

# Real Time Data Ingestion Platform

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User Documentation

Real Time Data Ingestion Platform

AMOS Group 1

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# 1. Installation

The RTDIP SDK is a PyPi package which can be found [here](#), to install it run the following command:

```
pip install rtdip-sdk
```

## 2. Machine Learning

### 2.1 DataBinning

Bases: `MachineLearningInterface`

Data binning using clustering methods. This method partitions the data points into a specified number of clusters (bins) based on the specified column. Each data point is assigned to the nearest cluster center.

Example

```
from src.sdk.python.rtdip_sdk.pipelines.machine_learning.spark.data_binning import DataBinning

df = ... # Get a PySpark DataFrame with features column

binning = DataBinning(
    df=df,
    column_name="features",
    bins=3,
    output_column_name="bin",
    method="kmeans"
)
binned_df = binning.train().predict()
binned_df.show()
```

Parameters:

Name	Type	Description	Default
<code>df</code>	<code>DataFrame</code>	Dataframe containing the input data.	<i>required</i>
<code>column_name</code>	<code>str</code>	The name of the input column to be binned (default: "features").	<code>'features'</code>
<code>bins</code>	<code>int</code>	The number of bins/clusters to create (default: 2).	<code>2</code>
<code>output_column_name</code>	<code>str</code>	The name of the output column containing bin assignments (default: "bin").	<code>'bin'</code>
<code>method</code>	<code>str</code>	The binning method to use. Currently only supports "kmeans".	<code>'kmeans'</code>
2.1.1 <code>system_type()</code>	<code>staticmethod</code>		

Attributes:

Name	Type	Description
<code>SystemType</code>	<code>Environment</code>	Requires PYSPARK
2.1.2 <code>train()</code>		

Filter anomalies based on the k-sigma rule

### 2.2 LinearRegression

Bases: `MachineLearningInterface`

This function uses `pyspark.ml.LinearRegression` to train a linear regression model on time data. And the uses the model to predict next values in the time series.

#### Parameters:

Name	Type	Description	Default
<code>df</code>	<code>Dataframe</code>	DataFrame containing the features and labels.	<i>required</i>
<code>features_col</code>	<code>str</code>	Name of the column containing the features (the input). Default is 'features'.	<code>'features'</code>
<code>label_col</code>	<code>str</code>	Name of the column containing the label (the input). Default is 'label'.	<code>'label'</code>
<code>prediction_col</code>	<code>str</code>	Name of the column to which the prediction will be written. Default is 'prediction'.	<code>'prediction'</code>

Returns: `PySparkDataFrame`: Returns the original PySpark DataFrame without changes.

#### 2.2.1 `evaluate(test_df)`

Evaluates the trained model using RMSE.

#### Parameters:

Name	Type	Description	Default
<code>test_df</code>	<code>DataFrame</code>	The testing dataset to evaluate the model.	<i>required</i>

#### Returns:

#### Name Type Description

<code>float</code>		The Root Mean Squared Error (RMSE) of the model.
--------------------	--	--

#### 2.2.2 `predict(prediction_df)`

Predicts the next values in the time series.

#### 2.2.3 `split_data(train_ratio=0.8)`

Splits the dataset into training and testing sets.

#### Parameters:

Name	Type	Description	Default
<code>train_ratio</code>	<code>float</code>	The ratio of the data to be used for training. Default is 0.8 (80% for training).	<code>0.8</code>

#### Returns:

#### Name Type Description

<code>DataFrame</code>		Returns the training and testing datasets.
------------------------	--	--

#### 2.2.4 `system_type()` `staticmethod`

#### Attributes:

#### Name Type Description

<code>SystemType</code>	<code>Environment</code>	Requires PYSPARK
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#### 2.2.5 `train(train_df)`

Trains a linear regression model on the provided data.

