

Analysis of Stock Price Fluctuation Based on Linear AlexNet and DNN

Peng Liang^{1,a}, Jie Yang^{2,b}, Jian Zhou^{3,c}, Zongyuan Tan^{4,d}, Zhenpei Shan^{5,e}

¹College of Economics Northwest Normal University Lanzhou 730070, China

²Research Institute of Information Technology Tsinghua University Beijing 100084, China

³School of Computer Science and Technology, Dalian University of Technology Dalian 116024, China

⁴College of Electrical Engineering Northwest Minzu University Lanzhou 730000, China

⁵School of Information Science and Technology Xiamen University Xiamen 361005, China

^aplbwdgw@126.com; ^btotoroyang@tsinghua.edu.cn; ^czhoujian@mail.dlut.edu.cn; ^dtanzongyuansmil@163.com; ^e23020170155537@stu.xmu.edu.cn

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Abstract. This paper aims to propose a method called linear Alexnet to analyze the fluctuation of stock price. In this study, the fluctuation of stock price can be summarized as three main factors. Based on the simulation results, we found that deep learning network is suitable to simulating and analyzing the current economic models, in particular certain fluctuation models. Of course, to further boost the performance of training, we add certain Gauss noises for avoiding the generalization of dataset.

Introduction and Setting

The stock market has a prominent role in optimizing resource allocation and industrial structure adjustment, in terms of investment and financing system reform and the establishment of modern enterprise operating mechanisms [1, 2]. China's stock market has the so-called late-comer advantage, but inevitably there are various characteristics of the initial stage [3]. How to improve the stock market, especially how to improve the market efficiency, is the key to whether the stock market can rationally allocate risks and benefits, and whether it can play its due role [4, 5]. However, the assumption that investment returns satisfy a normal distribution is increasingly criticized because the normal distribution of positive and negative dispersions of income is significantly different from the actual psychological perception of actual investors, while using variance to measure risk, its indicators are non-independent [6, 7]. A key to market effectiveness of testing is the treatment of revenue errors. The initial study assumed that the variance of returns remained constant at different times. The theory of market effectiveness has been challenged in the past 30 years [8]. The first is the discovery of abnormal phenomena such as the week effect and the small company effect, followed by the development of behavioral finance theory, and the research on market nonlinearity has also impacted the validity theory [8, 9]. The policy implication of our research is that the policy management model should try to get rid of the wandering between the norms 0 and 1 development and continue to cause shocks (although decreasing) [10], so that the market should fully exert its self-adaptation and self-control. Recovery mechanism; The focus of supervision should be on protecting the interests of investors, improving and perfecting the information disclosure system, ensuring investors' fair access to information, and punishing the use of insider information, insider trading, and false statements to promote profitability. The stock market flows fully, quickly, accurately, and symmetrically [11,12]. At the same time, the establishment of some securities information centers should be encouraged to enable investors to obtain information in a timely and low-cost manner. In addition, the conclusions of the effectiveness study mean that investors can only rely on technical analysis to obtain long-term, stable excess returns based on fundamental analysis.

If the frequency of both overreaction and underreaction is roughly similar, the market is still valid. Empirical studies have confirmed that the probability of occurrence of these two situations is very similar [13]. At the same time, to overthrow the theory of market effectiveness, it is necessary to specify a hypothesis against it as the basis for the test. Behavioral finance theory is difficult to do this, so the theory of validity cannot be overturned [14]. We believe that the theory of market

effectiveness reflects the ideal state that financial scientists dream of. Although there is a vision in reality, it reflects the deviation of the realization state from the ideal state. The challenge cannot fundamentally negate the theory of market effectiveness, and the theory provides a frame of reference for research questions [15, 16]. Prices often rise in a single direction, which inevitably results in fewer runs, thus increasing the difference between the number of runs and the standard normal distribution, so that the number of runs caused by the initial stage of the market will always affect the validity of the test, making the test pass. An effective way to overcome this drawback is to divide the annual test and the progressive validity test, and at the same time to find out the evolutionary trend of market effectiveness. The current stock market has developed to a certain scale and level, providing more samples and technically meeting the needs of more measurement models. Furthermore, please note that we mainly utilize SIFT and PCA to model big datasets.

