Problem: Predicting Airplane Delays

The goals of this notebook are:

- Process and create a dataset from downloaded ZIP files
- Exploratory data analysis (EDA)
- Establish a baseline model and improve it

Introduction to business scenario

You work for a travel booking website that is working to improve the customer experience for flights that were delayed. The company wants to create a feature to let customers know if the flight will be delayed due to weather when the customers are booking the flight to or from the busiest airports for domestic travel in the US.

You are tasked with solving part of this problem by leveraging machine learning to identify whether the flight will be delayed due to weather. You have been given access to the a dataset of on-time performance of domestic flights operated by large air carriers. You can use this data to train a machine learning model to predict if the flight is going to be delayed for the busiest airports.

Dataset

The provided dataset contains scheduled and actual departure and arrival times reported by certified US air carriers that account for at least 1 percent of domestic scheduled passenger revenues. The data was collected by the Office of Airline Information, Bureau of Transportation Statistics (BTS). The dataset contains date, time, origin, destination, airline, distance, and delay status of flights for flights between 2014 and 2018. The data are in 60 compressed files, where each file contains a CSV for the flight details in a month for the five years (from 2014 - 2018). The data can be downloaded from this link (https://ucstaff-my.sharepoint.com/:f:/g/personal/ibrahim_radwan_canberra_edu_au/EhWeqeQsh-9Mr1fneZc9_0sBOBzEdXngvxFJtAIla-eAgA?e=8ukWwa). Please download the data files and place them on a relative path. Dataset(s) used in this assignment were compiled by the Office of Airline Information, Bureau of Transportation Statistics (BTS), Airline On-Time Performance Data, available with the following link (https://www.transtats.bts.gov/Fields.asp?gnoyr_VQ=FGJ).

Step 1: Problem formulation and data collection

Start this project off by writing a few sentences below that summarize the business problem and the business goal you're trying to achieve in this scenario. Include a business metric you would like your team to aspire toward. With that information defined, clearly write out the machine learning problem statement. Finally, add a comment or two about the type of machine learning this represents.

Machine learning is suitable for this problem because of a few reasons:

- Complexity of Patterns: flight delays due to weather depend on many interconnected factors like season, airport, airline, or time of day. Patterns that are too complex for traditional rule-based systems.
- Large Dataset: dataset consists of 60 compressed files with detailed information about delays, routes, airlines, and timing. ML algorithms are good at discovering patterns in large historical datasets that humans might miss.

2. Formulate the business problem, success metrics, and desired ML output.

- **Business Problem**: Flight delays, especially those caused by weather, create inconvenience for customers and operational challenges for airlines. The company wants to alert customers during booking if their flight is likely to be delayed due to weather.
- **Business Goal + Success metrics**: Build a machine learning model that predicts whether a scheduled flight will be delayed due to weather conditions.
- Accuracy: ≥ 80%
- Recall: ≥ 70%
- Precision: ≥ 75%
- **Desired ML output**: A binary prediction:

1 means Flight delayed due to weather while **0** means Flight not delayed due to weather

This output can be used to inform travelers during the booking process, helping them make better decisions and improving trust in the platform.

3. Identify the type of ML problem you’re dealing with.

This is a supervised learning problem, specifically it is Classification.

This is because the dataset includes labeled examples (each flight record shows whether it was delayed or not.

Setup

Now that we have decided where to focus our energy, let's set things up so you can start working on solving the problem.

In [1]:
```
import os
from pathlib2 import Path
from zipfile import ZipFile
import time

import pandas as pd
import numpy as np
import subprocess

import matplotlib.pyplot as plt
import seaborn as sns

sns.set()

import warnings
warnings.filterwarnings('ignore')

%matplotlib inline

# <please add any other library or function you are aiming to import here>
```

In [2]:
```
# pip install pathlib2
```

Step 2: Data preprocessing and visualization

In this data preprocessing phase, you should take the opportunity to explore and visualize your data to better understand it. First, import the necessary libraries and read the data into a Pandas dataframe. After that, explore your data. Look for the shape of the dataset and explore your columns and the types of columns you're working with (numerical, categorical). Consider performing basic statistics on the features to get a sense of feature means and ranges. Take a close look at your target column and determine its distribution.

Specific questions to consider

1. What can you deduce from the basic statistics you ran on the features?
2. What can you deduce from the distributions of the target classes?
3. Is there anything else you deduced from exploring the data?

Start by bringing in the dataset from an Amazon S3 public bucket to this notebook environment.

In [3]:
```
# download the files

# <note: make them all relative, absolute path is not accepted>
zip_path = 'data_compressed'
base_path = '.'
csv_base_path = 'datasets'

!mkdir -p {csv_base_path}
```

In [4]:
```
# How many zip files do we have? write a code to answer it.

import os

count_files = 0
zip_files=[]

all_files = os.listdir(zip_path)
# print(all_files[:3])

for file in all_files:
    if file.lower().endswith(".zip"):
        count_files = count_files + 1
        zip_files.append(file)
#         print(count_files)

print("Number of zip files:", count_files)
```

```
Number of zip files: 60
```

Extract CSV files from ZIP files

In [5]:
```
def zip2csv(zipFile_name , file_path):
    """
    Extract csv from zip files
    zipFile_name: name of the zip file
    file_path : name of the folder to store csv
    """

    try:
        with ZipFile(zipFile_name, 'r') as z:
            print(f'Extracting {zipFile_name} ')
            z.extractall(path=file_path)
    except:
        print(f'zip2csv failed for {zipFile_name}')

for file in zip_files:
    zip_file_path = os.path.join(zip_path, file)
    zip2csv(zip_file_path, csv_base_path)

print("Files Extracted")
```

```
Extracting data_compressed/On_Time_Reporting_Carrier_On_Time_Performance_1987_present_2014_1.zip
Extracting data_compressed/On_Time_Reporting_Carrier_On_Time_Performance_1987_present_2016_3.zip
Extracting data_compressed/On_Time_Reporting_Carrier_On_Time_Performance_1987_present_2016_2.zip
Extracting data_compressed/On_Time_Reporting_Carrier_On_Time_Performance_1987_present_2014_2.zip
Extracting data_compressed/On_Time_Reporting_Carrier_On_Time_Performance_1987_present_2016_1.zip
Extracting data_compressed/On_Time_Reporting_Carrier_On_Time_Performance_1987_present_2014_3.zip
Extracting data_compressed/On_Time_Reporting_Carrier_On_Time_Performance_1987_present_2014_7.zip
Extracting data_compressed/On_Time_Reporting_Carrier_On_Time_Performance_1987_present_2016_5.zip
Extracting data_compressed/On_Time_Reporting_Carrier_On_Time_Performance_1987_present_2016_4.zip
Extracting data_compressed/On_Time_Reporting_Carrier_On_Time_Performance_1987_present_2014_6.zip
Extracting data_compressed/On_Time_Reporting_Carrier_On_Time_Performance_1987_present_2014_4.zip
Extracting data_compressed/On_Time_Reporting_Carrier_On_Time_Performance_1987_present_2016_6.zip
Extracting data_compressed/On_Time_Reporting_Carrier_On_Time_Performance_1987_present_2018_9.zip
Extracting data_compressed/On_Time_Reporting_Carrier_On_Time_Performance_1987_present_2018_8.zip
Extracting data_compressed/On_Time_Reporting_Carrier_On_Time_Performance_1987_present_2016_7.zip
Extracting data_compressed/On_Time_Reporting_Carrier_On_Time_Performance_1987_present_2014_5.zip
Extracting data_compressed/On_Time_Reporting_Carrier_On_Time_Performance_1987_present_2017_10.zip
Extracting data_compressed/On_Time_Reporting_Carrier_On_Time_Performance_1987_present_2015_2.zip
Extracting data_compressed/On_Time_Reporting_Carrier_On_Time_Performance_1987_present_2015_3.zip
```

In [6]:
```
# How many csv files have we extracted? write a code to answer it.

count_csv = 0
csv_files=[]

all_csv_files = os.listdir(csv_base_path)
# print(all_csv_files[:3])


for file in all_csv_files:
    if file.lower().endswith(".csv"):
        count_csv = count_csv + 1
        csv_files.append(file)
#       print(count_csv)

print("Number of csv files:", count_csv)
```

```
Number of csv files: 60
```

Before loading the CSV file, read the HTML file from the extracted folder. This HTML file includes the background and more information on the features included in the dataset.

In [7]:
```
from IPython.display import IFrame

IFrame(src=os.path.relpath(f"{csv_base_path}/readme.html"), width=1000, height=600)
```

Out[7]:

Load sample CSV

Before combining all the CSV files, get a sense of the data from a single CSV file. Using Pandas, read the `On_Time_Reporting_Carrier_On_Time_Performance_(1987_present)_2018_9.csv` file first. You can use the Python built-in `read_csv` function (documentation (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.read_csv.html)).

In [8]:
```
df_temp = pd.read_csv(f'{csv_base_path}/On_Time_Reporting_Carrier_On_Time_Performance_(1987_present)_2018_9.c
```

Question: Print the row and column length in the dataset, and print the column names.

In [9]:
```
df_shape = df_temp.shape
print(f'Rows and columns in one csv file is {df_shape}')
```

```
Rows and columns in one csv file is (585749, 110)
```

Question: Print the first 10 rows of the dataset.

In [10]:
```
first_ten_rows = df_temp[:10]

print(first_ten_rows)
first_ten_rows
```

	Year	Quarter	Month	DayofMonth	DayOfWeek	FlightDate	Reporting_Airline	\
0	2018	3	9	3	1	2018-09-03	9E	
1	2018	3	9	9	7	2018-09-09	9E	
2	2018	3	9	10	1	2018-09-10	9E	
3	2018	3	9	13	4	2018-09-13	9E	
4	2018	3	9	14	5	2018-09-14	9E	
5	2018	3	9	16	7	2018-09-16	9E	
6	2018	3	9	17	1	2018-09-17	9E	
7	2018	3	9	20	4	2018-09-20	9E	
8	2018	3	9	21	5	2018-09-21	9E	
9	2018	3	9	23	7	2018-09-23	9E	

	DOT_ID_Reporting_Airline	IATA_CODE_Reporting_Airline	Tail_Number	...	\
0	20363	9E	N908XJ	...	
1	20363	9E	N315PQ	...	
2	20363	9E	N582CA	...	
3	20363	9E	N292PQ	...	
4	20363	9E	N600LR	...	
5	20363	9E	N316PQ	...	
6	20363	9E	N916XJ	...	
7	20363	9E	N371CA	...	
8	20363	9E	N601LR	...	
9	20363	9E	N906XJ	...	

	Div4TailNum	Div5Airport	Div5AirportID	Div5AirportSeqID	Div5WheelsOn	\
0	NaN	NaN	NaN	NaN	NaN	
1	NaN	NaN	NaN	NaN	NaN	
2	NaN	NaN	NaN	NaN	NaN	
3	NaN	NaN	NaN	NaN	NaN	
4	NaN	NaN	NaN	NaN	NaN	
5	NaN	NaN	NaN	NaN	NaN	
6	NaN	NaN	NaN	NaN	NaN	
7	NaN	NaN	NaN	NaN	NaN	
8	NaN	NaN	NaN	NaN	NaN	
9	NaN	NaN	NaN	NaN	NaN	

	Div5TotalGTime	Div5LongestGTime	Div5WheelsOff	Div5TailNum	Unnamed: 109
0	NaN	NaN	NaN	NaN	NaN
1	NaN	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN	NaN

```
4   NaN   NaN   NaN   NaN   NaN
5   NaN   NaN   NaN   NaN   NaN
6   NaN   NaN   NaN   NaN   NaN
7   NaN   NaN   NaN   NaN   NaN
8   NaN   NaN   NaN   NaN   NaN
9   NaN   NaN   NaN   NaN   NaN

[10 rows x 110 columns]
```

Out[10]:

	Year	Quarter	Month	DayofMonth	DayOfWeek	FlightDate	Reporting_Airline	DOT_ID_Reporting_Airline	IATA_CODE_Reporting_Airline	Tail_Numbe
0	2018	3	9	3	1	2018-09-03	9E	20363	9E	N908X
1	2018	3	9	9	7	2018-09-09	9E	20363	9E	N315P
2	2018	3	9	10	1	2018-09-10	9E	20363	9E	N582C
3	2018	3	9	13	4	2018-09-13	9E	20363	9E	N292P
4	2018	3	9	14	5	2018-09-14	9E	20363	9E	N600L
5	2018	3	9	16	7	2018-09-16	9E	20363	9E	N316P
6	2018	3	9	17	1	2018-09-17	9E	20363	9E	N916X
7	2018	3	9	20	4	2018-09-20	9E	20363	9E	N371C
8	2018	3	9	21	5	2018-09-21	9E	20363	9E	N601L
9	2018	3	9	23	7	2018-09-23	9E	20363	9E	N906X

10 rows × 110 columns

Question: Print all the columns in the dataset. Use `<dataframe>.columns` to view the column names.

In [11]:
```
print(f'The column names are :')
print('')
for col in df_temp.columns:
    print(col)
```

```
The column names are :

Year
Quarter
Month
DayofMonth
DayOfWeek
FlightDate
Reporting_Airline
DOT_ID_Reporting_Airline
IATA_CODE_Reporting_Airline
Tail_Number
Flight_Number_Reporting_Airline
OriginAirportID
OriginAirportSeqID
OriginCityMarketID
Origin
OriginCityName
OriginState
```

Question: Print all the columns in the dataset that contain the word 'Del'. This will help you see how many columns have delay data in them.

Hint: You can use a Python list comprehension to include values that pass certain `if` statement criteria.

For example: `[x for x in [1,2,3,4,5] if x > 2]`

Hint: You can use the `in` keyword (documentation (https://www.w3schools.com/python/ref_keyword_in.asp)) to check if the value is in a list or not.

For example: `5 in [1,2,3,4,5]`

In [12]:
```
del_columns = [x for x in df_temp.columns if 'Del' in x]
print(del_columns)
```

```
['DepDelay', 'DepDelayMinutes', 'DepDel15', 'DepartureDelayGroups', 'ArrDelay', 'ArrDelayMinutes', 'ArrDel1
5', 'ArrivalDelayGroups', 'CarrierDelay', 'WeatherDelay', 'NASDelay', 'SecurityDelay', 'LateAircraftDelay',
'DivArrDelay']
```

Here are some more questions to help you find out more about your dataset.

Questions

1. How many rows and columns does the dataset have?
2. How many years are included in the dataset?
3. What is the date range for the dataset?
4. Which airlines are included in the dataset?
5. Which origin and destination airports are covered?

