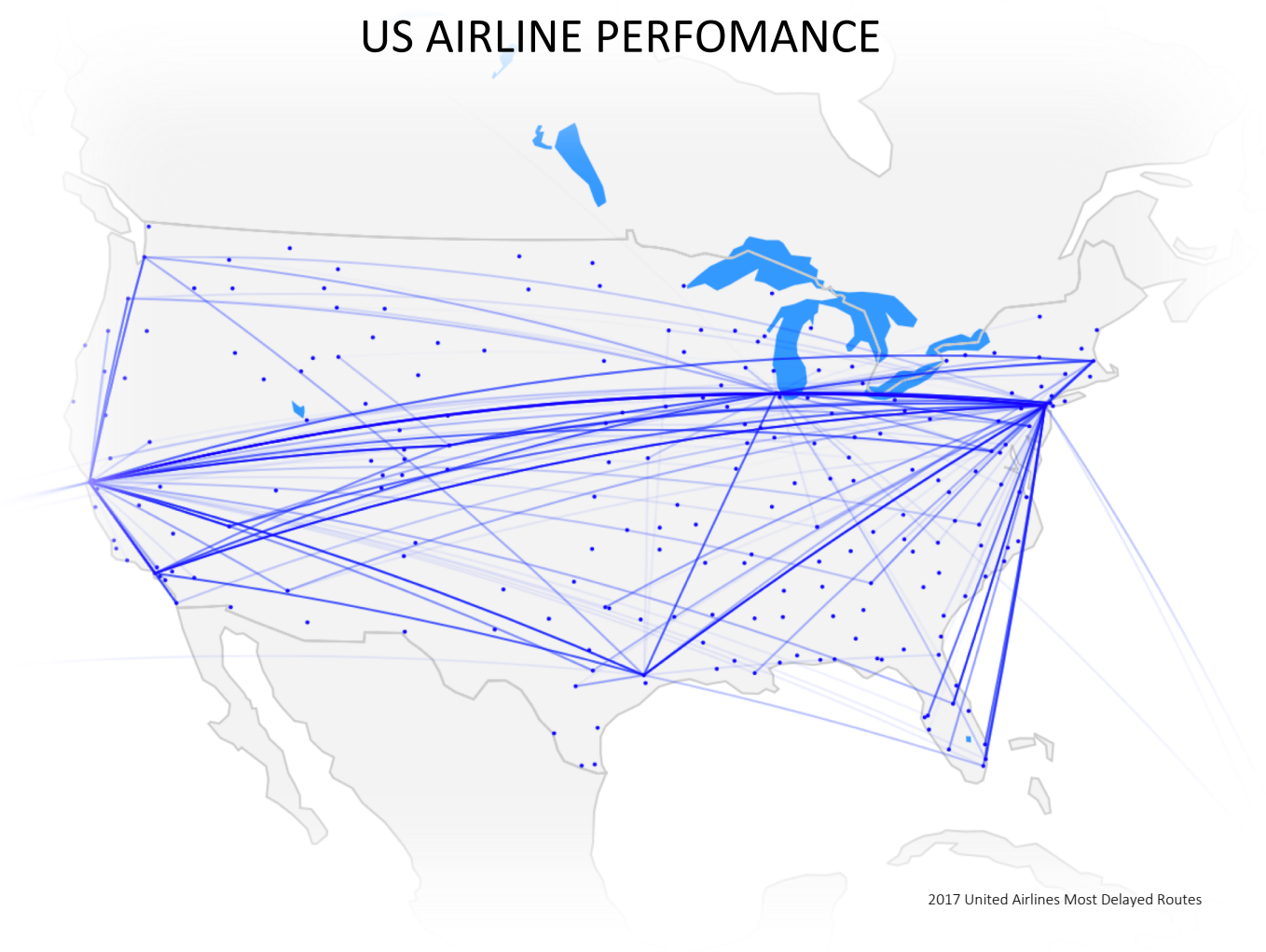
US AIRLINE PERFOMANCE



2017 United Airlines Most Delayed Routes

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1. Introduction and Executive Summary

Air travel has always been and still is a headache for many travelers. The unknowns of delays and cancellations are some of the biggest contributors to the stress. In this analysis we'll attempt to shine a light on the unknowns and try to predict the probability of delay and even the delay length of a given future flight. We'll take a look at 15 years of airline performance data, containing over 75 million flights in a dataset available from US Department of Transportation.

2. Acquiring and Aggregating the Data

The data was obtained from United States Department of Transportation. Unfortunately, the data are only available by month in a zipped file, which presents a challenge when it comes to downloading and concatenating. Additionally, the website utilizes a webapp to click on checkboxes and buttons to activate the download, which makes scraping impossible. As such, the data was acquired manually. Due to limitations in available data in years prior to 2004, only data for 2004 - 2018 was obtained for a total of 12 zipped files per year (for a total of 12 files x 15 years = 180 files). The data was then combined into a set of files organized by year and then into one complete csv file. The dataset will be uploaded to Google BigQuery for further analysis. For this analysis we will be using the 2017 Dataset. The code to combine all the files is available on github.

In summary, the following steps were taken:

a. Create a list of files in each year directory via glob method.
b. Loop through each file, unzip, and read into a Pandas Dataframe via pd.read_csv, utilizing the "compression='zip'" parameter.
c. Since each year's file will be ~3GB in memory, convert the datatypes in each column to reduce size.
d. Repeat the process for each year by looping through year folders.
e. Concatenate all csv files into one via shell and upload to Google BigQuery.

2.1. Adding Weather Data

Additional data were obtained during the feature engineering stage in order to compute precipitation information for a specific airport and departure time. The precip_sum column was created in the flight data frame. This column includes the sum of four hours' worth of precipitation data prior to the departure hour.

	station	network	valid	precip_in
0	LAX	CA_ASOS	2016-12-31 22:00:00	0.0
1	LAX	CA_ASOS	2016-12-31 23:00:00	0.0
2	LAX	CA_ASOS	2017-01-01 00:00:00	0.0
3	LAX	CA_ASOS	2017-01-01 01:00:00	0.0
4	LAX	CA_ASOS	2017-01-01 02:00:00	0.0

CRSElapsedTime	Distance	DistanceGroup	precip_sum
120.0	574.0	3	0.0
115.0	574.0	3	0.0
250.0	1865.0	8	0.0
150.0	999.0	4	0.0
85.0	391.0	2	0.0

Figure 1 Mapping Precipitation Data to the Main Flight DataFrame

2.2. Adding Airport Coordinates

We're also going to need airport coordinates in order to create extra features for the modeling portion of the project. We'll first import a csv file with all US airport latitude and longitude data and join it with our flights data frame.

locationID	Latitude	Longitude
YUM	32.6686	-114.5991
MQT	46.3497	-87.3873
SCE	40.8500	-77.8487
ECP	30.3553	-85.7991
ADK	51.8781	-176.6461

start_lat	start_lon	end_lat	end_lon	airline	airport1	airport2
39.8617	-104.6731	29.9844	-95.3414	UA	DEN	IAH
33.9425	-118.4072	29.9844	-95.3414	UA	LAX	IAH
33.9425	-118.4072	38.9475	-77.4600	UA	LAX	IAD
32.7336	-117.1897	39.8617	-104.6731	UA	SAN	DEN
38.8522	-77.0378	29.9844	-95.3414	UA	DCA	IAH

Figure 2 Mapping Airport Coordinates to the Main DataFrame

Spot checking DEN & IAH (Denver International & Houston International):

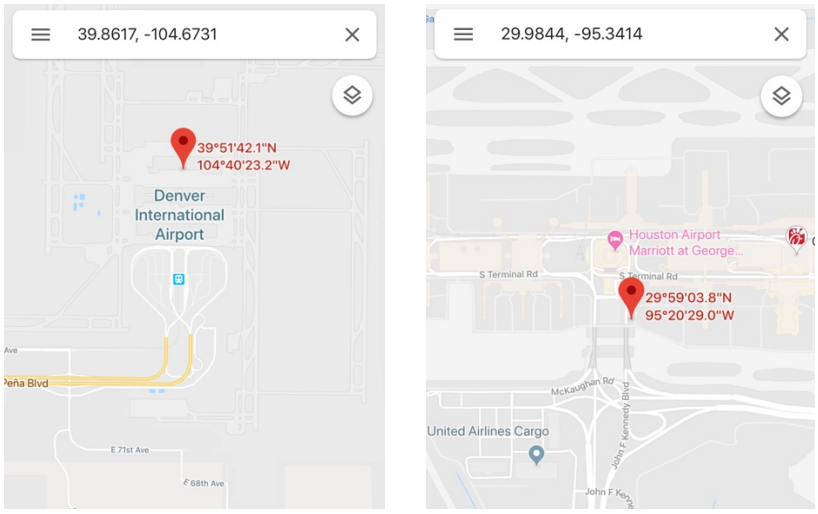


Figure 3 Denver and Houston Aiprots Check Against DataFrame Information

3. Cleaning the data

The dataset is relatively clean from the perspective of missing data. Only 1.5% of rows have missing values, which can be removed without significant impact on the analysis. As we go through EDA and ML portions of this analysis, the data will need to be formatted to fit the needs of the approach. As an example, time of day is presented in the dataset as a float-type number, ranging from 00 to 59 mins, which leaves 60 to 99 blank. This can be problematic when visualizing the data or converting to a timestamp. This will be addressed through a custom method which will convert the float-type number to a proper format.

```
df.DEP_TIME.head()
```

```
0    1031.0
1    1420.0
2    1203.0
3     758.0
4    1041.0
Name: DEP_TIME, dtype: float32
```

