A multi objective optimization algorithm for recommender system based on PSO

Zhao-Xing Li[1, 2*], Li-le He[1]

[1]*School of Mechanical and Electrical Engineering, Xi'an University of Architecture and Technology, Xi'an 710055, China*

[2]*School of Information Engineering, Yulin University, Yulin 719000, China*

Received 3 March 2014, www.tsi.lv

Abstract

In order to follow the development of Internet information service and improve the accuracy of recommender systems and recommendation algorithm. An optimal selection approach of multi-objective and particle swarm optimization (MOP-PSO) was put forward based on PSO algorithm. Furthermore, through two sets are combined and repeated dynamic adjustments, to achieve a better balance in algorithm efficiency and accuracy. Proposed a weighted cosine similarity method to calculate the user similarity, and then optimizing the weight by the PSO algorithm. Simulation results show that the algorithm has a better effective and can effectively improve the scoring accuracy, effectively improve the quality of the recommendation system.

Keywords: particle swarm optimization, recommended system, multi objective optimization

1 Introduction

Along with the degree rise of Internet service socialization, as well as the popularity of the mobile Internet, the one-way service mode of traditional Internet is affected by new Internet service mode, Users are no longer satisfied with traditional passive network service information received in the role, but also hope that the manufacture and dissemination of information in the network activities, such network applications are driving the demand for services in the form of bi-many Internet applications transition mode, thus make the network information services into web 2.0 application stage [1]. In particular, such as blog and micro blogging and other social networking applications in the form of attracting a large number of individual users and business users and even has become an important way to national government agencies as well as politicians and the public to communicate and exchange.

In order to retrieve information on the Internet resources as soon as possible, search engines technology has become the preferred solution for users [2]. The major search engines are based on information retrieval technology, user manual input to keyword based on information and search [3]. In addition, the traditional information service model is a passive mode of service; information service providers can only passively wait for the user's service request and to provide users with personalized information free.

In response to these problems, and limitations of information overload, academia and industry search engine and information service mode passive proposed recommendation system solution [4]. Recommended system can be based on user preferences historical interest, the initiative to provide users with information resources in line with their needs and interests. Recommended system has become a hot research direction of data mining, machine learning and human interface areas. However, with the further development of Internet applications, the traditional recommendation system and its algorithm is difficult to adapt to the user scale, the concept of the rapid growth of the number of projects recommended data and user history score, score data sparsity and user interest drift problems caused Recommend decreased quality, user satisfaction, reduced, or even the loss of a large number of users, which have seriously hampered the further promotion and application of the recommendation system. Therefore, the current recommendation algorithm to solve the problems and improve the recommendation accuracy of the recommendation system theory and practice has very important significance [5]. In this background, this paper will be recommended for the target accuracy of the recommendation system, drift issues and concepts for the sparsity recommendation system to carry out research work, and propose an improved recommendation algorithm has some innovative. In order to improve the accuracy of prediction, we propose a new similarity calculation method-weighted cosine similarity, and through PSO optimization calculation it weights. Experiments show that this method can effectively improve the accuracy of predictions. Figure 1 shows the general model of recommendation systems; recommender systems play an important role in modern daily life.

* ***Corresponding author:*** e-mail: 39812767@qq.com

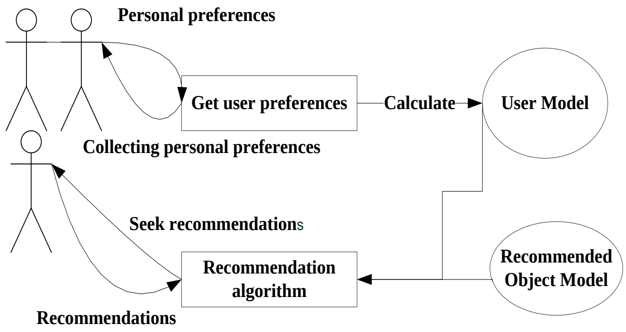


FIGURE 1 Recommended system model

2 Recommendation algorithm

2.1 PARTICLE SWARM OPTIMIZATION ALGORITHM

Particle swarm optimization algorithm (PSO) is proposed by Kenney and Eberhart in 1995 population parallel search algorithm based on global optimization [6, 7], through cooperation and competition between groups in the community to achieve optimal particle. Mathematical description of PSO: a population size is n, the i particles in m dimensional search space representation of $X_i=(X_{i1},X_{i2},...,X_{ij},...,X_{im})$, flight speed is $V_i=(V_{i1},V_{i2},...,V_{ij},...,V_{im})$, the optimal position of individual so far to search is $P_i=(p_{i1},P_{i2},...,P_{ij},...,P_{im})$. The particle swarm optimal position is $P_{gbesti}=(p_{gbest1},P_{gbest2},...,P_{gbestm})$. It can update the particle velocity and position according to the formula (1) and (2):

