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Collaborative Filtering Recommendation Algorithm Based on Sparse Bilinear Convolution

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In the process of personalized dynamic web page tag information detection, the amount of data errors caused by the disturbance of the fuzzy state feature is quite high. A personalized dynamic web page tag information collaborative filtering recommendation algorithm based on sparse bilinear convolution is proposed. The sparse bilinear convolution feature reconstruction method is adopted for the feature reconstruction of personalized dynamic web page tag information, the non-linear state information optimization analysis method is combined for regression analysis and point cloud structure reorganization of personalized dynamic web page tag information, the combined feature quantity of personalized dynamic web page tag information is extracted, the average mutual information feature quantity of personalized dynamic web page tag information is then extracted by feature extraction technology. Combined with the association rule mining method, the principal component analysis of personalized dynamic web page tag information is carried out, the similarity attribute category component of personalized dynamic web page tag information is mined, and the depth learning method is adopted to carry out adaptive optimization in the collaborative filtering recommendation process of personalized dynamic web page tag information, thus realizing a collaborative filtering recommendation of personalized dynamic web page tag information. The simulation results show that the attribute classification and identification of personalized dynamic web page tag information using this method are better, the feature resolution ability is stronger, and the intelligent recommendation ability of a personalized dynamic web page is improved.

Keywords: Thinning; Bilinear convolution; Collaborative filtering; Recommendation

1. INTRODUCTION

Personalized dynamic web page tag information is stored on a large scale in the cloud database, and effective collaborative filtering recommendation of personalized dynamic web page tag information is the key to ensure effective access and retrieval from the cloud database. Through feature space reconstruction and dimension reduction processing of personalized dynamic web page tag information, association rule feature quantities of personalized dynamic web page tag information are extracted, and a collaborative filtering recommendation of personalized dynamic web page tag information is realized [1]. In order to improve access to the cloud database and the ability of automatic retrieval, and to study the recommendation model of personalized dynamic web tag information, collaborative filtering recommendation algorithms have important application value in realizing the optimal distribution design of a personalized dynamic web tag information base and the design of the cloud combination model. The research on relevant collaborative filtering recommendation algorithms of personalized dynamic web tag information has received great attention [2].

From the perspective of database display, there are a few papers about the picture dominance effect in web design in China in the past decade, most of which are psychological studies on the picture dominance effect. Li Tonggui discusses whether there is picture superiority effect in metamemory, and points out that there is an obvious picture superiority effect in the judgment level of sense of knowing, but there is a picture inferiority effect in the accuracy of judgment and recognition accuracy. Xiao Ying also found that the

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clarity and fuzziness of learning materials can affect the picture dominance effect. Domestic research on the picture advantage effect is mostly based on the foreign theoretical basis, and puts forward some picture advantage effects and picture disadvantage effects under certain circumstances. When displayed on a web page, pictures can be roughly divided into four categories: photographic pictures, vector cartoons, abstract graphics and icon graphics. Photography pictures come from photography, which can express the theme intuitively. It is required in the web page that photography pictures are clear and recognizable, and clear pictures can convey the story of the web page well. Vector cartoon pictures usually have strong color contrast and strong decorative effect. The pictures are mostly represented by cartoon images, increasing the page's liveliness and vitality. Web page types can be divided into several types including product or service query and display, brand promotion, enterprise foreign business, online shopping, enterprise portal, comprehensive information, communication and exchange platform, and government portal information. Different types of websites have different requirements for pictures. Portal information websites are rich and complex in content because of people's needs for different information, so web pages are mainly presented with text-based information. Due to the demand of the users for the details of goods, online shopping web pages are usually presented with picture based information. The demand for the presentation of the web page depends on the needs of the viewer. Therefore, excellent web design meets people's needs and promotes a good user experience.

A collaborative filtering recommendation for personalized dynamic web page tag information is based on the analysis of the characteristics of personalized dynamic web page tag information and the reorganization of data structure. By mining the effective characteristic values of personalized dynamic web page tag information and adopting the distributed topology structure design method, the optimized topology design of personalized dynamic web page tag information is carried out, the graph model structure design of personalized dynamic web page tag information is realized, and the collaborative filtering recommendation for personalized dynamic web page tag information is realized through application in database retrieval. The traditional personalized dynamic web page tag information recommendation method has several issues including a high computational cost and fuzzy recommendation [3]. A personalized dynamic web tag information collaborative filtering recommendation algorithm based on sparse bilinear convolution is proposed. The sparse bilinear convolution feature reconstruction method is used to reconstruct the characteristics of personalized dynamic web page tag information. The feature extraction technology is used to extract the average mutual information feature quantity of personalized dynamic web page tag information [4, 5]. The association rule mining method is combined to carry out the principal component analysis of personalized dynamic web page tag information to realize collaborative filtering recommendation and optimal access of personalized dynamic web page tag information. Finally, the simulation experiment analysis shows the superior performance of the method in improving the collaborative filtering recommendation capability of personalized dynamic web page tag information.