In [13]:
```
# to answer above questions, complete the following code
print("The #rows and #columns are ", df_temp.shape[0] , " and ",  df_temp.shape[1])
print("The years in this dataset are: ", df_temp["Year"].unique())
print("The months covered in this dataset are: ", df_temp["Month"].unique())
print("The date range for data is :" , min(df_temp['FlightDate']), " to ", max(df_temp['FlightDate']))
print("The airlines covered in this dataset are: ", list(df_temp['IATA_CODE_Reporting_Airline'].unique()))
print("The Origin airports covered are: ", list(df_temp['Origin'].unique()))
print("The Destination airports covered are: ", list(df_temp['Dest'].unique()))
```

```
The #rows and #columns are  585749  and  110
The years in this dataset are:  [2018]
The months covered in this dataset are:  [9]
The date range for data is : 2018-09-01  to  2018-09-30
The airlines covered in this dataset are:  ['9E', 'B6', 'WN', 'YV', 'YX', 'EV', 'AA', 'AS', 'DL', 'HA', 'U
A', 'F9', 'G4', 'MQ', 'NK', 'OH', 'OO']
The Origin airports covered are:  ['DFW', 'LGA', 'MSN', 'MSP', 'ATL', 'BDL', 'VLD', 'JFK', 'RDU', 'CHS', 'D
TW', 'GRB', 'PVD', 'SHV', 'FNT', 'PIT', 'RIC', 'RST', 'RSW', 'CVG', 'LIT', 'ORD', 'JAX', 'TRI', 'BOS', 'CW
A', 'DCA', 'CHO', 'AVP', 'IND', 'GRR', 'BTR', 'MEM', 'TUL', 'CLE', 'STL', 'BTV', 'OMA', 'MGM', 'TVC', 'SA
V', 'GSP', 'EWR', 'OAJ', 'BNA', 'MCI', 'TLH', 'ROC', 'LEX', 'PWM', 'BUF', 'AGS', 'CLT', 'GSO', 'BWI', 'SA
T', 'PHL', 'TYS', 'ACK', 'DSM', 'GNV', 'AVL', 'BGR', 'MHT', 'ILM', 'MOT', 'IAH', 'SBN', 'SYR', 'ORF', 'MK
E', 'XNA', 'MSY', 'PBI', 'ABE', 'HPN', 'EVV', 'ALB', 'LNK', 'AUS', 'PHF', 'CHA', 'GTR', 'BMI', 'BQK', 'CI
D', 'CAK', 'ATW', 'ABY', 'CAE', 'SRQ', 'MLI', 'BHM', 'IAD', 'CSG', 'CMH', 'MCO', 'MBS', 'FLL', 'SDF', 'TP
A', 'MVY', 'LAS', 'LGB', 'SFO', 'SAN', 'LAX', 'RNO', 'PDX', 'ANC', 'ABQ', 'SLC', 'DEN', 'PHX', 'OAK', 'SM
F', 'SJU', 'SEA', 'HOU', 'STX', 'BUR', 'SWF', 'SJC', 'DAB', 'BQN', 'PSE', 'ORH', 'HYA', 'STT', 'ONT', 'HR
L', 'ICT', 'ISP', 'LBB', 'MAF', 'MDW', 'OKC', 'PNS', 'SNA', 'TUS', 'AMA', 'BOI', 'CRP', 'DAL', 'ECP', 'EL
P', 'GEG', 'LFT', 'MFE', 'MDT', 'JAN', 'COS', 'MOB', 'VPS', 'MTJ', 'DRO', 'GPT', 'BFL', 'MRY', 'SBA', 'PS
P', 'FSD', 'BRO', 'RAP', 'COU', 'STS', 'PIA', 'FAT', 'SBP', 'FSM', 'HSV', 'BIS', 'DAY', 'BZN', 'MIA', 'EY
W', 'MYR', 'HHH', 'GJT', 'FAR', 'SGF', 'HOB', 'CLL', 'LRD', 'AEX', 'ERI', 'MLU', 'LCH', 'ROA', 'LAW', 'MH
K', 'GRK', 'SAF', 'GRI', 'JLN', 'ROW', 'FWA', 'CRW', 'LAN', 'OGG', 'HNL', 'KOA', 'EGE', 'LIH', 'MLB', 'JA
C', 'FAI', 'RDM', 'ADQ', 'BET', 'BRW', 'SCC', 'KTN', 'YAK', 'CDV', 'JNU', 'SIT', 'PSG', 'WRG', 'OME', 'OT
Z', 'ADK', 'FCA', 'FAY', 'PSC', 'BIL', 'MSO', 'ITO', 'PPG', 'MFR', 'EUG', 'GUM', 'SPN', 'DLH', 'TTN', 'BK
G', 'SFB', 'PIE', 'PGD', 'AZA', 'SMX', 'RFD', 'SCK', 'OWB', 'HTS', 'BLV', 'IAG', 'USA', 'GFK', 'BLI', 'EL
M', 'PBG', 'LCK', 'GTF', 'OGD', 'IDA', 'PVU', 'TOL', 'PSM', 'CKB', 'HGR', 'SPI', 'STC', 'ACT', 'TYR', 'AB
I', 'AZO', 'CMI', 'BPT', 'GCK', 'MQT', 'ALO', 'TXK', 'SPS', 'SWO', 'DBQ', 'SUX', 'SJT', 'GGG', 'LSE', 'LB
E', 'ACY', 'LYH', 'PGV', 'HVN', 'EWN', 'DHN', 'PIH', 'IMT', 'WYS', 'CPR', 'SCE', 'HLN', 'SUN', 'ISN', 'CM
X', 'EAU', 'LWB', 'SHD', 'LBF', 'HYS', 'SLN', 'EAR', 'VEL', 'CNY', 'GCC', 'RKS', 'PUB', 'LBL', 'MKG', 'PA
H', 'CGI', 'UIN', 'BFF', 'DVL', 'JMS', 'LAR', 'SGU', 'PRC', 'ASE', 'RDD', 'ACV', 'OTH', 'COD', 'LWS', 'AB
R', 'APN', 'ESC', 'PLN', 'BJI', 'BRD', 'BTM', 'CDC', 'CIU', 'EKO', 'TWF', 'HIB', 'BGM', 'RHI', 'ITH', 'IN
L', 'FLG', 'YUM', 'MEI', 'PIB', 'HDN']
The Destination airports covered are:  ['CVG', 'PWM', 'RDU', 'MSP', 'MSN', 'SHV', 'CLT', 'PIT', 'RIC', 'IA
H', 'ATL', 'JFK', 'DCA', 'DTW', 'LGA', 'TYS', 'PVD', 'FNT', 'LIT', 'BUF', 'ORD', 'TRI', 'IND', 'BGR', 'AV
P', 'BWI', 'LEX', 'BDL', 'GRR', 'CWA', 'TUL', 'MEM', 'AGS', 'EWR', 'MGM', 'PHL', 'SYR', 'OMA', 'STL', 'TV
C', 'ORF', 'CLE', 'ABY', 'BOS', 'OAJ', 'TLH', 'BTR', 'SAT', 'JAX', 'BNA', 'CHO', 'VLD', 'ROC', 'DFW', 'GN
V', 'ACK', 'PBI', 'CHS', 'GRB', 'MOT', 'MKE', 'DSM', 'ILM', 'GSO', 'MCI', 'SBN', 'BTV', 'MVY', 'XNA', 'RS
T', 'EVV', 'HPN', 'RSW', 'MDT', 'ROA', 'GSP', 'MCO', 'CSG', 'SAV', 'PHF', 'ALB', 'CHA', 'ABE', 'BMI', 'MS
Y', 'IAD', 'GTR', 'CID', 'CAK', 'ATW', 'AUS', 'BQK', 'MLI', 'CAE', 'CMH', 'AVL', 'MBS', 'FLL', 'SDF', 'TP
A', 'LNK', 'SRQ', 'MHT', 'BHM', 'LAS', 'SFO', 'SAN', 'RNO', 'LGB', 'ANC', 'PDX', 'SJU', 'ABQ', 'SLC', 'DE
N', 'LAX', 'PHX', 'OAK', 'SMF', 'SEA', 'STX', 'BUR', 'DAB', 'SJC', 'SWF', 'HOU', 'BQN', 'PSE', 'ORH', 'HY
A', 'STT', 'ONT', 'DAL', 'ECP', 'ELP', 'HRL', 'MAF', 'MDW', 'OKC', 'PNS', 'SNA', 'AMA', 'BOI', 'GEG', 'IC
T', 'LBB', 'TUS', 'ISP', 'CRP', 'MFE', 'LFT', 'VPS', 'JAN', 'COS', 'MOB', 'DRO', 'GPT', 'BFL', 'COU', 'SB
```

```
P', 'MTJ', 'SBA', 'PSP', 'FSD', 'FSM', 'BRO', 'PIA', 'STS', 'FAT', 'RAP', 'MRY', 'HSV', 'BIS', 'DAY', 'BZ
N', 'MIA', 'EYW', 'MYR', 'HHH', 'GJT', 'FAR', 'MLU', 'LRD', 'CLL', 'LCH', 'FWA', 'GRK', 'SGF', 'HOB', 'LA
W', 'MHK', 'SAF', 'JLN', 'ROW', 'GRI', 'AEX', 'CRW', 'LAN', 'ERI', 'HNL', 'KOA', 'OGG', 'EGE', 'LIH', 'JA
C', 'MLB', 'RDM', 'BET', 'ADQ', 'BRW', 'SCC', 'FAI', 'JNU', 'CDV', 'YAK', 'SIT', 'KTN', 'WRG', 'PSG', 'OM
E', 'OTZ', 'ADK', 'FCA', 'BIL', 'PSC', 'FAY', 'MSO', 'ITO', 'PPG', 'MFR', 'DLH', 'EUG', 'GUM', 'SPN', 'TT
N', 'BKG', 'AZA', 'SFB', 'LCK', 'BLI', 'SCK', 'PIE', 'RFD', 'PVU', 'PBG', 'BLV', 'PGD', 'SPI', 'USA', 'TO
L', 'IDA', 'ELM', 'HTS', 'HGR', 'SMX', 'OGD', 'GFK', 'STC', 'GTF', 'IAG', 'CKB', 'OWB', 'PSM', 'ABI', 'TY
R', 'ALO', 'SUX', 'AZO', 'ACT', 'CMI', 'BPT', 'TXK', 'SWO', 'SPS', 'DBQ', 'SJT', 'GGG', 'LSE', 'MQT', 'GC
K', 'LBE', 'ACY', 'LYH', 'PGV', 'HVN', 'EWN', 'DHN', 'PIH', 'WYS', 'SCE', 'IMT', 'HLN', 'ASE', 'SUN', 'IS
N', 'EAR', 'SGU', 'VEL', 'SHD', 'LWB', 'MKG', 'SLN', 'HYS', 'BFF', 'PUB', 'LBL', 'CMX', 'EAU', 'PAH', 'UI
N', 'RKS', 'CGI', 'CNY', 'JMS', 'DVL', 'LAR', 'GCC', 'LBF', 'PRC', 'RDD', 'ACV', 'OTH', 'COD', 'LWS', 'AB
R', 'APN', 'PLN', 'BJI', 'CPR', 'BRD', 'BTM', 'CDC', 'CIU', 'ESC', 'EKO', 'ITH', 'HIB', 'BGM', 'TWF', 'RH
I', 'INL', 'FLG', 'YUM', 'MEI', 'PIB', 'HDN']
```

Question: What is the count of all the origin and destination airports?

Hint: You can use the Pandas `values_count` function (documentation (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.Series.value_counts.html)) to find out the values for each airport using the columns `Origin` and `Dest`.

In [14]:
```
counts = pd.DataFrame({
    'Origin': df_temp['Origin'].value_counts(),
    'Destination':df_temp['Dest'].value_counts()})
counts
```

Out[14]:

	Origin	Destination
ABE	303	303
ABI	169	169
ABQ	2077	2076
ABR	60	60
ABY	79	79
...	...	...
WRG	60	60
WYS	52	52
XNA	1004	1004
YAK	60	60
YUM	96	96

346 rows × 2 columns

Question: Print the top 15 origin and destination airports based on number of flights in the dataset.

Hint: You can use the Pandas `sort_values` function (documentation (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.sort_values.html)).

In [15]:
```
counts.sort_values(by='Origin', ascending=False).head(15)
```

Out[15]:

	Origin	Destination
ATL	31525	31521
ORD	28257	28250
DFW	22802	22795
DEN	19807	19807
CLT	19655	19654
LAX	17875	17873
SFO	14332	14348
IAH	14210	14203
LGA	13850	13850
MSP	13349	13347
LAS	13318	13322
PHX	13126	13128
DTW	12725	12724
BOS	12223	12227
SEA	11872	11877

Question: Given all the information about a flight trip, can you predict if it would be delayed?

Yes, I think flight delays can be predicted using the information in the dataset. Features like the airline, origin/destination airports, day of week, month, and scheduled departure time could capture patterns like certain airlines having more delays, specific airports being prone to congestion, seasonal weather impacts (winter storms, summer thunderstorms), or even peak travel times.

Variable like ArrDel15 could potentially be used as the target variable.

In [ ]:

Now, assume you are traveling from San Francisco to Los Angeles on a work trip. You want to have an ideas if your flight will be delayed, given a set of features, so that you can manage your reservations in Los Angeles better. How many features from this dataset would you know before your flight?

Columns such as `DepDelay`, `ArrDelay`, `CarrierDelay`, `WeatherDelay`, `NASDelay`, `SecurityDelay`, `LateAircraftDelay`, and `DivArrDelay` contain information about a delay. But this delay could have occured at the origin or destination. If there were a sudden weather delay 10 minutes before landing, this data would not be helpful in managing your Los Angeles reservations.

So to simplify the problem statement, consider the following columns to predict an arrival delay:

`Year`, `Quarter`, `Month`, `DayofMonth`, `DayOfWeek`, `FlightDate`, `Reporting_Airline`, `Origin`, `OriginState`, `Dest`, `DestState`, `CRSDepTime`, `DepDelayMinutes`, `DepartureDelayGroups`, `Cancelled`, `Diverted`, `Distance`, `DistanceGroup`, `ArrDelay`, `ArrDelayMinutes`, `ArrDel15`, `AirTime`

You will also filter the source and destination airports to be:

- Top airports: ATL, ORD, DFW, DEN, CLT, LAX, IAH, PHX, SFO
- Top 5 airlines: UA, OO, WN, AA, DL

This should help in reducing the size of data across the CSV files to be combined.

Combine all CSV files

Hint:
First, create an empy dataframe that you will use to copy your individual dataframes from each file. Then, for each file in the `csv_files` list:

1. Read the CSV file into a dataframe
2. Filter the columns based on the `filter_cols` variable

```
columns = ['col1', 'col2']
df_filter = df[columns]
```

3. Keep only the subset_vals in each of the subset_cols. Use the `isin` Pandas function (documentation (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.isin.html)) to check if the `val` is in the dataframe column and then choose the rows that include it.

```
df_eg[df_eg['col1'].isin('5')]
```

4. Concatenate the dataframe with the empty dataframe

In [16]:
```
def combine_csv(csv_files, filter_cols, subset_cols, subset_vals, file_name):
    """
    Combine csv files into one Data Frame
    csv_files: list of csv file paths
    filter_cols: list of columns to filter
    subset_cols: list of columns to subset rows
    subset_vals: list of list of values to subset rows
    """
    # Create an empty dataframe
    df = pd.DataFrame()

    for file in csv_files:

        file_path = f"datasets/{file}"

        df_temp = pd.read_csv(file_path)

        # Filter the columns (keep only the columns we want)
        df_temp = df_temp[filter_cols]

        # Filter rows - keep only rows where Origin is in first list
        df_temp = df_temp[df_temp['Origin'].isin(subset_vals[0])]

        # Filter rows - keep only rows where Dest is in second list
        df_temp = df_temp[df_temp['Dest'].isin(subset_vals[1])]

        # Filter rows - keep only rows where Reporting_Airline is in third list
        df_temp = df_temp[df_temp['Reporting_Airline'].isin(subset_vals[2])]

        # Add this filtered data to our main dataframe
        df = pd.concat([df, df_temp])

    # Save the combined data to a CSV file
    df.to_csv(file_name, index=False)


    #<complete the code of this function>
```

In [17]:
```
#cols is the list of columns to predict Arrival Delay
cols = ['Year','Quarter','Month','DayofMonth','DayOfWeek','FlightDate',
        'Reporting_Airline','Origin','OriginState','Dest','DestState',
        'CRSDepTime','Cancelled','Diverted','Distance','DistanceGroup',
        'ArrDelay','ArrDelayMinutes','ArrDel15','AirTime']

subset_cols = ['Origin', 'Dest', 'Reporting_Airline']

# subset_vals is a list collection of the top origin and destination airports and top 5 airlines
subset_vals = [['ATL', 'ORD', 'DFW', 'DEN', 'CLT', 'LAX', 'IAH', 'PHX', 'SFO'],
               ['ATL', 'ORD', 'DFW', 'DEN', 'CLT', 'LAX', 'IAH', 'PHX', 'SFO'],
               ['UA', 'OO', 'WN', 'AA', 'DL']]
```

Use the function above to merge all the different files into a single file that you can read easily.

Note: This will take 5-7 minutes to complete.

