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Review

How machine learning informs ride-hailing services: A survey

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ABSTRACT

In recent years, online ride-hailing services have emerged as an important component of urban transportation system, which not only provide significant ease for residents' travel activities, but also shape new travel behavior and diversify urban mobility patterns. This study provides a thorough review of machine-learning-based methodologies for on-demand ride-hailing services. The importance of on-demand ride-hailing services in the spatio-temporal dynamics of urban traffic is first highlighted, with machine-learning-based macro-level ride-hailing research demonstrating its value in guiding the design, planning, operation, and control of urban intelligent transportation systems. Then, the research on travel behavior from the perspective of individual mobility patterns, including carpooling behavior and modal choice behavior, is summarized. In addition, existing studies on order matching and vehicle dispatching strategies, which are among the most important components of on-line ride-hailing systems, are collected and summarized. Finally, some of the critical challenges and opportunities in ride-hailing services are discussed.

1. Introduction

Due to the expansion of the sharing economy, especially the increase in travel demand for shared mobility among residents, the global ride-hailing market is witnessing rapid growth, with industry reports expecting a compound annual growth rate of over 8.75% from 2021 to 2026, reaching USD 230 billion (Research and Markets, 2022). On-line ride-hailing services are constantly generating a huge amount of location-based data every day, including on-line orders data, trajectory information, map query data, and geo-tagged check-in data. By learning and understanding these multi-source data, further development of on-line taxi services is expected to reduce traffic congestion and improve the level of service for urban transportation. Fortunately, machine learning and deep learning methods provide a potential solution, as they are adept at mining latent patterns in data, and have been trailed by ride-hailing service providers like DiDi Chuxing in an attempt to improve passenger satisfaction and reduce vehicle idle time (Qin et al., 2020).

This paper focuses on how machine learning informs on-line taxi services. The accurate prediction of future traffic spatio-temporal dynamics is one of the machine learning application topics related to on-line ride-hailing services. The ride-hailing services discussed in this study basically consists of two aspects. The first aspect is the user-based demand problem which is called "on-demand ride-hailing services" is this paper. Based on an accurate estimation of urban ride-hailing demand, the platforms can produce precise and timely recommendations for matching and allocating idle vehicles and routing the ride-sharing vehicles in the fleet (Agarwal et al., 2022). And the second aspect is the system-based supply problem including order matching and dispatching problem which is called "on-line ride-hailing services" in this paper. And when a passenger submits a ride request, the order matching system assigns it to an available driver and follows specific assignment policies such as maximizing the driver's revenue or minimizing the passenger's waiting time (Yan et al., 2020). Most related research focused on macroscopic traffic prediction tasks, such as ride-hailing demand prediction (Tang et al., 2021; Huang et al., 2021) and travel time estimation (Mao et al., 2021; Sun et al., 2021). On-line ride-hailing services can not only provide convenience for the travel activities of residents, but also shape new travel behavior and emerging urban mobility patterns (Acheampong et al., 2020). Apart from the macroscopic level, another line of research focused on the microscopic level, at which individual mobility patterns can be identified. There have been many studies on the travelers' personalized travel behavior analysis, such as carpooling

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behavior (Qin et al., 2021; Al-Abbasi et al., 2019), and modal choice behavior (Tong et al., 2018; Mäenpää et al., 2017). In this review, we assess the literature related to on-line ride-hailing services from both perspectives of spatio-temporal dynamics and individual mobility patterns, covering both macro and micro-level studies.

The remainder of this survey is organized as follows: Section 2 reviews the literature on on-line ride-hailing services from the perspective of spatio-temporal dynamics. Section 3 presents the micro-level study, i.e., individual mobility patterns. Section 4 collects and summarizes existing approaches involving two of the most critical parts of on-line ride-hailing systems, i.e., order matching and vehicle dispatching. Finally, Section 5 discusses promising future research directions in ride-hailing services.

2. The spatio-temporal dynamics of traffic

To tackle the difficulties of mobility and sustainability in megacities, understanding the spatio-temporal dynamics of traffic is critical for guiding the design, planning, operation, and control of urban transportation systems (He et al., 2020).

2.1. Ride-hailing demand prediction

Based on an accurate short-term estimate of urban ride-hailing demand, the platforms can produce precise and timely recommendations for matching and allocating idle vehicles and routing the ride-sharing vehicles in the fleet (Agarwal et al., 2022).

Early traffic demand prediction studies focused on time series modeling by discretizing time and then using historical data to forecast future demand. The most widely studied model is the autoregressive integrated moving average model (ARIMA) and its variants (Smith et al., 2002; Lippi et al., 2013). In addition to the classic ARIMA-family model, many other data-driven models have been proposed, such as the support vector machine (Castro-Neto et al., 2009), k-nearest neighbor (Cai et al., 2016), linear regression (Tong et al., 2017), and a Gaussian process (Gammelli et al., 2020). Tong et al. (2017) proposed a unified linear regression model with 200 million multidimensional features, and a set of optimization strategies for model training and updating efficiency. Ride-hailing demand is highly dependent on supply, and the observed ride-hailing demand from historical data does not exceed supply, so the existing demand is only a subset of the true demand. Gammelli et al. (2020) explored this issue and proposed a Gaussian process model to estimate the latent demand of ride-hailing services.

In recent years, innovations at the algorithm level and rapid development of computing ability have brought about the rise of deep learning techniques. Urban ride-hailing demand data usually contains spatial and temporal attributes, and this type of data is also referred to as spatio-temporal data. The spatio-temporal correlation of traffic dynamics has been the focus of many studies on traffic demand prediction using deep learning. Emerging deep learning techniques, such as the convolution neural network (CNN), graph convolution neural network (GCN), and recurrent neural network (RNN), have been widely used for prediction of traffic demands.

There are two common structures for representing spatio-temporal traffic data. The first one is in the form of a picture where each pixel point in the picture represents an area of the city. Researchers have focused on how to employ CNNs to capture both spatial and temporal patterns from traffic data as computer vision technology has progressed, particularly after the creation of the fully convolutional network (FCN) (Long et al., 2015). FCN first emerged for the task of semantic segmentation of images in computer vision. Unlike the classical CNN, which uses a fully-connected layer after the convolution layer to obtain a fixed-length feature vector for classification, FCN takes any size input image and utilizes a deconvolution layer to up-sample the final convolution layer's feature map, which is restored to the input size, thus generating pixel-wise predictions. Fig. 1(a) is an original remote sensing image, and Fig. 1(b) demonstrates the result of semantic segmentation, which classifies each pixel in Fig. 1(a) into four categories: buildings, farmlands, roads, and water networks. In the study of traffic demand prediction, the study area is often partitioned into an $m \times n$ traffic grid map, using FCN, the sizes of model inputs and outputs can both be complete traffic grid maps. Fig. 2 displays two different sizes of traffic grid maps. Fig. 2(a) illustrates a coarse-grained division with a traffic grid map of length and width 20 (Liu et al., 2019), and in Fig. 2(b), the city is partitioned into a traffic grid map of 436×495, representing a fine-grained division (Liu et al., 2021).

The first deep learning-based spatio-temporal data prediction model (DeepST) proposed by Zhang et al. (2016) can capture both temporal and spatial dependencies and use an FCN architecture where the output of the model is a full-size image. To improve performance, Ke et al. (2017) merged the long short-term memory (LSTM) with CNN, which becomes a landmark approach in spatio-temporal traffic data prediction. In contrast to previous works, Yao et al. (2018) suggested a deep multi-view spatio-temporal network that included semantic views is better to represent the correlation between regions with similar temporal patterns. Guo et al. (2019) introduced a 3D convolution to model the correlation of traffic data in both spatial and temporal dimensions automatically and proposed a new recalibration block to allow for the differences in spatial correlation contributions in explicit terms. Almost all studies so far have divided urban areas into square grids. Ke et al. (2018) designed a novel segmentation model by dividing the study area into regular hexagonal grids, taking full advantage of the fact that this segmentation has well-defined neighborhoods, smaller edge area ratios and isotropy, and further proposed a hexagonal-based CNN. Ensemble learning can

(a) original remote sensing image (b) the result of semantic segmentation

Fig. 1. Illustration of semantic segmentation.

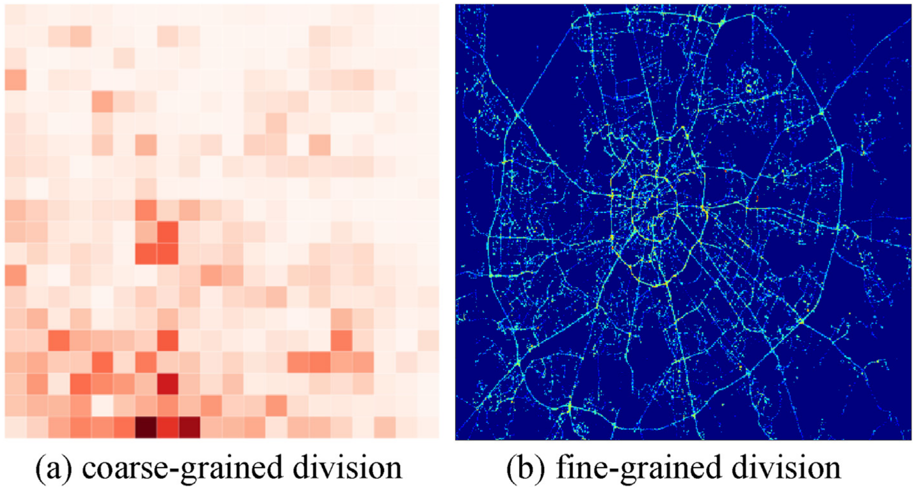

Fig. 2. Illustration of traffic grid map division.

integrate the results of multiple basic models and thus enhancing the accuracy of the models. Liu et al. (2019) designed a CNN based ensemble method for spatio-temporal data prediction, where the output of different basic models is used as a channel of the image and then integrated adaptively using convolutional networks. Based on the attention mechanism in computer vision, Liu et al. (2020) established a personalized ride-hailing demand prediction model, where personalized implies that the model learns a set of weights specifically for different regions and time periods, and they further evaluated the effects of network structure on the demand prediction accuracy. Understanding the propagation of traffic states helps to tailor deep learning network architectures. Liu et al. (2021) studied the propagation process of traffic states in both temporal and spatial dimensions and designed the corresponding neural network structure for experimental validation. The backbone network was designed based on U-net (Ronneberger et al., 2015), which can significantly relief the computational effort and increase the receptive field of the convolutional kernel.

Another approach for representing spatio-temporal traffic data is to visualize the traffic network as a graph, where nodes indicate intersections and edges indicate road segments. Non-Euclidean pairwise correlations between regions are encoded into several graphs by Geng et al. (2019), who modeled the explicit correlations using static multi-graph convolutions. To overcome the inability of static maps to model the real-time dynamic correlation of passenger flows between regions over time, Chen et al. (2021) constructed a spatial-temporal dynamic multi-graph attention network, where the feature similarities between regions and passenger flows are encoded into multiple static and dynamic graphs. Graph neural networks (GNNs) are often used in fusion with other neural networks. Jin et al. (2020) proposed multiple spatio-temporal information fusion networks, which integrate the structures of graph CNNs, variational autoencoder, and sequence-to-sequence learning models to capture the spatio-temporal dynamics of traffic flows. On-line ride-hailing platforms usually provide multiple service modes (e.g., solo ride or carpooling services). When predicting demand for multiple service modes, Ke et al. (2021b) employed many multi-graph convolutional networks and created a multi-task learning module for inter-network knowledge transfer. Some researchers have also studied the problem of origin-destination (OD) demand prediction based on GNNs (Feng et al., 2022). Zhang et al. (2021a) established a joint learning framework called a dynamic automatic structured GNN to tackle the OD demand prediction problem. In their later work, Zhang et al. (2021b) created a dynamic OD graph to describe taxi demand data and constructed a dynamic node-edge attention network to deal with the nuances of OD demand prediction from the perspective of demand creation and attraction.

RNNs have a wide range of applications in language modeling, text generation, and machine translation, and specialize in capturing the hidden patterns in sequential data (e.g., text sequences). More refined origin-destination ride-sourcing demand prediction is more valuable, but also more complex. The existing study region partitioning methods usually partition the whole city into several square grids. Niu et al. (2019) examined the effects of various regional partitioning approaches on the model and developed a regional partition assisted LSTM neural network for predicting ride-hailing service demand. To overcome this challenge, Ke et al. (2021a) designed a residual multigraph convolutional model to encode spatial dependencies, and an LSTM network to encode temporal dependencies. There is heterogeneity in ride-hailing demand between different regions. Zhang et al. (2021) used zone clustering as well as inter-regional heterogeneity to improve the prediction. They designed a taxi zone clustering algorithm and extracted intra-cluster and inter-cluster features separately as the input of multi-level RNNs. Deep learning approximates a black box, and there are many scholars who aim to design interpretable neural network models. Kim et al. (2020) proposed a step-wise interpretable deep learning framework combining linear regression (LR) and RNNs for predicting the demand for taxis in New York City.

2.2. Estimated time of arrival

Estimated time of arrival (ETA) refers to the travel time inferred from the origin to the destination along a given route (Fig. 3). Calculating ETA is one of the most critical modules of ride-hailing services. Given billion-level number of requests every day on ride-hailing platforms, an accurate and efficient ETA module provides greater decision-making system efficiency, a positive customer experience, and significant operational cost savings (Fang et al., 2020).

Most road segments may not have been traversed by any Global Positioning System (GPS)-equipped car during the current time period, as the trajectory data are sparse. To address this problem, Wang et al. (2014) used a three-dimensional tensor to represent the journey times of each driver on each road segment at each time periods, and then used tensor decomposition to fill in the missing values. Tang et al. (2018) similarly used a tensor-based approach to overcome the sparsity of trajectory data and designed a tensor-based Bayesian probabilistic model for city-wide travel time estimation. Lin et al. (2019) proposed attribute-related hybrid trajectory networks to address this data sparsity problem, which uses multi-source hybrid trajectory datasets that include other types of vehicle trajectories for travel time estimation. There are also some variants of the ETA task, such as in the parcel delivery problem, where a trip contains multiple destinations and the order of dispatch,

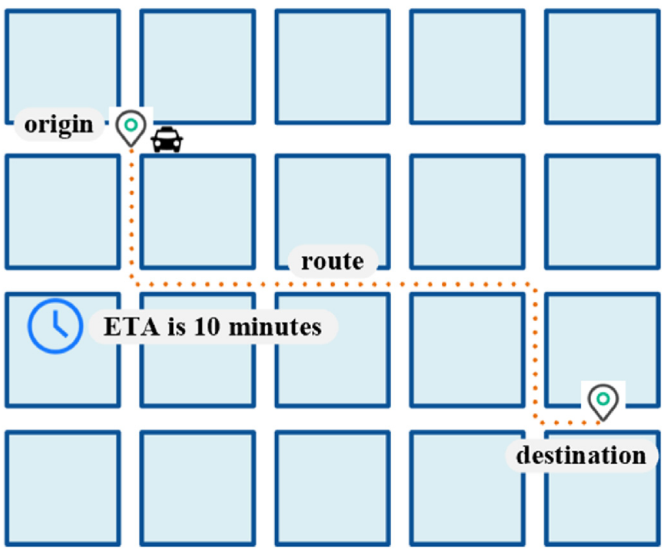

Fig. 3. Illustration of ETA.

delivery mode, *inter alia* exert a significant influence on travel time. Wu and Wu (2019) developed a spatio-temporal sequential neural network model (DeepETA) to overcome such effects.

The vast majority of travel time estimation research used deep learning to learn trajectory information. Wang et al. (2018) defined ETA learning and combined the benefits of linear models, deep neural networks, and RNNs to create a wide-deep-recurrent model for calculating travel time. Many studies have focused on travel time estimation of individual road segments and the accumulation of them, which can lead to accumulated local errors. Wang et al. (2018) presented an end-to-end deep learning framework (DeepTTE) which introduces a geo-convolution that can directly predict the travel time of the entire path. The ETA task is mainly to mine the trajectory data, which is a time series of GPS coordinates, so there are many studies based on RNNs. A few researchers have utilized CNN to extract features from trajectory-transformed images. For instance, Fu and Lee (2019) mapped paths as a sequence of 'generalized images' containing information like sub-paths, traffic states, road networks, and traffic signals. The heterogeneity of traffic networks was considered in the ETA task by Hong et al. (2020). They transformed the road map into a multi-relational network, where traffic behavior patterns are incorporated based on trajectories. Sun et al. (2022) pioneered the introduction of an auxiliary task in the ETA task, i.e., learning not only the ETA but also the driver's personalized driving behavior in a multi-task learning framework, which in turn improved the accuracy of the model. The temporal complexity of trip time inference is extremely important to the on-line ride-hailing platform. In most ETA tasks, researchers concentrate solely on data such as origin, destination, departure time, and traffic conditions, neglecting the driver's own behavior. Fu et al. (2020) focused on the representation of the data by encoding the higher-order spatial and temporal dependencies of the road network through graph attention networks and then using a simple multilayer perceptron model to accelerate the inference time. Most studies on travel time estimation rely on GPS trajectories, but the trajectory data are not accurate enough to reflect the details of individual driving behavior, such as sharp turns, frequent lane changes, and overtaking. To address this problem, Gao et al. (2022) combined GPS trajectories, inertial data from smartphones, and road networks to design a deep RNN.

3. Individual mobility patterns

Patterns of human mobility provide information about urban functions. Understanding individual mobility patterns are important for solving many urban problems, such as urban planning and traffic management (J. Zhang et al., 2021).

3.1. Understanding carpooling behavior

Carpooling, also known as ride-pooling, allows travelers to share a car to their destination (as shown in Fig. 4), which has a positive effect on relieving traffic congestion, which is helpful in saving travel time for ride-hailing users and other travelers on the road (Ke et al., 2020a).

To minimize both the trip delay and waiting time of carpooling passengers, Yu and Shen (2019) proposed a spatial and temporal decomposition heuristic method, which can dynamically dispatch idle drivers to passengers and provide routes for pick-up and drop-off. Trip fares, fleet size, and acceptable detour time are three determinant factors of carpooling service efficiency in an online ride-hailing system. Ke et al. (2020b) managed to model the complex relationships between various variables and decisions in carpooling markets, which guided the development of ride-hailing services. Ma and Koutsopoulos (2022) introduced an advance-request operating model for carpooling, in which users can request a ride before their desired departure time and developed a platform with request matching, vehicle routing, and other features. Carpooling can provide flexible and personalized transportation services and greatly reduces the number of vehicle-kilometers travelled (VKT). Zhu and Mo (2022) used real data from the DiDi Chuxing platform to simulate the carpooling process of travelers, and quantified the contribution of carpooling to VKT reduction and carbon emission reduction. Existing solutions to the real-time carpooling problem are short-sighted as only the objective of the current time step is optimized without considering the impact on the allocation of future time steps. Shah et al. (2020) proposed an approximate dynamic programming approach and built a neural network to handle the complexity of passenger request combinations. Carpooling has numerous advantages, but it increases the uncertainty of the system. Kucharski et al. (2021) analyzed theoretically and experimentally how late passengers affect the performance of ride-hailing services. In a carpooling scenario, an *en-route* driver who is providing service to a passenger may be notified to pick up a passenger wanting to travel in the same direction. Li and Liu (2021) formulated this *en-route* order matching as a multi-stage integer planning model. To encourage carpooling, discounted fees are used to motivate users.

3.2. Understanding modal choice behavior

Smart phones and mobile Internet have fundamentally changed

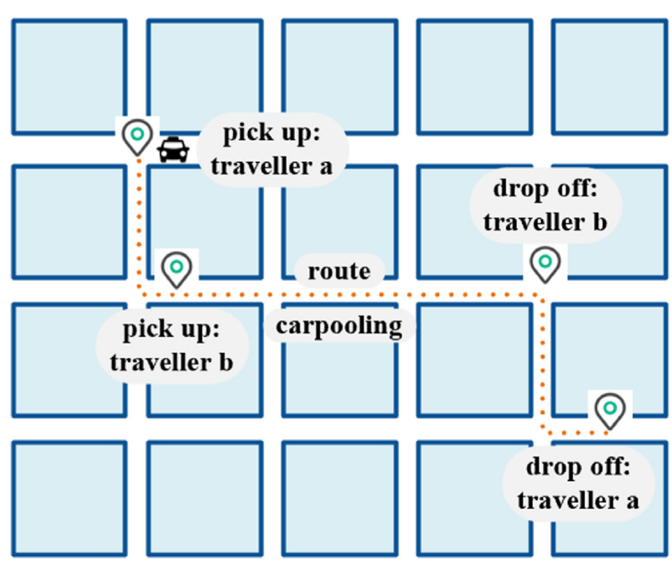

Fig. 4. Illustration of carpooling.

modern life, including people's travel preferences and modal choice. A large amount of travel data helps researchers understand the real travel choice behavior of users, thus providing more intelligent travel decision services (Chen et al., 2017; Ge et al., 2019). As shown in Fig. 5, in intelligent transportation systems, typical travel decision services include route planning, travel mode recommendation, destination recommendation, etc.

The route planning algorithm gives the best travel route and transportation mode between known origins and destinations (Li et al., 2012). Yuan et al. (2011) proposed a clustering algorithm based on variance entropy to estimate the distribution of travel time of two landmarks in different time periods and designed a routing algorithm to provide travelers with the actual fastest routes and customized routes. Yousaf et al. (2014) formalized the ride-sharing problem into a multi-source-destination route planning problem, used social media to obtain users' preferences and then modeled them. The model not only generates optimal routes, but also generates sub-optimal paths for drivers to choose according to demand. Most routing recommendations still provide only the shortest distance or shortest travel time routes, ignoring individual preferences and current conditions. With the help of navigation software, a more logical and reliable route plan is provided according to real-time traffic information like congestion status. Campigotto et al. (2016) proposed a context-aware route recommendation solution, which leverages current traffic conditions and personal preferences. Huang et al. (2018) considered both public transportation and carpooling in multi-modal route planning, and the proposed method can integrate static network and dynamic network while maintaining the flexibility of the carpooling network (static network). Yuen et al. (2019) proposed an algorithm to predict the route with the highest probability of finding compatible customers. By reducing the search space, the dynamic programming method is used to determine the best route. Jia et al. (2020) combined the weighted shortest path problem with deep learning for route recommendation. They used deep neural networks to learn weights from drivers' historical choices to minimize the total weighted cost of historical routes and maximize the cost of unselected routes. Multi-request assignment and multi-point planning are key challenges in the design and operation of ride-sharing services. Zuo et al. (2021) proposed a clustering algorithm for vehicle matching and route planning, which combines ride-sharing candidates through a single clustering process.

Recommending a combination of multiple travel modes for users (e.g., a recommended travel plan that includes more than one travel mode, e.g., recommending travelers take the subway before transferring

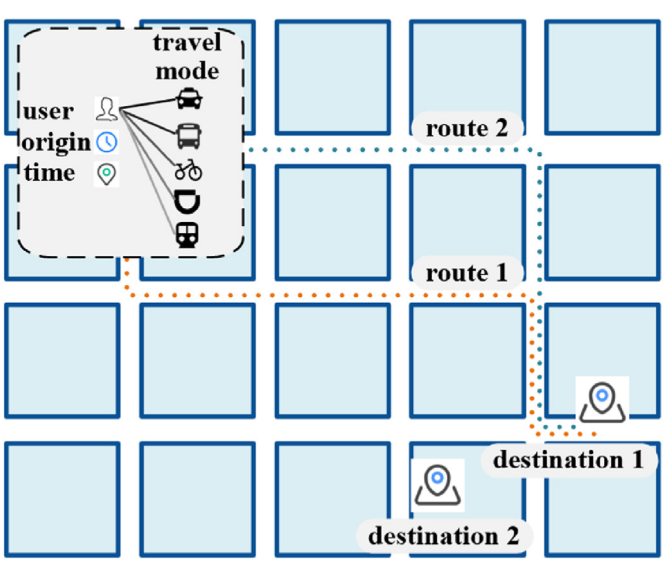

Fig. 5. Illustration of intelligent travel decision services.

to a bus) is an emerging feature in navigation applications. Zou et al. (2016) built an agent-based passenger travel mode and departure time selection method to accumulate experience and update their spatial and temporal knowledge through the use of a Bayesian learning process. Liu et al. (2019a) extracted a graph containing multiple travel modes out of large-scale Baidu Maps queries to discover the relationship between users, OD pairs, and travel modes. Liu et al. (2019b) then proposed a multi-modal recommendation system of travel modes (also known as Hydra), and deployed it on Baidu Maps. Liu et al. (2021a) et al. explored the large-scale multi-modal transportation recommendation problem; they modeled it from multiple perspectives such as user, travel mode, location, and time. OD pairs, user-OD pairs are modeled by a bipartite graph such that their co-occurrence can be better learned from the data. They also proposed a post-processing algorithm to address the inconsistency between the objective function and evaluation metrics. Liu et al. (2021b) further proposed a method of embedding the user's personalized travel behavior into a vector, and applied it to the case scenario of travel mode selection.

Inferring the destination of the traveler is a fundamental problem in location-based services, such as personalized service recommendations (Xue et al., 2013), and public transport dispatching (Besse et al., 2017). Neto et al. (2018) combined Markov models and partial matching prediction techniques to build a route and destination prediction model and avoided congestion by suggesting users deviate from the route where appropriate. Khezerlou et al. (2019) predicted future gathering events through trajectory destination prediction, and they fused historical trajectories with recent sparse trajectories to build a dynamic mixture model to predict future gathering events on a continuous basis. Zhu et al. (2021) proposed a tensor factorization model to classify travel choice based on Bayesian supervised learning, which was evaluated on a real ride-hailing dataset. Jiang et al. (2022) proposed the concept of virtual docks based on POI and designed a probabilistic trip-based destination prediction method to solve the resource rebalancing problem for the dock-less bicycle system, and the model was unaffected by data sparsity. Although destination prediction is the basis of location-based services, it will infringe on users' location privacy. Faced with the privacy-preserving problem in the destination prediction problem, Jiang et al. (2021) specifically designed a data-driven privacy-preserving model to achieve the trade-off between privacy preservation and accuracy of prediction results by controlling the addition of noise. Modeling the behavior of taxi drivers based on the initial partial trajectory plays an important role in location-based services. Rossi et al. (2019) proposed an RNN approach to estimate the precise location of the next destination. This approach models the behavior of taxi drivers using geographic information from social networks and semantically encodes their visited locations. Song et al. (2020) designed a taxi destination prediction model based on an echo state network, in which RNN is modified as an echo state network by forming the hidden layer of the network by randomly deploying massively and sparsely connected neurons. Ebel et al. (2020) discretized GPS locations based on *k-d* trees, then trained a RNN to predict destinations based on partial trajectory sequences, and finally computed the route to the most likely destination.

4. On-line ride-hailing services

In on-line ride-hailing services, passengers are matched with a driver through a mobile application. A typical on-line ride-hailing system consists of the two most important modules: order matching and vehicle dispatching (Yan et al., 2020).

4.1. Order matching

When a passenger submits a ride request, the order matching system assigns it to an available driver and follows specific assignment policies (Fig. 6), such as maximizing the driver's revenue or minimizing the passenger's waiting time (Yang and Lai, 2021). Specifically, after

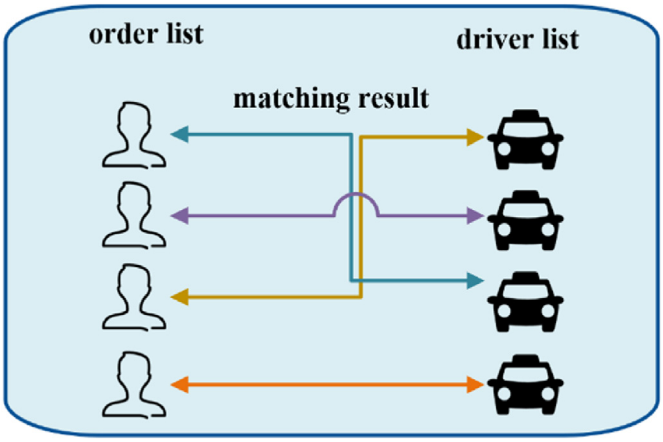

Fig. 6. Illustration of order matching.

observing spatial-temporal patterns and the inherently hierarchical structure of the data, the order matching models help to separately predict the matching probabilities of passengers' trip requests between the order list and driver list.

In some classic order matching work, static matching strategies are used, e.g., Bailey and Clark (1987) matched the nearest driver to order. Meanwhile, the combinatorial optimization methods also play a key role in order matching tasks. Özkan and Ward (2020) studied dynamic order matching by assuming time-varying driver and order arrival rates and proposed a continuous linear program model. For driver-order matching, Xu et al. (2018) characterized the problem as a large-scale sequential decision task and employed a combinatorial optimization strategy. Haliem et al. (2021) proposed a dynamic order matching and route planning model, which considers (in real time) the on-line demand for ride-hailing, pricing, and the location of the vehicle to generate planned routes. During the decision-making process, drivers can also propose different prices based on the expected return of one specific trip and future trip destinations. Gao et al. (2021) demonstrated an order matching method that combines an active guidance strategy with batch matching optimization to increase the matching rate and decrease passenger waiting time. Order matching (i.e., driver-customer matching) and vehicle scheduling are two critical components of a ride-hailing company's operation. Most of previous research considers these two components separately, and the performance of the vehicle dispatching model depends on the accuracy of future demand forecasts. Guo et al. (2021) incorporated order matching into the vehicle dispatching problem to stipulate better dispatching strategies.

The general trend of sequence matching research is the transition from combinatorial optimization methods to DRL methods. Qin et al. (2020) explored how to progress from a combinatorial optimization method to a semi-Markovian decision process model and a deep reinforcement learning (DRL) method. For large-scale ride-sharing platforms, it is a challenge to handle highly concurrent order matching, where thousands of ride requests need to be matched with drivers each second. For the large-scale order matching problem, using multi-agent reinforcement learning, Zou et al. (2016) proposed a decentralized implementation of the order matching algorithm. Jin et al. (2019) studied the joint decision challenge of order matching and vehicle scheduling by formulating a ride-hailing service as the problem of large-scale parallel sorting. They proposed a multi-agent reinforcement learning model, which regards each region as one single agent. Hierarchical reinforcement learning based on the geographical hierarchy of regions was used to coordinate agents from various regions for long-term gains. The matching efficiency was significantly improved by adaptively adjusting the order matching interval significantly for delay matching. Qin et al. (2021) designed a reinforcement learning framework to determine the best delayed matching strategy and overcome the dimensional explosion and sparse reward problems.

The order matching process relies on the user's location, which may lead to the privacy breach of the user's personal data Huang et al., 2021). How to protect users' privacy in the process of order matching has become a focus of much recent research. Yu et al. (2019, 2020) proposed a cryptographic distance calculation method that matches the nearest driver and passenger without revealing the privacy of the passenger and driver locations. Instead of directly using the physical locations of passengers and drivers, Luo et al. (2018) developed a strategy to estimate the shortest distance between passengers and drivers in a road network using road network embedding techniques and cryptographic concepts.

4.2. Vehicle dispatching

Vehicle dispatching, also called vehicle repositioning, is an algorithm through which on-line taxi platforms can adjust their operation and management strategies according to the dynamic changes in demand and supply, and reallocate idle vehicles in advance to areas with large demand gaps, so as to achieve the balance between supply and demand (Lei et al., 2020). Real-world on-line ride-hailing service providers (e.g., DiDi Chuxing) divide their operating area into several hexagonal dispatch units; Fig. 7 shows an illustration of the vehicle dispatching process.

To increase the expected acceptance rate of future requests and minimize the travel time during dispatch, Pouls et al. (2022) designed a demand prediction-driven mixed integer programming model that uses the demand forecast and the current fleet configuration as inputs to provide suitable dispatch destinations for idle vehicles. Ma et al. (2019) proposed a travel strategy that integrates ride-hailing with public transportation service, in which the ride-hailing service is used to solve the last-mile problem. They designed a vehicle dispatching and idle vehicle relocation algorithm based on queuing theory. More trips can be satisfied by optimizing the vehicle dispatching process in the case of limited vehicles. Xu et al. (2022) developed a network flow-based vehicle dispatching algorithm to search for the optimal dispatch sequence of vehicles to requests by establishing the minimum cost flow.

In the on-line ride-hailing market, supply and demand are the two most critical factors, and the relationship between demand and supply is complex and dynamic. Reinforcement learning is suitable when solving the continuous dynamic decision-making challenges in vehicle dispatching tasks. Both model-based and model-free reinforcement learning methods are widely used for vehicle dispatching tasks. Research using model-based approaches usually relies on value iterations to solve a Markov Decision Process (MDP). Rong et al. (2016) modeled the taxicab dispatching task as an MDP and then learned the MDP parameters in different time periods in the data to find the optimal action in terms of improving driver revenue.

Model-free approach to solving problems related to on-line ride-hailing services is the prevailing line of research. Transportation

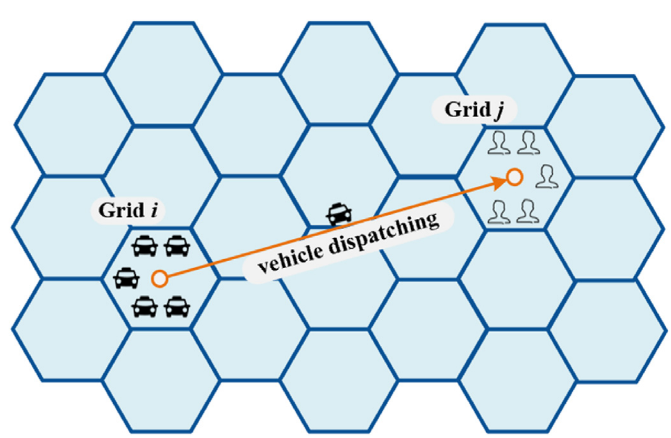

Fig. 7. Illustration of vehicle dispatching.

electrification is a major trend nowadays and electric vehicles will occupy a higher share of the future on-line vehicle market. Shi et al. (2019) evaluated fleet management problems when using electric vehicles and investigated a reinforcement learning -based algorithm to operate a fleet of electric vehicles with the overall goal of reducing customer waiting time, electricity cost, and vehicle operating cost. Holler et al. (2019) proposed a DRL approach to jointly solve the problems of fleet management and vehicle dispatching. In addition to modeling drivers as independent agents, a central fleet management agent was used in charge for the drivers' decisions. Instead of simply partitioning the study area into a grid map, Liu et al. (2022a) proposed a clustering algorithm that divides the road network map into regions, incorporating the road topology. Through accurate taxi demand prediction and frequent updates of driver status, a full study of taxi demand and supply at the regional level was performed in order to improved DRL modeling. Liang et al. (2021) proposed a hybrid structure involving reinforcement learning and centralized programming to solve order matching and vehicle dispatching tasks. Intelligent transportation systems are closely related to other disciplines: Liu et al. (2022b) designed a single-agent DRL model by analogizing the vehicle dispatching problem in a real-world on-line ride-hailing platform to a load balancing problem in a computer network and validated it on real data.

5. Summary and discussion

The literature survey shows that various machine-learning methodological approaches are framed to develop on-demand and on-line ride-hailing systems.

5.1. Joint optimization of multiple functional modules in an integrated system

The on-line taxi platform integrates several functional modules involving supply and demand prediction, ETA, travel plan recommendation, carpooling, order matching, vehicle dispatching, dynamic pricing, and other underlying algorithms. Each functional module has its own set of evaluation metrics and independent optimization procedures. However, even if each module reaches its optimal state, the overall performance may not be optimal after being stitched into an integrated system. The joint optimization of multiple functional modules is a potential solution to ensure the overall optimality of the integrated system (Qin et al., 2021).

5.2. Designing and explaining machine-learning-based travel decision models inspired by discrete choice models

Given that ride-hailing services have accumulated a massive amount of trip data, the travel decision models reviewed in this paper are data-driven models based on machine learning, however, in transportation engineering, travel decisions are usually modeled using discrete choice models, which are also widely applied in both economics and sociology (Leong and Hensher, 2012). Researchers have gained a wealth of knowledge and expertise in the application of discrete choice models, which can help to understand the operation mechanism of machine-learning-based travel recommendation models and improve model interpretability; however, related studies are scarce and these warrants further investigation.

5.3. Establishing model-controlled traffic prediction so that prediction and control become a closed-loop

This paper reviews the research on the spatio-temporal dynamics in traffic data. Existing traffic prediction algorithms rely on previous data to extract potential patterns. However, in intelligent transportation system scenarios, they are vulnerable to the influences of external control factors, such as signal control strategy and train timetables, which can invalidate the patterns learned based on historical data. Model predictive control is a well-known model that considers both prediction and control in modeling, which greatly improves the performance of optimal control (Li et al., 2022). Nevertheless, model predictive control is limited to dealing with control problems, rather than problems in intelligent transportation systems such as traffic prediction, which are extensively required to serve traffic operation, design, management, and planning. Therefore, it is necessary to introduce control factors into the traffic prediction task so that the two form a closed loop for model-controlled traffic prediction.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Yang Liu reports financial support was provided by European Union.

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References

Acheampong, R.A., Siiba, A., Okyere, D.K., Tuffour, J.P., 2020. Mobility-on-demand: an empirical study of internet-based ride-hailing adoption factors, travel characteristics and mode substitution effects. Transport. Res. C Emerg. Technol. 115, 102638.
Agarwal, S., Charoenwong, B., Cheng, S.F., Keppo, J., 2022. The impact of ride-hail surge factors on taxi bookings. Transport. Res. C Emerg. Technol. 136, 103508.
Al-Abbasi, A.O., Ghosh, A., Aggarwal, V., 2019. Deeppool: distributed model-free algorithm for ride-sharing using deep reinforcement learning. IEEE Trans. Intell. Transport. Syst. 20 (12), 4714–4727.
Bailey Jr., W.A., Clark Jr., T.D., 1987. A simulation analysis of demand and fleet size effects on taxicab service rates. In: Proceedings of the 19th Conference on Winter Simulation, pp. 838–844.
Besse, P.C., Guillouet, B., Loubes, J.M., Royer, F., 2017. Destination prediction by trajectory distribution-based model. IEEE Trans. Intell. Transport. Syst. 19 (8), 2470–2481.
Cai, P., Wang, Y., Lu, G., Chen, P., Ding, C., Sun, J., 2016. A spatiotemporal correlative k-nearest neighbor model for short-term traffic multistep forecasting. Transport. Res. C Emerg. Technol. 62, 21–34.
Campigotto, P., Rudloff, C., Leodolter, M., Bauer, D., 2016. Personalized and situation-aware multimodal route recommendations: the FAVOUR algorithm. IEEE Trans. Intell. Transport. Syst. 18 (1), 92–102.
Castro-Neto, M., Jeong, Y.S., Jeong, M.K., Han, L.D., 2009. Online-SVR for short-term traffic flow prediction under typical and atypical traffic conditions. Expert Syst. Appl. 36 (3), 6164–6173.
Chen, X.M., Zahiri, M., Zhang, S., 2017. Understanding ridesplitting behavior of on-demand ride services: an ensemble learning approach. Transport. Res. C Emerg. Technol. 76, 51–70.
Chen, Y., Jiang, W., Fu, H., Liu, G., 2021, December. Spatio-temporal dynamic multi-graph attention network for ride-hailing demand prediction. In: International Conference on Neural Information Processing. Springer, Cham, pp. 133–144.
Ebel, P., Göl, I.E., Lingenfelder, C., Vogelsang, A., 2020. Destination prediction based on partial trajectory data. In: 2020 IEEE Intelligent Vehicles Symposium (IV). IEEE, pp. 1149–1155.
Fang, X., Huang, J., Wang, F., Zeng, L., Liang, H., Wang, H., 2020. Constgat: contextual spatial-temporal graph attention network for travel time estimation at Baidu maps. In: Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 2697–2705.
Feng, S., Ke, J., Yang, H., Ye, J., 2022. A multi-task matrix factorized graph neural network for co-prediction of zone-based and OD-based ride-hailing demand. IEEE Trans. Intell. Transport. Syst. 23 (6), 5704–5716.
Fu, T.Y., Lee, W.C., 2019. Deepist: deep image-based spatio-temporal network for travel time estimation. In: Proceedings of the 28th ACM International Conference on Information and Knowledge Management, pp. 69–78.
Fu, K., Meng, F., Ye, J., Wang, Z., 2020. Compacteta: a fast inference system for travel time prediction. In: Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 3337–3345.
Gammelli, D., Peled, I., Rodrigues, F., Pacino, D., Kurtaran, H.A., Pereira, F.C., 2020. Estimating latent demand of shared mobility through censored Gaussian processes. Transport. Res. C Emerg. Technol. 120, 102775.
Gao, J., Li, X., Wang, C., Huang, X., 2021. BM-DDPG: an integrated dispatching framework for ride-hailing systems. IEEE Trans. Intell. Transport. Syst.
Gao, R., Sun, F., Xing, W., Tao, D., Fang, J., Chai, H., 2022. CTTE: customized travel time estimation via mobile crowdsensing. IEEE Trans. Intell. Transport. Syst.

Ge, Y., Li, H., Tuzhilin, A., 2019. Route recommendations for intelligent transportation services. IEEE Trans. Knowl. Data Eng. 33 (3), 1169–1182.
Geng, X., Li, Y., Wang, L., Zhang, L., Yang, Q., Ye, J., Liu, Y., 2019. Spatiotemporal multi-graph convolution network for ride-hailing demand forecasting. Proc. AAAI Conf. Artif. Intell. 33, 3656–3663, 01.
Guo, S., Lin, Y., Li, S., Chen, Z., Wan, H., 2019. Deep spatial–temporal 3D convolutional neural networks for traffic data forecasting. IEEE Trans. Intell. Transport. Syst. 20 (10), 3913–3926.
Guo, X., Caros, N.S., Zhao, J., 2021. Robust matching-integrated vehicle rebalancing in ride-hailing system with uncertain demand. Transp. Res. Part B Methodol. 150, 161–189.
Haliem, M., Mani, G., Aggarwal, V., Bhargava, B., 2021. A distributed model-free ride-sharing approach for joint matching, pricing, and dispatching using deep reinforcement learning. IEEE Trans. Intell. Transport. Syst. 22 (12), 7931–7942.
He, Z., Chow, C.Y., Zhang, J.D., 2020. STNN: a spatio-temporal neural network for traffic predictions. IEEE Trans. Intell. Transport. Syst. 22 (12), 7642–7651.
Holler, J., Vuorio, R., Qin, Z., Tang, X., Jiao, Y., Jin, T., et al., 2019. Deep reinforcement learning for multi-driver vehicle dispatching and repositioning problem. In: 2019 IEEE International Conference on Data Mining (ICDM). IEEE, pp. 1090–1095.
Hong, H., Lin, Y., Yang, X., Li, Z., Fu, K., Wang, Z., et al., 2020. Heteta: heterogeneous information network embedding for estimating time of arrival. In: Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 2444–2454.
Huang, H., Bucher, D., Kissling, J., Weibel, R., Raubal, M., 2018. Multimodal route planning with public transport and carpooling. IEEE Trans. Intell. Transport. Syst. 20 (9), 3513–3525.
Huang, Z., Wang, D., Yin, Y., Li, X., 2021. A spatiotemporal bidirectional attention-based ride-hailing demand prediction model: a case study in beijing during COVID-19. IEEE Trans. Intell. Transport. Syst.
Huang, J., Luo, Y., Fu, S., Xu, M., Hu, B., 2021. pRide: privacy-preserving online ride hailing matching system with prediction. IEEE Trans. Veh. Technol. 70 (8), 7413–7425.
Jia, H., Fang, J., Tan, N., Liu, X., Huo, Z., Ma, N., et al., 2020, July. Context-aware route recommendation with weight learning through deep neural networks. In: 2020 American Control Conference (ACC). IEEE, pp. 4040–4045.
Jiang, M., Li, C., Li, K., Liu, H., 2022. Destination prediction based on virtual POI docks in dockless bike-sharing system. IEEE Trans. Intell. Transport. Syst. 23 (3), 2457–2470.
Jiang, H., Wang, M., Zhao, P., Xiao, Z., Dustdar, S., 2021. A utility-aware general framework with quantifiable privacy preservation for destination prediction in LBSs. IEEE/ACM Trans. Netw. 29 (5), 2228–2241.
Jin, G., Cui, Y., Zeng, L., Tang, H., Feng, Y., Huang, J., 2020. Urban ride-hailing demand prediction with multiple spatio-temporal information fusion network. Transport. Res. C Emerg. Technol. 117, 102665.
Jin, J., Zhou, M., Zhang, W., Li, M., Guo, Z., Qin, Z., et al., 2019. Coride: joint order dispatching and fleet management for multi-scale ride-hailing platforms. In: Proceedings of the 28th ACM International Conference on Information and Knowledge Management, pp. 1983–1992.
Ke, J., Zheng, H., Yang, H., Chen, X.M., 2017. Short-term forecasting of passenger demand under on-demand ride services: a spatio-temporal deep learning approach. Transport. Res. C Emerg. Technol. 85, 591–608.
Ke, J., Yang, H., Zheng, H., Chen, X., Jia, Y., Gong, P., Ye, J., 2018. Hexagon-based convolutional neural network for supply-demand forecasting of ride-sourcing services. IEEE Trans. Intell. Transport. Syst. 20 (11), 4160–4173.
Ke, J., Yang, H., Zheng, Z., 2020a. On ride-pooling and traffic congestion. Transp. Res. Part B Methodol. 142, 213–231.
Ke, J., Yang, H., Li, X., Wang, H., Ye, J., 2020b. Pricing and equilibrium in on-demand ride-pooling markets. Transp. Res. Part B Methodol. 139, 411–431.
Ke, J., Qin, X., Yang, H., Zheng, Z., Zhu, Z., Ye, J., 2021a. Predicting origin-destination ride-sourcing demand with a spatio-temporal encoder-decoder residual multi-graph convolutional network. Transport. Res. C Emerg. Technol. 122, 102858.
Ke, J., Feng, S., Zhu, Z., Yang, H., Ye, J., 2021b. Joint predictions of multi-modal ride-hailing demands: a deep multi-task multi-graph learning-based approach. Transport. Res. C Emerg. Technol. 127, 103063.
Khezerlou, A.V., Zhou, X., Tong, L., Li, Y., Luo, J., 2019. Forecasting gathering events through trajectory destination prediction: a dynamic hybrid model. IEEE Trans. Knowl. Data Eng. 33 (3), 991–1004.
Kim, T., Sharda, S., Zhou, X., Pendyala, R.M., 2020. A stepwise interpretable machine learning framework using linear regression (LR) and long short-term memory (LSTM): city-wide demand-side prediction of yellow taxi and for-hire vehicle (FHV) service. Transport. Res. C Emerg. Technol. 120, 102786.
Kucharski, R., Fielbaum, A., Alonso-Mora, J., Cats, O., 2021. If you are late, everyone is late: late passenger arrival and ride-pooling systems' performance. Transportmetrica: Transport. Sci. 17 (4), 1077–1100.
Lei, Z., Qian, X., Ukkusuri, S.V., 2020. Efficient proactive vehicle relocation for on-demand mobility service with recurrent neural networks. Transport. Res. C Emerg. Technol. 117, 102678.
Leong, W., Hensher, D.A., 2012. Embedding decision heuristics in discrete choice models: a review. Transport Rev. 32 (3), 313–331.
Li, J.Q., Zhou, K., Zhang, L., Zhang, W.B., 2012. A multimodal trip planning system with real-time traffic and transit information. J. Intell. Transport. Syst. 16 (2), 60–69.
Li, Y., Liu, Y., 2021. Optimizing flexible one-to-two matching in ride-hailing systems with boundedly rational users. Transport. Res. E Logist. Transport. Rev. 150, 102329.
Li, S., Liu, Y., Qu, X., 2022. Model controlled prediction: a reciprocal alternative of model predictive control. IEEE/CCA J. Autom. Sin. 9 (6), 1–4.
Liang, E., Wen, K., Lam, W.H., Sumalee, A., Zhong, R., 2021. An integrated reinforcement learning and centralized programming approach for online taxi dispatching. IEEE Transact. Neural Networks Learn. Syst.
Lin, X., Wang, Y., Xiao, X., Li, Z., Bhowmick, S.S., 2019, November. Path travel time estimation using attribute-related hybrid trajectories network. In: Proceedings of the 28th ACM International Conference on Information and Knowledge Management, pp. 1973–1982.
Lippi, M., Bertini, M., Frasconi, P., 2013. Short-term traffic flow forecasting: an experimental comparison of time-series analysis and supervised learning. IEEE Trans. Intell. Transport. Syst. 14 (2), 871–882.
Liu, Y., Liu, Z., Lyu, C., Ye, J., 2019. Attention-based deep ensemble net for large-scale online taxi-hailing demand prediction. IEEE Trans. Intell. Transport. Syst. 21 (11), 4798–4807.
Liu, H., Tong, Y., Zhang, P., Lu, X., Duan, J., Xiong, H., 2019a. Hydra: a personalized and context-aware multi-modal transportation recommendation system. In: Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 2314–2324.
Liu, H., Li, T., Hu, R., Fu, Y., Gu, J., Xiong, H., 2019b. Joint representation learning for multi-modal transportation recommendation. Proc. AAAI Conf. Artif. Intell. 33 (No. 01), 1036–1043.
Liu, Z., Liu, Y., Lyu, C., Ye, J., 2020. Building personalized transportation model for online taxi-hailing demand prediction. IEEE Trans. Cybern. 51 (9), 4602–4610.
Liu, Z., Li, J., Wu, K., 2022a. Context-aware taxi dispatching at city-scale using deep reinforcement learning. IEEE Trans. Intell. Transport. Syst. 23 (3), 1996–2009.
Liu, Y., Lyu, C., Zhang, Y., Liu, Z., Yu, W., Qu, X., 2021. DeepTSP: deep traffic state prediction model based on large-scale empirical data. Commun. Transport. Res. 1, 100012.
Liu, Y., Lyu, C., Liu, Z., Cao, J., 2021a. Exploring a large-scale multi-modal transportation recommendation system. Transport. Res. C Emerg. Technol. 126, 103070.
Liu, Y., Wu, F., Lyu, C., Li, S., Ye, J., Qu, X., 2022b. Deep dispatching: a deep reinforcement learning approach for vehicle dispatching on online ride-hailing platform. Transport. Res. E Logist. Transport. Rev. 161, 102694.
Liu, Y., Wu, F., Lyu, C., Liu, X., Liu, Z., 2021b. Behavior2vector: embedding users' personalized travel behavior to vector. IEEE Trans. Intell. Transport. Syst. https://doi.org/10.1109/TITS.2021.3078229.
Long, J., Shelhamer, E., Darrell, T., 2015. Fully convolutional networks for semantic segmentation. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 3431–3440.
Luo, Y., Jia, X., Fu, S., Xu, M., 2018. pRide: privacy-preserving ride matching over road networks for online ride-hailing service. IEEE Trans. Inf. Forensics Secur. 14 (7), 1791–1802.
Ma, T.Y., Rasulkhani, S., Chow, J.Y., Klein, S., 2019. A dynamic ridesharing dispatch and idle vehicle repositioning strategy with integrated transit transfers. Transport. Res. E Logist. Transport. Rev. 128, 417–442.
Ma, Z., Koutsopoulos, H.N., 2022. Near-on-demand mobility. The benefits of user flexibility for ride-pooling services. Transport. Res. C Emerg. Technol. 135, 103530.
Mäenpää, H., Lobov, A., Lastra, J.L.M., 2017. Travel mode estimation for multi-modal journey planner. Transport. Res. C Emerg. Technol. 82, 273–289.
Mao, X., Cai, T., Peng, W., Wan, H., 2021. Estimated time of arrival prediction via modeling the spatial-temporal interactions between links and crosses. In: Proceedings of the 29th International Conference on Advances in Geographic Information Systems, pp. 658–661.
Neto, F.D.N., de Souza Baptista, C., Campelo, C.E., 2018. Combining Markov model and prediction by partial matching compression technique for route and destination prediction. Knowl. Base Syst. 154, 81–92.
Niu, K., Wang, C., Zhou, X., Zhou, T., 2019. Predicting ride-hailing service demand via RPA-LSTM. IEEE Trans. Veh. Technol. 68 (5), 4213–4222.
Özkan, E., Ward, A.R., 2020. Dynamic matching for real-time ride sharing. Stoch. Syst. 10 (1), 29–70.
Pouls, M., Ahuja, N., Glock, K., Meyer, A., 2022. Adaptive forecast-driven repositioning for dynamic ride-sharing. Ann. Oper. Res. 1–34.
Qin, Z., Tang, X., Jiao, Y., Zhang, F., Xu, Z., Zhu, H., Ye, J., 2020. Ride-hailing order dispatching at DiDi via reinforcement learning. Inf. J. Appl. Anal. 50 (5), 272–286.
Qin, Z.T., Zhu, H., Ye, J., 2021. Reinforcement learning for ridesharing: a survey. In: 2021 IEEE International Intelligent Transportation Systems Conference (ITSC). IEEE, pp. 2447–2454.
Qin, X., Yang, H., Wu, Y., Zhu, H., 2021. Multi-party ride-matching problem in the ride-hailing market with bundled option services. Transport. Res. C Emerg. Technol. 131, 103287.
Qin, G., Luo, Q., Yin, Y., Sun, J., Ye, J., 2021. Optimizing matching time intervals for ride-hailing services using reinforcement learning. Transport. Res. C Emerg. Technol. 129, 103239.
Research and Markets, 2022. Ride-hailing market - growth, trends, COVID-19 impact, and forecasts, 2022 - 2027). Accessed April 19th, 2022. https://www.researchandmarkets.com/reports/5239571/ride-hailing-market-growth-trends-covid-19.
Rong, H., Zhou, X., Yang, C., Shafiq, Z., Liu, A., 2016. The rich and the poor: a Markov decision process approach to optimizing taxi driver revenue efficiency. In: Proceedings of the 25th ACM International on Conference on Information and Knowledge Management, pp. 2329–2334.
Ronneberger, O., Fischer, P., Brox, T., 2015. U-net: convolutional networks for biomedical image segmentation. In: International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, Cham, pp. 234–241.
Rossi, A., Barlacchi, G., Bianchini, M., Lepri, B., 2019. Modelling taxi drivers' behaviour for the next destination prediction. IEEE Trans. Intell. Transport. Syst. 21 (7), 2980–2989.

Shah, S., Lowalekar, M., Varakantham, P., 2020, April. Neural approximate dynamic programming for on-demand ride-pooling. Proc. AAAI Conf. Artif. Intell. 34 (No. 01), 507–515.
Shi, J., Gao, Y., Wang, W., Yu, N., Ioannou, P.A., 2019. Operating electric vehicle fleet for ride-hailing services with reinforcement learning. IEEE Trans. Intell. Transport. Syst. 21 (11), 4822–4834.
Song, Z., Wu, K., Shao, J., 2020. Destination prediction using deep echo state network. Neurocomputing 406, 343–353.
Smith, B.L., Williams, B.M., Oswald, R.K., 2002. Comparison of parametric and nonparametric models for traffic flow forecasting. Transport. Res. C Emerg. Technol. 10 (4), 303–321.
Sun, Y., Fu, K., Wang, Z., Zhou, D., Wu, K., Ye, J., Zhang, C., 2022. CoDriver ETA: combine driver information in estimated time of arrival by driving style learning auxiliary task. IEEE Trans. Intell. Transport. Syst. 23 (5), 4037–4048.
Sun, Y., Wang, Y., Fu, K., Wang, Z., Yan, Z., Zhang, C., Ye, J., 2021. FMA-ETA: estimating travel time entirely based on FFN with attention. In: ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, pp. 3355–3359.
Tang, K., Chen, S., Liu, Z., Khattak, A.J., 2018. A tensor-based Bayesian probabilistic model for citywide personalized travel time estimation. Transport. Res. C Emerg. Technol. 90, 260–280.
Tang, J., Liang, J., Liu, F., Hao, J., Wang, Y., 2021. Multi-community passenger demand prediction at region level based on spatio-temporal graph convolutional network. Transport. Res. C Emerg. Technol. 124, 102951.
Tong, Y., Chen, Y., Zhou, Z., Chen, L., Wang, J., Yang, Q., et al., 2017. The simpler the better: a unified approach to predicting original taxi demands based on large-scale online platforms. In: Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 1653–1662.
Tong, Y., Zeng, Y., Zhou, Z., Chen, L., Ye, J., Xu, K., 2018. A unified approach to route planning for shared mobility. Proc. VLDB Endow. 11 (11), 1633.
Wang, Y., Zheng, Y., Xue, Y., 2014. Travel time estimation of a path using sparse trajectories. In: Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 25–34.
Wang, Z., Fu, K., Ye, J., 2018. Learning to estimate the travel time. In: Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 858–866.
Wang, D., Zhang, J., Cao, W., Li, J., Zheng, Y., 2018. When will you arrive? estimating travel time based on deep neural networks. In: Thirty-Second AAAI Conference on Artificial Intelligence.
Wu, F., Wu, L., 2019, July. DeepETA: a spatial-temporal sequential neural network model for estimating time of arrival in package delivery system. Proc. AAAI Conf. Artif. Intell. 33 (No. 01), 774–781.
Xu, Z., Li, Z., Guan, Q., Zhang, D., Li, Q., Nan, J., et al., 2018. Large-scale order dispatch in on-demand ride-hailing platforms: a learning and planning approach. In: Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 905–913.
Xu, Y., Wang, W., Xiong, G., Liu, X., Wu, W., Liu, K., 2022. Network-flow-based efficient vehicle dispatch for city-scale ride-hailing systems. IEEE Trans. Intell. Transport. Syst. 23 (6), 5526–5538.
Xue, A.Y., Zhang, R., Zheng, Y., Xie, X., Huang, J., Xu, Z., 2013. Destination prediction by sub-trajectory synthesis and privacy protection against such prediction. In: 2013 IEEE 29th International Conference on Data Engineering (ICDE). IEEE, pp. 254–265.
Yan, C., Zhu, H., Korolko, N., Woodard, D., 2020. Dynamic pricing and matching in ride-hailing platforms. Nav. Res. Logist. 67 (8), 705–724.
Yang, R., Lai, M., 2021. Multi-level analyses on the nearest-first matching policy of on-demand chauffeured ride-hailing service. Int. J. Sustain. Transport. 15 (10), 749–767.
Yao, H., Wu, F., Ke, J., Tang, X., Jia, Y., Lu, S., et al., 2018, April. Deep multi-view spatial-temporal network for taxi demand prediction. Proc. AAAI Conf. Artif. Intell. 32 (1).
Yousaf, J., Li, J., Chen, L., Tang, J., Dai, X., 2014. Generalized multipath planning model for ride-sharing systems. Front. Comput. Sci. 8 (1), 100–118.
Yu, X., Shen, S., 2019. An integrated decomposition and approximate dynamic programming approach for on-demand ride pooling. IEEE Trans. Intell. Transport. Syst. 21 (9), 3811–3820.
Yu, H., Shu, J., Jia, X., Zhang, H., Yu, X., 2019. LpRide: lightweight and privacy-preserving ride matching over road networks in online ride hailing systems. IEEE Trans. Veh. Technol. 68 (11), 10418–10428.
Yu, H., Zhang, H., Yu, X., Du, X., Guizani, M., 2020. PGRide: privacy-preserving group ridesharing matching in online ride hailing services. IEEE Internet Things J. 8 (7), 5722–5735.
Yuan, J., Zheng, Y., Xie, X., Sun, G., 2011. T-drive: enhancing driving directions with taxi drivers' intelligence. IEEE Trans. Knowl. Data Eng. 25 (1), 220–232.
Yuen, C.F., Singh, A.P., Goyal, S., Ranu, S., Bagchi, A., 2019. Beyond shortest paths: route recommendations for ride-sharing. In: The World Wide Web Conference, pp. 2258–2269.
Zhang, J., Zheng, Y., Qi, D., Li, R., Yi, X., 2016. DNN-based prediction model for spatio-temporal data. In: Proceedings of the 24th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, pp. 1–4.
Zhang, C., Zhu, F., Lv, Y., Ye, P., Wang, F.Y., 2021. MLRNN: taxi demand prediction based on multi-level deep learning and regional heterogeneity analysis. IEEE Trans. Intell. Transport. Syst.
Zhang, D., Xiao, F., 2021a. Dynamic auto-structuring graph neural network: a joint learning framework for origin-destination demand prediction. IEEE Trans. Knowl. Data Eng. https://doi.org/10.1109/TKDE.2021.3135898.
Zhang, D., Xiao, F., Shen, M., Zhong, S., 2021b. DNEAT: a novel dynamic node-edge attention network for origin-destination demand prediction. Transportation Research Part C: Emerg. Technol. 122, 102851.
Zhang, J., Hasan, S., Yan, X., Liu, X., 2021c. Spatio-temporal mobility patterns of on-demand ride-hailing service users. Transport. Lett. 1–12.
Zhu, Z., Sun, L., Chen, X., Yang, H., 2021. Integrating probabilistic tensor factorization with Bayesian supervised learning for dynamic ridesharing pattern analysis. Transport. Res. C Emerg. Technol. 124, 102916.
Zhu, P., Mo, H., 2022. The potential of ride-pooling in VKT reduction and its environmental implications. Transport. Res. Transport Environ. 103, 103155.
Zou, M., Li, M., Lin, X., Xiong, C., Mao, C., Wan, C., et al., 2016. An agent-based choice model for travel mode and departure time and its case study in Beijing. Transport. Res. C Emerg. Technol. 64, 133–147.
Zuo, H., Cao, B., Zhao, Y., Shen, B., Zheng, W., Huang, Y., 2021. High-capacity ride-sharing via shortest path clustering on large road networks. J. Supercomput. 77 (4), 4081–4106.

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