

Predicting Flight Delays

—

By: Sunny & Wes

Table of Contents

Introduction

Workflow

Model Selection

Results

Challenges

Introduction

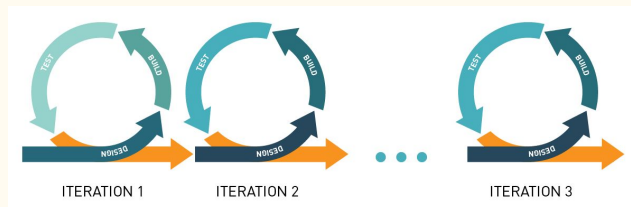
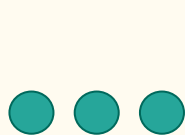
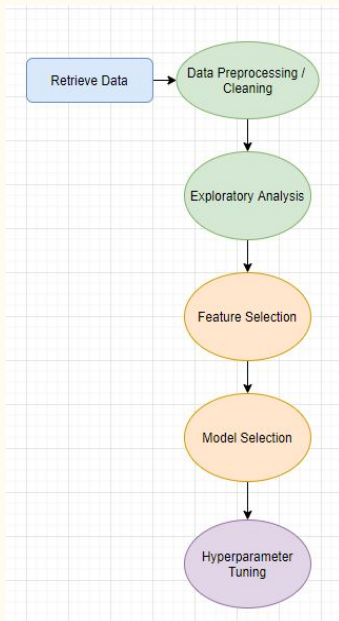
Company: Sunley Airlines

Problem: Customer satisfaction is down due to an increase in flight delays.

Solution: Machine Learning modelling to retrieve insights into the cause of these delays.

