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RESEARCH ARTICLE

REHREC: Review Effected Heterogeneous Information Network Recommendation System

FARHAD KHALILZADEH AND ILYAS CICEKLI
Department of Computer Engineering, Hacettepe University, 06800 Ankara, Turkey
Corresponding author: Farhad Khalilzadeh (khalilzadeh.f@hacettepe.edu.tr)

ABSTRACT Heterogeneous Information Networks have bunches of rich secret information that assist us in the creation of successful recommendation frameworks. A Heterogeneous Information Network (HIN) includes useful knowledge required for a recommendation system, and the network embedding is the common strategy for getting useful knowledge out of a HIN to be used in recommendation platforms. Although user and business nodes have been used in HINs, review contents have not been used. In this work, we use review nodes in HINs in addition to user and business nodes. Since written reviews provide valuable insights into points of interest within recommendation systems, integrating review nodes into HINs allows us to assess their impact on recommendation systems. Specifying meaningful meta-paths aids in extracting hidden information within a heterogeneous information network. While user and business nodes are typically utilized for specifying meaningful meta-paths, review nodes have been overlooked. We introduce new meta-paths incorporating review nodes to uncover hidden information in heterogeneous information networks. These meta-paths are leveraged to enhance the recommendation system's performance. This study endeavors to amalgamate rich written reviews with heterogeneous information networks and analyze their effects on recommendation systems. Our experiments demonstrate that incorporating review texts improves the recommendation system, particularly when selecting meaningful meta-paths. Augmenting HINs with reviews facilitates the capture of additional relational information between users and businesses, thereby enhancing the recommendation model. This underscores the benefits of consolidating interaction information within HIN features for superior recommendation outcomes.

INDEX TERMS Heterogeneous information networks, recommendation systems, network embedding, meta-path base random walk.

I. INTRODUCTION

Alongside the advancement of data with web innovation, people have experienced the data overburden problem. In particular, the web delivers a lot of information which are very complex and also useful. Finding the point of their interests are progressively hard. The information in the web is large-scale and it consists of different types. Constructing a graphical relationship between them leads to a structured model which is named as Heterogeneous Information Network (HIN) [1]. HINs are constructed by various entities and links which are huge in numbers [2], [3].

The framework of a recommendation system, which assists humans in discovering items users may be keen on, plays an imperative role in online commerce and services [4]. The old fashion recommendation systems which produce recommendations uses one of the typical methods such as collaborative filtering (CF) [5], [6], [7], [8], [9]. In these recommendation systems, only the history of the clients and their bought objects are considered in the recommendation process.

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On the other hand, a HIN includes useful knowledge required for a recommendation system. The HIN's data utilization power and the ability of combining more data makes it a powerful tool as a data mining technique [10], [11]. Besides, it is a major problem to separate and use legitimate information from HIN. The network embedding is the common strategy for getting useful data out of a HIN to be used in recommendation platforms. The HIN embeddings accurately depict the originality and semantics of the data, encompassing all aspects within the network. In this context, a conversion of HIN into a homogeneous information network is constructed with embeddings.

With the assistance of HIN embedding, numerous recommendation systems have been recently developed [12]. In social networking recommendations, a customized recommendation system is constructed using both HIN embedding and a recommendation AI engine [13]. There are several papers that are based on this method, and one of them [14] employs random walk groupings on user embeddings and point of interest meta-paths. In this regard, it applies the classical matrix factorization method to estimate ratings over a point of interest. Their exploratory findings validate the successful enhancement effect of using HIN embedding within a recommendation model, leading to better results.

Review contents have not been used in HINs. In this work, we also use reviews as nodes in HINs in addition to user and business nodes. Then we use these review nodes to create new meta-paths and these meta-paths are used in order to improve the performance of the designed recommendation system. With the inclusion of review nodes in HINs and the usage of their meta-paths, we obtain better results than the results of other HIN based recommendation systems. Other meta-path based recommendation systems do not use review information as an input to the system therefore there are no review meta-paths in their solution. Our aim is to show the effect of review nodes and their dependent meta-paths over the recommendation system performance.

Our experimental results have showed that including the review graph to the recommendation system and using appropriate meta-paths increases the recommendation performance. Our proposed model is tested in many different conditions and it outperformed all baselines. In particular, the proposed model showed more positive results than the base HERec model [14], with improved results ranging from 3.87% to 9.61% for the Yelp dataset.

The rest of the paper is organized as follows. In Section II, we review related works from various perspectives that are relevant to our proposed recommendation system. In Section III, we discuss our approach named as Review Effected HREC (REHREC). Section IV presents new meta-paths based on reviews, which are discussed in detail. In Section V, we discuss how the recommendation candidates that are generated using review meta-paths are ranked. Section VI presents our evaluation results and the effects of the usage of the review meta-paths in the recommendation system. Finally, Section VII gives the concluding remarks and future work.

