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RESEARCH PAPER

A personalized point-of-interest recommendation system for O2O commerce

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Abstract

Online-to-offline (O2O) commerce, e.g., the internet celebrity economy, provides a seamless service experience between online commerce and offline bricks-and-mortar commerce. This type of commerce model is closely related to location-based social networks (LBSNs), which incorporate mobility patterns and human social ties. Personalized point-of-interest (POI) recommendations are crucial for O2O commerce in LBSNs; such recommendations not only help users explore new venues but also enable many location-based services, e.g., the targeting of mobile advertisements to users. However, producing personalized POI recommendations for O2O commerce is highly challenging, since LBSNs involve heterogeneous types of data and the user-POI matrix is very sparse. LBSNs have substantially altered how people interact by sharing a wide range of user information, such as the products and services that users use and the places and events that users visit. To address these challenges in O2O commerce LBSNs, we analyze users' check-in behaviors in detail and introduce the concept of a heterogeneous information network (HIN). Then, we propose a HIN-based POI recommendation system, which consists of two components: an improved singular value decomposition (SVD++) and factorization machines (FMs). The results of experiments on two real-world O2O commerce websites, namely, Gowalla and Foursquare, demonstrate that our method is more accurate than baseline methods. Additionally, a case study of the bricks-and-mortar brand of internet celebrity indicates that our proposed POI recommendation system can be used to conduct online promotion and purchasing to drive offline marketing and consumption.

Keywords POI recommendation system · O2O commerce · Internet celebrity economy · Location-based social networks · Heterogeneous information networks

JEL classification C90 · M31

Introduction

Online-to-offline (O2O) commerce increasingly draws the attention of the whole commerce industry. O2O commerce provides a seamless service experience between online commerce and offline bricks-and-mortar commerce, e.g., catering and entertainment. In O2O commerce, customers seek and order products or services online and then consume them in the corresponding bricks-and-mortar stores (Xiao and Dong 2015). After consumption, customers share their experiences and express their feelings online, such as through ratings and comments. The internet celebrity economy, or wanghong economy, is a type of O2O commerce model where online or offline sales are promoted by an online celebrity (Li 2018). According to the data company CBNData, the internet celebrity economy was projected to be worth

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approximately $8.4 billion in 2016 and surpassed $21 billion in 2018, thus making the sector even more valuable than the domestic film industry. Moreover, as the overall size of the internet celebrity economy grows, the influence of internet celebrities extends beyond the fashion and pan-entertainment industry (Chang and Woo 2019). An increasing number of internet celebrities are also building a burgeoning influence in education, food, travel, parenting, and childcare. Internet celebrities have more diversified ways to boost their revenues, which have grown considerably through advertising, online tipping, paid subscription services, bricks-and-mortar brands, etc. In particular, the bricks-and-mortar brands of internet celebrity have grown rapidly, thereby becoming an important source of income (CBNData report 2018). According to current research, the internet celebrity economy can be divided into two categories: The first category consists of online shops or brands set up by influential internet celebrities, such as Papi Jiang and Zhang Dayi, who target a large growing segment of internet users. The second category consists of the bricks-and-mortar brands of internet celebrity; these brands, e.g., Heytea, Baoshifu, and Nayuki, are popular because of their unique look and the consumption experience that they provide. In this paper, we principally focus on the second category. Figure 1 shows an example of a bricks-and-mortar brand of internet celebrity.

With the popularization of information technology, O2Ocommercehasdeveloped a close relationship with location-based social networks (LBSNs), which incorporate mobility patterns and human social ties (Interdonato et al. 2019; Shen et al. 2019). As users would like to survey others' opinions online before consumption, LBSN services have substantially altered how people make purchasing decisions by sharing a wide range of user information, such as the products and services that users use and the places and events that users visit (Duan et al. 2019). Thus, the effectiveness of O2O commerce can be significantly improved by considering the rich information in LBSNs, which provide an important research environment for O2O commerce. In particular, Alex Rampell (2010) observed that the "key to O2O commerce is that it finds consumers online and brings them into real-world stores". Point-of-interest (POI) recommendation systems, which recommend fascinating new places, bridge the gap between the physical and virtual online world (Bao et al. 2015). Therefore, POI recommendation systems are important to O2O commerce in LBSNs because they not only satisfy users' personalized preferences for visiting new places but also help O2Owebsites increase revenue by providing users with intelligent location services.

Two major challenges presented by POI recommendation systems are data sparsity and cold start, which dramatically degrade recommendation performance (Eirinaki et al. 2018). The cold start problem occurs if the recommendation system does not have sufficient knowledge to provide effective suggestions to a new user, who has limited check-in records. Data sparsity occurs when the data are insufficient for identifying similar users or POIs. For POI recommendation systems in LBSNs, each user's check-in records are limited, whereas the number of POIs is large.

To address these challenges, we propose a heterogeneous information network based POI recommendation system that fully utilizes diverse information and is extremely suitable for the recommendation scenarios for bricks-and-mortar brands of internet celebrity. In summary, our work makes the following contributions:

(1) We identify the challenges of producing POI recommendations in O2O commerce by exploring the unique mobility and social characteristics of O2O commerce. We use 8 time slots to represent the covisitation events in O2O commerce LBSNs.
(2) To address the problems of data sparsity and cold start, we employ a weighted meta path to encode the influences of geography, social relations, and temporal effects. Additionally, we explore the utility of the above

Fig. 1 An example of a bricks-and-mortar brand of internet celebrity

information in the personalized POI recommendation tasks of O2O commerce.

(3) We utilize the FM to capture the interactions between and among inter-meta path features, thereby increasing prediction accuracy.

The remainder of this paper is organized as follows: Section 2 summarizes related works. Section 3 elaborates the problem to be addressed in this paper. Section 4 presents the research methodology in detail. Section 5 introduces the optimization and complexity analysis of our method. The experiment framework is presented in Section 6, while the results of the experiments are presented in Section 7. Finally, we present the discussion and conclusions of this study in Sections 8 and 9, respectively.

Related work

In general, there are several categories for current POI recommendation approaches in O2O commerce. Some works belong to more than one category, since they combine different recommendation algorithms with different information. In this section, we review the current literature in three related research streams, namely, O2O service recommendations, POI recommendations in LBSNs, and HIN-based POI recommendations. Overall, the three parts compose our ultimate theme: a HIN-based POI recommendation system in LBSNs in O2O commerce.

O2O service recommendation

As increasingly more enterprises encapsulate their business modules into web services, O2O commerce becomes popular in current service applications. Faced with so many items, customers who suffer from serious information overloading find it difficult to choose appropriate services to meet their needs. Personalized recommendation methods are the most common and efficient approaches to solving information overload (Adomavicius and Tuzhilin 2005). In this subsection, we summarize the state of the art in O2O service recommendation research by the data sources used and the methodology employed to generate recommendations.

