

flight delays

May 23, 2025

Background You work for a major airline operating flights across the USA. Flight delays are a significant challenge for both the airline and passengers, causing disruptions, financial losses, and dissatisfaction. As part of the airline's data analytics team, your goal is to analyze historical flight data to uncover delay patterns, identify operational inefficiencies, and predict delays before they occur. By identifying delay patterns, predicting delays, and uncovering the factors that contribute most to delays, you'll be able to drive operational efficiency and enhance the overall passenger experience. Your insights will help the airline make data-driven decisions to optimize scheduling, improve on-time performance, and enhance passenger satisfaction.

Can you crack the code behind flight delays and revolutionize air travel?

Challenge Create a report summarizing your insights. Your report should explore the following questions:

1. How do different airlines compare in terms of their departure and arrival times? Are there noticeable trends in their on-time performance over the year? A well-structured visualization could help uncover patterns.
2. Are there particular months/weeks/time of day where there is a general trend of greater delays in flights across all carriers? If so, what could be the reasons?
3. Some airports seem to operate like clockwork, while others are notorious for disruptions. How do different airports compare when it comes to departure and arrival punctuality? Could location, traffic volume, or other factors play a role? Are there patterns that emerge when looking at delays across various airports?
4. [Optional 1] Predict whether a flight will have a delay of 15 minutes or more at departure.
5. [Optional 2] What underlying factors influence flight delays the most? Are some routes more prone to disruptions than others? Do external variables like time of day, distance, or carrier policies play a significant role? By analyzing the relationships between different features, you might discover unexpected insights.

```
[1]: import pandas as pd
flight_data = pd.read_csv('flights_data/flights.csv')
print(flight_data.head().to_string(index=False))
```

id	year	month	day	dep_time	sched_dep_time	dep_delay	arr_time	sched_arr_time	arr_delay	carrier	flight	tailnum	origin	dest	air_time	distance	hour	minute	time_hour	name
0	2013	1	1	517.0	515	2.0	830.0													
819		11.0		UA	1545	N14228	EWB	IAH	227.0	1400	5									
15	2013-01-01	05:00:00		United Air Lines Inc.																
1	2013	1	1	533.0	529	4.0	850.0													

```

830      20.0      UA      1714 N24211      LGA IAH      227.0      1416      5
29 2013-01-01 05:00:00 United Air Lines Inc.
   2 2013      1      1      542.0      540      2.0      923.0
850      33.0      AA      1141 N619AA      JFK MIA      160.0      1089      5
40 2013-01-01 05:00:00 American Airlines Inc.
   3 2013      1      1      544.0      545      -1.0      1004.0
1022      -18.0      B6      725 N804JB      JFK BQN      183.0      1576      5
45 2013-01-01 05:00:00 JetBlue Airways
   4 2013      1      1      554.0      600      -6.0      812.0
837      -25.0      DL      461 N668DN      LGA ATL      116.0      762      6
0 2013-01-01 06:00:00 Delta Air Lines Inc.

```

```
[3]: flight_data.columns
```

```
[3]: Index(['id', 'year', 'month', 'day', 'dep_time', 'sched_dep_time', 'dep_delay',
          'arr_time', 'sched_arr_time', 'arr_delay', 'carrier', 'flight',
          'tailnum', 'origin', 'dest', 'air_time', 'distance', 'hour', 'minute',
          'time_hour', 'name'],
          dtype='object')
```

```
[4]: flight_data.info()
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 336776 entries, 0 to 336775
Data columns (total 21 columns):
#   Column                Non-Null Count  Dtype
---  -
0   id                    336776 non-null  int64
1   year                  336776 non-null  int64
2   month                 336776 non-null  int64
3   day                   336776 non-null  int64
4   dep_time              328521 non-null  float64
5   sched_dep_time        336776 non-null  int64
6   dep_delay             328521 non-null  float64
7   arr_time              328063 non-null  float64
8   sched_arr_time        336776 non-null  int64
9   arr_delay             327346 non-null  float64
10  carrier               336776 non-null  object
11  flight                336776 non-null  int64
12  tailnum               334264 non-null  object
13  origin                336776 non-null  object
14  dest                  336776 non-null  object
15  air_time              327346 non-null  float64
16  distance              336776 non-null  int64
17  hour                  336776 non-null  int64
18  minute                336776 non-null  int64
19  time_hour             336776 non-null  object
20  name                  336776 non-null  object

