3022_classification_notebook

April 13, 2022

[1]:
```
%matplotlib inline
import calendar
from sklearn.preprocessing import Normalizer
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
import scipy
import scipy.stats as stats
import math

# Jupyter notebook settings
import warnings
warnings.filterwarnings('ignore')
plt.rcParams['figure.figsize'] = [24, 8]

# Dataset feature constants
TARGET_CLASS = ["DEP_DEL15"]
CATEGORICAL = ["CARRIER_NAME", "DEPARTING_AIRPORT", "PREVIOUS_AIRPORT",␣
 ↪"DEP_TIME_BLK"]
CONTINUOUS = ["FLT_ATTENDANTS_PER_PASS", "GROUND_SERV_PER_PASS", "LATITUDE",␣
 ↪"LONGITUDE",
              "PRCP", "SNOW", "SNWD", "TMAX", "AWND"]
DISCRETE = ["MONTH", "DAY_OF_WEEK", "DISTANCE_GROUP", "SEGMENT_NUMBER",
            "CONCURRENT_FLIGHTS", "NUMBER_OF_SEATS", "AIRPORT_FLIGHTS_MONTH",␣
 ↪"AIRLINE_FLIGHTS_MONTH",
            "AIRLINE_AIRPORT_FLIGHTS_MONTH", "AVG_MONTHLY_PASS_AIRPORT",␣
 ↪"AVG_MONTHLY_PASS_AIRLINE", "PLANE_AGE"]
```

1 Semester Project - Part 2

CSPB 3022 Data Science Algorithms - Spring 2022

- Author: Thomas Cochran
- Github: https://github.com/t-cochran/CSPB-3022-Data-Science-Project

1.1 Project Topic

Project goal:

The goal of this project is to create a binary classifier that predicts whether a domestic flight will be delayed or not.

Type of problem:

This is a binary classification problem. The target class `DEP_DEL15` labels flights as on-time `0` or delayed `1` if the departure time exceeds 15 minutes.

Project motivation:

The motivation for this project is to identify when flight delays might not occur given a set of weather and transportation conditions. If we anticipate a delay, perhaps we could plan around it ahead of time. Or, at the very least, we could mentally prepare ourselves and hope we get an aisle seat.

1.2 Dataset

Dataset Source:

The dataset used in this project is from kaggle (source) and is located in file: `dataset/full_data_flightdelay.csv`

Each row of the dataset corresponds to a domestic airline departure flight and its associated weather for the year of 2019. This dataset has been wrangled and merged by the kaggle source from the following primary sources:

1. Bureau of Transportation statistics: Link
2. National Centers for Environmental Information (NOAA): Link

The departure data from the Bureau of Transportation statistics consists of monthly performance reports that contain a plethora of features for domestic departure flights. This is merged with the NOAA data which adds some interesting features that may contribute to flight delays, such as departure wind, snowfall, and precipitation.

Dataset size and features:

The dataset is quite large. Each row corresponds to a single domestic departure and the dataset contains over 6 million domestic departures. Here is a summary of the dataset's contents:

- 1.27 GB size
- 6,489,062 rows
- 26 features

There are 5 categorical and 21 numeric features. A description of each feature can be found in the file `dataset/documentation.md`.

[2]:
```
# Load the dataset
df = pd.read_csv('../dataset/full_data_flightdelay.csv', dtype='unicode')

# A brief look at a random sample of departure flights and some of their␣
↪features
```

```
display(df[['MONTH', 'DEP_DEL15', 'CARRIER_NAME', 'NUMBER_OF_SEATS',
            'DEPARTING_AIRPORT', 'PLANE_AGE', 'FLT_ATTENDANTS_PER_PASS',␣
 ↪'PRCP', 'SNOW']].sample(n=8, replace=False))
```

```
        MONTH DEP_DEL15            CARRIER_NAME NUMBER_OF_SEATS  \
3111605     6         0      Mesa Airlines Inc.              76
3658787     7         1       Endeavor Air Inc.              76
6143797    12         0    SkyWest Airlines Inc.             66
1572326     4         0  Southwest Airlines Co.             143
1860569     4         0  Frontier Airlines Inc.             180
1525081     4         1    United Air Lines Inc.            120
3032008     6         0             Comair Inc.              70
5248182    10         0  American Airlines Inc.             128

                         DEPARTING_AIRPORT PLANE_AGE FLT_ATTENDANTS_PER_PASS  \
3111605              Norfolk International         5                     0.0
3658787      John F. Kennedy International         6                     0.0
6143797            General Mitchell Field        14    3.419267401443636e-05
1572326     Austin - Bergstrom International        8    6.178236301460919e-05
1860569             Stapleton International         8   0.00011572564827677376
1525081         Chicago O'Hare International        18   0.00025380424062159367
3032008  Ronald Reagan Washington National        17                     0.0
5248182                   Douglas Municipal        19     9.82082928995461e-05

         PRCP SNOW
3111605   0.0  0.0
3658787   0.0  0.0
6143797   0.0  0.0
1572326   0.0  0.0
1860569   0.0  0.0
1525081   1.3  0.0
3032008  0.74  0.0
5248182  0.19  0.0
```

1.3 Data cleaning:

Setting data types

The data types for each feature are listed as `object` which means they are encoded as a string of varying length. The first cleaning step will be to cast each feature to an appropriate type that we can work with.

