Efficient Ridesharing Framework for Ride-matching via Heterogeneous Network Embedding

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Ridesharing has attracted increasing attention in recent years, and combines the flexibility and speed of private cars with the reduced cost of fixed-line systems to benefit alleviating traffic pressure. A major issue in ridesharing is the accurate assignment of passengers to drivers, and how to maximize the number of rides shared between people being assigned to different drivers has become an increasingly popular research topic. There are two major challenges facing ride-matching: scalability and sparsity. Here, we show that network embedding drives the optimal matches between drivers and riders. Contrary to existing approaches that merely depend on the proximity between passengers and drivers, we employ a heterogeneous network to learn the latent semantics from different choices in two types of ridesharing, and extract features in terms of user trajectories and sentiment. A novel framework for ridesharing, RShareForm, which encodes not only the objects but also a variety of semantic relationships between them, is proposed. This article extends the existing skip-gram model to incorporate meta-paths over a proposed heterogeneous network. It allows diverse features to be used to search for similar participants and then ranks them to improve the quality of ride-matching. Extensive experiments on a large-scale dataset from DiDi in Chengdu, China show that by leveraging heterogeneous network embedding with meta paths, RShareForm can significantly improve the accuracy of identifying the participants for ridesharing over existing methods, including both meta-path guided similarity search methods and variants of embedding methods.

CCS Concepts: • **Human-centered computing** → **Empirical studies in ubiquitous and mobile computing**;

Additional Key Words and Phrases: Ridesharing matching, network embedding, heterogeneous network, meta-path, skip-gram

ACM Reference format:

Lei Tang, Zihang Liu, Yaling Zhao, Zongtao Duan, and Jingchi Jia. 2020. Efficient Ridesharing Framework for Ride-matching via Heterogeneous Network Embedding. *ACM Trans. Knowl. Discov. Data* 14, 3, Article 27 (March 2020), 24 pages.
<https://doi.org/10.1145/3373839>

This work was funded by the Key Science and Technological Innovation Team of Shanxi Province, China (Grant No. 2017KCT-29) and the Key Research and Development Plan Project of the Shaanxi Province, China (Grant No. 2019ZDLGY17-08, 2019ZDLGY03-09-01).

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1556-4681/2020/03-ART27 \$15.00

<https://doi.org/10.1145/3373839>

1 INTRODUCTION

With a one-time transaction, ridesharing allows passengers to be assigned to a nearby driver and be shuttled to their destination [1]. Due to the increasing empirical evidence indicating ridesharing's usage and impact [2], much strategic investment, such as that by Zipcar and Lyft in the USA, and DiDi in China, has been made to effectively participate in on-demand ridesharing delivery. Ridesharing raises a number of public interest questions. Rayle et al. [3] collected completed surveys on the use of public transit and ridesharing in San Francisco. They showed that speed (e.g., short waiting time) and convenience (e.g., ease of calling a car) were the main attractions for ridesharing. Thus, the development of a ridesharing service must take into account the participants' requirements, which also include origins and destinations, trip purpose, and acceptable waiting time, as well as passenger willingness in matching drivers.

In this work, we focus on the problem of ridesharing matching [4], where passengers with similar travel plans are matched to the same driver in real time. In ridesharing, the participants are commonly divided into servers/drivers and clients/passengers [5]; thus, we address this issue by formulating a participant searching problem that aims at designing a method to automatically assign potential passengers to a driver. Instead of dealing with proximity, we treat the information of a ridesharing plan as nodes in a network. An illustration of the problem appears in Figure 1.

Current harvesting techniques can extract different types of travel-related information from trajectories [6, 7] or a social network [8–10] and fuse them to find a ride-share partner. Various kinds of auxiliary data (e.g., spatial dispersion, temporal duration, and movement velocity) become available in ridesharing matching systems. It is difficult to model and utilize this heterogeneous and complex travel-related information. Furthermore, it is more challenging to develop a relatively general approach to model these varying data in different ride-matching systems or platforms. Besides, the potential of information harvesting to automatically (or semi-automatically) abstract data and latent relations between the features that may impact ridesharing behavior is still unexplored. For example, existing approaches can match drivers and passengers by assessing the similarity of their origin-destination (OD) pair [6, 11, 12], or by using demographic information (e.g., gender and estimated income) as well as individual interests [13, 14]. Such explicit markers are obviously difficult to directly obtain in many practical environments due to privacy concerns or technological limitations. It is also difficult for these approaches to characterize complex travel features (e.g., on-demand pickup time in unexpected circumstances) and the associations between them, such as when and where the participants should meet to minimize the waiting time of passengers [15].

To measure the relevance of the driver and passenger for ride-matching, neighborhood-based measures such as common neighbors and Jaccard's coefficient have been proposed. Other graph-theoretic measures that are based on random walks between objects include Personalized PageRank and SimRank. These measures do not consider multiple types of relationships connecting participants with their attributes, which we represent in a heterogeneous information network (HIN) [16]. Hence, the idea of our work is to leverage meta-path-based semantic relatedness between participants over HINs for ride-matching. Returning to the earlier example, by constructing a HIN, passengers are connected with a driver through links including a set of locations, timestamps, and text contents through online activities.

However, meta-path-based similarities mainly characterize semantic relations defined over HINs, and may not be directly applicable to ridesharing matching systems. To address the above-mentioned challenges, we propose a framework, RShareForm, in this article. We first learn the complicated mapping mechanism of ridesharing HIN information, taking into account user trajectories and willingness. We then characterize nodes from HINs with low-dimensional vectors,

Fig. 1. Illustration of participant searching problem.

i.e., embeddings. In our framework, nodes are first embedded as vectors along with the meta-paths derived from a ridesharing HIN. Then, the embeddings are shared and jointly trained to rank possible passengers for a given driver. Instead of relying on existing network embedding, we derive the meta-paths that have explicit impacts on matching performance and learn effective heterogeneous network representations for summarizing important structural characteristics of HINs and participants' attributes. Considering that passengers may refuse a ridesharing arrangement without sufficient comfort, a driver in the underlying proximity can be dispatched to serve passengers and further improve the effectiveness of ride-matching services in the existing platform. This is especially beneficial when people share rides with strangers, where it helps to create a capacity to improve travel satisfaction.

The contributions of this article are summarized as follows.