```

```
dtypes: float64(5), int64(10), object(6)
memory usage: 54.0+ MB
```

```
[5]: flight_data.describe
```

```
[5]: <bound method NDFrame.describe of
      sched_dep_time  dep_delay  \
0          0  2013      1      1      517.0          515          2.0
1          1  2013      1      1      533.0          529          4.0
2          2  2013      1      1      542.0          540          2.0
3          3  2013      1      1      544.0          545         -1.0
4          4  2013      1      1      554.0          600         -6.0
...
336771  336771  2013      9     30          NaN          1455          NaN
336772  336772  2013      9     30          NaN          2200          NaN
336773  336773  2013      9     30          NaN          1210          NaN
336774  336774  2013      9     30          NaN          1159          NaN
336775  336775  2013      9     30          NaN           840          NaN

      arr_time  sched_arr_time  arr_delay  ... flight  tailnum origin dest  \
0      830.0          819      11.0  ...  1545    N14228    EWR   IAH
1      850.0          830      20.0  ...  1714    N24211    LGA   IAH
2      923.0          850      33.0  ...  1141    N619AA    JFK   MIA
3     1004.0         1022     -18.0  ...   725    N804JB    JFK   BQN
4      812.0          837     -25.0  ...   461    N668DN    LGA   ATL
...
336771      NaN          1634      NaN  ...  3393      NaN    JFK   DCA
336772      NaN          2312      NaN  ...  3525      NaN    LGA   SYR
336773      NaN          1330      NaN  ...  3461    N535MQ    LGA   BNA
336774      NaN          1344      NaN  ...  3572    N511MQ    LGA   CLE
336775      NaN          1020      NaN  ...  3531    N839MQ    LGA   RDU

      air_time  distance  hour  minute  time_hour  \
0      227.0      1400      5      15  2013-01-01 05:00:00
1      227.0      1416      5      29  2013-01-01 05:00:00
2      160.0      1089      5      40  2013-01-01 05:00:00
3      183.0      1576      5      45  2013-01-01 05:00:00
4      116.0       762      6       0  2013-01-01 06:00:00
...
336771      NaN       213      14      55  2013-09-30 14:00:00
336772      NaN       198      22       0  2013-09-30 22:00:00
336773      NaN       764      12      10  2013-09-30 12:00:00
336774      NaN       419      11      59  2013-09-30 11:00:00
336775      NaN       431       8      40  2013-09-30 08:00:00

      name
0  United Air Lines Inc.
```

```

1      United Air Lines Inc.
2      American Airlines Inc.
3      JetBlue Airways
4      Delta Air Lines Inc.
...
336771      Endeavor Air Inc.
336772      Endeavor Air Inc.
336773      Envoy Air
336774      Envoy Air
336775      Envoy Air

```

```
[336776 rows x 21 columns]>
```

```
[6]: missing = flight_data.isnull().sum()
print(missing[missing > 0])
```

