Research on personalized information recommendation platform for CSA users

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Abstract

This paper analyses the demand in personalized recommendation service and the characteristics of classification content for CSA users. Then it proposes a personalized information recommendation platform based on the interests of agricultural users. For the interest update in push service, we integrate mathematical modeling, three-dimensional synthetic techniques and the quantization techniques, to establish user interest model. For the distribution problem in push service of agricultural information, we propose an improved classification model based on genetic algorithm, BP neural network and multiple linear regressions. The process of feature extraction and algorithm implementation are also provided in this paper. The experiments show our recommendation algorithm based on user interest has obvious improvement in precision and recall compared to traditional algorithms. It can further excavate the users' interest to cater to the preferences and make effective and in-time information recommendation.

Keywords: recommendation service, data miming, interest, neural network, agricultural information

1 Introduction

The new community support agriculture (CSA) has become the hotspot for agricultural user. CSA integrates social network and actual land in a novel pattern. However, in order to perform network-based community support agriculture, the management company is required to be powerful in organic agriculture, network, logistics with large-scaled investment and highly effective management [1]. The farmers determine the varieties of production, management, items by obtaining supply and demand information of market agricultural products, before and after production. Meanwhile, according to agricultural materials, planting and aqua cultural information, they can reasonably arrange their productions. These information becomes the source for farmers' competition in agricultural production. For instance, vegetable farmers can rationally assemble market supply varieties by sales of various vegetables, price and inventories in market. Grain farmers can make correct management choice according to requirement information of national various grain-oil exchange market. We can also adjust the aquaculture plans by aquaculture information of related varieties. However, production-based agriculture production information, planting-breeding information and supply-demand information of agricultural products have obvious difference with different requirement types of agricultural workers in their regions. Most technologies in traditional recommendation systems are general models without combining recommendation models with domain feature [2, 3]. Thus, this paper creates a users' knowledge base of regional characteristics and integrates the users' features to establish users' interest model, based on regional advantage model in agricultural field. It provides personalized recommendation service of agricultural information, which is more accurate than traditional models for personalized recommendation.

With the development of personalized service and further research, the researchers are conscious of important position of user modeling technology on personalized service and start related research in recent days. The main results of foreign research achievements on information acquisition and modeling include: Pazzani in literature [4] proposes a news guidance agent *NewsDude* which advocates a special theme to sort pages. According to users' feedback, it learns and updates user's model and recommends users news by interest model. Fab in literature [5] requires users sort the rank page in person and it discovers user model by webpage rank and content. Literature [6] makes use of vector space model to express users' interest and it is represented by a group of keywords feature vectors. However, domestic scholars also carry out corresponding researches in relative field and they focus on the user expression, user modeling, feedback update, etc. For instance, Ying [7] proposes a client-side fine-grained user interest modeling method for personalized service. This method integrates users' background knowledge and adopts word frequency to select the feature subset. Then it applies the improved K-nearest classifier to constitute user model to get better experiment effect. Wang in literature [8] adopts implicit feedback and reinforcement learning to adjust user interest model and

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update users' interest. Cheng in literature [9] applies agent technology to screen and filter Web information. It integrates the log mining with Web content mining to analyze the log file at server and establish user model, providing selective service of information.

From the perspective of current and future development, the key point in personalized service research field is extracting and expressing true interest of users effectively. Thus, based on relevant principles and technologies in personalized recommendation systems, this paper analyzes regional and service classification characteristics of personalized recommendation service object information requirement in agricultural information. Then it proposes a personalized agricultural information recommendation platform based on users' interest. For the problems of interest update in agricultural information push service, this paper integrates mathematical modeling, three-dimensional synthetic and quantization techniques to establish a user interest updating model. For the problems of user classification in agricultural information push service, we propose a user classification model based on the integration of genetic algorithm, BP neural network and multiple linear regressions. The experiments show that our model is better than traditional methods such as by multiple regression and BP neural network only. It can offer efficient and timely information recommendation, providing support for detailed implementation on CSA information recommendation.

2 Information push platforms for CSA

This platform mainly adopts content-based recommendation technology and implements personalized agricultural information push service by establishing interest model and document feature model. With traditional content-based recommendation technology, we fully take into account different interest requirements and the adaptive correction of the whole module. It promotes the recommendation module on this platform to be more consistent with farmers' requirements. Its overall framework is shown as Figure 1.

