A STUDY ON NEW YORK CITY TAXI RIDES – Fare and Duration Prediction

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Course: Big Data Technologies and Applications
Term: Summer – 2018
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ABSTRACT

In this paper, our aim is to develop a predictive model for 'NYC Taxi Data' which contains approximately 200 million yellow taxi trips between 2009 and 2017. The raw data is reachable from the NYC Taxi & Limousine Commission website month by month and it represents 17-21 variables for each taxi ride. The size of the raw data is nearly 217 GB in total.

Possible predictive analyses can be performed on;

- fare amount (average, maximum or minimum)
- tip amount or
- duration

of a trip by threating one of them as a dependent (target) variable. In this study, we decided "fare amount and trip duration" to be estimated, since they would be valuable for taxi vendors optimizing their incomes/operations and for passengers managing their expenditures/times.

Statistical regressive models (linear/nonlinear) and machine learning methods (Decision Tree, Support Vector Machine and Convolutional Neural Network) will be used to produce predictions on the chosen target variable.

Information obtained from this study can be used by numerous authorities and industries for their own purpose. Gained insight about data that can be beneficial in Turkey especially for entities provides taxi services (e.g. BiTaksi).

This paper includes only;

- ✓ Data Processing (Infrastructure),
- ✓ Data Collection,
- ✓ Data Manipulation,
- ✓ EDA[1] and
- ✓ Data Imputation

[1] Exploratory Data Analysis

parts of the study. We will exhibit further parts (Feature Engineering, Feature Selection, Collinearity Detection, Model Selection and Result Interpretation) at the end of the final semester.

A- Data Processing (Infrastructure)

Platforms and tools that are used in this study can be shown as the below graph.

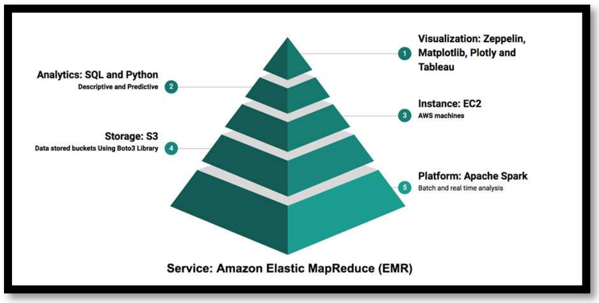

Visualization: Zeppelin, Matplotlib, Plotly and Tableau
1
Analytics: SQL and Python
Descriptive and Predictive
2
Instance: EC2
AWS machines
3
Storage: S3
Data stored buckets Using Boto3 Library
4
Platform: Apache Spark
Batch and real time analysis
5
Service: Amazon Elastic MapReduce (EMR)

Figure 1

All platforms and tools are provided by Amazon Web Services (AWS). Due to the size of our data, it is considered that using Hadoop/Spark base system would be efficient to store and analyze our data. We have created a S3-Bucket (s3://ludditiesnyctaxi/….) in AWS and downloaded raw data from NYC official website[2]. EC2-Instances and EMR-Clusters are used for analysis via AWS-CLI (terminal), Zeppelin, JupterHub and Spark interfaces with the help of the Spark API's (Pyspark and SparkSQL). We also used 'Bootstrap action' to install abovementioned interfaces and related libraries and to configure clusters' instances easily at each time they created.

[2] http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml

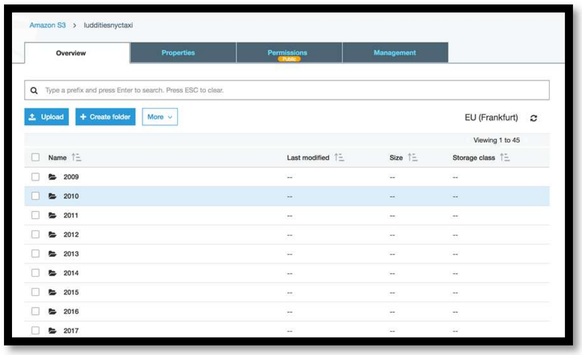
B- Data Collection

We had three options to collect the data, which are;

- downloading data to local machine/external hard disk by using web browser,
- downloading data to HDFS by using '-wget' function on AWS-CLI or
- downloading data directly to S3-Bucket by using 'Boto3' dictionary on python library.

We have succeeded two of them (a and c) and decided to use option (a) for getting 200 GB data due to the time constraint.