2. BASIC DEFINITIONS

Identifiers need to be filtered out when extracting text information. It is not difficult to filter identifiers, as there are certain rules for them, as long as the corresponding information is obtained according to the different identifiers. However, many pieces of layout information must be recorded synchronously, including the font size of the text and whether the text is a title, is bold, or is a key word of the page, all of which helps to calculate the importance of the words in the web page. At the same time, for HTML web pages, in addition to the title and body, there will be many advertising links and public channel links. These links have no relationship with the text body at all. When extracting the content of the page, these useless links must be filtered out. For example, if a website has a “product introduction” channel and it is shown in the navigation bar, it will be displayed on every page in the website. Without filtering the navigation bar links, a search for “product introduction” will display every page in the website, negating the usefulness of the search function entirely. To filter these invalid links, a large number of page structure rules must be counted, common features need to be extracted, and then uniformly filtered; for some specific websites, these invalid links must be dealt with individually. This requires that the design of web spider has expansibility. For multimedia, picture and other files, the content of these files is generally judged by the linked anchor text (i.e. the linked text) and the related file annotation. For example, if there is a link with the text “Zhang Manyu's photo” and the link points to a picture in BMP format, the web spider will know that the content of this picture is “Zhang Manyu's photo”. In this way, when searching for “Zhang Manyu” and “photos”, the search engine can find this picture. In addition, many multimedia files have file attributes. Considering these attributes, we can better understand the content of the file.

Dynamic web pages have always been a problem for web spiders. The so-called dynamic web page is relative to the static web page, which is automatically generated by the program. The advantage of a dynamic web page is that it can change the style of web page quickly and uniformly, and it can also reduce the server space occupied by a web page, but it also causes issues for web spiders. Web spiders find it more difficult to deal with some script language generated web pages, including those generated by VBScript and JavaScript. In order to deal with these pages well, web spiders need to have their own script interpreter. For many sites, data is placed in a database that needs to be searched to retrieve information; this causes great difficulties to the web spiders. For this kind of website, if the website designer wants the data to be indexed by the search engine, they need to provide a way to traverse the entire database content. Web content extraction has become an important technology in web spiders. The whole system is generally in the form of plug-ins. Through a plug-in management service program, web pages with different formats are processed by different plug-ins. The advantage of this method is that it has good extensibility. Every time a new type is found, it can be treated as a plug-in and added to the plug-in management service program.

By using the established dictionary base or knowledge base to expand the query term, the recall rate and precision rate of search engine can be improved. After analyzing the initial query feature words of users properly, the query extension adds the feature words with the same concept attribute to the initial query words to form a richer user query, in order to improve the query accuracy. For example: "information retrieval" → "information retrieval" and "search engine"; "computer" → "computer" or "electronic information". The main process is as follows:

The methods of query extension can be divided into three categories: based on the user's registered interest, based on the user's feedback on the result set operation, and based on the global information of the search result document set. These methods expand the initial query through different ways to improve the user proximity of the query results. The user interest registration method is the most accurate and easy to implement, but the user must register first. The user feedback information mining method does not require any additional information from the user, but the workload of search engine will be greater, the accuracy of the mining is difficult to control, and mining itself also involves the problem of user privacy permission. The method global information based on search result document set has been very popular. Good implementation solves the problem of query expansion to a large extent. The query expansion method based on word frequency statistics does not rely on dictionaries, but on the frequency statistics of the co-occurrence of consecutive strings in the article. The strings whose co-occurrence frequency is greater than a chosen standard are regarded as a word. The so-called co-occurrence frequency is a measure unit that uses the word frequency statistical method to determine whether a string is a word. It is generally considered that the co-occurrence frequency is directly proportional to the length of the string and the number of times the string appears in the article. The accuracy of word segmentation is comparatively low, but by using this method, proper nouns, that are not included in some dictionaries, such as people's names and place names can be extracted. For those articles with strong specialization, this word segmentation method can extract the words that reflect the theme of the article more effectively.

The user interface is responsible for the events in direct contact with the user, and the main function points include:

(1) The user query interface must be simple and clear. If the user wants to get personalized query results, they must first log in to the system.

(2) In order for a user to log in to the system for the first time, the user needs to register, the system records the user's relevant information, such as background knowledge and research fields for the subsequent analysis of the user's interests. Through registration, the system will establish a unique account for each user, and information about the user's personal interests will be stored in the user interest database with this unique account as the identifier. The system analyzes this data through a personalized and intelligent algorithm in order to provide personalized query responses for users.

(3) Registered users can select a personalized interface; the page can be set according to the user's customized requirements meeting the personalized requirements of different users.

(4) Registered users can choose their interest types when they register. The model stores these interest classes in the user interest database, so as to provide personalized query results for users.

(5) Analysis of the user's interest in the database provides a reasonable display sequence of the user's results.

