WJCMS

Wasit Journal of Computer and Mathematics Science

Journal Homepage: https://wjcm.uowasit.edu.iq/index.php/WJCM

e-ISSN: 2788-5879 p-ISSN: 2788-5879

An Effective Algorithm to Improve Recommender Systems using Evolutionary Computation Algorithms and Neural Network

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DOI: https://doi.org/10.31185/wjcm.Vol1.Iss1.20
Received: January 2022; Accepted: March 2022; Available online: March 2022

ABSTRACT: The growing Internet access and easy access to it have resulted in a significant increase in e-content, which, along with many benefits, has caused problems for users. Internet users simply cannot find the content they need from this massive amount of data. Users are faced with a lot of suggestions for choosing goods, buying items, selecting music and videos, and more. Advantage systems can be used to overcome these problems. Today, with the spread of people's use of cyberspace, such as web sites and social networks, and increasing the need for conscious and clever selection of people, recommender systems has been extensively investigated. Although the neural network can identify the connections between the inputs and outputs of a dataset, but in order to achieve the proper performance of the neural network, a proper structure should be considered. We will use the mantle algorithm to determine this structure. The mantle algorithm is a form of traditional genetic algorithm that uses local search to reduce the time to achieve optimal response. Genetic algorithms are created to search across the search space, while the local search, the neighborhood of the neighborhood, finds every response found by the genetic algorithm to find better answers. This algorithm seeks to find the optimal values for the parameters of the neural network method, so optimal solutions of the memetic algorithm is considered to be used to set parameters for the neural network method. The results of this study show the desirable performance of the proposed approach in this study.

Keywords: Effective Algorithm, Recommender Systems, Evolutionary Computation Algorithms, Neural Network

1. INTRODUCTION

The growing Internet access and easy access to it have resulted in a significant increase in e-content, which, along with numerous benefits, has created problems for users. Internet users simply cannot find the content they need from this massive amount of data. That's why the need for systems that can guide users to their needs is felt more than ever. Advisory systems have been developed on this basis. These systems are used to refine the information [1].

Advisory systems use several methods to provide the best possible suggestions to users. One of these methods is based on the opinions and opinions of other users. One of these methods, known as collaborative refinement, is considered in this research [2].

In this research we are looking for a new method to improve the performance of the advisory systems. For this purpose, we use the neural network method to construct the model. The neural network is taken from the human brain and processes data into small and large units that interact in parallel and in parallel with each other to solve a problem. These small neurons are called neurons.

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Although the neural network can identify the connections between the inputs and outputs of a dataset, but in order to achieve the proper performance of the neural network, a proper structure should be considered. We will use the mantle algorithm to determine this structure. The mantle algorithm is a form of traditional genetic algorithm that uses local search to reduce the time to achieve optimal response. Genetic algorithms are created to search across the search space, while the local search, the neighborhood of the neighborhood, finds every response found by the genetic algorithm to find better answers. Selection of Generation Operators in the Genetic Section of a Memetic Algorithm and the type and method of local search used in it will result in very different results.

2. RELATED WORKS:

The Memetic algorithm was introduced by a Dawkins genealogy in the field of cultural evolution. The term memetic is derived from the term meme, which is a cultural or behavioral element transmitted by non-genetic factors from generation to generation.

One of the important features of this algorithm is the introduction of a group of its own inventive factors, that is, the chromosomes have the chance of living and learning from the environment. In addition, creating new knowledge to speed up the search process is another feature of this algorithm. Individual learning and life-long learning through local searches are done by each chromosome.

There are two methods of learning Lamarck and Baldwin in existing meme strategies. In the Lamarck learning method, the optimal response replaces the original chromosome after the local search process. In other words, the concepts learned directly enter the gene sequence of the chromosome. While in the Baldwin learning method, the fit or satisfaction of the improved response after the local search process replaces the fit of the original chromosome. In other words, the learned concepts cannot directly enter the gene structure. Only the combination and mutation operators are allowed to change genes [3]. The use of the mantle algorithm can be done according to the type of problem using any of the above methods or in a combination of them.

The mantle algorithm is considered to be part of the class of innovative algorithms and computational intelligence. Although the mantle algorithm follows the principles of evolutionary algorithms, it cannot be considered entirely as an evolutionary method. The mantle algorithm has a functional similarity to the Baldwin evolutionary algorithm, Lamarck's evolutionary algorithm, hybrid evolutionary algorithms, and cultural algorithms. In this way, the use of the idea of behavioral patterns and the memetic algorithm in optimization is known as the mathematical calculus [4].

