Step Out of Your Comfort Zone: More Inclusive Content Recommendation for Networked Systems

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ABSTRACT

Networked systems are widely applicable in real-world scenarios such as social networks, infrastructure networks, and biological networks. Among those applications, we are interested in social networks due to their complexity and popularity. One crucial task on the social network is to recommend new content based on special characteristics of the graph structure. In this project, we aim to enhance the recommender systems by preventing the recommendations from leaning towards contents from closed communities. To counteract the bias, we will consider information dissemination across network as a metric to assess the recommendation for contents e.g. new connections and news feed. We use academic collaboration network and user-item interaction datasets from Yelp to simulate an environment for connection recommendations and to validate the proposed algorithm.

1 INTRODUCTION

Graphs have been utilized in a wide variety of practical applications, including but not limited to social networks, biology networks, and interconnected large-scale systems. In the applications of social networks, graphs are composed of individuals and their relationships with others, represented as nodes and edges. Similarly, warehouses and routes of a supply chain network can be modeled as a directed graph with nodes and edges. For those graphical systems, especially for social networks, one important application is how to accurately recommend contents or connections for existing users. Profound research has been conducted to establish reliable and efficient recommender systems. For example, Konstas et al. [11] introduce a collaborative filtering recommendation system. In their work, they utilize network information including personal preferences and underlying users’ communities to enhance the performance of the recommender system. Yang et al. [24] demonstrate that the accuracy of the recommendation system can be increased by learning the category-specific social trust circles from the network data. Moreover, Fan et al. [2] apply the graphical neural network to predict user-item rating. The model separately learns the user and item latent variables from the two user-user and user-item graphs, and train the predictor on these latent variables.

All the aforementioned works try to improve the recommender systems’ performance by applying additional information from the graphs, such as communities of users, trust circles as well as users’ interactions. Nonetheless, such additional information tends to be community-specific; as a consequence, the users would likely connect within their community or heavily receive homogeneous recommendations. The cycle of a user interacting based on recommendations and recommendations constructed from the user’s interactions leads to an undesirably disconnected graph. The overall utility of such recommendation is questionable: out-of-community recommendations can be more preferable for users. Furthermore, the dissemination of information should not be limited by specific communities identified. For example, on Youtube, a user may prefer to have coverings for the same subject from different perspectives; or on TikTok, the user may want to discover new contents different from his/her “learned” interests. As a result, in this project, we want to avoid the over-constrained recommender systems by considering information dissemination crossing the entire network via user-item interaction graph.

Information dissemination has been used as a measure in the literature to evaluate the structure of the graph. For instance, Tong et al. [19] have demonstrated an algorithm to increase the information dissemination by adding edges to the graph. However, it assumes that all edges have the same addition cost, which is false in the recommendation problem; in particular, target users have a preference for each connection. Generalizing the idea for the social network settings, out-of-community connections should be recommended based on information dissemination metrics together with the likelihood of users’ interactions.

Thus, we adopt DiffNet Wu et al. [22] to formulate an appropriate optimization model to recommend potential user-item connections based on social network or user-user interactions (Section 2). We also study information dissemination in existing graphs and propose an integration of dissemination into aforementioned optimization problem to train DiffNet in order to optimize recommendation accuracy and dissemination capability simultaneously (Section 3). We then empirically study the effect of dissemination factor and draw DiffNet’s Pareto front on accuracy-dissemination trade-off (4). In general, we are able to formulate a recommender algorithm to smoothly incorporate information dissemination as an additional criterion.
2 NETWORK DIFFUSION FOR RECOMMENDATION

As for traditional recommendation tasks, many studies have been conducted to find sophisticated user and item embeddings in latent space and thus to directly predict users’ preferences based on the embedded representations. Guo et al. [6], He et al. [8], Rendle [16]. However, the performance of the embedding based recommendation technique is usually deteriorated because of the sparsity of the user-item interactions. This drawback motivates the research about how to incorporate external information other than user/item embeddings to enhance the recommendation system. For instance, with the abundant information from the social networks, interactions between the users can be utilized to learn the user’s preference towards a specific item even tough the user-item interaction of such a pairwise relation is missing. The intuition is that people who are in close contact may share similar interests and such social network information can be utilized to tackle the data sparsity issue. Thus, how to leverage the underlying information in the social networks becomes a promising direction in the recent literature Guo et al. [4], Jiang et al. [10], Tang et al. [18]. Among all those social network aided recommendation frameworks, in this study, we first adopt the influence diffusion neural network (DiffNet) proposed by Wu et al. [22] to analyze the applicability of using social network information in the recommender system.

