Toward Stock Price Prediction using Deep Learning

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ABSTRACT

Three methods including LSTM, Seq2seq and WaveNet are implemented in this study. We compare the performance of different deep learning methods in predicting stock prices. We use the correlation between the predicted price and the actual price as the performance metric to evaluate the effectiveness of these methods.

CCS CONCEPTS

CCS → Computing methodologies → Machine learning → Machine learning approaches → Neural networks

KEYWORDS

Deep Learning, stock prediction, LSTM, Seq2seq, WaveNet

I. INTRODUCTION

Predicting changes in financial markets is a challenging task. Market volatility in recent years has brought serious problems to economic and financial market forecasts. The purpose of investors investing in the stock market is to make a profit from it, so predicting the rise or fall of financial markets in the future will play an important role in determining the returns of investors.

In recent years, deep learning techniques have been applied to different time series data (including manufacturing, transportation, weather, energy, and stock trading, etc.) [1,2,3] Various deep learning techniques (such as LSTM[4], Seq2seq[5], WaveNet[6]) have been applied to time series data prediction. These methods have achieved different level of successes. However, in the context of stock price prediction, these prior studies used different stock data and evaluated them using different performance metrics. It is difficult to compare which of these methods is more effective in predicting stock price and providing users with better information.

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On the other hand, there are quite a few stock price prediction Apps available in the market [7,8]. But these Apps generally do not provide any information about prediction accuracy to the users so that it unclear how much one can trust the generated predictions from these Apps.

In this work, we collect 932 Taiwan stock price information for the past 13 years (from 2007 To 2019) and use these data to train a prediction model based on LSTM, Seq2seq, WaveNet respectively. We use the correlation between the predicted price and the actual price as the performance metric to evaluate the effectiveness of these methods and find that WaveNet outperforms the other two methods. In addition, given the same prediction model (e.g. based on WaveNet) different stocks could vary significantly in terms of their predictability (indicated by the correlation between the predicted price and the actual price). For example, the average correlation per year can range from 0.1 to 0.75 for different stocks.

II. METHOD

Our goal is to compare the performance of different deep learning methods in predicting stock prices. Three methods including LSTM, Seq2seq and WaveNet are implemented in this study. 932 Taiwan stock data from 2007 to 2019 are collected using Yahoo Finance API. We used data from 2007 to 2016 as the training data, and data from 2017-2019 as the testing data. We built a stock forecasting system using Keras, a deep learning framework, and all experiments are run on a 64-bit Ubuntu 16.04 system using INTEL i7-4790 CPUs with GEFORCE GTX 1080.GPU and 16GB RAM. data source

We select three sets of variables as the input features. Table 1 gives the specific details. The first set of variables (A) are the historical trading data for each index. These data include Open, High, Low, and Closing prices (OHLC variables) as well as the trading volumes. These variables present the basic trading information for each stock. Another set of inputs include 13 widely used technical indicators for each stock, as shown in (B). The final set of inputs are the macroeconomic variables as shown in (C). Generally speaking, the macroeconomic conditions across regions also play a critical role in the performance of the stock prediction.

III. RESULT

We use five of the top Taiwan stocks in 2017 to evaluate the performance of different deep learning methods. They are (1) CATHAY HOLDINGS (2) Fubon Financial (3) CTBC HOLDINGS (4) E.S.F.H (5) FFHC. As shown in Table 2 an Table 3, we can see WaveNet outperforms the other 2 methods in terms of RMSE and correlation (based on the comparison of predicted price and the actual price). These results are based on a prediction for one particular week in 2017. Prediction for other periods of time in 2017 also show similar results. We also try with different prediction period, including 7 days, 14 days and 21 days. On average, 21-day prediction period give us the best results.

Name	Definition/Implication
	A. Daily Trading Data
Open/Close Price	nominal daily open/close price
High/Low Price	nominal daily highest/lowest price
Trading volume	Daily trading volume
	B. Technical Indicator
MACD	Moving average convergence divergence: displays trend following characteristics and momentum characteristics.
CCI	Commodity channel index: helps to find the start and the end of a trend.
ATR	Average true range: measures the volatility of price
BOLL	Bollinger Band: provides a relative definition of high and low, which aids in rigorous pattern recognition
EMA12/20	12/20 day Exponential Moving Average
MA5/MA10	5/10 day Moving Average
MOM6/MOM12	6/12 month Momentum: helps pinpoint the end of a decline or advance
ROC	Price rate of change: shows the speed at which a stock's price is changing
RSI	The relative strength index (RSI) is a momentum indicator that measures the magnitude of recent price changes to evaluate overbought or oversold conditions in the price of a stock or other asset.
WVAD	Williams's Variable Accumulation/Distribution: measures the buying and selling pressure.
	C. Macroeconomic Variable
Exchange rate	TWD dollar Index
Interest rate	Interbank Offered Rate

Table1 Description of input features

	LSTM	Seq2seq	WaveNet
CATHAYHOLDINGS	1.074	3.811	**0.989**
Fubon Financial	0.908	6.757	**0.799**
CTBC HOLDING	0.416	3.570	**0.505**
E.S.F.H	1.802	3.357	**0.188**
FFHC	1.915	1.146	**0.952**

Table 2 Comparison of RMSE for different deep learning methods

	LSTM	Seq2seq	WaveNet
CATHAYHOLDINGS	0.857	0.847	**0.938**
Fubon Financial	0.888	0.897	**0.930**
CTBC HOLDING	0.895	0.837	**0.958**
E.S.F.H	0.958	0.506	**0.986**
FFHC	0.896	0.579	**0.970**

Table 3 Comparison of correlation for different deep learning methods

In addition, as shown in Figure 1, we can see different stocks have different level of predictability (based on the correlation between the predicted price and the actual price). The x-axis shows the stock ID of different stocks.

IV. CONCLUSION

In this study, we use 13 years' Taiwan stock data to evaluate the performance of three deep learning methods, including LSTM, Seq2seq and WaveNet, in stock prediction. We find that WaveNet outperforms the other two methods. In addition, contrary to the common perception of that stock prices are difficult to predict, we find that some stocks actually can be predicted with a certain level of accuracy. In this work, we only use the basic historical stock price information as the input features to train the model. It is possible to create a better prediction model when more relevant parameters are considered, which will be a future direction of our study.

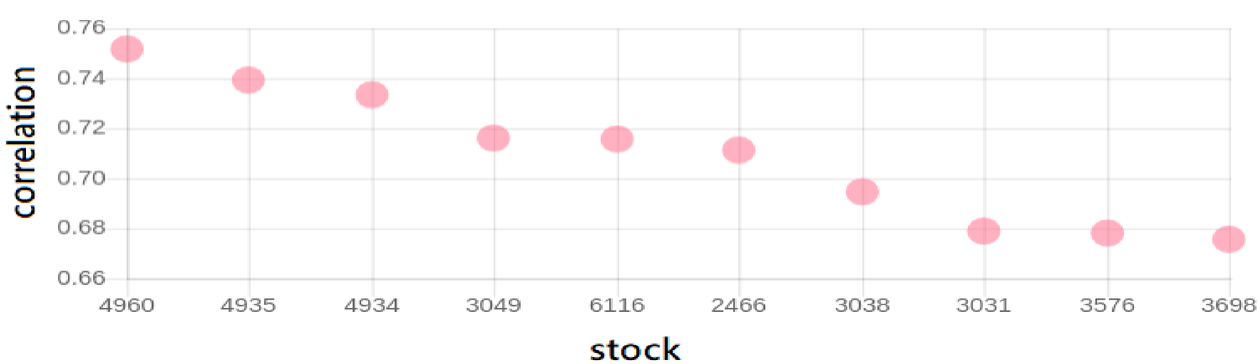

Figure 1 Correlation of the Top ten stocks in photonics industry in Taiwan

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