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Prediction of Stock Closing Price of SVR Model Based on Multi-scale Kernel Function

Xiufang Yuan

School of Mathematics and Statistics, Sichuan University of Science & Engineering, China

yxiufang1990@163.com

Abstract: Multi-scale wavelet kernel is constructed as SVR kernel function by combining wavelet analysis knowledge with kernel function knowledge. Firstly, MWK kernel function expression is constructed through Morlet wavelet and multi-scale kernel function; then adopting MWK kernel function, SVR model is used to predict the stock closing price. The experiments show that the SVR model adopting multi-scale kernel function has better performance than the single SVR model.
Keywords: Support vector regression; Wavelet analysis; Multi-scale kernel.

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1. INTRODUCTION

At present, with the deepening of people's understanding of the stock market, as well as the continuous improvement of advanced computer algorithms and technologies, people's enthusiasm for the study of stock prices is growing, so they begin to rely on various forecasting methods.

There are few researches on stock price in constructing kernel function and few researches on constructing proper multi-scale kernel function to predict stock price. Jin Debao [1] established a two-stage prediction stock market model based on financial kernel. Compared with the traditional SVM prediction model, it has obvious advantages in both learning ability and generalization ability. In literature [2-3], a Wavelet SVM (WSVM) based on gaussian frequency-modulated Wavelet kernel is proposed. Its approximation accuracy and pattern recognition rate are both better than that of gaussian kernel SVM. However, literature [4] points out that WSVM currently proposed is not necessarily the best. Based on this, Ren Shijin and Wu Tiejun [5] proposed a multi-scale WSVM learning algorithm based on radial basis wavelet kernel, which could improve the training speed and approximation accuracy of WSVM. Jiang Bo[6]constructed multi-scale wavelet kernel and compared the prediction effects of multi-scale wavelet kernel ν-SVM, single-scale wavelet kernel ν-SVM, wavelet neural network and RBF kernel ε-SVM function on Shanghai composite index in view of the fact that the CV method used in literature [5] was sensitive to the number of parameters, which made the literature only able to optimize the parameters of two-scale wavelet kernel.

As we all know, the key of SVR model is the choice of kernel function. This paper first constructs a special kernel function, multi-scale kernel function, and then establishes a SVR model based on

multi-scale kernel function to predict the closing price of stocks. The effectiveness and superiority of RBF ε-SVR model and combinatorial model are proved by comparing them. The research of this paper enriches and expands the current research content of stock price prediction, and its conclusion can provide scientific reference for investors to effectively invest and manage money, and has a broad application prospect.

2. MUlTISCALE KERNEL FUNCTION

Define2.1 Multiscale Kernel[7] Set $\varphi : R^d \to R$ is a function with a tight support, bounded, satisfy the double scale equation, such that $\forall x \in R^d$, exist $k \in Z^d$, satisfy $\varphi(x-k) \neq 0$. Furthermore, it is assumed that the sequence $\{h_k\}_{k \in Z^d}$ in the two-scale equation is of finite length, that is, there are only a finite number of, so that $h_k \neq 0$.Fixed $l \in Z$ and $\lambda \triangleq \{\lambda_j\}_{j=l}^{\infty}$, where $\lambda_j > 0$, and $\sum_{j=l}^{\infty} \lambda_j < \infty$, then the function

$$\Phi_l(x,y) \triangleq \sum_{j=l}^{\infty} \lambda_j (\sum_{k \in Z^d} \varphi(2^j x - k)(2^j y - k)) \tag{1}$$

It is Mercer kernel function, called multi-scale kernel function.

Define2.2 Finite Multiscale Krne [7] Assuming that φ and λ have the same definition as in definition 2.1, then for some $u \geq l, u \in Z$, the following Finite Multiscale Krnel function is defined:

$$\Phi_l^u(x,y) \triangleq \sum_{j=l}^{u} \lambda_j (\sum_{k \in Z^d} \varphi(2^j x - k)(2^j y - k)) \tag{2}$$

Among them, u and l respectively represent the upper and lower bounds of the scale contained in the kernel function.

Now, the necessary and sufficient condition of Mercer condition is given: a translation invariant kernel $k(x,z) = k(x-z)$ is an admissible SVM kernel function if and only if its Fourier transform satisfies:

$$F(\omega) = (2\pi)^{-\frac{d}{2}} \int_{-\infty}^{\infty} e^{-\omega t} k(t) dt \geq 0 \tag{3}$$

If the one-dimensional wavelet function is denoted as $\varphi(x)$, then the wavelet function in the n dimensional space can be expressed as:

$$\varphi_n(x) = \Pi_{i=1}^{n} \varphi(x_i) \tag{4}$$

Since Morlet wavelet function meets Mercer condition, it can be used as the kernel function of SVM. The following is the proof of its corresponding kernel function.

