PROJECT REPORT ON:

Dynamic Pricing Prediction for Cabs Using IBM Watson

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1. **INTRODUCTION:**

Many organizations do not have a direct role in travel and tourism but offer related products and services. Some examples would be offering travel insurance, parking facilities at airports, theatre and event tickets, car hire, and travel by rail or coach to airports, etc. at competitive rates. There are various different forms of dynamic pricing:

1. Peak Pricing – This is a strategy that is common in transportation businesses. Airlines are a good example. Airlines often charge a higher price to travel during rush hour mostly on weekdays and sometimes on weekends.

2. Surge Pricing – Companies such as Uber respond dynamically to changes in supply and demand in order to price their services differently. Like most of us have noticed, this frequently happens on stormy evenings and nights when more people request for cabs. Taxify also not so long ago introduced dynamic pricing to ensure the drivers are encouraged to go online and offer services when the demand is high.

2. LITERATURE REVIEW

We know the popularity of uber in the recent years and about the urban citizens who are benefited by the uber. Later the author compares the difference between the competitive taxis and uber and defines new way of calling and also the new way of paying for cabs, the author also tells us about the importance of data produced by the cabs daily and also about the visualization and analysis of data. After that the author tells how the different time and different environments will have an effect on passengers to make different choices.

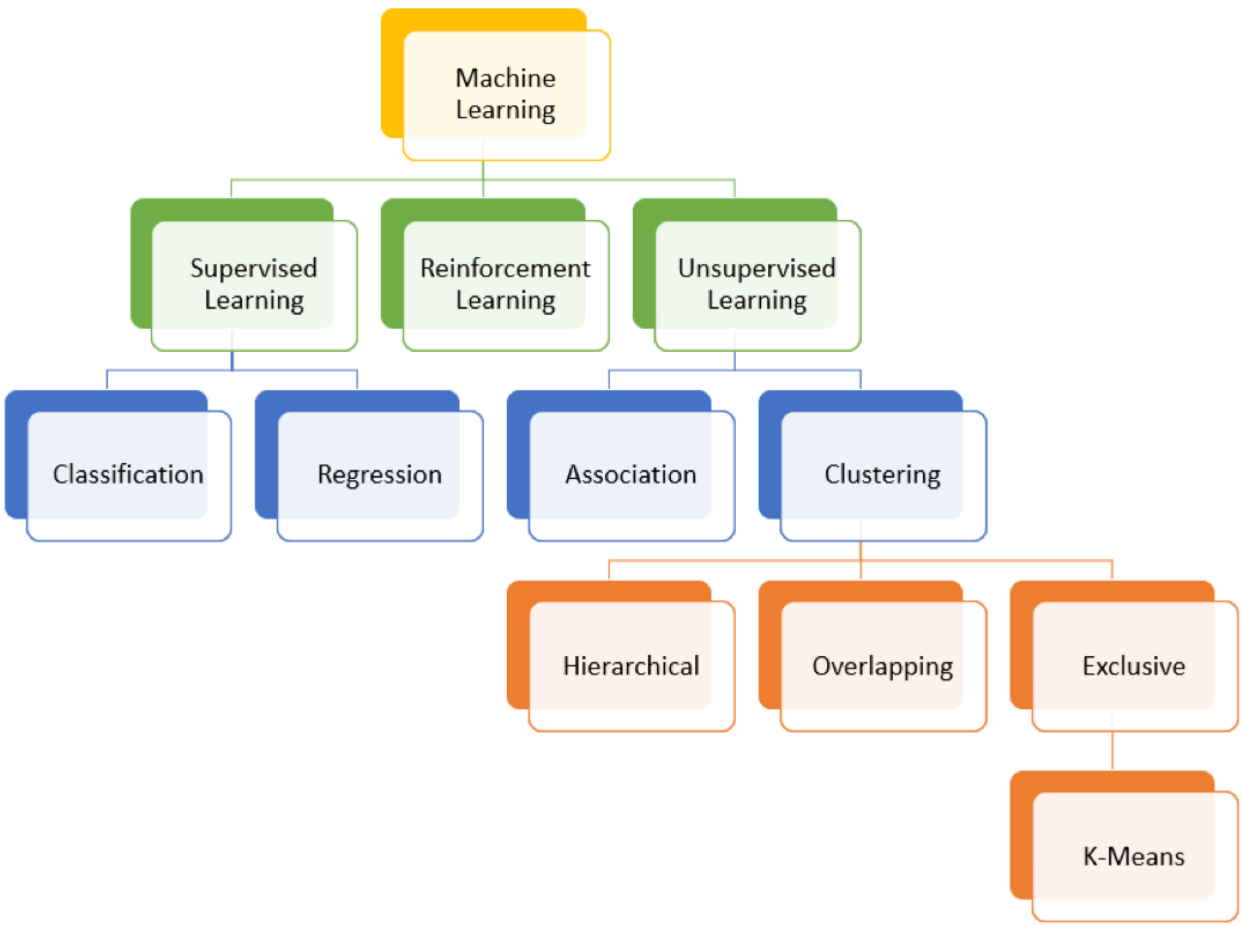
3. THEORITICAL ANALYSIS:

After analyzing the different parameters, here are a few pointers that we can conclude. If you were a Business Analyst or a data scientist working for either Uber or Lyft, you could draw the following conclusions:

1. Uber is more economical; however, Lyft also provides fair competition.
2. People prefer to have shared rides during the nighttime.
3. People avoid taking rides when it rains.
4. When traveling long distances, the price does not increase linearly. However, based on the time and demand, a surge can affect the cost.
5. Uber can be the first choice for long distances.