Xue et al. (2016) proposed a computational experiment-based evaluation method for O2O service recommendation strategies; this method consists mainly of three parts: a customization of O2O service strategies, a modeling of the experiment system, and an evaluation of the experiment. Pan et al. (2017) proposed an O2O service recommendation method based on multidimensional similarity measurements; this method encompasses three similarity measures: collaborative similarity, preference similarity and trajectory similarity. In addition, Pan et al. (2019) proposed a rating-based O2O service recommendation model that, by considering user activity, can better reflect the differences in customers' behavioral characteristics. Yu (2018) proposed a personal recommendation method based on the O2O sports community; this method establishes various compact relationships among exercisers, activities, and commodities. Wang and Yi (2019) proposed a recommendation algorithm, based on the rank-order centroid/analytic hierarchy process, for transforming the recent booking preferences of users into the takeaway service standard weight. Hu et al. (2019) proposed an item-oriented recommendation algorithm to maximize revenue by discovering users who can purchase the target item.

As proposed by Gorgoglione et al. (2019), the incorporation of contextual information is helpful for enhancing the accuracy of the recommendation system. Nevertheless, the number of studies on the utilization of multidimensional information for O2Ocommerce recommendations is limited. Therefore, it is crucial to introduce LBSNs and HIN to O2O service recommendations.

POI recommendation in LBSNs

LBSNs have popularized the concept of POI recommendations, which detect relevant POIs for target users based on their preferences. Users typically utilize LBSN-based websites or applications to detect POIs that are close to their current location and to identify venues that are popular in the users' social networks. According to the type of contextual information involved in LBSNs, there are three types of influential factors for POI recommendations: geographical influence, temporal effect, and social influence.

Geographical Influence. In LBSNs, the geographical property, which is associated with locations, is important in the user's choice of location (Liu et al. 2013; Li et al. 2015). Due to the restriction of human mobility, a user typically prefers a nearby POI over a faraway one. Furthermore, geographically adjacent users may share similar interests and influence check-in behaviors. Therefore, considering the geographical property of POIs enables us to capture user preferences more precisely.

Temporal Effect. Human geographical movement exhibits strong temporal patterns in LBSNs (Gao et al. 2013). For example, a user regularly chooses a restaurant next to her workplace for convenience on weekdays, while she goes to a bar for entertainment on weekends. Such temporal cyclic patterns are often observed in check-in data and provide us a perspective from which to investigate user mobility. Thus, mining the temporal patterns in check-in data in terms of where a user would like to go enables us to better investigate user check-in behaviors (Duan et al. 2019).

Social Influence. Online social connections offer the user opportunities to view her friends' historical check-in behaviors. Some friends have a positive impact on a user's check-in at a location, while others may influence a user's check-in negatively. Hence, a user's check-ins can be highly affected by a group of friends. Considering such social influence creates the potential to design more advanced POI recommendation systems in LBSNs (Zhang and Chow 2015).

Considering all the works currently available related to the POI recommendation in LBSNs, we conclude that the performance of a POI recommendation system can be improved by considering three additional dimensions beyond the usual preference dimension: geographical, temporal and social dimensions. However, how to efficiently integrate the three types of influences in LBSNs deserves further study.

HIN-based POI recommendation

Many previous works deal with the problem of POI recommendations, and we present the main algorithmic categories, i.e., collaborative filtering (CF), factorization models, graph-based models, semantic-based models, and deep learning (Symeonidis et al. 2014). However, except for deep learning methods, the other models are not flexible in modeling data heterogeneity and incorporating auxiliary information for POI recommendations (Shi et al. 2018), while deep learning methods are time consuming and require a large-scale dataset to iterate parameters (Huo et al. 2017). With a certain computational cost, HINs naturally model complex objects and their rich relations in recommender systems, in which objects are of different types and links among objects represent different relations (Sun and Han 2013). Additionally, several path-based similarity measures are proposed to evaluate the similarity of objects in HINs (Kang et al. 2018). Therefore, some researchers have begun to be aware of the importance of HIN-based POI recommendations. For example, Hang et al. (2018) presented an analysis of students' mobility and social characteristics, including temporal dynamics of user preferences, covisitation behavior and exploration behavior; this analysis is based on data from Wi-Fi access logs that were collected at Purdue University. The authors adapted bipartite graph embedding and negative sampling to encode the correlations among users, POIs, and activities and to jointly learn embedding for the vertices. Ke et al. (2018) utilized the preferences of tourists to recommend a tourism POI solution in a heterogeneous information network. The proposed recommendation framework consists of density-based clustering, the skyline method, and the genetic algorithm. Qiao et al. (2018) proposed a hybrid location suggestion algorithm that fully considers a user's familiarity and preference similarity along with online relationships. In the proposed model, the authors introduce three feature variables: the number of mutual friends, the Jaccard coefficient and the cosine similarity. In addition, the maximum likelihood estimation approach is employed to calculate the weights of each feature, and logistic regression is used to calculate the familiarity. Xing et al. (2018) utilized geographical influences, review information, and user social relations that were captured from check-in records to identify users' latent factors. Then, the authors model these three types of information under a unified POI recommendation framework that is based on convolution matrix factorization, which integrates a convolutional neural network into a probability matrix factorization. Tang et al. (2019) searched for similar users of the same regions of interest to optimize the user acceptance rate for POI recommendations. The authors employed a variable-order Markov model to determine the distribution of a user's POIs and applied linear discriminant analysis to cluster the "Travel" topics. Thus, POIs that correspond to the same topics are connected to users with suitable social interests and travel preferences.

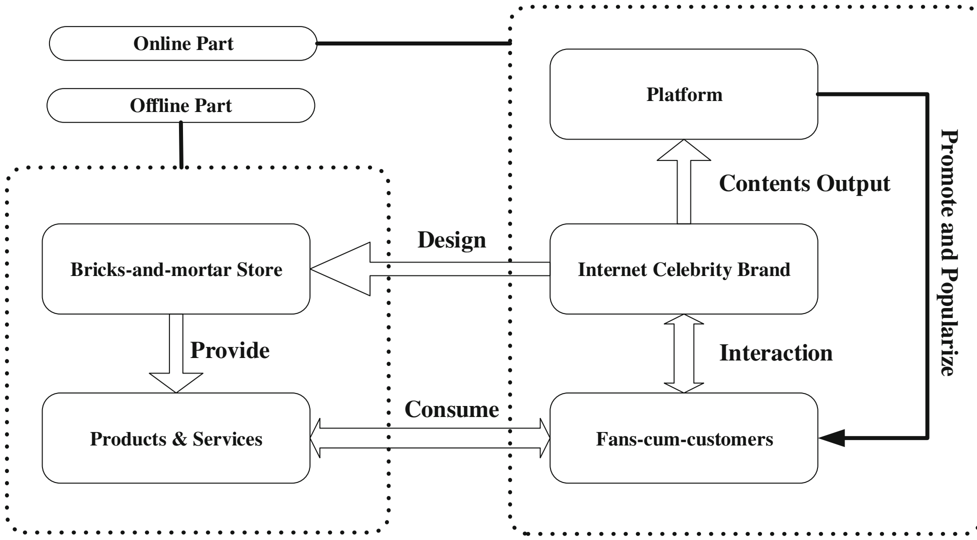
To the best of our knowledge, most studies utilize only part of the information in anO2O commerce LBSN to generate POI recommendations. Fully considering all three factors, namely, geographical influence, temporal effect, and social influence, not only helps to alleviate the problems of cold start and data sparsity but also comprehensively represents user preferences from an overall perspective, thereby improving recommendation accuracy. However, there is a gap between theory and practice mainly because of the computational cost. As all of the features are generated by matrix factorization, the dense features increase the computational cost of parameter learning. In addition, current algorithms fail to fully exploit the information that is contained in the latent features of O2O commerce LBSNs. To overcome these problems, we model the three dimensions with a weighted meta path and propose an "SVD++ & factorization machine" approach for O2O commerce recommendations.

