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Heterogeneous Trust-based Social Recommendation via Reliable and Informative Motif-based Attention

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***Abstract*—Recently, social recommender systems are promising to enhance the quality of recommendations by integrating user-user social networks and user-item bipartite networks. However, there are very little success in that direction. Pessimistic findings are ascribed mainly to three factors. (1) Very few works focus on the identification of implicit neighbors to overcome the sparsity problem of explicit links. Furthermore, these works do not consider higher-order and complex patterns of interactivity among users. (2) Very less number of trust-based social recommender systems integrate heterogeneous trust relationships, and this heterogeneity is considered for explicit social links only. Moreover, these works ignore user-user heterogeneous trust relationships of higher-order network structure and user-item heterogeneous interactivity. (3) Existing works overlook the reliability (or lack of that) problem of links in higher-order and complex patterns of interactivity. To address the above mentioned challenges, we develop, a Graph $\bar{C}$onvolutional $\bar{N}$etworks via $\bar{R}$eliable and $\bar{I}$nformative $\bar{M}$otif-based Attention Model *(CNRIM)*. To the best of our knowledge, it is the first work that investigates user-user heterogeneous trust relationships and user-item heterogeneous interactivity via reliable, informative motif-based attention mechanisms. Varying reliability and informative motifs introduce the heterogeneity. The experiments on publicly available real-world datasets, and empirical analyses present the superiority of our model over popular baselines.**

I. Introduction

Recommender systems recommend items to the target users according to their preferences. Users can share their feedback about their purchased items through social medias [1], [2] to reflect their preferences. The social trust-related information among users is vital because we generally share opinions with our neighbors or we take feedback from our reliable online neighborhoods regarding their purchased items [3].

Due to the rapid growth and proliferation of online social media platforms, explicitly observed social relations are integrated into recommender systems to enhance their performances. In social correlation theories [4], [5], it is mentioned that a user is influenced by or the user's taste is similar to the user's directly connected neighborhoods. Based on this theory, the traditional social recommender systems incorporate only explicitly observed social relations [1], [6]. In [6], [7], the authors propose linear and non-linear kernels-based methodologies to understand users' preferences more accurately by integrating social network information and purchasing history.

But, recent studies show that the effectiveness of social recommender systems is poor because there are very less number of explicit friends of most of the users in social networks. However, direct consideration of explicit links may degrade the performances of social recommendation due to the unreliability of observed links. A series of works [3], [8] propose to identify effective explicit neighbors or extract explicit links into fine-grained classes and apply that filtered information. However, due to the sparsity problem of social network structure, the filtered social links are too sparse to successfully enhance the accuracy of recommended items [9], [10].

Interestingly, the aforementioned methodologies have a strong belief that directly connected neighbors have the same preferences while the tastes of unconnected friends may vary. In reality, a user may also have the same taste as other users who are at distant in social networks. This kind of user pairs are defined as *implicit neighbors* [11]. In recent studies, authors have given attention to identify effective reliable implicit neighbors and proposed techniques to incorporate explicit links and implicit social relation in social recommender systems [11]–[13]. Following their strategies, we can overcome the sparsity of explicit links but at the same time this augmentation unavoidably initiates noises [12], [14]. Importantly, these implicit neighborhood identifying techniques are not suitable for the recommendation process, because such techniques struggle to integrate higher order and complex interactivity patterns among nodes. None of these methods give importance to the multi-faced problem on social relations.

Users feel comfortable sharing feedback with strong ties (neighborhoods) rather than with weak ties [5]. Most of the existing trust-related social recommender systems and the aforementioned methodologies [11]–[13] overlook the heterogeneous trust links among users. The heterogeneity in trust links of users and the heterogeneous weightage of interactivity between users and items can be utilized in improving social recommendations. Very limited works consider heterogeneous trust relationships [15]–[17]. Specifically, heterogeneous trust relation is applied only on explicit links [3]. In [18] the authors follow alternative neighborhood generation techniques to identify authentic neighbors. None of these methods considers the unreliability problem of links and heterogeneous trust relationships on higher-order structures in complex networks. Some works [19], [20] apply motifs to capture higher order complex patterns of interactivity among nodes but they overlook indepth analyses on reliable and informative motifs.

To overcome the drawbacks of the existing works on social recommendations, we develop a Graph $\bar{C}$onvolutional $\bar{N}$etworks via $\bar{R}$eliable and $\bar{I}$nformative $\bar{M}$otif-based Attention Model *(CNRIM)* which explicitly investigates heterogeneous trust relationship and heterogeneous interactivity via reliable and informative motif-based attention mechanism on higher-order complex interactivity patterns. We open out our work by discussing the following questions:

(i) How does our model capture higher-order and complex patterns of interactivity? In [11], [21], [22], the authors have given attention to the identification of implicit neighbors to overcome the sparsity problem of explicit links. But our investigation claims that such works face problems to integrate high-order and complex interactivity between nodes because these works only capture from an immediate neighbor or random walk-based neighborhood [11], [22]. Based on some predefined motif structure [20], our model explicitly captures different higher-order structures, aggregates information from motif-induced neighborhoods with the attention mechanism that assigns high weight values to informative and reliable motifs. This strategy considers not only explicit observed links but also implicit neighbors via motif-based attention mechanism.

