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Research Article

Web Service Applications and Consumer Environments Based on ICT-Driven Optimization

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Networking is the use of physical links to connect individual isolated workstations or hosts together to form data links for the purpose of resource sharing and communication. In the field of web service application and consumer environment optimization, it has been shown that the introduction of network embedding methods can effectively alleviate the problems such as data sparsity in the recommendation process. However, existing network embedding methods mostly target a specific structure of network and do not collaborate with multiple relational networks from the root. Therefore, this paper proposes a service recommendation model based on the hybrid embedding of multiple networks and designs a multinetwork hybrid embedding recommendation algorithm. First, the user social relationship network and the user service heterogeneous information network are constructed; then, the embedding vectors of users and services in the same vector space are obtained through multinetwork hybrid embedding learning; finally, the representation vectors of users and services are applied to recommend services to target users. To verify the effectiveness of this paper's method, a comparative analysis is conducted with a variety of representative service recommendation methods on three publicly available datasets, and the experimental results demonstrate that this paper's multinetwork hybrid embedding method can effectively collaborate with multirelationship networks to improve service recommendation quality, in terms of recommendation efficiency and accuracy.

1. Introduction

At present, the world has entered the era of driven technological innovation. Digital technology and information and communication technology (ICT) have become an important basis for a country's economic and social development and an important symbol of industrial and trade competitiveness. It is also the most intense key area for countries to seize the high ground of the new round of scientific and technological revolution and industrial revolution and has an extremely important strategic position in all countries [1]. With the vigorous development of the global digital economy, ICT service trade has become the leading force in the development of global service trade and is also an important support to promote the digital development of trade [2–5]. Since its reform and opening up, China's ICT industry has effectively combined global information technology innovation resources through the introduction of technology, and ICT service trade has achieved leapfrog development from scratch, from small to large, and from weak to strong and has formed strong international competitiveness, becoming the largest source of knowledge-intensive service trade in China [6]. China will face more severe global technological competition and challenges, especially due to the impact of Sino-US trade friction and technology decoupling; ICT service trade and industrial development will encounter more difficulties. However, China has the advantage of the world's super large-scale consumer market, and the ICT industry already has a strong foundation and the advantage of technological advancement [7]. Especially after the epidemic, a new infrastructure plan to accelerate the layout of a new generation of digital technology infrastructure will be conducive to grasp the strategic opportunities of the new round of information technology revolution. It promotes the development of ICT service trade to a new level and plays a major role in building a new pattern of the domestic and international dual cycle.

International Data Corporation believes that by 2021, 75% of the world's commercial enterprises will use artificial intelligence [8]. At the same time, cloud computing, big data, artificial intelligence, blockchain, and other new generation information technologies are penetrating into industry, service industry and agriculture on a large scale, providing huge space for innovation activities and driving the global value chain revolution into a new stage of globalization of knowledge and innovation [9]. The global new crown epidemic will bring a new round of explosive growth of the digital economy. And ICT will play an important supporting role in global epidemic prevention and control, especially the application scenarios and scale effects of new business models such as e-commerce platforms, telemedicine, telecommuting, and online education, which will surely bring scale growth and model innovation of ICT service trade in the postepidemic era [10].

Consumers always want to choose the goods they need the most in the market with the least time and the least steps. The development of ICT then provides a solid material basis for the upgrading of web service applications [11]. This allows web service applications to expand the computing power and information acquisition dimension of the application itself through the powerful communication capability of ICT, so as to organize and predict consumers' preferences and habits, allowing consumers to detach themselves from the clutter of information and focus on the goods they are interested in [12]. Thus, the service environment of information is optimized.

The recommendation method commonly used in web service applications is the collaborative filtering recommendation algorithm first proposed by Goldberg in 1992, which has rapidly attracted the attention of many researchers since its introduction [13]. Especially in personalized recommendation technology, collaborative filtering has been widely used, and is one of the most widely used and successful recommendation techniques in recommendation systems [14, 15]. This method makes full use of the user's large amount of history information for analysis and modelling, so as to predict the items that may be of interest to the user. Its recommendation results rely heavily on the user-item relationship based on the user-item rating matrix to achieve recommendations.

