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3 authors:

Oleksii Ivanov
Kherson State University

Oleksandr Snihovyi
Kherson State University

Vitaliy Kobets
Kherson State University

Implementation of Robo-Advisors Tools for Different Risk Attitude Investment Decisions

Oleksii Ivanov[1], Oleksandr Snihovyi[1], and Vitaliy Kobets[1][0000-0002-4386-4103]

[1] Kherson State University, 27, 40 Universitetska st. Kherson, 73000, Ukraine
sink2385@gmail.com, snegovoy@hotmail.com, vkobets@kse.org.ua

Abstract. We researched: how to use Machine Learning in the financial industry on an example of Robo-Advisors; defined the basic functionality of Robo-Advisor; an implementation of Robo-Advisors based on analysis of the most popular financial services such as Betterment, FutureAdvisor, Motif Investing, Schwab Intelligent and Wealthfront. We compared their functionality, formulated a list of critical features and described the high-level architecture design of a general robo-advisor tool. Using Markowitz model we prepared a proof of concept of a robo-advisor application for investors with different attitudes to risks. Results of our investigation proposed data processing automatization from open sources of cryptocurrencies as the top trend nowadays.

Keywords: robo-advisor, Markowitz model, financial instruments.

1 Introduction

Intelligent data analysis is one of the areas of artificial intelligence, which solves the problem of learning automatic systems without their explicit programming, focuses on developing algorithms that are self-learning based on the proposed data [1].

Financial corporations that need to adapt quickly to the environment have realized that it is more efficient to develop self-learning systems that manually improve existing systems as needed. It saves the resources of the company and optimizes the process of developing a financial software product.

However, according to a Bloomberg survey in 2017 in New York, only 16% of firms have introduced Machine Learning into their investment strategies and software [2].

The **purpose** of this paper is to review the financial software that uses Machine Learning to consider the working principle and formulate the main functionality of the regular Robo Advisor as software for managing investment portfolios [2, 3], and to implement a proof of concept of the robo advising algorithm.

The paper has the following structure: it consists of 4 main parts. Part 2 examines the main ways of using data mining in the financial sector, especially in the concept of constant living income. Part 3 examines the functionality and capabilities of existing tools and formulates a list of main features. Part 4 includes experiment of robo-advisor application for investors with different attitudes to risks. The last part is the conclusion, which summed up the results of the research.

2 Machine Learning role in the financial industry

The ability of computer programs to learn and improve themselves has become a conventional technology continuously growing in all industries. Large companies like Google, Facebook, Amazon, use Machine Learning (ML) to improve performance, user experience, and data security. In the financial industry, the following areas were affected by ML [4]:

- Fraud Prevention;
- Risk Management;
- Customer Service;
- Virtual Assistant;
- Network Security;
- Algorithmic Trading;
- Investment Portfolio Management.

All of these areas combine such a process as forecasting. Also, they all carry a vast array of data that can be combined to create a detailed view [4]. It is the primary component of ML. Having an extensive multi-layered data where each layer affects others the goal is to find a pattern and to forecast the next values, or based on found values provide the most profitable solution. Also, it is not the only one advantage, because the ML's knowledge base always increases, the later forecasts will be much accurate than were in the beginning. Let's consider some examples of situations and possible scenarios of using ML in FinTech. For example, Virtual Assistant (VA) is an integral part of any high-quality product, especially financial software like online banking. VA can save bank's money and minimize the cost of real assistance. However, even it cannot resolve all issues and acts as the "first barrier" between the customer and the real assistant who participates in case of VA's impossibility to resolve the issue. So, what kind of issues the VA can solve? For example, instruction about how to open a deposit in a bank, help with closing an account, actual offers. The main "trump card" of the virtual assistant is not only easy access to all information in the bank, and it is personalization to the customer, but also training on customer's actions. In a case of regular money receipt to a customer's account and positive account balance after all withdrawals; well-trained VA can propose a profitable type of deposit. Also if the bank has an assignment in partnership with MasterCard (or any other company), VA may offer to all owners of MasterCard cards some unique bonus. However, if the customer regularly rejects the same bonuses in the past, VA can mark such customer as not a part of the target audience (but of course he can find all information about bonuses by himself). Another excellent example of using intelligent data analysis is algorithmic trading – a method of executing a large order using a programmed algorithm based on trading instructions. Usually, to succeed such software should have a big dataset with all values even those which affect the main one (for example, goods prices, the costs of raw materials, the costs for creating and sale) for an extended period. Having so much information to learn, the ML algorithm can forecast numbers, and traders will know either they need to buy or to sell or to wait.