In [18]:
```
start = time.time()

combined_csv_filename = f"{base_path}/combined_files.csv"

df_combined = combine_csv(csv_files, cols, subset_cols, subset_vals, combined_csv_filename)

print(f'csv\'s merged in {round((time.time() - start)/60,2)} minutes')
```

```
csv's merged in 2.07 minutes
```

Load dataset

Load the combined dataset.

In [19]:
```
data = pd.read_csv(combined_csv_filename)
```

Print the first 5 records.

In [20]:
```
print(data)

data
```

```
         Year  Quarter  Month  DayofMonth  DayOfWeek  FlightDate  \
0        2014        4     10           1          3  2014-10-01
1        2014        4     10           2          4  2014-10-02
2        2014        4     10           3          5  2014-10-03
3        2014        4     10           4          6  2014-10-04
4        2014        4     10           5          7  2014-10-05
...       ...      ...    ...         ...        ...         ...
1658125  2017        3      9           5          2  2017-09-05
1658126  2017        3      9           5          2  2017-09-05
1658127  2017        3      9           5          2  2017-09-05
1658128  2017        3      9           5          2  2017-09-05
1658129  2017        3      9           5          2  2017-09-05

       Reporting_Airline Origin OriginState Dest DestState  CRSDepTime  \
0                     AA    DFW          TX  SFO        CA         755
1                     AA    DFW          TX  SFO        CA         755
2                     AA    DFW          TX  SFO        CA         755
3                     AA    DFW          TX  SFO        CA         755
4                     AA    DFW          TX  SFO        CA         755
...                  ...    ...         ...  ...       ...         ...
1658125               UA    ORD          IL  SFO        CA         950
1658126               UA    IAH          TX  PHX        AZ         909
1658127               UA    IAH          TX  LAX        CA         910
1658128               UA    LAX          CA  ORD        IL        1347
1658129               UA    ATL          GA  SFO        CA         716

         Cancelled  Diverted  Distance  DistanceGroup  ArrDelay  \
0              0.0       0.0    1464.0              6      -9.0
1              0.0       0.0    1464.0              6      40.0
2              0.0       0.0    1464.0              6       9.0
3              0.0       0.0    1464.0              6     -16.0
4              0.0       0.0    1464.0              6      -8.0
...            ...       ...       ...            ...       ...
1658125        0.0       0.0    1846.0              8     -36.0
1658126        1.0       0.0    1009.0              5       NaN
1658127        1.0       0.0    1379.0              6       NaN
1658128        0.0       0.0    1744.0              7      -9.0
1658129        0.0       0.0    2139.0              9     -22.0

         ArrDelayMinutes  ArrDel15  AirTime
0                    0.0       0.0    195.0
```

```
1                  40.0       1.0    199.0
2                   9.0       0.0    196.0
3                   0.0       0.0    195.0
4                   0.0       0.0    192.0
...                 ...       ...      ...
1658125             0.0       0.0    228.0
1658126             NaN       NaN      NaN
1658127             NaN       NaN      NaN
1658128             0.0       0.0    221.0
1658129             0.0       0.0    263.0

[1658130 rows x 20 columns]
```

Out[20]:

	Year	Quarter	Month	DayofMonth	DayOfWeek	FlightDate	Reporting_Airline	Origin	OriginState	Dest	DestState	CRSDepTime	Cancelle
0	2014	4	10	1	3	2014-10-01	AA	DFW	TX	SFO	CA	755	0
1	2014	4	10	2	4	2014-10-02	AA	DFW	TX	SFO	CA	755	0
2	2014	4	10	3	5	2014-10-03	AA	DFW	TX	SFO	CA	755	0
3	2014	4	10	4	6	2014-10-04	AA	DFW	TX	SFO	CA	755	0
4	2014	4	10	5	7	2014-10-05	AA	DFW	TX	SFO	CA	755	0
...	...	...	...	...	...	...	...	...	...	...	...	...	
1658125	2017	3	9	5	2	2017-09-05	UA	ORD	IL	SFO	CA	950	0
1658126	2017	3	9	5	2	2017-09-05	UA	IAH	TX	PHX	AZ	909	1
1658127	2017	3	9	5	2	2017-09-05	UA	IAH	TX	LAX	CA	910	1
1658128	2017	3	9	5	2	2017-09-05	UA	LAX	CA	ORD	IL	1347	0
1658129	2017	3	9	5	2	2017-09-05	UA	ATL	GA	SFO	CA	716	0

1658130 rows × 20 columns

Here are some more questions to help you find out more about your dataset.

Questions

1. How many rows and columns does the dataset have?
2. How many years are included in the dataset?
3. What is the date range for the dataset?
4. Which airlines are included in the dataset?
5. Which origin and destination airports are covered?

In [21]:
```
# to answer above questions, complete the following code
print("The #rows and #columns are ", data.shape[0] , " and ", data.shape[1])
print("The years in this dataset are: ", list(data["Year"].unique()))
print("The months covered in this dataset are: ", sorted(list(data["Month"].unique())))
print("The date range for data is :" , min(data['FlightDate']), " to ", max(data['FlightDate']))
print("The airlines covered in this dataset are: ", list(df_temp['IATA_CODE_Reporting_Airline'].unique()))
print("The Origin airports covered are: ", list(data['Origin'].unique()))
print("The Destination airports covered are: ", list(data['Dest'].unique()))
```

```
The #rows and #columns are  1658130  and  20
The years in this dataset are:  [2014, 2017, 2018, 2015, 2016]
The months covered in this dataset are:  [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12]
The date range for data is : 2014-01-01  to  2018-12-31
The airlines covered in this dataset are:  ['9E', 'B6', 'WN', 'YV', 'YX', 'EV', 'AA', 'AS', 'DL', 'HA', 'U
A', 'F9', 'G4', 'MQ', 'NK', 'OH', 'OO']
The Origin airports covered are:  ['DFW', 'SFO', 'DEN', 'PHX', 'IAH', 'ATL', 'ORD', 'LAX', 'CLT']
The Destination airports covered are:  ['SFO', 'DFW', 'DEN', 'PHX', 'ORD', 'IAH', 'ATL', 'LAX', 'CLT']
```

Let's define our **target column : is_delay** (1 - if arrival time delayed more than 15 minutes, 0 - otherwise). Use the `rename` method to rename the column from `ArrDel15` to `is_delay` .

Hint: You can use the Pandas `rename` function (documentation (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.rename.html)).

For example:

```
df.rename(columns={'col1':'column1'}, inplace=True)
```

In [22]:
```
# data.columns

data.rename(columns={'ArrDel15': 'is_delay'}, inplace=True)

data.columns
```

Out[22]:
```
Index(['Year', 'Quarter', 'Month', 'DayofMonth', 'DayOfWeek', 'FlightDate',
       'Reporting_Airline', 'Origin', 'OriginState', 'Dest', 'DestState',
       'CRSDepTime', 'Cancelled', 'Diverted', 'Distance', 'DistanceGroup',
       'ArrDelay', 'ArrDelayMinutes', 'is_delay', 'AirTime'],
      dtype='object')
```

Look for nulls across columns. You can use the `isnull()` function (documentation (https://pandas.pydata.org/pandas-docs/version/0.17.0/generated/pandas.isnull.html)).

Hint: `isnull()` detects whether the particular value is null or not and gives you a boolean (True or False) in its place. Use the `sum(axis=0)` function to sum up the number of columns.

In [23]:
```
data.isnull().sum(axis=0)
```

Out[23]:
```
Year                    0
Quarter                 0
Month                   0
DayofMonth              0
DayOfWeek               0
FlightDate              0
Reporting_Airline       0
Origin                  0
OriginState             0
Dest                    0
DestState               0
CRSDepTime              0
Cancelled               0
Diverted                0
Distance                0
DistanceGroup           0
ArrDelay            22540
ArrDelayMinutes     22540
is_delay            22540
AirTime             22540
dtype: int64
```

The arrival delay details and airtime are missing for 22540 out of 1658130 rows, which is 1.3%. You can either remove or impute these rows. The documentation does not mention anything about missing rows.

Hint: Use the `~` operator to choose the values that aren't null from the `isnull()` output.

For example:

```
null_eg = df_eg[~df_eg['column_name'].isnull()]
```

In [24]:
```
### Remove null columns
data = data[~data['is_delay'].isnull()] # I just remove is_delay because the rest missing values (AirTime,Arr


data.isnull().sum(axis=0)
```

Out[24]:
```
Year                0
Quarter             0
Month               0
DayofMonth          0
DayOfWeek           0
FlightDate          0
Reporting_Airline   0
Origin              0
OriginState         0
Dest                0
DestState           0
CRSDepTime          0
Cancelled           0
Diverted            0
Distance            0
DistanceGroup       0
ArrDelay            0
ArrDelayMinutes     0
is_delay            0
AirTime             0
dtype: int64
```

Get the hour of the day in 24-hour time format from CRSDepTime.

In [25]:
```
# data['DepHourofDay'] = # Enter your code here

data['DepHourofDay'] = (data['CRSDepTime'] // 100).astype(int)
```

The ML problem statement

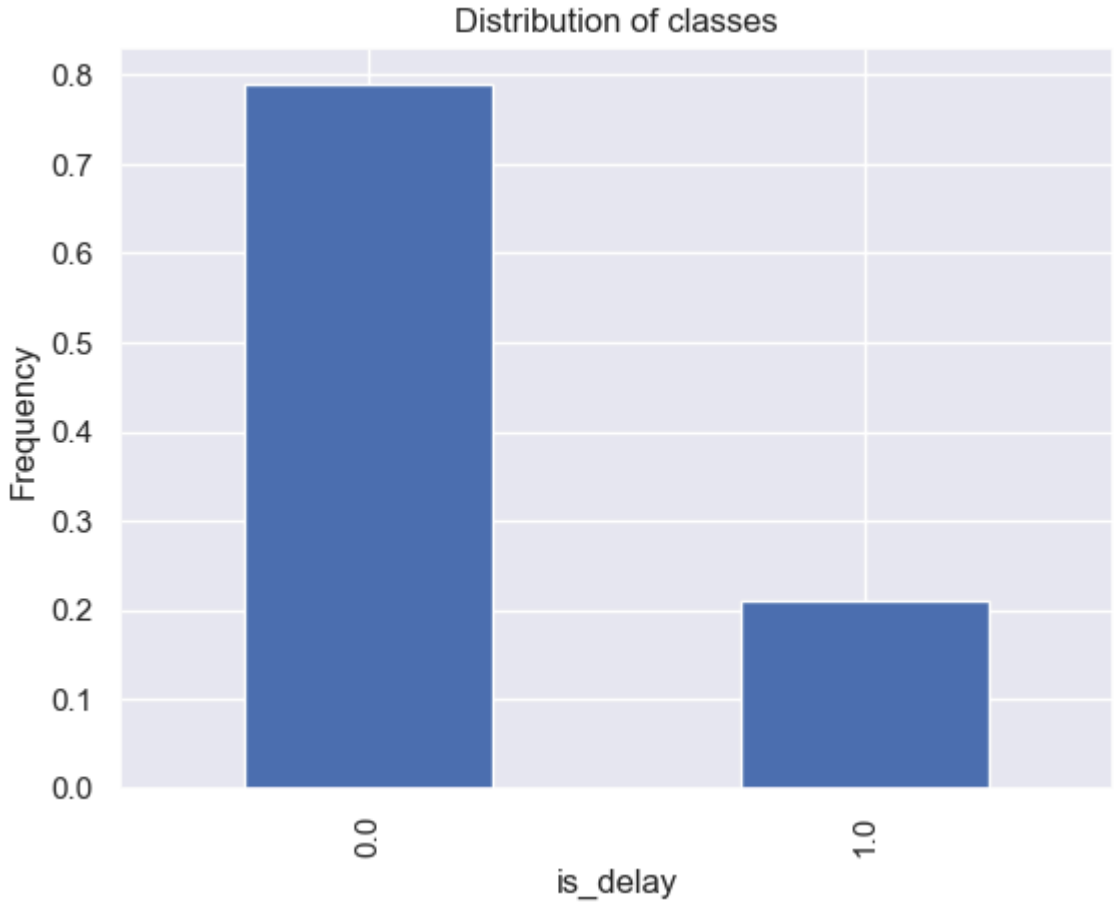
- Given a set of features, can you predict if a flight is going to be delayed more than 15 minutes?
- Because the target variable takes only 0/1 value, you could use a classification algorithm.

Data exploration

Check class delay vs. no delay

Hint: Use a `groupby` plot (documentation (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.groupby.html)) with a `bar` plot (documentation (https://matplotlib.org/tutorials/introductory/pyplot.html)) to plot the frequency vs. distribution of the class.

In [26]:
```
(data.groupby(["is_delay"]).size()/len(data) ).plot(kind='bar')# Enter your code here
plt.ylabel('Frequency')
plt.title('Distribution of classes')
plt.show()
```



Question: What can you deduce from the bar plot about the ratio of delay vs. no delay?

From that bar plot, I can deduce that:

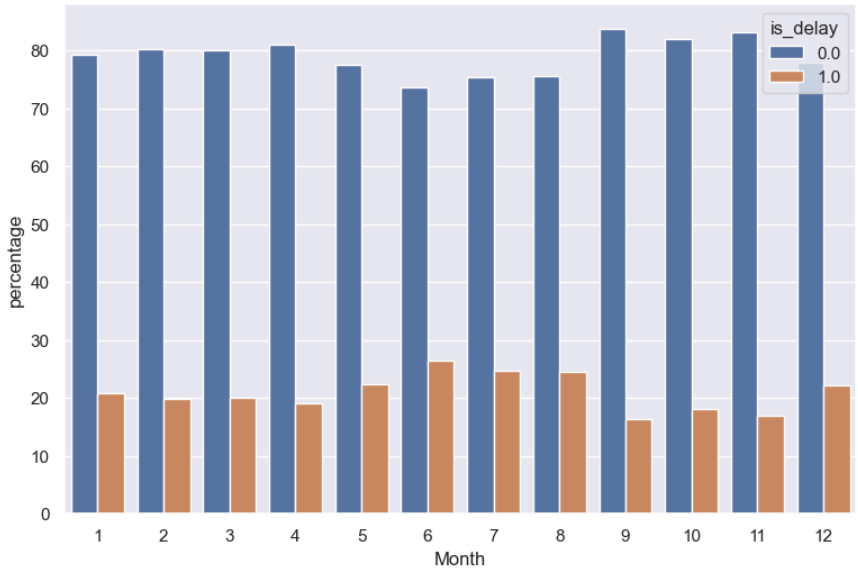
The dataset shows a significant class imbalance between delay and no delay cases. No delay cases have around 80% of the observations while delay cases have only approximately 20%.

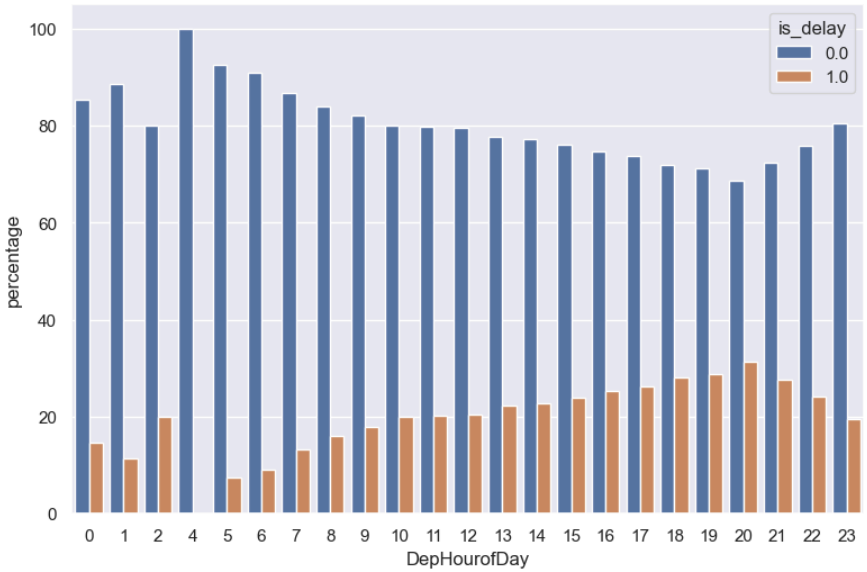
So, the majority class (no delay) dominates the dataset, and the minority class (delay) is underrepresented. This imbalance may cause machine learning models to be biased toward predicting no delays.

