Assignment1

July 21, 2025

Objective :

The goal is to predict food delivery times based on customer location, restaurant location, weather, traffic, and other factors. This involves both data preprocessing and building predictive models using linear regression and logistic regression.

Phase 1Data Collection and Exploratory Data Analysis

contains 3 steps

Step 1 - Data Import and Preprocessing

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler, LabelBinarizer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error,␣
↪accuracy_score, precision_score, recall_score, f1_score, confusion_matrix,␣
↪ConfusionMatrixDisplay, roc_curve, auc, classification_report
from scipy import stats
```

[2]:
```
data=pd.read_csv('Food_Delivery_Time_prediction.csv')
d=data.copy()
d.head()
```

[2]:

	Order_ID	Customer_Location	Restaurant_Location	Distance	\
0	ORD0001	(17.030479, 79.743077)	(12.358515, 85.100083)	1.57	
1	ORD0002	(15.398319, 86.639122)	(14.174874, 77.025606)	21.32	
2	ORD0003	(15.687342, 83.888808)	(19.594748, 82.048482)	6.95	
3	ORD0004	(20.415599, 78.046984)	(16.915906, 78.278698)	13.79	
4	ORD0005	(14.786904, 78.706532)	(15.206038, 86.203182)	6.72	

	Weather_Conditions	Traffic_Conditions	Delivery_Person_Experience	\
0	Rainy	Medium	4	
1	Cloudy	Medium	8	
2	Snowy	Medium	9	

```
3              Cloudy                Low                           2
4               Rainy               High                           6

  Order_Priority Order_Time Vehicle_Type  Restaurant_Rating  Customer_Rating  \
0         Medium  Afternoon          Car                4.1              3.0
1            Low      Night          Car                4.5              4.2
2           High      Night         Bike                3.3              3.4
3         Medium    Evening         Bike                3.2              3.7
4            Low      Night         Bike                3.5              2.8

   Delivery_Time  Order_Cost  Tip_Amount
0          26.22     1321.10       81.54
1          62.61      152.21       29.02
2          48.43     1644.38       64.17
3         111.63      541.25       79.23
4          32.38      619.81        2.34
```

[3]:
```
d.isnull().sum()
```

[3]:
```
Order_ID                      0
Customer_Location             0
Restaurant_Location           0
Distance                      0
Weather_Conditions            0
Traffic_Conditions            0
Delivery_Person_Experience    0
Order_Priority                0
Order_Time                    0
Vehicle_Type                  0
Restaurant_Rating             0
Customer_Rating               0
Delivery_Time                 0
Order_Cost                    0
Tip_Amount                    0
dtype: int64
```

Null values do not exist in any column Now checking for incorrect data

[4]:
```
#drop duplicate and empty rows of Order_ID column
d.dropna(subset=['Order_ID'])
d.drop_duplicates(subset='Order_ID', keep='first')
# drop incorrect data for Order_ID column
d.drop(d[ d['Order_ID'].str.match(r'^ORD\d{4}$')==False ].index, inplace=True)
# here if inplace=True not used then the changes will not be applied to the␣
 ↪original dataframe

#drop rows with null values in Customer_Location column
d.dropna(subset=['Customer_Location'], inplace=True)
```

```
#drop rows with null values in Restaurant_Location column
d.dropna(subset=['Restaurant_Location'], inplace=True)

# # distance values all greater than 0
# d.loc[d['Distance']<=0,'Distance']=np.mean(d[d['Distance']>0]['Distance'])

# fill null values in Weather_Conditions with 'Sunny'
# Weather_Conditions values should be one of the following
d['Weather_Conditions'].fillna('Sunny')
valid_weather_conditions = ['Sunny', 'Rainy', 'Snowy', 'Cloudy']
d.loc[~d['Weather_Conditions'].isin(valid_weather_conditions),␣
 ↪'Weather_Conditions'] = 'Sunny'

# fill null values in Traffic_Conditions with 'Medium'
# Traffic_Conditions values should be one of the following
d['Traffic_Conditions'].fillna('Medium')
valid_traffic_conditions = ['Low', 'Medium', 'High']
d.loc[~d['Traffic_Conditions'].isin(valid_traffic_conditions),␣
 ↪'Traffic_Condisions'] = 'Medium'

# # Deliver_Person_Experience values should be positive and non-zero
# d.loc[d['Delivery_Person_Experience']<=0,'Delivery_Person_Experience']=np.
 ↪mean(d.loc[d['Delivery_Person_Experience']>0,'Delivery_Person_Experience'])

# fill null values in Order_Priority with 'Medium'
# Order_Priority values should be one of the following
d['Order_Priority'].fillna('Medium')
valid_order_priority = ['Low', 'Medium', 'High']
d.loc[~d['Order_Priority'].isin(valid_order_priority), 'Order_Priority'] =␣
 ↪'Medium'

# fill null values in Order_Time with 'Night'
# Order_Time values should be one of the following
d['Order_Time'].fillna('Night')
valid_order_time = ['Afternoon', 'Night', 'Evening', 'Morning']
d.loc[~d['Order_Time'].isin(valid_order_time), 'Order_Time'] = 'Night'

# fill null values in Vehicle_Type with 'Bike'
# Vehicle_Type values should be one of the following
d['Vehicle_Type'].fillna('Bike')
valid_vehicle_type = ['Car', 'Bike', 'Bicycle']
d.loc[~d['Vehicle_Type'].isin(valid_vehicle_type), 'Vehicle_Type'] = 'Bike'

# # Restaurant_Rating values all greater than 0
# d.loc[d['Restaurant_Rating']<=0,'Restaurant_Rating']=np.
 ↪mean(d[d['Restaurant_Rating']>0]['Restaurant_Rating'])
```

```
# # Restaurant_Rating values all should be less than or equal to 5
# d.loc[d['Restaurant_Rating']>5,'Restaurant_Rating']=np.
 ↪mean(d[(d['Restaurant_Rating'] >= 2.5) & (d['Restaurant_Rating'] <␣
 ↪5)]['Restaurant_Rating'])

# # Customer_Rating values all greater than 0
# d.loc[d['Customer_Rating']<=0,'Customer_Rating']=np.
 ↪mean(d[d['Customer_Rating']>0]['Customer_Rating'])
# # Customer_Rating values all should be less than or equal to 5
# d.loc[d['Customer_Rating']>5,'Customer_Rating']=np.
 ↪mean(d[(d['Customer_Rating'] >= 2.6) & (d['Customer_Rating'] <␣
 ↪5)]['Customer_Rating'])

# # Delivery_Time values all greater than 0
# d.loc[d['Delivery_Time']<=0,'Delivery_Time']=np.
 ↪mean(d[d['Delivery_Time']>0]['Delivery_Time'])

# # Order_Cost values all greater than 0
# d.loc[d['Order_Cost']<=0,'Order_Cost']=np.
 ↪mean(d[d['Order_Cost']>0]['Order_Cost'])

# # Tip_Amount values all greater than 0
# d.loc[d['Tip_Amount']<=0,'Tip_Amount']=np.
 ↪mean(d[d['Tip_Amount']>0]['Tip_Amount'])
```

[5]:
```
d
```

[5]:
```
     Order_ID       Customer_Location     Restaurant_Location  Distance  \
0    ORD0001  (17.030479, 79.743077)  (12.358515, 85.100083)      1.57
1    ORD0002  (15.398319, 86.639122)  (14.174874, 77.025606)     21.32
2    ORD0003  (15.687342, 83.888808)  (19.594748, 82.048482)      6.95
3    ORD0004  (20.415599, 78.046984)  (16.915906, 78.278698)     13.79
4    ORD0005  (14.786904, 78.706532)  (15.206038, 86.203182)      6.72
..       …                     …                     …       …
195  ORD0196   (17.910045, 81.56199)  (18.098924, 87.896124)     23.82
196  ORD0197   (21.66459, 82.226635)  (16.892341, 80.554716)      6.09
197  ORD0198   (14.575401, 82.55641)  (13.625369, 82.418092)     20.61
198  ORD0199  (12.094497, 82.893369)  (19.135509, 86.659978)     24.06
199  ORD0200  (19.360304, 84.132424)   (20.941636, 77.01334)      9.18

    Weather_Conditions Traffic_Conditions  Delivery_Person_Experience  \
0                Rainy             Medium                          4
1               Cloudy             Medium                          8
2                Snowy             Medium                          9
3               Cloudy                Low                          2
4                Rainy               High                          6
..                 …                  …                        …
```

```
195             Cloudy              High                          8
196              Snowy            Medium                          8
197              Snowy              High                          4
198              Rainy              High                          9
199              Snowy               Low                          2

    Order_Priority Order_Time Vehicle_Type  Restaurant_Rating  \
0           Medium  Afternoon          Car                4.1
1              Low      Night          Car                4.5
2             High      Night         Bike                3.3
3           Medium    Evening         Bike                3.2
4              Low      Night         Bike                3.5
..             …        …           …                  …
195         Medium      Night         Bike                4.7
196            Low      Night      Bicycle                3.0
197         Medium  Afternoon         Bike                2.9
198            Low      Night          Car                3.9
199            Low    Morning         Bike                4.6

     Customer_Rating  Delivery_Time  Order_Cost  Tip_Amount Traffic_Condisions
0                3.0          26.22     1321.10       81.54                NaN
1                4.2          62.61      152.21       29.02                NaN
2                3.4          48.43     1644.38       64.17                NaN
3                3.7         111.63      541.25       79.23                NaN
4                2.8          32.38      619.81        2.34                NaN
..               …            …          …          …                  …
195              4.0          50.39     1432.26       66.34                NaN
196              3.6          90.54     1720.25       40.27                NaN
197              3.4          73.20     1356.58        5.10                NaN
198              4.8          53.94      354.39       85.25                NaN
199              3.2          78.58      323.73       48.91                NaN

[200 rows x 16 columns]
```

[6]:
```python
# Setting numeric values to column Weather_Conditions
weather_map = {'Sunny': 0, 'Rainy': 1, 'Snowy': 2, 'Cloudy': 3}
d['Weather_Conditions'] = d['Weather_Conditions'].map(weather_map)

# Setting numeric values to column Traffic_Conditions
traffic_map = {'Low': 0, 'Medium': 1, 'High': 2}
d['Traffic_Conditions'] = d['Traffic_Conditions'].map(traffic_map)

# Setting numeric values to column Order_Priority
order_priority_map = {'Low': 0, 'Medium': 1, 'High': 2}
d['Order_Priority'] = d['Order_Priority'].map(order_priority_map)

# Setting numeric values to column Order_Time
```

```
order_time_map = {'Morning': 0, 'Afternoon': 1, 'Evening': 2, 'Night': 3}
d['Order_Time'] = d['Order_Time'].map(order_time_map)

# Setting numeric values to column Vehicle_Type
vehicle_type_map = {'Bicycle': 0, 'Bike': 1, 'Car': 2}
d['Vehicle_Type'] = d['Vehicle_Type'].map(vehicle_type_map)
```

[7]:
```
d
```

[7]:
```
    Order_ID       Customer_Location     Restaurant_Location  Distance  \
0    ORD0001  (17.030479, 79.743077)  (12.358515, 85.100083)      1.57
1    ORD0002  (15.398319, 86.639122)  (14.174874, 77.025606)     21.32
2    ORD0003  (15.687342, 83.888808)  (19.594748, 82.048482)      6.95
3    ORD0004  (20.415599, 78.046984)  (16.915906, 78.278698)     13.79
4    ORD0005  (14.786904, 78.706532)  (15.206038, 86.203182)      6.72
..       …                      …                     …       …
195  ORD0196   (17.910045, 81.56199)  (18.098924, 87.896124)     23.82
196  ORD0197   (21.66459, 82.226635)  (16.892341, 80.554716)      6.09
197  ORD0198   (14.575401, 82.55641)  (13.625369, 82.418092)     20.61
198  ORD0199  (12.094497, 82.893369)  (19.135509, 86.659978)     24.06
199  ORD0200  (19.360304, 84.132424)   (20.941636, 77.01334)      9.18

