Data Scientist Nano Degree (Capstone Project)

Car Booking Analysis and Prediction

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Project Definition

Project Overview

In Egypt transportation represent a major challenge, which has been partially relieved after new players entered the market (car booking companies like Uber, Careem, SWVL…etc).

These new players used technology to offer a more reliable, secured and intelligent transportation options.

The competition in this business area is fierce, and the winner will be the one who employ data analytics to provide better customer service with minimal cost.

The objective of this project is to support car booking companies with analysis and prediction to offer better service to the customer.

Unfortunately, dataset from these companies is not publicly available, so in this project I will use NYC Taxi and Limousine Commission dataset as an alternative.

Problem Statement

Provide car booking companies with analytics to maximize profit and provide customers with superb customer experience with minimal cost, and also find new business opportunities:

- Fleet management:
    - Deploy the fleet at the most demanding areas at specific time.
    - Deploy the fleet based on driver's preferences for drop off locations (a driver may prefer a drop off near his home)
- Fare prediction:

    Customer need to know the estimated fare for his trip before start

- Trips scheduling:

    Suggest best trip time within a specific time window defined by the customer, this best trip time should have lowest trip duration and fare amount.

Metrics

The success of this project is measured by providing answers for our business questions, where some of them will be answered by statistical analysis like:

- What are the top pick up locations per specific time?
- What are the top pick up locations per specific times and favorite drop off list?
- Suggest best time to for a specific trip.

More over to predict the fare amount with high accuracy where I will try different models (Linear regression and XGBoost) with different parameters and measure them against each other by comparing the R-squared score and Root Mean Squared Error to identify the best model.

Analysis

Data Exploration

Unfortunately, dataset is not available for the Egyptian market, so I will use a similar data from other markets to build and test the use case.

The data used were collected and provided to the NYC Taxi and Limousine Commission (TLC) by technology providers authorized under the Taxicab & Livery Passenger Enhancement Programs (TPEP/LPEP).

The dataset is publicly available under the following link:

https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page

I'll use Yellow Taxi trips data from year 2019 to avoid the impact of Covid-19; this subset has over 40 million trips (42821916 trips, with 18 columns)

Data Structure:

The dataset structure and features descriptions are publicly available, and below are the main tables with their data structure.

- Table "yellow_tripdata" (each month has a separate file):

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.

- Table "taxi+_zone_lookup":
  This is the lookup table to map Pickup and DropOff Location IDs to Boroughs, Zones and service_zone names.

Data Exploration:

I started with basic data exploration; dataset size, columns names and types, data description, count missing values…etc

The data shape is (42821916, 18).

The columns are confirmed as in the data structure documentation:

```
VendorID                 float64
tpep_pickup_datetime      object
tpep_dropoff_datetime     object
passenger_count          float64
trip_distance            float64
RatecodeID               float64
store_and_fwd_flag        object
PULocationID               int64
DOLocationID               int64
payment_type             float64
fare_amount              float64
extra                    float64
mta_tax                  float64
tip_amount               float64
tolls_amount             float64
improvement_surcharge    float64
total_amount             float64
congestion_surcharge     float64
dtype: object
```

And upon initial data exploration missing values and un-logical values (-ve values or extreme outliers) were found which would affect the data visualization and would affect any conclusion derived from the data.

	count	mean	std	min	25%	50%	75%	max
VendorID	42706377.0	1.644342	0.501307	1.00	1.00	2.00	2.00	4.00
passenger_count	42706377.0	1.562970	1.210514	0.00	1.00	1.00	2.00	9.00
trip_distance	42821916.0	2.986702	4.856197	-18739.24	0.97	1.61	3.02	831.80
RatecodeID	42706377.0	1.061002	0.742314	1.00	1.00	1.00	1.00	99.00
PULocationID	42821916.0	163.280894	66.043385	1.00	116.00	162.00	233.00	265.00
DOLocationID	42821916.0	161.517654	70.257471	1.00	107.00	162.00	233.00	265.00
payment_type	42706377.0	1.288448	0.477927	1.00	1.00	1.00	2.00	5.00
fare_amount	42821916.0	13.278955	186.922325	-530.00	6.50	9.50	14.50	943274.80
extra	42821916.0	1.015128	1.219016	-60.00	0.00	0.50	2.50	535.38
mta_tax	42821916.0	0.494820	0.063083	-0.50	0.50	0.50	0.50	75.00
tip_amount	42821916.0	2.167272	21.801100	-221.00	0.00	1.78	2.86	141492.02
tolls_amount	42821916.0	0.377244	1.839576	-70.00	0.00	0.00	0.00	3288.00
improvement_surcharge	42821916.0	0.298692	0.026992	-0.30	0.30	0.30	0.30	1.00
total_amount	42821916.0	18.831406	204.270166	-530.80	10.80	14.16	20.30	1084772.17
congestion_surcharge	37965935.0	2.109704	0.917122	-2.50	2.50	2.50	2.50	4.50

