Reinforcement Learning for Ridesharing: A Survey

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Abstract

In this paper, we present a comprehensive, in-depth survey of the literature on reinforcement learning approaches to ridesharing problems. Papers on the topics of rideshare matching, vehicle repositioning, ride-pooling, and dynamic pricing are covered. Popular data sets and open simulation environments are also introduced. Subsequently, we discuss a number of challenges and opportunities for reinforcement learning research on this important domain.

1 Introduction

The emergence of ridesharing, led by companies such as DiDi, Uber, and Lyft, has revolutionized the form of personal mobility. It is projected that the global rideshare industry will grow to a total market value of \$218 billion by 2025 [MarketsAndMarkets, 2018]. Auto industry experts expect that ride-hailing apps would eventually make individual car ownership optional [Choi, 2020]. However, operational efficiency is a tough challenge for rideshare platforms, e.g., long passenger waiting time Smith [2019], and as high as 41% vacant time for ridesharing vehicles in a large city [Brown, 2020].

Reinforcement learning (RL) is a machine learning paradigm that trains an agent to take optimal actions (measured by total cumulative reward) through interaction with the environment and getting feedback signals. It is a class of optimization methods for solving sequential decision-making problems with a long-term objective.

There are excellent surveys on RL for intelligent transportation [Haydari and Yilmaz, 2020; Yau et al., 2017], mostly covering traffic signals control, autonomous driving, and routing. There has been no comprehensive review of the literature on RL for ridesharing, although the field has attracted much attention and interest from the research communities for both RL and transportation just within the last few years. This paper aims to fill that gap by surveying the literature of this domain published in top conferences and journals. We describe the research problems associated with the various aspects of a ridesharing system, review the existing RL approaches proposed to tackle each of them, and discuss the challenges and opportunities.

Reinforcement learning has close relationship with other families of methods, such as stochastic optimization, approximate dynamic programming, and model predictive control. Although it is not our goal in this paper to have a comprehensive review of those methods for problems in ridesharing, we aim to point the readers to the representative works so that they can refer to the further literature therein.

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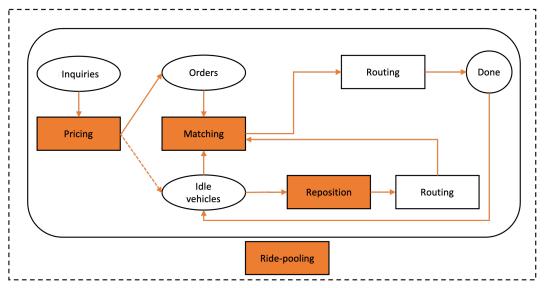


Figure 1: The process flow of ridesharing operations. The solid rectangular boxes represent the modules described in Section 2. The literature on the optimization problems associated with the modules in orange are reviewed in the paper.

2 Ridesharing

A ridesharing service, in contrast to taxi hailing, matches passengers with drivers of vehicles for hire using mobile apps. When each driver takes only one passenger request at a time, i.e. only one passenger shares the ride with the driver, this mode is more commonly called 'ride-hailing'. Ridesharing can refer to both ride-hailing and ride-pooling, where multiple passengers share a vehicle. In a typical mobile ridesharing system, there are three major characteristic modules: pricing, matching, and repositioning. When a potential passenger submits a trip request, the *pricing* module offers a quote, which the passenger either accepts or rejects. Upon acceptance, the matching module attempts to assign the request to an available driver. Depending on driver pool availability, the request may have to wait in the system until a successful match. Pre-match cancellation may happen during this time. The assigned driver then travels to pick up the passenger, during which time post-match cancellation may also occur. After the driver successfully transports the passenger to the destination, she receives the trip fare and becomes available again. The repositioning module guides idle vehicles to specific locations in anticipation of fulfilling more requests in the future. In the *ride-pooling* mode, multiple passengers with different trip requests can share one single vehicle, so the pricing, matching, and repositioning problems are different from those for ride-hailing and require specific treatment. The downstream *routing* module provides navigation to the driver and finally executes the matching and reposition decisions on the road network. Figure 1 illustrates the process and decision modules described above.

Since the trip fare determines not only the price that the passenger has to pay for the trip but also the income for the driver, pricing decisions influence both demand and supply distributions through price sensitivities of users, e.g., the use of surge pricing during peak hours. This is illustrated by the solid and dotted arrows pointing from the pricing module to orders and idle vehicles respectively in Figure 1. The pricing problem in the ridesharing literature is in most cases dynamic pricing, which adjusts trip prices in real-time in view of the changing demand and supply. The pricing modules sits at the upstream position with respect to the other modules and is a macro-level lever to achieve SD balance.