- We formalize two types of ridesharing, end-points and en route, and extract features in terms of user trajectories and sentiment. Instead of using the features only, we further analyze multiple types of semantic relationships between them.
- To the best of our knowledge, we are the first to employ heterogeneous networks to utilize the latent semantics from different choices in two types of ridesharing. Based on the features extracted, the ridesharing will be represented by a structural HIN.
- We investigate the ride-matching problem of embedding for heterogeneous networks, which incorporate meta-paths derived from a ridesharing HIN to link the drivers and passengers. We propose a framework, RShareForm, that learns a unique embedding representation to encode the travel information on the participants, and evaluates the similarity of participants, taking into account the multiple types of proximities.
- Through extensive experiments, we demonstrate the efficacy of the presented method in ridesharing matching problems, such as network embedding, achieving relative improvements of at least 9.5% over baselines, and similar participant searching, achieving relative gains of 25% over benchmarks. The novel framework may be welcome for an online system, such as Didi Chuxing, due to its higher matching efficiency.

2 RELATED WORK

The implementation of ridesharing is based on the dynamic and real-time matching of passenger and driver [17]. On-demand ride-matching is where passengers with similar origins and destinations are matched to the same driver in real time, and the ride and costs are split among the passengers. Some commercial matching agencies, such as ZimRide, Avego, and Carticipate, help people to establish ride-shares at short notice. However, several constraints on the feasibility of

matches must be observed. Besides the timing of rides and the availability of spare seats, driver preferences (e.g., a maximum deviation from a direct route) [18] must be accounted for in the ride-matching. A good matching system helps decrease the driver's pressure-based risk factors associated with rushing to accept matches and pick up passengers. In addition, many forms of social media are used in ride-matching. For example, Twitter data were used to extract OD trips as used in some ridesharing group query models. Lee et al. [19] conducted trip planning by harvesting geolocations from tweets in the Greater Los Angeles metropolitan area. For the OD trips, designed to recognize ridesharing behavior, cell phone data, often containing and storing the call description record (CDR) over time and from different Base Transceiver Station (BTS) towers [20] can also provide a different point of view on the duration of OD trips compared with social media. The subjects gave consent to be geotagged and have their data aggregated to identify their home and work locations as well as their commuting routes. Many existing works on rideshare matching rely on similar trajectory clustering [21–24]. For example, Galland et al. created a private social network (PrivNet) [25] to denote each participant's profile including their role and relationships with others. PrivNet identified the preferred candidates for ride-matching, in terms of start location, OD, interests, and requirements from the profile. However, it is difficult to model and utilize this heterogeneous and complex information. Furthermore, it is more challenging to develop a relatively general approach to model these varying data in different mobility systems. Thus, HIN, which contains multiple types of entities connected by different types of relations, can be adopted in the ride-matching systems to characterize rich data [26]. In this article, we adopt a HIN for representing the multiple types of semantic relationships between different objects in ridesharing, such as a passenger and his travel time, that would enable extraction of significant semantic knowledge for ride-matching. Under the HIN-based representation, the ride-matching problem can be considered a similar participant search task over the HIN.

Many works have been devoted to mining heterogeneous networks in the past few years [27–30] to study such networks with multiple types of nodes and links, i.e., heterogeneous network embedding has been proposed, as well as studies like metapath2vec, Predictive text embedding (PTE) [31], and Embedding of Embedding (EOE) [32]. Some existing network embedding methods are applied in e-commerce, e.g., to identify the enterprise customer [33] and to recommend items [34]; as well as bibliographic, e.g., to identify the author-article [35] and to label the article [36]; and social networks [37]. However, heterogeneous network embedding methods are seldom used in transportation studies. Li et al. learned the representations from the raw historical trips to predict OD travel time [38]. The MURAT model they proposed utilized the underlying road network structure and the spatio-temporal property as prior knowledge, rather than estimating the travel time on the most likely path. In [39], Liu et al. proposed the Leader-Writer network for dialogue summarization used in the customer service of DiDi. Each word in the dialogues was embedded into a low-dimension vector and was fed as input into the hierarchical encoder/decoder network, which generated the prediction for summary tasks. One common limitation of these approaches is that the trip features (e.g., origin, destination, and departure time) are represented and learned independently, and thus the proximity between trips is difficult to generalize to cases in which no or a very limited number of similar features are available. Thus, to deal with the insufficiency of relationships between a driver and passenger and discover the proximity well, it is desirable to learn a feature representation that preserves the proximity in low-dimensional space. To address this problem, in this article we propose a ridesharing framework that can generate proximities. As a result, the generated proximity can help discover potential passengers for a driver to benefit ridesharing. To the best of our knowledge, existing works make a straightforward use of raw features to build models, and very limited attention has been paid to finding a proper representation for transportation problems, especially for ridesharing matching.

3 PRELIMINARIES

3.1 Heterogeneous Information Network

Definition 1. A HIN [40] is defined as a network with multiple types of nodes and/or multiple types of links. It can be denoted $H = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ is a set of nodes and $\mathcal{E}$ is a set of links. The links can be weighted, unweighted, directed, and undirected. A node-type mapping function $f_v : \mathcal{V} \rightarrow \mathcal{A}$ maps the node to a predefined type, and a link-type mapping function $f_e : \mathcal{E} \rightarrow \mathcal{R}$ maps the link to a predefined link type.

A heterogeneous network is comprised of different but related nodes that are connected by inter-network edges. The term “different” means that vertices of networks are of different types, while the term “related” means that two nodes have a particular type of interaction or relationship.

3.2 Ridesharing Matching Problem

Our approach to ridesharing matching is by formulating the participant searching problem using heterogeneous networks. Given a network, our goal is to learn a representation for each node and determine the assignment of passengers to drivers considering the similarities between participants. For each driver $d \in \mathcal{V}$, we represent its neighborhood in network H as $N_d = \{N_d^{(1)}, N_d^{(2)}, \dots, N_d^{(T)}\}$, where $N_d^{(t)}$ is a set of neighbor nodes of the t th-node type. The node types include the OD pair, departure time, pick-up and drop-off locations of passengers, and so on. We use N_d to denote the set of passengers that can be assigned to the driver.

Ridesharing Matching Problem. Given a set of drivers and passengers represented as (N, P) where $N = \{N_d\}$ and $P = \{P_d\}$, the goal is to learn a model to rank potential passengers for every driver d based on information in N_d and such that its top ranked passengers are in P_d .

Detailed information about the notation used in Sections 3 and 4 is provided in the Appendix.

4 PROPOSED METHOD

In this section, we introduce the approach to the way we model the ridesharing features in HIN, and how to solve the matching problem based on the representation using RShareForm.

