



Stock Market Price Forecasting by Using Deep Learning

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Abstract

Stock market forecasts are an attempt to determine the future value of corporate capital or other financial products consumed in the stock market. If the future stock price forecast succeeds, you can gain great profit. The efficient market presents all the current stock price information, which shows that price fluctuations are not the basis for unnecessary new information. Others disagree that people who have these ideas have many methods and techniques to help them get future information. [1]

Keywords: stock market; prediction;

1. Introduction

Forecasting the stock price is one of the most important topics in the financial sector. Many researchers have considered how to use technical analysis, statistical analysis and various methods to profit from market prices using a variety of methods. ANN is one of data mining techniques for learning human brain function. [7] The current artificial neural network (ANN) is used to forecast the substitution index. ANN is one of data mining techniques that are learning capability of the human brain [8]. Because sophisticated financial data is used, data patterns are unpredictable that can make dynamic changes. A number of studies have been conducted to improve the efficiency of stock value. Kimoto used ANN's methods to use one of the first projects to predict the TOPIX [9]

2. Prediction methods

Forecast methods are divided into three main categories that can (and often do) interact. They are (i) fundamental analysis, (ii) technical analysis (chart) and (iii) technological techniques. [30]

A. Fundamental Analysis

This analysis deals with a company that manages its own stock. They evaluate the corporation's past performance and reliability of its accounts. Many performance ratios have been created to help basic analysts evaluate the validity of such stocks such as p/e ratio. [30]

B. Technical Analysis:

Technical analysts and chartists are not interested in the company's basic principles. They are looking for the current

(potential) price based on the original price that determines the future stock price (using time series analysis).

These days people are relied on technical analysts, who determine the company's future. Thus, here have been introduced a lot of techniques to predict the market commodities. [30]

C. Technological Methods

Data Mining Technologies: With the advent of digital computers, stock market forecasts have entered the technical field. The most important method involves the use of artificial neural networks (ANNs) and transmissible processes. The researchers found that the method of improving bacterial chemotherapy may be much better than GA. [30] [1]

3. Artificial Neural Network (ANN)

Artificial neural network (ANNs) information processing systems were originally inspired by mathematical generalization of human neurons. ANNs are approximations to mathematical functions. The most common form of ANN used for stock market forecasting is a feedforward network that updates network weights using error backpropagation. Unfortunately, stock market is essentially complicated, non-linear, dynamic, non parametric, and chaotic in nature [3]. The time series are random, noisy, multi-stationary, and has frequent structural breaks [6]. In addition, stock market's movements are affected by many macro-economical factors [5] such as movements of other stock market, general economic conditions, firms' policies, bank rate, commodity price index, political events, bank exchange rate, investors' expectations, general economic conditions, institutional investors' choices, psychology of investors, etc. [1] Historical and present stock index data to predict future prices are used to model the most artificial neural network. Due to inherent capabilities to approximate any non-linear function to a high level of accuracy, ANN has gained a lot of popularity. [4]. However, ANN is particularly pre-dispersed with a lot of noise and ignorance Characteristics of stock market volatility in backpropagation. [13]

Tsoi, Lawrence and Giles pointed [1] out that, When data noise makes BP formation difficult, such a network will always be a naive solution for predicting the most common result. [5] Miao et al. believes that BP solutions are generally ,The gradient descent algorithm is used to obtain connection weights.. [1]

4. Linear Regression

In statistics, linear regression is a linear method of modeling the relationship between a scalar dependent variable y and one or more explanatory variables (or independent variables) labeled with X . The relationship in the linear regression is modeled using a linear prediction function, and the model parameters that cannot be known from the data are estimated in the linear prediction function. These models are called linear models. The purpose of our linear regression is to predict the target y value in the input value vector, from

$$x \in \mathbb{R}^n$$

to find a function $y = h(x)$ so that we have

$$y^{(i)} \approx h(x^{(i)})$$

,for each training example. To find a function $h(x)$. we use the the equation

$$Index(x) = \frac{(Index(x) - Min(Index))}{(Max(Index) - Min(Index))}$$

$$h_{\theta}(x) = \sum_j \theta_j x_j = \theta^T x$$

$h_{\theta}(x)$ represents a large family of functions parametrized by the choice of θ

Here the θ improves and minimizes the $y(i)$. so the function of θ is taken as

$$J(\theta) = \frac{1}{2} \sum_i (h_{\theta}(x^{(i)}) - y^{(i)})^2 = \frac{1}{2} \sum_i (\theta^T x^{(i)} - y^{(i)})^2$$

There are many algorithms for minimizing the function. the most common used one is Gradient Descent. we use the gradient to optimize the output. to compute the gradient we use

$$\frac{\partial J(\theta)}{\partial \theta_j} = \sum_i x_j^{(i)} (h_{\theta}(x^{(i)}) - y^{(i)})$$

$J(\theta)$ is called the cost function.

5. Methodology

The project can be divided into three main parts

- (1) Training process
- (2) Testing process
- (3) Comparison

A. Training Process

Training process are used as pre-parameters for the weights and optimal values of the network. The learning model used in MLP is characterized by changes in specific input patterns and connection weights. This model assigns the input signal to the optimal value of the network. The connection weight passes the signal. The hidden and output layers contain vectors of processing elements that have activation capabilities. Either weight or bias network is ready to be trained. Compare the deliverables and goals in the process of education and coordinate the network.

The training process requires an example of proper network behavior and target output. weights and biased networks are repeated during training to minimize network performance. Mean squared error (MSE) is a performance function used when learning feedforward neural networks. MSE is the mean square error between the network output and the target output. training is the process of backpropagation errors to the system via the output layer. Backpropagation is an important way of the training process. Because hidden units do not have training

to use target values, they need to be trained based on previous layer mistakes.

B. Testing Process

Training continues until all differences between the updated weight and the old weight of the previous epoch are below the threshold. MLP (Multilayer Perception) is the most common feedforward network In this setting, the input vector and the target vector are randomly divided into two groups, 80% learning. 20% will be used to confirm that the network has generalized and completed before the training is over. This last 20% is also used as a completely independent network standardization test.

C. Comparison

Exchange statistics were collected by the Standard & Poor's 500 (S & P 500). The sample size of each stock index is 5 years. In each sample, the closing price, the starting price, the lowest price, the highest price, the total number of shares traded

One of the most important problems is to improve the artificial neural network. Each input variable should be preprocessed. Mean value, average of the training set is small compared to its standard deviation. Index rage is between -1 and +1 . We are able to use simple formula which is

It can be clearly seen the regression plot of the training set. Each of the figures corresponds to the target from the output array. Regression values (correlation coefficients) are very close to 1. It means that the correlation between the outputs and the target is very high.

6. Conclusion

In this document we have developed a new Framework for predicting stock market values .This Framework is able to learn structural representation from training data support all types of stocks efficiently computes all values i.e it can predicts the stock values. This implementation process consists of different steps like data collection, data preprocessing, classification and model evaluation. Each approach to stock prediction. is used back propagation with feed forward network

Table 1: Source From S& P 500, 2013

date	open	high	low	close	volume
08-02-2013	15.07	15.12	14.63	14.75	8407500
11-02-2013	14.89	15.01	14.26	14.46	8882000
12-02-2013	14.45	14.51	14.1	14.27	8126000
13-02-2013	14.3	14.94	14.25	14.66	10259500
14-02-2013	14.94	14.96	13.16	13.99	31879900
15-02-2013	13.93	14.61	13.93	14.5	15628000
19-02-2013	14.33	14.56	14.08	14.26	11354400
20-02-2013	14.17	14.26	13.15	13.33	14725200
21-02-2013	13.62	13.95	12.9	13.37	11922100
22-02-2013	13.57	13.6	13.21	13.57	6071400
25-02-2013	13.6	13.76	13	13.02	7186400
26-02-2013	13.14	13.42	12.7	13.26	9419000
27-02-2013	13.28	13.62	13.18	13.41	7390500
28-02-2013	13.49	13.63	13.39	13.43	6143600
01-03-2013	13.37	13.95	13.32	13.61	7376800
04-03-2013	13.5	14.07	13.47	13.9	8174800
05-03-2013	14.01	14.05	13.71	14.05	7676100
06-03-2013	14.52	14.68	14.25	14.57	13243200
07-03-2013	14.7	14.93	14.5	14.82	9125300
08-03-2013	14.99	15.2	14.84	14.92	10593700
11-03-2013	14.85	15.15	14.71	15.13	6961800
12-03-2013	15.14	15.6	14.95	15.5	8999100
13-03-2013	15.54	16.2	15.48	15.91	11380000
14-03-2013	15.98	16.36	15.93	16.25	8383300
15-03-2013	16.45	16.54	15.88	15.98	17667700
18-03-2013	15.8	16.33	15.71	16.29	6514100
19-03-2013	16.48	16.85	16.41	16.78	11805300
20-03-2013	17.13	17.33	16.87	17.23	10819800
21-03-2013	17.21	17.43	16.87	17	10740800