Table 1 Example of Departure Time representation in the dataset (e.g. 1031.0 should be 10.52 as float)

Furthermore, we are going to be dealing with a lot of categorical data, such as airline names and airport codes, which will have an impact on predicting performance. In order apply modeling techniques these data will need to be converted into numerical values, as the solvers rely on mathematical algorithms. When encoding these values, we'll have to be mindful of memory space required as there are over 300 unique origins and destinations and over 10 unique airlines. A possible solution to this is the use of a sparse matrix.

4. Exploratory Data Analysis (EDA)

In this section we'll explore the data statistically and visually to understand any trends or features we should focus on during the modeling stage. The code for this section is available on github with a sample data set on Google drive:
Code:
https://github.com/dmitriykats1/Springboard/blob/master/Capstone1/EDA-2017.ipynb

Data:
https://drive.google.com/file/d/15PXxxTY9X4w0exxu6vMEReJm3Pwcn4TE/view?usp=sharing

4.1. Distribution of Arrival Delays

Let's begin with the most important feature, delay time at the destination, represented as ArrDelay in our data set. This feature set has both negative and positive values, representing early and late arrival times, respectively. Let's take a look at the distribution:

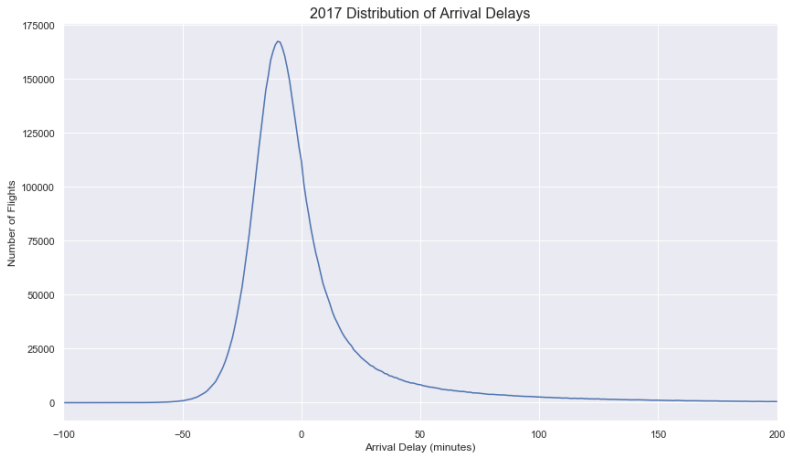


Figure 4 Distribution of delays for all US flights in 2017

From the above we see that majority of flights being on time or early, and the distribution is also skewed and non-normal. With the mean arrival delay of 4.3mins., median of -6.0mins, and a standard deviation of 45.5mins. The next obvious questions we can ask is: Do long and short flights have same distributions? To answer this, we'll split the dataset into long flights with durations longer than 3hrs and remainder will be short flights.

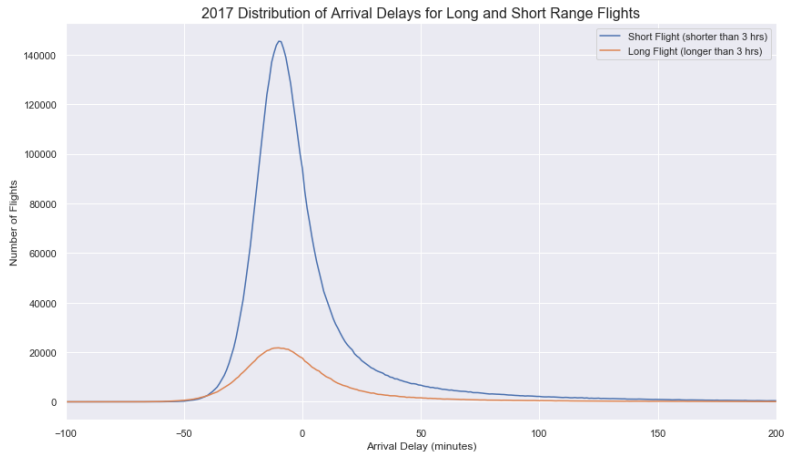


Figure 5 Distribution of delays for all US flights in 2017 for short and long rage flights

The short- and long-range flights seem to have the same distributions with slightly different means which we can investigate use to investigate any statistical differences, with long range flights having a mean delay of 3.8mins and short-range flights having a mean delay of 4.4mins. Since majority of flights are on time or early, taking an average of arrival delay does not paint a full picture due to the skew. This can be better visualized below:

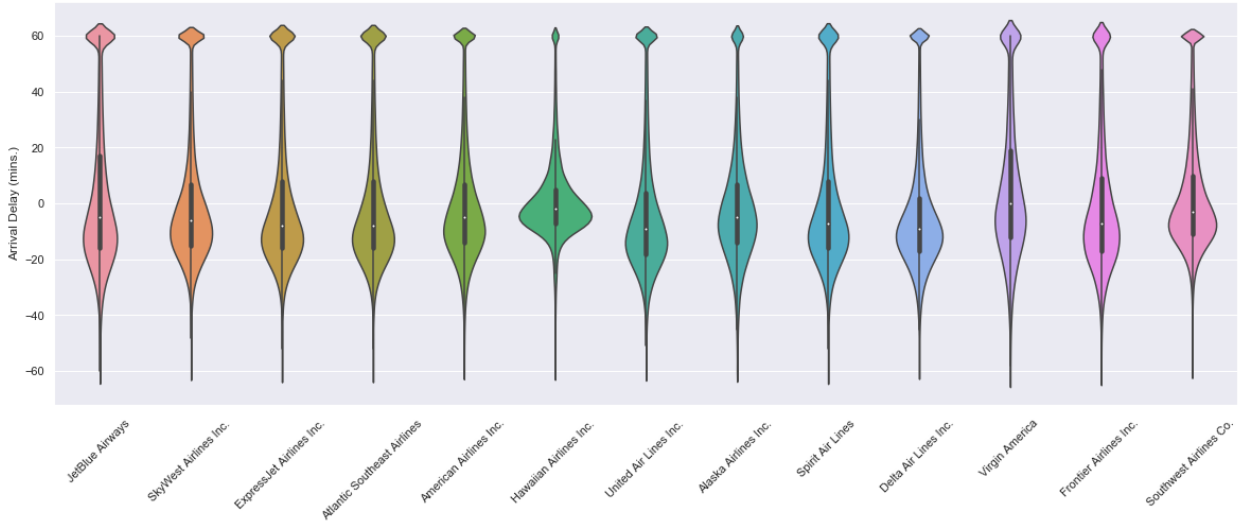


Figure 6 Arrival delay distribution split by airlines

Next, we can take a look at ONLY delayed flights, or flights that are delayed 15 mins or more as defined by the FAA. One of the questions we can ask is if there is any correlation between arrival delays and other features. First let's look at departure delays and arrival delays:

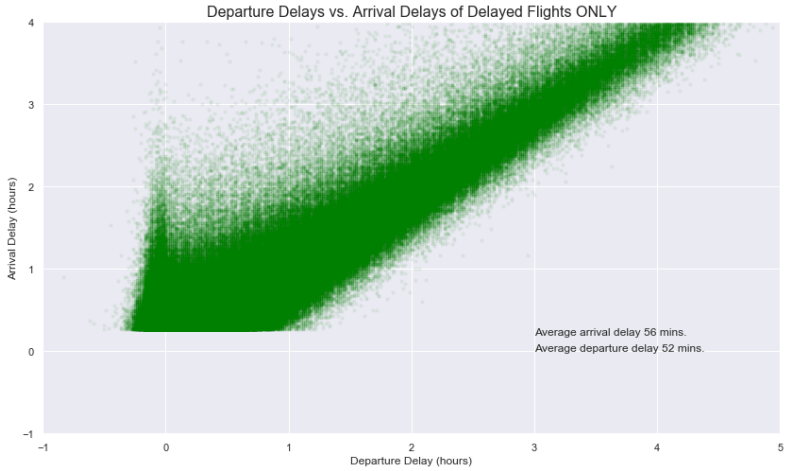
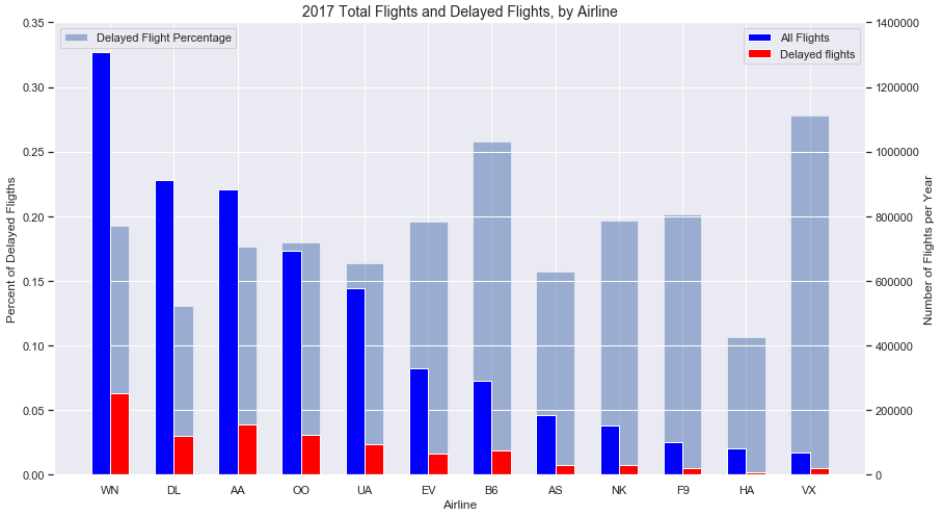


Figure 7 Correlation of departure and arrival times for all delayed flights in 2017

There is a positive linear relationship between departure delays and arrival delays, this makes sense intuitively and we'll need to keep this in mind when modeling our data. We do notice a small spike in arrival delays around the 0-minute mark for departure delays. This may be due to airlines trying to get out on time and closing the aircraft door in order to have an on-time departure. Only finding themselves waiting in taxi lines to depart and subsequently be delayed on arrival.

4.2. Airport and Airline On-Time Performance

Another set of features that may impact on-time performance are the airlines and airports. Let's take a look at the summary of top airlines and on-time performance:



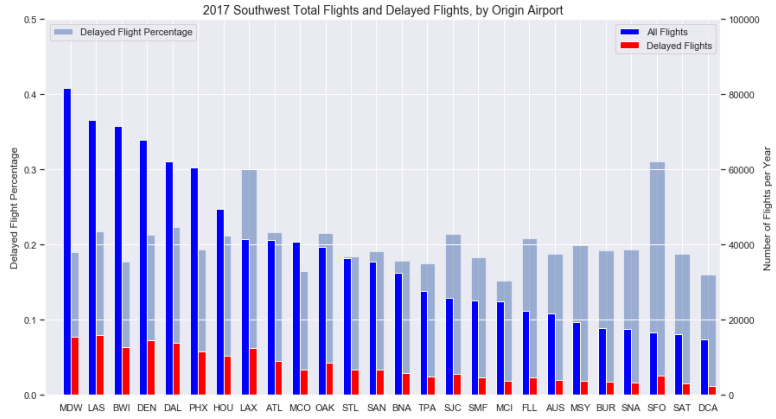
	Delay Percentage
VX	0.277877
B6	0.257856
F9	0.201811
NK	0.196220
EV	0.195932
WN	0.192491
OO	0.179436
AA	0.176565
UA	0.163890
AS	0.157340
DL	0.130984
HA	0.106147

Figure 8 Summary of Airline Performance for 2017

Above figure gives us a glimpse of how each airline performed in 2017, the data above is sorted by flight volume. It's interesting that airlines with most flights don't necessarily have the worst delay record, as we can see from the delay percentage bars. Delay percentages will certainly change as we break this data down by origin airport. Let's see if there is a list of airports that have consistently high delays when broken down by airline.

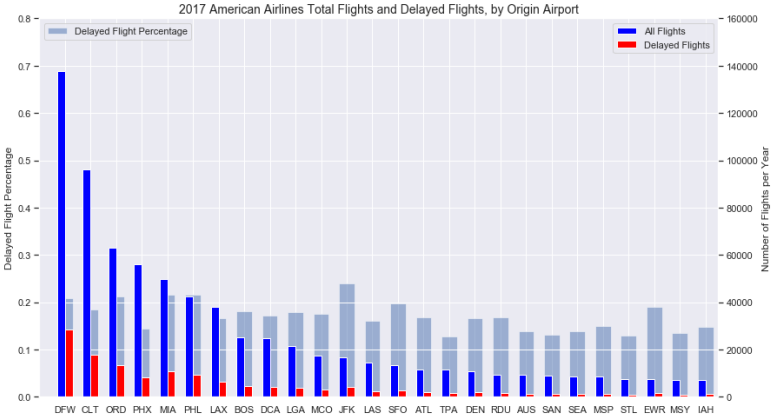
Initial analysis looked at Southwest, American, and United Airlines (which make up 50% of all US flights) and delay percentages as a function of origin airport.

Southwest Airlines



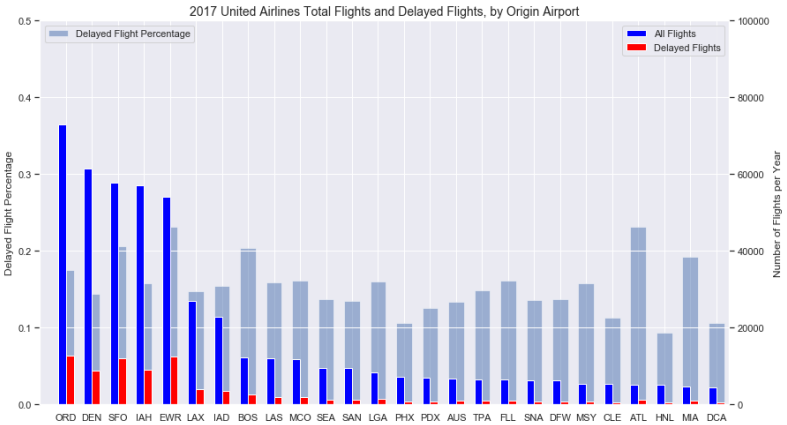
SFO	0.311330
LAX	0.300265
EWR	0.271363
DAL	0.223535
LAS	0.218197
ATL	0.216150
OAK	0.215234
SJC	0.214712
DEN	0.213428
HOU	0.212105

American Airlines



JFK	0.239166
MIA	0.215648
PHL	0.215173
ORD	0.212090
DFW	0.207660
IAD	0.203976
SFO	0.197801
EWR	0.189142
CLT	0.184354
BOS	0.180293

United Airlines

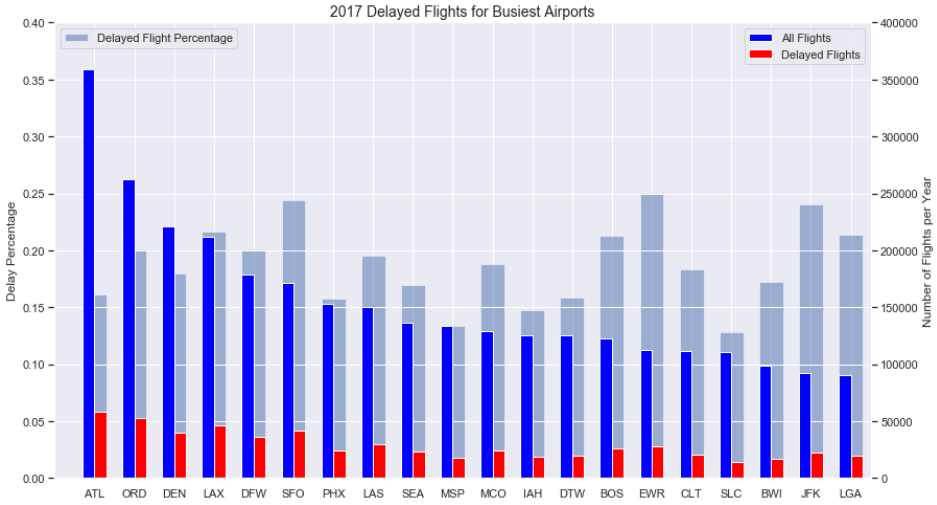


PBI	0.263673
EWR	0.231172
ATL	0.230904
BNA	0.219697
SFO	0.206219
BOS	0.204175
EUG	0.198057
SJU	0.197797
MIA	0.192012
ORD	0.174702

Figure 9 Top Airlines by flight volume and origin airport on-time performance

We see EWR and SFO appear on the list for all three airlines. We can further investigate these airports and surrounding airports to see if regional air congestion impacts other airports in the area. But first let's confirm these airports appear on the top delayed airports list.

