Development of Robo-Advisor System for Personalized Investment and Insurance Portfolio Generation

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Abstract

We researched how to use financial technology in the finance industry on the example of robo-advisors; defined the basic functionality of robo-advisor; got the robo-advisors implementation based on analysis of the most popular financial services. We compared their functionality, composed a list of critical features and described the high-level architectural design of a general robo-advisor tool, scope of application of robo-advisors, their key features, and a brief overview of existing solutions. Using Markowitz model, we set up a concept of a robo-advisor application for investors who have different attitudes towards risks. Our goal is to cover the main features of financial robo-advisor and to describe a high-level architecture for such applications. We have defined the main modules that represent the architecture of a typical robo-advisor. We also described different techniques, which could be applied for building a personalized investment and insurance portfolio.

Keywords 1

Robo-advisor, investment portfolio, Markowitz model, financial instruments.

1. Introduction

Various digital financial instruments find their application in many areas of the financial industry. The most popular use cases are credit scoring, insurance estimating, fraud detection, risk management, etc. Robo-advisors (RAs) have become another popular type of financial instrument in the last decade [1].

Robo-advisors are the part of asset management segment of financial technologies industry (FinTech). FinTech means the use of information technology in such areas as banking, insurance, and investing [2]. RAs allow starting making investments even for those who do not have a large start-up capital. A lot of RAs do not have a minimum portfolio size limit, which expands their potential audience.

Another advantage of using RAs is that, unlike classical financial consulting companies that offer to compose a personalized investment portfolio for a quite high price, RA services charge a relatively small transaction fee and some only have fixed annual fees. This attracts novice investors and lowers the entry threshold for potential customers.

Robo-advisor (RA) is a type of financial adviser that gives investment advice and provides online access to the investment management dashboard. It consists of interactive and intelligent user assistance components [3]. Most RAs are designed for personal use. They provide an intuitive user interface to such features as choosing investment goals, risk preferences, budget, and desired investment assets. The output of RA is an investment portfolio plan, based on input information provided by a user.

General attributes of robo-advisors are next:

- Robo-advisors offer on-line investment advice based on the user's responses to a questionnaire filled out online [4];

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- Complete absence or minimum of human contact between investors and the platform;
- The ability to dynamically change personal settings (expected rate of return, risk attitude, etc.) and rebalance the investment portfolio.

The main advantages of RA systems compared to traditional financial advising institutions (availability, low entry budget level for new clients, ability to fine-tune the parameters of the investment portfolio, ability to plan funded pension system) stimulate the active interest of potential investors in such services. As a result, this leads to the emergence of many fintech startups offering financial advisory services in the markets of North America, Europe, and Asia. However, such systems are not yet widely available in Eastern Europe and in particular, in Ukraine.

RA developers should keep in mind that most people are unfamiliar with professional economic terms and rules and they cannot compose their personal investment goals, which should include short, medium and long-term personal financial goals, by their own. Therefore, the first task of RA application is to collect as much input about the user as possible. This should include age, annual income, amount of spending, investment goal, investment period, an acceptable level of risk, preferable assets, etc. The output information should contains a detailed investment plan with the percentage of each assets in the portfolio, expected rate of return, and possible portfolio annual drawdowns. It is also important that all this information be presented in a clear and understandable form to increase the level of users' trust.

The **purpose** of this paper is to develop high-level architecture of the robo-advisor as software for managing investment portfolios.

We organise the remainder of our paper as follows: in part, 2 we consider related works. In part, 3 we revealed the high-level architecture of robo-advisor. Part 4 is devoted to asset yield prediction using machine-learning techniques through model of investment portfolio. Finally, the last section concludes.

2. Related Works

2.1. Analysis of FinTech-services

Different legal restrictions had not allowed traditional financial institutions to respond to new consumer needs, which led to the emergence of so-called FinTech companies. Changes in the traditional concept of investing and insurance form a new sphere in the financial services market (FinTech-services). FinTech services are provided by technology companies using special software and focused on the financial needs of customers [5].

Analysis of FinTech-services [6] is presented in table 1.

