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(article starts on next page)

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Full Length Article

A personalized recommendation system for multi-modal transportation systems

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ABSTRACT

Recommendation system has recently experienced widespread applications in fields like advertising and streaming platforms. Its ability of extracting valuable information from complex data makes it a promising tool for multi-modal transportation system. In this paper, we propose a conceptual framework for proactive travel mode recommendation combining recommendation system and transportation engineering. The proposed framework works by learning from historical user behavioral preferences and ranking the candidate travel modes. In this framework, an incremental scanning method with multiple time windows is designed to acquire multi-scale features from user behaviors. In addition, to alleviate the computational burden brought by the large data size, a hierarchical behavior structure is developed. To further allow for social benefits, the proposed framework proposes to adjust the candidate modes according to real-time traffic states, which is potential in promoting the use of public transport, alleviating traffic congestion, and reducing environmental pollution.

1. Introduction

Recommendation system has gained extensive attention over the past decade, and its applications are widespread in a variety of areas, such as e-commerce stores and streaming platforms (Covington et al., 2016; Deldjoo et al., 2015; Van den Oord et al., 2013; Wang et al., 2018; Liu et al., 2018). By pushing more relevant items to users, service providers are expected to increase users' satisfaction to their products and make more profit. At the same time, trip planning and navigation services are growing to become an indispensable component of the intelligent transportation system (Jenelius and Koutsopoulos, 2018; Li et al., 2010; Yuan et al., 2013). As a type of product directly connecting transportation services to travelers, exclusive attention needs to be placed on providing personalized guidance catering to each individual's preference (Borole et al., 2013; Ge et al., 2019; Shang et al., 2016). To achieve this goal, it can be promising to introduce recommendation system, which is capable of identifying users' preferences from massive historical behavioral interactions. This paper aims to propose a personalized recommendation system for multi-model transportation system, in order to provide users with active travel mode guidance. Currently, there have been some navigation platforms like Baidu Maps and Google Maps that manages to provide recommendation services. For instance, Hydra, the system proposed by Baidu Maps, was verified on datasets of two cities, significantly outperforming traditional baselines (Liu et al., 2019).

However, existing methods focus mainly on improving the click through rates of the recommendation system without allowing for factors related to social benefits. Multi-modal transportation system consists of diverse travel modes, including both public transport

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and private transport (Qin et al., 2021). It is inappropriate to encourage users to choose private transport like taxis when road traffic is congested even though the user is insensitive to travel cost, since it may aggravate the traffic state (Peled et al., 2021). Therefore, apart from attending to users' propensity of travel modes, it is also expected that the recommendation system can help promote the use of public transport instead of encouraging users to drive.

E-commerce recommendation systems have grown mature nowadays. In the era of big data, when there is an explosive increase in the amount of information, the recommendation system is essentially helping users filter information to prevent information overload. People are also getting used to shopping and watching videos based on the recommended results. The item ranking given by the recommendation model plays a key role in users' final choices. Similarly, the proposed recommendation system can provide results favoring public transport, thus implicitly guiding users to use public transport. Faced with this issue, our proposed framework will work together with real-time traffic state information, whereby the results of candidate trip plans will be adjusted when road traffic experiences severe congestion.

The major contributions of this study can be summarized as follows,

1. Develop a conceptual personalized mode recommendation framework for multi-model transportation system based on both user preferences and real-time traffic state information.
2. Design an incremental scanning method with multiple time windows in order to extract multi-scale features from user behaviors within different time horizons.
3. Develop a hierarchical behavior structure to alleviate the computational burden caused by the large data size.

2. Problem statement

Two types of data are required for the personalized mode recommendation system, including the historical user interaction data collected by the navigation application and traffic state indicator. The user interaction data can be further decomposed into four subsets, i.e., the user query data, the candidate data, the selection data, and the user attribute data. Detailed definitions of these data are provided below.

Definition 1: User query data Q. A query includes the full process when a user searches trip plans for a given pair of origin and destination (OD) on the navigation application. The information contained in a set of user query data are the user ID, the query ID, the query time, and the locations of OD.

