Predicting Departure Delay Durations

Denver RTD Light Rail

Jason Summer

2020

Agenda

01 Executive Summary

02 Problem Statement and Proposed Solution

03 Data Wrangling Effort

04 Data Exploration Analysis & Inferential Statistical Analysis

05 Predictive Modeling Evaluation

06 Conclusion & Opportunities for Improvement

Executive Summary

Improve train efficiency and ridership through more transparent and widely available train departure times

A year’s worth of RTD light rail departures were studied, alongside of surrounding weather and local sporting events. Correlating factors were identified, but more importantly 2 predictive models were pursued.

One model with a goal of supporting real-time predictions for immediate riders showed promising results. This model was able to estimate whether train departures would be 5-10, 10-15, or 15-20 minutes delayed with roughly 80% accuracy and 30-60 minutes delayed with 89% accuracy.

While areas of improvement are highlighted following the subsequent analysis, this real time model would be an effective addition to any real-time rider alert system.

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Light Rail Challenges

RTD faced increasing adversity in 2019 impacting train performance, ridership, and subsequently the brand's reliability.

51% of train departures are over a minute late with the average train 1 minute and 42 seconds delayed.

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NEWS > TRANSPORTATION

RTD cancels about 100 light rail trips Monday, days ahead of discussion on driver operator shortage

RTD says it's working to recruit more people, address service issues

NEWS > TRANSPORTATION

Frozen switch leads to 15 to 20 minute delays for light rail passengers

NEWS > TRANSPORTATION • News

More than 500 Denver International Airport flights canceled or delayed as snow rolls in

RTD bus and light rail service delays reported

NEWS > TRANSPORTATION • News

Icy conditions slow Denver's bus, light rail and commuter rail systems

Traffic crashes on icy highways close major highway lanes during commute

NEWS > TRANSPORTATION

Light rail service restored after power issues disrupted Wednesday rush hour service

Train riders should plan for additional travel time between affected stations

Evolving Challenges

Driver Shortage

In November 2019, RTD surveyed riders to determine if service cuts or delays and cancellations are preferred in wake of a driver shortage

Weather Conditions

Riders seeked refuge in public transportation during harsh weather conditions but experienced unexpected delays without notice

Outages

While rare, outages have left unknowing riders stranded, as seen on September 11th, 2019.

Real Time Signage

RTD's mobile ticketing app and real-time location website are limited in their delay notifications. Station signage reports schedule times. RTD has recommended enrolling in email alerts or following their twitter account.

Proposal

Provide RTD and riders alike with model outputs that can provide estimated delays in future train departures

Input Data Sources

Past Performance

Approximately 30% of light rail vehicles' and all commuter rail vehicles' station departures are tracked with some days removed by RTD due to extreme weather. The data was sourced directly from RTD.

Weather

Hourly weather was sourced from visualcrossing.com for 13 cities in Colorado. Data included information about ice, snow, rain, wind, heat index, temperature, humidity, etc.

Local Events

The starting day and time of games hosted locally by the Denver Nuggets, Colorado Avalanche, Denver Broncos, and Colorado Rockies were sourced from the Denver Post, sports-reference.com, and Altitude TV. Some schedules spanned multiple seasons.

Prior Delays

From the RTD data itself, the departure delays at prior stations were derived and included as lag feature consideration.

Currently, RTD's mobile ticketing **app does not alert riders of disruptions** and it cannot send texts. The **real-time location website is limited** and the electronic signs at **stations show scheduled times** instead of updated times.

RTD has indicated **investment in improved real-time alerting,** which was estimated to be a couple months out as of September 2019. Being able to **predict both immediate delays and high-risk delays further in the future** could fill the void of real-time and accurate delay updates or improve any current efforts to do so.

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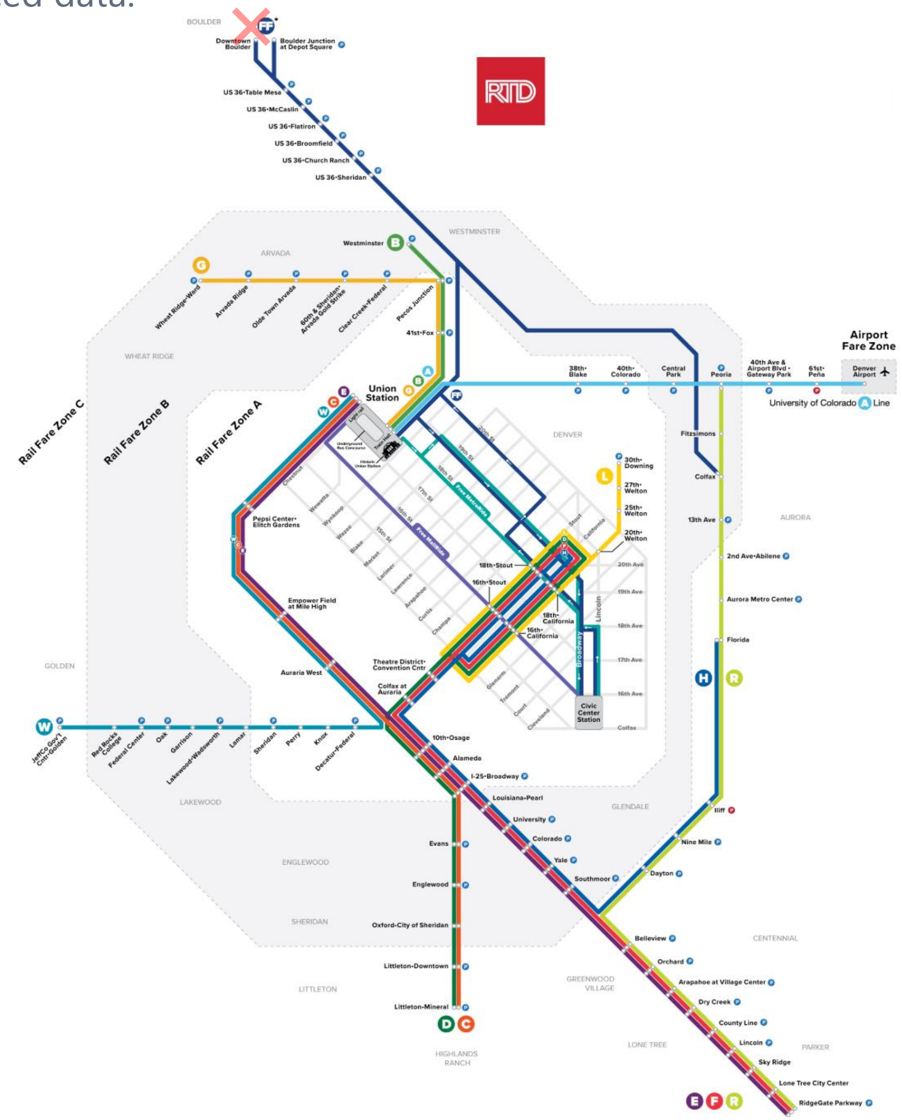
Key RTD Data Wrangling