     Weather_Conditions  Traffic_Conditions  Delivery_Person_Experience  \
0                     1                   1                           4
1                     3                   1                           8
2                     2                   1                           9
3                     3                   0                           2
4                     1                   2                           6
..                  …                   …                           …
195                   3                   2                           8
196                   2                   1                           8
197                   2                   2                           4
198                   1                   2                           9
199                   2                   0                           2

     Order_Priority  Order_Time  Vehicle_Type  Restaurant_Rating  \
0                 1           1             2                4.1
1                 0           3             2                4.5
2                 2           3             1                3.3
3                 1           2             1                3.2
4                 0           3             1                3.5
..              …           …             …                …
195               1           3             1                4.7
196               0           3             0                3.0
197               1           1             1                2.9
198               0           3             2                3.9
199               0           0             1                4.6
```

```
     Customer_Rating  Delivery_Time  Order_Cost  Tip_Amount Traffic_Condisions
0                3.0          26.22     1321.10       81.54                NaN
1                4.2          62.61      152.21       29.02                NaN
2                3.4          48.43     1644.38       64.17                NaN
3                3.7         111.63      541.25       79.23                NaN
4                2.8          32.38      619.81        2.34                NaN
..               …            …          …         …                  …
195              4.0          50.39     1432.26       66.34                NaN
196              3.6          90.54     1720.25       40.27                NaN
197              3.4          73.20     1356.58        5.10                NaN
198              4.8          53.94      354.39       85.25                NaN
199              3.2          78.58      323.73       48.91                NaN

[200 rows x 16 columns]
```

[8]:
```
# Standardization
s=StandardScaler()
d['Distance_Scaled'] = s.fit_transform(d[['Distance']])
d['Delivery_Time_Scaled'] = s.fit_transform(d[['Delivery_Time']])
d['Order_Cost_Scaled'] = s.fit_transform(d[['Order_Cost']])
# StandardScaler().fit_transform() expects a 2D array or DataFrame, but you␣
 ↪passed a Series (d['Distance']), which is 1D.
# So pass a DataFrame with double brackets d[['Distance']]
```

[9]:
```
d
```

[9]:
```
    Order_ID       Customer_Location     Restaurant_Location  Distance  \
0    ORD0001  (17.030479, 79.743077)  (12.358515, 85.100083)      1.57
1    ORD0002  (15.398319, 86.639122)  (14.174874, 77.025606)     21.32
2    ORD0003  (15.687342, 83.888808)  (19.594748, 82.048482)      6.95
3    ORD0004  (20.415599, 78.046984)  (16.915906, 78.278698)     13.79
4    ORD0005  (14.786904, 78.706532)  (15.206038, 86.203182)      6.72
..       …                        …                     …       …
195  ORD0196   (17.910045, 81.56199)  (18.098924, 87.896124)     23.82
196  ORD0197   (21.66459, 82.226635)  (16.892341, 80.554716)      6.09
197  ORD0198   (14.575401, 82.55641)  (13.625369, 82.418092)     20.61
198  ORD0199  (12.094497, 82.893369)  (19.135509, 86.659978)     24.06
199  ORD0200  (19.360304, 84.132424)   (20.941636, 77.01334)      9.18

     Weather_Conditions  Traffic_Conditions  Delivery_Person_Experience  \
0                     1                   1                           4
1                     3                   1                           8
2                     2                   1                           9
3                     3                   0                           2
4                     1                   2                           6
..                  …                   …                           …
```

```
195                 3                 2                          8
196                 2                 1                          8
197                 2                 2                          4
198                 1                 2                          9
199                 2                 0                          2

     Order_Priority  Order_Time  Vehicle_Type  Restaurant_Rating  \
0                 1           1             2                4.1
1                 0           3             2                4.5
2                 2           3             1                3.3
3                 1           2             1                3.2
4                 0           3             1                3.5
..              ...         ...           ...                ...
195               1           3             1                4.7
196               0           3             0                3.0
197               1           1             1                2.9
198               0           3             2                3.9
199               0           0             1                4.6

     Customer_Rating  Delivery_Time  Order_Cost  Tip_Amount  \
0                3.0          26.22     1321.10       81.54
1                4.2          62.61      152.21       29.02
2                3.4          48.43     1644.38       64.17
3                3.7         111.63      541.25       79.23
4                2.8          32.38      619.81        2.34
..               ...            ...         ...         ...
195              4.0          50.39     1432.26       66.34
196              3.6          90.54     1720.25       40.27
197              3.4          73.20     1356.58        5.10
198              4.8          53.94      354.39       85.25
199              3.2          78.58      323.73       48.91

    Traffic_Condisions  Distance_Scaled  Delivery_Time_Scaled  \
0                  NaN        -1.454738             -1.487932
1                  NaN         1.439192             -0.264987
2                  NaN        -0.666417             -0.741529
3                  NaN         0.335835              1.382411
4                  NaN        -0.700119             -1.280915
..                 ...              ...                   ...
195                NaN         1.805512             -0.675660
196                NaN        -0.792431              0.673647
197                NaN         1.335157              0.090908
198                NaN         1.840679             -0.556356
199                NaN        -0.339659              0.271711

     Order_Cost_Scaled
0             0.501852
```

```
1            -1.634294
2             1.092646
3            -0.923323
4            -0.779755
..                 …
195           0.704997
196           1.231298
197           0.566692
198          -1.264810
199          -1.320841

[200 rows x 19 columns]
```

Step 2 - Exploratory Data Analysis (EDA)

[10]:
```
# keepdims=True makes sure the result is always an array, even if there is only one mode.
# Without keepdims=True, the output might be a scalar if the input is 1D, which can sometimes cause issues in further processing.

dist_mean=np.mean(d['Distance'])
dist_mode=stats.mode(d['Distance'], keepdims=True).mode[0]
dist_median=np.median(d['Distance'])
dist_var=np.var(d['Distance'])

weather_mode = stats.mode(d['Weather_Conditions'], keepdims=True).mode[0]
weather_median = np.median(d['Weather_Conditions'])

Traffic_mode = stats.mode(d['Traffic_Conditions'], keepdims=True).mode[0]
Traffic_median = np.median(d['Traffic_Conditions'])

delivery_person_experience_mean=np.mean(d['Delivery_Person_Experience'])
delivery_person_experience_mode=stats.mode(d['Delivery_Person_Experience'],keepdims=True).mode[0]
delivery_person_experience_median=np.median(d['Delivery_Person_Experience'])
delivery_person_experience_var=np.var(d['Delivery_Person_Experience'])

Order_priority_mode = stats.mode(d['Order_Priority'], keepdims=True).mode[0]
Order_priority_median = np.median(d['Order_Priority'])

Order_time_mode = stats.mode(d['Order_Time'], keepdims=True).mode[0]
Order_time_median = np.median(d['Order_Time'])

Vehicle_Type_mode = stats.mode(d['Vehicle_Type'], keepdims=True).mode[0]
Vehicle_Type_median = np.median(d['Vehicle_Type'])

restaurant_rating_mean=np.mean(d['Restaurant_Rating'])
```

```
restaurant_rating_mode=stats.mode(d['Restaurant_Rating'], keepdims=True).mode[0]
restaurant_rating_median=np.median(d['Restaurant_Rating'])
restaurant_rating_var=np.var(d['Delivery_Person_Experience'])

customer_rating_mean=np.mean(d['Customer_Rating'])
customer_rating_mode=stats.mode(d['Customer_Rating'], keepdims=True).mode[0]
customer_rating_median=np.median(d['Customer_Rating'])
customer_rating_var=np.var(d['Customer_Rating'])

Delivery_Time_mean=np.mean(d['Delivery_Time'])
Delivery_Time_mode=stats.mode(d['Delivery_Time'], keepdims=True).mode[0]
Delivery_Time_median=np.median(d['Delivery_Time'])
Delivery_Time_var=np.var(d['Delivery_Time'])

Order_Cost_mean=np.mean(d['Delivery_Time'])
Order_Cost_mode=stats.mode(d['Delivery_Time'], keepdims=True).mode[0]
Order_Cost_median=np.median(d['Order_Cost'])
Order_Cost_var=np.var(d['Order_Cost'])

Tip_Amount_mean=np.mean(d['Tip_Amount'])
Tip_Amount_mode=stats.mode(d['Tip_Amount'], keepdims=True).mode[0]
Tip_Amount_median=np.median(d['Tip_Amount'])
Tip_Amount_var=np.var(d['Tip_Amount'])
```

[11]:
```
print('Mean of Distance : ', dist_mean)
print('Median of Distance : ', dist_median)
print('Mode of Distance : ', dist_mode)
print('Variance of Distance : ', dist_var)

print('')
print('Mode of Weather_Conditions : ', weather_mode)
print('Median of Weather_Conditions : ', weather_median)

print('')
print('Mode of Traffic_Conditions : ', Traffic_mode)
print('Median of Traffic_Conditions : ', Traffic_median)

print('')
print('Mean of Delivery_Person_Experience : ', delivery_person_experience_mean)
print('Median of Delivery_Person_Experience : ',␣
 ↪delivery_person_experience_median)
print('Mode of Delivery_Person_Experience : ', delivery_person_experience_mode)
print('Variance of Delivery_Person_Experience : ',␣
 ↪delivery_person_experience_var)

print('')
print('Mode of Order_Priority : ', Order_priority_mode)
```

```
print('Median of Order_Priority : ', Order_priority_median)

print('')
print('Mode of Order_Time : ', Order_time_mode)
print('Median of Order_Time : ', Order_time_median)

print('')
print('Mode of Vehicle_Type : ', Vehicle_Type_mode)
print('Median of Vehicle_Type : ', Vehicle_Type_median)

print('')
print('Mean of Restaurant_Rating : ', restaurant_rating_mean)
print('Median of Restaurant_Rating : ', restaurant_rating_median)
print('Mode of Restaurant_Rating : ', restaurant_rating_mode)
print('Variance of Restaurant_Rating : ', restaurant_rating_var)

print('')
print('Mean of Customer_Rating : ', customer_rating_mean)
print('Median of Customer_Rating : ', customer_rating_median)
print('Mode of Customer_Rating : ', customer_rating_mode)
print('Variance of Customer_Rating : ', customer_rating_var)

print('')
print('Mean of Delivery_Time : ', Delivery_Time_mean)
print('Median of Delivery_Time : ', Delivery_Time_median)
print('Mode of Delivery_Time : ', Delivery_Time_mode)
print('Variance of Delivery_Time : ', Delivery_Time_var)

print('')
print('Mean of Order_Cost : ', Order_Cost_mean)
print('Median of Order_Cost : ', Order_Cost_median)
print('Mode of Order_Cost : ', Order_Cost_mode)
print('Variance of Order_Cost : ', Order_Cost_var)

print('')
print('Mean of Tip_Amount : ', Tip_Amount_mean)
print('Median of Tip_Amount : ', Tip_Amount_median)
print('Mode of Tip_Amount : ', Tip_Amount_mode)
print('Variance of Tip_Amount : ', Tip_Amount_var)
```

