```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns


from sklearn.preprocessing import LabelEncoder, StandardScaler


from sklearn.cluster import KMeans


import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

Importing Liberries

Data Source & Data pre Processing

```
import pandas as pd


file_path = 'YourCabs_training.csv'
data = pd.read_csv(file_path)


missing_values = data.isnull().sum()
print("Missing values in each column:\n", missing_values)

data.fillna(data.mean(numeric_only=True), inplace=True)


for column in data.select_dtypes(include=['object']).columns:
    data[column].fillna(data[column].mode()[0], inplace=True)


duplicates = data.duplicated().sum()
print(f"Number of duplicate rows: {duplicates}")


data_cleaned = data.drop_duplicates()


print("Data types of columns:\n", data.dtypes)

if 'Booking_DateTime' in data.columns:
    data['Booking_DateTime'] = pd.to_datetime(data['Booking_DateTime'], errors='coerce')


for col in data.columns:
    if data[col].dtype == 'object':

        data[col] = pd.to_numeric(data[col], errors='ignore')


numeric_columns = data.select_dtypes(include=['float64', 'int64']).columns
for col in numeric_columns:
    mean = data[col].mean()
    std = data[col].std()
    data_cleaned = data_cleaned[(data_cleaned[col] > mean - 3*std) & (data_cleaned[col] < mean + 3*std)]

columns_to_drop = ['some_irrelevant_column']
data_cleaned = data_cleaned.drop(columns=columns_to_drop, axis=1, errors='ignore')

# Final cleaned data
print("Cleaned data preview:")
print(data_cleaned.head())

# Save cleaned data to a new CSV file
data_cleaned.to_csv('YourCabs_cleaned.csv', index=False)
```

```
from_lat                  93
from_long                 93
to_lat                  9138
to_long                 9138
Car_Cancellation           0
Cost_of_error              0
dtype: int64
Number of duplicate rows: 0
Data types of columns:
 id                      int64
user_id                 int64
vehicle_model_id        int64
package_id            float64
travel_type_id          int64
from_area_id          float64
to_area_id            float64
from_city_id          float64
to_city_id            float64
from_date              object
to_date               float64
online_booking          int64
mobile_site_booking     int64
booking_created        object
from_lat              float64
from_long             float64
to_lat                float64
to_long               float64
Car_Cancellation        int64
Cost_of_error         float64
dtype: object
Cleaned data preview:
       id  user_id  vehicle_model_id  package_id  travel_type_id  \
0  132512    22177                28    2.030066               2
1  132513    21413                12    2.030066               2
2  132514    22178                12    2.030066               2
3  132515    13034                12    2.030066               2
4  132517    22180                12    2.030066               2

   from_area_id  to_area_id  from_city_id  to_city_id      from_date  \
0          83.0       448.0     14.915081   68.537783  1/1/2013 2:00
1        1010.0       540.0     14.915081   68.537783  1/1/2013 9:00
2        1301.0      1034.0     14.915081   68.537783  1/1/2013 3:30
3         768.0       398.0     14.915081   68.537783  1/1/2013 5:45
4        1365.0       849.0     14.915081   68.537783  1/1/2013 9:00

       to_date  online_booking  mobile_site_booking booking_created  \
0  41507.97484               0                    0   1/1/2013 1:39
1  41507.97484               0                    0   1/1/2013 2:25
2  41507.97484               0                    0   1/1/2013 3:08
3  41507.97484               0                    0   1/1/2013 4:39
4  41507.97484               0                    0   1/1/2013 7:53

    from_lat  from_long     to_lat    to_long  Car_Cancellation  Cost_of_error
0  12.924150  77.672290  12.927320  77.635750                 0            1.0
1  12.966910  77.749350  12.927680  77.626640                 0            1.0
2  12.937222  77.626915  13.047926  77.597766                 0            1.0
3  12.989990  77.553320  12.971430  77.639140                 0            1.0
4  12.845653  77.677925  12.954340  77.600720                 0            1.0
```

Cleaned Data

```
df = pd.read_csv('YourCabs_cleaned.csv')
```

```
print(df.head())
```

```
       id  user_id  vehicle_model_id  package_id  travel_type_id  \
0  132512    22177                28    2.030066               2
1  132513    21413                12    2.030066               2
2  132514    22178                12    2.030066               2
3  132515    13034                12    2.030066               2
4  132517    22180                12    2.030066               2

   from_area_id  to_area_id  from_city_id  to_city_id      from_date  \
0          83.0       448.0     14.915081   68.537783  1/1/2013 2:00
1        1010.0       540.0     14.915081   68.537783  1/1/2013 9:00
2        1301.0      1034.0     14.915081   68.537783  1/1/2013 3:30
3         768.0       398.0     14.915081   68.537783  1/1/2013 5:45
```

