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A Decision Support System for Mongolian Portfolio Selection

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Abstract

Investors aim to increase their profits by investing in the stock market. One possible strategy for minimization of risk is by enlarging or varying its field of operation for the portfolio. In this paper, we propose a six-step stocks portfolio selection model. This model is based on data mining clustering techniques that reflect the impact of Mongolian political, economic, legal, and corporate governance. As a dataset, we have selected stock exchange trading price, financial statements, and operational report information of TOP-20 highly capitalized stocks traded at the Mongolian Stock Exchange from 2013-to 2017. To cluster stock returns and risks, we have used K-means clustering techniques. We have combined both K-means clustering with Markowitz's portfolio theory to create an optimal, efficient portfolio. We constructed an efficient frontier, 15 portfolios created, and calculated the weight of stocks in each portfolio. From these portfolio options, the investor can choose according to his behavior.

Keywords

Data mining, Decision support system, K-means clustering

1. Introduction

The rapidly increasing volume, velocity, variety, and complexity of data are due to the rapid development of information technology and IoT devices, such as growing the day-to-day operations of all sectors, including research institutions, businesses, trade, and industry. It is challenging to use traditional data analysis techniques to accurately and efficiently process large amounts of data generated in each sector. The traditional data analysis methods that rely heavily on the workforce can no longer effectively process, analyze extensive data and make decisions [1,2]. The main methods of analyzing large amounts of data are gradually becoming data mining, artificial intelligence, and cloud computing technology [3-5].

Since the dawn of human history, financial markets have played an essential role in economic activity and social organization [6,7]. Financial activities play an essential role in the current economic development of many countries worldwide, and they contribute to the development of the world economy. Financial markets depend on many factors [8]. Researchers working in data mining, finance, and mathematics area have focused on investing in financial markets in the past decades. Therefore, some data mining algorithms have been proposed to support investors in different financial markets [9].

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Financial markets are risky and sensitive, so it is essential to base your long-term investment decisions on research. There is a growing difficulty in dealing with complex financial data using statistical methods. For this reason, researchers use data mining methods and machine learning methods to process complex financial data [10].

The banking sector accounts for 95% of the financial market in Mongolia. Although companies can use long-term financing from the stock market at a lower cost than bank lending rates, in Mongolia, companies make up the majority of their investments from high-interest bank loans due to the development of this market. Due to the weak development of the stock market, long-term, low-cost financing channels to support real economic growth are limited, economic growth is inaccessible, and asset valuation is not well developed. As a result, capital is not circulating in the economy, foreign investment in non-mining sectors is relatively low, and foreign exchange inflows are low. The World Bank publishes an annual Competitiveness Index report for 137 countries. In this report, Mongolia ranked 82nd in terms of public decision-making, 123rd in corporate ethics, 128th in audit and reporting standards, 132nd in board efficiency, 131st protection of small shareholders' rights, 6.8th in terms of investor protection (maximum score 10), 114th consumer awareness and information, and 131st in securities trading regulation as of 2017-2018. These indicators show that corporate governance, corporate ethics, board efficiency-related information, and the information needed by investors are insufficient in Mongolia. Besides, most of the stocks of listed companies are held by a few shareholders. As a result, corporate governance is underdeveloped, and investors are reluctant to invest in the company.

We do not have enough systematic software or decision support systems to process the information on listed companies and stock companies, provide investors with valuable and accurate information through qualitative and technical analysis, and assist them in making investment decisions. Therefore, it is mandatory to develop an integrated approach to diversify stock market products, process big data of the stock market, and build decision-making systems for stock portfolio selection methodology.

Markowitz's model offers suggestions based on the correlation of stock. Our proposed method is more accurate than existing methodologies; we have used data mining techniques to support decision-makers. Investors can select a portfolio based on stocks. We calculated financial, corporate governance, and bankruptcy indicators to identify the stock ranking. We identified the stock rankings by the TOPSIS method of the multicriteria decision-making method.

