
pandera

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Apr 30, 2022

INTRODUCTION

1	Install	3
1.1	Extras	3
2	Quick Start	5
3	Schema Model	7
4	Informative Errors	9
5	Contributing	11
6	Issues	13
7	Need Help?	15
7.1	DataFrame Schemas	15
7.1.1	Column Validation	16
7.1.1.1	Null Values in Columns	16
7.1.1.2	Coercing Types on Columns	17
7.1.1.3	Required Columns	18
7.1.1.4	Ordered Columns	19
7.1.1.5	Stand-alone Column Validation	19
7.1.1.6	Column Regex Pattern Matching	19
7.1.1.7	Handling Dataframe Columns not in the Schema	21
7.1.1.8	Validating the order of the columns	22
7.1.1.9	Validating the joint uniqueness of columns	22
7.1.2	Index Validation	23
7.1.3	MultiIndex Validation	24
7.1.3.1	MultiIndex Columns	24
7.1.3.2	MultiIndex Indexes	24
7.1.4	Get Pandas Data Types	25
7.1.5	DataFrameSchema Transformations	26
7.2	Schema Models	28
7.2.1	Basic Usage	28
7.2.2	Validate on Initialization	29
7.2.3	Converting to DataFrameSchema	30
7.2.4	Excluded attributes	31
7.2.5	Supported dtypes	31
7.2.5.1	Dtype aliases	31
7.2.5.2	Type Vs instance	31
7.2.5.3	Parametrized dtypes	32
7.2.5.3.1	Annotated	32

7.2.5.3.2	Field	33
7.2.6	Required Columns	33
7.2.7	Schema Inheritance	34
7.2.8	Config	34
7.2.9	MultiIndex	35
7.2.10	Custom Checks	36
7.2.10.1	Column/Index checks	36
7.2.10.2	DataFrame Checks	37
7.2.10.3	Inheritance	37
7.2.11	Aliases	38
7.3	Series Schemas	40
7.4	Checks	40
7.4.1	Checking column properties	40
7.4.2	Built-in Checks	41
7.4.3	Vectorized vs. Element-wise Checks	41
7.4.4	Handling Null Values	42
7.4.5	Column Check Groups	42
7.4.6	Wide Checks	43
7.4.7	Raise UserWarning on Check Failure	44
7.4.8	Registering Custom Checks	45
7.5	Hypothesis Testing	45
7.5.1	Overview	45
7.5.2	Wide Hypotheses	47
7.6	Pandera Data Types	48
7.6.1	Motivations	48
7.6.2	Data Type basics	49
7.6.3	Example	49
7.6.4	Parametrized data types	51
7.6.5	Defining the <code>coerce_value</code> method	51
7.7	Decorators for Pipeline Integration	52
7.7.1	Check Input	52
7.7.2	Check Output	53
7.7.3	Check IO	54
7.7.4	Decorate Functions and Coroutines	55
7.8	Schema Inference	56
7.8.1	Schema Persistence	57
7.8.1.1	Write to a Python script	57
7.8.1.2	Write to YAML	58
7.9	Lazy Validation	59
7.10	Data Synthesis Strategies	62
7.10.1	Basic Usage	62
7.10.2	Usage in Unit Tests	62
7.10.3	Strategies and Examples from Schema Models	63
7.10.4	Checks as Constraints	64
7.10.4.1	Check Strategy Chaining	64
7.10.4.2	In-line Custom Checks	65
7.10.5	Defining Custom Strategies	65
7.11	Extensions	65
7.11.1	Registering Custom Check Methods	65
7.11.2	Specifying a Check Strategy	66
7.11.3	Check Types	68
7.11.3.1	Element-wise Checks	68
7.11.3.2	Groupby Checks	68
7.11.4	Registered Custom Checks with the Class-based API	69

7.12	Data Format Conversion	70
7.12.1	The <code>to/from_format</code> Configuration Options	71
7.12.2	Takeaway	72
7.13	Supported DataFrame Libraries	72
7.13.1	Domain-specific Data Validation	72
7.13.1.1	Data Validation with GeoPandas	72
7.13.2	Scaling Up Data Validation	74
7.13.2.1	Data Validation with Dask	74
7.13.2.2	Data Validation with Fugue	76
7.13.2.2.1	What is Fugue?	76
7.13.2.2.2	Example	76
7.13.2.2.3	Validation by Partition	78
7.13.2.3	Data Validation with Koalas	79
7.13.2.4	Data Validation with Pyspark (New)	79
7.13.2.5	Data Validation with Modin	80
7.14	Integrations	82
7.14.1	FastAPI	82
7.14.1.1	Using SchemaModels to Validate Endpoint Inputs and Outputs	82
7.14.1.2	Reading File Uploads	83
7.14.1.3	Takeaway	84
7.14.2	Reading Third-Party Schema	84
7.14.2.1	Frictionless Data Schema	84
7.14.3	Mypy	87
7.14.3.1	Limitations	89
7.14.4	Pydantic	89
7.14.4.1	Using Pandera Schemas in Pydantic Models	89
7.14.4.2	Using Pydantic Models in Pandera Schemas	90
7.15	API	92
7.15.1	Core	92
7.15.1.1	Schemas	92
7.15.1.1.1	<code>pandera.schemas.DataFrameSchema</code>	92
7.15.1.1.1.1	<code>pandera.schemas.DataFrameSchema.__init__</code>	94
7.15.1.1.1.2	<code>pandera.schemas.DataFrameSchema.add_columns</code>	96
7.15.1.1.1.3	<code>pandera.schemas.DataFrameSchema.coerce_dtype</code>	96
7.15.1.1.1.4	<code>pandera.schemas.DataFrameSchema.example</code>	97
7.15.1.1.1.5	<code>pandera.schemas.DataFrameSchema.from_yaml</code>	97
7.15.1.1.1.6	<code>pandera.schemas.DataFrameSchema.get_dtypes</code>	97
7.15.1.1.1.7	<code>pandera.schemas.DataFrameSchema.remove_columns</code>	97
7.15.1.1.1.8	<code>pandera.schemas.DataFrameSchema.rename_columns</code>	98
7.15.1.1.1.9	<code>pandera.schemas.DataFrameSchema.reset_index</code>	99
7.15.1.1.1.10	<code>pandera.schemas.DataFrameSchema.select_columns</code>	100
7.15.1.1.1.11	<code>pandera.schemas.DataFrameSchema.set_index</code>	101
7.15.1.1.1.12	<code>pandera.schemas.DataFrameSchema.strategy</code>	103
7.15.1.1.1.13	<code>pandera.schemas.DataFrameSchema.to_script</code>	103
7.15.1.1.1.14	<code>pandera.schemas.DataFrameSchema.to_yaml</code>	103
7.15.1.1.1.15	<code>pandera.schemas.DataFrameSchema.update_column</code>	103
7.15.1.1.1.16	<code>pandera.schemas.DataFrameSchema.update_columns</code>	104
7.15.1.1.1.17	<code>pandera.schemas.DataFrameSchema.validate</code>	105
7.15.1.1.1.18	<code>pandera.schemas.DataFrameSchema.__call__</code>	106
7.15.1.1.2	<code>pandera.schemas.SeriesSchema</code>	107
7.15.1.1.2.1	<code>pandera.schemas.SeriesSchema.__init__</code>	108
7.15.1.1.2.2	<code>pandera.schemas.SeriesSchema.validate</code>	108
7.15.1.1.2.3	<code>pandera.schemas.SeriesSchema.__call__</code>	109
7.15.1.2	Schema Components	109

7.15.1.2.1	pandera.schema_components.Column	110
7.15.1.2.1.1	pandera.schema_components.Column.__init__	111
7.15.1.2.1.2	pandera.schema_components.Column.coerce_dtype	112
7.15.1.2.1.3	pandera.schema_components.Column.example	112
7.15.1.2.1.4	pandera.schema_components.Column.get_regex_columns	113
7.15.1.2.1.5	pandera.schema_components.Column.set_name	113
7.15.1.2.1.6	pandera.schema_components.Column.strategy	113
7.15.1.2.1.7	pandera.schema_components.Column.strategy_component	113
7.15.1.2.1.8	pandera.schema_components.Column.validate	113
7.15.1.2.1.9	pandera.schema_components.Column.__call__	114
7.15.1.2.2	pandera.schema_components.Index	114
7.15.1.2.2.1	pandera.schema_components.Index.example	115
7.15.1.2.2.2	pandera.schema_components.Index.strategy	115
7.15.1.2.2.3	pandera.schema_components.Index.strategy_component	116
7.15.1.2.2.4	pandera.schema_components.Index.validate	116
7.15.1.2.2.5	pandera.schema_components.Index.__call__	116
7.15.1.2.3	pandera.schema_components.MultiIndex	116
7.15.1.2.3.1	pandera.schema_components.MultiIndex.__init__	118
7.15.1.2.3.2	pandera.schema_components.MultiIndex.coerce_dtype	119
7.15.1.2.3.3	pandera.schema_components.MultiIndex.example	119
7.15.1.2.3.4	pandera.schema_components.MultiIndex.strategy	120
7.15.1.2.3.5	pandera.schema_components.MultiIndex.validate	120
7.15.1.2.3.6	pandera.schema_components.MultiIndex.__call__	120
7.15.1.3	Checks	121
7.15.1.3.1	pandera.checks.Check	121
7.15.1.3.1.1	pandera.checks.Check.eq	124
7.15.1.3.1.2	pandera.checks.Check.equal_to	125
7.15.1.3.1.3	pandera.checks.Check.ge	125
7.15.1.3.1.4	pandera.checks.Check.greater_than	125
7.15.1.3.1.5	pandera.checks.Check.greater_than_or_equal_to	126
7.15.1.3.1.6	pandera.checks.Check.gt	126
7.15.1.3.1.7	pandera.checks.Check.in_range	126
7.15.1.3.1.8	pandera.checks.Check.isin	127
7.15.1.3.1.9	pandera.checks.Check.le	127
7.15.1.3.1.10	pandera.checks.Check.less_than	127
7.15.1.3.1.11	pandera.checks.Check.less_than_or_equal_to	128
7.15.1.3.1.12	pandera.checks.Check.lt	128
7.15.1.3.1.13	pandera.checks.Check.ne	128
7.15.1.3.1.14	pandera.checks.Check.not_equal_to	129
7.15.1.3.1.15	pandera.checks.Check.notin	129
7.15.1.3.1.16	pandera.checks.Check.str_contains	129
7.15.1.3.1.17	pandera.checks.Check.str_endswith	130
7.15.1.3.1.18	pandera.checks.Check.str_length	130
7.15.1.3.1.19	pandera.checks.Check.str_matches	130
7.15.1.3.1.20	pandera.checks.Check.str_startswith	130
7.15.1.3.1.21	pandera.checks.Check.__call__	131
7.15.1.3.2	pandera.hypotheses.Hypothesis	131
7.15.1.3.2.1	pandera.hypotheses.Hypothesis.__init__	133
7.15.1.3.2.2	pandera.hypotheses.Hypothesis.one_sample_ttest	135
7.15.1.3.2.3	pandera.hypotheses.Hypothesis.two_sample_ttest	136
7.15.1.3.2.4	pandera.hypotheses.Hypothesis.__call__	138
7.15.2	Data Types	139
7.15.2.1	Library-agnostic dtypes	139
7.15.2.1.1	pandera.dtypes.DataType	140

7.15.2.1.1.1	pandera.dtypes.DataType.__init__	140
7.15.2.1.1.2	pandera.dtypes.DataType.check	140
7.15.2.1.1.3	pandera.dtypes.DataType.coerce	140
7.15.2.1.1.4	pandera.dtypes.DataType.coerce_value	140
7.15.2.1.1.5	pandera.dtypes.DataType.try_coerce	141
7.15.2.1.1.6	pandera.dtypes.DataType.__call__	141
7.15.2.1.2	pandera.dtypes.Bool	141
7.15.2.1.2.1	pandera.dtypes.Bool.__init__	141
7.15.2.1.2.2	pandera.dtypes.Bool.check	142
7.15.2.1.2.3	pandera.dtypes.Bool.coerce	142
7.15.2.1.2.4	pandera.dtypes.Bool.coerce_value	142
7.15.2.1.2.5	pandera.dtypes.Bool.try_coerce	142
7.15.2.1.2.6	pandera.dtypes.Bool.__call__	142
7.15.2.1.3	pandera.dtypes.Timestamp	142
7.15.2.1.3.1	pandera.dtypes.Timestamp.__init__	143
7.15.2.1.3.2	pandera.dtypes.Timestamp.check	143
7.15.2.1.3.3	pandera.dtypes.Timestamp.coerce	143
7.15.2.1.3.4	pandera.dtypes.Timestamp.coerce_value	143
7.15.2.1.3.5	pandera.dtypes.Timestamp.try_coerce	143
7.15.2.1.3.6	pandera.dtypes.Timestamp.__call__	144
7.15.2.1.4	pandera.dtypes.DateTime	144
7.15.2.1.5	pandera.dtypes.Timedelta	144
7.15.2.1.5.1	pandera.dtypes.Timedelta.__init__	144
7.15.2.1.5.2	pandera.dtypes.Timedelta.check	144
7.15.2.1.5.3	pandera.dtypes.Timedelta.coerce	145
7.15.2.1.5.4	pandera.dtypes.Timedelta.coerce_value	145
7.15.2.1.5.5	pandera.dtypes.Timedelta.try_coerce	145
7.15.2.1.5.6	pandera.dtypes.Timedelta.__call__	145
7.15.2.1.6	pandera.dtypes.Category	145
7.15.2.1.6.1	pandera.dtypes.Category.__init__	146
7.15.2.1.6.2	pandera.dtypes.Category.check	146
7.15.2.1.6.3	pandera.dtypes.Category.coerce	146
7.15.2.1.6.4	pandera.dtypes.Category.coerce_value	146
7.15.2.1.6.5	pandera.dtypes.Category.try_coerce	146
7.15.2.1.6.6	pandera.dtypes.Category.__call__	146
7.15.2.1.7	pandera.dtypes.Float	146
7.15.2.1.7.1	pandera.dtypes.Float.__init__	147
7.15.2.1.7.2	pandera.dtypes.Float.check	147
7.15.2.1.7.3	pandera.dtypes.Float.coerce	147
7.15.2.1.7.4	pandera.dtypes.Float.coerce_value	147
7.15.2.1.7.5	pandera.dtypes.Float.try_coerce	148
7.15.2.1.7.6	pandera.dtypes.Float.__call__	148
7.15.2.1.8	pandera.dtypes.Float16	148
7.15.2.1.8.1	pandera.dtypes.Float16.__init__	148
7.15.2.1.8.2	pandera.dtypes.Float16.check	149
7.15.2.1.8.3	pandera.dtypes.Float16.coerce	149
7.15.2.1.8.4	pandera.dtypes.Float16.coerce_value	149
7.15.2.1.8.5	pandera.dtypes.Float16.try_coerce	149
7.15.2.1.8.6	pandera.dtypes.Float16.__call__	149
7.15.2.1.9	pandera.dtypes.Float32	149
7.15.2.1.9.1	pandera.dtypes.Float32.__init__	150
7.15.2.1.9.2	pandera.dtypes.Float32.check	150
7.15.2.1.9.3	pandera.dtypes.Float32.coerce	150
7.15.2.1.9.4	pandera.dtypes.Float32.coerce_value	150

7.15.2.1.9.5	pandera.dtypes.Float32.try_coerce	150
7.15.2.1.9.6	pandera.dtypes.Float32.__call__	151
7.15.2.1.10	pandera.dtypes.Float64	151
7.15.2.1.10.1	pandera.dtypes.Float64.__init__	151
7.15.2.1.10.2	pandera.dtypes.Float64.check	151
7.15.2.1.10.3	pandera.dtypes.Float64.coerce	152
7.15.2.1.10.4	pandera.dtypes.Float64.coerce_value	152
7.15.2.1.10.5	pandera.dtypes.Float64.try_coerce	152
7.15.2.1.10.6	pandera.dtypes.Float64.__call__	152
7.15.2.1.11	pandera.dtypes.Float128	152
7.15.2.1.11.1	pandera.dtypes.Float128.__init__	153
7.15.2.1.11.2	pandera.dtypes.Float128.check	153
7.15.2.1.11.3	pandera.dtypes.Float128.coerce	153
7.15.2.1.11.4	pandera.dtypes.Float128.coerce_value	153
7.15.2.1.11.5	pandera.dtypes.Float128.try_coerce	153
7.15.2.1.11.6	pandera.dtypes.Float128.__call__	153
7.15.2.1.12	pandera.dtypes.Int	153
7.15.2.1.12.1	pandera.dtypes.Int.__init__	154
7.15.2.1.12.2	pandera.dtypes.Int.check	154
7.15.2.1.12.3	pandera.dtypes.Int.coerce	154
7.15.2.1.12.4	pandera.dtypes.Int.coerce_value	154
7.15.2.1.12.5	pandera.dtypes.Int.try_coerce	155
7.15.2.1.12.6	pandera.dtypes.Int.__call__	155
7.15.2.1.13	pandera.dtypes.Int8	155
7.15.2.1.13.1	pandera.dtypes.Int8.__init__	155
7.15.2.1.13.2	pandera.dtypes.Int8.check	156
7.15.2.1.13.3	pandera.dtypes.Int8.coerce	156
7.15.2.1.13.4	pandera.dtypes.Int8.coerce_value	156
7.15.2.1.13.5	pandera.dtypes.Int8.try_coerce	156
7.15.2.1.13.6	pandera.dtypes.Int8.__call__	156
7.15.2.1.14	pandera.dtypes.Int16	156
7.15.2.1.14.1	pandera.dtypes.Int16.__init__	157
7.15.2.1.14.2	pandera.dtypes.Int16.check	157
7.15.2.1.14.3	pandera.dtypes.Int16.coerce	157
7.15.2.1.14.4	pandera.dtypes.Int16.coerce_value	157
7.15.2.1.14.5	pandera.dtypes.Int16.try_coerce	157
7.15.2.1.14.6	pandera.dtypes.Int16.__call__	158
7.15.2.1.15	pandera.dtypes.Int32	158
7.15.2.1.15.1	pandera.dtypes.Int32.__init__	158
7.15.2.1.15.2	pandera.dtypes.Int32.check	158
7.15.2.1.15.3	pandera.dtypes.Int32.coerce	159
7.15.2.1.15.4	pandera.dtypes.Int32.coerce_value	159
7.15.2.1.15.5	pandera.dtypes.Int32.try_coerce	159
7.15.2.1.15.6	pandera.dtypes.Int32.__call__	159
7.15.2.1.16	pandera.dtypes.Int64	159
7.15.2.1.16.1	pandera.dtypes.Int64.__init__	160
7.15.2.1.16.2	pandera.dtypes.Int64.check	160
7.15.2.1.16.3	pandera.dtypes.Int64.coerce	160
7.15.2.1.16.4	pandera.dtypes.Int64.coerce_value	160
7.15.2.1.16.5	pandera.dtypes.Int64.try_coerce	160
7.15.2.1.16.6	pandera.dtypes.Int64.__call__	160
7.15.2.1.17	pandera.dtypes.UInt	160
7.15.2.1.17.1	pandera.dtypes.UInt.__init__	161
7.15.2.1.17.2	pandera.dtypes.UInt.check	161

7.15.2.1.17.3	pandera.dtypes.UInt.coerce	161
7.15.2.1.17.4	pandera.dtypes.UInt.coerce_value	161
7.15.2.1.17.5	pandera.dtypes.UInt.try_coerce	162
7.15.2.1.17.6	pandera.dtypes.UInt.__call__	162
7.15.2.1.18	pandera.dtypes.UInt8	162
7.15.2.1.18.1	pandera.dtypes.UInt8.__init__	162
7.15.2.1.18.2	pandera.dtypes.UInt8.check	163
7.15.2.1.18.3	pandera.dtypes.UInt8.coerce	163
7.15.2.1.18.4	pandera.dtypes.UInt8.coerce_value	163
7.15.2.1.18.5	pandera.dtypes.UInt8.try_coerce	163
7.15.2.1.18.6	pandera.dtypes.UInt8.__call__	163
7.15.2.1.19	pandera.dtypes.UInt16	163
7.15.2.1.19.1	pandera.dtypes.UInt16.__init__	164
7.15.2.1.19.2	pandera.dtypes.UInt16.check	164
7.15.2.1.19.3	pandera.dtypes.UInt16.coerce	164
7.15.2.1.19.4	pandera.dtypes.UInt16.coerce_value	164
7.15.2.1.19.5	pandera.dtypes.UInt16.try_coerce	164
7.15.2.1.19.6	pandera.dtypes.UInt16.__call__	165
7.15.2.1.20	pandera.dtypes.UInt32	165
7.15.2.1.20.1	pandera.dtypes.UInt32.__init__	165
7.15.2.1.20.2	pandera.dtypes.UInt32.check	165
7.15.2.1.20.3	pandera.dtypes.UInt32.coerce	166
7.15.2.1.20.4	pandera.dtypes.UInt32.coerce_value	166
7.15.2.1.20.5	pandera.dtypes.UInt32.try_coerce	166
7.15.2.1.20.6	pandera.dtypes.UInt32.__call__	166
7.15.2.1.21	pandera.dtypes.UInt64	166
7.15.2.1.21.1	pandera.dtypes.UInt64.__init__	167
7.15.2.1.21.2	pandera.dtypes.UInt64.check	167
7.15.2.1.21.3	pandera.dtypes.UInt64.coerce	167
7.15.2.1.21.4	pandera.dtypes.UInt64.coerce_value	167
7.15.2.1.21.5	pandera.dtypes.UInt64.try_coerce	167
7.15.2.1.21.6	pandera.dtypes.UInt64.__call__	167
7.15.2.1.22	pandera.dtypes.Complex	167
7.15.2.1.22.1	pandera.dtypes.Complex.__init__	168
7.15.2.1.22.2	pandera.dtypes.Complex.check	168
7.15.2.1.22.3	pandera.dtypes.Complex.coerce	168
7.15.2.1.22.4	pandera.dtypes.Complex.coerce_value	168
7.15.2.1.22.5	pandera.dtypes.Complex.try_coerce	169
7.15.2.1.22.6	pandera.dtypes.Complex.__call__	169
7.15.2.1.23	pandera.dtypes.Complex64	169
7.15.2.1.23.1	pandera.dtypes.Complex64.__init__	169
7.15.2.1.23.2	pandera.dtypes.Complex64.check	170
7.15.2.1.23.3	pandera.dtypes.Complex64.coerce	170
7.15.2.1.23.4	pandera.dtypes.Complex64.coerce_value	170
7.15.2.1.23.5	pandera.dtypes.Complex64.try_coerce	170
7.15.2.1.23.6	pandera.dtypes.Complex64.__call__	170
7.15.2.1.24	pandera.dtypes.Complex128	170
7.15.2.1.24.1	pandera.dtypes.Complex128.__init__	171
7.15.2.1.24.2	pandera.dtypes.Complex128.check	171
7.15.2.1.24.3	pandera.dtypes.Complex128.coerce	171
7.15.2.1.24.4	pandera.dtypes.Complex128.coerce_value	171
7.15.2.1.24.5	pandera.dtypes.Complex128.try_coerce	171
7.15.2.1.24.6	pandera.dtypes.Complex128.__call__	172
7.15.2.1.25	pandera.dtypes.Complex256	172

7.15.2.1.25.1	pandera.dtypes.Complex256.__init__	172
7.15.2.1.25.2	pandera.dtypes.Complex256.check	172
7.15.2.1.25.3	pandera.dtypes.Complex256.coerce	173
7.15.2.1.25.4	pandera.dtypes.Complex256.coerce_value	173
7.15.2.1.25.5	pandera.dtypes.Complex256.try_coerce	173
7.15.2.1.25.6	pandera.dtypes.Complex256.__call__	173
7.15.2.1.26	pandera.dtypes.String	173
7.15.2.1.26.1	pandera.dtypes.String.__init__	174
7.15.2.1.26.2	pandera.dtypes.String.check	174
7.15.2.1.26.3	pandera.dtypes.String.coerce	174
7.15.2.1.26.4	pandera.dtypes.String.coerce_value	174
7.15.2.1.26.5	pandera.dtypes.String.try_coerce	174
7.15.2.1.26.6	pandera.dtypes.String.__call__	174
7.15.2.2	Pandas Dtypes	174
7.15.2.2.1	pandera.engines.pandas_engine.BOOL	175
7.15.2.2.1.1	pandera.engines.pandas_engine.BOOL.__init__	175
7.15.2.2.1.2	pandera.engines.pandas_engine.BOOL.check	176
7.15.2.2.1.3	pandera.engines.pandas_engine.BOOL.coerce	176
7.15.2.2.1.4	pandera.engines.pandas_engine.BOOL.coerce_value	176
7.15.2.2.1.5	pandera.engines.pandas_engine.BOOL.try_coerce	176
7.15.2.2.1.6	pandera.engines.pandas_engine.BOOL.__call__	176
7.15.2.2.2	pandera.engines.pandas_engine.INT8	176
7.15.2.2.2.1	pandera.engines.pandas_engine.INT8.__init__	177
7.15.2.2.2.2	pandera.engines.pandas_engine.INT8.check	177
7.15.2.2.2.3	pandera.engines.pandas_engine.INT8.coerce	177
7.15.2.2.2.4	pandera.engines.pandas_engine.INT8.coerce_value	178
7.15.2.2.2.5	pandera.engines.pandas_engine.INT8.try_coerce	178
7.15.2.2.2.6	pandera.engines.pandas_engine.INT8.__call__	178
7.15.2.2.3	pandera.engines.pandas_engine.INT16	178
7.15.2.2.3.1	pandera.engines.pandas_engine.INT16.__init__	179
7.15.2.2.3.2	pandera.engines.pandas_engine.INT16.check	179
7.15.2.2.3.3	pandera.engines.pandas_engine.INT16.coerce	179
7.15.2.2.3.4	pandera.engines.pandas_engine.INT16.coerce_value	179
7.15.2.2.3.5	pandera.engines.pandas_engine.INT16.try_coerce	179
7.15.2.2.3.6	pandera.engines.pandas_engine.INT16.__call__	179
7.15.2.2.4	pandera.engines.pandas_engine.INT32	179
7.15.2.2.4.1	pandera.engines.pandas_engine.INT32.__init__	180
7.15.2.2.4.2	pandera.engines.pandas_engine.INT32.check	180
7.15.2.2.4.3	pandera.engines.pandas_engine.INT32.coerce	180
7.15.2.2.4.4	pandera.engines.pandas_engine.INT32.coerce_value	181
7.15.2.2.4.5	pandera.engines.pandas_engine.INT32.try_coerce	181
7.15.2.2.4.6	pandera.engines.pandas_engine.INT32.__call__	181
7.15.2.2.5	pandera.engines.pandas_engine.INT64	181
7.15.2.2.5.1	pandera.engines.pandas_engine.INT64.__init__	182
7.15.2.2.5.2	pandera.engines.pandas_engine.INT64.check	182
7.15.2.2.5.3	pandera.engines.pandas_engine.INT64.coerce	182
7.15.2.2.5.4	pandera.engines.pandas_engine.INT64.coerce_value	182
7.15.2.2.5.5	pandera.engines.pandas_engine.INT64.try_coerce	182
7.15.2.2.5.6	pandera.engines.pandas_engine.INT64.__call__	182
7.15.2.2.6	pandera.engines.pandas_engine.UINT8	182
7.15.2.2.6.1	pandera.engines.pandas_engine.UINT8.__init__	183
7.15.2.2.6.2	pandera.engines.pandas_engine.UINT8.check	183
7.15.2.2.6.3	pandera.engines.pandas_engine.UINT8.coerce	183
7.15.2.2.6.4	pandera.engines.pandas_engine.UINT8.coerce_value	184

7.15.2.2.6.5	pandera.engines.pandas_engine.UINT8.try_coerce	184
7.15.2.2.6.6	pandera.engines.pandas_engine.UINT8.__call__	184
7.15.2.2.7	pandera.engines.pandas_engine.UINT16	184
7.15.2.2.7.1	pandera.engines.pandas_engine.UINT16.__init__	185
7.15.2.2.7.2	pandera.engines.pandas_engine.UINT16.check	185
7.15.2.2.7.3	pandera.engines.pandas_engine.UINT16.coerce	185
7.15.2.2.7.4	pandera.engines.pandas_engine.UINT16.coerce_value	185
7.15.2.2.7.5	pandera.engines.pandas_engine.UINT16.try_coerce	185
7.15.2.2.7.6	pandera.engines.pandas_engine.UINT16.__call__	185
7.15.2.2.8	pandera.engines.pandas_engine.UINT32	185
7.15.2.2.8.1	pandera.engines.pandas_engine.UINT32.__init__	186
7.15.2.2.8.2	pandera.engines.pandas_engine.UINT32.check	186
7.15.2.2.8.3	pandera.engines.pandas_engine.UINT32.coerce	186
7.15.2.2.8.4	pandera.engines.pandas_engine.UINT32.coerce_value	187
7.15.2.2.8.5	pandera.engines.pandas_engine.UINT32.try_coerce	187
7.15.2.2.8.6	pandera.engines.pandas_engine.UINT32.__call__	187
7.15.2.2.9	pandera.engines.pandas_engine.UINT64	187
7.15.2.2.9.1	pandera.engines.pandas_engine.UINT64.__init__	188
7.15.2.2.9.2	pandera.engines.pandas_engine.UINT64.check	188
7.15.2.2.9.3	pandera.engines.pandas_engine.UINT64.coerce	188
7.15.2.2.9.4	pandera.engines.pandas_engine.UINT64.coerce_value	188
7.15.2.2.9.5	pandera.engines.pandas_engine.UINT64.try_coerce	188
7.15.2.2.9.6	pandera.engines.pandas_engine.UINT64.__call__	188
7.15.2.2.10	pandera.engines.pandas_engine.STRING	188
7.15.2.2.10.1	pandera.engines.pandas_engine.STRING.__init__	189
7.15.2.2.10.2	pandera.engines.pandas_engine.STRING.check	189
7.15.2.2.10.3	pandera.engines.pandas_engine.STRING.coerce	189
7.15.2.2.10.4	pandera.engines.pandas_engine.STRING.coerce_value	190
7.15.2.2.10.5	pandera.engines.pandas_engine.STRING.from_parametrized_dtype	190
7.15.2.2.10.6	pandera.engines.pandas_engine.STRING.try_coerce	190
7.15.2.2.10.7	pandera.engines.pandas_engine.STRING.__call__	190
7.15.2.2.11	pandera.engines.numpy_engine.Object	190
7.15.2.2.11.1	pandera.engines.numpy_engine.Object.__init__	191
7.15.2.2.11.2	pandera.engines.numpy_engine.Object.check	191
7.15.2.2.11.3	pandera.engines.numpy_engine.Object.coerce	191
7.15.2.2.11.4	pandera.engines.numpy_engine.Object.coerce_value	191
7.15.2.2.11.5	pandera.engines.numpy_engine.Object.try_coerce	191
7.15.2.2.11.6	pandera.engines.numpy_engine.Object.__call__	191
7.15.2.2.12	pandera.engines.pandas_engine.DateTime	191
7.15.2.3	GeoPandas Dtypes	192
7.15.2.3.1	pandera.engines.pandas_engine.Geometry	192
7.15.2.3.1.1	pandera.engines.pandas_engine.Geometry.__init__	193
7.15.2.3.1.2	pandera.engines.pandas_engine.Geometry.check	193
7.15.2.3.1.3	pandera.engines.pandas_engine.Geometry.coerce	193
7.15.2.3.1.4	pandera.engines.pandas_engine.Geometry.coerce_value	193
7.15.2.3.1.5	pandera.engines.pandas_engine.Geometry.try_coerce	193
7.15.2.3.1.6	pandera.engines.pandas_engine.Geometry.__call__	193
7.15.2.4	Pydantic Dtypes	193
7.15.2.4.1	pandera.engines.pandas_engine.PydanticModel	194
7.15.2.4.1.1	pandera.engines.pandas_engine.PydanticModel.__init__	194
7.15.2.4.1.2	pandera.engines.pandas_engine.PydanticModel.check	194
7.15.2.4.1.3	pandera.engines.pandas_engine.PydanticModel.coerce	194
7.15.2.4.1.4	pandera.engines.pandas_engine.PydanticModel.coerce_value	195
7.15.2.4.1.5	pandera.engines.pandas_engine.PydanticModel.try_coerce	195

7.15.2.4.1.6	<code>pandera.engines.pandas_engine.PydanticModel.__call__</code>	195
7.15.2.5	Utility functions	195
7.15.2.5.1	<code>pandera.dtypes.is_subdtype</code>	196
7.15.2.5.2	<code>pandera.dtypes.is_float</code>	196
7.15.2.5.3	<code>pandera.dtypes.is_int</code>	196
7.15.2.5.4	<code>pandera.dtypes.is_uint</code>	196
7.15.2.5.5	<code>pandera.dtypes.is_complex</code>	196
7.15.2.5.6	<code>pandera.dtypes.is_numeric</code>	196
7.15.2.5.7	<code>pandera.dtypes.is_bool</code>	197
7.15.2.5.8	<code>pandera.dtypes.is_string</code>	197
7.15.2.5.9	<code>pandera.dtypes.is_datetime</code>	197
7.15.2.5.10	<code>pandera.dtypes.is_timedelta</code>	197
7.15.2.5.11	<code>pandera.dtypes.immutable</code>	197
7.15.2.6	Engines	198
7.15.2.6.1	<code>pandera.engines.engine.Engine</code>	198
7.15.2.6.1.1	<code>pandera.engines.engine.Engine.dtype</code>	198
7.15.2.6.1.2	<code>pandera.engines.engine.Engine.get_registered_dtypes</code>	198
7.15.2.6.1.3	<code>pandera.engines.engine.Engine.register_dtype</code>	198
7.15.2.6.1.4	<code>pandera.engines.engine.Engine.__call__</code>	199
7.15.2.6.2	<code>pandera.engines.numpy_engine.Engine</code>	199
7.15.2.6.2.1	<code>pandera.engines.numpy_engine.Engine.dtype</code>	200
7.15.2.6.3	<code>pandera.engines.pandas_engine.Engine</code>	200
7.15.2.6.3.1	<code>pandera.engines.pandas_engine.Engine.dtype</code>	200
7.15.2.6.3.2	<code>pandera.engines.pandas_engine.Engine.numpy_dtype</code>	200
7.15.3	Schema Models	200
7.15.3.1	Schema Model	200
7.15.3.1.1	<code>pandera.model.SchemaModel</code>	201
7.15.3.1.1.1	<code>pandera.model.SchemaModel.example</code>	202
7.15.3.1.1.2	<code>pandera.model.SchemaModel.strategy</code>	202
7.15.3.1.1.3	<code>pandera.model.SchemaModel.to_schema</code>	203
7.15.3.1.1.4	<code>pandera.model.SchemaModel.to_yaml</code>	203
7.15.3.1.1.5	<code>pandera.model.SchemaModel.validate</code>	203
7.15.3.2	Model Components	204
7.15.3.2.1	<code>pandera.model_components.Field</code>	204
7.15.3.2.2	<code>pandera.model_components.check</code>	205
7.15.3.2.3	<code>pandera.model_components.dataframe_check</code>	205
7.15.3.3	Typing	206
7.15.3.3.1	<code>pandera.typing</code>	206
7.15.3.3.1.1	<code>pandera.typing.fastapi.UploadFile</code>	207
7.15.3.3.1.2	<code>pandera.typing.formats.Formats</code>	208
7.15.3.4	Config	210
7.15.3.4.1	<code>pandera.model.BaseConfig</code>	210
7.15.4	Decorators	211
7.15.4.1	<code>pandera.decorators.check_input</code>	211
7.15.4.2	<code>pandera.decorators.check_output</code>	212
7.15.4.3	<code>pandera.decorators.check_io</code>	213
7.15.4.4	<code>pandera.decorators.check_types</code>	214
7.15.5	Schema Inference	215
7.15.5.1	<code>pandera.schema_inference.infer_schema</code>	215
7.15.6	IO Utilities	215
7.15.6.1	<code>pandera.io.from_yaml</code>	215
7.15.6.2	<code>pandera.io.to_yaml</code>	215
7.15.6.3	<code>pandera.io.to_script</code>	216
7.15.7	Data Synthesis Strategies	216

7.15.7.1	pandera.strategies	216
7.15.8	Extensions	223
7.15.8.1	pandera.extensions	223
7.15.9	Errors	224
7.15.9.1	pandera.errors.SchemaError	224
7.15.9.2	pandera.errors.SchemaErrors	224
7.15.9.3	pandera.errors.SchemaInitError	224
7.15.9.4	pandera.errors.SchemaDefinitionError	224
7.16	Contributing	224
7.16.1	Getting Started	225
7.16.2	Contributing to the Codebase	225
7.16.2.1	Environment Setup	225
7.16.2.1.1	Option 1: <code>miniconda</code> Setup	225
7.16.2.1.2	Option 2: <code>virtualenv</code> Setup	225
7.16.2.1.3	Run Tests	225
7.16.2.1.4	Build Documentation Locally	226
7.16.2.1.5	Adding New Dependencies	226
7.16.2.1.6	Set up <code>pre-commit</code>	226
7.16.2.2	Making Changes	226
7.16.2.3	Run the Full Test Suite Locally	226
7.16.2.3.1	Using <code>mamba</code> (optional)	227
7.16.2.4	Project Releases	227
7.16.2.5	Contributing Documentation	227
7.16.2.6	Contributing Bugfixes	227
7.16.2.7	Contributing Enhancements	227
7.16.2.8	Making Pull Requests	227
7.16.2.8.1	Bugfixes	228
7.16.2.8.2	Documentation	228
7.16.2.8.3	Enhancements	228
7.16.2.9	Questions, Ideas, General Discussion	228
7.16.2.10	Dataframe Schema Style Guides	228
7.16.3	Deprecation policy	229
8	How to Cite	231
8.1	Paper	231
8.2	Software Package	231
9	License and Credits	233
10	Indices and tables	235
	Python Module Index	237
	Index	239

A data validation library for scientists, engineers, and analysts seeking correctness.

pandera provides a flexible and expressive API for performing data validation on dataframes to make data processing pipelines more readable and robust.

Dataframes contain information that pandera explicitly validates at runtime. This is useful in production-critical data pipelines or reproducible research settings. With pandera, you can:

1. Define a schema once and use it to validate *different dataframe types* including pandas, dask, modin, and pyspark.pandas.
2. *Check* the types and properties of columns in a `pd.DataFrame` or values in a `pd.Series`.
3. Perform more complex statistical validation like *hypothesis testing*.
4. Seamlessly integrate with existing data analysis/processing pipelines via *function decorators*.
5. Define schema models with the *class-based API* with pydantic-style syntax and validate dataframes using the typing syntax.
6. *Synthesize data* from schema objects for property-based testing with pandas data structures.
7. *Lazily Validate* dataframes so that all validation rules are executed before raising an error.
8. *Integrate* with a rich ecosystem of python tools like pydantic, fastapi and mypy.

INSTALL

Install with pip:

```
pip install pandera
```

Or conda:

```
conda install -c conda-forge pandera
```

1.1 Extras

Installing additional functionality:

pip

```
pip install pandera[hypotheses] # hypothesis checks
pip install pandera[io]         # yaml/script schema io utilities
pip install pandera[strategies] # data synthesis strategies
pip install pandera[mypy]       # enable static type-linting of pandas
pip install pandera[dask]       # validate dask dataframes
pip install pandera[pyspark]    # validate pyspark dataframes
pip install pandera[modin]      # validate modin dataframes
pip install pandera[modin-ray]  # validate modin dataframes with ray
pip install pandera[modin-dask] # validate modin dataframes with dask
pip install pandera[geopandas]  # validate geopandas geodataframes
```

conda

```
conda install -c conda-forge pandera-hypotheses # hypothesis checks
conda install -c conda-forge pandera-io         # yaml/script schema io utilities
conda install -c conda-forge pandera-strategies # data synthesis strategies
conda install -c conda-forge pandera-mypy       # enable static type-linting of pandas
conda install -c conda-forge pandera-fastapi    # fastapi integration
conda install -c conda-forge pandera-dask       # validate dask dataframes
conda install -c conda-forge pandera-pyspark    # validate pyspark dataframes
conda install -c conda-forge pandera-modin      # validate modin dataframes
conda install -c conda-forge pandera-modin-ray  # validate modin dataframes with ray
conda install -c conda-forge pandera-modin-dask # validate modin dataframes with dask
```


QUICK START

```
import pandas as pd
import pandera as pa

# data to validate
df = pd.DataFrame({
    "column1": [1, 4, 0, 10, 9],
    "column2": [-1.3, -1.4, -2.9, -10.1, -20.4],
    "column3": ["value_1", "value_2", "value_3", "value_2", "value_1"],
})

# define schema
schema = pa.DataFrameSchema({
    "column1": pa.Column(int, checks=pa.Check.le(10)),
    "column2": pa.Column(float, checks=pa.Check.lt(-1.2)),
    "column3": pa.Column(str, checks=[
        pa.Check.str_startswith("value_"),
        # define custom checks as functions that take a series as input and
        # outputs a boolean or boolean Series
        pa.Check(lambda s: s.str.split("_", expand=True).shape[1] == 2)
    ]),
})

validated_df = schema(df)
print(validated_df)
```

```
   column1  column2  column3
0         1    -1.3  value_1
1         4    -1.4  value_2
2         0    -2.9  value_3
3        10   -10.1  value_2
4         9   -20.4  value_1
```

You can pass the built-in python types that are supported by pandas, or strings representing the legal pandas datatypes, or pandera's `DataType`:

```
schema = pa.DataFrameSchema({
    # built-in python types
    "int_column": pa.Column(int),
    "float_column": pa.Column(float),
    "str_column": pa.Column(str),
```

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```
# pandas dtype string aliases
"int_column2": pa.Column("int64"),
"float_column2": pa.Column("float64"),
# pandas > 1.0.0 support native "string" type
"str_column2": pa.Column("str"),

# pandera DataType
"int_column3": pa.Column(pa.Int),
"float_column3": pa.Column(pa.Float),
"str_column3": pa.Column(pa.String),
})
```

For more details on data types, see [DataType](#)

SCHEMA MODEL

pandera also provides an alternative API for expressing schemas inspired by [dataclasses](#) and [pydantic](#). The equivalent *SchemaModel* for the above DataFrameSchema would be:

```
from pandera.typing import Series

class Schema(pa.SchemaModel):

    column1: Series[int] = pa.Field(le=10)
    column2: Series[float] = pa.Field(lt=-1.2)
    column3: Series[str] = pa.Field(str_startswith="value_")

    @pa.check("column3")
    def column_3_check(cls, series: Series[str]) -> Series[bool]:
        """Check that column3 values have two elements after being split with '_'"""
        return series.str.split("_", expand=True).shape[1] == 2

Schema.validate(df)
```


INFORMATIVE ERRORS

If the dataframe does not pass validation checks, `pandera` provides useful error messages. An `error` argument can also be supplied to `Check` for custom error messages.

In the case that a validation `Check` is violated:

```
import pandas as pd

from pandera import Column, DataFrameSchema, Int, Check

simple_schema = DataFrameSchema({
    "column1": Column(
        Int, Check(lambda x: 0 <= x <= 10, element_wise=True,
                    error="range checker [0, 10]"))
})

# validation rule violated
fail_check_df = pd.DataFrame({
    "column1": [-20, 5, 10, 30],
})

simple_schema(fail_check_df)
```

```
Traceback (most recent call last):
...
SchemaError: <Schema Column: 'column1' type=<class 'int'>> failed element-wise validator.
->0:
<Check <lambda>: range checker [0, 10]>
failure cases:
   index  failure_case
0      0             -20
1      3              30
```

And in the case of a mis-specified column name:

```
# column name mis-specified
wrong_column_df = pd.DataFrame({
    "foo": ["bar"] * 10,
    "baz": [1] * 10
})

simple_schema.validate(wrong_column_df)
```

```
Traceback (most recent call last):
...
pandera.SchemaError: column 'column1' not in dataframe
   foo  baz
0  bar   1
1  bar   1
2  bar   1
3  bar   1
4  bar   1
```


CONTRIBUTING

All contributions, bug reports, bug fixes, documentation improvements, enhancements and ideas are welcome.

A detailed overview on how to contribute can be found in the [contributing guide](#) on GitHub.

ISSUES

Submit issues, feature requests or bugfixes on [github](#).

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7.1 DataFrame Schemas

The `DataFrameSchema` class enables the specification of a schema that verifies the columns and index of a pandas DataFrame object.

The `DataFrameSchema` object consists of `Columns` and an `Index`.

```
import pandera as pa

from pandera import Column, DataFrameSchema, Check, Index

schema = DataFrameSchema(
    {
        "column1": Column(int),
        "column2": Column(float, Check(lambda s: s < -1.2)),
        # you can provide a list of validators
        "column3": Column(str, [
            Check(lambda s: s.str.startswith("value")),
            Check(lambda s: s.str.split("_", expand=True).shape[1] == 2)
        ]),
    },
    index=Index(int),
    strict=True,
    coerce=True,
)
```

You can refer to [Schema Models](#) to see how to define dataframe schemas using the alternative pydantic/dataclass-style syntax.

7.1.1 Column Validation

A *Column* must specify the properties of a column in a dataframe object. It can be optionally verified for its data type, *null values* or duplicate values. The column can be *coerced* into the specified type, and the *required* parameter allows control over whether or not the column is allowed to be missing.

Similarly to pandas, the data type can be specified as:

- a string alias, as long as it is recognized by pandas.
- a python type: *int*, *float*, *double*, *bool*, *str*
- a numpy data type
- a pandas extension type: it can be an instance (e.g *pd.CategoricalDtype(["a", "b"])*) or a class (e.g *pandas.CategoricalDtype*) if it can be initialized with default values.
- a pandera *DataType*: it can also be an instance or a class.

Column checks allow for the DataFrame's values to be checked against a user-provided function. Check objects also support *grouping* by a different column so that the user can make assertions about subsets of the column of interest.

Column Hypotheses enable you to perform statistical hypothesis tests on a DataFrame in either wide or tidy format. See *Hypothesis Testing* for more details.

7.1.1.1 Null Values in Columns

By default, SeriesSchema/Column objects assume that values are not nullable. In order to accept null values, you need to explicitly specify `nullable=True`, or else you'll get an error.

