

# Testing Data Quality with Great Expectations

In this lab, you will work on defining some expectations and validations over a dataset in a MySQL Database. You will implement your validation workflow using the different components of Great Expectations: Data Context, Data Sources, Expectations and suites, and Checkpoints.

```
• Expectations store:
expectations_store:
  class_name: ExpectationsStore
  store_backend:
    class_name: TupleS3StoreBackend
    bucket: <GX-ARTIFACTS-BUCKET>
    prefix: expectations/

• Validations store:
validations_store:
  class_name: ValidationsStore
  store_backend:
    class_name: TupleS3StoreBackend
    bucket: <GX-ARTIFACTS-BUCKET>
    prefix: validations/

• Checkpoint store:
checkpoint_store:
  class_name: CheckpointStore
  store_backend:
    class_name: TupleS3StoreBackend
    suppress_store_backend_id: false
    bucket: <GX-ARTIFACTS-BUCKET>
    prefix: checkpoints/
```

## Table of Contents

- 1 - Introduction and Setup
- 2 - Data Context
- 3 - Data Source
- 4 - Batch Request
  - Exercise 1
- 5 - Expectation Suite and Validator
  - Exercise 2
  - Exercise 3
  - Exercise 4
- 6 - Creating the Batch Requests and the Validations List
  - Exercise 5
- 7 - Checkpoints and Computing Validations over the Dataset
  - Exercise 6

### 1 - Introduction and Setup

**Great Expectations (GX)** enables you to define expectations for your data and to automatically validate your data against these expectations. It can also notify you of any inconsistencies detected, and you can use it to validate your data at any stage of your data pipeline. You can find GX documentation [here](#).

1.1. Let's start by configuring GX. In the terminal, run the following command to set up the environment:

```
source scripts/setup.sh
```

Take the output that has the form:

```
MYSQL_CONNECTION_STRING: mysql+pymysql://<DBUSER>:<DBPASSWORD>@<DBHOST>:<DBPORT>/<DBNAME>
```

and save it as you will use it later. Then, initialize your GX project with this command:

```
great_expectations init
```

You will be shown an output indicating the folder structure that the library is going to create in your local filesystem, which looks as follows:

```
great_expectations
|-- great_expectations.yml
|-- expectations
|-- checkpoints
|-- plugins
|-- .gitignore
|-- uncommitted
    |-- config_variables.yml
    |-- data_docs
    |-- validations
```

Type **v** to proceed. Even though the output shows `great_expectations` as the root folder, you will find that the actual root folder is named `gx`.

#### Configuring the Backend stores

The previous command initialized the data context object and created your backend stores, such as the checkpoints, expectations, data\_docs and validations stores, as local directories. Let's configure these stores as S3 buckets. For that, you are provided with two S3 buckets:

- `GXartifacts3bucket`: you will use this bucket to store information about your expectations, validations and checkpoints;
- `GXdocs3bucket`: you will use this bucket to store your DataDocs, which are human readable documentations that contain reports on Expectations, Checkpoints and Validation results.

There are several advantages for storing your project metadata in an S3 bucket. These advantages include:

- Accessibility**: S3 buckets are highly accessible from various environments and by other team members or stakeholders.
- Scalability**: You can continue storing your project metadata seamlessly as your metadata grows over time.
- Durability**: Your metadata are reliably stored and protected.

1.2. Run the following code to get the link to the AWS console.

*Note*: For security reasons, the URL to access the AWS console will expire every 15 minutes, but any AWS resources you created will remain available for the 2 hour period. If you need to access the console after 15 minutes, please rerun this code cell to obtain a new active link.

```
from IPython.display import HTML

with open('../aws/aws_console_url', 'r') as file:
    aws_url = file.read().strip()

HTML(f'<a href="{aws_url}" target="_blank">GO TO AWS CONSOLE</a>')
```

[GO TO AWS CONSOLE](#)

*Note*: If you see the window like in the following printscreen, click on **logout** link, close the window and click on console link again.

AWSLogout

Go to the AWS console, and search for **CloudFormation**. Click on the alphanumeric stack name and then click on the **Outputs** tab. In the list of outputs, you will see the buckets with the CloudFormation *Key* `GXartifacts3bucket` and `GXdocs3bucket`. You will need to copy the corresponding bucket names, that you can find under the column *Value*, in order to replace the placeholders below.

Alternatively, you can also run the following command in the terminal to list all available S3 buckets and gather the information directly: `aws s3 ls`.

1.3. Open the file `gx/great_expectations.yml`. This YAML file represents the central configuration file used by GX, and contains various settings that control the behavior of your GX project. Search for the stores key; you will find several subkeys associated with each type of store. Replace the sections of the YAML file that correspond to the expectation, validations and checkpoint stores with the following configurations. Make sure to replace the placeholder `<GX-ARTIFACTS-BUCKET>` with the corresponding bucket name in those sections.

*Note*: the YAML file is indentation-sensitive, so make sure to keep the same indentation level when you replace the configuration information (otherwise you will get some errors when you run the command in 1.5).