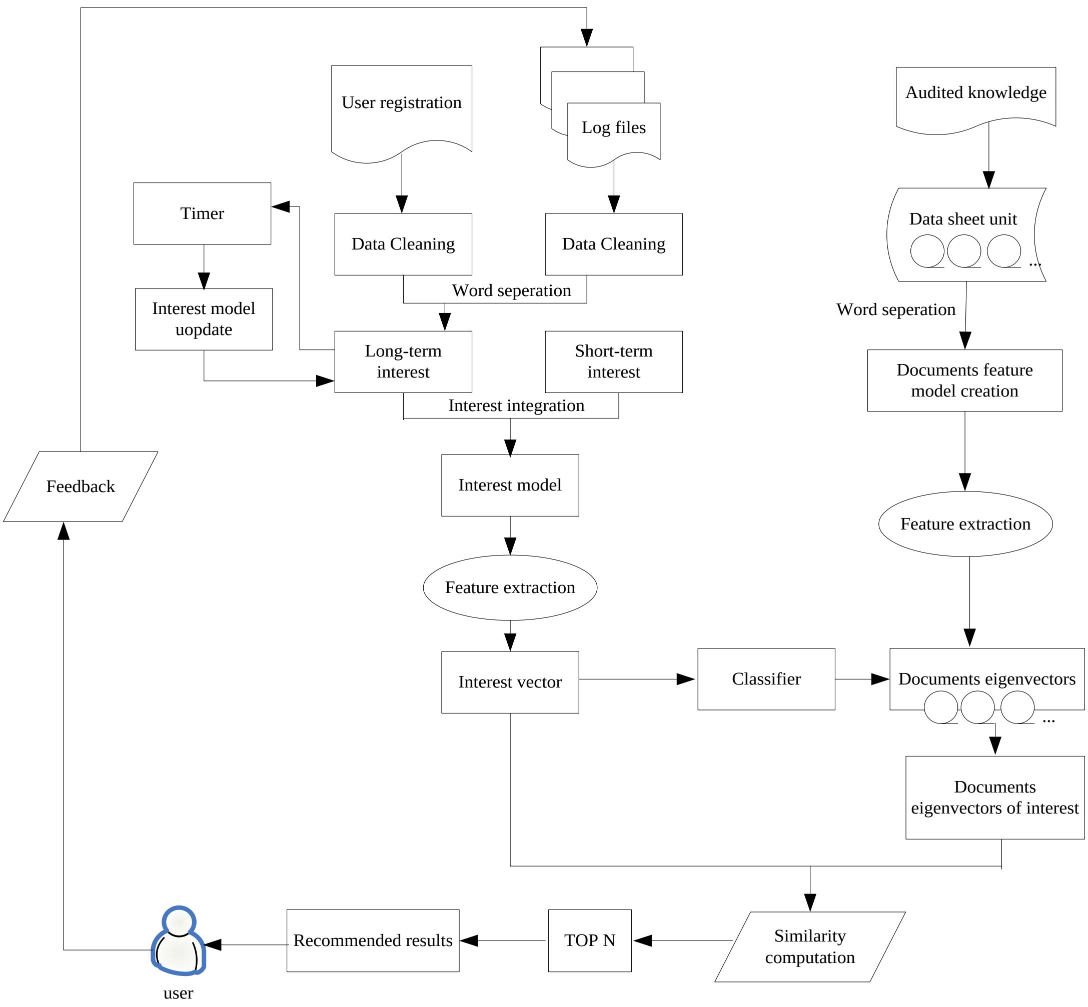

FIGURE 1 Overall structure of agricultural information recommendation model

The principle technical measures include:

1) Data acquisition and pre-treatment. In order to establish accurate and practical interest feature model, the system need to collect information reflecting the users' interest. This is mainly based on the registration information and log data, which are taken as original data of user interest feature model. For large amounts of webpage information, they clean it and remove HTML labels in the webpage. Then, the word segmentation is applied to filter words and to clean the stop words and useless words during segmentation.

2) User classification. User is the object of information service and user classification is the basis and precondition of personalized information service. User classification module classifies the information service object based on requirement analysis and performs differential management for different types of users. Rational and detailed user classification is helpful to improve the personalized level of information service, to improve the quality of information service. If one agricultural service system is accepted by farmers, it must deeply comprehend current situations and establish more reasonable user classification based on investigation.

