Shared Scooters - a Fad or the Future?

An Investigation of their Usage & Viability

by

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This capstone is dedicated to our families, husband and friends who have supported us while we dedicated long hours, nights and weekends throughout this journey.

A special thanks to our advisor Nasrin Khansari who shared her work that helped guide us through this process and Dean Author O'Connor who provided great guidance as we went through this program.

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Abstract

This capstone project focused on the newest trend in urban transport – scooters. An open data set obtained from the city of Austin, Texas contains over 3.5 million records spanning 9 months, from 2018 to 2019, with one row for each trip taken. Variables of note include origin, destination, timestamps, distance traveled, and trip duration among others. The purpose of this capstone was to forecast future ridership, industry revenue and losses, and the aggregate consumption of vehicle hardware. The overall findings note that the new mode of transportation, although privatized, behaves like a government agency with losses due to affordable pricing that attracts low-income riders *en masse* and forecasting was treated like a stock index pricing model due to the daily variability of riders.

Keywords: scooters, data698, Austin, capstone, LSTM

Introduction

In the summer of 2017, a former Uber employee started a new transport service. Instead of people using their own cars, the company would rent electric kick scooters to the public. The scooters would be left in public view, and accessed via an app.

Travis VanderZanden started his scooter service in Santa Monica and Venice, two beaches on the doorstep of America's second biggest city. The scooters quickly caught on, allowing VanderZanden to raise tens and then hundreds of millions of dollars to expand the service, known as Bird, to other cities. Other rivals since have also appeared, including Lime and Spin, as well variants from ridehail firms Uber & Lyft.

The scooters have elicited contempt and joy in great measure - much like any new form of transport. The charges against them range from putting pedestrians in harm's way, to injuring riders with unsafe hardware. More poignantly, the shared bike services, on which Bird et al. are based, have mostly disappeared from American cities because scooters have proven more popular.

With Lime allegedly spending $23 million monthly[1], it's worth considering if rented scooters are financially viable, and if not, whether they can become so. With constant location tracking and internet access, the scooters generate copious data, most of which is held in private by operators. The city of Austin, Texas has released trip data which can shed light on the performance of scooters to date.

The purpose of this capstone is to assess the usage of scooters in Austin, as well as their financial viability and environmental sustainability; this was achieved by using a combination of revenue analysis and a predictive model to help operators determine their daily supply and demand needs.

[1] *The Information*, 09-Dec-2018

Data Exploration

Data Cleaning and Preparation: Filtering Out Questionable Trips

The trips dataset contains 4.4 million raw trip records, as of May 3, 2019. 16% of these trips were found to be questionable, leaving 3.7 million available for analysis; the discarded trips were physically impossible, unlikely, or not indicative of a real trip (e.g. the trip had zero distance).

In reviewing the various trip statistics, such as duration and distance, bounds were set for the minimum and maximum acceptable values. Identifying outliers using the interquartile range (IQR) ratios was considered, but transportation-specific thresholds were deemed more precise and reliable.

Trips must be at least 1 minute, 0.1 miles, and 1 mile per hour. They also must be less than 90 minutes, 25 miles, and 25 mph in average speed. The upper bounds correspond to the maximum limits of the scooters, which are capped at 15 or 18 mph on flat ground, 20-25 miles of range when fully charged.

The lower bounds were more restrictive, resulting in 15% of raw trips removed, while an additional 1% of the original trips were removed for passing the upper thresholds. The high volume of lower outliers (15%, approximately 600 thousand) is likely due to sensors detecting a trip where none occurred, or due to riders unlocking, but not quite riding the scooter to a destination.

Summary Statistics

This section describes the data obtained and discern useful statistics and information that will feed in to the forecasting and viability sections of this capstone.

The distribution of filtered trip duration, distance and speed are shown below. The statistics shown in text are from all filtered trips, while the graphics are from a 50,000-unit sample (~1.4% of the total data) of those trips (A sample was drawn to avoid long processing times for generating graphs).

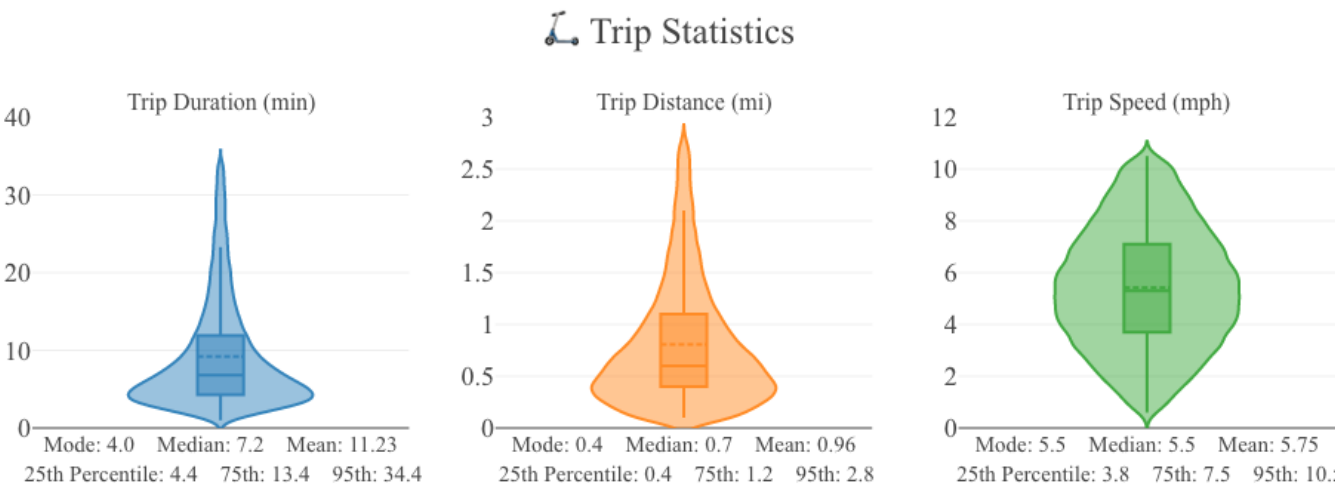

Figure 1. Trip Statistics for Duration, Distance and Speed

Most operators offer the same pricing structure across operators of $1 per ride + $0.15 a minute[2]; the median ride fare amounts to $2.20, the average, $2.75. At a median of $3.14 per mile, that is approximately seven times (7x) the average cost per mile of driving.[3] Low-income riders may apply to receive large (~50%) discounts, but the data available does not identify the share of trips attributable to these riders.

Variation in Scooter Trip Volume Over Time

For the initial pilot month of April in 2018, there were ~2,000 trips per day; scooters were removed for most of May 2018, and then returned by June. By August, scooters were seeing ~9,500

[2] Lime, Lyft, Razor and Spin have these rates; JUMP, which primarily offers ebikes, does not charge an unlock fee, but $0.15 per minute; Bird has recently increased their fee in Austin to $1 + $0.27 per minute.
[3] $0.43 per mile; $8,427 average spent on cars per household, 2016; 53.8 miles traveled per household per day, p12

trips daily; trips peaked in March 2019, thanks to a large festival, at ~22,500 trips per day. For the latest period available, April and early May, Austin saw some 16,000 scooter trips daily.

