Bikeshare DC

GEORGETOWN CERTIFICATE IN DATA SCIENCE
CAPSTONE PROJECT — COHORT 11

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Abstract

In September 2017, the DC Department of Transportation began a dockless bikeshare pilot program. The pilot program allowed 6 different dockless bikeshare operators to enter the DC market and begin offering their services, effectively putting them in direct competition with the 7.5 year old Capital Bikeshare system. Our project seeks to analyze the dockless pilot program to determine if the introduction of dockless bikes has impacted the demand among users for Capital Bikeshare (CaBi). We accomplish this analysis by gathering data on CaBi, the dockless bikeshare operators and external factors that we believe impact the DC bikeshare demand. Using historical data on Capital Bikeshare and the external factors we create two machine learning models using Lasso and Random Forest to predict the number of Capital Bikeshare rides that we would expect to see during the first eight months of the dockless pilot program. Then we compare our models' predicted values to the actual number of rides that occurred during the pilot program to determine if our models realistically estimated the impact that the dockless bikeshare pilot program has had an impact on Capital Bikeshare.

Introduction

In September 2010, Capital Bikeshare (CaBi) began operating in the Washington, DC region with 1,100 bikes and 114 stations in Washington, DC and Arlington, VA (Motivate International, Inc, 2017). Since then CaBi has grown to approximately 437 stations and 4,500 bikes. It has expanded its coverage to include, Alexandria, VA, Montgomery County, MD, and Fairfax County, VA. The system, which sees an average of over 10,000 trips per day, has grown to be the third largest bikeshare system currently operating in the United States.

In September 2017, the DC department of Transportation (DDOT) began a pilot program in Washington, DC which allowed for five dockless bikeshare companies to begin operating in the city (Sturdivant, 2017). Dockless bikeshare bikes differ notably from CaBi in that the bikes do not need to be taken from or returned to physical docking stations. Instead, the dockless bikes can be left anywhere in the city as long as they are on public property and they are not obstructing roadways or pedestrian walkways. The lack of infrastructural prerequisites meant that seemingly overnight several fleets of brightly colored bikes appeared on the streets. Under regulations established by DDOT for the dockless bikeshare pilot program, each operator is permitted to have a maximum of 400 vehicles on the street at any given time (Ryan, 2017). For the first several months of the pilot program, vehicle was synonymous with bike until electric scooters were introduced in March and Lime reduced the number of bikes in their fleet in order to increase the number of scooters (Seher, 2018). The pilot program presented a unique opportunity to study the effect that the introduction of a new mode of might have on the demand for a well-established bikeshare system. In this paper we use machine learning to predict the demand for CaBi through the duration of the pilot program, and by comparing the predicted demand with the actual demand, we attempt to determine to what extent the dockless bikeshare operators have been able to disrupt the status quo.

Data Sources

The data that was gathered for this project fell into one of three categories:

1. CaBi Data - Publicly available system data and API
2. Dockless Bikeshare Data - Data provided by DDOT and API
3. Misc Data - Data on a variety of factors, such as weather and population, that we believe would have an impact on the demand for bikeshares in Washington, DC.

Most of the data that was used for this project is publicly available data which we either downloaded, scraped or used an API to pull down from a website. Exceptionally, we received dockless trip data from DDOT and dockless bikes available data from Daniel Schep who had already put together a site to track all the bikeshare systems in DC. He was kind enough to share his stored API data with us so that we could actually analyze dockless bikeshare utilization rates, as the data we received from the operators was not reliable. As we began sourcing our data, we set up a meeting with DDOT to explain to them the goals and scope of our project and offer our assistance to help analyze the efficacy of the pilot program. DDOT agreed to share the data that they had with us on the condition that we share our findings with them at the end of our analysis and we sign a nondisclosure agreement agreeing not to divulge any of the dockless data to the general public.

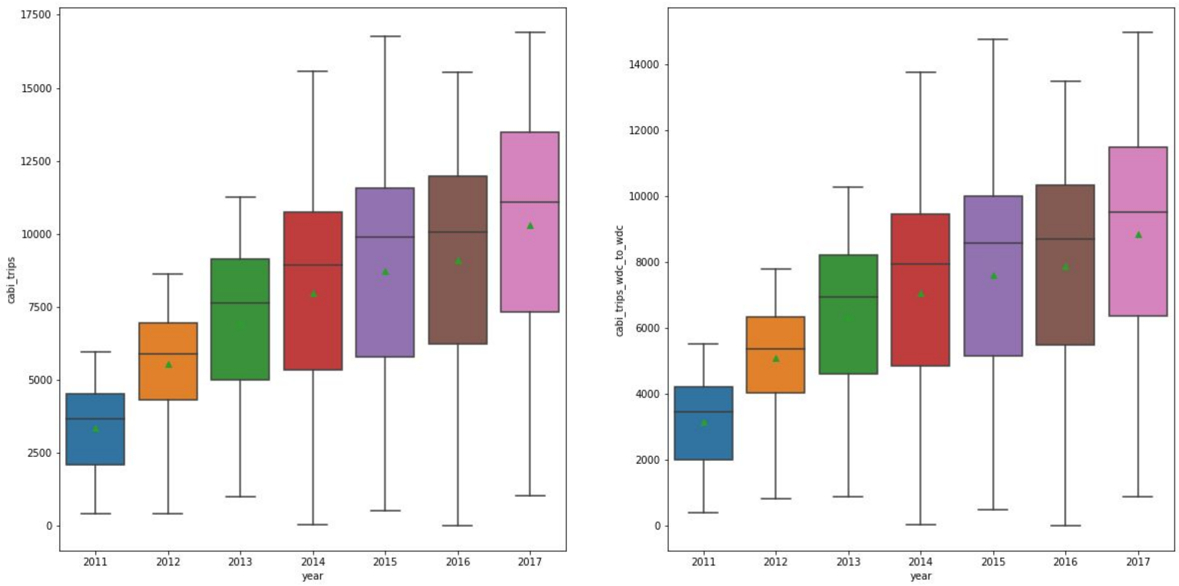
Under the rules of the pilot program, the dockless bikeshare operators are required to self-report data on a monthly basis to DDOT. The monthly reports include data on trip start and stop times, trip start and stop locations, and user id among other fields. The CSVs that we received required a significant amount of processing. For example, not every operator reported latitude and longitude trips starts/ends to the enough precision to determine actual location, which impacted our ability to compare trip locations across operators. There were also inconsistencies with the start and end times for trips in the data that the dockless operators were self-reporting. In one extreme case it was discovered that the hours were missing from the timestamps for all trips for a particular operator. In another case, there were instances where the reported end time occurred before the reported start time which resulted in calculations for negative trip durations.

Table descriptions and data dictionaries of all the data sources we used as can be found in our Github repo's data dictionary. Additionally, a full system architecture can be found in our repo's README file.

Exploratory Analysis

We began our exploratory analysis by looking at the growth in the CaBi daily trips for from 2011 through 2017. Our goal was to determine the best time frame for our machine learning analysis by identifying when CaBi became well established in Washington, DC. Figure 1 shows that the number of trips per day increased fairly rapidly during the first four years of operation. During that time, approximately 222 new docking stations were added to the system. Beginning in 2014, the average number of trips taken each day has increased a slower rate, suggesting that the rapid expansion of the earlier years has ended as CaBi has become a fixture within DC's public transportation system.