1.4. Now, you will configure the storage for the documentation files Data Docs. In the same `YAML` file, search for the key `data_docs_sites` and replace the `local_site` subkey with the following configuration. Make sure to replace the placeholder `<GX-DOCS-BUCKET>` with the corresponding bucket name, using the name that is for the docs bucket not the artifacts bucket.

```
S3_site:
  class_name: SiteBuilder
  store_backend:
    class_name: TupleS3StoreBackend
    bucket: <GX-DOCS-BUCKET>
  site_index_builder:
    class_name: DefaultSiteIndexBuilder
```

Save changes in the `YAML` file `ctrl+s` or `cmd+s`.

1.5. To check that your stores have been properly configured, execute the following command in the terminal:

```
great_expectations store list
```

This command lists the available Stores and shows information such as name, type, and location. Note that the Data Docs Sites is not listed by this command.

1.6. Load the required packages and set the variable `LAB_PREFIX` that will be used in the lab:

```
from dotenv import load_dotenv
import boto3
import time
import os

import great_expectations as gx
from great_expectations.checkpoint import Checkpoint
LAB_PREFIX='de-c2a3a1'
```

Now you will use the GX components to set up the validation workflow, starting with the Data Context.

### 2 - Data Context

The data context serves as the entry point for the Great Expectations API, which consists of classes and methods that allow you to create objects to connect to your data sources, create expectations and validate your data. So using the data context, you can connect to the Data source, define your expectations, create a validator, run your checkpoints, and access the metadata of your Great Expectations project.

The Data Context can be ephemeral - existing only in memory and not persisting beyond the current Python session - or it can be backed by the configuration files so that it can persist between Python sessions and can be saved for later usage (File Data Context). In this lab, GX was set up so that your data context is a File Data Context backed by an AWS S3 Bucket.

2.1. Use the `gx.get_context()` method of great expectations to load your Data Context.

```
context = gx.get_context()
```

2.2. Inspect the content of the Data Context that you just created. You will see information about the stores you just configured.

```
context

Something went wrong when trying to use SQLAlchemy to obfuscate URL: Could not parse SQLAlchemy URL from string '${MYSQL_CONNECTION_STRING}'

{
  "anonymous_usage_statistics": {
    "usage_statistics_url": "https://stats.greatexpectations.io/great_expectations/v1/usage_statistics",
    "enabled": true,
    "explicit_url": false,
    "explicit_id": true,
    "data_context_id": "bb7edbc7-b702-460b-afb0-af638c91765b"
  },
  "checkpoint_store_name": "checkpoint_store",
  "config_variables_file_path": "uncommitted/config_variables.yml",
  "config_version": 3.0,
  "data_docs_sites": {
    "local_site": {
      "class_name": "SiteBuilder",
      "store_backend": {
        "class_name": "TupleS3StoreBackend",
```

```
    "bucket": "de-c2b3a1-891377276567-us-east-1-gx-docs"
  },
  "site_index_builder": {
    "class_name": "DefaultSiteIndexBuilder"
  }
},
"site": {
  "class_name": "SiteBuilder",
  "store_backend": {
    "class_name": "TupleS3StoreBackend",
    "bucket": "de-c2b3a1-891377276567-us-east-1-gx-docs"
  },
  "site_index_builder": {
    "class_name": "DefaultSiteIndexBuilder"
  }
}
},
"datasources": {},
"evaluation_parameter_store_name": "evaluation_parameter_store",
"expectations_store_name": "expectations_store",
"fluent_datasources": {
  "de-c2b3a1-db-datasource": {
    "type": "sql",
    "assets": {
      "de-c2b3a1-trips": {
        "type": "table",
        "order_by": [],
        "batch_metadata": {},
        "splitter": {
          "column_name": "vendor_id",
          "method_name": "split_on_column_value"
        },
        "table_name": "trips"
      }
    },
    "connection_string": "://None:***@None$MYSQL_CONNECTION_STRING"
  }
},
"include_rendered_content": {
  "expectation_suite": false,
  "expectation_validation_result": false,
  "globally": false
},
"plugins_directory": "plugins/",
"stores": {
  "expectations_store": {
    "class_name": "ExpectationsStore",
    "store_backend": {
      "class_name": "TupleS3StoreBackend",
      "bucket": "de-c2b3a1-891377276567-us-east-1-gx-artifacts",
      "prefix": "expectations/"
    }
  },
  "validations_store": {
    "class_name": "ValidationsStore",
    "store_backend": {
      "class_name": "TupleS3StoreBackend",
      "bucket": "de-c2b3a1-891377276567-us-east-1-gx-artifacts",
      "prefix": "validations/"
    }
  },
  "evaluation_parameter_store": {
    "class_name": "EvaluationParameterStore"
  },
  "checkpoint_store": {
    "class_name": "CheckpointStore",
    "store_backend": {
      "class_name": "TupleS3StoreBackend",
      "suppress_store_backend_id": false,
      "bucket": "de-c2b3a1-891377276567-us-east-1-gx-artifacts",
      "prefix": "checkpoints/"
    }
  },
  "profiler_store": {
    "class_name": "ProfilerStore",
    "store_backend": {
      "class_name": "TupleFileSystemStoreBackend",
      "suppress_store_backend_id": true,
      "base_directory": "profilers/"
    }
  }
},
"validations_store_name": "validations_store"
}
```

Additionally, in the content of the Artifacts S3 bucket, you will see a folder for each of the different stores that you have configured, one for the Expectations, another for Validations, and one for Checkpoints.