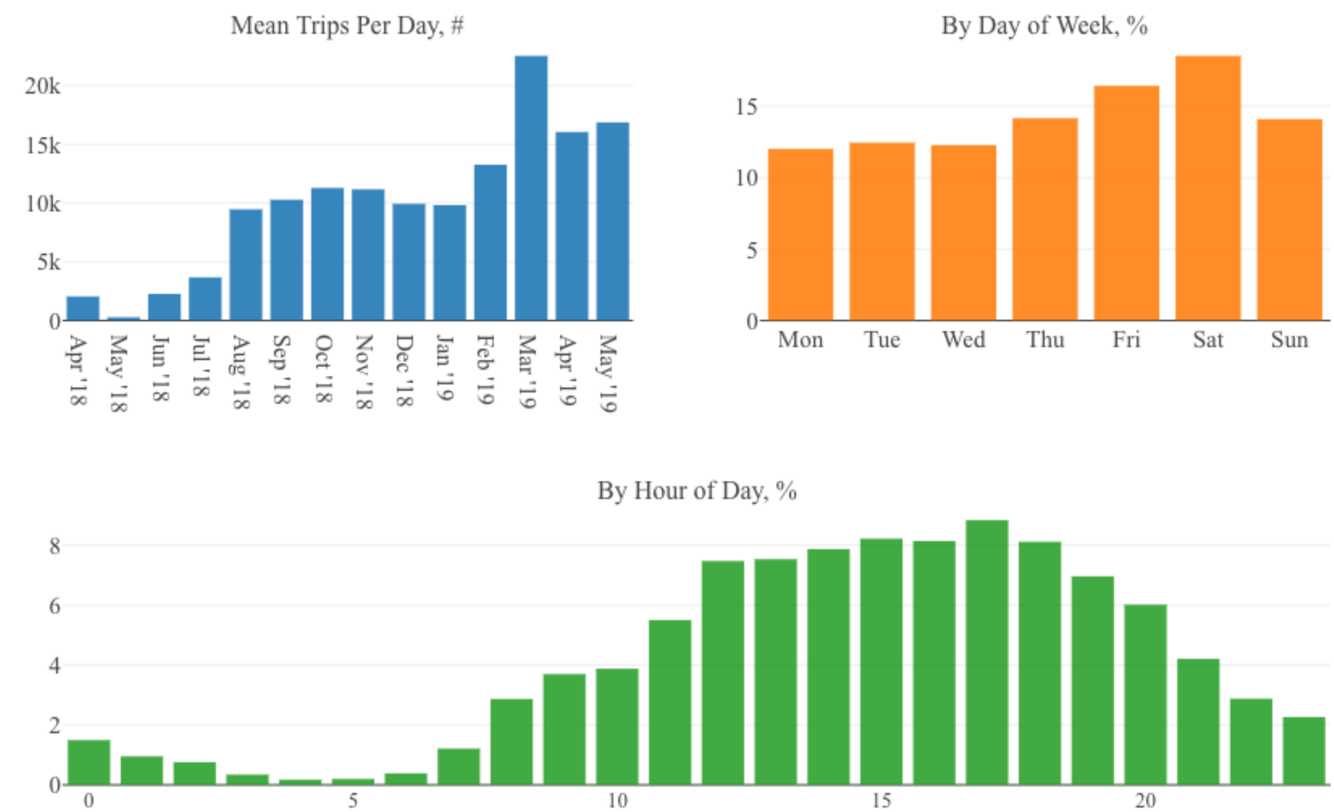

Figure 2. Trips Over Time by Month, Weekday and Year (n = 3.7 million)

Notably, Austin is home to the University of Texas and its 50,000 students, whose classes run from the end of August until mid-December, and again from late January until mid-May.

Ridership is not only a weekend affair - on Monday through Wednesday, 12-13% of rides occur daily. Rides increase sequentially from 14% on Thursday to 16% on Friday to a Saturday peak of 18% of rides on Saturday, then 14% on Sunday. The relatively even distribution of trips by weekday suggests people are using it for personal trips throughout the week, such as personal errands, weekend socializing and recreation. The classic morning and evening peaks in usage, as seen in cycling, transit and driving, are not observed, however.

Dataset Limitations: Estimating Daily Vehicle Deployments & Utilization

The original dataset shows a record of trips taken, not of vehicles per se, and their deployment status. Therefore, vehicle counts can only be estimated, since a vehicle will not appear in the dataset on a given date, if it had no trips that day. Moreover, the number of vehicles out on a given day is necessarily an underestimate, because some number of vehicles will have zero rides that day, and thus will not appear as being active that day in the trips database.

Similarly, estimates are made of vehicle utilization - the number of rides per scooter per day; but these estimates are necessarily an overestimate, since they do not include scooters that had zero trips on a given date. Utilization is considered a barometer of financial sustainability by operators. At least three trips per day is necessary, according to operators[4].

Daily Trips, Deployments, and Utilization

A rolling average of seven days was used to consider trends in trip volumes, vehicle deployments, and utilization.

Up to a certain point, increased deployments of vehicles can induce more demand, by increasing the visibility of the scooters to passersby, and by decreasing the average distance of vehicles to potential riders. Greater proximity to vehicles translates into higher effective trip speeds. Additionally, competition among operators may lead to faster trip growth, based on research of dockless bike-sharing in China[5].

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[4] Brekke, Dan. “Bird Pushes Back Against S.F. Proposal to Limit Scooter Fleets.” April 25, 2018.
[5] Guangyu Cao & Ginger Zhe Jin & Xi Weng & Li-An Zhou, 2018