$$v_{ij}(t+1)=\omega.v_{ij}(t)+c_1.r_1.(p_{ij}-x_{ij}(t))+ c_2.r_2.(p_{gbestj}-x_{ij}(t)), \quad (1)$$

$$x_{ij}(t+1)+x_{ij}(t)+v_{ij}(t+1)\,. \quad (2)$$

where t represents the t iteration, j=1,2,…,n; j=l,2,…,m; $c_1,c_2>0$ are respectively the individual learning factor and social learning factors; t is the current number of iterations, r_1 and r_2 are uniformly distributed random numbers in the range of [0,1]. ω is the inertia weight coefficient, used to control the effect of history on current speed. In order to balance the global and local search ability, make the ω along with the increase in the number of iterations decreases linearly, can significantly improve the performance of the PSO algorithm, it is given

$$\omega=\omega_{\min}+(iter_{\max}-iter)\times (\omega_{\max}-\omega_{\min})/iter_{\max}, \quad (3)$$

wherein $\omega_{\min}$, $\omega_{\max}$ respectively the maximum and minimum weighting factor, $iter$ is the current iteration number, $iter_{\max}$ is the total number of iterations.

In the formula (3), $\omega_{\max}$ is the initial inertia weight; $\omega_{\min}$ is the last inertia weight; $t_{\max}$ is the maximum number of iterations. Flight speed is $v_i \in -V_{\max},V_{\max}$, the constraint conditions to prevent particle speed missed optimal solutions, through the improvement of the algorithm further improves the global searching ability of particle swarm.

2.2 MULTI-OBJECTIVE OPTIMIZATION

Objective optimization problem was originated in the design of many complex systems, modelling, planning issues. Since the 1960s, multi-objective optimization problem attracted the attention of a growing number of researchers from different backgrounds [8]. Especially in recent years, multi-objective evolutionary algorithm is to obtain the optimization of the more widely used and studied, resulting in a series of novel algorithms and get a good application. Multi-objective optimization proposition is generally no unique global optimal solution, so this is actually a multi-objective optimization proposition is often how the process of seeking Pareto set. Traditional multi-objective algorithm is often converted into a single objective proposition after the use of sophisticated single-objective optimization algorithm, the drawback is that the optimal solution can only be determined once a solution. And now the multi-objective evolutionary strategy tends to be more parallel computing can be solved once a sufficient number of solutions distributed on the Pareto front provides decision-makers to the next decision. Which PSO as a novel evolutionary computing strategy has been more and more widely used in multi-objective optimization problem. Multi-objective optimization is described as follows:

Definition 1:

$\min\ f(x)=[f_1(x),f_2(x),...,f_n(x)]$,

$st.\ g_i(x)\le 0, i=1,2,...,m$

$h_j(x)=0\ \ j=1,2,...,n$,

where $x=[x_1,x_2,...,x_D]\in R^D$,

$f_1(x)(i=1,2,...,n)$ is the objective function;

$g_1(x)(i=1,2,...,m)$ is the inequality constraint;

$h_1(x)(i=1,2,...,p)$ is the equality constraints.

Definition 2: global optimum

Given a multi-objective optimization of the overall proposition $f(x), f(\bar{x})$ is called optimal if and only if $\forall x\in\Omega$, have $f(\bar{x})\le f(x)$.

3 Multi objective optimization recommendation algorithm based on PSO

3.1 MULTI OBJECTIVE PARTICLE SWARM OPTIMIZATION ALGORITHM

In order to improve the quality of recommendation system, the paper-based multi-objective optimization PSO algorithm recommended by the relevant principles, we propose a means of optimizing the recommendation system. Entire score prediction algorithm roughly as follows:

(1) Initial population, the initial population size is denoted by n. Based on the idea of fitness domination, it is divided into two sub-groups, and the initial population size is denoted by n. A subset of non-dominated is called (p_Set), referred to dominate another subset is (NP_Set), wherein (p_Set) and (NP_Set) are referred to as a base, respectively n_1, n_2, and satisfy $n_1 + n_2 = n\ (1 \le n_1, n_2 < n)$.

