Abstract

Destination prediction has been a critical topic in transportation research, and there are a large number of studies. However, almost all existing studies are based on high predictability data conditions while pay less attention to the data condition with low predictability, where the regularity of single individuals is not exposed. Based on a certain period of observation, there is a fact that individuals may choose destinations beyond observation, which we call “potential destinations”. The number of potential destinations is very large and can’t be ignored for the data condition with low predictability formed by short-term observation. To reveal the choice pattern of potential destination of individuals under the data condition with low predictability, we propose a global optimization method based on knowledge graph embedding. First, we joint the trip data of all individuals by constructing Trip Knowledge Graph (TKG). Next, we optimize the general algorithm of knowledge graph embedding for our data and task in training strategy and objective function, then implement it on TKG. It can achieve global optimization for association paths that exist between almost any two entities in TKG. On this basis, a method for potential destination prediction is proposed, giving the possible ranking of unobserved destinations for each individual. In addition, we improve the performance by fusing static statistical information that is not passed to TKG. Finally, we validate our method in a real-world dataset, and the prediction results are highly consistent with individuals’ potential destination choice behaviour.

Keywords: Potential destination prediction · Low predictability · Knowledge graph embedding · Globally optimized

1 Introduction

Destination prediction has always been a focus of research in the transportation field. In recent years, the sensing environment of transportation has changed dramatically. Vehicle-borne devices and sensing devices deployed in cities can collect many individual trips and movement data. With the huge amount of data available, a large quantity of data-driven destination prediction studies have been proposed, covering a wide range of scenes and different data types. However, we found that their task is similar: to make an accurate prediction, such as predicting the destination of an ongoing trip based on information such as the trip origin.
If we observe an individual’s trips and record the destinations continuously, there is the fact that we will observe destinations that the individual has not chosen. In other words, the limited observations do not cover all the possible destinations that an individual may choose. We refer to such destination that an individual may choose but lack of observation based on limited observations as “Potential Destination”. The existence of potential destinations for individuals is a common phenomenon, especially when we have very limited observations of individuals, such as short-term observation conditions. To confirm it in the real world, we observed trips destinations extracted from the data collected by Automatic Vehicle Identification(AVI) for each individual. We found that the trip regularity of individuals varies, but when the observation period is short enough, almost all vehicle individuals have a large proportion of potential destinations. Therefore, the potential destinations cannot be ignored in the early stages of observation, or only a short observation period is available. Then it raises the question of “How to make predictions about the potential destinations of individuals based on limited observations?”. However, we found that despite a large amount of destination prediction studies already present, little attention has been paid to potential destinations, and no studies have been conducted to answer the above questions. In some studies, potential destinations have been entirely ignored by some ways like limiting the candidate set of destination (Neto et al. [2018]), such as Hariharan and Toyama [2004], it defined the destination as places where an individual have experienced a stay. Krumm and Horvitz [2006] was an early study that introduced the concept of potential destination, which was called “new destination” by it. Just as a part of the overall prediction task, it only constructed a discrete distribution through rules based on distances and similarity of regions and does not verify its validity. Similarly, some of the recent studies referred to its ability to predict unobserved destinations like Jiang et al. [2019] also simply added potential destinations to the candidate set, while destinations observed are given a higher probability. To find the reason, we analyzed the data condition and methods of the relevant studies further. Ultimately, we found that the potential destination is unnecessary in their data conditions. In other words, the individual destinations were almost completely observed. And it is also the reason why they can achieve good results even if ignoring potential destinations. Specifically, existing studies are generally based on long-term observation, and for those based on relatively short-term observations, their scene is usually very simple, such as Zhao et al. [2021]. In addition, we note that most studies default or assume that individuals trip or mobility following a certain pattern like Zong et al. [2019]. Based on the findings of Gonzalez et al. [2008], such an assumption is reasonable if the condition that long-term observations are available. In terms of methodology, although the existing studies use very diverse methods, the ideas are pretty much the same. They basically learn the patterns or regularities of individuals and make predictions based on them by constructing sequence models, neural networks, etc. On this basis, we can conclude that the patterns and regularities of individual trips are exposed under the data conditions of the existing studies. We categorize such data conditions with regular exposure as “data condition with high predictability”. Then we can summarize the existing studies as accurate prediction of destinations based on pattern discovery method under high predictability data condition. While the issue that some studies focusing on the predictability of human mobility like Song et al. [2010], Kulkarni et al. [2019] discussed is essentially the limits can be achieved by methods under data condition with high predictability.

Relatively, for the data conditions in which regularity and patterns are not exposed, we define it as “data condition with low predictability”. For human mobility and trip, according to Gonzalez et al. [2008], the low predictability is mainly due to short-term observations. Potential destinations are vastly present with such data conditions and can not be ignored. It is extremely difficult to make accurate predictions under low predictability data conditions unlike highly predictable data conditions. Assuming that there are two individuals, for the first individual, we have its 30 trip destination observations that cover 2 traffic zones, showing a significant commuting pattern. While we only have its 1 trip destination observation for the second one. Then for the first individual, it seems little difficult to accurately predict its next destination based on its current location. Nonetheless, even predicting where they might go in the next period is very challenging for the second individual. That is the difference in the difficulty and limit of making predictions based on individuals with different predictability. Obviously, the study of prediction under low predictability data conditions is worth researching for the data condition with high predictability are not always available in the real world. It can provide valid information for short term prediction, personalized recommendation and individual-level OD estimation. More importantly, it can help respond to the doubt that data with how low predictability is still predictable and the what extent it can achieve. However, few studies have essentially paid attention to destination prediction with low predictability data so far. One reason may be that it is difficult to make an accurate prediction with a high practical value under the condition of low predictability data. On the other hand, existing methods treat individuals with low predictability as unpredictable and eliminate them. For example, to ensure model convergence, Mai et al. [2018] filtered out individuals whose trip number is less than 5, which account for a considerable proportion in low predictability data condition. In addition, we have tried to use the method based on high predictability data conditions to deal with the prediction problem under low predictability data conditions and found it really doesn’t work. Therefore, we need a new way of thinking about prediction under the condition of low predictability data.

In this paper, we focus on the potential destination prediction of the individual under the data conditions with low predictability formed by short term observation. The challenge of this task mainly comes from the extreme sparsity
and randomness of individual data, which are unacceptable to the existing methods proposed based on data with high predictability. If there are only a few observations of a single individual, we also think it is almost unpredictable. However, [Gonzalez et al. 2008] has found that humans mobility follow simple reproducible patterns and it also found that the travel pattern of humans has inherent similarity despite the diversity of their travel history. Hence we consider that if we have the observation of multiple low predictability individuals, we believe that they are predictable as a whole. Specifically, we can assume that the observed data of each individual under short-term observation reflects a part of a similar pattern. On this basis, we think that the data of individuals should be associated and analysed from a global perspective. Therefore, three core issues are exposed. The first is how to model the data of all individuals to make them joint. The second is how to make the data model capable of prediction from a global perspective. The last is how to infer and get the result. Faced with these issues, we propose the method based on Knowledge Graph Embedding. First, given the powerful expressiveness of knowledge graphs for associations, we adopt it to model individual trip data to obtain Trip Knowledge Graph(TKG), in which different individuals and different types of data are associated. To make the TKG computable, we map its entities and relations to a continuous space. On this basis, we improve the general algorithm in terms of training strategy and optimisation objectives and perform it on TKG. Since almost all data of individuals in TKG are associated, the training process can achieve the effect of global optimisation. Finally, based on the model trained to convergence, we designed the prediction methods and improved its performance by combining static information. It can obtain the ranking of the possibility of their potential destinations being chosen in the future. To validate our method, we constructed a completely low-predictability data condition using real-world AVI data and adopted our method in this scene. Experiments demonstrate that the ranking given by the method is highly consistent with the pattern of individual potential destination choices.

2 Literature review

Over the last two decades, researchers have devoted a great deal of work to destination and human mobility prediction. This section reviews mainly recent data-driven-based studies, while we have selected some representative studies for the earlier studies. In this section, we focus on their methods and corresponding data conditions. To present the above information more intuitively, we summarize the reviewed literature and form Table 1. Some studies similar to the literature in the table are omitted, such as studies that use similar methods for the same task on the same dataset. In Table 1, we present the data condition of the study by “Scene”, “Data Type” and “Data Scale”, while the method is summarized and presented by “Method”. Scene indicates the specific scene of the study. In general, the difficulty of prediction varies from scene to scene. For example, since sharing bike mainly serves the last/first kilometer trip, its destination is usually limited to the nearby station of the departure, while the prediction of taxi and vehicle scene is relatively more difficult. Data Type is used to describe the type of data used in the study. Different studies may use data from various sources, such as LBS-based GPS data, Bluetooth data, smart card data, and so on. Here we ignore the collection devices and abstract them into two types, i.e., “Trajectory data” and “OD-only” data. The difference between the two is whether information about the mobility or trip process is recorded. For example, in addition to the start and end point, GPS data also records the point of the path, so it belongs to trajectory data. The trajectory data is usually more informative for the “OD-only” data is equivalent to containing only the trajectory data’s start and end information. Data Scale is used to describe the scale of data. According to the description of the experimental data scale in different studies, we mainly used two presentation ways in Table 1: the observation period and the average number of records for an individual.

