

Clipboard Health Pricing Case Study One

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[Link to Github repository](#)

1. Introduction

The Pricing Team is assessing the feasibility of launching a ride-hailing service for riders from the Toledo Airport to Downtown Toledo, Ohio. The service will only be active for 12 months and is subject to the following assumptions and constraints:

- Riders are acquired into the service at a cost of \$30 per rider
- The price offered to the driver pool is variable, but affects the probability of the ride being accepted by a driver¹
- Riders may or may not end up hailing trips during their customer lifetime
- If a rider does not make any ride requests in a given month, they churn from the service and will not hail any more trips in future months²
- If a rider makes ride requests in a given month but none are accepted, the rider churns from the service and will not hail any trips in future months
- The number of successful rides hailed in a given month for a customer will affect the frequency at which they request trips the following month³
- There is no limit to the number of drivers available on the service
- There are a maximum of 10 000 riders that can be acquired into the service with a monthly maximum of 1 000 in any given month
- The service starts with 0 riders

1.1. What is our goal?

Our goal is to provide a pricing strategy that maximises the profits of the service given the assumed set of constraints. The two input factors that we have control over are:

- The price at which to offer the ride to the driver pool, affecting the probability of a driver accepting the trip and the profit that we can make
- The number of riders to acquire each month, each of which costs \$30 to acquire

2. Analysis

The first step of our analysis involves the investigation of the relationship between the cost of the trip paid to the driver (assumed fixed), the number of riders acquired in a year (assumed homogeneous across months) and overall profitability.

¹ The probability of a driver accepting a trip for a given offered price is determined by a logistic regression model, detailed further in the [Appendix](#).

² The number of trips that a new customer will call is determined by a Poisson distribution with $\lambda = 1$.

³ The number of trips that a returning customer will call is determined by a Poisson distribution with lambda equal to the number of successful trips they hailed in the previous month. This is detailed further in the [Appendix](#).

The profitability of the service was determined using the following equation:

$$Profit = (N_{rides} \times Price_{ride}) - (N_{rides} \times Price_{driver}) - (N_{riders\ acquired} \times Cost_{acquisition})$$

Where:

N_{rides}	The number of rides successfully hailed on the service
$Price_{ride}$	The cost of a ride to the customer, fixed at \$30
$Price_{driver}$	The expense of paying the driver for the ride
$N_{riders\ acquired}$	The number of riders acquired into the service, evenly distributed over 12 months
$Cost_{acquisition}$	The cost of acquiring a new customer, fixed at \$30

2.1. Two scenarios for determining the likelihood of the driver pool accepting a ride

Two separate scenarios for determining the likelihood of drivers accepting a ride were considered:

- Scenario one assumes that the probability of a driver accepting a ride is directly applied to the number of customers calling a ride.
 - An example of this would be, if 100 riders hailed a ride and there was a 75% likelihood of a driver accepting the trip for a given price, 75 riders will have their rides accepted and 25 riders will have their rides rejected.
- Scenario two assumes that the probability of a driver accepting a ride is either 0% or 100%, depending on whether the calculated probability is above the threshold of 50%.
 - An example of this would be, if 100 riders hailed a ride and there was a 75% likelihood of a driver accepting the trip for a given price, all 100 riders will have their rides accepted as the 75% probability is greater than the 50% threshold.

2.2. How many riders stay in the service

The number of riders retained in the service is impacted by the probability of them hailing N_{rides} in a given month as well as the probability that a driver will accept the price of the ride.

The equations for the number of riders retained in the service are provided in the [Appendix](#).

2.3. Scenario 1: continuous probability of drivers accepting rides

Relationship between driver price, number of customers acquired and overall profitability

The effect of driver price on the overall profitability of the service, for a varying number of riders acquired, is shown in the following diagram.



The above graph shows that, as the number of riders on-boarded into the service per year increases (acquisition spaced equally across 12 months), the profitability of the operation decreases. This is likely due to the large expense of customer acquisition (at \$30 a person) increasing the margin that operating profits must overcome for the service to be profitable. For all sets of yearly acquired riders, the profitability follows a similar pattern of not being profitable after 12 months, no matter the amount paid to the driver.

