Adaptive Residual Attention Recommendation Model Based on Interest Social Influence

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***Abstract*—Existing social recommendation models mostly directly use original social data in the social space. However, original social data may contain a large amount of redundant and noisy social relationships. Additionally, existing feature fusion methods struggle to adaptively fuse features between nodes deeply, which can degrade the recommendation performance of the model. Addressing these issues, this paper proposes an Adaptive Residual Attention Recommendation Model based on Interest Social Influence. Firstly, we construct a novel Interest Social Mapping Module to model the confidence of social relationships based on user interests and map original social data to interest social space, thereby gaining a deeper understanding of user interest relationships in social networks. Secondly, we introduce a unique Social Selection Mechanism that dynamically filters and removes meaningless social interactions in the interest social space using social confidence scores, effectively filtering out social information that may interfere with or mislead users. Finally, we design an Adaptive Residual Attention Mechanism to flexibly adjust the feature fusion method of nodes, thereby obtaining more effective node information to improve recommendation accuracy. Experimental results show that compared to several state-of-the-art methods, the proposed model exhibits significant improvements on the Ciao and Epinions datasets.**

Keywords*—*Social recommendation; redundant and noisy; interest social mapping; social selection mechanism; adaptive residual attention mechanism

I. Introduction

Recommendation systems, as an integral part of today's information age, aim to assist users in discovering and obtaining personalized content that aligns with their preferences. Among these systems, collaborative filtering stands out as a common recommendation algorithm. It works by analyzing user behavior and preferences to identify groups of users with similar interests from a large pool, thereby recommending items or content that users might find interesting. However, traditional collaborative filtering algorithms perform poorly when confronted with data sparsity and cold start issues [1]. To overcome the challenges posed by data sparsity and cold start, scholars have proposed various solutions. With the advent of post-quantum cryptography [2]-[5], one approach is to incorporate additional auxiliary information to enhance the performance of recommendation systems.

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With the rise of social networks, researchers began to turn their attention to the field of social recommendation, trying to incorporate information from social networks into recommendation systems to improve the personalization of recommendations. Early social recommendation methods primarily employed matrix factorization [6]-[8]. These methods tend to recommend items similar to a user's historical behavior, potentially overlooking novel items that might be of interest. Subsequently, significant progress has been made in the development of graph neural networks for social recommendations. Fan et al. [9] proposed the GraphRec model, pioneering the use of Graph Neural Networks (GNNs) to capture representations of nodes in user-item interaction graphs and user-user social graphs for social recommendations. Fan et al. [10] proposed the GraphRec+ model, incorporating the capture of item-item relationships for rating prediction. This enhancement provides a more holistic view of interactions but may introduce additional computational overhead.

Besides, there are some GNN models that are innovative in addressing selection bias, but they also add complexity and time overhead to the model. Chen et al. [11] introduced the GDSRec model, treating rating biases as vectors and integrating them into user and item representations, addressing statistical bias offset issues for users (items). Jia et al. [12] proposed the SoGCLR model, capturing latent relationships between social neighbors through social relation attention layers and utilizing graph contrastive learning to map representations of similar nodes to nearby embedding spaces, thus achieving smoother representations and alleviating exposure bias issues. Cai et al. [13] introduced the REST model, employing a variable autoencoder to reconstruct latent exposure strategies and designing a recommendation algorithm based on counterfactual inference using recovered exposure strategies to address selection bias issues in recommendation systems. Zhang et al. [14] proposed the GL-HGNN model, modeling fine-grained heterogeneous global graphs through heterogeneous graph neural networks to capture complex semantic relationships and rich topological information.

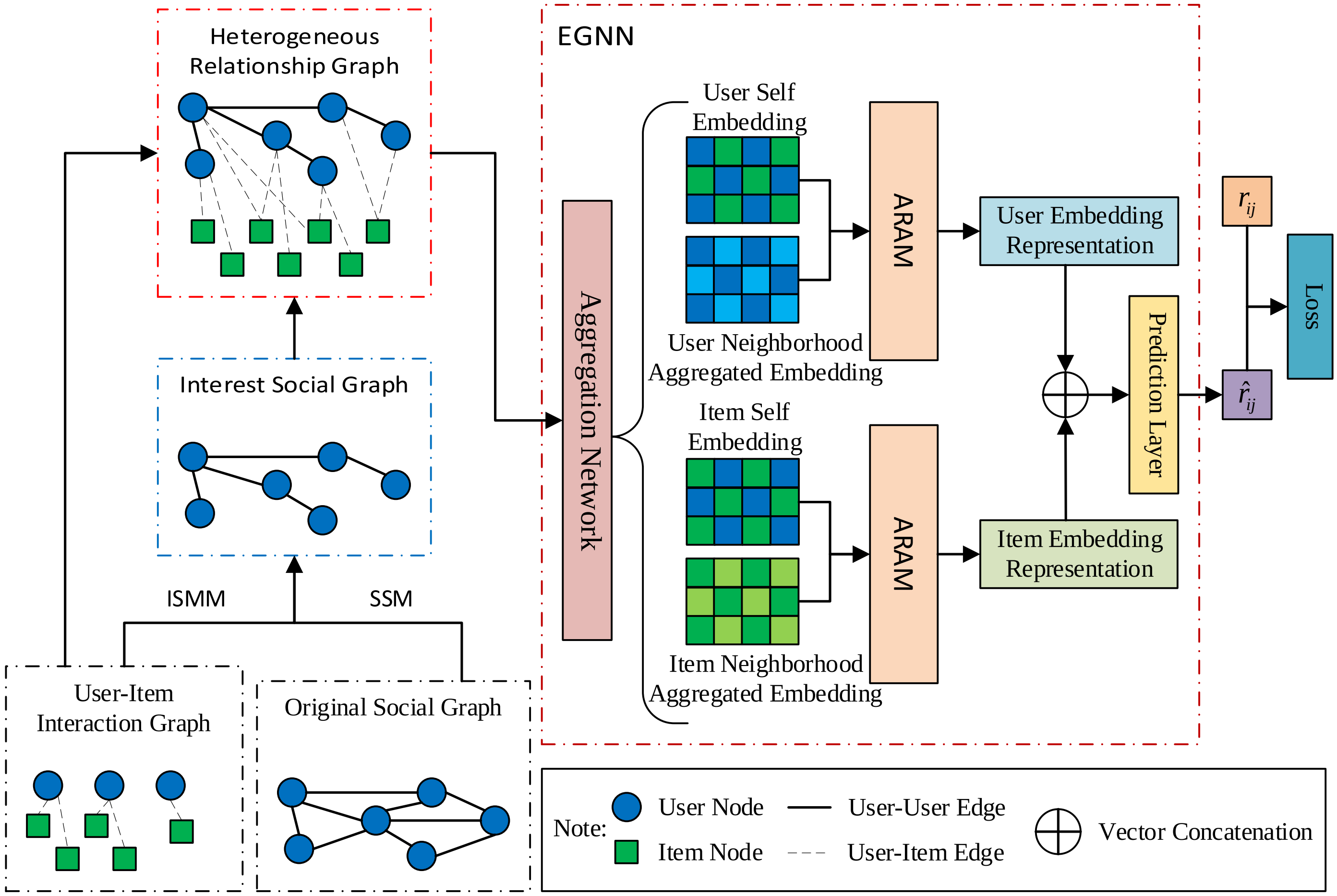

Fig. 1. ARAR-ISI overall framework

Despite the good results achieved by current graph neural network-based social recommendation models for rating prediction tasks, however, inspired by the literature [14], most of the existing social recommendation models use the original social data directly in the social space, ignoring the reliability of the original social data. In this paper, we argue that a large portion of social relationships in original social data is redundant or even noisy, partly because original social connections usually only record social relationships among users without reflecting similarities among user preferences. For example, some of the social friends are likely to lack common interests in specific domains, or are even unrelated to each other in terms of interests, which results in a large portion of social relationships being meaningless for the recommendation task. These meaningless social relationships not only bring a huge computational and storage burden to the recommender system, but also reduce the accuracy and computational efficiency of the recommender system, which ultimately has a negative impact on the overall performance of the recommender system. In addition, the existing feature fusion methods are difficult to deeply adaptively fuse the features between the target node and the neighbor nodes.

In order to solve the above problems, this paper proposes an Adaptive Residual Attention Recommendation Model based on Interest Social Influence (ARAR-ISI) inspired by the literature [10]-[23]. First, a new Interest Social Mapping Module (ISMM) is constructed, which is capable of modeling social relationships with confidence based on users' interests and mapping original social data to the interest social space as a way to understand users' interest relationships in social networks. Second, a unique Social Selection Mechanism (SSM) is introduced, which dynamically filters and removes meaningless socialization in the interest social space based on social confidence scores, and effectively filters social information that may disturb or mislead users. Finally, an Adaptive Residual Attention Mechanism (ARAM) is designed, which flexibly adjusts the feature fusion of the nodes and more effectively extracts the node information for prediction, so as to improve the accuracy of the recommendation.

II. The Proposed Framework

A. Definitions and Notations

Let $U=\{u_1,u_2,...,u_p\}$ and $V=\{v_1,v_2,...,v_q\}$ respectively denote the sets of users and items, where p and q represent the total number of users and items. O denotes the observed user-item ratings, $R\in \mathbb{R}^{i\times j}$ represents the matrix of ratings for user-item pairs, $r_{ij}\in R$ is the true rating of user u_i for item v_j. $S(u_i)$ represents the original social matrix of user u_i. $I(u_i)$ represents the item interaction matrix of user u_i. $U(v_j)$ represents the matrix of interacting users for item v_j. $X(u_i)$

represents the interest social matrix of user u_i . $N(m)$ represents the neighborhood matrix of target node m . h_{u_i} represents the embedding of user u_i . d is the embedding size. h_{v_j} represents the embedding of item v_j . The objective of this paper is to accurately predict the rating of user u_i for item v_j given the provided information such as R , S , etc.

B. An Overview of the Proposed Framework

The overall framework of the ARAR-ISI model is illustrated in Fig. 1. Firstly, based on the user-item interaction data, the Interest Social Mapping Module (ISMM) and Social Selection Mechanism (SSM) are jointly utilized to remove meaningless social interactions from the original social data as accurately as possible in the interest social space, thereby obtaining reliable interest social relationships. Subsequently, an Enhanced Graph Neural Network (EGNN) with Adaptive Residual Attention Mechanism (ARAM) is employed to model the heterogeneous relationship graph composed of interest social relationships and user-item relationships. After obtaining user embedding representation and item embedding representation, both are fed into the prediction layer for the final rating prediction.

C. The Interest Social Mapping Module

To effectively identify meaningless social interactions in the original social data, this paper introduces the concept of the "interest social space" to describe the interest relationships between users in the social network. In this study, a new Interest Social Mapping Module is constructed.

Firstly, considering that user-item interaction data to some extent represents user interests, we utilize the historical interaction data between users and their social connections to model social confidence. Additionally, the Transformer module [15] is effective in modeling the similarity between two sequences of user interaction history. Therefore, in the Interest Social Mapping Module, we design a Transformer-based method for modeling social confidence. Specifically, we use the interaction items between users and their social connections to calculate the confidence of their social relationships, as shown in the following formula:

$$\text{Score} = \text{Tf}(\boldsymbol{E}_{u_i v} \oplus \boldsymbol{E}_{u_k v} \mid \forall u_i \in U, \forall u_k \in S(u_i)) \tag{1}$$

Where $\boldsymbol{E}_{u_i v}$ represents the historical interaction item embedding of user u_i , $\oplus$ denotes the concatenation of two vectors, $\boldsymbol{E}_{u_k v}$ represents the historical interaction item embedding of user u_j , U represents the user matrix, $S(u_i)$ represents the original social matrix of user u_i , Tf denotes the Transformer module, and Score represents the confidence score of the social relationship between user u_i and their social user u_k . A higher Score indicates that user u_i has a greater interest similarity with their social user u_k .

After calculating the confidence score for each user's social relationships, each user sorts their original social relationships based on their social confidence scores and maps them one by one to the interest social space. In this way, users' interest relationships in the social network can be presented in the interest social space, facilitating the discovery of meaningful interest social relationships and elimination of meaningless social interactions in the original social data.

D. The Social Selection Mechanism

Relatively speaking, social relationships with high confidence in the interest social space represent meaningful interest social connections in the original social data, while those with low confidence represent meaningless social interactions in the original social data. However, it's important to note a question here: how much is "low"? This paper considers "low" as a relative concept in this context because each user's social relationships are diverse and unique. Some users have very complex social relationships, while others have relatively simple ones. This makes the adoption of a fixed threshold for uniform discarding methods potentially unsuitable for all users, as it may result in some users losing their true interest social friends, thus hindering the effective learning of social features and impacting the final recommendation performance.

Dunbar's Number theory [16] suggests that the true number of close social friends for a person is around 5. The more friends one has, the more likely some of them are distant friends, as human intelligence allows for a limited number of stable social connections. Additionally, in daily life, individuals are genuinely interested in a relatively small circle and can only focus their interactions on meaningful information. Based on these, this paper believes that in the interest space, a user's interest social friends only account for a small portion of it. Therefore, it is decided to retain all relationships for sparsely connected users while reducing more unreliable relationships for densely connected users. This consideration of social quantity in the non-uniform discarding method is more robust than the uniform discarding method with a fixed threshold.

Addressing the challenge of extracting meaningful interest social and meaningless social interactions from original social data in the interest social space, inspired by the Dynamic Neighborhood Sampling Mechanism [17] and Dunbar's Number theory [16], this paper introduces a Social Selection Mechanism. Firstly, it adaptively obtains the number of social connections to be removed for each user based on their social quantity. Then, based on the social confidence scores, it dynamically filters and removes low-confidence social relationships in the interest social space for each user, thereby eliminating meaningless social interactions. The specific method is shown in the following formula:

$$\text{drop\_num} = \begin{cases} 0 & \text{if } n_s < \varepsilon \\ [\log_{10} n_s]^{\alpha} \times \beta & \text{else} \end{cases} \tag{2}$$

Where ε , α , and β are three hyperparameters used to control the degree of social relationship reduction, n_s represents the original number of social relationships for a certain user, and drop_num represents the number of social relationships that the user is advised to remove.

In summary, the Interest Social Mapping and Social Selection Mechanism proposed in this paper effectively map original social data to the interest social space and dynamically filter and remove meaningless social interactions for each user within this space. The Social Selection Mechanism aims to efficiently filter out information that may cause interference or misdirection to users, thereby enabling social aggregation to focus more on valuable and meaningful social interactions. This contributes to faster acquisition of superior user embeddings, thereby enhancing the overall prediction accuracy and speed. In theory, this feature is expected to significantly improve the accuracy and efficiency of recommendation systems.

E. EGNN with Adaptive Residual Attention Mechanism

After filtering out meaningless social relationships in the interest social space using the adaptive residual attention mechanism, relatively reliable interest social relationships are obtained. The next step is to utilize Graph Neural Networks (GNNs) to propagate and aggregate information on user interaction graphs and interest social graphs. In this process, this paper considers two issues:

- For user target nodes, it's necessary to aggregate not only user-item information but also interest social information. However, for item target nodes, merely aggregating item-user information is far from sufficient. This is due to data sparsity, specifically the long-tail effect in user-item interactions, where many items are not widely attended to by users, resulting in these item target nodes being unable to aggregate item-user information. Therefore, it is advisable to introduce auxiliary information to enhance the embedding representation of item target nodes.

- In addition to distinguishing the varying importance of each neighboring node in aggregating towards the target node, the combination of the target node's features with its aggregated neighborhood features significantly influences the representation of the final node features. However, common methods such as vector addition or concatenation have not yielded the best results.

To further enhance recommendation performance, inspired by the Graph Neural Networks proposed by Fan et al. [9]-[10], [17]-[19] this paper designs an Enhanced Graph Neural Network (EGNN) to model the interest social graph and user interaction graph. It consists of an aggregation network and an Adaptive Residual Attention Mechanism. Specifically, in the aggregation network, this paper introduces item category information to improve the embedding quality of item target nodes. That is, item target nodes aggregate item-user information and item category information, while user target nodes aggregate user interaction information and interest social information. An attention mechanism [10] is used to distinguish the importance of each neighboring node. After obtaining the aggregated neighborhood features, the Adaptive Residual Attention Mechanism flexibly integrates the target node features and neighborhood aggregation features based on learned weight parameters for different nodes and situations. This ensures that each user (item) node obtains a satisfactory final embedding representation.

1) Aggregation network: Inspired by existing work [9]-[10], [17], the model employs an embedding layer $\boldsymbol{E} \in R^{d\times(m+n)}$, where each column represents a trainable embedding for each node, with d being a predetermined parameter indicating the embedding size. In the subsequent sections, $\boldsymbol{e}_u$ represents a user embedding, $\boldsymbol{e}_v$ represents an item embedding, $\boldsymbol{e}_r$ denotes a rating embedding, and $\boldsymbol{e}_c$ signifies an embedding of item category. To acquire feature embeddings of the target node, the model needs to first obtain feature embeddings of its neighboring nodes. For the user target node u_i, the model extracts the feature embedding $\boldsymbol{e}_{N_n(u_i)}$ of its neighboring nodes based on the interaction information and interest social information of u_i, as shown in the following formula:

$$\boldsymbol{e}_{N_n(u_i)} = \boldsymbol{W}_2^{\,T} \cdot \sigma(\boldsymbol{W}_1 \cdot [\boldsymbol{e}_{N_n(u_i)} \oplus \boldsymbol{e}_{r(N_n(u_i))}] + \boldsymbol{b}_1) + \boldsymbol{b}_2 \tag{3}$$

Where $N_n(u_i)$ represents any neighboring node of user u_i, and $N_n(u_i) \in I(u_i) \cup S(u_i)$, $I(u_i)$ denotes the item interaction matrix of user u_i, and $S(u_i)$ represents the interest-based social matrix of user u_i. $r(N_n(u_i))$ represents the rating given by user u_i to its neighboring nodes, taking interaction ratings when the neighboring nodes are item nodes, and interest confidence ratings when they are user nodes. $\boldsymbol{e}_{N_n(u_i)}$ and $\boldsymbol{e}_{r(N_n(u_i))}$ respectively denote the embedding vectors of neighboring nodes of user u_i and rating embedding vectors. $\oplus$ signifies vector concatenation, while $\boldsymbol{W}_1 \in \mathbb{R}^{d\times 2d}$ and $\boldsymbol{W}_2$, $\boldsymbol{b}_1$, $\boldsymbol{b}_2 \in \mathbb{R}^{d}$ are trainable weights.

$$\boldsymbol{e}_{N_n(v_j)} = \boldsymbol{W}_4^{\,T} \cdot \sigma(\boldsymbol{W}_3 \cdot [\boldsymbol{e}_{N_n(v_j)} \oplus \boldsymbol{e}_{r(N_n(v_j))}] + \boldsymbol{b}_3) + \boldsymbol{b}_4 \tag{4}$$

For the item target node v_j, it is necessary to first aggregate the item category information to obtain the intrinsic features of the item target node. Then, the embeddings of its neighboring nodes, $\boldsymbol{e}_{N_n(v_j)}$, are obtained by utilizing the interactions and ratings provided by users to v_j. The specific formula is as follows:

$$\hat{\alpha}_{mn} = \boldsymbol{W}_6^{\,T} \cdot \sigma(\boldsymbol{W}_5 \cdot [\boldsymbol{e}_m \oplus \boldsymbol{e}_n] + \boldsymbol{b}_5) + \boldsymbol{b}_6 \tag{5}$$

$$\alpha_{mn} = \frac{\exp(\hat{\alpha}_{mn})}{\sum_{n\in N(m)} \exp(\hat{\alpha}_{mn})} \tag{6}$$

$$\boldsymbol{e}_{N(m)} = \sum_{n\in N(m)} \alpha_{mn} \boldsymbol{e}_n \tag{7}$$

Where $\boldsymbol{e}_m \in R^d$ represents the intrinsic feature embedding of the target node, and $\boldsymbol{e}_n \in R^d$ signifies the feature embeddings of its neighboring nodes. It's worth noting that when the target node is a user node, the embedding of neighborhood nodes is denoted as $\boldsymbol{e}_n = \boldsymbol{e}_{N_n(u_i)}$, whereas when the target node is an item node, the embedding of neighborhood nodes is denoted as $\boldsymbol{e}_n = \boldsymbol{e}_{N_n(v_j)}$. $\sigma(\cdot)$ denotes the ReLU activation function, $N(m)$ denotes the matrix of neighboring nodes of the user (or item) target node, and α_{mn} is used to distinguish the importance of each neighboring node to the target node.

2) The adaptive residual attention mechanism: Through aggregation networks, the aggregated embeddings of the target node's neighborhood have been obtained. However, to achieve satisfactory embeddings of the target node, the model needs to more deeply adaptively fuse the intrinsic features of the target node with its aggregated neighborhood features. In the field of social recommendations, existing methods typically employ various approaches to fuse these two types of features, such as average pooling, addition, concatenation, as well as gating mechanism [18], and even combinations of concatenation and multi-layer perceptrons [19]. However, these methods have certain limitations: either they are difficult to dynamically adjust, or the trainable weight matrices used are insufficient to fully extract the unique information of each user, ultimately resulting in the inability to ensure that each target node obtains a satisfactory final embedding representation.

Inspired by the gating mechanism [18], the residual idea of Resnet [20] and other efficient implementations [21]-[22], this paper proposes an Adaptive Residual Attention Mechanism. It can flexibly adjust the feature fusion method by learning weight parameters for different nodes and situations, thereby better capturing node information. The specific formula is as follows:

$$\boldsymbol{f}_m = \tanh(\boldsymbol{W}_7^G(\boldsymbol{e}_m \oplus \boldsymbol{e}_{N(m)}) + \boldsymbol{b}_7^G) \tag{8}$$

$$\boldsymbol{g}_m = \mathrm{sigmoid}(\boldsymbol{W}_8^G(\boldsymbol{e}_m \oplus \boldsymbol{e}_{N(m)}) + \boldsymbol{b}_8^G) \tag{9}$$

$$\boldsymbol{h}_m = \boldsymbol{g}_m \odot \boldsymbol{f}_m + (1-\boldsymbol{g}_m) \odot \boldsymbol{W}_m(\boldsymbol{e}_m) \tag{10}$$

Where $\boldsymbol{e}_m$ represents the intrinsic feature embedding of the target node, $\boldsymbol{e}_{N(m)}$ represents the aggregated embedding of the neighborhood of the target node, $\boldsymbol{g}_m$ is used to adjust the influence of each feature on the overall feature, $\odot$ represents the Hadamard product, $\tanh(\cdot)$ and $\mathrm{sigmoid}(\cdot)$ represent activation functions, while $\boldsymbol{W}_m \in \mathbb{R}^{d\times d}, \boldsymbol{b}_7^G, \boldsymbol{b}_8^G \in \mathbb{R}^d$ and $\boldsymbol{W}_7^G, \boldsymbol{W}_8^G \in \mathbb{R}^{d\times 2d}$ are trainable parameters. In this way, we can obtain more satisfactory embeddings $\boldsymbol{h}_m$ of user or item target nodes, thus improving the final predictive performance.

F. Scoring Prediction and Training

Through the Enhanced Graph Neural Network (EGNN), we obtained the embedded representations of user target nodes, denoted as $\boldsymbol{h}_{u_i}$, and item target nodes, denoted as $\boldsymbol{h}_{v_j}$. Next, through the prediction layer, we calculate the predicted rating $\hat{r}_{ij}$ of user u_i for item v_j:

$$\hat{r}_{ij} = \mathrm{MLP}(\boldsymbol{h}_{u_i} \oplus \boldsymbol{h}_{v_j}) \tag{11}$$

where $\mathrm{MLP}(\cdot)$ is a Multilayer Perceptron with a three-layer structure.

