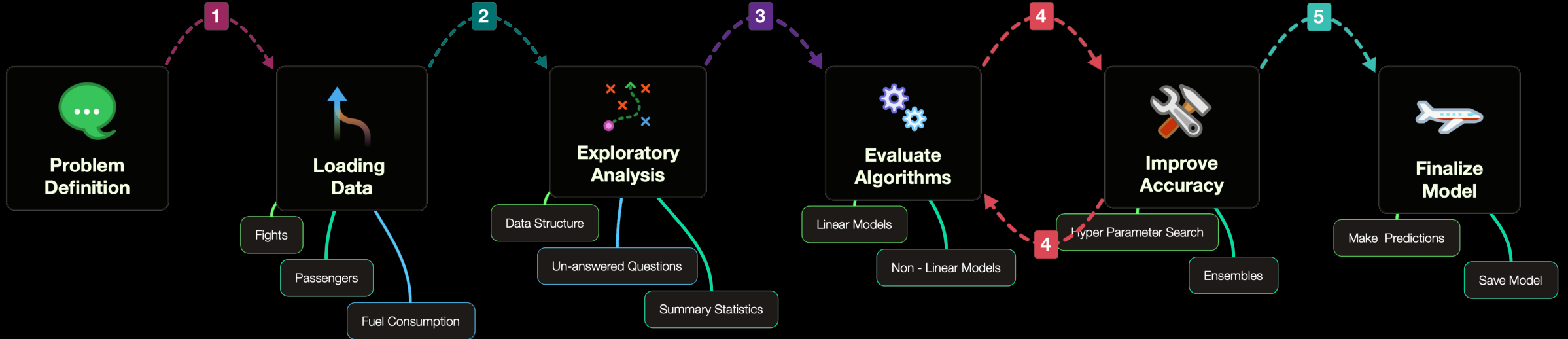


# PREDICTING FLIGHT DELAYS

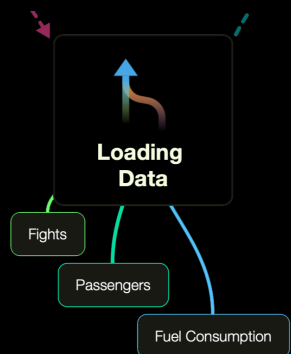
SUPERVISED MACHINE LEARNING

# PROCESS



# WHAT IS THE PROBLEM?

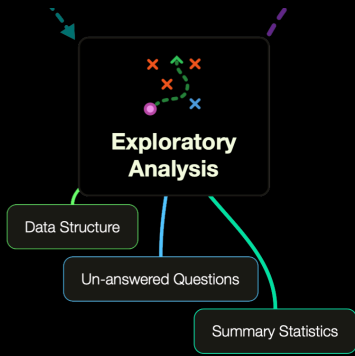
- Significant implications for airlines, affecting their profitability and customer satisfaction.
- Accurate estimation is crucial for airlines to make informed decisions and optimize their operations.
- Understanding the factors affecting flight delays is essential for developing accurate prediction models.



# DATASETS

Four separate tables related to US the air travel industry.

- Flights — departure and arrival information 2018 and 2019.
- Fuel Consumption — different airlines from years 2015-2019 aggregated per month.
- Passengers — totals on different routes from years 2015-2019 aggregated per month.
- Flights test — test dataset for flights in January 2020

