Title:-Exploratory-Data-Analysis-on-Indian-Flight-Prices.

Extraction of Zip file.

☑ ZIP Extraction Completed!

Data Loading.

```
import pandas as pd
import glob

# Find all CSV files in extracted folder
csv_files = glob.glob(extract_folder + "/*.csv")

# Read and combine into single DataFrame
df_list = [pd.read_csv(file) for file in csv_files]
df = pd.concat(df_list, ignore_index=True)

print(f" Data Loaded! Combined shape: {df.shape}")
df.head()
```

Data Loaded! Combined shape: (404, 8)

Out[9]:		FlightName	FlightCode	DepartingCity	DepartingTime	ArrivingCity	ArrivingTime	1
	0	Air India	AI 621	Mumbai	03:55	Bengaluru	05:50	
	1	AirAsia	15 670	Mumbai	19:55	Bengaluru	21:45	
	2	AirAsia	15 2992	Mumbai	23:55	Bengaluru	01:45\r\n+ 1 DAY	
	3	IndiGo	6E 5388	Mumbai	21:30	Bengaluru	23:15	
	4	Akasa Air	QP 1103	Mumbai	00:45	Bengaluru	02:20	
	4						•	•

Data Preprocessing.

```
In [14]: # Check for null values
    print("\nNull values per column:")
    print(df.isnull().sum())

# Remove commas from Price column safely (if any)
    df['Price'] = df['Price'].apply(lambda x: int(str(x).replace(',', '')))

# Strip whitespace from text fields
    df['FlightName'] = df['FlightName'].astype(str).str.strip()
    df['DepartingCity'] = df['DepartingCity'].astype(str).str.strip()
    df['ArrivingCity'] = df['ArrivingCity'].astype(str).str.strip()

    print(" Data Preprocessing Done")
    df.head()

Null values per column:
```

FlightName 0
FlightCode 0
DepartingCity 0
DepartingTime 0
ArrivingCity 0
ArrivingTime 0
Duration 0
Price 0
dtype: int64

☑ Data Preprocessing Done

Out[14]:		FlightName	FlightCode	DepartingCity	DepartingTime	ArrivingCity	ArrivingTime	I
	0	Air India	AI 621	Mumbai	03:55	Bengaluru	05:50	
	1	AirAsia	15 670	Mumbai	19:55	Bengaluru	21:45	
	2	AirAsia	15 2992	Mumbai	23:55	Bengaluru	01:45\r\n+ 1 DAY	
	3	IndiGo	6E 5388	Mumbai	21:30	Bengaluru	23:15	
	4	Akasa Air	QP 1103	Mumbai	00:45	Bengaluru	02:20	
	4						•	

Feature Engineering.

```
In [18]: # Create 'Route' column
    df['Route'] = df['DepartingCity'] + " → " + df['ArrivingCity']

# Convert 'DepartingTime' to datetime to extract hour
    df['DepartureHour'] = pd.to_datetime(df['DepartingTime']).dt.hour

print(" ▼ Feature Engineering Done")
    df.head()
```

☑ Feature Engineering Done

C:\Users\SHREYA DAS\AppData\Local\Temp\ipykernel_15488\349626817.py:5: UserWarnin g: Could not infer format, so each element will be parsed individually, falling b ack to `dateutil`. To ensure parsing is consistent and as-expected, please specify a format.

df['DepartureHour'] = pd.to datetime(df['DepartingTime']).dt.hour

Out[18]:		FlightName	FlightCode	DepartingCity	DepartingTime	ArrivingCity	ArrivingTime
	0	Air India	AI 621	Mumbai	03:55	Bengaluru	05:50
	1	AirAsia	15 670	Mumbai	19:55	Bengaluru	21:45
	2	AirAsia	I5 2992	Mumbai	23:55	Bengaluru	01:45\r\n+ 1 DAY
	3	IndiGo	6E 5388	Mumbai	21:30	Bengaluru	23:15
	4	Akasa Air	QP 1103	Mumbai	00:45	Bengaluru	02:20
	4						•

