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the World Financial Market»

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## INTRODUCTION

Brief range of key issues. Financial markets play huge role in facilitating the smooth operation of capitalist economies by allocating resources and creating liquidity for businesses and entrepreneurs. Markets are making easier for buyers and sellers to trade their financial holdings. Prices of securities on financial markets are driven by supply and demand, but there is no strict equitation, which can tell us the future price of the security. Though, there are known forces which drive prices, such as Economic Strength of Market and Peers, Incidental Transactions, Demographics, Trends, News, psychology of market participants and many more, all these forces are affecting market price in a very complex way. As neural networks are very good function approximators and, they can analyze a lot of data, they are in fact used by credit organization in the financial markets to improve its financial results. But the huge leap in the past years in development of neural networks architectures and deep leaning approaches might change the role of neural networks in the financial markets.

Actuality. Trading and investment on the financial markets play key role in the modern economy. For an effective trading and investment, it is required to predict prices of the securities in the future and even though they are heavily studied in the economics, there is no simple formula to correctly determine future prices, because it is affected by a lot of factors in a very complex way. On the other hand, neural networks are types of machine learning technique which were able to solve multiple data analysis tasks for the past years, which were considered unsolvable for decades, like time series forecasting, natural language processing, image classification and others complex problems. That is why this area of machine learning is developing very rapidly today. So, it is an open question, how modern architectures of neural networks are able to trade on financial markets and how they perform compared to other popular approaches in investing and trading.

Degree of research. Neural networks are the field of machine learning study, they are investigated by lot of researches all over the world, so there are plenty of scientific papers studying issue of using neural networks in financial markets. On the

other hand, deep learning is very young field, so a lot of those researches are outdated and do not use modern architectures. Also, it is a concern that huge credit organization might do not share results of their researches in this field and keep it as a secret.

Aim:

- Explore how modern neural networks can be used by credit institutions in the financial market and what prospects do they have.

Objectives:

- Research current state of economics concerned with financial markets.
- Study features of modern approaches used by credit organization in financial markets.
- Research of modern neural networks characteristics and architectures.
- Analyze research state of modern deep neural networks usage in the financial markets and highlight the trends in the academic field.
- Create modern deep neural network model based on conducted research and analysis.
- Test, how modern mathematical models based on neural networks are able to forecast prices and make meaningful transactions on the global stock market.
- Compare result of neural network-based investment strategies with more established ones.
- Reveal features of using reinforcement learning based on neural network in financial market on practice.
- Suggests further improvements which can be done to increase model efficacy
- Explore possibility of using modern artificial neural network models for forex markets.

Object of research. Usage of neural networks by credit organizations in the financial markets

Subject of research. Neural networks, used in the field of financial markets

# 1. THEORETICAL FOUNDATIONS OF ANALYSIS AND FORECASTING OF THE DYNAMICS OF FINANCIAL MARKETS

## 1.1 Concept and structure of the world financial market.

Financial markets refer broadly to any marketplace where the trading of securities occurs, including the stock market, bond market, forex market, and derivatives market, among others. Financial markets are vital to the smooth operation of capitalist economies<sup>1</sup>.

Financial markets play an important role in the smooth management of capital economies by allocating resources and creating liquidity for businesses and entrepreneurs. The marketplace makes it easier for buyers and sellers to trade financial assets. Financial markets create stock products, provide income to surplus funds - investors and lenders, and make this money available to those who need more - borrowers. Financial markets essentially rely on buying and selling a variety of financial instruments including stocks, bonds, currencies, and derivatives. Financial markets rely heavily on information transparency to ensure that markets set reasonable and efficient prices. Due to macroeconomic factors such as taxes, the market price of securities may not reflect their real value. Some financial markets are small and inactive, while others, such as the New York Stock Exchange or NYSE, trade trillions of dollars in stocks daily. A stock exchange is a financial market where investors can buy and sell shares of listed companies. The new shares are traded on a major exchange known as an initial public offering. Subsequent stocks are traded in the secondary market, where investors buy and sell stocks they already own.<sup>2</sup>

Presented overview of basic market concepts has shown their importance for the economy and uncovered its fundamentals for the further exploration, such as structural

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<sup>1</sup> Financial Markets. Date Views 03.03.2021 [www.encyclopedia.com/social-sciences/applied-and-social-sciences-magazines/financial-markets#E](http://www.encyclopedia.com/social-sciences/applied-and-social-sciences-magazines/financial-markets#E).

<sup>2</sup> Hull, JH., 2014. Options, Futures, and Other Derivatives; 9th Edition. Pearson, pp: [www.amazon.com/Options-Futures-Other-Derivatives-9th/dp/0133456315](http://www.amazon.com/Options-Futures-Other-Derivatives-9th/dp/0133456315).

organization analysis. The financial market can be classified in different ways to show the characteristics of the each market:

- Financial markets can be classified by the type of security, which is traded on the market, such as bonds, stocks, commodities, derivatives, futures, currencies, and cryptocurrencies. Also, it includes spot market, where commodities for immediate delivery are traded, interbank lending market, where banks lend funds to one another, and money markets, which deal with short-term loans, generally for a period less than a year.

- One of the ways financial markets can be classified is by the expiration date of financial assets. The money market is a financial market in which only short-term debt securities are traded with an initial maturity of one year. The capital market is a market for trading long-term debt securities with an original maturity of one year or more and equity instruments. Money market securities generally have a wider trading range and greater liquidity.

- Other way to categorize financial markets is whether financial instruments are newly issued. The primary market is the financial market in which borrowers release securities with money from new investors. Once the securities have been sold to sellers, they can be sold on the secondary market. The secondary market can be organized in two ways. One is a regulated market that brings together buyers and sellers of securities through its agents in a central trading venue. The other is other the counter or OTC market, where OTC traders located in different places but connected to each other by a computer network trade securities. Many common stocks are traded over the counter and corporate transactions are traded on regulated exchanges such as the New York Stock Exchange.

As it has been shown, market are complex systems, and the analysis of their structure has unveiled their environmental characteristics. However, as it was shown, there exists much more functional mechanisms behind its operation. For example, by bringing money from investors to issuers and borrowers, the financial markets improve the efficiency of production and distribution throughout the economy. Financial markets also have significant price features. The activities of buyers and sellers in the

financial markets determine the price of liquid assets. This gives an idea of how to allocate the financial assets to the financial assets in an economy. In addition, financial markets have risk management mechanisms. Different financial assets traded in the financial markets have different forms of payment. This distributes and diversifies the risks associated with future cash flows between issuers and investors. Financial markets also provide liquidity by giving investors a mechanism for buying and selling financial assets. Having a regulated financial market lowers the cost of research and transactional data, such as money spent on announcing demand for buying and selling financial assets. In an effective market, the market price reflects the total participation of all market participants.

Through the conducted review of market participants, it is clear that credit organizations play role of lenders in the financial markets, and they seek to gain profit by investing in different kind of financial instruments. Another conclusion drawn according to performed research is that the analysis of financial market is highly studied topic in the scientific field.

One of the most important aspects of investment in financial market is the price. Fundamentally, prices of securities and other financial instruments on the financial markets are determined by law of supply and demand, according to the modern economics theory. So, market price is the result of interaction between investors and traders, and dealers on the market. Market price reflects the bid, that buyer and seller of the financial assets are agreed to buy and sell the asset. It has been observed that over the past century economy is constantly growing. As it is shown on figure 1.1 and 1.2, for the last 100 years, stock financial markets are constantly growing on average.

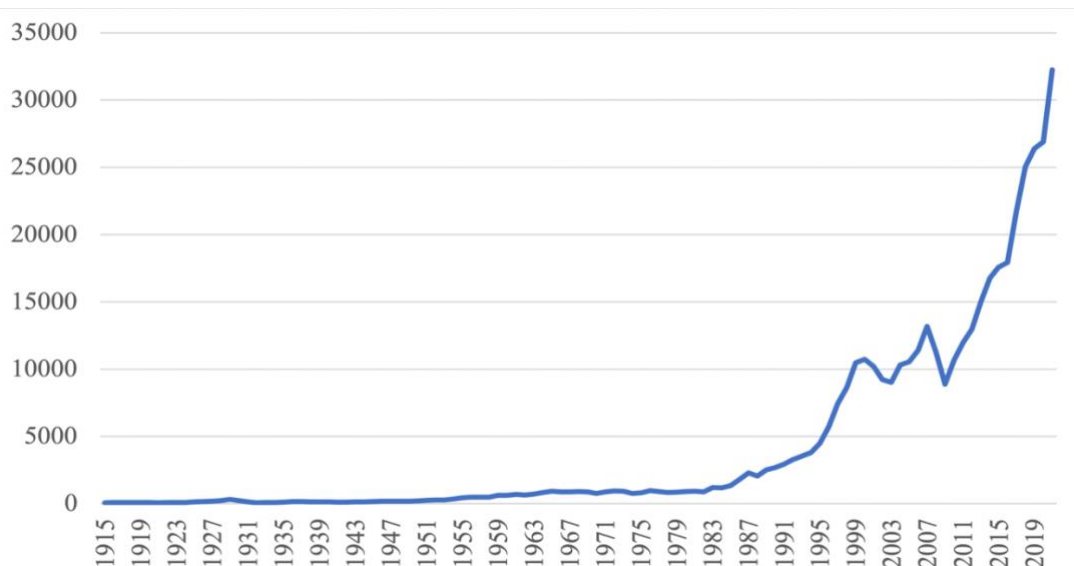


Figure 1.1. Dow Jones Industrial Average

Source: Dow Jones - DJIA - 100 Year Historical Chart // macro trends URL:

<https://www.macrotrends.net/1319/dow-jones-100-year-historical-chart> (дата обращения: 23.02.2021).

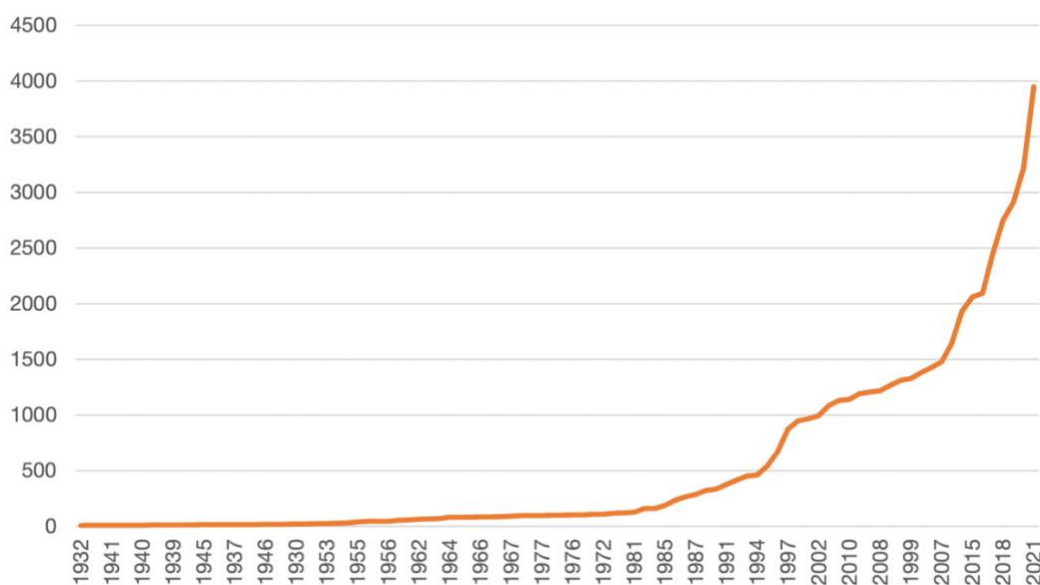


Figure 1.2. S&P 500

Source: S&P 500 // finance.yahoo URL: <https://finance.yahoo.com/quote/%5EGSPC/> (date of the application: 23.02.2021).

Economists refer to an increase in economic growth caused by more efficient use of productivity of labor, physical capital, energy, and materials. This growth is beneficial for investors, as they can gain profit by investing in a long-term and ignore short-term



volatility. In fact if the market is perfectly efficient, long-term investment is the best possible investment strategy. But how efficient price settling in the market is still an open question.

According to the efficient-market hypothesis, created by a famous economists of 20<sup>th</sup> century Eugene Fama, at any given moment of time, prices in the market reflect all publicly known information and it changes accordingly as new information became available <sup>3</sup>. Therefore, it is impossible to outperform market, based on the publicly available information and gain profit by any mean other than luck. There exist evidence for this theory, which are:

- Prediction future price of an asset is not always accurate;
- As new information become available, market prices change quickly;
- Most investors could not outperform market.

On the other hand, there are also evidences for market inefficiency, such as:

- It has been identified in the literature in academics field of economy, that momentum effect exists on the market. For example, it was identified by Jegadeesh and Titman<sup>4</sup>. Stocks that have been successful or unsuccessful in the last 3-12 months will continue to do well or poorly in the next 3-12 months. A proactive strategy is to take a long position with the closest losers and generate an average return adjusted for positive risk. It provides compelling evidence of past market price affecting future and is presented in many markets, industry returns and national stock market indices all over the world. Fama also admits that this dynamic is anomaly.

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<sup>3</sup> Eugene, F. Efficient Capital Markets: A Review of Theory and Empirical Work. Vol 25 New York: American Finance Association, 1970. from. 383–417.

<sup>4</sup> Jegadeesh, N., Titman, S. "Returns to Buying winners and selling losers: Implications for stock market efficiency". Vol 48 Journal of Finance, 1993. from. 65–91.

- January effect. It is a hypothesis that there is anomaly in financial market that in month of January stock prices increase more than in any other month. This effect was first observed in 1942 by a banker, Sidney B. Wachtel.<sup>5</sup>
- Different kind of bubbles on the financial markets.
- There are investors, who are able to outperform market, such as Warren Buffet and other institutional investors.
- Sometimes prices in consumer credit market don't adjust to legal changes in the law that affect future losses which indicate how inefficient markets can be.

In the light of such evidences, I would rather agree with professor Shiller, a Nobel prize laureate in economics<sup>6</sup>, that markets are not perfectly efficient, however at the same time they are able to allocate resources unbelievably efficient for a raised from human interactions, self-organized entity.

As it has been shown, financial markets are essential part of economy and is heavily studied topic in economics. Multiple characteristics of financial markets has been analyzed. One of key concepts concerned by economists is financial efficiency of a market, and as it was stated there is no concrete consensus among economists, though it is mostly believed, that markets are neither efficient in the absolute sense, nor extremely inefficient, while it is disagreed at what degree does they efficient or not. Reviewed evidences has confirmed given opinion. This is why credit organization are trying to come up with any approach to consistently win the market.

## 1.2 Evaluation of data analysis methods used by credit institutions.

As it was discussed earlier, that one of the main aims of credit organization on the financial markets is to get high return and they achieve this by investing in different

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<sup>5</sup> Sidney B. Wachtel; Investment Banker // Washingtonpost URL: <https://www.washingtonpost.com/wp-dyn/content/article/2008/10/02/AR2008100203726.html> (date of the application: 25.02.2021).

<sup>6</sup> Speculative Asset Prices. Date Views 01.03.2021 [www.nobelprize.org/uploads/2018/06/shiller-lecture.pdf](http://www.nobelprize.org/uploads/2018/06/shiller-lecture.pdf).

instruments of financial markets. Investment is allocation of capital with the expectation of a future financial return to gain an advantage.

There are plenty of approaches to investment, which can be classified by long or short-term period of time, by high or low risk absorption, by types of investments include equity, debt securities, real estate and many more. Portfolio management play one of the key roles in investing. Function of portfolio management is to maximize the expected return and minimize the risk. Diversification of assets is the essence for creation of portfolio, which has the statistical effect of reducing overall risk. In the financial sector, diversification refers to the process of allocating funds to reduce exposure to assets and risks. A typical way to diversify is to reduce risk and volatility by investing in multiple assets. If the price of an asset cannot fully fluctuate at the same time, then the variance of a diversified portfolio is less than the weighted average variance of its constituent assets, and volatility is usually less than the least volatile factor.

Portfolio investment may be divided into two main categories:

- Strategic investment involves buying financial assets for their long-term growth potential or their income yield, or both, with the intention of holding onto those assets for a long time.
- The tactical approach requires active buying and selling activity in hopes of achieving short-term gains.

If efficient-market hypothesis or EMH is right, it would mean that Strategic investment is best possible investment strategy. This strategy does not consider volatility of assets, and it should gain return as financial market in the long term as prices are correlated with GDP growth, as it was stated earlier. While tactical approach or value investing try to beat the market and predict future prices of financial assets, which is impossible according to EMH. But as it was stated earlier, there are evidences against EMH.

To get return, value investing usually based on fundamental, technical, and quantitative analysis or all of them.

Fundamental analysis in finance<sup>7</sup> is the analysis of business financial statement, overall business health and perspective, competitors and market situation. Also, fundamental analysis consider overall state of economy and it concerned with such factors as GDP, interest rates, earnings, production, employment. Goal of analyzing all this data is to try to understand intrinsic value of stocks and predicts their possible evolution in future. Some investors believe that security can be valued incorrectly in the short-term, but it will be corrected eventually by the market. Investors, which are using fundamental analysis, can use either bottom-up or top-down approach<sup>8</sup>:

- Bottom-up investor start its analysis with a specific business with such tools like financial analysis also known as financial statement analysis or accounting analysis. Its main aim is to understand profitability, stability, viability of a company. It performed by professionals with ratios methods and other techniques that make use of information taken from financial statements. Then, investor continue with analysis of market sectors and continue with analysis of overall economical situation.
- Top-down investor starts its analysis with global economy, macro-economical indicators like GDP, inflation, interest rate and others. Then, they narrow area of research to an industry indicators, prices, competition, make industry specific technical analysis and then begin to study business in the area of research, gradually moving from overall economy to exact companies.

Fundamental analysis is concerned with financial statements of companies. It includes financial ratios, cash flows, capita financing, growth rates, risks. Discounted cash flow model is used to calculate present value by taking into account dividends paid, earning and cash flow of company. All these procedures are time consuming, so

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<sup>7</sup> Mabrouk, AM., HH. Hassan and AW. Wafi, 2015. Fundamental Analysis Models in Financial Markets – Review Study. *Procedia Economics and Finance*, 30(939-947). Date Views 10.05.2021 [www.sciencedirect.com/science/article/pii/S2212567115013441](http://www.sciencedirect.com/science/article/pii/S2212567115013441).

<sup>8</sup> Zurek, MZ. and LH. Heinrich, 2021. Bottom-up versus top-down factor investing: an alpha forecasting perspective. *Journal of Asset Managemen*, 22((1):1-19). Date Views 9.05.2021 [www.researchgate.net/publication/346534317\\_Bottom-up\\_versus\\_top-down\\_factor\\_investing\\_an\\_alpha\\_forecasting\\_perspective](http://www.researchgate.net/publication/346534317_Bottom-up_versus_top-down_factor_investing_an_alpha_forecasting_perspective).

software solutions are used in order to digitalize the fundamental analysis, making it easier and more powerful. These are most common features of fundamental analysis software:

- Alerts features notify if financial asset enters or exit investor's saving strategy
- Backtesting feature<sup>9</sup> allows to test, how given investment strategy will behave, given market information from the past years. It will typically show total and annualized return in comprising with standard benchmark, such as S&P500. It can also show volatility statistics or average beta and maximum drawdown.
- Data feed feature provides information about end of date close, open, high and low price for the given and it usually is updatet once per day.
- Build in strategy feature will backtest built in strategy in order to show their return on average. Built in strategies are usually well-know strategies among investments community like IBD Stable 70 or Dividend Champions. User can choose build in strategy that aligns with needed intertreatment goals and can choose those stock, which pass the strategy.
- Scanner feature allows user to investigate the market, be it stocks, options, futures or currencies in order to identify opportunities for investment. Scanner also give opportunity to scan the market, for example, for stocks with below industry average PE ratio.
- Many fundamental analysis software includes brokerage platform, which allow to make trades.

