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Personalized Recommendation Model for Cross-border E-commerce Incorporating Social Network Contexts

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Abstract. Current cross-border e-commerce platforms mainly pay attention to mine potential needs and preferences from users' behavioral data, but there is no differentiation study of user interest representation for the diversity of commodity categories in social networks, which affects user satisfaction. Intending to the above issues, this article designs a cross-border e-commerce personalized recommendation model that incorporates the social network context. First, the matrix factor decomposition technique is enhanced, and the regularization parameter is optimized to adjust the distribution of users' ratings for various product categories in the social network. Second, the attention mechanism of Graph Attention Network (GAN) is utilized to aggregate the feature information of users and products to mine potential implicit social relationships, and the cosine similarity between users is calculated to obtain the top TOP-N implicit friendships. Then, the aggregated information of users is fed into the feed-forward neural network to cluster similar user groups, find the product categories that target users may be interested in, and form a diversified recommendation list. Finally, the two recommendation lists are integrated into matrix factorization for score prediction to meet the diversity and accuracy of product recommendation outcome. The experimental outcome indicate that compared with the comparison model, the suggested model has higher NDCG, HitRate, Recall, Topic coverage and Diversity, which proves the efficiency of the designed model.
Keywords: Cross-border e-commerce; Personalized recommendation; Matrix factor decomposition; Social network; Graph attention network

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1. **Introduction.** As the cross-border e-commerce platforms and Internet technologies deeply integrating, the users on the network show exponential growth, the variety of commodities is more diverse, and it is more and more tough for users to find the commodities they are interested in from them [1, 2]. It has been found that understanding users' preferences through social networks can effectively alleviate the above problems. Behavioral

data such as content and comments shared by users on social media can reveal hidden shopping needs and potential preferences.

Many scholars have directly integrated explicit social relationships into cross-border e-commerce recommender systems, but the explicit relationships contain a lot of noise, which leads to unsatisfactory recommendation effects [3, 4]. Explicit social relations refers to the intimate relationship links clearly established between users in social networks, such as friends and concerns. This explicit social relationship can directly reflect the user's social circle and potential interest preferences. In addition, the recommendation information and product categories received by users are getting narrower and narrower [5], which may trigger a series of problems such as too single recommendation results, decreased user satisfaction, and lack of platform stickiness [6, 7]. In cross-border e-commerce, how to identify the real purchase intention of users and mine their preferences based on the characteristics of their behavioral information to provide diversified recommendation services for users is of strong significance for improving the market competitiveness of cross-border e-commerce enterprises.

1.1. **Related work.** Loeb and Terry [8] started to try to use the attributes or features of cross-border goods to recommend similar goods to users. Ji [9] in modeling users' interest preferences Considering that users have different tendencies to different products and calculating the similarity between users or items, and then determining whether the user is interested in goods he/she has not been exposed to before. In recent years, various model-based Matrix Factorization (MF) techniques have been developed, i.e., Bayesian Networks [10], Neural Networks [11], Support Vector Machines [12], and Fuzzy-based systems [13]. However, matrix decomposition models are considered the most advanced recommendation algorithm models currently available due to their advantages in accuracy and scalability, but when rating data is lacking, matrix decomposition often leads to poor recommendation quality [14]. García-Sánchez et al. [15] used additional content data, such as merchandise information, to address the problem of ratings sparsity. Li et al. [16] proposed an approach that considered the introduction of user implicit feedback behavioral data and related bias terms to mitigate interaction data sparsity. Yang [17] extended MF by identifying the top-N semantic friends of each user and adding nearest-neighbor information to the matrix decomposition process to improve recommendation accuracy.

With the growth of social platforms, cross-border e-commerce platforms must provide more personalized and diversified recommendation services in order to better meet users' needs. Ma et al. [18] utilized users' explicit social relationships to improve the recommendation effect of cross-border e-commerce products. Di Noia et al. [19] used the attributes of cross-border goods to calculate the diversity, and adopted decision tree prediction to get the final recommendation results, which improved the diversity of recommendation, but the accuracy was not high. Guan et al. [20] applied greedy reordering strategy in the traditional collaborative over-recommendation algorithm, and outputted cross-border e-commerce recommendation results through a deep learning network, but the recommended goods were of a single type. Recently, Tian et al. [21] utilized node embedding on graph neural network to mine the potential social relationship of users, and then utilized potential friends for cross-border goods recommendation, which achieved good recommendation accuracy, but the user satisfaction was not high. Chen et al. [22] designed an objective function as the value of the difference between predicted results and the original sorting results by learning the user factor and product factor. Minimize the objective function value to the final result.

