



Predicting the Price of an Uber/Lyft ride

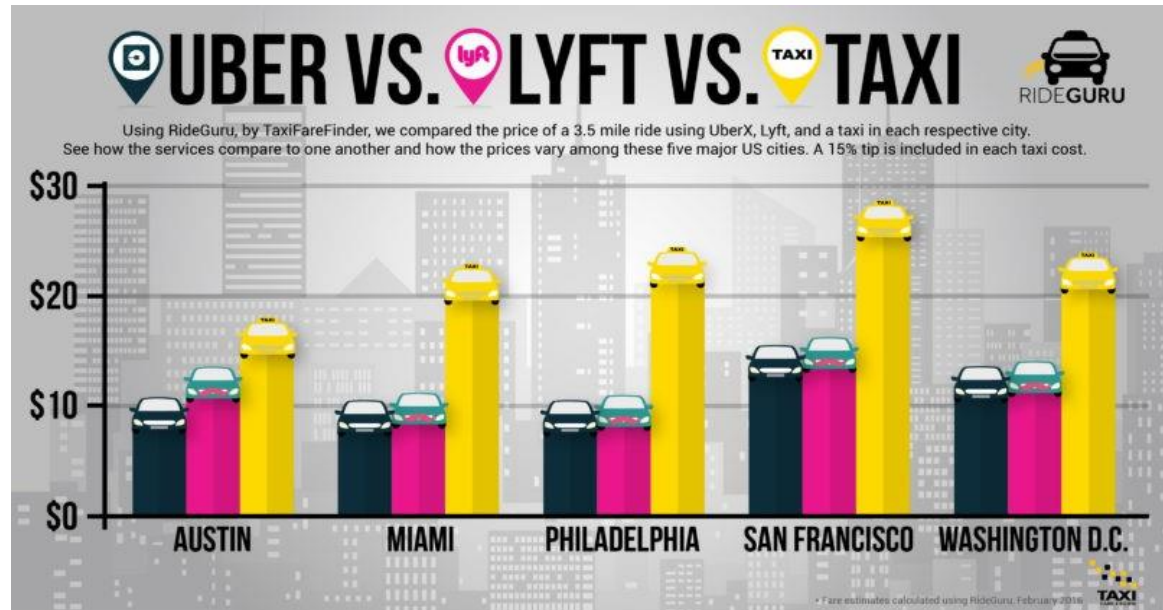
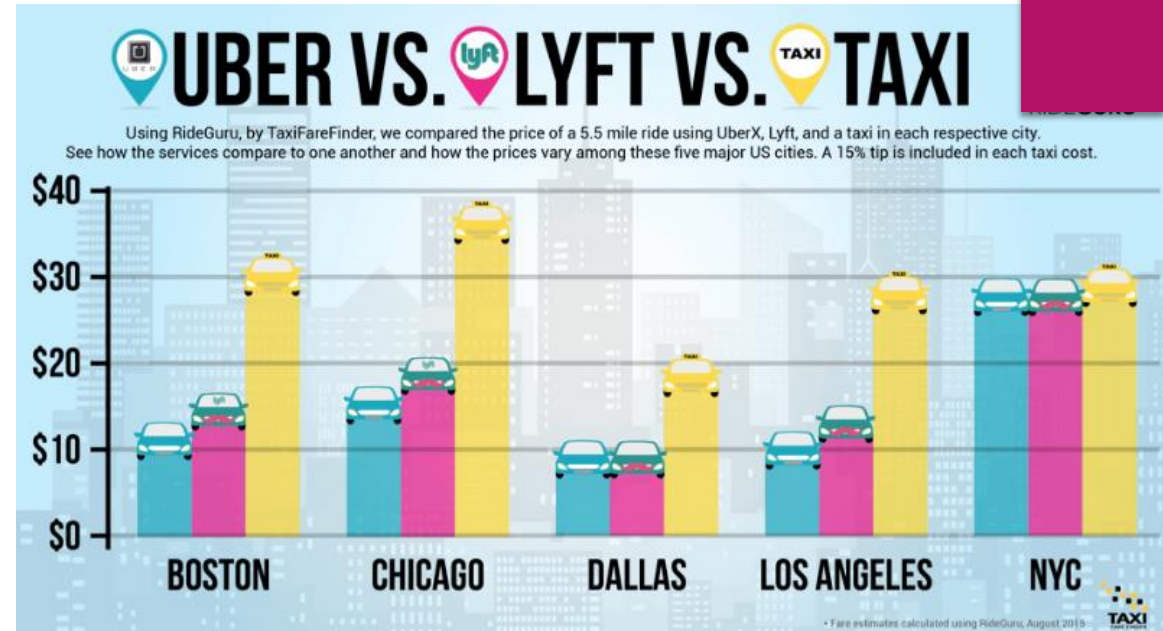
BY DEVESH GOKALGANDHI

THANKS TO SPRINGBOARD MENTOR: NADAV RINDLER

The Problem

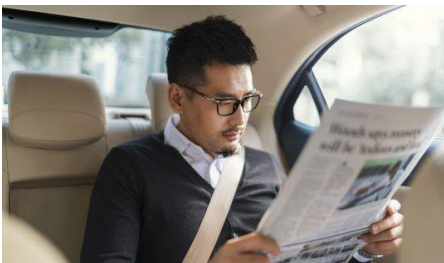
- ▶ Uber and Lyft dominate the ride-service industry, with over 100 million users across both applications.
- ▶ Rides, offered by these applications, are a much cheaper alternative to standard yellow taxis in major cities.

What factors influence the price of Uber/Lyft rides?



Who might care?

Riders



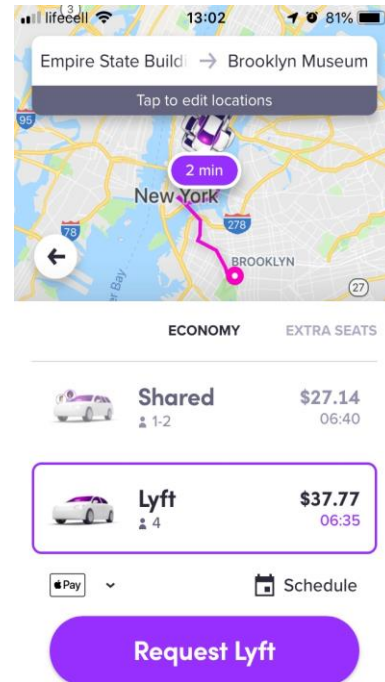
Competing Ride-Service Applications



What factors might influence price?

