Group Members and Matric Number

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Introduction

For this project, We are exploring a dataset containing detailed records of flights departing from the three main New York City airports in 2023, along with metadata on airlines, airports, weather, and planes. The primary focus of our analysis is to uncover patterns, trends, and insights within the dataset while addressing key questions related to flight delays and cancellations. My analysis will also involve building predictive models to forecast flight delays and classify flight cancellations using supervised learning techniques.

Before diving into the specifics of this project, let’s briefly discuss the concept of **Data Analytics**. Data Analytics is the process of cleaning, transforming, and analyzing raw data to extract meaningful insights that support decision-making. This process often involves generating visualizations such as charts, graphs, and tables to effectively communicate findings. Data Analytics is a critical tool for identifying trends, improving operational efficiency, and reducing uncertainty in decision-making.

This project is structured into several key tasks. The first task focuses on **data cleaning**, where I ensure the dataset is free from inconsistencies, missing values, or outliers that could compromise the analysis. Next, I conduct an **exploratory data analysis (EDA)** to understand the relationships between various features and identify factors influencing flight delays and cancellations. Following this, I preprocess the data by encoding categorical variables and scaling numerical features to prepare it for modeling.

The second part of the project involves applying supervised learning techniques to address two specific objectives:

1. **Regression Analysis**: Predicting a continuous target variable (e.g., arrival delay) using features such as departure delay, distance, air time, weather conditions, and more.
2. **Classification Analysis**: Categorizing flights as canceled or not canceled by deriving a binary target variable based on flight delay information.

Throughout the project, we employed various Python libraries such as pandas for data manipulation, seaborn and matplotlib for visualization, scikit-learn for machine learning models, and other tools to streamline the analysis process. We also evaluated the performance of our predictive models using appropriate metrics for both regression (e.g., RMSE and R-squared) and classification (e.g., accuracy and F1-score).

This project aims to provide a comprehensive understanding of how different factors influence flight operations while enhancing my skills in data cleaning, exploratory analysis, feature engineering, and supervised learning. I welcome any comments or feedback on this project as I embark on this exciting journey through data!

Background

The dataset for this project contains comprehensive information about flights departing from the three main New York City airports (JFK, LaGuardia, and Newark) in 2023, along with associated metadata. This rich dataset encompasses a wide range of attributes related to flight operations, weather conditions, aircraft specifications, and airline information. Each of these factors contributes to the complex dynamics of flight performance, including potential delays and cancellations.

The dataset is composed of five main CSV files, each providing unique and interconnected information:

1. Flights: This core dataset contains detailed records of individual flights, including departure and arrival times, delays, flight numbers, and route information.
2. Weather: This file provides hourly weather data for each airport, including temperature, wind speed, precipitation, and visibility.
3. Planes: This dataset contains specifications for each aircraft, such as manufacturer, model, number of seats, and engine type.
4. Airports: This file includes information about airports, such as location coordinates, altitude, and time zone.
5. Airlines: This dataset provides details about the airlines operating the flights, including carrier codes and full names.

These interconnected datasets allow for a comprehensive analysis of how various factors - from weather conditions to aircraft types - influence flight performance and scheduling.

Key variables of interest include:

- Departure and arrival delays

- Flight cancellations
- Air time and distance
- Weather conditions at departure
- Aircraft specifications
- Carrier information

By analyzing these variables and their relationships, we aim to uncover patterns and build predictive models that can forecast flight delays and classify potential cancellations. This analysis has practical implications for improving flight scheduling, enhancing passenger experience, and optimizing airline operations.

Importing Required Libraries

```
import pandas as pd  # For data manipulation
import numpy as np  # For numerical operations
import matplotlib.pyplot as plt  # For data visualization
import seaborn as sns  # For advanced visualizations
from sklearn.model_selection import train_test_split  # For splitting data
from sklearn.preprocessing import StandardScaler, LabelEncoder  # Data preprocessing
from sklearn.linear_model import LinearRegression  # For regression task
from sklearn.ensemble import RandomForestClassifier  # For classification task
from sklearn.metrics import mean_squared_error, accuracy_score, confusion_matrix
```

Loading Datasets

```
# Load datasets with error handling and specific delimiters
flights = pd.read_csv('flights.csv', sep=';')
weather = pd.read_csv('weather.csv', sep=';')
airports = pd.read_csv('airports.csv', sep=';')
planes = pd.read_csv('planes.csv', sep=';')
airlines = pd.read_csv('airlines.csv', sep=';')
```

Observing our datasets by looking at each top 10 rows

```
# Set pandas option to display all columns
pd.set_option('display.max_columns', None)
```

```
flights.head(10)
```

	Unnamed: 0	year	month	day	dep_time	sched_dep_time	dep_delay	arr_time	sched_arr_time	arr_delay	carrier	flight	tailnum	origin
0	1	2023	1	1	1.0	2038	203.0	328.0	3	205.0	UA	628	N25201	EWR
1	2	2023	1	1	18.0	2300	78.0	228.0	135	53.0	DL	393	N830DN	JFK
2	3	2023	1	1	31.0	2344	47.0	500.0	426	34.0	B6	371	N807JB	JFK
3	4	2023	1	1	33.0	2140	173.0	238.0	2352	166.0	B6	1053	N265JB	JFK
4	5	2023	1	1	36.0	2048	228.0	223.0	2252	211.0	UA	219	N17730	EWR
5	6	2023	1	1	503.0	500	3.0	808.0	815	-7.0	AA	499	N925AN	EWR
6	7	2023	1	1	520.0	510	10.0	948.0	949	-1.0	B6	996	N2043J	JFK
7	8	2023	1	1	524.0	530	-6.0	645.0	710	-25.0	AA	981	N918AN	EWR
8	9	2023	1	1	537.0	520	17.0	926.0	818	68.0	UA	206	N13113	EWR
9	10	2023	1	1	547.0	545	2.0	845.0	852	-7.0	NK	225	N912NK	EWR

```
weather.head(10)
```

	Unnamed: 0	origin	year	month	day	hour	temp	dewp	humid	wind_dir	wind_speed	wind_gust	precip	pressure	visib	time_hour
0	1	JFK	2023	1	1	0	NaN	NaN	NaN	0.0	0	0	NaN	NaN	0,25	2023-01-01 09:00:00
1	2	JFK	2023	1	1	1	NaN	NaN	NaN	190.0	4,60312	5,2971784336	NaN	NaN	2,5	2023-01-01 10:00:00
2	3	JFK	2023	1	1	2	NaN	NaN	NaN	190.0	5,7539	6,621473042	NaN	NaN	0,25	2023-01-01 11:00:00
3	4	JFK	2023	1	1	3	NaN	NaN	NaN	250.0	5,7539	6,621473042	0,02	NaN	4	2023-01-01 12:00:00
																2023-01-

Next steps: Generate code with weather | View recommended plots | New interactive sheet

```
airports.head(10)
```

	Unnamed: 0	faa	name	lat	lon	alt	tz	dst	tzone
0	1	AAF	Apalachicola Regional Airport	29,72750092	-85,02749634	20	-5.0	A	America/New_York
1	2	AAP	Andrau Airpark	29,7224998474	-95,5883026123	79	-6.0	A	America/Chicago
2	3	ABE	Lehigh Valley International Airport	40,652099609375	-75,440803527832	393	-5.0	A	America/New_York
3	4	ABI	Abilene Regional Airport	32,4113006592	-99,6819000244	1791	-6.0	A	America/Chicago
4	5	ABL	Ambler Airport	67,1063	-157,856989	334	-9.0	A	America/Anchorage
5	6	ABQ	Albuquerque International Sunport	35,040199	-106,609001	5355	-7.0	A	America/Denver
6	7	ABR	Aberdeen Regional Airport	45,4491004943848	-98,4217987060547	1302	-6.0	A	America/Chicago
7	8	ABY	Southwest Georgia Regional Airport	31,5354995727539	-84,1945037841797	197	-5.0	A	America/New_York
8	9	ACK	Nantucket Memorial Airport	41,25310135	-70,06020355	47	-5.0	A	America/New_York
9	10	ACT	Waco Regional Airport	31,6112995147705	-97,2304992675781	516	-6.0	A	America/Chicago

Next steps: Generate code with `airports` View recommended plots New interactive sheet

```
planes.head(10)
```

	Unnamed: 0	tailnum	year	type	manufacturer	model	engines	seats	speed	engine
0	1	N101DQ	2020.0	Fixed wing multi engine	AIRBUS	A321-211	2	199	0	Turbo-fan
1	2	N101DU	2018.0	Fixed wing multi engine	C SERIES AIRCRAFT LTD PTNRSP	BD-500-1A10	2	133	0	Turbo-fan
2	3	N101HQ	2007.0	Fixed wing multi engine	EMBRAER-EMPRESA BRASILEIRA DE	ERJ 170-200 LR	2	80	0	Turbo-fan
3	4	N101NN	2013.0	Fixed wing multi engine	AIRBUS INDUSTRIE	A321-231	2	379	0	Turbo-fan
4	5	N102DN	2020.0	Fixed wing multi engine	AIRBUS	A321-211	2	199	0	Turbo-fan
5	6	N102DU	NaN	Fixed wing multi engine	C SERIES AIRCRAFT LTD PTNRSP	BD-500-1A10	2	133	0	Turbo-fan

Next steps: Generate code with `planes` View recommended plots New interactive sheet

```
airlines.head(10)
```

	Unnamed: 0	carrier	name
0	1	9E	Endeavor Air Inc.
1	2	AA	American Airlines Inc.
2	3	AS	Alaska Airlines Inc.
3	4	B6	JetBlue Airways
4	5	DL	Delta Air Lines Inc.
5	6	F9	Frontier Airlines Inc.
6	7	G4	Allegiant Air
7	8	HA	Hawaiian Airlines Inc.
8	9	MQ	Envoy Air
9	10	NK	Spirit Air Lines

Next steps: Generate code with `airlines` View recommended plots New interactive sheet

Data Preprocessing

Now, let's take a closer look at our dataset and explore the shape, variables along with their types. Additionally, we will assess whether any data cleaning is necessary, such as removing null or missing values, dropping unnecessary columns, and considering changes to the data types of variables if needed.

```
flights.shape
```

```
(435352, 20)
```

```
flights.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 435352 entries, 0 to 435351
Data columns (total 20 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   Unnamed: 0      435352 non-null  int64  
 1   year            435352 non-null  int64  
 2   month           435352 non-null  int64  
 3   day             435352 non-null  int64  
 4   dep_time        424614 non-null  float64
 5   sched_dep_time  435352 non-null  int64  
 6   dep_delay       424614 non-null  float64
 7   arr_time        423899 non-null  float64
 8   sched_arr_time  435352 non-null  int64  
 9   arr_delay       422818 non-null  float64
 10  carrier         435352 non-null  object 
 11  flight          435352 non-null  int64  
 12  tailnum         433439 non-null  object 
 13  origin          435352 non-null  object 
 14  dest            435352 non-null  object 
 15  air_time        422818 non-null  float64
 16  distance        435352 non-null  int64  
 17  hour            435352 non-null  int64  
 18  minute          435352 non-null  int64  
 19  time_hour       435352 non-null  object 
dtypes: float64(5), int64(10), object(5)
memory usage: 66.4+ MB
```

```
weather.shape
```

```
(26204, 16)
```

```
weather.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26204 entries, 0 to 26203
Data columns (total 16 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Unnamed: 0  26204 non-null  int64  
 1   origin      26204 non-null  object 
 2   year        26204 non-null  int64  
 3   month       26204 non-null  int64  
 4   day         26204 non-null  int64  
 5   hour        26204 non-null  int64  
 6   temp        668 non-null    object 
 7   dewp        668 non-null    object 
 8   humid       668 non-null    object 
 9   wind_dir    24984 non-null  float64
 10  wind_speed  25171 non-null  object 
 11  wind_gust   25171 non-null  object 
 12  precip      1593 non-null   object 
 13  pressure    572 non-null    object 
 14  visib       26180 non-null  object 
 15  time_hour   26204 non-null  object 
dtypes: float64(1), int64(5), object(10)
memory usage: 3.2+ MB
```

```
airports.shape
```

```
(1251, 9)
```

```
airports.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1251 entries, 0 to 1250
Data columns (total 9 columns):
```

```
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Unnamed: 0  1251 non-null   int64  
 1   faa         1251 non-null   object 
 2   name        1251 non-null   object 
 3   lat         1251 non-null   object 
 4   lon         1251 non-null   object 
 5   alt         1251 non-null   int64  
 6   tz          1203 non-null   float64
 7   dst         1203 non-null   object 
 8   tzone       1132 non-null   object 
dtypes: float64(1), int64(2), object(6)
memory usage: 88.1+ KB
```

```
planes.shape
```

```
(4840, 10)
```

```
planes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4840 entries, 0 to 4839
Data columns (total 10 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Unnamed: 0    4840 non-null   int64  
 1   tailnum       4840 non-null   object 
 2   year          4751 non-null   float64
 3   type          4840 non-null   object 
 4   manufacturer  4840 non-null   object 
 5   model         4840 non-null   object 
 6   engines       4840 non-null   int64  
 7   seats         4840 non-null   int64  
 8   speed         4840 non-null   int64  
 9   engine        4840 non-null   object 
dtypes: float64(1), int64(4), object(5)
memory usage: 378.2+ KB
```

```
airlines.shape
```

```
(14, 3)
```

```
airlines.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14 entries, 0 to 13
Data columns (total 3 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   Unnamed: 0  14 non-null     int64 
 1   carrier     14 non-null     object
 2   name        14 non-null     object
dtypes: int64(1), object(2)
memory usage: 464.0+ bytes
```

NOTE: We have several types of variables, ranging from integers, objects, and floats.

```
# We would like to see a descriptive analysis of my dataset. For this We use a describe function.

flights.describe()
```

