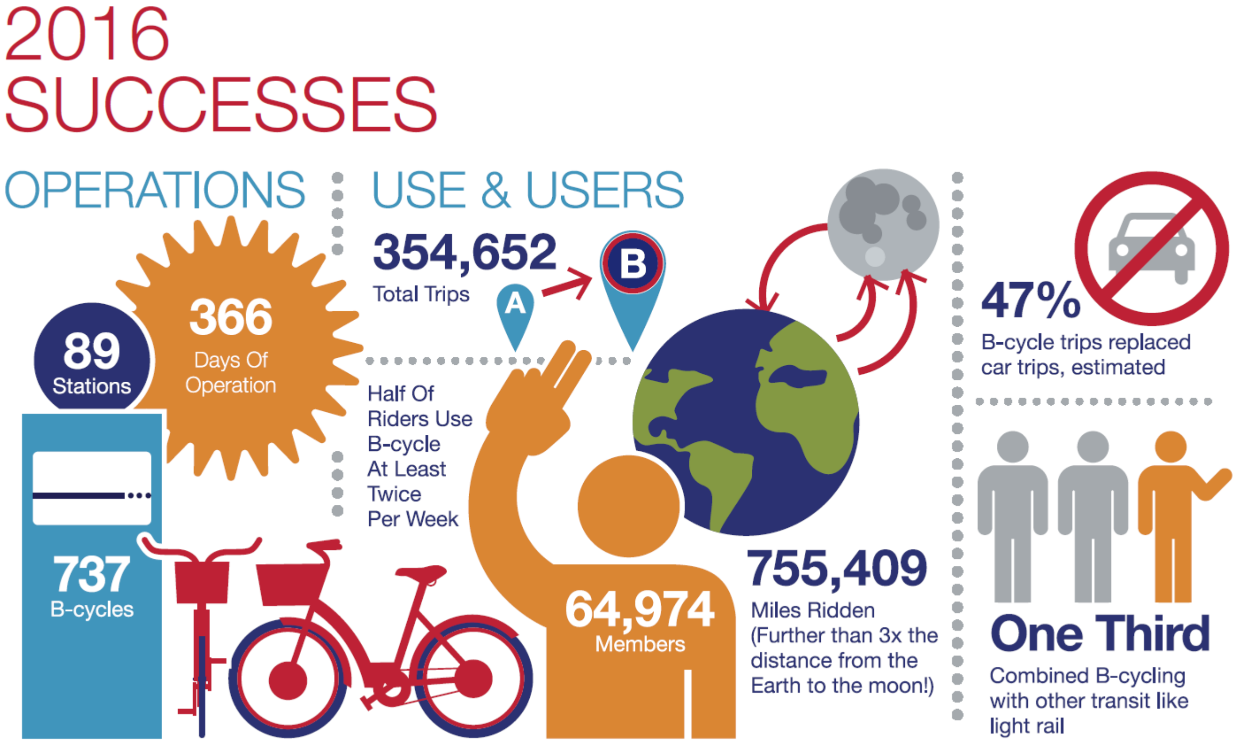
Denver 2016 B-cycle Ridership Data Exploration



Source: http://denver.bcycle.com/docs/librariesprovider34/default-document-library/dbs_annualreport_2016_05.pdf

Denver B-cycle is a non-profit public bike sharing organization operating an automated bike sharing system called Denver B-cycle. Its mission is to "serve as a catalyst to fundamentally transform public thinking and behavior by operating a bike sharing system in Denver to enhance mobility while promoting all aspects of sustainability: quality of life, equity, the environment, economic development, and public health" its purpose, its organization and discuss its relevance to this exploration.

Denver B-cycle posts its trips data set on its website as soon as its annual report is released. Trips data have been available since 2010. The 2016 annual report and its associated dataset for this report were obtained from Denver B-Cycle website. The original plan was to use the 2015 dataset to continue the effort by Tyler Byler who published a report, Exploring 2014 Denver B-cycle Ridership. In his study Tyler indicated that "most calendar and clock variables were highly significant when predicting ridership, and weather variables such as temperature and amount of cloud cover appear to be as well". The original plan for this report was to use 2015 data to continue Tyler's work. However, the 2016 data became available at the end of February 2017, so gears had to be rapidly shifted to use this data instead. To this end, the reporting style will follow Tyler's study to provide seamless continuity and good reference on trends and analyses.

This study has three parts:

1. Explore the Trips datasets and visualize the data to provide useful and interesting information.
2. Deploy a variety of regression models to train and test the data.
3. Deploy a variety of classification models to train and test the data.

Part 1: Data Exploration

Data Acquisition

Data for this study was downloaded from several sources and combined using the following steps:

1. Downloaded B-cycle 2016 Trips and Kiosk data from Denver B-Cycle website. The columns names were changed to comply with Python code best practices.
2. Created a list of the 7921 combinations of the 89 checkout/return kiosks. Used Google Distance Matrix API to provide the bicycling distance and time between each checkout and return kiosk. Adopted Tyler's method of finding the average distance by taking the distance from each checkout-return pair's distance separately then averaging it. As he pointed out in his study, this approach was taken "because of the large number of one-way streets in the Denver downtown area where the kiosks are highly clustered". Google only supports a maximum of 2500 requests a day, it took four days to obtain this data.
3. Obtained daily and hourly weather data via Dark Sky API for all of 2016. Dark Sky supports up to 1000 requests per day.

Basic Ridership Statistics

Number of Rides

The B-cycle data, as downloaded, contained 419,611 rows of trips data. Under normal circumstances this would mean that 419,611 B-cycle trips were taken in 2016. However, the 2016 Denver B-cycle annual report acknowledged 354,652 total trips for the year. The breakdown was as follows:

Membership Type	Number of Trips
Annual (And Annual Plus)	193,113
Flex Pass	3,565
30 Day	54,004
24 hour online	117
24-hour Kiosk	103,853
Total Trips	**354,652**

The Trips dataset reported the following breakdown:

Membership Type	Number of Trips
Annual (Denver B-cycle)	82,199
Annual Plus (Denver B-cycle)	84,271
Flex Pass	3,565
Monthly (Denver B-cycle)	54,004
24 hour online (Denver B-cycle)	117
24-hour Kiosk Only (Denver B-cycle)	87,315
Total Trips	**311,471**

There were several other Membership Types that were also listed under “Denver B-cycle” in the User’s Program:

Membership Type	Number of Trips
Denver B-cycle Founder (Denver B-cycle)	18,003
Not Applicable	64,959
Single Ride (Denver B-cycle)	16,526

In particular, the “Not Applicable” membership type accounted for more than 15% of the 419,611 trips. Perhaps some of these trips were used in the Denver B-cycle annual report.

Also over 2.3% of the Denver B-cycle rides (9,954 rides) had the same checkout station as return station with a trip duration of only 1 minute (Figure 1). Again, Tyler’s explanation of why these trips should be removed from the dataset makes sense - “I believe these should be filtered out because I believe the majority of these “rides” are likely people checking out a bike, and then deciding after a very short time that this particular bike doesn’t work for them. I believe that most of the same-kiosk rides under 5 minutes or so likely shouldn’t count, but only culled the ones that were one minute long”.

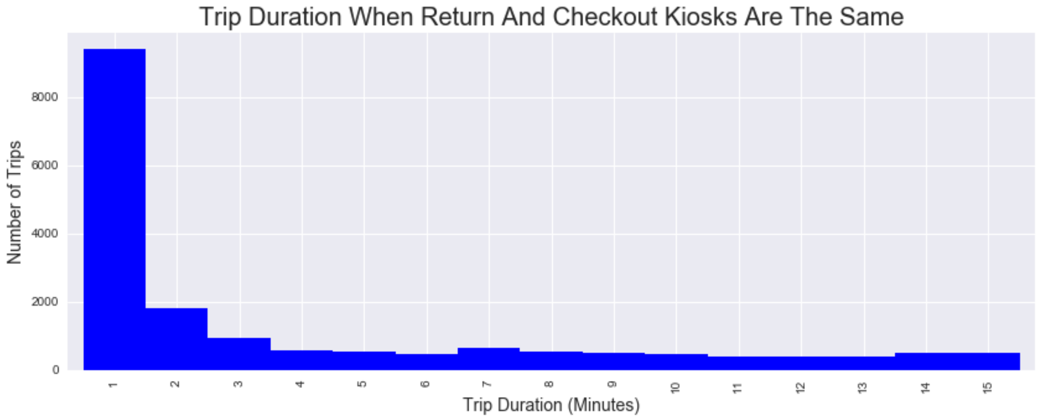


FIGURE 1: TRIP DURATION WHEN CHECKOUT AND RETURN KIOSKS ARE THE SAME

There were 6574 rows in the Trips dataset that had kiosk names not in the Kiosk Master List. These 6574 rows were removed accordingly.

Removing the 9,954 rows with a trip duration of 1 minute and 6574 rows with invalid kiosk names resulted in **394,431 Denver B-cycle rides in 2016**.

Distance Traveled

To estimate the distance between checkout and return kiosks when they are the same, Tyler's method of using the "average speed of all the other rides (nominal distance ridden divided by the duration), and then applying this average speed to the same-kiosk trip durations" was adopted. This resulted in **670,802 miles ridden in 2016**.

Most Popular and Least Popular Checkout and Return Kiosks

Most Popular

The following ten kiosks were the most popular checkout kiosks by number of total bike checkouts in 2016.

Checkout Kiosk	Number of Checkouts
16th & Wynkoop	11,174
16th & Broadway	3,565
1350 Larimer	10,837
18th & California	9,865
1550 Glenarm	9,441
18th & Arapahoe	**8,531**
20th & Chestnut	8,240
13th & Speer	8,228
REI	8,218
16th & Little Raven	8,198

The following ten kiosks were the most popular return kiosks by number of total bike checkouts in 2016.

Return Kiosk	Number of Checkouts
16th & Wynkoop	11,289
1350 Larimer	10,920
16th & Broadway	10,870
18th & California	9,863
1550 Glenarm	9,501
18th & Arapahoe	8,549
20th & Chestnut	8,356
REI	8,284
13th & Speer	8,272
16th & Little Raven	8,267

Least Popular

The following ten kiosks were the least popular checkout kiosks by number of total bike checkouts in 2016.

Checkout Kiosk	Number of Checkouts
Pepsi Center	1,795
32nd & Julian	1,755
25th & Lawrence	1,736
Colfax & Garfield	1,725
4th & Walnut	1.663
Decatur Federal Light Rail	1,508
Denver Zoo	1,490
Colfax & Gaylord	1,421
17th & Curtis	615
39th & Fox	332

The following ten kiosks were the least popular return kiosks by number of total bike checkouts in 2016.

Return Kiosk	Number of Checkouts
21st & Market	1,795
32nd & Julian	1,767
25th & Lawrence	1,758
Colfax & Garfield	1,743
4th & Walnut	1,686
Decatur Federal Light Rail	1,537
Denver Zoo	1,468
Colfax & Gaylord	1,433
17th & Curtis	632
39th & Fox	345

Map of Station Popularity

Checkout Kiosks

The use of Tableau aided in the creation of the following map showing the popularity of the various Checkout Kiosks (Figure 2). The size of the circle is proportional to the number of checkouts from that kiosk in 2016.

