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Optimisation of e-commerce personalised recommendation algorithms driven by neural network models

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ABSTRACT

With the rise of major e-commerce, how to make more customer groups choose to buy items in their own websites is the goal that major e-commerce platforms have been relying on. Therefore, a set of personalised recommendation system that can intelligently explore customers' needs comes into being. In this paper, a graph neural network model is used to sort out the multi-path fusion neighbourhood relationship among three objects: user, product and query. The utility matrix is established and the collaborative filtering algorithm is used to derive the user's preference situation for commodities. Subtractive clustering is combined with fuzzy C-means to obtain the clustering centre of gravity and cluster e-commerce users. Graph neural network is introduced to ensure that the data sparsity of the user dataset is within a reasonable range. The practical application effect of the model is evaluated through simulation experiments and empirical analysis, respectively. In this paper, according to the age of the users, the users are clustered and analysed, and three clustering centres of gravity are obtained, which are (3.16, 32.73), (45.35, 40.25), and (14.03, 52.89), so the users are classified into three clusters, and the analysis of simulation experiments is carried out. The training effect of this paper's model is fitted, and the adjusted R^2 = 0.8292, which shows that the accuracy of personalised recommendation is high. Meanwhile, comparing with other algorithms, this paper's method reaches a recommendation satisfaction level of 100% when the number of learning times is 60, which is significantly better than other algorithms.

Keywords: graph neural network, user preference, fuzzy C-mean clustering, e-commerce personalised recommendation

1. Introduction

In computer e-commerce systems, the practice and exploration of personalised recommendation algorithms is increasingly becoming an important development direction in the industry. This technology is based on users' historical behaviours, preferences and real-time data to provide users

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with accurate recommendations of goods or services, and to enhance the user experience and sales conversion rate [1-2]. E-commerce platforms need to establish a good recommendation system to ensure that the recommendation results match the actual needs of users.

On the one hand, e-commerce recommendation system facilitates enterprises to make reasonable use of consumers' demographic information, consumers' previous shopping information, and website transaction data, so as to analyse consumers' potential demand preferences and recommend the right products for consumers at the right time, thus improving the conversion rate and promoting enterprises' profits [3-5]. On the other hand, e-commerce recommender system also meets the consumer's decision support needs, consumers do not need to spend a lot of their own time and energy in product search and comparison, e-commerce platforms are able to intelligently mine the products that users need, effectively avoiding information overload [6-9]. E-commerce recommendation system mainly includes three parts: recommendation input, recommendation algorithm, and recommendation output, in which the recommendation algorithm is the core of the whole recommendation system, which determines the degree of personalisation, speed and accuracy of the recommendation [10-11].

In recent years, deep neural network technology has made a big breakthrough, and has gained very good results in the fields of image, natural language processing, speech and so on. After sweeping through the fields of image and speech, deep neural networks are also making inroads into the field of personalised recommender systems, where deeper models can better model user intentions, better discover matches between users and items, and can solve the novelty problem in recommendation to a certain extent [12-15].

The practice and exploration of personalised recommendation algorithms in computer e-commerce systems is increasingly becoming an important development in the industry [16]. Alamdari, P. M. et al. clarified that e-commerce platforms that rely on Internet platforms for services and exchanges with electronic devices generate a large amount of information and recommender systems can effectively address this information overload by providing personalised recommendation services to users to increase their satisfaction [17]. Jiang, L. et al. illustrated the necessity of building e-commerce recommender systems that automatically provide users with items they may be interested in, so automation of the recommendation process is fundamental to personalised recommender systems and has accuracy requirements for recommendation algorithms [18]. Liao, M. et al. investigated the significance of content filtering methods and collaborative filtering methods for the algorithm design of e-commerce recommendation systems in different product positioning, and for experiential products, consumers prefer the recommendation method based on content filtering, while for search products, collaborative filtering leads to more positive reviews by triggering the "herd effect" [19].

Personalised recommendation algorithms for e-sub-commerce are mainly classified as collaborative filtering recommendation, content based recommendation and hybrid recommendation. Collaborative filtering recommendation is a method of recommendation based on the similarity between users or items.Shoja, B. M. et al. developed a feature vocabulary for e-commerce products using deep neural networks to extract deep features from processed user comments, based on which matrix decomposition is applied as a collaborative filtering method to provide recommendations [20]. Jing, N. et al. improved the traditional collaborative filtering recommendation method by proposing an enhanced collaborative filtering method for sentiment assessment, which uses feature words extracted from online customer reviews with sentiment polarity scores to compute user preferences and user similarity for personalised recommendation of services and products [21]. Karabila, I. et al. combined collaborative filtering with sentiment analysis, used BERT fine-tuning model to classify users' text data by sentiment, and built a hybrid collaborative filtering recommendation model to effectively improve the recommendation accuracy of the recommendation system and provide customised and reliable recommendation services for users in the e-commerce domain [22]. Vullam, N. et al. investigated the user clustering analysis of a multi-agent recommender system for personalised e-commerce product recommendation, which uses user ratings of product categories as a clustering metric to search for as many domain objects as possible and to achieve a highly accurate recommendation of the system [23]. Wang, K. et al. proposed a personalised recommendation system for e-commerce based on learning clustering, which combines recurrent neural network and attention mechanism to solve the limitations of the model in the selection of neighbourhood object set, and the effectiveness of the system was verified through experiments [24].

Content-based recommendation algorithms make recommendations by analysing product content features and user preferences.Guo, Y. et al. designed a mobile e-commerce recommendation system based on an improved Apriori algorithm, which improves the efficiency of mining user data and achieves the unity of real-time and accuracy of recommendations [25]. Necula, S. C. et al. showed that combining AI with other technologies such as blockchain, virtual reality and augmented reality can enhance the user's consumer experience during e-commerce, whereas the e-commerce recommendation process varies in terms of the type of data and the type of task, leading to differences in the form of personalised recommendations based on algorithms and technologies [26]. Zhou, M. et al. argued that micro-behaviours resulting from macroscopic interactions between users and items can deepen the understanding of users at a fine-grained level, and therefore proposed an interpretable recommendation framework, RIB, to improve the effectiveness of e-commerce recommender systems by modelling sequences of micro-behaviours and their impact [27].

