# MGNN: Mutualistic Graph Neural Network for Joint Friend and Item Recommendation



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# MGNN: Mutualistic Graph Neural Network for Joint Friend and Item Recommendation

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**Abstract**—Many social studies and practical cases suggest that people's consumption behaviors and social behaviors are not isolated but interrelated in social network services. However, most existing research either predicts users' consumption preferences or recommends friends to users without dealing with them simultaneously. We propose a holistic approach to predict users' preferences on friends and items jointly and thereby make better recommendations. To this end, we design a graph neural network that incorporates a mutualistic mechanism to model the mutual reinforcement relationship between users' consumption behaviors and social behaviors. Our experiments on the two-real world datasets demonstrate the effectiveness of our approach in both social recommendation and link prediction.

**Index Terms**—Joint Recommendation, Social Networks, Mutualistic Model, Graph Neural Networks

## 1 Introduction

The past decades have witnessed the prosperity of social network service platforms such as Epinions and Facebook. These platforms facilitate the establishment of social relationship among people who share similar preferences, activities, or real-life interactions. A social network service platform typically supports two types of user behaviors: consumption behaviors (e.g., purchasing an item, rating an item, or checking-in at certain locations) and social behaviors (e.g., befriending by linking to another user). Social studies reveal that the two types of behaviors are correlated, instead of being isolated. These observations perfectly align with the social influence theory: a user' preference for items or locations can be easily influenced by its social links while users with similar interests are likely to build a relationship. In fact, users' consumption and social behaviors can mutually reinforce each other, and further drives the continuous development of social network services. We use an example (Fig.1) to illustrate the mutual reinforcement relationship: Bob may purchase a pair of sports shoes from Adidas after seeing his friend David did that; Alice may make friends with Bob, knowing that he is also fond of photography.

Most existing studies focus on either of the two types of behaviors. They either totally ignore the other behavior type or leverage the information about one behavior to improve the task performance in the other behavior type. For example, some work [1], [2] incorporates users' social relationship to predict users' consumption preference; others [3], [4], [5],

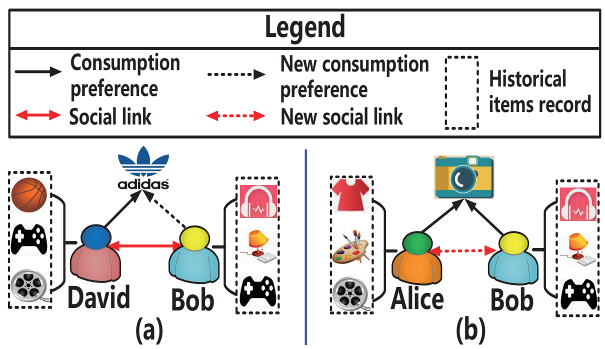


Fig. 1. An illustrative example

[6] take users' historical consumption information as additional features to mine unknown social connections among users. The limited studies that solve social recommendation and link prediction tasks jointly appear only very recently [7], [8], and they simply use concatenation or weighted sum to aggregate users' consumption and social behavior information. Such operations cannot explore the mutual relationship well.

We design a Mutualistic Graph Neural Network (MGNN) for joint friend and item recommendation (Section 4). MGNN contains four layers: the spatial layer, the spectral layer, the mutualistic layer and the predicted layer. The spatial layer and spectral layer first extract latent embeddings from user-item and user-user data, then the mutualistic layer merges the two embeddings and transmits the new generated embeddings to the predicted layer, which finally accomplishes the joint tasks. In particular, MGNN incorporates a mutualistic mechanism in the graph neural network to represent and leverage the mutual relationship among the two types of user behaviors. Our mutualistic mechanism (Section 3) is inspired by the mutualistic model, which originates from exploring the implicit interactive relationship between two species. The mutualistic model

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focuses on simulating the growth rate in the real nature and digging up the latent elements in biology dynamically. It has plenty of theoretic support [9] for modeling the mutual-reinforcement relationship in broader contexts. To the best of our knowledge, this is the first effort on applying the mutualistic model to recommendation problems. We have reviewed the related work (Section 2) and conducted extensive experiments (Section 5) to demonstrate the advantages of our approach.

## 2 Related Work

The previous studies either consider the social influence for item recommendation [1], [2], [10], [11], [12], [13], [14], [15], [16] or explore users' explicit social data (via matrix factorization or representative learning) for link prediction [3], [4], [6]. Only very limited work have studied friend and item recommendation as a joint problem: Shu et al. [7] first use transfer learning to extract user features from existing social media and then predict users' consumption preference and suggest new links on the newly launched social websites; Wu et al. [8] propose a general neural framework to jointly model the evolution of users' consumption preference and social links. The existing studies have two drawbacks. First, the work based on matrix factorization (e.g., [7]) are susceptible to data sparsity. Second, the approaches either use simple concatenation [8] or weighted sum operation [7]) to combine users' consumption and social link information; therefore, they cannot well model the sophisticated relationship between users' consumption preference and social behaviors.

In this paper, we propose a novel approach that incorporates the mutualistic mechanism to overcome the above drawbacks in addressing the joint recommendation tasks.

## 3 Preliminaries

This section introduces some background knowledge of our work. Table 1 shows the main notations used in this paper.

### 3.1 Mutualisitic Model

The Mutualistic model describes the ecological interaction between two or more species where each species benefits [9]. Examples of mutualism include flowering plants being pollinated by animals, vascular plants being dispersed by animals, and corals with zooxanthellae. A popular way to dynamically simulate the variation between species behind the mutualistic phenomenon is via partial differential equations [9] such as the *Lotka-Volterra* equations [9]. *Lotka-Volterra* assumed that the growth of a species depends on its self-interaction and the benefits obtained from the interaction with the other species, which is formulated as follows:

$$\begin{cases} \dot{N_1} = r_1 N_1 + \alpha_1 N_1 N_2 \\ \dot{N_2} = r_2 N_2 + \alpha_2 N_1 N_2 \end{cases} \tag{1}$$

where $N_1$, $N_2$ represent the quantity of two species; $\dot{N_i}$ ($i$=1,2) denotes the growth velocity of each species; $r_1, r_2, \alpha_1, \alpha_2$ are positive parameters. The *Lotka-Volterra* equations aim to find an equilibrium from, rather than solving Eq. (1). Such an insight lowers the complexity of research on mutualism because not all the partial differential equations have a unique solution [9].