The data sparsity problem and the cold start problem have been hot topics for scholars in the research and discussion of collaborative filtering recommendation algorithms. The literature proposed a collaborative filtering recommendation algorithm that fuses item scores, which is based on the idea of item score prediction fusion and calculates the similarity between items by correcting the conditional probability [16]. The method was experimentally validated to make the recommendation results more accurate and improve the recommendation quality. Traditional service recommendation methods (e.g., collaborative filtering and matrix decomposition) mainly consider the relationship between users and services with direct influence [17]. However, in reality, this direct relationship data is often sparse and with it comes problems such as cold starts. To solve the problem, there is a tendency to consider multiple relationships and elements of users and services in an integrated manner [18, 19]. Although the integrated consideration of multiple relationships can improve the quality of service recommendation, there are still many challenges to effectively collaborate various relationships. With the rapid iteration of information and communication technologies, a large amount of network data can be easily accessed and further processed by deep learning techniques [20]. As a result, network embedding has been gaining attention as a convenient and effective method for learning network representations and has recently become a popular research problem based on neural networks and deep learning [21]. Network embedding learning can project the information network to the low-dimensional vector space Rd, which can effectively extract the multidimensional features of the information network [22]. These features are incorporated into the embedding vectors of nodes. Using the embedding vectors for service recommendation is more efficient than directly and mechanically using the structural information of the information network [23, 24]. Different relational networks with different structures apply different network embedding methods. For homogeneous information networks, converting the network into a vertex sequence library by random wandering and then borrowing text features to learn the model training are a common approach [25]. For modelling heterogeneous information networks, applying random walks directly to heterogeneous information networks does not work well. Most heterogeneous information network embedding methods generate metapaths by wandering in the network and learn the different metapaths separately by embedding them [26]. There are now many representative network embedding algorithms: Node2vec, LINE, SDNE, and BINE. The main contributions are summarized as follows: (1) In the field of web service application and consumer environment optimization, the introduction of the network embedding method can effectively alleviate the problems of data sparsity in the recommendation process. (2) The user social relationship network and user service heterogeneous information network are constructed, which are used in the consumer environment and improve the network service quality. (3) Experiments verify the efficiency and quality of the algorithm.

This paper first introduces the user services system of consumers in the consumption process from the consumer habits and web application characteristics. Then, the web embedding method is introduced. On this basis, the service recommendation method of network hybrid embedding is proposed in order to improve the recommendation effect. In order to improve the efficiency of recommendation, the random wandering method in embedding learning is optimized to ensure that the feature information of the original network can be extracted and retained more effectively. Finally, the comparison is performed by under multiple datasets. The F-measure values can be improved by 21% and 15%, respectively, compared with the service recommendation methods based on a single relational network and a simple fused multirelational network. The experimental results demonstrate that this hybrid multinetwork embedding method can effectively collaborate with multirelational networks to improve the quality of service recommendation.

The rest of this paper is organized as follows. Section 2 discusses service recommendation method for multinetwork hybrid embedding, followed by the multinetwork hybrid embedding recommendation algorithm design which is discussed in Section 3. Section 4 shows the simulation experimental results, and Section 5 concludes the paper with summary and future research directions.

2. Service Recommendation Method for Multinetwork Hybrid Embedding

The central idea of the learning method of network embedding is to find a mapping function that converts each node in the network into a low-dimensional potential representation. Although it can better avoid the problems caused by traditional recommendation methods such as cold start, it cannot avoid the limitations of the network itself and the problem of conflicting results recommended by different networks [27, 28]. Therefore, the network embedding method does not have good robustness and scalability. Therefore, it is necessary to solve the problem of embedding several different kinds of relational networks into the same low-dimensional vector space to get a unified vector representation. But the existing network embedding methods are only for a specific kind of information networks, such as homogeneous information networks and heterogeneous information networks.

To address the above problems, in this paper, we propose a multiple network hybrid embedding for recommendation method, which embeds the nodes of multiple relational networks into the same vector space to get a unified vector representation [29]. So that the embedding vectors of the same kind of nodes contain the features of multiple relationship networks, and the embedding vectors of different types of nodes contain the direct influence relationship, and considering the scalability of the method, the relationship between users and services is divided into two categories, as shown in Figure 1. One kind of relationship is vertical: it refers to the direct association between users and services, as shown by the straight line in the figure. Although this relationship is sparse, it can directly reflect the user's preference characteristics. Another kind of parallel relationship: refers to the interaction between users and services, which is shown by the arc in the figure, for example, the social relationship between users and the shared label relationship between services. These relationships can indirectly provide more basis for service recommendation.

The method in this paper is divided into three parts. (1) constructing information networks: constructing user service heterogeneous information networks, service labelled common networks, and user social relationship networks; (2) multinetwork hybrid embedding: embedding the three types of information networks obtained in the previous step into the same low-dimensional vector space to obtain user and service embedding vectors; (3) user-based collaborative recommendation: using the learned user and service embedding vectors for service rating prediction and finally recommending top-K service sequences by considering the influence of similar users' preferences. As shown in Figure 2, we need to recommend movies that users are interested in. We can build a user-movie heterogeneous information network based on users' scores of movies, a movie tag common network using the genre information of movies, and a user social network based on the attention and interaction information among users. Then, we get the embedding vectors of users and movies through multinetwork hybrid embedding, and finally, we use the user-based collaborative recommendation to recommend the movies that users are interested in.

User service heterogamous information network: heterogeneous information network is simply understood as a network with two or more types of nodes or connected edges, as shown in Figure 3.

Service cotag network: in reality, each service will be assigned multiple tags. By calculating the number of tags shared between different services, we can build a service cotag network.

User social network: there are many public service platforms, such as Yelp and Douban. Through these platforms, users can not only rate different services but also communicate with other users. According to the provided user interaction data, if a user u_i follows another user u_j, then a social association is visible between the two users. Thus, the social relationship network between users $\mathrm{Net}_{\mathrm{social}} = (U, E)$, $U = \{u_i \mid i = 1, 2, \cdots m\}$ is the set of users, and $E = \{e_j \mid i, j = 1, 2, \cdots m\}$ is the set of connected edges, considering that the closeness between users in a virtual social platform and the weight of influence is a complex factor. We treat the social network between users as an undirected unweighted network only. That is, if there is interaction between users u_i and u_j, $e_{ij} = 1$, otherwise 0.