3) Feature Extraction. When original data is used to segment words by word segmentation, the dimensions in original feature space are very huge and some of them can reach thousands. These high-dimension feature spaces will directly result in data sparsity and this largely increases response time and space complexity of machine learning. There is still much interference information in original feature vector and it has more obvious effect on machine learning accuracy. Therefore, the technology of dimensionality reduction must be used to reduce the size of original vector space.

4) Similarity computation. In order to find out users' genuine interesting information correctly, the system needs to perform similarity computation between user interest vector and document feature vector, to provide final recommendation service according to similarity results. At present, most similarity computations in use include the cosine similarity and Pearson correlation coefficients, etc.

5) Push mechanism. In order to push recommendation candidate items which represent users' interest to target user, the system will adopt an appropriate push mechanism for recommendation. There are two ways generally. The system sets a threshold value w in advance and pushes all candidate items which are larger than the closed value w to all target users. It is very important to choose the closed value w while using this method since it is one of the important factors to determine recommendation efficiency. However, during actual operation, it is difficult for us to quantify the suitable value so it does not have effective practicality for implementation. The second way is TOP-N principle [10] which is one of the most broadly applied push mechanisms. Its basic idea is directly pushing the most upfront N candidate items to users. This method can effectively control the size of result set and has better manoeuvrability.

6) Model updating. In the push models, users' interest is not invariable and it will develop with various environment factors such as the change of time and users. This may cause that users' original interest content strength will get weak and new interest strength may get enhanced gradually. This requires that our model should take users' interest correction into account. So the design of modules should consider correlated strategies of users' interest model.

3 Researches on key technologies of recommendation service model

3.1 UPDATE OF INTEREST MODEL FOR FARMERS

First we adopt three-dimensional synthetic techniques to classify the information [11]. Three-dimensional synthetic agricultural information has accurate generality and vivid figurativeness. It raised the perception of users to the information but it still lacks necessary mathematical features. Therefore, three-dimensional synthetic agricultural information needs another quantization to solve the problems by scientific and mathematical methods, improving the personalized degree of information push. The quantization process in detail.

1) Axis digitizing of three-dimensional space. The synthetic agricultural information has three attributes: *Time*, *Content* and *Relation*. They are mapped respectively mapped to x-axis- x-axis and z- x-axis. Each point on the axis corresponds to one attribute of *Time*, *Content* and *Relation.* The value rang is $X \in [0,\infty)$, $Y \in [0,\infty)$, $Z \in [0,\infty)$.

2) Blocks in three-dimensional space. The space is divided into several independent cube spaces. The point in each cube space has only correspondence to the coordinate in the space.

3) Classification of the agricultural information. The agricultural information are classified based on their classes and the classifying records are marked by class.

4) Determination of the storage space. According to the first-class NO we can assign independent storage space for all kinds of information. The size is determined by the second-class NO of information. The second-class NO of the same class are centralized in the storage space where the first-class NO is assigned.

5) Information quantization of storage space. When the agricultural information is storage to corresponding space, the quantization only needs simple mapping process. In the information space, we assign a three-dimensional coordinate (x, y, z) for the information, so this formation can be quantized as one point in the space.

After above procedures, the interest migration can provide more explicit representation. As an example shown in Figure 2, we use planting, livestock and forestry to demonstrate the process of interest migration. C1, C2, C3, C4, C5, C6, C7 and C8 are migrating vectors of users. Cl, C4 and C7 denote the interest of user is migrated inside the information with second-class 014, 025 and 037. C2, C5 and C8 denote the interest of user is migrated inside the information with different second-class of first class 01, 02 and 03. C3, C6 and C9 denote the interest of user is migrated inside the information with second-class 01, 02 and 03. So the interest migration can be expressed by migrated vector C and the migrated strength S.