Figure 1 Average daily CaBi Trips by Year (Left: System Wide, Right: DC to DC trips)



We also wanted to determine if behavior differed between the two user categories, member and casual. Members are defined as CaBi users that have purchased either an annual or monthly membership. Casual users are defined as users that have purchased a three-day, 24-hour pass or single trip pass (starting in June 2016). We examined the behavior of these two user types by plotting the bike utilization rate for members and casual users by year, month and day of the week in order to determine if there were significant differences in the usage patterns between these two groups. The *bike utilization rate* is defined as $\frac{Total\ number\ of\ trips\ per\ day}{Total\ number\ of\ available\ bikes}$. In Figure 2, we examine the average *bike utilization rate* by year by creating one subplot which shows the bike utilization rate for members and another subplot for the bike utilization rate of casual riders. In 2011, CaBi members accounted for a little under 2.5 rides per day for each active bike. That number grew to around 2.6 rides per day in 2012 before it slowly started declining to a little over 1.5 in 2017. What this shows is that by 2011 there was already a strong demand among members when CaBi had a relatively small fleet. CaBi has added bikes to their fleet over the years at a rate which has outpaced the growth in rides per day by CaBi members. The bike utilization rate for casual users has remained fairly constant since 2011. The third subplot in Figure 2 shows that from 2011 until 2016 around 80% of CaBi's usage is coming from members. This percentage begins to dip in 2016 and 2017; one possible explanation being that CaBi introduced $2 single trip 30 minute rides in June 2016. This makes it easier for casual users to use CaBi, as they no longer need to purchase a 24-hour or 3 day pass.

FIGURE 2 BIKE UTILIZATION RATE FOR CABI BY YEAR

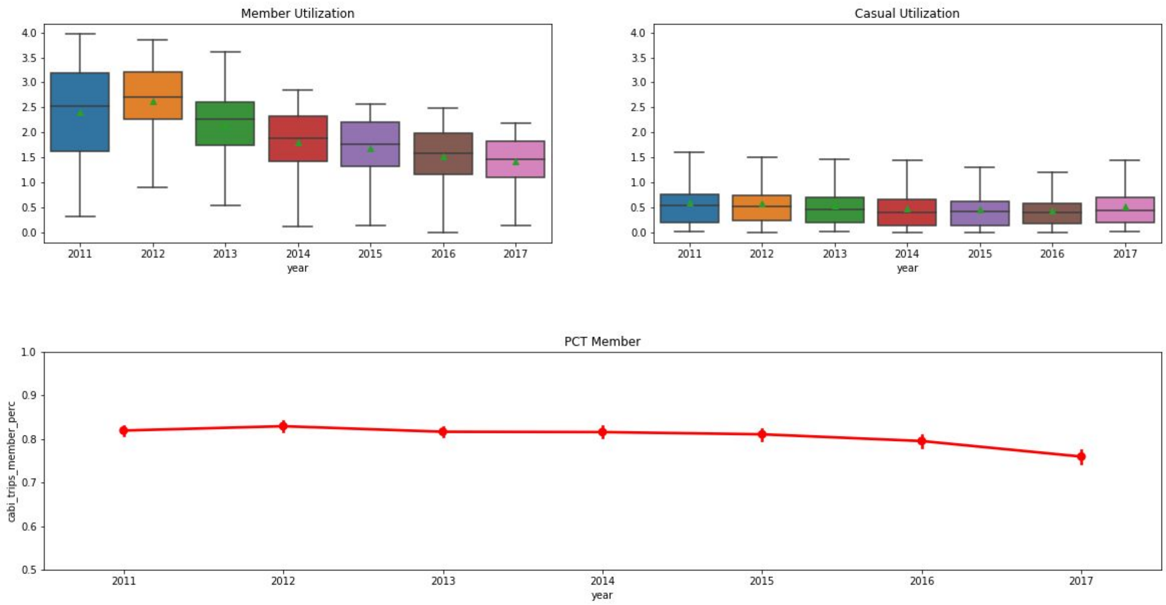


Figure 3 shows the bike utilization rate by month for the two user types. The subplots clearly demonstrate the seasonality of usage for both members and casual users. For both user types, the utilization rate of the bikes is depressed during the colder winter months and peaks in the warmer summer months. However, the drop off in the utilization rate during the winter months for casual users is more substantial than it is for members. Members account for around 90% of trips during the months of December, January, and February, as seen in the third subplot of figure 3. However, that rate falls to a little over 75% in the summer months once the usage among casual riders begins to increase, starting around March. It's important to note that our analysis of the dockless pilot program does not include the summer months since it began in September and has only been running for the past 9.5 months.

Figure 4 shows the bike utilization rate for members and casual users by day of the week. The subplots show that there is a difference in the usage patterns of members and casual users. For members the bike utilization rate is highest on weekdays and lower on the weekends, suggesting that CaBi members may be using the bikes to commute to and from work. For casual users, the bike utilization rate peaks on the weekends and is significantly lower during the week. It is possible that some of the casual users are people coming to DC for tourism and purchasing one of the passes that CaBi offers or DC residents engage in non-habitual usage in their leisure time. The third subplot shows that trips taken by CaBi members account for about 85% of bike usage during the work week, while during the weekend that rate drops to less than 70%. Figures 3 and 4 suggest that usage patterns differ in a significant way between members and casual users.

FIGURE 3 BIKE UTILIZATION RATE FOR CABI BY MONTH

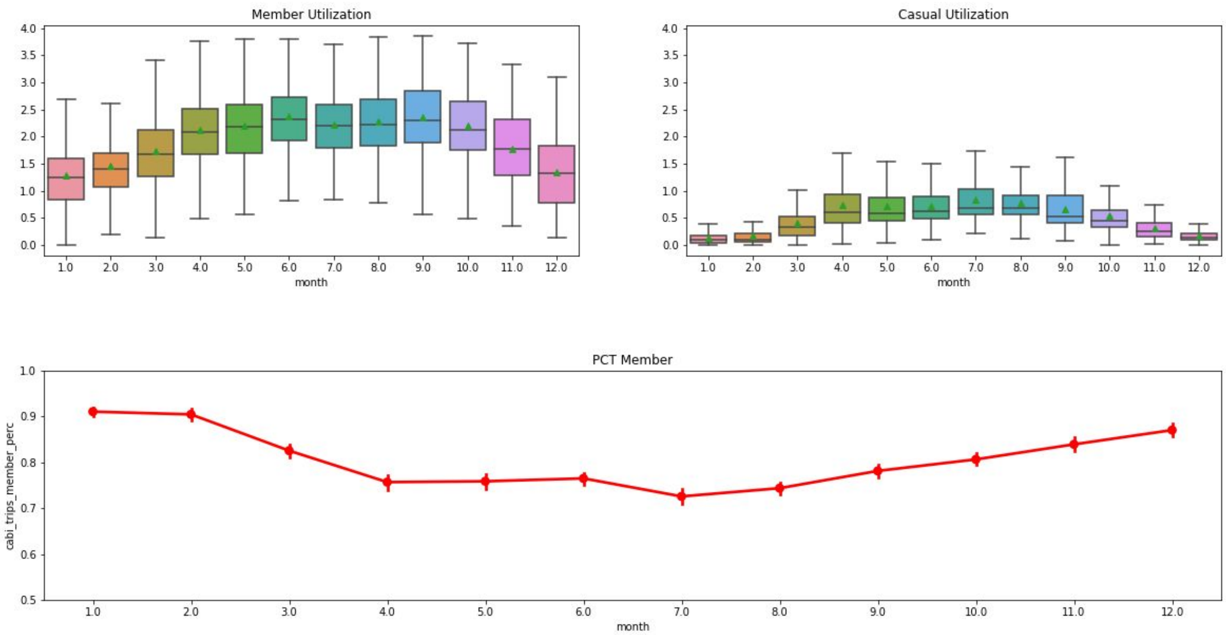
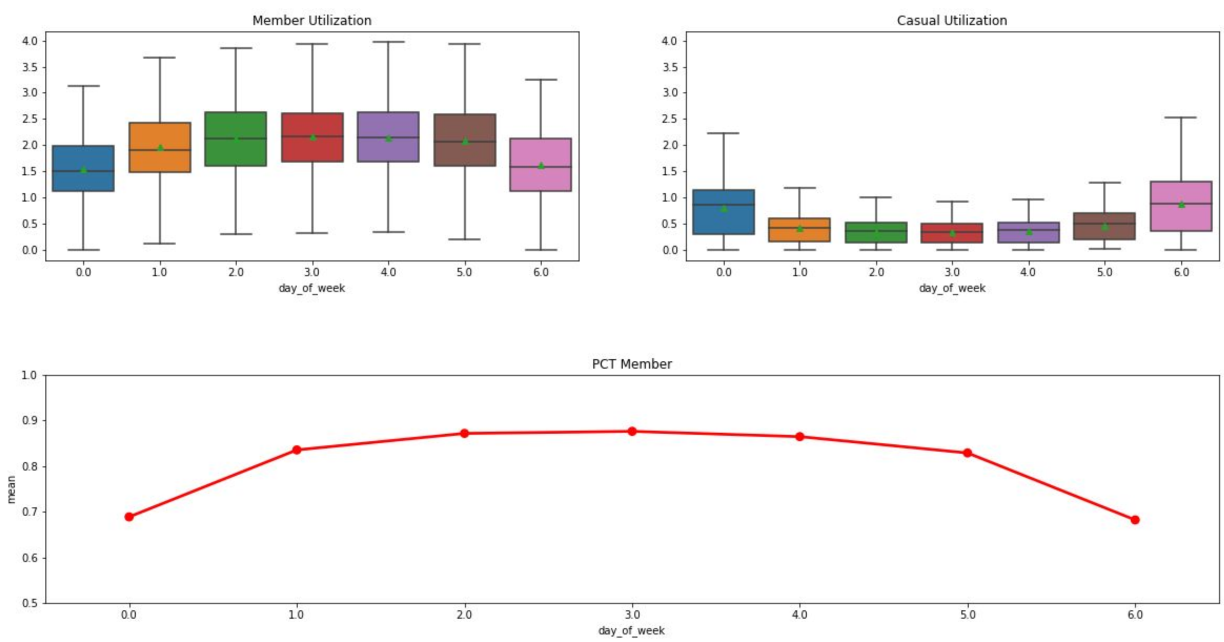