[3]:
```
# Cast groups of features from strings to an appropriate data type
df[TARGET_CLASS] = df[TARGET_CLASS].astype(int)
df[CATEGORICAL] = df[CATEGORICAL].astype(str)
df[CONTINUOUS] = df[CONTINUOUS].astype(float)
df[DISCRETE] = df[DISCRETE].astype(int)
```

```
# List the features of the first 8 columns and their datatypes
display(df.iloc[:, 0:7].dtypes)
```

```
MONTH                    int32
DAY_OF_WEEK              int32
DEP_DEL15                int32
DEP_TIME_BLK            object
DISTANCE_GROUP           int32
SEGMENT_NUMBER           int32
CONCURRENT_FLIGHTS       int32
dtype: object
```

Checking for missing values

Next I will look for any missing values by looking for features with `np.nan` values:

[4]:
```
# Sum NaN values in all columns
missing_vals = df.isnull().sum()
print(f"Total missing values in dataset: {missing_vals.sum()}")
```

```
Total missing values in dataset: 0
```

There don't appear to be any missing values in the form of `np.nan`, however there are some empty categorical features listed with `NONE`:

[5]:
```
# Search the dataframe for "NONE" string values
none_vals = df[df.eq("NONE").any('columns')]

# Print the name of columns with NONE value and the percentage of the dataset␣
↪with NONE values
print(f"Columns with NONE values: {df.columns[df.eq('NONE').any('rows')]}")
print(f"Percent of dataset with NONE values: {(len(none_vals) / len(df) * 100):.
↪2f}%")
```

```
Columns with NONE values: Index(['PREVIOUS_AIRPORT'], dtype='object')
Percent of dataset with NONE values: 22.33%
```

22.3% of the dataset has rows with `NONE` values, so it would be costly to drop all rows with this missing value. However, this affects only one feature: `PREVIOUS_AIRPORT`. Given these circumstances, I will keep these rows and note that the feature `PREVIOUS_AIRPORT` is imbalanced.

1.4 Exploratory Data Analysis (EDA):

Overview: Why EDA?

Exploratory data analysis is a collection of methods that investigate characteristics and patterns in the dataset which can improve our understanding of the features and their relationships.

How EDA will be performed:

I will be using EDA to visualize a variety of relationships between features and the target class `DEP_DEL15`, such as:

1. What numeric features are highly correlated? Are any redundant?
2. How does the frequency of flight delays vary by month or day of the week?
3. Are there certain airlines that experience more frequent delays?

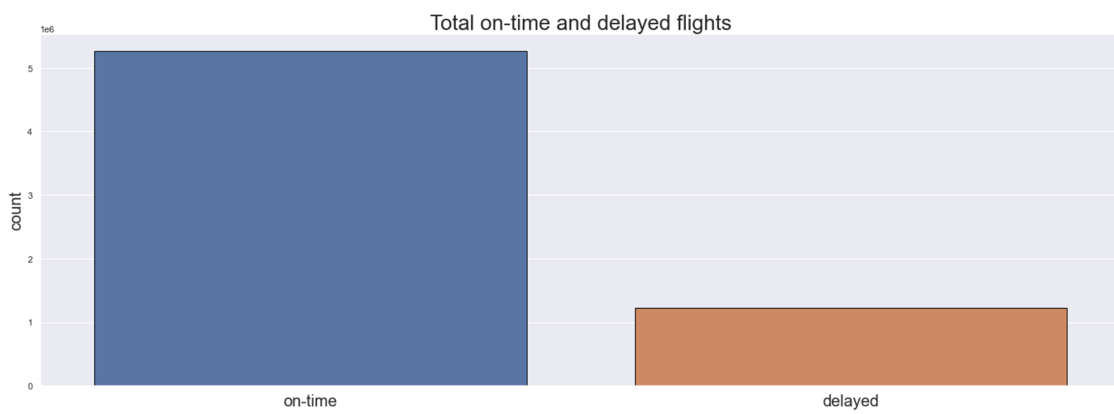
I will begin by looking at the distribution of the target class DEP_DEL15.

Target class distribution

The distribution of the target class is important because it can affect model selection. If the target class is imbalanced, then the predictive model could be more sensitive to biases and errors.

[110]:
```
# Create a countplot of our target class
sns.set_theme(style="darkgrid")
ax = sns.countplot(x="DEP_DEL15", edgecolor='black', data=df)
ax.set_xticks([0, 1], ["on-time", "delayed"], size=20)
ax.set_ylabel("count", fontsize = 20)
ax.set_title("Total on-time and delayed flights", fontdict={'fontsize':26})
ax.set_xlabel(None)

# Print the proportion of each target
class_targets = df.groupby(['DEP_DEL15']).size()
print(f"On-time flights in the dataset: {class_targets[0]/len(df)*100:.2f}%")
print(f"Delayed flights in the dataset: {class_targets[1]/len(df)*100:.2f}%")
```

```
On-time flights in the dataset: 81.09%
Delayed flights in the dataset: 18.91%
```



There is a clear bias towards on-time flights, whose proportion is more than 4-times the proportion of delayed flights. This imbalance will need to be considered when we select our model.