Apparently satisfied: $\forall x_i \in NP\_Set$, at least $\exists x_j \in P\_Set$, then x_i control x_j, where $1 \le j \le n_i, 1 \le i \le n_2$.

Nearest neighbour choice is personalized recommendation system is a very important step, multi-target system depends largely on the quality of the recommendation algorithm to find the neighbour effect. During each iteration, only the particles NP_Set and position update rate, and updated based on the particles NP_Set disposable Thought fitness particle P_Set comparison, if $\forall x_i \in NP\_Set, \exists x_j \in P\_Set$, made x_j control x_i. Then the switch x_i, x_j position, that is $x_j \in NP\_Set, x_i \in P\_Set$.

Then build the project configuration file, build the project configuration file contains basic user information, project information, rating, and other features of values based on the characteristics of the project, the project configuration file is a comprehensive reflection characteristics of the project.

(2) Nearest neighbour extract candidate set. Using the maximum intersection method using matrix operations to extract maximum current projects of common user items rated as the nearest neighbour candidate sets.

(3) The optimal project similarity calculation. The idea of this paper is that the weight of each set of eigenvalues first project configuration file attributes heavy initial project, and then build the weighted cosine similarity function between the current project and the project's neighbours, and through PSO optimization algorithm in the training set of weights value optimization, prediction error when the score reaches the most hours of the nearest weight value, calculate the current project and the project's neighbours according to a recent weights recently similarity solution.

(4) Current Ratings forecasts. According to the characteristics of the optimization project between the neighbours being the best score and after the two projects worth similarity to recent experiments focused solutions to existing projects predicted score. In the prediction process, first select the current project does not score and score on a neighbour project users, according to a recent candidate set of previously established neighbours to the right of the current project is the recent similarity profiles and project configuration files between neighbours weight score to predict the current project.

(5) Make recommendations. In the user - after item rating matrix to fill, select a user forecast projects a higher score to make recommendations for the current user.

Realization of the program algorithm is as follows:

Step l: Initial population, $x_1, x_2, ..., x_n, (n = Pop\_Max)$, where set the dimension is *D*.

Step 2: Initialization fitness populations, $for\ \ i = 1\ to\ n$.

Calculate $f(x_i) = [f_i(x_i), f_2(x_i), ..., f_n(x_i)]$.

Based on the concept of fitness dominance, the initial population is divided into two subgroups, referred to as non-dominated subset of a subset of P_Set and NP_Set domination, P_Set subset of cardinality Pareto denoted n_1, N_Pareto subset NP_Set of cardinality denoted n_2.

Step 3: Velocity and position of each particle in the conduct of particles NP_Set update, location update: $\mathrm{V_p} = \omega \times V_{id} + c_1 \times r_1 \times (P_{id} - x_{id}) + c_2 \times r_2 \times (P_d - x_{id})$.

Speed update: $x_{id} = x_{id} + V_{id}$, where P_{gd} is the entire population from a randomly selected subset of P_Set.

Step 4: Dynamic exchange strategy: NP_Set subset of each particle and each particle P_Set comparing each subset, and the subset of NP_Set. Vocabulary particles is $x_1, ..., x_i, ..., x_{n2}$, P_Set is a subset of particles is $x_1, ..., x_j, ..., x_{n1}$.

$for\ (k = 1\ to\ n_2)$

$for (t = 1\ \ to\ \ n_1)$

$if\ (f(x_i) \le f(x_j))$

Swap x_i and x_j, and update their number and location in the collection.

End if

End for

Comparison of x_i and x_j after all, there is j made the $f(x_i) \le f(x_j)$ established, and then clearly, x_i may be a non-dominated solutions. Therefore, the x_i also joined P_Set subset. It is to Update P_Set and NP_Set subset, if P_Set has *k* elements duplicate, delete and re-initialized k particles in NP_Set; if there are duplicate *k* elements in NP_Set, for a similar operation.

Update n_1, n_2.

If $n_1 \ne n$ or the maximum number of iterations is not reached, then jump to Step 3.

3.2 WEIGHT OPTIMIZATION MULTI-OBJECTIVE PARTICLE SWARM ALGORITHM

In the experiment, it is assumed that each item characteristic is stable weight value, and therefore optimization of the process, an optimal solution this project there is only the weight value, i.e., there is only a single fitness function. This adaptation function, which is defined as the average of the prediction error rates between the two items. Thus, the goal of the optimization is to calculate each current project W. Adapted as a function of the expression (4) below, where n is the number of users of the T and j exists between the joint score. T representative of the current project, j represents a neighbourhood of T, av_T on behalf of T being the mean score, $similar(T, j)$ is the similarity of T and j, $VT(i, j)$ represents for i users on the project of the j score, av_i on behalf of all users of the mean score of i,

$$fitness = \frac{1}{n}\left\{(av_T + u\sum_{i=1}^{m} similar(T, j)\times (VT(j,i) - av_i)) - VT(T,i)\right. , \quad (4)$$

where $similar(T, j) = \sum_{i=1}^{n} \frac{TW \cdot jW}{|TW| \times |jW|}$, (5)

where T represents the current project configuration file; j on behalf of the project selection process to select the configuration file out of the neighbourhood project configuration file, and $T \neq j$; W is a $K \times K$ diagonal matrix, the diagonal matrix for each value represents the value of the heavy weight of each feature, n represents the total number between two projects have a common score users.

PSO optimization procedure is divided into three steps, first, initialization of the particle velocity and position, using an experimental paper initialize random process; Secondly, the rules according to the dynamic movement of particles, establishing a new position of particles and particle velocity iteration; then establish each step local optimum and the global optimum particle, by the position of each particle, and the fitness function to get the value of the particle positions, and decide whether to update the local optimum and the global optimum.

3.3 USER RATING PREDICTION AND RECOMMENDATION

After establishing the nearest neighbour recent and current projects right profile heavy, you can start score prediction.

(1) Score prediction. Score prediction formula as formula (6) are shown, Wherein $C\_VT(T,i)$ is a prediction of the current score of the item, av_T Q is the average of all the scores of the project T, $VT(T,i)$ Q is the user i to the project T scores of the configuration file, j is the user i to the project j scores of the configuration file, $similar(T, j)$ is the training set optimized project configuration files T and j recently cosine similarity value, $VT(i, j)$ is user i to the project of the j score, av_i is the average user i all items on the score, n is the number of neighbour selection, k as the standard parameters.

$$C\_VT(T,i) = av_i + u\sum_{j=1}^{n} similar(T, j)\times (VT(j,i) - av_i)) . \quad (6)$$

(2) Be recommended. Recommended system recommended by different algorithms based on differ mainly in two ways: First, when extracting the most similar to the current nearest neighbour user interest, users will be interested in the project's neighbours to recommend to the current user; its Second, the presence of score recommendation system, the nearest neighbour first extracted, and then the prediction of the current project, or user rating score according to the neighbour, then the current user of the prediction score ranking, for extracting several high recommendation rating.

4 Experiment and Analysis

In this paper, experiments using Jingdong online shopping evaluation data set (http://www.jd.com/). The dataset contains 123,883 users and 2190 project (this paper is to mobile phones) and those users detailed information on the project 200,000 votes.

During the experiment, in order to verify the accuracy of the predicted score, the whole data set were randomly divided into A, B two parts, crossover turns twice. In each experiment, the selected item as a two-part test ratings training set for training right weighted cosine similarity weight; remainder Grading set of experiments to verify the validity as to optimize the results.

Specifically, we use a randomly selected set of methods currently selected item from the data sequence A, B, as the training set, B, A set of experiments was performed twice crossover, divided into two groups in each experiment as follows:

(1) Randomly extracted 20 project as the active item, using the maximum number of items extracted intersection nearest neighbour candidate set of n (n = 5, 15, 35).

(2) The number of items randomly extracted 20 items as the active item, randomly extracted nearest neighbour candidate set of n (n = 5,15,35). When the experiment 1 and experiment 2, the nearest neighbour is different extraction candidate sets to verify the maximum extraction of the intersection nearest neighbour candidate

set, the accuracy of the prediction score increased. By experiments 1 and 2, a different number of neighbours recently extracted to determine the size of the nearest neighbour extraction.

In the training set, the same set of parameters for the PSO, as follows:

(1) The number of particles: N = 50; learning factor: $c_1 = 1$, $c_2 = 1$; inertia weight: W = 0.6; maximum number of iterations: M = 2 000.