```
4       1365.0       849.0     14.915081   68.537783  1/1/2013 9:00

      to_date  online_booking  mobile_site_booking booking_created  \
0  41507.97484               0                    0   1/1/2013 1:39
1  41507.97484               0                    0   1/1/2013 2:25
2  41507.97484               0                    0   1/1/2013 3:08
3  41507.97484               0                    0   1/1/2013 4:39
4  41507.97484               0                    0   1/1/2013 7:53

    from_lat  from_long     to_lat    to_long  Car_Cancellation  Cost_of_error
0  12.924150  77.672290  12.927320  77.635750                 0            1.0
1  12.966910  77.749350  12.927680  77.626640                 0            1.0
2  12.937222  77.626915  13.047926  77.597766                 0            1.0
3  12.989990  77.553320  12.971430  77.639140                 0            1.0
4  12.845653  77.677925  12.954340  77.600720                 0            1.0
```

```
df.shape
```

```
(36552, 20)
```

Information of Dataset

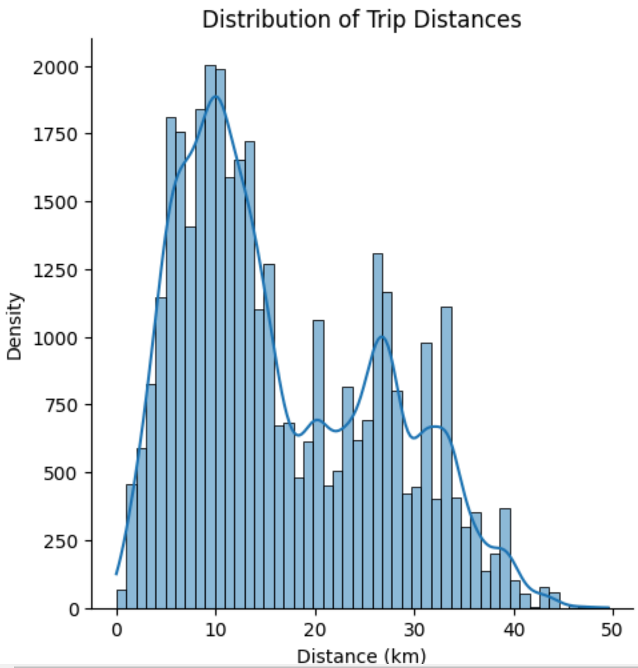
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 36552 entries, 0 to 36551
Data columns (total 20 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   id                   36552 non-null  int64
 1   user_id              36552 non-null  int64
 2   vehicle_model_id     36552 non-null  int64
 3   package_id           36552 non-null  float64
 4   travel_type_id       36552 non-null  int64
 5   from_area_id         36552 non-null  float64
 6   to_area_id           36552 non-null  float64
 7   from_city_id         36552 non-null  float64
 8   to_city_id           36552 non-null  float64
 9   from_date            36552 non-null  object
 10  to_date              36552 non-null  float64
 11  online_booking       36552 non-null  int64
 12  mobile_site_booking  36552 non-null  int64
 13  booking_created      36552 non-null  object
 14  from_lat             36552 non-null  float64
 15  from_long            36552 non-null  float64
 16  to_lat               36552 non-null  float64
 17  to_long              36552 non-null  float64
 18  Car_Cancellation     36552 non-null  int64
 19  Cost_of_error        36552 non-null  float64
dtypes: float64(11), int64(7), object(2)
memory usage: 5.6+ MB
```

```
# Import necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

# Function to calculate distance between two coordinates (Haversine formula)
def haversine(lat1, lon1, lat2, lon2):
    # Convert decimal degrees to radians
    lat1, lon1, lat2, lon2 = map(np.radians, [lat1, lon1, lat2, lon2])

    # Haversine formula
    dlat = lat2 - lat1
    dlon = lon2 - lon1
    a = np.sin(dlat/2)**2 + np.cos(lat1) * np.cos(lat2) * np.sin(dlon/2)**2
    c = 2 * np.arcsin(np.sqrt(a))
    km = 6371 * c  # Radius of earth in kilometers is 6371
    return km

# Load the dataset
file_path = 'YourCabs_cleaned.csv'
data = pd.read_csv(file_path)

# Data Preprocessing (Dropping rows with missing coordinates)
data_cleaned = data.dropna(subset=['from_lat', 'from_long', 'to_lat', 'to_long'])
```

```
# Apply the Haversine formula to calculate distance and add as a new column
data_cleaned['distance'] = data_cleaned.apply(lambda row: haversine(row['from_lat'], row['from_long'],
                                                                     row['to_lat'], row['to_long']), axis=1)

# Visualize the distribution of distances using a kernel density estimate (KDE)
plt.figure(figsize=(10, 6))
sns.displot(data_cleaned['distance'], kde=True)
plt.title('Distribution of Trip Distances')
plt.xlabel('Distance (km)')
plt.ylabel('Density')
plt.show()
```

