Ride Booking Company- Exploratory Data Analysis (EDA)

Objective:

Perform exploratory data analysis (EDA) on the given dataset from a ride-booking company operating in multiple Indian cities. The aim is to gain insights into customer behavior, ride trends, vehicle preferences, and fare distributions.

Dataset Description:

The dataset contains 10,000 ride bookings with the following columns: -

1)**Date:** The date of the ride.

2)**Time:** The time of the ride.

3)**Booking ID:** Unique identifier for each booking.

4)**Booking Status:** Whether the ride was Completed, Cancelled, or Ongoing.

5) **Customer ID:** Unique identifier for each customer.

6)**Vehicle Type:** Type of vehicle chosen for the ride.

7)**City:** The city where the ride was booked.

8)**Pickup Location:** Starting point of the ride.

9)**Drop Location:** Ending point of the ride.

10) **Fare (INR):** Total fare charged for the ride.

Tasks to Perform:

1. Load and clean the dataset (check for missing values, duplicates, etc.).

2. Analyze booking trends over time (daily/weekly/monthly).

3. Identify the most popular vehicle types and cities.

4. Examine fare distributions across different vehicle types and cities.

5. Visualize booking status frequencies.

6. Segment customers based on booking patterns.

7. Identify any anomalies or interesting patterns in the data.

Bonus: Try clustering, feature engineering, or predictive modeling (e.g., fare prediction or cancellation prediction) based on EDA results.

1. **Load and clean the dataset**

```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
df = pd.read_csv("EDA_project_dataset.csv")
print(df.info())
print("Missing values:", df.isnull().sum())
print("Duplicate rows:", df.duplicated().sum())
```

output:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 10 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Date             10000 non-null  object
 1   Time             10000 non-null  object
 2   Booking ID       10000 non-null  object
 3   Booking Status   10000 non-null  object
 4   Customer ID      10000 non-null  object
 5   Vehicle Type     10000 non-null  object
 6   City             10000 non-null  object
 7   Pickup Location  10000 non-null  object
 8   Drop Location    10000 non-null  object
 9   Fare (INR)       10000 non-null  float64
dtypes: float64(1), object(9)
memory usage: 781.4+ KB
None
Missing values: Date               0
Time               0
Booking ID         0
Booking Status     0
Customer ID        0
Vehicle Type       0
City               0
Pickup Location    0
Drop Location      0
Fare (INR)         0
dtype: int64
Duplicate rows: 0
```

Drop duplicates if any

df.drop_duplicates(inplace=True)

df.head(3)

output:

Date	Time	Booking ID	Booking Status	Customer ID	Vehicle Type	City	Pickup Location	Drop Location	Fare (INR)	
0	6/25/2025	12:00:51	be09ad20-1048-4d52-b2b3-2cb3aec12bd9	Ongoing	1887efac-cbe3-422b-b154-97bbf86a1eba	Auto	Ahmedabad	Viswanathan Marg	Iyengar Ganj	675.56
1	6/20/2025	1:09:13	5076e372-2770-4f3e-9eb8-65eb83dafccc	Completed	ac2f1ddd-fb1f-4e6f-864d-413d639926b8	Prime Sedan	Lucknow	Dhingra Street	Kohli Road	969.37
2	7/4/2025	13:45:18	bc126a53-9ff2-493b-8878-dece53ce4b7e	Completed	78ab7ccc-88a9-4dbd-b35e-27003b9294c8	Auto	Lucknow	Korpal Circle	Tata Ganj	1252.80

Convert date columns if needed (adjust column name)

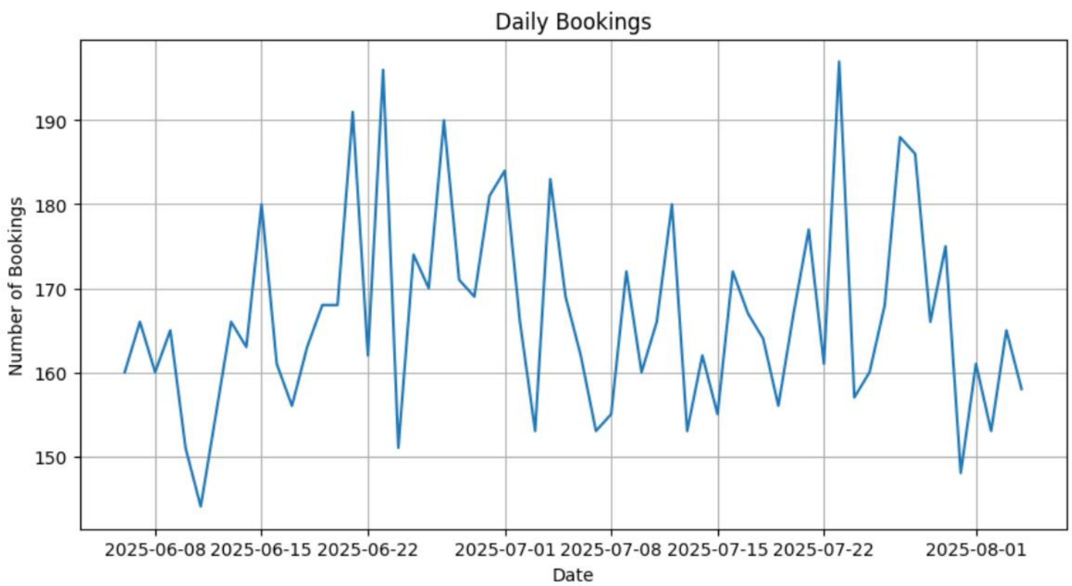
df['Date'] = pd.to_datetime(df['Date'])

2. **Analyze booking trends over time**

