NYC Taxi – Data exploration and cleaning

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1. Introduction

This document briefly explains the main issues encountered downloading and treating with the datasets and decisions we can made for further analysis.

The notebook “*data_exploration_cleaning*” shows how it has been implemented all the process.

2. Data sources

We have 3 main data sources:

- Yellow Taxi Trip Records:
  - Description: Data about yellow taxis in NYC, that includes include fields capturing pick-up and drop-off dates/times, pick-up and drop-off locations, trip distances
  - URL: https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page
  - Data dictionary: https://www1.nyc.gov/assets/tlc/downloads/pdf/data_dictionary_trip_records_yellow.pdf
- Taxi Zone Lookup Table:
  - Description: Table that groups different zones in NYC
  - URL: https://s3.amazonaws.com/nyc-tlc/misc/taxi+_zone_lookup.csv
- Taxi Zone Shapefile:
  - Description: Shepefile with the geographic polygons of the zones in NYC
  - URL: https://s3.amazonaws.com/nyc-tlc/misc/taxi_zones.zip

3. Data extraction

3.1. Memory issues

When loading the Yellow Taxi Trip Records we can suffer from memory problems, especially if we want to increase the periods to analyse. So, it has been decided to use Spark to load the Taxi datasets.

3.2. Downloading pipeline

A script helper (extraction.py) has been created that manages the data extraction from the URLs. The method saves the data in local folders, so it avoids always downloading the data from the website.

With the help of a configuration file (config.yml) we can specify the URLs, file names, local folders, etc. For the case of taxi data we can also specify the periods, so we can increase the months and years whenever we want.

NOTE: For the case of taxi data, even with Spark, we are suffering from some strange errors when we include all the months of 2017. We have added a parameter in config.yml (*sample_fraction*) to only work with a fraction of the dataset. Even with this we suffer from the following error, that for the lack of time it hasn't been furtherly investigated:

```
Output exceeds the size limit. Open the full output data in a text editor
---------------------------------------------------------------------------
Py4JJavaError                             Traceback (most recent call last)
    [... skipping hidden 1 frame]

c:\Users\joan.borras\sourcecode\NYCTaxi\notebooks\test.ipynb Cell 2' in <cell line: 27>()
     25 psdf_taxi = prep.clean_taxi_data(psdf_taxi, cfg)
---> 27 print(f"SPDF Taxi size: {psdf_taxi.count()}")

File c:\ProgramData\Anaconda3\envs\py39\lib\site-packages\pyspark\sql\dataframe.py:804, in DataFrame.count(self)
    795 """Returns the number of rows in this :class:`DataFrame`.
    796
    797 .. versionadded:: 1.3.0
   (...)
    802 2
    803 """
--> 804 return int(self._jdf.count())

File c:\ProgramData\Anaconda3\envs\py39\lib\site-packages\py4j\java_gateway.py:1321, in JavaMember.__call__(self, *args)
   1320 answer = self.gateway_client.send_command(command)
-> 1321 return_value = get_return_value(
   1322     answer, self.gateway_client, self.target_id, self.name)
   1324 for temp_arg in temp_args:

File c:\ProgramData\Anaconda3\envs\py39\lib\site-packages\pyspark\sql\utils.py:190, in capture_sql_exception.<locals>.deco(*a, **kw)
    189 try:

...
--> 438 self.socket.connect((self.java_address, self.java_port))
    439 self.stream = self.socket.makefile("rb")
    440 self.is_connected = True

ConnectionRefusedError: [WinError 10061] No se puede establecer una conexión ya que el equipo de destino denegó expresamente dicha conexión
```

By the way, working with a fraction of 10% of the dataset for the months 1, 3, 6, 9, 11 and 12 in 2017, worked perfectly. Reducing the fraction, and increasing the months, surprisingly still caused problems.

4. Main statistics

We have added a new feature ("*duration_in_min*") which measures in minutes the duration of the trip, based on the "*tpep_pickup_datetime*" and "*tpep_dropoff_datetime*" features.

We have analysed the distribution of different variables and how they correlate with tip_amount variable. We have detected that payment_type different from 1 does not provide values to tip amount. So we will only keep rows with payment_type is 1.