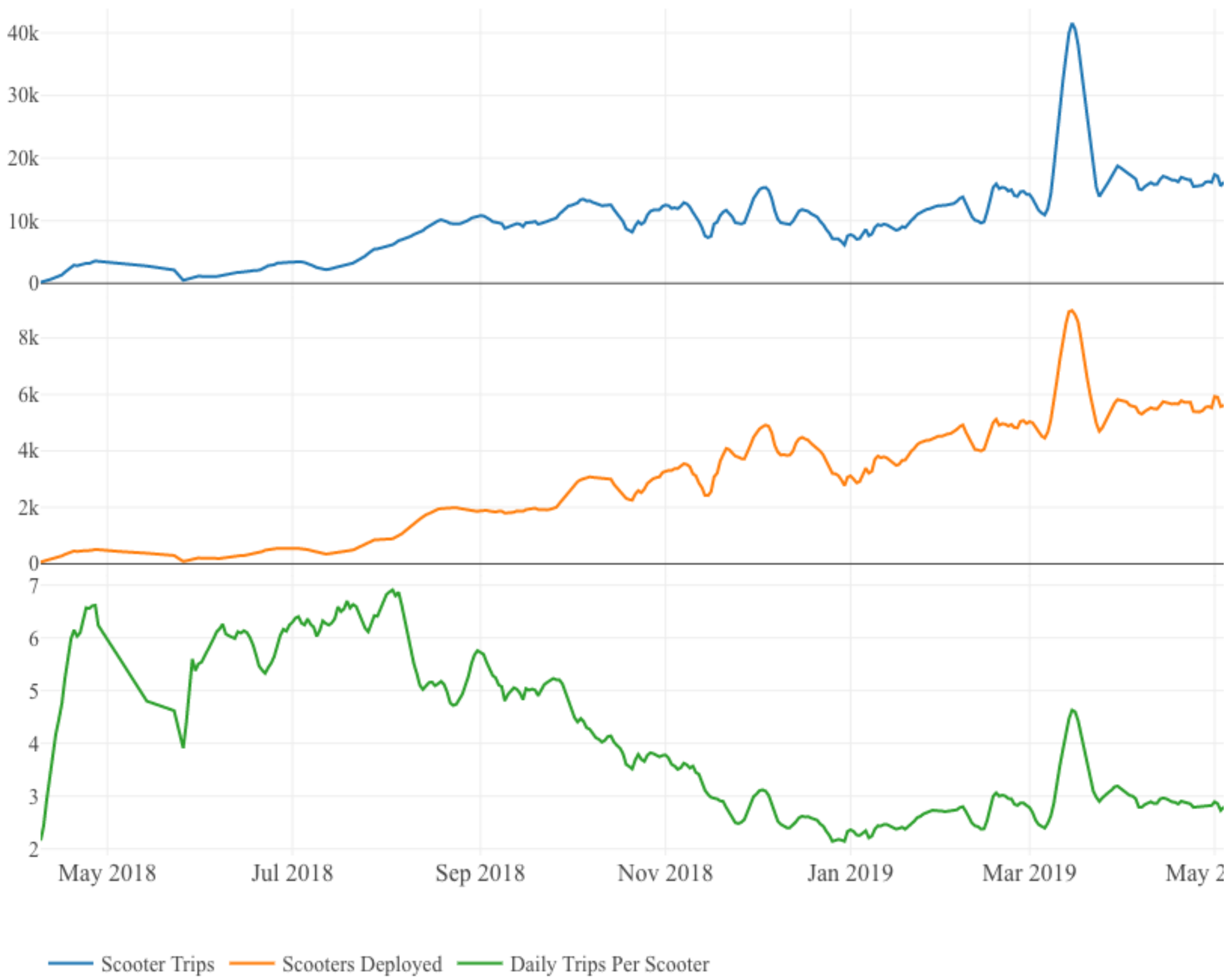


Figure 3. Daily Scooter Trips, Deployment & Utilization

These metrics can be decomposed into three phases:

Phase 1: Introduction **Months: Apr - Aug, 2018**

Less than 500 scooters are deployed daily, and the latent demand for short distance transport (1-2 miles) leads to a high utilization of 6 rides per scooter per day. In August, vehicle deployment increases to 2,000, though trips increase as well to keep utilization above 5. Trips surge from 2-3,000 daily to 10,000 by the end of Phase 1.

Phase 2: Saturation of Supply, Plateauing Demand **Months: Sep - Jan 2019**

Operators continue to increase the supply of vehicles, albeit faster than the growth in trips, leading utilization to plummet from 7 in July and 6 in August to ~2.5 trips per day by January. Trip volumes are plateauing, and more scooters are chasing the same number of trips, approximately 10,000 per day. University is out of session for most of December and January.

Phase 3: **Spring Rebound** **Months: Feb - May 2019**

Ridership recovers to 13,000 per day in February, and to 16,000 by April. Utilization has recovered, but only slightly, to approximately 3 rides daily. A spike in trips, deployments and utilization occurs during this period for the large festival South by Southwest (SXSW), but performance quickly returns to trend. Even during SXSW, utilization briefly surpasses 4 rides a day, far below the utilization of Phase 1

The graphs below show the number of distinct scooters that appeared in Austin per month; despite the arrival of spring, and the SXSW festival aside, scooter vehicle growth appears to have moderated.

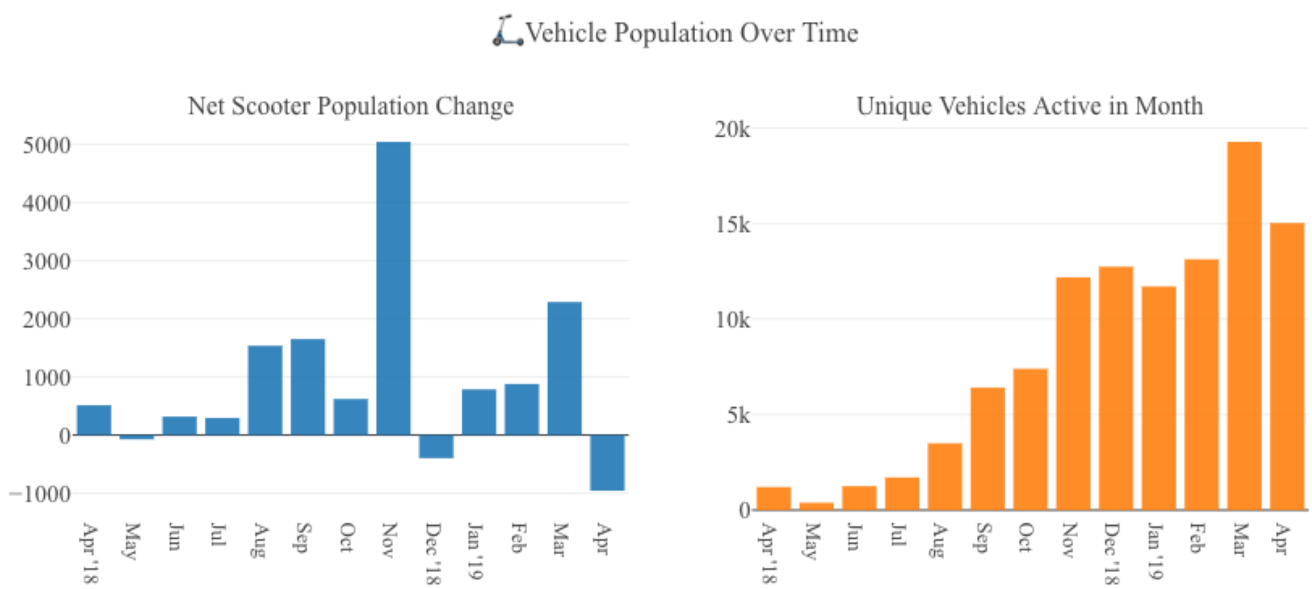


Figure 4. Scooter Vehicle Population Over Time

Performance per Vehicle Analysis

Beyond just analyzing trip statistics, one can also consider how vehicles performed, since the dataset includes persistent unique vehicle IDs that enable tracking a vehicle from one trip to the next.

After two weeks of inactivity, a scooter is classified as defunct. If a scooter later reappears in the trips database after a hiatus of 2+ weeks, its status is reverted to active; the pool of defunct scooters are analyzed to estimate the volume of usage a shared scooter will see over its life.

Why scooters disappear from the dataset is unclear. Possible reasons include vandalism, hardware failures, long term storage, and relocation to other cities.

Barometers of Longevity

Longevity is considered with four metrics:

- *Rides Completed*: the number of valid trips associated with a unique vehicle ID
- *Total Ride Time (hours):* hours of active ride time
- *Distance Traveled (miles):* total miles traveled across all trips
- *Days Active:* the number of distinct dates on which the scooter completed rides

The four longevity metrics share a similar distribution - a high share of scooters with low lifetime usage, tapering off to fewer and fewer scooters with higher longevity. As a result, mean longevity figures are considerably higher than the median figures. The distribution for each metric, in a violin plot, is shown below.

