

The Research on the Prediction of the Network Traffic Based on the Improved PSOSVM Algorithm

Xu Yan

Xi'an Physical Education University, Shaanxi, China, 710068.
xuyanmini13@163.com

To predict the network traffic can make us understand the dynamic situation of the network operation to forecast the actual network traffic. It can also adjust and manage the business needs of the service quality assurance. In addition, it operates the network performance. PSO and SVM are two methods in common use. In this paper, we combine the PSO with the SVM. We use the PSO method to optimize the parameters in SVM. We propose an improved PSOSVM method to predict the network traffic. Compared with other prediction methods, this method has the higher accurate. And it is an effective network traffic prediction method.

1. Introduction

Prediction is an important part in our life (Mingyue Zhao et al (2015)). With the continuous expansion of the internet scale and the continuous emergence of the diversified network services, the network traffic data shows more and more complex behavior and characteristic. How to manage effectively and make the network provide better service becomes a problem that people more and more concern.

There were many scholars studying the network traffic prediction. In 2012, Yue Huichen, Bin Yang, Qing Fangmeng used the flexible neural tree (FNT) model to predict the network traffic. The author optimized the parameters with the Particle Swarm Optimization algorithm to predict the small-time scale traffic measurements data. The experiment showed that the method was very effective to forecast the small scale network traffic. In 2013, Dong-Chul Park (2013) applied the BiLinear Recurrent Neural Network (BLRNN) successfully to the prediction of the network traffic. The BLRNN could reduce about half in terms of the number of weights while preserving its generalization ability through the structure simplification procedure and the application of the GA. The experiment showed that the method could reduce half of the training time and the prediction accuracy was also improved a lot. Then, A combined method which was based on the local mean decomposition (LMD) by Ji Yimu et al (2015) and the generalized autoregressive conditional heteroscedasticity (GARCH) was put forward to forecast the traffic rate of the Flash P2P. In addition, there were many scientists having studied the network traffic prediction such as Jun Jiang, Symeon Papavassiliou (2006), Chang, Hsiu Fen Tsa (2009), Yingxu Lai et al (2015).

In this paper, we combine the PSO with VSM and propose a kind of improved PSOSVM algorithm. Then, we apply this algorithm to the network traffic prediction. The structure of this paper is as follows. The first part is the introduction. The second part is the SVM. In this part, we introduce mainly the basic knowledge of the SVM. The third part is the improved PSOSVM algorithm. In this part, we combine the PSO with the SVM. And we propose the improved PSOSVM algorithm. The fourth part is the experiment and the last part is the conclusion.

2. SVM

The research group which led by the professor V.Vapnik Bell proposed the statistical learning theory aiming at the small sample problem. With the development of the statistical learning theory, it produced the support vector machine (SVM).

We assume that $(X, y_i), (i = 1, 2, \dots, n, X \in R^d)$ is the linear separable sample. $g(X) = W \cdot X + b$ is the general form of the linear discriminant function in d dimension. The classification plane is $W \cdot X + b = 0$.

For the non-support vector, it meets $\alpha_i = 0$. Therefore, the optimal classification plane function only needs to aim at the support vectors. And for the b^* , it can be solved according to the constraint conditions of any support vector. For the linear non-separable problem, we usually introduce the kernel function. we can use the kernel function to instead of the inner product operation in the above function. That is,

$$\begin{aligned} \min Q(\alpha) &= \frac{1}{2} \sum_{i,j=1}^n \alpha_i \alpha_j y_i y_j K(X_i X_j) - \sum_{i=1}^n \alpha_i \\ \text{s.t. } \alpha_i &\geq 0, i = 1, 2, \dots, n \\ \sum_{i=1}^n y_i \alpha_i &= 0 \end{aligned} \quad (1)$$

Accordingly, the classification function becomes,

$$f(x) = \text{sgn}\left\{ \sum_{i=1}^n \alpha_i^* y_i K(X_i \cdot X) + b^* \right\} \quad (2)$$

We can select any support vector and can find out b^* according to the following function.

$$y_i \left[\sum_{i=1}^n \alpha_i^* y_i K(X_i, X) + b^* \right] = 1 \quad (3)$$

The training set is $(x_i, y_i), i = 1, 2, \dots, N$. x_i is the input vector and y_i is the corresponding output. For each sample, we use the nonlinear function ϕ to map to the high feature space. The regression function can be expressed as follows.

$$f(x) = \omega \phi(x) + b \quad (4)$$

In order to get the following parameters, we can adopt the SRM principle and transform the original problem to the following problem.