```
Mean of Distance :  11.498050000000001
Median of Distance :  10.265
Mode of Distance :  1.32
Variance of Distance :  46.5755686975

Mode of Weather_Conditions :  1
Median of Weather_Conditions :  1.0
```

```
Mode of Traffic_Conditions :  0
Median of Traffic_Conditions :  1.0

Mean of Delivery_Person_Experience :  5.25
Median of Delivery_Person_Experience :  5.0
Mode of Delivery_Person_Experience :  8
Variance of Delivery_Person_Experience :  7.4975

Mode of Order_Priority :  0
Median of Order_Priority :  1.0

Mode of Order_Time :  1
Median of Order_Time :  2.0

Mode of Vehicle_Type :  0
Median of Vehicle_Type :  1.0

Mean of Restaurant_Rating :  3.7384999999999997
Median of Restaurant_Rating :  3.8
Mode of Restaurant_Rating :  3.8
Variance of Restaurant_Rating :  7.4975

Mean of Customer_Rating :  3.6864999999999997
Median of Customer_Rating :  3.7
Mode of Customer_Rating :  2.6
Variance of Customer_Rating :  0.4834677499999999

Mean of Delivery_Time :  70.49494999999999
Median of Delivery_Time :  72.775
Mode of Delivery_Time :  66.84
Variance of Delivery_Time :  885.4209709974999

Mean of Order_Cost :  70.49494999999999
Median of Order_Cost :  1035.9499999999998
Mode of Order_Cost :  66.84
Variance of Order_Cost :  299423.22280130995

Mean of Tip_Amount :  46.61665
Median of Tip_Amount :  47.53
Mode of Tip_Amount :  2.22
Variance of Tip_Amount :  857.7992592775001
```

Annot value in matrix greater than 0.05 both + and - then they have importance or correlation or dependancy with each other more the value more they are correlated

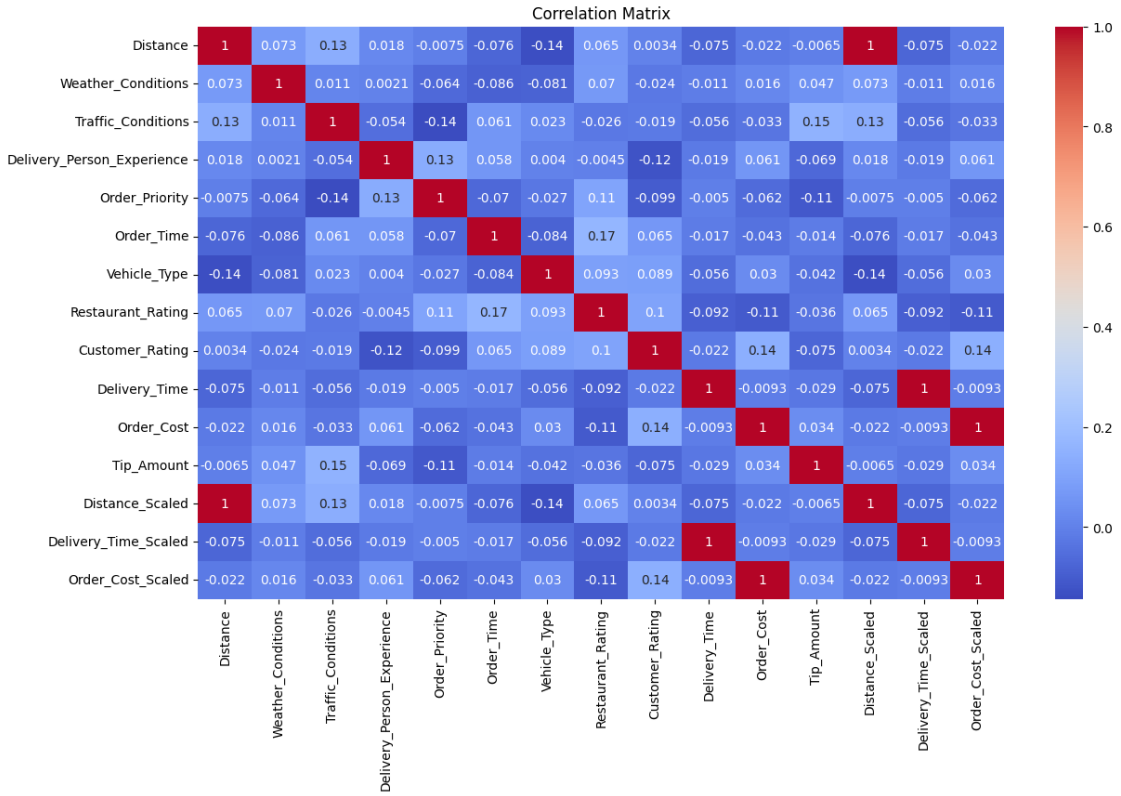
A negative correlation means that as one variable increases, the other decreases A positive correlation means that as one variable increases, the other also increases

Feature means column

There is a target_feature and other features If among other features if they are highly correlated (+ve) (more than 0.9 or values greater than 0.7 or 0.8) with each other then among them only one of them should be kept and drop the other(s)

A feature highly correlated with target_feature should not be removed

[12]:
```
correlation_matrix = d.corr(numeric_only=True)
plt.figure(figsize=(14, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()

# Table
correlation_with_target = correlation_matrix['Delivery_Time'].sort_values()
print("Correlation of features with Delivery_Time : ")
print(correlation_with_target)
```




```
Correlation of features with Delivery_Time :
Restaurant_Rating           -0.091855
Distance                    -0.075143
Distance_Scaled             -0.075143
Traffic_Conditions          -0.055840
Vehicle_Type                -0.055576
```

```
Tip_Amount                   -0.029154
Customer_Rating              -0.021952
Delivery_Person_Experience   -0.019098
Order_Time                   -0.017476
Weather_Conditions           -0.010518
Order_Cost_Scaled            -0.009307
Order_Cost                   -0.009307
Order_Priority               -0.004982
Delivery_Time_Scaled          1.000000
Delivery_Time                 1.000000
Name: Delivery_Time, dtype: float64
```

Outliers -> some values that are either too big or too small than the most of the values in that column

They affect the output soo much Output that should have come is affected

Z-score or IQR method is used to remove outliers

[13]:
```
d
```

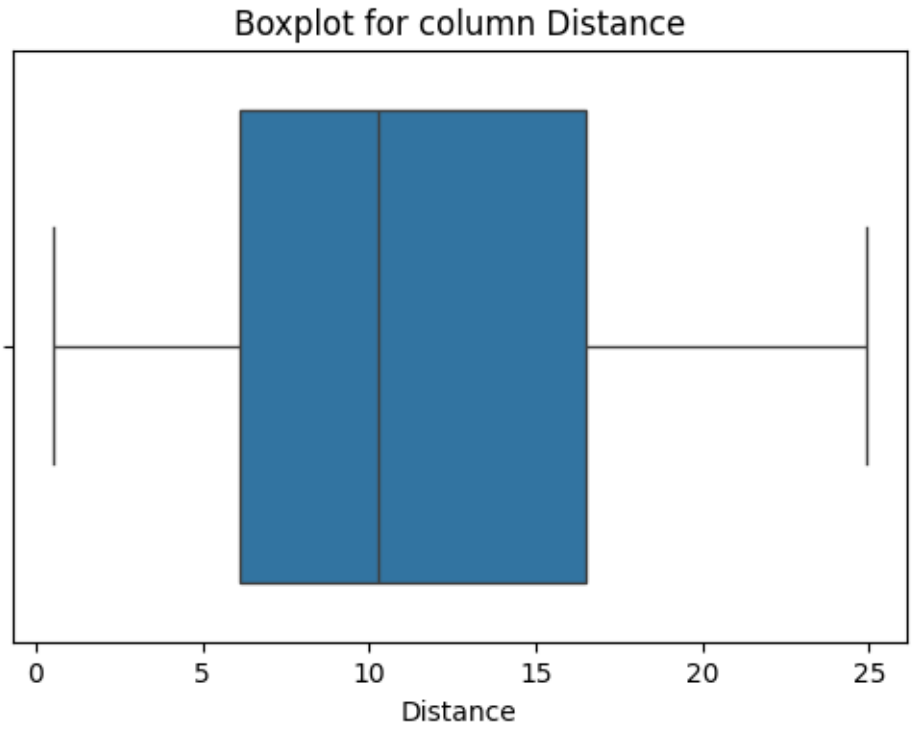
[13]:
```
    Order_ID       Customer_Location     Restaurant_Location  Distance  \
0    ORD0001  (17.030479, 79.743077)  (12.358515, 85.100083)      1.57
1    ORD0002  (15.398319, 86.639122)  (14.174874, 77.025606)     21.32
2    ORD0003  (15.687342, 83.888808)  (19.594748, 82.048482)      6.95
3    ORD0004  (20.415599, 78.046984)  (16.915906, 78.278698)     13.79
4    ORD0005  (14.786904, 78.706532)  (15.206038, 86.203182)      6.72
..       …                       …                       …       …
195  ORD0196   (17.910045, 81.56199)  (18.098924, 87.896124)     23.82
196  ORD0197   (21.66459, 82.226635)  (16.892341, 80.554716)      6.09
197  ORD0198   (14.575401, 82.55641)  (13.625369, 82.418092)     20.61
198  ORD0199  (12.094497, 82.893369)  (19.135509, 86.659978)     24.06
199  ORD0200  (19.360304, 84.132424)   (20.941636, 77.01334)      9.18

     Weather_Conditions  Traffic_Conditions  Delivery_Person_Experience  \
0                     1                   1                           4
1                     3                   1                           8
2                     2                   1                           9
3                     3                   0                           2
4                     1                   2                           6
..                  …                   …                           …
195                   3                   2                           8
196                   2                   1                           8
197                   2                   2                           4
198                   1                   2                           9
199                   2                   0                           2

     Order_Priority  Order_Time  Vehicle_Type  Restaurant_Rating  \
0                 1           1             2                4.1
```

```
1                 0           3             2                4.5
2                 2           3             1                3.3
3                 1           2             1                3.2
4                 0           3             1                3.5
..              …           …             …                …
195               1           3             1                4.7
196               0           3             0                3.0
197               1           1             1                2.9
198               0           3             2                3.9
199               0           0             1                4.6

     Customer_Rating  Delivery_Time  Order_Cost  Tip_Amount  \
0                3.0          26.22     1321.10       81.54
1                4.2          62.61      152.21       29.02
2                3.4          48.43     1644.38       64.17
3                3.7         111.63      541.25       79.23
4                2.8          32.38      619.81        2.34
..               …            …          …         …
195              4.0          50.39     1432.26       66.34
196              3.6          90.54     1720.25       40.27
197              3.4          73.20     1356.58        5.10
198              4.8          53.94      354.39       85.25
199              3.2          78.58      323.73       48.91

    Traffic_Condisions  Distance_Scaled  Delivery_Time_Scaled  \
0                  NaN        -1.454738             -1.487932
1                  NaN         1.439192             -0.264987
2                  NaN        -0.666417             -0.741529
3                  NaN         0.335835              1.382411
4                  NaN        -0.700119             -1.280915
..                 …               …                     …
195                NaN         1.805512             -0.675660
196                NaN        -0.792431              0.673647
197                NaN         1.335157              0.090908
198                NaN         1.840679             -0.556356
199                NaN        -0.339659              0.271711

     Order_Cost_Scaled
0             0.501852
1            -1.634294
2             1.092646
3            -0.923323
4            -0.779755
..                 …
195           0.704997
196           1.231298
197           0.566692
```