Mean and standard deviation of numeric features

Next I will have a quick look at some descriptive statistics for numeric features to get a handle on where the averages are. It may be interesting to see where some differences exist for delayed flights, however we cannot say whether any differences are statistically significant without further analysis.

First I will compute the mean and standard deviation for delayed flights:

[7]:
```
# Select numeric features, exluding month and day of week
numeric = df[TARGET_CLASS + CONTINUOUS + DISCRETE]
numeric = numeric.loc[:, ~numeric.columns.isin(['MONTH', 'DAY_OF_WEEK'])]

# Select delayed flights only
delayed_numeric = numeric[numeric['DEP_DEL15'] == 1]

# Compute the mean and standard deviation for numeric features of delayed␣
↪flights
print("DELAYED FLIGHTS:")
display(delayed_numeric.describe().loc[['mean', 'std']].applymap('{:.2f}'.
↪format))
```

DELAYED FLIGHTS:

	DEP_DEL15	FLT_ATTENDANTS_PER_PASS	GROUND_SERV_PER_PASS	LATITUDE
mean	1.00	0.00	0.00	36.71
std	0.00	0.00	0.00	5.25

	LONGITUDE	PRCP	SNOW	SNWD	TMAX	AWND	DISTANCE_GROUP	SEGMENT_NUMBER
mean	-93.25	0.16	0.06	0.13	71.13	8.72	3.90	3.47
std	16.81	0.43	0.49	0.86	19.24	3.78	2.38	1.77

	CONCURRENT_FLIGHTS	NUMBER_OF_SEATS	AIRPORT_FLIGHTS_MONTH
mean	28.24	134.88	13174.01
std	21.30	46.48	8731.56

	AIRLINE_FLIGHTS_MONTH	AIRLINE_AIRPORT_FLIGHTS_MONTH
mean	63211.75	3579.94
std	35100.32	4094.56

	AVG_MONTHLY_PASS_AIRPORT	AVG_MONTHLY_PASS_AIRLINE	PLANE_AGE
mean	1645375.69	7828102.68	11.62
std	1095573.89	5043404.98	6.77

Next, I will compute the same for on-time flights:

[8]:
```
# Select on-time flights only
ontime_numeric = numeric[numeric['DEP_DEL15'] == 0]

# Compute the mean and standard deviation for numeric features of on-time␣
↪flights
print("ON-TIME FLIGHTS:")
display(ontime_numeric.describe().loc[['mean', 'std']].applymap('{:.2f}'.
↪format))
```

ON-TIME FLIGHTS:

```
     DEP_DEL15 FLT_ATTENDANTS_PER_PASS GROUND_SERV_PER_PASS LATITUDE  \
mean      0.00                    0.00                 0.00    36.70
std       0.00                    0.00                 0.00     5.56

     LONGITUDE  PRCP  SNOW  SNWD   TMAX  AWND DISTANCE_GROUP SEGMENT_NUMBER  \
mean    -94.49  0.09  0.02  0.08  71.55  8.25           3.80           2.95
std      18.15  0.32  0.26  0.69  18.14  3.56           2.38           1.74

     CONCURRENT_FLIGHTS NUMBER_OF_SEATS AIRPORT_FLIGHTS_MONTH  \
mean              27.74          133.47              12570.41
std               21.56           46.44               8860.97

     AIRLINE_FLIGHTS_MONTH AIRLINE_AIRPORT_FLIGHTS_MONTH  \
mean              62901.99                       3431.10
std               34212.30                       4286.35

     AVG_MONTHLY_PASS_AIRPORT AVG_MONTHLY_PASS_AIRLINE PLANE_AGE
mean               1575403.75               7811906.61     11.51
std                1129931.10               5047687.73      6.97
```

The average daily percipitation and snow (`PRCP`, `SNOW`; in inches) is lower for on-time flights, but both feature means have a relatively large variance. There is a difference between the average monthly passengers at the airport (`AVG_MONTHLY_PASS_AIRPORT`), which is larger for delayed flights.