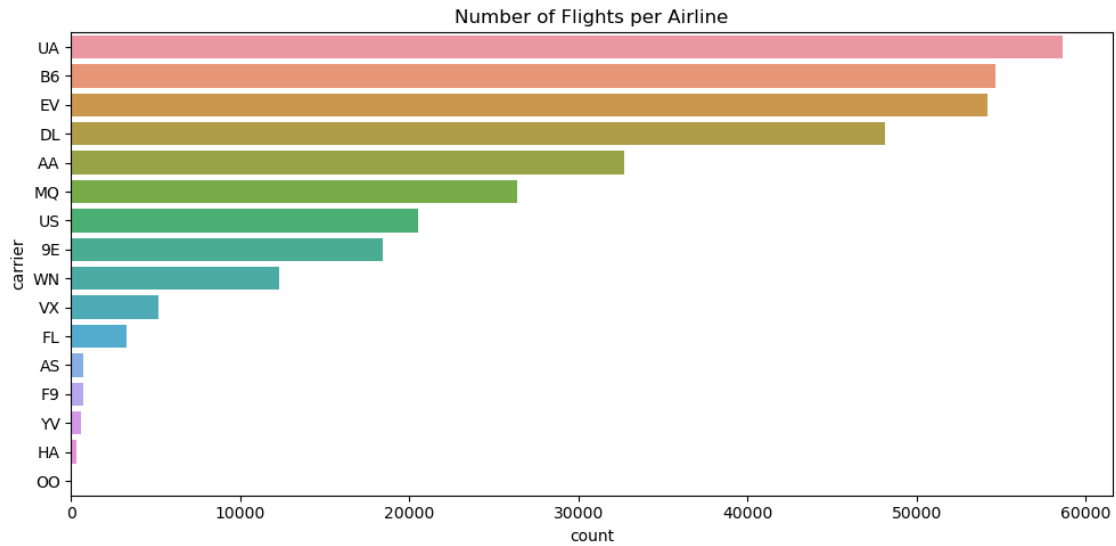
```

dep_time      8255
dep_delay     8255
arr_time      8713
arr_delay     9430
tailnum       2512
air_time      9430
dtype: int64

```

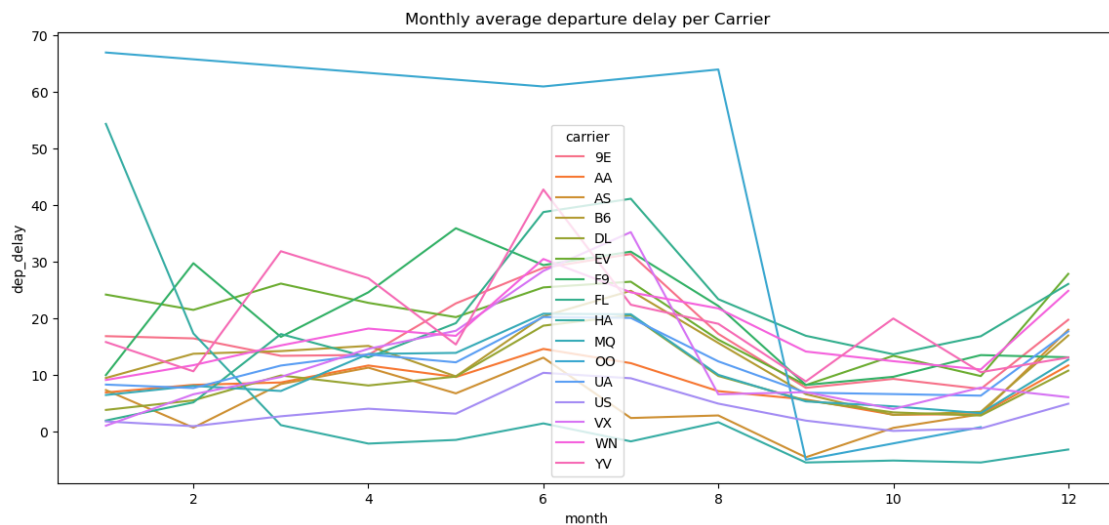
```
[7]: import matplotlib.pyplot as plt
import seaborn as sns

#count flights per airline
plt.figure(figsize=(10,5))
sns.countplot(y='carrier', data=flight_data, order=flight_data['carrier'].
    ↪value_counts().index)
plt.title("Number of Flights per Airline")
plt.tight_layout()
plt.show()
```