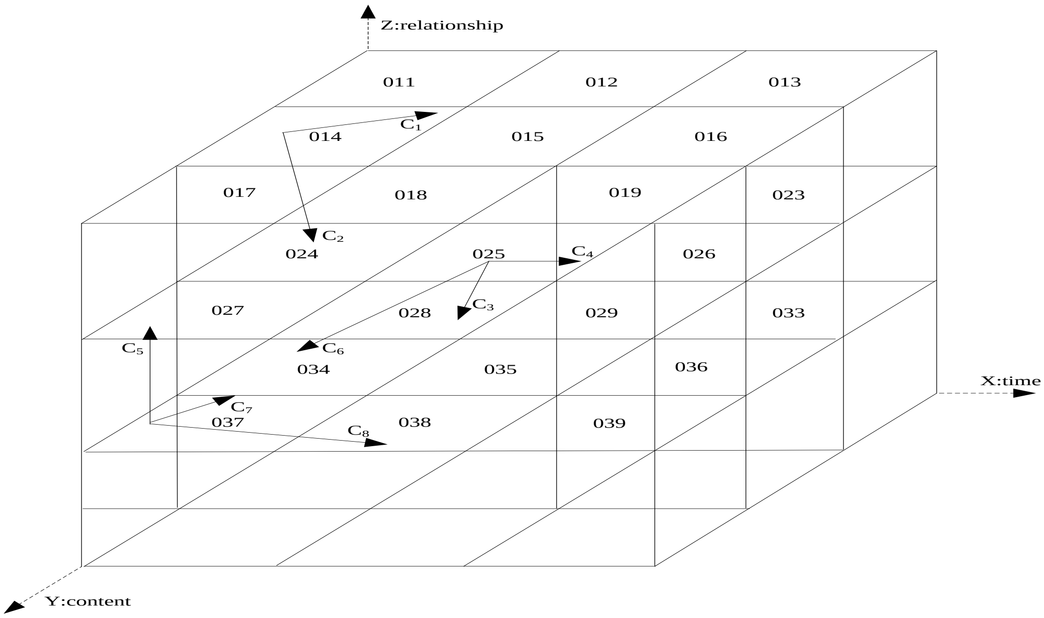

FIGURE 2 Interest migration

The interest update can be summarized by explicit equation, that is, if the information which is interested by user $I_s = I_q(x_0, y_0, z_0)$, t is time variable and $0 \le t \le \infty$. Then the information interested at the next time is $I_s^{'} = I_q(x_0 + c_1 t, y_0 + c_2 t, z_0 + c_3 t)$. Based on the mathematical model of updating process by users' interests, we can excavate the rules for interest migration by data miming. So it can reflect and track the migration of users' interest objectively, for update and prediction of the interest. The push service for information is also modified and updated in time.

3.2 CLASSIFICATION ALGORITHM DESIGN

Based on above techniques we take the three key attributes concerned by uses as the arguments, and the attributes uses belonging to as the dependent variables. Data mining algorithms are used for accurate classification of users. Genetic algorithm, BP neural network and multiple regression are the methods which are widely adopted [12]. This paper integrates the advantage of them and proposed a hybrid-BP neural network and it performs genetic algorithm optimization to mix the initial weight of BP neural network. So the deficiency of three algorithms which are used respectively can be avoided. First, we use association analysis to separate the data to be treated into two parts: linear and nonlinear. Then according to the characteristics of BP neural network and multiple regression, we maximize their advantage: BP neural network processes the nonlinear part of data, and multiple regression processes the linear parts. Finally they are mixed together and the global optimization of genetic algorithm is also adopted to optimize their weights.

Assuming the data to be processed is X and each record of X have n dependent variables. n_1 Arguments have linear relation with n_2 ($n_1 + n_2 = n$).

1) X is separated into two parts X_1 and X_2. n_2 is composed of n_1 arguments which have nonlinear relation with it; X_2 is composed of n_2 arguments which have linear relation with it.

2) Establish a BP neural network model based on X_1. The number of nodes in input layer is n_1 and that of the output layer is 1. The number of nodes in hidden layer is determined by the size of training samples.

3) Establish a BP neutral network model based on X_2.

4) The output value of hybrid-BP neural network is taken as the input value to establish a new BP neural network model, with 2 input nodes, 3 hidden layer nodes and 1 output node. Then the genetic algorithm is adopted to optimize the weight of this model.

If the neurons of these three layers are denoted by r, q, m respectively, a three-layer network is $BP(r, q, m)$, and the final model structure of BP neural network is $BP(n_1, q, m)$. The active function of hidden layer can adopts the derivable function transit, and the output layer adopts linear function purelin to ensure the stability and accuracy. We take 0 and 3 as the final learning rate. The mathematical expression is:

$$Y1 = purelin[W^{(2)} \cdot \tan sig(W^{(1)} \cdot X1, B1]), B2] . \quad (1)$$

$W^{(1)}$, $W^{(2)}$ are weights matrix and $B1$, $B2$ are threshold matrix. $X1$ is composed of dependent variable and n_2 arguments which have linear relationship with it.

Let $X2$ be processing data. We establish a multiple linear regression model with n_2 arguments and one dependent variable. Its expression is:

$$Y2 = W^{(3)} * X2 + C . \quad (2)$$

$W^{(3)}$ is weighted matrix; C is a constant; $X2$ is composed of the dependent variable and n_2 arguments which have linear relationship with it.

Then we set the output value of B neural network as $Y1$ and that of the multiple linear regression model as $Y2$. Both $Y1$ and $Y2$ are taken as arguments to establish a BP neural network with 2 input nodes, 3 hidden layer nodes and 1 output node. The active function of hidden layer is tansig, and the output layer adopts linear function purelin. 0 and 3 is determined as the final learning rate. So the mathematical expression of hybrid BP neural network model is:

$$Y = purelin[W^{(5)} \cdot \tan sig(W^{(4)} \cdot X2, B4]), B5] . \quad (3)$$

$W^{(4)}$, $W^{(5)}$ are weights matrix and $B4$, $B5$ are threshold matrix. $X = \{Y1, Y2\}$.

Next, we adopt genetic algorithm to optimize the weight and threshold, aiming for the minimum network error. The principle ideas is describing the weight and threshold as chromosome, and choosing suitable target functions to perform genetic iteration, until it satisfies some convergence condition [13]. Our genetic algorithm arranges all the initial weights of BP neural network in one population. After the first generation of population is generated, following the theory "survival of the fittest", better approximate solution can be acquired by evolution of generations. In each generation, we choose the individual according to the size of fitness of individuals in the problem domain. Drawing support from the intersection and mutation of genetic factors in nature genetics, we create the populations representing new solutions.

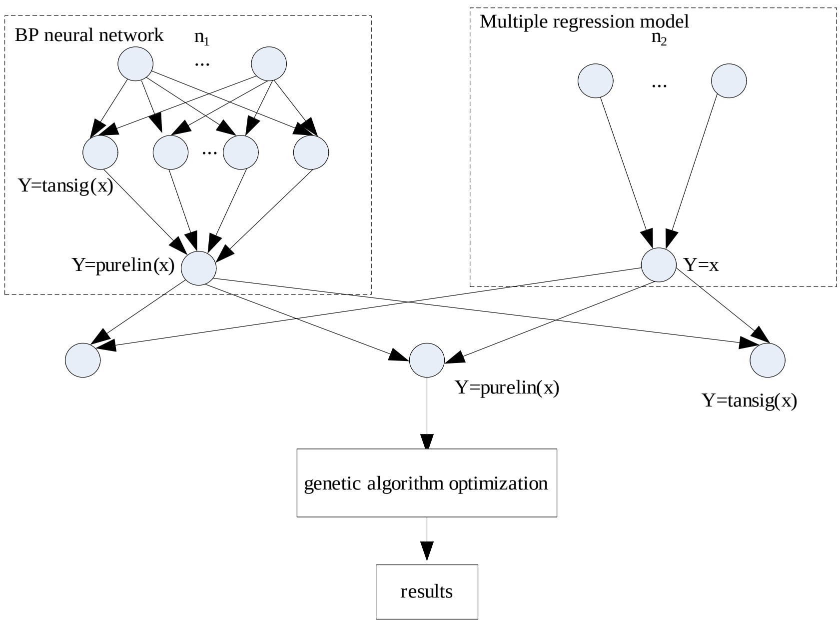

FIGURE 3 Hybrid neural network based on optimized genetic algorithm

In our experiment, we set the number of generations as 1000. The size of population is 100 and the fitness function $Fit = 1/ESS$ (ESS denotes the error square sum of output value with true value). Finally we can get a hybrid BP neural network based on optimized genetic algorithm. Its structure is depicted as Figure 3 and parts of the codes of genetic algorithm are:

```
Function [W1,B1,W2,B2,Fit] = gadecod(x)
Global p,t,R,S1,S2,S
  For i=1:S1
    For k-1:R
      W1(i,k) = x(R*(i-1)+k)
    End
  End
For i=1:S2
```

```
    W2(i,k) = x(S1*(i-1)+k+R*S1)
  End
End
```

