Cab Fare Prediction

In this challenge we are given a training set of Cab trips train data and test data. The goal of this challenge is to predict the fare of a Cab trip given information about the pickup and drop off locations, the pickup date time and number of passengers travelling.

In any analytics project 80% of the time and effort is spent on data cleaning, exploratory analysis and deriving new features. We aim to clean the data, visualize the relationship between variables and also figure out new features that are better predictors of taxi fare.

Here we take the city to be NEW YORK.

The Data

The fields that are present in the data are as below:-

Feature Name	Feature Description	Feature Data Type
Key	This is the unique identifier. This is combination of pickup datetime and an unique identifier	string
pickup_datetime	Date time when trip started	timestamp
pickup_longitude	longitude coordinate of where trip started	float
pickup_latitude	latitude coordinate of where the trip started	float
dropoff_longitude	longitude coordinate of where trip ended	float
dropoff_latitude	latitude coordinate of where the trip ended	float
passenger_count	number of passengers in taxi ride	integer
fare_amount	cost of the taxi ride in dollars. This is the value to be predicted. It is not present in the test data	float

Hypothesis Generation

The next step to solve any analytics problems is to list down a set of hypothesis, which in our case are factors that will affect the cost of a taxi trip.

1. **Trip distance** : If the distance to be traveled is more, then fare should be higher.
2. **Time of Travel** : During peak traffic hours, the taxi fare may be higher.
3. **Day of Travel** : Fare amount may differ on weekday and weekends
4. **Weather Conditions** : If it is snowing, there may be lower availability of cabs and hence higher fares.

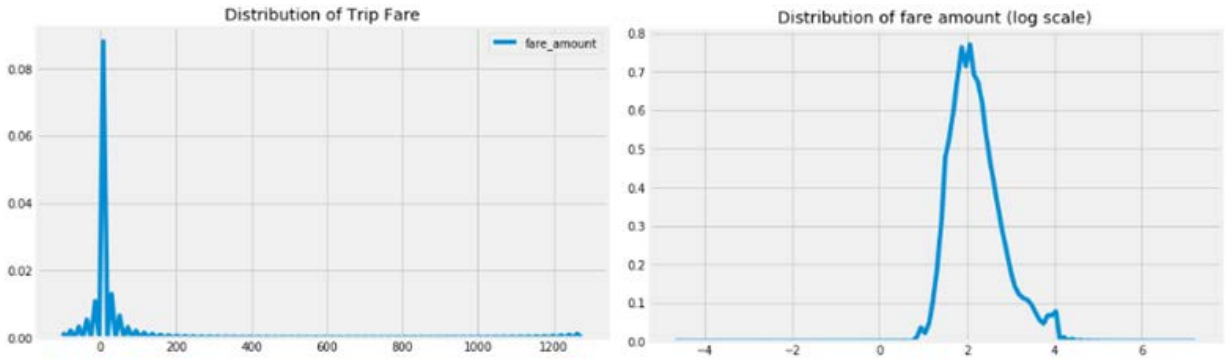
5. **Is it a trip to/from airport** : Trips to/from airport generally have a fixed fare.
6. **Pickup or Drop-off Neighborhood** : Fare may be different based on the kind of neighborhood.
7. **Availability of taxi** : If a particular location has a lot of cabs available, the fares may be lower.

Data Cleaning and Exploration

In this section, we will discuss various steps used to clean the data and understand the relationship between variables and use this understanding to create better features

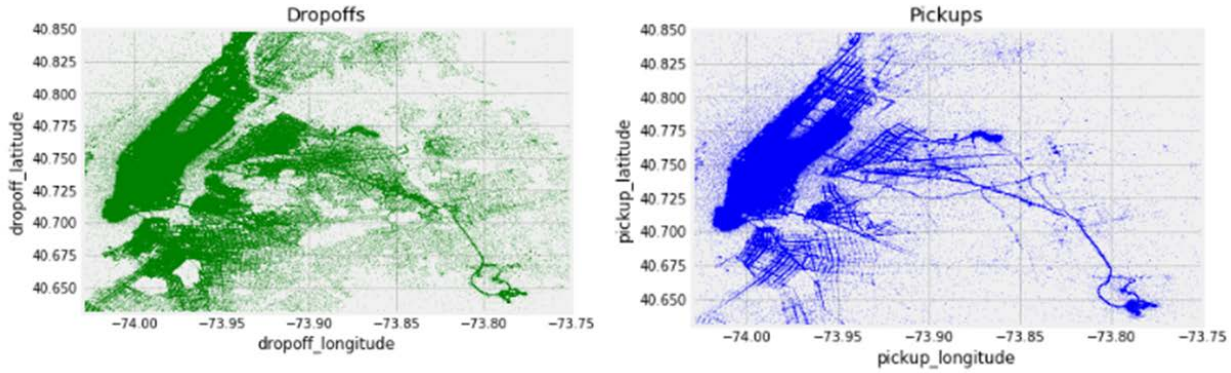
Distribution of fare amount

We first looked at the distribution of fare amount and found that there were 1 record where the fare was negative. Since, cost of a trip cannot be negative we removed such instances from the data. Also, fare amount follows long tail distribution.To understand the distribution of fare amount better we take a log transformation after removing the negative fares- this makes the distribution close to normal