3. Multinetwork Hybrid Embedding Recommendation Algorithm Design

3.1. Multinetwork Hybrid Embedding Algorithm. The method of projecting nodes in a network into a low-dimensional vector space Rd has been effectively validated in the field of machine learning. The network embedding method can effectively extract the multidimensional features of the information network and incorporate these features into the embedding vectors of the nodes [30]. We divide multinetwork modeling into two levels: vertical relationship modeling and parallel relationship modeling.

Vertical relationships are the direct association relationships between users and services. In the heterogeneous information network $\mathrm{Net}_{\mathrm{HIN}} = (U, S, W)$, there are direct connected edges between two nodes u_i and s_j. This explicit relationship is modeled using the local proximity between nodes. The probability of union of node u_i with s_j is defined as

$$p(u_i, s_j) = \frac{w_{ij}}{\sum w_{ij}}, \quad (1)$$

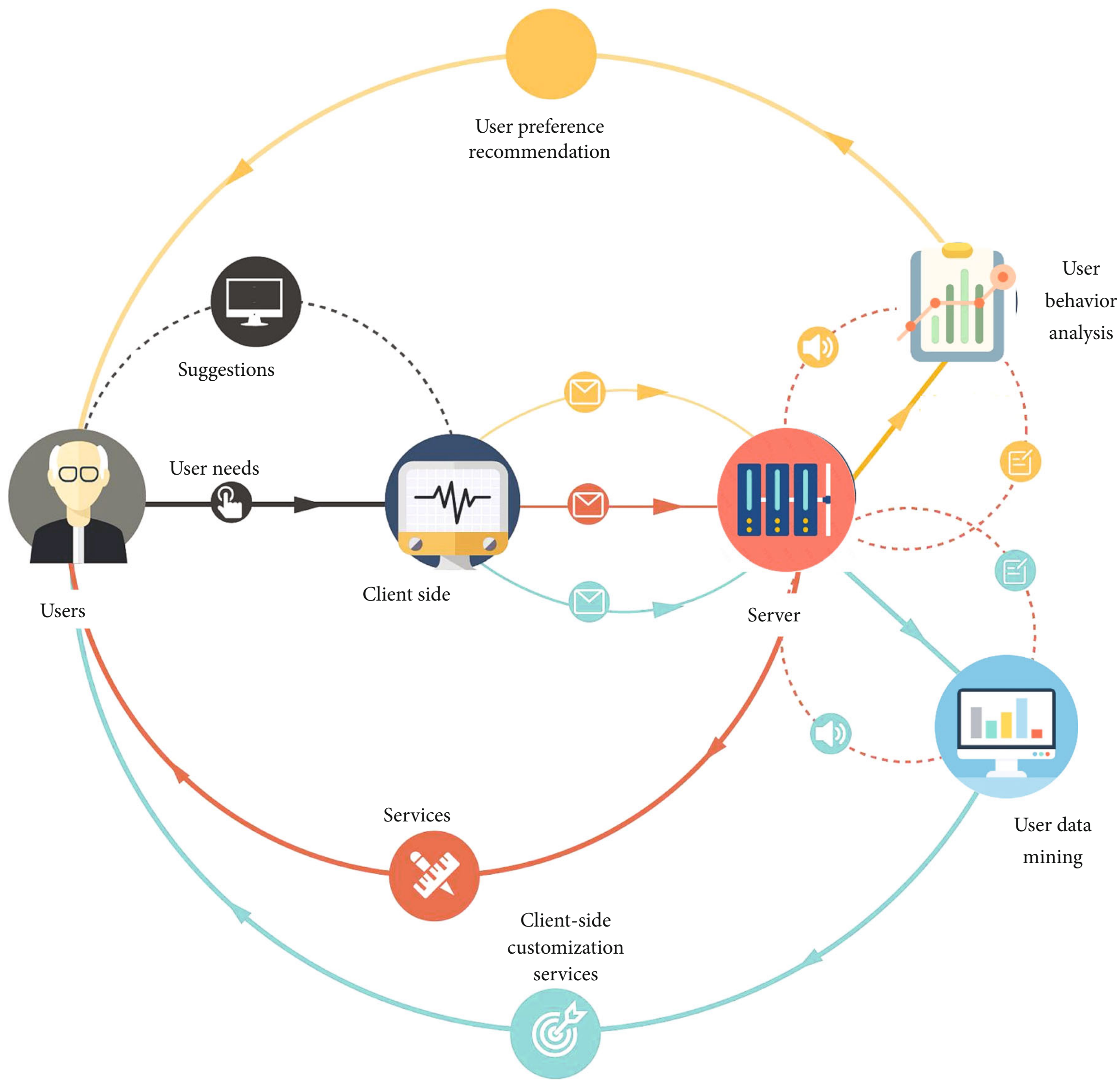


Figure 1: User service network based on ICT technology.

where w_{ij} denotes the weight of the connected edge between u_i and s_j. Obviously, if the value of w_{ij} is larger, the probability of u_i and s_j uniting is larger. Drawing on the popular Word2vec model, the linkage between the embedding vectors is converted into probabilities using the sigmoid function.

$$p(u_i, s_j) = \frac{1}{1 + \exp\left(\vec{u}_i^T \cdot \vec{s}_j\right)}, \quad (2)$$

where note $\vec{u}_i, \vec{s}_j \in \mathbb{R}^d$ are the embedding vectors of nodes. By minimizing $p(u_i, s_j)$, if the weight of the connected edges of two nodes is larger, the connection between the embedding vectors of two nodes is also stronger. Therefore, the explicit relationship between two nodes can be incorporated into the embedding vectors of the nodes.

