Night Owls Get the Worms: The Lifetime Value of Overnight Lyft Drivers

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Abstract

After close inspections of the dataset, we recommend deriving the lifetime value (LTV) of a driver with the formula defined in 3. We find that the gross fare, full-time/part-time working schedule, total number of rides, and rides efficiency contribute most to a driver's LTV (and other factors defined in section 3). The average projected lifetime for a driver is about 2 years. Different segments of drivers have different performance while driving, such as shift preference and total number of rides. Insightful business recommendations such as a preference for day/night-time workers and an algorithm to efficiently distribute customer requests are described in section 5.

1 Average Projected Lifetime of a Driver

By definition, the projected lifetime of Lyft drivers is the time interval that they continue to drive once onboard. In order to determine the drivers' projected lifetime, their activity level is an important factor to examine. By looking at the proportion of days the drivers used the platform, we get to examine how loyal the drivers are.

In our analysis, we built features *active days* and *total days with Lyft* to represent the drivers' level of adherence to Lyft: *active days* captures the amount of distinct days for a driver accepting rides, and *total days with Lyft* captures the amount of distinct days for a driver riding with Lyft since the day onboard to the last ride appeared in the dataset *ridetimestamps.csv*.

To measure their level of engagement, a retention rate score is calculated for each driver as follows

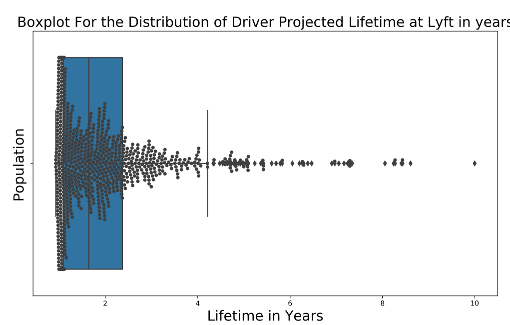
$$Retention\ Rate = \frac{Active\ Days}{Total\ Days\ since\ onboard} \tag{1}$$

By modifying a formula suggested by [1], we demonstrated the projected lifetime for each driver as follows:

$$Projected\ Lifetime = \frac{1}{1.1 - Retention\ Rate} \tag{2}$$

By standardizing the margin lifetime to be 1 year, we weighted the margin with a coefficient of the reciprocal of the loss rate of the drivers. By using this metric, an engaged driver will have a higher retention rate and a lower loss rate, leading to a higher coefficient multiplying the standardized margin, which in other words, a higher projected lifetime.

Figure 1: Distribution of Projected Lifetime



In our data, we obtained the sample mean of 2.02 years, with a standard deviation of 1.32 years. By Strong Law of Large Number, the population mean and standard deviation is estimated to be close to the sample's. Hence, we conclude that once a driver is onboard, they typically continue driving with Lyft for **2.02 years** on average with a standard deviation of **1.32 years**.

2 Driver's LTV

$$LTV = Fare \times Lifetime \times RetentionRate \quad (3)$$

Based on the formula created for drivers' projected lifetime and after a close analysis on the dataset, we define the LTV of a driver as in equation (3), where *Fare* denotes the total amount of revenue a driver brings to Lyft in a fixed amount of time (4 months in this case), *RetentionRate* is defined in equation (1), and *Lifetime* is defined in equation (2). This formula captures most essences when we consider a driver's value to Lyft for the following reasons. First, the biggest factor we consider is a driver's ability to bring profit to Lyft. Second, we evaluate the loyalty of a driver to Lyft, i.e. how long and how efficient a driver tends to work for Lyft.

3 Main factors that Affect a Driver's LTV

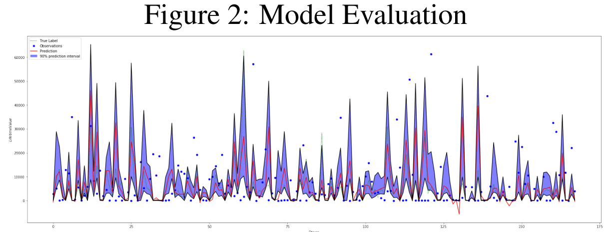
Two biggest factors that determine drivers' LTV are the gross profit and their adherence, as defined in the LTV formula. Also, interesting factors, such as total number of rides a driver makes, average daily working time, time spent to pick up a customer after accepting a ticket, day/night-time worker, etc, also affect a driver's LTV. Here we implement a few regression models such as Lasso, Ridge, Gradient-Boosting and Ordinary Least Squares Regressor [2] to extract significant features that affect a driver's value to Lyft. First we use Lasso Regressor to obtain the most significant features due to the construction of its regularization term. Because one-norm regularization is used in Lasso Regression to constrain the weight(feature) vector, most important feature is conserved while less essential features are thrown. The main factors we extract out from this regression model are total number of rides, daily active time, and time spent to pick up a customer after accepting a ticket. If a driver completes more rides, drives more often, and let a customer wait for less time after requesting a ride, then this driver tends to have a higher LTV for Lyft. Another regression model yields more compelling results. As showed in Table 1, five bold features are the main factors to determine a driver's LTV.