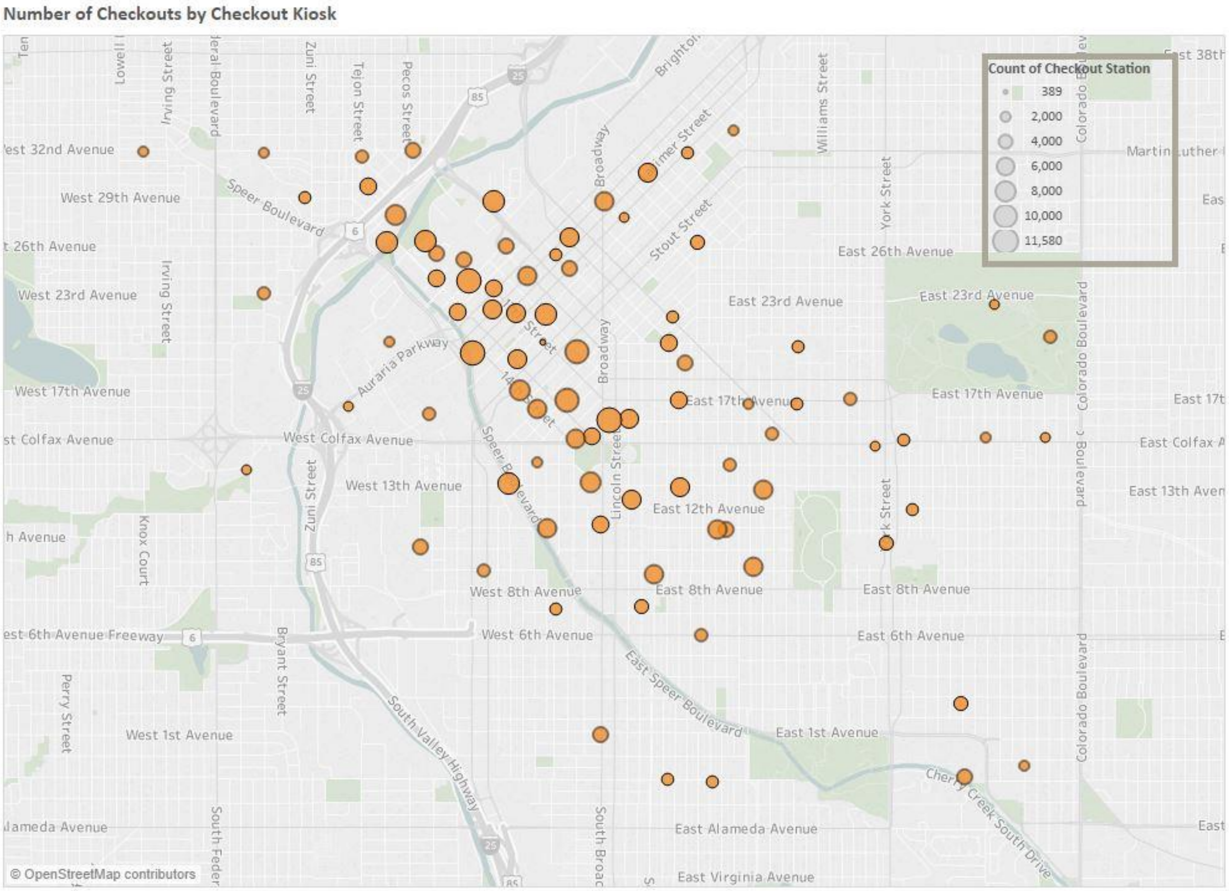


FIGURE 2: CHECKOUT KIOSK LOCATIONS AND NUMBER OF CHECKOUTS IN 2016

Return Kiosks

Similarly, the use of Tableau aided in the creation of the following map showing the popularity of the various Return Kiosks (Figure 3). The size of the circle corresponds to the number of checkouts returned to that kiosk in 2016.

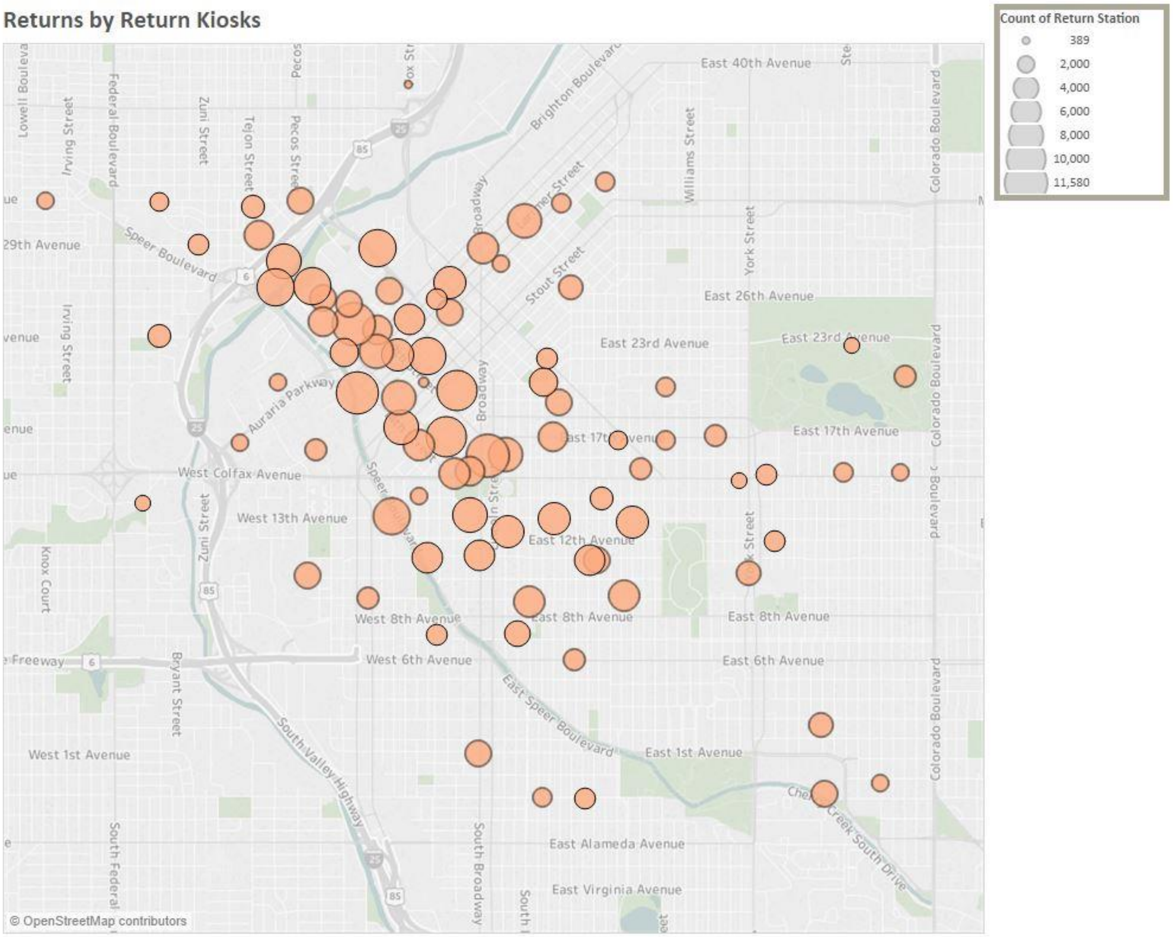


FIGURE 3: RETURN KIOSK LOCATIONS AND NUMBER OF RETURNS IN 2016

Checkouts per Membership Type

Denver B-cycle has a number of different membership passes. The following were the top ten by number of checkouts in 2016 (Figure 4).

Membership Type	Number of Checkouts
24-hour Kiosk Only (Denver B-cycle	85,680
Annual Plus (Denver B-cycle)	82,202
Annual (Denver B-cycle)	80,093
Not Applicable	56,250

Monthly (Denver B-cycle)	52,811
Denver B-cycle Founder (Denver B-cycle)	17,675
Single Rider (Denver B-cycle)	16,291
Republic Rider (Annual) (Boulder B-cycle)	5,930
Flex Pass (Denver B-cycle)	3,507
Republic Rider (Boulder B-cycle)	1,229

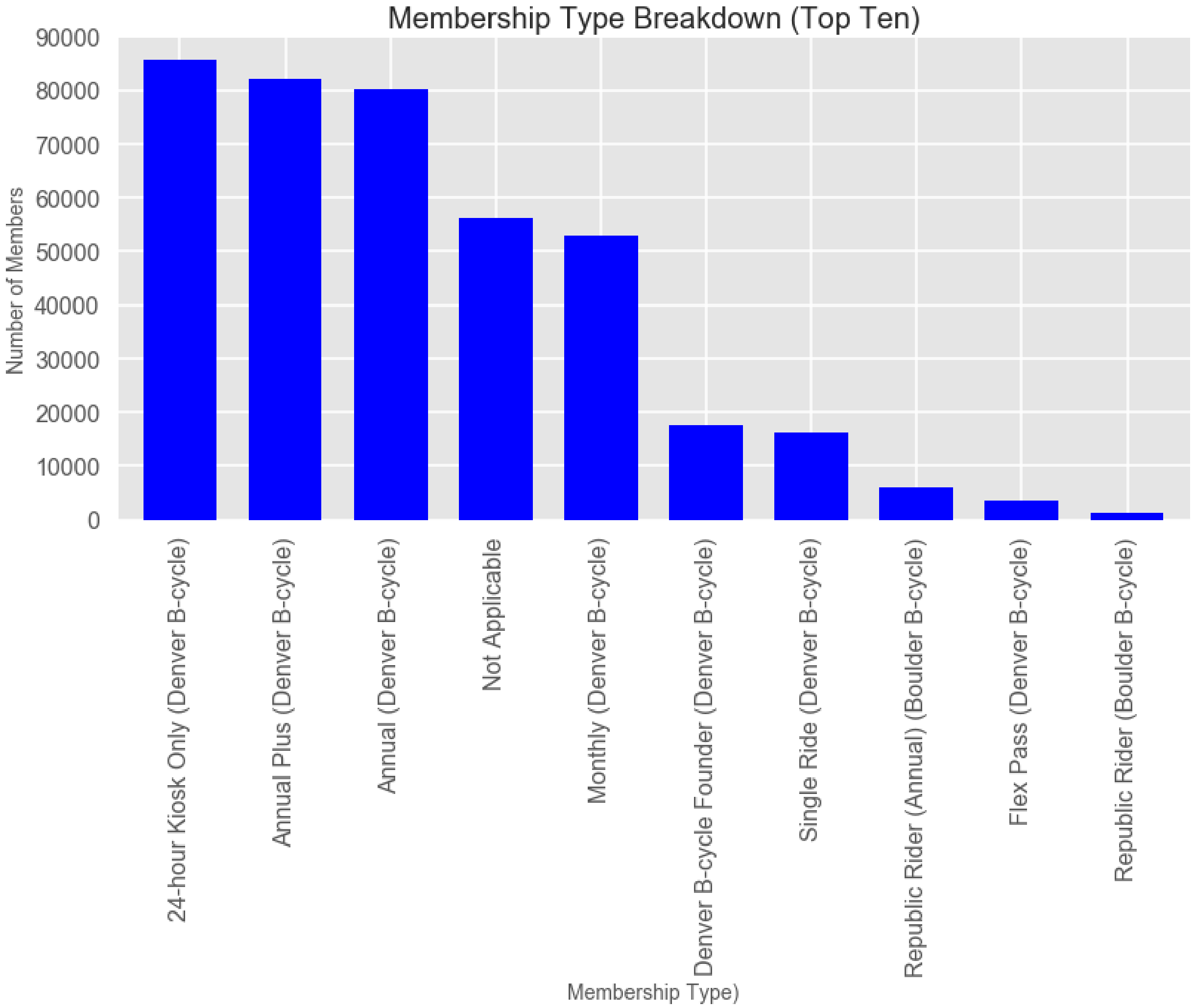


FIGURE 4: NUMBER OF CHECKOUTS BY MEMBERSHIP TYPE IN 2016

Ridership by Calendar and Clock Variables

Ridership by Hour

Bike checkout time is probably the most important attribute in the Trips dataset. Each checkout time was converted into its integer hour. For example, 7:02 AM or 7:59 AM would be converted to an integer of 7. In this way, total number of checkouts could be aggregated for the year and plotted against their hours of the day, as shown in Figure 5.