```
import numpy as np
import pandas as pd
import pandera as pa

from pandera import Check, Column, DataFrameSchema

df = pd.DataFrame({"column1": [5, 1, np.nan]})

non_null_schema = DataFrameSchema({
    "column1": Column(float, Check(lambda x: x > 0))
})

non_null_schema.validate(df)
```

```
Traceback (most recent call last):
...
SchemaError: non-nullable series contains null values: {2: nan}
```

```
null_schema = DataFrameSchema({
    "column1": Column(float, Check(lambda x: x > 0), nullable=True)
})

print(null_schema.validate(df))
```

```

column1
0      5.0
1      1.0
2      NaN

```

7.1.1.2 Coercing Types on Columns

If you specify `Column(dtype, ..., coerce=True)` as part of the `DataFrameSchema` definition, calling `schema.validate` will first coerce the column into the specified `dtype` before applying validation checks.

```

import pandas as pd
import pandera as pa

from pandera import Column, DataFrameSchema

df = pd.DataFrame({"column1": [1, 2, 3]})
schema = DataFrameSchema({"column1": Column(str, coerce=True)})

validated_df = schema.validate(df)
assert isinstance(validated_df.column1.iloc[0], str)

```

Note: Note the special case of integers columns not supporting nan values. In this case, `schema.validate` will complain if `coerce == True` and null values are allowed in the column.

```

df = pd.DataFrame({"column1": [1., 2., 3, np.nan]})
schema = DataFrameSchema({
    "column1": Column(int, coerce=True, nullable=True)
})

validated_df = schema.validate(df)

```

Traceback (most recent call last):

```

...
pandera.errors.SchemaError: Error while coercing 'column1' to type int64: Cannot convert_
↪non-finite values (NA or inf) to integer

```

The best way to handle this case is to simply specify the column as a `Float` or `Object`.

```

schema_object = DataFrameSchema({
    "column1": Column(object, coerce=True, nullable=True)
})
schema_float = DataFrameSchema({
    "column1": Column(float, coerce=True, nullable=True)
})

print(schema_object.validate(df).dtypes)
print(schema_float.validate(df).dtypes)

```

```

column1    object
dtype: object

```

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```
column1    float64
dtype: object
```

If you want to coerce all of the columns specified in the `DataFrameSchema`, you can specify the `coerce` argument with `DataFrameSchema(..., coerce=True)`.

7.1.1.3 Required Columns

By default all columns specified in the schema are required, meaning that if a column is missing in the input `DataFrame` an exception will be thrown. If you want to make a column optional, specify `required=False` in the column constructor:

```
import pandas as pd
import pandera as pa

from pandera import Column, DataFrameSchema

df = pd.DataFrame({"column2": ["hello", "pandera"]})
schema = DataFrameSchema({
    "column1": Column(int, required=False),
    "column2": Column(str)
})

validated_df = schema.validate(df)
print(validated_df)
```

```
   column2
0    hello
1  pandera
```

Since `required=True` by default, missing columns would raise an error:

```
schema = DataFrameSchema({
    "column1": Column(int),
    "column2": Column(str),
})

schema.validate(df)
```

```
Traceback (most recent call last):
...
pandera.SchemaError: column 'column1' not in dataframe
   column2
0    hello
1  pandera
```


7.1.1.4 Ordered Columns

7.1.1.5 Stand-alone Column Validation

In addition to being used in the context of a `DataFrameSchema`, `Column` objects can also be used to validate columns in a dataframe on its own:

```
import pandas as pd
import pandera as pa

df = pd.DataFrame({
    "column1": [1, 2, 3],
    "column2": ["a", "b", "c"],
})

column1_schema = pa.Column(int, name="column1")
column2_schema = pa.Column(str, name="column2")

# pass the dataframe as an argument to the Column object callable
df = column1_schema(df)
validated_df = column2_schema(df)

# or explicitly use the validate method
df = column1_schema.validate(df)
validated_df = column2_schema.validate(df)

# use the DataFrame.pipe method to validate two columns
validated_df = df.pipe(column1_schema).pipe(column2_schema)
```

For multi-column use cases, the `DataFrameSchema` is still recommended, but if you have one or a small number of columns to verify, using `Column` objects by themselves is appropriate.

7.1.1.6 Column Regex Pattern Matching

In the case that your dataframe has multiple columns that share common statistical properties, you might want to specify a regex pattern that matches a set of meaningfully grouped columns that have `str` names.

```
import numpy as np
import pandas as pd
import pandera as pa

categories = ["A", "B", "C"]

np.random.seed(100)

dataframe = pd.DataFrame({
    "cat_var_1": np.random.choice(categories, size=100),
    "cat_var_2": np.random.choice(categories, size=100),
    "num_var_1": np.random.uniform(0, 10, size=100),
    "num_var_2": np.random.uniform(20, 30, size=100),
})

schema = pa.DataFrameSchema({
```

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```

"num_var_.+": pa.Column(
    float,
    checks=pa.Check.greater_than_or_equal_to(0),
    regex=True,
),
"cat_var_.+": pa.Column(
    pa.Category,
    checks=pa.Check.isin(categories),
    coerce=True,
    regex=True,
),
})

print(schema.validate(dataframe).head())

```

	cat_var_1	cat_var_2	num_var_1	num_var_2
0	A	A	6.804147	24.743304
1	A	C	3.684308	22.774633
2	A	C	5.911288	28.416588
3	C	A	4.790627	21.951250
4	C	B	4.504166	28.563142

You can also regex pattern match on `pd.MultiIndex` columns:

```

np.random.seed(100)

dataframe = pd.DataFrame({
    ("cat_var_1", "y1"): np.random.choice(categories, size=100),
    ("cat_var_2", "y2"): np.random.choice(categories, size=100),
    ("num_var_1", "x1"): np.random.uniform(0, 10, size=100),
    ("num_var_2", "x2"): np.random.uniform(0, 10, size=100),
})

schema = pa.DataFrameSchema({
    ("num_var_.+", "x.+"): pa.Column(
        float,
        checks=pa.Check.greater_than_or_equal_to(0),
        regex=True,
    ),
    ("cat_var_.+", "y.+"): pa.Column(
        pa.Category,
        checks=pa.Check.isin(categories),
        coerce=True,
        regex=True,
    ),
})

print(schema.validate(dataframe).head())

```

	cat_var_1	cat_var_2	num_var_1	num_var_2
	y1	y2	x1	x2
0	A	A	6.804147	4.743304

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1	A	C	3.684308	2.774633
2	A	C	5.911288	8.416588
3	C	A	4.790627	1.951250
4	C	B	4.504166	8.563142

7.1.1.7 Handling Dataframe Columns not in the Schema

By default, columns that aren't specified in the schema aren't checked. If you want to check that the DataFrame *only* contains columns in the schema, specify `strict=True`:

```
import pandas as pd
import pandera as pa

from pandera import Column, DataFrameSchema

schema = DataFrameSchema(
    {"column1": Column(int)},
    strict=True)

df = pd.DataFrame({"column2": [1, 2, 3]})

schema.validate(df)
```

Traceback (most recent call last):

```
...
SchemaError: column 'column2' not in DataFrameSchema {'column1': <Schema Column: 'None'
↳ type=DataType(int64)>}
```

Alternatively, if your DataFrame contains columns that are not in the schema, and you would like these to be dropped on validation, you can specify `strict='filter'`.

```
import pandas as pd
import pandera as pa

from pandera import Column, DataFrameSchema

df = pd.DataFrame({"column1": ["drop", "me"], "column2": ["keep", "me"]})
schema = DataFrameSchema({"column2": Column(str)}, strict='filter')

validated_df = schema.validate(df)
print(validated_df)
```

```
   column2
0      keep
1         me
```

7.1.1.8 Validating the order of the columns

For some applications the order of the columns is important. For example:

- If you want to use [selection by position](#) instead of the more common [selection by label](#).
- Machine learning: Many ML libraries will cast a Dataframe to numpy arrays, for which order becomes crucial.

To validate the order of the Dataframe columns, specify `ordered=True`:

```
import pandas as pd
import pandera as pa

schema = pa.DataFrameSchema(
    columns={"a": pa.Column(int), "b": pa.Column(int)}, ordered=True
)
df = pd.DataFrame({"b": [1], "a": [1]})
print(schema.validate(df))
```

```
Traceback (most recent call last):
...
SchemaError: column 'b' out-of-order
```

7.1.1.9 Validating the joint uniqueness of columns

In some cases you might want to ensure that a group of columns are unique:

```
import pandas as pd
import pandera as pa

schema = pa.DataFrameSchema(
    columns={col: pa.Column(int) for col in ["a", "b", "c"]},
    unique=["a", "c"],
)
df = pd.DataFrame.from_records([
    {"a": 1, "b": 2, "c": 3},
    {"a": 1, "b": 2, "c": 3},
])
schema.validate(df)
```

```
Traceback (most recent call last):
...
SchemaError: columns>('a', 'c') not unique:
column index failure_case
0      a      0          1
1      a      1          1
2      c      0          3
3      c      1          3
```

7.1.2 Index Validation

You can also specify an *Index* in the *DataFrameSchema*.

```
import pandas as pd
import pandera as pa

from pandera import Column, DataFrameSchema, Index, Check

schema = DataFrameSchema(
    columns={"a": Column(int)},
    index=Index(
        str,
        Check(lambda x: x.str.startswith("index_")))

df = pd.DataFrame(
    data={"a": [1, 2, 3]},
    index=["index_1", "index_2", "index_3"])

print(schema.validate(df))
```

```
      a
index_1  1
index_2  2
index_3  3
```

In the case that the DataFrame index doesn't pass the Check.

```
df = pd.DataFrame(
    data={"a": [1, 2, 3]},
    index=["foo1", "foo2", "foo3"])

schema.validate(df)
```

```
Traceback (most recent call last):
...
SchemaError: <Schema Index> failed element-wise validator 0:
<lambda>
failure cases:
      index  count
failure_case
foo1      [0]     1
foo2      [1]     1
foo3      [2]     1
```

7.1.3 MultiIndex Validation

pandera also supports multi-index column and index validation.

7.1.3.1 MultiIndex Columns

Specifying multi-index columns follows the pandas syntax of specifying tuples for each level in the index hierarchy:

```
import pandas as pd
import pandera as pa

from pandera import Column, DataFrameSchema, Index

schema = DataFrameSchema({
    ("foo", "bar"): Column(int),
    ("foo", "baz"): Column(str)
})

df = pd.DataFrame({
    ("foo", "bar"): [1, 2, 3],
    ("foo", "baz"): ["a", "b", "c"],
})

print(schema.validate(df))
```

```
foo
bar baz
0    1  a
1    2  b
2    3  c
```

7.1.3.2 MultiIndex Indexes

The *MultiIndex* class allows you to define multi-index indexes by composing a list of `pandera.Index` objects.

```
import pandas as pd
import pandera as pa

from pandera import Column, DataFrameSchema, Index, MultiIndex, Check

schema = DataFrameSchema(
    columns={"column1": Column(int)},
    index=MultiIndex([
        Index(str,
              Check(lambda s: s.isin(["foo", "bar"])),
              name="index0"),
        Index(int, name="index1"),
    ])
)

df = pd.DataFrame(
```

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```

data={"column1": [1, 2, 3]},
index=pd.MultiIndex.from_arrays(
    ["foo", "bar", "foo"], [0, 1, 2 ]],
    names=["index0", "index1"]
)
)
print(schema.validate(df))

```

		column1
index0	index1	
foo	0	1
bar	1	2
foo	2	3

7.1.4 Get Pandas Data Types

Pandas provides a *dtype* parameter for casting a dataframe to a specific dtype schema. *DataFrameSchema* provides a *dtypes* property which returns a dictionary whose keys are column names and values are *DataTypes*.

Some examples of where this can be provided to pandas are:

- https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.read_csv.html
- <https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.astype.html>

```

import pandas as pd
import pandera as pa

schema = pa.DataFrameSchema(
    columns={
        "column1": pa.Column(int),
        "column2": pa.Column(pa.Category),
        "column3": pa.Column(bool)
    },
)

df = (
    pd.DataFrame.from_dict(
        {
            "a": {"column1": 1, "column2": "valueA", "column3": True},
            "b": {"column1": 1, "column2": "valueB", "column3": True},
        },
        orient="index",
    )
    .astype({col: str(dtype) for col, dtype in schema.dtypes.items()})
    .sort_index(axis=1)
)

print(schema.validate(df))

```

	column1	column2	column3
a	1	valueA	True
b	1	valueB	True

7.1.5 DataFrameSchema Transformations

Once you've defined a schema, you can then make modifications to it, both on the schema level – such as adding or removing columns and setting or resetting the index – or on the column level – such as changing the data type or checks.

This is useful for re-using schema objects in a data pipeline when additional computation has been done on a dataframe, where the column objects may have changed or perhaps where additional checks may be required.

```
import pandas as pd
import pandera as pa

data = pd.DataFrame({"col1": range(1, 6)})

schema = pa.DataFrameSchema(
    columns={"col1": pa.Column(int, pa.Check(lambda s: s >= 0))},
    strict=True)

transformed_schema = schema.add_columns({
    "col2": pa.Column(str, pa.Check(lambda s: s == "value")),
    "col3": pa.Column(float, pa.Check(lambda x: x == 0.0)),
})

# validate original data
data = schema.validate(data)

# transformation
transformed_data = data.assign(col2="value", col3=0.0)

# validate transformed data
print(transformed_schema.validate(transformed_data))
```

	col1	col2	col3
0	1	value	0.0
1	2	value	0.0
2	3	value	0.0
3	4	value	0.0
4	5	value	0.0

Similarly, if you want dropped columns to be explicitly validated in a data pipeline:

```
import pandera as pa

schema = pa.DataFrameSchema(
    columns={
        "col1": pa.Column(int, pa.Check(lambda s: s >= 0)),
        "col2": pa.Column(str, pa.Check(lambda x: x <= 0)),
        "col3": pa.Column(object, pa.Check(lambda x: x == 0)),
    },
```

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```

    strict=True,
)

new_schema = schema.remove_columns(["col2", "col3"])
print(new_schema)

```

```

<Schema DataFrameSchema(
  columns={
    'col1': <Schema Column(name=col1, type=DataType(int64))>
  },
  checks=[],
  coerce=False,
  dtype=None,
  index=None,
  strict=True
  name=None,
  ordered=False,
  unique_column_names=False
)>

```

If during the course of a data pipeline one of your columns is moved into the index, you can simply update the initial input schema using the `set_index()` method to create a schema for the pipeline output.

```

import pandera as pa

from pandera import Column, DataFrameSchema, Check, Index

schema = DataFrameSchema(
    {
        "column1": Column(int),
        "column2": Column(float)
    },
    index=Index(int, name = "column3"),
    strict=True,
    coerce=True,
)
print(schema.set_index(["column1"], append = True))

```

```

<Schema DataFrameSchema(
  columns={
    'column2': <Schema Column(name=column2, type=DataType(float64))>
  },
  checks=[],
  coerce=True,
  dtype=None,
  index=<Schema MultiIndex(
    indexes=[
      <Schema Index(name=column3, type=DataType(int64))>
      <Schema Index(name=column1, type=DataType(int64))>
    ]
  )
  coerce=False,
  strict=False,
)

```

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```
        name=None,
        ordered=True
    )>,
    strict=True
    name=None,
    ordered=False,
    unique_column_names=False
)>
```

The available methods for altering the schema are: `add_columns()`, `remove_columns()`, `update_columns()`, `rename_columns()`, `set_index()`, and `reset_index()`.

7.2 Schema Models

new in 0.5.0

pandera provides a class-based API that's heavily inspired by `pydantic`. In contrast to the *object-based API*, you can define schema models in much the same way you'd define `pydantic` models.

Schema Models are annotated with the `pandera.typing` module using the standard `typing` syntax. Models can be explicitly converted to a `DataFrameSchema` or used to validate a `DataFrame` directly.

Note: Due to current limitations in the pandas library (see discussion [here](#)), `pandera` annotations are only used for **run-time** validation and **cannot** be leveraged by static-type checkers like `mypy`. See the discussion [here](#) for more details.

7.2.1 Basic Usage

```
import pandas as pd
import pandera as pa
from pandera.typing import Index, DataFrame, Series

class InputSchema(pa.SchemaModel):
    year: Series[int] = pa.Field(gt=2000, coerce=True)
    month: Series[int] = pa.Field(ge=1, le=12, coerce=True)
    day: Series[int] = pa.Field(ge=0, le=365, coerce=True)

class OutputSchema(InputSchema):
    revenue: Series[float]

@pa.check_types
def transform(df: DataFrame[InputSchema]) -> DataFrame[OutputSchema]:
    return df.assign(revenue=100.0)

df = pd.DataFrame({
    "year": ["2001", "2002", "2003"],
    "month": ["3", "6", "12"],
```

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```

    "day": ["200", "156", "365"],
})

transform(df)

invalid_df = pd.DataFrame({
    "year": ["2001", "2002", "1999"],
    "month": ["3", "6", "12"],
    "day": ["200", "156", "365"],
})
transform(invalid_df)

```

```

Traceback (most recent call last):
...
pandera.errors.SchemaError: <Schema Column: 'year' type=DataType(int64)> failed element-
↪wise validator 0:
<Check greater_than: greater_than(2000)>
failure cases:
   index  failure_case
0      2      1999

```

As you can see in the example above, you can define a schema by sub-classing `SchemaModel` and defining column/index fields as class attributes. The `check_types()` decorator is required to perform validation of the dataframe at run-time.

Note that `Field`s apply to both `Column` and `Index` objects, exposing the built-in `Check`s via key-word arguments.

(*New in 0.6.2*) When you access a class attribute defined on the schema, it will return the name of the column used in the validated `pd.DataFrame`. In the example above, this will simply be the string `"year"`.

```

print(f"Column name for 'year' is {InputSchema.year}\n")
print(df.loc[:, [InputSchema.year, "day"]])

```

```

Column name for 'year' is year

```

```

   year  day
0  2001  200
1  2002  156
2  2003  365

```

7.2.2 Validate on Initialization

new in 0.8.0

Pandera provides an interface for validating dataframes on initialization. This API uses the `pandera.typing.pandas.DataFrame` generic type to validated against the `SchemaModel` type variable on initialization:

```

import pandas as pd
import pandera as pa

from pandera.typing import DataFrame, Series

```

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```

class Schema(pa.SchemaModel):
    state: Series[str]
    city: Series[str]
    price: Series[int] = pa.Field(in_range={"min_value": 5, "max_value": 20})

df = DataFrame[Schema](
    {
        'state': ['NY', 'FL', 'GA', 'CA'],
        'city': ['New York', 'Miami', 'Atlanta', 'San Francisco'],
        'price': [8, 12, 10, 16],
    }
)
print(df)

```

	state	city	price
0	NY	New York	8
1	FL	Miami	12
2	GA	Atlanta	10
3	CA	San Francisco	16

Refer to *Supported DataFrame Libraries* to see how this syntax applies to other supported dataframe types.

7.2.3 Converting to DataFrameSchema

You can easily convert a *SchemaModel* class into a *DataFrameSchema*:

```
print(InputSchema.to_schema())
```

```

<Schema DataFrameSchema(
  columns={
    'year': <Schema Column(name=year, type=DataType(int64))>
    'month': <Schema Column(name=month, type=DataType(int64))>
    'day': <Schema Column(name=day, type=DataType(int64))>
  },
  checks=[],
  coerce=False,
  dtype=None,
  index=None,
  strict=False
  name=InputSchema,
  ordered=False,
  unique_column_names=False
)>

```

You can also use the *validate()* method to validate dataframes:

```
print(InputSchema.validate(df))
```

	year	month	day
0	2001	3	200

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```
1 2002     6 156
2 2003    12 365
```

Or you can use the `SchemaModel()` class directly to validate dataframes, which is syntactic sugar that simply delegates to the `validate()` method.

```
print(InputSchema(df))
```

```
   year  month  day
0  2001     3  200
1  2002     6  156
2  2003    12  365
```

7.2.4 Excluded attributes

Class variables which begin with an underscore will be automatically excluded from the model. `Config` is also a reserved name. However, *aliases* can be used to circumvent these limitations.

7.2.5 Supported dtypes

Any dtypes supported by pandera can be used as type parameters for `Series` and `Index`. There are, however, a couple of gotchas.

7.2.5.1 Dtype aliases

```
import pandera as pa
from pandera.typing import Series, String

class Schema(pa.SchemaModel):
    a: Series[String]
```

7.2.5.2 Type Vs instance

You must give a **type**, not an **instance**.

✓ Good:

```
import pandas as pd

class Schema(pa.SchemaModel):
    a: Series[pd.StringDtype]
```

Bad:

```
class Schema(pa.SchemaModel):
    a: Series[pd.StringDtype()]
```

```
Traceback (most recent call last):
...
TypeError: Parameters to generic types must be types. Got string[python].
```

7.2.5.3 Parametrized dtypes

Pandas supports a couple of parametrized dtypes. As of pandas 1.2.0:

Kind of Data	Data Type	Parameters
tz-aware datetime	DatetimeTZDtype	unit, tz
Categorical	CategoricalDtype	categories, ordered
period	PeriodDtype	freq
sparse	SparseDtype	dtype, fill_value
intervals	IntervalDtype	subtype

7.2.5.3.1 Annotated

Parameters can be given via `typing.Annotated`. It requires python > 3.9 or `typing_extensions`, which is already a requirement of Pandera. Unfortunately `typing.Annotated` has not been backported to python 3.6.

✓ Good:

```
try:
    from typing import Annotated # python 3.9+
except ImportError:
    from typing_extensions import Annotated

class Schema(pa.SchemaModel):
    col: Series[Annotated[pd.DatetimeTZDtype, "ns", "est"]]
```

Furthermore, you must pass all parameters in the order defined in the dtype's constructor (see [table](#)).

Bad:

```
class Schema(pa.SchemaModel):
    col: Series[Annotated[pd.DatetimeTZDtype, "utc"]]

Schema.to_schema()
```

```
Traceback (most recent call last):
...
TypeError: Annotation 'DatetimeTZDtype' requires all positional arguments ['unit', 'tz'].
```

7.2.5.3.2 Field

✓ Good:

```
class SchemaFieldDatetimeTZDtype(pa.SchemaModel):
    col: Series[pd.DatetimeTZDtype] = pa.Field(dtype_kwargs={"unit": "ns", "tz": "EST"})
```

You cannot use both `typing.Annotated` and `dtype_kwargs`.

Bad:

```
class SchemaFieldDatetimeTZDtype(pa.SchemaModel):
    col: Series[Annotated[pd.DatetimeTZDtype, "ns", "est"]] = pa.Field(dtype_kwargs={
↪ "unit": "ns", "tz": "EST"})

Schema.to_schema()
```

Traceback (most recent call last):

```
...
TypeError: Cannot specify redundant 'dtype_kwargs' for pandera.typing.Series[typing_
↪ extensions.Annotated[pandas.core.dtypes.dtypes.DatetimeTZDtype, 'ns', 'est']].
Usage Tip: Drop 'typing.Annotated'.
```

7.2.6 Required Columns

By default all columns specified in the schema are *required*, meaning that if a column is missing in the input DataFrame an exception will be thrown. If you want to make a column optional, annotate it with `typing.Optional`.

```
from typing import Optional

import pandas as pd
import pandera as pa
from pandera.typing import Series

class Schema(pa.SchemaModel):
    a: Series[str]
    b: Optional[Series[int]]

df = pd.DataFrame({"a": ["2001", "2002", "2003"]})
Schema.validate(df)
```

7.2.7 Schema Inheritance

You can also use inheritance to build schemas on top of a base schema.

```
class BaseSchema(pa.SchemaModel):
    year: Series[str]

class FinalSchema(BaseSchema):
    year: Series[int] = pa.Field(ge=2000, coerce=True) # overwrite the base type
    passengers: Series[int]
    idx: Index[int] = pa.Field(ge=0)

df = pd.DataFrame({
    "year": ["2000", "2001", "2002"],
})

@pa.check_types
def transform(df: DataFrame[BaseSchema]) -> DataFrame[FinalSchema]:
    return (
        df.assign(passengers=[61000, 50000, 45000])
        .set_index(pd.Index([1, 2, 3]))
        .astype({"year": int})
    )

print(transform(df))
```

	year	passengers
1	2000	61000
2	2001	50000
3	2002	45000

7.2.8 Config

Schema-wide options can be controlled via the `Config` class on the `SchemaModel` subclass. The full set of options can be found in the `BaseConfig` class.

```
class Schema(pa.SchemaModel):

    year: Series[int] = pa.Field(gt=2000, coerce=True)
    month: Series[int] = pa.Field(ge=1, le=12, coerce=True)
    day: Series[int] = pa.Field(ge=0, le=365, coerce=True)

    class Config:
        name = "BaseSchema"
        strict = True
        coerce = True
        foo = "bar" # Interpreted as dataframe check
```

It is not required for the `Config` to subclass `BaseConfig` but it **must** be named ‘`Config`’.

See *Registered Custom Checks with the Class-based API* for details on using registered dataframe checks.

7.2.9 MultiIndex

The *MultiIndex* capabilities are also supported with the class-based API:

```
import pandera as pa
from pandera.typing import Index, Series

class MultiIndexSchema(pa.SchemaModel):

    year: Index[int] = pa.Field(gt=2000, coerce=True)
    month: Index[int] = pa.Field(ge=1, le=12, coerce=True)
    passengers: Series[int]

    class Config:
        # provide multi index options in the config
        multiindex_name = "time"
        multiindex_strict = True
        multiindex_coerce = True

index = MultiIndexSchema.to_schema().index
print(index)
```

```
<Schema MultiIndex(
  indexes=[
    <Schema Index(name=year, type=DataType(int64))>
    <Schema Index(name=month, type=DataType(int64))>
  ]
  coerce=True,
  strict=True,
  name=time,
  ordered=True
)>
```

```
from pprint import pprint

pprint({name: col.checks for name, col in index.columns.items()})
```

```
{'month': [<Check greater_than_or_equal_to: greater_than_or_equal_to(1)>,
           <Check less_than_or_equal_to: less_than_or_equal_to(12)>],
 'year': [<Check greater_than: greater_than(2000)>]}
```

Multiple Index annotations are automatically converted into a *MultiIndex*. *MultiIndex* options are given in the *Config*.

7.2.10 Custom Checks

Unlike the object-based API, custom checks can be specified as class methods.

7.2.10.1 Column/Index checks

```
import pandera as pa
from pandera.typing import Index, Series

class CustomCheckSchema(pa.SchemaModel):

    a: Series[int] = pa.Field(gt=0, coerce=True)
    abc: Series[int]
    idx: Index[str]

    @pa.check("a", name="foobar")
    def custom_check(cls, a: Series[int]) -> Series[bool]:
        return a < 100

    @pa.check("^a", regex=True, name="foobar")
    def custom_check_regex(cls, a: Series[int]) -> Series[bool]:
        return a > 0

    @pa.check("idx")
    def check_idx(cls, idx: Index[int]) -> Series[bool]:
        return idx.str.contains("dog")
```

Note:

- You can supply the key-word arguments of the `Check` class initializer to get the flexibility of *groupby checks*
- Similarly to pydantic, `classmethod()` decorator is added behind the scenes if omitted.
- You still may need to add the `@classmethod` decorator *after* the `check()` decorator if your static-type checker or linter complains.
- Since checks are class methods, the first argument value they receive is a `SchemaModel` subclass, not an instance of a model.

```
from typing import Dict

class GroupbyCheckSchema(pa.SchemaModel):

    value: Series[int] = pa.Field(gt=0, coerce=True)
    group: Series[str] = pa.Field(isin=["A", "B"])

    @pa.check("value", groupby="group", regex=True, name="check_means")
    def check_groupby(cls, grouped_value: Dict[str, Series[int]]) -> bool:
        return grouped_value["A"].mean() < grouped_value["B"].mean()

df = pd.DataFrame({
    "value": [100, 110, 120, 10, 11, 12],
```

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```

    "group": list("AAABBB"),
})

print(GroupbyCheckSchema.validate(df))

```

```

Traceback (most recent call last):
...
pandera.errors.SchemaError: <Schema Column: 'value' type=DataType(int64)> failed series_
↳ validator 1:
<Check check_means>

```

7.2.10.2 DataFrame Checks

You can also define dataframe-level checks, similar to the *object-based API*, using the `dataframe_check()` decorator:

```

import pandas as pd
import pandera as pa
from pandera.typing import Index, Series

class DataFrameCheckSchema(pa.SchemaModel):

    col1: Series[int] = pa.Field(gt=0, coerce=True)
    col2: Series[float] = pa.Field(gt=0, coerce=True)
    col3: Series[float] = pa.Field(lt=0, coerce=True)

    @pa.dataframe_check
    def product_is_negative(cls, df: pd.DataFrame) -> Series[bool]:
        return df["col1"] * df["col2"] * df["col3"] < 0

df = pd.DataFrame({
    "col1": [1, 2, 3],
    "col2": [5, 6, 7],
    "col3": [-1, -2, -3],
})

DataFrameCheckSchema.validate(df)

```

7.2.10.3 Inheritance

The custom checks are inherited and therefore can be overwritten by the subclass.

```

import pandas as pd
import pandera as pa
from pandera.typing import Index, Series

class Parent(pa.SchemaModel):

    a: Series[int] = pa.Field(coerce=True)

    @pa.check("a", name="foobar")

```

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```

def check_a(cls, a: Series[int]) -> Series[bool]:
    return a < 100

class Child(Parent):

    a: Series[int] = pa.Field(coerce=False)

    @pa.check("a", name="foobar")
    def check_a(cls, a: Series[int]) -> Series[bool]:
        return a > 100

is_a_coerce = Child.to_schema().columns["a"].coerce
print(f"coerce: {is_a_coerce}")

```

```
coerce: False
```

```
df = pd.DataFrame({"a": [1, 2, 3]})
print(Child.validate(df))

```

```

Traceback (most recent call last):
...
pandera.errors.SchemaError: <Schema Column: 'a' type=DataType(int64)> failed element-
↪wise validator 0:
<Check foobar>
failure cases:
   index  failure_case
0      0             1
1      1             2
2      2             3

```

7.2.11 Aliases

SchemaModel supports columns which are not valid python variable names via the argument *alias* of *Field*.

Checks must reference the aliased names.

```

import pandera as pa
import pandas as pd

class Schema(pa.SchemaModel):
    col_2020: pa.typing.Series[int] = pa.Field(alias=2020)
    idx: pa.typing.Index[int] = pa.Field(alias="_idx", check_name=True)

    @pa.check(2020)
    def int_column_lt_100(cls, series):
        return series < 100

df = pd.DataFrame({2020: [99]}, index=[0])

```

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```
df.index.name = "_idx"
print(Schema.validate(df))
```

```
      2020
_idx
0      99
```

(New in 0.6.2) The *alias* is respected when using the class attribute to get the underlying *pd.DataFrame* column name or index level name.

```
print(Schema.col_2020)
```

```
2020
```

Very similar to the example above, you can also use the variable name directly within the class scope, and it will respect the alias.

Note: To access a variable from the class scope, you need to make it a class attribute, and therefore assign it a default *Field*.

```
import pandera as pa
import pandas as pd

class Schema(pa.SchemaModel):
    a: pa.typing.Series[int] = pa.Field()
    col_2020: pa.typing.Series[int] = pa.Field(alias=2020)

    @pa.check(col_2020)
    def int_column_lt_100(cls, series):
        return series < 100

    @pa.check(a)
    def int_column_gt_100(cls, series):
        return series > 100

df = pd.DataFrame({2020: [99], "a": [101]})
print(Schema.validate(df))
```

```
      2020   a
0      99  101
```

7.3 Series Schemas

The *SeriesSchema* class allows for the validation of pandas Series objects, and are very similar to *columns* and *indexes* described in *DataFrameSchemas*.

```
import pandas as pd
import pandera as pa

# specify multiple validators
schema = pa.SeriesSchema(
    str,
    checks=[
        pa.Check(lambda s: s.str.startswith("foo")),
        pa.Check(lambda s: s.str.endswith("bar")),
        pa.Check(lambda x: len(x) > 3, element_wise=True)
    ],
    nullable=False,
    unique=False,
    name="my_series")

validated_series = schema.validate(
    pd.Series(["foobar", "foobar", "foobar"], name="my_series"))
print(validated_series)
```

```
0    foobar
1    foobar
2    foobar
Name: my_series, dtype: object
```

7.4 Checks

7.4.1 Checking column properties

Check objects accept a function as a required argument, which is expected to take a *pa.Series* input and output a boolean or a Series of boolean values. For the check to pass, all of the elements in the boolean series must evaluate to True, for example:

```
import pandera as pa

check_lt_10 = pa.Check(lambda s: s <= 10)

schema = pa.DataFrameSchema({"column1": pa.Column(int, check_lt_10)})
schema.validate(pd.DataFrame({"column1": range(10)}))
```

Multiple checks can be applied to a column:

```
schema = pa.DataFrameSchema({
    "column2": pa.Column(str, [
        pa.Check(lambda s: s.str.startswith("value")),
```

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```

        pa.Check(lambda s: s.str.split("_", expand=True).shape[1] == 2)
    ]),
})

```

7.4.2 Built-in Checks

For common validation tasks, built-in checks are available in pandera.

```

import pandera as pa
from pandera import Column, Check, DataFrameSchema

schema = DataFrameSchema({
    "small_values": Column(float, Check.less_than(100)),
    "one_to_three": Column(int, Check.isin([1, 2, 3])),
    "phone_number": Column(str, Check.str_matches(r'^[a-z0-9-]+$')),
})

```

See the [Check](#) API reference for a complete list of built-in checks.

7.4.3 Vectorized vs. Element-wise Checks

By default, *Check* objects operate on `pd.Series` objects. If you want to make atomic checks for each element in the Column, then you can provide the `element_wise=True` keyword argument:

```

import pandas as pd
import pandera as pa

schema = pa.DataFrameSchema({
    "a": pa.Column(
        int,
        checks=[
            # a vectorized check that returns a bool
            pa.Check(lambda s: s.mean() > 5, element_wise=False),

            # a vectorized check that returns a boolean series
            pa.Check(lambda s: s > 0, element_wise=False),

            # an element-wise check that returns a bool
            pa.Check(lambda x: x > 0, element_wise=True),
        ]
    ),
})

df = pd.DataFrame({"a": [4, 4, 5, 6, 6, 7, 8, 9]})
schema.validate(df)

```

`element_wise == False` by default so that you can take advantage of the speed gains provided by the `pd.Series` API by writing vectorized checks.

7.4.4 Handling Null Values

By default, pandera drops null values before passing the objects to validate into the check function. For `Series` objects null elements are dropped (this also applies to columns), and for `DataFrame` objects, rows with any null value are dropped.

If you want to check the properties of a pandas data structure while preserving null values, specify `Check(..., ignore_na=False)` when defining a check.

Note that this is different from the nullable argument in `Column` objects, which simply checks for null values in a column.

7.4.5 Column Check Groups

`Column` checks support grouping by a different column so that you can make assertions about subsets of the column of interest. This changes the function signature of the `Check` function so that its input is a dict where keys are the group names and values are subsets of the series being validated.

Specifying `groupby` as a column name, list of column names, or callable changes the expected signature of the `Check` function argument to:

```
Callable[Dict[Any, pd.Series] -> Union[bool, pd.Series]
```

where the dict keys are the discrete keys in the `groupby` columns.

In the example below we define a `DataFrameSchema` with column checks for `height_in_feet` using a single column, multiple columns, and a more complex `groupby` function that creates a new column `age_less_than_15` on the fly.

```
import pandas as pd
import pandera as pa

schema = pa.DataFrameSchema({
    "height_in_feet": pa.Column(
        float, [
            # groupby as a single column
            pa.Check(
                lambda g: g[False].mean() > 6,
                groupby="age_less_than_20"),

            # define multiple groupby columns
            pa.Check(
                lambda g: g[(True, "F")].sum() == 9.1,
                groupby=["age_less_than_20", "sex"]),

            # groupby as a callable with signature:
            # (DataFrame) -> DataFrameGroupBy
            pa.Check(
                lambda g: g[(False, "M")].median() == 6.75,
                groupby=lambda df: (
                    df.assign(age_less_than_15=lambda d: d["age"] < 15)
                    .groupby(["age_less_than_15", "sex"])),
            ]),
    "age": pa.Column(int, pa.Check(lambda s: s > 0)),
    "age_less_than_20": pa.Column(bool),
    "sex": pa.Column(str, pa.Check(lambda s: s.isin(["M", "F"])))
})
```

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```

})

df = (
    pd.DataFrame({
        "height_in_feet": [6.5, 7, 6.1, 5.1, 4],
        "age": [25, 30, 21, 18, 13],
        "sex": ["M", "M", "F", "F", "F"]
    })
    .assign(age_less_than_20=lambda x: x["age"] < 20)
)

schema.validate(df)

```

7.4.6 Wide Checks

pandera is primarily designed to operate on long-form data (commonly known as [tidy data](#)), where each row is an observation and each column is an attribute associated with an observation.

However, pandera also supports checks on wide-form data to operate across columns in a DataFrame. For example, if you want to make assertions about height across two groups, the tidy dataset and schema might look like this:

```

import pandas as pd
import pandera as pa

df = pd.DataFrame({
    "height": [5.6, 6.4, 4.0, 7.1],
    "group": ["A", "B", "A", "B"],
})

schema = pa.DataFrameSchema({
    "height": pa.Column(
        float,
        pa.Check(lambda g: g["A"].mean() < g["B"].mean(), groupby="group")
    ),
    "group": pa.Column(str)
})

schema.validate(df)

```

Whereas the equivalent wide-form schema would look like this:

```

df = pd.DataFrame({
    "height_A": [5.6, 4.0],
    "height_B": [6.4, 7.1],
})

schema = pa.DataFrameSchema(
    columns={
        "height_A": pa.Column(float),
        "height_B": pa.Column(float),
    }
)

```

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```

    },
    # define checks at the DataFrameSchema-level
    checks=pa.Check(
        lambda df: df["height_A"].mean() < df["height_B"].mean()
    )
)

schema.validate(df)

```

You can see that when checks are supplied to the `DataFrameSchema` `checks` key-word argument, the check function should expect a pandas `DataFrame` and should return a `bool`, a `Series` of booleans, or a `DataFrame` of boolean values.

7.4.7 Raise `UserWarning` on Check Failure

In some cases, you might want to raise a `UserWarning` and continue execution of your program. The `Check` and `Hypothesis` classes and their built-in methods support the keyword argument `raise_warning`, which is `False` by default. If set to `True`, the check will raise a `UserWarning` instead of raising a `SchemaError` exception.

Note: Use this feature carefully! If the check is for informational purposes and not critical for data integrity then use `raise_warning=True`. However, if the assumptions expressed in a `Check` are necessary conditions to considering your data valid, do not set this option to true.

One scenario where you'd want to do this would be in a data pipeline that does some preprocessing, checks for normality in certain columns, and writes the resulting dataset to a table. In this case, you want to see if your normality assumptions are not fulfilled by certain columns, but you still want the resulting table for further analysis.

```

import warnings

import numpy as np
import pandas as pd
import pandera as pa

from scipy.stats import normaltest

np.random.seed(1000)

df = pd.DataFrame({
    "var1": np.random.normal(loc=0, scale=1, size=1000),
    "var2": np.random.uniform(low=0, high=10, size=1000),
})

normal_check = pa.Hypothesis(
    test=normaltest,
    samples="normal_variable",
    # null hypotheses: sample comes from a normal distribution. The
    # relationship function checks if we cannot reject the null hypothesis,
    # i.e. the p-value is greater or equal to alpha.
    relationship=lambda stat, pvalue, alpha=0.05: pvalue >= alpha,
)

```

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```

    error="normality test",
    raise_warning=True,
)

schema = pa.DataFrameSchema(
    columns={
        "var1": pa.Column(checks=normal_check),
        "var2": pa.Column(checks=normal_check),
    }
)

# catch and print warnings
with warnings.catch_warnings(record=True) as caught_warnings:
    warnings.simplefilter("always")
    validated_df = schema(df)
    for warning in caught_warnings:
        print(warning.message)

```

```

<Schema Column(name=var2, type=None)> failed series or dataframe validator 0:
<Check _hypothesis_check: normality test>

```

7.4.8 Registering Custom Checks

pandera now offers an interface to register custom checks functions so that they're available in the `Check` namespace. See [the *extensions* document](#) for more information.

7.5 Hypothesis Testing

pandera enables you to perform statistical hypothesis tests on your data.

Note: The hypothesis feature requires a pandera installation with `hypotheses` dependency set. See the [installation instructions](#) for more details.

7.5.1 Overview

The `Hypothesis` class defines built in methods, which can be called as in this example of a two-sample t-test:

```

import pandas as pd
import pandera as pa

from pandera import Column, DataFrameSchema, Check, Hypothesis

from scipy import stats

df = (
    pd.DataFrame({

```

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```

        "height_in_feet": [6.5, 7, 6.1, 5.1, 4],
        "sex": ["M", "M", "F", "F", "F"]
    })
)

schema = DataFrameSchema({
    "height_in_feet": Column(
        float, [
            Hypothesis.two_sample_ttest(
                sample1="M",
                sample2="F",
                groupby="sex",
                relationship="greater_than",
                alpha=0.05,
                equal_var=True),
        ]),
    "sex": Column(str)
})

schema.validate(df)

```

```

Traceback (most recent call last):
...
pandera.SchemaError: <Schema Column: 'height_in_feet' type=float64> failed series_
↳ validator 0: hypothesis_check: failed two sample ttest between 'M' and 'F'

```

You can also define custom hypotheses by passing in functions to the `test` and `relationship` arguments.

The `test` function takes as input one or multiple array-like objects and should return a `stat`, which is the test statistic, and `pvalue` for assessing statistical significance. It also takes key-word arguments supplied by the `test_kwargs` dict when initializing a `Hypothesis` object.

The `relationship` function should take all of the outputs of `test` as positional arguments, in addition to key-word arguments supplied by the `relationship_kwargs` dict.

Here's an implementation of the two-sample t-test that uses the [scipy implementation](#):

```

def two_sample_ttest(array1, array2):
    # the "height_in_feet" series is first grouped by "sex" and then
    # passed into the custom `test` function as two separate arrays in the
    # order specified in the `samples` argument.
    return stats.ttest_ind(array1, array2)

def null_relationship(stat, pvalue, alpha=0.01):
    return pvalue / 2 >= alpha

schema = DataFrameSchema({
    "height_in_feet": Column(
        float, [
            Hypothesis(
                test=two_sample_ttest,

```

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```

        samples=["M", "F"],
        groupby="sex",
        relationship=null_relationship,
        relationship_kwargs={"alpha": 0.05}
    )
]),
"sex": Column(str, checks=Check.isin(["M", "F"]))
})

schema.validate(df)

```

7.5.2 Wide Hypotheses

pandera is primarily designed to operate on long-form data (commonly known as [tidy data](#)), where each row is an observation and columns are attributes associated with the observation.

However, pandera also supports hypothesis testing on wide-form data to operate across columns in a `DataFrame`.

For example, if you want to make assertions about `height` across two groups, the tidy dataset and schema might look like this:

```

import pandas as pd
import pandera as pa

from pandera import Check, DataFrameSchema, Column, Hypothesis

df = pd.DataFrame({
    "height": [5.6, 7.5, 4.0, 7.9],
    "group": ["A", "B", "A", "B"],
})

schema = DataFrameSchema({
    "height": Column(
        float, Hypothesis.two_sample_ttest(
            "A", "B",
            groupby="group",
            relationship="less_than",
            alpha=0.05
        )
    ),
    "group": Column(str, Check(lambda s: s.isin(["A", "B"])))
})

schema.validate(df)

```

The equivalent wide-form schema would look like this:

```

import pandas as pd
import pandera as pa

from pandera import DataFrameSchema, Column, Hypothesis

```

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```
df = pd.DataFrame({
    "height_A": [5.6, 4.0],
    "height_B": [7.5, 7.9],
})

schema = DataFrameSchema(
    columns={
        "height_A": Column(Float),
        "height_B": Column(Float),
    },
    # define checks at the DataFrameSchema-level
    checks=Hypothesis.two_sample_ttest(
        "height_A", "height_B",
        relationship="less_than",
        alpha=0.05
    )
)

schema.validate(df)
```

7.6 Pandera Data Types

new in 0.7.0

7.6.1 Motivations

Pandera defines its own interface for data types in order to abstract the specifics of dataframe-like data structures in the python ecosystem, such as Apache Spark, Apache Arrow and xarray.

Note: In the following section Pandera `Data Type` refers to a `pandera.dtypes.DataType` object whereas `native data type` refers to data types used by third-party libraries that Pandera supports (e.g. pandas).

Most of the time, it is transparent to end users since pandera columns and indexes accept native data types. However, it is possible to extend the pandera interface by:

- modifying the **data type check** performed during schema validation.
- modifying the behavior of the **coerce** argument for `DataFrameSchema`.
- adding your **own custom data types**.

7.6.2 DataType basics

All pandera data types inherit from `pandera.dtypes.DataType` and must be hashable.

A data type implements three key methods:

- `pandera.dtypes.DataType.check()` which validates that data types are equivalent.
- `pandera.dtypes.DataType.coerce()` which coerces a data container (e.g. `pandas.Series`) to the data type.
- The dunder method `__str__()` which should output the native alias. For example `str(pandera.Float64) == "float64"`

For pandera's validation methods to be aware of a data type, it has to be registered with the targeted engine via `pandera.engines.Engine.register_dtype()`. An engine is in charge of mapping a pandera `DataType` with a native data type counterpart belonging to a third-party library. The mapping can be queried with `pandera.engines.Engine.Engine.dtype()`.

As of pandera 0.7.0, only the pandas `Engine` is supported.

7.6.3 Example

Let's extend `pandas.BooleanDtype` coercion to handle the string literals "True" and "False".

```
import pandas as pd
import pandera as pa
from pandera import dtypes
from pandera.engines import pandas_engine

@pandas_engine.Engine.register_dtype # step 1
@dtypes.immutable # step 2
class LiteralBool(pandas_engine.BOOL): # step 3
    def coerce(self, series: pd.Series) -> pd.Series:
        """Coerce a pandas.Series to date types."""
        if pd.api.types.is_string_dtype(series):
            series = series.replace({"True": 1, "False": 0})
        return series.astype("boolean")

data = pd.Series(["True", "False"], name="literal_bools")

# step 4
print(
    pa.SeriesSchema(LiteralBool(), coerce=True, name="literal_bools")
    .validate(data)
    .dtype
)
```

```
boolean
```

The example above performs the following steps:

1. Register the data type with the pandas engine.
2. `pandera.dtypes.immutable()` creates an immutable (and hashable) `dataclass()`.

3. Inherit `pandera.engines.pandas_engine.BOOL`, which is the pandera representation of `pandas.BooleanDtype`. This is not mandatory but it makes our life easier by having already implemented all the required methods.
4. Check that our new data type can coerce the string literals.

So far we did not override the default behavior:

```
import pandera as pa

pa.SeriesSchema("boolean", coerce=True).validate(data)
```

Traceback (most recent call last):

```
...
pandera.errors.SchemaError: Error while coercing 'literal_bools' to type boolean: Need
↳to pass bool-like values
```

To completely replace the default `BOOL`, we need to supply all the equivalent representations to `register_dtype()`. Behind the scenes, when `pa.SeriesSchema("boolean")` is called the corresponding pandera data type is looked up using `pandera.engines.engine.Engine.dtype()`.

