Implementation of Robo-Advisors Using Neural Networks for Different Risk Attitude Investment Decisions

Oleksandr Snihovyi
Department of Computer Science
Kherson State University
Kherson, Ukraine
snegovoy@hotmail.com

Oleksyi Ivanov
Department of Computer Science
Kherson State University
Kherson, Ukraine
sink2385@gmail.com

Vitaliy Kobets
Department of Computer Science
Kherson State University
Kherson, Ukraine
vkobets@kse.org.ua

***Abstract*—This paper is a sequel to our previous works related to Robo-advisors and cryptocurrencies. Our goal now is to build two application modules for a single Robo-advisor. The first module is a Long short-term memory (LSTM) neural network which forecasts cryptocurrencies prices daily. The second module uses Robo-advising approach to build an investment plan for novice cryptocurrencies investors with different risk attitude investment decisions. The third module does ETL (Extract-Transform-Load) for a statistics dataset and neural networks models. Results of the investigation show that investing in cryptocurrencies can give 23.7% per year for risk-averse, 31.8% per year for risk-seeking investors and 16.5% annually for risk-neutral investors**.

Keywords—robo-advisor, Markowitz model, financial instruments, neural networks, machine learning.

I. Introduction

Robo-advisor is a favorite tool for novice investors which builds an investment plan and calibrate it from time to time based on a current market state. Robo-advisors are digital platforms consisting of interactive and intelligent user assistance components [1]. Investment goals of a client, risk preferences are quantified by algorithms using automated processes. Robo Advisor differs from existing online investment platforms with two issues: customer assessment (online questionnaires) and customer portfolio management (which includes several financial instruments that require no active decision concerning portfolio management like Exchange Traded Funds) [2]. This combination of financial instruments and algorithms can considerably reduce management cost through full automation.

Generally, it allows investing in stocks, bonds, ETFs and mutual funds. However, now there is one additional way to invest money – cryptocurrencies. They had become famous from the beginning of 2017 when most of the cryptocurrencies were created, and their prices started increasing. Most of the people think that investments in cryptocurrencies are too risky because of hype, for example, Bitcoin (the most popular cryptocurrency) has raised more than $19,000 only to fall sharply within minutes at the end of 2017. Currently, a price of Bitcoin for USD is much less than it was (according to Coindesk.com the price of Bicoin on September 6, 2018 is $6,402.69). Those people who have invested their money in this cryptocurrency in the middle of 2017 still have profit, but not as much as they could have. Most novice cryptocurrencies investors do not know to which coin they should invest and how much. It leads to losing money in a long-run period.

The **purpose** of the paper is to investigate the architecture of a regular robo-advisor and how they work with cryptocurrencies to help novice investors to invest without fear of losing money. The **goal** is to use robo-advising approach through a minimum viable product (MPV) for cryptocurrencies trading composed of three modules: the first will be responsible for prices forecasting via LSTM neural network; the second will build an investment plan based on forecasted data from the first module; the third will parse and manage models for the first module.

The paper is organized as follows: part two describes related works, part three describes application modules for our Robo-Advisor, part four describes the results of the investigation after experiment, and the last part concludes.

II. Related Works

A. Robo-advisors

The first cryptocurrency was born in 2008. In the same year, the first robo-advisors were launched. Both of them were invented to develop and improve the financial industry. Cryptocurrencies can be used to prevent fraud [3], de-corrupt charities [4], and many other things. Robo-advisors help to automate investment portfolio rebalancing, wealth management and get rid of brokers and human financial advisors. Also, they are great for risk-averse investors who do not want to invest much money in the beginning, by offering a minimum investment sum. Some of them do not have the minimum investment sum at all.

V. Kobets, V. Yatsenko, A. Mazur and M. Zubrii have analyzed robo-advisors to find their strengths, weaknesses, opportunities, and threats [5]. As the result of their research robo-advisors have more strengths and opportunities than weaknesses and threats. The primary challenge for robo-advisors now is a necessity of face-to-face interaction with advisors for users, especially for novice investors and robo-advisors inability to follow up with questions and make recommendations based on the answers.