Aforementioned official link had been used to download data, monthly. Then, we have transferred these monthly files to S3-Buckets by dragging it to AWS interface. The interface appearance of our S3-Bucket is shown below.



Name	Last modified	Size	Storage class
2009	--	--	--
2010	--	--	--
2011	--	--	--
2012	--	--	--
2013	--	--	--
2014	--	--	--
2015	--	--	--
2016	--	--	--
2017	--	--	--

Figure 2

Our S3-Bucket is public, so one can reach it from any IP in the world.

C- Data Understanding

In order to understand what our data represents, drawing graphs/charts is an easy and efficient way. We produced them using platforms and tools mentioned in 'Data Processing' part of the report.

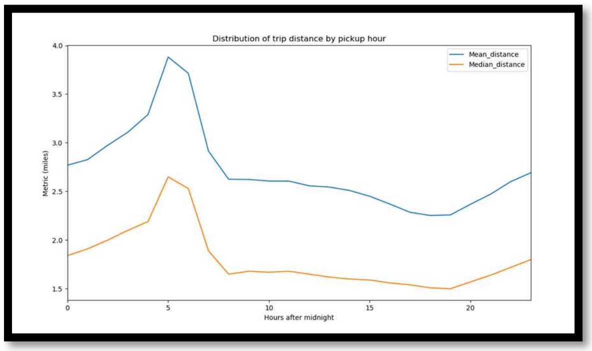


Figure 3

Plot is suggesting that the mean trip distances is longer in morning and evening hours. This could be the population that uses cabs to commute for work. But if so the evening commuter are much less than morning commuters. This indicates that the people who takes taxi in the morning to work do not use it when they go back home.

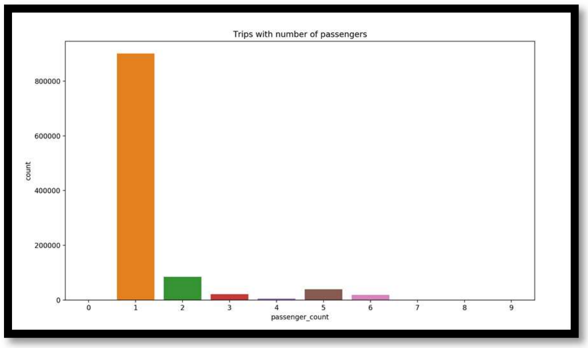


Figure 4

Big part of the total rides is single passenger rides. This seems to be working individuals.

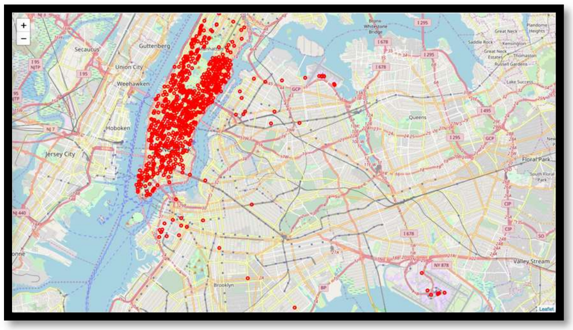


Figure 5

Above map indicates yellow taxi's pickup locations for 2016/01. Yellow cabs are allowed to serve only in City center, as can be seen from the re circle distribution in the map. A detailed one is located on 'Appendix' part of the report which is named "nyc_map.html".

A dictionary of the data is also added to the 'Appendix' part of the report. It might be helpful to grasp meaning of each variable of the data.

D- Data Manipulation

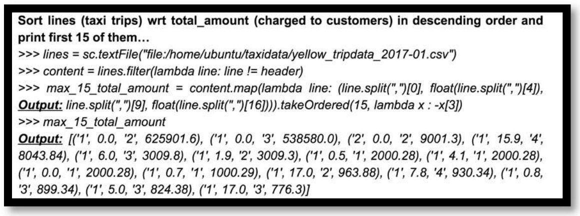
In the Data Manipulation process, one should handle;

i. Outliers
ii. Missing Values
iii. Repeated Rows (Uniqueness)

in the dataset.