Correlation matrix

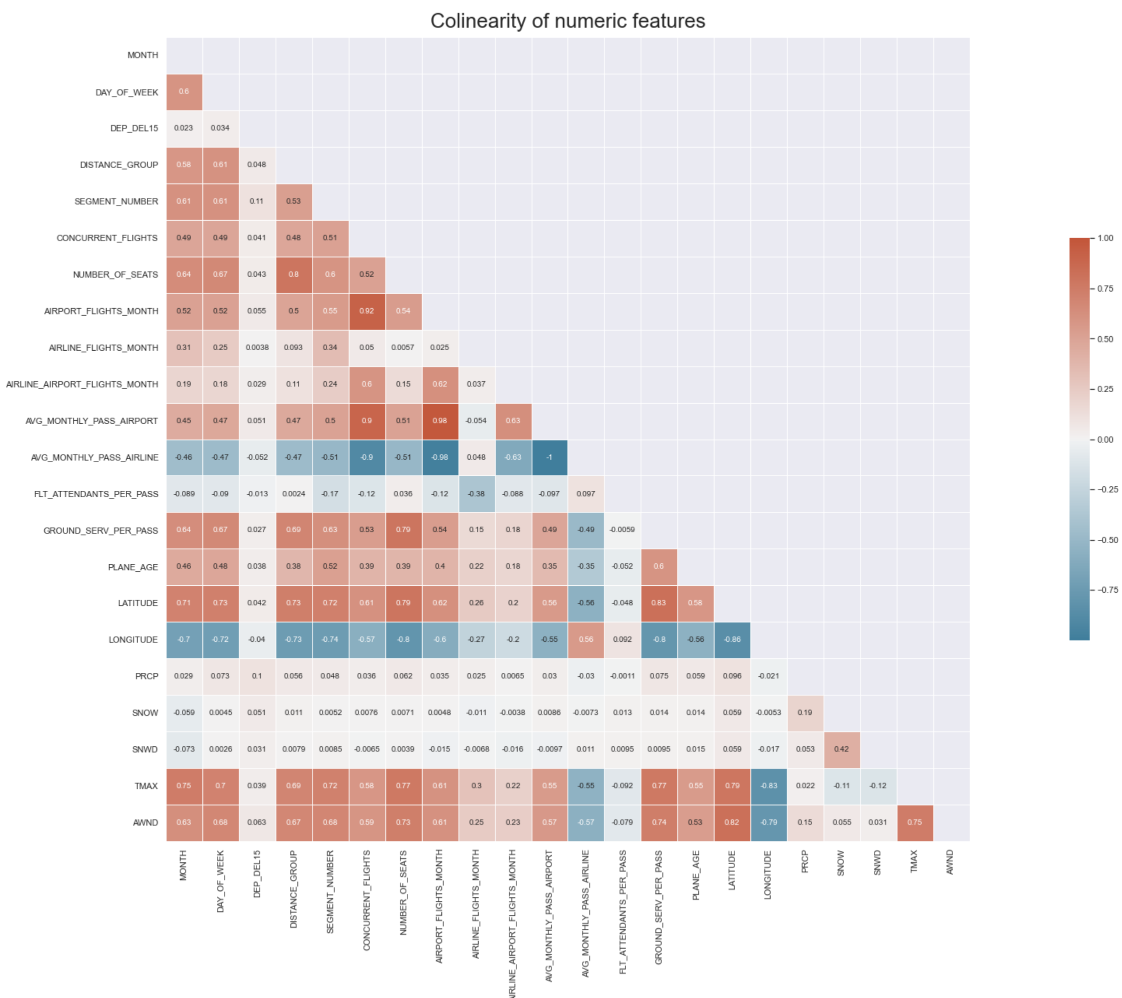
A correlation matrix is a collection of correlation coefficients between features in a dataset. This is useful because it can identify strong positive or negative linear relationships between features. If a pair of features have a very strong linear relationship, then they may be redundant; that is, one can be substituted for the other.

In this section, I will pair numeric features and then create a correlation matrix. Using the correlation matrix, I will identify which features are highly correlated and then remove redundant features using a simple heuristic: If two features have $|\rho| >= 0.90$, I will remove the feature with a lower correlation to our target class.

[9]:

```
# Seaborn heatmap reference:
# https://seaborn.pydata.org/examples/many_pairwise_correlations.html

# Select only the numeric features from the dataset
numeric_features_df = df.select_dtypes(['int32', 'float64'])

# Normalize and then compute a pairwise correlation of numeric columns
normalized_pd = pd.DataFrame(Normalizer().fit_transform(numeric_features_df),␣
 ↪columns = numeric_features_df.columns)
corr = normalized_pd.corr('spearman')

# Mask the upper triangle of the heatmap and create a diverging colormap
mask = np.triu(np.ones_like(corr, dtype=bool))
```

```python
cmap = sns.diverging_palette(230, 20, as_cmap=True)

# Create the heatmap
f, ax = plt.subplots(figsize=(46, 19))
corr_heatmap = sns.heatmap(corr, mask=mask, cmap=cmap, vmax=1, center=0, square=True,
                           linewidths=.5, cbar_kws={"shrink": .5}, annot=True,
                           annot_kws={"fontsize":10})

# Set the heatmap title
corr_heatmap.set_title('Colinearity of numeric features', fontdict={'fontsize': 26}, pad=12);
```



The heatmap shows some highly correlated numeric features. For example, the average airport flights per month (`AIRPORT_FLIGHTS_MONTH`) is highly correlated with the average airport departing passengers per month (`AVG_MONTHLY_PASS_AIRPORT`), which we may expect.

The following algorithm should target and remove highly correlated features from the dataset using the heuristic above.