However, constant living income (CLI) can be the most common usage of ML in the financial industry. It is a type of income that does not depend on daily activities. (e.g., investment, ownership or deposits). CLI combined all ML areas used in financial industry. ML can automate the process of getting CLI through offering new types of income, different forecasts, and metrics) and this process will be improved continuously.

3 Robo-Advisors as financial software

A good example of financial software for making passive income and managing a financial investment portfolio is Robo Advisor (RA). Now, this software is common, but until 2008, this term did not even exist [2, 3].

RA is a set of algorithms, which calibrates investment portfolio based on customer's goals and risks. The customer enters his goal, age, current income and financial assets. For example, 30 years old man with a salary of $120 000 per year has accumulated $100 000, and he wants to retire at the age of 50 with $10 000 000 savings. The system begins to offer the expansion of investment between classes of assets and financial instruments to achieve customer's goals. Also, it calibrates the expansion based on changes to the customer's goals and market changes in real time. So, Robo-Advisor always tries to find what is most closely related to the goals of the client [5, 6].

Unfortunately, RAs algorithms are unknown to the public because they are a commercial secret. However, there are few techniques what they can use [7].

Firstly, it can be Modern Portfolio Theory (MTP) as a theory of optimizing or maximizing expected return by risk-averse investors based on a given level of market risk. The algorithm of portfolio construction could use MTP if the customer is a risk-averse person [4]:

$$E(R_p) = \sum_i w_i E(R_i), \tag{1}$$

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 (that is the proportion of asset "i" in the portfolio).

Also, RAs can use Fisher equation to show the customer's real interest rate under inflation [8]:

$$i \approx r + \pi, \tag{2}$$

where r is the real interest rate, i is the nominal interest rate and π is the inflation rate.

However, the Black-Litterman model also can help to optimize the portfolio, and also can be used in RAs [3]. E. g. Betterment and Wealthfront use this model to predict the expected rates of return, but Schwab Intelligent uses completely different approach [9].

$$E[R] = [(r\Sigma)^{-1} + P^{\tau}\Omega^{-1}P^{-1}]^{-1}[(r\Sigma)^{-1}\Pi + P^{\tau}\Omega^{-1}Q], \quad (3)$$

where τ is a scaling factor, Σ is a yield covariance matrix of instrument ($N \times N$ matrix). P is the is the assets identifying matrix that is the subject of investor's forecasts ($K \times N$ matrix). Ω is a diagonal covariance matrix of standard forecast errors that is reflecting forecasts uncertainty ($K \times K$ matrix). Π is the expected equilibrium return vector ($N \times 1$ vector-column). Q is the forecast's vector ($K \times 1$ vector-column). K is investor's forecasts number and N is the assets number in the portfolio. Of course, there might be completely different formulas, especially because of using them with ML. There are many of RAs, but only 5 of them were chosen, as the most popular, to review and to define the main functionality. Bellow the comparison of some features is shown in the following table 1.

Table 1. Ras features comparison

Feature	Betterment	FutureAdvisor	Motif Investing	Schwab Inteligent	Wealthfront
The user can create own account.	+	+	+	+	+
Two-factor authentication	+ (sms only)	-	-	-	-
Portfolio rebalancing	+	+	-	+	+
Advice	+ (Human)	+ (Automated)	+ (Automated)	+ (Huma)	+ (Automated)
Customer Service	+	+	+	+	+
Mutual funds	+	+	-	-	+
Fees	Digital - 0.25%/year ; Premium – 0.40%/year	0.50%/year	$9.95/trade	0.28%; $900 quarterly cap	0.25%, but first $10,000 is free
Retirement Planning	+	+	+	+	+
Automated Investments	+	+	+	+	+

Betterment is the one of the oldest RA (dashboard screen is shown in the following fig.2). The company has developed reliable software to help novice investors. The user should set how much they plans to invest into ETFs (Exchange Trade Fund, the investment fund), and how much into ETFs bonds. There is no minimum deposit to open an account. One commission is charged in the range of 0.15% to 0.35% based on the balance of the account. RA has easy-to-use tools which help investors decide on the distribution of stocks, bonds and other financial instruments as cryptocurrencies [7, 10].

