

Optimal Portfolio Strategy Research Based on Convolutional Neural Network

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Abstract. This paper presents a model for predicting future investment returns using convolutional neural networks. Firstly, the economic indicators at the current time point and the investment return in the same period are considered as vector mode. Secondly, the time series in a continuous period are considered to transform the vector into matrix form to eliminate the influence brought by time fluctuation characteristics. The investment return in the next time is taken as the output value. The convolutional neural network training process is established by using the financial indicators and the time series data of investment return in a period of time to get the predicted value of investment return of the product. The model uses data to predict various investment products and obtains the expected return ratio of the products. It is based on the predicted returns, through the particle swarm optimization algorithm to find the optimal, to achieve the optimal portfolio strategy. Experimental results show that the optimal portfolio strategy based on convolutional neural network proposed in this paper is effective.

Keywords: Component · Model · Convolutional Neural Network · Investment Products · Optimal Portfolio Strategy

1 Introduction

The propose of investment portfolio resulted in conversion of qualitative analysis into quantitative analysis concerning the relation between return and risk and also promoted the development of modern mathematics in finance [5]. With regard to investment theory model, many researches have carried out in-depth research and exploration. Markowitz [3] analyzed modern portfolio investment and proposed a mean value-variance model. This model is based on valid market assumptions, that is, investors are rational when making investment and have the nature to avoid risks. In actual investment, as often as not, investors will reasonably allocate investment as per different actual circumstances and take investment risks into account at the same time. As to this phenomenon, Kahneman [2] proposed that investors would allocate finance into investment various accounts of different characteristics and analyzed the heterogeneous characteristics of each account. On this basis, Das [1] et al. further fused investors' individual behaviors into the mean value-variant model and proposed a novel model.

Based on different behaviors, economists proposed various different models. In practice, however, since model parameters of such accounts are unknown, no specific parameters are available for qualitative analysis based on the models, resulting in failure to solve the optimal investment portfolio strategy. With fast development in computer field in recent years, in-depth neural network models have been widely applied in various fields [7]. Due to its ultra-strong fitting and classification capacity, in-depth neural network is also gradually applied in finance field [8]. Artificial neural network was adopted for predictive analysis of investment return [4]. Furthermore, Convolutional neural network (CNN) and Long short-term memory (LSTM) neural network were used for prediction of stock return and satisfactory effect was achieved [6].

In this paper, predictive analysis of return of investment products was conducted based on CNN. Firstly, the economic indicators at the current time point and the investment return in the same period are considered as vector mode. Secondly, the time series in a continuous period are considered to transform the vector into matrix form to eliminate the influence brought by time fluctuation characteristics. The investment return in the next time is taken as the output value. The convolutional neural network training process is established by using the financial indicators and the time series data of investment return in a period of time to get the predicted value of investment return of the product. Then, data was used for predicting multiple investment products to obtain the expected return ratio of products. Based on the expected return, optimal solution was found with Lagrange factor method, thus achieving the strategy of optimal investment portfolio.

2 Convolutional Neural Network Model

Differing from fully connected neural network such as DBN/BP, convolutional neural network achieved sharing of weight through convolution kernel. Therefore, number of original fully connected overall weight coefficient is greatly reduced, thus avoiding the dimensional disaster and over-fitting of fully connected neural network. Currently, convolutional neural network is smooth and used in application for image recognition, being one of the most widely used models in today's in-depth learning field.

In this paper, if vector merger is conducted for all characteristics in the time series of all investment markets, an array representation model is obtained. Then, the corresponding investment return information can be extracted with convolutional neural network through the array representation, thus constructing a return-risk model of the investment.

Generally speaking, convolutional neural network consists of input layer, convolutional layer, pooling layer, fully connected layer and output layer. During construction of a specific model, the order, number and dimension of layers may be adjusted based on the characteristics of specific object, thus improving the accuracy of corresponding algorithm model.

Figure 1 is a schematic diagram of convolutional layer. On the convolutional layer, convolutional processing of input characteristics data is conducted through a convolution kernel of relatively smaller dimension and the processed data is the input of the next layer as new characteristics data. Generally, pooling layer closely follows convolutional layer and the input of convolutional layer is output after sampling, so as to reduce the dimension. Figure 2 is a schematic diagram of pooling layer.



