Butterfree Documentation

Release 1.0.2

QuintoAndar

Aug 21, 2023

CONTENTS

Made with by the **MLOps** team from QuintoAndar.

The library is centered on the following concetps:

- **ETL**: central framework to create data pipelines. Spark-based Extract, Transform and Load modules ready to use.
- **Declarative Feature Engineering**: care about what you want to compute and not how to code it.
- **Feature Store Modeling**: the library easily provides everything you need to process and load data to your Feature Store.

CHAPTER

ONE

NAVIGATION

1.1 Welcome to the Butterfree Docs!

The main idea is for this repository to be a set of tools for easing ETLs. The idea is using Butterfree to upload data to a Feature Store, so data can be provided to your machine learning algorithms.

1.1.1 Table of Contents

1.1.2 What is going on here

Besides introducing Butterfree itself, it's necessary to define some concepts that will be presented throughout this Docs.

The feature store is where features for machine learning models and pipelines are stored. A feature is an individual property or characteristic of a data-sample, such as the height of a person, the area of a house or an aggregated feature as the average prices of houses seen by a user within the last day. A feature set can be thought of as a set of features. Finally, an entity is a unity representation of a specific business context.

This repository holds all scripts that will extract data from necessary sources (S3 and Kafka, for instance), transform all of this raw data into feature sets and, finally, upload these results in a feature store.

Scripts use Python and Apache's Spark.

It's important to highlight that a feature store incurs some challenging concerns, such as:

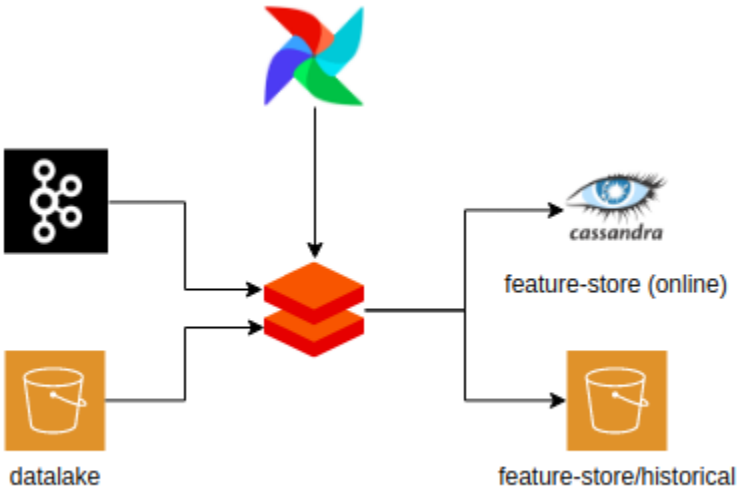
- Dealing with big volumes of data;
- Retroactively computing new features;
- Loading historical and online data for consumption;
- Keeping it simple to add new features and functionality;

- Making it easy to share code.

1.1.3 Service Architecture

Regarding this architecture, some requisites can be emphasized, for instance:

- We currently support Amazon S3 and Apache Kafka as data sources;
- A hive metastore is required within your Spark session;
- An Apache Cassandra database should be up and running.



Some important core concepts regarding this service are features, feature sets and entities, discussed previously. Besides, it's possible to draw attention to other two major ideas:

- Historical Feature Store: all features are calculated over time and stored at S3;
- Online Feature Store: hot/latest data stored at a low latency data storage, such as Apache Cassandra.

1.1.4 Extract

Basically, the extract step is performed with a `Source` object, by defining the desired data sources. You can learn more about it in the *Extract Session*.

1.1.5 Transform

The transform step is defined within a `FeatureSet`, by explicitly defining the desired transformations. More information about the transformations can be found at the *Transform Session*.

1.1.6 Load

It's the last step of the ETL process, and it's defined by a `Sink` object. Please, refer to the *Sink Session* to know more.

1.1.7 Streaming

We also support streaming pipelines in Butterfree. More information is available at the *Streaming Session*.

1.1.8 Setup Configuration

Some configurations are needed to run your ETL pipelines. Detailed information is provided at the *Configuration Section*

1.1.9 Command-line Interface

Butterfree has its own command-line interface, to manage your feature sets. Detailed information provided by the *Command-line Interface* section.

1.2 Getting Started

Butterfree depends on **Python 3.7+** and it is **Spark 3.0 ready**.

Python Package Index hosts reference to a pip-installable module of this library, using it is as straightforward as including it on your project's requirements.

```
pip install butterfree
```

Or after listing `butterfree` in your `requirements.txt` file:

```
pip install -r requirements.txt
```

1.2.1 Discovering Butterfree

Welcome to **Discovering Butterfree** tutorial series! Click on the following links to open the tutorials:

#1 Feature Set Basics

#2 Spark Functions and Window

#3 Aggregated Feature Set

#4 Streaming Feature Set

1.3 Source

Regarding the extract step, we can define a `Source` as a set of data sources in order to join your raw data for the transform step.

Currently, we support three different data sources or, as it's called within `Butterfree`, `readers`:

- `FileReader`: this reader loads data from a file, as the name suggests, and returns a dataframe. It can be instantiated as:

```
file_reader = FileReader(
                id="file_reader_id",
                path="data_path",
                format="json"
              )
```

- `TableReader`: this reader loads data from a table registered in spark metastore and returns a dataframe. It can be instantiated as:

```
table_reader = TableReader(
                    id="table_reader_id",
                    database="table_reader_db",
                    table="table_reader_table"
               )
```

- `KafkaReader`: this reader loads data from a kafka topic and returns a dataframe. It can be instantiated as:

```
kafka_reader = KafkaReader(
                id="kafka_reader_id",
                topic="topic",
                value_schema=value_schema
                connection_string="host1:port,host2:port",
               )
```

After defining all your data sources, it's important to write a query in order to define the relation between them, something like this:

```
source = Source(
   readers=[
       TableReader(
           id="table_reader_id",
           database="table_reader_db",
           table="table_reader_table",
       ),
       FileReader(id="file_reader_id", path="data_sample_path", format="json"),
   ],
   query=f"select a.*, b.feature2 "
   f"from table_reader_id a "
   f"inner join file_reader_id b on a.id = b.id ",
)
```

It's important to state that we have some pre-processing methods as well, such as filter and pivot. Feel free to check them here.

1.4 Feature Sets

Regarding the transform step, we can define a `FeatureSet` as a set of features in order to apply the suggested transformations to your data.

It's possible to use three different kinds of features:

- `KeyFeature`: a `FeatureSet` must contain one or more `KeyFeatures`, which will be used as keys when storing the feature set dataframe as tables. The `FeatureSet` may validate keys that are unique for the latest state of a feature set.
- `TimestampFeature`: a `FeatureSet` must contain one `TimestampFeature`, which will be used as a time tag for the state of all features. By containing a timestamp feature, users may time travel over their features. The `FeatureSet` may validate that the set of keys and timestamp are unique for a feature set. By defining a timestamp column, the feature set will always contain a data column called "timestamp" of `TimestampType` (spark dtype).
- `Feature`: a `Feature` is the result of a transformation over one (or more) data columns over an input dataframe. Transformations can be as simple as renaming, casting types, mathematical expressions or complex functions/models. It can be instantiated as:

```
feature = Feature(
   name="new_feature",
   description="simple feature renaming",
   from_column="feature"
)
```

It's possible to define the desired transformation to be applied over your input data by defining the `transformation` parameter within the `Feature` instantiation. The following transform components can be used in `Butterfree`:

- `SparkFunctionTransform`: this component can bem used when a pyspark sql function needs to be used. It can be instantiated as:

```
feature = Feature(
   name="feature",
   description="Spark function transform usage example",
   transformation=SparkFunctionTransform(
      functions=[Function(functions.cos, DataType.DOUBLE)])
)
```

Feel free to check more here.

- `SQLExpressionTransform`: as the name suggests, this component can be used when a user wants to define the feature's transformation using SQL. It can be instantiated as:

```
feature = Feature(
   name="feature",
   description="SQL expression transform usage example",
   transformation=SQLExpressionTransform(expression="feature1/feature2"),
)
```

You can find more info here.

- `CustomTransform`: this component can be used when an user wants to define a custom transformation by defining a method. For instance:

```
def divide(df, parent_feature, column1, column2):
    name = parent_feature.get_output_columns()[0]
```

(continues on next page)

(continued from previous page)

```
    df = df.withColumn(name, F.col(column1) / F.col(column2))
    return df

feature = Feature(
   name="feature",
   description="custom transform usage example",
   transformation=CustomTransform(
       transformer=divide, column1="feature1", column2="feature2",
   )
)
```

You can take a look at the code here.

- `H3HashTransform`: this component can be used when an user wants to convert latitude and longitude values into a hash. You can learn more about H3 here. For instance:

```
feature = Feature(
   name="feature",
   description="h3 hash transform usage example",
   transformation=H3HashTransform(
       h3_resolutions=[6, 7, 8, 9, 10, 11, 12],
       lat_column="lat",
       lng_column="lng",
   )
)
```

You can read the code here.

- `StackTransform`: this component can be used when an user wants to create a stack column based on some given values. For instance:

```
feature = Feature(
    name="stack_ids",
    description="id_a and id_b stacked in a single column.",
    transformation=StackTransform("id_a", "id_b"),
)
```

Feel free to check it out here.

Finally, an example of a `FeatureSet` is provided:

```
feature_set = FeatureSet(
   name="feature_set",
   entity="entity",
   description="description",
   features=[
       Feature(
           name="feature1",
           description="test",
           transformation=SparkFunctionTransform(
                functions=[
                           Function(F.avg, DataType.DOUBLE),
                           Function(F.stddev_pop, DataType.DOUBLE)]
            ).with_window(
```

(continues on next page)

(continued from previous page)

```
                partition_by="id",
                order_by=TIMESTAMP_COLUMN,
                mode="fixed_windows",
                window_definition=["2 minutes", "15 minutes"],
            ),
        ),
        Feature(
            name="divided_feature",
            description="unit test",
            transformation=CustomTransform(
                transformer=divide, column1="feature1", column2="feature2",
            ),
        ),
    ],
    keys=[KeyFeature(name="id", description="The user's Main ID or device ID")],
    timestamp=TimestampFeature(),
)
```

1.5 Aggregated Feature Sets

When an user desires to use aggregated features, an `AggregatedFeatureSet` can be used. Besides `KeyFeature`, `TimestampFeature` and `Feature` classes, we're going to use a new component regarding the transformations, called `AggregatedTransform`.

- `AggregatedTransform`: this transformation needs to be used within an `AggregatedFeatureSet`. Unlike the other transformations, this class won't have a transform method implemented. The idea behind aggregating is that, in spark, we should execute all aggregation functions after in a single group by. So an `AggregateFeatureSet` will have many features with an associated `AggregatedTransform`. If each one of them needs to apply a `groupby.agg()`, then we must join all the results in the end, making this computation extremely slow. It's important to say that the `AggregatedFeatureSet` can be used with both time and row windows.

Some examples are provided below:

```
feature_set = AggregatedFeatureSet(
    name="aggregated_feature_set",
    entity="entity",
    description="description",
    features=[
        Feature(
            name="feature1",
            description="test",
            transformation=AggregatedTransform(
                 functions=[
                    Function(F.avg, DataType.DOUBLE),
                    Function(F.stddev_pop, DataType.DOUBLE)],
             ),
             from_column="rent",
        ),
    ],
    keys=[KeyFeature(name="id", description="some key")],
```

(continues on next page)

(continued from previous page)

```
    timestamp=TimestampFeature(from_column="ts"),
)
```

You could also add a time window, like this:

```
feature_set.with_windows(definitions=["3 days"])
```

Also, you can add a `pivot` operation:

```
feature_set.with_pivot(
    column="status",
    values=["publicado", "despublicado", "alugado"]
).with_windows(definitions=["1 day", "2 weeks"])
```

Please refer to this code in order to understand more. Also, check our examples section.

1.6 Sink

The Load step is the `Sink` method, where we define the destinations for the feature set pipeline, that is, it is the process of recording the transformed data after the transformation step.

Declaring the sink:

```
sink = Sink(
            writers = [HistoricalFeatureStoreWriter(), OnlineFeatureStoreWriter()]
       ),
```

Currently, you can write your data into two types of `writers`:

- `HistoricalFeatureStoreWriter`: The Historical Feature Store will write the data to an AWS S3 bucket.
- `OnlineFeatureStoreWriter`: The Online Feature Store will write the data to a Cassandra database.

If you declare your writers without a database configuration, they will use their default settings. But we can also define this configuration, such as:

- `HistoricalFeatureStoreWriter`:

```
config = S3Config(bucket="my_bucket", mode="append", format_="parquet")
writers = [HistoricalFeatureStoreWriter(db_config=config)]
```

- `OnlineFeatureStoreWriter`:

```
config = CassandraConfig(
                        mode="overwrite",
                        format_="org.apache.spark.sql.cassandra",
                        keyspace="keyspace_name"
         )
writers = [OnlineFeatureStoreWriter(db_config=config)]
```

You can see the writers here and database configuration here.

It's also important to highlight that our writers support a `debug_mode` option:

```
writers = [HistoricalFeatureStoreWriter(debug_mode=True), OnlineFeatureStoreWriter(debug_
↪mode=True)]
sink = Sink(writers=writers)
```

When `debug_mode` assumes `True`, then a temporary view will be created, therefore no data will be actually saved to both historical and online feature store. Feel free to check our examples section, in order to learn more about how to use this mode.

1.7 Streaming Feature Sets in Butterfree

1.7.1 Introduction

Spark enables us to deal with streaming processing in a very powerful way. For an introduction of all Spark's capabilities in streaming you can read more in this link. As the core Spark, Butterfree also let you declare pipelines to deal with streaming data. The best is that the pipeline declaration is almost the same as dealing with batch use-cases, so there isn't too complex to deal with this type of challenge using Butterfree tools.

Streaming feature sets are the ones that have at least one streaming source of data declared in the `Readers` of a `FeatureSetPipeline`. The pipeline is considered a streaming job if it has at least one reader in streaming mode (`stream=True`).

1.7.2 Readers

Using readers in streaming mode will make use of Spark's `readStream` API instead of the normal `read`. That means it will produce a stream dataframe (`df.isStreaming == True`) instead of a normal Spark's dataframe.

The currently supported readers in stream mode are `FileReader` and `KafkaReader`. For more information about the specifications read their docstrings, here and here respectively.

1.7.3 Online Feature Store Writer

`OnlineFeatureStoreWriter` is currently the only writer that supports streaming dataframes. It will write, in real time, and upserts to Cassandra. It uses `df.writeStream` and `foreachBatch` Spark functionality to do that. You can read more about `forachBatch` here.

Debug Mode

You can use the `OnlineFeatureStoreWriter` in debug mode (`debug_mode=True`) with streaming dataframes. So instead of trying to write to Cassandra, the data will be written to an in-memory table. So you can query this table to show the output as it is being calculated. Normally this functionality is used for the purpose of testing if the defined features have the expected results in real time.

1.7.4 Pipeline Run

Differently from a batch run, a pipeline running with a streaming dataframe will not "finish to run". The pipeline will continue to get data from the streaming, process the data and save it to the defined sink sources. So when managing a job using this feature, an operation needs to be designed to support a continuously-up streaming job.

1.8 Setup Configuration

To perform a ETL pipeline, some configurations are needed. For example: credentials to connect to data sources and default paths. This chapter will cover the main setup configurations on Butterfree.

Some of the configurations are possible to set trough environment variables, the API or both. The priority is first trying to use the parameters used in the instantiation, with the environment variables as fallback. Check the following examples:

1.8.1 Kafka Reader

Configurations:

- Kafka Consumer Connection String: connection string to use to connect to the Kafka.

Setup by instantiation:

```
from butterfree.extract.readers import KafkaReader

kafka_reader = KafkaReader(
    id="reader_id",
    topic="topic_name",
    value_schema=schema,
    connection_string="host1:port,host2:port"
)
```

Setup by environment variables:

Setup the following environment variable in the Spark Cluster/Locally: `KAFKA_CONSUMER_CONNECTION_STRING`

After setting this variables you can instantiate `KafkaReader` easier:

```
from butterfree.extract.readers import KafkaReader

kafka_reader = KafkaReader(
    id="reader_id",
```

(continues on next page)

(continued from previous page)

```
    topic="topic_name",
    value_schema=schema
)
```

1.8.2 Online Feature Store

Cassandra Configuration

Configurations:

- Cassandra Username: username to connect to CassandraDB.
- Cassandra Password: password to connect to CassandraDB.
- Cassandra Host: host to connect to CassandraDB.
- Cassandra Keyspace: keyspace to connect to CassandraDB.
- Stream Checkpoint Path: path on S3 to save the checkpoint for the streaming query. Only need when performing streaming writes.

Setup by instantiation:

```
from butterfree.configs.db import CassandraConfig
from butterfree.load.writers import OnlineFeatureStoreWriter

db_config  = CassandraConfig(
    username="username",
    password="password",
    host="host",
    keyspace="keyspace",
    stream_checkpoint_path="path"
)
writer = OnlineFeatureStoreWriter(db_config=db_config)
```

Setup by environment variables:

Setup the following environment variables in the Spark Cluster/Locally: `CASSANDRA_USERNAME`, `CASSANDRA_PASSWORD`, `CASSANDRA_HOST`, `CASSANDRA_KEYSPACE`, `STREAM_CHECKPOINT_PATH`

After setting this variables you can instantiate `CassandraConfig` and `OnlineFeatureStoreWriter` easier:

```
from butterfree.configs.db import CassandraConfig
from butterfree.load.writers import OnlineFeatureStoreWriter

db_config  = CassandraConfig()
writer = OnlineFeatureStoreWriter(db_config=db_config)

# or just
writer = OnlineFeatureStoreWriter()
```

Kafka Configuration

Configurations:

- Kafka topic: Kafka topic name.
- Kafka connection string: string with hosts and ports to connect.
- Stream Checkpoint Path: path on S3 to save the checkpoint for the streaming query. Only need when performing streaming writes.

Setup by instantiation:

```
from butterfree.configs.db import KafkaConfig
from butterfree.load.writers import OnlineFeatureStoreWriter

custom_kafka_config  = KafkaConfig(
    kafka_topic="custom_topic",
    kafka_connection_string="kafka_connection_string",
    stream_checkpoint_path="path"
)
writer = OnlineFeatureStoreWriter(db_config=custom_kafka_config)
```

or

```
from butterfree.configs.db import KafkaConfig
from butterfree.load.writers import OnlineFeatureStoreWriter

kafka_config  = KafkaConfig(
    kafka_connection_string="kafka_connection_string",
    stream_checkpoint_path="path"
)
writer = OnlineFeatureStoreWriter(db_config=kafka_config)
```

Setup by environment variables:

Setup the following environment variables in the Spark Cluster/Locally: `KAFKA_CONSUMER_CONNECTION_STRING`, `STREAM_CHECKPOINT_PATH`

After setting this variables you can instantiate `KafkaConfig` and `OnlineFeatureStoreWriter` easier:

```
from butterfree.configs.db import KafkaConfig
from butterfree.load.writers import OnlineFeatureStoreWriter

kafka_config  = KafkaConfig()
writer = OnlineFeatureStoreWriter(db_config=kafka_config)
```

1.8.3 Historical Feature Store (Spark Metastore and S3)

Configurations:

- Feature Store S3 Bucket: Bucket on S3 to use for the Historical Feature Store.
- Feature Store Historical Database: Database on Spark metastore to use to write the tables from Historical Feature Store.

Setup by instantiation:

```
from butterfree.configs.db import S3Config
from butterfree.load.writers import HistoricalFeatureStoreWriter

db_config  = S3Config(bucket="bucket")
writer = HistoricalFeatureStoreWriter(
    db_config=db_config,
    database="database"
)
```

Setup by environment variables:

Setup the following environment variables in the Spark Cluster/Locally: `FEATURE_STORE_S3_BUCKET`, `FEATURE_STORE_HISTORICAL_DATABASE`

After setting this variables you can instantiate `S3Config` and `HistoricalFeatureStoreWriter` easier:

```
from butterfree.configs.db import S3Config
from butterfree.load.writers import HistoricalFeatureStoreWriter

db_config  = S3Config()
writer = HistoricalFeatureStoreWriter(db_config=db_config)

# or just
writer = HistoricalFeatureStoreWriter()
```

1.8.4 Important Considerations

API information

For more detailed information on the API arguments is better to check their own docstrings.

Troubleshoot checks

- Check if Spark cluster machines have all the permissions to read/write/modify on the Historical FeatureStore Bucket
- Check if Spark cluster machines can reach the all the configured hosts
- Check if the configured credentials have all the needed permissions on CassandraDB

1.9 API Specification

1.9.1 butterfree package

Subpackages

butterfree.clients package

Submodules

Abstract class for database clients.

class butterfree.clients.abstract_client.**AbstractClient**

Bases: ABC

Abstract base class for database clients.

abstract property conn: Any

Returns a connection object.

abstract get_schema(*table: str*, *database: Optional[str] = None*) → Any

Returns desired table schema.

table

desired table.

Returns

A list of dictionaries in the format [{"column_name": "example1", type: "Spark_type"}, ...]

abstract sql(*query: str*) → Any

Runs a query.

Parameters

query – client query.

Returns

Set of records.

CassandraClient entity.

class butterfree.clients.cassandra_client.**CassandraClient**(*host: List[str]*, *keyspace: str*, *user: Optional[str] = None*, *password: Optional[str] = None*)

Bases: *AbstractClient*

Cassandra Client.

user

username to use in connection.

password

password to use in connection.

keyspace

key space used in connection.

host

cassandra endpoint used in connection.

property conn: Session

Establishes a Cassandra connection.

create_table(*columns: List[CassandraColumn]*, *table: str*) → None

Creates a table.

columns

a list dictionaries in the format [{"column_name": "example1", type: "cql_type", primary_key: True}, ...]

get_schema(*table: str*, *database: Optional[str] = None*) → List[Dict[str, str]]

Returns desired table schema.

table

desired table.

Returns

A list dictionaries in the format [{"column_name": "example1", type: "cql_type"}, ...]

sql(*query: str*) → ResponseFuture

Executes desired query.

query

desired query.

class butterfree.clients.cassandra_client.**CassandraColumn**(***kwargs*)

Bases: dict

Type for cassandra columns.

It's just a type abstraction, we can use it or a normal dict

```
>>> def function(column: CassandraColumn) -> CassandraColumn:
...     return column
>>> # The following two lines will pass in the type checking
>>> function({'column_name': 'test', 'type': 'integer', 'primary_key': False})
>>> function(CassandraColumn(column_name='test', type='integer', primary_key=False))
```

column_name: str

primary_key: bool

type: str

SparkClient entity.

class butterfree.clients.spark_client.**SparkClient**

Bases: *AbstractClient*

Handle Spark session connection.

Get query results with SQL, reads and writes data on external systems.

add_table_partitions(*partitions: List[Dict[str, Any]]*, *table: str*, *database: Optional[str] = None*) → None

Add partitions to an existing table.

Parameters

- **partitions** – partitions to add to the table. It's expected a list of partition dicts to add to the table. Example: *[{"year": 2020, "month": 8, "day": 14}, ...]*
- **table** – table to add the partitions.
- **database** – name of the database where the table is saved.

property conn: SparkSession

Gets or creates an SparkSession.

Returns
Spark session

static create_temporary_view(*dataframe: DataFrame*, *name: str*) → Any

Create a temporary view from a given dataframe.

Parameters

- **dataframe** – dataframe to be be queried by the view.
- **name** – name of the temporary view.

get_schema(*table: str*, *database: Optional[str] = None*) → List[Dict[str, str]]

Returns desired table schema.

table

desired table.

Returns
A list of dictionaries in the format [{"column_name": "example1", type: "Spark_type"}, ...]

read(*format: str*, *path: Optional[Union[str, List[str]]] = None*, *schema: Optional[StructType] = None*, *stream: bool = False*, ***options: Any*) → DataFrame

Use the SparkSession.read interface to load data into a dataframe.

Check docs for more information:
https://spark.apache.org/docs/latest/sql-data-sources-load-save-functions.html#generic-loadsave-functions

Parameters

- **format** – string with the format to be used by the DataframeReader.
- **path** – optional string or a list of string for file-system.
- **stream** – flag to indicate if data must be read in stream mode.
- **schema** – an optional pyspark.sql.types.StructType for the input schema.
- **options** – options to setup the DataframeReader.

Returns
Dataframe

read_table(*table: str*, *database: Optional[str] = None*) → DataFrame

Use the SparkSession.read interface to read a metastore table.

Parameters

- **database** – name of the metastore database/schema
- **table** – name of the table in metastore

Returns
Dataframe

sql(*query: str*) → DataFrame

Run a query using Spark SQL.

Parameters
query – Spark SQL query.

Returns
Dataframe

static write_dataframe(*dataframe: DataFrame*, *format_: str*, *mode: str*, ***options: Any*) → None

Receive a spark DataFrame and write it.

Parameters

- **dataframe** – dataframe containing data from a feature set.
- **format** – format used to save the dataframe.
- **mode** – writing modem can be "error", "append", "overwrite" or "ignore". For more information: [here](https://spark.apache.org/docs/2.3.0/sql-programming-guide.html#save-modes).
- ****options** – all other options that can be used in a DataFrameWriter.

write_stream(*dataframe: DataFrame*, *processing_time: str*, *output_mode: str*, *checkpoint_path: Optional[str]*, *format_: str*, *mode: str*, ***options: Any*) → StreamingQuery

Starts streaming data writing job.

Parameters

- **dataframe** – Spark dataframe containing data from a feature set.
- **processing_time** – a processing time interval as a string. E.g. '5 seconds', '1 minute'. Set a trigger that runs the mini-batch periodically based on the processing time. If the effect of processing data as soon as the data arrives, without having to wait for the time frame, is desired, the value '0 seconds' can be set.
- **output_mode** – specifies how data of a streaming DataFrame/Dataset is written to a streaming sink destination.
- **checkpoint_path** – path on S3 to save checkpoints for the stream job. These checkpoint can be used on the the job re-start to return from where it stops.
- **format** – format used to save the dataframe.
- **mode** – writing modem can be "error", "append", "overwrite" or "ignore". For more information: [here](https://spark.apache.org/docs/2.3.0/sql-programming-guide.html#save-modes).

- ****options** – all other options that can be used in a DataFrameWriter.