978-1-5386-7097-2/18/$31.00 ©2018 IEEE

T. D. Cocca in his research [6] says that currently, robo-advisors can manage only low-complexity financial decisions. From our side in previous research, we defined the basic functionality for a regular robo-advisor and described its general high-level architecture [7]. We defined couple modules there, but the most important are: Investment plan module, Calculations module, and Parser module. These three modules are major. The most crucial job belongs to them: Parser module gets and updates data regularly, which is vital for keeping users investment plans up to date; Calculations module predict prices based on up to date data; Investment plan module uses data from Calculations module to rebuild users investment plans daily.

M.L. Fein studied robo-advisors in 2015 [8] and described that they offer advice based on responses to specific questions, portfolio rebalancing or reallocating of investments, what primarily represents the main functionality of such tools.

Based on studied works we have found out that separating on modules as we did in our previous research will help robo-advisors to do their job better in term of performance. So, we used our previous approach here in the section number three.

B. *Cryptocurrencies*

We studied criteria which affect prices of cryptocurrencies [9] and found out that combination of supply, mining difficulty, trading volume, and news reaction for each date, can predict more than 70% of the price (we used Bitcoin for research).

R.C. Philips and D. Gorse studied how to predict cryptocurrency prices bubbles using epidemic modeling and human reaction on social media [10].

Also, S. Colianni, S. Rosales, and M. Signorotti investigated cryptocurrencies algorithmic trading techniques based on Twitter sentiments analysis [11]. C. Lamon, E. Nielsen, and E. Redondo studied cryptocurrency price changes based on news and Reddit sentiments [12]. Kim YB et al in 2016 did significant research about how users activities in communities affect prices of cryptocurrencies [13].

All researches we have mentioned above show that users activities affect prices. However, we applied a different approach in this research. Our idea was to predict cryptocurrencies prices based on their daily trading volume. The results are in the section number four.

III. Modules of a Robo-Advisor

We used our previous architecture approach with small modifications:

- To make things look clear, we have merged Parser module and Clean Up module in ETL (Extract-Transform-Load) because this is what it does, Parsed Data on Dataset & Models and User Data to Investment Plans;
- We have connected Investment Plan modules with Investment Plans storage.

The reason is that we want to keep the high-level design simple and as high-level as possible. We also understand that each particular implementation will separate these modules on more, because of a specific set of features, specific infrastructure, and other things. Also, the current architecture does not have a security module, and the reason for this is that we decided to move it from the application level to the infrastructure level. It provides simplified architecture and connection between services in general.

On the following Fig. 1 high-level architecture is described.

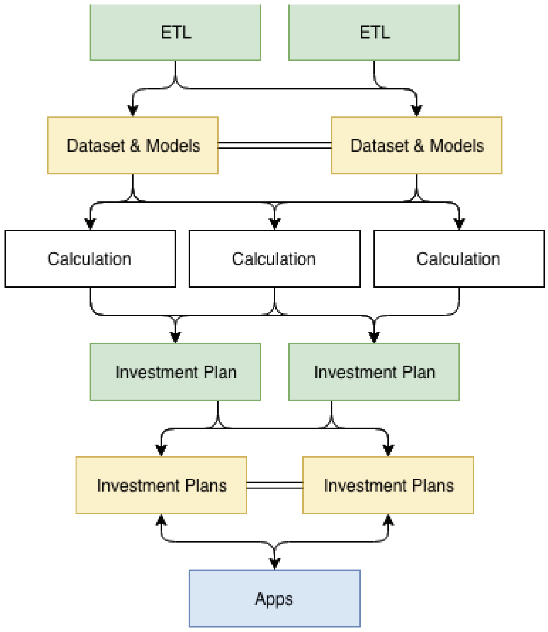

Fig. 1. High-level MVP architecture.

Some of the modules are replicated databases modules and CRUD (Create-Read-Update-Delete) APIs (yellow color blocks), some are running by schedule (green color blocks), some do computations (while color blocks), and some are apps (blue color block).

