Assignment

September 30, 2024

1 Interview Task – Data Engineering & Analytics

[1]:
```
# imports
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
import scipy.stats as stats
import warnings

warnings.filterwarnings("ignore")
```

1.0.1 Import the datasets

[2]:
```
df = pd.read_csv("aviation_data.csv")
print(df.head())
```

```
  FlightNumber DepartureDate DepartureTime ArrivalDate ArrivalTime  \
0       AA1234    09/01/2023      08:30 AM  09/01/2023    10:45 AM
1       DL5678    09/01/2023      01:15 PM  09/01/2023    03:30 PM
2       UA9101    09/01/2023      05:00 PM  09/01/2023    07:15 PM
3       AA1234    09/01/2023      08:30 AM  09/01/2023    10:45 PM
4       DL5678    09/02/2023      02:00 PM  09/02/2023    04:10 PM

             Airline  DelayMinutes
0  American Airlines          15.0
1              Delta           5.0
2    United Airlines          25.0
3  American Airlines          30.0
4              Delta           NaN
```

1.0.2 Insert the datasets and fetch values from MySQL database

[3]:
```
from sqlalchemy import create_engine, text
import os
from dotenv import load_dotenv

# Load environment variables from the .env file
```

```python
load_dotenv()

# Retrieve database credentials from environment variables
DB_USERNAME = os.getenv("DB_USERNAME")
DB_PASSWORD = os.getenv("DB_PASSWORD")
DB_HOST = os.getenv("DB_HOST")
DB_NAME = os.getenv("DB_NAME")
DB_PORT = os.getenv("DB_PORT")


connection_string = (
    f"mysql+pymysql://{DB_USERNAME}:{DB_PASSWORD}@{DB_HOST}:{DB_PORT}/{DB_NAME}"
)

try:
    engine = create_engine(connection_string)
    # create table
    create_table_query = text(
        """
    CREATE TABLE IF NOT EXISTS aviation_data (
        id INT AUTO_INCREMENT PRIMARY KEY,
        FlightNumber TEXT,
        DepartureDate TEXT,
        DepartureTime TEXT,
        ArrivalDate TEXT,
        ArrivalTime TEXT,
        Airline TEXT,
        DelayMinutes FLOAT
    )"""
    )

    with engine.connect() as connection:
        connection.execute(create_table_query)

    # insert data
    df.to_sql("aviation_data", engine, if_exists="append", index=False)

    # fetch data
    df_fetched = pd.read_sql("SELECT * FROM aviation_data", engine)

    print(df_fetched.head())

except Exception as e:
    print(f"Error: {e}")

finally:
    engine.dispose()
```

```
   id FlightNumber DepartureDate DepartureTime ArrivalDate ArrivalTime  \
0   1       AA1234    09/01/2023      08:30 AM  09/01/2023    10:45 AM
1   2       DL5678    09/01/2023      01:15 PM  09/01/2023    03:30 PM
2   3       UA9101    09/01/2023      05:00 PM  09/01/2023    07:15 PM
3   4       AA1234    09/01/2023      08:30 AM  09/01/2023    10:45 PM
4   5       DL5678    09/02/2023      02:00 PM  09/02/2023    04:10 PM

             Airline  DelayMinutes
0  American Airlines          15.0
1              Delta           5.0
2    United Airlines          25.0
3  American Airlines          30.0
4              Delta           NaN
```

1.1 DATA CLEANING

- a. Identify and handle any missing or inconsistent values in the dataset.

Data Cleaning : Missing Values

[4]:
```python
df = df_fetched



# Missing Values
def check_missing_values(df):
    print("Missing values before handling:")
    print(df.isnull().sum())

    df["DelayMinutes"] = df["DelayMinutes"].fillna(0)

    print("\nMissing values after handling:")
    print(df.isnull().sum())
    return df


df = check_missing_values(df)
```

```
Missing values before handling:
id               0
FlightNumber     0
DepartureDate    0
DepartureTime    0
ArrivalDate      0
ArrivalTime      0
Airline          0
DelayMinutes     2
dtype: int64

Missing values after handling:
```

```
id               0
FlightNumber     0
DepartureDate    0
DepartureTime    0
ArrivalDate      0
ArrivalTime      0
Airline          0
DelayMinutes     0
dtype: int64
```