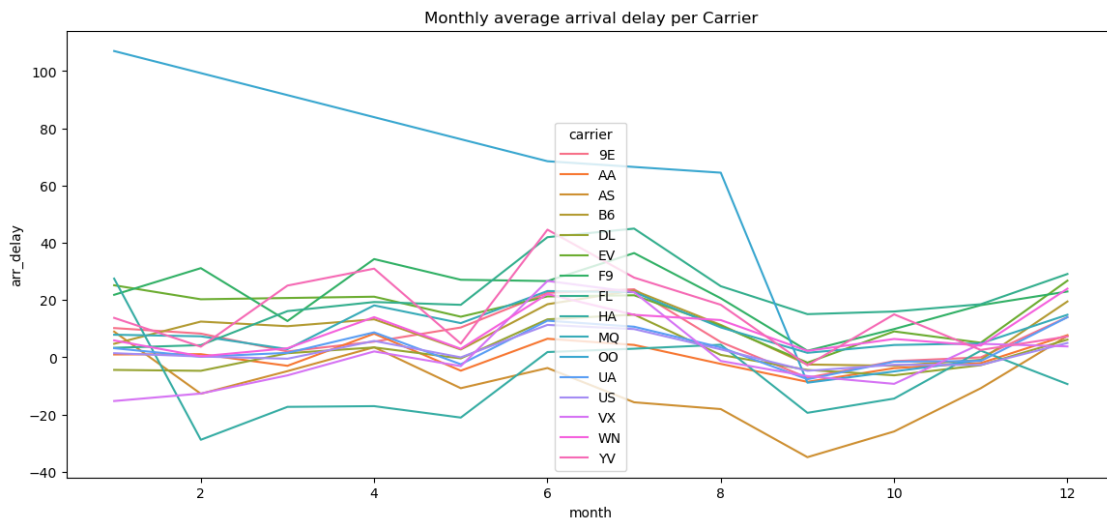
```
[8]: # Monthly trend per carrier
monthly_delay = flight_data.groupby(['month', 'carrier'])[['dep_delay', 'arr_delay']].mean().reset_index()

plt.figure(figsize=(14,6))
sns.lineplot(data=monthly_delay, x='month', y='dep_delay', hue='carrier')
plt.title("Monthly average departure delay per Carrier")
plt.show()
```



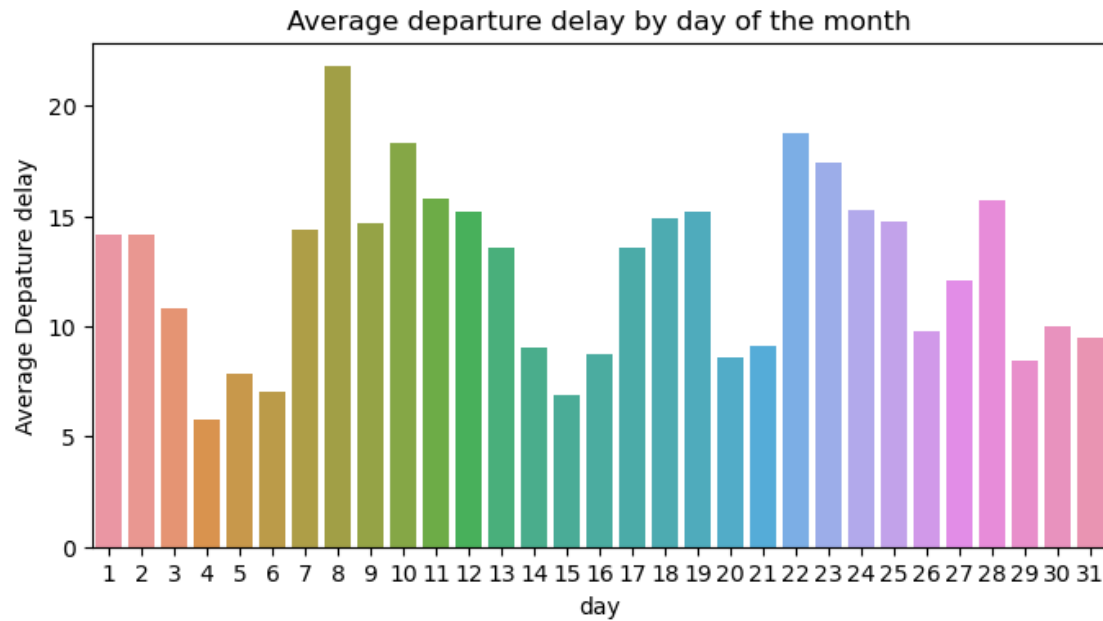
```
[11]: # Monthly trend per carrier
monthly_delay = flight_data.groupby(['month', 'carrier'])[['dep_delay', 'arr_delay']].mean().reset_index()

plt.figure(figsize=(14,6))
sns.lineplot(data=monthly_delay, x='month', y='arr_delay', hue='carrier')
plt.title("Monthly average arrival delay per Carrier")
plt.show()
```