Reviewed analysis technique has been characterized and it features have been unveiled, different approaches have been identified. As it can be concluded through the conducted research, fundamental analysis as a class of investment techniques

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<sup>9</sup> Zhang, CJ. and JN. Ni, 2005. An Efficient Implementation of the Backtesting of Trading Strategies. Parallel and Distributed Processing and Applications (issue 3758), ISPA Date Views 09.05.2021  
[www.researchgate.net/publication/220945302\\_An\\_Efficient\\_Implementation\\_of\\_the\\_Backtesting\\_of\\_Trading\\_Strategies](http://www.researchgate.net/publication/220945302_An_Efficient_Implementation_of_the_Backtesting_of_Trading_Strategies).

usually directed toward a long-term perspective and it is evolving toward a more technically advanced solution.

Technical analysis<sup>10</sup> is another term used by investors to describe wide range of price forecasting techniques. Technical analysis primarily is the study of past market prices, usually prices and volume, which are used for forecasting direction of price movements in the future. In technical analysis, trading rules and patterns are based on transformations of prices and quantities such as relative strength index, moving averages, regressions, inter-market and intra-market price correlations, business cycles, stock market cycles or, classically, through recognition of chart patterns. Charts are used widely by technical analytics as they seek to identify patterns such as head and shoulder, double top/bottom, reversal pattern, study technical indicators and moving averages, look for line of support and resistance, flags, pennants and cup and handle pattern in the charts with previous market price data. Many types of market indicators are widely used by technical analysts, some of which are mathematical price fluctuations, which usually include volume fluctuations, data fluctuations, and other inputs. These indicators are used to assess if an asset is trending, and if so, to continue the trend. Technicians are also looking for the relationship between price / volume ratio and market indicators. Examples are moving averages, RSI and MACD. Other research approaches include the correlation between options changes or so-called implied volatility and the relationship between buying and selling and prices. Emotional indicators such as buy-sell ratios, high-low ratios, short-term interest rates, and implied volatility are also important.

There are many methods of technical analysis. Proponents of various methods, for example, candlestick analysis, the oldest form of technical analysis developed by Japanese grain traders, harmonics, Dow theory, Elliott Wave theory and many others may ignore other methods. Some technical analysts use subjective judgments to

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<sup>10</sup> de Souza, M.J.S., Ramos, D.G.F., Pena, M.G. *et al.* Examination of the profitability of technical analysis based on moving average strategies in BRICS. *Financ Innov* 4, 3 (2018). <https://doi.org/10.1186/s40854-018-0087-z>

determine the patterns that a particular instrument reflects at a given point in time and to interpret this pattern. Others use rigorous mechanical or methodological methods to identify and interpret patterns.

Technical analysis software automatically performs planning, analysis, and reporting functions to help technical analysts to analyze and forecast financial markets such as stock markets. In addition to installable desktop-based software packages in the traditional sense, the industry has seen an emergence of cloud-based applications and application programming interfaces or APIs that deliver technical indicators e.g., MACD, Bollinger Bands via RESTful HTTP or intranet protocols. The latest technical analysis software can usually be used as a web or smartphone app without downloading and installing a software package. Particular type of software is the Execution Management System or EMS which is an application that traders use to view market data and provide their trading partners with quick and seamless access. The app includes independent algorithms offered by brokers such as TWAP and VWAP, global market data, and technologies that can be used to predict certain market conditions. One of the main functions of the EMS system is the ability to manage orders on multiple exchanges. Stock broker and networking between electronic networks and networks. In addition to commercial vendors, there are many open source projects that can be classified as EMS, but their scope varies.

Performed overview of technical analysis has gave understanding of essences of proposed technique and intrudes to its tools. As it can be concluded through the conducted research, technical analysis as a class of investment techniques, which are directed toward a shot-term perspective and it is evolving toward a more technically advanced solution as well as fundamental analysis.

Quantitative analysis <sup>11</sup> is another tool used for data analysis by credit organizations for the purposes of investment. Quantitative analysis is the use of mathematical and statistical methods in finance. Process of analyzing is usually consist

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<sup>11</sup> Horst, UH. and FR. Riedel, 2021. Mathematics and Financial Economics Volume 15. Transformative Journal.

of searching financial databases for patterns. It is typical for mathematically oriented quantum analysts to develop sophisticated models for pricing, hedging, and risk management of derivatives. This quantitative analysis is based on numerical analysis, not statistics or econometrics. Stochastic Calculus is one of the most important mathematical tools in quantitative finance. For quantitative statisticians, it is common to develop a model to identify relatively cheap and relatively expensive stocks. The model may include the company's book value to price ratio, the final price-earnings ratio, and other accounting factors. Investment managers can perform this analysis by buying undervalued stocks, selling overvalued stocks, or both. Statistically oriented quantitative analysts rely on statistics and econometrics rather than sophisticated numerical methods and object-oriented programming. All types of quantitative analyzers require a deep understanding of complex math and computer programming skills. These models might be based on the idea of behavioral economics which studies the effects of psychological, cognitive, emotional, cultural and social factors on the decisions of individuals and institutions and how those decisions vary from those implied by classical economic theory.

Neural networks are also used in the field of quantitative analysis because they can learn to detect complex patterns in data. In mathematical terms, they are universal function approximators, meaning that given the right data and configured correctly, they can capture and model any input-output relationships. While the advanced mathematical nature of such adaptive systems has kept neural networks for financial analysis mostly within academic research circles, in recent years more user-friendly neural network software has made the technology more accessible to traders and investors.

Another popular method, used by many traders in credit organization is sentiment analysis, which refers to the use of natural language processing, text analysis, computational linguistics, and biometrics to systematically identify, extract, quantify, and study affective states and subjective information. Example of sentimental analysis



is trading news investment strategy. Trading the news is a technique to trade equities, currencies, and other financial instruments on the financial markets.

As it can has been observed, tools of financial analysis are usually divided into fundamental and technical. Quantitative analysis was shown as another unique method for investment, which concerned more with a complex mathematical model of markets. All of them combined are used by credit organizations to solve multiple tasks in the financial markets. For the past years, digitalized software solutions have become the preferred options for investors as it makes process of analysis much easier and quicker, allow for more possibilities. Further direction of financial analysis will probably continue to move toward digitalization and more technically advanced solutions.

### 1.3 Concept, basic characteristics, and principles of building neural networks.

“Artificial neural networks or ANNs, usually simply called neural networks or NNs, are computing systems vaguely inspired by the biological neural networks that constitute animal brains. An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron that receives a signal then processes it and can signal neurons connected to it. So-called signal at a connection is a real number, and the output of each neuron is computed by some non-linear function of the sum of its inputs. The connections are called edges.”<sup>12</sup> Neurons and edges typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold. Typically, neurons are aggregated into layers. Different layers may perform different transformations on their inputs. Signals travel from the first layer or the input layer, to the last layer or the output layer, possibly

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<sup>12</sup> Neural network. Date Views 10.05.2021 [www.en.wikipedia.org/wiki/Neural\\_network](http://www.en.wikipedia.org/wiki/Neural_network).

after traversing the layers multiple times. Figure 1.3 shows visualization of a simple model of neural network.

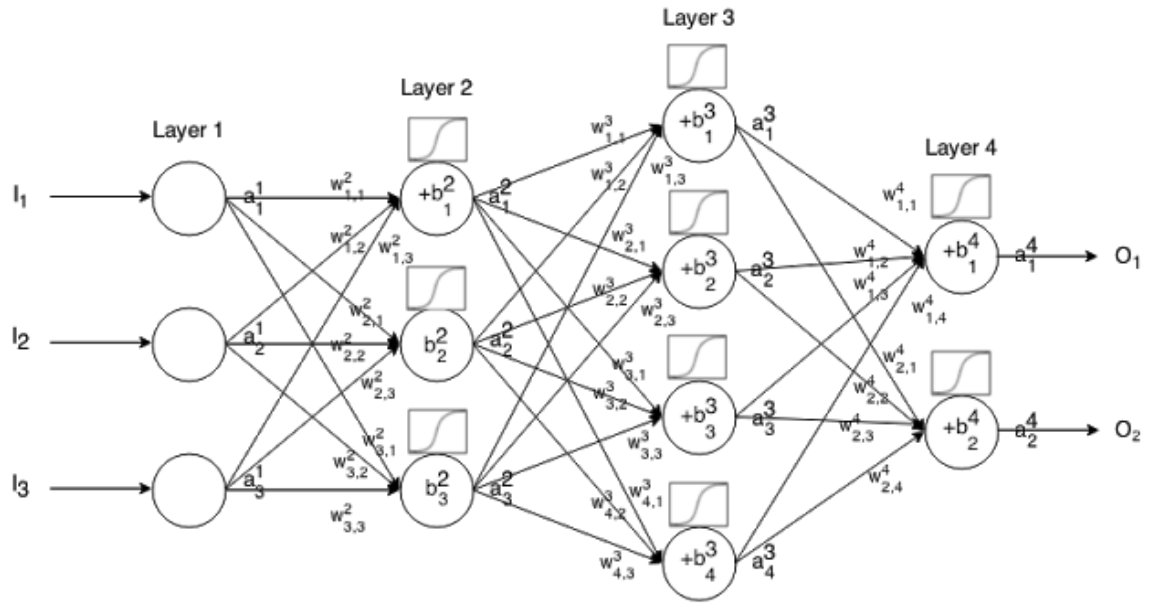


Figure 1.3. Simple Neural Network Visualization

Source: Nielsen, MN., 2015. Neural Networks and Deep Learning. Determiation Press.

Input layer represent input to a neural network as a one dimensional vector  $\vec{L}$ , where each neuron represent number  $li$  and is an element of  $\vec{L}$ . Second layer is a hidden layer, which take as input vector  $\vec{L}$  and output a new vector  $\vec{A}$ . Each neuron from hidden layer takes as input all neurons from previous layers. Neuron  $a$  of hidden layer can be described as (1.1):

$$a_i = \sum_{a=0}^n F(w_{ai} \times l_a + b_i) , \quad (1.1)$$

where  $a_i$  is a neuron,  $l_a$  is previous layer neuron,  $w$  is weight value, which is assigned to every connection of the network,  $b$  is bias value, which is assigned to every neuron in the network and  $F(x)$  is an activation functions, which introduce non-linearity into neural network. Weight and biases are initialized randomly, and when neural network is training, these parameters are changing, that is why they are called trainable

parameters. Output of hidden layer is vector  $\vec{A}$ , which is simply consist of every output of each neuron of hidden layer  $a_0, a_1 \dots a_n$ . Second hidden layer and output layer are the same, expect that they take as input preceding layer and have their own trainable parameters. So, neural network can be represented as (1.2):

$$F(L, W, B) = Y, \quad (1.2)$$

where  $L$  is just an input vector,  $W$  is three-dimensional vector of weights, and  $B$  is a matrix of biases, where each vector of  $W$  and element of  $B$  are assigned to exact neuron. Basically, neural network represents a function which maps an input of  $L$  with a corresponding output of  $Y$  with parameters  $W$  and  $B$ . As it was said, neural networks were inspired by biological neural networks, which can be seen on the figure 1.3. In fact, it has been proven by universal approximation theorem<sup>13</sup> that this type of neural network in theory can approximate any function. Speaking about financial markets it means that in theory neural network with high amount of nodes and appropriate parameters is able to find the best possible strategy of investment. On the other hand, theorem do not provide a construction for the weights, but merely state that such a construction is possible.

The way neural network can solve tasks is not fully understood and often heuristics is used to describe how artificial neural networks works. Mathematically speaking, neural network represents complex multivariable function. So, for each input  $L$ , there exists multidimensional graph of this function with a maximum point on the  $Y$  axes, which approximate the best possible solution for a given task. Finding this point in multidimensional space of parameters is called training of neural network.

In practice, training of neural network is including constriction of cost function, which is created to measure accuracy of neural network forecast and is used for

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<sup>13</sup> Balázs C.C. Approximation with Artificial Neural Networks: Computer science: 122. Budapest, 2001.

gradient descent training technique. Cost function construction depends on the problem, which neural network solves, but it always should represent how good or bad ANN does its task. For example, in classical machine learning task like computer vision, quadratic cost function can be used. Quadratic cost function takes as input the output from the neural network  $\check{Y}$  and expected result, which we seek to find  $\check{Y}$ . Quadratic cost function can be described by this formula (1.3):

$$Cost = \sum_{i=0}^n (\check{Y} - \check{Y})^2 . \quad (1.3)$$

And as (1.4):

$$F(L, W, B) = \check{Y} \Rightarrow Cost = g(F(L, W, B)). \quad (1.4)$$

So, if we know  $\check{Y}$ , we can find parameters  $W, B$  with some kind of optimization algorithm. Classical method is to use gradient descent. Via using derivative of each element in vector  $\check{Y}$ , we can find gradient of a cost function  $\nabla C(W, B)$ . Then, we can use this gradient in order to find local minimum of a cost function, so that  $\check{W}$  and  $\check{B}$  parameters will satisfy equation (1.5):

$$C \left( L, \check{W}, \check{B} \right) \approx 0, \quad (1.5)$$

which means that (1.6):

$$F \left( L, \check{W}, \check{B} \right) \approx \check{Y}. \quad (1.6)$$

This is a backbone behind training process of neural networks. But this exact technique is only able to find such parameters  $W$  and  $B$ , which solve task for only one possible input, whereas we would like neural network to map arbitrary input into  $Y$ , even if network has never seen such  $L$ . This characteristic of neural networks is called generalization. Generalization is reached, by going over the training data and averaging gradient of cost function  $\nabla C(W, B)$  over the training data of  $n$  samples (1.7):

$$\frac{\sum_{i=0}^n \nabla C_i(W_i, B_i)}{n}, \quad (1.7)$$

for the efficiency of the process, instead of averaging gradient decent over the whole training data, data can be divided into minibatches, to fasten the process of learning, so that average gradient is (1.8):

$$\frac{\sum_{i=0}^n \nabla C_i(W_i, B_i)}{n}, \quad (1.8)$$

being calculated only for mini batch, rather than for the whole training data. This whole idea is called stochastic gradient decent. After repeating gradient decent optimization algorithm for each mini batch of training data, neural network is able to generalize and learns parameters  $W$  and  $B$ , which can be used to map data into some true value  $Y$ , even if neural network has never seen this example before. Described process of training of neural network is called backpropagation, as it requires derivatives of cost function to propagate backward through neural network in order to find gradient. This neural network architecture and training technique was developed during second half of 20<sup>th</sup> century. In fact, this simple architecture can solve a lot of machine learning problems, but it is far from being ideal. Thanks to latest evolution of neural networks,

machine learning made a huge progress over the past years and some problems, which were considered unsolvable, were solved. These are number of computer vision tasks, text and audio recognition tasks, computer, and board game play, and many more. But even though ANN has changed, the fundamental principles behind neural networks remain unchanged.

Modern architectures and approaches to neural network construction and training are usually attributed to the field of deep learning. Deep learning refers to the idea of training big neural networks with multiplicity hidden layers. It has been a challenge for decades to train deep neural networks due to such problems as vanishing and explosive gradient descent, but they become solvable. Modern field of neural network study includes:

- Convolutional neural network. In deep learning, a convolutional neural network or CNN is a class of deep neural networks, most commonly applied to analyze visual data, but more generally can be used as data feature extractors. They have applications in image and video recognition, recommender systems, image classification, image segmentation, medical image analysis, natural language processing, brain-computer interfaces, and financial time series.
- Recurrent neural networks or RNN is a type of artificial neural network in which connections between nodes form a graph oriented chronologically. This allows to exhibit dynamic behavior over time. RNNs are derived from power neural networks and can use their internal state memory to process a variable length input data stream. This makes it suitable for tasks such as handwriting recognition and speech recognition.
- Transformer is a deep learning model that was introduced in 2017 and is primarily used in the field of natural language processing or NLP.
- Like recurrent neural networks, switches are designed to process sequential data, such as natural language, to perform tasks such as translating and synthesizing text. However, unlike RNNs, switches do not have to process serial data sequentially. For example, if the input is a natural language declaration, it is not

processed from start to finish. With this feature, Transformer provides more RNN concurrency and reduces training time.

- Reinforcement learning is a field of machine learning related to the concept of how intelligent agents work in an environment to maximize overall reward. Reinforcement learning is usually concerned with unsupervised learning, where expected policy is unknown.
- A generative adversarial network or GAN is a type of machine learning framework developed by Ian Goodfellow and colleagues in 2014. Two neural networks compete with each other in a game in the form of a zero-sum game in which the agent's gain is equal to the other's loss.
- Given the training set, this method learns to generate new data with the same statistics as the training set.

During the analysis of neural network-based approaches, deep learning has shown itself as a famous research field which came up with different solutions to approach previously unsolvable tasks. Newly created architecture became more sophisticated and can squeeze much more performance from a smaller number of parameters. It has been shown that very hard tasks can be solved by implementing more advanced techniques. Newly created approaches make possible to solve very big class of problems and combination of different models or so-called hybrid models of different kind can be used to achieve better results, for example in the reinforcement learning field.

#### 1.4 Analysis of modern research, dedicated to the application of machine learning for trading in the global financial market.

A lot of works in the academic literature are concerned about usage of neural network in the financial markets. For this chapter I will use Applications of deep

learning in stock market prediction: recent progress scientific paper<sup>14</sup> by Weiwei Jiang, from Department of Electronic Engineering, Tsinghua University, Beijing, China. This paper is dedicated to literature review of scientific papers about neural network in financial markets. This article reviewed total of 154 papers, 124 of which are published in the past 4 years. Another paper I will use is Neural networks for option pricing and hedging: a literature review<sup>15</sup> by Johannes Ruf and Weiguan Wang of more than 100 scientific works dedicated to ANN in financial market.

Different types or raw data are accompanied with different levels of difficulty for obtaining and processing, and the usage of different data types. For deep learning models, a huge amount of input data is necessary for the training of a complex neural network model. In this case, market data is the best choice and used for the most as it provides the largest amount of data sample, while the other data types usually have a smaller size. Text data is used for the second most, with the popularity of social media and online news, website, and the easier use of web crawlers to get the text data. An extreme case is the analytics data, which is never used in the surveyed studies, because of both the data sparsity and the high cost to access. There is also a trend that more diverse data types are used in 2018 and 2019, compared to the studies in 2017. It indicates the fact that it is harder to get a better prediction result based only on the market data.

Various modern prediction models can be classified into three types: standard models and their variants, hybrid models, and other models. Adversarial network, transfer learning, and reinforcement learning only appear in recent years and are still in an early stage of being applied for stock market prediction. While standard models perform well at early stages of research, their variants are further developed to improve the prediction performance. As an overall trend it can be remarked that more recent papers use more complex architectures, in line with improved availability of

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<sup>14</sup> Weiwei J. Applications of deep learning in stock market prediction: recent progress // Elsevier. 2020. № 0957-4174.

<sup>15</sup> Johannes R., Weiguan W. Neural networks for option pricing and hedging: a literature review // Journal of Computational Finance. 2020. №1460-1559.



computational resources. With the further exploration of deep learning models for stock prediction, their ratio as baselines keeps increasing in the past three years. The attention mechanism and generative adversarial networks has got a huge space for exploration. For example, for sentiment analysis of text data, Transformer and pre-trained BERT are widely used in natural language processing, but is less discussed for financial news analysis

A simple baseline investment strategy used is the Buy&Hold Strategy, which buys the asset at the beginning and hold it to the end of the testing period, without any further buying or selling operation. Technical indicators are also often used for designing baseline trading strategies, e.g., momentum strategy, which is introduced in Jegadeesh & Titman<sup>16</sup>, is a simple strategy of buying winners and selling losers.

