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CNN-driven cross-border e-commerce intelligent recommendation model performance optimization

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Abstract With the advancement of economic globalization, the development of cross-border e-commerce is becoming increasingly prosperous. In this paper, we design a cross-border e-commerce product artificial intelligence recommendation model based on convolutional neural network, which integrates the logistics spatio-temporal data and user portrait features to optimize the recommendation effect. After preprocessing the historical user data, clustering analysis is used to construct a multi-dimensional user portrait. The Embedding layer is utilized to process the high-dimensional features of the data, and the convolutional neural network model is trained by combining the MSE loss function. The study shows that the model in this paper gradually improves the recall rate and other three indicators from about 0.4 to about 0.9 in the product recommendation scenarios of Top5, 10, 15 and 20. The time used to complete the recommendation is around 61-64s. The product recommendation accuracy rates are all greater than 0.75.

Index Terms convolutional neural network, logistics spatio-temporal data, user profile clustering, cross-border e-commerce, product recommendation

I. Introduction

In today's era of information explosion, although there is information with great potential value contained in massive information, there is no very obvious boundary between important information and unimportant information [1], [2]. How to mine and analyze the huge amount of network information so that users can quickly obtain the information they are interested in the vast sea of data has become a recognized hot and difficult problem, and cross-border e-commerce in the network environment is even more so [3]-[5].

Recommender system, as a tool that can effectively filter and screen data information, is widely used in today's era to mine valuable information in the massive data information [6]. Its appearance can be said to be extremely effective in solving the thorny problem of information overload, which mines the massive data on the basis of understanding the user's demand information through some algorithms and provides the user with information data that meets his or her personalized needs [7]-[10]. In addition, as a link between users' personalized needs and data information, the recommender system can not only help users find information that meets their own wishes, but also in turn can realize that the data information can be displayed in front of the users who are interested in it, so as to achieve the mutually beneficial win-win effect of the data information provider and the data information demander [11]-[14]. The goodness of a recommender system depends largely on the goodness of the recommendation algorithm used. A good recommendation algorithm can well improve the recommendation efficiency and have a high recommendation accuracy, on the contrary, a relatively poor recommendation algorithm has more serious internal consumption, and the recommended information is likely to be not in line with the user's wishes [15], [16]. Therefore, it is of great significance to construct a recommendation model for the cross-border e-commerce market domain.

This paper builds an artificial intelligence recommendation framework to improve the comprehensive recommendation effect of complex cross-border e-commerce products. Pre-processing multiple heterogeneous data, unified quantification of logistics geographic information and user behavior data. Perform data clustering, extract user portrait features, and analyze the evolution law of consumption preference by combining feature vectorization. Train the artificial intelligence recommendation model based on convolutional neural network to realize the accurate recommendation of e-commerce products through deep learning of data features. Take the historical user data of the enterprise as the research object to verify the advantages of the proposed preprocessing method, portrait feature extraction technology, and model recommendation performance.