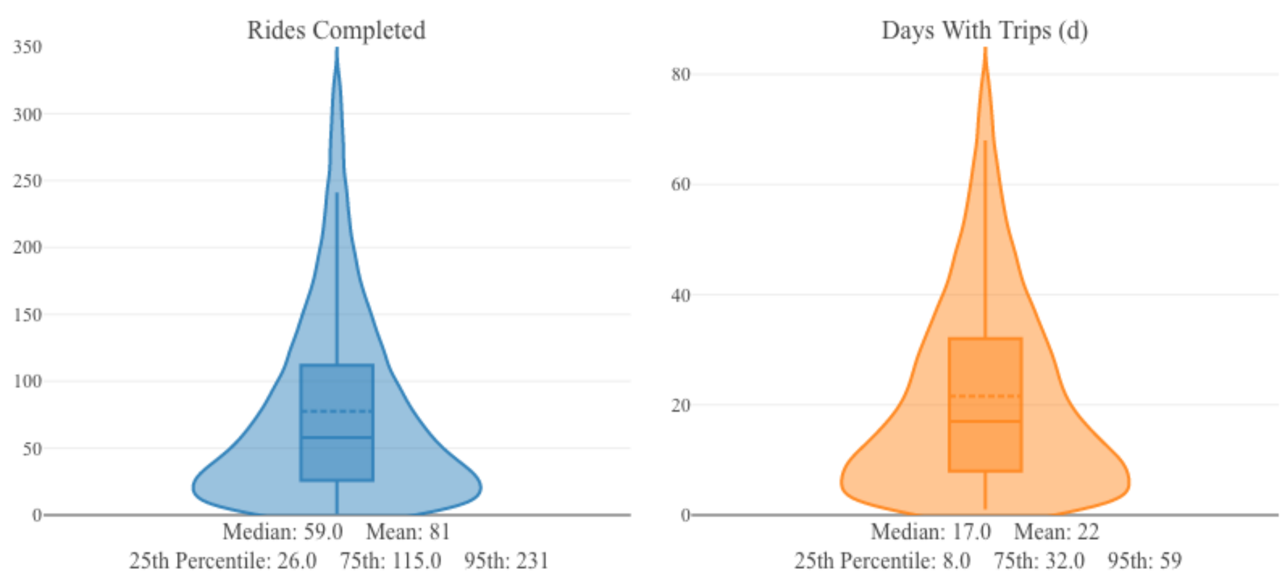


Figure 5. Defunct Scooter Lifetime Vehicle Usage Statistics

To evaluate lifetime vehicle statistics, medians are used, since a median can be computed accurately on a sample whose vehicles are only 50% defunct. Mean figures would require all of the sample to have reached their 'end-of-life.' Also, some vehicles may have anomalously low lifespans, skewing the mean. Vehicles from April 2018 through January 2019 are mostly defunct, and vehicles first deployed in February 2019 are nearly there.

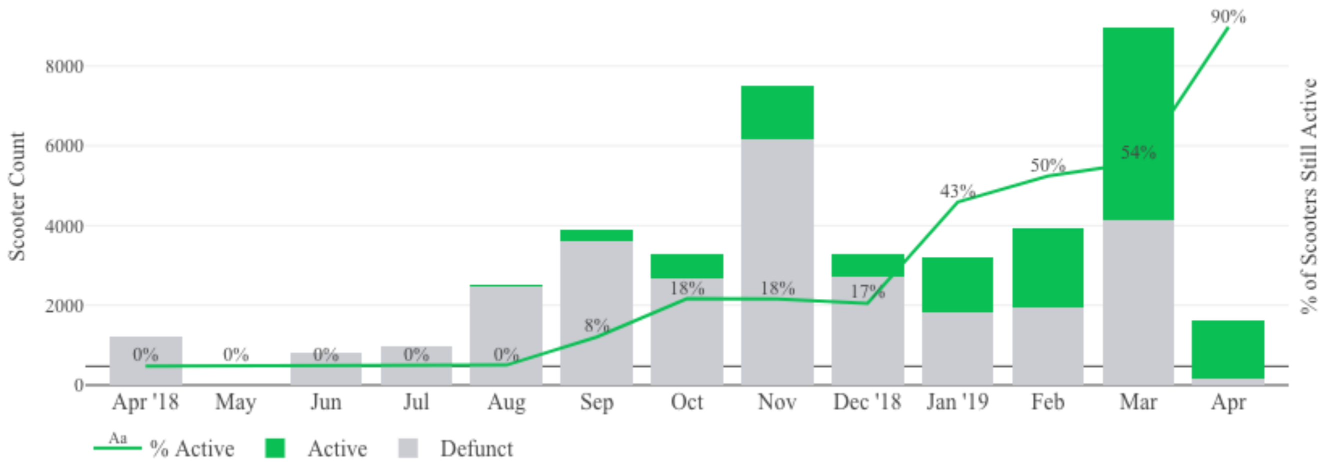


Figure 6. Scooters, Active & Defunct by Start Month

While one might expect new technology to mature, and see longevity grow over time, this has not occurred with scooters. Scooters deployed in February fare worse than those released in July.

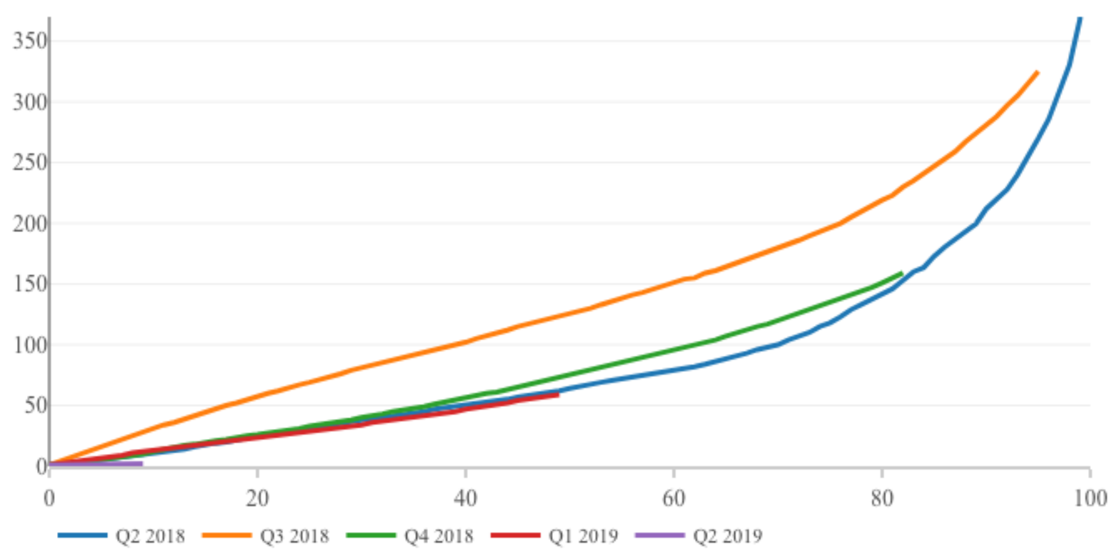


Figure 7. Percentile Distribution of Lifetime Rides by Quarter Deployed, Defunct Scooters Only

Interestingly, scooter longevity peaked in July 2018, and has not recovered. Wear and tear on the scooter can come from two primary sources - time being ridden, and days deployed out on the street. It appears the second factor, days active, predominates. July scooters had a median of nearly 250 rides each, vastly outpacing figures from the ensuing months, while its longevity in terms of days active was less exceptional, compared to scooters first deployed in other months.

These results from July suggest that the number of days active is more influential to longevity. While these vehicles have been known to go for a thousand miles and more when privately owned, being left out in the sun and rain, and being jostled around in vans and pickups (for regular electric charging) is likely taking their toll.

One can also consider the median lifetime rides and days active per defunct scooter, on a rolling basis over time (Figure 8). For a rolling window of 500 scooters, the median rides and days active per scooter are shown. On the x-axis the number of the scooter in sequence, eg the 1st defunct scooter, the second, etc is shown; for both metrics, no consistent trend appears, though since the 21,000th dead scooter (occurring in early March), median rides and days active has ticked steadily upwards, to 76 rides and 24 days, respectively.