2. Related Work

The development trends of the world's stock exchanges have changed due to the global economic crisis and other factors. Until the 1980s, stock trading was traditional, and since then, with the rapid development of computer technology, electronic commerce has begun. With the advent of computer systems, data was stored in databases, and large amounts of data were created. The concept of "big data" has emerged since 1990, and the research work of scientists is focused on how this large amount of data can be processed efficiently to meet human needs and help people make informed decisions.

Hsu implemented a hybrid of Self Organizing Map and genetic programming to predict stock prices on the Taiwan Stock Exchange [11]. Research has also used the Artificial Neural Network for stock market prediction [12-14]. Nanda, Mahanty, Tiwari used K-means, Self-Organizing Map (SOM), and Fuzzy C-Means to cluster stocks listed on the Bombay Stock Exchange (BSE) [15]. Using genetic algorithm (GA), Oh, Kim, and Min’s study proposes a portfolio optimization scheme for index fund management in 2005 [16]. Topaloglou, Vladimir, and Zenios worked on a dynamic stochastic programming model for global portfolio management [17]. Amitava Ghosh and Ambuj Mahanti studied mathematical and econometric models used in 63 research papers and studies conducted between 2009 and 2014 under securities portfolio management. More than 30 algorithms were used in these works, with 24% using mathematical modelling algorithms. Sharp ratios were used the most, or 39.68%, to measure the performance of a portfolio [18].

Recent financial theories have also shown that it is essential to consider investor behavior in portfolio selection. Researchers proposed a financial risk indicator system based on similarity measurement and item clustering. They constructed a financial risk model [19] on the clustering algorithm to classify and optimize financial risks [20,21]. Data mining and machine learning algorithms are being used to analyze financial activities for the past decade [22-25]. Recent financial theories have also shown that it is essential to consider investor behavior in portfolio selection.

3. Proposed Methodology

Based on the comparative analysis of optimal risky portfolio selection research papers, and by considering Mongolia's political, economic, legal, and corporate governance indicators, we have developed the following six steps methodology.
The overall structure of the DSS developed for stock portfolio selection in the Mongolian stock exchange is shown in Fig. 1.

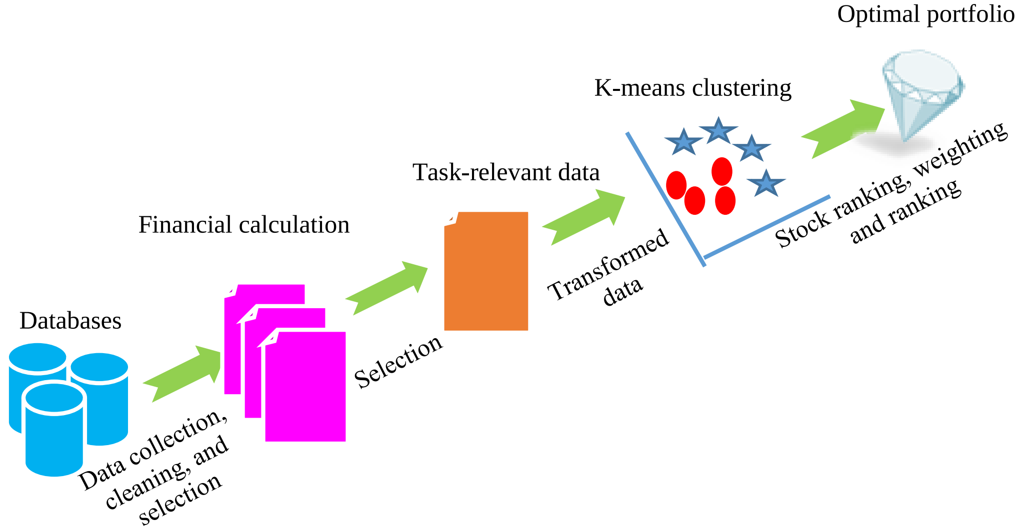

Fig. 1. The process of the DSS.