FIGURE 4 CABI BIKE UTILIZATION RATE BY DAY OF WEEK



Machine Learning

For our analysis, we use two competing machine learning models. In our models an instance is a single day and our goal is to predict the number of CaBi trips that start in DC and end in DC, taken on each day of the pilot program from September 9, 2017 to April 30, 2018. We only included DC to DC trips in our model because the pilot program restricts the dockless bikeshare operators to operate within the District of Columbia. We were able to determine the region where trips started and ended by using data that we collected from the CaBi API. The time frame of our training data is limited to the period of time from January 1, 2013 to September 8, 2017. We started the training set in 2013 because of the rapid growth during the first two years of operation as shown in Figure 1, as well as data availability issues from the same time period.

Lasso

We identified 18 features that we believed would be important to incorporate into our model. These features included daylight hours, apparent high temperature, U.S. holidays, and Washington Nationals games. We decided to use a smaller feature set with the Lasso model in order to minimize the chances of including collinear variables as features in our model. Multicollinearity among explanatory features in a linear model can have detrimental effects on coefficient estimates. We also dropped some features because of leakage issues - for example, some of our features are related to the duration that CaBi stations are empty or full in each day. Although these features are extremely predictive of CaBi trips, trips and empty duration are simultaneously co-determined, so we drop these features because of endogeneity issues.

Next, we preprocessed the data. In order to incorporate data from multiple years into our model, we performed cyclical encoding on the day of year to ensure continuity between December and January. Figure 5 shows a ranking of feature importance for the 18 features that were selected for the lasso model when we ran it initially, without including any polynomial variables or interaction terms in the model. We did not achieve a good fit due to the model's simplicity, however because of this simplicity it is easier to identify the explanatory power of each variable. For example, apparent high temperature had the strongest positive effect on the number of CaBi trips while whether or not the day was a US holiday had the strongest negative effect. Intuitively, this makes sense that as temperature rises so do the number of CaBi trips. It also seems intuitive that the CaBi system would see fewer rides on US holidays due to the absence of commuters.

We used the Rank2D visualizer from the Yellowbrick package in order to visualize which of our 18 features had the strongest correlation. Not surprisingly, variables like daylight and apparent high temperature were positively correlated. Figure 6 shows a simplified Pearson ranking of the 18 features that were selected for the lasso model before applying PolynomialFeatures. It does not show all of the 180 features that were used in our final model after creating the interaction terms and polynomial features.

FIGURE 5 FEATURE IMPORTANCE OF 18 FEATURES SELECTED FOR LASSO MODEL

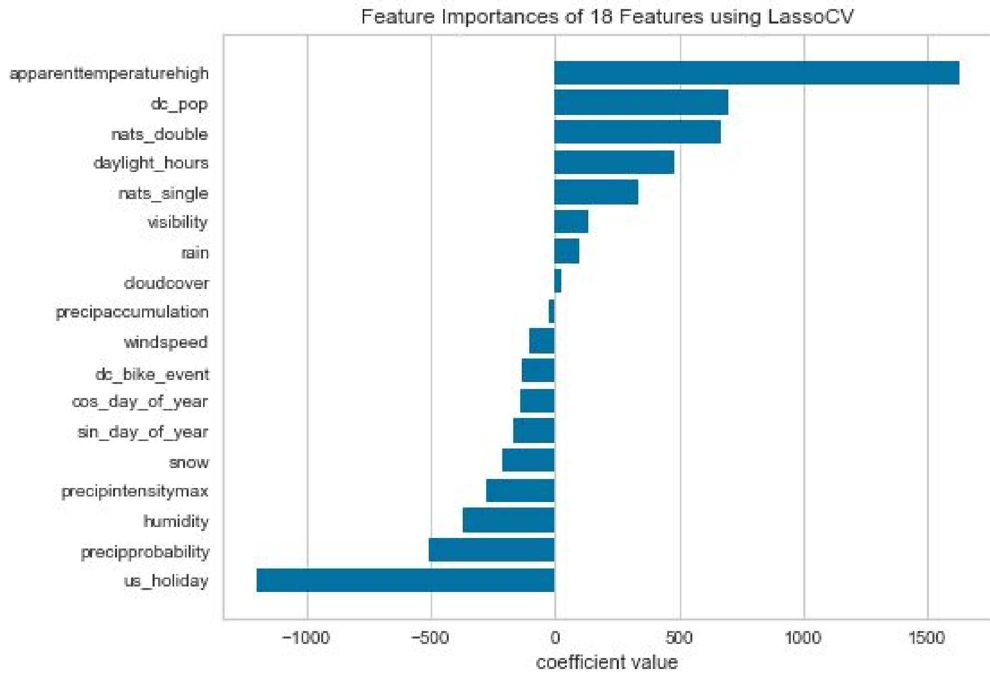
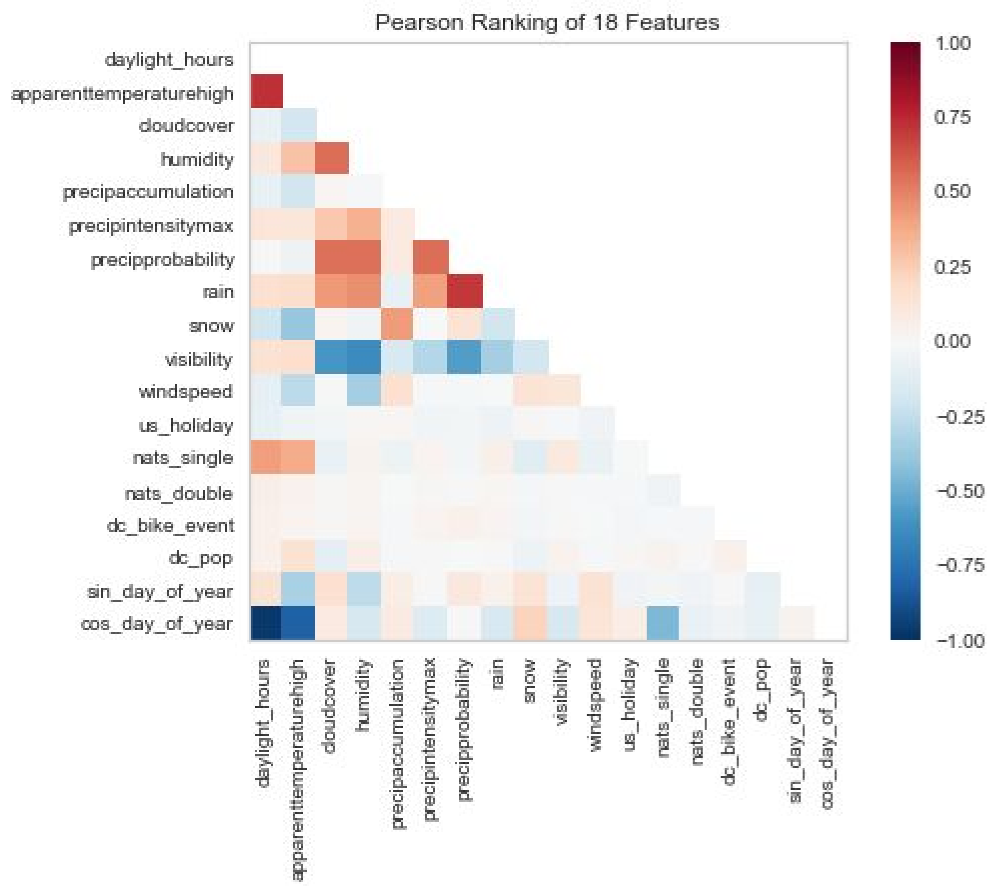