Table 1: Coefficient(feature) Analysis

Features	Sign	Importance
Rides	+	**0**
Prime	+	**0.239**
Active	-	**0**
Completion	+	0.502
Arriving	+	**0.061**
Speed	+	0.867
Distance	-	0.827
Duration	+	0.680
Work Period	-	**0.275**

Notes: Rides—total number of rides; Prime—prime time ride percentage; Active—daily working time; Completion—completion rate; Arriving—time spent to pick up a customer; Speed/Distance/Duration—average speed/distance/duration of a ride; Work Period: day/night-time worker. Sign: '+' means positive effect while '-' means negative effect. Importance denotes the p value of the feature: the closer it is to 0, the more important the feature is.

Figure 2: Model Evaluation



It seems that night-time drivers who accept more rides during prime time will have higher value. Furthermore, more interesting results are generated from different segments of drivers. For night-time worker, cancellation/abnormal ride have positive effects toward LTV (Note: we define abnormal ride here as those rides which have distance ≤ 0). This may be caused by unbalanced data in the dataset (only 2 drivers have abnormal rides). Moreover, when we split the drivers into high/medium/low-value sections, we found that the main factor that affects low-value drivers is ride distance, while medium-value drivers is ride duration and speed and high-value drivers is prime time ride percentage (more insights in section 5). We split all drivers into train/validation and test data. After training, the result on test data is shown in Figure 2, which shows 90% confidence level (expected LTV) of each test driver.

4 Driver Behavior Analysis

To further assess how drivers act and contribute values differently to Lyft, we decided to focus on the number of total rides they completed and how their shift is spanned through a 24-hour window.

Figure 3: Distribution of Average Single Ride Distance

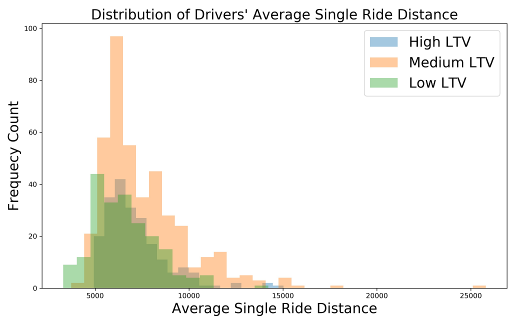
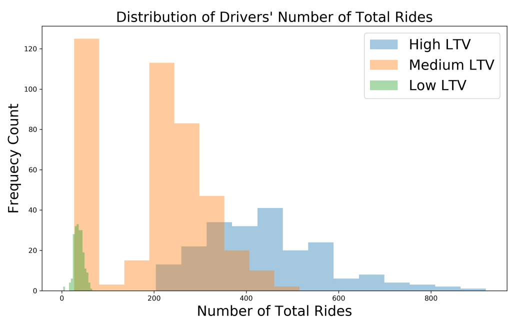


Figure 4: Distribution of Total Number of Rides



Number of Rides We first categorize the drivers in our sample into three groups: High LTV(LTV), Medium LTV, and Low LTV. Drivers who generate LTV less than 25 percentile of population are categorized into Low LTV, drivers that generate LTV higher than 75 percentile of the population are categorized into High LTV, and the rest of the drivers are categorized into Medium LTV.

By our definition of LTV, it remains unclear if the reason behind the outstanding contribution of the drivers with high LTV is due to their preferences of long rides that generate many profits or the accumulation of short rides. By comparing the distribution of average single ride distance Fig 3 and number of total rides Fig 4 across the three groups of drivers, we observed that all three distributions approximately center on the same mean, with medium LTV drivers' mean value being slightly larger than the rest of the two groups. On the contrary, the distribution of the total number of rides completed for three contributions vary differently. As expected, we observed that drivers with a higher LTV tends to drive more number of rides than the ones who generated low LTV. At the same time, the average single ride distance doesn't seem to differ much across groups.

Shift Preference Since Lyft offers drivers options to drive full-time and part-time, we were interested in how drivers schedule their shift and if the differences in shift scheduling make an impact on their LTV contribution to Lyft.

The timestamps of drivers accepting rides were used as the measurement approximating the hours the drivers started working. In order to better demonstrate the full working intervals and the distribution of ride events, the hour were shifted to a 6AM to 6AM interval. Figure 5 below illustrates how drivers act differently in terms of driving habits. Twenty drivers were randomly sampled from the pool of drivers. For the purpose of privacy protection, the driver ids were anonymized. For example, Driver 2 from the Figure 5 demonstrates a part-time night shift driver's schedule that starts around midnight and goes to the morning; Driver 6 shows a schedule of a full-time driver accepting rides primarily in the morning; Driver 16 shows a schedule of a part-time day shift driver's schedule that picks up customers primarily in the rush hours.