Table 2: Stock High Value

Actual High Value	Predicted High Value
	920.5639038
924.9909734	929.7027588
937.1526831	932.8369751
937.7684709	947.2979126
937.8290402	947.932251
942.1395554	948.2165527
937.7280914	953.2165527
935.5779822	948.3103638
940.443615	946.3339233
941.9477526	952.3509521
950.2659364	954.0079346
930.6414834	963.432312
931.2572712	940.1343384
943.6235032	941.71521
947.6614565	956.4824219
955.3083306	960.9164429
962.2990373	969.0296631
968.3256826	976.0913086
977.976391	982.3723145
982.4787089	993.3452759
973.0803726	998.3088989
972.9087596	987.3178711
978.9555946	987.7561646
988.1419384	995.4026489
988.1823179	1006.27887
988.8182956	1005.864075
990.2618639	1006.126526
948.2974342	1007.628052
927.7066989	959.3088989
956.8377054	937.9016113
954.9802469	973.8860474
937.0012598	971.270752
944.2241488	949.2855835
961.8447675	956.9157104
962.8138763	976.6952515
963.5709925	977.2593994
967.3969533	977.6177368
967.0436324	981.4330444
963.6012772	981.0328369
939.4341267	977.5479126
928.4811783	950.0905762
923.0501311	938.9729614
920.7182131	934.1507568

Table 3: Stock Low Values

Actual Low Value	Predicted Low Value
909.4526	910.4526
912.5426	913.5426
924.59	925.59
925.2	926.2
925.26	926.26
929.53	930.53
925.16	926.16
923.0301	924.0301
927.85	928.85
929.34	930.34
937.58	938.58
918.14	919.14
918.75	919.75
931	932
935	936
942.575	943.575
949.5	950.5
955.47	956.47
965.03	966.03
969.49	970.49
960.18	961.18
960.01	961.01
966	967
975.1	976.1
975.14	976.14
975.77	976.77
977.2	978.2
935.63	936.63

915.2328	916.2328
944.09	945.09
942.25	943.25
924.44	925.44
931.595	932.595
949.05	950.05
950.01	951.01
950.76	951.76
954.55	955.55
954.2	955.2
950.79	951.79
926.85	927.85
916	917
910.62	911.62
908.31	909.31

Table 4: Stock Close Value

Actual Close Value	Predicted Close Value
913.7460414	912.4527588
916.8309397	921.4907837
928.8584491	924.5903931
929.4674419	938.8917236
929.5273429	939.519104
933.7902929	939.800293
929.427508	944.7450562
927.3011245	939.8930664
932.1130667	937.9384155
933.6006066	943.8890381
941.8270021	945.527771
922.4190982	954.8480835
923.0280911	931.807251
935.2578659	933.3706665
939.2512618	947.9749146
946.8137552	952.3599854
953.7273218	960.383667
959.6874652	967.3674316
969.2316813	973.5791626
973.6843177	984.4310303
964.3896888	989.3398438
964.2199695	978.4700928
970.2000798	978.9035645
979.2850554	986.4656372
979.3249893	997.2218628
979.9539492	996.8117065
981.3815882	997.071228
939.8802216	998.5562134
919.5166981	950.7702026
948.3262539	929.5991821
946.4892918	965.1864624
928.7086967	962.6000366
935.8518836	940.8574829
953.2780648	948.4034424
954.2364798	967.9647217
954.9852415	968.522644
958.7689841	968.8770142
958.419562	972.6502686
955.015192	972.2544556
931.1147177	968.8079224

Table 5: Stock Open Value

Actual Open Value	Predicted Open Value
915.470023	914.1778564
918.5521673	923.2078247
930.5689392	926.3046265
931.1773884	940.5932617
931.2372359	941.2200317
935.4963803	941.5009766
931.1374901	946.4413452
929.013005	941.593689
933.8206514	939.6407471
935.3068633	945.5861206
943.5259148	947.2233276
924.1353371	956.5353394
924.7437863	933.5150757
936.9626431	935.0770874
940.9524739	949.6682739

948.508216	954.0494995
955.4156106	962.065979
961.3704331	969.0435181
970.9061287	975.2496948
975.35479	986.0918579
966.0684588	990.9963379
965.898891	980.1362305
971.8736627	980.5693359
980.9505277	988.1246948
980.9904261	998.8713379
981.6188244	998.4614868
983.0451889	998.7207642
941.5808723	1000.204407
921.235528	952.4610596
950.0193644	931.30896
948.1840423	966.864502
930.4193206	964.2803955
937.5561304	942.557251
954.9667546	950.0964355
955.924314	969.6402588
956.6724073	970.1976318
960.452772	970.5517578
960.1036618	974.3215942
956.702331	973.9261475
932.8231937	970.4827271
922.0007776	943.3526611

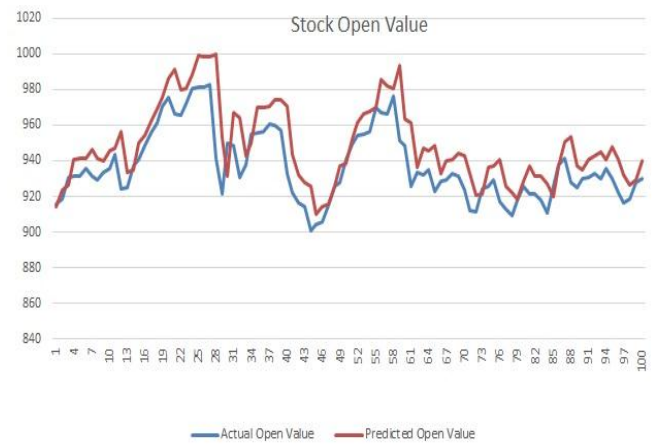


Fig. 3: Stock Open values comparison.

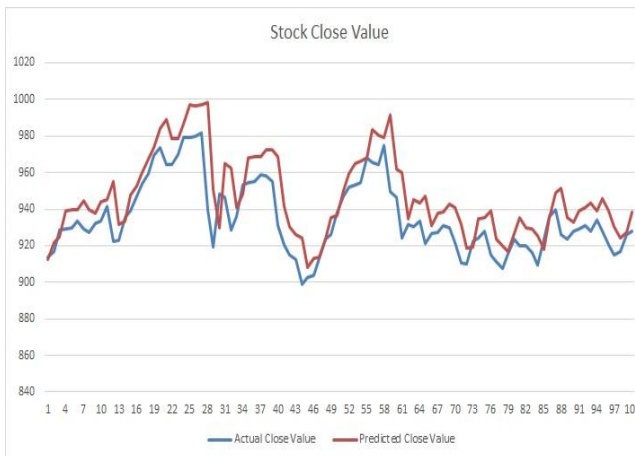


Fig. 1: Stock Close values comparison

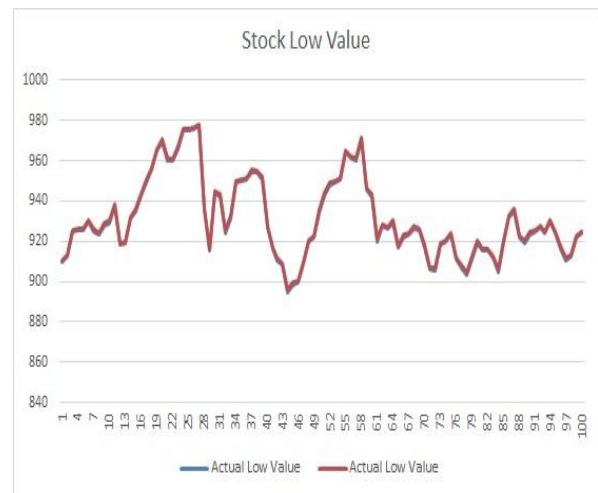


Fig. 4: Stock Low values comparison

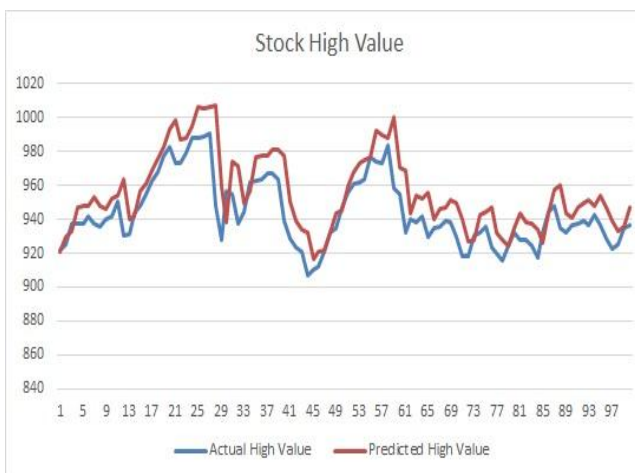


Fig. 2: Stock High values comparison

The model can be very beneficial for financial analysis and corporate investors and uses for financial media . They can provide a futuristic plan our behaviour and moment and that properly in their trading.This act properly is for trading to profit and prevent loss. In future work, We intend to optimise the impact of fundamental analysis in predict the quality of the stock prediction.We also would like to predict the stock not only using the data stock but all so newsfeed from online or other social media

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