Evaluating the impact of fare capping and guaranteed best fare policies using smart card validations data and machine learning

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Introduction

Declining ridership, increasing operating budget, disruption in payment technology and increasing emphasis on customer experience, integrated mobility and affordability for low-income customers lead transit authorities to explore alternative fare policies (Stuntz et al., 2019). Among them is the introduction of fare capping and guaranteed best fare.

Fare capping and guaranteed best fare are two tightly related concepts. Generally speaking, fare capping limits the amount of fare that can be charged to a transit user within a given time period. Customers who use single fares would benefit from discounted or free fare after the threshold is reached. There can be multiple thresholds and levels of discount. The policy of guaranteed best fare ensures that the users would never pay more than any other available fare options within a given period. In both cases, users do not need to commit to choose a prepaid fare or make a payment in advance in order to benefit the discount. The latter even renders prepaid pass irrelevant. The risks on fare revenue and fare payment collection lie entirely on transit authorities. In exchange, the improved customer experience may increase user satisfaction and ridership.

Some transit authorities in North America, for example those in Dallas, Portland, Oregon (TriMet, 2019) and the State of Connecticut, have adopted the guaranteed best fare policy (although they do not explicitly distinguish fare capping from guaranteed best fare). Impacts on revenue and ridership are not well studied and documented. Tri-Met of Portland estimated in 2017 the introduction of fare capping could reduce fare revenue between 1.0 and 1.5 percent (TransitCenter, 2017). This paper, using fare validation data from a smart card system in Montreal, Canada, will analyze the impact of such policies on system revenue and ridership; estimate the relative importance and sensibility of parameters of the policies; and explore individual fare choice decision using machine learning algorithms.

Data and methodology

Several parameters in the fare table would have an impact on the revenue and ridership:

- The capping threshold: the number of trips (or the amount of fare) beyond which an additional trip would not be charged a fare
- The duration of the capping: the period (using in number of days) in which the number of trips or the amount of fare is accumulated
- The multiplier of existing passes: the number of trips priced at regular fare needed to be made in order to break even the cost of an unlimited travel pass

By varying each of these parameters one at a time on a fixed demand, one can isolate the impact of the parameters on fare revenue and determine their sensitivity in a fare capping or guaranteed best fare policy. To achieve some degree of realism, revealed demand from the smart card system is used (Chu, 2014). The dataset contains several millions of fare validations in a disaggregated format and can be organized by card. A large random sample of cards, each covering a month worth of transit use from different time of the year, will be selected to simulate the actual demand patterns. Individuals whose number of trips are close to the capping threshold are more susceptible to modify their travel frequency in a view to reduce their fare payment. Those cards will be analyzed in detail for their impact on ridership.

The other aspect of the paper is to explore individual fare choice decision using the same dataset. Additional variables on the individual, such as the fare category; and on the travel pattern, such as the trip frequency, the trip intensity, the trips characteristics regarding the day of the week, the location (urban or suburban) and the transit modes, are derived (Chu & Chapleau, 2008). The enriched dataset is then submitted to machine learning algorithms such as decision tree and clustering (Spurr et al., 2019). The resulting models identify factors that drive the individuals' decision to commit to a prepaid pass while the prediction anomalies can be studied in order to gain insights of missing variable in the decision-making process.

Expected results and conclusion

The two experiments proposed in the paper will generate the results related to:

- The impact of each parameter in a fare capping or guaranteed best fare policy on revenue
- The number and characteristics of individuals that pose a potential risk on decreased ridership
- An algorithm that can explain and predict fare choice decision
- Insights on elements not captured by the fare choice algorithm in the decision-making process

These results will provide valuable information to transit authorities regarding the benefits or risks of offering a fare capping or guaranteed best fare option; the parameters that minimize the risk on revenue and ridership; as well as the required incentives to maintain the attractiveness of prepaid passes, which from a transit authority perspective, guarantee a predictable level of revenue and promote ridership.

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