# PREDICTIVE
# Flight Delays

GROUP 2

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# PROJECT OVERVIEW

## PROPOSAL

Using historical flight and weather data, build a machine learning model that predicts probability of flight being delayed by 15 minutes or more.

The user interface also features real-time weather forecasts for both the departure and destination airports, enabling travelers to better prepare for their trips.

## DATASET

Kaggle Dataset - **2019 Airline Delays w/Weather and Airport Details**

Classification dataset with detailed airline, weather, airport and employment information for 2019.

*Sourced:* ***Bureau of Transportation statistics***
***National Centers for Environmental Information (NOAA)***

# KAGGLE DATA

## 26 Columns — 6,489,062 Rows

| | | | | | | |
|---|---|---|---|---|---|---|
| MONTH | DAY OF WEEK | DEPARTURE DELAY OVER 15 MIN | DEPARTING FLIGHT DISTANCE (IN TIME) | DEPARTING FLIGHT DISTANCE TO BE FLOWN | SEGMENT NUMBER | CONCURRENT FLIGHTS |
| NUMBER OF SEATS | CARRIER AIRLINE | AVG. # OF MONTHLY FLIGHTS (AIRPORT) | AVG. # OF MONTHLY FLIGHTS (AIRLINE) | MONTHLY FLIGHTS (AIRLINE/AIRPORT) | AVG. MONTHLY PASSENGERS (DEPARTING AIRPORT) | |
| AVG. MONTHLY PASSENGERS (AIRLINE) | FLIGHT ATTENDANTS PER PASSENGER | GROUND EMPLOYEES PER PASSENGER | PLANE AGE | DEPARTING AIRPORT | LATITUDE (DEPARTING AIRPORT) | |
| LONGITUDE (DEPARTING AIRPORT) | PREVIOUS AIRPORT | PRECIPITATION DAILY (INCHES) | SNOWFALL DAILY (INCHES) | SNOW ON GROUND PER DAY (INCHES) | MAX DAILY TEMP | MAX DAILY WIND SPEED |

**Source:** https://www.kaggle.com/datasets/threnjen/2019-airline-delays-and-cancellations

# DATA PREPROCESSING

## POTENTIAL FEATURES IMPACTING FLIGHT DELAYS

### WEATHER CONDITIONS

- ✈ Flight Visibility
- ✈ Precipitation
- ✈ Extreme Temperature
- ✈ Wind and Speed Direction
- ✈ Snowfall/Snow on Ground
- ✈ Severe Weather Storms

### INSTANCES OF PEAK TRAVEL

- ✈ Peak Travel Times
- ✈ Holiday Seasonality
- ✈ Busy Days for Travel (weekends, Mondays)
- ✈ Concurrent Flights (tarmac congestion)