5. Check for errors

With the statistics observed above, and with some filtering analysis made at the notebebook, we can see several data inconsistency:

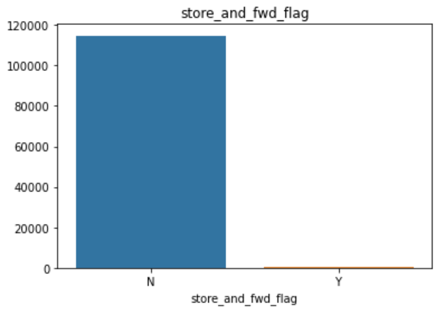
- We can see some features with negative values: *fare_amount, duration_in_min, extra, MTA_Tax, Improvement_surcharge, tip_amount, tolls_amount, total_amount.*
- The features *Passenger_count* and *trip_distance* have values equal to 0 but they should be above 0.
- The features "Congestion_Surcharge" and "Airport_fee" contain only null values.
- *RateCodeID* has 8 rows with values not between the available options (1 and 6). They will have to be removed from the dataset.
- The feature *extra* only accepts values of 0.5$ and 1$. It has been detected in 0.01% of cases that the values are not modulo of 0.5$.
- *MTA_Tax* should be always 0.5$ but it in 0.05% of cases we find different values.
- Adding all expenses should be equal to *total_amount*. But this is not always true in 0.17% of rows.

- *Improvement_surcharge* is different that 0.3$ in 0.07% of observations.
- 0.09% of observations have a pickup datetime greater than the drop off datetime.
- 0.02% of observations have the year different from the requested, and 0.19% have different months.

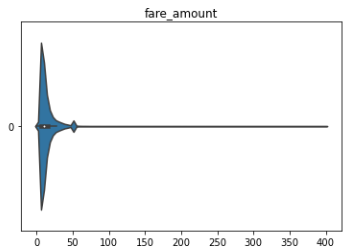
Important: for this test we remove values based on the percentile. However, in a production environment we would remove values that do not accomplish specific predefined values.

All the values that do not accomplish the above conditions are removed by the "*clean_taxi_data*" function created at the module "*preprocessing.py*".

We can also check the frequency of the category variables and discover how they are represented. Looking at the following example we see that *store_and_fwd_flag* are mainly equal to *N* (more charts are available at the notebook).



Checking the distribution of the numeric variables we can see a right-skewed distribution with extremely large and low values in some variables as shown below.



fare_amount

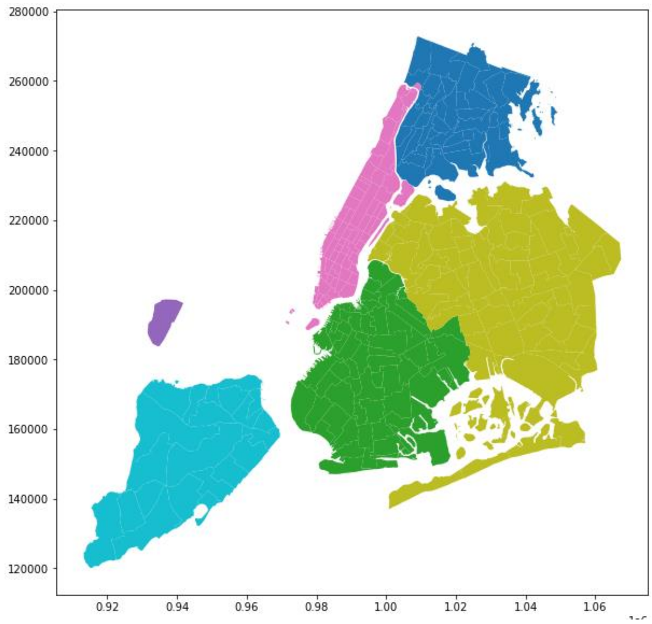
0%	0.1%	0.5%	1%	5%	10%	25%	50%	75%	90%	95%	99%	99.5%	99.9%	100%
0.01	3.0	3.5	3.5	4.5	5.0	6.5	9.5	15.0	26.0	37.5	52.0	60.0	94.5	825.0

We assign NaN the values from those variables that we detect as probably not correct (either for being too high or too low):

- trip_distance values below percentile 1% and above 99.9% are probably not correct
- fare_amount values below percentile 0.1% and above 99.9% are probably not correct
- tolls_amount values above 99.9% are probably not correct
- total_amount values below percentile 0.1% and above 99.9% are probably not correct
- duration_in_min values below percentile 0.5% and above 99.5% are probably not correct
- tip_amount values above 99.9% are probably not correct

Checking for ID duplicates, it has been discovered that LocationID in SHP has duplicates. In fact, the IDs of LocationID and OBJECTID are always the same, except for those that have duplicates. For this reason, we can conclude that we should use OBJECTID instead for the SHP dataframe.

Finally, we plot some geo maps, to see if the grouped areas are well identified with their boroughs. As we can see in the figure below, the boroughs seem to be correctly classified.



It appears to be a borough and a service zone with the name "Unknown". With some domain knowledge of the region, it would be good to identify the reason.

6. Data cleaning

With the decisions made above, it has been created a function named *clean_taxi_data*, that performs 3 main steps:

- Removes all the observations with values not allowed for each feature
- Remove outliers for the feature *duration_in_min*
- Remove trips that are not paid card

This method can be requested later for data exploration or modelling.