The ridesharing matching problem [Yan et al., 2020; Özkan and Ward, 2020; Qin et al., 2020a] may appear under different names in the literature, e.g., order dispatching, order-driver assignment. It is an online bipartite matching problem where both supply and demand are dynamic, with the uncertainty coming from demand arrivals, travel times, and the entrance-exit behavior of the drivers. Matching can be done continuously or at fixed review windows (i.e., batching). Online request matching is not entirely unique to ridesharing. Indeed, ridesharing matching falls into the family of more general

dynamic matching problems for on-demand markets [Hu and Zhou, 2020]. A distinctive feature of the ridesharing problem is its spatiotemporal nature. A driver's eligibility to match and serve a trip request depends in part on her spatial proximity to the request. Trip requests generally take different amount of time to finish, and they change the spatial states of the drivers, affecting the supply distribution for future matching. The drivers and passengers generally exhibit asymmetric exit behaviors in that drivers usually stay in the system for an extended period of time, whereas passenger requests are lost after a much shorter waiting period in general.

Single-vehicle repositioning may refer to as taxi routing or passenger seeking in the literature. Taxi routing slightly differs in the setting from repositioning a rideshare vehicle in that a taxi typically has to be at a visual distance from the potential passenger to take the request whereas the matching radius of a mobile rideshare request is considerably longer, sometimes more than a mile. System-level vehicle repositioning, also known as driver dispatching, vehicle rebalancing/reallocation, or fleet management, aims to rebalance the global supply-demand (SD) distributions by proactively dispatching idle vehicles to different locations. Repositioning and matching are similar in that both relocate a vehicle to a different place as a consequence. In theory, one can treat repositioning as matching a vehicle to a virtual trip request, the destination of which is that of the reposition action, so that both matching and repositioning can be solved in a single problem instance. Typically in practice, these two problems are solved separately because they are separate system modules on most ridesharing platforms with different review intervals and objective metrics among other details. In some cases, the reposition policy directly provides link-level turn-by-turn guidance with the goal of maximizing the driver's income, thus covering the role of dynamic routing (or route choice) albeit with a different objective.

Some literature refers to the mode of multiple passengers sharing a ride as 'ridesharing'. In this paper, we use term 'ride-pooling' (or 'carpool') to disambiguate the concept, as 'ridesharing' can refer to both single- and multiple-passenger rides. The seminal paper of [Alonso-Mora et al., 2017a] shows that through ride-pooling optimization, the number of taxis required to meet the same trip demand can be significantly reduced with limited impact on passenger waiting times. In a pooling-enabled rideshare system, the matching, repositioning, and pricing modules all have to adapt to additional complexity. In this case, the set of available vehicles are augmented, including both idle vehicles and occupied ones not at capacity. It is non-trivial to determine the set of feasible actions (one or more passengers to be assigned to a vehicle) for matching. Every time a new passenger is to be added to a non-idle vehicle, the route has to be recalculated using a vehicle routing problem (VRP) solver [Nazari et al., 2018; James et al., 2019; Peng et al., 2019] to account for the additional pick-up and drop-off, the travel times for all the passengers already on board are updated, and the vehicle capacity, the waiting time and detour distance constraints are checked.

The downstream routing module is typically a standard module that provides turn-by-turn guidance on the road network to drivers in service or performing a reposition to go from a given origin to a given destination with the shortest time. Shortest-time dynamic route choice and VRP are more general problems that are not specific to ridesharing. Interested readers can refer to [Shou and Di, 2020a; Haydari and Yilmaz, 2020] for the references therein. In-service routing in the context of ride-pooling is discussed in Section 4.4.

3 Reinforcement Learning

We briefly review the RL basics and the major algorithms, especially those used in the papers in the subsequent sections. For a complete reference, see, e.g., [Sutton and Barto, 2018].

3.1 Why Reinforcement Learning?

We have seen in Section 2 that the operational decisions in ridesharing are sequential in nature and have strong spatiotemporal dependency, offering excellent applications of RL. Thanks to the rapid advancement in deep learning research and computing capabilities, the integration of deep neural networks and RL has generated explosive progress in the latter for solving complex large-scale learning problems [Silver and Hassabis, 2016; Berner *et al.*, 2019], attracting huge amount of renewed interests in the recent years. We are witnessing a similar trend in the ridesharing domain.