Hybrid recommendation algorithm combines collaborative filtering and content recommendation to improve recommendation accuracy and matching.Guo, Y. et al. evaluated the performance of hybrid recommendation algorithms in e-commerce product recommendation.The interactive assignment of weights method based on customer feedback better meets the consumer needs and improves the consumer coverage, consumer discovery accuracy, and recommendation recall of recommendation system [28]. Yang, F . introduced a hybrid recommendation algorithm that integrates content recommendation algorithm, collaborative recommendation algorithm and demographic-based recommendation algorithm, which makes up for the deficiency of a single recommendation algorithm by expanding the recommendation dimensions, and the experimental results show that the hybrid recommendation algorithm has a better e-commerce recommendation effect [29].

In this paper, we construct a personalised recommendation model for e-commerce based on graph neural network, which is oriented to meta-paths, defines neighbouring nodes as the set of all visited objects, and infers the path itself. The item utility matrix is constructed, and the UserCF algorithm under collaborative filtering algorithm is used to calculate the cosine similarity of the user to the rest of the users according to their preferences. Predict the interest degree of the target user in the item according to the preference profile of the similar users and derive the preference degree of the target user for the item based on this. The improved algorithm is used to solve the data sparsity problem of the dataset generated by the e-commerce personalised recommendation process. Combining subtractive clustering with fuzzy C-means and introducing graph neural networks on this basis, the genetic fuzzy clustering algorithm is optimised to improve the practicality of the e-commerce personalised recommendation model. The optimised model is applied to the actual e-commerce personalised recommendation, and the implementation process is evaluated to evaluate the personalised recommendation effect of the model in e-commerce scenarios.

2. Fuzzy clustering algorithm based on hybrid genetic

2.1. Fuzzy clustering

Traditional cluster analysis is a hard division, which strictly classifies each object to be recognized into a certain category, with the nature of "either/or", so the boundaries of this kind of category division are clear. Users can only belong to a single category, and it is not possible to record the multi-interest characteristics of users. In addition, the ultra-high dimensionality of the data degrades the recommendation performance. Since fuzzy clustering obtains the degree of uncertainty of the samples belonging to each category and expresses the mediation of the sample's class, i.e., establishes a description of the sample's uncertainty with respect to the category, it reflects the real world more objectively, thus becoming the mainstream of cluster analysis research. The fuzzy clustering process can be carried out offline, which does not burden the real-time performance of the recommender system. At the same time fuzzy clustering is also effective in solving the cold-start problem caused by data sparsity.

Fuzzy clustering (FCM) divides n vector $(i=1,2,\cdots,n)$ into c fuzzy groups and seeks the centre of clustering of each group such that the value function of the non-similarity metrics is minimised [30]. FCM uses fuzzy partitioning to allow each given data point to determine the extent to which it belongs to each group using an affiliation degree with a value between 0 and 1. In keeping with the introduction of fuzzy partitioning, the affiliation matrix U is allowed to have elements with values between 0, 1. However, together with the normalisation provision, the sum of the degrees of affiliation of a data set is always equal to 1:

$$\sum_{i=1}^{c} u_{ij} = 1, \forall j = 1,\cdots,n \tag{1}$$

Then, the generalised form of the value function (or objective function) of the FCM:

$$J(U,c_1,\cdots,c_c) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c}\sum_{j}^{n} u_{ij}^m d_{ij}^2 \tag{2}$$

Here u_{ij} lies between 0, 1, c_i is the clustering centre of the fuzzy group, $d_{ij} = \|c_i - x_j\|$ is the Euclidean distance between the i th clustering centre and the j th data point, and $m \in [1,\infty)$ is a weighted index.

Constructing the following new objective function, the necessary conditions to minimise equation (2) can be found:

$$\begin{aligned} &\bar{J}(U,c_1,\cdots,c_c,\lambda_1,\cdots,\lambda_n) \\ &= J(U,c_1,\cdots,c_c) + \sum_{j=1}^{n}\lambda_j\left(\sum_{i=1}^{c}u_{ij}-1\right) \\ &= \sum_{i=1}^{c}\sum_{j}^{n}u_{ij}^m d_{ij}^2 + \sum_{j=1}^{n}\lambda_j\left(\sum_{i=1}^{c}u_{ij}-1\right) \end{aligned} \tag{3}$$

Here λ_j, $j=1\sim n$, are the Lagrange multipliers of the n constraint equations of Eq. (1). The necessary condition to minimise Eq. (2) is derived for all input parameters:

$$c_i = \frac{\sum_{i=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m} \tag{4}$$

and:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{kj}}\right)^{2/(m-1)}} \tag{5}$$

From the above two necessary conditions, the fuzzy C-mean clustering algorithm is a simple iterative process. When run in batch mode, the FCM determines the clustering centre c_i and the affiliation matrix U using the following steps:

Step 1: Initialise the affiliation matrix U with random numbers with values between 0, 1 so that it satisfies the constraints in equation (1).

Step 2: Calculate c clustering centres c_i, $i=1,\cdots,c$ using equation (4).

Step 3: Calculate the value function according to equation (2). The algorithm stops if it is less than some determined threshold or if the amount of change in it relative to the last value function value is less than some threshold.

Step 4: Calculate the new U matrix using equation (5). Return to step 2.

The above algorithm can also initialise the clustering centres before performing the iterative process. Since there is no guarantee that the FCM converges to an optimal solution. The performance of the algorithm depends on the initial clustering centre, so some improvements are made in using it.

