Towards Tailored Carpooling in Gig-based Ride-Sharing Platforms*

CHRISTINE BASSEM, Wellesley College, USA

Recently the gig economy has become a popular choice among workers, specifically within ride-sharing applications such as Uber and Lyft. Although popular, current service models in these applications mainly benefit the platform itself. In this work, our goal is to improve the experiences of customers, *i.e.*, drivers and passengers alike, within the ecosystem of the existing gig applications, via coordinated carpooling. In this paper, we present two models for carpool coordination, tailored to the needs of the drivers and the passengers, which allows them to benefit further from using such gig applications.

CCS Concepts: • **Information systems** → **Spatial-temporal systems**; • **Human-centered computing** → *Ubiquitous and mobile computing design and evaluation methods*;

Additional Key Words and Phrases: ride-sharing, carpool, sustainability, future-of-work, gig economy

1 INTRODUCTION

With the launch of Amazon Mechanical Turk in 2005 [Barr 2005] and Uber in 2011 [Inc. 2022], the gig economy has crept into a variety of fields, creating work models that are changing the shape of the future-of-work. More workers have found themselves relying on these gig applications, with 34% of the workforce being gig workers in 2017 and the total projected to rise to 43% in 2020 [Bose 2021].

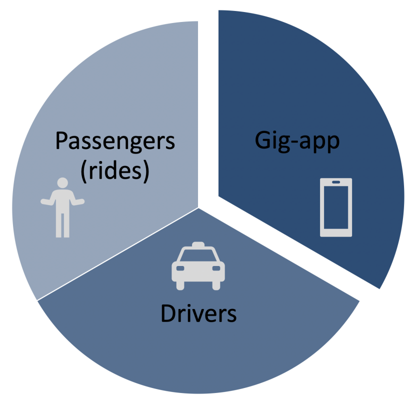

Fig. 1. Who stands to benefit from gig ride-sharing applications?

In gig-based ride-sharing platforms, such as Uber [Inc. 2022] and Lyft [Lyft 2022], drivers are not employed or controlled by the platform, but join willingly for their own gain. Albeit seeming to benefit the drivers and passengers, the service models in these gig applications end up only working for the benefit of the application itself [Sonnemaker 2021].

As evident with the recent global events, the decrease in the number of drivers led to price surges and increased delays [Allyn 2021; Dickler 2022], which has led to increased negative emotions towards these platforms [Morshed et al. 2021]. Thus, forcing these companies to increasing driver incentives [Kerr 2022; Paul 2021] and bringing back carpool options [Peters 2021], in attempts to reduce costs. With the return of carpooling, customers can benefit from reduced fares, but drivers may still experience lower income and reduced gain due to wasted time deadheading, *i.e.*, circling around idly looking for the next passenger [Bensinger 2021].

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Author's address: Christine Bassem, Wellesley College, Wellesley, MA, 02481, USA, cbassem@wellesley.edu.

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In this work, believe that one way to improve the future-of-work within such ride-sharing gig applications is via coordinated carpooling. Our goal is to provide solutions that are tailored to the needs of both the drivers and the passengers, within the ecosystem of the existing gig applications. These models not only provide clear incentives for both drivers and passengers, they are also designed to leverage existing gig applications. Thus, not forcing any of the drivers or passengers to switch to unfamiliar and less-trustworthy platforms.

In this paper, we present our work in progress towards that goal, and define two models for carpool coordination, which are tailored to accommodate the drivers' and the passengers' preferences respectively. The first model aims to guide drivers to better paths that could potentially increase their income as they interact with the gig application. The second model aims to pool passengers together based on their social preferences before interacting with the gig application, to provide them with better prices and safer carpooling options.

2 RELATED WORK

Existing work on ride-sharing can be generally classified into three main categories based on the model of driver availability in the system; taxi-based services [Liu et al. 2021; Verma et al. 2017], dial-a-ride services [Cordeau and Laporte 2007], and ride-sharing with private cars [Lin et al. 2018]. For most of these platforms, the work on ride-sharing generally focuses on either ride assignments, route planning, or a hybrid of both.