```
198          -1.264810
199          -1.320841

[200 rows x 19 columns]
```

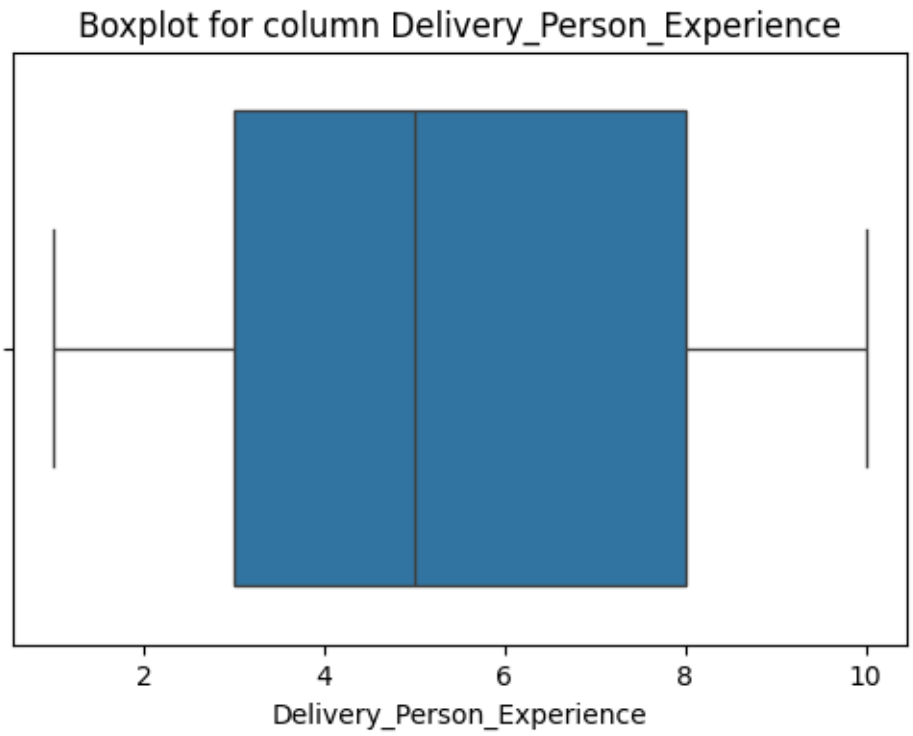
To see outliers clearly using box plot

[14]:
```
plt.figure(figsize=(6, 4))
sns.boxplot(x=d['Distance'])
plt.title('Boxplot for column Distance')
plt.show()
```



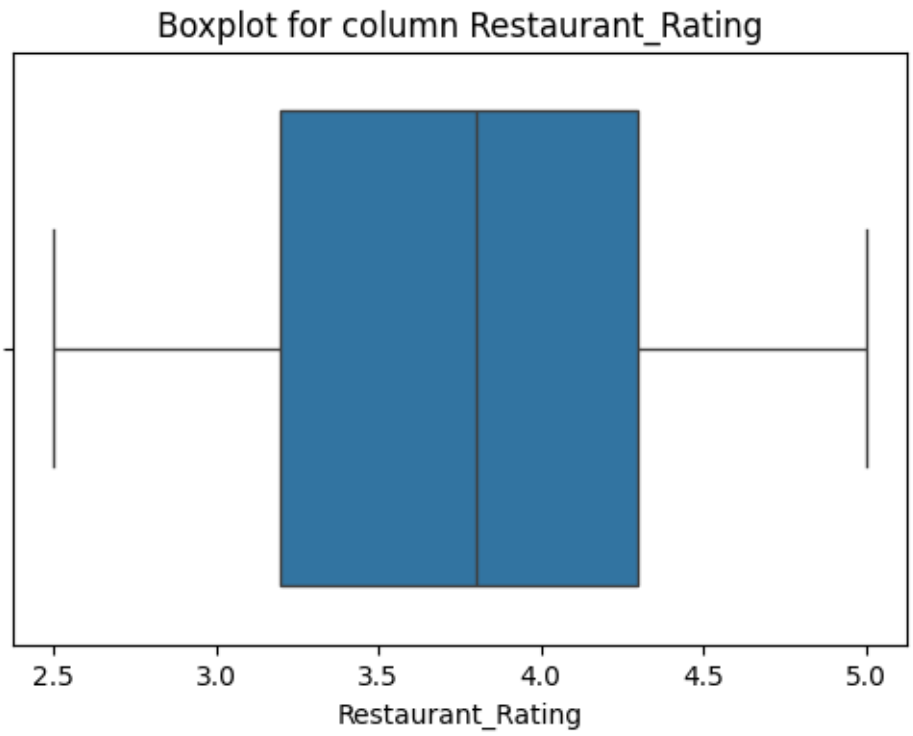
No outliers for column Distance

[15]:
```
plt.figure(figsize=(6, 4))
sns.boxplot(x=d['Delivery_Person_Experience'])
plt.title('Boxplot for column Delivery_Person_Experience')
plt.show()
```



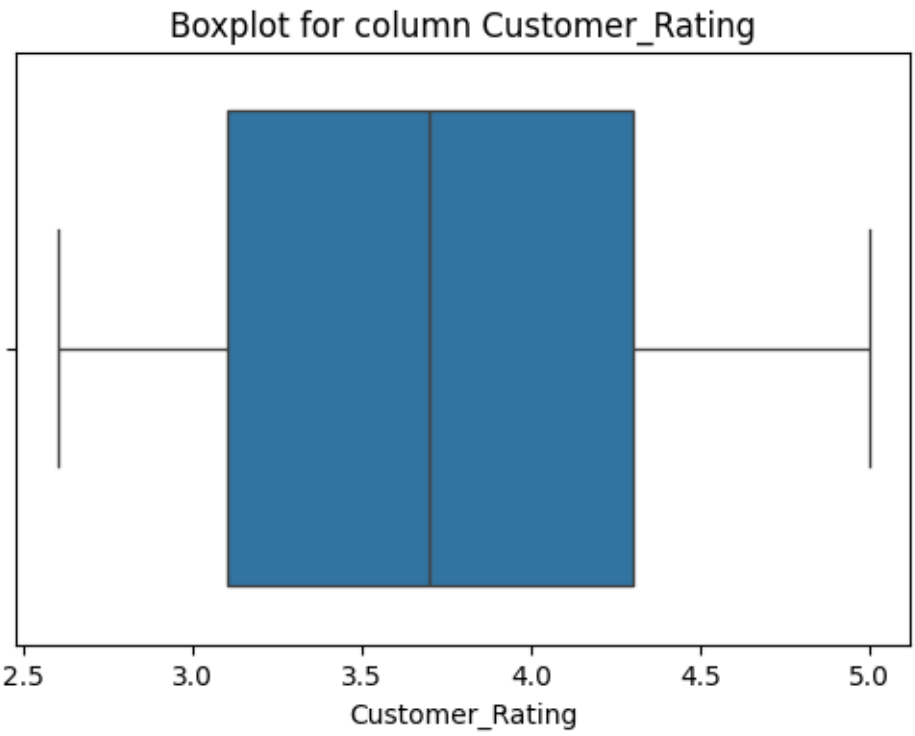
No outliers for column Delivery_Person_Experience

[16]:
```
plt.figure(figsize=(6, 4))
sns.boxplot(x=d['Restaurant_Rating'])
plt.title('Boxplot for column Restaurant_Rating')
plt.show()
```



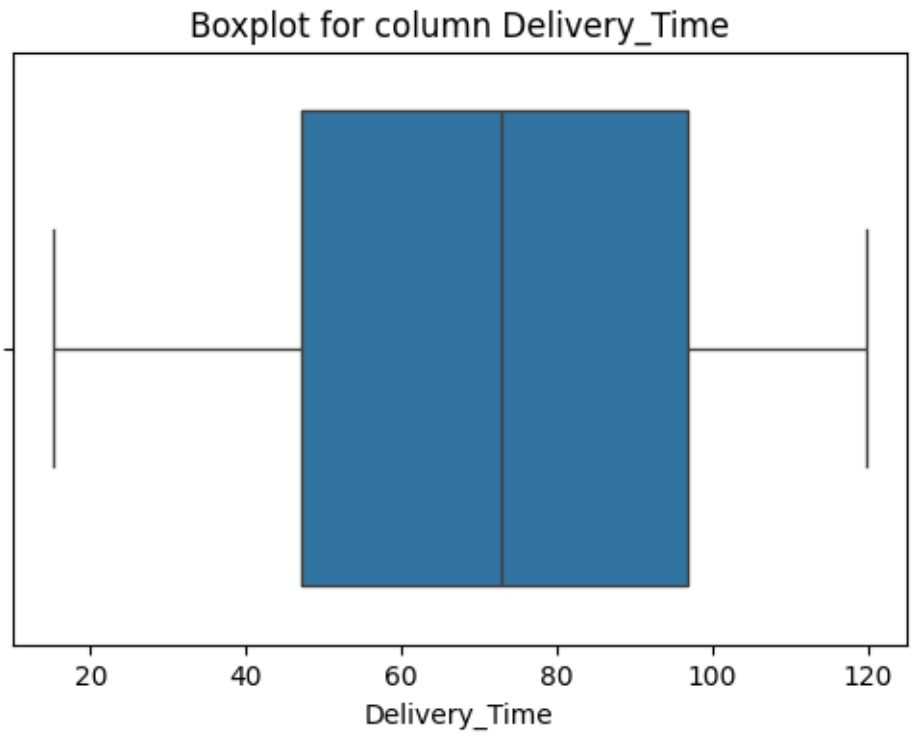
No outliers for column Restaurant_Rating

[17]:
```
plt.figure(figsize=(6, 4))
sns.boxplot(x=d['Customer_Rating'])
plt.title('Boxplot for column Customer_Rating')
plt.show()
```



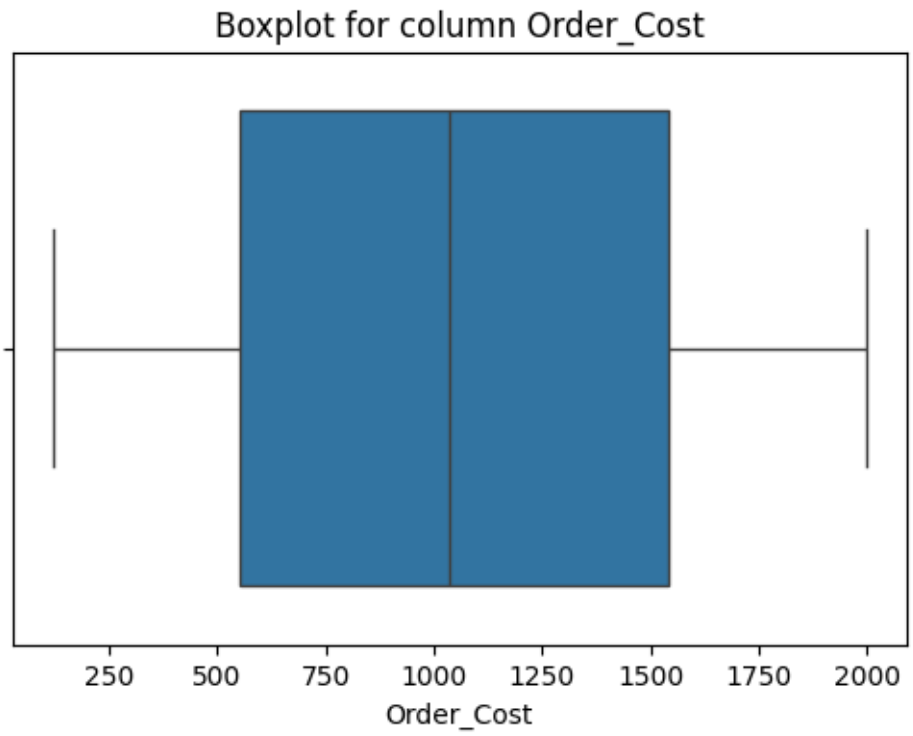
No outliers for column Customer_Rating

[18]:
```
plt.figure(figsize=(6, 4))
sns.boxplot(x=d['Delivery_Time'])
plt.title('Boxplot for column Delivery_Time')
plt.show()
```



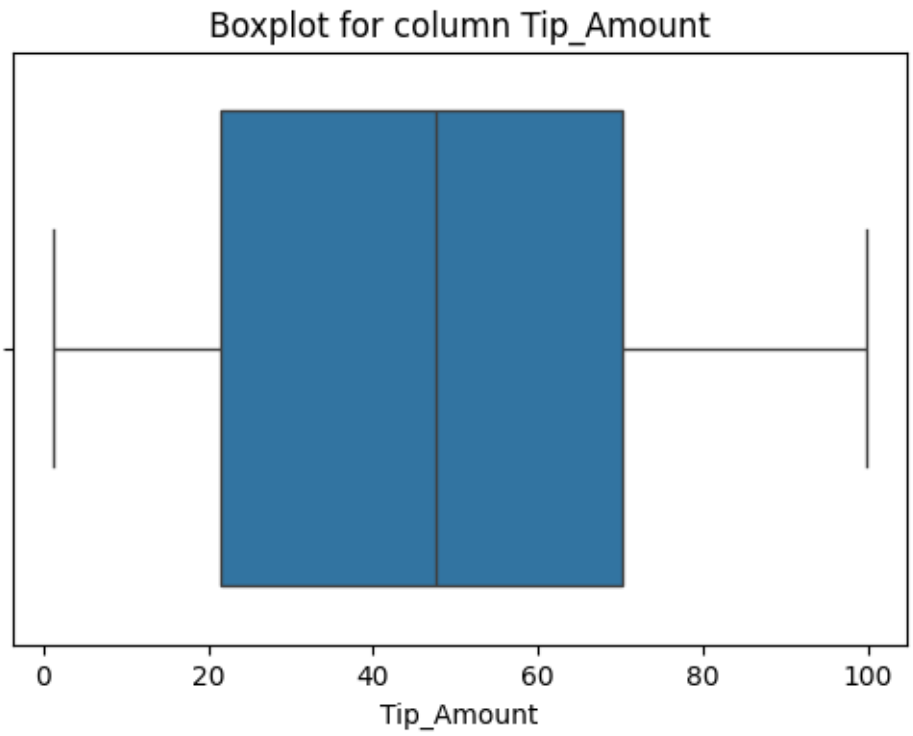
No outliers for column Delivery_Time

[19]:
```
plt.figure(figsize=(6, 4))
sns.boxplot(x=d['Order_Cost'])
plt.title('Boxplot for column Order_Cost')
plt.show()
```



No outliers for column Order_Cost

[20]:
```
plt.figure(figsize=(6, 4))
sns.boxplot(x=d['Tip_Amount'])
plt.title('Boxplot for column Tip_Amount')
plt.show()
```



No outliers for column Tip_Amount

None of the columns have outliers

Step 3 - Feature Engineering

[21]:
```
def haversine_formula(coords_array1, coords_array2):
    lat1 = coords_array1[:,0]
    lon1 = coords_array1[:,1]
    lat2 = coords_array2[:,0]
    lon2 = coords_array2[:,1]
    # Convert decimal degrees to radians
    lat1=np.radians(lat1)
    lon1=np.radians(lon1)
    lat2=np.radians(lat2)
    lon2=np.radians(lon2)
    # Haversine formula
    lat_diff = lat2 - lat1
    lon_diff = lon2 - lon1
    a = np.sin(lat_diff/2)**2 + np.cos(lat1) * np.cos(lat2) * np.sin(lon_diff/
 ↪2)**2
    c = 2 * np.asin(np.sqrt(a))
    r = 6371  # Radius of earth in km
    return c * r
```

