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A quantitative trading method using deep convolution neural network

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A quantitative trading method using deep convolution neural network

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Abstract. All Deep convolution neural network has been a great success in field of image processing,but rarely applied in market portfolios.Whether it can be transplanted into quantitative trading ,and how is its actual effect? In this paper,an empirical research is present on this problem.Three data processing methods for HS300 in China stock market were investigated to train and test the neural network based on ResNet50.By comparing the loss, efficiency, and accuracy, the results show that the convolution neural network has a limited ability to predict the time series data. No matter which data processing method is used,the TOP-1 prediction accuracy of convolution neural network is always between 32% and 38%,and the TOP-5 accuracy is always over 96%. Inspired by this training characteristics,a quantitative trading strategy is designed.The back test shows that this strategy can achieve SHARP ratio of 2.204.

1. Introduction

Convolutional neural network[1] and recurrent neural network[2] are two powerful types of deep neural network.The latter is widely developed in the field of financial quantification[3,4,5], whereas the former is seldom applied in this field,though has been successful in image processing[6].So far there is no statistics data on the forecasting efficiency of Chinese stock market trend using DCNN. In this paper,an empirical research is present on this problem.Three data processing methods for HS300 in China stock market were investigated to train and test the neural network based on ResNet50.By comparing the loss, efficiency, and accuracy, the results show that the convolution neural network has a limited ability to predict the time series data,and no matter which data processing method is adopted, the prediction accuracy is always stable in a fixed range. Inspired by training characteristics,a quantitative trading strategy is designed.The market regression test shows that this strategy can achieve SHARP ratio of 2.204.

.The rest of the paper is outlined as follows. Section 2 describes three time series data conversion methods and analyzes the training and test results. In section 3,a quantitative strategy called PLSCNN based on the convolution neural network is proposed and the test results are discussed .Section 4 concludes with directions for future research.

2. Convolutional neural network for time series data

DCNN can be applied to the prediction of time series data[7,9].However, in the common models of DCNN, such as lenet-5, AlexNet, ZFNet, vgg-16, GoogLeNet and ResNet[8], images are directly input to the neural network.Does time series data need to be transformed into two dimensional images to facilitate convolution? [9] carry out one dimensional convolution operations directly on time series data derived from large-scale,high-frequency trading orders..Different from [9], one dimensional

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convolution and two kinds of two-dimensional convolution are evaluated for the efficiency in prediction of the price movement of China's stock market in this paper .

One hundred stocks were randomly selected from HS300 in China's stock market.The data from January 1, 2016 to May 31, 2017 are taken as training samples, and the data from June 1, 2017 to December 31, 2017 are taken as test samples.According to the rate of return within 30 days after buying the stock, the samples are divided into 10 categories, and the classification labels are specified as shown in Table 1.

Table 1. Labels.

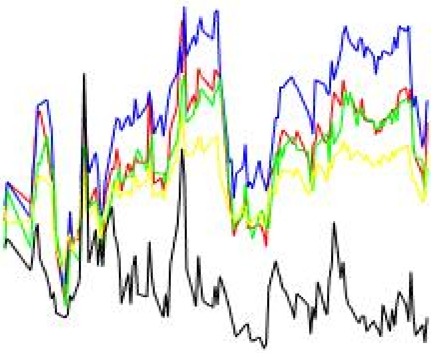
label	C01	C02	C03	C04	C05	C06	C07	C08	C09	C10
return	>35%	>25%	>15%	>5%	>0%	>-5%	>-15%	>-25%	>-35%	<-35%

Three types of samples are processed for training.

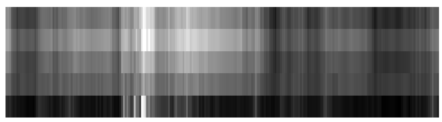
Training samples1:After the normalization for closing price, one dimensional convolution is directly carried out.Length of convolution kernel is 224.

Training samples2:For each day,the highest price,lowest price,opening price,closing price and volume of the previous 240 days were drawn in line chart after normalization,then converted to image with size of 240X240, as shown in figure 1A.

Training samples3:The x-coordinates take 240 days,and the y-coordinates take the highest price, the lowest price, the opening price, the closing price and the turnover volume,therefore A matrix of 240X5 is constructed. the values of the matrix were normalized and scaled to 0 to 255, as shown in figure 1B.