# 3. Monitoring

## 3.1 FlatlineDetection

Bases: `MonitoringBaseInterface`

Detects flatlining in specified columns of a PySpark DataFrame and logs warnings.

Flatlining occurs when a column contains consecutive null or zero values exceeding a specified tolerance period. This class identifies such occurrences and logs the rows where flatlining is detected.

### Parameters:

Name	Type	Description	Default
<code>df</code>	<code>DataFrame</code>	The input DataFrame to monitor for flatlining.	<i>required</i>
<code>watch_columns</code>	<code>list</code>	List of column names to monitor for flatlining (null or zero values).	<i>required</i>
<code>tolerance_timespan</code>	<code>int</code>	Maximum allowed consecutive flatlining period. If exceeded, a warning is logged.	<i>required</i>

### • Example

```

from rtdip_sdk.pipelines.monitoring.spark.data_quality.flatline_detection import FlatlineDetection
from pyspark.sql import SparkSession

spark = SparkSession.builder.master("local[1]").appName("FlatlineDetectionExample").getOrCreate()

# Example DataFrame
data = [
    (1, 1),
    (2, 0),
    (3, 0),
    (4, 0),
    (5, 5),
]
columns = ["ID", "Value"]
df = spark.createDataFrame(data, columns)

# Initialize FlatlineDetection
flatline_detection = FlatlineDetection(
    df,
    watch_columns=["Value"],
    tolerance_timespan=2
)

# Detect flatlining
flatline_detection.check()

```

### 3.1.1 `check()`

Detects flatlining in the specified columns and logs warnings if detected.

Returns:

Type	Description
DataFrame	pyspark.sql.DataFrame: The original PySpark DataFrame unchanged.
3.1.2 system_type()	staticmethod

Attributes:

Name	Type	Description
SystemType	Environment	Requires PYSPARK
3.2 CheckValueRanges		

Bases: MonitoringBaseInterface

Monitors data in a DataFrame by checking specified columns against expected value ranges. Logs events when values exceed the specified ranges.

Parameters:

Name	Type	Description	Default
df	DataFrame	The DataFrame to monitor.	required
columns_ranges	dict	A dictionary where keys are column names and values are dictionaries specifying 'min' and/or 'max', and optionally 'inclusive' values. Example: { 'temperature': {'min': 0, 'max': 100, 'inclusive': 'both'}, 'pressure': {'min': 10, 'max': 200, 'inclusive': 'left'}, 'humidity': {'min': 30} # Uses default inclusive }	required
default_inclusive	str	Default inclusivity setting if not specified per column. Can be 'both', 'neither', 'left', or 'right'. Default is 'both'. - 'both': min <= value <= max - 'neither': min < value < max - 'left': min <= value < max - 'right': min < value <= max	'both'

• Example

```
from pyspark.sql import SparkSession
from rtdip_sdk.pipelines.monitoring.spark.data_quality.check_value_ranges import CheckValueRanges

spark = SparkSession.builder.master("local[1]").appName("CheckValueRangesExample").getOrCreate()

data = [
    (1, 25, 100),
    (2, -5, 150),
    (3, 50, 250),
    (4, 80, 300),
    (5, 100, 50),
]

columns = ["ID", "temperature", "pressure"]

df = spark.createDataFrame(data, columns)

columns_ranges = {
    "temperature": {"min": 0, "max": 100, "inclusive": "both"},
    "pressure": {"min": 50, "max": 200, "inclusive": "left"},
}

check_value_ranges = CheckValueRanges(
    df=df,
```

```
        columns_ranges=columns_ranges,
        default_inclusive="both",
    )

    result_df = check_value_ranges.check()
```

3.2.1 `check()`

Executes the value range checking logic. Identifies and logs any rows where specified columns exceed their defined value ranges.

Returns:

Type	Description
DataFrame	pyspark.sql.DataFrame: Returns the original PySpark DataFrame without changes.

