

Describing & Forecasting Flight delays



At Chicago O'Hare International Airport

TEAM #14

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MBC638 Final Project Presentation

PROJECT OBJECTIVE

→ Analyze **2015 US flights data** to uncover insights and attempt to explain/predict flight delays

Presentation
overview:

About the data

I. Descriptive
analysis

II. Forecasting



Data source



Data: 2015 Flight Delays and Cancellations

- available on Kaggle at <https://www.kaggle.com/usdot/flight-delays>
- originally came from the Department of Transportation Statistics website
(available at <https://www.transtats.bts.gov/> > Data Finder[By Mode [Aviation]] > Airline On-Time Performance Data > On-Time Performance > [all months from 2015 can be downloaded from this page])

The folder downloaded (592 MB) contained 3 datasets : **airlines.csv** (2 columns), **airports.csv** (7 columns), **flights.csv** (31 columns) (main dataset, about 6 millions rows; lots of missing values)

- 2015 only (all 12 months)
- US airports only
- US airlines only

The dataset was **cleaned** extensively, only **Chicago Airport (ORD)** was kept as the origin

- Note that the month of October (10) was omitted due to the absence of airport codes (departure and destination) for the entire month of October in the original dataset
- Some data preprocessing was done (e.g. times were discretized: morning, afternoon, evening, etc.)

MONT	DAY	DAY_C	AIRLIN	ORIGIN	DESTI	FLIGH	SCHEDULI	SCHEDULI	STATUS	DEPAF	ARRIV.
1	1	4	B6	ORD	BOS	867	night	morning	on time	-11	-33
1	1	4	NK	ORD	LGA	733	night	morning	delayed	-9	27
1	1	4	DL	ORD	ATL	606	night	morning	on time	2	-21
1	1	4	UA	ORD	MCO	1005	morning	morning	on time	-5	-21
1	1	4	UA	ORD	SFO	1846	morning	morning	on time	8	-12
1	1	4	UA	ORD	LAX	1744	morning	morning	on time	0	0

Weather data



In the city of Chicago, we expected **weather** to be a very good predictor of flight delays.

- Retrieved weather data from the National Oceanic and Atmospheric Administration
<https://www.ncdc.noaa.gov/cdo-web/>
 - The data consisted of many weather stations' records at different points in time



- It was very **noisy** and many **values were missing** → a pivot table was created with averages aggregated by day

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	Date	AWND	PRCP	SNOW	TAVG	Fog	Heavy	Thund	Ice_pe	Hail	Glaze	Haze	Blowir	Tornac	Damag
2	1/1/15	13.6433333	0	0	20	0	0	0	0	0	0	0	0	0	0
3	1/2/15	4.02666667	0.00208333	0	26	0	0	0	0	0	0	0	0	0	0
4	1/3/15	4.69666667	0.21463158	0.30140845	31	1	0	0	1	0	1	0	0	0	0
5	1/4/15	14.24	0.58297872	0.76835443	29	1	0	0	0	0	1	1	1	0	0
6	1/5/15	9.91666667	0.07940476	0.93636364	2	1	0	0	0	0	0	1	0	0	0
7	1/6/15	12.38	0.1616129	2.40714286	5	1	0	0	0	0	0	1	1	0	0
8	1/7/15	16.25666667	0.00197802	0.20682927	3	0	0	0	0	0	0	1	0	0	0
9	1/8/15	16.4033333	0.00336957	0.08915663	-2	0	0	0	0	0	0	1	1	0	0
10	1/9/15	15.2833333	0.10822222	1.83823253	8	0	0	0	0	0	0	1	1	0	0

- Finally, **key variables** (both qualitative and quantitative) that were expected to impact delays were selected and **merged** to our main dataset (VLOOKUP)

About the variables in the final dataset



ORIGINAL VARIABLES

WEATHER VARIABLES WE ADDED

DATE	MONT	DAY	DAY_OF_WEEK	AIRLINE	ORIGIN	DESTI	FLIGHT_DISTANCE	SCHEDULED_DEPARTURE	SCHEDULED_ARRIVAL	STATUS	DEPAI	ARRIV	AWND	PRCP	SNOW	TAVG	Fog	Heavy_fog	Thunder	Ice_pellets	Hail	Glaze	Haze	Blowing_snow	Tornado	Damaging_winds
1/1/15	1	1	4	B6	ORD	BOS	867	night	morning	on time	-11	-33	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0
1/1/15	1	1	4	NK	ORD	LGA	733	night	morning	delayed	-9	27	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0
1/1/15	1	1	4	DL	ORD	ATL	606	night	morning	on time	2	-21	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0
1/1/15	1	1	4	UA	ORD	MCO	1005	morning	morning	on time	-5	-21	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0
1/1/15	1	1	4	UA	ORD	SFO	1846	morning	morning	on time	8	-12	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0
1/1/15	1	1	4	UA	ORD	LAX	1744	morning	morning	on time	0	0	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0
1/1/15	1	1	4	NK	ORD	LAX	1744	morning	morning	on time	-6	-12	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0
1/1/15	1	1	4	F9	ORD	ATL	606	morning	morning	delayed	65	61	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0
1/1/15	1	1	4	UA	ORD	MCO	1005	morning	morning	on time	14	3	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0

CANDIDATE DEPENDENT
VARIABLES FOR MODELING

VARIABLE DICTIONARY

DATE → we created based on MONTH and DAY variables
MONTH → (categorical) month of year (1 = Jan, 2 = Feb, etc.)
DAY → (categorical) day of the month (1, 2, 3, ..., 29, 30, 31)
DAY_OF_WEEK → (categorical) weekday (1 = Mon, 2 = Tue, etc.)
AIRLINE → (categorical) airline IATA code
ORIGIN → (categorical) origin airport IATA code (ORD only)
DESTINATION → (categorical) destination airport IATA code
FLIGHT_DISTANCE → (quantitative) flight distance range for given flight (miles)
SCHEDULED_DEPARTURE → (categorical) scheduled departure time of day
SCHEDULED_ARRIVAL → (categorical) scheduled arrival time of day
STATUS (categorical) → we created using delay variable & official FAA definition
DEPARTURE_DELAY → (quantitative) departure delay (minutes)
ARRIVAL_DELAY → (quantitative) arrival delay (minutes)

VARIABLE DICTIONARY

AWND → (quantitative) average daily wind speed (mph)
PRCP → (quantitative) precipitation average for the day (inches)
SNOW → (quantitative) snowfall average for the day (inches)
TAVG → (quantitative) temperature average for the day (Fahrenheit)
Fog, Heavy_fog, Thunder, Ice_pellets, Hail, Glaze, Haze, Blowing_snow, Tornado, Damaging_winds → (dummy) all these weather dummy variables indicate whether the corresponding condition occurred that day. By including all these dummies in a regression, the baseline would be "normal weather conditions".

“ The Federal Aviation Administration (FAA) considers a flight to be delayed when it takes off and/or lands **15 minutes** later than its scheduled time.

Wikipedia

About the data

- Our dataset is **unique**
- **Population of interest:** all domestic flights departing from the Chicago O'Hare International Airport (ORD)
- The data collected is a **sample** (non random) which should be representative of the population of interest (**not** accounting for international flights)

I. Main dataset (our focus):

(# of rows: 59,644)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA
1	DATE	MONT	DAY	DAY_C	AIRLIN	ORIGI	DESTI	FLIGH	SCHEDUL	SCHEDUL	STATUS	DEPAF	ARRIV	AWND	PRCP	SNOW	TAVG	Fog	Heavy	Thund	Ice_pe	Hail	Glaze	Haze	Blowir	Tornac	Damag
2	1/1/15	1	1	4	B6	ORD	BOS	867	night	morning	on time	-11	-33	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0
3	1/1/15	1	1	4	NK	ORD	LGA	733	night	morning	delayed	-9	27	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0
4	1/1/15	1	1	4	DL	ORD	ATL	606	night	morning	on time	2	-21	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0
5	1/1/15	1	1	4	UA	ORD	MCO	1005	morning	morning	on time	-5	-21	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0
6	1/1/15	1	1	4	UA	ORD	SFO	1846	morning	morning	on time	8	-12	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0
7	1/1/15	1	1	4	UA	ORD	LAX	1744	morning	morning	on time	0	0	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0
8	1/1/15	1	1	4	NK	ORD	LAX	1744	morning	morning	on time	-6	-12	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0
9	1/1/15	1	1	4	F9	ORD	ATL	606	morning	morning	delayed	65	61	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0
10	1/1/15	1	1	4	UA	ORD	MCO	1005	morning	morning	on time	14	3	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0

II. Additional datasets (to answer specific questions in descriptive section):

a. Delayed flights with a breakdown of delays

(# of rows: 15,048)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U								
1	DATE	MONT	DAY	DAY_C	AIRLIN	ORIGI	DESTI	FLIGH	SCHEDUL	SCHEDUL	STATUS	DEPAF	ARRIV	AIR_SYSTEM_D	SECURITY_D	AIRLINE_D	LATE_AIRCRAFT_D	WEAT	AWND	PRCP	SNOW_T								
2	1/1/15	1	1	4	NK	ORD	LGA	733	night	morning	delayed	-9	27	27	0	0	0	0	0	0	0	13.6	0.0	0.0	0.0	0.0	0.0		
3	1/1/15	1	1	4	F9	ORD	ATL	606	morning	morning	delayed	65	61	0	0	61	0	0	0	13.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0		
4	1/1/15	1	1	4	UA	ORD	LAX	1744	morning	morning	delayed	21	16	0	0	0	16	0	0	0	13.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
5	1/1/15	1	1	4	OO	ORD	ATL	606	morning	morning	delayed	100	88	0	0	0	63	25	0	0	13.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
6	1/1/15	1	1	4	UA	ORD	SFO	1846	afternoon	afternoon	delayed	46	44	0	0	44	0	0	0	13.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
7	1/1/15	1	1	4	US	ORD	PHL	678	afternoon	afternoon	delayed	25	15	0	0	0	2	13	0	0	13.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
8	1/1/15	1	1	4	UA	ORD	MCO	1005	afternoon	evening	delayed	133	121	0	0	93	28	0	0	13.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
9	1/1/15	1	1	4	AA	ORD	LGA	733	afternoon	evening	delayed	65	53	0	0	53	0	0	0	13.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
10	1/1/15	1	1	4	OO	ORD	DCA	612	afternoon	evening	delayed	35	15	0	0	0	15	0	0	0	13.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

b. Canceled flights

(# of rows: 1,303)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z		
1	DATE	MONT	DAY	DAY_C	AIRLIN	ORIGI	DESTI	FLIGH	SCHEDUL	SCHEDUL	STATUS	CANCELLATION_F	AWND	PRCP	SNOW	TAVG	Fog	Heavy	Thund	Ice_pe	Hail	Glaze	Haze	Blowir	Tornac	Damag		
2	1/1/15	1	1	4	UA	ORD	PHL	678	morning	afternoon	cancelled	airline/carrier	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0	0	
3	1/3/15	1	3	6	F9	ORD	ATL	606	morning	morning	cancelled	airline/carrier	4.7	0.2	0.3	31.0	1	0	0	1	0	0	0	0	0	0	0	0
4	1/3/15	1	3	6	AA	ORD	SFO	1846	morning	afternoon	cancelled	airline/carrier	4.7	0.2	0.3	31.0	1	0	0	1	0	0	0	0	0	0	0	0
5	1/3/15	1	3	6	AA	ORD	MCO	1005	afternoon	afternoon	cancelled	airline/carrier	4.7	0.2	0.3	31.0	1	0	0	1	0	0	0	0	0	0	0	0
6	1/3/15	1	3	6	AA	ORD	LGA	733	afternoon	afternoon	cancelled	airline/carrier	4.7	0.2	0.3	31.0	1	0	0	1	0	0	0	0	0	0	0	0
7	1/3/15	1	3	6	UA	ORD	LAX	1744	afternoon	evening	cancelled	airline/carrier	4.7	0.2	0.3	31.0	1	0	0	1	0	0	0	0	0	0	0	0
8	1/4/15	1	4	7	MQ	ORD	ATL	606	morning	morning	cancelled	airline/carrier	14.2	0.6	0.8	29.0	1	0	0	0	0	0	1	1	1	0	0	0
9	1/4/15	1	4	7	AA	ORD	LGA	733	morning	morning	cancelled	airline/carrier	14.2	0.6	0.8	29.0	1	0	0	0	0	0	1	1	1	0	0	0
10	1/4/15	1	4	7	AA	ORD	DCA	612	afternoon	afternoon	cancelled	airline/carrier	14.2	0.6	0.8	29.0	1	0	0	0	0	0	1	1	1	0	0	0

