Spotify Machine Learning Project

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Outline

- Goals
- Datasets
- Exploratory data analysis
- Flight delays modelling
- Conclusions

Goals

Goals and Impacts

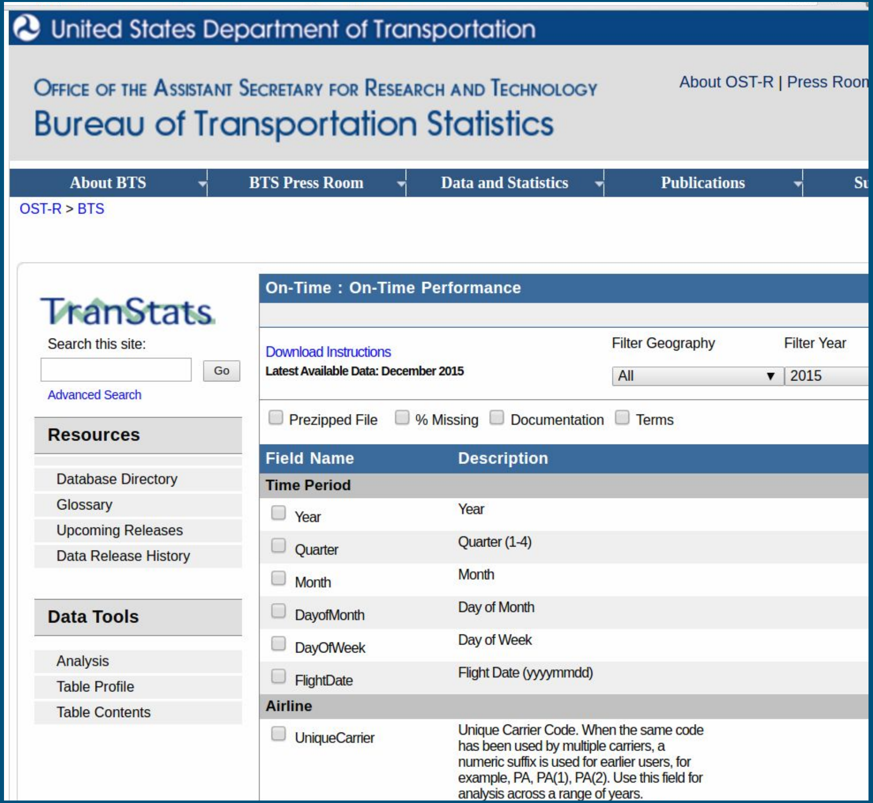
- Depict global pictures of US flight transportations in recent years.
- Develop an accurate flight delays prediction system based on transportation and weather data.
- Save billion of dollars every years of flights delays due to additional hotel/ taxi/ tickets expenses [1].
- Provide more than 800 million per year US air travelers a reliable timeline when scheduling flights & travels [2].

Datasets

Bureau of Transportation Flights Statistics

US Flights data since 2005 include:

- Flight schedule date.
- Carrier.
- Flight/ tail numbers.
- Flight origin/ destination.
- Actual departure/ arrival time.
- Cancellation code.
- Cause of Delay (5 categories).



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Bureau of Transportation Statistics

Search this site:

On-Time : On-Time Performance

Download Instructions

Latest Available Data: December 2015

Filter Geography: All

Filter Year: 2015

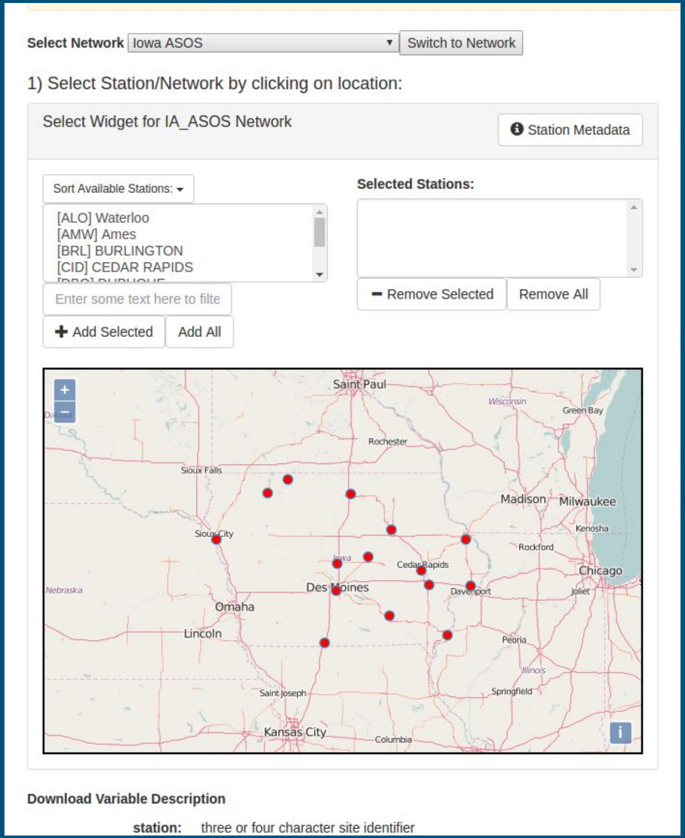
□ Prezipped File □ % Missing □ Documentation □ Terms

Field Name	Description
Time Period	
□ Year	Year
□ Quarter	Quarter (1-4)
□ Month	Month
□ DayofMonth	Day of Month
□ DayOfWeek	Day of Week
□ FlightDate	Flight Date (yyyymmdd)
Airline	
□ UniqueCarrier	Unique Carrier Code. When the same code has been used by multiple carriers, a numeric suffix is used for earlier users, for example, PA, PA(1), PA(2). Use this field for analysis across a range of years.

ASOS-AWOS-METAR Data

Detailed hourly weather data of US airports:

- Air Temperature
- Dew Point Temperature
- Humidity
- Wind speed
- One hour precipitation
- Pressure altimeter
- Visibility
- Wind gust



Select Network Iowa ASOS ▾ Switch to Network

1) Select Station/Network by clicking on location:

Select Widget for IA_ASOS Network

Sort Available Stations:

[ALO] Waterloo
[AMW] Ames
[BRL] BURLINGTON
[CID] CEDAR RAPIDS

Enter some text here to filte

Selected Stations:

Download Variable Description

station: three or four character site identifier

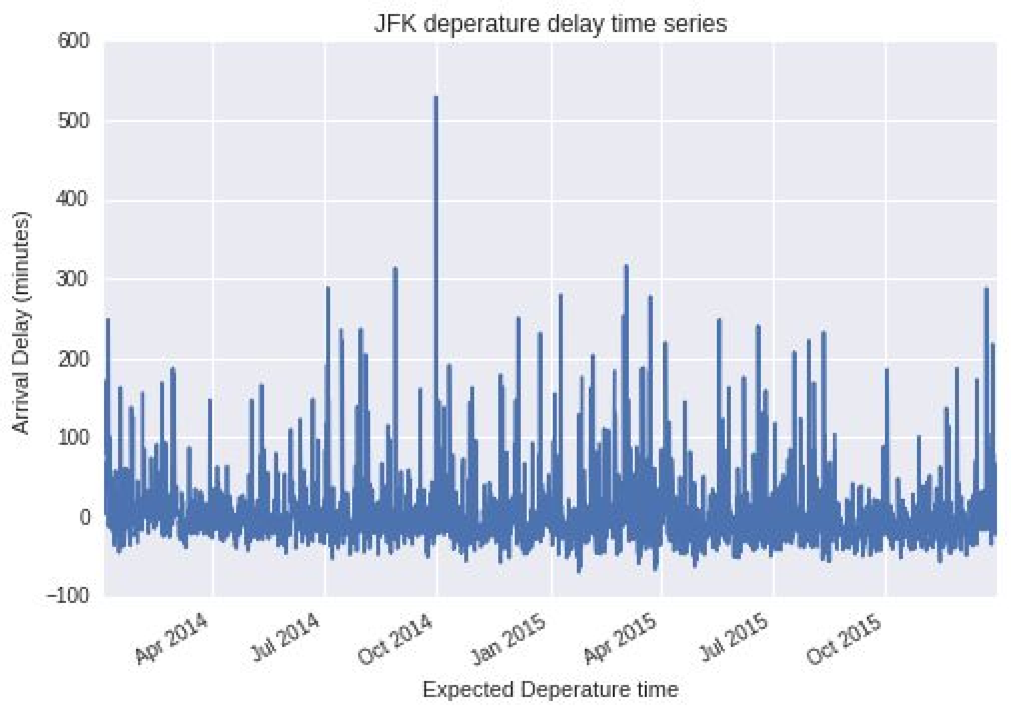
Exploratory Data Analysis

Flight delays at JFK, 2014-2015

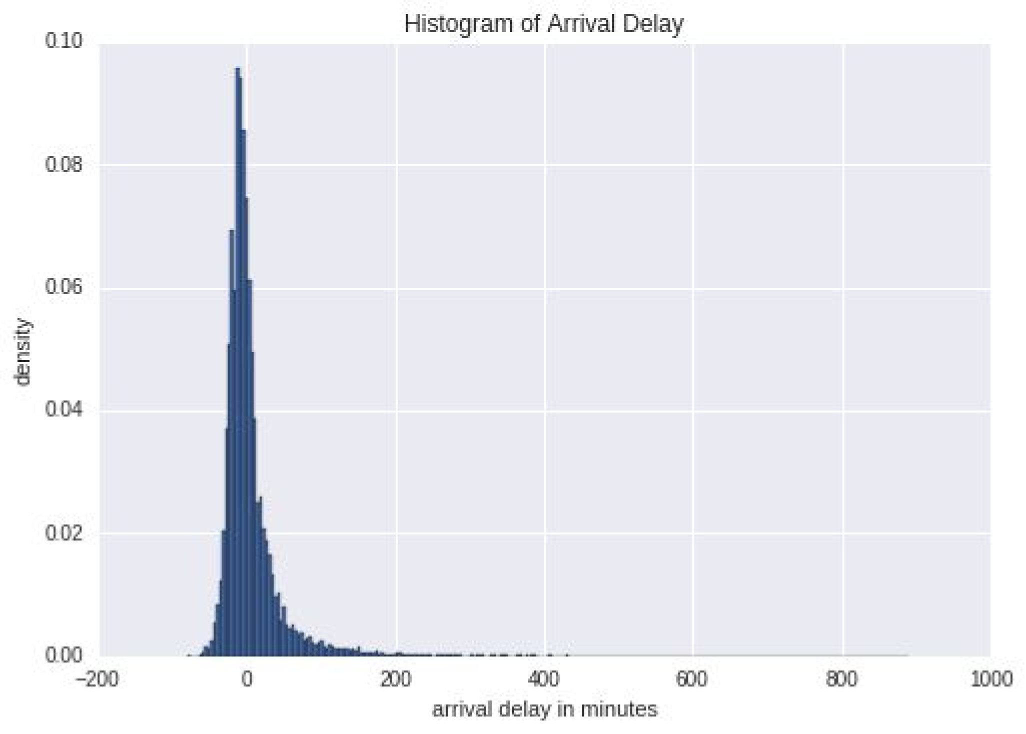
- Delay time series includes all flights in JFK in 2014-2015.

- Hardly to find any periodicity of this series, in other words, overall temporal trend of delays seems to be quite weak.

- One goal of this project is modelling the ‘outliers’, where delays more than 200 minutes.



Flights delay distribution



- Actually nearly 60% flights arrive before the schedule, among these early arrival flights, their average is 15 mins earlier.

- However, delays distribution is skewed: if delayed, on average 35 minutes is expected, and it can be as worse as hours (90% percentile).