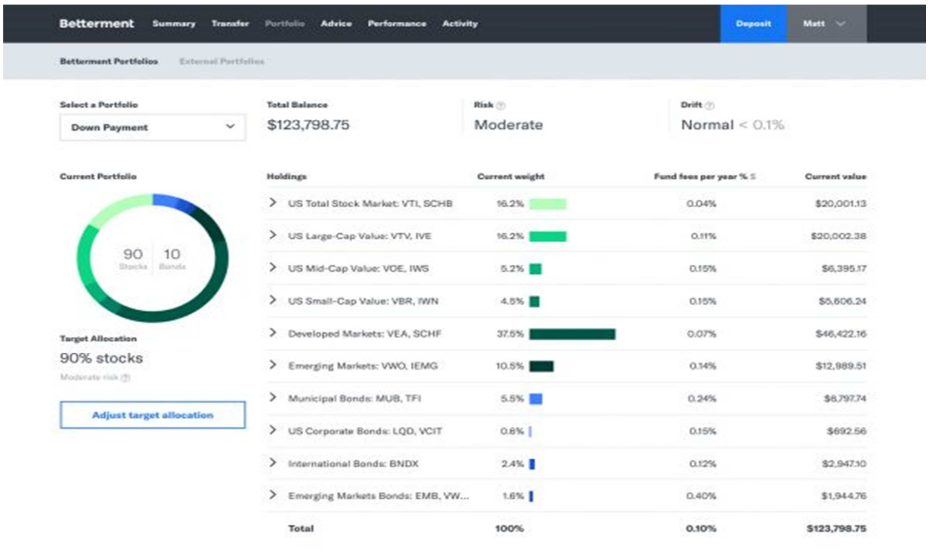

Fig. 1. Betterment dashboard screen [11].

FutureAdvisor (dashboard screen is shown in the following fig. 2) is the RA that works with Fidelity, an American holding company, one of the largest asset management companies in the world, and TD Ameritrade, an American company that set up an electronic trading platform. This RA offers a reliable investment evaluation tool. Users can associate existing investment account in the system for free. It assesses the investments feasibility based on productivity, diversification, commissions, and taxes. Also, this product may provide guidance on changing the investor’s assets distribution [12].

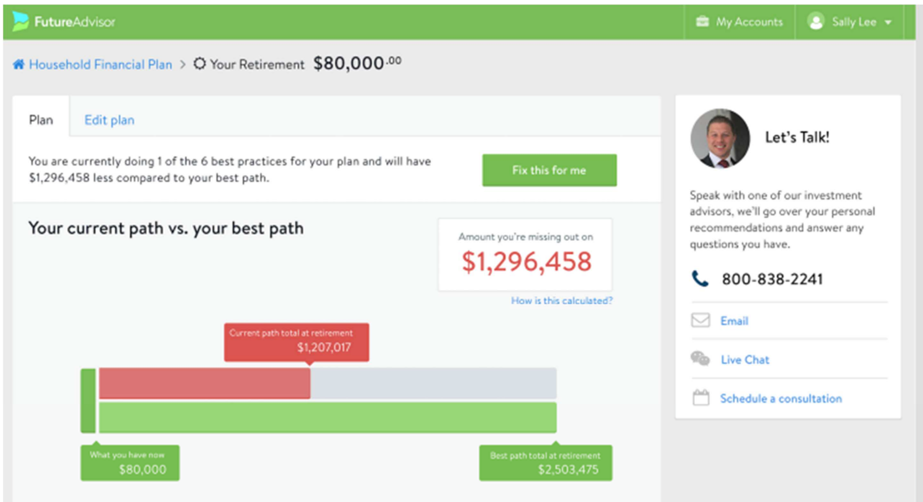

Fig. 2. FutureAdvisor dashboard screen [13].

Motif Investing is a product for active traders which allows users to create stock baskets and ETFs (dashboard screen is shown in the following fig. 3). After the creating, the user can buy up to 30 stocks of ETFs for $9.95. Investors can create their baskets; invest money in other ones which were created by the service itself or in those created by other users [14, 15].