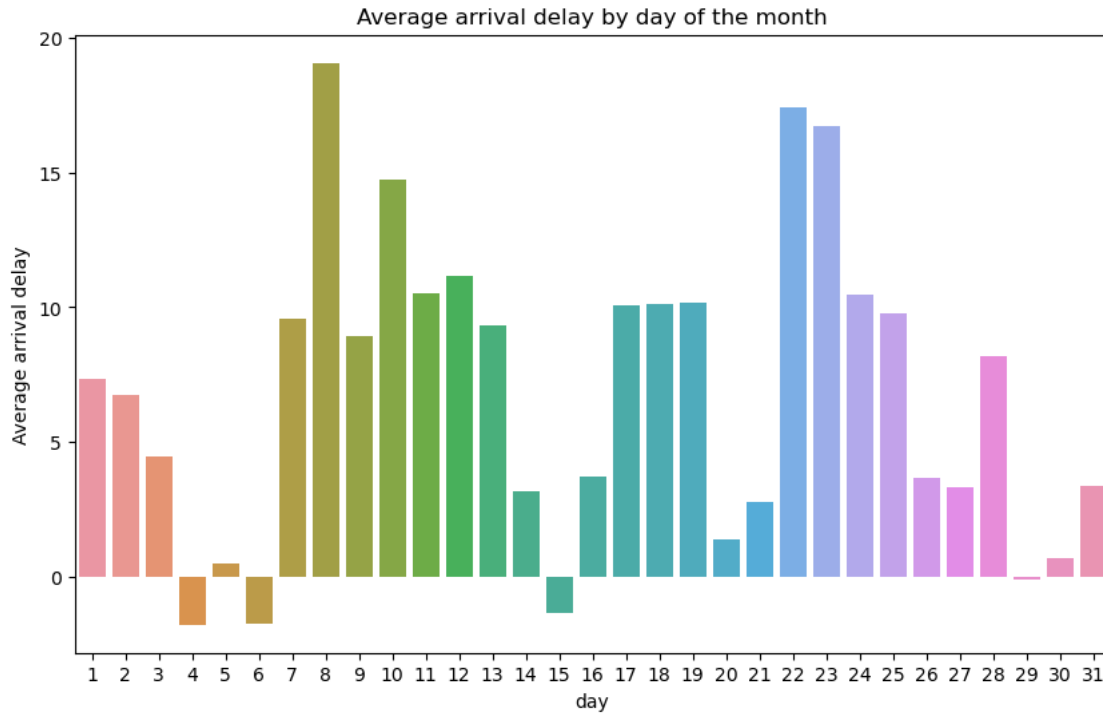
```
[ ]: # Departure delay by day of the month
day_delay = flight_data.groupby('day')[['dep_delay', 'arr_delay']].mean().reset_index()

plt.figure(figsize=(8,4))
sns.barplot(data=day_delay, x='day', y='dep_delay')
plt.title("Average departure delay by day of the month")
plt.ylabel("Average Departure delay")
plt.show()
```