► Ride Factors

- Distance
- Surge-Multiplier
- Ride-Type
- Pickup/Dropoff Location
- Pickup Time of Day
- Pickup Day of Week



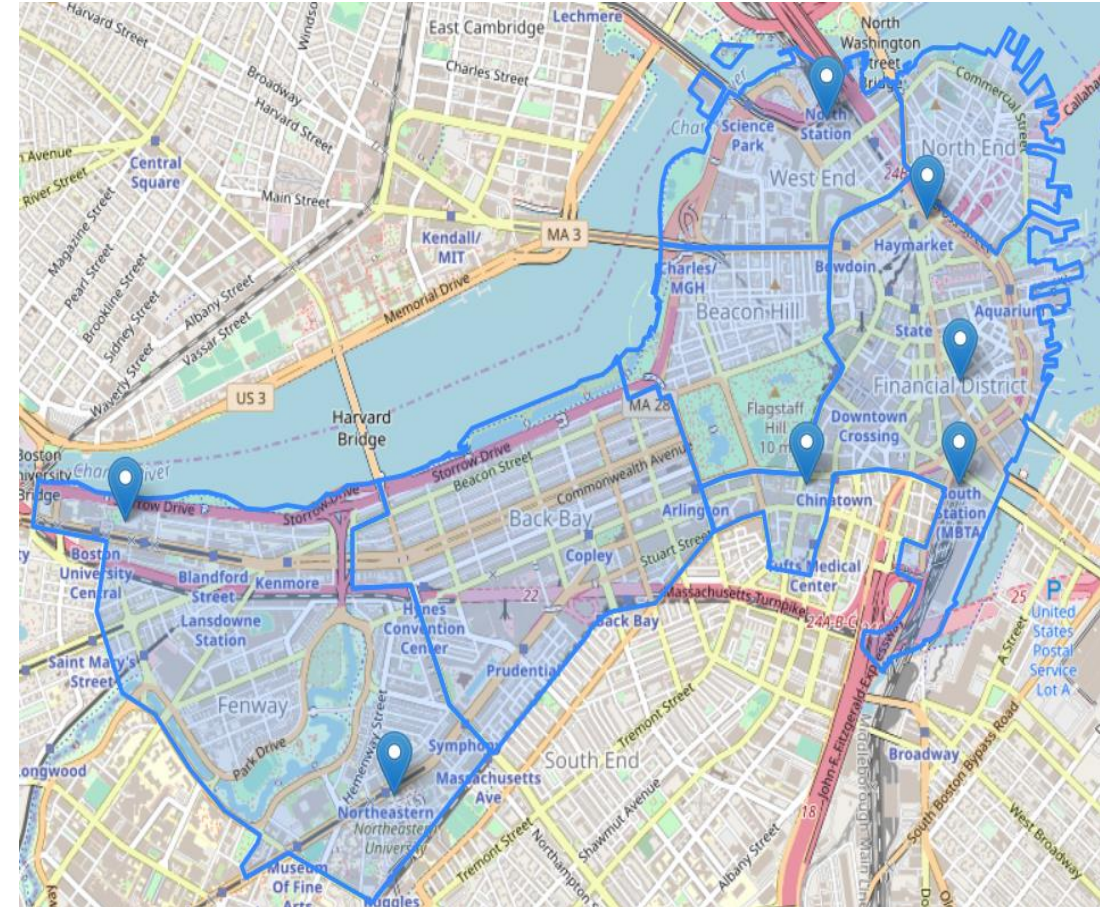
► Weather Factors

- Temperature
- Rain
- Humidity
- Pressure
- Wind
- Clouds



Data Information

- ▶ Ride pickup and dropoff occurring within 6 major Boston neighborhoods: North End, West End, Back Bay, Beacon Hill, Fenway, and Downtown.
- ▶ Within these areas: Boston University and Northeastern University (in Fenway), North Station (in North End), Haymarket Square, Financial District, South Station, and Theatre District (in Downtown)



Data Information

Ride Data Specifics

- ▶ Acquired through real time API queries
- ▶ Ranges from Nov 26 – Dec 18, 2018
- ▶ File Format: csv
- ▶ Over 600000 ride instances (approx. 50000 for each of 12 ride-types). Each row is a unique ride instance from either Uber or Lyft

Weather Data Specifics

- ▶ Acquired through wunderground.com
- ▶ Ranges from Nov 26 – Dec 18, 2018
- ▶ File Format: csv
- ▶ Each weather instance describes the measurement of each weather feature (temp, rain, wind, etc.) at specific time



Merging

Weather instance merged by time-stamp, occurring within 1 hour of pickup, on ride pickup location

Sport Occurrence

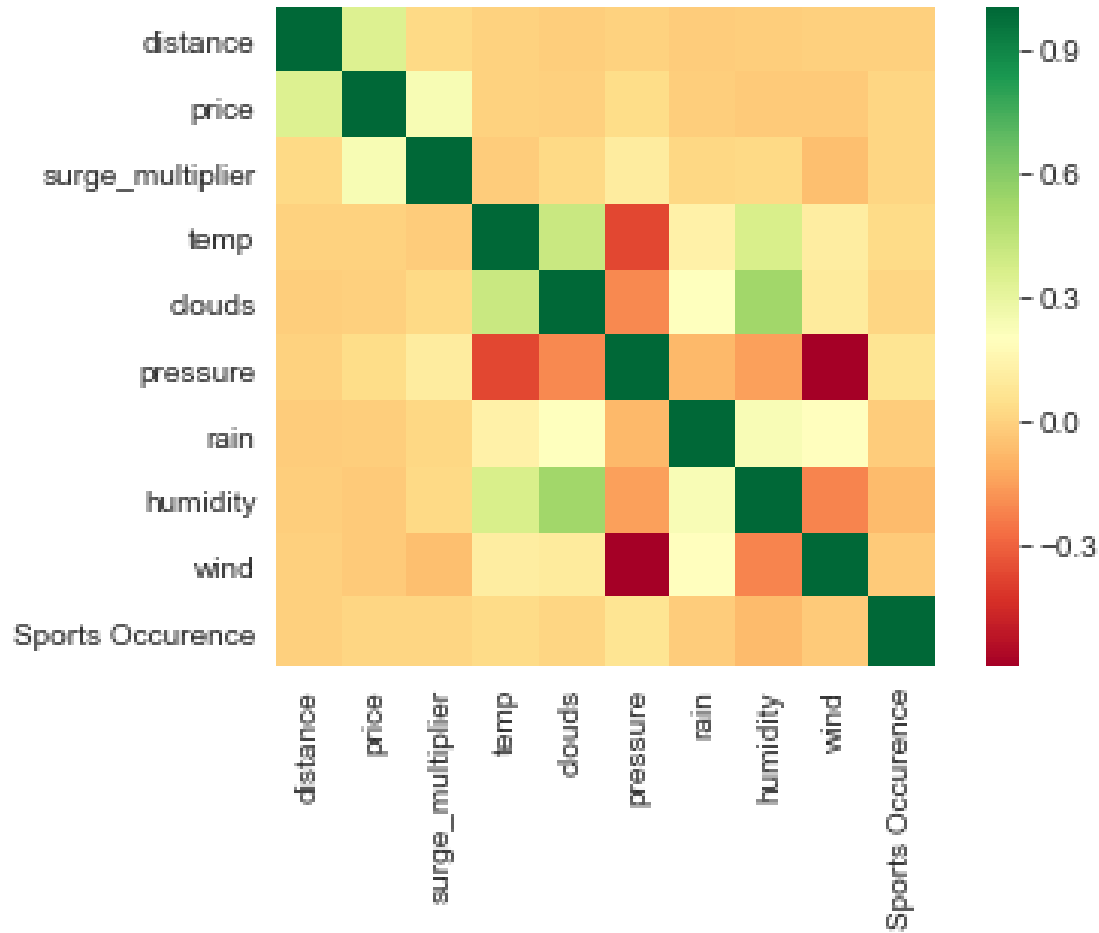
- ▶ Dummy variable column added to dataset representing the occurrence of a Celtics game or Bruins game.
- ▶ 1 if game occurred within 2 hours of ride pickup or ride drop-off, 0 otherwise.
- ▶ Only for rides going to and coming from North Station (where TD Garden is located).