### 3 - Data Source

The next step is to configure your Data Source. In this lab, you are provided with a MySQL database labeled as `taxi_trips` which contains a sample of the [TLC trip record data set](#). The database contains one table named `trips`, which has the following schema:

ER Diagram trips

3.1. Now that you have a general understanding of the data schema you will use, let's connect to the database.

Using the `context` object, you can connect to a SQL database using the method: `context.sources.add_sql()`. This method expects a name for your data source (which can be of your choice) and a connection string that consists of the database credentials that are needed to establish a connection to the database. GX supports passing Data Source [connection credentials](#) through environment variables or setting them through the GX configuration files. In this lab, you will set the `config_variables.yml` configuration file.

Open the `gx/unused/config_variables.yml` file and at the end of the file, append the output that you got from the execution of the script located at `scripts/setup.sh`. Append it in the following way:

```
MYSQL_CONNECTION_STRING: mysql+pymysql://DBUSER@:DBPASSWORD@DBHOST:DBPORT/DBNAME
```

Save changes. Then, run the following cell to create the data source object.

```
# Create the data source to represent the data available in the MySQL DB
mysql_datasource = context.sources.add_sql(
    name=f'{LAB_PREFIX}-db-datasource', connection_string=f'{MYSQL_CONNECTION_STRING}'
)
```

3.2. Let's now define a Data Asset from your data source. Remember that a Data Asset represents collections of records stored within a Data Source. It could be a table in a SQL database or a file in a file system. It could be also a query asset that joins data from more than one table or it could be a collection of files matching a particular regular expressions pattern. In other words, by defining your data asset, you tell GX on which part of your data you want to focus on.

Since the given database consists of only the trips table, you will create a Table Data Asset from your data source using the method `add_table_asset`. This method expects a name for the data asset (in this case, we used the lab prefix followed by the table name) and the actual name of the table in the source database.

Run the following cell to create your data asset.

```
# Add a Data Asset to represent a discrete set of data
trips = mysql_datasource.add_table_asset(
    name=f'{LAB_PREFIX}-trips', table_name='trips'
)

#trips = mysql_datasource.get_asset("de-c2b3a1-trips")
```

### 4 - Batch Request

The next thing you need to create is the Batch Request, which represents the primary way to retrieve data from your data asset. It can retrieve your data asset as a single batch or as multiple batches. In this lab, you will define your data asset as batches based on the `vendor_id` column.

#### Exercise 1

1. To create batches on your Table Data Asset trips, call the method `add_splitter_column_value()` on your data asset, and pass the `"vendor_id"` column as the splitter column.

Note: GX offers several ways to split your data, according to different conditions.

2. Create the batch request, using the `build_batch_request()` method of your Table Data Asset.

3. To inspect the batches, get the batches using the `get_batch_list_from_batch_request()` method of your Table Data Asset. This method expects as input the batch request. You can inspect the information about each batch, such as the Table Data Asset name, the type of splitter used, and the batch identifier according to the column selected as the splitter.

```
### START CODE HERE ### (~ 3 lines of code)
# Use the "vendor_id" column as splitter column
trips.add_splitter_column_value("vendor_id")

# Build the batch request
batch_request = trips.build_batch_request()

# Get the batches
batches = trips.get_batch_list_from_batch_request(batch_request)

### END CODE HERE ###

for batch in batches:
    print(batch.batch_spec)

{'type': 'table', 'data_asset_name': 'de-c2b3a1-trips', 'table_name': 'trips', 'schema_name': None, 'batch_identifiers': {'vendor_id': 1}, 'splitter_method': 'split_on_column_value', 'splitter_kwargs': {'column_name': 'vendor_id'}}
{'type': 'table', 'data_asset_name': 'de-c2b3a1-trips', 'table_name': 'trips', 'schema_name': None, 'batch_identifiers': {'vendor_id': 2}, 'splitter_method': 'split_on_column_value', 'splitter_kwargs': {'column_name': 'vendor_id'}}
{'type': 'table', 'data_asset_name': 'de-c2b3a1-trips', 'table_name': 'trips', 'schema_name': None, 'batch_identifiers': {'vendor_id': 4}, 'splitter_method': 'split_on_column_value', 'splitter_kwargs': {'column_name': 'vendor_id'}}
```