Parallel relationships refer to the relationships between nodes of the same class that influence each other, i.e., social networks between users and shared networks of labels between services. The projection networks $\mathrm{Net}_{\mathrm{HIN}}^U$ and $\mathrm{Net}_{\mathrm{HIN}}^S$ of users and services can be obtained by projecting the heterogeneous information network. Referring to PageRank, we define the projection operation as

$$w_{ij}^U = \frac{\sum_{k\in S}\left(\left(w_{ik} + w_{kj}\right)/2\right)}{|S|}, \quad w_{ij}^S = \frac{\sum_{k\in U}\left(\left(w_{ik} + w_{kj}\right)/2\right)}{|U|}. \quad (3)$$

After processing by Equation (4), two projection matrices w^U andw^S, which are two homogeneous information networks, can be obtained. These two homogeneous information networks can be further transformed into a sequence of nodes for embedding learning.

3.2. WalkGenerator Algorithm. The random walk method is the most commonly used method to transform the network

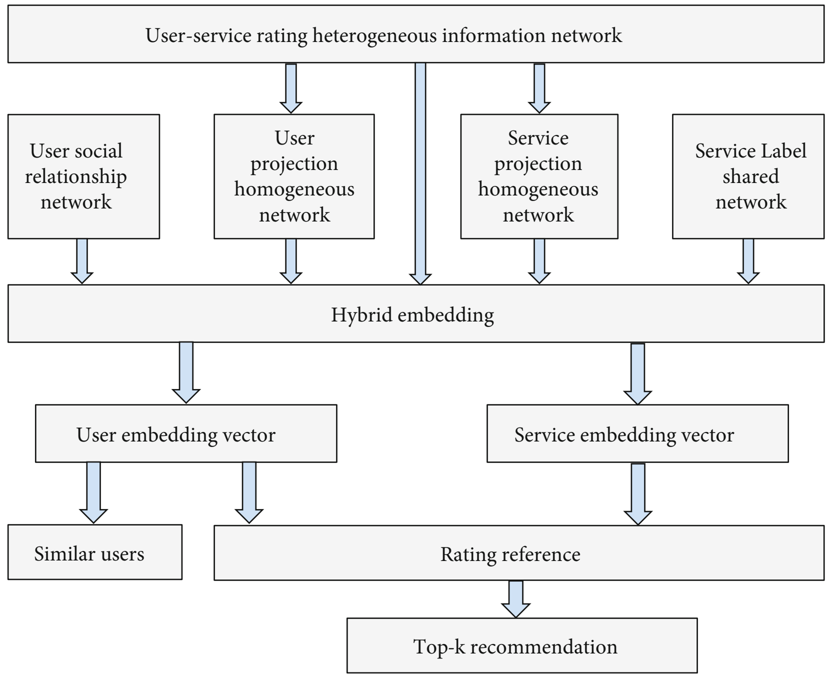


Figure 2: Multinetwork fitted embedding learning model.

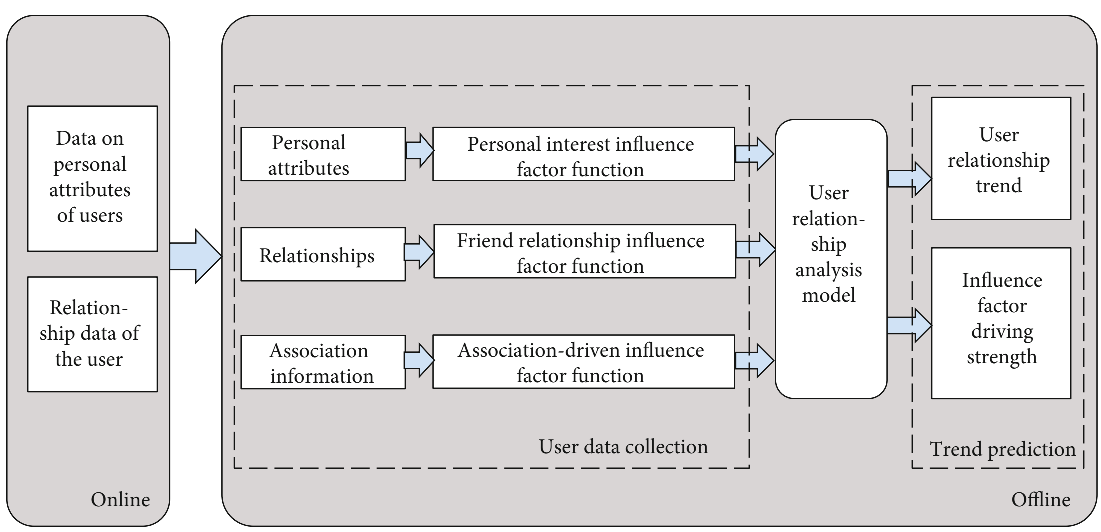


Figure 3: User service rating heterogeneous information network.

into a sequence of nodes, but the traditional random walk method DeepWalk does not effectively preserve the distribution characteristics of the nodes in the network [31]. Optimization is performed in BINE by considering the centrality of the nodes and Node2vec by considering the local network structure. In this paper, the above two optimization methods are combined to propose a more effective random wandering algorithm as shown in Figure 4.