(ii) How can our model guarantee the reliability of weighted motifs? Most of the existing works overlook the problem of the unreliability of social links. Limited research paid attention to identifying valid relations for each user based on degree matrix, but these works ignore to analyze the characteristic of each user separately, whether the user is reliable or biased. To understand the characteristic of users, we propose a technique to evaluate the reliability of each user based on (a) the helpful score of her posted feedback and (b) the feedback's quality. Varying reliability introduces user-user heterogeneous trust relationships and user-item heterogeneous interactivity.

(iii) How does our model capture heterogeneous information from user-user social networks and user-item bipartite network? We integrate a user-user social network and a user-item bipartite network. In our model, a social attention technique is applied to assign high weightage value to reliable and informative motifs. Additionally, our model also considers heterogeneous interactivity between users and items. Interestingly, by not considering the reliability of users, existing recommender systems undermine the effects of negative users (who give negative feedback). There are some biased negative users who randomly give feedback, and some reliable negative users who post feedbacks according to their satisfaction level regarding their bought items. From the negative feedback of a user to a particular item, the existing recommendations assume that this item is not included in the user's preferences. But practically, it is not always true. We should look into whether the item is not included in the user's preferences or whether the user is not happy with the particular item's quality or whether the user is biased. Similar characteristic is also applicable for positive users. From the existing literature works we can say that our work is the first work that investigates user-user heterogeneous trust relationships and user-item heterogeneous interactivity via reliable, informative motif-based attention mechanisms.

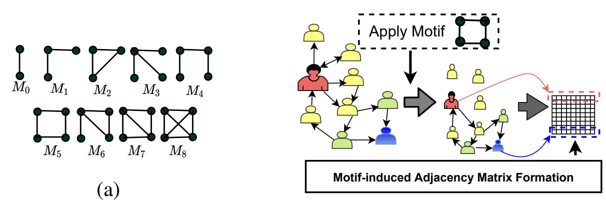
The remaining part of this paper is organized as follows: Section II illustrates the proposed social recommendation framework. In section III, we present the results of our experiments. Finally, we conclude our work in section IV.

II. The Proposed Architecture

A. Motif-induced Adjacency Matrix Formation

Inspired by [19], we construct motif based user-user social networks. In Fig. 1a, a directed graph $G = (V, E)$ and a set of T different motifs $M = \{M_0, M_1, ..., M_{T-1}\}$ are shown. Point to be noted that here we consider network motifs of size 2-4 only. More motifs can extract more diverse high-order features. So we perform a experiment on network motifs of size 5. But there is no improvement and its details discussion is omitted due to page limitation. Here, T different motif-induced adjacency matrices $A = \{A_0, A_1, ..., A_{T-1}\}$ are constructed, where

$$(A_t)_{i,k} = \begin{cases} 1 & i = k \\ 1 & i, k \textit{ are in the same } M_t \\ 0 & \textit{otherwise.} \end{cases} \tag{1}$$



(a) (b)

Fig. 1: (a) Undirected network motifs or graphlets of sizes 2-4. (b) Illustration of motif-induced adjacency matrix formation from directed social network.

An example of motif-induced matrix formation is shown in Fig. 1b, where motif network (undirected) M_5 is applied. Being motivated from [6], we keep the motifs undirected. M_5 motif is applied on (left) original network and the links of original network, that can match with M_5 motif are presented in the (right) motif-induced network and then we form an adjacency matrix from it. For link matching, we ignore the link direction of the original network to induce less parameters and it has been decided after the investigation.

B. Informative Motifs

We observe that our model assigns higher attention weights to M_2, M_5, M_7 and M_8 compare to other motifs, because the degrees of nodes in M_2, M_5, M_7 and M_8 are all greater than 1. It indicates strong ties among nodes. So, M_2, M_5, M_7 and M_8 are more informative motifs. The informative motifs are effective to extract useful connections. However, the nodes in rest of the motifs are sparsely connected and these are treated as uninformative.

C. Users' Reliability with Authenticity Score

Based on helpful votes and quality of a users' posted feedback, we evaluate authenticity score and this score indicates the user's reliability.

1) Helpfulness of a feedback: Generally, users are habituated to read posted feedback to get an idea about the quality of their preferable items. Just below each feedback, there is a posted query, "Was this feedback helpful? (Choose Yes/No)". To measure the effectiveness of a feedback, helpfulness score is calculated. The helpfulness a_{ij}^h of user u_i for item p_j (i.e., u_i wrote feedback c_{ij} on p_j) is normalized based on how many other users are satisfied from the feedback and it is formulated as follows:

$$a_{ij}^h = \frac{f_{ij}}{\sum_{x=1}^{n_{p_j}} f_{xj}}, where \tag{2}$$

$$f_{ij} = \frac{(\#helpful \text{ “}yes\text{” } responses \ on \ feedback \ c_{ij})^2}{total \ \#responses \ on \ feedback \ c_{ij}}. \tag{3}$$

Here, n_{p_j} is the number of users who purchase p_j. The Eq. 3 is quadratic equation because we want to give more weightage value to the users whose feedbacks score more helpful responses "yes". Point to be noted that, if there is no information about the total votes in any experimental dataset and contains only the information about helpful votes "yes", then the denominator part of Eq. 3 will be replaced by the maximum number of "yes" votes scored by any feedback on p_j.