More information about processing_time, output_mode and checkpoint_path can be found in Spark documentation: [here](https://spark.apache.org/docs/latest/structured-streaming-programming-guide.html)

Returns
Streaming handler.

static write_table(*dataframe: DataFrame*, *database: Optional[str]*, *table_name: str*, *path: str*, *format_: Optional[str] = None*, *mode: Optional[str] = None*, *partition_by: Optional[List[str]] = None*, ***options: Any*) → None

Receive a spark DataFrame and write it as a table in metastore.

Parameters

- **dataframe** – spark dataframe containing data from a feature set.
- **database** – specified database name.
- **table_name** – specified table name.
- **path** – string with the local to save the table.
- **format** – string with the format used to save.
- **mode** – writing mode, it can be: "error", "append", "overwrite" or "ignore". More information: [here](https://spark.apache.org/docs/2.3.0/sql-programming-guide.html#save-modes).
- **partition_by** – names of partitioning columns.
- **options** – all other options that can be used in a DataFrameWriter.

Module contents

Holds connection clients.

class butterfree.clients.**AbstractClient**

Bases: ABC

Abstract base class for database clients.

abstract property conn: Any

Returns a connection object.

abstract get_schema(*table: str*, *database: Optional[str] = None*) → Any

Returns desired table schema.

table

desired table.

Returns
A list of dictionaries in the format [{"column_name": "example1", type: "Spark_type"}, ...]

abstract sql(*query: str*) → Any

Runs a query.

Parameters
query – client query.

Returns
Set of records.

class butterfree.clients.**CassandraClient**(*host: List[str]*, *keyspace: str*, *user: Optional[str] = None*, *password: Optional[str] = None*)

Bases: *AbstractClient*

Cassandra Client.

user
username to use in connection.

password
password to use in connection.

keyspace
key space used in connection.

host
cassandra endpoint used in connection.

property conn: Session
Establishes a Cassandra connection.

create_table(*columns: List[CassandraColumn]*, *table: str*) → None
Creates a table.

columns
a list dictionaries in the format [{"column_name": "example1", type: "cql_type", primary_key: True}, ...]

get_schema(*table: str*, *database: Optional[str] = None*) → List[Dict[str, str]]
Returns desired table schema.

table
desired table.

Returns
A list dictionaries in the format [{"column_name": "example1", type: "cql_type"}, ...]

sql(*query: str*) → ResponseFuture
Executes desired query.

query
desired query.

class butterfree.clients.**SparkClient**

Bases: *AbstractClient*

Handle Spark session connection.

Get query results with SQL, reads and writes data on external systems.

add_table_partitions(*partitions: List[Dict[str, Any]]*, *table: str*, *database: Optional[str] = None*) → None
Add partitions to an existing table.

Parameters

- **partitions** – partitions to add to the table. It's expected a list of partition dicts to add to the table. Example: *[{"year": 2020, "month": 8, "day": 14}, ...]*
- **table** – table to add the partitions.
- **database** – name of the database where the table is saved.

property conn: SparkSession

Gets or creates an SparkSession.

Returns
Spark session

static create_temporary_view(*dataframe: DataFrame*, *name: str*) → Any

Create a temporary view from a given dataframe.

Parameters

- **dataframe** – dataframe to be be queried by the view.
- **name** – name of the temporary view.

get_schema(*table: str*, *database: Optional[str] = None*) → List[Dict[str, str]]

Returns desired table schema.

table

desired table.

Returns
A list of dictionaries in the format [{"column_name": "example1", type: "Spark_type"}, ...]

read(*format: str*, *path: Optional[Union[str, List[str]]] = None*, *schema: Optional[StructType] = None*, *stream: bool = False*, ***options: Any*) → DataFrame

Use the SparkSession.read interface to load data into a dataframe.

Check docs for more information:
https://spark.apache.org/docs/latest/sql-data-sources-load-save-functions.html#generic-loadsave-functions

Parameters

- **format** – string with the format to be used by the DataframeReader.
- **path** – optional string or a list of string for file-system.
- **stream** – flag to indicate if data must be read in stream mode.
- **schema** – an optional pyspark.sql.types.StructType for the input schema.
- **options** – options to setup the DataframeReader.

Returns
Dataframe

read_table(*table: str*, *database: Optional[str] = None*) → DataFrame

Use the SparkSession.read interface to read a metastore table.

Parameters

- **database** – name of the metastore database/schema
- **table** – name of the table in metastore

Returns
Dataframe

`sql`(*query: str*) → DataFrame

Run a query using Spark SQL.

Parameters
query – Spark SQL query.

Returns
Dataframe

`static write_dataframe`(*dataframe: DataFrame*, *format_: str*, *mode: str*, ***options: Any*) → None

Receive a spark DataFrame and write it.

Parameters

- **dataframe** – dataframe containing data from a feature set.
- **format** – format used to save the dataframe.
- **mode** – writing modem can be "error", "append", "overwrite" or "ignore". For more information: [here](https://spark.apache.org/docs/2.3.0/sql-programming-guide.html#save-modes).
- ****options** – all other options that can be used in a DataFrameWriter.

`write_stream`(*dataframe: DataFrame*, *processing_time: str*, *output_mode: str*, *checkpoint_path: Optional[str]*, *format_: str*, *mode: str*, ***options: Any*) → StreamingQuery

Starts streaming data writing job.

Parameters

- **dataframe** – Spark dataframe containing data from a feature set.
- **processing_time** – a processing time interval as a string. E.g. '5 seconds', '1 minute'. Set a trigger that runs the mini-batch periodically based on the processing time. If the effect of processing data as soon as the data arrives, without having to wait for the time frame, is desired, the value '0 seconds' can be set.
- **output_mode** – specifies how data of a streaming DataFrame/Dataset is written to a streaming sink destination.
- **checkpoint_path** – path on S3 to save checkpoints for the stream job. These checkpoint can be used on the the job re-start to return from where it stops.
- **format** – format used to save the dataframe.
- **mode** – writing modem can be "error", "append", "overwrite" or "ignore". For more information: [here](https://spark.apache.org/docs/2.3.0/sql-programming-guide.html#save-modes).
- ****options** – all other options that can be used in a DataFrameWriter.

More information about processing_time, output_mode and checkpoint_path can be found in Spark documentation: [here](https://spark.apache.org/docs/latest/structured-streaming-programming-guide.html)

Returns
Streaming handler.

`static write_table`(*dataframe: DataFrame*, *database: Optional[str]*, *table_name: str*, *path: str*, *format_: Optional[str] = None*, *mode: Optional[str] = None*, *partition_by: Optional[List[str]] = None*, ***options: Any*) → None

Receive a spark DataFrame and write it as a table in metastore.

Parameters

- **dataframe** – spark dataframe containing data from a feature set.
- **database** – specified database name.
- **table_name** – specified table name.
- **path** – string with the local to save the table.
- **format** – string with the format used to save.
- **mode** – writing mode, it can be: "error", "append", "overwrite" or "ignore". More information: [here](https://spark.apache.org/docs/2.3.0/sql-programming-guide.html#save-modes).
- **partition_by** – names of partitioning columns.
- **options** – all other options that can be used in a DataFrameWriter.

butterfree.configs package

Subpackages

butterfree.configs.db package

Submodules

Abstract classes for database configurations with spark.

class butterfree.configs.db.abstract_config.**AbstractWriteConfig**

Bases: ABC

Abstract class for database write configurations with spark.

abstract property database: str

Database name.

abstract property format_: Any

Config option "format" for spark write.

Args:

Returns
format.

Return type
str

abstract property mode: Any

Config option "mode" for spark write.

Args:

Returns
mode.

Return type
str

abstract translate(*schema: Any*) → List[Dict[Any, Any]]

Translate feature set spark schema to the corresponding database.

Parameters
schema – feature set schema

Returns
Corresponding database schema.

Holds configurations to read and write with Spark to Cassandra DB.

class butterfree.configs.db.cassandra_config.**CassandraConfig**(*username: Optional[str] = None*, *password: Optional[str] = None*, *host: Optional[str] = None*, *keyspace: Optional[str] = None*, *mode: Optional[str] = None*, *format_: Optional[str] = None*, *stream_processing_time: Optional[str] = None*, *stream_output_mode: Optional[str] = None*, *stream_checkpoint_path: Optional[str] = None*, *read_consistency_level: Optional[str] = None*, *write_consistency_level: Optional[str] = None*, *local_dc: Optional[str] = None*)

Bases: *AbstractWriteConfig*

Configuration for Spark to connect on Cassandra DB.

References can be found [here](https://docs.databricks.com/data/data-sources/cassandra.html).

username
username to use in connection.

password
password to use in connection.

host
host to use in connection.

keyspace
Cassandra DB keyspace to write data.

mode
write mode for Spark.

format_
write format for Spark.

stream_processing_time
processing time interval for streaming jobs.

stream_output_mode
specify the mode from writing streaming data.

stream_checkpoint_path

path on S3 to save checkpoints for the stream job.

read_consistency_level

read consistency level used in connection.

write_consistency_level

write consistency level used in connection.

More information about processing_time, output_mode and checkpoint_path can be found in Spark documentation: [here](https://spark.apache.org/docs/latest/structured-streaming-programming-guide.html)

property database: str

Database name.

property format_: Optional[str]

Write format for Spark.

get_options(*table: str*) → Dict[Optional[str], Optional[str]]

Get options for connect to Cassandra DB.

Options will be a dictionary with the write and read configuration for spark to cassandra.

Parameters

table – table name (keyspace) into Cassandra DB.

Returns

Configuration to connect to Cassandra DB.

property host: Optional[str]

Host used in connection to Cassandra DB.

property keyspace: Optional[str]

Cassandra DB keyspace to write data.

property local_dc: Optional[str]

Local DC for Cassandra connection.

property mode: Optional[str]

Write mode for Spark.

property password: Optional[str]

Password used in connection to Cassandra DB.

property read_consistency_level: Optional[str]

Read consistency level for Cassandra.

property stream_checkpoint_path: Optional[str]

Path on S3 to save checkpoints for the stream job.

property stream_output_mode: Optional[str]

Specify the mode from writing streaming data.

property stream_processing_time: Optional[str]

Processing time interval for streaming jobs.

translate(*schema: List[Dict[str, Any]]*) → List[Dict[str, Any]]

Get feature set schema to be translated.

The output will be a list of dictionaries regarding cassandra database schema.

Parameters
schema – feature set schema in spark.

Returns
Cassandra schema.

property username: Optional[str]
Username used in connection to Cassandra DB.

property write_consistency_level: Optional[str]
Write consistency level for Cassandra.

Holds configurations to read and write with Spark to Kafka.

class butterfree.configs.db.kafka_config.**KafkaConfig**(*kafka_topic: Optional[str] = None*, *kafka_connection_string: Optional[str] = None*, *mode: Optional[str] = None*, *format_: Optional[str] = None*, *stream_processing_time: Optional[str] = None*, *stream_output_mode: Optional[str] = None*, *stream_checkpoint_path: Optional[str] = None*)

Bases: *AbstractWriteConfig*

Configuration for Spark to connect to Kafka.

kafka_topic
string with kafka topic name.

kafka_connection_string
string with hosts and ports to connect.

mode
write mode for Spark.

format_
write format for Spark.

stream_processing_time
processing time interval for streaming jobs.

stream_output_mode
specify the mode from writing streaming data.

stream_checkpoint_path
path on S3 to save checkpoints for the stream job.

More information about processing_time, output_mode and checkpoint_path can be found in Spark documentation: [here](https://spark.apache.org/docs/latest/structured-streaming-programming-guide.html)

property database: str
Database name.

property format_: Optional[str]
Write format for Spark.

get_options(*topic: str*) → Dict[Optional[str], Optional[str]]
Get options for connecting to Kafka.

Options will be a dictionary with the write and read configuration for spark to kafka.

Parameters
topic – topic related to Kafka.

Returns
Configuration to connect to Kafka.

property kafka_connection_string: Optional[str]
Kafka connection string with hosts and ports to connect.

property kafka_topic: Optional[str]
Kafka topic name.

property mode: Optional[str]
Write mode for Spark.

property stream_checkpoint_path: Optional[str]
Path on S3 to save checkpoints for the stream job.

property stream_output_mode: Optional[str]
Specify the mode from writing streaming data.

property stream_processing_time: Optional[str]
Processing time interval for streaming jobs.

translate(*schema: List[Dict[str, Any]]*) → List[Dict[str, Any]]
Get feature set schema to be translated.

The output will be a list of dictionaries regarding cassandra database schema.

Parameters
schema – feature set schema in spark.

Returns
Kafka schema.

Holds configurations to read and write with Spark to AWS S3.

class butterfree.configs.db.metastore_config.**MetastoreConfig**(*path: Optional[str] = None*, *mode: Optional[str] = None*, *format_: Optional[str] = None*, *file_system: Optional[str] = None*)

Bases: *AbstractWriteConfig*

Configuration for Spark metastore database stored.

By default the configuration is for AWS S3.

path
database root location.

mode
writing mode used be writers.

format_
expected stored file format.

file_system
file schema uri, like: s3a, file.

property database: str
Database name.

property file_system: Optional[str]

Writing mode used be writers.

property format_: Optional[str]

Expected stored file format.

get_options(*key: str*) → Dict[Optional[str], Optional[str]]

Get options for Metastore.

Options will be a dictionary with the write and read configuration for Spark Metastore.

Parameters
key – path to save data into Metastore.

Returns
Options configuration for Metastore.

get_path_with_partitions(*key: str*, *dataframe: DataFrame*) → List

Get options for AWS S3 from partitioned parquet file.

Options will be a dictionary with the write and read configuration for Spark to AWS S3.

Parameters

- **key** – path to save data into AWS S3 bucket.
- **dataframe** – spark dataframe containing data from a feature set.

Returns
A list of string for file-system backed data sources.

property mode: Optional[str]

Writing mode used be writers.

property path: Optional[str]

Bucket name.

translate(*schema: List[Dict[str, Any]]*) → List[Dict[str, Any]]

Translate feature set spark schema to the corresponding database.

Module contents

This module holds database configurations to be used by clients.

class butterfree.configs.db.**AbstractWriteConfig**

Bases: ABC

Abstract class for database write configurations with spark.

abstract property database: str

Database name.

abstract property format_: Any

Config option "format" for spark write.

Args:

Returns
format.

Return type
str

`abstract property mode: Any`

Config option "mode" for spark write.

Args:

Returns
mode.

Return type
str

`abstract translate(schema: Any) → List[Dict[Any, Any]]`

Translate feature set spark schema to the corresponding database.

Parameters
schema – feature set schema

Returns
Corresponding database schema.

`class butterfree.configs.db.CassandraConfig(username: Optional[str] = None, password: Optional[str] = None, host: Optional[str] = None, keyspace: Optional[str] = None, mode: Optional[str] = None, format_: Optional[str] = None, stream_processing_time: Optional[str] = None, stream_output_mode: Optional[str] = None, stream_checkpoint_path: Optional[str] = None, read_consistency_level: Optional[str] = None, write_consistency_level: Optional[str] = None, local_dc: Optional[str] = None)`

Bases: *AbstractWriteConfig*

Configuration for Spark to connect on Cassandra DB.

References can be found [here](https://docs.databricks.com/data/data-sources/cassandra.html).

username
username to use in connection.

password
password to use in connection.

host
host to use in connection.

keyspace
Cassandra DB keyspace to write data.

mode
write mode for Spark.

format_
write format for Spark.

stream_processing_time
processing time interval for streaming jobs.

stream_output_mode

specify the mode from writing streaming data.

stream_checkpoint_path

path on S3 to save checkpoints for the stream job.

read_consistency_level

read consistency level used in connection.

write_consistency_level

write consistency level used in connection.

More information about processing_time, output_mode and checkpoint_path can be found in Spark documentation: [here](https://spark.apache.org/docs/latest/structured-streaming-programming-guide.html)

property database: str

Database name.

property format_: Optional[str]

Write format for Spark.

get_options(*table: str*) → Dict[Optional[str], Optional[str]]

Get options for connect to Cassandra DB.

Options will be a dictionary with the write and read configuration for spark to cassandra.

Parameters
table – table name (keyspace) into Cassandra DB.

Returns
Configuration to connect to Cassandra DB.

property host: Optional[str]

Host used in connection to Cassandra DB.

property keyspace: Optional[str]

Cassandra DB keyspace to write data.

property local_dc: Optional[str]

Local DC for Cassandra connection.

property mode: Optional[str]

Write mode for Spark.

property password: Optional[str]

Password used in connection to Cassandra DB.

property read_consistency_level: Optional[str]

Read consistency level for Cassandra.

property stream_checkpoint_path: Optional[str]

Path on S3 to save checkpoints for the stream job.

property stream_output_mode: Optional[str]

Specify the mode from writing streaming data.

property stream_processing_time: Optional[str]

Processing time interval for streaming jobs.

translate(*schema: List[Dict[str, Any]]*) → List[Dict[str, Any]]

Get feature set schema to be translated.

The output will be a list of dictionaries regarding cassandra database schema.

Parameters
schema – feature set schema in spark.

Returns
Cassandra schema.

property username: Optional[str]

Username used in connection to Cassandra DB.

property write_consistency_level: Optional[str]

Write consistency level for Cassandra.

class butterfree.configs.db.**KafkaConfig**(*kafka_topic: Optional[str] = None*, *kafka_connection_string: Optional[str] = None*, *mode: Optional[str] = None*, *format_: Optional[str] = None*, *stream_processing_time: Optional[str] = None*, *stream_output_mode: Optional[str] = None*, *stream_checkpoint_path: Optional[str] = None*)

Bases: *AbstractWriteConfig*

Configuration for Spark to connect to Kafka.

kafka_topic

string with kafka topic name.

kafka_connection_string

string with hosts and ports to connect.

mode

write mode for Spark.

format_

write format for Spark.

stream_processing_time

processing time interval for streaming jobs.

stream_output_mode

specify the mode from writing streaming data.

stream_checkpoint_path

path on S3 to save checkpoints for the stream job.

More information about processing_time, output_mode and checkpoint_path can be found in Spark documentation: [here](https://spark.apache.org/docs/latest/structured-streaming-programming-guide.html)

property database: str

Database name.

property format_: Optional[str]

Write format for Spark.

get_options(*topic: str*) → Dict[Optional[str], Optional[str]]

Get options for connecting to Kafka.

Options will be a dictionary with the write and read configuration for spark to kafka.

Parameters
topic – topic related to Kafka.

Returns
Configuration to connect to Kafka.

property kafka_connection_string: Optional[str]
Kafka connection string with hosts and ports to connect.

property kafka_topic: Optional[str]
Kafka topic name.

property mode: Optional[str]
Write mode for Spark.

property stream_checkpoint_path: Optional[str]
Path on S3 to save checkpoints for the stream job.

property stream_output_mode: Optional[str]
Specify the mode from writing streaming data.

property stream_processing_time: Optional[str]
Processing time interval for streaming jobs.

translate(*schema: List[Dict[str, Any]]*) → List[Dict[str, Any]]
Get feature set schema to be translated.

The output will be a list of dictionaries regarding cassandra database schema.

Parameters
schema – feature set schema in spark.

Returns
Kafka schema.

class butterfree.configs.db.**MetastoreConfig**(*path: Optional[str] = None*, *mode: Optional[str] = None*, *format_: Optional[str] = None*, *file_system: Optional[str] = None*)

Bases: *AbstractWriteConfig*

Configuration for Spark metastore database stored.

By default the configuration is for AWS S3.

path
database root location.

mode
writing mode used be writers.

format_
expected stored file format.

file_system
file schema uri, like: s3a, file.

property database: str
Database name.

property file_system: Optional[str]

Writing mode used be writers.

property format_: Optional[str]

Expected stored file format.

get_options(*key: str*) → Dict[Optional[str], Optional[str]]

Get options for Metastore.

Options will be a dictionary with the write and read configuration for Spark Metastore.

Parameters
key – path to save data into Metastore.

Returns
Options configuration for Metastore.

get_path_with_partitions(*key: str*, *dataframe: DataFrame*) → List

Get options for AWS S3 from partitioned parquet file.

Options will be a dictionary with the write and read configuration for Spark to AWS S3.

Parameters

- **key** – path to save data into AWS S3 bucket.
- **dataframe** – spark dataframe containing data from a feature set.

Returns
A list of string for file-system backed data sources.

property mode: Optional[str]

Writing mode used be writers.

property path: Optional[str]

Bucket name.

translate(*schema: List[Dict[str, Any]]*) → List[Dict[str, Any]]

Translate feature set spark schema to the corresponding database.

Submodules

Holds functions for managing the running environment.

exception butterfree.configs.environment.UnspecifiedVariableError(*variable_name: str*)

Bases: RuntimeError

Environment variables not set error.

variable_name

environment variable name.

butterfree.configs.environment.get_variable(*variable_name: str*, *default_value: Optional[str] = None*) → Optional[str]

Gets an environment variable.

The variable comes from it's explicitly declared value in the running environment or from the default value declared in specification or from the default_value.

Parameters

- **variable_name** – environment variable name.
- **default_value** – default value to use in case no value is set in the environment nor in the environment.yaml specification file.

Returns
The variable's string value

Logger funcion.

Module contents

Holds configuration/setup for Butterfree components.

butterfree.constants package

Submodules

Holds common column names, constant through all Butterfree.

DataType Enum Entity.

class butterfree.constants.data_type.**DataType**(*value*)

Bases: Enum

Holds constants for data types within Butterfree.

ARRAY_BIGINT = (ArrayType(LongType(), True), 'frozen<list<bigint>>', 'ARRAY<BIGINT>')

ARRAY_FLOAT = (ArrayType(FloatType(), True), 'frozen<list<float>>', 'ARRAY<FLOAT>')

ARRAY_STRING = (ArrayType(StringType(), True), 'frozen<list<text>>', 'ARRAY<STRING>')

BIGINT = (LongType(), 'bigint', 'BIGINT')

BINARY = (BinaryType(), 'boolean', 'BINARY')

BOOLEAN = (BooleanType(), 'boolean', 'BOOLEAN')

DATE = (DateType(), 'timestamp', 'DATE')

DECIMAL = (DecimalType(10,0), 'decimal', 'DECIMAL')

DOUBLE = (DoubleType(), 'double', 'DOUBLE')

FLOAT = (FloatType(), 'float', 'FLOAT')

INTEGER = (IntegerType(), 'int', 'INT')

STRING = (StringType(), 'text', 'STRING')

TIMESTAMP = (TimestampType(), 'timestamp', 'TIMESTAMP')

Migrations' Constants.

Holds common spark constants, present through all Butterfree.

Allowed windows units and lengths in seconds.

Module contents

Holds constant attributes that are common for Butterfree.

class butterfree.constants.**DataType**(*value*)

Bases: Enum

Holds constants for data types within Butterfree.

ARRAY_BIGINT = (ArrayType(LongType(), True), 'frozen<list<bigint>>', 'ARRAY<BIGINT>')

ARRAY_FLOAT = (ArrayType(FloatType(), True), 'frozen<list<float>>', 'ARRAY<FLOAT>')

ARRAY_STRING = (ArrayType(StringType(), True), 'frozen<list<text>>', 'ARRAY<STRING>')

BIGINT = (LongType(), 'bigint', 'BIGINT')

BINARY = (BinaryType(), 'boolean', 'BINARY')

BOOLEAN = (BooleanType(), 'boolean', 'BOOLEAN')

DATE = (DateType(), 'timestamp', 'DATE')

DECIMAL = (DecimalType(10,0), 'decimal', 'DECIMAL')

DOUBLE = (DoubleType(), 'double', 'DOUBLE')

FLOAT = (FloatType(), 'float', 'FLOAT')

INTEGER = (IntegerType(), 'int', 'INT')

STRING = (StringType(), 'text', 'STRING')

TIMESTAMP = (TimestampType(), 'timestamp', 'TIMESTAMP')

butterfree.dataframe_service package

Submodules

IncrementalStrategy entity.

class butterfree.dataframe_service.incremental_strategy.**IncrementalStrategy**(*column: Optional[str] = None*)

Bases: object

Define an incremental strategy to be used on data sources.

Entity responsible for defining a column expression that will be used to filter the original data source. The purpose is to get only the data related to a specific pipeline execution time interval.

column

column expression on which incremental filter will be applied. The expression need to result on a date or timestamp format, so the filter can properly work with the defined upper and lower bounds.

filter_with_incremental_strategy(*dataframe: DataFrame*, *start_date: Optional[str] = None*, *end_date: Optional[str] = None*) → DataFrame

Filters the dataframe according to the date boundaries.

Parameters

- **dataframe** – dataframe that will be filtered.
- **start_date** – date lower bound to use in the filter.
- **end_date** – date upper bound to use in the filter.

Returns

Filtered dataframe based on defined time boundaries.

from_milliseconds(*column_name: str*) → *IncrementalStrategy*

Create a column expression from ts column defined as milliseconds.

Parameters

column_name – column name where the filter will be applied.

Returns

IncrementalStrategy with the defined column expression.

from_string(*column_name: str*, *mask: Optional[str] = None*) → *IncrementalStrategy*

Create a column expression from ts column defined as a simple string.

Parameters

- **column_name** – column name where the filter will be applied.
- **mask** – mask defining the date/timestamp format on the string.

Returns

IncrementalStrategy with the defined column expression.

from_year_month_day_partitions(*year_column: str = 'year'*, *month_column: str = 'month'*, *day_column: str = 'day'*) → *IncrementalStrategy*

Create a column expression from year, month and day partitions.

Parameters

- **year_column** – column name from the year partition.
- **month_column** – column name from the month partition.
- **day_column** – column name from the day partition.

Returns

IncrementalStrategy with the defined column expression.

get_expression(*start_date: Optional[str] = None*, *end_date: Optional[str] = None*) → str

Get the incremental filter expression using the defined dates.

Both arguments can be set to defined a specific date interval, but it's only necessary to set one of the arguments for this method to work.

Parameters

- **start_date** – date lower bound to use in the filter.
- **end_date** – date upper bound to use in the filter.

Returns

Filter expression based on defined column and bounds.

Raises

- **ValuerError** – If both arguments, start_date and end_date, are None.
- **ValueError** – If the column expression was not defined.

Module defining partitioning methods.

butterfree.dataframe_service.partitioning.**extract_partition_values**(*dataframe: DataFrame*, *partition_columns: List[str]*) → List[Dict[str, Any]]

Extract distinct partition values from a given dataframe.

Parameters

- **dataframe** – dataframe from where to extract partition values.
- **partition_columns** – name of partition columns presented on the dataframe.

Returns

distinct partition values.

Module where there are repartition methods.

butterfree.dataframe_service.repartition.**repartition_df**(*dataframe: DataFrame*, *partition_by: List[str]*, *num_partitions: Optional[int] = None*, *num_processors: Optional[int] = None*) → DataFrame

Partition the DataFrame.