Definition 2: Candidate data C. Each time when a user starts a query, the routing engine of the navigation application will provide the user with several candidate trip plans of different travel modes. These plans are displayed in a particular order, and the most appropriate plan will be placed on the top of the candidate list. The information contained in a set of candidate data are the attributes of each plan, including estimated travel distance (ETD), estimated time of arrival (ETA), estimated travel cost (ETC), the plan ID, and the query ID.

Definition 3: Selection data S. Being given a list of candidate trip plans, a user will select one plan that conforms most to their preference to check the details. The information contained in a set of selection data are the query ID, and the selected plan ID.

Definition 4: User attribute data U. The attributes of a user indicate the basic information about this user, such as gender, age, and occupation. However, for the sake of privacy protection, these attributes are usually not directly accessible. Instead, they are stored in an anonymous way, in the form of a set of normalized numbers.

Definition 5: Traffic state indicator D. Traffic state indicator refers to a critical number that indicates the phase transition of traffic flow from free flow to congestion. For commercial navigation applications like Baidu Maps, average travel speed is used to identify traffic states.

Problem Statement: Given the user ID, the query time, and a pair of OD, the personalized mode recommendation system has to recommend the travel mode that conforms the most to the users' preference. In addition, the generated candidate trip plans should allow for the constraint of traffic states.

Our goal is not to force users to travel in the recommended way, but something like traffic guidance. Given the costs of different candidate trip plans, the user will subjectively choose the trip plan with the lower cost (Gao et al., 2020; Gao et al., 2021). The inherent random behaviors are part of the unavoidable error brought by the data itself. Since none of travel behavior models, including machine learning models, can achieve an accuracy of 100%, the existence of such error is reasonable (Liu et al., 2019).

Note that recommendation systems are not equivalent to supervised learning models. Taking an operations research task as an example, we can model the problem, define the objectives, constraints and then solve it using a solver such as Cplex. In a recommendation system, a supervised learning model only acts in the role of Cplex. We need to first define a completely new problem that translates into a problem that can be solved by machine learning, i.e., modeling. In addition to that, a personalized candidate set has to be generated and personalized features have to be designed, where personalization is a concept in recommender systems indicating that the recommendation given to each individual user in our model is completely different by allowing for their preferences.

3. Methodology

3.1. Framework overview

Recommendation system usually includes two fundamental steps, namely candidate generation and item ranking, where our primary focus is on the second. To address the personalized mode recommendation problem, the proposed framework transforms the item ranking into a supervised learning problem. A model is built and trained using historical user interaction data to learn users' preferences on mode choice. The input of the supervised learning model includes historical user behaviors and the context of the current session, and the output of the model is the mode choice of this user. Feature engineering is required to construct feature vectors from the unorganized historical behavior data. Two novel techniques, i.e., incremental feature scanning with multiple time windows and hierarchical behavior structure, are used to help extract valuable information from the raw data and improve the efficiency of the extraction process. To accomplish the supervised learning task, an improved algorithm of gradient boosting tree, LightGBM, is adopted to learn the complex relationship between input feature vectors and output labels (Ke et al., 2017). It should be noted that, in this paper, we are actually presenting an idea of innovation, briefly describing the background and related technologies. Real-world applications can be found in two of our previous works. Note that in our previous works, our innovation was mainly in the design of a multi-modal recommendation system (Liu et al., 2021a), and focused on learning the behavior of travelers using unsupervised learning (Liu et al., 2021b). In this paper, we focus on proposing a personalized recommendation system for the multi-modal transportation system, in order to provide users with active travel mode guidance.