II. Artificial Intelligence Recommendation Model for Cross-Border E-commerce

II. A. Technical architecture of cross-border e-commerce recommendation system

The technical architecture of cross-border e-commerce recommendation system is an important foundation to support the realization of the recommendation function, and the system technical architecture usually contains several key components. Figure 1 shows the technical architecture of cross-border e-commerce recommendation system. Specific analysis is as follows: first, data collection and storage. The massive data generated by cross-border e-commerce platforms need to be effectively collected and stored, which include users' browsing history, purchase records, evaluation information and so on. Common data storage solutions include relational databases, distributed file systems, etc. for storing different types of data. Second, data preprocessing and feature extraction. Before the data enters the recommender system, it is usually necessary to carry out preprocessing and feature extraction, which mainly includes data cleaning, de-duplication, normalization and other steps, as well as feature extraction of users and commodities. At the same time, feature extraction can also be based on the user's behavior, the attributes of the commodity and other information. Third, deep learning model design and training. The cross-border e-commerce recommendation system uses deep learning algorithms for recommendation, which requires the design and training of deep learning models applicable to the recommendation task. Common models include neural network-based convolutional neural network (CNN), recurrent neural network (RNN), long short-term memory network (LSTM) and so on. Fourth, recommendation result generation and evaluation. After model training, the recommendation system can generate personalized recommendation results for the user, and the generated recommendation results can be based on the user's historical behavior, interest preferences and other information. In order to ensure the quality of the recommendation, usually need to evaluate the recommendation results, evaluation indicators include accuracy, recall, coverage, etc. Fifth, real-time recommendation and feedback. With the changes in user behavior, the recommendation system needs to be able to respond to user feedback in a timely manner and adjust the recommendation results. Therefore, real-time recommendation and feedback mechanism is an important part of the recommendation system architecture.

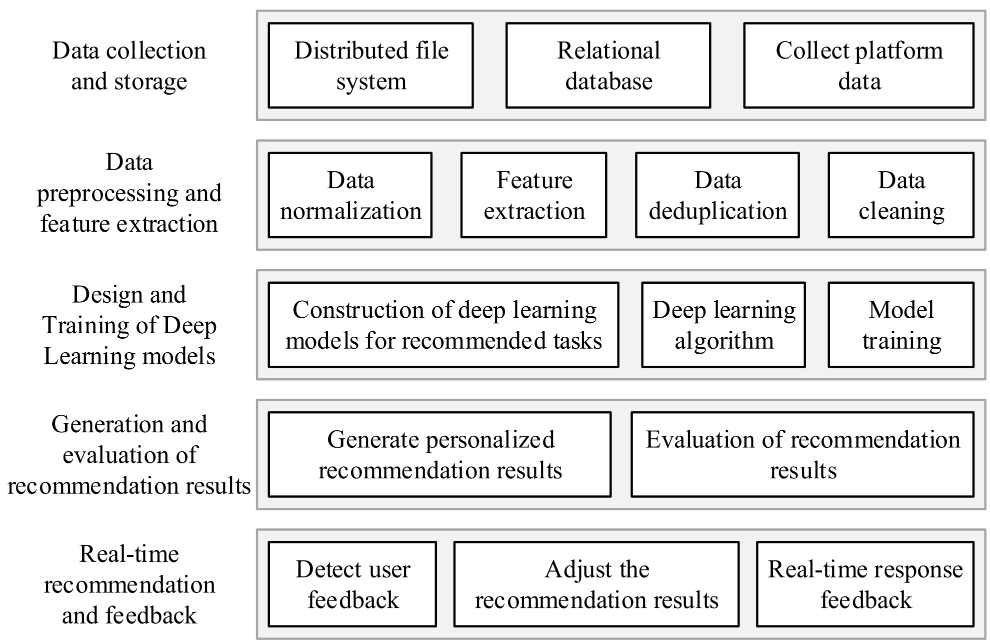

Figure 1: Architecture of Cross-border E-commerce Recommendation System

II. B. Data pre-processing

II. B. 1) Data sources and analysis

Due to the cross-border e-commerce business for many years, there is a large amount of data stored in the database of which includes the logistics information of the goods, product information, order information, customs declaration information and so on. There is a lot of important information needed for this experiment, and at the same time, the information also contains some unwanted interference information. Therefore, the information is preprocessed to eliminate some interference, and the data needed for the final experiment are extracted. After the pre-processing, it is used as the feature data of the experiment.

II. B. 2) Pre-processing of logistics information

The logistics information table contains a lot of information related to the logistics of consumers after purchasing items, and there are only two fields required for this experiment, namely the province CP and city CC fields. Figure 2 shows the E-R display of the logistics information table.