Pandas, numpy, matplotlib, seaborn, datetime, and dateutil packages were used for manipulation of sourced data.



Station Identifier

A location mapping file was provided, however, not all station codes were accounted for from the rail data. A one source of truth of readable station names were coalesced from the mapping file’s names and rail data’s native cross street information.

Arrival and Departure Times

Dates of scheduled station departures were merged with timestamps of actual arrivals and departures. The date stamps were adjusted accordingly in instances that the arrival/departure straddled midnight. New wait times and departure delays were calculated.

Time Delta Fields

Time delta fields including station dwell times, delay durations, and delay flags were re-calculated based on new timestamps.

End of Line Departures

Evaluation of the native sort order field indicated that some stations were missing, others out of order, and departure delays were captured for final stations. Thus, end of line stations were flagged to avoid skewing departure predictions

Unnecessary Field Removal

RTD uses a similar data schemas to track non-rail vehicles. These extraneous fields and other unnecessary fields were removed for size reduction.

Key Weather Data Wrangling

Pandas, numpy, matplotlib, seaborn, datetime, and dateutil packages were used for manipulation of sourced data.

NOAA Weather by County

Initial weather information was obtained from NOAA and sourced by county. Empty, duplicative, and inaccurate county values were researched and updated.

Visual Crossing Weather by City

NOAA weather data was scarce and replaced by data sourced from visualcrossing.com by city. Again, city values had to be researched and updated and dummy indicator fields were created for 22 unique weather descriptors.

Weather Data Merge

The visualcrossing.com weather data were merged into the train dataset by applying the closest hourly record of weather data to each scheduled train station departure time.

Weather Descriptors

A combination of 22 unique weather descriptors were included in the weather data, such as ‘thunderstorm’ or ‘hail’. 22 hot key indicator columns were initially created for each unique description. Subsequently for modeling preparation, ordinal weather fields were created for varying degrees of rain, ice, and snow.

Hourly Weather Data

- precipitation type and volume
- snow type and depth
- ice / hail type
- wind speed
- relative humidity
- temperature
- visibility

Key Sporting Event Data Wrangling

Pandas, numpy, matplotlib, seaborn, datetime, and dateutil packages were used for manipulation of sourced data.

Rockies Schedule Sourcing

The 2019 Rockies game scores were obtained from sports-reference.com. However, start times were not included and were subsequently sourced separately from the Denver Post. Changes in the regular schedule were identified when these 2 sources were merged.

Rockies Schedule Corrections

Research indicated 2 double-header days were played after prior game cancellations. Additional validation was performed by matching the opponent field of both the score and schedule files (mentioned above).

Away Games

All away regular and postseason games were removed from the Rockies, Broncos, Avalanche, and Nuggets schedules.

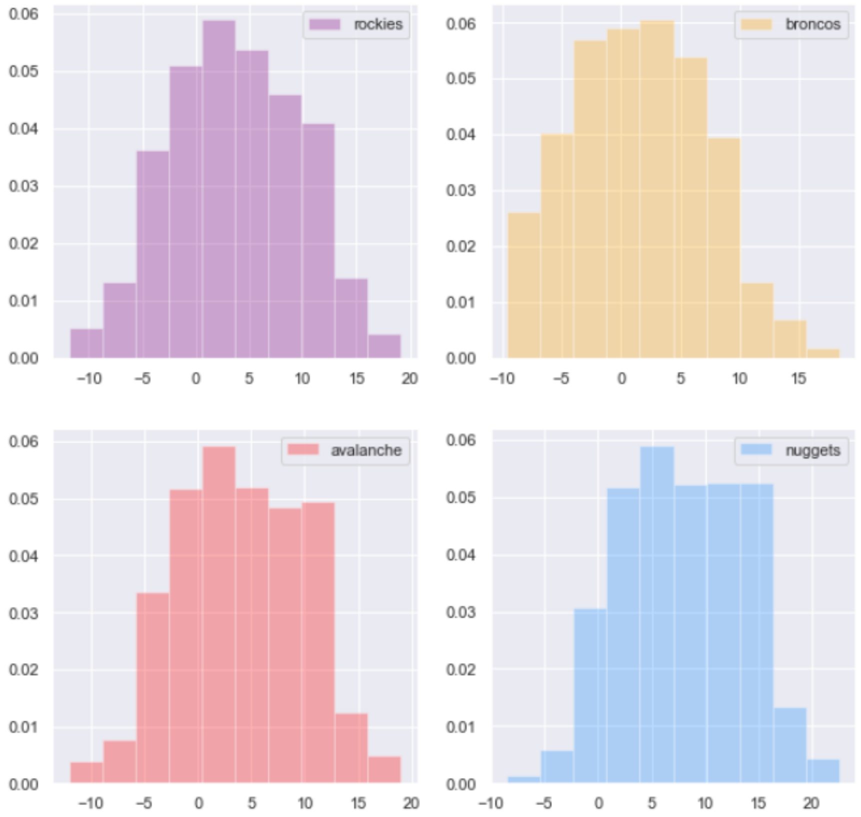
Consistent Datetimes

All game start times were re-formatted to a 24-hour clock. The Rockies data required additional correction for an inconsistent format and the 2nd game in a double-header did not have a published start time and was eventually removed. The Broncos schedule required conversion to local time.

Hours Until Game Time

During modeling preparation, new fields were introduced to capture train departures occurring on the same day as local professional sporting games. The field captured the hours between scheduled departure and game start times.

Hours between Scheduled Departure and Sporting Events



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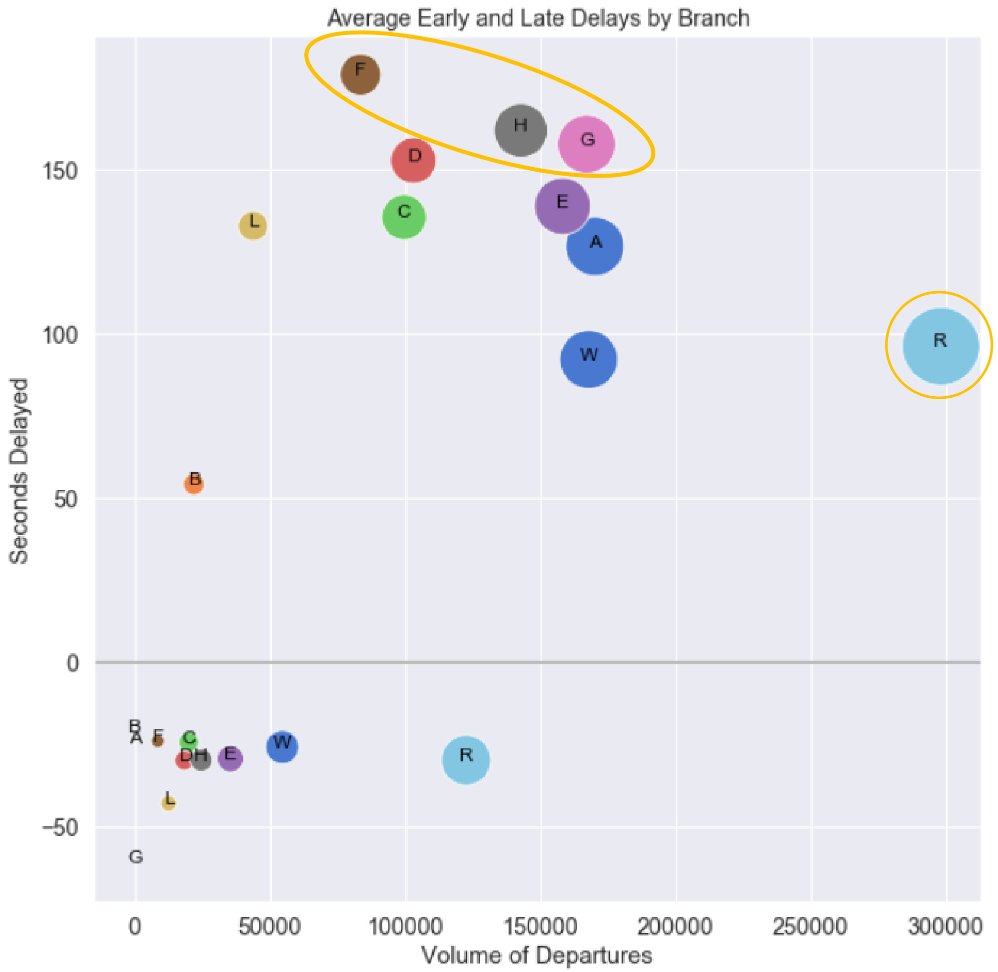
Route Analysis

Certain routes show far more common delays while others reveal more extreme delays

Route Comparison

Route / Line	Overall Avg Seconds Delay
A	127
B	54
C	108
D	125
E	108
F	160
G	157
H	133
L	93
R	59
W	63



Nearly every route shows an average departure above 1 minute.

While lines F, G, and H show the highest average delays, respectively, F does not feature the highest volume of delays. On the contrary, G and H shows a high number of departures, thus extrapolating the impact of their delays.

Line R seems to feature the most departures with the average delayed departure around a minute and a half and the average on-time/early departure roughly 30 seconds before scheduled.

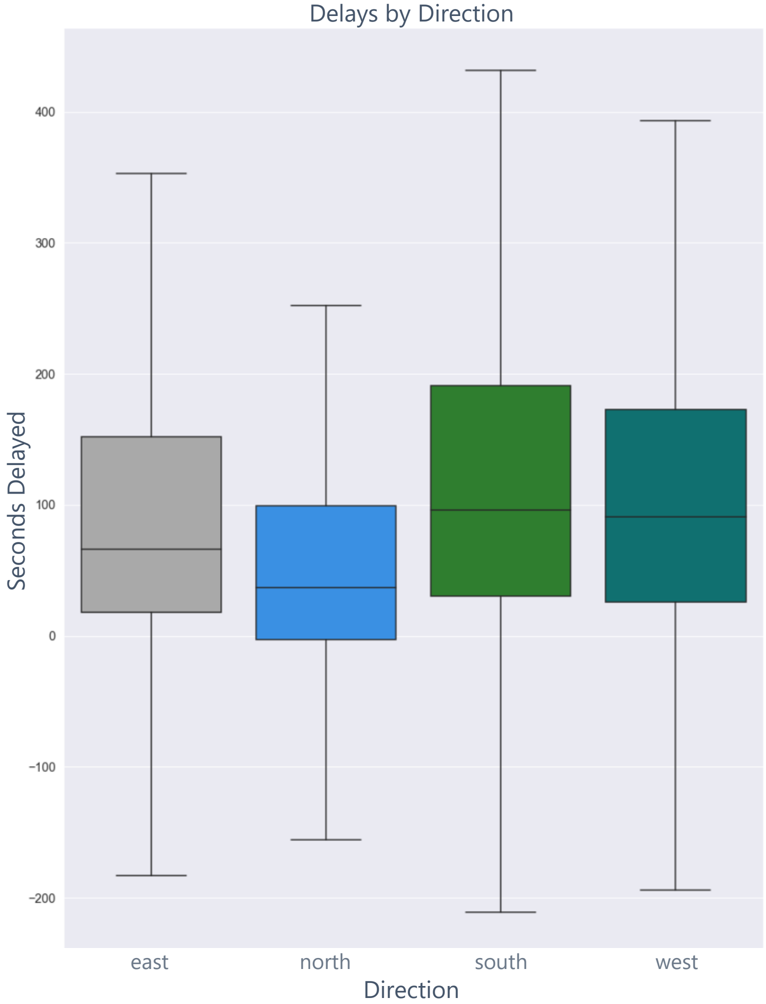
A one-way F test indicated a statistical significance (p-value ~ 0.00) in the difference in average departure delay among the different lines.