The mantle algorithm is inspired by the interactions carried out in the genetic evolution and the evolution of the mantle. The gene's generalization in the mantle algorithm goes beyond other biologically based systems, in which each system inherits separate information units after the selection process and creates diversity. The term meme or mem is used to refer to a fragment of discrete cultural information and shows the interactions of genetic and cultural evolution.

The purpose of this information processing strategy is to exploit a nation-wide population-based search technique that most widely places the best response in good areas of search, through repeated use of a localized exploration through a solution. Ideally, the mantle algorithm has the duality of genetic and cultural evolution, which allows transmission, selection, inheritance and variety of behavioral and genetic patterns in the population to be preserved.

An artificial neural network (ANN) is an idea for information processing that is inspired by the biological nervous system and deals with the processing of information like the brain. The key element of this idea is the new structure of the information processing system. This system consists of a large number of super-interconnected processing elements called neurons that work together to solve a problem. ANNs, like humans, learn from the example. An ANN is set to perform specific tasks, such as identifying patterns and classifying information, during a learning process. In biological learning systems, there is a synergistic connection between the nerves. This is also the method of ANNs [5]. Various types of advisory systems have been investigated by researchers. For example, content-centric, knowledge-based and collaborative refinement systems can be mentioned. We will focus on these systems on collaborative refinement systems. This is because the collaborative refinement methods do not require additional content information about the user and recommendations, and are only registered based on existing privileges and advice people using the Saber experience. Based on the experiences of other similar people and the discovery of communication between users, these systems produce personalized recommendations for individuals. Several studies have been carried out on these types of systems, and some of them are listed below:

Yin et al. (2012) have introduced a methodology that, given their personal interests and local interests, introduces a specific user to a set of restaurants, concerts, and more. In particular, LCARS consists of two offline modeling components and online recommendations. The offline section is designed to learn the interests of each user and local preferences for each location. The online section automatically combines the interests learned about users and local preferences for positions for producing the best recommendations [6].

In 2011, Bobadilla and colleagues have come up with a new benchmark for assessing similarity between users. In this research, the genetic algorithm has been used to find the optimal similarity function [7].

In 2012, Walter et al. presented a knowledge-based, social-based compilation of a knowledge-based advocacy system. The evaluation of the results of this research in the field of cinema has yielded excellent results compared to other similar work [9].

The goal of the paper presented by Huawa and colleagues in 2011 was to propose a comprehensive approach to improving the advocacy systems by combining social networking information. To accomplish this, a matrix framework framed with social settings is presented in this study. The method presented in this article is quite general and can be easily extended by combining other textual information, such as social tags, etc. [10].

In a research by Ricci et al. In 2010, an interaction framework has been proposed. The authors of this paper examined the implications and advantages of using the New Recommender Method based on Markov Decision Processing and the Enhancement Learning System, which allows the interactive system to independently improve its initial interaction strategy in order to effectively and efficiently learn.]

A Hoang study presented in 2014 presents a systematic mathematical definition of the fuzzy recommendation system, which includes theoretical analysis of algebraic operations and extracted features. This paper presents a new fuzzy user-based combination method based on collaborative refinement that obtains the degree of fuzzy similarity between users based on statistical information and, based on the scores provided by them, has discovered the final similarity and In order to obtain high precision predictions [12].

Manjula et al., Released in 2015, have introduced a real time system for music data. The proposed real-time system is a combination of these content-based techniques and interactive genetic algorithms by providing a real-time, real-time solution. This system is based on the user's preferences and also allows each user to share their favorite songs with other users and thus make a better result for other users [13].

3. PROPOSED ALGORITHM

The Memetic algorithm in the proposed hybrid system of this research seeks to find the most suitable values for artificial neural network parameters. To achieve this, the objective function of the algorithm is to achieve the highest accuracy of the artificial neural network. Each of the algorithm solutions will specify certain values for the neural network parameters. Evaluating the suitability of each solution is also done by calculating the accuracy of the corresponding neural network corresponding to the solution.

Finally, the goal of the Memetic algorithm is to find the optimal solution that offers the best values for the neural network. The flowchart of the proposed system, which is composed of an artificial neural network and Memetic algorithm, is shown in Fig. 1.

```
Procedure BeeColonyCommunityDetection
Input:  M, nPop, MaxIt,BestSolution, ParetoFront
Output: CP; // the community partition
Begin
l ←0;// l is the iteration number
∀v∈V, COM(l)←── v ; // initialize the Community of all vertices
    For g=1:N
       Compute FitnessFunc;
    End
 Do
    l ← l+1;
    For j = 1: nPop
     Assign a rank to each individual and sort;
     Create a new population of offspring;
     Combine the parents and offspring;
        For g=1:N
          Compute FitnessFunc;
        End
    End
   CP ← COM(l);
Until (l= MaxIt)
Q ← Compute the value of the modularity for CP;
CP ← COM;
End
```

FIGURE 1. Proposed Method's Algorithm

In the remainder of this section, the various stages of the implementation of the Memetic algorithm are explained. The main steps of the algorithm are the definition of the population of solutions, the evaluation of solutions, and the implementation of algorithm operators.

Define population of solutions

Each of the solutions of the Memetic algorithm represents the structure of a unique neural network. In fact, the values in each solution set the parameters of the neural network configuration. The values given to the initial solutions in this algorithm are calculated randomly and during the execution of the mantle algorithm, the values of each of the parameters will be optimized.

Operators of the mantle algorithm

The operation that must be applied to the Memetic algorithm's solutions is to apply selections, recombines, mutations and local search operators. In this research, a roulette wheel is used to perform selection operations. This luck-based approach is done so that all individuals are mapped to neighborhoods based on their suitability. The size of the area per person will be determined according to its suitability. Then a random number is generated and, depending on the size of the number, the person is selected.

The recombination operation in the proposed method will be based on the multiple recombination method. In this way, by selecting a few points for combining the solutions, the search space is more explicitly explored and the search will be more efficient.

Mutant operations are performed to avoid trapping local optimal solutions. Performing this operation, select a number of solution components randomly and modify each of them in its defined range. In this way, the mutation operation also makes it possible to better explore the possible search space.

The local search operator is an operator whose existence in the mantle algorithm is one of the main reasons for its differentiation from other evolutionary algorithms such as genetics and will increase the efficiency of the search algorithm process. In this way, this operator eventually leads to increased intelligence and increased speed of the convergence of the algorithm to improve the optimal response. In this operator, a subset of the Memetic is first selected for the operation and a local search operation is performed on this subset.

Investigate the appropriateness of solutions

In this study, to evaluate the appropriateness of each solution that represents the specified values to the artificial neural network parameters, the neural network is first constructed corresponding to the solution. After constructing the corresponding neural network, the accuracy of the constructed neural network will be examined and recorded as the proportion of the solution.

Check the stop criterion

At this point, the stopping algorithm is considered; if this criterion is met, the algorithm will be terminated and the optimized members will be presented as the final solution. One of the things that can be considered as a stopping point is to reach the specified number of repetitions or to obtain the desired accuracy. In this research, if the number of loop repeats exceeds the maximum number of replicates, the algorithm ends; otherwise, a new round of repetition begins.

4. IMPLEMENTATION RESULTS

In this research, the MovieLens dataset was used to conduct experiments. The core of this dataset is a list of ratings (privileges) given for different movies. The information contained in the MovieLens dataset is compiled by genuine scores collected from a user group. Each person has scored at least twenty films. The videos in this dataset are scored by users from 1 to 5, which mean 1- bad, 2- medium, 3- good, 4- very good and 5- excellent.

This dataset contains 100,000 records, in which 943 users gave 1682 videos rating 1 to 5. The data in the dataset used in this dataset was collected through the MovieLens website (movielens.umn.edu) during a seven-month period from September 1997 to April 1998. In this dataset, the data for users who had made less than 20 rankings or complete information about them in the system was not removed from this dataset.

The results of the experiments carried out in this experiment for the second case are presented in Fig. 2. As can be seen in this figure, the efficiency of the neural network method will be improved by determining the optimal values for its parameters using the mantle algorithm during the implementation of the algorithm. In this case, the average proportions obtained at the end of the training process are about 86%.

For the first comparison, Gedikli et al has been used. This article, similar to the proposed system of the study, uses the MovieLens data set to evaluate its results. It is stated in this article that 75% of the samples for the dataset were used to train the system and the remaining 25% was used to test the system. Therefore, in this experiment, the same kind of work as the set of training and test data sets will be selected. The criterion used in this research is the F-Measure criterion, which is expressed as a relationship.

$$F_{measures} = \frac{2 \times Precision \times recall}{Precision + recall}$$

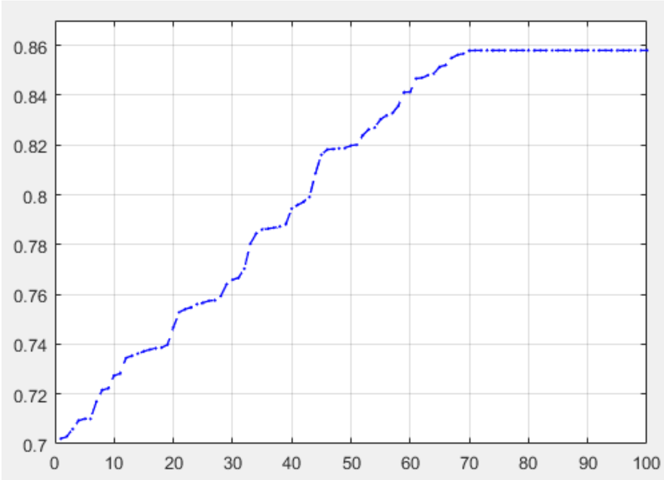

FIGURE 2. Improvement of education accuracy in the case of use of a combination of neural network method and memetic algorithm

Therefore, this criterion will be used in this experiment. The results of this experiment are presented in Table 1. As can be seen from the results recorded in this table, the proposed system of the research has been able to achieve better results in similar situations with Gedikly and colleagues.

Table 1. Comparison of proposed system with Gedikli method [14] in terms of F-Measure

System	Training data	Test data	F-Measure
Gedikli et al	75 percent	25%	81.75%
recommended system	75 percent	25%	86.4%

For the second comparison, Christakou et al. has been selected. This article, similar to the proposed system of the study, uses the MovieLens data set to evaluate its results. This article states that 70% of the samples for the dataset were used to train the system and the remaining 30% was used to test the system. Therefore, in this experiment, the same kind of work as the set of training and test data sets will be selected. The evaluation criterion used in the review article is the precision and recall criteria. The Precision criterion is obtained by dividing the number of real positive system samples into the total number of positive system samples (positive samples known from the system viewpoint). The Recall criterion is obtained based on the number of real positive system instances identified by the algorithm on the total number of positive real samples.

The results of this experiment are presented in Table 2 and Table 3. As can be seen from the results recorded in this table, the proposed system of the research has been able to achieve better results in terms similar to those of Christakou et al.

Table 2. Comparison of the proposed system with the Christakou et al. Method [15] in terms of Precision

System	Training data	Test data	Precision
Christakou et al	70 percent	30%	72%
recommended system	70 percent	30%	80.6%

Table 3. Comparison of the proposed system with the Christakou et al. Method [15] in terms of the Recall criterion

System	Training data	Test data	Recall
Christakou et al	70 percent	30%	78.5%
recommended system	70 percent	30%	83.9%

5. CONCLUSION

The growing Internet access and easy access to it have resulted in a significant increase in e-content, which, along with many benefits, has caused problems for users. Internet users simply cannot find the content they need from this massive amount of data. Users are faced with a lot of suggestions for choosing goods, buying items, selecting music and videos, and more. Advantage systems can be used to overcome these problems.

Today, with the spread of people's use of cyberspace, such as web sites and social networks, and increasing the need for conscious and clever selection of people, recommender systems has been extensively investigated. Recommender system analyzes user behavior and other users. It proposes the most suitable items, such as data, place or goods. Several studies conducted in the field of advisory systems; however, there is still space for new things, which can provide better accuracy and performance.

In the proposed system of this research, the neural network method uses the existing data set to learn the pattern in the data set under consideration. In addition, the mimetic algorithm is used to improve the performance of the neural network method. This algorithm seeks to find the optimal values for the parameters of the neural network method, in such a way that optimal solutions of the mantle algorithm are finally considered to be used to set parameters for the neural network method.

The proposed approach in this research has been implemented in MATLAB environment and the results have been tested and evaluated by implementing several different tests. The results of the experiments and comparison made show that the approach presented in this study has been shown to increase the accuracy of the effect and the performance and accuracy of the algorithm are acceptable to similar systems.

FUNDING

None

ACKNOWLEDGEMENT

None

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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