1.2. **Contribution.** Personalized recommendation technology has become the main technology of recommendation systems for cross-border e-commerce platforms, which can provide users with products, services and activities of interest. Existing research mainly focuses on recommendation accuracy, resulting in poor diversity of recommended results. Therefore, it is a great challenge to balance the accuracy and diversity of recommendations. This paper designs a personalized recommendation model for cross-border e-commerce that incorporates the social network context.

First, the user-commodity rating matrix is decomposed into the product of two low-rank matrices, the potential feature vectors of users and commodities are learned, and the personalized diversity regular term is introduced to adjust the differences in user ratings for different categories of commodities. Second, the graph attention network is utilized to aggregate the feature information of users and commodities in the social network, and the cosine similarity between users is calculated to obtain the top TOP-N implicit friendships. Then, the aggregated information of users is fed into the feed-forward neural network to cluster similar user groups and form a diverse recommendation list. At last, the two recommendation lists are integrated into the matrix factorization for score prediction, in order to meet the diversity and accuracy of product recommendation results. Experimental results show that, compared with the comparison model, the performance of NC@20, HR@20, Rec@20, CC@20 and ILD@20 on the experimental data set is improved by 10.99%, 9.16%, 5.78%, 5.06% and 6.17%, which proves the efficiency of the suggested model.

2. Theoretical analysis.

2.1. **Basic concepts of social networks.** Social network is a product of people's online socialization, and the network structure is usually represented by a graph [23], which consists of nodes and edges, where nodes can refer to people, movies, books, etc. The connected edges reflect the relationships between nodes in the social network. Therefore, a social network can be abstracted as $G = (W, E)$, where G is a binary consisting of sets W and E, where $W = \{w_1, w_2, \ldots, w_n\}$ represents the nonempty set of points, $E = \{e_1, e_2, \ldots, e_n\}$ is an abstract set of relational edges, and the maximum total number of edges is $n(n-1)/2$. Figure 1 illustrates a simple social network.

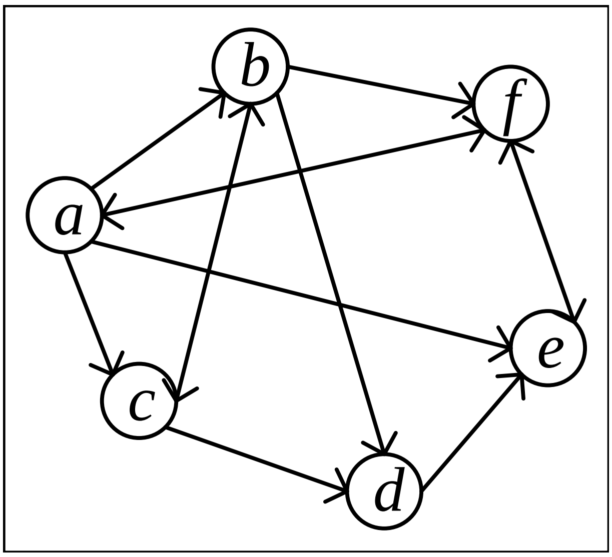

Figure 1. The structure of social network

In graph theory, the degree of node w_i is represented by c_i, which refers to the total number of edges connected to w_i. The computation equation is as bellow. In a social network, the greater the degree of the user, the greater its importance, the wider the scope of social interaction, the greater its influence.

$$c_i = \sum_i e_{i,j} \tag{1}$$

The clustering coefficient is used to reflect the closeness between neighboring nodes. Let e_{ij} denote node w_i pointing to node w_j. The neighbor node of node w_i is defined as $N_i = \{w_i : e_{ij} \in E\}$ and the number of neighbors is l_i. The maximum value of the possible edges of the neighbor nodes of w_i is $l_i(l_i - 1)/2$. The clustering coefficient $D(i)$ of vertex w_i in the graph is defined as below.

$$D(i) = \frac{2|\{\, e_{jl} : w_j, w_l \in N_i \wedge e_{jl} \in E\}|}{l_i(l_i - 1)} \tag{2}$$

2.2. **Matrix factorization techniques.** Matrix factorization technique [24] is to decompose the original large matrix into a number of small matrices multiplied by two, as indicated in Figure 2. It is the most common model-based collaborative filtering technique, which maps the information of users and commodities into a linkage and latent feature space of dimension f. The interaction between the user and the product is represented by the product of two potential feature vectors. These potential features can reflect some characteristic information of the user and the product, which is usually uninterpretable.