II. RELATED WORK

We discuss the related work from four different point of views which consists of recommendation systems, heterogeneous information networks, HIN embeddings and network embeddings.

A. RECOMMENDATION SYSTEMS

When faced with numerous items to choose from, people require assistance in quickly narrowing down their wish list. Recommendation systems are developed to aid individuals in identifying items they may prefer among a vast array of objects or points of interest. Recommendation systems are widely applied in internet-based social networking and have also been successfully implemented in targeted advertisements through online digital platforms.

In order to produce recommendations, recommendation systems collect the required knowledge from the recorded user behaviors and the properties of the items that users interested. There are many different approaches for implementing a recommendation system. Two main approaches are collaborative filtering (CF) and Content-based filtering approaches.

In content-based filtering recommendation systems, item features and the items that users interested in are mainly utilized in the recommendation process. They produce recommendations depending on the similarities between candidate recommendations and items. This approach uses item features for a specific user in order to recommend. The content based filtering is especially useful when all items features are available and the recommendation is needed to be more user specific. This approach does not use information hidden in user's similarity or friendship graph.

On the other hand, collaborative filtering (CF) recommendation systems estimate evaluations based on knowledge of user-item associations [15]. In collaborative filtering recommendation systems, similarities between users are evaluated according to user features, and these user similarities are utilized in the recommendation process. Similar items are recommended to users with similar preferences in collaborative filtering recommendation systems.

Our approach, based on Heterogeneous Information Network (HIN), identifies user and item similarities using the underlying HIN structure. Similarities are determined through meta-paths within the underlying HIN structure. Subsequently, the identified user and item similarities are employed in the recommendation process. Since we also utilize user and item similarities in the recommendation process, our approach can be regarded as a collaborative filtering recommendation system.

Using collaborative filtering in our system we need to solve some issues that exists in this method. Using collaborative filtering in the recommendation system can lead us to a very good recommendation performance but the cold start issue is one of the impediments in which the collaborative filtering still faces [16]. HIN based recommendation systems partially solves the cold start problem.

Many studies have explored strategies for addressing the cold start problem. In these investigations, scientists have gathered positive data and valuable insights from heterogeneous information networks as part of efforts to resolve the issue. For example, one of the studies [18] implements a cross-domain model which recommends through gathering data of different domains, while other paper [17] examine data from the text comments and ratings to resolve the problem. In another study [19], a framework which is named as smooth neighborhood is introduced to solve the cold-start issue. A kernel which detects the similarity is implemented in order to fetch the locality information through some specific networks, such as friendship network of users. Additionally, there are heterogeneous information network based recommendation models [20], [21], [22] that implemented the deep neural network learning methods to try improving the results and solving the issue.

B. HETEROGENEOUS INFORMATION NETWORK (HIN)

The world that we live consists of different and heterogeneous kinds of entities and their collaborations. These entities and their integration makes a network which is named as a HIN (Heterogeneous Information Network). When these HINs are analyzed, we can notice that there are lots of powerful information that can be reached in the below layers of HINs which semantically are connected. HINs are naturally created by e-commerce platforms or the other network based platforms such as Facebook.

To understand the difference between HINs and homogeneous networks, there should be mentioned that all the nodes in a homogeneous network are in the same type and all the links between them are in the same type too. Links in homogenous networks represent the relations between same type nodes representing entities in a particular type. The similarities between the nodes of a homogeneous network can be measured by some traditional distance metrics such as Euclidean distance, Cosine similarity and Jaccard index. On the other hand, the nodes in a heterogeneous information network (HIN) can represent entities in different types and the links between these nodes can be also in different types [3]. Essentially, the direct usage of traditional distance metrics to measure similarities in HINs may not be appropriate. As an example, the straightforward usage of k-means algorithm [23] in order to cluster the entities in a HIN is not logical since the entities in a HIN may belong to different categories. Generally, a HIN carries more information than a homogeneous network and different approaches are used to measure the similarities in HINs [24].

To solve the similarity detection problem in HINs, the meta-paths are used by many different researchers [25], [37]. In a single heterogeneous information network, there can exist many separate meta-paths and all of them can reveal different similarities based on their semantic meanings. Meta-paths between the nodes in different types indicate the relations between the entities in different categories. Using these meta-paths, the hidden relation between the nodes that belongs to a same category can be revealed.

Numerous researchers [25], [37] propose various meta-path models to serve as measurement tools for comparing nodes of similar or different classes. For instance, in one study [26], the random path method is implemented to establish a sampling technique for evaluating distance, based on the fundamental concept of "similar neighbors" in both heterogeneous and homogeneous information networks.