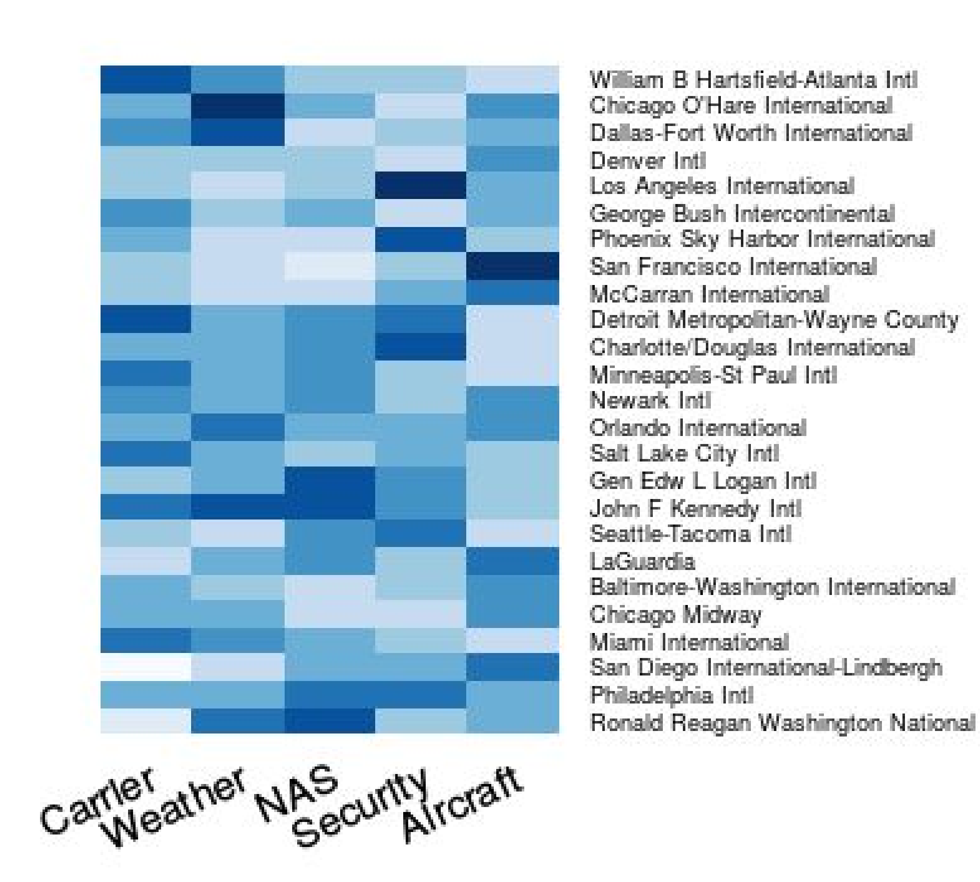
- Maybe this is why many of us remember these awful delays instead of on-time experiences.

Heatmap

- Weather delays are much more common in Chicago and New York (JFK) than in Phoenix and San Francisco.

