Chicago Taxi Rides

Proposal Paper

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PROBLEM STATEMENT & MOTIVATION

The database that we will be using was taken from the Chicago Taxi Cabs which recorded the locations of pickup and drop off, time of day, duration, fees, method of payment and tips of each ride in 2016. This database can be used to predict how much tip each location offers, tips vs the duration of the trip, frequently traveled locations, etc. From these knowledge that we can gain from this database, we can combine it with the Census data of Chicago that we found to compare the frequency of routes taken to the income of those locations. This information could be used to help Cab companies to change their fees, such as lowering the initial pickup fee for locations with low income and low frequency to get more customers to take their cabs as their main method of transportation. Our hope is to find connections, such as frequency of the routes and number of pickups and drop-offs at each location, with the Census data to help taxi companies be more profitable by gaining more customers and strategizing their routes.

1 LITERATURE SURVEY

Some studies and surveys have indeed already been conducted on the Chicago taxi service, mostly by city transportation/commerce departments. Our group looked at three conducted by the City of Chicago Business Affairs and Consumer Protection office, the NYC Data Science Academy, and Todd W. Schneider, a Yale software engineer. These studies looked at pickup frequencies, rates, and pick up/drop off locations. Our study also aims to study these attributes; however, unlike these studies, we're looking to find relations between them.

The Chicago BACP study (2014) looked at taxi rates in relation to value to the consumer as well as fairness of income for taxi drivers. The purpose was to develop a model that the city could use to determine the effect of fare changes on taxi drivers' income. This model accounted for different taxi ownerships (part time/full time, lease/ownership). However, the study didn't take into account locations of taxi service and looked at the Chicago taxi service as a whole. Also, the study combined fares and tips into revenue, not looking at each individually [1].

The NYC Data Science Academy study (2016) was more in line with our study (and used our same dataset). It looked at locations in Chicago and the average taxi pickup frequencies at those locations. Another part of this study mapped the ratio of pickups to drop offs in each community as well as average trip ranges. The study found that the airports and central section of the city receive the most frequent pickups and have the highest ratio of pickups to drop-offs. The trip ranges from the airports were consistently high, while the trip ranges from the city center were consistently low. So, in every location besides the airports, trip range seems to increase as pickup frequency decreases [2].

Todd W. Schneider conducted a survey on a similar dataset, but from 2013 to 2016 instead of just one year. His study seemed to be more aimed at trends in the Chicago taxi service as a whole. The study found that the taxi business in Chicago is declining faster than New York City's (55% decrease since 2013). However, his study did look at pickup frequency in certain locations of Chicago as well. Schneider mapped taxis' percent chance of a pickup within 30

minutes to each community in Chicago. Strangely, the study suggests that the airports were areas of very low pickup frequency, completely contradictory to the NYC Data Science Academy study. The rest of the data seems consistent, but this anomaly will be something to focus on in our study. As a side not, his percentage based prediction model could serve as a useful metric in our analysis. Schneider's study was built on his previous analysis of New York City taxis [3].

2 PROPOSED WORK

2.1 Preprocessing

The taxi rides dataset has already undergone some cursory preprocessing before being released to the public. All of the changes made are documented in the press release from the City of Chicago [5]. Major changes include masking time, location, and taxi medallion number for privacy. Pickup and drop-off time is rounded to the nearest 15 minutes, and location is given to the accuracy of the census tract. Implausible values were removed from the data, including negative lengths or costs, or extremely long trips. Some duplicates were also removed.

To get the data into a workable state, we will also need to continue with preprocessing and cleaning. First, the twelve distinct months will be merged into a single dataset to evaluate the data for the entire year. Some features from the dataset are not needed for our purposes and will be dropped. Our analysis of pickup and drop-off location will be on the community area level, so the census tract and geolocation columns for pickup and drop-off location will be removed. Any rows without the pickup or drop-off location in the community area level will be removed. The payment extras column is sparse and without specifics on what the extra payment is for, so it will be removed. The taxi ID column will not provide us with any meaningful insights, so it will also be removed.