It appears that the highest number of checkouts occur between 4 PM and 5 PM with ridership increasing steadily from 10 AM onwards.

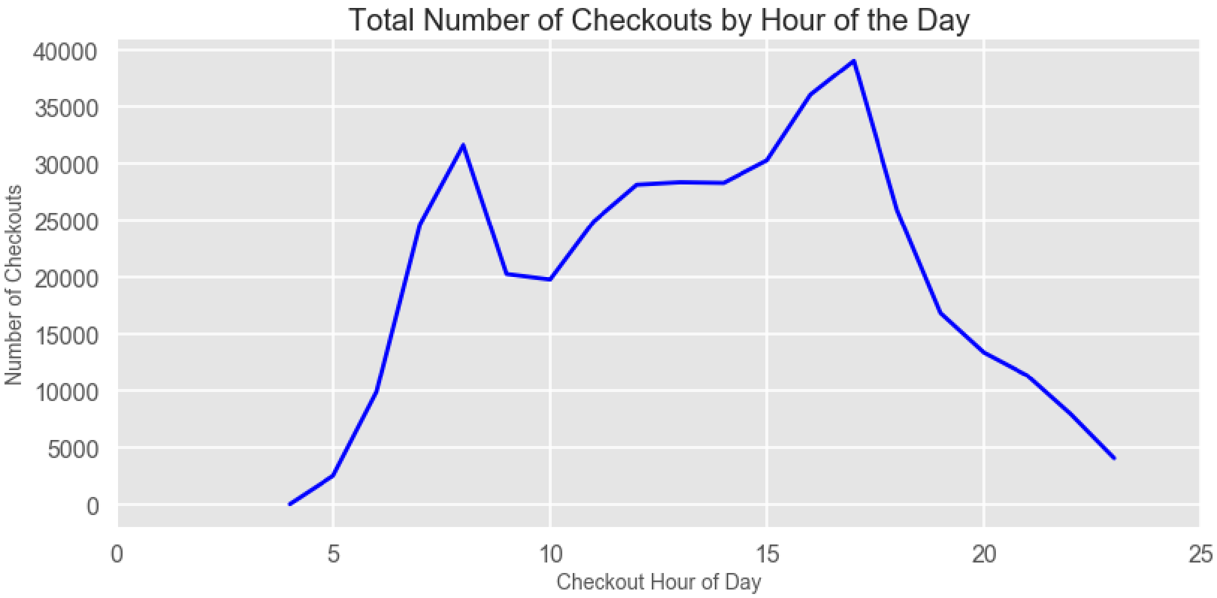


FIGURE 5: NUMBER OF CHECKOUTS BY HOUR IN 2016

Figure 6 shows the average distance ridden by the hour of the day in 2016. More distance is covered during the 10 AM period and declining steadily after 3 PM.

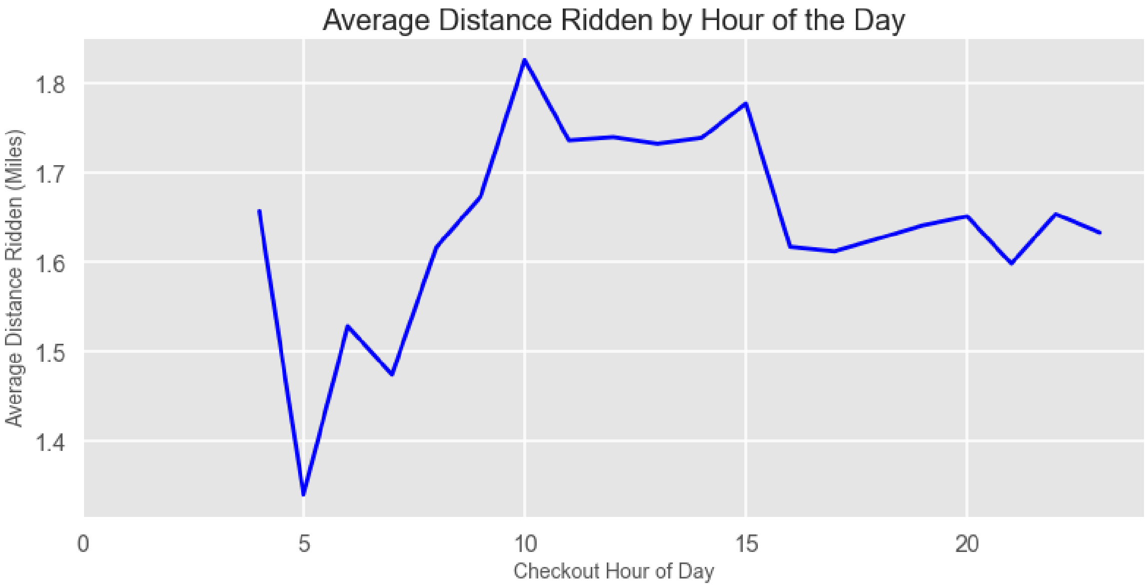


FIGURE 6: ESTIMATED AVERAGE MILES RIDDEN BY HOUR OF CHECKOUT IN 2016

Ridership by Hour and Weekday

Figure 7 shows that weekday ridership patterns are similar. On the other hand weekend ridership demonstrate a busy afternoon (between 12 PM and 3 PM)

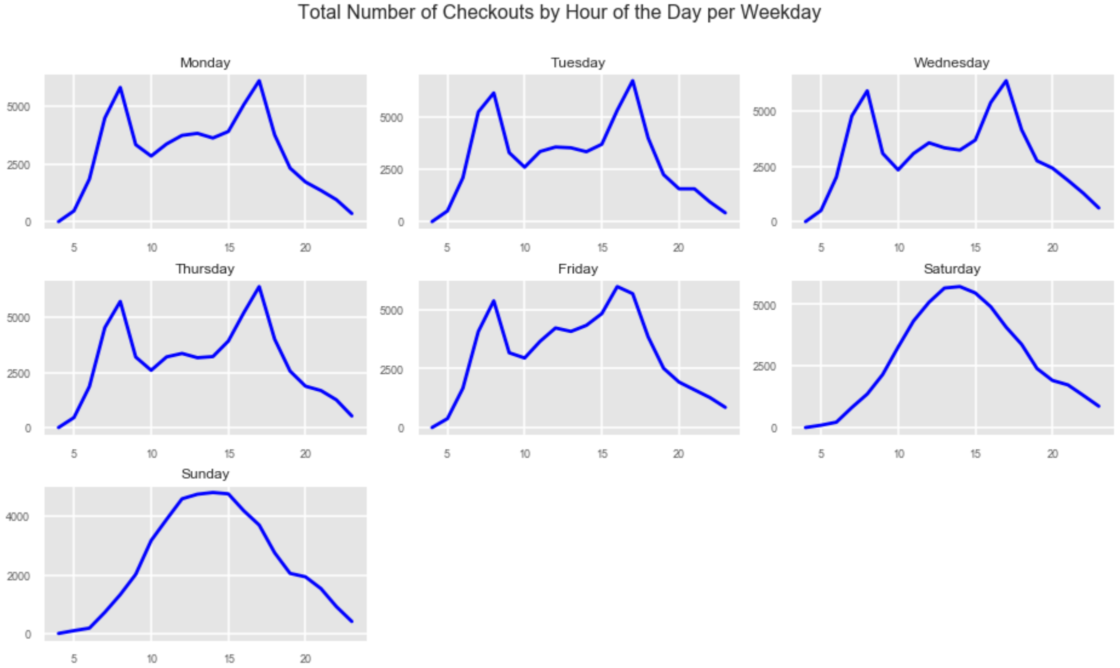


FIGURE 7: CHECKOUTS BY HOUR OF DAY PER WEEKDAY IN 2016

Ridership by Month

Monthly checkouts, as shown in Figure 8, suggest high ridership during the summer months and low ridership during the winter months.

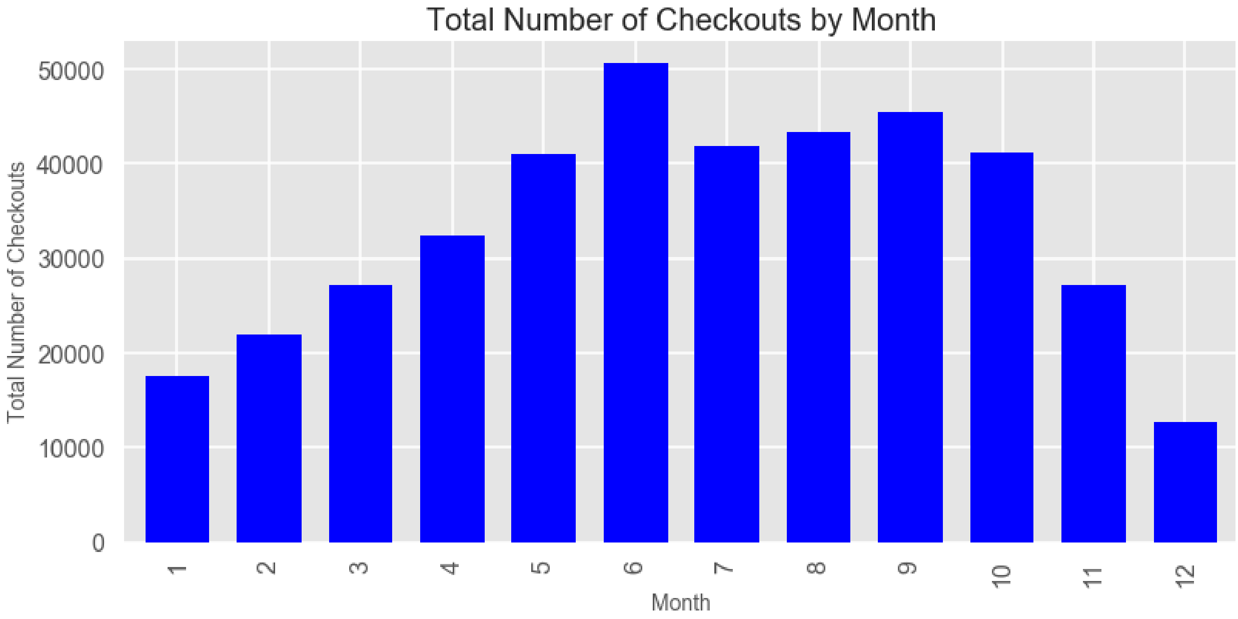


FIGURE 8: TOTAL CHECKOUTS BY MONTH IN 2016

Merging with Weather

It is highly likely that weather plays a very important role in bike ridership and bike checkout times. This was shown in the previous plots on total checkouts per hour of the day, by weekday, and by month. To verify this, weather data obtained from Dark Sky API was merged with the Trips dataset and several graphs plotted to visualize the relationships.