2) Quality of feedback: It is obvious that feedback with minimal misspelled words and less grammatical mistakes is treated as more reliable to users. After reading good quality feedback, sometimes some users may skip giving any vote to feedback (the long tail phenomenon of social systems). For this reason, there are some high-quality feedback that get less number of helpful votes or no helpful votes. So, a user's reliability does not only depend on helpfulness score but also relates to the user's posted feedback's quality.

Spelling error score: To identify misspelled words, **pyspellchecker**[1] is used. The non-English words presented in the feedback are discarded. The spelling error score (ss_{ij}) of feedback c_{ij} regarding p_j posted by u_i is evaluated as follows:

$$ss_{ij} = \frac{number \ of \ misspelled \ words \ of \ c_{ij}}{the \ length \ of \ c_{ij} \ (in \ words)}. \tag{4}$$

Readability: Several metrics can compute readability of feedback, we choose Flesch-Kincaid Grade level of the feedback *(FK)* [23]. These metrics indicate how easy to read feedback for users. The feedback's quality c_{ij} for item p_j, posted by u_i is formulated as $a_{ij}^q = FK_{ij} - ss_{ij}$. Before evaluating a_{ij}^q, we normalize the $FK_{ij} \in (0, 1]$ by the maximum value.

[1]https://pyspellchecker.readthedocs.io/en/latest/.

The authenticity score is derived from feedbacks as follows:

$$a_{ij} = \frac{a_{ij}^h + a_{ij}^q}{2}, \quad and \tag{5}$$

$$a_i^{avg} = \frac{\sum_{j \in \theta(i)} a_{ij}}{|\theta(i)|}, \tag{6}$$

where $a_{ij} \in (0,\ 1)$ indicates the reliability of u_i for p_j. Here a_i^{avg} indicates the reliability of u_i based on her posted feedbacks. Here, $\theta(i)$ is the set of u_i's posted feedbacks and $|\theta(i)|$ is the number of u_i's posted feedbacks. The higher value of authenticity score indicates more reliability of the user.

D. User Latent Factor

The information of feedback c_{ij} given by user u_i on item p_j is used as an input of our methodology. Here, interactivity score is denoted by q_{ij}. This score indicates that the user rates on the item or not. Here q_{ij} is either 0 or 1, where 1 means u_i rates on p_j, otherwise 0. Rating score (degree of satisfaction) is denoted by R_{ij} and reliability is defined by authenticity score a_{ij}. The number of users is denoted by n and m is the number of items. If u_i rates p_j, then R_{ij} is the satisfaction degree (rating value) of u_i for p_j and q_{ij} = 1. If there is no rating, then both R_{ij} and q_{ij} = 0.

In this subsection, we have discussed how we learn user latent factors based on user-item heterogeneous interactivity and motif-induced neighborhood as presented in Fig. 2 (a-I, a-II), respectively. The user latent factor based on motif-induced neighborhood is defined as $e_i^{us} \in \mathbb{R}^d$ for u_i, where d denotes the embedding size. The user latent factor based on user-item interactivity is indicated as $e_i^{up} \in \mathbb{R}^d$ for u_i. Final user latent factor $\theta_i^U \in \mathbb{R}^d$ is evaluated based on e_i^{us} and e_i^{up} discussed as follows:

1) User Latent Factor based on Motif-induced Neighborhood: The user latent factor $e_i^{us} \in \mathbb{R}^d$ is evaluated based on motif-induced neighborhood for u_i as shown in Fig. 2(a-II). To extract information (network structure and authenticity score) from explicit and motif-induced neighborhoods, we construct a general graph convolution network using layer-wise propagation [24]. The embedding matrix of node features based on network topology of motif-induced social network is evaluated as follows:

$$(E_t^{L+1})^{s1} = \sigma_{ReLU}\left\{F_t^{-1/2} A_t F_t^{-1/2} (E_t^L)^{s1} b^L\right\}, \tag{7}$$

where σ_{ReLU} is the *ReLU* activation function (after experimental observation, it is chose); $(E_t^L)^{s1}$ is embedding matrix of node features, which is extracted from the motif-induced adjacency matrix A_t, inputted to the L^{th} layer. A_t = A_t^* + I (I indicates an identity matrix with size n ; n = number of node in G) is the updated adjacency matrix of the input graph including self-loops; A_t^* is the original adjacency matrix of directed G graph. Here F_t is the diagonal degree matrix of A_t; $(F_t)_{i,i}$ = $\sum_{k \in \mathcal{N}^{A_t}} (A_t)_{i,k}$, where $\mathcal{N}^{A_t}$ is the set of u_i's neighborhood defined by the matrix A_t - which includes itself. Here, b^L is a trained embedding matrix applied to the embedded inputs with a lower dimension.

The embedding matrix of node features based on the authenticity score of explicit and motif-induced neighborhoods is evaluated as follows:

$$(E_t^{L+1})^{s2} = \sigma_{ReLU}\left\{({}^*F_t^{-1/2})A_t({}^*F_t^{-1/2})(E_t^L)^{s2}(b^{*L})\right\} \tag{8}$$

where, $({}^*F_t)_{i,i} = \frac{1}{|\mathcal{N}^{A_t}|}\sum_{k\in\mathcal{N}^{A_t}}\left\{(A_t)_{i,k} * a_k^{avg}\right\}$. Here, $(E_t^L)^{s2}$ is the embedding matrix of node features based on the reliability of explicit and motif-induced neighborhoods, inputted to the L^{th} layer. Here, (b^{*L}) is a trainable embedding matrix applied to embed the given inputs (typically to a lower dimension).