3.2 CLASS FEATURE EXTRACTION

When users' interests are classified, we cannot recommend all the information of the same kind to the user. Parts of the webpages that has higher similarity according to the similarity of webpage and topic class will be selected to recommend to the user. This paper chooses cosine method to compute the correlation between webpage and topics. It needs the features vector to denote the topics. So we create the features vectors of the topics for each class, according to training samples. This paper chooses the common feature selection method DF to get litter computation and better evaluation effects [14]. The process of algorithm is: first, for each class, we count up the times of frequency of each word that appears in the training samples. Then all the entries are ordered by above statistical results and we choose prior m entries as the feature words of this class. Finally the total times of training sample set is divided by the times of frequency, to acquire the weight of each feature word in the feature vectors. The procedures in detail are:

```
Algorithm: Feature vectors extraction

Input: training samples of one kind of class
Output: Feature vectors of one class
    Initialize the entry library wordSet;
    Initialize total numbers of entry totalWordNumber;
    For each training sample Sa
     {
        Make word separation of Sa and acquire entry vectors
        if the samples;
        Delete the stopwords of entry vectors;
        For each entry of the vectors such as Ea
        {
          If wordSet includes Ea
          {
            Add 1 to the frequency number of Ea;
            }
            Else
            {
              Add 1 to the frequency number of Sa;
              Add Sa to wordSet;
            }
        }
     }
     Order all the entries of wordSet by the size of
     word frequency ;
     Select prior m entries as feature words and compute
     the weight of each entry;
    Return the feature vectors constructed by features and
    their weights;
```

FIGURE 4 Class feature extraction

4 Experimental analyses

4.1 SIMULATIONS OF CLASSIFICATION ALGORITHMS

The tests select 4 different types of user data. Four regions are respectively calibrated as 1, 2, 3 and 4. The data of attentions on information of various attributes' are the same as that in literature [15]. A_1-A_4 are taken as test data and A_5-A_{20} are taken as training data. The obtained classification predicted values are 3.9926, 2.9996, 0.9998 and 1.9997, so they are very approximate to true values 4, 3, 1 and 2. The error comparisons between true values and predicted values are shown as Table 1. Fitting chart of true values and predicted values are seen as Figure 5. Our experiment results show that the user classification model based on three-dimensional synthetic information in this paper is feasible and practical with higher classification precision.

TABLE 1 Analysis on errors of true value and predicted value

	A_1	A_2	A_3	A_4
Predicted value	3.9817	2.9898	0.9889	1.9999
True value	4	3	1	2
Absolute error	0.0183	0.0102	0.0111	0.0001
Predicted classification	4	3	1	2
True classification	4	3	1	2
Error	0	0	0	0

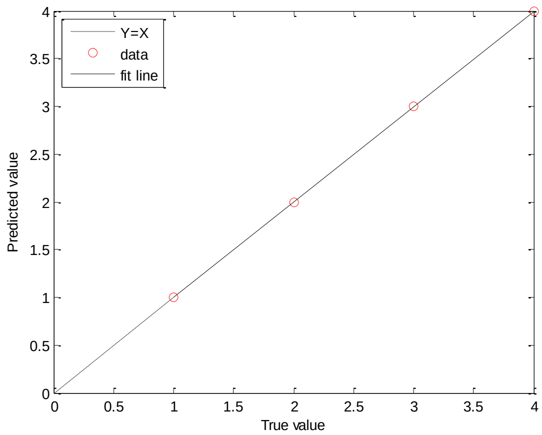

FIGURE 5 Fitting results of predicted value and true value

The absolute error of predictive values and true values between new methods and several mainstream methods are compared as shown in Table 2. The absolute value of difference between predicted value and true value is taken as observation data of Wilcoxon signed rank test. Then we use signed rank test on the method in this paper and current mainstream methods, to get the results shown in Table 3.

TABLE 2 Absolute error of true value and predicted value

Absolute error	Hybrid-BP	SVMK	BP-NN	libSVR
A_1	0.0079	0.0753	0.0099	0.6051
A_2	0.0003	0.0753	0.4201	0.1499
A_3	0.0005	0.0753	0.0248	0.1492
A_4	0.0001	0.0753	1.5004	0.1461
Average	0.0022	0.0753	0.4888	0.3756

TABLE 3 Results of Wilcoxon sign rank test

	Mean	Median	Max	RMS	Hybrid-BP	SVMK	BP-NN	libSVR
Hybrid-BP	0.0021	0.00034	0.0074	0.0038		+	+	+
SVMK	0.0074	0.07501	0.0749	0.0699	-		+	+
BP-NN	0.4568	0.2230	1.4260	0.7384	-	-		-
libSVR	0.2260	0.14501	0.6053	0.3297	-	-	+	

From the results in Table 2 we see that the hybrid BP network in this paper is the most ideal one on predicted effect among these four methods. The average absolute error rate between predicted value and true value is only 0.0022 and the error is obviously smaller than the other three algorithms. With Wilcoxon signed rank test results in Table 3, it is found that the hybrid-BP network model based on genetic algorithm optimization is superior to the other three methods. Their order sequence is hybrid BP network based on genetic algorithm, SVMK, BP-NN and libSVR.

