Journal of Computers Vol. 30 No. 3, 2019, pp. 82-101
doi:10.3966/199115992019063003007

Research on Weibo Public Opinion Prediction Using Improved Genetic Algorithm Based BP Neural Networks

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Received 24 August 2017; Revised 8 December 2017; Accepted 1 February 2018

Abstract. With the increase in Weibo users, the Weibo platform produces large amounts of data every day. The rapid propagation of data would result in an extensive change in public opinion. Thus, correctly predicting public opinion from Weibo is an urgent challenge. For this purpose, an approach to public opinion prediction from Weibo using an improved BP is proposed in this paper. First, according to the characteristics of Weibo public opinion, this paper constructs nine public opinion indexes to analyze Weibo public opinion. Third, because the BP is susceptible to the choice of initial weights and has a poor rate of convergence, GA is introduced to optimize the BP. However, the GA easily gets stuck in local optimal solutions. Therefore, the Metropolis acceptance criterion is employed to improve the local searching ability of GA. Then, the IGABP algorithm, which is based on the improved GA, is proposed. Finally, from extracting and normalizing the Weibo data, the validity of the IGABP algorithm is verified. The experimental result shows that the IGABP algorithm is feasible in the prediction of Weibo public opinion. In addition, the IGABP algorithm has better generalization ability and higher accuracy in Weibo public opinion prediction.

Keywords: BP neural network, improved genetic algorithm, metropolis acceptance criterion, public opinion prediction

1 Introduction

With the popularity of Web2.0 technology, Weibo has become the main source of public opinion. Weibo public opinion was proliferated and disseminated through the Weibo platform. Weibo [1] can lead to the rapid spread of public opinion and result in a huge social influence [2]. Therefore gains relevant information timely for public opinion analysis and prediction [3] has far-reaching significance for business and government agencies. Considering the adaptability of the algorithm to the varying Weibo data, the error reverse propagation algorithm for artificial neural networks is adopted as the public opinion prediction algorithm. A back-propagation neural network (BP) [4] is one of the most maturely studied neural network algorithms; it has good self-learning, self-adapting, robustness and generalization ability. This paper focuses on public opinion prediction from Weibo data based on an optimized BP algorithm.

In recent years, many researchers have proposed using a BP [5-9] to analyze public opinion from Weibo. On the one hand, these approaches are used to analyze Weibo, which have poor accuracy rates in public opinion prediction because BP easily gets stuck in local minima. On the other hand, these approaches do not analyze the process of dissemination, and the construction of public opinion indexes is not reasonable. Some of them take the forwarding amount into account so that the trend of public opinion cannot be reflected. There are many factors that affect the spread of Weibo public opinion, such as the comments on a topic and the tendency degree of an opinion. According to the characteristics of Weibo,

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this paper constructed reasonable Weibo public opinion indexes. In addition, to improve the accuracy rate of prediction, a novel BP algorithm (IGABP) based on an improved genetic algorithm is adopted.

The Genetic algorithm (GA) [4], one of the evolutionary algorithms, is a heuristic stochastic search algorithm. In our research, to avoid the GA getting stuck in local minima, the Metropolis acceptance criterion is introduced. The Metropolis acceptance criterion can also prevent GA's premature convergence. The improved GA is used to train the initial weights and thresholds of a BP. The obtained optimal weights and thresholds are taken as the input of a BP, by which the new BP model can be constructed. Finally, the experimental result shows that the new model has higher accuracy for Weibo public opinion prediction.

The rest of this paper is organized as follows. In section 2, related works are reviewed. In section 3, the character of Weibo and Weibo public opinion is illustrated to show our research motivation. In section 4, the basic knowledge of BP and GA are introduced compactly. In section 5, the improved GA is proposed to get the optimal solution in the iterative process, and the improved GA can optimize the BP. Section 6 analyses the experiment results. In section 7, the research is summarized, and future works are discussed.

2 Related Work

Weibo is the abbreviation of Microblog, which is a platform based on data sharing, dissemination and acquisition. Weibo public opinion is influenced by the speech situation where posts about an event break out and spread in Weibo. Users can post Weibo data through the client or web page anytime and anywhere. When major events occur, the Weibo data can spread throughout the world within a few hours. Then, public opinion can have extensive social impact and create enormous public pressure. If the guidance is poor, the negative network public opinion will be a great threat to social order and public safety.

Weibo public opinion prediction research has become a hot topic for study. Chen [5] developed a Weibo public opinion forecasting system, which can automatically collect and process data. They predict Weibo public opinion using a BP, but the system's forecasting rate was slow. To address public opinion of the Weibo community, Pan [6] constructed a prevention-monitoring model based on a BP, but this model did not relate to public opinion prediction. According to the characters of Weibo, Yang [7] proposed a method of public opinion prediction based on Neural Networks. They took the amount of Weibo data in a unit of time as a quantitative index of a time trend forecast and predicted the burst point and the amount of posting. Through the Neural Network method, He [8] predicted the forwarding quantity of the emergencies. Shi [9] combined a GA and a simulated annealing algorithm to optimize a BP and constructed a public opinion prediction model.

Wang [10] proposed a method of public opinion prediction based on a Neural Network, which took the amount of Weibo data in a unit of time as a quantitative index to predict the burst and posting of events. Through the Neural Network method, [11] predicted the forwarding quantity of the emergencies. The experimental results have some reference value, but the forwarding amount prediction may have some limitations.

BP is one of the tools in processing intelligent information, which is widely used for computers and various other disciplines and can also be applied in the health field [12]. It can also be used as a method of credit appraisal for architecture enterprises [13] and can be used in the field of marketing [14], as well as in other fields [15-18]. In summary, the BP is a feasible method of forecasting Weibo public opinion. However, there are some disadvantages of using a BP [19-20]. Thus, researchers considered optimizing BP before predicting public opinion [21], combining GA and simulated annealing algorithms to optimize the BP and constructing a public opinion prediction model. This method improved the accuracy of public opinion forecasts, but since only the amount of discussion is considered, it still has some defects.

In view of the above problems in addition to the reward of improving the methodology, this paper takes eight other indexes into account to analyze and predict public opinion from Weibo data. The BP [22] is susceptible to being affected by the choice of initial weights, has poor rates of convergence and easily gets stuck in local minima. This paper proposed to use an improved GA optimizing BP. The Metropolis acceptance criterion, which was introduced to improve the GA, prevents GA from getting trapped in local optimal solutions and prevents premature convergence. Then, the BP model was constructed by the improved GA, giving it higher accuracy in predicting public opinion from Weibo data.

3 Problem Analyses

3.1 Characteristics of Weibo

Sina Weibo was taken as a data source in this paper. From observing the Sina Weibo home page of a user (Fig. 1), it would be found that the top of the home page displays the user's head portrait, nickname, profile, etc. The left side of the home page shows the number of the user's concerns, the number of fans, the number of Weibo, the presence of Certification, Weibo level, whether or not the user has a membership, location, school, profile, mailbox, tags, registration time and so on. The user's details are usually complemented in the "See more" section. "See more" includes basic information, contact information, work information, education information and tag information.