TABLE 1
Notations

| Symbols | Description |
|---|---|
| $\mathcal{R}$ | The user-item rating matrix (i.e., user-item graph) |
| $\mathcal{U}$, $\mathcal{I}$, $\mu_i$, $i_j$ | User set, Item set, the $i$th user, the $j$th item |
| $r_{ij}$ | The rating of $i_j$ by $\mu_i$ |
| $\mathcal{S}$, $s_{iv}$ | The user-user social graph, the link between $\mu_i$ and $\mu_v$ |
| $d$ | The length of embedding vector |
| $\boldsymbol{P}$, $\boldsymbol{p}_i$ | User-specific matrix, the user-specific embedding of $\mu_i$ |
| $\boldsymbol{Q}$, $\boldsymbol{q}_j$ | Item-specific matrix, the item-specific embedding of $i_j$ |
| $\boldsymbol{F}$, $\boldsymbol{f}_i$ | User latent social matrix, the latent social embedding of $\mu_i$ |
| $\mathcal{N}_{\mu_i}$ | The set of items rated by $\mu_i$ |
| $\mathcal{N}_{i_j}$ | The set of users rated $i_j$ |
| $\mathcal{N}_{\mu_i}^f$ | The set of users directly linked with $\mu_i$ |
| $\boldsymbol{z}_i^{\mathcal{I}}$ | The item influence embedding of $\mu_i$ |
| $\boldsymbol{z}_i^{\mathcal{S}}$ | The social item embedding of $\mu_i$ |
| $\boldsymbol{z}_i^{pre\_\mathcal{I}}$ | The consumption preference embedding of $\mu_i$ |
| $\boldsymbol{z}_i^{pre\_\mathcal{S}}$ | The social preference embedding of $\mu_i$ |
| $\boldsymbol{z}_i^{uP}$ | The user preference embedding of $\mu_i$ |
| $\boldsymbol{z}_i^{uS}$ | The user social embedding of $\mu_i$ |
| $\boldsymbol{z}_i^{u\_m}$ | The mutual embedding of $\mu_i$ |
| $\boldsymbol{z}_i^{u\_mP}$ | The mutual preference embedding of $\mu_i$ |
| $\boldsymbol{z}_i^{u\_mS}$ | The mutual social embedding of $\mu_i$ |
| $\boxplus$, $\otimes$, $\odot$ | Concatenation operation, dot production, element-wise $\times$ |
| $MLP(\cdot)$, $\boldsymbol{\phi}$ | Multi-Layer Perceptron, activation function |
| $\boldsymbol{W}/\boldsymbol{W_j}$, $\boldsymbol{b}/\boldsymbol{b_j}$ | The weights and biases of neural network |

### 3.2 Motivation for Applying the Mutualistic Model

The mutual reinforcement relationship between users' consumption preference and social links has been validated to exist by multiple studies [7], [8]: on the one hand, a user prefers to contact or share its shopping experience with those who have similar interests or hobbies, which strengthens their connections; on the other hand, user's social relationship can enhance the recommendation performance [1], [2], [10].

The mutualistic model has been extensively studied [9] and has the advantage of modeling the mutual interaction between species via exploring the latent mutual interactive elements, which makes it a perfect fit for modeling the above mutual reinforcement relationship in social networks. In particular, we design our strategy by adapting *Lotka-Volterra* equations as follows:

$$\begin{cases} \boldsymbol{z}_i^{mP} = \boldsymbol{z}_i^{\mu P} \boxplus \boldsymbol{z}_i^{\mu P} \odot \boldsymbol{z}_i^{\mu S} \\ \boldsymbol{z}_i^{mS} = \boldsymbol{z}_i^{\mu S} \boxplus \boldsymbol{z}_i^{\mu P} \odot \boldsymbol{z}_i^{\mu S} \end{cases} \tag{2}$$

where $\boldsymbol{z}_i^{\mu P}$ and $\boldsymbol{z}_i^{\mu S}$ denote the $\mu_i$'s preference embedding and social embedding; $\boldsymbol{z}_i^{mP}$ and $\boldsymbol{z}_i^{mS}$ are the mutual embedding for social recommendation and link prediction tasks, respectively; $\boxplus$ denotes the concatenation operation; $\odot$ is the element-wise mutiplication for simulating the mutual interaction.

### 3.3 Problem Formulation

We consider both the rating of users on items and social relationship among users. We denote by $\mathcal{R} = \{r_{ij}\}_{m \times n}$ the user-item rating matrix that contains $m$ users and $n$ items, where $r_{ij} = 1$ if user $\mu_i$ rated item $i_j$ and 0 otherwise. We denote by $\mathcal{N}_{\mu_i}$ and $\mathcal{N}_{i_j}$ the set of items rated by $\mu_i$ and the set of users who have rated $i_j$, respectively. We use $\mathcal{S} = \{s_{iv}\}_{m \times m}$ to represent a social graph, where $s_{iv} = 1$ if $\mu_i$

has a relationship with $\mu_v$ and 0 otherwise. Sicne $\mathcal{S}$ is a bi-directional graph, $\mathcal{S}$ is a symmetric matrix.

Given rating matrix $\mathcal{R}$ and social graph $\mathcal{S}$, our objectives are: 1) obtaining the feature representation of each user's consumption preference and social preference; 2) quantifying the social influence on user preference and homophily influence on social links; 3) predicting unobserved ratings and social links in $\mathcal{R}$ and $\mathcal{S}$, or more precisely, the probability of $\mu_i$ clicking a new item $i_j^+$ and the probability of $\mu_i$ establishing a new link with a new user $\mu_v^+$.

## 4 Proposed Scheme

Fig. 2 shows the overall structure of MGNN, which contains four parts: spatial layer, spectral layer, mutualistic layer, and predicted layer.