Sketch of decision support system is as follows:
STEP-1. Data collection, cleaning, and portfolio creation
STEP-2. Stock clustering
STEP-3. Stock ranking
STEP-4. Stock weighting
STEP-5. Portfolio ranking
STEP-6. Selection of optimal portfolio
The main steps of our proposed methodology are described in detail as follows:

STEP-1. Data collection, cleaning, and portfolio creation

We have selected records from stock exchange information, financial statements, and activity report information of TOP-20 highly capitalized stocks traded at the Mongolian Stock Exchange from 2013- to 2017. And then, we cleaned the data for further analysis. After that, we have duplicated and regenerated some records for preprocessing. Finally, 16018 records were used in our experiment. Also, we manually selected the required information from the company's financial statements and corporate governance reports. Of these, we have used around one hundred records of data with 15 indicators.

STEP-2. Stock clustering

Many research has shown that k-means are appropriate for investors to make investment decisions based on stock returns and risk. Therefore, we clustered the stocks according to their return and risk using the k-means clustering analysis [26].

Algorithm Basic K-means algorithm

1. Select K points as initial centroids.
2. **repeat**
3. Form K clusters by assigning each point to its closest centroid.
4. Recompute the centroid of each cluster
5. **until** centroids do not change

STEP-3. Stock ranking

We calculated financial, corporate governance, and bankruptcy indicators to identify the stock ranking. We identified the stock rankings by the TOPSIS method of the multicriteria decision-making method.

- Company Financial Indicators: One of the most critical factors for investors to consider when investing in a company's stock is the company's financial performance. A company's financial statements show the company's financial position over time, determine future profits and dividends, and contain information needed to assess the company's prospects. As a result of our research, the following financial ratios are considered in determining the ranking of stocks: Return on Equity (ROE), Return on Assets (ROA), Earnings per share (EPS), Price-earnings ratio (P/E ratio), and Debt ratio;
- Financial ratios that affect a company's bankruptcy: Private and corporate investors make investment decisions by anticipating the company's financial difficulties and bankruptcy. In other words, it is essential for a company to trade before the stock price falls and to predict changes in the value of stocks and additional stocks in the portfolio. S. Tsolmon developed a bankruptcy prediction model and identified four independent variables that significantly impact a company's bankruptcy [27]. These include: Interest and pre-tax profit / Total assets or EBITTA, Equity / Total assets or ETA, Liabilities / Equity or LE, Logarithm of total assets or LOGTA;
- Corporate governance and its indicators: In Mongolia, there is no clear understanding of what corporate governance is, but in our research, we have selected essential factors in corporate governance by considering: Board size, Independent board of directors, Institutional shareholder, Audit committee, Percentage of shareholders over 5 percent and Firm size, which means that there are no more devices to be discovered in the partition. Go to the next partition.

The weight of the criteria influencing decision-making is highly dependent on the subjective judgment of the decision-maker. The emotional weight of the indicators consists of the decision-maker’s experience, knowledge, and understanding of the issue. For this reason, a variety of subjective weighting methods have been developed. The results of these methods are not reliable. The critical method, which does not have an emotional nature, was proposed by Diakoulaki. The technique uses a standard deviation of the criteria and a correlation between the indicators [28].

The stocks were prioritized based on the TOPSIS method of the multicriteria decision-making method. TOPSIS sketches are as follows:

Step 1. Create of decision matrix, and the standard decision matrix (R)
Step 3. Calculate the weighted (R) matrix.
Step 4. Determine the best solutions, and worst solutions
Step 5. Compute the distance of each alternative from the positive ideal solution and the distance of each alternative from the negative ideal solution.
Step 6. Calculate the similarity to the worst condition

Hwang and Yoon developed the Technique for Order Preference by Similarity to Ideal Solution (after this TOPSIS) based on choosing a decision option close to the positive solution of the criterion and far from the negative ideal solution [29].

STEP-4. Stock weighting

Markowitz [30,31] developed the portfolio selection theory in uncertain conditions, identified the difference between risks of particular assets and portfolios in the math equation and proved that the risk of a portfolio depends on the covariance of assets in that portfolio. For risk and return characteristics of a portfolio, the model developed by Markowitz suggests the maximization of expected return and minimization of the portfolio's risk.

