# Lyft Analysis

## Churn at Lyft

- → Definition
- → Insight
- → Opportunity
- → Experiment Design

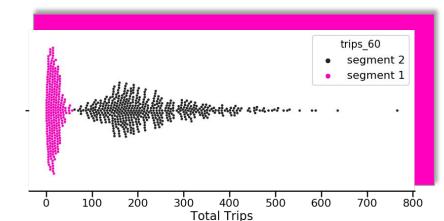
## Driver Churn @ USA

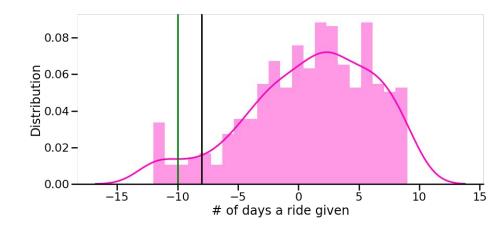
#### **Definition:**

Driver with only 2 rides or less in 21 days.



- Accommodates drivers that drive consistently yet infrequently
- Takes into account vacation time
- 2 rides is two std from # of rides given in 21 days
- Do not want to label our low ride, consistent, active drivers as churned





# 28%

### **Driver Churn**

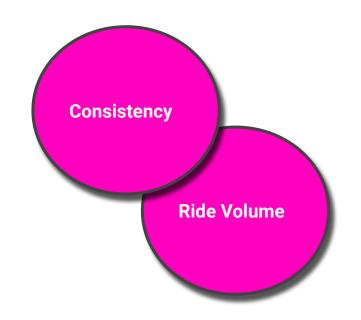
## **Impact of Churn**

- Revenue Loss | \$1.64M
- Leased cars depreciated in value
- Marketing / Attracting drivers is the single biggest operating expense
  - \$105 / driver \$22,300
- \$89,000 in 1 year

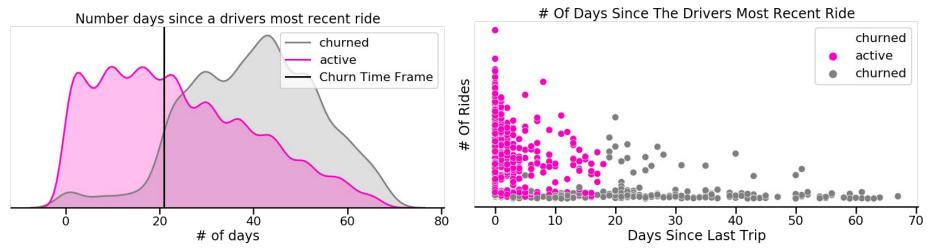
## **Factors Impacting Churn**

#### Top 5

- 1. Number of days given a ride in the past 3 weeks
- 2. Total number of trips
- 3. Number of trips per week
- 4. Number of trips in the first 30 days
- 5. Number of weeks a driver is active

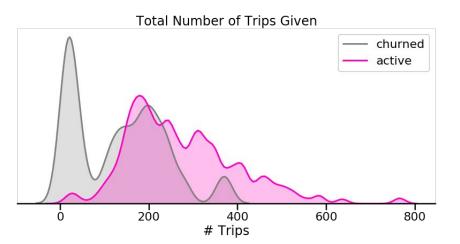


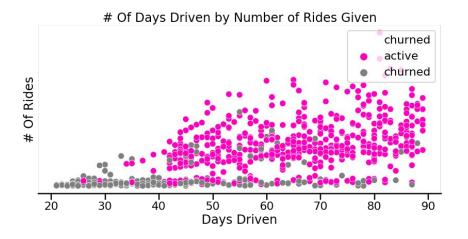
## Insights on Segments - Days Preceding Churn



- We want to be cognizant of drivers that are consistent, but have low rides/wk
- Churned drivers on average had 39 days since their most recent ride
- Active average was 24

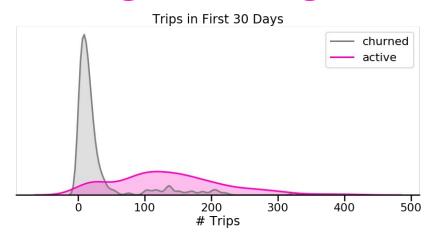
## Insights on Segments - Total Number of Trips

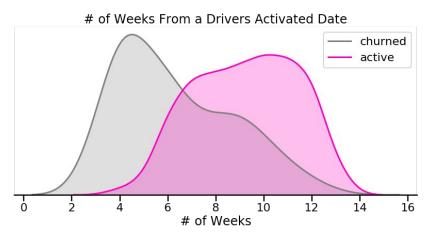




- We want to be cognizant of drivers that are consistent, but have low rides/wk
- Churned drivers on average had 134 total rides
- Active drivers averaged was 275
- 30% of Drivers had 40 rides or less