project

user

	v_1	v_2	v_3
u_1		5	
u_2	4		3
u_3	2	1	

user rating $R^{m\times n}$

=

	k_1	k_2
u_1	1.2	0.4
u_2	0.5	0.6
u_3	0.7	0.8

user matrix $U^{m\times k}$

×

	v_1	v_2	v_3
k_1	0.4	0.5	0.6
k_2	0.7	0.5	0.9

project matrix $V^{k\times n}$

Figure 2. Example diagram of matrix factorization

Specifically, each item i is associated with an f-dimensional potential feature vector $q_i \in R^f$, and each user u is associated with an f-dimensional potential feature vector $P_u \in R^f$.

The magnitude of the latitude value of the latent feature vector indicates the extent to which the item or user matches the corresponding latent feature. The dot product $P_u^T q_i$ describes the interaction between the user and the item, i.e., the user's entire interest in the item.

The matrix decomposition decomposes the user rating matrix $R^{m\times n}$ into a user matrix $U^{m\times l}$ and an item matrix $V^{l\times n}$, where m is the number of users in the matrix, n is the number of items in the matrix, and l is the number of implicit eigenvectors. Calculate the user ratings of the items as bellow.

$$P(u,i) = r_{ui} = P_u^T x_i = \sum_{l=1}^{L} P_u^l x_i^l \tag{3}$$

Its corresponding objective optimization function is as follows.

$$L = \sum_{u=1}^{m} \sum_{i=1}^{n} \left(r_{u,i} - \hat{r}_{u,i}\right) + \mu\left(\|P\|^2 + \|X\|^2\right) \tag{4}$$

3. **Matrix factorization technique for incorporating commodity diversity in social networks.** In this paper, we suggest a matrix decomposition model that takes into account the differences in users' personalized interests and the diversity regularity term of social network products. By introducing product category difference scores and user interest diversity scores to the traditional Funk-SVD model, we construct a diversity regularization factor to regulate the distribution of users' ratings for different products, so as to enhance the diversity of recommendations while guaranteeing the accuracy of recommendations.

(1) Base matrix factorization part. By decomposing the user-product rating matrix into the product of two low-rank matrices, the potential characteristic vectors of users and products are learned to achieve personalized recommendation. In this article, Funk-SVD [25] is utilized to decompose the rating interaction matrix, and the objective function is indicated in Equation (5).

$$L(P,Q) = \sum_{u \in U} \sum_{j \in I} \left(r_{uj} - \langle p_u, q_j \rangle\right)^2 + \mu_r\left(\|P\|^2 + \|Q\|^2\right) \tag{5}$$

where P denotes the matrix of user hidden vectors, Q denotes the matrix of item hidden vectors, r_{uj} denotes the rating of item j by user u, and μ_r is used to control overfitting. Funk-SVD learns a potential vector p_u for each user as well as a potential vector q_j for each item.

(2) Diversity regularization of social network commodities. In this paper, the distance matrix $D_{n^I \times n^I}$ between any two commodities is calculated by the different categories of social network commodities, and the element $d_{i,j}$ $(i, j \in I)$ in the matrix represents the Euclidean distance between commodity i and commodity j, as bellow.

$$d_{i,j(i \neq j)} = \|W_i^I - W_j^I\| \tag{6}$$

where I represents the set of commodities, $W^I_{I \times m_{sd}}$ is the commodity representation matrix obtained from the semantic labeling of commodity categories, and m_{sd} is the number of semantic topics in the commodity domain of the social network.

For the goal of realizing the diversity of goods in the social network, this paper introduces an indicator of the intensity of the demand for diversity by user u. Firstly, the semantic vectors of the items that are highly rated by user u in the set of goods are summed up to obtain a semantic preference vector L_u that represents the semantic preference of user u, as indicated below.

$$L_u = \sum W^I_{\xi(u)} \tag{7}$$

where $\xi(u)$ is the favorable item of user u.

Then, the idea of information entropy [26] is used to measure the degree of users' demand for diversity of goods in the social network $G \in R^{|U|}$. U is the number of users.

The vector G_u can represent the intensity of diversity demand of user u, as indicated bellow.

$$G_u = \Big(-\sum_{i=1}^{n_{sd}} \frac{L_{u_i}}{\sum_i L_{u_i}} \cdot \lg\big(\tfrac{L_{u_i}}{\sum_i L_{u_i}}\big)\Big) \tag{8}$$

where L_{u_i} is the i-th element of vector L_u. The larger G_u is, the more dispersed the distribution of highly rated items in the product category is, indicating that user u has a greater need for thematic diversity.

At last, this article introduces a personalized diversity regular term that adjusts the difference in ratings of different categories of goods in the social network goods domain. Specifically, if the thematic distance between two items is large (e.g., $d_{i,j}$ is large), and the diversity demand G_u of user u is large, the proposed regular term can reduce the difference between the ratings of u on items i and j by constraining the hidden vectors of user u and the related items to achieve the personalized adjusting of the intensity of diversity recommendation as indicated in Equation (9).

$$\min \mu_d \sum_u F_u \sum_{j_1,j_2 \in I} d(j_1, j_2)\big(p_u^T(q_{j_1} - q_{j_2})\big)^2 \tag{9}$$

where $\mu_d > 0$ is the adaptive diversity regularity parameter, which controls the output strength of the personalized diversity regularity term, the larger its value, the stronger the overall demand for diversity of recommended topics.

4. A personalized recommendation model for cross-border e-commerce incorporating social network contexts.

4.1. Social network user information aggregation. On the ground of the above matrix factorization technique incorporating diversity, this article designs a cross-border e-commerce personalized recommendation model incorporating social network context. Firstly, the multi-channel attention mechanism of GAN is utilized to aggregate the feature information of users and commodities in the social network, mine the potential implicit social relationships, obtain more comprehensive user characteristics, and calculate the cosine similarity between users to get the top TOP-N implicit friendships. Secondly, the aggregated information of users is fed into the feed-forward neural network to cluster similar user groups, and the similar user groups are used to find the product categories that the target users may be interested in to form a diversified recommendation list. Finally, the two recommendation lists are integrated into matrix factorization for personalized cross-border product recommendation to meet the diversity and accuracy of product recommendation results. The whole model is implied in Figure 3.

User information aggregation in social networks mainly aggregates information from user channel and commodity channel. Firstly, for the user channel, the user's node features $\{\vec{g}_{u1}, \vec{g}_{u2}, \dots, \vec{g}_{uM}\}$ are aggregated and passed to the input by feed-forward neural network [26], where $g_i \in \mathbb{R}^C$, M is the number of users and C_u is the number of features for each user. To obtain a rich feature representation, the input features are changed to include more user-level information features, and a shared linear transformation is applied to each user, parameterized by a weight matrix $V \in \mathbb{R}^{C' \times C}$. The input features are then used for the user's nodes, and the user's node features are then used for the user's nodes. Then, the attention coefficient is computed at the node using the shared attention mechanism $\beta : \mathbb{R}^{C'} \times \mathbb{R}^{C'} \to \mathbb{R}$.

$$h_{ij} = \beta\big(V\vec{g}_{ui}, V\vec{g}_{uj}\big) \tag{10}$$

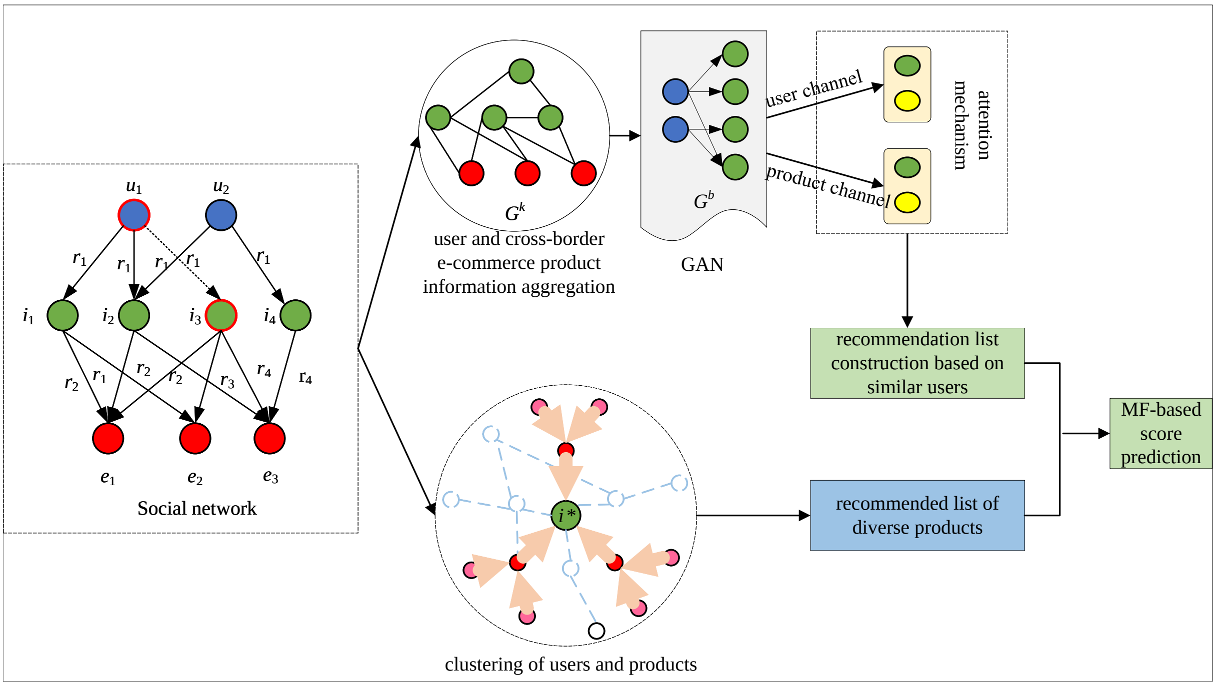

Figure 3. The whole structure of the purposed model

where h_{ij} denotes the importance of user j for user i. These coefficients need to be computed only for nodes that are actually connected. To ensure that only the attention coefficients of close neighbors are computed, masked attention is used as follows.

$$\beta_{ij} = \text{softmax}_j(h_{ij}) = \frac{\exp(h_{ij})}{\sum_{l \in M_i} \exp(h_{il})} \tag{11}$$

By computing a linear combination of the attention coefficients and the corresponding node features and applying the nonlinearities, the output of the attention layer can be achieved as follows.

$$\vec{g}_i' = \delta\Big(\sum_{j \in M_i} \beta_{ij} V \vec{g}_{uj}\Big) \tag{12}$$

where δ is the ReLU activation function.

The use of a single attention is unstable and sometimes results in the loss of valuable information. In order to stabilize the learning process and increase the model's representational power, multiple attention was used, employing L independent attention heads and linking the results.

$$\vec{g}_i' = \prod_{l=1}^{L} \delta\Big(\sum_{j \in N_i} \beta_{ij}^l V^l \vec{g}_{uj}\Big) \tag{13}$$

Next, information collection is performed from the commodity channel. Suppose the input of commodity features is $\{\vec{g}_{i1}, \vec{g}_{i2}, \dots, \vec{g}_{iN}\}$, where N is the total number of commodities and C_i is the feature of each commodity. The output of the commodity aggregator is the feature set $\{\vec{g}_{i1}', \vec{g}_{i2}', \dots, \vec{g}_{iN}'\}$, where each node has the features of C_i'.

$$\vec{g}_i' = \text{ReLu}\big(V(\vec{g}_u' \,\Box\, \vec{g}_i')\big) \tag{14}$$

4.2. **Diversified cross-border e-commerce product list construction.** In terms of the above aggregated user information, for the goal of enhancing user satisfaction, this article will construct a recommendation list based on similar users and a product recommendation list relied on product diversity.

(1) Recommendation list construction relied on similar users. The aggregated feature information of the users is fed into the feed-forward network, which is used to predict whether the two users are in the same trust network or not. F_u is the final aggregated feature of the users, m and n represent different users, and the prediction is made using the following equation.

$$R = \mathrm{ReLu}\big(V(F_{um} \Box F_{un})\big) \tag{15}$$

Two users in the same social network are considered as each other's implicit friends and the remaining string similarity is calculated. And find the most similar Top-N implicit friends for each user.

(2) The user vector is represented as an m-dimensional vector $U = [u_1, u_2, \ldots, u_m]$. Assuming that the total number of input product categories is m and the competitive layer users are categorized into N categories, the inner product vector a, of the input vector U and weights V is indicated below.

$$a = [a_1, a_2, \ldots, a_N] = VU = [v_1^T u,\ v_2^T u,\ \ldots,\ v_N^T u]^T \tag{16}$$

where $v_i^T u$ is the inner product of the connection weights between the user vectors and the item i. The user interests obtained from the clustering of a winning neuron have similar coarse-grained category interests. Users clustered by a winning neuron have similar coarse-grained category interests. The inner product vector a is computed using the winning equation.

$$A = \mathrm{compet}(a) = \begin{cases} 1, & i = i^* \\ 0, & i \neq i^* \end{cases} \tag{17}$$

where $a_{i*} \geq a_i$, $\forall i$, $i^* \leq i$, $\forall a_i = a_{i*}$. The neuron is able to indicate the features of the input vector, and only one neuron wins at the end, similarly the result is $A = [0, 0, \ldots, 1, 0, \ldots, 0]$. The neuron is labeled as the winning neuron.

Then, centered on i^*, the number of iterations is determined as the weight adjustment for y, as bellow.

$$V_i(y) = V_i(y-1) + \tau(y)\big(U_j(y) - V_i(y-1)\big) \tag{18}$$

where $V_i(y)$ and $V_i(y-1)$ denote the weight vectors of neuron i at iteration numbers y and $y-1$, respectively, and $\tau(y)$ denotes the learning rate at moment y, i.e., $\tau(y) = \tau(0) \times (1 - y/T)$, T is the total number of iterations.

Finally, all user vectors are fed into the feed-forward neural network to find the set $S_{1,2,\ldots,x} = S_1 \cup S_2 \cup \cdots \cup S_x$ of products that may be of interest to the target user.

To recommend a product to user x, sort the product category $O_{1,2,\ldots,x} = O_1 \cup O_2 \cup \cdots \cup O_x$ in set $S_{1,2,\ldots,x}$ with its total hotness r_s, and then sort the hotness of the products in the cross-border e-commerce product category to obtain a diversified product recommendation set.

4.3. **Score prediction based on matrix factorization technique.** The Top-N implicit friends that are most similar to the user and the diverse set of product recommendations O are added into the MF as social regularization terms to constrain the objective function of the MF. The Matrix Factorization is used to predict the scores of users and cross-border e-commerce products, and then personalized recommendations are made for users relied on the predicted scores.

First, a scoring matrix $R^{n\times m}$ composed of users and goods is given, where n represents the number of all users and m represents the number of all items. It is decomposed into the form of the multiplication of the user matrix U of $n \times l$ and the commodity matrix V of $l \times m$, i.e. $R = U^T V$, where l is the dimension of the implicit vector. The inner product of the user's potential vector u_i and the weight vector v_j of the item is used to predict the user's rating of the missing item, i.e. $\hat{r} = u_i^T v_j$. The objective function can be defined as bellow.

$$\begin{aligned} L = &\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{m} J_{i,j}^R\left(r_{ij} - U_i^T V_j\right)^2 + \frac{\mu_U}{2}\sum_{i=1}^{n} U_i^T U_i + \frac{\mu_O}{2}\sum_{j=1}^{m} V_j^T V_j \\ &+ \frac{\mu_S}{2}\sum_{i=1}^{n}\sum_{j=1}^{m} sim(i,q)sim(j,O)(U_i - U_{fr})^T(V_i - V_{fr}) \end{aligned} \tag{19}$$

where $J_{i,j}^R$ is a marker function, when the value is 1, it means that user i has rated commodity j, and when the value is 0, it means that user i has not rated commodity j. μ_U and μ_O are the regularization parameters of the set of implicit friends and diversified commodities, respectively, which are used to prevent the overfitting of ratings. μ_S controls the degree of social constraints. q denotes the implicit friends of user i. In addition, to distinguish all Top-N implicit friends, $\mathrm{sim}(i,q)$ and $\mathrm{sim}(j,O)$ are added in this article to compute the cosine similarity by embedding user j, implicit friend q, user j, and commodity category O into the objective function. Finally, the local minimum is obtained using gradient descent method as bellow.

$$\frac{\partial L}{\partial U_i} = \sum_{j=1}^{m} J_{i,j}^R\left(r_{ij} - U_i^T V_j\right)V_j + \mu_U U_i + \mu_S\sum_{i=1}^{n}(U_i - U_{fr}) + \mu_S\sum_{j=1}^{m}(U_j - U_{fr}) \tag{20}$$

$$\frac{\partial L}{\partial V_j} = \sum_{i=1}^{n} J_{i,j}^R\left(r_{ij} - U_i^T V_j\right)U_i + \mu_O V_j \tag{21}$$

5. **Performance testing and analysis.**

5.1. **Comparison of classification performance.** For the purpose of validating the performance of a cross-border e-commerce personalized recommendation model that incorporates a social network context, this article obtains 8,152 e-commerce platform users (overlapping users of the e-commerce platform) logged in with social accounts from a large cross-border e-commerce platform, as well as their unique ID numbers on the social network context, this article obtains 8,152 e-commerce platform users (overlapping users of the e-commerce platform) logged in with social accounts from a large cross-border e-commerce platform, as well as their unique ID numbers on the social networking site and their e-commerce data on the e-commerce platform over a period of time. The e-commerce data spans from January 2019 to June 2022 and contains a total of 17.14 million purchase records for 6,558 items from these 8,152 users. Table 1 gives the statistics of the experimental dataset.

In this article, 70% for training, 20% for validation and 10% for testing are selected from the above dataset. To validate the performance of the method designed in this paper, comparative experiments are conducted, for the convenience of analysis, the model in this article is denoted as CBSN, in literature [9] as RLDB, in literature [19] as AMAD, in

Table 1. Statistics of the experimental dataset

Item	Consumer	Commodity	Commodity category	Score
quantity	8152	6558	200	3957

literature [21] as EGIF, and in literature [27] as HRAC. All the experiments are conducted under Python 2.7.18 programming environment. In order to prevent the risk of overfitting, a dropout strategy was used with dropout value set to 0.5. The learning rate was set to 0.001 and the regular term coefficient was set to 0.05 using the Adam optimization function.

To evaluate the accuracy of the models, this paper conducts a comparative analysis of the accuracy of different recommendation models using the NDCG@N (NC@N), HitRate@N (HR@N), and Recall@N (Rec@N) [28] evaluation metrics, where N represents the length of the recommendation list. In this paper, the length of recommendation list N is set to 10 and 20 respectively, and the experimental outcomes are indicated in Table 1 by conducting experiments on the four comparison models.

Table 2. Comparison of recommendation accuracy of different Models

Model	NC@10	NC@20	HR@10	HR@20	Rec@10	Rec@20
RLDB	0.058	0.203	0.029	0.119	0.612	0.648
AMAD	0.091	0.236	0.071	0.173	0.677	0.693
EGIF	0.179	0.355	0.152	0.282	0.758	0.796
HRAC	0.142	0.309	0.108	0.256	0.715	0.739
CBSN	0.216	0.394	0.174	0.317	0.781	0.842

The suggested model CBSN has achieved the best performance on all indexes. Among them, NC@20, HR@20 and Rec@20 have increased by 10.99%, 12.41% and 5.78% compared with EGIF model, and by 27.51%, 23.83% and 13.94% compared with HRAC model. This indicates that compared with EGIF and HRAC models that do not utilize implicit social relations, the recommendation algorithm that integrates implicit social relations in social networks is superior. The multi-faceted search for implicit social relations through the attention mechanism of GAN can more comprehensively capture the interaction information between users and items, which can effectively improve the performance of the recommendation model. EGIF is the suboptimal algorithm, HRAC is the second. RLDB and AMAD models have the worst recommendation accuracy, because RLDB only uses the traditional collaborative filtering algorithm to recommend cross-border e-commerce goods, without considering the characteristics of users and sacred products, resulting in the lowest accuracy.

5.2. **Recommended results diversity analysis.** To further validate the effectiveness of the proposed model in diversity recommendation, this paper uses topic coverage (CC@N) [29] and recommendation list diversity (ILD@N) [30] to compare and analyze the diversity of different models. Figure 4 demonstrates the diversity performance of different models.

From Figure 4, it can be seen that the proposed model CBSN performs the best in this paper, followed by the EGIF model, and has similar results to the HRAC model. On the four metrics CC@10, CC@20, ILD@10, and ILD@20, the CBSN model improved 7.46%, 5.06%, 4.17%, and 6.17% relative to the suboptimal EGIF model; 16.13%, 10.67%, 13.64%, and 11.69% compared to the HRAC model; 41.18%, 33.83%, 41.51%, and 34.38% compared to the RLDB model; and 26.32%, 20.29%, 29.31%, and 22.86% compared to the AMAD model. It is well illustrated that the introduction of a clustering mechanism in