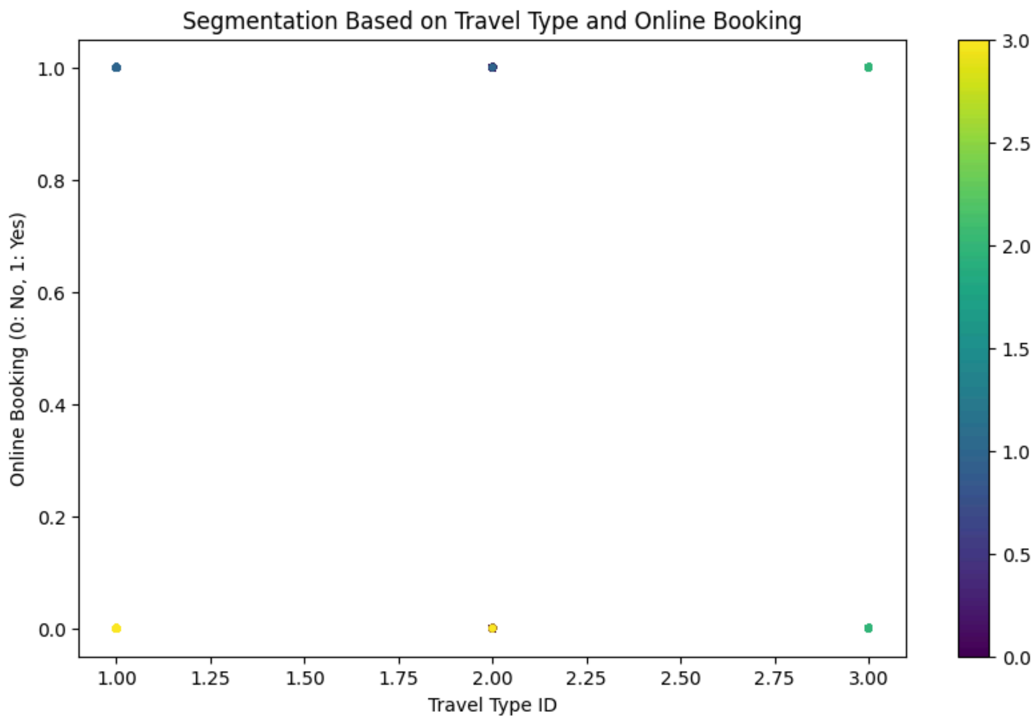
```
<Figure size 1000x600 with 0 Axes>
```