However, acquiring and analyzing similar data is only a tipping point for several companies. There are several enterprises in the market that can help bring data from multiple sources and in different formats into the data warehouse of your choice.

a. **Block Diagram:**



b. **Hardware / Software designing:**

- python

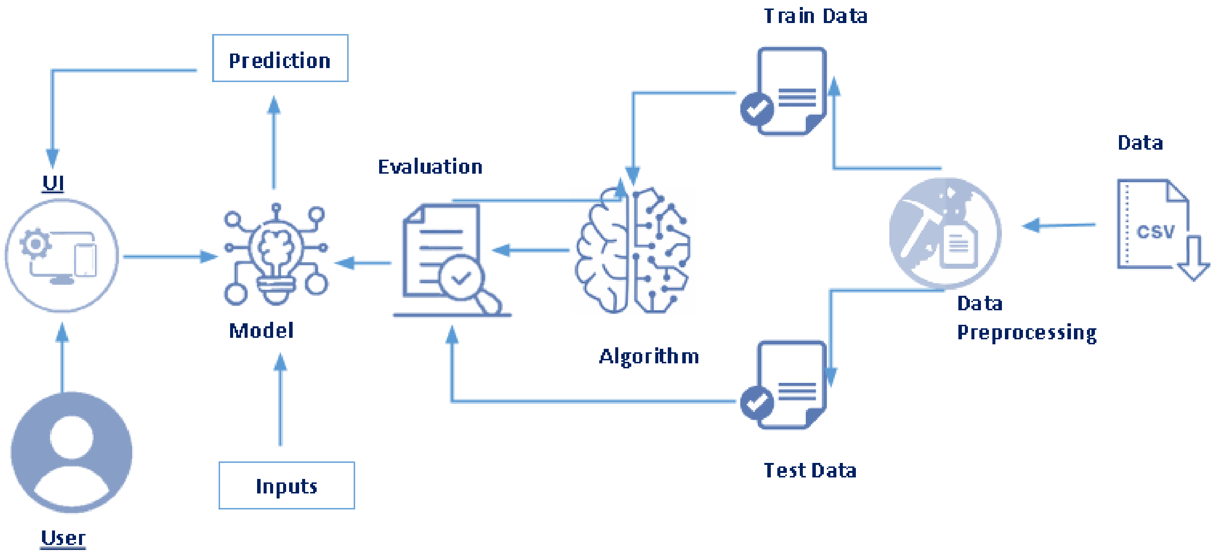
- HTML
- Google Chrome
- IBM Cloud
- Microsoft Excel

4. EXPERIMENTAL INVESTIGATIONS:

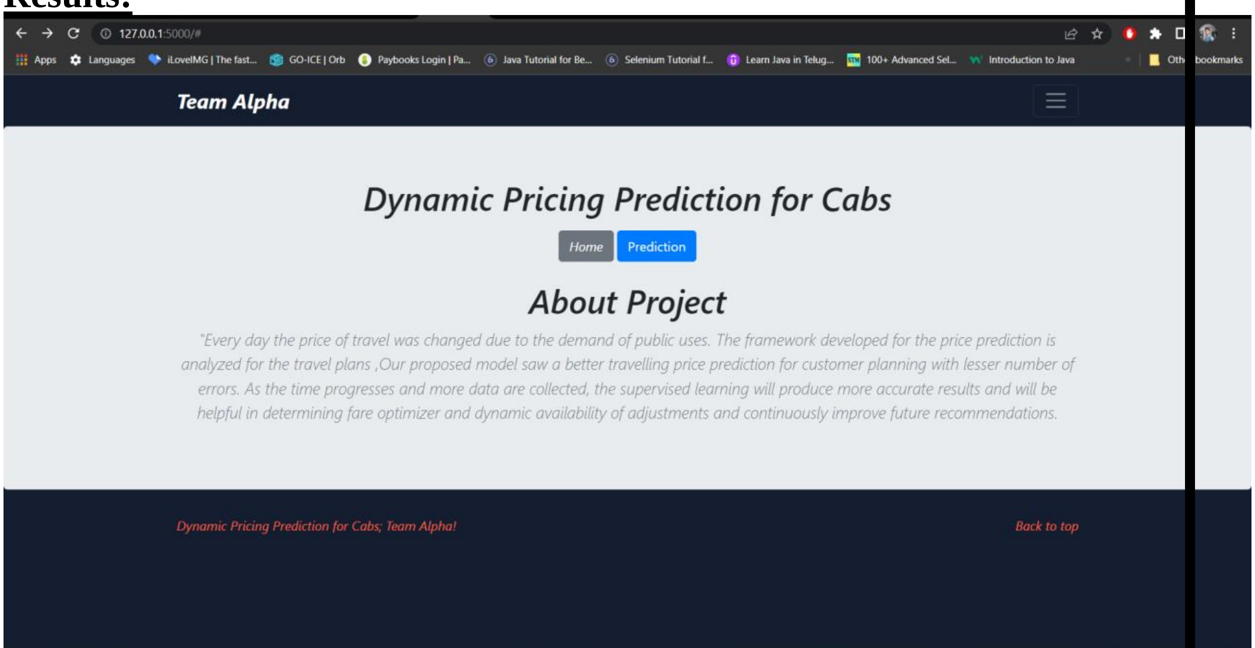
After collecting the segmentation data set, required data preprocessing and data visualizations are done to our data set and later on we checked the accuracy of our data set by applying different machine learning algorithms like H-clustering, k-means clustering Decision tree, Random Forest, KNN, and xgboost. As we used here different machine learning techniques like Supervised and Unsupervised Machine learning algorithms, we got different accuracies accordingly and from that we got highest accuracy for xgboost Supervised machine learning algorithm. We stored that model in pickle file and by running that file in flask with required python code with extracting the saved pickle file and by coding in HTML for the web pages i.e., for user interface we got the required output for our project. Later on we deployed our model in IBM Watson cloud and after deploying we got the python code according to that deployment and after merging with our python code we got the same output as before i.e., by giving the required values the model predicts whether the customer is highly potential or potential or not potential.

