Stock Market Prediction Using Radial Basis Function Network

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Abstract

In the stock exchange, the market volatility is highly volatile, and it is difficult to predict the stock price. In this paper, we use the radial basis function network (RBFN) as the learning mathematical model; and the k-Means with silhouette coefficient (SC) is implemented to select the number of clusters for the hidden layer. The optimization on the error to determine the best fitting basis function among several radial basis functions (RBF), and the simulation results suggest that the RBFN with inverse quadratic (IQ) function is the best in predicting the market prices.

Motivation

We study the RBFN (a kind of artificial neural network) for using in time-series prediction in the stock market. Our goal is to predict stock prices and the tendency of stocks.

Data sources

The analysis data were downloaded from the *yahoo finance* website included the daily stock prices, including open, high, low, close, adjusted close, volume values. The study stocks are for the Apple Inc. (AAPL) and the Bitcoin USD (BTC-USD), and the stock exchange's period is from 2017/8/1 to 2018/7/31.

Methods

We use the RBFN, developed by [1] as the neural network model (see Fig. 1) will use below 4 kinds of basis function kernels (φ) to approximate for the predicted price as follows:

$$\varphi^G = e^{\frac{-(x-c)^2}{2\gamma^2}}, \quad \varphi^{MQ} = \sqrt{1+\gamma^2(x-c)^2}, \quad \varphi^{IQ} = \frac{1}{1+\gamma^2(x-c)^2}, \quad \varphi^{IMQ} = \frac{1}{\sqrt{1+\gamma^2(x-c)^2}},$$

for basis functions Gaussian (G), multiquadric (MQ), inverse quadratic (IQ), inverse multiquadric (IMQ), where γ is the width of distribution, c is the center. The approximate predicted price function can be expressed as $\hat{y} = \sum_{j=1}^{k} w_j \varphi_j$, w_j is the j^{th} linear weight.

For implementing the RBFN, the 70% of time-series data are for training and 30% for testing. The k-Means algorithm via the SC [3] is used for selecting the number k of clusters (see Fig. 2-3), and let the selected number k is equal to the number of nodes in the hidden layer. Here we use the mean square error (MSE) as the loss function and minimize the least square problem:

$$min \frac{1}{n} \sum_{i=1}^{n} \|\hat{y}_i - y_i\|_2^2$$

where y_i is the real price from the training data. And hereby employ the mean absolute error (MAE) to determine the performance of the model, where the MAE is as:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |\hat{y}_i - y_i| .$$

Results

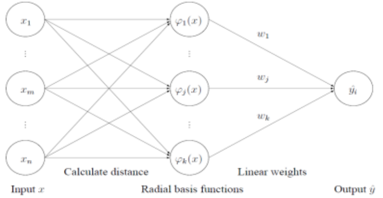

Fig. 1. The RBFN model

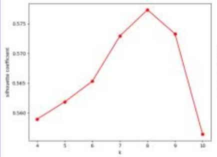

Fig. 2. Use SC to determine k for AAPL

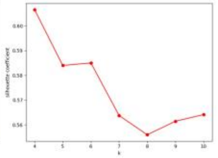

Fig. 3. Use SC to determine k for BTC-USD

Tab. 1. The errors (MAE) of RBFN with various RBFs for AAPL

RBF	MAE
G	2.2056
MQ	1.7811
IQ	1.6877
IMQ	2.0672

Tab. 2. The errors (MAE) of RBFN with various RBFs for BTC-USD

RBF	MAE
G	254.69
MQ	320.40
IQ	249.44
IMQ	269.57

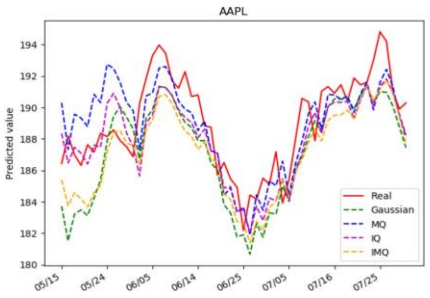

Fig. 4. RBFN with various basis functions for AAPL

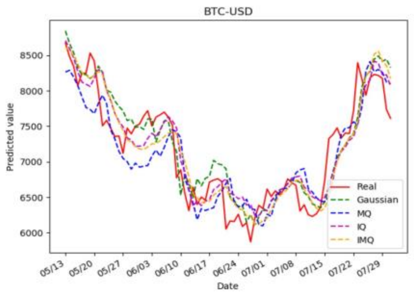

Fig. 5. RBFN with various basis functions for BTC-USD

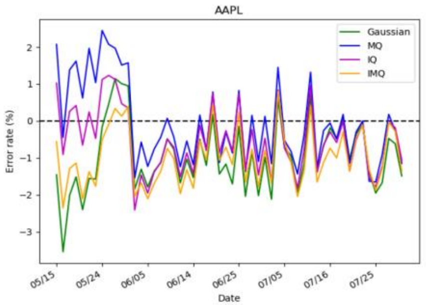

Fig. 6. Error rate for various basis functions for AAPL

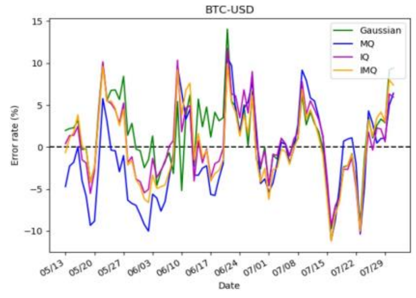

Fig. 7. Error rate for various basis functions for BTC-USD

Conclusions

We concluded that it is practicable to select the cluster number k as the number of nodes in the hidden layer, and following Tab. 1-2 and Fig. 4-7 show that the best RBF kernel for our proposed method is the IQ function, which gives the most accurate in the stock price prediction. RBFN with k-Means and SC estimates accurately trend of stocks and forecasts.

References

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[3] P. T. Rousseeuw, " *Silhouettes: A graphical aid to the interpretation and validation of cluster analysis* ", Journal of Computational and Applied Mathematics, vol. 20, pp. 53-65, 1987.