4.1 Feature Extraction

Ridesharing takes on different characteristics depending on whether or not drivers have their own original trip plan and preferences. The differences bring about the notion of single- versus double-sided matching [4]. The driver and all the passengers must agree on the costs and schedules, including the OD, departure time, and pick-up and drop-off locations of passengers in the latter case. Here we analyze the different behaviors of passengers and drivers participating in ridesharing and classify ridesharing types. In the literature [4], Furuhashi et al. classified ridesharing according to how the differences influence matching. Here, we extend their classification to extract how a variety of features impact ridesharing behavior.

We now present some symbols and notation for the features. Here, we formulate the end-points of ridesharing among people where both the origin and destination of a passenger are on the original route of the driver. All the trips are accomplished by ridesharing. In addition, a driver might be able to pick up several passengers that have routes “covered” by his own. Thus, the effectiveness of ride-sharing can be greatly enhanced by picking up additional passengers en route where ridesharing is only a part of the passenger’s trip. When we say a driver’s original route, we mean the route they would have taken if not participating in ridesharing. Figure 2 presents an illustrative example of en route ridesharing trips in Chengdu, China. To facilitate sharing a ride, passengers may be asked to meet at a designated location (e.g., the geometric center of an area or

Fig. 2. Illustration of en route ridesharing in Chengdu, China, assuming each bundle of trips are spatially close enough. In the figure, trips T₁, T₂, and T₃ have nearby trip origins, destinations, and departure times (same for trips T₄ and T₅). Consequently, these trips can be grouped into the same ride. Trips T₆ and T₇, however, have different departure dates, and there is no matching ride for trip T₈.

a landmark near their point of origin) to take the ride and will be dropped off at a place that is a compromise between the needs of all people on board.

Instead of classifying the patterns only given by Furuhashi, we further use the following representations to clarify this difference. We denote d as a driver and p as a passenger. Each driver and passenger have their preferred origin and destination. We denote x as a pick-up location and y as a drop-off location. We assume that each driver has his or her original route $R(d)$. Let $TT(O, D)$ denote the travel time between the origin and destination of passenger p or driver d and $Dtime$ denote the departure time of passenger p or driver d from a location. Suppose a passenger is maximal and all others in P can take a ride. Further, if only p 's departure time is before that of d , d can take them to the destination. Suppose a passenger n is among the last to depart, i.e., $Dtime_n = \forall p, \max_p Dtime_p$. We can conclude that $Dtime_n \leq Dtime_d$. Thus, a driver d can have p as a passenger for end-point ridesharing only if $\forall p, \max_p TT(O_p, D_p) < TT(O_d, D_d)$ and $\max_p Dtime_p \leq Dtime_d$. En route ridesharing is a typical form of travel in which passengers walk to a pick-up location (e.g., the origin of the driver) on the original route of driver, take the trip at the departure time, debark at the driver's destination or drop-off location, and then walk to their final destination [13]. The vehicle will pass by somewhere within walking distance of the passenger's route. We denote MT_p as the maximum walking time of passenger p between the location of origin/pick-up and destination/drop-off; that is, $MT_p = \forall p, \max_p (TT(O_p, x_p), TT(y_p, D_p))$. Effective ride-matching may help achieve the reduction in total saved travel time. Thus, a driver can pick-up if $TT(O_p, x_p) + TT(y_p, D_p) + TT(x_p, y_p) < TT(O_p, D_p)$. We can also conclude that $\forall p, TT(O_p, x_p) + TT(y_p, D_p) \leq 2MT_p < TT(O_p, D_p) - TT(x_p, y_p)$.

We classify two modes of ridesharing as illustrated in Table 1. Note that en route ridesharing is an end-point type while $MT_p \neq 0$. In the following, we extract the features in terms of trips and preferences based on the descriptions of ridesharing types.

4.1.1 Trajectory-related Extraction. In selecting between different ridesharing types, travellers usually consider a number of criteria, such as cost, travel time, and convenience, including the location of the pick-up and drop-off points [2]. Therefore, they can be used as representations of the behavior of participants in a rideshare. To extract these features from vehicular trajectory data,

Table 1. Different Types of Ridesharing

	Types	Representation
end-points ridesharing	$O_p, D_p \in R(d)$	$\forall p, \max_p TT(O_p, D_p) < TT(O_d, D_d)$ $\max_p DTime_p \leq DTime_d$
en route ridesharing	$x_p, y_p \in R(d) \& \neg(O_p \in R(d) \& D_p \in R(d))$	$MT_p < \frac{TT(O_p, D_p) - TT(x_p, y_p)}{2}$ $\forall p, MT_p = \max_p (TT(O_p, x_p), TT(y_p, D_p))$

Fig. 3. Schematic example of order records converted in daily trips for one passenger. Activities are inferred in stay locations and daily trips are measured by time of day between these stays. The number in the circle represents the probability a passenger performs an activity in a location.

we first collect OD pairs, stay points, and then trips that occur between these stays. To generate an activity type for a trip, all OD-related locations are labelled as home, work, or other, using the time of day. Based on our previous work [41], we can transform daily trajectories into separate individual trips with labelled locations, assigned departure times, and activity types.

Note that the sample subject of Figure 3 generates different trips in the 3 days of observation. These trips would be distributed across the day based on the observed departure time of the stays. This conversion procedure aims to generate a representative sample of trips from passengers to account for the choices of the total population.

4.1.2 Ride Sentiment Extraction. En route ridesharing presents further complications for the instantaneous decision-making for passengers due to the additional travel cost incurred by the request of the pick-up and/or drop-off locations. Here, each driver or passenger has his/her own origin and destination.

Example. Suppose a driver d and a passenger p aim to travel from O_d to D_d and O_p to D_p , respectively. The locations at $O_d(D_d)$ and $O_p(D_p)$ cover different regions. If p can pass close to the regions covered by the $O_d(D_d)$, the two can meet at some point (i.e., l_m) between if it saves overall travel costs, even though it requires a detour. In addition to the costs of the two original paths $\mathcal{P}^1 = O_d \rightarrow l_m^1 \rightarrow D_d$, and $\mathcal{P}^2 = O_p \rightarrow l_m^2 \rightarrow D_p$, the time cost introduced by the “meeting” path $\mathcal{P}^3 = l_m^1 \rightarrow l_m^2$ should also be taken into consideration (where $\rightarrow$ represents a sub-path). We consider the situation where d and p may meet and go to their destinations along the ridesharing path by treating O_p, l_m^2 as the same location. Therefore, the “meeting” path is converted to $\mathcal{P}^3 = O_p \rightarrow l_m^1$. There is a drop-off location l_m^3 on d ’s path for passenger p , the “separating” path

Fig. 4. Find a meeting point for en route ridesharing.