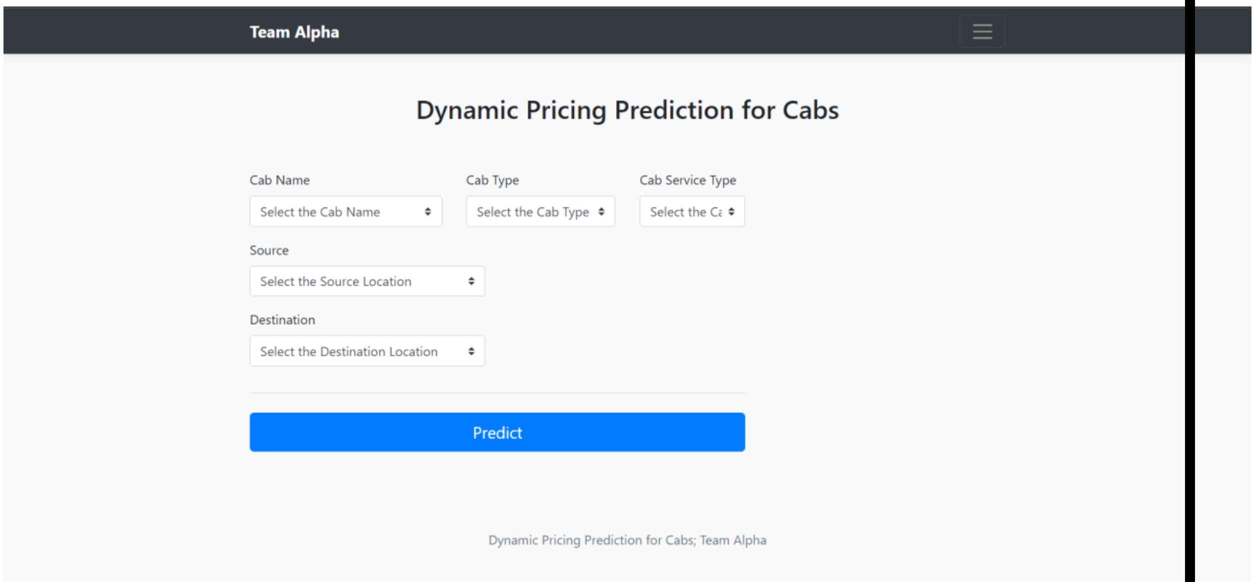
5. FLOWCHART:

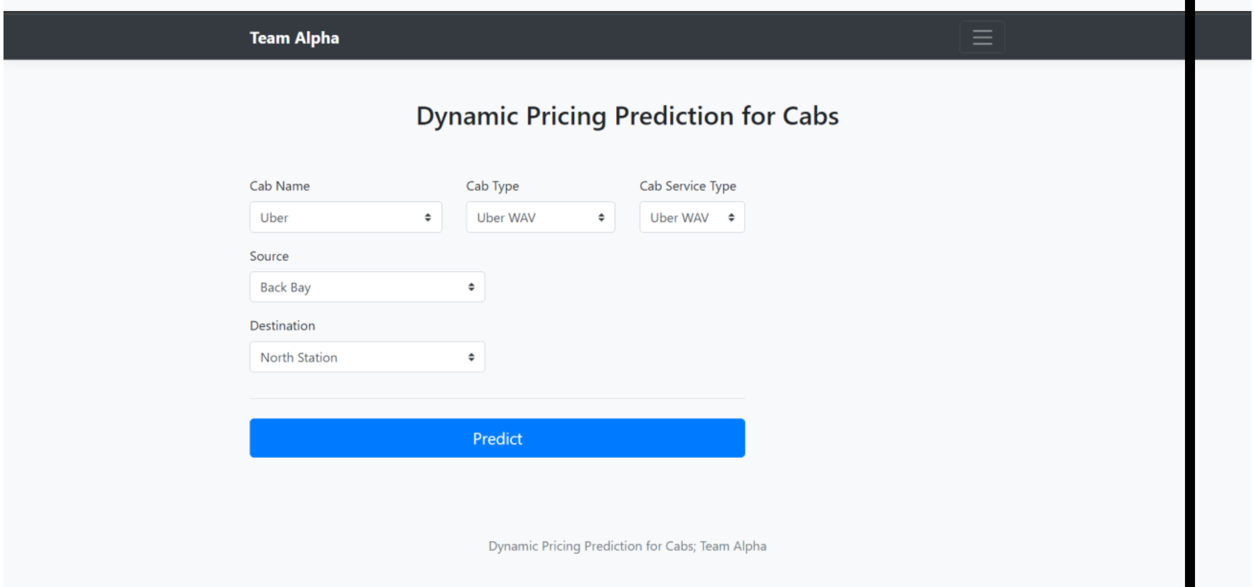
5. <u>FlowChart</u>

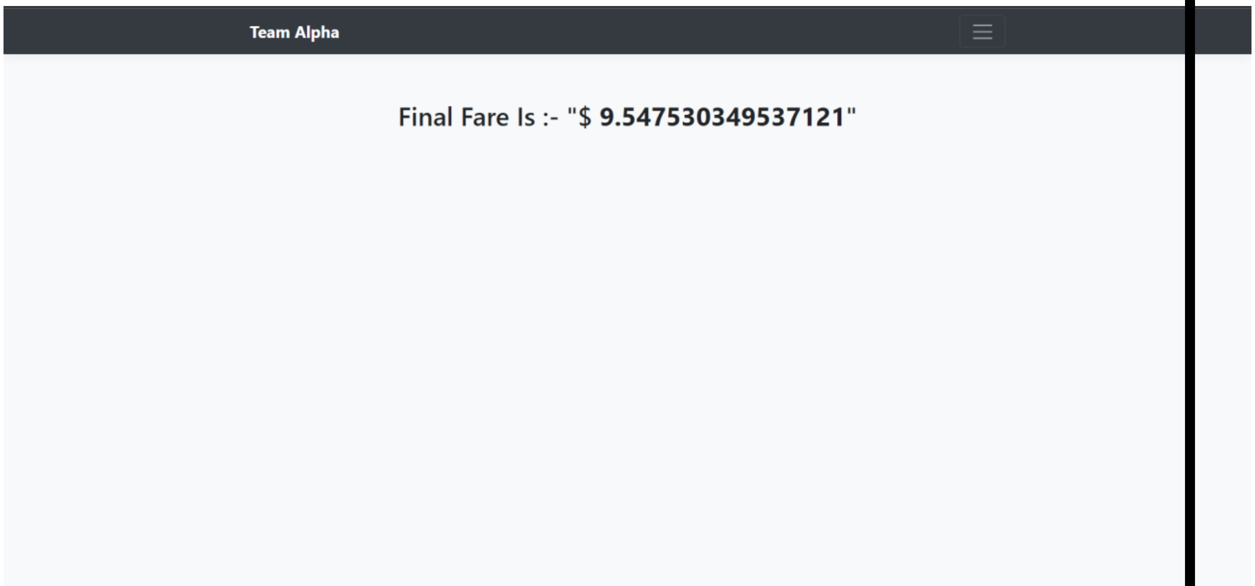


6. Results:




Team Alpha
Dynamic Pricing Prediction for Cabs
Cab Name
Select the Cab Name
Cab Type
Select the Cab Type
Cab Service Type
Select the Ca
Source
Select the Source Location
Destination
Select the Destination Location
Predict
Dynamic Pricing Prediction for Cabs; Team Alpha


Team Alpha
Dynamic Pricing Prediction for Cabs
Cab Name
Uber
Cab Type
Uber WAV
Cab Service Type
Uber WAV
Source
Back Bay
Destination
North Station
Predict
Dynamic Pricing Prediction for Cabs; Team Alpha



7. ADVANTAGES & DISADVANTAGES:

As for the relative pros and cons, it’s vital to comprehend the notion that the seller usually wins: dynamic pricing algorithms ideally allow for maximizing the profits out of every single client. The seller can establish some discriminatory policies that are going to reflect his or her subjective overview of the market, even though the customers may realize that they are overpaying for the same solution, factually speaking. Such an approach may turn away some of the clients, yet still, allow the seller to receive the utmost benefit. Otherwise, if the demand for the product is relatively low, it’s still possible to generate some revenue by offering promotions for appreciating the general supply/demand chart. In such a scenario, it will be the customer who “gains” the most. Even though the real-life models may contain slightly more variables that influence the pricing, it always comes down to these rooting rules and principles.

8. CONCLUSION

This project gives us basic understanding of how we can use machine learning in order to predict the cab fare from given source to destination before starting the cab ride. The model created is able to give us the predictions which are not exactly equal to the actual the price fluctuation is around the difference of ten to twenty rupees compared to the actual price. Since the model is good but not the best, we can improve the predictions of the model by using the Fine-tuning technique. If fine tuning is applied to the existing model, we are able to get higher accuracy than the proposed model.

9. Future Scope

From a long cycle perspective, the ride demand may first increase and then decrease, or first decrease and then increase, so the benchmark model may not be intuitive. In this section, we construct a general model to extend our benchmark model in Section 4, which can provide reference for the ride-hailing platform enterprises when the situation in which there is increasing or decreasing fluctuation of market demand (e.g., first increasing and then decreasing). In addition, we find the characteristics of the optimal dynamic price trajectory in the general model are consistent with those of the benchmark model, that is, the other forms of requirement functions will not change the correctness of the conclusion.

10. BIBILORAPHY

[1] J. Guo, "Analysis and comparison of Uber, Taxi and Uber request via Transit,," IIJRD, vol. 4, no. 2, pp. 60- 62, 2015.
[2] N. G. G. K. Uyanik, "A study on multiple linear regression analysis," Procedia- Social and Behavioral Sciences, vol. 106, pp. 234-240, 2013.
[3] Y. J. Y. Zhang, "A data-driven quantitative assessment model for taxi industry: the scope of business ecosystem’s health," Eur. Transp. Res., vol. 9, pp. 1-23, 2017.
[4] U. Patel, "NYC Taxi Trip and Fare Data Analytics using BigData," Department of Computer Science and Engineering University of Bridgeport, USA, 2018.
[5] J. Chao, "Modeling and Analysis of Uber’s Rider Pricing," Advances in Economics, Business and Management Research, vol. 109, pp. 639-711, 2019.