The importance of the motif-induced network structure of a user may differ from motif to motif. Assigning the same weight value for all motif networks of a user could degrade a recommender system's performance. It is more practical to identify different motif networks by setting an individual weight value. We adopt an attention mechanism to fuse T multi-view graph embedding, which can ensure that high weights are assigned to informative and reliable ones:

$$e_i^{us} = \sigma_{ReLU}(W\left\{\sum_{t=0}^{T-1}\lambda_{it}[(e_t^{L+1})_{u_i}^{s1}]\oplus[(e_t^{L+1})_{u_i}^{s2}]\right\}+b). \tag{9}$$

Here, $(e_t^{L+1})_{u_i}^{s1}$ is the feature vector embedding of user u_i at layer $L+1$ based on network topology of $motif$-t-induced social network, where $(e_t^{L+1})_{u_i}^{s2}$ is the feature vector embedding of user u_i at layer $L+1$ based on reliability of explicit and $motif$-t-induced neighborhoods. Here in the network, the weight is denoted as W and b is bias. Here $\oplus$ indicates concatenation operation. The attention coefficient λ_{it} of $motif$-t network is evaluated as follows:

$$\lambda_{it}^* = w_2^T\sigma_{ReLU}(W_1[(e_t^{L+1})_{u_i}^{s1}]\oplus[(e_t^{L+1})_{u_i}^{s2}]+b_1)+b_2 \tag{10}$$

$$\lambda_{it} = \frac{exp(\lambda_{it}^*)}{\sum_{t=0}^{T-1}exp(\lambda_{it}^*)}. \tag{11}$$

2) User Latent Factor based on User-Item interactivity: User latent factor e_i^{up} is evaluated based on heterogeneous interactivity of u_i on her purchased items based on the degree of satisfaction and reliability. Following the technique demonstrated in [25], we form user-item embedding.

Based on interactivity, u_i and p_j's embedding vector are represented by o_i^q and o_j^q, respectively (same technique is followed mentioned in [25]). Similarly, based on rating activities, u_i's and p_j's embedding vector are represented by o_i^r and o_j^r, respectively. Similarly, based on authenticity score on posted feedbacks, u_i's and p_j's embedding vector are represented by o_i^a and o_j^a, respectively.

To indicate each type of ratings as a dense vector representation, satisfaction embedding is used. Here, $ev_{ij}^r \in \mathbb{R}^d$ indicates the satisfaction embedding vector of the posted rating of u_i on item p_j. Similarly, the reliability vector embedding is denoted as $ev_{ij}^a \in \mathbb{R}^d$. Initially, based on the users' interactivity, rating and authenticity score of their posted feedbacks, e_i^u and $e_j^p \in \mathbb{R}^d$ are evaluated as follows:

$$e_i^u = \alpha_1([o_i^r \oplus o_i^a \oplus o_i^q]), \quad and \tag{12}$$

$$e_j^p = \alpha_2([o_j^r \oplus o_j^a \oplus o_j^q]), \tag{13}$$

where the embedding of u_i is represented by e_i^u and the item embedding of p_j is represented by e_j^p. It is evaluated based on embedding vector o_i^r, o_i^a and o_i^q through a Multi-Layer Perceptron *(MLP)*. Here, α_1 and α_2 fuse these vectors.

The interactivity between u_i and p_c with rating r_{ic} and authenticity a_{ic}, reliability based interactivity embedding y_{ic}^u is evaluated as follows:

$$y_{ic}^u = \alpha_3([e_c^p \oplus ev_{ic}^r \oplus ev_{ic}^a]), \tag{14}$$

where α_3 fuses the three vectors as presented in fig. 2(a-I). The interactivity of a user may differ from item to item. We identify users by setting an individual weightage value for each (u_i, p_c) pair. Here, e_i^{up} is evaluated as

$$e_i^{up} = \sigma(W\left\{\sum_{c\in\beta(i)}\delta_{ic}y_{ic}^u\right\}+b), \tag{15}$$

where $\beta(i)$ is the set of items that are purchased by u_i. Here, σ indicates the Sigmoid activation function. Here, δ_{ic} is the weightage of interactivity between u_i, p_c pair and this weightage is calculated through an attention mechanism as presented in Fig. 2(a-I). The attention mechanism and final attention weights are evaluated as follows:

$$\delta_{ic}^* = w_2^T\sigma(W_1[y_{ic}^u \oplus e_i^u]+b_1)+b_2 \tag{16}$$

$$\delta_{ic} = \frac{exp(\delta_{ic}^*)}{\sum_{c\in\beta(i)}exp(\delta_{ic}^*)}. \tag{17}$$

3) Learning User Latent Factor: The concatenation operation of two embeddings e_i^{up} and e_i^{us} is performed via fully connected layers as shown in Fig. 2(c). At the end θ_i^U is evaluated as follows:

$$\Phi_1 = [e_i^{up} \oplus e_i^{us}] \tag{18}$$

$$\Phi_2 = \sigma(W_2.\Phi_1 + b_2) \tag{19}$$

$$\theta_i^U = \sigma(W_L.\Phi_{L-1} + b_L) \tag{20}$$

where, L is the index of a hidden layer.