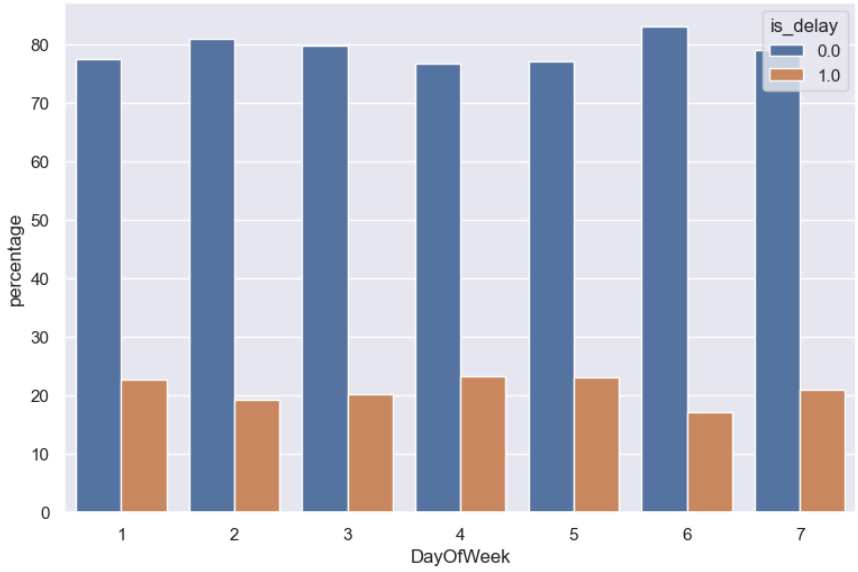
Questions:

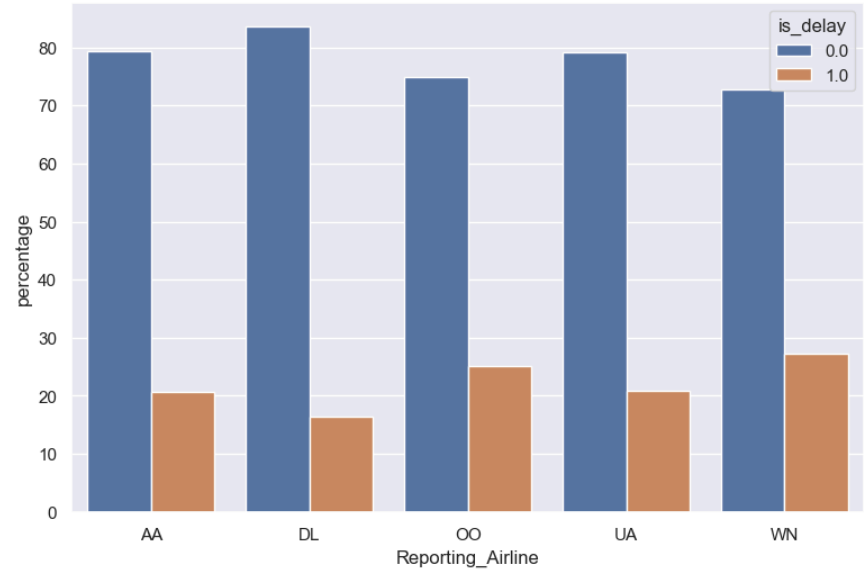
- Which months have the most delays?
- What time of the day has the most delays?
- What day of the week has the most delays?
- Which airline has the most delays?
- Which origin and destination airports have the most delays?
- Is flight distance a factor in the delays?

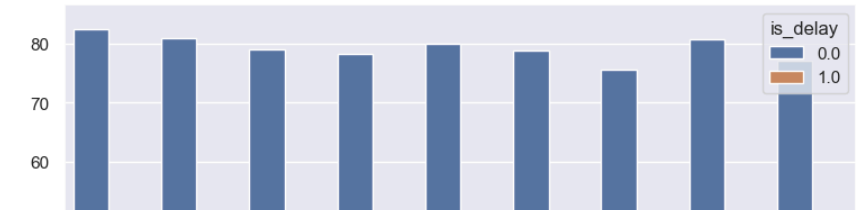
In [27]:
```
viz_columns = ['Month', 'DepHourofDay', 'DayOfWeek', 'Reporting_Airline', 'Origin', 'Dest']
fig, axes = plt.subplots(3, 2, figsize=(20,20), squeeze=False)
# fig.autofmt_xdate(rotation=90)

for idx, column in enumerate(viz_columns):
    ax = axes[idx//2, idx%2]
    temp = data.groupby(column)['is_delay'].value_counts(normalize=True).rename('percentage').\
    mul(100).reset_index().sort_values(column)
    sns.barplot(x=column, y="percentage", hue="is_delay", data=temp, ax=ax)
    plt.ylabel('% delay/no-delay')


plt.show()
```

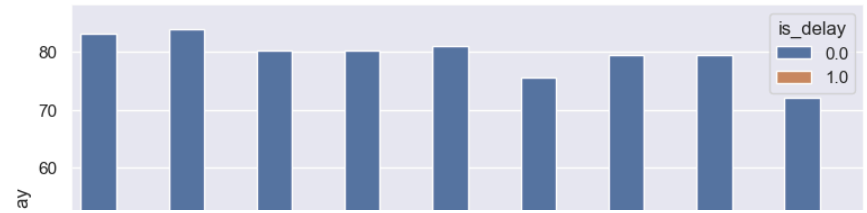

is_delay
0.0
1.0
percentage
Month
1 2 3 4 5 6 7 8 9 10 11 12

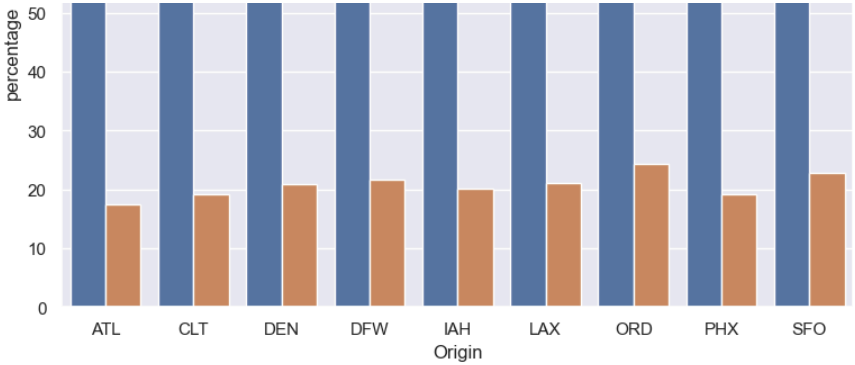

is_delay
0.0
1.0
percentage
DepHourofDay
0 1 2 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23

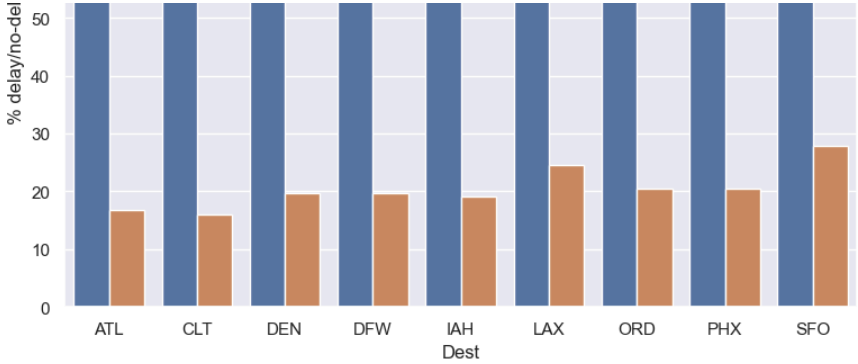

is_delay
0.0
1.0
percentage
DayOfWeek
1 2 3 4 5 6 7


is_delay
0.0
1.0
percentage
Reporting_Airline
AA DL OO UA WN

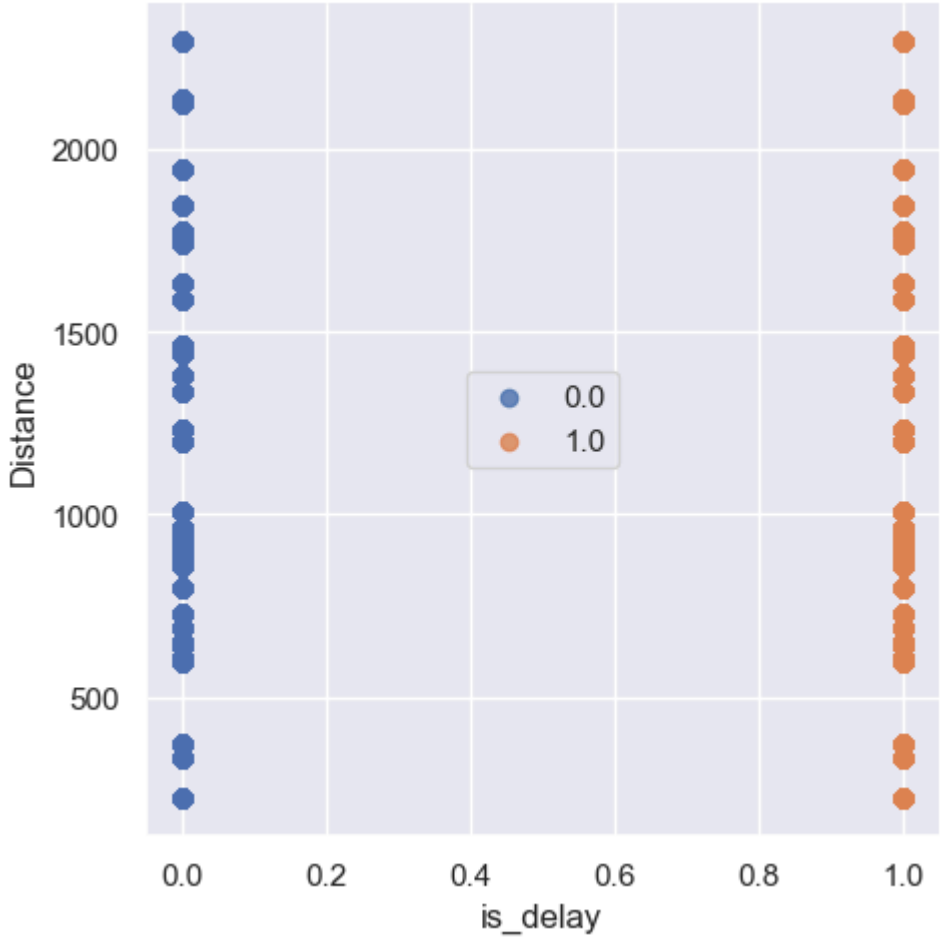

is_delay
0.0
1.0


is_delay
0.0
1.0


percentage
0
10
20
30
40
50
ATL
CLT
DEN
DFW
IAH
LAX
ORD
PHX
SFO
Origin


% delay/no-del
0
10
20
30
40
50
ATL
CLT
DEN
DFW
IAH
LAX
ORD
PHX
SFO
Dest

In [28]:
```
sns.lmplot( x="is_delay", y="Distance", data=data, fit_reg=False, hue='is_delay', legend=False)
plt.legend(loc='center')
plt.xlabel('is_delay')
plt.ylabel('Distance')
plt.show()
```



Which months have the most delays?

- June has the highest delays, after that, July, August and December.

What time of the day has the most delays?

- 8pm has the most delays, but delays starts to increase from 6pm-9pm.

What day of the week has the most delays?

- It seems like Monday(1), Thursday(4), and Friday(5) have the most delays.

Which airline has the most delays?

- WN and then OO have the most delays.

Which origin and destination airports have the most delays?

- origin: ORN and destination: SFO

Is flight distance a factor in the delays

- Flight distance is NOT a determining factor in whether a flight will be delayed.
- Both delayed flights and non-delayed flights show nearly identical distance distributions. The points overlap extensively across all distance ranges.

Features

Look at all the columns and what their specific types are.

In [29]:
```
data.columns
```

Out[29]:
```
Index(['Year', 'Quarter', 'Month', 'DayofMonth', 'DayOfWeek', 'FlightDate',
       'Reporting_Airline', 'Origin', 'OriginState', 'Dest', 'DestState',
       'CRSDepTime', 'Cancelled', 'Diverted', 'Distance', 'DistanceGroup',
       'ArrDelay', 'ArrDelayMinutes', 'is_delay', 'AirTime', 'DepHourofDay'],
      dtype='object')
```

In [30]:
```
data.dtypes
```

Out[30]:
```
Year                 int64
Quarter              int64
Month                int64
DayofMonth           int64
DayOfWeek            int64
FlightDate          object
Reporting_Airline   object
Origin              object
OriginState         object
Dest                object
DestState           object
CRSDepTime           int64
Cancelled          float64
Diverted           float64
Distance           float64
DistanceGroup        int64
ArrDelay           float64
ArrDelayMinutes    float64
is_delay           float64
AirTime            float64
DepHourofDay         int64
dtype: object
```

Filtering the required columns:

- Date is redundant, because you have Year, Quarter, Month, DayofMonth, and DayOfWeek to describe the date.
- Use Origin and Dest codes instead of OriginState and DestState.
- Because you are just classifying whether the flight is delayed or not, you don't need TotalDelayMinutes, DepDelayMinutes, and ArrDelayMinutes.

Treat DepHourofDay as a categorical variable because it doesn't have any quantitative relation with the target.

- If you had to do a one-hot encoding of it, it would result in 23 more columns.
- Other alternatives to handling categorical variables include hash encoding, regularized mean encoding, and bucketizing the values, among others.
- Just split into buckets here.

Hint: To change a column type to category, use the `astype` function (documentation (https://pandas.pydata.org/pandas-

In [31]:
```
data_orig = data.copy()
data = data[[ 'is_delay', 'Quarter', 'Month', 'DayofMonth', 'DayOfWeek',
       'Reporting_Airline', 'Origin', 'Dest','Distance','DepHourofDay']]

# I did the BUCKETIZE DepHourofDay before treating as categorical
def bucket_hour(hour):
    if 0 <= hour < 6:
        return 'Night'
    elif 6 <= hour < 12:
        return 'Morning'
    elif 12 <= hour < 18:
        return 'Afternoon'
    else:  # 18 <= hour < 24
        return 'Evening'

# Create the bucketed column and drop the original
data['DepHourBucket'] = data['DepHourofDay'].apply(bucket_hour)
data.drop('DepHourofDay', axis=1, inplace=True)

# categorical_columns  = ['Quarter', 'Month', 'DayofMonth', 'DayOfWeek',
#        'Reporting_Airline', 'Origin', 'Dest', 'DepHourofDay']

# Update categorical_columns to use DepHourBucket instead of DepHourofDay
categorical_columns = ['Quarter', 'Month', 'DayofMonth', 'DayOfWeek',
                       'Reporting_Airline', 'Origin', 'Dest', 'DepHourBucket']


for c in categorical_columns:
    data[c] = data[c].astype('category')


# Verify the changes
print(data.dtypes)
print(f"\nDataset shape: {data.shape}")
print(f"\nFirst few rows:\n{data.head()}")
```

```
is_delay              float64
Quarter              category
Month                category
DayofMonth           category
DayOfWeek            category
Reporting_Airline    category
Origin               category
Dest                 category
Distance              float64
DepHourBucket        category
dtype: object

Dataset shape: (1635590, 10)

First few rows:
   is_delay Quarter Month DayofMonth DayOfWeek Reporting_Airline Origin Dest  \
0       0.0       4    10          1         3                 AA    DFW  SFO
1       1.0       4    10          2         4                 AA    DFW  SFO
2       0.0       4    10          3         5                 AA    DFW  SFO
3       0.0       4    10          4         6                 AA    DFW  SFO
4       0.0       4    10          5         7                 AA    DFW  SFO

   Distance DepHourBucket
0    1464.0       Morning
1    1464.0       Morning
2    1464.0       Morning
3    1464.0       Morning
4    1464.0       Morning
```

To use one-hot encoding, use the Pandas `get_dummies` function for the categorical columns that you selected above. Then, you can concatenate those generated features to your original dataset using the Pandas `concat` function. For encoding categorical variables, you can also use *dummy encoding* by using a keyword `drop_first=True` . For more information on dummy encoding, see https://en.wikiversity.org/wiki/Dummy_variable_(statistics) (https://en.wikiversity.org/wiki/Dummy_variable_(statistics)).