The overall profitability of the service experiences a local maximum at around \$24 paid to the driver for all sets of yearly riders acquired, with the effect being more noticeable for larger sets of acquired riders. This is because, as the drivers are paid more, the probability of them accepting the trip increases, reducing the churn rate of customers in the service. However, as the price paid to the driver increases, the profitability per trip begins to decrease. Churned customers are also a massive drain on profitability because of their cost of acquisition and this may not be made up in operating profits by the time they churn from the service.

As the profitability of the service is largest (albeit negative) at a low number of yearly acquired riders and for a driver price between \$22 and \$26, it is prudent to show the profitability graphically within this range.



From this data, it is evident that profitability of the service is not possible for the provided input parameters (price to charge rider, ride request probability and cost of customer acquisition). The profitability reaches a maximum as the number of riders acquired tends towards zero, showing that there are fundamental problems with the ability of the service to overcome the cost of customer acquisition through ride profitability (the difference between the cost to the rider and the expense to pay the driver).

Relationship between driver price and churn rate

The effect of driver price on the churn rate of customers leaving the service, for a varying number of riders acquired, is shown in the following diagram.

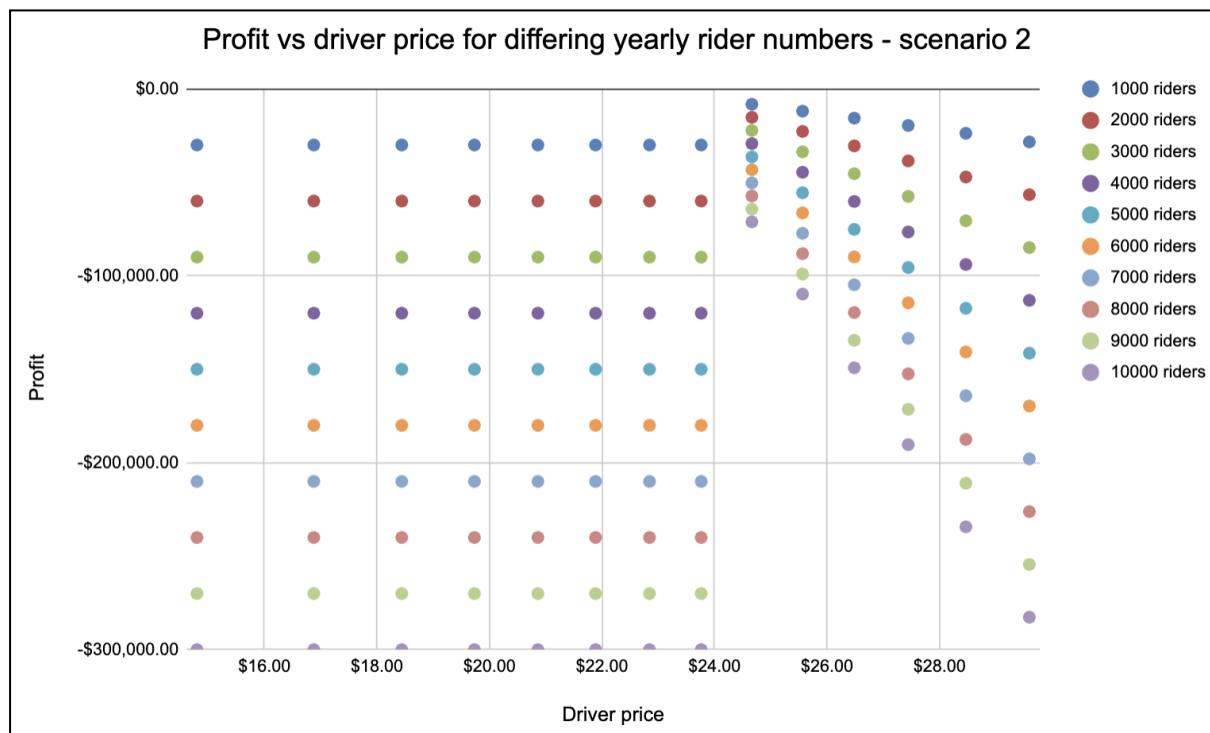


This graph shows that, as the amount paid to the driver increases, the churn rate of customers leaving the service decreases. This is logical, as the more a driver is paid, the less likely they are to reject a trip offered to them. As the number of riders acquired per year increases, the churn rate decreases slightly, as more riders in the earlier months are likely to hail at least one trip, keeping them in the service for longer.