i. <u>Outliers:</u>

Outliers have potential to create noise in our data variance. So, we have checked them for columns such as "fare_amount" by using Pyspark RDD data structure like below.



```
Sort lines (taxi trips) wrt total_amount (charged to customers) in descending order and
print first 15 of them…
>>> lines = sc.textFile("file:/home/ubuntu/taxidata/yellow_tripdata_2017-01.csv")
>>> content = lines.filter(lambda line: line != header)
>>> max_15_total_amount = content.map(lambda line: (line.split(",")[0], float(line.split(",")[4]),
Output: line.split(",")[9], float(line.split(",")[16]))).takeOrdered(15, lambda x : -x[3])
>>> max_15_total_amount
Output: [('1', 0.0, '2', 625901.6), ('1', 0.0, '3', 538580.0), ('2', 0.0, '2', 9001.3), ('1', 15.9, '4',
8043.84), ('1', 6.0, '3', 3009.8), ('1', 1.9, '2', 3009.3), ('1', 0.5, '1', 2000.28), ('1', 4.1, '1', 2000.28),
('1', 0.0, '1', 2000.28), ('1', 0.7, '1', 1000.29), ('1', 17.0, '2', 963.88), ('1', 7.8, '4', 930.34), ('1', 0.8,
'3', 899.34), ('1', 5.0, '3', 824.38), ('1', 17.0, '3', 776.3)]
```

Figure 6

As can be seen from above output, some trips can be treated as outliers, since they have enormously high "fare_amount" than others even they do not represents any trip distances. So, values which behave distinguishably different will be deleted/detached from our data, manually.

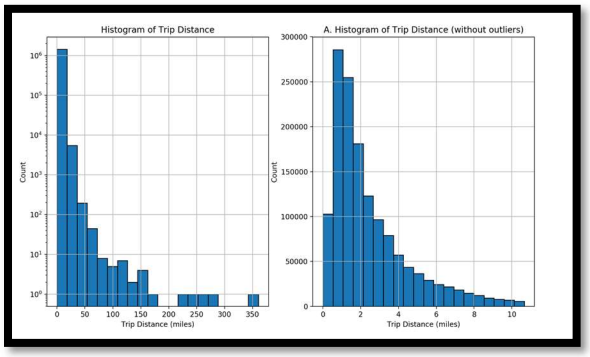
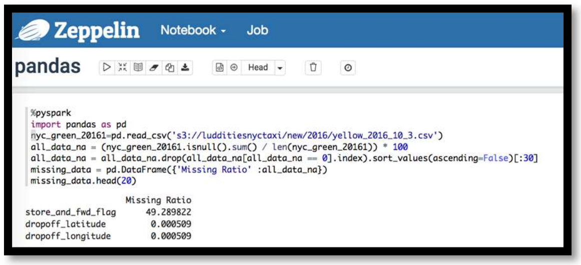


Figure 7

First graph in Figure-7 is a "trip_distance" histogram with outliers. But, second one is the same without outliers. We did exclude any data point located further than 3 standard deviations of the median point.

ii. <u>Missing Values:</u>

To handle missing values in our data, firstly, we detect the percentage of null values at each column by using below python code.



```
%pyspark
import pandas as pd
nyc_green_20161=pd.read_csv('s3://ludditiesnyctaxi/new/2016/yellow_2016_10_3.csv')
all_data_na = (nyc_green_20161.isnull().sum() / len(nyc_green_20161)) * 100
all_data_na = all_data_na.drop(all_data_na[all_data_na == 0].index).sort_values(ascending=False)[:30]
missing_data = pd.DataFrame({'Missing Ratio' :all_data_na})
missing_data.head(20)

                   Missing Ratio
store_and_fwd_flag     49.289822
dropoff_latitude        0.000509
dropoff_longitude       0.000509
```

Figure 8

We adopted the policy of removing a column whose missing ratio is greater than %20. With respect to this policy;

- 'Ehail_fee' is removed since 99% of the data are missing,
- 'store_and_fwd_flag' is removed since nearly half of it is missing,
- 'mta_tax' is removed since approximately whole of it is missing.

Variables did not exceed the 20% threshold but still having missing values will be filled by applying some statistical techniques (6-Sigma Imputation or Direct Imputation) in 'Data Imputation' part of the report.

In addition to these, we have found some abnormalities (invalid data) in other variables which we will repair by applying some operations in 'Data Imputation' part, too.

Figure-8 represents one-month implementation. One can adapt this code to whole data by using loop logic via EMR-Cluster platform. We got "Out of Memory/ Java Heap Space/GC Overhead Limit Exceeded" errors while trying mentioned implementation on even 1-year data.