11. APPENDIX:

a. After Importing necessary libraries and loading the data set.

```
rides_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 693071 entries, 0 to 693070
Data columns (total 10 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   distance          693071 non-null  float64
 1   cab_type          693071 non-null  object
 2   time_stamp        693071 non-null  int64
 3   destination       693071 non-null  object
 4   source            693071 non-null  object
 5   price             637976 non-null  float64
 6   surge_multiplier  693071 non-null  float64
 7   id                693071 non-null  object
 8   product_id        693071 non-null  object
 9   name              693071 non-null  object
dtypes: float64(3), int64(1), object(6)
memory usage: 52.9+ MB
```

```
weather_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6276 entries, 0 to 6275
Data columns (total 8 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   temp        6276 non-null   float64
 1   location    6276 non-null   object
 2   clouds      6276 non-null   float64
 3   pressure    6276 non-null   float64
 4   rain        894 non-null    float64
 5   time_stamp  6276 non-null   int64
 6   humidity    6276 non-null   float64
 7   wind        6276 non-null   float64
dtypes: float64(6), int64(1), object(1)
memory usage: 392.4+ KB
```

```
df_joined.info()
```

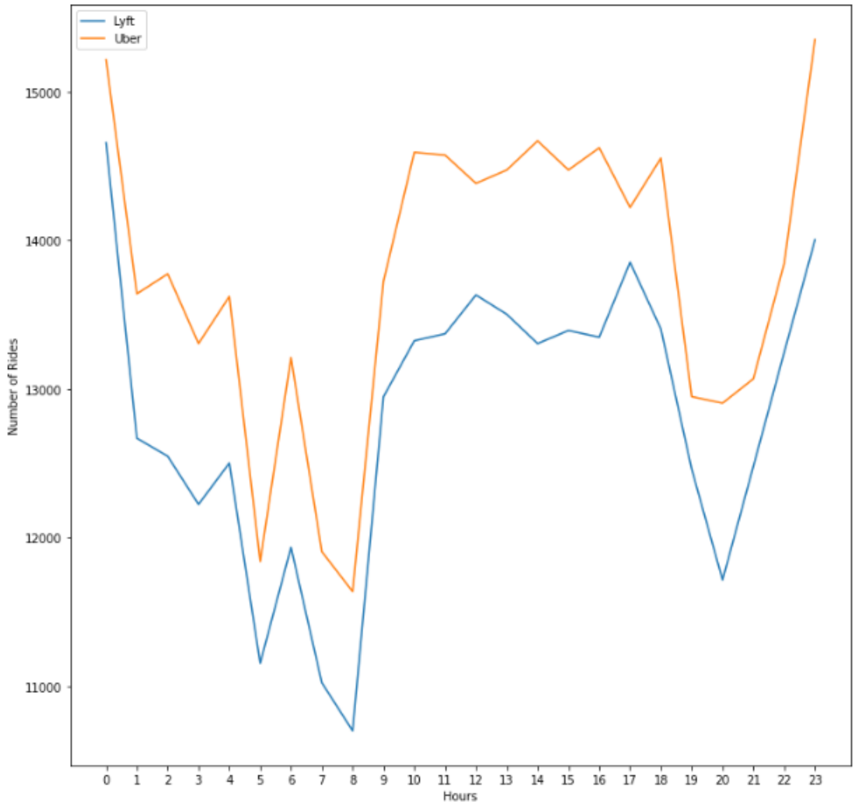
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1167730 entries, 0 to 637975
Data columns (total 22 columns):
 #   Column            Non-Null Count    Dtype
---  ------            --------------    -----
 0   distance          1167730 non-null  float64
 1   cab_type          1167730 non-null  object
 2   time_stamp        1167730 non-null  int64
 3   destination       1167730 non-null  object
 4   source            1167730 non-null  object
 5   price             1167730 non-null  float64