Analyzing flight volume / delay volume percentages can give us a better picture of how the delays are weighted.



EWR	0.250590
SFO	0.244134
JFK	0.240389
LAX	0.216559
LGA	0.213504
BOS	0.212972
DFW	0.201238
ORD	0.200680
LAS	0.195448
MCO	0.187614

Figure 10 Top Airlines by flight volume and origin airport on-time performance

We can see, that EWR and SFO are top offending airports in 2017. But this list is sorted by flight volume, so we don't get the full picture. Surrounding airports may be impacted. We can also note that all three major airports in the NYC area appear on the list: EWR, JFK, and LGA. Let's look at EWR and airports within 30-mile radius and compare the performance to the national average.

4.3. Regional Analysis

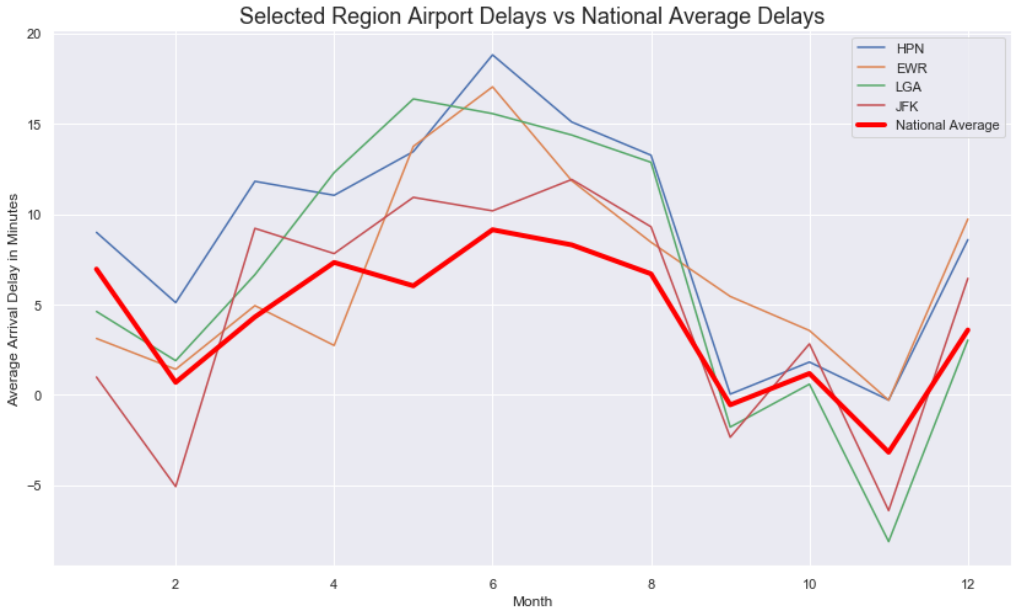


Figure 11 NYC Area average delays compared to a national average, by month

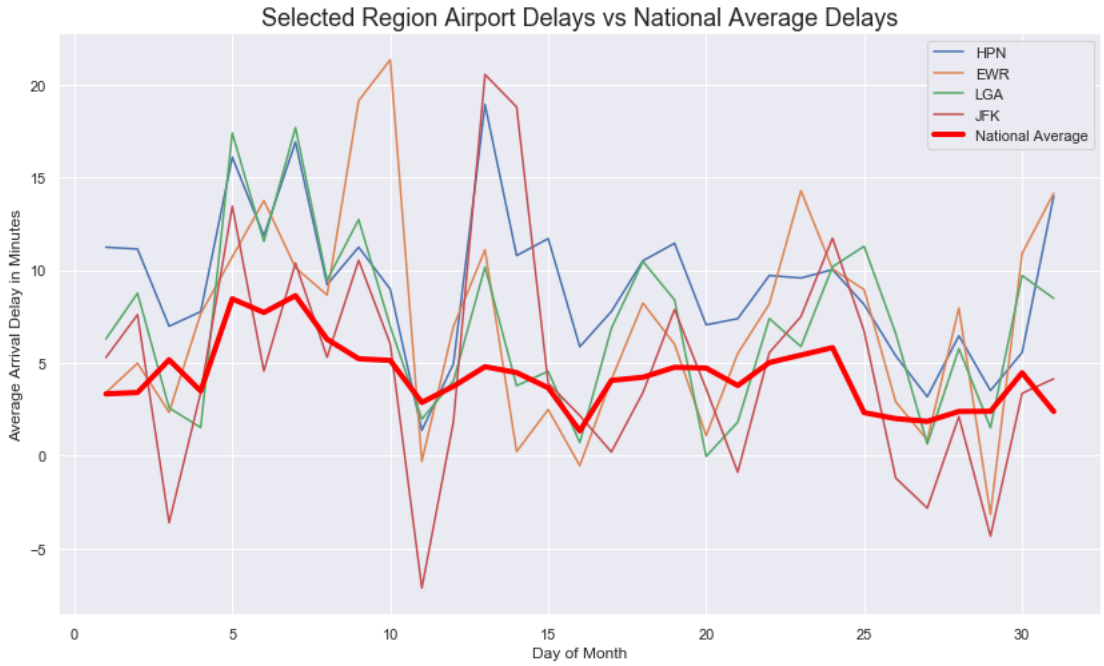


Figure 12 NYC Area average delays compared to a national average, by day of month

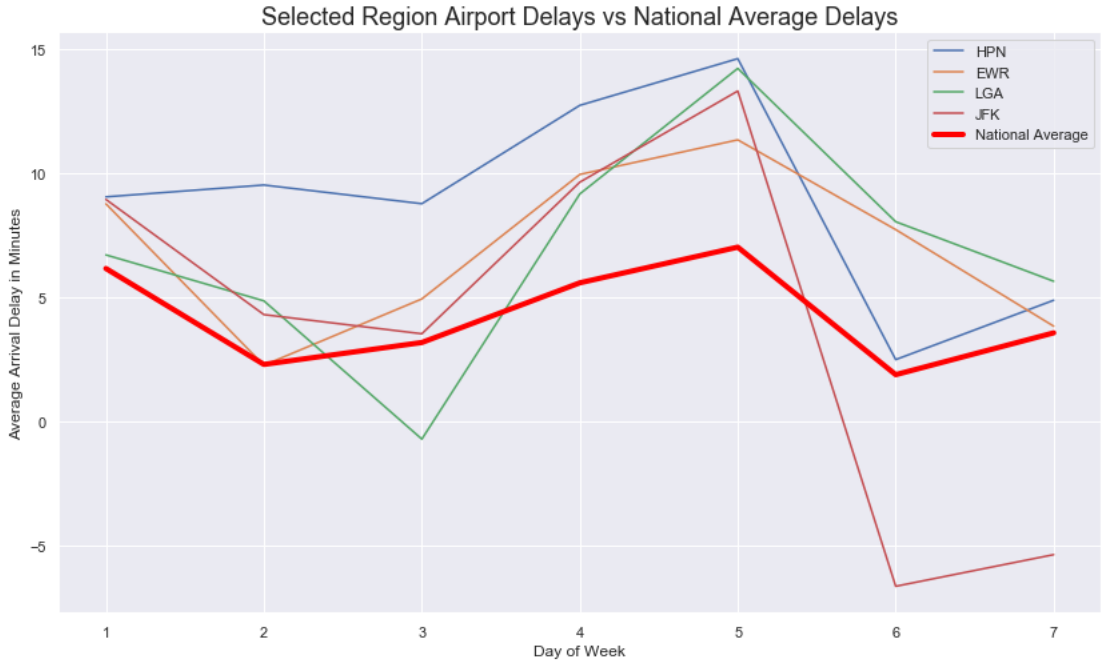


Figure 13 NYC Area average delays compared to a national average, by day of week

We can see that all airports in the area tracks along with the national average on all charts, which was expected. However, regional airports tend to perform worse, on average. Note, that this analysis shows delays by minutes whereas last set of charts focused on percent of flights that were delayed. Next let's take a look at how the delays break down, what is causing these delays?