We first pay attention to the data conditions of existing studies. Trajectory data and OD-only data are the core data types for human mobility and destination prediction, of which studies based on trajectory data account for the vast majority. Data such as weather and temperature are also used for activity-based methods, while such data are not discussed much here. Through Table 1, we can see that regardless of the type of data used, the existing studies are all based on a large number of historical data of individuals under long-term observations. There are some studies that described its data conditions as “sparse data” like [Xue et al. 2013], and others like [Imai et al. 2018] claimed they focused on “early destination prediction” that recognition in destination prediction has not been fully explored. Essentially, they all want to show their data scales are small and it can be seen according to Table 1 if we compared data scales of them with studies of the same scene. The prediction under the data condition of small scale is usually considered a more difficult task and there are studies to solve the data sparsity problem in destination prediction like [Xue et al. 2015]. However, we note that the data scale of such studies is only relatively small and none of them explains why and how their data are sparse. The data scale of [Xue et al. 2013] is actually larger than that of [Zong et al. 2019], but [Zong et al. 2019] did not describe the data condition as sparse data. So the criteria for data sparsity seem to be ambiguous. With further analysis, we found that almost all existing studies considered that the mobility of individuals follows a certain pattern. For example, [Alvarez-Garcia et al. 2010] indicated it directly in the text. Other studies like [Chen et al. 2019] mined individual mobility patterns in its methodology, and [Liang and Zhao 2021] excluded individuals with different routing patterns from the target group. Besides, we also found no studies profiled the regularity or randomness of
Table 1: Representative studies of human mobility and destination prediction.

| Study                | Scene                     | Data Type | Data Scale | Method                   |
|---------------------|---------------------------|-----------|------------|--------------------------|
| Ashbrook and Starner [2002] | Human Mobility          | Trajectory | 4 months   | Markov model             |
| Krumm and Horvitz [2006]     | Vehicle                  | Trajectory | 43 records/id | Bayesian inference       |
| Burbea and Martin [2008]     | Human Mobility           | Trajectory | 11 weeks   | Partial-match            |
| Nadembega et al. [2012]      | Human Mobility           | Trajectory | 9 months   | Cluster-Based            |
| Noulas et al. [2012]         | Human Mobility           | Trajectory | 5 months   | M5 model tree            |
| Xue et al. [2015]            | Taxi                     | Trajectory | 3 months   | Bayesian Inference       |
| Chen et al. [2019]           | Taxi                     | Trajectory | 12 months  | Deep Learning            |
| Wang et al. [2020]           | Sharing bike             | OD-only    | 40 records/id | Deep Learning            |
| Besse et al. [2017]          | Taxi                     | Trajectory | 12 months  | Distribution-Based       |
| Imai et al. [2018]           | Human Mobility           | Trajectory | 2 months   | Probabilistic model      |
| Neto et al. [2018]           | Vehicle                  | Trajectory | 3 months   | Markov model             |
| Dai et al. [2018]            | Sharing bike             | Trajectory | 12 months  | Cluster-Based            |
| Zhao et al. [2018]           | Public Transportation    | OD-only    | 24 Months  | Markov model             |
| Rossi et al. [2019]          | Taxi                     | Trajectory | 12 Months  | RNN                      |
| Zong et al. [2019]           | Vehicle                  | Trajectory | 2 Months   | Hidden Markov model       |
| Rathore et al. [2019]        | Taxi                     | Trajectory | 869 records/id | Markov chain             |
| Ebel et al. [2020]           | Taxi                     | Trajectory | 1731 records/id | LSTM                 |
| Mo et al. [2021]             | Subway                   | OD-only    | 30 months  | Hidden Markov Model       |
| Liang and Zhao [2021]        | Vehicle                  | Trajectory | 528 records/id | Machine Learning        |
| Jiang et al. [2021]          | Vehicle                  | OD-only    | 7 months   | Bayesian-Based           |
| Sun and Kim [2021]           | Vehicle                  | Trajectory | 11 months  | LSTM                    |
| Zhao et al. [2021]           | Subway                   | OD-only    | over 1 months | Deep Learning       |

individuals' mobility. Nevertheless, we still summarised some information by analysing the experimental results. First, we found that the method used in some studies like Zhao et al. [2018] does not have the ability to predict destinations where individuals lack observations, but the method still works well experimentally under its data condition. Secondly, in analysing the comparative methods studied, we found that very simple regularity-based methods can also achieve good results under their data conditions such as Jiang et al. [2021]. The above information indicates that under the existing studies’ data conditions, the destination or trajectory is almost completely observed and the regularity of the data is exposed. Combining the above analysis and the definition of data predictability in Section [1], we considered that the reason why such large scale data was needed is to guarantee the regularity of individual data exposed. More specifically, the data scale of each existing study can ensure the data condition is “high predictability” for its scene and task. Data scale is a critical factor affecting the predictability of data, so when data scale decreases, the predictability of the data decreases accordingly. Based on such recognition, we can understand sparse data as data with relatively low predictability. However, the randomness of the data is also a factor that affects predictability. Hence even the data scale that is relatively small in Wang et al. [2020] is enough to create a data condition with high predictability since it is a simple scene and the important information that origin station is used as input in its task. It is worth mentioning that even for existing studies that claim to be performed under sparse, small-scale data conditions, their data conditions are still of high predictability. This point will be developed in the analysis of the existing studies’ methods. In addition to large data scales, there are also studies that ensure high predictability in other ways. For example, Manasseh and Sengupta [2013], Krumm and Horvitz [2006] and Neto et al. [2018] only made prediction for specific highly regular individuals. Jiang et al. [2019] combined with other information such as wind direction to ensure high predictability under relatively short-term observation. In summary, almost all existing studies was developed based on highly predictable data conditions.

Next, we focus on the methods used in existing studies. Nearly all method used for human mobility and destination prediction was covered in Table [1]. We can see that the method is dominated by the sequence model like the Markov model, Recurrent Neural Network (RNN) and its variants like Long Short-Term Memory (LSTM), especially when the data is of the trajectory type. In addition, there are also some studies that used methods based on Bayesian and decision tree and others like clustering. Although many methods have been proposed, we found nearly all of them aimed to learn the pattern of the data and based on which to make the prediction. More plainly, they both tend to reproduce historical or training sequences. So whichever method is used, they treat the data in the same way that is not essentially different from matching directly based on historical trajectories like early-stage study Burbey and Martin [2008], as well as explicitly giving a higher probability to destinations that have historically occurred. Based on such analysis, we can explain why data with high predictability is needed in existing studies for having a stable pattern is a fundamental requirement of these methods for data. On the other hand, almost all these studies seek higher prediction
accuracy. Hence, we can summarize the tasks of the existing study as methodological study based on data with high predictability to obtain better or even close to the limit of predictability. And Song et al. [2010] was a discussion of the upper limit of predictability under highly predictable data conditions.

These methods can be divided into two categories according to the way dealing with potential destinations. The one is ignoring such destinations completely. Part of these studies excluded potential destinations directly by the definition of the destination like Hanharan and Toyama [2004]. The others are because the method itself does not have the ability to predict potential destinations. For example, partial studies based on the general Markov model usually use individual observed trajectory data for training. Without adding corresponding parameters, the Markov model will not export an untrained destination, i.e. potential destination. Even if the mechanism of generating an untrained sequence is designed, it is essentially treated as noise. The other category studies usually acknowledge the existence of potential destinations and describe the prediction of potential destinations as an extremely difficult task. Finally, they explicitly expressed their methods can infer the destinations that are not observed. However, these studies make the methods have this capability in a very rough way. In other words, they are not specifically designed for potential destination prediction. For example, Jiang et al. [2019] simply by adding all destinations to the alternative set, the corresponding probabilities of unobserved destinations are given by statistical information on groups. More significantly, none of these studies analysed and demonstrated the prediction results of potential destinations. Since they also use data with high predictability, the proportion of potential destinations is so low that even complete abandonment would have little effect on the results. Therefore, in the absence of a corresponding analysis, it is difficult to judge whether the method really predicts the potential destinations well.

The potential destination is unimportant and can even be ignored for its low proportion of data with high predictability. However, it is crucial to study under low predictability data conditions. Then comes a question: Can the existing methods proposed under high predictability data conditions be migrated to low predictability data conditions? Intuitively, there is no stable pattern in low predictability data, so existing methods or models like RNN will not perform well and even converge. Through analysis of the literature and experiments, we confirmed this idea. Existing studies usually pre-process the data before the experiment is conducted. This process mainly removes some of the "problem data". We found that the removed data was partly the real problem data, like duplicated records. But most of them are the problem data from the method or model perspective. For example, Zhao et al. [2021] claimed that its purpose is to predict the destinations of occasional trips, which have more randomness and uncertainty, especially for an individual with few historical trip records. However, individuals whose activate days are less than 2 are excluded when making the prediction. On the other hand, in this data condition, the top ten frequency of OD pairs account for nearly total trips. So it is a very easy scene for destination prediction. Similarly, Imai et al. [2018] which claimed it is making predictions at an early stage when the destination has not been fully observed. But it filtered out individuals whose trip number is less than 5. In addition, Wang et al. [2020] exclude records with shorter travel time. Dai et al. [2018] excluded stations with less than 70 trips. Liang and Zhao [2021] excluded trips of the individual who have different routing patterns from target individuals. It can be seen that these excluded data are not objectively problematic and the reason for their exclusion is only because they would affect the effectiveness of their methods. However, these excluded data are exactly the subject of the data condition with low predictability. We can also think that the data with low predictability is considered unpredictable by existing methods.

3 Methodology

3.1 Preliminaries and notations

The basic elements of the knowledge graph are “Entity” and “Relation”. A complete knowledge graph usually contains multiple types of entities and relations constructed between entities to express their relations. So knowledge graph can be described as a multi-relational graph composed of entities and relations with different types. (Wang et al. [2017]). As for the definition of the knowledge graph, we will follow the previous study [Ji et al. [2021]). We use $G$ to represent a knowledge graph, and it can be expressed as $G = \{E, R, F\}$ where $E$, $R$, and $F$ are sets of entities, relations and facts, respectively. A fact is denoted as a triple $h, r, t \in F$, where $h$ and $t$ are elements of the entity set $E$ and $r$ is element of $R$. For the triple $(h, r, t)$, $r$ is generally has direction that from $h$ to $t$. The triple with a directional relation shown in Figure 1(a) can be represented as “(h: Entity) $\rightarrow$ [r: Relation] $\rightarrow$ (t: Entity)”, in which entities represented by $h$ and $t$ are called “head entity” and “tail entity” respectively. The triple is the unit structure in the knowledge graph and the information expressed by it is called “Fact”. A specific triple will express a specific fact. For example, the triple that “(h: Jobs) $\rightarrow$ [r: Founder] $\rightarrow$ (t: Apple)” whose entities and relations have a specific meaning, describes the fact that “Jobs is the founder of Apple”.

A single triple can express the direct association between two entities, and the indirect association information between entities can also be expressed in the knowledge graph. by “Association Path” (or “Meta Path”). Entities that are not
directly related but can be associated through one or more other entities are considered to be indirectly associated. The path that makes indirectly associated entities are associated through other entities is called the “Association Path”. Association path can be considered as a chain of multiple connected triples. From a structure perspective, it is a sequence of alternating entities and relations as shown in Figure 1(b). The formation of an association path depends on different triples containing the same entity, and it should as the head entity and tail entity, respectively.