Datasets overview

Airlines in the data

IATA_AIRLINE
UA United Air Lines Inc.
AA American Airlines Inc.
US US Airways Inc.
F9 Frontier Airlines Inc.
B6 JetBlue Airways
OO Skywest Airlines Inc.
AS Alaska Airlines Inc.
NK Spirit Air Lines
DL Delta Air Lines Inc.
EV Atlantic Southeast Airlines
MQ American Eagle Airlines Inc.
VX Virgin America

Airports in the data

IATA_AIRPORT	CITY	STATE
ATL	Hartsfield-Jackson Atlanta	GA
BOS	Gen. Edward Lawr Boston	MA
DCA	Ronald Reagan W Arlington	VA
LAS	McCarran Internat Las Vegas	NV
LAX	Los Angeles Intern Los Angele	CA
LGA	LaGuardia Airport (New York	NY
MCO	Orlando Internat Orlando	FL
ORD	Chicago O'Hare In Chicago	IL
PHL	Philadelphia Intern Philadelph	PA
SEA	Seattle-Tacoma Int Seattle	WA
SFO	San Francisco Int San Franci	CA

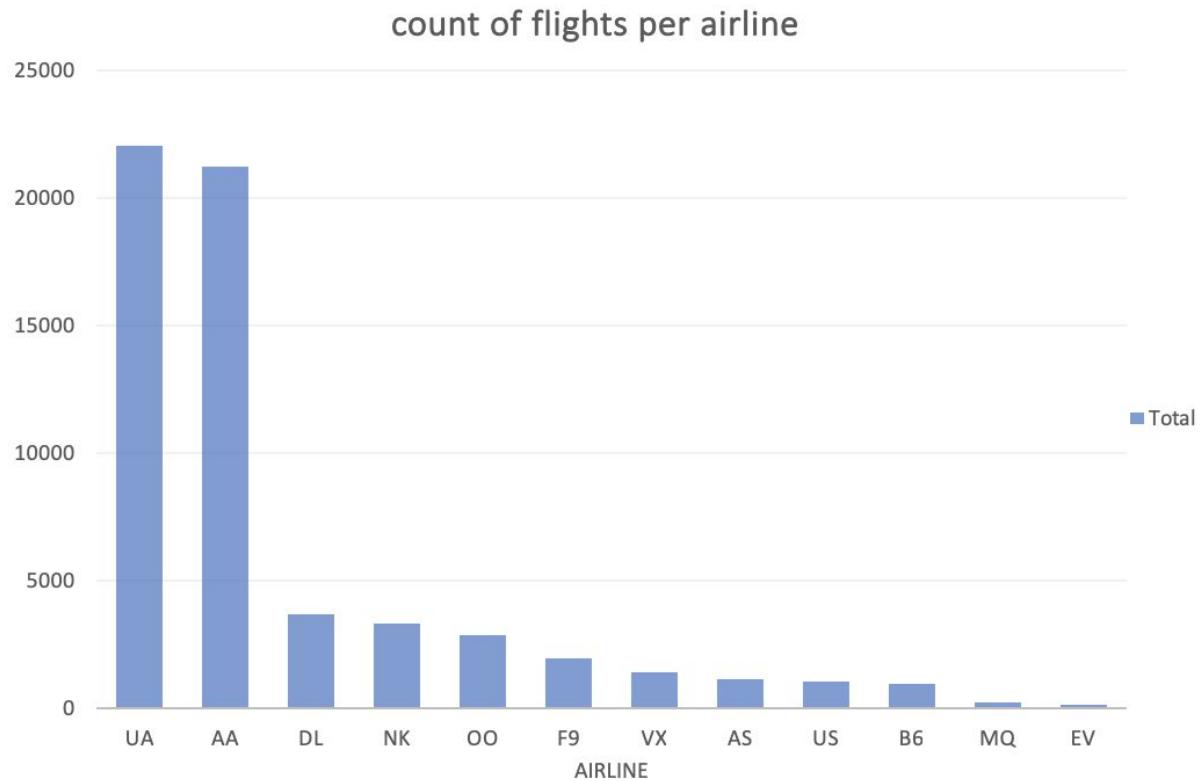
A

DESCRIPTIVE ANALYSIS



Objective: use descriptive methods to learn from and understand past data

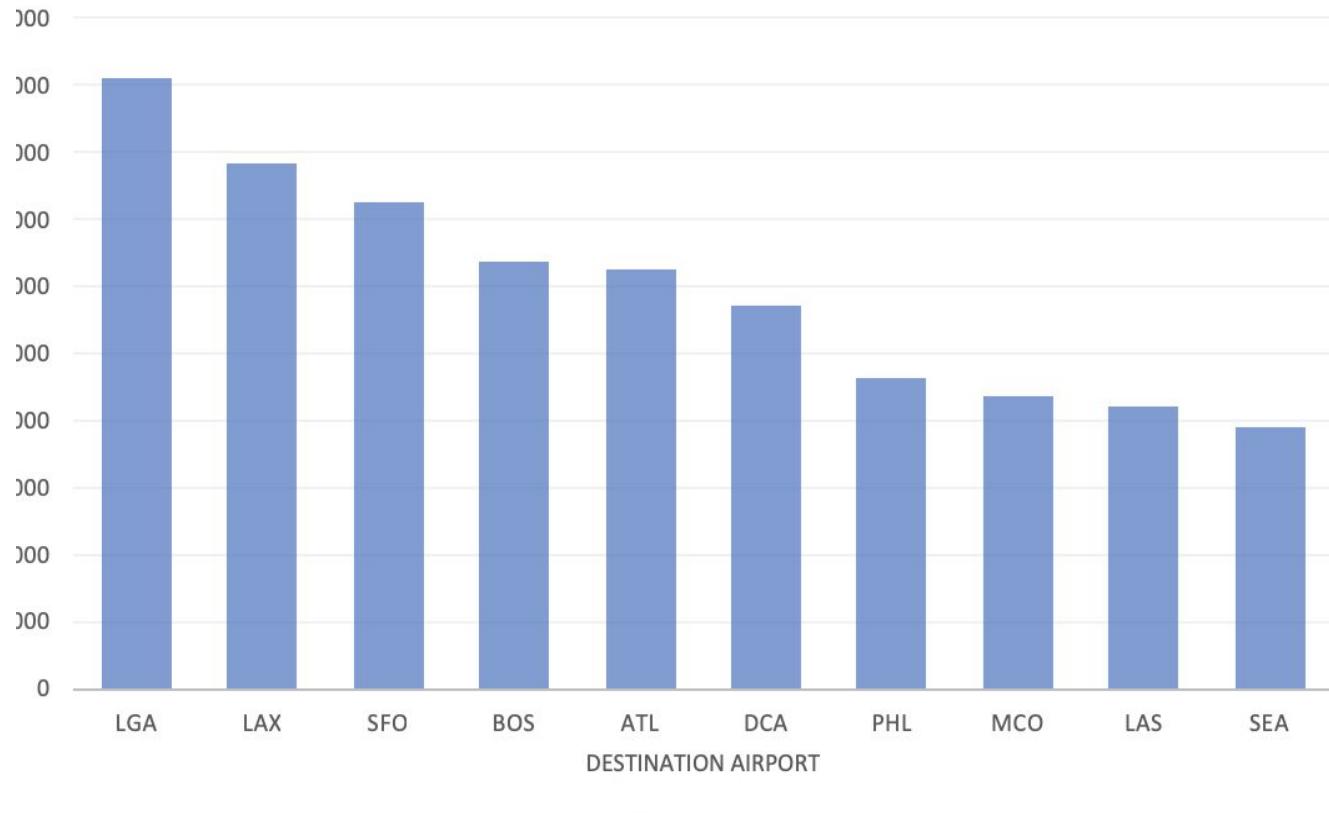
Row Labels	Count of /
UA	22012
AA	21217
DL	3627
NK	3328
OO	2864
F9	1892
VX	1373
AS	1110
US	1021
B6	954
MQ	181
EV	66
Grand Total	59645



→ Since Chicago airport (ORD) is known to be the largest hub for United Airlines and American Airlines, this graph clearly shows that the count of flights for these airlines are the highest

How many flights per airline are there in the data?

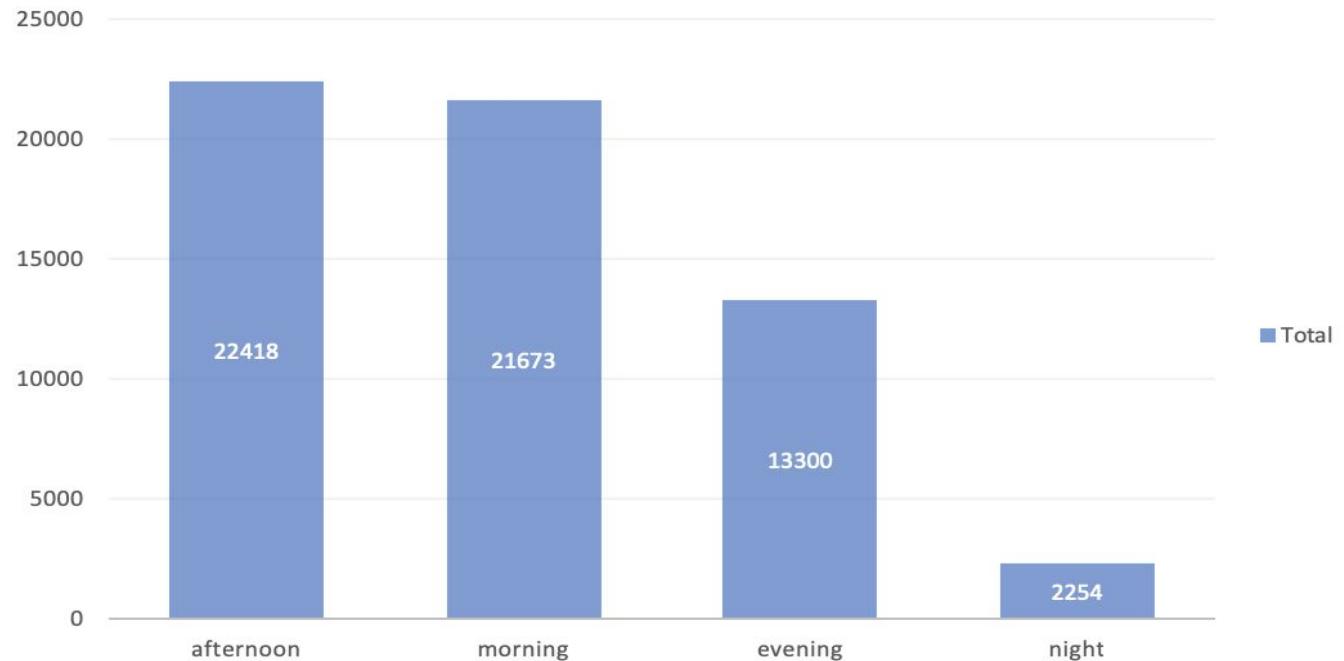
count of flights per destination airport



→ The highest number of flights leaving from Chicago airport are the ones departing to LGA, LAX and SFO

How many flights per scheduled destination are there in the data?