Checkouts vs. Daily Temperature

Figure 9 shows the total number of checkouts against maximum and minimum daily temperature. It clearly suggests that ridership increases as the temperature increases and vice-versa.

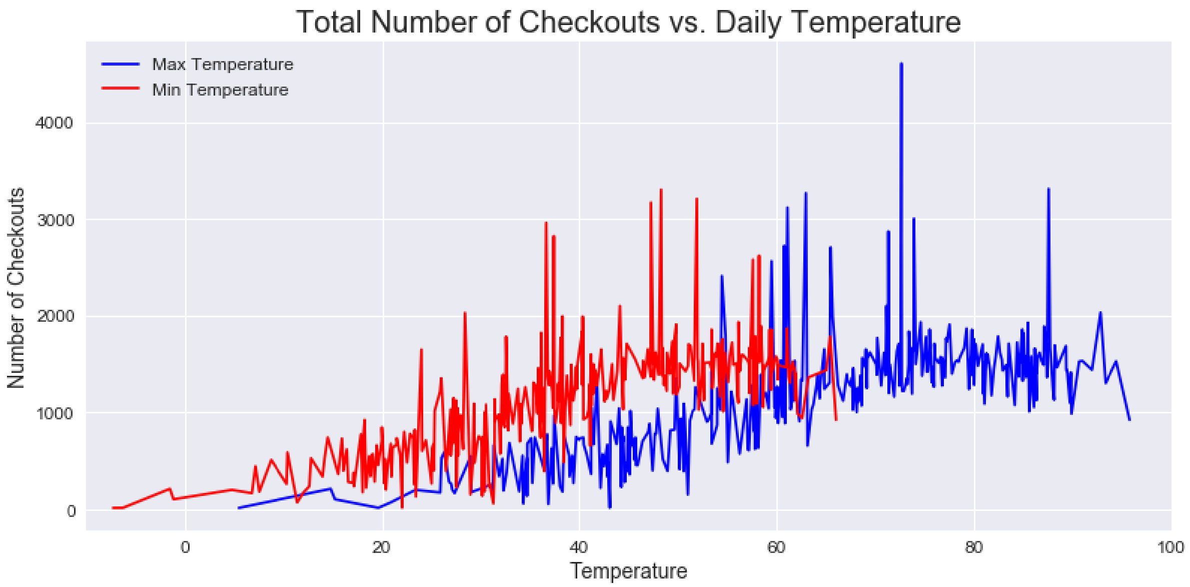


FIGURE 9: TOTAL CHECKOUTS BY DAILY TEMPERATURE IN 2016

Apparent temperature, as defined by Dark Sky, is “apparent (or “feels like”) temperature in degrees Fahrenheit”. It appears to have a subtle effect on bike ridership as shown in Figure 10.

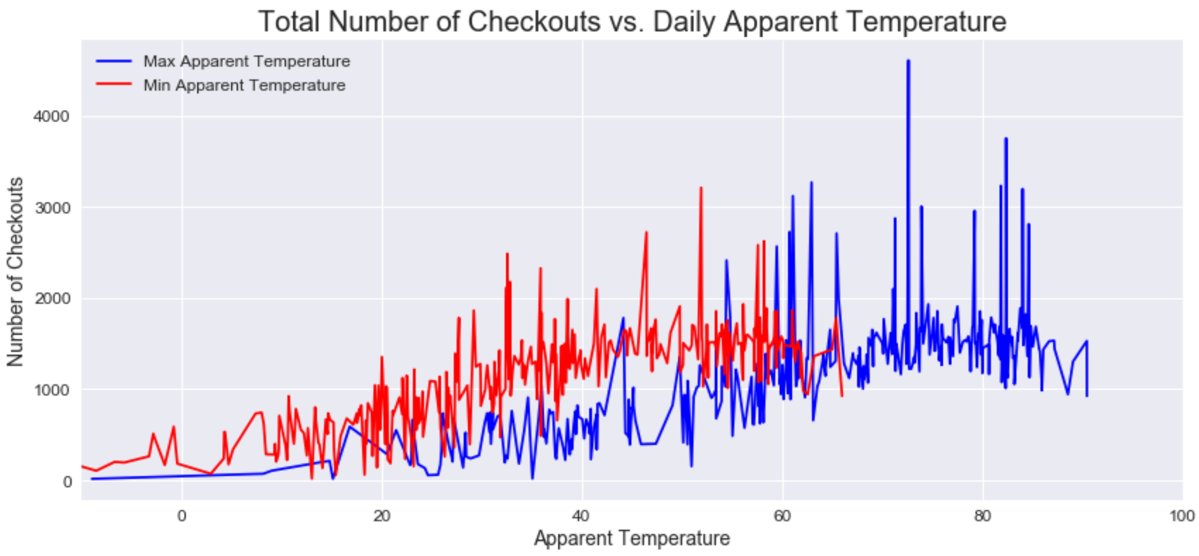


FIGURE 10: TOTAL CHECKOUTS BY DAILY APPARENT TEMPERATURE IN 2016

Checkouts vs. Daily Cloud Cover

Dark Sky defines Cloud Cover as “the percentage of sky occluded by clouds, between 0 and 1, inclusive”. Figures 11 shows the total number of checkouts against daily cloud cover. They clearly suggest that ridership is highest as the cloud cover stays at around 0.15.

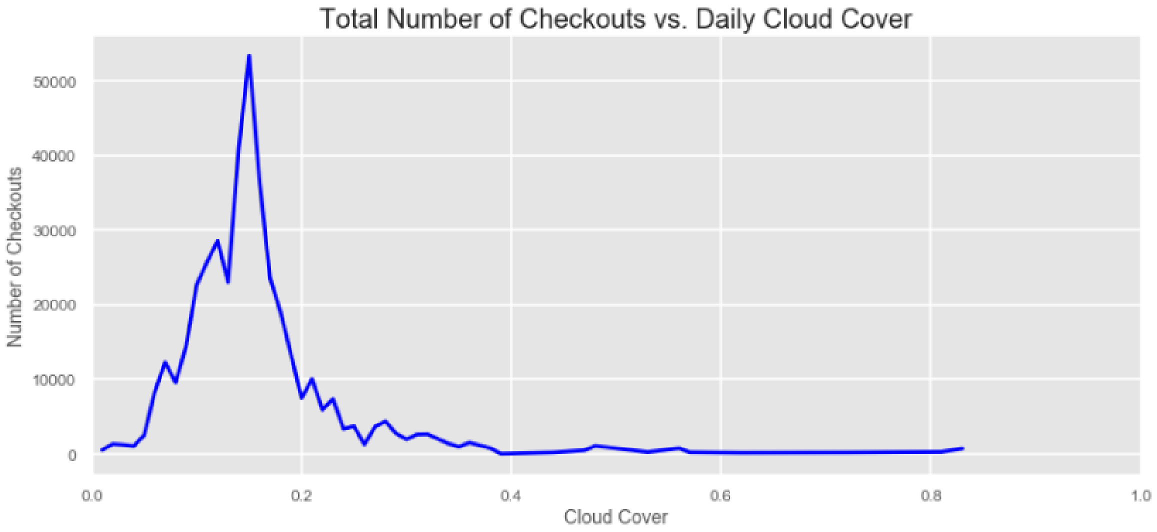


FIGURE 11: TOTAL CHECKOUTS BY DAILY CLOUD COVER IN 2016

Checkouts vs. Daily Wind Speed

Wind speed is reported in miles per hour. As shown in Figure 12, ridership does not seem to be somewhat impacted by higher wind speeds.

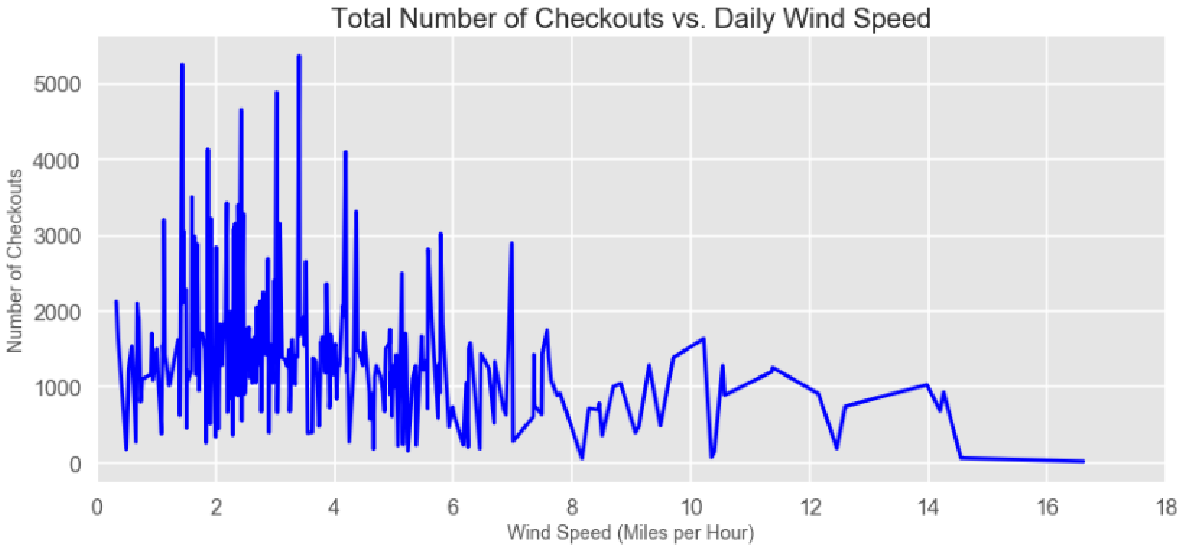


FIGURE 12: TOTAL CHECKOUTS BY DAILY WIND SPEED IN 2016

Checkouts vs. Daily Humidity

Humidity is defined by Dark Sky as “relative humidity, between 0 and 1. Figure 13 shows decreased ridership at higher humidity levels.