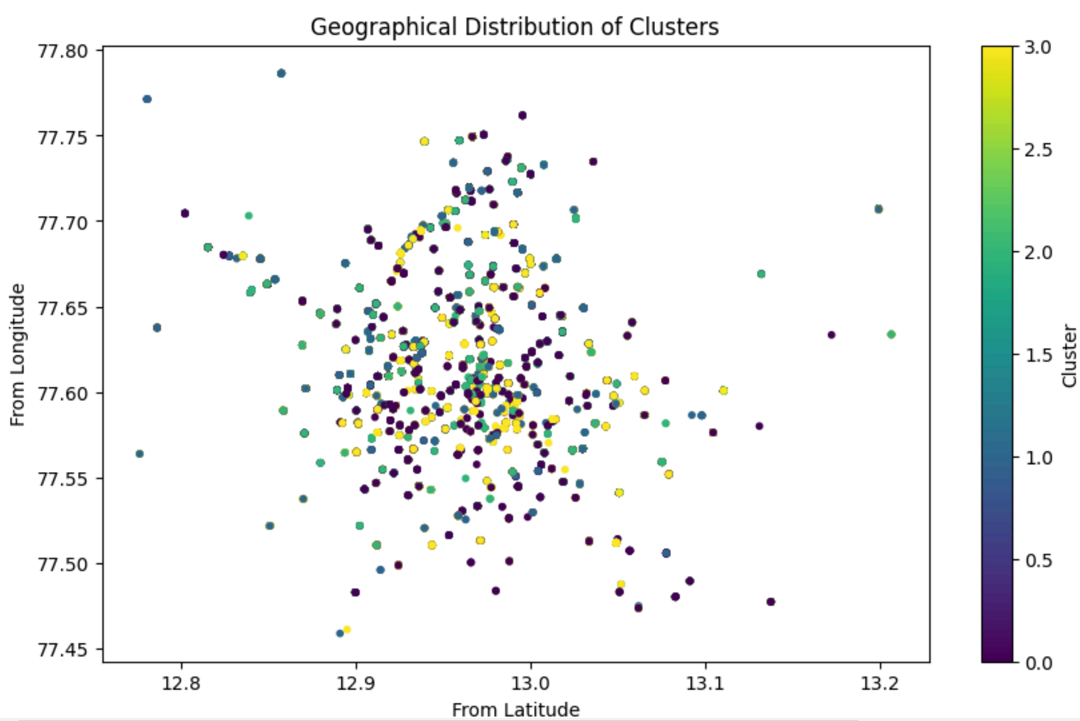


Market Segmentation Based on Travel Type

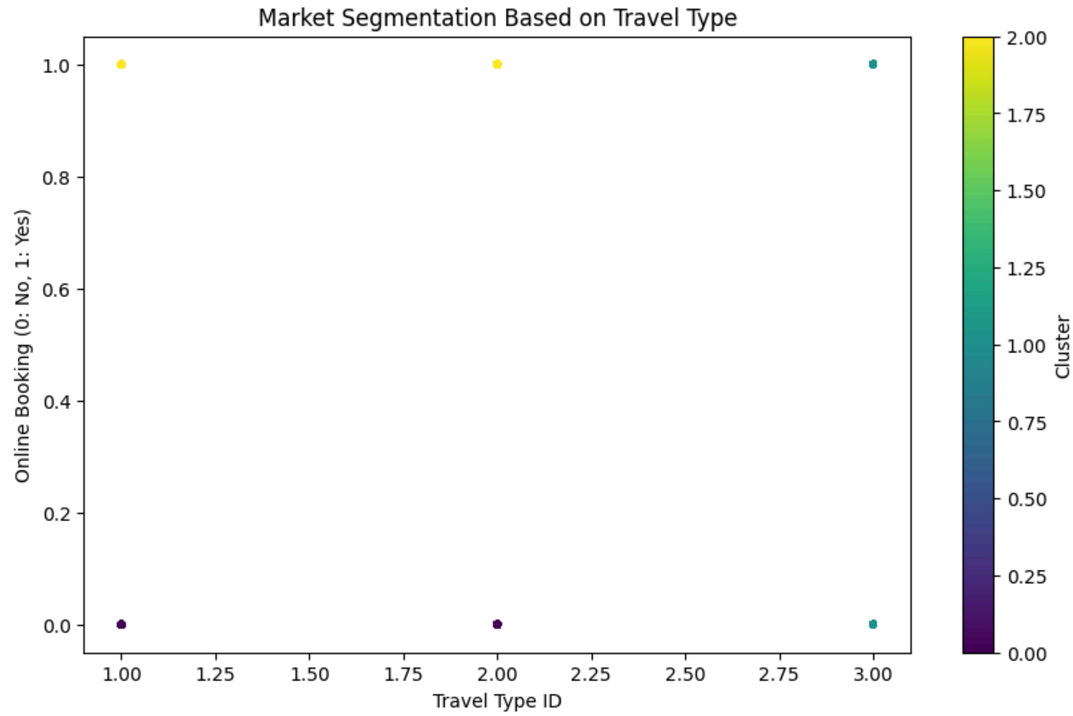
```
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

# Load the dataset
file_path = 'YourCabs_cleaned.csv'
data = pd.read_csv(file_path)

# Step 1: Preprocessing
# Selecting relevant columns and dropping rows with missing values
cluster_data_full = data[['travel_type_id', 'online_booking', 'mobile_site_booking',
                          'from_lat', 'from_long', 'to_lat', 'to_long', 'Car_Cancellation', 'Cost_of_error']].dropna()

# Step 2: Normalizing the data
scaler = StandardScaler()
cluster_data_full_scaled = scaler.fit_transform(cluster_data_full)

# Step 3: K-Means Clustering
kmeans_full = KMeans(n_clusters=4, random_state=42)
clusters_full = kmeans_full.fit_predict(cluster_data_full_scaled)

# Adding the cluster labels to the dataset
cluster_data_full['cluster'] = clusters_full

# Step 4: Visualization
# Visualization 1: Based on travel type and online booking
plt.figure(figsize=(10, 6))

plt.scatter(cluster_data_full['travel_type_id'], cluster_data_full['online_booking'],
            c=cluster_data_full['cluster'], cmap='viridis', s=10)
plt.colorbar(label='Cluster')
```

```
plt.title('Segmentation Based on Travel Type and Online Booking')
plt.xlabel('Travel Type ID')
plt.ylabel('Online Booking (0: No, 1: Yes)')
plt.show()

# Visualization 2: Geographical distribution (latitude and longitude)
plt.figure(figsize=(10, 6))

plt.scatter(cluster_data_full['from_lat'], cluster_data_full['from_long'],
            c=cluster_data_full['cluster'], cmap='viridis', s=10)
plt.colorbar(label='Cluster')
plt.title('Geographical Distribution of Clusters')
plt.xlabel('From Latitude')
plt.ylabel('From Longitude')
plt.show()
```





```
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

# Load the dataset
file_path = 'YourCabs_cleaned.csv'
data = pd.read_csv(file_path)

# Step 1: Preprocessing
# Selecting travel_type_id and related attributes for segmentation
cluster_data_travel_type = data[['travel_type_id', 'online_booking', 'mobile_site_booking',
                                 'Car_Cancellation', 'Cost_of_error']].dropna()

# Step 2: Normalizing the data
scaler = StandardScaler()
cluster_data_travel_type_scaled = scaler.fit_transform(cluster_data_travel_type)

# Step 3: K-Means Clustering
kmeans_travel_type = KMeans(n_clusters=3, random_state=42)  # Assuming 3 clusters for segmentation
clusters_travel_type = kmeans_travel_type.fit_predict(cluster_data_travel_type_scaled)

# Adding the cluster labels to the dataset
cluster_data_travel_type['cluster'] = clusters_travel_type

# Step 4: Visualization
plt.figure(figsize=(10, 6))

# Scatter plot based on travel type and online booking
plt.scatter(cluster_data_travel_type['travel_type_id'], cluster_data_travel_type['online_booking'],
            c=cluster_data_travel_type['cluster'], cmap='viridis', s=10)
plt.colorbar(label='Cluster')
plt.title('Market Segmentation Based on Travel Type')
plt.xlabel('Travel Type ID')
plt.ylabel('Online Booking (0: No, 1: Yes)')
plt.show()

# Optional: View cluster statistics
print(cluster_data_travel_type.groupby('cluster').mean())
```