 6   surge_multiplier  1167730 non-null  float64
 7   id                1167730 non-null  object
 8   product_id        1167730 non-null  object
 9   name              1167730 non-null  object
 10  date              1167730 non-null  datetime64[ns]
 11  merged_date       1167730 non-null  object
 12  temp              1164996 non-null  float64
 13  location          1164996 non-null  object
 14  clouds            1164996 non-null  float64
 15  pressure          1164996 non-null  float64
 16  rain              1164996 non-null  float64
 17  time_stamp_w      1164996 non-null  float64
 18  humidity          1164996 non-null  float64
 19  wind              1164996 non-null  float64
 20  date_w            1164996 non-null  datetime64[ns]
 21  merged_date_w     1164996 non-null  object
dtypes: datetime64[ns](2), float64(10), int64(1), object(9)
memory usage: 204.9+ MB
```

b. We can also see count,standard deviation,mean,min,max,25%,50%,75% with data.describe() command.

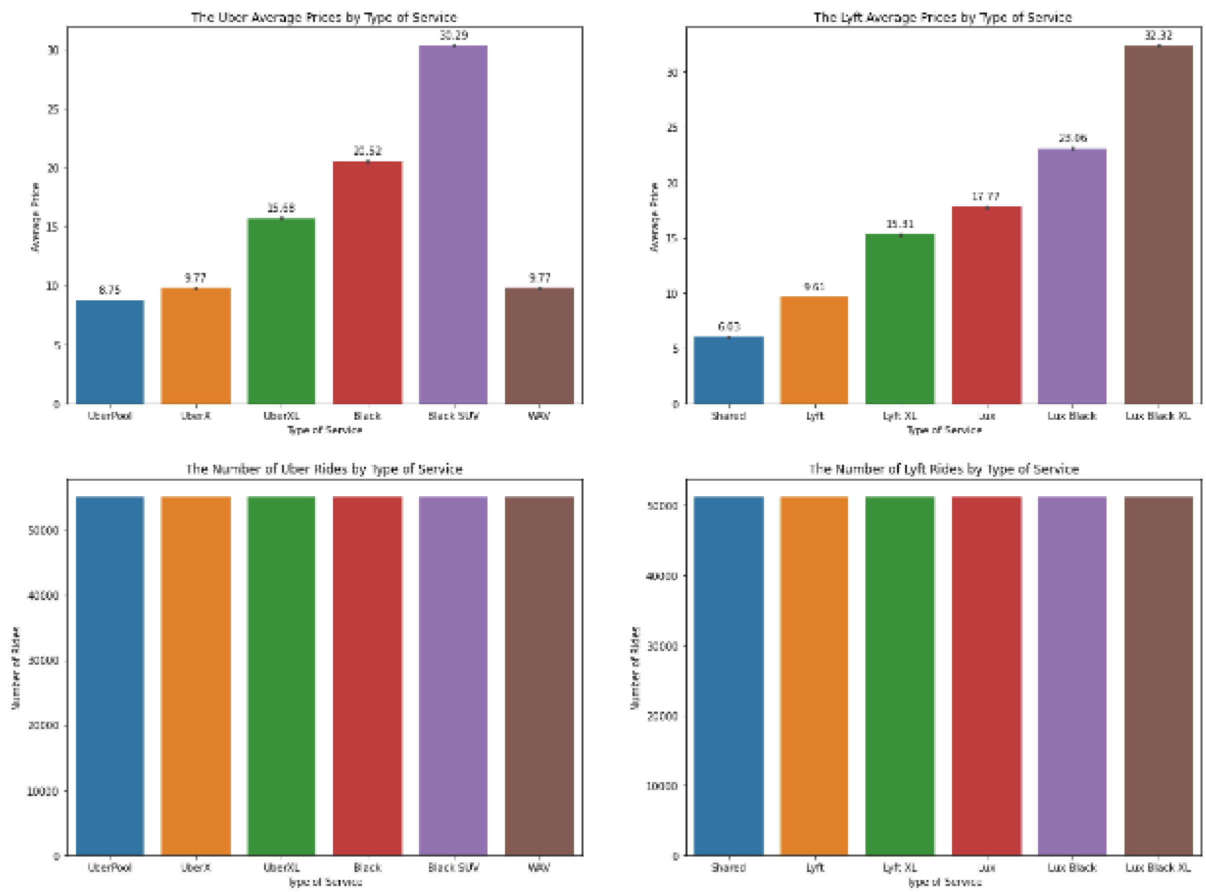
c. We can see about our data by checking the info, here we can also see that there are no null values mentioned in our columns.

d. Next we perform Data visualization.

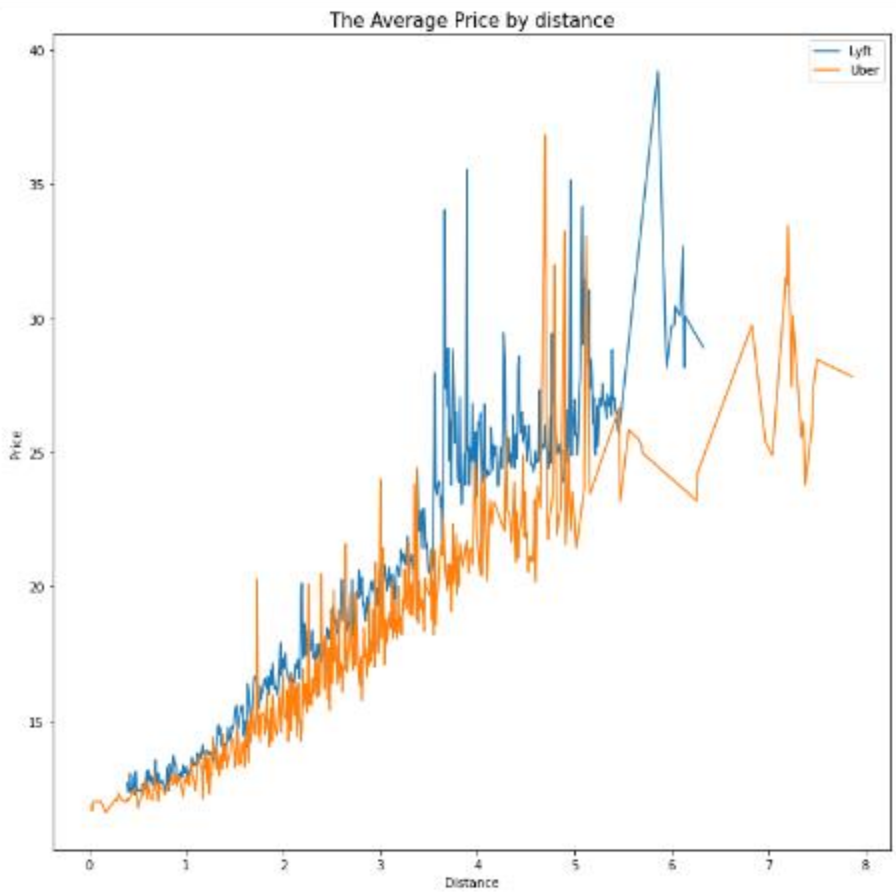
```
In [25]: # The ride distribution in one day
         fig , ax = plt.subplots(figsize= (12,12))
         ax.plot(df_rides_weather[df_rides_weather['cab_type'] == 'Lyft'].groupby('Hour').Hour.count().index, df_rides_weather[df_rides_w
         ax.plot(df_rides_weather[df_rides_weather['cab_type'] == 'Uber'].groupby('Hour').Hour.count().index, df_rides_weather[df_rides_w
         ax.legend()
         ax.set(xlabel = 'Hours', ylabel = 'Number of Rides')
         plt.xticks(range(0,24,1))
         plt.show()
```



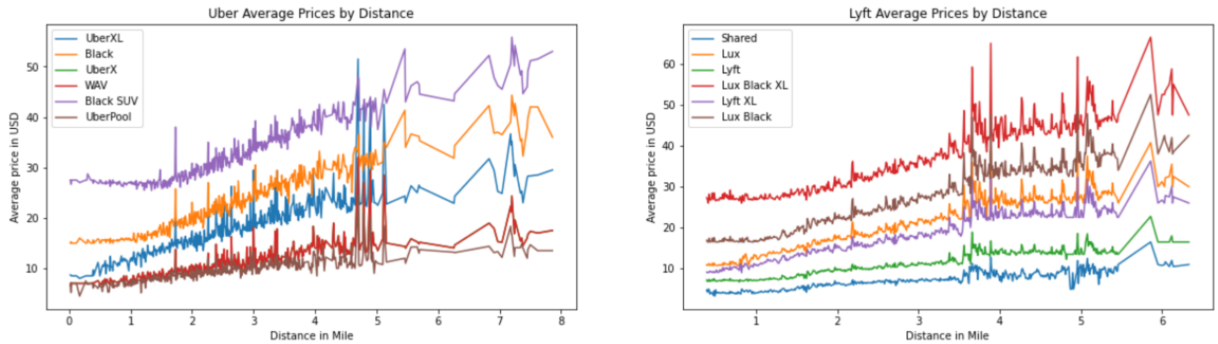
```
# The Average price of rides by type of service
import seaborn as sns