3.2.2 `system_type()` `staticmethod`

Attributes:

Name	Type	Description
SystemType	Environment	Requires PYSPARK

3.3 `IdentifyMissingDataInterval`

Bases: `MonitoringBaseInterface`

Detects missing data intervals in a DataFrame by identifying time differences between consecutive measurements that exceed a specified tolerance or a multiple of the Median Absolute Deviation (MAD). Logs the start and end times of missing intervals along with their durations.

Parameters:

Name	Type	Description	Default
df	Dataframe	DataFrame containing at least the 'EventTime' column.	<i>required</i>
interval	str	Expected interval between data points (e.g., '10ms', '500ms'). If not specified, the median of time differences is used.	None
tolerance	str	Tolerance time beyond which an interval is considered missing (e.g., '10ms'). If not specified, it defaults to 'mad_multiplier' times the Median Absolute Deviation (MAD) of time differences.	None
mad_multiplier	float	Multiplier for MAD to calculate tolerance. Default is 3.	3
min_tolerance	str	Minimum tolerance for pattern-based detection (e.g., '100ms'). Default is '10ms'.	'10ms'

• Example

```
from rtdip_sdk.pipelines.monitoring.spark.data_quality import IdentifyMissingDataInterval
from pyspark.sql import SparkSession

missing_data_monitor = IdentifyMissingDataInterval(
    df=df,
    interval='100ms',
    tolerance='10ms',
)
```

```
df_result = missing_data_monitor.check()
```

3.3.1 `check()`

Executes the identify missing data logic.

Returns:

Type	Description
DataFrame	pyspark.sql.DataFrame: Returns the original PySpark DataFrame without changes.

3.3.2 `system_type()` `staticmethod`

Attributes:

Name	Type	Description
SystemType	Environment	Requires PYSPARK

3.4 `IdentifyMissingDataPattern`

Bases: `MonitoringBaseInterface`

Identifies missing data in a DataFrame based on specified time patterns. Logs the expected missing times.

Parameters:

Name	Type	Description	Default
df	Dataframe	DataFrame containing at least the 'EventTime' column.	<i>required</i>
patterns	List of dict	List of dictionaries specifying the time patterns. - For 'minutely' frequency: Specify 'second' and optionally 'millisecond'. Example: [{ 'second': 0}, { 'second': 13}, { 'second': 49}] - For 'hourly' frequency: Specify 'minute', 'second', and optionally 'millisecond'. Example: [{ 'minute': 0, 'second': 0}, { 'minute': 30, 'second': 30}]	<i>required</i>
frequency	str	Frequency of the patterns. Must be either 'minutely' or 'hourly'. - 'minutely': Patterns are checked every minute at specified seconds. - 'hourly': Patterns are checked every hour at specified minutes and seconds.	'minutely'
tolerance	str	Maximum allowed deviation from the pattern (e.g., '1s', '500ms'). Default is '10ms'.	'10ms'

• Example

```
from pyspark.sql import SparkSession

spark = SparkSession.builder.master("local[1]").appName("IdentifyMissingDataPatternExample").getOrCreate()

patterns = [
    {"second": 0},
    {"second": 20},
]

frequency = "minutely"
tolerance = "1s"

identify_missing_data = IdentifyMissingDataPattern(
    df=df,
```



```

patterns=patterns,
frequency=frequency,
tolerance=tolerance,
)

identify_missing_data.check()

```

### 3.4.1 `check()`

Executes the missing pattern detection logic. Identifies and logs any missing patterns based on the provided patterns and frequency within the specified tolerance.

**Returns:**

**Type**      **Description**

`DataFrame` `pyspark.sql.DataFrame`: Returns the original PySpark DataFrame without changes.