$$\begin{aligned} \min_{\omega, \xi} & \left[\frac{1}{2} [\omega]^2 + C \sum_{i=1}^L (\xi_i^+ + \xi_i^-) \right] \\ \text{s.t. } & y_i - \omega_i - b \leq \varepsilon + \xi_i^- \\ & \omega_i + b - y_i \leq \varepsilon + \xi_i^+ \\ & \xi_i^-, \xi_i^+ \geq 0 \end{aligned} \quad (5)$$

For solving the above convex optimization problem, the core idea is to use the Lagrange multiplier method to transform the above optimal question to its dual form.

$$\begin{aligned} \min & \left[-\frac{1}{2} \sum_{i,j=1}^L (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)(x_i, x_j) - \varepsilon (\alpha_i - \alpha_i^*) + \sum_{i=1}^L y_i (\alpha_i - \alpha_i^*) \right] \\ \text{s.t. } & \sum_{i=1}^L y_i (\alpha_i - \alpha_i^*) = 0 \end{aligned} \quad (6)$$

In general, the selection of the kernel function is as follows.

(1) Radial Basis Function

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \quad (7)$$

(2) Exponential Radial Basis Function

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|}{2\sigma^2}\right) \quad (8)$$

3. The improved PSOSVM algorithm

PSO algorithm is a kind of evolutionary algorithm (Tao Lin et al (2015)). The advantage of the PSO algorithm is to achieve simply. And there are not many parameters needing to adjust. In PSO algorithm, the location vector of the particle is $u_i = (u_{i1}, u_{i2}, \dots, u_{im})$. The best location for the i is $p_g = (p_{g1}, p_{g2}, \dots, p_{gm})$. The speed and the update formula for the particle is as follows.

$$v_{im}^{k+1} = wv_{im}^k + c_1r_2(p_{im} - u_{im}^k) + c_2r_2(p_{gm} - u_{im}^k) \quad (9)$$

$$u_{im}^{k+1} = u_{im}^k + v_{im}^{k+1} \quad (10)$$

Where, r_1 and r_2 are the random numbers between $[0,1]$. w is the inertia weight. w is the key parameter in the particle swarm algorithm. They can balance the global search ability and the local search ability of the algorithm. In the initial stage of the evolution, we hope that the particle has the better exploration ability. With the increase of the iterations, in the latter part of the evolution, we hope that the particle has the better development ability. Therefore, during the evolution process, we need to adjust dynamically the inertia weight. Therefore, the inertia weight that this paper adopts is as follows.

$$w = w_{\max} - (w_{\max} - w_{\min}) \frac{iter}{iter_{\max}} \quad (11)$$

Where, $iter$ is the current iteration number. $iter_{\max}$ is the maximum iteration number. w_{\max} and w_{\min} are the maximum value and the minimum value of the weights.

In the particle swarm optimization algorithm, c_1 and c_2 are the self-learning factor and the social learning factor. In general, they are taken as 2. There is little people studying the influence of c_1 and c_2 on the particle swarm optimization algorithm. We know that, in the early stage of the algorithm, we require that the particle has the larger self-learning ability and the less social learning ability. It can make the particle fly in the whole search space. However, in the latter of the algorithm, we require that the particle has the less self-learning ability and the larger social learning ability. It can make the particle fly to the global optimal solution. In order to improve the convergence performance of the algorithm, this paper adjusts dynamically the self-learning factor c_1 and the social learning factor c_2 .

$$c_1 = (c_{1e} - c_{1s}) \frac{iter}{iter_{\max}} + c_{1s} \quad (12)$$

$$c_2 = (c_{2e} - c_{2s}) \frac{iter}{iter_{\max}} + c_{2s} \quad (13)$$

c_{1s} and c_{1e} are the initial value and the final value of c_1 . c_{2s} and c_{2e} are the initial value and the final value of c_2 . We assume that we forecasting observed value is t_i . The forecasting value is y_i . Therefore, we can get the following function.

$$SS_{tot} = \sum_{i=1}^n (t_i - \bar{t})^2 \quad (14)$$

$$SS_{reg} = \sum_{i=1}^n (y_i - \bar{t})^2 \tag{15}$$

$$SS_{err} = \sum_{i=1}^n (t_i - y_i)^2 \tag{16}$$

SS_{tot} is the total sum of squares, proportional to the sample variance. SS_{reg} is the regression sum of squares, namely the explained sum of squares. SS_{err} is the residual sum of squares.

We assume that $\bar{t} = \frac{1}{n} \sum_{i=1}^n t_i$. Therefore, we determine the coefficient,

$$R^2 = 1 - \frac{SS_{err}}{SS_{tot}} \tag{17}$$

The algorithm flow chart of the improved PSOSVM is shown in the following diagram.