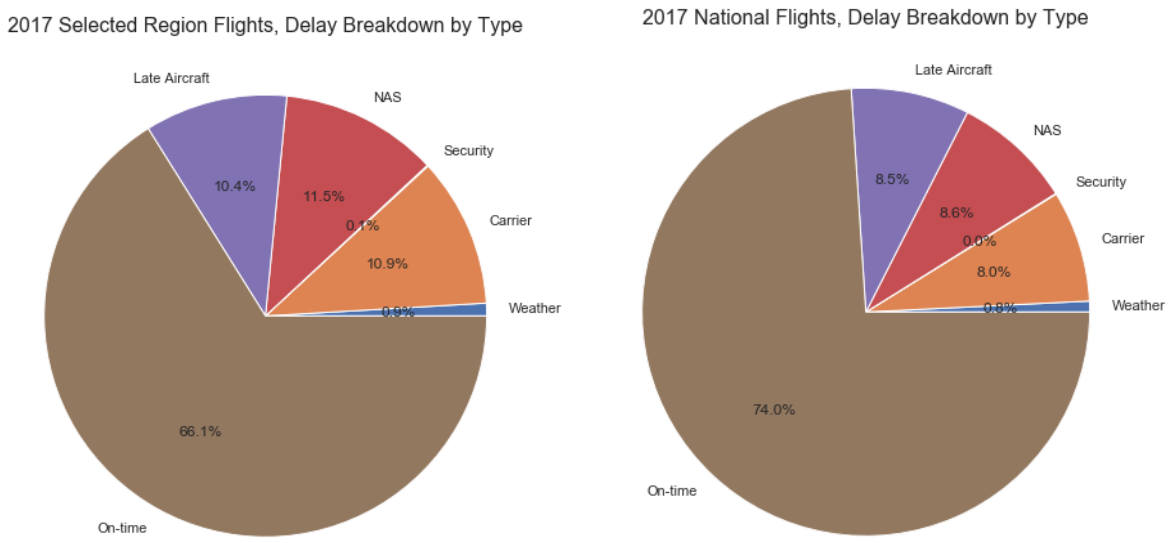
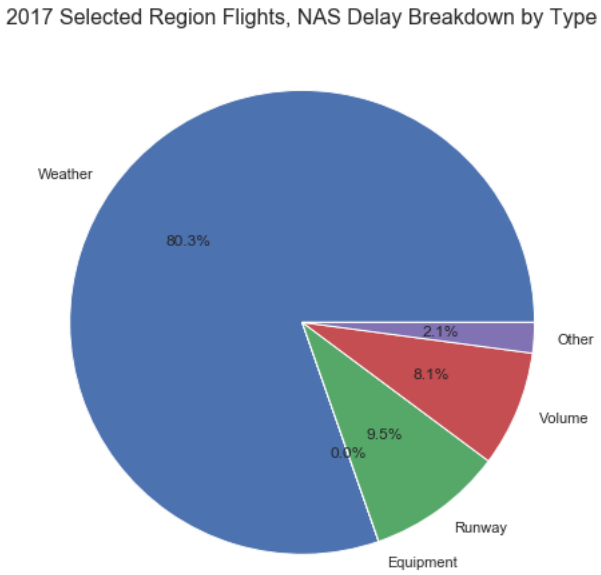


Figure 14 NYC Area vs National delay breakdown by cause

Since NAS data is further broken down into sub-categories, we can download the actual data from FAA. Breaking down the FAA data (NAS delays section from above):



NAS - We can continue to look at patterns for heavy traffic or trends in increasing air traffic patterns areas and look for constancies. Additionally, extreme events are not considered here, normal weather patterns that cause air traffic slowdowns are. Looking at weather patterns may be beneficial. FAA has a database breaking down the NAS delays by cause. (FAA OPSNET)

Carrier - carrier performance can be further analyzed by location and see if there are patterns

Late Aircraft - This can be handled with arrival delay information. This field highly depends on the other delay causes.

Weather - only extreme weather events are considered here. These events are rare and would result in region-wide cancellations, as such, these can be ignored as outliers.

Figure 15 NYC Area delay breakdown of NAS delay data

NYC Area had an on-time performance of only 66% in 2017 (as measured by arrival delay), which is lower than the national average of 74%. We can note that late aircraft, carrier, and NAS delays made up an overwhelming majority of delays. We'll keep this in mind for further EDA and feature engineering stages of this project.

4.4. Regional Traffic Volume and Delays

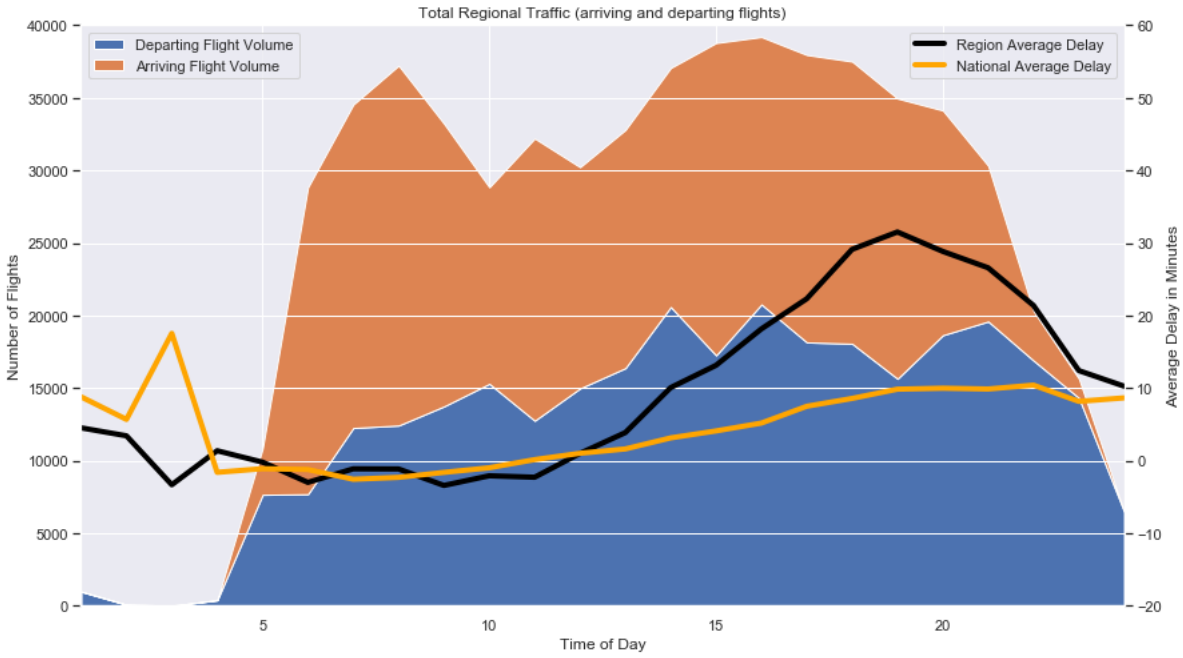


Figure 16 Air traffic volume and average delay time, throughout the day

Taking into account arriving and departing flights in the NYC Area, we can see that air traffic is relatively flat throughout the day, however the average delay in minutes tends to increase towards the afternoon and evening hours. Although, the same can be seen on a national scale, the delays peak at ~30mins for NYC area.

We can further breakdown the delay times by day and hour to get a full picture of performance of all airlines in the NYC Area:

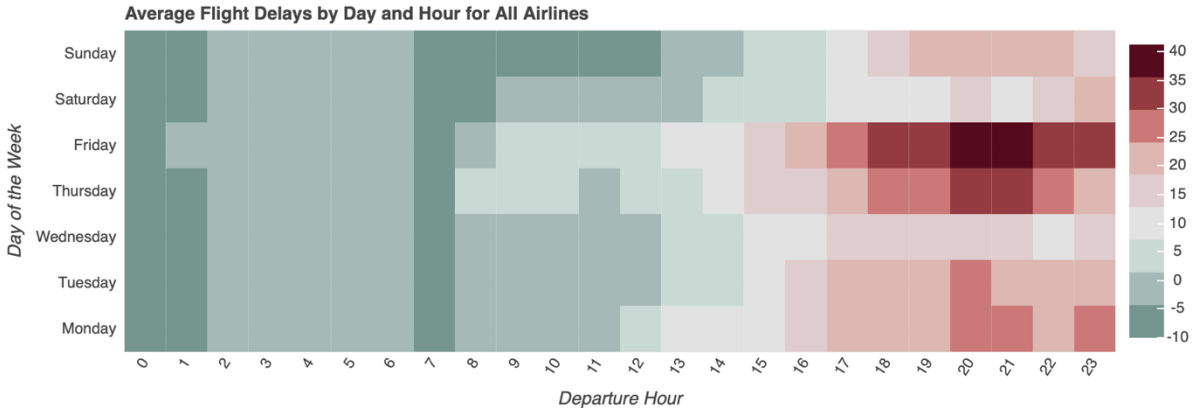


Figure 17 Heatmap of arrival delays broken out by hour and day of week

It looks like NYC Area sees an increased delay time during Thursday and Friday afternoons/evenings. This could be due to increase in passenger loading during those hours and days or more flights. We can look into this next.