Ride Assignment. Most works that explore ride assignment consider one-to-one matching, where a rider is matched to at most one driver, and a driver is matched to at most one rider at a time, as in [Ta et al. 2018]. Some works deviate from this model, as in SHAREK [Cao et al. 2020], in which a rider is matched to a set of drivers that they can choose from. Although our algorithms and models can be used for ride assignment, the focus of this project is on improving the future-of-work of drivers and passengers without interfering with the ride choice process.

Route Planning. Although minimum cost routing algorithms are usually adopted to route drivers towards their assigned rides, as in [Ta et al. 2018], some algorithms adopted in taxi services are developed with the goal of sending drivers to areas with the greatest number of riders based on historical data to minimize their idle time [Verma et al. 2017]. Other types of routing algorithms focus on inserting a new ride (pick up and drop off locations) into an existing route of a vehicle while optimizing for a certain objective [Cheng et al. 2017; Tong et al. 2018]. However, this approach was observed to not be as efficient long-term, and Wang et al. developed a dynamic programming algorithm that consider where rides may appear in the nearest future based on historical data [Wang et al. 2020] to improve the routing results.

Recently, the problem of routing planning with detours have been proposed in the context of ride-sharing. For example, Yuen et. al proposed a routing recommendation algorithm that maximizes the chance to find compatible rides with a minimum detour using historical data [Yuen et al. 2019]. Our work in the first proposed model directly contributes to this category.

Pooling Rides. Most existing works have focused on pooling rides together to optimize ride-sharing based on the spatio-temporal characteristics of the rides [Agatz et al. 2012; Tafreshian et al. 2020], with a few designed considering the social preferences of their passengers and/or drivers [Cici et al. 2014; Saisubramanian et al. 2019]. With recent works on modeling the social preferences of riders in such platforms [Cui et al. 2021], there is an opportunity to leverage such models to personalize the carpooling process, which is the goal of our second proposed model.

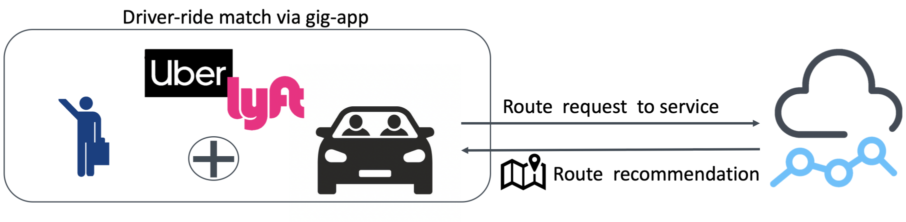

Fig. 2. Tailoring routes for drivers to increase their chances of picking up more rides along the way.

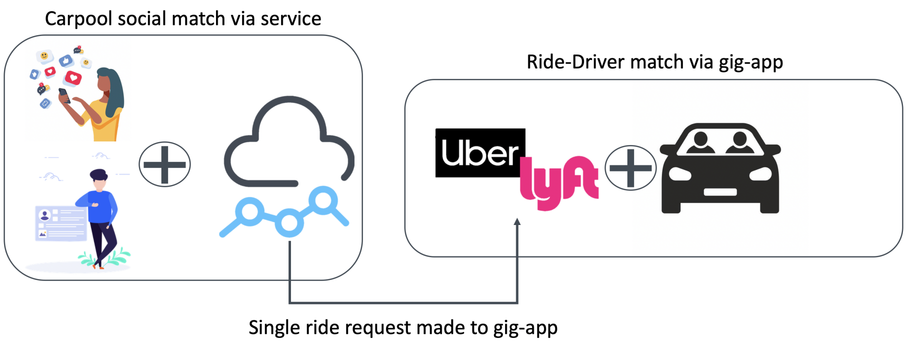

Fig. 3. Tailoring carpools among passengers based on their social and spatio-temporal preferences.