C. EMBEDDING FOR HINS

To extract more valuable information from HINs, we must utilize node embeddings within them. In this subsection, we explain some of works in the literature concerning this topic. There exist many approaches aimed at extracting sufficient meaningful data from HINs. Through the adoption of embedding techniques or novel similarity detection approaches, the efficiency of recommendation frameworks is enhanced, leading to the acquisition of more useful information from recommendation systems.

For example, in one study [27], certain sub-items and users are constrained to be comparable within the HIN. These constrained nodes are then incorporated into the matrix factorization process to enhance the overall workflow and achieve improved results. In another study [28], the detection of resemblance between nodes, the implementation of meta-paths, and their integration into a matrix factorization model are conducted for HINs. Unlike similarity-based strategies, which measure similarities between nodes, embedding-based techniques are adept at overcoming sparsity and noisy data. An illustrative example of such work proposes an embedding strategy that utilizes meta-path-driven results within the item rating workflow [14]. Conversely, in another study [12], authors utilize a model based on artificial neural networks structured on graphs to enhance recommendation systems. Additionally, another study [21] designs an algorithm to learn embeddings capable of condensing or extracting data from various meta-paths. Similarly, deep learning approaches are employed in embedding-based models.

D. EMBEDDING A NETWORK TO REDUCE THE DIMENSION

The embedding of a network can get the nodes in the network and convert them as a smaller node from the dimensional point of view at the cost of the thickness in its space complexity. Keeping the main network properties, designing the recommendation system using this method is proved its effectiveness in many studies [29], [30].

Fundamentally, the first embedding algorithms are about to reduce the dimension of the nodes [31]. Somewhat recently, the embedding is improved into adaptable embedding of the graph in new papers. For example, one paper [32] constrains neighboring nodes in the graph and thus proposes a graph factorization method. In another paper, this technique is improved by accumulating a quadratic resemblance among knots [33]. Another paper [34] used the auto-encoders to find the resulting embedding, detecting the information that is not linear. Two of the papers [35], [36], creatively use the random walking method to take the samples of the network and introduce the nodes based on these samples.

Not all of the methods to execute an embedding, are suitable for implementing over the HINs. Specially, distinctive meta-paths from one node to another one can mean different from semantic point of view, because the nodes in a HIN have varied properties which leads to this semantic difference. In addition, it is not sensible and logical to put the various nodes with different properties into a same space which means they are similar in the heterogeneous graph.

Based on the above facts, the analysts created new algorithms to better adapt to the heterogeneous graphs [38], [39], [40]. For example, to learn the fundamental of the graph connections, one of them [37] introduces implementing skip-gram method, and proposes a model to embed the nodes by using random walks based on the selected meta-paths. Another research [14] uses deep walking over the network. The embedding in this method learns from successive nodes produced by random walking on meta-pathways in the graph.

III. THE REVIEW EFFECTED HREC (REHREC) APPROACH

In this part, we introduce the structure of our suggested "Review Effected Heterogeneous Information Network Embedding for Recommendation" (REHREC) framework exhaustively, which is basically made out of three steps. The initial step is to produce the review graph, dependent on some similarity estimation between reviews. Consequently, we blend this review graph with our HIN network to create a heterogeneous network comprising of User, Business, Category and Review nodes together with their edges. We produce a meta-path driven HIN embedding strategy to become familiar with the embeddings of different nodes such as users and businesses [14].

Here the outer product is used to produce the matrix related to the feature relationship among user and item embeddings over the heterogeneous graph [41]. At the end, a rating estimation function for matrix factorization (MF) is obtained. It is based on the approach described in the paper [14] by some review option additions. In the rest of this section, we discuss these steps one by one.

A. REVIEW GRAPH GENERATION

To extract features from textual information, various algorithms are available. Given that the linguistic context of the content is crucial in review texts, the Doc2Vec embedding technique is selected to preserve this essential information. A two-layer Neural Network serving as a Doc2Vec framework is utilized and fed with continuous bag of words. After preparing the model, we can obtain the vector representation of a review. This vector can then be utilized as a feature vector for the review to be fed into any classification algorithm. Our aim is to explore the semantic connections between reviews to generate a review graph based on their semantic similarities.

Finding the sentiment of a review is treated as a binary classification problem. The training dataset contains review texts with ratings and review ratings between 0 and 5. A review whose review rating is lower than 3 is treated as a negative review and it is treated as a positive review otherwise. The SVM classifier is used as a learning algorithm to classify reviews based on their vectors as positive or negative. To generate our review graph, we put an edge between two reviews if their semantics are same (whether both are negative or both are positive).