ETL here is a parser which grabs cryptocurrencies statistics from open sources and saves it to the database called Dataset & Modules in the Fig. 1. Also, it analyzes which cryptocurrencies are “dead” using services such as DeadCoins and CryptoCompare and removes them from the database. We have found that CryptoCompare provides API for all the statistics we need (has data from more than 90 exchanges and does updates regularly). Our goal was to get data for each day from the beginning of trading for each live cryptocurrency. We managed to get data for more than 500 live cryptocurrencies at all using the next algorithm for ETL services:

1. Get the list of coins;
2. Walk through all coins:
    a. If the coin appears as “dead”, then remove it from the database if exists and go the next coin;
    b. If a coin is not in the database, get statistics for the maximum period, otherwise for the last day;
3. Save all the values to the database;
4. If there is no LSTM model in the database for this coin, then create one for trading volume and one for a price depending on trading volume, otherwise get these models and continue training with the newest data;

5. Save these models to the database;
6. Shutdown till the next run.

There are many coins, so by default it is good to provide the most common for portfolio such as Bitcoin (BTC), Litecoin (LTC), Etherium (ETH), BitcoinCash (BCH) and others. Those which have more than a billion USD market capitalization because they are trusted.

Calculation modules forecast price of selected cryptocurrency for few days related to the US Dollar based on forecasted volume. It is required for choosing the most diverse and sustainable options for the investment portfolio rebalancing. Generally, these modules use LSTM neural network (because it is well-known, suitable for financial predictions neural network) developed with Keras (high-level neural networks API developed on top of TensorFlow). The algorithm has several steps:

1. Trading Volume forecasting:
   a. Get a trading volume LSTM model from Dataset & Models for the selected cryptocurrency;
   b. Predict for some days;
   c. Go to the last step if fails;
   d. Save the result for the price prediction temporary;
2. Price forecasting:
   a. Get a price LSTM model from Dataset & Models for the selected cryptocurrency;
   b. Predict for some days using previously predicted trading volume;
   c. Go to the last step if fails;
   d. Return predicted price;
3. Finish.

For the testing purpose we got BTC dataset [14] and predicted values for both trading volume and price from June 24th, 2018 to June 30th, 2018.

Results of forecasting are on the Fig. 2 and Fig. 3 below:

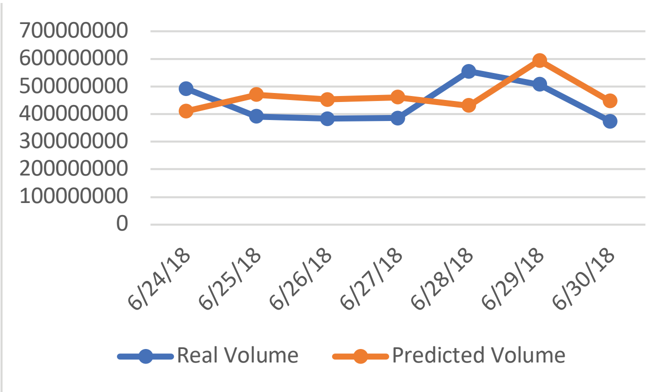

Fig. 2. BTC trading volume chart[15].

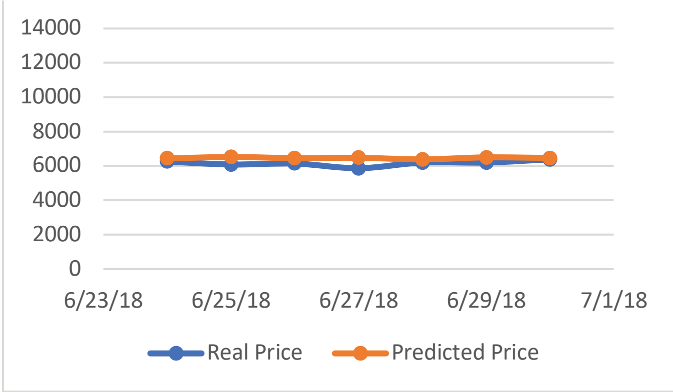

Fig. 3. BTC prices chart[16].

Investment Plan services use Markowitz model described by equation bellow (1), to build the investment portfolio for risk-averse, risk-seeking and risk-neutral investors based on forecasted prices via Calculation services:

$$E(R_p) = \sum_i w_i E(R_i) \quad (1)$$

Where R_p is a return of the portfolio, R_i is a return on asset and w_i is the weighting of a component asset i [6]. The algorithm and experiment for the Investment Plan services are described in the following part.

IV. Experiment

For experiment [17, 18, 19], we have selected five popular cryptocurrencies and settle over them three times: for risk-averse, risk-seeking and risk-neutral investors. The primary goal of RA is to support investors by converting their specific requirements into an adequate portfolio of financial instruments without human intervention. We used active and passive robo-advisor because our investment strategy and portfolio construction are not fixed (dynamic approach), and only RA decides about the actual execution of investment (rebalancing) process (passive approach).

We can describe, on the followng Fig. 4, robo-advisory process as sequence of following steps: configuration (proposals for different ration average income-risk), matching (correspondence between type of client and type of proposal) and maintenance (algorithm of execution for chosen investment proposal).

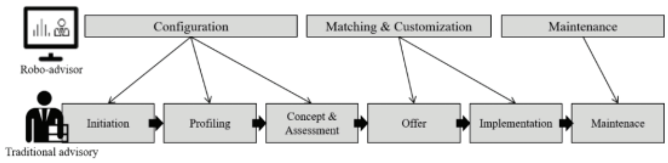

Fig. 4. Discrete robo-advisory process[1].

We have chosen the following cryptocurrencies:

- BTC;
- ETH;

- LTC;
- NEO;
- BCH.

Also, we have chosen days for which data is available for all of the cryptocurrencies. This is a date range from August 2017 to June 2018 including the last week of June 2018 which were forecasted using Calculation module in the previous section.

Our steps were next:

- Calculate a percentage change of an exchange rate for each day;
- For each chosen cryptocurrency:
  - Calculate the average diurnal variation (average d_i).

After performing the steps above, we got the following values: for BTC it was 0.003403692319; for ETH it was 0.003610395455; for LTC it was 0.004613528809, for NEO it was 0.007199503207, and for BCH it was 0.008653971527.

Then we calculated a covariance matrix for the selected cryptocurrencies for the risk-averse investor in the Table 1.

TABLE I. THE COVARIANCE MATRIX FOR THE RISK-AVERSE INVESTOR

	BTC	*ETH*	*LTC*	*NEO*	*BCH*
BTC	0,002877727	0,00206006	0,0025224	0,0023779	0,00188176
ETH	0,002060057	0,00358836	0,0035501	0,0034209	0,0029448
LTC	0,002522413	0,0035501	0,0062318	0,0031385	0,00304327
NEO	0,002377913	0,00342086	0,0031385	0,0102438	0,00350223
BCH	0,001881761	0,0029448	0,0030433	0,0035022	0,01061673
X'	29%	0%	7%	25%	39%
$X'V$	0,00233852	0,00284791	0,0031334	0,0048325	0,00578812

We also made calculations for the risk-seeking and risk-neutral (hybrid) investors and the following results described in the Table 2 and the Table 3 bellow.

TABLE II. THE COVARIANCE MATRIX FOR THE RISK-SEEKING INVESTOR

	BTC	*ETH*	*LTC*	*NEO*	*BCH*
BTC	0,002877727	0,00206006	0,0025224	0,0023779	0,00188176
ETH	0,002060057	0,00358836	0,0035501	0,0034209	0,0029448
LTC	0,002522413	0,0035501	0,0062318	0,0031385	0,00304327
NEO	0,002377913	0,00342086	0,0031385	0,0102438	0,00350223
BCH	0,001881761	0,0029448	0,0030433	0,0035022	0,01061673
X'	0%	0%	0%	0%	100%
$X'V$	0,001881761	0,0029448	0,0030433	0,0035022	0,01061673

TABLE III. THE COVARIANCE MATRIX FOR HYBRID TYPE OF INVESTOR

	BTC	*ETH*	*LTC*	*NEO*	*BCH*
BTC	0,002877727	0,00206006	0,0025224	0,0023779	0,00188176
ETH	0,002060057	0,00358836	0,0035501	0,0034209	0,0029448
LTC	0,002522413	0,0035501	0,0062318	0,0031385	0,00304327
NEO	0,002377913	0,00342086	0,0031385	0,0102438	0,00350223
BCH	0,001881761	0,0029448	0,0030433	0,0035022	0,01061673
X'	47%	24%	9%	9%	12%
$X'V$	0,002490112	0,002783817	0,003227083	0,00350813	0,003407631

In the end we calculated daily yield for each cryptocurrency using (2):

$$Y = d_i * X'V \tag{2}$$

We got the following results for the risk-averse investor: for BTC it was 0.001033391, for ETH it was 0, for LTC it was 0.00033303 for NEO it was 0.0018735, and for BCH it was: 0.00347921.