Based on the quantity of connected head and tail entities, the knowledge graph’s relations will have different complex degrees. It can be roughly divided into two categories: simple relation and complex relation. The simple relation is the relation with only one head and one tail entity called “1-1”. The complex relation can be divided into three types: “1-N”, “N-1” and “N-N”. The former represents the number of head entities connected by the relation, and the latter represents the tail entities. For example, the relation of type “1-N” means that the head entity of it is only one while there are multiple tail entities connected to its tail as shown in Figure 1(c). “N-N” is the most complex type of relation, it connects more than one head entity, as well as multiple tail entities, as shown in Figure 1(d).

According to the fields covered, knowledge graphs can be divided into general knowledge graphs and expertise knowledge graphs. Here we would like to emphasize the differences between them in terms of construction. Knowledge graph construction is the process of organizing data expressed in other forms such as structured data into knowledge graphs. When constructing a general knowledge graph, the data are mostly unstructured data such as text, and the “Bottom-Up” construction method is mostly be used. In this process, entities and relations are extracted directly, hence there is no need to design the structure of the knowledge graph. For expertise knowledge graphs, which are mainly constructed based on structured data, a “Top-Down” construction method is generally used. In this process, it is required first to design a structure of the expertise knowledge graph and then abstract the data into the entity and build the relation between them according to the structure design. For the same data, different structures can lead to a different performance of the knowledge graph in various tasks.

### 3.2 Construction of the Trip Knowledge Graph

The trip data collected by the device is usually expressed in the form of structured data, of which a trip record describes each individual trip. It is efficient for describing trip information from an individual perspective, and most studies have been conducted based on this form of data. Nevertheless, it is not able to directly and efficiently express the information about the association between different individual trips. According to the analysis of Section 2, for low predictability data conditions, we have no way to predict from an individual perspective, while from a global perspective may work. Hence, first we need to associate the data of all individuals. Given the powerful ability of knowledge graphs to represent associative information, we adopted it to organize individual trip data to make them associated. The knowledge graph about individual trip that we need to construct is an expertise knowledge graph. As the introduction of Section 3.1, the work that designing the structure of the knowledge graph is necessary, and it is the central work. It includes the design of entity and relation, which correspond to the entity extracting and relation building of the construction process, respectively. Next, we will describe these two parts in detail.
### 3.2.1 Entity extracting

At the step of entity extracting, the critical issue to consider is “What types of entities should be included in the knowledge graph”. Obviously, we should select effective elements according to the specific task. Therefore, the factors related to individual destination choice should be extracted as entities in our trip knowledge graph. Theoretically, the more relevant factors are considered, the better the prediction will be. However, the data of some elements are extremely difficult to obtain. In addition, we aim to provide a generic method, so only the basic factors considered in this paper are like data can be collected directly from the device or obtained from the internet easily.

The granularity of the prediction is at the individual level, hence the trip knowledge graph should have a type of entity that can represent the individual’s identity. In AVI-based detection data, the vehicle’s plate is used to identify the identity of the individual, and it is a field in the original structured trip data. So we extract it as a type of entity that reflects the vehicle’s identity, denoted as “Veh_id”. Each entity of the “Veh_id” type corresponds to a specific vehicle individual. Next, considering that the task of the study is to predict the destination, hence the entity representing destinations is necessary. According to the description in Section 4.1 traffic zone is used to represent the trip destination (and origin) in this study and we extract it as entity of “Zone” type. Next, we considered information relevant to the choice of trip destination. We refer to related studies to get this information by filtering while avoiding the interference of invalid information. First, it is the points of interest(POI) within traffic zones that really attract vehicle individuals to trip. Therefore, we believe that the POI is valid information for inferring destinations. And it is straightforward to obtain from the internet. In addition, we refer to a study by Yuan et al. [2013] on POI recommendation. It pointed out the significance of the time factor in the POI recommendation task. Therefore, the time of the trip is another element that should be considered. Finally, Zong et al. [2019] boosted the effectiveness of the Hidden Markov Model(HMM) on the next location prediction task by adding weekday versus holiday information. Therefore, this information is also valid for destination prediction. Many other elements are relevant to the choice of trip destination, such as an individual’s occupation. However, this information is beyond the scope of trip data and is extremely difficult to obtain, so it is not considered.

In summary, we determined the entity types and the meaning of different entities is shown in Table 2. When extracting entities, what needs to be emphasized is to ensure their consistency with the real world. In other words, the different entities in the knowledge graph must uniquely represent one thing of the real world. For example, a zone may be taken as a destination or origin of the trip by different individuals and appears in multiple records. Even so, they all correspond to the same zone in the real world. Therefore, when extracting entities, the zone is expressed by only one entity instead of abstracting one entity for each occurrence. This is the key to ensuring the knowledge graph’s powerful associative representation capability.

| Entity   | Meaning                                      |
|----------|----------------------------------------------|
| Veh_id   | Unique identification of individual         |
| Day_nat  | Nature of the day, including “working” day and “holiday” |
| Time_span| Time span of the day, e.g. “Morning peak”    |
| Zone     | Traffic zone                                 |
| POI      | Point of Interest                            |

### 3.2.2 Relation building

After the extraction of entities, the knowledge graph possesses the basic elements of the entity, but the relation between them was not described. So building the relation between entities is needed to complete the trip knowledge graph. The specific work required to do in this step is defining relation types between different entity types. According to the introduction of Section 3.1, entities and the relation between them form the triple, which describes the fact. Hence, defining relations between different types of entities is essentially constructing various types of triples for describing facts. Therefore, we need to consider “Which facts we want the trip knowledge graph to express” and define corresponding relations. According to the data condition and the types of entities extracted, the facts that need to be described in the trip knowledge graph are divided into two categories. (1) Individual historical trips, including the choice of historical trip destinations, etc. (2) Traffic zone contains POI.

The fact described in natural language contains the types of entities that should be related. For example, the fact “Traffic zone contains POI” indicates that a relation should be defined between Zone and POI entities to describe this fact. Then comes the most critical issue, that is “How to define the relation between entities”. Through the introduction of section 3.1, we know that the relation has different degrees of complexity, such as the simple relation of “1 − 1” and the most complex relation of “N − N”. Relations of different degrees of complexity have almost no impact on
humans’ understanding of knowledge graphs. Instead, this concept is introduced mainly because of its effects on knowledge graph representation learning. Representation learning is the process of mapping the entities and relations of the knowledge graph to a continuous space to obtain its mathematical representation. Many methods and models can implement this process. In general, models that can handle the complex relation are usually more complex, while some simple models can only handle the simple relation. In addition, the more complex a relation is, the higher the optimal dimension required to describe it is usually. The knowledge graph embedding algorithm that we will subsequently perform based on the trip knowledge graph is one of the representation learning methods. Therefore, when defining the relations between entities, we need to focus on their complexity to ensure that there exist a model that can process it by finite dimension. Specifically, there are the following requirements for defining relations of the trip knowledge graph.
(1) The complexity of different types of relations should be Balanced since the dimensions of the model describing different types of relations are usually the same. On this basis, to reduce the complexity of relations as much as possible.
(2) To ensure migration and generality, make the complexity of the relations as independent of the scale of the data as possible.

First, we considered the definition of the relation between entities Zone and POI to describe the fact that “Traffic zone contains POI”. A common way is to define the relation Has_POI between entities Zone and POI, forming the triple (Zone) → [Has_POI] → (POI) to describe this fact. A traffic zone may contain multiple POIs, and the same POI may be distributed in different zones, hence the relation Has_POI is a complex relation of type “N – N”. Nonetheless, since it has a small number of both head and tail entity types, it is not yet more complex than the capabilities of existing models. Next, we use the same idea of defining relations to describe the fact of the individual historical trip. To describe this fact requires defining relations between veh_id entities and Time_span, Day_nat, and Zone entities respectively. We use the fact that “A vehicle individual has chosen a certain traffic zone as the destination in history” as an example. Following the same idea, we can define the relation “Choose_D” between Veh_id and Zone entities. Then we will get the triple “(Veh_id) → [Choose_D] → (Zone)”. An individual may choose more than one zone as the destination, and a zone will be chosen by multiple individuals as the destination. So relation “Choose_D” is also of the “N – N” type. However, in contrast to the Has_POI relation, the complexity of relation “Choose_D” varies with the scale of the trip data. For example, as more individuals are considered, the number of its head entities increases accordingly. This means that when the data scale changes, the trained model will be invalid and it cannot migrate to other datasets of different data scales for their optimal dimensions will be different. Furthermore, when the number of individuals considered is very large, the dimension required to express this relation becomes unacceptable. On the other hand, it is difficult to keep its complexity in line with the relation “Has_POI” whose complexity is stable. Therefore, it is not ideal for defining the relation “Choose_D” between Veh_id and Zone entities directly.

To address the problem, we propose the concept of individual private relation. We define the “Choose_D_id” relation as a group of relations rather than a relation like “Choose_D”. Each relation of “Choose_D_id” corresponds to a specific individual, i.e., the head entity of each relation is only one individual. In other words, each individual has a private relation of type “Choose_D_id”. There is little difference in the way the above two relations are defined for human understanding. But they are fundamentally different about the complexity of the relation. In the way “Choose_D_id” relation is defined, there is only one head entity for each relation, while individuals may have chosen different zones as their destination, i.e., the tail entity may be more than one. Thus the relations of “Choose_D_id” type is “1 → N”, which greatly reduces the complexity of the relation versus “Choose_D”. On the other hand, when the amount of individuals changes, the number of “Choose_D_id” relation changes accordingly, but the complexity of each relation is not affected. Therefore the complexity of “Choose_D_id” is independent of the number of individuals. This ensures the migration of the optimal dimensions of the model. We have the same problem in defining the relations between Veh_id and Time_span, Day_nat, and Zone entities to describe facts that “individuals have chosen zones as origin”, etc. Thus, we also adopt the private relation when defining these relations. Then we obtained all types of triple and facts described by them in the Trip Knowledge Graph as shown in Table 3. The triple that describes destination choice behaviour is marked with *, calling it “core triple” in the next. By the way, if we only seek to construct simple relation, we can make a simple “1 → 1” relation by privatizing the type Zone entities, etc. as well. But then the data between individuals cannot be associated. Therefore, when designing the trip knowledge graph, the association of the data and the complexity of the relation should be considered.

| Triple | Described fact |
|--------|----------------|
| (Veh_id)-[Choose_D_id]→(Zone)* | The vehicle chooses the zone as destination to trip |
| (Veh_id)-[Trip_O_id]→(Zone) | The vehicle trips with the zone as origin |
| (Veh_id)-[Trip_Time_id]→(Time_span) | The vehicle trips during the time span |
| (Veh_id)-[Trip_Day]→(Day_nat) | The vehicle trips on the day with the day nature |
| (Zone)-[Has_POI]→(POI) | The zone contains the point of interest |
So far, we have completed the construction of the Trip Knowledge Graph of individual, which we refer to as “TKG” for short in the next. The structure of TKG is shown in Figure 2. In TKG, all types of entities have the association path, and the microscopic association between different types of entities is shown in Figure 3.