3.4.2 `system_type()`    `staticmethod`

**Attributes:**

**Name**      **Type**      **Description**

`SystemType`    `Environment`    Requires PYSPARK

## 4. Data Wranglers

### 4.1 `MissingValueImputation`

Bases: `WranglerBaseInterface`

Imputes missing values in a univariate time series creating a continuous curve of data points. For that, the time intervals of each individual source is calculated, to then insert empty records at the missing timestamps with NaN values. Through spline interpolation the missing NaN values are calculated resulting in a consistent data set and thus enhance your data quality.

Example

```

from pyspark.sql import SparkSession
from pyspark.sql.dataframe import DataFrame
from pyspark.sql.types import StructType, StructField, StringType
from src.sdk.python.rtdip_sdk.pipelines.data_wranglers.spark.data_quality.missing_value_imputation import (
    MissingValueImputation,
)

```

```

@pytest.fixture(scope="session")
def spark_session():
    return SparkSession.builder.master("local[2]").appName("test").getOrCreate()

```

```
spark = spark_session()
```

```

schema = StructType([
    StructField("TagName", StringType(), True),
    StructField("EventTime", StringType(), True),
    StructField("Status", StringType(), True),
    StructField("Value", StringType(), True)
])

```

```

data = [
    # Setup controlled Test
    ("A2PS64V0J.:ZUX09R", "2024-01-01 03:29:21.000", "Good", "1.0"),
    ("A2PS64V0J.:ZUX09R", "2024-01-01 07:32:55.000", "Good", "2.0"),
    ("A2PS64V0J.:ZUX09R", "2024-01-01 11:36:29.000", "Good", "3.0"),

```

```
("A2PS64V0J.:ZUX09R", "2024-01-01 15:39:03.000", "Good", "4.0"), ("A2PS64V0J.:ZUX09R", "2024-01-01 19:42:37.000", "Good", "5.0"), #("A2PS64V0J.:ZUX09R", "2024-01-01 23:46:11.000", "Good", "6.0"), # Test values #("A2PS64V0J.:ZUX09R", "2024-01-02 03:49:45.000", "Good", "7.0"), ("A2PS64V0J.:ZUX09R", "2024-01-02 07:53:11.000", "Good", "8.0"), ("A2PS64V0J.:ZUX09R", "2024-01-02 11:56:42.000", "Good", "9.0"), ("A2PS64V0J.:ZUX09R", "2024-01-02 16:00:12.000", "Good", "10.0"), ("A2PS64V0J.:ZUX09R", "2024-01-02 20:13:46.000", "Good", "11.0"), # Tolerance Test ("A2PS64V0J.:ZUX09R", "2024-01-03 00:07:20.000", "Good", "10.0"), #("A2PS64V0J.:ZUX09R", "2024-01-03 04:10:54.000", "Good", "9.0"), ("A2PS64V0J.:ZUX09R", "2024-01-03 08:14:28.000", "Good", "8.0"), ("407LSSAM_3EA02:2GT7E02I_R_MP", "31.12.2023 00:01:43", "Good", "4686.259766"), ("407LSSAM_3EA02:2GT7E02I_R_MP", "31.12.2023 00:02:44", "Good", "4691.161621"), ("407LSSAM_3EA02:2GT7E02I_R_MP", "31.12.2023 00:04:44", "Good", "4686.259766"), ("407LSSAM_3EA02:2GT7E02I_R_MP", "31.12.2023 00:05:44", "Good", "4691.161621"), ("407LSSAM_3EA02:2GT7E02I_R_MP", "31.12.2023 00:11:46", "Good", "4686.259766"), ("407LSSAM_3EA02:2GT7E02I_R_MP", "31.12.2023 00:13:46", "Good", "4691.161621"), ("407LSSAM_3EA02:2GT7E02I_R_MP", "31.12.2023 00:16:47", "Good", "4691.161621"), ("407LSSAM_3EA02:2GT7E02I_R_MP", "31.12.2023 00:19:48", "Good", "4696.063477"), ("407LSSAM_3EA02:2GT7E02I_R_MP", "31.12.2023 00:20:48", "Good", "4691.161621"), ]
```

```
df = spark.createDataFrame(data, schema=schema)

missing_value_imputation = MissingValueImputation(spark, df) imputed_df = missing_value_imputation.filter()

print(imputed_df.show(imputed_df.count(), False))

...
```