4.2 TEST OF PUSH RESULTS

In this experiment, the detection and evaluation index recommended by information adopts general accuracy, recall and F-measure value in current information retrieval field. It is taken as the detection basis of this paper. If a denotes the number of information correctly recommended by the system to users; b denotes the number of information wrongly recommended by the system to users; c denotes the number of information which are not recommended by the system to users. Their calculation equations are shown as

$$P = \frac{a}{a+b} \times 100\% \,, \tag{4}$$

$$R = \frac{a}{a+c} \times 100\% \,. \tag{5}$$

$$F_\beta = \frac{(\beta^2+1) \times p \times r}{\beta^2 \times p + r} \,. \tag{6}$$

P, R and F_β denotes the accuracy, recall and F-measure. β is a parameter which has weight in the evaluation function to adjust the accuracy and recall. Generally $\beta = 1$, then the evaluation index is:

$$F_1 = \frac{2pr}{p+r} \,. \tag{7}$$

After the number of interest information obtains by users' manual management on information after system recommendations, above equations are used to initially judge the performance of system recommendation.

This experiment makes comparisons between improved interest expression model and vector space-based user interest expression model to verify the influence of two different models on recommendation effect. During the comparison, we adopt users' interest models constructed by two kinds of different expressions, after obtaining users' interest models. Then they are reused to match and filter the webpage resources which are grasped by information crawler. In addition, the descending order of similarity between users' interest model and webpage in resources data is recommended to users. The experiment respectively performs a series of weekly information recommendation and its accurate rate, recall rate and F-measure results of information recommendation results, as shown in Table 4.

TABLE 4 Recommendation results comparison of two models

Effect / Models	$a+b$	a	b	c	Accuracy	Recall	F_1 measure
Interest-based model	105	99	6	42	95.3	71.8	82.1
Vector space model	105	97	8	47	90.6	66.9	7837

From Table 4 we can see that the model based on users' interest has better accuracy, recall and F_1 measure value in the personalized information recommendation system, than the effects of traditional measures based on VSM. We have adopt the vector space with classified interest to establish the users' interest model. The interest of users is classified first. Then the feature vectors of interest are extracted for expressions. According these classifications the similarities are matched, which reduces the interference of the feature vectors of the same kind, to some extent. It helps to improve the accuracy of information recommendation. In the experiment of personalized information recommendation, we use the method in this paper to crawl the news on the same webs. 1500 webpages are collected totally as the data source of user recommendation. Based on the user interest model the information is filtered. At the same time, we add the function of "without loading user interest model recommendation" to the recommendation module. Then, under two cases with and without loading the user interest model files, we perform user information recommendation. The results are shown in Figures 6 and 7.