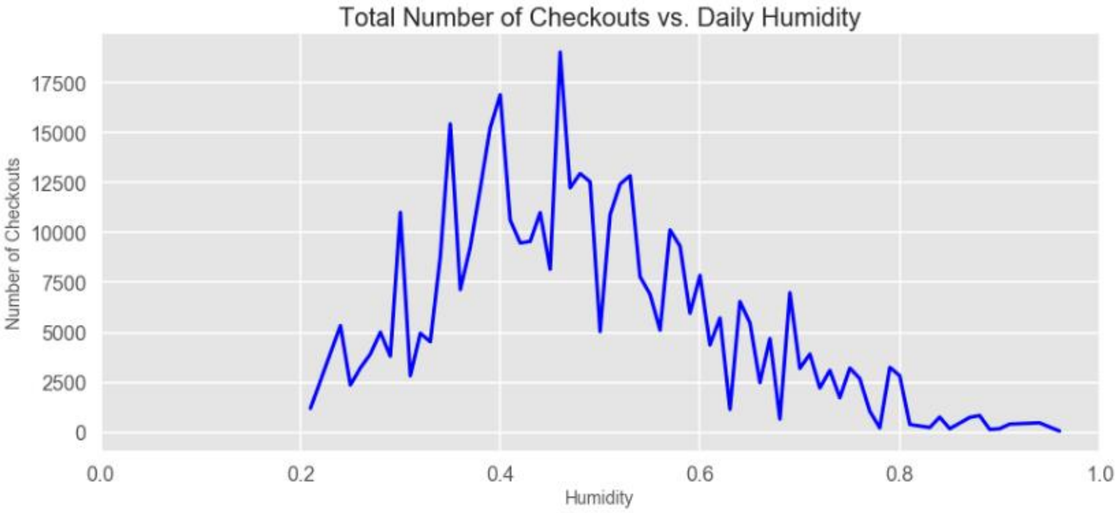


FIGURE 13: TOTAL CHECKOUTS BY DAILY HUMIDITY IN 2016

Checkouts vs. Daily Visibility

Visibility is measured in miles and capped at 10 miles, according to Dark Sky. As Figure 14 shows, ridership peaks when visibility is at 10 miles.

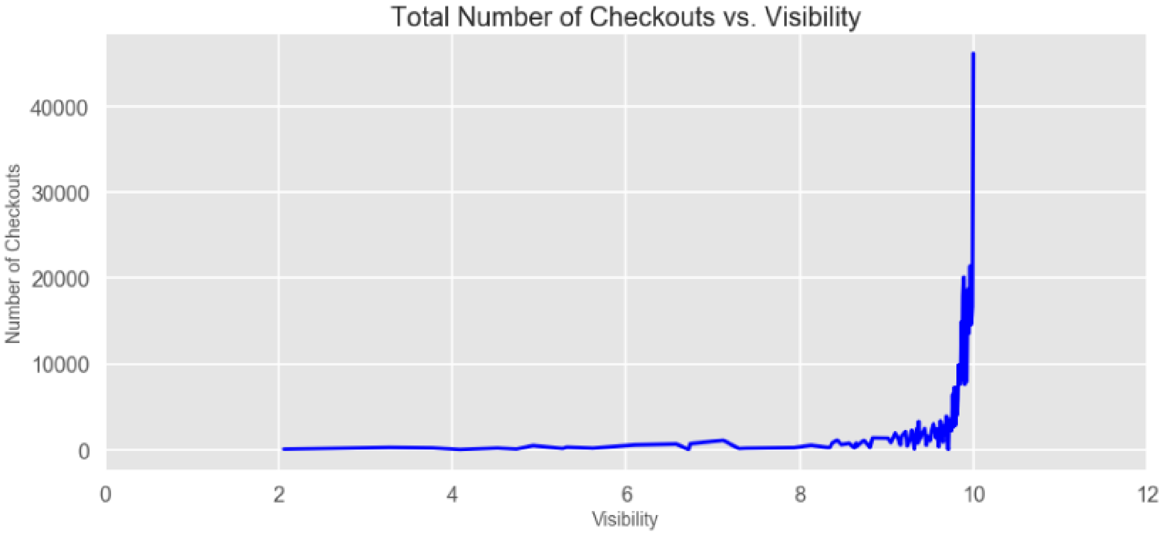


FIGURE 14: TOTAL CHECKOUTS BY DAILY VISIBILITY IN 2016

Days with Highest/Lowest Ridership

Another interesting data discovery was the fact that Saturdays and Sundays had the highest and lowest ridership depending upon the weather. In his study, Tyler suggests that this may be due to "'weekend warriors' who rent B-cycles for pleasure and are highly affected by the weather in their decision to ride". This may well be the case.

Highest Ridership

Checkout Week Day	Checkout Date	Max Temperature	Min Temperature	Number of Checkouts
Sunday	2016-05-29	71.090	44.100	2,100
Saturday	2016-05-28	65.650	40.330	1,990
Friday	2016-06-03	74.600	56.120	1,933
Wednesday	2016-06-15	85.430	51.980	1,927
Saturday	2016-06-21	77.510	49.790	1,909
Monday	2016-06-27	87.060	58.440	1,868
Saturday	2016-06-25	79.230	61.040	1,868
Saturday	2016-06-04	75.500	53.410	1,857
Thursday	2016-03-23	84.860	59.280	1,857
Friday	2016-09-02	79.770	59.500	1,855

Lowest Ridership

Checkout Week Day	Checkout Date	Max Temperature	Min Temperature	Number of Checkouts
Saturday	2016-12-24	50.960	28.940	154
Sunday	2016-04-17	34.710	30.140	140
Sunday	2016-01-31	31.260	23.430	133
Wednesday	2016-12-07	15.250	-1.110	105
Tuesday	2016-02-02	20.870	11.430	72
Saturday	2016-04-16	34.430	31.310	61
Sunday	2016-12-25	36.860	25.290	56
Wednesday	2016-03-23	43.070	22.040	18
Sunday	2016-12-18	19.640	-6.220	17
Saturday	2016-12-17	5.490	-7.220	16

Checkouts vs. Hourly Weather Variables

Hourly weather conditions provide better resolution than daily weather conditions. To investigate this, number of checkouts against hourly weather variables were also plotted and compared with the plots using daily weather variables.

Checkouts vs. Hourly Temperature

The scatter plots in Figure 15 and 16 show that the relationship between the number of checkouts and the hourly temperatures are not linear.

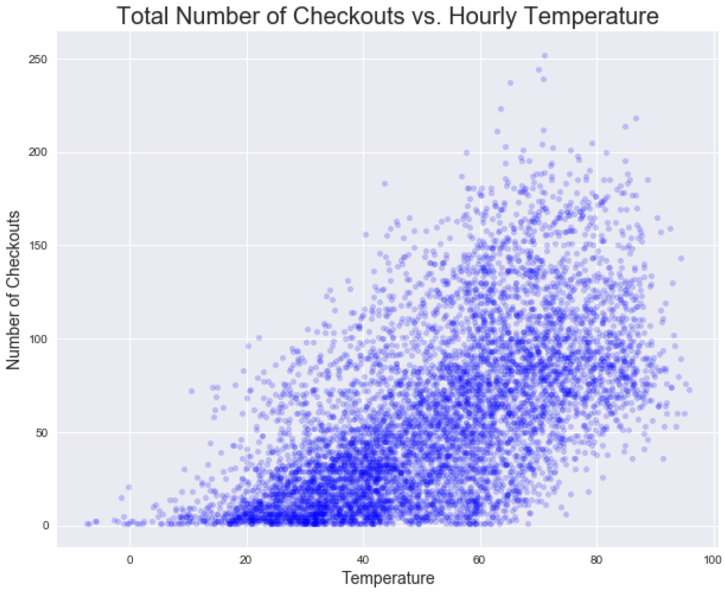


FIGURE 15: TOTAL CHECKOUTS BY HOURLY TEMPERATURE IN 2016

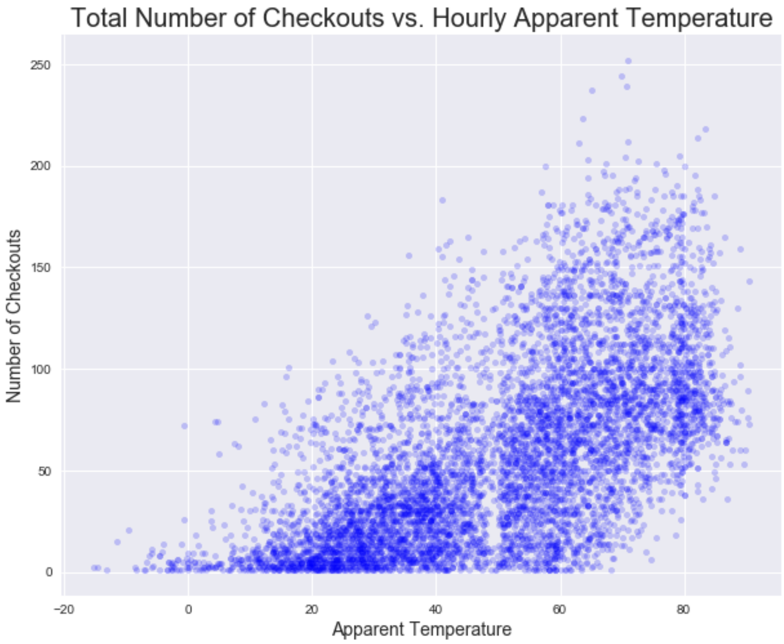


FIGURE 16: TOTAL CHECKOUTS BY HOURLY APPARENT TEMPERATURE IN 2016

Checkouts vs. Hourly Humidity

Figure 17 shows that humidity affects ridership significantly.

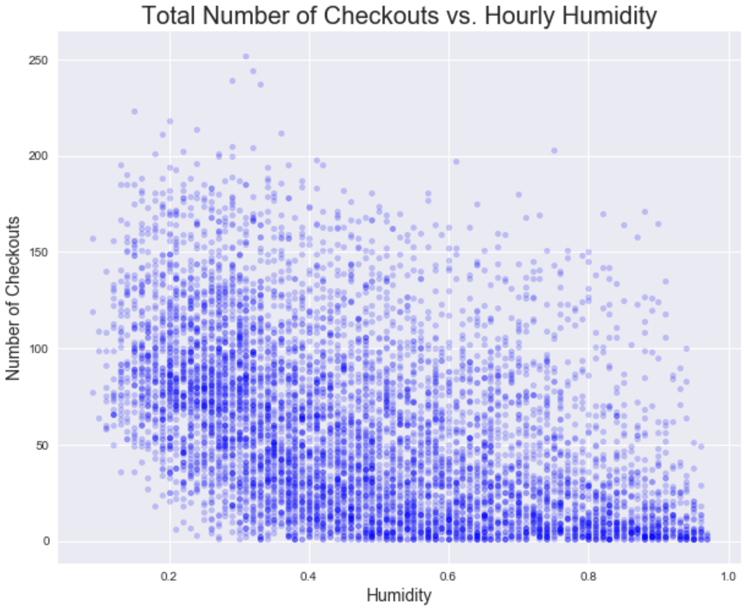


FIGURE 17: TOTAL CHECKOUTS BY HOURLY HUMIDITY IN 2016

Checkouts vs. Hourly Cloud Cover

As shown in Figure 18 Cloud Cover certainly impacts ridership.