Data Exploration

[HTTPS://GITHUB.COM/DGOKALGA/SPRINGBOARD-DATA-SCIENCE/BLOB/MASTER/CAPSTONE-1/DATASTORYTELLING.IPYNB](https://github.com/dgokalga/springboard-data-science/blob/master/capstone-1/datastorytelling.ipynb)

1. VALUE PER DISTANCE
2. TEMPORAL FACTORS
3. SPORTS OCCURRENCE
4. WEATHER FACTORS



What quantitative features correlate with ride price?

Distance and surge-multiplier positively correlate with the ride price.

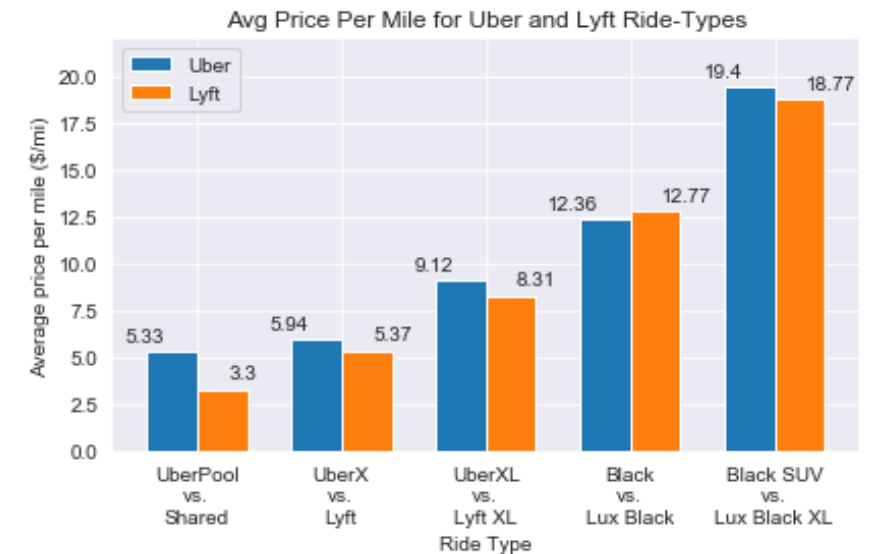
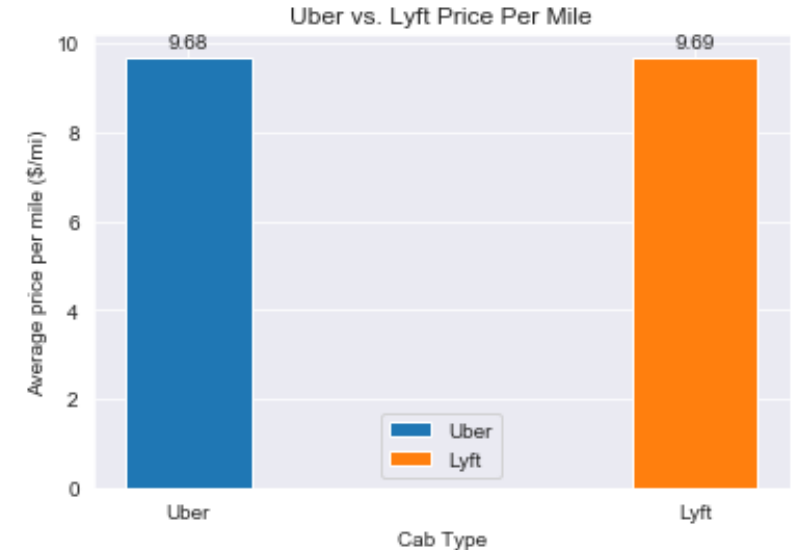
Some correlation between weather features.