### 4.1 Spatial Layer

The spatial layer aims to learn the users' consumption preference embedding from the rating matrix $\mathcal{R}$. Since a user's consumption preference depends on both the items preferred by itself and the items preferred by its friends in a social network [1], we learn users' consumption preference embedding from two aspects: item influence embedding and social item embedding. Our idea of considering the neighborhood influence in this layer is inspired by GraphSage [5]. Such consideration enables to leverage the graph structure as the input to replace the sparse matrix, thus mitigating the adverse effect of data sparsity. Meanwhile, it enables to aggregate a portion of (sampled neighbor) nodes instead of all the nodes during extracting embeddings, thus relieving the computation cost for large transductive graphs. We construct the spatial layer as follows:

**Item influence embedding $\boldsymbol{z}_i^I$**: We learn item influence embedding $\boldsymbol{z}_i^I$ from $\mu_i$'s historical records of items. Each $\mu_i$ has a direction connection with every item that $\mu_i$ rated in $\mathcal{R}$. Given a $\mu_i$, we denote $\mathcal{N}_{\mu_i}$ as the set of items rated by $\mu_i$; Similarly, given an item $i_j$, we denote $\mathcal{N}_{i_j}$ as the set of users who rated item $i_j$. For example, in Fig. 2, user $\mu_i$ (denoted by a filled red circle) purchased two items (denoted by yellow hexagons): $i_1$ and $i_4$; therefore, $\mathcal{N}_{\mu_i} = \{i_1, i_4\}$. Since both $\mu_i$ and $\mu_3$ (denoted by a plain circle) purchased $i_1$, $\mathcal{N}_{i_1}$={$\mu_i$,$\mu_3$}.

Let $\boldsymbol{h}_{i_j}$ be the aggregated feature vector of item $i_j$, we first aggregate the feature of users in $\mathcal{N}_{i_j}$:

$$\boldsymbol{h}_{i_j} = \boldsymbol{\phi}\left(\boldsymbol{W}\sum_{\mu_k\in\mathcal{N}_{i_j}}\boldsymbol{p}_k + \boldsymbol{b}\right) \tag{3}$$

Then, we aggregate all the $\boldsymbol{h}_{i_j}$ ($\forall i_j \in \mathcal{N}_{\mu_i}$) to generate item influence embedding $\boldsymbol{z}_i^I$:

$$\boldsymbol{z}_i^I = \boldsymbol{\phi}\left(\boldsymbol{W_1}\sum_{i_j\in\mathcal{N}_{\mu_i}}\boldsymbol{h}_{i_j} + \boldsymbol{b}_1\right) \tag{4}$$

**Social item embedding $\boldsymbol{z}_i^S$**: Social item embedding $\boldsymbol{z}_i^S$ reflects the preference influence of $\mu_i$'s friends on $\mu_i$. We use $\mathcal{N}_{\mu_i}^f$ to denote the set of $\mu_i$'s friends. Each user $\mu_l$ in $\mathcal{N}_{\mu_i}^f$ has its own historical records on items, denoted by $\mathcal{N}_{\mu_l}$. For example, in the up-left of Fig.2, user $\mu_i$ has two friends: $\mu_1$ and $\mu_2$ (colored in blue in the user-item ratings graph), where their purchased items are marked by $\mathcal{N}_{\mu_1}$ and $\mathcal{N}_{\mu_2}$, respectively. In order to efficiently learn $\boldsymbol{z}_i^S$, we adopt the similar structure applied in $\boldsymbol{z}_i^I$. Let $\boldsymbol{h}_{\mu_l}$ be the aggregated feature vector of user $\mu_l$, We first aggregate the features of items in $\mathcal{N}_{\mu_l}$ ($\mu_l \in \mathcal{N}_{\mu_i}^f$):

$$\boldsymbol{h}_{\mu_l} = \boldsymbol{\phi}\left(\boldsymbol{W_2}\sum_{i_j\in\mathcal{N}_{\mu_l}}\boldsymbol{q}_j + \boldsymbol{b_2}\right) \tag{5}$$

Given all $\boldsymbol{h}_{\mu_l}$ ($\forall \mu_l \in \mathcal{N}_{\mu_i}^f$), we aggregate them to generate social item embedding $z_i^S$:

$$\boldsymbol{z}_i^S = \boldsymbol{\phi}\left(\boldsymbol{W_3}\sum_{\mu_l\in\mathcal{N}_{\mu_i}^f}\boldsymbol{h}_{\mu_l} + \boldsymbol{b}_3\right) \tag{6}$$

Then $\mu_i$'s consumption preference embedding $\boldsymbol{z}_i^{pre\_I}$ is computated as follows:

$$\boldsymbol{z}_i^{pre\_I} = MLP(\boldsymbol{z}_i^I \boxplus \boldsymbol{z}_i^S) \tag{7}$$

### 4.2 Spectral Layer

The spectral layer focuses on learning user's social preference embedding from the social graph $\mathcal{S}$. We apply the spectral layer for two reasons: 1) spectral graph convolution networks can take into account implicit connections between nodes when extracting features, thus relieving the adverse effect of data sparsity; 2) building a spectral graph convolution network requires constructing a spectral kernel, which demands the input to be an asymmetric matrix, while the social graph $\mathcal{S}$, is a symmetric matrix that readily meet the requirements.

Given a social graph $\mathcal{S}$, we construct the graph convolution kernel (denoted by $\widehat{\mathcal{S}}$) as follows:

1) Constructing a normalized Laplacian matrix $\mathcal{L}$ via $\mathcal{L} = \boldsymbol{I}_m - \boldsymbol{D}^{-\frac{1}{2}}\mathcal{S}\boldsymbol{D}^{-\frac{1}{2}}$, where $I_m$ is an $m \times m$ identity matrix, $\boldsymbol{D}$ is the $m \times m$ diagonal degree matrix defined as $D_{nn} = \sum_j S_{m,j}$.
2) Constructing $\widehat{\mathcal{S}}$ via $\widehat{\mathcal{S}} = \boldsymbol{U}\boldsymbol{U}^\top + \boldsymbol{U}\Lambda\boldsymbol{U}^\top$, where $\boldsymbol{U}$ and $\lambda$ are the eigen-vector matrix and eigen-value matrix of $\mathcal{L}$.