	Total	Percent
VendorID	115539	0.002698
tpep_pickup_datetime	0	0.000000
tpep_dropoff_datetime	0	0.000000
passenger_count	115539	0.002698
trip_distance	0	0.000000
RatecodeID	115539	0.002698
store_and_fwd_flag	115539	0.002698
PULocationID	0	0.000000
DOLocationID	0	0.000000
payment_type	115539	0.002698
fare_amount	0	0.000000
extra	0	0.000000
mta_tax	0	0.000000
tip_amount	0	0.000000
tolls_amount	0	0.000000
improvement_surcharge	0	0.000000
total_amount	0	0.000000
congestion_surcharge	4855981	0.113399

Moreover, to explore that data, some feature engineering is needed first.

So I started with the basic engineered features and basic data cleaning to be able to visualize the data.

Data Preprocessing

Feature Engineering:

From first look we can notice that the following engineered features can be derived from the Pickup and Dropoff times:

- tripduration_mins
- year, month, day, hour of the trip
- dayofweek
- weekendflag
- holidayflag

Initial Data Cleaning:

Based on the ranges of the data I have applied the following:

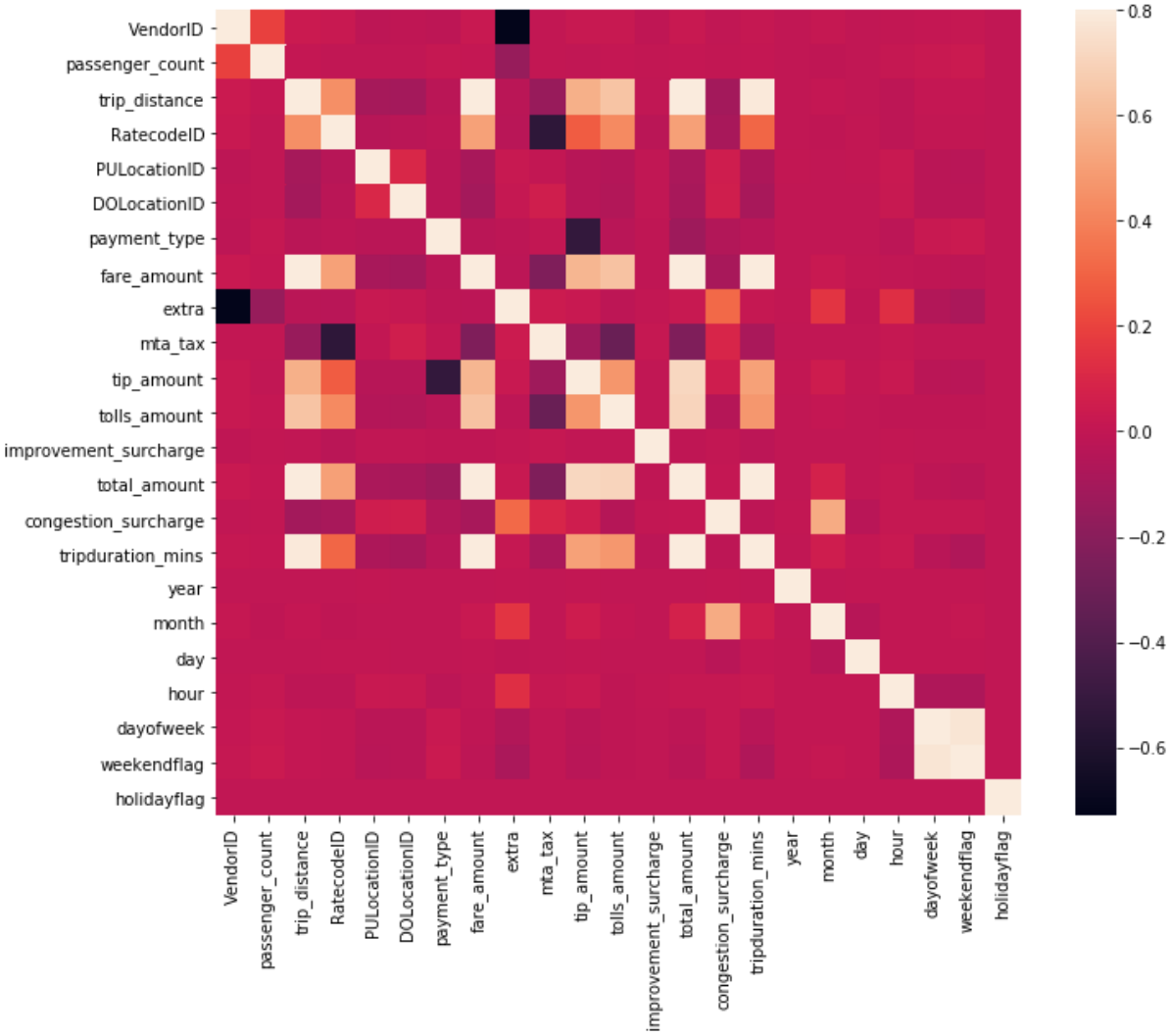
- drop rows with –ve values for 'fare_amount', 'total_amount', 'tripduration_mins', 'tip_amount', 'tolls_amount', 'improvement_surcharge', 'congestion_surcharge', 'trip_distance', 'extra', 'mta_tax'
- drop rows with 'passenger_count' > 6 and 'RatecodeID' > 6