```
def parse_location(loc_str):
    # Remove parentheses and split by comma
    lat, lon = loc_str.strip("()").split(",")
    return float(lat), float(lon)

coords_array1 = d['Customer_Location'].apply(parse_location).tolist()
coords_array1 = np.array(coords_array1)

coords_array2 = d['Restaurant_Location'].apply(parse_location).tolist()
coords_array2 = np.array(coords_array2)

d['Calculated_Distance'] = haversine_formula(coords_array1, coords_array2)
```

[22]:
```
d[['Calculated_Distance']]
```

[22]:
```
     Calculated_Distance
0              775.651198
1             1042.385597
2              476.220706
3              389.912629
4              806.505886
..                    …
195            670.130652
196            558.891202
197            106.686689
198            880.580093
199            763.581776

[200 rows x 1 columns]
```

[23]:
```
d
```

[23]:
```
    Order_ID       Customer_Location     Restaurant_Location  Distance  \
0    ORD0001  (17.030479, 79.743077)  (12.358515, 85.100083)      1.57
1    ORD0002  (15.398319, 86.639122)  (14.174874, 77.025606)     21.32
2    ORD0003  (15.687342, 83.888808)  (19.594748, 82.048482)      6.95
3    ORD0004  (20.415599, 78.046984)  (16.915906, 78.278698)     13.79
4    ORD0005  (14.786904, 78.706532)  (15.206038, 86.203182)      6.72
..       …                       …                       …       …
195  ORD0196   (17.910045, 81.56199)  (18.098924, 87.896124)     23.82
196  ORD0197   (21.66459, 82.226635)  (16.892341, 80.554716)      6.09
197  ORD0198   (14.575401, 82.55641)  (13.625369, 82.418092)     20.61
198  ORD0199  (12.094497, 82.893369)  (19.135509, 86.659978)     24.06
199  ORD0200  (19.360304, 84.132424)   (20.941636, 77.01334)      9.18

     Weather_Conditions  Traffic_Conditions  Delivery_Person_Experience  \
```

```
0                    1                   1                           4
1                    3                   1                           8
2                    2                   1                           9
3                    3                   0                           2
4                    1                   2                           6
..                 …                   …                         …
195                  3                   2                           8
196                  2                   1                           8
197                  2                   2                           4
198                  1                   2                           9
199                  2                   0                           2

     Order_Priority  Order_Time  Vehicle_Type  Restaurant_Rating  \
0                 1           1             2                4.1
1                 0           3             2                4.5
2                 2           3             1                3.3
3                 1           2             1                3.2
4                 0           3             1                3.5
..              …           …             …                …
195               1           3             1                4.7
196               0           3             0                3.0
197               1           1             1                2.9
198               0           3             2                3.9
199               0           0             1                4.6

     Customer_Rating  Delivery_Time  Order_Cost  Tip_Amount  \
0                3.0          26.22     1321.10       81.54
1                4.2          62.61      152.21       29.02
2                3.4          48.43     1644.38       64.17
3                3.7         111.63      541.25       79.23
4                2.8          32.38      619.81        2.34
..               …            …         …         …
195              4.0          50.39     1432.26       66.34
196              3.6          90.54     1720.25       40.27
197              3.4          73.20     1356.58        5.10
198              4.8          53.94      354.39       85.25
199              3.2          78.58      323.73       48.91

    Traffic_Condisions  Distance_Scaled  Delivery_Time_Scaled  \
0                  NaN        -1.454738             -1.487932
1                  NaN         1.439192             -0.264987
2                  NaN        -0.666417             -0.741529
3                  NaN         0.335835              1.382411
4                  NaN        -0.700119             -1.280915
..                 …              …                     …
195                NaN         1.805512             -0.675660
196                NaN        -0.792431              0.673647
```

```
197                NaN         1.335157              0.090908
198                NaN         1.840679             -0.556356
199                NaN        -0.339659              0.271711

     Order_Cost_Scaled  Calculated_Distance
0             0.501852           775.651198
1            -1.634294          1042.385597
2             1.092646           476.220706
3            -0.923323           389.912629
4            -0.779755           806.505886
..                 …                    …
195           0.704997           670.130652
196           1.231298           558.891202
197           0.566692           106.686689
198          -1.264810           880.580093
199          -1.320841           763.581776

[200 rows x 20 columns]
```

[24]:
```
d["Order_Time"].unique()
```

[24]:
```
array([1, 3, 2, 0])
```

[25]:
```
print(np.sum(d['Order_Time']==0))
print(np.sum(d['Order_Time']==1))
print(np.sum(d['Order_Time']==2))
print(np.sum(d['Order_Time']==3))
```

```
39
59
57
45
```

[26]:
```
d.loc[(d['Order_Time'] == 1) | (d['Order_Time'] == 2), 'Hour_Type'] = 'Rush␣
 ↪Hour'
d.loc[(d['Order_Time'] == 0) | (d['Order_Time'] == 3), 'Hour_Type'] = 'Non-Rush␣
 ↪Hour'
d[['Hour_Type']]
```

[26]:
```
          Hour_Type
0         Rush Hour
1     Non-Rush Hour
2     Non-Rush Hour
3         Rush Hour
4     Non-Rush Hour
..              …
195   Non-Rush Hour
196   Non-Rush Hour
```

```
197      Rush Hour
198  Non-Rush Hour
199  Non-Rush Hour

[200 rows x 1 columns]
```

[27]:
```
# Setting numeric values to column Hour_Type
Hour_Type_map = {'Non-Rush Hour': 0, 'Rush Hour': 1}
d['Hour_Type'] = d['Hour_Type'].map(Hour_Type_map)
d[['Hour_Type']]
```

[27]:
```
     Hour_Type
0            1
1            0
2            0
3            1
4            0
..         …
195          0
196          0
197          1
198          0
199          0

[200 rows x 1 columns]
```

Phase 2Predictive Modeling

contains 2 steps

Step 4 - Linear Regression Model

[28]:
```
d
```

[28]:
```
    Order_ID       Customer_Location     Restaurant_Location  Distance  \
0    ORD0001  (17.030479, 79.743077)  (12.358515, 85.100083)      1.57
1    ORD0002  (15.398319, 86.639122)  (14.174874, 77.025606)     21.32
2    ORD0003  (15.687342, 83.888808)  (19.594748, 82.048482)      6.95
3    ORD0004  (20.415599, 78.046984)  (16.915906, 78.278698)     13.79
4    ORD0005  (14.786904, 78.706532)  (15.206038, 86.203182)      6.72
..       …                       …                       …       …
195  ORD0196   (17.910045, 81.56199)  (18.098924, 87.896124)     23.82
196  ORD0197   (21.66459, 82.226635)  (16.892341, 80.554716)      6.09
197  ORD0198   (14.575401, 82.55641)  (13.625369, 82.418092)     20.61
198  ORD0199  (12.094497, 82.893369)  (19.135509, 86.659978)     24.06
199  ORD0200  (19.360304, 84.132424)   (20.941636, 77.01334)      9.18

     Weather_Conditions  Traffic_Conditions  Delivery_Person_Experience  \
0                     1                   1                           4
```

```
1                    3                    1                          8
2                    2                    1                          9
3                    3                    0                          2
4                    1                    2                          6
..                 …                    …                        …
195                  3                    2                          8
196                  2                    1                          8
197                  2                    2                          4
198                  1                    2                          9
199                  2                    0                          2