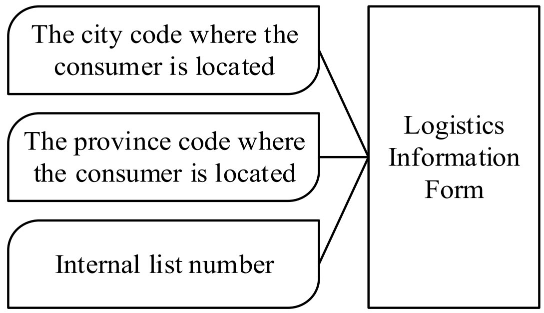

Figure 2: Logistics information table E-R chart

The main fields used in the logistics information table for this experiment are the consumer's province code, the consumer's city code and the internal list number. The preprocessing process of the logistics information table is to first find out the province where the consumer is located according to the province field which can be based on the province code comparison table, and to derive the grade of the city where the consumer is located according to the city field and the city grade division table. According to the latest city level table, the city level is divided into 5 levels, and 1.0 to 5.0 indicates the first tier to the fifth tier cities. Based on the province code information, the consumer's region information is obtained and represented by north, cast, south, northcast, northwest, southwest, and central codes.

II. C. Extracting user profile features

User profiling is a comprehensive description of user attributes and behaviors, which can help cross-border e-commerce platforms understand user needs and behavioral patterns more deeply. Through the use of data mining and machine learning technologies, key user characteristics are extracted from the pre-processed data. These features will reflect the static attributes of users and reveal their dynamic behavioral patterns, providing support for building personalized marketing strategies.

In the field of e-commerce, this carefully constructed user profile model based on clustering analysis can deeply excavate the potential needs and unique preferences of users, create a personalized recommendation system tailored for cross-border e-commerce platforms, and lay a solid foundation for the implementation of strategies. The user profile construction system stands firmly on two pillars: one is the fine portrayal of the user attribute dimension, which accurately captures and fixes the user's static characteristics, such as age, gender and other core labels.

The second is to deeply analyze and refine the massive and complex user data with the help of advanced machine learning technology, from which multi-dimensional and standardized feature vectors are extracted. According to the analysis goal, the user data is labeled. Extract the significant features and group differences of users through cluster analysis. For cluster analysis, especially K-means clustering, the goal is to find a partition $C = \{C_1, C_2, \cdots, C_I\}$, where I denotes the number of clusters, and C_I denotes the set of i th cluster. The mean vector (or center of mass) of each cluster C_i is denoted as μ_i.

$$WCSS = \sum_{i=1}^{I} \sum_{m \in C_i} \| m - \mu_i \|^2 \tag{1}$$

where m denotes a data point in the cluster C_i. Based on the extracted features, user profiles are constructed. Use visualization tools (e.g., bar charts, pie charts, radar charts) to present the user features to form an intuitive and easy-to-understand user portrait.

II. D. Training models

Immediately after obtaining the similarity data in the previous step, the model needs to be trained, and the process is summarized as follows: the similarity data obtained in the previous step is used to train the convolutional neural network model using the training dataset, and the network parameters are updated by the back-propagation algorithm using the mean-square error (MSE) as the loss function, so that the loss function is minimized.

The specific steps are as follows:

Step 1 Forward propagation: input the training samples and calculate the output values of the neural network through forward propagation.

The forward propagation is divided into the following steps:

(1) Input processing: the input data is processed to transform the IDs of users and products into vector representations. Specifically, for the convolutional neural network model, the input consists of two similar samples, so each sample needs to be processed and computed separately. Suppose our model has two inputs, user ID and item ID, which we can convert into corresponding vector representations. Suppose we use Embedding layer to convert each ID into a d-dimensional vector, then we can convert user ID and product ID into two d-dimensional vectors, denoted as u and v, respectively.

(2) Neural network computation: the processed input data is fed into the neural network for computation, and the output value of the network is finally obtained.