```
df['Month'] = df['Date'].dt.to_period('M')
df['Week'] = df['Date'].dt.to_period('W')
df['Day'] = df['Date'].dt.date

daily_trend = df.groupby('Day').size()
monthly_trend = df.groupby('Month').size()
```

```python
weekly_trend = df.groupby('Week').size()

plt.figure(figsize=(10, 5))
daily_trend.plot(title="Daily Bookings")
plt.xlabel("Date")
plt.ylabel("Number of Bookings")
plt.grid()
plt.show()
```

output:



3. **Most popular vehicle types and cities**

```python
print("\nTop Vehicle Types:\n", df['Vehicle Type'].value_counts())
print("\nTop Cities:\n", df['City'].value_counts())

output:
```

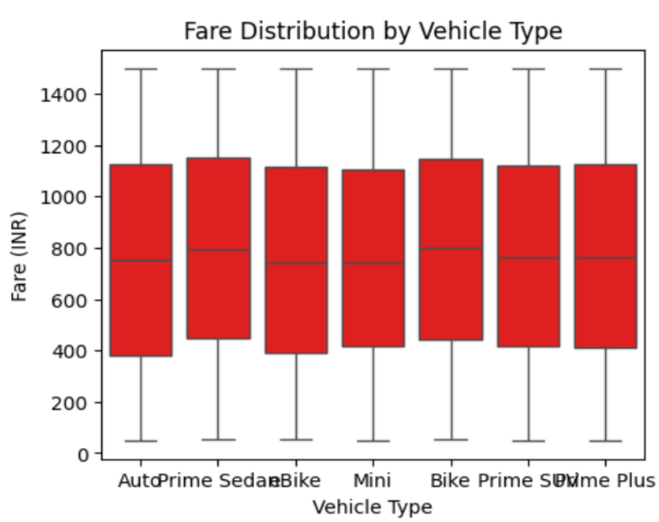
Top Vehicle Types:
 Vehicle Type
eBike 1483
Mini 1472
Auto 1431
Prime Plus 1428
Prime Sedan 1418
Prime SUV 1401
Bike 1367
Name: count, dtype: int64

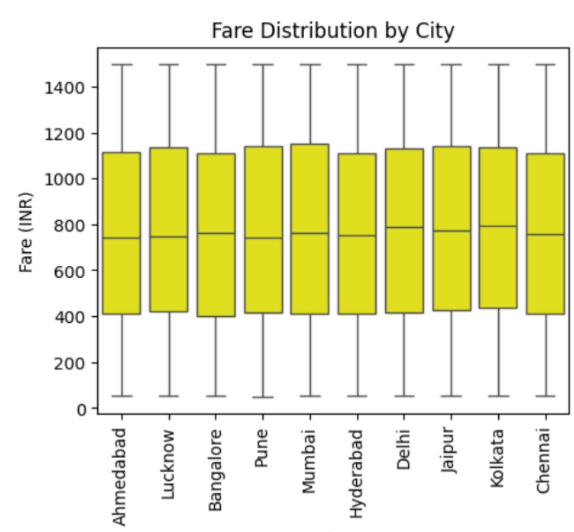
Top Cities:
 City
Bangalore   1092
Mumbai   1044
Delhi   1017
Kolkata   1016
Ahmedabad   1015
Lucknow   984
Hyderabad   984
Jaipur   950
Pune   949
Chennai   949
Name: count, dtype: int64

4. Fare distributions