For example:

```
pd.get_dummies(df[['column1','columns2']], drop_first=True)
```

In [32]:
```
data_dummies = pd.get_dummies(data[categorical_columns], drop_first=True)
data = pd.concat([data, data_dummies], axis = 1)
data.drop(categorical_columns,axis=1, inplace=True)
```

Check the length of the dataset and the new columnms.

In [33]:
```
# Verify the changes
print("New dataset shape:", data.shape)
```

```
New dataset shape: (1635590, 75)
```

In [34]:
```
print("\nData types:")
print(data.dtypes)

print("\nColumn names:")
print(data.columns)
```

```
Data types:
is_delay                 float64
Distance                 float64
Quarter_2                   bool
Quarter_3                   bool
Quarter_4                   bool
                            ...
Dest_PHX                    bool
Dest_SFO                    bool
DepHourBucket_Evening       bool
DepHourBucket_Morning       bool
DepHourBucket_Night         bool
Length: 75, dtype: object

Column names:
Index(['is_delay', 'Distance', 'Quarter_2', 'Quarter_3', 'Quarter_4',
       'Month_2', 'Month_3', 'Month_4', 'Month_5', 'Month_6', 'Month_7',
       'Month_8', 'Month_9', 'Month_10', 'Month_11', 'Month_12',
       'DayofMonth_2', 'DayofMonth_3', 'DayofMonth_4', 'DayofMonth_5',
       'DayofMonth_6', 'DayofMonth_7', 'DayofMonth_8', 'DayofMonth_9',
       'DayofMonth_10', 'DayofMonth_11', 'DayofMonth_12', 'DayofMonth_13',
       'DayofMonth_14', 'DayofMonth_15', 'DayofMonth_16', 'DayofMonth_17',
       'DayofMonth_18', 'DayofMonth_19', 'DayofMonth_20', 'DayofMonth_21',
       'DayofMonth_22', 'DayofMonth_23', 'DayofMonth_24', 'DayofMonth_25',
       'DayofMonth_26', 'DayofMonth_27', 'DayofMonth_28', 'DayofMonth_29',
       'DayofMonth_30', 'DayofMonth_31', 'DayOfWeek_2', 'DayOfWeek_3',
       'DayOfWeek_4', 'DayOfWeek_5', 'DayOfWeek_6', 'DayOfWeek_7',
       'Reporting_Airline_DL', 'Reporting_Airline_OO', 'Reporting_Airline_UA',
       'Reporting_Airline_WN', 'Origin_CLT', 'Origin_DEN', 'Origin_DFW',
       'Origin_IAH', 'Origin_LAX', 'Origin_ORD', 'Origin_PHX', 'Origin_SFO',
       'Dest_CLT', 'Dest_DEN', 'Dest_DFW', 'Dest_IAH', 'Dest_LAX', 'Dest_ORD',
       'Dest_PHX', 'Dest_SFO', 'DepHourBucket_Evening',
       'DepHourBucket_Morning', 'DepHourBucket_Night'],
      dtype='object')
```

Sample Answer:

```
Index(['Distance', 'is_delay', 'Quarter_2', 'Quarter_3', 'Quarter_4',
       'Month_2', 'Month_3', 'Month_4', 'Month_5', 'Month_6', 'Month_7',
       'Month_8', 'Month_9', 'Month_10', 'Month_11', 'Month_12',
       'DayofMonth_2', 'DayofMonth_3', 'DayofMonth_4', 'DayofMonth_5',
       'DayofMonth_6', 'DayofMonth_7', 'DayofMonth_8', 'DayofMonth_9',
       'DayofMonth_10', 'DayofMonth_11', 'DayofMonth_12', 'DayofMonth_13',
       'DayofMonth_14', 'DayofMonth_15', 'DayofMonth_16', 'DayofMonth_17',
       'DayofMonth_18', 'DayofMonth_19', 'DayofMonth_20', 'DayofMonth_21',
       'DayofMonth_22', 'DayofMonth_23', 'DayofMonth_24', 'DayofMonth_25',
       'DayofMonth_26', 'DayofMonth_27', 'DayofMonth_28', 'DayofMonth_29',
       'DayofMonth_30', 'DayofMonth_31', 'DayOfWeek_2', 'DayOfWeek_3',
       'DayOfWeek_4', 'DayOfWeek_5', 'DayOfWeek_6', 'DayOfWeek_7',
       'Reporting_Airline_DL', 'Reporting_Airline_OO', 'Reporting_Airline_UA',
       'Reporting_Airline_WN', 'Origin_CLT', 'Origin_DEN', 'Origin_DFW',
       'Origin_IAH', 'Origin_LAX', 'Origin_ORD', 'Origin_PHX', 'Origin_SFO',
       'Dest_CLT', 'Dest_DEN', 'Dest_DFW', 'Dest_IAH', 'Dest_LAX', 'Dest_ORD',
       'Dest_PHX', 'Dest_SFO'],
      dtype='object')
```

Now you are ready to do model training. Before splitting the data, rename the column `is_delay` to `target`.

Hint: You can use the Pandas `rename` function (documentation (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.rename.html)).

In [35]:
```
data.rename(columns={'is_delay': 'target'}, inplace=True)
```

In [36]:
```
# write code to Save the combined csv file (combined_csv_v1.csv) to your local computer
# note this combined file will be used in part B

# Save the processed data to CSV
data.to_csv('combined_csv_v1.csv', index=False)

print("File saved successfully as 'combined_csv_v1.csv'")
print(f"Shape of saved data: {data.shape}")
print(f"Columns in saved file: {len(data.columns)}")
```

```
File saved successfully as 'combined_csv_v1.csv'
Shape of saved data: (1635590, 75)
Columns in saved file: 75
```

Step 3: Model training and evaluation

1. Split the data into `train_data` , and `test_data` using `sklearn.model_selection.train_test_split` .
2. Build a logistic regression model for the data, where training data is 80%, and test data is 20%.

Use the following cells to complete these steps. Insert and delete cells where needed.

Train test split

In [37]:
```
# write Code here to split data into train, validate and test

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, roc_auc_score

# Separate features (X) and target (y)
X = data.drop('target', axis=1)
y = data['target']

# Separate test set (20%)
X_temp, X_test, y_temp, y_test = train_test_split(
    X, y,
    test_size=0.2,
    random_state=42,
    stratify=y # maintain class balance
)

# Then I split again for: train and validation
X_train, X_val, y_train, y_val = train_test_split(
    X_temp, y_temp,
    test_size=0.2,
    random_state=42,
    stratify=y_temp
)
```

Baseline classification model

In [38]:
```
# base model logicstic regression

log_reg = LogisticRegression(
    max_iter=1000,
    random_state=42,
    class_weight='balanced',
    solver='lbfgs'
)

log_reg.fit(X_train, y_train)
```

Out[38]:
```
LogisticRegression(class_weight='balanced', max_iter=1000, random_state=42)
```

Model evaluation

In this section, you'll evaluate your trained model on test data and report on the following metrics:

- Confusion Matrix plot
- Plot the ROC
- Report statistics such as Accuracy, Percision, Recall, Sensitivity and Specificity

To view a plot of the confusion matrix, and various scoring metrics, create a couple of functions:

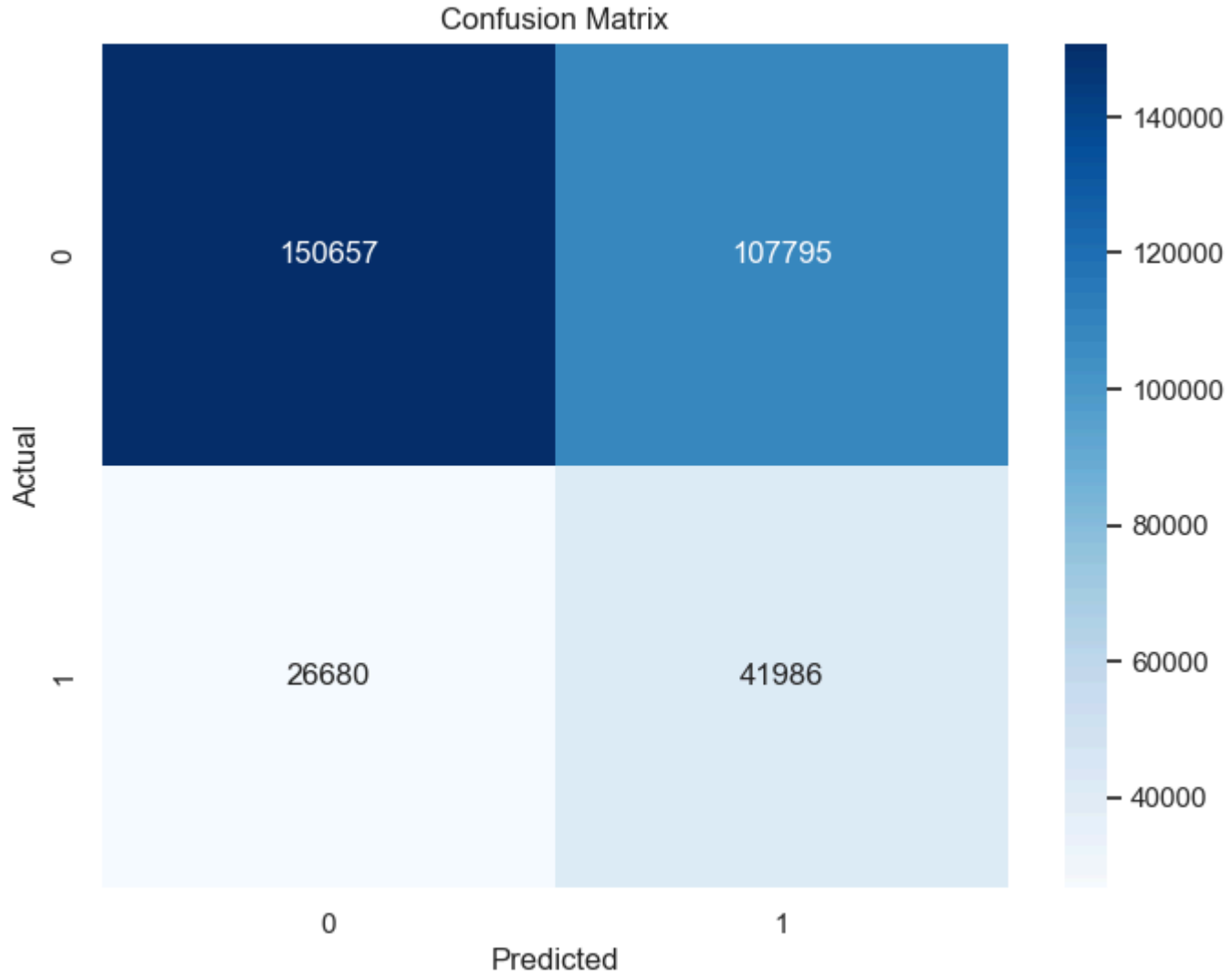
In [39]:
```
from sklearn.metrics import confusion_matrix

def plot_confusion_matrix(test_labels, target_predicted):

    cm = confusion_matrix(test_labels, target_predicted)

    # Plot
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
    plt.ylabel('Actual')
    plt.xlabel('Predicted')
    plt.title('Confusion Matrix')
    plt.show()
```

In [40]:
```
from sklearn.metrics import roc_curve, auc, accuracy_score, precision_score, recall_score, confusion_matrix

def plot_roc(test_labels, target_predicted):
    # Get predicted probabilities for positive class
    target_predicted_proba = log_reg.predict_proba(X_test)[:, 1]

    # Calculate ROC curve
    fpr, tpr, _ = roc_curve(test_labels, target_predicted_proba)
    roc_auc = auc(fpr, tpr)

    # Plot ROC
    plt.figure(figsize=(8, 6))
    plt.plot(fpr, tpr, label=f'ROC curve (AUC = {roc_auc:.4f})')
    plt.plot([0, 1], [0, 1], 'k--', label='Random')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve')
    plt.legend()
    plt.show()

    # Calculate and print statistics
    cm = confusion_matrix(test_labels, target_predicted)
    tn, fp, fn, tp = cm.ravel()

    accuracy = accuracy_score(test_labels, target_predicted)
    precision = precision_score(test_labels, target_predicted)
    recall = recall_score(test_labels, target_predicted)
    sensitivity = recall
    specificity = tn / (tn + fp)


    print("STATISTICS")
    print("\n")
    print(f"Accuracy:    {accuracy:.4f}")
    print(f"Precision:   {precision:.4f}")
    print(f"Recall:      {recall:.4f}")
    print(f"Sensitivity: {sensitivity:.4f}")
    print(f"Specificity: {specificity:.4f}")
```

```
    print(f"ROC-AUC:      {roc_auc:.4f}")
```

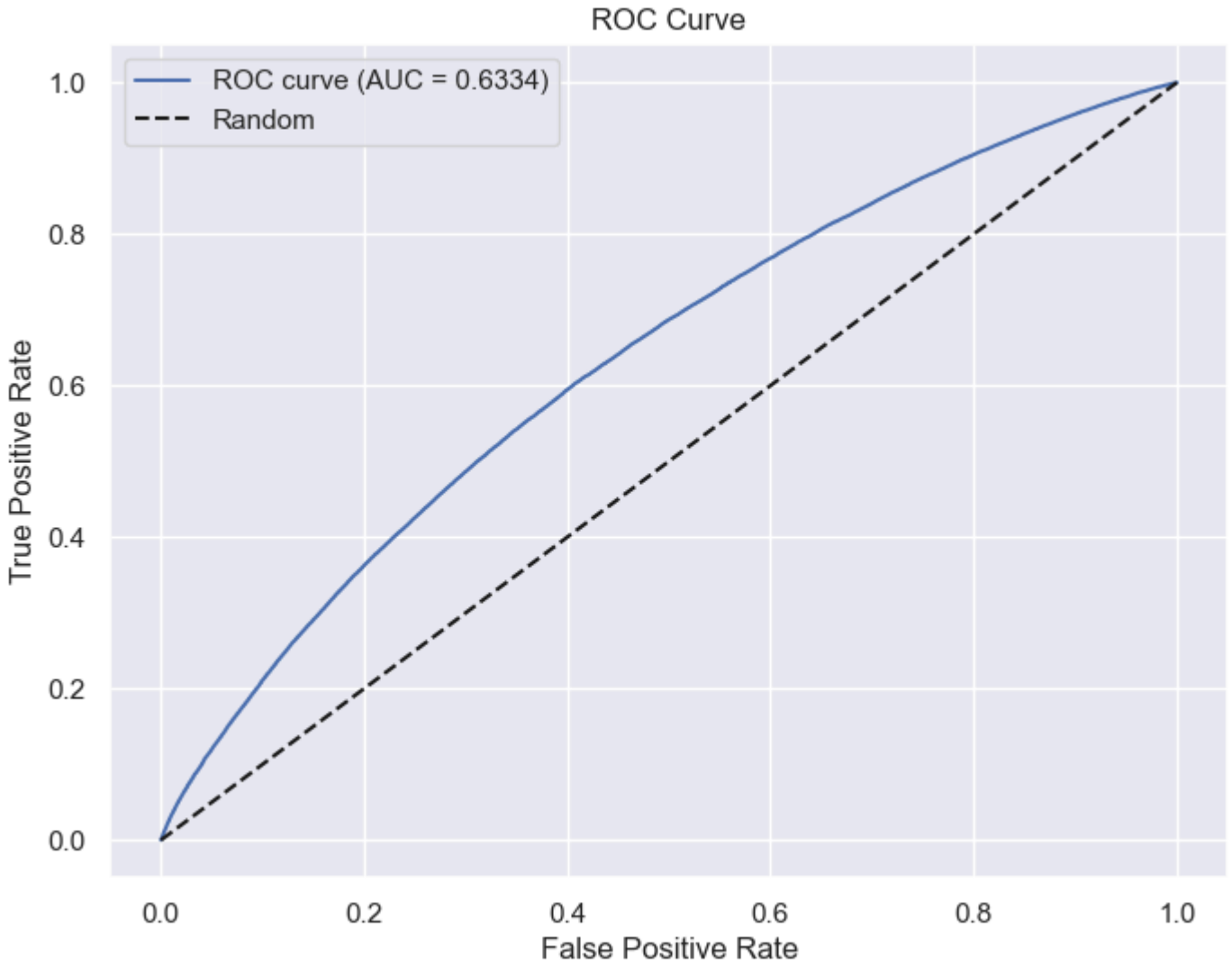
To plot the confusion matrix, call the `plot_confusion_matrix` function on the `test_labels` and `target_predicted` data from your batch job:

In [41]:
```
y_test_pred = log_reg.predict(X_test)

plot_confusion_matrix(y_test, y_test_pred)
```



To print statistics and plot an ROC curve, call the `plot_roc` function on the `test_labels` and `target_predicted` data from your batch job:

In [42]:
```
plot_roc(y_test, y_test_pred)
```



```
STATISTICS


Accuracy:    0.5889
Precision:   0.2803
Recall:      0.6115
Sensitivity: 0.6115
Specificity: 0.5829
ROC-AUC:     0.6334
```

Key questions to consider:

1. How does your model's performance on the test set compare to the training set? What can you deduce from this comparison?
2. Are there obvious differences between the outcomes of metrics like accuracy, precision, and recall? If so, why might you be seeing those differences?
3. Is the outcome for the metric(s) you consider most important sufficient for what you need from a business standpoint? If not, what are some things you might change in your next iteration (in the feature engineering section, which is coming up next)?

