Optimization of Simulated Annealing Algorithm to the Parameters of SVM Prediction Model

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Abstract
In the standard SVM algorithm still exists the problem of low accuracy when demand forecast, this article puts forward a kind of talent demand forecasting model based on simulated annealing algorithm to optimize the SVM algorithm. First of all, introduce the simulated annealing algorithm, use Cauchy distribution as the distance of disturbance to disturbance optimization it, then changing the annealing schedule, properly controlling the cooling process, combining with the method of success - failure and the method of variable metric to optimize convergence. At last, we introduced the improved simulated annealing algorithm into the parameter selection of support vector machines, improving accuracy which is supporting vector machine algorithm. According to the simulation results, the improved simulated annealing algorithm from this paper has better convergence.sa for accuracy, the talent demand forecasting model based on simulated annealing algorithm to optimize the SVM algorithm is higher than the original SVM algorithm.
Key words: *SVM ALGORITHM, CAUCHY DISTRIBUTION, SIMULATED ANNEALING ALGORITHM, PREDICTION MODEL*

1. Introduction

Talent forecast includes ownership forecast, demand forecast, construction of ownership forecast, construction of demand forecast and talent evaluation system, etc. which is a complex social system engineering [1]. Horng-Jiun Lin found that as a traditional tool for prediction, Delphi method has been accepted widely and used in technology forecast, talent forecast and trend forecast, etc [2]. To meet the requirements of random and non-stationary service, Righter developed Markov decision process model. This model has been applied to the service organization to solve the problem of talent requirement, and achieved effective results [3]. After research on the combinatorial problems, Shen thought that if there are several methods that can predict the same problem, we can use a combinatorial forecast method [4]. Jin Y Q studied from the increment of labor supply and demand aspect, considering the impact of the financial crisis and the upgrading of industrial structure to the demand of employment. She forecasted the supply and demand of the labor of 2001-2020 and called on the government to take positive measures to solve the employment problem [5]. From the unsuitability of university professional structure and economic development, Wang Y R predicted the number of talent from university as well as the quality, level and structure, finding it can't meet the demand of social development, as a result of the trend of the diversification of industrial and technological structures. Thus the author forecasts that adjusting professional structure has become the inevitable choice to universities to culture talents [6]. Zhao X predicted the number of employees on the marine using gray prediction model GM (1, 1). Results showed that the demand for marine employees will reach 459.55millon and marine technology talent 68.93millon [7]. Zhao H analyzed the percentage of various foreign talents in the market in Henan, concluding that, in the coming decades, it will be saturated for the talents familiar with only one foreign language, while compound talents who are familiar with basic knowledge and theory on foreign affairs, foreign trade, economics, law, news, political, etc. will be very popular [8]. Zhu Y G analyzed the current human resources in Xinjiang, making full use of the function of human resources planning, combining the local real demand for talent, using multiple linear regression model and obtained the specific number of technical talents specific in coal, coal electric and chemical industry, according to which he made a realistic talent training objectives and the specific programs [9].

In this paper, to compensate for the flaws in forecasting the demand of talent using SVM, a model for forecasting the demand of talent based on simulated annealing algorithm SVM was put forward.

2. Demand forecast model based on SVM

Supporting vector machine is based on the principle of structural risk minimization. The structural risk minimization principle solves the anti-excessive study problem in traditional learning algorithms. SVM algorithm is higher both in precision and efficiency [10].

Given the training set

$$T = \{(x_1, y_1), \ldots, (x_l, y_l)\} \in (R^n \times \gamma)^l \qquad (1)$$

$$x_i \in R^n,\ y_i \in \gamma = \{1, -1\},\ i = 1, \ldots, l\,.$$

Classification problem is looking for a real-valued function in space, through the decision function.

$$f(x) = \mathrm{sgn}(g(x)) \qquad (2)$$

Infer the output according to the either input x.

