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SVR Model Used for Economic Fluctuation Analysis

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Abstract: *The purpose of this study is to find an optimal algorithm for the prediction of market value and the analysis of economic fluctuations. We propose an ensemble learning algorithm based on SVR and apply it to market value prediction and economic fluctuation analysis. It was found that in most situations, the smaller the window value of short-term learning model is, the smaller the weight of long-term learning model is, and the better the performance of ensemble learning model is. However, with the decrease of weight value, ensemble learning model will have the problem of over-fitting, which makes the performance of the model decline. This paper proposes a market value forecasting model based on long-term and short-term ensemble learning. In the theory of SVR model, the validity and superiority of the model are verified through a large number of experiments. [1]*

Keywords: *SVR Model, Economic Fluctuation, long-term, short-term*

1. Background

Alibaba's market value also rose from HK $560 billion in 2015 to HK $6 trillion in 2020, more than ten times in five years, with an annual compound interest rate of 60.7%. Tencent's market value has risen 500 times since it went public 13 years ago. It took 31 months for its market value to go from 1 trillion yuan to 2 trillion yuan, and only 11 months to go from 2 trillion yuan to 3 trillion yuan.

Factors affecting market value.

1) Whether there is capital when operating

For the 336 listed companies with capital operations in China this year, their total market capitalization has increased by just 1.17 percent, compared with an average of 8.36 percent for companies without capital operations. In the structural bull market of blue chip stocks, it is more important for an enterprise to do a good job of its own brand and investment management. Capital operation cannot greatly improve the market value of the company, at least in the short term

2) The impact of company performance on market capitalization.

Performance is an important factor in stock price growth, but it's not that the higher the growth, the higher the stock price. As we all know, it's better to be able to grow steadily from year to year than it is to be able to fluctuate, mature value companies with steady growth.

3) Changes between various sectors are different.

The steel industry and non-ferrous metals appear "duopoly" situation, the overall rise of more than 30%, media and clothing fell by more than 13%. Companies with a total market capitalization of more than $100 billion rose an average of 20%, while those with a total market capitalization of less than $5 billion fell 11%.[2]

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2. Method

Support vector regression (SVR) is an application of Support Vector Machine (SVM) to regression problems. In this study, we propose an integrated learning algorithm based on SVR, which integrates the following two models:

- A long-term learning model, which uses all available market value historical data as the training set to train the SVR model;

- The short-term learning model, which uses the most recent N days of market capitalization history data as the training set to train the SVR model.

Specifically, after obtaining and processing the data, the algorithm first uses all the data for training to obtain the long-term learning model then extracts the most recent N days of historical data for training to obtain the short-term learning model, and finally uses both models to forecast the closing price on the same day (N + 1 days), and uses the weighted average of the forecast results as the final forecast value, the larger the weight, the more the final forecast model is biased towards the long-term learning model.

The introduction of the short-term learning model allows the algorithm to simulate the trend of the market value within the time period more accurately when the market value is more volatile, thus improving the prediction accuracy; while the retention of the long-term learning model allows the algorithm to maintain a certain degree of generalization ability when the market value is unusually volatile. [3]

3. Data acquisition and pre-processing

In this experiment, we use yfinance module to obtain the market value data of Yahoo Finance from August 2004 to August 2020. After the data is obtained, we eliminated the invalid data and added a new column to store the market value of the next day as the target variable of machine learning. Table 1 is an example of market value data of Google after processing.

Table 1

	SVR Model	Integrated Model
RMSE	0.0685	0.0318
	273.8356	82.43232
R2	0.5341	0.8998
	0.5505	0.9592
Cross_val_score	0.1220	0.8998
	0.5379	0.9593

4. Influence of short-term learning model window on model performance

Influence of short-term learning model window on model performance

In this experiment, we tested the influence of different short-term learning model windows on the model performance under the same weight, and the figure 1 a-f show the experimental results.

The data and figures indicate that with the increase of N, the number of days one window contains in short-term learning model, integrated learning model's RMSE value also increases, and R^2 decreases, and the smaller the weight value, the greater the change of model evaluation indicators. For example, when weight equals to 0, we can see that two indicators change greatly along with the change of N. However, when weight equals to 1, the two indicators almost do not change alone with the change of N. Therefore, it can be concluded that for most industries, the smaller the window of short-term learning model, the better the model performance, and the lower the weight, the greater the influence of the window value on the model performance. This is because the weight allocation directly reflects the influence of the two models on the ensemble model. When weight equals to 0, the ensemble learning model is completely consistent with the short-term learning model, and the window has the maximum influence on the model performance. When weight equals to 1, the ensemble learning model is completely consistent with the long-term learning. In fact, the window will not affect the model performance, and the change in model performance is only related to the random disturbance in the process of training the SVR model. [4]