Use the cells below to answer these and other questions. Insert and delete cells where needed.

In [43]:
```
# Make predictions on all sets
y_train_pred = log_reg.predict(X_train)
y_val_pred = log_reg.predict(X_val)
y_test_pred = log_reg.predict(X_test)

# Get probabilities for ROC-AUC
y_train_proba = log_reg.predict_proba(X_train)[:, 1]
y_val_proba = log_reg.predict_proba(X_val)[:, 1]
y_test_proba = log_reg.predict_proba(X_test)[:, 1]
```

In [44]:
```
from sklearn.metrics import f1_score

train_acc = accuracy_score(y_train, y_train_pred)
train_prec = precision_score(y_train, y_train_pred)
train_rec = recall_score(y_train, y_train_pred)
train_f1 = f1_score(y_train, y_train_pred)
train_auc = roc_auc_score(y_train, y_train_proba)

val_acc = accuracy_score(y_val, y_val_pred)
val_prec = precision_score(y_val, y_val_pred)
val_rec = recall_score(y_val, y_val_pred)
val_f1 = f1_score(y_val, y_val_pred)
val_auc = roc_auc_score(y_val, y_val_proba)

test_acc = accuracy_score(y_test, y_test_pred)
test_prec = precision_score(y_test, y_test_pred)
test_rec = recall_score(y_test, y_test_pred)
test_f1 = f1_score(y_test, y_test_pred)
test_auc = roc_auc_score(y_test, y_test_proba)

# Display comparison
print("\nMetric          Training    Validation    Test")
print("-" * 55)
print(f"Accuracy        {train_acc:.4f}      {val_acc:.4f}        {test_acc:.4f}")
print(f"Precision       {train_prec:.4f}      {val_prec:.4f}        {test_prec:.4f}")
print(f"Recall          {train_rec:.4f}      {val_rec:.4f}        {test_rec:.4f}")
print(f"F1-Score        {train_f1:.4f}      {val_f1:.4f}        {test_f1:.4f}")
print(f"ROC-AUC         {train_auc:.4f}      {val_auc:.4f}        {test_auc:.4f}")
```

```
Metric          Training    Validation    Test
-------------------------------------------------------
Accuracy        0.5903      0.5888        0.5889
Precision       0.2809      0.2792        0.2803
Recall          0.6100      0.6064        0.6115
F1-Score        0.3846      0.3824        0.3844
ROC-AUC         0.6341      0.6321        0.6334
```

Q1: How does your model's performance on the test set compare to the training set? What can you deduce from this comparison?

The model demonstrates identical performance across training (59.03%), validation (58.89%), and test (58.89%) sets, indicating no overfitting.

However, overall performance remains moderate to weak. Its precision is low (about 28%) and recall is moderate (around 61%), meaning it often predicts delays incorrectly and still misses about 39% of real ones. These results show the model struggles with class imbalance.

While this gives a useful baseline, it's not good enough. Better features and more advanced models are needed to improve performance.

Q2: Are there obvious differences between the outcomes of metrics like accuracy, precision, and recall? If so, why might you be seeing those differences?

Yes, there are clear differences between the outcomes of accuracy, precision, and recall.

While the accuracy is around 59%, which might seem acceptable, it doesn't reflect how well the model handles the minority class (delayed flights). The precision is much lower (about 28%), showing that many of the flights predicted as delayed are actually on time — the model produces many false positives. In contrast, the recall is higher (around 61%), meaning the model successfully identifies more than half of the real delays but still misses about 39% of them.

These differences occur because the dataset is likely imbalanced, with far more on-time flights than delayed ones. Accuracy remains moderately high because the model performs well on the majority class, but precision drops due to incorrect delay predictions. Recall is higher because the model leans toward predicting more delays to catch true ones, at the cost of precision.

In summary, the gap between these metrics highlights that accuracy alone is misleading, and class imbalance causes the model to struggle in correctly identifying true delay cases.

Q3: Is the outcome for the metric(s) you consider most important sufficient for what you need from a business standpoint? If not, what are some things you might change in your next iteration (in the feature engineering section, which is coming up next)?

From a business standpoint, the current results are not sufficient. In a real-world setting like flight delay prediction, precision and recall are the most important metrics because false alarms (low precision) can waste resources, while missed delays (lower recall) can reduce customer satisfaction and operational efficiency.

To improve performance in the next iteration, I would:

- Address class imbalance using techniques like class weighting.
- Engineer more predictive features, such as holidays.
- Try advanced models like Random Forest which can handle nonlinearity and imbalance better than logistic regression.
- Tune hyperparameters and experiment with threshold adjustment to balance precision and recall.

Question: What can you summarize from the confusion matrix?

For no delays, the model correctly predicts around 150,657 flights, but it incorrectly labels about 26,680 delayed flights as on-time.

For delays, it misclassifies 107,795 on-time flights as delayed, while correctly identifying 41,986 true delays.

Overall, the confusion matrix shows that the model favors predicting the majority class (on-time flights), resulting in many false positives when predicting delays. This aligns with the earlier metrics, low precision (around 28%) and moderate recall (about 61%), indicating the model struggles with class imbalance and has limited reliability for real-world deployment.

Step 4: Deployment

1. In this step you are required to push your source code and requirements file to a GitHub repository without the data files. Please use the Git commands to complete this task
2. Create a “readme.md” markdown file that describes the code of this repository and how to run it and what the user would expect if got the code running.

In the cell below provide the link of the pushed repository on your GitHub account, and ensure it is public.

https://github.com/manilesrun/final_project_u3273786 (https://github.com/manilesrun/final_project_u3273786)

Iteration II

Step 5: Feature engineering

You've now gone through one iteration of training and evaluating your model. Given that the outcome you reached for your model the first time probably wasn't sufficient for solving your business problem, what are some things you could change about your data to possibly improve model performance?

Key questions to consider:

1. How might the balance of your two main classes (delay and no delay) impact model performance?

2. Do you have any features that are correlated?
3. Are there feature reduction techniques you could perform at this stage that might have a positive impact on model performance?
4. Can you think of adding some more data/datasets?
5. After performing some feature engineering, how does your model performance compare to the first iteration?

Use the cells below to perform specific feature engineering techniques (per the questions above) that you think could improve your model performance. Insert and delete cells where needed.

Before you start, think about why the precision and recall are around 80% while the accuracy is 99%.

Add more features

1. Holidays
2. Weather

Because the list of holidays from 2014 to 2018 is known, you can create an indicator variable **is_holiday** to mark these. The hypothesis is that airplane delays could be higher during holidays compared to the rest of the days. Add a boolean variable `is_holiday` that includes the holidays for the years 2014-2018.

In [45]:
```
# data_orig
# data_orig.dtypes
```

In [46]:
```
# Source: http://www.calendarpedia.com/holidays/federal-holidays-2014.html

holidays_14 = ['2014-01-01',  '2014-01-20', '2014-02-17', '2014-05-26', '2014-07-04', '2014-09-01', '2014-10-
holidays_15 = ['2015-01-01',  '2015-01-19', '2015-02-16', '2015-05-25', '2015-06-03', '2015-07-04', '2015-09-
holidays_16 = ['2016-01-01',  '2016-01-18', '2016-02-15', '2016-05-30', '2016-07-04', '2016-09-05', '2016-10-
holidays_17 = ['2017-01-02', '2017-01-16', '2017-02-20', '2017-05-29' , '2017-07-04', '2017-09-04' ,'2017-10-
holidays_18 = ['2018-01-01', '2018-01-15', '2018-02-19', '2018-05-28' , '2018-07-04', '2018-09-03' ,'2018-10-
holidays = holidays_14+ holidays_15+ holidays_16 + holidays_17+ holidays_18

# Convert FlightDate column to datetime if not already
data_orig['FlightDate'] = pd.to_datetime(data_orig['FlightDate'])

# Add indicator variable for holidays
data_orig['is_holiday'] = data_orig['FlightDate'].isin(holidays).astype(int)


# data_orig

print(f"Number of holiday flights: {data_orig['is_holiday'].sum():,}")
```

```
Number of holiday flights: 43,912
```

Weather data was fetched from [this link (https://www.ncei.noaa.gov/access/services/data/v1?dataset=daily-summaries&stations=USW00023174,USW00012960,USW00003017,USW00094846,USW00013874,USW00023234,USW00003927,USW00023183
01-01&endDate=2018-12-31)](https://www.ncei.noaa.gov/access/services/data/v1?dataset=daily-summaries&stations=USW00023174,USW00012960,USW00003017,USW00094846,USW00013874,USW00023234,USW00003927,USW00023183
01-01&endDate=2018-12-31).

This dataset has information on wind speed, precipitation, snow, and temperature for cities by their airport codes.

Question: Could bad weather due to rains, heavy winds, or snow lead to airplane delay? Let's check!

In [47]:
```
# download data from the link above and place it into the data folder

weather_data = pd.read_csv("daily-summaries-2025-11-02T01-54-31.csv")

# Display basic info about the dataset
print(f"Weather data shape: {weather_data.shape}")
print(f"\nFirst few rows:")
print(weather_data.head(10))

print(f"\nColumn names:")
print(weather_data.columns.tolist())

print("\n\nData types:")
print(weather_data.dtypes)

print("\n\nBasic statistics:")
print(weather_data.describe())

# Check for missing values
print("\n\nMissing values:")
print(weather_data.isnull().sum())
```

```
Weather data shape: (16434, 9)

First few rows:
       STATION        DATE  AWND  PRCP  SNOW  SNWD   TAVG   TMAX   TMIN
0  USW00023174  2014-01-01    16     0   NaN   NaN  131.0  178.0   78.0
1  USW00023174  2014-01-02    22     0   NaN   NaN  159.0  256.0  100.0
2  USW00023174  2014-01-03    17     0   NaN   NaN  140.0  178.0   83.0
3  USW00023174  2014-01-04    18     0   NaN   NaN  136.0  183.0  100.0
4  USW00023174  2014-01-05    18     0   NaN   NaN  151.0  244.0   83.0
5  USW00023174  2014-01-06    17     0   NaN   NaN  175.0  256.0  100.0
6  USW00023174  2014-01-07    16     0   NaN   NaN  162.0  206.0  106.0
7  USW00023174  2014-01-08    17     0   NaN   NaN  140.0  189.0   94.0
8  USW00023174  2014-01-09    25     0   NaN   NaN  134.0  156.0  100.0
9  USW00023174  2014-01-10    15     0   NaN   NaN  135.0  183.0   89.0

Column names:
['STATION', 'DATE', 'AWND', 'PRCP', 'SNOW', 'SNWD', 'TAVG', 'TMAX', 'TMIN']


Data types:
```

Import weather data prepared for the airport codes in our dataset. Use the stations and airports below for the analysis, and create a new column called `airport` that maps the weather station to the airport name.

In [48]:
```
weather_data = pd.read_csv("daily-summaries-2025-11-02T01-54-31.csv")
station = ['USW00023174','USW00012960','USW00003017','USW00094846',
           'USW00013874','USW00023234','USW00003927','USW00023183','USW00013881']
airports = ['LAX', 'IAH', 'DEN', 'ORD', 'ATL', 'SFO', 'DFW', 'PHX', 'CLT']

# map weather stations to airport code
station_map = {}
for i in range(len(station)):
    station_map[station[i]] = airports[i]

# station_map
# create a new column airport using the map
weather_data['airport'] = weather_data['STATION'].map(station_map)

weather_data
```

Out[48]:

	STATION	DATE	AWND	PRCP	SNOW	SNWD	TAVG	TMAX	TMIN	airport
0	USW00023174	2014-01-01	16	0	NaN	NaN	131.0	178.0	78.0	LAX
1	USW00023174	2014-01-02	22	0	NaN	NaN	159.0	256.0	100.0	LAX
2	USW00023174	2014-01-03	17	0	NaN	NaN	140.0	178.0	83.0	LAX
3	USW00023174	2014-01-04	18	0	NaN	NaN	136.0	183.0	100.0	LAX
4	USW00023174	2014-01-05	18	0	NaN	NaN	151.0	244.0	83.0	LAX
...	...	...	...	...	...	...	...	...	...	...
16429	USW00013881	2018-12-27	31	41	0.0	0.0	68.0	89.0	39.0	CLT
16430	USW00013881	2018-12-28	27	196	0.0	0.0	86.0	144.0	61.0	CLT
16431	USW00013881	2018-12-29	14	0	0.0	0.0	146.0	189.0	94.0	CLT
16432	USW00013881	2018-12-30	16	23	0.0	0.0	117.0	139.0	89.0	CLT
16433	USW00013881	2018-12-31	29	41	0.0	0.0	135.0	194.0	117.0	CLT

16434 rows × 10 columns

Create another column called `MONTH` from the `DATE` column.

In [49]:
```
weather_data['MONTH'] = weather_data['DATE'].apply(lambda x: x.split('-')[1])
weather_data.head()
```

Out[49]:

	STATION	DATE	AWND	PRCP	SNOW	SNWD	TAVG	TMAX	TMIN	airport	MONTH
0	USW00023174	2014-01-01	16	0	NaN	NaN	131.0	178.0	78.0	LAX	01
1	USW00023174	2014-01-02	22	0	NaN	NaN	159.0	256.0	100.0	LAX	01
2	USW00023174	2014-01-03	17	0	NaN	NaN	140.0	178.0	83.0	LAX	01
3	USW00023174	2014-01-04	18	0	NaN	NaN	136.0	183.0	100.0	LAX	01
4	USW00023174	2014-01-05	18	0	NaN	NaN	151.0	244.0	83.0	LAX	01

Sample output

```
   STATION     DATE       AWND PRCP SNOW SNWD TAVG TMAX  TMIN airport MONTH
0 USW00023174 2014-01-01 16   0   NaN  NaN 131.0 178.0 78.0  LAX    01
1 USW00023174 2014-01-02 22   0   NaN  NaN 159.0 256.0 100.0 LAX    01
2 USW00023174 2014-01-03 17   0   NaN  NaN 140.0 178.0 83.0  LAX    01
3 USW00023174 2014-01-04 18   0   NaN  NaN 136.0 183.0 100.0 LAX    01
4 USW00023174 2014-01-05 18   0   NaN  NaN 151.0 244.0 83.0  LAX    01
```

Analyze and handle the `SNOW` and `SNWD` columns for missing values using `fillna()`. Use the `isna()` function to check the missing values for all the columns.