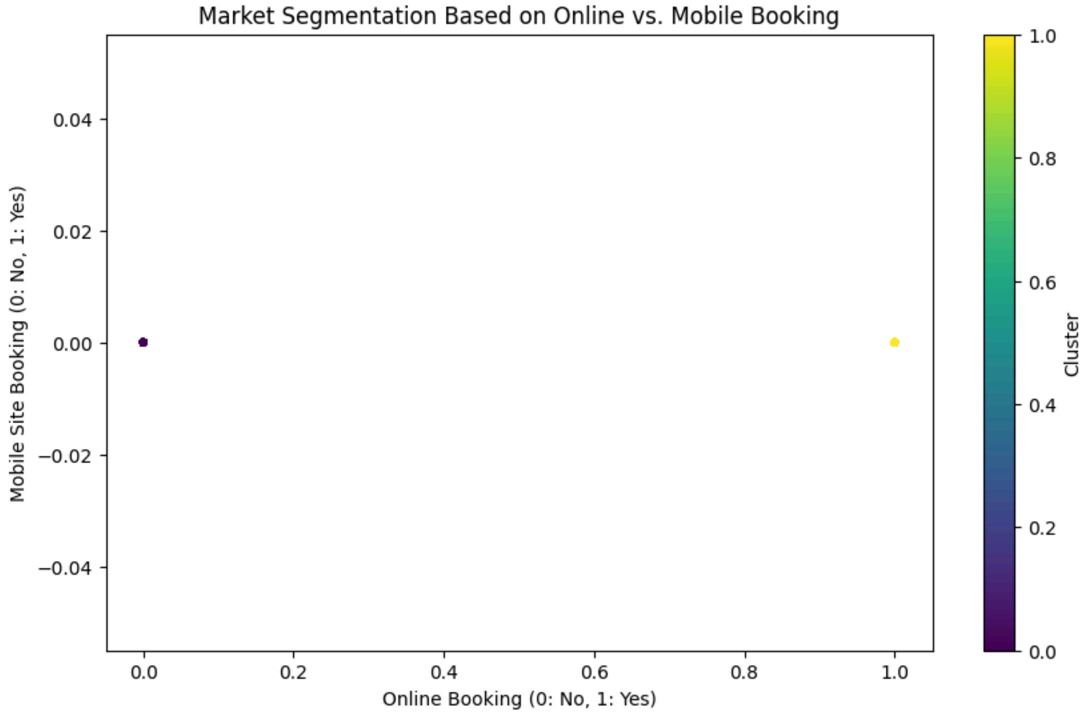

```
         travel_type_id  online_booking  mobile_site_booking  \
cluster
0              1.987446        0.000000                  0.0
1              3.000000        0.281455                  0.0
2              1.986731        1.000000                  0.0

         Car_Cancellation  Cost_of_error
cluster
0                     0.0            1.0
1                     0.0            1.0
```