Problem definition

As discussed in the introduction, the business model of the bricks-and-mortar brand of internet celebrity is illustrated in Fig. 2. The bricks-and-mortar brands of internet celebrity attract consumers through social network marketing, and consumers share their consumption experiences and express their feelings in a private community of social networks. Hence, the bricks-and-mortar brands of internet celebrity form a cycle of online marketing and offline sales to expand business scale. In this paper, we aim to develop a POI recommendation system to bridge the gap between the online and offline part of the bricks-and-mortar brands of internet celebrity.

By constructing heterogeneous networks for LBSNs, one can effectively integrate all types of information; such networks have demonstrated the potential for improving recommendation performance. The concept of heterogeneous

Fig. 2 Business model of the bricks-and-mortar brand of internet celebrity



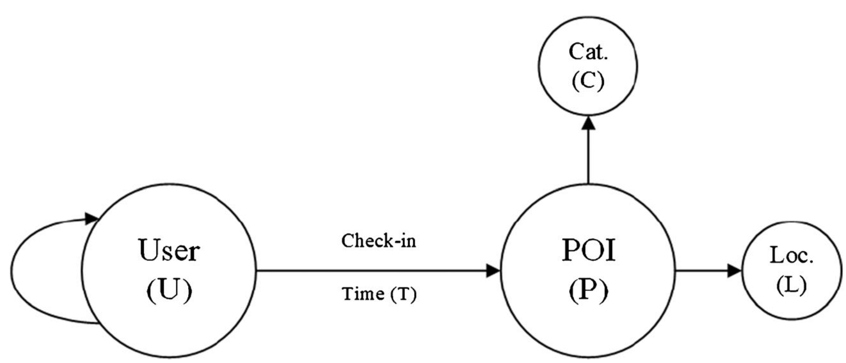
information network arises from sophisticated real-world networks, which are difficult to represent with standard network topologies. An LBSN, which incorporates the mobility patterns and social ties of humans, is a typical example of a HIN. Figure 3 illustrates a HIN schema of an LBSN.HINs contain not only various nodes (e.g., users and POIs) but also diverse links (such as check-in information, social relations, and geographical attributes). Moreover, the nodes and links in HINs represent various semantics, which can be explored to identify the subtle relations among nodes.

As a mainstream approach, HINs have been used in POI recommender systems to characterize complex and heterogeneous recommendation settings (Shi et al. 2016). Various types of information can be modeled by a HING $=(V, E)$. Concerning recommendation-oriented HIN, two kinds of entities (i.e., users and POIs) together with the relations between them are our focus. Let $u \subset V$and $p \subset V$ denote the sets of users and POIs, respectively; a triplet $\langle u, p, r_{u,\ p}\rangle$ denote a record where a user u assigns a rating of $r_{u,\ p}$ to a POI p; and $R=\{\langle u, p, r_{u,\ p}\rangle\}$ denote the set of rating records. Then, the goal is to predict the rating score $r_{u,\ p'}$that user $u$will assign to an unvisited POI p'.

Research methodology

In this section, we formally present the framework of a POI recommendation for O2O commerce, which is illustrated in Fig. 4.We employ a weighted meta path to better represent the temporal characteristics of user mobility patterns and develop an "SVD++&FM" approach that integrates geographical, social and temporal influences. Based on a comprehensive analysis of users' check-in behaviors, we interpret user preferences in O2O commerce LBSNs from a three-dimensional perspective, namely, geographical influence, temporal effect, and social influence. To fully utilize this information, we employ the meta path to model geographical and social influences and the weighted meta path to model the temporal effect. To incorporate all the latent factors in the meta paths into our prediction problem, we compute the user-POI similarity matrix for each meta path (see Appendix A.1). Then, SVD++ is used to factor the matrices into a set of user and POI latent vectors (see Appendix A.2). With a variety of sets of user and POI vectors, we exploit the factorization machine (FM) to assemble these vectors and learn from the rating matrix (see Appendix A.3). Finally, the predicted ratings are ranked in

Fig. 3 Example of a HIN schema for an LBSN. Cat (C): category of the POI; Loc (L): location; and Time (T): time slot



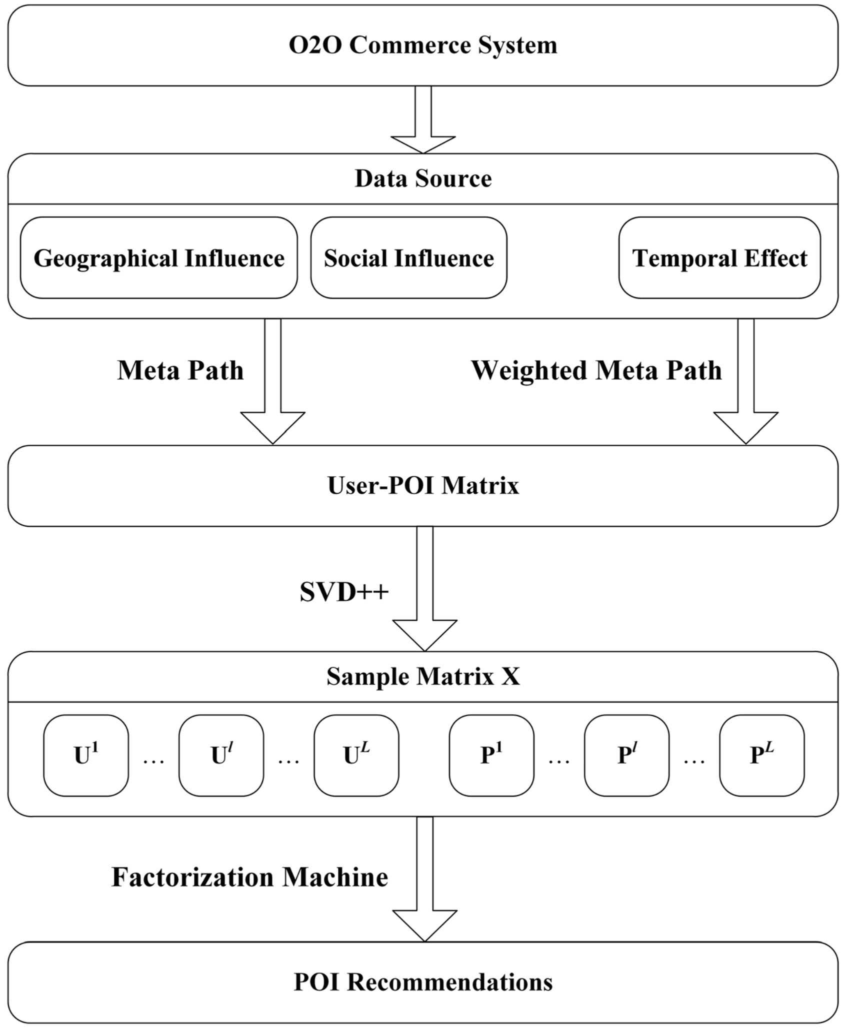


Fig. 4 Framework of a POI recommendation system in O2O commerce

descending order, and several top POIs are recommended to the target user in accordance with the marketing plan of O2O platforms. The corresponding optimization of this model is presented in Appendix A.4.

