A Method for Maximizing Human Satisfaction in Ridesharing

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Abstract. Transportation services play a crucial part in the development of modern smart cities. In particular, on-demand ridesharing services, which group together passengers with similar itineraries, are already operating in several metropolitan areas. We argue that user satisfaction should be the main objective when trying to find the best assignment of passengers to vehicles and the determination of their routes. Moreover, the model of user satisfaction should be rich enough to capture the traveling time, cost, and other factors as well. We show that it is more important to capture a rich model of human satisfaction than peruse an optimal performance. That is, we developed a practical algorithm for assigning passengers to vehicles, which outperforms assignment algorithms that are optimal, but use a simpler satisfaction model.

Keywords: Ride-sharing · Modeling Human Behaviour · Human-Agent Interaction · Smart-Cities.

1 Introduction

The National Household Travel Survey performed in the U.S. in 2009 [18] revealed that approximately 83.4% of all trips in the U.S. were in a private vehicle (other options being public transportation, walking, etc.). The average vehicle occupancy was only 1.67 when compensating for the number of passengers (i.e., if two people travel in the same vehicle, their travel distance is multiplied by two). This extremely low average vehicle occupancy entails a very large number of vehicles on the road that collectively contribute to carbon dioxide emissions, fuel consumption, air pollution and an increase in traffic load, which in turn requires additional investment in enlarging the road infrastructure. In recent years, ride hailing services such as Uber and Lyft have gained popularity and an increasing number of passengers use these services as one of their main means of transportation [20]. Both Uber and Lyft are now also offering ridesharing options, and other companies, such as Super-Shuttle and Via, are explicitly targeted at customers who want to share their ride.

The deployment of autonomous vehicles in the near future will have a significant impact on the way people are traveling. The implication of this revolutionary way of transportation is not fully known nowadays [9], but it is safe to claim that autonomous vehicles will have a positive effect on the development of ridesharing services. Indeed, it will be easier and cheaper for a company to handle a fleet of autonomous vehicles that can serve the demands of different passengers. It can also rule-out some negative human-driver factors, such as driver's fatigue from the long travels and the driver's inconvenience from having multiple pick-up and drop stops along his route.

The basic challenge of a ridesharing service is how to assign the passengers' requests for a ride to vehicles and define the routes for the fleet of vehicles in an optimal manner. This problem belongs to the generic class of Vehicle Routing and scheduling Problems (VRPs), which have been extensively studied over the past 50 years, mainly in the operation research and transportation science communities. Several variants with different characteristics have been developed.

Many works integrate quality of service and user satisfaction considerations as additional constraints of the problem. For example, a time window restricts the waiting time a passenger is willing to face before being picked up [8], and it is usually combined with a bound on the maximum user ride time [15]. However, to the best of our knowledge, there are no works in the ridesharing domain that exclusively focus on maximizing a complex user satisfaction function, which captures the traveling time, cost, and other factors as well.

We investigate a comprehensive human-centric approach for the ridesharing problem. Our basic claim is that the user satisfaction should be the main objective of the ridesharing service. Moreover, the model of user satisfaction should be rich enough to capture the complex interdependencies among several factors. Therefore, we develop a method for modeling and maximizing a complex user satisfaction function.

Since our rich objective function models user satisfaction, we propose a human-centric, approach. Specifically, we investigate machine learning methods for modeling the rich satisfaction function from real humans. Clearly, it is unrealistic to elicit the exact user satisfaction for each passenger and every ride, and we thus propose to build a general model for user satisfaction, which is based on multiple features. These features include both ride specific features (e.g. cost, travel time) and person specific features (e.g. age, gender) and thus two people may obtain different satisfaction levels from similar rides.