Parameters

- **dataframe** – Spark DataFrame.
- **partition_by** – list of partitions.
- **num_processors** – number of processors.
- **num_partitions** – number of partitions.

Returns

Partitioned dataframe.

butterfree.dataframe_service.repartition.**repartition_sort_df**(*dataframe: DataFrame*, *partition_by: List[str]*, *order_by: List[str]*, *num_processors: Optional[int] = None*, *num_partitions: Optional[int] = None*) → DataFrame

Partition and Sort the DataFrame.

Parameters

- **dataframe** – Spark DataFrame.
- **partition_by** – list of columns to partition by.
- **order_by** – list of columns to order by.
- **num_processors** – number of processors.
- **num_partitions** – number of partitions.

Returns
Partitioned and sorted dataframe.

Module contents

Dataframe optimization components regarding Butterfree.

class butterfree.dataframe_service.**IncrementalStrategy**(*column: Optional[str] = None*)

Bases: object

Define an incremental strategy to be used on data sources.

Entity responsible for defining a column expression that will be used to filter the original data source. The purpose is to get only the data related to a specific pipeline execution time interval.

column

column expression on which incremental filter will be applied. The expression need to result on a date or timestamp format, so the filter can properly work with the defined upper and lower bounds.

filter_with_incremental_strategy(*dataframe: DataFrame*, *start_date: Optional[str] = None*, *end_date: Optional[str] = None*) → DataFrame

Filters the dataframe according to the date boundaries.

Parameters

- **dataframe** – dataframe that will be filtered.
- **start_date** – date lower bound to use in the filter.
- **end_date** – date upper bound to use in the filter.

Returns
Filtered dataframe based on defined time boundaries.

from_milliseconds(*column_name: str*) → *IncrementalStrategy*

Create a column expression from ts column defined as milliseconds.

Parameters
column_name – column name where the filter will be applied.

Returns
IncrementalStrategy with the defined column expression.

from_string(*column_name: str*, *mask: Optional[str] = None*) → *IncrementalStrategy*

Create a column expression from ts column defined as a simple string.

Parameters

- **column_name** – column name where the filter will be applied.
- **mask** – mask defining the date/timestamp format on the string.

Returns
IncrementalStrategy with the defined column expression.

from_year_month_day_partitions(*year_column: str = 'year'*, *month_column: str = 'month'*, *day_column: str = 'day'*) → *IncrementalStrategy*

Create a column expression from year, month and day partitions.

Parameters

- **year_column** – column name from the year partition.

- **month_column** – column name from the month partition.
- **day_column** – column name from the day partition.

Returns
IncrementalStrategy with the defined column expression.

get_expression(*start_date: Optional[str] = None*, *end_date: Optional[str] = None*) → str

Get the incremental filter expression using the defined dates.

Both arguments can be set to defined a specific date interval, but it's only necessary to set one of the arguments for this method to work.

Parameters

- **start_date** – date lower bound to use in the filter.
- **end_date** – date upper bound to use in the filter.

Returns
Filter expression based on defined column and bounds.

Raises

- **ValuerError** – If both arguments, start_date and end_date, are None.
- **ValueError** – If the column expression was not defined.

butterfree.dataframe_service.**extract_partition_values**(*dataframe: DataFrame*, *partition_columns: List[str]*) → List[Dict[str, Any]]

Extract distinct partition values from a given dataframe.

Parameters

- **dataframe** – dataframe from where to extract partition values.
- **partition_columns** – name of partition columns presented on the dataframe.

Returns
distinct partition values.

butterfree.dataframe_service.**repartition_df**(*dataframe: DataFrame*, *partition_by: List[str]*, *num_partitions: Optional[int] = None*, *num_processors: Optional[int] = None*) → DataFrame

Partition the DataFrame.

Parameters

- **dataframe** – Spark DataFrame.
- **partition_by** – list of partitions.
- **num_processors** – number of processors.
- **num_partitions** – number of partitions.

Returns
Partitioned dataframe.

butterfree.dataframe_service.**repartition_sort_df**(*dataframe: DataFrame*, *partition_by: List[str]*, *order_by: List[str]*, *num_processors: Optional[int] = None*, *num_partitions: Optional[int] = None*) → DataFrame

Partition and Sort the DataFrame.

Parameters

- **dataframe** – Spark DataFrame.
- **partition_by** – list of columns to partition by.
- **order_by** – list of columns to order by.
- **num_processors** – number of processors.
- **num_partitions** – number of partitions.

Returns

Partitioned and sorted dataframe.

butterfree.extract package

Subpackages

butterfree.extract.pre_processing package

Submodules

Explode json column for dataframes.

butterfree.extract.pre_processing.explode_json_column_transform.**explode_json_column**(*df: DataFrame*, *column: str*, *json_schema: StructType*) → DataFrame

Create new columns extracting properties from a JSON column.

Example:

```
>>> from pyspark import SparkContext
>>> from pyspark.sql import session
>>> from butterfree.testing.dataframe import create_df_from_collection
>>> from butterfree.extract.pre_processing import explode_json_column
>>> from pyspark.sql.types import (
...     ArrayType,
...     IntegerType,
...     StringType,
...     StructField,
...     StructType,
... )
>>> spark_context = SparkContext.getOrCreate()
>>> spark_session = session.SparkSession(spark_context)
>>> data = [{"json_column": '{"a": 123, "b": "abc", "c": "123", "d": [1, 2, 3]}'}]
>>> df = create_df_from_collection(data, spark_context, spark_session)
>>> df.collect()
```

[Row(json_column='{"a": 123, "b": "abc", "c": "123", "d": [1, 2, 3]}')]

```
>>> json_column_schema = StructType(
... [
...     StructField("a", IntegerType()),
...     StructField("b", StringType()),
...     StructField("c", IntegerType()),
...     StructField("d", ArrayType(IntegerType())),
... ]
>>> explode_json_column(
...     df, column='json_column', json_schema=json_column_schema
... ).collect()
```

[

Row(
json_column='{"a": 123, "b": "abc", "c": "123", "d": [1, 2, 3]}', a=123, b='abc', c=123, d=[1, 2, 3]

)

]

Parameters

- **df** – input dataframe with the target JSON column.
- **column** – column name that is going to be exploded.
- **json_schema** – expected schema from that JSON column. Not all "first layer" fields need to be mapped in the json_schema, just the desired columns. If there is any JSON field that is needed to be cast to a struct, the declared expected schema (a StructType) need to have the exact same schema as the presented record, if don't, the value in the resulting column will be null.

Returns
dataframe with the new extracted columns from the JSON column.

Module where filter DataFrames coming from readers.

butterfree.extract.pre_processing.filter_transform.**filter**(*dataframe: DataFrame*, *condition: str*) → DataFrame

Filters DataFrame's rows using the given condition and value.

Parameters

- **dataframe** – Spark DataFrame.
- **condition** – SQL expression with column, operation and value to filter the dataframe.

Returns
Filtered dataframe

Forward Fill Transform for dataframes.

butterfree.extract.pre_processing.forward_fill_transform.**forward_fill**(*dataframe: DataFrame*, *partition_by: Union[str, List[str]]*, *order_by: Union[str, List[str]]*, *fill_column: str*, *filled_column: Optional[str] = None*) → DataFrame

Applies a forward fill to a single column.

Filling null values with the last known non-null value, leaving leading nulls alone.

butterfree.extract.pre_processing.forward_fill_transform.**dataframe**
dataframe to be transformed.

butterfree.extract.pre_processing.forward_fill_transform.**partition_by**
list of columns' names to be used as partition for the operation.

butterfree.extract.pre_processing.forward_fill_transform.**order_by**
list of columns' names to be used when sorting column values.

butterfree.extract.pre_processing.forward_fill_transform.**fill_column**
column to be forward filled.

butterfree.extract.pre_processing.forward_fill_transform.**filled_column**
new column name. Optional. When none, operation will be inplace.

Example

```
>>> dataframe.orderBy("ts", "sensor_type", "location").show()
+-----------+-------------------+--------+-----------+
|sensor_type|                 ts|location|temperature|
+-----------+-------------------+--------+-----------+
|          1|2017-09-09 12:00:00|   shade|   18.83018|
|          1|2017-09-09 12:00:00|     sun|       null|
|          2|2017-09-09 12:00:00|   shade|   18.61258|
|          2|2017-09-09 12:00:00|     sun|    25.4986|
|          1|2017-09-09 13:00:00|   shade|   18.78458|
|          1|2017-09-09 13:00:00|     sun|   25.68457|
|          2|2017-09-09 13:00:00|   shade|       null|
|          2|2017-09-09 13:00:00|     sun|       null|
|          1|2017-09-09 14:00:00|   shade|   17.98115|
|          1|2017-09-09 14:00:00|     sun|   24.15754|
|          2|2017-09-09 14:00:00|   shade|   18.61258|
|          2|2017-09-09 14:00:00|     sun|       null|
+-----------+-------------------+--------+-----------+
```

```
>>> filled_df = forward_fill(
...     dataframe,
...     ["sensor_type", "location"],
...     "ts",
...     "temperature",
...     "temperature_filled"
... )
>>> filled_df.orderBy("ts", "sensor_type", "location").show()
+-----------+-------------------+--------+-----------+------------------+
|sensor_type|                 ts|location|temperature|temperature_filled|
+-----------+-------------------+--------+-----------+------------------+
|          1|2017-09-09 12:00:00|   shade|   18.83018|          18.83018|
|          1|2017-09-09 12:00:00|     sun|       null|              null|
|          2|2017-09-09 12:00:00|   shade|   18.61258|          18.61258|
```

(continues on next page)

(continued from previous page)

```
|          2|2017-09-09 12:00:00|     sun|    25.4986|           25.4986|
|          1|2017-09-09 13:00:00|   shade|   18.78458|          18.78458|
|          1|2017-09-09 13:00:00|     sun|   25.68457|          25.68457|
|          2|2017-09-09 13:00:00|   shade|       null|          18.61258|
|          2|2017-09-09 13:00:00|     sun|       null|           25.4986|
|          1|2017-09-09 14:00:00|   shade|   17.98115|          17.98115|
|          1|2017-09-09 14:00:00|     sun|   24.15754|          24.15754|
|          2|2017-09-09 14:00:00|   shade|   18.61258|          18.61258|
|          2|2017-09-09 14:00:00|     sun|       null|           25.4986|
+-----------+-------------------+--------+-----------+------------------+
>>> # inplace forward fill
>>> filled_df = forward_fill(
...     dataframe,
...     ["sensor_type", "location"],
...     "ts",
...     "temperature"
... )
>>> filled_df.orderBy("ts", "sensor_type", "location").show()
+-----------+-------------------+--------+-----------+
|sensor_type|                 ts|location|temperature|
+-----------+-------------------+--------+-----------+
|          1|2017-09-09 12:00:00|   shade|   18.83018|
|          1|2017-09-09 12:00:00|     sun|       null|
|          2|2017-09-09 12:00:00|   shade|   18.61258|
|          2|2017-09-09 12:00:00|     sun|    25.4986|
|          1|2017-09-09 13:00:00|   shade|   18.78458|
|          1|2017-09-09 13:00:00|     sun|   25.68457|
|          2|2017-09-09 13:00:00|   shade|   18.61258|
|          2|2017-09-09 13:00:00|     sun|    25.4986|
|          1|2017-09-09 14:00:00|   shade|   17.98115|
|          1|2017-09-09 14:00:00|     sun|   24.15754|
|          2|2017-09-09 14:00:00|   shade|   18.61258|
|          2|2017-09-09 14:00:00|     sun|    25.4986|
+-----------+-------------------+--------+-----------+
```

Pivot Transform for dataframes.

butterfree.extract.pre_processing.pivot_transform.**pivot**(*dataframe: DataFrame*, *group_by_columns: List[str]*, *pivot_column: str*, *agg_column: str*, *aggregation: Callable*, *mock_value: Optional[Union[float, str]] = None*, *mock_type: Optional[Union[DataType, str]] = None*, *with_forward_fill: bool = False*) → DataFrame

Defines a pivot transformation.

butterfree.extract.pre_processing.pivot_transform.**dataframe**

dataframe to be pivoted.

butterfree.extract.pre_processing.pivot_transform.**group_by_columns**

list of columns' names to be grouped.

butterfree.extract.pre_processing.pivot_transform.**pivot_column**

column to be pivoted.

butterfree.extract.pre_processing.pivot_transform.**agg_column**

column to be aggregated by pivoted category.

butterfree.extract.pre_processing.pivot_transform.**aggregation**

desired spark aggregation function to be performed. An example: spark_agg(col_name). See docs for all spark_agg: https://spark.apache.org/docs/2.3.1/api/python/_modules/pyspark/sql/functions.html

butterfree.extract.pre_processing.pivot_transform.**mock_value**

value used to make a difference between true nulls resulting from the aggregation and empty values from the pivot transformation.

butterfree.extract.pre_processing.pivot_transform.**mock_type**

mock_value data type (compatible with spark).

butterfree.extract.pre_processing.pivot_transform.**with_forward_fill**

applies a forward fill to null values after the pivot operation.

Example

```
>>> dataframe.orderBy("ts", "id", "amenity").show()
+---+---+-------+-----+
| id| ts|amenity|  has|
+---+---+-------+-----+
|  1|  1| fridge|false|
|  1|  1|   oven| true|
|  1|  1|   pool|false|
|  2|  2|balcony|false|
|  1|  3|balcony| null|
|  1|  4|   oven| null|
|  1|  4|   pool| true|
|  1|  5|balcony| true|
+---+---+-------+-----+
```

```
>>> pivoted = pivot(dataframe, ["id", "ts"], "amenity", "has", functions.first)
>>> pivoted.orderBy("ts", "id").show()
+---+---+-------+------+----+-----+
| id| ts|balcony|fridge|oven| pool|
+---+---+-------+------+----+-----+
|  1|  1|   null| false|true|false|
|  2|  2|  false|  null|null| null|
|  1|  3|   null|  null|null| null|
|  1|  4|   null|  null|null| true|
|  1|  5|   true|  null|null| null|
+---+---+-------+------+----+-----+
```

But, sometimes, you would like to keep the last values that some feature has assumed from previous modifications. In this example, amenity "oven" for the id=1 was set to null and "pool" was set to true at ts=4. All other amenities should then be kept to their actual state at that ts. To do that, we will use a technique called forward fill:

```
>>> pivoted = pivot(
...     dataframe,
...     ["id", "ts"],
...     "amenity",
...     "has",
...     functions.first,
...     with_forward_fill=True
...)
>>> pivoted.orderBy("ts", "id").show()
+---+---+-------+------+----+-----+
| id| ts|balcony|fridge|oven| pool|
+---+---+-------+------+----+-----+
|  1|  1|   null| false|true|false|
|  2|  2|  false|  null|null| null|
|  1|  3|   null| false|true|false|
|  1|  4|   null| false|true| true|
|  1|  5|   true| false|true| true|
+---+---+-------+------+----+-----+
```

Great! Now every amenity that didn't have been changed kept it's state. BUT, the force change to null for amenity "oven" on id=1 at ts=4 was ignored during forward fill. If the user wants to respect this change, it must provide a mock value and type to be used as a signal for "true nulls". In other words, we want to forward fill only nulls that were created by the pivot transformation.

In this example, amenities only assume boolean values. So there is no mock values for a boolean. It is only true or false. So users can give a mock value of another type (for which the column can be cast to). Check this out:

```
>>> pivoted = pivot(
...     dataframe,
...     ["id", "ts"],
...     "amenity",
...     "has",
...     functions.first,
...     with_forward_fill=True,
...     mock_value=-1,
...     mock_type="int"
...)
>>> pivoted.orderBy("ts", "id").show()
+---+---+-------+------+----+-----+
| id| ts|balcony|fridge|oven| pool|
+---+---+-------+------+----+-----+
|  1|  1|   null| false|true|false|
|  2|  2|  false|  null|null| null|
|  1|  3|   null| false|true|false|
|  1|  4|   null| false|null| true|
|  1|  5|   true| false|null| true|
+---+---+-------+------+----+-----+
```

During transformation, this method will cast the agg_column to mock_type data type and fill all "true nulls" with the mock_value. After pivot and forward fill are applied, all new pivoted columns will then return to the original type with all mock values replaced by null.

Replace transformer for dataframes.

butterfree.extract.pre_processing.replace_transform.**replace**(*dataframe: DataFrame*, *column: str*, *replace_dict: Dict[str, str]*) → DataFrame

Replace values of a string column in the dataframe using a dict.

Example:

```
>>> from butterfree.extract.pre_processing import replace
... from butterfree.testing.dataframe import (
...     assert_dataframe_equality,
...     create_df_from_collection,
... )
>>> from pyspark import SparkContext
>>> from pyspark.sql import session
>>> spark_context = SparkContext.getOrCreate()
>>> spark_session = session.SparkSession(spark_context)
>>> input_data = [
...     {"id":1, "type": "a"}, {"id":2, "type": "b"}, {"id":3, "type": "c"}
... ]
>>> input_df = create_df_from_collection(input_data, spark_context, spark_session)
>>> input_df.collect()
```

[Row(id=1, type='a'), Row(id=2, type='b'), Row(id=3, type='c')]

```
>>> replace_dict = {"a": "type_a", "b": "type_b"}
>>> replace(input_df, "type", replace_dict).collect()
```

[Row(id=1, type='type_a'), Row(id=2, type='type_b'), Row(id=3, type='c')]

Parameters

- **dataframe** – data to be transformed.
- **column** – string column on the dataframe where to apply the replace.
- **replace_dict** – dict with values to be replaced. All mapped values must be string.

Returns

Dataframe with column values replaced.

Module contents

Pre Processing Components regarding Readers.

butterfree.extract.pre_processing.**explode_json_column**(*df: DataFrame*, *column: str*, *json_schema: StructType*) → DataFrame

Create new columns extracting properties from a JSON column.

Example:

```
>>> from pyspark import SparkContext
>>> from pyspark.sql import session
>>> from butterfree.testing.dataframe import create_df_from_collection
>>> from butterfree.extract.pre_processing import explode_json_column
>>> from pyspark.sql.types import (
...     ArrayType,
```

(continues on next page)

(continued from previous page)

```
...     IntegerType,
...     StringType,
...     StructField,
...     StructType,
... )
>>> spark_context = SparkContext.getOrCreate()
>>> spark_session = session.SparkSession(spark_context)
>>> data = [{"json_column": '{"a": 123, "b": "abc", "c": "123", "d": [1, 2, 3]}'}]
>>> df = create_df_from_collection(data, spark_context, spark_session)
>>> df.collect()
```

[Row(json_column='{“a”: 123, “b”: “abc”, “c”: “123”, “d”: [1, 2, 3]}')]

```
>>> json_column_schema = StructType(
... [
...    StructField("a", IntegerType()),
...    StructField("b", StringType()),
...    StructField("c", IntegerType()),
...    StructField("d", ArrayType(IntegerType())),
... ]
>>> explode_json_column(
...     df, column='json_column', json_schema=json_column_schema
... ).collect()
```

[

Row(
json_column='{“a”: 123, “b”: “abc”, “c”: “123”, “d”: [1, 2, 3]}', a=123, b='abc', c=123, d=[1, 2, 3]

)

]

Parameters

- **df** – input dataframe with the target JSON column.
- **column** – column name that is going to be exploded.
- **json_schema** – expected schema from that JSON column. Not all “first layer” fields need to be mapped in the json_schema, just the desired columns. If there is any JSON field that is needed to be cast to a struct, the declared expected schema (a StructType) need to have the exact same schema as the presented record, if don't, the value in the resulting column will be null.

Returns
dataframe with the new extracted columns from the JSON column.

butterfree.extract.pre_processing.**filter**(*dataframe: DataFrame*, *condition: str*) → DataFrame

Filters DataFrame's rows using the given condition and value.

Parameters

- **dataframe** – Spark DataFrame.
- **condition** – SQL expression with column, operation and value to filter the dataframe.

Returns
Filtered dataframe

butterfree.extract.pre_processing.**forward_fill**(*dataframe: DataFrame*, *partition_by: Union[str, List[str]]*, *order_by: Union[str, List[str]]*, *fill_column: str*, *filled_column: Optional[str] = None*) → DataFrame

Applies a forward fill to a single column.

Filling null values with the last known non-null value, leaving leading nulls alone.

butterfree.extract.pre_processing.**dataframe**
dataframe to be transformed.

butterfree.extract.pre_processing.**partition_by**
list of columns' names to be used as partition for the operation.

butterfree.extract.pre_processing.**order_by**
list of columns' names to be used when sorting column values.

butterfree.extract.pre_processing.**fill_column**
column to be forward filled.

butterfree.extract.pre_processing.**filled_column**
new column name. Optional. When none, operation will be inplace.

Example

```
>>> dataframe.orderBy("ts", "sensor_type", "location").show()
+-----------+-------------------+--------+-----------+
|sensor_type|                 ts|location|temperature|
+-----------+-------------------+--------+-----------+
|          1|2017-09-09 12:00:00|   shade|   18.83018|
|          1|2017-09-09 12:00:00|     sun|       null|
|          2|2017-09-09 12:00:00|   shade|   18.61258|
|          2|2017-09-09 12:00:00|     sun|    25.4986|
|          1|2017-09-09 13:00:00|   shade|   18.78458|
|          1|2017-09-09 13:00:00|     sun|   25.68457|
|          2|2017-09-09 13:00:00|   shade|       null|
|          2|2017-09-09 13:00:00|     sun|       null|
|          1|2017-09-09 14:00:00|   shade|   17.98115|
|          1|2017-09-09 14:00:00|     sun|   24.15754|
|          2|2017-09-09 14:00:00|   shade|   18.61258|
|          2|2017-09-09 14:00:00|     sun|       null|
+-----------+-------------------+--------+-----------+
```

```
>>> filled_df = forward_fill(
...     dataframe,
...     ["sensor_type", "location"],
...     "ts",
...     "temperature",
...     "temperature_filled"
... )
>>> filled_df.orderBy("ts", "sensor_type", "location").show()
```

(continues on next page)

(continued from previous page)

```
+-----------+-------------------+--------+-----------+-----------------+
|sensor_type|                 ts|location|temperature|temperature_filled|
+-----------+-------------------+--------+-----------+-----------------+
|          1|2017-09-09 12:00:00|   shade|   18.83018|          18.83018|
|          1|2017-09-09 12:00:00|     sun|       null|              null|
|          2|2017-09-09 12:00:00|   shade|   18.61258|          18.61258|
|          2|2017-09-09 12:00:00|     sun|    25.4986|           25.4986|
|          1|2017-09-09 13:00:00|   shade|   18.78458|          18.78458|
|          1|2017-09-09 13:00:00|     sun|   25.68457|          25.68457|
|          2|2017-09-09 13:00:00|   shade|       null|          18.61258|
|          2|2017-09-09 13:00:00|     sun|       null|           25.4986|
|          1|2017-09-09 14:00:00|   shade|   17.98115|          17.98115|
|          1|2017-09-09 14:00:00|     sun|   24.15754|          24.15754|
|          2|2017-09-09 14:00:00|   shade|   18.61258|          18.61258|
|          2|2017-09-09 14:00:00|     sun|       null|           25.4986|
+-----------+-------------------+--------+-----------+-----------------+
>>> # inplace forward fill
>>> filled_df = forward_fill(
...     dataframe,
...     ["sensor_type", "location"],
...     "ts",
...     "temperature"
... )
>>> filled_df.orderBy("ts", "sensor_type", "location").show()
+-----------+-------------------+--------+-----------+
|sensor_type|                 ts|location|temperature|
+-----------+-------------------+--------+-----------+
|          1|2017-09-09 12:00:00|   shade|   18.83018|
|          1|2017-09-09 12:00:00|     sun|       null|
|          2|2017-09-09 12:00:00|   shade|   18.61258|
|          2|2017-09-09 12:00:00|     sun|    25.4986|
|          1|2017-09-09 13:00:00|   shade|   18.78458|
|          1|2017-09-09 13:00:00|     sun|   25.68457|
|          2|2017-09-09 13:00:00|   shade|   18.61258|
|          2|2017-09-09 13:00:00|     sun|    25.4986|
|          1|2017-09-09 14:00:00|   shade|   17.98115|
|          1|2017-09-09 14:00:00|     sun|   24.15754|
|          2|2017-09-09 14:00:00|   shade|   18.61258|
|          2|2017-09-09 14:00:00|     sun|    25.4986|
+-----------+-------------------+--------+-----------+
```

butterfree.extract.pre_processing.**pivot**(*dataframe: DataFrame*, *group_by_columns: List[str]*, *pivot_column: str*, *agg_column: str*, *aggregation: Callable*, *mock_value: Optional[Union[float, str]] = None*, *mock_type: Optional[Union[DataType, str]] = None*, *with_forward_fill: bool = False*) → DataFrame

Defines a pivot transformation.

butterfree.extract.pre_processing.**dataframe**

dataframe to be pivoted.

butterfree.extract.pre_processing.**group_by_columns**

list of columns' names to be grouped.

butterfree.extract.pre_processing.**pivot_column**

column to be pivoted.

butterfree.extract.pre_processing.**agg_column**

column to be aggregated by pivoted category.

butterfree.extract.pre_processing.**aggregation**

desired spark aggregation function to be performed. An example: spark_agg(col_name). See docs for all spark_agg: https://spark.apache.org/docs/2.3.1/api/python/_modules/pyspark/sql/functions.html

butterfree.extract.pre_processing.**mock_value**

value used to make a difference between true nulls resulting from the aggregation and empty values from the pivot transformation.

butterfree.extract.pre_processing.**mock_type**

mock_value data type (compatible with spark).

butterfree.extract.pre_processing.**with_forward_fill**

applies a forward fill to null values after the pivot operation.