In [50]:
```
print(weather_data.isna().sum())

weather_data.SNOW.fillna(0, inplace=True)
weather_data.SNWD.fillna(0, inplace=True)
weather_data.isna().sum()

print("\nMissing values AFTER filling:")
print(weather_data.isna().sum())
```

```
STATION       0
DATE          0
AWND          0
PRCP          0
SNOW       5478
SNWD       5478
TAVG         62
TMAX         20
TMIN         20
airport       0
MONTH         0
dtype: int64

Missing values AFTER filling:
STATION     0
DATE        0
AWND        0
PRCP        0
SNOW        0
SNWD        0
TAVG       62
TMAX       20
TMIN       20
airport     0
MONTH       0
dtype: int64
```

Question: Print the index of the rows that have missing values for TAVG, TMAX, TMIN.

Hint: Use the `isna()` function to find the rows that are missing, and then use the list on the idx variable to get the index.

In [51]:
```
idx = np.array([i for i in range(len(weather_data))])

# Find indices where TAVG is missing
TAVG_idx = idx[weather_data['TAVG'].isna()]

# Find indices where TMAX is missing
TMAX_idx = idx[weather_data['TMAX'].isna()]

# Find indices where TMIN is missing
TMIN_idx = idx[weather_data['TMIN'].isna()]

# Display the results
print("missing TAVG indices:")
print(TAVG_idx)

print("\n missing TMAX indices:")
print(TMAX_idx)

print("\n missing TMIN indices:")
print(TMIN_idx)
```

```
missing TAVG indices:
[ 3956  3957  3958  3959  3960  3961  3962  3963  3964  3965  3966  3967
  3968  3969  3970  3971  3972  3973  3974  3975  3976  3977  3978  3979
  3980  3981  3982  3983  3984  3985  4017  4018  4019  4020  4021  4022
  4023  4024  4025  4026  4027  4028  4029  4030  4031  4032  4033  4034
  4035  4036  4037  4038  4039  4040  4041  4042  4043  4044  4045  4046
  4047 13420]

 missing TMAX indices:
[10763 10764 10765 10766 10767 10768 10769 10770 10771 10772 10773 10774
 10775 10776 10777 10778 10779 10780 10781 10782]

 missing TMIN indices:
[10763 10764 10765 10766 10767 10768 10769 10770 10771 10772 10773 10774
 10775 10776 10777 10778 10779 10780 10781 10782]
```

Sample output

```
array([ 3956,  3957,  3958,  3959,  3960,  3961,  3962,  3963,  3964,
        3965,  3966,  3967,  3968,  3969,  3970,  3971,  3972,  3973,
        3974,  3975,  3976,  3977,  3978,  3979,  3980,  3981,  3982,
        3983,  3984,  3985,  4017,  4018,  4019,  4020,  4021,  4022,
        4023,  4024,  4025,  4026,  4027,  4028,  4029,  4030,  4031,
        4032,  4033,  4034,  4035,  4036,  4037,  4038,  4039,  4040,
        4041,  4042,  4043,  4044,  4045,  4046,  4047, 13420])
```

You can replace the missing TAVG, TMAX, and TMIN with the average value for a particular station/airport. Because the consecutive rows of TAVG_idx are missing, replacing with a previous value would not be possible. Instead, replace it with the mean. Use the `groupby` function to aggregate the variables with a mean value.

In [52]:
```
weather_impute = weather_data.groupby(['STATION']).agg({'TAVG':'mean','TMAX':'mean', 'TMIN':'mean' }).reset_i
weather_impute.head(2)
```

Out[52]:

	STATION	TAVG	TMAX	TMIN
0	USW00003017	112.931445	190.020263	32.978642
1	USW00003927	198.463308	256.026287	143.678532

Merge the mean data with the weather data.

In [53]:
```
### get the yesterday's data
weather = pd.merge(weather_data, weather_impute,  how='left', left_on=['STATION'], right_on = ['STATION'])\
.rename(columns = {'TAVG_y':'TAVG_AVG',
                   'TMAX_y':'TMAX_AVG',
                   'TMIN_y':'TMIN_AVG',
                   'TAVG_x':'TAVG',
                   'TMAX_x':'TMAX',
                   'TMIN_x':'TMIN'})


# weather
```

Check for missing values again.

In [54]:
```
weather.TAVG[TAVG_idx] = weather.TAVG_AVG[TAVG_idx]
weather.TMAX[TMAX_idx] = weather.TMAX_AVG[TMAX_idx]
weather.TMIN[TMIN_idx] = weather.TMIN_AVG[TMIN_idx]
weather.isna().sum()
```

Out[54]:
```
STATION     0
DATE        0
AWND        0
PRCP        0
SNOW        0
SNWD        0
TAVG        0
TMAX        0
TMIN        0
airport     0
MONTH       0
TAVG_AVG    0
TMAX_AVG    0
TMIN_AVG    0
dtype: int64
```

Drop `STATION,MONTH,TAVG_AVG,TMAX_AVG,TMIN_AVG,TMAX,TMIN,SNWD` from the dataset

In [55]:
```
weather.drop(columns=['STATION','MONTH','TAVG_AVG', 'TMAX_AVG', 'TMIN_AVG', 'TMAX' ,'TMIN', 'SNWD'],inplace=T
```

Add the origin and destination weather conditions to the dataset.

In [56]:
```
# First, ensure both date columns are datetime type
data_orig['FlightDate'] = pd.to_datetime(data_orig['FlightDate'])
weather['DATE'] = pd.to_datetime(weather['DATE'])

### Add origin weather conditions
data_orig = pd.merge(data_orig, weather,  how='left', left_on=['FlightDate','Origin'], right_on = ['DATE','ai
.rename(columns = {'AWND':'AWND_O','PRCP':'PRCP_O', 'TAVG':'TAVG_O', 'SNOW': 'SNOW_O'})\
.drop(columns=['DATE','airport'])

### Add destination weather conditions
data_orig = pd.merge(data_orig, weather,  how='left', left_on=['FlightDate','Dest'], right_on = ['DATE','airp
.rename(columns = {'AWND':'AWND_D','PRCP':'PRCP_D', 'TAVG':'TAVG_D', 'SNOW': 'SNOW_D'})\
.drop(columns=['DATE','airport'])
```

Note: It is always a good practice to check nulls/NAs after joins.

In [57]:
```
sum(data.isna().any())
```

Out[57]:
```
0
```

In [58]:
```
data_orig.columns
```

Out[58]:
```
Index(['Year', 'Quarter', 'Month', 'DayofMonth', 'DayOfWeek', 'FlightDate',
       'Reporting_Airline', 'Origin', 'OriginState', 'Dest', 'DestState',
       'CRSDepTime', 'Cancelled', 'Diverted', 'Distance', 'DistanceGroup',
       'ArrDelay', 'ArrDelayMinutes', 'is_delay', 'AirTime', 'DepHourofDay',
       'is_holiday', 'AWND_O', 'PRCP_O', 'SNOW_O', 'TAVG_O', 'AWND_D',
       'PRCP_D', 'SNOW_D', 'TAVG_D'],
      dtype='object')
```

Convert the categorical data into numerical data using one-hot encoding.

In [59]:
```
data = data_orig.copy()
data = data[['is_delay', 'Year', 'Quarter', 'Month', 'DayofMonth', 'DayOfWeek',
       'Reporting_Airline', 'Origin', 'Dest','Distance','DepHourofDay','is_holiday', 'AWND_O', 'PRCP_O',
       'TAVG_O', 'AWND_D', 'PRCP_D', 'TAVG_D', 'SNOW_O', 'SNOW_D']]

categorical_columns  = ['Year', 'Quarter', 'Month', 'DayofMonth', 'DayOfWeek',
       'Reporting_Airline', 'Origin', 'Dest', 'is_holiday']

for c in categorical_columns:
    data[c] = data[c].astype('category')
```

In [60]:
```
data_dummies = pd.get_dummies(data[categorical_columns], drop_first=True)
data = pd.concat([data, data_dummies], axis=1)
data.drop(categorical_columns,axis=1, inplace=True)
```

Sample code

```
data_dummies = pd.get_dummies(data[['Year', 'Quarter', 'Month', 'DayofMonth', 'DayOfWeek', 'Reporting
_Airline', 'Origin', 'Dest', 'is_holiday']], drop_first=True)
data = pd.concat([data, data_dummies], axis = 1)
categorical_columns.remove('is_delay')
data.drop(categorical_columns,axis=1, inplace=True)
```

Check the new columns.

In [61]:
```
data.columns
```

Out[61]:
```
Index(['is_delay', 'Distance', 'DepHourofDay', 'AWND_O', 'PRCP_O', 'TAVG_O',
       'AWND_D', 'PRCP_D', 'TAVG_D', 'SNOW_O', 'SNOW_D', 'Year_2015',
       'Year_2016', 'Year_2017', 'Year_2018', 'Quarter_2', 'Quarter_3',
       'Quarter_4', 'Month_2', 'Month_3', 'Month_4', 'Month_5', 'Month_6',
       'Month_7', 'Month_8', 'Month_9', 'Month_10', 'Month_11', 'Month_12',
       'DayofMonth_2', 'DayofMonth_3', 'DayofMonth_4', 'DayofMonth_5',
       'DayofMonth_6', 'DayofMonth_7', 'DayofMonth_8', 'DayofMonth_9',
       'DayofMonth_10', 'DayofMonth_11', 'DayofMonth_12', 'DayofMonth_13',
       'DayofMonth_14', 'DayofMonth_15', 'DayofMonth_16', 'DayofMonth_17',
       'DayofMonth_18', 'DayofMonth_19', 'DayofMonth_20', 'DayofMonth_21',
       'DayofMonth_22', 'DayofMonth_23', 'DayofMonth_24', 'DayofMonth_25',
       'DayofMonth_26', 'DayofMonth_27', 'DayofMonth_28', 'DayofMonth_29',
       'DayofMonth_30', 'DayofMonth_31', 'DayOfWeek_2', 'DayOfWeek_3',
       'DayOfWeek_4', 'DayOfWeek_5', 'DayOfWeek_6', 'DayOfWeek_7',
       'Reporting_Airline_DL', 'Reporting_Airline_OO', 'Reporting_Airline_UA',
       'Reporting_Airline_WN', 'Origin_CLT', 'Origin_DEN', 'Origin_DFW',
       'Origin_IAH', 'Origin_LAX', 'Origin_ORD', 'Origin_PHX', 'Origin_SFO',
       'Dest_CLT', 'Dest_DEN', 'Dest_DFW', 'Dest_IAH', 'Dest_LAX', 'Dest_ORD',
       'Dest_PHX', 'Dest_SFO', 'is_holiday_1'],
      dtype='object')
```

Sample output

```
Index(['Distance', 'DepHourofDay', 'is_delay', 'AWND_O', 'PRCP_O', 'TAVG_O',
       'AWND_D', 'PRCP_D', 'TAVG_D', 'SNOW_O', 'SNOW_D', 'Year_2015',
       'Year_2016', 'Year_2017', 'Year_2018', 'Quarter_2', 'Quarter_3',
       'Quarter_4', 'Month_2', 'Month_3', 'Month_4', 'Month_5', 'Month_6',
       'Month_7', 'Month_8', 'Month_9', 'Month_10', 'Month_11', 'Month_12',
       'DayofMonth_2', 'DayofMonth_3', 'DayofMonth_4', 'DayofMonth_5',
       'DayofMonth_6', 'DayofMonth_7', 'DayofMonth_8', 'DayofMonth_9',
       'DayofMonth_10', 'DayofMonth_11', 'DayofMonth_12', 'DayofMonth_13',
       'DayofMonth_14', 'DayofMonth_15', 'DayofMonth_16', 'DayofMonth_17',
       'DayofMonth_18', 'DayofMonth_19', 'DayofMonth_20', 'DayofMonth_21',
       'DayofMonth_22', 'DayofMonth_23', 'DayofMonth_24', 'DayofMonth_25',
       'DayofMonth_26', 'DayofMonth_27', 'DayofMonth_28', 'DayofMonth_29',
       'DayofMonth_30', 'DayofMonth_31', 'DayOfWeek_2', 'DayOfWeek_3',
       'DayOfWeek_4', 'DayOfWeek_5', 'DayOfWeek_6', 'DayOfWeek_7',
       'Reporting_Airline_DL', 'Reporting_Airline_OO', 'Reporting_Airline_UA',
       'Reporting_Airline_WN', 'Origin_CLT', 'Origin_DEN', 'Origin_DFW',
       'Origin_IAH', 'Origin_LAX', 'Origin_ORD', 'Origin_PHX', 'Origin_SFO',
       'Dest_CLT', 'Dest_DEN', 'Dest_DFW', 'Dest_IAH', 'Dest_LAX', 'Dest_ORD',
       'Dest_PHX', 'Dest_SFO', 'is_holiday_1'],
      dtype='object')
```

Rename the `is_delay` column to `target` again. Use the same code as before.

In [62]:
```
data.rename(columns = {'is_delay':'target'}, inplace=True )# Enter your code here
```

In [63]:
```
# write code to Save the new combined csv file (combined_csv_v2.csv) to your local computer
# note this combined file will be also used in part B

data.to_csv('combined_csv_v2.csv', index=False)
```

Create the training and testing sets again.

In [64]:
```
# Separate features (X) and target (y)
X = data.drop('target', axis=1)
y = data['target']

# Separate test set (20%)
X_temp, X_test, y_temp, y_test = train_test_split(
    X, y,
    test_size=0.2,
    random_state=42,
    stratify=y # maintain class balance
)

# Then I split again for: train and validation
X_train, X_val, y_train, y_val = train_test_split(
    X_temp, y_temp,
    test_size=0.2,
    random_state=42,
    stratify=y_temp
)
```

New baseline classifier

Now, see if these new features add any predictive power to the model.