Memory allocation problem is the one that we have faced frequently in our study as expected. Although it is not necessary to use all data while establishing a predictive model[3], we need it as a whole for manipulation (cleaning and imputing) and EDA processes. This problem might be solved by;

- ➢ using advance instances ('p' or 'r' type) as workers/nodes,
- ➢ increasing number of workers,
- ➢ using Kyro Serialization[4],
- ➢ tuning driver and executor memory parameters of spark environment,
- ➢ using GC1 garbage collector method[5],
- ➢ implementing 'chunk-size' functionality of Pandas,
- ➢ implementing 'repartition' functionality of Pyspark and
- ➢ applying 'broadcasting' method of Pyspark.

These methods have been tried both individually and simultaneously to get rid of memory allocation restrictions of our big data tools. Up to this report, we have achieved to use one-year data which has approximately 10-20 GB size.

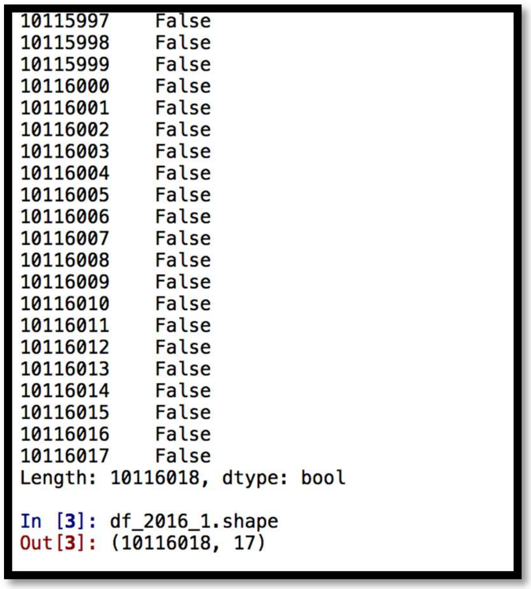
iii. <u>Uniqueness:</u>

[3] Randomly chosen sample of 10.000 data from 2009 – 2017 would be enough to create a statistically robust models.

[4] Spark is using 'Java serialization' as default

[5] Spark is using 'Java Paralel GC' as default

Every data may have duplicates in it, thus, it is important to check its uniqueness. We checked our data in terms of uniqueness with the help of Pandas library. We found that there are no repeating rows in our data. There is an example below.



```
10115997    False
10115998    False
10115999    False
10116000    False
10116001    False
10116002    False
10116003    False
10116004    False
10116005    False
10116006    False
10116007    False
10116008    False
10116009    False
10116010    False
10116011    False
10116012    False
10116013    False
10116014    False
10116015    False
10116016    False
10116017    False
Length: 10116018, dtype: bool

In [3]: df_2016_1.shape
Out[3]: (10116018, 17)
```

Figure 9

After performing the operations describing in this part of the report, we have reduced the size of raw data approximately 13,7%, which corresponds roughly 30 GB.

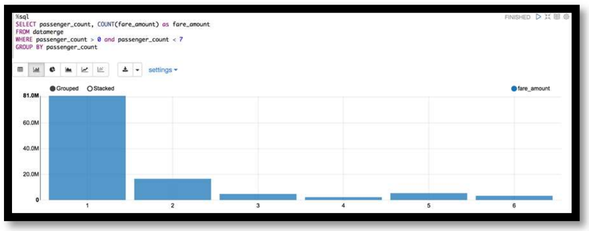
E- Exploratory Data Analysis (EDA)

EDA is an open-ended process where we make plots and calculate statistics in order to explore our data. The purpose of this process is to find anomalies, patterns, trends, or relationships between independent and target variables.

EDA generally starts out with a high-level overview, and then narrows in to specific parts of the dataset once as we find interesting areas to examine. To begin with EDA, we will focus on a single variable, "fare_amount", since it has chosen as the target value that our machine learning models will try to predict.

Outputs of EDA will offer us some insights about the relationships in our data and drive us to "Feature Engineering" process where we will shape our data to strengthen correlations between independent variables and dependent variable.