Example

```
>>> dataframe.orderBy("ts", "id", "amenity").show()
+---+---+-------+-----+
| id| ts|amenity|  has|
+---+---+-------+-----+
|  1|  1| fridge|false|
|  1|  1|   oven| true|
|  1|  1|   pool|false|
|  2|  2|balcony|false|
|  1|  3|balcony| null|
|  1|  4|   oven| null|
|  1|  4|   pool| true|
|  1|  5|balcony| true|
+---+---+-------+-----+
```

```
>>> pivoted = pivot(dataframe, ["id", "ts"], "amenity", "has", functions.first)
>>> pivoted.orderBy("ts", "id").show()
+---+---+-------+------+----+-----+
| id| ts|balcony|fridge|oven| pool|
+---+---+-------+------+----+-----+
|  1|  1|   null| false|true|false|
|  2|  2|  false|  null|null| null|
|  1|  3|   null|  null|null| null|
|  1|  4|   null|  null|null| true|
|  1|  5|   true|  null|null| null|
+---+---+-------+------+----+-----+
```

But, sometimes, you would like to keep the last values that some feature has assumed from previous modifications. In this example, amenity "oven" for the id=1 was set to null and "pool" was set to true at ts=4. All other amenities should then be kept to their actual state at that ts. To do that, we will use a technique called forward fill:

```
>>> pivoted = pivot(
...     dataframe,
...     ["id", "ts"],
...     "amenity",
...     "has",
...     functions.first,
...     with_forward_fill=True
...)
>>> pivoted.orderBy("ts", "id").show()
+---+---+-------+------+----+-----+
| id| ts|balcony|fridge|oven| pool|
+---+---+-------+------+----+-----+
|  1|  1|   null| false|true|false|
|  2|  2|  false|  null|null| null|
|  1|  3|   null| false|true|false|
|  1|  4|   null| false|true| true|
|  1|  5|   true| false|true| true|
+---+---+-------+------+----+-----+
```

Great! Now every amenity that didn't have been changed kept it's state. BUT, the force change to null for amenity "oven" on id=1 at ts=4 was ignored during forward fill. If the user wants to respect this change, it must provide a mock value and type to be used as a signal for "true nulls". In other words, we want to forward fill only nulls that were created by the pivot transformation.

In this example, amenities only assume boolean values. So there is no mock values for a boolean. It is only true or false. So users can give a mock value of another type (for which the column can be cast to). Check this out:

```
>>> pivoted = pivot(
...     dataframe,
...     ["id", "ts"],
...     "amenity",
...     "has",
...     functions.first,
...     with_forward_fill=True,
...     mock_value=-1,
...     mock_type="int"
...)
>>> pivoted.orderBy("ts", "id").show()
+---+---+-------+------+----+-----+
| id| ts|balcony|fridge|oven| pool|
+---+---+-------+------+----+-----+
|  1|  1|   null| false|true|false|
|  2|  2|  false|  null|null| null|
|  1|  3|   null| false|true|false|
|  1|  4|   null| false|null| true|
|  1|  5|   true| false|null| true|
+---+---+-------+------+----+-----+
```

During transformation, this method will cast the agg_column to mock_type data type and fill all "true nulls" with the mock_value. After pivot and forward fill are applied, all new pivoted columns will then return to the original type with all mock values replaced by null.

butterfree.extract.pre_processing.**replace**(*dataframe: DataFrame*, *column: str*, *replace_dict: Dict[str, str]*) → DataFrame

Replace values of a string column in the dataframe using a dict.

Example:

```
>>> from butterfree.extract.pre_processing import replace
... from butterfree.testing.dataframe import (
...     assert_dataframe_equality,
...     create_df_from_collection,
... )
>>> from pyspark import SparkContext
>>> from pyspark.sql import session
>>> spark_context = SparkContext.getOrCreate()
>>> spark_session = session.SparkSession(spark_context)
>>> input_data = [
...     {"id":1, "type": "a"}, {"id":2, "type": "b"}, {"id":3, "type": "c"}
... ]
>>> input_df = create_df_from_collection(input_data, spark_context, spark_session)
>>> input_df.collect()
```

[Row(id=1, type='a'), Row(id=2, type='b'), Row(id=3, type='c')]

```
>>> replace_dict = {"a": "type_a", "b": "type_b"}
>>> replace(input_df, "type", replace_dict).collect()
```

[Row(id=1, type='type_a'), Row(id=2, type='type_b'), Row(id=3, type='c')]

Parameters

- **dataframe** – data to be transformed.
- **column** – string column on the dataframe where to apply the replace.
- **replace_dict** – dict with values to be replaced. All mapped values must be string.

Returns

Dataframe with column values replaced.

butterfree.extract.readers package

Submodules

FileReader entity.

class butterfree.extract.readers.file_reader.**FileReader**(*id: str*, *path: str*, *format: str*, *schema: Optional[StructType] = None*, *format_options: Optional[Dict[Any, Any]] = None*, *stream: bool = False*)

Bases: *Reader*

Responsible for get data from files.

id

unique string id for register the reader as a view on the metastore.

path

file location.

format

can be one of the keys: json, parquet, orc, or csv.

schema

an optional pyspark.sql.types.StructType for the input schema.

format_options

additional options required by some formats. Check docs: https://spark.apache.org/docs/latest/sql-data-sources-load-save-functions.html#manually-specifying-options

Example

Simple example regarding FileReader class instantiation.

```
>>> from butterfree.extract.readers import FileReader
>>> from butterfree.clients import SparkClient
>>> from butterfree.extract.pre_processing import filter
>>> spark_client = SparkClient()
>>> file_reader = FileReader(
...                 id="file_reader_id",
...                 path="data_path",
...                 format="json"
...               )
>>> df = file_reader.consume(spark_client)
```

However, we can define the schema and format_options, like header, and provide them to FileReader.

```
>>> spark_client = SparkClient()
>>> schema_csv = StructType([
...            StructField("column_a", LongType()),
...            StructField("column_b", DoubleType()),
...            StructField("coumn_c", StringType())
...          ])
>>> file_reader = FileReader(
...                 id="file_reader_id",
...                 path="data_path",
...                 format="csv",
...                 schema=schema_csv,
...                 format_options={
...                    "header": True
...                 }
...               )
>>> df = file_reader.consume(spark_client)
```

This last method will use the Spark Client, as default, to read the desired file, loading data into a dataframe, according to FileReader class arguments.

It's also possible to define simple transformations within the reader's scope:

```
>>> file_reader.with_(filter, condition="year = 2019").build(spark_client)
```

In this case, however, a temp view will be created, cointaining the transformed data.

consume(*client:* SparkClient) → DataFrame

Extract data from files stored in defined path.

Try to auto-infer schema if in stream mode and not manually defining a schema.

Parameters
client – client responsible for connecting to Spark session.

Returns
Dataframe with all the files data.

KafkaSource entity.

class butterfree.extract.readers.kafka_reader.**KafkaReader**(*id: str*, *topic: str*, *value_schema: StructType*, *connection_string: Optional[str] = None*, *topic_options: Optional[Dict[Any, Any]] = None*, *stream: bool = True*)

Bases: *Reader*

Responsible for get data from a Kafka topic.

id

unique string id for register the reader as a view on the metastore

value_schema

expected schema of the default column named "value" from Kafka.

topic

string with the Kafka topic name to subscribe.

connection_string

string with hosts and ports to connect. The string need to be in the format: host1:port,host2:port,...,hostN:portN. The argument is not necessary if is passed as a environment variable named KAFKA_CONSUMER_CONNECTION_STRING.

topic_options

additional options for consuming from topic. See docs: https://spark.apache.org/docs/latest/structured-streaming-kafka-integration.html.

stream

flag to indicate the reading mode: stream or batch

The default df schema coming from Kafka reader of Spark is the following:
key:string value:string topic:string partition:integer offset:long timestamp:timestamp timestampType:integer

But using this reader and passing the desired schema under value_schema we would have the following result:

With value_schema declared as:

```
>>> value_schema = StructType(
...     [
...         StructField("ts", LongType(), nullable=True),
...         StructField("id", LongType(), nullable=True),
...         StructField("type", StringType(), nullable=True),
...     ]
... )
```

The output df schema would be:

ts:long id:long type:string kafka_metadata:struct

key:string topic:string value:string partition:integer offset:long timestamp:timestamp timestampType:integer

Instantiation example:

```
>>> from butterfree.extract.readers import KafkaReader
>>> from butterfree.clients import SparkClient
>>> from pyspark.sql.types import StructType, StructField, StringType, LongType
>>> spark_client = SparkClient()
>>> value_schema = StructType(
...     [
...         StructField("ts", LongType(), nullable=True),
...         StructField("id", LongType(), nullable=True),
...         StructField("type", StringType(), nullable=True),
...     ]
... )
>>> kafka_reader = KafkaReader(
...                  id="kafka_reader_id",
...                  topic="topic",
...                  value_schema=value_schema
...                  connection_string="host1:port,host2:port",
...                 )
>>> df = kafka_reader.consume(spark_client)
```

This last method will use the Spark Client, as default, to read the desired topic, loading data into a dataframe, according to KafkaReader class arguments.

In this case, however, a temp view will be created, containing the transformed data.

KAFKA_COLUMNS = ['key', 'topic', 'value', 'partition', 'offset', 'timestamp', 'timestampType']

consume(*client:* SparkClient) → DataFrame

Extract data from a kafka topic.

When stream mode it will get all the new data arriving at the topic in a streaming dataframe. When not in stream mode it will get all data available in the kafka topic.

Parameters

client – client responsible for connecting to Spark session.

Returns

Dataframe with data from topic.

Reader entity.

class butterfree.extract.readers.reader.**Reader**(*id: str*, *incremental_strategy: Optional[*IncrementalStrategy*] = None*)

Bases: ABC, *HookableComponent*

Abstract base class for Readers.

id

unique string id for register the reader as a view on the metastore.

transformations

list os methods that will be applied over the dataframe after the raw data is extracted.

build(*client: SparkClient*, *columns: Optional[List[Any]] = None*, *start_date: Optional[str] = None*, *end_date: Optional[str] = None*) → None

Register the data got from the reader in the Spark metastore.

Create a temporary view in Spark metastore referencing the data extracted from the target origin after the application of all the defined pre-processing transformations.

The arguments start_date and end_date are going to be use only when there is a defined *IncrementalStrategy* on the *Reader*.

Parameters

- **client** – client responsible for connecting to Spark session.
- **columns** – list of tuples for selecting/renaming columns on the df.
- **start_date** – lower bound to use in the filter expression.
- **end_date** – upper bound to use in the filter expression.

abstract consume(*client: SparkClient*) → DataFrame

Extract data from target origin.

Parameters
client – client responsible for connecting to Spark session.

Returns
Dataframe with all the data.

Returns
Spark dataframe

with_(*transformer: Callable[[...], DataFrame]*, **args: Any*, ***kwargs: Any*) → Any

Define a new transformation for the Reader.

All the transformations are used when the method consume is called.

Parameters

- **transformer** – method that receives a dataframe and output a dataframe.
- ***args** – args for the transformer.
- ****kwargs** – kwargs for the transformer.

Returns
Reader object with new transformation

with_incremental_strategy(*incremental_strategy: IncrementalStrategy*) → *Reader*

Define the incremental strategy for the Reader.

Parameters
incremental_strategy – definition of the incremental strategy.

Returns
Reader with defined incremental strategy.

TableSource entity.

class butterfree.extract.readers.table_reader.**TableReader**(*id: str*, *table: str*, *database: Optional[str] = None*)

Bases: *Reader*

Responsible for get data from tables registered in the metastore.

id

unique string id for register the reader as a view on the metastore.

database

name of the metastore database/schema.

table

name of the table.

Example

Simple example regarding TableReader class instantiation.

```
>>> from butterfree.extract.readers import TableReader
>>> from butterfree.clients import SparkClient
>>> from butterfree.extract.pre_processing import filter
>>> spark_client = SparkClient()
>>> table_reader = TableReader(
...                     id="table_reader_id",
...                     database="table_reader_db",
...                     table="table_reader_table"
...                 )
>>> df = table_reader.consume(spark_client)
```

This last method will use the Spark Client, as default, to read the desired table, loading data into a dataframe, according to TableReader class arguments.

It's also possible to define simple transformations within the reader's scope:

```
>>> table_reader.with_(filter, condition="year = 2019").build(spark_client)
```

In this case, however, a temp view will be created, cointaining the transformed data.

consume(*client:* SparkClient) → DataFrame

Extract data from a table in Spark metastore.

Parameters

client – client responsible for connecting to Spark session.

Returns

Dataframe with all the data from the table.

Module contents

The Reader Component of a Source.

class butterfree.extract.readers.**FileReader**(*id: str*, *path: str*, *format: str*, *schema: Optional[StructType] = None*, *format_options: Optional[Dict[Any, Any]] = None*, *stream: bool = False*)

Bases: *Reader*

Responsible for get data from files.

id

unique string id for register the reader as a view on the metastore.

path

file location.

format

can be one of the keys: json, parquet, orc, or csv.

schema

an optional pyspark.sql.types.StructType for the input schema.

format_options

additional options required by some formats. Check docs: https://spark.apache.org/docs/latest/sql-data-sources-load-save-functions.html#manually-specifying-options

Example

Simple example regarding FileReader class instantiation.

```
>>> from butterfree.extract.readers import FileReader
>>> from butterfree.clients import SparkClient
>>> from butterfree.extract.pre_processing import filter
>>> spark_client = SparkClient()
>>> file_reader = FileReader(
...                 id="file_reader_id",
...                 path="data_path",
...                 format="json"
...               )
>>> df = file_reader.consume(spark_client)
```

However, we can define the schema and format_options, like header, and provide them to FileReader.

```
>>> spark_client = SparkClient()
>>> schema_csv = StructType([
...             StructField("column_a", LongType()),
...             StructField("column_b", DoubleType()),
...             StructField("coumn_c", StringType())
...           ])
>>> file_reader = FileReader(
...                 id="file_reader_id",
...                 path="data_path",
```

(continues on next page)

(continued from previous page)

```
...                     format="csv",
...                     schema=schema_csv,
...                     format_options={
...                         "header": True
...                     }
...                 )
>>> df = file_reader.consume(spark_client)
```

This last method will use the Spark Client, as default, to read the desired file, loading data into a dataframe, according to FileReader class arguments.

It's also possible to define simple transformations within the reader's scope:

```
>>> file_reader.with_(filter, condition="year = 2019").build(spark_client)
```

In this case, however, a temp view will be created, cointaining the transformed data.

consume(*client:* SparkClient) → DataFrame

Extract data from files stored in defined path.

Try to auto-infer schema if in stream mode and not manually defining a schema.

Parameters

client – client responsible for connecting to Spark session.

Returns

Dataframe with all the files data.

class butterfree.extract.readers.**KafkaReader**(*id: str*, *topic: str*, *value_schema: StructType*, *connection_string: Optional[str] = None*, *topic_options: Optional[Dict[Any, Any]] = None*, *stream: bool = True*)

Bases: *Reader*

Responsible for get data from a Kafka topic.

id

unique string id for register the reader as a view on the metastore

value_schema

expected schema of the default column named "value" from Kafka.

topic

string with the Kafka topic name to subscribe.

connection_string

string with hosts and ports to connect. The string need to be in the format: host1:port,host2:port,...,hostN:portN. The argument is not necessary if is passed as a environment variable named KAFKA_CONSUMER_CONNECTION_STRING.

topic_options

additional options for consuming from topic. See docs: https://spark.apache.org/docs/latest/structured-streaming-kafka-integration.html.

stream

flag to indicate the reading mode: stream or batch

The default df schema coming from Kafka reader of Spark is the following:

key:string value:string topic:string partition:integer offset:long timestamp:timestamp timestampType:integer

But using this reader and passing the desired schema under value_schema we would have the following result:

With value_schema declared as:

```
>>> value_schema = StructType(
...     [
...         StructField("ts", LongType(), nullable=True),
...         StructField("id", LongType(), nullable=True),
...         StructField("type", StringType(), nullable=True),
...     ]
... )
```

The output df schema would be:

ts:long id:long type:string kafka_metadata:struct

key:string topic:string value:string partition:integer offset:long timestamp:timestamp timestampType:integer

Instantiation example:

```
>>> from butterfree.extract.readers import KafkaReader
>>> from butterfree.clients import SparkClient
>>> from pyspark.sql.types import StructType, StructField, StringType, LongType
>>> spark_client = SparkClient()
>>> value_schema = StructType(
...     [
...         StructField("ts", LongType(), nullable=True),
...         StructField("id", LongType(), nullable=True),
...         StructField("type", StringType(), nullable=True),
...     ]
... )
>>> kafka_reader = KafkaReader(
...                 id="kafka_reader_id",
...                 topic="topic",
...                 value_schema=value_schema
...                 connection_string="host1:port,host2:port",
...                )
>>> df = kafka_reader.consume(spark_client)
```

This last method will use the Spark Client, as default, to read the desired topic, loading data into a dataframe, according to KafkaReader class arguments.

In this case, however, a temp view will be created, containing the transformed data.

KAFKA_COLUMNS = ['key', 'topic', 'value', 'partition', 'offset', 'timestamp', 'timestampType']

consume(*client:* SparkClient) → DataFrame

Extract data from a kafka topic.

When stream mode it will get all the new data arriving at the topic in a streaming dataframe. When not in stream mode it will get all data available in the kafka topic.

Parameters
client – client responsible for connecting to Spark session.

Returns
Dataframe with data from topic.

transformations: List[Dict[str, Any]]

class butterfree.extract.readers.**TableReader**(*id: str*, *table: str*, *database: Optional[str] = None*)

Bases: *Reader*

Responsible for get data from tables registered in the metastore.

id

unique string id for register the reader as a view on the metastore.

database

name of the metastore database/schema.

table

name of the table.

Example

Simple example regarding TableReader class instantiation.

```
>>> from butterfree.extract.readers import TableReader
>>> from butterfree.clients import SparkClient
>>> from butterfree.extract.pre_processing import filter
>>> spark_client = SparkClient()
>>> table_reader = TableReader(
...                     id="table_reader_id",
...                     database="table_reader_db",
...                     table="table_reader_table"
...                 )
>>> df = table_reader.consume(spark_client)
```

This last method will use the Spark Client, as default, to read the desired table, loading data into a dataframe, according to TableReader class arguments.

It's also possible to define simple transformations within the reader's scope:

```
>>> table_reader.with_(filter, condition="year = 2019").build(spark_client)
```

In this case, however, a temp view will be created, cointaining the transformed data.

consume(*client:* SparkClient) → DataFrame

Extract data from a table in Spark metastore.

Parameters
client – client responsible for connecting to Spark session.

Returns
Dataframe with all the data from the table.

Submodules

Holds the SourceSelector class.

class butterfree.extract.source.**Source**(*readers: List[*Reader*]*, *query: str*)

Bases: *HookableComponent*

The definition of the the entry point data for the ETL pipeline.

A FeatureSet (the next step in the pipeline) expects a single dataframe as input. This dataframe is built from a data composition of one or more readers defined in the Source. There is only one Source for pipeline.

TODO refactor query into multiple query components TODO make it harder to do query injection

readers
list of readers from where the source will get data.

query
Spark SQL query to run against the readers.

Example

Simple example regarding Source class instantiation.

```
>>> from butterfree.extract import Source
>>> from butterfree.extract.readers import TableReader, FileReader
>>> from butterfree.clients import SparkClient
>>> spark_client = SparkClient()
>>> source = Source(
...     readers=[
...         TableReader(
...             id="table_reader_id",
...             database="table_reader_db",
...             table="table_reader_table",
...         ),
...         FileReader(id="file_reader_id", path="data_sample_path", format="json"),
...     ],
...     query=f"select a.*, b.feature2 "
...     f"from table_reader_id a "
...     f"inner join file_reader_id b on a.id = b.id ",
...)
>>> df = source.construct(spark_client)
```

This last method will use the Spark Client, as default, to create temporary views regarding each reader and, after, will run the desired query and return a dataframe.

construct(*client: SparkClient*, *start_date: Optional[str] = None*, *end_date: Optional[str] = None*) → DataFrame

Construct an entry point dataframe for a feature set.

This method will assemble multiple readers, by building each one and querying them using a Spark SQL. It's important to highlight that in order to filter a dataframe regarding date boundaries, it's important to define a IncrementalStrategy, otherwise your data will not be filtered. Besides, both start and end dates parameters are optional.

After that, there's the caching of the dataframe, however since cache() in Spark is lazy, an action is triggered in order to force persistence.

Parameters

- **client** – client responsible for connecting to Spark session.
- **start_date** – user defined start date for filtering.
- **end_date** – user defined end date for filtering.

Returns

DataFrame with the query result against all readers.

Module contents

The Source Component of a Feature Set.

class butterfree.extract.**Source**(*readers: List[Reader]*, *query: str*)

Bases: *HookableComponent*

The definition of the the entry point data for the ETL pipeline.

A FeatureSet (the next step in the pipeline) expects a single dataframe as input. This dataframe is built from a data composition of one or more readers defined in the Source. There is only one Source for pipeline.

TODO refactor query into multiple query components TODO make it harder to do query injection

readers

list of readers from where the source will get data.

query

Spark SQL query to run against the readers.

Example

Simple example regarding Source class instantiation.

```
>>> from butterfree.extract import Source
>>> from butterfree.extract.readers import TableReader, FileReader
>>> from butterfree.clients import SparkClient
>>> spark_client = SparkClient()
>>> source = Source(
...     readers=[
...         TableReader(
...             id="table_reader_id",
...             database="table_reader_db",
...             table="table_reader_table",
```

(continues on next page)

(continued from previous page)

```
...         ),
...         FileReader(id="file_reader_id", path="data_sample_path", format="json"),
...     ],
...     query=f"select a.*, b.feature2 "
...     f"from table_reader_id a "
...     f"inner join file_reader_id b on a.id = b.id ",
...)
>>> df = source.construct(spark_client)
```

This last method will use the Spark Client, as default, to create temporary views regarding each reader and, after, will run the desired query and return a dataframe.

construct(*client: SparkClient*, *start_date: Optional[str] = None*, *end_date: Optional[str] = None*) → DataFrame

Construct an entry point dataframe for a feature set.

This method will assemble multiple readers, by building each one and querying them using a Spark SQL. It's important to highlight that in order to filter a dataframe regarding date boundaries, it's important to define a IncrementalStrategy, otherwise your data will not be filtered. Besides, both start and end dates parameters are optional.

After that, there's the caching of the dataframe, however since cache() in Spark is lazy, an action is triggered in order to force persistence.

Parameters

- **client** – client responsible for connecting to Spark session.
- **start_date** – user defined start date for filtering.
- **end_date** – user defined end date for filtering.

Returns

DataFrame with the query result against all readers.

butterfree.hooks package

Subpackages

butterfree.hooks.schema_compatibility package

Submodules

Cassandra table schema compatibility Hook definition.

class butterfree.hooks.schema_compatibility.cassandra_table_schema_compatibility_hook.**CassandraTableSch**

Bases: *Hook*

Hook to verify the schema compatibility with a Cassandra's table.

Verifies if all columns presented on the dataframe exists and are the same type on the target Cassandra's table.

cassandra_client
client to connect to Cassandra DB.

table
table name.

run(*dataframe: DataFrame*) → DataFrame
Check the schema compatibility from a given Dataframe.

This method does not change anything on the Dataframe.

Parameters
dataframe – dataframe to verify schema compatibility.

Returns
unchanged dataframe.

Raises
ValueError if the schemas are incompatible. –

Spark table schema compatibility Hook definition.

class butterfree.hooks.schema_compatibility.spark_table_schema_compatibility_hook.**SparkTableSchemaCompa**

Bases: *Hook*

Hook to verify the schema compatibility with a Spark's table.

Verifies if all columns presented on the dataframe exists and are the same type on the target Spark's table.

spark_client
client to connect to Spark's metastore.

table
table name.

database
database name.

run(*dataframe: DataFrame*) → DataFrame
Check the schema compatibility from a given Dataframe.

This method does not change anything on the Dataframe.

Parameters
dataframe – dataframe to verify schema compatibility.

Returns
unchanged dataframe.

Raises
ValueError if the schemas are incompatible. –

Module contents

Holds Schema Compatibility Hooks definitions.

class butterfree.hooks.schema_compatibility.**CassandraTableSchemaCompatibilityHook**(*cassandra_client: CassandraClient*, *table: str*)

Bases: *Hook*

Hook to verify the schema compatibility with a Cassandra's table.

Verifies if all columns presented on the dataframe exists and are the same type on the target Cassandra's table.

cassandra_client
client to connect to Cassandra DB.

table
table name.

run(*dataframe: DataFrame*) → DataFrame
Check the schema compatibility from a given Dataframe.

This method does not change anything on the Dataframe.

Parameters
dataframe – dataframe to verify schema compatibility.

Returns
unchanged dataframe.

Raises
ValueError if the schemas are incompatible. –

class butterfree.hooks.schema_compatibility.**SparkTableSchemaCompatibilityHook**(*spark_client: SparkClient*, *table: str*, *database: Optional[str] = None*)

Bases: *Hook*

Hook to verify the schema compatibility with a Spark's table.

Verifies if all columns presented on the dataframe exists and are the same type on the target Spark's table.

spark_client
client to connect to Spark's metastore.

table
table name.

database

database name.

run(*dataframe: DataFrame*) → DataFrame

Check the schema compatibility from a given Dataframe.

This method does not change anything on the Dataframe.

Parameters
dataframe – dataframe to verify schema compatibility.

Returns
unchanged dataframe.

Raises
ValueError if the schemas are incompatible. –

Submodules

Hook abstract class entity.

class butterfree.hooks.hook.**Hook**

Bases: ABC

Definition of a hook function to call on a Dataframe.

abstract run(*dataframe: DataFrame*) → DataFrame

Run interface for Hook.

Parameters
dataframe – dataframe to use in the Hook.

Returns
dataframe result from the Hook.

Definition of hookable component.

class butterfree.hooks.hookable_component.**HookableComponent**

Bases: object

Defines a component with the ability to hold pre and post hook functions.

All main module of Butterfree have a common object that enables their integration: dataframes. Spark's dataframe is the glue that enables the transmission of data between the main modules. Hooks have a simple interface, they are functions that accepts a dataframe and outputs a dataframe. These Hooks can be triggered before or after the main execution of a component.

Components from Butterfree that inherit HookableComponent entity, are components that can define a series of steps to occur before or after the execution of their main functionality.

pre_hooks

function steps to trigger before component main functionality.

post_hooks

function steps to trigger after component main functionality.

enable_pre_hooks

property to indicate if the component can define pre_hooks.

enable_post_hooks

property to indicate if the component can define post_hooks.

add_post_hook(**hooks:* Hook) → *HookableComponent*

Add a post-hook steps to the component.

Parameters
hooks – Hook steps to add to post_hook list.

Returns
Component with the Hook inserted in post_hook list.

Raises
ValueError – if the component does not accept post-hooks.

add_pre_hook(**hooks:* Hook) → *HookableComponent*

Add a pre-hook steps to the component.

Parameters
hooks – Hook steps to add to pre_hook list.

Returns
Component with the Hook inserted in pre_hook list.