Next, the two vectors are fed into a shared neural network for computation. This shared neural network consists of multiple fully connected layers and can use an architecture similar to a multilayer perceptual machine. In each fully connected layer, the ReLU activation function is computed using the ReLU activation function. Since this neural network includes 3 fully connected layers, the output dimensions of each layer are h_1, h_2 and h_3. We can pass the input vectors u and v through each of these three fully connected layers to obtain the output vectors o_1, o_2 and o_3 denoted as:

$$\begin{aligned} o_1 &= ReLU(W_1[u,v]+b_1) \\ o_2 &= ReLU(W_2[o_1]+b_2) \\ o_3 &= ReLU(W_3[o_2]+b_3) \end{aligned} \tag{2}$$

where W_1, W_2, W_3 denote the weights of the fully-connected layer and b_1, b_2, b_3 denote the bias, respectively. The $[u,v]$ denotes the splicing of the two vectors to obtain a 2dimensional vector.

Finally, we can use the output vector o_3 as the output value of the neural network. During the training process, we need to compare this output value with the actual value to calculate the loss function.

Step 2 Calculate the loss: use the loss function to calculate the error between the model output and the real label.

The loss function of the convolutional neural network model here uses the Mean Square Error (MSE) to measure the error between the predicted value and the true value, which is calculated as follows:

$$loss = \frac{1}{2m}\sum_{i=1}^{m}(\hat{y}_i - y_i)^2 \tag{3}$$

where m denotes the number and quantity of samples in the model, $\hat{y}_i$ denotes the predicted value of the model for the i th sample, and y_i denotes the true value of the i th sample.

Step 3 Backpropagation error: backpropagate the error from the output layer to the input layer and calculate the contribution of each parameter to the error. In the backpropagation algorithm, the partial derivatives of each parameter to the error need to be calculated, and then the parameters are updated according to these partial derivatives. Assuming that our loss function is the mean square error (MSE), then for a convolutional neural network model, the following steps can be used for backpropagation to calculate the error in the last layer:

$$\delta_L = \frac{\partial L}{\partial z_L} = \frac{\partial L}{\partial y_1}\frac{\partial y_1}{\partial z_L} \tag{4}$$

where L is the loss function, y_1 is the predicted value of the model output, and z_L is the input to the last layer.

Calculate the error from the penultimate to the second layer:

$$\delta_i = \frac{\partial L}{\partial z_i} = \frac{\partial L}{\partial z_{i+1}}\frac{\partial z_{i+1}}{\partial z_i} = \delta_{i+1} W_{i+1} \frac{\partial f_i(z_i)}{\partial z_i} \tag{5}$$

where W_{i+1} is the weight from the $i+1$ th layer to the i th layer and $f_i(z_i)$ is the activation function of the i th layer.

Compute the partial derivatives of the weights and the bias:

$$\frac{\partial L}{\partial W_i} = a_{i-1}^T \delta_i \tag{6}$$

$$\frac{\partial L}{\partial b_i} = \delta_i \tag{7}$$

where a_{i-1} is the output of the $i-1$ th layer, w_i is the weight of the i th layer, and b_i is the bias of the i th layer.

Update the weights and biases:

$$W_i = W_i - \eta \frac{\partial L}{\partial W_i} \tag{8}$$

$$b_i = b_i - \eta \frac{\partial L}{\partial b_i} \tag{9}$$

where η is the learning rate.

Step 4 Update the parameters: on this basis, the inverse gradient correction of each parameter is carried out by using the gradient descent method to reduce the loss of the system. When the gradient descent method is used to correct the parameters, the loss function is firstly biased so as to obtain the gradient of each parameter; when the gradient descent method and its deformation method are used for the parameter correction, the gradient of each parameter must be calculated. Specifically, assuming that the model has L layers, the parameter of the l th layer is $\theta^{(l)}$, and the loss function is J, the gradient of the parameter can be calculated by the chain rule:

$$\frac{\partial J}{\partial \theta^{(l)}} = \frac{\partial J}{\partial z^{(L)}} \frac{\partial z^{(L)}}{\partial a^{(L-1)}} \frac{\partial a^{(L-1)}}{\partial z^{(L-1)}} \cdots \frac{\partial z^{(l)}}{\partial \theta^{(l)}} \tag{10}$$

where $z^{(l)}$ denotes the weighted input of the l th layer, $a^{(l)}$ denotes the output of the l th layer, and $\frac{\partial J}{\partial z^{(l)}}$ denotes the derivative of the loss function with respect to the output of the last layer. According to the chain rule, the gradient of the parameters can be obtained by continuously calculating the gradient of each layer and propagating forward layer by layer.

Based on the gradient values and the learning rate, the model parameters are updated. Specifically, assuming that the loss function is $L(w)$ and w is the model parameter vector, the parameter update formula is:

$$w_{i+1} = w_i - \eta \frac{\partial L(w_i)}{\partial w} \tag{11}$$

where η is the learning rate and i is the number of iterations. The gradient can be computed using the chain rule, e.g. in a neural network, for a weight w_{ij}, the gradient is:

$$\frac{\partial L(w)}{\partial w_{ij}} = \frac{\partial L(w)}{\partial y} \frac{\partial y}{\partial w_{ij}} \tag{12}$$

where y is the network output value, $\frac{\partial L(w)}{\partial y}$ is the partial derivative of the loss function with respect to the output value, and $\frac{\partial y}{\partial w_{ij}}$ is the partial derivative of the output value with respect to the weight w_{ij}. Depending on the specific neural network structure, the gradient of each parameter can be computed in turn using the chain rule and the parameters can be updated.

III. Application of Artificial Intelligence Recommendation Models in Cross-border E-commerce Marketplace

III. A. User Value Label Creation

III. A. 1) Sample data calculation

Taking the historical user data of a large cross-border e-commerce enterprise as the base sample data, 12,000 data entries for the period of 2023-2024 were selected, excluding orders with incomplete transactions such as refunded orders and canceled orders, in order to ensure the completeness and accuracy of the selected data, and to prepare for the subsequent data analysis.

Based on the historical user data, the recent purchase behavior (R), the overall frequency of purchase (F), and the amount of money spent (M) of each customer are calculated, and these three indicators are used to describe the value status of this customer, while the number of times of consumption within 7 months is specified as the frequency. Four fields, order number, user ID, time of order placement, and payment amount were used to calculate the RFM metrics, and data from December 2023 to June 2024 was chosen as the timeframe. The number of days between “December 30, 2023” and the most recent purchase is used as an indicator of recent purchase behavior. Table 1 shows some of the calculated sample data. The historical behavioral data show that the sample customers' consumption frequency ranges from 1-4 times, the average payment amount ranges from 12.73 yuan to 50.16 yuan, and the interval between the last purchase ranges from 13 to 263 days, which is a large difference in the overall behavioral data, and it meets the requirements of the subsequent experiments.

Table 1: The calculated partial sample data

User ID	Consumption frequency F	Average payment amount (RMB) M	Interval from the last purchase(days) R
Aal1123	1	46.32	143
Aa27241	3	50.16	26
Aa126075	2	32.65	47
Aa1237	4	4.69	263
Ab11582	3	25.71	102
Ab82945	1	38.36	70
Ab13667	1	31.72	45
Ab232617	1	12.73	62
Ab17264	2	30.68	147
Ab75621	3	34.79	13

III. A. 2) Preprocessed sample data

R (Recently Purchased Time), F (Frequency of Purchase) and M (Amount of Purchase) are three important metrics in the RFM model. Since the value ranges of these indicators may differ significantly, for example, R is a number in terms of days while M is a number in terms of amount, the influence of certain indicators may become unbalanced when calculating the RFM score, thus affecting the accuracy of the RFM model.