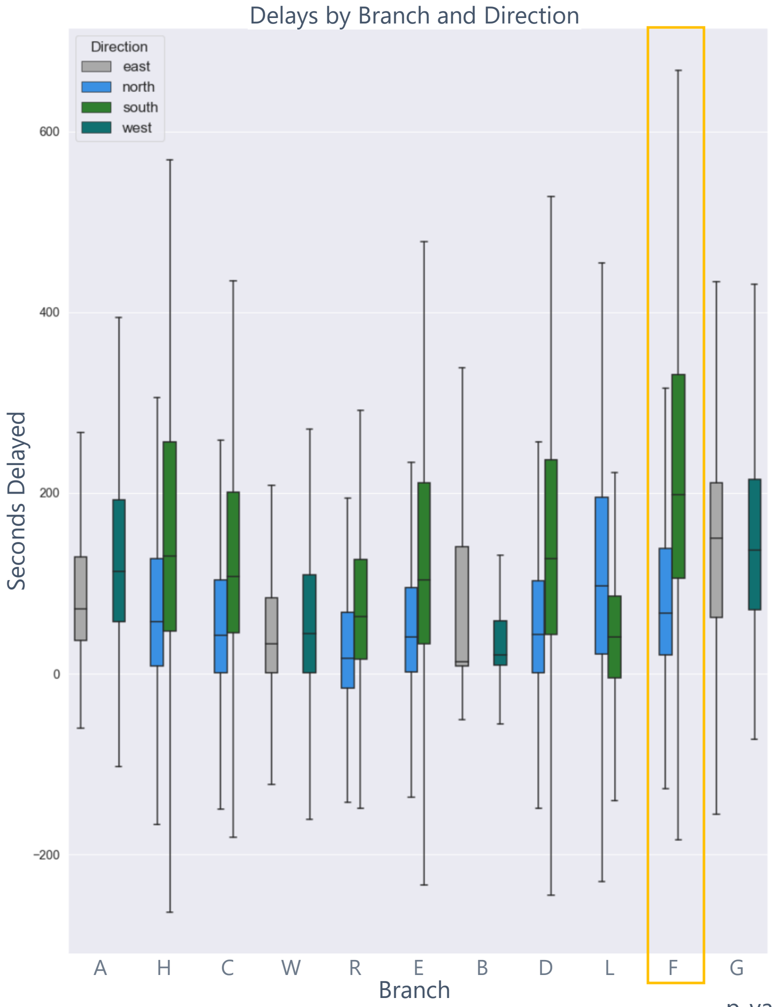
Left chart considers the average of both early and late departures
p-value of ~0.0 indicates the numpy minimum threshold of 1E-16 was exceeded

Direction Analysis

Train direction affects on-time departures, indicating the same route in a different direction can be less reliable

Direction Analysis





Simply comparing train direction shows significant overlap. However, northbound performance seems to show the lowest delays while southbound trains show the highest delays and most variability.

However, comparing train performance by direction for each line shows much higher separation between north and southbound trains. The greatest separation can be seen with line F.

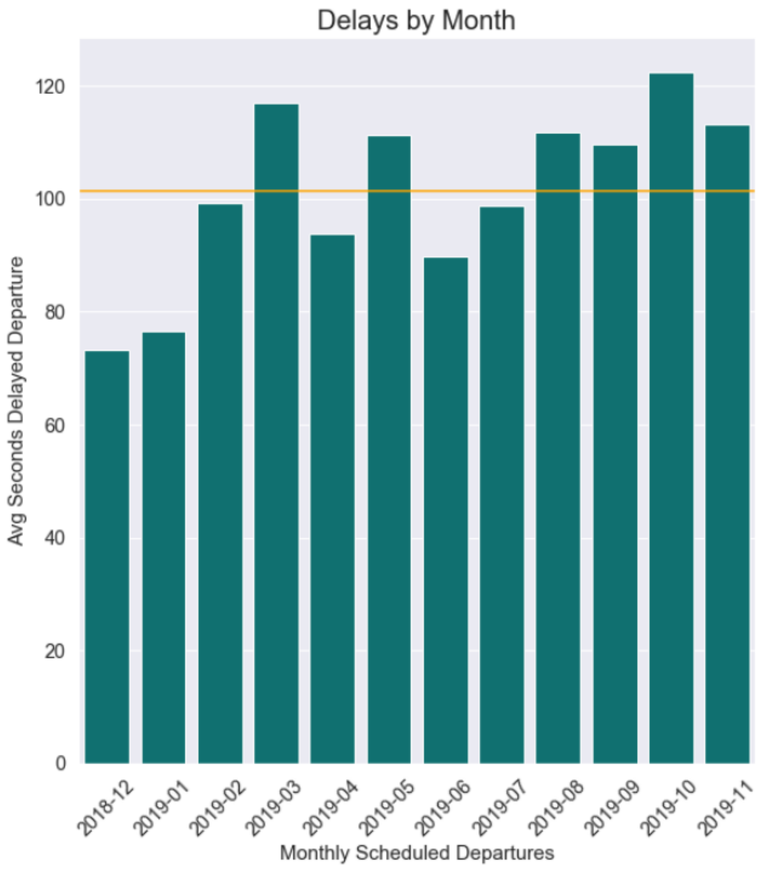
A permutation resampling technique used to compare the mean delay of southbound trains with all other directions resulted in a p-value of ~0.00, indicating a significant difference between southbound trains and other directions.