Data Cleaning: Duplicate Values

[5]:
```python
# Check for duplicates
def check_duplicates(df):
    duplicate_count = df.duplicated(
        subset=[
            "FlightNumber",
            "DepartureDate",
            "DepartureTime",
            "ArrivalDate",
            "ArrivalTime",
            "Airline",
            "DelayMinutes",
        ]
    ).sum()
    print(f"\nNumber of duplicate entries: {duplicate_count}")

    # Remove duplicates
    df = df.drop_duplicates(
        subset=[
            "FlightNumber",
            "DepartureDate",
            "DepartureTime",
            "ArrivalDate",
            "ArrivalTime",
            "Airline",
            "DelayMinutes",
        ]
    )

    print(f"Number of entries after removing duplicates: {df.shape[0]}")
    return df


df = check_duplicates(df)
```

```
Number of duplicate entries: 0
Number of entries after removing duplicates: 12
```

Data Cleaning: Inconsistent Time Entries

```
[6]: def convert_to_24hr(time_str):
         return datetime.strptime(time_str, "%I:%M %p").strftime("%H:%M")


     # Check for inconsistent time entries
     def check_inconsistent_time_entries(df):
         # Inconsistent time entries
         inconsistent_time_entries = pd.DataFrame()

         inconsistent_time_entries = df[df["DepartureTime"] > df["ArrivalTime"]]
         df = df[df["DepartureTime"] <= df["ArrivalTime"]]

         # Convert DepartureTime and ArrivalTime to 24-hour format
         df["DepartureTime_24"] = df["DepartureTime"].apply(convert_to_24hr)
         df["ArrivalTime_24"] = df["ArrivalTime"].apply(convert_to_24hr)

         # Combine DepartureDate and DepartureTime into a single datetime
         df["DepartureDateTime"] = pd.to_datetime(
             df["DepartureDate"] + " " + df["DepartureTime"], format="%m/%d/%Y %I:%M␣
      ↪%p"
         )
         df["ArrivalDateTime"] = pd.to_datetime(
             df["ArrivalDate"] + " " + df["ArrivalTime"], format="%m/%d/%Y %I:%M %p"
         )

         # Identify duplicate flights based on specific columns
         duplicates = df[df.duplicated(
             subset=['FlightNumber', 'Airline', 'DepartureDate', 'ArrivalDate',␣
      ↪'DepartureTime'])]

         inconsistent_time_entries = pd.concat(
             [inconsistent_time_entries, duplicates])

         df = df.drop_duplicates(
             subset=['FlightNumber', 'Airline', 'DepartureDate', 'ArrivalDate',␣
      ↪'DepartureTime'])
         print(
             f"Number of inconsistent time entries: {inconsistent_time_entries.
      ↪shape[0]}")
         print(f"Number of entries after removing inconsistent time entries: {df.
      ↪shape[0]}")

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

```
df = check_inconsistent_time_entries(df)
```

```
Number of inconsistent time entries: 2
Number of entries after removing inconsistent time entries: 10
   id FlightNumber DepartureDate DepartureTime ArrivalDate ArrivalTime  \
0   1       AA1234    09/01/2023      08:30 AM  09/01/2023    10:45 AM
1   2       DL5678    09/01/2023      01:15 PM  09/01/2023    03:30 PM
2   3       UA9101    09/01/2023      05:00 PM  09/01/2023    07:15 PM
4   5       DL5678    09/02/2023      02:00 PM  09/02/2023    04:10 PM
5   6       UA9101    09/02/2023      05:00 PM  09/02/2023    07:15 PM

             Airline  DelayMinutes DepartureTime_24 ArrivalTime_24  \
0  American Airlines          15.0            08:30          10:45
1              Delta           5.0            13:15          15:30
2    United Airlines          25.0            17:00          19:15
4              Delta           0.0            14:00          16:10
5    United Airlines          20.0            17:00          19:15