Some trips recorded a 0 value both for trip length in miles and trip length in seconds. When the value is 0 for both columns, the row will be removed. When only one of the columns is 0, the value will be extrapolated using the prediction technique described in section 4. Tips are only recorded for credit card payments, so any analysis on tip amount will not include cash payments. Because tips are not recorded for cash payments, the fare column will be used for cost analysis rather than the total column, therefore the tolls and trip totals will be removed. Any rows with negative values for trip seconds, trip miles, or fares will also be removed.

The selected socioeconomic factors from our secondary dataset will be merged to the taxi rides dataset using a key of community area. Analysis and evaluation methods are described in depth in section 4.

2.2 Difference from prior work

The Chicago BACP study focused on overall Chicago taxi service value and income balance. The NYC Data Science Academy study focused on the relationship between pickup frequency and trip range [2]. Todd Schneider's study looked at the trend of decline in the Chicago taxi business overall as well as pickup frequencies in different locations. Unlike the BACP study - as well as Schneider's - we will focus on trends per community in Chicago [1,3]. Connecting pickup frequency and range per location will be important, but we will also be looking at average tips and payment trends in each location as well. Alongside this, we also aim to study correlations between these communities' taxi trends and their poverty ratings.

3 DATA SET

The primary dataset for this project is the Chicago Taxi Rides dataset provided on Kaggle by the City of Chicago [4]. The dataset includes information about every taxi ride taken within the city for the year of 2016. The features of this dataset include a start and end timestamp, trip length in seconds and miles, pickup and drop-off locations in the form of census tract, community area, and geolocation, payment information including fare, tip, tolls, extras, and trip total, and the taxi company. It is divided into 12 separate files, one for each month of 2016. Each month contains around 1.7 million taxi trips.

We will also use a secondary dataset containing socioeconomic information about the different areas in the city. This dataset is also provided by the City of Chicago [6], and is divided by the same community areas as the taxi rides dataset. The other features of this dataset include the community area name, percent of housing crowded, percent of households below poverty, unemployment information, per capita income, percent aged under 18 or over 64, and a hardship index.

4 EVALUATION METHODS

After we complete the pre-processing of the data in our dataset as described in the Proposed Work, we will apply several different pattern evaluation methods to mine possible patterns we are interested in. It is extremely important to select highly corrective measures to produce accurate and quality results, derived from understanding in depth the characteristics of the data such as the types of attributes and completeness, validity, accuracy, consistency, availability and timeliness of the data in our dataset.

As a result of insignificant correlation between Trip Seconds and Trip Miles, the prediction model was no longer applied to fill in some of the unknown or missing values in these attributes. Likewise, any of the missing numeric codes in Pickup Community Area or Dropoff Community Area was not filled due to the insignificant correlation between them.

We also used relevant samples of our dataset to generate our statistics and data visualizations, instead of random samples of a particular month-data.

Next, we will apply the Relim Algorithm to derive the frequent 2-itemsets of pickup and drop-off community area as well as the frequency of pickup in a specific time of a day and a year. Relim is a recursive elimination algorithm inspired by FP-growth, designed to be simple in structure. An implementation of Relim is available in PyMining. We believe that these will be strongly perceptive indicators to justify the possible best or worst places and time blocks for a taxi to make a pickup and/or drop-off, thus again could use the outcomes to generate a more profitable business.

We will also look at how Per Capita Income by Each Community Area is correlated with the frequency of pickup and tips as a part of trip total cost. It is very important to perceive cash tips are not recorded mainly because they do not go through the payment systems. As a result, we will closely monitor if this does not result in a possibly skewed outcome.

Subsequently, we will do a Cluster Analysis to see how similar in the frequency of pickup and/or drop-off from one area to another and one time block to another. In order to measure the magnitude of similarities we will also apply one of the distance functions such as Euclidian or Manhattan Distance.

To make sure the selective methods we applied are consistently validated, we will lastly try to replicate some of statistics that are studied in the previous work for comparison.