2.2. Subtractive Clustering and Fuzzy C-means

Among the many algorithms for fuzzy cluster analysis, the fuzzy C-mean algorithm (FCM) can be said to be the most widely used and sensitive one. However, the fuzzy C-mean algorithm is very sensitive to the initial value when performing fuzzy clustering, and a poorly set initial value will lead to a local optimal solution. In this paper, the initial value of fuzzy C-mean clustering is set by subtractive clustering before using it, which can not only obtain the optimal solution, but also speed up the convergence speed, and automatically obtain the best number of clusters.

2.2.1. Subtractive clustering. The subtractive clustering method uses all the data points as candidates for the centre of clustering. It is a fast and independent approximation of the clustering method, with which the computation, the amount of computation is simply linear with the number of data points and independent of the dimension of the problem under consideration.

Consider q data points $\left(X_1, X_2, \cdots, X_q\right)$ in R-dimensional space and assume that the data have been normalised into a hypercube. The density metric at data point X_i is defined as:

$$D_i = \sum_{j=1}^{q} \exp\left(-\frac{\left\|X^i - X^j\right\|^2}{\left(A/2\right)^2}\right) \tag{6}$$

After calculating the density metrics of each data point, the data point with the highest density metric is selected as the first clustering centre, so that X_{c1} is the selected point and D_{c1} is its density metric. Then the density index of each data point X_i can be corrected by Eq. where C is a positive number, and generally $C = 1.5A$ can be selected.

$$D_i = D_i - D_{c_1} \sum_{j=1}^{q} \exp\left(-\frac{\left\|X^i - X^j\right\|^2}{\left(C/2\right)^2}\right) \tag{7}$$

After correcting the density metrics for each data point, the next clustering centre X_{c2} is selected and all density metrics for the data points are corrected again. This process is repeated until a sufficient number of clustering centres are produced, or the number of clusters can be determined automatically based on certain conditions.

2.2.2. Subtractive clustering combined with fuzzy C-means. Before performing the calculation, the number of data points n, the radius of the neighbourhood A, C and the error allowance ε should be set according to the specific requirements of the problem.

1) Firstly, the density indexes of n data points are calculated using equation (6), and then the one

with the highest density index among all the density indexes is found as the first cluster centre point X_{c1}.

2) After finding the first clustering centre, use the density metrics of X_{c1} to further calculate the density metrics of the remaining $1-n$ data points according to Eq. (7), and then find out the highest as the second clustering centre X_{c2}, and so on, and so on, and keep on finding the clustering centre of q. Here, q is determined by the magnitude of the influence of the various dimensions on the selection of the centre in each data on its own, and does not need to be determined in advance.

3) Initialise the fuzzy partition matrix $U(0)$

4) For each step use equation (7) to calculate the q centres V_i

5) Modify the partition matrix $U(r)$ for step r as follows: when $I_k=\Phi$.

When $I_k=\Phi$:

$$u_{ik}^{(r+1)}=\frac{1}{\sum_{j=1}^{q}\left(\frac{d_{ij}^{(r)}}{d_{kj}^{(r)}}\right)^{2/(m-1)}} \tag{8}$$

6) If $\left\|u^{(r+1)}-u^{(r)}\right\|\le\varepsilon_L$, stop, otherwise, set $r=r+1$ and return to step (4).

3. Personalised recommendation algorithm for e-commerce based on graph neural network

3.1. *Basic concepts of graph neural networks*

3.1.1. Graph Neural Network Modelling Commodity Recommendation. The Web consists of multiple types of objects (e.g., users (Y), goods (S), queries (C)) and their rich interaction relationships. The relationships between these three constitute a number of meta-paths that can represent the semantic relationships between users and queries.

3.1.2. Neighbourhood relations for multi-path fusion. Given an object o and a meta-path κ (starting from o) in a heterogeneous network, when object o walks along a given meta-path κ, the meta-path oriented neighboring nodes are defined as the set of all visited objects. In addition, the i th order neighboring node of object o is called $N_\kappa^i(o)$ in this paper, so it can be introduced that $N_\kappa^0(o)$ is o itself.

Given the meta-path "user-commodity-query (YSC)" and user y_2, we can obtain:

$$N_{YSC}^1(y_2)=\{s_1,s_2\} \tag{9}$$

$$N_{YSC}^2(y_2)=\{c_1,c_3,c_4\} \tag{10}$$

Then, all meta-path oriented neighbourhoods of y_2 are represented as:

$$\{N_{YSC}^0(y_2),N_{YSC}^1(y_2),N_{YSC}^2(y_2)\}=\{y_2,s_1,s_2,c_1,c_3,c_4\} \tag{11}$$

3.2. *Personalised Recommendations*

The set of users Y and the set of goods S have been defined previously. Let W denote the set of all keywords. Each item $s\in S$ has a set of selling point vocabulary (MD), denoted $T_a=\{t_1,t_2,\dots,t_m\}$, where $t_i\in W$. When a user $y\in Y$ submits a query $c=\{w_1,w_2,\dots,w_s\}(w_i\in W)$, the search engine returns a set of items. The goal is to predict $p(t_i|y,c)$ for each returned good s, i.e., the probability that each $t_i\in T_a$ attracts y given the query c. The selling point terms with the highest probability can then be added to the results of the search in the list of search results. Note that the conditions in $p(t_i|y,c)$ do not contain any goods. This is because after submitting a query, the user's preference for a product feature is deterministic and independent of the particular commodity title, and does not change in preference because of the commodity title.

In this paper, $p\left(t_i \middle| y,c\right)$ is estimated by a personalised recommendation model [31]. Since no reliable dataset of explicit user feedback on preference settings in selling keywords is collected in this paper, the model is trained using information on user clicks on common feature keywords (CMs). There is a set of labelled CM click data $S^{CM}=\left\{\left(y,c,v,d\right)\right\}$, where $v \in W$ denotes a CM and d is a binary label indicating whether y clicked on v. The problem then becomes to train the neural model for estimating $p\left(t_i \middle| y,c\right)$ under the supervision of S^{CM}.