- drop rows with outliers ('fare_amount' > 100, 'tripduration_mins' > 180, 'tip_amount' > 20, 'tolls_amount' > 30, 'extra' > 5, 'mta_tax' > 1, 'improvement_surcharge' > 1 OR 'trip_distance' > 30
- Fill na values in 'congestion_surcharge' with 0.

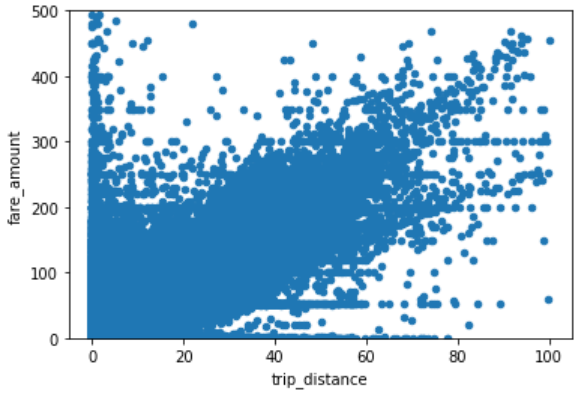
Data Visualization

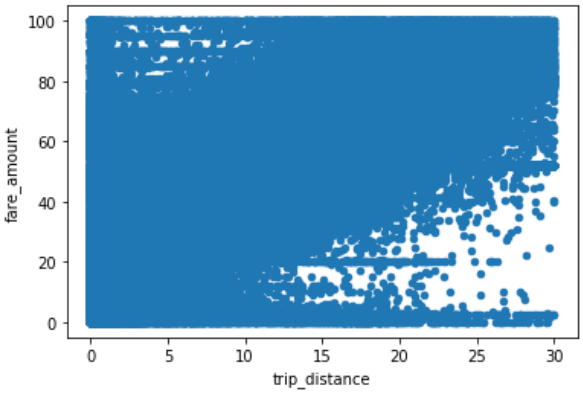
I have started with the Correlation matrix for all features

As expected for example, fare_amount has strong correlation to the trip distance and trip duration.