count of flights per scheduled time of day for departure



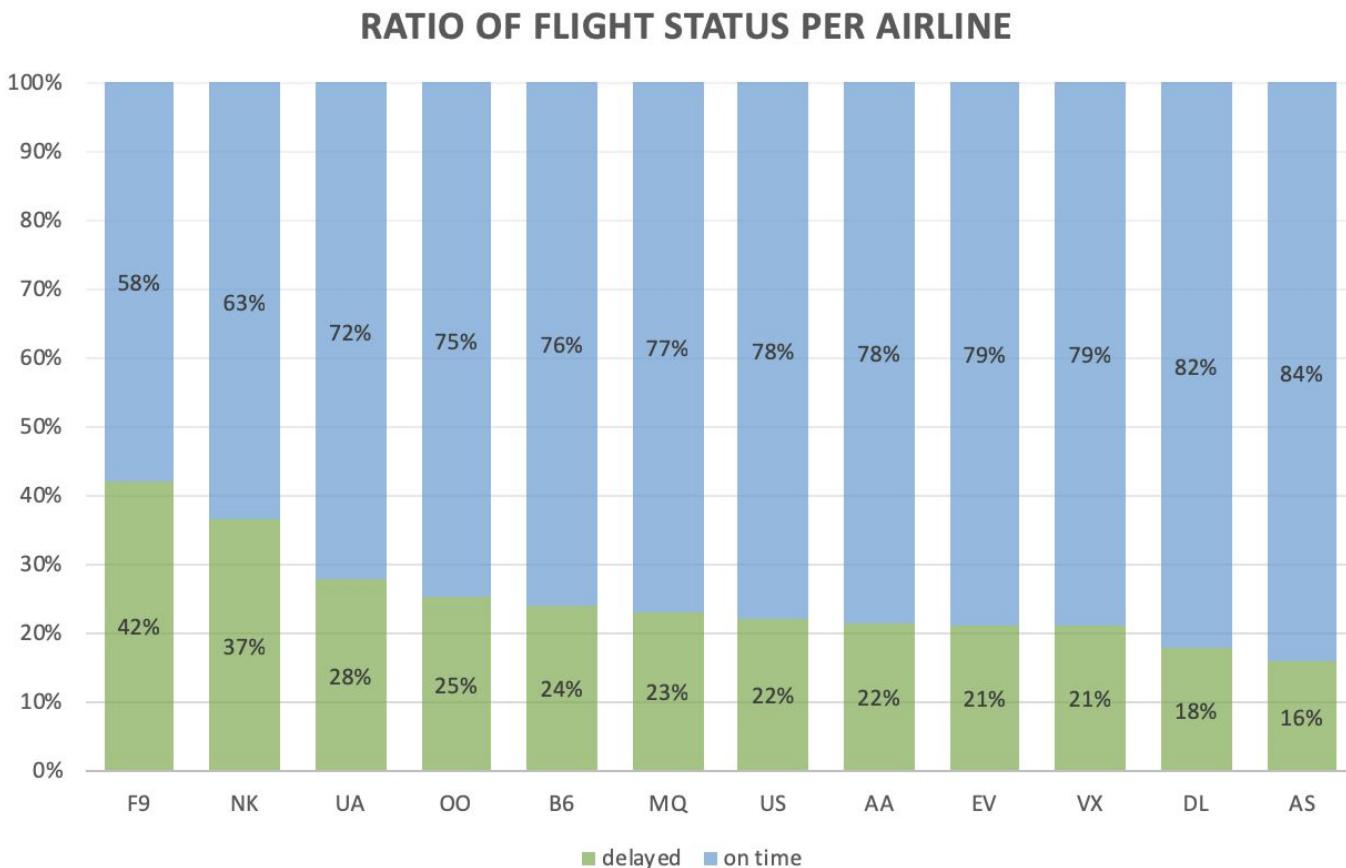
→ The highest number of flights leave from Chicago airport are in the afternoon and morning

How many flights per scheduled departure time of day are there in the data?

1. Which **airlines** typically have significant flight delays? (1) → SUMMARY STATISTICS

AIRLINE	delayed flights count	on time flight counts	delay mean	delay median	delay st dev	delay min	delay max	% delayed flights	% on time flights
AA	4569	16648	3.35	-8.00	41.18	-63	859	22%	78%
AS	176	934	2.30	-6.00	45.42	-51	820	16%	84%
B6	230	724	12.35	-4.00	60.27	-38	1002	24%	76%
DL	646	2981	6.17	-8.00	62.88	-39	1184	18%	82%
EV	14	52	4.24	-9.00	35.28	-30	152	21%	79%
F9	798	1094	27.66	8.00	62.73	-48	762	42%	58%
MQ	42	139	8.53	-5.00	45.76	-32	277	23%	77%
NK	1216	2112	18.57	4.00	46.46	-46	405	37%	63%
OO	725	2139	10.88	-1.00	38.92	-35	396	25%	75%
UA	6115	15897	12.06	-2.00	47.79	-55	623	28%	72%
US	227	794	5.44	-6.00	38.95	-41	289	22%	78%
VX	291	1082	5.38	-3.00	38.71	-48	342	21%	79%

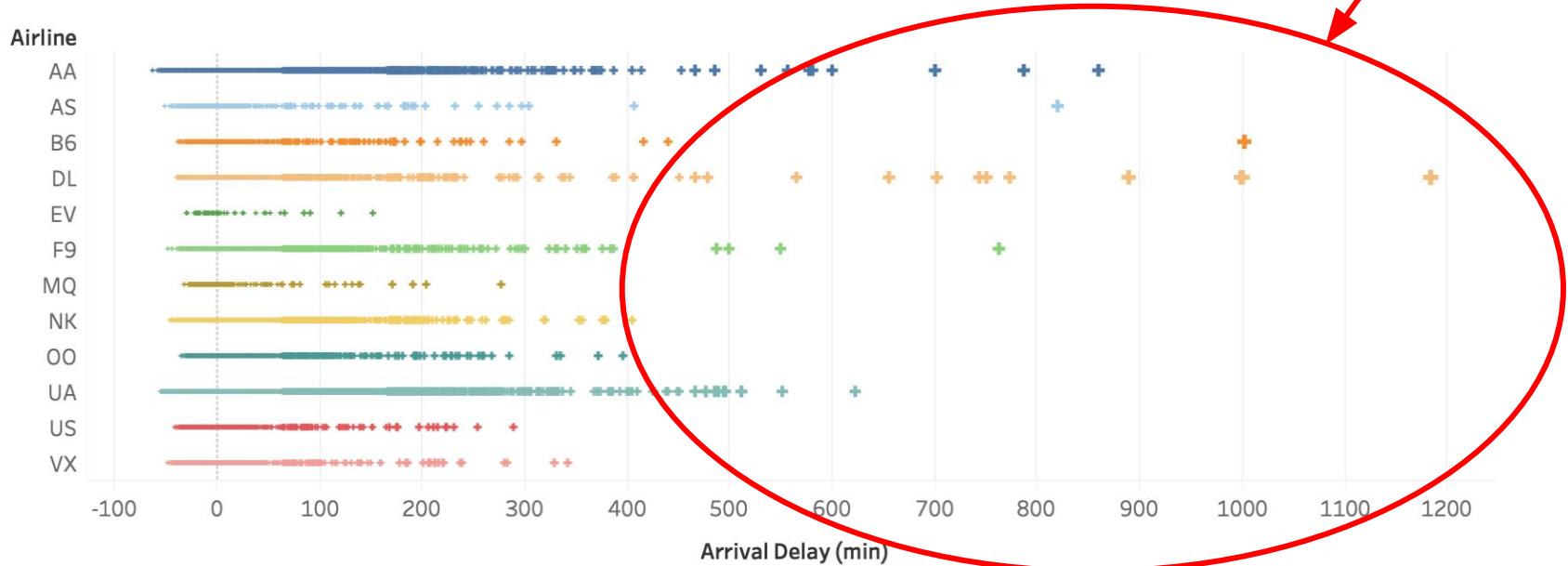
1. Which **airlines** typically have significant flight delays? (1) → RATIOS OF STATUS PER AIRLINE



	Row L delayed	on time	Grand Total
F9	42%	58%	100%
NK	37%	63%	100%
UA	28%	72%	100%
OO	25%	75%	100%
B6	24%	76%	100%
MQ	23%	77%	100%
US	22%	78%	100%
AA	22%	78%	100%
EV	21%	79%	100%
VX	21%	79%	100%
DL	18%	82%	100%
AS	16%	84%	100%

→ The airlines most commonly delayed are F9 (Frontier), NK (Spirit), and UA (United)

1. Which **airlines** typically have significant flight delays? (1) → DOT PLOT FOR LONGEST DELAYS



Feel free to use our VLOOKUP query tables to answer questions about delays and airlines:

MIN TO HOUR CONVERSION

How many minutes? **1180** (please update the value in the yellow cell -- the value can be positive or negative.)

For your information, 1180 minutes is approximately equal to 19.7 hour(s).

Therefore, the flight you selected arrived approximately 19.7 hour(s) after the original schedule.

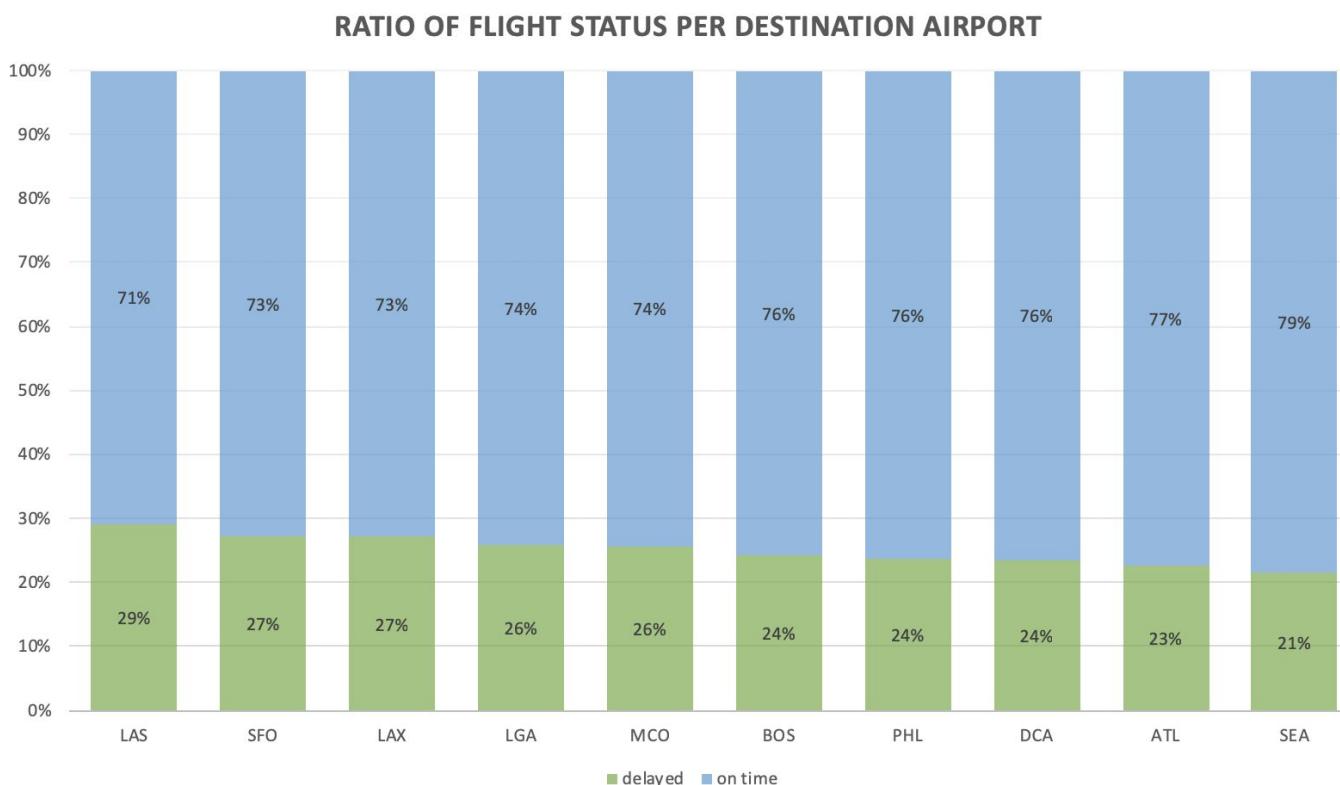
In other words, this flight was delayed.