[10]:
```
# Select the upper triangle of correlation matrix using our mask
corr_matrix = corr.where(cond=mask)

# Remove redundant features according to heuristic:
# If |p| >= 0.90 remove the feature less correlated to target class 'DEP_DEL15'
redundant_features = []
for col in corr_matrix:
    current_column = corr_matrix[col]       # Iterate over columns in the␣
 ↪correlation matrix
    if current_column.name == 'DEP_DEL15':  # Ignore our target class
        continue
    else:
        for row in current_column.index:    # Select each row in the current␣
 ↪column
            if current_column.name == row:  # Ignore correlation between the␣
 ↪same row and column
                continue
            if np.abs(current_column[row]) >= 0.90:                 # Select␣
 ↪highly correlated |p|>=0.90 features
                target_class_row = corr_matrix.loc['DEP_DEL15'][row] # Check␣
 ↪the correlation with our target class
                target_class_col = corr_matrix.loc['DEP_DEL15'][col]
                if target_class_row >= target_class_col:             # Remove␣
 ↪feature with lower correlation to target
                    redundant_features.append(current_column.name)
                else:
                    redundant_features.append(row)

# Print and drop redundant features
df.drop(set(redundant_features), axis=1, inplace=True)
print(f"Dropped redundant features:\n{set(redundant_features)}")
```

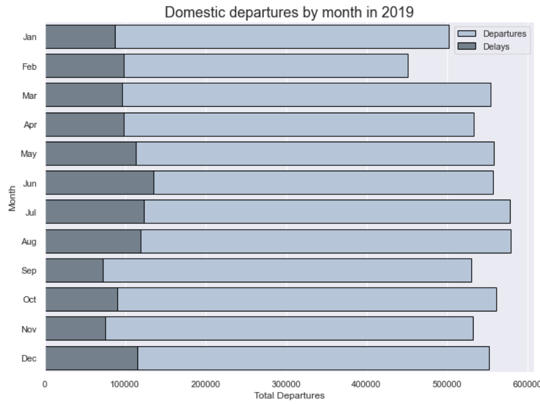
```
Dropped redundant features:
{'AVG_MONTHLY_PASS_AIRLINE', 'AVG_MONTHLY_PASS_AIRPORT', 'CONCURRENT_FLIGHTS'}
```

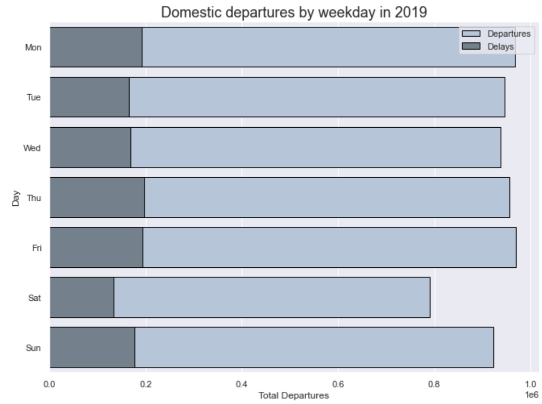
Flight delays by month and weekday

In this section, I will be investigating how delays vary over months and days of the week. My intuition tells me that holiday months and Mondays should have a higher incidence of delays due to more congestion at the airport.

[121]:
```
# Create dataframes to organize and sort the frequency data
month_df = pd.DataFrame({
    'MONTHLY_TOTAL'  :  df.groupby(['MONTH']).size(),
    'MONTHLY_DELAYS' :  df[df['DEP_DEL15'] == 1].groupby(['MONTH']).size(),
```

```
})
day_df = pd.DataFrame({
    'WEEKDAY_TOTAL'   :  df.groupby(['DAY_OF_WEEK']).size(),
    'WEEKDAY_DELAYS' :  df[df['DEP_DEL15'] == 1].groupby(['DAY_OF_WEEK']).size()
})

# Plot frequency of monthly delays
fig, (ax1, ax2) = plt.subplots(1, 2)
sns.barplot(x="MONTHLY_TOTAL", y=month_df.index, data=month_df, ax=ax1,␣
 ↪order=month_df.index,
            edgecolor='black', color="lightsteelblue", label="Departures",␣
 ↪orient="h")
sns.barplot(x="MONTHLY_DELAYS", y=month_df.index, data=month_df, ax=ax1,␣
 ↪order=month_df.index,
            edgecolor='black', color="slategray", label="Delays", orient="h")

# Plot frequency of week day delays
sns.barplot(x="WEEKDAY_TOTAL", y=day_df.index, data=day_df, ax=ax2,␣
 ↪order=day_df.index,
            edgecolor='black', color="lightsteelblue", label="Departures",␣
 ↪orient="h")
sns.barplot(x="WEEKDAY_DELAYS", y=day_df.index, data=day_df, ax=ax2,␣
 ↪order=day_df.index,
            edgecolor='black', color="slategray", label="Delays", orient="h")

# Configure plot labels
ax1.set_title('Domestic departures by month in 2019', fontdict={'fontsize':18})
ax2.set_title('Domestic departures by weekday in 2019', fontdict={'fontsize':
 ↪18})
ax1.set_yticklabels(['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug',␣
 ↪'Sep', 'Oct', 'Nov', 'Dec'])
ax2.set_yticklabels(['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat', 'Sun'])
ax1.legend(ncol=1, loc="upper right", frameon=True), ax2.legend(ncol=1,␣
 ↪loc="upper right", frameon=True)
ax1.set_xlabel("Total Departures"), ax1.set_ylabel("Month")
ax2.set_xlabel("Total Departures"), ax2.set_ylabel("Day");
```