A Samples2



B Samples3

Figure 1. training samples.

The Resnet50 model is selected to train the samples, and the test samples is uesed to validate model. The accuracy and loss of training are analyzed. The results are shown in Table 2 and Figure 2.

Table 2 Experimental results for different samples

Cataory	Top-1			Top-5		
	Sample1	Sample2	Sample3	Sample1	Sample2	Sample3
C01	0/50	4/26	0/26	23/50	24/26	10/26
C02	0/62	0/50	3/50	42/62	9/50	43/50
C03	4/182	9/143	7/143	143/182	123/143	143/143
C04	546/973	368/816	329/816	973/973	816/816	813/816
C05	329/1015	444/905	400/905	1009/1015	905/905	905/905
C06	17/374	0/316	11/316	374/374	313/316	287/316
C07	82/198	78/173	74/173	197/198	173/173	173/173
C08	32/76	3/49	0/49	68/76	39/49	42/49
C09	0/62	0/6	0/6	58/62	4/6	5/6
C10	0/10	0/0	0/0	5/10	0/0	0/0
all	0.3365	0.3647	0.3316	0.9636	0.9686	0.9744

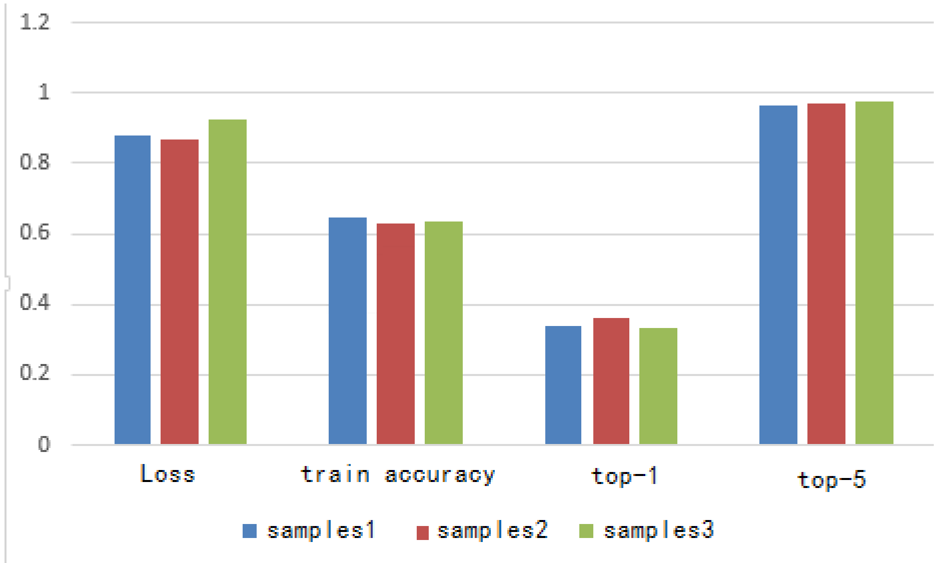


Figure 2 Performance comparison of three samples

The foregoing model training and test results can be summarized as follows:

A.The result of forecasting price trend using CNN is the same no matter what kind of data processing method is adopted.The TOP-1 prediction accuracy of convolution neural network is always between 32% and 38%.Using ImageNet,AlexNet model, and changing stock varieties and time range, the same result was obtained.

B.There is a significant difference between TOP1 accuracy rate and TOP5 accuracy rate, among which the accuracy of TOP5 is always over 96%

3. Quantitative trading strategy based on CNN

Although convolution operation is very limited in predicting the time series data in stock market, its accuracy in TOP5 is relatively high. Based on this feature, a new quantitative trading strategy called PLSCNN is proposed, in which the PLS factor analysis method[10,11] is combined to guess the correct classification in Top5 of CNN.

For those stocks with a positive return of less than 2 classes in top-5, PLS factor analysis was used to predict their expected return, and the top 10% to 20% were selected according to the ranking of the predicted results from high to low.The prediction calculation is shown in formula 1.

$$\begin{aligned} \mathrm{R}_{t+1} &= u_t + \varepsilon_{t+1} = B_t \times \Gamma_t \\ X_{t-1} &= \lambda_{t-1} \times B_t \end{aligned} \tag{1}$$

Where is expected returns and is unexpected returns, is observe firm characteristics variable,is the cross-sectional average of the factor,is returns of implicit variables.and the algorithm of separate cross-sectional regressions is used to predict stock returns.