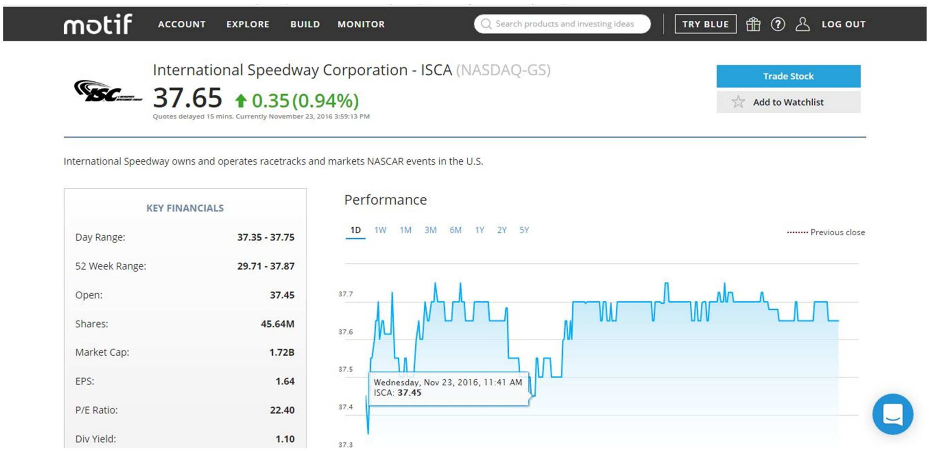

Fig. 3. Motif Investing dashboard screen [16].

Schwab Intelligent is one of the best RA according to NerdWallet's review [17] at the beginning of 2018. It offers advisory service with automated portfolio management and unlimited access to certified financial planners including personal financial guidance (dashboard screen is shown in the following fig. 4). However, generated portfolios have high allocation in cash (means a part of a customer's money remains not invested permanently) and investors must be comfortable with it.

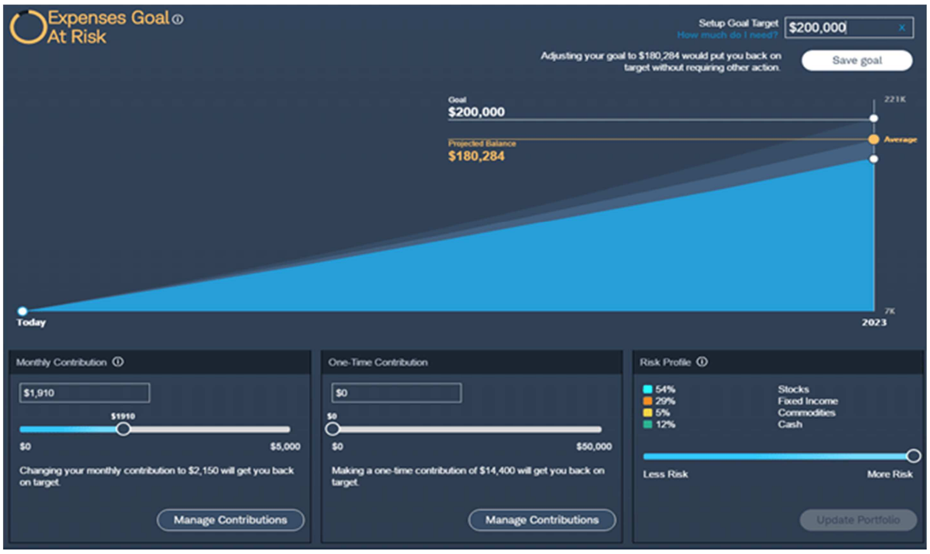

Fig. 4. Schwab Intelligent Portfolios dashboard [18].

Wealthfront (dashboard is shown in the following fig. 5) is a crucial force in the online advisor industry what offers one of the most robust tax-optimization services available with no human advice offering at all (strict robo-advisor as the opposite to the Betterment) [19].

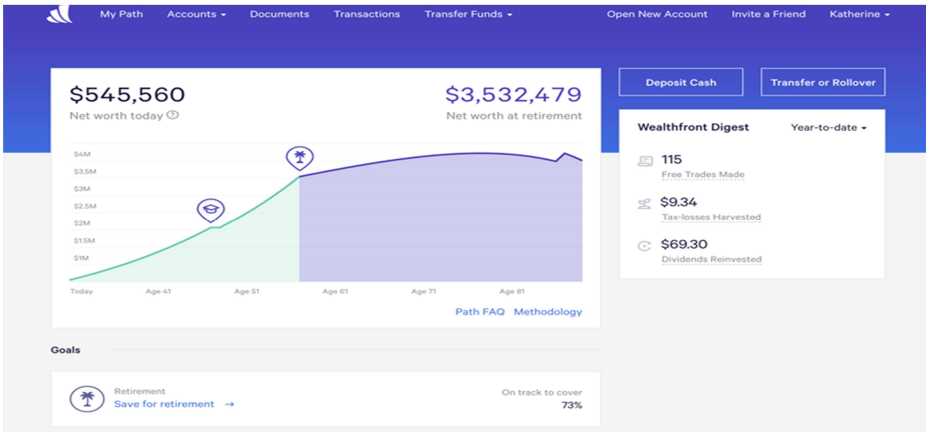

Fig. 5. Wealthfront dashboard [20].