    DepartureDateTime     ArrivalDateTime
0 2023-09-01 08:30:00 2023-09-01 10:45:00
1 2023-09-01 13:15:00 2023-09-01 15:30:00
2 2023-09-01 17:00:00 2023-09-01 19:15:00
4 2023-09-02 14:00:00 2023-09-02 16:10:00
5 2023-09-02 17:00:00 2023-09-02 19:15:00
```

- b. Ensure all column data types are appropriate (e.g., dates as date types, times as time types).

[7]:
```
# Ensure all column data types are appropriate (e.g., dates as date types, times as time types).
df["FlightNumber"] = df["FlightNumber"].astype(str)
df["DepartureDate"] = pd.to_datetime(df["DepartureDate"])
df["ArrivalDate"] = pd.to_datetime(df["ArrivalDate"])
df["DepartureTime"] = pd.to_datetime(df["DepartureTime"])
df["ArrivalTime"] = pd.to_datetime(df["ArrivalTime"])
df["DelayMinutes"] = df["DelayMinutes"].astype(int)
df["Airline"] = df["Airline"].astype(str)
print(df.dtypes)
```

```
id                               int64
FlightNumber                    object
DepartureDate           datetime64[ns]
DepartureTime           datetime64[ns]
ArrivalDate             datetime64[ns]
ArrivalTime             datetime64[ns]
Airline                         object
DelayMinutes                     int64
DepartureTime_24                object
ArrivalTime_24                  object
```

```
DepartureDateTime    datetime64[ns]
ArrivalDateTime      datetime64[ns]
dtype: object
```

- Correct any inconsistencies or errors in times (e.g., arrival time should be later than departure time).

[8]:
```
# Correct any inconsistencies or errors in times (e.g., arrival time should be␣
↪later than departure time).
df = df[df["DepartureDateTime"] <= df["ArrivalDateTime"]]
print(df.head())
```

```
   id FlightNumber DepartureDate       DepartureTime ArrivalDate  \
0   1       AA1234    2023-09-01 2024-09-30 08:30:00  2023-09-01
1   2       DL5678    2023-09-01 2024-09-30 13:15:00  2023-09-01
2   3       UA9101    2023-09-01 2024-09-30 17:00:00  2023-09-01
4   5       DL5678    2023-09-02 2024-09-30 14:00:00  2023-09-02
5   6       UA9101    2023-09-02 2024-09-30 17:00:00  2023-09-02

          ArrivalTime            Airline  DelayMinutes DepartureTime_24  \
0 2024-09-30 10:45:00  American Airlines            15            08:30
1 2024-09-30 15:30:00              Delta             5            13:15
2 2024-09-30 19:15:00    United Airlines            25            17:00
4 2024-09-30 16:10:00              Delta             0            14:00
5 2024-09-30 19:15:00    United Airlines            20            17:00

  ArrivalTime_24   DepartureDateTime     ArrivalDateTime
0          10:45 2023-09-01 08:30:00 2023-09-01 10:45:00
1          15:30 2023-09-01 13:15:00 2023-09-01 15:30:00
2          19:15 2023-09-01 17:00:00 2023-09-01 19:15:00
4          16:10 2023-09-02 14:00:00 2023-09-02 16:10:00
5          19:15 2023-09-02 17:00:00 2023-09-02 19:15:00
```

1.1.1 Data Normalization

- a. Convert DepartureDate and ArrivalDate columns to a standard YYYY-MM-DD format.

[9]:
```
# Convert DepartureDate and ArrivalDate to datetime and format as YYYY-MM-DD
df["DepartureDate"] = pd.to_datetime(
    df["DepartureDate"], format="%m/%d/%Y"
).dt.strftime("%Y-%m-%d")
df["ArrivalDate"] = pd.to_datetime(df["ArrivalDate"], format="%m/%d/%Y").dt.
↪strftime(
    "%Y-%m-%d"
)