B. HIN NETWORK GENERATION

To generate our heterogeneous network, we need to know how to put edges between nodes with different types. Our HIN network contains user nodes and business nodes together with review nodes. The edges between user nodes come from user friendship graph. The edges between business nodes come from their physical distances based on their location (longitude and latitude), and the edges between review nodes came from the review graph based on their sentiment analysis. Any edges between different node types came from the relationship between those nodes that exists in the dataset. For example, if *User1* goes to *Business1* and writes *Review1* for that location, there will be edges between these specific nodes.

C. HIN EMBEDDING

There are 3 main steps during executing the embedding over heterogeneous networks. In the initial one, we get the walking order with a random walk along the determined path. In the second step, starting from this point, nodes with an alternative kind of starting node based on the specific meta-path should be eliminated sequentially and run the homogeneous network embedding strategy to learn how to embed the nodes in a particular path. As the last step, we get the result HIN embedding by including the embedding of vertexes in various paths using some aggregation function.

To begin with, a random walk which is based on the meta-path-driven method is described below. Here we represent a heterogeneous information network as G consisting of V as vertices and E as edges. The following meta-path (mp) describes relations $R_1,\ldots,R_t$ between node types $T_1,\ldots,T_{t+1}$ of nodes $v_1,\ldots,v_{t+1}$:

$$\mathrm{mp} : T_1 \xrightarrow{R_1} \cdots T_k \xrightarrow{R_k} T_{k+1} \cdots \xrightarrow{R_t} T_{t+1} \quad (1)$$

We can produce sequence as indicated by the walking methodology in underneath condition:

$$P\left(v_{k+1}|v_k\right) = \left\{ \begin{array}{cc} \frac{1}{|N\left(v_k\right)|} & \left(v_k, v_{k+1}\right) \in E \wedge \varphi\left(v_{k+1}\right) = T_{k+1} \\ 0 & otherwise \end{array} \right\} \tag{2}$$

In (2) the distribution probability P is calculated, where v_k and v_{k+1} introduces k-th, k+1-th vertex with kinds of T_k and T_{k+1} regarding the mp meta-path and $N(v_k)$ appear for set of neighbors that exists in the first reaching edge connected to v_k node with the type of T_{k+1}. According to the equation structure, we are able to create a series of random walks by taking into account the length of the walk and the starting point.

Mentioning about the series of random walk, it has various properties and consists of different types of nodes. Likewise, it is irrational to map nodes with various property to a similar dimension space. Therefore, we need to eliminate nodes unique to vertex that is the meta-path starts with. Thus, the walk set automatically is converted to a homogeneous graph which the embedding representation of the nodes can be learned using the homogeneous network embedding technique. Subsequently, we can obtain embedding nodes belonging to different meta-paths.

$$\left\{e_v^{(b)}\right\}_{b=1}^{|MP|} \tag{3}$$

The set of meta-paths inside the equation, is demonstrated as MP. The count of MP is illustrated as |MP| and finally the vertex embedding of b-th meta-path is representing as $e_v^{(b)}$.

As the final step, a combination function can be obtained to perform the HIN embedding of the nodes. We name this combining function as "aggregation function". There are several "aggregation functions" which we use one type of them as "The non-linear aggregation function" which is (user specific).

Aggregations which are linear do not have the capacity handling the complication that resists in the information interactions. To preserve the valuable information encoded in node embeddings, we implement the utilization phase using non-linear functions. This approach helps retain the beneficial information within the system. Below is our function to fuse the node embeddings which is to be obtained from training phase:

$$\mathrm{K}\left(\{e_u^{(n)}\}\right) = \delta\left(\sum_{n=1}^{\mathrm{MP}} \Omega_u^{(n)} \delta(\Pi^{(n)} e_u^{(n)} + b^{(n)})\right) \tag{4}$$

K is our aggregation result, δ shows mathematical sigmoid expression which is a nonlinear function. The count of meta-paths related to users are shown as |MP|.