We retain the computerized mechanism of local network structure and modify the fixed number of wanderings to be dynamically calculated according to node centrality. There are many node centrality metrics, which will be comparatively analyzed in the experimental part of this paper. The probability parameter p that controls the wander stop is added so that the length of the resulting node sequence is irregular, where mw is the minimum number of wanderings.

The sequence of nodes and the C^U, C^S, C^{UR}, C^{SR} sequence are obtained using the improved random walk algorithm for $\mathrm{Net}_{\mathrm{HIN}}^U$, $\mathrm{Net}_{\mathrm{HIN}}^S$, and $\mathrm{Net}_{\mathrm{social}}$, respectively. The obtained node sequences are learned by embedding them using the Skip-gram text embedding model, which is based on the idea that the embedding vectors of nodes in the same sequence should be similar. Taking C^U as an example, for node $u_i \in U$ and node sequence $\mathrm{seq}^U \in C^U$, so the conditional probability of $\mathrm{seq}_{u_i}^U$ out of union with u_i should

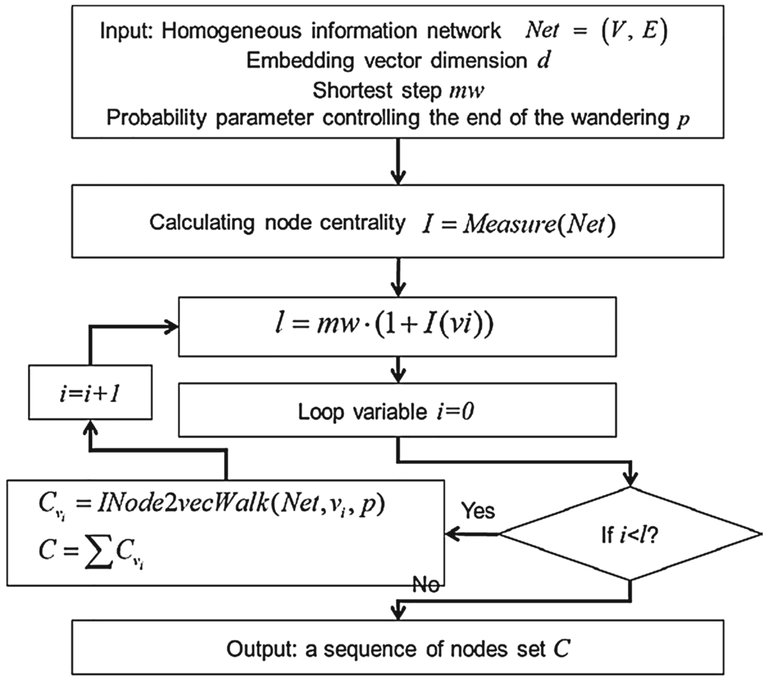


Figure 4: Flowchart of WalkGenerator algorithm.

be maximized, and the objective function after log-optimal learning is as follows.

$$\max O_2 = \sum_{u_i \in U} \sum_{k=1}^{\left|\mathrm{seq}_{u_i}^{U}\right|} \lg p_U(u_k \mid u_i), \tag{4}$$

where $\mathrm{seq}_{u_i}^{U}$ denotes the set of nodes that are in the same node sequence as node u_i. In order to jointly embed user nodes and service nodes in a multinetwork into the same vector space from both vertical and horizontal perspectives, we combine their objective functions and propose a joint training objective function as follows.

$$\max f = \alpha(O_2 + O_4) + \alpha(O_3 + O_5) - \omega O_1. \tag{5}$$

Considering the generality of this method, we divide the horizontal relationship into two categories of users and services. And the minimization O_1 is transformed to seek maximization consistent with other objective functions. To maximize the joint objective function, we use Stochastic Gradient Ascent (SGA) to optimize it. Since the three parts of the joint objective function are different objective functions, we design a combined training model.

Step 1: for the vertical relationship, such as two nodes u, with s, we train the embedding vector by forward accumulative gradient (SGA) to maximize it. The specific calculation is as follows.

$$\overrightarrow{u_i} = \overrightarrow{u_i} + \lambda \cdot \left(\omega \cdot w_{ij} \cdot \frac{\exp\left(-\overrightarrow{u}_i^{T} \cdot \overrightarrow{s}_j\right)}{1 + \exp\left(-\overrightarrow{u}_i^{T} \cdot \overrightarrow{s}_j\right)} \cdot \overrightarrow{s_j} \right),$$

Table 1: Experimental dataset.