3.2 Basics & Algorithms

RL is based on the Markov decision process (MDP) framework, where the agent (the decision-making entity) has a *state* s in the state space $\mathcal S$ and can perform an action a defined by an action space $\mathcal A$. After executing the action, the agent receives an immediate reward R(s,a) from the environment, and its state changes according to the transition probabilities $P(\cdot|s,a)$. The process repeats until a terminal state or the end of the horizon is reached, giving a sequence of the triplets $(s_t,a_t,r_t)_{t=0}^{t=T}$, where t is the epoch index, T is the final epoch at the terminal state or the end of the horizon, and r_t is a sample of R. The objective of the MDP is to maximize the cumulative reward over the horizon. A key quantity to compute is the value function

$$V(s) := E\left[\sum_{t=0}^{t=T} \gamma^t r_t | s_0 = s\right],$$

which satisfies the Bellman equation,

$$V(s_t) = \sum_{a_t} P(s_{t+1}, r_t | s_t, a_t) \left(r_t(s_t, a_t) + \gamma V(s_{t+1}) \right). \tag{1}$$

Similarly, we have the action-value function

$$Q(s,a) := E\left[\sum_{t=0}^{t=T} \gamma^t r_t | s_0 = s, a_0 = a\right],$$

which conditions on both s and a. A policy is a function $\pi(s): \mathcal{S} \to \mathcal{A}$.

Given P and R, we can compute V(s) by the value iterations,

$$V(s) \leftarrow \max_{a} \sum_{s',r} P(s',r|s,a) \left(r + \gamma V(s')\right). \tag{2}$$

If we estimate (P,R) from data, we have a basic model-based RL method. A model-free method learns the value function and optimizes the policy directly from data without learning and constructing a model of the environment. A common example is *temporal-difference* (TD) *learning*, which iteratively updates V by TD-errors using trajectory samples and bootstrapping,

$$V(s) \leftarrow V(s) + \alpha(r + \gamma V(s') - V(s)), \tag{3}$$

where α is the step size (or learning rate). If learning the optimal action-values for control is the goal, we similarly have *Q-learning*, which updates Q by

$$Q(s,a) \leftarrow Q(s,a) + \alpha(r + \gamma \max_{a'} Q(s',a') - Q(s,a)). \tag{4}$$

The deep Q-network (DQN) [Mnih et al., 2015] approximates Q(s,a) by a neural network along with a few heuristics to improve training stability. These are all value-based methods.

A policy-based method directly learns π by computing the policy gradient (PG), the gradient of the cumulative reward with respect to the policy parameters θ ,

$$\sum_{s} \mu(s) \sum_{a} Q^{\pi}(s, a) \nabla \pi(a|s, \theta), \tag{5}$$

where μ is the on-policy distribution under π . REINFORCE [Williams, 1992] is a classical PG method. The value function (V,Q), or the advantage Q(s,a)-V(s) can be learned simultaneously to compute the PG, and we have an *actor-critic* (AC) method. The proximal policy optimization (PPO) [Schulman *et al.*, 2017] optimizes a clipping surrogate objective with respect to the advantage to promote conservative updates to π and is a popular choice of training algorithm for RL problems.

An MDP can be extended to a Markov game involving multiple agents to form the basis for multiagent RL (MARL). Many MARL algorithms, e.g., [Yang et al., 2018; Lowe et al., 2017] focus on agent communication and coordination, in view of the intractable action space in MARL.

A family of methods closely related to RL is approximate dynamic programming (ADP) [Powell, 2007] for solving stochastic dynamic programs (DP), of which the Bellman equation for MDP is an instance.

4 Reinforcement Learning for Ridesharing

We review the RL literature for ridesharing in this section grouped by the core operational problems. We first cover pricing, matching, and repositioning in the context of ride-hailing. Then, we will review works on those problems specific to ride-pooling.

4.1 Pricing

RL-based approaches have been developed for dynamic pricing in one-sided retail markets [Raju et al., 2003; Bertsimas and Perakis, 2006], where pricing changes only the demand pattern per customers' price elasticity. The ridesharing marketplace, however, is more complex due to its two-sided nature and spatiotemmporal dimensions. In this case, pricing is also a lever to change the supply (driver) distribution if price changes are broadcast to the drivers in advance. Because of its close ties to SD distributions, dynamic pricing is often jointly optimized with order matching or vehicle repositioning. Prior to using RL, dynamic pricing for ridesharing has already been studied and analyzed in conjunction with matching [Yan et al., 2020; Özkan and Ward, 2020] and from the spatiotemporal perspective [Ma et al., 2020; Bimpikis et al., 2019; Hu et al., 2021], covering optimality and equilibrium analyses.