In order to optimize the design of the collaborative filtering recommendation algorithm for personalized dynamic web page tag information combined with the distributed structure reorganization method of personalized dynamic web page tag information storage nodes, the personalized dynamic web page tag information architecture is established on the basis of web-based mobile social networks (MSNs, WMSNs) and decentralized mobile social networks (DMSNs) [6], and the vector quantization analysis method. An optimal distribution model of personalized dynamic web page label information storage nodes is constructed, and a graph model structure of personalized dynamic web page label information is represented by a binary directed graph, wherein $G = (V,\ E)$ is a vertex set deployed at the distribution nodes of the data graph model; V is a collection of all edges of personalized dynamic web page tag information in a limited domain distribution area [7]. Assuming $M_1, M_2 \cdots M_N$ are Sink nodes of personalized dynamic web tag information, Euclidean distance is used to represent the phase trajectory spacing of personalized dynamic web page tag information transmission nodes [8]. Under the initial link distribution model of personalized dynamic web tag information community nodes, the distributed topology model of sparse data is shown in Figure 2.

Combined with the topological structure model shown in Figure 1, a limited coverage area model of personalized dynamic web page tag information is constructed. In the personalized dynamic web page tag information storage structure network, the weighted coefficient of the directed graph vector of the collaborative filtering recommendation model is $W = \{u, w_1, w_2, \cdots, w_k\}$, in the information coverage area of personalized dynamic web page tag information, assuming that the link layer data transmitted by m network nodes of personalized dynamic web page tag information is $x(k-1), \ldots, x(k-M)$, and the estimated value of the initial position $x_s = [x(\eta_1, \ldots, x(\eta_N))]^T$ of harmonic feature distribution nodes:

$$\hat{x}_s = W_s^T y \tag{1}$$

Based on the service priority division method, the load model of the personalized dynamic web page label information transmission node is obtain as follows:

$$\begin{aligned} r(t) &= \sum_i \sum_{j=0}^{N_f-1} \sum_{l=0}^{L-1} b_i \alpha_l p\left(t - iT_s - jT_f - c_j T_c - \tau_l\right) + \omega(t) \\ &= \sum_i \sum_{j=0}^{N_f-1} b_i p_h\left(t - iT_s - jT_f - c_j T_c - \tau_0\right) + \omega(t) \end{aligned} \tag{2}$$

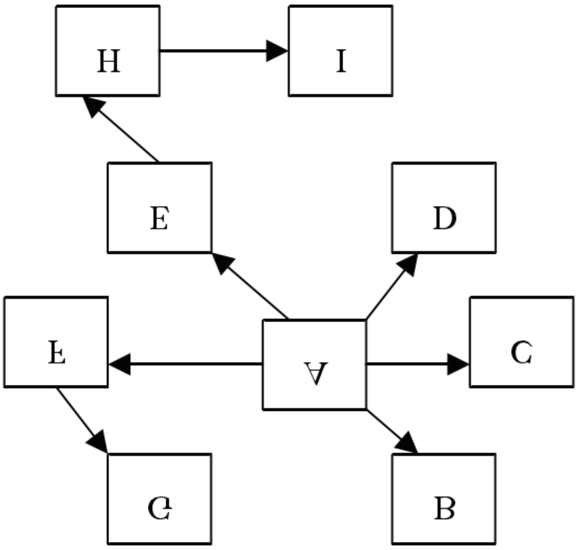

Figure 1 Schematic diagram of information extraction steps.

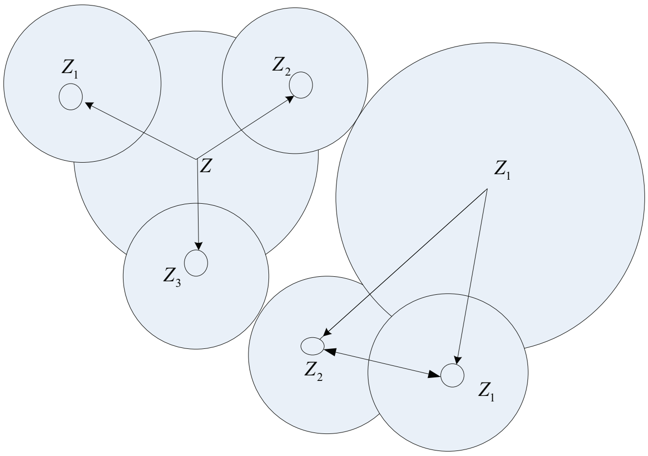

Figure 2 Distributed topology model of high-dimensional sparse data.

wherein

$$p_h(t) = \sum_{l=0}^{L-1} \alpha_l p\left(t - \tau_{l,0}\right) \tag{3}$$

In addition, $\omega(t)$ is the data dimension of the virtual node, $p_h(t)$ is the distance between the personalized dynamic web page label information Source and Sink nodes. The sparse bilinear convolution feature reconstruction method is adopted for the feature reconstruction of personalized dynamic web page tag information, and the non-linear state information optimization analysis method is combined for regression analysis and point cloud structure reorganization of the personalized dynamic web page tag information [9].