2.4. Scenario 2: binary probability of drivers accepting rides

Relationship between driver price, number of customers acquired and overall profitability

The effect of driver price on the overall profitability of the service, for a varying number of riders acquired, is shown in the following diagram. The key difference between this scenario and that of scenario 1 is that the probability of a driver accepting the ride is either 0% or 100%, depending on whether or not the logistic regression probability (P) is larger than 0.5 (ride accepted) or less than 0.5 (ride rejected). See the [Appendix](#) for further details.



The above graph shows that, as the number of riders on-boarded into the service per year increases (acquisition spaced equally across 12 months), the profitability of the operation decreases, similar to scenario 1. The cause for this is the same as that of scenario 1 – the large expense of customer acquisition (at \$30 a person) creates a large margin for operating profits to overcome. Furthermore, as the drivers are paid more per trip, the profit made per ride decreases, the overall profitability decreases and this margin cannot be closed.

For all sets of yearly acquired riders, the profitability follows a similar pattern to that of scenario 1 of not being profitable after 12 months, no matter the amount paid to the driver. A key difference between this graph and that of scenario 1 is that the profitability is the same for all driver prices that are too low to be accepted ($P < 0.5$, \$24.66).

The profitability of the service experiences a local maximum at around \$24.66 ($P = 0.5$) for all sets of yearly riders acquired, with the effect being more noticeable for larger sets of acquired riders. This is because the threshold for drivers always accepting the trip is set to $P \geq 0.5$ with the most profitable rides being those at $P = 0.5$. As the price paid to drivers increases and P is above 0.5, there is no benefit to offering the drivers more per trip as they will always accept the price and the profitability per ride decreases. In this scenario, the effect of customer churn as a result of rejected trips is always felt at $P < 0.5$ ($< \$24.66$ to driver) and never felt at $P \geq 0.5$ ($\geq \$24.66$ to driver).

Relationship between driver price and churn rate

The effect of driver price on the churn rate of customers leaving the service, for a varying number of riders acquired, is shown in the following diagram.



This graph shows that, if the amount paid to the driver is in the range of \$24.66 to \$30.00, the churn rate is lower than if the amount paid to the driver is below \$24.66. This is because the threshold for drivers always accepting or rejecting trips is based on whether they are paid above or below \$24.66 ($P=0.5$).

As the number of riders acquired per year increases, the churn rate decreases slightly, as more riders in the earlier months are likely to hail at least one trip, keeping them in the service for longer.

3. Discussion

3.1. Scenario 1 vs scenario 2

Although scenario 2 has more favourable profitability outcomes when compared to scenario 1, it is less representative of the likely behaviour of drivers because of its assumption that

drivers will always accept a ride when offered \$24.66 and more. It is more likely that some drivers will accept the trips for that price and some will not, as reflected in the raw dataset used to populate the logistic regression model. For that reason, only scenario 1 outcomes will be discussed for the remainder of this analysis.

3.2. Customer acquisition cost and the price charged to riders

The high customer acquisition cost of \$30 creates a margin that is difficult to overcome with per-ride profit when the maximum that can be charged to riders is \$30. Drivers already have a 50% chance of rejecting a trip that pays them \$24.66 (for a profit of only \$5.34 to the service). The competing interests of having drivers reject as few trips as possible whilst also attempting to maximise per-ride profitability negatively impacts either customer churn rate or per-ride profit, which both negatively impact the overall profitability of the service.

3.2.1. Customer acquisition cost vs service profitability

Driver price vs service profitability for varying customer acquisition costs (CAC) at a constant 1000 yearly riders acquired and \$30 rider price is shown in the graph below.