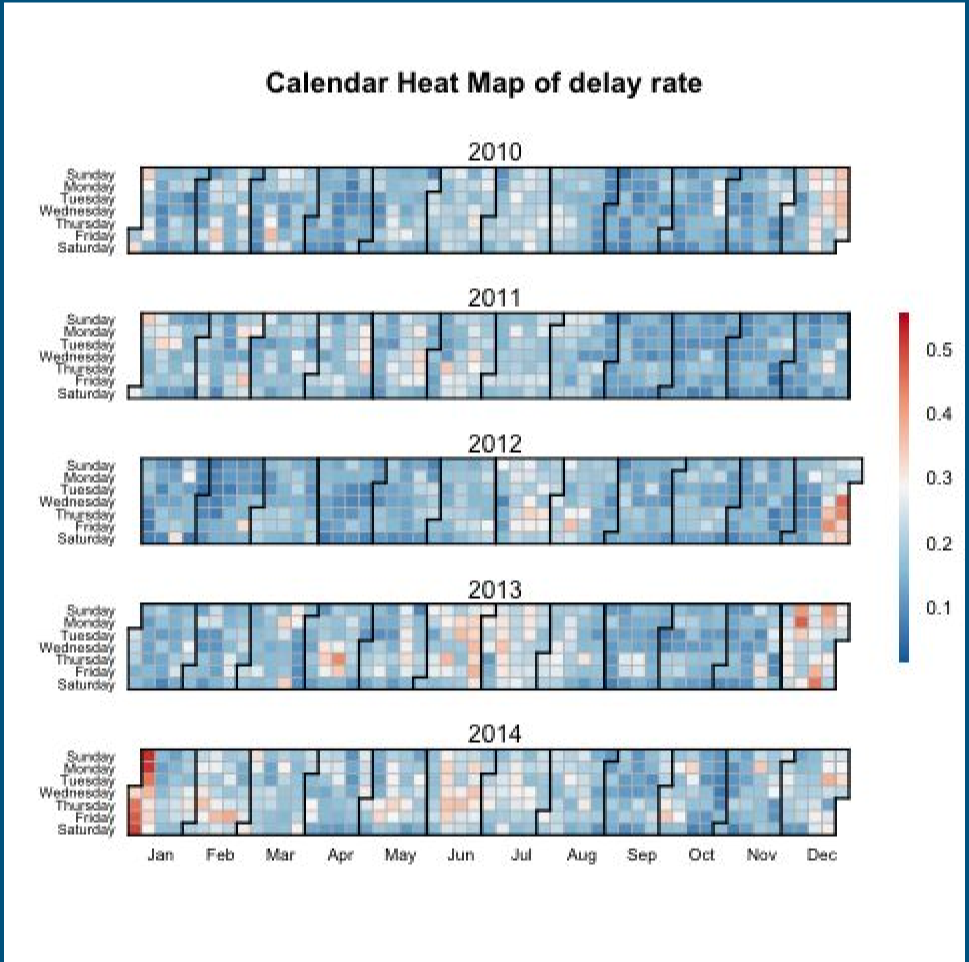
- Security is a major reason for delay in LAX but not in Denver.

- San Diego and Ronald Reagan Washington airports may have good carrier control management, resulting in less carrier delays.

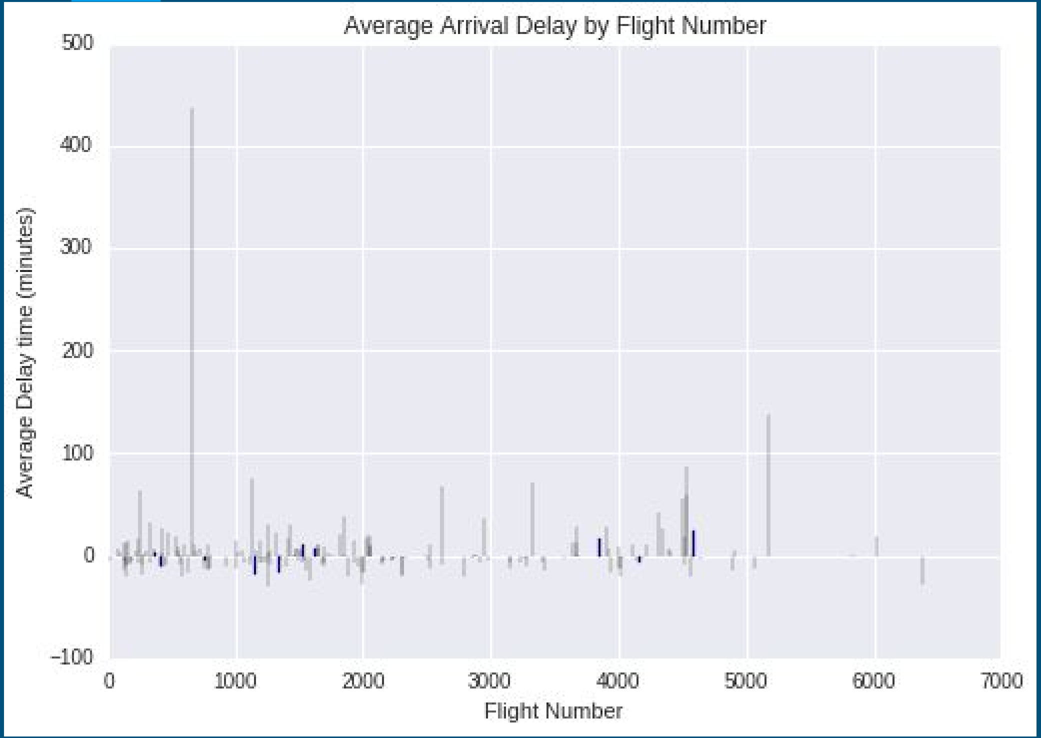


Calendar Plot of delay rates

- On each date, (# delays) / (# flights) is reported and colored.
- Higher rates in Jan, July and Aug, match the traveling seasons. Sometimes delays are overwhelming, e.g. in the first week of 2014, more than 50% flights were delayed.
- From 2012-2014, the rate goes up gradually. The causes of this needs to be verified in further studies.