Raises
ValueError – if the component does not accept pre-hooks.

property enable_post_hooks: bool

Property to indicate if the component can define post_hooks.

property enable_pre_hooks: bool

Property to indicate if the component can define pre_hooks.

property post_hooks: List[*Hook*]

Function steps to trigger after component main functionality.

property pre_hooks: List[*Hook*]

Function steps to trigger before component main functionality.

run_post_hooks(*dataframe: DataFrame*) → DataFrame

Run all defined post-hook steps from a given dataframe.

Parameters
dataframe – data to input in the defined post-hook steps.

Returns
dataframe after passing for all defined post-hooks.

run_pre_hooks(*dataframe: DataFrame*) → DataFrame

Run all defined pre-hook steps from a given dataframe.

Parameters
dataframe – data to input in the defined pre-hook steps.

Returns
dataframe after passing for all defined pre-hooks.

Module contents

Holds Hooks definitions.

class butterfree.hooks.**Hook**

Bases: ABC

Definition of a hook function to call on a Dataframe.

abstract run(*dataframe: DataFrame*) → DataFrame

Run interface for Hook.

Parameters
dataframe – dataframe to use in the Hook.

Returns
dataframe result from the Hook.

class butterfree.hooks.**HookableComponent**

Bases: object

Defines a component with the ability to hold pre and post hook functions.

All main module of Butterfree have a common object that enables their integration: dataframes. Spark's dataframe is the glue that enables the transmission of data between the main modules. Hooks have a simple interface, they are functions that accepts a dataframe and outputs a dataframe. These Hooks can be triggered before or after the main execution of a component.

Components from Butterfree that inherit HookableComponent entity, are components that can define a series of steps to occur before or after the execution of their main functionality.

pre_hooks

function steps to trigger before component main functionality.

post_hooks

function steps to trigger after component main functionality.

enable_pre_hooks

property to indicate if the component can define pre_hooks.

enable_post_hooks

property to indicate if the component can define post_hooks.

add_post_hook(**hooks:* Hook) → *HookableComponent*

Add a post-hook steps to the component.

Parameters
hooks – Hook steps to add to post_hook list.

Returns
Component with the Hook inserted in post_hook list.

Raises
ValueError – if the component does not accept post-hooks.

add_pre_hook(**hooks:* Hook) → *HookableComponent*

Add a pre-hook steps to the component.

Parameters
hooks – Hook steps to add to pre_hook list.

Returns
Component with the Hook inserted in pre_hook list.

Raises
ValueError – if the component does not accept pre-hooks.

property enable_post_hooks: bool
Property to indicate if the component can define post_hooks.

property enable_pre_hooks: bool
Property to indicate if the component can define pre_hooks.

property post_hooks: List[*Hook*]
Function steps to trigger after component main functionality.

property pre_hooks: List[*Hook*]
Function steps to trigger before component main functionality.

run_post_hooks(*dataframe: DataFrame*) → DataFrame
Run all defined post-hook steps from a given dataframe.

Parameters
dataframe – data to input in the defined post-hook steps.

Returns
dataframe after passing for all defined post-hooks.

run_pre_hooks(*dataframe: DataFrame*) → DataFrame
Run all defined pre-hook steps from a given dataframe.

Parameters
dataframe – data to input in the defined pre-hook steps.

Returns
dataframe after passing for all defined pre-hooks.

butterfree.load package

Subpackages

butterfree.load.processing package

Submodules

Json conversion for writers.

butterfree.load.processing.json_transform.**json_transform**(*dataframe: DataFrame*) → DataFrame
Filters DataFrame's rows using the given condition and value.

Parameters
dataframe – Spark DataFrame.

Returns
Converted dataframe.

Module contents

Pre Processing Components regarding Readers.

butterfree.load.processing.**json_transform**(*dataframe: DataFrame*) → DataFrame

Filters DataFrame's rows using the given condition and value.

Parameters
dataframe – Spark DataFrame.

Returns
Converted dataframe.

butterfree.load.writers package

Submodules

Holds the Historical Feature Store writer class.

class butterfree.load.writers.historical_feature_store_writer.**HistoricalFeatureStoreWriter**(*db_config: Optional[AbstractV = None, database: Optional[str] = None, num_partitions: Optional[int] = None, validation_threshold: float = 0.01, debug_mode: bool = False, interval_mode: bool = False, check_schema_h Optional[Hook] = None, row_count_valid bool = True*)

Bases: *Writer*

Enable writing feature sets into the Historical Feature Store.

db_config

Datalake configuration for Spark, by default on AWS S3. For more information check module 'butterfree.db.configs'.

database

database name to use in Spark metastore. By default FEATURE_STORE_HISTORICAL_DATABASE environment variable.

num_partitions

value to use when applying repartition on the df before save.

validation_threshold

lower and upper tolerance to using in count validation. The default value is defined in DEFAULT_VALIDATION_THRESHOLD property. For example: with a validation_threshold = 0.01 and a given calculated count on the dataframe equal to 100000 records, if the feature store return a count equal to 995000 an error will not be thrown. Use validation_threshold = 0 to not use tolerance in the validation.

debug_mode

"dry run" mode, write the result to a temporary view.

Example

Simple example regarding HistoricalFeatureStoreWriter class instantiation. We can instantiate this class without db configurations, so the class get the S3Config() where it provides default configurations about AWS S3 service.

```
>>> spark_client = SparkClient()
>>> writer = HistoricalFeatureStoreWriter()
>>> writer.write(feature_set=feature_set,
...              dataframe=dataframe,
...              spark_client=spark_client)
```

However, we can define the db configurations, like write mode, file format and S3 bucket, and provide them to HistoricalFeatureStoreWriter.

```
>>> spark_client = SparkClient()
>>> config = MetastoreConfig(path="my_s3_bucket_name",
...                  mode="overwrite",
...                  format_="parquet")
>>> writer = HistoricalFeatureStoreWriter(db_config=config)
>>> writer.write(feature_set=feature_set,
...              dataframe=dataframe,
...              spark_client=spark_client)
```

For what settings you can use on S3Config and default settings, to read S3Config class.

We can write with interval mode, where HistoricalFeatureStoreWrite will need to use Dynamic Partition Inserts, the behaviour of OVERWRITE keyword is controlled by spark.sql.sources.partitionOverwriteMode configuration property. The dynamic overwrite mode is enabled Spark will only delete the partitions for which it has data to be written to. All the other partitions remain intact.

```
>>> spark_client = SparkClient()
>>> writer = HistoricalFeatureStoreWriter(interval_mode=True)
>>> writer.write(feature_set=feature_set,
...              dataframe=dataframe,
...              spark_client=spark_client)
```

We can instantiate HistoricalFeatureStoreWriter class to validate the df to be written.

```
>>> spark_client = SparkClient()
>>> writer = HistoricalFeatureStoreWriter()
>>> writer.validate(feature_set=feature_set,
...                 dataframe=dataframe,
...                 spark_client=spark_client)
```

Both methods (write and validate) will need the Spark Client, Feature Set and DataFrame, to write or to validate, according to the Writer's arguments.

P.S.: When writing, the HistoricalFeatureStoreWrite partitions the data to improve queries performance. The data is stored in partition folders in AWS S3 based on time (per year, month and day).

DEFAULT_VALIDATION_THRESHOLD = 0.01

PARTITION_BY = ['year', 'month', 'day']

check_schema(*client: Any*, *dataframe: DataFrame*, *table_name: str*, *database: Optional[str] = None*) → DataFrame

Instantiate the schema check hook to check schema between dataframe and database.

Parameters

- **client** – client for Spark or Cassandra connections with external services.
- **dataframe** – Spark dataframe containing data from a feature set.
- **table_name** – table name where the dataframe will be saved.
- **database** – database name where the dataframe will be saved.

validate(*feature_set:* FeatureSet, *dataframe: DataFrame*, *spark_client:* SparkClient) → None

Calculate dataframe rows to validate data into Feature Store.

Parameters

- **feature_set** – object processed with feature_set informations.
- **dataframe** – spark dataframe containing data from a feature set.
- **spark_client** – client for spark connections with external services.

Raises

AssertionError – if count of written data doesn't match count in current feature set dataframe.

write(*feature_set:* FeatureSet, *dataframe: DataFrame*, *spark_client:* SparkClient) → None

Loads the data from a feature set into the Historical Feature Store.

Parameters

- **feature_set** – object processed with feature_set informations.
- **dataframe** – spark dataframe containing data from a feature set.
- **spark_client** – client for spark connections with external services.

If the debug_mode is set to True, a temporary table with a name in the format: historical_feature_store__{feature_set.name} will be created instead of writing to the real historical feature store.

Holds the Online Feature Store writer class.

class butterfree.load.writers.online_feature_store_writer.**OnlineFeatureStoreWriter**(*db_config: Optional[AbstractWriteConfi = None*, *database: Optional[str] = None*, *debug_mode: bool = False*, *write_to_entity: bool = False*, *interval_mode: bool = False*, *check_schema_hook: Optional[Hook] = None*)

Bases: *Writer*

Enable writing feature sets into the Online Feature Store.

db_config

Spark configuration for connect databases. For more information check the module 'butterfree.db.configs'.

debug_mode

"dry run" mode, write the result to a temporary view.

write_to_entity

option to write the data to the entity table. With this option set to True, the writer will write the feature set to a table with the name equal to the entity name, defined on the pipeline. So, it WILL NOT write to a table with the name of the feature set, as it normally does.

Example

Simple example regarding OnlineFeatureStoreWriter class instantiation. We can instantiate this class without db configurations, so the class get the CassandraConfig() where it provides default configurations about CassandraDB.

```
>>> spark_client = SparkClient()
>>> writer = OnlineFeatureStoreWriter()
>>> writer.write(feature_set=feature_set,
...              dataframe=dataframe,
...              spark_client=spark_client)
```

However, we can define the db configurations and provide them to OnlineFeatureStoreWriter.

```
>>> spark_client = SparkClient()
>>> config = CassandraConfig(mode="overwrite",
    ...                       format_="parquet",
    ...                       keyspace="keyspace_name")
```

```
>>> writer = OnlineFeatureStoreWriter(db_config=config)
>>> writer.write(feature_set=feature_set,
   ...           dataframe=dataframe,
   ...           spark_client=spark_client)
```

For what settings you can use on CassandraConfig and default settings, to read CassandraConfig class.

We can instantiate OnlineFeatureStoreWriter class to validate the writers, using the default or custom configs.

```
>>> spark_client = SparkClient()
>>> writer = OnlineFeatureStoreWriter()
>>> writer.validate(feature_set=feature_set,
   ...              dataframe=dataframe,
   ...              spark_client=spark_client)
```

Both methods (writer and validate) will need the Spark Client, Feature Set and DataFrame, to write or to validate, according to OnlineFeatureStoreWriter class arguments.

There's an important aspect to be highlighted here: if you're using the incremental mode, we do not check if your data is the newest before writing to the online feature store.

This behavior is known and will be fixed soon.

check_schema(*client: Any*, *dataframe: DataFrame*, *table_name: str*, *database: Optional[str] = None*) → DataFrame

Instantiate the schema check hook to check schema between dataframe and database.

Parameters

- **client** – client for Spark or Cassandra connections with external services.
- **dataframe** – Spark dataframe containing data from a feature set.
- **table_name** – table name where the dataframe will be saved.
- **database** – database name where the dataframe will be saved.

static filter_latest(*dataframe: DataFrame*, *id_columns: List[Any]*) → DataFrame

Filters latest data from the dataframe.

Parameters

- **dataframe** – spark dataframe containing data from a feature set.
- **id_columns** – unique identifier column set for this feature set.

Returns

contains only latest data for each unique id in the
feature set.

Return type
dataframe

get_db_schema(*feature_set:* FeatureSet) → List[Dict[Any, Any]]

Get desired database schema.

Parameters
feature_set – object processed with feature set metadata.

Returns
Desired database schema.

validate(*feature_set:* FeatureSet, *dataframe: DataFrame*, *spark_client:* SparkClient) → None

Calculate dataframe rows to validate data into Feature Store.

Parameters

- **feature_set** – object processed with feature set metadata.
- **dataframe** – Spark dataframe containing data from a feature set.
- **spark_client** – client for Spark connections with external services.

Raises
AssertionError – if validation fails.

write(*feature_set:* FeatureSet, *dataframe: DataFrame*, *spark_client:* SparkClient) → Optional[StreamingQuery]

Loads the latest data from a feature set into the Feature Store.

Parameters

- **feature_set** – object processed with feature set metadata.
- **dataframe** – Spark dataframe containing data from a feature set.
- **spark_client** – client for Spark connections with external services.

Returns
Streaming handler if writing streaming df, None otherwise.

If the debug_mode is set to True, a temporary table with a name in the format: *online_feature_store__my_feature_set* will be created instead of writing to the real online feature store. If dataframe is streaming this temporary table will be updated in real time.

Writer entity.

class butterfree.load.writers.writer.**Writer**(*db_config:* AbstractWriteConfig, *debug_mode: bool = False*, *interval_mode: bool = False*, *write_to_entity: bool = False*, *row_count_validation: bool = True*)

Bases: ABC, *HookableComponent*

Abstract base class for Writers.

Parameters
spark_client – client for spark connections with external services.

abstract check_schema(*client: Any*, *dataframe: DataFrame*, *table_name: str*, *database: Optional[str] = None*) → DataFrame

Instantiate the schema check hook to check schema between dataframe and database.

Parameters

- **client** – client for Spark or Cassandra connections with external services.
- **dataframe** – Spark dataframe containing data from a feature set.
- **table_name** – table name where the dataframe will be saved.

- **database** – database name where the dataframe will be saved.

abstract validate(*feature_set:* FeatureSet, *dataframe: DataFrame*, *spark_client:* SparkClient) → Any

Calculate dataframe rows to validate data into Feature Store.

Parameters

- **feature_set** – object processed with feature set metadata.
- **dataframe** – Spark dataframe containing data from a feature set.
- **spark_client** – client for Spark connections with external services.

Raises

AssertionError – if validation fails.

with_(*transformer: Callable[[...], DataFrame]*, **args: Any*, ***kwargs: Any*) → *Writer*

Define a new transformation for the Writer.

All the transformations are used when the method consume is called.

Parameters

- **transformer** – method that receives a dataframe and output a dataframe.
- ***args** – args for the transformer.
- ****kwargs** – kwargs for the transformer.

Returns

Reader object with new transformation

abstract write(*feature_set:* FeatureSet, *dataframe: DataFrame*, *spark_client:* SparkClient) → Any

Loads the data from a feature set into the Feature Store.

Feature Store could be Online or Historical.

Parameters

- **feature_set** – object processed with feature set metadata.
- **dataframe** – Spark dataframe containing data from a feature set.
- **spark_client** – client for Spark connections with external services.

Module contents

Holds data loaders for historical and online feature store.

class butterfree.load.writers.**HistoricalFeatureStoreWriter**(*db_config: Optional[AbstractWriteConfig] = None*, *database: Optional[str] = None*, *num_partitions: Optional[int] = None*, *validation_threshold: float = 0.01*, *debug_mode: bool = False*, *interval_mode: bool = False*, *check_schema_hook: Optional[Hook] = None*, *row_count_validation: bool = True*)

Bases: *Writer*

Enable writing feature sets into the Historical Feature Store.

db_config

Datalake configuration for Spark, by default on AWS S3. For more information check module 'butterfree.db.configs'.

database

database name to use in Spark metastore. By default FEATURE_STORE_HISTORICAL_DATABASE environment variable.

num_partitions

value to use when applying repartition on the df before save.

validation_threshold

lower and upper tolerance to using in count validation. The default value is defined in DEFAULT_VALIDATION_THRESHOLD property. For example: with a validation_threshold = 0.01 and a given calculated count on the dataframe equal to 100000 records, if the feature store return a count equal to 995000 an error will not be thrown. Use validation_threshold = 0 to not use tolerance in the validation.

debug_mode

"dry run" mode, write the result to a temporary view.

Example

Simple example regarding HistoricalFeatureStoreWriter class instantiation. We can instantiate this class without db configurations, so the class get the S3Config() where it provides default configurations about AWS S3 service.

```
>>> spark_client = SparkClient()
>>> writer = HistoricalFeatureStoreWriter()
>>> writer.write(feature_set=feature_set,
   ...           dataframe=dataframe,
   ...           spark_client=spark_client)
```

However, we can define the db configurations, like write mode, file format and S3 bucket, and provide them to HistoricalFeatureStoreWriter.

```
>>> spark_client = SparkClient()
>>> config = MetastoreConfig(path="my_s3_bucket_name",
    ...                mode="overwrite",
    ...                format_="parquet")
>>> writer = HistoricalFeatureStoreWriter(db_config=config)
>>> writer.write(feature_set=feature_set,
   ...           dataframe=dataframe,
   ...           spark_client=spark_client)
```

For what settings you can use on S3Config and default settings, to read S3Config class.

We can write with interval mode, where HistoricalFeatureStoreWrite will need to use Dynamic Partition Inserts, the behaviour of OVERWRITE keyword is controlled by spark.sql.sources.partitionOverwriteMode configuration property. The dynamic overwrite mode is enabled Spark will only delete the partitions for which it has data to be written to. All the other partitions remain intact.

```
>>> spark_client = SparkClient()
>>> writer = HistoricalFeatureStoreWriter(interval_mode=True)
>>> writer.write(feature_set=feature_set,
...              dataframe=dataframe,
...              spark_client=spark_client)
```

We can instantiate HistoricalFeatureStoreWriter class to validate the df to be written.

```
>>> spark_client = SparkClient()
>>> writer = HistoricalFeatureStoreWriter()
>>> writer.validate(feature_set=feature_set,
...                 dataframe=dataframe,
...                 spark_client=spark_client)
```

Both methods (write and validate) will need the Spark Client, Feature Set and DataFrame, to write or to validate, according to the Writer's arguments.

P.S.: When writing, the HistoricalFeatureStoreWrite partitions the data to improve queries performance. The data is stored in partition folders in AWS S3 based on time (per year, month and day).

DEFAULT_VALIDATION_THRESHOLD = 0.01

PARTITION_BY = ['year', 'month', 'day']

check_schema(*client: Any*, *dataframe: DataFrame*, *table_name: str*, *database: Optional[str] = None*) → DataFrame

Instantiate the schema check hook to check schema between dataframe and database.

Parameters

- **client** – client for Spark or Cassandra connections with external services.
- **dataframe** – Spark dataframe containing data from a feature set.
- **table_name** – table name where the dataframe will be saved.
- **database** – database name where the dataframe will be saved.

transformations: List[Dict[str, Any]]

validate(*feature_set:* FeatureSet, *dataframe: DataFrame*, *spark_client:* SparkClient) → None

Calculate dataframe rows to validate data into Feature Store.

Parameters

- **feature_set** – object processed with feature_set informations.
- **dataframe** – spark dataframe containing data from a feature set.
- **spark_client** – client for spark connections with external services.

Raises

AssertionError – if count of written data doesn't match count in current feature set dataframe.

write(*feature_set:* FeatureSet, *dataframe: DataFrame*, *spark_client:* SparkClient) → None

Loads the data from a feature set into the Historical Feature Store.

Parameters

- **feature_set** – object processed with feature_set informations.
- **dataframe** – spark dataframe containing data from a feature set.
- **spark_client** – client for spark connections with external services.

If the debug_mode is set to True, a temporary table with a name in the format: historical_feature_store__{feature_set.name} will be created instead of writing to the real historical feature store.

class butterfree.load.writers.**OnlineFeatureStoreWriter**(*db_config: Optional[AbstractWriteConfig] = None*, *database: Optional[str] = None*, *debug_mode: bool = False*, *write_to_entity: bool = False*, *interval_mode: bool = False*, *check_schema_hook: Optional[Hook] = None*)

Bases: *Writer*

Enable writing feature sets into the Online Feature Store.

db_config

Spark configuration for connect databases. For more information check the module 'butterfree.db.configs'.

debug_mode

"dry run" mode, write the result to a temporary view.

write_to_entity

option to write the data to the entity table. With this option set to True, the writer will write the feature set to a table with the name equal to the entity name, defined on the pipeline. So, it WILL NOT write to a table with the name of the feature set, as it normally does.

Example

Simple example regarding OnlineFeatureStoreWriter class instantiation. We can instantiate this class without db configurations, so the class get the CassandraConfig() where it provides default configurations about CassandraDB.

```
>>> spark_client = SparkClient()
>>> writer = OnlineFeatureStoreWriter()
>>> writer.write(feature_set=feature_set,
...              dataframe=dataframe,
...              spark_client=spark_client)
```

However, we can define the db configurations and provide them to OnlineFeatureStoreWriter.

```
>>> spark_client = SparkClient()
>>> config = CassandraConfig(mode="overwrite",
...                          format_="parquet",
...                          keyspace="keyspace_name")
```

```
>>> writer = OnlineFeatureStoreWriter(db_config=config)
>>> writer.write(feature_set=feature_set,
...              dataframe=dataframe,
...              spark_client=spark_client)
```

For what settings you can use on CassandraConfig and default settings, to read CassandraConfig class.

We can instantiate OnlineFeatureStoreWriter class to validate the writers, using the default or custom configs.

```
>>> spark_client = SparkClient()
>>> writer = OnlineFeatureStoreWriter()
>>> writer.validate(feature_set=feature_set,
...                 dataframe=dataframe,
...                 spark_client=spark_client)
```

Both methods (writer and validate) will need the Spark Client, Feature Set and DataFrame, to write or to validate, according to OnlineFeatureStoreWriter class arguments.

There's an important aspect to be highlighted here: if you're using the incremental mode, we do not check if your data is the newest before writing to the online feature store.

This behavior is known and will be fixed soon.

check_schema(*client: Any*, *dataframe: DataFrame*, *table_name: str*, *database: Optional[str] = None*) → DataFrame

Instantiate the schema check hook to check schema between dataframe and database.

Parameters

- **client** – client for Spark or Cassandra connections with external services.
- **dataframe** – Spark dataframe containing data from a feature set.
- **table_name** – table name where the dataframe will be saved.
- **database** – database name where the dataframe will be saved.

static filter_latest(*dataframe: DataFrame*, *id_columns: List[Any]*) → DataFrame

Filters latest data from the dataframe.

Parameters

- **dataframe** – spark dataframe containing data from a feature set.
- **id_columns** – unique identifier column set for this feature set.

Returns

contains only latest data for each unique id in the
feature set.

Return type
dataframe

get_db_schema(*feature_set:* FeatureSet) → List[Dict[Any, Any]]

Get desired database schema.

Parameters
feature_set – object processed with feature set metadata.

Returns
Desired database schema.

validate(*feature_set:* FeatureSet, *dataframe: DataFrame*, *spark_client:* SparkClient) → None

Calculate dataframe rows to validate data into Feature Store.

Parameters

- **feature_set** – object processed with feature set metadata.
- **dataframe** – Spark dataframe containing data from a feature set.
- **spark_client** – client for Spark connections with external services.

Raises

AssertionError – if validation fails.

write(*feature_set:* FeatureSet, *dataframe: DataFrame*, *spark_client:* SparkClient) → Optional[StreamingQuery]

Loads the latest data from a feature set into the Feature Store.

Parameters

- **feature_set** – object processed with feature set metadata.
- **dataframe** – Spark dataframe containing data from a feature set.
- **spark_client** – client for Spark connections with external services.

Returns

Streaming handler if writing streaming df, None otherwise.

If the debug_mode is set to True, a temporary table with a name in the format: *online_feature_store__my_feature_set* will be created instead of writing to the real online feature store. If dataframe is streaming this temporary table will be updated in real time.

Submodules

Holds the Sink class.

class butterfree.load.sink.**Sink**(*writers: List[*Writer*]*, *validation: Optional[*Validation*] = None*)

Bases: *HookableComponent*

Define the destinations for the feature set pipeline.

A Sink is created from a set of writers. The main goal of the Sink is to trigger the load in each defined writers. After the load the entity can be used to make sure that all data was written properly using the validate method.

writers

list of Writers to use to load the data.

validation

validation to check the data before starting to write.

flush(*feature_set:* FeatureSet, *dataframe: DataFrame*, *spark_client:* SparkClient) → List[StreamingQuery]

Trigger a write job in all the defined Writers.

Parameters

- **dataframe** – spark dataframe containing data from a feature set.
- **feature_set** – object processed with feature set metadata.
- **spark_client** – client used to run a query.

Returns
Streaming handlers for each defined writer, if writing streaming dfs.

validate(*feature_set: FeatureSet*, *dataframe: DataFrame*, *spark_client: SparkClient*) → None

Trigger a validation job in all the defined Writers.

Parameters

- **dataframe** – spark dataframe containing data from a feature set.
- **feature_set** – object processed with feature set metadata.
- **spark_client** – client used to run a query.

Raises
RuntimeError – if any on the Writers returns a failed validation.

property validation: Optional[*Validation*]

Validation to check the data before starting to write.

property writers: List[*Writer*]

List of Writers to use to load the data.

Module contents

Holds the Sink component of a feature set pipeline.

class butterfree.load.**Sink**(*writers: List[Writer]*, *validation: Optional[Validation] = None*)

Bases: *HookableComponent*

Define the destinations for the feature set pipeline.

A Sink is created from a set of writers. The main goal of the Sink is to trigger the load in each defined writers. After the load the entity can be used to make sure that all data was written properly using the validate method.

writers
list of Writers to use to load the data.

validation
validation to check the data before starting to write.

flush(*feature_set: FeatureSet*, *dataframe: DataFrame*, *spark_client: SparkClient*) → List[StreamingQuery]

Trigger a write job in all the defined Writers.

Parameters

- **dataframe** – spark dataframe containing data from a feature set.
- **feature_set** – object processed with feature set metadata.
- **spark_client** – client used to run a query.

Returns
Streaming handlers for each defined writer, if writing streaming dfs.

validate(*feature_set: FeatureSet*, *dataframe: DataFrame*, *spark_client: SparkClient*) → None

Trigger a validation job in all the defined Writers.

Parameters

- **dataframe** – spark dataframe containing data from a feature set.
- **feature_set** – object processed with feature set metadata.

- **spark_client** – client used to run a query.

Raises

RuntimeError – if any on the Writers returns a failed validation.

property validation: Optional[*Validation*]

Validation to check the data before starting to write.

property writers: List[*Writer*]

List of Writers to use to load the data.

butterfree.migrations package

Subpackages

butterfree.migrations.database_migration package

Submodules

Cassandra Migration entity.

class butterfree.migrations.database_migration.cassandra_migration.**CassandraMigration**

Bases: *DatabaseMigration*

Cassandra class for performing migrations.