For the risk-seeking investor results were next: for BTC, EHT, LTC, and NEO it was 0, but for BCH it was 0.00865397.

For the hybrid type of investor results were following: for BTC, EHT, LTC, and NEO were correspondingly 0.001583487, 0.00085866, 0.0004303, 0.0006218, 0.00101527. For hybrid type of investor both risk level and profitability is lower than for 2 previous types of investors.

Thus profitability of the risk-averse investor is 0.67% daily or 24.5% annually with 0.44% risk.

For the risk-seeking investor, the yield will be higher – 0.87% daily or 31.6% annually with 1.06% risk.

For hybrid type of investor the yield will be 0.45% daily or 16.5% annually with 0.28% risk.

If we divide data on a monthly basis, we get the following schedule of optimal investments in financial instruments on the Fig. 5 bellow.

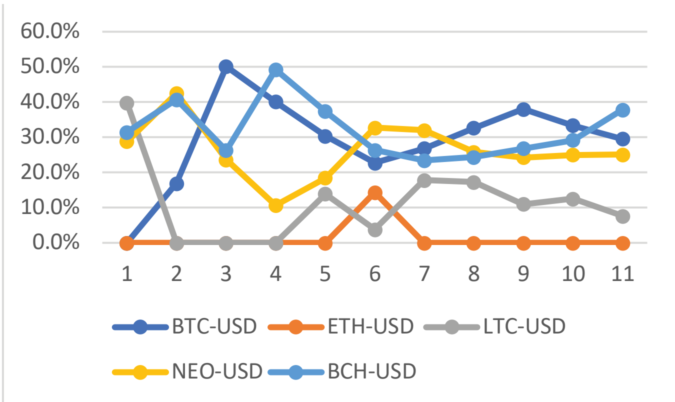

Fig. 5. Dynamic of optimal invextments in financial instruments.

In the ETH it is better not to invest at all, it is better to invest in BTC on the level of 30%. NEO and BCH are promising financial instruments for investing at a level of 25-30% each.

V. Conclusions

So, we have developed MVP of a cryptocurrencies robo-advisor with Investment plan, Calculations and ETL modules. ETL module used data from CryptoCompare and DeadCoins to continue LSTM models training and clean database from scam, Calculation module did forecasts for trading volume and for price for each cryptocurrency. Investment plan module built investment plans using Markowitz model for risk-averse, risk-seeking and risk-neutral investors.

As the result we have got 5 cryptocurrencies and found out that if the user is risk-averse they should invest into 4 of them to gain 23.7% annually with 0.44% risk. If the user is risk-seeking they should invest into 1 of them to gain 31.7% annually with 1.06% risk. Finally if the user is risk-neutral they should invest into all of the five to gain 16.5% annually with 0.28% risk.

On this base, we plan to improve general robo-advisor architecture to the real-market product and to study cryptocurrencies and robo-advisors more and how they can be combined together.

References

[1] Maedche, A., Morana, S., Schacht, S., Werth, D., Krumeich, J. 2016 Advanced User Assistance Systems. Business and Information Systems Engineering 58(5). pp. 367-370.

[2] Jung, D., Dorrner, V., Glaser, F., Morana, S. 2018. Catchword Robo-Advisory – Digitalization and Automation of Financial Advisory, Business and Information Systems Engineering, BISE, p.p. 1-8.

[3] N. Firth, Want to make your vote really count? Stick a blockchain on it. September 6, 2017., https://www.newscientist.com/article/mg23531424-500-bitcoin-tech-to-put-political-power-in-the-hands-of-voters/, last visited: June 30, 2018.