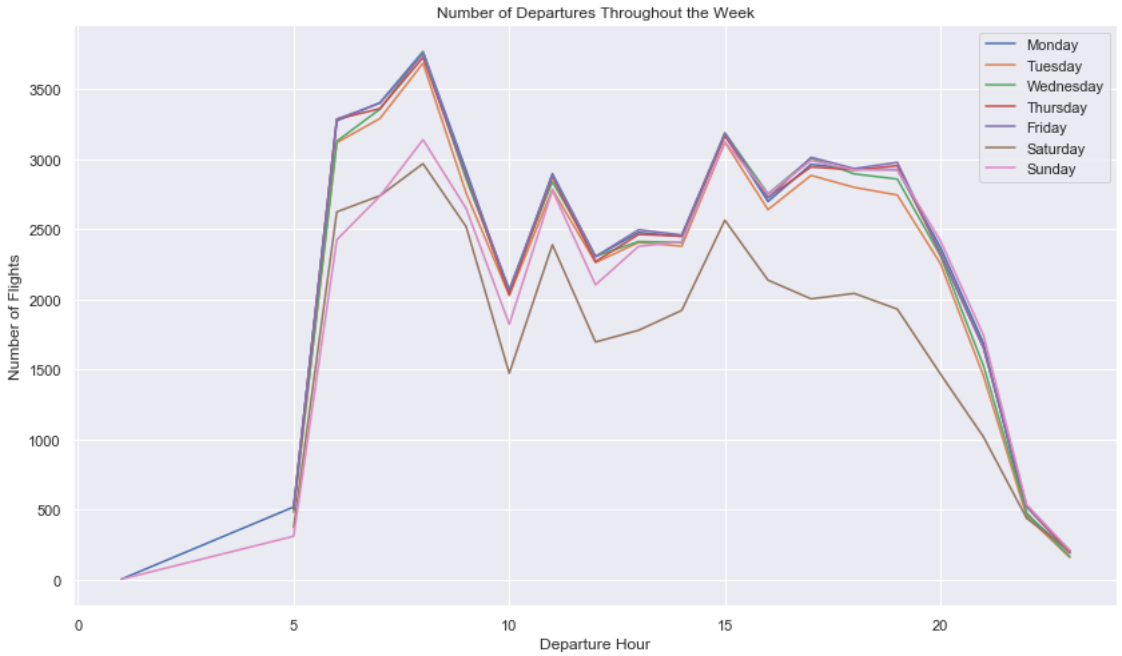


Figure 18 Number of Departing Flights in the NYC Area Throughout the Week

There does not seem to be any spikes during evening / night hours for Thursday and Friday. Scheduling seems relatively consistent.
Let's take a look at the passenger loading data by month and see if there is a trend relative to delays:

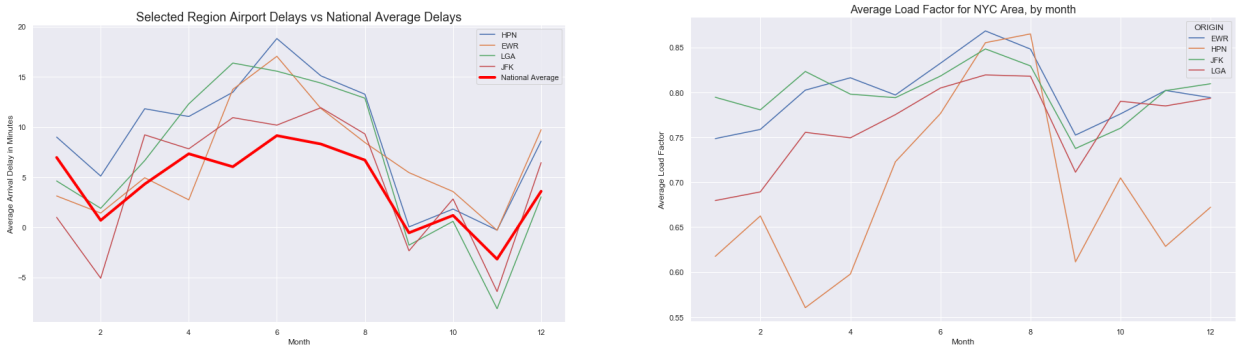


Figure 19 Average Delay (left) and Passenger Load Factor (right), by month

There seems to be a trend between delay and passenger loading, the more passengers fly, the higher the average delay. Unfortunately, only monthly aggregated Load Factor data are available, and we cannot compare loading data to hourly performance.

4.5. Individual Route Analysis

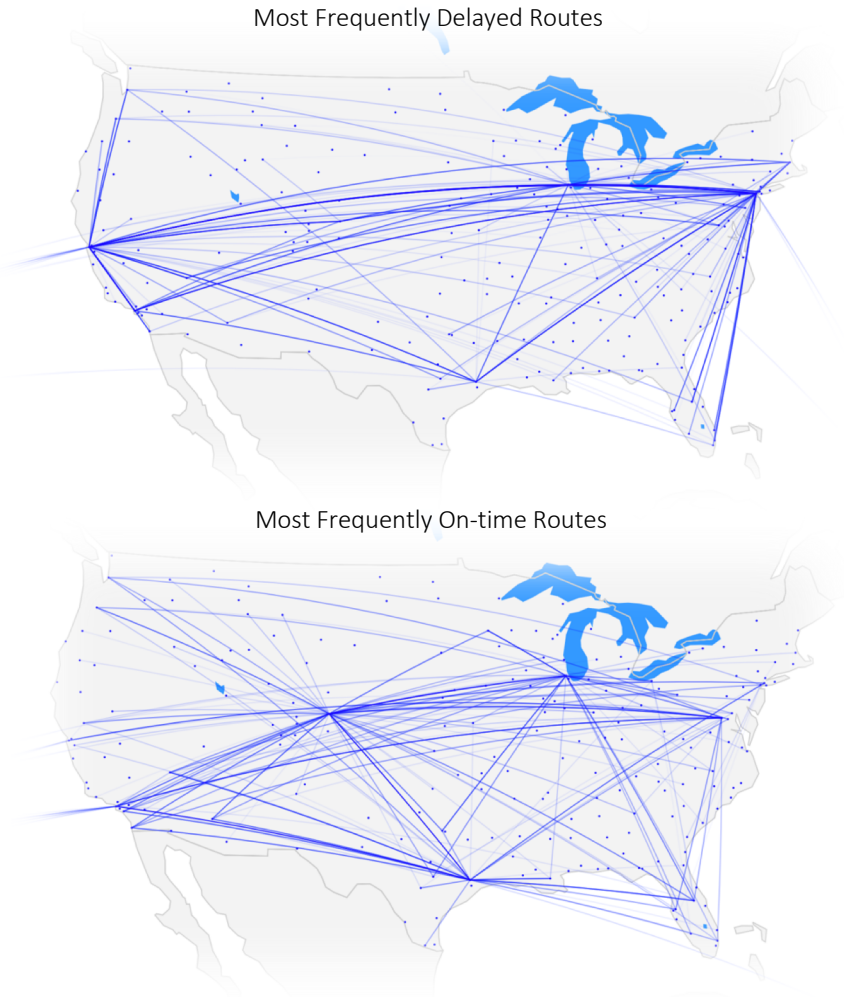
Now we can take a look at specific routes and their historic performance throughout the year. Are there routes that are prone to delays and are there ones that are always on-time? We'll first filter and create a data frame that we can use to answer our questions:
First we'll group the data by airline, origin, and destination airport, to see what are the most flown routes for the specific airline and then add the average delay time for each route, we can do this for on-time flights, as well:

airline	airport1	airport2	cnt	avg_del
UA	EWR	SFO	4885	10.128557
UA	ORD	SFO	4397	14.556516
UA	DEN	SFO	3912	14.054448
UA	ORD	EWR	3151	15.589971
UA	EWR	BOS	3069	14.160964

airline	airport1	airport2	cnt	avg_del
UA	DEN	IAH	3625	-3.664552
UA	LAX	IAH	3556	-3.771372
UA	LAX	IAD	2457	-6.881563
UA	SAN	DEN	1557	-8.271676
UA	DCA	IAH	1478	-8.714479

Figure 20 Most Delayed(left) and On-time(right) Routes for United Airlines

Now we can merge the data with latitude and longitude information as described in section 2.2 and visualize what this looks like on a map.