3.3. Collaborative Filtering Algorithm

Assume that the rating matrix of n user for m items is shown in Figure 1, which is also known as the utility matrix, and the question marks in the figure indicate the rating values to be predicted.

	I_1	I_2	I_3	…	I_m
U_1	r_{11}	r_{12}	r_{13}	…	r_{1m}
U_2	r_{21}	r_{22}	?	…	r_{2m}
U_3	r_{31}	?	r_{33}	…	r_{3m}
…	…	…	…	…	…
U_n	r_{n1}	r_{n2}	r_{n3}	…	r_{nm}

Fig. 1. User - object scoring matrix

The algorithmic idea of UserCF under collaborative filtering algorithm is [32]:

1) Do similarity calculation between user u and the rest of the users based on the preferences of user u and find the most similar K users.

The similarity of users u_j and u_k can be measured by cosine distance:

$$sim\left(u_j,u_k\right)=\cos\left(u_j,u_k\right)=\frac{u_j \cdot u_k}{\left\|u_j\right\|\left\|u_k\right\|} \tag{12}$$

Where u_j, u_k are both m-dimensional vectors, further, in order to eliminate the problem of each user's rating scale, one can subtract one's own average rating for each user, and the resulting similarity is calculated as:

$$sim\left(u_j,u_k\right)=\frac{\sum_{c\in I_{\mu}}\left(r_{j,c}-\bar{r}_j\right)\left(r_{k,c}-\bar{r}_k\right)}{\sqrt{\sum_{c\in l_j}\left(r_{j,c}-\bar{r}_j\right)^2}\sqrt{\sum_{c\in I_k}\left(r_{k,c}-\bar{r}_k\right)^2}} \tag{13}$$

$r_{j,c}$ in Equation (13) is the rating of item c by user u_j. The shorter the cosine distance, the more similar the two users are. After obtaining the similarity value of each user with user u, the most similar K users are selected for user u.

2) Based on the preferences of these K users for item i, predict user u's interest in item i. The degree of preference of user u for item i can be deduced:

$$preference(u,i)=\sum_{v\in S(u,K)\cap N(i)} w_{tu}r_{vi} \tag{14}$$

where $s(u,K)$ denotes the set of K users who are most similar to user u, and $s(u,K)\cap N(i)$ is the subset of these K users who have rated item i. w_{uv} denotes the similarity between users u and v, and r_{vi} is the preference value for item i for each user v in the set. Equation (14) is a combination of the preferences of these K users for item i and the similarity of these K users to the target user to make recommendations for the user.

The recommendation performance of UserCF is also related to the size of the value of K. If the value of K is too small, it cannot form a user scale and loses the meaning of collaborative filtering. The value of K is too large, when recommending for the user to refer to too many similar users, although the group effect can be formed, but the recommended items tend to be popular items, can not effectively tap the items in the long tail, resulting in the coverage of the recommendation is not high. Therefore, choosing the right size of K values is crucial for the actual UserCF recommendation algorithm. In addition to this, the number of users in an e-commerce business is usually huge, and the overhead of finding K users similar to each user would be unacceptable.

3.4. Optimisation ideas introduced based on graph neural networks

1) Definition of relevant symbols. Definition 1: User-project evaluation matrix:

$$R=\begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ r_{31} & r_{32} & \cdots & r_{3m} \\ \vdots & \vdots & & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix} \tag{15}$$

where the rating of item j by user i is denoted by $r_{ij}\left(1\le i\le n,1\le j\le m\right)$:

$$R=\left[R_1R_2R_3\cdots R_n\right]^T \tag{16}$$

where the rating vectors (i.e., row vectors) for user i are $R_i\left(1\le i\le n\right)$, $R_i=\left(R_i,R_{i2},R_{i3},\cdots,R_{im}\right)$:

$$R_j=\left[I_1I_2I_3\cdots I_m\right] \tag{17}$$

where the rating vectors (i.e., column vectors) for item j_T are $I_j\left(1\le j\le m\right)$, $I_j=I_j\left(R_{1j},R_{2j},R_{3j},\cdots R_{nj}\right)$.

Definition 2: Sparsity of the user-item rating matrix

$S=1$ -Number of evaluated information in the rating matrix/total number of elements in the rating matrix

Definition 3: α -Operation

$$\alpha\left(P,u\right)=\begin{cases} true,u\in P,u\ne\phi \\ false,u\in P,u=\phi \end{cases} \tag{18}$$

Any class of scoring vectors (row vectors or column vectors or subsets thereof) is denoted by P.

Definition 4: β operates on

$\beta\left(P\right)=\left\{u\middle|\alpha\left(P,u\right)=ture\right\}$ and obviously $\beta\left(P\right)$ is a subset of P.

Definition 5: γ operations and ϕ operations

$$\gamma\left(P_1,P_2,\cdots,P_n\right)=\beta\left(P_1\right)\cup\beta\left(P_2\right)\cup\ldots\cup\beta\left(P_n\right) \tag{19}$$

$$\phi\left(P_1,P_2,\cdots,P_n\right)=\beta\left(P_1\right)\cap\beta\left(P_2\right)\cap\ldots\cap\beta\left(P_n\right) \tag{20}$$

Definition 6: A vector space operates on its operations θ

$P=[P_1,P_2,\cdots,P_n]$, where any two vectors P_i and P_j are not necessarily of equal length $(1\le i,j\le m)$. $\theta(P)=\theta([P_1,P_2,\cdots,P_n])=([P_1',P_2',\cdots,P_n'])$. where $P_i'=\{\, p/p\in\beta(P_i)$ whose value is the value of $p\,\}$ $\cup\{p/p\not\subset\beta(P_i)\, and p\in\gamma(P_1,P_2,\cdots,P_{i-1},P_{i+1},\cdots,P_n)$, the value is null}.