AIRLINE CODE TO AIRLINE NAME

Enter airline code: **DL** (please update the value in the yellow cell -- enter an airline code.)

This airline is: **Delta Air Lines Inc.**

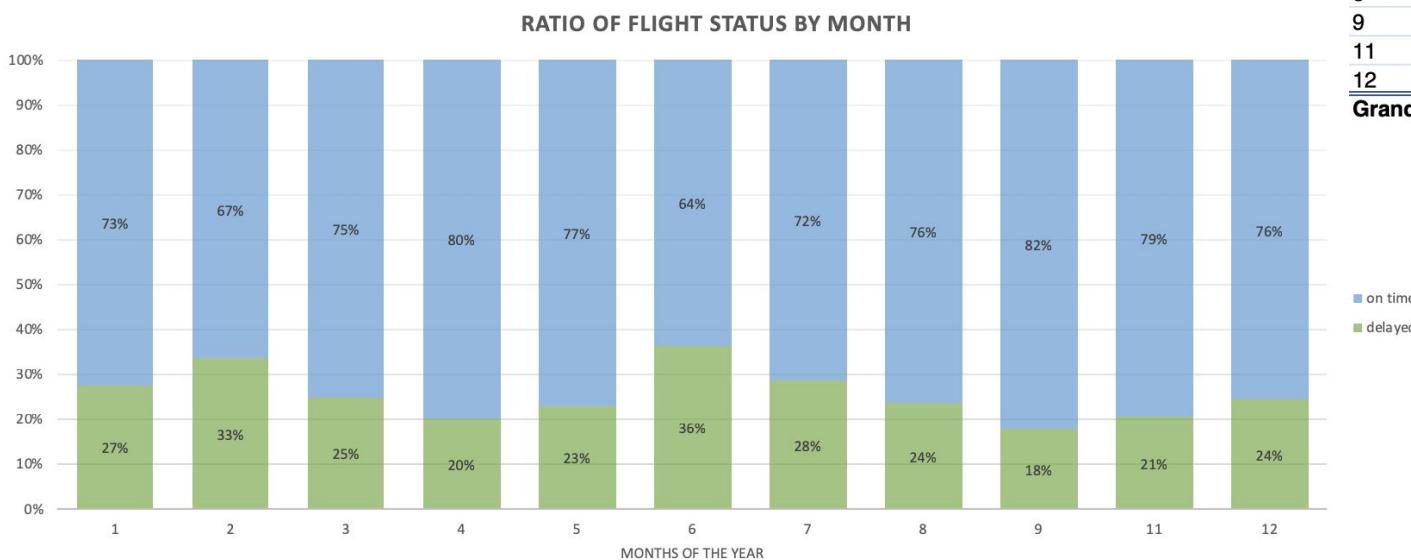
2. Which **scheduled destination airports** typically have significant flight delays?



Row Labels	Count of SCHEDULE Column		
	delayed	on time	Grand Total
LGA	25.85%	74.15%	100.00%
LAX	27.10%	72.90%	100.00%
SFO	27.20%	72.80%	100.00%
BOS	24.22%	75.78%	100.00%
ATL	22.70%	77.30%	100.00%
DCA	23.55%	76.45%	100.00%
PHL	23.76%	76.24%	100.00%
MCO	25.70%	74.30%	100.00%
LAS	29.19%	70.81%	100.00%
SEA	21.46%	78.54%	100.00%
Grand Total	25.23%	74.77%	100.00%

→ The top destination airports for which there tends to be more delays are LAS, SFO, and LAX

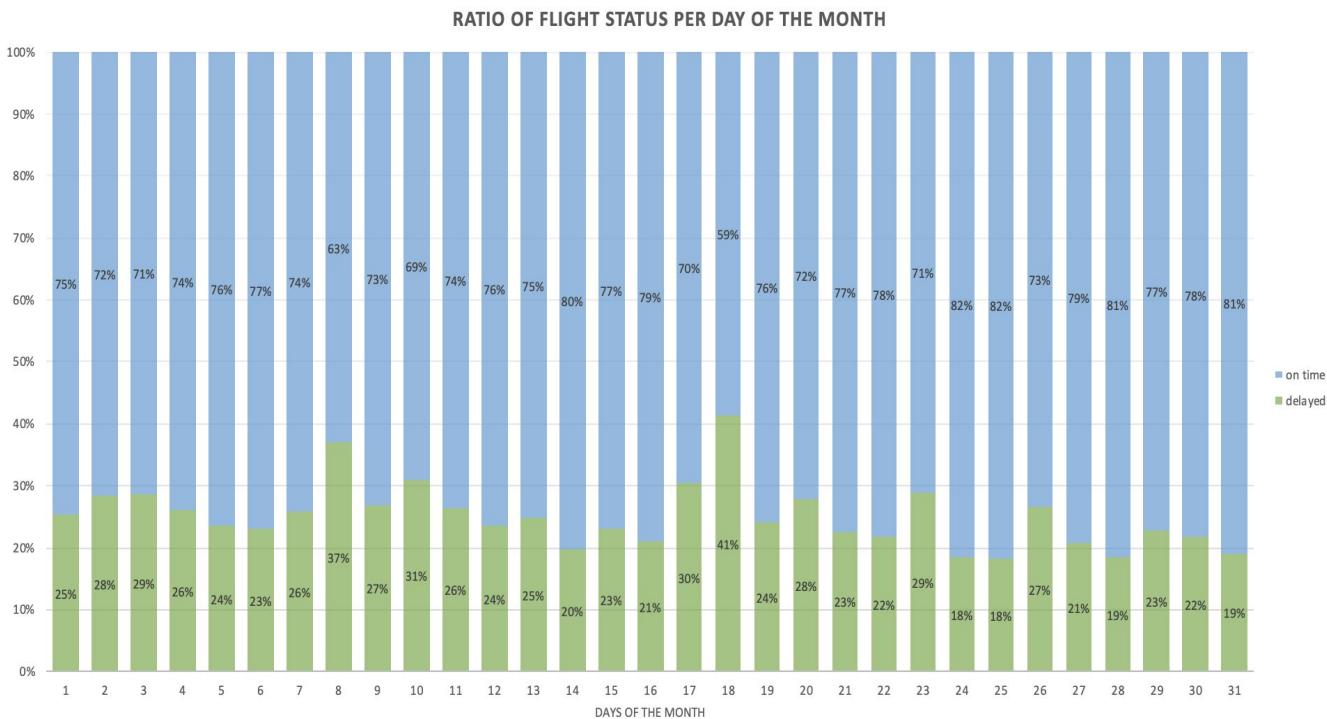
3. Which time of year, month, and day have the most flight delays? (month)



Row Labels	Count of MONTH		
	delayed	on time	Grand Total
1	27%	73%	100%
2	33%	67%	100%
3	25%	75%	100%
4	20%	80%	100%
5	23%	77%	100%
6	36%	64%	100%
7	28%	72%	100%
8	24%	76%	100%
9	18%	82%	100%
11	21%	79%	100%
12	24%	76%	100%
Grand Total	25%	75%	100%

→ The months with most flight delays are December, January, and February (Holiday season), and June and July (summer vacation season)

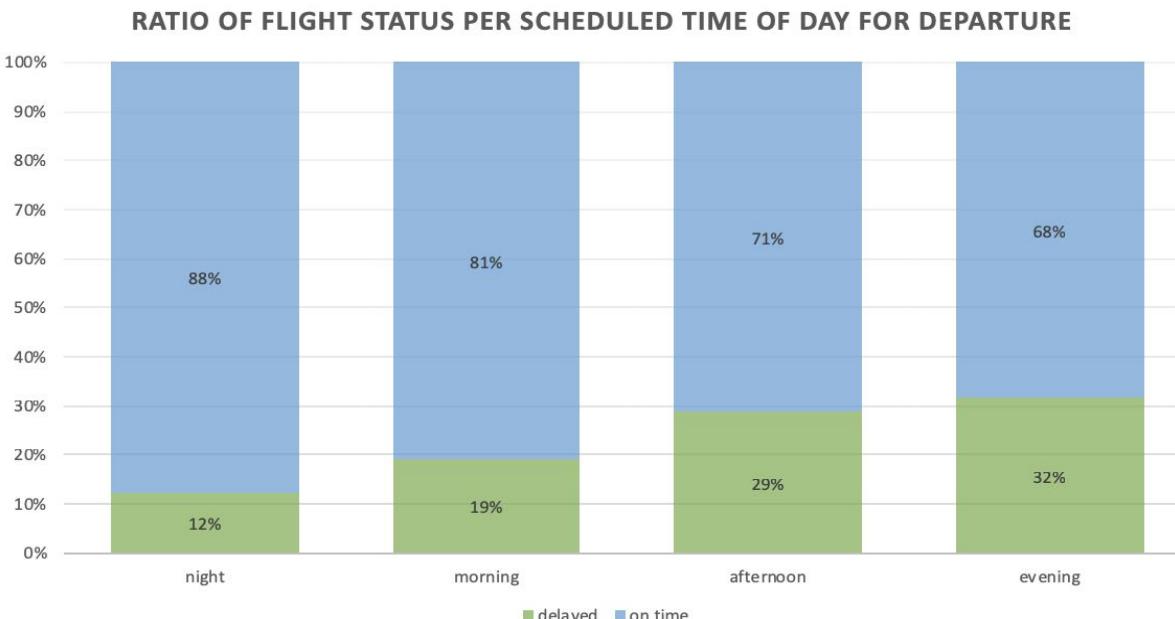
3. Which time of year, month, and day have the most flight delays? (day)



Row	Count	Column	delayed	on time	Grand Total
1	25%	75%	100%		
2	28%	72%	100%		
3	29%	71%	100%		
4	26%	74%	100%		
5	24%	76%	100%		
6	23%	77%	100%		
7	26%	74%	100%		
8	37%	63%	100%		
9	27%	73%	100%		
10	31%	69%	100%		
11	26%	74%	100%		
12	24%	76%	100%		
13	25%	75%	100%		
14	20%	80%	100%		
15	23%	77%	100%		
16	21%	79%	100%		
17	30%	70%	100%		
18	41%	59%	100%		
19	24%	76%	100%		
20	28%	72%	100%		
21	23%	77%	100%		
22	22%	78%	100%		
23	29%	71%	100%		
24	18%	82%	100%		
25	18%	82%	100%		
26	27%	73%	100%		
27	21%	79%	100%		
28	19%	81%	100%		
29	23%	77%	100%		
30	22%	78%	100%		
31	19%	81%	100%		
Grand	25%	75%	100%		

→ The patterns shown do not reveal any particularly useful insights, as some specific months must have skewed the data