# Verify the changes
df[["DepartureDate", "ArrivalDate"]].head()
```

[9]:

	DepartureDate	ArrivalDate
0	2023-09-01	2023-09-01
1	2023-09-01	2023-09-01
2	2023-09-01	2023-09-01
4	2023-09-02	2023-09-02
5	2023-09-02	2023-09-02

- b. Convert DepartureTime and ArrivalTime columns to a 24-hour time format (e.g., "08:30" for 8:30 AM).

[10]:
```
# Optionally, replace the original time columns with 24-hour format
df["DepartureTime"] = df["DepartureTime_24"]
df["ArrivalTime"] = df["ArrivalTime_24"]

# Drop the temporary 24-hour columns
df = df.drop(["DepartureTime_24", "ArrivalTime_24"], axis=1)

# Verify the changes
df[["DepartureTime", "ArrivalTime"]].head()
```

[10]:

	DepartureTime	ArrivalTime
0	08:30	10:45
1	13:15	15:30
2	17:00	19:15
4	14:00	16:10
5	17:00	19:15

- c. Create a new column for FlightDuration by calculating the difference between DepartureTime and ArrivalTime on the same day.

[11]:
```
# Calculate FlightDuration in minutes
df["FlightDuration"] = (df["ArrivalDateTime"] - df["DepartureDateTime"]).dt.
↪total_seconds() / 60

df[["FlightNumber", "DepartureDateTime", "ArrivalDateTime", "FlightDuration"]].
↪head()
```

[11]:

	FlightNumber	DepartureDateTime	ArrivalDateTime	FlightDuration
0	AA1234	2023-09-01 08:30:00	2023-09-01 10:45:00	135.0
1	DL5678	2023-09-01 13:15:00	2023-09-01 15:30:00	135.0
2	UA9101	2023-09-01 17:00:00	2023-09-01 19:15:00	135.0
4	DL5678	2023-09-02 14:00:00	2023-09-02 16:10:00	130.0
5	UA9101	2023-09-02 17:00:00	2023-09-02 19:15:00	135.0

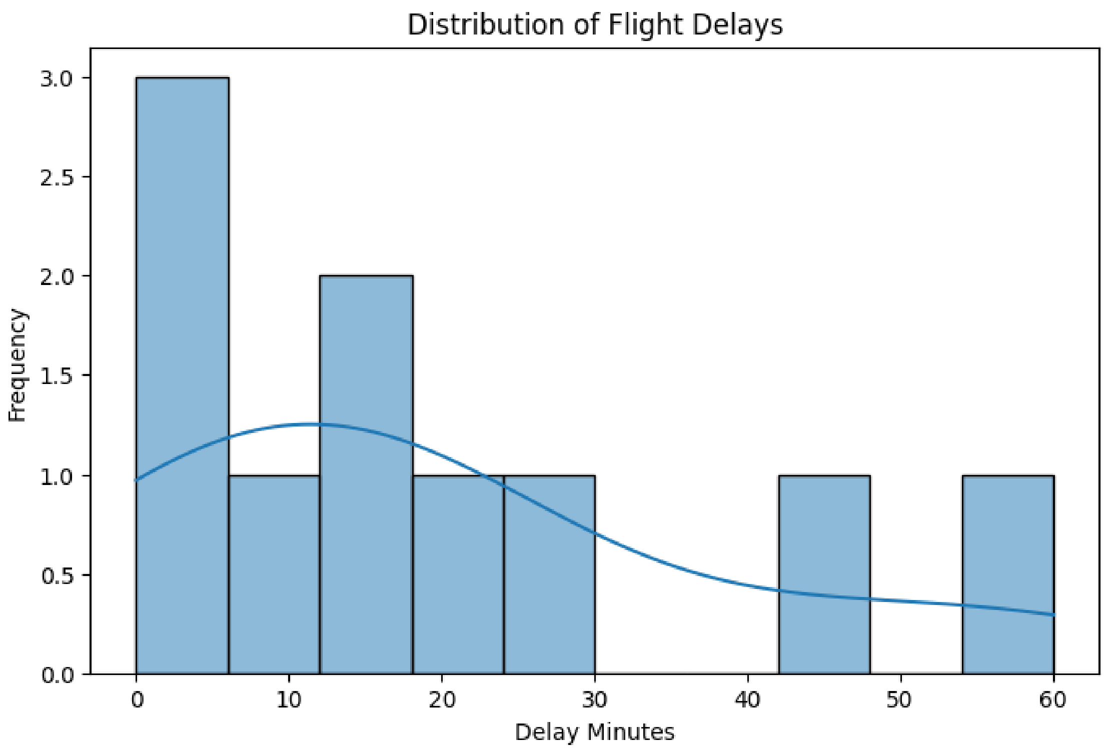
1.2 DATA ANALYSIS

- Analyze the distribution of delays and identify any trends or patterns.

[12]:

```
# Summary statistics of DelayMinutes
delay_summary = df["DelayMinutes"].describe()
print("Delay Minutes Summary:")
print(delay_summary)

# Plot distribution of delays
plt.figure(figsize=(8, 5))
sns.histplot(df["DelayMinutes"],bins=10, kde=True)
plt.title("Distribution of Flight Delays")
plt.xlabel("Delay Minutes")
plt.ylabel("Frequency")
plt.show()

print('Insights:')
print("1. The distribution shows that the majority of flights had delays␣
↪between 0 and 10 minutes, with the highest frequency in this range.")
print("2. The overall shape of the histogram suggests a right-skewed␣
↪distribution. Most delays are concentrated at the lower end, with fewer␣
↪flights experiencing significant delays (over 30 minutes).")
print("3. A significant proportion of flights face relatively short delays␣
↪(below 15 minutes).")
```

```
Delay Minutes Summary:
count    10.000000
mean     19.500000
std      19.500712
min       0.000000
25%       6.250000
50%      15.000000
75%      23.750000
max      60.000000
Name: DelayMinutes, dtype: float64
```



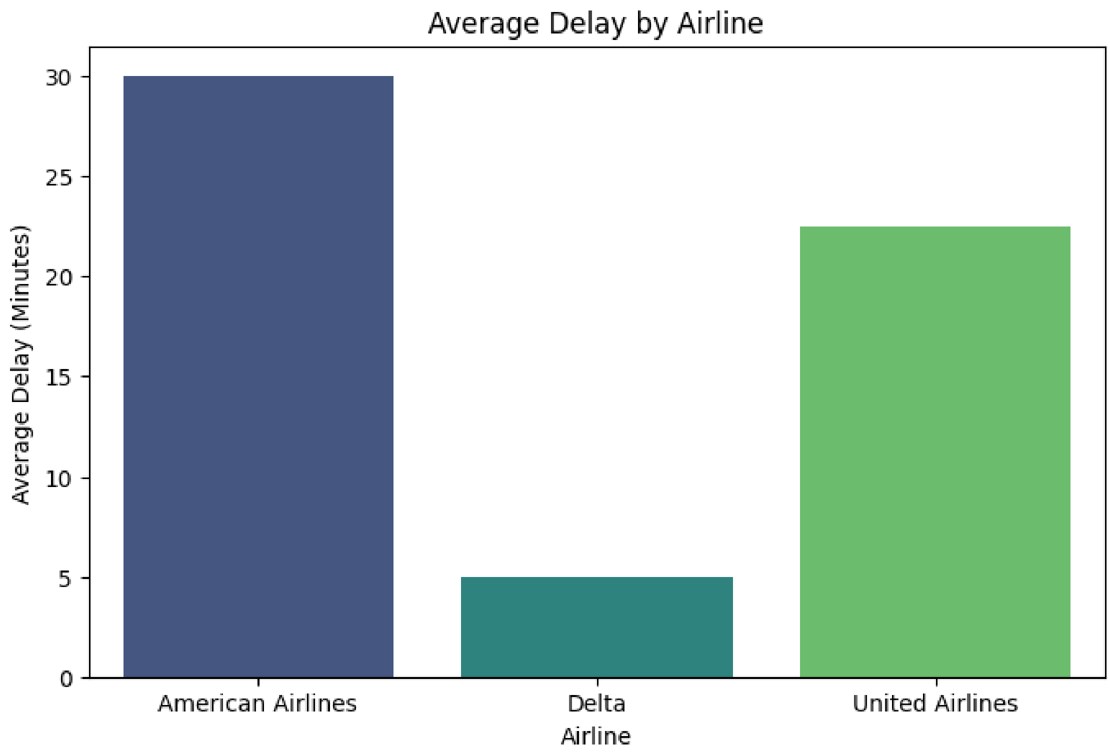