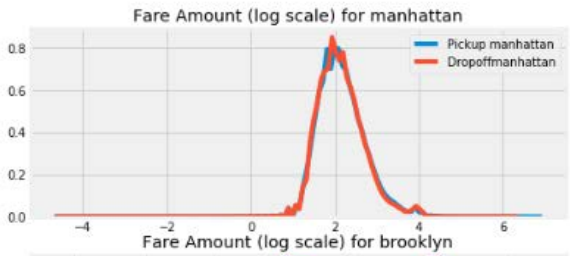
2. **Distribution of Geographical Features**

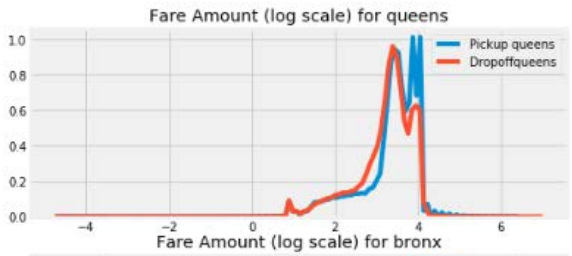
The range of latitudes and longitudes are between -90 to 90 and -180 to 180 respectively. But in the training data set we observed latitudes and longitudes in range of (-3488.079513, 3344.459268) which is not possible. On further exploration, we also identified a set of records which had both pickup and drop-off coordinates at the Equator. Since, this data is for taxi rides in New York, we remove these rows from our analysis. Such anomalies where not found in the test data.

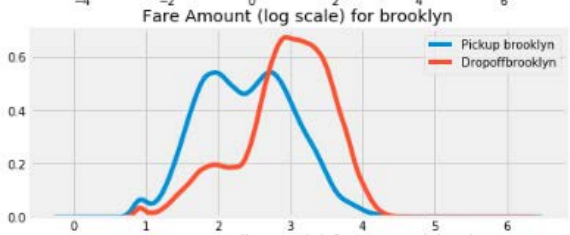


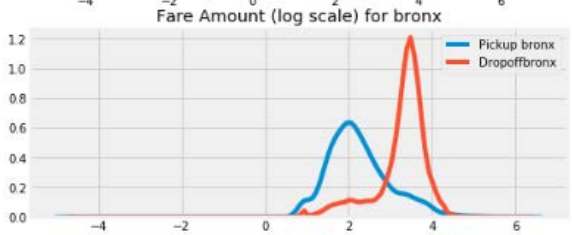
We can see that there is a high density of pickups near JFK and La Guardia Airport. We then looked at what is the average fare amount for pickups and drop offs to JFK, compared to all trips in the train data and observed that fare was higher for airport trips. Based on this observations we created features to check whether a pickup or a drop-off was to any one of the three airports in New York — JFK, EWR or LaGuardia

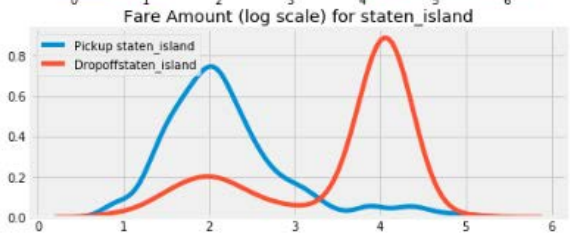
The next step was to check whether our hypothesis of fare from certain neighborhoods are higher than the rest, based on the 5 Boroughs New York city is divided — Manhattan, Queens, Brooklyn, Staten Island and Bronx, each pickup and drop off location was grouped into these 5 neighborhoods. And yes our hypothesis was right- except for Manhattan which had most of the pickups and drop offs, for every other neighborhood, there was a difference in the pickup and drop off fare distribution. Also, Queens had a higher mean pickup fare compared to other neighborhoods.