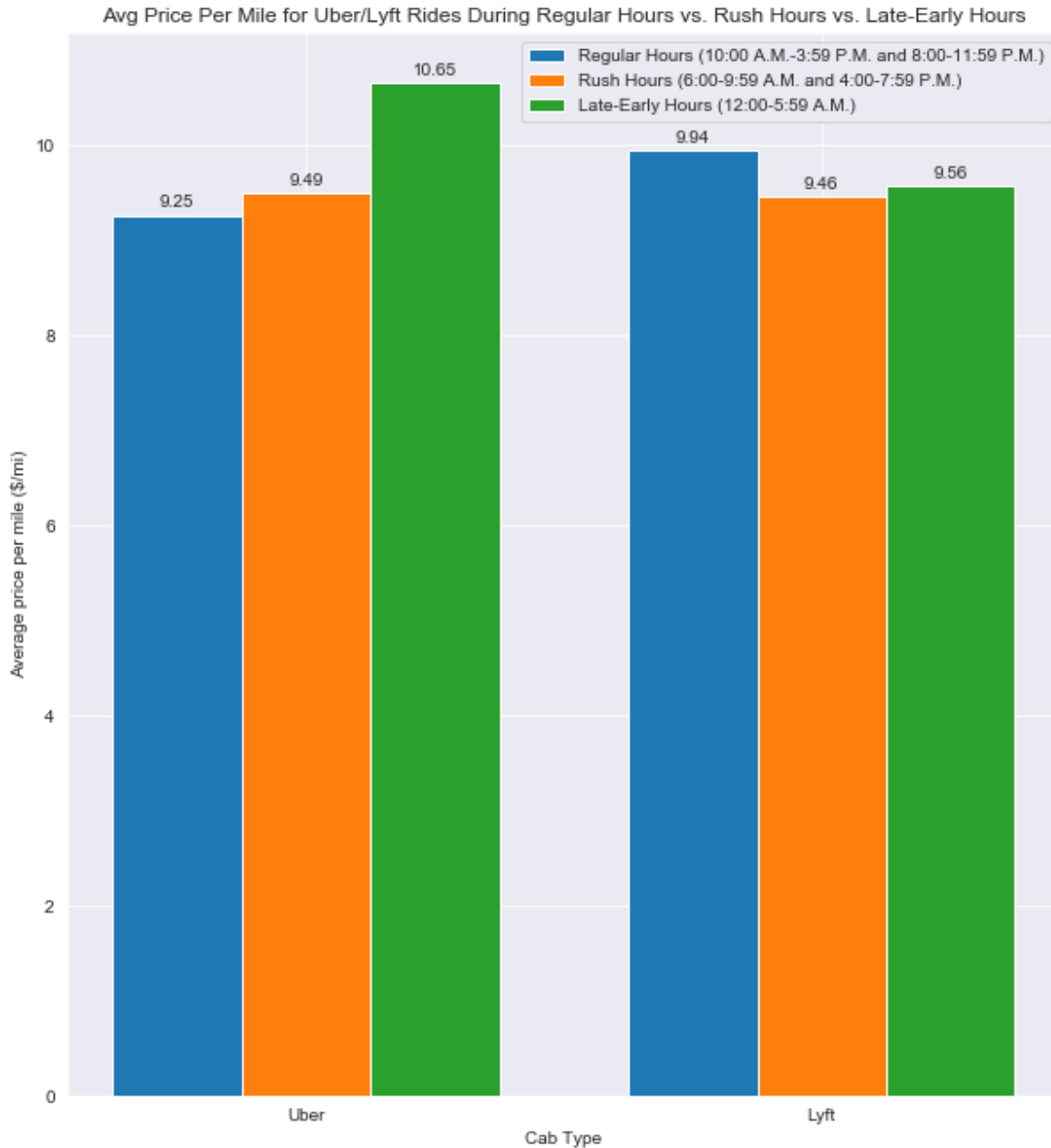
Value Per Distance

Looking at the value of a ride per distance for both Uber and Lyft ride-service applications, on average, both cost relatively the same per mile.

When comparing similar ride-types between Uber and Lyft, four of the five Uber ride-types: UberPool, UberX, UberXL, Black SUV are the more expensive option per mile, on average, compared to their Lyft counterpart.

Lux Black, on average, was found to be the more expensive option per mile than its Uber counterpart, Uber Black.

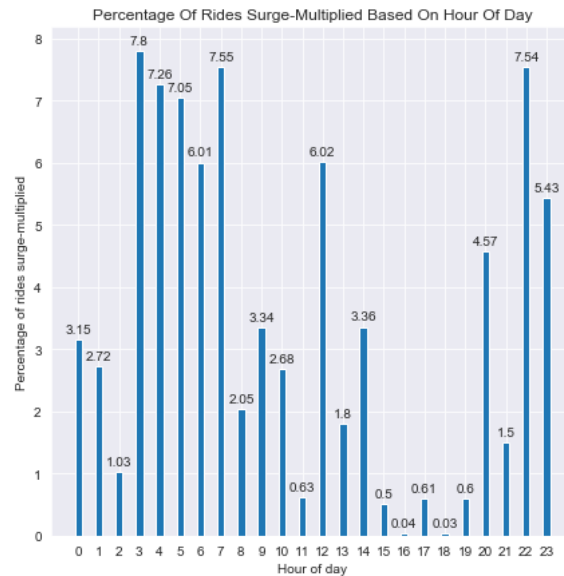
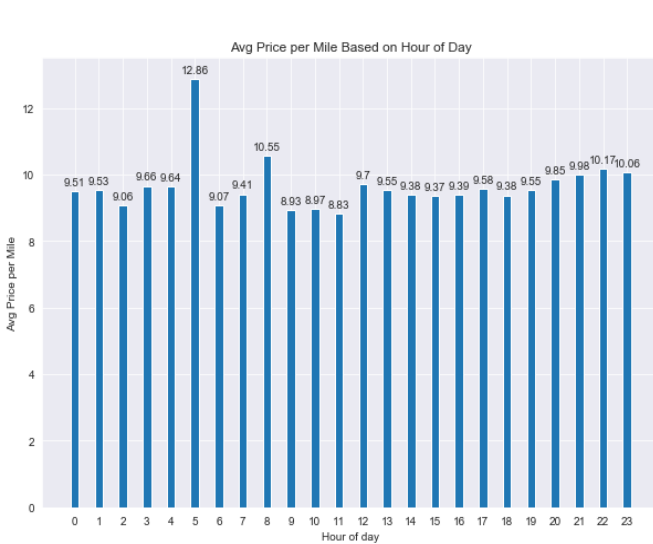




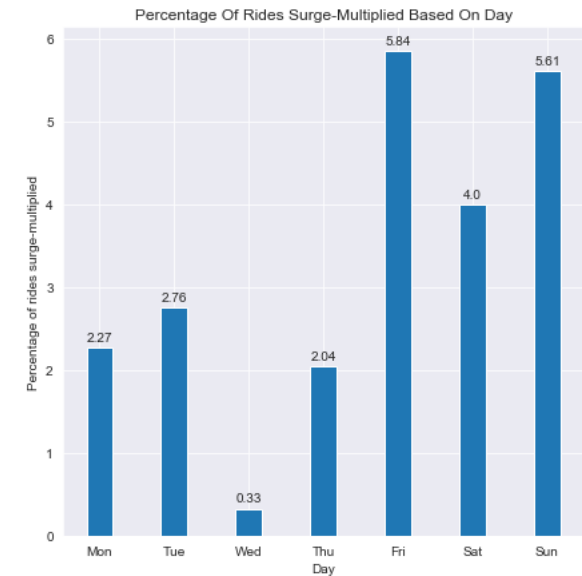
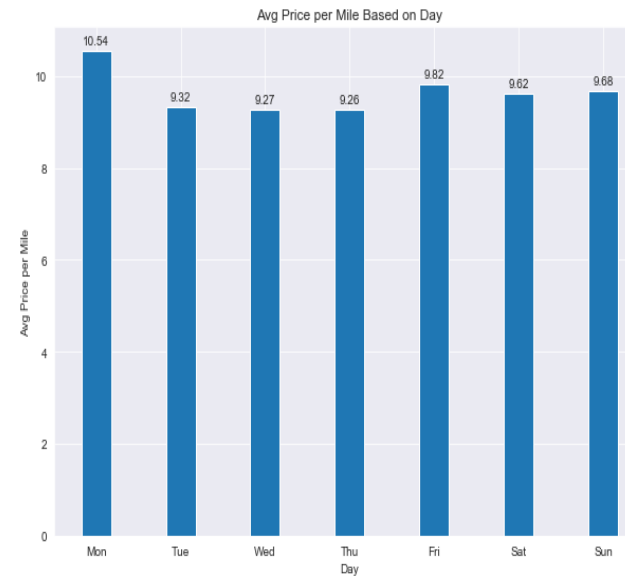
Prices Higher
During Late-Early
Hours for Uber
and Regular
Hours for Lyft