$$\Pi^{(n)} \in R^{D_U \times d_U} \quad and \quad b^{(n)} \in R^{D_U} \tag{5}$$

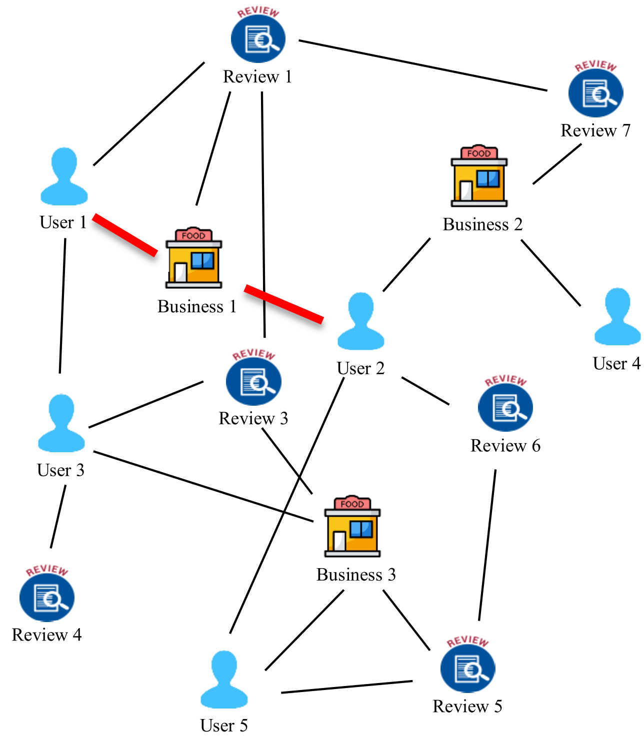

FIGURE 1. Sample HIN network of yelp dataset.

Π shows the matrix that contains the weights belonging to the embeddings from n-th meta-path. The b is a vector that contains all biases of n-th meta-path. Ω is chosen weight of specific user in the n-th meta-path

IV. REHREC META PATHS

To generate samples using meta-path based method with the random walk technique, specifying the meaningful meta-paths is needed to help us extract the hidden information exists in the heterogeneous information network. Below is the list of used meta-paths in the REHREC method:

UBU (User – Business - User): A path that starts from a user node goes to a business node and then ends with a user node. The aim of this meta-path is to extract user – user relation that does not exist in user friendship graph. Figure 1 shows a hidden link between User1 and User2. Since both User1 and User2 goes to the same business, a relation between these two users is extracted using this meta-path.

BUB (Business – User - Business): A path that starts from a business node goes to a user node and then ends with a business node. The aim of this meta-path is to extract business – business relation that does not exist in business graph. If there is at least one user goes to both businesses, a relation between these two businesses is extracted using BUB meta-path.

URRU (User - Review – Review - User): A path that starts from a User node goes to a Review node and using another Review node, ends with a User node. The aim of this meta-path is to extract User – User relation that does not exist in the user friendship graph. If two users' review classes are same, a relation between these two users will be extracted using this meta-path. Two users' review classes are same if their majority of their reviews are in the same sentiment class (positive, negative). This means that if both User1 and User2 write mainly positive reviews, a relation between User1 and User2 will be created using URRU meta-path. Similarly, if they write mainly negative reviews, a relation between them will be also extracted.

BRRB (Business - Review – Review - Business): A path that starts from a Business node goes to a Review node and using another Review node, ends with a Business node. The aim of this meta-path is to extract Business – Business relation that does not exist in Business graph. If the majority of the reviews of two businesses are in the same sentiment class, a relation between these two businesses will be extracted by BRRB meta-path.

UBRRBU (User - Business - Review – Review – Business – User): A path that starts from a User, goes to Business node then using a Review node goes to another Review node and then goes to a Business node, and finally ends with a User node. The aim of this meta-path is to extract User – User relation that does not exist in user friendship graph. If User1 goes to Business1, User2 goes to Business2 and the majority of the reviews of these two businesses are in the same sentiment class, a relation between these two users will be extracted using UBRRBU meta-path.

BURRUB (Business - User - Review – Review – User - Business): A path that starts from a Business, goes to User node then using a Review node goes to another Review node and then goes to a User node, and finally ends with a Business node. The aim of this meta-path is to extract Business – Business relation that does not exist in user friendship graph. If User1 goes to Business1, User2 goes to Business2 and the majority of the reviews of these two users are in the same sentiment class, a relation between these two businesses will be extracted using BURRUB meta-path.

Filtering Phase for Random-Walk Series: It must be noted that the random-walk series comprises different types of vertices, each possessing various properties. Similarly, when we place vertices with distinct types and properties within the same dimensional space, we compromise the logic and coherence of the system. Consequently, when establishing a path sequence of same node types, nodes whose node types are different than the starting node type should be excluded.

Here, for a random walk sequence given as "user1 bussiness1 user2 bussiness2 user3 bussiness3", the nodes which are in different type than "user" are removed from this sequence and the sequence "user1 user2 user3" where all nodes have same type as the type of the starting node is obtained. Thus, the remaining sequences that are obtained from random walk sequences are resulted as a homogeneous graph. The resulted embedding representation of the nodes can be learned using the homogeneous network embedding technique. The conversion steps from Heterogeneous Network to homogeneous network is illustrated in Figure 2.