Expected Output

```
{'type': 'table', 'data_asset_name': 'de-c2b3a1-trips', 'table_name': 'trips', 'schema_name': None, 'batch_identifiers': {'vendor_id': 1}, 'splitter_method': 'split_on_column_value', 'splitter_kwargs': {'column_name': 'vendor_id'}}
{'type': 'table', 'data_asset_name': 'de-c2b3a1-trips', 'table_name': 'trips', 'schema_name': None, 'batch_identifiers': {'vendor_id': 2}, 'splitter_method': 'split_on_column_value', 'splitter_kwargs': {'column_name': 'vendor_id'}}
{'type': 'table', 'data_asset_name': 'de-c2b3a1-trips', 'table_name': 'trips', 'schema_name': None, 'batch_identifiers': {'vendor_id': 4}, 'splitter_method': 'split_on_column_value', 'splitter_kwargs': {'column_name': 'vendor_id'}}
```

You can see in the output a key named `'batch_identifiers'` with a dictionary as a value. The dictionary contains the splitter column name as a key and the value of the column that identifies the batch. Now, let's create a batch request list for each of the batches generated before.

```
batch_request_list = [batch.batch_request for batch in batches]
```

### 5 - Expectation Suite and Validator

#### Expectation Suite

In order to define expectations for your data, you need to create an Expectation Suite which is a collection of expectations or assertions about your data.

#### Exercise 2

Use the `add_or_update_expectation_suite()` method of the context object to create a new Expectation Suite. Pass the name stored in the variable `expectation_suite_name` to the parameter `expectation_suite_name` in the same method.

```
# Add an expectation suite name to the context
expectation_suite_name = f'{LAB_PREFIX}-expectation-suite-trips-taxi-db'

### START CODE HERE ### (~ 1 line of code)
context.add_or_update_expectation_suite(expectation_suite_name=expectation_suite_name)

### END CODE HERE ###

{
  "expectation_suite_name": "de-c2b3a1-expectation-suite-trips-taxi-db",
  "ge_cloud_id": null,
  "expectations": [],
  "data_asset_type": null,
  "meta": {
    "great_expectations_version": "0.18.22"
  }
}
```

```
}
}

Expected Output

{
  "expectation_suite_name": "de-c2w3a1-expectation-suite-trips-taxi-db",
  "ge_cloud_id": null,
  "expectations": [],
  "data_asset_type": null,
  "meta": {
    "great_expectations_version": "0.18.22"
  }
}
```

**Validator**

In GX, a Validator is the component responsible for validating your data against your expectations. You can directly interact with the validator to manually validate your data. OR you can streamline the validation process using checkpoints. For now, let's directly interact with the validator to explore the manual process of validating your data.

**Exercise 3**

Instantiate the validator by calling the `get_validator()` method of the `context` object; store it in the `validator` variable. Make sure to pass the following parameters:

- `batch_request_list` as the list with batch requests you generated previously, which is stored in `batch_request_list`.
- `expectation_suite_name` as the Expectation Suite name you used in the previous cell.

```
## START CODE HERE ## (~ 4 lines of code)

validator = context.get_validator(
    batch_request_list=batch_request_list,
    expectation_suite_name=expectation_suite_name,
)

## END CODE HERE ##
```

**Setting the Expectations**

Now you have the expectation suite and the validator objects both ready. But you still did not define any expectations for your data. An Expectation is a statement about your data that can be validated, serving to improve data quality and facilitating clearer communication about data features. Similar to assertions in Python unit tests, Expectations offer a descriptive language for specifying the conditions the data should meet. However, unlike conventional unit tests, GX applies these Expectations directly to your data rather than to code. There are several types of expectations, such as

- `expect_column_values_to_not_be_null`
- `expect_column_values_to_be_unique`
- `expect_table_row_count_to_be_between`
- `expect_column_values_to_be_between`

And so on. You will use only a pair of those expectations for this lab. You can also check the [Expectations Gallery](#) to see the available expectations depending on the type of Data Source you are using.

**Exercise 4**

Using the validator, add three expectations:

1. First, check that in the dataset, the "pickup\_datetime" does not contain any null values. Call the `expect_column_values_to_not_be_null()` method of the validator and pass the "pickup\_datetime" column to the `column` parameter.
2. Check that the "passenger\_count" column does not contain nulls. Use the same approach as in the previous step.
3. Check that the column "congestion\_surcharge" has values between 0 and 1000. Use the `expect_column_values_to_be_between()` method to add this expectation.

These expectations will be automatically added to your expectation suite and evaluated on your current Data Asset.