FIGURE 6 PEARSON RANKING OF 18 FEATURES SELECTED BEFORE POLYNOMIALFEATURES



In order to improve the fit of our Lasso model, we had to increase its complexity. This was achieved by using PolynomialFeatures to create quadratic and interaction terms that we could incorporate into our model to introduce complexity by increasing the number of features in our model to 180. We initially tried using PolynomialFeatures of orders 2 and 3, but ultimately found that PolynomialFeatures(2) was most performant. Creating interaction terms for our analysis was an important step because we believed that combinations of certain variables could have different impacts on CaBi demand, and these terms allow for a more complex linear relationship between our features and target variable. For example, behavior might differ between a cold day with rain and a warm day with rain. We dropped any quadratic variables that were redundant such as those created from our binary features, e.g. U.S. holiday squared. We also standardized our continuous variables by passing them through StandardScaler so that they would all have a mean of 0 and standard deviation of 1. For our binary features, we used MinMaxScaler to ensure that if any changes were made to those features when we applied PolynomialFeatures to them, they would be returned to 0 and 1.

In order to fit our model, we used 5-fold cross-validation and an alpha search space of 250 logarithmically spaced points between .01 and 10. The highest performance we got from the lasso model had an alpha of approximately 4.6 and a mean R^2 value of 0.852 with a standard deviation of 0.0175. The model tended to over-predict the number of CaBi rides taken per day which is evidenced by the sum of the residuals being negative. Table 1 shows a ranking of feature importance for the top 10 features out of the 75 that were selected for the lasso model. The interpretation of these feature interactions is difficult due to the increased complexity of the model. However, there is cross-over between several of the features that were identified as important in our simplified model and features that were incorporated into the more complicated Lasso model, suggesting that these may be important. Features such as apparent high temperature, population, humidity and precipitation probability appear on both lists.

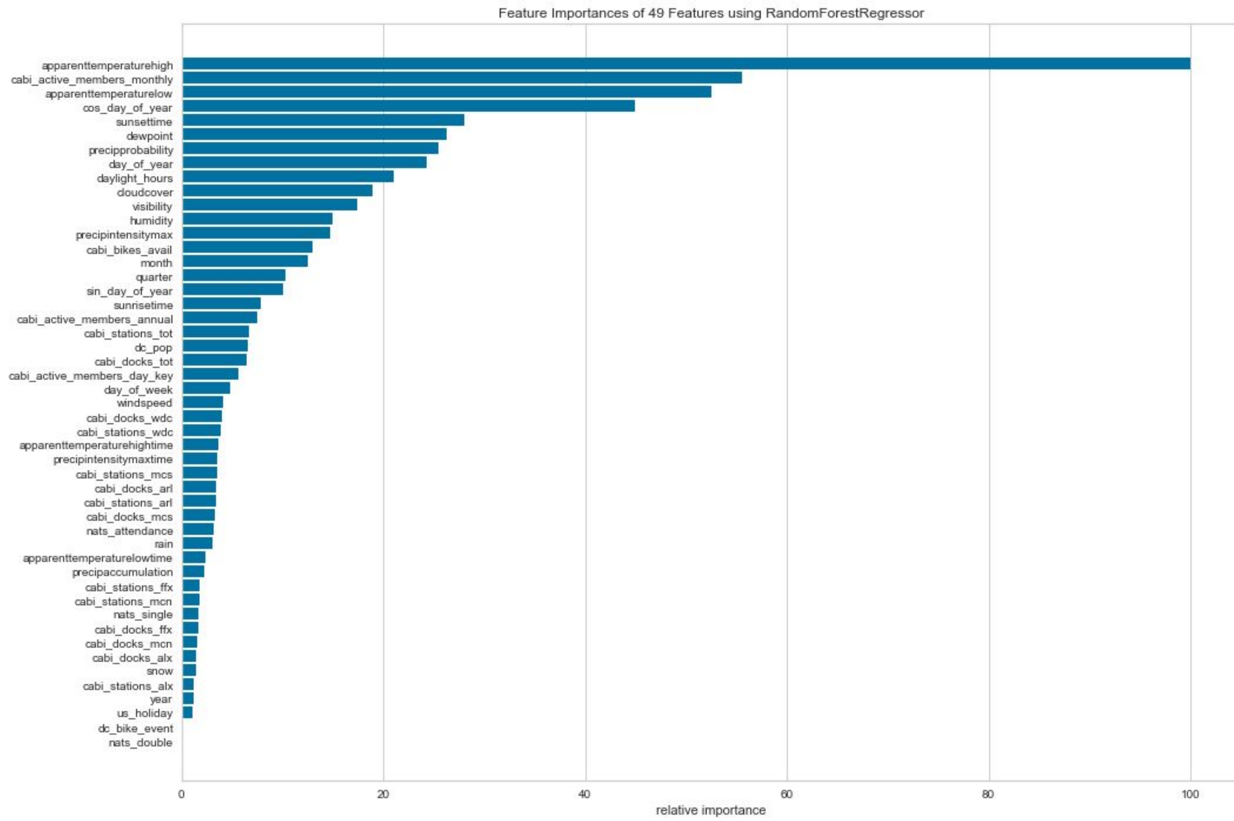
Table 1 Importance of Top 10 Features and Interaction Terms

		0	sorted
Apparenttemperaturehigh	dc_pop	2400.061	2400.061
dc_pop	cos_day_of_year	-2266.03	2266.027
daylight_hours	cos_day_of_year	1422.029	1422.029
Visibility	cos_day_of_year	-1253.97	1253.968
Apparenttemperaturehigh	sin_day_of_year	1252.191	1252.191
apparenttemperaturehigh^2		-1242.4	1242.399
Apparenttemperaturehigh	cos_day_of_year	1121.388	1121.388
Humidity	precipprobability	-1003.04	1003.04
Visibility	sin_day_of_year	-732.413	732.4135
Precipprobability	visibility	588.3362	588.3362

Random Forest

We wanted to experiment with a nonlinear regression method since we had already employed a linear regression model by using Lasso. Random forest, which uses bagging, seemed like a better option than using a boosting algorithm which could have potentially resulted in overfitting. Additionally, random forest had the added bonus of not being negatively affected by multicollinearity among features like Lasso is. This enabled us to incorporate a larger set of 49 features into the model. We also did not need to do any preprocessing in terms of scaling or creating polynomial features to deal with interaction terms because of how decision trees consider features sequentially. Figure 7 shows the features ranked by importance, which basically means these features were used to create partitions. The five most important features for this model were apparent high temperature, number of active monthly CaBi users, apparent low temperature, the day of the year, and the sunset time. Note that these feature importances are less informative than those returned by Lasso since they don't tell us anything about the direction of the effect, just relative magnitude.