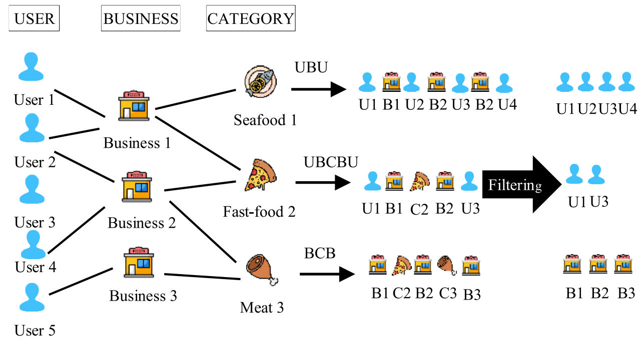

FIGURE 2. Sample mata path based filtering operations.

V. RATING PREDICTION FUNCTION AND RECOMMENDATION

Beneficial information from heterogeneous information networks is extracted as user-type embeddings and business-type embeddings using meta-paths. This extracted information serves as the basis for developing a recommendation system.

During this stage, these embeddings are consolidated to generate rating estimations within the recommendation system. The proposed REHREC model, an extension of the HERec model [14], employs the Matrix Factorization (MF) method. As depicted in Figure 3, we derive node embeddings from the heterogeneous network using meta-path-based random walks. Multiple meta-paths starting with the same node type result in the generation of multiple embeddings for a single node, as illustrated in the node embedding phase. To obtain a unique single node embedding generated by different meta-paths, a fusion step is introduced as the final phase of the embedding workflow. These fused embeddings are then employed in matrix factorization to perform the recommendation task.

In Matrix Factorization, the rating of the user point of interest (POI) which is business here (point of interest/business) is obtained using the user matrix and the POI matrix. We may name these low dimensional matrices as latent factor matrices. The row indices of these two matrix shows the relation between users and POIs in the latent factors. The mathematical expression belonging to a rating of particular user (u) over b-th POI is as follows,

$$\mathrm{Rating}_{u,b} = U_u^T . V_b \tag{6}$$

where $\mathrm{U_u}$ is showing the latent factor of user and $\mathrm{V_b}$ is showing the latent factor related to POI. On the other hand, the HERec model, adds embedding of user and item into the MF. The prediction of ratings is done using below function in the REHREC algorithm.

$$\mathrm{Rating}_{u,b} = U_u^T . V_b + \lambda \cdot {e_u^{(U)}}^T \cdot \Omega_u^{(U)} + \mu \cdot {\Omega_b^{(I)}}^T \cdot e_b^{(I)} \tag{7}$$

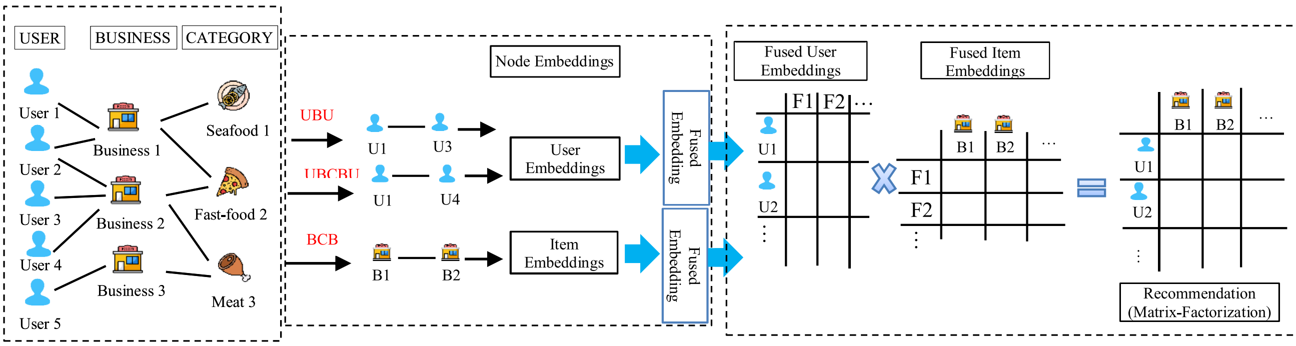

FIGURE 3. Diagram which illustrates the workflow of the approach.

In the equation, Ω_u shows the weight belonging to user embedding and Ω_b shows the weight belonging to business embedding. Also, in the formula the coefficients λ and μ play the role of integration from the embeddings into matrix factorization functionality.

The recommendation is done based on the predicted ratings which is a number between 0 and 5. We place a threshold for this purpose. The ratings that are predicted as 3 and above are recommended to the user and others are eliminated.

Cold-Start Issue: The cold-start issue arises when there are insufficient rating values associated with a specific user-business relation. In such scenarios, HINs can potentially aid us by offering rich contextual information even in the absence of rating records.