### AIRLINE & AIRCRAFT IMPACT

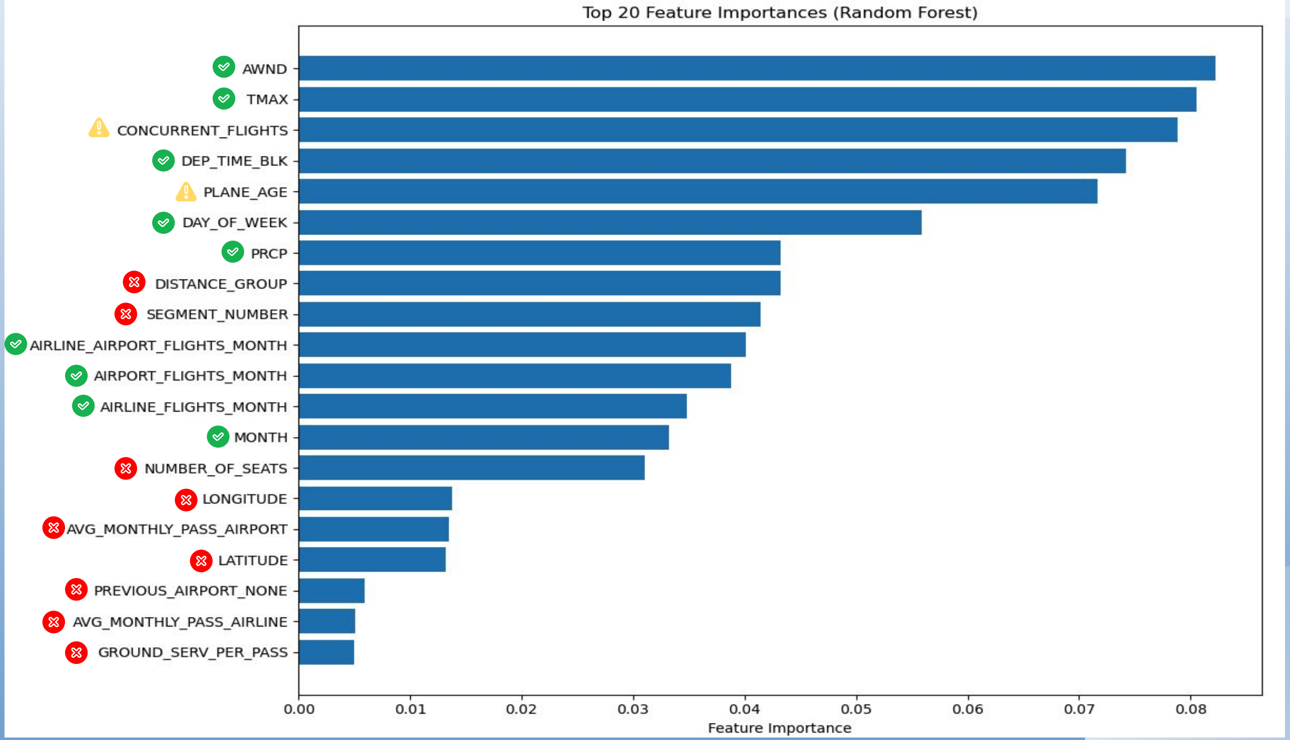
- ✈ Airline Carrier (are there specific airlines that see flight delays more often?)
- ✈ Age of Departing Aircraft (does this assumption of increased maintenance times cause higher levels of delay?)
- ✈ Prior Flights to Departure (subsequent flights for an aircraft allows for possibility of prior flight delay)
- ✈ Departing Airport (busier airports, with higher traffic levels can more commonly result in flight delays)
- ✈ Flight Distance for Departing Aircraft (will a flights' length impact likelihood of delay - *maintenance factors*?)

# FEATURE IMPORTANCE

### Feature Availability

Current database structure and access to necessary APIs for live data to user input prevented certain features from being utilized in our model to dashboard design.

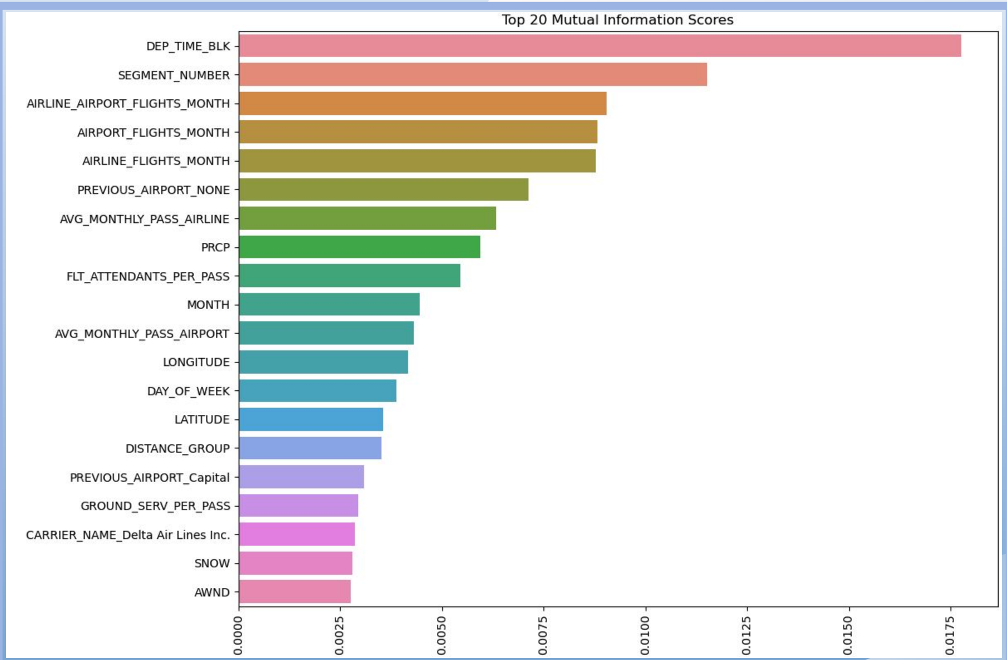
| | |
|---|---|
| | *Feature Used* |
| | *Use Restricted* |
| | *Not Included in Model Training* |