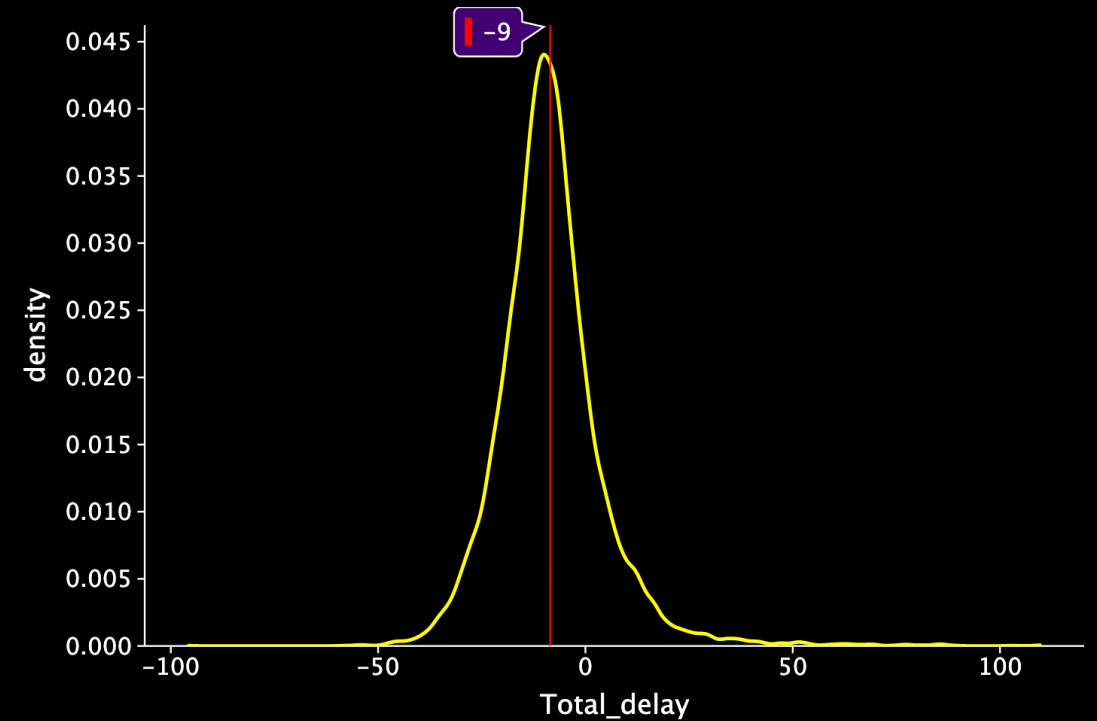


# EDA

Is distribution of delays normal?

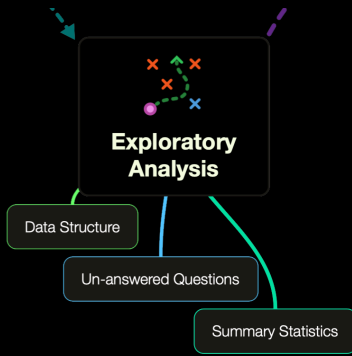
- By day of week, most flights leave on time, by on average 7 mins earlier.
- ATL was the busiest airport with 1602 flights with 179K passengers passing through in just one month.
- Flights that left late night were more likely to be delayed

## Shapiro - Wilk Test

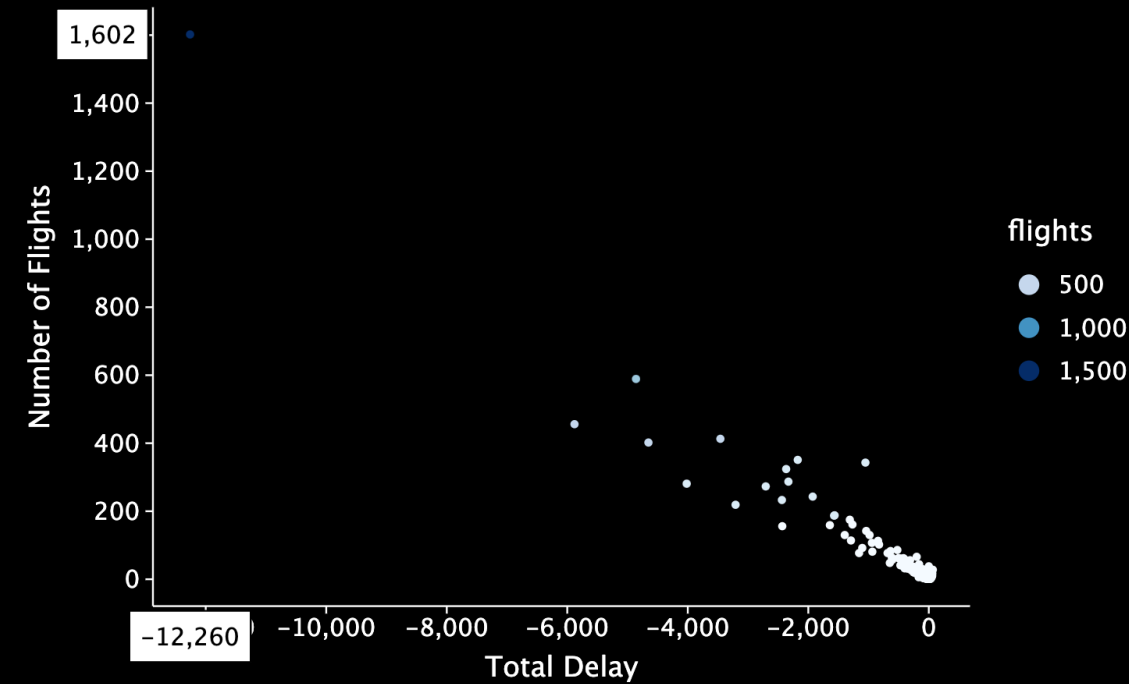


$P > \alpha = 0.05$   
Mean total delay is not 0 (-9 minutes)