```
Insights:
1. The distribution shows that the majority of flights had delays between 0 and
10 minutes, with the highest frequency in this range.
2. The overall shape of the histogram suggests a right-skewed distribution. Most
delays are concentrated at the lower end, with fewer flights experiencing
significant delays (over 30 minutes).
3. A significant proportion of flights face relatively short delays (below 15
minutes).
```

- Calculate the average delay for each airline.

[13]:
```python
# Average delay per airline
average_delay_airline = df.groupby("Airline")["DelayMinutes"].mean().
↪reset_index()

# Display the results
print("Average Delay per Airline:")
print(average_delay_airline)

# Plot average delay per airline
plt.figure(figsize=(8, 5))
sns.barplot(
    data=average_delay_airline, x="Airline", y="DelayMinutes", palette="viridis"
```

```
)
plt.title("Average Delay by Airline")
plt.xlabel("Airline")
plt.ylabel("Average Delay (Minutes)")
plt.show()

print('Insights:')
print("1. The average delay times vary significantly across different airlines.
 ↪")
print("2. American Airlines has the highest average delay, while Delta Airline␣
 ↪has the lowest average delay.")
print("3. The difference in average delay times suggests variations in␣
 ↪operational efficiency and performance among airlines.")
```

```
Average Delay per Airline:
             Airline  DelayMinutes
0  American Airlines          30.0
1              Delta           5.0
2    United Airlines          22.5
```

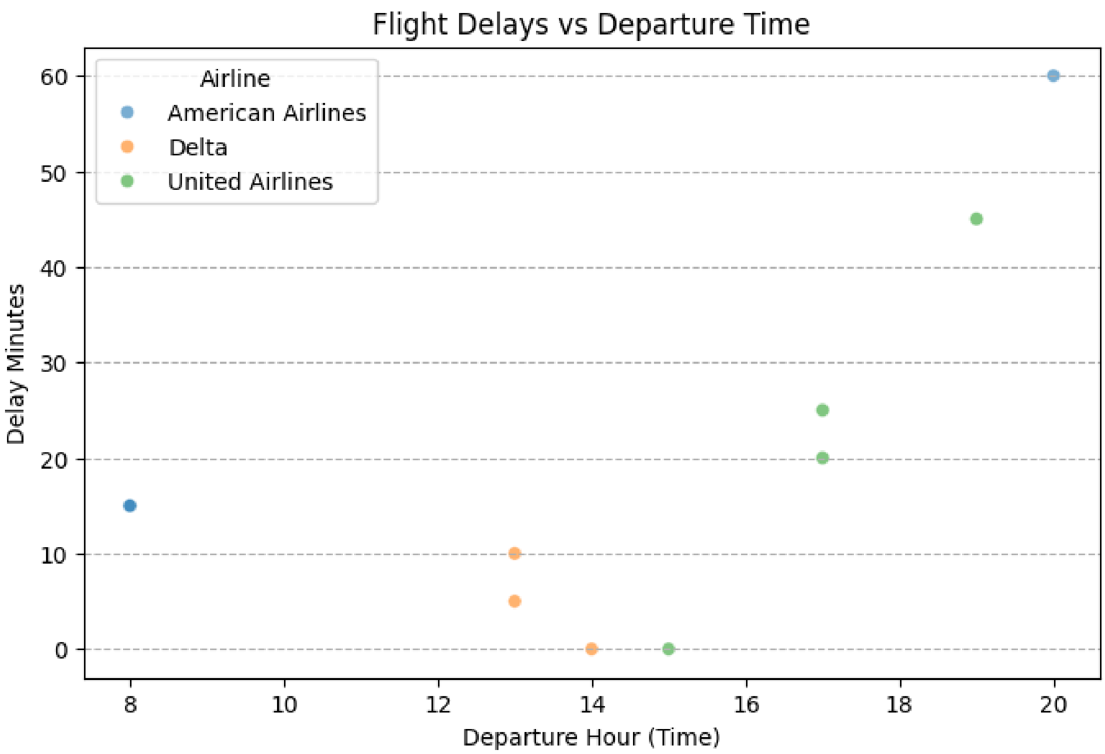