Table 1
Analysis of FinTech-services

Potential benefits of FinTech services	Risks of FinTech services
Decentralization and diversification of financial services led by increased competition between traditional and robo-advisors, improving the quality of services, reduction of market impact of individual financial companies, easy access and low minimum investment amount for low-budget investors.	**Cyber risks** (wider use of technology and digital solutions expands the range and number of entry points that could be attacked by hackers).
Efficiency – due to modern technological approaches (using machine learning techniques and artificial intelligence to improve decision-making processes and to reduce costs), lower	**Legal / regulatory risks** (there are different legal uncertainties in some countries with smart contracts or robo-advisors).

charges. RAs do not make decisions based on emotions.	
Stability of fintech services due to reduction of information asymmetry between financial service providers and clients, use of smart contracts to reduce risks, crowdfunding for fintech startups.	**Systemic risk** (complex algorithmic trading cause new shocks in the financial markets). Uncertain result of RA's algorithm due to extreme market crashes and/or extreme market shifts.

First robo-advisors in their modern form of Internet-based applications were created in the late 2000s during the financial crisis of 2007–2008 [1, 7]. Nowadays there are over 100 robo-advisory services [7], which have a wide range of features. Some of them are focused on novice investors and have a small minimum account size, while others are focused on more experienced investors and have restrictions on the minimum size of the investment.

2.2. Main features of robo-advisors

Basel Committee on Banking Supervision (BCBS) states that FinTech-services for asset management (robo-advisers) have next key features [8]:

- services operate only in the form of web application or software application for a smartphone or PC;
- all services are provided without the participation of traditional financial intermediaries;
- services use an automated mechanism based on mathematical algorithms;
- services provide high speed of operations.

Robo-advisor is a service of online portfolio management, which provides automated, algorithm-based consulting advices. Within the next several years, we may expect that robo-advice platforms will became a means of accessing other channels of distribution and new clients will be offered life insurance and connected products [9]. Technological innovations and competition in finance industry enforce the market to provide fully automated investment solutions subject to individually customized risk investors who has very different income.

Currently, robo-advice platforms do not provide solutions for more complex financial needs, such as insurances or pensions, which constitute all other aspects of personal financial planning handled by financial human advisers. The insurance-specific module of robo-advisor, that is InsurTech, is still non-existent.

Based on studied works [10, 11] we concluded that some of the most popular RAs (Betterment, FutureAdvisor, Motif Investing, Schwab Intelligent, and Wealthfront) have almost the same key features, which include investment advice, automated investments, retirement planning, and customer service. However, there are some unique features, which are present only in some of them:

- Mutual funds (available only in Betterment, FutureAdvisor and Wealthfront);
- Portfolio rebalancing isn't available in Motif Investing;
- Two-factor authentication is available only in Betterment.

Differences between automated and human financial are shown in table 2.

Table 2

Comparison of automated and human financial advisors' characteristics

Characteristics of a financial consultant	Automated robo-advisor	Human finance advisor
Customer Service	investor interacts remotely with the online service and answers general RA questions through a web interface or mobile application	personal communication with a financial advisor, filling in the questionnaire by the investor individually with the financial advisor

Goal based investing	automated assessment of typical investor goals for short-run and medium-run purposes	individual assessment of the investor's goals for long-run and short-run goals
Advisor service	lack of a "live" advisor, online service offers automated recommendations for the formation of the investment portfolio	asset managers are involved in the process of managing the client's assets and forming his investment portfolio
Fees	0.25%-0,50%/year	1%-2%/year
	Low (zero) entry threshold and low commission (creates opportunities for investors with low savings)	High entry threshold and higher commission (available for high-income investors) with individual trust management
Methods of investment portfolio formation	algorithmic methods on the basis of modern portfolio theory, Markowitz-Tobin model, Black-Litterman model for optimization of profitability and risk (mean-variance optimization)	analytical methods based on the experience of financial advisers, statistical indicators of profitability and risk of financial instruments
Finance instruments	exchange traded funds (ETFs), cryptocurrencies, stocks, bonds	deposits, stocks, bonds, mutual funds
Strategies	passive index strategies (RA follows the ETF index, including its forecast) with fewer transactions per year	active asset manager strategies with more transactions per year
Portfolio rebalancing	automated rebalancing within certain limits of deviation	determined by the asset management considering the requirements of the investor
Working hours	24/7	working hours for an asset manager
Report	dashboards with graphs, charts, cost of services, dynamics of profitability, portfolio structure	periodic (annual) report through e-mail

Robo-advisors have to operate in accordance with the financial laws of the markets in which they are available. This also includes accounts insuring. Robo-advisors that, for example, work on the United States market, are not insured by the Federal Deposit Insurance Corporation (FDIC), because they do not operate bank deposits but securities held for investment purposes. Instead, they, like regular financial advisors, insure their accounts via the Securities Investor Protection Corporation (SIPC) [12].