Based on the selected RAs the following functionality can be defined as the basic [10, 12, 15]:

- Account creation and goals setup;
- Personal data analysis;
- Recommendations for investing and distributing assets;
- Communications between users for mutual investments;
- Active trading and investing in ETFs, stocks, bonds;
- User's data protection;
- Portfolio rebalancing;
- Retirement planning.

As described above the basic functionality is quite suitable for ML due to their perfect matching to the areas of usage. RAs even should include all possible ML use cases for Financial Industry. This fact makes RA one of the most difficult systems from development perspective. Based on the described functionality we can define the high-level architecture design for a general RA in the following fig. 6.

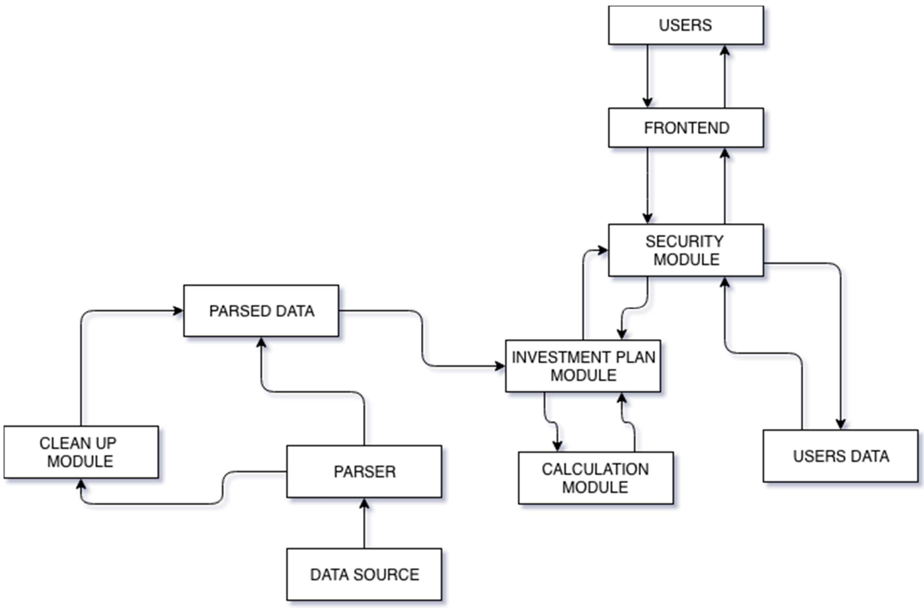

Fig. 6. High-level architecture design for a general RA.

Data Source is either stocks data, cryptocurrencies statistics etc. (means it is what RA will use to build investment plan). Parser module should do ETL (Extract-Transfor-Load) work and process valid and appropriate data to the Parse Data or run Clean Up module to remove invalid records. Investment Plan Module will build and keep updated users investments plans. Calculation module will do all required calculations for the Investment Plan Module. Security Module is a hub between the Investment Plan Module, Front-end module and Users Data storage. It is necessary to keep users data safe and visible only to them. Front-end module is a UI (user interface) of RA application (web and/or mobile client). Users Data is a storage of personal users data and their investments plans.

4 Robo-Advisor in Action: Experimental Results

The purpose of an investor is to increase its capital through the formation of a set of financial instruments (investment portfolio) [21, 22]. Portfolio value is formed as the total value of all components of financial instruments. If the value of the portfolio is P, then through the time interval t the profitability of the portfolio will be $\frac{P'-P}{P}$. Let's x_i is a share of capital spent on the purchase of a financial instrument i; d_i is a return of the financial instrument per 1 invested dollar. Then the return on investment portfolio will be:

$$d_p = \sum_{i=1}^{n} d_i \tag{4}$$

The profitability and risk of the investment portfolio is measured by the mathematical expectation m_p and the variance $\sigma = r_p$ respectively, where:

$$m_p = x_1 \cdot E(d_1) + \ldots + x_n \cdot E(d_n) = \sum_{i=1}^{n} x_i \cdot m_i \tag{5}$$

$$r_p = \sum_{i=1}^{n} \sum_{j=1}^{n} x_i \cdot x_j \cdot v_{ij} \tag{6}$$

where v_{ij} is the covariance of financial instruments. Since the returns of financial instruments are random, then the return of the portfolio is also a random variable.