These are evaluation metrics for the prediction models mostly used by researchers:

- Classification metrics. Classification metrics are used to measure the model's performance on movement prediction, which is modeled as a classification problem. Common used metrics include accuracy precision, recall, sensitivity, specificity, F1 score, macro-average F-score, Matthews correlation coefficient which is a discrete case for Pearson correlation coefficient, hit ratio, average relative variance, etc.
- Regression metrics. Regression metrics are used to measure the model's performance on stock/index price prediction, which is modeled as a regression problem. Common used metrics include mean absolute error (MAE), root mean absolute error (RMAE), mean squared error (MSE), normalized MSE (NMSE), root mean squared error (RMSE), relative RMSE, normalized RMSE (NRMSE), mean absolute percentage error (MAPE), root mean squared relative error (RMSRE), mutual information,  $R^2$

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<sup>16</sup> Narasimhan J., Sheridan T. Profitability of Momentum Strategies: An Evaluation of Alternative Explanations // The Journal of Finance. 2001. №56.

- Profit Analysis. Profit analysis evaluates whether the predicted-based trading strategy can bring a profit or not. It is usually evaluated from two aspects, the return and the risk. Risk can be evaluated by maximum drawdown, which is the largest peak-to-trough decline in the value of a portfolio and represents the max possible loss, or the annualized volatility. Sharpe Ratio is a comprehensive metric with both the return and risk into consideration.
- Significance Analysis. In order to determine if there is significant difference in terms of predictions when comparing the deep learning models to the baselines.

Most of the existing studies focus on only one stock market, in the sense that stock markets differ from each other because of the trading rules, while different markets may share some common phenomenon that can be leveraged for prediction by approaches such as transfer learning. There are already a few studies showing positive results for cross-market analysis and it is worth exploring in the following studies. In Lee et al. (2019)<sup>17</sup>, the model is trained only on US stock market data and tested on the stock market data of 31 different countries over 12 years. Even though the authors do not use the terminology of transfer learning, it is a practice of model transfer.

The prediction is not the end of the journey. Good prediction is one factor to make money in the stock market, but not the whole story. Some of the studies have evaluated the profit and risk of the trading strategies based on the prediction result. However, these strategies are simple and intuitive, which may be impractical limited by the trading rules. The transaction cost is often omitted or simplified, which makes the conclusion less persuasive. Another problem is the adaption for different market styles, as the training of deep learning models is time-consuming. These studies are not sufficient for building a practical algorithmic trading system. One possible direction is deep reinforcement learning, which has recent successes in a variety of applications and is also been used in a few studies for stock prediction and trading. It has advantages

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<sup>17</sup> J L., Raehyun K., Yookyung K., Jaewoo K. Global Stock Market Prediction Based on Stock Chart Images Using Deep Q-Network // Statistical Finance. 2019. №56..

of simulating more possible cases and making a faster and better trading choice than human traders.

It was shown that neural network models, used in reviewed researches are evolving as new papers became available and their architecture is moving toward a more advanced networks and hybridizations of multiple different architectures. Also, data diversity improving over time - news, macroeconomic indicators, social networks and other new data types and sources starting to be used in recent papers in contrast to older ones. It is hard to conclude a paper-by-paper summary of specific conclusions been drawn, but more than half of the paper abstracts explicitly emphasize the positive performance of ANNs in the option pricing, hedging task, stock prices prediction and portfolio management.

## 2. PROBLEMS AND FEATURES OF THE USE OF NEURAL NETWORKS BY PARTICIPANTS IN THE GLOBAL FINANCIAL MARKET.

### 2.1 Statements of problems solved by modern neural networks in the financial market.

As it was said, ANN can be used to solve huge amount of different tasks faced by credit organizations, from sentiment analysis and patter recognition problems up to big class of reinforcement problems, such a decision making. On the other hand, due to the fast pace of progress in the field of study of neural networks and implementation of neural network on the financial markets, there is a lack of information about usage of deep learning in financial markets to solve real world tasks. Thought, modern neural networks can be used to solve large variety of problems, so there are lots of research on their implantation.

Usage of neural network is always a concern of big data, as it is one of the main issues, when it comes to study neural networks. ANN should be trained to perform their task and they are data hungry algorithms. On the other hand, if there is enough data to train ANN, they can quickly process new information, find hidden patterns, and extract other useful information. So, neural network is usually used with big data and the most obvious usage of this feature is financial data analysis.

Neural networks are able to find trends and patterns in macro-economical data, ANN can be trained from analysis of oil well and S&P 500 to internet of things data. Then, this trained ANN can make predictions on different stock markets and be used as macro and micro economical indictor. Contrary to many researchers in the field, this study<sup>18</sup> argues that neural networks should be considered as a powerful complement to standard econometric methods, rather than a substitute. The full potential of neural networks can probably be exploited by using them in conjunction with linear regression models. Hence, neural networks should be viewed as an additional tool to be included

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<sup>18</sup> Gonzalez, SG., 2007. Neural Networks for Macroeconomic Forecasting: A Complementary Approach to Linear Regression Models, 2000-2007. Department of Finance.

in the toolbox of macroeconomic forecasters<sup>19</sup>. Being such a powerful data analysis tool, obvious neural network usage in fundamental, technical, and quantitative analysis.

As far as technical analysis is concerned, neural networks are a new, unique but complicated method. Usage of neural network can be made with investment decision based on thoroughly examined data, which is not necessarily the case when using traditional technical analysis methods. Neural networks are a next-generation tool in technical analysis with great potential that can detect subtle non-linear interdependencies and patterns that other methods of technical analysis are unable to uncover. It is intended for providing the most trustworthy and precise information possible on how effective certain investment strategy is. Neural network based model usage as technical analysis tool has a lifespan and cannot be used indefinitely. The longevity of a model's life span depends on the market situation and on how long the market interdependencies reflected in it remain topical. However, sooner or later any model becomes obsolete as new technical data became available. When this happens, models are either retrained using completely new data, add some new data to the existing data set and train the model again, or simply retire the model altogether.

The simplest approach is to forecast the price a few bars ahead and base a software system on such forecast. Other approach is to forecast price change or percentage of the price change. This approach seldom yields better results than forecasting the price directly. Both the simplistic approaches fail to uncover and gainfully exploit most of the important longer-term interdependencies and, as a result, the model quickly becomes obsolete as the global driving forces change. A more advanced technique of usage is to focus on governing input items for their neural network and adjusting their parameters. Several weeks and sometimes up to several months can be spent deploying the network. ANN used for technical analysis are set

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<sup>19</sup> CAMERON, NC. and SM. MOSHIRI, 2000. NORMAN CAMERON. 1999 Journal of Forecasting, 19(201-217). Date Views 05.04.2020  
[www.researchgate.net/publication/249759889\\_Neural\\_Network\\_vs\\_Econometric\\_Models\\_in\\_Forecasting\\_Inflation](http://www.researchgate.net/publication/249759889_Neural_Network_vs_Econometric_Models_in_Forecasting_Inflation).

appropriately for changing conditions throughout its lifespan. Because each neural network can only cover a relatively small aspect of the market, neural networks should also be used in a committee.

Another issue is an ability to employ several nets at once. In this way, each of these multiple nets can be responsible for some specific aspect of the market and give a major advantage across the board. However, it is the case to keep the number of nets used within the range of five to ten. Finally, neural networks for technical analysis can be combined with one of the classical approaches. This will allow a better leverage the results achieved in accordance with investment preferences. Key to usage of neural networks for technical analyses enrichment lies not in the network itself, but in the strategy. Therefore, neural networks usually used in combination with classical filters and money management rules.

Neural networks are a very powerful tool in modern quantitative finance. They are present in the fields related to semi and non-parametric regression and pattern classification, like time series prediction, risk estimation and credit scoring, estimation from conditional volatilities and estimation from implied volatility surfaces. For estimation of conditional volatilities, historical time series and estimation of surfaces of underlying asset volatilities implied on option prices is used. A deeper comprehension of the mechanisms and techniques used on the development of neural networks is necessary and decisive to its successful implementation in the field of quantitative analysis. Concerning networks applications, studies in the field are directed toward another practical financial problems: estimation of conditional Value at Risk, development of automatization of strategies for trading and portfolio hedging, development of credit scoring and default prediction tools. Neural networks in the framework of statistical learning and quantitative financial analysis remain as an interesting and challenging field.

As it was said, it can be used by credit organizations for finding trends, stock market prediction, quantitatively trading, algorithmic trading, risk management and many more. However, one of the big achievements of last years for the neural networks

is natural language processing. Unlike other algorithms, they can extract information not only from numerical data, but they also can be used for different type of texts, like news articles and social network information. They can extract meaningful features depending on the task. For example, on some datasets it has been shown that simple one-layer LSTM can extract, whether given text is has positive or negative sentiment with an accuracy of almost 100%<sup>20</sup>, which is higher than human average. And the latest achievement of open-ai, with the use of latest transformer architectures, was able to create GPT-3 ANN<sup>21</sup>, which can achieve state of the art accuracy on different variety of text analysis benchmark without prior training. This shows that ANN are very powerful tool for text analysis and in fact there are no comparable tools for such analysis apart from neural networks. This technique can be used for financial statements or news articles to conduct fundamental analysis and to understand the current situation on the markets, like in the study of Roberts S.<sup>22</sup>. In another study<sup>23</sup>, neural network was used to extract sentiment dynamics in related companies. It was found that there exists a clear positive relationship between the sentiment of the individual company and the group sentiment for several company groups, although the strength of this relationship varies across groups.

Hu et al.<sup>24</sup> did a comprehensive literature review in 2015 and concluded that most existing studies which apply soft computing and neural network for financial prediction are based on technical analysis. A much fewer studies explored ANN

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<sup>20</sup> Sentiment Analysis on IMDb. Date Views 12.04.2021 [www.paperswithcode.com/sota/sentiment-analysis-on-imdb](http://www.paperswithcode.com/sota/sentiment-analysis-on-imdb).

<sup>21</sup> Amodei, AD., SL. Sutskever, RA. Radford, MS. McCandlish and BT. Brown, 2020. Language Models are Few-Shot Learners. 1, 1. Date Views 05.04.2021 [www.arxiv.org/abs/2005.14165](http://www.arxiv.org/abs/2005.14165).

<sup>22</sup> Roberts, SR., DK. Kaiser, JC. Calliess and AA. Amel-Zadeh, 2020. Machine Learning-Based Financial Statement Analysis. SSRN, 41. Date Views 07.04.2020 [www.papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3520684](http://www.papers.ssrn.com/sol3/papers.cfm?abstract_id=3520684).

<sup>23</sup> Dong, XD., SZ. Zohren, JC. Calliess and XW. Wan, 2020. Sentiment correlation in financial news networks and associated market movements. *Nature*, 3062(11). Date Views 07.04.2020 [www.nature.com/articles/s41598-021-82338-6](http://www.nature.com/articles/s41598-021-82338-6).

<sup>24</sup> Y. Hu, K. Liu, X. Zhang, L. Su, E.W.T. Ngai, M. Liu, Application of evolutionary computation for rule discovery in stock algorithmic trading: A literature review. *Applied Soft Computing*, 36, 534-551, 2015.

assisted stock selection based on fundamental analysis. Shen and Tzeng<sup>25</sup> proposed a combined soft computing model for value stock selection. They concluded that their model could distinguish value stocks with satisfactory financial returns. Eakins and Stansell<sup>26</sup> applied FNN model for stock selection based on a set of fundamental financial ratios. They backtested their model for a 20-year period and achieved an investment return superior to that of benchmark stock index. Quah and Srinivasan<sup>27</sup> did a similar experiment using FNN for stock selection based on fundamental financial ratios. They also achieved above benchmark returns over their test period. In 2008, Quah<sup>28</sup> again compared FNN and ANFIS for stock selection based on fundamental analysis. Quah classified stocks into two classes based on their yearly return and converted the prediction problem into a classification problem. Eight years of quarterly data were used for training and 2 years for testing in Quah's study. His results show that ANN achieved high prediction results. Usage of neural networks for fundamental analysis is a very promising field, much less studied compared to technical and quantitative analysis, where neural network application is strait forward.

Another examples of ANN usages on different data types is convolutional neural networks, which can extract features from images. So, in this work<sup>29</sup>, CNN was used to for analyzing 2D images of stock charts.

Apart from being a very powerful data analysis tool, deep neural networks can be taught to act, according to environment conditions. This field of research is

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<sup>25</sup> K.Y. Shen, G.H. Tzeng, Combined soft computing model for value stock selection based on fundamental analysis, *Applied Soft Computing*, 37, 142-155, 2015.

<sup>26</sup> S.G. Eakins, S.R. Stansell, Can value-based stock selection criteria yield superior risk-adjusted returns: an application of neural networks, *International Review of Financial Analysis*, 12, 83-97, 2003.

<sup>27</sup> T.S.Quah,B.Srinivasan,Improvingreturnsonstockinvestmentthrough neural network selection, *Expert Systems with Applications*, 17, 295-301, 1999

<sup>28</sup> T.S. Quah, DJIA stock selection assisted by neural network, *Expert Systems with Applications*, 35, 50-58, 2008.

<sup>29</sup> Kim, R., So, C. H., Jeong, M., Lee, S., Kim, J., & Kang, J. (2019). Hats: A hierarchical graph attention network for stock movement prediction. arXiv preprint arXiv:1908.07999



reinforcement learning or RL. RL agent can perform actions, given the observable environment. They can be used on the financial market for portfolio management, by observing the stock prices, market condition and economic indicators and other data analysis. In fact, neural network as a reinforcement learning agent can use CNN and transformer networks, to extract feature from different type of data and then use them to perform actions, such networks are very powerful. They used for the self-driving cars, robotics and given a big data available in the financial field, they are greatly adopted for portfolio management.

As it was shown, neural networks are able to solve huge classes of problems in the financial market like price prediction, portfolio management, sentimental analysis. Deep learning base approaches in the area of sentiment analyses is the only option for extracting meaningful features from the text, as no other technique is able to achieve such a high result in this field. It was demonstrated in multiple researches, that in some cases, especially in very narrow tasks, neural networks are outperforming human experts even in intellectual tasks like data analysis. Given a big dataset for training, they can be a very powerful tool used by credit organizations for multiple classes of tasks, and different architectures of neural network can be combined for accomplishing big and at the same time diverse class of goals on the financial market.

## 2.2. Modern approaches to improving the quality of neural network forecast.

Since the breakthrough of AlexNet architecture<sup>30</sup> in vision recognition benchmark in 2012, deep neural networks gained an ability to solve huge amount different classes of tasks and achieved state of the art results, so they became heavily studied topic for the last decade. This brought up huge number of approaches for improving their results.

Unlike most neural networks in the past, modern neural networks usually use Relu as an activation function. Its derivative, unlike previously popular sigmoid

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<sup>30</sup> Rectified Linear Units. Date Views 09.04.2021 [www.paperswithcode.com/method/relu](http://www.paperswithcode.com/method/relu).

function<sup>31</sup>, has great property of not equal to zero, when argument is rather high. This significantly reduces vanishing gradient decent problem<sup>32</sup>. Relu activation function is shown on figure 2.1

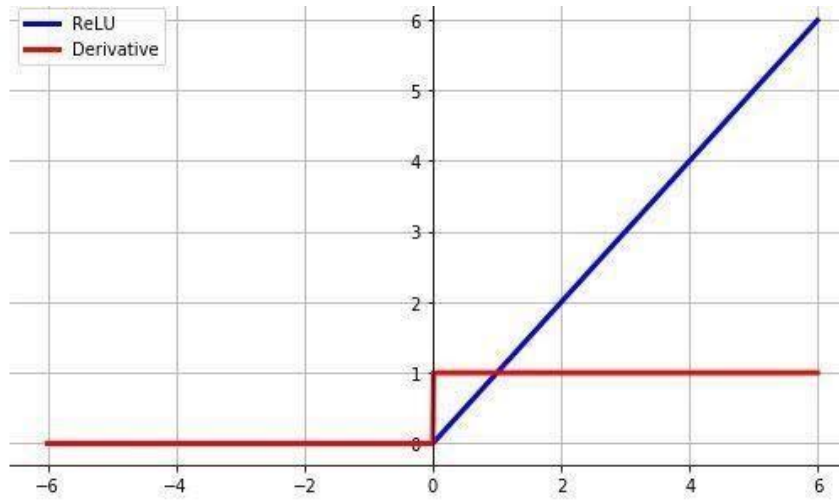


Figure 2.1. Relu activation function

Source: Bengio, YB., AB. Bordes and XG. Glorot, 2011. Deep Sparse Rectifier Neural Networks. Proceedings of Machine Learning Research, Neil Lawrence and Mark Reid Date Views 10.04.2020  
[www.proceedings.mlr.press/v15/glorot11a/glorot11a.pdf](http://www.proceedings.mlr.press/v15/glorot11a/glorot11a.pdf).

Vanishing gradient decent problem occurs if input signal is high and neural network performs very poorly. In such case gradients based on sigmoid function are very small and do not allow for an effective learning, whereas relu gradients would allow to learn without significant performance drop.

Another improvement of neural networks forecast accuracy relates to optimization algorithm. As neural networks can be represented as (2.1):

$$F(L, W, B) = Y, \quad (2.1)$$

<sup>31</sup> Han, Jun; Morag, Claudio, 1995. The influence of the sigmoid function parameters on the speed of backpropagation learning. In Mira, José; Sandoval, Francisco. From Natural to Artificial Neural Computation. Lecture Notes in Computer Science. 930. pp. 195–201. doi:10.1007/3-540-59497-3\_175. ISBN 978-3-540-59497-0.

<sup>32</sup> Hinton, GH., IS. Sutskever and AK. Krizhevsky, 2012. ImageNet Classification with Deep Convolutional Neural Networks. Advances in Neural Information Processing Systems, 25(2). Date Views 09.04.2021  
[www.researchgate.net/publication/267960550\\_ImageNet\\_Classification\\_with\\_Deep\\_Convolutional\\_Neural\\_Networks](http://www.researchgate.net/publication/267960550_ImageNet_Classification_with_Deep_Convolutional_Neural_Networks).

where  $L$  is just input vector,  $W$  is three-dimensional vector of weights, and  $B$  is a matrix of biases, where each vector of  $W$  and element of  $B$  are assigned to exact neuron.

For training this network, stochastic gradient descent or SGD is used as it was described in chapter 1.3. One of the issues with SGD is that it has a tendency to converges to local minima. Neural network can be represented visually, as a complex function of its parameters  $W$  and  $B$ . While training, neural network's parameters tries to reach global minima via SGD, but it can be stuck in local minima or in saddle point, for example. Simplified ANN version with only two parameters is shown on figure 2.2.