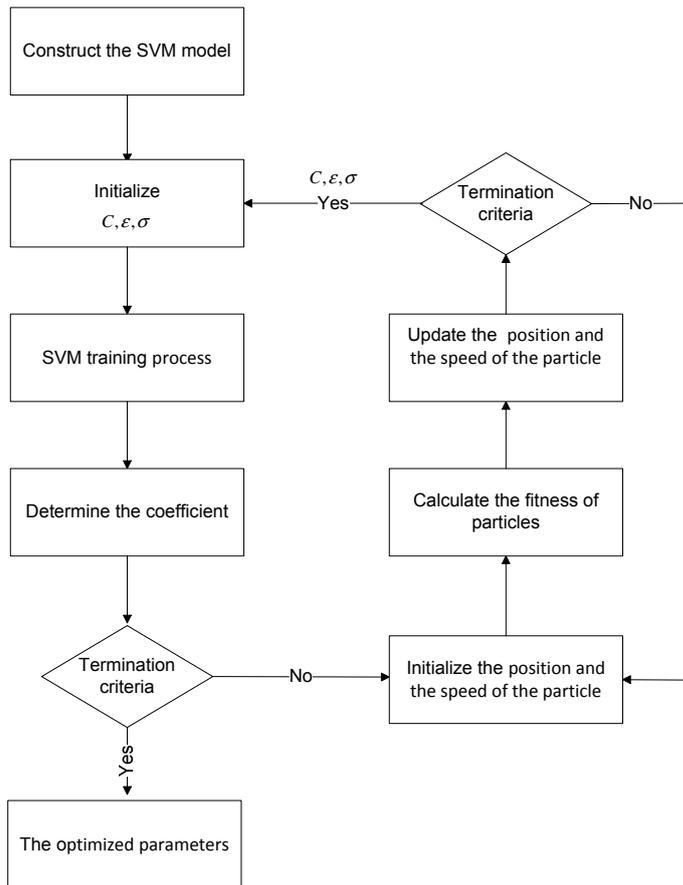


Figure 1: The flow chart of the PSOSVM

4. Experiment

In the experimental part, we apply the improved PSOSVM algorithm to forecast the network traffic. We select the network traffic of one college from July1, 2014 to July 20, 2014 as the experimental data. Among them, the data of the first 19days is as the training set. And the data of the last day is as the prediction set. We use the improved PSOSVM method to predict and the results are as follows.

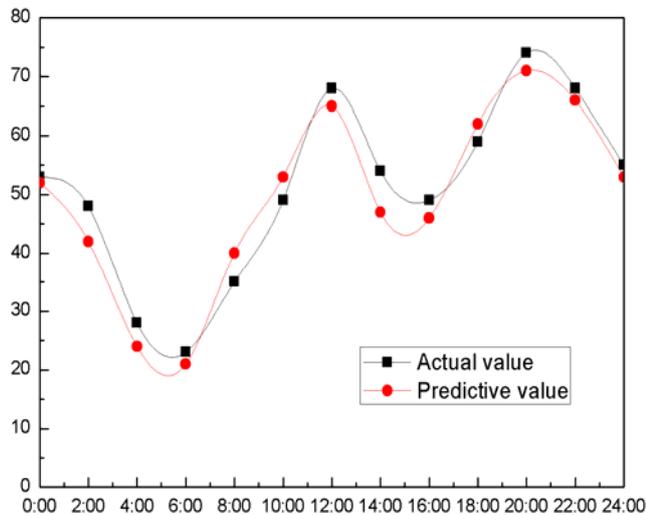


Figure 2: The predicted result

From the figure 3, we can see that the predicted results of the improved PSOSVM model are very similar to the actual results. It shows that the method is effective.

In order to verify the prediction accuracy of the improved PSOSVM algorithm, we compare the predicted results of the algorithm with other algorithms. The comparison results are as follows.

Table 1: The comparison of PSOSVM, SVM and linear regression

	PSOSVM	SVM	linear regression
Average relative error	7.28%	21.05%	28.32%
Prediction accuracy	92.72%	78.95	71.38%

From the above table, we can know that the predicted results of the PSOSVM model are very good. At the same time, compared with other predicted algorithms, the accuracy of the PSOSVM network traffic model is higher. Therefore, the model can use to predict the network traffic and it achieves the better prediction accuracy.

5. Conclusions

It has the important significance to predict the network traffic, control the network congestion and security the business. This paper combines the SVM with the PSO and proposes an improved method. Then, this paper uses this method to predict the network traffic. The main works of this paper are as follows. Firstly, this paper introduces the development status of the network traffic. Secondly, this paper introduces the basic knowledge of the SVM. Thirdly, this paper proposes the improved PSOSVM method. The experimental shows that the method has the higher accuracy. And it is an effective network traffic prediction model.

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