The structural model of the phase space reconstruction of personalized dynamic webpage tag information is as follows:

$$\begin{aligned} X &= [s_1, s_2, \cdots s_K] \\ &= \begin{bmatrix} x_1 & x_2 & \cdots & x_K \\ x_{1+x} & x_{2+\tau} & \cdots & x_{K+\tau} \\ \cdots & \cdots & \cdots & \cdots \\ x_{1+(m-1)\tau} & x_{2+(m-1)\tau} & \cdots & x_{M+(m-1)\tau} \end{bmatrix} \end{aligned} \tag{4}$$

where $K = N - (m-1)\tau$, which represents the embedding dimension of the personalized dynamic web page label information search feature space, τ is the time delay, m is the number of virtual nodes and virtual link layers, and $s_i = \left(x_i, x_{i+\tau}, \cdots, x_{i+(m-1)\tau}\right)^T$ is called the time slot set. Data feature extraction is carried out in the reconstructed phase space to improve the collaborative filtering recommendation capability of the data [10].

3. COMBINED FEATURE EXTRACTION OF PERSONALIZED DYNAMIC WEB LABEL INFORMATION

The application of pictures is very important for web page design, but different types of web pages have different needs. Therefore, the advantage effect of pictures in web page design is not absolute. In product display, brand promotion, enterprise foreign business and online shopping web sites, more consideration should be given to the application of pictures in the web page design in order to take full advantage of the effect of the pictures. In portal information websites, the balance between pictures and words should be carefully considered. There should not be a large number of pictures that clutter the web page and cause it to load slowly. Excessive use of pictures leads to the disadvantage effect of pictures. Most of the pictures in the web page are not decorative; they are often related to the text. Pictures need to co-operate with the text to convey the information of the web page. For example, the proportion of ads, pictures and text on Apple's official iPad Air website is the same, which jointly expresses the information of their products.

According to the research on the definition of web page pictures, different types of web pages have different requirements on the clarity of their pictures. Pictures with high definition can have an advantageous effect on shopping websites, while pictures with low definition can have an advantageous effect in pages where the text is more important. There are many styles of pictures in web pages; the authenticity and veracity of pictures are very important for users who browse web pages. The research and application of the image advantage effect in web design is not very common, which is not conducive to brand promotion and product display for website enterprises. The color content of a picture is a major feature that distinguishes a picture from a text. Although there are also color fonts and black-and-white pictures, in a web page, pictures are often attached with rich colors, while the text mostly exists in black. Therefore, web page pictures and colors are more closely related. Vibrant colors can enhance people's arousal and attract more attention. Therefore, from the perspective of color, pictures on web pages are often more attractive than the text, due to the color advantage effect. A picture can often show a variety of colors, and for text, in addition to the visual design of artistic fonts, a line of words usually only has one color. Pictures can attract people's attention and have an advantageous effect due to the characteristics of color; however, the advantage effect of pictures is often restricted. For example, in a web page with a minimalist style, adding too many bright and colorful pictures will affect the simple visual effect of the whole web page, detracting from the visitor experience. Web images can therefore have a disadvantageous effect in this situation. On a food web page, warm color food pictures can often attract people's attention, affect people's taste experience and stimulate people's appetite. However, if the color of the picture is dim, not only are the characteristics of the food itself not shown, but this can also affect people's mood, which is not conducive to the information transmission of the web page. The dim picture color becomes the factor that restricts the picture superiority effect. As different types of web pages have different needs for pictures, the picture advantage effect is limited within web design, and has constraints. There are obvious advantages in product display, brand promotion, online shopping and enterprise foreign-related business websites. However, for portal websites with complex information, the advantage effects of pictures are reduced. Excessive use of pictures for these websites will cause a disadvantageous effect. The advantage effect of pictures in related web pages can also be restricted by internal and external factors. If there is a contradiction between the pictures and text it will make the contents of the pictures untrustworthy and restrict the advantageous effect of the pictures; the irregular layout of some web pages can also make pictures become interference factors that affect the reading flow of users and distract their attention; in shopping websites, low-resolution or fuzzy pictures cannot express product details and reduce users' trust; in social websites, virtual avatars do not accurately portray the user. A real user portrait is effective, but also to a certain extent restricts the image in having the maximum advantage effect; the content and color of the image also affect the image advantage effect, the advantage of the image only occurs when high-quality content and appropriate color are selected. Therefore, the existence of the image superiority effect in web design is conditional. The type of web page, the relationship between the image and the other visual elements of web page, and the characteristics of image itself all need to be considered. In web page design, the type and goal of web page needs to be understood, and the relationship between the pictures and the text, the content, color, layout and other elements must all be considered. Finally, the application mode of the pictures can be determined. Therefore, to maximize the advantage effect of pictures, the relationship between various factors needs to be weighed. A good web design is the balance among the elements of picture, text, layout and content.