As one of the early works, Wu et al. [2016] consider a simplified ridesharing environment which captures only the two-sidedness of the market but not the spatiotemporal dimensions. The state of the MDP is the current price plus SD information. The action is to set a price, and the reward is the generated profit. A O-learning agent is trained in a simple simulator, and empirical advantage in the total profit is demonstrated against other heuristic approaches. Chen et al. [2019a] integrate contextual bandits and the spatiotemporal value network developed in [Tang et al., 2019] for matching to jointly optimize pricing and matching decisions. In particular, the pricing actions are the discretized price percentage changes and are selected by a contextual bandits algorithm, where the long-term values learned by the value network are incorporated into the bandit rewards. In [Turan et al., 2020], the RL agent determines both the price for each origin-destination (OD) pairs and the reposition/charging decisions for each electric vehicle in the fleet. The state contains global information such as the electricity price in each zone, the passenger queue length for OD pair, and the number of vehicles in each zone and their energy levels. The reward accounts for trip revenue, penalty for the queues, and operational cost for charging and repositioning. Due to the multi-dimensional continuous action space, PPO is used to train the agent in a simulator. Song et al. [2020] perform a case study of ridesharing in Seoul. They use a tabular Q-learning agent to determine spatiotemporal pricing, and extensive simulations are performed to analyze the impact of surge pricing on alleviating the problem of marginalized zones (areas where it is consistently hard to get a taxi) and on improving spatial equity. Mazumdar et al. [2017] study from a different perspective of the pricing problem. The proposed risk-sensitive inverse RL method [Ng et al., 2000] recovers the policies of different types of passengers (risk-averse, risk-neutral, and risk-seeking) in view of surge pricing. The policy determines whether the passenger should wait or take the current ride.

4.2 Online Matching

The rideshare matching problem and its generalized forms have been investigated extensively in the field of operations research (see e.g., [Özkan and Ward, 2020; Hu and Zhou, 2020; Lowalekar *et al.*, 2018] and the references therein). Lowalekar *et al.* [2018] approach the problem through stochastic optimization and use Bender's decomposition to solve it efficiently. To account for the temporal dependency of the decisions, Hu and Zhou [2020] formulate the problem as a stochastic DP and propose heuristic policies to compute the optimal matching decisions. For a related problem, the truckload carriers assignment problem, Simao *et al.* [2009] also formulate a dynamic DP but with post-decision states so that they are able to solve the problem using ADP. In each iteration, a demand path is sampled, and the value function is approximated in a linear form and updated using the dual variables from the LP solution to the resulting optimization problem.

The RL literature for rideshare matching typically aims to optimize the platform revenue (or total driver income) and the service quality over an extended period of time. Service quality can be quantified by *response rate* and *fulfillment rate*. Response rate is the ratio of the matched requests to all trip requests. Since the probability of pre-match cancellation is primarily a function of response time (pre-match waiting time), the total response time is an alternative metric to response rate.

Fulfillment rate is the ratio of completed requests to all requests and is no higher to the response rate. The gap is due to post-match cancellation, usually because of the waiting for pick-up. Hence, the average pick-up distance is also a relevant quantity to observe.

In terms of the MDP formulation, modeling the agent as a driver is convenient choice for its straightforward definition of state, action, and reward, in contrast to system-level modeling where the action space is exponential. In this case, the rideshare platform is naturally a multi-agent system with a global objective. A common approach is to crowdsource all drivers' experience trajectories to train a single agent and apply it to all the drivers to generate their matching policies [Xu et al., 2018; Wang et al., 2018; Tang et al., 2019]. Since the system reward is the sum of the drivers' rewards, the system value function does decompose into the individual drivers' value functions computed by each driver's own trajectories. The approximation here is using a single value function learned from all drivers' data. See [Qin et al., 2020a] for detailed discussions. Specifically, Xu et al. [2018] learn a tabular driver value function using TD(0), and Wang et al. [2018]; Tang et al. [2019]; Holler et al. [2019] apply DQN-type of training to learn a value network. In particular, Tang et al. [2019] design a spatiotemporal state-value network using hierarchical coarse coding and cerebellar embedding memories for better state representation and training stability. Holler et al. [2019] develop an action-value network that leverages global SD information, which is embedded into a global context by attention.

This type of single-agent approach avoids dealing explicitly with the multi-agent aspect of the problem and the interaction among the agents during training. Besides simplicity, this strategy has the additional advantage of being able to easily handle a dynamic set of agents (and hence, a changing action space) [Ke *et al.*, 2020b]. On the other hand, order matching requires strong system-level coordination in that a feasible solution has to satisfy the one-to-one constraints. To address this issue, Xu *et al.* [2018]; Tang *et al.* [2019] use the learned state values to populate the edge weights of a bipartite assignment problem to generate a collective-greedy policy [Qin *et al.*, 2020a] with respect to the state values. Holler *et al.* [2019] assume a setting where drivers are matched or repositioned sequentially so that the policy output always satisfies the matching constraints.