For $\forall \mu_i$, we can get its links set as $\mathcal{N}_{\mu_i}^f$. We can then proceed to obtain its friends' social features $\boldsymbol{Soc}_i$:

$$\boldsymbol{Soc}_i = \{soc_i^k |\ soc_i^k \in MLP(\widehat{\mathcal{S}}\boldsymbol{F}),\ \mu_k \in \mathcal{N}_{\mu_i}^f\} \tag{8}$$

Finally, we obtain the social preference embedding $\boldsymbol{z}_i^{pre\_S}$ of $\mu_i$ by the following:

$$\boldsymbol{z}_i^{pre\_S} = \boldsymbol{\phi}\left(\boldsymbol{W}_4\sum_{\mu_k\in\mathcal{N}_{\mu_i}^f} soc_i^k + \boldsymbol{b_4}\right) \tag{9}$$

### 4.3 Mutualistic Layer

The mutualistic layer aims to model the mutual implicit reinforcement relationship between user's consumption preference and social links [7], inspired by the *mutualistic model*. We include the mutualistic layer based on three considerations. First, users' consumption behavior and social

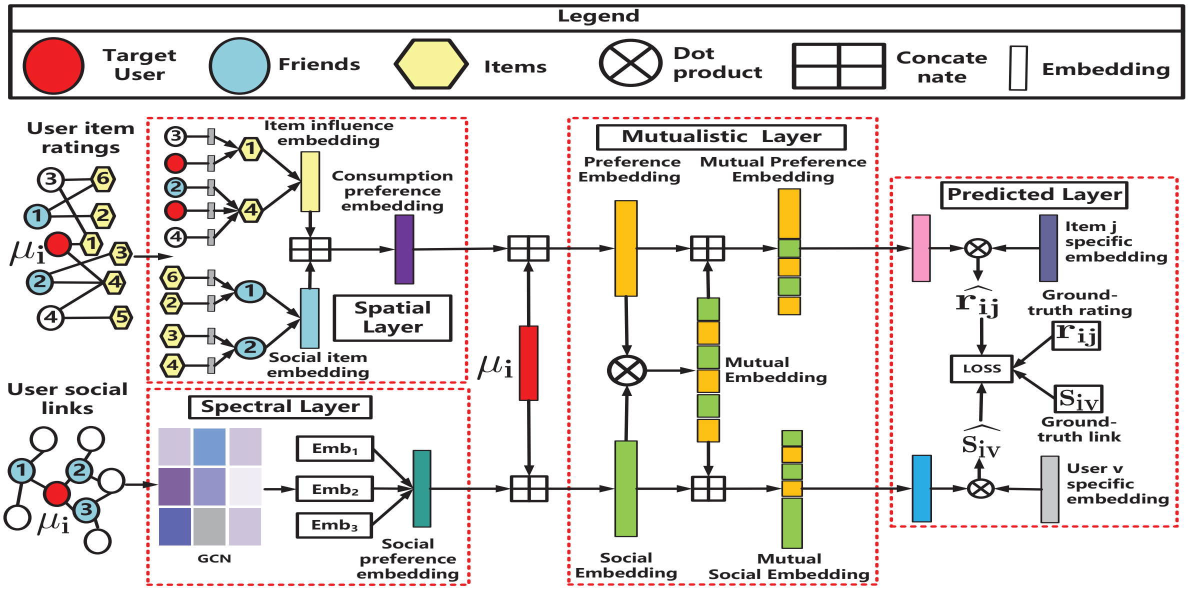



Fig. 2. The architecture of MGNN. It contains four components: spatial layer, spectral layer, mutualistic layer, and predicted layer.

behavior are interactively influenced between each other, according to the social influence theory [1], [10]. Second, the effectiveness of applying users' social links to item recommendation has been validated to improve recommendation performance [1], [2], [10]. Third, the mutualistic model inherently models the mutual reinforcement relationship between species by exploring the latent mutual elements that positively influence the growth of species, making it a perfect fit for handling joint recommendation tasks.

We construct the input of the mutualistic layer, including user preference embedding $z_i^{uP}$ and user social embedding $z_i^{uS}$, based on $\mu$'s consumption preference embedding ($\boldsymbol{z_i}^{pre\_I}$) and social preference embedding ($\boldsymbol{z_i}^{pre\_S}$):

$$\begin{cases} \boldsymbol{z}_i^{uP} = MLP(\boldsymbol{z}_i^{pre\_I} \boxplus \boldsymbol{p}_i) \\ \boldsymbol{z}_i^{uS} = MLP(\boldsymbol{z}_i^{pre\_S} \boxplus \boldsymbol{f}_i) \end{cases} \tag{10}$$

Then, we construct a new generating embedding called mutual embedding ($\boldsymbol{z}_i^m$) to capture the mutual influence between user's consumption preference and social links according to Section 3.2:

$$\boldsymbol{z}_i^m = \boldsymbol{z}_i^{uP} \odot \boldsymbol{z}_i^{uS} \tag{11}$$

Finally, we produce $\mu_i$'s mutual preference embedding $\boldsymbol{z}_i^{\mu\_mP}$ and mutual social embedding $\boldsymbol{z}_i^{\mu\_mS}$ as follows:

$$\begin{cases} \boldsymbol{z}_i^{\mu\_mP} = \boldsymbol{z}_i^{mP} \boxplus \boldsymbol{z}_i^{uP} \\ \boldsymbol{z}_i^{\mu\_mS} = \boldsymbol{z}_i^{mS} \boxplus \boldsymbol{z}_i^{uS} \end{cases} \tag{12}$$

### 4.4 Predicted Layer

The predicted layer predicts $\mu_s$'s consumption preference towards a new item and linking preference towards a new user based on $\mu$'s mutual preference embedding ($\boldsymbol{z}_i^{\mu\_mP}$) and mutual social embedding ($\boldsymbol{z}_i^{\mu\_mS}$). To this end, we first transform $\boldsymbol{z}_i^{\mu\_mP}$ and $\boldsymbol{z}_i^{\mu\_mS}$ into the appropriate input for the predicted layer as follows:

$$\begin{cases} \boldsymbol{z}_i^{New\_P} = MLP(\boldsymbol{z}_i^{\mu\_mP}) \\ \boldsymbol{z}_i^{New\_S} = MLP(\boldsymbol{z}_i^{\mu\_mS}) \end{cases} \tag{13}$$