# EDA

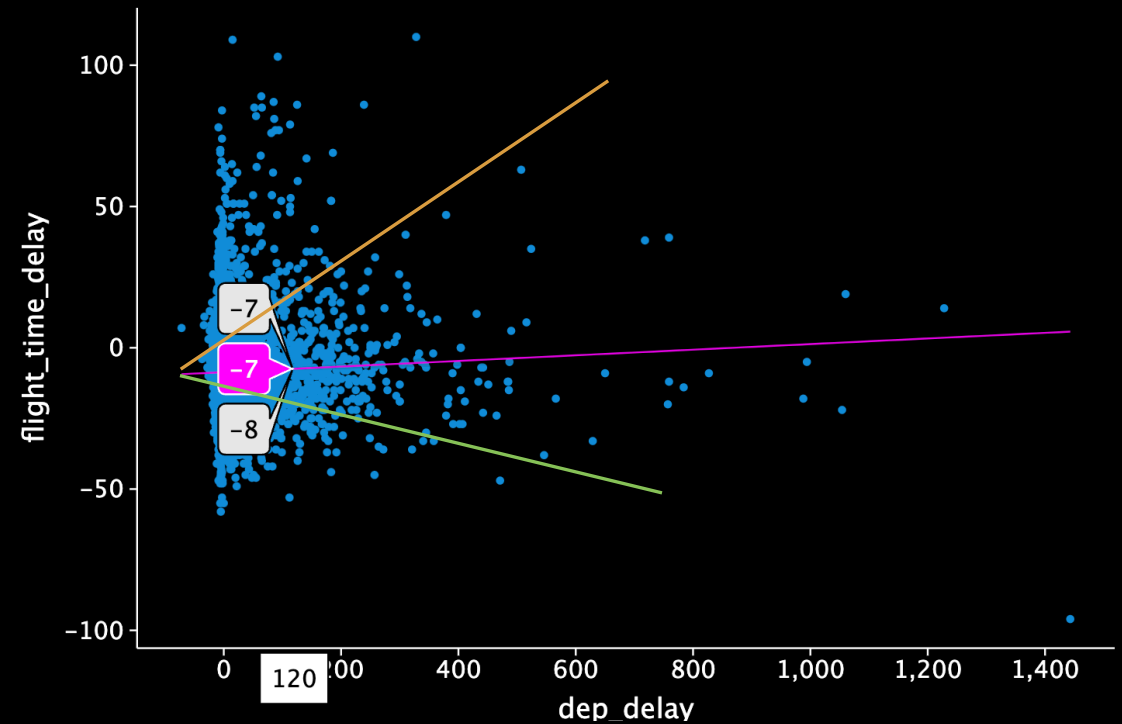


Delay Vs Number of Previous Flights



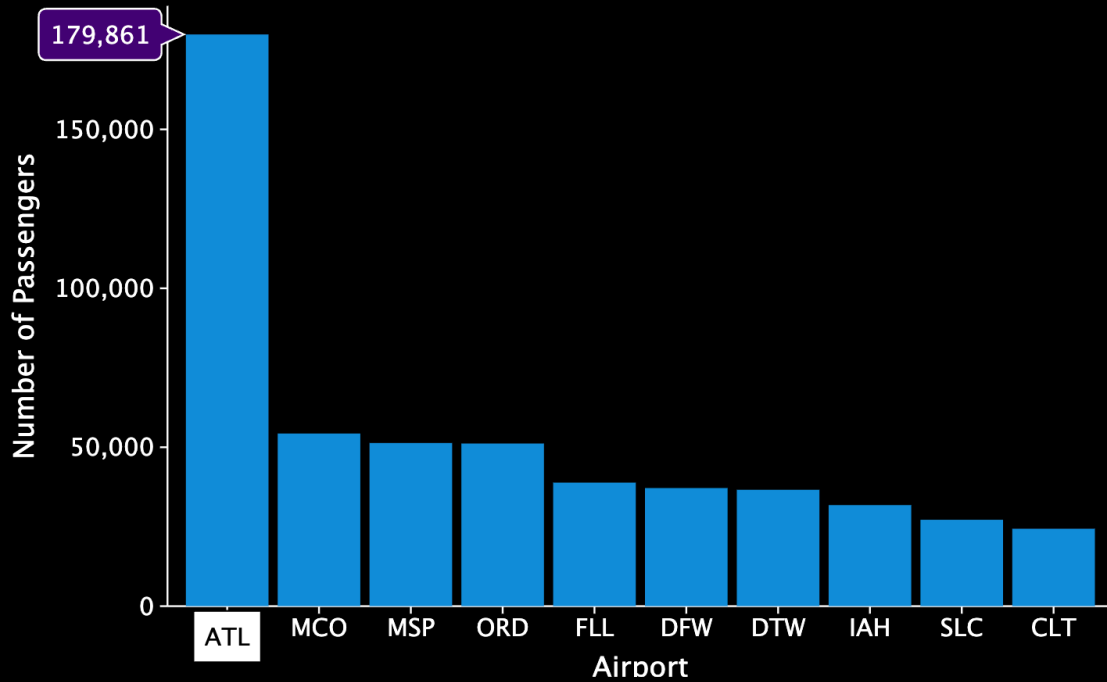
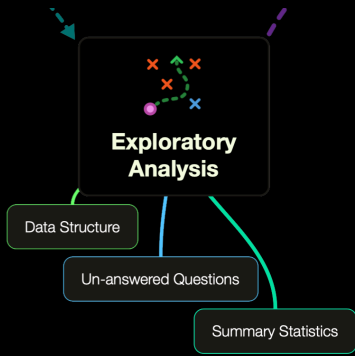
There is a strong association between total delay and Number of previous flights.