3 TAILORED CARPOOLING

3.1 Working around the gig-app

The first model for carpooling is designed for the drivers' benefit After a driver chooses their ride directly from the gig-app, they are typically provided with the shortest route towards that ride's pick up location. In our proposed model, as shown in Figure 2, we direct the driver through a route that is not necessary the shortest, but one that maximizes their chances of picking up other rides along the way, similar to the work in [Chen et al. 2021; Yuen et al. 2019]. That path would be tailored for the driver's preferences and ride choice, while not violating the ride's constraints.

In such a model, drivers have the incentive to follow these route recommendations, as they increase their chances of picking up multiple rides along their paths. Meanwhile, passengers have the incentive to carpool, as they pay reduced fares for shared rides with a delay that is constrained to some threshold of their choice. Moreover, the same algorithms could be used to guide an idle driver towards more lucrative locations to minimize deadheading.

3.2 Piggybacking on the gig-app

The second model for carpooling is designed for the passengers' benefit, while piggybacking on the existing gig application. In this model, we recognize that carpool participation is low due to a series of challenges - one of which is the "Stranger Danger" problem [Hong et al. 2019], in which riders are less willing to share rides with strangers. Current ride-sharing platforms fail to recognize that humans are social beings with feelings and attitudes, and their matching algorithms focus mainly on the spatio-temporal aspects of the rides, *i.e.* the ride's endpoints and duration, rather than the passengers themselves [Agatz et al. 2012].

As shown in Figure 3, this model of carpooling is designed such that passengers interact with the offered service directly instead of the gig application. The objective of the service is to tailor carpool matches among the passengers based on their social attributes, preferences, as well as the spatio-temporal properties of their rides, before they start their rides. After a match is found, the passengers are notified of the details. If a match is accepted, the service piggybacks on the gig application, and requests the rides on the behalf of both passengers.

In such a model, passengers have the incentive to use the service since they would be aware of who they are pooled with ahead of their rides, thus providing them with some sense of safety and happiness in addition to the reduced fares. On the other hand, drivers would benefit from well-coordinated carpooled rides.

3.3 Discussion

The models described above are current works-in-progress as part of a larger project that aims to improve the experiences of users, *i.e.*, drivers and passengers alike, in ride-sharing gig applications. In this presentation, we aim to discuss our solutions and their potential in improving the future-of-work within the gig economy, as well as discuss the challenges that arise in such a project. These challenges can be generally clustered into three categories,

- **Algorithmic challenges.** Ride-sharing algorithms must be efficiently designed to offer split-second decisions in real time, given thousands of requests per hour and processing of extremely large-scale geo-spatial maps.
- **Evaluation of defined solutions.** Although evaluations of algorithms can be done via simulations and theoretical models when applicable, the same cannot said on evaluating solutions for matching individuals. Efficient and re-usable models of evaluation are needed to effectively measure the quality of various matching mechanisms. Currently, we are developing a campus-scale experiment on facilitating the process of carpooling among students, which will allow us to further evaluate our matching algorithms qualitatively.
- **Ethical considerations.** There are various ethical considerations to be considered within ride-sharing platforms, especially when carpooling is involved. Matching algorithms need to be designed in a way that avoids bias towards certain social factors, including gender, ethnicity, etc. They also need to be incentive-compatible and rational, *i.e.*, provide valid incentives for participants, passengers and drivers alike, to get involved and provide truthful information about their preferences. Moreover, such algorithms need to consider the social and cultural factors affecting the participants' decisions and behaviors within the platform.

4 CONCLUSION AND FUTURE WORK

In this paper, we presented our vision to coordinate carpooling in current ride-sharing gig applications to improve the future-of-work of the parties involved in such platforms. We proposed two models for tailored carpooling that leverage existing gig applications, which we hope to discuss further in the workshop. Our current work involves developing efficient algorithms for a seamless interaction with the gig application users in real-time, as well as the design of interactive evaluation models to ensure the integrity and happiness of the participants in these models. Moreover, our future work involves investigating the implications of the varying cultural and societal backgrounds of the participants on their interaction with the proposed models.

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