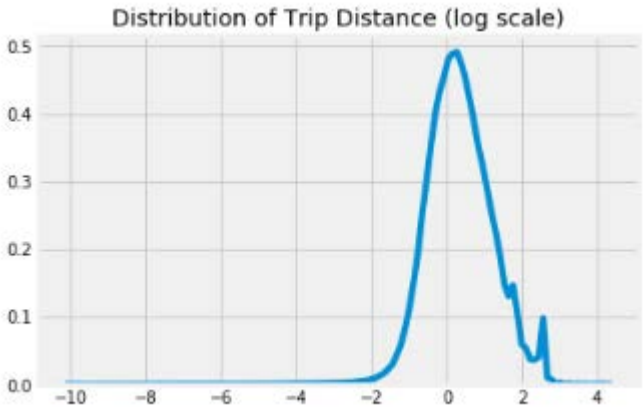




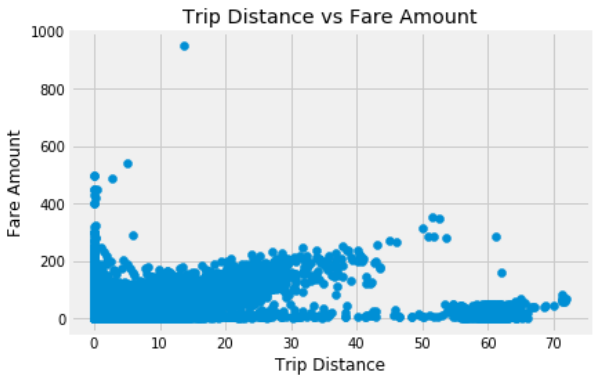


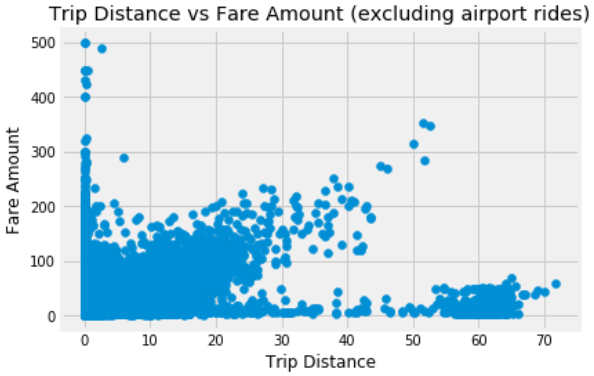
3. **Distribution of Trip Distance**

Using the pickup and drop-off coordinates we calculate the trip distance in miles based on **Haversine Distance.** Trip distance just like fare amount follows long tail distribution, we take a log transformation to make it close to normal distribution