Since this paper focuses on the score prediction task, it is trained using the loss function commonly used in the score prediction task:

$$Loss = \frac{1}{2|O|}\sum_{i,j\in O}(\hat{r}_{ij} - r_{ij})^2 \tag{12}$$

Where $|O|$ represents the observed number of user-item ratings, r_{ij} denotes the true rating given by user u_i to item v_j.

To facilitate readers in quickly grasping the structure of this paper and replicating the study, we have introduced the pseudocode of the ARAR-ISI model, as shown in Table I.

TABLE I. PSEUDO-CODE OF ARAR-ISI

Input: User-Item rating matrix R, User-User social matrix S
Output: Predict the rating r_{ij} of user u_i for item v_j
1: **While** ARAR-ISI Not Convergence **do:**
2: Initialize embedding vectors for user and item nodes;
3: **For** each user and their social connections in S **do**:
4: Calculate historical interaction item embeddings $\boldsymbol{E}_{u_i v}$ and $\boldsymbol{E}_{u_k v}$ based on R;
5: Calculate social trust score;
6: Sort and map original social relationships based on the score;
7: Obtain the list of interest social connections;
8: Retrieve the original social quantity;
9: Calculate the drop_num of social connections to be removed;
10: Remove meaningless social connections based on the list and drop_num;
11: Obtain the interest social matrix X;
12: Combine X with R to obtain the heterogeneous graph;
13: Aggregate neighborhood embedding for user and item target nodes;
14: Adaptively fuse the intrinsic features of target node with its aggregated neighborhood features to obtain $\boldsymbol{h}_m$;
15: Feed the final embedded representations $\boldsymbol{h}_{u_i}$ and $\boldsymbol{h}_{v_j}$ of u_i and item v_j into the prediction layer to obtain the predicted rating r_{ij};
16: Calculate the loss value based on r_{ij} and $\hat{r}_{ij}$;
17 Optimize the model using gradient descent algorithm;
18: **end while**

G. Complexity Analysis

In this paper, we compare the complexity of the ARAR-ISI model with important components of the baseline model such as GDSRec [11]. In terms of spatial complexity, compared to the baseline models, the ARAR-ISI model introduces an additional 28 categories of item information embedding. Besides this, other trainable parameters are consistent with the baseline models. In contrast, the 28 categories of item information embedding are far fewer than the sum of user embeddings and item embeddings (at least 170,000). Therefore, it is considered that they are consistent in spatial complexity.

Next, the main analysis focuses on the time complexity during the model training process, which mainly includes three parts: Social Selection, GNN embedding propagation and aggregation, and Loss Calculation, with specific time complexities as shown in Table II. Assuming $|E|$ represents the number of edges in the user-item interaction graph, $|E_1|$ represents the number of user-user edges in the interest social graph, d represents the embedding size, ρ represents the average drop ratio of the ARAR-ISI model for the original social relationships, and ρ_1 represents the sampling ratio of the GDSRec model for the original neighbors.

TABLE II. THE COMPARISON OF TIME COMPLEXITY

Component	GDSRec	ARAR-ISI
Social Selection	-	$O(2\|E\|d+(3+\rho)\|E_1\|)$
GNN Operation	$O(\rho_1(2\|E\|+\|E_1\|)Ld)$	$O((2\|E\|+\rho\|E_1\|)Ld)$
Loss Calculation	$O(\|E\|d)$	$O(\|E\|d)$

The Social Selection of the ARAR-ISI model consists of Interest Social Mapping module and Social Selection Mechanism. Therefore, the overall time complexity of social selection is $O(2|E|d+(3+\rho)|E_1|)$. For the L-layer GNN embedding propagation and aggregation, since $(1-\rho)$ proportion of meaningless social connections has been removed, the time complexity reduces from $O((2|E|+|E_1|)Ld)$ to $O((2|E|+\rho|E_1|)Ld)$, where ρ <1. Regarding the Loss Calculation, the time complexity is $O(|E|d)$. Hence, the overall time complexity of the model is $O((2|E|+\rho|E_1|)Ld+3|E|d+(3+\rho)|E_1|)$.

This paper intentionally includes constants in the time complexity shown in Table II to facilitate fine-grained comparisons. From Table II, it can be observed that although the model proposed in this paper requires some time for social selection operations, this time is comparable to the time saved by GNN operations. Therefore, it can be considered that the time complexity of the model proposed in this paper is consistent with that of other GNN-based social recommendation models.

III. EXPERIMENT

This section describes the experimental procedure of the study including dataset description, baseline model description, experimental settings, experimental results and conclusions to validate the effectiveness of the proposed ARAR-ISI model.

A. Datasets

This paper evaluates the effectiveness of the proposed model on two widely used datasets, Ciao and Epinions, both sourced from real social networking platforms, with rating scales ranging from {1, 2, 3, 4, 5}. The Ciao dataset stores user ratings for various products and the connections between users, providing rich social relationships. The Epinions dataset is extensive and contains diverse information relationships, covering user ratings for movies and social information among users. The statistical information for these two datasets is shown in Table III.

TABLE III. STATISTICAL INFORMATION OF THE DATASET

Dataset	Ciao	Epinions
#of Users	7317	18088
#of Items	104975	261649
#of Ratings	283319	764352
#Density(Ratings)	0.0368%	0.0161%
#of Social Connections	111781	355813
#of Density(Social Relations)	0.2087%	0.1087%
#of Item Category	28	27

B. Evaluation Metrics

In order to evaluate the rating prediction performance of the proposed model, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used as the evaluation metrics for the experiments in this paper. The smaller values of MAE and RMSE indicate better prediction accuracy.

C. Baselines

To validate the effectiveness of the ARAR-ISI model proposed in this paper, it is compared with other state-of-the-art recommendation models in the rating prediction task. These include classic CF models (PMF [7], SoRec [8]) and GNN recommendation models (GraphRec [9], ConsisRec [17], GraphRec+ [10], GSFR [23], GDSRec [11], MGMASR [24], REST [13], FIR-REC [25]).

D. Experimental Settings

For two dataset, 80% is used as the training set, 10% as the validation set, and 10% for the final performance comparison test set. Through grid search, the batch size is set to 128, embedding size to 16, learning rate to 0.001, and the model is trained using the Adam optimizer with a weight decay of 0.0001. To address overfitting, early stopping strategy is employed. If the RMSE metric on the validation set does not decrease for five consecutive rounds, training is halted.

E. Experimental Results and Analysis

This paper presents a comprehensive comparison of the experimental results between ARAR-ISI and other recommendation models on the Ciao and Epinions datasets. The experimental results are summarized in Table IV, revealing the following observations:

TABLE IV. COMPARISON OF EXPERIMENTAL RESULTS OF VARIOUS MODELS

Model	Ciao		Epinions	
	MAE	***RMSE***	***MAE***	***RMSE***
PMF	0.9021	1.1238	0.9952	1.2128
SoRec	0.8410	1.0652	0.8961	1.1437
GraphRec	0.7387	0.9794	0.8168	1.0631
ConsisRec	0.7394	0.9722	0.8046	1.0495
GSFR	0.7297	0.9718	0.8018	1.0501
GDSRec	0.7323	0.9740	0.8047	1.0566
MGMASR	0.7365	0.9816	0.8257	1.0640
REST	0.7320	<u>0.9635</u>	<u>0.8013</u>	<u>1.0413</u>
FIR-REC	<u>0.7234</u>	0.9658	0.8020	1.0512
ARAR-ISI	**0.7059**	**0.9463**	**0.7835**	**1.0307**
Improvement	2.42%	1.79%	2.22%	1.02%

From the experimental results, it is evident that SoRec outperforms PMF, indicating that user trust information in social networks can effectively enhance recommendation performance. In contrast, graph neural network-based models such as GraphRec, ConsisRec, GraphRec+, GSFR, GDSRec, MGMASR, REST, and FIR-REC significantly outperform previous models. This demonstrates that GNNs have a strong potential for representation learning on graph-structured data.

The evaluation metrics of the proposed ARAR-ISI model on the two datasets significantly outperform all baseline models. Compared to the state-of-the-art performance of current mainstream models, on the Ciao dataset, the MAE and RMSE metrics respectively improved by 2.42% and 1.79%, while on the Epinions dataset, they improved by 2.22% and 1.02%. This superiority can be attributed to the effectiveness of the proposed model. The Interest Social Mapping Module proposed in this paper is able to map the original social data to the interest social space according to the user's interests, and deeply understand the user's interest relationships in the social network. Combined with the Social Selection Mechanism, it can dynamically filter and remove meaningless social interactions in the interest social space, effectively filter social information that may interfere with or mislead the user, and retain only meaningful interest social relationships, which enables social aggregation to focus on more valuable and meaningful social interactions, thus improving the quality and efficiency of the recommendation system. In addition, the EGNN based on adaptive residual attention mechanism can obtain more accurate embedding of user and item target nodes, which further improves the accuracy of the recommender system.

F. Ablation Study

The ablation experiments were designed to investigate the impact of each key component of the ARAR-ISI model on the final recommended performance.

1) Effect of interest social mapping module: To verify the effectiveness of the proposed Interest Social Mapping Module (ISMM), this study designed three variant models, as shown in Table V. Specifically, the ARARISI-I variant model was designed, representing the model without the ISMM. This means that the original social data is not modeled for confidence and ordered arrangement, but instead, the confidence scores of all users' social relationships in the original social data are set to a score of 1, and the social relationships are randomly sorted. Since ISMM mainly maps based on the confidence scores of social relationships, to verify the effectiveness of the Transformer-based social confidence modeling method in ISMM, two variant models, ARARISI-P and ARARISI-M, were designed. Here, ARARISI-P represents its replacement with a pooling-based item merge confidence modeling method, while ARARISI-M represents its replacement with an MLP-based social user node representation modeling method. Specific results are shown in Fig. 2.

TABLE V. VARIANT DESCRIPTION OF INTEREST SOCIAL MAPPING MODULE

Variant Models	Variant Description
ARARISI-I	ARARISI Removes ISMM
ARARISI-P	ISMM replaced with Pooling-based item merge confidence modeling method
ARARISI-M	ISMM replaced with MLP-based social user node representation modeling method

From the results in Fig. 2, it can be seen that ARAR-ISI outperforms the ARARISI-I variant in terms of metrics on both datasets, indicating that the proposed Interest Social Mapping Module is effective, which is due to the fact that the Interest Social Mapping Module maps the original social data from the social space to the interest social space based on the user's interests, enabling the model to remove the social noise based on the confidence scores. In addition to this, it can be seen that the metrics of ARAR-ISI on both datasets are better than the two variants of the model, ARARISI-P and ARARISI-M, which indicates that the Transformer-based social confidence modeling approach is more effective than the other two variants of the approach due to the fact that the user-item interaction data characterizes the user's interests to some degree, and that the Transformer module is able to model the similarity between historical sequences of user interactions well.

2) Effect of social selection mechanism: To verify the effectiveness of the proposed Social Selection Mechanism (SSM), this study designed two variant models, as shown in Table VI. Specifically, the ARARISI-S variant model was designed to represent the model without the Social Selection Mechanism, meaning that social data information was not filtered out. Additionally, the ARARISI-G variant model was designed to represent the adoption of the traditional fixed threshold uniform dropout method to replace the Social Selection Mechanism proposed in this paper. It is worth noting that the fixed thresholds in the Ciao and Epinions datasets were set to 4 and 10, respectively, and these thresholds are consistent with the average number of social interactions removed in the Social Selection Mechanism. Specific results are shown in Fig. 3.

TABLE VI. VARIANT DESCRIPTION OF SOCIAL MAPPING MODULE

Variant Models	Variant Description
ARARISI-S	ARARISI Removes SSM
ARARISI-G	SSM replaced with traditional fixed threshold uniform dropout method

From Fig. 3, it can be observed that ARAR-ISI outperforms the two major variant models on both datasets, indicating that the proposed Social Selection Mechanism is not only effective but also superior to the traditional uniform dropout method. This is because the Social Selection Mechanism can dynamically remove unreliable social connections for each user in the interest social space, retaining only interest social users to improve accuracy. Furthermore, considering the diversity of social connections for each user, the idea of sparse connection users retaining all relationships and dense connection users cutting more unreliable relationships is adopted, which is more robust than uniform dropout without considering the quantity of social connections.

3) Effect of adaptive residual attention mechanism: To validate the effectiveness of the proposed Adaptive Residual Attention Mechanism (ARAM) in E-GNN, this paper designs three variant models, as shown in Table VII. Specifically, ARARISI-cat represents its replacement with vector concatenation, ARARISI-gate represents its replacement with gate mechanism, and ARARISI-mlp represents replacement with combination of concatenation and multi-layer perceptron. Specific results are illustrated in Fig. 4.

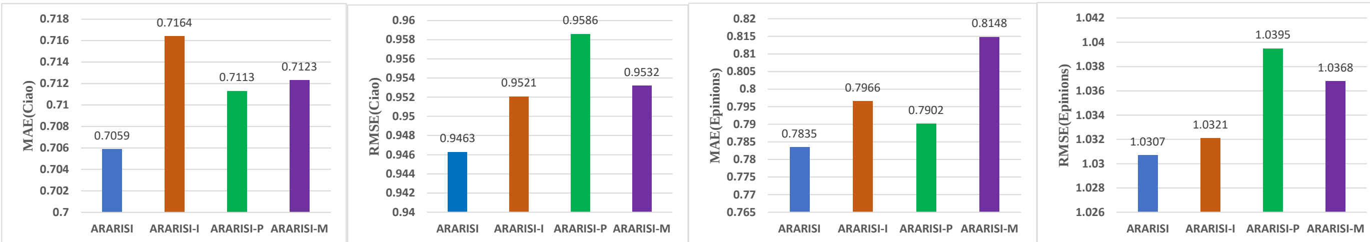

Fig. 2. Effectiveness analysis of interest social mapping module

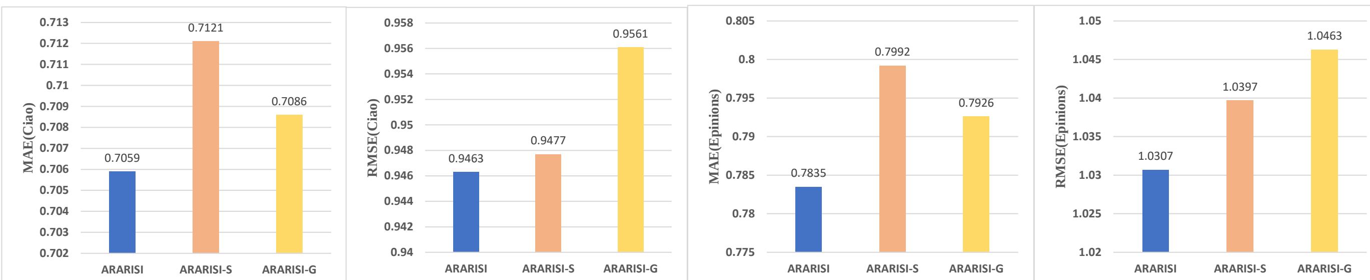

Fig. 3. Effectiveness analysis of social selection mechanism

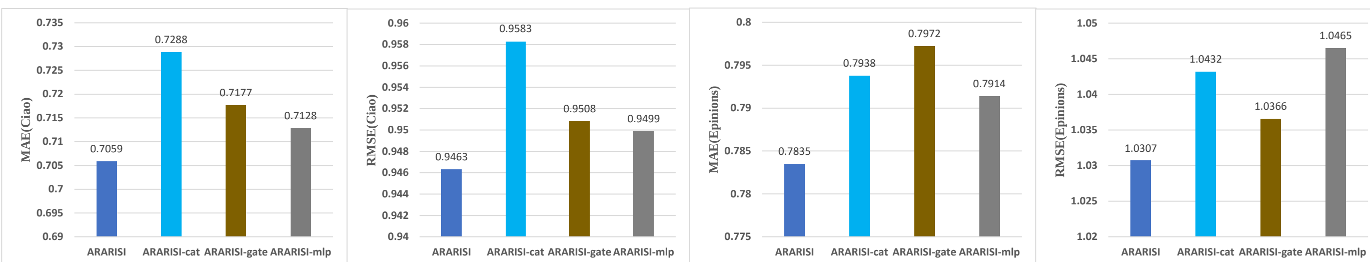

Fig. 4. Effectiveness analysis of adaptive residual attention mechanism

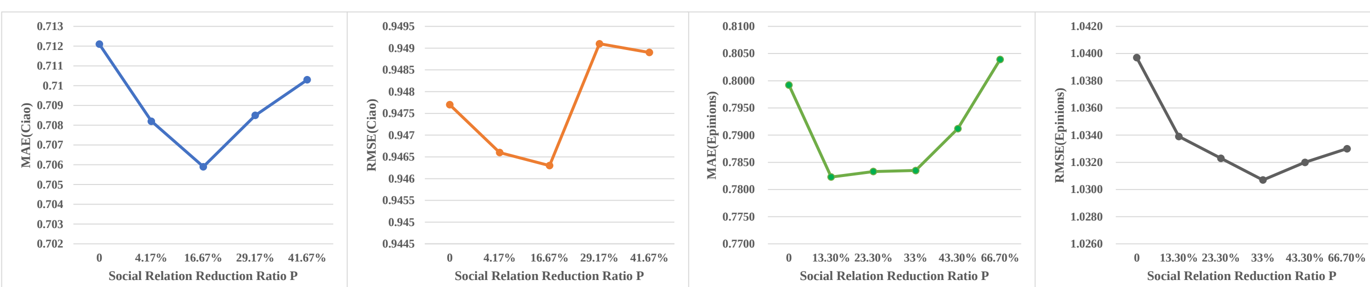

Fig. 5. The Impact of social relationship reduction ratio on evaluation indicators

TABLE VII. VARIANT DESCRIPTION OF ADAPTIVE RESIDUAL ATTENTION MECHANISM

Variant Models	Variant Description
ARARISI-cat	ARAM replaced with vector concatenation
ARARISI-gate	ARAM replaced with gating mechanism
ARARISI-mlp	ARAM replaced with combination of concatenation and multi-layer perceptron

From Fig. 4, it is evident that the performance metrics of ARAR-ISI outperform those of the three major variant models across both datasets. This indicates that the proposed adaptive residual attention mechanism can better integrate the features of target nodes with their aggregated neighborhood features, thereby enhancing the representation capability and robustness of the target node embedding vectors. Consequently, each target node can obtain a satisfactory final embedding representation, thus improving the ultimate predictive performance.

G. *Effect of Social Relationship Reduction Ratio*

The Social Selection Mechanism is a method of non-uniform discard that considers the quantity of user social connections, where three hyperparameters, ε, α, and β, are used to control the degree of social relationship reduction. The social relationship reduction ratio refers to the ratio of the average number of social connections removed per user to the average original number of social connections per user. To observe the influence of the degree of social relationship reduction on the final predictive performance of the model, this paper conducted related experiments, and the results are shown in Fig. 5 and 6.

Fig. 5 illustrates the impact of the social relationship reduction ratio (denoted as p) on the evaluation metrics. As shown in Fig. 5, on both the Ciao and Epinions datasets, the optimal predictive performance is achieved when the social relationship reduction ratio is around 16% and 33%, respectively. Taking the Ciao dataset as an example, as the reduction ratio p increases from 0 to 16%, an improvement in the metrics is observed, attributed to the removal of meaningless social connections in the Ciao dataset. However, when the reduction ratio p increases from 16% to 29%, a significant deterioration in the metrics is evident. This is because excessive reduction in social relationships removes reliable interest-based connections, leading to the failure to aggregate some meaningful social interactions, thus decreasing the model's accuracy.

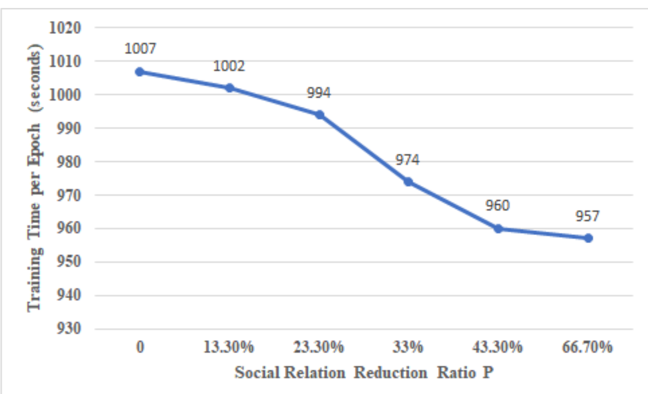

Fig. 6. Effect of social relationship reduction ratio on computational efficiency

Fig. 6 illustrates the relationship between the time spent on one training cycle and the reduction ratio p on the Epinions dataset. As shown in Fig. 6, reducing social connections by 33% on the Epinions dataset results in a decrease in training time of 3.28% per cycle. Moreover, as the reduction ratio p of social connections increases, the time spent on model training decreases, and the computational efficiency of the model increases. This is because the model can generate a more concise social graph based on user interests, retaining only meaningful social connections.

H. Effect of Embedding Size

In order to observe the effect of the embedding size of users and items on the prediction performance of the model, this paper designs relevant experiments, and Fig. 7 demonstrates the performance comparison of the ARAR-ISI model of this paper with the change of embedding size on the Ciao and Epinions datasets.

From the experimental results in Fig. 7, it can be seen that the model performance first increases and then decreases as the embedding size increases. Increasing the embedding size from 8 to 16 significantly improves the performance. However, when the embedding size is increased from 16 to 32, the performance starts to decrease and further decreases when it is increased to 256. It can be seen that the model performs best on the Ciao and Epinions datasets when the embedding size is 16. This is due to the fact that smaller embedding sizes are not sufficient to represent the node information, while larger embedding sizes increase the complexity of the model, resulting in a tendency to overfitting problems. Therefore, we need to find a suitable embed size to balance the performance and the complexity as much as possible.

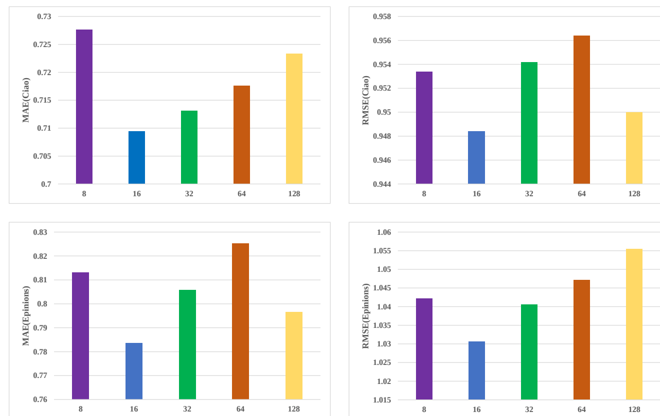

Fig. 7. Effect of embedding size on ciao and Epinions datasets

IV. Conclusions and Future Work

This study proposes an Adaptive Residual Attention-based Recommendation Model with Interest Social Influence (ARAR-ISI). Firstly, the Interest Social Mapping Module designed in this paper can map the original social data from the social space to the interest social space based on interest confidence modeling, thereby deepening the understanding of interest relationships among social users in the social network. Combined with the Social Selection Mechanism, it effectively filters out meaningless social interactions in the interest social space, retaining only meaningful interest social relationships. This resolves the issue of a large amount of redundant and noisy social relationships in the original social data. Additionally, the adaptive residual attention mechanism designed in this paper can flexibly adjust the feature fusion method through learned weight parameters, thereby obtaining more effective node information to improve recommendation accuracy. Compared to traditional fusion methods, this mechanism has more advantages and can further enhance the representation ability of node embedding vectors. Experimental results on the Ciao and Epinions datasets demonstrate the effectiveness of the proposed ARAR-ISI model. It can reliably reduce meaningless social relationships, retain only meaningful interest-social relationships, and generate more concise interest social networks. This feature not only contributes to improving the computational efficiency of recommendation algorithms but also enhances recommendation accuracy, thus having significant practical value in recommendation systems. Considering that ratings and social information in real life are dynamic, future work will delve into dynamic graph neural networks to enhance the practicality of recommendation systems.

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