     Order_Priority  Order_Time  Vehicle_Type  …  Customer_Rating  \
0                 1           1             2  …             3.0
1                 0           3             2  …             4.2
2                 2           3             1  …             3.4
3                 1           2             1  …             3.7
4                 0           3             1  …             2.8
..              …         …           …  …              …
195               1           3             1  …             4.0
196               0           3             0  …             3.6
197               1           1             1  …             3.4
198               0           3             2  …             4.8
199               0           0             1  …             3.2

     Delivery_Time  Order_Cost  Tip_Amount  Traffic_Condisions  \
0            26.22     1321.10       81.54                 NaN
1            62.61      152.21       29.02                 NaN
2            48.43     1644.38       64.17                 NaN
3           111.63      541.25       79.23                 NaN
4            32.38      619.81        2.34                 NaN
..             …         …          …                   …
195          50.39     1432.26       66.34                 NaN
196          90.54     1720.25       40.27                 NaN
197          73.20     1356.58        5.10                 NaN
198          53.94      354.39       85.25                 NaN
199          78.58      323.73       48.91                 NaN

    Distance_Scaled  Delivery_Time_Scaled  Order_Cost_Scaled  \
0         -1.454738             -1.487932           0.501852
1          1.439192             -0.264987          -1.634294
2         -0.666417             -0.741529           1.092646
3          0.335835              1.382411          -0.923323
4         -0.700119             -1.280915          -0.779755
..              …                     …                …
195        1.805512             -0.675660           0.704997
196       -0.792431              0.673647           1.231298
197        1.335157              0.090908           0.566692
```

```
198        1.840679             -0.556356          -1.264810
199       -0.339659              0.271711          -1.320841

     Calculated_Distance  Hour_Type
0              775.651198          1
1             1042.385597          0
2              476.220706          0
3              389.912629          1
4              806.505886          0
..                    …         …
195            670.130652          0
196            558.891202          0
197            106.686689          1
198            880.580093          0
199            763.581776          0

[200 rows x 21 columns]
```

[29]:
```
features1=['Calculated_Distance', 'Order_Priority', 'Hour_Type',␣
 ↪'Traffic_Conditions', 'Distance', 'Weather_Conditions', 'Order_Time',␣
 ↪'Vehicle_Type']
x1 = d[features1]
y1 = d['Delivery_Time'].values.reshape(-1,1)
```

[30]:
```
x1_train, x1_test, y1_train, y1_test = train_test_split(x1, y1, test_size=0.2,␣
 ↪random_state=42)
```

[31]:
```
model1=LinearRegression()
model1.fit(x1_train, y1_train)
```

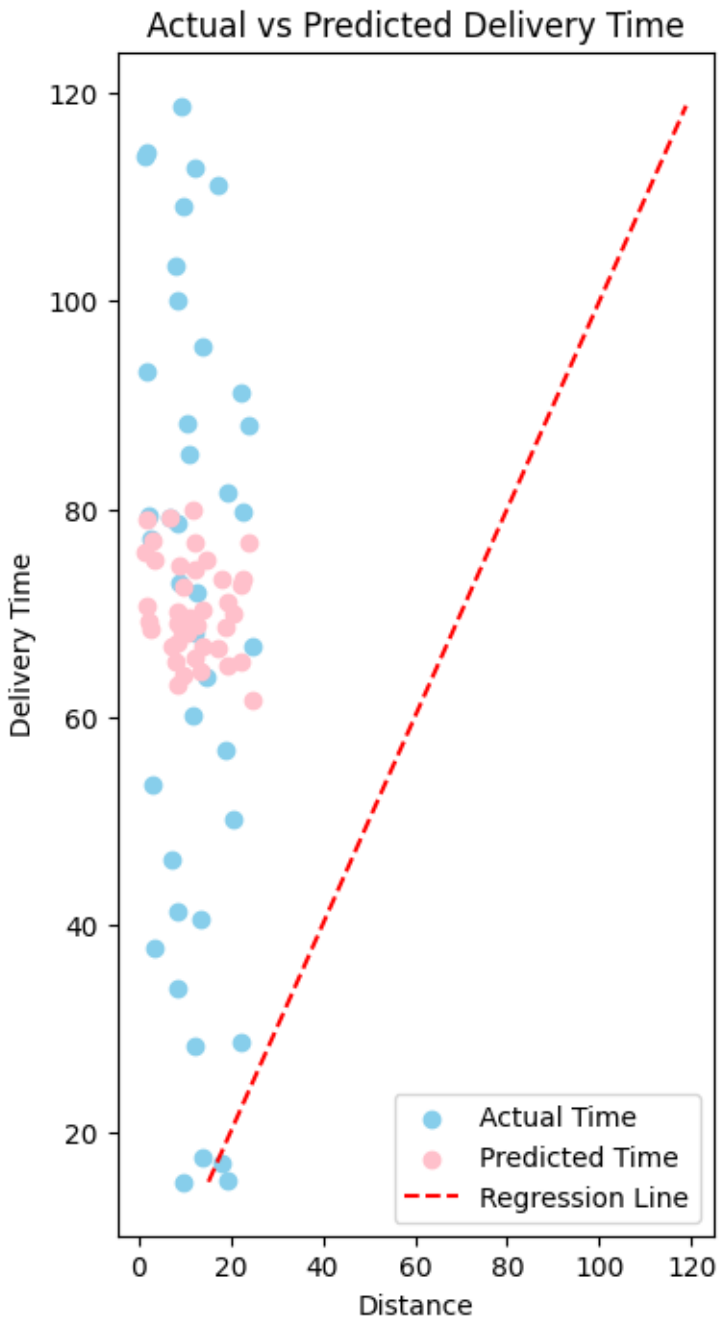
[31]:
```
LinearRegression()
```

[32]:
```
y1_pred=model1.predict(x1_test)
y1_pred
```

[32]:
```
array([[65.38769861],
       [69.91274107],
       [76.85336904],
       [70.38494607],
       [73.17633753],
       [75.13550136],
       [74.60017305],
       [70.70943681],
       [79.05965283],
       [65.72732621],
       [61.58958746],
       [68.54998666],
```

```
       [63.02809109],
       [79.96379449],
       [75.15506435],
       [66.55010947],
       [65.01215338],
       [68.94450298],
       [64.00757063],
       [77.0237123 ],
       [72.77246244],
       [66.73099907],
       [66.75165826],
       [67.10549902],
       [69.54848976],
       [68.5129306 ],
       [68.4822748 ],
       [68.89987917],
       [64.36055246],
       [75.85486299],
       [70.98672602],
       [70.15976751],
       [74.13732224],
       [69.20527439],
       [68.15818663],
       [76.71161811],
       [73.29715265],
       [72.52772064],
       [65.38620191],
       [79.20417865]])
```

[33]:
```
plt.figure(figsize=(4,8))
plt.scatter(x1_test['Distance'], y1_test, color='skyblue', label='Actual Time')
plt.scatter(x1_test['Distance'], y1_pred, color='pink', label='Predicted Time')
plt.plot([y1_test.min(), y1_test.max()], [y1_test.min(), y1_test.max()], 'r--',␣
 ↪label='Regression Line')  # Reference line
plt.xlabel('Distance')
plt.ylabel('Delivery Time')
plt.legend()
plt.title('Actual vs Predicted Delivery Time')
plt.show()
```



[34]:
```
mse = mean_squared_error(y1_test, y1_pred)
r2_score = model1.score(x1_test, y1_test)
mae = mean_absolute_error(y1_test, y1_pred)

print('Mean Squared Error : ', mse)
print('R sqyared (Accuracy for regression) : ', r2_score)
```

```
print('Mean Absolute Error : ', mae)
```

```
Mean Squared Error :  888.6648291609388
R sqyared (Accuracy for regression) :  0.03916826098779047
Mean Absolute Error :  25.33245221650145
```

Step 5 - Logistic Regression Model (for Categorization)

[35]:
```
d
```

[35]:
```
    Order_ID       Customer_Location     Restaurant_Location  Distance  \
0    ORD0001  (17.030479, 79.743077)  (12.358515, 85.100083)      1.57
1    ORD0002  (15.398319, 86.639122)  (14.174874, 77.025606)     21.32
2    ORD0003  (15.687342, 83.888808)  (19.594748, 82.048482)      6.95
3    ORD0004  (20.415599, 78.046984)  (16.915906, 78.278698)     13.79
4    ORD0005  (14.786904, 78.706532)  (15.206038, 86.203182)      6.72
..       …                       …                       …       …
195  ORD0196   (17.910045, 81.56199)  (18.098924, 87.896124)     23.82
196  ORD0197   (21.66459, 82.226635)  (16.892341, 80.554716)      6.09
197  ORD0198   (14.575401, 82.55641)  (13.625369, 82.418092)     20.61
198  ORD0199  (12.094497, 82.893369)  (19.135509, 86.659978)     24.06
199  ORD0200  (19.360304, 84.132424)   (20.941636, 77.01334)      9.18

     Weather_Conditions  Traffic_Conditions  Delivery_Person_Experience  \
0                     1                   1                           4
1                     3                   1                           8
2                     2                   1                           9
3                     3                   0                           2
4                     1                   2                           6
..                  …                   …                           …
195                   3                   2                           8
196                   2                   1                           8
197                   2                   2                           4
198                   1                   2                           9
199                   2                   0                           2

     Order_Priority  Order_Time  Vehicle_Type  …  Customer_Rating  \
0                 1           1             2  …              3.0
1                 0           3             2  …              4.2
2                 2           3             1  …              3.4
3                 1           2             1  …              3.7
4                 0           3             1  …              2.8
..              …           …           …  …              …
195               1           3             1  …              4.0
196               0           3             0  …              3.6
197               1           1             1  …              3.4
198               0           3             2  …              4.8
199               0           0             1  …              3.2
```

```
     Delivery_Time  Order_Cost  Tip_Amount  Traffic_Condisions  \
0            26.22     1321.10       81.54                 NaN
1            62.61      152.21       29.02                 NaN
2            48.43     1644.38       64.17                 NaN
3           111.63      541.25       79.23                 NaN
4            32.38      619.81        2.34                 NaN
..             …          …          …                   …
195          50.39     1432.26       66.34                 NaN
196          90.54     1720.25       40.27                 NaN
197          73.20     1356.58        5.10                 NaN
198          53.94      354.39       85.25                 NaN
199          78.58      323.73       48.91                 NaN

    Distance_Scaled  Delivery_Time_Scaled  Order_Cost_Scaled  \
0         -1.454738             -1.487932           0.501852
1          1.439192             -0.264987          -1.634294
2         -0.666417             -0.741529           1.092646
3          0.335835              1.382411          -0.923323
4         -0.700119             -1.280915          -0.779755
..              …                     …                  …
195        1.805512             -0.675660           0.704997
196       -0.792431              0.673647           1.231298
197        1.335157              0.090908           0.566692
198        1.840679             -0.556356          -1.264810
199       -0.339659              0.271711          -1.320841

     Calculated_Distance  Hour_Type
0             775.651198          1
1            1042.385597          0
2             476.220706          0
3             389.912629          1
4             806.505886          0
..                   …          …
195           670.130652          0
196           558.891202          0
197           106.686689          1
198           880.580093          0
199           763.581776          0

[200 rows x 21 columns]
```

[36]:
```
d.loc[d['Delivery_Time']>=Delivery_Time_median,'Delivery_Status']='Delayed'
d.loc[d['Delivery_Time']<Delivery_Time_median,'Delivery_Status']='Fast'
```

[37]:
```
d[['Delivery_Status']]
```

[37]:
```
    Delivery_Status
0              Fast
1              Fast
2              Fast
3           Delayed
4              Fast
..              …
195            Fast
196         Delayed
197         Delayed
198            Fast
199         Delayed