	Unnamed: 0	year	month	day	dep_time	sched_dep_time	dep_delay	arr_time	sched_arr_time
count	435352.000000	435352.0	435352.000000	435352.000000	424614.000000	435352.000000	424614.000000	423899.000000	435352.000000
mean	217676.500000	2023.0	6.422713	15.736475	1365.698738	1363.634668	13.837372	1496.509204	1551.548744
std	125675.441533	0.0	3.414399	8.767280	498.044482	478.278174	54.313852	550.498310	513.311580
min	1.000000	2023.0	1.000000	1.000000	1.000000	500.000000	-50.000000	1.000000	1.000000
25%	108838.750000	2023.0	3.000000	8.000000	931.000000	930.000000	-6.000000	1105.000000	1135.000000
50%	217676.500000	2023.0	6.000000	16.000000	1357.000000	1359.000000	-2.000000	1519.000000	1551.000000
75%	326514.250000	2023.0	9.000000	23.000000	1804.000000	1759.000000	10.000000	1946.000000	2007.000000
max	435352.000000	2023.0	12.000000	31.000000	2400.000000	2359.000000	1813.000000	2400.000000	2359.000000

We observed a wide range of flight distances and durations, suggesting diverse route types. The delay statistics indicate that while most flights experience some delay, there's significant variability, with some extreme cases of long delays. The presence of missing values in departure and arrival times suggests potential cancellations or data recording issues that will need further investigation. The distribution of scheduled departure times across the day provides insights into peak flying hours.

```
weather.describe()
```

	Unnamed: 0	year	month	day	hour	wind_dir
count	26204.000000	26204.0	26204.000000	26204.000000	26204.000000	24984.000000
mean	13102.500000	2023.0	6.511449	15.679515	11.501336	188.123199
std	7564.587563	0.0	3.440720	8.772079	6.921984	111.752334
min	1.000000	2023.0	1.000000	1.000000	0.000000	0.000000
25%	6551.750000	2023.0	4.000000	8.000000	6.000000	80.000000
50%	13102.500000	2023.0	7.000000	16.000000	12.000000	200.000000
75%	19653.250000	2023.0	10.000000	23.000000	18.000000	290.000000
max	26204.000000	2023.0	12.000000	31.000000	23.000000	360.000000

The data covers all months, days, and hours, providing a thorough representation of weather conditions. The wind direction data, while mostly complete, has some missing values that may require attention in further analysis. The distribution of wind directions, with a mean around 188 degrees (roughly south-southwest), could be indicative of prevailing wind patterns at the airports. This weather data will be crucial in analyzing how meteorological conditions correlate with flight delays and cancellations, potentially offering valuable insights for predictive modeling.

```
airports.describe()
```

	Unnamed: 0	alt	tz
count	1251.000000	1251.000000	1203.000000
mean	626.000000	1121.992006	-6.501247
std	361.276902	1602.521826	1.585277
min	1.000000	-115.000000	-10.000000
25%	313.500000	96.000000	-8.000000
50%	626.000000	551.000000	-6.000000
75%	938.500000	1226.000000	-5.000000
max	1251.000000	9070.000000	8.000000

The wide altitude range suggests the dataset includes airports from various geographical settings, from coastal areas to mountainous regions. The time zone distribution indicates a focus on airports in the Western Hemisphere, particularly in North America. The presence of some missing time zone data might require attention in further analysis. This airport data will be valuable in understanding how geographical and time zone factors might influence flight operations, delays, and cancellations when combined with the flight and weather datasets.

```
planes.describe()
```

	Unnamed: 0	year	engines	seats	speed
count	4840.000000	4751.000000	4840.000000	4840.000000	4840.0
mean	2420.500000	2010.158072	2.000413	189.839050	0.0
std	1397.331982	8.370654	0.028748	92.697687	0.0
min	1.000000	1990.000000	1.000000	4.000000	0.0
25%	1210.750000	2002.000000	2.000000	140.000000	0.0
50%	2420.500000	2012.000000	2.000000	182.000000	0.0
75%	3630.250000	2017.000000	2.000000	200.000000	0.0
max	4840.000000	2023.000000	3.000000	563.000000	0.0

The aircraft age distribution suggests regular fleet updates. The consistent zero value for speed is anomalous and may require further investigation or data correction. This planes data will be crucial in analyzing how aircraft characteristics might influence flight performance, potentially offering insights into factors affecting delays or cancellations when combined with the flight data.

```
airlines.describe()
```

	Unnamed: 0
count	14.0000
mean	7.5000
std	4.1833
min	1.0000
25%	4.2500
50%	7.5000
75%	10.7500
max	14.0000

It has just a column, hence the brief description

Checking Datasets for missing values

Checking Flights Dataset for missing values

```
flights.isnull()
```

	Unnamed: 0	year	month	day	dep_time	sched_dep_time	dep_delay	arr_time	sched_arr_time	arr_delay	carrier	flight	tailnum
0	False	False	False	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...	...	...	...
435347	False	False	False	False	False	False	False	False	False	False	False	False	False
435348	False	False	False	False	False	False	False	False	False	False	False	False	False
435349	False	False	False	False	False	False	False	False	False	False	False	False	False
435350	False	False	False	False	False	False	False	False	False	False	False	False	False
435351	False	False	False	False	False	False	False	False	False	False	False	False	False

435352 rows × 20 columns

```
print(flights.isnull().sum())
```

```
Unnamed: 0           0
year                 0
month                0
day                  0
dep_time         10738
sched_dep_time       0
dep_delay        10738
arr_time         11453
sched_arr_time       0
arr_delay        12534
carrier              0
flight               0
tailnum           1913
origin               0
dest                 0
air_time         12534
distance             0
hour                 0
minute               0
time_hour            0
dtype: int64
```

```
# Replace missing dep_time and arr_time with 0
flights['dep_time'] = flights['dep_time'].fillna(0)
flights['arr_time'] = flights['arr_time'].fillna(0)

# Create Flight Status column
flights['Flight_Status'] = np.where((flights['dep_time'] == 0) & (flights['arr_time'] == 0), 'Cancelled',
                                    np.where((flights['dep_delay'] > 15) | (flights['arr_delay'] > 15), 'Delayed', 'On Time'))

# Handle dep_delay and arr_delay
flights['dep_delay'] = flights['dep_delay'].fillna(0)
flights['arr_delay'] = flights['arr_delay'].fillna(0)

# Impute missing air_time values
median_air_time = flights.groupby(['origin', 'dest'])['air_time'].transform('median')
flights['air_time'] = flights['air_time'].fillna(median_air_time)

# If there are still missing air_time values, fill with overall median
overall_median_air_time = flights['air_time'].median()
flights['air_time'] = flights['air_time'].fillna(overall_median_air_time)

# Handle missing tailnum
flights['tailnum'] = flights['tailnum'].fillna('Unknown')

# Reset index after processing
flights = flights.reset_index(drop=True)



# Verify the results
print(flights.isnull().sum())
```

```
Unnamed: 0       0
year             0
month            0
day              0
dep_time         0
sched_dep_time   0
dep_delay        0
arr_time         0
sched_arr_time   0
arr_delay        0
carrier          0
flight           0
tailnum          0
origin           0
dest             0
air_time         0
distance         0
hour             0
minute           0
time_hour        0
Flight_Status    0
dtype: int64
```

```
flights.shape
```

(435352, 21)

```
flights.head(10)
```

	Unnamed: 0	year	month	day	dep_time	sched_dep_time	dep_delay	arr_time	sched_arr_time	arr_delay	carrier	flight	tailnum	origin
0	1	2023	1	1	1.0	2038	203.0	328.0	3	205.0	UA	628	N25201	EWR
1	2	2023	1	1	18.0	2300	78.0	228.0	135	53.0	DL	393	N830DN	JFK
2	3	2023	1	1	31.0	2344	47.0	500.0	426	34.0	B6	371	N807JB	JFK
3	4	2023	1	1	33.0	2140	173.0	238.0	2352	166.0	B6	1053	N265JB	JFK
4	5	2023	1	1	36.0	2048	228.0	223.0	2252	211.0	UA	219	N17730	EWR
5	6	2023	1	1	503.0	500	3.0	808.0	815	-7.0	AA	499	N925AN	EWR
6	7	2023	1	1	520.0	510	10.0	948.0	949	-1.0	B6	996	N2043J	JFK
7	8	2023	1	1	524.0	530	-6.0	645.0	710	-25.0	AA	981	N918AN	EWR
8	9	2023	1	1	537.0	520	17.0	926.0	818	68.0	UA	206	N13113	EWR
9	10	2023	1	1	547.0	545	2.0	845.0	852	-7.0	NK	225	N912NK	EWR

Checking Weather Dataset for missing values

```
weather.isnull()
```

	Unnamed: 0	origin	year	month	day	hour	temp	dewp	humid	wind_dir	wind_speed	wind_gust	precip	pressure	visib	time_hour
0	False	False	False	False	False	False	True	True	True	False	False	False	True	True	False	False
1	False	False	False	False	False	False	True	True	True	False	False	False	True	True	False	False
2	False	False	False	False	False	False	True	True	True	False	False	False	True	True	False	False
3	False	False	False	False	False	False	True	True	True	False	False	False	False	True	False	False
4	False	False	False	False	False	False	True	True	True	False	False	False	True	True	False	False
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
26199	False	False	False	False	False	False	True	True	True	False	False	False	True	True	False	False
26200	False	False	False	False	False	False	True	True	True	False	False	False	True	True	False	False
26201	False	False	False	False	False	False	True	True	True	False	False	False	True	True	False	False
26202	False	False	False	False	False	False	True	True	True	False	False	False	True	True	False	False
26203	False	False	False	False	False	False	True	True	True	False	False	False	True	True	False	False

```
print(weather.isnull().sum())
```

```
Unnamed: 0        0
origin            0
year              0
month             0
day               0
hour              0
temp          25536
dewp          25536
humid         25536
wind_dir       1220
wind_speed     1033
wind_gust      1033
precip        24611
pressure      25632
visib            24
time_hour         0
dtype: int64
```

```
# Convert 'time_hour' to datetime, handling inconsistent formats
weather['time_hour'] = pd.to_datetime(weather['time_hour'], format='mixed', errors='coerce')

# Ensure continuous columns are numeric
continuous_columns = ['temp', 'dewp', 'humid', 'precip', 'pressure', 'visib']
for col in continuous_columns:
    weather[col] = pd.to_numeric(weather[col], errors='coerce')

# Set 'time_hour' as the index for time-based interpolation
weather = weather.set_index('time_hour')

# Temporal Interpolation for continuous variables
for col in ['temp', 'dewp', 'humid', 'precip', 'pressure']:
    weather[col] = weather[col].interpolate(method='time')

# Reset the index back to the original form
weather = weather.reset_index()

# Forward and Backward Fill for wind-related variables
for col in ['wind_dir', 'wind_speed', 'wind_gust']:
    weather[col] = weather[col].ffill().bfill()

# Mean Imputation for visibility
weather['visib'] = weather['visib'].fillna(weather['visib'].mean())

# Print final missing value counts
print("\nFinal missing value counts:")
print(weather.isnull().sum())
```

```
Final missing value counts:
time_hour        0
Unnamed: 0       0
origin           0
year             0
month            0
day              0
hour             0
temp           390
dewp           393
humid          608
wind_dir         0
wind_speed       0
wind_gust        0
precip         390
pressure      1924
visib            0
dtype: int64
```

1. **Convert 'time_hour' to Datetime**: This ensures the 'time_hour' column is in a proper datetime format, facilitating time-based operations and interpolation.
2. **Ensure Numeric Data Types**: The specified continuous columns (temperature, dew point, humidity, precipitation, pressure, visibility) are converted to numeric types, with non-numeric values set to NaN, which is crucial for mathematical operations.
3. **Set 'time_hour' as Index**: By setting 'time_hour' as the index, the dataset can utilize time-based interpolation methods effectively.

4. **Temporal Interpolation**: Missing values in continuous variables are filled using time-based interpolation, which is appropriate for weather data due to its temporal nature.
5. **Reset Index**: The index is reset to bring 'time_hour' back as a regular column after interpolation.
6. **Forward and Backward Fill**: For wind-related variables, missing values are filled using forward fill (last known value) and backward fill (next known value), which suits the discrete nature of these measurements.
7. **Mean Imputation for Visibility**: Remaining missing visibility values are filled with the mean of the column, appropriate given the relatively low number of missing entries.

Based on the above, we still have missing values. Hence, further cleaning.

```
# Convert 'time_hour' to datetime, handling inconsistent formats
weather['time_hour'] = pd.to_datetime(weather['time_hour'], errors='coerce')

# Ensure continuous columns are numeric
continuous_columns = ['temp', 'dewp', 'humid', 'precip', 'pressure', 'visib']
for col in continuous_columns:
    weather[col] = pd.to_numeric(weather[col], errors='coerce')

# Set 'time_hour' as the index for time-based operations
weather = weather.set_index('time_hour')

# Calculate humidity from temp and dewp where possible
def calculate_humidity(temp, dewp):
    return 100 * (np.exp((17.625 * dewp) / (243.04 + dewp)) / np.exp((17.625 * temp) / (243.04 + temp)))

weather['humid'] = weather.apply(
    lambda row: calculate_humidity(row['temp'], row['dewp'])
    if pd.notnull(row['temp']) and pd.notnull(row['dewp']) else row['humid'],
    axis=1
)

# Temporal Interpolation for continuous variables
for col in ['temp', 'dewp', 'humid', 'precip', 'pressure']:
    weather[col] = weather[col].interpolate(method='time')

# Use rolling mean for pressure (24-hour window)
weather['pressure'] = weather['pressure'].rolling(window=24, center=True, min_periods=1).mean()

# Forward and Backward Fill for wind-related variables
for col in ['wind_dir', 'wind_speed', 'wind_gust']:
    weather[col] = weather[col].ffill().bfill()

# Mean Imputation for visibility
weather['visib'] = weather['visib'].fillna(weather['visib'].mean())

# Final interpolation to catch any remaining NaNs
weather = weather.interpolate(method='time', limit_direction='both')

# Reset the index back to the original form
weather = weather.reset_index()

# Print final missing value counts
print("\nFinal missing value counts:")
print(weather.isnull().sum())
```

```
Final missing value counts:
time_hour     0
Unnamed: 0    0
origin        0
year          0
month         0
day           0
hour          0
temp          0
dewp          0
humid         0
wind_dir      0
wind_speed    0
wind_gust     0
precip        0
pressure      0
visib         0
```

```
dtype: int64
<ipython-input-37-b75ccf62fced>:37: FutureWarning: DataFrame.interpolate with object dtype is deprecated and will raise in a future vers
  weather = weather.interpolate(method='time', limit_direction='both')
```

For further cleaning, we did the following:

---

1. **Convert `'time_hour'` to Datetime**

The `time_hour` column is converted to a datetime format using `pd.to_datetime`. Any invalid or unparseable dates are replaced with `NaT` (Not a Time) due to `errors='coerce'`. Time-based operations (like interpolation or rolling means) require the data to have a valid `DatetimeIndex` or datetime column. Handling inconsistent formats ensures that further operations do not fail.