When running the following cell you may get a pop-up like the one shown in the image

```
img><

Just click on Enable downloads. The cell should run without any issues.

## START CODE HERE ## (~ 3 lines of code)

validator.expect_column_values_to_not_be_null(column="pickup_datetime")
validator.expect_column_values_to_not_be_null(column="passenger_count")
validator.expect_column_values_to_be_between(column="congestion_surcharge", min_value=0, max_value=1000)

## END CODE HERE ##

{"model_id": "7e05cb76734dc1b63c82e0ba38ee1a", "version_major": 2, "version_minor": 0}
{"model_id": "abafaf6bf7047089180aeb0a5c1df8d", "version_major": 2, "version_minor": 0}
{"model_id": "f0f0800796b84c3b0fb04424d064af3", "version_major": 2, "version_minor": 0}

{
  "success": true,
  "result": {
    "element_count": 96,
    "unexpected_count": 0.0,
    "unexpected_percent": 0.0,
    "partial_unexpected_list": [],
    "missing_count": 0.0,
    "missing_percent": 0.0,
    "unexpected_percent_total": 0.0,
    "unexpected_percent_nonmissing": 0.0
  },
  "meta": {},
  "exception_info": {
    "raised_exception": false,
    "exception_traceback": null,
    "exception_message": null
  }
}

Expected Output
```

*Note:* The actual values in the output may change.

```
{
  "success": true,
  "result": {
    "element_count": 96,
    "unexpected_count": 0.0,
    "unexpected_percent": 0.0,
    "partial_unexpected_list": [],
    "missing_count": 0.0,
    "missing_percent": 0.0,
    "unexpected_percent_total": 0.0,
    "unexpected_percent_nonmissing": 0.0
  },
  "meta": {},
  "exception_info": {
    "raised_exception": false,
    "exception_traceback": null,
    "exception_message": null
  }
}
```

This corresponds to the output of the last batch that the validator has taken. Don't worry, GX actually has validated the other batches but only shows the output of the last one.

Run the following cell to save your Expectation Suite to the S3 bucket (expectation store), so you can use the expectations you just defined in another session.

```
validator.save_expectation_suite(discard_failed_expectations=False)
```

You can inspect your artifacts bucket. Inside the `expectations/` folder you will find a `json` file named as your Expectation Suite (`de-c2w3a1-expectation-suite-trips-taxi-db`). If you download it, you will see the expectations you have added, which will look as follows:

```
{
  "data_asset_type": null,
  "expectation_suite_name": "de-c2w3a1-expectation-suite-trips-taxi-db",
  "expectations": [
    {
      "expectation_type": "expect_column_values_to_not_be_null",
      "kwargs": {
        "column": "pickup_datetime"
      },
      "meta": {}
    },
    {
      "expectation_type": "expect_column_values_to_not_be_null",
      "kwargs": {
        "column": "passenger_count"
      },
      "meta": {}
    },
    {
      "expectation_type": "expect_column_values_to_be_between",
      "kwargs": {
        "column": "congestion_surcharge",
        "max_value": 1000,
        "min_value": 0
      },
      "meta": {}
    }
  ],
  "ge_cloud_id": null,
  "meta": {
    "great_expectations_version": "0.18.9"
  }
}
```

**6 - Creating the Batch Requests and the Validations List**

Now in a production environment, you can't manually validate your data the way you did in the previous exercise. What you can instead do, is to load into your new environment the expectation suite that you stored, and then pass it with your batch requests to a Checkpoint object. The checkpoint will automatically create a validator to validate your data against your expectations.

*Optional Notes*

You may be wondering why you need to compute the validations independently of the creation of the expectations; some of the advantages of that approach are:

- **Modularity and Reusability:** Separating the creation and computation of expectations allows you to modularize your workflow. You can create a set of reusable expectation definitions that can be applied across different batches of your dataset rewriting them each time.
- **Workflow Flexibility:** Separating expectation creation and computation provides flexibility in how you orchestrate your data quality pipeline. You can trigger expectation computation based on different events or schedules, integrate it with other data processing steps, or parallelize computations across multiple environments.
- **Resource Optimization:** Running and computing expectations may require different computational resources or environments compared to expectation creation. Separating these processes allows you to optimize resource allocation and scale each part of the workflow independently based on its specific requirements.
- **Error Isolation and Debugging:** If errors occur during expectation computation, separating the creation process makes it easier to isolate and debug issues. You can focus on troubleshooting the computation step without affecting the expectation definitions themselves.

*End of optional Notes*

A checkpoint object expects a collection of data batches and their corresponding expectation suite. We will call this collection a validations list. So before you create the checkpoint object, let's first create the validations list.

First, create a batch request from your Data Asset as you did in [Exercise 1](#). Call the `build_batch_request()` in your Data Asset and store it in the variable `batch_request`. Then, create the batches from your Data Asset by using the `get_batch_list_from_batch_request()` method and passing the `batch_request` as a parameter.

```
# Build the batch request
batch_request = trips.build_batch_request()

# Create your batches using the batch_request from the previous cell
batches = trips.get_batch_list_from_batch_request(batch_request)
```

For the expectation suite, run the following cell to retrieve the Expectation Suite's name from the context object. In this case you only have one expectation suite that you can access from the list of Expectations Suite returned by the `list_expectation_suite_names()` method.

```
expectation_suite_name = context.list_expectation_suite_names()[0]
```

Exercise 5

Let's now create the validations list. This list consists of a collection of a batch request and expectation suite pairs. In other words, each element in the validations list is a dictionary that defines the batch request and its expectation suite.