Parameters: df (DataFrame): Dataframe containing the raw data. tolerance\_percentage (int): Percentage value that indicates how much the time series data points may vary in each interval

4.1.1 filter()

Impute missing values based on [Spline Interpolation, ]

4.1.2 system\_type() staticmethod

Attributes:

Name	Type	Description
SystemType	Environment	Requires PYSPARK

4.2 IntervalFiltering

Bases: WranglerBaseInterface

Cleanses a DataFrame by removing rows outside a specified interval window. Example:

Parameters:

Name	Type	Description	Default
spark	SparkSession	A SparkSession object.	required
df	DataFrame	PySpark DataFrame to be converted	required
interval	int	The interval length for cleansing. interval_unit (str): 'hours', 'minutes', 'seconds' or 'milliseconds' to specify the unit of the interval.	required

4.2.1 filter()

Filters the DataFrame based on the interval

## 4.2.2 system\_type() staticmethod

## Attributes:

Name	Type	Description
SystemType	Environment	Requires PYSPARK

## 4.3 ArimaPrediction

Bases: WranglerBaseInterface

Extends a column in given DataFrame with a ARIMA model.

- **ARIMA-Specific parameters can be viewed at the following statsmodels documentation page**  
<https://www.statsmodels.org/dev/generated/statsmodels.tsa.arima.model.ARIMA.html>

## Example

```
df = pandas.DataFrame()

numpy.random.seed(0)
arr_len = 250
h_a_l = int(arr_len / 2)
df['Value'] = np.random.rand(arr_len) + np.sin(np.linspace(0, arr_len / 10, num=arr_len))
df['Value2'] = np.random.rand(arr_len) + np.cos(np.linspace(0, arr_len / 2, num=arr_len)) + 5
df['index'] = np.asarray(pandas.date_range(start='1/1/2024', end='2/1/2024', periods=arr_len))
df = df.set_index(pd.DatetimeIndex(df['index']))

learn_df = df.head(h_a_l)

# plt.plot(df['Value'])
# plt.show()

input_df = spark_session.createDataFrame(
    learn_df,
    ['Value', 'Value2', 'index'],
)
arima_comp = ArimaPrediction(input_df, column_name='Value', number_of_data_points_to_analyze=h_a_l, number_of_data_points_
                             order=(3,0,0), seasonal_order=(3,0,0,62))
forecasted_df = arima_comp.filter()
```

**Parameters:**

Name	Type	Description	Default
<code>past_data</code>	<code>DataFrame</code>	PySpark DataFrame to extend	<i>required</i>
<code>column_name</code>	<code>str</code>	Name of the column to be extended	<i>required</i>
<code>timestamp_column_name</code>	<code>str</code>	Name of the column containing timestamps	
		<code>external_regressor_column_names</code> (List[str]): Names of the columns with data to use for prediction, but not extend	<code>None</code>
<code>number_of_data_points_to_predict</code>	<code>int</code>	Amount of most recent rows used to create the model	<code>50</code>
<code>number_of_data_points_to_analyze</code>	<code>int</code>	Amount of rows to predict with the model	<code>None</code>
<code>order</code>	<code>tuple</code>	ARIMA-Specific setting	<code>(0, 0, 0)</code>
<code>seasonal_order</code>	<code>tuple</code>	ARIMA-Specific setting	<code>(0, 0, 0, 0)</code>
<code>trend</code>	<code>str</code>	ARIMA-Specific setting	<code>'c'</code>
<code>enforce_stationarity</code>	<code>bool</code>	ARIMA-Specific setting	<code>True</code>
<code>enforce_invertibility</code>	<code>bool</code>	ARIMA-Specific setting	<code>True</code>
<code>concentrate_scale</code>	<code>bool</code>	ARIMA-Specific setting	<code>False</code>
<code>trend_offset</code>	<code>int</code>	ARIMA-Specific setting	<code>1</code>
<code>missing</code>	<code>str</code>	ARIMA-Specific setting	<code>'None'</code>

**4.3.1** `filter()`

Predicts value to predict and extends the in the constructor inputted Dataframe.