θ After the operation, any two vectors in vector space $[P_1',P_2',\cdots,P_n']$ are of equal length, and the vectors are either unfilled or the values of the elements of the corresponding vector space V are preserved. Note that the θ operation requires preserving the values of the vectors or elements in the vector space.

2) Collaborative filtering recommendation algorithm based on BP neural network. The collaborative filtering recommendation algorithm based on BP neural network mainly uses BP neural network to fill in the unrated items other than the target user's rating of the target item, so that the data sparsity is under a certain standard.

4. Personalised recommendation results for e-commerce

4.1. Simulation experiment results

4.1.1. Algorithm implementation process. The source data is the information of the products in an e-commerce platform and the data is preprocessed to standardise it. Since the research object is less diverse and more users, this paper adopts a collaborative filtering algorithm, which in turn recommends products to a certain user. First of all, basic observation and summary of the collected basic user data, and then according to the collaborative filtering algorithm in this paper, fuzzy clustering of the user's age attributes, users with similar age groups are gathered in the same cluster, and when recommending, the similarity between the products of other similar users in the cluster where the user is located is calculated, and the top 10 products with the highest similarity are recommended to the user.

Figure 2 shows the results of the clustering experiment, the paper uses fuzzy clustering to cluster the age attribute in the data and roughly divides the distribution of user's age into three clusters, namely: users aged 25-35 years old, who are skilled in the application of product e-commerce, users aged 36-45 years old, who are first time to buy agricultural products with the network, and users aged 46-55 years old, who are attempting to use the network, i.e., the parameter K=3 in fuzzy clustering is set in the paper. Using the tool Clustering is performed on the preprocessed data. It can be seen that the three clusters centre of gravity are (3.16, 32.73), (45.35, 40.25), (14.03, 52.89), there is no overlap between the user clusters, and the clustering effect is better.

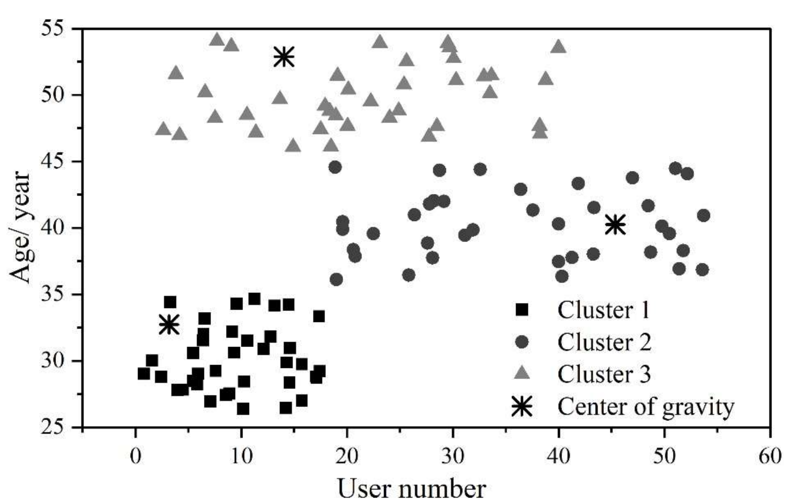

Fig. 2. Clustering experiment results

After many experiments, the experimental results in Fig. 2 are more consistent with the reality. That is, different clusters are labelled with different labels, and similar users in the same cluster are given the same label, and finally the labels are added to the standard data. Table 1 shows some of the standard data, so that the cluster of users aged 25-35 years old is 1, the cluster of users aged 36-45 years old is 2, and the cluster of users aged 46-55 years old is 3. For example, if the age of user number 1 is 27 years old, and the item number is 15, then the cluster class number is categorised as 1.

Table 1. Data after clustering

User number	User age	Item number	Cluster number
1	27	15	1
1	27	14	1
1	27	29	1
2	30	49	1
2	30	16	1
2	30	42	1
3	45	54	2
3	45	68	2
3	45	41	2
4	55	68	3
4	55	40	3
4	55	12	3
5	28	21	1
5	28	23	1
5	28	25	1
...	...	...	...

4.1.2. User preferences. Mainstream recommendation algorithms mainly include collaborative filtering, content-based and hybrid recommendation methods. And among them, the most influential is the collaborative filtering algorithms, such as user-based collaborative filtering, commodity-based collaborative filtering and model-based collaborative filtering, which is mainly based on the decomposition of user-commodity scoring matrix and discovers the preferences of similar users for recommendation. First, user preferences evolve over time, and dynamic changes in commodity recommendations are difficult to handle in time, and recommended commodities become outdated quickly. Figure 3 shows the evolution of user preferences over time, with the passage of time, the user's preference for commodity type/attribute characteristics will change. Comparing week 1 and week 10, the click-through rate of pharmaceutical and healthcare decreases from 32% to 13%. Thus, both commodity characteristics and commodity candidate sets are changing rapidly. Users' preference interests for different commodities change over time, thus, regular updating of the model is necessary.