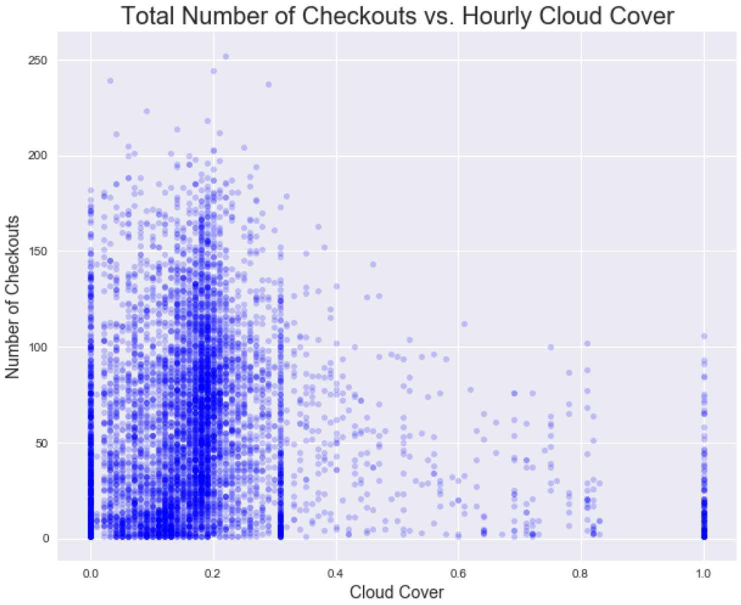


FIGURE 18: TOTAL CHECKOUTS BY HOURLY CLOUD COVER IN 2016

Checkouts vs. Hourly Wind Speed

Data on wind speed indicates it is clustered heavily in 0 to 8 miles per hour range, as shown in Figure 19.

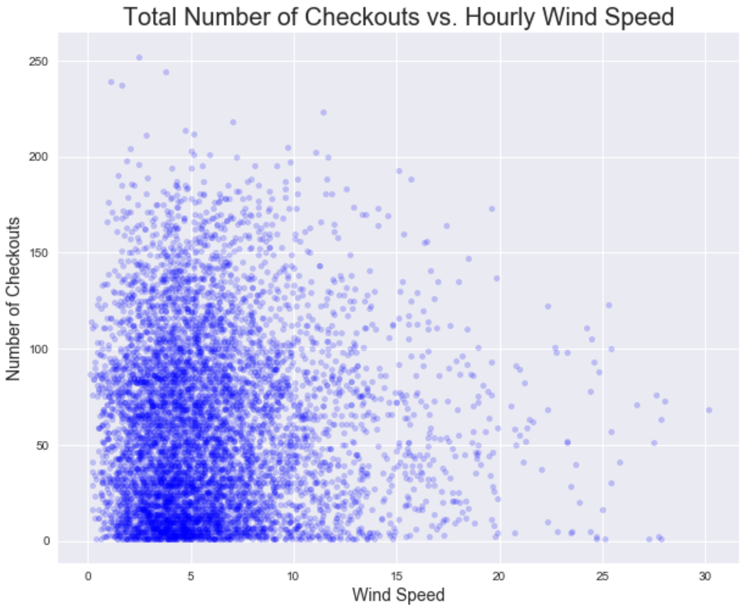


FIGURE 19: TOTAL CHECKOUTS BY HOURLY WIND SPEED IN 2016

Checkouts vs. Hourly Visibility

As shown in Figure 20 visibility at 10 miles has the greatest impact on ridership.

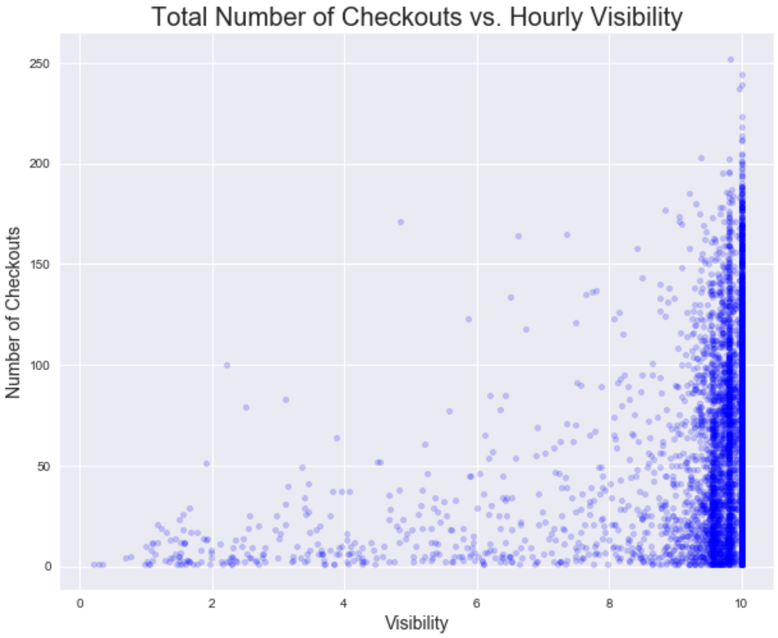


FIGURE 20: TOTAL CHECKOUTS BY HOURLY VISIBILITY IN 2016

Part 2: Regression Modeling

In his study, Tyler attempted to create a linear regression model using a number of calendar and weather variables. Using temperature, temperature squared, humidity, month, weekday, hour of day, holiday and cloud cover as input variables he arrived at an R squared value of 0.7382 which meant that approximately 73.8% of the variation in the hourly ridership could be explained by the selected variables and the linear model he used to fit the data.

In this section various linear and non-linear regression models were used to test and train the Trips data that was merged with the weather data to try to predict the number of checkouts based on weather conditions.

The following regression models with their brief explanation were used in this study:

- Linear Regression
  - Most widely used statistical and machine learning technique to model relationship between two sets of variables typically using a straight line. Simple to use and fast performance but lacks high accuracy when compared to non-linear models.
- Lasso Regression
  - A type of linear regression that uses shrinkage to reduce data values toward the mean. Well suited for automating feature selection.
- Ridge Regression
  - Well suited for data that suffers from multicollinearity, i.e. features with high correlation.
- Bayesian Ridge Regression
  - An approach to linear regression in which the statistical analysis is undertaken using Bayesian inference.
- Decision Tree Regression
  - Uses a tree like structure to derive a final decision on the outcome of the analysis.
- Random Forest Regression
  - An ensemble learning method that operates by constructing a multitude of decision trees to arrive at the mean prediction.
- Extra Trees Regression
  - An extremely randomized tree regressor. Builds a totally random decision tree.
- Nearest Neighbors Regression
  - A simple algorithm that uses a similarity measure (e.g. distance between neighbors) to predict the outcome.

Regression Modeling with Categorical Feature Set

The Checkout Month, Week Day and Hour numeric variables were converted to categorical features resulting in 45 total features for regression modeling.

Prior to applying the models a feature correlation was performed on all the features to see if any of the features were highly correlated to one another. As shown in Figure 21, Temperature and Apparent Temperature were highly correlated suggesting that one of them could be removed from the features in the model application.

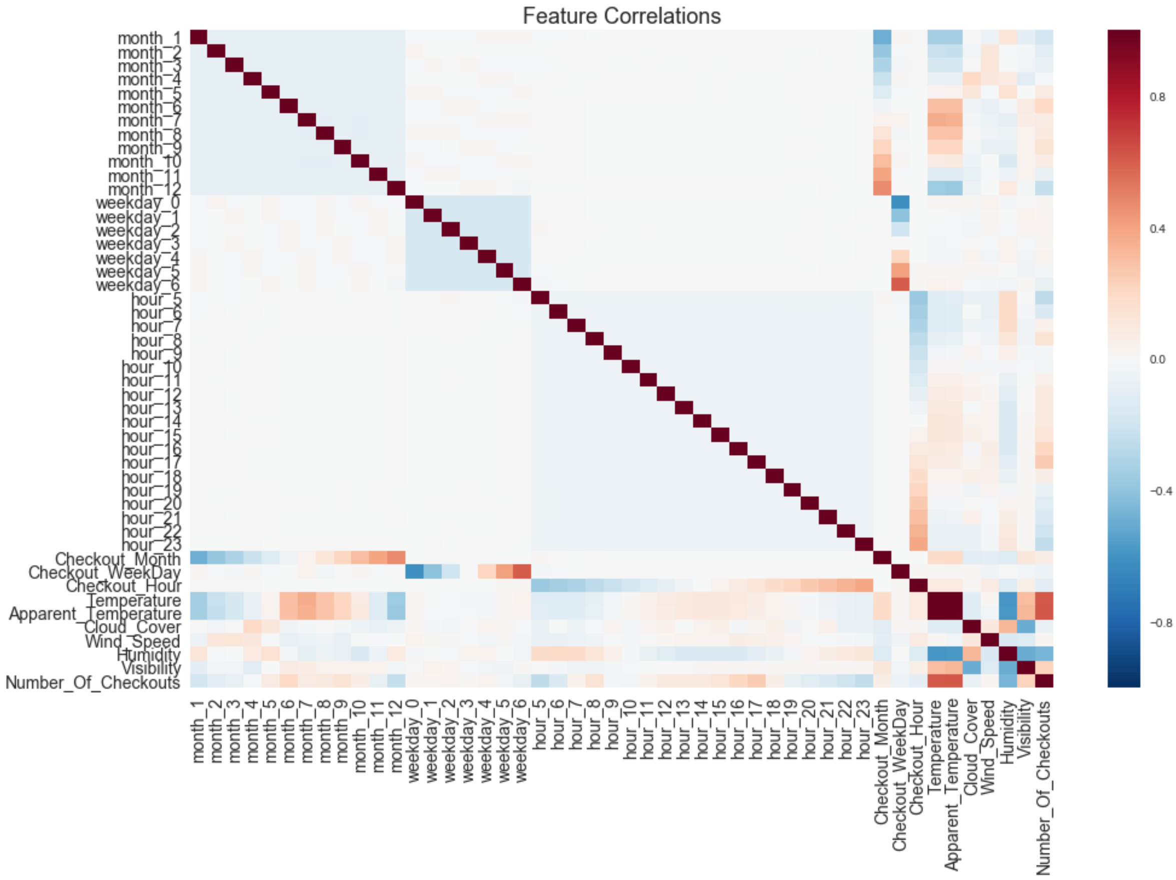


FIGURE 21: FEATURE CORRELATIONS

The models used for regression supported the use of several parameters that could be used to adjust or tune them for better performance. In most cases in this study, the parameters were set to default.

The dataset was randomly spilt into 70% for training and 30% for testing. For each model the training and test scores, R Squared and RMSE results were collected and summarized. In addition, the Decision Tree, Random Forest and Extra Trees models also had their Feature Importance bar charts plotted. The chart for Extra Tree model is shown in Figure 22.