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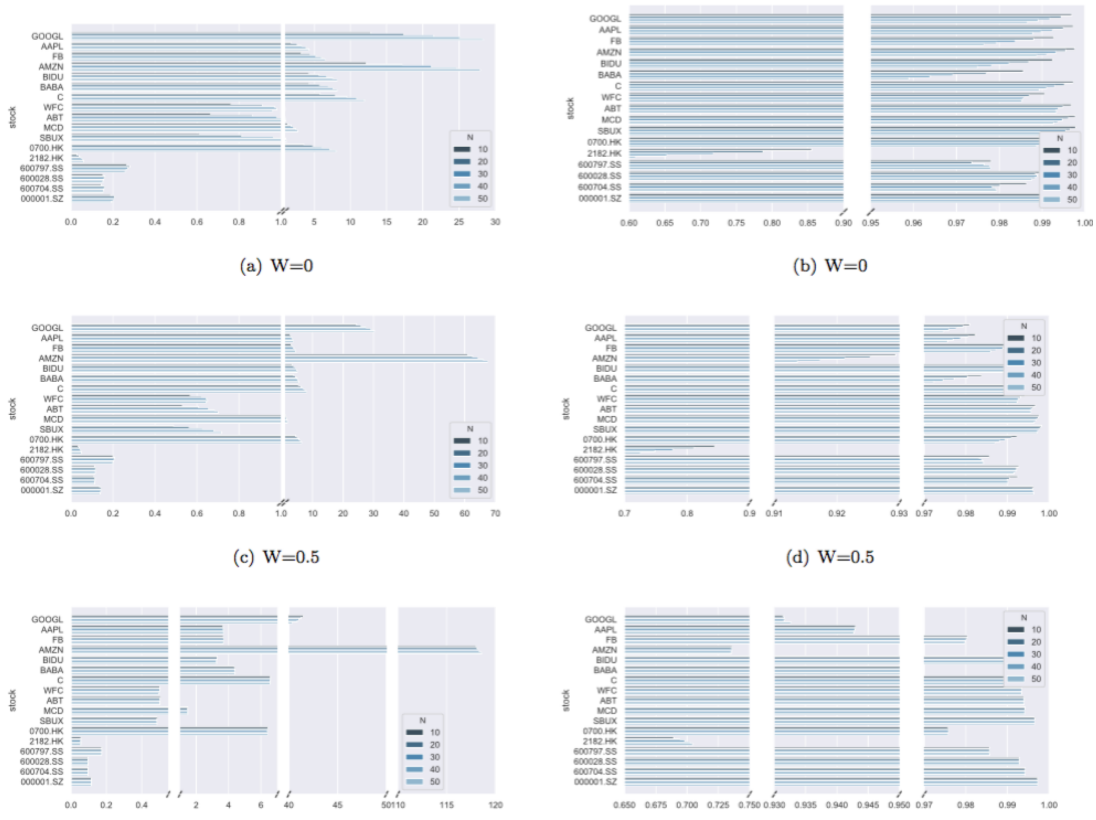

(a) W=0 (b) W=0

(c) W=0.5 (d) W=0.5

(e) W=1 (f) W=1

Figure 1: RMSE and R2 of the learning model corresponding to different windows with weights of 0, 0.5,1 respectively (RMSE on the left, R2 on the Right)

5. Influence of weights on model performance

In this experiment, we test the influence of different weights on the model performance under the same window. Figure 1 shows the experimental results. By analyzing the data, we can find that, for most industries, the RMSE value of the ensemble learning model shows an upward trend with the increase of weight value, while the R2 value shows a downward trend and the rate of change is getting faster and faster. However, the value of the window of the short-term learning model has little influence on this rangeability. On the other hand, when the value of the short-term learning model's window is significant, the R2 value of some industrial ensemble learning models will show a trend of increasing firstly and then decreasing. Therefore, it can be concluded that the smaller the weight of the long-term learning model is, the better the model performance is. However, with the decrease of weight value, the ensemble learning model that inclines exclusively to the short-term learning model will lead to an overfitting problem, and the prediction accuracy will decrease instead.

6. Discussion

This paper proposes a market value forecasting model based on long-term and short-term ensemble learning. In the theory of SVR model, the validity and superiority of the model are verified through a large number of experiments. The final conclusion is: In most situations, the smaller the window value of short-term learning model is, the smaller the weight of long-term learning model is, and the better the performance of ensemble learning model is. However, with the decrease of weight value, ensemble learning model will have the problem of over-fitting, which makes the performance of the model decline. This paper only uses the SVR model with default parameters. We will analyze the shadow response of the kernel function and hyperparameters of the SVR model to the final predicted results in our further research.

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