Leveraging MARL, Li *et al.* [2019]; Jin *et al.* [2019]; Zhou *et al.* [2019] directly optimize the multi-agent system. One significant challenge is scalability since any realistic ridesharing setting can easily involve thousands of agents, precluding the possibility of dealing with an exact joint action space. Li *et al.* [2019] apply mean-field MARL to make the interaction among agents tractable, by taking the 'average' action of the neighboring agents to approximate the joint actions. Zhou *et al.* [2019] argue that no explicit communication among agents is required for order matching due to the asynchronous nature of the transitions and propose independent Q-learning with centralized KL divergence (of the supply and demand distributions) regularization. Both Li *et al.* [2019]; Zhou *et al.* [2019] follow the centralized training decentralized execution paradigm. Jin *et al.* [2019] take a different approach treating each spatial grid cell as a worker agent and a region of a set of grid cells as a manager agent, and they adopt hierarchical RL to jointly optimize order matching and vehicle repositioning.

Besides the driver-passenger pairing decisions, there have also been research on using RL to learn when to match a request (or a batch of requests). This can be done from the perspective of a request itself [Ke et al., 2020b] or the system [Wang et al., 2019]. In [Ke et al., 2020b], an agent is modeled as a trip request. An agent network is trained centrally using pooled experience from all agents to decide whether or not to delay the matching of a request to the next review window, and all the agents share the same policy. To encourage cooperation among the agents, a specially shaped reward function is used to account for both local and global reward feedback. Wang et al. [2019] take a system's view and train an agent using Q-learning to determine the length of the current review window (or batch size). They also show theoretical analysis results on the performance guarantee in terms of competitive ratio for dynamic bipartite graph matching with adaptive windows.

Because of its generalizability, order matching for ridesharing is closed related to a number of online matching problems in other domains, the RL methods to which are also relevant and can inform the research in ridesharing matching. Some examples are training a DQN agent to dispatch trucks for mining tasks [Zhang *et al.*, 2020], learning a decentralized value function using PPO to dispatch couriers for pick-up services [Chen *et al.*, 2019b], and designing a self-attention, pointer network-based policy network for assignment in mobile crowdsourcing [Shen *et al.*, 2020].

4.3 Vehicle Repositioning

Vehicle repositioning from a single-driver perspective (i.e., taxi routing) has a relatively long history of research since taxi service has been in existence long before the emergence of rideshare platforms. Likewise, research on RL-based approaches for this problem also appeared earlier than that on system-level vehicle repositioning.

For the taxi routing problem, the agent is naturally modeled as a driver, and the objective thus focuses on optimizing individual reward. Common reward definitions include trip fare [Rong et al., 2016], net profit (income - operational cost) [Verma et al., 2017], idle cruising distance [Garg and Ranu, 2018], and ratio of trip mileage to idle cruising mileage [Gao et al., 2018]. Earlier works Han et al. [2016]; Wen et al. [2017]; Verma et al. [2017]; Garg and Ranu [2018] optimize the objective within a horizon up to the next successful match, but it is now more common to consider a long-term horizon, where an episode usually consists of a trajectory over one day.

The type of actions of an agent depends on the physical abstraction adopted. A simpler and more common way of representing the spatial world is a grid system, square or hexagonal² [Han *et al.*, 2016; Wen *et al.*, 2017; Verma *et al.*, 2017; Gao *et al.*, 2018; Lin *et al.*, 2018; Rong *et al.*, 2016; Jiao *et al.*, 2020; Shou *et al.*, 2020]. In this setting, the action space is the set of neighboring cells (often including the current cell). Shou and Di [2020b] explain the justification for this configuration. Determination of the specific destination point is left to a separate process, e.g., pick-up points service [Jiao *et al.*, 2020]. The more realistic abstraction is a road network, in which the nodes can be intersections or road segments [Garg and Ranu, 2018; Yu *et al.*, 2019; Zhou *et al.*, 2018; Schmoll and Schubert, 2020]. The action space is the adjacent nodes or edges of the current node. This approach supports a turn-by-turn guiding policy (like routing) but requires more map information at run time.

Most of the papers adopt a tabular value function, so the state is necessarily low-dimensional, including spatiotemporal information and sometimes additional categorical statuses. Shou *et al.* [2020] has a boolean in the state to indicate if the driver is assigned to consecutive requests since its setting allows a driver to be matched before completing a trip request. Rong *et al.* [2016]; Zhou *et al.* [2018] have the direction from which the driver arrives at the current location. For deep RL-based approaches [Wen *et al.*, 2017; Jiao *et al.*, 2020], richer contextual information, such as SD distributions in the neighborhood, can go into the state.

