Journal of Soft Computing and Artificial Intelligence
JSCAI, 1(2): pp:78-85 (2020), www.dergipark.org.tr/en/pub/jscai
JSCAI
ISSN: 2717-8226
Received: September 22 2020 Accepted: October 9 2020

RGBSticks: A New Deep Learning Based Framework for Stock Market Analysis and Prediction

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ABSTRACT We present a novel intuitive graphical representation for daily stock prices, which we refer to as RGBSticks, a variation of classical candle sticks. This representation allows the usage of complex deep learning based techniques, such as deep convolutional auto encoders and deep convolutional generative adversarial networks to produce insightful visualizations for market's past and future states. We believe RGBStick representation has great potential to integrate human decision process and deep learning for stock market analysis and forecasting. The traders who are highly familiar with candlesticks are able to evaluate the results generated by deep learning algorithms by inspecting the varying color shades in a compact, instinctual and rapid fashion.

KEYWORDS: deep learning, forecasting, time series.

1. INTRODUCTION

Candlestick charts have been by far the most widespread way of visualizing the daily stock market and exchangeable currency, derivative or commodity values for a long time. According to many sources, they can be traced back to Japan's Meiji period in the 18th century, developed for rice trading. Some academics particularly credit it to Munehisa Homma, a prominent rice broker of the era [1, 2]. The very fact that they have been used uninterruptedly and unchanged throughout the history of modern trading hints us about the effectiveness of the method. Even with today's complex cutting edge digital infrastructure and automated trading algorithms; they are still among the most valuable elements of a broker's toolbox; and this is likely to last for years. Possibly, it's effectiveness comes from its simplicity, where the overall image of many consecutive days (or any other intended time period) can abstract many hidden and latent factors of market dynamics inside a broker's mind. The human brain's preference for visual data to rapidly process complex tasks subconsciously is a well-studied phenomenon [3, 4].

Based on this observation, we propose to process the candlestick charts as an image, in contrast to many deep learning and data science based stock price analysis and forecasting techniques, which approaches the issue as raw tabular or temporal feature extraction [5-8].

The proposed method's advantage appears to be twofold. Firstly, it may allow the deep learning algorithms to capture the complex patterns that raw data processing cannot provide; an insight stemming from the success of candlesticks that drove human traders to make correct decisions in a highly chaotic environment throughout three centuries. Second, as the results provided by the deep learning methods are also candlestick like presentations; the human traders can gain insights on the past and the future market and conclude with interpretable artificial intelligence support.

After we have come up with the idea, firstly we have reviewed the literature to check whether a similar approach was followed before. To the best of our knowledge, [9] is the only one to mention the encoding of stock price movements as candlestick images, however it still does not propose a pure visual representation like the method explained in this paper. The authors use Gramian Angular Fields to encode the stock market time series and apply deep Convolutional Neural Networks (CNN).

Candlestick approach is highly straightforward: The value of the traded entity (currency, commodity, contract etc.) in a time period (a day, a business week, 5 minutes etc.) are represented with four values. *Open* and *Close* are the first and last are the prices at the beginning and end of the period, respectively. *High* and *Low* values correspond to the highest and the lowest ever price in the particular period of interest. If the close value is lower than the open value, it is considered as a *bearish* period and the inner candle of the candlestick is colored red. The inverse case corresponds to a *bullish* period and is represented with a green candle. A large gap between high and low indicates a high volatility in that particular period.

In this paper, we present *RGBSticks*, a novel framework to transform candlestick market prices to a structure, where it is still both readable for human agents and also in the form which benefits the deep learning methods. The name comes from the encoding of open, close, low and high prices on red, green and blue channels of a digital image. After explaining this visual representation, we analyze the daily stock price of a company by using a dense deep neural network based auto encoder. By using the same architecture the next day is tried to be predicted. Finally, a Deep Convolutional Generative Adversarial Network (DC-GAN) architecture is applied to simulate artificial market periods.

2. RGBSticks

An RGBStick is visually almost identical to a conventional candlestick as it can be seen Fig. 1, with the exception that the outer sticks have the same width with the inner candle and are encoded in blue channel. This allows the deep learning based computer vision algorithms to process and output human readable three dimensional (width, height indices and 3 channel color) images. Thanks to this representation, we can proliferate the performance of deep learning algorithms which use this kind of input shape, forcing the synaptic and convolutional weights to be tuned to plausible and distinctive ranges by assigning the information to highest values of a single channel.

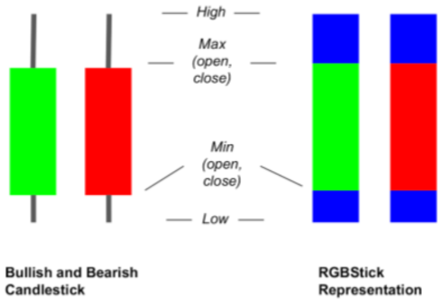

Figure 1. A traditional candlestick representation and an RGBStick representation for a bullish and bearish period.

A candlestick transforms the open, close, low, high values into 5 semantic visual features : high, low, maximum and minimum of the open and close price and whether the close value was higher than the open or not, where the last is represented with red or green color.

Temporal deep Learning algorithms, whether they process images (e.g. video frame prediction) or not require the supervision of the sequential data in to a tabular structure, where the lagged instances are grouped together. This procedure is sometimes referred to as time series supervision or lagged/sliding window feature generation. The maximum length of each lagging window is called the *look back* parameter, that being also the expression used in this paper. Similarly, the output data point length is referred to as look after, the number of instances in future we want to predict. In this paper, look back and look after values are determined as 16 and 1, meaning we want our machine learning algorithms to forecast the next day based on previous 16 days. So, each input data point in our system is a square image, as in Fig. 2.. And the output data point is a rectangular image representing a day. For each 16 days, we first calculate the maximum and minimum of all 4 indicators. Without loss of generality, we assume that the values of the next day will not be larger than the 10% of the maximum and smaller than 10% of the minimum value of the previous 16 days. Thanks to this defined global maximum and minimum, we can normalize and place RGBSticks in the vertical axis for a specific time block. In case, for the relatively rarer cases where the next day is out of these ranges its values are clipped. The image size of 64x64 pixels is determined for this paper, thus the width and height of a single RGBStick is normalized according to.

As you can see, the candlesticks are placed on a total black image plane, where all the 3 channel values have 0 intensity. As the information on being bullish or bearish and the volatility (the outer limits of a RGBStick) are encoded as the highest intensity of all independent 3 channels; this permits the machine learning algorithms to capture and exploit the most important features of the data by enforcing optimization process to iterate through the extrema.

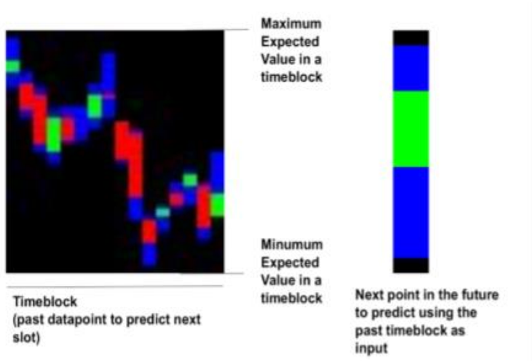

Figure 2. A time block of look back long days from the whole stock price data.

This corresponds to a single data point of the input batches both for training and testing segments. The output data point is similarly the following look after long block, which is assigned as the output. A look back value of 16 is determined for this work. For forecasting task, we have defined the look after value as one, which means that we want our deep learning model to predict the next day by evaluating the previous 16 days. In case of auto encoding and adversarial networks the output data point is the same with the input.

3. Deep Neural Network Forecasting of Future Market

Based on the explained framework, as a first attempt, we have built a regular dense deep neural network to predict the next days based on the previous 16 days. An hourglass shaped, auto encoder like architecture is preferred to reduce dimensionality on latent feature space to mitigate the highly volatile nature of stock market data. The details of the used neural network can be inspected in Fig. 3. We present the results of our work for a single company's daily stock market prices for a calendar year. The first 90% of the days are used as training, whilst the remaining last days of the years are evaluated for testing purposes. As it can be seen from the figures, our RGBStick backed deep learning framework not only provides accurate results, it also permits the human trader to develop a market strategy by evaluating the results based on the color shades, similar to traditional candlestick charts, where he/she already is familiar.

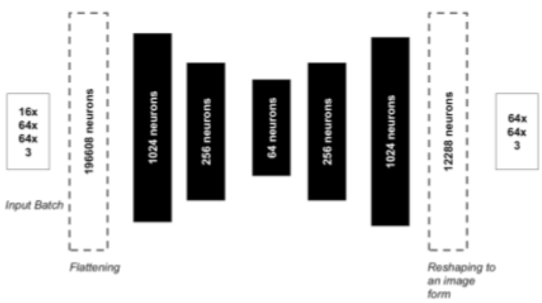

Figure 3. The hourglass shaped deep dense neural network used for predicting the next days' RGBsticks based on previous 16 days. The relu layers are used in all layers, except the last layer, where logistic regression probability is preferred for matching the output.

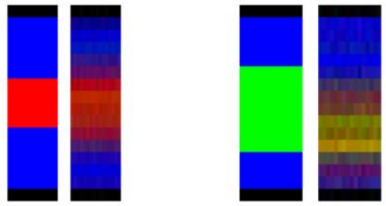

Figure 4. Real RGBStick and the predicted one with our dense deep neural network for a bearish and bullish day in the test dataset.

As it can be noted, the algorithm performs quite efficiently to predict the tendency and volatility. A human interpreter can have an insight on the volatility and the tendency of the forecast by evaluating the difference hue variations. Intensity of the blue on the outer edges signal the limits and confidence of the volatility. Similarly, stronger reddish or greenish hue give an idea on the upper and lower limits of close and open values. For instance yellowish hue would mean the mixture of green and blue; where open/close values are close to each other for a bullish day. In contrast, violet hue pixels can be interpreted for the same effect for a bearish day. Brownish pixels can be interpreted as the confidence on bearish/bullish decision is lower as mixture of red and green.

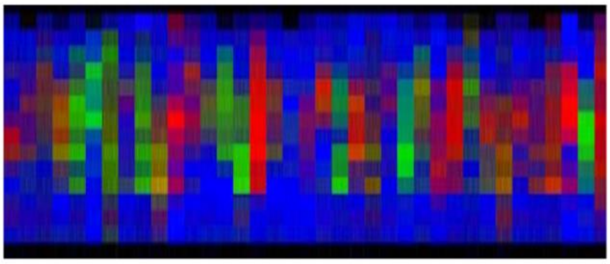

Figure 5. The predicted RGBSticks days of the test part.

This kind of concatenated view permits the human trader to evaluate the forecasts and the short to mid term tendency in the market in a global fashion with the parameters such as confidence, volatility and extrema are encoded in color shades.

4. Deep Autoencoders for Understanding Dynamics of Market

We have used the above mentioned architecture as a deep autoencoder, with the intentions to extract information out of the history of the stock prices. As the architecture was chosen primarily as an hourglass structure it suits well to the concept. As it is known, autoencoders takes the same input and output data points to be trained, thus they are classified as self-supervised. The data is projected in to a lower dimensional latent feature space, which is called as the bottleneck for extracting the most valuable information, eliminating the noisy parts.

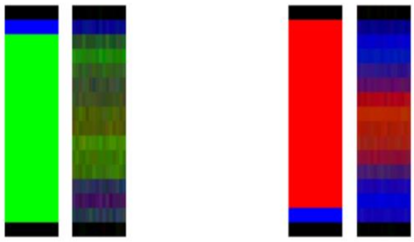

Figure 6. The days in the past of the stock prices with real and the predicted RGBSticks using deep auto encoder. The auto encoder allows us to interpret that on these specific two days open/close values would actually meant to be more closer to each other based on the overall dynamics of the environment.

5. Market Analysis and Simulation with Deep Convolutional Generative Adversarial Networks

Generative Adversarial Networks (GAN) are relatively new architectures in deep learning research, being started to be developed a few years ago [10-12]. They are one of the most innovative breakthroughs in artificial intelligence. With these state-of-the-art models we are now capable of generating highly sophisticated artificial data, such as deep fakes or artificial human faces or transfer styles between batches of images. The central idea is to have two separate neural networks connected to each other called a generative network and a discriminator network. In the case for convolutional networks for images, the generator network takes randomized inputs for its latent space and maps it to the images of the intended size through deconvolution layers. As for the variational auto encoders, GAN also learns the distribution via latent space rather than the direct processing of input data. The discriminator's task is to be fed with real training input images and the artificial outputs of the generative network, and classify it as a real one or fake one. Throughout training, generative network learns gradually to produce more real like artificial outputs, whilst discriminative network gets better to discriminate the fake ones. Thanks to this adversarial concept, at the end we are able to produce realistic fake images. Even though it is an adversarial setting, the nature is cooperative, where at the end generator network is able to generate realistic fake images. The DC-GAN architecture is highly efficient when you consider the fact that the latent vector is fed with random inputs. Adversarial setting and deep convolutional and dense layers is capable of being trained in short time to produce plausible results [12].

We have trained a deep convolutional generative adversarial network with the daily stock prices represented as RGBStick images. The details of the used architecture can be seen in Fig. 7. We provide 32 arbitrary real RGBStick time blocks of the stock price history of the company and 24 fake time blocks generated by the DC-GAN architecture in Fig. 8. Note the fact that, the deep generator has grasped the sharp upside and downside trends and high volatility in the data.

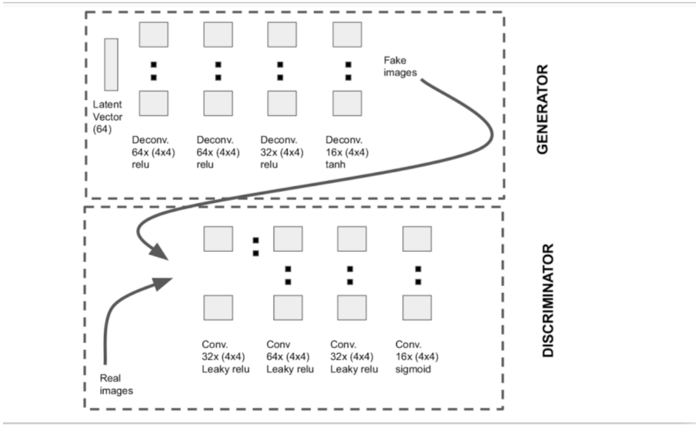

Figure 7. DC-GAN architecture used to train our RGBStick representations of stock market which allows us to simulate the dynamics of the market but also understand its underlying complex statistical structure by inspecting the variations of different random numbers on the latent vector of the generator.

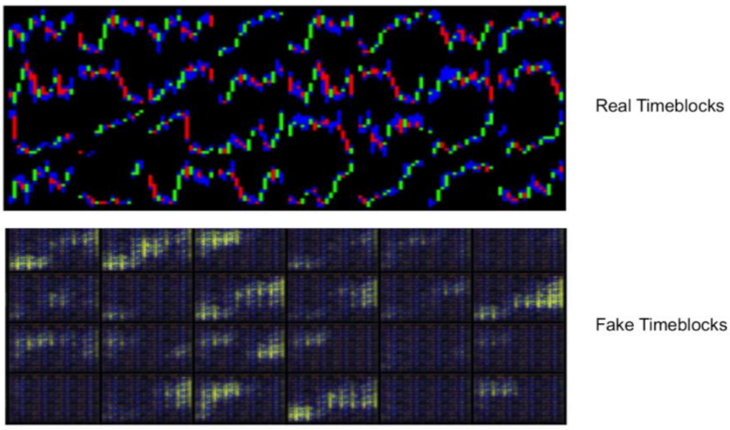

Figure 8. 32 arbitrary real RGBStick time blocks of the stock price history of the company and 24 fake time blocks generated by the DC-GAN architecture.

6. CONCLUSION

Candlestick charts has been used extensively for a long time for the analysis of trading markets. The success of this kind of a chart comes from its effective visual abstraction for human traders, who can have a wide angle view of the history. This has encouraged us to theorize that there might be a powerful latent information encoded visually. Thus, we propose to represent open, close, high and low prices as candlestick like graphical representation, which we refer as RGBSticks. The outer sticks defining the difference between the high and low values, i.e. the limits of the volatility in the time period is encoded as full intensity in the blue channel (thus, zero intensity in the other 2 color channels). The bearish and bullish inner candles are represented as full intensity in the green and red channels. This encoding of important information on the extrema of color channels helps deep learning algorithms to reach more optimal weights for intended tasks. We have tested a dense neural network to predict the RGBStick of the next day based on previous 16 days. The same architecture is used also to evaluate the history of the stock prices by auto encoding. Finally, a DC-GAN architecture is applied to simulate and understand the stock prices of a company.

We believe RGBStick representation has great potential to integrate human decision process and deep learning for stock market analysis and forecasting. The traders who are highly familiar with candlesticks are able to evaluate the results generated by deep learning algorithms by inspecting the varying color shades in a compact, instinctual and rapid fashion.

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