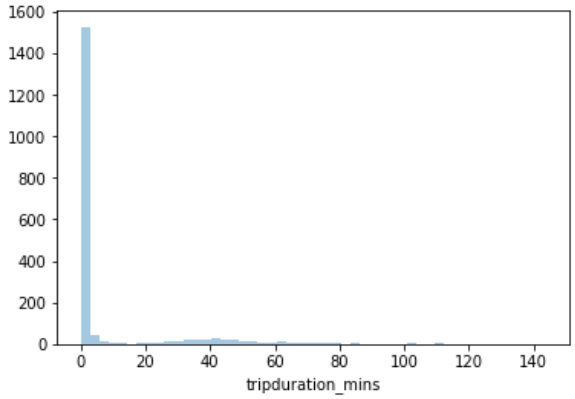


And from the below “Fare vs. Trip Distance” charts we can find that fare amount is correlated to the trip distance with minor exceptions. However, after data cleaning the view is much better and logical.

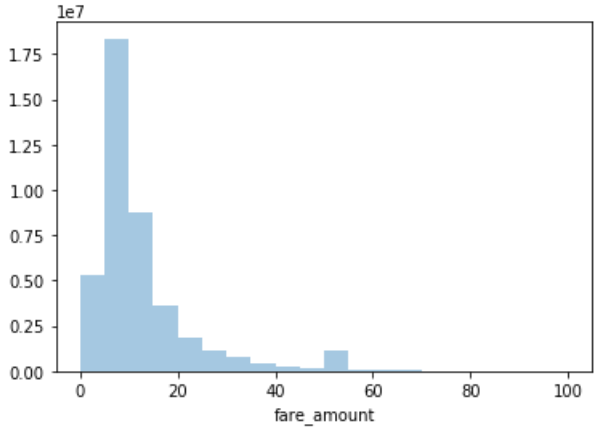


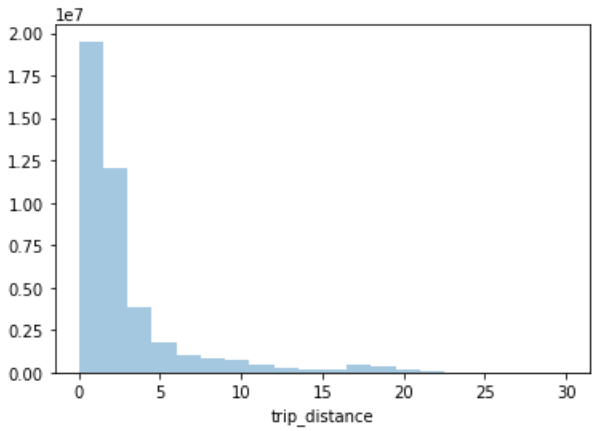


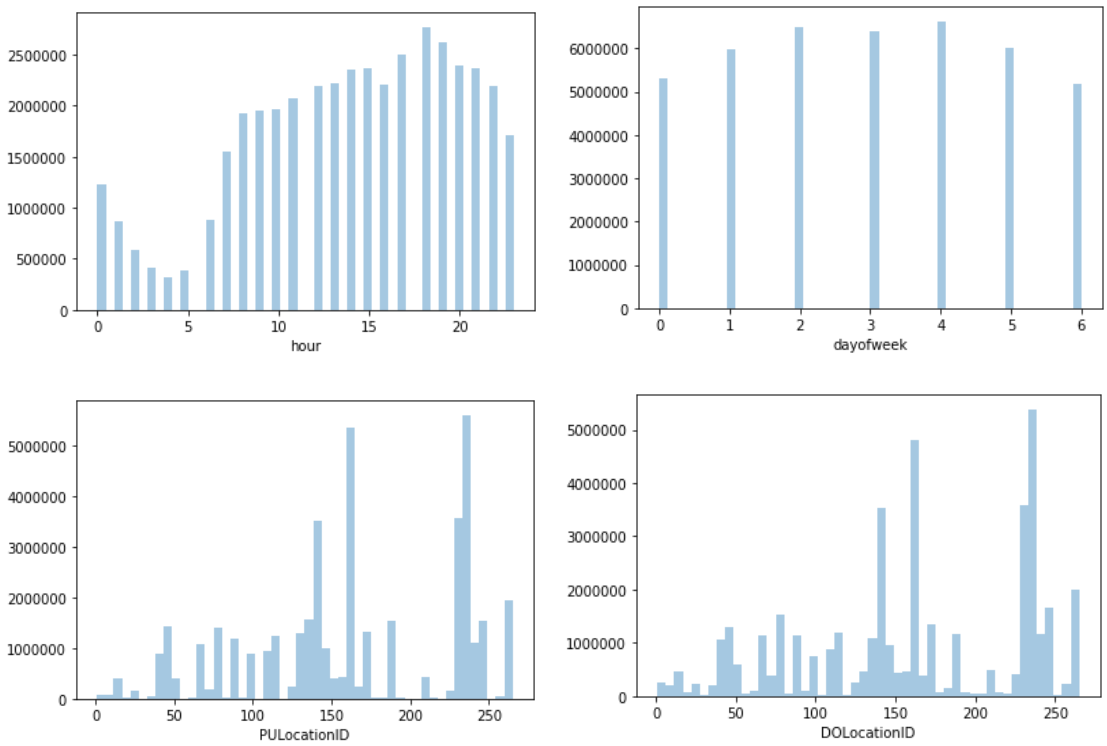
And for the trips with long distance and low fare amount, below its trip time distribution (seems these trips were on free roads and took short time, that's why the fare was low).