To create the validations list, you are given a list comprehension that you will use to iterate over each batch in the batches list. For each batch, define a dictionary with two keys:

- `"batch_request"`: use the `batch_request` property of the current batch to define the value for this key
- `"expectation_suite_name"`: use the name of the expectation suite you just retrieved. This value is the same for all elements.

```
### START CODE HERE ### (~ 4 lines of code)

validations = [

    {'batch_request': batch.batch_request, "expectation_suite_name": expectation_suite_name}
    for batch in batches

]

### END CODE HERE ###

validations

[['batch_request': BatchRequest(datasource_name='de-c2w3a1-db-datasource', data_asset_name='de-c2w3a1-trips', options={'vendor_id': 1}),
 'expectation_suite_name': 'de-c2w3a1-expectation-suite-trips-taxi-db'],
 {'batch_request': BatchRequest(datasource_name='de-c2w3a1-db-datasource', data_asset_name='de-c2w3a1-trips', options={'vendor_id': 2}),
 'expectation_suite_name': 'de-c2w3a1-expectation-suite-trips-taxi-db'},
 {'batch_request': BatchRequest(datasource_name='de-c2w3a1-db-datasource', data_asset_name='de-c2w3a1-trips', options={'vendor_id': 4}),
 'expectation_suite_name': 'de-c2w3a1-expectation-suite-trips-taxi-db'}]]

Expected Output

[['batch_request': BatchRequest(datasource_name='de-c2w3a1-db-datasource', data_asset_name='de-c2w3a1-trips', options={'vendor_id': 1}), 'expectation_suite_name': 'de-c2w3a1-expectation-suite-trips-taxi-db'], ('batch_request': BatchRequest(datasource_name='de-c2w3a1-db-datasource',
data_asset_name='de-c2w3a1-trips', options={'vendor_id': 2})), 'expectation_suite_name': 'de-c2w3a1-expectation-suite-trips-taxi-db'], ('batch_request': BatchRequest(datasource_name='de-c2w3a1-db-datasource', data_asset_name='de-c2w3a1-trips', options={'vendor_id': 4})), 'expectation_suite_name': 'de-
c2w3a1-expectation-suite-trips-taxi-db']]]
```

7 - Checkpoints and Computing Validations over the Dataset

Let's create a Checkpoint to validate the expectations you created over your dataset. Use the Checkpoint instantiation and pass the following parameters:

- `name` as the `checkpoint_name` variable. Take a look at how the checkpoint name is created, taking into account the current timestamp. Using a way to differentiate checkpoints will be helpful to avoid overwriting the results of the validation executions
- `data_context`: Use the data context object context that you already loaded.
- `expectation_suite_name`: The expectation suite name that you loaded.
- `validations`: Pass the validations list that you generated for each of your batch requests.

Take a look at the `action_list` parameter. You will see a list of different actions that will be performed after the validations are computed. Check the values associated with the `"class_name"` key:

- `StoreValidationResultAction`: This action stores the validation results in your Validation Store. Remember that this has been set up to be saved in S3.
- `UpdateDataDocsAction`: This action updates the data docs with the result of the validations.

You can see more Actions in the documentation.

```
# Create the Checkpoint configuration that uses your Data Context

timestamp = time.time()
checkpoint_name = f'{LAB_PREFIX}-checkpoint-trips-{timestamp}'

checkpoint = Checkpoint(
    name=checkpoint_name,
    run_name_template='trips XY-XM-Xd XM:XM:XS',
    data_context=context,
    expectation_suite_name=expectation_suite_name,
    validations=validations,
    action_list=[
        {
            "name": "store_validation_result",
            "action": {"class_name": "StoreValidationResultAction"},
        },
        {"name": "update_data_docs", "action": {"class_name": "UpdateDataDocsAction"}},
    ],
)
```

Exercise 6

Add the created checkpoint to the data context by using the `add_or_update_checkpoint()` method and passing the checkpoint object that you created.

```
### START CODE HERE ### (~ 1 line of code)

context.add_or_update_checkpoint(checkpoint=checkpoint)

### END CODE HERE ###

{
  "action_list": [
    {
      "name": "store_validation_result",
      "action": {
        "class_name": "StoreValidationResultAction"
      }
    },
    {
      "name": "update_data_docs",
      "action": {
        "class_name": "UpdateDataDocsAction"
      }
    }
  ],
  "batch_request": {},
  "class_name": "Checkpoint",
  "config_version": 1.0,
  "evaluation_parameters": {},
  "expectation_suite_name": "de-c2w3a1-expectation-suite-trips-taxi-db",
  "module_name": "great_expectations.checkpoint",
  "name": "de-c2w3a1-checkpoint-trips-1753380499.8075445",
  "profiles": {},
  "run_name_template": "trips XY-XM-Xd XM:XM:XS",
  "runtime_configuration": {},
  "validations": [
    {
      "batch_request": {
        "datasource_name": "de-c2w3a1-db-datasource",
        "data_asset_name": "de-c2w3a1-trips",
        "options": {
          "vendor_id": 1
        }
      },
      "expectation_suite_name": "de-c2w3a1-expectation-suite-trips-taxi-db"
    },
    {
      "batch_request": {
        "datasource_name": "de-c2w3a1-db-datasource",
        "data_asset_name": "de-c2w3a1-trips",
        "options": {
          "vendor_id": 2
        }
      },
      "expectation_suite_name": "de-c2w3a1-expectation-suite-trips-taxi-db"
    },
    {
      "batch_request": {
        "datasource_name": "de-c2w3a1-db-datasource",
        "data_asset_name": "de-c2w3a1-trips",
        "options": {
          "vendor_id": 4
        }
      },
      "expectation_suite_name": "de-c2w3a1-expectation-suite-trips-taxi-db"
    }
  ]
}
```