```
print(f"before: {pandas_engine.Engine.dtype('boolean').__class__}")

@pandas_engine.Engine.register_dtype(
    equivalents=["boolean", pd.BooleanDtype, pd.BooleanDtype()],
)
@dtypes.immutable
class LiteralBool(pandas_engine.BOOL):
    def coerce(self, series: pd.Series) -> pd.Series:
        """Coerce a pandas.Series to date types."""
        if pd.api.types.is_string_dtype(series):
            series = series.replace({"True": 1, "False": 0})
        return series.astype("boolean")

print(f"after: {pandas_engine.Engine.dtype('boolean').__class__}")

for dtype in ["boolean", pd.BooleanDtype, pd.BooleanDtype()]:
    pa.SeriesSchema(dtype, coerce=True).validate(data)
```

```
before: <class 'pandera.engines.pandas_engine.BOOL'>
after: <class 'LiteralBool'>
```

Note: For convenience, we specified both `pd.BooleanDtype` and `pd.BooleanDtype()` as equivalents. That gives us more flexibility in what pandera schemas can recognize (see last for-loop above).

7.6.4 Parametrized data types

Some data types can be parametrized. One common example is `pandas.CategoricalDtype`.

The `equivalents` argument of `register_dtype()` does not handle this situation but will automatically register a `classmethod()` with signature `from_parametrized_dtype(cls, equivalent:...)` if the decorated `DataType` defines it. The `equivalent` argument must be type-annotated because it is leveraged to dispatch the input of `dtype` to the appropriate `from_parametrized_dtype` class method.

For example, here is a snippet from `pandera.engines.pandas_engine.Category`:

```
import pandas as pd
from pandera import dtypes

@classmethod
def from_parametrized_dtype(
    cls, cat: Union[dtypes.Category, pd.CategoricalDtype]
):
    """Convert a categorical to
    a Pandera :class:`pandera.dtypes.pandas_engine.Category`."""
    return cls(categories=cat.categories, ordered=cat.ordered) # type: ignore
```

Note: The dispatch mechanism relies on `functools.singledispatch()`. Unlike the built-in implementation, `typing.Union` is recognized.

7.6.5 Defining the `coerce_value` method

For pandera datatypes to understand how to correctly report coercion errors, it needs to know how to coerce an individual value into the specified type.

All pandas data types are supported: `numpy`-based datatypes use the underlying `numpy` dtype to coerce an individual value. The pandas-native datatypes like `CategoricalDtype` and `BooleanDtype` are also supported.

As an example of a special-cased `coerce_value` implementation, see `coerce_value()`:

```
"""Coerce an value to a particular type."""
if value not in self.categories: # type: ignore
    raise TypeError(
        f"value {value} cannot be coerced to type {self.type}"
    )
return value
```

And `coerce_value()`:

```
"""Coerce an value to specified datatype type."""
if value not in self._bool_like:
    raise TypeError(
        f"value {value} cannot be coerced to type {self.type}"
    )
return super().coerce_value(value)
```

7.7 Decorators for Pipeline Integration

If you have an existing data pipeline that uses pandas data structures, you can use the `check_input()` and `check_output()` decorators to easily check function arguments or returned variables from existing functions.

7.7.1 Check Input

Validates input pandas DataFrame/Series before entering the wrapped function.

```
import pandas as pd
import pandera as pa

from pandera import DataFrameSchema, Column, Check, check_input

df = pd.DataFrame({
    "column1": [1, 4, 0, 10, 9],
    "column2": [-1.3, -1.4, -2.9, -10.1, -20.4],
})

in_schema = DataFrameSchema({
    "column1": Column(int,
                      Check(lambda x: 0 <= x <= 10, element_wise=True)),
    "column2": Column(float, Check(lambda x: x < -1.2)),
})

# by default, check_input assumes that the first argument is
# dataframe/series.
@check_input(in_schema)
def preprocessor(dataframe):
    dataframe["column3"] = dataframe["column1"] + dataframe["column2"]
    return dataframe

preprocessed_df = preprocessor(df)
print(preprocessed_df)
```

	column1	column2	column3
0	1	-1.3	-0.3
1	4	-1.4	2.6
2	0	-2.9	-2.9
3	10	-10.1	-0.1
4	9	-20.4	-11.4

You can also provide the argument name as a string

```
@check_input(in_schema, "dataframe")
def preprocessor(dataframe):
    ...
```

Or an integer representing the index in the positional arguments.

```
@check_input(in_schema, 1)
def preprocessor(foo, dataframe):
    ...
```

7.7.2 Check Output

The same as `check_input`, but this decorator checks the output DataFrame/Series of the decorated function.

```
import pandas as pd
import pandera as pa

from pandera import DataFrameSchema, Column, Check, check_output

preprocessed_df = pd.DataFrame({
    "column1": [1, 4, 0, 10, 9],
})

# assert that all elements in "column1" are zero
out_schema = DataFrameSchema({
    "column1": Column(int, Check(lambda x: x == 0))
})

# by default assumes that the pandas DataFrame/Schema is the only output
@check_output(out_schema)
def zero_column_1(df):
    df["column1"] = 0
    return df

# you can also specify in the index of the argument if the output is list-like
@check_output(out_schema, 1)
def zero_column_1_arg(df):
    df["column1"] = 0
    return "foobar", df

# or the key containing the data structure to verify if the output is dict-like
@check_output(out_schema, "out_df")
def zero_column_1_dict(df):
    df["column1"] = 0
    return {"out_df": df, "out_str": "foobar"}

# for more complex outputs, you can specify a function
@check_output(out_schema, lambda x: x[1]["out_df"])
def zero_column_1_custom(df):
    df["column1"] = 0
    return ("foobar", {"out_df": df})
```

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```
zero_column_1(preprocessed_df)
zero_column_1_arg(preprocessed_df)
zero_column_1_dict(preprocessed_df)
zero_column_1_custom(preprocessed_df)
```

7.7.3 Check IO

For convenience, you can also use the `check_io()` decorator where you can specify input and output schemas more concisely:

```
import pandas as pd
import pandera as pa

from pandera import DataFrameSchema, Column, Check, check_input

df = pd.DataFrame({
    "column1": [1, 4, 0, 10, 9],
    "column2": [-1.3, -1.4, -2.9, -10.1, -20.4],
})

in_schema = DataFrameSchema({
    "column1": Column(int),
    "column2": Column(float),
})

out_schema = in_schema.add_columns({"column3": Column(float)})

@pa.check_io(df1=in_schema, df2=in_schema, out=out_schema)
def preprocessor(df1, df2):
    return (df1 + df2).assign(column3=lambda x: x.column1 + x.column2)

preprocessed_df = preprocessor(df, df)
print(preprocessed_df)
```

	column1	column2	column3
0	2	-2.6	-0.6
1	8	-2.8	5.2
2	0	-5.8	-5.8
3	20	-20.2	-0.2
4	18	-40.8	-22.8

7.7.4 Decorate Functions and Coroutines

All pandera decorators work on synchronous as well as asynchronous code, on both bound and unbound functions/coroutines. For example, one can use the same decorators on:

- sync/async functions
- sync/async methods
- sync/async class methods
- sync/async static methods

All decorators work on sync/async regular/class/static methods of metaclasses as well.

```
import pandera as pa
from pandera.typing import DataFrame, Series

class Schema(pa.SchemaModel):
    col1: Series[int]

    class Config:
        strict = True

@pa.check_types
async def coroutine(df: DataFrame[Schema]) -> DataFrame[Schema]:
    return df

@pa.check_types
async def function(df: DataFrame[Schema]) -> DataFrame[Schema]:
    return df

class SomeClass:
    @pa.check_output(Schema.to_schema())
    async def regular_coroutine(self, df) -> DataFrame[Schema]:
        return df

    @classmethod
    @pa.check_input(Schema.to_schema(), "df")
    async def class_coroutine(cls, df):
        return Schema.validate(df)

    @staticmethod
    @pa.check_io(df=Schema.to_schema(), out=Schema.to_schema())
    def static_method(df):
        return df
```

7.8 Schema Inference

New in version 0.4.0

With simple use cases, writing a schema definition manually is pretty straight-forward with pandera. However, it can get tedious to do this with dataframes that have many columns of various data types.

To help you handle these cases, the `infer_schema()` function enables you to quickly infer a draft schema from a pandas dataframe or series. Below is a simple example:

```
import pandas as pd
import pandera as pa

from pandera import Check, Column, DataFrameSchema

df = pd.DataFrame({
    "column1": [5, 10, 20],
    "column2": ["a", "b", "c"],
    "column3": pd.to_datetime(["2010", "2011", "2012"]),
})
schema = pa.infer_schema(df)
print(schema)
```

```
<Schema DataFrameSchema(
  columns={
    'column1': <Schema Column(name=column1, type=DataType(int64))>
    'column2': <Schema Column(name=column2, type=DataType(object))>
    'column3': <Schema Column(name=column3, type=DataType(datetime64[ns]))>
  },
  checks=[],
  coerce=True,
  dtype=None,
  index=<Schema Index(name=None, type=DataType(int64))>,
  strict=False
  name=None,
  ordered=False,
  unique_column_names=False
)>
```

These inferred schemas are **rough drafts** that shouldn't be used for validation without modification. You can modify the inferred schema to obtain the schema definition that you're satisfied with.

For `DataFrameSchema` objects, the following methods create modified copies of the schema:

- `add_columns()`
- `remove_columns()`
- `update_column()`

For `SeriesSchema` objects:

- `set_checks()`

The section below describes two workflows for persisting and modifying an inferred schema.

7.8.1 Schema Persistence

The schema persistence feature requires a pandera installation with the `io` extension. See the *installation* instructions for more details.

There are two ways of persisting schemas, inferred or otherwise.

7.8.1.1 Write to a Python script

You can also write your schema to a python script with `to_script()`:

```
# supply a file-like object, Path, or str to write to a file. If not
# specified, to_script will output the code as a string.
schema_script = schema.to_script()
print(schema_script)
```

```
from pandas import Timestamp
from pandera import DataFrameSchema, Column, Check, Index, MultiIndex

schema = DataFrameSchema(
    columns={
        "column1": Column(
            dtype=pandera.engines.numpy_engine.Int64,
            checks=[
                Check.greater_than_or_equal_to(min_value=5.0),
                Check.less_than_or_equal_to(max_value=20.0),
            ],
            nullable=False,
            unique=False,
            coerce=False,
            required=True,
            regex=False,
        ),
        "column2": Column(
            dtype=pandera.engines.numpy_engine.Object,
            checks=None,
            nullable=False,
            unique=False,
            coerce=False,
            required=True,
            regex=False,
        ),
        "column3": Column(
            dtype=pandera.engines.pandas_engine.DateTime,
            checks=[
                Check.greater_than_or_equal_to(
                    min_value=Timestamp("2010-01-01 00:00:00")
                ),
                Check.less_than_or_equal_to(
                    max_value=Timestamp("2012-01-01 00:00:00")
                ),
            ],
            nullable=False,
```

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```

        unique=False,
        coerce=False,
        required=True,
        regex=False,
    ),
},
index=Index(
    dtype=pandera.engines.numpy_engine.Int64,
    checks=[
        Check.greater_than_or_equal_to(min_value=0.0),
        Check.less_than_or_equal_to(max_value=2.0),
    ],
    nullable=False,
    coerce=False,
    name=None,
),
coerce=True,
strict=False,
name=None,
)

```

As a python script, you can iterate on an inferred schema and use it to validate data once you are satisfied with your schema definition.

7.8.1.2 Write to YAML

You can also write the schema object to a yaml file with `to_yaml()`, and you can then read it into memory with `from_yaml()`. The `to_yaml()` and `from_yaml()` is a convenience method for this functionality.

```

# supply a file-like object, Path, or str to write to a file. If not
# specified, to_yaml will output a yaml string.
yaml_schema = schema.to_yaml()
print(yaml_schema.replace(f"{{pa.__version__}}", "{{PANDERA_VERSION}}"))

```

```

schema_type: dataframe
version: {{PANDERA_VERSION}}
columns:
  column1:
    dtype: int64
    nullable: false
    checks:
      greater_than_or_equal_to: 5.0
      less_than_or_equal_to: 20.0
    unique: false
    coerce: false
    required: true
    regex: false
  column2:
    dtype: object
    nullable: false
    checks: null

```

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```

unique: false
coerce: false
required: true
regex: false
column3:
  dtype: datetime64[ns]
  nullable: false
  checks:
    greater_than_or_equal_to: '2010-01-01 00:00:00'
    less_than_or_equal_to: '2012-01-01 00:00:00'
  unique: false
  coerce: false
  required: true
  regex: false
checks: null
index:
- dtype: int64
  nullable: false
  checks:
    greater_than_or_equal_to: 0.0
    less_than_or_equal_to: 2.0
  name: null
  unique: false
  coerce: false
coerce: true
strict: false
unique: null

```

You can edit this yaml file by specifying column names under the `column` key. The respective values map onto key-word arguments in the `Column` class.

Note: Currently, only built-in `Check` methods are supported under the `checks` key.

7.9 Lazy Validation

New in version 0.4.0

By default, when you call the `validate` method on schema or schema component objects, a `SchemaError` is raised as soon as one of the assumptions specified in the schema is falsified. For example, for a `DataFrameSchema` object, the following situations will raise an exception:

- a column specified in the schema is not present in the dataframe.
- if `strict=True`, a column in the dataframe is not specified in the schema.
- the `data` type does not match.
- if `coerce=True`, the dataframe column cannot be coerced into the specified `data` type.
- the `Check` specified in one of the columns returns `False` or a boolean series containing at least one `False` value.

For example:

```
import pandas as pd
import pandera as pa

from pandera import Check, Column, DataFrameSchema

df = pd.DataFrame({"column": ["a", "b", "c"]})

schema = pa.DataFrameSchema({"column": Column(int)})
schema.validate(df)
```

Traceback (most recent call last):

```
...
SchemaError: expected series 'column' to have type int64, got object
```

For more complex cases, it is useful to see all of the errors raised during the `validate` call so that you can debug the causes of errors on different columns and checks. The `lazy` keyword argument in the `validate` method of all schemas and schema components gives you the option of doing just this:

```
import pandas as pd
import pandera as pa

from pandera import Check, Column, DataFrameSchema

schema = pa.DataFrameSchema(
    columns={
        "int_column": Column(int),
        "float_column": Column(float, Check.greater_than(0)),
        "str_column": Column(str, Check.equal_to("a")),
        "date_column": Column(pa.DateTime),
    },
    strict=True
)

df = pd.DataFrame({
    "int_column": ["a", "b", "c"],
    "float_column": [0, 1, 2],
    "str_column": ["a", "b", "d"],
    "unknown_column": None,
})

schema.validate(df, lazy=True)
```

Traceback (most recent call last):

```
...
pandera.errors.SchemaErrors: A total of 5 schema errors were found.
```

Error Counts

```
-----
- column_not_in_schema: 1
- column_not_in_dataframe: 1
- schema_component_check: 3
```

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```

Schema Error Summary
-----

```

schema_context	column	check	failure_cases	n_failure_cases
DataFrameSchema	<NA>	column_in_dataframe	[date_column]	1
		column_in_schema	[unknown_column]	1
Column	float_column	dtype('float64')	[int64]	1
	int_column	dtype('int64')	[object]	1
	str_column	equal_to(a)	[b, d]	2

Usage Tip

Directly inspect all errors by catching the exception:

```

...
try:
    schema.validate(dataframe, lazy=True)
except SchemaErrors as err:
    err.failure_cases # dataframe of schema errors
    err.data # invalid dataframe
...

```

As you can see from the output above, a `SchemaErrors` exception is raised with a summary of the error counts and failure cases caught by the schema. You can also see from the **Usage Tip** that you can catch these errors and inspect the failure cases in a more granular form:

```

try:
    schema.validate(df, lazy=True)
except pa.errors.SchemaErrors as err:
    print("Schema errors and failure cases:")
    print(err.failure_cases)
    print("\nDataFrame object that failed validation:")
    print(err.data)

```

```

Schema errors and failure cases:
  schema_context  column  check  check_number  \
0 DataFrameSchema  None    column_in_schema  None
1 DataFrameSchema  None  column_in_dataframe  None
2      Column  int_column  dtype('int64')  None
3      Column  float_column  dtype('float64')  None
4      Column  float_column  greater_than(0)  0
5      Column  str_column    equal_to(a)  0
6      Column  str_column    equal_to(a)  0

  failure_case index
0 unknown_column  None
1   date_column  None
2      object  None
3      int64  None
4          0    0
5          b    1

```

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```

6           d      2

DataFrame object that failed validation:
  int_column  float_column  str_column  unknown_column
0           a             0           a             None
1           b             1           b             None
2           c             2           d             None

```

7.10 Data Synthesis Strategies

new in 0.6.0

pandera provides a utility for generating synthetic data purely from pandera schema or schema component objects. Under the hood, the schema metadata is collected to create a data-generating strategy using [hypothesis](#), which is a property-based testing library.

7.10.1 Basic Usage

Once you've defined a schema, it's easy to generate examples:

```

import pandera as pa

schema = pa.DataFrameSchema(
    {
        "column1": pa.Column(int, pa.Check.eq(10)),
        "column2": pa.Column(float, pa.Check.eq(0.25)),
        "column3": pa.Column(str, pa.Check.eq("foo")),
    }
)
print(schema.example(size=3))

```

```

   column1  column2  column3
0         10      0.25      foo
1         10      0.25      foo
2         10      0.25      foo

```

Note that here we've constrained the specific values in each column using [Check](#) s in order to make the data generation process deterministic for documentation purposes.

7.10.2 Usage in Unit Tests

The `example` method is available for all schemas and schema components, and is primarily meant to be used interactively. It *could* be used in a script to generate test cases, but [hypothesis](#) recommends against doing this and instead using the `strategy` method to create a [hypothesis](#) strategy that can be used in `pytest` unit tests.

```

import hypothesis

def processing_fn(df):
    return df.assign(column4=df.column1 * df.column2)

```

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```
@hypothesis.given(schema.strategy(size=5))
def test_processing_fn(dataframe):
    result = processing_fn(dataframe)
    assert "column4" in result
```

The above example is trivial, but you get the idea! Schema objects can create a strategy that can then be collected by a `pytest` runner. We could also run the tests explicitly ourselves, or run it as a `unittest.TestCase`. For more information on testing with hypothesis, see the [hypothesis quick start guide](#).

A more practical example involves using *schema transformations*. We can modify the function above to make sure that `processing_fn` actually outputs the correct result:

```
out_schema = schema.add_columns({"column4": pa.Column(float)})

@pa.check_output(out_schema)
def processing_fn(df):
    return df.assign(column4=df.column1 * df.column2)

@hypothesis.given(schema.strategy(size=5))
def test_processing_fn(dataframe):
    processing_fn(dataframe)
```

Now the `test_processing_fn` simply becomes an execution test, raising a `SchemaError` if `processing_fn` doesn't add `column4` to the dataframe.

7.10.3 Strategies and Examples from Schema Models

You can also use the *class-based API* to generate examples. Here's the equivalent schema model for the above examples:

```
from pandera.typing import Series, DataFrame

class InSchema(pa.SchemaModel):
    column1: Series[int] = pa.Field(eq=10)
    column2: Series[float] = pa.Field(eq=0.25)
    column3: Series[str] = pa.Field(eq="foo")

class OutSchema(InSchema):
    column4: Series[float]

@pa.check_types
def processing_fn(df: DataFrame[InSchema]) -> DataFrame[OutSchema]:
    return df.assign(column4=df.column1 * df.column2)

@hypothesis.given(InSchema.strategy(size=5))
def test_processing_fn(dataframe):
    processing_fn(dataframe)
```

7.10.4 Checks as Constraints

As you may have noticed in the first example, *Check*s further constrain the data synthesized from a strategy. Without checks, the `example` method would simply generate any value of the specified type. You can specify multiple checks on a column and pandera should be able to generate valid data under those constraints.

```
schema_multiple_checks = pa.DataFrameSchema({
    "column1": pa.Column(
        float, checks=[
            pa.Check.gt(0),
            pa.Check.lt(1e10),
            pa.Check.notin([-100, -10, 0]),
        ]
    )
})

for _ in range(5):
    # generate 10 rows of the dataframe
    sample_data = schema_multiple_checks.example(size=3)

    # validate the sampled data
    schema_multiple_checks.validate(sample_data)
```

One caveat here is that it's up to you to define a set of checks that are jointly satisfiable. If not, an `Unsatisfiable` exception will be raised:

```
schema_multiple_checks = pa.DataFrameSchema({
    "column1": pa.Column(
        float, checks=[
            # nonsensical constraints
            pa.Check.gt(0),
            pa.Check.lt(-10),
        ]
    )
})

schema_multiple_checks.example(size=3)
```

```
Traceback (most recent call last):
```

```
...
Unsatisfiable: Unable to satisfy assumptions of hypothesis example_generating_inner_
↪function.
```

7.10.4.1 Check Strategy Chaining

If you specify multiple checks for a particular column, this is what happens under the hood:

- The first check in the list is the *base strategy*, which `hypothesis` uses to generate data.
- All subsequent checks filter the values generated by the previous strategy such that it fulfills the constraints of current check.

To optimize efficiency of the data-generation procedure, make sure to specify the most restrictive constraint of a column as the *base strategy* and build other constraints on top of it.

7.10.4.2 In-line Custom Checks

One of the strengths of `pandera` is its flexibility with regard to defining custom checks on the fly:

```
schema_inline_check = pa.DataFrameSchema({
    "col": pa.Column(str, pa.Check(lambda s: s.isin({"foo", "bar"})))
})
```

One of the disadvantages of this is that the fallback strategy is to simply apply the check to the generated data, which can be highly inefficient. In this case, `hypothesis` will generate strings and try to find examples of strings that are in the set `{"foo", "bar"}`, which will be very slow and most likely raise an `Unsatisfiable` exception. To get around this limitation, you can register custom checks and define strategies that correspond to them.

7.10.5 Defining Custom Strategies

All built-in `Check`s are associated with a data synthesis strategy. You can define your own data synthesis strategies by using the `extensions API` to register a custom check function with a corresponding strategy.

7.11 Extensions

new in 0.6.0

7.11.1 Registering Custom Check Methods

One of the strengths of `pandera` is its flexibility in enabling you to defining in-line custom checks on the fly:

```
import pandera as pa

# checks elements in a column/dataframe
element_wise_check = pa.Check(lambda x: x < 0, element_wise=True)

# applies the check function to a dataframe/series
vectorized_check = pa.Check(lambda series_or_df: series_or_df < 0)
```

However, there are two main disadvantages of schemas with inline custom checks:

1. they are not serializable with the *IO interface*.
2. you can't use them to *synthesize data* because the checks are not associated with a `hypothesis` strategy.

`pandera` now offers a way to register custom checks so that they're available in the `Check` class as a check method. Here let's define a custom method that checks whether a pandas object contains elements that lie within two values.

```
import pandera as pa
import pandera.extensions as extensions
import pandas as pd

@extensions.register_check_method(statistics=["min_value", "max_value"])
def is_between(pandas_obj, *, min_value, max_value):
    return (min_value <= pandas_obj) & (pandas_obj <= max_value)

schema = pa.DataFrameSchema({
```

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```

    "col": pa.Column(int, pa.Check.is_between(min_value=1, max_value=10))
})

data = pd.DataFrame({"col": [1, 5, 10]})
print(schema(data))

```

```

   col
0    1
1    5
2   10

```

As you can see, a custom check's first argument is a pandas series or dataframe by default (more on that later), followed by keyword-only arguments, specified with the `*` syntax.

The `register_check_method()` requires you to explicitly name the check statistics via the keyword argument, which are essentially the constraints placed by the check on the pandas data structure.

7.11.2 Specifying a Check Strategy

To specify a check strategy with your custom check, you'll need to install the `strategies extension`. First let's look at a trivially simple example, where the check verifies whether a column is equal to a certain value:

```

def custom_equals(pandas_obj, *, value):
    return pandas_obj == value

```

The corresponding strategy for this check would be:

```

from typing import Optional
import hypothesis
import pandera.strategies as st

def equals_strategy(
    pandera_dtype: pa.DataType,
    strategy: Optional[st.SearchStrategy] = None,
    *,
    value,
):
    if strategy is None:
        return st.pandas_dtype_strategy(
            pandera_dtype, strategy=hypothesis.strategies.just(value),
        )
    return strategy.filter(lambda x: x == value)

```

As you may notice, the pandera strategy interface has two arguments followed by keyword-only arguments that match the check function keyword-only check statistics. The `pandera_dtype` positional argument is useful for ensuring the correct data type. In the above example, we're using the `pandas_dtype_strategy()` strategy to make sure the generated value is of the correct data type.

The optional `strategy` argument allows us to use the check strategy as a *base strategy* or a *chained strategy*. There's a detail that we're responsible for implementing in the strategy function body: we need to handle two cases to account for *strategy chaining*:

1. when the strategy function is being used as a *base strategy*, i.e. when `strategy` is `None`

2. when the strategy function is being chained from a previously-defined strategy, i.e. when `strategy` is not `None`.

Finally, to register the custom check with the strategy, use the `register_check_method()` decorator:

```
@extensions.register_check_method(
    statistics=["value"], strategy>equals_strategy
)
def custom_equals(pandas_obj, *, value):
    return pandas_obj == value
```

Let's unpack what's going in here. The `custom_equals` function only has a single statistic, which is the `value` argument, which we've also specified in `register_check_method()`. This means that the associated check strategy must match its keyword-only arguments.

Going back to our `is_between` function example, here's what the strategy would look like:

```
def in_between_strategy(
    pandera_dtype: pa.DataType,
    strategy: Optional[st.SearchStrategy] = None,
    *,
    min_value,
    max_value
):
    if strategy is None:
        return st.pandas_dtype_strategy(
            pandera_dtype,
            min_value=min_value,
            max_value=max_value,
            exclude_min=False,
            exclude_max=False,
        )
    return strategy.filter(lambda x: min_value <= x <= max_value)

@extensions.register_check_method(
    statistics=["min_value", "max_value"],
    strategy=in_between_strategy,
)
def is_between_with_strat(pandas_obj, *, min_value, max_value):
    return (min_value <= pandas_obj) & (pandas_obj <= max_value)
```

7.11.3 Check Types

The extensions module also supports registering *element-wise* and *groupby* checks.

7.11.3.1 Element-wise Checks

```
@extensions.register_check_method(
    statistics=["val"],
    check_type="element_wise",
)
def element_wise_equal_check(element, *, val):
    return element == val
```

Note that the first argument of `element_wise_equal_check` is a single element in the column or dataframe.

7.11.3.2 Groupby Checks

In this groupby check, we're verifying that the values of one column for `group_a` are, on average, greater than those of `group_b`:

```
from typing import Dict

@extensions.register_check_method(
    statistics=["group_a", "group_b"],
    check_type="groupby",
)
def groupby_check(dict_groups: Dict[str, pd.Series], *, group_a, group_b):
    return dict_groups[group_a].mean() > dict_groups[group_b].mean()

data = pd.DataFrame({
    "values": [20, 10, 1, 15],
    "groups": list("xyxy"),
})

schema = pa.DataFrameSchema({
    "values": pa.Column(
        int,
        pa.Check.groupby_check(group_a="x", group_b="y", groupby="groups"),
    ),
    "groups": pa.Column(str),
})

print(schema(data))
```

	values	groups
0	20	x
1	10	x
2	1	y
3	15	y

7.11.4 Registered Custom Checks with the Class-based API

Since registered checks are part of the `Check` namespace, you can also use custom checks with the *class-based API*:

```
from pandera.typing import Series

class Schema(pa.SchemaModel):
    col1: Series[str] = pa.Field(custom_equals="value")
    col2: Series[int] = pa.Field(is_between={"min_value": 0, "max_value": 10})

data = pd.DataFrame({
    "col1": ["value"] * 5,
    "col2": range(5)
})

print(Schema.validate(data))
```

```
   col1  col2
0  value    0
1  value    1
2  value    2
3  value    3
4  value    4
```

DataFrame checks can be attached by using the `Config` class. Any field names that do not conflict with existing fields of `BaseConfig` and do not start with an underscore (`_`) are interpreted as the name of registered checks. If the value is a tuple or dict, it is interpreted as the positional or keyword arguments of the check, and as the first argument otherwise.

For example, to register zero, one, and two statistic dataframe checks one could do the following:

```
import pandera as pa
import pandera.extensions as extensions
import numpy as np
import pandas as pd

@extensions.register_check_method()
def is_small(df):
    return sum(df.shape) < 1000

@extensions.register_check_method(statistics=["fraction"])
def total_missing_fraction_less_than(df, *, fraction: float):
    return (1 - df.count().sum().item() / sum(df.shape)) < fraction

@extensions.register_check_method(statistics=["col_a", "col_b"])
def col_mean_a_greater_than_b(df, *, col_a: str, col_b: str):
    return df[col_a].mean() > df[col_b].mean()

from pandera.typing import Series
```

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```

class Schema(pa.SchemaModel):
    col1: Series[float] = pa.Field(nullable=True, ignore_na=False)
    col2: Series[float] = pa.Field(nullable=True, ignore_na=False)

    class Config:
        is_small = ()
        total_missing_fraction_less_than = 0.6
        col_mean_a_greater_than_b = {"col_a": "col2", "col_b": "col1"}

data = pd.DataFrame({
    "col1": [float('nan')] * 3 + [0.5, 0.3, 0.1],
    "col2": np.arange(6.),
})

print(Schema.validate(data))

```

```

  col1  col2
0   NaN   0.0
1   NaN   1.0
2   NaN   2.0
3   0.5   3.0
4   0.3   4.0
5   0.1   5.0

```

7.12 Data Format Conversion

new in 0.9.0

The class-based API provides configuration options for converting data to/from supported serialization formats in the context of `check_types()`-decorated functions.

Note: Currently, `pandera.typing.pandas.DataFrame` is the only data type that supports this feature.

Consider this simple example:

```

import pandera as pa
from pandera.typing import DataFrame, Series

class InSchema(pa.SchemaModel):
    str_col: Series[str] = pa.Field(unique=True, isin=["abcd"])
    int_col: Series[int]

class OutSchema(InSchema):
    float_col: pa.typing.Series[float]

@pa.check_types
def transform(df: DataFrame[InSchema]) -> DataFrame[OutSchema]:
    return df.assign(float_col=1.1)

```

With the schema type annotations and `check_types()` decorator, the `transform` function validates DataFrame inputs and outputs according to the `InSchema` and `OutSchema` definitions.

But what if your input data is serialized in parquet format, and you want to read it into memory, validate the DataFrame, and then pass it to a downstream function for further analysis? Similarly, what if you want the output of `transform` to be a list of dictionary records instead of a pandas DataFrame?

7.12.1 The `to/from_format` Configuration Options

To easily fulfill the use cases described above, you can implement the read/write logic by hand, or you can configure schemas to do so. We can first define a subclass of `InSchema` with additional configuration so that our `transform` function can read data directly from parquet files or buffers:

```
class InSchemaParquet(InSchema):
    class Config:
        from_format = "parquet"
```

Then, we define subclass of `OutSchema` to specify that `transform` should output a list of dictionaries representing the rows of the output dataframe.

```
class OutSchemaDict(OutSchema):
    class Config:
        to_format = "dict"
        to_format_kwargs = {"orient": "records"}
```

Note that the `{to/from}_format_kwargs` configuration option should be supplied with a dictionary of key-word arguments to be passed into the respective pandas `to_{format}` method.

Finally, we redefine our `transform` function:

```
@pa.check_types
def transform(df: DataFrame[InSchemaParquet]) -> DataFrame[OutSchemaDict]:
    return df.assign(float_col=1.1)
```

We can test this out using a buffer to store the parquet file.

Note: A string or path-like object representing the filepath to a parquet file would also be a valid input to `transform`.

```
import io
import json

buffer = io.BytesIO()
data = pd.DataFrame({"str_col": ["abc"], "int_col": range(3)})
data.to_parquet(buffer)
buffer.seek(0)

dict_output = transform(buffer)
print(json.dumps(dict_output, indent=4))
```

```
[
  {
    "str_col": "a",
```

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```
        "int_col": 0,
        "float_col": 1.1
    },
    {
        "str_col": "b",
        "int_col": 1,
        "float_col": 1.1
    },
    {
        "str_col": "c",
        "int_col": 2,
        "float_col": 1.1
    }
]
```

7.12.2 Takeaway

Data Format Conversion using the `{to/from}_format` configuration option can modify the behavior of `check_types()`-decorated functions to convert input data from a particular serialization format into a dataframe. Additionally, you can convert the output data from a dataframe to potentially another format.

This dovetails well with the *FastAPI Integration* for validating the inputs and outputs of app endpoints.

7.13 Supported DataFrame Libraries

Pandera started out as a pandas-specific dataframe validation library, and moving forward its core functionality will continue to support pandas. However, pandera's adoption has resulted in the realization that it can be a much more powerful tool by supporting other dataframe-like formats.

7.13.1 Domain-specific Data Validation

The pandas ecosystem provides support for *domain-specific data manipulation*, and by extension pandera can provide access to data types, methods, and data container types specific to these libraries.

<i>GeoPandas</i>	An extension of pandas that adds geospatial data processing capabilities.
------------------	---

7.13.1.1 Data Validation with GeoPandas

new in 0.9.0

GeoPandas is an extension of Pandas that adds support for geospatial data. You can use pandera to validate `GeoDataFrame()` and `GeoSeries()` objects directly. First, install pandera with the `geopandas` extra:

```
pip install pandera[geopandas]
```

Then you can use pandera schemas to validate geodataframes. In the example below we'll use the *class-based API* to define a `SchemaModel` for validation.

```

import geopandas as gpd
import pandas as pd
import pandera as pa
from shapely.geometry import Polygon

geo_schema = pa.DataFrameSchema({
    "geometry": pa.Column("geometry"),
    "region": pa.Column(str),
})

geo_df = gpd.GeoDataFrame({
    "geometry": [
        Polygon(((0, 0), (0, 1), (1, 1), (1, 0))),
        Polygon(((0, 0), (0, -1), (-1, -1), (-1, 0)))
    ],
    "region": ["NA", "SA"]
})

print(geo_schema.validate(geo_df))

```

```

                geometry region
0  POLYGON ((0.00000 0.00000, 0.00000 1.00000, 1....    NA
1  POLYGON ((0.00000 0.00000, 0.00000 -1.00000, -...    SA

```

You can also use the GeometryDtype data type in either instantiated or un-instantiated form:

```

geo_schema = pa.DataFrameSchema({
    "geometry": pa.Column(gpd.array.GeometryDtype),
    # or
    "geometry": pa.Column(gpd.array.GeometryDtype()),
})

```

If you want to validate-on-instantiation, you can use the GeoDataFrame generic type with the schema model defined above:

```

from pandera.typing import Series
from pandera.typing.geopandas import GeoDataFrame, GeoSeries

class Schema(pa.SchemaModel):
    geometry: GeoSeries
    region: Series[str]

# create a geodataframe that's validated on object initialization
df = GeoDataFrame[Schema](
    {
        'geometry': [
            Polygon(((0, 0), (0, 1), (1, 1), (1, 0))),
            Polygon(((0, 0), (0, -1), (-1, -1), (-1, 0)))
        ],
        'region': ['NA', 'SA']
    }
)

```

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```
)
print(df)
```

```

                                geometry region
0  POLYGON ((0.00000 0.00000, 0.00000 1.00000, 1....    NA
1  POLYGON ((0.00000 0.00000, 0.00000 -1.00000, -...
```

7.13.2 Scaling Up Data Validation

Pandera provides multiple ways of scaling up data validation to dataframes that don't fit into memory. Fortunately, pandera doesn't have to re-invent the wheel. Standing on shoulders of giants, it integrates with the existing ecosystem of libraries that allow you to perform validations on out-of-memory dataframes.

<i>Dask</i>	Apply pandera schemas to Dask dataframe partitions.
<i>Fugue</i>	Apply pandera schemas to distributed dataframe partitions with Fugue.
<i>Koalas [Deprecated]</i>	A pandas drop-in replacement, distributed using a Spark backend.
<i>Pyspark</i>	Exposes a <code>pyspark.pandas</code> module, distributed using a Spark backend.
<i>Modin</i>	A pandas drop-in replacement, distributed using a Ray or Dask backend.

7.13.2.1 Data Validation with Dask

new in 0.8.0

Dask is a distributed compute framework that offers a pandas-like dataframe API. You can use pandera to validate `DataFrame()` and `Series()` objects directly. First, install pandera with the dask extra:

```
pip install pandera[dask]
```

Then you can use pandera schemas to validate dask dataframes. In the example below we'll use the *class-based API* to define a `SchemaModel` for validation.

```
import dask.dataframe as dd
import pandas as pd
import pandera as pa

from pandera.typing.dask import DataFrame, Series

class Schema(pa.SchemaModel):
    state: Series[str]
    city: Series[str]
    price: Series[int] = pa.Field(in_range={"min_value": 5, "max_value": 20})

ddf = dd.from_pandas(
    pd.DataFrame(
        {
            'state': ['FL', 'FL', 'FL', 'CA', 'CA', 'CA'],
            'city': [
                'Orlando',
```

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```

        'Miami',
        'Tampa',
        'San Francisco',
        'Los Angeles',
        'San Diego',
    ],
    'price': [8, 12, 10, 16, 20, 18],
}
),
npartitions=2
)
pandera_ddf = Schema(ddf)

print(pandera_ddf)

```

```

Dask DataFrame Structure:
                state  city  price
npartitions=2
0              object  object  int64
3                ...    ...    ...
5                ...    ...    ...
Dask Name: validate, 4 tasks

```

As you can see, passing the dask dataframe into `Schema` will produce another dask dataframe which hasn't been evaluated yet. What this means is that pandera will only validate when the dask graph is evaluated.

```
print(pandera_ddf.compute())
```

```

state      city  price
0  FL      Orlando    8
1  FL      Miami     12
2  FL      Tampa     10
3  CA  San Francisco  16
4  CA   Los Angeles  20
5  CA   San Diego    18

```

You can also use the `check_types()` decorator to validate dask dataframes at runtime:

```

@pa.check_types
def function(ddf: DataFrame[Schema]) -> DataFrame[Schema]:
    return ddf[ddf["state"] == "CA"]

print(function(ddf).compute())

```

```

state      city  price
3  CA  San Francisco  16
4  CA   Los Angeles  20
5  CA   San Diego    18

```

And of course, you can use the object-based API to validate dask dataframes:

```

schema = pa.DataFrameSchema({
    "state": pa.Column(str),
    "city": pa.Column(str),
    "price": pa.Column(int, pa.Check.in_range(min_value=5, max_value=20))
})
print(schema(ddf).compute())

```

	state	city	price
0	FL	Orlando	8
1	FL	Miami	12
2	FL	Tampa	10
3	CA	San Francisco	16
4	CA	Los Angeles	20
5	CA	San Diego	18

7.13.2.2 Data Validation with Fugue

Validation on big data comes in two forms. The first is performing one set of validations on data that doesn't fit in memory. The second happens when a large dataset is comprised of multiple groups that require different validations. In pandas semantics, this would be the equivalent of a `groupby-validate` operation. This section will cover using pandera for both of these scenarios.

Pandera only supports pandas DataFrames at the moment. However, the same pandera code can be used on top of Spark or Dask engines with [Fugue](#). These computation engines allow validation to be performed in a distributed setting. Fugue is an open source abstraction layer that ports Python, pandas, and SQL code to Spark and Dask.

7.13.2.2.1 What is Fugue?

Fugue serves as an interface to distributed computing. Because of its non-invasive design, existing Python code can be scaled to a distributed setting without significant changes.

To run the example, Fugue needs to be installed separately. Using pip:

```
pip install fugue[spark]
```

This will also install PySpark because of the `spark` extra. Dask is available with the `dask` extra.

7.13.2.2.2 Example

In this example, a pandas DataFrame is created with `state`, `city` and `price` columns. Pandera will be used to validate that the `price` column values are within a certain range.

```

import pandas as pd

data = pd.DataFrame(
    {
        'state': ['FL', 'FL', 'FL', 'CA', 'CA', 'CA'],
        'city': [
            'Orlando', 'Miami', 'Tampa', 'San Francisco', 'Los Angeles', 'San Diego'
        ],
    }
)

```

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```

        'price': [8, 12, 10, 16, 20, 18],
    }
)
print(data)

```

```

  state      city  price
0  FL      Orlando    8
1  FL      Miami    12
2  FL      Tampa    10
3  CA  San Francisco  16
4  CA   Los Angeles  20
5  CA   San Diego    18

```

Validation is then applied using pandera. A `price_validation` function is created that runs the validation. None of this will be new.

```

from pandera import Column, DataFrameSchema, Check

price_check = DataFrameSchema(
    {"price": Column(int, Check.in_range(min_value=5,max_value=20))}
)

def price_validation(data:pd.DataFrame) -> pd.DataFrame:
    return price_check.validate(data)

```

The transform function in Fugue is the easiest way to use Fugue with existing Python functions as seen in the following code snippet. The first two arguments are the `DataFrame` and function to apply. The keyword argument `schema` is required because schema is strictly enforced in distributed settings. Here, the `schema` is simply `*` because no new columns are added.

The last part of the transform function is the engine. Here, the `SparkExecutionEngine` is used to run the code on top of Spark. Fugue also has a `DaskExecutionEngine`, and passing nothing uses the default pandas-based `ExecutionEngine`. Because the `SparkExecutionEngine` is used, the result becomes a Spark `DataFrame`.

```

from fugue import transform
from fugue_spark import SparkExecutionEngine

spark_df = transform(data, price_validation, schema="*", engine=SparkExecutionEngine)
spark_df.show()

```

```

+-----+-----+-----+
|state|      city|price|
+-----+-----+-----+
|  FL|   Orlando|   8|
|  FL|    Miami|  12|
|  FL|    Tampa|  10|
|  CA|San Francisco| 16|
|  CA| Los Angeles| 20|
|  CA|   San Diego| 18|
+-----+-----+-----+

```

7.13.2.2.3 Validation by Partition

There is an interesting use case that arises with bigger datasets. Frequently, there are logical groupings of data that require different validations. In the earlier sample data, the price range for the records with state FL is lower than the range for the state CA. Two `DataFrameSchema` will be created to reflect this. Notice their ranges for the `Check` differ.

```
price_check_FL = DataFrameSchema({
    "price": Column(int, Check.in_range(min_value=7,max_value=13)),
})

price_check_CA = DataFrameSchema({
    "price": Column(int, Check.in_range(min_value=15,max_value=21)),
})

price_checks = {'CA': price_check_CA, 'FL': price_check_FL}
```

A slight modification is needed to our `price_validation` function. Fugue will partition the whole dataset into multiple pandas DataFrames. Think of this as a `groupby`. By the time `price_validation` is used, it only contains the data for one state. The appropriate `DataFrameSchema` is pulled and then applied.

To partition our data by state, all we need to do is pass it into the `transform` function through the `partition` argument. This splits up the data across different workers before they each run the `price_validation` function. Again, this is like a `groupby-validation`.

```
def price_validation(df:pd.DataFrame) -> pd.DataFrame:
    location = df['state'].iloc[0]
    check = price_checks[location]
    check.validate(df)
    return df

spark_df = transform(data,
    price_validation,
    schema="*",
    partition=dict(by="state"),
    engine=SparkExecutionEngine)

spark_df.show()
```

```
SparkDataFrame
state:str|city:str                                |price:long
-----+-----+-----
CA      |San Francisco                                |16
CA      |Los Angeles                                  |20
CA      |San Diego                                    |18
FL      |Orlando                                       |8
FL      |Miami                                        |12
FL      |Tampa                                        |10
Total count: 6
```

Note: Because operations in a distributed setting are applied per partition, statistical validators will be applied on each partition rather than the global dataset. If no partitioning scheme is specified, Spark and Dask use default partitions. Be careful about using operations like `mean`, `min`, and `max` without partitioning beforehand.

All row-wise validations scale well with this set-up.

7.13.2.3 Data Validation with Koalas

Note: Koalas has been deprecated since version *0.10.0*. Please refer to the *pyspark page* for validating pyspark dataframes.

7.13.2.4 Data Validation with Pyspark (New)

new in 0.10.0

Pyspark is a distributed compute framework that offers a pandas drop-in replacement dataframe implementation via the `pyspark.pandas` API. You can use pandera to validate `DataFrame()` and `Series()` objects directly. First, install pandera with the `dask extra`:

```
pip install pandera[pyspark]
```

Then you can use pandera schemas to validate pyspark dataframes. In the example below we'll use the *class-based API* to define a `SchemaModel` for validation.

```
import pyspark.pandas as ps
import pandas as pd
import pandera as pa

from pandera.typing.pyspark import DataFrame, Series

class Schema(pa.SchemaModel):
    state: Series[str]
    city: Series[str]
    price: Series[int] = pa.Field(in_range={"min_value": 5, "max_value": 20})

# create a pyspark.pandas dataframe that's validated on object initialization
df = DataFrame[Schema](
    {
        'state': ['FL', 'FL', 'FL', 'CA', 'CA', 'CA'],
        'city': [
            'Orlando',
            'Miami',
            'Tampa',
            'San Francisco',
            'Los Angeles',
            'San Diego',
        ],
        'price': [8, 12, 10, 16, 20, 18],
    }
)
print(df)
```

```

state      city  price
0  FL      Orlando    8
1  FL      Miami     12
2  FL      Tampa     10
3  CA  San Francisco  16
4  CA  Los Angeles   20
5  CA  San Diego     18

```

You can also use the `check_types()` decorator to validate pyspark pandas dataframes at runtime:

```

@pa.check_types
def function(df: DataFrame[Schema]) -> DataFrame[Schema]:
    return df[df["state"] == "CA"]

print(function(df))

```

```

state      city  price
3  CA  San Francisco  16
4  CA  Los Angeles   20
5  CA  San Diego     18

```

And of course, you can use the object-based API to validate dask dataframes:

```

schema = pa.DataFrameSchema({
    "state": pa.Column(str),
    "city": pa.Column(str),
    "price": pa.Column(int, pa.Check.in_range(min_value=5, max_value=20))
})
print(schema(df))

```

```

state      city  price
0  FL      Orlando    8
1  FL      Miami     12
2  FL      Tampa     10
3  CA  San Francisco  16
4  CA  Los Angeles   20
5  CA  San Diego     18

```

7.13.2.5 Data Validation with Modin

new in 0.8.0

Modin is a distributed compute framework that offers a pandas drop-in replacement dataframe implementation. You can use pandera to validate `DataFrame()` and `Series()` objects directly. First, install pandera with the dask extra:

```

pip install pandera[modin]           # installs both ray and dask backends
pip install pandera[modin-ray]      # only ray backend
pip install pandera[modin-dask]     # only dask backend

```

Then you can use pandera schemas to validate modin dataframes. In the example below we'll use the *class-based API* to define a `SchemaModel` for validation.