Prices Higher During Late-Early Hours, and Weekends (except Mon)

Hour of Day

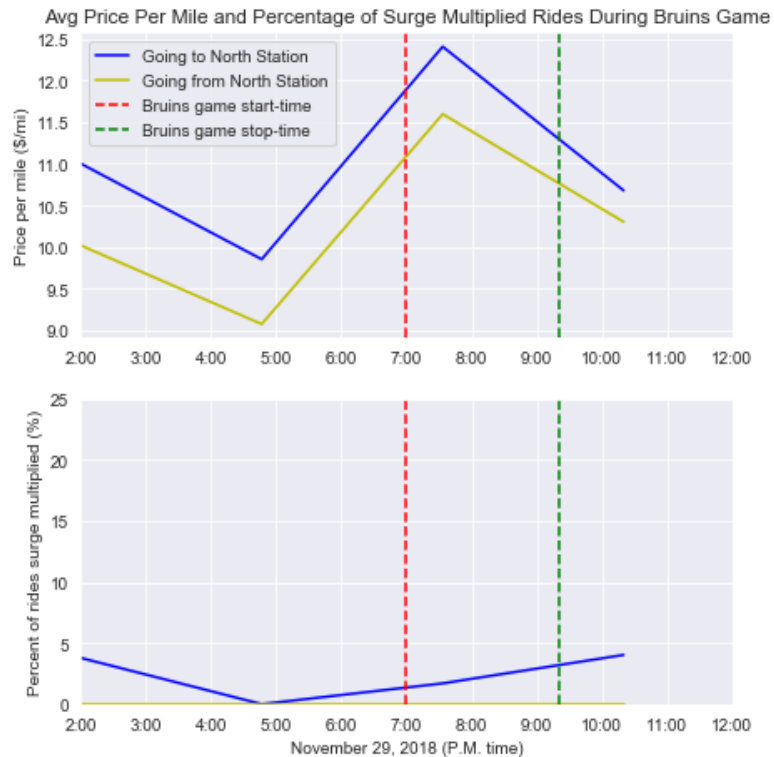


Day of Week

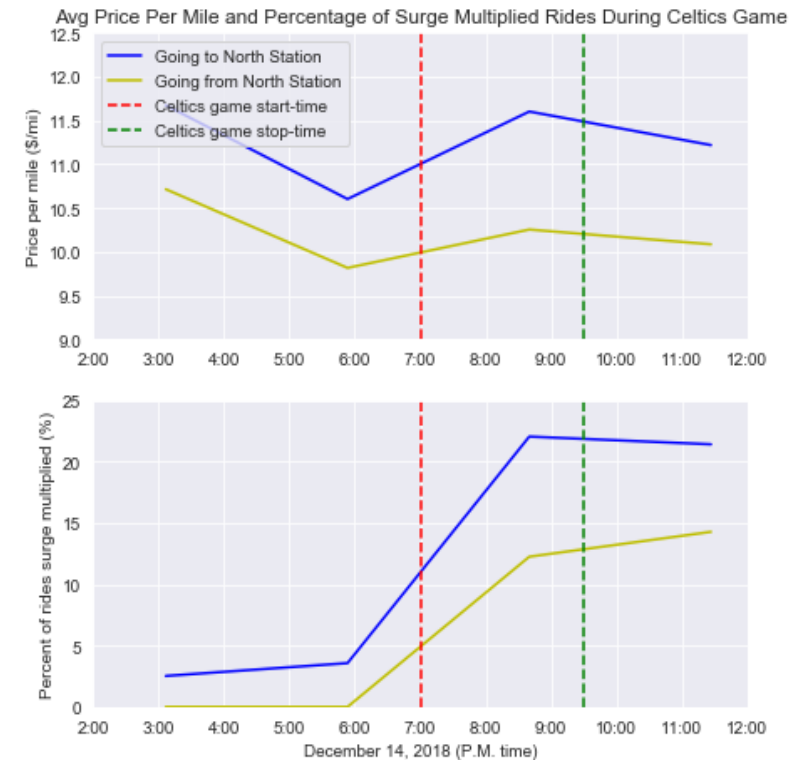


Prices Higher and Surged During and After the Game

Bruins Game



Celtics Game





Prices
cheaper
under
rainy and
cloudy
weather

Regression Modeling

[HTTPS://GITHUB.COM/DGOKALGA/SPRINGBOARD-DATA-SCIENCE/BLOB/MASTER/CAPSTONE-1/UBERLYFT_REGRESSION.IPYNB](https://github.com/dgokalga/springboard-data-science/blob/master/capstone-1/uberlyft_regression.ipynb)

REGRESSION MODELS IMPLEMENTED
(USING SCIKIT-LEARN AND STATSMODEL):

1. MULTIVARIATE LINEAR REGRESSION
2. LASSO REGRESSION
3. RIDGE REGRESSION

METRICS CALCULATED:

1. R-SQUARED
2. MEAN ABSOLUTE ERROR (MAE)
3. MEAN ABSOLUTE PERCENTAGE ERROR (MAPE)
4. ROOT MEAN SQUARED ERROR (RMSE)

Modeling Pre-Processing

Remove ID Features from Dataset



Create time-range, day of week, and general weather feature columns



Create dummy columns for categorical features



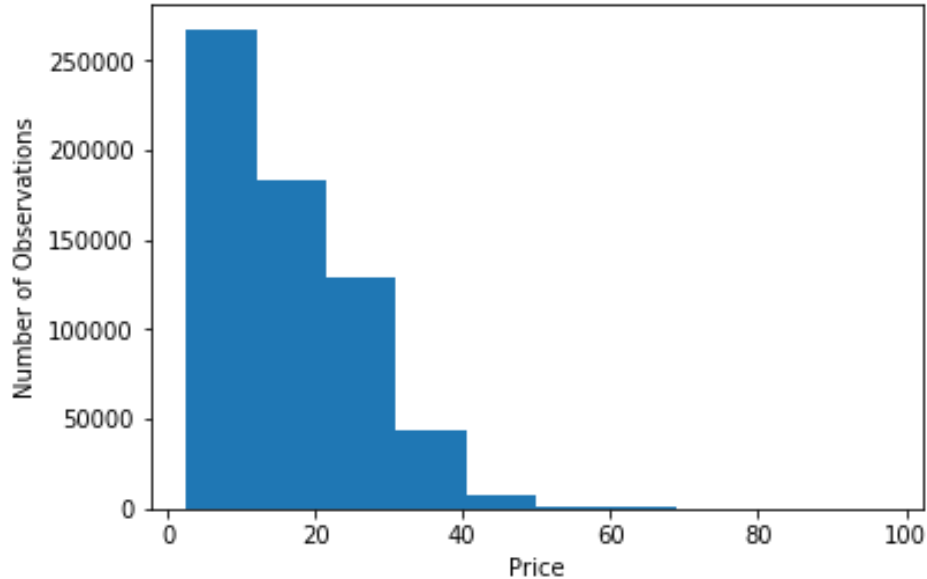
Create 2D array for independent features and 1D array for dependent feature (price)