United Airlines Most Delayed(top) and Most On-time(bottom) flight routes in 2017.

The averages are weighted based on number of flights for the particular route. Darker lines represent higher delay frequency.

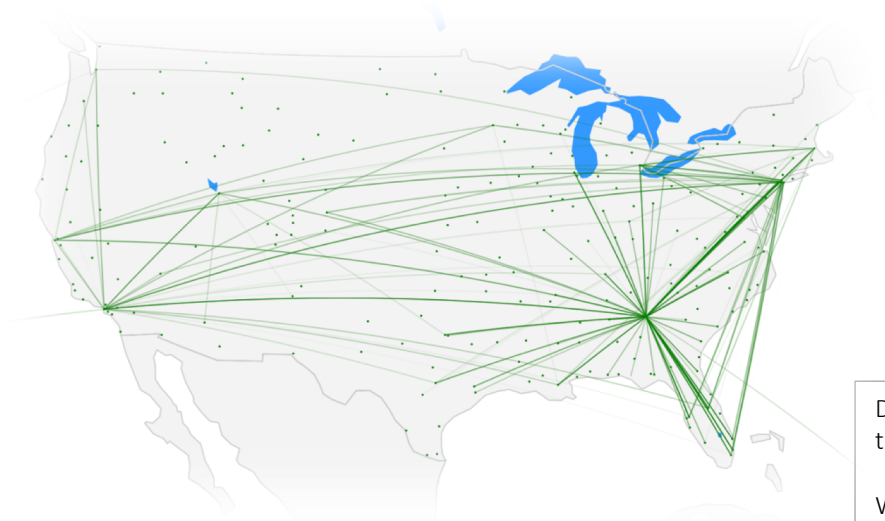
There is a clear difference in performance based on the route chosen. Coast to coast or long-haul flights tend to represent routes that are most delayed. This will be considered during the modeling stage. As simple average delay will not isolate problematic routes. This can be seen in Figure 3.1 and the distribution of arrival delays based on length of flight.

These routes were somewhat expected as the airports that appear in the delayed routes list are problematic for all airlines as can be seen in Figure 10.

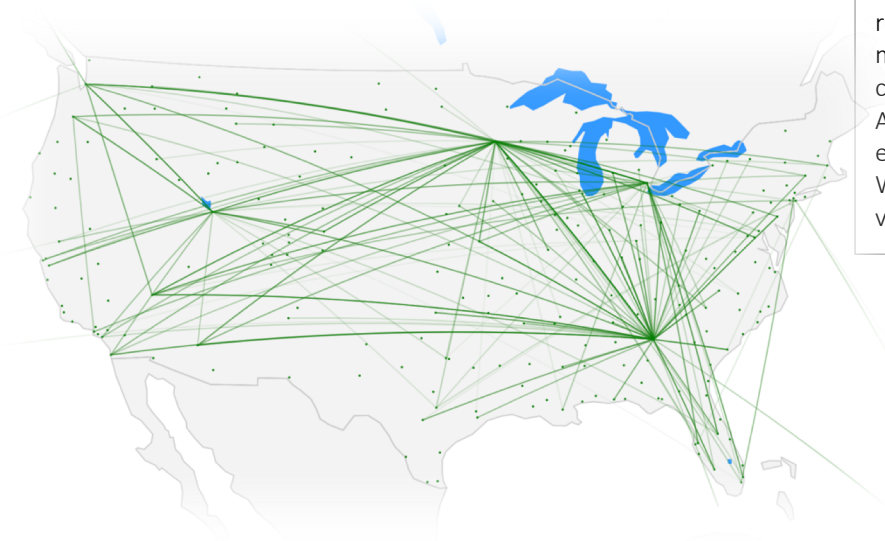
Dmitriy Kats
Capstone 1 – On-Time Airline Performance

Delta Airlines

Most Frequently Delayed Routes



Most Frequently On-time Routes



Delta Airlines Most Delayed(top) and Most On-time(bottom) flight routes in 2017

We see the same pattern for Delta Airlines, long-haul flights seem to dominate most delayed routes. And although Atlanta is not one of the most frequently delayed airports, routes that connect to JFK and LAX, for example, are. Additionally, Delta has three hubs with exceptional performance: MSP, DTW, and SLC. Which do not appear on the delayed route visualization.

5. EDA Conclusions

The intent of the EDA was to find any patterns in the data by creating visualizations which can later be used to create additional features and consequently a more robust model. We found a lot of trends and insights during this EDA but when we find these insights it's important to stop and ask: why are we seeing these trends? What is the underlying cause?

Possible questions to answer from EDA:

From route analysis:

1. Is there a link between origin airports / destination airports and these delayed routes?
2. Do other airlines have similar performance for a given route?
3. Does a given dominate a given airport?

From flight delay percentage comparison between Bay Area and National:

1. Why does NYC area have more delays than the national average?
2. Is there a statistically significant difference between number of delays in the NYC vs National average?
3. What region has lowest percentage of flight delays?

From the delayed percentage chart by airport:

1. Why do EWR, SFO, and JFK have the highest percentage of delayed flights?
2. Do these airports have most coast to coast flights? If so, why would these flights be delayed?
3. International traffic was not considered for this analysis which could have a huge impact on airport loading, especially major airport hubs such as EWR, SFO, and JFK.

Datasets

Passenger Loading Data
https://www.transtats.bts.gov/DL_SelectFields.asp?Table_ID=311

Complete Datasets
https://www.transtats.bts.gov/DL_SelectFields.asp?Table_ID=236

Weather:
https://mesonet.agron.iastate.edu/ASOS/

Airline Info (automatic download)
https://www.transtats.bts.gov/Download_Lookup.asp?Lookup=L_UNIQUE_CARRIERS

Airport Coordinates:
https://drive.google.com/file/d/1bMVXqd8Tm30RwmYLBgKk8RMr786IuDoK/view?usp=sharing

FAA OPSNET:
https://aspm.faa.gov/opsnet/sys/Delays.asp

6. Modeling

There are many classification algorithms available to predict whether a flight will be delayed or not. Below is a table with ones we'll focus in this analysis.

	Advantages	Disadvantages
Logistic Regression	Can incorporate future data into the model easily. Fast and good for probabilistic approaches.	Not as accurate as random forest. Almost no tuning capabilities.
Naïve Bayes	Super simple and fast.	Can't learn about interactions between features. Not as accurate as some other models.
Random Forest	Easy to implement, use, and tune. Very easy to interpret and explain as this is an ensemble of decision trees. Not a lot of parameters to tune. Very fast and proven to be accurate.	Although not necessary, some tuning is required to achieve optimal performance.
XGBoost	High model performance and execution speed.	A lot of parameters to tune.

Table 2 Modeling Techniques

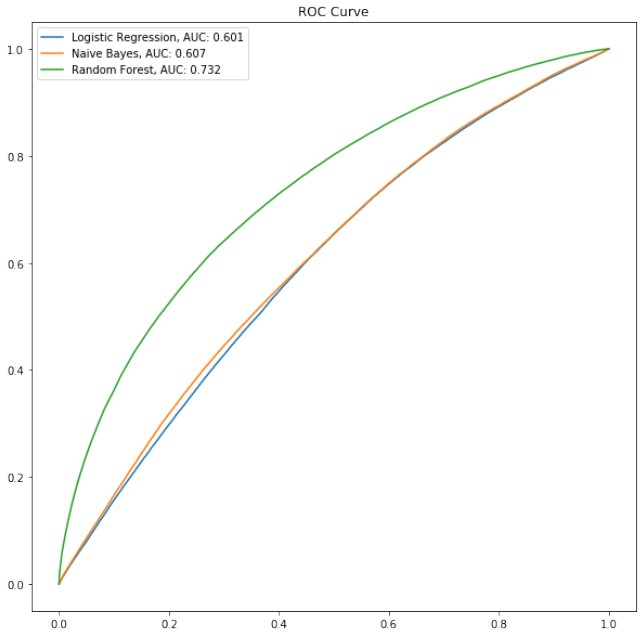
We started with the fastest and easiest implementation of Logistic Regression and Naïve Bayes classifiers. An 80/20 test/train split was utilized initially. We don't have a concern about not having enough training data as the there are over 2M samples. Additionally, since there is a class imbalance in the dataset, only ~18% of flights tend to be delayed, we want to make sure this is taken into account. The goal is to be able to predict as many delayed flights accurately as possible, but also without sacrificing on-time predictions.