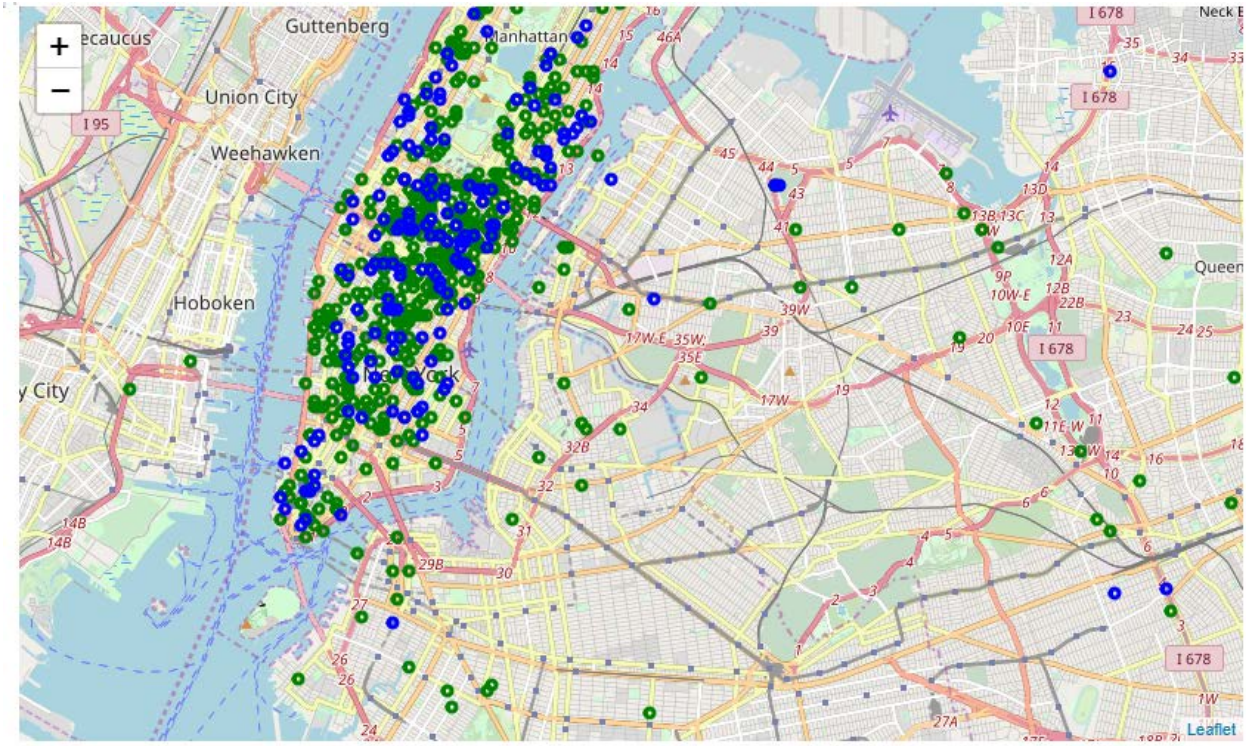


One of our hypothesis was just the fare amount should ideally increase with trip distance. A scatter plot between trip distance and fare amount showed that though there is a linear relationship,the fare per mile (slope) was lower, and there were a lot of trips whose distance was greater than 50 miles, but fare was very low. To check if this was the case because of airport trips, we removed the airport trips and plotted the distribution. We then observed that fare per mile was higher and another small cluster with trip distance >50 miles was observed.





The next step was to see if there was a particular region where the trip distance>50 miles was observed. This showed that, there were a lot of pickups and dropoffs from lower Manhattan. This led to a new feature — pickup_is_lower_manhattan and dropoff_is_low_manhattan.

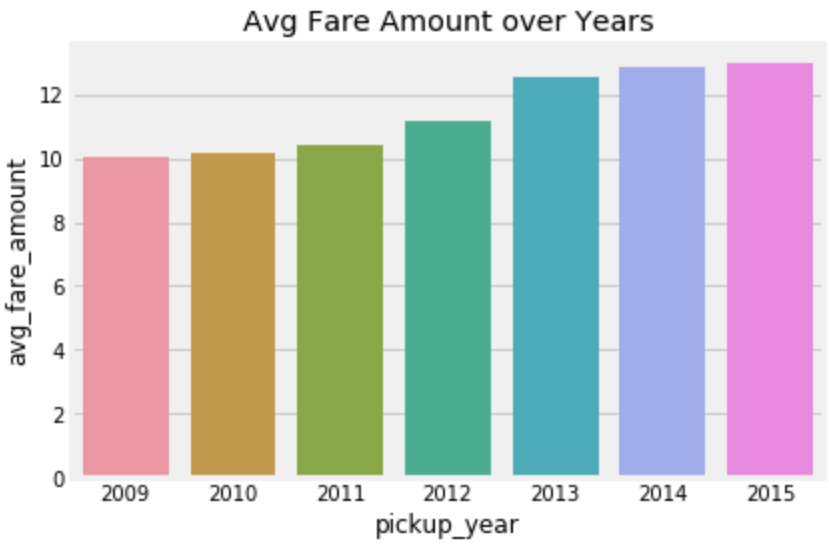


4. Distribution of Pickup date time

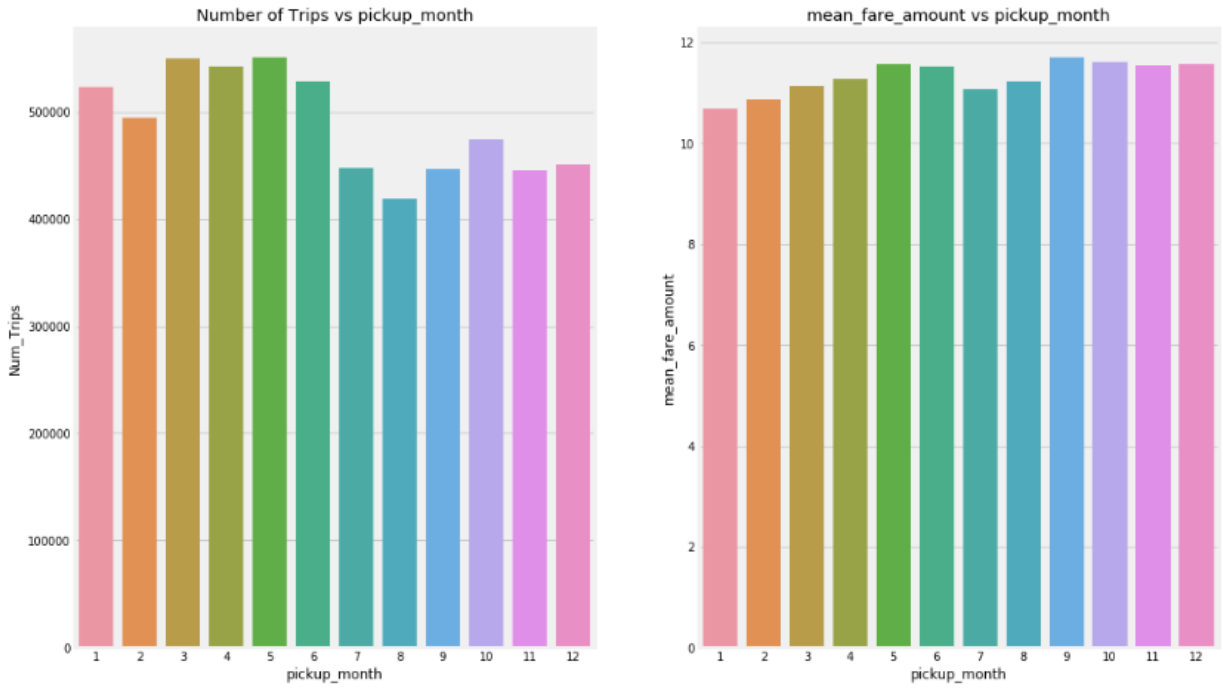
The first step to analyse how the fares have changed over time, is to create features like hour, day of the week, day, month, year from pickup datetime. The code to extract these features is as below

```
train['pickup_datetime']=pd.to_datetime(train['pickup_datetime'],format='%Y-%m-%d %H:%M:%S UTC')
train['pickup_date']= train['pickup_datetime'].dt.date
train['pickup_day']=train['pickup_datetime'].apply(lambda x:x.day)
train['pickup_hour']=train['pickup_datetime'].apply(lambda x:x.hour)
train['pickup_day_of_week']=train['pickup_datetime'].apply(lambda x:calendar.day_name[x.weekday()])
train['pickup_month']=train['pickup_datetime'].apply(lambda x:x.month)
train['pickup_year']=train['pickup_datetime'].apply(lambda x:x.year)
```