E. Item Latent Factor

In this subsection, we have discussed how we evaluate item latent factor $\theta_j^P \in \mathbb{R}^d$ for item p_j based on user-item heterogeneous interactivity.

1) Item Latent Factor based on User-Item interactivity: User u_k purchases item p_j with rating R_{jk} and reliability is a_{jk} for her posted feedback regarding the same item. Here the degree of satisfaction and reliability based interactivity embedding y_{jk}^p is evaluated as follows:

$$y_{jk}^p = \alpha_4([e_k^u \oplus ev_{jk}^r \oplus ev_{jk}^a]). \tag{21}$$

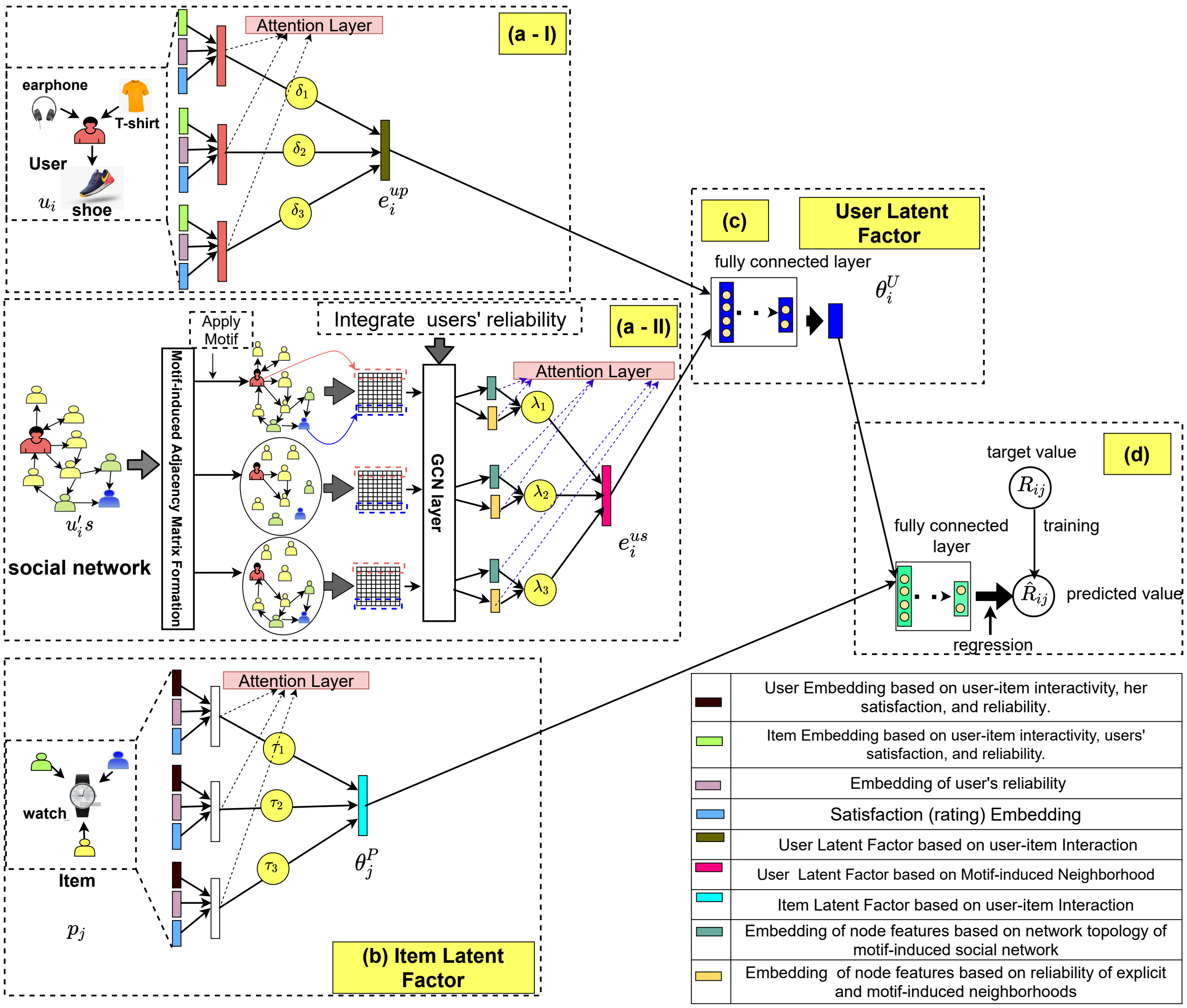


Fig. 2: Our proposed model architecture. (a-I): User Latent Factor based on user-item interactivity; (a-II): User Latent Factor based on Motif-induced Neighbourhood; (b): Item Latent Factor based on user-item interactivity; (c): Learning of Final User Latent Factor; (d): Rating Prediction.