Figure 7 Feature Importance of 49 Features Selected for Random Forest Model



In order to tune our hyperparameters for this model, we used RandomizedSearchCV to identify which hyperparameters to tune. There were 5,760 unique combinations of hyperparameters possible through the randomized search, and we tried 100 iterations over 5 folds. After confirming that this new model performed better than the untuned model, we used GridSearchCV with a smaller set of hyperparameters to then select the most performant combination. After performing 5-fold shuffled cross-validation we achieved a mean R2 value of 0.902 with a standard deviation of 0.007. This model also tended to overpredict the number of CaBi rides.

Results

Figure 8 plots the predicted values and the actual values for the number of CaBi rides for every date of the pilot program from September 9, 2017 to April 30, 2018. It also plots the prediction error for each day of the pilot program. Our model tended to overpredict the number of rides, as evidenced by the fact that the error term is less than 0 for most of the days within the pilot program. This suggests that the dockless pilot program might have had an impact on the demand for CaBi since there were fewer CaBi trips taken during the dockless period than our model predicted.

Figure 8 Actual vs. Predicted CaBi Rides during Dockless Pilot

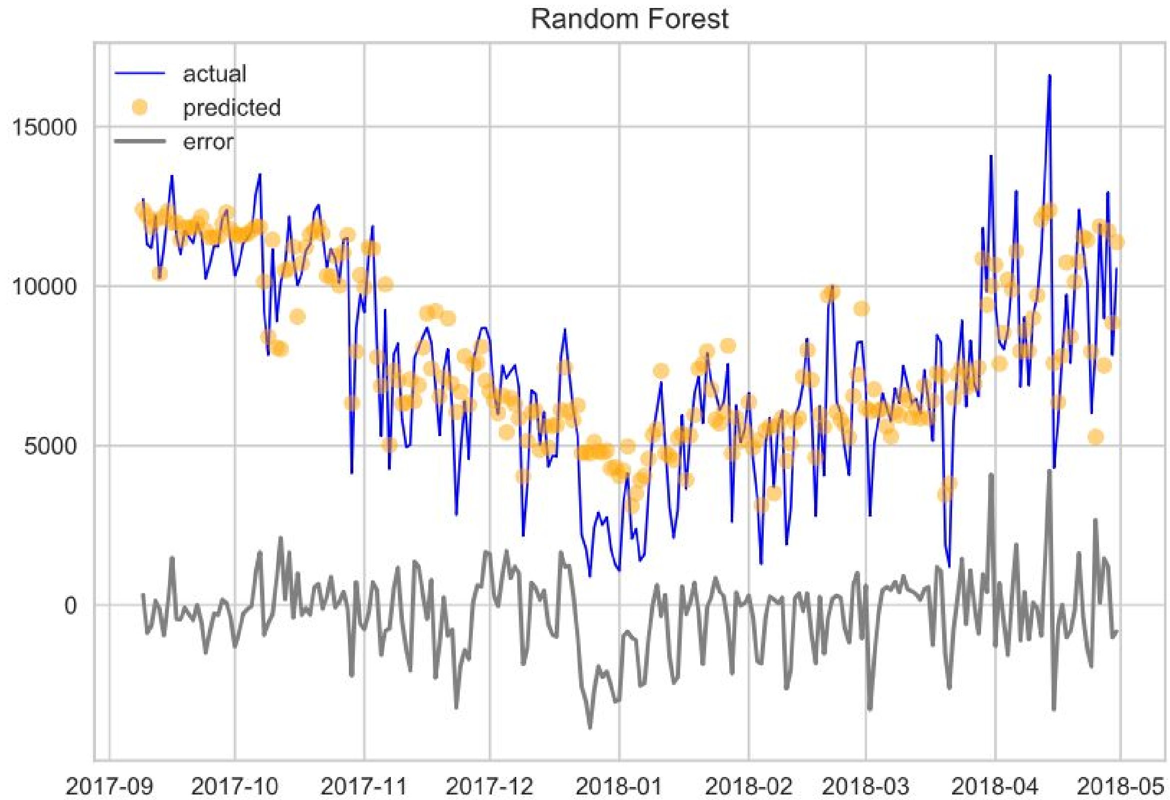
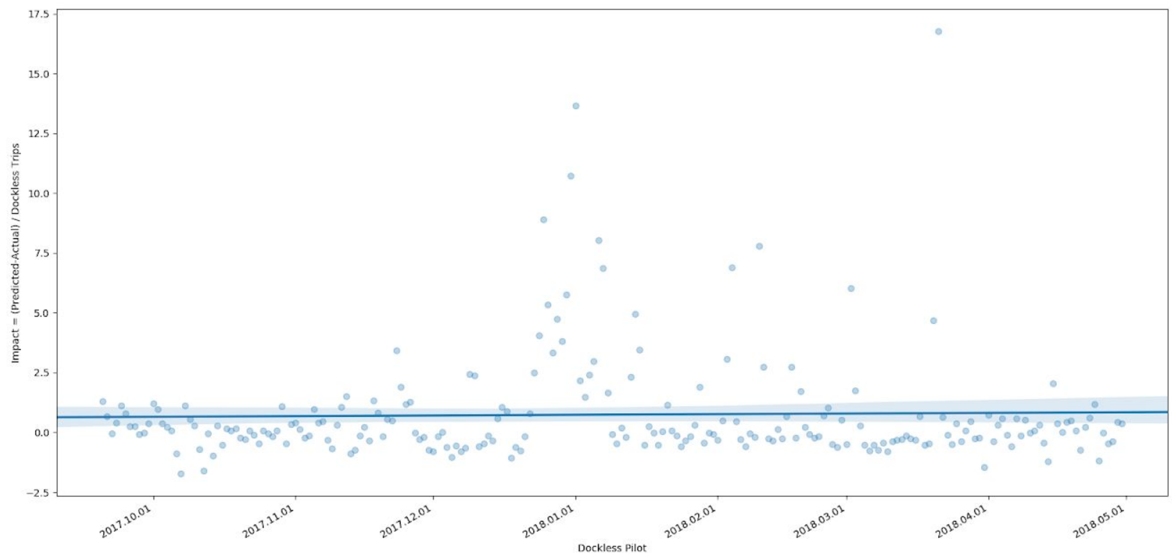


Figure 9 shows the *impact score* of the Dockless pilot program on the demand for CaBi. The *impact score* is defined as $\frac{Predicted\ CaBi\ Trips - Actual\ CaBi\ Trips}{Actual\ Dockless\ Trips}$. In the this figure, the average impact score hovers around 0.5 which could be interpreted as on average, our model's overprediction is equivalent to 50% of dockless trips on a given day. We cannot say for certain that dockless trips is the sole factor causing this overprediction, but there is certainly strong signal in that direction. Figure 9 also makes it clear that there were several days where the impact score was significantly greater than the average impact score for the pilot program. This is due to the fact that our model greatly overpredicted the demand for CaBi on these days.