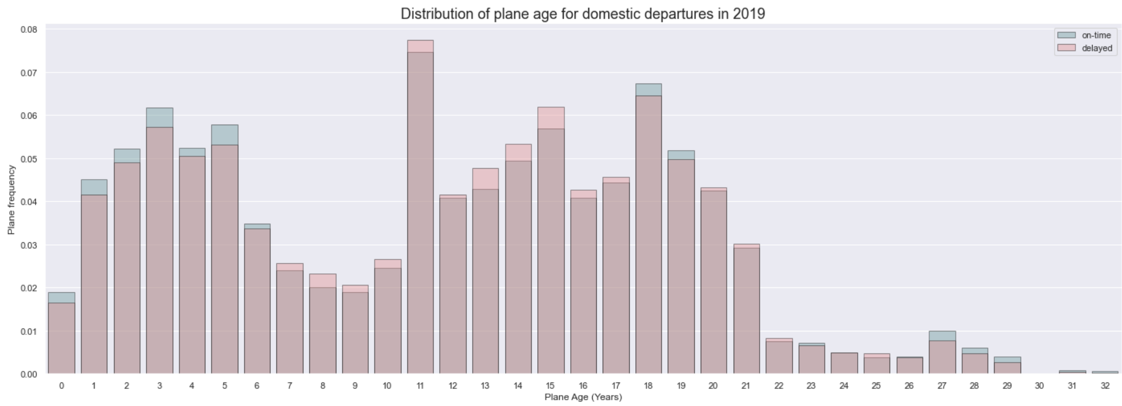


The month of August has the most departures, followed by July. The fewest departures occur on Saturday's. The largest number of delays occur on June and on Thursday. However, the all days of the week appear to have a comparable number of delays relative to their total departures.

Distribution of plane age

Next I will investigate whether delayed flights involve more older planes. In order to do this, I will plot the relative frequency of planes by age for both delayed and on-time flights.

[129]:
```
# Select delayed and ontime departures and sort by plane age
ontime_df = df[df['DEP_DEL15'] == 0].sort_values(['PLANE_AGE'], ascending=True)
delay_df = df[df['DEP_DEL15'] == 1].sort_values(['PLANE_AGE'], ascending=True)

# Compute the relative frequency of planes for each age group
ontime_df['AGE_PCT'] = ontime_df['PLANE_AGE'].map(ontime_df['PLANE_AGE'].
 ↪value_counts(normalize=True))
delay_df['AGE_PCT'] = delay_df['PLANE_AGE'].map(delay_df['PLANE_AGE'].
 ↪value_counts(normalize=True))

# Pair the age percentage with each unique plane age
ontime_df = ontime_df.groupby(['PLANE_AGE']).head(n=1)[['PLANE_AGE', 'AGE_PCT']]
delay_df = delay_df.groupby(['PLANE_AGE']).head(n=1)[['PLANE_AGE', 'AGE_PCT']]

# Plot the percentage of planes in each age group for delayed and on-time␣
 ↪flights
ax = plt.subplots()
ax = sns.barplot(x=ontime_df.PLANE_AGE,y=ontime_df.
 ↪AGE_PCT,color='cadetblue',edgecolor='black',label='on-time',alpha=0.4)
ax = sns.barplot(x=delay_df.PLANE_AGE,y=delay_df.
 ↪AGE_PCT,color='lightcoral',edgecolor='black',label='delayed',alpha=0.4)
ax.set_title('Distribution of plane age for domestic departures in 2019',␣
 ↪fontdict={'fontsize':18})
ax.set_xlabel("Plane Age (Years)"), ax.set_ylabel("Plane frequency")
plt.legend();
```

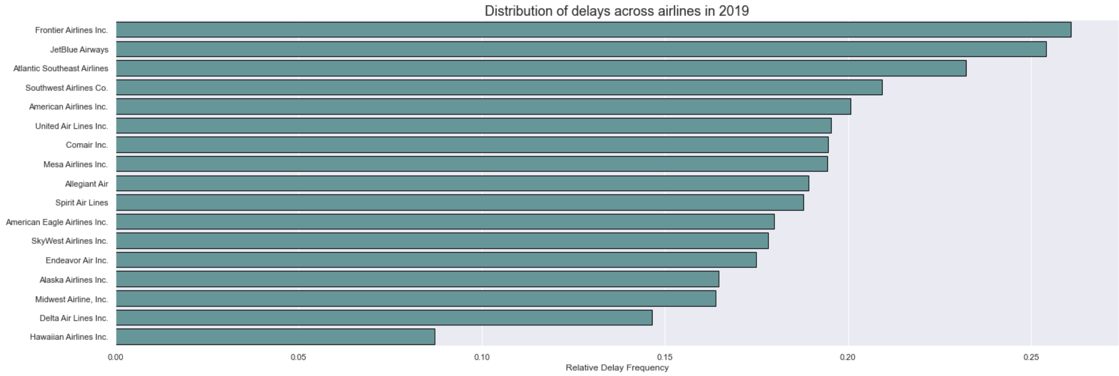


The difference between on-time and delayed departures appears to be quite small. The left hand side of the graph suggests that on-time flights use younger aircraft slightly more frequently. The middle of the graph suggests that delayed flights use older aircraft slightly more frequently.