Will my pilot fly faster when departure was delayed?



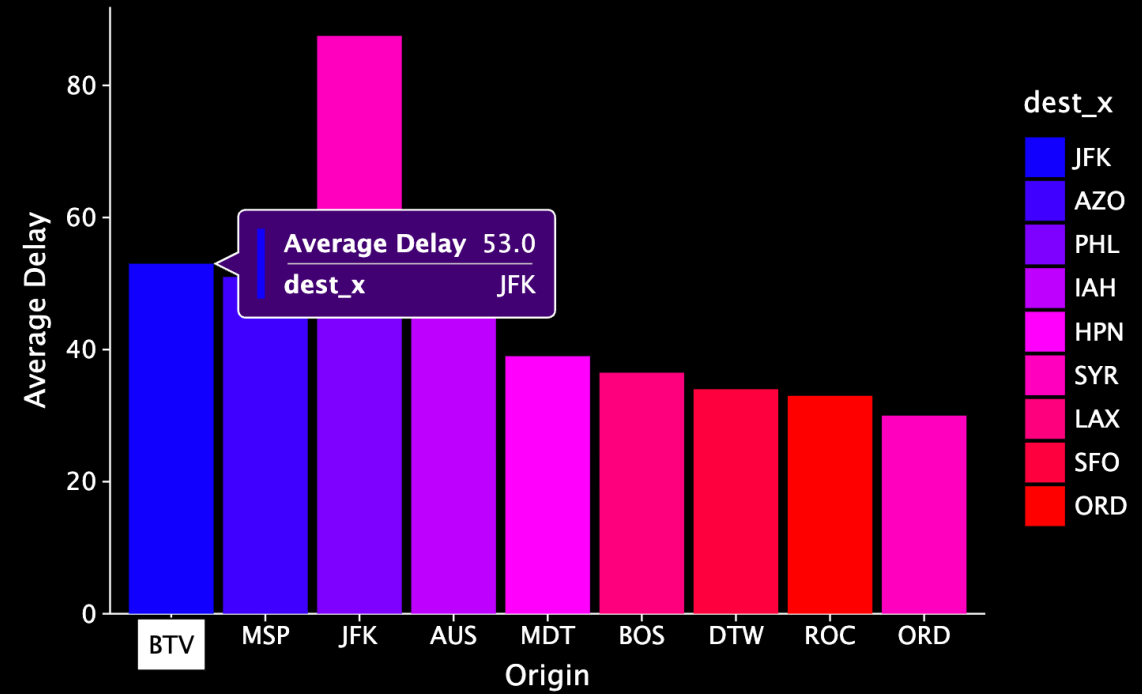
There is a positive linear relationship, but very Close to zero. At 2 hours late, they'll only fly faster By 7 minutes.

# EDA



Atlanta - home to Delta Airways was the busiest airport 179,000 passengers and 1,602 flights in one month

## Origin - Destination Average Delay



Flying between BTV and JFK has highest average Delay of 53 minutes. Worse combination possible

# FEATURE IMPORTANCE

- Origin city average departure delay (both origin and dest).
- Day of week.
- Day of week average departure delay (both origin and dest).
- op\_unique\_carrier average arrival delay.
- Airtime avg of distance group.
- Number of passenger average of distance group.
- Payload average of distance group.



# MODEL SELECTION

- Grid Search for finding best hyper-parameters.
- Use Ridge and Lasso Model.
- Use three Ensemble Techniques : 1) Random Forest Regressor 2) Gradient Boosting 3) XGBoost
- In which Random Forest Regressor gives minimum mean squared error
- Use linear regression model and find summary in which we observed
  - 1)  $R^2$  of model is 0.1031937
  - 2) Saturday has largest positive coefficient.
  - 3) Monday has smallest negative coefficient.

# CHALLENGES

- Weather related data was not readily available.
- Disjoint in table keys. The most important key (flight number) was missing in the flight dataset. When merged we lost a good chunk of data.

# CONCLUSION

- An okay project - not the results we were expecting.
- Sample across multiple years, data enrichment.

# CONCLUSION