The focus in the following analysis is on the differences between **night-time drivers and day-time drivers**. To distinguish the working periods, we calculated the 2.5%, 5%, 10%, 12.5%, 25%, 50%, 75%, 90%, 95% and 97.5% of starting time of rides each driver has completed. Further, the mid 95%, 90%, 80%, and 50% duration was measured.

By our definition (Figure 6), in order for a driver to be categorized as a night-time driver, the driver needs to satisfy the following conditions:

1. The 2.5 percentile of ride starting time should be after and within 4 hours of the 97.5 percentile.

2. The mid 95% duration between 2.5 percentile of ride starting time and the 97.5 percentile should be at least 15 hours.

3. The mid 50% duration between 75 percentile

of ride starting time and the 25 percentile should be at least 8 hours.

Figure 5: Drivers' Work Hour Span

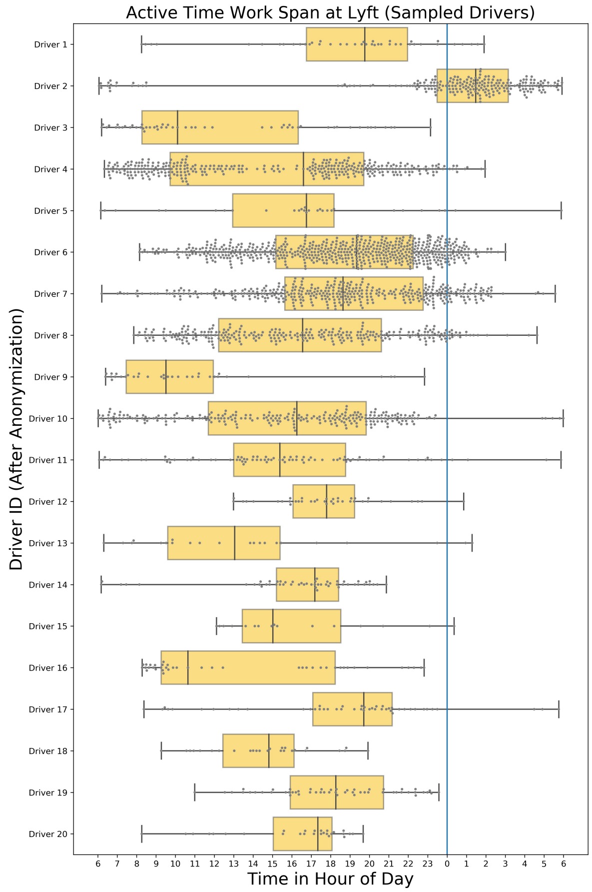
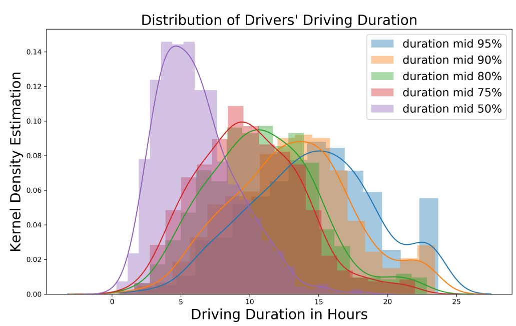


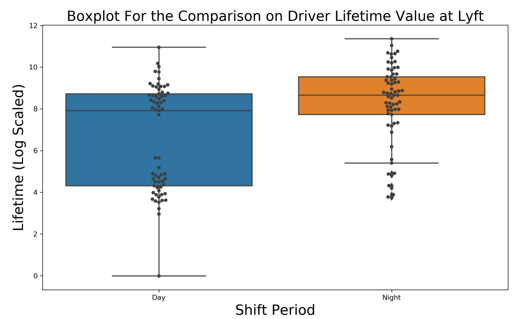
Figure 6: Distribution of Drivers' Work Span



The reason why the above restrictions were set is to ensure the night-time workers we defined work primarily, periodically, and continuously from night to morning: The percentile measurement greatly reduces the case of outliers; The restrictions on duration restricts the case of full-time workers working overnight from the first day to the next morning.

The limitation of setting a strict standard for night-shift workers is a high false negative rates on classifying night-shift workers. Hence, it is likely that when we compare the differences in the two distributions, the differences between distributions are harder to be observed. However, from the boxplot and the results from statistical testings conducted below, the difference between distributions of LTV in night-time workers and day-time workers is considered statistically significant.