---

2. **Ensure Continuous Columns are Numeric**

Non-numeric values (e.g., strings or errors) in the specified continuous columns are converted to `NaN` using `errors='coerce'`. Continuous variables like temperature, pressure, or visibility need to be numeric for mathematical operations such as interpolation, imputation, and rolling calculations. Ensuring numeric types avoids type-related errors.

---

3. **Set `time_hour` as the Index**

The `time_hour` column is set as the index of the DataFrame. Time-based operations (like `interpolate(method='time')` and `rolling`) require a `DatetimeIndex`. This step enables the proper execution of those methods.

---

4. **Calculate Humidity from Temp and Dewpoint**

Humidity is recalculated using temperature (`temp`) and dewpoint (`dewp`) where both values are present. If either value is missing, the original `humid` value is retained. Humidity is derived from the relationship between temperature and dewpoint. This recalculation ensures consistency and fills gaps where possible.

---

5. **Temporal Interpolation for Continuous Variables**

Missing values in continuous columns are filled using **time-weighted interpolation**. Time-based interpolation considers the datetime index and ensures missing values are filled smoothly by looking at adjacent timestamps.

---

6. **Rolling Mean for Pressure (24-Hour Window)**

A rolling mean with a 24-hour window is applied to the `pressure` column. The `center=True` option centers the window around each row. The rolling mean smooths out short-term fluctuations in `pressure` while retaining the overall trend. This is useful for reducing noise in the data.

---

7. **Forward and Backward Fill for Wind-Related Variables**

Missing values in wind-related columns are filled using **forward fill (ffill)** and **backward fill (bfill)**. Wind-related variables may have missing values that are more consistent over short time spans. Forward and backward filling ensures gaps are filled without drastic changes.

---

8. **Mean Imputation for Visibility**

Missing values in `visib` (visibility) are replaced with the column mean. Mean imputation is a simple and effective method for filling missing data when values are randomly missing and no time-based interpolation is needed.

---

9. **Final Temporal Interpolation**

A final time-based interpolation is performed to ensure no `NaN` values remain in the dataset. This step ensures that any remaining gaps (after earlier operations) are filled using time-weighted interpolation.

---

10. **Reset Index**

The `DatetimeIndex` (`time_hour`) is reset back as a regular column. After time-based operations are complete, restoring the original structure makes the dataset easier to work with.

Checking Planes Dataset for missing values

```
planes.isnull()
```

	Unnamed: 0	tailnum	year	type	manufacturer	model	engines	seats	speed	engine
0	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...
4835	False	False	False	False	False	False	False	False	False	False
4836	False	False	False	False	False	False	False	False	False	False
4837	False	False	False	False	False	False	False	False	False	False
4838	False	False	False	False	False	False	False	False	False	False
4839	False	False	False	False	False	False	False	False	False	False

4840 rows × 10 columns

```
print(planes.isnull().sum())
```

```
Unnamed: 0      0
tailnum         0
year           89
type            0
manufacturer    0
model           0
engines         0
seats           0
speed           0
engine          0
dtype: int64
```

From the above, we can see that just the year column has some missing values, hence we shall replace with the mean value of the year.

```
mean_year = planes['year'].mean()
planes['year'] = planes['year'].fillna(value=mean_year)
```

```
print("\nMissing values after handling:")
print(planes.isnull().sum())
```

```

Missing values after handling:
Unnamed: 0      0
tailnum         0
year            0
type            0
manufacturer    0
model           0
engines         0
seats           0
speed           0
engine          0
dtype: int64
```

Now, we have no missing value

Checking Airlines Dataset for Missing Values

```
airlines.isnull()
```

	Unnamed: 0	carrier	name
0	False	False	False
1	False	False	False
2	False	False	False
3	False	False	False
4	False	False	False
5	False	False	False
6	False	False	False
7	False	False	False
8	False	False	False
9	False	False	False
10	False	False	False
11	False	False	False
12	False	False	False
13	False	False	False

```
print(airlines.isnull().sum())
```

```
Unnamed: 0    0
carrier       0
name          0
dtype: int64
```

Here, we have no missing values

Checking Missing Values for Airport Dataset

```
airports.isnull()
```

	Unnamed: 0	faa	name	lat	lon	alt	tz	dst	tzone
0	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...
1246	False	False	False	False	False	False	False	False	False
1247	False	False	False	False	False	False	False	False	False
1248	False	False	False	False	False	False	False	False	False
1249	False	False	False	False	False	False	False	False	False
1250	False	False	False	False	False	False	True	True	True

1251 rows × 9 columns

```
print(airports.isnull().sum())
```

```
Unnamed: 0      0
faa             0
name            0
lat             0
lon             0
alt             0
tz             48
dst            48
tzone         119
dtype: int64
```

```
!pip install timezonefinder
```

```
Collecting timezonefinder
  Downloading timezonefinder-6.5.7-cp310-cp310-manylinux_2_17_x86_64.manylinux_2_5_x86_64.manylinux1_x86_64.manylinux2014_x86_64.whl.met
Requirement already satisfied: cffi<2,>=1.15.1 in /usr/local/lib/python3.10/dist-packages (from timezonefinder) (1.17.1)
Collecting h3>4 (from timezonefinder)
  Downloading h3-4.1.2-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (18 kB)
Requirement already satisfied: numpy<3,>=1.23 in /usr/local/lib/python3.10/dist-packages (from timezonefinder) (1.26.4)
Requirement already satisfied: pycparser in /usr/local/lib/python3.10/dist-packages (from cffi<2,>=1.15.1->timezonefinder) (2.22)
Downloading timezonefinder-6.5.7-cp310-cp310-manylinux_2_17_x86_64.manylinux_2_5_x86_64.manylinux1_x86_64.manylinux2014_x86_64.whl (50.7
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 50.7/50.7 MB 18.2 MB/s eta 0:00:00
Downloading h3-4.1.2-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (993 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 993.5/993.5 kB 49.7 MB/s eta 0:00:00
Installing collected packages: h3, timezonefinder
Successfully installed h3-4.1.2 timezonefinder-6.5.7
```

```
import pandas as pd
from timezonefinder import TimezoneFinder

# Convert 'lat' and 'lon' to strings, replace commas with dots
airports['lat'] = airports['lat'].astype(str).str.replace(',', '.', regex=False)
airports['lon'] = airports['lon'].astype(str).str.replace(',', '.', regex=False)

# Convert 'lat' and 'lon' back to numeric
airports['lat'] = pd.to_numeric(airports['lat'], errors='coerce')
airports['lon'] = pd.to_numeric(airports['lon'], errors='coerce')


# Function to get timezone info based on lat/lon
def get_timezone_info(lat, lon):
    tf = TimezoneFinder()
    if pd.notnull(lat) and pd.notnull(lon):
        timezone_str = tf.timezone_at(lat=lat, lng=lon)
        if timezone_str:
            tz = pd.Timestamp.now(tz=timezone_str).utcoffset().total_seconds() / 3600
            dst = 'Y' if abs(tz) != int(abs(tz)) else 'N'
            return tz, dst, timezone_str
    return None, None, None

# Fill missing values for 'tz' and 'dst'
for index, row in airports[airports['tz'].isnull()].iterrows():
    tz, dst, tzone = get_timezone_info(row['lat'], row['lon'])
    if tz is not None:
        airports.loc[index, 'tz'] = tz  # Use loc to avoid FutureWarning
        airports.loc[index, 'dst'] = dst

# Fill any remaining NaNs with mode values
airports.loc[:, 'tz'] = airports['tz'].fillna(airports['tz'].mode()[0])
airports.loc[:, 'dst'] = airports['dst'].fillna(airports['dst'].mode()[0])
airports.loc[:, 'tzone'] = airports['tzone'].fillna(airports['tzone'].mode()[0])

# Print final missing value counts
print(airports.isnull().sum())
```

```
Unnamed: 0    0
faa           0
name          0
lat           0
lon           0
alt           0
tz            0
dst           0
tzone         0
dtype: int64
```

What we did:

1. **Replace Commas in `lat` and `lon`:**
   - The `lat` and `lon` columns are converted to strings, and commas (`','`) are replaced with dots (`'.'`) to standardize decimal formatting.
   - The columns are then converted back to numeric using `pd.to_numeric`, replacing invalid values with `NaN` using `errors='coerce'`.
2. **Define `get_timezone_info` Function:**

- Takes `lat` and `lon` as inputs.
- Uses the `TimezoneFinder` library to find the timezone.
- Calculates the offset (`tz`) and checks for daylight saving time (`dst`).

3. **Fill Missing `tz` and `dst`:**
   - Iterates through rows where `tz` is missing.
   - Uses `get_timezone_info` to compute and update `tz` and `dst` values.
4. **Handle Remaining Missing Values:**
   - Any remaining `NaN` values in `tz`, `dst`, and `tzone` are filled with the **mode** (most common value) of their respective columns.
5. **Output Missing Value Summary:**
   - Prints the count of missing values after the cleaning and filling process.

Hence, no missing values anymore

Removing Duplicates

```
flights.drop_duplicates(inplace=True)
weather.drop_duplicates(inplace=True)
planes.drop_duplicates(inplace=True)
airports.drop_duplicates(inplace=True)
airlines.drop_duplicates(inplace=True)
```

Verifying Cleaned Datasets

```
# Verify cleaned datasets
print("Flights dataset after cleaning:", flights.shape)
print("Weather dataset after cleaning:", weather.shape)
print("Planes dataset after cleaning:", planes.shape)
print("Airports dataset after cleaning:", airports.shape)
print("Airlines dataset after cleaning:", airlines.shape)
```

```
Flights dataset after cleaning: (435352, 21)
Weather dataset after cleaning: (26204, 16)
Planes dataset after cleaning: (4840, 10)
Airports dataset after cleaning: (1251, 9)
Airlines dataset after cleaning: (14, 3)
```