The first "high impact" period came in the few days before and after January 1. There are two factors that might explain why our model was not able to accurately predict the demand for CaBi on these days. The first explanation is that our model did not account for the days before or after U.S. holidays, it just looked at whether or not the day for which it was predicting demand was a U.S. Holiday. Anecdotally speaking, during the winter holidays of Christmas and New Year's people are more likely to take additional days off of work to travel. Also, some companies may close their offices for the week between Christmas and New Year's. The second possible explanation is that the days at the end of 2017 and the beginning of 2018 were unseasonably cold. Our model did account for apparent high and low temperatures, but it is possible that our training set did not include enough instances with extremely cold temperatures to be able to accurately predict the demand for CaBi on these cold days.

The second period of the pilot program where the calculated impact was significantly higher than the average occurred around March 21, 2018. This is when Washington, DC received several inches of snow which caused extensive school and work closures. CaBi even suspended service on this day because of the snowfall. Again, even though snow and precipitation accumulation were features in our model it is possible that there were not enough high snowfall days in our training set for the model to be able to accurately predict or account for a complete system closure by CaBi.

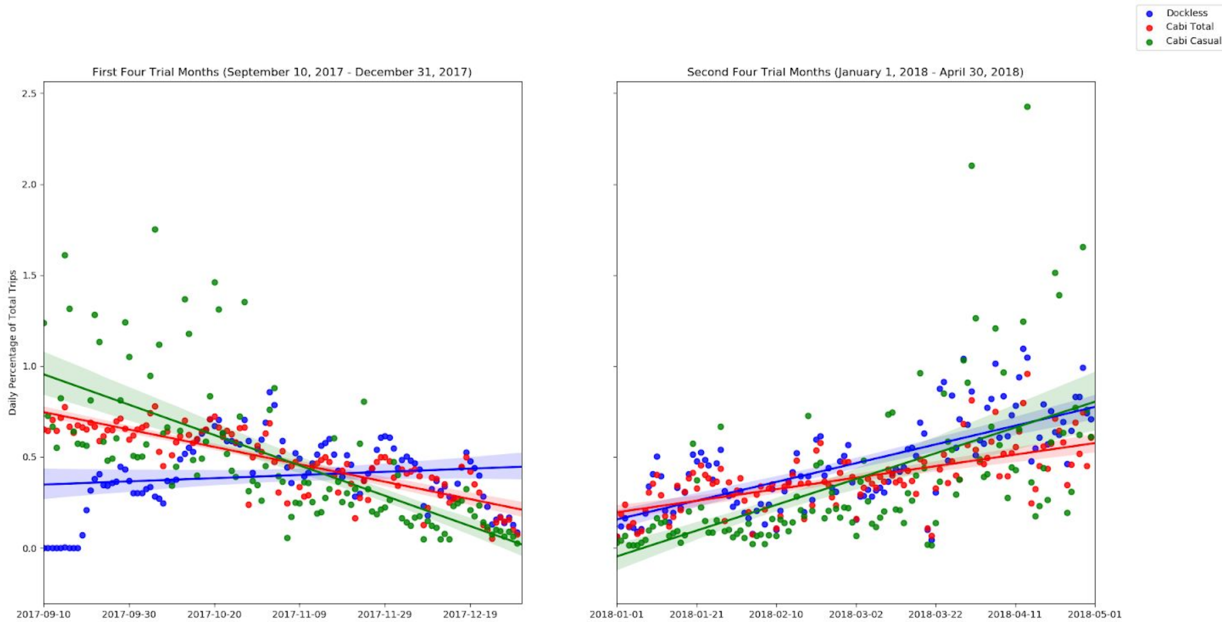
Figure 9 Dockless Impact on CaBi



Limitations & Areas for Future Study

It is difficult to draw any definitive conclusions from the analysis that we conducted for several reasons. First, the pilot program is still in its infancy. Our analysis only examined the first 8 months dockless bikeshare pilot and each operator was only allowed 400 bikes, a number well below what they would be outside the restrictions of the pilot. During this time period, the dockless bikes were new and exciting for users which could have impacted their behavior. There has not been enough time yet for this “novelty” effect to wear off and demand to normalize among users. Figure 10 illustrates this novelty effect. It splits the pilot program period into the first four months (September through December) and the next four months (January through April) and plots the percentage of total trips during the dockless pilot that were taken on each day by all CaBi users, CaBi casual users and all dockless bikeshare users. The subplot on the left, which shows the first four months of the pilot program, shows a gradual increase in the percentage of total trips through the end of December for dockless bikeshare users, while for all CaBi users and CaBi casual users there is a negative trend going into the cooler winter months. In the next four months of the pilot program, the daily percentage of total trips for the dockless bikeshare users has a trend line with a slightly more positive slope than that of the first four months. This is expected as this follows the monthly bike utilization trends of CaBi that were exhibited in figure 3. The subplot on the right shows that the slope of the Dockless trendline lies between that of all Capital Bike users and Casual CaBi users.

Figure 10 Daily Percentage of Total Trips over the Dockless Pilot Period



The novelty effect is again demonstrated in Figure 11, which shows the percentage of dockless users who have taken five trips or less compared to those who have taken more than five trips over the course of the pilot program. Only around 7% of users have regularly returned to the dockless bikeshare; taking more than 5 trips over the course of 8 months. This differs significantly from CaBi where most of the trips are taken by members. Mobike trips was not included in this plot because the data that they reported to DDOT did not include user IDs, so it was not possible to determine how many individual users were taking more than 5 trips.

Figure 11 also suggests that the behavior of dockless bikeshare users is more akin to CaBi casual users than CaBi members. Figure 12 shows the time of day CaBi members, casual user and dockless user trips are taken. The majority of CaBi member trips are taken on weekdays. During mid-week, the majority of the trips occur during peak metro operating hours, suggesting that members are commuting to and from work. CaBi casual users of follow a distinctly different usage pattern with the majority of their trips occur on the weekend. For trips that do occur mid-week, a slightly greater portion of those are occurring during off-peak hours. Dockless trip usage pattern seems to fall somewhere in the middle of CaBi members and CaBi casual users. While the dockless bikeshare rides occur mostly on weekdays, the split between peak and off-peak hours is relatively even, suggesting that commuters usage is not as strong for the dockless bikeshare operators. There is also higher usage on the weekends by the dockless users compared to CaBi members.

Figure 11 Percentage of Dockless Trips by Users that Have Taken More than 5 Trips by Operator