Distribution of delays across airlines

Next I will plot the distribution of delays across different airlines to see if there are any particular carriers that are better or worse at avoiding delays.

[107]:
```
# Select departures grouped by CARRIER_NAME then compute the relative frequency␣
↪of delays
delay_df = df.groupby(['CARRIER_NAME'])['DEP_DEL15'].
↪value_counts(normalize=True).sort_values(ascending=False)

# Select only delayed flights
delay_df = delay_df.iloc[delay_df.index.get_level_values('DEP_DEL15') == 1]

# Get x and y axis from the delay_df series
x = delay_df.values
y = delay_df.index.get_level_values('CARRIER_NAME')

# Plot the distribution of delays
ax = plt.subplots()
ax = sns.barplot(x=x,y=y,color='cadetblue', edgecolor='black', orient="h")
ax.set_title('Distribution of delays across airlines in 2019',␣
↪fontdict={'fontsize':18})
ax.set_xlabel("Relative Delay Frequency"), ax.set_ylabel("");
```

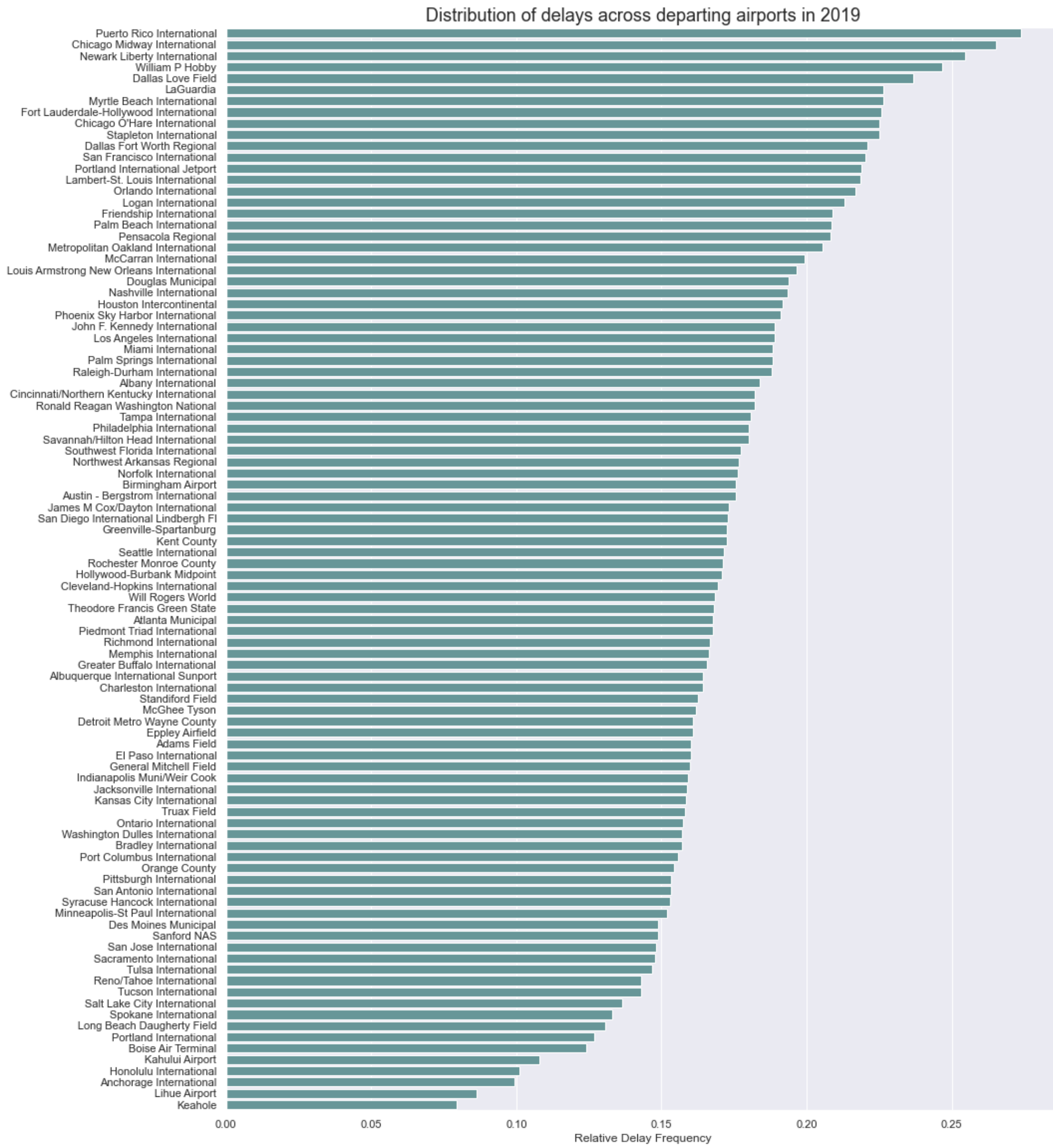


The clear winner here is Hawaiin Airlines which has the lowest relative delay frequency. The top two airlines are Frontier and Jetblue. I find this a little amusing because I often booked Frontier for flights to CU Boulder and I often encountered delays.