Expected Output

```
{
  "action_list": [
    {
      "name": "store_validation_result",
      "action": {
        "class_name": "StoreValidationResultAction"
      }
    },
    {
      "name": "update_data_docs",
      "action": {
        "class_name": "UpdateDataDocsAction"
      }
    }
  ],
  "batch_request": {},
  "class_name": "Checkpoint",
  "config_version": 1.0,
  "evaluation_parameters": {},
  "expectation_suite_name": "de-c2w3a1-expectation-suite-trips-taxi-db",
  "module_name": "great_expectations.checkpoint",
  "name": "de-c2w3a1-checkpoint-trips-1718883980.7753274",
  "profiles": {},
  "run_name_template": "trips XY-XM-Xd XM:XM:XS",
  "runtime_configuration": {},
  "validations": [
    {
      "batch_request": {
        "datasource_name": "de-c2w3a1-db-datasource",
        "data_asset_name": "de-c2w3a1-trips",
        "options": {
          "vendor_id": 1
        }
      },
      "expectation_suite_name": "de-c2w3a1-expectation-suite-trips-taxi-db"
    },
    {
      "batch_request": {
        "datasource_name": "de-c2w3a1-db-datasource",
        "data_asset_name": "de-c2w3a1-trips",
        "options": {
          "vendor_id": 2
        }
      },
      "expectation_suite_name": "de-c2w3a1-expectation-suite-trips-taxi-db"
    },
    {
      "batch_request": {
        "datasource_name": "de-c2w3a1-db-datasource",
        "data_asset_name": "de-c2w3a1-trips",
        "options": {
          "vendor_id": 4
        }
      },
      "expectation_suite_name": "de-c2w3a1-expectation-suite-trips-taxi-db"
    }
  ]
}
```

```
    },
    "expectation_suite_name": "de-c2w3a1-expectation-suite-trips-taxi-db"
  }
}
```

Take a look at your Artifacts S3 bucket in the checkpoints/ folder. After this command run, there should be a subfolder with the same name as your checkpoint, like de-c2w3a1-checkpoint-trips-<TIMESTAMP> and inside of it, you will find a YAML file that contains the same configuration that you saw in the previous output:

```
name: de-c2w3a1-checkpoint-trips-<TIMESTAMP>
config_version: 1.0
template_name:
module_name: great_expectations.checkpoint
class_name: Checkpoint
run_name_template: trips %Y-%m-%d %H:%M:%S
expectation_suite_name: de-c2w3a1-expectation-suite-trips-taxi-db
batch_requests: {}
action_list:
  - name: store_validation_result
    action:
      class_name: StoreValidationResultAction
  - name: update_data_docs
    action:
      class_name: UpdateDataDocsAction
evaluation_parameters: {}
runtime_configuration: {}
validations:
  - batch_request:
      datasource_name: de-c2w3a1-db-datasource
      data_asset_name: de-c2w3a1-trips
      options:
        vendor_id: 1
      expectation_suite_name: de-c2w3a1-expectation-suite-trips-taxi-db
  - batch_request:
      datasource_name: de-c2w3a1-db-datasource
      data_asset_name: de-c2w3a1-trips
      options:
        vendor_id: 2
      expectation_suite_name: de-c2w3a1-expectation-suite-trips-taxi-db
  - batch_request:
      datasource_name: de-c2w3a1-db-datasource
      data_asset_name: de-c2w3a1-trips
      options:
        vendor_id: 4
      expectation_suite_name: de-c2w3a1-expectation-suite-trips-taxi-db
profilers: {}
gs_cloud_id:
expectation_suite_gs_cloud_id:
```

Now, it is time to run your validations. Execute the following command to compute the expectations over your dataset. This step can take some time as validations are computed for all batches, so you will see a progress bar showing the computation of the metrics for each of the batches.

```
checkpoint_result = checkpoint.run()

{"model_id": "5d81ed0bac994c6aaf12d23b054d6a03", "version_major": 2, "version_minor": 0}
{"model_id": "c7b047de246d41ce9d2ac739acaf0718", "version_major": 2, "version_minor": 0}
{"model_id": "127932f8534b4f0808084825c03e909de", "version_major": 2, "version_minor": 0}
```

Once the checkpoint has run the validations, go to your artifacts bucket. Open the validations folder and you will find a folder with the expectation suite name and then a folder named with the same `run_time_template` format that was set in the checkpoint: `trips %Y-%m-%d %H:%M:%S`. Open such a folder, inside there will be another subfolder with a Datetime format and finally some json files. The format of the name is composed of the Data Source, Data Asset, and will end with the column name used to perform the splits for the batches and the value for the batch itself. You can download one of them to inspect it.