Model Formulation

We first give some parameters and structure diagram of AlexNet as follows:

- 1) Convolution layer: 5 layers
- 2) Fully connected layer: 3 layers
- 3) Depth: 1 layer
- 4) Number of parameters: 60M
- 5) Number of neurons: 784k
- 6) Output layer: 10
- 7) Input layer: 8 (784 neurons)
- 8) Number of categories: 1000 categories

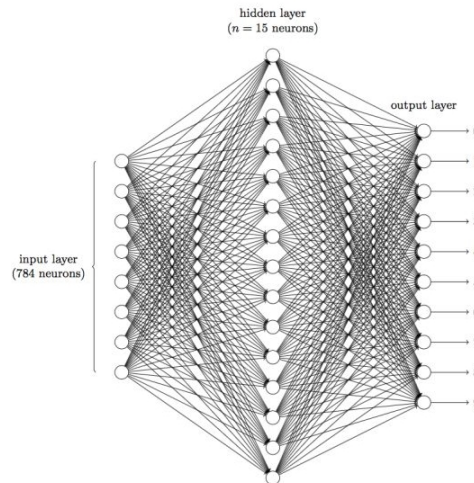


Fig. 1 Structure of AlexNet Learning

As shown in Fig. 1, one can see that the structure of Alexnet is mainly consisted by 3 layers. In the following, we attempt to analysis and compute the Softmax function, as noted in [7, 8], the defination of Softmax function can be written as follows:

$$\sigma(Z)_j = \frac{e^{Z_j}}{\sum_{k=1}^K e^{Z_k}} \quad (1)$$

$$x^k = \arg \min_x \Gamma(x, \beta) = \frac{\beta^{(k)}}{2} \|Ax - b + \frac{\lambda^k}{\beta^{(k)}}\|_2^2 \quad (2)$$

We then calculate the fuction of connectted networks, the equation can be denoted as follows:

$$\begin{cases} \dot{x}_i = f(x_i) - c \sum_{j=1}^N a_{ij} \Gamma x_j + u_i, i = 1, 2, \dots, l \\ \dot{x}_i = f(x_i) - c \sum_{j=1}^N a_{ij} \Gamma x_j, i = l+1, l+2, \dots, N \end{cases} \quad (3)$$

Stability is also a significant research direction of network topologies and combine controllability, which form theoretical foundation of most system analysis and synthetical problems. Therefore, the controllability and stability analysis of agents of network topologies could contribute to further research the properties of network topology. According to the above analysis, and as found in [8], the Lipschitz continuous can be defined as following form:

$$\|\nabla f(x) - \nabla f(y)\| \leq L \|x - y\|, \forall x, y \in \mathbb{R}^p \quad (4)$$

The block diagonal matrix $\text{Diag} \{A_i\}$ has its block on the diagonal matrix. The constant c controls a trade-off between an approximation error and the weight vector norm $\|w\|$. Minimizing the risk R is equivalent to minimizing the risk shown in Eq. (5) and Eq. (6) respectively, as found in [14].

$$R = \frac{1}{2} \|w\|^2 + c \left(\sum_{i=1}^m |y - f(x, w)|_{\varepsilon} \right) \quad (5)$$

$$R = \frac{1}{2} \|w\|^2 + c \sum_{i=1}^m (\xi + \xi^*) \quad (6)$$

Similar to SVM, above constrained optimization problem is solved using Lagrangian theory and the Karush–Kuhn–Tucker conditions to obtain the desired weight vector of the regression function. Here, ξ_i and ξ are slack variables, one for exceeding the target value by more than ε and other for being more than ε below the target.

Simulation and Test

The neural network is an efficient identification method that has been developed in recent years and has attracted widespread attention. Recently, they found that their unique network structure can effectively reduce the complexity of the feedback neural network, and then proposed a convolutional neural network (Convolutional Neural Networks - CNN for short). Nowadays, CNN has become one of the research hotspots in many scientific fields, especially in the field of pattern classification. Because the network avoids the complicated pre-processing of images, it can directly input the original image, so it has been widely used. Subsequently, more researchers have improved the network. Among them, representative research results are the “improvement of cognitive machines” proposed by Alexander and Taylor, which combines the advantages of various improved methods and avoids time-consuming error back propagation. The correlation of expected function and price on dataset is shown in Fig. 2 and Fig.3.

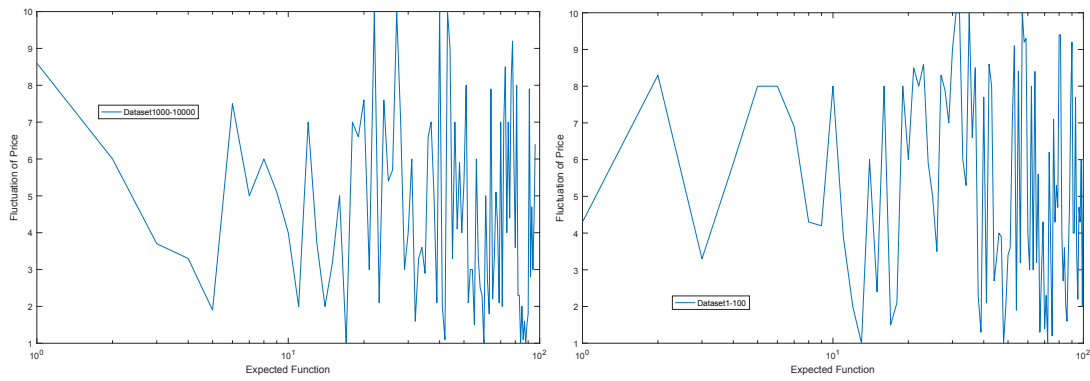


Fig. 2 Correlation of Expected Function and Price on Dataset (1-100 and 1000-10000)