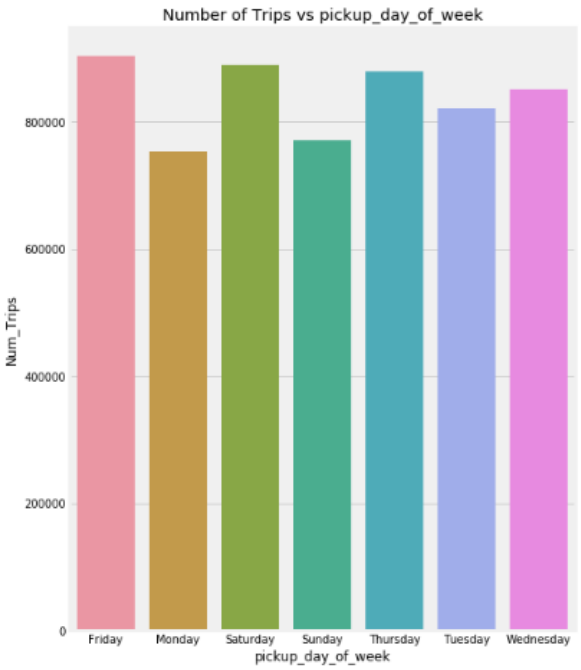
As expected, over years the average taxi fare has increased.

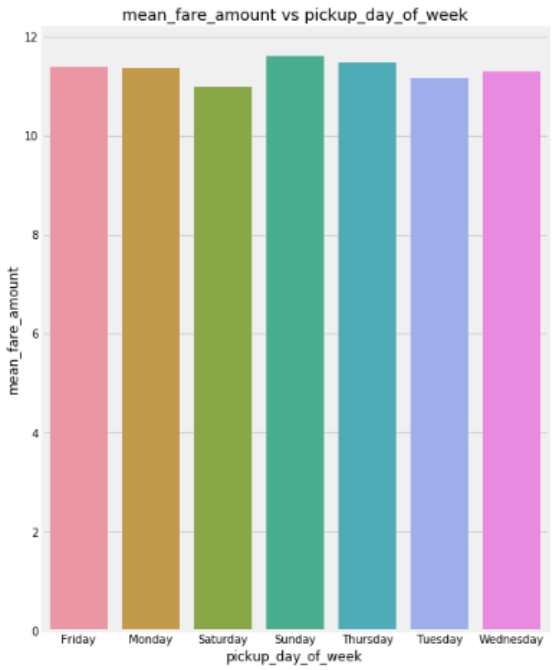


Over months, though there have been fewer pickups from July to December, the average fare is almost constant across months