uber_order =[ 'UberPool', 'UberX', 'UberXL', 'Black','Black SUV','WAV' ]
lyft_order = ['Shared', 'Lyft', 'Lyft XL', 'Lux', 'Lux Black', 'Lux Black XL']
fig, ax = plt.subplots(2,2, figsize = (20,15))
ax1 = sns.barplot(x = df_rides_weather[df_rides_weather['cab_type'] == 'Uber'].name, y = df_rides_weather[df_rides_weather['cab_
ax2 = sns.barplot(x = df_rides_weather[df_rides_weather['cab_type'] == 'Lyft'].name, y = df_rides_weather[df_rides_weather['cab_
ax3 = sns.barplot(x = df_rides_weather[df_rides_weather['cab_type'] == 'Uber'].groupby('name').name.count().index, y = df_rides_
ax4 = sns.barplot(x = df_rides_weather[df_rides_weather['cab_type'] == 'Lyft'].groupby('name').name.count().index, y = df_rides_
for p in ax1.patches:
    ax1.annotate(format(p.get_height(), '.2f'), (p.get_x() + p.get_width() / 2., p.get_height()), ha = 'center', va = 'center',
for p in ax2.patches:
    ax2.annotate(format(p.get_height(), '.2f'), (p.get_x() + p.get_width() / 2., p.get_height()), ha = 'center', va = 'center',
ax1.set(xlabel = 'Type of Service', ylabel = 'Average Price')
ax2.set(xlabel = 'Type of Service', ylabel = 'Average Price')
ax3.set(xlabel = 'Type of Service', ylabel = 'Number of Rides')
ax4.set(xlabel = 'Type of Service', ylabel = 'Number of Rides')
ax1.set_title('The Uber Average Prices by Type of Service')
ax2.set_title('The Lyft Average Prices by Type of Service')
ax3.set_title('The Number of Uber Rides by Type of Service')
ax4.set_title('The Number of Lyft Rides by Type of Service')
plt.show()
```



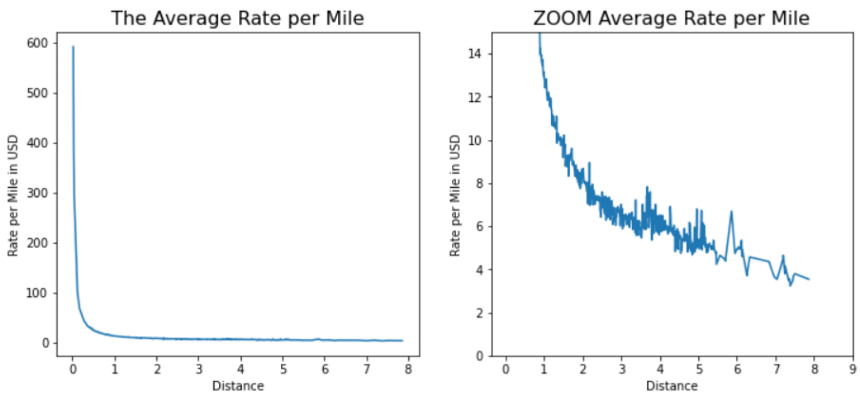
```python
# The average price by distance
fig , ax = plt.subplots(figsize = (12,12))
ax.plot(df_rides_weather[df_rides_weather['cab_type'] == 'Lyft'].groupby('distance').price.mean().index, df_rides_weather[df_r
ax.plot(df_rides_weather[df_rides_weather['cab_type'] == 'Uber'].groupby('distance').price.mean().index, df_rides_weather[df_r
ax.set_title('The Average Price by distance', fontsize= 15)
ax.set(xlabel = 'Distance', ylabel = 'Price' )
ax.legend()
plt.show()
```

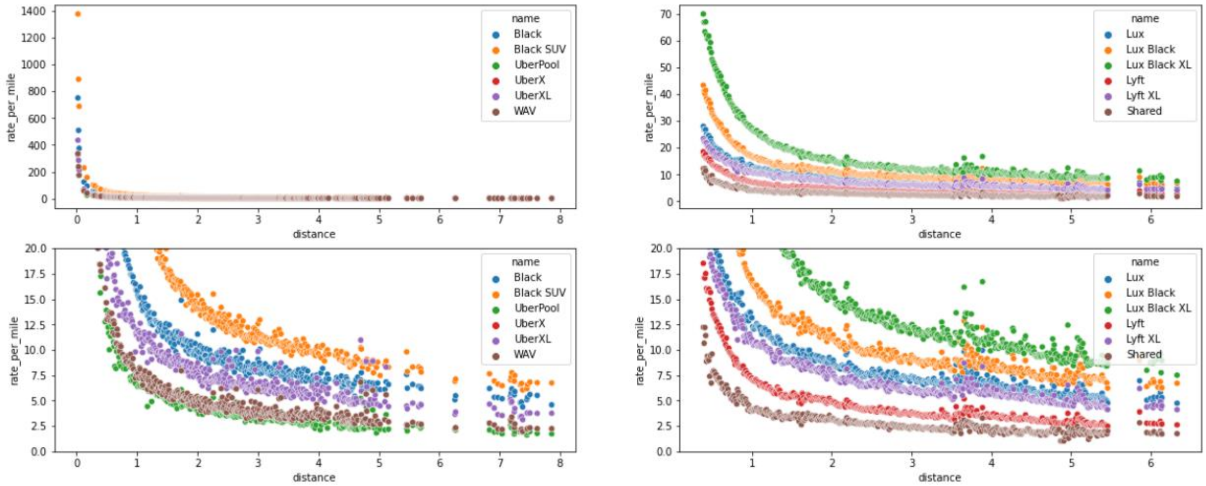