Given an item-specific embedding $\boldsymbol{q}_j$ or user latent social embedding $\boldsymbol{f}_v$, we derive the predicted rating $\hat{r}_{ij}$ and link $\hat{s}_{iv}$ as follows:

$$\begin{cases} \hat{r}_{ij} = \boldsymbol{z}_i^{New\_P} \boldsymbol{q}_j^\top \\ \hat{s}_{iv} = \boldsymbol{z}_i^{New\_S} \boldsymbol{p}_v^\top \end{cases} \tag{14}$$

Then, we use a BPR loss to estimate model parameters and to guarantee the recommendation performance. Basically, the BPR loss is a pair-wise loss function that considers the relative order between observed and unobserved user-item/user-user interactions. It has been widely used to optimize recommendation approaches [3]. We define the following loss function for optimizing MGNN:

$$loss = -\sum_{(i,j,k)\in\mathcal{O}} ln\sigma(\hat{r}_{ij} - \hat{r}_{ik}) - \sum_{(i,v,y)\in\mathcal{O}^f} ln\sigma(\hat{s}_{iv} - \hat{s}_{iy}) + \lambda \parallel \Theta \parallel_2^2 \tag{15}$$

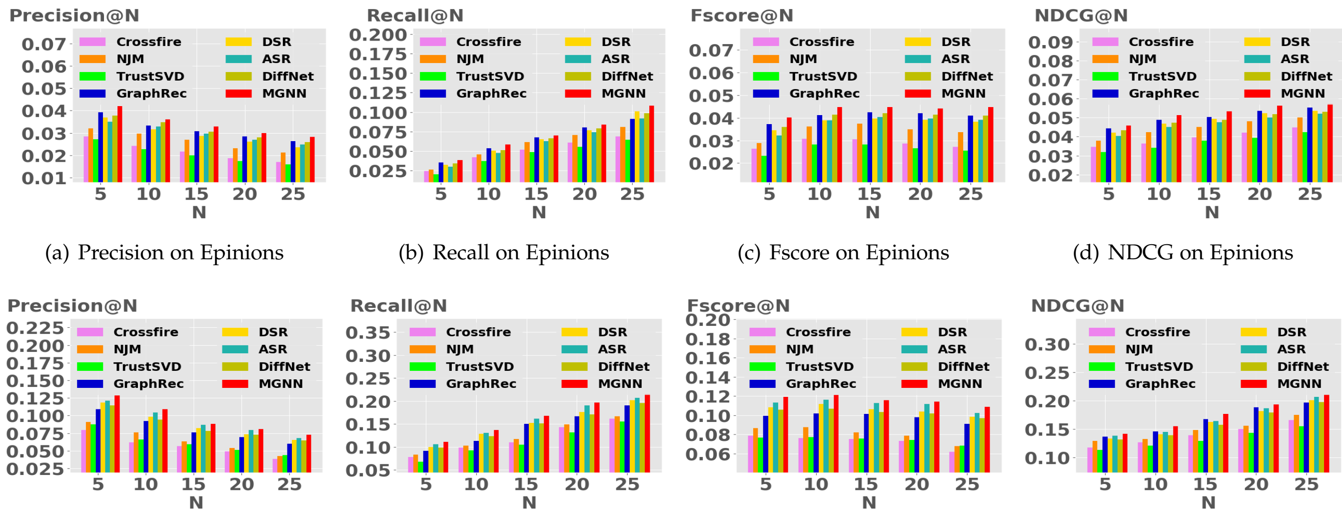
where $\mathcal{O} = \{(i,j,k)|(i,j) \in \mathcal{R}^+, (i,k) \in \mathcal{R}^-\}$ and $\mathcal{O}^f = \{(i,v,y)|(i,v) \in \mathcal{S}^+, (i,y) \in \mathcal{S}^-\}$ denote the training set for social recommendation and link prediction; '+' denotes the observed data in graph; '−' denotes the unobserved data sampled from graph; $\sigma(\cdot)$ is the sigmoid function; $\Theta = \{\boldsymbol{P}, \boldsymbol{Q}, \boldsymbol{F}\}$ is the regularization term to avoid overfitting. We conduct $\boldsymbol{L}_2$ regularization parameterized by $\lambda$ on $\Theta$. Finally, we adopt Adam optimizer to minimize the loss function and to update model parameters. Compared with other optimizers such as RMSprop and AdaGrad, Adam optimizer yields faster convergence and mitigates the burden of fine-tuning the learning rate.

## 5 Experiments

### 5.1 Datasets

We conducted experiments on Epinions[1] and Flixster[2] datasets, where we preserved only active users and items,

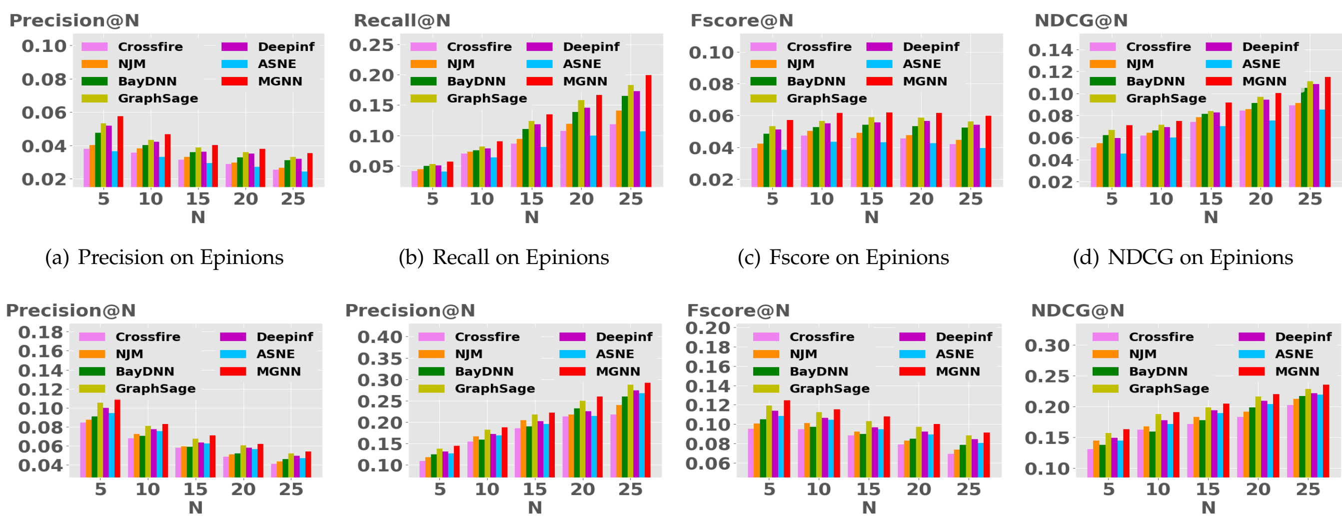
1. http://www.trustlet.org/downloaded_epinions.html
2. http://drive.google.com/file/d/1nTKRWJ63-2EnRtiyGwDdKd9RKGDHcBA3/view