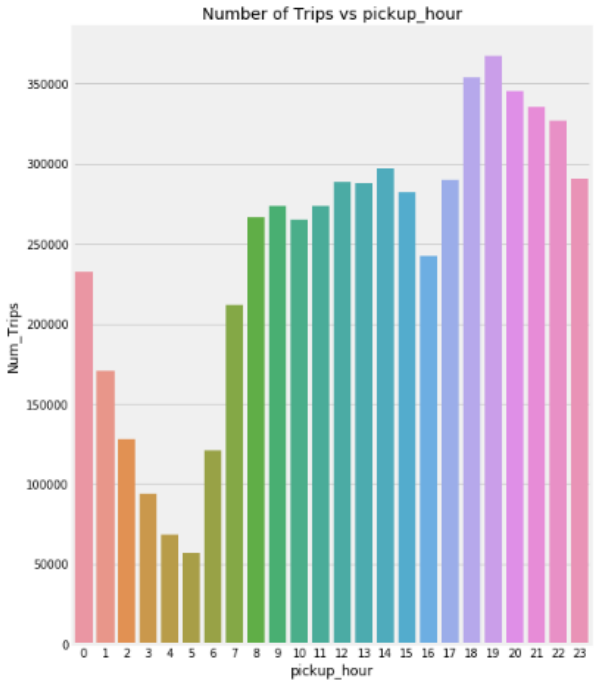


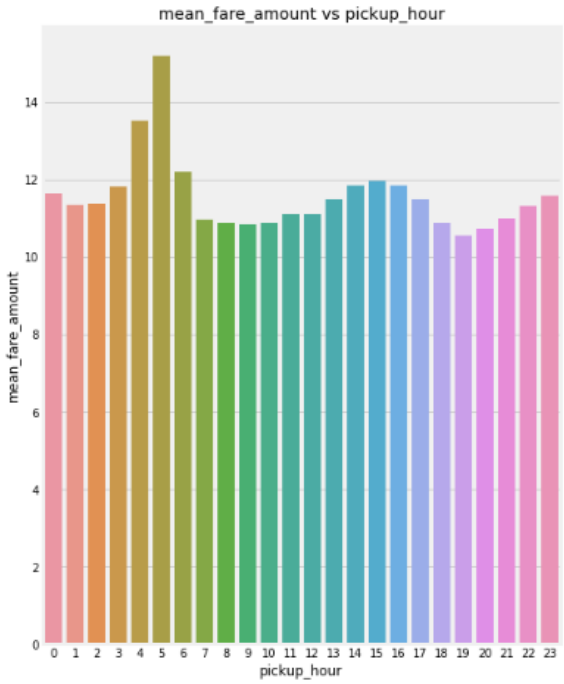
We observed that though the number of pickups are higher on Saturday, the average fare amount is lower. On Sunday and Monday though the number of trips are lower, avg fare amount is higher





The average fare amount at 5 am is the highest while the number of trips at 5 am are the least. This is because, at 5 AM 83% of the trips are to the airport.The number of trips are highest in 18 and 19 hours





Based on the features created using this Exploratory Analysis, the baseline model using XGBoost scored a RMSE of 3.03760 on the public leaderboard, which is in the Top 15 percentile.

we will understand how to build machine learning models to predict taxi fare and look at the significant impact feature engineering plays in this process. The code for this article can be found here.

Roadmap

After the Data Cleaning and Exploratory Analysis phase, we have finally arrived at the Model Building phase. The quality of results at the end of this phase depends on the data quality and features

used for modelling. In this article, we are going to understand the below steps in detail:

1. Data Preparation for model building
2. Creating a baseline prediction
3. Building Models without Feature Engineering
4. Building Models with Feature Engineering

Data Preparation

This step involves cleaning the data, dropping unwanted columns, converting the categorical variables to machine-understandable format, and finally splitting of training data into train and validation sets.

We will remove all negative fare amount, and passenger counts greater than 7, as we did in part 1.

The next step in data preparation is dividing the training data into train and validation data sets. This step is followed in almost all machine learning projects and is one of the most critical steps that allows us to evaluate models.

The validation dataset helps us understand how the model, fit using training data, works on any unseen data. This helps us gauge whether the model is overfitting or underfitting. Overfitting is the term used when training error is low, but the testing error is high. This is a common problem with complex models because they tend to memorize the underlying data and hence perform poorly on unseen data.