The study, which covered 219 systems that could be considered as robo-advisors [2], says that most of them use Harry Markowitz's Modern Portfolio Theory as a basic framework for building personalized investment portfolios.

Customers point out the following weaknesses of robo-advisers [2]:

- no full fit to individual needs;
- no contact with a human advisor;
- low trust from customers;
- low transparency;
- limited offer.

These must be taken into account when designing the architecture and user interface of the RA.

Ernst & Young's classification of FinTech-services includes insurance (car insurance, health insurance), but does not contain the specifics of insurance for robo-advisor services [13]. The distribution of investments in FinTech-services shows the interest level in insurance technologies equals 8%, which is significantly higher than investments in robo-advisors (2%) (Fig. 1).

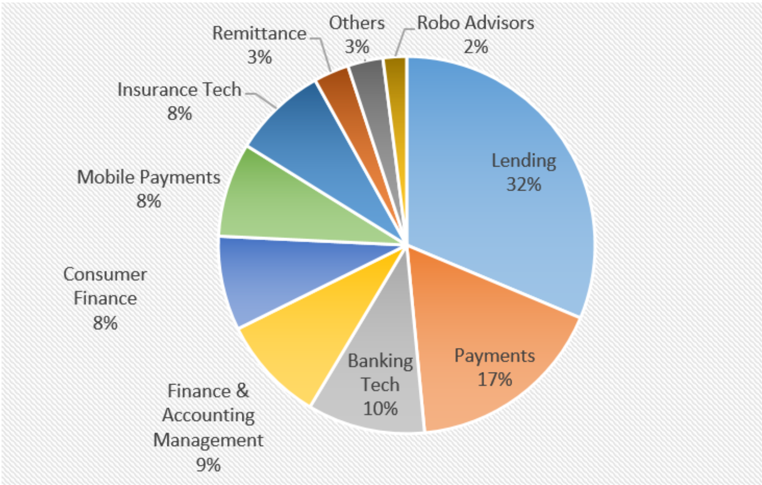

Figure 1: Global investments in FinTech-company. Source: Global State of FinTech PWC 2017

The result shows that the demand of investors, who want to minimize their risk, is gradually increasing for insurance fintech services (InsurTech). Portfolio insurance techniques (stop-loss, synthetic put, constant proportion portfolio insurance) depend on utility function of investor, especially for risk averse ones [14]. 'All three strategies provide significantly better risk-return trade-offs and downside protection than a buy-and-hold strategy' [14].

The Insurance microservice of RA can use functionality of an external insurance service (e.g., Sanitas Active, AXA Drive Recorder, Allianz and Panasonic etc.). The digital insurance firm Lemonade allows integrating their insurance services into websites and apps by providing third parties with an API and widgets, while Simplesurance is able to gain expertise in selling insurance online by evaluating on a large basis across insurance products. P2P insurance models (e.g., Lemonade) charge a fixed percentage of insurance premium [15]. It means that integrating insurance service with RA, which are less affected by regulation, can be an efficient way to increase customer engagement and economies of scale. This drift towards personalized finance and insurance advisory services (Fig. 2).

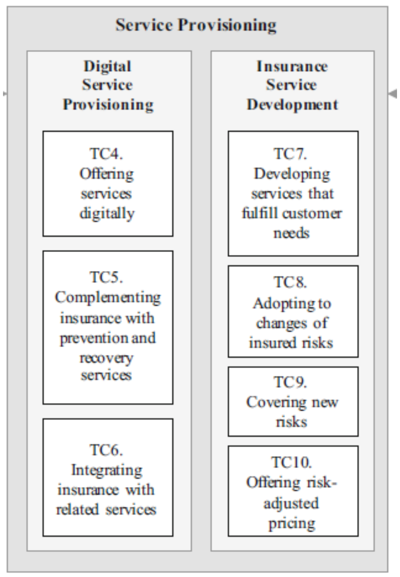

Figure 2: InsurTech service of RA [15]

Application of machine learning (ML) to exchange traded fund (ETF) investments in the finance instruments contributes a predictive support that can detect long or short investment signals [16]. Substantial growth of ETF arose from their tax advantage, low cost, and liquidity, because algorithmic ETF trading model can produce more returns by using AI and machine learning methods compared to the traditional equity mutual funds [17]. Time series momentum trading strategy is helpful in constructing ETF portfolios and in forecasting ETF returns [18]. Support vector machine is effective in analyzing financial times series data and beneficial for capturing momentum effects in the financial markets [19]. Example of architecture of machine learning RA system for finance instruments is presented on fig. 3.