The model of optimization problems can be expressed as follow

$$\max_a -\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} y_i y_j (x_i \cdot x_j) a_i a_j + \sum_{j=1}^{l} a_j \qquad (3)$$

According to the SVM algorithm above, talent demand forecast model was built and simulation experiment was put on it. Three parameters were assigned to SVM manually, $C = 100$, $\varepsilon = 0.00054$, $\sigma = 0.0036$, the predicted effect figure was obtained as follow:

From the simulation results, it can be seen that the talent demand prediction model based on SVM algorithms also has some defects as follows:

Standard SVM, in time series forecasting and applications in other fields, is same for error penalty parameter C and request parameter of different samples, that is, for different sample data, its accuracy, precision deviation punishment is non-discriminatory.

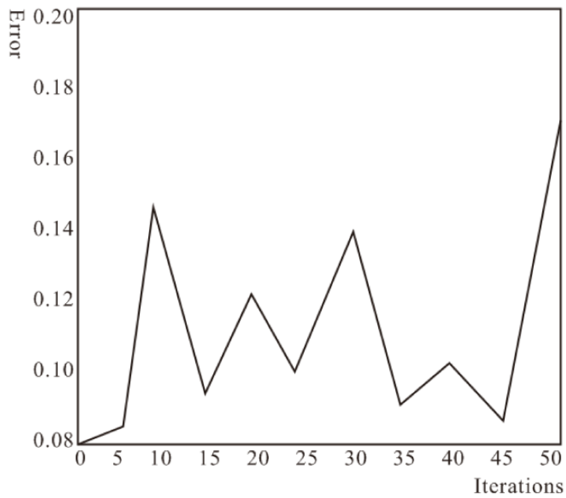

Figure 1. SVM-based prediction algorithms talent

However, in practice, it is often found that some date has big importance and small demand training error, while these dates have less importance and allow certain training error. For example, in reliability prediction, the recent dates of the sample are often consistent with the environment of the dates to be predicted, thus it can provide more information.

3. Parameter optimization of SVM algorithm

3.1. Convergence optimization of simulated annealing algorithm

The simulated annealing algorithm originated from the simulation of complex compound optimization problem and the annealing of solid. This paper firstly did convergence optimization to the simulated annealing algorithm.

(1) Convergence optimization based on Disturbance

This paper used a new disturbance model, which use Cauchy as the theory of disturbance distance. It can be expressed as:

$$p(\Delta x) = \frac{1}{\pi}\frac{T}{T^2 + (\Delta x)^2} \qquad (4)$$

It can be deduced as

$$\Delta x = T\tan(\pi \cdot z) \qquad (5)$$

Where z is a random number ranging from 0 to 0.5. In the task diagram, Δx represents the number of the node changed when moved from current division to the new division, that is the distance between the current and the new. Because there are differences between the total node and annealing temperature, it needs to make normalization process. However the obtained Δx∈[0, N], the upper limit of the inner loop calculation complexity of the algorithm is o(K.N), where N represent the number of task, K is the number of annealing under each temperature and it is a constant. Obviously the complex of the inner loop calculation is only related to N, and it will increase when N is big.

Set the outer cooling times of random disturbance model simulated annealing algorithm as M, then the calculated complex is o(M.K.N) using the algorithm of disturbance model. Therefore, in extreme cases, the computation time in improved perturbation model algorithm is bigger than that in random disturbance model, thus this paper dealt with Δx, so that so complex of inner loop can be reduced and Δx will change as T changed. The improved method is as follow:

$$\Delta x = \varepsilon \Delta x \tag{6}$$

Where ε is a small number. The complex of the improved inner loop is o(K). The computation decreased sharply and Δx is also the function of T after treatment, having larger distance when in higher temperature. It can search in bigger range and can accelerate the convergence when in lower temperature, searching in the current division.

The convergence optimization based on annealing progress

Annealing progress is an important parameters controlling algorithm convergence rate. From the pseudo-code of the simulated annealing algorithm, it can be seen that temperature is one of the two conditions that control the algorithm termination. However temperature is controlled by the speed of annealing, the speed of annealing affecting the convergence rate directly. The method of annealing rapidly is as follow:

$$T_k = \frac{T}{k} \tag{7}$$

But the annealing progress is:

$$T_k = (\alpha)^k T \tag{8}$$

T represents temperature, and k represents the k-th cooling process. αis cool factor ranging from 0.92 to 0.99 and usually value 0.96. It can be derived that Tk is the exponential function of k which decrease slowly for $\alpha \to 1$. But annealing schedule function is inverse function which decreases more rapidly than annealing process of standard simulated annealing algorithm. Therefore, annealing progress can accelerates the termination of algorithm but will decreases the frequency of outer loop algorithm. The algorithm does not search enough solution space. Algorithm may have ended not finding approximate global optimal solution. Therefore this paper modifies annealing schedule, properly controlling cooling process and decreases the cooling rate by multiplying k a weight A (A<1), so that the algorithm can fully iterative. The improved annealing process is as follow:

$$T_k = \frac{T}{A \cdot K} \tag{9}$$

The improved annealing schedule solved the problem that there is little space because of the fast annealing rate, which will lead to the algorithm end before getting approximate optimal solution. And the rate is faster than standard simulate annealing algorithm, making it possible to get approximate optimal solution in the case the algorithm iterates fully.

(2) Convergence optimization base on effective offset

In the style of solution generation, this paper put forward the concept of effective offset, combine with the success—failure method and variable scale method. Effective offset refers to the offset when the current solution is accepted. If the previous offset is not effective offset, then the improved function of the solution is as follow:

$$Y_i^k = X_i^k + Z_i^k \tag{10}$$

$$Z_i^k = \frac{W_i T_i (b_i - a_i)/10}{\sqrt{\sum_{j=1}^{n} W_j^2}} \left| \frac{1}{|U_i|^m} - 1 \right|, i = 1, 2, \ldots \tag{11}$$

Where X is iterative initial solution, Y is iterative new solution. U, W is random variable in [-1, 1]. i is vector component. a_i and b_i are upper and lower limits of the i-th vector. m is a constant and it is bigger than 1, in this paper, m=3.

If the previous offset is effective, then implement success—failure method to it; If the accepted value of penalty function of the current solution decreased, offset marked sign of success, if not, sign of failure. This paper put forward a generation function of iterative offset as follow:

$$Z_i^k = \begin{cases} 2.3 Z_i^k, Z_i^k \le 1.0e10 \\ -Z_i^k / 1.7, Z_i^k \ge 1.0e-8 \end{cases} \tag{12}$$

Formula (18), (19), (20) can improve the calculating effective and reliability of simulation annealing algorithm. On the on hand, it keeps the temperature decrease properly, on the other hand, it make the generated vectors maintain a certain degree of spread.

To find the chemotactic search effect increasing the minimum, random number and the current optimal variable metric was adopted. This paper put forward to a new search interval calculation method.

$$b_i' = \begin{cases} l_i + (b_i - a_i)/n_i, b_i' \le b_i \\ b_i \qquad , b_i' > b_i \end{cases} \tag{13}$$

$$a_i' = \begin{cases} l_i + (b_i - a_i)/n_i, a_i' \ge b_i \\ a_i \qquad , a_i' < b_i \end{cases} \tag{14}$$

Where l_i is the component of the current optimal solutions; n_i is pseudo-random number ranging from 1 to 20, using for Shortening the search range and improving search efficiency. In the topical search stage, narrow adaptive factor at a certain ratio while cooling, K: K=K/1.01.

3.2. SVM parameter optimization based on simulated annealing algorithm

This paper introduced simulation annealing algorithm to SVM parameter selection, which will greatly improve SVM accuracy. When the simulated annealing algorithm used to the parameters selection of SVM, the concrete steps are as follows:

(1)To set upper limit for the three parameters supporting vector machines and then give initial numbers and feedback to the SVM model. The absolute value of the prediction error is defined as system state (E). Here it can reach the initial state (E0).

(2)Move randomly so that the system translates from initial state to critical state. There will be a collection of three parameters appear during this period.

(3)Decide whether accept or reject the critical state using the following formula State []:

$$\begin{cases} accept, E(S_{new}) > E(S_{old})\ \&\ p < P(accept\ S_{new}) \\ accept, E(S_{new}) \le E(S_{old}) \\ refuse, other \end{cases} \tag{15}$$

In formula (20), p is a random number deciding whether accept critical state or not. If accepting the critical state, set critical state as the current state.