Modeling training is completed in the offline stage using solely historical data. For the online stage when the model is used in practical cases, the model will accept the context of the session as the input and output the estimated ranking of each candidate mode. However, as discussed in Introduction, merely catering to users' preferences fail to allow for social benefits. Moreover, the purpose of existing recommendation algorithms only focus on recommendation, which, however, is unreasonable in the field of traffic engineering. For example, if we recommend the same route to a group of users with the same start and end locations, congestion may occur even on roads previously uncongested. Therefore, in online implementation, the generated candidate modes will be adjusted according to the real-time traffic states. First, K different trip plans using different travel modes will be generated as the initial scheme. Next, the generated candidates will be examined one by one concerning whether the traffic state relating to this mode reaches the critical value, in other words, whether serving another traveler using this mode will aggravate the traffic state. Provided that several users start concurrent sessions with similar plans, priority will be given to the earlier user following the first-in-first-out rule. We will recommend the sub-optimal travel plan to the remaining travelers to alleviate/reduce traffic congestion for the roads in the optimal travel plan. The output of the model is the predicted probability of the traveler using different trip plans. To prioritize public transport, we can multiply the probability of travel plans with public transport by a factor. In this way, travel plans of public transport will be ranked higher, which actively induces/recommends travelers to use public transport.

This paper does not propose a specific method, but a class of methods. Therefore, the objective function and output can be designed according to actual requirements, for example, the practical application can be a binary classification task or a multi-classification task. The input raw data are information mentioned in the problem statement, and it is worth noting that one of the key components of machine learning workflow is feature engineering, where algorithm experts can define different features according to their needs. The users' preferences are quantified by hundreds of features, which can be simple statistics (e.g., travel frequency), expert-defined indicators, and even the output of other models.

3.2. Incremental feature scanning with multiple time windows

As a supervised learning problem, it is critical to extract valuable information from historical data, i.e., historical user interactions in the navigation application. For a recommendation system, feature extraction is usually realized by calculating various statistics of behavioral indicators from a specific time range (Liu et al., 2021a; Liu et al., 2020a; Liu et al., 2020b). Here, suppose the range of time used to construct the feature vector of a sample is m days. Then, the label corresponding to this sample will be the user behavior on the $(m+1)$-th day.

The extracted information is closely connected with the time range, which is also referred as the time window. Normally, the larger the window size, the richer the information obtained from historical user behaviors. A small window size like $m = 1$ will be insufficient to accurately capture the individual preference of a user, and is easily affected by sudden events or occasional behaviors. In contrast, a large window size can be robust in feature extraction as the results are not prone to be influenced by outliers. On the other hand, smaller window size can be advantageous over the large one since users' preferences can change over time.

However, determining the window size is not a trivial task because of heterogeneity in users' behaviors. In response to this issue, we propose to use an incremental feature scanning method, which utilizes multiple time windows with different sizes for feature extraction, as illustrated in Fig. 1. Compared with single time window, both advantages of large window size and small window size can be leveraged.

3.3. Hierarchical behavior structure

In addition to the amount of extracted information, the window size is also correlated with the computational cost. For navigation services serving millions of users, the size of user interaction data can be extremely large. A large time window indicates computations with a huge amount of data, leading to massive memory usage. To ensure the feasibility of the incremental feature scanning method, it is therefore imperative to limit the computational pressure involved in large-scale feature engineering. It should be noted that the features obtained by dimensionality reduction are weak features, while the features carefully designed by expert experience-based feature engineering are strong features. However, designing and calculating these strong features are computational exhaustive, and the hierarchical behavioral structure in this paper is proposed for this situation.

The hierarchical behavior structure is introduced to address the above issue. This structure is designed in resemblance to the memory hierarchy of computers. In modern computers, the storages are organized in a hierarchical way, where massive data are