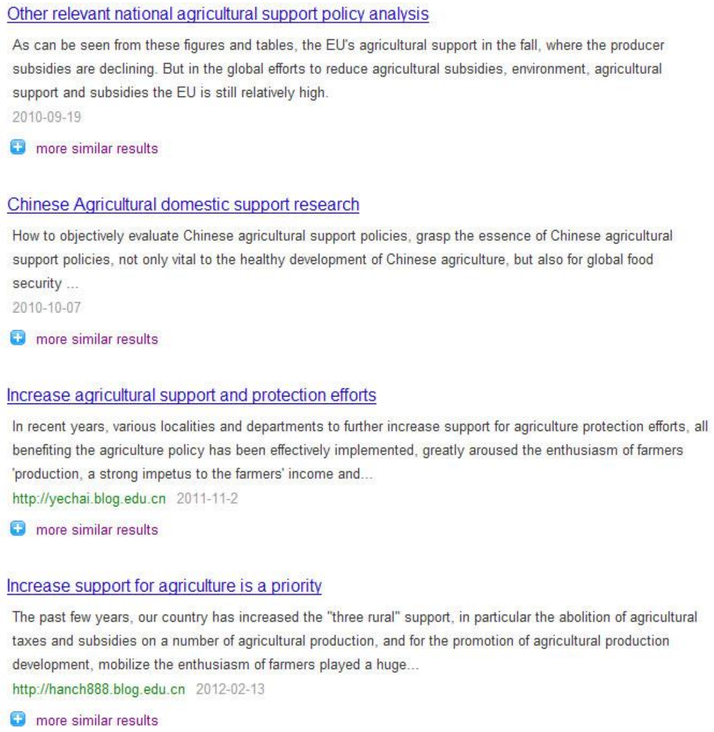

FIGURE 6 Recommendation results with interest model

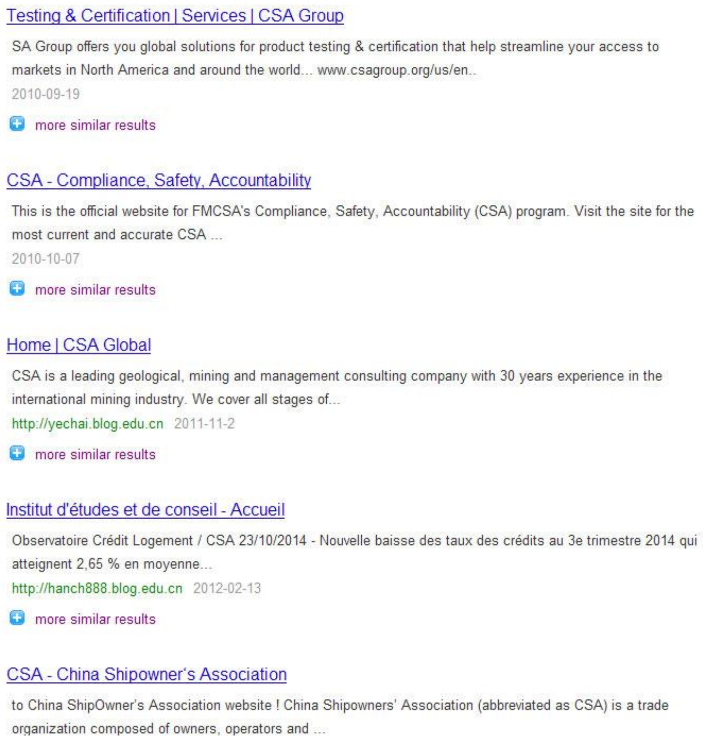

FIGURE 7 Recommendation results without interest mode

From above Figures it can be seen that, when user interest model is loaded, “agriculture” is the class attracting most interest of users, so the information about “education” is recommended to users preferentially; when user interest model is not loaded, the system will not differentiate the news. It selects the information which has new release date to recommend to the users. However, there is much news that are not interested by users.

To verify the effect of the personalized interest model, this paper tracks the using situation in one week for users. It invites the users to provide evaluation on the recommended information. The accuracy comparison of recommended information is shown in Figure 8.

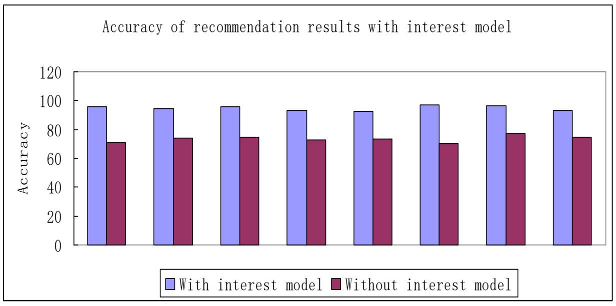

FIGURE 8 Recommendation effects comparison

The effect of personalized information recommendation is obviously with interest model is superior to that without interest model. Because when the user interest model is loaded, all the recommended information are special for the individual’s interest; on the contrary, the system will recommend the same information to all the users, which cause large deviation to the users’ interest and lower accuracy.

5 Conclusion

Our research focuses on relevant theory and technology of personalized information recommendation system. We analyze the specialty of users’ demand for recommendation service, and the features of service content classification. Then an active personalized recommendation platform for CSA users is proposed in this paper. It aims for user information classification and feature extraction in agriculture information push service, integrating the mathematical modeling, information three-dimensional synthetic technique and quantification techniques. For the user classification problems we put forward a hybrid-BP neural network based on genetic algorithm and multiple linear regressions, to improve the user interest update model. By the comparisons in experiment, it is verified that our model can make personalized information recommendation for the users and has better effect in precision.

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