Experimental framework

In this section, we describe the experimental framework, including the datasets, evaluation metric, baseline models and experimental settings, used to verify the effectiveness of the recommendation results.

Datasets

To evaluate the effectiveness of our proposed approach for the recommendation task, we use two real-world datasets collected from O2O commerce LBSNs, namely, Gowalla and Foursquare, both of which contain rich heterogeneous information. Table 1 summarizes the statistics on the datasets that were obtained from Gowalla and Foursquare.

Gowalla is a famous O2O commerce website where users share their location check-ins with friends. The website enables users to check in at venues with a dedicated mobile application or through the mobile website. Gowalla has a user base of more than 6.4 million and was acquired by Facebook in December 2011.The Gowalla dataset, which contains 6442,890 check-in records from February 2009 to October 2010, was collected by Cho et al. (2011). The user friendship

Table 1 Dataset description

Statistic	Gowalla	Foursquare
Time period	569 days	1186 days
Number of users	196,591	78,837
Number of POIs	1,280,956	298,711
Number of check-ins	6,442,890	637,700
Number of friendship links	950,327	4,118,477
Average check-ins per user	32.8	8.1
Average check-ins per POI	5.0	2.1
Average friends per user	4.8	52.2

network in the Gowalla dataset consists of 196,591 users and 950,327 relations.

Similar to Gowalla, Foursquare is also a popular O2O commerce website. Using Foursquare, we establish a dynamic heterogeneous network in four USA cities. The Foursquare dataset contains637,700 check-ins that were generated by 78,837 users in 298,711 POIs from May 2008 to July 2011, and each check-in record is associated with a POI ID, comments, and a timestamp (Bao et al. 2012). We also obtained 4118,477 friendship links among 78,837 users for building social relations.

Evaluation metric

We evaluate the performance of our approach according to two metrics—precision and recall, which are denoted as *Precision* @ *N*and *Recall* @ *N*, respectively:

$$Precision@N = \frac{\left|R_{u,N} \cap T_u\right|}{N} \tag{1}$$

$$Recall@N = \frac{\left|R_{u,N} \cap T_u\right|}{T_u} \tag{2}$$

where$R_{u,\ N}$is the set of top-N recommended POIs for user u and T_u represents the set of new POIs that will be visited by user u. Thus, when the number of requested recommendations is defined as N, *Precision* @ N denotes the accuracy of the recommendation, and *Recall* @ N denotes the comprehensiveness of the recommendation. Precision and recall are mutually constrained. Thus, the two indices enable a comprehensive acquisition of the recommendation results for O2O commerce.

Baseline models

To evaluate the performance of our proposed approach, we compare it with the following baseline models:

SVD++ (Singular value decomposition ++): SVD++ is a state-of-the-art matrix factorization algorithm that belongs to the family of latent factor models, which utilize implicit feedback from users for prediction. In this paper, we run the implementation that was introduced by Koren (2008) and exploit only the user-POI rating matrix.

PMF (Probabilistic matrix factorization): We compare our proposed approach with the baseline PMF method that was proposed by Mnih and Salakhutdinov (2008); this method uses only the user-POI rating matrix for recommendations and does not consider any social factors.

FM (Factorization machine): FM denotes the factorization machine with L2 regularization. We use the method and code that are provided by Rendle (2012) to model the prediction task.

SemRec (Semantic path-based personalized recommendation): As a meta path-based recommendation method applied to WHINs, SemRec flexibly integrates the heterogeneous information of users and items. Through a weight regularization term, the path weights of users with little rating information are learned from the weights of similar users. In our work, we consider the algorithm that was implemented by Shi et al. (2019).

All these baseline approaches are implemented, and the acquired data are preprocessed.

Experimental settings

To evaluate the performance of our proposed model, we utilize the meta paths that are listed in Table 7 (see Appendix A.1). For a fair comparison, we fix the parameters in all experiments and show the parameters in Table 2.

As numerous users checked in at a POI less than once, our datasets contain millions of check-in records but are highly sparse. Thus, we preprocess each dataset by filtering the inactive users and unpopular POIs, namely, the users with fewer than 5 check-in records and the POIs that were checked into by fewer than 80 users. To conduct experiments, 70% of the data in the datasets are used as training data to learn user preferences, while 10% are used as validation data for parameter tuning. The remaining 20% of the data in the datasets are used as testing data to evaluate the accuracy of the methods. In terms of cross-validation, we repeat the learning and testing process five times, and the average performances of the five rounds are presented as the final results. Table 3 presents the implementation environments of our model.

Experimental results

In this section, we present the experimental results and an analysis of the model performance.

Recommendation performance

In this subsection, we present the experimental results of all recommendation methods with well-tuned parameters. The prediction performance in terms of precision and recall is presented in Table 4, and our method is denoted by SVD++

Table 2 Summary of notations

Symbol	Description	value
N	number of recommended POIs	10
F	rank of user-POI similarity matrices	10
K	number of latent factors	15
λ_w, λ_v	group lasso weight	0.01

Table 3 Implementation environments and parameters

Implementation environments	Parameters
Operating system	64-bit Windows 10
Platform	Python 3.6.5
CPU	Intel Core i3 @ 2.53 GHz
RAM	8 GB

&FMRec. From the results, we draw the following conclusions.

According to the results for the two datasets, the recommendation performance for Gowalla is always better than that for Foursquare. This difference is probably due to the data density of latent features. As the recommendations are generated by a group of latent factors, the datasets differ in terms of data density for latent factors, thus leading to differences in prediction accuracy values. We will further discuss this observation in the next section. However, the performance is consistent across algorithms.

According to the results, the lowest performing model is the PMF model; the SVD++ and FM methods perform better. Our method and SemRec outperform SVD++, the FM and PMF mainly because SVD++, the FM and PMF employ only the rating matrix to model user preferences, while the FM and SemRec utilize extra heterogeneous information that is provided by meta paths.

Although the performance gap between our method and SemRec is not large, our method performs the best; hence, the FM is more efficient in integrating heterogeneous information for two reasons: a weighted ensemble of inner products of latent factors tends to lose the information among meta paths, and SemRec fails to remove the useless meta paths.

Selected meta paths

This section analyzes the selected meta paths by using the group lasso. Table 5 lists selected meta paths for the Gowalla and Foursquare datasets.

According to Table 5, $\Phi_7$is useful for both datasets, thus demonstrating that the weighted meta path and the temporal effect contain rich semantic information. The semantic meaning of $\Phi_7$is that two userssimultaneously visit the same POIs; we refer to this behavior as covisitation, which is a noisy indicator of common preferences among users. A larger set of user pairwise covisitation events is likely to characterize user friendship. Similarly, $\Phi_1$plays the same role as $\Phi_7$in POI recommendation tasks. Hence,direct relationships between users and POIs are necessary for improving recommendation performance.