The essential component of the DiffNet is to capture the user’s interest and to model the propagation process of the user’s influence to his/her neighbors k-hops away. Such an iterative interest/influence diffusion process can change the latent user embeddings at each propagation step. And it’s beneficial to comprehend the precise user/item embeddings during the diffusion process to improve the recommendation performance. In the following sections, we first briefly summarize the key components of the DiffNet, and demonstrate it’s original performance on the real world dataset.

2.1 DiffNet Architecture

There are four major components of the DiffNet: embedding layer, fusion layer, influence diffusion layer, and prediction layer. And the overall flowchart of the DiffNet is depicted in Figure 1.

Embedding layer: Similar to the collaborative filtering, free embeddings of the user and item can be obtained from e.g. matrix factorization and neural network based filtering. Let \( P \in \mathbb{R}^{M \times D} \) and \( Q \in \mathbb{R}^{N \times D} \) represent the embeddings of the users and items, where \( M/N \) is the number of users/items and \( D \) is the dimension of the latent space. These two free embeddings are treated as the initial inputs to the DiffNet.

Fusion layer: Besides the embeddings of the users/items, other useful features can also be used as the input. For instance, by using the Word2vec model, features can be constructed from the embedding of each word in the reviews given to businesses on Yelp, the comments left on posts on Twitter, or the descriptions of images on Instagram. Once the corpus of a given dataset has been analyzed, the feature vector of each user/item can be constructed by averaging all the learned word vectors for the user/item. For the user \( a \), let \( x_a \) denote the feature vector. Then the free embedding of the user \( P_a \) can be fused with the \( x_a \) by employing a simple neural network with one fully connected layer:

\[
h^0_a = g(W^0 \times (x_a, P_a)),
\]

where \( W \) is the weight; \( g \) is a nonlinear function e.g. a fully connected layer; \( x_a \) and \( P_a \) have been concatenated first. Similarly, the fusion layer for the item \( i \) can be expressed as:

\[
v_i = g(W \times (y_i, Q_i)).
\]

Influence diffusion layer: After we obtain the initial fused user embedding \( h^0_a \), then we need to diffuse such a user’s influence information in the social network. And the influence diffusion layer models the dynamic diffusion process for the user’s latent preference. This process can be represented as a \( k \)-layer structure: each layer takes the user embedding \( h^{k-1}_a \) from the previous layer and outputs the updated embedding \( h^k_a \) as the propagation goes on. And the propagation forwards by one hop at each layer. Specifically, the updated user embedding consists of two parts: the previous embedding and the influence diffusion from the trusted users at current layer. Notice that, in a connected social network, a user \( a \) trusts every user if \( k \) is large enough. Let \( S_a \) denote the set of trusted users of user \( a \), then the influence diffusion from trusted users for user \( a \) is

\[
h^{k+1}_{S_a} = Pool(h^k_b | b \in S_a),
\]

where \( pool \) is a pooling operation, e.g. taking the maximum of or averaging the input. Then the overall updated user embedding can be formulated as a nonlinear mapping:

\[
h^k_a = g(W^k \times (h^{k+1}_{S_a} , h^k_a)),
\]

where again \( g \) is a nonlinear function and \( W^k \) is trainable weights.

Prediction layer: With both the user embedding \( h^k_a \) after \( K \)-hops diffusion and the fused item vector \( v_i \) on hand, the final user representation can be obtained from

\[
u_a = h^k_a + \sum_{i \in R_a} \frac{v_i}{|R_a|}
\]

where \( R_a \) is the set of items that user \( a \) has shown interest. This equation states that the latent representation of each user has two parts: the user embedding from the social network diffusion process, and the average item embedding from his/her known preferences in the dataset. This user embedding is more comprehensive by considering both the information of the social network and the user’s historical preferences. And in order to make predictions for potential user-item interactions, we can adopt the traditional approach of taking the inner product of the item embedding and the final user representation:

\[
\hat{r}_{ai} = v^T_i u_a.
\]

This \( \hat{r}_{ai} \) can be interpreted as the predicted probability of having a connection between the user \( a \) and the item \( i \). And in this way, based on the recommendation prediction results, a new graph \( G := (V := \{a, i\}, E := a \times i) \) can be established.