Merge Datasets for Analysis

```
# Clean column names by stripping whitespace and removing unwanted characters
flights.columns = flights.columns.str.replace(';', '').str.replace('"', '').str.strip()
planes.columns = planes.columns.str.replace(';', '').str.replace('"', '').str.strip()
airlines.columns = airlines.columns.str.replace(';', '').str.replace('"', '').str.strip()
weather.columns = weather.columns.str.replace(';', '').str.replace('"', '').str.strip()
airports.columns = airports.columns.str.replace(';', '').str.replace('"', '').str.strip()

# Check cleaned column names again
print("Cleaned Flights columns:", flights.columns)
```

```
Cleaned Flights columns: Index(['Unnamed: 0', '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', 'Flight_Status'],
      dtype='object')
```

```
# Step 1: Clean column names (remove spaces, special characters, and ensure lowercase)
def clean_columns(df):
    df.columns = df.columns.str.strip().str.lower().str.replace(r'[;"\s]', '', regex=True)
    return df

flights = clean_columns(flights)
planes = clean_columns(planes)
```

```
airlines = clean_columns(airlines)
weather = clean_columns(weather)
airports = clean_columns(airports)

# Step 2: Remove any unnamed columns (e.g., 'unnamed: 0')
for df in [flights, planes, airlines, weather, airports]:
    df.drop(columns=[col for col in df.columns if 'unnamed' in col], inplace=True, errors='ignore')

# Step 3: Convert 'time_hour' to datetime format in both DataFrames
flights['time_hour'] = pd.to_datetime(flights['time_hour'], errors='coerce')
weather['time_hour'] = pd.to_datetime(weather['time_hour'], errors='coerce')

# Step 4: Merge flights with planes on 'tailnum'
flights_planes = flights.merge(planes, on='tailnum', how='left')

flights_planes = flights.merge(planes, on='tailnum', how='left')
print(f"Shape after merging flights with planes: {flights_planes.shape}")


# Step 5: Merge with airlines on 'carrier'
flights_planes_airlines = flights_planes.merge(airlines, on='carrier', how='left')

flights_planes_airlines = flights_planes.merge(airlines, on='carrier', how='left')
print(f"Shape after merging with airlines data: {flights_planes_airlines.shape}")


# Step 6: Merge with weather using 'origin' and 'time_hour'
flights_weather = flights_planes_airlines.merge(
    weather,
    on=['origin', 'time_hour'],
    how='left'
)

flights_weather = flights_planes_airlines.merge(
    weather,
    on=['origin', 'time_hour'],
    how='left'
)
print(f"Shape after merging with weather data: {flights_weather.shape}")


# Step 7: Merge with airports dataset twice
# - First for origin airport
merged_with_origin = flights_weather.merge(
    airports,
    left_on='origin',
    right_on='faa',
    how='left',
    suffixes=('', '_origin')
)

merged_with_origin = flights_weather.merge(
    airports,
    left_on='origin',
    right_on='faa',
    how='left',
    suffixes=('', '_origin')
)
print(f"Shape after merging with origin airports: {merged_with_origin.shape}")


# - Then for destination airport
airports_dest = airports.rename(columns=lambda col: f"{col}_dest" if col != 'faa' else col)
final_merged_df = merged_with_origin.merge(
    airports_dest,
    left_on='dest',
    right_on='faa',
    how='left'
)


final_merged_df = merged_with_origin.merge(
    airports_dest,
    left_on='dest',
    right_on='faa',
    how='left'
)
print(f"Shape of the final merged DataFrame: {final_merged_df.shape}")
```

```
print(f"Shape of the final merged DataFrame: {final_merged_df.shape}")


# Step 8: Drop redundant columns
final_merged_df.drop(columns=['faa'], errors='ignore', inplace=True)
```

```
Shape after merging flights with planes: (435352, 28)
Shape after merging with airlines data: (435352, 29)
Shape after merging with weather data: (435352, 42)
Shape after merging with origin airports: (435352, 50)
Shape of the final merged DataFrame: (435352, 58)
```

```
# Missing values summary
print("\nMissing Values Summary:")
print(final_merged_df.isnull().sum())
```

```
month_x              0
day_x                0
dep_time             0
sched_dep_time       0
dep_delay            0
arr_time             0
sched_arr_time       0
arr_delay            0
carrier              0
flight               0
tailnum              0
origin               0
dest                 0
air_time             0
distance             0
hour_x               0
minute               0
time_hour            0
flight_status        0
year_y           11284
type             11284
manufacturer     11284
model            11284
engines          11284
seats            11284
speed            11284
engine           11284
name                 0
year               894
month_y            894
day_y              894
hour_y             894
temp               894
dewp               894
humid              894
wind_dir           894
wind_speed         894
wind_gust          894
precip             894
pressure           894
visib              894
faa_x                0
name_origin          0
lat                  0
lon                  0
alt                  0
tz                   0
dst                  0
tzone                0
faa_y             7484
name_dest         7484
lat_dest          7484
lon_dest          7484
alt_dest          7484
tz_dest           7484
dst_dest          7484
tzone_dest        7484
dtype: int64
```

```
final_merged_df.shape
```

```
(435352, 58)
```

```
# Function to remove commas and convert to numeric
def remove_commas_and_convert(df, columns):
    for col in columns:
        # Remove commas and convert to float
        df[col] = df[col].replace({',': ''}, regex=True)
        df[col] = pd.to_numeric(df[col], errors='coerce')  # Convert to numeric, set invalid parsing to NaN
    return df

# List of columns that may contain commas (you can adjust this based on your dataset)
columns_with_commas = ['wind_speed', 'wind_gust', 'distance', 'temp', 'precip', 'pressure', 'visib', 'lat', 'lon', 'alt']

# Apply the function to remove commas and convert to numeric
final_merged_df = remove_commas_and_convert(final_merged_df, columns_with_commas)

# Check the first few rows to verify
print(final_merged_df.head())
```

```
3           2352      166.0      B6    1053  N265JB    JFK  CHS     108.0
4           2252      211.0      UA     219  N17730    EWR  DTW      80.0

   distance  hour_x  minute           time_hour flight_status  year_y  \
0      2500      20      38 2023-01-01 20:00:00       Delayed  1999.0
1       760      23       0 2023-01-01 23:00:00       Delayed  2014.0
2      1576      23      44 2023-01-01 23:00:00       Delayed  2012.0
3       636      21      40 2023-01-01 21:00:00       Delayed  2006.0
4       488      20      48 2023-01-01 20:00:00       Delayed  1999.0

                      type manufacturer           model  engines  seats  \
0  Fixed wing multi engine       BOEING         737-824      2.0  149.0
1  Fixed wing multi engine       BOEING       737-932ER      2.0  222.0
2  Fixed wing multi engine       AIRBUS        A320-232      2.0  200.0
3  Fixed wing multi engine      EMBRAER  ERJ 190-100 IGW      2.0   20.0
4  Fixed wing multi engine       BOEING         737-724      2.0  149.0

   speed     engine                    name    year  month_y  day_y  hour_y  \
0    0.0  Turbo-fan  United Air Lines Inc.  2023.0      1.0    1.0    11.0
1    0.0  Turbo-fan   Delta Air Lines Inc.  2023.0      1.0    1.0    14.0
2    0.0  Turbo-fan        JetBlue Airways  2023.0      1.0    1.0    14.0
3    0.0  Turbo-fan        JetBlue Airways  2023.0      1.0    1.0    12.0
4    0.0  Turbo-fan  United Air Lines Inc.  2023.0      1.0    1.0    11.0

   temp  dewp      humid  wind_dir  wind_speed     wind_gust  precip  \
0  32.0  18.0  43.375308     220.0   1035702.0  1.191865e+11  0.0001
1  32.0  18.0  43.375308     230.0    805546.0  9.270062e+10  0.0001
2  32.0  18.0  43.375308     230.0    805546.0  9.270062e+10  0.0001
3  32.0  18.0  43.375308     260.0    920624.0  1.059436e+11  0.0001
4  32.0  18.0  43.375308     220.0   1035702.0  1.191865e+11  0.0001

      pressure  visib faa_x                           name_origin        lat  \
0  1028.166667    7.0   EWR  Newark Liberty International Airport  40.692501
1  1029.000000   10.0   JFK  John F Kennedy International Airport  40.639801
2  1029.000000   10.0   JFK  John F Kennedy International Airport  40.639801
3  1029.000000    8.0   JFK  John F Kennedy International Airport  40.639801
4  1028.166667    7.0   EWR  Newark Liberty International Airport  40.692501

         lon  alt   tz dst            tzone faa_y  \
0 -74.168701   18 -5.0   A  America/New_York   SMF
1 -73.778900   13 -5.0   A  America/New_York   ATL
2 -73.778900   13 -5.0   A  America/New_York   NaN
3 -73.778900   13 -5.0   A  America/New_York   CHS
4 -74.168701   18 -5.0   A  America/New_York   DTW

                                         name_dest   lat_dest    lon_dest  \
0                  Sacramento International Airport  38.695400 -121.591003
1  Hartsfield Jackson Atlanta International Airport  33.636700  -84.428101
2                                              NaN        NaN         NaN
3   Charleston Air Force Base-International Airport  32.898602  -80.040497
4         Detroit Metropolitan Wayne County Airport  42.212399  -83.353401

   alt_dest  tz_dest dst_dest           tzone_dest
0      27.0     -8.0        A  America/Los_Angeles
1    1026.0     -5.0        A     America/New_York
2       NaN      NaN      NaN                  NaN
3      46.0     -5.0        A     America/New_York
4     645.0     -5.0        A     America/New_York
```

```
# Drop NaNs or fill them with appropriate values
numeric_columns = final_merged_df.select_dtypes(include=[np.number]).columns
print(numeric_columns)
final_merged_df = final_merged_df.dropna(subset=numeric_columns)  # Drop rows with NaN in numeric columns
```

```
Index(['year_x', 'month_x', 'day_x', 'dep_time', 'sched_dep_time', 'dep_delay',
       'arr_time', 'sched_arr_time', 'arr_delay', 'flight', 'air_time',
       'distance', 'hour_x', 'minute', 'year_y', 'engines', 'seats', 'speed',
       'year', 'month_y', 'day_y', 'hour_y', 'temp', 'dewp', 'humid',
       'wind_dir', 'wind_speed', 'wind_gust', 'precip', 'pressure', 'visib',
       'lat', 'lon', 'alt', 'tz', 'lat_dest', 'lon_dest', 'alt_dest',
       'tz_dest'],
      dtype='object')
```

Identifying Outliers

Using IQR Method

The IQR method identifies outliers based on the interquartile range. Values below $Q1-1.5\times IQR$ or above $Q3+1.5\times IQR$ are considered outliers.

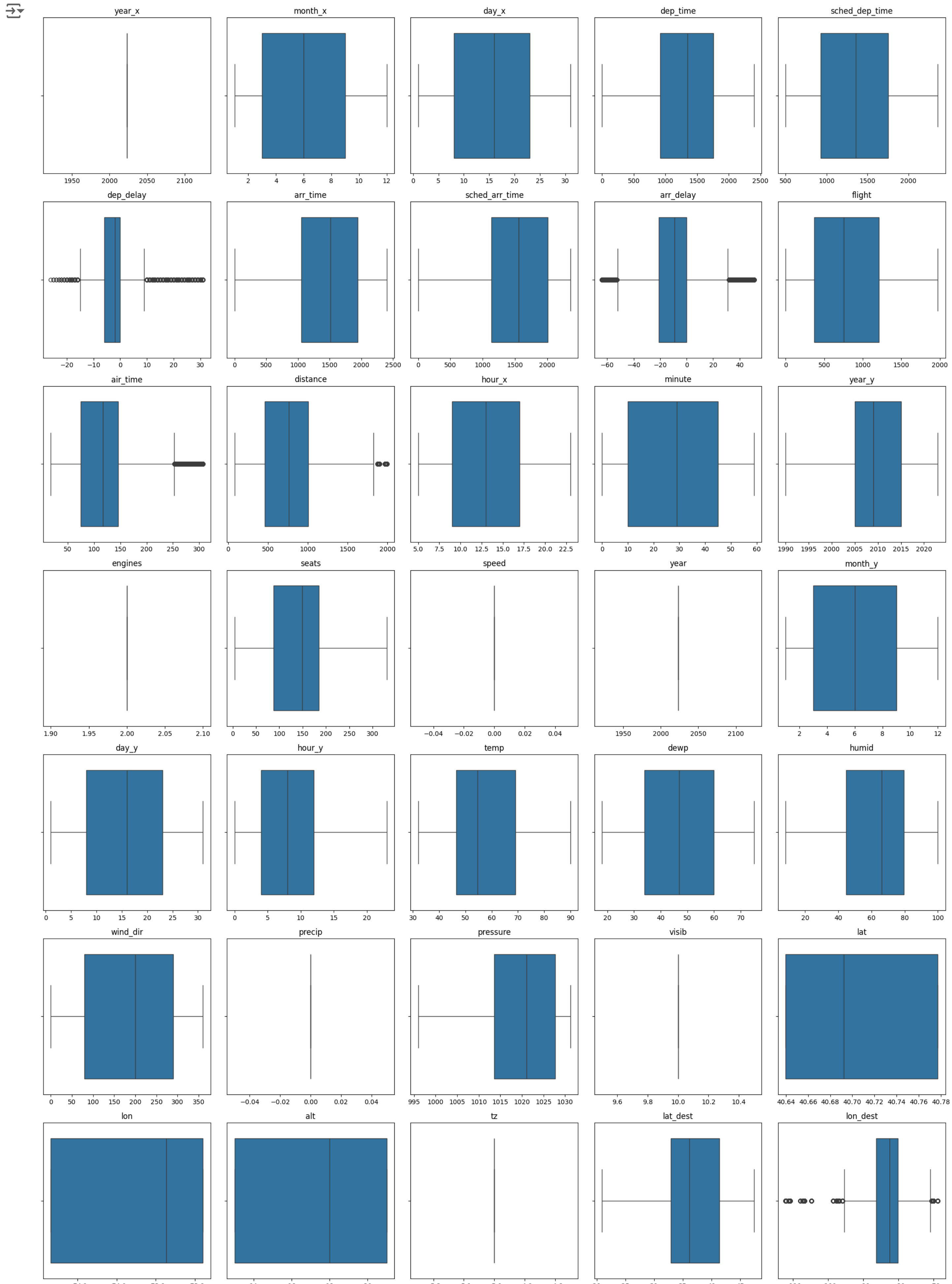
```
# IQR filtering for numeric columns
numeric_columns = final_merged_df.select_dtypes(include=[np.number]).columns

# Identify and remove outliers based on IQR
for col in numeric_columns:
    Q1 = final_merged_df[col].quantile(0.25)
    Q3 = final_merged_df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    # Replace outliers with median (alternative approach to removal)
    final_merged_df[col] = np.where(
        (final_merged_df[col] < lower_bound) | (final_merged_df[col] > upper_bound),
        final_merged_df[col].median(), final_merged_df[col]
    )

print("Remaining rows after IQR filtering:", final_merged_df.shape)
```

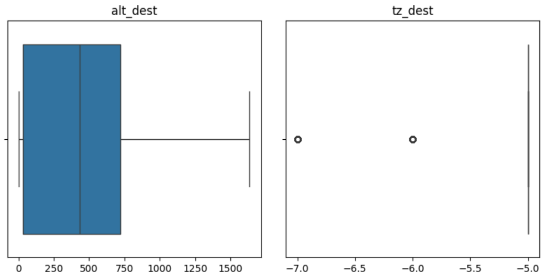
```
Remaining rows after IQR filtering: (415865, 58)
```

Visualze Outliers with Boxplot

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import math

# Specify numerical columns to visualize for outliers
numeric_columns = ['year_x', 'month_x', 'day_x', 'dep_time', 'sched_dep_time', 'dep_delay',
      'arr_time', 'sched_arr_time', 'arr_delay', 'flight', 'air_time',
      'distance', 'hour_x', 'minute', 'year_y', 'engines', 'seats', 'speed',
      'year', 'month_y', 'day_y', 'hour_y', 'temp', 'dewp', 'humid',
      'wind_dir', 'precip', 'pressure', 'visib', 'lat', 'lon', 'alt', 'tz',
      'lat_dest', 'lon_dest', 'alt_dest', 'tz_dest']

# Calculate the number of rows needed
n_cols = 5  # You can adjust this number
n_rows = math.ceil(len(numeric_columns) / n_cols)