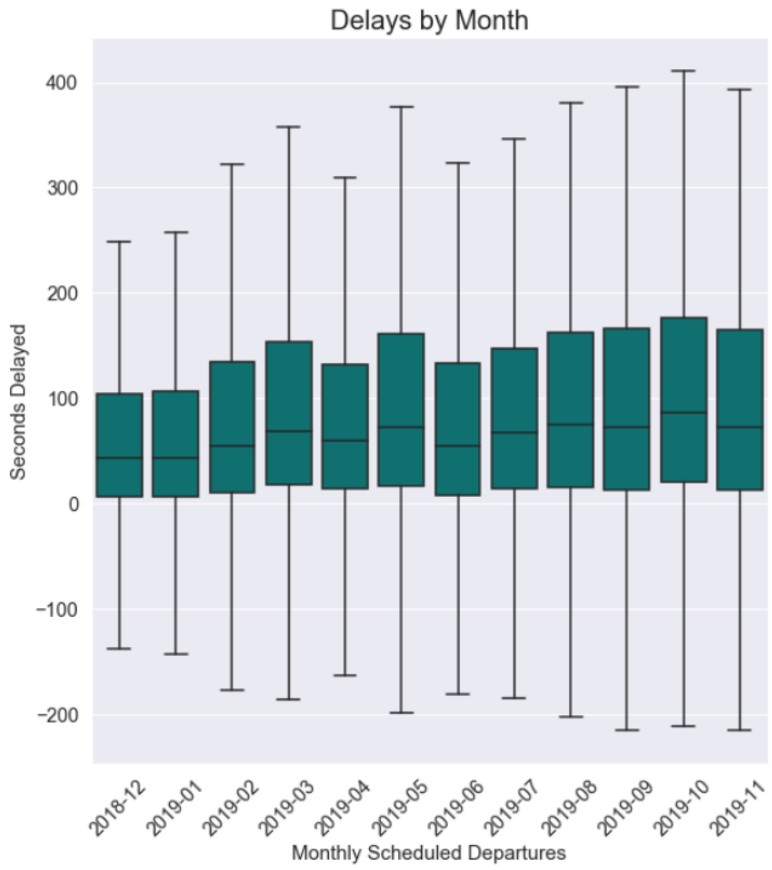
p-value of ~0.0 indicates the numpy minimum threshold of 1E-16 was exceeded

Time of Year Exploration

While seasonality cannot be confidently determined with 12 months of data, there is a slight uptick in delays around Q4 2019

Calendar Analysis





There seems to be differences among the months. However, year-over-year is not possible for comparison.

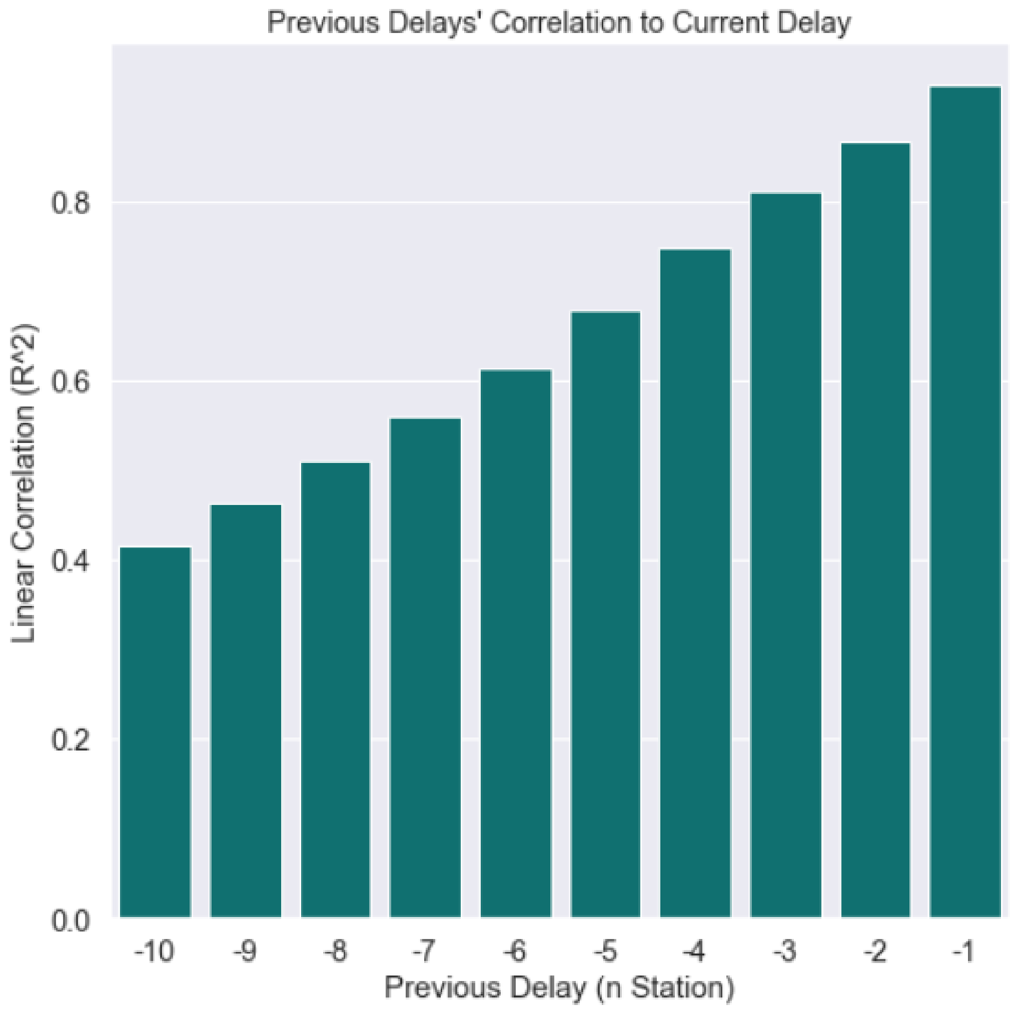
Interestingly, September through November 2019 show higher than average delays. Media circulation of RTD operator shortages started around September and October 2019.