The key formula for maximization of the expected rate of return of the portfolio is:

$$E\left(R_p\right) = \sum_{i=1}^{n} \omega_i \, E(R_i) \tag{1}$$

Where ω(i) must satisfy the following constraint.

$$\begin{cases} var\left(R_p\right) = \sum_{i=1}^{n} \omega_i^2 \, var(R_i) + \sum_{i=1}^{n} \sum_{\substack{j=1 \\ i \neq j}}^{n} \omega_i \omega_j \, cov\left(R_i, R_j\right) \leq \sigma_p^2 \\ \omega_1 + \omega_2 + \cdots + \omega_n = 1 \\ \omega_i \geq 0 \end{cases} \tag{2}$$

where ω_i – i is the weight of asset in the portfolio, $E(R_i)$ - i is the expected return of asset in the portfolio, $cov(R_i, R_j)$ is the covariance between asset i and j.

STEP-5. Portfolio ranking

The portfolio's ranking considers the weight of the stock in the portfolio, the return on the portfolio, the risk, the portfolio beta, the Sharpe ratio, and the Treynor ratio.

A web-based decision support system automatically saves each creation of an optimal risky portfolio. The software module shows the ranked portfolio to the user.

STEP-6. Selection of optimal portfolio

We resolved the risk minimization problem at the desired return level and established a threshold for the stock return curve. An investor can select the appropriate one of these portfolios in accordance with their sentiment and how to behave concerning portfolio management and react to market conditions.

4. Experimental Results

We developed the web-based decision support system named "A decision support system for stock investment" using PHP. We wrote 650 lines of code with a total of nine modules. As a database management system, we used MySQL. Our database contains nine tables with 16018 records.

We have developed a web application named: "A decision support system for stock investment" Version: 1.0. Hardware Requirement for this application is as follows: Intel(R) Core(TM) i7-4790 CPU @ 3.60GHz processor, 64-bit operating system, RAM-8 GB.

Appropriate for Settings such as investment fund management, financial advisers or brokers, mutual fund According to the industry classification, we have classified the MSE listed companies into five sectors: production, construction, transportation, mining, agriculture, trade & services, and 14 subsectors.

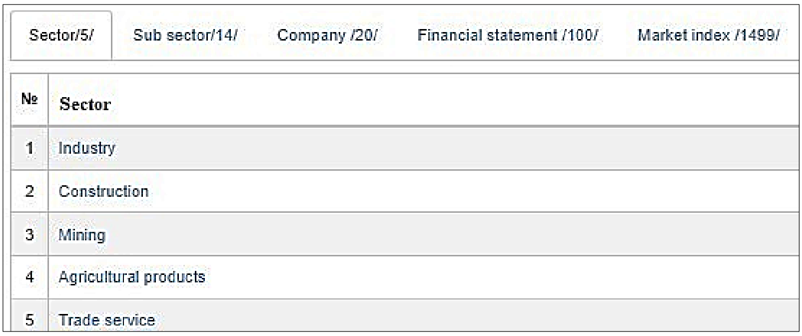

Fig. 2. System settings window.

Figure 2 shows the system settings window, with the following tabs: sector, sub-sectors, companies, financial indicators, and market index. Update, delete, insert, select operations are available on each tab. We calculated the financial ratio from the company's financial statements, and governance indicators are taken from the company's operational report. The system allows users to manually enter, import, and enter data into a database.

A. Results of stock ranking processing using the TOPSIS method of multivariate decision making

The stability of a joint-stock company and its sound financial performance are indicators of a company's suitable governance mechanism. The weight of the factors influencing the stocks' ranking was calculated using the critical method.