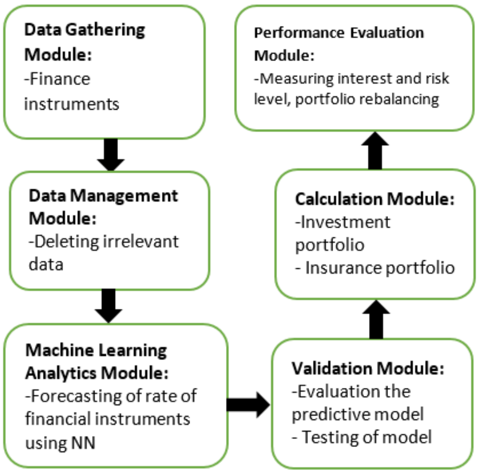

Figure 3: Architecture of the machine learning RA system for finance instruments [19].

Robo-advisor explores various approaches to the selection of the corresponding financial instruments (e.g. shares, bonds, currencies, real estate, ETF) and its weights, pursuant to an individualized risk profile of investor [20]. Comparison of time series prediction algorithms using machine learning is presented in table 3 [21].

Table 3

Comparison of time series prediction algorithms using machine learning

Algorithm	Advantages	Disadvantages
Linear regression	Ability to process various components and predictors of the time series; High interpretability.	Sensitivity to emissions; Strong assumptions
Random Forest	Intuitive decision-making rules; Takes into account the interaction between predictors; Can handle nonlinear predictors	There is no rating at the output; High bias towards the training sample
K-Nearest Neighbors	Ability to handle levels with variables, trends and seasonal components; Automated optimization	Sensitivity to emissions; Narrow confidence intervals
Support Vectors Machines	High interpretability; Realistic confidence intervals; Realistic forecasts.	Requires more data; Strict restrictions and assumptions; It is difficult to automate.
Long short-term memory (LSTM)	A small number of limitations and assumptions; Ability to process complex nonlinear templates;	Low interpretability; It is difficult to derive confidence intervals for the forecast; Requires more data.

	Ability to memorize long-term predictors and High quality forecast; Easily automated.	

The main disadvantage of traditional investment advice is limited availability due to the required amount of assets and high management costs. These disadvantages are answered by robo-advice, using artificial intelligence and algorithms without the participation of a physical adviser, thereby reducing or abolishing minimal assets and reducing costs [9]. Robo-advisors are not a threat to traditional financial advisors, but their complement, which makes the hybrid model connecting a physical advisor assisted by technological solutions (robo-advisors) most likely [9].

These tools support users in:

- taking financial decisions,
- defining products portfolio,
- monitoring incomes and expenditures,
- purchasing finance instruments,
- rebalancing of investment portfolio.

Investors' perceptions of human vs. robo-advisor for US market is demonstrated on fig. 4.