```

import modin.pandas as pd
import pandas as pd
import pandera as pa

from pandera.typing.modin import DataFrame, Series

class Schema(pa.SchemaModel):
    state: Series[str]
    city: Series[str]
    price: Series[int] = pa.Field(in_range={"min_value": 5, "max_value": 20})

# create a modin dataframe that's validated on object initialization
df = DataFrame[Schema](
    {
        'state': ['FL', 'FL', 'FL', 'CA', 'CA', 'CA'],
        'city': [
            'Orlando',
            'Miami',
            'Tampa',
            'San Francisco',
            'Los Angeles',
            'San Diego',
        ],
        'price': [8, 12, 10, 16, 20, 18],
    }
)
print(df)

```

	state	city	price
0	FL	Orlando	8
1	FL	Miami	12
2	FL	Tampa	10
3	CA	San Francisco	16
4	CA	Los Angeles	20
5	CA	San Diego	18

You can also use the `check_types()` decorator to validate modin dataframes at runtime:

```

@pa.check_types
def function(df: DataFrame[Schema]) -> DataFrame[Schema]:
    return df[df["state"] == "CA"]

print(function(df))

```

	state	city	price
3	CA	San Francisco	16
4	CA	Los Angeles	20
5	CA	San Diego	18

And of course, you can use the object-based API to validate dask dataframes:

```
schema = pa.DataFrameSchema({
    "state": pa.Column(str),
    "city": pa.Column(str),
    "price": pa.Column(int, pa.Check.in_range(min_value=5, max_value=20))
})
print(schema(df))
```

```
state      city  price
0    FL      Orlando    8
1    FL      Miami     12
2    FL      Tampa     10
3    CA  San Francisco   16
4    CA   Los Angeles   20
5    CA      San Diego   18
```

Note: Don't see a library that you want supported? Check out the [github issues](#) to see if that library is in the roadmap. If it isn't, open up a [new issue](#) to add support for it!

7.14 Integrations

Pandera ships with integrations with other tools in the Python ecosystem, with the goal of interoperating with libraries that you know and love.

<i>FastAPI</i>	Use pandera SchemaModels in your FastAPI app
<i>Frictionless</i>	Convert frictionless schemas to pandera schemas
<i>Hypothesis</i>	Use the hypothesis library to generate valid data under your schema's constraints.
<i>Mypy</i>	Type-lint your pandas and pandera code with mypy for static type safety [experimental]
<i>Pydantic</i>	Use pandera SchemaModels when defining your pydantic BaseModel

7.14.1 FastAPI

new in 0.9.0

Since both FastAPI and Pandera integrates seamlessly with Pydantic, you can use the *SchemaModel* types to validate incoming or outgoing data with respect to your API endpoints.

7.14.1.1 Using SchemaModels to Validate Endpoint Inputs and Outputs

Suppose we want to process transactions, where each transaction has an *id* and *cost*. We can model this with a pandera schema model:

```
# pylint: skip-file
from typing import Optional

from pydantic import BaseModel, Field
```

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```
import pandera as pa

class Transactions(pa.SchemaModel):
    id: pa.typing.Series[int]
    cost: pa.typing.Series[float] = pa.Field(ge=0, le=1000)

    class Config:
        coerce = True
```

Also suppose that we expect our endpoint to add a name to the transaction data:

```
class TransactionsOut(Transactions):
    id: pa.typing.Series[int]
    cost: pa.typing.Series[float]
    name: pa.typing.Series[str]
```

Let's also assume that the output of the endpoint should be a list of dictionary records containing the named transactions data. We can do this easily with the `to_format` option in the schema model `BaseConfig`.

```
class TransactionsDictOut(TransactionsOut):
    class Config:
        to_format = "dict"
        to_format_kwargs = {"orient": "records"}
```

Note that the `to_format_kwargs` is a dictionary of key-word arguments to be passed into the respective pandas `to_{format}` method.

Next we'll create a FastAPI app and define a `/transactions/` POST endpoint:

```
from fastapi import FastAPI, File
from pandera.typing import DataFrame

app = FastAPI()

@app.post("/transactions/", response_model=DataFrame[TransactionsDictOut])
def create_transactions(transactions: DataFrame[Transactions]):
    output = transactions.assign(name="foo")
    ... # do other stuff, e.g. update backend database with transactions
    return output
```

7.14.1.2 Reading File Uploads

Similar to the `TransactionsDictOut` example to convert dataframes to a particular format as an endpoint response, pandera also provides a `from_format` schema model configuration option to read a dataframe from a particular serialization format.

```
class TransactionsParquet(Transactions):
    class Config:
        from_format = "parquet"
```

Let's also define a response model for the `/file/` upload endpoint:

```
class TransactionsJsonOut(TransactionsOut):
    class Config:
        to_format = "json"
        to_format_kwargs = {"orient": "records"}

class ResponseModel(BaseModel):
    filename: str
    df: pa.typing.DataFrame[TransactionsJsonOut]
```

In the next example, we use the pandera `UploadFile` type to upload a parquet file to the `/file/` POST endpoint and return a response containing the filename and the modified data in json format.

```
from pandera.typing.fastapi import UploadFile

@app.post("/file/", response_model=ResponseModel)
def create_upload_file(
    file: UploadFile[DataFrame[TransactionsParquet]] = File(...),
):
    return {
        "filename": file.filename,
        "df": file.data.assign(name="foo"),
    }
```

Pandera's `UploadFile` type is a subclass of FastAPI's `UploadFile` but it exposes a `.data` property containing the pandera-validated dataframe.

7.14.1.3 Takeaway

With the FastAPI and Pandera integration, you can use Pandera `SchemaModel` types to validate the dataframe inputs and outputs of your FastAPI endpoints.

7.14.2 Reading Third-Party Schema

new in 0.7.0

Pandera now accepts schema from other data validation frameworks. This requires a pandera installation with the `io` extension; please see the [installation](#) instructions for more details.

7.14.2.1 Frictionless Data Schema

Note: Please see the [Frictionless schema](#) documentation for more information on this standard.

`pandera.io.from_frictionless_schema(schema)`

Create a `DataFrameSchema` from either a frictionless json/yaml schema file saved on disk, or from a frictionless schema already loaded into memory.

Each field from the frictionless schema will be converted to a pandera column specification using `FrictionlessFieldParser` to map field characteristics to pandera column specifications.

Parameters `schema` (`Union[str, Path, Dict, Schema]`) – the frictionless schema object (or a string/Path to the location on disk of a schema specification) to parse.

Return type *DataFrameSchema*

Returns dataframe schema with frictionless field specs converted to pandera column checks and constraints for use as normal.

Example

Here, we're defining a very basic frictionless schema in memory before parsing it and then querying the resulting *DataFrameSchema* object as per any other Pandera schema:

```
>>> from pandera.io import from_frictionless_schema
>>>
>>> FRICTIONLESS_SCHEMA = {
...     "fields": [
...         {
...             "name": "column_1",
...             "type": "integer",
...             "constraints": {"minimum": 10, "maximum": 99}
...         },
...         {
...             "name": "column_2",
...             "type": "string",
...             "constraints": {"maxLength": 10, "pattern": "\S+"}
...         },
...     ],
...     "primaryKey": "column_1"
... }
>>> schema = from_frictionless_schema(FRICTIONLESS_SCHEMA)
>>> schema.columns["column_1"].checks
[<Check in_range: in_range(10, 99)>]
>>> schema.columns["column_1"].required
True
>>> schema.columns["column_1"].unique
True
>>> schema.columns["column_2"].checks
[<Check str_length: str_length(None, 10)>, <Check str_matches: str_matches(re.
↪ compile('^\S+$'))>]
```

under the hood, this uses the *FrictionlessFieldParser* class to parse each frictionless field (column):

class `pandera.io.FrictionlessFieldParser`(*field*, *primary_keys*)

Parses frictionless data schema field specifications so we can convert them to an equivalent Pandera *Column* schema.

For this implementation, we are using field names, constraints and types but leaving other frictionless parameters out (e.g. foreign keys, type formats, titles, descriptions).

Parameters

- **field** – a field object from a frictionless schema.
- **primary_keys** – the primary keys from a frictionless schema. These are used to ensure primary key fields are treated properly - no duplicates, no missing values etc.

property checks: `Optional[Dict]`

Convert a set of frictionless schema field constraints into checks.

This parses the standard set of frictionless constraints which can be found [here](#) and maps them into the equivalent pandera checks.

Return type `Optional[Dict]`

Returns a dictionary of pandera *Check* objects which capture the standard constraint logic of a frictionless schema field.

property coerce: `bool`

Determine whether values within this field should be coerced.

This currently returns `True` for all fields within a frictionless schema.

Return type `bool`

property dtype: `str`

Determine what type of field this is, so we can feed that into *DataType*. If no type is specified in the frictionless schema, we default to string values.

Return type `str`

Returns the pandas-compatible representation of this field type as a string.

property nullable: `bool`

Determine whether this field can contain missing values.

If a field is a primary key, this will return `False`.

Return type `bool`

property regex: `bool`

Determine whether this field name should be used for regex matches.

This currently returns `False` for all fields within a frictionless schema.

Return type `bool`

property required: `bool`

Determine whether this field must exist within the data.

This currently returns `True` for all fields within a frictionless schema.

Return type `bool`

to_pandera_column()

Export this field to a column spec dictionary.

Return type `Dict`

property unique: `bool`

Determine whether this field can contain duplicate values.

If a field is a primary key, this will return `True`.

Return type `bool`

7.14.3 Mypy

new in 0.8.0

Pandera integrates with mypy to provide static type-linting of dataframes, relying on [pandas-stubs](#) for typing information.

```
pip install pandera[mypy]
```

Then enable the plugin in your `mypy.ini` or `setug.cfg` file:

```
[mypy]
plugins = pandera.mypy
```

Note: Mypy static type-linting is supported for only pandas dataframes.

Warning: This functionality is experimental. Since the [pandas-stubs](#) type stub annotations don't always match the official [pandas effort to support type annotations](#), installing the `pandera[mypy]` extra may yield false positives in your pandas code, many of which are documented in `tests/mypy/modules`.

We encourage beta users to [file an issue](#) if they find any false positives or negatives being reported by mypy. A list of such issues can be found [here](#).

In the example below, we define a few schemas to see how type-linting with pandera works.

```
from typing import cast

import pandas as pd

import pandera as pa
from pandera.typing import DataFrame, Series

class Schema(pa.SchemaModel):
    id: Series[int]
    name: Series[str]

class SchemaOut(pa.SchemaModel):
    age: Series[int]

class AnotherSchema(pa.SchemaModel):
    id: Series[int]
    first_name: Series[str]
```

The mypy linter will complain if the output type of the function body doesn't match the function's return signature.

```
def fn(df: DataFrame[Schema]) -> DataFrame[SchemaOut]:
    return df.assign(age=30).pipe(DataFrame[SchemaOut]) # mypy okay
```

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```

def fn_pipe_incorrect_type(df: DataFrame[Schema]) -> DataFrame[SchemaOut]:
    return df.assign(age=30).pipe(DataFrame[AnotherSchema]) # mypy error
    # error: Argument 1 to "pipe" of "NDFrame" has incompatible type
    ↪ "Type[DataFrame[Any]]"; # noqa
    # expected "Union[Callable[..., DataFrame[SchemaOut]], Tuple[Callable[...],
    ↪ DataFrame[SchemaOut]], str]" [arg-type] # noqa

def fn_assign_copy(df: DataFrame[Schema]) -> DataFrame[SchemaOut]:
    return df.assign(age=30) # mypy error
    # error: Incompatible return value type (got "pandas.core.frame.DataFrame",
    # expected "pandera.typing.pandas.DataFrame[SchemaOut]") [return-value]

```

It'll also complain if the input type doesn't match the expected input type. Note that we're using the `pandera.typing.pandas.DataFrame` generic type to define dataframes that are validated against the `SchemaModel` type variable on initialization.

```

schema_df = DataFrame[Schema]({"id": [1], "name": ["foo"]})
pandas_df = pd.DataFrame({"id": [1], "name": ["foo"]})
another_df = DataFrame[AnotherSchema]({"id": [1], "first_name": ["foo"]})

fn(schema_df) # mypy okay

fn(pandas_df) # mypy error
# error: Argument 1 to "fn" has incompatible type "pandas.core.frame.DataFrame"; # noqa
# expected "pandera.typing.pandas.DataFrame[Schema]" [arg-type]

fn(another_df) # mypy error
# error: Argument 1 to "fn" has incompatible type "DataFrame[AnotherSchema]";
# expected "DataFrame[Schema]" [arg-type]

```

To make mypy happy with respect to the return type, you can either initialize a dataframe of the expected type:

```

def fn_pipe_dataframe(df: DataFrame[Schema]) -> DataFrame[SchemaOut]:
    return df.assign(age=30).pipe(DataFrame[SchemaOut]) # mypy okay

```

Note: If you use the approach above with the `check_types()` decorator, pandera will do its best to not to validate the dataframe twice if it's already been initialized with the `DataFrame[Schema](**data)` syntax.

Or use `typing.cast()` to indicate to mypy that the return value of the function is of the correct type.

```

def fn_cast_dataframe(df: DataFrame[Schema]) -> DataFrame[SchemaOut]:
    return cast(DataFrame[SchemaOut], df.assign(age=30)) # mypy okay

```

7.14.3.1 Limitations

An important caveat to static type-linting with pandera dataframe types is that, since pandas dataframes are mutable objects, there's no way for mypy to know whether a mutated instance of a `SchemaModel`-typed dataframe has the correct contents. Fortunately, we can simply rely on the `check_types()` decorator to verify that the output dataframe is valid.

Consider the examples below:

```
def fn_pipe_dataframe(df: DataFrame[Schema]) -> DataFrame[SchemaOut]:
    return df.assign(age=30).pipe(DataFrame[SchemaOut]) # mypy okay

def fn_cast_dataframe(df: DataFrame[Schema]) -> DataFrame[SchemaOut]:
    return cast(DataFrame[SchemaOut], df.assign(age=30)) # mypy okay

@pa.check_types
def fn_mutate_inplace(df: DataFrame[Schema]) -> DataFrame[SchemaOut]:
    out = df.assign(age=30).pipe(DataFrame[SchemaOut])
    out.drop(["age"], axis=1, inplace=True)
    return out # okay for mypy, pandera raises error

@pa.check_types
def fn_assign_and_get_index(df: DataFrame[Schema]) -> DataFrame[SchemaOut]:
    return df.assign(foo=30).iloc[:3] # okay for mypy, pandera raises error
```

Even though the outputs of these functions are incorrect, mypy doesn't catch the error during static type-linting but pandera will raise a `SchemaError` or `SchemaErrors` exception at runtime, depending on whether you're doing *lazy validation* or not.

```
@pa.check_types
def fn_cast_dataframe_invalid(df: DataFrame[Schema]) -> DataFrame[SchemaOut]:
    return cast(
        DataFrame[SchemaOut], df
    ) # okay for mypy, pandera raises error
```

7.14.4 Pydantic

new in 0.8.0

7.14.4.1 Using Pandera Schemas in Pydantic Models

`SchemaModel` is fully compatible with `pydantic`. You can specify a `SchemaModel` in a `pydantic BaseModel` as you would any other field:

```
import pandas as pd
import pandera as pa
from pandera.typing import DataFrame, Series
import pydantic
```

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```

class SimpleSchema(pa.SchemaModel):
    str_col: Series[str] = pa.Field(unique=True)

class PydanticModel(pydantic.BaseModel):
    x: int
    df: DataFrame[SimpleSchema]

valid_df = pd.DataFrame({"str_col": ["hello", "world"]})
PydanticModel(x=1, df=valid_df)

invalid_df = pd.DataFrame({"str_col": ["hello", "hello"]})
PydanticModel(x=1, df=invalid_df)

```

```

Traceback (most recent call last):
...
ValidationError: 1 validation error for PydanticModel
df
series 'str_col' contains duplicate values:
1    hello
Name: str_col, dtype: object (type=value_error)

```

Other pandera components are also compatible with pydantic:

Note: The `SeriesSchema`, `DataFrameSchema` and `schema_components` types validates the type of a schema object, e.g. if your pydantic `BaseModel` contained a schema object, not a pandas object.

- `SchemaModel`
- `DataFrameSchema`
- `SeriesSchema`
- `MultiIndex`
- `Column`
- `Index`

7.14.4.2 Using Pydantic Models in Pandera Schemas

new in 0.10.0

You can also use a pydantic `BaseModel` in a pandera schema. Suppose you had a `Record` model:

```

from pydantic import BaseModel

import pandera as pa

class Record(BaseModel):
    name: str

```

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```
xcoord: str
ycoord: int
```

The PydanticModel datatype enables you to specify the Record model as a row-wise type.

```
import pandas as pd
from pandera.engines.pandas_engine import PydanticModel

class PydanticSchema(pa.SchemaModel):
    """Pandera schema using the pydantic model."""

    class Config:
        """Config with dataframe-level data type."""

        dtype = PydanticModel(Record)
        coerce = True # this is required, otherwise a SchemaInitError is raised
```

Note: By combining `dtype=PydanticModel(...)` and `coerce=True`, pandera will apply the pydantic model validation process to each row of the dataframe, converting the model back to a dictionary with the `BaseModel.dict()` method.

The equivalent pandera schema would look like this:

```
class PanderaSchema(pa.SchemaModel):
    """Pandera schema that's equivalent to PydanticSchema."""

    name: pa.typing.Series[str]
    xcoord: pa.typing.Series[int]
    ycoord: pa.typing.Series[int]
```

Note: Since the PydanticModel datatype applies the BaseModel constructor to each row of the dataframe, using PydanticModel might not scale well with larger datasets.

If you want to help benchmark, consider [contributing a benchmark script](#)

Note: Don't see a library that you want supported? Check out the [github issues](#) to see if that library is in the roadmap. If it isn't, open up a [new issue](#) to add support for it!

7.15 API

<i>Core</i>	The core objects for defining pandera schemas
<i>Data Types</i>	Data types for type checking and coercion.
<i>Schema Models</i>	Alternative class-based API for defining pandera schemas.
<i>Decorators</i>	Decorators for integrating pandera schemas with python functions.
<i>Schema Inference</i>	Bootstrap schemas from real data
<i>IO Utilities</i>	Utility functions for reading/writing schemas
<i>Data Synthesis Strategies</i>	Module of functions for generating data from schemas.
<i>Extensions</i>	Utility functions for extending pandera functionality
<i>Errors</i>	Pandera-specific exceptions

7.15.1 Core

7.15.1.1 Schemas

<code>pandera.schemas.DataFrameSchema</code>	A light-weight pandas DataFrame validator.
<code>pandera.schemas.SeriesSchema</code>	Series validator.

7.15.1.1.1 `pandera.schemas.DataFrameSchema`

```
class pandera.schemas.DataFrameSchema(columns=None, checks=None, index=None, dtype=None,
coerce=False, strict=False, name=None, ordered=False,
unique=None, unique_column_names=False, title=None,
description=None)
```

A light-weight pandas DataFrame validator.

Initialize DataFrameSchema validator.

Parameters

- **columns** (*mapping of column names and column schema component.*) – a dict where keys are column names and values are Column objects specifying the datatypes and properties of a particular column.
- **checks** (*CheckList*) – dataframe-wide checks.
- **index** – specify the datatypes and properties of the index.
- **dtype** (*PandasDtypeInputTypes*) – datatype of the dataframe. This overrides the data types specified in any of the columns. If a string is specified, then assumes one of the valid pandas string values: <http://pandas.pydata.org/pandas-docs/stable/basics.html#dtypes>.
- **coerce** (*bool*) – whether or not to coerce all of the columns on validation. This has no effect on columns where `dtype=None`
- **strict** (*Union[bool, str]*) – ensure that all and only the columns defined in the schema are present in the dataframe. If set to ‘filter’, only the columns in the schema will be passed to the validated dataframe. If set to filter and columns defined in the schema are not present in the dataframe, will throw an error.
- **name** (*Optional[str]*) – name of the schema.
- **ordered** (*bool*) – whether or not to validate the columns order.

- **unique** (*Optional[Union[str, List[str]]*) – a list of columns that should be jointly unique.
- **unique_column_names** (*bool*) – whether or not column names must be unique.
- **title** (*Optional[str]*) – A human-readable label for the schema.
- **description** (*Optional[str]*) – An arbitrary textual description of the schema.

Raises *SchemaInitError* – if impossible to build schema from parameters

Examples

```
>>> import pandera as pa
>>>
>>> schema = pa.DataFrameSchema({
...     "str_column": pa.Column(str),
...     "float_column": pa.Column(float),
...     "int_column": pa.Column(int),
...     "date_column": pa.Column(pa.DateTime),
... })
```

Use the pandas API to define checks, which takes a function with the signature: `pd.Series -> Union[bool, pd.Series]` where the output series contains boolean values.

```
>>> schema_withchecks = pa.DataFrameSchema({
...     "probability": pa.Column(
...         float, pa.Check(lambda s: (s >= 0) & (s <= 1))),
...     # check that the "category" column contains a few discrete
...     # values, and the majority of the entries are dogs.
...     "category": pa.Column(
...         str, [
...             pa.Check(lambda s: s.isin(["dog", "cat", "duck"])),
...             pa.Check(lambda s: (s == "dog").mean() > 0.5),
...         ]),
... })
```

See [here](#) for more usage details.

Attributes

<code>coerce</code>	Whether to coerce series to specified type.
<code>description</code>	An arbitrary textual description of the schema.
<code>dtype</code>	Get the dtype property.
<code>dtypes</code>	A dict where the keys are column names and values are <i>DataTypes</i> for the column.
<code>ordered</code>	Whether or not to validate the columns order.
<code>title</code>	A human-readable label for the schema.
<code>unique</code>	List of columns that should be jointly unique.
<code>unique_column_names</code>	Whether multiple columns with the same name can be present.

Methods

<code>__init__</code>	Initialize <code>DataFrameSchema</code> validator.
<code>add_columns</code>	Create a copy of the <code>DataFrameSchema</code> with extra columns.
<code>coerce_dtype</code>	Coerce dataframe to the type specified in <code>dtype</code> .
<code>example</code>	Generate an example of a particular size.
<code>from_yaml</code>	Create <code>DataFrameSchema</code> from yaml file.
<code>get_dtypes</code>	Same as the <code>dtype</code> property, but expands columns where <code>regex == True</code> based on the supplied dataframe.
<code>remove_columns</code>	Removes columns from a <code>DataFrameSchema</code> and returns a new copy.
<code>rename_columns</code>	Rename columns using a dictionary of key-value pairs.
<code>reset_index</code>	A method for resetting the Index of a <code>DataFrameSchema</code>
<code>select_columns</code>	Select subset of columns in the schema.
<code>set_index</code>	A method for setting the Index of a <code>DataFrameSchema</code> , via an existing Column or list of columns.
<code>strategy</code>	Create a hypothesis strategy for generating a DataFrame.
<code>to_script</code>	Create <code>DataFrameSchema</code> from yaml file.
<code>to_yaml</code>	Write <code>DataFrameSchema</code> to yaml file.
<code>update_column</code>	Create copy of a <code>DataFrameSchema</code> with updated column properties.
<code>update_columns</code>	Create copy of a <code>DataFrameSchema</code> with updated column properties.
<code>validate</code>	Check if all columns in a dataframe have a column in the Schema.
<code>__call__</code>	Alias for <code>DataFrameSchema.validate()</code> method.

7.15.1.1.1.1 pandera.schemas.DataFrameSchema.__init__

`DataFrameSchema.__init__` (*columns=None, checks=None, index=None, dtype=None, coerce=False, strict=False, name=None, ordered=False, unique=None, unique_column_names=False, title=None, description=None*)

Initialize `DataFrameSchema` validator.

Parameters

- **columns** (*mapping of column names and column schema component.*) – a dict where keys are column names and values are `Column` objects specifying the datatypes and properties of a particular column.
- **checks** (*CheckList*) – dataframe-wide checks.
- **index** – specify the datatypes and properties of the index.
- **dtype** (*PandasDtypeInputTypes*) – datatype of the dataframe. This overrides the data types specified in any of the columns. If a string is specified, then assumes one of the valid pandas string values: <http://pandas.pydata.org/pandas-docs/stable/basics.html#dtypes>.

- **coerce** (*bool*) – whether or not to coerce all of the columns on validation. This has no effect on columns where `dtype=None`
- **strict** (*Union[bool, str]*) – ensure that all and only the columns defined in the schema are present in the dataframe. If set to ‘filter’, only the columns in the schema will be passed to the validated dataframe. If set to filter and columns defined in the schema are not present in the dataframe, will throw an error.
- **name** (*Optional[str]*) – name of the schema.
- **ordered** (*bool*) – whether or not to validate the columns order.
- **unique** (*Optional[Union[str, List[str]]]*) – a list of columns that should be jointly unique.
- **unique_column_names** (*bool*) – whether or not column names must be unique.
- **title** (*Optional[str]*) – A human-readable label for the schema.
- **description** (*Optional[str]*) – An arbitrary textual description of the schema.

Raises `SchemaInitError` – if impossible to build schema from parameters

Examples

```
>>> import pandera as pa
>>>
>>> schema = pa.DataFrameSchema({
...     "str_column": pa.Column(str),
...     "float_column": pa.Column(float),
...     "int_column": pa.Column(int),
...     "date_column": pa.Column(pa.DateTime),
... })
```

Use the pandas API to define checks, which takes a function with the signature: `pd.Series -> Union[bool, pd.Series]` where the output series contains boolean values.

```
>>> schema_withchecks = pa.DataFrameSchema({
...     "probability": pa.Column(
...         float, pa.Check(lambda s: (s >= 0) & (s <= 1))),
...     # check that the "category" column contains a few discrete
...     # values, and the majority of the entries are dogs.
...     "category": pa.Column(
...         str, [
...             pa.Check(lambda s: s.isin(["dog", "cat", "duck"])),
...             pa.Check(lambda s: (s == "dog").mean() > 0.5),
...         ]),
... })
```

See [here](#) for more usage details.

7.15.1.1.1.2 pandera.schemas.DataFrameSchema.add_columns

`DataFrameSchema.add_columns(extra_schema_cols)`

Create a copy of the `DataFrameSchema` with extra columns.

Parameters `extra_schema_cols` (`DataFrameSchema`) – Additional columns of the format

Return type `ForwardRef`

Returns a new `DataFrameSchema` with the `extra_schema_cols` added.

Example

To add columns to the schema, pass a dictionary with column name and `Column` instance key-value pairs.

```
>>> import pandera as pa
>>>
>>> example_schema = pa.DataFrameSchema(
...     {
...         "category": pa.Column(str),
...         "probability": pa.Column(float),
...     }
... )
>>> print(
...     example_schema.add_columns({"even_number": pa.Column(pa.Bool)})
... )
<Schema DataFrameSchema(
  columns={
    'category': <Schema Column(name=category, type=DataType(str))>
    'probability': <Schema Column(name=probability, type=DataType(float64))>
    'even_number': <Schema Column(name=even_number, type=DataType(bool))>
  },
  checks=[],
  coerce=False,
  dtype=None,
  index=None,
  strict=False
  name=None,
  ordered=False,
  unique_column_names=False
)>
```

See also:

`remove_columns()`

7.15.1.1.1.3 pandera.schemas.DataFrameSchema.coerce_dtype

`DataFrameSchema.coerce_dtype(obj)`

Coerce dataframe to the type specified in `dtype`.

Parameters `obj` (`DataFrame`) – dataframe to coerce.

Return type `DataFrame`

Returns dataframe with coerced dtypes

7.15.1.1.1.4 `pandera.schemas.DataFrameSchema.example`

`DataFrameSchema.example` (*size=None, n_regex_columns=1*)

Generate an example of a particular size.

Parameters `size` (`Optional[int]`) – number of elements in the generated DataFrame.

Return type `DataFrame`

Returns pandas DataFrame object.

7.15.1.1.1.5 `pandera.schemas.DataFrameSchema.from_yaml`

classmethod `DataFrameSchema.from_yaml` (*yaml_schema*)

Create `DataFrameSchema` from yaml file.

Parameters `yaml_schema` – str, Path to yaml schema, or serialized yaml string.

Return type `ForwardRef`

Returns dataframe schema.

7.15.1.1.1.6 `pandera.schemas.DataFrameSchema.get_dtypes`

`DataFrameSchema.get_dtypes` (*dataframe*)

Same as the `dtype` property, but expands columns where `regex == True` based on the supplied dataframe.

Return type `Dict[str, DataType]`

Returns dictionary of columns and their associated dtypes.

7.15.1.1.1.7 `pandera.schemas.DataFrameSchema.remove_columns`

`DataFrameSchema.remove_columns` (*cols_to_remove*)

Removes columns from a `DataFrameSchema` and returns a new copy.

Parameters `cols_to_remove` (`List`) – Columns to be removed from the `DataFrameSchema`

Return type `ForwardRef`

Returns a new `DataFrameSchema` without the `cols_to_remove`

Raises `SchemaInitError`: if column not in schema.

Example

To remove a column or set of columns from a schema, pass a list of columns to be removed:

```
>>> import pandera as pa
>>>
>>> example_schema = pa.DataFrameSchema(
...     {
...         "category" : pa.Column(str),
...         "probability": pa.Column(float)
...     }
... )
```

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```

>>>
>>> print(example_schema.remove_columns(["category"]))
<Schema DataFrameSchema(
  columns={
    'probability': <Schema Column(name=probability, type=DataType(float64))>
  },
  checks=[],
  coerce=False,
  dtype=None,
  index=None,
  strict=False
  name=None,
  ordered=False,
  unique_column_names=False
)>

```

See also:`add_columns()`

7.15.1.1.1.8 pandera.schemas.DataFrameSchema.rename_columns

`DataFrameSchema.rename_columns(rename_dict)`

Rename columns using a dictionary of key-value pairs.

Parameters `rename_dict` (`Dict[str, str]`) – dictionary of ‘old_name’: ‘new_name’ key-value pairs.**Return type** `ForwardRef`**Returns** `DataFrameSchema` (copy of original)**Raises** `SchemaInitError` if column not in the schema.**Example**

To rename a column or set of columns, pass a dictionary of old column names and new column names, similar to the pandas DataFrame method.

```

>>> import pandera as pa
>>>
>>> example_schema = pa.DataFrameSchema({
...     "category" : pa.Column(str),
...     "probability": pa.Column(float)
... })
>>>
>>> print(
...     example_schema.rename_columns({
...         "category": "categories",
...         "probability": "probabilities"
...     })
... )
<Schema DataFrameSchema(
  columns={

```

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```

        'categories': <Schema Column(name=categories, type=DataType(str))>
        'probabilities': <Schema Column(name=probabilities,
↳ type=DataType(float64))>
    },
    checks=[],
    coerce=False,
    dtype=None,
    index=None,
    strict=False
    name=None,
    ordered=False,
    unique_column_names=False
)>

```

See also:`update_column()`**7.15.1.1.1.9 pandera.schemas.DataFrameSchema.reset_index**`DataFrameSchema.reset_index(level=None, drop=False)`A method for resetting the Index of a *DataFrameSchema***Parameters**

- **level** (Optional[List[str]]) – list of labels
- **drop** (bool) – bool, default True

Return type `ForwardRef`**Returns** a new *DataFrameSchema* with specified column(s) in the index.**Raises** *SchemaInitError* if no index set in schema.**Examples**

Similar to the pandas `reset_index` method on a pandas `DataFrame`, this method can be used to to fully or partially reset indices of a schema.

To remove the entire index from the schema, just call the `reset_index` method with default parameters.

```

>>> import pandera as pa
>>>
>>> example_schema = pa.DataFrameSchema(
...     {"probability" : pa.Column(float)},
...     index = pa.Index(name="unique_id", dtype=int)
... )
>>>
>>> print(example_schema.reset_index())
<Schema DataFrameSchema(
  columns={
    'probability': <Schema Column(name=probability, type=DataType(float64))>
    'unique_id': <Schema Column(name=unique_id, type=DataType(int64))>
  },
  checks=[],

```

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```

coerce=False,
dtype=None,
index=None,
strict=False
name=None,
ordered=False,
unique_column_names=False
)>

```

This reclassifies an index (or indices) as a column (or columns).

Similarly, to partially alter the index, pass the name of the column you would like to be removed to the `level` parameter, and you may also decide whether to drop the levels with the `drop` parameter.

```

>>> example_schema = pa.DataFrameSchema({
...     "category" : pa.Column(str)},
...     index = pa.MultiIndex([
...         pa.Index(name="unique_id1", dtype=int),
...         pa.Index(name="unique_id2", dtype=str)
...     ]
... )
... )
>>> print(example_schema.reset_index(level = ["unique_id1"]))
<Schema DataFrameSchema(
  columns={
    'category': <Schema Column(name=category, type=DataType(str))>
    'unique_id1': <Schema Column(name=unique_id1, type=DataType(int64))>
  },
  checks=[],
  coerce=False,
  dtype=None,
  index=<Schema Index(name=unique_id2, type=DataType(str))>,
  strict=False
  name=None,
  ordered=False,
  unique_column_names=False
)>

```

See also:

[`set_index\(\)`](#)

7.15.1.1.10 `pandera.schemas.DataFrameSchema.select_columns`

`DataFrameSchema.select_columns(columns)`

Select subset of columns in the schema.

New in version 0.4.5

Parameters `columns` (`List[Any]`) – list of column names to select.

Return type `ForwardRef`

Returns `DataFrameSchema` (copy of original) with only the selected columns.

Raises *SchemaInitError* if column not in the schema.

Example

To subset a schema by column, and return a new schema:

```
>>> import pandera as pa
>>>
>>> example_schema = pa.DataFrameSchema({
...     "category" : pa.Column(str),
...     "probability": pa.Column(float)
... })
>>>
>>> print(example_schema.select_columns(['category']))
<Schema DataFrameSchema(
  columns={
    'category': <Schema Column(name=category, type=DataType(str))>
  },
  checks=[],
  coerce=False,
  dtype=None,
  index=None,
  strict=False
  name=None,
  ordered=False,
  unique_column_names=False
)>
```

Note: If an index is present in the schema, it will also be included in the new schema.

7.15.1.1.11 pandera.schemas.DataFrameSchema.set_index

`DataFrameSchema.set_index(keys, drop=True, append=False)`

A method for setting the Index of a *DataFrameSchema*, via an existing Column or list of columns.

Parameters

- **keys** (`List[str]`) – list of labels
- **drop** (`bool`) – bool, default True
- **append** (`bool`) – bool, default False

Return type `ForwardRef`

Returns a new *DataFrameSchema* with specified column(s) in the index.

Raises *SchemaInitError* if column not in the schema.

Examples

Just as you would set the index in a pandas DataFrame from an existing column, you can set an index within the schema from an existing column in the schema.

```

>>> import pandera as pa
>>>
>>> example_schema = pa.DataFrameSchema({
...     "category" : pa.Column(str),
...     "probability": pa.Column(float)})
>>>
>>> print(example_schema.set_index(['category']))
<Schema DataFrameSchema(
  columns={
    'probability': <Schema Column(name=probability, type=DataType(float64))>
  },
  checks=[],
  coerce=False,
  dtype=None,
  index=<Schema Index(name=category, type=DataType(str))>,
  strict=False
  name=None,
  ordered=False,
  unique_column_names=False
)>

```

If you have an existing index in your schema, and you would like to append a new column as an index to it (yielding a Multiindex), just use `set_index` as you would in pandas.

```

>>> example_schema = pa.DataFrameSchema(
...     {
...         "column1": pa.Column(str),
...         "column2": pa.Column(int)
...     },
...     index=pa.Index(name = "column3", dtype = int)
... )
>>>
>>> print(example_schema.set_index(["column2"], append = True))
<Schema DataFrameSchema(
  columns={
    'column1': <Schema Column(name=column1, type=DataType(str))>
  },
  checks=[],
  coerce=False,
  dtype=None,
  index=<Schema MultiIndex(
    indexes=[
      <Schema Index(name=column3, type=DataType(int64))>
      <Schema Index(name=column2, type=DataType(int64))>
    ]
    coerce=False,
    strict=False,
    name=None,
    ordered=True
  )>,
  strict=False
  name=None,
  ordered=False,

```

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```
unique_column_names=False
)>
```

See also:`reset_index()`

7.15.1.1.1.12 `pandera.schemas.DataFrameSchema.strategy`

`DataFrameSchema.strategy(*, size=None, n_regex_columns=1)`

Create a hypothesis strategy for generating a DataFrame.

Parameters

- **size** (`Optional[int]`) – number of elements to generate
- **n_regex_columns** (`int`) – number of regex columns to generate.

Returns a strategy that generates pandas DataFrame objects.

7.15.1.1.1.13 `pandera.schemas.DataFrameSchema.to_script`

`DataFrameSchema.to_script(fp=None)`

Create DataFrameSchema from yaml file.

Parameters `path` – str, Path to write script**Return type** `ForwardRef`**Returns** dataframe schema.

7.15.1.1.1.14 `pandera.schemas.DataFrameSchema.to_yaml`

`DataFrameSchema.to_yaml(stream: None = None) → str``DataFrameSchema.to_yaml(stream: os.PathLike) → None`

Write DataFrameSchema to yaml file.

Parameters `stream` (`Optional[PathLike]`) – file stream to write to. If None, dumps to string.**Return type** `Optional[str]`**Returns** yaml string if stream is None, otherwise returns None.

7.15.1.1.1.15 `pandera.schemas.DataFrameSchema.update_column`

`DataFrameSchema.update_column(column_name, **kwargs)`Create copy of a `DataFrameSchema` with updated column properties.**Parameters**

- **column_name** (`str`) –
- **kwargs** – key-word arguments supplied to `Column`

Return type `ForwardRef`

Returns a new *DataFrameSchema* with updated column

Raises *SchemaInitError*: if column not in schema or you try to change the name.

Example

Calling `schema.1` returns the *DataFrameSchema* with the updated column.

```
>>> import pandera as pa
>>>
>>> example_schema = pa.DataFrameSchema({
...     "category" : pa.Column(str),
...     "probability": pa.Column(float)
... })
>>> print(
...     example_schema.update_column(
...         'category', dtype=pa.Category
...     )
... )
<Schema DataFrameSchema(
  columns={
    'category': <Schema Column(name=category, type=DataType(category))>
    'probability': <Schema Column(name=probability, type=DataType(float64))>
  },
  checks=[],
  coerce=False,
  dtype=None,
  index=None,
  strict=False
  name=None,
  ordered=False,
  unique_column_names=False
)>
```

See also:

`rename_columns()`

7.15.1.1.16 `pandera.schemas.DataFrameSchema.update_columns`

`DataFrameSchema.update_columns(update_dict)`

Create copy of a *DataFrameSchema* with updated column properties.

Parameters `update_dict` (`Dict[str, Dict[str, Any]]`) –

Return type `ForwardRef`

Returns a new *DataFrameSchema* with updated columns

Raises *SchemaInitError*: if column not in schema or you try to change the name.

Example

Calling `schema.update_columns` returns the *DataFrameSchema* with the updated columns.

```
>>> import pandera as pa
>>>
```

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```

>>> example_schema = pa.DataFrameSchema({
...     "category" : pa.Column(str),
...     "probability": pa.Column(float)
... })
>>>
>>> print(
...     example_schema.update_columns(
...         {"category": {"dtype":pa.Category}}
...     )
... )
<Schema DataFrameSchema(
  columns={
    'category': <Schema Column(name=category, type=DataType(category))>
    'probability': <Schema Column(name=probability, type=DataType(float64))>
  },
  checks=[],
  coerce=False,
  dtype=None,
  index=None,
  strict=False
  name=None,
  ordered=False,
  unique_column_names=False
)>

```

7.15.1.1.17 pandera.schemas.DataFrameSchema.validate

`DataFrameSchema.validate`(*check_obj*, *head=None*, *tail=None*, *sample=None*, *random_state=None*, *lazy=False*, *inplace=False*)

Check if all columns in a dataframe have a column in the Schema.

Parameters

- **check_obj** (*pd.DataFrame*) – the dataframe to be validated.
- **head** (*Optional[int]*) – validate the first *n* rows. Rows overlapping with *tail* or *sample* are de-duplicated.
- **tail** (*Optional[int]*) – validate the last *n* rows. Rows overlapping with *head* or *sample* are de-duplicated.
- **sample** (*Optional[int]*) – validate a random sample of *n* rows. Rows overlapping with *head* or *tail* are de-duplicated.
- **random_state** (*Optional[int]*) – random seed for the *sample* argument.
- **lazy** (*bool*) – if True, lazily evaluates dataframe against all validation checks and raises a `SchemaErrors`. Otherwise, raise `SchemaError` as soon as one occurs.
- **inplace** (*bool*) – if True, applies coercion to the object of validation, otherwise creates a copy of the data.

Return type `DataFrame`

Returns validated `DataFrame`

Raises *SchemaError* – when DataFrame violates built-in or custom checks.

Example

Calling `schema.validate` returns the dataframe.

```
>>> import pandas as pd
>>> import pandera as pa
>>>
>>> df = pd.DataFrame({
...     "probability": [0.1, 0.4, 0.52, 0.23, 0.8, 0.76],
...     "category": ["dog", "dog", "cat", "duck", "dog", "dog"]
... })
>>>
>>> schema_withchecks = pa.DataFrameSchema({
...     "probability": pa.Column(
...         float, pa.Check(lambda s: (s >= 0) & (s <= 1))),
...     # check that the "category" column contains a few discrete
...     # values, and the majority of the entries are dogs.
...     "category": pa.Column(
...         str, [
...             pa.Check(lambda s: s.isin(["dog", "cat", "duck"])),
...             pa.Check(lambda s: (s == "dog").mean() > 0.5),
...         ]),
... })
>>>
>>> schema_withchecks.validate(df)[["probability", "category"]]
probability category
0          0.10      dog
1          0.40      dog
2          0.52      cat
3          0.23      duck
4          0.80      dog
5          0.76      dog
```

7.15.1.1.18 pandera.schemas.DataFrameSchema.__call__

`DataFrameSchema.__call__(dataframe, head=None, tail=None, sample=None, random_state=None, lazy=False, inplace=False)`

Alias for `DataFrameSchema.validate()` method.

Parameters

- **dataframe** (*pd.DataFrame*) – the dataframe to be validated.
- **head** (*int*) – validate the first n rows. Rows overlapping with *tail* or *sample* are de-duplicated.
- **tail** (*int*) – validate the last n rows. Rows overlapping with *head* or *sample* are de-duplicated.
- **sample** (*Optional[int]*) – validate a random sample of n rows. Rows overlapping with *head* or *tail* are de-duplicated.
- **random_state** (*Optional[int]*) – random seed for the sample argument.

- **lazy** (`bool`) – if True, lazily evaluates dataframe against all validation checks and raises a `SchemaErrors`. Otherwise, raise `SchemaError` as soon as one occurs.
- **inplace** (`bool`) – if True, applies coercion to the object of validation, otherwise creates a copy of the data.

7.15.1.1.2 pandera.schemas.SeriesSchema

```
class pandera.schemas.SeriesSchema(dtype=None, checks=None, index=None, nullable=False,
                                     unique=False, coerce=False, name=None, title=None,
                                     description=None)
```

Series validator.

Initialize series schema base object.

Parameters

- **dtype** (`Union[str, type, DataType, Type, ExtensionDtype, dtype, None]`) – datatype of the column. If a string is specified, then assumes one of the valid pandas string values: <http://pandas.pydata.org/pandas-docs/stable/basics.html#dtypes>
- **checks** (`Union[Check, Hypothesis, List[Union[Check, Hypothesis]], None]`) – If `element_wise` is True, then callable signature should be:
`Callable[Any, bool]` where the `Any` input is a scalar element in the column. Otherwise, the input is assumed to be a `pandas.Series` object.
- **index** – specify the datatypes and properties of the index.
- **nullable** (`bool`) – Whether or not column can contain null values.
- **unique** (`bool`) – Whether or not column can contain duplicate values.
- **coerce** (`bool`) – If True, when `schema.validate` is called the column will be coerced into the specified dtype. This has no effect on columns where `dtype=None`.
- **name** (`Optional[str]`) – series name.
- **title** (`Optional[str]`) – A human-readable label for the series.
- **description** (`Optional[str]`) – An arbitrary textual description of the series.

Attributes

<code>checks</code>	Return list of checks or hypotheses.
<code>coerce</code>	Whether to coerce series to specified type.
<code>description</code>	An arbitrary textual description of the series.
<code>dtype</code>	Get the pandas dtype
<code>name</code>	Get <code>SeriesSchema</code> name.
<code>nullable</code>	Whether the series is nullable.
<code>title</code>	A human-readable label for the series.
<code>unique</code>	Whether to check for duplicates in check object

Methods

<code>__init__</code>	Initialize series schema base object.
<code>validate</code>	Validate a Series object.
<code>__call__</code>	Alias for <code>SeriesSchema.validate()</code> method.

7.15.1.1.2.1 pandera.schemas.SeriesSchema.__init__

`SeriesSchema.__init__(dtype=None, checks=None, index=None, nullable=False, unique=False, coerce=False, name=None, title=None, description=None)`

Initialize series schema base object.

Parameters

- **dtype** (`Union[str, type, DataType, Type, ExtensionDtype, dtype, None]`) – datatype of the column. If a string is specified, then assumes one of the valid pandas string values: <http://pandas.pydata.org/pandas-docs/stable/basics.html#dtypes>
- **checks** (`Union[Check, Hypothesis, List[Union[Check, Hypothesis]], None]`) – If `element_wise` is `True`, then callable signature should be:
`Callable[Any, bool]` where the `Any` input is a scalar element in the column. Otherwise, the input is assumed to be a `pandas.Series` object.
- **index** – specify the datatypes and properties of the index.
- **nullable** (`bool`) – Whether or not column can contain null values.
- **unique** (`bool`) – Whether or not column can contain duplicate values.
- **coerce** (`bool`) – If `True`, when `schema.validate` is called the column will be coerced into the specified dtype. This has no effect on columns where `dtype=None`.
- **name** (`Optional[str]`) – series name.
- **title** (`Optional[str]`) – A human-readable label for the series.
- **description** (`Optional[str]`) – An arbitrary textual description of the series.