5 TOOLS

5.1 Python3 and iPython

The rich features of the high performance in preprocessing, statistics, and graphics using iPython (interactive form of Python3) provided by Jupyter Notebook will allow us to more readily focus and solve domain problems, rapid-prototype code and more quickly and easily experiment with ideas. In this interactive notebook environment, Python 3, Pandas, Numpy, Scipy, and PyMining will be used primarily for preprocessing, mining, and analysis of the data in our dataset. As data visualization tools, we will use Matplotlib and Seaborn for simple graphical representations and Bokeh and possibly Plotly for rich and interactive visualizations.

5.2 Git and Github

We will use Git and Github to manage source code. It will allow us to easily and seamlessly collaborate and keep track of the various changes through version control.

5.3 Slack

We will use Slack for better team communication, especially as a venue to share any resources such as ideas, documents, and tools that enable our team to produce quality results.

6 MILESTONES

6.1 Milestones Completed

6.1.1 Data Cleaning: We made our final decision on how much data cleaning to do and applied it to all months, which we combined into one file. We took out the columns: taxi_id, pickup_census_tract, dropoff_census_tract, extras, tolls, trip_total, company, pickup_latitude, pickup_longitude, dropoff_latitude, and dropoff_longitude. We also removed any data missing either pickup_community_area or dropoff_community_area. Then we included data with trip_second, trip_miles, or fares that were greater than 0.

6.1.2 Integration with Income: We integrated our data set with the income of each community

area and found a positive correlation between income and the ride count of each area.

6.1.3 Frequent Rides: We applied the Relim Algorithm to the full data set to find the most common areas that were traveled. This does not include traveling within the same community area.

6.2 Milestones Remaining

6.2.1 Graphs of Frequency by April 12th: Create a graph displaying hour of day vs frequency of rides traveled and the month vs the frequency of rides traveled for the top five pickup locations.

6.2.2 Graphs of K-Means Clustering by April 12th: Create a k-means clustering graph displaying how similar in the frequency of pickup from top 5 central downtown areas vs top 5 suburban areas applying Euclidean distance function

6.2.3 Part 5 by April 15th: Upload all project source codes into Github and create a 5 minute or less video discussing the project and results.

6.2.4 Presentation Slides by April 24th: Finish the presentation slides and practice for the final presentation.

6.2.5 Presentation on April 27th: Presentation in front of the whole class.

6.2.6 Part 4 and Part 7 by April 30th: Finish the Final report and Peer Evaluation.

7 RESULTS SO FAR

7.1 Income and ride count correlation

The counts of all rides starting or ending in a certain community area were summed to get an idea of the total taxi traffic volume going in and out of certain community areas. With information about the income levels for each community area, we were able to compare the total number of rides for each area to the income in that area. A positive correlation was discovered between the number of rides and the income in a community area with the correlation coefficient 0.708. This relationship is shown in Fig. 1. The graph is dominated primarily by the extreme high values for ride count and income for the central Chicago community areas, specifically Near North Side, the Loop, Near West Side, and Lincoln Park.

Figure 1: Comparison between number of dies and the income in a community area with the correlation coefficient.

7.2 Frequent rides by community area

The Relim algorithm was applied to the cleaned full dataset to determine which community areas were the most frequently traveled between. The Table 1 shows five of the most frequent community areas for pickup and drop-off. A ride is considered a member of the itemset when the pickup is in either area 1 or area 2, and the drop-off is in the other area out of the pair.

Area 1	Area 2	Count
Near North Side	Loop	2281451
Near North Side	Near West Side	899440
Near West Side	Loop	814120
Lincoln Park	Near North Side	475912
Near North Side	O'Hare	453597

Table 1: Five most frequently traveled community areas for drop-off and pickup.

Most of the discovered frequently traveled community areas are around the downtown area of Chicago. Around 23.67% of rides pickup and drop off in the same community area. Those rides are not included in the frequent pattern analysis. The top four frequently traveled community areas are also adjacent to each other. The exception to most of the frequent community areas being downtown is O'Hare. There is also strong support for taxi rides going to or from the downtown area to the O'Hare airport. The trend of downtown areas with higher support counts continues down the full list of frequently traveled community areas, with a similar deviation for Midway airport. There are also high support counts for rides going to or from downtown and the Midway airport, with 139746 rides between Midway and Near North Side. For reference, Fig. 2 displays a map of the Chicago community areas is included below.

Figure 2: Map of the Chicago Community Areas.

7.3 Tip amounts per community area

To begin, a simple association study between tip amounts and communities was performed on the cleaned dataset. Since tips weren't recorded for cash transactions, rows with cash transactions were omitted. Outliers made the mean an unreliable method for looking at the average tip in each community area, so median values were used. Data based on pick-up location vs. drop-off location tended to be pretty similar, but drop-off data was more complete (since some areas don't seem to have regular taxi pick-ups), so it was the primary source for this data. Fig. 3 is a map of the plain tip amounts per area.

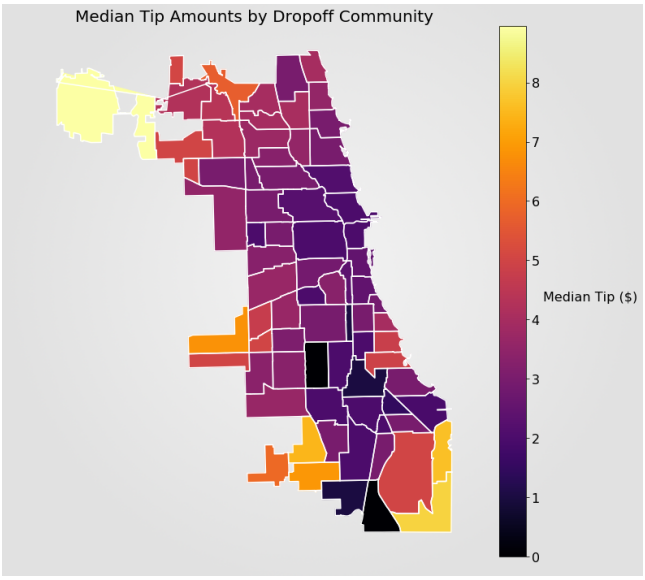

Figure 3: Map of the median tip amounts of each community area at drop-off

Based just on this, the area in the top left (O'Hare Airport) and the areas in the southwest corner (Hegewisch and East Side) hand out the biggest tips, while the downtown areas seem to hand out very little. This is because the trips from these "hot" areas are typically much longer than most. Instead, then, the fare to tip percentage was analyzed. Also appended is a map of drop-off frequencies per area. Obviously, taxi drivers can only choose where to pick up customers and not where to drop them off, so a map of pickup tip percentages and frequencies is also included. However, this data seems to be similar enough to draw conclusions from either.

What we can see is that O'Hare Airport turns out to be pretty average in tip giving, as well as the couple areas in the southwest. Most of the North and West Sides, in fact, look to be fairly average with tips. Austin and Garfield Park are subpar (Upper West Side) as well as a number of areas in the South Side. Obviously, the ride frequencies in the downtown areas (the Loop, Near North Side, Near West Side) are much higher than any other area. However, the median tip percentages also seem to peak in these

areas compared to other adjacent areas. One last small thing to note is the somewhat anomalous area, Roseland, in the south which hits the peak tip percentage, unlike any other non-downtown community. The most frequently ridden areas are 6, 7, 8, 28, and 32. (See Fig. 4 and 5)