The learning algorithms are fairly diverse but are all value-based. By estimating the various parameters (e.g., matching probability, passenger destination probability) to compute the transition probabilities, Rong *et al.* [2016]; Yu *et al.* [2019]; Shou *et al.* [2020]; Zhou *et al.* [2018] adopt a model-based approach and use value iterations to solve the MDP. Model-free methods are also common, e.g., Monte Carlo learning [Verma *et al.*, 2017], Q-learning [Han *et al.*, 2016; Gao *et al.*, 2018], and DQN [Wen *et al.*, 2017]. Jiao *et al.* [2020] is a hybrid approach in that it performs a action tree search at the online planning stage using estimated matching probabilities and a separately learned state value network. Garg and Ranu [2018] is in a similar spirit by augmenting the multi-arm bandits with Monte Carlo tree search.

The problem formulation most relevant to the ridesharing service provider is system-level vehicle repositioning. The agent can be either the platform or a vehicle, latter of which calls for a MARL approach. All the works in this formulation have global SD information (each vehicle and request's status or SD distributions) in the state of the MDP, with a vehicle agent additionally has its spatiotemporal status. The rewards are mostly the same as in the taxi routing case, except that Mao *et al.* [2020] consider the monetized passenger waiting time. The actions are all based on grid or taxi zone systems.

The system-agent RL formulation has only been studied very recently, in view of the intractability of the joint action space of all the vehicles. To tackle this challenge of scalability, Feng $et\ al.\ [2020]$ decompose the system action into a sequence of atomic actions corresponding to passenger-vehicle matches and vehicle repositions. The MDP encloses a 'sequential decision process' in which all feasible atomic actions are executed to represent one system action, and the MDP advances its state upon complete of the system action. They develop a PPO algorithm for the augmented MDP to determine the sequence of the atomic actions. The system policy in [Mao $et\ al.\ 2020$] produces a reposition plan that specifies the number of vehicles to relocate from zone i to j so that the action space is independent from the number of agents (at the expense of extra work at execution). The agent

²The hexagonal grid system is the industry standard.

network, trained by a batch AC method, outputs a value for each OD pair, which after normalization gives the percentage of vehicles from each zone to a feasible destination.

The vehicle-agent approaches have to address the coordination issue among the agents. Lin et al. [2018] develop contextual DQN and AC methods, in which coordination is achieved by masking the action space based on the state context and splitting the reward accrued in a grid cell among the multiple agents within the same cell. Oda and Joe-Wong [2018] treat the global state in grid as image input and develop an independent DQN method. They argue that independent learning, equipped with global state information, works quite well compared to an MPC-based approach. The zone structure in [Liu et al., 2020] is constructed by clustering a road-connectivity graph. A single vehicle agent is trained with contextual deep RL and generates sequential actions for the vehicles. Zhang et al. [2020] also train a single DQN agent for all agents, but with global KL distance between the SD distributions similar to [Zhou et al., 2019]. The DQN agent is put in tandem with QRewriter, another agent with a Q-table value function that converts the output of DQN to an improved action. Shou and Di [2020b] approach the MARL problem with bilevel optimization: The bottom level is a mean-field AC method [Li et al., 2019] with the reward function coming from a platform reward design mechanism, which is tuned by the top level Bayesian optimization. Agent coordination is done by a central module in [Chaudhari et al., 2020], where a vehicle agent executes a mix of independent and coordinated actions. The central module determines the need for coordination based on SD gaps, and explicit coordination is achieved by solving an assignment problem to move vehicles from excess zones to deficit zones.

Existing literature typically assumes the drivers' full compliance to reposition, i.e., the autonomous vehicle setting. How non-compliance affects the overall performance of a reposition algorithm still requires further investigation.

4.4 Ride-pooling (Carpool)

Ride-pooling optimization typically concerns with matching, repositioning, routing (see e.g., [Zheng et al., 2018; Alonso-Mora et al., 2017b,a; Tong et al., 2018]). The RL literature has primarily focused on the first two problems. Many works have multiple objectives and define the reward as a weighted combination of several quantities, with hand-tuned weight parameters. Passenger wait time is the duration between the request time and the pick-up time. Detour delay is the extra time a passenger spends on the vehicle due to the participation in the ride-pooling. In some cases, these two quantities define the feasibility of a potential pooled trip instead of appearing in the reward [Shah et al., 2020]. Effective trip distance is the travel distance between the origin and destination of a trip request, should it be fulfilled without ride-pooling. Yu and Shen [2019] consider minimizing passenger wait time, detour delay, and lost demand. Guériau and Dusparic [2018] maximize the number of passengers served. Jindal et al. [2018] maximize the total effective trip distance within an episode. Considering a fixed number of requests within an episode (hence fixed total effective distance), the total effective distance is just the number of served requests weighted by individual trip distance. Alabbasi et al. [2019]; Haliem et al. [2020a]; Singh et al. [2019]; Haliem et al. [2020b] all attempt to minimize the SD mismatch, passenger wait time, reposition time, detour delay, and the number of vehicles used. Singh et al. [2019] study a more general form of ride-pooling, where a passenger can hop among different vehicles to complete a trip, with each vehicle completing one leg. They further consider the number of hops and the delay due to hopping.