Simple models like Linear Regression do not memorize the underlying data, but instead have straightforward assumptions about the data. Therefore, these models have a very high error (high bias), but low variance. The validation data set will help us evaluate the models based on variance and bias. In this analysis, we will keep 25% of our data as validation data.

```
from sklearn.model_selection import train_test_split
X=train.drop([fare_amount],axis=1)
y=train[fare_amount]
X_train, X_test, y_train, y_test = train_test_split(X,y,
test_size=0.25,random_state=123)#test_size is the proportion of
data that is to be kept aside for validation
```

Baseline Model

A baseline model is a solution to a problem without applying any machine learning techniques. **Any model we build must improve upon this solution.** Some ways of building a baseline model are taking the most common value in case of classification, and calculating the average in a regression problem. In this analysis, since we are predicting fare amount (which is a quantitative variable)— we will predict the average fare amount. **This resulted in an RMSE of 9.71. So any model we build should have an RMSE lower than 9.71.**

```
avg_fare=round(np.mean(y_train),2) #11.31
baseline_pred=np.repeat(avg_fare,y_test.shape[0])
baseline_rmse=np.sqrt(mean_squared_error(baseline_pred, y_test))
print("Basline RMSE of Validation data :",baseline_rmse)
```

Model Building and Evaluation

1. Without Feature Engineering

In this step, we will use only DateTime features, without including any of the additional features like the trip distance, or distance from airports, or pickup distance from a borough. To understand and evaluate the models, we will consider the following ML algorithms:

- Linear Regression
- Random Forest
- Light GBM

Except for Linear Regression, the rest of the models are ensembles of decision trees, but they differ in the way the decision trees are created. Before we discuss further, let us understand the definitions of a couple of key terms we will be using.

1. **Bagging**: In this method, multiple models are created, and the output prediction is the average predictions of the different models. In Bagging, you take bootstrap samples (with replacement) of your data set and each sample trains a weak learner. Random Forest uses this method for predictions. In Random Forest, multiple decision trees are created, and the output is the average prediction by each of these trees. For this method to work, the baseline models must have a lower bias (error rate).
2. **Boosting**: In this method, multiple weak learners are ensembled to create strong learners. Boosting uses all data to

train each learner. But instances that were misclassified by the previous learners are given more weight, so that subsequent learners can give more focus to them during training. XGBoost and Light GBM are based on this method. Both of them are variations of the Gradient Boosting Decision Trees (GBDTs). In GBDTs, the decision trees are trained iteratively — i.e., one tree at a time. XGBoost and Light GBM use the **leaf-wise** growth strategy when growing the decision tree. When training each decision tree and splitting the data, XGBoost follows level-wise strategy, while Light GBM follows leaf-wise strategy.

It's finally time to build our models!

1. **Linear Regression:** It is used to find a linear relationship between the target and one or more predictors. The main idea is to identify a line that best fits the data. The best fit line is the one for which the prediction error is the least. This algorithm is not very flexible, and has a very high bias. Linear Regression is also highly susceptible to outliers as it tries to minimize the sum of squared errors.

```
lm = LinearRegression()
lm.fit(X_train,y_train)
y_pred=np.round(lm.predict(X_test),2)
lm_rmse=np.sqrt(mean_squared_error(y_pred, y_test))
lm_train_rmse=np.sqrt(mean_squared_error(lm.predict(X_train),
y_train))
lm_variance=abs(lm_train_rmse - lm_rmse)
print("Test RMSE for Linear Regression is ",lm_rmse)
print("Train RMSE for Linear Regression is ",lm_train_rmse)
print("Variance for Linear Regression is ",lm_variance)
```

The test RMSE for Linear Regression model was 8.14, and the training RMSE was 8.20. This model is an improvement on the baseline prediction. Still, the error rate is very

high in this model, though the variance is very low (0.069). Let's try a more complex model next.

2. **Random Forest**

Random Forest is far more flexible than a Linear Regression model. This means lower bias, and it can fit the data better. Complex models can often memorize the underlying data and hence will not generalize well. Parameter tuning is used to avoid this problem.

```
rf = RandomForestRegressor(n_estimators = 100, random_state =
883,n_jobs=-1)
rf.fit(X_train,y_train)
rf_pred= rf.predict(X_test)
rf_rmse=np.sqrt(mean_squared_error(rf_pred, y_test))
print("RMSE for Random Forest is ",rf_rmse)
```

The Random Forest model gave an RMSE of 3.72 on validation data and train RMSE of 1.41. There is a huge variation in the training and validation RMSE, indicating overfitting. To reduce overfitting, we can tune this model.

3. **LightGBM**

LightGBM is a boosting tree based algorithm. The difference between Light GBM and other tree-based algorithms, is that Light GBM grows leaf-wise instead of level-wise. This algorithm chooses the node which will result in maximum delta loss to split. Light GBM is very fast, takes quite less RAM to run, and focuses on the accuracy of the result.

```
train_data=lgb.Dataset(X_train,label=y_train)
param = {'num_leaves':31,
```

```
'num_trees':5000,'objective':'regression'}
param['metric'] = 'l2_root'
num_round=5000
cv_results = lgb.cv(param, train_data,
num_boost_round=num_round, nfold=10,verbose_eval=20,
early_stopping_rounds=20,stratified=False)
lgb_bst=lgb.train(param,train_data,len(cv_results['rmse-mean']))
lgb_pred = lgb_bst.predict(X_test)
lgb_rmse=np.sqrt(mean_squared_error(lgb_pred, y_test))
print("RMSE for Light GBM is ",lgb_rmse)
```