The inclusion of additional and useful meta-paths, augmented with review information, enhances the recommendation system by extracting even more contextual information from HINs. This contributes to better addressing the cold-start problem, which is already improved by utilizing HIN itself as a source of context.

VI. EXPERIMENTS

In this section, we demonstrate the execution of REHREC's proposal by analyzing a commonly used "Yelp" open dataset and comparing it with cutting-edge recommendation models. Through experimental studies conducted with the REHREC model, it is evident that the model exhibits positive performance.

We use Yelp dataset [44] which is also used in the paper [14] in order to evaluate the results. The Yelp dataset is a sparse dataset with a density of 0.08%. The Yelp dataset contains users, businesses, reviews and business ratings. Although Shi et al. [14] only used users and business information in the dataset, we also use review information in addition to them. The Yelp dataset contains 1 million users, 144820 businesses and 4.1 million reviews.

The following classical RMSE (Root Mean Square Error) is used as a tool to evaluate the models and rate the recommendation algorithms:

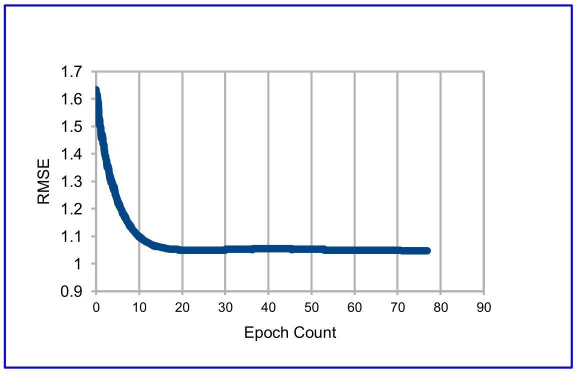

FIGURE 4. Error curve in different iterations.

$$RMSE=\sqrt{\frac{1}{|R_{test}|}\sum\nolimits_{(u,b,\text{rating}_{u,b})\in R_{test}}\left(\text{rating}_{u,b}-\text{pred}_{u,b}\right)^2} \quad (8)$$

In (8), R_{test} is a test set consisting of triplets (b, u, $\text{rating}_{u,b}$) where b is a business, u is a user and $\text{rating}_{u,b}$ is rating of that business by that user. $\text{pred}_{u,b}$ is the predicted rating by our model and $|R_{test}|$ is the size of the test set. In order to increase the model performance, the RMSE value should be as low as possible.

In Figure 4, the curve indicates RMSE values for the test set depending on Epoch counts on the training. The values in Figure 4 are obtained when 90% of the dataset is used as the training set and 10% of the dataset is used as the test set. The curve indicates that approximately 20 Epochs are enough to minimize RMSE.

Our model is compared with some cutting-edge recommendation systems to evaluate the presentation of the rating forecast. Since these recommendation systems use RMSE in their evaluations, we compare our model with these systems using obtained RMSE results. The model list is as follows:

- HERec: The given model is the main model that we are working on to improve it by adding reviews to the system [14].

TABLE 1. Results based on different algorithms and training set percentages.

Dataset	Training	Metric	HERec	NCF	MCRec	NGCF	Our REHREC Model
YELP	90%	RMSE	1.0907	1.0556	1.0823	1.0619	1.0500
	80%	RMSE	1.1117	1.0655	1.0997	1.0687	1.0560
	70%	RMSE	1.1256	1.0719	1.1072	1.0734	1.0706
	60%	RMSE	1.1488	1.0911	1.1241	1.0968	1.0754

TABLE 2. RMSE results using different meta paths in 90% training.

UBU, BUB, **URRU**, **BRRB**, **UBRRBU**, UBCaBU, BCaB	UBU, BUB, UBCaBU, BCaB	UBU, BUB, **URRU**, UBCaBU, BCaB	UBU, BUB, **BRRB**, UBCaBU, BCaB	UBU, BUB, **UBRRBU**, UBCaBU, BCaB	UBU, BUB, **BURRUB**, UBCaBU, BCaB
1.05 (Our REHREC Model)	1.0907 (Base HERec Paper)	1.08	1.09	1.06	1.14

- NCF: The specified model is a recommended neural network strategy that uses MLP in order to display user-item relation [42].
- MCRec: The specified model uses CNN to metapathize a complex model correlation inside HIN which leads to a better result [43].
- NGCF: This is one of the new methods of the graphical neural networks which is based on GCN to display the recommendation output [21].