Name	User	Service	Score	Relationship
Douban movie	13,367	12.677	1,068,278	4,085
Yelp	16,239	14,284	198,397	158,590
MovieLens	1,370	2,682	100,000	47,150

$$\overrightarrow{s_j} = \overrightarrow{s_j} + \lambda \cdot \left(\omega \cdot w_{ij} \cdot \frac{\exp\left(-\overrightarrow{u}_i^{T} \cdot \overrightarrow{s}_j\right)}{1 + \exp\left(-\overrightarrow{u}_i^{T} \cdot \overrightarrow{s}_j\right)} \cdot \overrightarrow{u_i} \right), \tag{6}$$

where 1 is the learning rate. The part in parentheses is the gradient of $-\omega O_1$ and the derivation process is omitted.

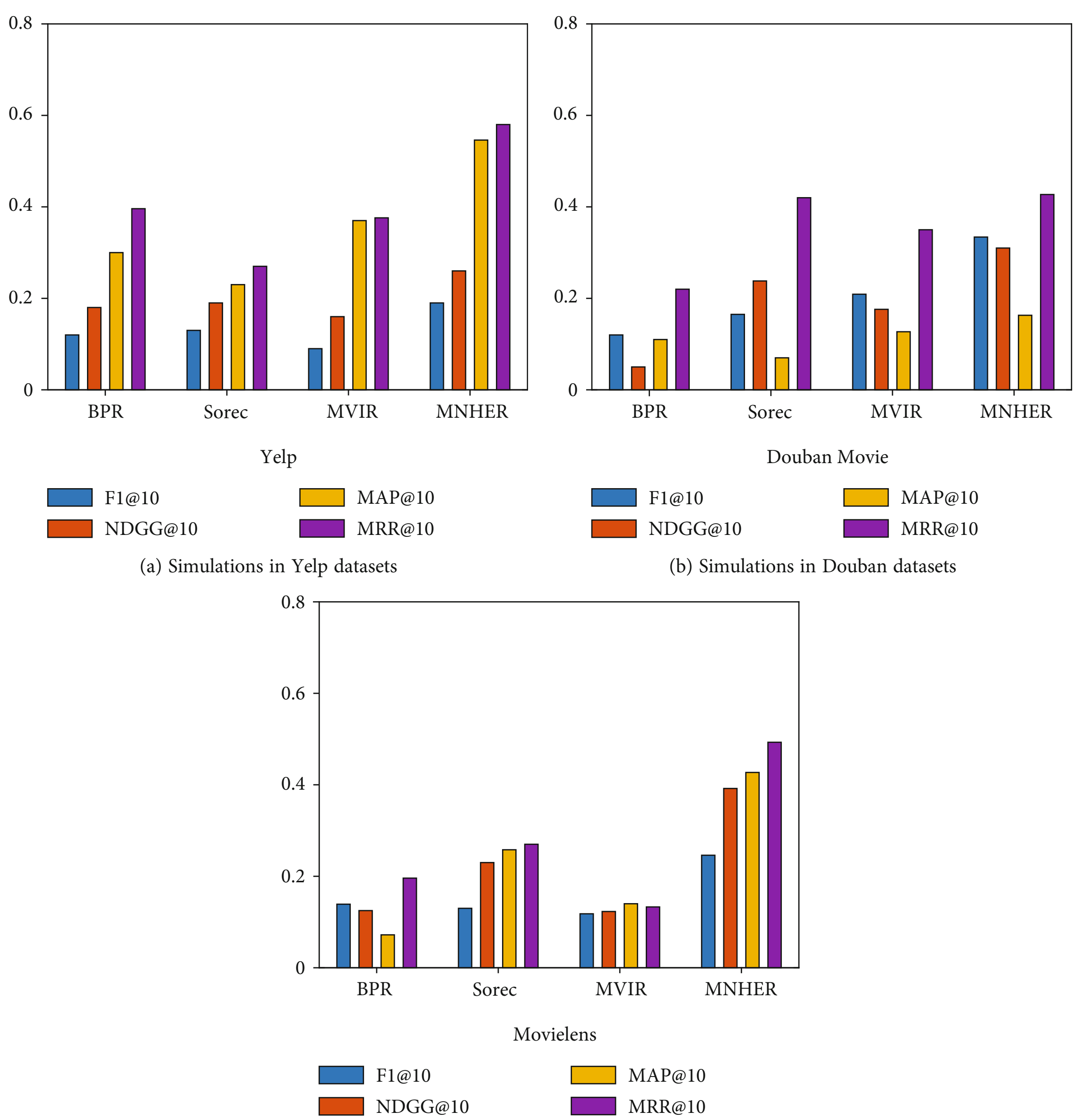
Step 2: for transversal relations, because the objective function types of these relations are the same, the same parameter training method is used. Taking O_2 as an example, for $u_i \in U$ and $z \in \{u_k\} \cup N_{\mathrm{seq}}^{ns}(u_i)$, the embedding vector is trained by forward cumulative gradient (SGA) to say that O_2 is maximized. The specific calculation method is as follows.