Data Summary.

```
In [19]: # Get unique airlines
         print("\nUnique Flight Names:", df['FlightName'].nunique())
         # Top airlines by frequency
         print("\nTop Airlines:\n", df['FlightName'].value_counts())
         # Price range
         print(f"\nPrice Range: ₹{df['Price'].min()} to ₹{df['Price'].max()}")
        Unique Flight Names: 6
        Top Airlines:
        FlightName
        IndiGo
               188
       Vistara
                    80
       Air India 77
Akasa Air 30
                    19
        SpiceJet
       AirAsia
                     10
        Name: count, dtype: int64
        Price Range: ₹2307 to ₹20581
```

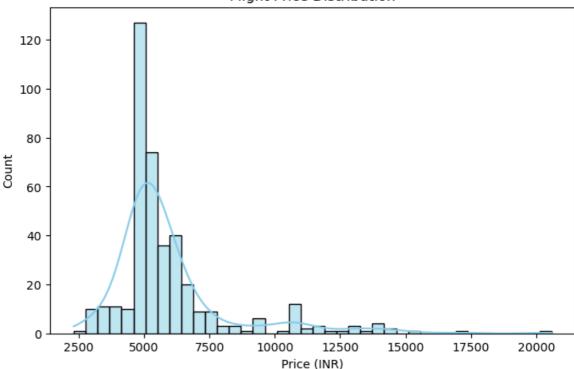
Data Visualization

Price Distribution

```
In [20]: import seaborn as sns
import matplotlib.pyplot as plt
```

```
plt.figure(figsize=(8,5))
sns.histplot(df['Price'], bins=40, kde=True, color='skyblue')
plt.title("Flight Price Distribution")
plt.xlabel("Price (INR)")
plt.ylabel("Count")
plt.show()
```





Average Price by Departing City

```
In [21]: plt.figure(figsize=(10,5))
    avg_depart_city = df.groupby('DepartingCity')['Price'].mean().sort_values()
    sns.barplot(x=avg_depart_city.values, y=avg_depart_city.index, palette='viridis'
    plt.title("Average Price by Departing City")
    plt.xlabel("Average Price (INR)")
    plt.ylabel("Departing City")
    plt.show()

C:\Users\SHREYA DAS\AppData\Local\Temp\ipykernel_15488\2703012239.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v
    0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.
```

sns.barplot(x=avg_depart_city.values, y=avg_depart_city.index, palette='viridi

s')



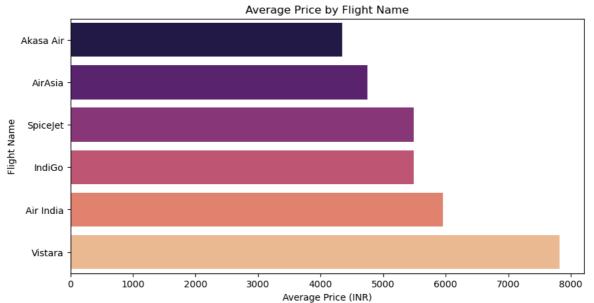
Average Price by Flight Name (Airline)

```
In [22]: plt.figure(figsize=(10,5))
    avg_airline = df.groupby('FlightName')['Price'].mean().sort_values()
    sns.barplot(x=avg_airline.values, y=avg_airline.index, palette='magma')
    plt.title("Average Price by Flight Name")
    plt.xlabel("Average Price (INR)")
    plt.ylabel("Flight Name")
    plt.show()
```

C:\Users\SHREYA DAS\AppData\Local\Temp\ipykernel_15488\2681216239.py:3: FutureWar
ning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v 0.14.0. Assign the \dot{y} variable to `hue` and set `legend=False` for the same effect.

sns.barplot(x=avg_airline.values, y=avg_airline.index, palette='magma')



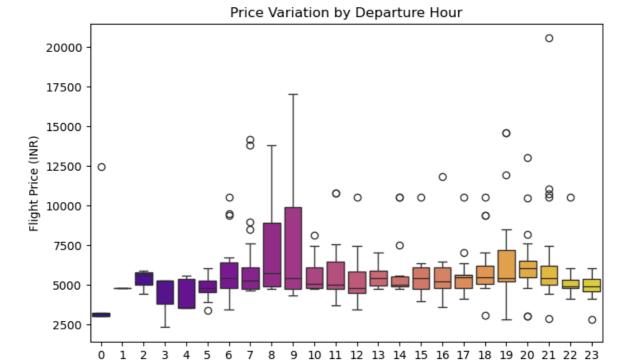
Departure Hour vs Price

```
In [24]: plt.figure(figsize=(8,5))
    sns.boxplot(x='DepartureHour', y='Price', data=df, palette='plasma')
    plt.title("Price Variation by Departure Hour")
    plt.xlabel("Hour of Departure")
    plt.ylabel("Flight Price (INR)")
    plt.show()

C:\Users\SHREYA DAS\AppData\Local\Temp\ipykernel_15488\69485880.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v
    0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

sns.boxplot(x='DepartureHour', y='Price', data=df, palette='plasma')
```