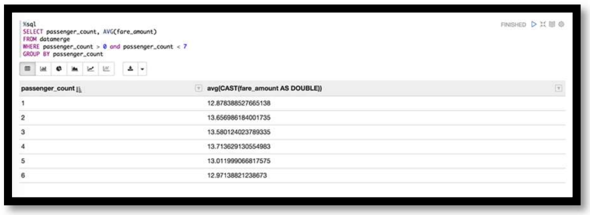
As a first step of this part, we have used some categorical variables as a separator to discover distinguishable behaviors of target variable if it exists. Below output is a sample and simple beginning of that kind of exploration.



```
%sql
SELECT passenger_count, COUNT(fare_amount) as fare_amount
FROM datamerge
WHERE passenger_count > 0 and passenger_count < 7
GROUP BY passenger_count
```

Figure 10

Graph tells us that taxi rides, which include one passenger only, are representing most of the total revenue in our dataset. So, we continue our journey with a deep look through this possible relationship between variables by taking averages.



```
%sql
SELECT passenger_count, AVG(fare_amount)
FROM datamerge
WHERE passenger_count > 0 and passenger_count < 7
GROUP BY passenger_count
```

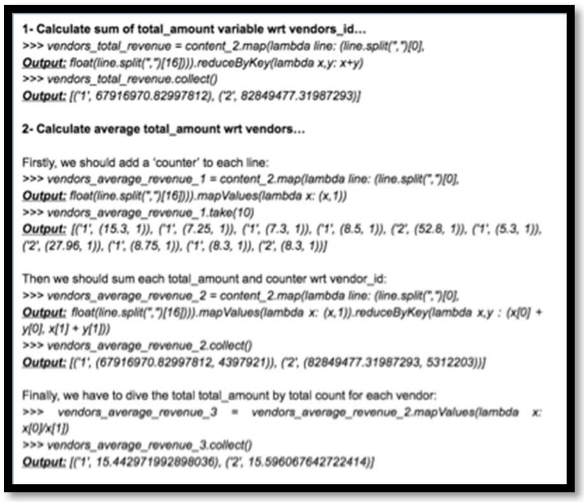
passenger_count	avg(CAST(fare_amount AS DOUBLE))
1	12.878388527665138
2	13.656986184001735
3	13.580124023789335
4	13.713629130554983
5	13.011999066817575
6	12.97138821238673

Figure 11

As can be seen from the above figure, there is no significant difference in terms of average 'fare_amount' with respect to count of passengers changing 1 to 6. So, 'passenger_count' will not be considered and threated as a useful discriminator of 'fare_amount'.

Another categoric variable, which we can check whether its subcategories indicate differentiation in terms of target variable, is 'vendor_id'. All taxi rides in our data are served by two vendors 'Creative Mobile Technologies' and 'VeriFone Inc.' having identity number '1' and '2', respectively.

Below figure comprises a Pyspark RDD experiment searching abovementioned differentiation.



1- Calculate sum of total_amount variable wrt vendors_id...

```
>>> vendors_total_revenue = content_2.map(lambda line: (line.split(",")[0],
Output: float(line.split(",")[16]))).reduceByKey(lambda x,y: x+y)
>>> vendors_total_revenue.collect()
Output: [('1', 67916970.82997812), ('2', 82849477.31987293)]
```

2- Calculate average total_amount wrt vendors...

Firstly, we should add a 'counter' to each line:

```
>>> vendors_average_revenue_1 = content_2.map(lambda line: (line.split(",")[0],
Output: float(line.split(",")[16]))).mapValues(lambda x: (x,1))
>>> vendors_average_revenue_1.take(10)
Output: [('1', (15.3, 1)), ('1', (7.25, 1)), ('1', (7.3, 1)), ('1', (8.5, 1)), ('2', (52.8, 1)), ('1', (5.3, 1)),
('2', (27.96, 1)), ('1', (8.75, 1)), ('1', (8.3, 1)), ('2', (8.3, 1))]
```

Then we should sum each total_amount and counter wrt vendor_id:

```
>>> vendors_average_revenue_2 = content_2.map(lambda line: (line.split(",")[0],
Output: float(line.split(",")[16]))).mapValues(lambda x: (x,1)).reduceByKey(lambda x,y : (x[0] +
y[0], x[1] + y[1]))
>>> vendors_average_revenue_2.collect()
Output: [('1', (67916970.82997812, 4397921)), ('2', (82849477.31987293, 5312203))]
```

Finally, we have to dive the total total_amount by total count for each vendor:

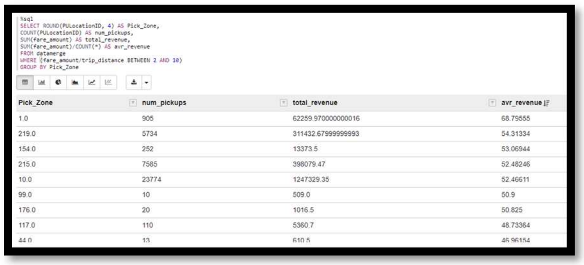
```
>>> vendors_average_revenue_3 = vendors_average_revenue_2.mapValues(lambda x:
x[0]/x[1])
>>> vendors_average_revenue_3.collect()
Output: [('1', 15.442971992898036), ('2', 15.596067642722414)]
```

Figure 12

In this example, we conclude that vendor 'VeriFone Inc.' has gained slightly (%1) more than 'Creative Mobile Technologies' for each trip. So, the dependent variable 'vendor_id' is considered to be useless for creating distinguishable subclasses of target variable.

Variables representing pickup and drop-off coordinates/zones of rides might be a good discriminator for 'fare_amount'. This type of variables are shown as discrete numeric in our dataset, but they can be easily transformed (Feature Engineering) into categoric type by creating buckets/intervals which symbolizes neighbor zones of the New York City.

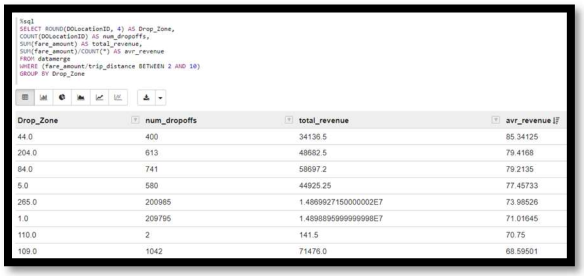
Below figures respectively stands for pickup and drop-off operation of taxi trips and they represent average 'fare_amount' for each zone.



```
%sql
SELECT ROUND(PULocationID, 4) AS Pick_Zone,
COUNT(PULocationID) AS num_pickups,
SUM(fare_amount) AS total_revenue,
SUM(fare_amount)/COUNT(*) AS avr_revenue
FROM datamerge
WHERE (fare_amount/trip_distance BETWEEN 2 AND 10)
GROUP BY Pick_Zone
```

Pick_Zone	num_pickups	total_revenue	avr_revenue
1.0	905	62259.970000000016	68.79555
219.0	5734	311432.67999999993	54.31334
154.0	252	13373.5	53.06944
215.0	7585	398079.47	52.48246
10.0	23774	1247329.35	52.46611
99.0	10	509.0	50.9
176.0	20	1016.5	50.825
117.0	110	5360.7	48.73364
44.0	13	610.5	46.96154

Figure 13



```
%sql
SELECT ROUND(DOLocationID, 4) AS Drop_Zone,
COUNT(DOLocationID) AS num_dropoffs,
SUM(fare_amount) AS total_revenue,
SUM(fare_amount)/COUNT(*) AS avr_revenue
FROM datamerge
WHERE (fare_amount/trip_distance BETWEEN 2 AND 10)
GROUP BY Drop_Zone
```

Drop_Zone	num_dropoffs	total_revenue	avr_revenue
44.0	400	34136.5	85.34125
204.0	613	48682.5	79.4168
84.0	741	58697.2	79.2135
5.0	580	44925.25	77.45733
265.0	200985	1.4869927150000002E7	73.98526
1.0	209795	1.4898895999999998E7	71.01645
110.0	2	141.5	70.75
109.0	1042	71476.0	68.59501

Figure 14

We can interpret these outputs that some zones including pickup or drop-off activity seems to have higher 'fare_amount' than others. For example, most profitable pickup zones in Figure-13 are Newark Airport, Springfield Garden and Marine Park respectively. These are social congregation locations in New York, as expected.

As a result, we realize that only the pickup and drop-off zone information may bring some useful variances for our target variable. So, we will focus on these types of variables in “Feature Engineering” part in order to sharp their separation capabilities on ‘fare_amount’.

Current Status & Waiting Challenges

During the analyses, we have used ‘SQL’ and ‘Python’ API’s of Apache Spark to handle with our huge data. It had been successfully finalized while working on only 1-month length data (2-3 GB) through both aforesaid libraries. On the other hand, enlarging the scope of the data (e.g. 1 year – 15 GB) has brought “Out of Memory” error, when using Python-Pandas library which offers advanced visualization capabilities with ‘plotly’ and ‘matplotlib’ dictionaries. SQL library, in contrast, could handle this challenge, but it has limited visualization capacity.