This graph shows that, if the cost charged to the rider remains at \$30 per trip, the customer acquisition cost would have to be drastically decreased to below \$5 per rider for the service to become profitable. As this is likely not a realistic target, changing the customer acquisition cost alone will not make the service profitable. Service profitability experiences a local maximum at around \$25 paid to the driver for all customer acquisition costs. This is because, as drivers are paid more per trip, they are less likely to reject the trip (reducing customer churn rate) but this decreases the profit made per ride.

3.2.2. Rider price vs service profitability

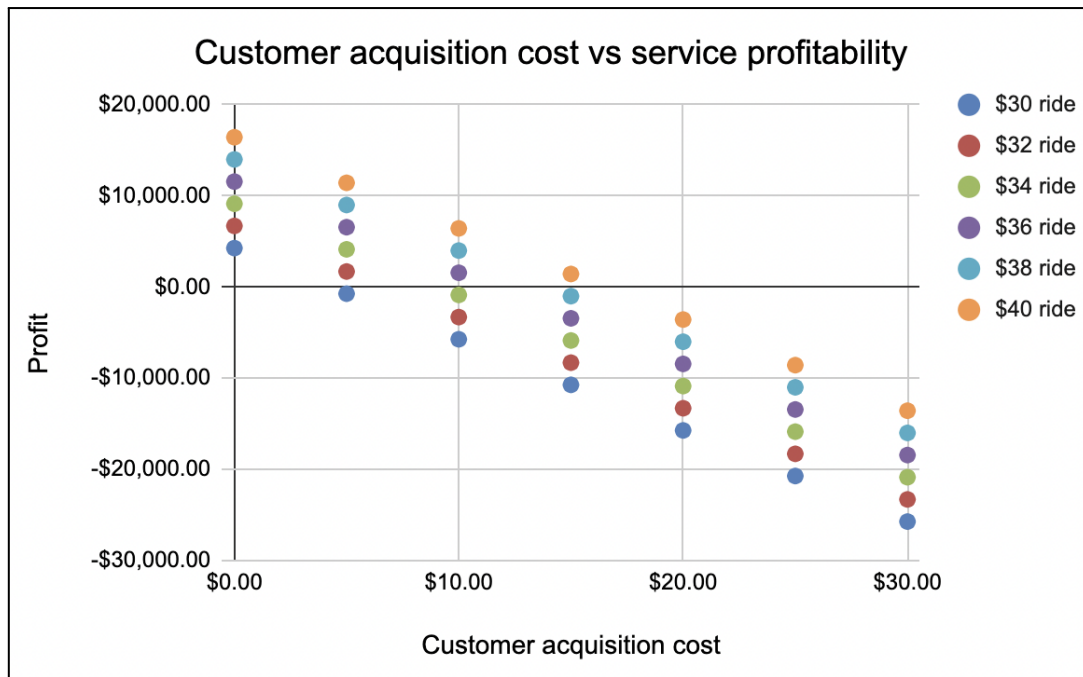
Driver price vs service profitability for varying rider prices at a constant 1000 yearly riders acquired and \$30 customer acquisition cost is shown in the graph below.



This graph shows that, if the customer acquisition cost remains at \$30 per rider, an increase in the price charged to the rider per trip increases the profitability of the service, but any amount less than or equal to \$40 per trip would still be unprofitable. As charging more than \$40 for the trip is likely unfeasible (especially if other ride services are readily available in the area), increasing this charge alone will not make the service profitable. As the price paid to the driver increases, the likelihood of them accepting rides increases, reducing the negative effect of customer churn on service profitability. Unfortunately, this also decreases the per-ride profitability of the service, making it difficult to overcome the high \$30 per-customer acquisition cost.

3.2.3. Customer acquisition cost vs service profitability for varying rider prices

Customer acquisition cost vs service profitability for varying rider prices at a constant 1000 yearly riders acquired and \$26.48 driver price ($P=0.6$) is shown in the graph below.



This graph shows that, for a fixed driver price, as the customer acquisition cost decreases and the price charged to riders increases, the profitability of the service increases. For this scenario where drivers are paid \$26.48 (giving them a 60% chance of accepting the trip), a feasible scenario would be an acquisition cost of \$10 per customer and a trip cost of \$36 to the rider. For varying driver pay rates (and therefore varying probabilities of them accepting trips), a set of feasible rider costs and customer acquisition costs can be found.