7.15.1.1.2.2 pandera.schemas.SeriesSchema.validate

`SeriesSchema.validate(check_obj, head=None, tail=None, sample=None, random_state=None, lazy=False, inplace=False)`

Validate a Series object.

Parameters

- **check_obj** (`Series`) – One-dimensional ndarray with axis labels (including time series).
- **head** (`Optional[int]`) – validate the first `n` rows. Rows overlapping with `tail` or `sample` are de-duplicated.
- **tail** (`Optional[int]`) – validate the last `n` rows. Rows overlapping with `head` or `sample` are de-duplicated.
- **sample** (`Optional[int]`) – validate a random sample of `n` rows. Rows overlapping with `head` or `tail` are de-duplicated.
- **random_state** (`Optional[int]`) – random seed for the `sample` argument.

- **lazy** (`bool`) – if True, lazily evaluates dataframe against all validation checks and raises a `SchemaErrors`. Otherwise, raise `SchemaError` as soon as one occurs.
- **inplace** (`bool`) – if True, applies coercion to the object of validation, otherwise creates a copy of the data.

Return type `Series`

Returns validated `Series`.

Raises `SchemaError` – when `DataFrame` violates built-in or custom checks.

Example

```
>>> import pandas as pd
>>> import pandera as pa
>>>
>>> series_schema = pa.SeriesSchema(
...     float, [
...         pa.Check(lambda s: s > 0),
...         pa.Check(lambda s: s < 1000),
...         pa.Check(lambda s: s.mean() > 300),
...     ])
>>> series = pd.Series([1, 100, 800, 900, 999], dtype=float)
>>> print(series_schema.validate(series))
0      1.0
1    100.0
2    800.0
3    900.0
4    999.0
dtype: float64
```

7.15.1.1.2.3 `pandera.schemas.SeriesSchema.__call__`

`SeriesSchema.__call__(check_obj, head=None, tail=None, sample=None, random_state=None, lazy=False, inplace=False)`

Alias for `SeriesSchema.validate()` method.

Return type `Series`

7.15.1.2 Schema Components

<code>pandera.schema_components.Column</code>	Validate types and properties of <code>DataFrame</code> columns.
<code>pandera.schema_components.Index</code>	Validate types and properties of a <code>DataFrame</code> Index.
<code>pandera.schema_components.MultiIndex</code>	Validate types and properties of a <code>DataFrame</code> <code>MultiIndex</code> .

7.15.1.2.1 pandera.schema_components.Column

```
class pandera.schema_components.Column(dtype=None, checks=None, nullable=False, unique=False,
                                       coerce=False, required=True, name=None, regex=False,
                                       title=None, description=None)
```

Validate types and properties of DataFrame columns.

Create column validator object.

Parameters

- **dtype** (`Union[str, type, DataType, Type, ExtensionDtype, dtype, None]`) – datatype of the column. The datatype for type-checking a dataframe. If a string is specified, then assumes one of the valid pandas string values: <http://pandas.pydata.org/pandas-docs/stable/basics.html#dtypes>
- **checks** (`Union[Check, Hypothesis, List[Union[Check, Hypothesis]], None]`) – checks to verify validity of the column
- **nullable** (`bool`) – Whether or not column can contain null values.
- **unique** (`bool`) – whether column values should be unique
- **coerce** (`bool`) – If True, when `schema.validate` is called the column will be coerced into the specified dtype. This has no effect on columns where `dtype=None`.
- **required** (`bool`) – Whether or not column is allowed to be missing
- **name** (`Union[str, Tuple[str, ...], None]`) – column name in dataframe to validate.
- **regex** (`bool`) – whether the name attribute should be treated as a regex pattern to apply to multiple columns in a dataframe.
- **title** (`Optional[str]`) – A human-readable label for the column.
- **description** (`Optional[str]`) – An arbitrary textual description of the column.

Raises `SchemaInitError` – if impossible to build schema from parameters

Example

```
>>> import pandas as pd
>>> import pandera as pa
>>>
>>>
>>> schema = pa.DataFrameSchema({
...     "column": pa.Column(str)
... })
>>>
>>> schema.validate(pd.DataFrame({"column": ["foo", "bar"]}))
   column
0    foo
1    bar
```

See [here](#) for more usage details.

Attributes

<code>checks</code>	Return list of checks or hypotheses.
<code>coerce</code>	Whether to coerce series to specified type.
<code>description</code>	An arbitrary textual description of the series.
<code>dtype</code>	Get the pandas dtype
<code>name</code>	Get SeriesSchema name.
<code>nullable</code>	Whether the series is nullable.
<code>properties</code>	Get column properties.
<code>regex</code>	True if <code>name</code> attribute should be treated as a regex pattern.
<code>title</code>	A human-readable label for the series.
<code>unique</code>	Whether to check for duplicates in check object

Methods

<code>__init__</code>	Create column validator object.
<code>coerce_dtype</code>	Coerce dtype of a column, handling duplicate column names.
<code>example</code>	Generate an example of a particular size.
<code>get_regex_columns</code>	Get matching column names based on regex column name pattern.
<code>set_name</code>	Used to set or modify the name of a column object.
<code>strategy</code>	Create a hypothesis strategy for generating a Column.
<code>strategy_component</code>	Generate column data object for use by DataFrame strategy.
<code>validate</code>	Validate a Column in a DataFrame object.
<code>__call__</code>	Alias for <code>validate</code> method.

7.15.1.2.1.1 `pandera.schema_components.Column.__init__`

`Column.__init__(dtype=None, checks=None, nullable=False, unique=False, coerce=False, required=True, name=None, regex=False, title=None, description=None)`

Create column validator object.

Parameters

- **dtype** (`Union[str, type, DataType, Type, ExtensionDtype, dtype, None]`) – datatype of the column. The datatype for type-checking a dataframe. If a string is specified, then assumes one of the valid pandas string values: <http://pandas.pydata.org/pandas-docs/stable/basics.html#dtypes>
- **checks** (`Union[Check, Hypothesis, List[Union[Check, Hypothesis]], None]`) – checks to verify validity of the column
- **nullable** (`bool`) – Whether or not column can contain null values.
- **unique** (`bool`) – whether column values should be unique
- **coerce** (`bool`) – If True, when `schema.validate` is called the column will be coerced into the specified dtype. This has no effect on columns where `dtype=None`.

- **required** (`bool`) – Whether or not column is allowed to be missing
- **name** (`Union[str, Tuple[str, ...], None]`) – column name in dataframe to validate.
- **regex** (`bool`) – whether the name attribute should be treated as a regex pattern to apply to multiple columns in a dataframe.
- **title** (`Optional[str]`) – A human-readable label for the column.
- **description** (`Optional[str]`) – An arbitrary textual description of the column.

Raises `SchemaInitError` – if impossible to build schema from parameters

Example

```
>>> import pandas as pd
>>> import pandera as pa
>>>
>>>
>>> schema = pa.DataFrameSchema({
...     "column": pa.Column(str)
... })
>>>
>>> schema.validate(pd.DataFrame({"column": ["foo", "bar"]}))
   column
0     foo
1     bar
```

See [here](#) for more usage details.

7.15.1.2.1.2 `pandera.schema_components.Column.coerce_dtype`

`Column.coerce_dtype(obj)`

Coerce dtype of a column, handling duplicate column names.

7.15.1.2.1.3 `pandera.schema_components.Column.example`

`Column.example(size=None)`

Generate an example of a particular size.

Parameters `size` – number of elements in the generated Index.

Return type `DataFrame`

Returns pandas DataFrame object.

7.15.1.2.1.4 `pandera.schema_components.Column.get_regex_columns`

`Column.get_regex_columns(columns)`

Get matching column names based on regex column name pattern.

Parameters `columns` (`Union[Index, MultiIndex]`) – columns to regex pattern match

Return type `Union[Index, MultiIndex]`

Returns matching columns

7.15.1.2.1.5 `pandera.schema_components.Column.set_name`

`Column.set_name(name)`

Used to set or modify the name of a column object.

Parameters `name` (`str`) – the name of the column object

7.15.1.2.1.6 `pandera.schema_components.Column.strategy`

`Column.strategy(*, size=None)`

Create a hypothesis strategy for generating a Column.

Parameters `size` – number of elements to generate

Returns a dataframe strategy for a single column.

7.15.1.2.1.7 `pandera.schema_components.Column.strategy_component`

`Column.strategy_component()`

Generate column data object for use by DataFrame strategy.

7.15.1.2.1.8 `pandera.schema_components.Column.validate`

`Column.validate(check_obj, head=None, tail=None, sample=None, random_state=None, lazy=False, inplace=False)`

Validate a Column in a DataFrame object.

Parameters

- **check_obj** (`DataFrame`) – pandas DataFrame to validate.
- **head** (`Optional[int]`) – validate the first n rows. Rows overlapping with `tail` or `sample` are de-duplicated.
- **tail** (`Optional[int]`) – validate the last n rows. Rows overlapping with `head` or `sample` are de-duplicated.
- **sample** (`Optional[int]`) – validate a random sample of n rows. Rows overlapping with `head` or `tail` are de-duplicated.
- **random_state** (`Optional[int]`) – random seed for the `sample` argument.
- **lazy** (`bool`) – if True, lazily evaluates dataframe against all validation checks and raises a `SchemaErrors`. Otherwise, raise `SchemaError` as soon as one occurs.

- **inplace** (*bool*) – if True, applies coercion to the object of validation, otherwise creates a copy of the data.

Return type `DataFrame`

Returns validated `DataFrame`.

7.15.1.2.1.9 `pandera.schema_components.Column.__call__`

`Column.__call__`(*check_obj*, *head=None*, *tail=None*, *sample=None*, *random_state=None*, *lazy=False*, *inplace=False*)

Alias for `validate` method.

Return type `Union[DataFrame, Series]`

7.15.1.2.2 `pandera.schema_components.Index`

class `pandera.schema_components.Index`(*dtype=None*, *checks=None*, *nullable=False*, *unique=False*, *coerce=False*, *name=None*, *title=None*, *description=None*)

Validate types and properties of a `DataFrame` `Index`.

Initialize series schema base object.

Parameters

- **dtype** (`Union[str, type, DataType, Type, ExtensionDtype, dtype, None]`) – datatype of the column. If a string is specified, then assumes one of the valid pandas string values: <http://pandas.pydata.org/pandas-docs/stable/basics.html#dtypes>
- **checks** (`Union[Check, Hypothesis, List[Union[Check, Hypothesis]], None]`) – If `element_wise` is True, then callable signature should be:
`Callable[Any, bool]` where the `Any` input is a scalar element in the column. Otherwise, the input is assumed to be a `pandas.Series` object.
- **nullable** (*bool*) – Whether or not column can contain null values.
- **unique** (*bool*) – Whether or not column can contain duplicate values.
- **coerce** (*bool*) – If True, when `schema.validate` is called the column will be coerced into the specified dtype. This has no effect on columns where `dtype=None`.
- **name** (`Optional[Any]`) – column name in dataframe to validate.
- **title** (`Optional[str]`) – A human-readable label for the series.
- **description** (`Optional[str]`) – An arbitrary textual description of the series.

Attributes

<code>checks</code>	Return list of checks or hypotheses.
<code>coerce</code>	Whether to coerce series to specified type.
<code>description</code>	An arbitrary textual description of the series.
<code>dtype</code>	Get the pandas dtype
<code>name</code>	Get SeriesSchema name.
<code>names</code>	Get index names in the Index schema component.
<code>nullable</code>	Whether the series is nullable.
<code>title</code>	A human-readable label for the series.
<code>unique</code>	Whether to check for duplicates in check object

Methods

<code>example</code>	Generate an example of a particular size.
<code>strategy</code>	Create a hypothesis strategy for generating an Index.
<code>strategy_component</code>	Generate column data object for use by MultiIndex strategy.
<code>validate</code>	Validate DataFrameSchema or SeriesSchema Index.
<code>__call__</code>	Alias for <code>validate</code> method.

7.15.1.2.2.1 `pandera.schema_components.Index.example`

`Index.example(size=None)`

Generate an example of a particular size.

Parameters `size` (`Optional[int]`) – number of elements in the generated Index.

Return type `Index`

Returns pandas Index object.

7.15.1.2.2.2 `pandera.schema_components.Index.strategy`

`Index.strategy(*, size=None)`

Create a hypothesis strategy for generating an Index.

Parameters `size` (`Optional[int]`) – number of elements to generate.

Returns index strategy.

7.15.1.2.2.3 pandera.schema_components.Index.strategy_component

`Index.strategy_component()`

Generate column data object for use by MultiIndex strategy.

7.15.1.2.2.4 pandera.schema_components.Index.validate

`Index.validate(check_obj, head=None, tail=None, sample=None, random_state=None, lazy=False, inplace=False)`

Validate DataFrameSchema or SeriesSchema Index.

Check_obj pandas DataFrame of Series containing index to validate.

Parameters

- **head** (`Optional[int]`) – validate the first n rows. Rows overlapping with *tail* or *sample* are de-duplicated.
- **tail** (`Optional[int]`) – validate the last n rows. Rows overlapping with *head* or *sample* are de-duplicated.
- **sample** (`Optional[int]`) – validate a random sample of n rows. Rows overlapping with *head* or *tail* are de-duplicated.
- **random_state** (`Optional[int]`) – random seed for the *sample* argument.
- **lazy** (`bool`) – if True, lazily evaluates dataframe against all validation checks and raises a `SchemaErrors`. Otherwise, raise `SchemaError` as soon as one occurs.
- **inplace** (`bool`) – if True, applies coercion to the object of validation, otherwise creates a copy of the data.

Return type `Union[DataFrame, Series]`

Returns validated DataFrame or Series.

7.15.1.2.2.5 pandera.schema_components.Index.__call__

`Index.__call__(check_obj, head=None, tail=None, sample=None, random_state=None, lazy=False, inplace=False)`

Alias for validate method.

Return type `Union[DataFrame, Series]`

7.15.1.2.3 pandera.schema_components.MultiIndex

`class pandera.schema_components.MultiIndex(indexes, coerce=False, strict=False, name=None, ordered=True, unique=None)`

Validate types and properties of a DataFrame MultiIndex.

This class inherits from `DataFrameSchema` to leverage its validation logic.

Create MultiIndex validator.

Parameters

- **indexes** (`List[Index]`) – list of Index validators for each level of the MultiIndex index.

- **coerce** (`bool`) – Whether or not to coerce the MultiIndex to the specified dtypes before validation
- **strict** (`bool`) – whether or not to accept columns in the MultiIndex that aren't defined in the `indexes` argument.
- **name** (`Optional[str]`) – name of schema component
- **ordered** (`bool`) – whether or not to validate the indexes order.
- **unique** (`Union[str, List[str], None]`) – a list of index names that should be jointly unique.

Example

```
>>> import pandas as pd
>>> import pandera as pa
>>>
>>>
>>> schema = pa.DataFrameSchema(
...     columns={"column": pa.Column(int)},
...     index=pa.MultiIndex([
...         pa.Index(str,
...             pa.Check(lambda s: s.isin(["foo", "bar"]))),
...         name="index0"),
...         pa.Index(int, name="index1"),
...     ])
... )
>>>
>>> df = pd.DataFrame(
...     data={"column": [1, 2, 3]},
...     index=pd.MultiIndex.from_arrays(
...         [["foo", "bar", "foo"], [0, 1, 2]],
...         names=["index0", "index1"],
...     )
... )
>>>
>>> schema.validate(df)
           column
index0 index1
foo     0         1
bar     1         2
foo     2         3
```

See [here](#) for more usage details.

Attributes

<code>coerce</code>	Whether or not to coerce data types.
<code>description</code>	An arbitrary textual description of the schema.
<code>dtype</code>	Get the dtype property.
<code>dtypes</code>	A dict where the keys are column names and values are <i>DataTypes</i> for the column.
<code>names</code>	Get index names in the MultiIndex schema component.
<code>ordered</code>	Whether or not to validate the columns order.
<code>title</code>	A human-readable label for the schema.
<code>unique</code>	List of columns that should be jointly unique.
<code>unique_column_names</code>	Whether multiple columns with the same name can be present.

Methods

<code>__init__</code>	Create MultiIndex validator.
<code>coerce_dtype</code>	Coerce type of a pd.Series by type specified in dtype.
<code>example</code>	Generate an example of a particular size.
<code>strategy</code>	Create a hypothesis strategy for generating a DataFrame.
<code>validate</code>	Validate DataFrame or Series MultiIndex.
<code>__call__</code>	Alias for <code>DataFrameSchema.validate()</code> method.

7.15.1.2.3.1 `pandera.schema_components.MultiIndex.__init__`

`MultiIndex.__init__(indexes, coerce=False, strict=False, name=None, ordered=True, unique=None)`
 Create MultiIndex validator.

Parameters

- **indexes** (`List[Index]`) – list of Index validators for each level of the MultiIndex index.
- **coerce** (`bool`) – Whether or not to coerce the MultiIndex to the specified dtypes before validation
- **strict** (`bool`) – whether or not to accept columns in the MultiIndex that aren't defined in the `indexes` argument.
- **name** (`Optional[str]`) – name of schema component
- **ordered** (`bool`) – whether or not to validate the indexes order.
- **unique** (`Union[str, List[str], None]`) – a list of index names that should be jointly unique.

Example

```
>>> import pandas as pd
>>> import pandera as pa
>>>
>>>
```

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```

>>> schema = pa.DataFrameSchema(
...     columns={"column": pa.Column(int)},
...     index=pa.MultiIndex([
...         pa.Index(str,
...             pa.Check(lambda s: s.isin(["foo", "bar"])),
...             name="index0"),
...         pa.Index(int, name="index1"),
...     ])
... )
>>>
>>> df = pd.DataFrame(
...     data={"column": [1, 2, 3]},
...     index=pd.MultiIndex.from_arrays(
...         [
...             ["foo", "bar", "foo"],
...             [0, 1, 2]
...         ],
...         names=["index0", "index1"],
...     )
... )
>>>
>>> schema.validate(df)

```

index0	index1	column
foo	0	1
bar	1	2
foo	2	3

See [here](#) for more usage details.

7.15.1.2.3.2 `pandera.schema_components.MultiIndex.coerce_dtype`

`MultiIndex.coerce_dtype(obj)`

Coerce type of a `pd.Series` by type specified in `dtype`.

Parameters `obj` (`MultiIndex`) – multi-index to coerce.

Return type `MultiIndex`

Returns `MultiIndex` with coerced data type

7.15.1.2.3.3 `pandera.schema_components.MultiIndex.example`

`MultiIndex.example(size=None)`

Generate an example of a particular size.

Parameters `size` – number of elements in the generated `DataFrame`.

Return type `MultiIndex`

Returns pandas `DataFrame` object.

7.15.1.2.3.4 `pandera.schema_components.MultiIndex.strategy`

`MultiIndex.strategy`(**, size=None*)

Create a hypothesis strategy for generating a DataFrame.

Parameters

- **size** – number of elements to generate
- **n_regex_columns** – number of regex columns to generate.

Returns a strategy that generates pandas DataFrame objects.

7.15.1.2.3.5 `pandera.schema_components.MultiIndex.validate`

`MultiIndex.validate`(*check_obj, head=None, tail=None, sample=None, random_state=None, lazy=False, inplace=False*)

Validate DataFrame or Series MultiIndex.

Parameters

- **check_obj** (`Union[DataFrame, Series]`) – pandas DataFrame of Series to validate.
- **head** (`Optional[int]`) – validate the first n rows. Rows overlapping with *tail* or *sample* are de-duplicated.
- **tail** (`Optional[int]`) – validate the last n rows. Rows overlapping with *head* or *sample* are de-duplicated.
- **sample** (`Optional[int]`) – validate a random sample of n rows. Rows overlapping with *head* or *tail* are de-duplicated.
- **random_state** (`Optional[int]`) – random seed for the *sample* argument.
- **lazy** (`bool`) – if True, lazily evaluates dataframe against all validation checks and raises a `SchemaErrors`. Otherwise, raise `SchemaError` as soon as one occurs.
- **inplace** (`bool`) – if True, applies coercion to the object of validation, otherwise creates a copy of the data.

Return type `Union[DataFrame, Series]`

Returns validated DataFrame or Series.

7.15.1.2.3.6 `pandera.schema_components.MultiIndex.__call__`

`MultiIndex.__call__`(*dataframe, head=None, tail=None, sample=None, random_state=None, lazy=False, inplace=False*)

Alias for `DataFrameSchema.validate()` method.

Parameters

- **dataframe** (`pd.DataFrame`) – the dataframe to be validated.
- **head** (`int`) – validate the first n rows. Rows overlapping with *tail* or *sample* are de-duplicated.
- **tail** (`int`) – validate the last n rows. Rows overlapping with *head* or *sample* are de-duplicated.

- **sample** (`Optional[int]`) – validate a random sample of `n` rows. Rows overlapping with `head` or `tail` are de-duplicated.
- **random_state** (`Optional[int]`) – random seed for the `sample` argument.
- **lazy** (`bool`) – if `True`, lazily evaluates dataframe against all validation checks and raises a `SchemaErrors`. Otherwise, raise `SchemaError` as soon as one occurs.
- **inplace** (`bool`) – if `True`, applies coercion to the object of validation, otherwise creates a copy of the data.

7.15.1.3 Checks

<code>pandera.checks.Check</code>	Check a pandas Series or DataFrame for certain properties.
<code>pandera.hypotheses.Hypothesis</code>	Special type of Check that defines hypothesis tests on data.

7.15.1.3.1 pandera.checks.Check

```
class pandera.checks.Check(check_fn, groups=None, groupby=None, ignore_na=True, element_wise=False,
                             name=None, error=None, raise_warning=False, n_failure_cases=None,
                             title=None, description=None, **check_kwargs)
```

Check a pandas Series or DataFrame for certain properties.

Apply a validation function to each element, Series, or DataFrame.

Parameters

- **check_fn** (`Union[Callable[[Series], Union[Series, bool]], Callable[[DataFrame], Union[DataFrame, Series, bool]]]`) – A function to check pandas data structure. For Column or SeriesSchema checks, if `element_wise` is `True`, this function should have the signature: `Callable[[pd.Series], Union[pd.Series, bool]]`, where the output series is a boolean vector.

If `element_wise` is `False`, this function should have the signature: `Callable[[Any], bool]`, where `Any` is an element in the column.

For `DataFrameSchema` checks, if `element_wise=True`, `fn` should have the signature: `Callable[[pd.DataFrame], Union[pd.DataFrame, pd.Series, bool]]`, where the output dataframe or series contains booleans.

If `element_wise` is `True`, `fn` is applied to each row in the dataframe with the signature `Callable[[pd.Series], bool]` where the series input is a row in the dataframe.

- **groups** (`Union[str, List[str], None]`) – The dict input to the `fn` callable will be constrained to the groups specified by `groups`.
- **groupby** (`Union[str, List[str], Callable, None]`) – If a string or list of strings is provided, these columns are used to group the Column series. If a callable is passed, the expected signature is: `Callable[[pd.DataFrame], pd.core.groupby.DataFrameGroupBy]`

The the case of `Column` checks, this function has access to the entire dataframe, but `Column.name` is selected from this `DataFrameGroupby` object so that a `SeriesGroupBy` object is passed into `check_fn`.

Specifying the `groupby` argument changes the `check_fn` signature to:

```
Callable[[Dict[Union[str, Tuple[str]], pd.Series]], Union[bool, pd.
Series]] # noqa
```

where the input is a dictionary mapping keys to subsets of the column/dataframe.

- **ignore_na** (*bool*) – If True, null values will be ignored when determining if a check passed or failed. For dataframes, ignores rows with any null value. *New in version 0.4.0*
- **element_wise** (*bool*) – Whether or not to apply validator in an element-wise fashion. If bool, assumes that all checks should be applied to the column element-wise. If list, should be the same number of elements as checks.
- **name** (*Optional[str]*) – optional name for the check.
- **error** (*Optional[str]*) – custom error message if series fails validation check.
- **raise_warning** (*bool*) – if True, raise a UserWarning and do not throw exception instead of raising a SchemaError for a specific check. This option should be used carefully in cases where a failing check is informational and shouldn't stop execution of the program.
- **n_failure_cases** (*Optional[int]*) – report the first n unique failure cases. If None, report all failure cases.
- **title** (*Optional[str]*) – A human-readable label for the check.
- **description** (*Optional[str]*) – An arbitrary textual description of the check.
- **check_kwargs** – key-word arguments to pass into `check_fn`

Example

```
>>> import pandas as pd
>>> import pandera as pa
>>>
>>>
>>> # column checks are vectorized by default
>>> check_positive = pa.Check(lambda s: s > 0)
>>>
>>> # define an element-wise check
>>> check_even = pa.Check(lambda x: x % 2 == 0, element_wise=True)
>>>
>>> # checks can be given human-readable metadata
>>> check_with_metadata = pa.Check(
...     lambda x: True,
...     title="Always passes",
...     description="This check always passes."
... )
>>>
>>> # specify assertions across categorical variables using `groupby`,
>>> # for example, make sure the mean measure for group "A" is always
>>> # larger than the mean measure for group "B"
>>> check_by_group = pa.Check(
...     lambda measures: measures["A"].mean() > measures["B"].mean(),
...     groupby=["group"],
... )
>>>
>>> # define a wide DataFrame-level check
>>> check_dataframe = pa.Check(
...     lambda df: df["measure_1"] > df["measure_2"])
```

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```

>>>
>>> measure_checks = [check_positive, check_even, check_by_group]
>>>
>>> schema = pa.DataFrameSchema(
...     columns={
...         "measure_1": pa.Column(int, checks=measure_checks),
...         "measure_2": pa.Column(int, checks=measure_checks),
...         "group": pa.Column(str),
...     },
...     checks=check_dataframe
... )
>>>
>>> df = pd.DataFrame({
...     "measure_1": [10, 12, 14, 16],
...     "measure_2": [2, 4, 6, 8],
...     "group": ["B", "B", "A", "A"]
... })
>>>
>>> schema.validate(df)[["measure_1", "measure_2", "group"]]
  measure_1  measure_2 group
0         10         2    B
1         12         4    B
2         14         6    A
3         16         8    A

```

See [here](#) for more usage details.

Attributes

<code>statistics</code>	Get check statistics.
<code>REGISTERED_CUSTOM_CHECKS</code>	

Methods

<code>eq</code>	Ensure all elements of a series equal a certain value.
<code>equal_to</code>	Ensure all elements of a series equal a certain value.
<code>ge</code>	Ensure all values are greater or equal a certain value.
<code>greater_than</code>	Ensure values of a series are strictly greater than a minimum value.
<code>greater_than_or_equal_to</code>	Ensure all values are greater or equal a certain value.
<code>gt</code>	Ensure values of a series are strictly greater than a minimum value.
<code>in_range</code>	Ensure all values of a series are within an interval.
<code>isin</code>	Ensure only allowed values occur within a series.
<code>le</code>	Ensure values are less than or equal to a maximum value.
<code>less_than</code>	Ensure values of a series are strictly below a maximum value.
<code>less_than_or_equal_to</code>	Ensure values are less than or equal to a maximum value.
<code>lt</code>	Ensure values of a series are strictly below a maximum value.
<code>ne</code>	Ensure no elements of a series equals a certain value.
<code>not_equal_to</code>	Ensure no elements of a series equals a certain value.
<code>notin</code>	Ensure some defined values don't occur within a series.
<code>str_contains</code>	Ensure that a pattern can be found within each row.
<code>str_endswith</code>	Ensure that all values end with a certain string.
<code>str_length</code>	Ensure that the length of strings is within a specified range.
<code>str_matches</code>	Ensure that string values match a regular expression.
<code>str_startswith</code>	Ensure that all values start with a certain string.
<code>__call__</code>	Validate pandas DataFrame or Series.

7.15.1.3.1.1 pandera.checks.Check.eq

classmethod `Check.eq(cls, value, **kwargs)`

Ensure all elements of a series equal a certain value.

New in version 0.4.5 Alias: `eq`

Parameters

- **value** – All elements of a given `pandas.Series` must have this value
- **kwargs** – key-word arguments passed into the `Check` initializer.

Return type `Check`

Returns `Check` object

7.15.1.3.1.2 `pandera.checks.Check.equal_to`

classmethod `Check.equal_to(cls, value, **kwargs)`

Ensure all elements of a series equal a certain value.

New in version 0.4.5 Alias: `eq`

Parameters

- **value** – All elements of a given `pandas.Series` must have this value
- **kwargs** – key-word arguments passed into the `Check` initializer.

Return type `Check`

Returns `Check` object

7.15.1.3.1.3 `pandera.checks.Check.ge`

classmethod `Check.ge(cls, min_value, **kwargs)`

Ensure all values are greater or equal a certain value.

New in version 0.4.5 Alias: `ge`

Parameters

- **min_value** – Allowed minimum value for values of a series. Must be a type comparable to the dtype of the `pandas.Series` to be validated.
- **kwargs** – key-word arguments passed into the `Check` initializer.

Return type `Check`

Returns `Check` object

7.15.1.3.1.4 `pandera.checks.Check.greater_than`

classmethod `Check.greater_than(cls, min_value, **kwargs)`

Ensure values of a series are strictly greater than a minimum value.

New in version 0.4.5 Alias: `gt`

Parameters

- **min_value** – Lower bound to be exceeded. Must be a type comparable to the dtype of the `pandas.Series` to be validated (e.g. a numerical type for float or int and a datetime for datetime).
- **kwargs** – key-word arguments passed into the `Check` initializer.

Return type `Check`

Returns `Check` object

7.15.1.3.1.5 `pandera.checks.Check.greater_than_or_equal_to`

classmethod `Check.greater_than_or_equal_to(cls, min_value, **kwargs)`

Ensure all values are greater or equal a certain value.

New in version 0.4.5 Alias: `ge`

Parameters

- **min_value** – Allowed minimum value for values of a series. Must be a type comparable to the dtype of the `pandas.Series` to be validated.
- **kwargs** – key-word arguments passed into the `Check` initializer.

Return type `Check`

Returns `Check` object

7.15.1.3.1.6 `pandera.checks.Check.gt`

classmethod `Check.gt(cls, min_value, **kwargs)`

Ensure values of a series are strictly greater than a minimum value.

New in version 0.4.5 Alias: `gt`

Parameters

- **min_value** – Lower bound to be exceeded. Must be a type comparable to the dtype of the `pandas.Series` to be validated (e.g. a numerical type for float or int and a datetime for datetime).
- **kwargs** – key-word arguments passed into the `Check` initializer.

Return type `Check`

Returns `Check` object

7.15.1.3.1.7 `pandera.checks.Check.in_range`

classmethod `Check.in_range(cls, min_value, max_value, include_min=True, include_max=True, **kwargs)`

Ensure all values of a series are within an interval.

Parameters

- **min_value** – Left / lower endpoint of the interval.
- **max_value** – Right / upper endpoint of the interval. Must not be smaller than `min_value`.
- **include_min** – Defines whether `min_value` is also an allowed value (the default) or whether all values must be strictly greater than `min_value`.
- **include_max** – Defines whether `min_value` is also an allowed value (the default) or whether all values must be strictly smaller than `max_value`.
- **kwargs** – key-word arguments passed into the `Check` initializer.

Both endpoints must be a type comparable to the dtype of the `pandas.Series` to be validated.

Return type `Check`

Returns *Check* object

7.15.1.3.1.8 pandera.checks.Check.isin

classmethod `Check.isin(cls, allowed_values, **kwargs)`

Ensure only allowed values occur within a series.

Parameters

- **allowed_values** (*Iterable*) – The set of allowed values. May be any iterable.
- **kwargs** – key-word arguments passed into the *Check* initializer.

Return type *Check*

Returns *Check* object

Note: It is checked whether all elements of a `pandas.Series` are part of the set of elements of allowed values. If allowed values is a string, the set of elements consists of all distinct characters of the string. Thus only single characters which occur in allowed_values at least once can meet this condition. If you want to check for substrings use `Check.str_is_substring()`.

7.15.1.3.1.9 pandera.checks.Check.le

classmethod `Check.le(cls, max_value, **kwargs)`

Ensure values are less than or equal to a maximum value.

New in version 0.4.5 Alias: `le`

Parameters

- **max_value** – Upper bound not to be exceeded. Must be a type comparable to the dtype of the `pandas.Series` to be validated.
- **kwargs** – key-word arguments passed into the *Check* initializer.

Return type *Check*

Returns *Check* object

7.15.1.3.1.10 pandera.checks.Check.less_than

classmethod `Check.less_than(cls, max_value, **kwargs)`

Ensure values of a series are strictly below a maximum value.

New in version 0.4.5 Alias: `lt`

Parameters

- **max_value** – All elements of a series must be strictly smaller than this. Must be a type comparable to the dtype of the `pandas.Series` to be validated.
- **kwargs** – key-word arguments passed into the *Check* initializer.

Return type *Check*

Returns *Check* object

7.15.1.3.1.11 `pandera.checks.Check.less_than_or_equal_to`

classmethod `Check.less_than_or_equal_to(cls, max_value, **kwargs)`

Ensure values are less than or equal to a maximum value.

New in version 0.4.5 Alias: `le`

Parameters

- **max_value** – Upper bound not to be exceeded. Must be a type comparable to the dtype of the `pandas.Series` to be validated.
- **kwargs** – key-word arguments passed into the `Check` initializer.

Return type `Check`

Returns `Check` object

7.15.1.3.1.12 `pandera.checks.Check.lt`

classmethod `Check.lt(cls, max_value, **kwargs)`

Ensure values of a series are strictly below a maximum value.

New in version 0.4.5 Alias: `lt`

Parameters

- **max_value** – All elements of a series must be strictly smaller than this. Must be a type comparable to the dtype of the `pandas.Series` to be validated.
- **kwargs** – key-word arguments passed into the `Check` initializer.

Return type `Check`

Returns `Check` object

7.15.1.3.1.13 `pandera.checks.Check.ne`

classmethod `Check.ne(cls, value, **kwargs)`

Ensure no elements of a series equals a certain value.

New in version 0.4.5 Alias: `ne`

Parameters

- **value** – This value must not occur in the checked `pandas.Series`.
- **kwargs** – key-word arguments passed into the `Check` initializer.

Return type `Check`

Returns `Check` object

7.15.1.3.1.14 `pandera.checks.Check.not_equal_to`

classmethod `Check.not_equal_to(cls, value, **kwargs)`

Ensure no elements of a series equals a certain value.

New in version 0.4.5 Alias: `ne`

Parameters

- **value** – This value must not occur in the checked `pandas.Series`.
- **kwargs** – key-word arguments passed into the `Check` initializer.

Return type `Check`

Returns `Check` object

7.15.1.3.1.15 `pandera.checks.Check.notin`

classmethod `Check.notin(cls, forbidden_values, **kwargs)`

Ensure some defined values don't occur within a series.

Parameters

- **forbidden_values** (`Iterable`) – The set of values which should not occur. May be any iterable.
- **raise_warning** – if True, check raises `UserWarning` instead of `SchemaError` on validation.

Return type `Check`

Returns `Check` object

Note: Like `Check.isin()` this check operates on single characters if it is applied on strings. A string as `paraforbidden_valuesmeter forbidden_values` is understood as set of prohibited characters. Any string of length > 1 can't be in it by design.

7.15.1.3.1.16 `pandera.checks.Check.str_contains`

classmethod `Check.str_contains(cls, pattern, **kwargs)`

Ensure that a pattern can be found within each row.

Parameters

- **pattern** (`str`) – Regular expression pattern to use for searching
- **kwargs** – key-word arguments passed into the `Check` initializer.

Return type `Check`

Returns `Check` object

The behaviour is as of `pandas.Series.str.contains()`.

7.15.1.3.1.17 `pandera.checks.Check.str_endswith`

classmethod `Check.str_endswith(cls, string, **kwargs)`

Ensure that all values end with a certain string.

Parameters

- **string** (`str`) – String all values should end with
- **kwargs** – key-word arguments passed into the *Check* initializer.

Return type *Check*

Returns *Check* object

7.15.1.3.1.18 `pandera.checks.Check.str_length`

classmethod `Check.str_length(cls, min_value=None, max_value=None, **kwargs)`

Ensure that the length of strings is within a specified range.

Parameters

- **min_value** (`Optional[int]`) – Minimum length of strings (default: no minimum)
- **max_value** (`Optional[int]`) – Maximum length of strings (default: no maximum)
- **kwargs** – key-word arguments passed into the *Check* initializer.

Return type *Check*

Returns *Check* object

7.15.1.3.1.19 `pandera.checks.Check.str_matches`

classmethod `Check.str_matches(cls, pattern, **kwargs)`

Ensure that string values match a regular expression.

Parameters

- **pattern** (`str`) – Regular expression pattern to use for matching
- **kwargs** – key-word arguments passed into the *Check* initializer.

Return type *Check*

Returns *Check* object

The behaviour is as of `pandas.Series.str.match()`.

7.15.1.3.1.20 `pandera.checks.Check.str_startswith`

classmethod `Check.str_startswith(cls, string, **kwargs)`

Ensure that all values start with a certain string.

Parameters

- **string** (`str`) – String all values should start with
- **kwargs** – key-word arguments passed into the *Check* initializer.

Return type *Check*

Returns *Check* object

7.15.1.3.1.21 `pandera.checks.Check.__call__`

`Check.__call__(df_or_series, column=None)`

Validate pandas DataFrame or Series.

Parameters

- **df_or_series** (`Union[DataFrame, Series]`) – pandas DataFrame of Series to validate.
- **column** (`Optional[str]`) – for dataframe checks, apply the check function to this column.

Return type `CheckResult`

Returns

CheckResult tuple containing:

`check_output`: boolean scalar, Series or DataFrame indicating which elements passed the check.

`check_passed`: boolean scalar that indicating whether the check passed overall.

`checked_object`: the checked object itself. Depending on the options provided to the Check, this will be a pandas Series, DataFrame, or if the `groupby` option is specified, a `Dict[str, Series]` or `Dict[str, DataFrame]` where the keys are distinct groups.

`failure_cases`: subset of the `check_object` that failed.

7.15.1.3.2 `pandera.hypotheses.Hypothesis`

```
class pandera.hypotheses.Hypothesis(test, samples=None, groupby=None, relationship='equal',
                                     test_kwargs=None, relationship_kwargs=None, name=None,
                                     error=None, raise_warning=False)
```

Special type of Check that defines hypothesis tests on data.

Perform a hypothesis test on a Series or DataFrame.

Parameters

- **test** (`Callable`) – The hypothesis test function. It should take one or more arrays as positional arguments and return a test statistic and a p-value. The arrays passed into the test function are determined by the `samples` argument.
- **samples** (`Union[str, List[str], None]`) – for *Column* or *SeriesSchema* hypotheses, this refers to the group keys in the *groupby* column(s) used to group the *Series* into a dict of *Series*. The *samples* column(s) are passed into the *test* function as positional arguments.

For *DataFrame*-level hypotheses, *samples* refers to a column or multiple columns to pass into the *test* function. The *samples* column(s) are passed into the *test* function as positional arguments.

- **groupby** (`Union[str, List[str], Callable, None]`) – If a string or list of strings is provided, then these columns are used to group the Column Series by *groupby*. If a callable is passed, the expected signature is `DataFrame -> DataFrameGroupby`. The function has access to the entire dataframe, but the `Column.name` is selected from this `DataFrameGroupby` object so that a `SeriesGroupBy` object is passed into the *hypothesis_check* function.

Specifying this argument changes the *fn* signature to: `dict[str[tuple[str], Series] -> bool|pd.Series[bool]`

Where specific groups can be obtained from the input dict.

- **relationship** (`Union[str, Callable]`) – Represents what relationship conditions are imposed on the hypothesis test. A function or lambda function can be supplied.

Available built-in relationships are: “greater_than”, “less_than”, “not_equal” or “equal”, where “equal” is the null hypothesis.

If callable, the input function signature should have the signature (`stat: float, pvalue: float, **kwargs`) where *stat* is the hypothesis test statistic, *pvalue* assesses statistical significance, and ***kwargs* are other arguments supplied via the ***relationship_kwargs* argument.

Default is “equal” for the null hypothesis.

- **test_kwargs** (`dict`) – Keyword arguments to be supplied to the test.
- **relationship_kwargs** (`dict`) – Keyword arguments to be supplied to the relationship function. e.g. *alpha* could be used to specify a threshold in a t-test.
- **name** (`Optional[str]`) – optional name of hypothesis test
- **error** (`Optional[str]`) – error message to show
- **raise_warning** (`bool`) – if True, raise a UserWarning and do not throw exception instead of raising a SchemaError for a specific check. This option should be used carefully in cases where a failing check is informational and shouldn’t stop execution of the program.

Examples

Define a two-sample hypothesis test using scipy.

```
>>> import pandas as pd
>>> import pandera as pa
>>>
>>> from scipy import stats
>>>
>>> schema = pa.DataFrameSchema({
...     "height_in_feet": pa.Column(float, [
...         pa.Hypothesis(
...             test=stats.ttest_ind,
...             samples=["A", "B"],
...             groupby="group",
...             # assert that the mean height of group "A" is greater
...             # than that of group "B"
...             relationship=lambda stat, pvalue, alpha=0.1: (
...                 stat > 0 and pvalue / 2 < alpha
...             ),
...             # set alpha criterion to 5%
...             relationship_kwargs={"alpha": 0.05}
...         )
...     ]),
...     "group": pa.Column(str),
... })
>>> df = (
...     pd.DataFrame({
```

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```

...     "height_in_feet": [8.1, 7, 5.2, 5.1, 4],
...     "group": ["A", "A", "B", "B", "B"]
...     })
... )
>>> schema.validate(df)[["height_in_feet", "group"]]
  height_in_feet group
0             8.1    A
1             7.0    A
2             5.2    B
3             5.1    B
4             4.0    B

```

See [here](#) for more usage details.

Attributes

RELATIONSHIPS	Relationships available for built-in hypothesis tests.
is_one_sample_test	Return True if hypothesis is a one-sample test.
statistics	Get check statistics.
REGISTERED_CUSTOM_CHECKS	

Methods

<code>__init__</code>	Perform a hypothesis test on a Series or DataFrame.
<code>one_sample_ttest</code>	Calculate a t-test for the mean of one sample.
<code>two_sample_ttest</code>	Calculate a t-test for the means of two samples.
<code>__call__</code>	Validate pandas DataFrame or Series.

7.15.1.3.2.1 pandera.hypotheses.Hypothesis.__init__

`Hypothesis.__init__(test, samples=None, groupby=None, relationship='equal', test_kwargs=None, relationship_kwargs=None, name=None, error=None, raise_warning=False)`

Perform a hypothesis test on a Series or DataFrame.

Parameters

- **test** (`Callable`) – The hypothesis test function. It should take one or more arrays as positional arguments and return a test statistic and a p-value. The arrays passed into the test function are determined by the `samples` argument.
- **samples** (`Union[str, List[str], None]`) – for `Column` or `SeriesSchema` hypotheses, this refers to the group keys in the `groupby` column(s) used to group the `Series` into a dict of `Series`. The `samples` column(s) are passed into the `test` function as positional arguments.

For `DataFrame`-level hypotheses, `samples` refers to a column or multiple columns to pass into the `test` function. The `samples` column(s) are passed into the `test` function as positional arguments.

- **groupby** (`Union[str, List[str], Callable, None]`) – If a string or list of strings is provided, then these columns are used to group the Column Series by *groupby*. If a callable is passed, the expected signature is `DataFrame -> DataFrameGroupby`. The function has access to the entire dataframe, but the `Column.name` is selected from this `DataFrameGroupby` object so that a `SeriesGroupBy` object is passed into the *hypothesis_check* function.

Specifying this argument changes the *fn* signature to: `dict[str|tuple[str], Series] -> bool|pd.Series[bool]`

Where specific groups can be obtained from the input dict.

- **relationship** (`Union[str, Callable]`) – Represents what relationship conditions are imposed on the hypothesis test. A function or lambda function can be supplied.

Available built-in relationships are: “greater_than”, “less_than”, “not_equal” or “equal”, where “equal” is the null hypothesis.

If callable, the input function signature should have the signature (`stat: float, pvalue: float, **kwargs`) where *stat* is the hypothesis test statistic, *pvalue* assesses statistical significance, and ***kwargs* are other arguments supplied via the *relationship_kwargs* argument.

Default is “equal” for the null hypothesis.

- **test_kwargs** (`dict`) – Keyword arguments to be supplied to the test.
- **relationship_kwargs** (`dict`) – Keyword arguments to be supplied to the relationship function. e.g. *alpha* could be used to specify a threshold in a t-test.
- **name** (`Optional[str]`) – optional name of hypothesis test
- **error** (`Optional[str]`) – error message to show
- **raise_warning** (`bool`) – if True, raise a `UserWarning` and do not throw exception instead of raising a `SchemaError` for a specific check. This option should be used carefully in cases where a failing check is informational and shouldn’t stop execution of the program.

Examples

Define a two-sample hypothesis test using `scipy`.

```
>>> import pandas as pd
>>> import pandera as pa
>>>
>>> from scipy import stats
>>>
>>> schema = pa.DataFrameSchema({
...     "height_in_feet": pa.Column(float, [
...         pa.Hypothesis(
...             test=stats.ttest_ind,
...             samples=["A", "B"],
...             groupby="group",
...             # assert that the mean height of group "A" is greater
...             # than that of group "B"
...             relationship=lambda stat, pvalue, alpha=0.1: (
...                 stat > 0 and pvalue / 2 < alpha
...             ),
...             # set alpha criterion to 5%
...             relationship_kwargs={"alpha": 0.05}
...         )
...     ])
... })
```

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```

...     ]),
...     "group": pa.Column(str),
... })
>>> df = (
...     pd.DataFrame({
...         "height_in_feet": [8.1, 7, 5.2, 5.1, 4],
...         "group": ["A", "A", "B", "B", "B"]
...     })
... )
>>> schema.validate(df)[["height_in_feet", "group"]]
  height_in_feet  group
0             8.1     A
1             7.0     A
2             5.2     B
3             5.1     B
4             4.0     B

```

See [here](#) for more usage details.