Figure 7: Drivers' Lifetime Value Comparison Across Different Shift Schedule



We first randomly sampled the same number of day-time drivers as the night-time drivers (Figure 7). Then, we log-scaled the LTV for the pattern in distributions being better observed. From the boxplot below, we found that in our sample, night-time drivers have a higher median and a narrower ranges of lifetime-value than the day-time drivers. Since the distribution of LTV we observed for both distributions on day-time drivers and night-time drivers are bi-modal, a one-sided non-parametric rank sum test, Mann-Whitney U-test, is used to assess whether two independent samples were selected from populations having the same distribution. The test is set such that the distributions of both populations are equal under the null hypothesis (Firgure 8), and a randomly selected value from the night-time drivers' LTV distribution will be greater or equal to a randomly selected value from a the day-time drivers'. We set our level of significance to be 0.05, and with a p-value of 0.0001, we are able to reject the null hypothesis and conclude that the difference in two populations is statistically significant.

To further illustrate the difference (Figure 9), a 100-fold permutation test is performed. We randomly shuffled the drivers' work-schedule labels and reassigned the new shuffled labels to the original population and calculated the population difference in means. After 100 times of experiments, we observed the probability of the observed difference being less than the distributions of theoretical differences to be 0.0. The difference leads us to a conclusion that the two distributions were not drawn from the same population, which further consolidated the results we derived from the Mann-Whitney U-Test.

Figure 8: Results of Mann-Whitney U-Test Assessing Differences on LTV Between Workers on Different Shift Schedule

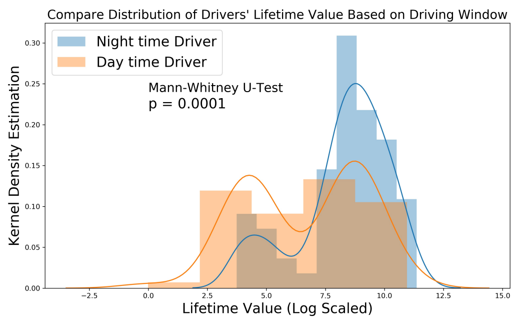
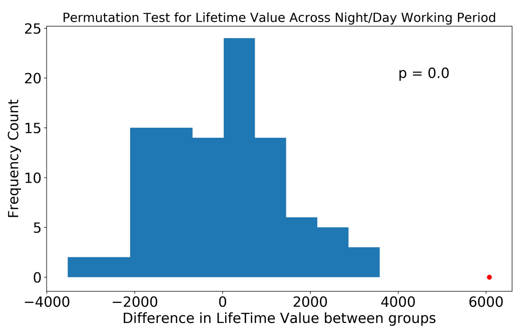


Figure 9: Results of Permutation Test Assessing Differences on LTV Between Workers on Different Shift Schedule



Therefore, we found that drivers who work primarily, periodically, and continuously overnight tend to behave differently than drivers who work in the day time. Further, the night-workers tend to generate a higher life-time value.

5 Business Recommendation

From the analysis above, we realized the profits of night-time workers and the differences among drivers who generate different levels of LTV to Lyft. We suppose the implicit reason of why night-time drivers generate more profits to Lyft is because they tend to accept rides continuously whenever they see a request. Since they were dedicated on driving throughout the night, they adhered to their schedule in a high efficiency. In order to optimize profits that are generated, we would like to give out the following recommendations:

1. Based on the night rides demand of the location, we would like to recommend a policy that increases drivers' incentives of extending the time driving at night time or the adherent period driving at day time. Prior to the making of policy, the we recommend designing an algorithms to classify drivers into night-time drivers and day-time drivers. Since the average daily driving time for each driver is 1.5 hours with a standard deviation of 0.67 hours, and the 75 percentile ride distance completed is at 8.095 kilometers, we propose to give night-time drivers bonus if they continuously drive for 4 hours between 9PM to 6AM, OR if completed 161.900 kilometers daily for five consecutive days between 6AM to 9PM.

2. Considering current drivers who generate different levels of LTV to Lyft, we recommend designing a new algorithm for distributing customer requests to effectively increase each driver's LTV. Based on the analysis, low-value drivers should drive longer distance to obtain higher value, while medium-value drivers should drive more efficiently to increase their value, such as increasing their ride speed in a fixed ride distance (under secure circumstances). And high-value drivers should try to increase their profit per ride, such as accepting more prime time tickets. In other words, the algorithm could distribute more ride requests which contains less uncertainties like traffics to current low-value drivers, assign more rides with potential profit such as the ones during prime time to more experienced drivers, i.e. high-value drivers, and let other medium-value drivers accept most of the rest requests.

References

[1] CLV-Calculator, Converting Retention Rate to Customer Lifetime Period `https://www.clv-calculator.com/customer-retention/converting-retention-rate/`

[2] Regression Models (Lasso, Ridge, OLS, GradientBoosting) `https://scikit-learn.org/stable/modules/linear_model.html`