The identification of different users by setting an individual weight value for each (u_k, p_j) pair is more practical. Here, θ_j^P is evaluated as

$$\theta_j^P = \sigma(W\left\{\sum_{k\in\mu(j)} \tau_{jk} y_{jk}^p\right\} + b), \tag{22}$$

where the set of users who buy an item p_j is denoted as $\mu(j)$. Here, the weightage of interactivity between u_k, p_j pair is represented as τ_{jk} and we evaluate this weight value through an attention mechanism as presented in Fig. 2(b). We design the attention mechanism as,

$$\tau_{jk}^* = w_2^T \sigma(W_1[y_{jk}^p \oplus e_j^p] + b_1) + b_2 \tag{23}$$

$$\tau_{jk} = \frac{exp(\tau_{jk}^*)}{\sum_{k\in\mu(j)} exp(\tau_{jk}^*)}. \tag{24}$$

F. Rating Prediction

As presented in Fig. 2(d), we perform concatenation between user latent factor θ_i^U and item latent factor θ_j^P and the output is passed via fully connected layers as

$$\Theta_1 = [\theta_i^U \oplus \theta_j^P] \tag{25}$$

$$\Theta_2 = \sigma(W_2.\Theta_1 + b_2) \tag{26}$$

$$\hat{rt}_{ij} = \sigma(W_L.\Theta_{L-1} + b_L). \tag{27}$$

The predicted rating ($\hat{R}_{ij}$) is evaluated through regression layer

$$\hat{R}_{ij} = w_{rg}\hat{rt}_{ij} + b_{rg}. \tag{28}$$

III. Experimental Result

A. Experimental Settings

1) Datasets: We evaluate the performances of our proposed model over three publicly available real-world datasets: Ciao, Epinions and LibraryThing [26], [27]. The information of a user for an item is included in these datasets if the user actually buys the item. Ciao and Epinions are general consumer review websites and LibraryThing is a book review website. In these social networking sites, the users share feedback on purchased items, post ratings/reviews, include friend circle, etc. The statistics of the experimental datasets are presented in Table I. Most of the popular baselines are using these three datasets.

TABLE I: Dataset Statistics

Dataset	Ciao	Epinions	LibraryThing
# of users	7,317	116,260	73,882
# of items	10,4975	41,269	337,561
# of feedbacks	283,319	181,394	979,053
# of social relations	111,781	181,304	120,536

2) Metrics: Based on *leave-one-out evaluation* [28], we evaluate all methods' performances. The latest interaction of each user is treated as the test data, two-thirds of the remaining is used as training and rest is used for validation. We execute random sampling independently five times and calculate the average as the final output for each execution. But to rank all items for each user is so much time taking. So we use the common strategy [28] that randomly samples 100 items which are not bought. Throughout experiments we rank the test items among the 100 items. *Hit Ratio (HR)* and *Normalized Discounted Cumulative Gain (NDCG)* are used to evaluate performance of a ranked list. In this paper, the ranked list is truncated at 10 for both metrics.

3) Baseline Models: To evaluate recommendation accuracy of *GNNTSR*, we select popular baseline models. For comparison purpose, we conduct experiments of the baseline models on the experimental data with the same experimental environment as directed in their corresponding literature. The baseline models are as follows:
i) SBRNE [1], **ii) TrustMF** [6], **iii) DeepSoR** [7], **iv) IF-BPR** [11], **v) RSGAN** [12], **vi) GraphRec** [3], **vii) EIRS** [13], **viii) ESRF** [18].

4) Details of Implementation: Our model is developed on the *Keras*. We randomly sample one interactivity between user-item as the validation for each user to calculate optimum value of the hyper-parameters of *CNRIM*. Then we tune the hyper-parameters on it. As an optimizer mini-batch, Adaptive Moment Estimation ($Adam$) is applied. After experimental observation, for all dataset, we fix embedding size d = 64. The number of layers in *GCN* is 2. The number of fully connected layers is 2 and architecture is $128->64$ as shown in Fig. 2(c). The number of fully-connected layers is 4 and architecture is $128->64->16->8$ as shown in Fig. 2(d). We test batch size of (128, 256, 512, 1024) and epochs of (1, 5, 10, 15, 20, 25, 30, 40, 50, 60). After experimental observation, 256 batch sizes and 40 epochs are used in our model.

B. Recommendation Performance

The experimental analyses of our model and baseline models *w.r.t HR@10* and *NDCG@10* on our experimental datasets are shown in Table II. The baselines *SBRNE* and *TrustMF* focus on users' social information with rating history. Considering both points of view; truster and trustee-based co-factorization strategy with social trust networks and rating matrix, *TrustMF* outperforms *SBRNE*. *DeepSoR* performs better than *TrustMF* model and *SBRNE*, because *DeepSoR* propose a deep neural model, that integrates all extracted features. The improvement of *DeepSoR* indicates the learning capability of deep neural model.

To overcome the data sparsity problem of the aforementioned three baselines, both baselines *IF-BPR* and *RSGAN* focus on explicit and implicit friends based on user-item purchasing activities and social relationships. The *RSGAN* model not only pays attention to explicit and implicit friends but also focuses on the reliability of social links based on user-item purchasing activities. For this reason and model learning capabilities, *RSGAN* obtains marginally better performance than *IF-BPR*. *RSGAN* and *IF-BPR* do not consider users' heterogeneous degree of preferences. Though *GraphRec* model only focuses on explicit neighbor, but it shows slightly better performances than *RSGAN* and *IF-BPR*. The reason is that *GraphRec* computes heterogeneous trust relationships (strong and weak social neighbors) among users in social networks and heterogeneous interactions between user-item based on users' degree of preferences, that are ignored by *RSGAN* and *IF-BPR*.