This class implements some methods of the parent DatabaseMigration class and has specific methods for query building.

The CassandraMigration class will be used, as the name suggests, for applying changes to a given Cassandra table. There are, however, some remarks that need to be highlighted:

- If an existing feature has its type changed, then it's extremely important to

make sure that this conversion would not result in data loss; - If new features are added to your feature set, then they're going to be added to the corresponding Cassandra table; - Since feature sets can be written both to a feature set and an entity table, we're not going to automatically drop features when using entity tables, since it means that some features belong to a different feature set. In summary, if data is being loaded into an entity table, then users can drop columns manually.

Migration entity.

class butterfree.migrations.database_migration.database_migration.**DatabaseMigration**(*client:* AbstractClient)

Bases: ABC

Abstract base class for Migrations.

apply_migration(*feature_set:* FeatureSet, *writer:* Writer, *debug_mode: bool*) → None

Apply the migration in the respective database.

Parameters

- **feature_set** – the feature set.
- **writer** – the writer being used to load the feature set.

- **debug_mode** – if active, it brings up the queries generated.

create_query(*fs_schema: List[Dict[str, Any]]*, *table_name: str*, *db_schema: Optional[List[Dict[str, Any]]] = None*, *write_on_entity: Optional[bool] = None*) → Any

Create a query regarding a data source.

Returns
The desired queries for the given database.

class butterfree.migrations.database_migration.database_migration.**Diff**(*column: str*, *kind: Kind*, *value: Any*)

Bases: object

DataClass to help identifying different types of diff between schemas.

class **Kind**(*value*)

Bases: Enum

Mapping actions to take given a difference between columns of a schema.

ADD = 1

ALTER_KEY = 2

ALTER_TYPE = 3

DROP = 4

column: str

kind: *Kind*

value: Any

Metastore Migration entity.

class butterfree.migrations.database_migration.metastore_migration.**MetastoreMigration**(*database: Optional[str] = None*)

Bases: *DatabaseMigration*

MetastoreMigration class for performing migrations.

This class implements some methods of the parent DatabaseMigration class and has specific methods for query building. The MetastoreMigration class will be used, as the name suggests, for applying changes to a given Metastore table. There are, however, some remarks that need to be highlighted:

- If an existing feature has its type changed, then it's extremely important to

make sure that this conversion would not result in data loss; - If new features are added to your feature set, then they're going to be added to the corresponding Metastore table; - Since feature sets can be written both to a feature set and an entity table, we're not going to automatically drop features when using entity tables, since it means that some features belong to a different feature set. In summary, if data is being loaded into an entity table, then users can drop columns manually.

Module contents

Holds available database migrations.

class butterfree.migrations.database_migration.**CassandraMigration**

Bases: *DatabaseMigration*

Cassandra class for performing migrations.

This class implements some methods of the parent DatabaseMigration class and has specific methods for query building.

The CassandraMigration class will be used, as the name suggests, for applying changes to a given Cassandra table. There are, however, some remarks that need to be highlighted:

- If an existing feature has its type changed, then it's extremely important to

make sure that this conversion would not result in data loss; - If new features are added to your feature set, then they're going to be added to the corresponding Cassandra table; - Since feature sets can be written both to a feature set and an entity table, we're not going to automatically drop features when using entity tables, since it means that some features belong to a different feature set. In summary, if data is being loaded into an entity table, then users can drop columns manually.

class butterfree.migrations.database_migration.**Diff**(*column: str*, *kind:* Kind, *value: Any*)

Bases: `object`

DataClass to help identifying different types of diff between schemas.

class Kind(*value*)

Bases: `Enum`

Mapping actions to take given a difference between columns of a schema.

ADD = 1

ALTER_KEY = 2

ALTER_TYPE = 3

DROP = 4

column: str

kind: *Kind*

value: Any

class butterfree.migrations.database_migration.**MetastoreMigration**(*database: Optional[str] = None*)

Bases: *DatabaseMigration*

MetastoreMigration class for performing migrations.

This class implements some methods of the parent DatabaseMigration class and has specific methods for query building. The MetastoreMigration class will be used, as the name suggests, for applying changes to a given Metastore table. There are, however, some remarks that need to be highlighted:

- If an existing feature has its type changed, then it's extremely important to

make sure that this conversion would not result in data loss; - If new features are added to your feature set, then they're going to be added to the corresponding Metastore table; - Since feature sets can be written both to a feature set and an entity table, we're not going to automatically drop features when

using entity tables, since it means that some features belong to a different feature set. In summary, if data is being loaded into an entity table, then users can drop columns manually.

Module contents

Holds available migrations.

butterfree.pipelines package

Submodules

FeatureSetPipeline entity.

class butterfree.pipelines.feature_set_pipeline.**FeatureSetPipeline**(*source:* Source, *feature_set:* FeatureSet, *sink:* Sink, *spark_client:* *Optional[*SparkClient*]* = *None*)

Bases: `object`

Defines a ETL pipeline for the construction of a feature set.

source

source of the data, the entry point of the pipeline.

feature_set

feature set composed by features and context metadata.

sink

sink used to write the output dataframe in the desired locations.

spark_client

client used to access Spark connection.

Example

This an example regarding the feature set pipeline definition. All sources, feature set (and its features) and writers are defined.

```
>>> import os
```

```
>>> from butterfree.pipelines import FeatureSetPipeline
>>> from butterfree.constants.columns import TIMESTAMP_COLUMN
>>> from butterfree.configs.db import MetastoreConfig
>>> from butterfree.extract import Source
>>> from butterfree.extract.readers import TableReader
>>> from butterfree.transform import FeatureSet
>>> from butterfree.transform.features import (
...     Feature,
...     KeyFeature,
...     TimestampFeature,
...)
```

(continues on next page)

(continued from previous page)

```
>>> from butterfree.transform.transformations import (
...     SparkFunctionTransform,
...     CustomTransform,
... )
>>> from butterfree.load import Sink
>>> from butterfree.load.writers import HistoricalFeatureStoreWriter
>>> from pyspark.sql import functions
```

```
>>> def divide(df, fs, column1, column2):
...     name = fs.get_output_columns()[0]
...     df = df.withColumn(name,
...             functions.col(column1) / functions.col(column2))
...     return df
```

```
>>> pipeline = FeatureSetPipeline(
...    source=Source(
...        readers=[
...            TableReader(
...                id="table_reader_id",
...                database="table_reader_db",
...                table="table_reader_table",
...            ),
...        ],
...        query=f"select * from table_reader_id ",
...    ),
...    feature_set=FeatureSet(
...        name="feature_set",
...        entity="entity",
...        description="description",
...        features=[
...            Feature(
...                name="feature1",
...                description="test",
...            transformation=SparkFunctionTransform(
...                 functions=[Function(functions.avg, DataType.DOUBLE),
...                         Function(functions.stddev_pop, DataType.DOUBLE)],
...             ).with_window(
...                 partition_by="id",
...                 order_by=TIMESTAMP_COLUMN,
...                 mode="fixed_windows",
...                 window_definition=["2 minutes", "15 minutes"],
...             ),
...            ),
...            Feature(
...                name="divided_feature",
...                description="unit test",
...                transformation=CustomTransform(
...                    transformer=divide,
...                    column1="feature1",
...                    column2="feature2",
...                ),
```

(continues on next page)

(continued from previous page)

```
...             ),
...         ],
...         keys=[
...             KeyFeature(
...                 name="id",
...                 description="The user's Main ID or device ID"
...             )
...         ],
...         timestamp=TimestampFeature(),
...     ),
...     sink=Sink(
...          writers=[
...             HistoricalFeatureStoreWriter(
...                 db_config=MetastoreConfig(
...                     format_="parquet",
...                     path=os.path.join(
...                         os.path.dirname(os.path.abspath(__file__))
...                     ),
...                 ),
...             )
...         ],
...     ),
...)
```

```
>>> pipeline.run()
```

This last method (run) will execute the pipeline flow, it'll read from the defined sources, compute all the transformations and save the data to the specified locations.

We can run the pipeline over a range of dates by passing an end-date

and a start-date, where it will only bring data within this date range.

```
>>> pipeline.run(end_date="2020-08-04", start_date="2020-07-04")
```

Or run up to a date, where it will only bring data up to the specific date.

```
>>> pipeline.run(end_date="2020-08-04")
```

Or just a specific date, where you will only bring data for that day.

```
>>> pipeline.run_for_date(execution_date="2020-08-04")
```

property feature_set: *FeatureSet*

Feature set composed by features and context metadata.

run(*end_date: Optional[str] = None*, *partition_by: Optional[List[str]] = None*, *order_by: Optional[List[str]] = None*, *num_processors: Optional[int] = None*, *start_date: Optional[str] = None*) → None

Runs the defined feature set pipeline.

The pipeline consists in the following steps: - Constructs the input dataframe from the data source. - Construct the feature set dataframe using the defined Features. - Load the data to the configured sink locations.

It's important to notice, however, that both parameters partition_by and num_processors are WIP, we intend to enhance their functionality soon. Use only if strictly necessary.

run_for_date(*execution_date: Optional[str] = None*, *partition_by: Optional[List[str]] = None*, *order_by: Optional[List[str]] = None*, *num_processors: Optional[int] = None*) → None

Runs the defined feature set pipeline for a specific date.

The pipeline consists in the following steps:

- Constructs the input dataframe from the data source.
- Construct the feature set dataframe using the defined Features.
- Load the data to the configured sink locations.

It's important to notice, however, that both parameters partition_by and num_processors are WIP, we intend to enhance their functionality soon. Use only if strictly necessary.

property sink: *Sink*

Sink used to write the output dataframe in the desired locations.

property source: *Source*

Source of the data, the entry point of the pipeline.

property spark_client: *SparkClient*

Client used to access Spark connection.

Module contents

ETL Pipelines.

class butterfree.pipelines.**FeatureSetPipeline**(*source: Source*, *feature_set: FeatureSet*, *sink: Sink*, *spark_client: Optional[SparkClient] = None*)

Bases: object

Defines a ETL pipeline for the construction of a feature set.

source

source of the data, the entry point of the pipeline.

feature_set

feature set composed by features and context metadata.

sink

sink used to write the output dataframe in the desired locations.

spark_client

client used to access Spark connection.

Example

This an example regarding the feature set pipeline definition. All sources, feature set (and its features) and writers are defined.

```
>>> import os
```

```
>>> from butterfree.pipelines import FeatureSetPipeline
>>> from butterfree.constants.columns import TIMESTAMP_COLUMN
>>> from butterfree.configs.db import MetastoreConfig
>>> from butterfree.extract import Source
>>> from butterfree.extract.readers import TableReader
>>> from butterfree.transform import FeatureSet
>>> from butterfree.transform.features import (
...     Feature,
...     KeyFeature,
...     TimestampFeature,
...)
>>> from butterfree.transform.transformations import (
...     SparkFunctionTransform,
...     CustomTransform,
... )
>>> from butterfree.load import Sink
>>> from butterfree.load.writers import HistoricalFeatureStoreWriter
>>> from pyspark.sql import functions
```

```
>>> def divide(df, fs, column1, column2):
...     name = fs.get_output_columns()[0]
...     df = df.withColumn(name,
...             functions.col(column1) / functions.col(column2))
...     return df
```

```
>>> pipeline = FeatureSetPipeline(
...    source=Source(
...        readers=[
...            TableReader(
...                id="table_reader_id",
...                database="table_reader_db",
...                table="table_reader_table",
...            ),
...        ],
...        query=f"select * from table_reader_id ",
...    ),
...    feature_set=FeatureSet(
...        name="feature_set",
...        entity="entity",
...        description="description",
...        features=[
...            Feature(
...                name="feature1",
...                description="test",
...            transformation=SparkFunctionTransform(
...                 functions=[Function(functions.avg, DataType.DOUBLE),
```

(continues on next page)

(continued from previous page)

```
...                         Function(functions.stddev_pop, DataType.DOUBLE)],
...             ).with_window(
...                 partition_by="id",
...                 order_by=TIMESTAMP_COLUMN,
...                 mode="fixed_windows",
...                 window_definition=["2 minutes", "15 minutes"],
...             ),
...             ),
...             Feature(
...                 name="divided_feature",
...                 description="unit test",
...                 transformation=CustomTransform(
...                     transformer=divide,
...                     column1="feature1",
...                     column2="feature2",
...                 ),
...             ),
...         ],
...         keys=[
...             KeyFeature(
...                 name="id",
...                 description="The user's Main ID or device ID"
...             )
...         ],
...         timestamp=TimestampFeature(),
...     ),
...     sink=Sink(
...          writers=[
...             HistoricalFeatureStoreWriter(
...                 db_config=MetastoreConfig(
...                     format_="parquet",
...                     path=os.path.join(
...                         os.path.dirname(os.path.abspath(__file__))
...                     ),
...                 ),
...             )
...         ],
...     ),
...)
```

```
>>> pipeline.run()
```

This last method (run) will execute the pipeline flow, it'll read from the defined sources, compute all the transformations and save the data to the specified locations.

We can run the pipeline over a range of dates by passing an end-date

and a start-date, where it will only bring data within this date range.

```
>>> pipeline.run(end_date="2020-08-04", start_date="2020-07-04")
```

Or run up to a date, where it will only bring data up to the specific date.

```
>>> pipeline.run(end_date="2020-08-04")
```

Or just a specific date, where you will only bring data for that day.

```
>>> pipeline.run_for_date(execution_date="2020-08-04")
```

property feature_set: *FeatureSet*

Feature set composed by features and context metadata.

run(*end_date: Optional[str] = None*, *partition_by: Optional[List[str]] = None*, *order_by: Optional[List[str]] = None*, *num_processors: Optional[int] = None*, *start_date: Optional[str] = None*) → None

Runs the defined feature set pipeline.

The pipeline consists in the following steps: - Constructs the input dataframe from the data source. - Construct the feature set dataframe using the defined Features. - Load the data to the configured sink locations.

It's important to notice, however, that both parameters partition_by and num_processors are WIP, we intend to enhance their functionality soon. Use only if strictly necessary.

run_for_date(*execution_date: Optional[str] = None*, *partition_by: Optional[List[str]] = None*, *order_by: Optional[List[str]] = None*, *num_processors: Optional[int] = None*) → None

Runs the defined feature set pipeline for a specific date.

The pipeline consists in the following steps:

- Constructs the input dataframe from the data source.
- Construct the feature set dataframe using the defined Features.
- Load the data to the configured sink locations.

It's important to notice, however, that both parameters partition_by and num_processors are WIP, we intend to enhance their functionality soon. Use only if strictly necessary.

property sink: *Sink*

Sink used to write the output dataframe in the desired locations.

property source: *Source*

Source of the data, the entry point of the pipeline.

property spark_client: *SparkClient*

Client used to access Spark connection.

butterfree.reports package

Submodules

Write feature set metadata.

class butterfree.reports.metadata.**Metadata**(*pipeline:* FeatureSetPipeline, *save: bool = False*)

Bases: object

Generate metadata for feature set pipeline.

pipeline

object processed with feature set pipeline.

save

bool value with default is False. When this value is True, it will generate a file.

Example

```
>>> pipeline = FeatureSetPipeline()
>>> metadata = Metadata(pipeline)
>>> metadata.to_json()
```

[

“feature_set”: “feature_set”, “description”: “description”, “source”: [

{

“reader”: “Table Reader”, “location”: “db.table”

}, {

“reader”: “File Reader”, “location”: “path”

}

], “sink”: [

{

“writer”: “Historical Feature Store Writer”

}, {

“writer”: “Online Feature Store Writer”

}

], “features”: [

{

“column”: {
“name”: “user_id”, “data_type”: “IntegerType”

}, “description”: “The user’s Main ID or device ID”

}, {

“column”: {
“name”: “timestamp”, “data_type”: “TimestampType”

}, “description”: “Time tag for the state of all features.”

}, {

“column”: {

“name”:
“listing_page_viewed__rent_per_month__avg_over_7_days_fixed_windows”,

“data_type”: “FloatType”

}, “description”: “Average of something.”

}, {

“column”: {

“name”:
“listing_page_viewed__rent_per_month__avg_over_2_weeks_fixed_windows”,
“data_type”: “FloatType”
}, “description”: “Average of something.”
}
]

}

to_json() → Any
Generate json file.

to_markdown() → Any
Generate markdown file.

Module contents

Reports module.

class butterfree.reports.Metadata(*pipeline:* FeatureSetPipeline, *save: bool = False*)
Bases: object

Generate metadata for feature set pipeline.

pipeline
object processed with feature set pipeline.

save
bool value with default is False. When this value is True, it will generate a file.

Example

```
>>> pipeline = FeatureSetPipeline()
>>> metadata = Metadata(pipeline)
>>> metadata.to_json()
```

[

“feature_set”: “feature_set”, “description”: “description”, “source”: [
{
“reader”: “Table Reader”, “location”: “db.table”
}, {
“reader”: “File Reader”, “location”: “path”
}
], “sink”: [

```
            {
                "writer": "Historical Feature Store Writer"
            }, {
                "writer": "Online Feature Store Writer"
            }
        ], "features": [
            {
                "column": {
                  "name": "user_id", "data_type": "IntegerType"
                }, "description": "The user's Main ID or device ID"
            }, {
                "column": {
                  "name": "timestamp", "data_type": "TimestampType"
                }, "description": "Time tag for the state of all features."
            }, {
                "column": {
                  "name":
                    "listing_page_viewed__rent_per_month__avg_over_7_days_fixed_windows",
                  "data_type": "FloatType"
                }, "description": "Average of something."
            }, {
                "column": {
                  "name":
                    "listing_page_viewed__rent_per_month__avg_over_2_weeks_fixed_windows",
                  "data_type": "FloatType"
                }, "description": "Average of something."
            }
        ]

}
```


to_json() → Any

Generate json file.

to_markdown() → Any

Generate markdown file.

butterfree.testing package

Subpackages

butterfree.testing.dataframe package

Module contents

Methods to assert properties regarding Apache Spark Dataframes.

butterfree.testing.dataframe.**assert_column_equality**(*output_df: DataFrame*, *target_df: DataFrame*, *output_column: Column*, *target_column: Column*) → None

Columns comparison method.

butterfree.testing.dataframe.**assert_dataframe_equality**(*output_df: DataFrame*, *target_df: DataFrame*) → None

Dataframe comparison method.

butterfree.testing.dataframe.**create_df_from_collection**(*data: List[Dict[Any, Any]]*, *spark_context: SparkContext*, *spark_session: SparkSession*, *schema: Optional[StructType] = None*) → DataFrame

Creates a dataframe from a list of dicts.

Module contents

Utilities to make testing of Butterfree tools easier.

butterfree.transform package

Subpackages

butterfree.transform.features package

Submodules

Feature entity.

class butterfree.transform.features.feature.**Feature**(*name: str*, *description: str*, *dtype: Optional[DataType] = None*, *from_column: Optional[str] = None*, *transformation: Optional[TransformComponent] = None*)

Bases: `object`

Defines a Feature.

A Feature is the result of a transformation over one (or more) data columns over an input dataframe. Transformations can be as simple as renaming, casting types, mathematical expressions or complex functions/models.

name

feature name. Can be use by the transformation to derive multiple output columns.

description

brief explanation regarding the feature.

dtype

data type for the output columns of this feature.

from_column

original column to build feature. Used when there is transformation or the transformation has no reference about the column to use for.

transformation

transformation that will be applied to create this feature.

property dtype: Any

Attribute dtype getter.

property from_column: Any

Attribute from_column getter.

get_output_columns() → List[str]

Get output columns that will be generated by this feature engineering.

Returns

Output columns names.

transform(*dataframe: DataFrame*) → DataFrame

Performs a transformation to the feature pipeline.

Parameters

dataframe – input dataframe for the transformation.

Returns

Transformed dataframe.

property transformation: Any

Attribute transformation getter.

KeyFeature entity.

class butterfree.transform.features.key_feature.**KeyFeature**(*name: str*, *description: str*, *dtype:* DataType, *from_column: Optional[str] = None*, *transformation: Optional[*TransformComponent*] = None*)

Bases: *Feature*

Defines a KeyFeature.

A FeatureSet must contain one or more KeyFeatures, which will be used as keys when storing the feature set dataframe as tables. The Feature Set may validate keys are unique for the latest state of a feature set.

name

key name. Can be use by the transformation to derive multiple key columns.

description

brief explanation regarding the key.

dtype

data type for the output column of this key.

from_column

original column to build a key. Used when there is transformation or the transformation has no reference about the column to use for.

transformation

transformation that will be applied to create this key. Keys can be derived by transformations over any data column. Like a location hash based on latitude and longitude.

TimestampFeature entity.

class butterfree.transform.features.timestamp_feature.**TimestampFeature**(*from_column: Optional[str] = None*, *transformation: Optional[TransformComponent] = None*, *from_ms: bool = False*, *mask: Optional[str] = None*)

Bases: *Feature*

Defines a TimestampFeature.

A FeatureSet must contain one TimestampFeature, which will be used as a time tag for the state of all features. By containing a timestamp feature, users may time travel over their features. The Feature Set may validate that the set of keys and timestamp are unique for a feature set.

By defining a TimestampColumn, the feature set will always contain a data column called "timestamp" of TimestampType (spark dtype).

from_column

original column to build a "timestamp" feature column. Used when there is transformation or the transformation has no reference about the column to use for. If from_column is None, the FeatureSet will assume the input dataframe already has a data column called "timestamp".

transformation

transformation that will be applied to create the "timestamp". Type casting will already happen when no transformation is given. But a timestamp can be derived from multiple columns, like year, month and day, for example. The transformation must always handle naming and typing.

from_ms

true if timestamp column presents milliseconds time unit. A

conversion is then performed.

mask

specified timestamp format by the user.

transform(*dataframe: DataFrame*) → DataFrame

Performs a transformation to the feature pipeline.

Parameters
dataframe – input dataframe for the transformation.

Returns
Transformed dataframe.

Module contents

Holds all feature types to be part of a FeatureSet.

class butterfree.transform.features.**Feature**(*name: str*, *description: str*, *dtype: Optional[DataType] = None*, *from_column: Optional[str] = None*, *transformation: Optional[TransformComponent] = None*)

Bases: object

Defines a Feature.

A Feature is the result of a transformation over one (or more) data columns over an input dataframe. Transformations can be as simple as renaming, casting types, mathematical expressions or complex functions/models.

name

feature name. Can be use by the transformation to derive multiple output columns.

description

brief explanation regarding the feature.

dtype

data type for the output columns of this feature.

from_column

original column to build feature. Used when there is transformation or the transformation has no reference about the column to use for.

transformation

transformation that will be applied to create this feature.

property dtype: Any

Attribute dtype getter.

property from_column: Any

Attribute from_column getter.

get_output_columns() → List[str]

Get output columns that will be generated by this feature engineering.

Returns

Output columns names.

transform(*dataframe: DataFrame*) → DataFrame

Performs a transformation to the feature pipeline.

Parameters

dataframe – input dataframe for the transformation.

Returns

Transformed dataframe.

property transformation: Any

Attribute transformation getter.

class butterfree.transform.features.**KeyFeature**(*name: str*, *description: str*, *dtype: DataType*, *from_column: Optional[str] = None*, *transformation: Optional[TransformComponent] = None*)

Bases: *Feature*

Defines a KeyFeature.

A FeatureSet must contain one or more KeyFeatures, which will be used as keys when storing the feature set dataframe as tables. The Feature Set may validate keys are unique for the latest state of a feature set.

name

key name. Can be use by the transformation to derive multiple key columns.

description

brief explanation regarding the key.

dtype

data type for the output column of this key.

from_column

original column to build a key. Used when there is transformation or the transformation has no reference about the column to use for.

transformation

transformation that will be applied to create this key. Keys can be derived by transformations over any data column. Like a location hash based on latitude and longitude.

class butterfree.transform.features.**TimestampFeature**(*from_column: Optional[str] = None*, *transformation: Optional[TransformComponent] = None*, *from_ms: bool = False*, *mask: Optional[str] = None*)

Bases: *Feature*

Defines a TimestampFeature.

A FeatureSet must contain one TimestampFeature, which will be used as a time tag for the state of all features. By containing a timestamp feature, users may time travel over their features. The Feature Set may validate that the set of keys and timestamp are unique for a feature set.

By defining a TimestampColumn, the feature set will always contain a data column called "timestamp" of TimestampType (spark dtype).

from_column

original column to build a "timestamp" feature column. Used when there is transformation or the transformation has no reference about the column to use for. If from_column is None, the FeatureSet will assume the input dataframe already has a data column called "timestamp".

transformation

transformation that will be applied to create the "timestamp". Type casting will already happen when no transformation is given. But a timestamp can be derived from multiple columns, like year, month and day, for example. The transformation must always handle naming and typing.

from_ms

true if timestamp column presents milliseconds time unit. A

conversion is then performed.

mask

specified timestamp format by the user.

transform(*dataframe: DataFrame*) → DataFrame

Performs a transformation to the feature pipeline.

Parameters
dataframe – input dataframe for the transformation.

Returns
Transformed dataframe.

butterfree.transform.transformations package

Subpackages

butterfree.transform.transformations.user_defined_functions package

Submodules

Module contents

Submodules

Aggregated Transform entity.

class butterfree.transform.transformations.aggregated_transform.**AggregatedTransform**(*functions: List[Function]*, *filter_expression: Optional[str]* = *None*)

Bases: *TransformComponent*

Specifies an aggregation.

This transformation needs to be used within an AggregatedFeatureSet. Unlike the other transformations, this class won't have a transform method implemented.

The idea behing aggregating is that, in spark, we should execute all aggregation functions after a single groupby. So an AggregateFeatureSet will have many Features with AggregatedTransform. If each one of them needs to apply a groupby.agg(), then we must join all the results in the end, making this computation extremely slow.

Now, the AggregateFeatureSet will collect all Features' AggregatedTransform definitions and run, at once, a groupby.agg(*aggregations).

This class helps defining on a feature, which aggregation function will be applied to build a new aggregated column. Allowed aggregations are registered under the

allowed_aggregations property.

functions

namedtuple with aggregation function and data type.

filter_expression

sql boolean expression to be used inside agg function. The filter expression can be used to aggregate some column only with records that obey certain condition. Has the same behaviour of the following SQL expression: *agg(case when filter_expression then col end)*

Example

```
>>> from butterfree.transform.transformations import AggregatedTransform
>>> from butterfree.transform.features import Feature
>>> from butterfree.constants import DataType
>>> from butterfree.transform.utils import Function
>>> import pyspark.sql.functions as F
>>> feature = Feature(
...     name="feature",
...     description="aggregated transform",
...     transformation=AggregatedTransform(
...         functions=[
...                    Function(F.avg, DataType.DOUBLE),
...                    Function(F.stddev_pop, DataType.DOUBLE)],
...     ),
...     from_column="somenumber",
...)
>>> feature.get_output_columns()
['feature__avg', 'feature__stddev_pop']
>>> feature.transform(anydf)
NotImplementedError: ...
```

property aggregations: List[Tuple]

Aggregated spark columns.

property output_columns: List[str]

Columns names generated by the transformation.

transform(*dataframe: DataFrame*) → DataFrame

(NotImplemented) Performs a transformation to the feature pipeline.