Other columns will be filled with NaN other similar None values.

**Returns:**

Name	Type	Description
<code>DataFrame</code>	<code>DataFrame</code>	A PySpark DataFrame with extended index and filled column_to_predict.

**4.3.2** `system_type()` `staticmethod`**Attributes:**

Name	Type	Description
<code>SystemType</code>	<code>Environment</code>	Requires PYSPARK

**4.4** `DuplicateDetection`

Bases: `WranglerBaseInterface`

Cleanses a PySpark DataFrame from duplicates.

**Example**

```
from rtdip_sdk.pipelines.monitoring.spark.data_quality.duplicate_detection import DuplicateDetection
from pyspark.sql import SparkSession
from pyspark.sql.dataframe import DataFrame
from pyspark.sql.functions import desc

duplicate_detection_monitor = DuplicateDetection(df)

result = duplicate_detection_monitor.filter()
```

**Parameters:**

Name	Type	Description	Default
df	DataFrame	PySpark DataFrame to be converted	<i>required</i>
4.4.1	filter()		

**Returns:**

Name	Type	Description
DataFrame	DataFrame	A cleansed PySpark DataFrame from all the duplicates.
4.4.2	system_type()	staticmethod

**Attributes:**

Name	Type	Description
SystemType	Environment	Requires PYSPARK

## 4.5 KSigmaAnomalyDetection

Bases: WranglerBaseInterface

Anomaly detection with the k-sigma method. This method either computes the mean and standard deviation, or the median and the median absolute deviation (MAD) of the data. The k-sigma method then filters out all data points that are k times the standard deviation away from the mean, or k times the MAD away from the median. Assuming a normal distribution, this method keeps around 99.7% of the data points when k=3 and use\_median=False.

**Example**

```
from src.sdk.python.rtdip_sdk.pipelines.data_wranglers.spark.data_quality.k_sigma_anomaly_detection import KSigmaAnomalyDe

spark = ... # SparkSession
df = ... # Get a PySpark DataFrame

filtered_df = KSigmaAnomalyDetection(
    spark, df, ["<column to filter>"]
).filter()

filtered_df.show()
```

**Parameters:**

Name	Type	Description	Default
spark	SparkSession	A SparkSession object.	<i>required</i>
df	DataFrame	Dataframe containing the raw data.	<i>required</i>
column_names	list[str]	The names of the columns to be filtered (currently only one column is supported).	<i>required</i>
k_value	float	The number of deviations to build the threshold.	3.0
use_median	bool	If True the median and the median absolute deviation (MAD) are used, instead of the mean and standard deviation.	False
4.5.1	filter()		

Filter anomalies based on the k-sigma rule

## 4.5.2 system\_type() staticmethod

**Attributes:**

Name	Type	Description
SystemType	Environment	Requires PYSPARK

## 4.6 Normalization

## 4.7 Denormalization

Bases: WranglerBaseInterface

### 4.7.1 TODO

Applies the appropriate denormalization method to revert values to their original scale.

