Ultimate Tech Take Home Challenge Report:

Part 1 - EDA:

Through exploration of the logins.json data, it was clear that there was a consistent pattern in the login activity. The most popular times on an average day were the late night/early morning hours when people use the service to avoid driving drunk. There is also a spike in logins around midday which is likely the result of the lunch rush. Figure 1 indicates the average logins for the whole dataset by hour and Figure 2 shows the activity on a Saturday.

Figure 1:

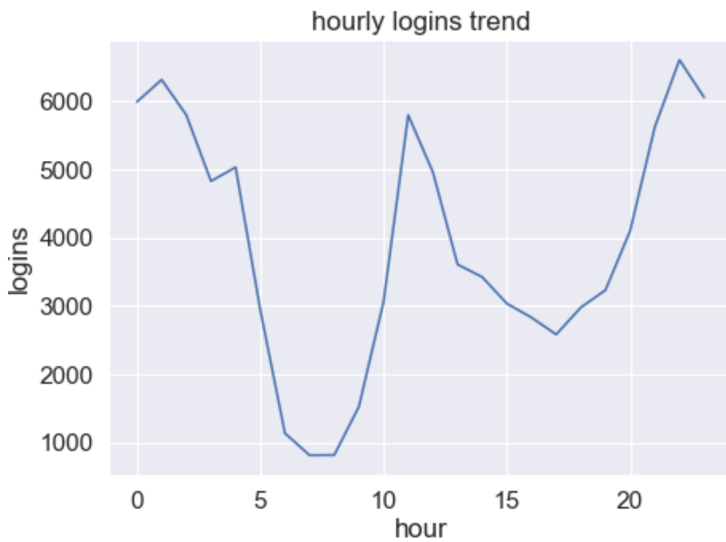
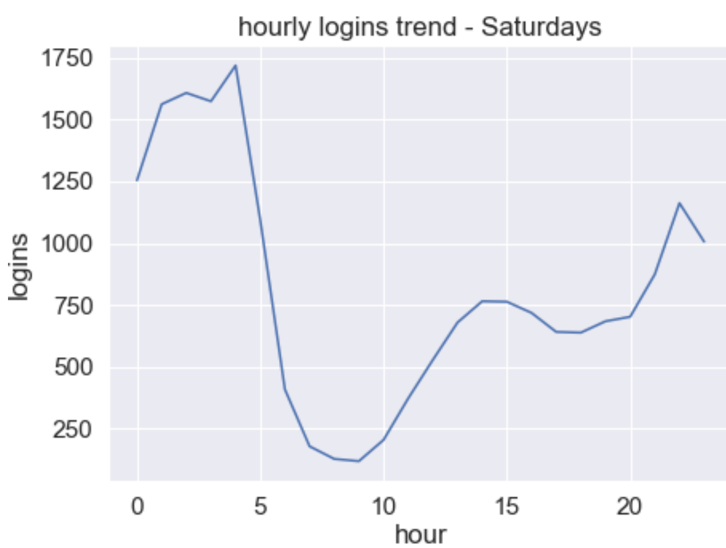
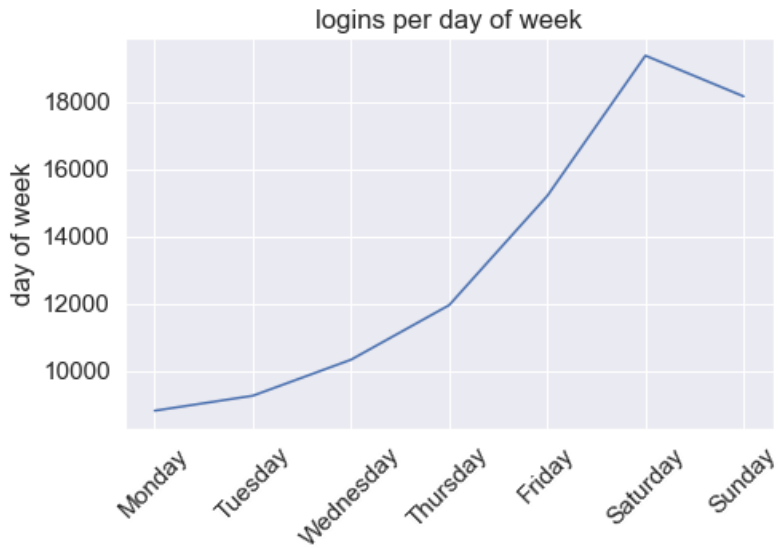


Figure 2:



As you can see in Figure 2, the login activity on Saturdays is more strictly isolated to the early hours of the morning which we would expect with a service like this. One trend that I did find interesting is that the activity consistently goes up through the week with logins on Thursday and Friday being much higher than days earlier in the week (see Figure 3).

Figure 3:



The biggest issue I find with the data is that we're analyzing the demand of a mobile rideshare application and the logins are dated before mobile apps existed in the 1970s. Another questionable thing I noticed was that of the 20 highest login periods, 10 of them happened on 4/4/1970 resulting in that being the most active day by almost 10% despite that not being a holiday or a day of much significance other than being a weekend. There were more normal dates appearing on that list, however. Namely the Saturday and Sunday before St. Patrick's Day being the 2nd and 4th most popular days respectively. There is also a clear

Part 2 - Experiment and Metrics Design:

To measure the success of the experiment of reimbursing the drivers' toll costs, I would analyze the growth in supply of drivers in each city compared to before the proposed experiment. To compare the proposed change, I would track drivers who would previously stick to driving in either Metropolis or Gotham and measure the rides they have completed in the other city in order to see if it is actually impacting driver behavior. To test this, I would use a paired t-test which would allow me to compare the means of drivers under two separate scenarios (not reimbursing tolls vs reimbursing tolls). If I was able to discern that there was a significant change in behavior among the drivers resulting in a greater supply in each city during the busy hours, I would recommend that the toll fees be reimbursed.

Part 3 - Predictive Modeling:

Once I imported the data, there were a couple columns that had null values that needed to be filled and I had to OneHot encode some categorical columns. Once I completed those steps, I had to create a column for my dependent variable indicating whether a rider was still “active” and their business had been retained. Once I had my data prepared, I split my data into training and test sets and tried a few different classification models to see what generated the best predictive results. For this exercise, I experimented with Random Forest, K Nearest Neighbors, Naive Bayes and Logistic Regression models and used Precision, Recall and F1-score as evaluation metrics to measure the model’s effectiveness at predicting rider retention. After running my four models, the best performer was the random forest model which had an F1-score of 0.81 when predicting rider attrition and 0.67 on retention. Once I tuned my hyperparameters, these figures improved to 0.84 and 0.70 respectively.

Ultimate could leverage my findings by looking at the output of the model and realizing that it is successful at predicting retention among riders. From there, one actionable item is the feature importances to the model success, the most important being ‘rides in first 30 days’ (Figure 4). If I were in charge at Ultimate, I would institute a sign up promotion to urge new users to take rides upon joining. If we can do that, we can prove our value as a service and retain more customers moving forward.

Figure 4: