Optimizing shared e-scooter pricing based on future demand

Group: 30
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1 Introduction and summary of the selected paper

The selected paper, "ADAPT-Pricing: A Dynamic And Predictive Technique for Pricing to Maximize Revenue in Ridesharing Platforms" [1], created a new way for ridesharing platforms (such as Uber and Lyft) to calculate the prices for a trip using their ridesharing platform..

Currently, Uber and Lyft calculate their prices for a trip based on the current demand [1]. If many people want a taxi, for example during an event, the price goes up. If fewer people want a taxi, for example during lunchtime, the price goes down. However, this price is only calculated using the *current* demand, and not on the *future* demand.

The ADAPT-Pricing paper has created a new algorithm for this, called ADAPT-pricing. These algorithm contains two types of ADAPT-pricing: predicting the future demand on the origin and predicting the future demand on the origin & destination.

For their experiments, they used one month of the New York City's Taxi and Limousine Commission (TLC) dataset [2]. This dataset contains 39,437 drivers and around 500,000 trips per day [1]. On this dataset, they performed their new ADAPT-pricing methods and presented their results. During their experiments, they saw an increase of 5-15% for the revenue and a decrease of 5% of the price for the customer [1], resulting in a win-win scenario for both the riders, companies and customers.

The new problem which will be addressed in this research is the pricing of E-scooters. E-scooters are a relatively new way of public transport, where people can hire an E-scooter to get to their destination. The current way of pricing for E-scooters is using a standard fee per minute. However, it would be interesting to see if the ADAPT-pricing method can be applied to lower the cost of E-scooters.

It should be mentioned that, contrary to ridesharing using an Uber, the E-scooters are from the company itself and not from other private individuals. However, the ADAPT-pricing results show that the prices for the customers could lower, and therefore it is still interesting to see if this can happen.

For this research we use an open-source dataset from the state Chicago which contains the "electronic scooter trips taken during the 2019 Chicago pilot program" [3]. This dataset contains information about the distance, duration and community numbers of the trip.

We expect different results with on this dataset than on the original dataset. People will use an E-scooter in other situations than when they are using a ridesharing service. For example: when the weather is bad, more people will call a taxi [1], but less people will use an E-scooter. Futhermore, an E-scooter will more often be used in crowded, urban places since it is easier to navigate through and can get to places where cars cant, such as a park. It is expected that an taxi will more often be called when the distance is larger. A third difference is the different in service: with ridesharing, the driver will pick the client up. With E-scooters, the client needs to first physically move to the scooter before it can use it. All these things can contribute to the decision to take an E-scooter or not and these factors need to be implemented in the current algorithm, since they are currently not..

The main research challenge will be by applying the algorithm described on this new dataset. The greatest difference between ridesharing platforms and E-scooters is that, with ridesharing, the client gets picked up by the driver. With E-scooters, the client needs to get to the E-scooter. All the differences explained in section

1 can influence the decision by the client to take an E-scooter and needs to be 'translated' into the algorithm. An extra challenge is that dynamic prices in the E-scooter market is currently not used. Therefore, we have no data where we can check on how the market responds on it (for example; how does the customer respond to it?), which makes it more difficult to create an simulation for this process to test our algorithm on.

2 Problem statement

Given the data set D representing E-scooter usage, where $D = \{(t_i, s_i, e_i, m_i, p_i) \mid i = 1, 2, \ldots, n\}$. Here, each tuple $(t_i, s_i, e_i, m_i, p_i)$ corresponds to the total time t_i (in minutes) of the ith ride, start and end location s_i, e_i where the ride takes place, a membership indicator m_i (where $m_i = 1$ if the user is a member and $m_i = 0$ otherwise), and the price p_i charged for that ride. The standard pricing model is given by $P(t) = 0.42 \times t + \text{tax}$, where t is the ride time in minutes.

The objective is to apply the algorithm described in paper [1] on the dataset D to propose a more equitable pricing model. This involves finding a function $F : D \to \mathbb{R}$ that maps each ride in the dataset to a new price, considering factors such as ride duration, location, and membership status. The goal is to optimize F such that the modified pricing formula $P'(t, s, e, m)$ decreases the average consumer price and increases the total revenue.

3 Research questions

What is the difference between average consumer price and total revenue, if we apply an updated version of the pricing algorithm from paper [1] to shared e-scooter rental data?

4 Methodology

As mentioned in previous sections, we will attempt to use the ADAPT pricing algorithm described in [1], to create more revenue for e-scooter companies and at the same time lower the cost for consumers. The ADAPT pricing algorithm considers both future demand and origin-destination pairs to find the optimal price for taxi rides (or e-scooter rentals). We will now introduce some notation needed to describe the ADAPT pricing algorithm:

- p_i^{*t}: Optimal price at time t for location i.
- $D_i^t(p)$: Demand at time t for location i.
- $S_i^t(.)$: Supply at time t for location i.
- V_i^t : potential drivers available at time t for location i
- $f^r(p)$: probability that passengers are willing to take a ride for price p.
- $f^w(p)$: probability that drivers are willing to participate for price p
- p_c: Price where supply and demand are equal.
- $T_i^t(p)$: Total trips at time t and location i

In figure 1 the ADAPT pricing algorithm is shown. To apply the algorithm to our e-scooter dataset we will have to make some assumptions. First of all, the ADAPT pricing algorithm assumes some probability function which returns the probability of drivers willing to participate. Of course, for e-scooters 'driver demand' is fixed. To replace this function, we will use a 'sufficient battery life' probability. For this we assume e-scooters are charged each night. We will calculate the distance travelled by each scooter using the start and end location of each trip to track e-scooters. We will assume the top 10% of the maximum kilometers per day, as the maximum battery life for e-scooters.

Furthermore, the dataset used does not contain pricing information. We will use the information from the city of Chicago to calculate prices [3]. We will assume all e-scooters follow the pricing lime with \$1.00 unlock + \$0.39/minute.

Algorithm 1 P-Pricing($\mathcal{R}_i^t, \mathcal{V}_i^t, \mathcal{R}_j^{t+1}$)

Input: $\mathcal{R}_i^t$, $\mathcal{V}_i^t$ as the number of requests and available drivers at time t and $\mathcal{R}_j^{t+1}$ as the predicted demand at time $t+1$.
Output: p^{*t}_i as the optimal prices at time t

for $i = 1 : n$ **do**
  $D_i^t(p) = \mathcal{R}_i^t \cdot (1 - F^r(p))$
  $S_i^t(p) = \mathcal{V}_i^t \cdot F^w(p)$
  $p_i^t =$ **LocalOptimal**$(D_i^t(p), S_i^t(p))$
  Compute $RevDec(\delta T_i^t)$ using Eq. (9)
end for
for $j = 1 : n$ **do**
  $D_j^{t+1}(p) = \mathcal{R}_j^{t+1} \cdot (1 - F^r(p))$
  Compute $\mathcal{V}_j^{t+1}(p_i^t)$ using Eq. (4)
  $S_j^{t+1}(p) = \mathcal{V}_j^{t+1} \cdot F^w(p)$
  $p_j^{t+1} =$ **LocalOptimal**$(D_j^{t+1}(p), S_j^{t+1}(p))$
  Compute $RevInc(\delta V_j^{t+1})$ using Eq. (14)
end for
Solve Eq. (15) and find optimal ΔT^t
for i 1:n **do**
  $\delta p_i^t = p_i^t - D_i^{t\,Inv}(D_i^t(p_i^t) - \delta T_i^t)$
  $p^{*t}_i = p_i^t - \delta p_i^t$
end for
return p^{*t}_i

Figure 1: ADAPT pricing algorithm

5 Evaluation approach

- **Metrics:** As with the original paper we will measure our performance based on revenue and average price.
- **Baselines:** We will compare the difference in price of the E-scooters to the difference of price for a ride using ridesharing after applying the updated algorithm. Since these two markets differs a lot from eachother, it is possible that calculating the price using predicted future demand does not make a difference for the E-scooter market, while it does for the ridesharing market. We tend to compare these two markets by using the % revenue increase and % price discount after applying the, respectively, original and updated algorithm on the original and the E-scooter dataset.

6 Data sources and other resources

Our dataset is available through the link at this source: [3].

Ethical statement

We do not think there are any privacy concerns for our project. The data is publicly available and fully anonymized.

Division of workload

We have divided the workload in two parts. Hidde will be responsible for implementing the algorithm and Rajeck will be responsible for building a simulation to evaluate our approach. To ensure we both understand these parts, we will switch these responsibilities for the report and presentation.

Code

https://github.com/hiddevr/uc_project

References

[1] Mohammad Asghari and Cyrus Shahabi. "ADAPT-Pricing: A Dynamic and Predictive Technique for Pricing to Maximize Revenue in Ridesharing Platforms". In: *Proceedings of the 26th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*. SIGSPATIAL '18. Seattle, Washington: Association for Computing Machinery, 2018, 189–198. ISBN: 9781450358897. DOI: 10.1145/3274895.3274928. URL: https://doi.org/10.1145/3274895.3274928.

[2] NYC Taxi Limousine Commision. 2013. URL: https://www.nyc.gov/site/tlc/about/tlc-trip-record-data.page.

[3] City of Chicago. 2020. URL: https://data.cityofchicago.org/Transportation/E-Scooter-Trips-2019-Pilot/2kfw-zvte.