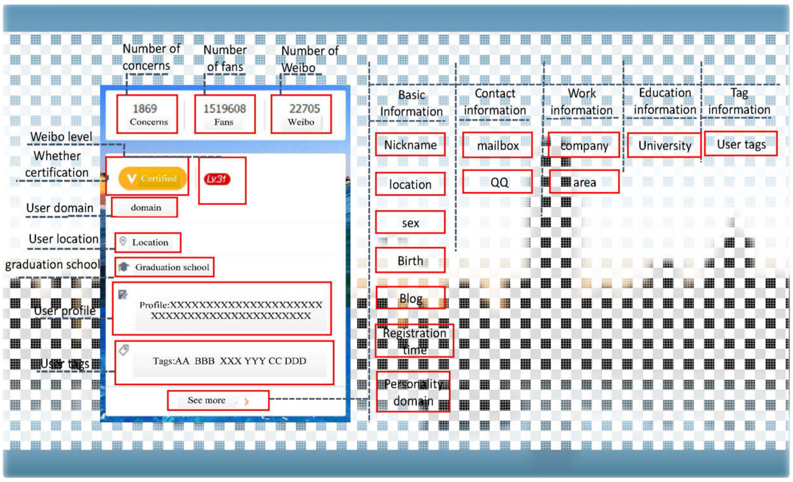

Fig. 1. Basic information of Weibo user

Generally, the personal information of an authenticated user is complete and credible. Moreover, the higher the users' reputation is, the more fans the users have. For example, some star actors have tens of millions or even hundreds of millions of fans. When a star actor posts a Weibo, the probability that the Weibo will be forwarded or commented on is higher than for ordinary people.

3.2 Weibo Public Opinion

In recent years, with the rapid development of the Internet, more and more people began to communicate through network platforms. Weibo users produce extensive Weibo data every day. Users use Weibo to participate in interactive topics and exchange data. Related data analyzed the source of public opinion and found that Weibo ranked first. Weibo has become a major source of public opinion.

Weibo public opinion data spread fast, and Internet users can release and receive Weibo data anytime and anywhere. The Weibo data can be published through the Internet or mobile phones. Weibo can not only publish text but also add pictures and video to complement. Weibo spread by forwarding, like a fission transmission, is different from traditional media. Through the client or web page, the data of Weibo are released real-time by users. Anyone can publish Weibo data, so Weibo public opinion data have a characteristic of arbitrariness.

Fig. 2 shows the process of the spread of Weibo public opinion data. The left part of Fig. 2 is a one-way communication mode. At the beginning of the data spread, most individuals have not yet come into contact with the public opinion data, so public opinion is a one-way communication. The right part of Fig. 2 is a two-way communication mode. With the number of individuals increased, the adjacent individuals interact with each other. It has evolved into a discussion instead of a one-way communication.

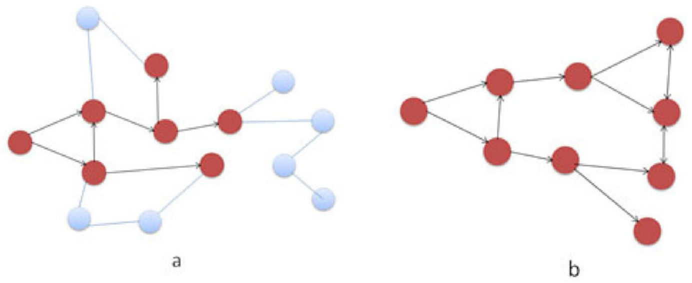

Fig. 2. Basic information of Weibo user

In the era of network information, people understand things from both their background and the impact of interpersonal communication. The influence degree of a user can be reflected by the quality of his fans. That is, if the fan influence of a user is greater, the user will have a greater influence. In this paper, the following formula can calculate the influence degree of a user.

$$Ir_i = (1-q) + q \sum_{i \in fw(i)} \frac{Ir_i}{|fri(j)|}. \quad \textbf{(1)}$$

In (1), Ir_i is the influence degree of user i, $fw(i)$ is the follower set of user i, $|fri(j)|$ is the user set user i focuses on, and q is the damping coefficient. The higher the value of q, the more the algorithm accounts for the social relations between the users. The damping coefficient is very useful in controlling the weight given to the social relations for the forwarding decision.

In the process of Weibo dissemination, a person may be affected by friends or surrounding people. If two people are supporters of the same team, they will be willing to exchange data about the team and affect each other's views. If two people hold opposing political views, they almost always do not agree with each other's views and almost always do not exchange with each other. The influence degree of a user is affected by his friends, which means that in (1), when the Ir_j increases, so does Ir_i. When a highly influential user forwarded a public opinion Weibo, the public opinion Weibo would be spread faster.

4 Basic Knowledge

4.1 Introduction of BP and GA

BP [23] was proposed by a group of scientists led by Rumelhart and McClelland in 1986. It is a multilayer feedforward network trained by an error inverse propagation algorithm. The BP is one of the most widely used Neural Network models and can learn and store a large number of input-output pattern mappings without revealing the mathematical equations. The learning rule of the BP is the gradient descent method. Network weights and thresholds are constantly adjusted through reverse propagation to ensure that the network error square sum is the minimum. The BP's topology is as shown in Fig. 3; it includes the input layer, hidden layer, and output layer.

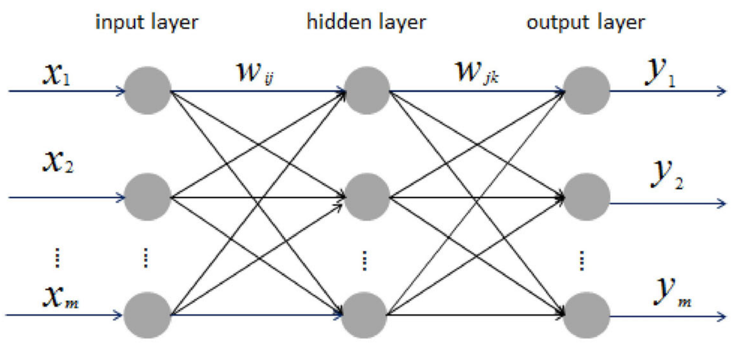

Fig. 3. Basic information of Weibo user

In Fig. 3, $x_1, x_2, x_3, ..., x_m$ is the input vector, $y_1, y_2, y_3, ..., y_n$ is the output vector, w_{ij} is the connection weight between the input layer and the hidden layer, w_{jk} is the connection weight between the hidden layer and the output layer, m is the number of input nodes, and n is the number of output nodes. If there is a standard result in advance, it will compare the output results with the standard result. According to the obtained error value, the connection weights of the BP will be reversed and corrected until a satisfying result is obtained.

GA [24] is a new global optimization algorithm developed in recent years. Professor Holland, in 1962, first proposed the idea of GA. GA borrowed the simulation of biological genetics and the natural selection mechanism and achieved the individual's adaptability through natural selection, a genetic algorithm, and mutation. To some extent, GA is a new attempt at the mathematical simulation of the biological evolution process.