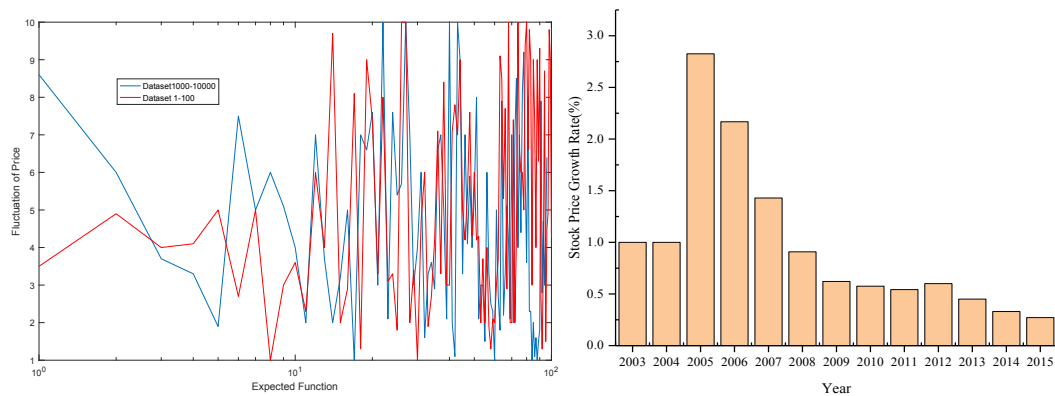


Fig. 3 Comparison of Expected Function and Price Function

As illustrated in Fig. 2 and Fig. 3, we conclude that the training method, different networks and training accuracy is statistics in Table 1 and Table2, respectively. Of course, it is worth remarking that the dataset is strongly affected by the different pooling functions.

Table 1 Effectiveness and Stability of the Real Networks and Model Networks

Type	Train Method	Stability (%)	Effectiveness (%)	Error Propagation (%)
Real Networks	CN	41.9	31.36	10.61
Model Networks	DN	48.1	55.32	-7.19
	N	3		

Table 2 Training Method and Test Accuracy

No.	Method	Sample Dataset	Training Dataset	di m. (St eps)	Er ror (%)	Acc uracy (%)
1	P	10	10	Hi	2.	97.2
2	CA	0	0	gh	8	86.8
3	FT	00	00	dium	.2	82.6
	NN	000	000	w	.4	

As a variable representing the component of the stock's return that is independent of the market's performance, the advantage of the random walk model is that it is a good first-approximation to real stock prices and provides a simple model based on which other important problems in finance and economy can be studied in a mathematically rigorous fashion, the simulation results are clearly

shown in Fig. 4.

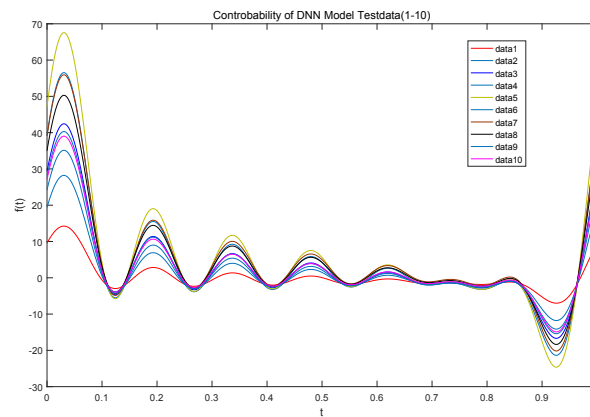


Fig. 4 Training Results of DNN Model on Dataset (1-10)

However, as far as we are concerned, there is no direct connection between prices and stock prices. In general, rising prices will cause stock prices to rise. This is because during the inflation period, since the bank deposit interest rate is often lower than the inflation rate, for investors holding cash, deposits are no different from currency depreciation, which in turn will turn the savings into other objects that can preserve value. Therefore, investors who buy stocks will increase accordingly. Despite this, the relationship between rising prices and rising stock prices is not very obvious.