3.3 Trip Knowledge Graph Embedding

In TKG, the information of all individuals’ trips and POIs contained in traffic zones have been associated. But TKG is so far described by natural language that it cannot be computed and does not have the ability of prediction. This section will use the knowledge graph embedding algorithm to map TKG to a continuous space and train it to obtain the parametric representation of entities and relations.
3.3.1 Introduction of knowledge graph embedding

The purpose of knowledge graph embedding is to map the entities and relations expressed in natural language to a continuous space. After embedding, entities and relations of the knowledge graph will have the parametric representation and then the knowledge graph is calculable. Translation model is a classical category of models for implementing knowledge graph embedding, which include many specific models. All these models consider the tail entity of the triple as a "translation" of the head entity through the relations. Their differences are mainly in the complexity of the models, or the number of parameters. This difference affects the ability of the models to handle complex relations. In general, the more complex the model, the better it is able to handle complex relations, while the simplest \textit{TransE} model can only handle the simple relation. Next, we will introduce the generic models of \textit{TransE} and \textit{TransH}. The former can most directly represent the principle of the translation model. And the latter deals with complex relations in an easy way relatively that matches the structure of TKG well. For a more comprehensive understanding of graph embedding algorithms and translation models, the \cite{Wang2017} can be consulted.

\textit{TransE} model is the first and the classic algorithm of translation models for knowledge graph embedding. It regards the relation in the knowledge graph as a translation vector between entities. As for each triple like $(h, r, t)$, \textit{TransE} model regards $l_r$ which represents the vector of relation $r$ as the translation between the head entities’ vector $l_h$ and tail entities’ vector $l_t$. Based on this idea, we can also regard $l_t$ as the translation of $l_h$ through relation $l_r$. As shown in Figure 4, for a triple $(h, r, t)$ which is short for (head $\rightarrow$ relation $\rightarrow$ tail), \textit{TransE} model will first give the initialization vector of the entity $(l_h, l_r)$ and relation $(l_r)$, then make $l_h + l_r \approx l_t$ through training. The loss function of general \textit{TransE} model is defined in Equation \ref{eq:1}. In the geometric sense, $|l_h + l_r - l_t|_{L_1/L_2}$ is the distance from the head entity of the triple $(h, r, t)$ to the tail entity through the translation of the relation $r$. So, the result of Equation \ref{eq:1} is also considered as the distance of the triple.

\begin{equation}
\|l_h + l_r - l_t\|_{L_1/L_2}
\end{equation}

\textit{TransE} is the most concise of the translation models, in which there is only one continuous space and each entity relation has a unique representation in it. However, since its concise, it is difficult for \textit{TransE} to handle complex relations. To enhance the ability of dealing with complex relations, a number of models were proposed after \textit{TransE}. As mentioned earlier, these models are more complex and more computationally intensive to train than \textit{TransE} models.

\textit{TransH} is the first proposed translation model that can handle complex relation types and its generic model was proposed by \cite{Wang2014}. There is only one type of parameter that “hyperplane” was added in \textit{TransH} compared to \textit{TransE} and it is the most concise of the translation models that can handle complex relations. \textit{TransH} enables the same entity to have different representations in triples composed of different relations by introducing hyperplanes. The idea of this

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{transh.png}
\caption{Translation Models}
\end{figure}
model to deal with complex relations specifically is as follows. As shown in Figure A2, for the relation $r$, TransH model uses the translation vector $l_r$ and the normal vector $w_r$ of the hyper-plane to express it at the same time. As for a triple $(h, r, t)$, TransH model projects the head entity vector $h_r$ and the tail entity vector $t_r$ along the normal to the hyper-plane corresponding to the relation $r$, by which $h_r$ and $t_r$ will be obtained and their calculation equation is shown in Equation 2,3. On this basis, the loss function(also the calculation of the triple distance) of TransH model is changed to Equation 4.

$$l_{hr} = h_r - w_r^T h_r w_r$$  \[2\]
$$l_{ht} = t_r - w_r^T t_r w_r$$  \[3\]
$$f_r(h, t) = ||l_{hr} + l_r - l_{tr}||_{L_1/L_2}$$  \[4\]

Negative sampling strategy is commonly adopted when training models in order to improve the efficiency of training and enhance the distinguishing ability such as Wang et al. [2020], especially for translation models. The triples constructed in the knowledge graph based on the observed data are considered to be the “correct” triples or positive samples. In other words, the facts described by correct triples are true. Triples other than positive samples are generally called “false” triples or negative samples, the “facts” described by which are objectively false or lack of observation. Unlike positive samples which are derived from modeling of observed data, negative samples need to be constructed artificially. The general method of generate the set of negative samples is that randomly replace one of the head entity, relation and tail entity of positive samples with other entities or relations. Denote the negative samples generated by this method as $S^-$, then it can be described by Equation 5.

$$S^- = \{(h', r, t) \cup (h', r', t) \cup (h, r, t')\}$$  \[5\]

Generic models of translation models typically consider negative sample strategy, and the optimization objective function is shown by Equation 6. In the Equation 6, $S$ is the set of positive samples, while $S^-$ is the set of negative samples. $max(x, y)$ returns the larger value of $x$ and $y$. $\gamma$ is the interval distance between the positive samples score and negative samples score.

$$\sum_{(h, r, t) \in S} \sum_{(h', r', t') \in S^-} max(0, f_r(h, t) + \gamma - f_r(h', t'))$$  \[6\]

3.3.2 Analysis and Optimization of knowledge graph embedding for the Trip Knowledge Graph

Analysis of knowledge graph embedding for the Trip Knowledge Graph. According to the optimization objective function shown in Equation 6. The target of translation model optimization is the triple(a pair of positive and negative samples) and there is no global optimization objective. Nevertheless, global optimization can be achieved by adopting the translation model or other models to TKG. The following will explains why. Through Figure 4, we know that association path is formed by multiple triples. Then considering a association path formed by two triples.

$$(h_m : Entity) - [r_m : relation] \rightarrow (e_c : Entity) - [r_n : Relation] \rightarrow (t_n : Entity)$$

This association path is formed by triple $f_m : (h_m, r_m, e_c)$ and $f_n : (e_c, r_n, t_n)$. If the vector representation of entities and relation of $f_n$ have been adjusted during training, then the $f_m$ triple will be affected for the tail entity $e_c$ is its head entity. Likewise, the adjustment of the $f_m$ triple affects the triples that form the associated path with it. That is, The training of a triple will affects all triples of the associated paths it forms. Through the introduction of Section 3.2 and Figure 3, almost all entities in TKG have association paths between them. Thus the training of each triple will indirectly affects the parameterized representation of the whole knowledge graph, while the convergence of the triple indicates the overall global convergence of TKG. So we say that using the knowledge graph embedding algorithm on TKG is essentially performing global optimization.

Due to the structure of TKG, Whichever model has been chosen, the global optimization can achieved. Then comes the issue that which model to choose for embedding the knowledge graph. Normally, the first factor to be considered is the type of relations contained in the knowledge graph. If complex relations was contained, then it is must choose a model that can handle complex relations, otherwise it will not be able to converge. The next factor to consider is the
The number of traffic zone it has not chosen will be chosen as a destination in the future for each individual gives the ranking can predict potential destinations for each individual in the TKG. Specifically, the distance of the triple. and the smaller the distance of the triple indicates the higher the possibility of the fact it describes by model without false. Otherwise, it would be misleading for training. Therefore, this requires that the artifically constructed negative sample should be truly negative, i.e., it should describe a fact that is objectively false, such as "the sun rises in the west". This is basically guaranteed for a relatively complete general knowledge graph but not for TKG. In TKG, the triples describing the facts of an individual’s historical trips are derived from the individual’s historical trip data. If our observed data can largely ensure that the facts described by such triples are complete, e.g., all possible destinations chosen by an individual have been observed, then there is no problem to introduce a negative sample sampling strategy. However, our data context is precisely short-term observed. Thus for TKG, some of the negative samples are not objectively false, but simply because they have not been observed. For example, negative sample $(Veh_{id} : V_i) \sim [Choose_D \rightarrow (Zone : Z_b)]$ may be constructed by random replacement method if $V_i$ has not chosen $Z_b$ as destination in history, but $Z_b$ may be a potential destination of the individual. On the other hand, our task is to infer unobserved facts, so if it occurs that the triple describing the unobserved facts is regarded as a negative sample during training, it will directly affect the performance of the model. To conclude, the negative sample sampling strategy is not suitable due to the data conditions of TKG and the specificity of the task. So we eliminate the sampling strategy of negative samples and modify the optimization objective to Equation[7]. The idea of this optimization objective is to describe only the observed facts and to consider that when the distance of a positive sample is less than $\gamma$, then the fact is considered to be well expressed by model without adjustment. In the experimental section we will also discuss the effect of introducing negative samples strategy during training.

$$\sum_{(h, r, t) \in S} \max(0, f_r(h, t) - \gamma) \quad (7)$$

### 3.4 Potential destination prediction based on the Trip Knowledge Graph Embedding model

In this section, we will introduce potential destination prediction of individual based on Trip Knowledge Graph Embedding model. According to Section[3.3.1] the process of training is actually a process of decreasing the distance of positive samples. That is, TKG’s embedding model portrays the possibility that the fact a triple describes holds by the distance of the triple. and the smaller the distance of the triple indicates the higher the possibility of the fact it describes. On this basis, we argue that the probability that the fact described by a triple holds when the model converges is negatively correlated with its distance, which draws on the knowledge graph complement task. Based on this idea, we can predict potential destinations for each individual in the TKG. Specifically, for each individual gives the ranking of the possibility that a traffic zone it has not chosen will be chosen as a destination in the future. Next, we will
present the method for potential destinations prediction in the following three steps and the framework is shown in Figure 5:

1. Identify potential destination candidate set of individual.
2. Calculate the distance of core triples formed by zones of potential destination candidate.
3. Get the ranking of zones of potential destination candidate based on distance.