2.2 Numerical Study

To evaluate the effectiveness of the DiffNet for recommending new contents, we utilize the well-known Yelp dataset ye [1]. This data set consists of two parts: a social network with 17237 users, 129455
edges and a matrix recording the rating from those users to 37378 businesses. The user/item feature matrix $X/Y$ is first derived from the Word2vec model by analyzing the reviews. The dimension of the feature is set to be 150 for both users and items. To evaluate the recommendation performance, we utilize two metrics: hit ratio (HR) and normalized discounted cumulative gain (NDCG). Given a top-N ranking list based on the recommendation result $\hat{r}_{ai}$, the HR measures the proportion of the number of recommendations that the user truly likes. And NDCG not only considers the occurrence of an appropriate recommendation but also takes the rank of each recommendation into consideration: the higher the rank of a correct recommendation, the larger the score.

Notice that there are two important parameters that can significantly affect the performance of the DiffNet: the dimension $D$ of the free embedding $P/Q$ and the top-N values $N$ in the evaluation metrics. Thus in Table 1 we show the numerical results of the HR and NDCG for different settings of $D$ and $N$. We include the recommendation performance from the traditional collaborative filtering based technique i.e. SVD++ Guo et al. [5] as a comparison. Moreover, comparing to other graph diffusion based approach, e.g. graphical convolutional network (GCN) based PinSage Ying et al. [25], the DiffNet provides better performance in terms of the HR and NDCG: the PinSage achieves a HR score around 0.30 for $D = 32$ and $N = 10$, while that for NDCG is 0.18, that are both worse than the results of DiffNet.

### 3.1 Information Dissemination

Information dissemination describes a characteristic of a graph in a stochastic process such as disease infection, news spreading, or data broadcasting. The prominent models to study these processes are the compartmental models which consider an ordinary differential equation (ODE) between states of nodes with interactions arising from the edges of the graph. As a simple variation, Susceptible-Infectious-Susceptible (SIS) models susceptible-to-infectious interaction via edges and probabilistic recovery to susceptible. Despite the complexity of the process, Wang et al. [21] have discovered that information dissemination can be summarized by one parameter: the largest eigenvalue $\lambda_1$ of the adjacent matrix. Moreover, the largest eigenvalue also indicates whether a spreading would evolve into an epidemic or disappear over time Prakash et al. [15].

To this end, we study the selected datasets from the information dissemination perspective. In this report, we include two datasets: the Yelp social graph yel [1] and the collaboration network of Arxiv High Energy Physics Theory (CA-HEPHT) Leskovec et al. [12]. To avoid an ill condition in the SIS model, we extract the largest connected subgraph from each dataset and remove all other connected components. The subgraphs contain 99.4% and 87.5% of all nodes. Table 2 shows the summary of dataset sizes and the information dissemination parameters $\lambda_1$. In addition, Figure 2 sums up the degree distributions of the two datasets. Node degrees in both Yelp
Parameter | Model | HR | NDCG
---|---|---|---
Free embedding dimension | DiffNet | 0.3272 | 0.1952 | 0.2075
| SVD++ | 0.2581 | 0.1545 | 0.1632
| PinSage | 0.2952 | 0.1758 | 0.1779
Top-N ranking | DiffNet | 0.2276 | 0.1779 | 0.2083
| SVD++ | 0.1868 | 0.1389 | 0.1511
| PinSage | 0.2099 | 0.1536 | 0.1868

Table 1: Testing results of the DiffNet on the Yelp dataset after 500 epochs of training: we consider two types of hyperparameters (1) the number of dimension of the free embedding $P_a/Q_i$ while $N$ is fixed at 10 (2) the number of the top-N ranking for the predicted recommendation while $D$ is fixed at 16.

| Dataset | Nodes | Edges | $\lambda_1$ |
|---|---|---|---|
| Yelp | 17138 | 129455 | 80.42 |
| Stars Topology | 17138 | 129455 | 357.53 |
| Next-K Neighborhood | 17138 | 129455 | 16.18 |
| Erdős–Rényi Model | 17138 | 129455 | 16.16 |
| Barabási–Albert Model | 17138 | 137040 | 43.54 |
| CA-HEPTH | 8638 | 24827 | 31.03 |
| Stars Topology | 8638 | 24827 | 156.40 |
| Next-K Neighborhood | 8638 | 24827 | 6.00 |
| Erdős–Rényi Model | 8638 | 24827 | 6.97 |
| Barabási–Albert Model | 8638 | 25905 | 20.52 |

Table 2: Summary of datasets and their similar synthetics.

and CA-HEPTH generally follow the power-law distribution but Yelp dataset contains some nodes with extremely high degrees.