$\mathcal{P}^4 = l_m^3 \rightarrow D_p$. Supposing a passenger p walks at an average speed of 3 mph, then they will join the routes with the extra cost $\frac{\text{distance}(\mathcal{P}^3) + \text{distance}(\mathcal{P}^4)}{3}$.

Ride sentiment [42, 43] measures the tendency of a passenger to join the route. We determine the optimal meeting point (i.e., l_m^1) and separating point (i.e., l_m^3) for a driver-passenger pair and identify the time (i.e., MT_p) taken by a passenger to meet with the driver. In this article, the time of a passenger is treated as the index for detecting ride sentiments in real time. A set of pairs of origin and destination points from the order records are extracted and then used to generate some short routes (i.e., $R(p)$) connecting these ODs respectively. We refer to the work of Huang et al. [44] to find a meeting point on the driver's original route that gives greatest reduction in total saved travel time.

Example. Figure 4 illustrates the meeting point identified on the urban street network using the order records from the dataset. Edges are represented using geographical distance as a weight. The red lines represent the shortest paths connecting two trajectory points, where x_p is on the original route of the driver. O_{p^1} and D_{p^1} are the origin and destination points of the passenger, respectively, while O_d and D_d are those of the driver, respectively. For a matching query $q_m = O_{p^1}, D_{p^1}, O_d, D_d$, the search starts from all nodes in q_m , and then expands from the closest one outwards. For the first iteration, $\omega(O_d) = \delta(O_d, O_d) + \delta(O_d, O_{p^1}) + \delta(O_d, D_{p^1}) + \delta(O_d, D_d) = 0 + 6 + 12 + 11 = 29$, where $\delta(\cdot)$ denotes the distance between two nodes. Similarly, $\omega(O_{p^1}) = 28$, $\omega(D_{p^1}) = 31$, $\omega(D_d) = 34$. Then, $M = \min(\omega(O_d), \omega(O_{p^1}), \omega(D_{p^1}), \omega(D_d)) = 28$, and the sum of distances due to the expansion on network, T , is set to 0. Owing to $M > T = 0$, it expands to the next nodes $q_m = v_2, v_9, v_{11}, x_p$, and M is updated as 25, for $\omega(x_p) = 25$. Since $M > T = 8$, it expands and continues until $M = T$, and the meeting point is x_p with weight 25, and then $\mathcal{P}^3 = \{(O_{p^1}, x_p, D_{p^1}), (O_d, x_p, D_d)\}$, $MT_p = \frac{\text{distance}(O_{p^1}, x_p)}{S}$, where S denotes the walking speed.

4.2 Exploiting Ridesharing HIN

Given the analysis of the rich features and relationship types for ridesharing matching, it is important to model them in a proper way so that different relations can be handled more effectively [45]. In this section, we introduce how to represent ridesharing by using the features extracted above. As argued above, a ridesharing network can be seen as a weighted heterogeneous network. It is centered by location a driver or passenger stayed, such as the OD pair and pick-up/drop-off point. The node types $\mathcal{A}$ in the network include *location(L)*, *activity(A)*, *time(T)*, and *user(U)*¹. The set

Fig. 5. Network schema of the ridesharing HIN. Each node denotes a node type and each link denotes a link type.

(a) Toy example of the ridesharing HIN.

(b) Red dotted lines denote ridesharing relationships, green dotted lines OD relationships, and yellow dotted lines travel time relationships.

Fig. 6. The purpose of introducing the ridesharing HIN is to create connections between drivers and passengers. The intuition is that the connected driver-passenger pairs should be more likely to have the same requirements. We provide the following definition of the term “meta-path.”

of link types $\mathcal{R}$ includes *occur* between activity and location, *route* between locations, and *range* between times. For each location $l \in L$, there are links to a set of users, an activity, and a set of departure times, belonging to a set of link types $\mathcal{R}$. It may also contain route information connecting two locations, and time interval information for some passengers walking toward meeting points for boarding. A meta path [40] is used to formulate the semantics of the higher-order relationships among entities. The network schema and associated meta-paths are shown in Figure 5.

¹To illustrate the ridesharing HIN, a simple example is shown in Figure 6. Suppose there are three people, where u_3 can offer a ride as a driver and the other two can make a request for transportation as passengers. They want to take part in ridesharing if their requirements (start and end locations, departure time, expected arrival time, and willingness to join) are satisfied. In addition to the user entities, there are the following three other types of entity in this network: locations (square nodes), activities (circular nodes), and time (polygonal nodes). In this example, we know that u_3 would like

¹We treat the driver and passenger as the user (i.e., Type-U) nodes in a ridesharing HIN.

Fig. 7. Illustration of RShareForm.

to travel from home to the university with a departure time of 8:00 and an arrival time of 9:00. u_1 submits a request from home to the university with a departure time of 8:30 and arrival time 9:00. u_2 submits a request to go to the library, which is on the original route of u_3 with a departure time of 8:10 and arrival time 8:40. Therefore, u_1 and u_3 are linked to the same location node of “university.” Similarly, users u_1 and u_2 are both interested in reading activity according to the location (“library”) and thus they are connected to the location node of “library” following the activity node of “reading.” These requests from u_1 and u_2 are on the route of driver u_3 , and thus can be assigned to u_3 to create a ridesharing match.

Definition 2 (Meta-path). A meta-path [40] is a path defined on the network schema $T_H = (\mathcal{A}, \mathcal{R})$ and is denoted in the form $V_1 \xrightarrow{r_1} V_2 \xrightarrow{r_2} V_a \xrightarrow{r_a} V_{a+1} \xrightarrow{r_{m-1}} V_m$, which represents the compositional relations between two given node types. Meta-paths are commonly used in a symmetric way; that is, its first node type V_1 is the same as the last one, V_m .

A typical meta-path for ridesharing matching is $user \xrightarrow{stays} location \xrightarrow{stays^{-1}} user$. This means that we want to match a driver with a passenger through the path containing the same location over the network. There can be multiple locations satisfying this meta-path constraint. Moreover, examples of meta paths defined in the network schema of Figure 5 include $location \rightarrow activity \leftarrow location$, and $location \rightarrow time \leftarrow location$. From these two examples, it is easy to see that in a ridesharing HIN, even comparing two nodes of the same type (e.g., location) going from different paths can lead to different meanings. Thus, we rank the potential passengers on the basis of information on a location (e.g., time range).