The below monthly rolling delay view shows this uptick more clearly.

Prior Delay Impact

As expected, immediately prior delays shows strong correlations to the current delay, but it is not constant across the route

Prior Delay Lag Indicators



The bar plot to the left shows the linear correlation between previous delays (up to the 10th prior station) on the current delay.

The average route has ~12 stations. However, showing the prior 10 delays shows an obvious pattern, in which the correlation increases as you approach the current delay. Similarly, prior stations further back are less linearly correlated to the current delay.

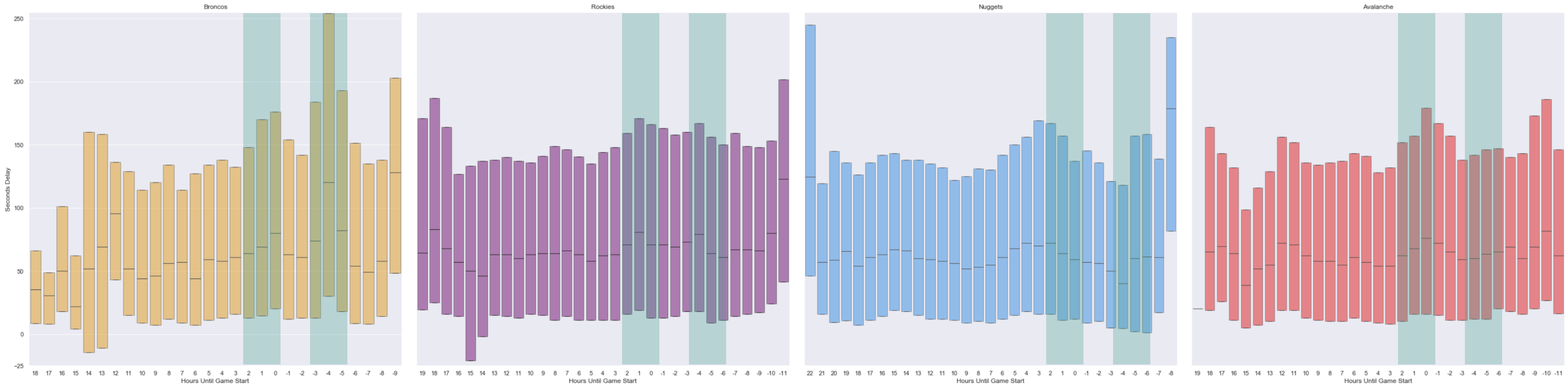
This pattern of increasing correlation indicates that delays in a line are not constant as one may expect. Instead, trains operators seem to make up for early delays as they progress in their route.

Some stations are marked as 'free running' indicating operators may leave earlier than scheduled. Providing notice of early departure can be just as important as late departure in many situations.

Local Sporting Event Impact

Identifying the departures that occur in the hours leading to the beginning of local sporting events and those following the sporting events may indicate an influx of riders and subsequent delay spikes.

Hours before Game Time



bars reflect the 25-75 percentile range, i.e. the middle 50% of departure delays

Delays tend to be rather variable throughout the entire dataset. However, showing delays before, during, and after local sporting events (occuring on the same calendar day), may allude to certain spikes in delays.

The 2 hours leading up to the beginning of Broncos and Avalanche games show obvious spikes in delays. A similar but less obvious pattern is seen with Rockies games. Interestingly, there is also a spike around where Broncos games would likely end, approximately 3-5 hours after kickoff.

Weather Impact

A simple comparison of clear days with snow or rainy days indicates a statistically significant difference in average delays

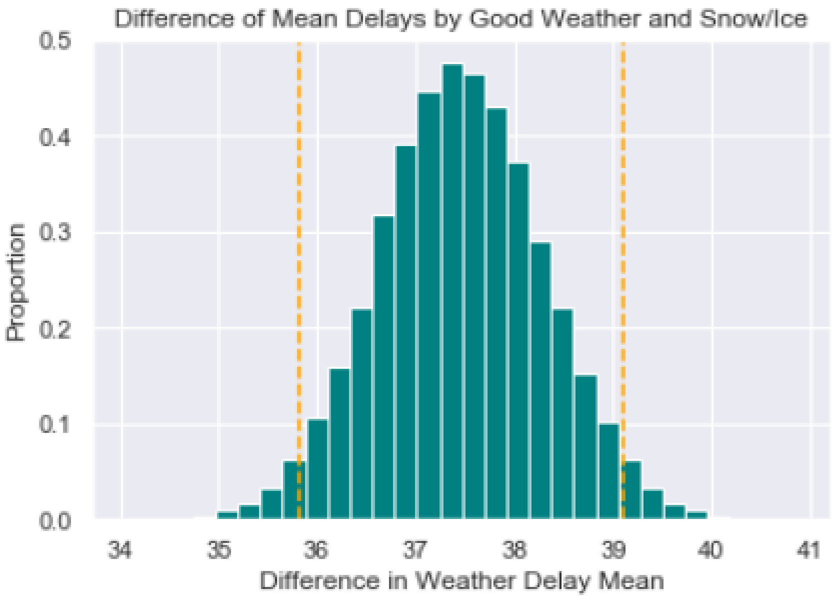
Fine Tuning and Comparing Weather

Rain Description	Ordinal Rank
Light Drizzle	1
Drizzle	2
Heavy Drizzle	3
Mist	4
Light Rain	5
Rain	6
Heavy Rain	7
Rain Showers	8
Thunderstorm	9

Ice Description	Ordinal Rank
Light Freezing Drizzle/Freezing Rain	1
Light Freezing Rain	2
Freezing Drizzle/Freezing Rain	3
Hail Showers	4

Snow Description	Ordinal Rank
Light Snow	1
Light Rain and Snow	2
Snow	3
Blowing or Drifting Snow	4
Heavy Snow	5

In addition to the quantitative fields for wind, temperature, etc., key weather descriptions were converted to ordinal indications of rain, ice, and snow conditions.