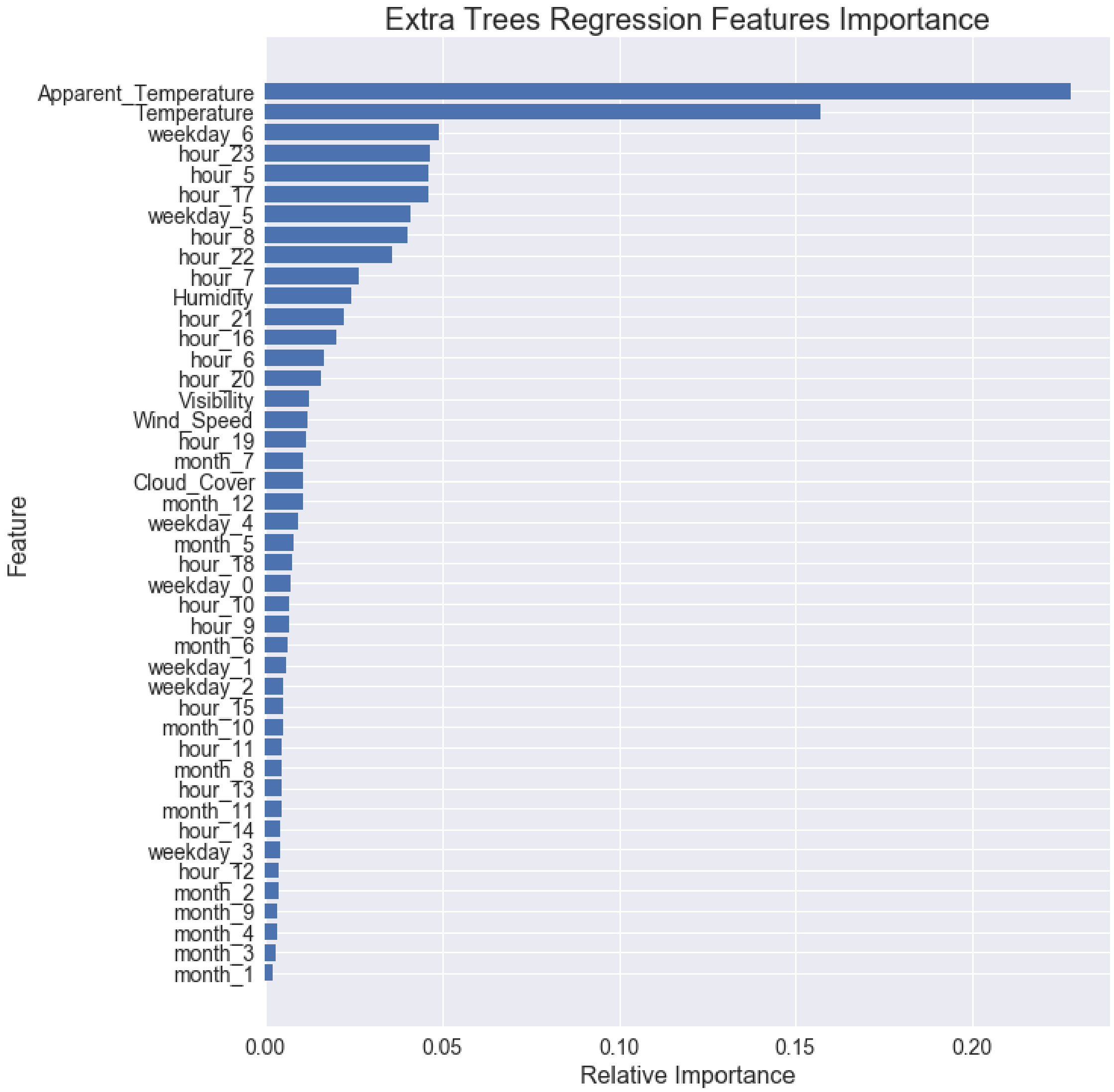


FIGURE 22: EXTRA TREES REGRESSION MODEL FEATURE IMPORTANCE CHART

Regression Modeling Summary – Categorical Feature Set

	Linear	Lasso	Ridge	Bayesian Ridge	Decision Tree	Random Forest	Extra Trees	Nearest Neighbors
Training Test Score	0.676	0.676	0.676	0.676	1.000	0.969	1.000	0.575
Test Set Score	0.696	0.696	0.696	0.696	0.718	0.825	0.840	0.476
R Squared	0.834519	0.834457	0.834457	0.834448	0.847276	0.908443	0.916278	0.690249
RMSE	627.95439	628.16826	628.16826	628.19832	583.57445	361.43485	331.86035	1082.98114

The Extra Trees regression model achieved the highest accuracy and the lowest RMSE. All the linear models (Linear, Lasso, Ridge and Bayesian Ridge) had twice the RMSE value of the Extra Trees model.

Regression Modeling with Numerical Feature Set

Using Checkout Month, Week Day and Hour numeric variables resulted in just 9 total features for regression modeling.

Prior to applying the models a feature correlation was performed on all the features to see if any of the features were highly correlated to one another. As shown in Figure 23, Temperature and Apparent Temperature were highly correlated suggesting that one of them could be removed from the features in the model application.

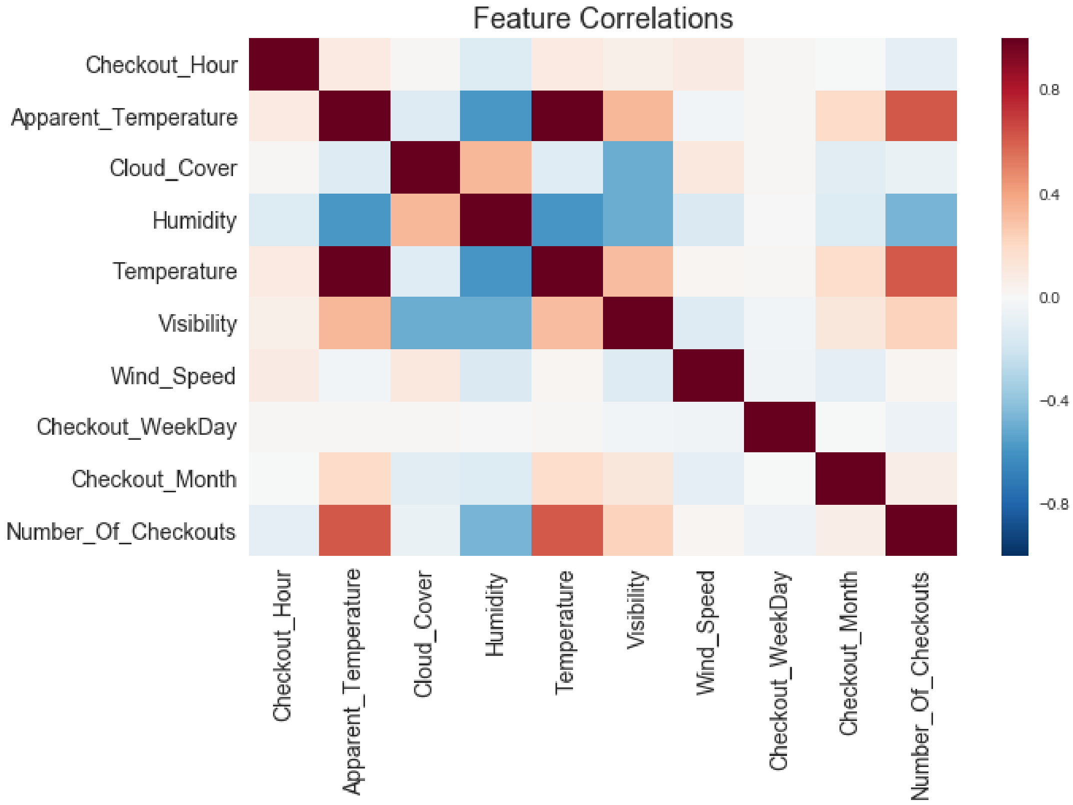


FIGURE 23: FEATURE CORRELATION

For each model the training and test scores, R Squared and RMSE results were collected and summarized. In addition, the Decision Tree, Random Forest and Extra Trees models also had their Feature Importance bar charts plotted. The chart for Extra Tree model is shown in Figure 24.

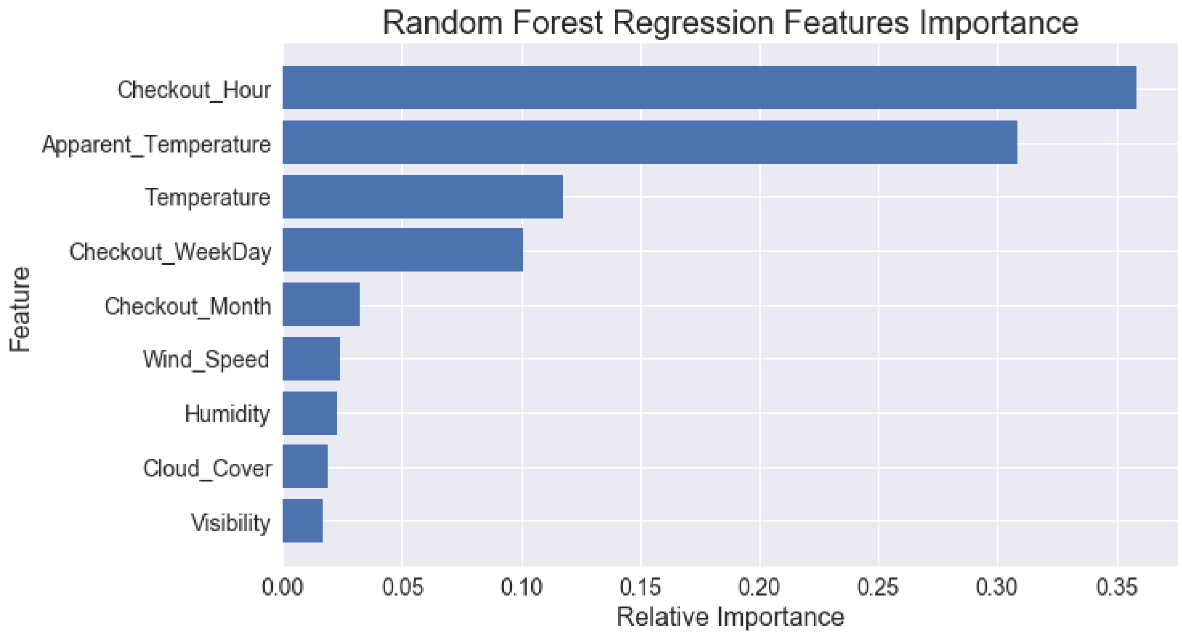


FIGURE 24: RANDOM FOREST REGRESSION MODEL FEATURE IMPORTANCE CHART

Regression Modeling Summary – Numerical Feature Set

	Linear	Lasso	Ridge	Bayesian Ridge	Decision Tree	Random Forest	Extra Trees	Nearest Neighbors
Training Test Score	0.433	0.433	0.433	0.433	1.000	0.975	1.000	0.880
Test Set Score	0.448	0.447	0.447	0.447	0.741	0.854	0.838	0.646
R Squared	0.669090	0.668243	0.668243	0.668785	0.861079	0.924077	0.915609	0.803447
RMSE	1142.475	1144.818	1144.818	1143.319	534.800	302.172	334.397	733.229

Regression Modeling Summary

- The data exploration phase of this study revealed the significance of weather variables on the ridership. The regression modeling phase confirmed this to be accurate. Looking at the feature importance graphs generated by the Extra Trees and Random Forest models, the weather attributes rank the highest.
- The non-linear regression models performed better than the linear models. In particular, even with a reduced feature set, the non-linear models such as the Random Forest and the Extra Trees were the best performers with R Squared values well above 0.9.