4.3 RShareForm Construction

In this section, we introduce the proposed framework in more detail. The basic idea of RShareForm is demonstrated in Figure 7. We consider that each user node is encoded into multiple pairs, and the node proximities of different pairs are preserved, which further are used to rank potential

passengers. This is different from conventional ridesharing matching methods, which present several criteria to search the similar participants. However, the semantics in the spatial layout (e.g., activity at certain locations) are ignored, leading to the inability to fully discover the participants [46]. RShareForm will learn the participant proximity from both local trajectories information and global ride sentiment through a network-embedding-based method.

4.3.1 Meta-path-based Embedding for Ridesharing Matching. We propose a novel network embedding for representing a ridesharing HIN. As in most of the existing representation learning methods [47], we represent each node $v \in \mathcal{V}$ as a d -dimensional vector in an embedded space via a projection function $f: \mathcal{V} \rightarrow \mathbb{R}^d$. The learned node representation can thus be used as the feature input of a similarity search task in ride-matching.

To model nodes and edges of different types in the ridesharing HIN, we consider the meta-paths that encode different meanings of links [35]. For example, connections between two users can encode multiple similarities for ridesharing matching; (1) they are associated with the same ride time, or (2) they are interested in the same pick-up location. Clearly, these two types of connections indicate different semantics. Therefore, we generalize the existing metapath2vec [48] embedding model to propose a meta-path-based network embedding that preserves proximities among user nodes.

There are two stages in constructing the feature representation induced by meta-paths. In the first stage, we conduct meta-path-based random walks to generate a sequence of nodes. Given a meta-path schema starting from a node v_a^i , the probability of selecting node v^{i+1} at step i will be conditioned on the given path $\mathcal{P}$, which is defined as follows:

$$p(v^{i+1}|v_a^i, \mathcal{P}) = \begin{cases} \frac{1}{|N_{a+1}(v_a^i)|} & (v^{i+1}, v_a^i \in \mathcal{E}, f_{\mathcal{V}} = a + 1) \\ 0 & (v^{i+1}, v_a^i \in \mathcal{E}, f_{\mathcal{V}} \neq a + 1), \\ 0 & (v^{i+1}, v_a^i \notin \mathcal{E}) \end{cases} \quad (1)$$

$$p(v^{i+1}|v_1^i, \mathcal{P}) = p(v^{i+1}|v_m^i, \mathcal{P}), \quad (2)$$

where $v_a^i \in V_a$ and $N_{a+1}(v_a^i)$ denote the neighborhood of node v_a^i along the predefined meta-path $\mathcal{P}$. As a result, the flow of the walker is conditioned on $\mathcal{P}$ only if $v^{i+1} \in V_{a+1}$. Taking Figure 6 as an example, meta-path “ULTLU” represents two users (U) who board at the same location (L) at the same time (T). Under “ULTLU,” the next step of a walker on node “home” is biased toward time nodes (T) given its previous step on at user node u_1 (U), following the semantics of this path.

In the second stage, we perform a heterogeneous skip-gram over the generated sequences to build a feature vector for each type-U node. For any node v_u in the sequence, assuming it appears in position j , we will take v_{j-c}, v_{j+c} as its neighbors with the a th type of nodes, where c is half of the window size. Thus, given a user node v_u , our objective is to maximize the conditional probability of having the heterogeneous neighbor’s context:

$$\arg \max_p \sum_{v \in \mathcal{V}} \sum_{a \in \mathcal{A}} \sum_{v_{j-c}, v_{j+c} \in N_a(v_u)} \log p(v_{j-c}, v_{j+c}|v_u; \theta), \quad (3)$$

where $\log p(v_{j-c}, v_{j+c}|v_u; \theta)$ can be further factorized as $\prod_{k=j-c}^{j-1} \log p(v_k|v_u; \theta) \cdot \prod_{k=j+1}^{j+c} \log p(v_k|v_u; \theta)$ given the conditional independence assumption. $p(v_k|v_u; \theta)$ defines the conditional probability of having a set of context nodes v_k given a node v_u using a softmax function:

$$p(v_k|v_u; \theta) = \frac{\exp(X_{v_k}^T \cdot X_{v_u})}{\sum_{v \in \mathcal{V}} \exp(X_v^T \cdot X_{v_u})}, \quad (4)$$

Fig. 8. Example of driver-passenger vector representation.

where X_{v_u} represents the embedding vector for node v_u . For illustration, considering the ridesharing network of Figure 6, the neighborhood of one user node u_1 can be physically close to another user's (e.g., u_2 or u_3), location (e.g., home, university, library, or park), time range (8:00–9:00, 8:30–9:00, and 8:10–8:40), as well as activity (e.g., reading).

To accelerate the optimization process [48], following word2vec [49], we use negative sampling to approximate the likelihood function. Equation (4) is updated as follows:

$$\mathcal{O}(X) \approx \log \sigma(X_{v_k}^T \cdot X_{v_u}) + \sum_{\mathbb{E}_{v'_u \sim p(v'_u)}} \log \sigma(-X_{v'_u}^T \cdot X_{v_u}) \quad (5)$$

$$\sigma(x) = \frac{1}{1 + e^{-x}}, \quad (6)$$

where $\mathcal{N}_{v_u}$ is the randomly sampled negative node set for v_u , where $v'_u \in \mathcal{N}_{v_u}$. We employ stochastic gradient descent (SGD) to maximize the likelihood function:

$$\frac{\partial \mathcal{O}(X)}{\partial X_{v_u}} = (\sigma(X_{v'_u}^T \cdot X_{v_u}) - \mathbb{F}_{v_k}[v'_u])X_{v_u}, \quad (7)$$

$$\frac{\partial \mathcal{O}(X)}{\partial X_{v_u}} = \sum_{v'_u \in \mathcal{N}_{v_u}} (\sigma(X_{v'_u}^T \cdot X_{v_u}) - \mathbb{F}_{v_k}[v'_u])X_{v'_u}, \quad (8)$$

where $\mathbb{F}_{v_k}[v'_u]$ is a function that indicates whether v'_u is the neighborhood context node v_k . The training procedure is as follows. We first sample a meta-path $\mathcal{P}$ following a uniform distribution, and then randomly sample a link (v_u, v_k) according to the network connectivity under $\mathcal{P}$. The set of negative nodes $\mathcal{N}_{v_u}$ including the type-U nodes are also sampled according to the noise distribution $p(v'_u)$. Finally, the parameter X is updated according to their gradients, such that the approximated sample log-likelihood $\mathcal{O}(X)$ can be maximized. As illustrated in Figure 8, v_j is assigned to v_i , $X_{v_k}^i$ and $X_{v_k}^j$ represent the neighborhood of v_i and v_j , respectively.