The model *EIRSN* focuses on explicit neighbor and implicit friends from observed links and unobserved social relationships. This model identifies the reliable one based on users' degree of preferences and at the same this model considers heterogeneous information in social recommendation. For considering two crucial factors in a model, the performance of *EIRSN* is better than *GraphRec*, *RSGAN* and *IF-BPR*. The *ESRF* model proposes a technique that captures high order and complex connectivity in social networks and it follows an alternative neighborhood generation technique to extract validate neighbors. For this reason, the best baseline *ESRF* outperforms other baselines. But unreliability problem of social links and heterogeneous interaction activities of user-item are totally ignored in *ESRF*.

Our proposed model *CNRIM* investigates heterogeneous trust relation via reliable and informative motif-based attention mechanism on high-order complex interaction patterns among users. In consideration of these important features, our model performs better than other baselines as shown in Table II.

C. Recommendation for Cold-Start Users

We also investigate the performances of our model for cold-start users who have posted feedbacks less than 6. Our observation is that 50 % of users are cold-start users. In Table III, it is shown that for all datasets our model performs more accurately compare to other baselines for cold-start users. The baselines *SBRNE*, *TrustMF*, *DeepSoR* and *GraphRec* only focus on explicit links. So, these models are not effective for cold-start users. *CNRIM* has the capability to capture reliable high order complex interaction patterns among users, where *IF-BPR* and *RSGAN* can not capture high order interactions and face problems to overcome noise issue of links. Our model not only captures reliable high order complex interactions but also considers heterogeneous interaction between users-items and heterogeneous trust relations among users, where *ESRF* only considers high order relations. As a result, *CNRIM* performs better than all baselines for cold-start users.

TABLE II: Performance comparison between *CNRIM* and baselines. The latest interaction of each user is treated as the test data and two-thirds of the remaining is used as training and rest is used for validation. We highlight the best performances in bold.

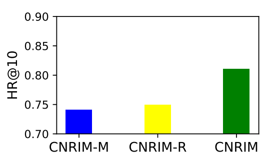
Dataset	Metrics	*SBRNE*	*TrustMF*	*DeepSoR*	*IF-BPR*	*RSGAN*	*GraphRec*	*EIRSN*	*ESRF*	*CNRIM*
Ciao	HR@10	0.422	0.481	0.521	0.601	0.687	0.691	0.747	0.763	**0.811**
	NDCG@10	0.316	0.373	0.417	0.447	0.483	0.488	0.549	0.561	**0.607**
Epinions	HR@10	0.441	0.511	0.544	0.636	0.693	0.700	0.705	0.711	**0.794**
	NDCG@10	0.401	0.471	0.521	0.537	0.543	0.547	0.553	0.557	**0.583**
LibraryThing	HR@10	0.478	0.517	0.521	0.601	0.612	0.619	0.678	0.701	**0.751**
	NDCG@10	0.317	0.359	0.389	0.411	0.469	0.473	0.546	0.579	**0.612**

TABLE III: Performance comparison for cold-start users between *CNRIM*. We highlight the best performances in bold.

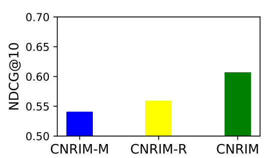
Dataset	Metrics	*SBRNE*	*TrustMF*	*DeepSoR*	*IF-BPR*	*RSGAN*	*GraphRec*	*EIRSN*	*ESRF*	*CNRIM*
Ciao	HR@10	0.303	0.312	0.343	0.523	0.561	0.351	0.601	0.621	**0.694**
	NDCG@10	0.211	0.227	0.244	0.317	0.330	0.252	0.417	0.459	**0.491**
Epinions	HR@10	0.320	0.327	0.350	0.543	0.571	0.359	0.617	0.637	**0.698**
	NDCG@10	0.201	0.221	0.234	0.307	0.328	0.244	0.404	0.437	**0.479**
LibraryThing	HR@10	0.331	0.342	0.355	0.529	0.561	0.377	0.600	0.623	**0.685**
	NDCG@10	0.211	0.227	0.239	0.322	0.341	0.242	0.417	0.441	**0.487**

D. Model Analysis

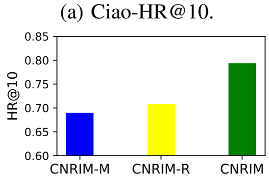
1) Effect of Motif-induced Social Network Structure and Users' Reliability: Here we examine the contribution of motif-induced social networks and users' reliability. In Fig. 3, *CNRIM-M* indicates our model's performances when motif-induced social network is not consider; we only consider original social network to evaluate e_i^{us}. *CNRIM-R* denotes our model's performances when we do not integrate reliability information in *GCN* layer and at the same time, we ignore reliability information in learning heterogeneous interactivity between user-item. The performances of *CNRIM*, *CNRIM-M* and *CNRIM-R* are presented in Fig. 3. From our experiment, our model claims that in the learning of heterogeneity in trust relationships on high-order complex interactivity patterns among users, users' reliability and motif-induced social network are two important factors.



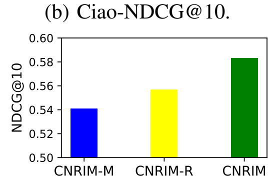
(a) Ciao-HR@10.