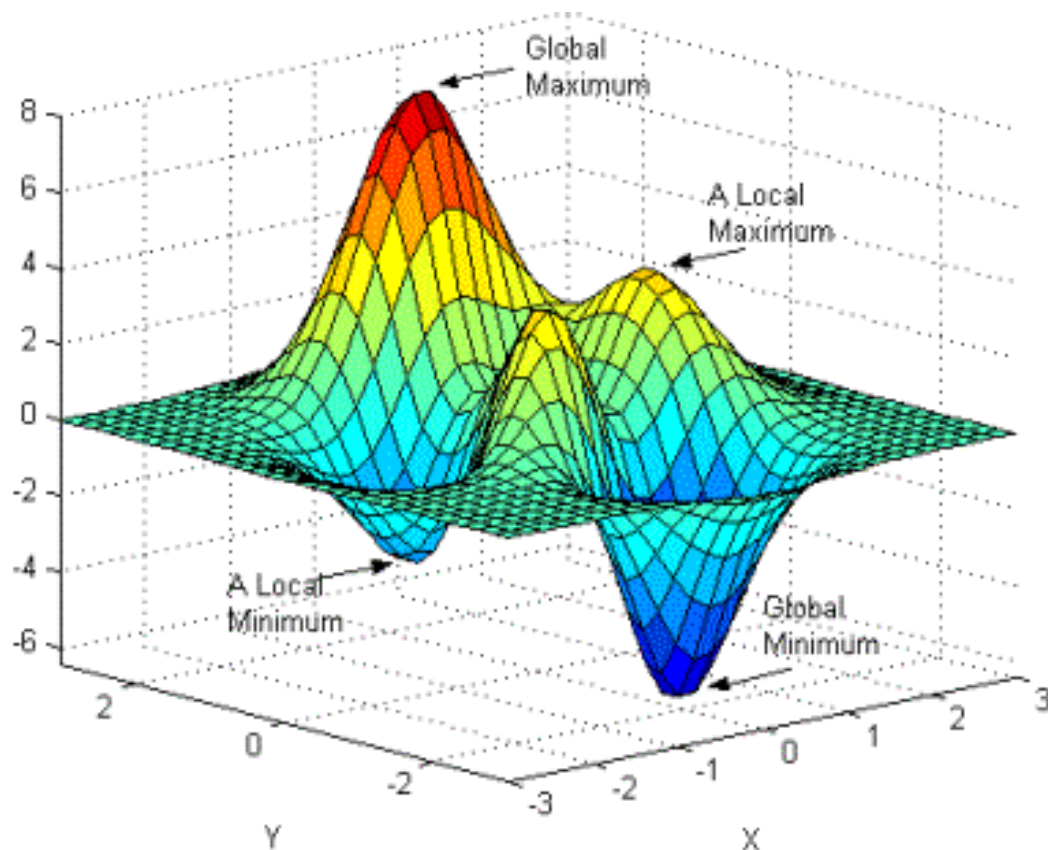


Figure 2.2. Oversimplified visualization of neural network

Source: Prepared by author

One of the Solutions for this issue is modified optimization algorithm like Adam. Adam tries to use both RMSprop<sup>33</sup> optimization algorithms and try to store both exponentially decaying average of the past squared gradients and the exponentially decaying average of past gradients<sup>34</sup>, thus, to compute the decaying average of past squared gradients and past gradients. This technique not only improves neural networks forecast, but also reduces the sensitivity of learning rate hyper-parameter.

One of the main issues when using neural networks for solving tasks is their architecture. Neural networks architectures overview is described in chapter 1.3. As it was stated, different architectures are used for different tasks. For example, convolutional neural networks are usually used for visual recognition but in fact idea of convolution can be adapted for any data. Convolutional neural networks are able to find pattern in data and often described as a features extractors as they are usually used to extract features from data, which are then used by another ANN to solve different tasks. Unlike traditional neural networks, where each layer consists of fully connected nodes, CNN uses convolutional operators, which significantly reduces number of parameters, allowing to create bigger and deeper neural networks. Another trick for learning neural networks is residual connections, which are shown on figure 2.3.

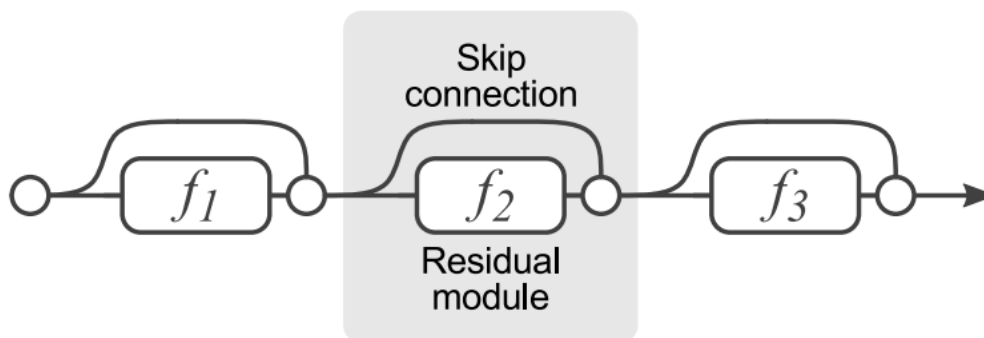


Figure 2.3. Residual connections

Source: Residual Neural Networks as Ensembles. Date Views 09.04.2021  
[www.codesachin.wordpress.com/tag/ensemble/](http://www.codesachin.wordpress.com/tag/ensemble/).

<sup>33</sup> RMSProp. Date Views 09.04.2021 [www.paperswithcode.com/method/rmsprop](http://www.paperswithcode.com/method/rmsprop).

<sup>34</sup> SGD with Momentum. Date Views 09.04.2021 [www.paperswithcode.com/method/sgd-with-momentum](http://www.paperswithcode.com/method/sgd-with-momentum).

Main idea behind residual networks, is that they give an ability for gradients  $\nabla f$  of neural network to be passed throughout a layer and so an ability to solve vanishing and exploding gradients problem when adding more layers to an already deep neural network.

Recurrent neural networks or RNN is another architecture, which provides an ability to neural network, to process sequential variable data. LSTM unit is shown of figure 2.4.

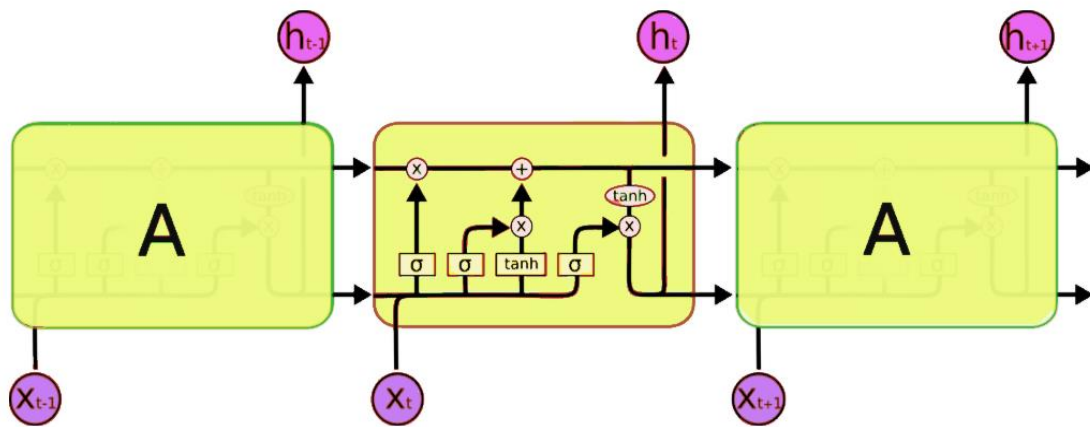


Figure 2.4. LSTM cell

Source: Long Short Term Memory (LSTM) Networks in a nutshell. Date Views 09.04.2021

[www.ahmetozlu93.medium.com/long-short-term-memory-lstm-networks-in-a-nutshell-363cd470ccac](https://www.ahmetozlu93.medium.com/long-short-term-memory-lstm-networks-in-a-nutshell-363cd470ccac).

LSTM which stands for Long Short Term Memory is an example of an advanced RNN. This figure illustrates how signal flow through a single LSTM cell, which can be stacked on top of each other. Red boxes are math operators, whereas yellow are neural network's single dense layer, with a corresponding activation function. Tanh is hyperbolic tangent activation function and  $\sigma$  is sigmoid activation function. Unlike other Neural network architecture, LSTM have multiple inputs and outputs. Those, illustrated on the sides are inner connections. During each time-step, it calculates so called inner state, which is then passed to the next time-step. In this way, LSTM can process sequential data by holding information about past time steps inside its inner state.

Another important area of research is reinforcement learning, where huge success has been made over past years. Reinforcement learning is concerned with how intelligent agents ought to take actions in an environment in order to maximize the notion of cumulative reward. Deep neural networks are used for state-of-the-art results in reinforcement learning field. Unlike most other fields, in reinforcement learning ANN should learn unsupervised. It means, that there is no predetermined right decision to learn. Usually, learning is presented in a form of Markov decision process, where agent should learn right moves or policy by interacting with the environment. There are a lot of approaches to achieve this. Standard one is policy gradients. Main idea is to push up the probabilities of actions that lead to higher return and push down the probabilities of actions that lead to lower return, until optimal policy is achieved. Let  $\pi_\theta$  denote a policy with parameters  $\theta$ , and  $J(\pi_\theta)$  denote the expected finite-horizon undiscounted return of the policy. The gradient of  $J(\pi_\theta)$  is (2.2):

$$\nabla_\theta J(\pi_\theta) = \mathbb{E}_{\tau \sim \pi_\theta} \left[ \sum_{t=0}^T \nabla_\theta \log \pi_\theta(a_t | s_t) A^{\pi_\theta}(s_t, a_t) \right], \quad (2.2)$$

where  $\tau$  is a trajectory and  $A^{\pi_\theta}$  is the advantage function for the current policy. In order to achieve high results, Actor-critic method, which is shown on the figure 2.5 is used.

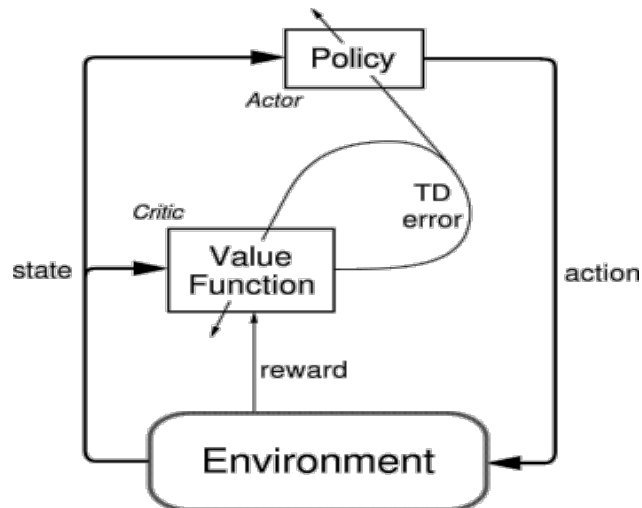


Figure 2.5. Markov decision process with Actor-critic method

Source: Long Short Term Memory (LSTM) Networks in a nutshell. Date Views 09.04.2021  
[www.ahmetozlu93.medium.com/long-short-term-memory-lstm-networks-in-a-nutshell-363cd470ccac](http://www.ahmetozlu93.medium.com/long-short-term-memory-lstm-networks-in-a-nutshell-363cd470ccac).

In general, idea is that advantage function  $A^{\pi_{\theta}}(s_t, a_t)$  is calculated as (2.3):

$$\sum_{t=1}^n \hat{R}_t - \hat{A}_t \quad (2.3)$$

Where  $\hat{R}$  is discounted reward,  $t$  is time-step,  $n$  is total amount of time-steps and  $\hat{A}$  is baseline values. It is calculated by another neural networks called critic, which evaluate how good was the action made, compared to what critics believed it was.

Evolution of artificial neural networks came a long way from the simple concept in the sixties, to a strong, multitasking, and promising tool in the nineties, to an extremely powerful, advanced, and ubiquitous class of approaches used by many companies' today. In the era of information and high technologies, artificial neural networks are used almost everywhere, from phones to cars and financial industries. Though, newly developed approaches are still looking for their application and given such a rapid growth, they will be used to solve even more tasks in different industries, including financial market.

2.3. Usage of neural networks to predict prices and execute transactions on the global stock market.

As it has been shown, deep neural networks are able to solve multiple tasks and achieve a very good performance and even exceed human possibilities and they are able to solve variety of problems on the financial market which are under concern of credit organizations. In this section, I would try to use deep neural network in a market environment and see how it would perform. Financial markets are stochastic environments with imperfect information, but as it was suggested chapter in 1.1, with strong evidence that financial markets probably not perfectly efficient. Given that they are affected by multiple different factors like Economic Strength of Market and Peers, Incidental Transactions, Demographics, Trends, News, psychology of market and many more variables in a very complex way, deep neural networks being a very good

function approximator, might find hidden patterns in big data, collected from multiple resources, so that it would be able to predict movements of securities on financial markets with relatively high accuracy. To test this hypothesis, I would try to use deep neural network to predict prices and to manage financial portfolio.

One approach would be to teach a neural network to predict stock prices using market historical data with supervised learning. However, it would be untrivial task to use such network to manage financial portfolio as it is unclear, how should neural network forecast be used in an investment strategy.

Another way to train a neural network is to use reinforcement learning approach and directly train neural network to manage financial portfolio. In this case, a reinforcement agent will be learning to execute transaction on the financial market and try to learn best investment strategy to gain maximum reward in a Markov environment. If there are patterns in the financial markets in the big data, which can help it to increase its reward, given a powerful agent and right learning techniques, it should learn to find those patterns and use them for portfolio management in best possible way, unlike supervised learning approach, where neural network predictions create another complex problem to solve. So, in this work I would use reinforcement learning, as it is less studied and more perspective.

To train neural network, I have collected historical data from different sources, including daily information about stock prices and volumes of S&P100, which are freely available on yahoo finance<sup>35</sup>. Also, I would use 13 economic indicators: NASDAQ BANK, KBW Nasdaq Bank Index, NASDAQ Industrial, NASDAQ Computer, NASDAQ Telecommunications, NASDAQ Biotechnology, PHLX Oil Service Sector, NYSE Arca Tech 100 Index, Russell 2000, PHLX Semiconductor, CBOE Volatility Index, PHLX GOLD and SILVER SECTOR I, NYSE ARCA SECURITIES BROKER/DEA. These indexes have been chosen due to their freely availability and a big historical archive, available on yahoo finance. Neural networks are data hungry algorithms, and they need a lot of data to train, especial in case

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<sup>35</sup> Yahoo Finance. Date Views 09.04.2021 [www.finance.yahoo.com](http://www.finance.yahoo.com).



reinforcement learning. Also, some patterns might be visible on the scale of years, so it is suggested that using data more than a decade, will be preferable. Beside stocks and economic indicators, I will use dataset of news, collected from 2003 up to 2020<sup>36</sup>. Sentiment analysis is a field, where neural networks perform much better than any other algorithm. Also, news trading is suggested to be a profitable strategy, so they might be useful for portfolio management. Simplified version of proposed neural network is shown in the figure 2.6 whereas full architecture is shown in the appendix 1.

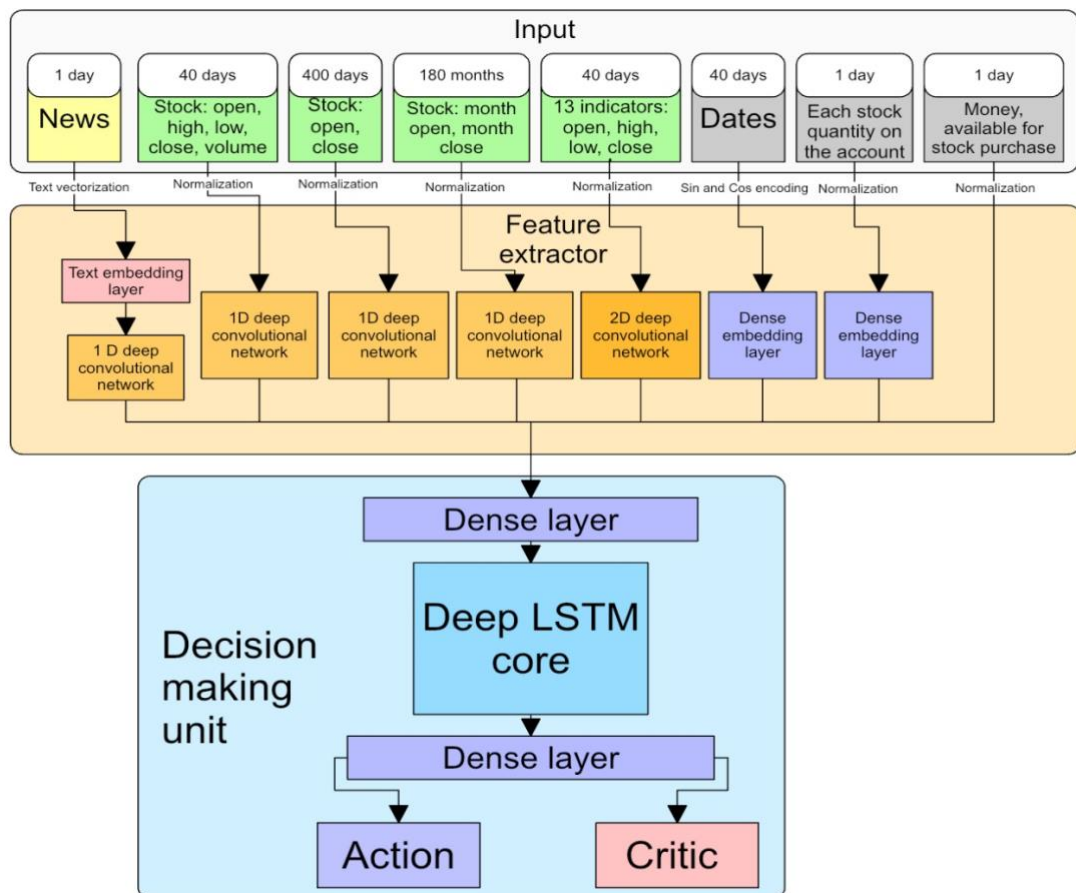


Figure 2.6 Neural Network Architecture

Source: Created by author

For reinforcement learning, I have chosen policy gradients. Policy gradients is a powerful learning policy, and its modifications has been used by OpenAi in their Open Ai Five neural network-based agent, which was able to beat world champions in the

<sup>36</sup> A Million News Headlines. Date Views 02.02.2021 [www.kaggle.com/therohk/million-headlines](http://www.kaggle.com/therohk/million-headlines).

video game of Dota 2<sup>37</sup>, which is a very complex game. Thought they have used modified version - Proximal Policy optimization, it has been shown in this study<sup>38</sup>, that a more classical vanilla gradients show better results on stock markets. In this work I will also use actor-critic method as it is currently state of the art approach. As for the Neural network architecture, I will use deep neural networks consisted of different blocks, including convolutional network, LSTM and classical dense or fully-connected layers. This architecture was inspired by Alphastar and Open AI Five, as they also have feature exactors networks and LSTM core, which make decisions. As it is shown on the diagram, to make forecast and explore strategies, deep neural network uses multiple inputs, some of which were already described. Data about the stocks is divided into 3 section: past 40 days detailed information about the stock market, past 400 days of open and close prices and past 180 months data points with monthly prices. As it was shown in this study, using different data time-frame windows is useful. Past 40 days dates are encoded so that model can be aware about the date. Also, in some learning strategies, it has information about each stock it holds at the moment, and money available to purchase new stocks. Deep neural network can only execute 2 actions at a time – buy or sell.

Three learning strategies were chosen:

1. Model learns to trade each individual stock at a time, where each learning batch consists of 180 days, after which model gradients are changed
2. Model learns to manage investment portfolio as a whole and choose to buy or sell each stock in a portfolio for seven days straight. In this case batch of training consists of 1 week, due to the much higher processing power needed for each day of training.

To explore the limits of proposed neural network, it was chosen to slightly modify second strategy to manage an investment portfolio, by choosing 15 most

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<sup>37</sup> Zhang, SZ., FW. Wolski, JT. Tang, IS. Sutskever and CB. Berner, 2019. Dota 2 with Large Scale Deep Reinforcement Learning. Date Views 09.04.2021 [www.cdn.openai.com/dota-2.pdf](http://www.cdn.openai.com/dota-2.pdf).

<sup>38</sup> Li, YL., KJ. Jiang, JZ. Zhu, HC. Chen and ZL. Liang, 2020. Adversarial Deep Reinforcement Learning in Portfolio Management. 747, 747. Date Views 09.04.2021 [www.arxiv.org/abc/1808.09940.pdf](http://www.arxiv.org/abc/1808.09940.pdf).

perspective stocks according to the probability distributions of an agent to limit the amount of total stock possible for buying at each step and so pushing learned strategy to its limits. Number 15 has been chosen by empirical tests made during the year 2018 as it showed to be most profitable.