The Morlet wavelet function is defined as

$$\varphi(x) = \cos(1.75x) \exp(-\frac{x^2}{2}) \tag{5}$$

Then Morlet wavelet kernel function is defined as

$$\varphi(x,z) = \Pi_{i=1}^{n} \cos(1.75 \frac{x_i - z_i}{a}) \exp(-\frac{\| x_i - z_i \|^2}{2a^2}) \tag{6}$$

The calculated $\varphi(x,z) = \varphi(x-z)$ Fourier transform is given

$$F(\omega)=\Pi_{i=1}^{n}(\frac{|a|}{2})(\exp(-\frac{(\omega_0-\omega_i a)^2}{2})+\exp(-\frac{(\omega_0+\omega_i a)^2}{2})) \tag{7}$$

And $a \neq 0$,therefore $F(\omega) \geq 0$, Morlet wavelet function can be used as kernel function of SVM. When taking wavelet function $\varphi(x)$ as the kernel function of SVR, the estimated function $f(x)$ can be expressed as follows:

$$f(x)=\sum_{i=1}^{N}(\beta_i^l-\beta_i)\Pi_{i=1}^{l}\varphi(\frac{x-x_i}{a})+b \tag{8}$$

Therefore, the form of multi-scale wavelet kernel function is:

$$\mathrm{MWK}(x,z)=\sum_{j=1}^{d}\mu_j\Pi_{i=1}^{n}\cos(1.75\frac{x_i-z_i}{a_j})\exp(-\frac{\|x_i-z_i\|^2}{2a_j^2}) \tag{9}$$

Among them, d is the scale number, μ_j is the weighting factor and a_j is j the scaling factor.

3. EXPERIMRNT OF MULTI-SCALE KERNEL FUNCTION SVR MODEL

In order to compare with the combined model arima-svr, the closing price of huayi brothers stock is still taken as the research object in this experiment. The model is obtained and predicted by the compiler of multi-scale wavelet kernel function. Table 1 lists the prediction data of 10 test samples of four models, and Table 2 gives its RMSE results. Figure 1 is drawn from Table 1, and the prediction effect of various models can be clearly seen.

Table 1 comparison of prediction results of four models

date	actual value	ARIMA model	SVR model	ARIMA-SVR model	Multi-scale wavelet kernel function model
2015-03-24	31.95	33.54	33.54	32.95	31.97
2015-03-25	32.05	32.83	32.83	32.21	32.01
2015-03-26	31.20	32.75	32.75	32.45	31.08
2015-03-27	30.96	31.57	31.57	31.16	31.03
2015-03-30	31.16	31.65	31.65	31.10	31.20
2015-03-31	31.28	31.88	31.88	31.27	31.25
2015-04-01	31.83	32.45	32.45	31.73	31.85
2015-04-02	34.00	33.46	33.46	32.98	33.87
2015-04-03	35.31	34.27	34.27	35.30	35.36
2015-04-07	36.02	35.82	35.82	36.02	36.00

Table 2 RMSE comparison table of four models

Model	RMSE
ARIMA model	2.88
SVR model	2.67
ARIMA-SVR model	1.92
Multi-scale wavelet kernel function model	0.21

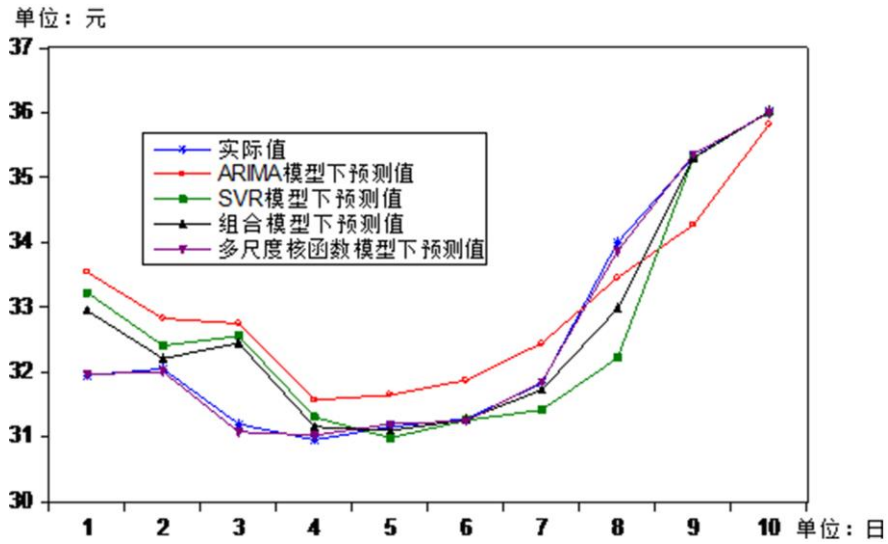

Fig. 1 trend chart of prediction results of various models

Observe table 1, 2 and Fig. 1 and find:

(1) the advantages of the combined model set SVR and ARIMA, its nonlinear approximation ability is obviously better than that of the single model, and the prediction results obtained are more accurate.

(2) the nonlinear approximation capability of multi-scale wavelet kernel function model is obviously better than that of SVR model, and in this data, it is better than the prediction result of combined model, which shows that it is a very promising model.

4. SUMMARY AND PROSPECT

Based on the selection and construction of SVM kernel function, a new kernel function, multi-scale wavelet kernel function, is proposed in this paper. Compared with other models, it is proved that it is a promising model.

In terms of prospects, there are other wavelet nuclei besides Morlet wavelet nuclei, and the prediction effect of other wavelet nuclei needs to be further studied. Based on the combined prediction model based on the wavelet transform, the method of kernel function selection in SVR model has not been studied so far, which is the best improvement and further exploration of this prediction model.

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