Compared with the traditional optimization algorithm, GA has its superiority. First, it is a search strategy based on population. The traditional optimization algorithm is a point-to-point search method. GA is a population search strategy, which makes it easier to achieve the global optimum. Second, GA is a heuristic evolutionary process, which has the characteristic of being simple, generic, and robust. Third, the objective function of the GA does not depend on gradient information, which is only needed to assess the fitness of the individuals. Therefore, it is widely used in complex and non-linear problems.

However, GA is also deficient. It depends on the probability of random operation. Although it avoids being stuck in local minima, it is limited to the optimization conditions. The GA generally only gets the global range of suboptimal solutions, and it is difficult to get the optimal solution.

4.2 Basics Definitions

Considering the regularity with which Weibo public opinion crises occur, this paper constructed the following nine public opinion indexes to analyze Weibo data.

4.2.1 Attention-Degree of Weibo Public Opinion

Index 1. The number of original public opinion Weibo (Num_WPO_i). This paper uses a triad described as $WPO_i = \{WPO_i\_event, WPO_i\_t, WPO_i\_user\}$, where WPO_i_event is the public opinion event, WPO_i_t is the time of post, and WPO_i_user is the user who posts the Weibo.

The original public opinion Weibo is the foundation of our research, and it is necessary. The original public opinion Weibo is the source that makes the public opinion shift break out. For example, in the event of Baoqiang Wang's divorce, the Chinese actor Baoqiang Wang in Weibo issued a statement that he was ending his marriage relationship with his wife Rong Ma, and revealed an improper relationship between his broker Zhe Song and Rong Ma. This statement immediately gained the attention of Internet users and media and quickly ignited public opinion. In this public opinion event, Baoqiang Wang is the user who released the original public opinion Weibo.

Index 2. The number of comments (Num_CPO_i).

$$Num\_CPO_i = \sum_{i=1}^{n} (PO\_CPO_{ij}) . \tag{2}$$

In (2), PO_CPO_{ij} is a comment on a Weibo public opinion event, Num_CPO_i is all of the comments about the event. If the Weibo is commented on by a user, it means the user was attracted by the public opinion event. When a person publishes a comment, the comment may attract more comments. When there are more and more comments, it may bring about a big public opinion event.

Index 3. The number of forwarding (Num_FPO_i). If a user forwards the Weibo from another, it represents the user's agreement with the opinion. Under normal circumstances, if someone does not strongly like or agree with the opinion, he simply gives a thumbs-up or just gives some comments. When a user forwards a Weibo, it means that all of his Weibo friends can see it, and they may comment or forward the Weibo. In addition, the scope of information dissemination is expanded.

4.2.2 Statement of Weibo Public Opinion

Index 4. Tendency degree of opinion (TPO_i).

$$TPO_i = \{(U_i, f(x)) \mid f(x) \in \{-1,0,1\}\}. \tag{3}$$

When $f(x) = -1$, it means user U_i is opposed to the opinion. When $f(x) = 0$, it means user U_i is neutral. When $f(x) = 1$, it means user U_i is supportive. The smaller the tendency degree of the view is, the greater the possibility that a network public opinion crisis occurs. The NLPIR/ICTCLAS Chinese word segmentation system can observe the proportion of positive and negative tendency degrees through a sentiment analysis.

Index 5. Intuition degree of the content (IPO_i):

$$IPO_i = \frac{\sum(PhotoCS(B\log_i) \cup VideoCS(B\log_i))}{\sum WPO_i\_e}. \tag{4}$$

Where $\sum WPO_i\_e$ is the total public opinion Weibo, $PhotoCS(B\log_i)$ is the set of Weibo that include pictures, and $VideoCS(B\log_i)$ is the set of Weibo that contains videos. It is not difficult for us to find that Weibo containing only text are relatively dull and boring. If the forwarded Weibo contains relevant pictures and videos, the Weibo content is more intuitive and attractive.

Index 6. True degree of Public Opinion:

$$RPO_i = Ir_i \frac{\sum WPO_i\_Auth}{\sum WPO_i\_e}. \tag{5}$$

In (5), WPO_i_Auth is the Weibo posted by certified users, WPO_i_e is the public opinion Weibo, and Ir_i is the influence degree of the user, which is proposed in (1). If a user's influence degree is high, the true degree of public opinion would be more convinced. Certified users are real-name authenticated, and they do not release fake public opinion information casually. Most importantly for the certified user's statement, other users can view the statement directly without logging in. Generally, certified users have better reputations, and their statements will cause more repercussions and public opinion.

4.2.3 Change Rate of Weibo Public Opinion

Index 7. Change rate of the comment amount:

$$RCPO_i = \sum_{j=1}^{n} \frac{Num\_CPO_{T_j} - Num\_CPO_{T_{j-1}}}{\mu e^{-\mu(T_j - T_{j-1})}}. \tag{6}$$

In (6), $Num\_CPO_{T_j}$ and $Num\_CPO_{T_{j-1}}$ are the amounts of comment at time T_j and T_{j-1}, and μ is the weight of the exponential decay. The higher $RCPO$ value indicates that many people are concerned about this public opinion event.

When the users scan the Weibo, if they are not interested in the topic, they will leave a comment randomly. Focusing on the change rate of the number of comments in a certain period of time can help us to analysis the trend of public opinion development.

Index 8. Change rate of the forwarding amount:

$$RFPO_i = \sum_{j=1}^{n} \frac{Num\_FPO_{T_j} - Num\_FPO_{T_{j-1}}}{\mu e^{-\mu(T_j - T_{j-1})}}. \tag{7}$$

In (7), $Num\_FPO_{T_j}$ and $Num\_FPO_{T_{j-1}}$ are the amounts of forwarding at time T_j and T_{j-1}, and μ is the weight of the exponential decay.

Index 9. Change rate of the original Weibo published amount:

$$RWPO_i = \sum_{j=1}^{n} \frac{Num\_WPO_{T_j} - Num\_WPO_{T_{j-1}}}{\mu e^{-\mu(T_j - T_{j-1})}}. \quad \textbf{(8)}$$

In (8), $Num\_WPO_{T_j}$ and $Num\_FPO_{T_{j-1}}$ are the amounts of original Weibo at time T_j and T_{j-1}, and μ is the weight of the exponential decay.

Through the nine constructed public opinion indexes, this paper uses the following formula to calculate public opinion value of an event:

$$\begin{aligned} KPO_i = {} & \beta_1 Num\_WPO_i + \beta_2 Num\_FPO_i + \beta_3 Num\_CPO_i + \beta_4 TPO_i \\ & + \beta_5 RPO_i + \beta_6 IPO_i + \beta_7 RFPO_i + \beta_8 RCPO_i + \beta_9 RWPO_i \end{aligned}. \quad \textbf{(9)}$$

In (9), KPO_i is the public opinion value of a topic event, β_i is the weight of each public opinion index, and $\beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 + \beta_6 + \beta_7 + \beta_8 + \beta_9 = 1$. In the practical application, the β_i will be assessed by the importance of each index.