Table 5 Selected Meta path for the Gowalla and Foursquare datasets

	Important	Useless
Gowalla	Φ_1,Φ_2,Φ_4,Φ_6,Φ_7	Φ_3,Φ_5
Foursquare	Φ_1,Φ_2,Φ_3,Φ_4,Φ_6,Φ_7	Φ_5

Another finding is that the meta paths of the form UP∗P outperform those of the form U∗UP. Here, we use UP∗P to represent meta graphs Φ_4, Φ_5 and Φ_6 and use U∗UP to represent meta graphs $\Phi_2$andΦ_3. As described in Table 7 (see Appendix A.1), UP∗P denotes the geographical influence, and U∗UP represents the social influence. For both datasets, Φ_4 and Φ_6 are preserved, while Φ_5 is eliminated becauseΦ_6 contains more specific and richer information than Φ_5. In addition,$\Phi_2$and$\Phi_3$are retained for Foursquare, whileΦ_3 is removed for Gowalla. This result agrees with the conclusion thatsocial influence outweighs geographical influence (Yu and Chen 2015). We argue that the check-in activitiesrequire physical interactions between users and POIs, thereby limiting the contributions of social influence, while activities in traditional recommendation systems, e.g., watching movies, listening to music and purchasing goods, are not restricted by physical interactions. Additionally, from the reduction of the meta paths, we can identify the characteristics of the two real-world datasets. For example, the elimination of $\Phi_3$reveals the sparsity of friendshipsin Gowalla, which provides lessuseful information than Foursquare; the average number of friends per user in Gowalla is 4.8, compared to 52.2 in Foursquare.

Discussion

Advances in digital technology are expanding e-commerce dimensions and reforming the way consumers shop and buy products and services (Park and Kim 2018). The findings in this article give us some insights into applying the POI

Table 4 Recommendation performance in terms of precision and recall for two datasets

		PMF	SVD++	FM	SemRec	SVD++&FMRec
Gowalla	Precision@10	0.0112	0.0152	0.0414	0.0564	0.0631
	Recall@10	0.0121	0.0163	0.0433	0.0483	0.0539
Foursquare	Precision@10	0.0091	0.0117	0.0411	0.0442	0.0427
	Recall@10	0.0083	0.0120	0.0310	0.0368	0.0456

recommendation system to O2O commerce, especially with respect to the bricks-and-mortar brands of internet celebrity.

From the dimension of age, the main consumers of the bricks-and-mortar brands of internet celebrity are between 24 and 28 (Li 2018). Online social networks have a strong impact on these consumers, and their decision-making process is affected mainly by friends (Xu and Pratt 2018). The younger consumer communities desire attention and generally prioritize the situational experience of consumption rather than the function of the product or service itself (CBNData report 2018). In particular, the consumption experience extends the mediated social connection so that younger consumers feel closer to each other and craft an identity based on the attitudes and values put forth by the bricks-and-mortar brands of internet celebrity (Alperstein 2019). These values, which appear as likes or dislikes, check-ins and comments, represent the collective consciousness of the younger consumers engaged on whichever platform is being utilized.

In terms of the factors that affect purchasing decisions on the O2O platform, in-depth research conducted by several scholars clearly shows that atmosphere, environment, location, and word of mouth are crucial (Chang et al. 2019; Tang and Zhu 2019). According to the theory of atmospheric cues, in bricks-and-mortar stores, the atmosphere and environment (which include architecture, window displays, store layout, and background music) significantly influence the perceived merchandise value and patronage intentions (Baker et al. 2002; Floh and Madlberger 2013). For the bricks-and-mortar brands of internet celebrity, it is possible to shape the environmental cues of the bricks-and-mortar store to match the online promotion of products or services. Therefore, each bricks-and-mortar brand of internet celebrity caters to the diverse, fragmented demands of consumers. Emotional-cognitive theory argues that consumer emotional integration, such as by word of mouth, is formed in the interaction between consumers and brands; this emotional integration is an extra input for the brands for consumers (Jordan 2003). Additionally, brand loyalty that originates from an emotional affinity may promote purchase decisions and shield brands against negative reviews (Kostyra et al. 2016). Moreover, the new digital world offers many opportunities to strengthen powerful word of mouth.

Therefore, O2O enterprises should make full use of O2O channel coordination capabilities to improve consumption experience and achieve a sustainable competitive advantage. Channel coordination is clustered into three purchase stages in terms of a customer purchase life cycle: pre-purchase, purchase, and post-purchase (Wollenburg et al. 2018). In the pre-purchase stage, a major strategy of channel coordination is to actively recommend personalized products or services to

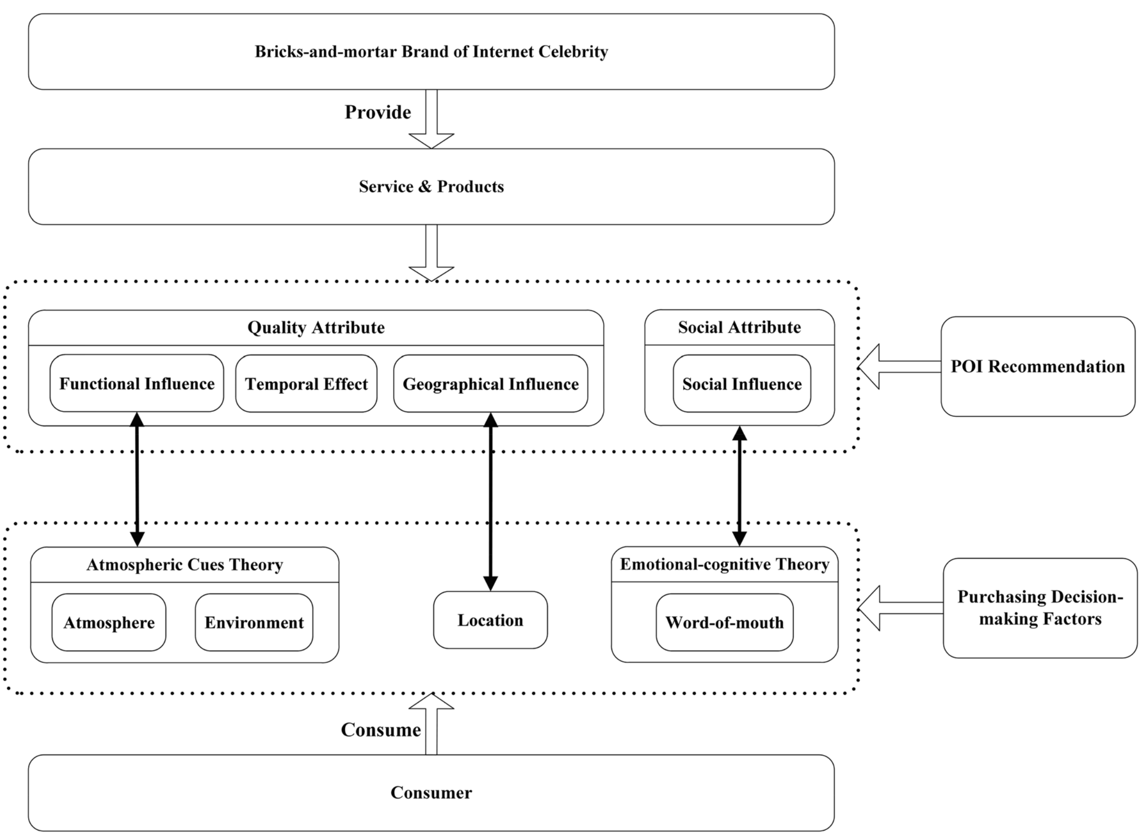


Fig. 5 Structural model of a POI recommendation system for the internet celebrity economy

consumers according to the historical consumption data by the using the POI recommendation system. Thus, we improve the ability of O2O channel integration in the pre-purchase stage to facilitate the purchase decision of consumers. Figure 5 shows how the POI recommendation system bridges the gap between the bricks-and-mortar brand of internet celebrity and consumers.