[4] D. Galeon, C. Reedy, Blockchain Is Helping Us Feed the World's Hungriest Families, March 21, 2017, https://futurism.com/blockchain-is-helping-us-feed-the-worlds-hungriest-families/, last visited: June 30, 2018.

[5] Kobets, V., Yatsenko, V., Mazur, A., Zubrii, M. Data analysis of private investment decision making using tools of Robo-advisers in long-run period Proceedings of the 14th International Conference on ICT in Education, Research and Industrial Applications. Integration, Harmonization and Knowledge Transfer, Kyiv, Ukraine, May 14-17, 2018, Vol.2104, 144-159 pp.

[6] Cocca, Teodoro, 2016. Potential and Limitations of Virtual Advice in Wealth Management, Journal of Financial Transformation, Capco Institute, vol. 44, pages 45-57.

[7] Ivanon, O., Snihovyi, O., Kobets V. Implementation of Robo-Advisors Tools for Different Risk Attitude Invesment Decisions, Proceedings of the 14th International Conference on ICT in Education, Research and Industrial Applications. Integration, Harmonization and Knowledge Transfer, Kyiv, Ukraine, May 14-17 2018, Vol.2104, 195-206 pp.

[8] Fein, Melanie L., Robo-Advisors: A Closer Look (June 30, 2015). http://dx.doi.org/10.2139/ssrn.2658701, last visited: June 30, 2018.

[9] Ivanov O., Snihovyi O., Kobets V., Cryptocurrencies Prices Forecasting With Anaconda Tool Using Machine Learning Techniques, Proceedings of the 14th International Conference on ICT in Education, Research and Industrial Applications. Integration, Harmonization and Knowledge Transfer, Kyiv, Ukraine, May 14-17 2018, Vol.2105, 453-456 pp.

[10] R. C. Phillips and D. Gorse, Predicting cryptocurrency price bubbles using social media data and epidemic modelling, *2017 IEEE Symposium Series on Computational Intelligence (SSCI)*, Honolulu, HI, 2017, pp. 1-7.

[11] Colianni, Stuart, Stephanie M. Rosales and Michael Signorotti. Algorithmic Trading of Cryptocurrency Based on Twitter Sentiment Analysis. (2015).

[12] Lamon, Connor, Eric Nielsen and Eric Redondo. Cryptocurrency Price Prediction Using News and Social Media Sentiment. (2017).

[13] Kim YB, Kim JG, Kim W, Im JH, Kim TH, Kang SJ, et al. (2016) Predicting Fluctuations in Cryptocurrency Transactions Based on User Comments and Replies. PLoS ONE 11(8): e0161197. https://doi.org/10.1371/journal.pone.0161197.

[14] Bitcoin's dataset used for forecasting, https://www.dropbox.com/s/dswj09nn3wc2crb/bitcoin_dataset.csv?dl=0, last accessed: June 30, 2018.

[15] Bitcoin's dataset used for comaprison real trading volume and forecasted, https://www.dropbox.com/s/e1fgz8oyuo1bfq4/bitcoin_trading_volume_predicted_dataset.csv?dl=0, last accessed: June 30, 2018.

[16] Bitcoin's dataset used for comparison real price and forecasted, https://www.dropbox.com/s/qzikltpfaud63mb/bitcoin_price_predicted_dataset.csv?dl=0, last accessed: June 30, 2018.

[17] Markowitz model Python implementation, https://gist.github.com/alekseysink/fca420a5e4e60bb010fbb1d21f628bf, last accessed: July 1, 2018.

[18] Kobets, V., Poltoratskiy, M.: Using an Evolutionary Algorithm to Improve Investment Strategies for Industries in an Economic System (2016), CEUR Workshop Proceedings, vol. 1614, P. 485-501 (Indexed by: Sci Verse Scopus, DBLP, Google Scholar). Available: CEUR-WS.org/Vol-1614/ICTERI-2016-CEUR-WS-Volume.pdf

[19] Kobets, V., Yatsenko, V., Poltoratskiy, M.: Dynamic Model of Double Electronic Vickrey Auction (2015), CEUR Workshop Proceedings, vol. 1356, P. 236-251 (Indexed by: Sci Verse Scopus, DBLP, Google Scholar). Available: CEUR-WS.org/Vol-1356