#### Strategy 1:

During testing, total timeframe of training was 15 years, from 1 January of 2003 up to 31 December of 2018. Evaluation was done separately on the year 2019. To evaluate the agent, it was compared with simple Buy and Hold S&P100 strategy. The result of the first learning strategy, where neural network was trained to trade one stock at a time is that neural networks has learned to always buy the stocks. In fact, neural network completely copied Buy and Hold strategy as this was the most profitable strategy developed by neural network. This behavior might be a consequence of a data bias because chosen stocks only include those companies, which exists today. There is not enough data on the companies, which went bankrupt during past 20 years to test this hypothesis. Also, at each timestep neural network was not able to trade multiple stocks at a time to give preferences to some, while exclude others, which is probably led to just copying Buy and Hold strategy.

Neural network behavior might indicate, that buy and hold strategy is the best strategy on the market possible for a single stock if not considering intraday trading. Also, it is possible, that model couldn't come up with a better strategy, due to its computational and architectural limitations. Important to notice is that in this case, RL agent was only trained with a chose to buy or sell one stock, so it does not have an ability to manage a portfolio.

#### Strategy 2:

According to second strategy, neural network is first fed with information about each stock from single timestep in a sequence, so that LSTM's inner state can understand situation of the whole market environment at the moment. Then, this process is repeated and on the second iteration, deep neural network outputs actions probability distributions for each stock, which are sampled and used to manage a

portfolio. One batch of training consists of 1 week, after that gradients are adjusted. Results are shown on figure 2.9.



Figure 2.9. RL agent and Buy&Hold strategy financial result comprising during the year 2019.

Source: Created by author

Y axis shows total gain received by investment strategies given the initial investment available of one million US dollars. X axis represents total timesteps available for the agent. Neural network had an ability to execute a transaction during the start and the end of each day, and it was trading for total of 50 weeks, so during the testing period total of 700 timesteps was made. As it can be seen on the graph, neural network results, market as RL agent, has almost copied the Buy and hold strategy. It was able to outperform Buy and Hold indicator by an insignificant margin. It can indicate that one epoch training on chosen data was not enough for a network to converge to any policy. However, during the testing it has been unveiled, that network output action distribution had different value during various market conditions, so in order to evaluate what network has learned, it was chosen to take only 15 highest signals from the network and artificially push neural network to choose only some of stocks for purchase. Number 15 has been chosen as this value has shown best results during the

testing on year 2018. And with such settings, neural network was able to outperform buy and hold strategy based on S&P100 index by total of 6%.

Figure 2.10 shows comprising of financial results after each week of testing.

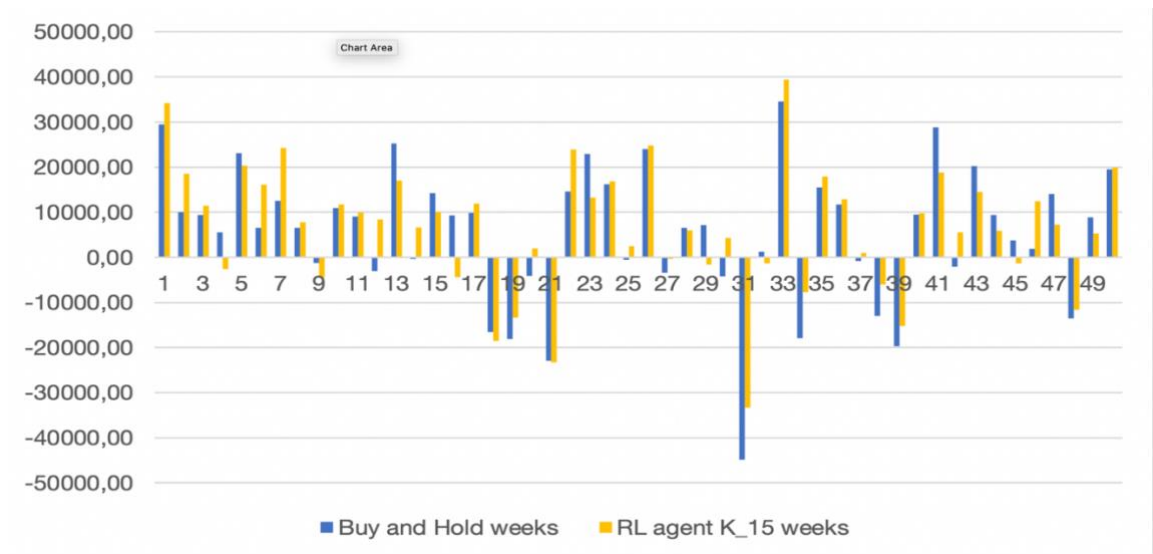


Figure 2.10 Comparing of B&H and RL agent weekly financial results.

Source: Created by author

Y axis represent financial results of both buy&hold strategy and RL agent during each week of year 2019. As it can be seen on the figure, lowest returns during the testing period belong to S&P100 index-based strategy. Such results suggest that neural network has learned to reduce its risks while managing a portfolio. And during the statistical analysis of conducted experiment, it has been shown that financial results of neural network has lower standard deviation, compared to Buy and Hold strategy, which are 4083 and 4305 correspondingly. So, neural network was not only able to outperform classical approach to portfolio management in terms of profitability, but also reduce the risks while only having 15 stock in its portfolio, compared to 100 in baseline strategy. Full table of results are attached in appendix 2.

On the figure 2.11 are shown financial results of the agent in year 2020.



Figure 2.11. RL agent and Buy&Hold strategy financial result comprising during the year 2020.

Source: Created by author

As it can be seen from the figure, this time results are quite different. RL agent again was able to outperform standard strategy by some marginal value. While the same agent, pushed to its limits performed not as good as S&P100 index. Interestingly enough, during most of the year, RL agent K 15 was outperforming baseline strategy, however closer to the end of the year during one of the months, it significantly underperformed. It can be visually seen in the figure 2.12., which represents weekly financial results.

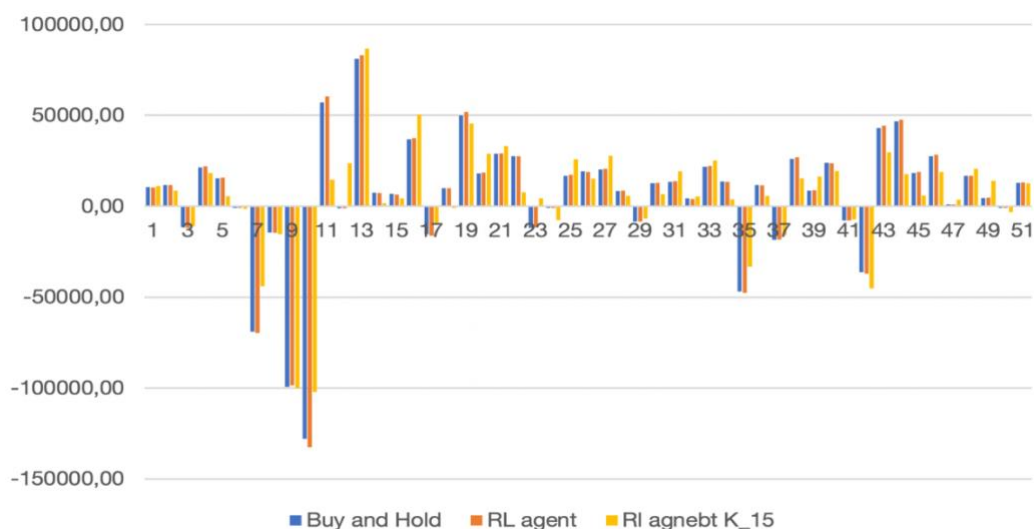


Figure 2.12 Comparing of B&H and RL agent weekly financial results.

Source: Created by author

Such a fluctuation might indicate that S&P100 index turned out to be more profitable due to stochastic volatility of the market. This hypothesis sounds convincing, given that standard deviation of proposed network strategy was lower in this year too, 11003 for buy and hold strategy, and 10638 for neural network-based strategy correspondingly. Important issue to notice is that neural network was not trained on the year 2019 before testing its performance during the year 2020, which might have affected the results.

Results of conducted experiment show how powerful modern deep neural network architectures are and how its combination with modern reinforcement learning approaches can be successfully used in modern financial market environment. It was able to outperform baseline benchmark of S&P100 index in profitability while reducing portfolio associated risks, even though there exists strong suggestion that this model seems to be undertrained and its result can be improved further with more epochs training. There are much more opportunities to explore as much bigger models with other architecture and training strategies can be used, more training data can be collected, including intraday market conditions and much more sources of information can be used to give neural network more understanding of what is happening the world to explore even more relationships and so significantly improve networks capabilities.

### 3. PROSPECTS FOR THE USE OF NEURAL NETWORKS BY CREDIT INSTITUTIONS IN THE GLOBAL FINANCIAL MARKET

3.1 Problems and features of the construction of artificial neural networks in the modern world financial market.

Neural networks are very complex systems and using them in the circumstances of modern financial markets might be very challenging. Training a deep reinforcement learning agents unveiled strong and weak sides of their usage in the markets but it has been shown that they can be effectively used for portfolio management.

There are modern instruments like TensorFlow and Pytorch, which significantly simplify usage of neural network for researchers and gives an ability to test different hypothesis and approaches, to try multiple architecture for certain task. In the modern financial environment with diverse big data availability and recent neural network developments, it is important to be able quickly test data and construct multiple neural network architecture and choose appropriate hyper parameters, in order to conduct researches. These frameworks allow to do so easily, without the need for attention to the low-level complex mathematical apparatus of the model itself.

Recent development of information technologies and their integration in the modern life was one of the key in the development of deep learning as it made big data available for the researchers. Study made by Weiwei J.<sup>39</sup> has shown diversity of data used for financial market related tasks. Today, datasets of market prices of different securities with the time scale of nanoseconds are available on the internet. People are using social networks, news and journals are published online, companies publish their financial statements on their web sites. All this data from diverse sources today can be used and analysed for the machine learning related problems including financial market.

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<sup>39</sup> Weiwei J. Applications of deep learning in stock market prediction: recent progress // Elsevier. 2020. № 0957-4174.



Data availability and quality play key role in neural network training. However, as it has been shown in the study of Grace Liu<sup>40</sup>, the data of commercial businesses and financial databases contain wide range of data quality issues, many of which have been systematically tested with statistical methods. It can greatly affects research quality and reliability. The presence of data quality problems can not only distort research results, destroy a research effort but also seriously damage management decisions based upon such research.

Another issue is dataset cost. Dataset of S&P100 with 17 years history for neural network training in this work has been collected using yahoo finance, with the help of scraper web harvesting or web data extraction, which are various methods of collecting information from across the internet. It is essentially a form of data mining. However, there is no such publicly available full dataset available ready for use. This limits the opportunities for the researchers. However, large historical dataset with intraday data is publicly unavailable. Some resources provide this data for substantial amount of money, which makes this data significantly less accessible for conducting a scientific study and creating market solutions by small organizations.

Another problem in the area of neural networks usage in financial markets is transaction cost. As it has been shown in chapter 2.3, ability of neural network to make decisions into the market environment has been significantly affected by transaction cost. This might be caused by the exploration algorithm of reinforcement learning agent. In this work, neural network explores different strategies, because a random sample has been taken from each action probability distribution output of a network at each timestep. When transaction cost has been included in the rewards function, reinforcement agent has been punished by exploring any new strategy which made it unable to explore different policies and to find optimal strategy.

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<sup>40</sup> Liu, GL., 2020. Data Quality Problems Troubling Business and Financial Researchers: A Literature Review and Synthetic Analysis. *Journal of Business & Finance Librarianship*, 10(1080). Date Views 10.04.2020  
[www.digitalcommons.wcupa.edu/cgi/viewcontent.cgi?article=1013&context=lib\\_facpub](http://www.digitalcommons.wcupa.edu/cgi/viewcontent.cgi?article=1013&context=lib_facpub).

Modern advanced machine learning approaches in the field of model-free reinforcement learning usually concerned with making one action at a time, however in case of solving portfolio management problem, they need to execute multiple action at each time step. This problem can be solved using multi-agent paradigm, where multiple agents are trying to solve complex task, and each learns to do execute only one action at a time. Another approach is to use multivariable probability distribution as an actor policy. In this work, portfolio management has been conducted by dividing single time-step into multiple steps, and an agent had a perception of a single stock at each sub-step, rather than the whole portfolio. However, other approaches can be used and might show better results.

Though, multi-agent approaches are more preferable in the research field, it is computationally expensive. Modern machine learning studies are often conducted by research groups with and access to huge computational resources. Latest achievement in the machine learning like GPT-3 language model, were made with huge resources and often costs millions of dollars' worth computation power. Such trends in the research community limits the possibilities of small entities to conduct research in the field of deep learning. ANN model used in this work have approximately four million trainable parameters and it took a week to train it on a modern personal computer, whereas GPT3 have got over a trillion parameters.

Another serious concern when using neural network by credit organizations is inability to understand the reason, why neural networks make such a prediction or action. More traditional approaches to stock market prediction, portfolio construction, risk management and other areas of financial market research use mathematical approaches to solve problems. These approaches are usually constructed for a specific task while neural network's ability to learn can be used for big class of problems and the solution is learned by the appropriate network with appropriate datasets. And if a more conservative approaches have been constructed with some underlying principles and understood mechanism of relationship, neural network are very complex mathematical models and all the principles of their work and especially their

architecture construction still not fully understood. Without the understanding of the technology, where it can fail and where is its limitations, it is very hard to calculate associated risks and use to solve real problems in the financial market environment.

Neural network has shown its ability to do multiple tasks in the financial markets. For example, as a function approximator they can be used to predict future prices, given a current state on the market. However, regarding its previously discussed complexity, it was identified in this work that its perdition capabilities can't be used directly for portfolio managements, risk calculations or forecast related tasks directly. Furthermore, it has been shown that even after training for 17 years staring for direct stock trading, it has just copied simple buy and hold strategies and further adjustments were required to gain higher results. Conducted work indicates, that neural networks usually unable to solve a specific task end-to-end and their usage is often narrow-limited in the circumstances of financial markets and further work should be made to acquire a satisfactory results. For instance, in case of stock perdition, neural network output has to be carefully embedded into investment strategy for financial results improvements.

Another concern for neural network usage is different market segments. Research of variety financial markets, neural network peculiar properties and their analysis unveiled that due to different market features, neural networks should be trained for a specific market. Even though it has been shown, that ANN trained on US stock market, can see patterns in many other stock markets all over the world, for instance currency market, bond market or spot market are just to different from each other for a neural network to generalize from one market to another.

Neural networks, being a very powerful tool in the financial market, are very complex systems and especially due to novelty of deep learning, they need to be properly adjusted for the exact task and there is not plug and go solutions yet. However, today there exist multiple libraries for deep learning which significantly simplify their usages. And modern development of technologies and their integration into society gives huge advances for the whole machine learning field and given further

development of the financial markets, businesses, and the whole world to the direction of informational technologies only increase the perspectives for neural networks.

### 3.2 Prospects for the use of neural networks for portfolio management.

Neural network has shown its ability to outperform basic S&P100 index so it can be used for portfolio management to increase financial results which is a concern about the future of portfolio management.

New technologies and methodologies, big data, advanced machine learning techniques and many more newly emerged tools in sciences, opens big perspectives for further development of economics. Better understanding of economics, relationship between economic factors and more precise analysis can cause an emergence of better portfolio management practices and contribute to improved machine learning financial results. All these new techniques became available, and it led economists to think in a more structured way and better understand how analysis should be made, how to extrapolate data from where it is a lot of evidence to where there is not much, which is a big generalization problem. Understanding of how different part of economics fit together will grow and it will have more implications. In the last decades, economics became a much bigger subject and erased new big economic areas such as behavioural economics<sup>41</sup>. Future development will continue and significantly affect the whole field of economics concerned with financial markets and as a consequence machine learning application.

As it has been shown multiple times, lately emerged big data in the field of data analysis gives more opportunities for researches and gives an ability to investigate previously inaccessible areas of human behaviour in different areas of society, like social interaction in social networks, news, trends in google search engine, web activity and many more. Further development of internet of things, informational technology

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<sup>41</sup> The Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel 2002. Nobel Foundation. Retrieved October 14, 2008.

and integration of computers and internet in the life of humans will continue and more sophisticated and accurate data will be available. Data analytics is expected to radically change the way people live and do business in the future. Although organizations are taking steps to turn data into insights, studies shows that organizations are still struggling with data quality and the problem to find the right resources to turn these insights into true value and become more data driven.

Expectations are that data analytics will make the impossible possible, but it is still in the early stages of the data era. Basically, every company is currently investing in data analytics capabilities to keep up with known or unknown developments and competition. The known data analytics development cycle is described in stages: from descriptive to diagnostic, to discovery, to predictive, and, finally, to prescriptive analytics. In general, organizations currently find themselves in the diagnostic and discovery stages. Data analytics initially supported the decision-making process but is now enabling better decisions than can be made by humans. Today analytics is applied to combine multiple data sources, resulting in new and better insights. If it turns out in the future that a decision-making process based on data analytics will produce better results, the step to automated decision-making will be small. New capabilities required to handle the availability and storage of data will emerge with cloud providers like Amazon Web Services, Google and Microsoft Azure. Organizations will not need to invest in data analytics platforms, because with the cloud all capabilities can easily be scaled to the organizational needs. This can include analytical building blocks, such as data lakes, machine learning tools and Hadoop, but also complete analytical visualization applications or apps readily available for variety of systems.

As with the froth of data, pure computational resources grow as well. Moore's law, which was empirically withdrawn in the sixties by the Intel founder Gordon Moore, forecast computational power to grow exponentially and doubles every 18 months. Actually, Moore's law is not a law of physics, rather it is an emergent trend in the history of semiconductor industry. However, it turned out to be correct even throughout decades. If Moore's trend will not stop, computational power of computers

will increase by more than two order of magnates during this decade. Such an increase in processing power can not only affect neural network models directly increasing their computation resources and accuracy, but they can also give ground for further development in machine learning. Modern neural networks were impossible twenty years ago due to computational issues, whereas today it is possible to train neural network on a laptop. Given exponential growth of processing powers, even bigger, more complex, and sophisticated models can be easily tested and build, and more data can be processed.

Another important future portfolio management aspect is evolution of deep learning. ANN achieved huge results during last decade, and solve tasks previously being unsolvable for decades. Given such big promises, large companies like Google, Apple and Facebook are spending billions of dollars on research and development in the field of machine learning. All these factors make current situation in the scientific field looks very promising and might empower further progress toward a more powerful models being available, not just in pure computation power, rather in an architectural and fundamental constructional way.

All proposed issues opens big opportunities for the future usage and development of deep neural network on the financial markets. There has been conducted multiple studies in reinforcement learning to test its performance for portfolio management. In the experiments of Lee et al., 2019<sup>42</sup>, influences of different optimizers and network structures on trading agents utilizing three kinds of deep reinforcement learning algorithms, deep deterministic policy gradient or DDPG, proximal policy optimization or PPO and policy gradient or PG. Experiments are conducted on China Stock data. In order to derive a general agent which is robust with different stocks, the price data was normalized. To be specific, it was chosen to divide the opening price, closing price, high price and low price by the close price at the last day of the period. For missing data which occurs during weekends and holidays, in

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<sup>42</sup> Lee, J., Kim, R., Koh, Y., & Kang, J. (2019). Global stock market pre- diction based on stock chart images using deep q-network. arXiv preprint arXiv:1902.10948

order to maintain the time series consistency, the empty price data was filled with the close price on the previous day and also set volume 0 to indicate the market is closed at that day. A fixed number, which is 5 in experiments of assets are randomly chosen from the assets pool. To ensure enough data is provided for learning, after a portfolio is formed, we check the intersection of their available trading history and only if it is longer than our pre-set threshold, which is 1200 days can we run our agent on it.