```
plt.figure(figsize=(5,4))
sns.boxplot(x='Vehicle Type', y='Fare (INR)', data=df,color='red')
plt.xlabel("Vehicle Type")
plt.ylabel("Fare (INR)")
plt.title("Fare Distribution by Vehicle Type")
plt.show()

plt.figure(figsize=(5,4))
sns.boxplot(x='City', y='Fare (INR)', data=df,color='yellow')
plt.xlabel("City")
plt.ylabel("Fare (INR)")
plt.title("Fare Distribution by City")
plt.xticks(rotation=90)
plt.show()
```

output:

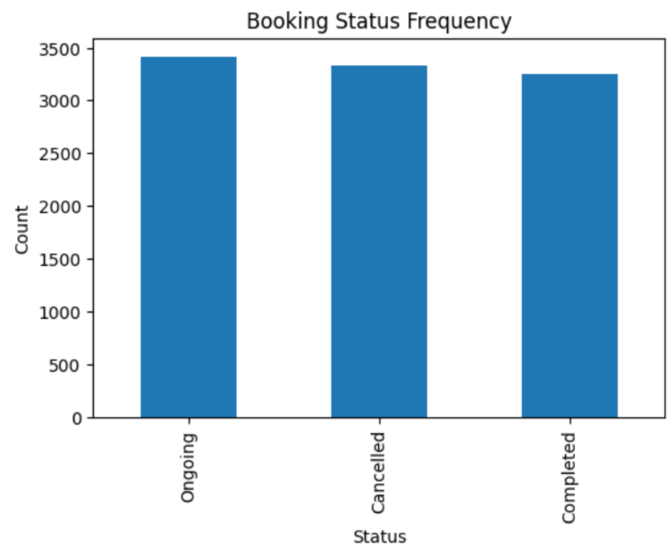




5. **Booking status frequencies**

```
plt.figure(figsize=(6, 4))
df['Booking Status'].value_counts().plot(kind='bar', title="Booking Status
Frequency")
plt.xlabel("Status")
plt.ylabel("Count")
plt.show()
```

output:



6. **Segment customers by booking patterns**

```
customer_seg = df.groupby('Customer ID').agg({
    'Booking ID': 'count',
    'Fare (INR)': 'mean',
    'Date': ['min', 'max']
}).reset_index()
customer_seg.columns = ['Customer ID', 'Total Bookings', 'Avg Fare', 'First
Booking', 'Last Booking']
print(customer_seg.head())
```

output:

	Customer ID	Total Bookings	Avg Fare \
0	00072147-69b1-49ac-8bcc-33c2234600a3	1	1046.91
1	000b2bac-f35e-4f30-bbee-690dfb5ec22d	1	152.30
2	000e67f4-2708-4b69-aa0b-a3ae31db5387	1	1216.03
3	001c2193-f920-4948-8c71-bd697cc80f8b	1	465.20
4	00242946-fb3c-4d37-948f-37d097acdb4c	1	1285.65

	First Booking	Last Booking
0	2025-06-27	2025-06-27
1	2025-06-21	2025-06-21
2	2025-06-23	2025-06-23
3	2025-07-11	2025-07-11
4	2025-07-11	2025-07-11

7.Anomalies or patterns

