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Study on the Support Vector Regression Model for Order's Prediction

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Abstract

The prediction for the order of enterprise is very important. Support vector machine is a kind of learning technique based on the structural risk minimization principle, and it is also a class of regression method with good generalization ability. In this paper, support vector machine is used to model of the prediction for the order. A simulation example is taken to demonstrate correctness and effectiveness of the proposed approach. The selection method of the model parameters is presented.

Keywords: Order;Support Vector Regression;Neural Network;Prediction

1. Introduction

Production according to the order standing for requirements from customers is the linchpin of improving flexibility and competitive strength of an enterprise. The prediction for the order of enterprise could effectively ahead of the schedule, improve agility and competitive strength, and make the enterprise achieve JIT (Just in Time)[1]. Prediction technologies in the field of economics management are numerous. There are two types: qualitative and quantitative method. The qualitative method has the experience to judge the law, the Del's Philippines law, the user survey law and so on. The common applications in quantitative method mainly include regression analysis method, time series method, neural network forecasting method[2] and the grey forecasting method[3] and so on. The return analytic method is high to the historical data material request. The time series method needs to have the massive historical observation value, and has the strong subjectivity and empirical in weighting factor's choice. The neural network forecasting method has the strong auto-adapted ability and learning capability, but requests to the

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data sample's quantity and the quality high, moreover also has strong empirical in the inserting dimension's determination. The commonly used model in gray forecasting method is GM(1,1) model, and it is suitable in the sequence of strong index rule, but can only describe the monotonous process of change. Support vector machines[4,5] (Support vector machines, SVM) based on structure risk minimum (Structural Risk Minimization, SRM) criterion, overcame the artificial neural networks (Artificial Neural Networks, ANN),which has the shortcoming relied on the experiences of designer, has solved congenital problems well such as dimension, local minimum, small sample of ANN and so on, and given dual attention to the merit. Its topology is decided by support vector. In this paper, SVM theory method is introduced in model of prediction for the order of enterprise, and explained the modeling process by example, confirmed validity of the model through forecasting result.

2. Support vector regression method

When utilizing the support vector regression (SVR) algorithm in the estimate regression function, its basic philosophy is that through a nonlinear mapping Φ, maps the data input into the space to a high dimension feature space, and then makes the linear regression in this high dimension space.

Assigning the training set $T = \{(x_i, y_i)\} \in (X \times Y)^n$, of which, x_i is the input victor, y_i is expected value, n is the sum of data point. SVM estimates the regression function with the below:

$$f(x) = (\omega \cdot \Phi(x)) + b \tag{1}$$

Where $\Phi(x)$ is a nonlinear mapping from input space to a high dimension feature space, The coefficient ω and b are estimated through the minimum equation

$$R_{reg}(f) = C\frac{1}{n}\sum_{i=1}^{n} L_\varepsilon(y_i, f(x_i)) + \frac{1}{2}\|\omega\|^2 \tag{2}$$

Where L_ε is a loss function. This article selects ε which is the insensitive loss function, and its expression is of the form:

$$L_\varepsilon(y, f(x)) = \begin{cases} 0, & if\ |y - f(x)| \le \varepsilon \\ |y - f(x)| - \varepsilon, & otherwise \end{cases} \tag{3}$$

Looking for the coefficient ω and b, this article needs to introduce the slack variable ξ_i and ξ_i^*, thus transforms to solve the raised optimized question in the following:

$$\min\ \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{4}$$

$$s.t\quad [\omega \cdot \Phi(x_i) + b] - y_i \le \varepsilon + \xi_i, y_i - [\omega \cdot \Phi(x_i) + b] \le \varepsilon + \xi_i, \xi_i, \xi_i^* \ge 0, \quad i = 1,2,\cdots,n \tag{5}$$

When solving the above equations, generally uses the antithesis theory, and transforms to two plan question, through establishing the Lagrange equation, and commanding $K(x, y) = \Phi(x) \cdot \Phi(y)$, than could obtain the dual form in optimized question:

$$\min \frac{1}{2}\sum_{i,j=1}^{n}(\alpha_i^* - \alpha_i)^T K(x_i, x_j)(\alpha_j^* - \alpha_j) - \sum_{i=1}^{n}[\alpha_i^*(y_i - \varepsilon) - \alpha_i(y_i + \varepsilon)] \tag{6}$$

$$s.t\quad \sum_{i=1}^{n}(\alpha_i - \alpha_i^*) = 0, \quad 0 \le \alpha, \alpha^* \le C, \quad i = 1,2,\cdots,n \tag{7}$$