Important aspect of any neural network model when training is learning rate. Learning rate plays an essential role in neural network training. However, it is also very subtle. A high learning rate will make training loss decrease fast at the beginning but drop into a local minimum occasionally, or even vibrate around the optimal solution but could not reach it. A low learning rate will make the training loss decrease very slowly even after a large number of epochs. Only a proper learning rate can help network achieve a satisfactory result. Therefore, DDPG was implemented and tested using different learning rates. The results show that learning rates have significant effect on critic loss even actor's learning rate does not directly control the critic's training. It was found that when the actor learns new patterns, critic loss would jump. This indicates that the critic has not sufficient generalization ability towards new states. Only when the actor becomes stable can the critic loss decreases.

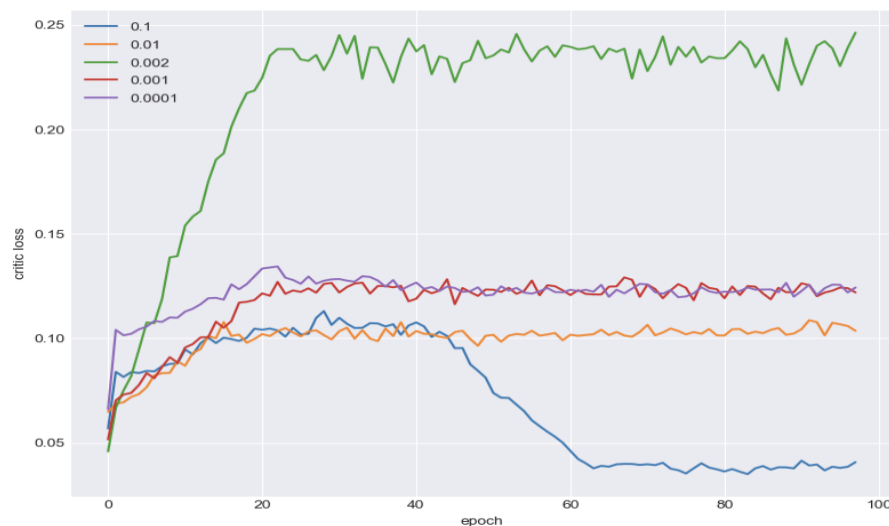


Figure 3.1. Loss under different actor learning rates

Source: Lee, J., Kim, R., Koh, Y., & Kang, J. (2019). Global stock market pre- diction based on stock chart images using deep q-network. arXiv preprint arXiv:1902.10948

Backtest of the agent was conducted on China data too. The unsatisfying performance of PPO algorithm uncovers the considerable gap between game playing or robot control and portfolio management. Random policy seems unsuitable in such an unstationary, low signal noise ratio financial market although its theoretical properties are appealing, including monotone improvement of policy and higher sample efficiency. All the detail experiments results, including the portfolio stocks codes, training time period, testing time period and average daily return, sharpe ratio and max drawdown of PG agent, UCRP agent, Follow-the-winner and Follow-the-loser agent can be viewed in figure

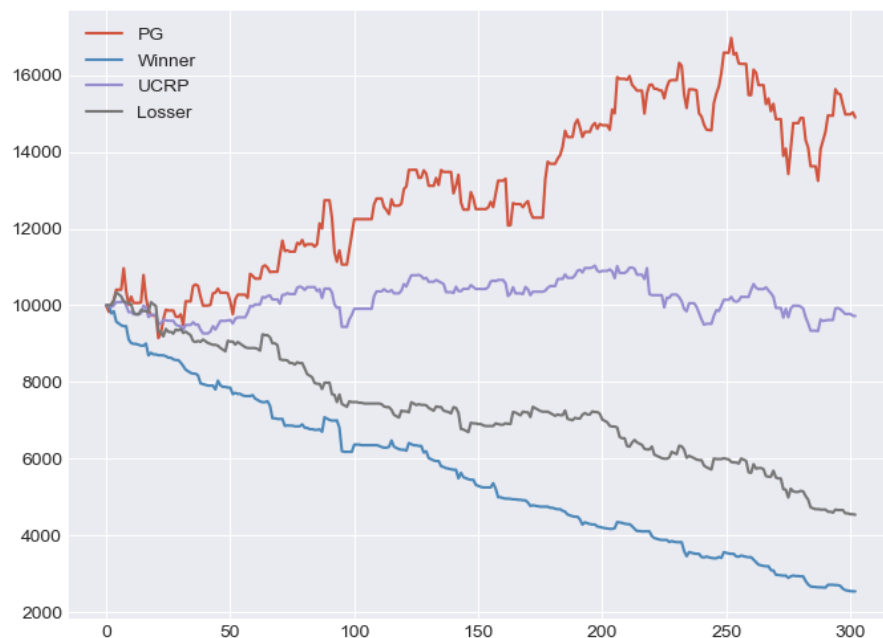


Figure 3.2. Backtest on China Stock Market

Source: Lee, J., Kim, R., Koh, Y., & Kang, J. (2019). Global stock market prediction based on stock chart images using deep q-network. arXiv preprint arXiv:1902.10948

The performances of DDPG, PPO and PG algorithms in hyper parameters were compared. The experiments show that the strategy obtained by PG algorithm can outperform UCRP in assets allocation. It's found that deep reinforcement learning can somehow capture patterns of market movements even though it is allowed to



observe limited data and features and self-improve its performance. All the numerical results are shown in table 3.3.

Table 3.3. Neural network performance comprising.

	ADR(%)	Sharpe	MMD	ADR(%)	Sharpe	MMD
1	0.416	1.171	0.416	0.226	0.678	0.22
2	0.242	0.647	0.417	0.31	0.885	0
3	0.242	0.724	0.224	0.249	0.753	0.13
4	0.298	0.859	0.349	0.304	0.921	0.119
5	0.262	0.765	0.45	0.254	0.802	0
6	0.413	1.142	0.305	0.323	0.903	0
7	0.213	0.668	0.449	0.202	0.667	0.231
8	0.187	0.554	0.347	0.276	0.836	0
9	0.471	1.107	0.649	0.308	0.873	0.277
10	0.32	0.795	0.546	0.297	0.812	0.279
11	0.312	0.837	0.195	0.338	0.924	0
12	0.17	0.741	0.242	0.202	0.715	0.19
13	0.313	0.825	0.341	0.26	0.691	0.34
14	0.345	0.931	0.263	0.307	0.892	0.096
15	0.573	1.499	0.609	0.354	0.993	0.272
16	0.493	1.337	0.42	0.328	0.91	0
17	0.348	0.911	0.307	0.364	1.002	0.23
18	0.198	0.601	0.251	0.244	0.756	0.086
19	0.306	0.813	0.46	0.295	0.863	0
20	0.377	1.099	0.419	0.313	0.949	0.165
21	0.325	0.876	0.23	0.308	0.828	0.237
22	0.301	0.918	0.123	0.269	0.824	0
23	0.373	1.176	0.514	0.245	0.819	0.138
24	0.487	1.257	0.461	0.33	0.914	0
25	0.426	1.14	0.386	0.415	1.127	0.408

Source: Lee, J., Kim, R., Koh, Y., & Kang, J. (2019). Global stock market pre- diction based on stock chart images using deep q-network. arXiv preprint arXiv:1902.10948

In experiments, deep reinforcement learning is highly sensitive so that its performance is unstable. What's more, the degeneration of our reinforcement learning agent, which often tends to buy only one asset at a time, indicates more modifications are needed for designing promising algorithms.

If more powerful models would be developed, with the further economics development, more data available and faster computers, portfolio management as a discipline probably will be almost fully devoted to algorithmic trading, powered by machine learning models. Humans will be unable to perform better in such task, as

computers can analyse terabits of information per second and process data in nanosecond scale. And with the more powerful ANN models, all these advantages of computers can be used for financial analysis of markets and even decision making, which is impossible for any human expert.

### 3.3. Possibilities of using neural networks for predicting exchange rates and making transactions in the global foreign exchange market.

Neural networks are class of algorithms, which can be used for very large and different classes of problems. It has been shown, how neural network can make transaction in the financial markets and outperform S&P100 index, so it is very like that model was able to extract some meaningful features from all the information it was feed with, during the training, and use it for managing a portfolio. These features should include various trends in the financial markets, words and phrases that affect the market situation, patterns in indicators that affect the stock market. This trained skill can be used for other purposes, with much less effort then training a new neural network for similar task from nothing. This process of using pretrained neural network on a slightly different task is called transfer learning, as it was already described. In such way, neural network trained to solve one exact task in the market, can be used to solve different task on the same market, or even different one. As it has been shown by researchers in the paper of Kang J.<sup>43</sup>, reinforcement learning agent, based on deep neural network trained to make transaction in the US market, was able to perform good in non-US markets. In this way, proposed model can be used for other markets, from tried-and-true blue-chip stocks to the fast-paced futures and foreign exchange markets with little training. However, different markets have key differences which should be considered and adopted for the new neural networks.

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<sup>43</sup> Jaewoo, JK., YK. Yookyung, RK. Raehyun and JL. Jinho, 2019. Global Stock Market Prediction Based on Stock Chart Images Using Deep Q-Network. Statistical Finance, 48. Date Views 12.04.2020 [www.arxiv.org/abs/1902.10948](http://www.arxiv.org/abs/1902.10948).

Currency markets have key differences to consider when using transfer learning, including:

1. Volatility or measure of short-term price fluctuations. While some trading strategies, particularly short-term and single day, rely on volatility in order to profit from quick price swings in the market, other ones are more comfortable with less volatile and less risky investments. As such, many short-term strategies are attracted to the forex markets, while buy-and-hold investors may prefer the stability offered by blue chips
2. A second consideration is leverage. In the United States, investors generally have access to 2:1 leverage for stocks. The forex market offers a substantially higher leverage of up to 50:1, and in parts of the world even higher leverage is available. Leverages certainly provides the springboard to build equity with a very small investment—forex accounts can be opened with as little as \$100.
3. Yet another difference is the time period that each is traded. Trade period for stocks are limited to exchange hours, generally 9:30 A.M. to 4pm Eastern Standard Time (EST), Monday through Friday with the exception of market holidays. The forex market, on the other hand, remains active round-the-clock from 5 P.M. EST Sunday, through 5 P.M. EST Friday, opening in Sydney, then traveling around the world to Tokyo, London and New York. The flexibility to trade during U.S., Asian and European markets with good liquidity virtually any time of day is a very important difference, when comparing to stock market
4. Another important difference is that, unlike the stock market, which usually rises, foreign exchange markets are not associated with economic growth in such a unique way, and there is no guarantee that a long-term strategy will be profitable in the foreign exchange market at all.

All these differences significantly change possible strategies and forex market player are usually prefer short-term strategies. However, as in the case of currency market, scientific studies on the topic strongly indicate that even in such environment,

reinforcement learning agent based on neural network are able gain profit<sup>44 45</sup>. Results show that direct reinforcement learning model can generate positive returns on certain currencies which rise the possibility of applying the model to a real-life trading environment. In the currency market, one important factor when executing trades is to limit negative risk. Therefore, the maximum downturn of the model should be restricted to a small number. It is possible to make the model risk-averse by restricting the amount of the transactions it can make. By incorporating the bid-ask spread, the model will learn to be more conservative since any type of position, long or short, is inherently risky because going to that position requires losing the spread.

Through experiments shows that direct reinforcement learning yields positive returns during all testing periods. The results are reasonable because used strategy is essentially a trend-following strategy and the features used resembles the factors in traditional factor models. Interesting issue is that Deep Q-network or DQN<sup>46</sup>, another popular approach for reinforcement learning along with policy gradients, does not work well on FX trading. Studies show that agent of the DQN learns to take neutral positions only and break even on the test set. The reasons may lie in the limited flexibility due to the discrete action set, the indirect learning objective, and confusing features. On the other hand, policy gradients models perform better. Also, implementation of direct reinforcement learning model with a single linear layer is not as effective as deep neural network. It is not surprising to find that deep model structures work better than naive shallow ones.

To further increase strategy profitability, incorporating better features can be used, like time series feature engineering. Also incorporate other advanced features like technical features to make the agent act more like a professional trader. Deep

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<sup>44</sup> João, JM., 2018. Reinforcement Learning Applied to Forex Trading. *Applied Soft Computing*, 73. Date Views 12.04.2020 [www.sciencedirect.com/science/article/abs/pii/S1568494618305349#!](http://www.sciencedirect.com/science/article/abs/pii/S1568494618305349#!).

<sup>45</sup> Xu, YX., IW. Wang, CW. Wang and YD. Dai, 2018. Reinforcement Learning for FX trading. *Applied Soft Computing*, 73. Date Views 11.04.2020 [www.sciencedirect.com/science/article/abs/pii/S1568494618305349#!](http://www.sciencedirect.com/science/article/abs/pii/S1568494618305349#!).

<sup>46</sup> Riedmiller, MR., DW. Wierstra, IA. Antonoglou, AG. Graves and VM. Mnih, 2015. Playing Atari with Deep Reinforcement Learning. *DeepMind Technologies*, -. Date Views 07.04.2020 [www.cs.toronto.edu/~vmnih/docs/dqn.pdf](http://www.cs.toronto.edu/~vmnih/docs/dqn.pdf).

neural network depends a lot on the number of parameters, which is affected by both width and depth of each layer, they can be further extended with residual blocks to build a deeper model, or with LSTM to learn with longer time lags. A good result is shown when continue training and hyperparameter tuning is used, so that training with data of a longer time span to increase the generalization ability of a model can be used. While currency trading is a difficult field to penetrate, reinforcement learning shows significant promise. With more diverse targeted knowledge such as important feature extraction and accurate architectural design, there is significant promise in the use of reinforcement learning in currency market and algorithmic trading become more and more technologically advanced and deep learning applications become more prevalent.

All the scientific studies, where model was executing transaction with different currencies suggests, that neural network is able to perform different types of task on a financial market and can be used by credit organizations to solve divergent task, as it was shown on both currency and stock markets. Even relatively small models able to execute meaningful transactions and though should be able to see alternative and recognize trends in markets, and then use it to come up with a profitable strategy and even outperform some indicators.

## CONCLUSION

In this work, financial markets were studied. It has been shown that financial markets are complex environments, and they play a key role in the smooth facilitation of economies. They are very complex systems with hierarchical structure.

During the market overview, it has been identified that credit organizations are essential participants in the financial markets which seek to gain profits and constantly try to beat the market. Multiple market characteristics, features and even relevant studies such as the efficient market hypothesis have been analyzed. Though markets have been heavily studied in the academia, there is still no consensus among scientists on the degree of market efficiency.

This caused many participants on the market including credit organizations to come up with multiple tools and approaches for efficient and accurate market analysis to achieve profit, for example fundamental, technical, and quantitative analysis, which were studied in this work and their fundamental features were identified and compared. It has been proposed in the study that all these techniques are currently developing even further to the more digitalized solutions. But still due to the complexity of the market systems, there is no single formula to predict market condition in the future.

And under such perspective, neural networks were presented in this work as a powerful tool to solve a lot of problems in other areas of research and open huge opportunities for credit organizations. Neural networks were scrupulously studied with all the mathematical apparatus behind their work. Modern architectures and approaches to neural networks constructions were explored. It has been shown that they are already used for technical, quantitative analysis and algorithmic trading, and there were a lot of developments in the field of deep neural networks during the past decade, which allowed to construct much more powerful models which are currently in the stage of finding their application, though their possibilities are often underestimated by investors.

Over a hundred recent studies on the usage of artificial neural networks in the financial market have been collected, reviewed, and analyzed. A lot of them suggest

that neural networks predictions can outperform more traditional tools of forecasting and with the reinforcement learning approach they can be used for transaction execution in a variety of financial markets. There are more possibilists for their usage by credit organization today and it might be the case that they are kept as a secret.

Modern deep neural network model was constructed and recently created state-of-the-art approaches were applied in order to get maximum performance and test model behavior in the circumstances of modern market environment. It has been experimentally proven, that deep neural network in fact can outperform standard investment strategies based on such index as S&P100 by managing an investment portfolio in the stock market though it need substation time and data for training. However, during the testing period, some features of neural network construction in the conditions of market environment has been unveiled, such as low public availability of data harden ANN training, though modern tools for machine learning make modern neural network model easily available for researchers. Also, it has been shown that neural networks are able to perform well in the currency markets and execute transactions in other environments which even further opens the possibilities of their use.

Conducted study reproduce the results of multiple other researches, where it was stated that reinforcement learning agent was able to outperform classical investment strategy and provides experimental results and developments which can be used in the future for financial market and especially portfolio management researches, and software constriction. It also studied the possibilities of neural networks usage across multiple market. It has been identified that neural network can solve tasks on the currency market.

New approaches were presented. Different neural network architectures and reinforcement learning paradigms can be further applied to understand the limits of modern neural networks. Presented artificial neural network was constructed with only four million parameters, which is not much compared with other researchers, and especially with the those conducted by big research groups such as google brain, deep

mind and OpenAi, which can have trillions of parameters per model, however there are no single research with such a big model in financial field. Other architectures, such as newly developed transformers can be applied for task solving on financial markets and a more sophisticated reinforcement learning techniques can be applied for further results improvements. Intraday data introduction should not only significantly enrich training data, but also enlarge generalization ability of the network.

Conducted work suggests, that with the further development of informational technologies and their integration in the everyday life and financial markets, there will be even more opportunities for the use of neural network in the future, especially due to economics science development, big data and computational power growth and further development of neural networks. If the technological progress will continue its pace and direction, neural networks-based systems will be used by credit organization to solve much more tasks in the financial market and in some critical areas, such as algorithmic trading, they can even fully absorb human's necessity in the field of investment.