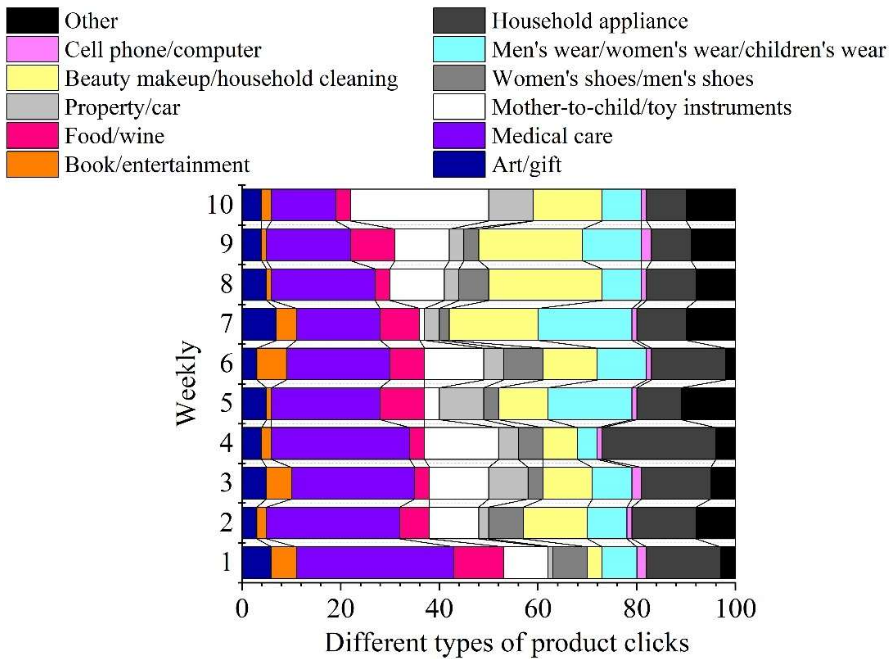

Fig. 3. User preferences change over time

4.2. Analysis of the Effectiveness of Personalised Recommendations in E-commerce

4.2.1. Effect of Personalised. Recommendation. In order to verify the accuracy and convergence of the method of this paper in achieving personalised recommendations for e-commerce, simulation experiments are conducted, which are designed using Matlab 7. The e-commerce data used in the experiment comes from the public data of Alibaba and Jingdong Mall on the web. The number of users in the test set is 2000, the optimization function for personalized recommendation is the ZDT series test function, the number of genetically evolved individuals in the D-dimensional space is 1000, the population size is set to 10, the simulation time for personalized recommendation of e-commerce is 120s, the number of running iterations is 3000, the clustering centre is $Q=40$, and the fuzzy control parameter is $c_1=120$, $c_2=350$. Based on the above simulation environment and parameter settings, a e-commerce personalised recommendation simulation analysis, and the sampled sample data set is obtained as shown in Fig. 4. When the time is 0.025s, the amplitude reaches a peak value of 0.6925.

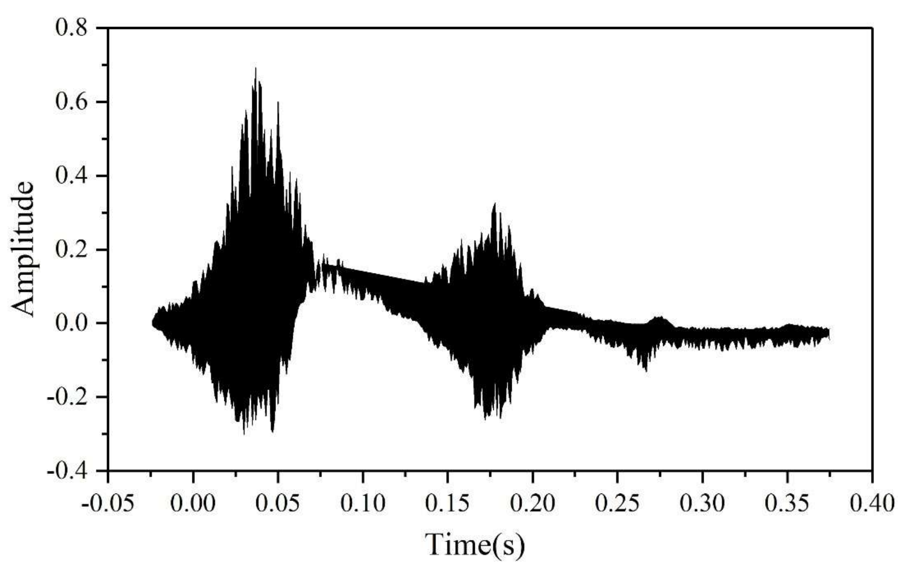

Fig. 4. Raw data sampling

Taking the e-commerce user information sampled in Fig. 4 as a sample, the personalised recommendation simulation test is carried out to test the convergence of the recommendation process and compare it with the traditional method, and the learning curve of personalised recommendation is obtained as shown in Fig. 5. The learning performance of e-commerce personalised recommendation using the method of this paper is better, with the adjusted R^2=0.8292, and the accuracy of recommendation is high.

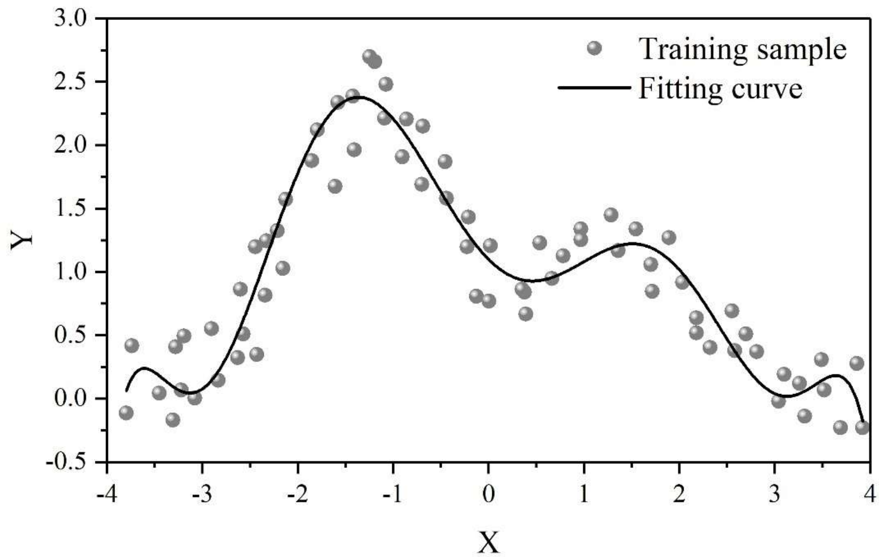

Fig. 5. The fitting curve of the personalized recommendation of the e-commerce

Figure 6 shows the satisfaction level comparison of e-commerce recommendation, comparing this paper's method with the traditional principal component analysis algorithm (PCA) and particle swarm recommendation algorithm (PSO) as well as the RFMT algorithm, where 1-4 represents RFMT, PCA, PSO, and this paper's method, respectively. From the figure, it can be seen that the method of this paper reaches 100% satisfaction level of recommendation when the number of learning times is 60 times, which is a better performance compared to other algorithms.