4.3.2 Participant Search for Ridesharing. Participant search attempts to match potential participants that have a similar OD pair and prefer on-going ridesharing [4, 37]. Recent work in this domain has mainly focused on linear models [50–52], which do not take complex relationships between features into account and strictly separate feature generation from modelling. Furthermore, traditional matching methods do not take the two types shown in Section 4 into account. Instead, matching is usually done via proximity rather than exact location [4]. In this article, we use network embedding to distinguish different ridesharing types and measure the similarity between two user nodes directly based on arithmetic operations on their embedding vectors. For any

pair of type-**U** vertices, v_i and v_j , their similarity is defined by the cosine similarity between X_i and X_j :

$$\text{Sim}(v_i, v_j) = \frac{X_i^T \cdot X_j}{\|X_i\| \cdot \|X_j\|}, \quad (9)$$

where cosine similarity is equivalent to Euclidean distance when $\|X_i\| = \|X_j\| = 1$, which allows the top-k similar vertices (passengers) of the given vertex v_i to be efficiently located using an approximate nearest-neighbor search after normalization [53].

Thus, given the previously learned user (driver) embeddings, potential passengers for a given driver are found by calculating the cosine similarity between their embedding vectors X_i and X_j . The K passengers with the greatest similarity are identified as ridesharing participants. We can then rank the candidates and observe the ridesharing types. The pseudo-code is listed in Algorithm 1.

ALGORITHM 1:

Inputs: Ridesharing HIN $H = (\mathcal{V}, \mathcal{E})$, meta-path scheme $\mathcal{P}$, walk length l , a set of passengers U , a set of drivers D , embedding vector for each node X

Outputs: Similarity between the embedding vectors of driver-passenger pairs

initialize X ;

for $i = 1 \rightarrow w$ do

 for each $v \in \mathcal{V}$ do

$MP = \text{RandomWalk}(H, \mathcal{P}, v, l)$;

$X = \text{SkipGram}(MP, X)$;

 end

end

extract vector embedding X_D, X_U

calculate the similarity between X_D, X_U according to Equation (9)

return $\text{Sim}(X_D, X_U)$;

5 EXPERIMENTAL RESULTS AND ANALYSIS

We next cover the details of training user embeddings, and then present the results of utilizing embeddings for ridesharing matching. We show five sets of experimental studies based on a real dataset to fully evaluate the performance of our developed RShareForm.

5.1 Data

The datasets used in this article were extracted from the on-demand ride service platform, *DiDi*², between November 1 and 14, 2016, in Chengdu, China¹. The total number of successful orders or completed trips during the time period was 2,742,827. An individual trip record includes the pick-up and drop-off location and time, order ID, and passenger ID. Any personally identifiable information of drivers and passengers has been properly anonymized to protect their privacy [54].²

Figure 9 shows the temporal distribution of ridesharing trips. Participants can make choices of whether to split rides with others. If a driver is willing to split rides and is successfully matched with another passenger(s), the ridesharing trip is initiated. A higher proportion of ridesharing requests are made in rush hours. The distributions enable us to infer the most likely path for pick-up passengers en route and improve the ride sentiment in the case of detour ridesharing. Figure 10 displays the distribution of trip distance and travel time. The average trip distance is

²DiDi is the world's leading mobile transportation platform.

Fig. 9. Origin and destination distribution of ridesharing trips.

3.7 km for a day, which indicates that ridesharing is more concentrated in urban areas due to its smaller trip distance. The overall statistics from the dataset for ridesharing show that the peak-hour (1–3 PM) mean travel distance is 3.94 km, while the off-peak hour (3–5 PM) mean travel distance is 4.01 km, which implies that ridesharing is more sensitive to the peak hours. In addition, in peak hours (1–3 PM), the mean travel time is 8.85 min, and the peak-hour standard deviation of travel time is 6.14 min. Off-peak-hour (3–5 PM) mean travel time is 10.61 min, and non-peak-hour standard deviation of travel time is 7.46 min. Figure 10 also shows that travel time does not increase as much as travel distance according to the distance of travel time rate (i.e., travel time per unit distance). This shows that passengers usually prefer to use the ridesharing service because it saves more time. Thus, it is interesting to identify the preferences of ridesharing partners and ridesharing trip types. A better understanding of this point should help in the development of successful ride-matching systems [4].

To prepare for the evaluation, we split all participants into a training and test set by the ratio 8:2, i.e., 80% of the entire dataset is used for training and the remaining 20% for testing. Figure 11 shows the better area-under-the-curve (AUC) and generalization performance of our proposed method when the ratio is set as 8:2.

Based on the training set, a ridesharing HIN is extracted. We first extract all participants that contain information about their OD pair and time from the dataset. The schema of the network is the same as in Figure 5. The extracted network contains millions of nodes and tens of millions of links. We consider various length-1 and length-2 meta-paths as candidate paths for the general heterogeneous network embedding. The detailed statistics of nodes and links for both training and testing sets can be found in Tables 2 and 3, respectively.

Fig. 10. Schematic example of order records converted in daily trips for 181,172 passengers. Activities are inferred in stay locations and daily trips are measured by time of day between these stays.

Table 2. Node Statistics

	U(driver)	U(passenger)	L(origin)	L(destination)	T
Train	61,141	72,432	49,979	50,460	48
Test	15,361	18,108	12,495	12,615	48

Table 3. Length-N link Statistics (N=1,2,3)

	U-L	L-L	L-T	U-L-T	U-L-L-T
Train	289,322	9,050,505	66,591	15,089,821	70,026,405
Test	72,331	2,262,627	16,648	3,772,455	17,506,601

5.2 Baselines and Experimental Settings

We select multiple meta-paths to see how they will reflect the participant search and affect the performance. We consider the following two types of baselines: (1) meta-path-guided similarity search methods and (2) variations of network embedding methods.

- PathSim [55] is a meta-path guided similarity search algorithm that utilizes the normalized count of path instances following the selected meta-path between any pair of vertices.

Fig. 11. AUC scores and generalization error for searching participants.