Interacting with humans and learning human behavior is a very complex task. Research into humans' behavior has found that people often deviate from what is thought to be the rational behavior, since they are affected by a variety of (sometimes conflicting) factors: a lack of knowledge of one's own preferences, the effects of the task complexity, framing effects, the interplay between emotion and cognition, the problem of self-control, the value of anticipation, future discounting, anchoring and many other effects [19, 12, 2, 7]. Therefore, algorithmic approaches that use a pure theoretically analytic objective often perform poorly with real humans [16, 3, 13]. On the other hand, several works have demonstrated that a machine learning approach, which builds upon psychological factors and human decision-making theory, is essential for developing a good model of true human behavior. The human behaviour model is in turn required for successfully implementing algorithms that interact with humans [17, 5, 10, 1, 4, 14, 6], and we follow this approach for modeling our user satisfaction function. We ran experiments with actual humans and build a deep learning based function to estimate user satisfaction. We introduce Simsat, an algorithm for assigning passengers to vehicles while maximizing a complex user satisfaction function as the objective. We show that Simsat outperforms optimal assignment methods that use a simpler objective function, indicating that it is more important to obtain a richer model of user satisfaction, than improving the performance of the assignment algorithm.

2 Experimental Evaluation

In order to develop a more realistic human satisfaction model, we use machine learning techniques based upon data collected from humans. To this end, we solicited 414 human subjects from Mechanical Turk to obtain satisfaction level data. The subjects were provided with the travel cost, travel time, number of passengers in vehicle, passenger's seat, and were asked for their Working status (employed or unemployed), age and gender. The subjects were asked to provide their satisfaction level. Based on this data, we use deep learning to build a satisfaction model.

We use a graph of the city of Toulouse as our simulation environment. This graph includes the actual distances between the different vertices. The graph also includes the Toulouse-Blagnac airport. Being a last mile problem, we set the origin vertex to be the same for all passengers, the Toulouse-Blagnac airport. The destination vertices were randomly sampled for every passenger using a uniform distribution over all vertices.

We compare the performance of the following five assignment algorithms in terms of relative user satisfaction (as obtain from the satisfaction model) in simulation:

1. **Optimal:** The optimal algorithm with the learned satisfaction function.
2. **M-Sat:** An algorithm starts with assigning every single passenger to a unique vehicle. It then considers all assignments that result from merging any pair of vehicles into a single vehicle.
3. **Simsat:** A stochastic algorithm that runs M-Sat multiple times.
4. **Cost:** The optimal algorithm that considers the travel cost only for determining the optimal assignment.
5. **Time:** The optimal algorithm that considers the travel time only for determining the optimal assignment. Clearly, this algorithm has trivial behavior; it assigns a private vehicle to each passenger.

All the algorithms were evaluated with the complete satisfaction function, regardless of the function actually used by the assignment algorithm.

Figure 1 presents our results. The results were obtained by averaging over 1000 samples of passenger destinations. Note that the Time assignment yields a constant user satisfaction of 0 since it assigns a private vehicle to each and every passenger. Due to the high volume of the data, all differences between *any* two methods are statistically significant ($p < 0.0001$). As depicted in the figures,

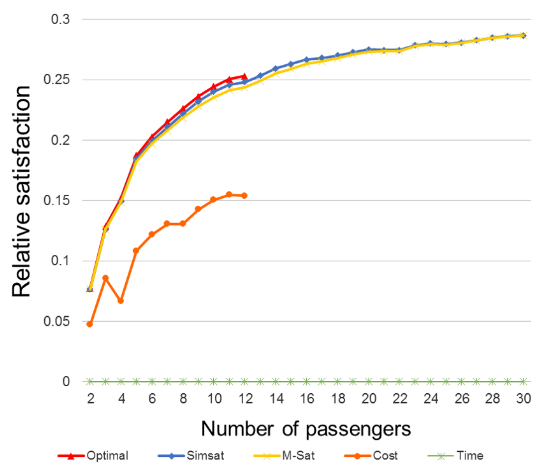

Fig. 1. Relative satisfaction in simulation for each of the assignment methods, averaged on 1000 assignments, for 2-30 passengers.

our satisfaction oriented assignment method (Simsat) obtains results that are very close to the optimal assignment. Simsat's average satisfaction level is much closer to the optimal assignment than that of the Cost and Time assignments, which are optimal assignments that use a simpler user-satisfaction model.

3 Conclusions

Ridesharing has a true potential for improving the quality of life for many people, and it is part of the general concept of sharing economy that is being evolved nowadays. However, despite both Uber and Lyft offering ridesharing options, not many users elect to share their rides with additional passengers [11]. Following the statement by Carnegie, "There is only one way to get anybody to do anything. And that is by making the other person want to do it.", we believe that the key ingredient required for a widespread adaptation of ridesharing is to focus on user satisfaction.

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