Данная работа выполнена мною самостоятельно

« \_\_\_\_ » \_\_\_\_\_ 2021 г. \_\_\_\_\_



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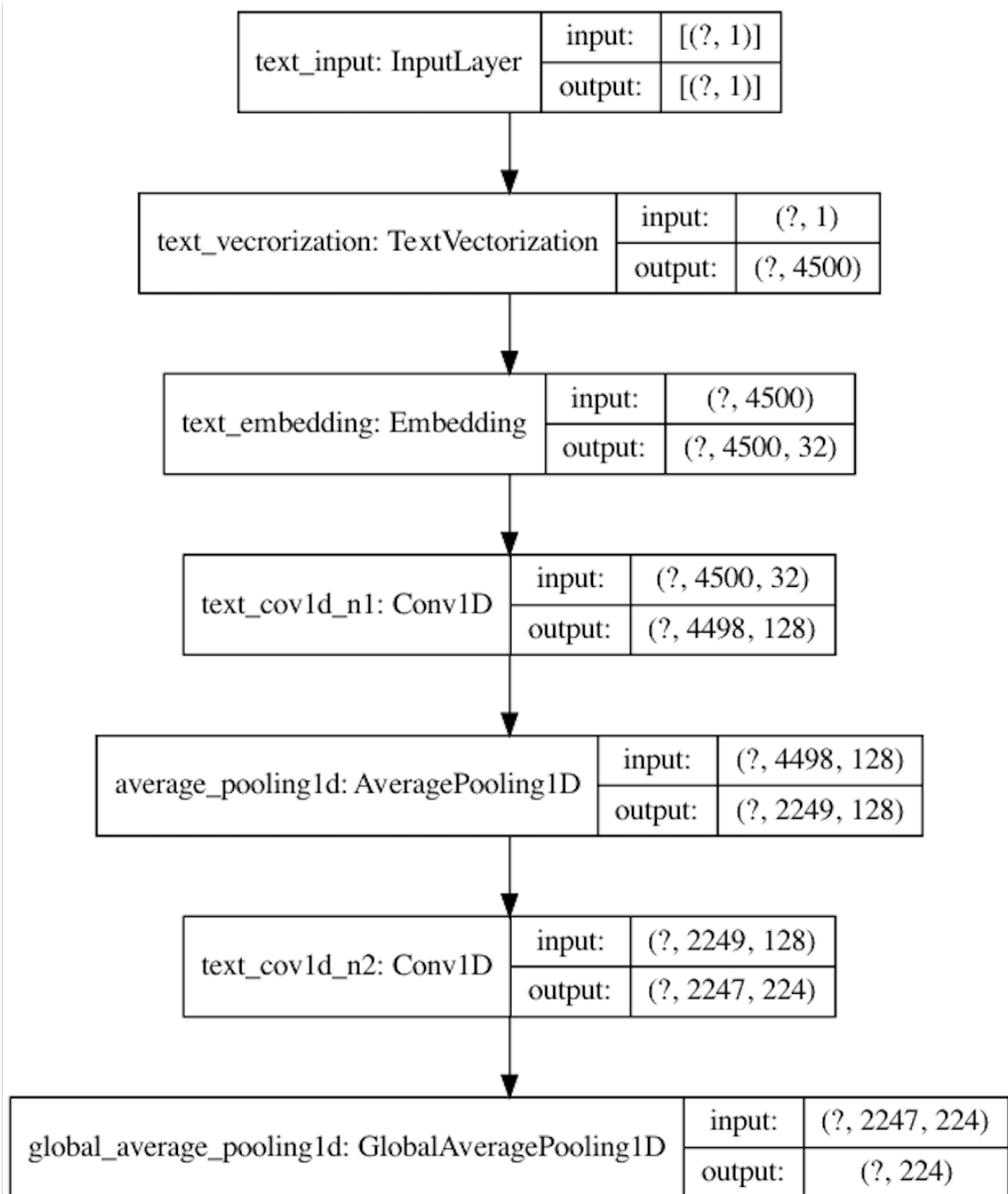
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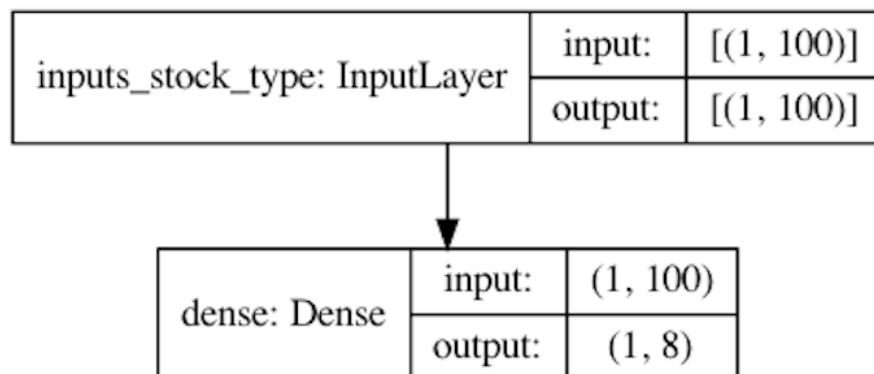
42.	Speculative	Asset	Prices.	Date	Views	
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43.	Neural	network.		Date	Views	
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49.	Long Short Term Memory (LSTM)	Networks	in a nutshell.	Date	Views	
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## Appendix 1.

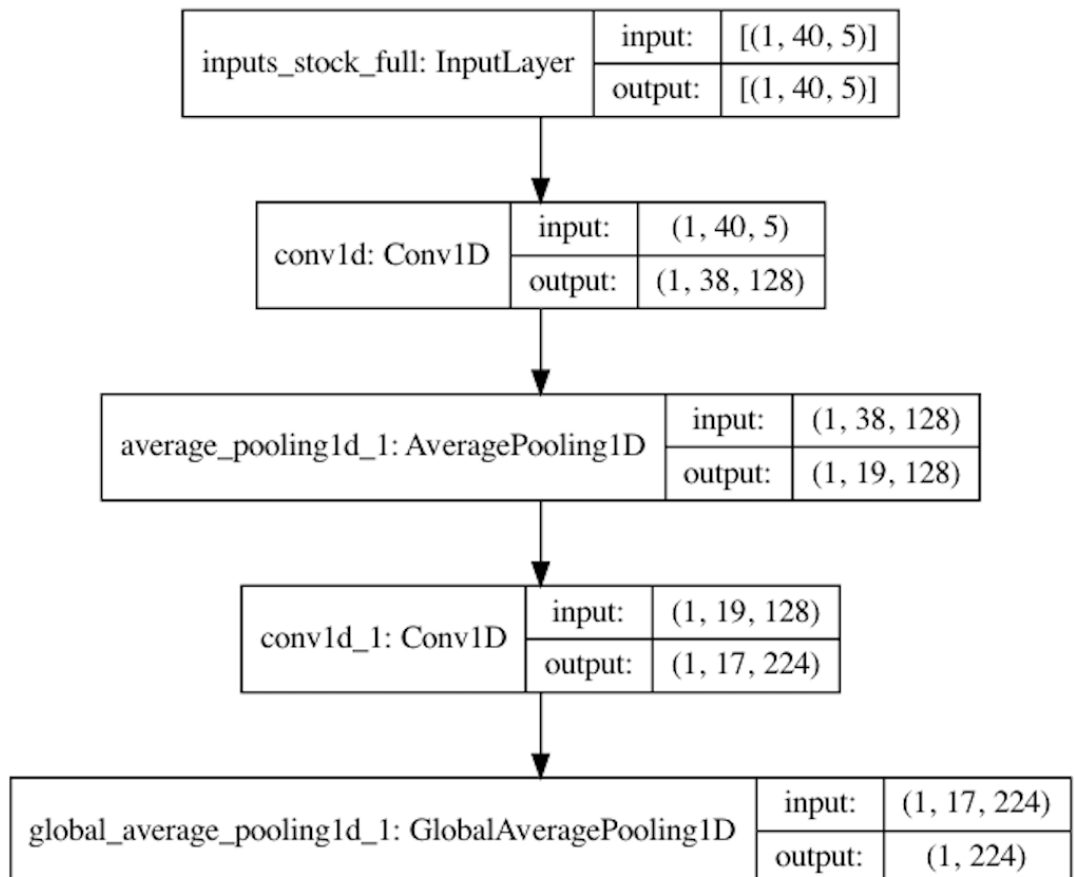
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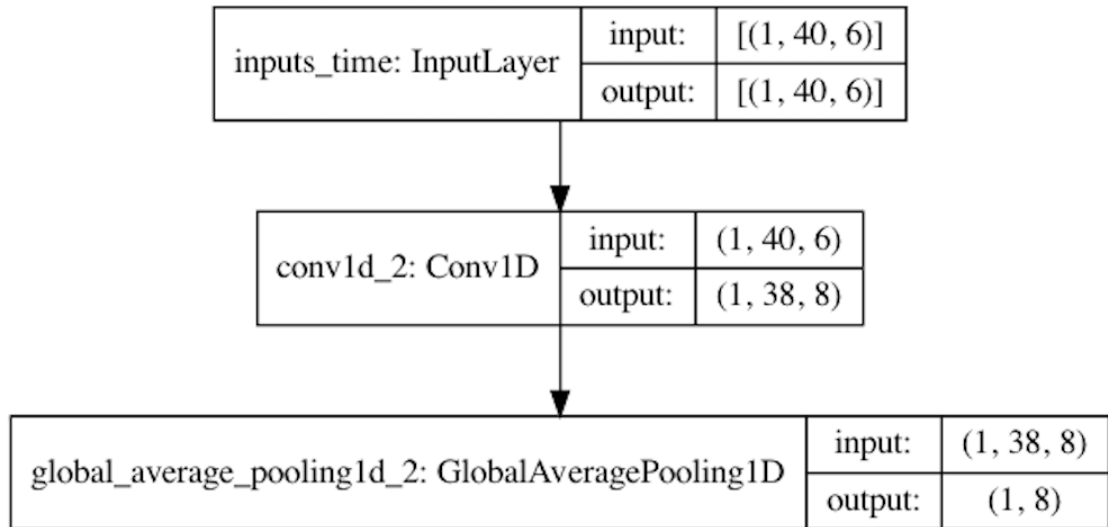
2. Stock type input:



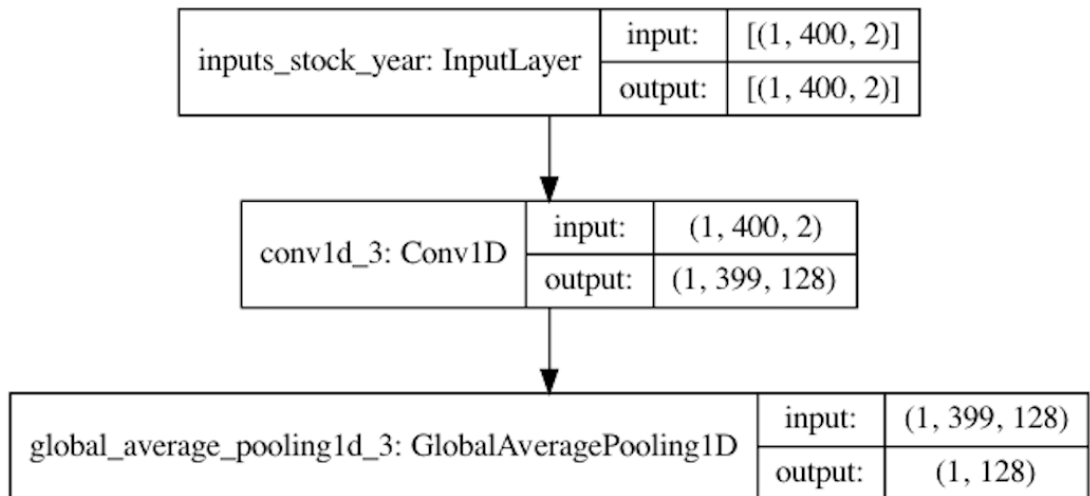
3. One stock market data input for the last 40 days



4. All dates encoded by with sinus and cosines functions for the past 40 days  
input:

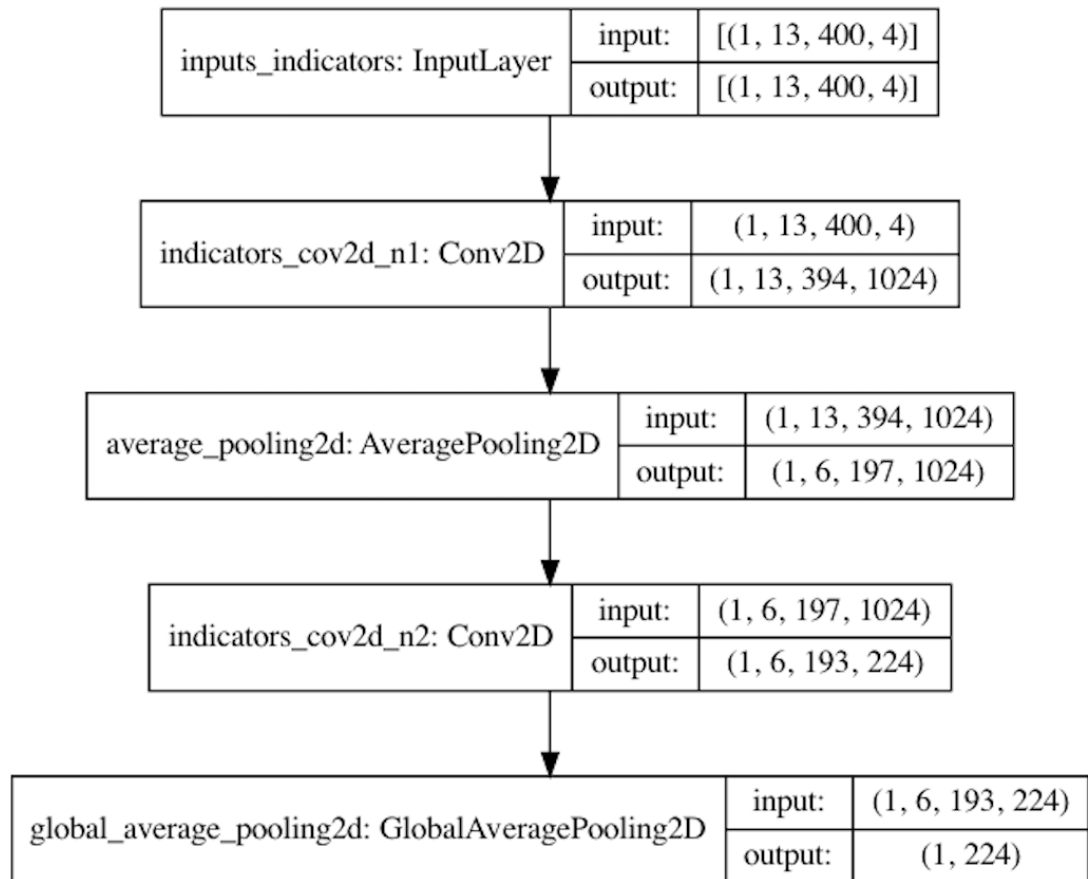


5. Data about one stock for the past 400 days, only open and close input:

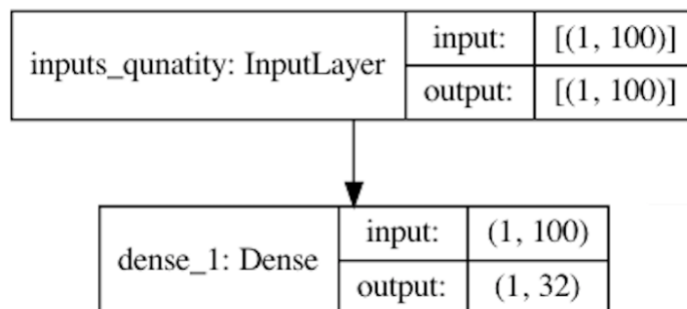




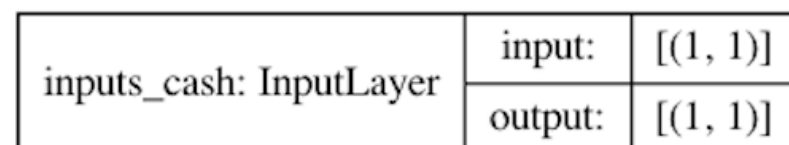
6. All indicators data for the past 40 days input:



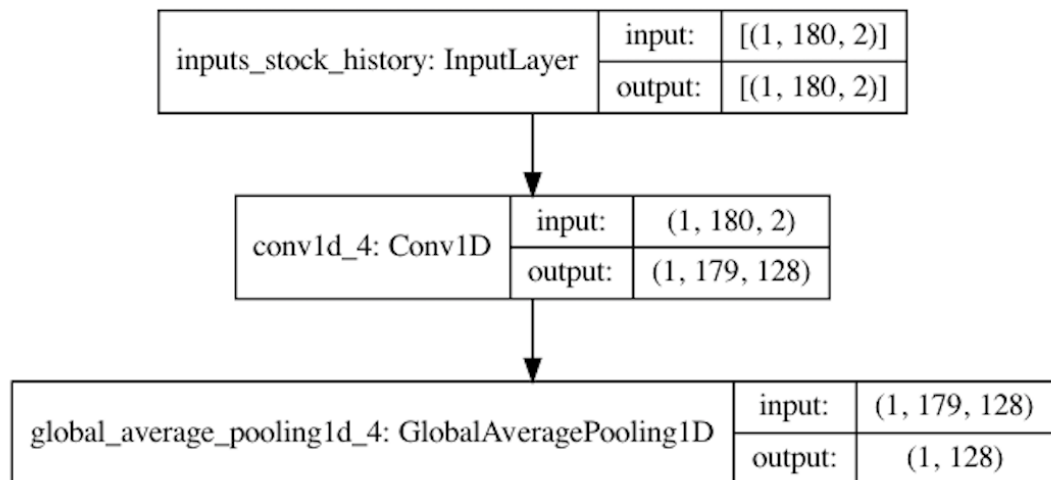
7. Quantity of each stock on the account input:



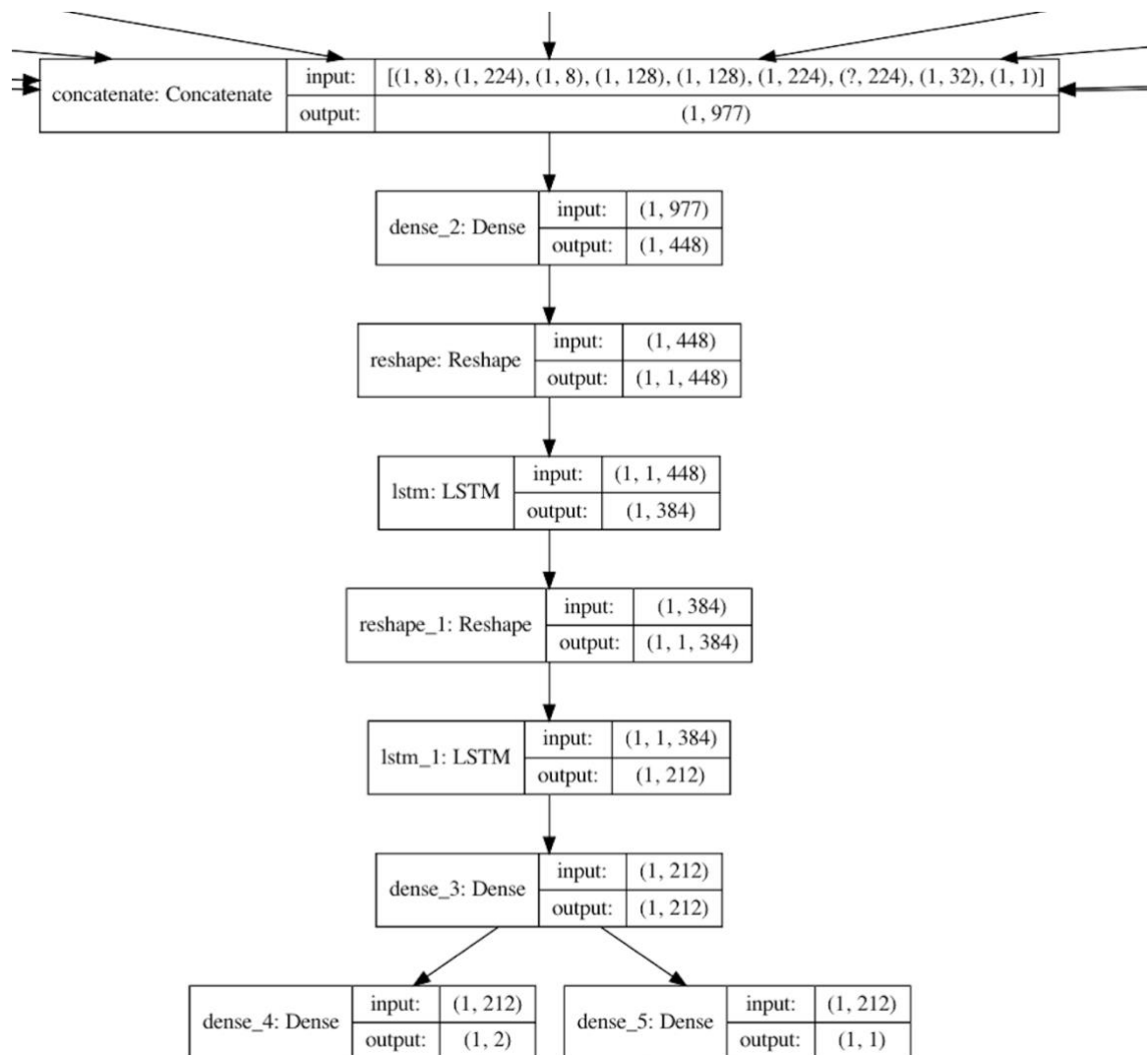
8. Amount of money, available for stock purchase at the moment input:



9. One stock history for the past 180 months, only monthly open close prices  
input:



#### 10. Decision making unit:



Appendix 2.