We compare these two real world graphs with 4 synthetic graphs with similar numbers of nodes and edges. Stars Topology refers to a graph where a few nodes connect to all other nodes. We connect the star’s edges as many as we can to match the number of edges in the original graph. Given nodes labeled with consecutive numbers in a ring, Next-K Neighborhood links each node to its adjacent neighborhood such that the total number of edges match. Erdős–Rényi model uniformly samples all possible edges. Finally, Barabási–Albert model generates a graph with power-law degree distribution by sampling edges with preferential attachment. We generate these 4 synthetic graphs for each dataset size, totaling 8 generated graphs. Alongside the original graphs, we also list the summary of these synthetic graphs in Table 2.

SIS simulations Miller and Ting [14] in Figure 3 empirically present the information dissemination process in all 10 graphs. Overall, the convergence rate of the infected fraction is consistent with the largest eigenvalues shown earlier: the higher $\lambda_1$ of the graph, the faster the convergence rate is initially. Stars Topology stands as the most information-disseminating graph. And this finding is consistent with the intuition: information is much easier to propagate in this setting since information from nodes with extremely high degrees can be quickly propagated to their numerous neighbors just one hop away. And the gap between the spreading in real world graphs and the artificial Stars Topology signifies some room for improvement for the real world network topology.

To further show that some of these graphs could have a wider spreading result, we replicate Gelling algorithm from Tong et al. [19] to suggest edges that would improve information dissemination the most. We choose to implement the full $O(n^2)$ version of the proposed algorithm, given the dataset size is tractable. Figure 4 outlines increasing largest eigenvalues after adding some edges via the Gelling technique. When we add $10^4$ edges, the information dissemination capability of the graph from Yelp dataset doubles while that of CA-HEPTH dataset improves by approximately 4
Figure 3: Fraction of infectious node over time in a SIS simulation of corresponding graph setting. Original graphs are Yelp (top) and CA-HEPTH (bottom). Lines of graphs in the legend are sorted by $\lambda_1$ without additional edge in descending order. The initial infectious fraction $\rho$, transmission rate $\tau$, and recovery rate $\gamma$ are denoted on the top of each plot.

3.2 Dissemination-aware Training

Now we see that there is a gap between ideally disseminating graph and existing ones. One can be tempted to substitute the recommender with dissemination optimizer; however, the most influential edge on dissemination is not guaranteed to be the best edge for recommendation task i.e. obtaining the highest HR or NDCG. Thus, our goal is to both accurately predict connections and improve dissemination in the graph to improve user’s exploration on new information.

To recommend new user-item pairwise relation via a neural network model, the most common approach is using the cross entropy loss to quantify the difference between the predicted edge connecting probability and the true edge connection status. In this case, the edge of interest is the predicted user-item interaction that has not been seen yet. However, we later find that using mean squared error (MSE) loss can significantly improve the performance of the model in terms of HR/NDCG. And the objective of the dissemination-aware recommendation model is shown as following:

$$
\min_{\hat{y}} \mathcal{L}(\hat{y}; y, \lambda) = \mathbb{E}_{a \sim \mathcal{A}, i \sim I} \left[ \frac{1}{2} S_a(a, i)(y_{a, i} - \hat{y}_{a, i})^2 \right]. \quad (7)
$$

where $\lambda(a, i)$ is the dissemination score and $S_a(a, i)$ is a dissemination factor between user $a$ in distribution $\mathcal{A}$ and item $i$ in distribution $I$. In this study, the $S_a(u, i)$ has the form:

$$
S_a(u, i) = \frac{1 + \lambda(a, i)e^\alpha}{1 + e^\alpha}.
$$

(8)

We assume a uniform distribution of user index. To mitigate the negative or unknown interactions dominating the training process, we construct an biased item distribution towards positive interactions similarly to other preceding evaluations He et al. [8], Wu et al. [22]. Specifically, we use all the positive ratings from each user provided in the Yelp dataset as the true positive connections. But we only uniformly sample 8 out of the remaining possible user-item connections for training and assign them as the negative interactions (since those connections have not been observed in the real dataset). As for evaluating the recommendation performance, we select 1000 users randomly and prepare the positive/negative connections in the same manner to compute HR and NDCG.