# Set up the matplotlib figure
plt.figure(figsize=(20, 4*n_rows))

# Create box plots for each numeric column
for i, col in enumerate(numeric_columns):
   plt.subplot(n_rows, n_cols, i + 1)
   sns.boxplot(x=final_merged_df[col])
   plt.title(f'{col}')
   plt.xlabel('')
```

```
plt.tight_layout()  # Adjust layout to prevent overlap
plt.show()
```


year_x
month_x
day_x
dep_time
sched_dep_time
dep_delay
arr_time
sched_arr_time
arr_delay
flight
air_time
distance
hour_x
minute
year_y
engines
seats
speed
year
month_y
day_y
hour_y
temp
dewp
humid
wind_dir
precip
pressure
visib
lat
lon
alt
tz
lat_dest
lon_dest



Remove Outliers

```
# Ensure the columns you're working with are numeric
for col in numeric_columns:
    final_merged_df[col] = pd.to_numeric(final_merged_df[col], errors='coerce')

# Remove rows with NaN values, if any
final_merged_df = final_merged_df.dropna(subset=numeric_columns)

# Remove outliers based on IQR method
for col in numeric_columns:
    Q1 = final_merged_df[col].quantile(0.25)
    Q3 = final_merged_df[col].quantile(0.75)
    IQR = Q3 - Q1
    final_merged_df = final_merged_df[~((final_merged_df[col] < (Q1 - 1.5 * IQR)) | (final_merged_df[col] > (Q3 + 1.5 * IQR)))]
```

```
final_merged_df.shape
```

```
(248111, 58)
```

```
# Define columns to drop based on redundancy and missing values
columns_to_drop = [
    'year_y',
    'month_y',
    'day_y',
    'hour_y',
    'name_origin',
    'name_dest', 'faa_x', 'faa_y', 'type', 'engine', 'engines', 'speed', 'dst_dest', 'time_hour', 'year'
]

# Drop columns from the final merged DataFrame
final_merged_df.drop(columns=columns_to_drop, errors='ignore', inplace=True)

# Check the remaining columns after dropping
print("\nRemaining Columns after Dropping:")
print(final_merged_df.columns)

# Optional: Check for missing values again after dropping
print("\nMissing Values Summary after Dropping:")
print(final_merged_df.isnull().sum())
```

```
       'tailnum', 'origin', 'dest', 'air_time', 'distance', 'hour_x', 'minute',
       'flight_status', 'manufacturer', 'model', 'seats', 'name', 'temp',
       'dewp', 'humid', 'wind_dir', 'wind_speed', 'wind_gust', 'precip',
       'pressure', 'visib', 'lat', 'lon', 'alt', 'tz', 'dst', 'tzone',
       'lat_dest', 'lon_dest', 'alt_dest', 'tz_dest', 'tzone_dest'],
      dtype='object')

Missing Values Summary after Dropping:
year_x            0
month_x           0
day_x             0
dep_time          0
sched_dep_time    0
dep_delay         0
arr_time          0
sched_arr_time    0
arr_delay         0
carrier           0
flight            0
tailnum           0
origin            0
dest              0
air_time          0
distance          0
hour_x            0
minute            0
flight_status     0
manufacturer      0
model             0
seats             0
name              0
temp              0
dewp              0
humid             0
wind_dir          0
wind_speed        0
wind_gust         0
precip            0
pressure          0
visib             0
lat               0
lon               0
alt               0
tz                0
dst               0
tzone             0
lat_dest          0
lon_dest          0
alt_dest          0
tz_dest           0
tzone_dest        0
dtype: int64
<ipython-input-61-4a3ec756ad56>:12: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a
  final_merged_df.drop(columns=columns_to_drop, errors='ignore', inplace=True)
```

```
final_merged_df.head(10)
```

	year_x	month_x	day_x	dep_time	sched_dep_time	dep_delay	arr_time	sched_arr_time	arr_delay	carrier	flight	tailnum	origin
0	2023.0	1.0	1.0	1.0	2038.0	-2.0	328.0	3.0	-9.0	UA	628.0	N25201	EWR
1	2023.0	1.0	1.0	18.0	2300.0	-2.0	228.0	135.0	-9.0	DL	393.0	N830DN	JFK
3	2023.0	1.0	1.0	33.0	2140.0	-2.0	238.0	2352.0	-9.0	B6	1053.0	N265JB	JFK
4	2023.0	1.0	1.0	36.0	2048.0	-2.0	223.0	2252.0	-9.0	UA	219.0	N17730	EWR
143	2023.0	1.0	1.0	851.0	900.0	-9.0	1142.0	1217.0	-35.0	B6	586.0	N323JB	LGA
146	2023.0	1.0	1.0	853.0	900.0	-7.0	1206.0	1229.0	-23.0	B6	855.0	N828JB	JFK
149	2023.0	1.0	1.0	854.0	900.0	-6.0	1240.0	1248.0	-8.0	AS	12.0	N431AS	JFK
151	2023.0	1.0	1.0	855.0	900.0	-5.0	1256.0	1310.0	-14.0	AA	55.0	N108NN	JFK
153	2023.0	1.0	1.0	855.0	900.0	-5.0	1200.0	1233.0	-33.0	AA	881.0	N316RK	LGA
156	2023.0	1.0	1.0	859.0	900.0	-1.0	1100.0	1121.0	-21.0	9E	1409.0	N336PQ	JFK

```python
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

# Select numerical columns
numerical_columns = final_merged_df.select_dtypes(include=[np.number]).columns

# Plot histograms for all numerical columns
plt.figure(figsize=(20, 15))  # Adjust figure size to fit multiple plots
for i, col in enumerate(numerical_columns):
   plt.subplot((len(numerical_columns) + 3) // 4, 4, i + 1)  # Arrange subplots in rows and columns
   sns.histplot(final_merged_df[col], kde=False, bins=30, color="skyblue", edgecolor="black")
   plt.title(f"Histogram of {col}")
   plt.xlabel(col)
   plt.ylabel("Frequency")

plt.tight_layout()
plt.show()
```

Boxplot for arrival delays by airline

Purpose: The boxplot compares the distribution of arrival delays across different airlines to assess performance and reliability.

Key Insights:

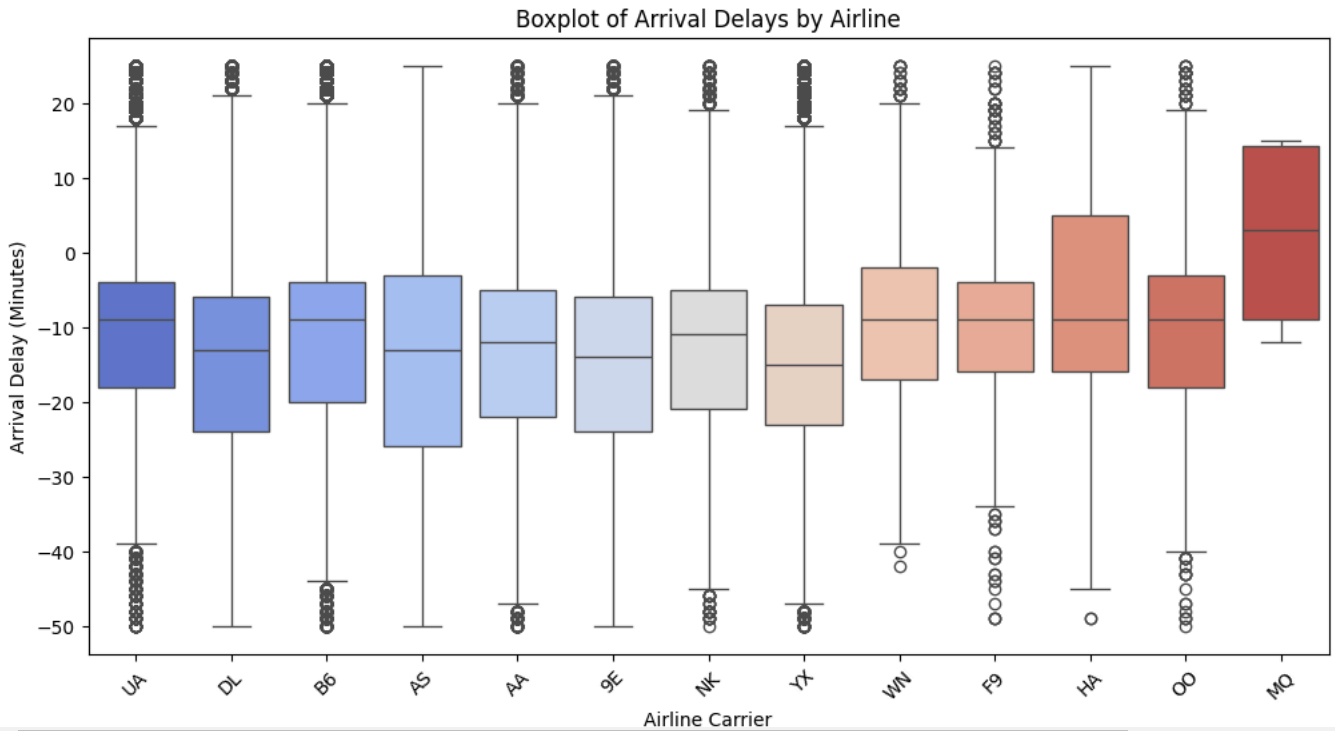
Highlights which airlines consistently have longer delays or better punctuality. Identifies outliers—extreme delays or highly inconsistent performance. Logic:

The sns.boxplot groups delay data (arr_delay) by airline (carrier). The box represents the interquartile range (IQR), while whiskers extend to 1.5x IQR, showing the spread of the data. Interpretation:

A narrow box with short whiskers indicates consistent performance with fewer delays. Outliers suggest exceptional circumstances or persistent issues requiring further investigation.

```
# Boxplot for arrival delays by airline
plt.figure(figsize=(12, 6))
sns.boxplot(data=final_merged_df, x='carrier', y='arr_delay', palette='coolwarm')
plt.title("Boxplot of Arrival Delays by Airline")
plt.xlabel("Airline Carrier")
plt.ylabel("Arrival Delay (Minutes)")
plt.xticks(rotation=45)
plt.show()
```

```
<ipython-input-64-58c80bac557e>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend

  sns.boxplot(data=final_merged_df, x='carrier', y='arr_delay', palette='coolwarm')
```



Heatmap:-Average Arrival Delays by Hour and Day

Purpose: The heatmap visualizes how average arrival delays vary by hour of the day and day of the week.

Key Insights:

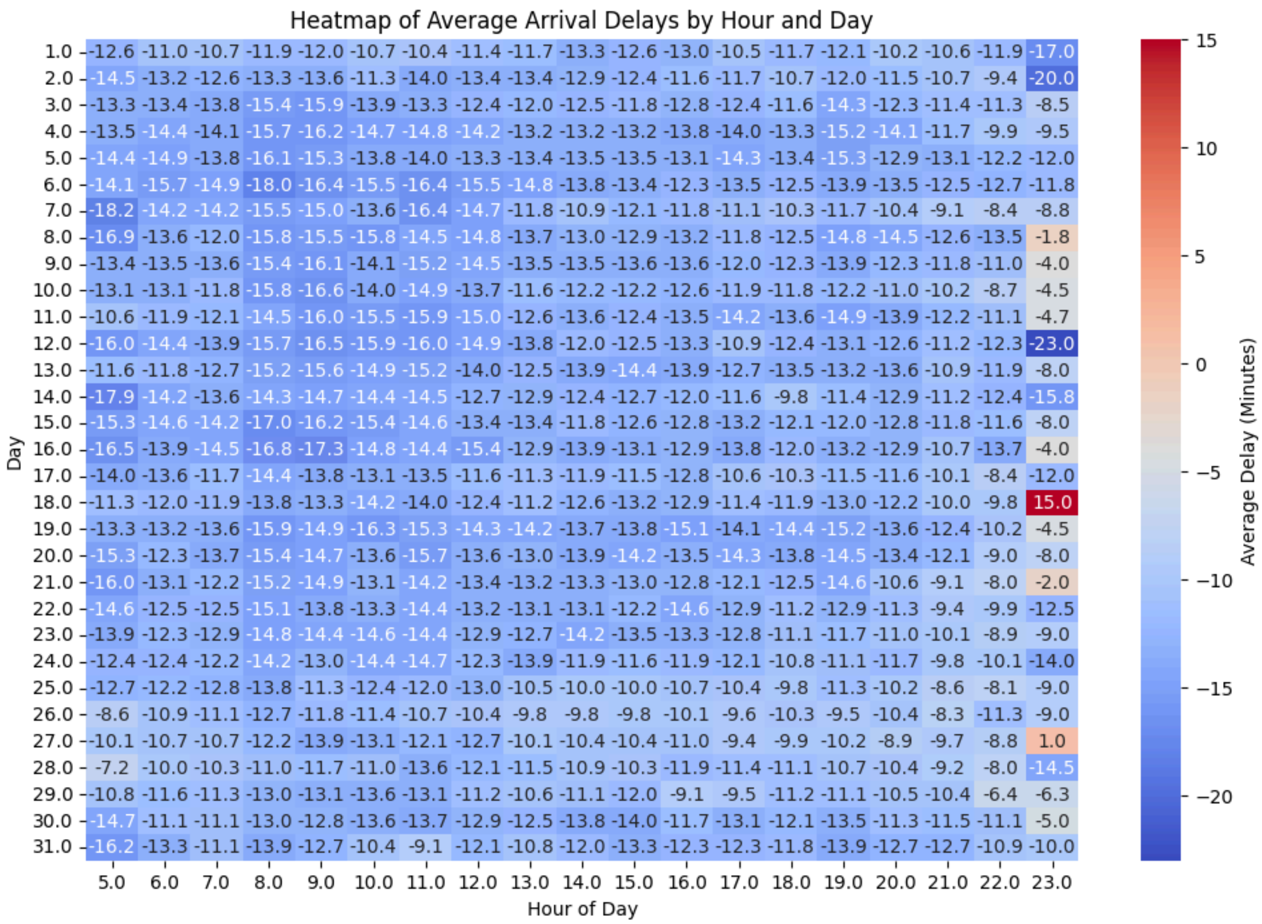
Helps identify trends in delays, such as specific hours or days with higher-than-average delays. Useful for understanding operational bottlenecks or peak congestion times at airports. Logic:

The pivot_table aggregates average arr_delay values grouped by hour (columns) and day (rows). The sns.heatmap visually represents this aggregated data using color gradients. Interpretation:

Darker colors indicate lower delays, while brighter colors highlight high delay periods. Look for patterns like consistent delays during certain hours or days, which can guide schedule adjustments or resource allocation.