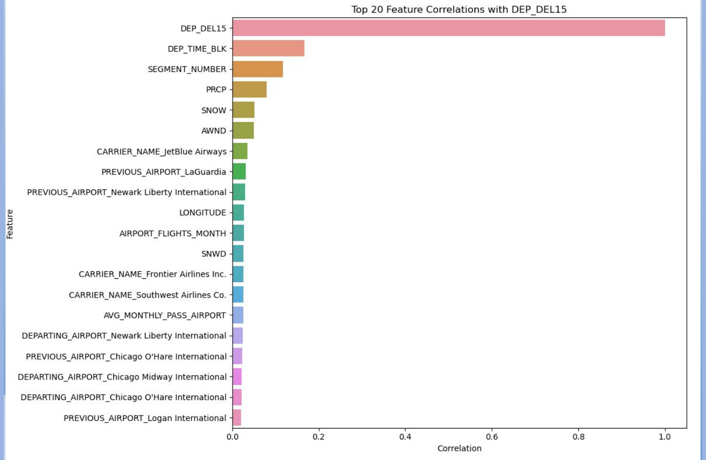


# FEATURE IMPORTANCE

## What can these charts tell us?

Further confirmation of feature selection, based on mutual dependence AND correlation between delays **[DEP_DEL15]** and each individual column in our dataset.



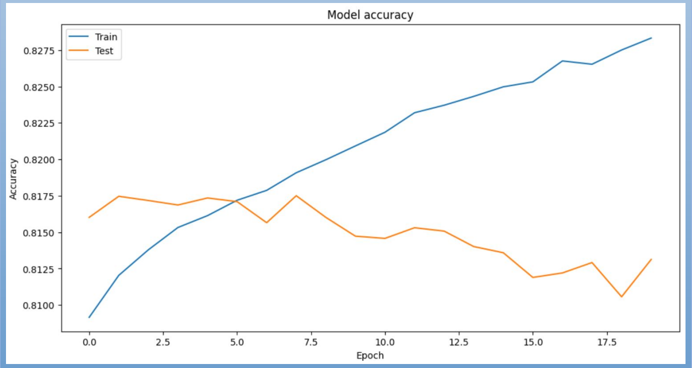
# MODEL SELECTION

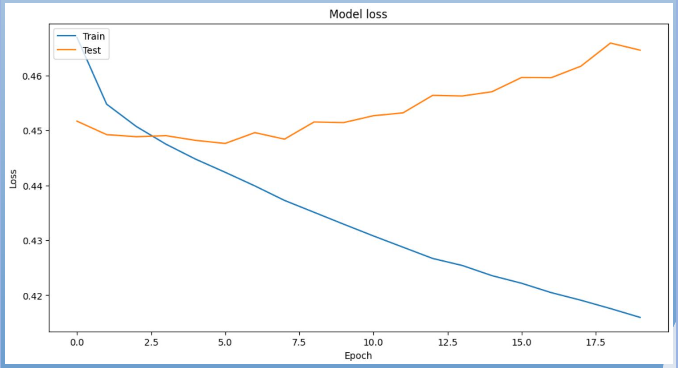
***2 Model Types Tested*** → ***13 Total Optimizations***

**XGBoost Model**

**Neural Network Model**

- ✈ Original Neural Network Model + increased number of neurons
- ✈ Original Neural Network Model + add hidden layer
- ✈ Original Neural Network Model + feature engineering