Hour of Departure

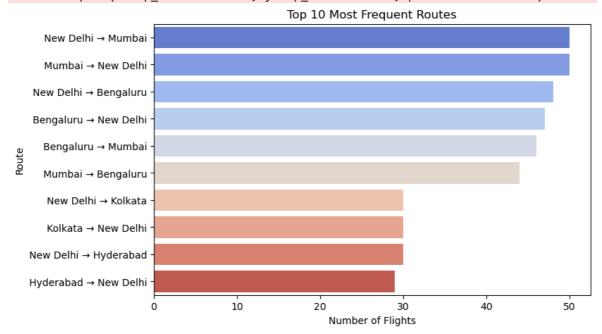
Top 10 Routes

```
In [25]: plt.figure(figsize=(8,5))
    top_routes = df['Route'].value_counts().head(10)
    sns.barplot(x=top_routes.values, y=top_routes.index, palette='coolwarm')
    plt.title("Top 10 Most Frequent Routes")
    plt.xlabel("Number of Flights")
    plt.ylabel("Route")
    plt.show()
```

C:\Users\SHREYA DAS\AppData\Local\Temp\ipykernel_15488\2883137815.py:3: FutureWar
ning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v 0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

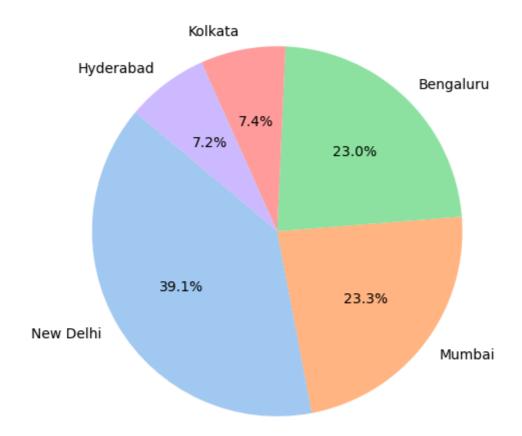
sns.barplot(x=top_routes.values, y=top_routes.index, palette='coolwarm')



Proportion of Flights by Departing City

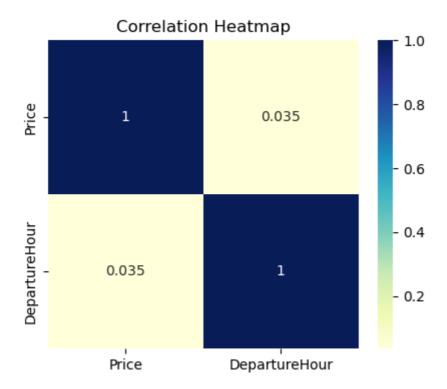
```
In [27]: plt.figure(figsize=(6,6))
    depart_counts = df['DepartingCity'].value_counts()
    plt.pie(depart_counts.values, labels=depart_counts.index, autopct='%1.1f%%', sta
    plt.title("Proportion of Flights by Departing City")
    plt.show()
```

Proportion of Flights by Departing City



Exploring Correlation Between Price & Schedule Attribute

```
In [28]: plt.figure(figsize=(5,4))
    corr = df[['Price', 'DepartureHour']].corr()
    sns.heatmap(corr, annot=True, cmap='YlGnBu')
    plt.title("Correlation Heatmap")
    plt.show()
```