[200 rows x 1 columns]
```

[38]:
```
features2=['Calculated_Distance', 'Order_Priority', 'Hour_Type',␣
 ↪'Traffic_Conditions', 'Distance', 'Weather_Conditions', 'Order_Time',␣
 ↪'Vehicle_Type']
x2=d[features2]
y2=d['Delivery_Status']
```

[39]:
```
x2_train, x2_test, y2_train, y2_test = train_test_split(x2, y2, train_size=0.2)
```

[40]:
```
model2 = LogisticRegression()
model2.fit(x2_train, y2_train)
```

```
c:\Users\Princy Pandya\AppData\Local\Programs\Python\Python310\lib\site-
packages\sklearn\linear_model\_logistic.py:470: ConvergenceWarning: lbfgs failed
to converge after 100 iteration(s) (status=1):
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT

Increase the number of iterations to improve the convergence (max_iter=100).
You might also want to scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

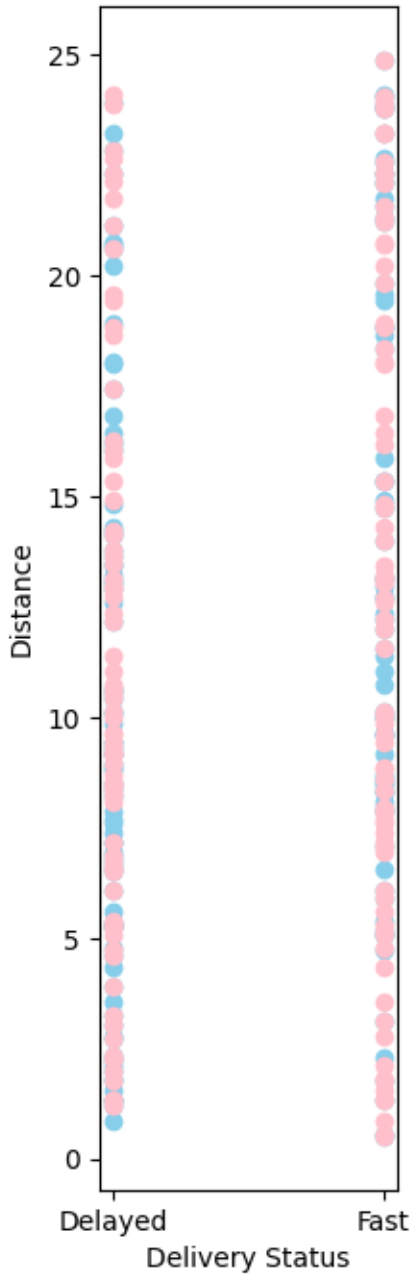
[40]:
```
LogisticRegression()
```

[41]:
```
y2_pred=model2.predict(x2_test)
y2_pred
```

[41]:
```
array(['Delayed', 'Delayed', 'Delayed', 'Fast', 'Delayed', 'Fast', 'Fast',
       'Delayed', 'Fast', 'Delayed', 'Fast', 'Delayed', 'Fast', 'Delayed',
       'Delayed', 'Delayed', 'Fast', 'Delayed', 'Fast', 'Delayed', 'Fast',
       'Delayed', 'Delayed', 'Delayed', 'Delayed', 'Delayed', 'Fast',
```

```
       'Fast', 'Delayed', 'Fast', 'Delayed', 'Delayed', 'Fast', 'Fast',
       'Fast', 'Delayed', 'Fast', 'Delayed', 'Fast', 'Fast', 'Delayed',
       'Delayed', 'Fast', 'Delayed', 'Fast', 'Fast', 'Delayed', 'Delayed',
       'Fast', 'Delayed', 'Delayed', 'Delayed', 'Delayed', 'Fast', 'Fast',
       'Delayed', 'Fast', 'Fast', 'Delayed', 'Delayed', 'Fast', 'Fast',
       'Fast', 'Fast', 'Delayed', 'Delayed', 'Fast', 'Fast', 'Delayed',
       'Delayed', 'Fast', 'Delayed', 'Delayed', 'Delayed', 'Fast',
       'Delayed', 'Fast', 'Fast', 'Delayed', 'Fast', 'Delayed', 'Fast',
       'Fast', 'Delayed', 'Delayed', 'Fast', 'Fast', 'Delayed', 'Delayed',
       'Fast', 'Delayed', 'Fast', 'Delayed', 'Delayed', 'Fast', 'Delayed',
       'Delayed', 'Delayed', 'Delayed', 'Delayed', 'Delayed', 'Fast',
       'Fast', 'Delayed', 'Delayed', 'Fast', 'Delayed', 'Fast', 'Delayed',
       'Fast', 'Delayed', 'Delayed', 'Fast', 'Delayed', 'Delayed', 'Fast',
       'Fast', 'Delayed', 'Delayed', 'Fast', 'Fast', 'Fast', 'Delayed',
       'Fast', 'Fast', 'Fast', 'Fast', 'Fast', 'Fast', 'Delayed', 'Fast',
       'Fast', 'Delayed', 'Delayed', 'Fast', 'Fast', 'Delayed', 'Delayed',
       'Delayed', 'Fast', 'Delayed', 'Delayed', 'Fast', 'Delayed',
       'Delayed', 'Fast', 'Delayed', 'Fast', 'Fast', 'Fast', 'Fast',
       'Delayed', 'Fast', 'Delayed', 'Delayed', 'Delayed', 'Delayed',
       'Delayed', 'Delayed', 'Delayed'], dtype=object)
```

[42]:
```
plt.figure(figsize=(2,8))
plt.scatter(y2_pred, x2_test['Distance'], color='skyblue', label='Predicted␣
 ↪Status')
plt.scatter(y2_test, x2_test['Distance'], color='pink', label='Actual Status')
plt.xlabel('Delivery Status')
plt.ylabel('Distance')
plt.legend
plt.show()
```



Phase 3:Reporting and Insights

contains 2 steps

Step 6 - Model Evaluation and Comparison

[43]:
```
accuracy = accuracy_score(y2_test, y2_pred)
precision = precision_score(y2_test, y2_pred, pos_label='Delayed')
recall = recall_score(y2_test, y2_pred, pos_label='Delayed')
```

```
f1 = f1_score(y2_test, y2_pred, pos_label='Delayed')

print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1-score:", f1)
```

```
Accuracy: 0.51875
Precision: 0.5172413793103449
Recall: 0.5625
F1-score: 0.5389221556886228
```

ROC Curve for Logistic Regression Receiver Operating Characteristic It is a graphical plot used to evaluate the performance of a binary classification model (has 2 outputs only) (like your logistic regression). The ROC curve shows the trade-off between the True Positive Rate (x-axis) (Sensitivity/Recall) and the False Positive Rate (y-axis) (1 - Specificity) at various threshold settings. True Positive Rate = True Positives/(True Positives + False Negatives) True Positive Rate = False Positives/(False Positives + True Negatives)

[44]:
```
y2_test
```

[44]:
```
154    Delayed
50        Fast
52        Fast
148       Fast
179    Delayed
        …
126       Fast
155       Fast
116    Delayed
89        Fast
51     Delayed
Name: Delivery_Status, Length: 160, dtype: object
```

These numbers are the original DataFrame indices for each test sample, and the value (“Delayed” or “Fast”) is the true label for that sample. for example : Row 180 in your original DataFrame has Delivery_Status = “Delayed” Row 37 in your original DataFrame has Delivery_Status = “Fast” Row 43 in your original DataFrame has Delivery_Status = “Delayed”

numbers printed ramdomly because train_test_split shuffles the data before splitting it into train and test sets

[45]:
```
lb = LabelBinarizer()
# converts y into numbers
# delayed = 1, fast = 0
y = lb.fit_transform(y2)
y=y.ravel()
x = x2.values
```

[46]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,␣
↪random_state=42)
```

[47]:
```
model1.fit(x_train, y_train)
y_pred = model1.predict(x_test)
y_pred
```

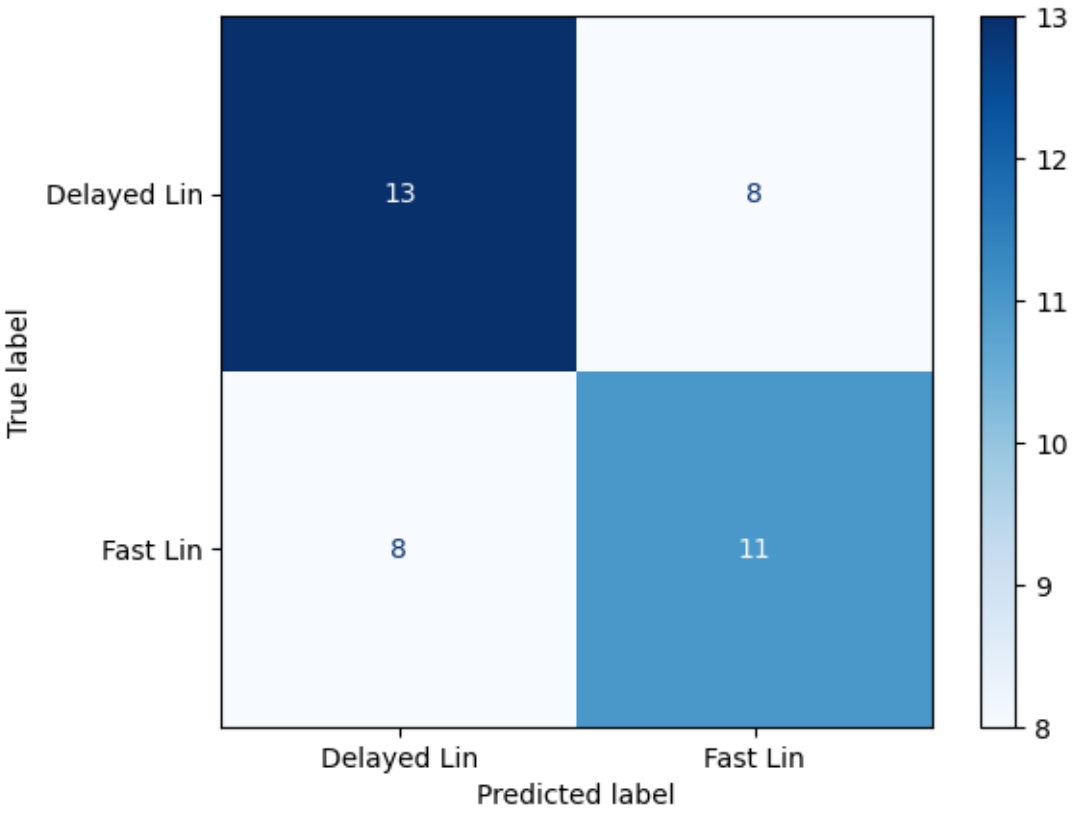
[47]:
```
array([0.74721902, 0.62297433, 0.41305978, 0.48218291, 0.50374511,
       0.43671382, 0.47212111, 0.47694589, 0.33238938, 0.66797094,
       0.7301367 , 0.65283339, 0.66327105, 0.24720314, 0.33677952,
       0.61057496, 0.62504165, 0.62153787, 0.70096819, 0.30291639,
       0.41590765, 0.57202788, 0.5172066 , 0.47816395, 0.60055172,
       0.44421179, 0.49317894, 0.54151593, 0.6482102 , 0.4197626 ,
       0.49907004, 0.39493781, 0.45822207, 0.4439889 , 0.59818562,
       0.42465846, 0.60742907, 0.339049  , 0.58430785, 0.25389288])
```

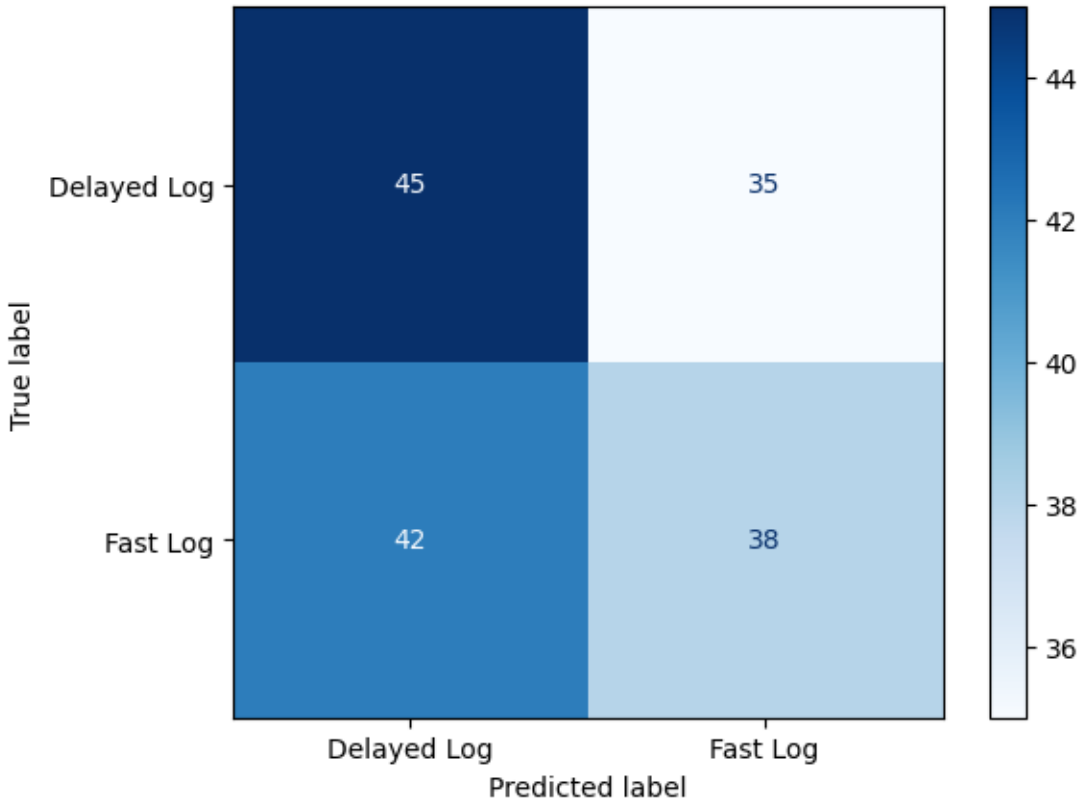
[48]:
```
y_pred_class = y_pred.round().astype(int).clip(0,2)
y_pred_class
```

[48]:
```
array([1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 1,
       1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0])
```

[49]:
```
# Confusion Matrices
cm_lin = confusion_matrix(y_test, y_pred_class)
ConfusionMatrixDisplay(confusion_matrix=cm_lin, display_labels=['Delayed Lin',␣
↪'Fast Lin']).plot(cmap='Blues')
cm_log = confusion_matrix(y2_test, y2_pred, labels=['Delayed', 'Fast'])
ConfusionMatrixDisplay(confusion_matrix=cm_log, display_labels=['Delayed Log',␣
↪'Fast Log']).plot(cmap='Blues')
```

[49]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x17be80643a0>
```