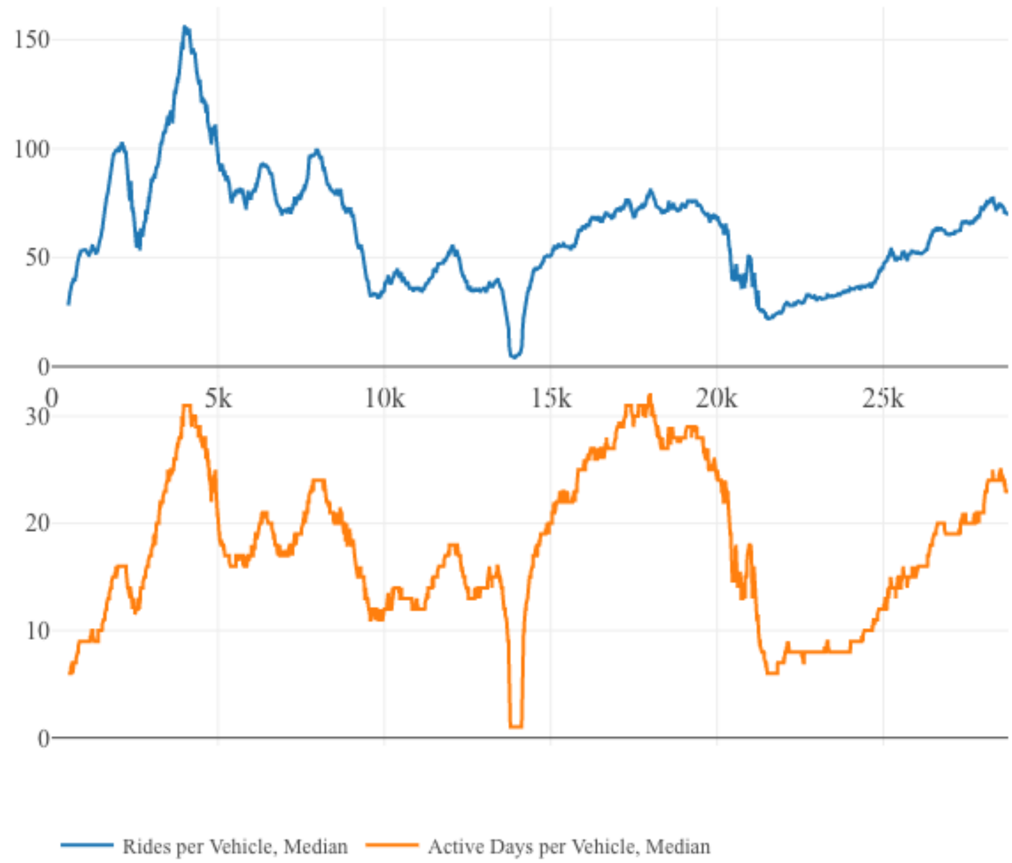


Figure 8. Rolling Median of Lifetime Rides & Active Days, per Scooter; the x-axis denotes the nth defunct scooter

Still, even with the recent rise in longevity, recently defunct scooters are still within the range of what was previously observed (50-150 lifetime rides, 10-30 lifetime days active).

One can segment scooters by their month of deployment (e.g., the 1,207 scooters released in April 2018), and compare the volume of their rides over time as in the Figure 9. The thickness of each line is proportional to the initial size of the cohort; thus the months with the thickest lines, November 2018 and March 2019, saw the biggest rollouts of new scooters. The slope of the line indicates the absolute rate of rides; since utilization is the ratio of rides to vehicles, utilization in the graphic below is the ratio of line thickness to line steepness. When utilization is constant between cohorts, a thicker line will also be steeper (as with the January and February 2019 cohorts).

Deployments in April and June were small and short-lived, with moderate utilization; July was similar, albeit with higher utilization; August resembled July, though with a bigger fleet and slightly lower utilization.

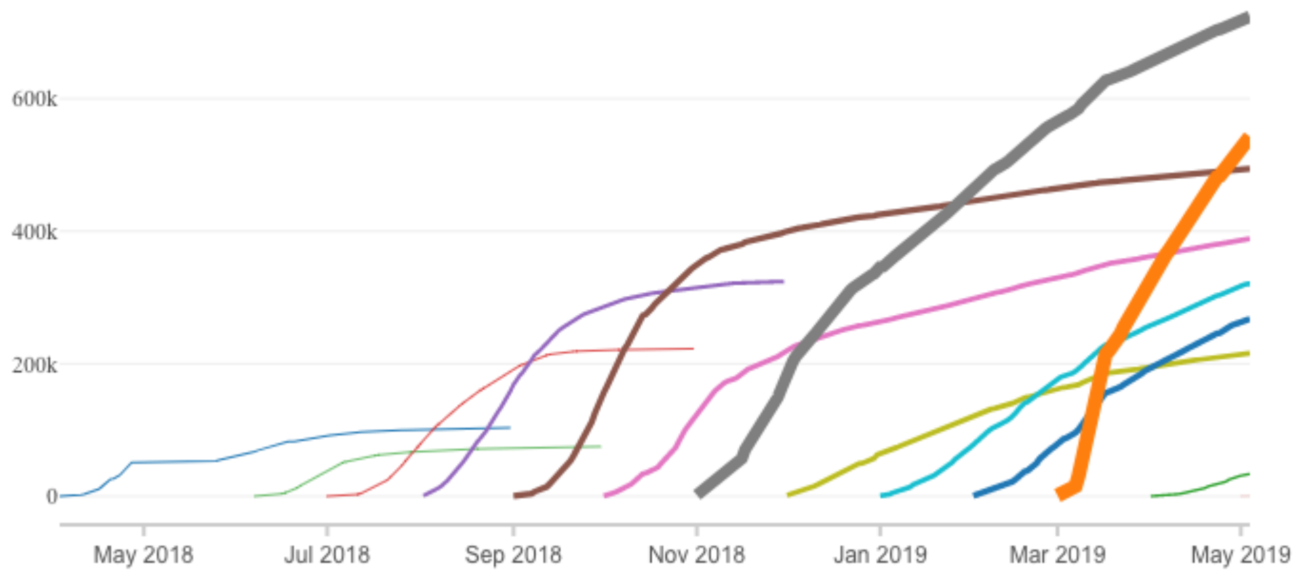


Figure 9. Cumulative Rides by Monthly Scooter Cohort

Starting in September, the cohorts endure longer, with long ‘tails’, and utilization (the ratio of line thickness to line slope) across cohorts is rather similar. Large deployments occurred in November and March (for the SXSW festival). In the wake of the large November and especially March deployments, new deployments thereafter were more modest.

More generally, this view indicates that while median longevity has not noticeably improved, a fraction of scooters persist for months, unlike in earlier months.

Models

This section describes the various types of models used for this capstone project. The models include two (2) forecasting types to predict expected trips the following day and one financial type to determine the financial viability of this new transportation mode in the hands of the private sector.

Forecasting

The purpose of this step is to take the modified dataset and begin exploring potential models that will be used to predict the expected trips in the City of Austin for the following day.

Various were explored including linear regression, supervised learning and time-series. In various types, daily variability of the data was smoothed out in many of these and ultimately the time-series model was chosen. Time-series forecasting is probably one of the more difficult models to create due to the nature of long short-term memory (LSTM) in the analysis. Unlike a moving average analysis, LSTM is highly valued in stock predictions where stockholders and trading companies can use these models to determine whether to buy or sell on any particular day. Similar to stocks, instead of determining whether to buy or sell, this model would help companies like Lime and Bird to be able to predict the number of units (scooters) to be deployed based upon the predicted demand. To that end the recurring neural network predictive model of LSTM was used to time-series forecast.

A visual representation of the data in Figure 10 (or copy the link into a browser) to the left to show the typical patterns over a day and the links visualized data to the right.