```
# Create pivot table for heatmap
delay_pivot = final_merged_df.pivot_table(
   index='day_x',
   columns='hour_x',
   values='arr_delay',
   aggfunc='mean'
)

# Check if pivot table is not empty
if not delay_pivot.empty:
    # Plot heatmap
   plt.figure(figsize=(12, 8))
   sns.heatmap(delay_pivot, cmap='coolwarm', annot=True, fmt='.1f', cbar_kws={'label': 'Average Delay (Minutes)'})
   plt.title("Heatmap of Average Arrival Delays by Hour and Day")
   plt.xlabel("Hour of Day")
   plt.ylabel("Day")
```

```
    plt.show()
else:
    print("The pivot table for delays is empty. Verify the data and column names.")
```



Scatter Plot: Weather Impact on Delays

Purpose: The scatter plot examines the relationship between temperature (temp) and arrival delays (arr_delay).

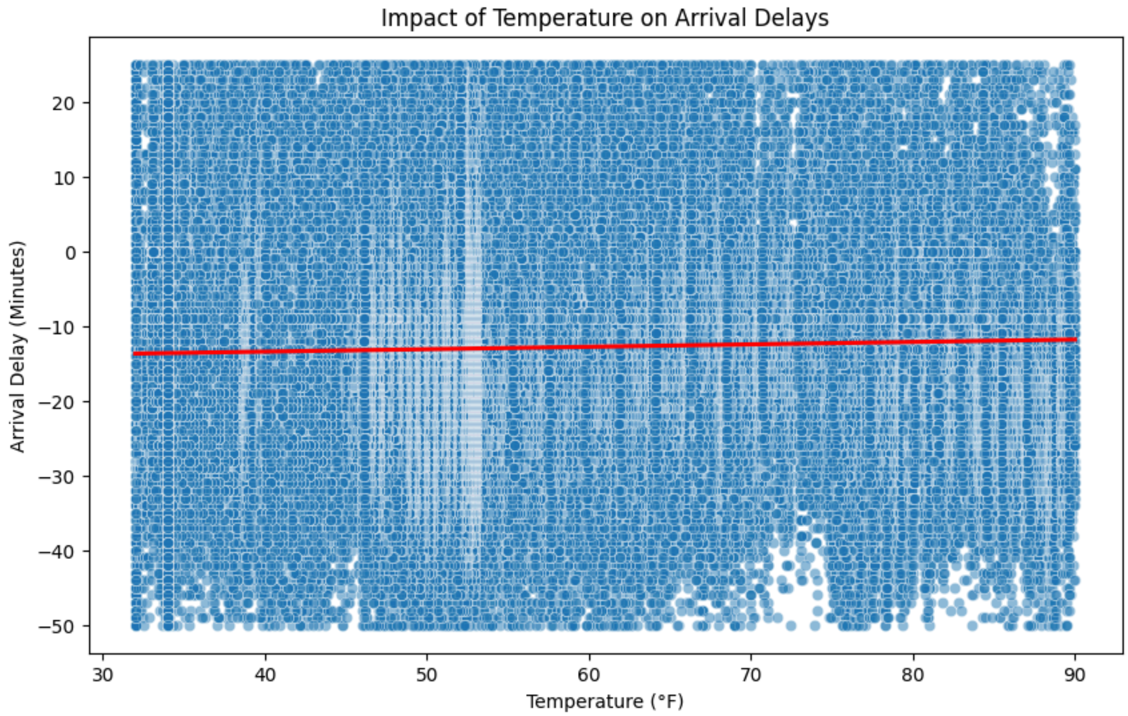
Key Insights:

Identifies how weather conditions, such as extreme temperatures, impact delays. Useful for predicting delays based on weather forecasts.
Logic:

The scatter plot visualizes individual flights, while a regression line overlays the general trend. Correlation can indicate whether delays increase (positive slope) or decrease (negative slope) with temperature changes. Interpretation:

A clear upward trend suggests that higher temperatures are associated with longer delays. Outliers (e.g., extreme delays) might indicate unusual weather events or operational disruptions.

```
# Scatter plot for temperature vs delay
plt.figure(figsize=(10, 6))
sns.scatterplot(data=final_merged_df, x='temp', y='arr_delay', alpha=0.5)
sns.regplot(data=final_merged_df, x='temp', y='arr_delay', scatter=False, color='red')
plt.title("Impact of Temperature on Arrival Delays")
plt.xlabel("Temperature (°F)")
plt.ylabel("Arrival Delay (Minutes)")
plt.show()
```



Bar Chart: Number of Flights per Airline

Purpose: The bar chart shows the total number of flights operated by each airline, helping assess their scale of operations.

Key Insights:

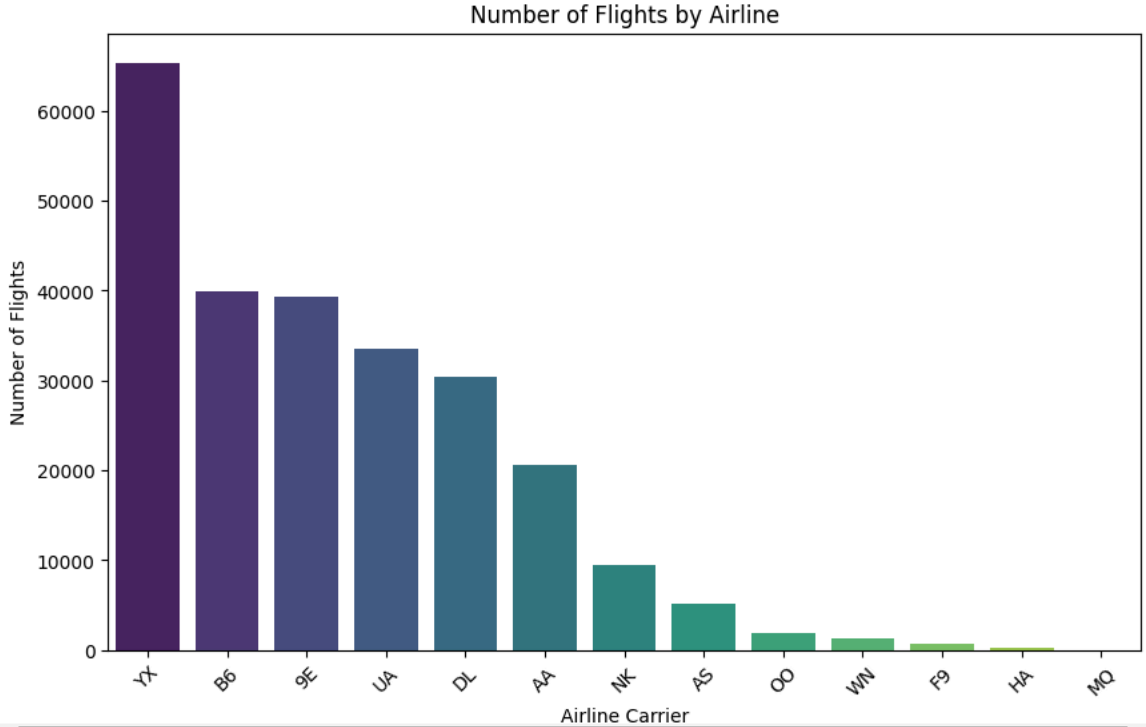
Indicates the busiest airlines in the dataset. Useful for correlating airline size with performance metrics (e.g., delays, cancellations). Logic:

The bar chart is created by counting the number of records for each airline (carrier) in the dataset. Interpretation:

Taller bars represent airlines with higher flight counts. Compare operational scale with other metrics, such as delays, to identify patterns.

```
# Bar chart for flight counts by airline
flight_counts = final_merged_df['carrier'].value_counts()

plt.figure(figsize=(10, 6))
sns.barplot(x=flight_counts.index, y=flight_counts.values, palette='viridis')
plt.title("Number of Flights by Airline")
plt.xlabel("Airline Carrier")
plt.ylabel("Number of Flights")
plt.xticks(rotation=45)
plt.show()
```

```
<ipython-input-69-c0179d4b1ad8>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend

  sns.barplot(x=flight_counts.index, y=flight_counts.values, palette='viridis')
```



Histogram: Distribution of Plane Ages

Purpose: The histogram shows the distribution of ages for planes in the fleet, providing insights into the modernization or aging of the aircraft.

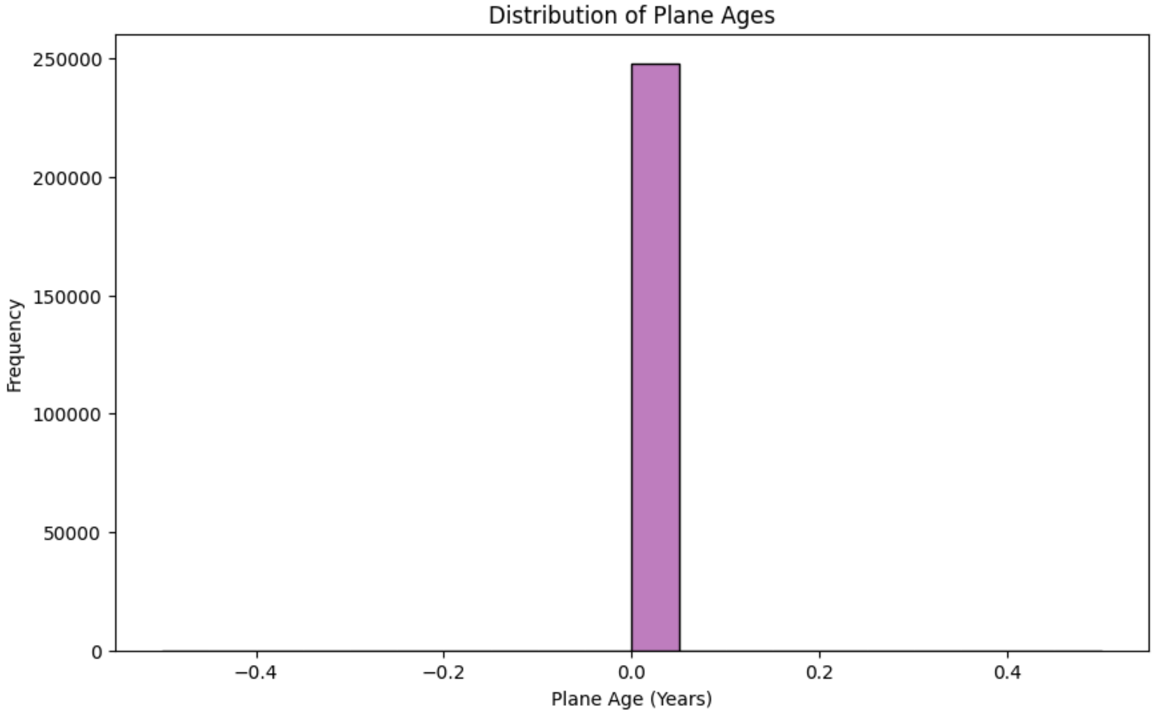
Key Insights:

Older planes may contribute to higher delays or maintenance issues. A younger fleet suggests investments in newer, more efficient aircraft. Logic:

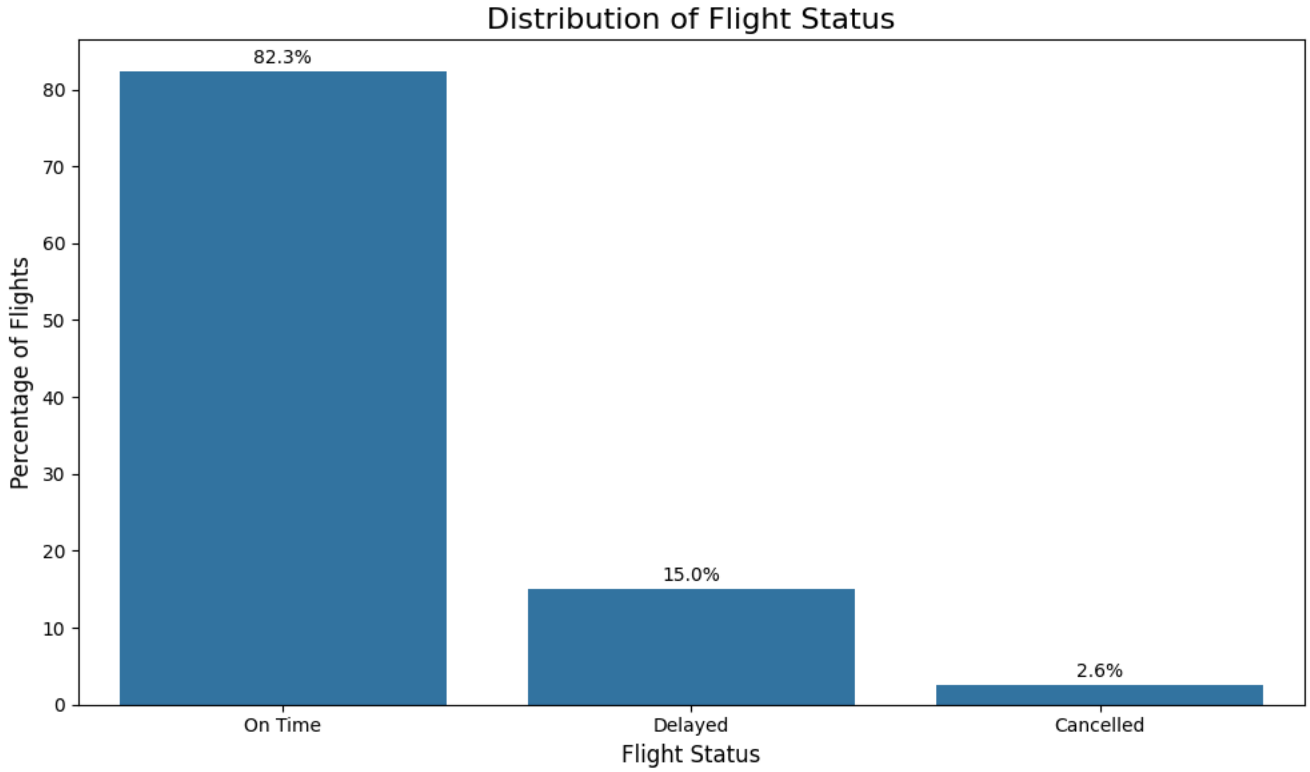
Plane age is calculated as the difference between the current year (e.g., 2023) and the year of manufacture. The histogram plots the frequency of planes by age, with a kernel density estimate (KDE) overlay to show the trend. Interpretation:

Peaks in the histogram indicate common plane ages, while a wider spread suggests diverse fleet age. Identify clusters of older planes that might require replacements or upgrades.