(4) If not accept critical state, return to (2). If the current state is not better than system state, then recycle (2) and (3) until the current state is better than system state. In the end, set the current state as the new state. Previous study thought that it should set the maximum number system returned N_{sa} should be $100d$ to avoid endless loop. Na represents dimension of problems. When determine the SVM parameter, three parameters(σ,C,ε) determine the system state, so set N_{sa} as 300.

(5) After acquire the new parameter, reduce the temperature. The temperature reduced can be acquired from the formula:

$$T_{new} = T_{old} \times \rho, 0 < \rho < 1 \tag{16}$$

In this paper, $\rho <$ was set as 0.9. If it reach the temperature determined previously, then the algorithm stop and the new state is approximate optimal solution. If not, return (2).

In the process of determining the optimal parameter of SA-SVM, we consider mean absolute percentage error (MAPE) as a criterion.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{d_i - y_i}{d_i}\right| \times 100\% \tag{17}$$

Where n represents the number in forecast period; d_i is the actual generated value in period I; y_i is the predictive value of talent demand in period i.

4. Algorithm simulation experiment

In order to verify the effectiveness of the improved algorithm is proposed in this paper, we take simulation experiments on it. First, we simulate the convergence of the improved simulated algorithm, the results are discussed:

Then, we regard the social demand data from 2008 to 2012 as input quantity, using the SVM algorithm which optimizes based on the simulation annealing algorithm proposed by this article to forecast the social talented person demand, the results are discussed:

Learning from the simulation result, improved simulated annealing algorithm proposed by this ar-

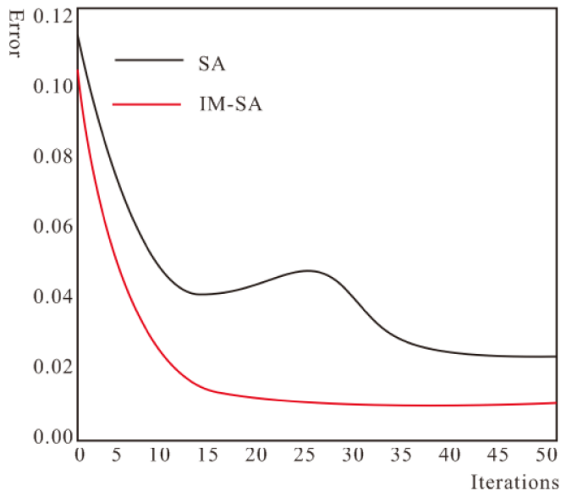

Figure 2. The convergence of simulated annealing algorithm simulation

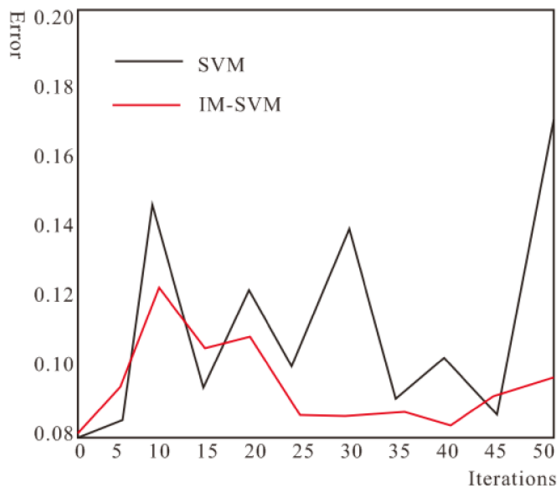

Figure 3. Improve the prediction accuracy of SVM algorithm simulation

ticle has better convergent, as for veracity, the SVM algorithm which optimizes based on the simulation annealing algorithm is higher than the original SVM algorithm.

5. Conclusion

In recent years, with the development of global economic, Global industry are rapidly transforming and optimizing. And in the same time, economic social demand more to talent to meet the economic development and change. Thus, it has been the urgent needs to forecast the demand of the talent market legitimately and effectively to employees, enterprises, region and global .This paper put a talent demand forecast model based on simulated annealing algorithm to optimize the SVM algorithm against the flaws in talent demand forecasting of SVM. Simulation results show that improved proposed model has better prediction accuracy.

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