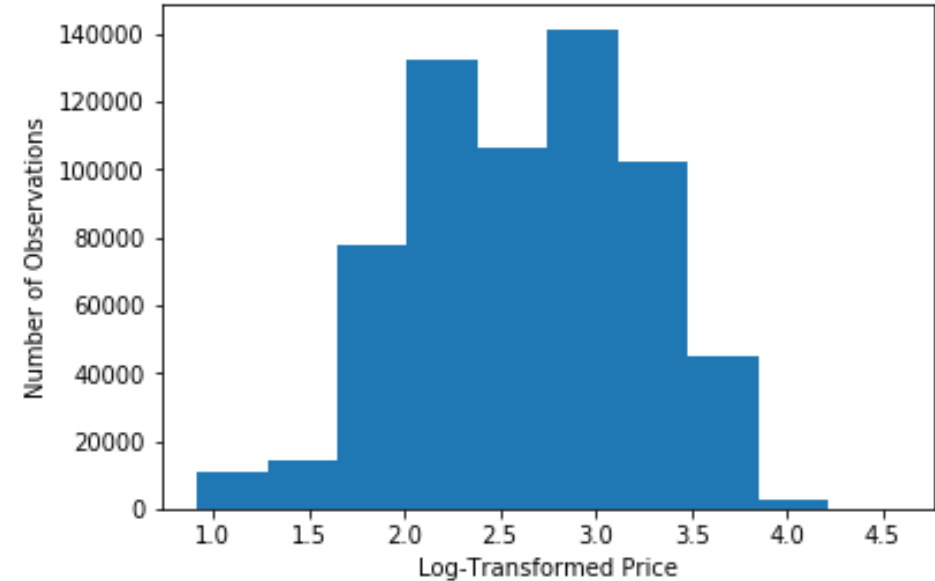
Create training and testing datasets (80/20 split)