Below charts also show the distribution analysis after data cleaning.



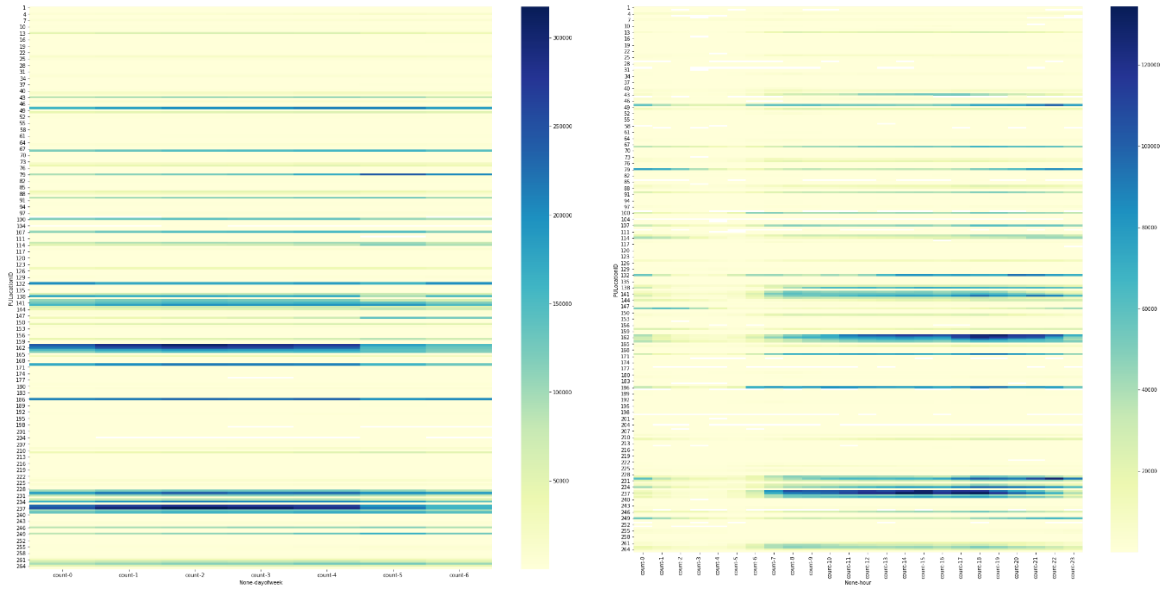




From the above distributions we find:

- The majority of the trips are short (below 5 km) with fare below 20$.
- Sunday and Monday have slightly lower number of trips.
- Distribution over day hours is logical in general (low after mid-night till working hours start)
- Pickup and Drop-off locations almost have the same distribution.

Below as well a heat map for the trips count for each pickup location over days of the week and over day hours as well.