Assuming that the statistical distribution sequence of personalized dynamic web page tag information flow to be recommended for collaborative filtering makes $\{x_1, x_2, \ldots, x_N\}$ a set of regression analysis feature quantities, sparse scattered point cloud mapping of personalized dynamic web page tag information is carried out in $x(n)$ dimension reconstruction phase space, and the distributed recombination structural formula of personalized dynamic webpage tag information is obtained as follows

$$\begin{aligned} \boldsymbol{X}(n) = \{&x(n), x(n+\tau), \cdots, \\ &x(n+(m-1)\tau)\} \quad n = 1, 2, \cdots, N \end{aligned} \tag{5}$$

The τ represents the embedding delay of personalized dynamic web page tag information in high-dimensional phase space [11], establishes a state transition model, and the expression of the feature evaluation concept set of personalized dynamic webpage tag information is expressed as follows:

$$p(y \mid \alpha, \theta) = \sum_{k=1}^{K} \alpha_k p_k \left(y \mid \mu_k, \sum_k \right) \tag{6}$$

Mining the association rule characteristic quantity of the recommendation attribute of the personalized dynamic web page label information:

$$\max_{x_{a,b,d,p}} \sum_{a\in A} \sum_{b\in B} \sum_{d\in D} \sum_{p\in P} x_{a,b,d,p} V_p \tag{7}$$

$$\text{s.t.} \sum_{a\in A} \sum_{d\in D} \sum_{p\in P} x_{a,b,d,p} R_p^{bw} \leq K_b^{bw}(S), b \in B \tag{8}$$

Using the method of cloud sparse evacuation random point structure reorganization, the scattered point set of the first personalized dynamic web page label information is $P_i = (p_{i1}, p_{i2}, \cdots p_{iD})$, in which:

$$j \in N_i(k), N_i(k) = \left\{ ||x_j(k) - x_i(k)|| < r_d(k) \right\} \tag{9}$$

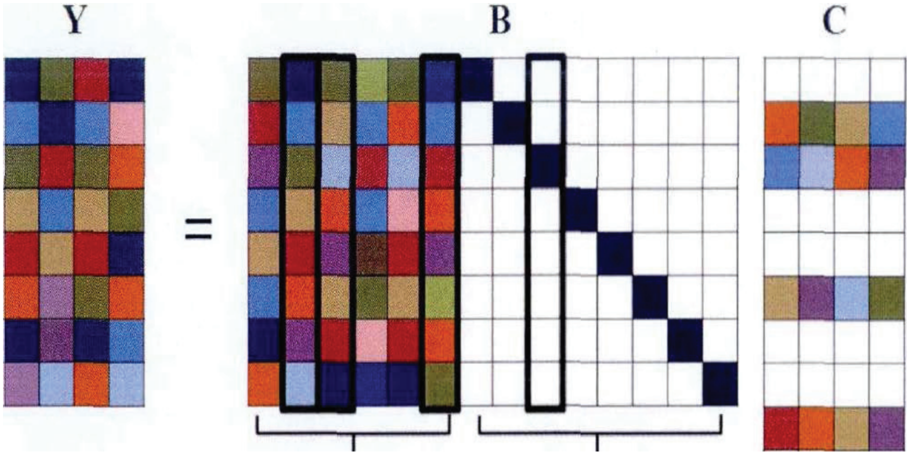

Figure 3 Multitask Joint Sparse Learning

Using the evolutionary time slot allocation mechanism, the attribute mixed recommendation value of personalized dynamic web page label information is calculated as:

$$x_i(k+1) = x_i(k) + s\left(\frac{x_j(k) - x_i(k)}{\left\|x_j(k) - x_i(k)\right\|}\right) \tag{10}$$

where: $\|\vec{x}\|$ represents the norm of $\vec{x}$, the combined characteristic quantity of user behavior is $P_{ij}^{best}(k)$, and the iteration step length is S.

The combined feature quantity is optimally extracted, and a depth learning algorithm is adopted to calculate the statistical feature quantity of personalized dynamic web page tag information in a dense scene at the starting time T_0, so that the trust value of the evolutionary time slot allocation in personalized dynamic web page tag information is obtained as follows:

$$ITrust_{a\to c} = \frac{\sum\limits_{b\in adj(a,c)} DTrust_{a\to b} \times (DTrust_{b\to c} \times \beta_d)}{\sum\limits_{b\in adj(a,c)} DTtrust_{a\to b}} \tag{11}$$

In the combination feature recommendation based on trust degree, the Gaussian distribution of spectrum Z-slave parameter β_d is obtained in the superframe structure, where:

$$\beta_d = (MPDist - d + 1)/MPDist, \quad d \in [2, MPDist] \tag{12}$$

where, $adj(a, c)$ represents the number of $a \to c$ paths, and is responsible for the number of paths for the client to process the data, $\beta \in (0, 1$, using the fuzzy directivity clustering method, carries out the combination feature mining and extraction of personalized dynamic web page label information. The collaborative filtering recommendation algorithm design of the data is realized according to the result of the feature extraction [12]. The application of the picture advantage effect in web page design is to make full use of pictures to assist the web page achieve its goal. The strategy of the web page image design can implement the virtual image advantage effect into the specific design, and guide the web page interface design through the use of advantageous images. Based on the two dominant effects of pictures in web design, cognitive advantage effect and emotional advantage effect, the strategies of web design can be studied and discussed from the cognitive and emotional levels. Through the study of the design strategy of the pictures, the purpose is to provide an effective design idea for the web design, and ultimately meet the cognitive and emotional needs of the web users. The cognitive design strategy and emotional design strategy of pictures have strong research values and design practice significance.

4. OPTIMIZATION DESIGN OF RECOMMENDATION ALGORITHM

4.1 Principal Component Analysis of Personalized Dynamic Web Label Information

Each task in sparse learning is independent of each other. As most of the candidate particles are distributed near the target position in the previous frame, there is a certain correlation between the particles. In sparse learning, the correlation between particles shows that the observations of all candidate particles based on the sparse representation of the hypercomplete dictionary are similar objects whose appearance can be approximately represented by a low dimensional subspace. In the tracking framework, such a seed space can be represented as a series of templates. For the first frame of the tracking sequence, the target region can be obtained by artificial calibration (i.e. manually selecting four corners of the target region) or by using the existing detection algorithm. The selected target area is then moved several pixels in each direction to generate target templates of the same size. The image region corresponding to the target template is extracted, and the extracted feature vectors are stored in columns, that is, the reconstruction of the target region. The graph of multi task joint sparse learning is shown in Figure 3.

In sparse learning, the area polluted or occluded by noise can be represented by micro template space. When the characteristic values of some pixels in the target area cannot be approximately represented by the target template, the badge template corresponding to its position will be excited.

Firstly, the one-dimensional micro template coefficient vector is reconstructed into a two-dimensional micro template coefficient image. Each pixel on the micro template coefficient image corresponds to the same position pixel in the normalized tracking result area. The image of the micro template coefficient is then binarized to get the occlusion map. On the binary occlusion map, the white pixel represents the occluded area, and the black pixel represents the unobstructed area. As the size of the occluder is much larger than the size of random noise, the occluder can be represented as a large white connected area on the occluder map.

In sparse learning, the correlation between features shows that the observations of candidate particles corresponding to each feature are similar based on the sparse representation of a hypercomplete dictionary. The basic idea of multi-task and multi-feature joint sparse learning is to force the observations of all candidate particles corresponding to each feature to be represented by as few of the same templates as possible in the super complete dictionary. Considering multiple features and the correlation between particles, on the basis of the above-mentioned feature reconstruction and feature extraction of personalized dynamic web page tag information using the sparse bilinear convolution feature reconstruction method [13], regression analysis and point cloud structure reorganization of personalized dynamic web page tag information are carried out in combination with the non-linear state information optimization analysis method, and the trust relationship of personalized dynamic web page tag information is expressed as $A \rightarrow B,\ B \rightarrow C$, and the regression analysis model is derived as follows:

$$MSD_{a\rightarrow b} = 1 - \frac{\sum_{i=1}^{|I_{a,b}|} \sqrt{\left(d_{a,i}-\bar{d}_a\right)^2 + \left(d_{b,i}-\bar{d}_b\right)^2}}{\left|I_{a,b}\right| \times \sum_{i=1}^{|I_{a,b}|} \left[\sqrt{\left(d_{a,i}-\bar{d}_a\right)^2} + \sqrt{\left(d_{b,i}-\bar{d}_b\right)^2}\right]} \tag{13}$$

Using feature extraction technology to extract the average mutual information feature quantity of personalized dynamic web page tag information, and outputting the mutual information of attribute distribution of personalized dynamic web page tag information is as follows:

$$I(Q,S) = H(Q) - H(Q|S) \tag{14}$$

wherein

$$H\left(Q \mid s_i\right) = -\sum_j \left[p_{sq}\left(s_i, q_j\right) \Big/ p_s\left(s_i\right)\right] \log_2 \left[p_{sq}\left(s_i, q_j\right) \Big/ p_s\left(s_i\right)\right] \tag{15}$$

Using feature extraction technology to extract the average mutual information feature quantity of personalized dynamic webpage tag information, in combination with the association rule mining method to carry out principal component analysis of personalized dynamic web page tag information, carrying out collaborative filtering recommendation according to the attribute mining result of personalized dynamic web page tag information, and obtaining that the decision criterion of data collaborative filtering recommendation meets the following requirements [14]:

Norm (1):

$$\sqrt{\frac{R_{(m+1)n}^2 - R_{mn}^2}{R_{(m+1)n}^2}} = \frac{\left|x_{\eta(n)+m\tau} - x_{n+m\tau}\right|}{R_{(m+1)n}} \geq R_{tol} \tag{16}$$

Norm (2):

$$\frac{R_{(m+1)n}}{\sqrt{\frac{1}{N}\sum_{k=1}^{N}\left[x_k - \frac{1}{N}\sum_{k=1}^{N} x_k\right]^2}} > A_{tol} \tag{17}$$

According to the recommended decision criteria of personalized dynamic web page tag information, the principal component analysis of personalized dynamic web page tag information is carried out. In the characteristic distribution attribute set of data, $\{u_1, \ldots, u_N\}$ is set to represent the class space distribution set of personalized dynamic web page tag information of the contained element node set, $\{v_1, \ldots, v_M\}$ is set to represent the untrusted node set, $R = R_{u,vN\times M}$ is set to represent the user behavior set of personalized dynamic web page tag information, and principal component analysis of data is carried out through carrier monitoring multi-access control method. Recurrence formula is as follows:

$$p_i^* = \frac{1}{\sum_{j=i}^{N} \frac{2m_j}{\sum_{k=j+1}^{N+1} L_k p_k - \sum_{k=j}^{N} E_k}} - 1, \quad i = 1, \ldots, N+1 \tag{18}$$

The $CIntra_i(n)$ is used to represent the optimal interval for the location of the personalized dynamic web page label information azimuth node i. The $CInter_i(n)$ represents the total time slot of the competitive node i. According to the above analysis, the principal component analysis of the personalized dynamic web page label information is carried out in combination with the association rule mining method to mine the similarity attribute class component of the personalized dynamic web page label information [15, 16].

4.2 Collaborative Filtering Recommended Output

An adaptive information fusion method is adopted to carry out the information fusion of the output characteristics of personalized dynamic web page tag information, and fuzzy clustering and feature mining processing of personalized dynamic web page tag information are carried out in a high-dimensional phase space. Assuming that the statistical feature sequence $\{X_n\}, n = 1, 2, \cdots, N$ of personalized dynamic web page tag information represent the original personalized dynamic web page tag information feature distribution set to be recommended, the feature distribution of personalized dynamic web page tag information recommended by collaborative filtering is obtained in a fuzzy grid area clustering environment, wherein the statistical feature quantity of observation data is $X_N = X_n + \eta$. In the

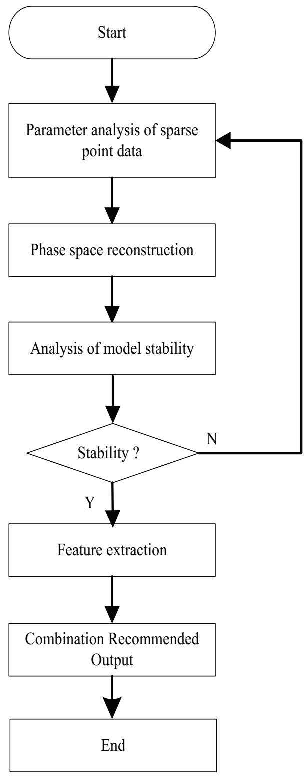

Figure 4 Realization flow of the algorithm.

distribution space of personalized dynamic web page tag information, the phase space reconstruction technology is adopted to reconstruct the characteristics of personalized dynamic web page tag information to obtain the current distributable maximum time slot distribution:

$$X_n = \left\{X_n, X_{n-\tau}, X_{n-2\tau}, \cdots, X_{n-(d-1)\tau}\right\} \tag{19}$$

The $R_{x\times L}$ is the matrix of the $d \times L$, and the average mutual information characteristic of the personalized dynamic web page tag information which is obtained through frequent item mining is:

$$R_1 = \{X_1, X - 2, X_3, \cdots, X_d\}^T \tag{20}$$

Using the depth learning method for adaptive optimization of the personalized dynamic web page tag information collaborative filtering recommendation process, the association rule vector set of personalized dynamic web tag information is:

$$R_1^T R_1 = \{X_1, X_2, \cdots, X_m\}\{X_1, X_2, \cdots, X_m\}^T \tag{21}$$

Under deep learning, the learning process of personalized dynamic web label information is iterative:

$$R_1^T R_1 = V_1 \sum{}_1 V_1^T \tag{22}$$

In the grid region of $L + 1$ to $2L$ dimension, the dimension reduction of the personalized dynamic page tag information is carried out. According to the above method, the recommended output eigenvalue of the personalized dynamic page tag information collaborative filtering is:

$$R_2^T R_2 = V_2 \sum_2 V_2^T \tag{23}$$

$$R_2 = \{X_{d+1}, X_{d+2}, \cdots X_{d+m}\}^T \tag{24}$$

$$R_2^T R_2 = \{X_{d+1}, X_{d+2}, \cdots X_{d+m}\}\{X_{d+1}, X_{d+2}, \cdots X_{d+m}\}^T \tag{25}$$

In the formula, the test set $V = [V_1, V_2, \cdots, V_m] \in R^{m\times m}$ of personalized dynamic web page label information is orthogonal, that is $VV^T = I_M$, $\sum = \mathrm{diag}(\sigma_1, \sigma_2, \cdots, \sigma_m) \in R^{m\times m}$, using feature extraction technology to extract the average mutual information characteristic of personalized dynamic web page label information, using the process feedback of the deep learning machine algorithm to realize error correction, so that the feature vector set $R^T R$ of the recommended output satisfies the balance between classes.