(a) Precision on Epinions (b) Recall on Epinions (c) Fscore on Epinions (d) NDCG on Epinions

(e) Precision on Flixster (f) Recall on Flixster (g) Fscore on Flixster (h) NDCG on Flixster

Fig. 3. Performance comparison on social recommendation




(a) Precision on Epinions (b) Recall on Epinions (c) Fscore on Epinions (d) NDCG on Epinions

(e) Precision on Flixster (f) Recall on Flixster (g) Fscore on Flixster (h) NDCG on Flixster

Fig. 4. Performance comparison on link prediction

TABLE 2
Statistics of datasets

| datasets | Epinions | Flixster |
|---|---|---|
| # Users | 6015 | 13552 |
| # Items | 16706 | 7237 |
| # Ratings | 222184 | 850038 |
| # Links | 129272 | 262432 |
| R-Density (%) | 0.44% | 0.86% |
| L-Density (%) | 0.71% | 0.29% |

i.e., users who provided more than four ratings or social records and items that were rated by more than four users. We then presented each rating using either 1 or 0: we set the rating to 1 if user $\mu_i$ rated item $i_j$ or 0 otherwise. Table 2 shows statistics of the datasets after the above filtering and presentation.

### 5.2 Evaluation Method

We applied a four-fold cross-validation to evaluate the performance of different approaches in our experiments. In each run, we randomly sampled 75% ratings and social links of each user to serve as training data and the rest as testing data. Then, we generated a ranked list of $N$ new items or links to each testing user to compare the recommendation results of approaches, where we varied $N$ from 5 to 25. We measure the recommendation quality via four metrics: *Precision@N*, *Recall@N*, *Fscore@N*, and *NDCG@N*, which have been extensively applied to evaluating the performance of recommended lists [3].

### 5.3 Compared Approaches

Our comparative experiments included two parts: social recommendation and link prediction. For social recommendation, we compared our approach with several competitive approaches as follows:

- **Crossfire** [7], a cross-social media framework based on matrix factorization, which simultaneously address friend and item recommendation.
- **NJM** [8], which jointly models the evolution of user feedback and social links for social network services platforms.
- **TrustSVD** [1], which capture user and item biases as well as the explicit and implicit influence of both rated items and trusted users when predicting unknown ratings.
- **DSR** [2], which learn informative yet compact binary codes for users and items in social recommendation.
- **ASR** [17], an adversarial training approach for social recommendation, which applies GCN in the discriminator.
- **DiffNet** [16], which is based on PinSage [18] via incorporating social relationship into the modelling during recommendation.
- **GraphRec** [10], a graph attention-based network approach that jointly captures interactions and opinions in a user-item bipartite graph by considering various sources of information, including social links and ratings.

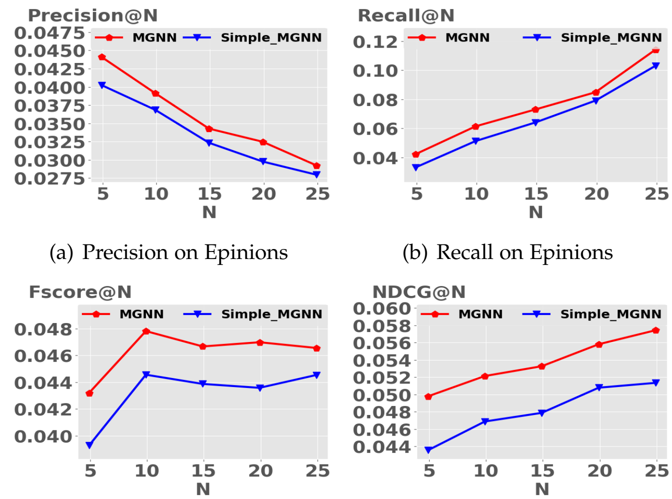
For social links prediction, we compared our approach with the following approaches besides CrossFire [7] and NJM [8]:

- **BayDNN** [3], a one-dimensional convolutional neural network that extracts latent feature representation and utilizes Bayesian ranking method to obtain users' preferences on unknown social links.
- **GraphSage** [5], which exploits the neighborhood structure through sampled paths on the graph and uses user-specific aggregaters to obtain the embedding of a target node.
- **ASNE** [4], a social network embedding framework which learns representations for a target user while preserving both the structural proximity and attribute proximity to recommend friends.
- **Deepinf** [6], which takes a user's local network as the input to a graph neural network and learns the user's latent social representation via incorporating network structures and user-specific features into convolutional neural attention networks.