```
# Ensure 'year_x' or 'year_y' exists and contains numeric data
if 'year_x' in final_merged_df.columns:
    # Calculate plane ages (assuming current year is 2023)
    final_merged_df['plane_age'] = 2023 - final_merged_df['year_x']  # Replace with correct column name

    # Plot histogram
    plt.figure(figsize=(10, 6))
    sns.histplot(final_merged_df['plane_age'], bins=20, kde=True, color='purple')
    plt.title("Distribution of Plane Ages")
    plt.xlabel("Plane Age (Years)")
    plt.ylabel("Frequency")
    plt.show()
else:
    print("The 'year_x' column is missing or invalid. Verify the dataset.")
```




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

# Assuming you've already run the code to prepare the DataFrame 'df'

# Calculate the percentage of each flight status
status_counts = final_merged_df['flight_status'].value_counts(normalize=True) * 100

# Create the bar plot
plt.figure(figsize=(10, 6))
sns.barplot(x=status_counts.index, y=status_counts.values)

# Customize the plot
plt.title('Distribution of Flight Status', fontsize=16)
plt.xlabel('Flight Status', fontsize=12)
plt.ylabel('Percentage of Flights', fontsize=12)

# Add percentage labels on top of each bar
for i, v in enumerate(status_counts.values):
    plt.text(i, v + 0.5, f'{v:.1f}%', ha='center', va='bottom')

# Display the plot
plt.tight_layout()
plt.show()
```




```
final_merged_df['average_speed'] = final_merged_df['distance'] / (final_merged_df['air_time'] / 60)
print(final_merged_df[['carrier', 'average_speed']].groupby('carrier').mean())
```

```
         average_speed
carrier
9E          349.674817
AA          384.693248
AS          390.769231
B6          384.453956
DL          403.231701
F9          417.786744
HA          390.769231
MQ          415.001994
NK          408.242264
OO          304.828259
UA          392.029892
WN          407.319241
YX          336.370445
```

Descriptive Statistics

Purpose: To summarize the key numerical and categorical features of the dataset, providing an overview of the data distribution, central tendencies, and variability.

Logic:

The describe() function generates basic statistics for each column: Numerical Columns: Count, mean, standard deviation (std), min, 25th percentile (Q1), median (50th percentile), 75th percentile (Q3), and max. Categorical Columns: Count, unique values, most frequent value (top), and its frequency (freq). Key Insights:

Identify the central tendency (mean, median) of numerical features. Assess variability (standard deviation, range) to detect dispersed data. Recognize potential issues such as skewed distributions, outliers, or sparse categories. Interpretation:

Numerical Example: A high standard deviation in arr_delay may indicate widely varying delay durations, suggesting potential operational issues. Categorical Example: A column with low unique values but a dominant category (high freq) may indicate an imbalance in the data.

```
# Descriptive statistics
descriptive_stats = final_merged_df.describe(include='all')
print("Descriptive Statistics:")
print(descriptive_stats)
```

```
Descriptive Statistics:
          year_x       month_x          day_x       dep_time  sched_dep_time  \
count   248111.0  248111.000000  248111.000000  248111.000000   248111.000000
unique       NaN           NaN            NaN            NaN             NaN
top          NaN           NaN            NaN            NaN             NaN
freq         NaN           NaN            NaN            NaN             NaN
mean      2023.0       6.412049      15.688756    1310.931220     1351.178747
std          0.0       3.438877       8.727546     536.907853      478.913571
min       2023.0       1.000000       1.000000       0.000000      500.000000
25%       2023.0       3.000000       8.000000     900.000000      929.000000
50%       2023.0       6.000000      16.000000    1323.000000     1345.000000
75%       2023.0       9.000000      23.000000    1738.000000     1735.000000
max       2023.0      12.000000      31.000000    2400.000000     2359.000000

            dep_delay       arr_time  sched_arr_time      arr_delay carrier  \
count   248111.000000  248111.000000   248111.000000  248111.000000  248111
unique            NaN            NaN             NaN            NaN      13
top               NaN            NaN             NaN            NaN      YX
freq              NaN            NaN             NaN            NaN   65356
mean        -3.701440    1443.983725     1545.374707     -12.892121     NaN
std          4.311008     587.099483      506.135835      13.674432     NaN
min        -15.000000       0.000000        1.000000     -50.000000     NaN
25%         -7.000000    1040.000000     1128.000000     -22.000000     NaN
50%         -4.000000    1446.000000     1536.000000     -12.000000     NaN
75%         -2.000000    1924.000000     1958.000000      -5.000000     NaN
max          9.000000    2400.000000     2359.000000      25.000000     NaN

               flight tailnum  origin    dest       air_time       distance  \
count   248111.000000  248111  248111  248111  248111.000000  248111.000000
unique            NaN    4420       3      75            NaN            NaN
top               NaN  N490PX     LGA     BOS            NaN            NaN
freq              NaN     531   90062   15783            NaN            NaN
mean       850.724329     NaN     NaN     NaN      95.314710     613.248868
std        521.883169     NaN     NaN     NaN      38.135163     296.493655
min          1.000000     NaN     NaN     NaN      18.000000      80.000000
25%        399.000000     NaN     NaN     NaN      62.000000     335.000000
50%        840.000000     NaN     NaN     NaN      96.000000     610.000000
75%       1298.000000     NaN     NaN     NaN     118.000000     762.000000
max       1972.000000     NaN     NaN     NaN     246.000000    1207.000000

               hour_x         minute flight_status manufacturer  \
count   248111.000000  248111.000000        248111       248111
unique            NaN            NaN             3           11
top               NaN            NaN       On Time       BOEING
freq              NaN            NaN        204284        56848
mean        13.225040      28.674706           NaN          NaN
std          4.766353      19.863219           NaN          NaN
min          5.000000       0.000000           NaN          NaN
25%          9.000000      10.000000           NaN          NaN
50%         13.000000      29.000000           NaN          NaN
75%         17.000000      45.000000           NaN          NaN
max         23.000000      59.000000           NaN          NaN

                model          seats             name           temp  \
count          248111  248111.000000           248111  248111.000000
unique             91            NaN               13            NaN
top    ERJ 170-200 LR            NaN  Republic Airline            NaN
freq            54478            NaN            65356            NaN
```

Specific Measures: Skewness and Kurtosis

Purpose: To assess the shape of the data distribution for numerical features, detecting asymmetry (skewness) and the presence of heavy tails or outliers (kurtosis).

Logic:

Skewness: Measures the symmetry of the data distribution: 0 indicates a symmetric distribution. Positive values suggest right-skewed data (longer tail on the right). Negative values suggest left-skewed data (longer tail on the left). Kurtosis: Measures the "tailedness" of the distribution: Values > 3 indicate heavy tails (more outliers). Values < 3 indicate light tails (fewer outliers). Key Insights:

High skewness in arr_delay may indicate delays with a long tail (extreme values). High kurtosis in distance may suggest routes with extreme lengths compared to the average. Interpretation:

Skewness Example: If arr_delay has a skewness of 2, most flights arrive close to the scheduled time, but a few have extreme delays. Kurtosis Example: A kurtosis of 6 for distance suggests a few very long-distance flights skew the distribution.

```
# Skewness and Kurtosis
specific_measures = {
   'Skewness': final_merged_df.skew(numeric_only=True),
   'Kurtosis': final_merged_df.kurt(numeric_only=True)
```

```
}
print("Specific Measures (Skewness & Kurtosis):")
print(specific_measures)
```

```
Specific Measures (Skewness & Kurtosis):
{'Skewness': year_x           0.000000
month_x          0.039820
day_x            0.015483
dep_time        -0.177536
sched_dep_time   0.074735
dep_delay        0.431490
arr_time        -0.541887
sched_arr_time  -0.272524
arr_delay        0.186097
flight           0.093577
air_time         0.085705
distance         0.090018
hour_x           0.083937
minute           0.008896
seats            0.346474
temp             0.238991
dewp            -0.141593
humid           -0.114757
wind_dir        -0.269222
wind_speed       0.518700
wind_gust        0.518700
precip           0.000000
pressure        -0.756199
visib            0.000000
lat              0.183552
lon             -0.638227
alt             -0.340147
tz               0.000000
lat_dest        -0.292790
lon_dest         1.051354
alt_dest         0.666175
tz_dest          0.000000
plane_age        0.000000
average_speed   -0.608295
dtype: float64, 'Kurtosis': year_x           0.000000
month_x         -1.232406
day_x           -1.175684
dep_time        -0.635541
sched_dep_time  -1.213121
dep_delay        0.485566
arr_time        -0.059027
sched_arr_time  -0.371473
arr_delay        0.099825
flight          -1.140309
air_time        -0.974437
distance        -1.159606
hour_x          -1.214938
minute          -1.219014
seats           -0.156866
temp            -0.901291
dewp            -1.066885
humid           -1.136787
wind_dir        -1.184610
wind_speed      -0.650315
wind_gust       -0.650315
precip           0.000000
pressure        -0.470302
```

Value Counts for Categorical Columns

Purpose: To determine the frequency of unique values in each categorical column, revealing data distribution and potential imbalances.

Logic:

The value_counts() function computes the frequency of each unique value in a categorical column. Often used for columns like carrier, origin, or dest. Key Insights:

Identify dominant categories (e.g., most common airline or airport). Detect imbalances that could affect analysis or modeling (e.g., underrepresented categories). Interpretation:

Example: If carrier has one airline making up 70% of flights, this could bias delay analysis toward that airline. Helps decide whether data balancing techniques (e.g., resampling) are necessary for modeling.

```
# Value counts for categorical columns
value_counts = {col: final_merged_df[col].value_counts() for col in final_merged_df.select_dtypes(include='object').columns}
```

```
print("Value Counts:")
for col, vc in value_counts.items():
    print(f"\n{col}:\n{vc}")
```

```
Value Counts:

carrier:
carrier
YX    65356
B6    39879
9E    39353
UA    33574
DL    30476
AA    20572
NK     9446
AS     5217
OO     1944
WN     1328
F9      717
HA      245
MQ        4
Name: count, dtype: int64

tailnum:
tailnum
N490PX    531
N915XJ    523
N491PX    514
N480PX    509
N482PX    493
         ...
N643UA      1
N429WN      1
N260WN      1
N8569Z      1
N552NW      1
Name: count, Length: 4420, dtype: int64

origin:
origin
LGA    90062
JFK    81140
EWR    76909
Name: count, dtype: int64

dest:
dest
BOS    15783
ATL    13510
MCO    13396
MIA    12702
CLT    11214
       ...
ANC       58
SBN       21
AGS       16
OGG       13
LEX        1
Name: count, Length: 75, dtype: int64

flight_status:
flight_status
```

Group Summaries

Purpose: To aggregate and analyze numerical features grouped by a categorical column, such as airline or airport, providing targeted insights.