So, working with 1 year or more sized data has the priority to be achieved for our study. We will focus on the possible solutions of memory error mentioned in “Data Manipulation” part of the report.

And surely, we are going to complete remaining parts of our study index, from F to K, listed below.

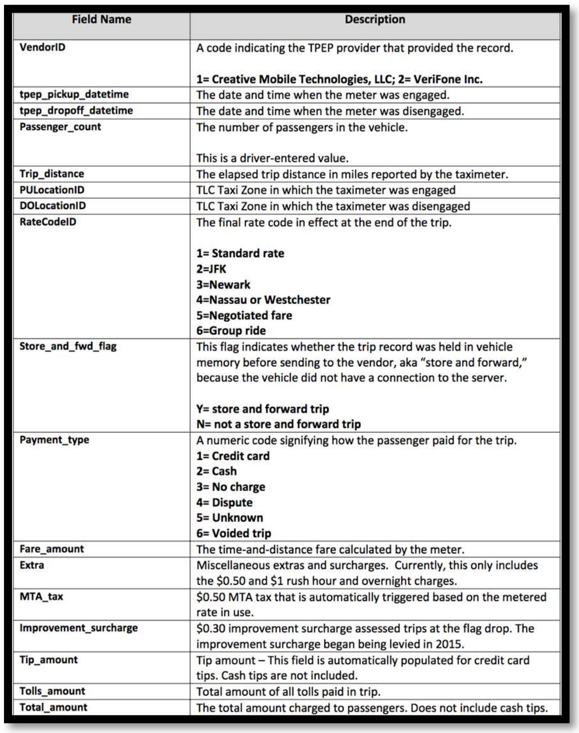
A- Data Processing (Infrastructure) ,
B- Data Collection,
C- Data Understanding,
D- Data Manipulation,
E- EDA,
F- Data Imputation,
G- Feature Engineering,
H- Feature Selection,
I- Collinearity Detection,
J- Model Selection and
K- Interpretation of the Results

To work on the prediction of trip duration, we will try to create it by taking subtraction of ‘pickup_datetime’ and ‘dropoff_datetime’ variables for whole data. Of course, this is a further task to be worked on after handling with memory errors.

APPENDIX

Data Dictionary

(http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml)



Field Name	Description
VendorID	A code indicating the TPEP provider that provided the record. **1= Creative Mobile Technologies, LLC; 2= VeriFone Inc.**
tpep_pickup_datetime	The date and time when the meter was engaged.
tpep_dropoff_datetime	The date and time when the meter was disengaged.
Passenger_count	The number of passengers in the vehicle. This is a driver-entered value.
Trip_distance	The elapsed trip distance in miles reported by the taximeter.
PULocationID	TLC Taxi Zone in which the taximeter was engaged
DOLocationID	TLC Taxi Zone in which the taximeter was disengaged
RateCodeID	The final rate code in effect at the end of the trip. **1= Standard rate** **2=JFK** **3=Newark** **4=Nassau or Westchester** **5=Negotiated fare** **6=Group ride**
Store_and_fwd_flag	This flag indicates whether the trip record was held in vehicle memory before sending to the vendor, aka "store and forward," because the vehicle did not have a connection to the server. **Y= store and forward trip** **N= not a store and forward trip**
Payment_type	A numeric code signifying how the passenger paid for the trip. **1= Credit card** **2= Cash** **3= No charge** **4= Dispute** **5= Unknown** **6= Voided trip**
Fare_amount	The time-and-distance fare calculated by the meter.
Extra	Miscellaneous extras and surcharges. Currently, this only includes the $0.50 and $1 rush hour and overnight charges.
MTA_tax	$0.50 MTA tax that is automatically triggered based on the metered rate in use.
Improvement_surcharge	$0.30 improvement surcharge assessed trips at the flag drop. The improvement surcharge began being levied in 2015.
Tip_amount	Tip amount – This field is automatically populated for credit card tips. Cash tips are not included.
Tolls_amount	Total amount of all tolls paid in trip.
Total_amount	The total amount charged to passengers. Does not include cash tips.

Figure 15

Table shows the most actual (2017) columns/variables in the data which might shows some differences between early years. For example;

- 'PULocationID' and 'DOLocationID' columns were represented by latitude and longitude coordinates in 2016/06 and before.
- 'trip_type' variable were dropped from dataset at the end of 2016.

NYC – Yellow_Taxi – Map:

nyc_map.html