Delays aggregated by Flight Number



- Flight number specifies a particular airline and route.
- Flight number is a good indicator for flight delays: some flights keep good on-time records, but some are notoriously bad.
- This feature will be used in advanced models next section.

Flight Delays Modelling

Methodologies

In order to build and test prototypes quickly, consider:

- Flights between 5 large US airports: Atlanta (ATL), Washington (IAH), New York (JFK), Los Angeles (LAX) and Chicago (ORD).
- Random sampling 10% of above data, use 2014 data as training data, 2015 data as testing data.
- Make predictions and access models based on (a) root mean square error (MAE), and (b) average absolute error (RMSE).

Naïve Approaches

Average of previous delays

- Report average delays on the same route.
- And same flight number?
- Same time? Same weather condition?
- Obviously, nearly impossible to find exact data points having the same conditions. This approach is limited.

Linear regression

- Regress flight delay on origin + dest airports + Flight Number + other features.
- However, tons of categorical variables makes regression computationally expensive.
- Easily overfitting.

Both models have MAE ~ 25 minutes and RMSE ~40 minutes.

Random forest approach

Random Forests regressions.

- Features include route, carrier, flight number and weather.
- Weather of both departure/ arrival airports closest to the scheduled departure time is considered.

Other benefits:

- Not using all the features each time making predictions to speed up the training.
- Prevent overfitting by averaging many decision trees.
- Reduce biases by selecting a few variables each time.

Results 1: Important features

Importance is measuring by the increase in mean-square-error of predictions (estimated with out-of-bag-CV) as a result of variable.

Most important features are:

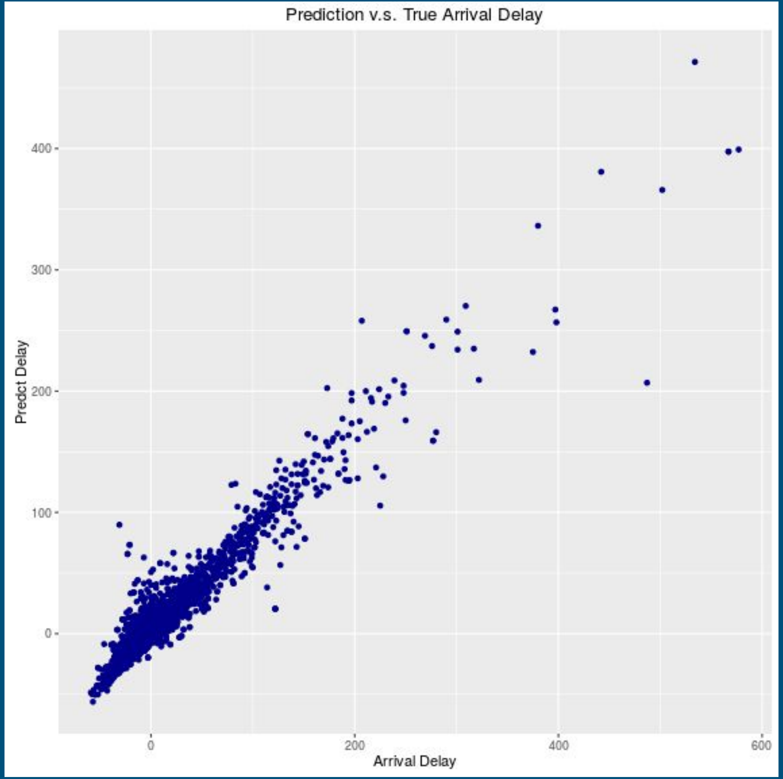
- Destination wind speed
- Destination dew point temperature
- Destination Pressure altimeter
- Carrier
- Origin Pressure altimeter
- Flight Number