This model gave an RMSE of 3.78 on validation data but the bias is higher than Random Forest. On the other hand, the variance of this model was 0.48 as compared to 2.31 in our Random Forest model.

	model_name	test_rmse	train_rmse	variance
0	Linear Regression	8.140288	8.209541	0.069252
1	Random Forest	3.722761	1.412086	-2.310674
2	Light GBM	3.789988	3.301217	-0.488771

Since Light GBM has a comparable error rate to Random Forest, and has a lower variance and runs faster than the latter, we will use LightGBM as our model for further analysis

2. Feature Engineering and Model Tuning

Feature Engineering is the process of transforming raw data into features that are input to the final models. The aim is to improve

the accuracy of the models. Having good features means we can use simple models for producing better results. Good features describe the structure inherent in the data.

As discussed in part 1, we will use features identified in the EDA phase, like the pickup and drop distance from airports, the pickup and drop distance from each borough (whether the pickup or drop was from or to the airport, and which borough the pickup or drop was from).

Applying the same Light GBM model discussed above on this feature engineered data resulted in an RMSE of 3.641 (drop from 3.78) and a variance of 0.48.

The next step is to tune this model. A good model has low bias and variance (to avoid overfitting). Few important features in LightGBM that can be optimized to reduce overfitting are:

1. **max_depth**: this indicates the maximum depth of the tree. Since LightGBM follows leaf-wise growth if not tuned, the depth can be much higher as compared to other tree-based algorithms.
2. **subsample**: This indicates what fraction of the data is to be used in each iteration, and it used to speed up the algorithm and control overfitting.
3. **colsample_bytree**: This is the fraction of features that are to be used in each iteration of the tree building process.
4. **min_child_samples:** This indicates the minimum number of samples that can be present in a leaf node. This helps to control overfitting.

I have used the *hyperopt* library in Python to tune the model. ***Hyperopt* is a hyperparameter search package that implements various search algorithms to find the best set of hyperparameters within a search space.** To use *Hyperopt*, we must specify an objective/loss function to minimize, the search space and trials database (optional, MongoTrials can be used to parallelise the search). For our problem, the objective is to minimise RMSE and identify the best set of parameters. We will tune the max_depth, subsample, and colsample_bytree parameters using hyperopt.

The objective function to be used for tuning is to minimize the RMSE in a LightGBM Regressor, given a set of parameters.

The search space defines the set of values a given parameter can take. After defining the objective function and the search space, we run 100 trials and evaluate the result of the trials on our validation data to identify the best parameters.

```
def objective(space):clf = lgb.LGBMRegressor(
          objective = 'regression',
          n_jobs = -1, # Updated from 'nthread'
          verbose=1,
          boosting_type='gbdt',
        num_leaves=60,
        bagging_freq=20,
       subsample_freq=100,
    max_depth=int(space['max_depth']),
    subsample=space['subsample'],
        n_estimators=5000,
    colsample_bytree=space['colsample'])
          #metric='l2_root')eval_set=[( X_train, y_train), (
X_test,y_test)]clf.fit(X_train, np.array(y_train),
            eval_set=eval_set,eval_metric='rmse',
            early_stopping_rounds=20)pred = clf.predict(X_test)
    rmse = np.sqrt(mean_squared_error(y_test, pred))
    print("SCORE:", rmse)return{'loss':rmse, 'status': STATUS_OK
}space ={
        'max_depth': hp.quniform("x_max_depth", 5, 30, 3),
```

```
        'subsample': hp.uniform ('x_subsample', 0.8, 1),
        'colsample':hp.uniform ('x_colsample', 0.3, 1)
    }trials = Trials()
best = fmin(fn=objective,
            space=space,
            algo=tpe.suggest,
            max_evals=100,
            trials=trials)print(best)
```

The best parameters that we got for LightGBM with feature engineering were:

```
{'max_depth': 24.0, 'subsample': 0.9988461076307639,
'colsample_bytree': 0.38429620148564814}
```

Using these parameters, the LightGBM model resulted in an RMSE of 3.633 and variance of 0.44. We can improve this model further by tuning other parameters like *num_leaves* and adding L1 and L2 regularisation parameters.

End Notes

Feature engineering significantly improved the predictive ability of our Machine Learning model. Another way to improve the model's accuracy is to increase the amount of training data, and/or building ensemble models. If we have a lot of dimensions (features) in the data, dimensionality reduction techniques can also help improve the model's accuracy.