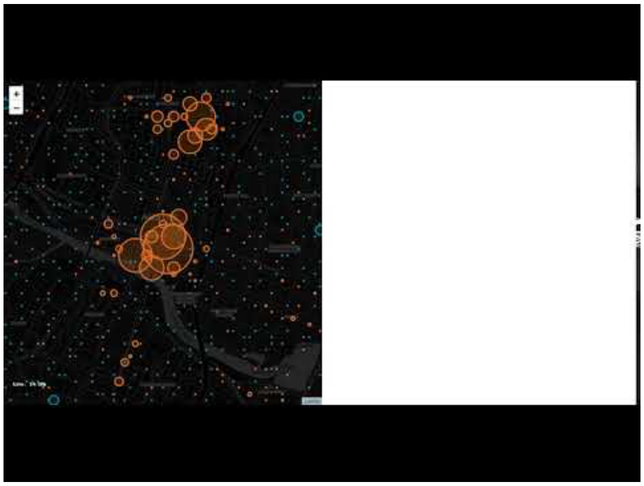
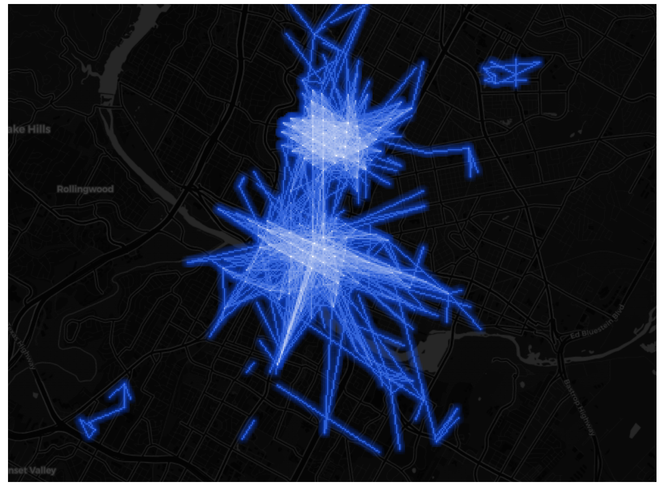
Origin Data Over Time Video	Link Visual
	

Figure 10. Video Visualizer of Origin and Destination Pairs of Trip Data and Link Visual of Pair (https://www.youtube.com/watch?v=VnsktKfSqUE)

As can be seen in the origin-destination link visual graphic, most of the trip is centralized around the main east-west strip in downtown Austin and around the University of Texas at Austin. The following information describes the two (2) models built for this step and the relevant analysis to provide reasons for model selection in the next step.

Model 1: Univariate LSTM Model

The perfect place to start is to use the univariate time step model which takes in the x variable of time normalized to units and the y variable is the number of scooter trips in a day.
The model was created using the LSTM model function within the keras package and had 1 shift in time step and was done over 100 simulations for each chunk of data. The full script can be found in Appendix B under *LSTM Univariate*. Figure 11 on the following page shows the results of the univariate model testing.

Walk Forward Validation　　　　LSTM Univariate Model

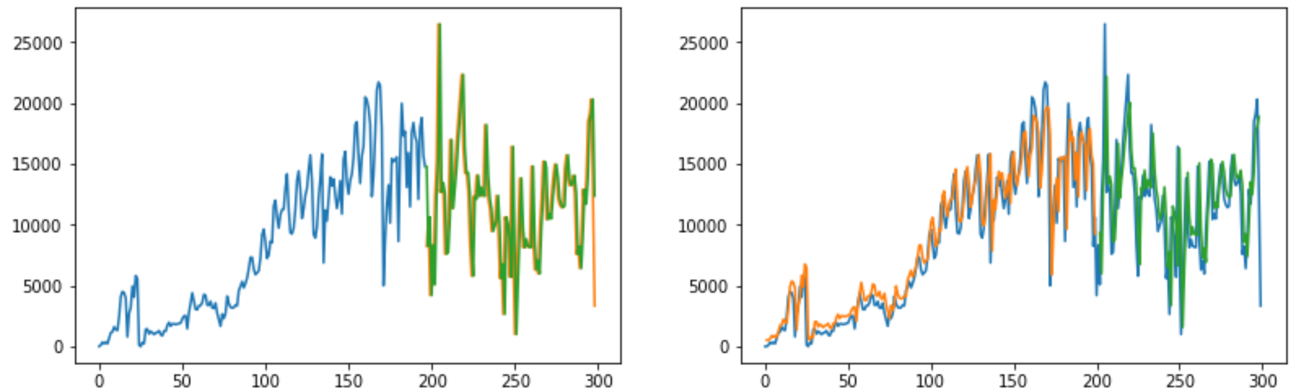


Figure 11. LSTM Univariate Model

For Model 1, the train score was 2174.30 RMSE and the test score was 3617.91 RMSE. This means that the average RMSE was 50% higher in the test data set which is a good starting point for our predictions.

Table 1. LSTM Univariate Last 3 Time Steps Comparison

Metric	Step 298	Step 299	Step 300
Actual	15,752	15,047	9,244
Predicted	17,722	18,114	18,870
Delta (# / %)	1,970 / 13%	3,067 / 20%	9,626 / 104%

With the above graphs, RMSE and time step comparisons, we can tell that Model 1 is a good predictor for short predictions as the expected number of trips for the region are within range. This behavior is sensible as the prior days seem to have been a spike in season due to an event which the model would self-regulate again once a few more days are in the short-term memory of the model. Next we will determine if a more complex model using more variables than just time will provide a better prediction model.

Model 2: Multivariate LSTM Model

The next place to explore is to determine if more variables would allow the model lower its RMSE without overfitting due to collinearity or other typical traps in model creation. For Model 2, three (3) additional variables will be used in addition to time normalized to units for this analysis; the output (CountID) variable stays the same as Model 1 and is the number of scooter trips in a day. The additional variables were daily means for Length of Trip, Length of Time of Trip, and Day of the Week and are represented in Figure 12.

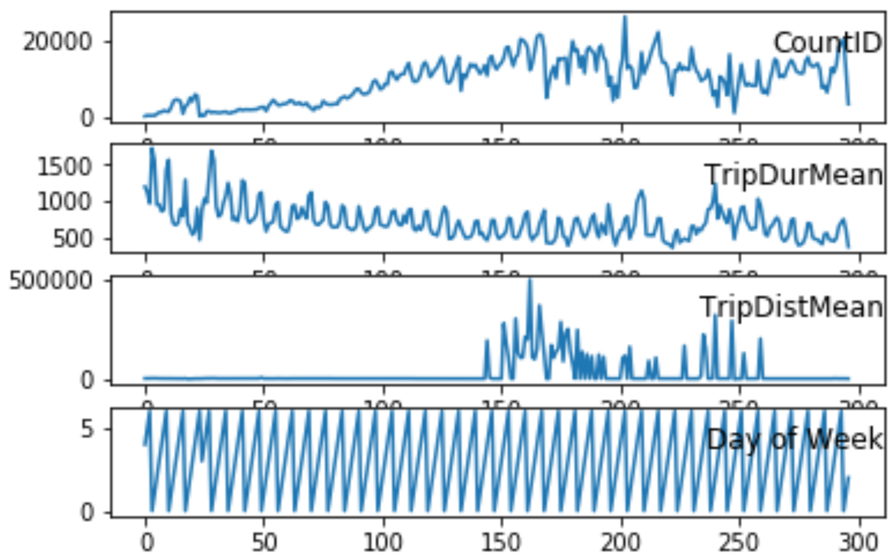


Figure 12. Visual Representation of Variables Selected for Multivariate Model

These variables were chosen based upon industry knowledge about the biggest factors that are also relevant to a scooter trip. The model was created by also using the LSTM model function within the keras package and had 1 shift in time step and was done over 50 simulations for each chunk of data. The full script can be found in Appendix B under *LSTM Multivariate*.

For Model 2, the test RMSE was 3919.99 which is about 10% higher from the test RMSE in Model 1 which was 3617.91. This means that multivariate model at first glance looks like a better model than the univariate model (i.e. $RMSE_{Model\ 2} > RMSE_{Model\ 1}$). However, in order to get the complete story, we need to look at the results of the losses in accuracy, similar to variances in linear regression, from the model comparing the test and train data set, the results of which are shown in Figure 13.