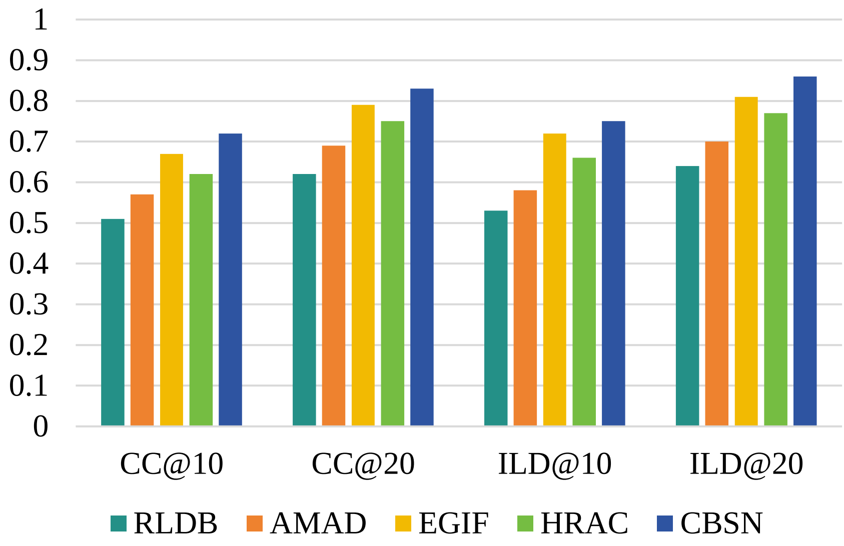

Figure 4. Comparison of diversity indicators in different models

the feed-forward neural network clusters the users, and the obtained similar users may be interested in the commodity categories, which improves the diversity of the recommended commodity categories. However, the RLDB and AMAD models perform generally, which is due to the fact that the diversity information such as commodity categories is not considered, resulting in poor diversity.

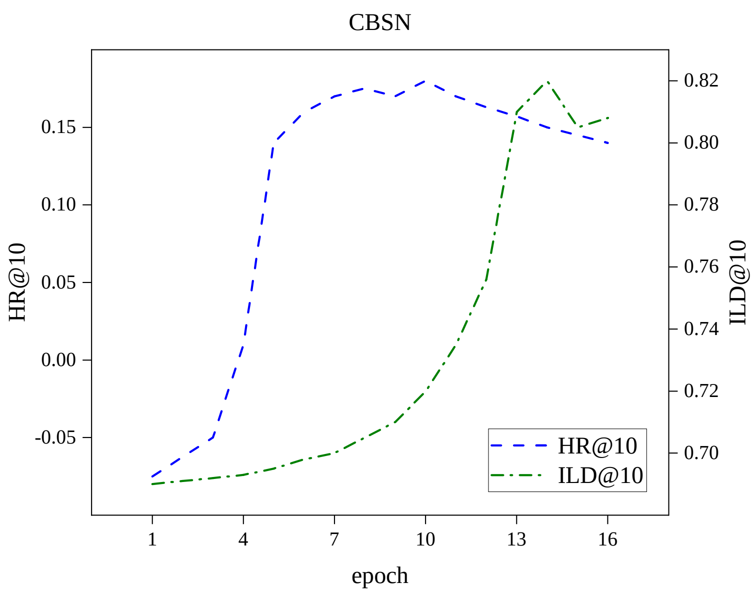

Figure 5. Sensitivity results for HR and ILD

5.3. **Sensitivity analysis.** This article analyzes the sensitivity of HR@10 and ILD@10 to the number of training iterations (epochs). The epoch size has a certain effect on the experimental results. When the epoch is 10, the CBSN model's HR@10 indicator has the highest result. After that, the accuracy of the model does not change much and the model converges. In this study, we take the results under epoch = 16 as the final experimental results. In addition, as the epoch rises, the ILD@10 metric rises the fastest around epoch

13, and the results do not change much when epoch ¿ 15. This indicates that HR and ILD are more sensitive before epoch 14, but gradually converge after epoch 15, which suggests that the model proposed in this paper can have a better balance between personalization and diversity.

6. **Conclusion.** Aiming at the current cross-border e-commerce personalized recommendation model, which is difficult to balance accuracy and diversity, this article designs a cross-border e-commerce personalized recommendation model that integrates the social network context. First, improving the MF technique by optimizing the regularization parameter to adjust the distribution of users' ratings for different product categories in the social network. Second, the GAN network with attention mechanism is utilized to aggregate the feature information of users and commodities in the social network to mine potential implicit social relationships, and the cosine similarity between users is calculated to obtain the top TOP-N implicit friendships. Then, the aggregated information of users is fed into the feed-forward neural network to cluster the similar user groups, find the product categories that the target users may be interested in, and form a diversified recommendation list. Finally, the two recommendation lists are integrated into matrix factorization for score prediction to satisfy the diversity and accuracy of product recommendation results. The experimental outcome indicates that the suggested model has better performance in NDCG, HitRate, Recall, Topic coverage and Diversity.

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