Using bootstrapped samples of 50,000, the mean delay of clear weather departures were compared to the mean delay of departures occurring around snow or icy conditions.

The 95% confidence interval of the difference of these means lies between the orange lines. The exclusion of 0 in this confidence interval indicates a statistically significant difference in the mean delays during clear and snowy/icy conditions.

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2-Model Approach

Differentiated by feature selection, a real time prediction model and a future prediction model were pursued using random forest regressors

Models Considered

1 Real Time Delay Model

Goal: Update riders with probabilities of delays for immediate and upcoming train departures

- current weather conditions
- local events and gatherings
- historic train performance
- preceding route delays

2 Future Delay Model

Goal: Help riders plan accordingly when the risk of extreme delays multiple hours or days in the future is high

- weather forecast
- local event schedules
- historic train performance

Algorithms Considered

While the Real Time Delay data was used in all 3 algorithms, the Future Delay data was only evaluated in the Random Forest algorithm as performance was lower than expected.

1 Lasso Linear Regression

Tuning: alpha constant for regularization

2 Random Forest Ensemble

Tuning: max_depth and prediction time comparison

3 Extreme Gradient Boosting

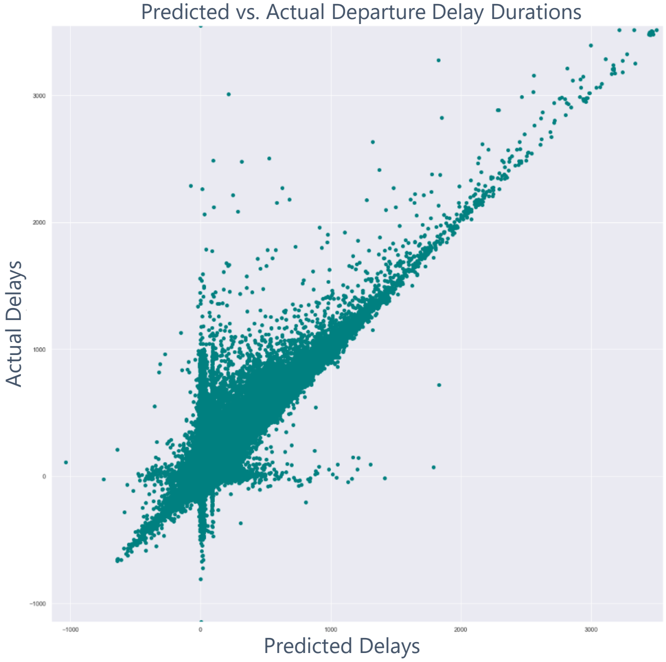
Tuning: max_depth, min_child_weight, gamma, colsample_bytree, subsample, reg_alpha, learning_rate, n_estimators

Real-Time Model Performance

Most of the prediction error lies between on-time departures and 1000 seconds delayed. In these high error scenarios, actual delays are often much greater than prediction as these may be due to unforeseen circumstances not discernible in the data, such as maintenance issues

Lasso Linear Regression

The regularization alpha was tuned using 6% of the data and 3-fold cross validation, while final training was done with 24% and predictions made on 70% of the data.



The summary mean squared error was 2373 or ~49 seconds. This was used as a baseline to improve upon for the models on the right.

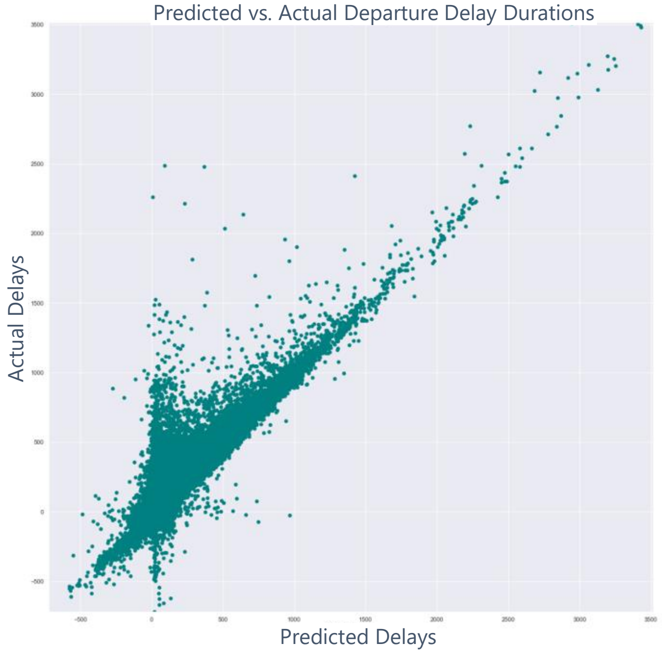
Random Forest Bagging

While the linear regression was rather effective, this tree-based ensemble method was explored with tuning of the max depth hyperparameter. The same training, validation, and testing samples and approach from lasso were used.

This method with rather minimal hyperparameter tuning resulted in an improved mean squared error of 1999 or ~ 47 seconds. Due to the high runtime of this model, prediction times for multiple max depths were compared.