As shown in Table 7 (see Appendix A.1) and Fig. 5, function influence, which is closely related to atmosphere and environment, implies the user preferences concerning the POI. Geographical influence means that the consumers have regular visit patterns and prefer to visit locations that are close to their usual locations (Brockmann et al. 2006). Social influence, which is closely associated with word of mouth, means that the preferences or behavioral patterns of the consumers may change when they are with friends (Ye et al. 2010). Temporal influence indicates that the consumers' preferences not only depend on the time of day but also differ during weekdays and weekends (Noulas et al. 2011).

There are numerous benefits to utilizing the POI recommendation system for the bricks-and-mortar brands of internet celebrity. From the perspective of consumers, the consumption experiences simultaneously satisfy both commodity and social demands. The social demands mean that every bricks-and-mortar brand of internet celebrity represents a different lifestyle, thus reflecting the distinctive cultural identities of the brand's fans-cum-customers. Cultural identity in a certain community is the basis for maintaining and extending the social network; thus, the consistency of cultural identity in consumption significantly affects subsequent purchase decisions. Therefore, consumers maintain a social community by consumption and further attract increasingly more consumers with the same preferences, thereby expanding the community. From the perspective of the bricks-and-mortar brands of internet celebrity, the process of consumption-social integration not only enhances the consumption experience but also improves the service chain. In addition, this process improves the loyalty of the consumer group and user stickiness by attaching the social characteristics of the commodity itself. From the perspective of the POI recommendation system, the recommended POI attracts many offline consumers to the bricks-and-mortar store of internet celebrity. Then, the check-in records shared by consumers enable a more precise recommendation result, which further pinpoints the target audience community.

Conclusions

This paper presents our analysis of geographical, temporal and social influences in LBSNs in O2O commerce and proposes a weighted meta path based method for handling the corresponding information. We employ this method for producing recommendations for bricks-and-mortar brands of internet celebrity. Extensive experiments are conducted to evaluate the POI recommendation performance for two real-world datasets: Gowalla and Foursquare. For both datasets, our proposed approach outperforms the baseline methods. Then, we depict the characters of main consumers of the bricks-and-mortar brands of internet celebrity and elaborate on the three factors that affect purchasing decisions on the O2O platform, namely, atmosphere, environment, location, and word of mouth. Furthermore, we reveal that the purchasing decision factors are well responded with the information employed in our proposed POI recommendation system and present the numerous benefits to utilizing the POI recommendation system for the bricks-and-mortar brands of internet celebrity. These results demonstrate the promise of modeling user check-in information with weighted meta paths for personalized bricks-and-mortar store of internet celebrity recommendations. Several areas still require further exploration. Since LBSNs contain rich semantics, we will exploit more information to enrich the features, e.g., the reviews that were written by consumers for POIs. In addition, we can further explore more applications of personalized POI recommendation systems in O2O commerce.

Appendix

Weighted meta path-based similarity

As described in related works, the temporal characteristics of user behavior in O2O commerce LBSNs contain two aspects: periodicity and preference variance. To capture the temporal cyclic pattern, a time-indexing scheme that encodes a standard time stamp to a specified time slot was devised. We consider the preference variance in a two-hierarchy category: time of day and day of the week. Therefore, as shown in Table 6, a week is divided into weekdays and the weekend, while a day is divided into four sessions. Hence, in total, there are 8 time slots, which can represent both weekly and daily preference variances.

Many real-world networks, especially O2O commerce LBSNs, contain attribute values on links. For instance, to represent covisitation events, the time slot is used as the weight for the user-POI link. However, few conventional HINs deal with attribute values on links. In this paper, we employ the concept of WHIN to handle this issue (Shi et al. 2019).

Table 6 Time-slot scheme of a twenty-four-hour clock

Session	Hours
Morning	06:00 - 11:59
Afternoon	12:00 - 16:59
Evening	17:00 - 23:59
Night	24:00 - 05:59

Definition 1. Weighted heterogeneous information network. A weighted heterogeneous information network is defined as a directed graph $G=(V, E, W)$ with schema $S=(\mathcal{A}, \mathcal{R}, \mathcal{W})$, where V is the node set, E is the link set, W is the attribute value (weight) set, $\mathcal{A}=\{A\}$ is the node type set, $\mathcal{R}=\{R\}$ is the link type set, and $\mathcal{W}=\{W\}$ is the attribute value type set. Each object $v \in V$ maps to an object type $\varphi(v) \in \mathcal{A}$ by function $\varphi: V \longrightarrow \mathcal{A}$, each link $e \in E$ maps to a relation $\psi(e) \in \mathcal{R}$ by function $\varphi: E \longrightarrow \mathcal{R}$, and each attribute value $w \in W$ maps to an attribute value type $\theta(w) \in \mathcal{W}$ via a function $\theta: W \longrightarrow \mathcal{W}$.

With the concept of WHIN, an intuitive strategy is to extend the conventional meta path to deal with attribute values on relations, namely, to a weighted meta path.

Definition 2. Weighted meta path. A weighted meta path is a meta path that is based on an attribute value constraint on relations; this constraint is denoted as $A_1 \longrightarrow^{\delta_1(R_1)} A_2 \longrightarrow^{\delta_2(R_2)} \cdots \longrightarrow^{\delta_l(R_l)} A_{l+1} | \mathcal{C}$. The attribute value function $\delta(R)$ is a set of values from the attribute value range of relation R. $A_i \longrightarrow^{\delta_i(R_i)} A_{i+1}$ represents the relation R_i between A_i and A_{i+1} that is based on the attribute values $\delta_i(R_i)$. The constraint $\mathcal{C}$ is a set of correlation constraints among attribute value functions.

Most similarity measures on meta paths are based on matrix multiplication, e.g., counting the probability of a random walk or the number of meta path instances. However, these similarity measures fail to handle the information of attribute value constraints on multiple relations of O2O commerce. To address this problem, we introduce the concept of an atomic meta path and use an ingenious solution to ensure that the existing path-based similarity measure remains available in the weighted meta path.

Definition 3 Atomic meta path. Given a weighted meta path $\mathcal{P}$, the atomic meta path is a subset of the weighted meta path $\mathcal{P}$ in which all attribute value functions $\delta(R)$ take a specified value. Namely, a weighted meta path is a complete set of atomic meta paths that satisfy the constraint $\mathcal{C}$.