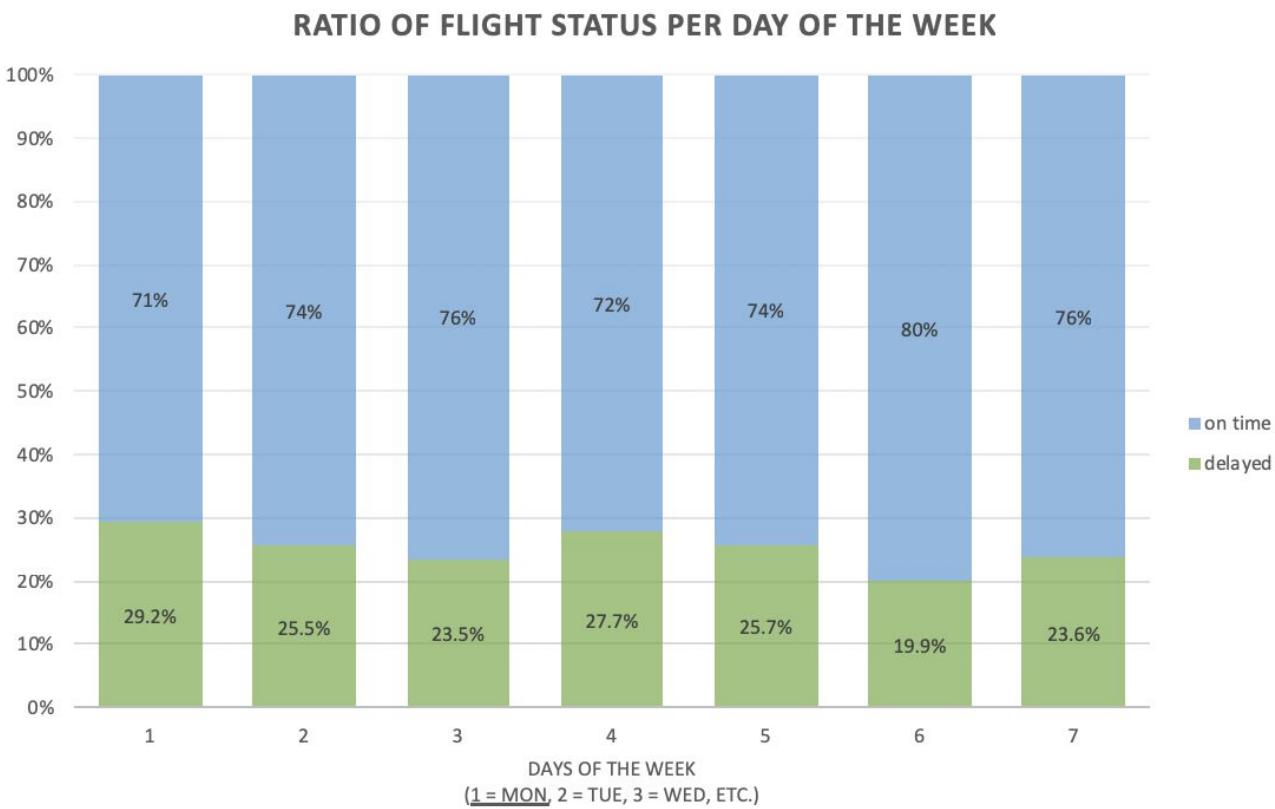
3. Which time of year, month, and day have the most flight delays? (time of day)



	Count	Column		
	Row	delayed	on time	Grand Total
night	12.29%	87.71%	100.00%	
morning	19.10%	80.90%	100.00%	
evening	31.56%	68.44%	100.00%	
afternoo	28.70%	71.30%	100.00%	
Grand	25.23%	74.77%	100.00%	

→ Although more flights leave from ORD in the morning and in the afternoon, the percentage of delayed flights is the highest in the evening and in the afternoon (which could be due to the accumulation of late aircraft over the day)

4. Which day(s) of the week typically have the most flight delays?

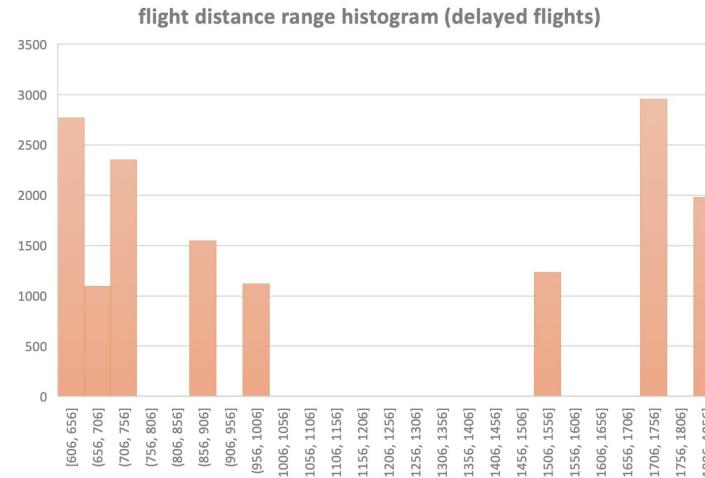
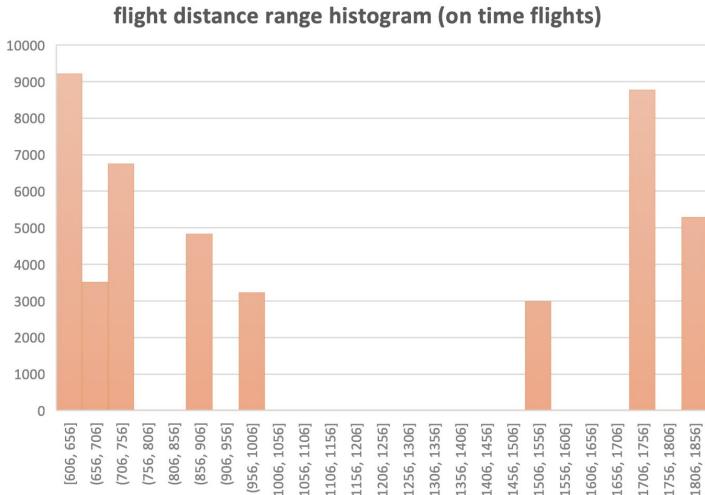


Count	Column	Row	delayed	on time	Grand Total
1			29.2%	71%	100%
2			25.5%	74%	100%
3			23.5%	76%	100%
4			27.7%	72%	100%
5			25.7%	74%	100%
6			19.9%	80%	100%
7			23.6%	76%	100%
Grand			25%	75%	100%

→ Flights tend to be delayed more on Mondays, Thursdays, and Fridays in comparison to other days of the week

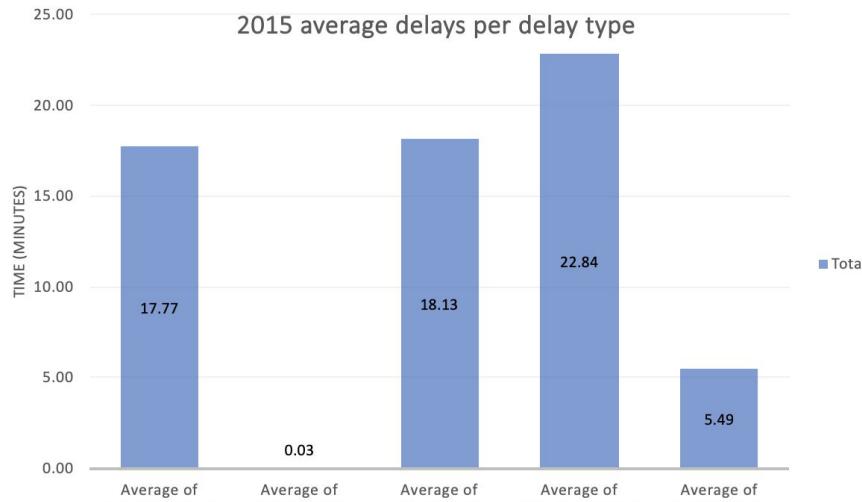
5. Which flight distance range(s) show(s) the largest number of flight delays?

→ These histograms show that the distributions of flight distance ranges for on time flights and delayed flights are similar



6. What are the most common delay reasons? What are the top cancellation reasons? (all data)

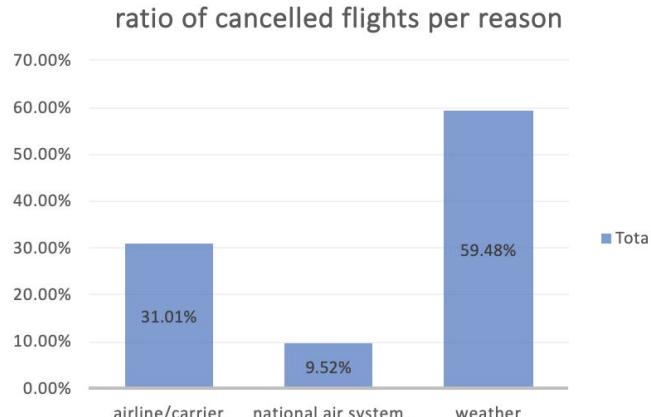
DELAYS



Values	
Average of AIR_SYS	17.77
Average of SECURIT	0.03
Average of AIRLINE_	18.13
Average of LATE_AIR	22.84
Average of WEATHE	5.49

→ In 2015, the average late aircraft delay was 22.84 minutes for flights departing from ORD. The average weather delay was 5.49 minutes.

CANCELLATIONS



Row Labels	Count of CANCELLATION
airline/carrier	31.01%
national air system	9.52%
weather	59.48%
Grand Total	100.00%

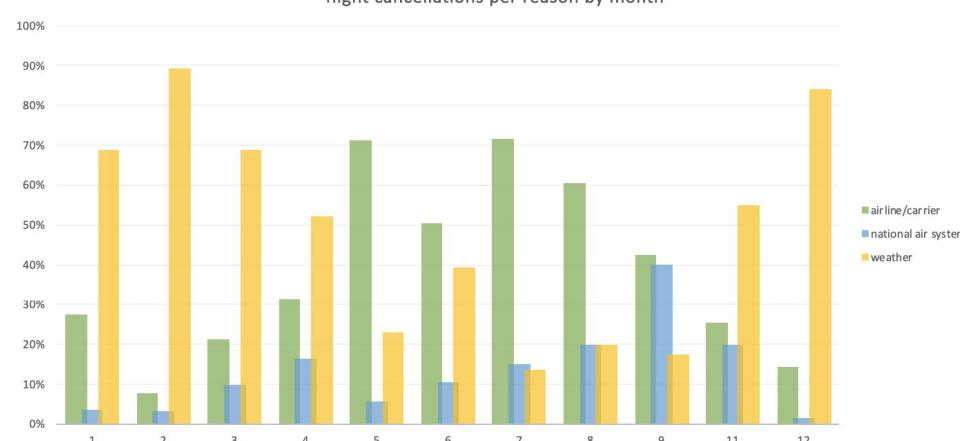
→ Weather contributes most to aircraft cancellations

6. What are the most common delay reasons? What are the top cancellation reasons? (by month)

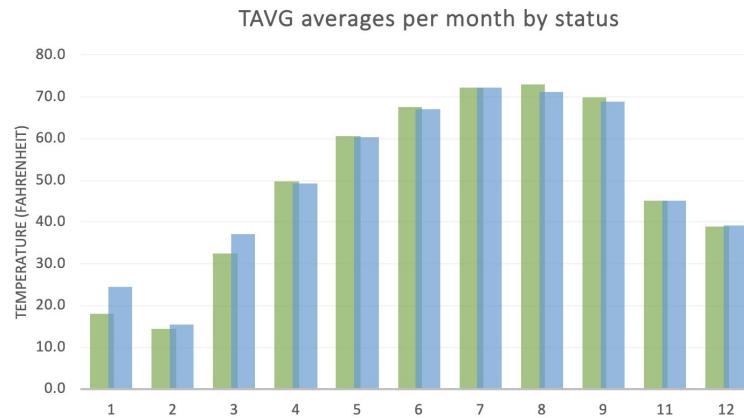
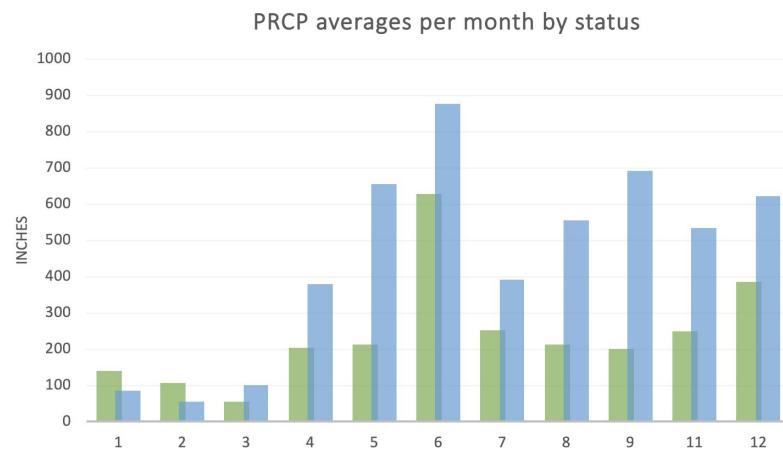
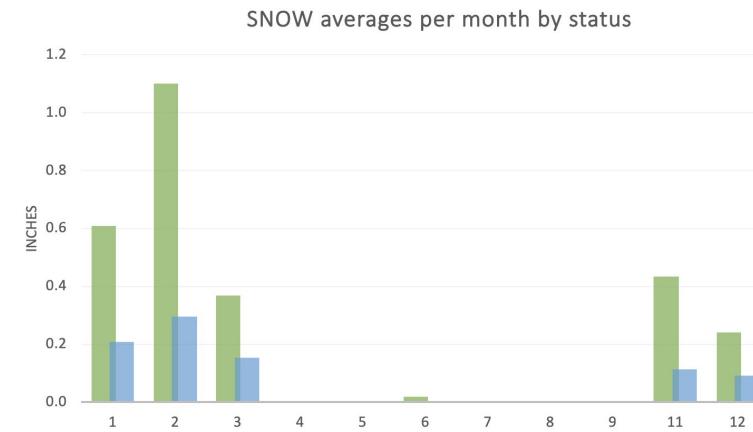
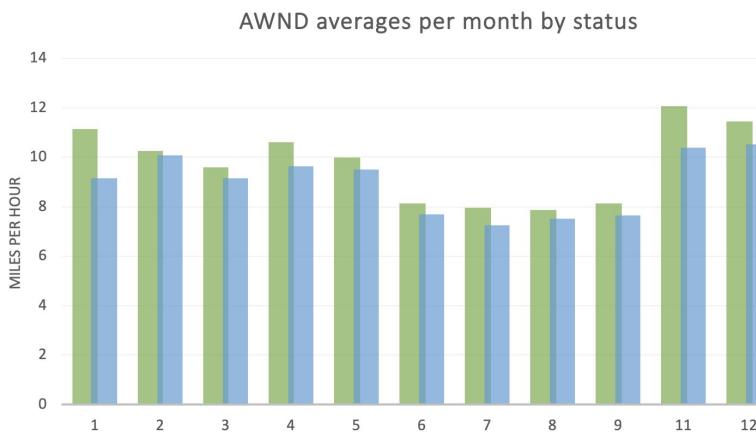
DELAYS