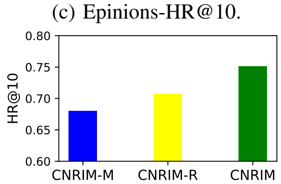
(b) Ciao-NDCG@10.



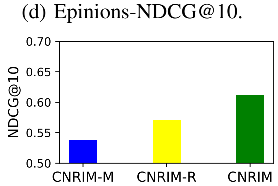
(c) Epinions-HR@10.



(d) Epinions-NDCG@10.



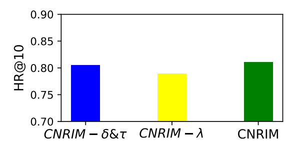
(e) LibraryThing-HR@10.



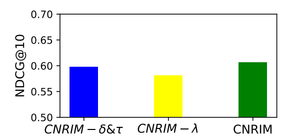
(f) LibraryThing-NDCG@10.

Fig. 3: Effect of Motif-induced Social Network and Users' Reliability.

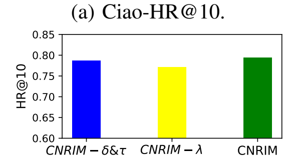
2) Effect of Attention Mechanisms: In this subsection, we examine the effectiveness of Attention Mechanisms in our model. In Fig. 4, *CNRIM-*δ *&* σ denotes our model's performances when user attention δ and item attention σ are eliminated; we only consider social attention λ. *CNRIM-*λ indicates our model's performances when social attention λ is eliminated; we only consider user attention δ and item attention σ. The performances of *CNRIM*, *CNRIM-*δ *&* σ and *CNRIM-*λ are presented in Fig. 4. From our experiment, we can claim that in the learning of heterogeneity in trust relationships on high-order complex interactivity patterns among users, attention mechanism is a crucial factor.



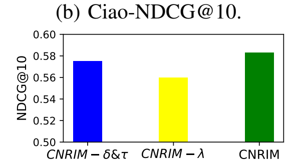
(a) Ciao-HR@10.



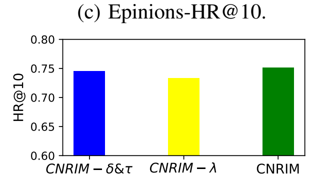
(b) Ciao-NDCG@10.



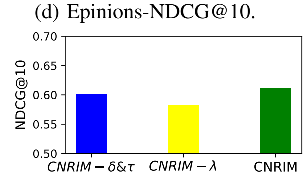
(c) Epinions-HR@10.



(d) Epinions-NDCG@10.



(e) LibraryThing-HR@10.



(f) LibraryThing-NDCG@10.

Fig. 4: Effect of Attention Mechanisms.

3) Effect of Informative Motifs: In this subsection, we further investigate the attention coefficients of different motif networks used in our model. In Table IV, it is observed that our attention mechanism assigns different attention weight values to different motif networks: Motif M_2, M_5, M_7 and M_8 receive comparatively high attention weight value.

One possible reason for assigning different weight values to different motifs is that informative motifs may help our model to improve performances, where uninformative motifs with low weights have limited contribution or created obstacles in performances improvement. To confirm this assumption, we experiment. In Table V, *CNRIM-M* denotes our model's performances when motif-induced social network is not consider; we only consider original social network to evaluate e_i^{us}.

CNRIM-IM indicates the performances when we do not consider informative motifs (M_2, M_5, M_7 and M_8) and *CNRIM-nIM* indicates the performances when we do not consider M_0, M_1, M_3, M_4 and M_6 motifs. The performances of *CNRIM* and the three variants *CNRIM-M*, *CNRIM-IM* and *CNRIM-nIM* are presented in Table V. In summary, informative motifs help our model to improve performances, where uninformative motifs with low weights have limited contribution and create obstacles in performances improvement wasting computational resources.

TABLE IV: Distribution of attention coefficients among motif networks

M_0	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8
0.021	0.052	0.117	0.085	0.102	0.174	0.115	0.207	0.213

TABLE V: Effect of Informative Motifs

Dataset	**Metrics**	***CNRIM-M***	***CNRIM-IM***	***CNRIM-nIM***	***CNRIM***
Ciao	HR@10	0.738	0.742	0.809	0.811
	NDCG@10	0.547	0.550	0.605	0.607
Epinions	HR@10	0.682	0.688	0.791	0.794
	NDCG@10	0.538	0.532	0.579	0.583
LibraryThing	HR@10	0.677	0.702	0.750	0.751
	NDCG@10	0.549	0.541	0.610	0.612

IV. Conclusion

In this paper, we propose *CNRIM* which investigates heterogeneous trust relationships via reliable and informative motif-based attention mechanism on high-order complex interactivity patterns among users. We perform experimental analyses on experimental data, and empirical analyses present the superiority of our model over popular baselines. Our model is also effective for cold-start users. We can apply our model in online merchandise sites that uses social network for recommendations.

We consider rating and social information static. However, rating, reliability and trust information are naturally dynamic. Hence, we will consider building dynamic graph neural networks for social recommendations with dynamic rating, reliability and trust value. In future we will focus on computational complexity analysis of dynamic graph neural network based model for social recommendations with dynamic rating, reliability and trust value and compare with *CNRIM*. In future, we will perform experiments on other datasets also.

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