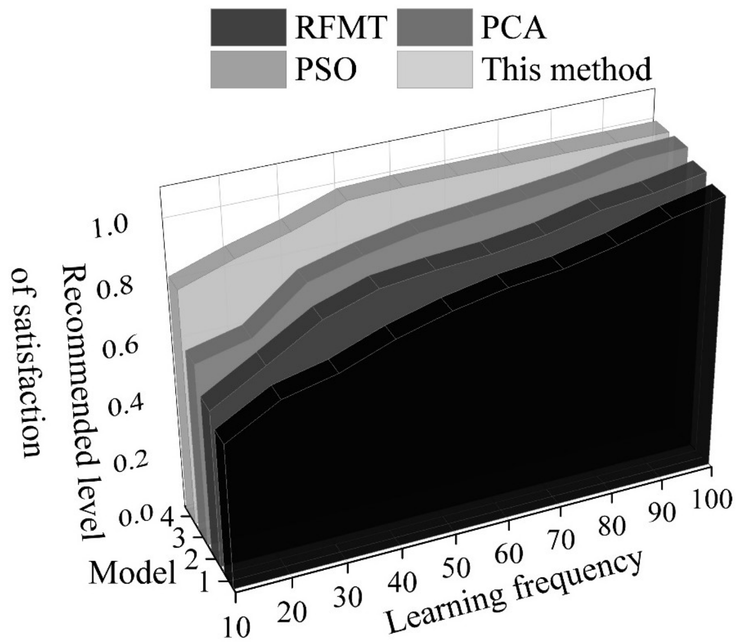

Fig. 6. Comparison of satisfaction recommended by e-commerce

4.2.2. Effectiveness of consumer adoption of recommended items. As this study focuses on exploring the impact of different recommended products on recommendation effectiveness. Therefore, after determining the experimental groups, the sales and ratings of the products recommended by the users were combined, resulting in four major categories of recommendation scenarios in this experiment. In each of these scenarios, the number of recommended products is divided into four different recommendation groups according to the proportion of recommended products. In the end, the experiment formed the following four categories with a total of 16 recommendation groups, as shown in Table 2.

Table 2. Recommendation scenario classification and specific Settings

Recommended situational classification	The proportion of recommended products			
Ⅰ Recommended product GZ&GL	GZ>GL		GZ<GL	
	GZ:GL=8:0	GZ:GL=6:2	GZ:GL=2:6	GZ:GL=0:8
Ⅱ Recommended product GZ&DZ	GZ>DZ		GZ<DZ	
	GZ:DZ=8:0	GZ:DZ=6:2	GZ:DZ=2:6	GZ:DZ=0:8
Ⅲ Recommended product GZ&DL	GZ>DL		GZ<DL	
	GZ:DL=8:0	GZ:DL=6:2	GZ:DL=2:6	GZ:DL=0:8
Ⅳ Recommended product GL&DZ	GZ>DZ		GZ<DZ	
	GZ:DZ=8:0	GZ:DZ=6:2	GZ:DZ=2:6	GZ:DZ=0:8

Note: GZ, representing high rating mainstream products, GL, which stands for high-scoring niche products,DZ stands for mainstream products with low ratings,DL, which stands for low-rated niche products.

This study argues that for search and experience products, the information and decision-making mindset that users pay attention to when choosing to buy these two products may be different.

Differences in consumers' use of online information for different types of products lead to different preferences for system-recommended products, which further has a different impact on the final recommendation effect. Therefore, when users choose and purchase experiential products, they are more likely to be influenced by system-recommended products. Separately, under each recommendation group in the four major types of recommendation scenarios, the number of consumers adopting the recommended search and experience products is analysed by two-sided t-tests, and the results of the adoption effect of consumers on search and experience products are shown in Table 3.

As shown in Table 3, under different recommendation groups in different recommendation scenarios, consumers' adoption of experiential products is better than that of search products, and the overall difference is significant, indicating that there is indeed a difference in the focus and decision-making mindset of users when choosing to buy search products and experiential products, and that under the 16 recommendation modes, only GZ:GL=6:2, GZ :GL=2:6, GZ:DZ=2:6, and GL:DZ=6:2, the t-values of the four modes are -0.9153, -1.5869, -0.7598, and -1.5264, respectively, and the rest of the modes are significantly different. For search products, consumers can easily understand the characteristics of the product by checking the description information of such products. For experiential products, on the other hand, they do not have such characteristics, and users need to query other consumers' purchasing and experiential experiences of such products to make judgements about them. Therefore, when users browse experiential products, they are more likely to be influenced by the products recommended by the system.

Table 3. Consumers' adoption of search and experience products

Recommended situation		The number of recommended products adopted by consumers		
		Search item	Experiential product	T
Ⅰ	GZ:GL=8:0	1.7956	2.2186	-1.9489*
	GZ:GL=6:2	2.5164	3.0951	-0.9153
	GZ:GL=2:6	2.1923	2.9456	-1.5869
	GZ:GL=0:8	1.5396	2.2954	-2.2498**
Ⅱ	GZ:DZ=8:0	1.9126	2.8168	-2.2598**
	GZ:DZ=6:2	1.9278	2.8162	-2.4687**
	GZ:DZ=2:6	1.9136	2.2465	-0.7598
	GZ:DZ=0:8	1.4856	2.1669	-2.2486**
Ⅲ	GZ:DL=8:0	1.5267	2.3486	-2.1687**
	GZ:DL=6:2	2.2489	3.0416	-1.9187*
	GZ:DL=2:6	1.9785	2.6879	-1.7156*
	GZ:DL=0:8	1.3895	2.0389	-1.8167*
Ⅳ	GZ:DZ=8:0	1.4265	2.1879	1.9248*
	GZ:DZ=6:2	2.1895	2.8326	-1.5264
	GZ:DZ=2:6	2.1964	2.8169	-1.8698*
	GZ:DZ=0:8	1.3194	2.0967	-2.3128**

Note: * means p<0.1, ** means p<0.05, *** means p<0.01.