After your validations have run, remember that the data docs have been updated as part of the actions that are executed as a later process. Run the following command to build your data docs.

```
context.build_data_docs()

{'local_site': 'https://s3.amazonaws.com/de-c2w3a1-891377276567-us-east-1-gx-docs/index.html',
 'S3_site': 'https://s3.amazonaws.com/de-c2w3a1-891377276567-us-east-1-gx-docs/index.html'}
```

To see the data docs, click on the link in the output.

*Note - alternative way to find the URL:* This URL can be also found in the properties of the docs S3 bucket. Go to the docs S3 bucket in the AWS console and then click on the **Properties** tab. Scroll down until you find the **Static website hosting** section and copy the URL that you will find in that section. Paste it into a new browser tab.

You will be redirected to the validation results which will look like the following image:

GX Data docs

You will have two tabs, one for the Validation Results and another one for the Expectation Suites. If you click the Expectation Suites tab, you will find the Expectation Suite name that you created, click on it and you will find an overview of the expectations that belong to that Suite, such as in the following image:

GX Data docs Expectation Suite

In the upper part, click on **Home** and click again on the Validation Results tab. In that tab, you will find the results of the validations performed over each batch. At this point, the Status of all your results should be **Succeeded**, indicating that all batches passed the proposed data quality expectation checks. Click on any of the rows shown to see a view with the results of the expectations over a particular batch. You should see something similar to this image:

GX Data docs validation results

You will find some statistics about the evaluated expectations, and successful and unsuccessful expectations. If you click on **Show more info...** you will see some metadata about the Checkpoint execution and the batch used. After that section, you will see each of the expectations and the result of the validation of each of them.

Now that you have explored the Data docs and realized that your expectations have run successfully, you will insert some data that violates one of the expectations. Go to the terminal and make sure you are located at `~/project`. Run the command to get the database endpoint:

```
aws rds describe-db-instances --db-instance-identifier de-c2w3a1-rds --output text --query "DBInstances[0].Endpoint.Address"
```

Then connect to the database replacing the `<RDS-DBHOST>` with the previous output:

```
mysql --host=<RDS-DBHOST> --user=admin --port=3306 --password=adminpurd --database=taxi_trips
```

Then, use the following command to insert some data that will violate one of the expectations:

```
INSERT INTO trips (vendor_id, pickup_datetime, dropoff_datetime, passenger_count, trip_distance, rate_code_id, store_and_fwd_flag, pickup_location_id, dropoff_location_id, payment_type, fare_amount, extra, mta_tax, tip_amount, tolls_amount, improvement_surcharge, total_amount, congestion_surcharge)
values (2, '2022-03-11 17:48:59', '2022-03-11 18:03:01', 6, 2.44, 1, 'N', 161, 236, 2, 11.0, 0.0, 0.5, 0.0, 0.0, 0.3, 11.5, 1001) ;
```

Now, back to the notebook, execute again the validation's computation:

```
checkpoint_bad_result = checkpoint.run()

{"model_id": "af3139ecb2614183a9c211681c9514e0", "version_major": 2, "version_minor": 0}
{"model_id": "1c777fc5476ab47d69a08e1039b1540bc", "version_major": 2, "version_minor": 0}
{"model_id": "b550191bc4aa4e70819f849e951b59b2", "version_major": 2, "version_minor": 0}
```

Inspect again the Data docs, you will see three additional rows as shown in the image:

GX Data docs validation bad

You will see that one of the last 3 batch runs has a Failed Status. Click on it, you will see that the expectation over the column `"congestion_surcharge"` has failed, as shown in the image:

GX Data docs validation bad results

You see the **Failed** status and that there is 1 Unsuccessful expectation. You can also see that the row of data that you inserted manually has a `"congestion_surcharge"` value of 1001, which violates your established expectation that the values of that particular column should be between 0 and 1000. The other two expectations were successful. That way, you can assess the quality of your data and the characteristics of those data rows that do not hold the expectations you have set.

In this lab, you worked with some of the core components of GX, configured the Data Context stores by modifying the `gx/great_expectations.yml` file, and created a SQL Data Source and the corresponding Table Data Asset from which you saw you can create your data batches. Then, you created an Expectation Suite and a Validator and added some Expectations to your Expectation Suite. Then, you created a validation list with the batch requests for each of your data batches and created a GX Checkpoint to run your expectations. Finally, you interacted with the Data Docs stored in your S3 bucket and assessed the quality of your data set.