![Figure 5: Framework of potential destination prediction of individuals.](image)

**Identify potential destination candidate set of individual.** To make prediction of the potential destination for each individual, the set of potential destinations candidate $Z_p$ needs to be identified first. According to the definition of potential destination in this study, each traffic zone that has not been chosen as the destination of the individual is possible to be its potential destination. Thus for each individual, we denoted its $Z_p$ as the set of traffic zones that have not been chosen by it. Specifically, denote the set of all traffic zones as $Z$. For each individual, the set of observed traffic zones chosen as destination $Z_o$ can be obtained by its historical trip data. Then the set of potential destination candidates $Z_p$ of the individual can be presented as Equation (8)

$$Z_p = Z - Z_o$$  

**Calculate the distance of core triples formed by zones of potential destination candidate.** We have mentioned that the embedding model of the knowledge graph describes the possibility of a fact holding by the distance of the triple. Then for any triple, including that not trained as positive samples, we can measure the possibility that the fact described by it holds by its distance. Among the triple types shown in Table 3, the triple of “(Vehicle Id) – [Choose D id] → (Zone)” type describes the fact that an individual chooses a traffic zone as its destination, which was marked as the core triple type. Therefore, the distance of this type of triple can measure the possibility that the individual (represented by the head entity) chooses the traffic zone (represented by the tail entity) as a destination. If the traffic zone of the triple belongs to its $Z_p$, then the distance of the triple describes the possibility that “**The individual will choose that zone as a destination in the future**”. This is the foundation for potential destinations prediction. Hence for each individual, the distance of its core triples formed by all zones of its $Z_p$ should be calculated. Specifically, we take the individual’s entity of Vehicle Id type as the head entity, its private relation of [Choose D id] type as the relation, and in turn take the entity of traffic zones in $Z_p$ as the tail entity to form the core triples of this individual. Then calculate the distances and record them.
Get the ranking of zones of potential destination candidate based on distance. With the previous step, we obtained the distance of the core triples consisting of the individual and its traffic zones in its $Z_p$. It is difficult to quantify the absolute value of the possibility by distance, but we can give the ranking of the possibility of holding based on the relative size of their distances. For example, for individual $v_n$, construct two triples $c_{ni} = (Veh_{id} : v_n) \rightarrow [Choose\_D\_n] \rightarrow (Zone : z_i)$, $c_{nj} = (Veh_{id} : v_n) \rightarrow [Choose\_D\_n] \rightarrow (Zone : z_j)$, where $z_i, z_j \in Z_p$. Next, calculate the distance of $c_{ni}$ and $c_{nj}$ and denote as $d_i$ and $d_j$ respectively. Then, although it is difficult to give quantitatively the probability that the fact described by $c_{ni}$ or $c_{nj}$ holds based on its distance. But if $d_i > d_j$, then we can completely think that the fact described by $c_{nj}$ is more likely to hold. In other words, $v_n$ is possible to choose traffic zone $z_j$ as its destination in the future. Therefore, based on the distances of the core triples calculated, we can obtain the possible ranking of the traffic zones in $Z_p$ for the individual. The smaller the distance, the more likely the traffic zone represented by the tail entity of the core triple is to be chosen as a destination in the future, and the higher it is ranked.

The flow of all steps of the above individual potential destination prediction can be summarized as Algorithm 1. It describes the process of predicting the possible ranking of a traffic zone for an individual based on the embedding model of TKG, which is the minimum granularity of the prediction.

**Algorithm 1**: Algorithm of potential destination prediction of an individual.

**Input**: Individual identity: $v_n$; The TKG Embedding model: $M$; Zone to be ranked: $z_j \in Z_p$

**Output**: The possible ranking of $z_j$ for $v_n$ given by embedding model: $k^e_j$

Get $Z_p$ of $v_n$:

$h_n \leftarrow Entity (Veh\_id : n)$;

$r_n \leftarrow Relation [Choose\_D\_n]$;

$S_n \leftarrow \emptyset$;

for $z_i$ in $Z_p$ do

$t_i \leftarrow Entity (Zone : z_i)$;

$c_{ni} \leftarrow Triple (h_n, r_n, t_i)$;

Calculate the distance of $c_{ni}$ according to $M$, denote as $d_i$;

$S_n \leftarrow d_i$;

$k^e_j \leftarrow 1$;

for $d$ in $S$ do

if $d < d_j$ then

$k^e_j \leftarrow k^e_j + 1$;

Return $S_n, k^e_j$

The ranking of zones given by the TKG embedding model is mainly based on the association information of individuals. Considering that there is static statistical information which we do not have and can hardly pass to TKG may be valid for destination prediction. We thought that fusing such information might improve the effectiveness of prediction. Thus we counted the frequency of different traffic zones being chosen as destinations by all individuals based on the observed data and obtained their hotness ranking by ranking them. The hotness ranking of the highest frequency chosen traffic zone is 1. The hotness ranking is static information that does not vary from individual to individual, while the ranking given by the TKG embedding model is personalized. We suppose that combining statistically-based static information and personalized information based on correlations will lead to better prediction results. Specifically, we integrated the ranking under the two ranking ways of the traffic zone and got its combined ranking. The algorithmic flow of the process is shown in Algorithm 2. So far, we have introduced three ranking ways: ranking given by the TKG embedding
model, which we call embedding ranking later, hotness ranking based on statistical information and combined ranking. The prediction performances of all ranking ways will be demonstrated and discussed in the experimental section.

Algorithm 2: Algorithm of calculating the combined ranking.

Input: Zone to be ranked: $z_j \in Z_p$
Output: The combined ranking of $z_j$: $k^c_j$

$L_n \leftarrow \emptyset$;

for $z_j$ in $Z_p$ do
  $k^e_j \leftarrow$ algorithm 1;
  Get the hotness ranking of $z_j$, denote as $k^h_j$;
  $k^c_j \leftarrow k^e_j + k^h_j$;
  if $k^c_j$ not in $L_n$ then
    $L_n \leftarrow k^c_j$;
  else
    $L_n \leftarrow k^c_j + 1$;

for $l$ in $L_n$ do
  if $l < k^c_j$ then
    $k^e_j \leftarrow k^e_j + 1$;

Return $k^c_j$

4 Experiments

4.1 Data Description

To verify the effectiveness of the method, we performed the method proposed in this paper in XuanCheng, a city of China, using real-world data. The original trip data was collated based on Automatic Vehicle Identification (AVI) deployed in the city road network. AVI is a new generation of sensing devices equipped on urban road networks. It can record the vehicle’s activity passively in the road network and its identity. In addition, AVI observes vehicle activities from the “trip” perspective directly without works like map matching. Hence the data collected by it is more suitable for analysing and understanding trip behaviour of vehicle individuals. The road network and AVI distribution of XuanCheng are shown in Figure 6. The fields of the original data are shown in Table 4. We use the “traffic zone” proposed in Wang et al. [2021] to describe the origin and destination of the trips. There are multiple points of interest (POI) inside of zones, and this information is publicly available on the Internet.

| Field      | Description                      |
|------------|----------------------------------|
| Vehicle_id | The id of vehicle, which is the identification of the vehicle. |
| Date       | The date of the trip.            |
| Ftime      | The starting time of the trip.   |
| Fzone      | The origin(zone) of the trip.    |
| Tzone      | The destination(zone) of the trip. |

To construct a purely low-predictability data condition, we first extracted trip data with a short time span from the original data to simulate short period observed conditions. Besides, We excluded individuals with strong trip regularity even under such short period observation conditions to ensure that our data condition is completely low predictable. Finally, the observation period we determined was one week, and the percentage of regular individuals is 18.44%, which was excluded. The remaining 81.56% of individuals who trip seem randomly formed our study’s target group, and its individual’s number is 95, 509. On the other hand, all of the traffic zones of the road network are considered, for a total of 191.

Next, we will show the sparsity of the data and demonstrate that the data conditions are low predictability by analyzing the trip data of the target group of the study.

First, we counted the frequency of trips of individuals in the target group during the observation period (one week) and obtained Figure 7. It can be seen that the number of trips observed of most individuals is less than 10, and for more
than 20% of individuals, we only observed no more than two trips for them. Thus for each individual, the data we have is sparse.

In order to demonstrate our data conditions is low predictability, we use the percentage of “accidental destination” and “potential destination” as indicators, whose definitions are given as follows.

- **Potential Destination**: Destination that chosen in the future but lack of observation period.
- **Accidental Destination**: Destinations chosen during the observation period but lack in the future.

Denote the two indicators as $P_o$ and $P_f$ respectively. Obviously, the values of $P_o$ and $P_f$ are related to the observation period $T_o$ and the period in the future $T_f$ considered. The value of $T_o$ can be determined as the observation period of our data is on one week. Hence, we show the percentage of target individuals for the above two types of destinations.
when $T_f$ takes different values. As for each individual, $P_o$ and $P_f$ can be calculated by Equations (9) and (10), of which $N_o$ and $N_f$ represent the number of destinations that the individual chose during $T_o$ and $T_f$ respectively. $N_{of}$ and $N_{fo}$ represent the number of "accidental destinations" and "potential destination". On this basis, we calculated and obtained the overall value of $P_o$, $P_f$ for the target group with different values of $T_f$ by averaging over individuals, see Table 5. Besides, for a specific demonstration, we drew a graph to show the distribution of the $P_o$ and $P_f$ of target individuals with $T_f = 14$ days, and result is shown in Figure 8.

$$P_o = \frac{N_{of}}{N_o} \times 100\%$$  
$$P_f = \frac{N_{fo}}{N_f} \times 100\%$$  

Table 5: The percentage of accidental destination and potential destination of target individuals.

| $T_o$=7days & $T_f$=7days | Percentage of Accidental destination | Percentage of Potential destination |
|--------------------------|-------------------------------------|-----------------------------------|
| $T_o$=7days & $T_f$=14days | 62.63%                              | 58.18%                            |
| $T_o$=7days & $T_f$=21days | 52.00%                              | 64.96%                            |
| $T_o$=7days & $T_f$=28days | 45.67%                              | 68.69%                            |
| $T_o$=7days & $T_f$=28days | 39.63%                              | 72.40%                            |

Figure 8: Proportional distribution of accidental and potential destination.