$$\overrightarrow{u}_i^{H} = \overrightarrow{u}_i^{H} + \lambda \cdot \sum_{z \in \{u_k\} \cup N_{\mathrm{seq}}^{ns}(u_i)} \alpha \cdot \left[b(z, u_i) - sig\left(\overrightarrow{u}_i^{H^T} \overrightarrow{\theta}_z^{H} \right) \right] \cdot \overrightarrow{\theta}_z^{H}. \tag{7}$$

Step 3: when step 2 is completed, $\overrightarrow{u}_i^{H}, \overrightarrow{u}_i^{R}, \overrightarrow{s}_j^{H}, \overrightarrow{s}_j^{R}$ is obtained. We assign $\overrightarrow{u}_i^{H}, \overrightarrow{u}_i^{R}$ and $\overrightarrow{s}_j^{H}, \overrightarrow{s}_j^{R}$ to $\overrightarrow{u_i}, \overrightarrow{s_j}$ by linear combination, respectively, and then proceed to the next

Table 2: Data statistics of information network.

Name	Network	Number of nodes	Number of consecutive sides
Douban movie	User homogeneous information network	10,279	78,311
	Service homogeneous information network	8,207	62,483
	User social network	9,032	3,357
Yelp	User homogeneous information network	13,279	87,137
	Service homogeneous information network	12,540	69,257
	User social network	14,367	98,573
MovieLens	User homogeneous information network	1,170	23,367
	Service homogeneous information network	2,194	17,621
	User social network	1,037	45,889

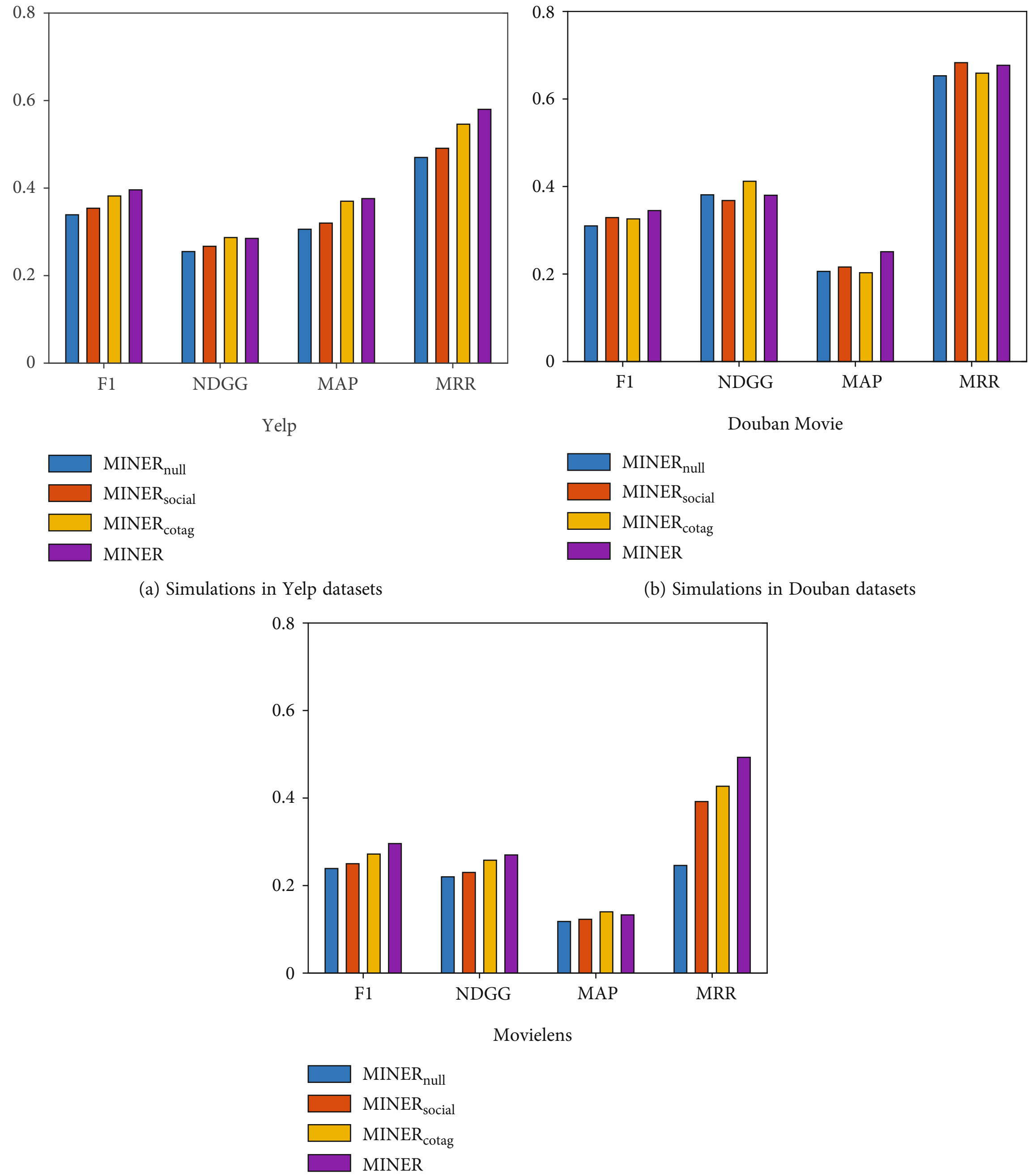


(a) Simulations in Yelp datasets

(b) Simulations in Douban datasets

(c) Simulations in MovieLens datasets

Figure 5: Performance comparisons with baselines on different datasets.