Methodology

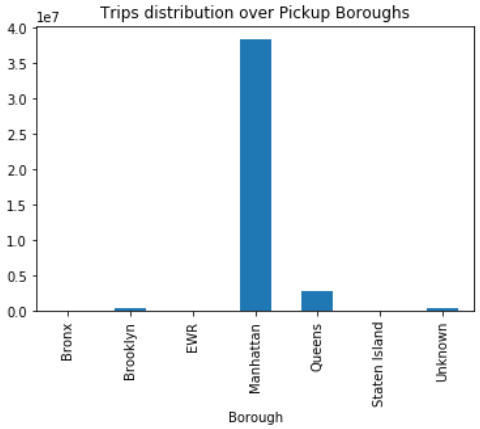
Implementation

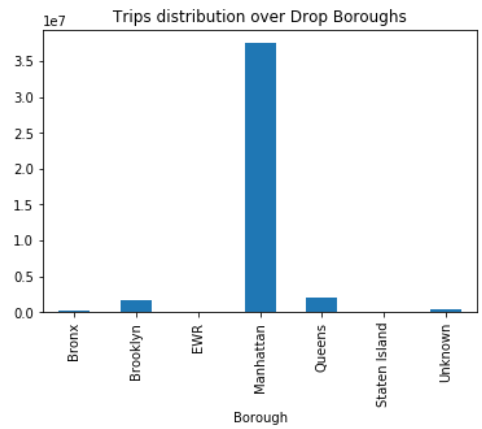
Some of the business questions introduced in this project can be answered by statistical analysis for the data, and some will need machine learning prediction.

So let's tackle the business questions one by one.

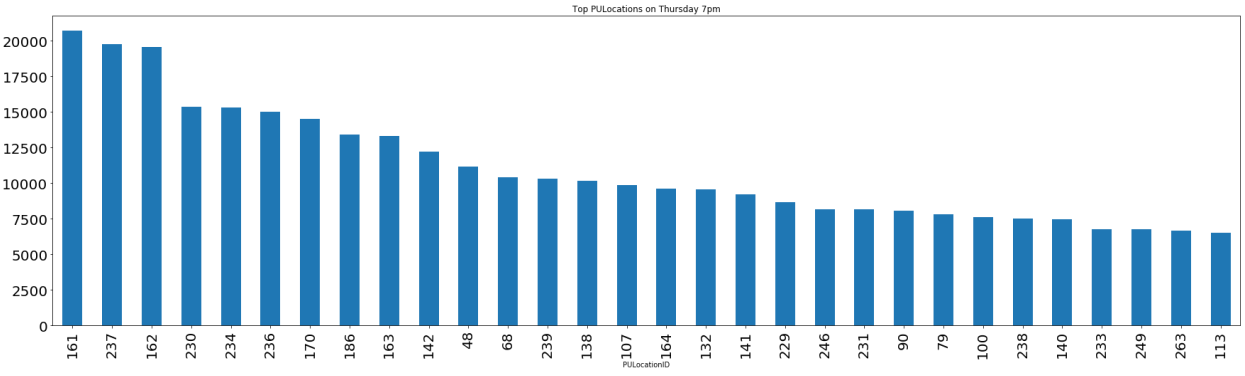
- Q1: What are the most demanding areas at specific time?

  First let's have a look at the trips distribution over New York Boroughs, we can find that Manhattan has the highest share in our dataset (as expected as per the yellow taxi service areas).



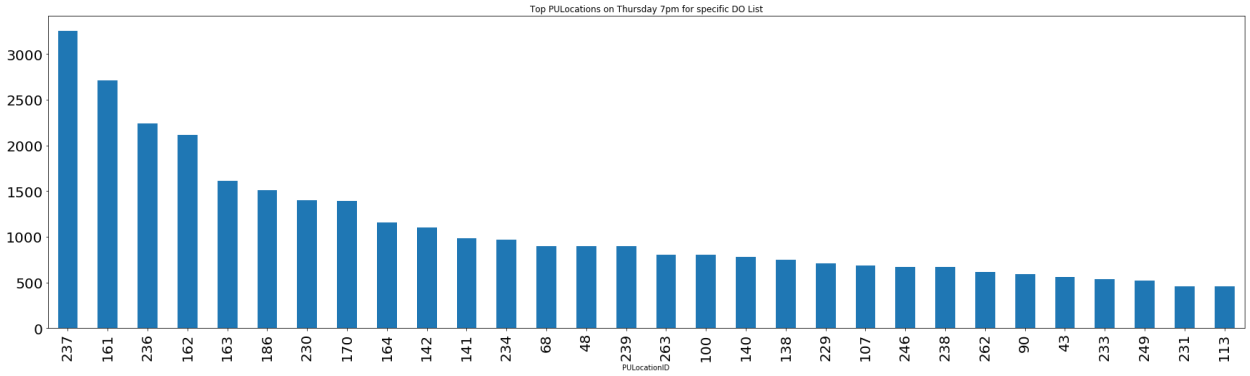


  And to answer our question we can build on the history we have in our dataset, for example below are top pick up locations for a specific day and hour (Thursday 7pm).