Table 5 and Figure 8 illustrate that both the percentage of potential destination and accidental destination of our target individuals are very high, which indicates the destination choosing behaviour of individuals seems to be very random. On the one hand, these individuals choose a large percentage of potential destinations that cannot be obtained by observing the individual’s historical trips. On the other hand, a large percentage of their chosen destinations have not been chosen at future periods. Thus for the destination prediction task, our data conditions are low predictability. It also shows that potential destinations are a very important research object worth studying in this data condition.

4.2 Experimental Setting

4.2.1 Data Setting

In this study, five weeks of data from 05/08/2019 to 08/09/2019 were used, of which only the first week data that we demonstrated in Section 4.1 was used for training which contains 1,047,061 trip records and the other data was used for testing.

According to the introduction of Section 3.2, the Trip Knowledge Graph(TKG) constructed using one week data has 95,728 unique entities, and the types of them are shown in Table 2. In addition, the number of relations of different types is 381,513 according to the structure shown in Figure 2 and all types of triples is shown in 5.
4.2.2 Parameter Setting

On the basis of the constructed Trip Knowledge Graph (TKG), we implemented the TransH model based on Pytorch 1.3.0 framework to embed the entity and relation of TKG. According to the characteristics of the training data and the structure of the knowledge graph, we have modified the general model, see Section 3.3.1. The crucial parameters are as follows.

| Parameter       | Value |
|-----------------|-------|
| Entity dimension| 148   |
| Relation dimension| 148 |
| $\gamma$        | 1.0   |
| Learning rate   | 0.003 |
| Batch size      | 1024  |
| Optimizer       | Adam  |

4.2.3 Output to be evaluated

The destination of target individuals chosen during the first week is regarded as "observed destination" and used for training. Then, when we retrieve the destination choices of target individuals after the first week, the potential destinations of each individual will be determined. Denote the set of individual potential destinations as $Z_c$ and $Z_p$. Based on the embedding model of TKG, for each potential destination of each individual, Algorithm 1-2 give the ranking of that destination under different ranking ways. The prediction effect varies among individuals. We cannot evaluate the effectiveness of prediction from the results of a single individual. Therefore, we consider the prediction results for all individuals and perform statistically. The process can be described as algorithm 3, of which “Count($K$)” means counting the proportion of elements of the set $K$, and it will output a hash table whose key is the element, and its value is the number proportion of this key.

Algorithm 3: Algorithm of potential destination prediction of individuals.

Input: Set of all individuals: $V$; Embedded TKG: $M$

Output: Hash Table of potential destination rankings: $R^e, R^h, R^c$

$R^e, R^h, R^c \leftarrow \emptyset$;

for $v_n$ in $V$ do

| $z_k$ in $Z_c$ do |
|------------------|
| $k^e_n \leftarrow$ algorithm1($z_k$); |
| $k^h_n, k^c_n \leftarrow$ algorithm2($z_k$); |
| $K^e \leftarrow k^e_n$; |
| $K^h \leftarrow k^h_n$; |
| $K^c \leftarrow k^c_n$; |
| $R^e, R^h, R^c \leftarrow \text{Count}(K^e), \text{Count}(K^h), \text{Count}(K^c)$; |

Return $R^e, R^h, R^c$

4.3 Experimental results and evaluation

4.3.1 Evaluation metrics.

The ranking hash table like $R^c$ can be considered a discrete distribution about the proportion of potential destinations predicted by different rankings. This distribution is the basis for our prediction performance evaluation, and the ideal distribution should have the following characteristics. First, the lower the ranking, the lower its corresponding proportion, which reflects the correctness of the prediction. If it cannot be strictly monotonous, then the evolution of its corresponding proportion should be smooth as the ranking varies. Second, most of the proportion should be concentrated in top rankings, which reflects the capability of the prediction model. On this basis, we denote the prediction output hash table and the proportion of ranking $r_i$ as $R$ and $P(r_i)$ respectively. Then we give the following three evaluation metrics.
Degree of ranking confusion. To evaluate the correctness of prediction, we introduce the metric that "degree of ranking confusion". First we extract the values of \( R \) to get the sequence \( A = [P(r_1), P(r_2), P(r_3), \ldots] \) and next sort it in descending order. Then the ranking of the \( P(r_i) \) in the sequence \( A \) can be obtained and denoted as \( r_i^R \). Then we can use the result of Equation \ref{eq:11} to quantify the Degree of ranking confusion.

\[
D_f = \sum_{r_i^R \in A} |(r_i^R - r_i) |
\tag{11}
\]

Degree of smoothing. To evaluate the smoothness of proportion evolution as ranking vary, we define the "Degree of smoothing" metric. Its equation is shown in Equation \ref{eq:12} in which \( P(r_i) \) represents the proportion of ranking \( r_i \) in ranking hash table \( R \).

\[
D_s = \sum_{R} (\max(0, P(r_{i+1}) - P(r_i)))
\tag{12}
\]

Degree of concentration. To evaluate the effectiveness of the prediction and the capability of the model, the metric that "degree of concentration" is introduced. It measures the concentration by calculating the cumulative proportion of the "Top-N" rankings, and it can be calculated by Equation \ref{eq:13}.

\[
D_c(N) = \frac{\sum_{n=1}^{N} (P(r_n))}{\sum_{r_i \in R} (P(r_i))} \times 100\%
\tag{13}
\]

Among the three metrics mentioned above, both \( D_f \) and \( D_s \) are the smaller the better, while for metric \( D_c \), the larger of it the better the model performance for the same \( N \).

4.3.2 Experimental results

In this section, we evaluate the performance of our method and comparison methods. Before making quantitative comparisons, visualization of the prediction output ranking hash table \( R \) can intuitively show the overall effectiveness of the prediction. Hence we will first visualize the \( R \) of different methods and then compare them using quantitative metrics.

First, We visualize the ranking hash table \( R^c \), \( R^h \) and \( R^e \) predicted under the three ranking ways obtained by Algorithm \ref{alg:3}, see Figure \ref{fig:9} Each of its bars represents the proportion of potential destinations caught by the ranking corresponding to its horizontal axis. Figure \ref{fig:9}(a) shows the performance of \( R^h \), which is predicted based on the statistical traffic zones hotness information. As we can see, the concentration of \( R^h \) is not bad, reflecting traffic zones with high hotness overall are usually more likely to be potential destinations for individuals. It also demonstrates that this information is valid for predicting potential destinations. However, intuitively, it is highly confusing and not smooth. More importantly, the prediction method is not personalized, i.e., it gives the same result for each individual. Figure \ref{fig:9}(b) illustrates the performance of \( R^e \), which is predicted based on our TKG embedding model. From the perspective of the correctness of the prediction results, our method is almost completely correct and very smooth. On this basis, Based on such prediction results, we can conclude that for an individual, the destination with a relatively high prediction ranking is indeed more likely to be chosen by that individual. Nevertheless, its concentration is not very high, considering the possible reason that the traffic zones hotness information is not added to the TKG and is not learned during the training process. So it is reasonable to assume that the combined ranking can have better results and it is illustrated in \ref{fig:9}(c). It can be seen that the prediction performance using the combined ranking incorporates the advantages of hotness ranking and embedding ranking only. It is almost monotonically decreasing and smooth with a high degree of concentration. The variation in the combined ranking performance proves that the two prediction ways are based on different dimensions of information, i.e., one based on statistics and one based on associated information. To summarize, our method has great performance for predicting potential destinations. In addition, the prediction is further improved by integrating the static statistical information of zones’ hotness. The correctness of the prediction results is sufficient to show that we have explored the choice patterns of individuals’ potential destinations. And the higher concentration level makes our method equally good practicality.

To demonstrate the superiority of our method, we compare the performance of different methods for the task of potential destination prediction. Considering methods that can implement this task, three types of methods are considered, and they all can achieve potential destination prediction personality.
Figure 9: Performances of different ranking ways.

1. **Random Choice (RC)**. “Random choice” simulates predicting potential destination in the absence of any context information. The method randomly gives the possible ranking of the zones in the potential destination candidate set for each individual.

2. **Matrix Decomposition (MD)**. “Matrix decomposition” is a typical class of methods for data repair and can be adapted to our task. We use the individual and the traffic zone as the two dimensions of the matrix and the number of trips that the individual chooses the traffic zone as the destination as the value of the matrix. By performing matrix decomposition, the 0 values in the matrix are filled. For each individual’s vector, the traffic zone corresponding to the original 0 value constitutes its candidate set of potential destinations, and the ranking can be given by comparing the size of these values after repair. We have implemented three common matrix decomposition methods that are UV decomposition, QR decomposition and SVD decomposition.

3. **Collaborative Filtering (CF)**. “Collaborative Filtering” is a classic method of recommendation system. For our task, we consider individual and traffic zone as user and item, respectively. The frequency of individuals choosing a traffic zone as the destination is regarded as the user’s score for the item. On this basis, we implemented two methods that “Collaborative Filtering User-based (CF-U)” and “Collaborative Filtering Item-based (CF-I)”. The former is based on the similarity of users, while the latter is based on the similarity of items.