One hundred stocks were randomly selected for the back test, starting from June 1, 2017 and ending on January 1, 2018. The PE factor strategy of HS300 was adopted as the benchmark.The period of strategy is 1 day.The cumulative return of the back test is shown in figure 3, where the black line is the benchmark strategy and the blue line is the PLSCNN strategy.

The results show that the PLSCNN strategy achieves 41.57% when the cumulative return of the benchmark strategy reaches 16.71%.Furthermore,The sharp ratio in months is calculated during the back test, as shown in table 3,and SHARP ratio of 2.204 can be achieved in this this strategy.

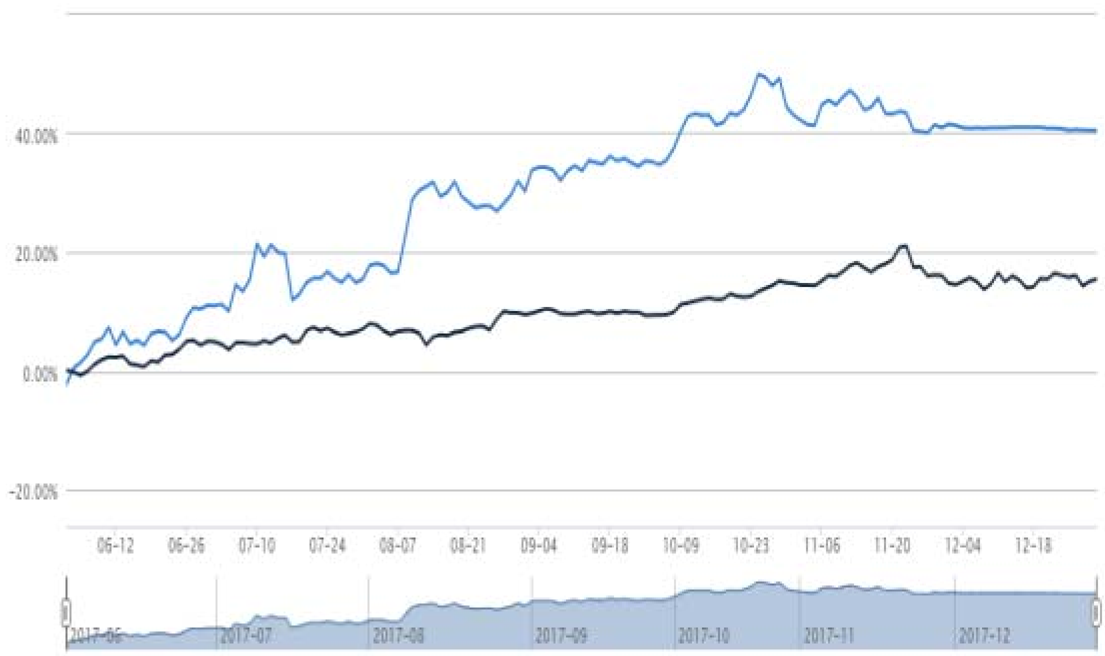


Figure 3. the cumulative return of PLSCNN.

Table 3. SHARP ratio of PLSCNN

date	Last month	Last 3 months	Last 6 months	Last 12 months
2017/06	4.917	-	-	-
2017/07	1.230	-	-	-
2017/08	4.788	3.736	-	-
2017/09	4.231	3.194	-	-
2017/10	2.553	4.216	-	-
2017/11	-0.955	1.888	3.208	-
2017/12	-9.260	0.379	2.204	-

4. Conclusion

The main contribution of this work is the empirical analysis of the predictive ability of deep convolution neural network in stock time series data.It can be concluded from the convolution operation of three kinds of time series data that the prediction ability of DCNN on stock market is very limited and the prediction accuracy of various methods is relatively stable.According to the characteristics of the large difference of TOP1 and TOP5 prediction accuracy,PLS factor analysis was used to guess the actual classification of top-5 in CNN, which achieved an ideal effect higher than the benchmark strategy.The next research direction is to use reinforcement learning method to further optimize predictive ability.

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