- SimRank [56] is an improvement from PageRank [57] and provides a similarity measurement based on network structure, with the intuition that two nodes are similar if nodes' in-neighbors are similar.
- Node2Vec [58] is an embedding algorithm specifically designed for homogeneous networks that applies negative sampling techniques.
- LINE [59] considers both first- and second-order information in a network (i.e., neighbors and neighbors of neighbors).
- PTE [60] learns the representation of text using the labeled data and different levels of word co-occurrence information. It works on a heterogeneous text network.
- HERec [26] is applied for HIN-based recommendation by measuring the relatedness between objects along the paths. HERec is most similar to our model.

To adapt Node2Vec and LINE to our settings, the method with the best performance from the work of Shang et al. [53] is used to project the ridesharing HIN to a weighted homogeneous network based on the selected meta-path. For example, we construct a directed network consisting of a type-U vertex and a “pick-up” type of relation among vertices. The weight of the edge between any pair of type-U vertexes that have the matching time window equal to the proximity to the requested pick-up location. In addition, we incorporate the semantic of meta-paths into the PTE and construct a heterogeneous network including user-co-occurrence networks, user-date networks, and user-departure time networks. Specifically, the type-U nodes that are measured by meta-paths can be linked according to whether the two users co-occur in the meta-paths for 1 d. We also utilize matrix factorization to generate the meta-path and obtain the node representation, as HERec does.

For all embedding methods, we use the same parameters. The dimension of the vertex embedding, d , is set to 128, the negative sampling ratio is set to 5, and the sampling times are set to 1,152,030 by default. The learning rate for parameters in RShareForm is initialized at 0.025 and warms up over the first 10% steps, and then linearly decays to zero. The number of walks starting from each vertex is set to 3, and the context window size c is set to 1. The following experiments on execution time were all conducted on a machine equipped with two Intel (R) Xeon (R) CPU E5-2620 v4 processors running at 2.10 GHz with 16 physical cores in total.

Since the ridesharing matching problem is implemented as a similar participant search and ranking problem, and usually only the top results are of interest, we adopt four commonly used ranking metrics, as shown in Table 4.

Table 4. Performance Indices of Ridesharing Matching

Indices	Description
TP	# of pairs correctly classified as being matched as ridesharing participants
FP	# of pairs mistakenly classified as being matched
FN	# of pairs mistakenly classified as being mismatched
TN	# of pairs correctly classified as being mismatched
$AP@K$	average precision at K, $AP@K = \sum_{k=1}^K P(k) / \min(L, K)$ for a single driver, where $P(k) = (TP \text{ in top } k) / (TP + FP)$, L is the total number of true passengers for this test driver
$MAP@K$	mean of $AP@K$ for each driver in the test set
$Recall@K$	recall at k, $Recall@K = (TP \text{ in top } K) / (TP + FN)$
Acc	$Acc = (TP + TN) / (TP + FP + FN + TN)$
AUC	probability that $TPR > FPR$, $TPR = TP / (TP + FN)$, $FPR = FP / (FP + TN)$
$Micro - F1$	micro-averaging, $Micro - F1 = 2 * \frac{\sum precision \cdot \sum recall}{\sum precision + \sum recall}$
$Macro - F1$	macro-averaging, $Macro - F1 = 2 * Average(\frac{precision \cdot recall}{precision + recall})$

Table 5. Similarity Search Performance Evaluation on Different Meta-paths

PID	Method	F1	ACC	TP	FP	TN	FN
1	ULU^T	0.3244	31.93%	5,197	5,043	4,957	16,600
2	$ULL^T U^T$	0.5004	51.24%	7,764	1,472	8,528	14,033
3	$ULTL^T U^T$	0.7274	60.02%	16,965	7,881	2,119	4,832
4	$ULLTL^T L^T U^T$	0.7600	71.77%	14,211	1,390	8,610	7,586

5.3 Performance Evaluation of RShareForm

In this set of experiments, four different kinds of relationships are generated, among them are (U, L, T) . We construct four meta-paths and compare their performance on similarity search by using RShareForm. From Table 5, it can be seen that different meta-paths indeed show different levels of performance. For example, some meta-paths, e.g., $ULTL^T U^T$ and $ULLTL^T L^T U^T$, perform well on the test set. Some other meta-paths do not perform well on their own, such as ULU^T , which may be because the semantics of the meta-path does not reflect the problem of ridesharing matching very well. However, when we combine these meta-paths with others, they still help improve the classification results.

5.3.1 Effectiveness of Network Embedding. With an embedding vector for each vertex, we can show meaningful visualizations using the t-SNE package [61]. The type-U vertices are projected onto a two-dimensional space with different colors to indicate their ridesharing group labels.

For different embedding-based methods (i.e., RShareForm, Node2Vec, and LINE (2nd)), we visualize a 10% random sample consisting of 28,972 passengers from four drivers for end-point ridesharing, as shown in Figure 12. Better embedding vectors should lead to a clearer figure in which the boundaries between differently colored points should be clean and not interfering with each other. Since Node2Vec and LINE work well for homogeneous networks, they yield inferior results when applied to particular multi-node classification tasks. As shown in Figure 12(d), one possible reason for the lower performance is that PTE learns the representation without differentiating the relations between two nodes widely separated, e.g., the header and trailer of user co-occurrences.

Fig. 12. Visualization of embedding vectors of 10% random sampled users when $\mathcal{P} = ULTL^T U^T$. Colors correspond to four drivers.

Fig. 13. Predictive performance on varying the ratio of training data.

Although HERec also introduces the meta-paths to measure the similarity of each node through a matrix, it represents the homogeneous neighborhood between type-U nodes without considering the different types of their neighbor nodes. Instead, RShareForm maps all types of travel-related entities into the same representation space using heterogeneous sequences. Based on the visualizations, one can easily observe that *RShareForm* provides the best embedding vectors as judged on this criterion.

We also compare our RShareForm method with LINE (2nd) and Node2Vec on the similar participant search. We repeat the training procedure three times and evaluate the performance of the different approaches in terms of average Micro-F1 and average Macro-F1 [62]. Figure 13 summarizes the performance of all methods. We have the following key observations and insights.

- (1) In most cases, the proposed RShareForm achieves better performance over the baseline models as measured by both Micro-F1 and Macro-F1. As the training ratio increases, RShareForm achieves > 9.5% and 24.1% improvements over Node2Vec and LINE (2nd), respectively, in terms of Micro-F1.

Fig. 14. Parameter sensitivity of RShareForm.