```
Insights:
1. The average delay times vary significantly across different airlines.
2. American Airlines has the highest average delay, while Delta Airline has the
```

```
lowest average delay.
3. The difference in average delay times suggests variations in operational
efficiency and performance among airlines.
```

- Identify any relationships between flight delays and departure times (e.g., are flights departing later in the day more likely to be delayed?).

[14]:
```python
# Extract hour from DepartureTime
df["DepartureHour"] = pd.to_datetime(df["DepartureTime"], format="%H:%M").dt.
 ↪hour

# Scatter plot of DepartureHour vs DelayMinutes
plt.figure(figsize=(8, 5))
sns.scatterplot(data=df, x="DepartureHour", y="DelayMinutes", hue="Airline",␣
 ↪alpha=0.6)
plt.title("Flight Delays vs Departure Time")
plt.xlabel("Departure Hour (Time)")
plt.ylabel("Delay Minutes")
plt.legend(title="Airline")
plt.grid(axis="y", linestyle="--")
plt.show()

print('Insights:')
print("1. Evening Delays: Delays increase significantly after 16:00, especially␣
 ↪for United and American Airlines.")
print("2. Delta's Punctuality: Delta consistently has minimal delays.")
print("3. American Airlines Peaks: American Airlines faces large delays around␣
 ↪morning 8:00 and night 20:00.")
```

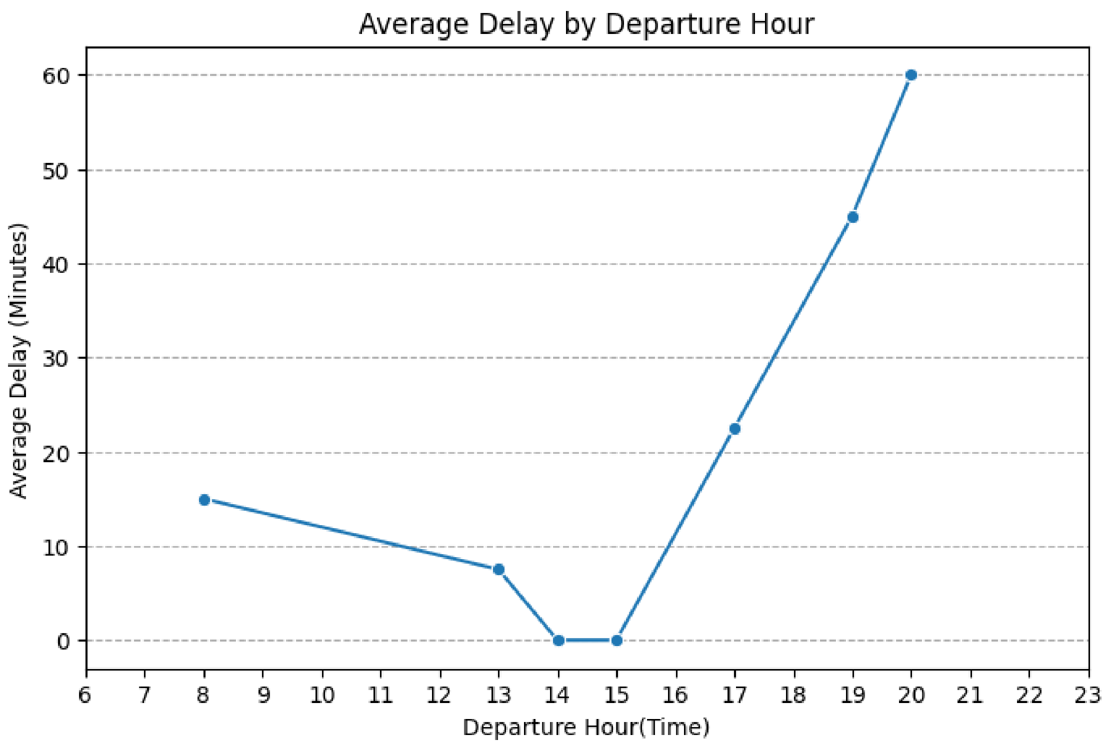