The visualization of the ranking hash table resulting from the prediction using the compared methods on our dataset is shown in Figure 10. We can see that the method of “Random Choice” almost obtains a uniform distribution about ranking and its proportion, which means the predicted ranking is invalid. The performance of “UV decomposition” is close to “Random Choice”, except for a significant decline in the tail. Both “QR decomposition” and “SVD decomposition” perform well in the head. However, they all suffer from predicting a large number of potential destinations as backward ranking. This phenomenon is most notable for “Collaborative Filtering-Item based”. The ranking it gives is almost the exact opposite of the actual individual choice behaviour. For the method of “Collaborative Filtering-User based”, its figure drops rapidly in the middle. This indicates that it can roughly distinguish the possibility of potential destinations.
Then we quantitatively evaluate all methods using the metrics introduced in Section 4.3.1. The degree of ranking confusion $D_f$ and the degree of smoothing $D_s$ of different methods are shown in Table 7. In this table, “Random Choice” is abbreviated to RC and our method that based on Trip Knowledge Graph Embedding is abbreviated to TKGE. The results under the two ranking ways of TKGE are identified by “Embedding” and “Combined”. Besides, The prediction results based on the statistical information of traffic zones’ hotness was also be shown in the table, noted as “Hotness”.

Table 7: Degree of ranking confusion and smoothing of different methods

| method          | RC   | Matrix decomposition | Collaborative Filtering | TKGE          |
|-----------------|------|----------------------|-------------------------|---------------|
|                 | UV   | QR                   | SVD                     | Embedding     |
| $D_f$           | 7899 | 5415                 | 7627                    | 11245         |
| $D_s$           | 0.0078 | 0.032 | 0.021 | 0.024 | 0.034 | 0.030 | 0.13 | **295** | 329 |
|                 | User based | Item based | Hotness | Combined |
|                 | 3828 | 14030 | 2120 | **0.006** | **0.005** |

As can be seen in Table 7, our method significantly outperforms the other methods in both $D_f$ and $D_s$. The performance on $D_f$ of “Collaborative Filtering-Item based” and “SVD decomposition” is even worse than “Random Choice”. The
performance of “Random Choice” on $D_s$ is well, but it is meaningless for its $D_f$ is high. The $D_s$ of the prediction results based on the traffic zones’ hotness is significantly higher than the other methods.

For the degree of concentration $D_s$, We draw the cumulative percentage curve of different methods, see Figure 11. It can be seen that based on the TKGE model proposed in this study, the prediction effect of using the combined ranking is better than all other methods. And if we rely only on the TKGE model, the concentration is inferior to the “Collaborative Filtering User-based”.

To summarize, our proposed method for predicting individual potential destinations based on the trip knowledge graph embedding model is significantly better than other methods in terms of correctness of prediction and has reached an excellent level. It means that the prediction results are consistent with the individual’s potential destination choice behaviour. In other words, from a statistical perspective, the relatively top-ranked traffic zones that we predict are indeed more likely to be chosen by the individual. Thus, our proposed method essentially discovers the pattern of individuals’ choice of potential destinations. On the other hand, the prediction results relying only on the T model do not perform particularly well in concentration. Still, by fusing statistical information, the concentration is significantly improved while hardly changing the correctness of the prediction and outperforms all other methods.

5 Discussion

5.1 Discussion of the Trip Knowledge Graph Embedding model

The Trip Knowledge Graph Embedding(TKGE) model proposed in this study is specifically presented for low predictability data conditions. It has excellent generality and scalability. Generality is reflected in the fact that its effect does not depend on finely processed, hard-to-access data types. The idea of TKGE can be easily transferred to other scenarios or tasks. Besides, the inputs to the model are not restricted. When new data types are available, they can be added to the knowledge graph without adjusting the training and prediction logic, which makes the model very scalable. Besides, It can be trained in the absence of other data types as long as the triple that performs the prediction task(core triple) is available. On the other hand, the TKGE model allows inconsistent inputs for training and prediction, i.e., we train using a variety of information such as POI, but the prediction is required to give only the individual’s identity. Other information influences the expression of the core triple during the training process. Next, we will thoroughly discuss the TKGE model and respond to the crucial points mentioned in the methodology.

5.1.1 Performance over a larger period

In Section 4 we used one week(7 days) of data for training and evaluated the effect with the following two weeks(14 days) of data. What if we predict the potential destination of the individual over a more extensive period? Figure 12 shows the results, which are almost consistent with the predicted two weeks. This is very well explained. As shown in Table 5, potential destinations have been exposed for the vast majority of the two weeks after that. Hence two weeks as the predicted period length is sufficient to evaluate the effect of the model.
5.1.2 Correlation between dimension and performance

The parameters of the knowledge graph embedding algorithm are not very large, while the dimension of embedding is the most critical of them. In general, an optimal dimension exists that makes the model perform best for a given data and task. If the dimension selection of the model is correlated with the effect, then it will significantly reduce the work of parameter adjusting. To explore it with the TKGE model, we selected different dimensions for a series of experiments. The results are shown in Figure 13. It illustrated the dimension of embedding has a remarkable correlation with the performance of the TKGE model. Limited by the expressiveness of the low dimension, the model is less effective when the dimension is very low. As the dimensions increase, the model becomes better until a specific dimension is reached (the optimal dimension, which may not be 148), and the model’s effectiveness decreases again. It would greatly facilitate the adjustments of the parameters. In combination with the definition of relations that take into account the migration of the optimal dimensions mentioned in Section 3.2, we can migrate to other datasets by calibrating the optimal dimensions on one dataset.

5.1.3 Validity of information external to the core triple

The TKGE model can perform the prediction task with only the core triple. We introduce additional information such as POI that is contained in non-core triples in the TKG for they are valid for potential destination prediction. Then comes the question that is this information really valid? Does our TKGE model make effective use of this information? We designed the model containing only the core triple and trained it with the same parameters to answer the above question. Its effect compared with the model containing non-core triples is shown in Figure 14. It can be seen that the improvement of the model effect by introducing non-core triples is noticeable. This proves that the additional
information we introduced is valid and can be used by our TKGE model. Then we have reason to believe that the model will perform better when new valid information is introduced.

![Figure 14: Performances of model with and without non-core triples.](image)

### 5.1.4 The effect of relation design

In Section 5.2, we propose the concept of “private relation”. But that’s not to suggest that public relation is entirely undesirable. We have adopted the public relation to constructing the core triple and trained it. Finally we got the effect similar to that of private relation(Figure 14(b)) as shown in 15(b). But its dimension reached 600. When the dimension is 148, its effect is shown in Figure 15(a). The experimental results show that the more complex the relation is, the larger the dimension needed to express it. In other words, the larger its optimal dimension is. Therefore, the reason why we adopt the private relation is to ensure the consistency of the complexity of relations so as to make the optimal dimensions of different types as close as possible. Further, it can guarantee the migration of the optimal dimension between datasets of different scales. For example, suppose public relations are adopted. In that case, when the number of individuals considered changes dramatically, the complexity of the relation will increase, and the optimal dimension will change accordingly, which is not the case with private relations. Thus, although feasible, public relation is not scientific for partial triples of TKG.

![Figure 15: Performance of the public relation.](image)

### 5.1.5 The effect of the negative sampling strategy

In Section 5.2, we have mentioned that the negative sampling strategy is not adapted to our data and task, and the reason is given. What would be the impact if we introduced a negative sampling mechanism for training the TKGE model? To explore it, we trained two models using two negative sampling strategies based on the same data and parameters. One of the negative samples is generated by the “random replacement” mentioned in Section 5.3.1. The other one is the sampling method we designed. It guarantees that the replaced entity or relation is of a different type from the original one based on the random replacement method, which we call “controlled replacement”. In addition, in the case of using the negative sampling strategy, the optimization objective of the model is Equation (5). These two models is shown in Figure 16. The performance of “Random replacement” can be explained by analysis in Section 5.3.1. However, the negative sample produced by “controlled replacement” must not be a positive sample, but experiments show that it destroys the overall effect of prediction. This is worth exploring.
5.2 Discussion of prediction under the data condition with low predictability

First, we would like to discuss the advantages of knowledge graphs for prediction under low predictability conditions along with comparison methods presented in Section 4.3. Knowledge graphs are very powerful in modelling and expressing associated information. Besides, it is able to organize heterogeneous information well. We have chosen matrix decomposition as a comparison method, but without actually adding supplementary information such as POI. This is actually limited by the matrix or tensor’s ability to express heterogeneous information. On the other hand, the embedding algorithm of the knowledge graph dealing with “N – N” relations such as transH we used implements the same entity with different representations on different relations. For TKG, this means that it allows individuals to look at the same traffic zone in different ways. And it actually does. We think the poor performance of the contrast methods is primarily due to they actually defaulting to entities having only one meaning. For example, two individuals have similar destination choices, but they are going for different purposes because there are multiple POIs within a traffic zone. These two individuals would be considered similar by the collaborative filtering method, which is lacking in reasonableness. In addition, the prediction logic of methods such as collaborative filtering for commodity recommendations is also not consistent with destination prediction. For example, suppose an individual is observed to frequent a traffic zone that contains a residence POI. In that case, a commodity-based recommendation method will recommend other traffic zones that also contain residences POI. This obviously makes no sense, and these are precisely the zones where the individual is unlikely to go, as that residence could be his home. We believe this is an important reason why the “Collaborative Filtering-Item based” method performs so poorly. Regarding the proposed methods under high predictability data conditions, in Section 2, we have discussed that these methods can barely handle low predictability data conditions. Despite knowing that the principles of these methods do not match our data and tasks, we have tried to use them to deal with potential destination prediction problems. During this process, we have identified the following specific issues. Basically, some methods are completely unachievable to predict unobserved potential destinations. It is difficult for some supervised learning methods to determine the truth value for our task. Besides, the prediction task in this study requires only the individual’s identity to be given, which means that only individual identities can be used for training for methods that require training inputs consistent with test inputs such as neural networks.

Next, we would like to discuss the understanding of prediction under the data condition of low predictability. From the perspective of the data-driven, it should have the upper limit of predictability under a specific data condition. Obviously, the upper limit of predictability of data conditions with low predictability is lower, for which accurate prediction is difficult to achieve. However, the inability to make accurate predictions does not mean that they are unpredictable. Our proposed method is not oriented to accurate prediction yet. But its greatest contribution is that it can statistically "correct" prediction results. It gives us confidence that our method has found a pattern for individuals to choose potential destinations. On the premise of keeping the prediction correct, optimizing and adding different types of data through algorithms may improve concentration performance. When the concentration is very high, the prediction effect will be close to accurate prediction. But, of course, it is unknown whether such data conditions can achieve accurate prediction with high accuracy. However, as long as we achieve a certain degree of prediction, we can say that such data condition has at least this degree of predictability. Finally, we would like to discuss how to improve the performance of our method, which is also our further work. According to Section 5.1, we can see our method can steadily obtain correct prediction results. Hence we mainly try to improve the model’s performance in the concentration. In Section 5.1.3, we have discussed the effectiveness of POI and other information to improve the performance. So next, we will consider introducing more types of data, such as the adjacency between traffic zones. It is worth mentioning that the knowledge graph is not good at expressing numerical information. This is why we do not consider the numerical
information of static statistics in the construction of TKG. Similarly, the distance information between traffic zones is also numerical and valid for destination prediction. Therefore, next we will also design an expression scheme for numerical information, so that it has good accuracy and can be well learned by the algorithm.