CANCELLATIONS

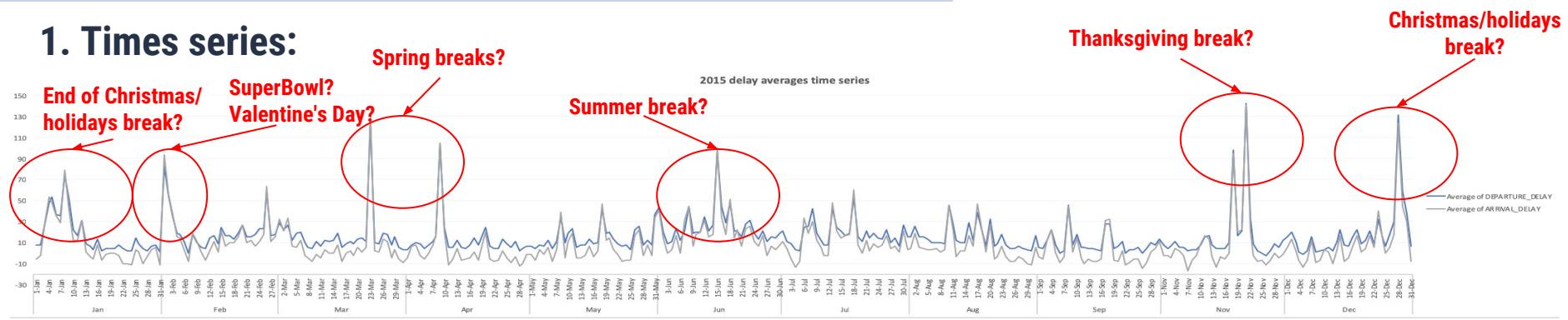


7. What was the **weather data** information by month?



7. Time series and 3D map

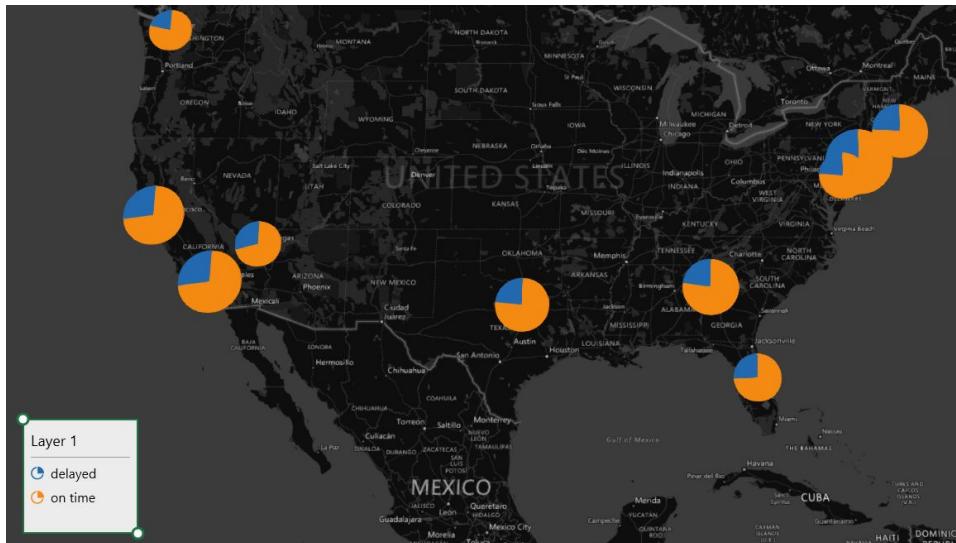
1. Times series:



→ The data is **non-stationary** (it shows no trend but has high volatility, and different cyclicity).

2. 3D map:

Orange = on time
Blue = delayed



B

FORECASTING



OBJECTIVE: Use regression models to discover good predictors of flight delays

Regression overview

We attempted to understand the **relationship** between **quantitative** variables in the data and conducting a **correlation analysis** of the second dataset (the one with a breakdown of delays)

The difference between **departure delay** vs. **arrival delay** was quite unclear. We conducted several experiments predicting both and the adj R² would always be higher when predicting **arrival delays**

	FLIGHT_DISTANCE	DEPART_DELAY	ARRIVAL_DELAY	AIR_SYSTEM_D	SECURITY_D	AIRLINE_D	LATE_AIRCRAFT_D	WEATHER_D	AWND	PRCP	SNOW	TAVG
FLIGHT_DISTANCE	1.00											
DEPARTURE_DELAY	-0.04	1.00										
ARRIVAL_DELAY	-0.05	0.95	1.00									
AIR_SYSTEM_D	-0.08	0.14	0.30	1.00								
SECURITY_D	0.02	-0.02	-0.01	-0.01	1.00							
AIRLINE_D	0.02	0.51	0.48	-0.15	-0.02	1.00						
LATE_AIRCRAFT_D	-0.04	0.61	0.58	-0.15	-0.02	-0.05	1.00					
WEATHER_D	0.00	0.34	0.35	-0.04	-0.01	-0.07	0.00	1.00				
AWND	-0.03	0.07	0.09	0.06	0.00	-0.02	0.04	0.10	1.00			
PRCP	-0.02	0.09	0.09	0.00	-0.01	0.02	0.07	0.06	0.17	1.00		
SNOW	-0.02	0.08	0.09	-0.02	-0.01	0.01	0.03	0.17	0.14	0.21	1.00	
TAVG	0.04	0.00	0.01	0.02	0.00	0.02	0.06	-0.13	-0.27	0.13	-0.33	1.00

IS	DEPAF	ARRIV	AIR_S	SECUF	AIRLIN	LATE_WEA	WEATI	AWNI
d	-9	27	27	0	0	0	0	13.1
d	65	61	0	0	61	0	0	13.1
d	21	16	0	0	16	0	0	13.1
d	100	88	0	0	63	25	0	13.1
d	46	44	0	0	44	0	0	13.1
d	25	15	0	0	2	13	0	13.1
d	133	121	0	0	93	28	0	13.1
d	65	53	0	0	53	0	0	13.1
d	35	15	0	0	15	0	0	13.1
d	64	59	0	0	59	0	0	13.1
d	39	17	0	0	14	3	0	13.1
d	55	35	0	0	35	0	0	13.1
d	91	87	0	0	87	0	0	13.1
	1	22	22	0	0	0	0	13.1

MODELING OVERVIEW

1. **Logistic regression** using all data (**Y = status**)
2. **Simple linear regression** (X=departure delay, **Y=arrival delay**)
3. **Multiple linear regression** (stepwise) (X=weather; weather+airlines(Dummy); weather+airlines(Dummy)+dayofweek(Dummy), etc. **Y=arrival delay**)

Feature engineering and dummy transformation

After discovering which airlines, days of week, destination airports, etc. had **the most significant delays** in the descriptive section and pivot tables, we decided to create dummy variables for the top #3 values with most delays in each category (e.g. AIRLINE: UA, F9, NK)

VARIABLE	DUMMIES CREATED FOR	BASELINE
MONTH	S_fall, S_winter, S_spring	S_summer
DAY	DAY_earlymonth, DAY_latemonth	DAY_middlemonth
DAY_OF_WEEK	DOW_mon, DOW_thu, DOW_fri	All other days of the week
AIRLINE	AIRLINE_UA, AIRLINE_F9, AIRLINE_NK	All other airlines in the data
DESTINATION	DEST_LAS, DEST_LAX, DEST_SFO	All other destination airports in the data
SCHEDULED_DEPARTURE	SD_morning, SD_evening, SD_night	SD_afternoon

Feature engineered dataset overview:

DATE	MO	S	T	W	F	S	DAY	DAY_OF_WEEK	DOY	DOY_OF_YEAR	DOY_OF_MONTH	DEP_DELAY	ARR_DELAY	DEP_DEL15	ARR_DEL15	ORIGIN_AIRPORT	DEST_AIRPORT	DEP_HOUR	DEP_MINUTE	FLIGHT	SCHEDULED_DEP	SD_HR	SD_MIN	SD_AMPM	SCHEDUL	STATUS	STA	DEPA	ARRIV	AVWD	PRCP	SNOW	TAVG	Fog	Hea	Thu	Ice	Hail	Gla	Haz	Biov	Torr	Dan																						
2/1/15	1	0	1	0	1	1	0	4	0	1	0	0	0	0	0	ORD	BOS	0	0	867	night	0	0	1	morning	on time	0	-11	-33	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0																
3/1/15	1	0	1	0	1	1	0	4	0	1	0	0	0	0	0	0	NK	1	0	0	1	ORD	LGA	0	0	0	733	night	0	0	1	morning	delayed	1	-9	-27	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0									
4/1/15	1	0	1	0	1	1	0	4	0	1	0	0	0	0	0	0	DL	0	0	0	0	ORD	ATL	0	0	0	609	night	0	0	1	morning	on time	0	2	-21	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0									
5/1/15	0	1	0	1	1	1	0	4	0	1	0	0	0	0	0	0	UA	1	0	0	0	ORD	MCI	0	0	0	1005	morning	1	0	0	morning	on time	0	-5	-21	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0								
6/1/15	0	1	0	1	1	1	0	4	0	1	0	0	0	0	0	0	UA	0	1	0	0	ORD	SFC	0	0	1	1744	morning	1	0	0	morning	on time	0	8	-12	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0								
7/1/15	0	1	0	1	1	1	0	4	0	1	0	0	0	0	0	0	NK	0	0	1	0	ORD	MIA	0	0	0	1744	morning	1	0	0	morning	on time	0	9	-12	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0								
8/1/15	0	1	0	1	1	1	0	4	0	1	0	0	0	0	0	0	NK	0	0	1	0	ORD	ATL	0	0	0	606	morning	1	0	0	morning	delayed	1	65	61	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0							
9/1/15	0	1	0	1	1	1	0	4	0	1	0	0	0	0	0	0	DL	0	1	0	0	ORD	ATL	0	0	0	606	morning	1	0	0	morning	on time	0	14	-3	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0							
10/1/15	0	1	0	1	1	1	0	4	0	1	0	0	0	0	0	0	UA	1	0	0	0	ORD	MCI	0	0	0	1005	morning	1	0	0	morning	on time	0	0	-21	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0								
11/1/15	0	1	0	1	1	1	0	4	0	1	0	0	0	0	0	0	UA	1	0	0	0	ORD	LGA	0	0	0	733	morning	1	0	0	morning	on time	0	0	-21	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0								
12/1/15	0	1	0	1	1	1	0	4	0	1	0	0	0	0	0	0	AS	0	0	0	0	ORD	SEA	0	0	0	1721	morning	1	0	0	morning	on time	0	-3	-27	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0							
13/1/15	0	1	0	1	1	1	0	4	0	1	0	0	0	0	0	0	CO	0	0	0	0	ORD	DCI	0	0	0	612	morning	1	0	0	morning	on time	0	0	-16	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0							
14/1/15	0	1	0	1	1	1	0	4	0	1	0	0	0	0	0	0	UA	1	0	0	0	ORD	LAS	1	0	0	1514	morning	1	0	0	morning	on time	0	7	-5	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0							
15/1/15	0	1	0	1	1	1	0	4	0	1	0	0	0	0	0	0	PHL	0	0	0	0	678	morning	1	0	0	morning	on time	0	-3	-28	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0							
16/1/15	0	1	0	1	1	1	0	4	0	1	0	0	0	0	0	0	ORD	LAX	0	1	0	1744	morning	1	0	0	morning	delayed	1	21	16	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0						
17/1/15	1	0	1	0	1	1	0	4	0	1	0	0	0	0	0	0	CO	0	0	0	0	606	morning	1	0	0	morning	delayed	1	100	88	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0						
18/1/15	0	1	0	1	0	1	1	0	4	0	1	0	0	0	0	0	UA	1	0	0	0	ORD	SFC	0	0	0	1846	morning	1	0	0	morning	on time	0	34	-8	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
19/1/15	0	1	0	1	0	1	1	0	4	0	1	0	0	0	0	0	DL	0	0	0	0	ORD	ATL	0	0	0	606	morning	1	0	0	morning	on time	0	2	-18	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0					
20/1/15	0	1	0	1	0	1	1	0	4	0	1	0	0	0	0	0	ORD	MCI	0	0	0	1005	morning	1	0	0	afternoon	on time	0	0	-18	13.6	0.0	0.0	20.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