### 5.4 Parameter Settings

We implemented MGNN using Pytorch[3]. All the experiments were conducted on a Titan Xp GPU. We trained all approaches for a maximum of 500 epochs or until convergence (i.e., none of the metrics improved after 50 epochs) and saved model parameters every 20 epochs. As for MGNN, we tuned the number of neighborhood sampling in spatial attention layer among {10, 20, 30, 40, 50} (defaulted to 20). For the embedding size $d$, we tested its value among {16, 24, 32, 64, 128}. We empirically set the size of the hidden layer the same to the embedding size and the activation function as LeakyReLU. The learning rate was tested on {0.001, 0.002, 0.005, 0.01}. As for NJM and ELJP related

3. https://pytorch.org/




(a) Precision on Epinions (b) Recall on Epinions

(c) Fscore on Epinions (d) NDCG on Epinions

Fig. 5. Self-Comparison on Social Recommendation

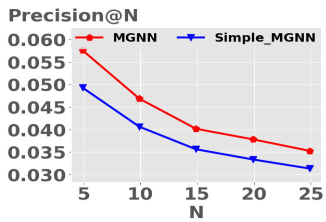
with time variation, we marked four timestamps according to the fold of datasets, i.e., we randomly marked the train set from 1 to 3 timestamps and the test set the 4th timestamp. For all the other approaches, we kept their configurations as described in the original papers. The batch size and regularization parameter $\lambda$ were fixed to 128 and 0.01 in all experiments.

### 5.5 Complexity Analysis

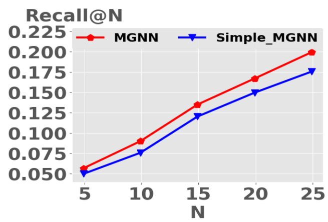
GNN contains four parts, as shown in Fig.2. For each user $\mu_i$, we first extracts the user's item influence embedding $z_i^I$ and social item embedding $z_i^S$, with the time complexity of $O(km)$, where $k$ and $m$ are fixed for the first layer and the second layer in the spatial layer. For social preference embedding, we use graph convolutional network to extract the latent representative with the time complexity of $O(1)$. The mutualistic layer and predicted layer also have the time complexity of $O(1)$ because they just execute the dot multiply and plus operations. For inference, we need $O(nkm)$ to implement MGNN for $n$ users, where $k$ and $m$ is rather smaller than $n$. Hence, MGNN can scale linearly with the time complexity of $O(n)$.

### 5.6 Comparison Results

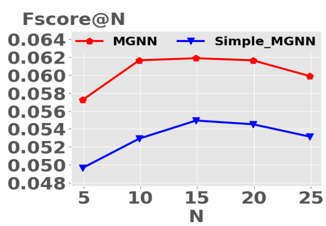
Fig.3 and Fig.4 show the performance of our approach in comparison with other schemes on the Epinions and Flixster datasets. The results show our proposed scheme significantly outperformed the compared approaches with respect to *Precision@N*, *Recall@N*, *Fscore@N*, and *NDCG@N* on both social recommendation or link prediction tasks. Besides, we had the following observations: 1) GraphRec, ASR, DiffNet and DSR attained better performance than the other three approaches in social recommendation. 2) Graph-based schemes (GraphSage and Deepinf) performed better than non-graph schemes (BayDNN, Crossfire, and NJM) in link prediction. 3) NJM performed better than Crossfire in solving joint tasks, indicating the advantages of neural network over matrix factorization in handling the joint tasks.



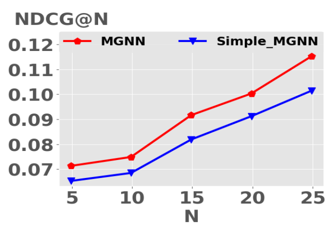

(a) Precision on Epinions




(b) Recall on Epinions




(c) Fscore on Epinions




(d) NDCG on Epinions

Fig. 6. Self-Comparison on Links Prediction

### 5.7 Mutualistic Mechnasm Analysis

In this experiment, we designed a concatenation layer to replace the mutualistic layer in our scheme to form the new scheme called Simple_MGNN. We used Simple_MGNN as the baseline to compared with MGNN to evaluate the impact of the mutualistic mechanism on our approach.

**Concatenation Layer**. We constructed the concatenate layer by concatenating user preference embedding $z_i^{uP}$ and user social embedding $z_i^{uS}$ to obtain a mixed representation, which were further used to generate a new mutual preference embedding $\overline{z_i^{mP}}$ and a new mutual social embedding $\overline{z_i^{mS}}$:

$$\begin{cases} z_{mix} = z_i^{uP} \boxplus z_i^{uS} \\ \overline{z_i^{mP}} = MLP(z_{mix}) \\ \overline{z_i^{mS}} = MLP(z_{mix}) \end{cases} \tag{16}$$

The predicted layer took the newly generated embedding ($\overline{z_i^{mP}}$ and $\overline{z_i^{mS}}$) as the input. Simple_MGNN followed the identical parameter settings of MGNN.

Fig.5 and Fig. 6 show MGNN outperformed Simple_MGNN by a large margin of 15% in both precision and NDCG for link prediction. Besides, performance comparisons of the same schemes under varied $N$ shows the variation tendency of precision is contrary to that of recall.

## 6 Conclusion

In this paper, we have proposed a novel framework for jointly modeling users' preferences and social interactions in social networks. Our proposed scheme first applies a spatial and spectral neural network layer to capture users' preference features and social features from observed data and then merges these two features via a mutualistic layer to solve social recommendation and link prediction tasks simultaneously. Our experiments on two real-world datasets demonstrate the superior performance of our approach over state-of-the-art approaches in both tasks. Our future work includes applying graph neural networks and merging knowledge graphs into graph neural networks for recommendations.

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# Revision of Manuscript ISSI-2019-09-0299

**"MGNN: Mutualistic Graph Neural Network for Joint Friend and Item Recommendation",** submitted to ***IEEE Intelligent Systems Magazine***

First, we express our deepest gratitude to the reviewers for their valuable comments on our paper, which have been fully considered in the revision of this article. To the best of our knowledge, every attempt has been made to address the comments raised by the reviewers.

In the remainder of this letter, we explain point-by-point how the issues raised by the reviewers were addressed, including details of the changes made to the paper (marked in **red**). We hope that these changes could satisfy the requirements of the reviewers and make the article acceptable for publication in the IEEE Intelligent Systems Magazine.