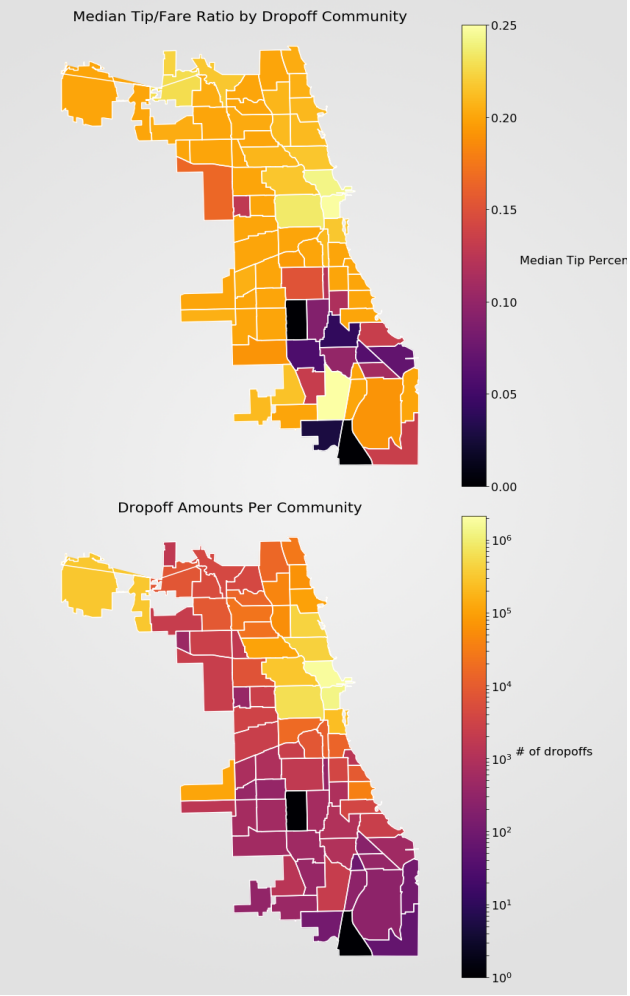

Figure 4: (Top) Map of the median tip/fare ratio by drop-off community area. (Bottom) Map of number of drop-offs at each community area.

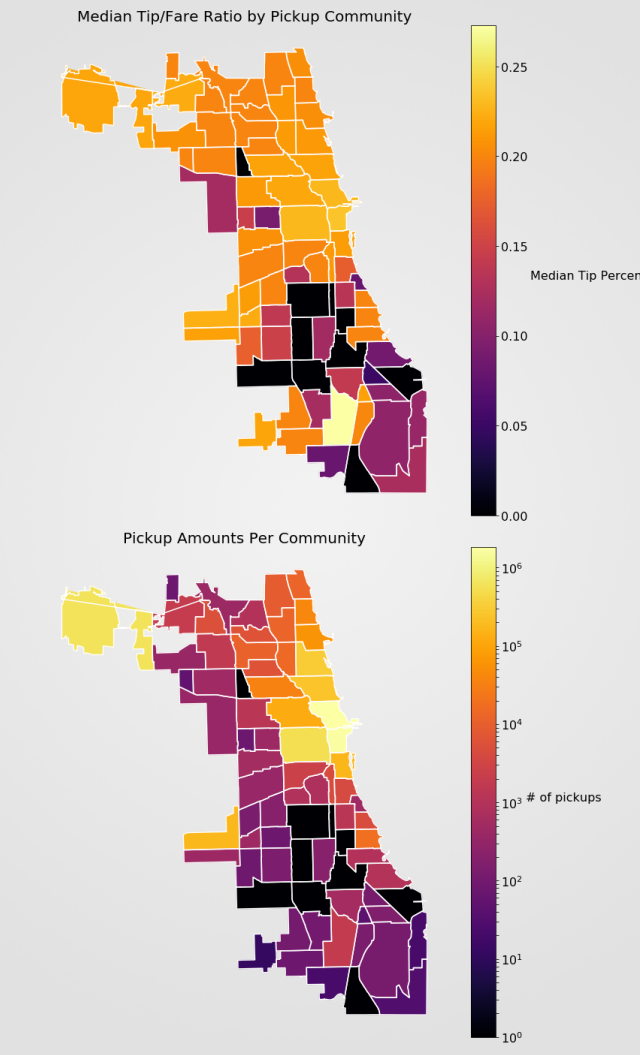

Figure 5: (Top) Map of the median tip/fare ratio by pickup community area. (Bottom) Map of number of pickups at each community area.

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