The state of an agent usually consists of global SD information, similar to that for matching and reposition, but the vehicle status contains key additional information of occupancy and OD's of the passengers on board.

The action space depends on whether the agent is modeled at vehicle level or system level. Existing works all require that a vehicle drops off all the passengers on board according to a planned route before a new round of pooling. An individual vehicle agent can then match to a feasible group of passengers (in terms of capacity and detour delay) [Jindal *et al.*, 2018], reposition to another location [Alabbasi *et al.*, 2019; Haliem *et al.*, 2020a,b], or both [Guériau and Dusparic, 2018]. A system-level agent has to make action decisions for the entire fleet together [Yu and Shen, 2019; Shah *et al.*, 2020].

Papers with vehicle-level policy commonly train a single agent and apply to all the vehicles independently (see e.g., [Haliem *et al.*, 2020b]). DQN is a convenient choice of training algorithm for this setting. For system-level decision-making, both Yu and Shen [2019] and Shah *et al.* [2020] employ

an ADP approach and consider matching decisions only. Yu and Shen [2019] follow a similar strategy as [Simao *et al.*, 2009] and use a linear approximation for the value function. In contrast, Shah *et al.* [2020] decompose the system value function into vehicle-level ones and adopts a neural network for the individual value function, which is updated in a DQN manner.

It has become increasingly clear that dynamic routing and route planning in the context of ride-pooling require specific attention. In particular, there are two aspects unique to ride-pooling. First, the trips are known only at request time. Hence, the routes taken by the pooled vehicles have to be updated dynamically to account for the newly joined passengers. Tong *et al.* [2018]; Xu *et al.* [2020] formulate the route planning problem for ride-pooling and develop efficient DP-based route insertion algorithms for carpool. Second, within a given route plan, the route taken by a pooled vehicle from an origin to a destination can affect the chance and quality of its future pooling. Hence, dynamic routing (or route choice) between an OD pair can be optimized in that direction, e.g., Yuen *et al.* [2019] goes beyond the shortest-path to make route recommendations for better chance of pooling. We expect to see more RL-based algorithms for the ride-pooling routing problems.

4.5 Related Methods

A related family of forward-looking methods that share a similar spirit with model-based RL is model predictive control (MPC). MPC exploits the environment dynamics model more explicitly in that it solves a multi-step planning problem over the prediction horizon at decision time. For ridesharing applications, both MPC and model-based RL involve online prediction of supply and demand using models trained on historical data. Model-based RL uses the prediction to learn the environment model, whereas MPC utilizes the information to generate the planning problem, which is typically solved by a mixed-integer-linear-programming solver [Iglesias *et al.*, 2018; Zhang *et al.*, 2016; Miao *et al.*, 2016; Cheng *et al.*, 2018; Riley *et al.*, 2020; Miller and How, 2017].

4.6 Data Sets & Environments

The problems in ridesharing are highly practice-oriented, and results from toy data sets or environments may present a very different picture from those in reality. Hence, real-world data sets and realistic simulators backed up by them are instrumental to research in RL algorithms for these problems.

The most commonly used data sets are those made available by NYC TLC (Taxi & Limousine Commission) [TLC, 2020]. This large public data repository contains trip records from several different services, Yellow Taxi, Green Taxi, and FHV (For-Hire Vehicle), from 2009 to 2020. The Yellow Taxi data is the most frequently used for various studies. The FHV trip records are submissions from the TLC-licensed bases (e.g., Uber, Lyft) and have a flag indicating pooled trips. The pick-up and drop-off locations are represented by taxi zones. A similar subset of the NYC FHV data is available at [Kaggle, 2017], with GPS coordinates for pick-up and drop-off locations. In addition, travel time data between OD pairs can be obtained through Uber Movement [Uber, 2021].

DiDi has published through [GAIA, 2020] a data set of trip records (both regular and pooled) and in-trip vehicle trajectories for the Chinese city of Chengdu. This data set, which powered KDD Cup 2020 RL track competition [Qin *et al.*, 2020b], also includes data on passenger trip cancellation and driver idle cruising behaviors. The evaluation simulation environment for the competition is available for public access through the competition platform [DiDi, 2020]. Although not yet open-sourced, this simulation environment supports both matching and vehicle repositioning tasks and accepts input algorithms through a Python API. Chaudhari *et al.* [2020] offer a Gym-compatible, open-source ride-hailing environment for trianing dispatching agents.