Market Segmentation based on Online Vs Mobile Booking

```
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

# Load the dataset
file_path = 'YourCabs_cleaned.csv'
data = pd.read_csv(file_path)

# Step 1: Preprocessing
# Selecting online and mobile booking related features for segmentation
cluster_data_booking = data[['online_booking', 'mobile_site_booking', 'Car_Cancellation', 'Cost_of_error']].dropna()

# Step 2: Normalizing the data
scaler = StandardScaler()
cluster_data_booking_scaled = scaler.fit_transform(cluster_data_booking)

# Step 3: K-Means Clustering
kmeans_booking = KMeans(n_clusters=3, random_state=42)  # Assuming 3 clusters for segmentation
clusters_booking = kmeans_booking.fit_predict(cluster_data_booking_scaled)

# Adding the cluster labels to the dataset
cluster_data_booking['cluster'] = clusters_booking

# Step 4: Visualization
plt.figure(figsize=(10, 6))

# Scatter plot based on online booking and mobile site booking
plt.scatter(cluster_data_booking['online_booking'], cluster_data_booking['mobile_site_booking'],
            c=cluster_data_booking['cluster'], cmap='viridis', s=10)
plt.colorbar(label='Cluster')
plt.title('Market Segmentation Based on Online vs. Mobile Booking')
plt.xlabel('Online Booking (0: No, 1: Yes)')
```

```
plt.ylabel('Mobile Site Booking (0: No, 1: Yes)')
plt.show()

# Optional: View cluster statistics
print(cluster_data_booking.groupby('cluster').mean())
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:1473: ConvergenceWarning: Number of distinct clusters (2) found smaller than n_c
  return fit_method(estimator, *args, **kwargs)
```