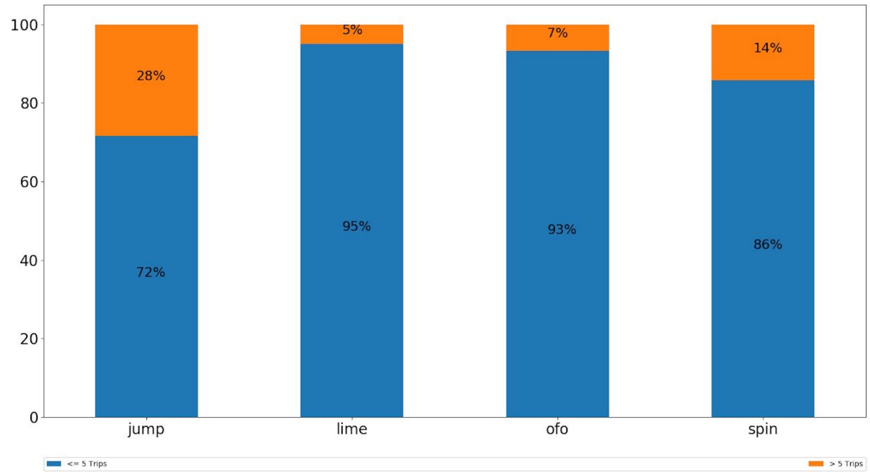


Figure 12 Trips by Day of Week Based on Metro Operating Status

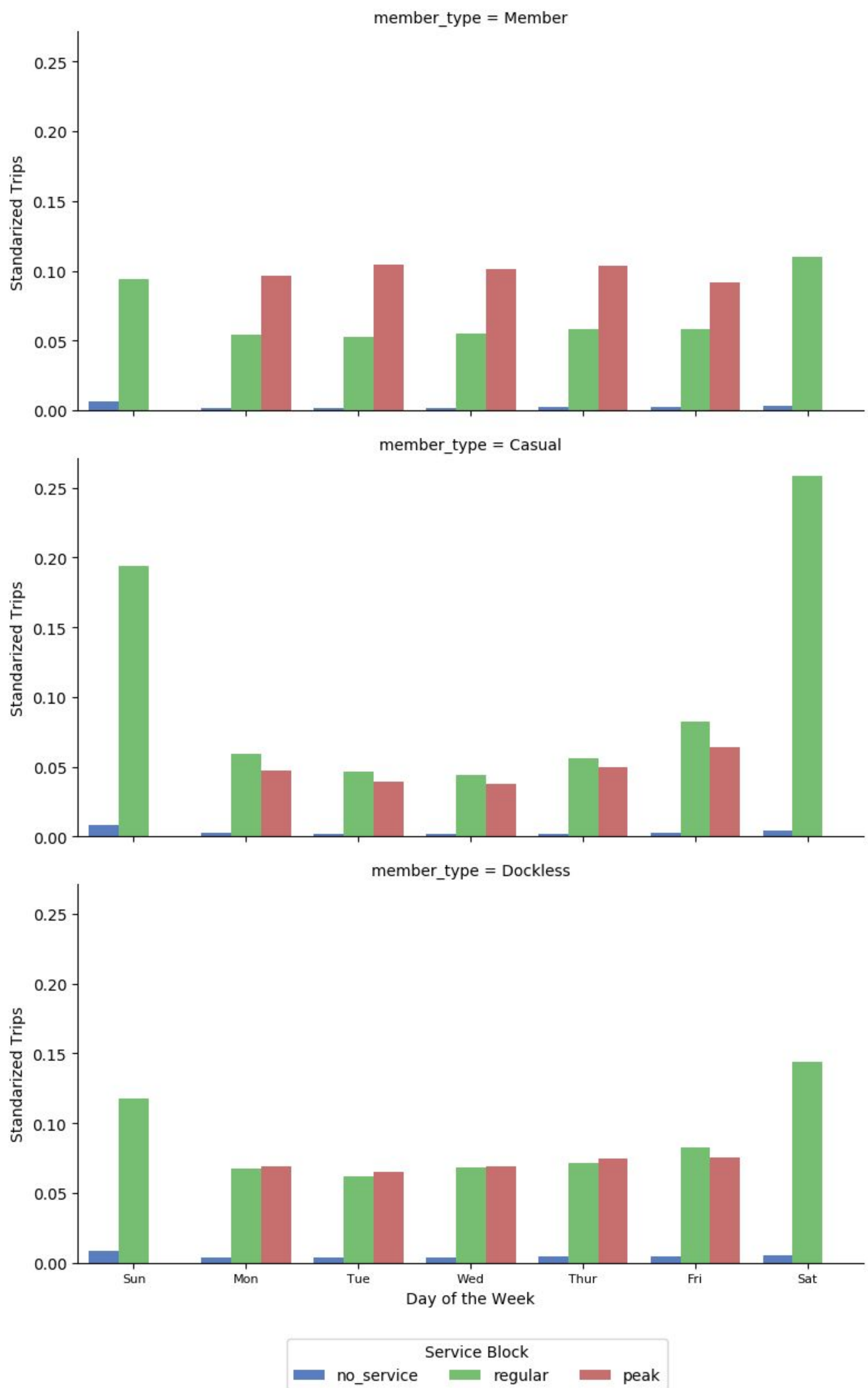
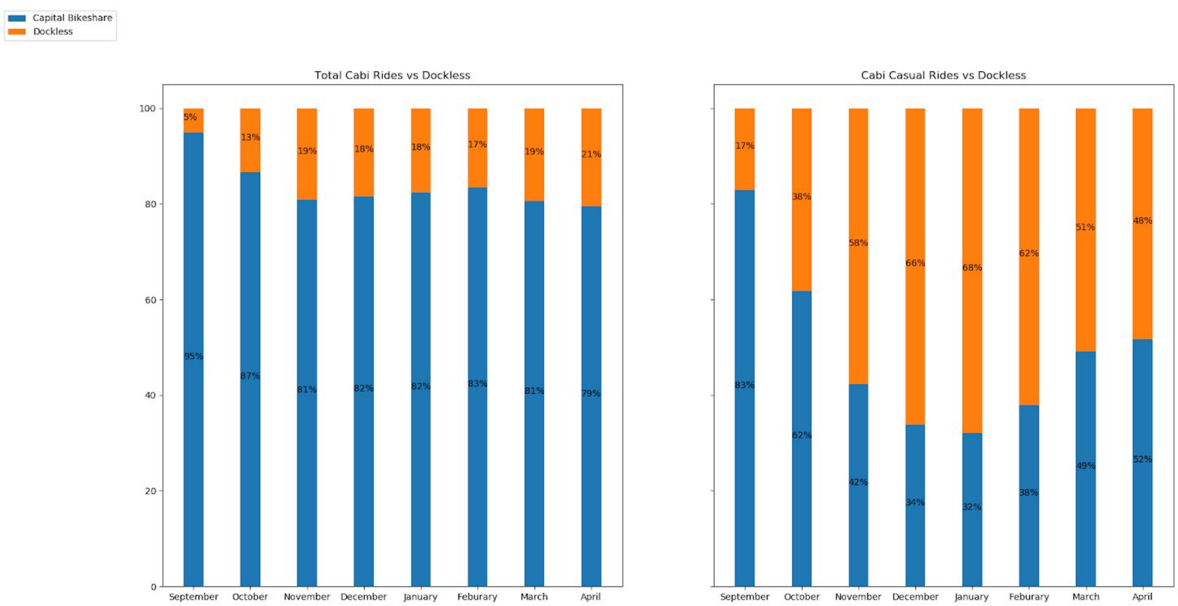


Figure 13 also supports the hypothesis that Dockless users are more similar to CaBi casual users than they are to CaBi members. The subplot on the left shows the market share for all CaBi and dockless bikeshare operators over the 8 months of the pilot program that we analyzed. The market share for the dockless bikeshare operators grows over the first three months before stabilizing at around 20% in November. The subplot on the right compares dockless bikeshare rides to CaBi casual users and demonstrates an expansion and contraction that takes place over the 8 months that we analyzed. The market share for the dockless operators in this subplot peaks in January at around 66% before shrinking back to about 42% in by April. This makes sense when compared with what was demonstrated in figure 10 where dockless rides increased slightly over the first four months while rides taken by CaBi casual users decreased. From January through April, the number of casual CaBi rides increased at a faster rate than dockless rides. Further research into the dockless bikeshare pilot program should exam the impact that the dockless bikeshare pilot has had on the demand for CaBi trips by casual users.

FIGURE 13 MARKET SHARE — CABI VS DOCKLESS



Another aspect that complicated our analysis was the introduction of electric scooters in March 2018. This past spring, DDOT expanded the pilot program to allow electric scooter shares to begin operating in DC. Most of the electric scooter companies were distinct from the dockless bikeshare operators, except in the case of Lime. In March, Lime began adding scooters to their fleet while taking bikes off the road to ensure that they did not exceed the 400 vehicle cap that was established as part of the pilot program. The introduction of electric scooters was particularly challenging for our analysis because the monthly reports that Lime submitted to DDOT did not differentiate trips by vehicle type. In other words, it was impossible to tell if a trip was taken by a Lime bike or a Lime scooter.