6 Conclusion

Potential destinations account for a large proportion and can not be ignored under the data condition with low predictability. In this paper, we proposed a method based on knowledge graph embedding for potential destination under data condition with low predictability formed by short-term observation. Firstly, we adopted the knowledge graph to organize individual trip data and obtain Trip Knowledge Graph(TKG). There are two crucial steps in the construction of TKG. First is entity extraction, in which we extracted the information related to the individual destination choice and modelled the trip scene in the real world through the one-to-one mapping between the entity and real-world subject. When designing the relation between entities, we introduce “private relation” to reduce the complexity of relations. In this way, data of different individuals are associated in TKG, and the complexity degree of its relations is similar. Next, we map the entity and relation of TKG to a continuous space by using the knowledge graph embedding algorithm. To adapt the algorithm to our data and tasks, we optimize the embedded general model. On the one hand, we changed the training strategy. On the other hand, the negative sample sampling strategy was canceled while the optimization object was modified. Since almost all data of individuals in TKG are associated, the training process can achieve the effect of global optimization. Based on Trip Knowledge Graph Embedding(TKGE) model, we designed the potential destination prediction methods. It can obtain the ranking of the possibility of their potential destinations being chosen in the future. Besides, we integrate the static statistical information by calculating the combined ranking. To validate our method, we construct a completely low-predictability data condition using real-world AVI data and adopted our method in this scene. Experiments demonstrate that whether the ranking given by embedding model or combined ranking is highly consistent with the pattern of individual potential destination choices, while combined ranking improved the model’s performance in the concentration metric. Finally, we have a thorough discussion of the method we proposed and respond to all changes to the general model in the methodology. In addition, we also discussed the task of prediction under the data condition with low predictability.
References

Francisco Dantas Nobre Neto, Cláudio de Souza Baptista, and Claudio EC Campelo. Combining markov model and prediction by partial matching compression technique for route and destination prediction. Knowledge-Based Systems, 154:81–92, 2018.

Ramaswamy Hariharan and Kentaro Toyama. Project lachesis: parsing and modeling location histories. In International Conference on Geographic Information Science, pages 106–124. Springer, 2004.

John Krumm and Eric Horvitz. Predestination: Inferring destinations from partial trajectories. In International Conference on Ubiquitous Computing, pages 243–260. Springer, 2006.

Jian Jiang, Fei Lin, Jin Fan, Hang Lv, and Jia Wu. A destination prediction network based on spatiotemporal data for bike-sharing. Complexity, 2019, 2019.

Juanjuan Zhao, Liutao Zhang, Jiexia Ye, and Chengzhong Xu. Mdlf: A multi-view-based deep learning framework for individual trip destination prediction in public transportation systems. IEEE Transactions on Intelligent Transportation Systems, 2021.

Fang Zong, Yongda Tian, Yanan He, Jinjun Tang, and Jianyu Lv. Trip destination prediction based on multi-day gps data. Physica A: Statistical Mechanics and its Applications, 515:258–269, 2019.

Marta C Gonzalez, Cesar A Hidalgo, and Albert-Laszlo Barabasi. Understanding individual human mobility patterns. nature, 453(7196):779–782, 2008.

Chaoming Song, Zehui Qu, Nicholas Blumm, and Albert-László Barabási. Limits of predictability in human mobility. Science, 327(5968):1018–1021, 2010.

Vaihav Kulkarni, Abhijit Mahalunkar, Benoit Garbinato, and John D Kelleher. Examining the limits of predictability of human mobility. Entropy, 21(4):432, 2019.

Ryo Imai, Kota Tsubouchi, Tatsuya Konishi, and Masamichi Shimosaka. Early destination prediction with spatiotemporal user behavior patterns. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 1(4):1–19, 2018.

Daniel Ashbrook and Thad Starner. Learning significant locations and predicting user movement with gps. In Proceedings. Sixth International Symposium on Wearable Computers, pages 101–108. IEEE, 2002.

Ingrid Burbey and Thomas L Martin. Predicting future locations using prediction-by-partial-match. In Proceedings of the first ACM international workshop on Mobile entity localization and tracking in GPS-less environments, pages 1–6, 2008.

Apollinaire Nadembega, Tarik Taleb, and Abdelhakim Hafid. A destination prediction model based on historical data, contextual knowledge and spatial conceptual maps. In 2012 IEEE International Conference on Communications (ICC), pages 1416–1420. IEEE, 2012.

Anastasios Noulas, Salvatore Scellato, Neal Lathia, and Cecilia Mascolo. Mining user mobility features for next place prediction in location-based services. In 2012 IEEE 12th international conference on data mining, pages 1038–1043. IEEE, 2012.

Andy Yuan Xue, Rui Zhang, Yu Zheng, Xing Xie, Jin Huang, and Zhenghua Xu. Destination prediction by subtrajectory synthesis and privacy protection against such prediction. In 2013 IEEE 29th international conference on data engineering (ICDE), pages 254–265. IEEE, 2013.

Meng Chen, Xiaohui Yu, and Yang Liu. Mpe: A mobility pattern embedding model for predicting next locations. World Wide Web, 22(6):2901–2920, 2019.

Wei Wang, Xiaofeng Zhao, Zhiguo Gong, Zhikui Chen, Ning Zhang, and Wei Wei. An attention-based deep learning framework for trip destination prediction of sharing bike. IEEE Transactions on Intelligent Transportation Systems, 2020.

Philippe C Besse, Brendan Guillouet, Jean-Michel Loubes, and François Royer. Destination prediction by trajectory distribution-based model. IEEE Transactions on Intelligent Transportation Systems, 19(8):2470–2481, 2017.

Pengcheng Dai, Changxiong Song, Huiping Lin, Pei Jia, and Zhipeng Xu. Cluster-based destination prediction in bike sharing system. In Proceedings of the 2018 Artificial Intelligence and Cloud Computing Conference, pages 1–8, 2018.

Zhan Zhao, Haris N Koutsopoulos, and Jinhua Zhao. Individual mobility prediction using transit smart card data. Transportation research part C: emerging technologies, 89:19–34, 2018.

Alberto Rossi, Gianni Barlacchi, Monica Bianchini, and Bruno Lepri. Modelling taxi drivers’ behaviour for the next destination prediction. IEEE Transactions on Intelligent Transportation Systems, 21(7):2980–2989, 2019.
Punit Rathore, Dheeraj Kumar, Sutharshan Rajasegarar, Marimuthu Palaniswami, and James C Bezdek. A scalable framework for trajectory prediction. *IEEE Transactions on Intelligent Transportation Systems*, 20(10):3860–3874, 2019.

Patrick Ebel, Ibrahim Emre Göl, Christoph Lingenfelder, and Andreas Vogelsang. Destination prediction based on partial trajectory data. In *2020 IEEE Intelligent Vehicles Symposium (IV)*, pages 1149–1155. IEEE, 2020.

Baichuan Mo, Zhan Zhao, Haris N Koutsopoulos, and Jinhua Zhao. Individual mobility prediction in mass transit systems using smart card data: An interpretable activity-based hidden markov approach. *IEEE Transactions on Intelligent Transportation Systems*, 2021.

Yuebing Liang and Zhan Zhao. Vehicle trajectory prediction in city-scale road networks using a direction-based sequence-to-sequence model with spatiotemporal attention mechanisms. *arXiv preprint arXiv:2106.11175*, 2021.

Feng Jiang, Zhen-ni Lu, Min Gao, and Da-ming Luo. Dp-bpr: Destination prediction based on bayesian personalized ranking. *Journal of Central South University*, 28(2):494–506, 2021.

Jie Sun and Jiwon Kim. Joint prediction of next location and travel time from urban vehicle trajectories using long short-term memory neural networks. *Transportation Research Part C: Emerging Technologies*, 128:103114, 2021.

Andy Yuan Xue, Jianzhong Qi, Xing Xie, Rui Zhang, Jin Huang, and Yuan Li. Solving the data sparsity problem in destination prediction. *The VLDB Journal*, 24(2):219–243, 2015.

Juan Antonio Alvarez-Garcia, Juan Antonio Ortega, Luis Gonzalez-Abril, and Francisco Velasco. Trip destination prediction based on past gps log using a hidden markov model. *Expert Systems with Applications*, 37(12):8166–8171, 2010.

Christian Manasseh and Raja Sengupta. Predicting driver destination using machine learning techniques. In *16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013)*, pages 142–147. IEEE, 2013.

Quan Wang, Zhendong Mao, Bin Wang, and Li Guo. Knowledge graph embedding: A survey of approaches and applications. *IEEE Transactions on Knowledge and Data Engineering*, 29(12):2724–2743, 2017.

Shaoxiong Ji, Shirui Pan, Erik Cambria, Pekka Marttinen, and S Yu Philip. A survey on knowledge graphs: Representation, acquisition, and applications. *IEEE Transactions on Neural Networks and Learning Systems*, 2021.

Quan Yuan, Gao Cong, Zongyang Ma, Aixin Sun, and Nadia Magnenat Thalmann. Time-aware point-of-interest recommendation. In *Proceedings of the 36th international ACM SIGIR conference on Research and development in information retrieval*, pages 363–372, 2013.

Zhen Wang, Jianwen Zhang, Jianlin Feng, and Zheng Chen. Knowledge graph embedding by translating on hyperplanes. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 28, 2014.

Yimin Wang, Yixian Chen, Guilong Li, Yuhuan Lu, Zhi Yu, and Zhaocheng He. City-scale holographic traffic flow data based on vehicular trajectory resampling. *arXiv preprint arXiv:2108.13376*, 2021.