We'll start with minimal data manipulation and no feature engineering to get a baseline. Encoding categorical values and limiting the data to top 20 airports and top 5 airlines by volume, we get our first results:

	Quarter	Month	DayofMonth	DayOfWeek	Reporting_Airline	Origin	Dest	ARR_HOUR	DEP_HOUR	STATUS
25	2	5	6	6	4	19	39	19	18	0
26	2	5	6	6	4	19	39	9	8	0
27	2	5	6	6	4	19	40	15	9	0
28	2	5	6	6	4	19	66	18	14	0
29	2	5	6	6	4	19	69	14	13	0

Table 3 DataFrame Used for Initial Model

Initial Results:



Logistic Regression		Actual		
		Positive	Negative	
Predicted	Positive	401,109	-	401,109
	Negative	90,673	-	90,673
		491,782	-	

Naïve Bayes		Actual		
		Positive	Negative	
Predicted	Positive	401,109	-	401,109
	Negative	90,673	-	90,673
		491,782	-	

Random Forest		Actual		
		Positive	Negative	
Predicted	Positive	399,344	1,765	401,109
	Negative	86,270	4,403	90,673
		485,614	6,168	

Figure 21 Initial ROC Curve and Confusion Matrices

ROC AUC does not look great and initial predictions don't look too promising. Both Logistic Regression and Naïve Bayes models did not predict any delayed flights, and Random Forest did relatively well, given the raw data. Let's focus on the Random Forest model and see if we can make improvements by engineering additional features, data balancing, hyper parameter tuning, and cross validation.

7. Feature Engineering and Data Balancing

7.1. Feature Engineering

In order to improve our model, we'll add extra features to our dataset.
Flight number / plane tail number were added back into the dataset. Note that this is not an engineered feature but provides historical significance to the model if certain flight numbers are historically delayed.

1. Weather data: we added 5-hour prior to departure precipitation sum, temperature at origin, 5-hour prior to departure average visibility, wind speed at origin.
2. Flight congestion: added a count of number of departing and arriving flights during the scheduled departure hour
3. Load factor: added monthly passenger loading factor for a given flight

7.2. Imbalanced Data

Since our flight data has only ~20% of flights delayed, the model tends to favor on-time arrivals. This can be seen in the initial results where our Random Forest model only predicted ~4k delayed flights out of 90k. In order to deal with this bias, we'll introduce a weight factor to the model. We'll assign a weight of 3 to the delayed flights and a weight of 1 to the on-time flights, then we'll adjust the weight of delayed flights to 5 and see how our predictions improve.

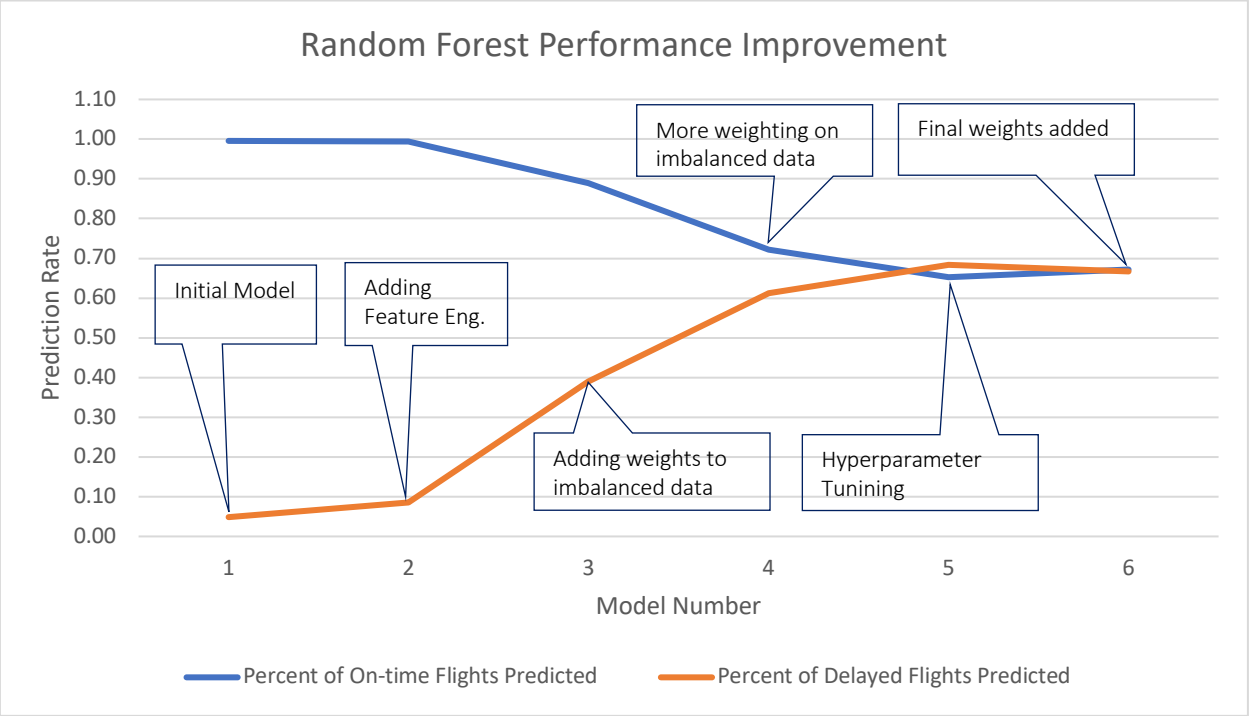


Figure 22 Random Forest Model Prediction Improvements

Engineered Features		Actual		
		Positive	Negative	
Predicted	Positive	398,512	2,597	401,109
	Negative	82,977	7,696	90,673
		481,489	10,293	

Adding Weights to Imbalanced Classes 1:3		Actual		
		Positive	Negative	
Predicted	Positive	356,400	44,709	401,109
	Negative	55,311	35,362	90,673
		411,711	80,071	

Additional Weights to Imbalanced Classes 1:4.5		Actual		
		Positive	Negative	
Predicted	Positive	289,448	111,661	401,109
	Negative	35,185	55,488	90,673
		324,633	167,149	

Tuned Model and Final Weights Added 1:4.85		Actual		
		Positive	Negative	
Predicted	Positive	269,557	131,552	401,109
	Negative	30,175	60,498	90,673
		299,732	192,050	

Figure 23 Confusion Matrices for Improved Random Forest Model

Interpreting the final results, we can calculate some key metrics:
Recall / Sensitivity: When the flight is actually on-time, how often does our model predict that it is on-time?
Recall = 269,557 / 401,109 = 0.67

Precision: When the flight is predicted to be on-time, how often is the model predicting it to be on-time correctly?
Precision = 269,557 299,732 = 0.90

False Positive Rate: When the flight is actually delayed, how often does it predict that it's not?
False Positive Rate = 131,552 / 90,673 = 1.45

True Negative Rate: When the flight is actually delayed, how often is the model correctly predicting that the flight is delayed?
True Negative Rate = 60,498 / 90,673 = 0.67

We were able to adjust and tune our model to predict ~67% of flights correctly whether it's delayed or on-time. This was the goal of the project, to maximize prediction rate for both types of flights.

8. Conclusions and Next Steps

In this analysis we aimed to shine a light on flight delays and predict weather a future flight would be delayed or not. The flight data were acquired from US Department of Transportation. We focused only on 2017 data for this analysis.

There are three major contributors to delayed flights, as we found in the EDA, Figure 14: NAS (mostly weather), Carrier delay (e.g. mechanical delay, flight crew, etc.), and Late Aircraft.
We had data on both, departure delays and arrival delays and we chose to focus on the latter, as this is the most important factor for travelers.

In order to improve our chances of prediction, we added a number of other datasets to the flight data. Passenger Load Factor data was added to account for delays due to more flyers. Weather data was included to account for weather delays. And additional features were engineered to account for airport traffic.
Since we wanted to predict whether a flight was going to be delayed or not, a classification algorithm was chosen. A number of methods were evaluated, and Random Forest was ultimately chosen for the reasons described in the Modeling Section.

Although the model performed relatively well, there a number of improvements that can be made. Adding passenger load factor data on an hourly basis, the intuition is that the predicted delayed flights will increase. The other key contribution to delays is Carrier performance, which can be explored via airline data on maintenance records and even age of aircraft based on the tail number and FAA data. Our model was only trained on 2017 data and can be further improved by introducing more training data. And finally, Late Aircraft delays can be traced using the tail number data and origin / destination information to better predict overall delays.