5. SIMULATION EXPERIMENT AND ANALYSIS OF RESULTS

In order to verify the application performance of the method in implementing collaborative filtering recommendation of personalized dynamic web page tag information, simulation experiments are carried out by combining Matlab and C++ programming software. The sample database of personalized dynamic web page tag information is from the cloud combination database Pearson Database, where Pearson linear correlation coefficient is set to 0.34 and Spearman rank correlation coefficient is set to 0.21. Using the K-S test to judge the convergence in the recommendation process, the dimension of personalized dynamic web page data is set

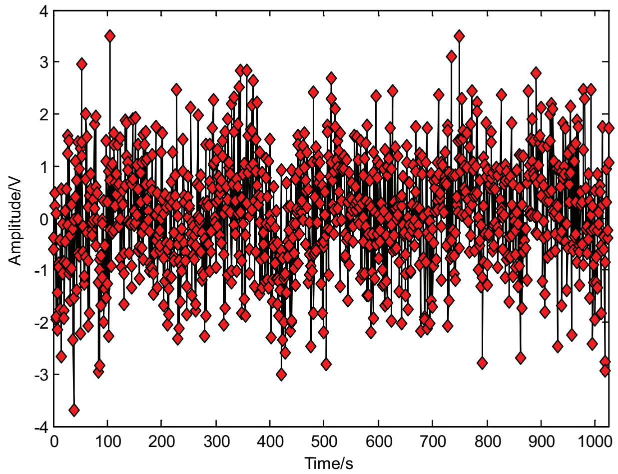

Figure 5 Sample distribution of personalized dynamic web page tag information.

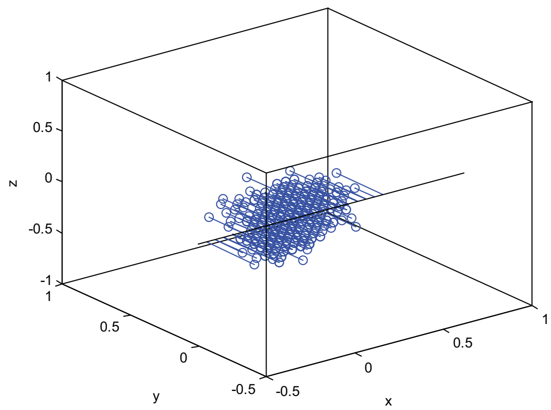

Figure 6 Co-filter recommendation output for personalized dynamic web page tag information.

to 40, the length of sampling samples is set to 1200, the size of personalized dynamic web page test set is 3000, and the optimal distribution type parameter is 23. According to the above simulation environment and parameter setting, the collaborative filtering recommendation simulation analysis of personalized dynamic web page tag information is carried out, and the sample distribution time domain diagram of personalized dynamic web page tag information is given in Figure 5.

Taking the above data as the research sample, the sparse bilinear convolution feature reconstruction method is used to reconstruct the features of the personalized dynamic web label information, and the combined feature quantity of the personalized dynamic web label information is extracted to realize the co-operative filtering recommendation of the data. The recommended output of the high-dimensional data is shown in Figure 6.

The analysis in Figure 4 shows that using this method can effectively realize the collaborative filtering recommendation of personalized dynamic web page label information, and the dimensionality reduction expression ability of the data is higher than that of Figure 3, and the recognition degree of the data in the high-dimensional phase space is more obvious and the recommendation ability is stronger. Table 1 and Table 2 show the outcomes of testing the time cost and accuracy of personalized dynamic web page tag information recommendation using different methods. The analysis shows that the time cost of this algorithm for personalized dynamic web page tag information recommendation is relatively short and the accuracy is high.

6. CONCLUSIONS

Effective collaborative filtering recommendation for personalized dynamic web page tag information is the key to ensure effective access and retrieval from a cloud database. The distributed topology model of high-dimensional sparse data was constructed, the regression analysis and point cloud structure reorganization of personalized dynamic web page label information were carried out by combining the non-linear state information optimization analysis method, the result of attribute mining of personalized dynamic web page label information was recommended, the decision criterion of data collaborative filtering recommendation was obtained, the similarity attribute category component of personalized dynamic web page label information was mined, and the feature distribution of personalized dynamic web page label information was obtained under the fuzzy grid area clustering environment. The research shows that the identification degree, accuracy and time cost of this method are higher than the existing methods.

Table 1 Comparison of recommended time- overhead performance for collaborative filtering of personalized dynamic web label information (Unit: s).

Sample	This method	Fuzzy algorithm	Load balancing algorithm
Group 1	0.556	3.454	1.365
Group 2	0.443	4.333	2.435
Group 3	0.756	3.557	5.678

Table 2 Comparison of recommended precision performance for collaborative filtering (%).

Sample	This method	Fuzzy algorithm	Load balancing algorithm
Group 1	98.554	93.435	84.678
Group 2	99.436	93.4678	93.545
Group 3	99.764	95.435	94.568

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