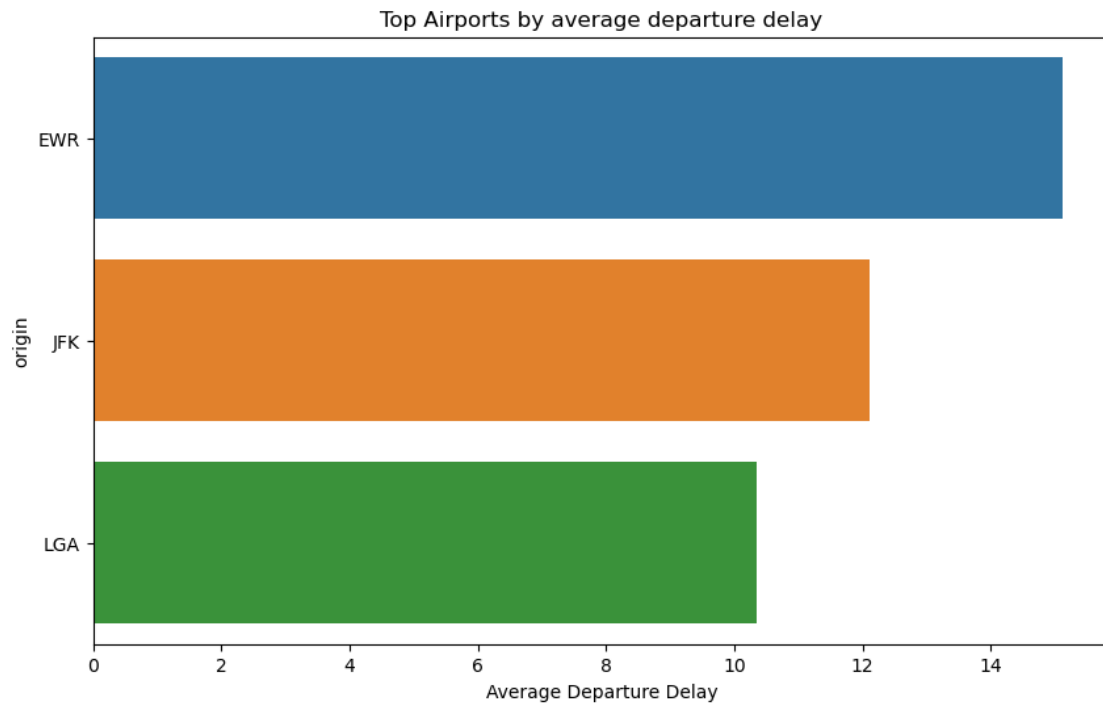
```
[ ]: # Arrival delay by day of the month

plt.figure(figsize=(10,6))
sns.barplot(data=day_delay, x='day', y='arr_delay')
plt.title("Average arrival delay by day of the month")
plt.ylabel("Average arrival delay")
plt.show()
```

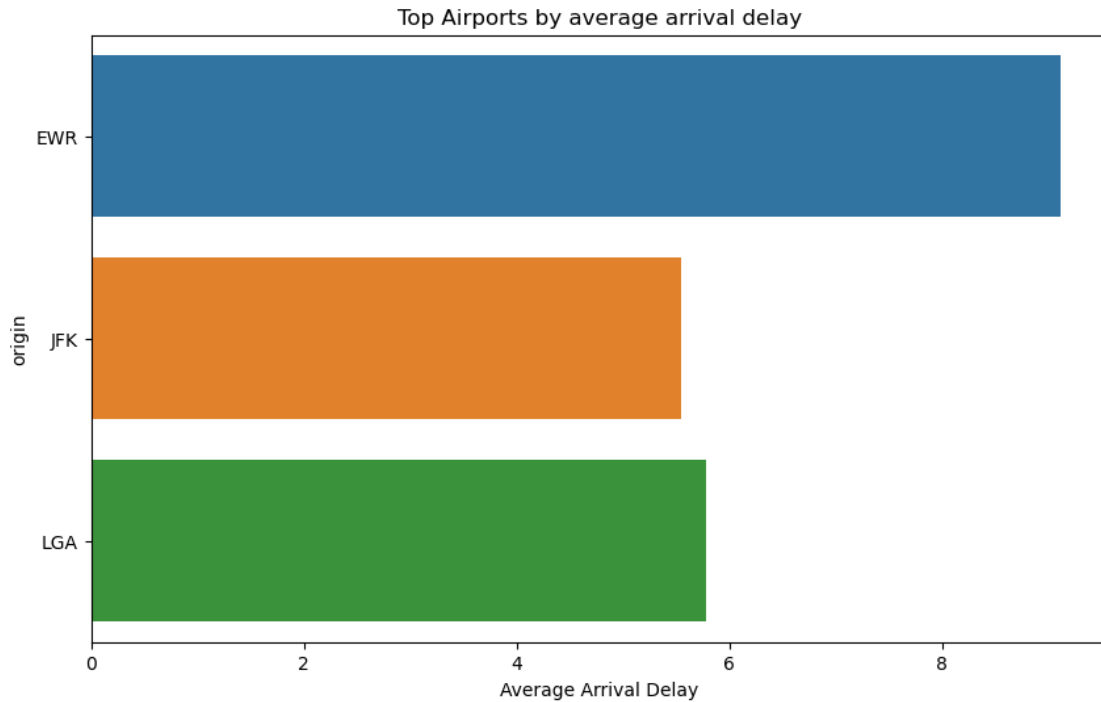


```
[29]: # Airport performance
origin_delays = flight_data.groupby('origin')[['dep_delay', 'arr_delay']].mean().
    ↪sort_values(by='dep_delay', ascending=False)

plt.figure(figsize=(10,6))
sns.barplot(x=origin_delays['dep_delay'], y=origin_delays.index)
plt.title("Top Airports by average departure delay")
plt.xlabel("Average Departure Delay")
plt.show()
```

```
[36]: plt.figure(figsize=(10,6))
sns.barplot(data=origin_delays,x='arr_delay',y=origin_delays.index)
plt.title("Top Airports by average arrival delay")
plt.xlabel("Average Arrival Delay")
plt.show()
```



```
[51]: # Predict a departure delay >=15 mins
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import classification_report

flight_data['delay_15'] = (flight_data['dep_delay'] >= 15).astype(int)

features = ['carrier', 'origin', 'dest', 'month', 'day']
X = flight_data[features].copy()
le = LabelEncoder()
for col in X.columns:
    X[col] = le.fit_transform(X[col])

y = flight_data['delay_15']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
    ↪random_state=42)
model = RandomForestClassifier(n_estimators=500, max_depth=10, random_state=42)
model.fit(X_train, y_train)

y_pred = model.predict(X_test)
print(classification_report(y_test, y_pred))
```