Another important term introduced in the Equation 7 is the dissemination score $\lambda(a, i)$. To obtain the score for each possible user-item pairwise relation, before training, we first combine the user-user social network and the user-item interactions and derive an $M+N$ by $M+N$ adjacency matrix. Then the first eigenvector $z \in \mathbb{R}^{M+N}$ of the aggregated adjacency matrix has been precomputed. Thus during the training process, we can use this eigenvector to compute the dissemination score $\lambda(a, i) = z[a]z[i]$.

Notice that the constant $\alpha \in \mathbb{R}$ in Equation 8 is an additional hyperparameter. It can be interpreted as a interpolation weight between the original MSE loss without considering dissemination and its fully dissemination-aware version, when $\alpha \to -\infty$ and $\alpha \to \infty$ respectively. In our experiment, we have analyzed the effects of this hyperparameter and have varied $\alpha$ to generate the
We have considered the HR/NDCG as well as the largest eigenvalue \( \lambda \) work that can be constructed quickly. The original HR/NDCG are different. And the final dissemination scores in are quite different. This indicates that the final topologies of the and the dissemination capability achieved from different settings all around the same level. However, the recommendation accuracy of newly introduced edges i.e. predicted user-item connections are eigenvalue increases significantly. For all levels of \( \alpha \) term is denoted as \( \lambda \) and the dissemination-aware DiffNet on the testing Yelp dataset with different weights \( \alpha \) edges. For any user-item pair, if the predicted \( r_{ai} \) is higher than 0.5, a corresponding edge \( e = (a, i) \) will be added to the original graph.

Table 3 summarizes the numerical results for the dissemination-aware DiffNet on the testing Yelp dataset with different weights \( \alpha \). We have considered the HR/NDCG as well as the largest eigenvalue of the graph to evaluate the recommendation performance. And the performance of the original DiffNet without any dissemination term is denoted as \( \alpha = -\infty \). It’s not surprising to see that the recommendation accuracy has been deteriorated after introducing the dissemination term in the objective function while the largest eigenvalue increases significantly. For all levels of \( \alpha \), the numbers of newly introduced edges i.e. predicted user-item connections are all around the same level. However, the recommendation accuracy and the dissemination capability achieved from different settings are quite different. This indicates that the final topologies of the user-item graph are different. And the final dissemination scores in

| \( \alpha \) | # edges added | HR  | NDCG | \( \lambda \) |
|---------|---------------|-----|------|----------|
| 3       | 18140         | 0.2077 | 0.1375 | 77.10    |
| 2       | 17078         | 0.2113 | 0.1378 | 74.50    |
| 1       | 19757         | 0.2376 | 0.1455 | 71.09    |
| 0       | 16405         | 0.2653 | 0.1645 | 71.03    |
| -1      | 19955         | 0.2839 | 0.1733 | 70.42    |
| -2      | 16590         | 0.3098 | 0.1792 | 66.28    |
| -3      | 16792         | 0.3044 | 0.1811 | 63.55    |

| DiffNet | 17217 | 0.3317 | 0.2083 | 58.97    |
| SVD++   | 17685 | 0.2631 | 0.1531 | 58.63    |
| PinSage | 16338 | 0.3065 | 0.1868 | 60.83    |

Table 3: Recommendation performance evaluated in HR and NDCG as well as the dissemination capability after introducing new connections based on the dissemination-aware DiffNet: for all tests, \( D = 16 \) and \( N = 10 \); last three rows correspond to results obtained from the original recommender systems without considering dissemination.

accuracy-dissemination Pareto front plot of the recommendation model.

4 EXPERIMENT RESULTS

Besides the established metrics for evaluating the recommendation performance e.g. HR and NDCG, we also need to analyze the information dissemination capability of the graph formed after obtaining the recommendation results. And the dissemination performance is quantified by the largest eigenvalue \( \lambda \) of the graph.