5 Improved GA Optimizing the BP Neural Network Model

5.1 BP Based on Improved GA

BP is sensitive to the selection of the initial weights. A change of the initial values will affect the convergence rate and accuracy of the network. Once the value is not proper, it will cause network oscillation and easily fall into local minima. Therefore, this paper considers using GA to optimize the BP. However, the GA can easily miss the optimal solution in the iterative process. Therefore, this paper introduces the Metropolis acceptance criterion to improve the GA, and then, the improved GA is used to optimize the BP.

Fig. 4 is the framework diagram for using improved GA to optimize the BP. At the beginning, the initial parameters are real coded, and the initial population is produced. Then, the fitness is calculated, and the fitness function uses the ranking fitness function.

After the selection operation, crossover operation and mutation operation, the Metropolis acceptance criterion is used to compare the fitness until the optimal connection weights and thresholds are obtained. Then, this paper uses the optimal connection weights and thresholds to optimize the BP.

Next, the optimized connection weights and thresholds are applied as the initial settings of the BP for public opinion prediction. Then, the outputs of the hidden layer and output layer are calculated, and the prediction error is also calculated. If the prediction error meets the terminate condition, the prediction value would be obtained. Otherwise, the connection weights and thresholds would be updated and returned by error back propagation.

Generally, as the learning and training ability of GA is far less than the BP, this paper combines the BP and improved GA organically to optimize the initial weights and thresholds of the BP. The global search performance of the improved GA is used to find the optimal solution, and then, the BP will find the optimal solution by error back propagation.

5.2 Improved GA Based on Metropolis Acceptance Criterion

GA [25] is a highly parallel and random adaptive search algorithm. Traditional GA can improve the overall ability of the search process but can easily miss the optimal solution in the iterative process. At the same time, the local spatial search ability of the GA is weakened, and the ability to convergence to the global optimal solution is affected. In the process of optimizing the BP based on the GA, it will have poor local convergence.

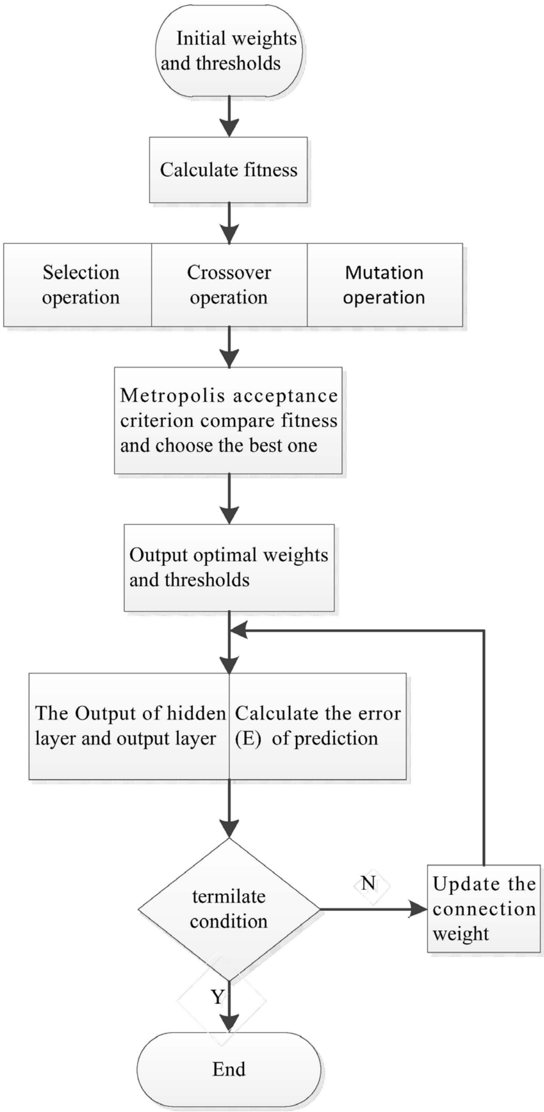

Fig. 4. The framework diagram of IGABP

For the problem mentioned above, this paper employed the Metropolis acceptance criterion to improve the traditional GA. Starting from the given initial value and changing the initial value repeatedly, finally, the relative optimal solution would be obtained. Then, the temperature T is gradually reduced, and the Metropolis algorithm is circularly executed. When the temperature T trends to zero, the optimal solution of the required problem will be obtained.

Given fit_i as the new fitness and fit_{i-1} as the fitness of last iteration, T is the initial temperature. When the GA produces a new fitness through selection, crossover and mutation, it uses the Metropolis acceptance criteria to compare fit_i and fit_{i-1}. Then, the optimal fitness will finally be selected, and the specific operation is as follows:

- When $\Delta fit > 0$ ($\Delta fit = fit_i - fit_{i-1}$), accept new solution.
- When $\Delta fit \le 0$, if the probability $P = \exp(-\Delta fit / T) < random[0,1)$, accept new solution. Otherwise, reduce the temperature parameter ∂ to adjust the temperature T, and then, accept the judgment again. The probability equation is as follows:

$$P = \begin{cases} 1, fit_i - fit_{i-1} > 0; \\ \exp(-\dfrac{fit_i - fit_{i-1}}{\partial T}) < random[0,1), fit_i - fit_{i-1} \le 0;. \\ 0, fit_i - fit_{i-1} \le 0. \end{cases} \quad \textbf{(10)}$$

The improved GA can increase the local search ability of the GA and get the optimal individual. When applying the improved GA to optimize the BP, the influence of the initial weights and thresholds to the BP can be reduced.

5.3 BP Model Based on Improved GA

The learning rule of traditional BP is gradient descent. Through reversing propagation to adjust the connection weights and thresholds constantly, the network error square sum achieves a minimum. However, it can easily fall into local optima and cannot obtain the global optimum. When a BP is used to predict Weibo public opinion, the accuracy is also affected. To overcome these disadvantages, this paper introduced improved GA to optimize BP.

When building a neural network, a connection threshold and a weight for each node are needed. However, in general, most people give them randomly. In the training process, the minimum is found through random search. When using the improved GA to optimize the BP, the neural network can be made from a closer level to start training.

Parameter initialization gives thresholds a and b a random value in the interval [-1, 1] and initializes the connection weights w_{ij}, w_{jk}, the population size, the evolutionary number, the crossover probability and the mutation probability. When using improved GA to optimize the BP, the population would be real coded. The length of population codes is calculated as follows:

$$S = RS1 + S1S2 + S1 + S2 . \quad \textbf{(11)}$$

In (11), R is the number of nodes in the input layer, $S1$ is the number of nodes in the hidden layer and $S2$ is the number of nodes in the output layer.

To make the residuals of the prediction value and the expected value as small as possible, the output of the objective function is calculated as follows:

$$F = \frac{1}{2}\sum_{t=1}^{S}\sum_{k=1}^{S2}(Pk - Ek)^2 . \quad \textbf{(12)}$$

In (12), Pk is the prediction value of the prediction sample and Ek is the norm of the error matrix of the expected value.