To ensure that different variables have the same weight and influence when calculating the RFM score, this study standardizes the three indicators of RFM. Variable standardization is the process of transforming data into standard distributions with specific means and standard deviations. Its function is to eliminate the difference in the scale between different variables, making the data comparable and easier to compare and analyze. Table 2 shows some of the data after standardization. The frequency of purchases after standardization ranges from 0.5912-0.8315, the amount of purchases ranges from 0.0027-1.1782, and the time of the most recent purchase ranges from 0.1035-1.2769, which makes it comparable.

Table 2: Some standardized data

User ID	Consumption frequency F	Average payment amount (RMB) M	Interval from the last purchase(days) R
Aal1123	0.5912	1.0241	0.9865
Aa27241	0.7223	1.1782	0.2184
Aa126075	0.6027	0.9226	0.1505
Aa1237	0.8315	0.0027	1.2769
Ab11582	0.7223	0.8235	0.8341
Ab82945	0.5912	0.9875	0.5724
Ab13667	0.5912	0.9015	0.3701
Ab232617	0.5912	0.5073	0.4416
Ab17264	0.6027	0.9017	0.9901
Ab75621	0.7223	0.9234	0.1035

III. B. User Profile Generation

Table 3 shows the three categories of user profiles generated based on the preprocessed data clustering. The sample users are clustered into 3 categories, which are high-value quality type, vigor quality type, and growth type. High-value premium accounted for 6%, vitality premium accounted for 10%, and growth type accounted for 84%. All three types of users were predominantly female, accounting for more than 60% of the users. The age of the users is concentrated in the stage of 25-50 years old, mainly Asian. 3 types of users' value labels and behavioral habits have a big difference.

Table 3: User portrait data of three types of groups

Information category	User type	Group 1: High-value high-quality type	Group 2: Dynamic and High-Quality Type	Group 3: Growth-oriented
User basic attributes	Number	300	500	4200
	Percentage	6%	10%	84%
	Gender	Male:30%	Male:35%	Male:32%
		Female:70%	Female:65%	Female:68%
	Annual income	<\50K:6%	<\50K:5%	<\50K:8%
		\50K-150K:76%	\50K-150K:70%	\50K-150K:70%
		>150K:18%	>150K:25%	>150K:22%
	Age group	<25:17%	<25:10%	<25:16%
		25-50:64%	25-50:69%	25-50:71%
		>50:19%	>50:21%	>50:13%
	Country/ Region	Europe:15%	Europe:10%	Europe:12%
		America:16%	America:18%	America:15%
		Asia:52%	Asia:59%	Asia:61%
		Other:17%	Other:13%	Other:12%
User value tag	Number of days since the last per capita consumption	207	53	274
	Per capita consumption amount	184	35	28
	Per capita order quantity	3	6	2
User consumption behavior	Comment activity level	Not frequently	Felatively frequently	Frequently
	Peak browsing period	12:00-13:30	19:30-22:00	20:30-23:00
	Peak ordering hours	Weekend or holiday period	Irregularity	During the promotion period
	Promotion sensitivity	Low	Relatively high	High

III. C. Cross-border e-commerce recommendation effect analysis of artificial intelligence recommendation models

III. C. 1) Recommended performance analysis

Using clustered user profile data and trained AI recommendation model for cross-border e-commerce product recommendation. Different Top recommendation numbers are counted separately, and the recommendation indicator data of the model is counted. Table 4 shows the statistical results of the model's recommendation indicators. In the cross-border e-commerce product recommendation using the AI model, when the number of recommended products is TOP5, its recommended recall rate and other three indicators are around 0.4, and when the number of recommendations rises to TOP15, its cross-border e-commerce product recommendation recall rate and other indicators reach more than 0.8, and when it reaches TOP20, its product recommendation recall rate and other indicators reach more than 0.9.