Extreme Gradient Boosting

Thorough hyperparameter tuning with a small sample of 10,000 records and 3-fold cross validation was conducted for this tree-based boosting algorithm. Final training was done with 70% and predictions on the remaining 30%

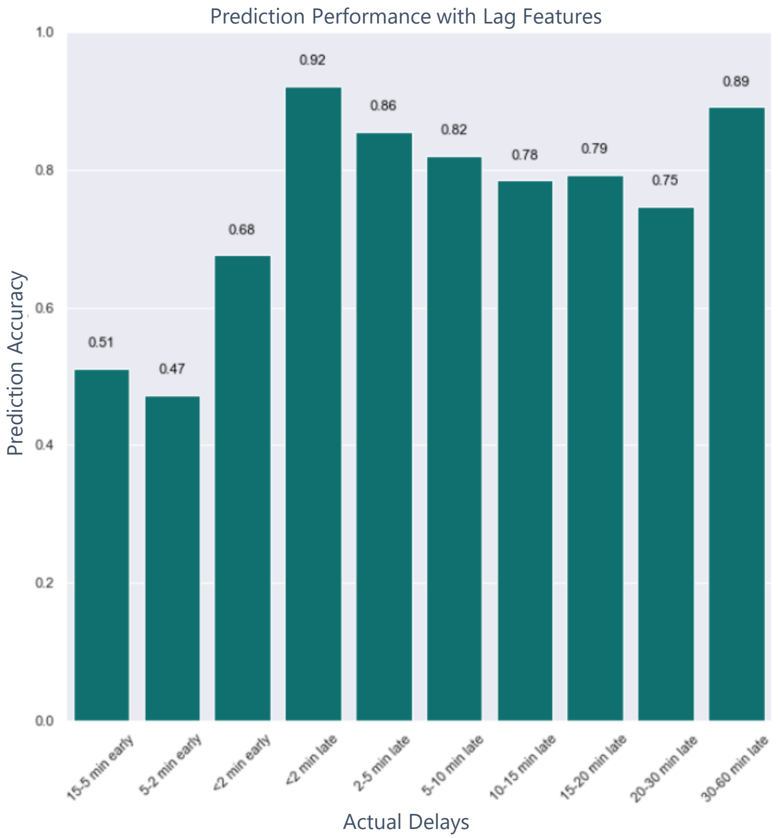


Tuning max depth, min child weight, gamma, colsample bytree, subsample, reg alpha, learning rate, n estimators resulted in an improved mean squared error of 1916 or ~ 44 seconds.

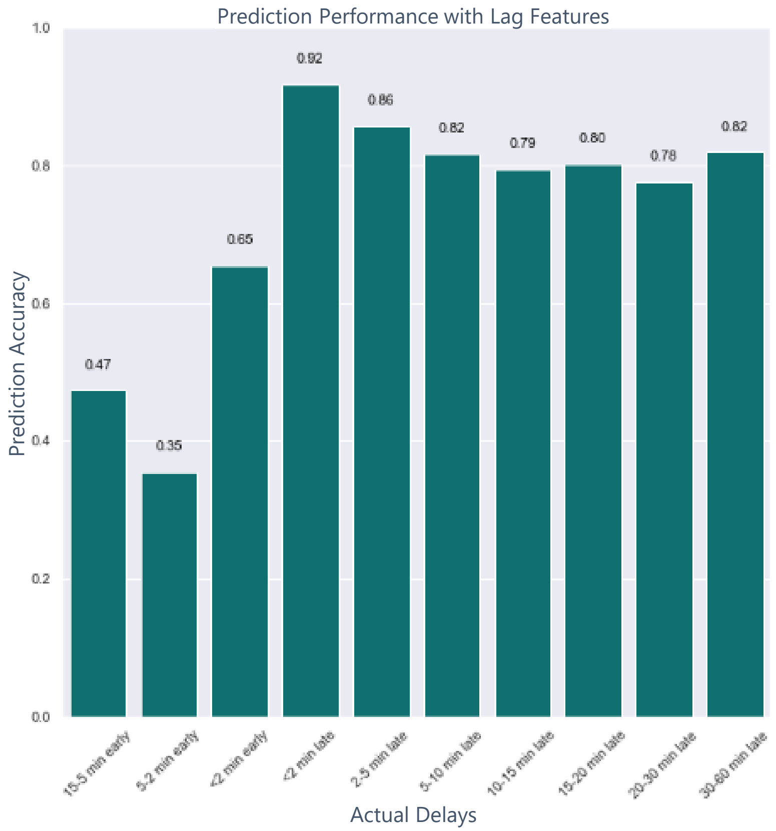
Model Evaluation

Categorizing departure delays into reasonable ranges shows prediction opportunity for delays between 2 minutes and 60 minutes using the real-time model

Random Forest Bagging



Extreme Gradient Boosting



Cutting delays into more digestible time estimates, as shown in the bar chart, indicates that delays between 2 minutes and 60 minutes can be appropriately categorized into their respective range with around 80% accuracy using either tree-based model.

Assuming model training is completed prior or during downtime, predictions could be made departure-by-departure in real time. This model could thus be used to update riders' probability distributions of potential delays as trains near.

The future delay model, however, did not perform well without the lag features included in the real-time model. See Appendix for similar benchmarking of this model and the Opportunities for Improvement section for ways to improve both models.

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Conclusion

The "real-time" predictive model(s) described above was able to **categorize delayed train departures as occurring 2-5 minutes, 5-10 minutes, 10-15 minutes, 20-30 minutes, and 30+ minutes with 78-89% accuracy**. The output of such predictions, and their associated probabilities, **would be an effective addition to any real-time rider alert system** deployed by RTD.

Opportunities for Improvement

Improved RTD Data

More comprehensive and inclusive RTD data would provide more representative train information.

Additional Local Events

Widening the consideration of local events, such as festivals, would further expand the model and its usage.

Seasonality Studies

Multi-year data would help to understand prospective changes due to seasonality and operator shortages in late 2019 and onward.

Alternative Time-Based Features or Models

Alternative time-based features or neural networks could have been used specifically for time-based components.

Ridership Information

Having estimated ridership would allow determination of capacity's affect on delays and identify high impact areas and times.

Geospatial Data

Including a spatial analysis of routes would allow assessment of impact from distances between stations and identify high variance areas.

Appendix

Future Delay Model Output