Distribution of the Target Variable

► Distribution of Price

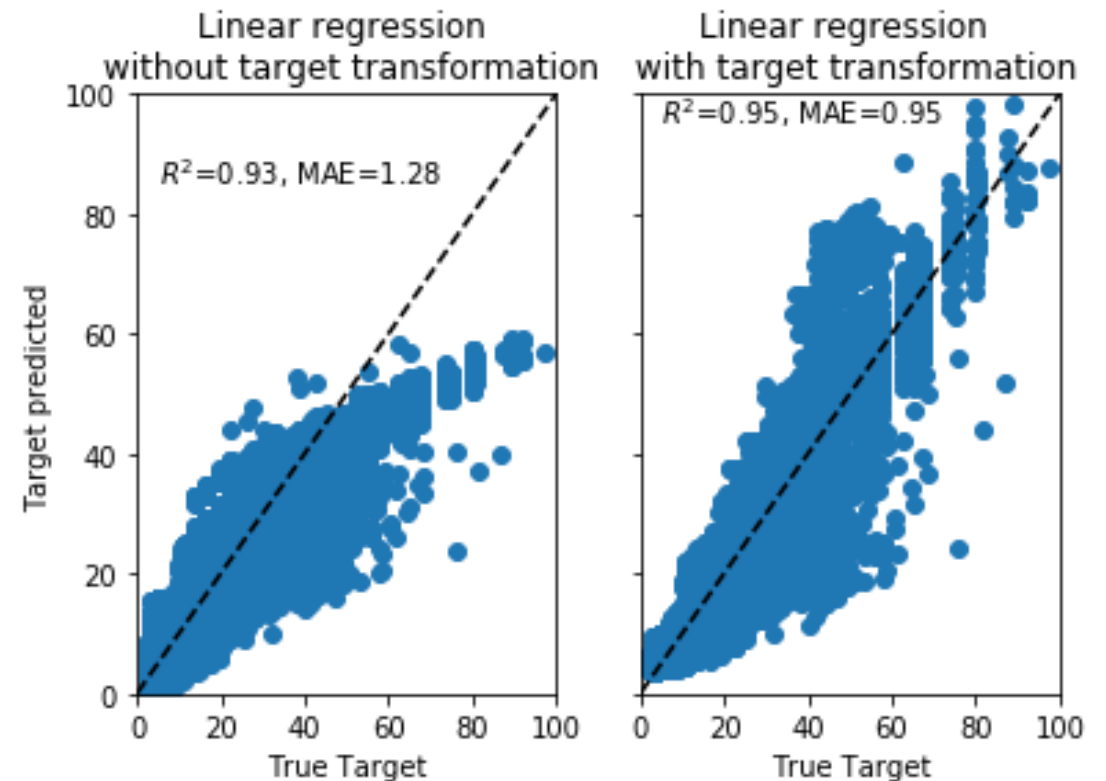


► Distribution of Log-Transformed Price



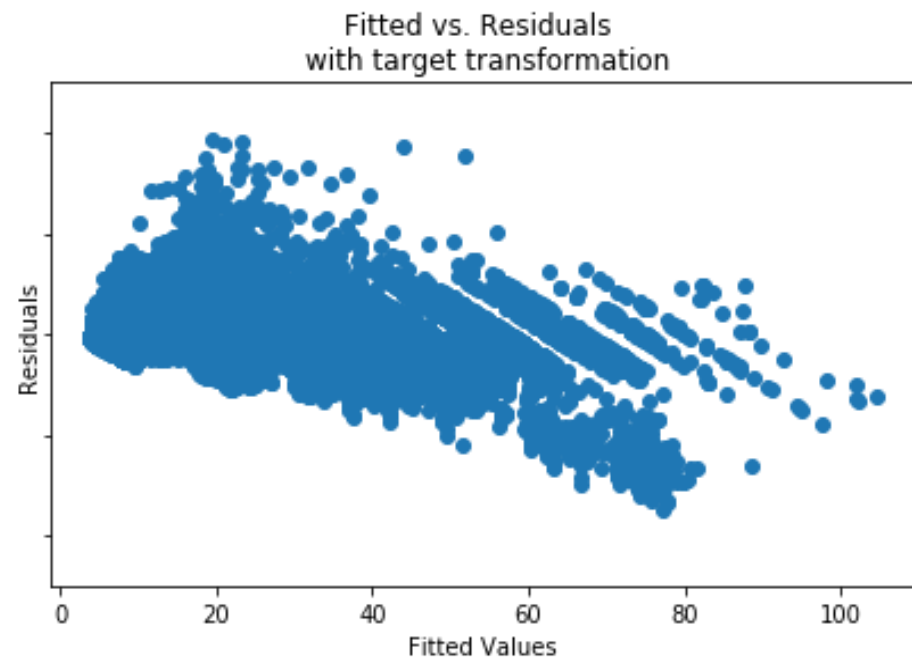
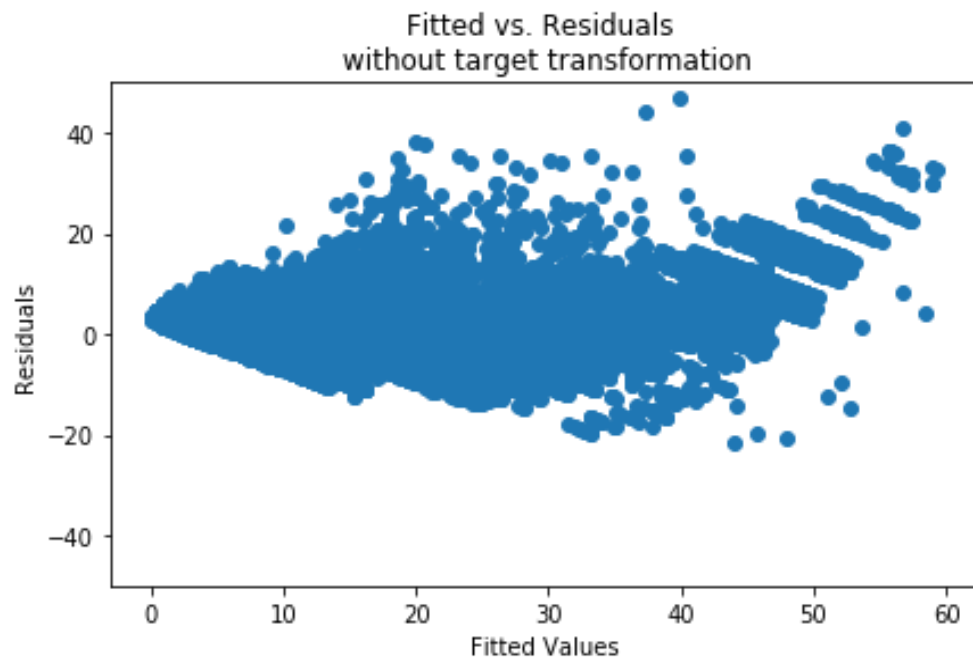
Multivariate Linear Regression

Regression performed on training data, for both non-transformed and transformed price

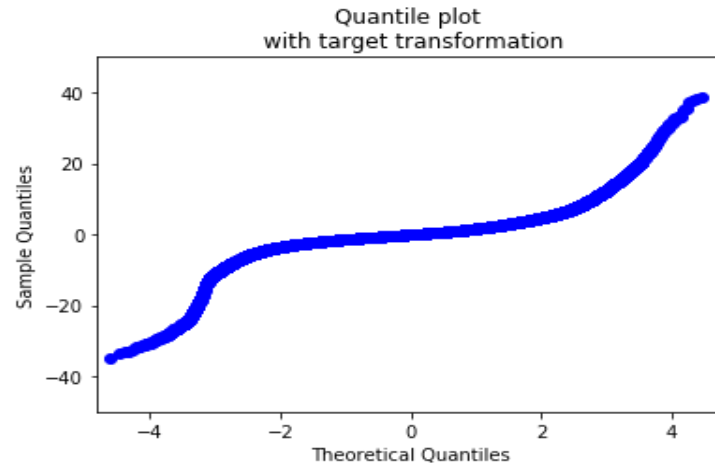


Multivariate Linear Regression (cont.)

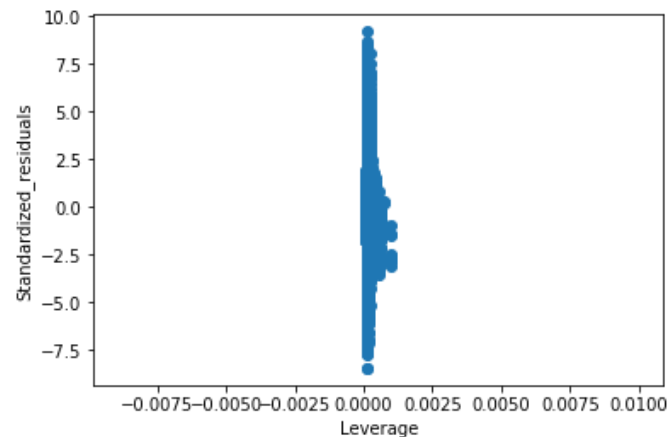
Transformed target variable model capture higher prices well



Residuals are normally distributed with heavy tails



No evidence of highly influential points, as high leveraged points have small standardized residuals



Multivariate
Linear
Regression
(cont.)

Lasso and Ridge Regression

Lasso Regression

- ▶ GridSearch and Cross Validation to determine best alpha. Price is log-transformed
- ▶ Best alpha value of 0, same as linear regression
- ▶ How model evaluates test data with lowering alpha values:

alpha	R-Squared	MAE	MAPE	RMSE
.01	.845	2.44	15.83	3.68
.001	.944	1.44	9.85	2.22
,0005	.945	1.41	9.64	2.20
0	.945	1.40	9,54	2.19

Ridge Regression

- ▶ GridSearch and Cross Validation to determine best alpha. Price is log-transformed
- ▶ Best alpha, with 5-fold cross validation: 2.778
- ▶ How the model evaluate test data:

Alpha	R-Squared	MAE	MAPE	RMSE
2.778	.945	1.40	9.54	2.19

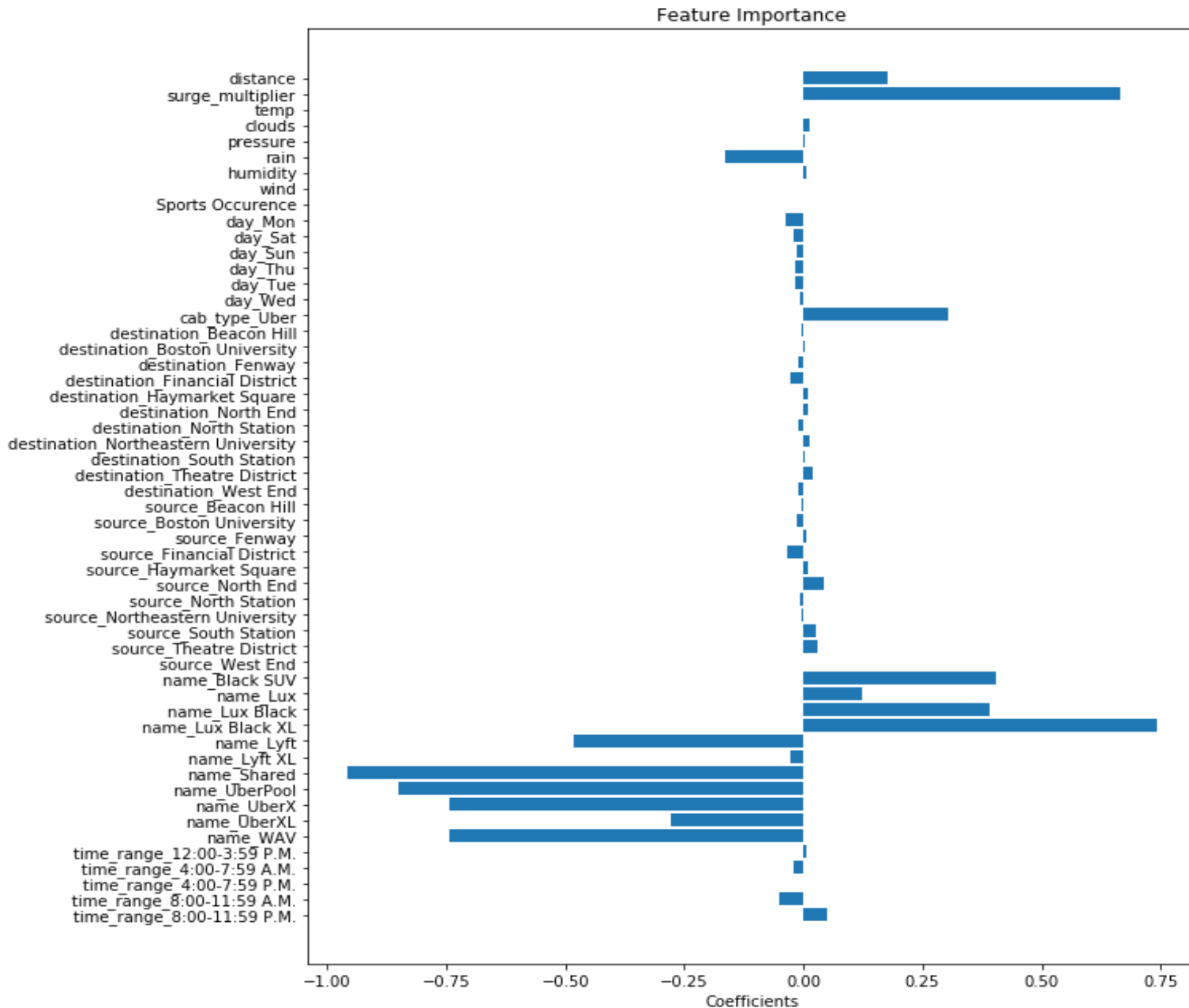
Model Comparisons on Test Data

When predicting for the training data or test data, the inverse function is applied to the predicted value for real valued prices on log transformed models.

Log-Linear Regression Model is the best model, as seen from its evaluation on test data, and simplicity compared to Lasso and Ridge regression.

Model	R-Squared	MAP	MAPE	RMSE
Linear Regression	.931	\$1.71	12.95%	2.47
Log-Linear Regression	.945	\$1.40	9.54%	2.19
*Lasso Regression	.945	\$1.40	9.54%	2.19
Ridge Regression	.945	\$1.40	9.54%	2.19

*Lasso regression with $\alpha = 0$, which is the same as linear regression



Feature Importance

Coefficients do not have a direct relationship with the dependent variable, price, because of the log-linear relationship

Feature Importance (cont.)

- ▶ Top 5 features:
 1. Ride-Type
 2. Surge Multiplier
 3. Distance
 4. Cab-Type
 5. Rain
- ▶ Two features, humidity and Sports Occurrence, have p-values > 0.05 , not statistically significant!
- ▶ These two features are removed from the dataset, and log-linear regression is re-ran.
- ▶ Model did not improve significantly.

Model	R-Squared	MAE	MAPE	RMSE
No features removed model	.945	1.40	9.54	2.19
Features removed model	.945	1.40	9.54	2.19

Recommendations to Clients

- ▶ Riders, when considering shared rides, solo rides, rides with up to 6 people, or premium black care service rides with up to 6 people, should choose Lyft over Uber.
- ▶ Otherwise, choose Uber for premium black car service rides for up to 4 people.

- ▶ Riders should expect prices to be cheaper under rainy weather, during daytime hours, or on most of the weekdays except Monday.
- ▶ More rides have a chance to be surged at late-early hours in the day, and generally on weekends.

- ▶ Competing ride service applications should use the model and offer discounted rides less than a \$1.40 less than the predicted price to drive demand.
- ▶ These competitors should also lower the surge multiplication of rides during late-early hours or weekends to provide a less expensive alternative to Uber and Lyft

Limitations and Future Improvements

- ▶ We assume all rides are independent, even though there may be some time-correlations.
 - ▶ We assume Uber and Lyft assign a price to a ride with the same algorithm.
 - ▶ Used only rides from Boston, and only occurring from a span of 2 weeks.
 - ▶ Missing Uber Taxi ride-type.
- ▶ To improve the model, we want to implement other regression models, such as regression trees, random forest, and gradient boosting, to capture some off the non-linear relationships.
 - ▶ We want to include other major cities ride data to lessen bias towards Boston.
 - ▶ Include data over the period of years and determine whether price trends change over time.
 - ▶ Include other features such as traffic data, latitude and longitude of ride-pickup and drop-off, or other transportation features to improve the model.

Conclusion

- ▶ Log-Linear Regression Model best evaluates unseen ride data, with an error of \$1.40, or a percentage error of 9.5%, within the actual ride price.
- ▶ 4 of the 5 Uber ride-types: UberPool, UberX, Uber XL, and Uber Black SUV, on average, are more expensive per mile than their Lyft counterparts. Lyft Black, on average, is more expensive per mile than Uber Black.
- ▶ Rides, on average, are cheaper under rainy and cloudy weather, than clear weather.
- ▶ All features, except humidity and Sports Occurrence, are used from both the ride and weather data.
- ▶ With more complex models, the evaluation of unseen data can be improved for the future.