Distribution of delays across departing airports

This section is similar to the last, however instead of airline carriers I am plotting the relative frequency of delays over departing airports in the dataset. As with airline carrier, this should be interesting to see if there exist certain airports that are rife with delays.

[109]:
```
# Select departures grouped by DEPARTING_AIRPORT then compute the relative␣
↪frequency of delays
delay_df = df.groupby(['DEPARTING_AIRPORT'])['DEP_DEL15'].
↪value_counts(normalize=True).sort_values(ascending=False)

# Select only delayed flights
delay_df = delay_df.iloc[delay_df.index.get_level_values('DEP_DEL15') == 1]

# Get x and y axis from the delay_df series
x = delay_df.values
y = delay_df.index.get_level_values('DEPARTING_AIRPORT')

# Plot the distribution of delays
ax = plt.subplots(figsize=(15,20))
ax = sns.barplot(x=x,y=y,color='cadetblue', orient="h")
ax.set_title('Distribution of delays across departing airports in 2019',␣
↪fontdict={'fontsize':18})
ax.set_xlabel("Relative Delay Frequency"), ax.set_ylabel("");
```



Summary of EDA findings

- The dataset is biased towards on-time flights.
- The largest number of departure delays occur on June and on Thursday.
- Airlines that are delayed most frequently are: Frontier and Jetblue.
- Airports with the most frequent delays are: Puerto Rico Intl., Chicago Midway, and Newark Liberty
- `SEGMENT_NUMBER` and `PRCP` have the largest positive correlation with target class `DEP_DEL15`.
- The numeric features `AVG_MONTHLY_PASS_AIRLINE`, `AVG_MONTHLY_PASS_AIRPORT`, `CONCURRENT_FLIGHTS` were dropped.

Discussion of forseen difficulties

EDA has identified foreseen difficulties to consider when selecting a model for this classification task:

1. The target class `DEP_DEL15` is imbalanced: 18.91% of the total flights in the dataset are delayed.
2. There remain an abundance of features after cleaning: 4 categorical, 18 numeric.
3. The dataset is large and may require algorithms with lower computational complexity.
4. Model input is heterogenous.

Each of these difficulties can be mitigated in different ways:

1. Class imbalance in `DEP_DEL15` may be mitigated by sampling methods, such as oversampling delayed or undersampling on-time flights.
2. Heterogenous input may require encoding categorical features, or selecting a model that can handle categorical and numeric features.
3. Since the input size is quite large, it will be important to select models whose complexity has a lower polynomial k of the input size n, i.e. n^k.

1.5 Plans for Model Approach:

For this project, I intend to train two different models and then compare their accuracy. One will be relatively simple and the other will be more advanced. In both cases, I want to preserve interpretability because it could be interesting to see how each model weighs features differently.

Model 1: Logistic regression

The first classification algorithm that I plan to use is simple logistic regression. The reasons for this are:

1. Target class `DEP_DEL15` is categorical and binary which is well suited for logistic regression.

2. The algorithm is simple to run, resistant to overfitting, and can act as a starting point before attempting more advanced classification models.

3. The interpretability is high which allows us to better understand how the model predicts delays from the features.

4. It has favorable training time complexity $\mathcal{O}(np)$ and test time complexity $\mathcal{O}(p)$ for the large input data n and predictors p in this dataset.

One important caveat with logistic regression is that real-world data isn't often modeled very well with a linear decision boundary. It's unlikely that flight delays are bounded by some linear combination of weather conditions, airline traffic, or airports.

Furthermore, logistic models perform poorly with highly correlated features. The correlation matrix in EDA did identify and remove some highly correlated features, but there remain features that are moderately correlated with $|\rho| >= 0.50$.

In light of these difficulties, I will relegate logistic regression as a first pass attempt at classifying flight delays. After training the model, I will asses the accuracy of its predictions and then see if a more advanced algorithm can achieve greater model accuracy.

Model 2: Random Forest

The second classification algorithm that I plan to use is the random forest ensemble method. The reasons for this are:

1. It handles non-linear parameters and is immune to highly correlated features, which are both improvements from the logistic model.
2. It can leverage the size of the dataset by generating larger bootstrapped sampling distributions with lower standard error.
3. As with logistic regression, interpretability of each decision tree is high and features can be ranked in terms of importance.
4. The training time complexity for k trees, n data points, and p predictors is $\mathcal{O}(n\log(n)pk)$ which is favorable for the large n in this dataset.

The random forest model will require some parameter tuning and that could create some challenges due to the size of the dataset. For example, increasing the total number of trees and their depth might improve model accuracy, but it could create large increases in space and time complexity.

Handling class imbalance

Both random forest and logistic regression will be sensitive to feature imbalances in the training data. This imbalance does exist. The target class `DEP_DEL15` labels 81.09% on-time flights and only 18.91% delayed flights, as was shown during EDA. If we were to train either model with a similarly imbalanced set of training data, the model could predict all flights as on-time and still be correct 81.09% of the time. Therefore, in both models, great care must be taken to balance the target class.

In the case of the logistic model, I will attempt to balance `DEP_DEL15` by using re-sampling methods, such as oversampling delayed flights or undersampling on-time flights. In the case of random forest, I can balance by using these re-sampling methods during the bootstrap step.