```
high_fare = df[df['Fare (INR)'] > df['Fare (INR)'].quantile(0.99)]
print("\nTop 1% High Fare Bookings:\n", high_fare)
```

output:

Top 1% High Fare Bookings:

	Date	Time	Booking ID \
172	2025-06-09	16:47:29	a795053e-25b2-4236-8c7a-634dff193396
194	2025-06-07	3:45:11	458c20a2-ed55-4a49-921c-1c59b0f312cf
327	2025-07-31	12:58:47	5e059511-ccd5-4128-9d66-52c1c1b849e4
406	2025-07-26	5:14:18	7b57ec3e-5814-440c-835a-1634392aa50c
499	2025-07-09	20:34:50	b194ead5-f7cd-41b8-b408-8e03c924581a
...	...	...	...
9604	2025-08-02	2:48:01	3f7c6c6a-25c7-4d13-811d-78bcffc83127
9837	2025-07-02	22:02:18	b5e17b62-119d-4d89-899b-a72b5c80a5c2
9942	2025-06-12	1:59:22	adaee2d6-d5db-4341-8b95-0d1a68e7510f
9982	2025-07-12	16:24:34	7a552a16-bf91-4035-990a-7dc3144a57c7
9990	2025-06-11	3:16:23	2db478fd-2989-4209-a7ff-35c519638727

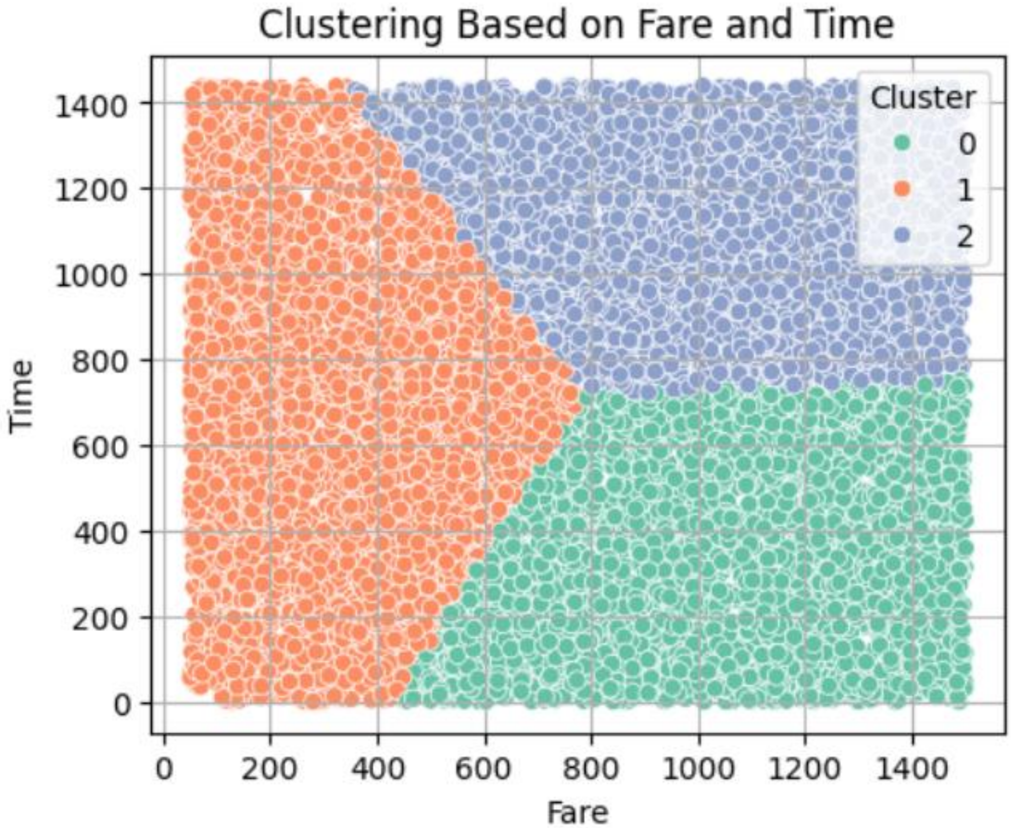
	Booking Status	Customer ID	Vehicle Type \
172	Completed	7235dbf6-83a2-47e7-aa25-d173c83680d3	Prime Plus
194	Cancelled	77101bdf-5ffa-4c1b-a40b-44a83f02dbce	Prime Plus
327	Ongoing	1fac66fd-2c41-4fda-afef-360c94425212	Mini
406	Ongoing	4102a7a5-ba74-47a5-9181-e44198e5ed00	Auto
499	Ongoing	810d7cdd-6756-41eb-b043-4944f795f5e0	Mini