3.3. Likelihood of riders requesting trips

For the current distribution of how new riders request trips⁴, 37% of customers never make a trip request and immediately churn from the service. Changing the probability distribution of how new riders request trips will likely require a high level of effort (marketing, customer segment targeting), but increasing the mean number of trips requested from 1 to 2 would more than halve the initial churn rate to 13.5%.

4. Recommendations

From the analysis, it was found that, if the customer acquisition cost and rider cost cannot be changed, no number of riders acquired into the service or driver pay rate would make the service profitable. This is because of the high customer acquisition cost creating a large expense that is difficult for per-ride profitability to overcome. This is made worse by the phenomenon of a decrease in the price paid to drivers increasing per-ride profitability, but increasing the likelihood of drivers rejecting the ride and customer churn. Customers churning from the service create a large expense as a result of their acquisition cost. The current distribution of the probability of riders hailing trips means that approximately 37% of riders are churned in their first month, negatively affecting service profitability due to their high acquisition cost.

⁴ Poisson distribution with $\lambda=1$, see [Appendix](#) for further details.

It is therefore recommended that the customer acquisition price be lowered in conjunction with an increase in the ride price charged to customers. The cost of customer acquisition should be analysed to see if this is on par with competitors in the same market and how this is overcome. It should also be investigated if the probability of customers hailing a trip in their first month on the service can be improved through marketing or customer segment targeting and if this is comparable to competitors.

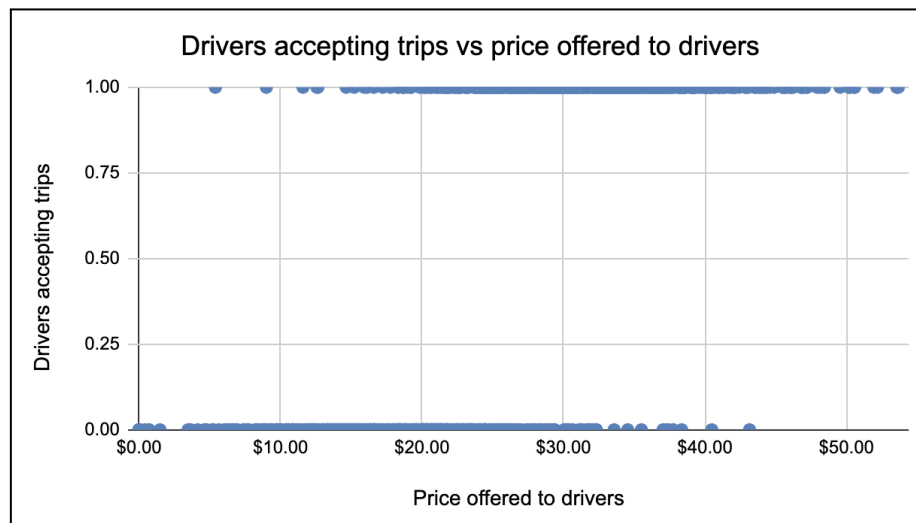
Other strategies for increasing the price charged to riders and offered to drivers should also be considered, for example surge pricing by fractional multiples when demand for the service is high so that there is a lower likelihood of the ride being rejected, reducing customer churn and frustration.

5. Appendix

[Link to Github repository](#) for attached code and data.

5.1. Modelling the likelihood of drivers accepting trips for a given price

A [dataset](#) of 1 000 trips from a similar ride-hailing service in the same market was used to model the likelihood of a driver accepting a trip (P) for a price offered to them (X). From this data, it can be seen that the more the driver pool is offered for a ride, the more likely they are to accept the trip. A graphical representation of the data is shown below, with 1 being an accepted trip and 0 being a rejected trip.