# FEATURE ENGINEERING

### *Steps to Improve Model Accuracy*

| Scenario | Features |
|---|---|
| 1 | With all Features |
| 2 | All features without Plane Age |
| 3 | All features without Concurrent Flights |
| 4 | All features without Prcp |
| 5 | All features without Plane Age & Concurrent flight |
| 6 | ['MONTH', 'DAY_OF_WEEK', 'DEP_TIME_BLK', 'CONCURRENT_FLIGHTS', 'PLANE_AGE','PRCP', 'TMAX', 'AWND'] |
| 7 | ['MONTH', 'DAY_OF_WEEK', 'DEP_TIME_BLK', 'CONCURRENT_FLIGHTS', 'PRCP', 'TMAX', 'AWND'] |
| 8 | ['MONTH', 'DAY_OF_WEEK', 'DEP_TIME_BLK','PLANE_AGE', ‘PRCP', 'TMAX', 'AWND'] |
| 9 | ['MONTH', 'DAY_OF_WEEK', 'DEP_TIME_BLK', 'PRCP', 'TMAX', 'AWND'] |
| 10 | [‘MONTH', 'DAY_OF_WEEK', 'DEP_TIME_BLK',  'TMAX', 'AWND'] |
| 11 | ['MONTH', 'DAY_OF_WEEK', 'DEP_TIME_BLK','TMAX', 'AWND' ,'AIRPORT_FLIGHTS_MONTH',  'AIRLINE_FLIGHTS_MONTH', 'AIRLINE_AIRPORT_FLIGHTS_MONTH'] |
| 12 | [‘MONTH', 'DAY_OF_WEEK', 'DEP_TIME_BLK','TMAX', 'AWND', 'AIRPORT_FLIGHTS_MONTH', 'AIRLINE_FLIGHTS_MONTH', 'AIRLINE_AIRPORT_FLIGHTS_MONTH',  'PRCP'] |

## Experimental Model - Outcome Plotted

# MODEL OPTIMIZATION

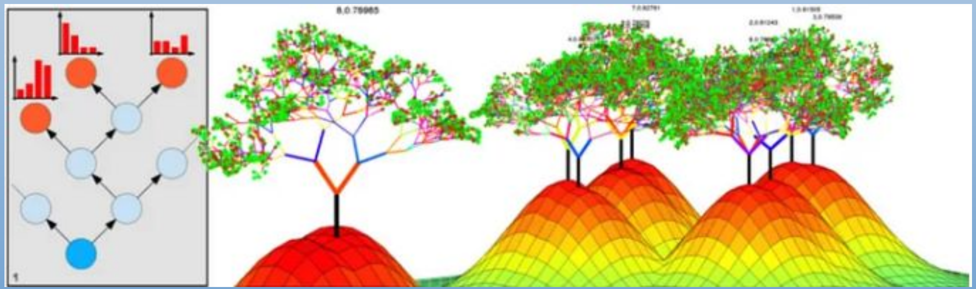
## Continuous Improvement

*Only 2 days until the presentation...*

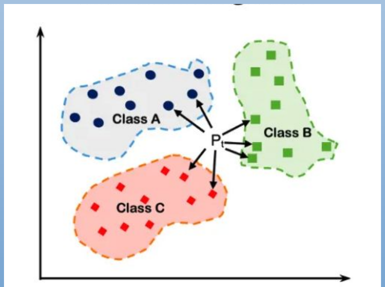
→ ***Not very happy with overall model performance, continue to optimize!***

Revert back to simpler models that work well with **classification** problems:

Random Forest



+ K Nearest Neighbors



# MODEL PERFORMANCE

## Random Forest

Classification Report:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.84 | 0.92 | 0.88 | 210437 |
| 1 | 0.42 | 0.24 | 0.30 | 49126 |
| accuracy | | | 0.79 | 259563 |
| macro avg | 0.63 | 0.58 | 0.59 | 259563 |
| weighted avg | 0.76 | 0.79 | 0.77 | 259563 |

**RF produced more balanced results and provides much higher chance of predicting true delays.**

## NNW

Classification Report:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.82 | 0.99 | 0.90 | 42286 |
| 1 | 0.54 | 0.06 | 0.11 | 9627 |
| accuracy | | | 0.82 | 51913 |
| macro avg | 0.68 | 0.52 | 0.50 | 51913 |
| weighted avg | 0.77 | 0.82 | 0.75 | 51913 |

## KNN

Classification Report:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.83 | 0.94 | 0.88 | 42286 |
| 1 | 0.39 | 0.17 | 0.24 | 9627 |
| accuracy | | | 0.80 | 51913 |
| macro avg | 0.61 | 0.55 | 0.56 | 51913 |
| weighted avg | 0.75 | 0.80 | 0.76 | 51913 |