7.15.1.3.2.2 `pandera.hypotheses.Hypothesis.one_sample_ttest`

classmethod `Hypothesis.one_sample_ttest`(*popmean*, *sample=None*, *groupby=None*, *relationship='equal'*, *alpha=0.01*, *raise_warning=False*)

Calculate a t-test for the mean of one sample.

Parameters

- **sample** (`Optional[str]`) – The sample group to test. For *Column* and *SeriesSchema* hypotheses, this refers to the *groupby* level that is used to subset the *Column* being checked. For *DataFrameSchema* hypotheses, refers to column in the *DataFrame*.
- **groupby** (`Union[str, List[str], Callable, None]`) – If a string or list of strings is provided, then these columns are used to group the *Column Series* by *groupby*. If a callable is passed, the expected signature is `DataFrame -> DataFrameGroupby`. The function has access to the entire dataframe, but the `Column.name` is selected from this `DataFrameGroupby` object so that a `SeriesGroupBy` object is passed into *fn*.

Specifying this argument changes the *fn* signature to: `dict[str|tuple[str], Series] -> bool|pd.Series[bool]`

Where specific groups can be obtained from the input dict.

- **popmean** (`float`) – population mean to compare *sample* to.
- **relationship** (`str`) – Represents what relationship conditions are imposed on the hypothesis test. Available relationships are: “`greater_than`”, “`less_than`”, “`not_equal`” and “`equal`”. For example, `group1 greater_than group2` specifies an alternative hypothesis that the mean of group1 is greater than group 2 relative to a null hypothesis that they are equal.
- **alpha** (`float`) – (Default value = 0.01) The significance level; the probability of rejecting the null hypothesis when it is true. For example, a significance level of 0.01 indicates a 1% risk of concluding that a difference exists when there is no actual difference.
- **raise_warning** – if True, check raises `UserWarning` instead of `SchemaError` on validation.

Example

If you want to compare one sample with a pre-defined mean:

```
>>> import pandas as pd
>>> import pandera as pa
>>>
>>>
>>> schema = pa.DataFrameSchema({
...     "height_in_feet": pa.Column(
...         float, [
...             pa.Hypothesis.one_sample_ttest(
...                 popmean=5,
...                 relationship="greater_than",
...                 alpha=0.1),
...         ]),
... })
>>> df = (
...     pd.DataFrame({
...         "height_in_feet": [8.1, 7, 6.5, 6.7, 5.1],
...     })
... )
>>> schema.validate(df)
height_in_feet
0             8.1
1             7.0
2             6.5
3             6.7
4             5.1
```

7.15.1.3.2.3 pandera.hypotheses.Hypothesis.two_sample_ttest

classmethod `Hypothesis.two_sample_ttest`(*sample1*, *sample2*, *groupby*=None, *relationship*='equal', *alpha*=0.01, *equal_var*=True, *nan_policy*='propagate', *raise_warning*=False)

Calculate a t-test for the means of two samples.

Perform a two-sided test for the null hypothesis that 2 independent samples have identical average (expected) values. This test assumes that the populations have identical variances by default.

Parameters

- **sample1** (`str`) – The first sample group to test. For *Column* and *SeriesSchema* hypotheses, refers to the level in the *groupby* column. For *DataFrameSchema* hypotheses, refers to column in the *DataFrame*.
- **sample2** (`str`) – The second sample group to test. For *Column* and *SeriesSchema* hypotheses, refers to the level in the *groupby* column. For *DataFrameSchema* hypotheses, refers to column in the *DataFrame*.
- **groupby** (`Union[str, List[str], Callable, None]`) – If a string or list of strings is provided, then these columns are used to group the Column Series by *groupby*. If a callable is passed, the expected signature is `DataFrame -> DataFrameGroupby`. The function has access to the entire dataframe, but the `Column.name` is selected from this `DataFrameGroupby` object so that a `SeriesGroupBy` object is passed into *fn*.

Specifying this argument changes the *fn* signature to: `dict[str[tuple[str], Series] -> bool|pd.Series[bool]`

Where specific groups can be obtained from the input dict.

- **relationship** (*str*) – Represents what relationship conditions are imposed on the hypothesis test. Available relationships are: “greater_than”, “less_than”, “not_equal”, and “equal”. For example, *group1 greater_than group2* specifies an alternative hypothesis that the mean of group1 is greater than group 2 relative to a null hypothesis that they are equal.
- **alpha** – (Default value = 0.01) The significance level; the probability of rejecting the null hypothesis when it is true. For example, a significance level of 0.01 indicates a 1% risk of concluding that a difference exists when there is no actual difference.
- **equal_var** – (Default value = True) If True (default), perform a standard independent 2 sample test that assumes equal population variances. If False, perform Welch’s t-test, which does not assume equal population variance
- **nan_policy** – Defines how to handle when input returns nan, one of { ‘propagate’, ‘raise’, ‘omit’ }, (Default value = ‘propagate’). For more details see: https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.ttest_ind.html
- **raise_warning** – if True, check raises UserWarning instead of SchemaError on validation.

Example

The the built-in class method to do a two-sample t-test.

```
>>> import pandera as pa
>>>
>>>
>>> schema = pa.DataFrameSchema({
...     "height_in_feet": pa.Column(
...         float, [
...             pa.Hypothesis.two_sample_ttest(
...                 sample1="A",
...                 sample2="B",
...                 groupby="group",
...                 relationship="greater_than",
...                 alpha=0.05,
...                 equal_var=True),
...         ]),
...     "group": pa.Column(str)
... })
>>> df = (
...     pd.DataFrame({
...         "height_in_feet": [8.1, 7, 5.2, 5.1, 4],
...         "group": ["A", "A", "B", "B", "B"]
...     })
... )
>>> schema.validate(df)[["height_in_feet", "group"]]
height_in_feet group
0             8.1    A
1             7.0    A
2             5.2    B
3             5.1    B
4             4.0    B
```

7.15.1.3.2.4 `pandera.hypotheses.Hypothesis.__call__`

`Hypothesis.__call__(df_or_series, column=None)`

Validate pandas DataFrame or Series.

Parameters

- **df_or_series** (`Union[DataFrame, Series]`) – pandas DataFrame or Series to validate.
- **column** (`Optional[str]`) – for dataframe checks, apply the check function to this column.

Return type `CheckResult`

Returns

`CheckResult` tuple containing:

`check_output`: boolean scalar, `Series` or `DataFrame` indicating which elements passed the check.

`check_passed`: boolean scalar that indicating whether the check passed overall.

`checked_object`: the checked object itself. Depending on the options provided to the `Check`, this will be a pandas `Series`, `DataFrame`, or if the `groupby` option is specified, a `Dict[str, Series]` or `Dict[str, DataFrame]` where the keys are distinct groups.

`failure_cases`: subset of the `check_object` that failed.

7.15.2 Data Types

7.15.2.1 Library-agnostic dtypes

<code>pandera.dtypes.DataType</code>	Base class of all Pandera data types.
<code>pandera.dtypes.Bool</code>	Semantic representation of a boolean data type.
<code>pandera.dtypes.Timestamp</code>	Semantic representation of a timestamp data type.
<code>pandera.dtypes.DateTime</code>	alias of <code>pandera.dtypes.Timestamp</code>
<code>pandera.dtypes.Timedelta</code>	Semantic representation of a delta time data type.
<code>pandera.dtypes.Category</code>	Semantic representation of a categorical data type.
<code>pandera.dtypes.Float</code>	Semantic representation of a floating data type.
<code>pandera.dtypes.Float16</code>	Semantic representation of a floating data type stored in 16 bits.
<code>pandera.dtypes.Float32</code>	Semantic representation of a floating data type stored in 32 bits.
<code>pandera.dtypes.Float64</code>	Semantic representation of a floating data type stored in 64 bits.
<code>pandera.dtypes.Float128</code>	Semantic representation of a floating data type stored in 128 bits.
<code>pandera.dtypes.Int</code>	Semantic representation of an integer data type.
<code>pandera.dtypes.Int8</code>	Semantic representation of an integer data type stored in 8 bits.
<code>pandera.dtypes.Int16</code>	Semantic representation of an integer data type stored in 16 bits.
<code>pandera.dtypes.Int32</code>	Semantic representation of an integer data type stored in 32 bits.
<code>pandera.dtypes.Int64</code>	Semantic representation of an integer data type stored in 64 bits.
<code>pandera.dtypes.UInt</code>	Semantic representation of an unsigned integer data type.
<code>pandera.dtypes.UInt8</code>	Semantic representation of an unsigned integer data type stored in 8 bits.
<code>pandera.dtypes.UInt16</code>	Semantic representation of an unsigned integer data type stored in 16 bits.
<code>pandera.dtypes.UInt32</code>	Semantic representation of an unsigned integer data type stored in 32 bits.
<code>pandera.dtypes.UInt64</code>	Semantic representation of an unsigned integer data type stored in 64 bits.
<code>pandera.dtypes.Complex</code>	Semantic representation of a complex number data type.
<code>pandera.dtypes.Complex64</code>	Semantic representation of a complex number data type stored in 64 bits.
<code>pandera.dtypes.Complex128</code>	Semantic representation of a complex number data type stored in 128 bits.
<code>pandera.dtypes.Complex256</code>	Semantic representation of a complex number data type stored in 256 bits.
<code>pandera.dtypes.String</code>	Semantic representation of a string data type.

7.15.2.1.1 pandera.dtypes.DataType

class pandera.dtypes.DataType

Base class of all Pandera data types.

Attributes

continuous	Whether the number data type is continuous.
------------	---

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.1.1 pandera.dtypes.DataType.__init__

`DataType.__init__()`

7.15.2.1.1.2 pandera.dtypes.DataType.check

`DataType.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.1.3 pandera.dtypes.DataType.coerce

`DataType.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.1.4 pandera.dtypes.DataType.coerce_value

`DataType.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.1.5 `pandera.dtypes.DataType.try_coerce`

`DataType.try_coerce(data_container)`

Coerce data container to the data type, raises a `~pandera.errors.ParserError` if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.1.6 `pandera.dtypes.DataType.__call__`

`DataType.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.2 `pandera.dtypes.Bool`

class `pandera.dtypes.Bool`

Semantic representation of a boolean data type.

Attributes

<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.

Methods

<code>__init__</code>	
<code>check</code>	Check that <code>pandera.DataType</code> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <code>~pandera.errors.ParserError</code> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.2.1 `pandera.dtypes.Bool.__init__`

`Bool.__init__()`

7.15.2.1.2.2 `pandera.dtypes.Bool.check`

`Bool.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.2.3 `pandera.dtypes.Bool.coerce`

`Bool.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.2.4 `pandera.dtypes.Bool.coerce_value`

`Bool.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.2.5 `pandera.dtypes.Bool.try_coerce`

`Bool.try_coerce(data_container)`

Coerce data container to the data type, raises a *~pandera.errors.ParserError* if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.2.6 `pandera.dtypes.Bool.__call__`

`Bool.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.3 `pandera.dtypes.Timestamp`

class `pandera.dtypes.Timestamp`

Semantic representation of a timestamp data type.

Attributes

<code>continuous</code>	Whether the number data type is continuous.
-------------------------	---

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.3.1 pandera.dtypes.Timestamp.__init__

`Timestamp.__init__()`

7.15.2.1.3.2 pandera.dtypes.Timestamp.check

`Timestamp.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.3.3 pandera.dtypes.Timestamp.coerce

`Timestamp.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.3.4 pandera.dtypes.Timestamp.coerce_value

`Timestamp.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.3.5 pandera.dtypes.Timestamp.try_coerce

`Timestamp.try_coerce(data_container)`

Coerce data container to the data type, raises a *pandera.errors.ParserError* if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.3.6 `pandera.dtypes.Timestamp.__call__`

`Timestamp.__call__(data_container)`
Coerce data container to the data type.

7.15.2.1.4 `pandera.dtypes.DateTime`

`pandera.dtypes.DateTime`
alias of `pandera.dtypes.Timestamp`

7.15.2.1.5 `pandera.dtypes.Timedelta`

class `pandera.dtypes.Timedelta`
Semantic representation of a delta time data type.

Attributes

<code>continuous</code>	Whether the number data type is continuous.
-------------------------	---

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.5.1 `pandera.dtypes.Timedelta.__init__`

`Timedelta.__init__()`

7.15.2.1.5.2 `pandera.dtypes.Timedelta.check`

`Timedelta.check(pandera_dtype)`
Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.5.3 `pandera.dtypes.Timedelta.coerce`

`Timedelta.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.5.4 `pandera.dtypes.Timedelta.coerce_value`

`Timedelta.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.5.5 `pandera.dtypes.Timedelta.try_coerce`

`Timedelta.try_coerce(data_container)`

Coerce data container to the data type, raises a `~pandera.errors.ParserError` if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.5.6 `pandera.dtypes.Timedelta.__call__`

`Timedelta.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.6 `pandera.dtypes.Category`

class `pandera.dtypes.Category(categories=None, ordered=False)`

Semantic representation of a categorical data type.

Attributes

<code>categories</code>	
<code>continuous</code>	Whether the number data type is continuous.
<code>ordered</code>	

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <code>DataType</code> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <code>~pandera.errors.ParserError</code> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.6.1 `pandera.dtypes.Category.__init__`

`Category.__init__(categories=None, ordered=False)`

7.15.2.1.6.2 `pandera.dtypes.Category.check`

`Category.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.6.3 `pandera.dtypes.Category.coerce`

`Category.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.6.4 `pandera.dtypes.Category.coerce_value`

`Category.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.6.5 `pandera.dtypes.Category.try_coerce`

`Category.try_coerce(data_container)`

Coerce data container to the data type, raises a *~pandera.errors.ParserError* if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.6.6 `pandera.dtypes.Category.__call__`

`Category.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.7 `pandera.dtypes.Float`

class `pandera.dtypes.Float`

Semantic representation of a floating data type.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.7.1 pandera.dtypes.Float.__init__

`Float.__init__()`

7.15.2.1.7.2 pandera.dtypes.Float.check

`Float.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.7.3 pandera.dtypes.Float.coerce

`Float.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.7.4 pandera.dtypes.Float.coerce_value

`Float.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.7.5 `pandera.dtypes.Float.try_coerce`

`Float.try_coerce(data_container)`

Coerce data container to the data type, raises a `~pandera.errors.ParserError` if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.7.6 `pandera.dtypes.Float.__call__`

`Float.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.8 `pandera.dtypes.Float16`

class `pandera.dtypes.Float16`

Semantic representation of a floating data type stored in 16 bits.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.

Methods

<code>__init__</code>	
<code>check</code>	Check that <code>pandera.DataType</code> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <code>~pandera.errors.ParserError</code> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.8.1 `pandera.dtypes.Float16.__init__`

`Float16.__init__()`

7.15.2.1.8.2 `pandera.dtypes.Float16.check`

`Float16.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.8.3 `pandera.dtypes.Float16.coerce`

`Float16.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.8.4 `pandera.dtypes.Float16.coerce_value`

`Float16.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.8.5 `pandera.dtypes.Float16.try_coerce`

`Float16.try_coerce(data_container)`

Coerce data container to the data type, raises a *~pandera.errors.ParserError* if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.8.6 `pandera.dtypes.Float16.__call__`

`Float16.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.9 `pandera.dtypes.Float32`

class `pandera.dtypes.Float32`

Semantic representation of a floating data type stored in 32 bits.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.9.1 pandera.dtypes.Float32.__init__

`Float32.__init__()`

7.15.2.1.9.2 pandera.dtypes.Float32.check

`Float32.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.9.3 pandera.dtypes.Float32.coerce

`Float32.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.9.4 pandera.dtypes.Float32.coerce_value

`Float32.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.9.5 pandera.dtypes.Float32.try_coerce

`Float32.try_coerce(data_container)`

Coerce data container to the data type, raises a *pandera.errors.ParserError* if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.9.6 pandera.dtypes.Float32.__call__

`Float32.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.10 pandera.dtypes.Float64

class `pandera.dtypes.Float64`

Semantic representation of a floating data type stored in 64 bits.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.10.1 pandera.dtypes.Float64.__init__

`Float64.__init__()`

7.15.2.1.10.2 pandera.dtypes.Float64.check

`Float64.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.10.3 `pandera.dtypes.Float64.coerce`

`Float64.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.10.4 `pandera.dtypes.Float64.coerce_value`

`Float64.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.10.5 `pandera.dtypes.Float64.try_coerce`

`Float64.try_coerce(data_container)`

Coerce data container to the data type, raises a `~pandera.errors.ParserError` if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.10.6 `pandera.dtypes.Float64.__call__`

`Float64.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.11 `pandera.dtypes.Float128`

class `pandera.dtypes.Float128`

Semantic representation of a floating data type stored in 128 bits.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.

Methods

<code>__init__</code>	
<code>check</code>	Check that <code>pandera.DataType</code> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <code>~pandera.errors.ParserError</code> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.11.1 `pandera.dtypes.Float128.__init__`

`Float128.__init__()`

7.15.2.1.11.2 `pandera.dtypes.Float128.check`

`Float128.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.11.3 `pandera.dtypes.Float128.coerce`

`Float128.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.11.4 `pandera.dtypes.Float128.coerce_value`

`Float128.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.11.5 `pandera.dtypes.Float128.try_coerce`

`Float128.try_coerce(data_container)`

Coerce data container to the data type, raises a *~pandera.errors.ParserError* if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.11.6 `pandera.dtypes.Float128.__call__`

`Float128.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.12 `pandera.dtypes.Int`

class `pandera.dtypes.Int`

Semantic representation of an integer data type.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.
<code>signed</code>	Whether the integer data type is signed.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.12.1 pandera.dtypes.Int.__init__

`Int.__init__()`

7.15.2.1.12.2 pandera.dtypes.Int.check

`Int.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.12.3 pandera.dtypes.Int.coerce

`Int.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.12.4 pandera.dtypes.Int.coerce_value

`Int.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.12.5 `pandera.dtypes.Int.try_coerce`

`Int.try_coerce(data_container)`

Coerce data container to the data type, raises a `~pandera.errors.ParserError` if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.12.6 `pandera.dtypes.Int.__call__`

`Int.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.13 `pandera.dtypes.Int8`

class `pandera.dtypes.Int8`

Semantic representation of an integer data type stored in 8 bits.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.
<code>signed</code>	Whether the integer data type is signed.

Methods

<code>__init__</code>	
<code>check</code>	Check that <code>pandera.DataType</code> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <code>~pandera.errors.ParserError</code> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.13.1 `pandera.dtypes.Int8.__init__`

`Int8.__init__()`

7.15.2.1.13.2 pandera.dtypes.Int8.check`Int8.check(pandera_dtype)`Check that pandera *DataType* are equivalent.**Return type** `bool`**7.15.2.1.13.3 pandera.dtypes.Int8.coerce**`Int8.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.13.4 pandera.dtypes.Int8.coerce_value`Int8.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.13.5 pandera.dtypes.Int8.try_coerce`Int8.try_coerce(data_container)`Coerce data container to the data type, raises a *~pandera.errors.ParserError* if the coercion fails**Raises** `ParserError`: if coercion fails**7.15.2.1.13.6 pandera.dtypes.Int8.__call__**`Int8.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.14 pandera.dtypes.Int16**class** `pandera.dtypes.Int16`

Semantic representation of an integer data type stored in 16 bits.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.
<code>signed</code>	Whether the integer data type is signed.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.14.1 pandera.dtypes.Int16.__init__

`Int16.__init__()`

7.15.2.1.14.2 pandera.dtypes.Int16.check

`Int16.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.14.3 pandera.dtypes.Int16.coerce

`Int16.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.14.4 pandera.dtypes.Int16.coerce_value

`Int16.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.14.5 pandera.dtypes.Int16.try_coerce

`Int16.try_coerce(data_container)`

Coerce data container to the data type, raises a *pandera.errors.ParserError* if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.14.6 pandera.dtypes.Int16.__call__

`Int16.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.15 pandera.dtypes.Int32

class `pandera.dtypes.Int32`

Semantic representation of an integer data type stored in 32 bits.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.
<code>signed</code>	Whether the integer data type is signed.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.15.1 pandera.dtypes.Int32.__init__

`Int32.__init__()`

7.15.2.1.15.2 pandera.dtypes.Int32.check

`Int32.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.15.3 `pandera.dtypes.Int32.coerce`

`Int32.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.15.4 `pandera.dtypes.Int32.coerce_value`

`Int32.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.15.5 `pandera.dtypes.Int32.try_coerce`

`Int32.try_coerce(data_container)`

Coerce data container to the data type, raises a `~pandera.errors.ParserError` if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.15.6 `pandera.dtypes.Int32.__call__`

`Int32.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.16 `pandera.dtypes.Int64`

class `pandera.dtypes.Int64`

Semantic representation of an integer data type stored in 64 bits.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.
<code>signed</code>	Whether the integer data type is signed.

Methods

<code>__init__</code>	
<code>check</code>	Check that <code>pandera.DataType</code> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <code>~pandera.errors.ParserError</code> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.16.1 `pandera.dtypes.Int64.__init__`

`Int64.__init__()`

7.15.2.1.16.2 `pandera.dtypes.Int64.check`

`Int64.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.16.3 `pandera.dtypes.Int64.coerce`

`Int64.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.16.4 `pandera.dtypes.Int64.coerce_value`

`Int64.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.16.5 `pandera.dtypes.Int64.try_coerce`

`Int64.try_coerce(data_container)`

Coerce data container to the data type, raises a *~pandera.errors.ParserError* if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.16.6 `pandera.dtypes.Int64.__call__`

`Int64.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.17 `pandera.dtypes.UInt`

class `pandera.dtypes.UInt`

Semantic representation of an unsigned integer data type.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.
<code>signed</code>	Whether the integer data type is signed.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.17.1 pandera.dtypes.UInt.__init__

`UInt.__init__()`

7.15.2.1.17.2 pandera.dtypes.UInt.check

`UInt.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.17.3 pandera.dtypes.UInt.coerce

`UInt.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.17.4 pandera.dtypes.UInt.coerce_value

`UInt.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.17.5 pandera.dtypes.UInt.try_coerce

`UInt.try_coerce(data_container)`

Coerce data container to the data type, raises a `~pandera.errors.ParserError` if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.17.6 pandera.dtypes.UInt.__call__

`UInt.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.18 pandera.dtypes.UInt8

class `pandera.dtypes.UInt8`

Semantic representation of an unsigned integer data type stored in 8 bits.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.
<code>signed</code>	Whether the integer data type is signed.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <code>DataType</code> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <code>~pandera.errors.ParserError</code> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.18.1 pandera.dtypes.UInt8.__init__

`UInt8.__init__()`

7.15.2.1.18.2 `pandera.dtypes.UInt8.check`

`UInt8.check(pandera_dtype)`

Check that `pandera.DataType` are equivalent.

Return type `bool`

7.15.2.1.18.3 `pandera.dtypes.UInt8.coerce`

`UInt8.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.18.4 `pandera.dtypes.UInt8.coerce_value`

`UInt8.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.18.5 `pandera.dtypes.UInt8.try_coerce`

`UInt8.try_coerce(data_container)`

Coerce data container to the data type, raises a `~pandera.errors.ParserError` if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.18.6 `pandera.dtypes.UInt8.__call__`

`UInt8.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.19 `pandera.dtypes.UInt16`

class `pandera.dtypes.UInt16`

Semantic representation of an unsigned integer data type stored in 16 bits.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.
<code>signed</code>	Whether the integer data type is signed.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.19.1 pandera.dtypes.UInt16.__init__

`UInt16.__init__()`

7.15.2.1.19.2 pandera.dtypes.UInt16.check

`UInt16.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.19.3 pandera.dtypes.UInt16.coerce

`UInt16.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.19.4 pandera.dtypes.UInt16.coerce_value

`UInt16.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.19.5 pandera.dtypes.UInt16.try_coerce

`UInt16.try_coerce(data_container)`

Coerce data container to the data type, raises a *pandera.errors.ParserError* if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.19.6 pandera.dtypes.UInt16.__call__

`UInt16.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.20 pandera.dtypes.UInt32

class `pandera.dtypes.UInt32`

Semantic representation of an unsigned integer data type stored in 32 bits.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.
<code>signed</code>	Whether the integer data type is signed.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.20.1 pandera.dtypes.UInt32.__init__

`UInt32.__init__()`

7.15.2.1.20.2 pandera.dtypes.UInt32.check

`UInt32.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.20.3 `pandera.dtypes.UInt32.coerce`

`UInt32.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.20.4 `pandera.dtypes.UInt32.coerce_value`

`UInt32.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.20.5 `pandera.dtypes.UInt32.try_coerce`

`UInt32.try_coerce(data_container)`

Coerce data container to the data type, raises a `~pandera.errors.ParserError` if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.20.6 `pandera.dtypes.UInt32.__call__`

`UInt32.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.21 `pandera.dtypes.UInt64`

class `pandera.dtypes.UInt64`

Semantic representation of an unsigned integer data type stored in 64 bits.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.
<code>signed</code>	Whether the integer data type is signed.

Methods

<code>__init__</code>	
<code>check</code>	Check that <code>pandera.DataType</code> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <code>~pandera.errors.ParserError</code> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.21.1 `pandera.dtypes.UInt64.__init__`

`UInt64.__init__()`

7.15.2.1.21.2 `pandera.dtypes.UInt64.check`

`UInt64.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.21.3 `pandera.dtypes.UInt64.coerce`

`UInt64.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.21.4 `pandera.dtypes.UInt64.coerce_value`

`UInt64.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.21.5 `pandera.dtypes.UInt64.try_coerce`

`UInt64.try_coerce(data_container)`

Coerce data container to the data type, raises a *~pandera.errors.ParserError* if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.21.6 `pandera.dtypes.UInt64.__call__`

`UInt64.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.22 `pandera.dtypes.Complex`

class `pandera.dtypes.Complex`

Semantic representation of a complex number data type.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.22.1 pandera.dtypes.Complex.__init__

`Complex.__init__()`

7.15.2.1.22.2 pandera.dtypes.Complex.check

`Complex.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.22.3 pandera.dtypes.Complex.coerce

`Complex.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.22.4 pandera.dtypes.Complex.coerce_value

`Complex.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.22.5 `pandera.dtypes.Complex.try_coerce`

`Complex.try_coerce(data_container)`

Coerce data container to the data type, raises a `~pandera.errors.ParserError` if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.22.6 `pandera.dtypes.Complex.__call__`

`Complex.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.23 `pandera.dtypes.Complex64`

class `pandera.dtypes.Complex64`

Semantic representation of a complex number data type stored in 64 bits.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.

Methods

<code>__init__</code>	
<code>check</code>	Check that <code>pandera.DataType</code> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <code>~pandera.errors.ParserError</code> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.23.1 `pandera.dtypes.Complex64.__init__`

`Complex64.__init__()`

7.15.2.1.23.2 pandera.dtypes.Complex64.check

`Complex64.check`(*pandera_dtype*)

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.23.3 pandera.dtypes.Complex64.coerce

`Complex64.coerce`(*data_container*)

Coerce data container to the data type.

7.15.2.1.23.4 pandera.dtypes.Complex64.coerce_value

`Complex64.coerce_value`(*value*)

Coerce an value to a particular type.

7.15.2.1.23.5 pandera.dtypes.Complex64.try_coerce

`Complex64.try_coerce`(*data_container*)

Coerce data container to the data type, raises a *~pandera.errors.ParserError* if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.23.6 pandera.dtypes.Complex64.__call__

`Complex64.__call__`(*data_container*)

Coerce data container to the data type.

7.15.2.1.24 pandera.dtypes.Complex128

class `pandera.dtypes.Complex128`

Semantic representation of a complex number data type stored in 128 bits.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.24.1 pandera.dtypes.Complex128.__init__

`Complex128.__init__()`

7.15.2.1.24.2 pandera.dtypes.Complex128.check

`Complex128.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.24.3 pandera.dtypes.Complex128.coerce

`Complex128.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.24.4 pandera.dtypes.Complex128.coerce_value

`Complex128.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.24.5 pandera.dtypes.Complex128.try_coerce

`Complex128.try_coerce(data_container)`

Coerce data container to the data type, raises a *pandera.errors.ParserError* if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.24.6 pandera.dtypes.Complex128.__call__

`Complex128.__call__(data_container)`
Coerce data container to the data type.

7.15.2.1.25 pandera.dtypes.Complex256

class `pandera.dtypes.Complex256`

Semantic representation of a complex number data type stored in 256 bits.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.25.1 pandera.dtypes.Complex256.__init__

`Complex256.__init__()`

7.15.2.1.25.2 pandera.dtypes.Complex256.check

`Complex256.check(pandera_dtype)`
Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.25.3 `pandera.dtypes.Complex256.coerce`

`Complex256.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.25.4 `pandera.dtypes.Complex256.coerce_value`

`Complex256.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.25.5 `pandera.dtypes.Complex256.try_coerce`

`Complex256.try_coerce(data_container)`

Coerce data container to the data type, raises a `~pandera.errors.ParserError` if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.25.6 `pandera.dtypes.Complex256.__call__`

`Complex256.__call__(data_container)`

Coerce data container to the data type.

7.15.2.1.26 `pandera.dtypes.String`

class `pandera.dtypes.String`

Semantic representation of a string data type.

Attributes

<code>continuous</code>	Whether the number data type is continuous.
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Methods

<code>__init__</code>	
<code>check</code>	Check that <code>pandera.DataType</code> are equivalent.
<code>coerce</code>	Coerce data container to the data type.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <code>~pandera.errors.ParserError</code> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.1.26.1 `pandera.dtypes.String.__init__`

`String.__init__()`

7.15.2.1.26.2 `pandera.dtypes.String.check`

`String.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.1.26.3 `pandera.dtypes.String.coerce`

`String.coerce(data_container)`

Coerce data container to the data type.

7.15.2.1.26.4 `pandera.dtypes.String.coerce_value`

`String.coerce_value(value)`

Coerce an value to a particular type.

7.15.2.1.26.5 `pandera.dtypes.String.try_coerce`

`String.try_coerce(data_container)`

Coerce data container to the data type, raises a *~pandera.errors.ParserError* if the coercion fails

Raises `ParserError`: if coercion fails

7.15.2.1.26.6 `pandera.dtypes.String.__call__`

`String.__call__(data_container)`

Coerce data container to the data type.

7.15.2.2 Pandas Dtypes

Listed here for compatibility with pandera versions < 0.7. Passing native pandas dtypes to pandera components is preferred.

<code>pandera.engines.pandas_engine.BOOL</code>	Semantic representation of a <code>pandas.BooleanDtype</code> .
<code>pandera.engines.pandas_engine.INT8</code>	Semantic representation of a <code>pandas.Int8Dtype</code> .
<code>pandera.engines.pandas_engine.INT16</code>	Semantic representation of a <code>pandas.Int16Dtype</code> .
<code>pandera.engines.pandas_engine.INT32</code>	Semantic representation of a <code>pandas.Int32Dtype</code> .
<code>pandera.engines.pandas_engine.INT64</code>	Semantic representation of a <code>pandas.Int64Dtype</code> .
<code>pandera.engines.pandas_engine.UINT8</code>	Semantic representation of a <code>pandas.UInt8Dtype</code> .
<code>pandera.engines.pandas_engine.UINT16</code>	Semantic representation of a <code>pandas.UInt16Dtype</code> .
<code>pandera.engines.pandas_engine.UINT32</code>	Semantic representation of a <code>pandas.UInt32Dtype</code> .
<code>pandera.engines.pandas_engine.UINT64</code>	Semantic representation of a <code>pandas.UInt64Dtype</code> .
<code>pandera.engines.pandas_engine.STRING</code>	Semantic representation of a <code>pandas.StringDtype</code> .
<code>pandera.engines.numpy_engine.Object</code>	Semantic representation of a <code>numpy.object_</code> .
<code>pandera.engines.pandas_engine.DateTime</code>	Semantic representation of a <code>pandas.DatetimeTZDtype</code> .

7.15.2.2.1 `pandera.engines.pandas_engine.BOOL`

class `pandera.engines.pandas_engine.BOOL`

Semantic representation of a `pandas.BooleanDtype`.

Attributes

<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.
<code>type</code>	Native pandas dtype boxed by the data type.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataTypes</i> are equivalent.
<code>coerce</code>	Pure coerce without catching exceptions.
<code>coerce_value</code>	Coerce an value to specified datatype type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <code>pandera.errors.ParserError</code> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.2.1.1 `pandera.engines.pandas_engine.BOOL.__init__`

`BOOL.__init__()`

7.15.2.2.1.2 `pandera.engines.pandas_engine.BOOL.check`

`BOOL.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.2.1.3 `pandera.engines.pandas_engine.BOOL.coerce`

`BOOL.coerce(data_container)`

Pure coerce without catching exceptions.

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.1.4 `pandera.engines.pandas_engine.BOOL.coerce_value`

`BOOL.coerce_value(value)`

Coerce an value to specified datetime type.

Return type `Any`

7.15.2.2.1.5 `pandera.engines.pandas_engine.BOOL.try_coerce`

`BOOL.try_coerce(data_container)`

Coerce data container to the data type, raises a `~pandera.errors.ParserError` if the coercion fails

Raises `ParserError`: if coercion fails

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.1.6 `pandera.engines.pandas_engine.BOOL.__call__`

`BOOL.__call__(data_container)`

Coerce data container to the data type.

7.15.2.2.2 `pandera.engines.pandas_engine.INT8`

`class pandera.engines.pandas_engine.INT8`

Semantic representation of a `pandas.Int8Dtype`.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.
<code>signed</code>	Whether the integer data type is signed.
<code>type</code>	Native pandas dtype boxed by the data type.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Pure coerce without catching exceptions.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.2.2.1 pandera.engines.pandas_engine.INT8.__init__

`INT8.__init__()`

7.15.2.2.2.2 pandera.engines.pandas_engine.INT8.check

`INT8.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.2.2.3 pandera.engines.pandas_engine.INT8.coerce

`INT8.coerce(data_container)`

Pure coerce without catching exceptions.

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.2.4 `pandera.engines.pandas_engine.INT8.coerce_value`

`INT8.coerce_value(value)`

Coerce an value to a particular type.

Return type `Any`

7.15.2.2.2.5 `pandera.engines.pandas_engine.INT8.try_coerce`

`INT8.try_coerce(data_container)`

Coerce data container to the data type, raises a `~pandera.errors.ParserError` if the coercion fails

Raises `ParserError`: if coercion fails

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.2.6 `pandera.engines.pandas_engine.INT8.__call__`

`INT8.__call__(data_container)`

Coerce data container to the data type.

7.15.2.2.3 `pandera.engines.pandas_engine.INT16`

class `pandera.engines.pandas_engine.INT16`

Semantic representation of a `pandas.Int16Dtype`.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.
<code>signed</code>	Whether the integer data type is signed.
<code>type</code>	Native pandas dtype boxed by the data type.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <code>DataTypes</code> are equivalent.
<code>coerce</code>	Pure coerce without catching exceptions.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <code>~pandera.errors.ParserError</code> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.2.3.1 `pandera.engines.pandas_engine.INT16.__init__`

`INT16.__init__()`

7.15.2.2.3.2 `pandera.engines.pandas_engine.INT16.check`

`INT16.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.2.3.3 `pandera.engines.pandas_engine.INT16.coerce`

`INT16.coerce(data_container)`

Pure coerce without catching exceptions.

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.3.4 `pandera.engines.pandas_engine.INT16.coerce_value`

`INT16.coerce_value(value)`

Coerce an value to a particular type.

Return type `Any`

7.15.2.2.3.5 `pandera.engines.pandas_engine.INT16.try_coerce`

`INT16.try_coerce(data_container)`

Coerce data container to the data type, raises a *~pandera.errors.ParserError* if the coercion fails

Raises `ParserError`: if coercion fails

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.3.6 `pandera.engines.pandas_engine.INT16.__call__`

`INT16.__call__(data_container)`

Coerce data container to the data type.

7.15.2.2.4 `pandera.engines.pandas_engine.INT32`

`class pandera.engines.pandas_engine.INT32`

Semantic representation of a `pandas.Int32Dtype`.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.
<code>signed</code>	Whether the integer data type is signed.
<code>type</code>	Native pandas dtype boxed by the data type.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Pure coerce without catching exceptions.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.2.4.1 `pandera.engines.pandas_engine.INT32.__init__`

`INT32.__init__()`

7.15.2.2.4.2 `pandera.engines.pandas_engine.INT32.check`

`INT32.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.2.4.3 `pandera.engines.pandas_engine.INT32.coerce`

`INT32.coerce(data_container)`

Pure coerce without catching exceptions.

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.4.4 `pandera.engines.pandas_engine.INT32.coerce_value`

`INT32.coerce_value(value)`

Coerce an value to a particular type.

Return type `Any`

7.15.2.2.4.5 `pandera.engines.pandas_engine.INT32.try_coerce`

`INT32.try_coerce(data_container)`

Coerce data container to the data type, raises a `~pandera.errors.ParserError` if the coercion fails

Raises `ParserError`: if coercion fails

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.4.6 `pandera.engines.pandas_engine.INT32.__call__`

`INT32.__call__(data_container)`

Coerce data container to the data type.

7.15.2.2.5 `pandera.engines.pandas_engine.INT64`

class `pandera.engines.pandas_engine.INT64`

Semantic representation of a `pandas.Int64Dtype`.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.
<code>signed</code>	Whether the integer data type is signed.
<code>type</code>	Native pandas dtype boxed by the data type.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <code>DataType</code> are equivalent.
<code>coerce</code>	Pure coerce without catching exceptions.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <code>~pandera.errors.ParserError</code> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.2.5.1 `pandera.engines.pandas_engine.INT64.__init__`

`INT64.__init__()`

7.15.2.2.5.2 `pandera.engines.pandas_engine.INT64.check`

`INT64.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.2.5.3 `pandera.engines.pandas_engine.INT64.coerce`

`INT64.coerce(data_container)`

Pure coerce without catching exceptions.

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.5.4 `pandera.engines.pandas_engine.INT64.coerce_value`

`INT64.coerce_value(value)`

Coerce an value to a particular type.

Return type `Any`

7.15.2.2.5.5 `pandera.engines.pandas_engine.INT64.try_coerce`

`INT64.try_coerce(data_container)`

Coerce data container to the data type, raises a *~pandera.errors.ParserError* if the coercion fails

Raises `ParserError`: if coercion fails

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.5.6 `pandera.engines.pandas_engine.INT64.__call__`

`INT64.__call__(data_container)`

Coerce data container to the data type.

7.15.2.2.6 `pandera.engines.pandas_engine.UINT8`

`class pandera.engines.pandas_engine.UINT8`

Semantic representation of a `pandas.UInt8Dtype`.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.
<code>signed</code>	Whether the integer data type is signed.
<code>type</code>	Native pandas dtype boxed by the data type.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Pure coerce without catching exceptions.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.2.6.1 pandera.engines.pandas_engine.UINT8.__init__

`UINT8.__init__()`

7.15.2.2.6.2 pandera.engines.pandas_engine.UINT8.check

`UINT8.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.2.6.3 pandera.engines.pandas_engine.UINT8.coerce

`UINT8.coerce(data_container)`

Pure coerce without catching exceptions.

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.6.4 `pandera.engines.pandas_engine.UINT8.coerce_value`

`UINT8.coerce_value(value)`

Coerce an value to a particular type.

Return type `Any`

7.15.2.2.6.5 `pandera.engines.pandas_engine.UINT8.try_coerce`

`UINT8.try_coerce(data_container)`

Coerce data container to the data type, raises a `~pandera.errors.ParserError` if the coercion fails

Raises `ParserError`: if coercion fails

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.6.6 `pandera.engines.pandas_engine.UINT8.__call__`

`UINT8.__call__(data_container)`

Coerce data container to the data type.

7.15.2.2.7 `pandera.engines.pandas_engine.UINT16`

`class pandera.engines.pandas_engine.UINT16`

Semantic representation of a `pandas.UInt16Dtype`.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.
<code>signed</code>	Whether the integer data type is signed.
<code>type</code>	Native pandas dtype boxed by the data type.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <code>DataTypes</code> are equivalent.
<code>coerce</code>	Pure coerce without catching exceptions.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <code>~pandera.errors.ParserError</code> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.2.7.1 `pandera.engines.pandas_engine.UINT16.__init__`

`UINT16.__init__()`

7.15.2.2.7.2 `pandera.engines.pandas_engine.UINT16.check`

`UINT16.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.2.7.3 `pandera.engines.pandas_engine.UINT16.coerce`

`UINT16.coerce(data_container)`

Pure coerce without catching exceptions.

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.7.4 `pandera.engines.pandas_engine.UINT16.coerce_value`

`UINT16.coerce_value(value)`

Coerce an value to a particular type.

Return type `Any`

7.15.2.2.7.5 `pandera.engines.pandas_engine.UINT16.try_coerce`

`UINT16.try_coerce(data_container)`

Coerce data container to the data type, raises a *pandera.errors.ParserError* if the coercion fails

Raises `ParserError`: if coercion fails

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.7.6 `pandera.engines.pandas_engine.UINT16.__call__`

`UINT16.__call__(data_container)`

Coerce data container to the data type.

7.15.2.2.8 `pandera.engines.pandas_engine.UINT32`

`class pandera.engines.pandas_engine.UINT32`

Semantic representation of a `pandas.UInt32Dtype`.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.
<code>signed</code>	Whether the integer data type is signed.
<code>type</code>	Native pandas dtype boxed by the data type.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Pure coerce without catching exceptions.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.2.8.1 pandera.engines.pandas_engine.UINT32.__init__

`UINT32.__init__()`

7.15.2.2.8.2 pandera.engines.pandas_engine.UINT32.check

`UINT32.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.2.8.3 pandera.engines.pandas_engine.UINT32.coerce

`UINT32.coerce(data_container)`

Pure coerce without catching exceptions.

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.8.4 `pandera.engines.pandas_engine.UINT32.coerce_value`

`UINT32.coerce_value(value)`

Coerce an value to a particular type.

Return type `Any`

7.15.2.2.8.5 `pandera.engines.pandas_engine.UINT32.try_coerce`

`UINT32.try_coerce(data_container)`

Coerce data container to the data type, raises a `~pandera.errors.ParserError` if the coercion fails

Raises `ParserError`: if coercion fails

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.8.6 `pandera.engines.pandas_engine.UINT32.__call__`

`UINT32.__call__(data_container)`

Coerce data container to the data type.

7.15.2.2.9 `pandera.engines.pandas_engine.UINT64`

class `pandera.engines.pandas_engine.UINT64`

Semantic representation of a `pandas.UInt64Dtype`.

Attributes

<code>bit_width</code>	Number of bits used by the machine representation.
<code>continuous</code>	Whether the number data type is continuous.
<code>exact</code>	Whether the data type is an exact representation of a number.
<code>signed</code>	Whether the integer data type is signed.
<code>type</code>	Native pandas dtype boxed by the data type.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <code>DataType</code> are equivalent.
<code>coerce</code>	Pure coerce without catching exceptions.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <code>~pandera.errors.ParserError</code> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.2.9.1 `pandera.engines.pandas_engine.UINT64.__init__`

`UINT64.__init__()`

7.15.2.2.9.2 `pandera.engines.pandas_engine.UINT64.check`

`UINT64.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.2.9.3 `pandera.engines.pandas_engine.UINT64.coerce`

`UINT64.coerce(data_container)`

Pure coerce without catching exceptions.

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.9.4 `pandera.engines.pandas_engine.UINT64.coerce_value`

`UINT64.coerce_value(value)`

Coerce an value to a particular type.

Return type `Any`

7.15.2.2.9.5 `pandera.engines.pandas_engine.UINT64.try_coerce`

`UINT64.try_coerce(data_container)`

Coerce data container to the data type, raises a *~pandera.errors.ParserError* if the coercion fails

Raises `ParserError`: if coercion fails

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.9.6 `pandera.engines.pandas_engine.UINT64.__call__`

`UINT64.__call__(data_container)`

Coerce data container to the data type.

7.15.2.2.10 `pandera.engines.pandas_engine.STRING`

`class pandera.engines.pandas_engine.STRING(storage='python')`

Semantic representation of a `pandas.StringDtype`.

Attributes

continuous storage	Whether the number data type is continuous.
type	Native pandas dtype boxed by the data type.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Pure coerce without catching exceptions.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>from_parametrized_dtype</code>	Convert a <code>pandas.StringDtype</code> to a Pandera <code>pandera.engines.pandas_engine.STRING</code> .
<code>try_coerce</code>	Coerce data container to the data type, raises a <code>pandera.errors.ParserError</code> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.2.10.1 pandera.engines.pandas_engine.STRING.__init__

`STRING.__init__(storage='python')`

7.15.2.2.10.2 pandera.engines.pandas_engine.STRING.check

`STRING.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.2.10.3 pandera.engines.pandas_engine.STRING.coerce

`STRING.coerce(data_container)`

Pure coerce without catching exceptions.

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.10.4 pandera.engines.pandas_engine.STRING.coerce_value

`STRING.coerce_value(value)`

Coerce an value to a particular type.

Return type `Any`

7.15.2.2.10.5 pandera.engines.pandas_engine.STRING.from_parametrized_dtype

classmethod `STRING.from_parametrized_dtype(pd_dtype)`

Convert a `pandas.StringDtype` to a Pandera `pandera.engines.pandas_engine.STRING`.

7.15.2.2.10.6 pandera.engines.pandas_engine.STRING.try_coerce

`STRING.try_coerce(data_container)`

Coerce data container to the data type, raises a `~pandera.errors.ParserError` if the coercion fails

Raises `ParserError`: if coercion fails

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.10.7 pandera.engines.pandas_engine.STRING.__call__

`STRING.__call__(data_container)`

Coerce data container to the data type.

7.15.2.2.11 pandera.engines.numpy_engine.Object

class `pandera.engines.numpy_engine.Object`

Semantic representation of a `numpy.object_`.

Attributes

<code>continuous</code>	Whether the number data type is continuous.
<code>type</code>	Native numpy dtype boxed by the data type.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <code>DataTypes</code> are equivalent.
<code>coerce</code>	Pure coerce without catching exceptions.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <code>~pandera.errors.ParserError</code> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.2.11.1 pandera.engines.numpy_engine.Object.__init__

`Object.__init__()`

7.15.2.2.11.2 pandera.engines.numpy_engine.Object.check

`Object.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.2.11.3 pandera.engines.numpy_engine.Object.coerce

`Object.coerce(data_container)`

Pure coerce without catching exceptions.

Return type `Union[Series, Index, DataFrame]`

7.15.2.2.11.4 pandera.engines.numpy_engine.Object.coerce_value

`Object.coerce_value(value)`

Coerce an value to a particular type.