- Q2: Deploy the fleet based on driver's preferences for drop off locations (a driver may prefer a drop off near his home).
  In this case the driver may enter his favorite drop off locations and based on historical data analysis we suggest top locations where he can work for specific time.

For example, below are top pick up locations for a specific day and hour (Thursday 7pm) which will most likely will lead to the favorite drop off locations [230, 234, 236]



- Q3: Fare prediction:

  To predict the fare amount I will test different machine learning regression model (Linear regression and XGBoost) using different features set trying to reach the optimum prediction scenario.

  Also I will split the dataset into training (70%) and testing (30%) to be able to evaluate the prediction models and features.

  Different features set were tried; I started with all features as a baseline then I started filtering the features based on its correlation with the label which is here the fare amount.

  Detailed results are discussed in the Model Evaluation and Validation section.

- Q4: Trips scheduling:

  Here to suggest best trip time within a specific time window defined by the customer, the system shall predict the trip duration and far amount for each hour in the window specified by the customer and based on this the best suitable time with minimum trip duration and fare amount shall be presented to the customer.

Refinement

To enhance the fare amount prediction results the following actions were taken:

- Tried two models (Linear regression and XGBoost).
- Evaluated different features sets; and some features were tested in the models as categorical and as numerical trying to reach the best option.
- Tried different hyper parameters to enhance the performance.

Results

Model Evaluation and Validation

Here I am listing all used scenarios for Fare amount prediction along with its R2 and RMSE scores to evaluate them

Scenario 1:

Here I used almost all the features with linear regression model as a baseline:

['trip_distance', 'RatecodeID', 'tripduration_mins', 'month', 'hour', 'weekendflag', 'holidayflag', 'passenger_count', 'PULocationID', 'DOLocationID', 'payment_type']

And I used all features as numerical (no categorical).

The output of this scenario was:

```
The r-squared score for our model on Training data is 0.9408655229497245 o
n 14712202 values.
The mean_squared_error score for our model on Training data is 6.879148895
127688 on 14712202 values.
The root_mean_squared_error score for our model on Training data is 2.6228
13164357631 on 14712202 values.

The r-squared score for our model on Testing data is 0.9409164098556393 on
6305230 values.
The mean_squared_error score for our model on Testing data is 6.8711970854
87989 on 6305230 values.
The root_mean_squared_error score for our model on Testing data is 2.62129
683276961 on 6305230 values.
```

And the coef_weights:

	est_int	coefs	abs_coefs
1	RatecodeID	4.877630	4.877630
0	trip_distance	1.789178	1.789178
6	holidayflag	-0.380822	0.380822
2	tripduration_mins	0.317012	0.317012
5	weekendflag	-0.079736	0.079736
3	month	0.021592	0.021592
4	hour	-0.006859	0.006859
10	payment_type	0.001454	0.001454
9	DOLocationID	-0.000803	0.000803

	est_int	coefs	abs_coefs
7	passenger_count	0.000387	0.000387
8	PULocationID	-0.000010	0.000010

Scenario 2:

Here I excluded some features based on the correlation matrix and scenario 1 coefficients and kept main features plus the datetime engineered features.

['trip_distance', 'RatecodeID', 'tripduration_mins', 'month', 'hour', 'weekendflag', 'holidayflag']

Also treated all features as numerical features (no categorical)

And also used Linear Regression; the output was almost the same

```
The r-squared score for our model on Training data is 0.9408385370477721 o
n 14712202 values.
The mean_squared_error score for our model on Training data is 6.882288181
156071 on 14712202 values.
The root_mean_squared_error score for our model on Training data is 2.6234
11553903823 on 14712202 values.

The r-squared score for our model on Testing data is 0.940890929867919 on
6305230 values.
The mean_squared_error score for our model on Testing data is 6.8741603112
65811 on 6305230 values.
The root_mean_squared_error score for our model on Testing data is 2.62186
19931769505 on 6305230 values.
```

	est_int	coefs	abs_coefs
1	RatecodeID	4.873097	4.873097
0	trip_distance	1.790674	1.790674
6	holidayflag	-0.357203	0.357203
2	tripduration_mins	0.317114	0.317114
5	weekendflag	-0.076037	0.076037
3	month	0.021624	0.021624
4	hour	-0.007014	0.007014

Scenario 3:

Here I used the same features from scenario 2, with linear regression model as well, but handled some features as categorical and applied one-hot-encoding on them.