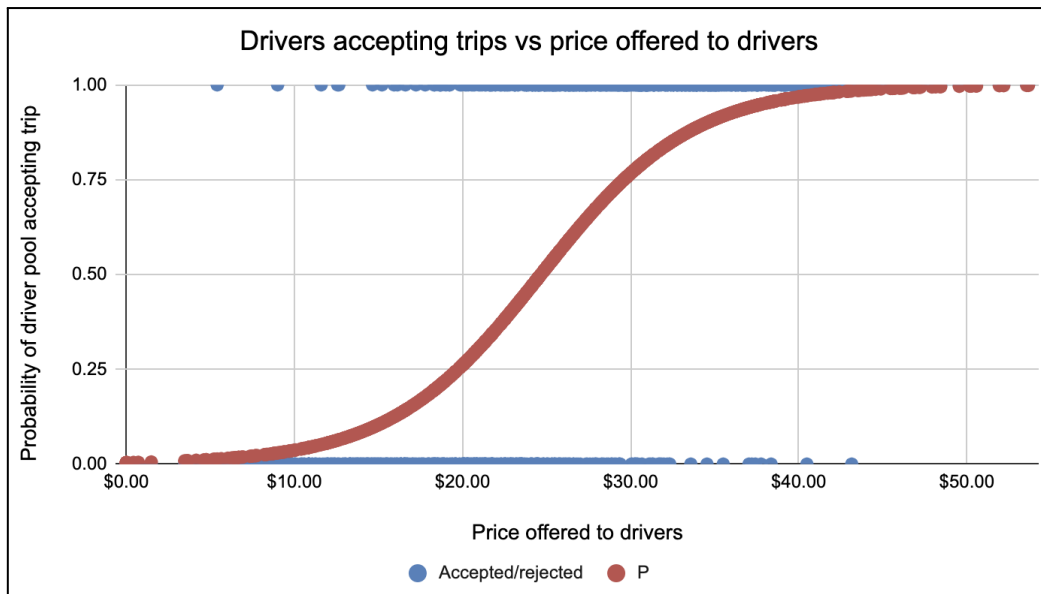
A binary logistic regression model with the following formula was fitted to the data:

$$P = \frac{e^{a+bX}}{1+e^{a+bX}}$$

Where:

- | | |
|-----|--|
| P | The probability of a driver accepting the ride |
| a | The bias or intercept term of the model, $a = -5.495$ |
| b | The coefficient term for X in the model, $b = 0.2228$ |
| X | The price offered to the driver in dollars, independent variable |

This model assumes that the dependent variable is binary (ride rejected or accepted), the observations from the dataset are independent of one another, there is linearity between the independent variable and log odds and that there is little to no multicollinearity amongst the independent variables. More detail on the parameters used to model this fit can be found in the attached code. A graphical representation of the model superimposed over the dataset is shown below, with 1 being an accepted trip and 0 being a rejected trip.

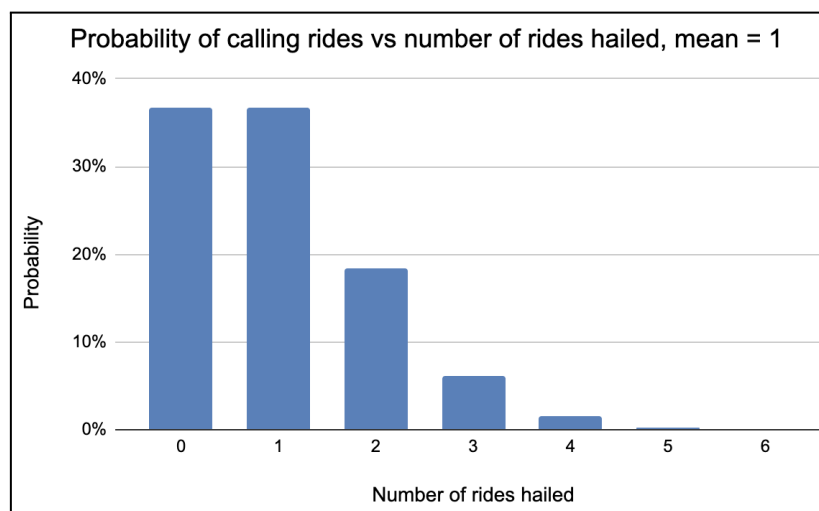


The model achieves a score of 83% of correctly modelling the driver acceptance/rejection outcomes for the dataset with the following confusion matrix:

	Predicted accept	Predicted reject
Actual accept	446	81
Actual reject	88	385

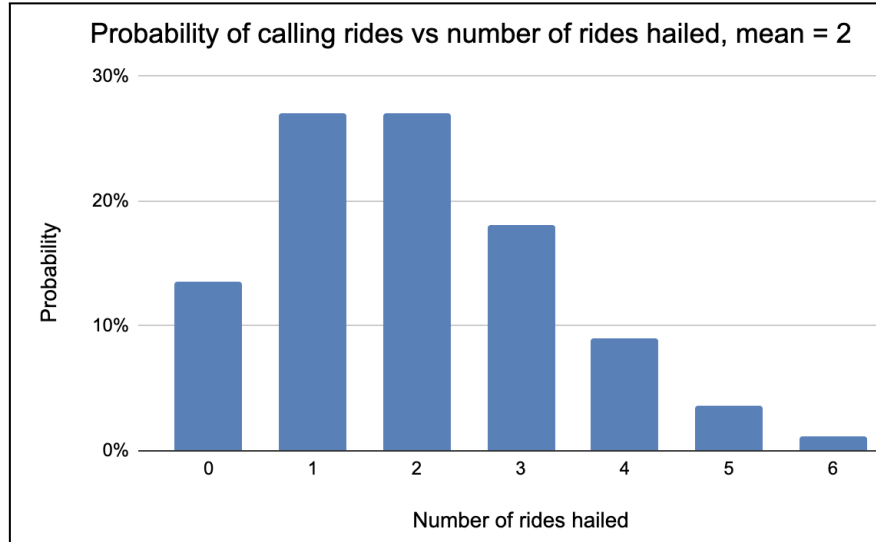
5.2. Modelling the likelihood of of riders hailing trips

Riders request rides according to a Poisson distribution where $\lambda = 1$ for their first month in the service and λ is updated the following month to how many rides they found a match for in the previous month. For example, if a rider requests two rides in their first month and finds a match for both rides, the following month they will request rides according to a Poisson distribution where $\lambda = 2$. An example of a Poisson distribution where $\lambda = 1$ is given below.



The above distribution shows that, in their first month on the service, 37% of riders will not hail any rides and will immediately churn from the service, 37% of riders will call one ride and 18% of riders will call two rides, etc.

An example of a Poisson distribution where $\lambda = 2$ is given below. This distribution would be applicable to riders who have successfully hailed two trips in the previous month.



5.3. Calculating the number of riders that successfully call trips

The number of customers that successfully call N_{rides} in a given month is determined by the following formula:

$$N_{customers} = N_{previous customers} \times \frac{i!}{j!(i-j)!} \times (P_{accept})^j \times (1 - P_{accept})^{(i-j)} \times P_{Poisson}(i)$$

Where:

$N_{customers}$ The number of customers that will successfully call j rides this month

$N_{previous customers}$ The number of customers that have successfully called λ rides in the previous month

i The number of rides called by the customer

j The number of rides accepted by the driver pool

P_{accept} The probability of the driver pool accepting the trip for a given driver price (X), determined by $P = \frac{e^{a+bX}}{1+e^{a+bX}}$

$P_{Poisson}(i)$ The Poisson distribution for i rides called, determined by

$$P_{Poisson}(i) = \frac{\lambda^i \times e^{-\lambda}}{i!} \text{ where } e \text{ is euler's number}$$

As the number of customers that call 6 or more rides month-over-month equals a fraction of a customer (<0.1 customers), these larger λ values are dropped before being inputted into the following month. More detail can be found in the attached code.

5.4. Calculating the churn rate

The churn rate is calculated using the following equation:

$$r_{churn} = \frac{N_{churned\ customers}}{N_{all\ customers}} \times 100$$

Where:

r_{churn} The churn rate of the service given an input of number of customers acquired, price to pay driver, price to charge rider and customer acquisition cost

$N_{churned\ customers}$ The number of customers that either never go on to hail a trip with the service, or who hail trips with the service but none are accepted by the driver pool

$N_{all\ customers}$ The number of customers acquired into the service