Delayed Lin
Fast Lin
True label
13
8
8
11
Delayed Lin
Fast Lin
Predicted label
13
12
11
10
9
8



[50]:
```
# Classification Reports
cr_lin = classification_report(y_test, y_pred_class, target_names=['Delayed',␣
↪'Fast'])
cr_log = classification_report(y2_test, y2_pred, target_names=['Delayed',␣
↪'Fast'])

# Print Classification Reports
print("Linear Regression Classification Report:\n", cr_lin)
print("Logistic Regression Classification Report:\n", cr_log)
```

```
Linear Regression Classification Report:
              precision    recall  f1-score   support

     Delayed       0.62      0.62      0.62        21
        Fast       0.58      0.58      0.58        19

    accuracy                           0.60        40
   macro avg       0.60      0.60      0.60        40
weighted avg       0.60      0.60      0.60        40

Logistic Regression Classification Report:
```

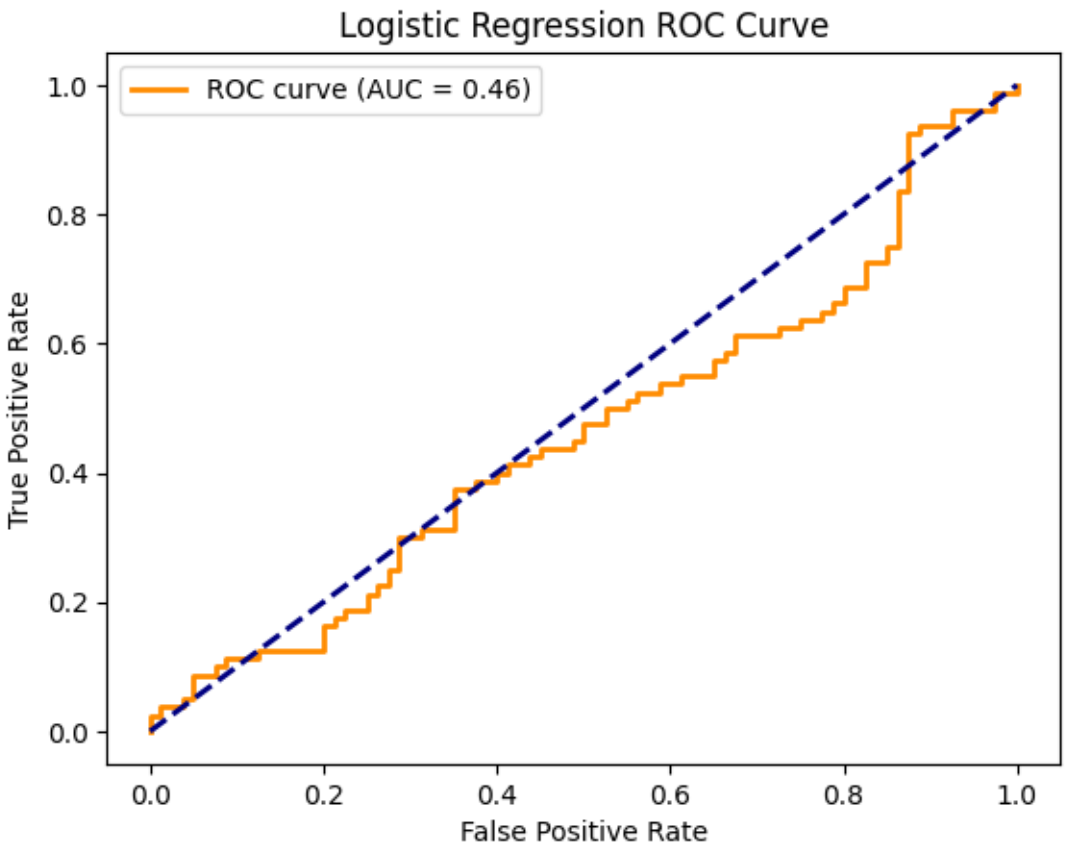
```
                precision    recall  f1-score   support

     Delayed       0.52      0.56      0.54        80
        Fast       0.52      0.47      0.50        80

    accuracy                           0.52       160
   macro avg       0.52      0.52      0.52       160
weighted avg       0.52      0.52      0.52       160
```

Logistic Regression will usually perform much better on classification tasks. Linear Regression, when rounded to the nearest class, might perform poorly due to treating labels as numeric values (e.g., 0, 1, 2).

Linear Regression performed better overall on this dataset: Higher accuracy, More balanced precision, recall, and f1-score

Logistic Regression : Features may not separate classes well Or the model needs tuning (e.g., better feature scaling, regularization, or hyperparameters)

[51]:
```
y2_test_bin = lb.fit_transform(y2_test)
# converts y2_test into numbers
# delayed = 1, fast = 0
if y2_test_bin.shape[1] == 1: # check if y2_test is binary
    # if y2_test is binary, then we need to convert it to 1D
    y2_test_bin = y2_test_bin.ravel() # convert to 1D array
    y2_pred_prob = model2.predict_proba(x2_test)[:, list(model2.classes_).
 ↪index('Delayed')] # get the probability of 'Delayed' class means that it␣
 ↪finds which column is "Delayed".
else: # if y2_test is not binary
    # If we had more than one column (multi-class), we just take the second␣
 ↪column (index 1).
    y2_pred_prob = model2.predict_proba(x2_test)[:, 1] # get the probability of␣
 ↪'Delayed' class

fpr, tpr, thresholds = roc_curve(y2_test_bin, y2_pred_prob)
roc_auc = auc(fpr, tpr)

plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.
 ↪2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Logistic Regression ROC Curve')
plt.legend()
plt.show()
```



Step 7 - Actionable Insights

[52]:
```
print("--> Optimize delivery routes using real-time traffic data and route␣
 ↪optimization tools to reduce delivery times,\n \tespecially for longer␣
 ↪distances or during high-traffic conditions.")
print("--> Increase staffing levels during identified rush hours and periods of␣
 ↪high traffic to ensure timely deliveries and reduce delays.")
print("--> Provide regular training and upskilling for delivery staff to␣
 ↪improve their efficiency, navigation, and customer interaction,\n \tleading␣
 ↪to faster and more reliable deliveries.")
```

```
--> Optimize delivery routes using real-time traffic data and route optimization
tools to reduce delivery times,
        especially for longer distances or during high-traffic conditions.
--> Increase staffing levels during identified rush hours and periods of high
traffic to ensure timely deliveries and reduce delays.
--> Provide regular training and upskilling for delivery staff to improve their
efficiency, navigation, and customer interaction,
        leading to faster and more reliable deliveries.
```

0.0.1 Final Summary

This project aimed to predict food delivery times using factors such as customer and restaurant locations, traffic, weather, and order-specific information. The workflow involved the following key stages:

- *Data Preparation:* The dataset was thoroughly cleaned by handling missing values, removing invalid entries, encoding categorical variables, and creating new features like calculated distance (using the Haversine formula) and time-of-day classification (Rush vs Non-Rush hour).
- *Exploratory Data Analysis (EDA):* We found weak individual correlations between delivery time and input features — distance, traffic conditions, and delivery experience had limited influence. Boxplots confirmed there were no major outliers.
- *Model Building:*
  - A *Linear Regression* model was trained to predict continuous delivery time, but it yielded a low R^2 *score of 0.039*, indicating very poor predictive performance.
  - A *Logistic Regression* model was then used to classify deliveries as either *"Fast"* or *"Delayed"* based on the median delivery time. This model achieved:
    - *Accuracy:* 51.87%
    - *Precision:* 51.72%
    - *Recall:* 56.25%
    - *F1-score:* 53.89% These results suggest that the logistic model performed slightly better but still lacked strong predictive power.
- *Insights & Recommendations:*
  - No single feature had a dominant effect on delivery time.
  - The data may be too limited or simplistic for accurate modeling using basic algorithms.

To address these challenges and improve delivery outcomes, we recommend: 1. Using *real-time traffic and route data* for better route optimization. 2. Increasing *delivery staff availability during peak (rush) hours*. 3. Providing *ongoing training* to delivery personnel to improve speed and customer service.