```
# The average price by distance
fig, ax = plt.subplots(1,2 , figsize = (20,5))
for i,col in enumerate(df_rides_weather[df_rides_weather['cab_type'] == 'Uber']['name'].unique()):
    ax[0].plot(df_rides_weather[ df_rides_weather['name'] == col].groupby('distance').price.mean().index, df_rides_weather[ df_ri
ax[0].set_title('Uber Average Prices by Distance')
ax[0].set(xlabel = 'Distance in Mile', ylabel = 'Average price in USD')
ax[0].legend()
for i,col in enumerate(df_rides_weather[df_rides_weather['cab_type'] == 'Lyft']['name'].unique()):
    ax[1].plot(df_rides_weather[ df_rides_weather['name'] == col].groupby('distance').price.mean().index, df_rides_weather[ df_ri
ax[1].set(xlabel = 'Distance in Mile', ylabel = 'Average price in USD')
ax[1].set_title('Lyft Average Prices by Distance')
ax[1].legend()
plt.show()
```




```
# the average rate per mile
df_rides_weather['rate_per_mile'] = round((df_rides_weather['price'] / df_rides_weather['distance'] ),2)
# The average rate per mile plot
fig, ax = plt.subplots(1,2,figsize = (12,5))
ax1 = sns.lineplot(x = df_rides_weather.groupby(['distance'])['rate_per_mile'].mean().index, y = df_rides_weather.groupby('distar
ax2 = sns.lineplot(x = df_rides_weather.groupby(['distance'])['rate_per_mile'].mean().index, y = df_rides_weather.groupby('distar
plt.xticks(range(0, 10,1))
ax1.set(xlabel = 'Distance', ylabel = 'Rate per Mile in USD')
ax2.set(xlabel = 'Distance', ylabel = 'Rate per Mile in USD', ylim = (0,15))
ax1.set_title('The Average Rate per Mile', fontsize = 16)
ax2.set_title('ZOOM Average Rate per Mile', fontsize = 16)
plt.show()
```





Using Random forest Algorithm

```
]: from sklearn.ensemble import RandomForestRegressor
rand=RandomForestRegressor(n_estimators=20,random_state=52,n_jobs=-1,max_depth=4)
rand.fit(x_train,y_train)
```

```
<ipython-input-64-57509395cdf7>:3: DataConversionWarning: A column-vector y was passed
nge the shape of y to (n_samples,), for example using ravel().
  rand.fit(x_train,y_train)
```

```
]: RandomForestRegressor(max_depth=4, n_estimators=20, n_jobs=-1, random_state=52)
```

Predecting the Result

```
: ypred=rand.predict(x_test)
print(ypred)
```

```
[33.44544798 19.16381383  9.54753035 ...  6.02421004 26.79738243
 17.55244465]
```

Score of the model

```
: rand.score(x_train,y_train)
```

```
: 0.7575275520145969
```