Results 2: Predictions

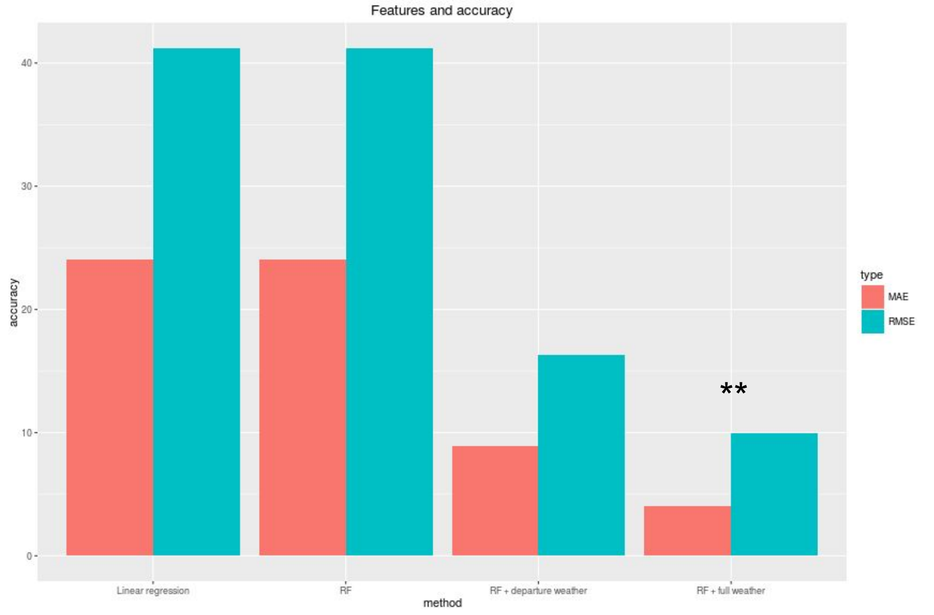
- Scatter plot of arrival delays vs predicted delays of the testing data.

- The random forest model forecasts early arrivals and short delays really well (prediction vs truth are on the x=y line).

- For long delays (>3 hours, less than 1% of data), the model is still able to make predictions with error ~30 minutes, achieving such accuracy for outliers is remarkable.



Results 3: Comparisons



- The chart: predictions mean absolute error (red) and root mean square error (green) of four models:
  - Linear regression
  - random forest (no weather)
  - random forest (+departure weather)
  - **random forest (+dept & destination weather)

- Weather data is extremely important for modelling flight delays. Without weather info, predictions can only reach 40 mins RMSE accuracy.

- Random forest full model has MAE 6 minutes and RMSE 10 minutes, >65% improvements from the naive approaches.

Conclusions

Summary and future work

- Mining useful information from massive flight and weather datasets, and demonstrate data visualization findings comprehensively.

- The random forest model predicts flight delays on average having less than 10 minutes , improving from 40+ minutes of empirical approaches.

- Similar approach can be used to model the cancellation rates (<1% of flights).

- The model can incorporate time series to capture temporal delays caused by traffic jams or special events such as Super Bowl.

- Modelling interactions between airports potentially will provide more instantaneous delay information.

Thank you

Any feedback would be greatly appreciated!

Appendix

- Bash scripts dealing with Bureau of Transportation data.
- Bash scripts dealing with ASOS weather data.
- Python scripts.
- R codes
- AWOS data https://mesonet.agron.iastate.edu/request/download.phtml
- Bureau of Transportation Flights Statistics.

- [1] all, M., Barnhart, C., Dresner, M., Hansen, M., Neels, K., Odoni, A., Peterson, E., Sherry, L., Trani, A. A., and Zou, B. (2010), “Total delay impact study: a comprehensive assessment of the costs and impacts of flight delay in the United States,” .
- [2] Total Passengers on U.S Airlines and Foreign Airlines U.S. Flights Increased 1.3% in 2012 from 2011, http: //www.rita.dot.gov/bts/press_releases/bts016_13