The fitness function uses the ranking fitness function, and a formal description is as follows:

$$Fit = ranking(obj) . \quad \textbf{(13)}$$

In (13), obj is the output of the objective function. In the GA, fitness reflects the quality of individuals. The greater the fitness is, the better the individuals are. In $ranking(a)$, the function allocates the fitness value according to the target key, which ranks from small to large. Therefore, this paper takes the reciprocal of F as the obj.

In the select operation, individuals with higher adaptability are inherited to the next generation with greater probability. The selection probability is calculated as follows:

$$P_i = \frac{fit_i}{\sum_{i=1}^{S} fit_i} . \quad \textbf{(14)}$$

The chromosomes in each generation were selected by the selection strategy based on the fitness ratio. This paper uses a single point crossover operator and basic bit mutation method to carry out the mutation operation. First, the individual genetic location of the mutation is determined, and then, the mutated genes were randomly selected according to a certain probability.

After GA's selection, crossover, and mutation, the new fitness was produced. The optimal fitness is selected by the improved GA. Therefore, it is effective to suppress the GA's premature convergence and improve the accuracy of the local optimization of GA.

When obtaining the optimal individuals through the improved GA, the individuals are taken as the connection weights of BP. and then, the output of the hidden layer is calculated according to the following formula:

$$H_i = f(\sum_{i=1}^{n} w_{ij}x_i - a_j) \quad j=1,2,3,...,S1 . \tag{15}$$

In (15), f is the activation function ($f(x)=1/(1+e^{-x})$). According to the expected output Y and the predicted output C , the prediction error is calculated as follows:

$$E_k = Y_k - C_k \qquad k = 1,2,3,...,m . \tag{16}$$

If the predicted error does not meet the conditions, then the network connection weights would be updated based on network error. The update formula is as follows:

$$\begin{aligned} W_{ij} &= w_{ij} + uH_j(1-H_j)x(i) \\ W_{jk} &= w_{jk} + uH_j e_p \end{aligned} . \tag{17}$$

In (17), u is the learning rate. Next, the thresholds a and b of network nodes are updated according to the prediction error.

$$\begin{aligned} a_j &= a_j + \theta H_j(1-H_j) \quad j=1,2,...,S1 \\ b_k &= b_k + e_k \qquad\qquad k=1,2,3,...,m \end{aligned} . \tag{18}$$

Finally, a judgment is made regarding whether the global error meets the accuracy requirements. If the conditions are satisfied, the solution would be obtained. The IGABP algorithm pseudo code is as follows.

Algorithm 1. IGABP algorithm pseudo code

Input: $x_1, x_2, x_3, ..., x_m$; $y_1, y_2, y_3, ..., y_n$

Output: E_k

1. Initializes parameters;
2. Real code the population;
3. Calculate Fit;
4. selection, crossover, mutation;
5. Metropolis compare the *fit*;
6. if (*bestfit*) calculate H_i
7. else update ∂ and turn to 2
8. Output C_k
9. Calculate E_k
10. If ($E_k >> Y_k$) turn to 11; Else turn to 12;
11. Update $W_{ij}; W_{jk}$

    Update a_j , b_p , turn to 12.
12. End.

The BP model is widely used as a forecasting model. However, the model can easily fall into local minima, and it has slow convergence and other shortcomings. To overcome these shortcomings, this paper optimizes the BP with an improved GA. However, there are some problems with GA. GA can easily get trapped in a local optimal solution and premature convergence. Therefore, this paper proposes an algorithm that uses the improved GA to optimize the BP. To begin with, it applies real coding to the population and takes the ranking fitness function as the fitness function. Through selection, crossover and mutation, it introduces the Metropolis acceptance criterion to compare the fitness with the previous iteration of GA to choose the optimal fitness. When it obtains the optimal individuals through the improved GA, the optimal individuals are taken as the input of BP. Next, the output of the hidden layer, the output of the output layer, and the prediction error are calculated. If the prediction error is within the allowable range, the solution was obtained. Otherwise, it is necessary to update the network connection weights and thresholds and calculate the output of the hidden layer and the output layer again. The

IGABP algorithm can be applied to the field of function approximation, pattern recognition, data classification and data prediction. In this paper, the IGABP algorithm is used for Weibo public opinion prediction.

The IGABP algorithm flow chart is shown in Fig. 5. At the beginning, the parameters were initialized, and the microblogging data were normalized. Then, the Population was real coded, and the fitness was calculated. After loops of the operations of choice, cross and mutation, the Metropolis criteria are used to compare the fitness to choose the optimal fitness until it reaches the number of evolution and obtains the optimal initial weights and thresholds. If the termination condition is met, the optimal value will be obtained. Otherwise, loop the operation. Construct the BP by the best initial weights and thresholds, and calculate the output of the hidden layer and the output of the output layer. Finally, the prediction error was calculated. If the error is within the acceptance range, the solution would be obtained. Otherwise, update the weights and thresholds, and then calculate again. The essence of IGABP is to take the optimal individuals as the initial weights and thresholds of the network. Then, the BP prediction model is constructed.

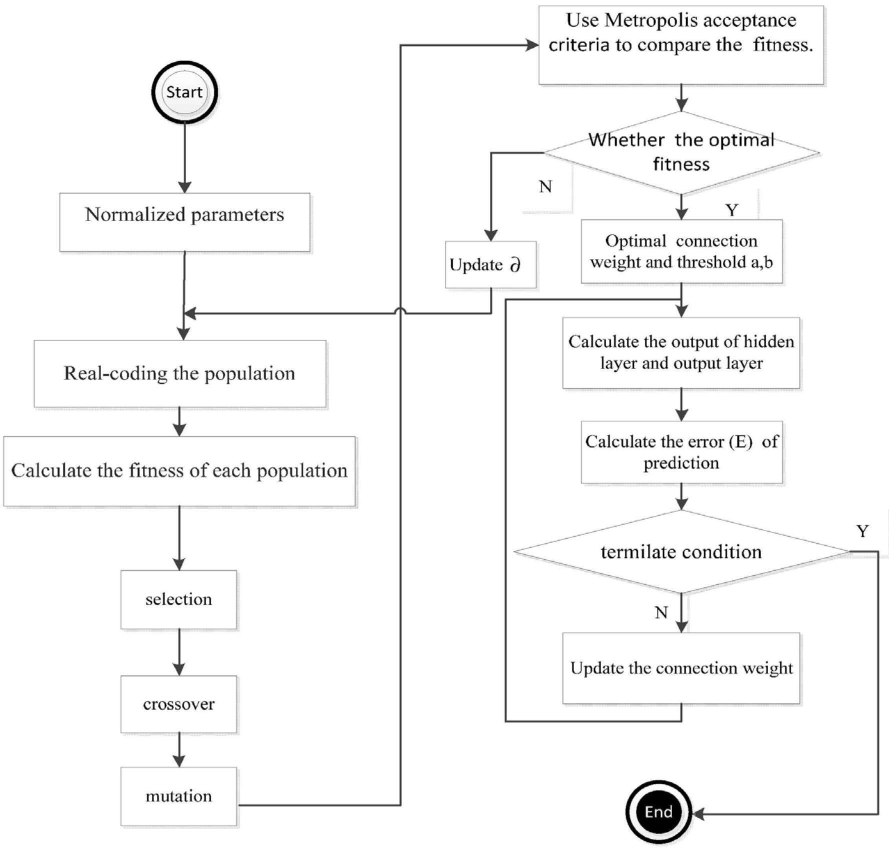

Fig. 5. The IGABP algorithm flow chart

6 Experiment Analysis

6.1 Dataset

This paper uses the Sina Weibo dataset on https://cn.aminer.org/billboard, which contains 300,000 original Weibo, including 23.7 million forwarding Weibo. Each Weibo has 80 forwards on average. The data set involved 1.77 million Weibo users, and it has 24 million follow relationships.

Through analysis and processing of the dataset, 10 public events were extracted to predict the public opinion. The 10 public events include the “Diaoyu Island incident”, when “Jiangnan style” swept the world, Zhiwen Wang drunk driving, etc. The extracted 10 events are shown in Table 1. The extent to which the extracted 10 events’ data are related is shown in Table 2.

Table 1. 10 topic events

No	Topic Event
1	"Diaoyu Island incident"
2	"Jiangnan style" swept the world
3	Zhiwen Wang drunk driving
4	"The Voice of China" hottest
5	London Olympics
6	"The Legend of ZhenHuan" hit
7	Jia Le injured in "You Are the One"
8	Yan Mo won the Nobel Prize in Literature
9	Shengyi Huang kneeling Benshan Zhao as teacher
10	Yifei Liu and Yike Zeng hand in hand to record program

Table 2. 10 topic events data Unit: million

Topic No	Original	Forwarding	Comments	Certified users
1	4.35	15.14	34.13	0.152
2	2.15	10.16	24.15	0.035
3	1.06	1.87	5.38	0.138
4	2.65	5.15	9.86	0.028
5	2.93	10.85	13.07	0.052
6	2.02	2.13	12.15	0.056
7	0.95	1.58	3.28	0.097
8	2.05	2.56	8.27	0.049
9	0.95	0.79	1.63	0.065
10	0.75	0.56	1.36	0.017

6.2 Data Normalization and Evaluation Criteria

To process the data conveniently, the min-max normalization method is employed to normalize the Weibo data. The min-max normalization method is also known as deviation normalization. It is the linear transformation of the original data, with the resulting value mapped to [0, 1]. The transfer function is as follows:

$$F(x) = \frac{x - \min}{\max - \min}. \tag{19}$$

In (19), $\max$ is the maximum value of the sample data, $\min$ is the minimum value of the sample data, x is the original sample data, and $F(x)$ is the normalized sample data. The public opinion indexes constructed in section 2.2 were marked as $x_1 \sim x_9$, and the 10 topic events were normalized by (19). The normalized sample data are as shown in Table 3.

Table 3. Normalization sample data

No	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9
1	0.053	0.041	0.136	0.052	0.065	0.098	0.159	0.052	0.085
2	0.158	0.162	0.057	0.035	0.029	0.074	0.065	0.054	0.066
3	0.062	0.074	0.082	0.138	0.095	0.065	0.038	0.056	0.058
4	0.152	0.052	0.065	0.028	0.037	0.041	0.056	0.039	0.052
5	0.036	0.156	0.074	0.052	0.045	0.062	0.052	0.039	0.041
6	0.029	0.032	0.057	0.056	0.072	0.039	0.054	0.065	0.025
7	0.056	0.085	0.086	0.097	0.052	0.029	0.073	0.057	0.098
8	0.052	0.065	0.075	0.049	0.056	0.085	0.095	0.038	0.029
9	0.052	0.095	0.038	0.065	0.062	0.039	0.075	0.052	0.095
10	0.052	0.062	0.068	0.097	0.159	0.183	0.067	0.059	0.062

In this paper, the prediction error is calculated by mean absolute error MAE and mean square error MSE. The formulas are as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}| f_i - y_i | . \quad \textbf{(20)}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(f_i - y_i)^2 . \quad \textbf{(21)}$$

$$MRE = \frac{1}{n}\sum_{i=1}^{n}| \frac{x_i - y_i}{x_i} | . \quad \textbf{(22)}$$

In (20)~(22), f_i is the predicted value and y_i is the true value. When the MAE, MSE and MRE are small, the accuracy rate of the prediction is high.

6.3 Parameter Settings

In the experiment, if the size of the population is huge, it is more favorable to find the global optimal solution. However, the calculation quantity and the time cost are increased. Therefore, to ensure the appropriate density, s (population size) = 30. When the crossover probability is high, the frequency of crossover operation will be fast, and it can converge to the optimal solution interval faster. However, it might converge to only one solution. Thus, this paper takes 0.5 as the crossover probability. The probability of mutation usually chooses a small value. If a relatively high mutation rate is chosen, it may cause instability. However, if too small of a mutation rate is chosen, it is more difficult to find the global optimal solution. Therefore, this paper takes the probability of mutation as 0.006. When the Metropolis acceptance criterion is employed to improve the GA, there is a higher probability that the higher temperature can lead to a higher quality solution. However, the time cost is greater, so the initial temperature is given as 100 ° C.

When calculating the public opinion value, the weight coefficients of the public opinion indexes are calculated by the analytic hierarchy process [26]. In the analytic hierarchy process, at the beginning, the judgment matrix A of the assessment index is constructed as follows.

$$A = \begin{bmatrix} 1 & a_{12} & \ldots & a_{1n} \\ a_{21} & 1 & \ldots & a_{2n} \\ \ldots & \ldots & 1 & \ldots \\ a_{n1} & a_{n2} & \ldots & 1 \end{bmatrix} \Rightarrow \begin{cases} a_{ij} = \dfrac{1}{a_{ji}} \\ a_{ij} \in \{1/9,1/7,1/5,1/3,1,3,5,7,9\} \end{cases} . \quad \textbf{(23)}$$

After comparing each two indicators according to the 9-bit ratio, the evaluation index matrix A is constructed. In (23), $a_{ij} \in \{1/9,1/7,1/5,1/3,1,3,5,7,9\}$. The value of a_{ij} is the degree of importance of the indicators. According to the judgment matrix, the weight coefficient of each index can be calculated as follows:

$$\overline{\beta}_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} (i = 1,2,...,n) . \quad \textbf{(24)}$$

Second, obtain the sum of each row from the normalized judgment matrix according to the following formula.

$$\overline{\beta}_i = \sum_{j=1}^{n} \overline{\beta}_{ij} (i = 1,2,...,n) . \quad \textbf{(25)}$$

Third, normalize the vector.

$$\beta_i = \frac{\beta_i}{\sum_{i=1}^{n} \overline{a}_{ij}} . \tag{26}$$

Then, the weight coefficient W is obtained.