**Example**

```
from src.sdk.python.rtdip_sdk.pipelines.data_wranglers import Denormalization
from pyspark.sql import SparkSession
from pyspark.sql.dataframe import DataFrame

denormalization = Denormalization(normalized_df, normalization)
denormalized_df = denormalization.filter()
```

**Parameters:**

Name	Type	Description	Default
df	DataFrame	PySpark DataFrame to be reverted to its original scale.	<i>required</i>
normalization_to_revert	NormalizationBaseClass	An instance of the specific normalization subclass (NormalizationZScore, NormalizationMinMax, NormalizationMean) that was originally used to normalize the data.	<i>required</i>

## 4.7.2 system\_type() staticmethod

**Attributes:**

Name	Type	Description
SystemType	Environment	Requires PYSPARK

## 4.8 NormalizationBaseClass

Bases: WranglerBaseInterface

A base class for applying normalization techniques to multiple columns in a PySpark DataFrame. This class serves as a framework to support various normalization methods (e.g., Z-Score, Min-Max, and Mean), with specific implementations in separate subclasses for each normalization type.

Subclasses should implement specific normalization and denormalization methods by inheriting from this base class.

**Example**

```
from src.sdk.python.rtdip_sdk.pipelines.data_wranglers import NormalizationZScore
from pyspark.sql import SparkSession
from pyspark.sql.dataframe import DataFrame

normalization = NormalizationZScore(df, column_names=["value_column_1", "value_column_2"], in_place=False)
normalized_df = normalization.filter()
```

Parameters:

Name	Type	Description	Default
df	DataFrame	PySpark DataFrame to be normalized.	required
column_names	List[str]	List of columns in the DataFrame to be normalized.	required
in_place	bool	If true, then result of normalization is stored in the same column.	False

NORMALIZATION\_NAME\_POSTFIX : str Suffix added to the column name if a new column is created for normalized values.

4.8.1 denormalize(input\_df)

Denormalizes the input DataFrame. Intended to be used by the denormalization component.

Parameters:

Name	Type	Description	Default
input_df	DataFrame	Dataframe containing the current data.	required

4.8.2 normalize()

Applies the specified normalization to each column in column\_names.

Returns:

Name	Type	Description
DataFrame	DataFrame	A PySpark DataFrame with the normalized values.

4.8.3 system\_type() staticmethod

Attributes:

Name	Type	Description
SystemType	Environment	Requires PYSPARK

4.9 NormalizationMean

Bases: NormalizationBaseClass

4.10 NormalizationMinMax

Bases: NormalizationBaseClass

4.11 NormalizationZScore

Bases: NormalizationBaseClass

# 5. Transformers

5.1 ColsToVector

Bases: TransformerInterface

Converts columns containing numbers to a column containing a vector.

Parameters:

Name	Type	Description	Default
df	DataFrame	PySpark DataFrame	required
input_cols	List[str]	List of columns to convert to a vector.	required
output_col	str	Name of the output column where the vector will be stored.	required
override_col	bool	If True, the output column can override an existing column.	False
5.1.1	system_type()	staticmethod	

Attributes:

Name	Type	Description
SystemType	Environment	Requires PYSPARK

5.2 PolynomialFeatures

Bases: TransformerInterface

This transformer takes a vector column and generates polynomial combinations of the input features up to the specified degree. For example, if the input vector is [a, b] and degree=2, the output features will be [a, b, a^2, ab, b^2].

Parameters:

Name	Type	Description	Default
df	DataFrame	PySpark DataFrame	required
input_col	str	Name of the input column in the DataFrame that contains the feature vectors	required
output_col	str		required
poly_degree	int	The degree of the polynomial features to generate	required
override_col	bool	If True, the output column can override an existing column.	False
5.2.1	system_type()	staticmethod	

Attributes:

Name	Type	Description
SystemType	Environment	Requires PYSPARK

6. Utilities

6.1 parse\_time\_string\_to\_ms(time\_str)

Parses a time string and returns the total time in milliseconds.

Parameters:

Name	Type	Description	Default
time_str	str	Time string (e.g., '10ms', '1s', '2m', '1h').	required

Returns:

Name	Type	Description
float	float	Total time in milliseconds.



Raises:

Type	Description
ValueError	If the format is invalid.