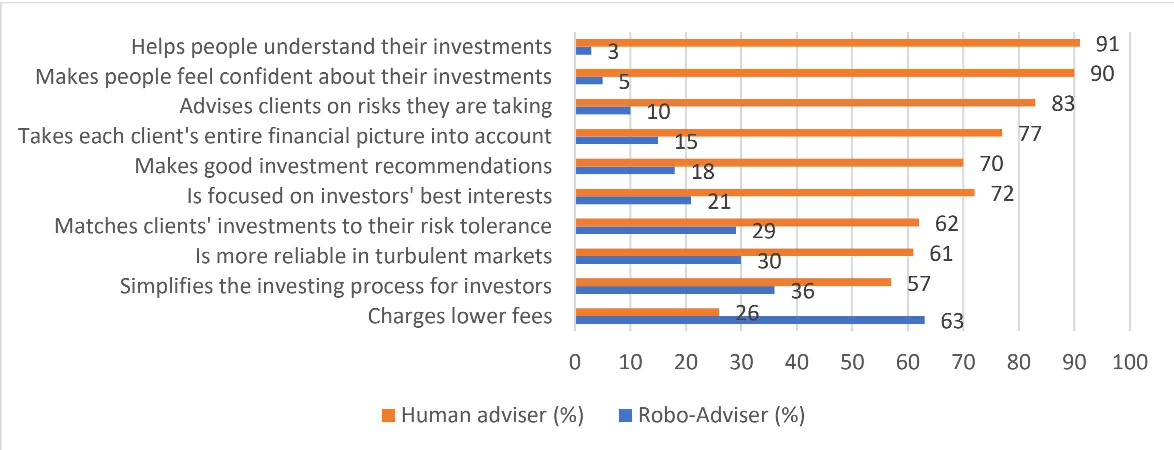

Figure 4: U.S. investors' perceptions of human vs. robo-advice [22]

Human advisers are leaders on almost all qualities measured in the survey, no matter what investors choose robo- over human advisers for charging lower fees. These results suppose that the hybrid model of cooperation between human and robo-advisors is currently the most realistic (e.g., Vanguard Personal Advisor Services and Schwab Intelligent Portfolios). Human financial advisers may use different tools for analysis of finance and insurances products and recommend robo-advice platforms for investments to their clients [9]. RA Betterment has introduced a call center with certified financial planners in order to monitor accounts and advise.

The Y/Millennials/tech-savvy generation is the core target group for RAs, which have relatively low charges, easy access and minimum investment [23]. The entire investment process carried out via robo-advice platforms is automated and does not require human activity to profile clients [9]. RAs monitor the target-based investment process automatically and are available 24/7.

Independent robo-advice operators will face an enormous international competition. There are growing fears by potential clients due to state regulations (rise of costs) of robo-advisors.

3. Developing the High-Level Architecture of Robo-Advisor

The RA system workflow consists of the following stages:

1. User survey. Determining the level of user's income rate, attitude to risk, investment goals, and time constraints.

2. Analysis of the information, which is received in the previous stage, for generating the personalized investment plan.
3. Presenting of the generated plan (investment portfolio) in the user interface with the ability to change certain parameters (e.g., the user can exclude a certain type of assets) and update the investment plan.
4. Providing access to the RA information dashboard.

We had analyzed each of the above steps and defined logical modules of the Robo-Advisor application. Summing up all the main features of RA, which are mentioned before, we propose the next high-level architecture of RA, described in fig. 5. This architecture assumes that RA is a web application that is accessed by the end-user through a web browser or a mobile app.