$$\beta = (\beta_1, \beta_2, ..., \beta_n)^T$$

For example, to illustrate the analytic hierarchy process, first, a judgment matrix is given as follows:

$$A = \begin{bmatrix} 1 & 1/3 & 4 \\ 3 & 1 & 1/2 \\ 1/4 & 2 & 1 \end{bmatrix}$$

Then, normalize each column element of the judgment matrix according to formula (24), and the calculation process is as follows:

$$\beta_{11} = 1/(1+3+1/4) = 0.24$$
$$\beta_{21} = 3/(1+3+1/4) = 0.71$$
$$\beta_{31} = (1/4)/(1+3+1/4) = 0.06$$
$$\beta_{12} = (1/3)/(1/3+1+2) = 0.10$$
$$\beta_{22} = 1/(1/3+1+2) = 0.30$$
$$\beta_{32} = 2/(1/3+1+2) = 0.60$$
$$\beta_{13} = 4/(4+1/2+1) = 0.73$$
$$\beta_{23} = (1/2)/(4+1/2+1) = 0.09$$
$$\beta_{33} = 1/(4+1/2+1) = 0.18$$

Through smoothing, the normalized matrix that is obtained as follows:

$$\overline{\beta} = \begin{bmatrix} 0.24 & 0.10 & 0.73 \\ 0.71 & 0.30 & 0.09 \\ 0.06 & 0.60 & 0.18 \end{bmatrix}$$

Next, obtain the sum of each row of the normalized judgment matrix as follows:

$$\overline{\beta_I} = \begin{bmatrix} 1.07 \\ 1.10 \\ 0.84 \end{bmatrix}$$

Normalize the vector according to formula (26), and the weight vector is as follows:

$$\beta = \begin{bmatrix} 1.07/(1.07+1.10+0.84) \\ 1.10/(1.07+1.10+0.84) \\ 0.84/(1.07+1.10+0.84) \end{bmatrix} = \begin{bmatrix} 0.36 \\ 0.37 \\ 0.28 \end{bmatrix}$$

According to the importance of each index, this paper constructed the analytic hierarchy Matrix, which is shown in Table 4.

Table 4. The judgment matrix of public opinion index

index	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9
x_1	1	1/3	3	1/2	3	1/2	4	1/3	3
x_2	3	1	1/2	1/3	2	1/3	1/3	2	3
x_3	1/3	2	1	1/2	3	2	1/2	2	1/3
x_4	2	3	2	1	2	1/3	1/3	3	1/2
x_5	1/3	1/2	3	1/2	1	1/2	3	1/2	2
x_6	2	1/3	1/2	3	2	1	2	1/3	3
x_7	1/4	3	2	3	1/3	1/2	1	1/2	2
x_8	3	1/2	1/2	1/3	2	3	2	1	1/2
x_9	1/3	1/3	3	2	1/2	1/3	1/2	2	1

Next, according to formula (24), normalize each column element of the analytic hierarchy Matrix in Table 3. The normalized matrix that is obtained as follows:

$$\overline{\beta} = \begin{bmatrix} 0.081 & 0.030 & 0.215 & 0.043 & 0.190 & 0.059 & 0.293 & 0.029 & 0.196 \\ 0.245 & 0.091 & 0.032 & 0.028 & 0.126 & 0.039 & 0.024 & 0.171 & 0.196 \\ 0.025 & 0.181 & 0.065 & 0.043 & 0.190 & 0.235 & 0.037 & 0.171 & 0.022 \\ 0.163 & 0.273 & 0.129 & 0.090 & 0.126 & 0.039 & 0.024 & 0.257 & 0.033 \\ 0.025 & 0.045 & 0.194 & 0.043 & 0.063 & 0.059 & 0.219 & 0.043 & 0.130 \\ 0.163 & 0.030 & 0.032 & 0.269 & 0.126 & 0.117 & 0.146 & 0.029 & 0.196 \\ 0.020 & 0.273 & 0.129 & 0.269 & 0.021 & 0.059 & 0.073 & 0.257 & 0.130 \\ 0.245 & 0.045 & 0.032 & 0.028 & 0.190 & 0.353 & 0.146 & 0.086 & 0.033 \\ 0.025 & 0.030 & 0.215 & 0.179 & 0.126 & 0.039 & 0.037 & 0.171 & 0.065 \end{bmatrix}$$

According to formula (25), obtain the sum of each row of the normalized judgment matrix, and the result is as follows:

$$\overline{\beta_1} = \begin{pmatrix} 1.136 \\ 0.852 \\ 0.969 \\ 1.134 \\ 0.821 \\ 1.108 \\ 1.231 \\ 1.158 \\ 0.887 \end{pmatrix}$$

According to formula (26), a normalization of the vector and the weight vector was obtained:

$$\beta = \left(0.108, 0.092, 0.104, 0.122, 0.088, 0.119, 0.132, 0.123, 0.095\right)^T$$

and through rounding, this is simplified as follows:

$$\beta = \left(0.12, 0.10, 0.10, 0.12, 0.09, 0.12, 0.13, 0.12, 0.09\right)^T$$

The weight coefficient is shown in Table 5.

Table 5. The Judgment Matrix of Public Opinion index

Weight	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
Coefficient	0.124	0.106	0.109	0.125	0.092	0.123	0.113	0.123	0.096

6.4 Experimental Result and Analysis

To verify the validity of the proposed algorithm in this paper, this paper constructed the BP model, the BP model based on GA (GABP), and the IGABP model. Then, the three models were applied to public opinion prediction from Weibo data. Moreover, the accuracy rate of public opinion prediction of BP, GABP and IGABP models is compared.

First, to verify the improved GA's validity, this paper compared the maximum fitness value of the GABP algorithm and the IGABP algorithm based on experimentation. Fitness [27] is generally used to evaluate the merits of an individual. The greater the fitness is, the better the individual is. If an individual has greater fitness, the individual will have more opportunities to reproduce, and the offspring inherit the fine characteristics.

The experiment results are shown in Fig. 6. In this experiment, it shows that when the number of iterations is between 10 and 55, the fitness of the traditional GABP algorithm increased gradually. The fitness of the IGABP algorithm is also growing, but the slope of IGABP is always higher than the GABP. When the number of iterations increased to 55, the maximum fitness of the GABP algorithm increases slowly and gradually becomes smooth. Because GA misses the optimal solution in the iterative process, the ability of convergence to the global optimal solution is affected. However, the max fitness value of the IGABP algorithm continues to increase. When the number of iterations increases to 73, the IGABP algorithm gradually became steady. In addition, the max fitness value of GABP is still smooth because by reducing the temperature parameter to adjust the temperature T constantly; the improved GA increased the local search ability of the GA and obtained the optimal solution. This showed that the introduction of the Metropolis acceptance criteria is effective.