Testing Regressor on unseen samples

The Random Forest Regressor with a predictive accuracy of 92.4% was used to predict 10 samples (with numerical feature set) from the dataset that had not been used neither in the training nor in the test sets. The results are tabulated below. The regressor predicted 1 of the 10 samples accurately. Of the remaining 9 samples, it predicted well within the 7.6% range based on its accuracy on 8 samples.

Sample Number	Actual Number of Checkouts	Predicted Number of Checkouts	+/-
1	92	96	+4
2	12	13	+1
3	55	56	+1
4	111	112	+1
5	76	72	-4
6	41	37	-4
7	8	14	+6
8	81	99	+18
9	65	64	-1
10	14	14	0

Part 3: Classification Modeling

In this section various classification models were used to test and train the Trips data that was merged with the weather data to try to predict the checkout hour based on weather conditions.

The following classification models were used in this study:

- Linear (Logistic) Classification
    - Similar to linear regression but used for classification

- Decision Tree Classification
    - Uses a tree like structure to derive at a final decision on the outcome of the analysis

- Random Forest Classification
    - Similar to random forest regression but used for classification

- Extra Trees Classification
    - Similar to extra trees regression but used for classification

- Naïve Bayes Classification
    - Uses the Bayes’ Theorem (i.e. assumes that the presence of a particular feature is unrela ted to the presence of any other feature)

- Gradient Boosting Classification
    - A machine learning method that produces a prediction model in the form of an ensembl e of weak prediction models, typically decision trees.

- Nearest Neighbors Classification

  - Similar to nearest neighbors regressor but used for classification

- Multi-layer Perceptron Classification
  - A feedforward artificial neural network mode that maps sets of input data onto a set of appropriate outputs.

The dataset was randomly spilt into 70% for training and 30% for testing. The class labels were defined as follows:

Class 0: Number of Checkouts >= 1 and <= 50

Class 1: Number of Checkouts >=51 and <= 100

Class 2: Number of Checkouts >= 101 and <= 150

Class 3: Number of Checkouts >=151

A cross validation using the Stratified Shuffle Split method was performed on the dataset for each model using a training sample size of 50% and a testing sample size of 50% with 10 splits.

Classification Modeling – Categorical Feature Set

As in the case of Regression modeling, feature correlation was carried out to determine if any features had a high correlation with one another. As shown in Figure 21, Temperature and Apparent Temperature were highly correlated suggesting that one of them could be removed from the features in the model application.

For each model the training and test scores, Accuracy, F1 (micro), F1 (macro), Precision (macro), Precision (micro), Recall (macro) and Recall (micro) results were collected and summarized. In addition, the Decision Tree, Random Forest and Extra Trees models also had their Feature Importance bar charts plotted.

Classification Modeling Summary – Categorical Feature Set

	Logistic	Decision Tree	Random Forest	Extra Trees	Naïve Bayes	Nearest Neighbors	Gradient Boosting	Multi-Layer Perceptron
Accuracy	0.728070	0.730119	0.786062	0.806043	0.457115	0.639864	0.756335	0.791423
F1 (macro)	0.560579	0.642804	0.670351	0.701782	0.371971	0.413859	0.651137	0.630989
F1 (micro)	0.728070	0.730119	0.786062	0.806043	0.457115	0.639864	0.756335	0.791423
Precision (macro)	0.622020	0.636731	0.710195	0.710991	0.440307	0.497978	0.682317	0.676773

Precision (micro)	0.728070	0.730119	0.786062	0.806043	0.457115	0.639864	0.756335	0.791423
Recall (macro)	0.538820	0.650152	0.646257	0.694738	0.515025	0.411259	0.630477	0.614739
Recall (micro)	0.728070	0.730119	0.786062	0.806043	0.457115	0.639864	0.756335	0.791423
Cross Validation	0.718655	0.722281	0.777895	0.797076	0.448012	0.624035	0.748538	0.750175
Execution Time (sec)	14.137227	0.304386	3.665370	3.346657	0.179008	0.977846	108.952438	9.298618

The Extra Trees model attained the highest accuracy in classifying the four classes. The Naïve Bayes model performed the poorest.

Classification Modeling – Numerical Feature Set

Using Checkout Month, Week Day and Hour numeric variables resulted in just 9 total features for regression modeling.

As in the case of Regression modeling, feature correlation was carried out to determine if any features had a high correlation with one another. As shown in Figure 22, Temperature and Apparent Temperature were highly correlated suggesting that one of them could be removed from the features in the model application.

For each model the training and test scores, Accuracy, F1 (micro), F1 (macro), Precision (macro), Precision (micro), Recall (macro) and Recall (micro) results were collected and summarized. In addition, the Decision Tree, Random Forest, Extra Trees and Gradient Boosting models also had their Feature Importance bar charts plotted. The chart for the Gradient Boosting model is shown in Figure 25.

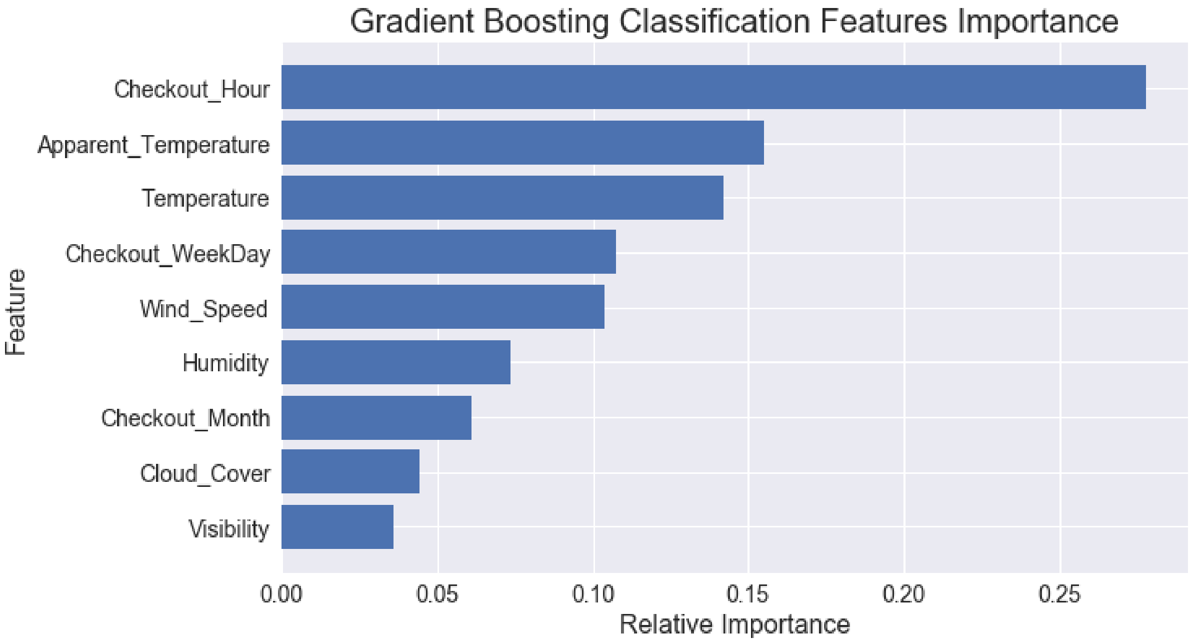


FIGURE 25: GRADIENT BOOSTING CLASSIFICATION MODEL FEATURE IMPORTANCE CHART

Classification Modeling Summary – Numerical Feature Set

	Logistic	Decision Tree	Random Forest	Extra Trees	Naïve Bayes	Nearest Neighbors	Gradient Boosting	Multi-Layer Perceptron
Accuracy	0.640351	0.732456	0.793372	0.791910	0.504386	0.688109	0.760234	0.687135
F1 (macro)	0.341939	0.629112	0.675405	0.684538	0.384729	0.463753	0.647997	0.437630
F1 (micro)	0.640351	0.732456	0.793372	0.791910	0.504386	0.688109	0.688109	0.687135
Precision (macro)	0.311641	0625842	0.732482	0.727647	0.395476	0.543086	0.658037	0.457347
Precision (micro)	0.640351	0.732456	0.793372	0.791910	0.504386	0.688109	0.688109	0.687135
Recall (macro)	0.380207	0.632630	0.646895	0.657962	0.411507	0.458458	0.639805	0.446176
Recall (micro)	0.640351	0.732456	0.793372	0.791910	0.504386	0.688109	0.688109	0.687135
Cross Validation	0.642573	0.727544	0.782407	0.778772	0.526725	0.684503	0.757427	0.664971
Execution Time (sec)	12.288280	0.190748	4.000826	3.295505	0.096340	0.941100	60.454736	3.061440

Both the Random Forest and the Extra Trees classifiers achieved the highest accuracy and the Naïve Bayes the lowest. The cross validation test accuracy were comparable to the F1 (micro), Precision (micro) and the Recall (micro) accuracies.

Classification Modeling Summary

- The multi-layer perceptron model attained the highest accuracy in classifying the four classes using the categorical feature set. The Naïve Bayes model performed the poorest.
- The Gradient Boosting Classifier achieved the highest accuracy and the Naïve Bayes the lowest with the numerical feature set. While the Multi-Layer Perceptron model had better accuracy than the Gradient Boosting with the categorical feature set it did not fare as well in the numerical feature set.
- None of the models used in this study were not able to achieve an accuracy greater than 71% either with the categorical or the numerical feature set.
- The non-linear regression models performed better than the linear models. In particular, even with a reduced feature set, the non-linear models such as the Random Forest and the Extra Trees were the best performers with R Squared values well above 0.9.

Testing Classifier on unseen samples

The Random Forest Classifier with a predictive accuracy of 79.3% was used to predict 10 samples (with numerical feature set) from the dataset that had not been used neither in the training nor in the test sets. The results are tabulated below. The classifier predicted 8 of the 10 samples accurately. Of the remaining 2 samples, it predicted one class below the actual class in both samples.

Sample Number	Actual Number of Checkouts	Class Number	Predicted Number of Checkouts	Class Number
1	Between 51 and 100	1	Between 51 and 100	1
2	Between 1 and 50	0	Between 1 and 50	0
3	Between 51 and 100	1	Between 1 and 50	0
4	Between 101 and 150	2	Between 101 and 150	2
5	Between 51 and 100	1	Between 51 and 100	1
6	Between 1 and 50	0	Between 1 and 50	0
7	Between 1 and 50	0	Between 1 and 50	0
8	Between 51 and 100	1	Between 1 and 50	0
9	Between 51 and 100	1	Between 51 and 100	1
10	Between 1 and 50	0	Between 1 and 50	0

Summary

This in-depth study on Denver 2016 Bike Share Trips data was undertaken to continue the work that Tyler started on the 2014 data. It agrees with his findings that by merging calendar, clock and weather attributes into the Trips dataset can reveal ridership patterns and allow regression and classification techniques to be applied for prediction purposes.

This study covered three areas:

1. Explored the Trips datasets and visualized the data and provided useful and interesting information.
2. Deployed a variety of supervised machine learning regression models to predict the number of checkouts using calendar, clock and weather attributes.
3. Deployed a variety of supervised machine learning classification models to predict the number of checkouts using calendar, clock and weather attributes.