Given the above definitions, an intuitive idea is to estimate the similarities between the source and the target nodes. In this paper, we employ PathSim (Sun et al. 2011) as the similarity measure, which can identify peer objects in the network. PathSim can be expressed as:

$$S(x, y|\mathcal{P}_\mathcal{C}) = \frac{2 \times \sum_{\mathcal{P}_\alpha \in \mathcal{P}_\mathcal{C}} \left| \left\{ p_{x \rightsquigarrow y} : p_{x \rightsquigarrow y} \in \mathcal{P}_\alpha \right\} \right|}{\sum_{\mathcal{P}_\alpha \in \mathcal{P}_\mathcal{C}} \left| \left\{ p_{x \rightsquigarrow x} : p_{x \rightsquigarrow x} \in \mathcal{P}_\alpha \right\} \right| + \sum_{\mathcal{P}_\alpha \in \mathcal{P}_\mathcal{C}} \left| \left\{ p_{y \rightsquigarrow y} : p_{y \rightsquigarrow y} \in \mathcal{P}_\alpha \right\} \right|} \quad (3)$$

where $\mathcal{P}_\mathcal{C}$ is a weighted meta path with attribute value constraint $\mathcal{C}$, $\mathcal{P}_\alpha$ is an atomic meta path of $\mathcal{P}_\mathcal{C}$, and $p_{x \rightsquigarrow y} \in \mathcal{P}_\alpha$ indicates a path instance connecting node x and y along atomic meta path $\mathcal{P}_\alpha$. As PathSim counts the number of path instances along the meta path with a normalized term, all users are treated identically. In particular, we should consider the effect of the normalized term in PathSim.

Since a weighted meta path is a combination of corresponding atomic meta paths, we regard the similarity measure that is based on a weighted meta path as the sum of the similarity measures that are based on the corresponding atomic meta paths. Moreover, the PathSim strategy along a weighted meta path can be described as the following steps: Initially, we count the number of path instances along each atomic meta path. Then, we sum the corresponding numbers along every atomic meta path before normalization. Therefore, our solution identifies similar users more accurately because they have the same preferences.

The longer the meta paths are, the less likely they are to generate satisfactory similarity measures because they fail to convey a distinct meaning (Sun et al. 2011). Thus, we employ 7 meaningful meta paths whose lengths are no longer than 4. All the weighted and unweighted meta paths that are used in this paper are listed in Table 7. These meta paths all begin from the source node U (user) and end at the target node P (POI), while intermediate nodes can be interpreted by various latent features in the LBSNs of O2O commerce, e.g., user preferences, temporal effects, and geographical and social influences.

Table 7 Meta paths that are used for the Gowalla and Foursquare datasets

Factor	ID	Weighted meta path	Semantic meaning
Preference	Φ_1	UP	Users visit POIs
Social	Φ_2	UUP	Users visit POIs that their friends visited previously
	Φ_3	UPUP	Users visit POIs that their latent friends visited previously
Geographic	Φ_4	UPCP	Users visit POIs that belong to the same category as previously visited POIs
	Φ_5	UPLsP	Users visit POIs that are in the same state as previously visited POIs
	Φ_6	UPLcP	Users visit POIs that are in the same city as previously visited POIs
Temporal	Φ_7	UT(i)PT(j)UP|i = j	Users visit the same POIs at the same time as the target user

By calculating the similarities between all users and all POIs along the meta paths $\mathcal{P}$, a user-POI similarity matrix $\widehat{R} \in \mathbb{R}^{m \times n}$ is obtained, where $\widehat{R_{ij}}$ represents the similarity between user $u_i$and POIp_j, and $m$and n denote the numbers of users and POIs, respectively. With L meta paths in an O2O commerce LBSN,we can obtain L user-POI similarity matrices that differ in terms of semantics and are denoted by $\widehat{R}^1, \cdots, \widehat{R}^L$.

Latent features in O2O commerce LBSNs

After user-POI similarity matrices have been obtained, we employ matrix factorization (MF) to identify the latent features of users and POIs in O2O commerce. Our MF approach is based on a state-of-the-art model, namely, SVD++, which was proposed by Koren (2008). To alleviate the noise problem and overcome the data sparsity in the user-POI similarity matrices, SVD++ considers user and POI biases and the influence of rated POIs, in addition to the user- and POI-specific vectors, for rating prediction. An SVD++ model associates each user u with a user-factor vector $p_u \in \mathbb{R}^F$ and each POI j with a POI-factor vector$q_j \in \mathbb{R}^F$. Formally, the rating for user $u$on POI j is predicted by:

$$\widehat{r}_{u,j} = \mu + b_u + b_j + q_j^{\mathrm{T}}\left(p_u + |N_u|^{-\frac{1}{2}}\sum_{i \in N_u}\mathcal{Y}_i\right) \tag{4}$$

where μ is the global average rating; b_u and b_j represent the user and POI biases, respectively; N_u is a set of POIs for which user $u$exhibited an implicit preference; and $\mathcal{Y}_i$ denotes the implicit influence of POIs that have been rated by user u in the past on the ratings of unknown POIs in the future. Thus, the feature vector of user u can also be represented by the set of rated POIs andmodeled as $\left(p_u + |N_u|^{-\frac{1}{2}}\sum_{i \in N_u}\mathcal{Y}_i\right)$ rather than simply being represented as p_u.

Assuming that user preferences in O2O commerce are controlled by few factors, we factor the similarity matrix $\widehat{R}$ into two low-rank matricesby solving the optimizing problem in (5):

$$\min_{b_u, b_j, q_j, p_u, y_i} \sum_{(u,j) \in \kappa}\left(r_{uj} - \widehat{r}_{uj}\right) + \lambda_{up}\left(b_u^2 + b_j^2 + \|p_u\|_F^2 + \|q_j\|_F^2 + \frac{\sum_{j \in N_u}\|y_j\|_F^2}{\|q_j\|_F^2}\right) \tag{5}$$

where κ is a set of (u, j)pairs for which r_{uj} is known and λ_{up}denotes the hyperparameter that controls the influence of the regularization to avoid overfitting. For L user-POI similarity matrices, we can obtain L groups of latent features of users and POIs; these features are denoted as $U^{(1)}, \cdots, U^{(L)}, P^{(1)}, \cdots, P^{(L)}$.

POI recommendation with factorization machine

With L groups of user and POI latent features in O2O commerce LBSNs, an intuitive strategy is to combine these features linearly to generate ratings. In previous approaches, the rating is predicted by a weighted ensemble of inner products of user-specific and POI-specific vectors from every meta path. However, this conventional approach fails to capture the interactions between and among inter-meta path features, thereby possibly decreasing prediction accuracy.