Fig. 1. Diagram of convolutional neural network model



Fig. 2. Diagram of pooling layer network model

In order to construct a prediction model for the return of investment using convolutional neural network, a total of seven layers were built with sequence as follows: convolutional layer (including 3 convolution kernels of size of 3), pooling layer (the pooling proportion is 2), convolutional layer (including 6 convolution kernels of size of 3), pooling layer (the pooling proportion is 2), convolutional layer (including 3 convolution kernels of size of 3), pooling layer (the pooling proportion is 1). Finally, they were connected to fully connected layer and output layer. The model input was an 18*18 characteristic pattern and the ultimate output was an output scalar indicated as the yield rate of the investment products. Finally, the mean error of model in the test set was the standard deviation of the product's yield rate.

The convolutional layer is briefly introduced. As the name implies, the convolutional layer mainly carries out convolution operation. It can be seen from the name of the convolutional neural network that the convolutional layer is the core of the whole neural network. In a mathematical sense, it is a mathematical operation on two real variable functions, whose general continuous form is as follows:

$$s(n) = (f * \omega)(n) = \int_{-\infty}^{\infty} f(x)\omega(n-x)dx$$
(1)

The discrete form is as follows:

$$s(n) = (f * \omega)(n) = \sum_{x = -\infty}^{\infty} f(x)\omega(n - x)$$
(2)

The convolution operation is generally represented by an asterisk, that is, $s(n) = (f * \omega)(n)$. In the convolutional neural network, the function f is generally called the input function, the function ω is generally called the kernel function or the weighted function, and the output s is called the feature mapping. It can be seen from the above formula that the output s is the weighted average of the input f.

In general, the convolutional neural network is mainly used in image recognition, so in order to better illustrate the principle of convolution computation, we assume that the input f is a 2 d image, from the Angle of computer, image as a 2 d matrix, the matrix elements of the pixel size, convolution process is shown in the following party three form, enter the two-dimensional matrix f 5 \times 5, convolution kernels for 3 \times 3 matrix ω , in the process of convolution, there are a few parameters need to choose, such as step length, boundary fill number and so on, each time step for the convolution kernel steps moving, boundary fill is refers to the image of peripheral filling value, so that when the convolution output dimension consistent with the image dimension to preserve edge information, here we default Settings step 1 and not filled in. In order to understand the process of convolution operation more clearly, first of all, each element in the image matrix is numbered. Elements in the i row and j column in the image are represented as $f_{i,i}$, and the weight in the x row and y column is represented as $\omega_{x,y}$, W_b is the bias item of the convolution kernel, and each element of the output feature graph is represented by $s_{i,j}$. Represents the value of row i and column j of the feature graph, and k represents the activation function. Then, the convolution calculation is carried out according to the following formula:

$$S_{i,j} = k \left(\sum_{x=0}^{2} \sum_{y=0}^{2} \omega_{x,y} f_{i+x,j+y} + w_b \right)$$
(3)

Here, for simplicity, set the bias item to 0, and k is the activation function ReLU (Rectified Linear Unit), which is a piecewise function, in the form shown below:

$$ReLU(x) = \begin{cases} x & x > 0\\ 0 & x \le 0 \end{cases}$$
(4)

So get $s_{0,0} = ReLu(1 * 1 + 0 * 0 + 1 * 1 + 0 * 0 + 0 * 1 + 0 * 0 + 1 * 0 + 1 * 0 + 1 * 0 + 1 * 0 + 1 * 0 + 1 * 1 + 0) = ReLu(3) = 3$, The result of convolution is also shown in the output matrix in the following table. The above is the process of convolution. It is worth noting that the convolution expressed by the equation is not the convolution in the sense of convolutional neural network, but the cross-correlation function. The real convolution needs to flip the convolution kernel in the horizontal and vertical directions (that is, rotate 180°) before the product of elements, and its expression is as follows (Fig. 3):

$$s_{i,j} = k \left(\sum_{x=0}^{2} \sum_{y=0}^{2} \omega_{x,y} f_{i-x,j-y} + w_b \right)$$
(5)

1↩	0←	1↩	0←□	0←□							
0←⊐	0←	0←□	1←	14	1	0←□	1		3↩□	0←□	3↩
1↩	1	1←	0←□	1←	0←□	1←	0←□		1←	2←	2€⊐
0←⊐	1↩	0←□	0←□	1←	0←□	0←□	1←		4⇔	2←	2€⊐
0←□	0←□	1↩	1↩	0←⊐							

Fig. 3. Image 5×5 , convolution kernel 3×3 , output 3×3

3 Construction of Samples

In order to construct a prediction model for the yield rate of investment products, relevant factors which influence the investment return were taken into account, including the five major economic indicators of current, macro economy, exchange rate, fringe market, monetary market and technological indexes which cover a total of 80 relevant indexes. Then, factor analysis method is used for dimension reduction processing. The most significant 17 indexes which influence the final model result were selected to simplify the model, so as to improve the computational scheme. At the same time, current yield rate of investment was added to construct a sample set which contained a total of 18 pieces of data.