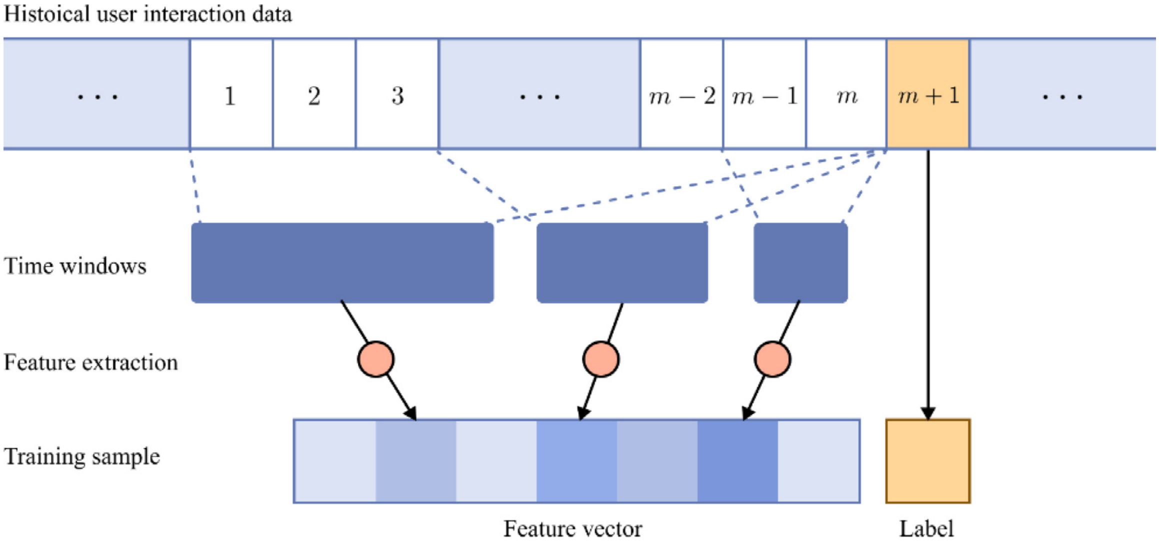

Fig. 1. Incremental feature scanning with multiple time windows.

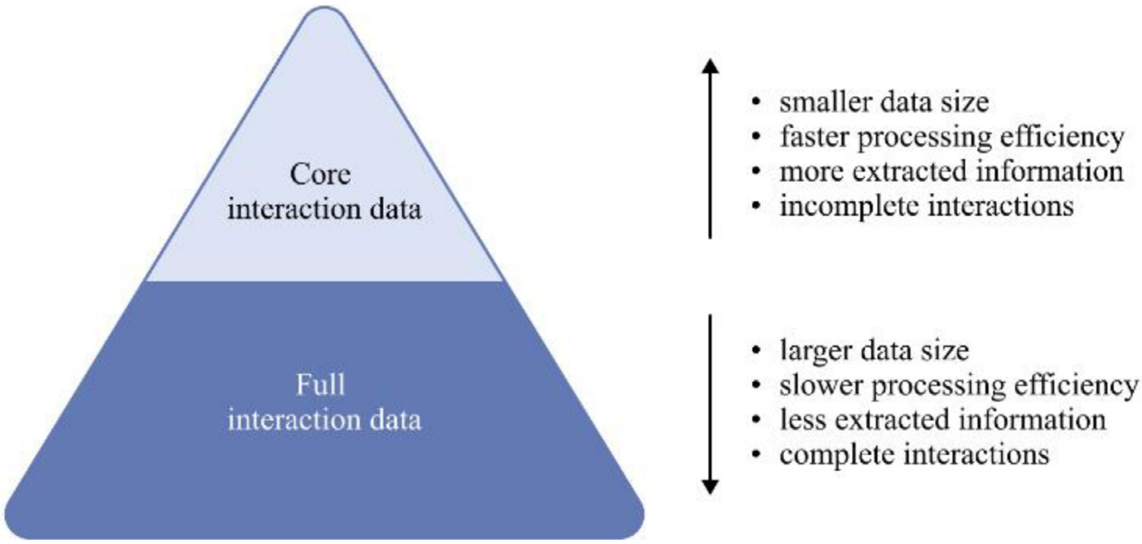

Fig. 2. Hierarchical behavior structure.

placed in the lower level with large capacity but low speed, while important data related to the task being currently executed are copied to the upper level with small capacity but high speed. Such design is useful to balance the demand for large capacity and high speed. Similar to the memory hierarchy, the proposed hierarchical behavior structure organizes the user interaction data into two ordered subsets, namely the core interaction data and the full interaction data. The premise of this structure is endorsed by the fact that, among all the candidate travel modes recommended to the user, only one of them will be finally selected. As demonstrated in Fig. 2, the full interaction data, which contains all the historical user interactions, sit on the lower level, while the core interaction data, which contains a part of the historical user interactions, sit on the upper level. Because of the difference in data size, the computational speed and memory efficiency for the core interaction data will be much higher than that for the full interaction data. Small data size and high processing efficiency allow the usage of large time window on the core interaction data. Therefore, compared with the full interaction data, more time windows can be applied on the core interaction data to extract richer information.