## Insights on Segments - Trips in First 30 Days / # of Active Weeks



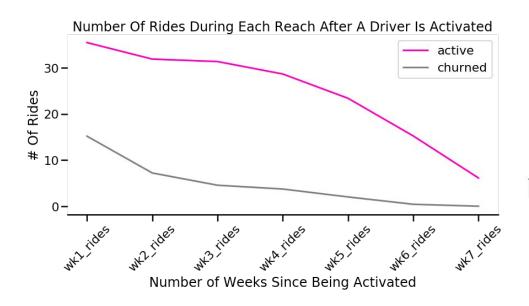


- We want to be cognizant of drivers that are consistent, but have low rides/wk
- Churned drivers on average had 117 total rides
- Active drivers average was 175
- 50% of Drivers had 100 rides or less in the first 30 days

- Churned drivers on average had total rides 6 Weeks
- Active drivers average was 9 Weeks

## Insights on Segments - Rides Per Week

- Number of rides every 7 days from activated date
- Both segments decline after the first week

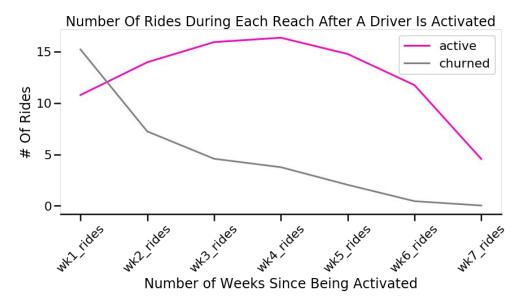


#### Average Number of Rides Per Week

	wk1_rides	wk2_rides	wk3_rides	wk4_rides	wk5_rides	wk6_rides	wk7_rides
churned							
active	35.454545	31.878182	31.347273	28.652727	23.400000	15.247273	6.138182
churned	15.198113	7.231132	4.575472	3.754717	2.042453	0.452830	0.033019

## Insights on Segments - Rides Per Week

- Filtered Active graph, limiting week 1 rides to 20 for week 1
- Captures the 'part time' driver
- Ride count increases for the first 2 weeks before decreasing



#### Average Number of Rides Per Week

	wk1_rides	wk2_rides	wk3_rides	wk4_rides	wk5_rides	wk6_rides	wk7_rides
churned							
active	10.766467	13.952096	15.910180	16.335329	14.754491	11.730539	4.550898
churned	7.709302	3.162791	1.680233	1.389535	0.482558	0.308140	0.040698

## **Opportunity**

Hypothesis 1 | <u>Doubling the number of rides in an activated driver's first week</u> will have a high opportunity in additional rides

#### **Size of Opportunity**

- 45,444 additional rides among 762 drivers.
- Average distance per ride is 7,034 meters. A total life of 320KM
- \$626,218 Lift
- Assuming all drivers hit KPI

#### **Long Term Consequences:**

- Dependent on how KPI is set. Setting a KPI/incentive at 60 trips would have a negative effect
- Current stigma are that rideshare companies are constantly making incentives harder, and paying less overall
- Does not address the declining number of rides after week 1
- Drivers would be demotivated

#### **Drivers Affected**

- You risk overlooking the 'part time' active driver
- 'Full time' drivers would need feel demotivated by the 'moving carrot'

## **Opportunity**

Hypothesis 2 | <u>Doubling the number of rides in an activated driver's second week over their first week\*</u> will have a high opportunity in additional rides

#### **Size of Opportunity**

- Lift of 24,404 rides moving an average of the week from 25 to 52
- Resulting in a lift of 144KM
- \$336,287 lift in revenue
- Assuming all drivers hit KPI

\*The 2x increase would be for drivers that had 20 or less rides their first week. Drivers with over 20 would have a multiplier of 1.7

#### **Long Term Consequences:**

- The hypothesis addresses the unattainable stigma. Adjusting goals based on driver performance. The increase is more attainable
- Will address consistency of drivers (churn)
- Will address an increase in trips (churn)
- Result: More attainable goals, addresses the top factors for churn

#### **Drivers Affected**

Meets all segments of riders

## **Experiment Design** "eliminating the Prime Time feature will decrease driver churn"

How you will divide observational units into control and treatment, and a description of the treatment and control conditions.

I'd randomly select a subset of drivers and randomly assign them to the control and treatment groups.

#### What are some potential second-order effects on the experience of drivers and passengers during this experiment.

Any conversation that may happen about Prime Time pricing when a rider enters the car. Tests that are impacted by the network effect of users are difficult to control. Drivers may ask riders if there is Prime Time, Drivers may cancel rides more often if they deem it not monetarily beneficial (distance)

#### What are the primary and secondary metrics you will track.

Response variable would be a ride given

The experimental unit would be driver/days ( observing the sum of rides per day for each driver)

Secondary metrics: # of canceled rides by driver, percentage of rides that are considered prime time

#### How long you will run the experiment and how you will choose the winning variant.

- The test will run for one month
- Verify the data was sufficiently random by segmenting the data by the variant to determine if there was any bias against any one group.
- Observe the total sum of rides per day/driver and churn for both groups
- Segment the data by quartile in each group and observe changes by quartile within the group and between groups
- determine statistical significance between the two groups.
- If churn is significantly lower in the variant group (no Prime Time feature) vs. the control group than we reject the null hypothesis and determine the variant group as the 'winning variant'

Assumption: The total fare (with prime time) is shown to the rider, however on the driver app the feature displaying Prime Time is turned off