# MODEL TESTING

```
input = [10.00, 7.00, 100.00,10.00, 20000.00,31600,1500, 50.0, "1900-1959"]
```

```
# Make the prediction
prediction_result = model.predict_proba(prepped_data) * 100
delay_percentage = prediction_result[0][1]  # Probability of class 1 (delay)
```

| | MONTH | DAY_OF_WEEK | TMAX | AWND | AIRPORT_FLIGHTS_MONTH | AIRLINE_FLIGHTS_MONTH | AIRLINE_AIRPORT_FLIGHTS_MONTH | PRCP | ENCODED_DEP_TIME_BLK |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 10.0 | 7.0 | 100.0 | 10.0 | 20000.0 | 31600 | 1500 | 50.0 | 14 |

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 102ms/step
Predicted delay percentage: 33.74%
```

✓ **Model passes testing → ready for flask connection and dashboard predictions**

# FLASK APPLICATION

## BACKEND

**Flask Application**

→ Parses Frontend User Inputs
→ Calculates and Returns Delay Probability
→ Database Queries for Multiple Endpoints

## FRONTEND

**HTML, CSS, JavaScript**

→ Predictive Flight Delay Dashboard
→ Historical Delay Trends (Interactive Visuals)
→ Navigation to Available Routes & Data

## DATABASE

**PostgresSQL - SQLAlchemy**

**Import:** *'full_data_flightdelay.csv.zip'*
**Database:** *flightpredict*

# APPLICATION DESIGN

## USER INPUT

User inputs available flight information; Origin and destination airport, date of flight, airline and flight number.

## VISUAL OUTPUT

Output visualizations are connected to model predictions and live flight & weather data from API.