The original Yelp dataset has been split into train, validation, and test dataset in a way that each partition contains non-overlapping user-item interactions. And the test dataset has around 18000 records correspond to 10622 users and 11948 items, which is a sparse network that can be constructed quickly. The original \( \lambda \) of the social network for the testing data is 70.47. To compare the information dissemination capability of the new networks, we have trained the dissemination-aware DiffNet for 500 epochs. Then we run the trained model on the testing dataset, obtain the recommendation results and expand the user-user social networks by adding user-item edges. For any user-item pair, if the predicted \( r_{ai} \) is higher than 0.5, a corresponding edge \( e = (a, i) \) will be added to the original graph.

Table 3 summarizes the numerical results for the dissemination-aware DiffNet on the testing Yelp dataset with different weights \( \alpha \). We have considered the HR/NDCG as well as the largest eigenvalue of the graph to evaluate the recommendation performance. And the performance of the original DiffNet without any dissemination term is denoted as \( \alpha = -\infty \). It’s not surprising to see that the recommendation accuracy has been deteriorated after introducing the dissemination term in the objective function while the largest eigenvalue increases significantly. For all levels of \( \alpha \), the numbers of newly introduced edges i.e. predicted user-item connections are all around the same level. However, the recommendation accuracy and the dissemination capability achieved from different settings are quite different. This indicates that the final topologies of the user-item graph are different. And the final dissemination scores in

some cases are worse than the original social networks without any recommendation e.g. when \( \alpha \leq -1 \). This is due to the fact that most of the predicted recommendations connect new item to existing users as an end node, which has a low nodal degree in the resulting graph.

Based on the numerical results in Table 3, we can see a clear trade-off between the recommendation accuracy and the information dissemination capability induced by the recommendation algorithm. To better comprehend the trade-off, Figure 5 illustrates the changes in NR/NDCG and the \( \lambda \) obtained from the new user-item graph. For both the NR and NDCG, the numerical results decrease with the increasing dissemination score \( \lambda \). And this observation is consistent with the objective function since larger \( \alpha \) makes the recommendation model focus more on establishing edges to maximize the information dissemination, while smaller \( \alpha \) leads to a model similar to the vanilla DiffNet. From Figure 5, we can see that the decreasing trend of the recommendation accuracy is not linear and there is a sharp change when the \( \alpha \) is set to be approximately 0. This could be the result of expressing the dissemination factor as an exponential term. And the plot suggests that an \( \alpha \) between 0 and -1 is a good choice for such a recommendation task on the Yelp dataset. Since the recommendation accuracy is acceptable (even higher than the SVD++ results) while the information dissemination capability has been maintained at a high level.

5 RELATED WORKS

Graph neural networks (GNNs) recently find their applications in recommender systems. Wu et al. [23] compiles an extensive survey
of these approaches based on different GNN structure (GCN Fu et al. [3], GraphSage Hamilton et al. [7], GAT Veličković et al. [20], and GGGN Li et al. [13]), temporal dependent (general recommendation, sequential recommendation), and considered information (user-item interactions, social network, knowledge graph). In terms of this taxonomy, DiffNet’s concept of influence diffusion is closely related to GCN approach. DiffNet performs a general recommendation and so assumes that recommendation is invariant to time. It also relies on social network to help learning user-item interactions.

Apart from dissemination, many other works enhance recommendation task with auxiliary properties to solve specific problems Ricci et al. [17]. Many objectives align well with our interest in explorative recommendations. For example, serendipity measures the surprising degree of successful recommendations which encourage recommendations out of the typical interactions. Novelty and diversity are also well-known desirable properties in a recommender systems which determine the distinction among the recommendations. Hurley and Zhang [9] explains various approaches to enhance existing frameworks towards these metrics. Instead of directly rewarding a diverse recommendation list, our algorithm globally focuses on the effect of successful recommendation on the user’s future exploration, reflected in the dissemination term.

6 CONCLUSION

In this project, we have studied existing recommender systems utilizing graph information such as user-user and user-item interactions. To improve the effectiveness of the recommendations in terms of both the accuracy and user’s exploration, we have considered the information dissemination of the graph as an aid in the recommendation algorithm. Case studies based on the Yelp dataset have successfully demonstrated the advantage of the proposed framework: comparing to baseline models such as SVD++, and PinSage, the recommendation accuracy has been maintained at desirable levels while the information dissemination capability of the formed user-item graph has been optimized. As for future directions, more comprehensive diffusion process for the network can be utilized: not only the user embedding can be evolved through the information propagation process but also the item embedding can be iteratively refined.

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