The two levels of data are constructed through a behavior filter that examines whether a session of user interaction contains the behavior of selection, and only the data with a selected travel mode will be put in the core interaction data. The behavior filter is able to reduce the million-scale data to thousand-scale. Fig. 3 illustrates the process of behavior filtering and feature extraction. For the full interaction data, only small time windows are used to ensure the computational time and memory consumption is acceptable. For the filtered core interaction data, apart from small time windows, large windows can also be used to capture more user preferences. Finally, the extracted features will be combined to form the training set and fed into the gradient boosting tree model.

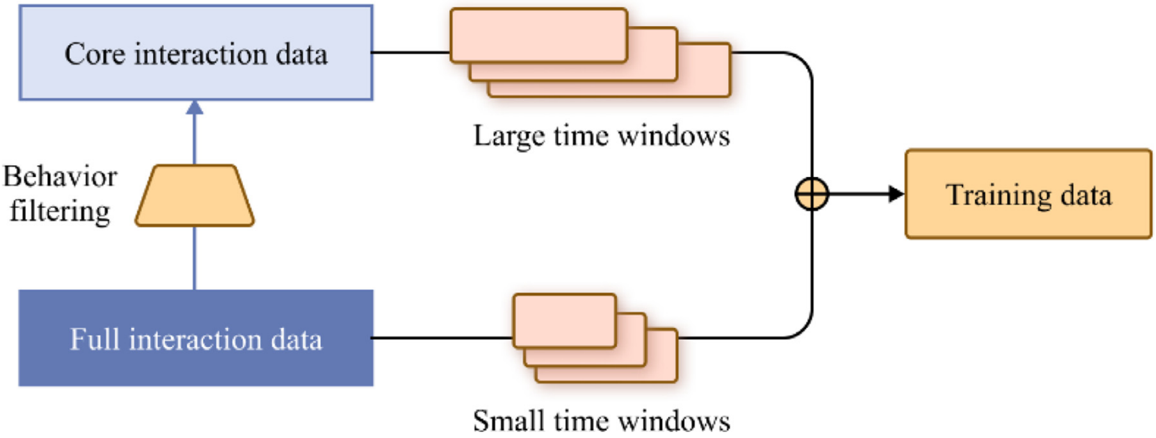

Fig. 3. Behavior filtering and feature extraction.

4. Conclusion and discussion

In this paper, we investigate the problem of personalized mode recommendation and propose a conceptual recommendation system for multi-modal transportation system. Two techniques, namely the incremental feature scanning with multiple time windows and the hierarchical behavior structure, are proposed to address issues relating to feature engineering and computational efficiency respectively. Specifically, the first technique leverages the advantages of both large time windows and small time windows to extract behavioral features in different scales, such that the general behavioral pattern and recent preference changes can be both captured. The second technique is targeted at the computational burden involved in the feature extraction with large time windows for large-scale data. Additionally, we also propose to adjust candidate modes according to real-time traffic states in the candidate generation step of the recommendation system in order to allow for social benefits. The model in this paper does not add more difficulty to the management of the transportation system. We are using existing data and existing travel modes to provide smarter services in order to achieve personalization.

The proposed framework is beneficial to various stakeholders. For common travelers, the user experience of navigation application can be improved by saving decision time for finding comfortable, convenient, and affordable trip plans. For transportation service providers, they can have better understanding about users' mode choice behaviors, whereby the service quality and pricing can be modified to improve their service efficiency and revenue. For government, the active guidance of the recommendation system can help promote the use of public transport, which is valuable in alleviating urban traffic congestion and environmental pollution.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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