Table 4: The recommended indicator data of the model

Indicators	Top 5	Top 10	Top 15	Top 20
Platform A				
Precision	0.4132	0.5671	0.8945	0.9012
Recall	0.4024	0.5519	0.8769	0.9352
MRR	0.4315	0.5436	0.8562	0.9146
Platform B				

Precision	0.3987	0.5135	0.8247	0.9028
Recall	0.4106	0.5239	0.8546	0.9745
MRR	0.4216	0.5341	0.8128	0.9614
Platform C				
Precision	0.4236	0.5029	0.8453	0.9236
Recall	0.3899	0.5148	0.8302	0.9173
MRR	0.4172	0.5237	0.8152	0.9257
Platform D				
Precision	0.4021	0.5245	0.8350	0.9148
Recall	0.4324	0.5173	0.8143	0.9265
MRR	0.4520	0.5628	0.8256	0.9674

III. C. 2) Recommended time analysis

Table 5 shows the recommendation time of the model under different number of product recommendations. 4 cross-border e-commerce platforms, the model in this paper recommends 5 products in about 61s, recommends 10 products in about 62s, recommends 15 products in about 63s, and recommends 20 products in about 64s. With the increase of the number of recommended products, the growth of the time used is very small, indicating that the model can accomplish the recommendation goal faster when accomplishing multiple product recommendation tasks at the same time.

Table 5: Recommendation time under different recommendation quantities

Cross-border E-commerce Platform	Number of product recommendations	Recommended time /s
Platform A	Top 5	61.39
	Top 10	62.41
	Top 15	63.37
	Top 20	64.14
Platform B	Top 5	61.28
	Top 10	62.15
	Top 15	63.26
	Top 20	64.12
Platform C	Top 5	61.30
	Top 10	62.78
	Top 15	63.49
	Top 20	64.25
Platform D	Top 5	61.24
	Top 10	62.26
	Top 15	63.15
	Top 20	64.38

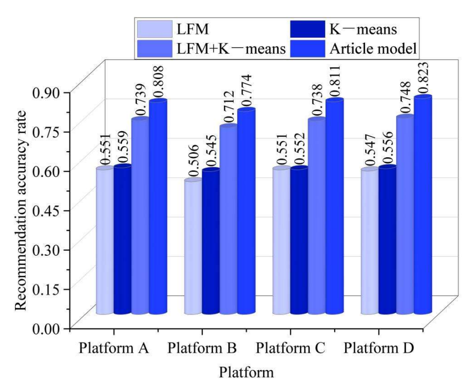

Figure 3: Comparison of recommendation accuracy rates of different models

III. C. 3) Recommendation accuracy analysis

LFM model, K-means model, LFM and K-means model, and this paper's model are used for cross-border e-commerce product recommendation, respectively, and Fig. 3 shows the results of the recommendation accuracy of this paper's model compared with that of the same type of model. The accuracy rate of this paper's model reaches 0.808, 0.774, 0.811, 0.823 in product recommendation in four cross-border e-commerce platforms, all of which are above 0.75, while in the comparison models, the highest accuracy rate is 0.748 in LFM and K-means model in platform D, which does not exceed 0.75.Therefore, this paper's model has a higher product recommendation accuracy rate in cross-border e-commerce platform with higher product recommendation accuracy. Taken together, the model in this paper can recommend suitable products for e-commerce customers more quickly and accurately.

IV. Conclusion

In this paper, we construct a cross-border e-commerce recommendation model that integrates convolutional neural network and user portrait features to effectively improve the precision of marketing. The value of indicators such as recall rate increases with the increase of recommendation volume, and when the recommendation volume increases to Top20, the value of three indicators reaches more than 0.9. The highest response time is around 64s, which meets the real-time recommendation requirements. The recommendation accuracy of 4 cross-border e-commerce platforms reaches 0.808, 0.774, 0.811, 0.823 respectively, which is higher than the comparison model, and has a good recommendation accuracy. In the future, we can try to develop edge computing architecture to continuously optimize the time required for recommendation and reduce the recommendation delay.

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