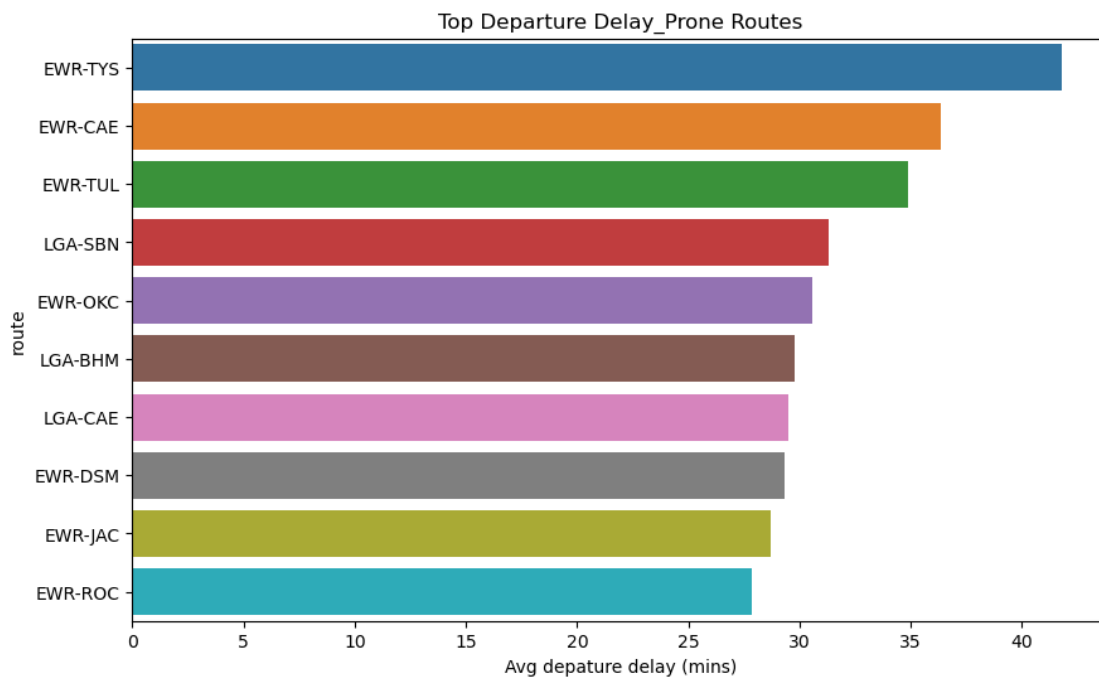
```
precision    recall  f1-score   support
```