Return type `Any`

7.15.2.2.11.5 pandera.engines.numpy_engine.Object.try_coerce

`Object.try_coerce(data_container)`

Coerce data container to the data type, raises a *~pandera.errors.ParserError* if the coercion fails

Raises `ParserError`: if coercion fails

Return type `Union[Series, Index, DataFrame, ndarray]`

7.15.2.2.11.6 pandera.engines.numpy_engine.Object.__call__

`Object.__call__(data_container)`

Coerce data container to the data type.

7.15.2.2.12 pandera.engines.pandas_engine.DateTime

`class pandera.engines.pandas_engine.DateTime(unit='ns', tz=None, to_datetime_kwargs=<factory>)`

Semantic representation of a `pandas.DatetimeTZDtype`.

Attributes

continuous	Whether the number data type is continuous.
type	Native pandas dtype boxed by the data type.
tz	The timezone.
unit	The precision of the datetime data.
to_datetime_kwargs	Any additional kwargs passed to <code>pandas.to_datetime()</code> for coercion.

Methods**7.15.2.3 GeoPandas Dtypes**

new in 0.9.0

`pandera.engines.pandas_engine.Geometry`

7.15.2.3.1 pandera.engines.pandas_engine.Geometry

class `pandera.engines.pandas_engine.Geometry`(*dtype: Any*)

Attributes

continuous	Whether the number data type is continuous.
type	Native pandas dtype boxed by the data type.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Pure coerce without catching exceptions.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.3.1.1 `pandera.engines.pandas_engine.Geometry.__init__`

`Geometry.__init__()`

7.15.2.3.1.2 `pandera.engines.pandas_engine.Geometry.check`

`Geometry.check(pandera_dtype)`

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.3.1.3 `pandera.engines.pandas_engine.Geometry.coerce`

`Geometry.coerce(data_container)`

Pure coerce without catching exceptions.

Return type `Union[Series, Index, DataFrame]`

7.15.2.3.1.4 `pandera.engines.pandas_engine.Geometry.coerce_value`

`Geometry.coerce_value(value)`

Coerce an value to a particular type.

Return type `Any`

7.15.2.3.1.5 `pandera.engines.pandas_engine.Geometry.try_coerce`

`Geometry.try_coerce(data_container)`

Coerce data container to the data type, raises a `~pandera.errors.ParserError` if the coercion fails

Raises `ParserError`: if coercion fails

Return type `Union[Series, Index, DataFrame]`

7.15.2.3.1.6 `pandera.engines.pandas_engine.Geometry.__call__`

`Geometry.__call__(data_container)`

Coerce data container to the data type.

7.15.2.4 Pydantic Dtypes

new in 0.10.0

`pandera.engines.pandas_engine.
PydanticModel`

A pydantic model datatype applying to rows in a dataframe.

7.15.2.4.1 pandera.engines.pandas_engine.PydanticModel

class pandera.engines.pandas_engine.PydanticModel(*model*)

A pydantic model datatype applying to rows in a dataframe.

Attributes

<code>continuous</code>	Whether the number data type is continuous.
<code>type</code>	Native pandas dtype boxed by the data type.

Methods

<code>__init__</code>	
<code>check</code>	Check that pandera <i>DataType</i> are equivalent.
<code>coerce</code>	Coerce pandas dataframe with pydantic record model.
<code>coerce_value</code>	Coerce an value to a particular type.
<code>try_coerce</code>	Coerce data container to the data type, raises a <i>pandera.errors.ParserError</i> if the coercion fails
<code>__call__</code>	Coerce data container to the data type.

7.15.2.4.1.1 pandera.engines.pandas_engine.PydanticModel.__init__

PydanticModel.**__init__**(*model*)

7.15.2.4.1.2 pandera.engines.pandas_engine.PydanticModel.check

PydanticModel.**check**(*pandera_dtype*)

Check that pandera *DataType* are equivalent.

Return type `bool`

7.15.2.4.1.3 pandera.engines.pandas_engine.PydanticModel.coerce

PydanticModel.**coerce**(*data_container*)

Coerce pandas dataframe with pydantic record model.

Return type `DataFrame`

7.15.2.4.1.4 `pandera.engines.pandas_engine.PydanticModel.coerce_value`

`PydanticModel.coerce_value(value)`

Coerce an value to a particular type.

Return type `Any`

7.15.2.4.1.5 `pandera.engines.pandas_engine.PydanticModel.try_coerce`

`PydanticModel.try_coerce(data_container)`

Coerce data container to the data type, raises a `~pandera.errors.ParserError` if the coercion fails

Raises `ParserError`: if coercion fails

Return type `Union[Series, Index, DataFrame]`

7.15.2.4.1.6 `pandera.engines.pandas_engine.PydanticModel.__call__`

`PydanticModel.__call__(data_container)`

Coerce data container to the data type.

7.15.2.5 Utility functions

<code>pandera.dtypes.is_subdtype</code>	Returns True if first argument is lower/equal in <code>DataType</code> hierarchy.
<code>pandera.dtypes.is_float</code>	Return True if <code>pandera.dtypes.DataType</code> is a float.
<code>pandera.dtypes.is_int</code>	Return True if <code>pandera.dtypes.DataType</code> is an integer.
<code>pandera.dtypes.is_uint</code>	Return True if <code>pandera.dtypes.DataType</code> is an unsigned integer.
<code>pandera.dtypes.is_complex</code>	Return True if <code>pandera.dtypes.DataType</code> is a complex number.
<code>pandera.dtypes.is_numeric</code>	Return True if <code>pandera.dtypes.DataType</code> is a complex number.
<code>pandera.dtypes.is_bool</code>	Return True if <code>pandera.dtypes.DataType</code> is a boolean.
<code>pandera.dtypes.is_string</code>	Return True if <code>pandera.dtypes.DataType</code> is a string.
<code>pandera.dtypes.is_datetime</code>	Return True if <code>pandera.dtypes.DataType</code> is a date-time.
<code>pandera.dtypes.is_timedelta</code>	Return True if <code>pandera.dtypes.DataType</code> is a timedelta.
<code>pandera.dtypes.immutable</code>	<code>dataclasses.dataclass()</code> decorator with different default values: <code>frozen=True</code> , <code>init=False</code> , <code>repr=False</code> .

7.15.2.5.1 `pandera.dtypes.is_subdtype`

`pandera.dtypes.is_subdtype(arg1, arg2)`

Returns True if first argument is lower/equal in `DataType` hierarchy.

Return type `bool`

7.15.2.5.2 `pandera.dtypes.is_float`

`pandera.dtypes.is_float(pandera_dtype)`

Return True if `pandera.dtypes.DataType` is a float.

Return type `bool`

7.15.2.5.3 `pandera.dtypes.is_int`

`pandera.dtypes.is_int(pandera_dtype)`

Return True if `pandera.dtypes.DataType` is an integer.

Return type `bool`

7.15.2.5.4 `pandera.dtypes.is_uint`

`pandera.dtypes.is_uint(pandera_dtype)`

Return True if `pandera.dtypes.DataType` is an unsigned integer.

Return type `bool`

7.15.2.5.5 `pandera.dtypes.is_complex`

`pandera.dtypes.is_complex(pandera_dtype)`

Return True if `pandera.dtypes.DataType` is a complex number.

Return type `bool`

7.15.2.5.6 `pandera.dtypes.is_numeric`

`pandera.dtypes.is_numeric(pandera_dtype)`

Return True if `pandera.dtypes.DataType` is a complex number.

Return type `bool`

7.15.2.5.7 pandera.dtypes.is_bool

`pandera.dtypes.is_bool(pandera_dtype)`

Return True if `pandera.dtypes.DataType` is a boolean.

Return type bool

7.15.2.5.8 pandera.dtypes.is_string

`pandera.dtypes.is_string(pandera_dtype)`

Return True if `pandera.dtypes.DataType` is a string.

Return type bool

7.15.2.5.9 pandera.dtypes.is_datetime

`pandera.dtypes.is_datetime(pandera_dtype)`

Return True if `pandera.dtypes.DataType` is a datetime.

Return type bool

7.15.2.5.10 pandera.dtypes.is_timedelta

`pandera.dtypes.is_timedelta(pandera_dtype)`

Return True if `pandera.dtypes.DataType` is a timedelta.

Return type bool

7.15.2.5.11 pandera.dtypes.immutable

`pandera.dtypes.immutable(pandera_dtype_cls=None, **dataclass_kwargs)`

`dataclasses.dataclass()` decorator with different default values: `frozen=True`, `init=False`, `repr=False`.

In addition, `init=False` disables inherited `__init__` method to ensure the `DataType`'s default attributes are not altered during initialization.

Parameters

- **dtype** – `DataType` to decorate.
- **dataclass_kwargs** (Any) – Keywords arguments forwarded to `dataclasses.dataclass()`.

Return type Union[Type[~_Dtype], Callable[[Type[~_Dtype]], Type[~_Dtype]]]

Returns Immutable `DataType`

7.15.2.6 Engines

<code>pandera.engines.engine.Engine</code>	Base Engine metaclass.
<code>pandera.engines.numpy_engine.Engine</code>	Numpy data type engine.
<code>pandera.engines.pandas_engine.Engine</code>	Pandas data type engine.

7.15.2.6.1 `pandera.engines.engine.Engine`

class `pandera.engines.engine.Engine`(*name*, *bases*, *namespace*, ***kwargs*)

Base Engine metaclass.

Keep a registry of concrete Engines.

Methods

<code>dtype</code>	Convert input into a Pandera <code>DataType</code> object.
<code>get_registered_dtypes</code>	Return the <code>pandera.dtypes.DataTypes</code> registered with this engine.
<code>register_dtype</code>	Register a Pandera <code>DataType</code> with the engine, as class decorator.
<code>__call__</code>	Call self as a function.

7.15.2.6.1.1 `pandera.engines.engine.Engine.dtype`

`Engine.dtype`(*data_type*)

Convert input into a Pandera `DataType` object.

Return type `~_DataType`

7.15.2.6.1.2 `pandera.engines.engine.Engine.get_registered_dtypes`

`Engine.get_registered_dtypes`()

Return the `pandera.dtypes.DataTypes` registered with this engine.

Return type `List[Type[DataType]]`

7.15.2.6.1.3 `pandera.engines.engine.Engine.register_dtype`

`Engine.register_dtype`(*pandera_dtype_cls=None*, ***, *equivalents=None*)

Register a Pandera `DataType` with the engine, as class decorator.

Parameters

- **`pandera_dtype`** – The `DataType` to register.
- **`equivalents`** (`Optional[List[Any]]`) – Equivalent scalar data type classes or non-parametrized data type instances.

Note: The classmethod `from_parametrized_dtype` will also be registered. See [here](#) for more usage details.

Example

```
>>> import pandera as pa
>>>
>>> class MyDataType(pa.DataType):
...     pass
>>>
>>> class MyEngine(
...     metaclass=pa.engines.engine.Engine,
...     base_pandera_dtypes=MyDataType,
... ):
...     pass
>>>
>>> @MyEngine.register_dtype(equivalents=[bool])
... class MyBool(MyDataType):
...     pass
```

Return type `Callable`

7.15.2.6.1.4 `pandera.engines.engine.Engine.__call__`

`Engine.__call__(*args, **kwargs)`

Call self as a function.

7.15.2.6.2 `pandera.engines.numpy_engine.Engine`

`class pandera.engines.numpy_engine.Engine`

Numpy data type engine.

Methods

<code>dtype</code>	Convert input into a numpy-compatible Pandera <code>DataType</code> object.
--------------------	---

7.15.2.6.2.1 `pandera.engines.numpy_engine.Engine.dtype`

classmethod `Engine.dtype(data_type)`

Convert input into a numpy-compatible Pandera *DataType* object.

Return type *DataType*

7.15.2.6.3 `pandera.engines.pandas_engine.Engine`

class `pandera.engines.pandas_engine.Engine`

Pandas data type engine.

Methods

<i>dtype</i>	Convert input into a pandas-compatible Pandera <i>DataType</i> object.
<i>numpy_dtype</i>	Convert a Pandera dtype.

7.15.2.6.3.1 `pandera.engines.pandas_engine.Engine.dtype`

classmethod `Engine.dtype(data_type)`

Convert input into a pandas-compatible Pandera *DataType* object.

Return type *DataType*

7.15.2.6.3.2 `pandera.engines.pandas_engine.Engine.numpy_dtype`

classmethod `Engine.numpy_dtype(pandera_dtype)`

Convert a Pandera dtype.

Return type *dtype*

7.15.3 Schema Models

7.15.3.1 Schema Model

<code>pandera.model.SchemaModel(*args, **kwargs)</code>	Definition of a DataFrameSchema.
---	----------------------------------

7.15.3.1.1 pandera.model.SchemaModel

class `pandera.model.SchemaModel(*args, **kwargs)`

Definition of a DataFrameSchema.

new in 0.5.0

See the *User Guide* for more.

Check if all columns in a dataframe have a column in the Schema.

Parameters

- **check_obj** (*pd.DataFrame*) – the dataframe to be validated.
- **head** – validate the first n rows. Rows overlapping with *tail* or *sample* are de-duplicated.
- **tail** – validate the last n rows. Rows overlapping with *head* or *sample* are de-duplicated.
- **sample** – validate a random sample of n rows. Rows overlapping with *head* or *tail* are de-duplicated.
- **random_state** – random seed for the *sample* argument.
- **lazy** – if True, lazily evaluates dataframe against all validation checks and raises a *SchemaErrors*. Otherwise, raise *SchemaError* as soon as one occurs.
- **inplace** – if True, applies coercion to the object of validation, otherwise creates a copy of the data.

Returns validated DataFrame

Raises *SchemaError* – when DataFrame violates built-in or custom checks.

Example

Calling `schema.validate` returns the dataframe.

```
>>> import pandas as pd
>>> import pandera as pa
>>>
>>> df = pd.DataFrame({
...     "probability": [0.1, 0.4, 0.52, 0.23, 0.8, 0.76],
...     "category": ["dog", "dog", "cat", "duck", "dog", "dog"]
... })
>>>
>>> schema_withchecks = pa.DataFrameSchema({
...     "probability": pa.Column(
...         float, pa.Check(lambda s: (s >= 0) & (s <= 1))),
...     # check that the "category" column contains a few discrete
...     # values, and the majority of the entries are dogs.
...     "category": pa.Column(
...         str, [
...             pa.Check(lambda s: s.isin(["dog", "cat", "duck"])),
...             pa.Check(lambda s: (s == "dog").mean() > 0.5),
...         ]),
... })
>>>
>>> schema_withchecks.validate(df)[["probability", "category"]]
```

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	probability	category
0	0.10	dog
1	0.40	dog
2	0.52	cat
3	0.23	duck
4	0.80	dog
5	0.76	dog

Methods

<i>example</i>	Create a hypothesis strategy for generating a DataFrame.
<i>strategy</i>	Create a hypothesis strategy for generating a DataFrame.
<i>to_schema</i>	Create DataFrameSchema from the SchemaModel .
<i>to_yaml</i>	Convert <i>Schema</i> to yaml using <i>io.to_yaml</i> .
<i>validate</i>	Check if all columns in a dataframe have a column in the Schema.

7.15.3.1.1.1 pandera.model.SchemaModel.example

classmethod `SchemaModel.example`(*cls*, *, *size=None*)

Create a hypothesis strategy for generating a DataFrame.

Parameters

- **size** (`Optional[int]`) – number of elements to generate
- **n_regex_columns** – number of regex columns to generate.

Return type DataFrameBase[~TSchemaModel]

Returns a strategy that generates pandas DataFrame objects.

7.15.3.1.1.2 pandera.model.SchemaModel.strategy

classmethod `SchemaModel.strategy`(*cls*, *, *size=None*)

Create a hypothesis strategy for generating a DataFrame.

Parameters

- **size** (`Optional[int]`) – number of elements to generate
- **n_regex_columns** – number of regex columns to generate.

Returns a strategy that generates pandas DataFrame objects.

7.15.3.1.1.3 `pandera.model.SchemaModel.to_schema`

classmethod `SchemaModel.to_schema()`

Create `DataFrameSchema` from the `SchemaModel`.

Return type `DataFrameSchema`

7.15.3.1.1.4 `pandera.model.SchemaModel.to_yaml`

classmethod `SchemaModel.to_yaml(stream=None)`

Convert `Schema` to yaml using `io.to_yaml`.

7.15.3.1.1.5 `pandera.model.SchemaModel.validate`

classmethod `SchemaModel.validate(check_obj, head=None, tail=None, sample=None, random_state=None, lazy=False, inplace=False)`

Check if all columns in a dataframe have a column in the Schema.

Parameters

- **check_obj** (`pd.DataFrame`) – the dataframe to be validated.
- **head** (`Optional[int]`) – validate the first n rows. Rows overlapping with `tail` or `sample` are de-duplicated.
- **tail** (`Optional[int]`) – validate the last n rows. Rows overlapping with `head` or `sample` are de-duplicated.
- **sample** (`Optional[int]`) – validate a random sample of n rows. Rows overlapping with `head` or `tail` are de-duplicated.
- **random_state** (`Optional[int]`) – random seed for the `sample` argument.
- **lazy** (`bool`) – if True, lazily evaluates dataframe against all validation checks and raises a `SchemaErrors`. Otherwise, raise `SchemaError` as soon as one occurs.
- **inplace** (`bool`) – if True, applies coercion to the object of validation, otherwise creates a copy of the data.

Return type `DataFrameBase[~TSchemaModel]`

Returns validated `DataFrame`

Raises `SchemaError` – when `DataFrame` violates built-in or custom checks.

Example

Calling `schema.validate` returns the dataframe.

```
>>> import pandas as pd
>>> import pandera as pa
>>>
>>> df = pd.DataFrame({
...     "probability": [0.1, 0.4, 0.52, 0.23, 0.8, 0.76],
...     "category": ["dog", "dog", "cat", "duck", "dog", "dog"]
... })
>>>
```

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```

>>> schema_withchecks = pa.DataFrameSchema({
...     "probability": pa.Column(
...         float, pa.Check(lambda s: (s >= 0) & (s <= 1))),
...     # check that the "category" column contains a few discrete
...     # values, and the majority of the entries are dogs.
...     "category": pa.Column(
...         str, [
...             pa.Check(lambda s: s.isin(["dog", "cat", "duck"])),
...             pa.Check(lambda s: (s == "dog").mean() > 0.5),
...         ]),
... })
>>>
>>> schema_withchecks.validate(df)[["probability", "category"]]
  probability category
0          0.10     dog
1          0.40     dog
2          0.52     cat
3          0.23    duck
4          0.80     dog
5          0.76     dog

```

7.15.3.2 Model Components

<code>pandera.model_components.Field(*[, eq, ne, ...])</code>	Used to provide extra information about a field of a SchemaModel.
<code>pandera.model_components.check(*fields[, regex])</code>	Decorator to make SchemaModel method a column/index check function.
<code>pandera.model_components.dataframe_check([_fn])</code>	Decorator to make SchemaModel method a dataframe-wide check function.

7.15.3.2.1 pandera.model_components.Field

`pandera.model_components.Field(*, eq=None, ne=None, gt=None, ge=None, lt=None, le=None, in_range=None, isin=None, notin=None, str_contains=None, str_endswith=None, str_length=None, str_matches=None, str_startswith=None, nullable=False, unique=False, coerce=False, regex=False, ignore_na=True, raise_warning=False, n_failure_cases=None, alias=None, check_name=None, dtype_kwargs=None, title=None, description=None, **kwargs)`

Used to provide extra information about a field of a SchemaModel.

new in 0.5.0

Some arguments apply only to numeric dtypes and some apply only to `str`. See the [User Guide](#) for more information.

The keyword-only arguments from `eq` to `str_startswith` are dispatched to the built-in [Check](#) methods.

Parameters

- **nullable** (`bool`) – Whether or not the column/index can contain null values.

- **unique** (*bool*) – Whether column values should be unique.
- **coerce** (*bool*) – coerces the data type if *True*.
- **regex** (*bool*) – whether or not the field name or alias is a regex pattern.
- **ignore_na** (*bool*) – whether or not to ignore null values in the checks.
- **raise_warning** (*bool*) – raise a warning instead of an Exception.
- **n_failure_cases** (*Optional[int]*) – report the first *n* unique failure cases. If *None*, report all failure cases.
- **alias** (*Optional[Any]*) – The public name of the column/index.
- **check_name** (*Optional[bool]*) – Whether to check the name of the column/index during validation. *None* is the default behavior, which translates to *True* for columns and multi-index, and to *False* for a single index.
- **dtype_kwargs** (*Optional[Dict[str, Any]]*) – The parameters to be forwarded to the type of the field.
- **title** (*Optional[str]*) – A human-readable label for the field.
- **description** (*Optional[str]*) – An arbitrary textual description of the field.
- **kwargs** – Specify custom checks that have been registered with the `register_check_method` decorator.

Return type *Any*

7.15.3.2.2 `pandera.model_components.check`

`pandera.model_components.check(*fields, regex=False, **check_kwargs)`

Decorator to make SchemaModel method a column/index check function.

new in 0.5.0

This indicates that the decorated method should be used to validate a field (column or index). The method will be converted to a classmethod. Therefore its signature must start with *cls* followed by regular check arguments. See the *User Guide* for more.

Parameters

- **_fn** – Method to decorate.
- **check_kwargs** – Keywords arguments forwarded to Check.

Return type `Callable[[Union[classmethod, Callable[... Any]]], classmethod]`

7.15.3.2.3 `pandera.model_components.dataframe_check`

`pandera.model_components.dataframe_check(_fn=None, **check_kwargs)`

Decorator to make SchemaModel method a dataframe-wide check function.

new in 0.5.0

Decorate a method on the SchemaModel indicating that it should be used to validate the DataFrame. The method will be converted to a classmethod. Therefore its signature must start with *cls* followed by regular check arguments. See the *User Guide* for more.

Parameters **check_kwargs** – Keywords arguments forwarded to Check.

Return type `Callable[[Union[classmethod, Callable[... Any]]], classmethod]`

7.15.3.3 Typing

<code>pandera.typing</code>	Typing module.
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7.15.3.3.1 pandera.typing

Typing module.

For backwards compatibility, pandas types are exposed to the top-level scope of the typing module.

Pandas Types

<code>DataFrame([data, index, columns, dtype, copy])</code>	A generic type for <code>pandas.DataFrame</code> .
<code>Index([data, dtype, copy, name, tupleize_cols])</code>	Representation of <code>pandas.Index</code> , only used for type annotation.
<code>Series([data, index, dtype, name, copy, ...])</code>	Representation of <code>pandas.Series</code> , only used for type annotation.

GeoPandas Types

<code>geopandas.GeoDataFrame([data, geometry, crs])</code>	A generic type for <code>geopandas.GeoDataFrame</code> .
<code>geopandas.GeoSeries([data, index, crs])</code>	Representation of <code>geopandas.GeoSeries</code> , only used for type annotation.

Dask Types

<code>dask.DataFrame(dsk, name, meta, divisions)</code>	Representation of <code>dask.dataframe.DataFrame</code> , only used for type annotation.
<code>dask.Series(dsk, name, meta, divisions)</code>	Representation of <code>pandas.Series</code> , only used for type annotation.
<code>dask.Index(dsk, name, meta, divisions)</code>	Representation of <code>pandas.Index</code> , only used for type annotation.

Pyspark Pandas Types

<code>pyspark.DataFrame([data, index, columns, ...])</code>	Representation of <code>dask.dataframe.DataFrame</code> , only used for type annotation.
<code>pyspark.Series([data, index, dtype, name, ...])</code>	Representation of <code>pandas.Series</code> , only used for type annotation.
<code>pyspark.Index([data, dtype, copy, name, ...])</code>	Representation of <code>pandas.Index</code> , only used for type annotation.

Modin Types

<code>pyspark.DataFrame([data, index, columns, ...])</code>	Representation of <code>dask.dataframe.DataFrame</code> , only used for type annotation.
<code>pyspark.Series([data, index, dtype, name, ...])</code>	Representation of <code>pandas.Series</code> , only used for type annotation.
<code>pyspark.Index([data, dtype, copy, name, ...])</code>	Representation of <code>pandas.Index</code> , only used for type annotation.

FastAPI Types

<code><i>fastapi.UploadFile</i>(data, filename, file, ...)</code>	Pandera-specific subclass of <code>fastapi.UploadFile</code> .
---	--

7.15.3.3.1.1 pandera.typing.fastapi.UploadFile

class `pandera.typing.fastapi.UploadFile`(*data, filename, file, *args, **kwargs*)

Pandera-specific subclass of `fastapi.UploadFile`.

This type uses `pandera.typing.DataFrame` to read files into dataframe format based on the `pandera.models.SchemaModel` configuration.

Initialize `UploadFile` object that has a `data` property that contains validated data.

Parameters `data` (*Any*) – pandera-validated data

Filename

__init__(*data, filename, file, *args, **kwargs*)

Initialize `UploadFile` object that has a `data` property that contains validated data.

Parameters `data` (*Any*) – pandera-validated data

Filename

Methods

<code>__init__(data, filename, file, *args, **kwargs)</code>	Initialize UploadFile object that has a <code>data</code> property that contains validated data.
<code>close()</code>	rtype <code>None</code>
<code>pydantic_validate(obj, field)</code>	Pydantic validation method for validating dataframes in the context of a file upload.
<code>read([size])</code>	rtype <code>Union[bytes, str]</code>
<code>seek(offset)</code>	rtype <code>None</code>
<code>validate(v)</code>	rtype <code>Any</code>
<code>write(data)</code>	rtype <code>None</code>

Attributes

<code>data</code>
<code>spool_max_size</code>

Serialization Formats

<code>formats.Formats(value)</code>	Data container serialization formats.
-------------------------------------	---------------------------------------

7.15.3.3.1.2 pandera.typing.formats.Formats

class `pandera.typing.formats.Formats`(*value*)

Data container serialization formats.

The values of this enum specify the valid values taken by the `to_format` and `from_format` attributes in [BaseConfig](#) when specifying a [SchemaModel](#).

`__init__()`

Attributes

csv	comma-separated values file
dict	python dictionary
json	json file
feather	feather file format.
parquet	parquet file format.
pickle	python pickle file format

DataTypes

Bool()	Semantic representation of a boolean data type.
DateTime	alias of <code>pandera.dtypes.Timestamp</code>
Timedelta()	Semantic representation of a delta time data type.
Category([categories, ordered])	Semantic representation of a categorical data type.
Float()	Semantic representation of a floating data type.
Float16()	Semantic representation of a floating data type stored in 16 bits.
Float32()	Semantic representation of a floating data type stored in 32 bits.
Float64()	Semantic representation of a floating data type stored in 64 bits.
Int()	Semantic representation of an integer data type.
Int8()	Semantic representation of an integer data type stored in 8 bits.
Int16()	Semantic representation of an integer data type stored in 16 bits.
Int32()	Semantic representation of an integer data type stored in 32 bits.
Int64()	Semantic representation of an integer data type stored in 64 bits.
UInt8()	Semantic representation of an unsigned integer data type stored in 8 bits.
UInt16()	Semantic representation of an unsigned integer data type stored in 16 bits.
UInt32()	Semantic representation of an unsigned integer data type stored in 32 bits.
UInt64()	Semantic representation of an unsigned integer data type stored in 64 bits.
INT8()	Semantic representation of a <code>pandas.Int8Dtype</code> .
INT16()	Semantic representation of a <code>pandas.Int16Dtype</code> .
INT32()	Semantic representation of a <code>pandas.Int32Dtype</code> .
INT64()	Semantic representation of a <code>pandas.Int64Dtype</code> .
UINT8()	Semantic representation of a <code>pandas.UInt8Dtype</code> .
UINT16()	Semantic representation of a <code>pandas.UInt16Dtype</code> .
UINT32()	Semantic representation of a <code>pandas.UInt32Dtype</code> .
UINT64()	Semantic representation of a <code>pandas.UInt64Dtype</code> .
Object()	Semantic representation of a <code>numpy.object_</code> .
String()	Semantic representation of a string data type.
STRING([storage])	Semantic representation of a <code>pandas.StringDtype</code> .

7.15.3.4 Config

`pandera.model.BaseConfig`Define DataFrameSchema-wide options.

7.15.3.4.1 `pandera.model.BaseConfig`**class** `pandera.model.BaseConfig`Bases: `object`

Define DataFrameSchema-wide options.

*new in 0.5.0***Attributes**

<code>coerce</code>	coerce types of all schema components
<code>description</code>	arbitrary textual description
<code>dtype</code>	datatype of the dataframe.
<code>from_format</code>	data format before validation.
<code>from_format_kwargs</code>	a dictionary keyword arguments to pass into the reader function that converts the object of type <code>from_format</code> to a pandera-validate-able data structure.
<code>multiindex_coerce</code>	coerce types of all MultiIndex components
<code>multiindex_name</code>	name of multiindex
<code>multiindex_ordered</code>	validate MultiIndex in order
<code>multiindex_strict</code>	make sure all specified columns are in validated MultiIndex - if "filter", removes indexes not specified in the schema
<code>name</code>	name of schema
<code>ordered</code>	validate columns order
<code>strict</code>	make sure all specified columns are in the validated dataframe - if "filter", removes columns not specified in the schema
<code>title</code>	human-readable label for schema
<code>to_format</code>	data format to serialize into after validation.
<code>to_format_kwargs</code>	a dictionary keyword arguments to pass into the writer function that converts the pandera-validate-able object to type <code>to_format</code> .
<code>unique</code>	make sure certain column combinations are unique
<code>unique_column_names</code>	make sure dataframe column names are unique

7.15.4 Decorators

<code>pandera.decorators.check_input</code>	Validate function argument when function is called.
<code>pandera.decorators.check_output</code>	Validate function output.
<code>pandera.decorators.check_io</code>	Check schema for multiple inputs and outputs.
<code>pandera.decorators.check_types</code>	Validate function inputs and output based on type annotations.

7.15.4.1 `pandera.decorators.check_input`

`pandera.decorators.check_input` (*schema*, *obj_getter=None*, *head=None*, *tail=None*, *sample=None*, *random_state=None*, *lazy=False*, *inplace=False*)

Validate function argument when function is called.

This is a decorator function that validates the schema of a dataframe argument in a function.

Parameters

- **schema** (`Union[DataFrameSchema, SeriesSchema]`) – dataframe/series schema object
- **obj_getter** (`Union[int, str, None]`) – (Default value = None) if int, `obj_getter` refers to the the index of the pandas dataframe/series to be validated in the args part of the function signature. If str, `obj_getter` refers to the argument name of the pandas dataframe/series in the function signature. This works even if the series/dataframe is passed in as a positional argument when the function is called. If None, assumes that the dataframe/series is the first argument of the decorated function
- **head** (`Optional[int]`) – validate the first n rows. Rows overlapping with *tail* or *sample* are de-duplicated.
- **tail** (`Optional[int]`) – validate the last n rows. Rows overlapping with *head* or *sample* are de-duplicated.
- **sample** (`Optional[int]`) – validate a random sample of n rows. Rows overlapping with *head* or *tail* are de-duplicated.
- **random_state** (`Optional[int]`) – random seed for the *sample* argument.
- **lazy** (`bool`) – if True, lazily evaluates dataframe against all validation checks and raises a `SchemaErrors`. Otherwise, raise `SchemaError` as soon as one occurs.
- **inplace** (`bool`) – if True, applies coercion to the object of validation, otherwise creates a copy of the data.

Return type `Callable[[~F], ~F]`

Returns wrapped function

Example

Check the input of a decorated function.

```
>>> import pandas as pd
>>> import pandera as pa
>>>
>>>
>>> schema = pa.DataFrameSchema({"column": pa.Column(int)})
>>>
```

(continues on next page)

```

>>> @pa.check_input(schema)
... def transform_data(df: pd.DataFrame) -> pd.DataFrame:
...     df["doubled_column"] = df["column"] * 2
...     return df
>>>
>>> df = pd.DataFrame({
...     "column": range(5),
... })
>>>
>>> transform_data(df)
   column  doubled_column
0         0                0
1         1                2
2         2                4
3         3                6
4         4                8

```

See [here](#) for more usage details.

7.15.4.2 pandera.decorators.check_output

`pandera.decorators.check_output` (*schema, obj_getter=None, head=None, tail=None, sample=None, random_state=None, lazy=False, inplace=False*)

Validate function output.

Similar to input validator, but validates the output of the decorated function.

Parameters

- **schema** (`Union[DataFrameSchema, SeriesSchema]`) – dataframe/series schema object
- **obj_getter** (`Union[str, int, Callable, None]`) – (Default value = None) if int, assumes that the output of the decorated function is a list-like object, where `obj_getter` is the index of the pandas data dataframe/series to be validated. If str, expects that the output is a dict-like object, and `obj_getter` is the key pointing to the dataframe/series to be validated. If a callable is supplied, it expects the output of decorated function and should return the dataframe/series to be validated.
- **head** (`Optional[int]`) – validate the first n rows. Rows overlapping with `tail` or `sample` are de-duplicated.
- **tail** (`Optional[int]`) – validate the last n rows. Rows overlapping with `head` or `sample` are de-duplicated.
- **sample** (`Optional[int]`) – validate a random sample of n rows. Rows overlapping with `head` or `tail` are de-duplicated.
- **random_state** (`Optional[int]`) – random seed for the `sample` argument.
- **lazy** (`bool`) – if True, lazily evaluates dataframe against all validation checks and raises a `SchemaErrors`. Otherwise, raise `SchemaError` as soon as one occurs.
- **inplace** (`bool`) – if True, applies coercion to the object of validation, otherwise creates a copy of the data.

Return type `Callable[[~F], ~F]`

Returns wrapped function

Example

Check the output a decorated function.

```

>>> import pandas as pd
>>> import pandera as pa
>>>
>>>
>>> schema = pa.DataFrameSchema(
...     columns={"doubled_column": pa.Column(int)},
...     checks=pa.Check(
...         lambda df: df["doubled_column"] == df["column"] * 2
...     )
... )
>>>
>>> @pa.check_output(schema)
... def transform_data(df: pd.DataFrame) -> pd.DataFrame:
...     df["doubled_column"] = df["column"] * 2
...     return df
>>>
>>> df = pd.DataFrame({"column": range(5)})
>>>
>>> transform_data(df)
   column  doubled_column
0         0                0
1         1                2
2         2                4
3         3                6
4         4                8

```

See [here](#) for more usage details.

7.15.4.3 pandera.decorators.check_io

`pandera.decorators.check_io`(*head=None, tail=None, sample=None, random_state=None, lazy=False, inplace=False, out=None, **inputs*)

Check schema for multiple inputs and outputs.

See [here](#) for more usage details.

Parameters

- **head** (`Optional[int]`) – validate the first *n* rows. Rows overlapping with *tail* or *sample* are de-duplicated.
- **tail** (`Optional[int]`) – validate the last *n* rows. Rows overlapping with *head* or *sample* are de-duplicated.
- **sample** (`Optional[int]`) – validate a random sample of *n* rows. Rows overlapping with *head* or *tail* are de-duplicated.
- **random_state** (`Optional[int]`) – random seed for the *sample* argument.
- **lazy** (`bool`) – if True, lazily evaluates dataframe against all validation checks and raises a `SchemaErrors`. Otherwise, raise `SchemaError` as soon as one occurs.
- **inplace** (`bool`) – if True, applies coercion to the object of validation, otherwise creates a copy of the data.

- **out** (`Union[DataFrameSchema, SeriesSchema, Tuple[Union[str, int, Callable], Union[DataFrameSchema, SeriesSchema]]]`, `List[Tuple[Union[str, int, Callable], Union[DataFrameSchema, SeriesSchema]]]`, `None`) – this should be a schema object if the function outputs a single dataframe/series. It can be a two-tuple, where the first element is a string, integer, or callable that fetches the pandas data structure in the output, and the second element is the schema to validate against. For multiple outputs, specify a list of two-tuples following the above structure.
- **inputs** (`Union[DataFrameSchema, SeriesSchema]`) – kwargs keys should be the argument name in the decorated function and values should be the schema used to validate the pandas data structure referenced by the argument name.

Return type `Callable[[~F], ~F]`

Returns wrapped function

7.15.4.4 `pandera.decorators.check_types`

```
pandera.decorators.check_types(wrapped: pandera.decorators.F, *, head: Optional[int] = 'None', tail:
    Optional[int] = 'None', sample: Optional[int] = 'None', random_state:
    Optional[int] = 'None', lazy: bool = 'False', inplace: bool = 'False') →
    pandera.decorators.F
```

```
pandera.decorators.check_types(wrapped: None = None, *, head: Optional[int] = 'None', tail: Optional[int] =
    'None', sample: Optional[int] = 'None', random_state: Optional[int] =
    'None', lazy: bool = 'False', inplace: bool = 'False') →
    Callable[[pandera.decorators.F], pandera.decorators.F]
```

Validate function inputs and output based on type annotations.

See the [User Guide](#) for more.

Parameters

- **wrapped** – the function to decorate.
- **with_pydantic** – use `pydantic.validate_arguments` to validate inputs. This function is still needed to validate function outputs.
- **head** (`Optional[int]`) – validate the first n rows. Rows overlapping with *tail* or *sample* are de-duplicated.
- **tail** (`Optional[int]`) – validate the last n rows. Rows overlapping with *head* or *sample* are de-duplicated.
- **sample** (`Optional[int]`) – validate a random sample of n rows. Rows overlapping with *head* or *tail* are de-duplicated.
- **random_state** (`Optional[int]`) – random seed for the *sample* argument.
- **lazy** (`bool`) – if True, lazily evaluates dataframe against all validation checks and raises a `SchemaErrors`. Otherwise, raise `SchemaError` as soon as one occurs.
- **inplace** (`bool`) – if True, applies coercion to the object of validation, otherwise creates a copy of the data.

Return type `Callable`

7.15.5 Schema Inference

<code>pandera.schema_inference.infer_schema</code>	Infer schema for pandas DataFrame or Series object.
--	---

7.15.5.1 pandera.schema_inference.infer_schema

`pandera.schema_inference.infer_schema(pandas_obj: pandas.core.series.Series) → pandera.schemas.SeriesSchema`

`pandera.schema_inference.infer_schema(pandas_obj: pandas.core.frame.DataFrame) → pandera.schemas.DataFrameSchema`

Infer schema for pandas DataFrame or Series object.

Parameters `pandas_obj` – DataFrame or Series object to infer.

Returns DataFrameSchema or SeriesSchema

Raises TypeError if pandas_obj is not expected type.

7.15.6 IO Utilities

The `io` module and built-in Hypothesis checks require a pandera installation with the corresponding extension, see the *installation* instructions for more details.

<code>pandera.io.from_yaml</code>	Create <i>DataFrameSchema</i> from yaml file.
<code>pandera.io.to_yaml</code>	Write <i>DataFrameSchema</i> to yaml file.
<code>pandera.io.to_script</code>	Write <i>DataFrameSchema</i> to a python script.

7.15.6.1 pandera.io.from_yaml

`pandera.io.from_yaml(yaml_schema)`

Create *DataFrameSchema* from yaml file.

Parameters `yaml_schema` – str or Path to yaml schema, or serialized yaml string.

Returns dataframe schema.

7.15.6.2 pandera.io.to_yaml

`pandera.io.to_yaml(dataframe_schema, stream=None)`

Write *DataFrameSchema* to yaml file.

Parameters

- **dataframe_schema** – schema to write to file or dump to string.
- **stream** – file stream to write to. If None, dumps to string.

Returns yaml string if stream is None, otherwise returns None.

7.15.6.3 pandera.io.to_script

`pandera.io.to_script(dataframe_schema, path_or_buf=None)`

Write *DataFrameSchema* to a python script.

Parameters

- **dataframe_schema** – schema to write to file or dump to string.
- **path_or_buf** – filepath or buf stream to write to. If None, outputs string representation of the script.

Returns yaml string if stream is None, otherwise returns None.

7.15.7 Data Synthesis Strategies

pandera.strategies

Generate synthetic data from a schema definition.

7.15.7.1 pandera.strategies

Generate synthetic data from a schema definition.

new in 0.6.0

This module is responsible for generating data based on the type and check constraints specified in a *pandera* schema. It's built on top of the *hypothesis* package to compose strategies given multiple checks specified in a schema.

See the *user guide* for more details.

`pandera.strategies.column_strategy(pandera_dtype, strategy=None, *, checks=None, unique=False, name=None)`

Create a data object describing a column in a DataFrame.

Parameters

- **pandera_dtype** (`Union[DataType, DataType]`) – *pandera.dtypes.DataType* instance.
- **strategy** (`Optional[SearchStrategy]`) – an optional hypothesis strategy. If specified, the pandas dtype strategy will be chained onto this strategy.
- **checks** (`Optional[Sequence]`) – sequence of *Check* s to constrain the values of the data in the column/index.
- **unique** (`bool`) – whether or not generated Series contains unique values.
- **name** (`Optional[str]`) – name of the Series.

Returns a *column* object.

`pandera.strategies.dataframe_strategy(pandera_dtype=None, strategy=None, *, columns=None, checks=None, unique=None, index=None, size=None, n_regex_columns=1)`

Strategy to generate a pandas DataFrame.

Parameters

- **pandera_dtype** (`Optional[DataType]`) – *pandera.dtypes.DataType* instance.
- **strategy** (`Optional[SearchStrategy]`) – if specified, this will raise a *BaseStrategyOnlyError*, since it cannot be chained to a prior strategy.

- **columns** (`Optional[Dict]`) – a dictionary where keys are column names and values are `Column` objects.
- **checks** (`Optional[Sequence]`) – sequence of `Check` s to constrain the values of the data at the dataframe level.
- **unique** (`Optional[List[str]]`) – a list of column names that should be jointly unique.
- **index** (`Optional[Any]`) – Index or MultiIndex schema component.
- **size** (`Optional[int]`) – number of elements in the Series.
- **n_regex_columns** (`int`) – number of regex columns to generate.

Returns hypothesis strategy.

`pandera.strategies.eq_strategy(pandera_dtype, strategy=None, *, value)`

Strategy to generate a single value.

Parameters

- **pandera_dtype** (`Union[DataType, DataType]`) – `pandera.dtypes.DataType` instance.
- **strategy** (`Optional[SearchStrategy]`) – an optional hypothesis strategy. If specified, the pandas dtype strategy will be chained onto this strategy.
- **value** (`Any`) – value to generate.

Return type `SearchStrategy`

Returns hypothesis strategy

`pandera.strategies.field_element_strategy(pandera_dtype, strategy=None, *, checks=None)`

Strategy to generate elements of a column or index.

Parameters

- **pandera_dtype** (`Union[DataType, DataType]`) – `pandera.dtypes.DataType` instance.
- **strategy** (`Optional[SearchStrategy]`) – an optional hypothesis strategy. If specified, the pandas dtype strategy will be chained onto this strategy.
- **checks** (`Optional[Sequence]`) – sequence of `Check` s to constrain the values of the data in the column/index.

Return type `SearchStrategy`

Returns hypothesis strategy

`pandera.strategies.ge_strategy(pandera_dtype, strategy=None, *, min_value)`

Strategy to generate values greater than or equal to a minimum value.

Parameters

- **pandera_dtype** (`Union[DataType, DataType]`) – `pandera.dtypes.DataType` instance.
- **strategy** (`Optional[SearchStrategy]`) – an optional hypothesis strategy. If specified, the pandas dtype strategy will be chained onto this strategy.
- **min_value** (`Union[int, float]`) – generate values greater than or equal to this.

Return type `SearchStrategy`

Returns hypothesis strategy

`pandera.strategies.gt_strategy(pandera_dtype, strategy=None, *, min_value)`

Strategy to generate values greater than a minimum value.

Parameters

- **pandera_dtype** (`Union[DataType, DataType]`) – `pandera.dtypes.DataType` instance.
- **strategy** (`Optional[SearchStrategy]`) – an optional hypothesis strategy. If specified, the pandas dtype strategy will be chained onto this strategy.
- **min_value** (`Union[int, float]`) – generate values larger than this.

Return type `SearchStrategy`

Returns hypothesis strategy

`pandera.strategies.in_range_strategy(pandera_dtype, strategy=None, *, min_value, max_value, include_min=True, include_max=True)`

Strategy to generate values within a particular range.

Parameters

- **pandera_dtype** (`Union[DataType, DataType]`) – `pandera.dtypes.DataType` instance.
- **strategy** (`Optional[SearchStrategy]`) – an optional hypothesis strategy. If specified, the pandas dtype strategy will be chained onto this strategy.
- **min_value** (`Union[int, float]`) – generate values greater than this.
- **max_value** (`Union[int, float]`) – generate values less than this.
- **include_min** (`bool`) – include `min_value` in generated data.
- **include_max** (`bool`) – include `max_value` in generated data.

Return type `SearchStrategy`

Returns hypothesis strategy

`pandera.strategies.index_strategy(pandera_dtype, strategy=None, *, checks=None, nullable=False, unique=False, name=None, size=None)`

Strategy to generate a pandas Index.

Parameters

- **pandera_dtype** (`Union[DataType, DataType]`) – `pandera.dtypes.DataType` instance.
- **strategy** (`Optional[SearchStrategy]`) – an optional hypothesis strategy. If specified, the pandas dtype strategy will be chained onto this strategy.
- **checks** (`Optional[Sequence]`) – sequence of `Check` s to constrain the values of the data in the column/index.
- **nullable** (`bool`) – whether or not generated Series contains null values.
- **unique** (`bool`) – whether or not generated Series contains unique values.
- **name** (`Optional[str]`) – name of the Series.
- **size** (`Optional[int]`) – number of elements in the Series.

Returns hypothesis strategy.

`pandera.strategies.isin_strategy(pandera_dtype, strategy=None, *, allowed_values)`

Strategy to generate values within a finite set.

Parameters

- **pandera_dtype** (`Union[DataType, DataType]`) – `pandera.dtypes.DataType` instance.
- **strategy** (`Optional[SearchStrategy]`) – an optional hypothesis strategy. If specified, the pandas dtype strategy will be chained onto this strategy.
- **allowed_values** (`Sequence[Any]`) – set of allowable values.

Return type SearchStrategy

Returns hypothesis strategy

`pandera.strategies.le_strategy(pandera_dtype, strategy=None, *, max_value)`

Strategy to generate values less than or equal to a maximum value.

Parameters

- **pandera_dtype** (`Union[DataType, DataType]`) – `pandera.dtypes.DataType` instance.
- **strategy** (`Optional[SearchStrategy]`) – an optional hypothesis strategy. If specified, the pandas dtype strategy will be chained onto this strategy.
- **max_value** (`Union[int, float]`) – generate values less than or equal to this.

Return type SearchStrategy

Returns hypothesis strategy

`pandera.strategies.lt_strategy(pandera_dtype, strategy=None, *, max_value)`

Strategy to generate values less than a maximum value.

Parameters

- **pandera_dtype** (`Union[DataType, DataType]`) – `pandera.dtypes.DataType` instance.
- **strategy** (`Optional[SearchStrategy]`) – an optional hypothesis strategy. If specified, the pandas dtype strategy will be chained onto this strategy.
- **max_value** (`Union[int, float]`) – generate values less than this.

Return type SearchStrategy

Returns hypothesis strategy

`pandera.strategies.multiindex_strategy(pandera_dtype=None, strategy=None, *, indexes=None, size=None)`

Strategy to generate a pandas MultiIndex object.

Parameters

- **pandera_dtype** (`Optional[DataType]`) – `pandera.dtypes.DataType` instance.
- **strategy** (`Optional[SearchStrategy]`) – an optional hypothesis strategy. If specified, the pandas dtype strategy will be chained onto this strategy.
- **indexes** (`Optional[List]`) – a list of `Index` objects.
- **size** (`Optional[int]`) – number of elements in the Series.

Returns hypothesis strategy.

`pandera.strategies.ne_strategy(pandera_dtype, strategy=None, *, value)`

Strategy to generate anything except for a particular value.

Parameters

- **pandera_dtype** (`Union[DataType, DataType]`) – `pandera.dtypes.DataType` instance.

- **strategy** (`Optional[SearchStrategy]`) – an optional hypothesis strategy. If specified, the pandas dtype strategy will be chained onto this strategy.
- **value** (`Any`) – value to avoid.

Return type `SearchStrategy`

Returns hypothesis strategy

`pandera.strategies.notin_strategy(pandera_dtype, strategy=None, *, forbidden_values)`

Strategy to generate values excluding a set of forbidden values

Parameters

- **pandera_dtype** (`Union[DataType, DataType]`) – `pandera.dtypes.DataType` instance.
- **strategy** (`Optional[SearchStrategy]`) – an optional hypothesis strategy. If specified, the pandas dtype strategy will be chained onto this strategy.
- **forbidden_values** (`Sequence[Any]`) – set of forbidden values.

Return type `SearchStrategy`

Returns hypothesis strategy

`pandera.strategies.numpy_complex_dtypes(dtype, min_value=0j, max_value=None, allow_infinity=None, allow_nan=None)`

Create numpy strategy for complex numbers.

Parameters

- **dtype** – numpy complex number datatype
- **min_value** (`complex`) – minimum value, must be complex number
- **max_value** (`Optional[complex]`) – maximum value, must be complex number

Returns hypothesis strategy

`pandera.strategies.numpy_time_dtypes(dtype, min_value=None, max_value=None)`

Create numpy strategy for datetime and timedelta data types.

Parameters

- **dtype** (`Union[dtype, DatetimeTZDtype]`) – numpy datetime or timedelta datatype
- **min_value** – minimum value of the datatype to create
- **max_value** – maximum value of the datatype to create

Returns hypothesis strategy

`pandera.strategies.pandas_dtype_strategy(pandera_dtype, strategy=None, **kwargs)`

Strategy to generate data from a `pandera.dtypes.DataType`.

Parameters

- **pandera_dtype** (`DataType`) – `pandera.dtypes.DataType` instance.
- **strategy** (`Optional[SearchStrategy]`) – an optional hypothesis strategy. If specified, the pandas dtype strategy will be chained onto this strategy.

Kwargs key-word arguments passed into `hypothesis.extra.numpy.from_dtype`. For datetime, timedelta, and complex number datatypes, these arguments are passed into `numpy_time_dtypes()` and `numpy_complex_dtypes()`.

Return type `SearchStrategy`

Returns hypothesis strategy

`pandera.strategies.register_check_strategy(strategy_fn)`

Decorate a Check method with a strategy.

This should be applied to a built-in *Check* method.

Parameters `strategy_fn` (`Callable[... SearchStrategy]`) – add strategy to a check, using check statistics to generate a hypothesis strategy.

`pandera.strategies.series_strategy(pandera_dtype, strategy=None, *, checks=None, nullable=False, unique=False, name=None, size=None)`

Strategy to generate a pandas Series.

Parameters

- **pandera_dtype** (`Union[DataType, DataType]`) – `pandera.dtypes.DataType` instance.
- **strategy** (`Optional[SearchStrategy]`) – an optional hypothesis strategy. If specified, the pandas dtype strategy will be chained onto this strategy.
- **checks** (`Optional[Sequence]`) – sequence of *Check*s to constrain the values of the data in the column/index.
- **nullable** (`bool`) – whether or not generated Series contains null values.
- **unique** (`bool`) – whether or not generated Series contains unique values.
- **name** (`Optional[str]`) – name of the Series.
- **size** (`Optional[int]`) – number of elements in the Series.

Returns hypothesis strategy.

`pandera.strategies.str_contains_strategy(pandera_dtype, strategy=None, *, pattern)`

Strategy to generate strings that contain a particular pattern.

Parameters

- **pandera_dtype** (`Union[DataType, DataType]`) – `pandera.dtypes.DataType` instance.
- **strategy** (`Optional[SearchStrategy]`) – an optional hypothesis strategy. If specified, the pandas dtype strategy will be chained onto this strategy.
- **pattern** (`str`) – regex pattern.

Return type `SearchStrategy`

Returns hypothesis strategy

`pandera.strategies.str_endswith_strategy(pandera_dtype, strategy=None, *, string)`

Strategy to generate strings that end with a specific string pattern.

Parameters

- **pandera_dtype** (`Union[DataType, DataType]`) – `pandera.dtypes.DataType` instance.
- **strategy** (`Optional[SearchStrategy]`) – an optional hypothesis strategy. If specified, the pandas dtype strategy will be chained onto this strategy.
- **string** (`str`) – string pattern.

Return type `SearchStrategy`

Returns hypothesis strategy

`pandera.strategies.str_length_strategy(pandera_dtype, strategy=None, *, min_value, max_value)`

Strategy to generate strings of a particular length

Parameters

- **pandera_dtype** (`Union[DataType, DataType]`) – `pandera.dtypes.DataType` instance.
- **strategy** (`Optional[SearchStrategy]`) – an optional hypothesis strategy. If specified, the pandas dtype strategy will be chained onto this strategy.
- **min_value** (`int`) – minimum string length.
- **max_value** (`int`) – maximum string length.

Return type `SearchStrategy`

Returns hypothesis strategy

`pandera.strategies.str_matches_strategy(pandera_dtype, strategy=None, *, pattern)`

Strategy to generate strings that patch a regex pattern.

Parameters

- **pandera_dtype** (`Union[DataType, DataType]`) – `pandera.dtypes.DataType` instance.
- **strategy** (`Optional[SearchStrategy]`) – an optional hypothesis strategy. If specified, the pandas dtype strategy will be chained onto this strategy.
- **pattern** (`str`) – regex pattern.

Return type `SearchStrategy`

Returns hypothesis strategy

`pandera.strategies.str_startswith_strategy(pandera_dtype, strategy=None, *, string)`

Strategy to generate strings that start with a specific string pattern.

Parameters

- **pandera_dtype** (`Union[DataType, DataType]`) – `pandera.dtypes.DataType` instance.
- **strategy** (`Optional[SearchStrategy]`) – an optional hypothesis strategy. If specified, the pandas dtype strategy will be chained onto this strategy.
- **string** (`str`) – string pattern.

Return type `SearchStrategy`

Returns hypothesis strategy

`pandera.strategies.to_numpy_dtype(pandera_dtype)`

Convert a `DataType` to numpy dtype compatible with hypothesis.

`pandera.strategies.verify_dtype(pandera_dtype, schema_type, name)`

Verify that `pandera_dtype` argument is not `None`.

7.15.8 Extensions

pandera.extensions

pandera API extensions

7.15.8.1 pandera.extensions

pandera API extensions

new in 0.6.0

This module provides utilities for extending the pandera API.

class `pandera.extensions.CheckType`(*value*)

Bases: `enum.Enum`

Check types for registered check methods.

VECTORIZED = 1

Check applied to a Series or DataFrame

ELEMENT_WISE = 2

Check applied to an element of a Series or DataFrame

GROUPBY = 3

Check applied to dictionary of Series or DataFrames.

`pandera.extensions.register_check_method`(*check_fn=None*, *, *statistics=None*, *supported_types=(`<class 'pandas.core.frame.DataFrame'>`, `<class 'pandas.core.series.Series'>`)*, *check_type='vectorized'*, *strategy=None*)

Registers a function as a *Check* method.

See the *user guide* for more details.

Parameters

- **check_fn** – check function to register. The function should take one positional argument for the object to validate and additional keyword-only arguments for the check statistics.
- **statistics** (`Optional[List[str]]`) – list of keyword-only arguments in the `check_fn`, which serve as the statistics needed to serialize/de-serialize the check and generate data if a strategy function is provided.
- **supported_types** (`Union[type, Tuple, List]`) – the pandas type(s) supported by the check function. Valid values are `pd.DataFrame`, `pd.Series`, or a list/tuple of (`pa.DataFrame`, `pa.Series`) if both types are supported.
- **check_type** (`Union[CheckType, str]`) – the expected input of the check function. Valid values are `CheckType` enums or `{"vectorized", "element_wise", "groupby"}`. The input signature of `check_fn` is determined by this argument:
 - if `vectorized`, the first positional argument of `check_fn` should be one of the `supported_types`.
 - if `element_wise`, the first positional argument of `check_fn` should be a single scalar element in the pandas Series or DataFrame.
 - if `groupby`, the first positional argument of `check_fn` should be a dictionary mapping group names to subsets of the Series or DataFrame.

- **strategy** – data-generation strategy associated with the check function.

Returns register check function wrapper.

7.15.9 Errors

<code>pandera.errors.SchemaError</code>	Raised when object does not pass schema validation constraints.
<code>pandera.errors.SchemaErrors</code>	Raised when multiple schema are lazily collected into one error.
<code>pandera.errors.SchemaInitError</code>	Raised when schema initialization fails.
<code>pandera.errors.SchemaDefinitionError</code>	Raised when schema definition is invalid on object validation.

7.15.9.1 `pandera.errors.SchemaError`