Workflow

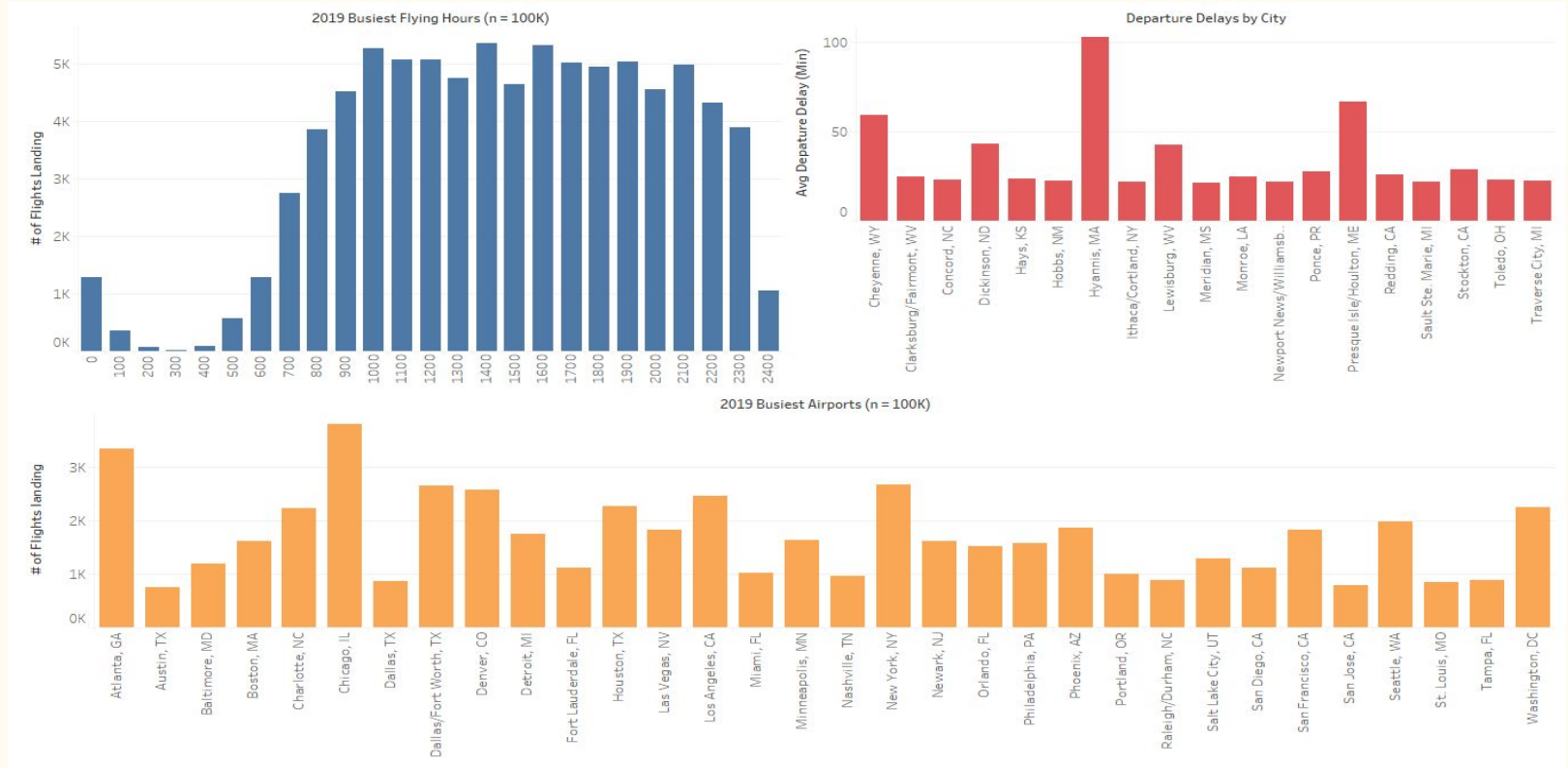
Model Process



= Final Model

- Adjust features
- Add weather data (type and severity)
- Merge with Fuel and Passenger tables

Potential Causes of Arrival Delays



Imbalanced Dataset / Outliers

Criteria: An arrival delay is defined as a delay greater than 15 minutes.

(<https://www.fly.faa.gov/flyfaa/usmap.jsp>)

Imbalance: 18.6% of our sample data is considered delayed.

Solution: Take a subsample of the data to perform our analysis.

Handling Outliers: Arrival delays that were greater than 180 minutes were removed.

Model 1 (Linear Regression)

```

=====
OLS Regression Results
=====
Dep. Variable:      arr_delay    R-squared:      0.014
Model:              OLS          Adj. R-squared: 0.014
Method:             Least Squares F-statistic:     28.93
Date:               Thu, 29 Jul 2021 Prob (F-statistic): 1.54e-50
Time:               12:37:40     Log-Likelihood:  -25866.
No. Observations:   18320       AIC:              5.175e+04
Df Residuals:       18310       BIC:              5.183e+04
Df Model:           9
Covariance Type:    nonrobust
=====

```

| | coef | std err | t | P> t | [0.025 | 0.975] |
|---------------------|-----------|---------|----------|-------|--------|--------|
| const | 1.561e-16 | 0.007 | 2.13e-14 | 1.000 | -0.014 | 0.014 |
| crs_dep_time | -0.0113 | 0.010 | -1.179 | 0.238 | -0.030 | 0.007 |
| arrival_hour | 0.0650 | 0.011 | 6.118 | 0.000 | 0.044 | 0.086 |
| arr_time | -0.0924 | 0.008 | -10.947 | 0.000 | -0.109 | -0.076 |
| actual_elapsed_time | -0.0648 | 0.020 | -3.256 | 0.001 | -0.104 | -0.026 |
| air_time | -0.0796 | 0.021 | -3.711 | 0.000 | -0.122 | -0.038 |
| distance | 0.0986 | 0.048 | 2.075 | 0.038 | 0.005 | 0.192 |
| miles_per_min | 0.0126 | 0.016 | 0.767 | 0.443 | -0.020 | 0.045 |
| total_taxi_time | 0.0452 | 0.009 | 4.828 | 0.000 | 0.027 | 0.063 |
| avg_dest_taxi_time | 0.0685 | 0.008 | 8.845 | 0.000 | 0.053 | 0.084 |
| dest_traffic | 0.0211 | 0.008 | 2.796 | 0.005 | 0.006 | 0.036 |

```

=====
Omnibus:      20711.105    Durbin-Watson:      1.959
Prob(Omnibus):    0.000    Jarque-Bera (JB):    2366131.014
Skew:            5.845    Prob(JB):            0.00
Kurtosis:        57.434    Cond. No.            4.44e+15
=====

```

Model 2 (Random Forest Regressor)

Feature Engineering

- Expected Miles per Minute
- Total Taxi Time
- Destination Traffic (Number of flights landing at each airport)
- Average Origin Taxi Time

Results

- $MAE = 33.7845$
- $R^2 = 0.5008$

Model 3 (Random Forest Regressor)

Feature Engineering (Exclusions)

- Total Taxi Time
- Destination Traffic

Feature Engineering (Additions)

- Average Destination Traffic Time
- Average Origin Departure Delay

Results

- $MAE = 12.5642$
- $R^2 = 0.5905$

Results

Feature Significance

- Average Origin Delay significantly improved the model.

Potential Scheduling Adjustments

- Prior to finalizing flight details, add additional time when departing from cities with a large departure delay.
- Plan flights from 12am-7am for the cities with the largest departure delays.
- Preemptively warn customers of potential delay to increase customer satisfaction

Challenges

Data Cleaning/Exploration

- Duplicate Data
- Missing Values
- Joining tables

Feature Selection/Engineering

- Over 80 different features
- Finding correlated features



References

- <https://github.com/lighthouse-labs/mid-term-project-I>
- <https://www.fly.faa.gov/flyfaa/usmap.jsp>
- https://en.wikipedia.org/wiki/Flight_length
- [Bureau of Transportation Statistics](#)