(a) Simulations in Yelp datasets

(b) Simulations in Douban datasets

(c) Simulations in MovieLens datasets

Figure 6: Comparison of experimental results considering different relations.

round. Thus, we give the algorithm to aid in illustrating the whole joint training process.

4. Experimental Results and Data Analysis

4.1. Experimental Setup. The experimental data were obtained from the GitHub platform. 13,367 users and 12,677 services (movie) were included in the Douban movie dataset. 16,239 users and 14,284 services (business) were included in the Yelp dataset. 1,370 users and 2,682 services (item) were included in the MovieLens dataset. The MovieLens dataset includes 1,370 users and 2,682 services (item). The experimental data information is shown in Table 1.

In the dataset, there are behavioral data of users' annotated ratings of services and interaction data between users. After modeling the user information network, the resulting network information statistics are shown in Table 2. To improve the quality of the experimental data, we filtered out users who focused on less than 5 services.

For a fair comparative analysis, all parameters of the benchmark method are taken as their default values. For the method in this paper, we refer to the parameter settings of several web embedding methods and set the dimensionality of the user vector and service vector to 128. We set the trade-off parameter ω to 0.01 and α and β to take values in the interval [0.01, 0.05, 0.1, 0.5, 1]. We set the minimum step size mw to take values from [4, 7, 9, 11, 13, 15]. We set the number of negative samples ns to be taken from [1, 2, 4, 7, 9, 11]. We set the probability p of wandering stop from [0.05, 0.1, 0.15, 0.2, 0.3, 0.4]. We set the linear combination weight $\delta = 0.6$ and the similar user set $|S(u)| = 25$. We set the learning rate to 0.1 according to the discussion of learning rates in the literature figure. We perform the empirical analysis on all three datasets, and the parameters remain consistent.

4.2. Comparative Analysis of Recommendation Quality. To prove the effectiveness of the proposed method in this paper, the experimental data with an 80% training ratio is taken, and the increase matrix is plotted as shown in Figure 5.

As shown in Figure 5, the experimental results show that the four metrics of the MNHER method proposed in this paper outperform the seven benchmark methods in the vast majority of cases. In particular, on the dataset MovieLens, MNHER has considerable improvement in the four metrics. When the training ratio is 80%, the improvement is 151% for F1@10, 145% for NDGG@10, 143% for MAP@10, and 159% for MRR@10 compared with the BPR method. Compared with the SoRec method, the improvement is 137% for F1@10, 138% for NDGG@10, and 196% for MAP@10 and 60% for MRR@10; compared to the MVIR method, 35% for Fl@10, 44% for NDGG@10, 28% for MAP@10, and 60% for MRR@10. Therefore, the recommendation quality of all the methods in this paper is better than that of a separate service recommendation method based on one type of relationship network. Considering multiple relationship networks in service recommendation helps to improve the recommendation quality, and the feature vectors of multiple relationship networks obtained by using the joint embedding method in this paper contain more positive factors of the target users.

4.3. Comparison of Consumer Environment Quality. For comparative analysis, the impact of adding consideration of other relational networks in the learning of representations of dichotomous heterogeneous information networks is considered. Four different combinations of relations were experimentally analyzed on three datasets, namely, $\text{MNHER}_{\text{null}}$, which considers only vertical relations between users and services; $\text{MNHER}_{\text{social}}$, which adds parallel relations between users, such as social relations; $\text{MNHER}_{\text{cotag}}$, which adds parallel relations between services, such as labeled shared relations; and MNHER, which combines the above parallel relations between users and between service relationships between users and services. The experimental results are shown in Figure 6.

After comparison, it is found that $\text{MNHER}_{\text{null}}$ is the method with the lowest quality of service recommendation under all three datasets. Increasing the consideration of parallel relationships between users or between services can improve the overall service recommendation quality. Therefore, increasing the consideration of parallelism in dichotomous heterogeneous information networks can help to explore the relationship between users and services. Second, by comparing the results of the last three experiments, it is found that the recommendation quality of the method that considers two parallel relationships together is better than that of the method that considers only one parallel relationship. Although there are some fluctuations in the data, it is still obvious that the optimal recommendation quality mostly comes from MNHER.

5. Conclusion

In this paper, we propose a multirelational network hybrid embedding method for service recommendation, in which a multirelational network mapped user and service representation vector is obtained using the hybrid network embedding method. The embedded vectors are then used to recommend services to target users. Comparative experiments are conducted with a variety of representative service recommendation methods on three publicly available datasets. The F-measure values can be improved by 21% and 15%, respectively, compared with the service recommendation methods based on a single relational network and a simple fused multirelational network. It is proven that the proposed multinetwork hybrid embedding method can effectively collaborate with multirelational networks and thus improve the service recommendation quality. It is also demonstrated that the proposed multinetwork hybrid embedding method can also effectively map the representation vectors of users and services, and the hybrid consideration of multiple relational networks can help improve the service recommendation quality. How to use the deep neural network to improve recommendation efficiency and recommendation quality is the focus of the next research.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of 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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