## PROCESS DATA

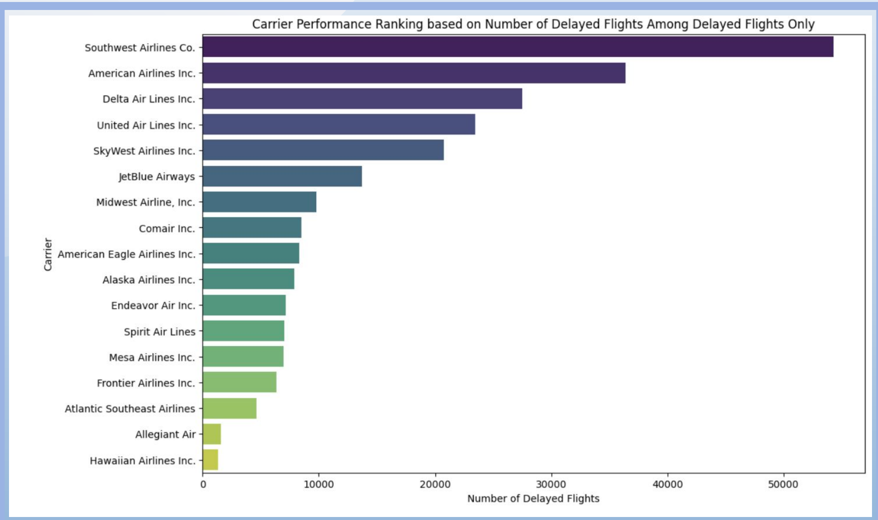
Machine learns from historical instances of flight delays, flagging for parameters that have produced past delays.

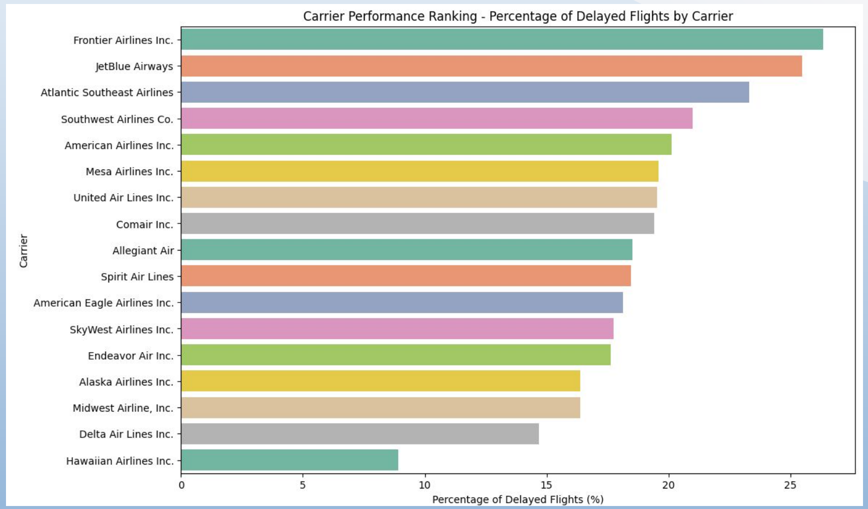
## PREDICT

Live weather forecast API is compared to historical data, outputting the probability of a flight delay.


FLASK APP
DEMO

# CARRIER PERFORMANCE




**Frontier**
**jetBlue**
**Atlantic Southeast**
**Southwest**
**American**

**Hawaiian**
**Delta**
**Midwest**
**Alaska**
**Endeavor Air**

# CONCLUSION & LIMITATIONS

## CONCLUSION

Flight delays are **highly unpredictable** due such wide variety of factors impacting the possibility of a flight being delayed *(think of the recent Crowdstrike outage).*

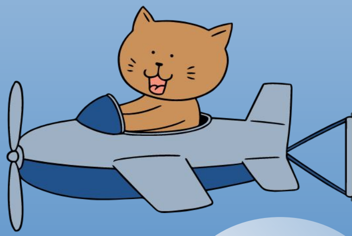
## LIMITATIONS

- ✈ Some features are retrieved from the database rather than live data
  *(This restricted our coverage to certain airports)*
- ✈ Two features deemed important were NOT attainable through user input
- ✈ Large size of database hinders performance in parts of the application
- ✈ Time frame of a prediction must be within 5 days of the current date
  *(Due to weather forecast availability through API)*

# FINAL THOUGHTS

## NEXT STEPS

- ✈ Find other data/variables not provided in initial dataset, *potentially impacting delays* (airlines being short staffed, cap on pilot flying hours, outdated systems, etc.)
- ✈ Source more than 1 year's worth of historical data