Therefore, an FM-based method is proposed for generating POI recommendations in O2O commerce LBSNs. First, we concatenate all the user and POI features from L meta paths. The result is denoted by X^n, which represents the feature vector of the n-th sample after concatenation.

$$X^n = u_i^1, \cdots, u_i^l, \cdots, u_i^L, p_j^1 \cdots, p_j^l, \cdots, p_j^L \tag{6}$$

where u_i^l and p_j^l represent user and POI features, respectively, that were generated from the l-th meta path. Given all of the latent features in Eq. (6), the formula for the FM is as follows:

$$\widehat{y}^n(W, V) = w_0 + \sum_{i=1}^{d} w_i x_i^n + \sum_{i=1}^{d}\sum_{j=i+1}^{d}\langle v_i, v_j\rangle x_i^n x_j^n \tag{7}$$

where $w_0$is the global bias, $W$is the first-order weights for modeling the strength of the latent features, V is the second-order weights for modeling the interactions among latent features, v_i represents the i-th variable with K factors, and x_i^n is the i-th feature in X^n.Particularly, $d = 2LF$ denotes the number of latent features that are generated by L meta paths, where F is a constant, namely, the rank that is used to factor every similarity matrix.

Although learning interactions between latent features substantially improves the performance of the recommendation model, the dense feature matrices that are generated by SVD++ increase the computational cost of learning parameters. Simultaneously, several meta paths help improve prediction accuracy only a little because the information that is contained in them can be covered by others. Therefore, it is crucial to select the most discriminating features for high-dimensional data in O2O commerce LBSNs.

To overcome this problem, we employ group lasso regularization for the FM method Meier et al. 2008). The group lasso is an extension of the lasso to variable selection on predefined groups of variables and is especially suitable for high-dimensional problems.

We denote the whole parameter vector by $\beta = \left(\beta_{\gamma_1}^{\mathrm{T}}, \cdots, \beta_{\gamma_g}^{\mathrm{T}}, \cdots, \beta_{\gamma_G}^{\mathrm{T}}\right)^{\mathrm{T}}$. Then, the group lasso regularization is defined as follows:

$$\phi(\beta) = \sum_{g=1}^{G}\left\|\beta_{\gamma_g}\right\|_2 \tag{8}$$

where $\|\cdot\|_2$ is the l_2-norm, β_{γ_g} is the parameter vector that correspondsto the g-th group of variables, and γ_g is the corresponding index set for $g = 1, 2, \cdots G$. In this model, the groups are the meta path-based features.

For the first-order parameters Win Eq. (7), we apply the group lasso to w_l. Therefore, the regularization can be reformulated as follows:

$$\phi_W(W) = \sum_{l=1}^{2L} \|W_l\|_2 \tag{9}$$

where $w_l \in \mathbb{R}^F$, which models the weights of the latent feature set for the l-th meta path. For the second-order parameters Vin Eq. (7), the corresponding regularizer is

$$\phi_V(V) = \sum_{l=1}^{2L} \|V_l\|_F \tag{10}$$

where $v_l \in \mathbb{R}^{F\times K}$ is the l-th block of V, which corresponds to the features of the l-th meta path; and where $\|\cdot\|_F$ is the Frobenius norm.

With group lasso regularizations, our model automatically preserves useful and removes redundant features in the unit of groups. Thus, the objective function to minimize is as follows:

$$h(W,V) = \sum_{n=1}^{N} \left(y^n - \hat{y}^n(W,V) \right)^2 + \lambda_w \phi_W(W) + \lambda_v \phi_V(V) \tag{11}$$

where $\lambda_W$and $\lambda_V$are the constants that control the regularization of $W$and V, respectively. As the constants increase, the corresponding regularization becomes heavier.

Model optimization

Due to the use of group lasso regularization, the objective function is non-smooth. The objective function is also not convex for V. An improved stochastic variance reduced gradient (SVRG++) can effectively solve non-convex objective functions with a non-smooth ℓ_2 regularizer (Allen-Zhu and Yuan 2016). Let us denote the initial vectors by w^{ϕ} and v^{ϕ}. Then, our algorithm can be divided into S epochs, where the s-th epoch consists of m_s-stochastic gradient steps. Within each epoch, we compute the full gradients $\widetilde{\mu}_{s-1} \longleftarrow \nabla f\left(\widetilde{w}^{s-1}\right)$ and $\widetilde{\mu}_{s-1} \longleftarrow \nabla f\left(\widetilde{v}^{s-1}\right)$, where $\widetilde{w}^{s-1}$ and $\widetilde{v}^{s-1}$ are the average points of the previous epochs, consecutively. Moreover, m_s doublesevery two consecutive epochs, thereby distinguishing SVRG++ from other variance-reduction-based methods. As shown in line 7, $\widetilde{\mu}_{s-1}$ is used to define the variance-reduced stochastic gradient ξin every stochastic gradient step. Finally, the starting vectors of the next epoch are set as $w^{s-1}_{m_s-1}$ and $v^{s-1}_{m_s-1}$, which is the ending vector of this epoch. SVRG++is presented as Algorithm 1, where η is the step length.

Algorithm 1 SVRG++

0 : Input: W and V

1 : $\tilde{w}^0 \leftarrow w^{\phi}, w_0^1 \leftarrow w^{\phi}, \tilde{v}^0 \leftarrow v^{\phi}, v_0^1 \leftarrow v^{\phi}$;

2 : for $s \leftarrow 1$ to S do

3 : $\quad \tilde{\mu}_{s-1} \leftarrow \nabla_w h\left(\tilde{w}^{s-1}, \tilde{v}^{s-1}\right), \tilde{\sigma}_{s-1} \leftarrow \nabla_v h\left(\tilde{w}^{s-1}, \tilde{v}^{s-1}\right)$;

4 : $\quad m_s \leftarrow 2^S \cdot m_0$;

5 : $\quad$ for $t \leftarrow 0$ *to* $m_s - 1|$ do

6 : $\qquad$ Pick i uniformly at random in $\{1, \cdots, n\}$;

7 : $\qquad \xi \leftarrow \nabla_w h_i\left(w_t^s, v_t^s\right) - \nabla_w h_i\left(\tilde{w}^{s-1}, \tilde{v}^{s-1}\right) + \tilde{\mu}_{s-1}, \zeta \leftarrow \nabla_v h_i\left(w_t^s, v_t^s\right) - \nabla_v h_i\left(\tilde{w}^{s-1}, \tilde{v}^{s-1}\right) + \tilde{\sigma}_{s-1}$;

8 : $\qquad w_{t+1}^s = \arg\min_{y \in \mathbb{R}^d} \left\{ \frac{1}{2\eta} \left\| w_t^s - y \right\|^2 + \Psi(y) + \langle \xi, y \rangle \right\}$,

9 : $\qquad v_{t+1}^s = \arg\min_{y \in \mathbb{R}^d} \left\{ \frac{1}{2\eta} \left\| v_t^s - y \right\|^2 + \Psi(y) + \langle \zeta, y \rangle \right\}$;

10 : $\quad$ end for

11 : $\quad \tilde{w}^{s-1} \leftarrow \frac{1}{m_s} \sum_{t=1}^{m_s} w_t^s,\ \tilde{v}^{s-1} \leftarrow \frac{1}{m_s} \sum_{t=1}^{m_s} v_t^s$;

12 : $\quad w_0^{s+1} \leftarrow w_{m_s}^s, v_0^{s+1} \leftarrow v_{m_s}^s$;

13 : end for

14 : return $\tilde{x}^S, \tilde{v}^S$

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