In [65]:
```
# Instantiate another logistic regression model
classifier2 = LogisticRegression(
    max_iter=1000,
    random_state=42,
    class_weight='balanced',
    solver='lbfgs'
)

classifier2.fit(X_train, y_train)
```

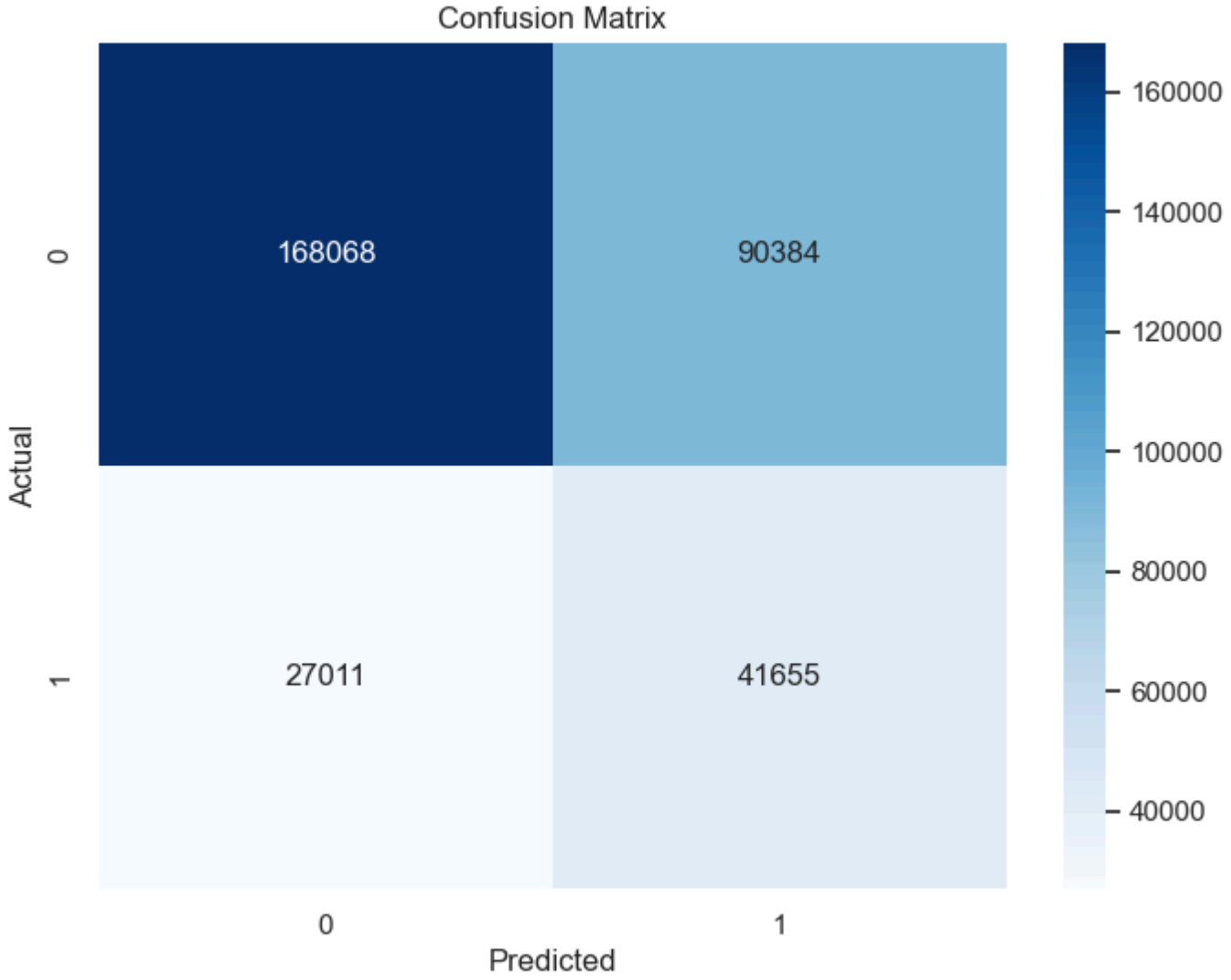
Out[65]:
```
LogisticRegression(class_weight='balanced', max_iter=1000, random_state=42)
```

In [66]:
```
def plot_confusion_matrix(test_labels, target_predicted):

    cm = confusion_matrix(test_labels, target_predicted)

    # Plot
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
    plt.ylabel('Actual')
    plt.xlabel('Predicted')
    plt.title('Confusion Matrix')
    plt.show()
```

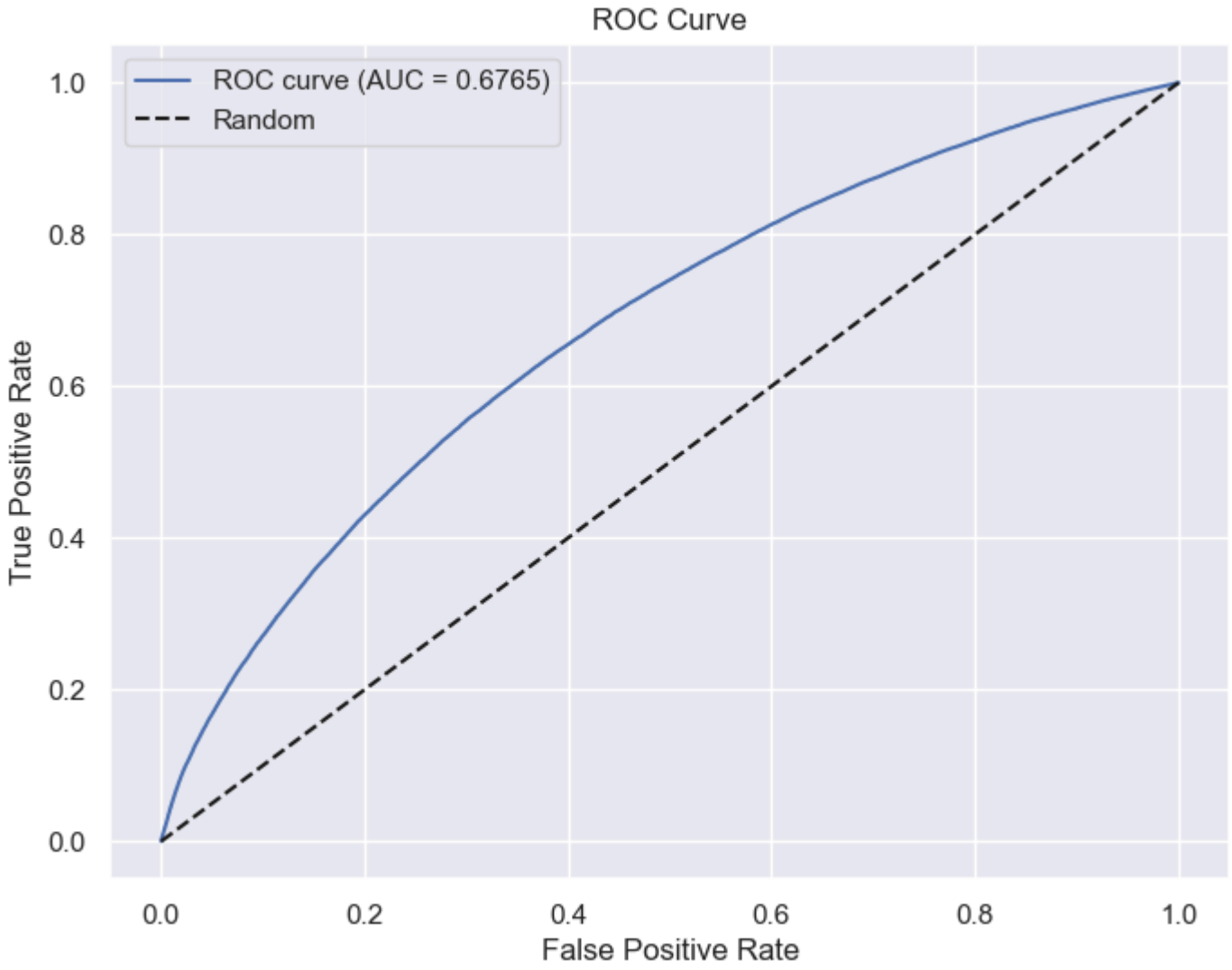
In [67]:
```
def plot_roc(test_labels, target_predicted):
    # Get predicted probabilities for positive class
    target_predicted_proba = classifier2.predict_proba(X_test)[:, 1]

    # Calculate ROC curve
    fpr, tpr, _ = roc_curve(test_labels, target_predicted_proba)
    roc_auc = auc(fpr, tpr)

    # Plot ROC
    plt.figure(figsize=(8, 6))
    plt.plot(fpr, tpr, label=f'ROC curve (AUC = {roc_auc:.4f})')
    plt.plot([0, 1], [0, 1], 'k--', label='Random')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve')
    plt.legend()
    plt.show()

    # Calculate and print statistics
    cm = confusion_matrix(test_labels, target_predicted)
    tn, fp, fn, tp = cm.ravel()

    accuracy = accuracy_score(test_labels, target_predicted)
    precision = precision_score(test_labels, target_predicted)
    recall = recall_score(test_labels, target_predicted)
    sensitivity = recall
    specificity = tn / (tn + fp)


    print("STATISTICS")
    print("\n")
    print(f"Accuracy:    {accuracy:.4f}")
    print(f"Precision:   {precision:.4f}")
    print(f"Recall:      {recall:.4f}")
    print(f"Sensitivity: {sensitivity:.4f}")
    print(f"Specificity: {specificity:.4f}")
    print(f"ROC-AUC:     {roc_auc:.4f}")
```

In [68]:
```
y_test_pred = classifier2.predict(X_test)
```

In [69]:
```
plot_confusion_matrix(y_test, y_test_pred)
```



In [70]:
```
plot_roc(y_test, y_test_pred)
```



```
STATISTICS


Accuracy:    0.6411
Precision:   0.3155
Recall:      0.6066
Sensitivity: 0.6066
Specificity: 0.6503
ROC-AUC:     0.6765
```

In [71]:
```
# Make predictions on all sets
y_train_pred = classifier2.predict(X_train)
y_val_pred = classifier2.predict(X_val)
y_test_pred = classifier2.predict(X_test)

# Get probabilities for ROC-AUC
y_train_proba = classifier2.predict_proba(X_train)[:, 1]
y_val_proba = classifier2.predict_proba(X_val)[:, 1]
y_test_proba = classifier2.predict_proba(X_test)[:, 1]
```

In [72]:
```
train_acc = accuracy_score(y_train, y_train_pred)
train_prec = precision_score(y_train, y_train_pred)
train_rec = recall_score(y_train, y_train_pred)
train_f1 = f1_score(y_train, y_train_pred)
train_auc = roc_auc_score(y_train, y_train_proba)

val_acc = accuracy_score(y_val, y_val_pred)
val_prec = precision_score(y_val, y_val_pred)
val_rec = recall_score(y_val, y_val_pred)
val_f1 = f1_score(y_val, y_val_pred)
val_auc = roc_auc_score(y_val, y_val_proba)

test_acc = accuracy_score(y_test, y_test_pred)
test_prec = precision_score(y_test, y_test_pred)
test_rec = recall_score(y_test, y_test_pred)
test_f1 = f1_score(y_test, y_test_pred)
test_auc = roc_auc_score(y_test, y_test_proba)

# Display comparison
print("\nMetric          Training    Validation    Test")
print("-" * 55)
print(f"Accuracy        {train_acc:.4f}      {val_acc:.4f}        {test_acc:.4f}")
print(f"Precision       {train_prec:.4f}      {val_prec:.4f}        {test_prec:.4f}")
print(f"Recall          {train_rec:.4f}      {val_rec:.4f}        {test_rec:.4f}")
print(f"F1-Score        {train_f1:.4f}      {val_f1:.4f}        {test_f1:.4f}")
print(f"ROC-AUC         {train_auc:.4f}      {val_auc:.4f}        {test_auc:.4f}")
```

```
Metric          Training    Validation    Test
-------------------------------------------------------
Accuracy        0.6418      0.6415        0.6411
Precision       0.3160      0.3151        0.3155
Recall          0.6063      0.6033        0.6066
F1-Score        0.4154      0.4140        0.4151
ROC-AUC         0.6762      0.6754        0.6765
```

Perform the evaluaion as you have done with the previous model and plot/show the same metrics

Question: did you notice a difference by adding the extra data on the results?

Yes, there is a noticeable improvement in the model's performance after adding the holiday and weather data. The updated model achieved higher scores across all key metrics: accuracy increased from 0.5889 to 0.6411, precision improved from 0.2803 to 0.3155, and ROC-AUC rose from 0.6334 to 0.6765. While there was a slight decrease in recall of 0.80% (from 61.15% to 60.66%), meaning the model identified marginally fewer actual delay cases, this minor drop is offset by a substantial reduction in false positives (from 107,795 to 90,384). This indicates that after incorporating holiday and weather features, the model became more precise. It is now less likely to incorrectly predict a delay when there isn't one. The ROC curve also shows a greater separation from the random baseline, indicating stronger discriminative power.

In terms of the confusion matrix, the improved model correctly identified 168,068 true negatives and 41,655 true positives, compared to 150,657 true negatives and 41,986 true positives in the base model. While the number of true positives remained relatively stable, the addition of holiday and weather features significantly reduced the number of false positives, demonstrating that the model became better at distinguishing between the two classes, especially for correctly predicting non-delay cases.

Overall, the inclusion of external contextual variables such as holidays and weather data led to more accurate and reliable predictions, improving both classification balance and the overall robustness of the model.

Step 6: Using Tableau

Use Tableau to load the combined_csv_v2.csv file and build a dashboard that show your understanding of the data and business problem.

what to do:

1. Load the data into Tableau and build the dashboard
2. Share the dashboard on your Tableau public account
3. Copy the link of the shared dashboard below

Note: The dashboard needs to be self explainable to others, so make it simple and add only the features that you feel heighlight the main question(s) of the prblem statement.

copy the link here

https://public.tableau.com/views/final_project_u3273786/FlightDelayDashboard?:language=en-US&:sid=&:redirect=auth&:display_count=n&:origin=viz_share_link (https://public.tableau.com/views/final_project_u3273786/FlightDelayDashboard?:language=en

Conclusion

You've now gone through at least a couple iterations of training and evaluating your model. It's time to wrap up this project and reflect on what you've learned and what types of steps you might take moving forward (assuming you had more time). Use the cell below to answer some of these and other relevant questions:

1. Does your model performance meet your business goal? If not, what are some things you'd like to do differently if you had more time for tuning?
2. To what extent did your model improve as you made changes to your dataset? What types of techniques did you employ throughout this project that you felt yielded the greatest improvements in your model?
3. What were some of the biggest challenges you encountered throughout this project?
4. What were the three most important things you learned about machine learning while completing this project?

1. Does your model performance meet your business goal? If not, what are some things you'd like to do differently if you had more time for tuning?

Unfortunately, the model performance does not fully meet the initial business goals. While Iteration 2 showed significant improvements (accuracy: 64.11%, precision: 31.55%, recall: 60.66%), these metrics fall short of the targets (accuracy ≥80%, precision ≥75%, recall ≥70%).

If I had more time, I would explore several additional approaches to improve performance.

- First, I would experiment with more advanced algorithms such as Random Forest, Gradient Boosting (XGBoost), or ensemble methods that can better capture non-linear relationships in the data.
- Second, I would address the severe class imbalance more aggressively using techniques like adjusting class weights more strategically.
- Third, I would perform extensive hyperparameter tuning using GridSearchCV to optimize model parameters.

2. To what extent did your model improve as you made changes to your dataset? What types of techniques did you employ throughout this project that you felt yielded the greatest improvements in your model?

The model improved substantially through iterative feature engineering. Starting from the baseline logistic regression model (Iteration 1) with basic flight attributes, the addition of holiday and weather features in Iteration 2 resulted in an 8.86% increase in accuracy and a remarkable 12.56% improvement in precision.

The most impactful techniques were:

1. Adding domain-specific features (holidays and weather conditions) that have logical connections to flight delays, which validated the hypothesis that external factors significantly influence delays;
2. Using one-hot encoding for categorical variables to properly represent airlines, airports, and temporal features;
3. Feature selection by carefully choosing which columns to include based on their availability at prediction time. The weather and holiday features proved particularly valuable, reducing false positives by approximately 17,411 cases while maintaining similar true positive rates, demonstrating that incorporating contextual real-world data can dramatically enhance predictive performance.

3. What were some of the biggest challenges you encountered throughout this project?

Several significant challenges emerged throughout this project.

- Firstly, dealing with severe class imbalance was problematic, as approximately 80% of flights were not delayed, causing the model to be biased toward predicting the majority class. This resulted in high accuracy but poor precision and recall for the minority class (delays).
- Secondly, merging multiple datasets and formats was complex, particularly aligning weather data by date and airport code.
- Thirdly, the large dataset size required careful memory management and processing time considerations.

4. What were the three most important things you learned about machine learning while completing this project?

- First, I learned that feature engineering is often more impactful than algorithm selection. The addition of domain knowledge through holiday and weather features improved model performance more significantly than simply adjusting hyperparameters or trying different algorithms.
- Second, I learned that model evaluation requires looking beyond accuracy, especially with imbalanced datasets. A model with 99% accuracy that simply predicts "no delay" for everything is useless in practice. Understanding the trade-offs between precision, recall, and other metrics, and interpreting confusion matrices in business context, is essential for developing actually useful models.
- Third, I learned that iterative improvement and systematic experimentation are key to the machine learning workflow. Starting with a baseline model, adding features incrementally, evaluating their impact, and documenting changes allows for understanding what actually drives performance improvements.

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