## Reviewer #1

**Comment 1:** "*The connection of mutualistic model with the proposed mutualistic mechanism is weak. The mutualistic model is based on partial differential equations, but the proposed mechanism is not related with a dynamic system. In spite of the advantage of mutualistic mechanism, it is difficult to understand the effectiveness in the current framework.*"

**Response:** Thank you for the comment. As a branch of partial differential equation, the mutualistic model explores the internal influence between two species that benefit from each other. Firstly, the mutual influence between users' consumption behavior and social relationship has been testified by many social studies, such as the following:

- Aiello L M, Barrat A, Schifanella R, et al. Friendship prediction and homophily in social media. ACM Transactions on the Web (TWEB), 2012, 6(2): 9;
- Libai B, Bolton R, Bügel M S, et al. Customer-to-customer interactions: broadening the scope of word of mouth research. Journal of service research, 2010, 13(3): 267-282.

Secondly, partial differential equations are an efficient tool to describe the dynamicity of the above interaction. When we regard our proposed MGNN as a dynamic system solved by neural network training, the mutualisitic model naturally provides the theory to support the design of the mutualistic layer. In the revised manuscript, we have stressed our motivation for applying the mutualistic model, i.e., to further model the implicit interaction between users' consumption behavior and social preference (**Section 3.2**).

**Comment 2:** *"The baselines are weak. As authors mentioned in introduction, there are two related work for joint friend and item recommendation, so these methods should be at least compared. And spectralCF, pinsage, and more advanced gcn-based models are also required for comparison."*

**Response:** Thank you for the suggestion. Actually, we have compared our model with two joint recommendation methods: Crossfire and NJM (**Section 5.3**), which were published in WSDM2018 and ICAJI 2018. We cannot use SpectralCF and Pinsage as baselines because both of them unrelated to social recommendation—including them would make the comparisons unfair. However, we have added two GCN-based models (**Section 5.3, Fig.3, Fig.4**) as baselines to make the experiments more solid.

- Krishnan A, Cheruvu H, Tao C, et al. A modular adversarial approach to social recommendation, Proceedings of the 28th ACM International Conference on Information and Knowledge Management. 2019: 1753-1762.
- L. Wu, P. Sun, Y. Fu, R. Hong, X. Wang, and M. Wang, “A neural influence diffusion model for social recommendation,” in Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval. ACM, 2019, pp. 235–244.

**Comment 3:** *“The paper do not provide complexity analysis. This is important for understand the efficiency of the proposed method.”*

**Response:** Thank you for the suggestion. In the revised manuscript, we have added complex analysis in **Section 5.5**.

**Comment 4:** *“There are only two datasets, and two datasets are very small. There are at most 222K ratings in the largest dataset. The authors are suggested to evaluate the proposed method against larger datasets.”*

**Response:** Thank you for pointing this out. In the revised manuscript, we have used Flixster, which contains more than 13500 users (see **Section 5.1 and Table 2** for details about the new dataset), to replace the smaller dataset and to re-conduct all the experiments. The Flixster dataset has been extensively used for recommendation studies. The following list some examples:

- Christakopoulou E, Karypis G. Local latent space models for top-n recommendation, Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. ACM, 2018: 1235-1243.
- Shokeen J, Rana C. Social recommender systems: techniques, domains, metrics, datasets and future scope. Journal of Intelligent Information Systems, 2019: 1-35.
- Fang H, Zhang Z, Shao Y, et al. Improved Bounded Matrix Completion for Large-Scale Recommender Systems[C]//IJCAI. 2017: 1654-1660.
- Zhou Y, Liu L, Zhang Q, et al. Enhancing Collaborative Filtering with Multi-label Classification, International Conference on Computational Data and Social Networks. Springer, Cham, 2019: 323-338.

**Reviewer #2**

**Comment 1:** *“The authors may need to add some literature on GNN, if possible.”*

**Response:** Thank you for your kind suggestion. Accordingly, we have added several latest literatures about GNN, e.g., [13], [14], in the revised manuscript.

**Comment 2:** *“In introduction, the authors should give a brief introduction of the proposed MGNN (e.g., its components) instead of focusing on the mutualistic mechanism.”*

**Response:** That is a good suggestion. Accordingly, we have added a brief introduction of MGNN, besides introducing the mutualistic insight in Section 1.

**Comment 3:** *"Some typo errors: e.g., in introduction, 'its social links' -> 'his/her social links', 'and further, driving' -> 'and further drives', 'The limited studies' -> 'limited studies',. In related work, 'that incorporate' -> 'that incorporates'."*

**Response:** Thank you for pointing them out. In the revised manuscript, we have carefully gone through the whole work and fixed the possible typos and errors, including those mentioned above.

**Reviewer #3**

**Comment 1:** *"The related work and reference is incomplete. I would suggest update the related work section. Social recommendation has been studied more than ten years. I would suggest to have a more detailed literature review which include some important pioneer work. For example:*

*1. Learning to Recommend with Social Trust Ensemble. SIGIR 2009*

*2. On social networks and collaborative recommendation. SIGIR 2009*

*3. SoRec: Social Recommendation Using Probabilistic Matrix Factorization. CIKM 2008*

*4. Recommender systems with social regularization. WSDM 2011*

*5. Exploring social influence for recommendation: a generative model approach SIGIR 2012"*

**Response:** Thank you for your invaluable suggestion. We had focused on the research in the joint task of social recommendation and social link prediction when presenting the related work in the original version. In light of your suggestion, we have included these papers and some latest work on social recommendation in the revised manuscript. This addition is also reflected in our responses to Reviewer 1 and Reviewer 2.

**Reviewer #4**

**Comment 1:** *"There are only some typos and grammatical mistakes that I would suggest the authors to benefit from proof reading their manuscript. I'll point out some in hear and will allow authors to take care of the rest:*
*on page2 section 3.2 paragraph 3: nad--> and*
*on page 6 section 5.4 for for-->for*
*on page 6 section 5.5 than should be removed from line4*
*on page 6 section 5.5 betterthen --> better than*
*section 5.5: This section seems to have been written in rush. consider rewriting this section to provide more insight on what you'll show as the result."*

**Response:** Thank you for careful examination of our manuscript. Accordingly, we have carefully gone through the whole manuscript again and rewritten **Section 5.5**.