The output has very minor improvement:

```
The r-squared score for our model on Training data is 0.9432230301501271 o
n 14712202 values.
The mean_squared_error score for our model on Training data is 6.604898679
993168 on 14712202 values.
The root_mean_squared_error score for our model on Training data is 2.5699
997431893196 on 14712202 values.

The r-squared score for our model on Testing data is 0.943321447117103 on
6305230 values.
The mean_squared_error score for our model on Testing data is 6.5915003882
98767 on 6305230 values.
The root_mean_squared_error score for our model on Testing data is 2.56739
1748116903 on 6305230 values.
```

Scenario 4:

Here I used XGBoost Regressor with the same features of scenario 3 and the following hyper parameters: colsample_bytree = 0.3, learning_rate = 0.1, vmax_depth = 5, alpha = 10, n_estimators = 10

and the output was with much lower score as following:

```
The r-squared score for our model on Training data is 0.3242116292704751 o
n 14712202 values.
The mean_squared_error score for our model on Training data is 78.61486320
225254 on 14712202 values.
The root_mean_squared_error score for our model on Training data is 8.8665
02309380659 on 14712202 values.

The r-squared score for our model on Testing data is 0.32425626984223854 o
n 6305230 values.
The mean_squared_error score for our model on Testing data is 78.586428784
23606 on 6305230 values.
The root_mean_squared_error score for our model on Testing data is 8.86489
869001536 on 6305230 values.
```

Scenario 5:

Here I just changed the n_estimators hyper parameter in scenario 4 from 10 to 50 and it gave the highest score among all scenarios as following:

```
The r-squared score for our model on Training data is 0.9636330518992762 o
n 14712202 values.
The mean_squared_error score for our model on Training data is 4.230588707
727396 on 14712202 values.
The root_mean_squared_error score for our model on Training data is 2.0568
39494887094 on 14712202 values.

The r-squared score for our model on Testing data is 0.9638064313943984 on
6305230 values.
The mean_squared_error score for our model on Testing data is 4.2091745357
480885 on 6305230 values.
```

```
The root_mean_squared_error score for our model on Testing data is 2.05162
72896771697 on 6305230 values.
```

Summary of different models scores:

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
R2 – on Training	0.9408655	0.9408385	0.9432230	0.3242116	0.9636330
RMSE – On Training	2.6228131	2.6234115	2.5699997	8.8665023	2.0568394
R2 – on Testing	0.9409164	0.9408909	0.9433214	0.3242562	0.9638064
RMSE – On Testing	2.6212968	2.6218619	2.5673917	8.8648986	2.0516272

Scenario #5 XGBoost gives the highest R-squared and lowest RMSE.

And in general Fare_amount prediction will be done with the following features set used for training.

['trip_distance', 'RatecodeID', 'tripduration_mins', 'month', 'hour', 'weekendflag', 'holidayflag']

Justification

All tested scenarios (except scenario 4) gave good results; and this is because we have highly correlated features to the fare amount, especially trip_distance and tripduration_mins.

Scenario 5 gave slightly better results after increasing the n_estimators hyber parameters.

Conclusion

Reflection

In this project we have applied different statistical analysis and prediction to answer our business questions that would help car booking companies provide better service to the customers.

The same analysis concepts can be applied when Egyptian car booking dataset is available, which would give insights on the Egyptian market and help solving the transportation problem in Egypt.

The main challenge here was the pre-processing of the dataset along with the feature engineering which consumed most of the project time.

Improvement

Still many use cases and analytics can be derived from the dataset analysis to improve customer experience and increase efficiency and service revenue.

The main analytics areas would lie under:

- Fleet management.
- Trip's scheduling
- Predictions like:
    - Move from fare amount predictions to total amount prediction considering all factors.
    - Tip amount prediction
- Find new business opportunities.

And so on.