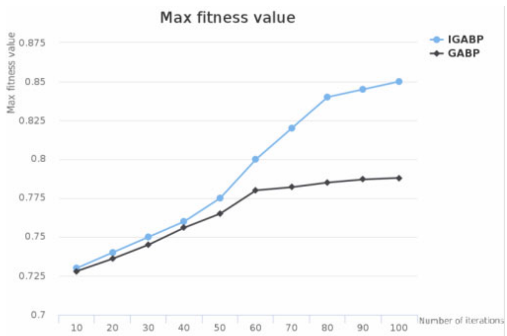

Fig. 6. The Max fitness value comparison

In summary, the traditional GA cannot effectively optimize the BP. However, when introducing the Metropolis acceptance criteria to improve the GA, the optimal max fitness value can be obtained.

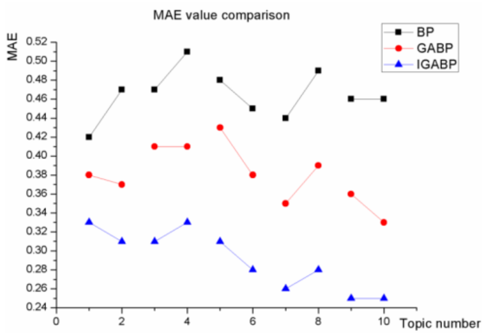

Fig. 7. MAE value comparison

After normalizing the 10 Weibo data samples, the Mean Absolute Error (MAE), the Mean Squared Error (MSE) and the Mean Relative Error (MRE) of each sample can be calculated by the formulas (20) ~ (22). In Fig. 8, it can be seen that the MAE points to a segment of the BP model, the MAE points to a segment of the GABP model, and the MAE points to a segment of IGABP model in public opinion prediction using Weibo data. It can be seen that the prediction accuracy of the traditional BP model is very poor. In topic 4, its error rate reached approximately 52 percent, while the lowest error rate is only approximately 42 percent in topic 1. Because the BP easily falls into local minima, the prediction accuracy rate in Weibo data is also affected. When this paper uses the GA to optimize the BP for public opinion prediction using Weibo data, it shows that the error rate reached 42 percent in topic 5, which is better than the traditional BP. When using improved GA to optimize the BP, in the best case, the MAE error rate reached approximately 25 percent. Because the improved GA helps the BP to get the optimal connection weights and thresholds, it reduces the impact of the initial weights and thresholds on the BP. The IGABP can handle the Weibo data better than the traditional BP.

Fig. 8 shows the MSE histograms of the BP model, the GABP model and the IGABP model for public opinion prediction using Weibo data. It shows that the mean square error of the traditional BP model is very large. The problem is that the BP algorithm can easily get stuck in local minima, which can affect the accuracy of public opinion data predictions. The mean square error of the GABP model is slightly reduced because GA rarely gets stuck in local minima. When combining GA with the BP to analyze Weibo data, the accuracy of the public opinion predictions was enhanced. It can be observed in Fig. 8 that the mean square error of the IGABP model is reduced to approximately 0.1. This shows that the IGABP is more effective and has better generalization ability. Through observing the MRE value in Fig. 8, the prediction value of the IGABP algorithm is closer to the true Weibo data.

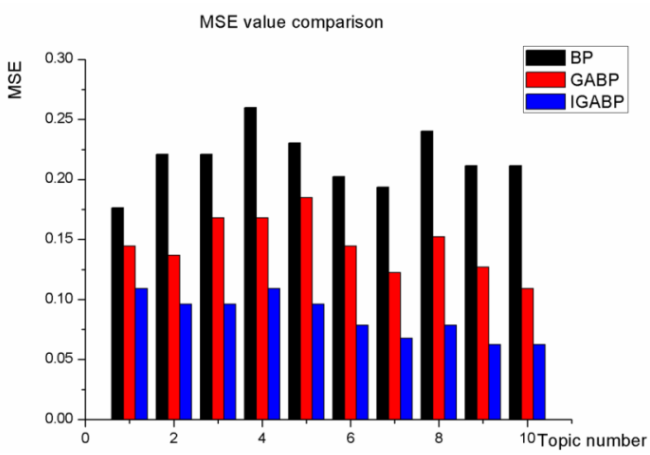

Fig. 8. MSE value comparison

Fig. 9 shows the MSE line chart of the BP model, the GABP model and the IGABP model in public opinion prediction using Weibo data. It shows that the MRE value is very poor for Weibo public opinion predictions when using a traditional BP. It can be seen that the MRE is more than 30 percent in all topics because the traditional BP has a poor rate of convergence in analyzing Weibo data and it gets stuck in local minima easily. When combining the GA with the BP to research Weibo data, the public opinion prediction MRE value is reduced to approximately 0.23, but the accuracy is still not very good. That is because in the iterative process, the GA missed the optimal solution. By combining the improved GA with the BP, the public opinion prediction results are much closer to the true data than those resulting from using the traditional BP model and the GABP model, and the MSE error rate is significantly reduced. The MSE result shows that the algorithm proposed in this paper is significantly helpful in improving the accuracy of Weibo public opinion prediction.

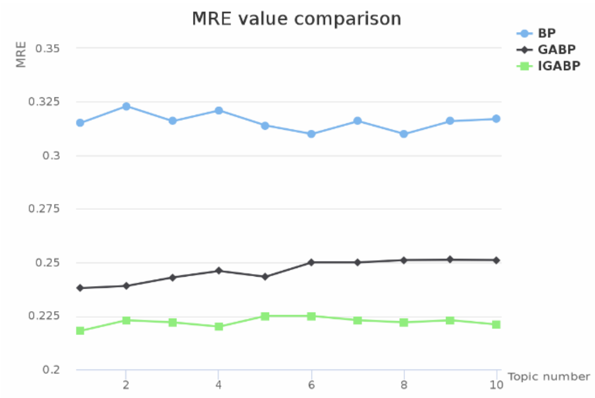

Fig. 9. MRE value comparison

7 Conclusion

As a new type of data dissemination platform, Weibo has greatly increased the propagation speed of data and extended the scope of data spreading. Therefore, extracting effective data from Weibo to analyze public opinion is necessary. This paper takes the transmission regularity of Weibo and characteristics of the Weibo into account, and the nine public opinion indexes are constructed. Moreover, the improved GA was used to optimize the BP. Next, the optimized BP is applied to public opinion prediction. From the experiment, it can be seen that the algorithm proposed in this paper has higher accuracy for Weibo public opinion prediction and has better generalization ability.

In the future, research on this issue will continue. On the one hand, we will focus on the big data produced in the Weibo. On the other hand, we will consider the preferences of users and make personalized recommendations for the specific users. Otherwise, the method can also be extended to other commercial applications, such as stock forecasts and crowd traffic forecasts.

Acknowledgments

This paper is supported by National Natural Science Foundation of China under Grant No. 61502294, CERNET Innovation Project under Grant No.NGII20160210, NGII20160614, NGII20160325, The Special Development Foundation of Key Project of Shanghai Zhangjiang National Innovation Demonstration Zone under Grant No. 201411-ZB-B204-012, and The Development Foundation for Cultural and Creative Industries of Shanghai under Grant No. 201610162.

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