5. Analysis of personalised recommendation strategies for e-commerce

5.1. Select recommendation strategies for different users

Information-rich users are those who have complete registration information and often purchase, for these users, shopping websites should extract and utilize this information as much as possible, and identify and categorize users based on this information. For example, if a user's browsing path is analyzed and found that the user tends to browse according to the price, and the usual entrance is the special area, then this user can be identified as a price-sensitive user, and recommendations generated for this type of user should fully consider the influence of price factors, such as recent discount information, promotional activities, and which products can enjoy certain benefits when purchased at the same time. For example, according to a user's browsing path, it is found that the user tends to browse according to the price, and the entrance is usually the special price area, so the user can be recognized as a price-sensitive user, and the recommendation generated for this type of user should take into account the influence of the price factor, such as the recent discount information, promotional activities, and which products can enjoy certain discounts when purchasing at the same time and so on. For those users who are passionate about fashion and prefer new products, they should be provided with information on new products or the latest trends with corresponding product descriptions. In addition, you can also form different user alliances according to the other characteristics of these users, such as often buy maternal and child goods "Mom Gang", like to buy books "book club" and so on, you can regularly provide these users with the appropriate shopping knowledge, information on hot commodities, the purchase of other members of the Information on commodities, other members of the purchase experience, you can also invite members of the Alliance for other users to introduce the corresponding experience, through these exchanges to speed up the flow of information to improve the efficiency of the recommendation.

For those users who are poor in information, mainly refers to those non-registered members, occasional browsing or buying users, most of them can become potential customers of the site through further browsing and understanding, so it should also get enough attention. But because we can not get more information about these users, so their recommendations should start from their browsing situation, such as recommending similar products, or similar browsing situation of the user's purchase of goods and so on. In addition, you can also put the site's discount promotions, the ranking of hot commodities, customer reviews of high product introductions and other links in a prominent position on the page, to attract the attention of these new users, reduce their search time and browsing costs.

5.2. Select recommendation strategies for different products

E-commerce sites have their own management and query for their commodity category system, for different categories of commodities, its display and recommendation strategy should be different.

For those users are very familiar with or often buy the goods, in the recommendation should pay more attention to the characteristics of the goods themselves, such as and similar commodities for comparison of what is special about the goods, whether the goods are in the period of discount promotions, etc., to facilitate the comparison of the same type of commodities and users can quickly choose to meet their own needs of the goods. In addition, you can also provide an introduction to often buy a piece of merchandise, such as accessories for digital products, beauty products of the same series of products, the corresponding holiday gift combinations, etc., or to provide promotional activities related to the product, such as how much money to buy similar products can be given free gifts, etc., through these ways to improve the browsing opportunities for other related products, and for the customer's browsing to bring convenience, increase their customer satisfaction. Satisfaction.

For those users do not often buy goods, such as new categories of goods, large home appliances, professional nature of the goods, etc., the user's understanding of these goods is often very limited, in this case should focus on increasing the introduction of experts on the goods and evaluation, and its functions and features to make a detailed description of the authoritative people through the explanation to help the user a better perception of these goods. Or by adding the corresponding commodity advertisements, how to use the introduction of the content of the video, you can also invite other users who have already purchased the goods to introduce their use, to bring users a more intuitive feeling, to help them make a purchase decision.

5.3. Selecting Recommendation Strategies for Different Websites

For the selection of recommendation strategies, e-commerce website operators can examine its performance from the following five aspects: the degree of personalisation, the recommendation system to give the recommended results whether it is in line with the interests of the current user, of course, the higher the degree of personalisation the better. The degree of automation, to reflect the amount of labour required by the user to get the recommended results or the ease of getting the recommended results. The degree of durability, mainly refers to whether the recommendations are based on the current user session or on multiple user sessions (current user session and previous user sessions). The degree of timeliness, users' online shopping time is often limited, whether the recommended information can be delivered in the effective time of the user's purchasing decision reflects the performance of the recommendation strategy to a certain extent. Degree of credibility, with the popularity of online social platforms, more and more recommendation information is obtained by users in their online communities, such as checking the evaluation information of related products, etc., the examination of this recommendation strategy has to be analysed in terms of its credibility.

6. Conclusion

This paper constructs a personalised product recommendation model based on the neighbourhood relationship of multi-path fusion. On this basis, it combines the algorithm of subtractive clustering and fuzzy C-mean, introduces graph neural network, and proposes an optimisation scheme for the e-commerce personalised recommendation algorithm.

1) Simulate the algorithm implementation, classify the e-commerce users according to their age, the three clustering centres of gravity after classification are (3.16, 32.73), (45.35, 40.25), (14.03, 52.89), there is no overlap between user clusters, and the clustering effect is good. The user preference of collaborative filtering algorithm is analysed, and the comparison from the first week to the tenth week shows that the click rate of medical insurance and health care decreases from 32% to 13%, which indicates that the user preference also pushes over with the change of time, so it is necessary to update the model periodically.

2) Simulation experiments are conducted to analyse the accuracy and convergence of this paper's method in e-commerce personalised recommendation, and the sample dataset obtained shows that the amplitude reaches the first peak at 0.6925s when the time is 0.025s, and the adjusted R^2 of the fitted curves = 0.8292, which indicates that the accuracy of the recommendation is high. Comparative analysis with other algorithms of recommended user satisfaction, this paper's method can reach 100% recommendation satisfaction level when the number of learning times is 60, which is better than other algorithms.

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