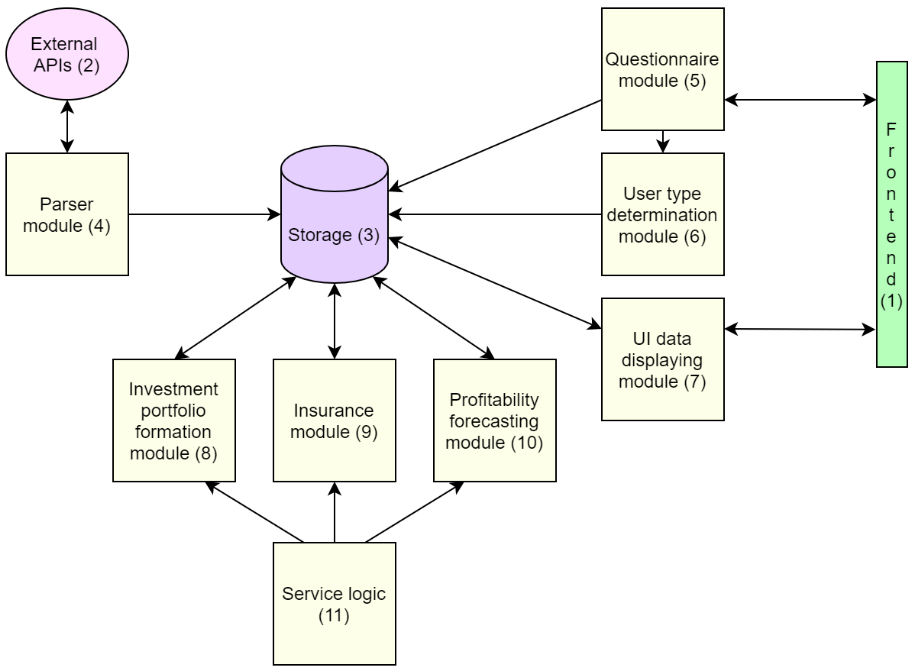

Figure 5: High-level architecture of RA

The module that provides an investment portfolio formation (8) is the main part of the application. It uses data collected by the Parser module (4) and input information about the user's expected rate of return, desired maximum risk level, etc. Insurance module (9) is a part of the application that is responsible for providing the insurance plan that is also based on the information, provided by the user. Its implementation may differ depending on local legislation. Profitability forecasting module (10) uses different machine-learning (ML) techniques to build models that could generate some predictions, for example, about shares profitability or average daily trading volume (ADTV). Service logic (11) is a module that runs scheduled tasks like periodic portfolios rebalancing, updating ML models and detects abnormal behavior of shares price in order to notify users.

UI data processing module (7) is a part of the application that provides all data shown in user interface. It could be divided into next logical blocks:

- the dynamics of changes in the price of assets that interest each user;
- setting and displaying the parameters of the user's investment plan (changing the level of acceptable risk, the level of expected profitability, setting the rebalancing period);
- notifications in case of a sharp fall or rise of any of the assets that are used in the user's portfolio.

Storage (3) is an abstract part of the architecture related to different data storing technologies. For each module we should use the type of storage that best suits the type of data that the module is working with. For the parser module it might be a time-series database. Document database or object storage is suitable for storing neural network models. For the rest of the modules we will use some relational database. Each of modules (4) – (11) could be implemented as a separate microservice. This approach will help scale the application in the future.

The RA application is supposed to be implemented using the following programming languages, frameworks and technologies:

- **Back-end**: Java programming language, Spring framework, relational and NoSQL databases, object storages.
- **Front-end**: JavaScript programming language, HTML and CSS for web client; Flutter, React Native or another cross-platform mobile application framework for mobile apps.
- **Profitability forecasting module**: Python programming language (with Machine-Learning and Data Analysis libraries such as NumPy, Scikit-learn, Pytorch, Pandas), TensorFlow.
- **Infrastructure layer**: Docker, AWS for cloud computations and services replication, Nginx web server.

Despite the fact that many papers state that fully automated processes of investment portfolio generation and the absence of any human interactions are one of the distinctive features of RAs [4, 8], a lot of customers note that they have a certain distrust of systems that are completely devoid of the ability of live connection with financial consultants [2]. Thereby, RA system also should have an additional module, which will provide the functionality of some kind of human interactions between customers and financial experts. Such interaction models that combine automated processes with human interactions are called bionic models. It could be an additional feature of RA system, which is not present in the base plan but could be executed on the user's demand. Such module is not present in the proposed in the paper architecture, but it should be added in further works.

4. Personalized investment portfolios formation approaches

4.1. Model of investment portfolio

The module that generates investment portfolios uses the Markowitz model and evolutionary algorithms. Markowitz model is a mathematical model for assembling a portfolio of assets such that the expected return is maximized and the level of risk is minimized (1). Formal notation for this task is

$$\begin{cases} R_p \to max \\ \sigma_p \to min \\ w_1 + w_2 + \cdots + w_N = 1 \\ w_i \geq 0 \end{cases} \tag{1}$$

where N is a number of assets, R_p is an expected return, σ_p is a level of risk (standard deviation), and w_i is a percentage of asset i in portfolio p. In general, such problem is hard to solve, so we should formulate the primal Markowitz problem for risk seeking investor (2) or the inverse Markowitz problem for risk-averse investor's type (3).

$$\begin{cases} R_p \to max \\ \sigma_p \leq \sigma_g \\ w_1 + w_2 + \cdots + w_N = 1 \\ w_i \geq 0 \end{cases} \tag{2}$$

$$\begin{cases} R_p \geq R_g \\ \sigma_p \to min \\ w_1 + w_2 + \cdots + w_N = 1 \\ w_i \geq 0 \end{cases} \tag{3}$$

where σ_g is a given level of risk and R_g is a given expected return rate. The primary problem is used to assemble a portfolio such that the expected return is maximized for a given level of risk, while the inverse problem is used to assemble a portfolio such that the level of risk is minimized for a given level of expected return [24]. We can also use target function, defined as $\frac{\sigma_p}{R_p} \to min$, to determine investment plan of risk neutral investor (4).

$$\begin{cases} \dfrac{\sigma_p}{R_p} \rightarrow min \\ w_1 + w_2 + \cdots + w_N = 1 \\ w_i \geq 0 \end{cases} \quad (4)$$

Thus, in any of the above cases, the Markowitz problem is an example of an optimization problem, solved by linear programming methods.