- ✈ Regularly update flight database with live results to track detailed delay trends
- ✈ Access to higher computing power and memory resources for model fine tuning
- ✈ Additional time debugging JavaScript to improve dashboard functionality
- ✈ Hosting application online for public use



**Surprising Discovery:**
*Spirit was NOT the worst airline carrier experiencing flight delays!*

# THANK YOU
# HAPPY GRADUATION!

## GROUP 2

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## REPOSITORY:

github.com/maddiebowman/predictive_flight_delays

# APPENDIX

## WEATHER ANALYSIS

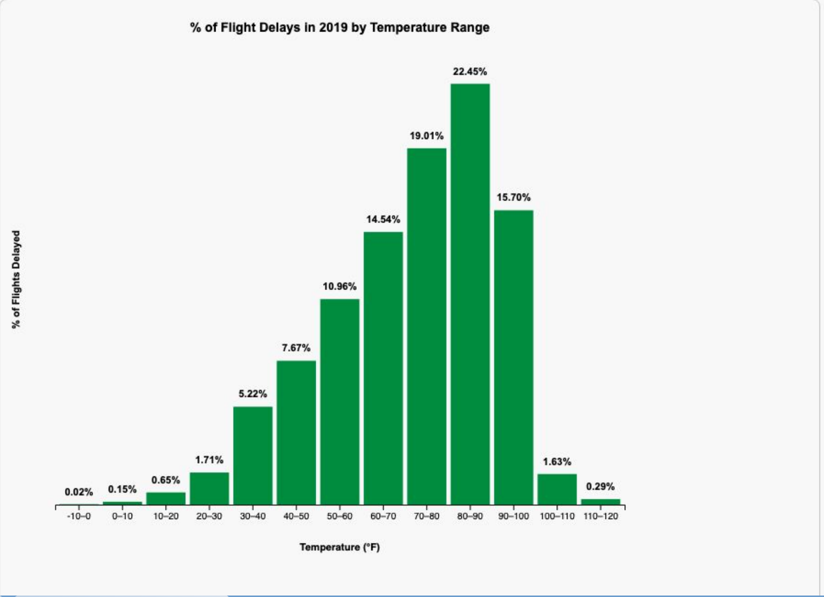
*Demystifying Predictive Flight Delays with Historical and Real-Time Data*

API sources: OpenWeatherMap + weather.gov

# WEATHER CONDITIONS

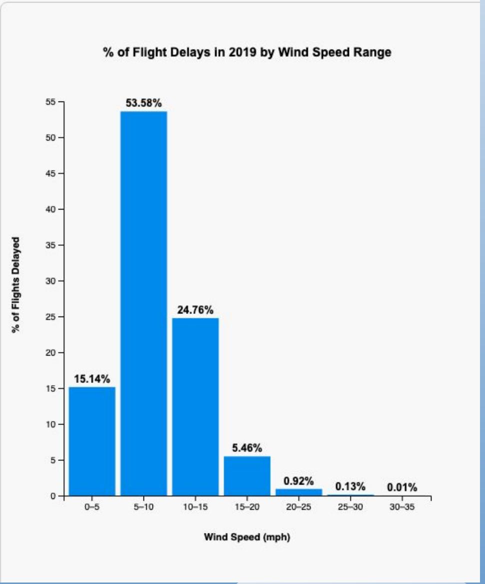
## Temperature

Temperature range between 80 F and 90 F had the highest impact on flight delays in 2019, followed by 70 F and 80 F.




## Wind Speed

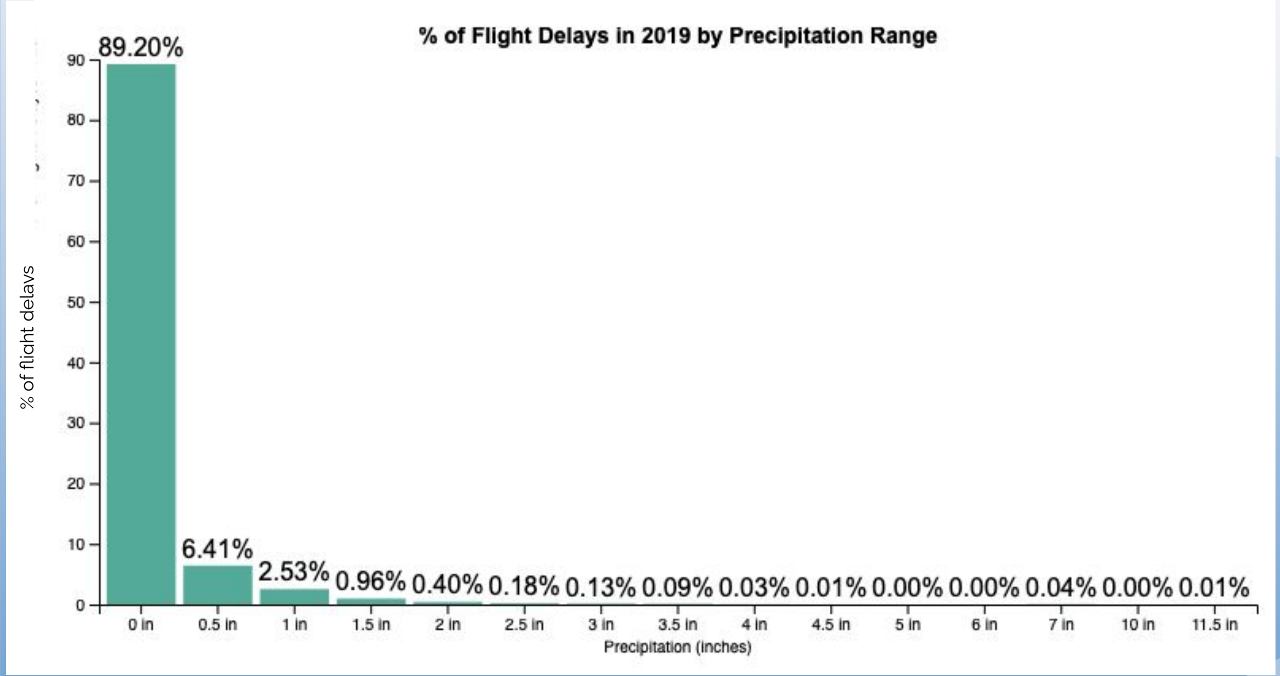
Wind speed range between 5 and 10 mph had the highest impact on flight delays in 2019.




Note: this could be because most flights are within this temp and wind range, which is why it's important for us to look at all factors when assessing flight delays rather than just a single factor.

API sources: OpenWeatherMap + weather.gov

# WEATHER CONDITIONS




## PRECIPITATION

Precipitation did not appear to be a factor in 2019 dataset, despite being an important factor in model prediction.