Conclusion

Our analysis suggests that the dockless pilot program has potentially had an impact on the demand for Capital Bikeshare within Washington, DC. However, there are several limiting factors that detract for the veracity of this conclusion. One of which is the length of the pilot program and our analysis. The pilot program that we analyzed did not include the summer months. Based on our research we believe that these months will be most critical for the pilot program because this is where Capital Bikeshare see the biggest shift in usage by casual riders. The data suggest that dockless bikeshare users tend to follow usage patterns similar to those of casual Capital Bikeshare users. If the docklesss bikeshare pilot program were to have a significant long-term impact on Capital Bikeshare demand, it would be most pronounced during the summer. It also remains to be seen if the dockless bike share operators themselves are sustainable in the long-term. Table 2 shows that the dockless operators have cycled through a sizeable amount of bikes in the short timeframe of the pilot program. On operator has gone through over 2,600 bikes, more than six times the number of bikes they are allowed to have on the road at any given time. With bikes that are damaged or in disrepair, it is difficult for users to see these operators as a reliable and viable alternative to Capital Bikeshare.

Table 2 Average Bike Age over Dockless Pilot Program (September - April)

Stat	Total Bikes	Replace Rate
Max	2,649	6.62
Avg	1,786	3.44
Min	211	1.51

Maps

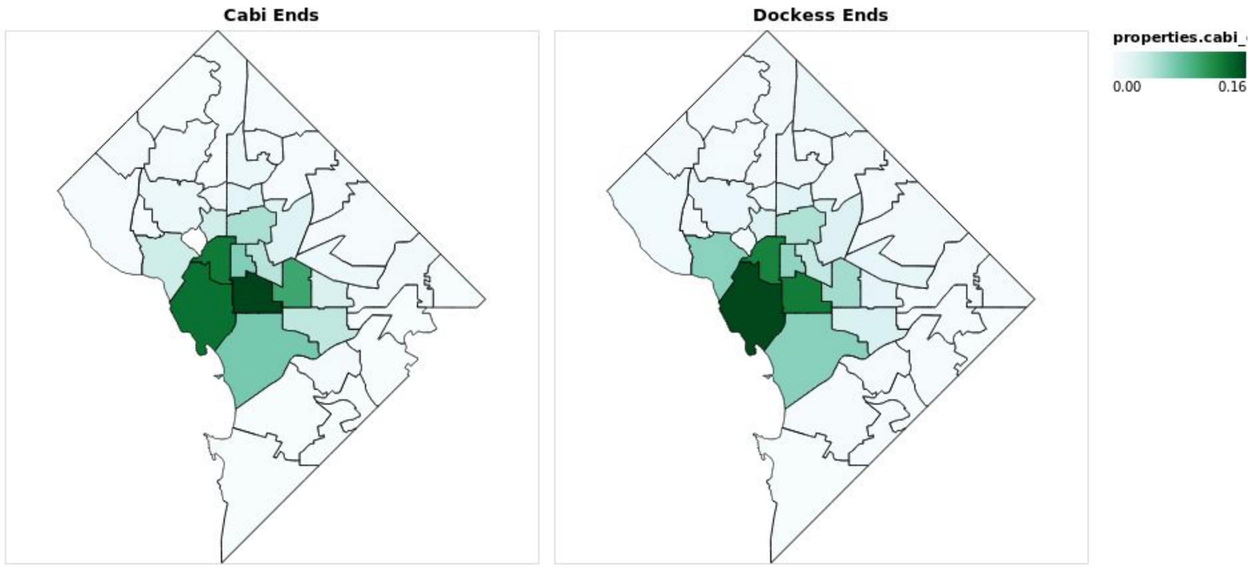
DDOT requested that we compare the service areas for CaBi and the dockless operators. To that end we put together a series of chloropeth maps that provide some interesting insights.

Map 1 shows DC's eight geo-political wards. These wards are further broken down into 40 Advisory Neighborhood Commissions (ANCs). These ANCs seemed to be about the right size to compare CaBi and the dockless operators and DDOT agreed when we presented these results to them.

Map 1 DC Wards

Appendix 2 shows two chloropeth maps of CaBi and dockless combined trip destinations split out by ANC for the entire dockless pilot period. We can see that the concentration area is approximately the same for both. The main difference between the two is that the dockless trip destinations are centered South and West along the National Mall, while CaBi trip destinations are centered more toward Downtown DC. This difference shows provides further evidence that dockless trips act trend toward more casual usage.

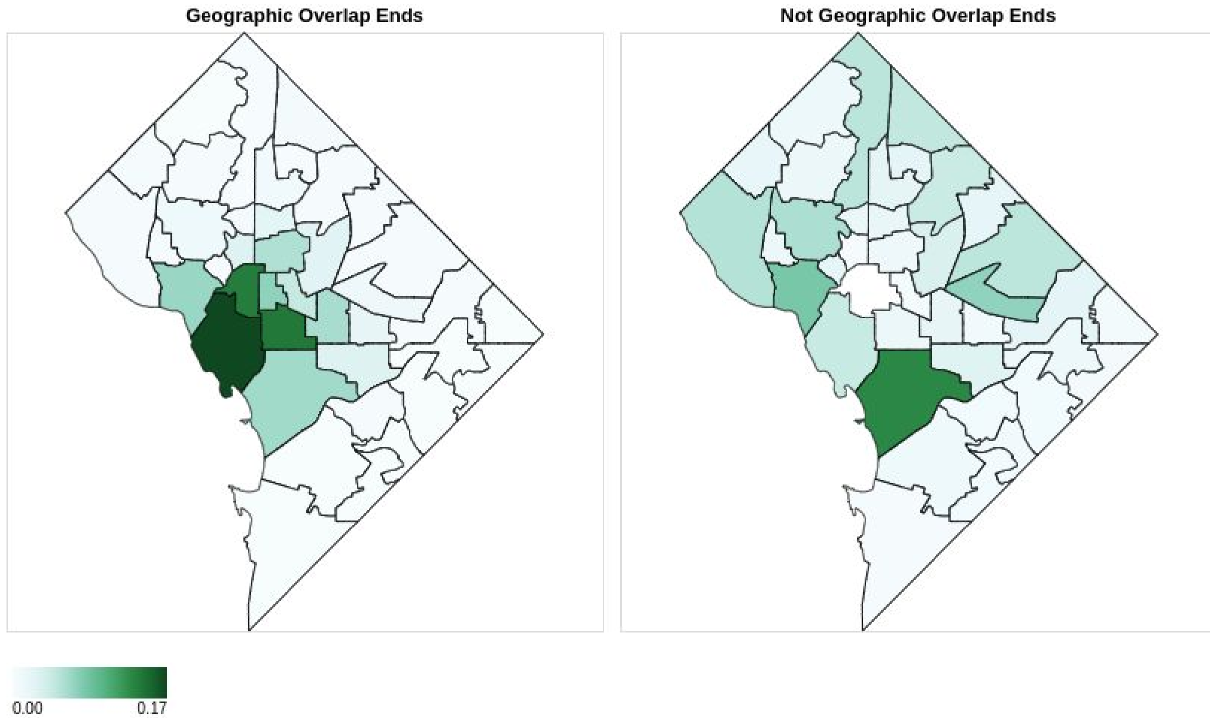
Appendix 2 Percent CaBi and Dockless Combined Trip Destinations by ANC



We define geographic overlap between a dockless trip and Cabi as either the trip starts or ends within a quarter mile of a CaBi station. Approximately 90% of all dockless trips are geographic ovelaps.

Appendix 3 shows the difference in ANC concentration for geographic overlap trips and non-geographic overlap trip destinations for all dockless operators combined for the dockless pilot period. The geographic overlaps look much like the original dockless chloropeth, as they comprise more than 90% of all dockless trip destinations. Non-Geographic overlaps are more spread out in Wards 3, 4 and 5, but still concentrated on the Mall. However, the Mall trips are more concentrated in the southeast section of the Mall that has less CaBi Stations. Regardless of geographic overlap, there is still no discernable presence detected in Wards 7 and 8.

APPENDIX 3 PERCENT DOCKLESS COMBINED TRIP DESTINATIONS GEOGRAPHIC OVERLAPS AND NOT BY ANC



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