```
Insights:
1. Evening Delays: Delays increase significantly after 16:00, especially for
United and American Airlines.
2. Delta's Punctuality: Delta consistently has minimal delays.
3. American Airlines Peaks: American Airlines faces large delays around morning
8:00 and night 20:00.
```

[15]:

```python
# Alternatively, analyze average delay by departure hour
average_delay_hour = df.groupby("DepartureHour")[
    "DelayMinutes"].mean().reset_index()

plt.figure(figsize=(8, 5))
sns.lineplot(data=average_delay_hour, x="DepartureHour",
             y="DelayMinutes", marker="o")
plt.title("Average Delay by Departure Hour")
plt.xlabel("Departure Hour(Time)")
plt.ylabel("Average Delay (Minutes)")
plt.grid(axis="y", linestyle="--")
plt.xticks(range(6, 24))
plt.show()

print('Insights:')
```

```python
print("1. High delays in the evening: Delays peak after 17:00, with the highest␣
↪around 20:00 (60+ minutes).")
print("2. Minimal delays at midday: Almost no delays between 14:00 and 15:00.")
print("3. Morning decline: Delays gradually decrease from 9:00 to 13:00.")
```




```
Insights:
1. High delays in the evening: Delays peak after 17:00, with the highest around
20:00 (60+ minutes).
2. Minimal delays at midday: Almost no delays between 14:00 and 15:00.
3. Morning decline: Delays gradually decrease from 9:00 to 13:00.
```

- Determine if there is a significant difference in delays between different airlines.

[16]:
```python
# Prepare data for ANOVA
airline_delays = [group["DelayMinutes"].values for name, group in df.
↪groupby("Airline")]

# Perform one-way ANOVA
anova_result = stats.f_oneway(*airline_delays)

print("ANOVA Result:")
print(f"F-statistic: {anova_result.statistic}, p-value: {anova_result.pvalue}")
```

```python
# Interpretation
if anova_result.pvalue < 0.05:
    print("There is a significant difference in delays between airlines.")
else:
    print("There is no significant difference in delays between airlines.")
```

```
ANOVA Result:
F-statistic: 1.4396907216494845, p-value: 0.29942565031587365
There is no significant difference in delays between airlines.
```

1.3 INSIGHTS:

1.3.1 Key Insights:

a. Provide a summary of the key findings from the data:

- **Delay Distribution**: Most flights experience delays of less than 30 minutes, with a significant portion facing delays under 10 minutes.
- **Average Delay by Airline**: American Airlines shows the highest average delay, followed by United Airlines, while Delta experiences the lowest delays.
- **Impact of Departure Time**: Flights departing later in the day tend to experience longer delays, particularly during the evening.
- **No Significant Differences Across Airlines**: ANOVA results indicate no statistically significant difference in delays between airlines (p-value: 0.225).

b. Analyze the impact of departure times on delays.:

- **Evening Delays**: Delays peak in the evening, especially after 17:00, with the highest around 20:00.
- **Minimal Delays at Midday**: Flights between 14:00 and 15:00 see the least delays.
- **Morning Decline**: Delays gradually reduce from 9:00 AM until early afternoon.

c. Compare delay distributions between airlines.:

- **American Airlines** faces the most significant delays, with an average of 30 minutes.
- **Delta Airlines** demonstrates operational efficiency with the lowest average delays at 5 minutes.
- **United Airlines** falls in the middle, averaging 22.5 minutes of delay.

d. Recommendations:

- **Operational Optimization**: American Airlines should focus on reducing delays, especially during high-delay periods (early morning and evening).
- **Resource Allocation**: Airlines should allocate more resources during peak delay times (late afternoon and evening) to improve punctuality.
- **Scheduling Adjustments**: Revising flight schedules around high-delay times (17:00-20:00) could help reduce bottlenecks.