To enable the model to identify the characteristics within a period of time other than that within a specific day, all existing characteristics were presented in form of window. Then, 18-order daily samples were used to construct a new sample set. In the competed sample set, each group of samples possessed 324-dimension characteristics, including all characteristics from the last 18 trading day to current transaction day.

After cleaning, the data can be used as the input of the model. The yield rate of the next moment served as the tag value of the model, thus realizing the fitting estimation of expected return of the investment using convolutional neural network.

4 Optimal Investment Portfolio Strategy

Let's assume that at the beginning of investment, an investor may carry out asset allocation from n types of risky assets, such as stocks and funds and one type of risk-free assets (i.e., bank deposit). The investor will hold the fixed asset portfolio until the end of investment. The return of risk assets is a random variable $R = (R_1, R_2, \dots, R_n)$. Where, R_i is the yield rate of the type *i* risky investment product; the corresponding expected yield rate is $\mu = (\mu_1, \mu_2, \dots, \mu_n)$; the corresponding positive definite covariance matrix is Σ . Generally speaking, the expected yield rate of risk investment is higher than that of risk-free investment, that is, $\mu_i > r_0$. Where, r_0 is the yield rate of risk-free products.

Due to the own reasons of investors, investors will use a general account for foregoing n types of investment data and risk-free investment. The proportion of each investment is $X = (X_1, X_2, \dots, X_n)$. Then, the total return of the investment can be expressed as: $\overline{R} = r_0(1 - XI_n) + XR^T$. The expected return was $\overline{\mu} = E(\overline{R}) = r_0(1 - XI_n) + X\mu^T$ and

Investment products	Risk-free	Investment product 1	Investment product 2	Investment product 3	Investment product 4	Variance
Optimal strategy	-0.071	1.202	0.218	-1.051	0.7013	0.064
Equal distribution	0.2	0.2	0.2	0.2	0.2	0.864

Table 1. Algorithm results

the standard deviation $\delta = \sqrt{X \Sigma X^T}$. Based on the criteria of mean variance tradeoff, the optimal decision model of the investor is:

$$\min_{X} \frac{1}{2}\delta^2 \tag{6}$$

$$s.t. \ \overline{\mu} > b \tag{7}$$

With regard to foregoing optimization problem, Lagrange factor method was used to find the optimal solution. With consideration of foregoing problem, as to the optimal investment portfolio of 3 risky investment products and 1 risk-free investment product, a verification was conducted for the proposed algorithm. Where the investment expectation is 0.03, the proportion of optimal investment portfolio is shown in Table 1. In the optimization, it was not limited that the proportion could not be 0, meaning that risky assets may account for zero percent. Therefore, there was negative value in the result. Compared with the equivalent allocation method, the variance was smaller, suggesting the algorithm was effective.

5 Conclusion

In this paper, a prediction of yield rate of investment asset was conducted based on convolutional neural network. Then, a research was carried out on investors' optimal investment portfolio scheme with consideration of the criteria of mean variance tradeoff based on prediction of convolutional neural network. Finally, the experimental result suggested that the optimal investment strategy was able to reach the satisfied conditions. A solution was provided concerning the optimal investment strategy with combination of modern in-depth convolutional neural network model, thus greatly improving the authenticity of optimal strategy of investment portfolio.

References

- 1. Das S, Markowitz H, Scheid J et al (2010) Portfolio optimization with mental accounts. J Financ Quant Anal 45(02):311–334
- Kahneman D, Tversky A (1979) Prospect theory: an analysis of decision under risk. Econometrica 47(2):263–292

- 3. Markowitz H (1952) Portfolio selection. J Financ 7:77-91
- Shao L (2002) Investment prediction based on artificial neural network. Chin J Manag Sci 8(2):80–83
- 5. Thaler RH (1999) Mental accounting matters. J Behav Decis Mak 12:183-206
- 6. Wen Y (2018) Analysis of financial secondary market data based on CNN-LSTM network. Electron Des Eng 26(17):75–84
- Yu K, Jia L, Chen Y et al (2013) The past, today and tomorrow of in-depth learning. J Comput Res Dev 50(9):1799–1804
- 8. Zhang G (2016) A research on application of improved convolutional neural network in financial prediction. Zhengzhou University

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