I. Logistic regression: predicting flight status using all data (1)

Logistic Regression for STATUS_D(1=delayed)							
Summary Measures							
Null Deviance	67381.9	https://stats.idre.ucla.edu/other/mult-pkg/faq/general/FAQ_N_00000000.html#Q1					
Model Deviance	61618.5	0.09 =-modeldeviance/nulldeviance					
Improvement	5763.47						
p-Value	< 0.0001						
Regression Coefficients		Standar	Wald	Lower	Upper		
	Coefficient	Error	Value	p-Value	Limit	Limit	
Constant	-0.5241	0.1	-6.4	< 0.0001	7.00E-0	-0.4	0.6
S_fall	-0.788	0	-22.5	< 0.0001	9.00E-0	-0.7	0.5
S_winter	-0.863	0	-17.9	< 0.0001	-1	-0.8	0.4
S_spring	-0.647	0	-19	< 0.0001	-0.7	-0.6	0.5
DAY_earlymonth	-0.025	0	-1	0.3378	-0.1	0	1
DAY_late month	-0.214	0	-8.5	< 0.0001	-0.3	-0.2	0.8
DOW_mon	0.23	0	7.9	< 0.0001	0.2	0.3	1.3
DOW_thu	0.238	0	8.1	< 0.0001	0.2	0.3	1.3
DOW_fri	0.266	0	9	< 0.0001	0.2	0.3	1.3
AIRLINE_UA	0.355	0	16.4	< 0.0001	0.3	0.4	1.4
AIRLINE_F9	0.935	0.1	18	< 0.0001	0.8	1	2.5
AIRLINE_NK	0.948	0	22.6	< 0.0001	0.9	1	2.6
DEST_LAS	0.052	0	1.1	0.2759	0	0.1	1.1
DEST_LAX	0.16	0	3.4	0.0006	0.1	0.3	1.2
DEST_SFO	0.199	0.1	3.9	< 0.0001	0.1	0.3	1.2
FLIGHT_DISTANCE	0	0	-3.3	0.001	0	0	1
SD_morning	-0.589	0	-24.8	< 0.0001	-0.6	-0.5	0.6
SD_evening	0.098	0	3.9	0.0001	0	0.1	1.1
SD_night	-1.268	0.1	-18.3	< 0.0001	-1.4	-1.1	0.3
AWND	0.046	0	13.9	< 0.0001	0	0.1	1
PRCP	0.097	0	2.4	0.0177	0	0.2	1.1
SNOW	0.231	0	9.9	< 0.0001	0.2	0.3	1.3
TAVG	-0.016	0	-17.2	< 0.0001	0	0	1
Fog	0.25	0	10.7	< 0.0001	0.2	0.3	1.3
Heavy_fog	0.53	0	11.4	< 0.0001	0.4	0.6	1.7
Thunder	0.62	0	20.2	< 0.0001	0.6	0.7	1.9
Ice_pellets	0.568	0.1	7	< 0.0001	0.4	0.7	1.8
Hail	0.032	0.1	0.4	0.6943	-0.1	0.2	1
Glaze	0.218	0.1	3.5	0.0005	0.1	0.3	1.2
Haze	-0.003	0	-0.1	0.9129	-0.1	0	1
Blowing_snow	1.002	0.1	11.8	< 0.0001	0.8	1.2	2.7
Tornado	1.555	0.2	7.8	< 0.0001	1.2	1.9	4.7
Damaging_winds	0.526	0.1	7.1	< 0.0001	0.4	0.7	1.7

GOAL: Understand how the data would affect the probability of getting delayed through the coefficients, and if the explanatory variables are good predictors for the classification task

Interpretation:

- Variables that increase $P(Y=1(\text{delay}))$ are in **green**.
 - Variables that decrease $P(Y=1(\text{delay}))$ are in **red**.
 - The brighter the color, the higher the increase or decrease in probability of $P(Y=1(\text{delay}))$.

Examples:

- The variables that increase the probability of delay the most are: Tornado (dummy), blowing_snow (dummy), airline_NK (dummy), etc.
 - The variables that decrease the probability of delay the most are: SD_night, S_winter, S_fall, S_spring, SD_morning, etc.

(always in comparison to the **baselines**, and **holding all other variables constant**.)

I. Logistic regression: predicting flight status using all data (2)

	Median	25th Percentile	75th Percentile	Logit (25th)	Logit (75th)	Prob (25th)	Prob (75th)	Difference
AWND	8.503	6.637	11.183	-1.090	-0.883	0.252	0.293	0.041
PRCP	0.008	0.000	0.133	-1.006	-0.993	0.268	0.270	0.003
SNOW	0.000	0.000	0.000					
TAVG	55.000	37.000	69.000	-0.720	-1.226	0.327	0.227	-0.100

$$\text{Equation: } \ln(p/(1-p)) = -0.52414074 + 0.046*\text{AWND} + 0.097*\text{PRCP} + 0.231*\text{SNOW} - 0.016*\text{TAVG}$$

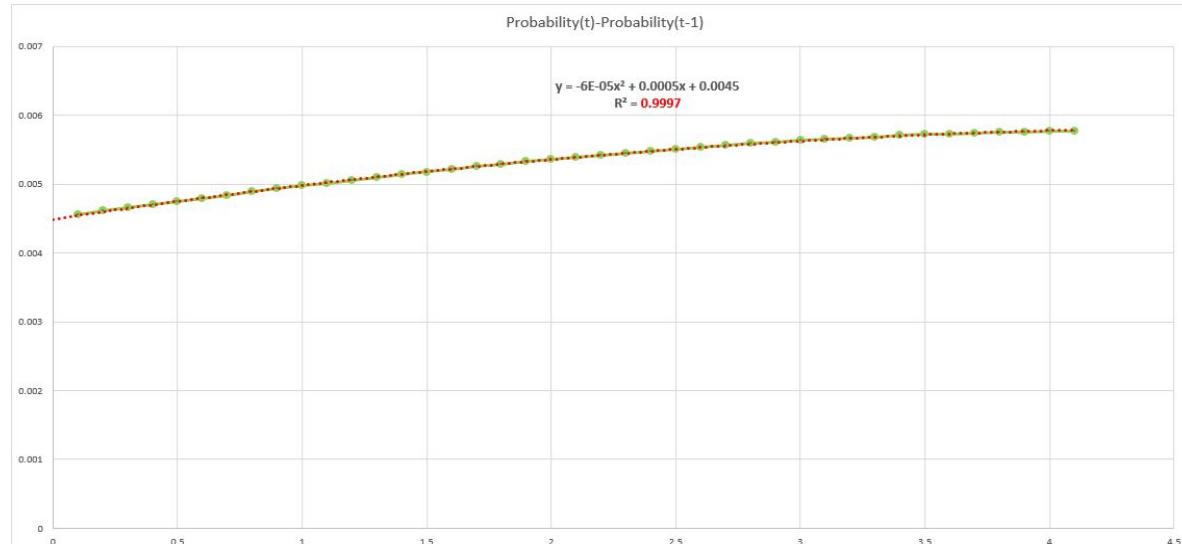
- In the equation above, to study the effect of one variable on the probability of delay, all the dummy variables are held constant (at baseline, i.e. all dummies =0) and median values were used for the remaining qualitative variables to keep them constant
e.g. while studying the effect of 'AWND' on probability of delay, we used median values of 'PRCP', 'SNOW' and 'TAVG'

Interpretation:

- While keeping everything else constant, an **increase of 1 mile per hour** in AWND will **increase the probability** of flight being delayed by **0.041**.
- While keeping everything else constant, **an increase of 1 inch** in PRCP will **increase the probability** of flight being delayed by **0.003**.
- While keeping everything else constant, **an increase of 1°F** in TAVG will **decrease the probability** of flight being delayed by **0.100**.

I. Logistic regression: predicting flight status using all data (3)

Snow(mm)	logits	Probability	Probability(t)-Probability(t-1)
0	-1.0049431	0.26797066	
0.1	-0.9818219	0.27253043	0.004559771
0.2	-0.9587007	0.27713841	0.004607985
0.3	-0.9355795	0.28179413	0.004655717
0.4	-0.9124583	0.28649706	0.004702931
0.5	-0.8893371	0.29124665	0.004749591
0.6	-0.8662158	0.29604231	0.00479566
0.7	-0.8430946	0.30088342	0.004841103
0.8	-0.8199734	0.3057693	0.004885882
0.9	-0.7968522	0.31069926	0.004929962
1	-0.773731	0.31567257	0.004973305
1.1	-0.7506098	0.32068844	0.005015876
1.2	-0.7274886	0.32574608	0.005057638
1.3	-0.7043674	0.33084463	0.005098555
1.4	-0.6812462	0.33598323	0.005138591
1.5	-0.658125	0.34116094	0.005177712
1.6	-0.6350038	0.34637682	0.005215881
1.7	-0.6118825	0.35162988	0.005253064
1.8	-0.5887613	0.35691911	0.005289228
1.9	-0.5656401	0.36224345	0.005324338
2	-0.5425189	0.36760181	0.005358362
2.1	-0.5193977	0.37299308	0.005391268
2.2	-0.4962765	0.3784161	0.005423023
2.3	-0.4731553	0.3838697	0.005453598
2.4	-0.4500341	0.38935266	0.005482962
2.5	-0.4269129	0.39486375	0.005511087
2.6	-0.4037917	0.40040169	0.005537944
2.7	-0.3806705	0.4059652	0.005563508
2.8	-0.3575492	0.41155295	0.005587752
2.9	-0.334428	0.4171636	0.005610652
3	-0.3113068	0.42279579	0.005632184
3.1	-0.2881856	0.42844811	0.005652326
3.2	-0.2650644	0.43411917	0.005671059
3.3	-0.2419432	0.43980753	0.005688361
3.4	-0.218822	0.44551175	0.005704216
3.5	-0.1957008	0.45123036	0.005718606
3.6	-0.1725796	0.45696187	0.005731517
3.7	-0.1494584	0.46270481	0.005742934
3.8	-0.1263372	0.46845765	0.005752847
3.9	-0.1032159	0.4742189	0.005761244
4	-0.0800947	0.47998701	0.005768116
4.1	-0.0569735	0.48576047	0.005773456



1. The data was sparse, most of it was 0. So we monitored the change in probability of delay for 0.1mm increment in snow.
2. The snow level (in mm) quadratically explained the change in probability.
3. For e.g., putting 0.3 as x in equation will give the probability change in delay when snow increases from 0.2mm to 0.3mm

$$\text{Equation: } y = -6E-05x^2 + 0.0005x + 0.0045$$

$$R^2 = 0.9997$$

I. Logistic regression: predicting flight status using all data (4)

Scenario #1

Vijet's uncle wants to go to Los Angeles on Friday to spend Christmas with his family on Sunday. He has a choice between traveling with Frontier Airlines or Delta airlines on Friday evening. The weather forecast indicates that there will only be wind on that night (10 mph) and that the the temperature average for the day will be 32 F.