```
...         ...                                   ...       ...
9604    Cancelled  34ea3322-f9ab-43d7-9a79-acdf95fa1df7        Mini
9837    Cancelled  252c998c-f29a-4efe-b31c-0d557f75d3b0   Prime SUV
9942    Cancelled  dc579349-12b4-4443-839e-f426abd27c38  Prime Plus
9982    Completed  db44da5e-8a20-4f11-a5e8-2ebd82adeeae        Bike
9990      Ongoing  66582f2d-7d9f-4b94-8b7e-7086d2d1e7ff        Auto

           City      Pickup Location   Drop Location  Fare (INR)    Month  \
172     Kolkata        Grewal Street     Kannan Zila     1497.11  2025-06
194   Hyderabad          Rama Nagar     Karpe Nagar     1496.28  2025-06
327       Delhi            Dey Road    Wagle Street     1491.67  2025-07
406   Ahmedabad       Mander Circle      Doshi Zila     1499.04  2025-07
499   Hyderabad         Sharaf Road      Setty Ganj     1491.68  2025-07
...         ...                 ...             ...         ...      ...
9604       Pune     Srivastava Path         De Road     1494.84  2025-08
9837  Hyderabad         Sangha Ganj      Andra Path     1488.60  2025-07
9942    Kolkata         Rege Street     Magar Chowk     1494.16  2025-06
9982  Bangalore         Garg Circle  Mallick Street     1497.12  2025-07
9990    Lucknow  Krishnamurthy Street      Deshmukh     1489.08  2025-06

                        Week         Day
172   2025-06-09/2025-06-15  2025-06-09
194   2025-06-02/2025-06-08  2025-06-07
327   2025-07-28/2025-08-03  2025-07-31
406   2025-07-21/2025-07-27  2025-07-26
499   2025-07-07/2025-07-13  2025-07-09
...                     ...         ...
9604  2025-07-28/2025-08-03  2025-08-02
9837  2025-06-30/2025-07-06  2025-07-02
9942  2025-06-09/2025-06-15  2025-06-12
9982  2025-07-07/2025-07-13  2025-07-12
9990  2025-06-09/2025-06-15  2025-06-11  [100 rows x 13 columns]
```

Bonus: Basic clustering

```
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans

df['Time'] = pd.to_timedelta(df['Time'])

# Extract total wait time in minutes
df['Time (min)'] = df['Time'].dt.total_seconds() / 60

features = df[['Fare (INR)', 'Time (min)']].dropna()

# Scale features
scaler = StandardScaler()
scaled = scaler.fit_transform(features)

# Clustering
kmeans = KMeans(n_clusters=3, random_state=42)
df['Cluster'] = kmeans.fit_predict(scaled)

# Visualize
plt.figure(figsize=(8, 6))
sns.scatterplot(x=features['Fare (INR)'], y=features['Time (min)'], hue=df['Cluster'], palette='Set2')
plt.title("Clustering Based on Fare and Time")
plt.xlabel("Fare")
plt.ylabel("Time")
plt.grid(True)
plt.show()
```

output:



Clustering Based on Fare and Time
Cluster
0
1
2
1400
1200
1000
800
600
400
200
0
Time
0
200
400
600
800
1000
1200
1400
Fare