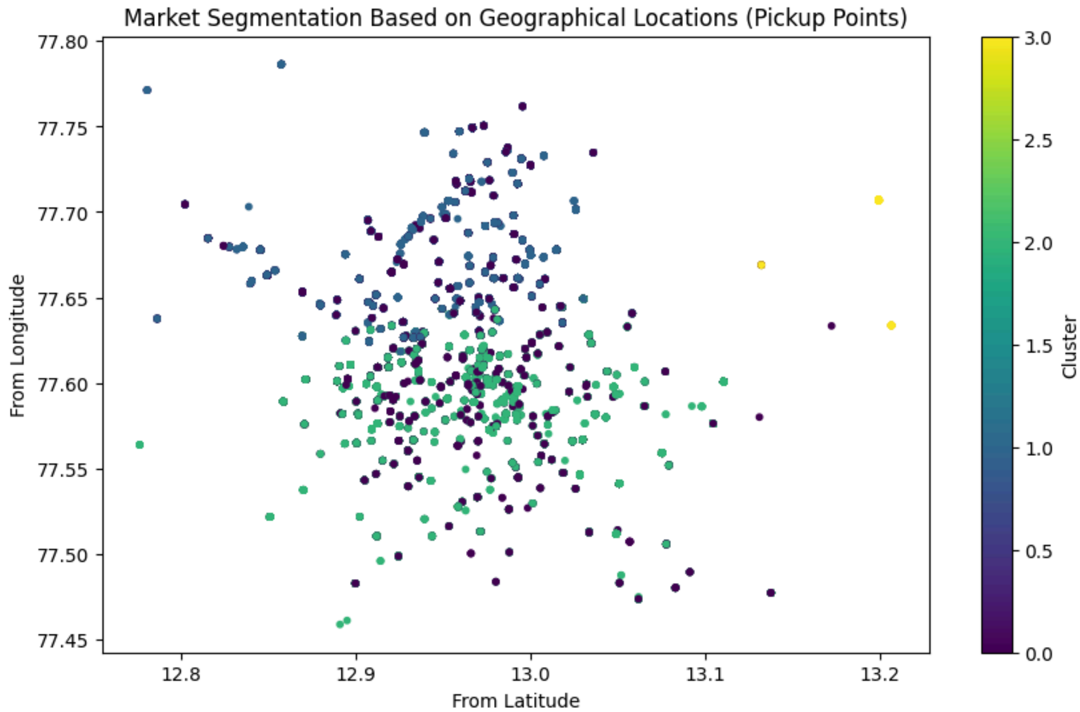


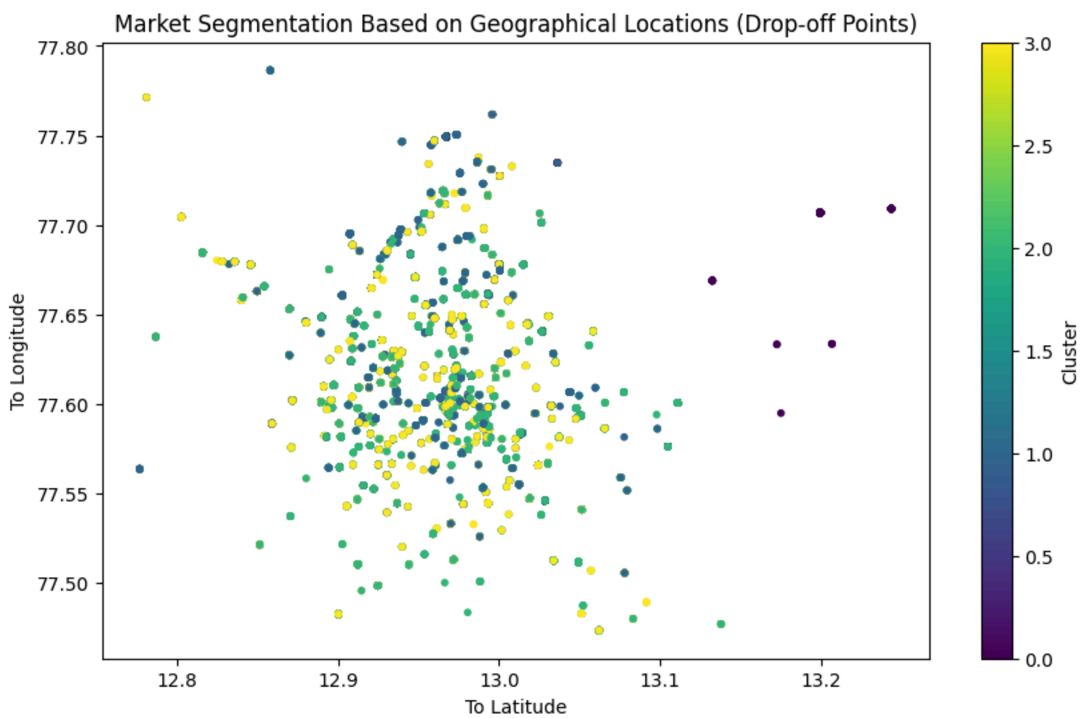

```
         online_booking  mobile_site_booking  Car_Cancellation  Cost_of_error
cluster
0                   0.0                  0.0               0.0            1.0
1                   1.0                  0.0               0.0            1.0
```

Market Segmentation Based on Geographical location

```
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

# Load the dataset
file_path = 'YourCabs_cleaned.csv'
data = pd.read_csv(file_path)

# Step 1: Preprocessing
# Selecting geographical features (latitude and longitude) for segmentation
cluster_data_geo = data[['from_lat', 'from_long', 'to_lat', 'to_long']].dropna()

# Step 2: Normalizing the data
scaler = StandardScaler()
cluster_data_geo_scaled = scaler.fit_transform(cluster_data_geo)

# Step 3: K-Means Clustering
kmeans_geo = KMeans(n_clusters=4, random_state=42)  # Assuming 4 clusters for geographical segmentation
clusters_geo = kmeans_geo.fit_predict(cluster_data_geo_scaled)

# Adding the cluster labels to the dataset
cluster_data_geo['cluster'] = clusters_geo

# Step 4: Visualization
plt.figure(figsize=(10, 6))

# Scatter plot based on 'from_lat' and 'from_long' to visualize geographical clusters
plt.scatter(cluster_data_geo['from_lat'], cluster_data_geo['from_long'],
            c=cluster_data_geo['cluster'], cmap='viridis', s=10)
```

```
plt.colorbar(label='Cluster')
plt.title('Market Segmentation Based on Geographical Locations (Pickup Points)')
plt.xlabel('From Latitude')
plt.ylabel('From Longitude')
plt.show()

# Visualization for drop-off locations
plt.figure(figsize=(10, 6))

# Scatter plot based on 'to_lat' and 'to_long' to visualize geographical clusters for drop-off points
plt.scatter(cluster_data_geo['to_lat'], cluster_data_geo['to_long'],
            c=cluster_data_geo['cluster'], cmap='viridis', s=10)
plt.colorbar(label='Cluster')
plt.title('Market Segmentation Based on Geographical Locations (Drop-off Points)')
plt.xlabel('To Latitude')
plt.ylabel('To Longitude')
plt.show()

# Optional: View cluster statistics
print(cluster_data_geo.groupby('cluster').mean())
```