Which airline should Vijet's uncle travel with?

AIRLINE	logit	prob(Y=1)
Frontier	-0.192124704	0.45
Delta	-1.128	0.24

He should travel with Delta Airlines.

Here's how the first probability was computed:

$\mathbf{z} = \text{constant} + S_{\text{winter}}*1 + \text{DAY}_{\text{latemonth}}*1 + \text{DOW}_{\text{fri}}*1 + \text{AIRLINE}_{\text{F9}}*1 + \text{DEST}_{\text{LAX}}*1 + \text{SD}_{\text{evening}}*1 + \text{AWND}*10 + \text{TAVG}*32$

$$P(Y=1(\text{delayed})) = 1/(1+e^{-\mathbf{z}})$$

Scenario #2

David's aunt also wants to go to Los Angeles on the day after, Saturday, and she will be traveling with United Airlines. She has a choice between flying in the morning or in the evening. The weather forecast indicates that there will only be blowing snow during the day and that the the temperature average for the day will be 32 F.

At what time of day should David's aunt travel?

TIME OF DAY	logit	prob(Y=1)
morning	-1.179	0.24
evening	-0.492	0.38

She should travel in the morning.

II. Simple linear regression: predicting arrival delays using departure delays

GOAL: Understand how departure delays affect arrival delays (2 quantitative variables)

I. Correlation coefficient and scatter plot

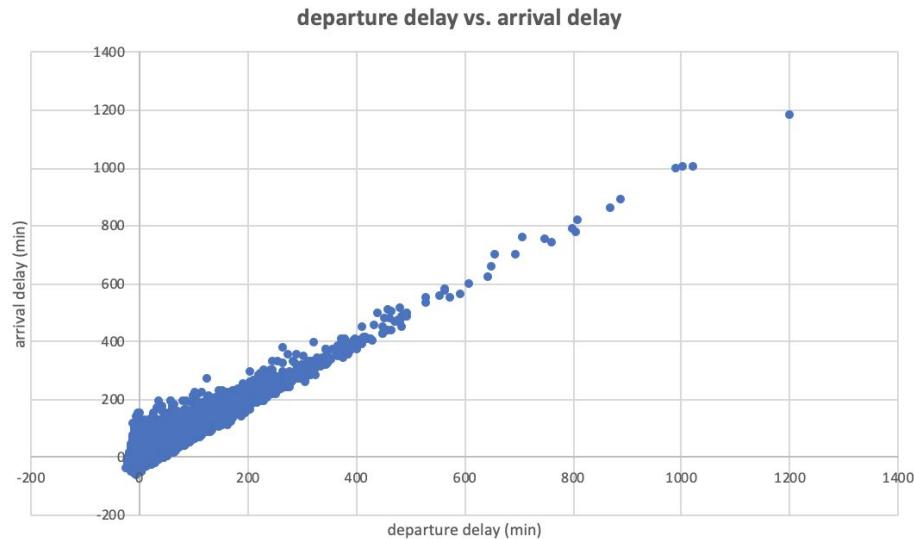
$r = 0.94 \rightarrow$ strong positive correlation
 \rightarrow strong linear positive relationship

II. Linear regression

$$\hat{Y} = -7.59 + 1.02 * X$$
$$R^2 = 0.8923$$

IV. Interpretation

- A flight with no departure delay ($X=0$) is predicted to arrive 7.59 minutes early.
- Every extra minute of departure delay is predicted to increase the arrival delay by 1.02 minutes.



Note: we attempted to add a quadratic term ($x + x^2$) to the regression to relax the assumption that the trend was linear ($R^2 \text{ adj} = 0.8924$), and a cubic term ($x + x^2 + x^3$) ($R^2 \text{ adj} = 0.8924$). The improvement was neglectable so we stuck with the linear model.

III. Multiple linear regression: predicting arrival delays using stepwise multiple linear regression (1)

GOAL: Understand how weather, airlines, destination airports, scheduled time of day, day of week, etc. all affect arrival delays and if they are good predictors using stepwise regression

X (predictors) for Y = ARRIVAL_DELAY	adj R-squared
all weather variables	0.0668
FLIGHT_DISTANCE + all weather variables (+ removed bad weather predictors: Hail (dummy) and Haze (dummy) (they had high p-values))	0.0673
[...] + AIRLINES	0.0810
[...] + DAY_OF_WEEK	0.0846
[...] + DAY (DAY_earlymonth, etc.)	0.0848
[...] + MONTH (S_winter, S_spring, etc.)	0.0918
[...] + DESTINATION (LAS, LAX, SFO)	0.0919
[...] + SCHEDULED_DEPARTURE (SD_morning, etc.)	0.1033
[...] + INTERACTION VARIABLES	0.1043

Interpretation

- Adding more variables consistently helped **improve the predictive power** of the model & **increase adj R²**
- Although for some chunks of variables (e.g. destination), some categories were **good predictors** (p-value<0.05, e.g. SFO) & some **were not** (p-value>0.05, e.g. LAX, LAS), the adj R² still increased
- As a last step, 3 **interactions variables** were added (categorical*quantitative variable): **morning*SNOW, evening*SNOW, night*SNOW**, to allow for the slope of delays to be different when it is snowing during different times of day (morning vs. night)

III. Multiple linear regression: predicting arrival delays using stepwise multiple linear regression (2)

Multiple Regression for ARRIVAL_DELAY						
Summary						
0.3237	0.1048	0.1043	4.4119241	0	0	
ANOVA Table						
Explained	33	1.00E+07	416927	211.378482	< 0.0001	
Unexplained	59611	1.00E+08	1972.4			
Coefficients						
Regression Tab	Coefficient	Error	t-Value	p-Value	Confidence Interval 95%	
Constant	15.005	1.5	10.2	< 0.0001	12.13	17.88
S_fall	-11.229	0.6	-18.8	< 0.0001	-12.4	-10.06
S_winter	-15.311	0.9	-17.5	< 0.0001	-17.02	-13.6
S_spring	-11.873	0.6	-19.4	< 0.0001	-13.07	-10.67
DAY_earlymonth	-1.013	0.5	-2.1	0.0342	-1.95	-0.08
DAY_latemonth	-2.713	0.5	-6	< 0.0001	-3.6	-1.82
DOW_mon	7.679	0.5	14.2	< 0.0001	6.62	8.74
DOW_thu	4.889	0.5	9	< 0.0001	3.83	5.95
DOW_fri	4.645	0.5	8.6	< 0.0001	3.59	5.7
AIRLINE_UA	7.487	0.4	18.9	< 0.0001	6.71	8.26
AIRLINE_F9	21.432	1.1	20	< 0.0001	19.33	23.53
AIRLINE_NK	16.049	0.8	19.3	< 0.0001	14.42	17.68
DEST_LAS	-1.149	0.9	-1.3	0.1922	-2.88	0.58
DEST_LAX	0.856	0.8	1	0.31	-0.8	2.51
DEST_SFO	2.173	0.9	2.4	0.0169	0.39	3.96
FLIGHT_DISTANCE	-0.004	0	-5.9	< 0.0001	-0.01	0
SD_morning	-9.372	0.4	-21.8	< 0.0001	-10.22	-8.53
SD_evening	0.872	0.5	1.8	0.0797	-0.1	1.85
SD_night	-15.639	1	-15.5	< 0.0001	-17.62	-13.66
AWND	1.106	0.1	18.6	< 0.0001	0.99	1.22
PRCP	3.374	0.8	4.1	< 0.0001	1.78	4.97
SNOW	4.637	0.5	9.2	< 0.0001	3.65	5.63
TAVG	-0.223	0	-13.7	< 0.0001	-0.25	-0.19
Fog	3.813	0.4	9.5	< 0.0001	3.03	4.6
Heavy_fog	17.652	0.9	19.2	< 0.0001	15.85	19.46
Thunder	10.082	0.6	17.2	< 0.0001	8.94	11.23
Ice_pellets	15.683	1.6	9.6	< 0.0001	12.48	18.89
Glaze	3.108	1.2	2.7	0.0078	0.82	5.4
Blowing_snow	31.212	1.7	18.3	< 0.0001	27.86	34.56
Tornado	74.911	3.8	19.9	< 0.0001	67.55	82.27
Damaging_winds	9.953	1.5	6.5	< 0.0001	6.95	12.96
SD_morning*SNOW	2.982	0.7	4.3	< 0.0001	1.64	4.33
SD_evening*SNOW	-3.073	0.8	-4	< 0.0001	-4.58	-1.57
SD_night*SNOW	-4.675	1.7	-2.8	0.0058	-8	-1.35

Adj R²: 0.1033

Interpretation of this model (examples)

- Flights that leave from ORD in seasons other than summer (baseline) are predicted to have a shorter arrival delay when holding other variables constant:
e.g. flights that leave in the Fall are predicted to have a delay of 15.01-11.23 = **3.78 min** when all the explanatory variables = 0
- Flights that leave from ORD on days of the week that are Mondays, Thursdays, and Fridays are predicted to have longer arrival delays than other days (baseline) when holding other variables constant:
e.g. flights that leave on Mondays are predicted to have a delay of 15.00+7.68 = **22.68 min** when all the explanatory variables = 0
- Flights that leave from ORD with severe weather conditions are predicted to have longer delays than with normal weather when holding other variables constant:
e.g. an increase in 1 mph of AWND is predicted to increase the arrival delay by **1.11 min**
- Flights that leave from ORD while it is snowing are predicted to have different delays based on the time of scheduled departure when holding other variables constant:
e.g. an increase in 1 inch of SNOW fall in the **morning** is predicted to increase the arrival delay by **2.9 min** in comparison to the delay triggered by SNOW in the afternoon
e.g. an increase in 1 inch of SNOW fall in the **evening** is predicted to decrease the arrival delay by **1.57 min** in comparison to the delay triggered by SNOW in the afternoon

RESULTS & CONCLUSIONS



SUMMARY

- With **logistic regression**, we were able to determine which factors play a key role in determining $P(Y=1(\text{delay}))$
- With **simple linear regression**, we were able to discover the impact of departure delay on arrival delay
- With **multiple linear regression**, we managed to reach the highest possible adjusted R-squared value by adding variables (quantitative, dummies, interactions) in a stepwise fashion

CONCLUSIONS

Based on the descriptive section, the models implemented, and the findings derived from those models, it can be concluded that:

- Although our task to build a models with a high predictive power was quite **ambitious** considering how little data we had, we found that the majority of variables we added (e.g. airlines, days of week, etc.) were **good predictors** for our linear & logistic regression models
- **Those predictors were found to greatly impact flight delays**

NEXT STEPS



- Collect **more precise weather data** (hourly averages instead of daily averages)
- Retrieve **more data** that could also play a crucial role in impacting flight delays:
 - ▷ Airport congestion
 - ▷ Fueling,
 - ▷ Maintenance Issues
 - ▷ Baggage and catering loading
 - ▷ Computer Glitches
 - ▷ Boarding times
 - ▷ Gate changes
 - ▷ etc.
- Attempt to implement **new models** for this highly categorical task (e.g. random forests, neural networks)
- Make predictions using a **training, validation, and testing** splits to evaluate accuracy of the best model

THANK YOU

If you have any questions, feel free to reach out to us.

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