For the AggregatedTransform, the transformation won't be applied without using an AggregatedFeatureSet.

Parameters
dataframe – input dataframe.

Raises
NotImplementedError. –

CustomTransform entity.

class butterfree.transform.transformations.custom_transform.**CustomTransform**(*transformer: Callable[[...], Any]*, ***kwargs: Any*)

Bases: *TransformComponent*

Defines a Custom Transform.

transformer

function to use for transforming the dataframe

****kwargs**
kwargs for the transformer

Example

It's necessary to instantiate the CustomTransform class using a custom method that must always receive a dataframe and the parent feature as arguments and the custom arguments must be passed to the builder through *kwargs.

```
>>> from butterfree.transform.transformations import CustomTransform
>>> from butterfree.transform.features import Feature
>>> from butterfree.constants import DataType
>>> from pyspark import SparkContext
>>> from pyspark.sql import session
>>> import pyspark.sql.functions as F
>>> sc = SparkContext.getOrCreate()
>>> spark = session.SparkSession(sc)
>>> df = spark.createDataFrame([(1, "2016-04-11 11:31:11", 200, 200),
...                             (1, "2016-04-11 11:44:12", 300, 300),
...                             (1, "2016-04-11 11:46:24", 400, 400),
...                             (1, "2016-04-11 12:03:21", 500, 500)]
...                            ).toDF("id", "timestamp", "feature1", "feature2")
>>> def divide(df, parent_feature, column1, column2):
...     name = parent_feature.get_output_columns()[0]
...     df = df.withColumn(name, F.col(column1) / F.col(column2))
...     return df
>>> feature = Feature(
...    name="feature",
...    description="custom transform usage example",
...    dtype=DataType.DOUBLE,
...    transformation=CustomTransform(
...        transformer=divide, column1="feature1", column2="feature2",
...    )
...)
>>> feature.transform(df).orderBy("timestamp").show()
+--------+--------+---+-------------------+--------+
|feature1|feature2| id|          timestamp|feature|
+--------+--------+---+-------------------+--------+
|     200|     200|  1|2016-04-11 11:31:11|    1.0|
|     300|     300|  1|2016-04-11 11:44:12|    1.0|
|     400|     400|  1|2016-04-11 11:46:24|    1.0|
|     500|     500|  1|2016-04-11 12:03:21|    1.0|
+--------+--------+---+-------------------+--------+
```

property output_columns: List[str]
Columns generated by transformation.

transform(*dataframe: DataFrame*) → DataFrame
Performs a transformation to the feature pipeline.

Parameters
dataframe – input dataframe to be transformed.

Returns
Transformed dataframe.

property transformer: Callable[[...], Any]

Function to use for transforming the dataframe.

H3 Transform entity.

class butterfree.transform.transformations.h3_transform.**H3HashTransform**(*h3_resolutions: List[int]*, *lat_column: str*, *lng_column: str*)

Bases: *TransformComponent*

Defines a H3 hash transformation.

h3_resolutions

h3 resolutions from 6 to 12.

lat_column

latitude column.

lng_column

longitude column.

Example

It's necessary to declare the desired h3 resolutions and latitude and longitude columns.

```
>>> from butterfree.transform.features import Feature
>>> from butterfree.transform.transformations.h3_transform import (
... H3HashTransform
...)
>>> from butterfree.constants import DataType
>>> from pyspark import SparkContext
>>> from pyspark.sql import session
>>> sc = SparkContext.getOrCreate()
>>> spark = session.SparkSession(sc)
>>> df = spark.createDataFrame([(1, 200, -23.554190, -46.670723),
...                             (1, 300, -23.554190, -46.670723),
...                             (1, 400, -23.554190, -46.670723),
...                             (1, 500, -23.554190, -46.670723)]
...                            ).toDF("id", "feature", "lat", "lng")
>>> feature = Feature(
...    name="feature",
...    description="h3 hash transform usage example",
...    dtype=DataType.STRING,
...    transformation=H3HashTransform(
...        h3_resolutions=[6, 7, 8, 9, 10, 11, 12],
...        lat_column="lat",
...        lng_column="lng",
...    )
... )
>>> feature.transform(df).show()
+-------+---+---------+----------+------------------+------------------+
|feature| id|      lat|       lng|lat_lng__h3_hash__6|lat_lng__h3_hash__7|
+-------+---+---------+----------+------------------+------------------+
|    200|  1|-23.55419|-46.670723|    86a8100efffffff|    87a8100eafffffff|
```

(continues on next page)

(continued from previous page)

```
|    300|  1|-23.55419|-46.670723|    86a8100effffffff|    87a8100eaffffff|
|    400|  1|-23.55419|-46.670723|    86a8100effffffff|    87a8100eaffffff|
|    500|  1|-23.55419|-46.670723|    86a8100effffffff|    87a8100eaffffff|
+-------+---+---------+----------+--------------------+--------------------+
```

property output_columns: List[str]

Columns generated by the transformation.

transform(*dataframe: DataFrame*) → DataFrame

Performs a transformation to the feature pipeline.

Parameters
dataframe – input dataframe.

Returns
Transformed dataframe.

with_stack() → *H3HashTransform*

Add a final Stack step to the transformation.

A new column will be created stacking all the the resolution columns generated by H3. The name of this column will be the parent name of H3Transform, for example, the name of the KeyFeature that has the H3 as a transformation.

butterfree.transform.transformations.h3_transform.**define_h3**(*lat: float*, *lng: float*, *resolution: int*) → Any

UDF for h3 hash retrieval.

butterfree.transform.transformations.h3_transform.**lat**

latitude column.

butterfree.transform.transformations.h3_transform.**lng**

longitude column.

butterfree.transform.transformations.h3_transform.**resolution**

desired h3 resolution.

Spark Function Transform entity.

class butterfree.transform.transformations.spark_function_transform.**SparkFunctionTransform**(*functions: List[*Function*]*)

Bases: *TransformComponent*

Defines an Spark Function.

function

namedtuple with spark function and data type.

Example

It's necessary to declare the function method, Any spark and user defined functions are supported.

```
>>> from butterfree.transform.transformations import SparkFunctionTransform
>>> from butterfree.constants.columns import TIMESTAMP_COLUMN
>>> from butterfree.transform.features import Feature
>>> from butterfree.transform.utils import Function
>>> from butterfree.constants import DataType
>>> from pyspark import SparkContext
>>> from pyspark.sql import session
>>> from pyspark.sql.types import TimestampType
>>> from pyspark.sql import functions
>>> sc = SparkContext.getOrCreate()
>>> spark = session.SparkSession(sc)
>>> df = spark.createDataFrame([(1, "2016-04-11 11:31:11", 200),
...                             (1, "2016-04-11 11:44:12", 300),
...                             (1, "2016-04-11 11:46:24", 400),
...                             (1, "2016-04-11 12:03:21", 500)]
...                            ).toDF("id", "timestamp", "feature")
>>> df = df.withColumn("timestamp", df.timestamp.cast(TimestampType()))
>>> feature = Feature(
...    name="feature",
...    description="spark function transform",
...    transformation=SparkFunctionTransform(
...       functions=[Function(functions.cos, DataType.DOUBLE)],)
...)
>>> feature.transform(df).orderBy("timestamp").show()
+---+-------------------+-------+--------------------+
| id|          timestamp|feature|        feature__cos|
+---+-------------------+-------+--------------------+
|  1|2016-04-11 11:31:11|    200|  0.4871876750070059|
|  1|2016-04-11 11:44:12|    300|-0.02209661927868...|
|  1|2016-04-11 11:46:24|    400|  -0.525296338642536|
|  1|2016-04-11 12:03:21|    500|  -0.883849273431478|
+---+-------------------+-------+--------------------+
```

We can use this transformation with windows.

```
>>> feature_row_windows = Feature(
...    name="feature",
...    description="spark function transform with windows",
...    transformation=SparkFunctionTransform(
...       functions=[Function(functions.avg, DataType.DOUBLE)],)
...                    .with_window(partition_by="id",
...                                 mode="row_windows",
...                                 window_definition=["2 events"],
...   )
...)
>>> feature_row_windows.transform(df).orderBy("timestamp").show()
+--------+---+-------------------+-------------------------------------+
|feature | id|          timestamp| feature_avg_over_2_events_row_windows|
+--------+---+-------------------+-------------------------------------+
|     200|  1|2016-04-11 11:31:11|                                200.0|
```

(continues on next page)

(continued from previous page)

```
|     300|  1|2016-04-11 11:44:12|                                      250.0|
|     400|  1|2016-04-11 11:46:24|                                      350.0|
|     500|  1|2016-04-11 12:03:21|                                      450.0|
+--------+---+-------------------+-------------------------------------------+
```

It's important to notice that transformation doesn't affect the dataframe granularity.

property output_columns: List[str]

Columns generated by the transformation.

transform(*dataframe: DataFrame*) → DataFrame

Performs a transformation to the feature pipeline.

Parameters

dataframe – input dataframe.

Returns

Transformed dataframe.

with_window(*partition_by: str*, *window_definition: List[str]*, *order_by: Optional[str] = None*, *mode: Optional[str] = None*) → *SparkFunctionTransform*

Create a list with windows defined.

SQL Expression Transform entity.

class butterfree.transform.transformations.sql_expression_transform.**SQLExpressionTransform**(*expression: str*)

Bases: *TransformComponent*

Defines an SQL Expression Transformation.

expression

SQL expression defined by the user.

Example

It's necessary to declare the custom SQL query, such that it corresponds to operations between existing columns in the dataframe. Besides, the usage of SparkSQL functions is also allowed. Finally, a "complete select statement", such as "select col_a * col_b from my_table", is not necessary, just the simple operations are required, for instance "col_a / col_b" or "col_a * col_b".

```
>>> from butterfree.transform.features import Feature
>>> from butterfree.transform.transformations import SQLExpressionTransform
>>> from butterfree.constants import DataType
>>> from pyspark import SparkContext
>>> from pyspark.sql import session
>>> import pyspark.sql.functions as F
>>> sc = SparkContext.getOrCreate()
>>> spark = session.SparkSession(sc)
>>> df = spark.createDataFrame([(1, "2016-04-11 11:31:11", 200, 200),
...                             (1, "2016-04-11 11:44:12", 300, 300),
...                             (1, "2016-04-11 11:46:24", 400, 400),
...                             (1, "2016-04-11 12:03:21", 500, 500)]
...                            ).toDF("id", "timestamp", "feature1", "feature2")
>>> feature = Feature(
```

(continues on next page)

(continued from previous page)

```
...     name="feature",
...     description="SQL expression transform usage example",
...     dtype=DataType.DOUBLE,
...     transformation=SQLExpressionTransform(expression="feature1/feature2"),
...)
>>> feature.transform(df).orderBy("timestamp").show()
+--------+--------+---+-------------------+----------------------+
|feature1|feature2| id|          timestamp|feature1_over_feature2|
+--------+--------+---+-------------------+----------------------+
|     200|     200|  1|2016-04-11 11:31:11|                   1.0|
|     300|     300|  1|2016-04-11 11:44:12|                   1.0|
|     400|     400|  1|2016-04-11 11:46:24|                   1.0|
|     500|     500|  1|2016-04-11 12:03:21|                   1.0|
+--------+--------+---+-------------------+----------------------+
```

property output_columns: List[str]

Columns generated by the transformation.

transform(*dataframe: DataFrame*) → DataFrame

Performs a transformation to the feature pipeline.

Parameters

dataframe – input dataframe.

Returns

Transformed dataframe.

Stack Transform entity.

class butterfree.transform.transformations.stack_transform.**StackTransform**(**columns_names: str*, *is_regex: bool = False*)

Bases: *TransformComponent*

Defines a Stack transformation.

For instantiation it is needed the name of the columns or a pattern to use to find the columns that need to be stacked. This transform generates just one column as output.

columns_names

full names or patterns to search for target columns on the dataframe. By default a single * character is considered a wildcard and can be anywhere in the string, multiple wildcards are not supported. Strings can also start with an *!* (exclamation mark), it indicates a negation, be it a regular string or simple pattern. When parameter :param is_regex: is *True*, simple patterns wildcards and negation are disabled and all strings are interpreted as regular expressions.

is_regex

boolean flag to indicate if columns_names passed are a Python regex string patterns.

Example

```
>>> from pyspark import SparkContext
>>> from pyspark.sql import session
>>> from butterfree.testing.dataframe import create_df_from_collection
>>> from butterfree.constants import DataType
>>> from butterfree.transform.transformations import StackTransform
>>> from butterfree.transform.features import Feature
>>> spark_context = SparkContext.getOrCreate()
>>> spark_session = session.SparkSession(spark_context)
>>> data = [
...     {"feature": 100, "id_a": 1, "id_b": 2},
...     {"feature": 120, "id_a": 3, "id_b": 4},
... ]
>>> df = create_df_from_collection(data, spark_context, spark_session)
>>> df.collect()
[Row(feature=100, id_a=1, id_b=2), Row(feature=120, id_a=3, id_b=4)]
>>> feature = Feature(
...     name="stack_ids",
...     description="id_a and id_b stacked in a single column.",
...     dtype=DataType.BIGINT,
...     transformation=StackTransform("id_a", "id_b"),
... )
>>> feature.transform(df).collect()
[
    Row(feature=100, id_a=1, id_b=2, stack_ids=1),
    Row(feature=100, id_a=1, id_b=2, stack_ids=2),
    Row(feature=120, id_a=3, id_b=4, stack_ids=3),
    Row(feature=120, id_a=3, id_b=4, stack_ids=4)
]
```

The StackTransform can be instantiated using a column pattern instead of the columns full names. Like this way:

```
>>> feature = Feature(
...     name="stack_ids",
...     description="id_a and id_b stacked in a single column.",
...     dtype=DataType.BIGINT,
...     transformation=StackTransform(columns_prefix="id_*"),
... )
```

property output_columns: List[str]

Columns generated by the transformation.

transform(*dataframe: DataFrame*) → DataFrame

Performs a transformation to the feature pipeline.

Parameters

dataframe – input dataframe.

Returns

Transformed dataframe.

Transform Abstract Class.

class butterfree.transform.transformations.transform_component.**TransformComponent**

Bases: ABC

Defines an abstract class for Transform entities.

parent

parent transform component.

abstract property output_columns: List[str]

Columns generated by the transformation.

property parent: Any

Parent transform component.

abstract transform(*dataframe: DataFrame*) → DataFrame

Performs a transformation to the feature pipeline.

Parameters
dataframe – input dataframe.

Returns
Transformed dataframe.

Module contents

Holds all transformations to be used by Features.

A transformation must inherit from a TransformComponent and handle data modification, renaming and cast types using parent's (a Feature) information.

class butterfree.transform.transformations.**AggregatedTransform**(*functions: List[Function]*, *filter_expression: Optional[str] = None*)

Bases: *TransformComponent*

Specifies an aggregation.

This transformation needs to be used within an AggregatedFeatureSet. Unlike the other transformations, this class won't have a transform method implemented.

The idea behing aggregating is that, in spark, we should execute all aggregation functions after a single groupby. So an AggregateFeatureSet will have many Features with AggregatedTransform. If each one of them needs to apply a groupby.agg(), then we must join all the results in the end, making this computation extremely slow.

Now, the AggregateFeatureSet will collect all Features' AggregatedTransform definitions and run, at once, a groupby.agg(*aggregations).

This class helps defining on a feature, which aggregation function will be applied to build a new aggregated column. Allowed aggregations are registered under the

allowed_aggregations property.

functions

namedtuple with aggregation function and data type.

filter_expression

sql boolean expression to be used inside agg function. The filter expression can be used to aggregate some column only with records that obey certain condition. Has the same behaviour of the following SQL expression: *agg(case when filter_expression then col end)*

Example

```
>>> from butterfree.transform.transformations import AggregatedTransform
>>> from butterfree.transform.features import Feature
>>> from butterfree.constants import DataType
>>> from butterfree.transform.utils import Function
>>> import pyspark.sql.functions as F
>>> feature = Feature(
...     name="feature",
...     description="aggregated transform",
...     transformation=AggregatedTransform(
...         functions=[
...                     Function(F.avg, DataType.DOUBLE),
...                     Function(F.stddev_pop, DataType.DOUBLE)],
...     ),
...     from_column="somenumber",
...)
>>> feature.get_output_columns()
['feature__avg', 'feature__stddev_pop']
>>> feature.transform(anydf)
NotImplementedError: ...
```

property aggregations: List[Tuple]

Aggregated spark columns.

property output_columns: List[str]

Columns names generated by the transformation.

transform(*dataframe: DataFrame*) → DataFrame

(NotImplemented) Performs a transformation to the feature pipeline.

For the AggregatedTransform, the transformation won't be applied without using an AggregatedFeatureSet.

Parameters
dataframe – input dataframe.

Raises
NotImplementedError. –

class butterfree.transform.transformations.**CustomTransform**(*transformer: Callable[[...], Any]*, ***kwargs: Any*)

Bases: *TransformComponent*

Defines a Custom Transform.

transformer

function to use for transforming the dataframe

****kwargs**

kwargs for the transformer

Example

It's necessary to instantiate the CustomTransform class using a custom method that must always receive a dataframe and the parent feature as arguments and the custom arguments must be passed to the builder through *kwargs.

```
>>> from butterfree.transform.transformations import CustomTransform
>>> from butterfree.transform.features import Feature
>>> from butterfree.constants import DataType
>>> from pyspark import SparkContext
>>> from pyspark.sql import session
>>> import pyspark.sql.functions as F
>>> sc = SparkContext.getOrCreate()
>>> spark = session.SparkSession(sc)
>>> df = spark.createDataFrame([(1, "2016-04-11 11:31:11", 200, 200),
...                             (1, "2016-04-11 11:44:12", 300, 300),
...                             (1, "2016-04-11 11:46:24", 400, 400),
...                             (1, "2016-04-11 12:03:21", 500, 500)]
...                            ).toDF("id", "timestamp", "feature1", "feature2")
>>> def divide(df, parent_feature, column1, column2):
...     name = parent_feature.get_output_columns()[0]
...     df = df.withColumn(name, F.col(column1) / F.col(column2))
...     return df
>>> feature = Feature(
...    name="feature",
...    description="custom transform usage example",
...    dtype=DataType.DOUBLE,
...    transformation=CustomTransform(
...        transformer=divide, column1="feature1", column2="feature2",
...    )
...)
>>> feature.transform(df).orderBy("timestamp").show()
+--------+--------+---+-------------------+--------+
|feature1|feature2| id|          timestamp|feature|
+--------+--------+---+-------------------+--------+
|     200|     200|  1|2016-04-11 11:31:11|     1.0|
|     300|     300|  1|2016-04-11 11:44:12|     1.0|
|     400|     400|  1|2016-04-11 11:46:24|     1.0|
|     500|     500|  1|2016-04-11 12:03:21|     1.0|
+--------+--------+---+-------------------+--------+
```

property output_columns: List[str]

Columns generated by transformation.

transform(*dataframe: DataFrame*) → DataFrame

Performs a transformation to the feature pipeline.

Parameters

dataframe – input dataframe to be transformed.

Returns

Transformed dataframe.

property transformer: Callable[[...], Any]

Function to use for transforming the dataframe.

class butterfree.transform.transformations.**SQLExpressionTransform**(*expression: str*)

Bases: *TransformComponent*

Defines an SQL Expression Transformation.

expression

SQL expression defined by the user.

Example

It's necessary to declare the custom SQL query, such that it corresponds to operations between existing columns in the dataframe. Besides, the usage of SparkSQL functions is also allowed. Finally, a "complete select statement", such as "select col_a * col_b from my_table", is not necessary, just the simple operations are required, for instance "col_a / col_b" or "col_a * col_b".

```
>>> from butterfree.transform.features import Feature
>>> from butterfree.transform.transformations import SQLExpressionTransform
>>> from butterfree.constants import DataType
>>> from pyspark import SparkContext
>>> from pyspark.sql import session
>>> import pyspark.sql.functions as F
>>> sc = SparkContext.getOrCreate()
>>> spark = session.SparkSession(sc)
>>> df = spark.createDataFrame([(1, "2016-04-11 11:31:11", 200, 200),
...                             (1, "2016-04-11 11:44:12", 300, 300),
...                             (1, "2016-04-11 11:46:24", 400, 400),
...                             (1, "2016-04-11 12:03:21", 500, 500)]
...                            ).toDF("id", "timestamp", "feature1", "feature2")
>>> feature = Feature(
...     name="feature",
...     description="SQL expression transform usage example",
...     dtype=DataType.DOUBLE,
...     transformation=SQLExpressionTransform(expression="feature1/feature2"),
...)
>>> feature.transform(df).orderBy("timestamp").show()
+--------+--------+---+-------------------+---------------------+
|feature1|feature2| id|          timestamp|feature1_over_feature2|
+--------+--------+---+-------------------+---------------------+
|     200|     200|  1|2016-04-11 11:31:11|                  1.0|
|     300|     300|  1|2016-04-11 11:44:12|                  1.0|
|     400|     400|  1|2016-04-11 11:46:24|                  1.0|
|     500|     500|  1|2016-04-11 12:03:21|                  1.0|
+--------+--------+---+-------------------+---------------------+
```

property output_columns: List[str]

Columns generated by the transformation.

transform(*dataframe: DataFrame*) → DataFrame

Performs a transformation to the feature pipeline.

Parameters

dataframe – input dataframe.

Returns

Transformed dataframe.

class butterfree.transform.transformations.**SparkFunctionTransform**(*functions: List[*Function*]*)

Bases: *TransformComponent*

Defines an Spark Function.

function

namedtuple with spark function and data type.

Example

It's necessary to declare the function method, Any spark and user defined functions are supported.

```
>>> from butterfree.transform.transformations import SparkFunctionTransform
>>> from butterfree.constants.columns import TIMESTAMP_COLUMN
>>> from butterfree.transform.features import Feature
>>> from butterfree.transform.utils import Function
>>> from butterfree.constants import DataType
>>> from pyspark import SparkContext
>>> from pyspark.sql import session
>>> from pyspark.sql.types import TimestampType
>>> from pyspark.sql import functions
>>> sc = SparkContext.getOrCreate()
>>> spark = session.SparkSession(sc)
>>> df = spark.createDataFrame([(1, "2016-04-11 11:31:11", 200),
...                             (1, "2016-04-11 11:44:12", 300),
...                             (1, "2016-04-11 11:46:24", 400),
...                             (1, "2016-04-11 12:03:21", 500)]
...                            ).toDF("id", "timestamp", "feature")
>>> df = df.withColumn("timestamp", df.timestamp.cast(TimestampType()))
>>> feature = Feature(
...    name="feature",
...    description="spark function transform",
...    transformation=SparkFunctionTransform(
...       functions=[Function(functions.cos, DataType.DOUBLE)],)
...)
>>> feature.transform(df).orderBy("timestamp").show()
+---+-------------------+-------+--------------------+
| id|          timestamp|feature|        feature__cos|
+---+-------------------+-------+--------------------+
|  1|2016-04-11 11:31:11|    200|  0.4871876750070059|
|  1|2016-04-11 11:44:12|    300|-0.02209661927868...|
|  1|2016-04-11 11:46:24|    400|  -0.525296338642536|
|  1|2016-04-11 12:03:21|    500|  -0.883849273431478|
+---+-------------------+-------+--------------------+
```

We can use this transformation with windows.

```
>>> feature_row_windows = Feature(
...    name="feature",
...    description="spark function transform with windows",
...    transformation=SparkFunctionTransform(
...       functions=[Function(functions.avg, DataType.DOUBLE)],)
...                    .with_window(partition_by="id",
```

(continues on next page)

(continued from previous page)

```
...                                 mode="row_windows",
...                                 window_definition=["2 events"],
...   )
...)
>>> feature_row_windows.transform(df).orderBy("timestamp").show()
+--------+---------------------+-------------------------------------+
|feature | id|          timestamp| feature_avg_over_2_events_row_windows|
+--------+---+-------------------+-------------------------------------+
|     200|  1|2016-04-11 11:31:11|                                200.0|
|     300|  1|2016-04-11 11:44:12|                                250.0|
|     400|  1|2016-04-11 11:46:24|                                350.0|
|     500|  1|2016-04-11 12:03:21|                                450.0|
+--------+---+-------------------+-------------------------------------+
```

It's important to notice that transformation doesn't affect the dataframe granularity.

property output_columns: List[str]

Columns generated by the transformation.

transform(*dataframe: DataFrame*) → DataFrame

Performs a transformation to the feature pipeline.

Parameters
dataframe – input dataframe.

Returns
Transformed dataframe.

with_window(*partition_by: str*, *window_definition: List[str]*, *order_by: Optional[str] = None*, *mode: Optional[str] = None*) → *SparkFunctionTransform*

Create a list with windows defined.

class butterfree.transform.transformations.**StackTransform**(**columns_names: str*, *is_regex: bool = False*)

Bases: *TransformComponent*

Defines a Stack transformation.

For instantiation it is needed the name of the columns or a pattern to use to find the columns that need to be stacked. This transform generates just one column as output.

columns_names

full names or patterns to search for target columns on the dataframe. By default a single * character is considered a wildcard and can be anywhere in the string, multiple wildcards are not supported. Strings can also start with an *!* (exclamation mark), it indicates a negation, be it a regular string or simple pattern. When parameter :param is_regex: is *True*, simple patterns wildcards and negation are disabled and all strings are interpreted as regular expressions.

is_regex

boolean flag to indicate if columns_names passed are a Python regex string patterns.