The dataset is separated into two parts named as test set and train set. Different sizes of training set are used in evaluations. We set four training proportions for our sparse Yelp dataset. These rates are starting from 60% of the dataset to 90% coverage and the increase percentage of the coverage at each dataset is 10% on top of the previous one. In evaluations, we used same parameters that are used by Shi et al. [14] in order to compare each method and validate the results. The embedding dimensions of our model for random walk are 128 and the hidden factor size of DNN (Deep Neural Network) is 100. Two hidden layers are used in MLP (Multi-Layer Perceptron). The number of neurons in the first layer is 64 and it decreases to 32 in the second hidden layer. We used the "ReLU" (Rectified Linear Unit) as the activation expression. In the Convolutional Neural Network structure, the pooling layer which is the first layer, the convolution layer and the full link layers makes our network. The neuron counts in layers are 128, 64 and 32, respectively. On the other hand, the filter size between layers is determined as 3. We also use the same-padding as padding type in convolutional layers which adds zeros in outer frame of the data. The pooling type is set to the max-pooling in the system. In order to obtain fair comparison, the parameters are same as the parameters that are revealed at Shi et al. paper [14]. In Table 1, the results of training set on different models are illustrated. As seen in Table 1, our model accomplishes the best results.

NCF and NGCF consistently outperforms the other baselines (HERec, MCRec). For the Yelp dataset, NCF out-performs HERec significantly, ranging from 3.33% to 8.03%, while MCRec obtains at most around 1% improvement over HERec.

Our proposed REHREC model is consistent in most of the conditions tested and outperforms all other systems. In particular, the proposed model shows more positive results than the base HERec model, with results ranging from 3.87% to 9.61% (for the Yelp dataset). Since our REHREC model is similar to HERec model except the usage of reviews, these improvements reflect the effect of reviews in the performance. The proposed model considers the semantic difference and impact between nodes in each POI (Point of Interest) compared to other methods.

Thus, our model can effectively extract more related information from heterogeneous information networks and it produces better recommendations. At the same time, it has been observed that the proposed model performs better for small training sets. The model showed RMSE improvement of over 9% over baseline HERec model when the training sample rate was as low as 60%. This result shows us the excellence of review insertion for small training sets and sparse datasets.

The recommendation system output results increase in performance while the percentage of the training set coverage increases. By evaluating our model with the original baseline work, we can see the relationship between the selected meta-path and the accuracy of the recommendation system in a positive manner. Table 2 shows the improvement rate based on the added meta-paths using reviews. As seen in Table 2, three of our new meta-paths using reviews (URRU, BRRB and UBRRBU) increase the performance of the system. As we can see only one meta-path (BURRUB) has reverse effect in the performance. The mentioned meta-path is BURRUB means starting from one business we try to reach another business using reviews and users in the middle. So it proves that this is not a good way of network preparation. In Table 2, we can see the results based on different meta-paths used in the proposed model and we obtain our best results (first column in Table 2) when we use three new review meta-paths.

VII. CONCLUSION

In this paper, we propose REHREC model for recommendation systems by adding review graph to enhance Heterogeneous Information Network. In the model, user HIN embedding, business HIN embedding, classical matrix factorization, and feature interaction matrix can be directly consolidated. Enhancing HIN with reviews leads to capture more relational information between users and more relational information between businesses. It proves that merging the information of interactions between the features inside a HIN leads to a better recommendation model. Our REHREC model captures more information between users (and businesses) using review included meta-paths and this leads the performance improvement in the recommendation system using our REHREC model.

Our experimental results indicate that the relations between users are captured more effectively than the relations between businesses as a result of usage of reviews in HINs. The usage of meta-paths URRU and UBRRBU improves the performance more drastically and those meta-paths captures the relations between users.

In terms of future work, we have identified the meta-path selection phase as crucial for leveraging the most relevant review context information within the recommendation system, thereby enhancing the quality of recommendations. Our ongoing research will focus on determining efficient meta-paths for reviews to maximize effectiveness and refine the overall system. Additionally, we plan to delve into analyzing reviews not solely based on their semantic positivity or negativity, but also from an interpretative standpoint, as part of our extended future endeavors.

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FARHAD KHALILZADEH was born in 1985. He received the B.S. degree in software engineering from UCNA, Iran, in 2008. He is currently pursuing the Ph.D. degree with the Department of Computer Engineering, Hacettepe University, Ankara, Turkey. His research interests include recommendation systems, text embedding, and deep neural networks.

ILYAS CICEKLI received the Ph.D. degree in computer science from Syracuse University, USA. He was a Visiting Faculty Member of Syracuse University, from 2017 to 2019, and the University of Central Florida, from 2001 to 2003. He currently holds the position of a Full Professor and the Chair of the Department of Computer Engineering, Hacettepe University, Ankara, Turkey. He has authored over 80 articles in the field of natural language processing, including more than 30 journal articles. His research interests include natural language processing, text summarization, example-based machine translation, question-answering, and information extraction.