0	0.79	1.00	0.88	79346
1	0.68	0.01	0.02	21687
accuracy			0.79	101033
macro avg	0.73	0.50	0.45	101033
weighted avg	0.76	0.79	0.69	101033

[47]: *# Route-based insights*

```
flight_data['route'] = flight_data['origin'] + "-" + flight_data['dest']
route_delay = flight_data.groupby('route')[['dep_delay', 'arr_delay']].mean().
    ↪sort_values(by='dep_delay', ascending=False).head(10)

plt.figure(figsize=(10,6))
sns.barplot(data=route_delay, x='dep_delay', y=route_delay.index)
plt.title("Top Departure Delay_Prone Routes")
plt.xlabel("Avg departure delay (mins)")
plt.show()
```



[48]: *# Route-based insights*

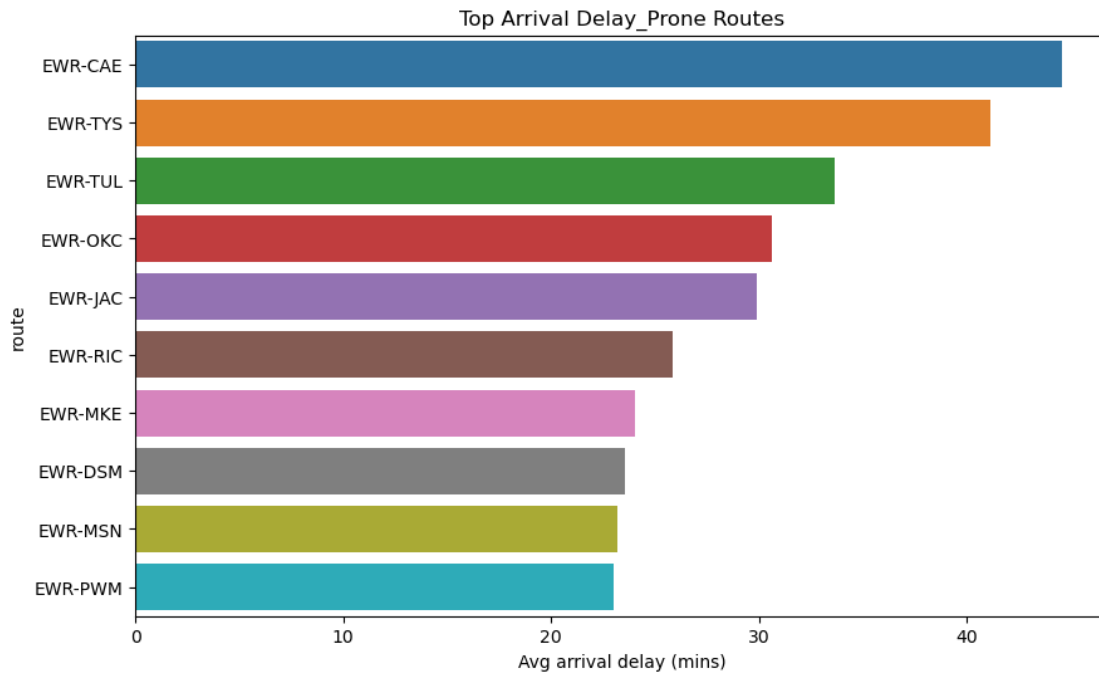
```
flight_data['route'] = flight_data['origin'] + "-" + flight_data['dest']
```

```

route_delay = flight_data.groupby('route')[['dep_delay', 'arr_delay']].mean().
    ↪sort_values(by='arr_delay', ascending=False).head(10)

plt.figure(figsize=(10,6))
sns.barplot(data=route_delay, x='arr_delay', y=route_delay.index)
plt.title("Top Arrival Delay_Prone Routes")
plt.xlabel("Avg arrival delay (mins)")
plt.show()

```



```

[38]: # Feature importance on delay prediction
importances = pd.Series(model.feature_importances_, index=features).
    ↪sort_values(ascending=False)

plt.figure(figsize=(8,4))
sns.barplot(x=importances, y=importances.index)
plt.title("Feature Importance For Delay Prediction")
plt.show()

```