- (2) Node2Vec becomes more comparable with RShareForm with 10% training data as measured by the two metrics, demonstrating that the meta-path-based random walk does not generate improvements because the number of neighbors decreases when sparsely labelled vertices are provided.

5.3.2 Parameter Sensitivity. We select *RShareForm* to study the parameter sensitivity, such as using $ULTL^T U^T$ in the end-point ridesharing matching and using ULU^T in en route ridesharing matching. We vary the parameter values to see how the AUC performance changes. Based on the curves in Figure 12(a), we can observe that setting the dimension (d) of the vertex embedding vectors to 128 is reasonable because too small a d cannot sufficiently capture the semantics, while too large a d may lead to some overfitting. Figure 12(b) indicates that the AUC scores are sensitive to the negative sample ratio K , and $K = 5$ for $ULTL^T U^T$ is a good choice. As shown in Figure 12(c), as more samples are optimized during training, the AUC scores keep increasing. We utilize a skip-gram with context window size 2 i.e., for embedding, which means only one neighbor at the front and back of each node in a meta-path-based sequence. For each iteration of training, we change the c and find that there is enough available contexts when due to a downward tendency of AUC in Figure 14(d).

5.4 Comparisons of RShareForm with Baselines

Table 6 shows a comparison of the performance between baselines and the proposed method, where $ULTL^T U^T$ is used in the end-point ridesharing matching. Our method significantly outperforms the meta-path-based baselines. This outcome is the result of SimRank's focus on analyzing models based on a bipartite graph structure and determining the similarity between objects having strong connections in different sets by multiple iterations. However, SimRank cannot describe the semantic relationships between objects, so it provided lower accuracy in calculating similarity than PathSim. Owing to the sparsity of data, the eigenvector on each meta-path with PathSim is iteratively calculated to be rather small, where some of those were very close to 0. Instead, RShareForm

Table 6. Ridesharing Matching Performance Comparison

Models	MAP@3	MAP@10	Recall@3	Recall@10
SimRank	0.3981	0.4442	0.4469	0.3652
PathSim	0.8433	0.6367	0.7378	0.6266
<i>RShareForm</i>	0.9722	0.8955	0.8056	0.7680

with the network embedding can reduce sparsity and further improve the ridesharing matching method.

5.5 Discussion

In our work, matching is done via proximity rather than the exact locations; that is, although there is a lack of information about drivers (e.g., only OD pairs are used), our method can still identify passengers with reasonable accuracy at top ranks. *RShareForm* can learn the proximity in the geographical space and preserve it in the low-dimensional space. We believe the framework can be further improved by incorporation with more complete trip and demographic information into meta paths. For the present and near future, our work may do a much more accurate job of dispatching a driver for passengers that they may trust.

An interesting observation from Figure 14 is that end-point ridesharing matching is easier for *RShareForm* to identify, while en route ridesharing is substantially more difficult. This suggests that dynamic real-time (i.e., en route) ridesharing is more difficult to provide since it must identify the optimal pick-up and drop-off locations in a very short matching time-window, considering the participants' itineraries and schedules. From this perspective, we think sharing the origins of drivers and passengers in some way facilitates ridesharing services.

6 CONCLUSIONS

In this article, we study the problem of ridesharing matching, which is implemented as a similar participant searching problem under a heterogeneous network. We propose a framework, *RShareForm*, to exploit heterogeneous networks with multiple types of nodes and links derived from real data on ridesharing behavior, and to embed a ridesharing network in the context of a ride-matching task. We extend the existing metapath2vec model to rank potential passengers under two types of meta-paths for different ridesharing types. To improve the accuracy of predictions of ride-matching, we explore real-world data extracted from the on-demand ride service platform DiDi, in Chengdu, China. Our experiments demonstrate that by using *RShareForm* with meta-paths, our method can obtain significantly better accuracy at ride-matching compared to existing methods.

There are several aspects that may be addressed in future works to further improve our study. First, to measure the proximity of drivers and passengers we assume ride-matching along the original route of drivers. In the real world, both pickup and delivery have time windows. Owing to the time windows for pick-ups, a ridesharing vehicle might have to wait at a passenger's pickup location while other passengers wait in the vehicle [63]. In the future, we will consider detour ridesharing, in which additional travel costs and detour time are incurred by the driver. Second, it is worth identifying the relationship between preferences, such as ridesharing partners and closeness of acquaintances. The current work only considers the hypothesis that all passengers in the data are willing to share their rides. Future efforts can be made to account for a scenario that incorporates social networks to form a social ridesharing community. Thus, a user's social links, interests, influences, [8] and concerns for the level of service quality, as well as travel activity patterns that influence ridesharing choices, can be utilized in a wide spectrum of ride-matching.

Similarly, drivers' willingness can be modeled as a logistical function with respect to subsidy and discount, rather than hypothetical thresholds in this study. Finally, since the behavior features in this study are obtained by an offline learning procedure, the framework may not fully capture the real-time information once the ridesharing-booking app is initiated and issues an online recommendation. To better improve the computational efficiency, online learning techniques are needed to quantify the behavioral features more accurately. Currently and in the near future, new types of data (e.g., social media, landmarks, or suggestions from other people) can be introduced to improve an existing ride-matching system. In this scenario, training data with new features will be added to the prediction system, while old features will be retained [64]. Online learning can be potentially more challenging than the existing work, as the model should be trained on the new data arriving sequentially and transfer useful knowledge from the universal model to personalize the matching for every individual in an online learning manner.

This article has shed some light on real-world on-demand ride-service-platform data for matching drivers and passengers. In the near future, we expect to extend this heterogeneous network-embedding approach to some other applications based on the ridesourcing data, including ridesharing group queries, classification of participants' satisfaction and dissatisfaction, and order dispatch.

APPENDIX

See Table 7.

Table 7. Symbols

Symbol	Description
d, p	driver, passenger
x_p, y_p	pick-up, drop-off location of a passenger
$R(d)$	original route of driver
$Dtime$	departure time
MT	time spent walking toward a pick-up location or destination
lm	optimal pick-up location
$\delta(,)$	road distance between two locations.
$H = (\mathcal{V}, \mathcal{E}), T_H = (\mathcal{A}, \mathcal{R})$	ridesharing HIN and its network schema, v, ε denote a node set and a link set, A, R denote a node-type set and link-type set
P	meta-path
x_v	vector representation of each node

ACKNOWLEDGMENTS

We thank Didi Chuxing GAIA Initiative for its dataset during the preparation of this manuscript.

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Received March 2019; revised September 2019; accepted November 2019