Consider the initial data of quotations of the two most popular cryptocurrencies (https://finance.yahoo.com/cryptocurrencies) (table 2):

Table 2. A fragment of quotation data of cryptocurrencies prices (in the US dollars) (from 26.01.2018 to 19.02.2018)

Day	Bitcoin	Etherium
26.01.2018	11459,71	1109,09
27.01.2018	11767,74	1231,58
28.01.2018	11233,95	1169,96
29.01.2018	10107,26	1063,75
30.01.2018	10226,86	1111,31
31.01.2018	9114,72	1026,19
01.02.2018	8870,82	917,47
02.02.2018	9251,27	970,87
03.02.2018	8218,05	827,59
04.02.2018	6937,08	695,08

05.02.2018	7701,25	758,01
06.02.2018	7592,72	751,81

Determine the returns of financial instruments using the formula $\frac{P'-P}{P}$ (table 3).

Table 3. A Fragment of return on cryptocurrencies (coefficients) (from 26.01.2018 till 19.02.2018)

Day	Bitcoin	Etherium
26.01.2018	0,032016	0,057707
27.01.2018	0,026879	0,110442
28.01.2018	-0,04536	-0,05003
29.01.2018	-0,10029	-0,09078
30.01.2018	0,011833	0,04471
31.01.2018	-0,10875	-0,07659
01.02.2018	-0,02676	-0,10595
02.02.2018	0,042888	0,058204
03.02.2018	-0,11168	-0,14758
04.02.2018	-0,15587	-0,16012
05.02.2018	0,110157	0,090536
06.02.2018	-0,01409	-0,00818

The average rate of return for Bitcoin and Etheruim equal correspondingly $d_1 = 0.0033$, $d_1 = -0.0038$. The average rate of return for bitcoin and etherium equal correspondingly $d_1 = 0.0033$, $d_1 = -0.0038$.

$$\begin{cases} r_p = \sum_{i=1}^{n}\sum_{j=1}^{n} x_i \cdot x_j \cdot v_{ij} \to min, \\ \sum_{i=1}^{n} x_i \cdot d_i = m_p\,, \\ \sum_{i=1}^{n} x_i = 1\,, x_i \geq 0. \end{cases} \tag{7}$$

The initial distribution of the financial instruments will be set at the level $x_1 = x_2 = 0.5$. The objective function in Markowitz model (7) is the quadratic form $r_p = X^T VX$, where X^T is the transposed matrix, V is the covariance matrix calculated according to the data of table 3:

$$V = \begin{pmatrix} 0.00545\ 0.00499 \\ 0.00499\ 0.00576 \end{pmatrix} \tag{8}$$

Adverse risk investor can achieve a certain level of return under minimal risk (7) 88% of the funds he/she needs to invest in Bitcoin and 12% in Etherium.

If investors are risk seeking and strive to maximize their returns under acceptable risk level (9), then all 100% of their investment fund they have to invest in Bitcoin.

$$\begin{cases} \sum_{i=1}^{n} x_i \cdot d_i = m_p \rightarrow max, \\ r_p = \sum_{i=1}^{n} \sum_{j=1}^{n} x_i \cdot x_j \cdot v_{ij} \,, \\ \quad \sum_{i=1}^{n} x_i = 1 \,, x_i \geq 0. \end{cases} \tag{9}$$

Over the time of investment portfolio formation using robo-advisor, these findings for each investor will significantly depend on the availability of alternative financial instruments and the volatility of their rates.

5 Conclusion

Machine Learning shows new ways how to develop various areas of the financial industry. It also can give a new life to old tools which help companies and individuals to invest, to trade and more using Robo Advisors. Even if it is not a young idea, it is still developing the financial industry. For example, it can: use personal data to prevent fraud (such as accounts duplicates, or a pre-arrangement for investing); does investment and asset allocation guidelines which is the ideal task for ML because of a significant amount of data to process and analyze. Despite the fact that RAs are often criticized [23] they make investments easier and provide new tools that can radically change an investment landscape. We implemented a proof of concept of the robo-advisor application for investment portfolio formation with financial instruments under adverse risk attitude and risk-seeking behavior of investors.

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