Logic:

The groupby() method aggregates numerical features based on categories: Mean: Average value per group. Median: Middle value per group. Count: Number of records per group. Sum: Total value per group. Often used to analyze performance metrics like delays by carrier or origin. Key Insights:

Compare average delays or flight counts across airlines or airports. Highlight the best-performing categories (e.g., airlines with the least delays). Uncover patterns in specific groups that might warrant further investigation. Interpretation:

Example: If the average arr_delay for carrier A is 5 minutes and carrier B is 30 minutes, carrier A is more reliable. Variations in flight counts can indicate operational scale differences between airlines or airports.

```
# Group summaries
group_summary = final_merged_df.groupby('carrier').agg({
   'arr_delay': ['mean', 'median', 'count'], # Replace 'arr_delay' as needed
   'distance': 'mean'
})
print("Group Summaries:")
print(group_summary)
```

```
Group Summaries:
         arr_delay                  distance
              mean median  count        mean
carrier
9E      -14.259447  -14.0  39353   432.420222
AA      -12.804589  -12.0  20572   718.567568
AS      -13.971823  -13.0   5217   762.000000
B6      -11.259259   -9.0  39879   738.384664
DL      -13.691757  -13.0  30476   809.905270
F9       -9.591353   -9.0    717   885.283124
HA       -6.669388   -9.0    245   762.000000
MQ        2.250000    3.0      4  1085.000000
NK      -12.220940  -11.0   9446   836.440927
OO      -10.213477   -9.0   1944   342.805041
UA      -10.413117   -9.0  33574   744.644934
WN       -9.228163   -9.0   1328   814.801205
YX      -14.218725  -15.0  65356   409.669181
```

Data Preprocessing

Encoding

```
from sklearn.preprocessing import LabelEncoder

# Make a copy of the original DataFrame for encoding
final_merged_df_encoded = final_merged_df.copy()

# Identify categorical columns
categorical_columns = final_merged_df.select_dtypes(include=['object']).columns

# Apply Label Encoding
label_encoder = LabelEncoder()
for col in categorical_columns:
    final_merged_df_encoded[col] = label_encoder.fit_transform(final_merged_df[col])

# Confirm encoding
final_merged_df_encoded.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 248111 entries, 0 to 434788
Data columns (total 45 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   year_x          248111 non-null  float64
 1   month_x         248111 non-null  float64
 2   day_x           248111 non-null  float64
 3   dep_time        248111 non-null  float64
 4   sched_dep_time  248111 non-null  float64
 5   dep_delay       248111 non-null  float64
 6   arr_time        248111 non-null  float64
 7   sched_arr_time  248111 non-null  float64
 8   arr_delay       248111 non-null  float64
 9   carrier         248111 non-null  int64
 10  flight          248111 non-null  float64
 11  tailnum         248111 non-null  int64
 12  origin          248111 non-null  int64
 13  dest            248111 non-null  int64
 14  air_time        248111 non-null  float64
 15  distance        248111 non-null  float64
 16  hour_x          248111 non-null  float64
 17  minute          248111 non-null  float64
 18  flight_status   248111 non-null  int64
 19  manufacturer    248111 non-null  int64
 20  model           248111 non-null  int64
 21  seats           248111 non-null  float64
 22  name            248111 non-null  int64
 23  temp            248111 non-null  float64
```

```
 24  dewp            248111 non-null  float64
 25  humid           248111 non-null  float64
 26  wind_dir        248111 non-null  float64
 27  wind_speed      248111 non-null  float64
 28  wind_gust       248111 non-null  float64
 29  precip          248111 non-null  float64
 30  pressure        248111 non-null  float64
 31  visib           248111 non-null  float64
 32  lat             248111 non-null  float64
 33  lon             248111 non-null  float64
 34  alt             248111 non-null  float64
 35  tz              248111 non-null  float64
 36  dst             248111 non-null  int64
 37  tzone           248111 non-null  int64
 38  lat_dest        248111 non-null  float64
 39  lon_dest        248111 non-null  float64
 40  alt_dest        248111 non-null  float64
 41  tz_dest         248111 non-null  float64
 42  tzone_dest      248111 non-null  int64
 43  plane_age       248111 non-null  float64
 44  average_speed   248111 non-null  float64
dtypes: float64(34), int64(11)
memory usage: 87.1 MB
```

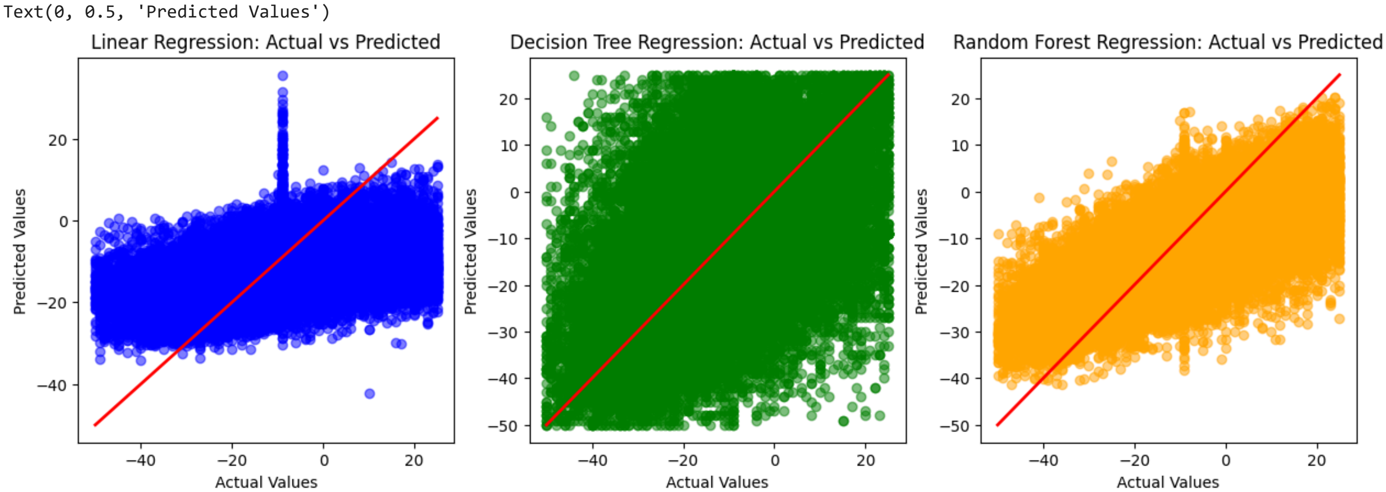
Most machine learning algorithms cannot work with categorical variables directly because they expect numeric input. Label Encoding helps by converting string labels into numbers. For example, a column representing countries (like ['Delayed', 'On Time', 'Cancelled']) will be transformed into [0, 1, 2]. This makes it possible to feed categorical data into machine learning models that require numeric features.

Regression Task

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error, r2_score
import xgboost as xgb

# Assuming final_merged_df_encoded is your DataFrame

# Step 1: Select target variable and features
target_column = 'arr_delay'

# Renaming X and y to X_regress and y_regress
X_regress = final_merged_df_encoded.drop(columns=[target_column, 'flight_status'])  # Drop target and categorical target
y_regress = final_merged_df_encoded[target_column]

# Step 2: Split the data into training and testing sets (80-20 split)
X_train, X_test, y_train, y_test = train_test_split(X_regress, y_regress, test_size=0.2, random_state=42)

# Step 3: Linear Regression Model
linear_reg = LinearRegression()
linear_reg.fit(X_train, y_train)
y_pred_linear = linear_reg.predict(X_test)

# Step 4: Decision Tree Regression Model
decision_tree = DecisionTreeRegressor(random_state=42)
decision_tree.fit(X_train, y_train)
y_pred_tree = decision_tree.predict(X_test)

# Step 5: Random Forest Regression Model
random_forest = RandomForestRegressor(random_state=42)
random_forest.fit(X_train, y_train)
y_pred_forest = random_forest.predict(X_test)


# Step 8: Evaluate Model Performance
# Linear Regression
linear_rmse = np.sqrt(mean_squared_error(y_test, y_pred_linear))
linear_r2 = r2_score(y_test, y_pred_linear)
```

```
# Decision Tree Regression
tree_rmse = np.sqrt(mean_squared_error(y_test, y_pred_tree))
tree_r2 = r2_score(y_test, y_pred_tree)

# Random Forest Regression
forest_rmse = np.sqrt(mean_squared_error(y_test, y_pred_forest))
forest_r2 = r2_score(y_test, y_pred_forest)


# Print performance metrics for all models
print(f"Linear Regression RMSE: {linear_rmse:.4f}, R2: {linear_r2:.4f}")
print(f"Decision Tree Regression RMSE: {tree_rmse:.4f}, R2: {tree_r2:.4f}")
print(f"Random Forest Regression RMSE: {forest_rmse:.4f}, R2: {forest_r2:.4f}")


# Step 9: Plotting Actual vs Predicted Values for all models
plt.figure(figsize=(15, 10))

# Linear Regression
plt.subplot(2, 3, 1)
plt.scatter(y_test, y_pred_linear, color='blue', alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], color='red', lw=2)
plt.title('Linear Regression: Actual vs Predicted')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')

# Decision Tree Regression
plt.subplot(2, 3, 2)
plt.scatter(y_test, y_pred_tree, color='green', alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], color='red', lw=2)
plt.title('Decision Tree Regression: Actual vs Predicted')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')

# Random Forest Regression
plt.subplot(2, 3, 3)
plt.scatter(y_test, y_pred_forest, color='orange', alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], color='red', lw=2)
plt.title('Random Forest Regression: Actual vs Predicted')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
```

```
Linear Regression RMSE: 12.0603, R2: 0.2244
Decision Tree Regression RMSE: 13.7902, R2: -0.0140
Random Forest Regression RMSE: 9.5610, R2: 0.5126
Text(0, 0.5, 'Predicted Values')
```



We trained and evaluated three different regression models (Linear Regression, Decision Tree Regression, and Random Forest Regression) on a dataset with arr_delay as the target variable.

Why Choose These Models and Target Variable?

Linear Regression: Chosen because it is simple and interpretable. It provides a good baseline for understanding the relationship between features and the target.

Decision Tree Regression: Chosen for its ability to capture non-linear relationships and its flexibility in fitting complex patterns.

Random Forest Regression: Chosen for its ensemble nature, which improves performance by combining multiple decision trees and helps prevent overfitting.

Evaluation:

RMSE (Root Mean Squared Error) is used to evaluate how close the predicted values are to the actual values.

R^2 score is used to determine how well the model explains the variance in the target variable.

Visualization:

The scatter plots compare the actual vs predicted values for each model to visually assess their performance.

Target Variable (arr_delay):

The target variable is arr_delay, representing the flight's arrival delay. This continuous variable is chosen because predicting delays is critical for airlines, and it has a real-world impact on operations, customer satisfaction, and logistics. Predicting arrival delays is a natural regression task because the target variable (arr_delay) is continuous and numerical.

Regression Task: Key Findings, Insights and Recommendation

From the regression results, we can draw the following conclusions about the performance of the models:

1. **Linear Regression**:
    - **RMSE**: 12.0603
    - **R^2**: 0.2244
    - Linear regression has a relatively high **RMSE**, indicating that the model has a significant error in its predictions. The **R^2 score** of 0.2244 suggests that only about **22.44%** of the variance in the target variable (`arr_delay`) is explained by the model. This suggests that linear regression is not capturing much of the underlying complexity in the data, likely due to the assumption of a linear relationship.
2. **Decision Tree Regression**:
    - **RMSE**: 13.7902
    - **R^2**: -0.0140
    - The **RMSE** of 13.7902 is higher than that of linear regression, indicating poorer performance. Additionally, the **R^2 score** is negative (-0.0140), which suggests that the decision tree model is performing worse than a simple mean-based model (i.e., it cannot even predict better than just predicting the mean of the target). This could be a sign of overfitting, where the decision tree has learned the noise in the training data instead of capturing the true underlying patterns.
3. **Random Forest Regression**:
    - **RMSE**: 9.5610
    - **R^2**: 0.5126
    - The **Random Forest** model has the **lowest RMSE**, indicating that it makes more accurate predictions compared to the other two models. With an **R^2 score** of 0.5126, it explains **51.26%** of the variance in the target variable, which is significantly better than both linear regression and decision tree regression. Random Forest is more robust and likely benefits from its ensemble nature, handling non-linear relationships better than the other models.

Overall Assessment:

- **Best Model**: **Random Forest Regression** is the best-performing model in terms of both **RMSE** and **R^2**, suggesting that it is capturing more complex patterns in the data and providing more accurate predictions.
- **Linear Regression** provides a reasonable baseline, but its performance could be improved by either using a more complex model or performing feature engineering.
- **Decision Tree Regression** shows the worst performance, likely due to overfitting or inability to generalize well on the data.

In summary, **Random Forest** is the most suitable model for this regression task among the three, but further tuning and testing with additional models or feature engineering could lead to even better results.

Classification Task

Splitting dataset into Training and Testing

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# Assuming final_merged_df is already prepared with all the features

# Step 2: Scale numerical features using StandardScaler
numerical_columns = ['dep_delay', 'arr_delay', 'air_time', 'distance', 'temp', 'dewp', 'humid', 'wind_dir', 'precip',
                     'pressure', 'visib', 'lat', 'lon', 'alt', 'plane_age', 'average_speed']

scaler = StandardScaler()
final_merged_df_encoded[numerical_columns] = scaler.fit_transform(final_merged_df_encoded[numerical_columns])

# Step 3: Split the data into features (X) and target variable (y)
# For Classification, we use 'flight_status' as the target variable
X_classification = final_merged_df_encoded.drop('flight_status', axis=1)
y_classification = final_merged_df_encoded['flight_status']

# Split into training and testing sets (80-20) for classification
X_train_class, X_test_class, y_train_class, y_test_class = train_test_split(X_classification, y_classification, test_size=0.2, random_state=

# Step 4: Classification models (Logistic Regression, Random Forest, SVM)

# Logistic Regression
log_reg = LogisticRegression(max_iter=1000, random_state=42)
log_reg.fit(X_train_class, y_train_class)
y_pred_log_reg = log_reg.predict(X_test_class)

# Random Forest
random_forest = RandomForestClassifier(random_state=42)
random_forest.fit(X_train_class, y_train_class)
y_pred_rf = random_forest.predict(X_test_class)

# Support Vector Machine (SVM)
svm = SVC(random_state=42)
svm.fit(X_train_class, y_train_class)
y_pred_svm = svm.predict(X_test_class)

# Step 5: Evaluate Classification Models
print("Classification Model Performance:")

def evaluate_model(y_true, y_pred):
    accuracy = accuracy_score(y_true, y_pred)
    precision = precision_score(y_true, y_pred, average='weighted')
    recall = recall_score(y_true, y_pred, average='weighted')
    f1 = f1_score(y_true, y_pred, average='weighted')
    return accuracy, precision, recall, f1

# Evaluate Logistic Regression
accuracy, precision, recall, f1 = evaluate_model(y_test_class, y_pred_log_reg)
print(f"Logistic Regression - Accuracy: {accuracy:.4f}, Precision: {precision:.4f}, Recall: {recall:.4f}, F1: {f1:.4f}")
```