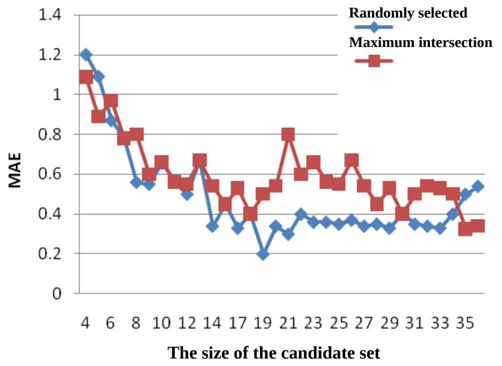
Figure 2 represents in *A*, *B* is the training set, *B*, *A* is the cross-experiment experimental set twice; In the two experiments, each randomly selected 30 current phones, and compare the intersection of law in accordance with the maximum of n bits select the nearest neighbours and randomly selected candidate n-bit nearest neighbour candidate scores received predictable results. In Figure 2, the horizontal axis represents the size of the nearest neighbour candidate set from 4-35, and the vertical axis represents the 30 current project a combined average score prediction error value MAE. Experimental results show that the maximum intersection nearest neighbour method is selected when the prediction accuracy of the obtained score is higher than the overall results of randomly selected, and the number of candidates is 21, 22, respectively, the prediction accuracy results stabilized.

Comprehensive experimental results show that the intersection of law and the maximum weighted cosine similarity score improved the accuracy of prediction, which can improve the quality of the system recommended by the recommendation.

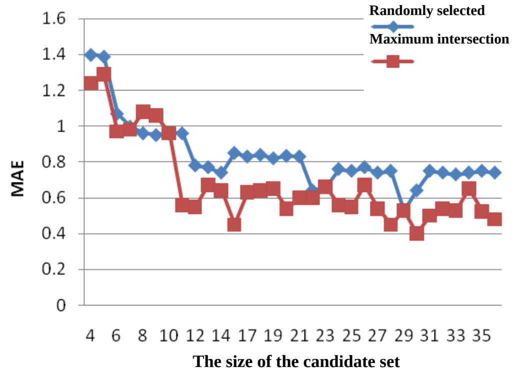
5 Conclusions

This paper starts from the status quo of Internet information service, introduces the application background of the recommender system, then the multi-objective particle swarm optimization algorithm of recommendation system is improved.

This paper makes the algorithm improvement goal focused mainly on the recommendation algorithm prediction accuracy, although the improvement and perfection of the recommendation algorithm increases the calculation task recommendation system in a certain extent, but from the computational complexity point of view, these improvements in computational performance of the recommendation system is very limited, remained in the recommended time the algorithm complexity level. In order to validate the proposed algorithm in this paper carry high recommendation accuracy, by comparing the prediction accuracy of each algorithm and the traditional recommendation algorithm, experimental results show that the algorithm proposed in this paper are different degree improves the prediction accuracy of the recommended, show that these algorithms are effective measures for improvement.



(a) B as the experimental set



(b) A as the experimental set

FIGURE 2 The maximum intersection method and random extraction experiments compare the results

Acknowledgments

This work is partially supported by the Research and Cooperation Project for Department of Yulin city of (**#Gy13-15**). Thanks for the help.

References

[1] Adomavicius G, Tuzhilin A 2005 *IEEE Transactions on Knowledge and Data Engineering* **17**(6) 734 - 49

[2] Kurkovsky S, Harihar K 2006 *Personal and Ubiquitous Computing* **10**(4) 227-40

[3] Cherkassky V, Yunqian Ma 2004 *Neural Networks* (S0893-6080) **17**(1) 113-26

[4] Zheng Y, Burke R 2012 Mobasher B. Optimal feature selection for context-aware recommendation using differential relaxation *ACM RecSys* **12**

[5] Üstün B, Melssen W J 2005 *Analytical Chimica Acta* (S0003-2670) **544**(1-2) 292-305

[6] Yaoyu Feng, Zhimin He 2003 *Enzyme and Microbial* **32**(2) 282-9

[7] Zhang Yong-Heng, Zhang Feng 2013 *Sensors and Transducers* **151**(4) 95-100

[8] Cao X, Chen S Y 2009 *Computer Standards and Interfaces* **31**(3) 579-85

Authors

Li Zhao-Xing, born on March 9, 1982, in Shannxi Yulin

Current position, grades: lecturer in Yulin University.
University studies: MS degree in Computer science from Xidian University in 2010.
Scientific interest: Cloud integrated manufacturing technology, big data, Evolutionary Algorithm

He Li-Le, born on March 18, 1966, in Shannxi Xi'an

Current position, grades: professor in Xi'an University of Architecture and Technology University
University studies: MS degree in Computer science from Xi'an University of Technology University in 2006.
Scientific interest: Image Understanding and Change Detection, Evolutionary Computation, Fuzzy Systems and Neural Networks