Table 1. Weight of decision-making indicators for each sector in 2016-2017

Indicators	Production sector		Mining sector		Trade and service sector	
	2016	2017	2016	2017	2016	2017
ROA	0.00092	0.00032	0.01085	0.01232	0.00004	0.00002
ROE	0.00293	0.00088	0.01919	0.0197	0.00015	0.00011
P/E	0.73074	0.85507	0.43549	0.61025	0.99094	0.98984
D/Equity	0.00528	0.01094	0.01275	0.05078	0.00031	0.00033
LOGTA	0.01743	0.00305	0.04456	0.01096	0.00031	0.00031
EBITTA	0.00107	0.00038	0.0136	0.0166	0.00004	0.00002
ETA	0.00498	0.00263	0.02934	0.02209	0.00024	0.00023
LE	0.0296	0.01718	0.19225	0.04056	0.00165	0.00217
BS	0.03863	0.02061	0.04387	0.04878	0.00091	0.00102
IS	0.02645	0.01414	0.03329	0.03694	0.00078	0.00083
OS	0.0133	0.00696	0.08927	0.07706	0.00094	0.00103
Audit	0.01067	0.0046	0.02484	0.02056	0.00028	0.00026
T5	0.00184	0.00092	0.00167	0.00174	0.00007	0.00007
Life	0.11617	0.06232	0.04903	0.05223	0.00334	0.00374

The weight of decision-making indicators for each sector is shown in Table 1. The ratio that has the most significant impact on decision-making is the P/E ratio. Financial and governance indicators for 2013-2017 are considered for each sector. The stock was ranked by the TOPSIS method. The following results were obtained for the ranking of companies based on the 2013-2017 financial and governance indicators of each sector.

Table 2. Stock rank calculated by the TOPSIS method

№	Company name/year	
	Sector	CV*
Production sector		
1	Arig gal	0.102
2	APU	0.225
3	Govi	0.092
4	Darkhan Nekhii	0.091
5	Makhimpex	0.088
6	Remicon	0.990
7	Suu	0.106
8	Talkh-Chikher	0.092
9	Khukh Gan	0.012
Construction and transportation sector		
1	Hermes centre	
Mining sector		
1	Aduunchuluun	0.258
2	Baganuur	0.012
3	Tavantolgoi	0.182
4	Sharyn Gol	0.982
Trade and service sector		
1	Bayangol Hotel	0.468
2	BDSec	0.903
3	Genco tour bureau	0.032
4	Materialimpex	0.369
5	Telecom Mongolia	0.814
6	Ulsyn ikh delguur	0.169

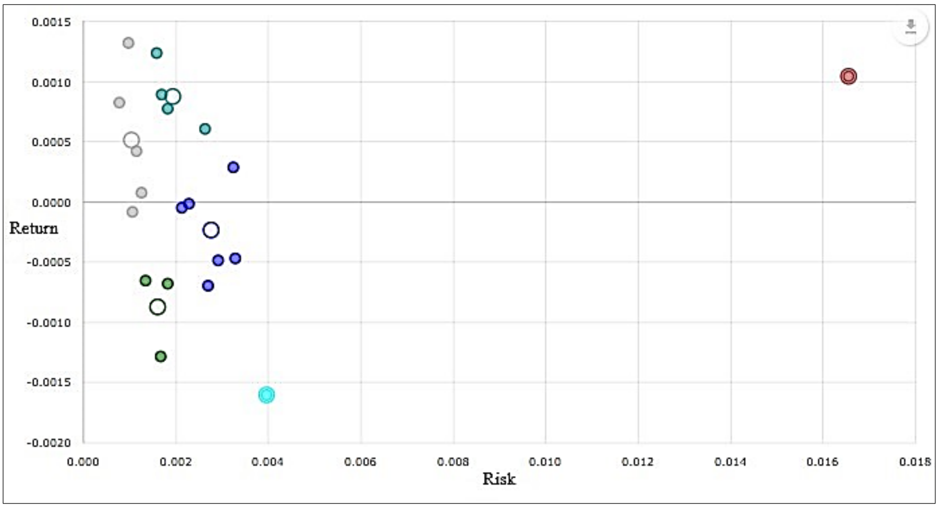

Fig. 3. Clustering by the K-means method.

Figure 3 shows a screenshot of K-means clustering. The cluster includes stocks of companies with similar financial characteristics. The number of clusters created by the investor should be less than the number of companies that we have registered in the web system. The stocks are placed in one cluster by descending order. The optimal portfolio can be created by selecting one stock from each cluster of investors. The system allows investors to create the most optimal portfolio by selecting one stock from each cluster according to their sentiment.