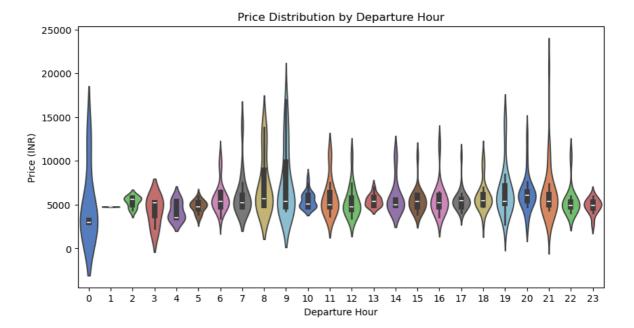
Distribution of Prices by Departure Hour

```
In [29]: plt.figure(figsize=(10,5))
    sns.violinplot(x='DepartureHour', y='Price', data=df, palette='muted')
    plt.title("Price Distribution by Departure Hour")
    plt.xlabel("Departure Hour")
    plt.ylabel("Price (INR)")
    plt.show()

C:\Users\SHREYA DAS\AppData\Local\Temp\ipykernel_15488\3170378440.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v 0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

sns.violinplot(x='DepartureHour', y='Price', data=df, palette='muted')
```



Flight Prices per Departing City

C:\Users\SHREYA DAS\AppData\Local\Temp\ipykernel_15488\1861346161.py:2: FutureWar
ning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v 0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

sns.swarmplot(x='DepartingCity', y='Price', data=df, palette='Set2')

C:\ProgramData\anaconda3\Lib\site-packages\seaborn\categorical.py:3399: UserWarning: 17.0% of the points cannot be placed; you may want to decrease the size of the markers or use stripplot.

warnings.warn(msg, UserWarning)

C:\ProgramData\anaconda3\Lib\site-packages\seaborn\categorical.py:3399: UserWarning: 45.6% of the points cannot be placed; you may want to decrease the size of the markers or use stripplot.

warnings.warn(msg, UserWarning)

C:\ProgramData\anaconda3\Lib\site-packages\seaborn\categorical.py:3399: UserWarning: 20.0% of the points cannot be placed; you may want to decrease the size of the markers or use stripplot.

warnings.warn(msg, UserWarning)

C:\ProgramData\anaconda3\Lib\site-packages\seaborn\categorical.py:3399: UserWarni ng: 19.1% of the points cannot be placed; you may want to decrease the size of the markers or use stripplot.

warnings.warn(msg, UserWarning)

C:\ProgramData\anaconda3\Lib\site-packages\seaborn\categorical.py:3399: UserWarni ng: 7.5% of the points cannot be placed; you may want to decrease the size of the markers or use stripplot.

warnings.warn(msg, UserWarning)

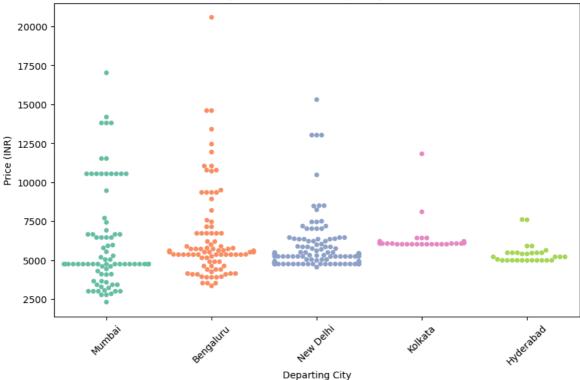
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\categorical.py:3399: UserWarning: 48.1% of the points cannot be placed; you may want to decrease the size of the markers or use stripplot.

warnings.warn(msg, UserWarning)

C:\ProgramData\anaconda3\Lib\site-packages\seaborn\categorical.py:3399: UserWarning: 26.7% of the points cannot be placed; you may want to decrease the size of the markers or use stripplot.

warnings.warn(msg, UserWarning)





Insights Summary

```
In [31]: print("Key Insights:")
    print("1 Majority of flights are concentrated in key cities like Delhi, Mumbai,
    print("2 Prices are generally higher during certain hours of the day.")
    print("3 Some airlines consistently show higher average prices.")
    print("4 Most frequent routes involve major metro cities.")
```

Key Insights:

- 1 Majority of flights are concentrated in key cities like Delhi, Mumbai, and Bangalore.
- 2 Prices are generally higher during certain hours of the day.
- Some airlines consistently show higher average prices.
- Most frequent routes involve major metro cities.

Save Cleaned Dataset

Cleaned dataset saved successfully.

Conclusion

This project successfully performed Exploratory Data Analysis on Indian flight ticket prices. Various visualizations helped analyze price distribution, airline pricing patterns, departure city trends, and time-based price fluctuations. The analysis identified key routes, peak hours for pricing, and differences across airlines. This project can be

extended further by applying machine learning models to predict flight prices based on historical data and additional features like holidays, seasons, and promotions.

In []: