UDC 330,3

Economics, Computer Science

Gagik VARDANYAN
Doctor of Sciences (Economics), Professor
Independent Expert
E-mail: gagik.v@yahoo.com,

Mher VARDANYAN
Master of Science in Computer & Information Science,
American University of Armenia
E-mail: mher.vardanyan.g@gmail.com

REFORMULATION OF AN EMPIRICAL INVESTMENT RULE IN TERMS OF ADVANCED ANALITICS AND ITS MODEL SELECTION

Գ. Վարդանյան, Մ. Վարդանյան

ԷՄՊԻՐԻԿ ՆԵՐԴՐՈՒՄԱՅԻՆ ԿԱՆՈՆԻ ՎԵՐԱՁԵՎԱԿԵՐՊՈՒՄՆ ԱՌԱՋԱԴԵՄ ՎԵՐԼՈՒԾԱԿԱՆ ԳՈՐԾԻՔՆԵՐԻ ԱՌՈՒՄՈՎ ԵՎ ԴՐԱ ՄՈԴԵԼԻ ԸՆՏՐՈՒԹՅՈՒՆԸ

Ներդրումներ կատարելու մասին գործնական խորհուրդներ և կանոններ պարունակող հայտնի գրքում՝ «Ցյուրիխյան աքսիոմներ»-ում, հեղինակը՝ Մաքս Գյունտերը նախանշում է ներդրումների կատարման երկու սկզբունք, որոնք սովորաբար շեշտադրվում են հայտնի ներդրողների կողմից: Հոդվածում փորձ է արվել ձևակերպել այդ սկզբունքները կարճատև և երկարատև միտումների բացահայտման խնդրի շրջանակում և այդ խնդիրը հասցեագրել առաջադեմ վերլուծական գործիքների կիրառմամբ: Հետազոտության ընթացքում մեզ հաջողվել է ուրվագծել բաժնետոմսերի կանխատեսման խնդրին անդրադառնալու նախկին փորձերը, ինչպես նաև վերլուծել մեր հետազոտության խնդրին առնչվող կոնկրետ մոտեցման առավելությունները և թերությունները: Մենք հանգել ենք այն եզրակացությանը, որ, օգտագործելով multi-kernel learning մոտեցումը, կարող ենք պատշաճ ձևով հասցեագրել հետազոտության հարցը, ինչպես նաև նմանատիպ արդյունքների կարելի է հասնել՝ օգտագործելով միայն տեխնիկական վերլուծության մոտեցումը LSTM մոդելի կիրառմամբ: Հետագա հետազոտության ընթացքում մենք

կշարունակենք մեր բացահայտումները՝ փորձարկելով և ավարտին հասցնելով սույն հոդվածում սկսված քննությունը:
Բանալի բառեր՝ Ցյուրիխյան աքսիոմներ, վերլուծական ֆինանսներ, արժեթղթերի շուկայի կանխատեսում, մեքենայական ուսուցում, խորը ուսուցում

Г. Варданян, М. Варданян

РЕФОРМУЛИРОВКА ПРАВИЛ ЭМПИРИЧЕСКОГО ИНВЕСТИРОВАНИЯ В УСЛОВИЯХ РАСШИРЕННОЙ АНАЛИТИКИ И ВЫБОРА ЕГО МОДЕЛИ

В популярной книге практических советов по инвестированию «Аксиомы Цюриха» авторвы деляет два принципа инвестирования, которые обычно подчеркиваются известными инвесторами. В этой статье мы попытались сформулировать эти принципы в виде задачи обнаружения краткосрочных и долгосрочных трендов и попытались решить эту проблему с помощью передовых аналитических инструментов. В ходе исследования мы смогли обрисовать предыдущие попытки решения проблемы прогнозирования акций, а также проанализировать плюсы и минусы конкретного подхода с точки зрения решения нашей исследовательской проблемы. Мы пришли к выводу, что с помощью многоядерного подхода к обучению мы можем решить сформулированный исследовательский вопрос, мы также указали, что аналогичные результаты могут быть достигнуты с помощью технического анализа только с учетом модели глубокого обучения LSTM. В будущих исследованиях мы продолжим проверку наших результатов и завершим обсуждение, начатое в этой статье.
Ключевые слова: Цюрихские аксиомы, LSTM, аналитические финансы, прогнозирование фондового рынка, многоядерное обучение.

In a popular book on practical investment tips “The Zurich Axioms”, the author outlines two principles of investment that are commonly underlined by famous investors. In this paper we tried to formulate those principles into a short-range and long-range trend detection problem and tried to address that problem using advanced analytical tools. Throughout the research we were able to outline the previous attempts of addressing the issue of stock predictions as well as to analyze the pros and cons of a specific approach in terms of addressing our research problem.We have concluded that using a multi-kernel learning approach we can address the formulated research question, we also pointed out that similar results can be achieved by using technical analysis only with LSTM deep learning model in mind. In the future research we will go on with testing our findings and will finish the discussion started in this paper.
Key words: Zurich Axioms, LSTM, analytical finance, stock market prediction, multi-kernel learning

Introduction

There is a popular book on the topic of investment called "The Zurich Axioms" by Max Gunther. The author discusses various strategies and general principles to follow for those who want to be successful investors just like, in his opinion, the Swiss. One of those principles or "axioms" is "always take your profit soon" (Max Gunther, 1985). More specifically, he points out the tendency of "what goes up must go down" and so, waiting for a rising stock to rise higher and higher, when one considers selling it, or waiting for a plunging stock to go lower and lower, when one considers buying it - is risky with every moment that the investor waits. This principle is then followed by a corollary principle where the author suggests deciding in advance what gain the investor wants to get from the investment [15]. The author suggests not wait until it is too late, although we must point out that the book was meant for the general public, so it is not at all technical by any means. That said, it is also crucial to underline the fact that those principles were backed by real world experience and the relevant history of investment decision making of the Swiss. Thus, the question really stands: can we quantify this "axiom"? And, most importantly, how far we can get, in terms of accuracy and efficiency, with the existing advanced analytical models? Also, we shall take under consideration the corollary principle, which is more directed towards interpretability and/or long-term trend detection than prediction accuracy for a short-term decision.Now we can formulate the topic of our research in a more cohesive and rigorous manner:

"*Finding the right time of selling a rising stock using advanced analytics*".

Let's notice that we have mentioned only the rising stock above, but that does not mean that those same principles will not apply for the opposite case. The reason we chose this formulation is that it conveys the meaning and the idea behind research topic to a large extent.

Generally speaking, stock market prediction has been a central topic of research for several decades. Time-series-analysis, various statistical measures have been at the core in providing investors with relevant descriptive and inferential summaries for the future trends of the market or specific stocks' performance. Advanced analytical tools such as Machine Learning algorithms, big data models, artificial neural networks etc. started to be used for financial data analysis as soon as they proved themselves worthwhile in other fields. Even the lately popularized advanced analytical models, such as deep neural networks, have been tried in the field with impressive results (Kumar et al., 2011). The tools have been getting better and better, and the levels of accuracy for the trend started to increase, for some models, for specific datasets passing 73% (Dixon et al., 2015). That said, as we have already mentioned above, we will not only be interested in accuracy but also in satisfying the corollary principle be that with a separate or integrated long-term trend detection or increased interpretability.

After a thorough literature review on the subject, we shall find the right approach for researching the topic from the three existing ones:

1) Financial data analysis (or technical analysis),
2) Investor sentiment analysis,
3) A mixture/hybrid analysis which includes the first two.

The challenges that we will face here would be involving the interpretability of the chosen models, the ability to generalize from the used models, the accuracy and efficiency of the models etc.

Depending on which approach(es) we choose, there are different advanced data analytic models to choose from. Several distinguishable models are discussed later. Most of them involve using Deep Learning methods which will be discussed in detail. Nevertheless, there is a gap for every approach, especially for the most promising one: the hybrid analysis. These gaps refer mostly to the interpretability and the ability to generalize the existing models for varying populations and samples. More specifically, it is not clear how different social and cultural dynamics are going to be dealt with in the sentiment analysis approach. The problem worsens as we try to combine the advantages of the first and the second approaches to form the third one, where the interpretability of the second approach turns into a significant impediment.

The justification of pursuing more efficient investing

Financial markets have become more efficient than ever. The transaction costs are drastically lowered due to the Internet-based financial services (Graham, 2006). This resulted in a more efficient market, as more capital can freely roam the fabric of the globalized financial world. Without a doubt, a more efficient market, in equal circumstances, has a potential of providing faster growth and development of economies worldwide. This will reduce poverty and other social issues and will make the world more prosperous. Thus, following this logic, we believe that lower risk factors for investors worldwide, will bring more efficiency to the financial system. What we mean by this is that when an investor has a functioning approach of dealing with the uncertainty of the market, as limited that approach might be, they will be keener to invest. Thus, some portion of the investment risk will be lowered, leading towards a more prosperous and developed world. The extent of the impact is not the subject of this research, although one thing is crystal clear from the above-described logic: the impact exists.

In addition, an analysis done with financial data, which is believed to be non-stationary, non-linear and noisy within the time series (Dixon, et al., 2017), will certainly have useful applications outside the financial world, as the type of data described above is not exclusive to the financial data.

The commonly accepted fact with regards to predictions of stock markets, is that financial markets are, in fact, unpredictable (Graham, 2006). Thus, we will state our hypothesis in the following manner:

Hypothesis 0: It is impossible to formulate a rule to determine the right time of selling a rising stock using advanced analytics with statistically significant accuracy, while satisfying corollary principle.

Hypothesis 1: It is possible to formulate a rule to determine the right time of selling a rising stock using advanced analytics with statistically significant accuracy, while satisfying the corollary principle.

Stock market prediction using advanced analytics

Since the advent of advanced analytical tools researchers and investors wanted to test those tools on predicting the financial markets. Financial markets were at the center of attention for a couple of main reasons. Firstly, having a better toolset for efficient and accurate predictions of financial markets, investment institutions and individuals interested in investing their money could have cut down on the risks they usually take. Secondly, the availability of data for analysis is very appealing. Useful statistical data on prices, earnings and dividends go back to 1871 [9].

As we have discussed above,financial assets can generally be divided into two parts: risky and risk-free. Usually, the investment portfolio consists of a specific weighted combination between non-risk assets, e.g., government bonds and risky assets, e.g., company stocks [10]. What we are looking for is not a good strategy for forming an investment portfolio, as that topic is very well discussed and analyzed within the disciplines of corporate finance and, more specifically, portfolio theory. The aim of this study is to understand which advanced analytical models and strategies have been used, so far, to predict the given asset's price on the market, within the confines of the research topic. *The accuracy as well as the extent at which the corollary principle is addressedare going to be the evaluation criteria for us.*

To understand the challenges of analyzing stock market data or doing a sentiment analysis based on public sentiment we have to underline the fact that financial data is believed to be non-stationary, non-linear and noisy within the time series [7]. Thus, making an accurate and efficient prediction will likely involve non-linear-capableapproaches such as Artificial Neural Networks (ANN). These models became popular mostly because they surpass conventional Machine Learning models' accuracy when sufficient dataand computational power is available [11]. In our case, as we stated above the data sufficiency is not a problem, and with the constantly increasing computational power the ANN models seem to be the perfect tools to predict stock market data.

Furthermore, it is important to distinguish the three main strategies aimed at predicting the stock market prices. Firstly, the stock market analysis done by analyzing the historical prices using linear and/or non-linear models (we can call this "the financial data analysis approach")[1]. The second one revolves around conducting a sentiment analysis for predicting stock prices via understanding the public perception with regards to those stocks (we can call this the "sentiment analysis approach"). The third strategy can be identified as a mixture or a hybrid between the first two strategies (we can call this "the hybrid analysis approach"), which promises to bring a multi-aspect analysis of stock prices, while making use of the conventional analysis and the "wisdom of the crowds" gained through sentiment analysis [6].

The financial data analysis approach

There are several strategies to consider under financial data analysis approach. Firstly, as Shen et al. noticed the globalization and connectivity among different financial markets allows us to assume that the trends noticeable in e.g., Tokyo Stock Exchange can be present in NASDAQ stock exchange in New York. Which means, that due to time-zone differences we can predict the behavior of a particular asset or assets in a certain financial market by analyzing data taken from another market [8]. Other approaches might include using large data sets and relying mostly on a careful feature selection for the analysis.

From a large array of possible models to use for analyzing financial data most common ones are support-vector machines (SVM), back propagation trained networks (BTN), artificial neural networks (ANN), class sensitive neural networks (CSNN) etc. In terms of

[1]*In some papers this type of approach is called "technical analysis" (Shangkun Deng et al, 2011).*

short-term trend prediction CSNN proved to be the best model [1]. That said, let's understand which model choice is the best for our task.

In recent years deep neural networks have been popularized and many analysts believe that DNN models are becoming the models of choice for financial data analysis. The most appealing part about DNN is that they demonstrate robustness against over fitting. Dixon et al. implemented a DNN for financial data analysis and reached a classification accuracy of 73% [3]. To understand better why this model is so accurate we can have a look at the diagram 1. Here we can see a feed-forward neural network where inputs are processed before entering to a next layer. The depth of the layers and the functions used to map the input for the next layer are at the core of this concept.

We also must underline the fact that feed-forward deep learning algorithms are not believed to be the best choice for time-series data. Moreover, Maknickiene et al. concluded in their study that for tackling recursive non-linearity of financial data Recurrent Neural Networks (RNN) are the best choice [2]. Thus, RNN are believed to be the state-of-the-art models for conducting financial data analysis with prediction as the main objective.

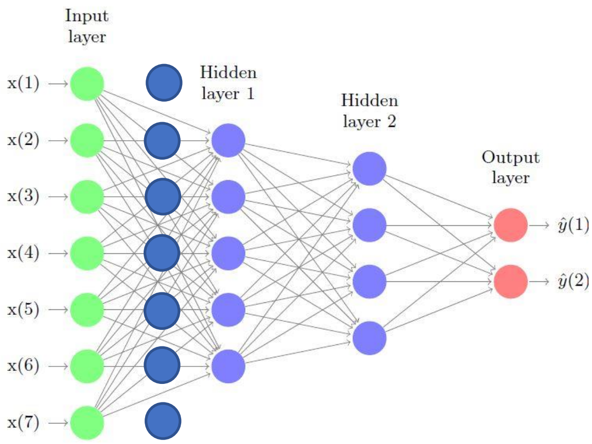

Diagram 1: Multi-layer feed-forward neural network [3].

With regards to the choice of a specific RNN model there is a phenomenon that needs to be addressed. RNNs generally utilize what's called a "short-term memory". Which is created in their internal state and is dynamically updated as the neural net goes from layer to layer.The issue here is that by using standard back propagation or real-time recurrent learning the gradient values (essentially weights gained by dynamically updating the short-term memory) will either vanish or "blow-up". So, what happens is that, e.g. in the case of a feed-forward net, while advancing to the next layer, the weights of the initial layers start to vanish. With back propagation, correspondingly, as we move back layer by layer the weights start to add up and eventually "blow up" in value yielding inefficient results. To address this issue S. Hochreiter and J. Schmidhuber suggested a more complex memory cell structure which will use gate units for getting rid of excess information and not letting go useful information throughout the layers of the network [14]. The essential structure of the memory cell can be seen in the diagram 2.

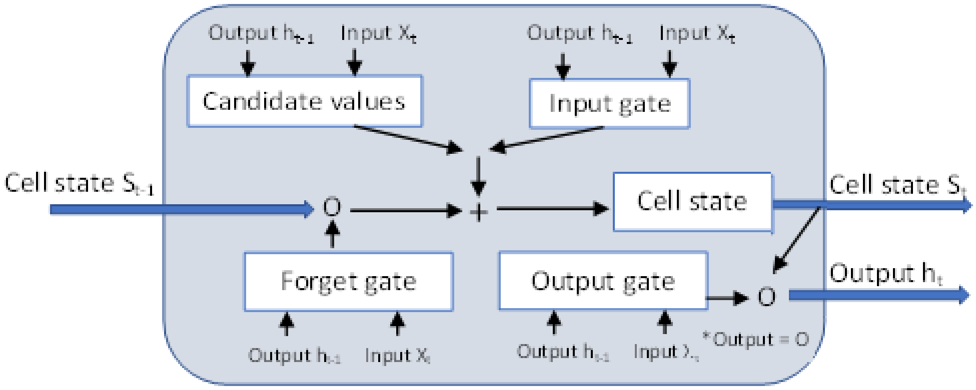

Diagram 2: The generalstructure of an LSTM memory cell [14].

Here we can see a high-level depiction of how the three gates: forget, input, output control the long-term trend maintenance by filtering the data with weights for the subsequent steps. So, firstly the data is passed to the forget state, where it gets a weight ranging from 0 to 1 (getting 1 will mean that it will not "forget" or diminish anything before it). Then it is processed through the input gate, after which it is transferred to the output gate to be processed in the next memory cell. By comparing this approach, specifically for financial analysis, T. Fischer, and C. Krauss found out that it outperformed benchmark models: random forest, deep net, and logistic regression, in most cases.

Thus, this approach proves to be efficient in conducting time-series analysis, music detection and other sequential data related tasks, and, more specifically, provides the functionality for addressing our research problem.

The limitations of the financial data analysis approach

We can assume that choosing an RNN model and using it wisely we can reach high accuracy and efficiency. When it comes to choosing the right quantity of epochs, the number of neurons and groups of parameters, we can rely on existing literature and in empirical results. With regards to interpretability, we can safely say that any neural network approach is generally regarded as a black-box-approach. However, if we address the corollary principle in terms of assessing the long-term performance of a given stock, an LSTM network would be the best model of choice among technical analysis approaches, as we will not require an interpretability criterion to be present anymore. That said, all models that derive conclusions from technical data suffer, to some extent, from the presumption of efficient markets, though the LSTM model does a great job at mitigating the adverse effects of that presumption [13].

The sentiment analysis approach

Sentiment analysis approach for predicting stock prices has generated significant interest based on some key processes that happened during the recent decade. Various online services allowed public to invest in companies with relatively small transaction costs. One of the most influential factors in this sense is the investors' reactions to the news disclosures [4], which can spread countrywide and even worldwide via social networks throughout the world.

There are different models that can be used for this purpose, including the combination of regression, classification models and lexicon-based sentiment analysis [6]. A remarkable result was achieved by Guo et al., when their model achieved 97.87% prediction accuracy for the upward trend of the stock market. An overall accuracy of 59.15% was reached by Chiong et al., with the use of Kraus and Feuerriegel's deep learning model.

The limitations of sentiment analysis approach

As we mentioned above, different accuracy figures can be noticed when we deal with upward trend vs downward trend. Which is a very interesting phenomenon to consider the limitations of this approach. You see, there are numerous factors that can affect the sentiment of an investor. Ranging from psychological, cultural, geographical etc. Moreover, the lingo-cultural differences from market to market should not be underestimated. This means that making generalizations from the sentiment analyses of investors is very challenging, if not impossible, on a global scale, across different markets. However, none of the studies reviewed addressed this problem adequately.

The hybrid analysis approach

Wang et al., proposed an interesting and promising approach of combining financial data analysis and investor sentiment analysis to predict stock prices [5]. The model they used was a two-stage multi-kernal SVR model. For all classifiers the hybrid solution had higher accuracy than the sentiment analysis by itself. Although this framework has been discussed by others, including the usage of Multiple Kernel Learning (MLK) [12], there was no emphasis put on using hybrid approach to create an interpretable, yet accurate, model. A model that will compromise financial data models within the hybrid approach to increase the interpretability while not losing accuracy with the usage of sentiment analysis. This approach will capitalize on the idea that deriving valuable inference from sentiment analysis is not that straightforward. As mentioned in the limitations of the sentiment analysis approach, any model working in this domain will not be interpretable to the extent at which the less accurate financial-data-driven models will be. Also, as we have said before this approach works best with deep learning models, which have multiple layers of neurons and are highly not interpretable.

The limitations of the hybrid analysis approach

Intuitively this approach seems to be the most promising one. On the other hand, if we take a closer look, the main two disadvantages can be spotted: finding the relevant data for different models and formulating the right model to form a more generalized approach. The problem is that although we have centuries worth of financial data, the availability of data for the sentiment analysis approach is far scarcer. This would not be a problem for specific usage of the sentiment approach for solving specific problems with regards to prediction. On the other hand, when it comes to the moment of combining the sentiment approach and the financial data approach, we might not be able to find adequate data for maximum synergy effect. Also, it is not clear which combination of various sentiment-analysis-related data should be taken for combining it with the technical analysis.

Conclusions and Areas for Future Research

We started with two, simple, industry proven, though not academically formulated principles to invest in stocks. The essential idea was that while it is important to know, guess or probabilistically evaluate when a rising stock is going to fall, it is likewise important to make sure that the long-term understanding or knowledge of the stock's performance is taken under consideration by the investor. This in mind, we formulated our research problems, accordingly,giving importance to the short-range accuracy and long-range interpretability/integration of long-range trends in our research for a capable advanced analytical model to address the research problem. We were able to point out that the sentiment analysis combined with a highly interpretable technical analysis model within a Multi Kernel setting is a perfect choice for us. Also, we realized that an LSTM model could help solve our problems with combining short-term and long-term trends within a single model. We choose to go on with the LSTM neural network model for reasons mentioned above. Thus, our following research will conclude this discussion with testing an LSTM implementation for a specific group of indexes.

References

1. Chen, C.H., 1994, June. Neural networks for financial prediction. In *Proceedings of 1994 IEEE International Con on Neural Networks (ICNN'94)* (Vol. 2, pp. 1199-1202). IEI
2. Maknickienė, N., Rutkauskas, A.V. and Maknickas, A. Investigation of financial market prediction by recurrent network. *Innovative Technologies for Science, Busines Education*, *2*(11), pp.3-8.
3. Dixon, M., Klabjan, D. and Bang, J.H., 2015, Nov Implementing deep neural networks for financial market pre on the Intel Xeon Phi. In *Proceedings of the 8th Workshop o Performance Computational Finance* (pp. 1-6).
4. Chiong, R., Fan, Z., Hu, Z., Adam, M.T., Lutz, Neumann, D., 2018, July. A sentiment analysis-based m learning approach for financial market prediction via disclosures. In *Proceedings of the Genetic and Evolu Computation Conference Companion* (pp. 278-279).
5. Wang, Q., Xu, W. and Zheng, H., 2018. Combini wisdom of crowds and technical analysis for financial prediction using deep random su ensembles. *Neurocomputing*, *299*, pp.51-61.
6. Guo, X. and Li, J., 2019, October. A Novel Twitter Ser Analysis Model with Baseline Correlation for Financial Prediction with Improved Efficiency. In *2019 Sixth Intern Conference on Social Networks Analysis, Managemer Security (SNAMS)* (pp. 472-477). IEEE.
7. Dixon, M., Klabjan, D. and Bang, J.H., 2017. Classifi based financial markets prediction using deep networks. *Algorithmic Finance*, *6*(3-4), pp.67-77.
8. Shen, S., Jiang, H. and Zhang, T., 2012. Stock forecasting using machine learning algorithms. *Departm Electrical Engineering, Stanford University, Stanford, CA*, p
9. Graham, B., 2006. *The intelligent investor*. Revised with new commentary by J. Zweig. Harper Business, pp.23,

10. Jonathan, B., Peter M DeMarzo, 2017. Corporate f
Fourth Global Edition. Pearson.
11. Aggarwal, C.C., 2018. *Neural networks and deep le*
Springer International Publishing AG.
12. Deng, S., Mitsubuchi, T., Shioda, K., Shimada, T. and S
A., 2011, December. Combining technical analysis with se
analysis for stock price prediction. In *2011 IEEE
international conference on dependable, autonomic and
computing* (pp. 800-807). IEEE.
13. Fischer, T. and Krauss, C., 2018. Deep learning wi
short-term memory networks for financial
predictions. *European Journal of Operational Research*,
pp.654-669.
14. Hochreiter, S. and Schmidhuber, J., 1997. Long sho
memory. *Neural computation*, *9*(8), pp.1735-1780.
15. Gunther, M., 1985. *The Zurich Axioms*. Unwin
Paperbacks, pp. 22-35.

Հոդվածը տպագրության է երաշխավորել խմբագրական խորհրդի անդամ, տ.գ.դ. Թ.Ն.Մանասերյանը։