Buy&hold	Buy&hold sum	Agent	Agent sum	Agent K_15	Agent K_15 sum
0	0	0	0	0	0
-	-	-	-	-	-
10072,96361	10072,96361	9863,947057	9863,947057	7527,990508	7527,990508
-	-	-	-	-	-
16732,18157	26805,14518	16626,65618	26490,60324	7050,501976	14578,49248
-	-	-	-	-	-
15253,94876	11551,19642	15139,64893	11350,95431	13386,88422	1191,608259
20405,37011	8854,173686	20268,83132	8917,877012	18387,46068	17195,85242
-	-	-	-	-	-
0	8854,173686	-3,26727E-05	8917,87698	0,005769257	17195,84666
0	8854,173686	0	8917,87698	0	17195,84666
0	8854,173686	0	8917,87698	0	17195,84666
0	8854,173686	0	8917,87698	0	17195,84666
-	-	-	-	-	-
1881,970564	10736,14425	1830,984084	10748,86106	1760,601904	15435,24475
6455,096601	17191,24085	6375,308307	17124,16937	8100,347425	23535,59218
10359,06044	27550,30129	10301,45475	27425,62412	8588,511713	32124,10389
-	-	-	-	-	-
1903,033648	25647,26764	1839,218634	25586,40549	425,6838572	32549,78775
3800,81616	29448,0838	3773,858368	29360,26386	1677,290395	34227,07814
0	29448,0838	0	29360,26386	0	34227,07814
-	-	-	-	-	-
6164,532609	23283,55119	6124,604288	23235,65957	5919,871414	28307,20673
11106,8615	34390,4127	11156,27097	34391,93054	9397,014546	37704,22127
-	-	-	-	-	-
5329,012683	29061,40001	5359,856699	29032,07384	3884,823768	33819,39751
5312,980154	34374,38017	5373,250184	34405,32402	6015,008651	39834,40616
-	-	-	-	-	-
0	34374,38017	-3,84292E-05	34405,32398	0,003819263	39834,40234
0	34374,38017	0	34405,32398	0	39834,40234
0	34374,38017	0	34405,32398	0	39834,40234
0	34374,38017	0	34405,32398	0	39834,40234
-	-	-	-	-	-
9347,602804	25026,77736	9418,298214	24987,02577	-7842,30643	31992,09591
1606,825575	26633,60294	1632,734771	26619,76054	4770,744861	36762,84077
1881,164864	28514,7678	1886,467817	28506,22836	2076,071326	38838,9121
7900,494438	36415,26224	7967,101928	36473,33028	9276,56874	48115,48084
3075,547605	39490,80985	3100,072936	39573,40322	4637,201382	52752,68222
0	39490,80985	0	39573,40322	0	52752,68222
-	-	-	-	-	-
4382,919549	35107,8903	4365,017387	35208,38583	3459,528593	49293,15362
10676,769	45784,65929	10786,65104	45995,03687	11240,69342	60533,84704
7311,013789	53095,67308	7401,956228	53396,9931	3228,673475	63762,52052
3895,335836	56991,00892	3971,070297	57368,0634	4087,167425	67849,68794
-	-	-	-	-	-
0	56991,00892	-4,38955E-05	57368,06335	0,000926934	67849,68702

0	56991,00892	0	57368,06335	0	67849,68702
0	56991,00892	0	57368,06335	0	67849,68702
0	56991,00892	0	57368,06335	0	67849,68702
0	56991,00892	0	57368,06335	0	67849,68702
0	56991,00892	0	57368,06335	0	67849,68702
-7619,475306	49371,53361	-7710,289327	49657,77403	-5666,156733	62183,53028
-6494,35199	42877,18162	-6579,633697	43078,14033	-4473,540862	57709,98942
5998,109027	48875,29065	6078,551128	49156,69146	6472,937283	64182,9267
0	48875,29065	0	49156,69146	0	64182,9267
188,383964	49063,67461	188,2175126	49344,90897	-314,2140459	63868,71266
2883,620948	51947,29556	2937,40306	52282,31203	740,079549	64608,79221
7168,267082	59115,56264	7272,221703	59554,53373	8340,087928	72948,88014
2130,308781	61245,87142	2190,391459	61744,92519	-325,2867039	72623,59343
0	61245,87142	-3,53847E-05	61744,92516	-1,652E-05	72623,59341
0	61245,87142	0	61744,92516	0	72623,59341
0	61245,87142	0	61744,92516	0	72623,59341
0	61245,87142	0	61744,92516	0	72623,59341
-12144,75305	49101,11838	-12335,9316	49408,99355	-14145,25537	58478,33805
1929,691032	51030,80941	1963,226715	51372,22027	1355,721408	59834,05945
-101,522843	50929,28657	-92,66475354	51279,55552	-36,69986381	59870,75932
-1752,576301	49176,71027	-1815,576993	49463,97852	-538,1907459	59332,56857
5252,458268	54429,16853	5344,456918	54808,43544	2217,273775	61549,84235
0	54429,16853	0	54808,43544	0	61549,84235
1431,478293	55860,64683	1401,839063	56210,2745	5455,918503	67005,76085
8947,969176	64808,616	8940,608006	65150,88251	17296,27852	84302,03937
1861,128305	66669,74431	1958,936836	67109,81935	-219,0067907	84083,03258
2,200816	66671,94512	9,94118688	67119,76053	-7433,557961	76649,47462
0	66671,94512	-4,07893E-05	67119,76049	-0,004156762	76649,47046
0	66671,94512	0	67119,76049	0	76649,47046
0	66671,94512	0	67119,76049	0	76649,47046
0	66671,94512	0	67119,76049	0	76649,47046
125,991248	66797,93637	132,751859	67252,51235	1778,552851	78428,02331
5489,542089	72287,47846	5501,443166	72753,95552	5043,156969	83471,18028
3527,809046	75815,28751	3530,94759	76284,90311	1139,97876	84611,15904
3621,459714	79436,74722	3619,161547	79904,06465	1492,060315	86103,21935
-1930,544547	77506,20267	-2011,047943	77893,01671	-4249,480448	81853,73891
0	77506,20267	0	77893,01671	0	81853,73891

- 6547,520444	70958,68223	- 6556,109597	71336,90711	- 4833,242355	77020,49655
- 4552,116697	66406,56553	- 4614,048406	66722,85871	- 1269,306632	75751,18992
-5637,53911	60769,02642	- 5721,587689	61001,27102	- 3007,268084	72743,92183
7892,625212	68661,65163	7957,964015	68959,23503	7923,970997	80667,89283
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0	68661,65163	0	68959,23499	0	80667,89242
2677,474191	71339,12583	2739,219963	71698,45496	2305,103212	82972,99564
- 2606,406968	68732,71886	- 2640,439474	69058,01548	- 2288,135809	80684,85983
6356,488765	75089,20762	6476,267268	75534,28275	4904,614956	85589,47478
6531,637972	81620,84559	6603,038777	82137,32153	8339,608376	93929,08316
2416,855931	84037,70153	2458,402479	84595,72401	4032,947441	97962,0306
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- 3791,492743	80246,20878	- 3782,978907	80812,7451	- 4136,427578	93825,60302
2693,554356	82939,76314	2756,650411	83569,39551	5796,640447	99622,24347
7335,297429	90275,06057	7431,392584	91000,7881	8549,796909	108172,0404
3415,847598	93690,90817	3459,706301	94460,4944	7009,183268	115181,2236
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- 3082,466782	90608,44138	- 3137,737239	91322,75713	- 2382,104207	112799,1171
4823,97548	95432,41686	4945,567808	96268,32493	6560,921756	119360,0388
1104,439374	96536,85624	1124,24461	97392,56954	2890,649487	122250,6883
0	96536,85624	0	97392,56954	0	122250,6883
- 2030,334954	94506,52128	- 2021,231259	95371,33828	- 3118,259752	119132,4286
- 1753,236112	92753,28517	- 1777,387822	93593,95046	- 535,1661561	118597,2624
3158,811002	95912,09617	3210,963541	96804,914	484,0930041	119081,3554
5545,512823	101457,609	5621,46677	102426,3808	10661,65619	129743,0116
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8320,272546	109777,8815	8459,30094	110885,6817	3183,358024	132926,3656
- 5375,818932	104402,0626	- 5475,878896	105409,8028	- 2689,459354	130236,9062

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2854,387045	101547,6756	2876,338447	102533,4643	6456,779763	123780,1264
3295,222669	104842,8982	3347,586401	105881,0507	6503,479896	130283,6063
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1794,851759	103048,0465	1816,301177	104064,7496	-269,946826	130013,6595
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295,708394	102291,0205	267,9861116	103308,921	124,4387752	127684,1053
5726,926236	108017,9467	5795,874199	109104,7952	5972,947101	133657,0524
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0	106444,7913	0	107521,1041	0	130986,7218
0	106444,7913	0	107521,1041	0	130986,7218
3622,239164	110067,0304	3651,566512	111172,6706	4590,882062	135577,6039
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7817,865581	102249,1648	7849,135363	103323,5353	10520,02117	125057,5827
257,539654	102506,7045	272,9536161	103596,4889	1220,296931	126277,8796
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		-			
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1693,703703	100093,0359	1707,130367	101142,1271	1895,205701	123639,5743
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5860,156982	94232,87891	5954,604838	95187,52223	4339,483447	119300,0908
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7987,887906	86244,99101	8158,133448	87029,38878	2525,575604	116774,5152
7418,277828	93663,26883	7567,313083	94596,70187	6089,613896	122864,1291
		-3,64024E-		-	
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0	93663,26883	0	94596,70183	0	122864,1289
0	93663,26883	0	94596,70183	0	122864,1289
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1499,991025	95163,25986	1554,734583	96151,43641	2165,961724	120698,1671
12022,56678	107185,8266	12267,67361	108419,11	8118,581106	128816,7483
1634,941355	108820,768	1684,870692	110103,9807	1215,267782	130032,016
636,618671	109457,3867	642,9781224	110746,9588	2566,130944	132598,147
3264,040063	112721,4267	3272,703821	114019,6627	4679,058953	137277,2059
0	112721,4267	0	114019,6627	0	137277,2059
		-		-	
-44,211518	112677,2152	43,29758832	113976,3651	1082,064916	136195,141
232,176986	112909,3922	206,9423474	114183,3074	1327,392112	137522,5331

2384,994891	115294,3871	2429,433839	116612,7413	-	137237,5905
3811,060374	119105,4475	3858,72162	120471,4629	284,9425837	139228,9421
0	119105,4475	-3,72421E-05	120471,4628	-	139228,9403
0	119105,4475	0	120471,4628	0,001790253	139228,9403
0	119105,4475	0	120471,4628	0	139228,9403
0	119105,4475	0	120471,4628	0	139228,9403
311,795195	119417,2427	337,670692	120809,1335	179,842758	139408,7831
2718,266623	122135,5093	2771,90381	123581,0373	6362,401315	145771,1844
4224,044092	126359,5534	4270,031591	127851,0689	4651,74108	150422,9255
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3650,478341	122709,075	-3719,37678	124131,6922	1662,091569	148760,8339
-987,197995	121721,877	-1009,27521	123122,4169	-1518,16883	147242,6651
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3279,998421	118441,8786	3295,028895	119827,3881	2850,600381	144392,0647
12139,94588	130581,8245	12289,87224	132117,2603	12968,434	157360,4987
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6220,862475	124360,962	6328,108299	125789,152	-3071,28976	154289,209
-13463,4159	110897,5461	-	112097,9909	-	143290,3531
0	110897,5461	-6,16927E-05	112097,9908	-2,61271E-05	143290,3531
0	110897,5461	0	112097,9908	0	143290,3531
0	110897,5461	0	112097,9908	0	143290,3531
0	110897,5461	0	112097,9908	0	143290,3531
-				-	
2120,471106	108777,075	2152,750139	109945,2407	-707,238798	142583,1143
1168,100269	109945,1753	1145,11899	111090,3597	4543,503287	147126,6175
7704,682519	117649,8578	7842,813638	118933,1733	6817,951572	153944,5691
995,740466	118645,5983	1036,425952	119969,5993	1708,239792	155652,8089
47,74908	118693,3474	43,90242918	120013,5017	-	155650,4078
0	118693,3474	0	120013,5017	2,401152986	155650,4078
2565,650817	121258,9982	2582,652319	122596,154	0	157872,5695
814,797114	122073,7953	827,9481757	123424,1022	2222,16171	158607,3373
4875,37949	126949,1748	4966,64544	128390,7476	734,7677965	161334,622
2014,305526	128963,4803	2054,731249	130445,4789	2727,284738	161975,9751
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0	128963,4803	0	130445,4788	0	161975,9751
8060,061364	137023,5417	8215,927828	138661,4066	7152,231018	169128,2061
3299,900579	140323,4422	3386,783682	142048,1903	938,6927608	170066,8988
-5,299827	140318,1424	-9,98063849	142038,2097	-	169733,9568
-748,974779	139569,1676	-	141293,8348	-	168552,3696
		744,3748974		1181,587241	

4394,545339	143963,713	4489,171625	145783,0064	4088,60545	172640,975
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322,080169	142714,7126	339,0241662	144560,7464	506,26468	173526,2773
3197,332295	145912,0449	3243,457031	147804,2035	3343,782232	176870,0595
396,637105	146308,682	369,3597022	148173,5632	1835,832225	178705,8917
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0	146308,682	0	148173,5631	0	178705,8917
0	146308,682	0	148173,5631	0	178705,8917
-		-		-	
1584,026602	144724,6554	1618,300259	146555,2629	1200,526563	177505,3651
3751,438148	148476,0935	3815,847852	150371,1107	8415,907565	185921,2727
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4874,895019	143601,1985	4945,147912	145425,9628	5322,115096	180599,1576
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1103,898017	142497,3005	-1110,59809	144315,3647	3205,775956	177393,3816
1244,805916	143742,1064	1254,789773	145570,1545	1836,419179	179229,8008
0	143742,1064	0	145570,1545	0	179229,8008
707,10803	144449,2144	699,7807152	146269,9352	305,8776151	179535,6784
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1339,920858	143109,2936	1357,491265	144912,444	-1677,2272	177858,4512
5610,996327	148720,2899	5680,46819	150592,9121	4065,275458	181923,7267
458,168069	149178,458	449,0394226	151041,9516	744,6951407	182668,4218
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0	149178,458	0	151041,9515	0	182668,4175
0	149178,458	0	151041,9515	0	182668,4175
0	149178,458	0	151041,9515	0	182668,4175
601,183262	149779,6412	620,621585	151662,5731	1215,554376	183883,9719
-		-		-	
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3652,444109	151956,2604	3704,878425	153870,3959	1316,804631	188779,9577
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389,61309	152345,8735	487,9924771	154358,3884	3166,354607	185613,6031
5580,982226	157926,8557	5726,855092	160085,2435	3651,282612	189264,8857
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2294,600059	160221,4558	2324,704881	162409,9484	3118,959519	192383,8452
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149,774824	160371,2306	145,8168826	162555,7653	4587,091236	187796,7539
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0	160371,2306	0,000241413	162555,765	-0,03093408	187796,723
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1237,05602	237891,8072	1212,131556	241102,9584	210,6763182	306746,6166
-633,634924	237258,1723	-620,119749	240482,8387	-4140,496552	302606,1201
1909,455412	239167,6277	1948,891566	242431,7302	2379,635434	304985,7555
-775,728506	238391,8992	-776,2854424	241655,4448	-213,1293359	304772,6262
0	238391,8992	-4,6825E-05	241655,4447	-0,009421823	304772,6168
0	238391,8992	0	241655,4447	0	304772,6168
0	238391,8992	0	241655,4447	0	304772,6168
0	238391,8992	0	241655,4447	0	304772,6168
4544,896073	242936,7953	4653,025751	246308,4705	3456,780088	308229,3968
3709,18034	246645,9756	3765,459917	250073,9304	346,3969966	308575,7938

545,03368	247191,0093	553,3172123	250627,2476	661,4685617	309237,2624
2242,608602	249433,6179	2239,916265	252867,1639	3242,89514	312480,1575
1254,325201	250687,9431	1284,862421	254152,0263	1331,068968	313811,2265
0	250687,9431	0	254152,0263	0	313811,2265
0	250687,9431	-	254151,9093	-	313811,1076
0	250687,9431	0,116968381	254151,9093	0,118892567	313811,1076
0	250687,9431	0	254151,9093	0	313811,1076
-	2418,976657	-	251736,342	-	312513,9861
2418,976657	248268,9664	-2415,56737	251736,342	1297,121491	312513,9861
-	1634,803412	-	250098,6268	-	310189,222
1634,803412	246634,163	1637,715201	250098,6268	2324,764117	310189,222
0	246634,163	-	250098,6265	-	310189,1915
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0	246634,163	0	250098,6265	0	310189,1915
0	246634,163	0	250098,6265	0	310189,1915
0	246634,163	0	250098,6265	0	310189,1915
182,061735	246816,2248	195,51796	250294,1445	1351,36703	311540,5585
-	9307,546475	-	240888,8949	-	305108,5633
9307,546475	237508,6783	9405,249598	240888,8949	6431,995222	305108,5633
-	-9782,10677	-	230960,4943	-	298246,0526
-9782,10677	227726,5715	9928,400584	230960,4943	6862,510699	298246,0526
4806,044238	232532,6158	4865,2034	235825,6977	2652,799372	300898,852
4649,729022	237182,3448	4719,737543	240545,4353	1233,901147	302132,7531
0	237182,3448	0	240545,4353	0	302132,7531
1732,800234	238915,145	1739,259171	242284,6944	530,8633182	302663,6164
-	1273,216627	-	241022,7563	-	303914,9918
1273,216627	237641,9284	1261,938073	241022,7563	1251,375356	303914,9918
7148,185855	244790,1142	7237,485466	248260,2418	5886,374946	309801,3667
1861,3690	246651,4833	1889,435913	250149,6777	-	307962,634
26	246651,4833	-4,69718E-	250149,6777	-	307962,6338
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0	246651,4833	0	250149,6777	0	307962,6338
0	246651,4833	0	250149,6777	0	307962,6338
0	246651,4833	0	250149,6777	0	307962,6338
-671,966894	245979,5164	-685,910373	249463,7673	511,054274	308473,6881
-	1295,450032	-	248151,3304	-	310356,3337
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480,867011	245164,9333	490,9923574	248642,3227	40,59115447	310396,9248
-	-476,707532	-	248195,2827	-	306869,1079
-476,707532	244688,2258	447,0400016	248195,2827	3527,816949	306869,1079
1341,13268	246029,3585	1368,519581	249563,8023	530,4358716	307399,5438
0	246029,3585	0	249563,8023	0	307399,5438
706,049799	246735,4083	707,8475003	250271,6498	770,6243033	308170,1681
9269,876095	256005,2844	9368,99326	259640,643	4266,843529	312437,0116
251,001642	256256,286	266,9852384	259907,6283	-	311674,376
846,906355	257103,1924	808,3182814	260715,9466	762,6355617	311674,376
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0	257103,1924	0	260715,9465	0	314493,1097

0	257103,1924	0	260715,9465	0	314493,1097
0	257103,1924	0	260715,9465	0	314493,1097
6159,438028	263262,6304	6259,852779	266975,7993	6518,167782	321011,2775
1970,920709	265233,5511	2010,692862	268986,4922	710,8408371	321722,1183
938,056445	266171,6076	945,0292605	269931,5214	2033,13283	323755,2512
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1050,91917	265566,9734	1675,588743	269309,4424	492,7124128	327271,3778
		1053,50972		4008,839043	