Example

```
>>> from pyspark import SparkContext
>>> from pyspark.sql import session
>>> from butterfree.testing.dataframe import create_df_from_collection
>>> from butterfree.constants import DataType
>>> from butterfree.transform.transformations import StackTransform
>>> from butterfree.transform.features import Feature
>>> spark_context = SparkContext.getOrCreate()
>>> spark_session = session.SparkSession(spark_context)
>>> data = [
...     {"feature": 100, "id_a": 1, "id_b": 2},
...     {"feature": 120, "id_a": 3, "id_b": 4},
... ]
>>> df = create_df_from_collection(data, spark_context, spark_session)
>>> df.collect()
[Row(feature=100, id_a=1, id_b=2), Row(feature=120, id_a=3, id_b=4)]
>>> feature = Feature(
...     name="stack_ids",
...     description="id_a and id_b stacked in a single column.",
...     dtype=DataType.BIGINT,
...     transformation=StackTransform("id_a", "id_b"),
... )
>>> feature.transform(df).collect()
[
    Row(feature=100, id_a=1, id_b=2, stack_ids=1),
    Row(feature=100, id_a=1, id_b=2, stack_ids=2),
    Row(feature=120, id_a=3, id_b=4, stack_ids=3),
    Row(feature=120, id_a=3, id_b=4, stack_ids=4)
]
```

The StackTransform can be instantiated using a column pattern instead of the columns full names. Like this way:

```
>>> feature = Feature(
...     name="stack_ids",
...     description="id_a and id_b stacked in a single column.",
...     dtype=DataType.BIGINT,
...     transformation=StackTransform(columns_prefix="id_*"),
... )
```

property output_columns: List[str]

Columns generated by the transformation.

transform(*dataframe: DataFrame*) → DataFrame

Performs a transformation to the feature pipeline.

Parameters

dataframe – input dataframe.

Returns

Transformed dataframe.

class butterfree.transform.transformations.**TransformComponent**

Bases: ABC

Defines an abstract class for Transform entities.

parent

parent transform component.

abstract property output_columns: List[str]

Columns generated by the transformation.

property parent: Any

Parent transform component.

abstract transform(*dataframe: DataFrame*) → DataFrame

Performs a transformation to the feature pipeline.

Parameters
dataframe – input dataframe.

Returns
Transformed dataframe.

butterfree.transform.utils package

Submodules

Utils for date range generation.

butterfree.transform.utils.date_range.**get_date_range**(*client: SparkClient*, *start_date: Union[str, datetime]*, *end_date: Union[str, datetime]*, *step: Optional[int] = None*) → DataFrame

Create a date range dataframe.

The dataframe returning from this method will containing a single column TIMESTAMP_COLUMN, of timestamp type, with dates between start and end.

Parameters

- **client** – a spark client.
- **start_date** – range beginning value (inclusive).
- **end_date** – range last value (exclusive)
- **step** – optional step, in seconds.

Returns
A single column date range spark dataframe.

Utils for custom or spark function to generation namedtuple.

class butterfree.transform.utils.function.**Function**(*func: Callable*, *data_type: DataType*)

Bases: object

Define a class Function.

Like a namedtuple:
Function = namedtuple("Function", ["function", "data_type"]).

func

custom or spark functions, such as avg, std, count. For more information check spark functions:

'https://spark.apache.org/docs/2.3.1/api/python/_modules/pyspark/sql/functions.html'

For custom functions, look the path:
'butterfree/transform/transformations/user_defined_functions'.

data_type
data type for the output columns.

property data_type: *DataType*
Function to be used in the transformation.

property func: Callable
Function to be used in the transformation.

Holds function for defining window in DataFrames.

class butterfree.transform.utils.window_spec.**FrameBoundaries**(*mode: Optional[str]*, *window_definition: str*)

Bases: object

Utility functions for defining the frame boundaries.

Parameters

- **mode** – available modes to be used in time aggregations.
- **window_definition** – time ranges to be used in the windows,
- **second** (*it can be*) –

get(*window: WindowSpec*) → Any
Returns window with or without the frame boundaries.

property window_size: int
Returns window size.

property window_unit: str
Returns window unit.

class butterfree.transform.utils.window_spec.**Window**(*window_definition: str*, *partition_by: Optional[Union[Column, str, List[str]]] = None*, *order_by: Optional[Union[Column, str]] = None*, *mode: Optional[str] = None*, *slide: Optional[str] = None*)

Bases: object

Utility functions for defining a window specification.

Parameters

- **partition_by** – he partitioning defined.
- **order_by** – the ordering defined.
- **mode** – available modes to be used in time aggregations.
- **window_definition** – time ranges to be used in the windows, it can be second(s), minute(s), hour(s), day(s), week(s) and year(s),

Use the static methods in *Window* to create a WindowSpec.

DEFAULT_SLIDE_DURATION: str = '1 day'

get() → Any

Defines a common window to be used both in time and rows windows.

get_name() → str

Return window suffix name based on passed criteria.

Module contents

This module holds utils to be used by transformations.

class butterfree.transform.utils.**Function**(*func: Callable*, *data_type:* DataType)

Bases: object

Define a class Function.

Like a namedtuple:
Function = namedtuple("Function", ["function", "data_type"]).

func

custom or spark functions, such as avg, std, count. For more information check spark functions:

'https://spark.apache.org/docs/2.3.1/api/python/_modules/pyspark/sql/functions.html'

For custom functions, look the path:
'butterfree/transform/transformations/user_defined_functions'.

data_type

data type for the output columns.

property data_type: *DataType*

Function to be used in the transformation.

property func: Callable

Function to be used in the transformation.

class butterfree.transform.utils.**Window**(*window_definition: str*, *partition_by: Optional[Union[Column, str, List[str]]] = None*, *order_by: Optional[Union[Column, str]] = None*, *mode: Optional[str] = None*, *slide: Optional[str] = None*)

Bases: object

Utility functions for defining a window specification.

Parameters

- **partition_by** – he partitioning defined.
- **order_by** – the ordering defined.
- **mode** – available modes to be used in time aggregations.
- **window_definition** – time ranges to be used in the windows, it can be second(s), minute(s), hour(s), day(s), week(s) and year(s),

Use the static methods in *Window* to create a WindowSpec.

DEFAULT_SLIDE_DURATION: str = '1 day'

get() → Any

Defines a common window to be used both in time and rows windows.

get_name() → str

Return window suffix name based on passed criteria.

Submodules

AggregatedFeatureSet entity.

class butterfree.transform.aggregated_feature_set.**AggregatedFeatureSet**(*name: str*, *entity: str*, *description: str*, *keys: List[KeyFeature]*, *timestamp: TimestampFeature*, *features: List[Feature]*)

Bases: *FeatureSet*

Holds metadata about the aggregated feature set.

This class overrides some methods of the parent FeatureSet class and has specific methods for aggregations.

The AggregatedTransform can only be used on AggregatedFeatureSets. The construct method will be responsible by collecting every feature's transformation definitions so it can run a groupby over the input dataframe, taking into account whether the user want's to run an rolling window aggregation, pivoting or just apply aggregation functions.

Example

This an example regarding the aggregated feature set definition. All features and its transformations are defined.

```
>>> from butterfree.transform.aggregated_feature_set import (
...       AggregatedFeatureSet
... )
>>> from butterfree.transform.features import (
...     Feature,
...     KeyFeature,
...     TimestampFeature,
...)
>>> from butterfree.transform.transformations import (
...     AggregatedTransform,
... )
>>> from butterfree.constants import DataType
>>> from butterfree.clients import SparkClient
>>> from butterfree.transform.utils import Function
>>> import pyspark.sql.functions as F
>>> client = SparkClient()
>>> client.conn.conf.set("spark.sql.session.timeZone", "UTC")
>>> dataframe = client.conn.createDataFrame(
...     [
...         (1, "2020-01-01 13:01:00+000", 1000, "publicado"),
...         (2, "2020-01-01 14:01:00+000", 2000, "publicado"),
...         (1, "2020-01-02 13:01:00+000", 2000, "alugado"),
```

(continues on next page)

(continued from previous page)

```
...         (1, "2020-01-03 13:01:00+000", 1000, "despublicado"),
...         (2, "2020-01-09 14:01:00+000", 1000, "despublicado"),
...     ],
...     ("id", "ts", "rent", "status"),
... )
>>> dataframe = dataframe.withColumn("ts", dataframe["ts"].cast("timestamp"))
>>> feature_set = AggregatedFeatureSet(
...    name="aggregated_feature_set",
...    entity="entity",
...    description="description",
...    features=[
...        Feature(
...            name="feature1",
...            description="test",
...            transformation=AggregatedTransform(
...                 functions=[
...                    Function(F.avg, DataType.DOUBLE),
...                    Function(F.stddev_pop, DataType.DOUBLE)],
...             ),
...             from_column="rent",
...        ),
...    ],
...    keys=[KeyFeature(name="id", description="lul")],
...    timestamp=TimestampFeature(from_column="ts"),
...)
>>> result = feature_set.construct(
...     dataframe=dataframe,
...     client=client,
...     end_date="2020-01-15"
... )
>>> result.show()
+---+-------------------+-------------+----------------+
| id|          timestamp|feature1__avg|feature1__stddev|
+---+-------------------+-------------+----------------+
|  1|2020-01-01 13:01:00|       1000.0|            null|
|  1|2020-01-03 13:01:00|       1000.0|            null|
|  1|2020-01-02 13:01:00|       2000.0|            null|
|  2|2020-01-09 14:01:00|       1000.0|            null|
|  2|2020-01-01 14:01:00|       2000.0|            null|
+---+-------------------+-------------+----------------+
```

Since you didn't define a window, the AggregateFeatureSet will always group by keys and timestamp feature columns. So in this example, there will be no changes to the dataframe, since it doesn't duplicate on id and timestamp :)

Let's run one example with windows:

```
>>> feature_set.with_windows(definitions=["3 days"])
>>> result = feature_set.construct(
...     dataframe=dataframe,
...     client=client,
...     end_date="2020-01-15"
... )
```

(continues on next page)

(continued from previous page)

```
>>> result.orderBy("timestamp", "id").show()
+---+-------------------+-----------------------------------------+
| id|          timestamp|feature1__avg_over_3_days_rolling_windows|
+---+-------------------+-----------------------------------------+
|  1|2020-01-01 00:00:00|                                     null|
|  2|2020-01-01 00:00:00|                                     null|
|  1|2020-01-02 00:00:00|                                   1000.0|
|  2|2020-01-02 00:00:00|                                   2000.0|
|  1|2020-01-03 00:00:00|                                   1500.0|
|  1|2020-01-04 00:00:00|                 1333.3333333333333|
|  1|2020-01-05 00:00:00|                                   1500.0|
|  2|2020-01-05 00:00:00|                                     null|
|  1|2020-01-06 00:00:00|                                   1000.0|
|  1|2020-01-07 00:00:00|                                     null|
|  2|2020-01-10 00:00:00|                                   1000.0|
|  2|2020-01-13 00:00:00|                                     null|
+---+-------------------+-----------------------------------------+
```

id	timestamp	feature1__stddev_over_3_days_rolling_windows
1 2 1 2 1 1 1 2 1 1 2 2	2020-01-01 00:00:00 2020-01-01 00:00:00 2020-01-02 00:00:00 2020-01-02 00:00:00 2020-01-03 00:00:00 2020-01-04 00:00:00 2020-01-05 00:00:00 2020-01-05 00:00:00 2020-01-06 00:00:00 2020-01-07 00:00:00 2020-01-10 00:00:00 2020-01-13 00:00:00	null null null null 707.1067811865476 577.3502691896258 707.1067811865476 null null null null null

(Had to break down the table result.)

And with pivot:

```
>>> feature_set.with_pivot(column="status", values=["publicado", "despublicado"])
+---+-------------------+----------------------+-------------------------+
| id|          timestamp|publicado_feature1__avg|publicado_feature1__stddev|
+---+-------------------+----------------------+-------------------------+
|  1|2020-01-01 13:01:00|                1000.0|                     null|
|  2|2020-01-01 14:01:00|                2000.0|                     null|
|  1|2020-01-02 13:01:00|                  null|                     null|
|  1|2020-01-03 13:01:00|                  null|                     null|
|  2|2020-01-09 14:01:00|                  null|                     null|
+---+-------------------+----------------------+-------------------------+
```

id	timestamp	despublicado_feature1__avg	despublicado_feature1__stddev
1 2 1 1 2	2020-01-01 13:01:00 2020-01-01 14:01:00 2020-01-02 13:01:00 2020-01-03 13:01:00 2020-01-09 14:01:00	null null null 1000.0 1000.0	null null null null null

As you can see, we need to pass the values you want to pivot. It optimizes this processing in spark and allows ignoring values when pivoting. If you wanted to get the pivot aggregation for "alugado" too, just use:

```
>>> feature_set.with_pivot(
...     column="status", values=["publicado", "despublicado", "alugado"]
... )
```

You can also run it with pivot AND windows:

```
>>> feature_set.with_pivot(
...     column="status",
...     values=["publicado", "despublicado", "alugado"]
... ).with_windows(definitions=["1 day", "2 weeks"])
```

The construct method will execute the feature set, computing all the defined aggregated transformations at once.

Remember: when using an AggregatedFeatureSet without window, the group will use the timestamp column.

construct(*dataframe: DataFrame*, *client:* SparkClient, *end_date: Optional[str] = None*, *num_processors: Optional[int] = None*, *start_date: Optional[str] = None*) → DataFrame

Use all the features to build the feature set dataframe.

After that, there's the caching of the dataframe, however since cache() in Spark is lazy, an action is triggered in order to force persistence, but we only cache if it is not a streaming spark dataframe.

Parameters

- **dataframe** – input dataframe to be transformed by the features.
- **client** – client responsible for connecting to Spark session.
- **end_date** – user defined max date for having aggregated data (exclusive).
- **num_processors** – cluster total number of processors for repartitioning.
- **start_date** – user defined min date for having aggregated data.

Returns

Spark dataframe with all the feature columns.

define_start_date(*start_date: Optional[str] = None*) → Optional[str]

Get aggregated feature set start date.

Parameters

start_date – start date regarding source dataframe.

Returns

start date.

property features: List[*Feature*]

Features to compose the feature set.

property features_columns: List[str]

Name of the columns of all features in feature set.

get_schema() → List[Dict[str, Any]]

Get feature set schema.

Returns

List of dicts with the feature set schema.

with_distinct(*subset: List*, *keep: str = 'last'*) → *AggregatedFeatureSet*

Add a distinct configuration for your aggregated feature set.

Parameters

- **subset** – the columns where it will identify duplicates.
- **keep** – determines which duplicates to keep. Default 'last'. - first : Ascending sorting by timestamp. - last : Descending sorting by timestamp.

Returns

An AggregatedFeatureSet configured with distinct.

with_pivot(*column: str*, *values: Optional[List[Union[bool, float, int, str]]]*) → *AggregatedFeatureSet*

Add a pivot configuration for your aggregated feature set.

This means we will group the input data, pivot over the column parameter and run each aggregation function over the columns within each value group in the values parameter. In spark it will be something like: dataframe.groupBy(*group).pivot(column, values).agg(*aggregations)

Parameters

- **column** – the column, containing categorical values, to pivot on.
- **values** – the distinct values you want to be pivoted.

Returns

An AggregatedFeatureSet configured with pivot.

with_windows(*definitions: List[str]*, *slide: Optional[str] = None*) → *AggregatedFeatureSet*

Create a list with windows defined.

FeatureSet entity.

class butterfree.transform.feature_set.**FeatureSet**(*name: str*, *entity: str*, *description: str*, *keys: List[*KeyFeature*]*, *timestamp:* TimestampFeature, *features: List[*Feature*]*)

Bases: *HookableComponent*

Holds metadata about the feature set and constructs the final dataframe.

name

name of the feature set.

entity

business context tag for the feature set, an entity for which we are creating all these features.

description

details about the feature set purpose.

keys

key features to define this feature set. Values for keys (may be a composition) should be unique on each moment in time (controlled by the TimestampFeature).

timestamp

A single feature that define a timestamp for each observation in this feature set.

features

features to compose the feature set.

Example

This an example regarding the feature set definition. All features and its transformations are defined.

```
>>> from butterfree.transform import FeatureSet
>>> from butterfree.transform.features import (
...     Feature,
...     KeyFeature,
...     TimestampFeature,
...)
>>> from butterfree.transform.transformations import (
...     SparkFunctionTransform,
...     CustomTransform,
... )
>>> from butterfree.constants import DataType
>>> from butterfree.transform.utils import Function
>>> import pyspark.sql.functions as F
```

```
>>> def divide(df, fs, column1, column2):
...     name = fs.get_output_columns()[0]
...     df = df.withColumn(name, F.col(column1) / F.col(column2))
...     return df
```

```
>>> feature_set = FeatureSet(
...    name="feature_set",
...    entity="entity",
...    description="description",
...    features=[
...        Feature(
...            name="feature1",
...            description="test",
...            transformation=SparkFunctionTransform(
...                 functions=[
...                            Function(F.avg, DataType.DOUBLE),
...                            Function(F.stddev_pop, DataType.DOUBLE)]
...             ).with_window(
...                 partition_by="id",
...                 order_by=TIMESTAMP_COLUMN,
...                 mode="fixed_windows",
...                 window_definition=["2 minutes", "15 minutes"],
...             ),
...        ),
...        Feature(
...            name="divided_feature",
...            description="unit test",
...            transformation=CustomTransform(
...                transformer=divide, column1="feature1", column2="feature2",
...            ),
...        ),
...    ],
...    keys=[KeyFeature(name="id", description="The user's Main ID or device ID")],
...    timestamp=TimestampFeature(),
...)
```

```
>>> feature_set.construct(dataframe=dataframe)
```

This last method (construct) will execute the feature set, computing all the defined transformations.

There's also a functionality regarding the construct method within the scope of FeatureSet called filter_duplicated_rows. We drop rows that have repeated values over key columns and timestamp column, we do this in order to reduce our dataframe (regarding the number of rows). A detailed explation of this method can be found at filter_duplicated_rows docstring.

property columns: List[str]

All data columns within this feature set.

This references all data columns that will be created by the construct method, given keys, timestamp and features of this feature set.

Returns

List of column names built in this feature set.

construct(*dataframe: DataFrame*, *client:* SparkClient, *end_date: Optional[str] = None*, *num_processors: Optional[int] = None*, *start_date: Optional[str] = None*) → DataFrame

Use all the features to build the feature set dataframe.

After that, there's the caching of the dataframe, however since cache() in Spark is lazy, an action is triggered in order to force persistence.

Parameters

- **dataframe** – input dataframe to be transformed by the features.
- **client** – client responsible for connecting to Spark session.
- **start_date** – user defined start date.
- **end_date** – user defined end date.
- **num_processors** – cluster total number of processors for repartitioning.

Returns

Spark dataframe with all the feature columns.

define_start_date(*start_date: Optional[str] = None*) → Optional[str]

Get feature set start date.

Parameters

start_date – start date regarding source dataframe.

Returns

start date.

property description: str

Details about the feature set purpose.

property entity: str

Business context tag for the feature set.

property features: List[*Feature*]

Features to compose the feature set.

property features_columns: List[str]

Name of the columns of all features in feature set.

get_schema() → List[Dict[str, Any]]

Get feature set schema.

Returns

List of dicts regarding cassandra feature set schema.

property keys: List[*KeyFeature*]

Key features to define this feature set.

property keys_columns: List[str]

Name of the columns of all keys in feature set.

property name: str

Name of the feature set.

property timestamp: *TimestampFeature*

Defines a timestamp for each observation in this feature set.

property timestamp_column: str

Name of the timestamp column in feature set.

Module contents

The Transform Component of a Feature Set.

class butterfree.transform.**FeatureSet**(*name: str*, *entity: str*, *description: str*, *keys: List[*KeyFeature*]*, *timestamp:* TimestampFeature, *features: List[*Feature*]*)

Bases: *HookableComponent*

Holds metadata about the feature set and constructs the final dataframe.

name

name of the feature set.

entity

business context tag for the feature set, an entity for which we are creating all these features.

description

details about the feature set purpose.

keys

key features to define this feature set. Values for keys (may be a composition) should be unique on each moment in time (controlled by the TimestampFeature).

timestamp

A single feature that define a timestamp for each observation in this feature set.

features

features to compose the feature set.

Example

This an example regarding the feature set definition. All features and its transformations are defined.

```
>>> from butterfree.transform import FeatureSet
>>> from butterfree.transform.features import (
...     Feature,
...     KeyFeature,
...     TimestampFeature,
...)
>>> from butterfree.transform.transformations import (
...     SparkFunctionTransform,
...     CustomTransform,
... )
>>> from butterfree.constants import DataType
>>> from butterfree.transform.utils import Function
>>> import pyspark.sql.functions as F
```

```
>>> def divide(df, fs, column1, column2):
...     name = fs.get_output_columns()[0]
...     df = df.withColumn(name, F.col(column1) / F.col(column2))
...     return df
```

```
>>> feature_set = FeatureSet(
...    name="feature_set",
...    entity="entity",
...    description="description",
...    features=[
...        Feature(
...            name="feature1",
...            description="test",
...            transformation=SparkFunctionTransform(
...                 functions=[
...                            Function(F.avg, DataType.DOUBLE),
...                            Function(F.stddev_pop, DataType.DOUBLE)]
...             ).with_window(
...                 partition_by="id",
...                 order_by=TIMESTAMP_COLUMN,
...                 mode="fixed_windows",
...                 window_definition=["2 minutes", "15 minutes"],
...             ),
...        ),
...        Feature(
...            name="divided_feature",
...            description="unit test",
...            transformation=CustomTransform(
...                transformer=divide, column1="feature1", column2="feature2",
...            ),
...        ),
...    ],
...    keys=[KeyFeature(name="id", description="The user's Main ID or device ID")],
...    timestamp=TimestampFeature(),
...)
```

```
>>> feature_set.construct(dataframe=dataframe)
```

This last method (construct) will execute the feature set, computing all the defined transformations.

There's also a functionality regarding the construct method within the scope of FeatureSet called filter_duplicated_rows. We drop rows that have repeated values over key columns and timestamp column, we do this in order to reduce our dataframe (regarding the number of rows). A detailed explation of this method can be found at filter_duplicated_rows docstring.

property columns: List[str]

All data columns within this feature set.

This references all data columns that will be created by the construct method, given keys, timestamp and features of this feature set.

Returns

List of column names built in this feature set.

construct(*dataframe: DataFrame*, *client:* SparkClient, *end_date: Optional[str] = None*, *num_processors: Optional[int] = None*, *start_date: Optional[str] = None*) → DataFrame

Use all the features to build the feature set dataframe.

After that, there's the caching of the dataframe, however since cache() in Spark is lazy, an action is triggered in order to force persistence.

Parameters

- **dataframe** – input dataframe to be transformed by the features.
- **client** – client responsible for connecting to Spark session.
- **start_date** – user defined start date.
- **end_date** – user defined end date.
- **num_processors** – cluster total number of processors for repartitioning.

Returns

Spark dataframe with all the feature columns.

define_start_date(*start_date: Optional[str] = None*) → Optional[str]

Get feature set start date.

Parameters

start_date – start date regarding source dataframe.

Returns

start date.

property description: str

Details about the feature set purpose.

property entity: str

Business context tag for the feature set.

property features: List[*Feature*]

Features to compose the feature set.

property features_columns: List[str]

Name of the columns of all features in feature set.

get_schema() → List[Dict[str, Any]]

Get feature set schema.

Returns
List of dicts regarding cassandra feature set schema.

property keys: List[*KeyFeature*]

Key features to define this feature set.

property keys_columns: List[str]

Name of the columns of all keys in feature set.

property name: str

Name of the feature set.

property timestamp: *TimestampFeature*

Defines a timestamp for each observation in this feature set.

property timestamp_column: str

Name of the timestamp column in feature set.

butterfree.validations package

Submodules

Validation implementing basic checks over the dataframe.

class butterfree.validations.basic_validaton.**BasicValidation**(*dataframe: Optional[DataFrame] = None*)

Bases: *Validation*

Basic validation suite for Feature Set's dataframe.

dataframe

object to be verified

check() → None

Check basic validation properties about the dataframe.

Raises
ValueError – if any of the verifications fail

validate_column_ts() → None

Check dataframe's ts column.

Raises
ValueError – if dataframe don't have a column named ts.

validate_df_is_empty() → None

Check dataframe emptiness.

Raises
ValueError – if dataframe is empty and is not streaming.

validate_df_is_spark_df() → None

Check type of dataframe object.

Raises
ValueError – if dataframe is not instance of pyspark.sql.DataFrame.

Abstract Validation class.

class butterfree.validations.validation.**Validation**(*dataframe: Optional[DataFrame] = None*)

Bases: ABC

Validate dataframe properties.

dataframe
data to be verified.

abstract check() → None
Check validation properties about the dataframe.

Raises
ValueError – if any of the verifications fail.

input(*dataframe: DataFrame*) → *Validation*
Input a dataframe to check.

Parameters
dataframe – data to check.

Module contents

Holds dataframe validate for multiple destinations.

class butterfree.validations.**BasicValidation**(*dataframe: Optional[DataFrame] = None*)

Bases: *Validation*

Basic validation suite for Feature Set's dataframe.

dataframe
object to be verified

check() → None
Check basic validation properties about the dataframe.

Raises
ValueError – if any of the verifications fail

validate_column_ts() → None
Check dataframe's ts column.

Raises
ValueError – if dataframe don't have a column named ts.

validate_df_is_empty() → None
Check dataframe emptiness.

Raises
ValueError – if dataframe is empty and is not streaming.

validate_df_is_spark_df() → None
Check type of dataframe object.

Raises
ValueError – if dataframe is not instance of pyspark.sql.DataFrame.

Module contents

Module docstring example, following Google's docstring style.

1.10 Command-line Interface (CLI)

Butterfree has now a command-line interface, introduced with the new automatic migration ability.

As soon as you install butterfree, you can check what's available through butterfree's cli with:

```
$~ butterfree --help
```

1.10.1 Automated Database Schema Migration

When developing your feature sets, you need also to prepare your database for the changes to come into your Feature Store. Normally, when creating a new feature set, you needed to manually create a new table in cassandra. Or, when creating a new feature in an existing feature set, you needed to create new column in cassandra too.

Now, you can just use `butterfree migrate apply ...`, butterfree will scan your python files, looking for classes that inherit from `butterfree.pipelines.FeatureSetPipeline`, then compare its schema with the database schema where the feature set would be written. Then it will prepare migration queries and run against the databases.

For more information, please, check `butterfree migrate apply --help` :)

1.10.2 Supported databases

This functionality currently supports only the **Cassandra** database, which is the default storage for an Online Feature Store built with Butterfree. Nonetheless, it was made with the intent to be easily extended for other databases.

Also, each database has its own rules for schema migration commands. Some changes may still require manual interference.

PYTHON MODULE INDEX

b

INDEX

C

D

E

F

G

H

I

J

K

L

M

N

O

P

Q

R

S

T

U

V

W