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Stock Movement Prediction Using Price Factor and Deep Learning

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Abstract—The development of machine learning methods and techniques has opened doors for investigation in many areas such as medicines, economics, finance, etc. One active research area involving machine learning is stock market prediction. This research paper tries to consider multiple techniques and methods for stock movement prediction using historical price or price factors. The paper explores the effectiveness of some deep learning frameworks for forecasting stock. Moreover, an architecture (TimeStock) is proposed which takes the representation of time into account apart from the price information itself. Our model achieves a promising result that shows a potential approach for the stock movement prediction problem.

Keywords—Classification, machine learning, time representation, stock prediction.

I. Introduction

THE importance of stock movement prediction has pushed this area into one of the interesting research problems around the world. However, the volatility of the stock price is the obstacle that prevents researchers from making accurate predictions. The high level of noise additionally contributes to the difficulties while predicting financial time series tasks [1]. Stock movement prediction has been categorized as a time series problem because it is influenced by new information and random walk pattern [2]. There are two types of analysis that impact the decisions in the stock market, which are Fundamental Analysis and Technical Analysis [3]. The historical stock prices are used in Technical Analysis to return the decisions. In contrast, Fundamental Analysis utilizes the information about the companies to gain valuable understandings [3]. However, using historical price itself is not sufficient to predict the stock movement. Recently, fundamental analysis has been taken into consideration for this type of problem. For instance, StockNet is proposed by [4], which is a deep generative model. It achieves significant results and proves as one of the exciting approaches to predict the stock market. Current research works show that the features and information from both Fundamental and Technical Analysis are necessary to generate the stock prediction. However, to the best of our knowledge, there has not been any research considering the representation of time. In this paper, we tackle another perspective of the problem, which is learning the time representation and using it as a feature. We adopted Time2Vec [5] as a method to learn the representation of time. To simplify our research and show the effectiveness of this step, we only consider the technical analysis or historical prices as our feature.

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The remainder of the paper is constructed as follows: Section II describes related work. Section III describes the problem setup. Methodology and Results are depicted in Sections IV and V, respectively. The last section is the conclusion of the paper.

II. Related Work

Many research projects have been conducted to address this area from theoretical approach to modern approach. For example, Modern Portfolio Theory and Black-Scholes are proposed as a theoretical method to this type of problem [6], [7]. Principal component analysis (PCA), which is one of the optimization techniques, was adopted in stock prediction [8]. With the emergence of Artificial Intelligence or Machine Learning, these techniques are implemented to address stock market prediction. Zhang et al. [9] use autoregressive integrated moving average model (ARIMA) to predict stock. Random forests and LSTM are utilized to forecast stock price for intraday trading [10]. Additionally, an attention mechanism is attached to the LSTM network to predict the stock is conducted by [11] and achieved promising results for Technical Analysis techniques. To forecast the stock market index, a hybrid neural network is proposed by [12], using a convolutional neural network-integrated with a bidirectional long short-term memory.

Fundamental Analysis has also been adapted, such as new articles analysis using RF, SVM, and Naive Bayes [13] then using this information to classify the articles into positive or negative. Another recent work is StockNet and Man-SF proposed by [4], [14] is to analyze Twitter information and historical prices simultaneously to return decisions. These methods have achieved potential accuracy for our problem.

All of the mentioned techniques have shown the importance of machine learning approaches to address the stock movement prediction problem. However, the representation of time is not included in consideration through these researches. Therefore, we try to implement Time2Vec [5] into our model to gain insights into this value. Although Recurrent Neural Networks indicate their effectiveness in modeling, these models do not consider time as a feature [5]. Therefore, Time2Vec is a technique to resolve this problem of various Recurrent Neural Networks. As mentioned in I, we consider only the technical information and adopt the StockNet dataset in [4] for our analysis.

III. Problem Setup

A. Problem Formulation

We formulate the problem similar to StockNet model in [4]. We consider the stock prices in the interval $[t - \Delta t, t]$ where Δt is the range of day we want to consider. The binary classification problem is proposed as:

$$y = \begin{cases} 1 & \text{if } (p_d^c > p_{d-1}^c) \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where d denotes trading day and p_d^c denotes the adjusted closing price, which is used to predict the stock movement. [4], [15]. However, there are days that are not eligible trading days. Thus, we implement trading day alignment suggested in to align information to T, where T is eligible trading days.

B. Dataset Setup

The StockNet dataset includes 88 stocks in 9 industries. We follow the setup proposed in the paper [4] where the time interval is from 01/01/2014 to 01/01/2016. To cut off movements with extreme low steps, the author introduces two numbers -0.5% and 0.55%, which serve as the lower and upper thresholds, respectively. Therefore, any movement above -0.5% and below 0.55% is removed. It returns 49.78% and 50.22% values in two classes of decreasing and increasing movements. The training set, validation set, and testing set are divided into 70:10:20 ratio from 01/01/2014 to 08/01/2015, from 08/01/2015 to 10/01/2015, and the rest in the time interval, respectively. The StockNet dataset comprises two main components, which are a historical price and Twitter information. However, since the paper targets the Technical Analysis, we only inherited the historical price dataset retrieved from Yahoo Finance [1].

TABLE I
Price Feature Vector Value

Technical Analysis	
Features	Description
p_d^o	The opening price
p_d^c	The closing price
p_d^h	The highest price

IV. Methodology

A. Price Encoder

1) Sequential Encoder: The price information contributes significantly to the stock movements. Thus, encoding useful features from price data is necessary to make accurate predictions. We have experienced different types of layers such as Long Short Term Memory [16] and Gated Recurrent Unit (GRU) [17]. However, through some experiments, we see that GRU performs better than LSTM in our problem. Therefore, we adopt GRU as our sequential encoder for the architecture. Apart from implementing GRU to gain features from sequential correlation among days, we adapt the attention mechanism into our architecture to learn the weights of days and representations of features indicated in [4], [14].

The GRU function is represented as:

$$s_t = GRU(p_d, s_{d-1})$$

where, p_d is the price vector on trading day d. s_t is the hidden state retrieved through the layer on trading day d. Moreover, the price feature vectors are normalized as:

$$p_d^n = \frac{p_d}{p_{d-1}^{\text{adj-c}}}$$

where p_d^n is the normalized value, p_d is the price vector and $p_{d-1}^{\text{adj-c}}$ is the adjusted closing price.

The step of temporal attention, which is a form of additive attention [14], [18] is presented as:

$$W_i = \sum_{t=1}^{t+\Delta t} \alpha_{ij} h_t$$

$$\alpha_{ij} = \frac{\exp(f(s_{i-1}, h_j))}{\sum_{k=1}^{\Delta t} \exp(f(s_{i-1}, h_k))}$$

where W_i depicts the attention weight, f is the attention function.

2) Time2Vec: According to [5], RNN models ignore time as a feature. Instead, they treat the inputs to the model separately. Time2Vec is the learnable vector representation of time with some benefits, such as being invariant to time rescaling. Moreover, it may capture periodic behavior [5]. Therefore, it can resolve the problem of RNN models.

The technique of Time2Vec is proposed in [5] as:

$$tv_i(t) = \begin{cases} \omega_i t + \phi_i & \text{if } i = 0 \\ \alpha(\omega_i t + \phi_i) & \text{if } 1 \le i \le k \end{cases}$$

$tv_i(t)$ is the ith element of $tv(t)$, The periodic function, frequency and phase-shift are denoted as α, ω and ϕ, respectively. The representation of time generated by Time2Vec is concatenated with the extracted price feature from Sequential Encoder.

The output from the price encoder is denoted f_s for stock s in Fig. 1.

B. Overall Architecture

The architecture considers the extracted features from the price encoder. Then, we implement a fully connected neural network (FCN) to classify the movement prediction into a binary value indicating the movement of stock price. The model is trained with Adam optimizer, and the cross-entropy loss function with y indicates the actual value:

$$L_{ce} = -(y \log(p) + (1 - y) \log(1 - p)) \tag{2}$$

The whole architecture is formulated in Fig. 2.

V. Results

To test the accuracy of our model, we compare our approach with other baseline models using only the historical dataset. The performance results is indicated in Table II.

- RAND: Random guess about the movement of stock

[1] https://finance.yahoo.com/industries

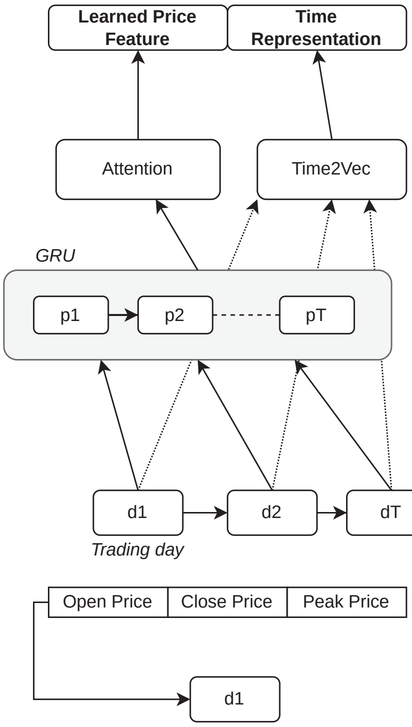

Fig. 1 Price Encoder

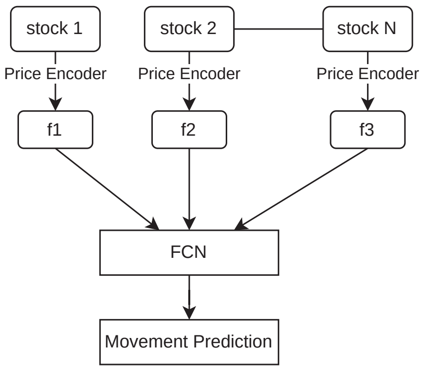

Fig. 2 TimeStock Architecture

- ARIMA: Autogressive Integrated Moving Average proposed in [19]
- StockNet-TECHNICALANALYST variation [4]: The StockNet model utilizes only historical prices

TABLE II
PERFORMANCE RESULTS

Baseline models	Accuracy
RAND	51
ARIMA [19]	51.4
StockNet-TECHNICALANALYST [4]	54.96
TimeStock	**56.4**

According to [20], when achieving the 56% of accuracy, it is a reasonable result for stock movement forecast. Moreover, with difficulties when predicting stocks, we can generate profits with light improvements. In our performance table, with the random guess, the accuracy gets around 51%. The ARIMA method returns a slightly higher accuracy of 51.4%, which is not a significant improvement and is below the 56% threshold of the promising result. On the other hand, a variation of StockNet, which is TECHNICALANALYST, with the accuracy of 54.96% is a potential result. However, without the fundamental analysis, the StockNet model's implementation can not reach the threshold of promising results for predicting stock movement. Through the table, we also show that our architecture achieved the best result among others in Technical Analysis. It shows another approach for stock movement prediction.

VI. Conclusion and Future Plan

Stock Movement Prediction is an exciting field to explore and address. With the importance of this area, we propose another way to stock market prediction. Although only considering the historical price dataset or Technical Analysis, the TimeStock model still achieved a significant result. This proves the effectiveness of the Time2Vec method for stock market prediction. It can capture time representation and enhance the features for the extracted price representation vectors. The future direction for this research is to consider the Fundamental Analysis approach. In addition, without considering each analysis separately, we aim to combine this information into a complete model, including the technical encoder (price encoder), the fundamental encoder (public information encoder), and the correlations between stock types (relationship encoder).

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