5 Challenges and Opportunities

Given the state of the current literature, we discuss a few challenges and opportunities that we feel crucial in advancing RL for ridesharing.

5.1 Ride-pooling

Methods for learning to make matching decisions are still computationally intensive [Shah *et al.*, 2020; Yu and Shen, 2019], in part due to the need to use VRP solver to determine feasible actions (combination of passengers). Moreover, all existing RL methods assume that the action set is predetermined, and some make only high-level decisions of reposition and serving new passengers or not. A more sophisticated agent may be called for to figure out, for example, how to dynamically determine the desirable passenger combination to match to a vehicle and the routes to take thereafter. Ride-pooling pricing [Ke *et al.*, 2020a], a hard pricing problem itself, is tightly coupled with matching. The share of the total trip fee that each passenger in a ride-pooled vehicle should be responsible for generally depends on the set of individual trips that are matched to that vehicle. A joint pricing-matching algorithm for ride-pooling is therefore highly pertinent.

5.2 Joint Optimization

The rideshare platform is an integrated system, so joint optimization of multiple decision modules leads to better solutions that otherwise unable to realize under separate optimizations, ensuring that different decisions work towards the same goal. We have already seen development on RL for joint matching-reposition [Holler *et al.*, 2019; Jin *et al.*, 2019] and with ride-pooling [Guériau and Dusparic, 2018], pricing-matching [Chen *et al.*, 2019a], and pricing-reposition [Turan *et al.*, 2020]. An RL-based method for fully joint optimization of all major modules is highly expected. Meanwhile, this also requires readiness from the rideshare platforms in terms of system architecture and organizational structure.

5.3 Heterogeneous Fleet

With the wide adoption of electric vehicles and the emergence of autonomous vehicles, we are facing an increasingly heterogeneous fleet on rideshare platforms. Electric vehicles have limited operational range per their battery capacities. They have to be routed to a charging station when the battery level is low (but sufficiently high to be able to travel to the station). Autonomous vehicles may run within a predefined service geo-fence due to their limited ability (compared to human drivers) to handle complex road situations. For an RL-based approach, a heterogeneous fleet means multiple types of agents with different state and action spaces. Specific studies are required to investigate how to make such a heterogeneous fleet cooperate well to complement each other and maximize the advantage of each type of vehicles.

5.4 Simulation & Sim2Real

Simulation environments are fundamental infrastructure for successful development of RL methods. Despite those introduced in Section 4.6, simulation continues to be a significant engineering and research challenge. We have not yet seen comparable simulation granularity as that of the environments for traffic management, (e.g., SUMO [Lopez et al., 2018], Flow [Wu et al., 2017]) or autonomous driving (e.g., SMARTS [Zhou et al., 2020], CARLA [Dosovitskiy et al., 2017]). The opportunity is an agent-based microscopic simulation environment for ridesharing that accounts for both ride-hailing and carpool, as well as driver and passenger behavior details, e.g., price sensitivity, cancellation behavior, driver entrance/exit behavior. None of the existing public/open-source simulators supports pricing decisions. Those simulators described in the pricing papers all have strong assumptions on passenger and driver price elasticities. A better way might be to learn those behaviors from data through, e.g., generative adversarial imitation learning [Shang et al., 2019] or inverse RL [Mazumdar et al., 2017].

No publicly known ridesharing simulation environment has sufficiently high fidelity to the real world to allow an agent trained entirely in it to deploy directly to production. Several deployed works [Qin et al., 2020a; Jiao et al., 2020] in Section 4 have all adopted offline RL for learning the state value functions and online planning. The robotics community has been extensively investigating ways to close the reality gap [Traoré et al., 2019; Mehta et al., 2020]. Sim2real transfer algorithms for ridesharing agents are urgently sought after.

5.5 Non-stationarity

We have seen in Sections 4.2 and 4.3 that RL algorithms deployed to real-world systems generally adopt offline training - once the value function or the policy is deployed, it is not updated until the next deployment. Value functions trained offline using a large amount of historical data are only able to capture recurring patterns resulted from SD changes from day to day. However, the SD dynamics can be highly non-stationary in that one-time abrupt changes can easily occur due to various events and incidents, e.g., concerts, matches, and even road blocks by traffic accidents. To fully unleash the power of RL, practical mechanisms for real-time on-policy updates of the value function is required. In view of the low risk tolerance of production systems in general, sample complexity, computational complexity, and robustness are the key challenges that such methods have to address.

6 Closing Remarks

We have surveyed the RL literature for the core problems in ridesharing and discussed some open challenges and future opportunities. As one may have noticed, most of the literature has just appeared in the last four years, and we expect it to continue growing and updating rapidly.

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