```
class pandera.errors.SchemaError(schema, data, message, failure_cases=None, check=None,
                                check_index=None, check_output=None)
```

Raised when object does not pass schema validation constraints.

7.15.9.2 `pandera.errors.SchemaErrors`

```
class pandera.errors.SchemaErrors(schema, schema_errors, data)
```

Raised when multiple schema are lazily collected into one error.

7.15.9.3 `pandera.errors.SchemaInitError`

```
class pandera.errors.SchemaInitError
```

Raised when schema initialization fails.

7.15.9.4 `pandera.errors.SchemaDefinitionError`

```
class pandera.errors.SchemaDefinitionError
```

Raised when schema definition is invalid on object validation.

7.16 Contributing

Whether you are a novice or experienced software developer, all contributions and suggestions are welcome!

7.16.1 Getting Started

If you are looking to contribute to the *pandera* codebase, the best place to start is the [GitHub “issues” tab](#). This is also a great place for filing bug reports and making suggestions for ways in which we can improve the code and documentation.

7.16.2 Contributing to the Codebase

The code is hosted on [GitHub](#), so you will need to use [Git](#) to clone the project and make changes to the codebase.

First create your own fork of *pandera*, then clone it:

```
# replace <my-username> with your github username
git clone https://github.com/<my-username>/pandera.git
```

Once you’ve obtained a copy of the code, create a development environment that’s separate from your existing Python environment so that you can make and test changes without compromising your own work environment.

An excellent guide on setting up python environments can be found [here](#). *Pandera* offers a `environment.yml` to set up a conda-based environment and `requirements-dev.txt` for a virtualenv.

7.16.2.1 Environment Setup

7.16.2.1.1 Option 1: miniconda Setup

Install [miniconda](#), then run:

```
conda create -n pandera-dev python=3.8 # or any python version 3.7+
conda env update -n pandera-dev -f environment.yml
conda activate pandera-dev
pip install -e .
```

7.16.2.1.2 Option 2: virtualenv Setup

```
pip install virtualenv
virtualenv .venv/pandera-dev
source .venv/pandera-dev/bin/activate
pip install -r requirements-dev.txt
pip install -e .
```

7.16.2.1.3 Run Tests

```
pytest tests
```

7.16.2.1.4 Build Documentation Locally

```
make docs
```

7.16.2.1.5 Adding New Dependencies

To add new dependencies to the project, make sure to alter the *environment.yml* file. Then to sync the dependencies from the *environment.yml* file to the *requirements-dev.txt* run the following command

```
python scripts/generate_pip_deps_from_conda.py
```

Moreover to add new dependencies in *setup.py*, it is necessary to add it to the `_extras_require` dictionary.

7.16.2.1.6 Set up pre-commit

This project uses `pre-commit` to ensure that code standard checks pass locally before pushing to the remote project repo. Follow the [installation instructions](#), then set up hooks with `pre-commit install`. After, `black`, `pylint` and `mypy` checks should be run with every commit.

Make sure everything is working correctly by running

```
pre-commit run --all
```

7.16.2.2 Making Changes

Before making changes to the codebase or documentation, create a new branch with:

```
git checkout -b <my-branch>
```

We recommend following the branch-naming convention described in *Making Pull Requests*.

7.16.2.3 Run the Full Test Suite Locally

Before submitting your changes for review, make sure to check that your changes do not break any tests by running:

```
# option 1: if you're working with conda (recommended)
$ make nox-conda

# option 2: if you're working with virtualenv
$ make nox
```

Option 2 assumes that you have python environments for all of the versions that pandera supports.

7.16.2.3.1 Using `mamba` (optional)

You can also use `mamba`, which is a faster implementation of `miniconda`, to run the `nox` test suite. Simply install it via `conda-forge`, and `make nox-conda` should use it under the hood.

```
$ conda install -c conda-forge mamba
$ make nox-conda
```

7.16.2.4 Project Releases

Releases are organized under `milestones`, which are be associated with a corresponding branch. This project uses `semantic versioning`, and we recommend prioritizing issues associated with the next release.

7.16.2.5 Contributing Documentation

Maybe the easiest, fastest, and most useful way to contribute to this project (and any other project) is to contribute documentation. If you find an API within the project that doesn't have an example or description, or could be clearer in its explanation, contribute yours!

You can also find issues for improving documentation under the `docs` label. If you have ideas for documentation improvements, you can create a new issue [here](#)

This project uses Sphinx for auto-documentation and RST syntax for docstrings. Once you have the code downloaded and you find something that is in need of some TLD, take a look at the `Sphinx` documentation or well-documented `examples` within the codebase for guidance on contributing.

You can build the html documentation by running `nox -s docs`. The built documentation can be found in `docs/_build`.

7.16.2.6 Contributing Bugfixes

Bugs are reported under the `bug` label, so if you find a bug create a new issue [here](#).

7.16.2.7 Contributing Enhancements

New feature issues can be found under the `enhancements` label. You can request a feature by creating a new issue [here](#).

7.16.2.8 Making Pull Requests

Once your changes are ready to be submitted, make sure to push your changes to your fork of the GitHub repo before creating a pull request. Depending on the type of issue the pull request is resolving, your pull request should merge onto the appropriate branch:

7.16.2.8.1 Bugfixes

- branch naming convention: `bugfix/<issue number>` or `bugfix/<bugfix-name>`
- pull request to: `dev`

7.16.2.8.2 Documentation

- branch naming convention: `docs/<issue number>` or `docs/<doc-name>`
- pull request to: `release/x.x.x` branch if specified in the issue milestone, otherwise `dev`

7.16.2.8.3 Enhancements

- branch naming convention: `feature/<issue number>` or `feature/<bugfix-name>`
- pull request to: `release/x.x.x` branch if specified in the issue milestone, otherwise `dev`

We will review your changes, and might ask you to make additional changes before it is finally ready to merge. However, once it's ready, we will merge it, and you will have successfully contributed to the codebase!

7.16.2.9 Questions, Ideas, General Discussion

Head on over to the [discussion](#) section if you have questions or ideas, want to show off something that you did with `pandera`, or want to discuss a topic related to the project.

7.16.2.10 Dataframe Schema Style Guides

We have guidelines regarding dataframe and schema styles that are encouraged for each pull request:

- If specifying a single column DataFrame, this can be expressed as a one-liner:

```
DataFrameSchema({"col1": Column(...)})
```

- If specifying one column with multiple lines, or multiple columns:

```
DataFrameSchema(  
    {  
        "col1": Column(  
            int,  
            checks=[  
                Check(...),  
                Check(...),  
            ],  
        ),  
    }  
)
```

- If specifying columns with additional arguments that fit in one line:

```
DataFrameSchema(  
    {"a": Column(int, nullable=True)},  
    strict=True  
)
```

- If specifying columns with additional arguments that don't fit in one line:

```
DataFrameSchema(  
    {  
        "a": Column(  
            int,  
            nullable=True,  
            coerce=True,  
            ...  
        ),  
        "b": Column(  
            ...,  
        )  
    },  
    strict=True)
```

7.16.3 Deprecation policy

This project adopts a rolling policy regarding the minimum supported version of its dependencies, based on [NEP 29](#):

- **Python**: 42 months
- **NumPy**: 24 months
- **Pandas**: 18 months

This means the latest minor (X.Y) version from N months prior. Patch versions (x.y.Z) are not pinned, and only the latest available at the moment of publishing the xarray release is guaranteed to work.

HOW TO CITE

If you use `pandera` in the context of academic or industry research, please consider citing the paper and/or software package.

8.1 Paper

```
@InProceedings{ niels_bantilan-proc-scipy-2020,  
  author    = { {N}iels {B}antilan },  
  title     = { pandera: {S}tatistical {D}ata {V}alidation of {P}andas {D}ataframes },  
  booktitle = { {P}roceedings of the 19th {P}ython in {S}cience {C}onference },  
  pages     = { 116 - 124 },  
  year      = { 2020 },  
  editor    = { {M}eghann {A}garwal and {C}hris {C}alloway and {D}illon {N}iederhut and  
↪{D}avid {S}hupe },  
  doi       = { 10.25080/Majora-342d178e-010 }  
}
```

8.2 Software Package

LICENSE AND CREDITS

pandera is licensed under the [MIT license](#). and is written and maintained by Niels Bantilan (niels@pandera.ci)

INDICES AND TABLES

- `genindex`

PYTHON MODULE INDEX

p

`pandera.extensions`, 223
`pandera.strategies`, 216
`pandera.typing`, 206

Symbols

- `__call__` () (*pandera.checks.Check* method), 131
- `__call__` () (*pandera.dtypes.Bool* method), 142
- `__call__` () (*pandera.dtypes.Category* method), 146
- `__call__` () (*pandera.dtypes.Complex* method), 169
- `__call__` () (*pandera.dtypes.Complex128* method), 172
- `__call__` () (*pandera.dtypes.Complex256* method), 173
- `__call__` () (*pandera.dtypes.Complex64* method), 170
- `__call__` () (*pandera.dtypes.DataType* method), 141
- `__call__` () (*pandera.dtypes.Float* method), 148
- `__call__` () (*pandera.dtypes.Float128* method), 153
- `__call__` () (*pandera.dtypes.Float16* method), 149
- `__call__` () (*pandera.dtypes.Float32* method), 151
- `__call__` () (*pandera.dtypes.Float64* method), 152
- `__call__` () (*pandera.dtypes.Int* method), 155
- `__call__` () (*pandera.dtypes.Int16* method), 158
- `__call__` () (*pandera.dtypes.Int32* method), 159
- `__call__` () (*pandera.dtypes.Int64* method), 160
- `__call__` () (*pandera.dtypes.Int8* method), 156
- `__call__` () (*pandera.dtypes.String* method), 174
- `__call__` () (*pandera.dtypes.Timedelta* method), 145
- `__call__` () (*pandera.dtypes.Timestamp* method), 144
- `__call__` () (*pandera.dtypes.UInt* method), 162
- `__call__` () (*pandera.dtypes.UInt16* method), 165
- `__call__` () (*pandera.dtypes.UInt32* method), 166
- `__call__` () (*pandera.dtypes.UInt64* method), 167
- `__call__` () (*pandera.dtypes.UInt8* method), 163
- `__call__` () (*pandera.engines.engine.Engine* method), 199
- `__call__` () (*pandera.engines.numpy_engine.Object* method), 191
- `__call__` () (*pandera.engines.pandas_engine.BOOL* method), 176
- `__call__` () (*pandera.engines.pandas_engine.Geometry* method), 193
- `__call__` () (*pandera.engines.pandas_engine.INT16* method), 179
- `__call__` () (*pandera.engines.pandas_engine.INT32* method), 181
- `__call__` () (*pandera.engines.pandas_engine.INT64* method), 182
- `__call__` () (*pandera.engines.pandas_engine.INT8* method), 178
- `__call__` () (*pandera.engines.pandas_engine.PydanticModel* method), 195
- `__call__` () (*pandera.engines.pandas_engine.STRING* method), 190
- `__call__` () (*pandera.engines.pandas_engine.UINT16* method), 185
- `__call__` () (*pandera.engines.pandas_engine.UINT32* method), 187
- `__call__` () (*pandera.engines.pandas_engine.UINT64* method), 188
- `__call__` () (*pandera.engines.pandas_engine.UINT8* method), 184
- `__call__` () (*pandera.hypotheses.Hypothesis* method), 138
- `__call__` () (*pandera.schema_components.Column* method), 114
- `__call__` () (*pandera.schema_components.Index* method), 116
- `__call__` () (*pandera.schema_components.MultiIndex* method), 120
- `__call__` () (*pandera.schemas.DataFrameSchema* method), 106
- `__call__` () (*pandera.schemas.SeriesSchema* method), 109
- `__init__` () (*pandera.dtypes.Bool* method), 141
- `__init__` () (*pandera.dtypes.Category* method), 146
- `__init__` () (*pandera.dtypes.Complex* method), 168
- `__init__` () (*pandera.dtypes.Complex128* method), 171
- `__init__` () (*pandera.dtypes.Complex256* method), 172
- `__init__` () (*pandera.dtypes.Complex64* method), 169
- `__init__` () (*pandera.dtypes.DataType* method), 140
- `__init__` () (*pandera.dtypes.Float* method), 147
- `__init__` () (*pandera.dtypes.Float128* method), 153
- `__init__` () (*pandera.dtypes.Float16* method), 148
- `__init__` () (*pandera.dtypes.Float32* method), 150
- `__init__` () (*pandera.dtypes.Float64* method), 151
- `__init__` () (*pandera.dtypes.Int* method), 154
- `__init__` () (*pandera.dtypes.Int16* method), 157
- `__init__` () (*pandera.dtypes.Int32* method), 158
- `__init__` () (*pandera.dtypes.Int64* method), 160
- `__init__` () (*pandera.dtypes.Int8* method), 155

__init__() (pandera.dtypes.String method), 174
 __init__() (pandera.dtypes.Timedelta method), 144
 __init__() (pandera.dtypes.Timestamp method), 143
 __init__() (pandera.dtypes.UInt method), 161
 __init__() (pandera.dtypes.UInt16 method), 164
 __init__() (pandera.dtypes.UInt32 method), 165
 __init__() (pandera.dtypes.UInt64 method), 167
 __init__() (pandera.dtypes.UInt8 method), 162
 __init__() (pandera.engines.numpy_engine.Object method), 191
 __init__() (pandera.engines.pandas_engine.BOOL method), 175
 __init__() (pandera.engines.pandas_engine.Geometry method), 193
 __init__() (pandera.engines.pandas_engine.INT16 method), 179
 __init__() (pandera.engines.pandas_engine.INT32 method), 180
 __init__() (pandera.engines.pandas_engine.INT64 method), 182
 __init__() (pandera.engines.pandas_engine.INT8 method), 177
 __init__() (pandera.engines.pandas_engine.PydanticModel method), 194
 __init__() (pandera.engines.pandas_engine.STRING method), 189
 __init__() (pandera.engines.pandas_engine.UINT16 method), 185
 __init__() (pandera.engines.pandas_engine.UINT32 method), 186
 __init__() (pandera.engines.pandas_engine.UINT64 method), 188
 __init__() (pandera.engines.pandas_engine.UINT8 method), 183
 __init__() (pandera.hypotheses.Hypothesis method), 133
 __init__() (pandera.schema_components.Column method), 111
 __init__() (pandera.schema_components.MultiIndex method), 118
 __init__() (pandera.schemas.DataFrameSchema method), 94
 __init__() (pandera.schemas.SeriesSchema method), 108
 __init__() (pandera.typing.fastapi.UploadFile method), 207
 __init__() (pandera.typing.formats.Formats method), 208

A

add_columns() (pandera.schemas.DataFrameSchema method), 96

B

BaseConfig (class in pandera.model), 210
 Bool (class in pandera.dtypes), 141
 BOOL (class in pandera.engines.pandas_engine), 175

C

Category (class in pandera.dtypes), 145
 Check (class in pandera.checks), 121
 check() (in module pandera.model_components), 205
 check() (pandera.dtypes.Bool method), 142
 check() (pandera.dtypes.Category method), 146
 check() (pandera.dtypes.Complex method), 168
 check() (pandera.dtypes.Complex128 method), 171
 check() (pandera.dtypes.Complex256 method), 172
 check() (pandera.dtypes.Complex64 method), 170
 check() (pandera.dtypes.DataType method), 140
 check() (pandera.dtypes.Float method), 147
 check() (pandera.dtypes.Float128 method), 153
 check() (pandera.dtypes.Float16 method), 149
 check() (pandera.dtypes.Float32 method), 150
 check() (pandera.dtypes.Float64 method), 151
 check() (pandera.dtypes.Int method), 154
 check() (pandera.dtypes.Int16 method), 157
 check() (pandera.dtypes.Int32 method), 158
 check() (pandera.dtypes.Int64 method), 160
 check() (pandera.dtypes.Int8 method), 156
 check() (pandera.dtypes.String method), 174
 check() (pandera.dtypes.Timedelta method), 144
 check() (pandera.dtypes.Timestamp method), 143
 check() (pandera.dtypes.UInt method), 161
 check() (pandera.dtypes.UInt16 method), 164
 check() (pandera.dtypes.UInt32 method), 165
 check() (pandera.dtypes.UInt64 method), 167
 check() (pandera.dtypes.UInt8 method), 163
 check() (pandera.engines.numpy_engine.Object method), 191
 check() (pandera.engines.pandas_engine.BOOL method), 176
 check() (pandera.engines.pandas_engine.Geometry method), 193
 check() (pandera.engines.pandas_engine.INT16 method), 179
 check() (pandera.engines.pandas_engine.INT32 method), 180
 check() (pandera.engines.pandas_engine.INT64 method), 182
 check() (pandera.engines.pandas_engine.INT8 method), 177
 check() (pandera.engines.pandas_engine.PydanticModel method), 194
 check() (pandera.engines.pandas_engine.STRING method), 189
 check() (pandera.engines.pandas_engine.UINT16 method), 185

- check() (*pandera.engines.pandas_engine.UINT32 method*), 186
- check() (*pandera.engines.pandas_engine.UINT64 method*), 188
- check() (*pandera.engines.pandas_engine.UINT8 method*), 183
- check_input() (*in module pandera.decorators*), 211
- check_io() (*in module pandera.decorators*), 213
- check_output() (*in module pandera.decorators*), 212
- check_types() (*in module pandera.decorators*), 214
- checks (*pandera.io.FrictionlessFieldParser property*), 85
- CheckType (*class in pandera.extensions*), 223
- coerce (*pandera.io.FrictionlessFieldParser property*), 86
- coerce() (*pandera.dtypes.Bool method*), 142
- coerce() (*pandera.dtypes.Category method*), 146
- coerce() (*pandera.dtypes.Complex method*), 168
- coerce() (*pandera.dtypes.Complex128 method*), 171
- coerce() (*pandera.dtypes.Complex256 method*), 173
- coerce() (*pandera.dtypes.Complex64 method*), 170
- coerce() (*pandera.dtypes.DataType method*), 140
- coerce() (*pandera.dtypes.Float method*), 147
- coerce() (*pandera.dtypes.Float128 method*), 153
- coerce() (*pandera.dtypes.Float16 method*), 149
- coerce() (*pandera.dtypes.Float32 method*), 150
- coerce() (*pandera.dtypes.Float64 method*), 152
- coerce() (*pandera.dtypes.Int method*), 154
- coerce() (*pandera.dtypes.Int16 method*), 157
- coerce() (*pandera.dtypes.Int32 method*), 159
- coerce() (*pandera.dtypes.Int64 method*), 160
- coerce() (*pandera.dtypes.Int8 method*), 156
- coerce() (*pandera.dtypes.String method*), 174
- coerce() (*pandera.dtypes.Timedelta method*), 145
- coerce() (*pandera.dtypes.Timestamp method*), 143
- coerce() (*pandera.dtypes.UInt method*), 161
- coerce() (*pandera.dtypes.UInt16 method*), 164
- coerce() (*pandera.dtypes.UInt32 method*), 166
- coerce() (*pandera.dtypes.UInt64 method*), 167
- coerce() (*pandera.dtypes.UInt8 method*), 163
- coerce() (*pandera.engines.numpy_engine.Object method*), 191
- coerce() (*pandera.engines.pandas_engine.BOOL method*), 176
- coerce() (*pandera.engines.pandas_engine.Geometry method*), 193
- coerce() (*pandera.engines.pandas_engine.INT16 method*), 179
- coerce() (*pandera.engines.pandas_engine.INT32 method*), 180
- coerce() (*pandera.engines.pandas_engine.INT64 method*), 182
- coerce() (*pandera.engines.pandas_engine.INT8 method*), 177
- coerce() (*pandera.engines.pandas_engine.PydanticModel method*), 194
- coerce() (*pandera.engines.pandas_engine.STRING method*), 189
- coerce() (*pandera.engines.pandas_engine.UINT16 method*), 185
- coerce() (*pandera.engines.pandas_engine.UINT32 method*), 186
- coerce() (*pandera.engines.pandas_engine.UINT64 method*), 188
- coerce() (*pandera.engines.pandas_engine.UINT8 method*), 183
- coerce_dtype() (*pandera.schema_components.Column method*), 112
- coerce_dtype() (*pandera.schema_components.MultiIndex method*), 119
- coerce_dtype() (*pandera.schemas.DataFrameSchema method*), 96
- coerce_value() (*pandera.dtypes.Bool method*), 142
- coerce_value() (*pandera.dtypes.Category method*), 146
- coerce_value() (*pandera.dtypes.Complex method*), 168
- coerce_value() (*pandera.dtypes.Complex128 method*), 171
- coerce_value() (*pandera.dtypes.Complex256 method*), 173
- coerce_value() (*pandera.dtypes.Complex64 method*), 170
- coerce_value() (*pandera.dtypes.DataType method*), 140
- coerce_value() (*pandera.dtypes.Float method*), 147
- coerce_value() (*pandera.dtypes.Float128 method*), 153
- coerce_value() (*pandera.dtypes.Float16 method*), 149
- coerce_value() (*pandera.dtypes.Float32 method*), 150
- coerce_value() (*pandera.dtypes.Float64 method*), 152
- coerce_value() (*pandera.dtypes.Int method*), 154
- coerce_value() (*pandera.dtypes.Int16 method*), 157
- coerce_value() (*pandera.dtypes.Int32 method*), 159
- coerce_value() (*pandera.dtypes.Int64 method*), 160
- coerce_value() (*pandera.dtypes.Int8 method*), 156
- coerce_value() (*pandera.dtypes.String method*), 174
- coerce_value() (*pandera.dtypes.Timedelta method*), 145
- coerce_value() (*pandera.dtypes.Timestamp method*), 143
- coerce_value() (*pandera.dtypes.UInt method*), 161
- coerce_value() (*pandera.dtypes.UInt16 method*), 164
- coerce_value() (*pandera.dtypes.UInt32 method*), 166
- coerce_value() (*pandera.dtypes.UInt64 method*), 167
- coerce_value() (*pandera.dtypes.UInt8 method*), 163

- `coerce_value()` (*pandera.engines.numpy_engine.Object* method), 191
- `coerce_value()` (*pandera.engines.pandas_engine.BOOL* method), 176
- `coerce_value()` (*pandera.engines.pandas_engine.Geometry* method), 193
- `coerce_value()` (*pandera.engines.pandas_engine.INT16* method), 179
- `coerce_value()` (*pandera.engines.pandas_engine.INT32* method), 181
- `coerce_value()` (*pandera.engines.pandas_engine.INT64* method), 182
- `coerce_value()` (*pandera.engines.pandas_engine.INT8* method), 178
- `coerce_value()` (*pandera.engines.pandas_engine.PydanticModel* method), 195
- `coerce_value()` (*pandera.engines.pandas_engine.STRING* method), 190
- `coerce_value()` (*pandera.engines.pandas_engine.UINT16* method), 185
- `coerce_value()` (*pandera.engines.pandas_engine.UINT32* method), 187
- `coerce_value()` (*pandera.engines.pandas_engine.UINT64* method), 188
- `coerce_value()` (*pandera.engines.pandas_engine.UINT8* method), 184
- `Column` (*class in pandera.schema_components*), 110
- `column_strategy()` (*in module pandera.strategies*), 216
- `Complex` (*class in pandera.dtypes*), 167
- `Complex128` (*class in pandera.dtypes*), 170
- `Complex256` (*class in pandera.dtypes*), 172
- `Complex64` (*class in pandera.dtypes*), 169
- ## D
- `dataframe_check()` (*in module pandera.model_components*), 205
- `dataframe_strategy()` (*in module pandera.strategies*), 216
- `DataFrameSchema` (*class in pandera.schemas*), 92
- `DataType` (*class in pandera.dtypes*), 140
- `DateTime` (*class in pandera.engines.pandas_engine*), 191
- `DateTime` (*in module pandera.dtypes*), 144
- `dtype` (*pandera.io.FrictionlessFieldParser* property), 86
- `dtype()` (*pandera.engines.engine.Engine* method), 198
- `dtype()` (*pandera.engines.numpy_engine.Engine* class method), 200
- `dtype()` (*pandera.engines.pandas_engine.Engine* class method), 200
- ## E
- `ELEMENT_WISE` (*pandera.extensions.CheckType* attribute), 223
- `Engine` (*class in pandera.engines.engine*), 198
- `Engine` (*class in pandera.engines.numpy_engine*), 199
- `Engine` (*class in pandera.engines.pandas_engine*), 200
- `eq()` (*pandera.checks.Check* class method), 124
- `eq_strategy()` (*in module pandera.strategies*), 217
- `equal_to()` (*pandera.checks.Check* class method), 125
- `example()` (*pandera.model.SchemaModel* class method), 202
- `example()` (*pandera.schema_components.Column* method), 112
- `example()` (*pandera.schema_components.Index* method), 115
- `example()` (*pandera.schema_components.MultiIndex* method), 119
- `example()` (*pandera.schemas.DataFrameSchema* method), 97
- ## F
- `Field()` (*in module pandera.model_components*), 204
- `field_element_strategy()` (*in module pandera.strategies*), 217
- `Float` (*class in pandera.dtypes*), 146
- `Float128` (*class in pandera.dtypes*), 152
- `Float16` (*class in pandera.dtypes*), 148
- `Float32` (*class in pandera.dtypes*), 149
- `Float64` (*class in pandera.dtypes*), 151
- `Formats` (*class in pandera.typing.formats*), 208
- `FrictionlessFieldParser` (*class in pandera.io*), 85
- `from_frictionless_schema()` (*in module pandera.io*), 84
- `from_parametrized_dtype()` (*pandera.engines.pandas_engine.STRING* class method), 190
- `from_yaml()` (*in module pandera.io*), 215
- `from_yaml()` (*pandera.schemas.DataFrameSchema* class method), 97
- ## G
- `ge()` (*pandera.checks.Check* class method), 125
- `ge_strategy()` (*in module pandera.strategies*), 217

- Geometry (class in *pandera.engines.pandas_engine*), 192
- get_dtypes() (*pandera.schemas.DataFrameSchema* method), 97
- get_regex_columns() (*pandera.schema_components.Column* method), 113
- get_registered_dtypes() (*pandera.engines.engine.Engine* method), 198
- greater_than() (*pandera.checks.Check* class method), 125
- greater_than_or_equal_to() (*pandera.checks.Check* class method), 126
- GROUPBY (*pandera.extensions.CheckType* attribute), 223
- gt() (*pandera.checks.Check* class method), 126
- gt_strategy() (in module *pandera.strategies*), 217
- ## H
- Hypothesis (class in *pandera.hypotheses*), 131
- ## I
- immutable() (in module *pandera.dtypes*), 197
- in_range() (*pandera.checks.Check* class method), 126
- in_range_strategy() (in module *pandera.strategies*), 218
- Index (class in *pandera.schema_components*), 114
- index_strategy() (in module *pandera.strategies*), 218
- infer_schema() (in module *pandera.schema_inference*), 215
- Int (class in *pandera.dtypes*), 153
- Int16 (class in *pandera.dtypes*), 156
- INT16 (class in *pandera.engines.pandas_engine*), 178
- Int32 (class in *pandera.dtypes*), 158
- INT32 (class in *pandera.engines.pandas_engine*), 179
- Int64 (class in *pandera.dtypes*), 159
- INT64 (class in *pandera.engines.pandas_engine*), 181
- Int8 (class in *pandera.dtypes*), 155
- INT8 (class in *pandera.engines.pandas_engine*), 176
- is_bool() (in module *pandera.dtypes*), 197
- is_complex() (in module *pandera.dtypes*), 196
- is_datetime() (in module *pandera.dtypes*), 197
- is_float() (in module *pandera.dtypes*), 196
- is_int() (in module *pandera.dtypes*), 196
- is_numeric() (in module *pandera.dtypes*), 196
- is_string() (in module *pandera.dtypes*), 197
- is_subdtype() (in module *pandera.dtypes*), 196
- is_timedelta() (in module *pandera.dtypes*), 197
- is_uint() (in module *pandera.dtypes*), 196
- isin() (*pandera.checks.Check* class method), 127
- isin_strategy() (in module *pandera.strategies*), 218
- ## L
- le() (*pandera.checks.Check* class method), 127
- le_strategy() (in module *pandera.strategies*), 219
- less_than() (*pandera.checks.Check* class method), 127
- less_than_or_equal_to() (*pandera.checks.Check* class method), 128
- lt() (*pandera.checks.Check* class method), 128
- lt_strategy() (in module *pandera.strategies*), 219
- ## M
- module
- pandera.extensions*, 223
 - pandera.strategies*, 216
 - pandera.typing*, 206
- MultiIndex (class in *pandera.schema_components*), 116
- multiindex_strategy() (in module *pandera.strategies*), 219
- ## N
- ne() (*pandera.checks.Check* class method), 128
- ne_strategy() (in module *pandera.strategies*), 219
- not_equal_to() (*pandera.checks.Check* class method), 129
- notin() (*pandera.checks.Check* class method), 129
- notin_strategy() (in module *pandera.strategies*), 220
- nullable (*pandera.io.FrictionlessFieldParser* property), 86
- numpy_complex_dtypes() (in module *pandera.strategies*), 220
- numpy_dtype() (*pandera.engines.pandas_engine.Engine* class method), 200
- numpy_time_dtypes() (in module *pandera.strategies*), 220
- ## O
- Object (class in *pandera.engines.numpy_engine*), 190
- one_sample_ttest() (*pandera.hypotheses.Hypothesis* class method), 135
- ## P
- pandas_dtype_strategy() (in module *pandera.strategies*), 220
- pandera.extensions* module, 223
- pandera.strategies* module, 216
- pandera.typing* module, 206
- PydanticModel (class in *pandera.engines.pandas_engine*), 194
- ## R
- regex (*pandera.io.FrictionlessFieldParser* property), 86
- register_check_method() (in module *pandera.extensions*), 223

- register_check_strategy() (in module *pandera.strategies*), 221
 register_dtype() (*pandera.engines.engine.Engine* method), 198
 remove_columns() (*pandera.schemas.DataFrameSchema* method), 97
 rename_columns() (*pandera.schemas.DataFrameSchema* method), 98
 required (*pandera.io.FrictionlessFieldParser* property), 86
 reset_index() (*pandera.schemas.DataFrameSchema* method), 99
- ## S
- SchemaDefinitionError (class in *pandera.errors*), 224
 SchemaError (class in *pandera.errors*), 224
 SchemaErrors (class in *pandera.errors*), 224
 SchemaInitError (class in *pandera.errors*), 224
 SchemaModel (class in *pandera.model*), 201
 select_columns() (*pandera.schemas.DataFrameSchema* method), 100
 series_strategy() (in module *pandera.strategies*), 221
 SeriesSchema (class in *pandera.schemas*), 107
 set_index() (*pandera.schemas.DataFrameSchema* method), 101
 set_name() (*pandera.schema_components.Column* method), 113
 str_contains() (*pandera.checks.Check* class method), 129
 str_contains_strategy() (in module *pandera.strategies*), 221
 str_endswith() (*pandera.checks.Check* class method), 130
 str_endswith_strategy() (in module *pandera.strategies*), 221
 str_length() (*pandera.checks.Check* class method), 130
 str_length_strategy() (in module *pandera.strategies*), 221
 str_matches() (*pandera.checks.Check* class method), 130
 str_matches_strategy() (in module *pandera.strategies*), 222
 str_startswith() (*pandera.checks.Check* class method), 130
 str_startswith_strategy() (in module *pandera.strategies*), 222
 strategy() (*pandera.model.SchemaModel* class method), 202
 strategy() (*pandera.schema_components.Column* method), 113
 strategy() (*pandera.schema_components.Index* method), 115
 strategy() (*pandera.schema_components.MultiIndex* method), 120
 strategy() (*pandera.schemas.DataFrameSchema* method), 103
 strategy_component() (*pandera.schema_components.Column* method), 113
 strategy_component() (*pandera.schema_components.Index* method), 116
 String (class in *pandera.dtypes*), 173
 STRING (class in *pandera.engines.pandas_engine*), 188
- ## T
- Timedelta (class in *pandera.dtypes*), 144
 Timestamp (class in *pandera.dtypes*), 142
 to_numpy_dtype() (in module *pandera.strategies*), 222
 to_pandera_column() (*pandera.io.FrictionlessFieldParser* method), 86
 to_schema() (*pandera.model.SchemaModel* class method), 203
 to_script() (in module *pandera.io*), 216
 to_script() (*pandera.schemas.DataFrameSchema* method), 103
 to_yaml() (in module *pandera.io*), 215
 to_yaml() (*pandera.model.SchemaModel* class method), 203
 to_yaml() (*pandera.schemas.DataFrameSchema* method), 103
 try_coerce() (*pandera.dtypes.Bool* method), 142
 try_coerce() (*pandera.dtypes.Category* method), 146
 try_coerce() (*pandera.dtypes.Complex* method), 169
 try_coerce() (*pandera.dtypes.Complex128* method), 171
 try_coerce() (*pandera.dtypes.Complex256* method), 173
 try_coerce() (*pandera.dtypes.Complex64* method), 170
 try_coerce() (*pandera.dtypes.DataType* method), 141
 try_coerce() (*pandera.dtypes.Float* method), 148
 try_coerce() (*pandera.dtypes.Float128* method), 153
 try_coerce() (*pandera.dtypes.Float16* method), 149
 try_coerce() (*pandera.dtypes.Float32* method), 150
 try_coerce() (*pandera.dtypes.Float64* method), 152
 try_coerce() (*pandera.dtypes.Int* method), 155
 try_coerce() (*pandera.dtypes.Int16* method), 157
 try_coerce() (*pandera.dtypes.Int32* method), 159
 try_coerce() (*pandera.dtypes.Int64* method), 160
 try_coerce() (*pandera.dtypes.Int8* method), 156

- `try_coerce()` (*pandera.dtypes.String* method), 174
`try_coerce()` (*pandera.dtypes.Timedelta* method), 145
`try_coerce()` (*pandera.dtypes.Timestamp* method), 143
`try_coerce()` (*pandera.dtypes.UInt* method), 162
`try_coerce()` (*pandera.dtypes.UInt16* method), 164
`try_coerce()` (*pandera.dtypes.UInt32* method), 166
`try_coerce()` (*pandera.dtypes.UInt64* method), 167
`try_coerce()` (*pandera.dtypes.UInt8* method), 163
`try_coerce()` (*pandera.engines.numpy_engine.Object* method), 191
`try_coerce()` (*pandera.engines.pandas_engine.BOOL* method), 176
`try_coerce()` (*pandera.engines.pandas_engine.Geometry* method), 193
`try_coerce()` (*pandera.engines.pandas_engine.INT16* method), 179
`try_coerce()` (*pandera.engines.pandas_engine.INT32* method), 181
`try_coerce()` (*pandera.engines.pandas_engine.INT64* method), 182
`try_coerce()` (*pandera.engines.pandas_engine.INT8* method), 178
`try_coerce()` (*pandera.engines.pandas_engine.PydanticModel* method), 195
`try_coerce()` (*pandera.engines.pandas_engine.STRING* method), 190
`try_coerce()` (*pandera.engines.pandas_engine.UINT16* method), 185
`try_coerce()` (*pandera.engines.pandas_engine.UINT32* method), 187
`try_coerce()` (*pandera.engines.pandas_engine.UINT64* method), 188
`try_coerce()` (*pandera.engines.pandas_engine.UINT8* method), 184
`two_sample_ttest()` (*pandera.hypotheses.Hypothesis* class method), 136

U

- UInt* (class in *pandera.dtypes*), 160
UInt16 (class in *pandera.dtypes*), 163
UINT16 (class in *pandera.engines.pandas_engine*), 184
UInt32 (class in *pandera.dtypes*), 165
UINT32 (class in *pandera.engines.pandas_engine*), 185
UInt64 (class in *pandera.dtypes*), 166
UINT64 (class in *pandera.engines.pandas_engine*), 187
UInt8 (class in *pandera.dtypes*), 162
UINT8 (class in *pandera.engines.pandas_engine*), 182
`unique` (*pandera.io.FrictionlessFieldParser* property), 86
`update_column()` (*pandera.schemas.DataFrameSchema* method), 103
`update_columns()` (*pandera.schemas.DataFrameSchema* method),

104

`UploadFile` (class in *pandera.typing.fastapi*), 207

V

- `validate()` (*pandera.model.SchemaModel* class method), 203
`validate()` (*pandera.schema_components.Column* method), 113
`validate()` (*pandera.schema_components.Index* method), 116
`validate()` (*pandera.schema_components.MultiIndex* method), 120
`validate()` (*pandera.schemas.DataFrameSchema* method), 105
`validate()` (*pandera.schemas.SeriesSchema* method), 108
VECTORIZED (*pandera.extensions.CheckType* attribute), 223
`verify_dtype()` (in module *pandera.strategies*), 222