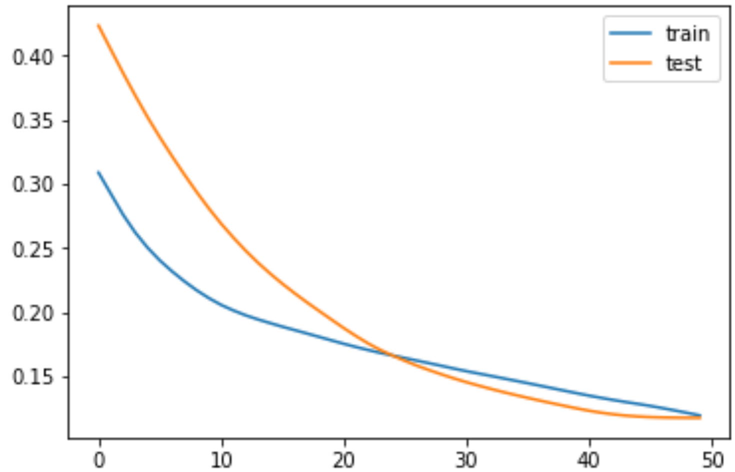


Figure 13. LSTM Multivariate Model Losses (Train vs Test)

A point of notice in Figure 13 is that the test data **dips below** the train data. In reviewing the model, this is the equivalent of getting a higher R^2 on a multiple regression model, but when diving deeper a high correlation between variables is found which causes the model to overfit and incorrectly assigns a higher R^2. The figure is showing the same concept when the **test** data goes below the train data - this means that the model is overfitting. Considering that this happens midway in the epochs time step analysis, this means that it overfits quickly. If the test data went below the the train data closer to the right-hand side, it would be less of a concern.

Table 2. LSTM Multivariate Last 3 Time Steps Comparison

Metric	Step 298	Step 299	Step 300
Actual	0.720	0.766	0.465
Predicted	0.558	0.427	0.342
Delta (# / %)	-0.162 / -0.22%	-0.338 / -0.44%	-0.123 / -0.26%

With the above graphs, RMSE and time step comparisons, we can tell that Model 2 may potentially be a good predictor, but the overfitting is a major concern.

Model Selection

With the above graphs, RMSE and time step comparisons between the two (2) models, we can tell that Model 1 is our best predictor for short predictions as the expected number of trips for the region are within range. This behavior is sensible as it is better to have a model that is not over-fitted and may have a lower predictive capability.

Financial Viability

Leading scooter sharing firm Bird optimistically projected[6] in a May 2018 report, that it would reach 33% gross margins would soon be achieved. Gross margin refers to the revenue left after accounting for the cost of goods sold (COGS), the direct costs associated with a ride such as charging, credit card processing, customer service and insurance.

Therefore, a $3 ride would have $1 in gross profit. The 33% margin figure was used to estimate cost and profit per ride for all operators. The industry standard pricing of $1 + $0.15 per minute is used to estimate revenue.

The same report mentioned that vehicles cost $551 each but would eventually cost $360 per piece; a figure of $400 was used, partly since scooter models have become more rugged and battery capacity has grown since the Bird report was written.

Therefore, at an average fare per ride of $2.75, each scooter would need to do 437 rides to break even. At a utilization rate of 3 rides per day, the lifespan required for break-even is approximately 150 days. Bird's founder and CEO said as much, "for Bird to eventually break even, the scooters will need to increase their lifespan to six months".[7]

Losses, at Scale

Of the 40,000+ scooters deployed, none have had more than 510 rides; approximately one in two thousand (0.05%) complete enough rides to break-even. For the median vehicle, losses per vehicle are approximately $340. The weighted average loss per ride is $4.07. Scooters first deployed in early

[6] (Efrati and Weinberg, 2018)
[7] (Hawkins, 2019)

September (n=1,373), the latest period with <1% of scooters remaining, saw an average loss of $2.97 per ride.

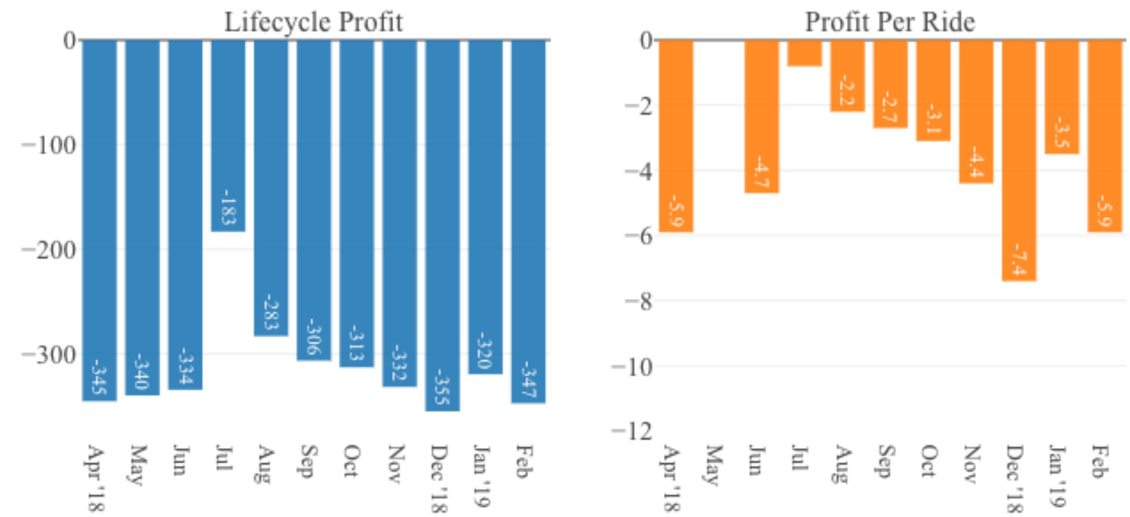


Figure 14. Vehicle Financial Statistics by Scooter Start Month

Among defunct scooters, the net total loss is $9.5m to date. The true profit levels are likely lower: gross margin figures don't account for costs that aren't directly tied to a ride, such as transporting the scooters from another city, developing the app, or staffing company headquarters.

Seventy-eight (78) days apart, Lime announced that it had done 34 and then 50 million rides, translating to an average of 205 thousand daily rides. At a loss of $2.97 a ride, that amounts to $609k in unit losses daily, or about $18.5M per month, without considering overhead costs. Lime is thought to provide 40-50% of US shared scooter rides overall, putting industry unit losses at $37-46m per month.

The gross profits above ultimately must still pay for overhead costs, to arrive at the net profits, the earnings left after overhead costs. Three scenarios were modeled, with net profit margins of 15%, 20% and 25%; and that a ruggedized scooter model would have a 25% higher acquisition cost ($500 per unit), we obtain the results shown below.