Another way is to build an investment strategy using an evolutionary algorithm (EA). The paper by Kobets, V., Poltoratskiy, M. [25] describes the way where evolutionary algorithm could be applied for selecting an optimal combination of investment share in different industries for improving of investment performance. In terms of evolutionary programming, population is a set of different combinations of distributions between assets; genotype is a concrete example of assets distribution; phenotype is a profitability of some assets distribution; progeny is those combinations that give better profitability on each iteration; fitness function corresponds to the expected return.

4.2. Asset Yield Prediction Using Machine-Learning Techniques

We can form an investment portfolio using not only already known statistical data, but also use the predicted values (value, trading volume, etc.) of assets. The profitability forecasting module could use various machine-learning techniques. We will give a brief description of two of them.

The first technique is Linear Regression (LR). Linear Regression is an approach to modeling the correspondence between some scalar value (dependent variable) and one or more explanatory variables (independent variables). If there is more than one explanatory variable then this process is called Multiple Linear Regression. To build a model using Multiple LR first we need to define which criteria have any impact on the forecasted value. For example, in the scope of shares price predicting it may be average daily price, trading volume, and total supply for some period of time. LR model also will help to understand which criteria affect the price most. The formal notation for Linear Regression is

$$\gamma = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n + u = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + u, \quad (5)$$

where γ is the dependent variable, β_0 is a constant, β_i is the scope (marginal impact) for the corresponding independent variable, x_i is the independent variable, n is the number of factors, and u is random errors of prediction.

Long short-term memory (LSTM) neural network is another machine learning option for asset yield forecasting. LSTM neural networks are subspecies of Recurrent Neural Networks (RNN). Their main difference from regular Feed Forward Neural Networks (FFNN) is that neurons receive information not only from the previous layer but also from their own previous pass. Thus, the order in which we provide data and train the network is important. A big challenge in RNNs is the explosive gradient problem, which leads to the rapid loss of information over time. LSTM neural networks try to solve this problem.

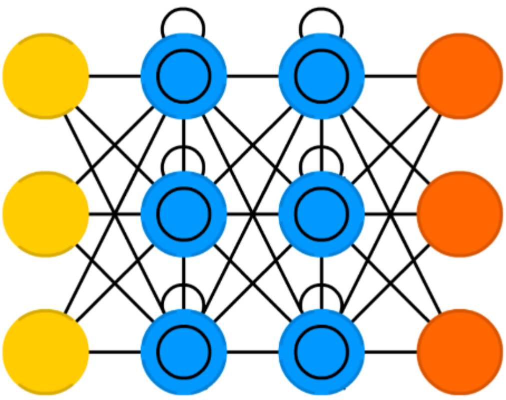

Figure 6: LSTM neural network scheme

Yellow cells are input cells, blue cells are recurrent memory cells, and orange ones are output cells. Each neuron from hidden layers has a special memory cell and filters that decide which and how much information would be stored and transferred to the next layer. LSTM networks are well suited to time-series predictions because they can determine and learn patterns in the behavior of the studied data that is repeated at certain time intervals [26].

5. Conclusions

Thus, we have analyzed key features of RA systems and provided a high-level architecture for a typical RA. This will be used for further development of the RA web application. We have also covered the main mathematical models for investment portfolio formation and machine-learning techniques used for asset yield forecasting.

This paper does not cover techniques that could be used to determine the risk readiness level of each client. This will be covered in further research. Other topics, which have not been examined in this paper, and which we are going to include in our further research include: more complex mathematical models for investment portfolio generation (Markowitz–Tobin model, Black–Litterman model); human support module in RA architecture; applying other machine learning techniques for analyzing and forecasting financial times series data (Support-Vector Machines, Decision Trees, etc.).

We are going to conduct an experimental effectiveness comparison of various methods of forming investment portfolios and predicting the return on assets. The next step is the choice of applied software technologies and the implementation of the main modules of the system according to the architecture proposed in our research.

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