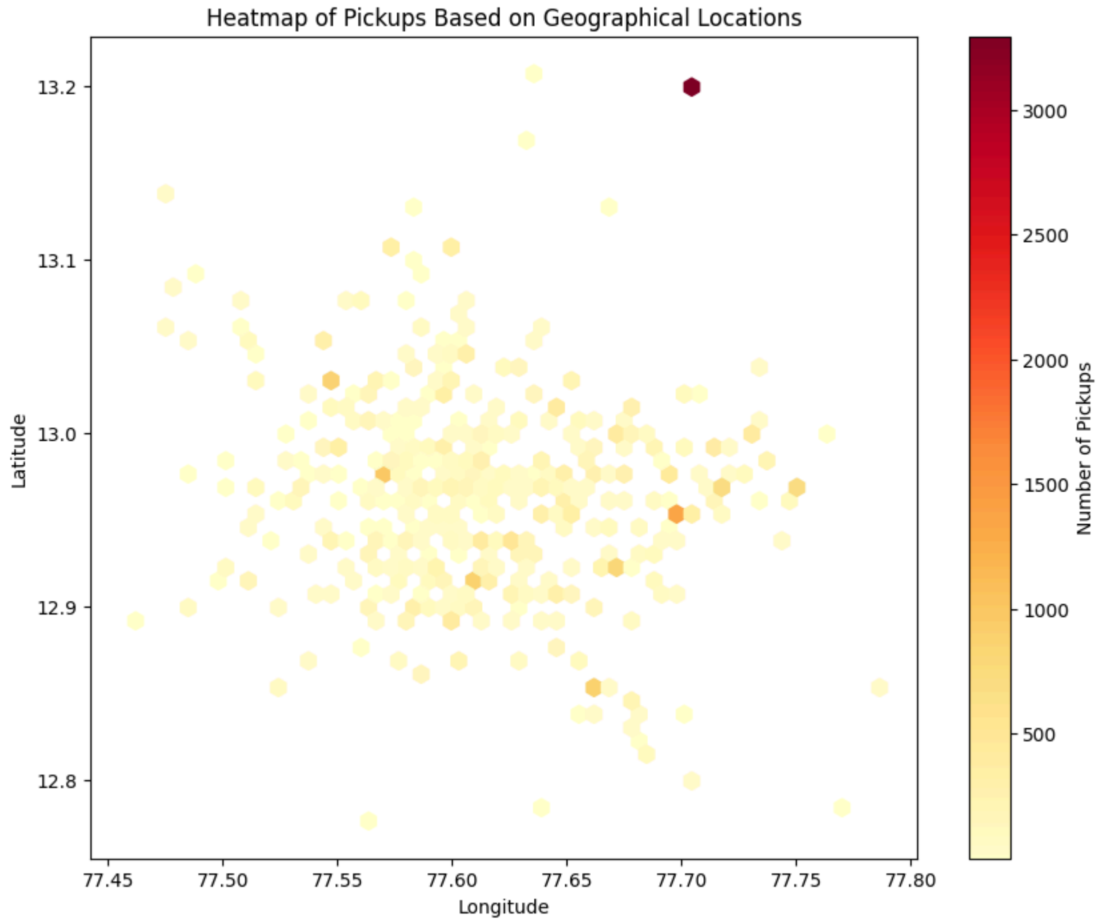



```
          from_lat   from_long     to_lat    to_long
cluster
0        12.957321  77.629688  13.195075  77.707520
1        12.950112  77.679668  12.983521  77.630422
2        12.975618  77.583259  12.981742  77.613523
```

HeatMap

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Load the dataset
file_path = 'YourCabs_cleaned.csv'
data = pd.read_csv(file_path)
```

```
# Step 1: Preprocessing
# Select the 'from_lat' and 'from_long' for pickups and drop NaN values
geo_data = data[['from_lat', 'from_long']].dropna()

# Step 2: Create a 2D histogram for density estimation (heatmap)
plt.figure(figsize=(10, 8))

# Using hexbin to plot density of pickups based on latitude and longitude
plt.hexbin(geo_data['from_long'], geo_data['from_lat'], gridsize=50, cmap='YlOrRd', mincnt=1)

# Add colorbar to show the intensity
plt.colorbar(label='Number of Pickups')

# Add labels and title
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.title('Heatmap of Pickups Based on Geographical Locations')

# Show plot
plt.show()

# Optional: Heatmap for drop-off locations
geo_data_dropoff = data[['to_lat', 'to_long']].dropna()

plt.figure(figsize=(10, 8))

# Using hexbin to plot density of drop-offs based on latitude and longitude
plt.hexbin(geo_data_dropoff['to_long'], geo_data_dropoff['to_lat'], gridsize=50, cmap='YlGnBu', mincnt=1)

# Add colorbar to show the intensity
plt.colorbar(label='Number of Drop-offs')

# Add labels and title
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.title('Heatmap of Drop-offs Based on Geographical Locations')

# Show plot
plt.show()
```




```
# Load the dataset
file_path = 'YourCabs_cleaned.csv'
data = pd.read_csv(file_path)

# Step 1: Check the column names
print(data.columns)  # Print the column names to identify the correct one for 'booking_timestamp'
```

```
Index(['id', 'user_id', 'vehicle_model_id', 'package_id', 'travel_type_id',
       'from_area_id', 'to_area_id', 'from_city_id', 'to_city_id', 'from_date',
       'to_date', 'online_booking', 'mobile_site_booking', 'booking_created',
       'from_lat', 'from_long', 'to_lat', 'to_long', 'Car_Cancellation',
       'Cost_of_error'],
      dtype='object')
```

```
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import seaborn as sns

# Load the dataset
file_path = 'YourCabs_cleaned.csv'
data = pd.read_csv(file_path)

# Step 1: Preprocessing
# Use 'booking_created' column instead of 'booking_timestamp'
data['booking_created'] = pd.to_datetime(data['booking_created'], errors='coerce')
```