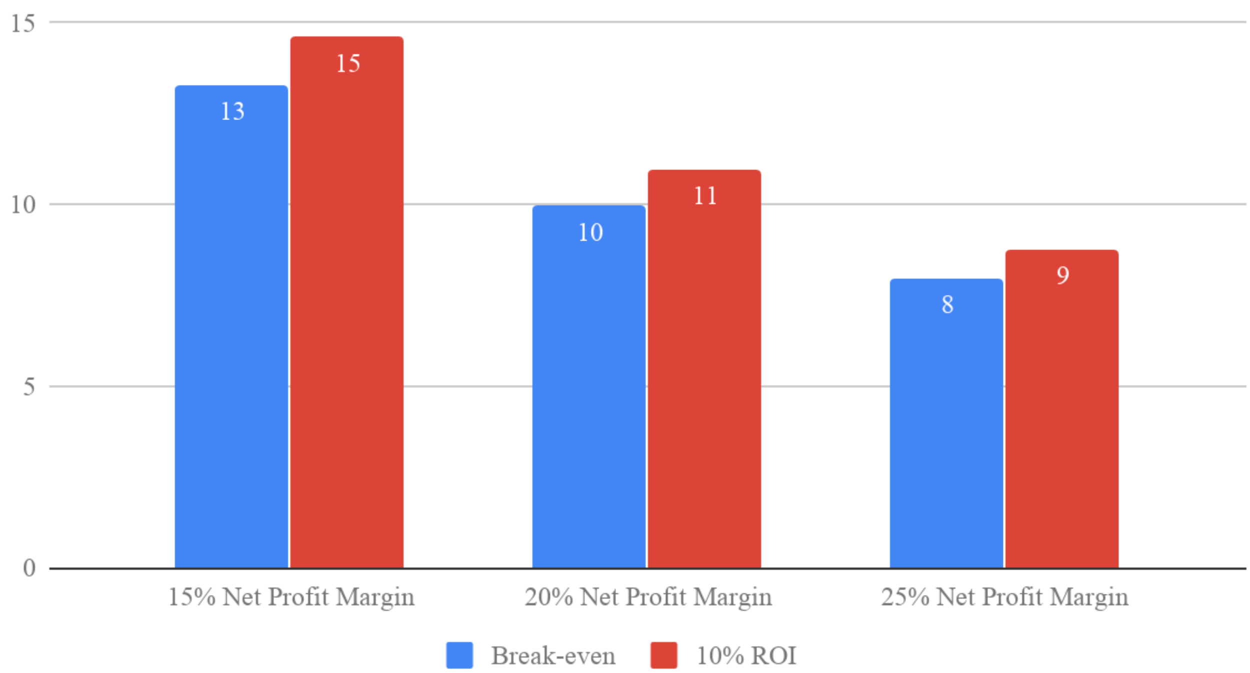


Figure 15. Months Required to Achieve Break Even and Achieve 10% ROI

If $1 of ride revenue nets $0.20 before vehicle hardware costs, it would take approximately 10 months to reach break-even, and one additional month to generate a 10% return on capital invested. For comparison, the design chief of leading electric bikeshare JUMP has said that its bikes are intended to last three years.

Sustainability

Transportation is now the largest source of greenhouse gas emissions, in the US and elsewhere. Shared scooters have been touted as one means of reducing emissions in transport. As electric vehicles without combustion engines, scooters appear well positioned to live up to this promise.

However, there are considerable emissions involved in the manufacture of lithium ion batteries - 150-200 kg[8] of CO2 per kilowatt-hour of capacity. We have estimated the CO2 emissions of scooter manufacture and operations for comparison to cars and find that each scooter would have to complete several times as much as the current 80-mile average, to attain parity with combustion engine cars.

[8] (Romare & Dahllöf, 2017)

If one considers the emissions from manufacturing of cars, as well as those from gas, the point of parity is about 320 miles, or quadruple the current scooter fleet average of 80 miles; new car sales have risen for 2018 despite the advent of scooter sharing. There is no evidence of the advent of scooter sharing reducing car ownership, nor are customers riding scooters frequently enough to replace a car they'd own otherwise.

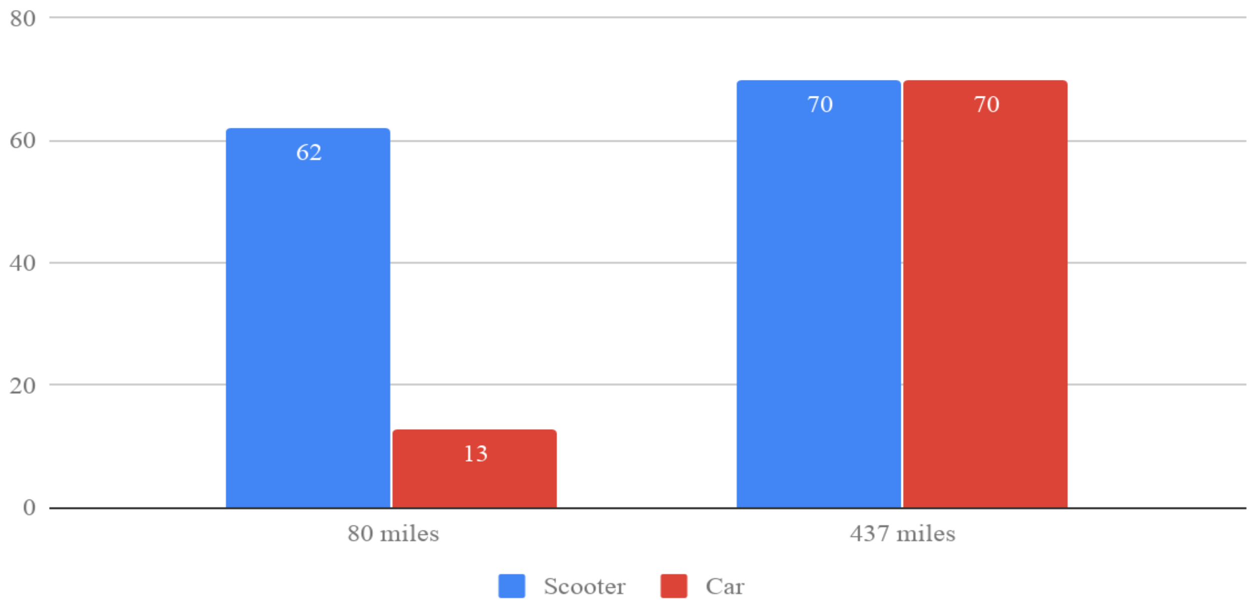


Figure 16. CO2 Emissions of Scooters vs Cars, at 80 (observed average) and 437 lifecycle miles

Removing the emissions from making cars from the comparison means that scooters would have to last ~400+ miles to emit fewer greenhouse gases than conventional cars. Yet today, few scooters come close to that mark. To attain parity with cars, shared scooter lifetime mileage would have to increase four to five times from current levels.

Conclusion

When scooters arrived in the United States, many were quick to dismiss it as an unsustainable toy, a dangerous ode to the Razor scooters of the 1990s, fuelled by venture capital and without profits of its own. These charges are not without merit. Based on the Austin, Texas data available, the industry is losing some $40-50 million a month, and the scooters do not last long enough to offer greenhouse gas emissions reductions, compared to the transport it replaces. As a silent confirmation of its financial woes, multiple major operators have already hiked prices 50%+ in select markets.

The Austin data contained numerous variables useful in generating the two (2) future ridership models, though the dataset does not identify the share of trips attributable to low income users with discounted pricing, which limits the ridership and financial analyses.

The two (2) models used the Long Short-Term Memory predictive model type from the Keras package: a univariate which only uses time as an input variable and predicts a specific set of time units forward or a multivariate model, which takes additional input variables and uses them in addition to the output to predict one (1) time unit (i.e. day) forward. After creating both models, it is clear that the univariate model is the best model for this exercise and reinforces the mantra that simplicity is best.

Major hurdles remain to the industry reaching financial and environmental sustainability, though the goal is clear - vehicles that last longer. With a typical longevity of three weeks and under 100 rides, while costing several times as much per mile as competing modes, shared scooters are not poised for any significant share of US vehicle miles traveled, for as long as these issues remain. There are early signs of improvement, with more recent cohorts of scooters showing longer staying power, but far from the 9 to 12-month vehicle longevity required. However, the quick consumer exposure highlights the mode's instinctive appeal, and these challenges are largely absent among scooters that are personally owned. Given the uncertainty around shared scooters and their promise, the Austin dataset is a welcome example of the government using its power to shed light on matters of public debate.

Appendix A. Python Code Summary Statistics.

The python code is available on the following Github repository:

https://github.com/cspitmit03/FinalThesis/blob/master/AppendixAPythonCodeSummaryStatistics.ipyn
b

Appendix B. Python Code Modeling/Forecasting.

The python code is available on the following Github repository:

https://github.com/cspitmit03/FinalThesis/blob/master/Appendix%20B.%20LSTM%20Code%20Analy
sis.pdf

Appendix C. References.

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