Second, there are three modes of change in intrinsic value: value growth, constant value, and value decline. For long-term growth stocks, their intrinsic value continues to grow due to their continuous increase in net profit will be stable or unchanged for a certain period of time; For a recession company, its intrinsic value is in a state of decline due to loss of performance. Third, there are three modes of change in speculative value: no speculative value, reasonable speculative value, and bubble speculative value. When the stock has no speculative value, the stock price does not have a premium space of intrinsic value, and the stock price can only operate in a range no higher than the intrinsic value. When stocks have reasonable speculative value, the stock price creates a premium space for intrinsic value, and the stock price can operate within a reasonable speculative value range.

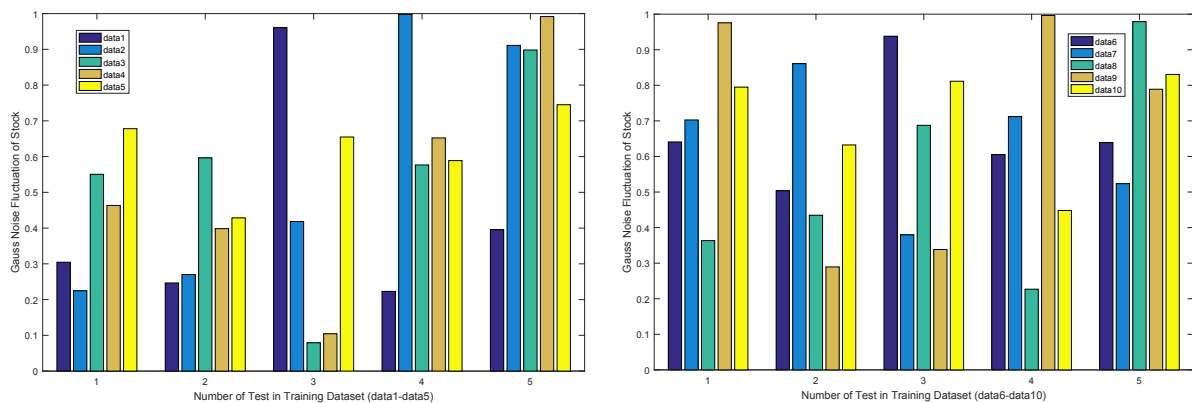


Fig. 5 Number of Test (data1-5 and data 6-10) and Gauss Noise Fluctuation of Stock

During the period of inflation, some listed companies' profits will increase, but some listed companies that are seriously affected by inflation will affect their profits due to excessive cost increases, causing their profits to fall or losses, and their share prices will fall. During the inflation period, the government will adopt methods such as raising interest rates and setting up value-added subsidies to encourage savings, which will affect the rise in stock prices. In this way, the price increase will not affect the stock price in the short term. However, in any cases, the rise in prices will cause the stock price to rise.



Fig. 6 Neural Network Training Error Confusion Matrix and Histogram

As shown in Fig. 6, we found that neural network training error in training dataset is ideal. Yet, with the increase of the epochs, the generalization of dataset would be strongly influenced and fluctuated. To further boost the performance of training, we utilized linear Alexnet to analyze the stock price. The nearby manifolds will affect the original data structure detecting LLE and PCA only considers the neighborhood similarities regardless of the structure of neighbors.

Conclusions and Discussion

According to the above analysis and simulation results, one can draw a conclusion that the fluctuation of stock price is primarily influenced by following aspects:

By perfecting the supporting system, the average income level of the stock market is moderately reduced.

Enhance the transparency of the stock issuance process, especially in the issuance and listing process, to clarify risks.

An important part of lowering the average income level is to weaken the impact of the weekend effect.

Encourage value-based investment consulting to raise investors' risk awareness and cultivate rational investment concepts.

There are three trends in the movement of stock prices, the most important of which is the basic trend of stocks, namely, the wide or comprehensive rise or fall of stock prices. Such moves typically last for a year or more, with a total rise (or fall) of more than 20 per cent. For investors, a sustained rise in the underlying trend leads to a long market, while a sustained decline leads to a short market. The second trend of stock price movement is called the secondary trend of stock price. The secondary trend is often contrary to the movement direction of the basic trend and has a certain constraint on it. This trend can last from three weeks to several months, and the share price generally rises or falls by one-third or two-thirds of the underlying trend. The third trend in the movement of the stock price is called the short-term trend, which reflects the movement of the stock price within a few days. A correction trend usually consists of three or more short-term trends. Of the three trends, long-term investors are most concerned with the underlying trend in share prices, with the aim of buying as many shares as possible in the long market and selling them in time before the short market takes hold. Speculators are more interested in the correction trend of stock prices. Their aim is to make short-term profits. Short-term trends are less important and more susceptible to manipulation, making them inconvenient for trend analysis. The fundamental and corrective trends of share prices are generally impossible to manipulate, and only the financial sector of the country is likely to make limited adjustments.

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