Markowitz's basic model calculates the expected average return and risk of a portfolio when the investor chooses the same weight of stocks to be included in the portfolio. The highest-ranked stocks will appear at the beginning of the clustering, from Cluster 2 BDSec and Baganuur from Cluster 4 Makhimpex, from Cluster 5 Darkhan Nekhii, from Cluster 6 APU.

The following results were obtained by calculating the expected average return and risk of a portfolio with the same weight or 20% of the stocks in the portfolio using the Markowitz model:

Expected return: - 0.00015 Expected risk: 0.00043

At the next step, we solved stock return maximization for these five stocks at the risk level of 0.00043 to estimate the optimal stock weights of each stock. as shown in Figure 4.

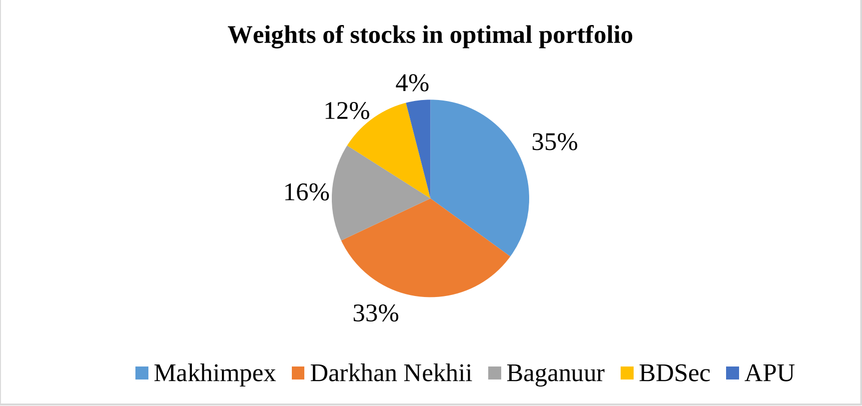

Fig. 4. Weights of stocks in optimal portfolio k-means clustering.

Table 3 shows the expected average return, risk, and weight of shares in a portfolio's efficiency margin curve.

Table 3. Portfolio options offered by the system

№	Expected return	Expected risk	BDSec	Makhimpex	Darkhan Nekhii	APU	Baganuur
min	-0.00015	0.00043	25.10%	29.53%	12.32%	15.59%	17.47%
1	-0.00011	0.00040	23.94%	30.05%	14.15%	14.52%	17.34%
2	-0.00006	0.00039	22.79%	30.57%	15.99%	13.45%	17.21%
3	-0.00001	0.00039	21.63%	31.09%	17.82%	12.38%	17.08%
4	0.00004	0.00039	20.47%	31.61%	19.66%	11.31%	16.95%
5	0.00009	0.00039	19.31%	32.13%	21.50%	10.24%	16.82%
6	0.00014	0.00039	18.15%	32.65%	23.33%	9.17%	16.69%
7	0.00019	0.00040	17.00%	33.17%	25.17%	8.11%	16.56%
8	0.00024	0.00040	15.84%	33.69%	27.00%	7.04%	16.43%
9	0.00029	0.00041	14.68%	34.21%	28.84%	5.97%	16.30%
10	0.00034	0.00042	13.52%	34.73%	30.67%	4.90%	16.17%
11	0.00039	0.00043	12.37%	35.25%	32.51%	3.83%	16.04%
12	0.00044	0.00046	11.21%	35.77%	34.35%	2.76%	15.91%
13	0.00049	0.00048	10.05%	36.29%	36.18%	1.69%	15.78%
14	0.00054	0.00050	8.89%	36.81%	38.02%	0.63%	15.65%

An investor can select the appropriate portfolio in accordance with his/her sentiment and how to behave concerning portfolio management and react to market conditions.

5. Conclusions

In our study, we proposed a six step decision support system for the optimal portfolio of stocks suitable for the conditions of Mongolia. This model is based on data mining clustering techniques that reflect the impact of Mongolian political, economic, legal, and corporate governance. We have developed a web-based decision support information system for financial intermediaries and investors which offers optimal risky portfolio options.

As a dataset, we have selected stock exchange information, financial statements, and activity report information of TOP-20 highly capitalized stocks traded at the Mongolian Stock Exchange from 2013- to 2017. Based on the research conducted by researchers, 15 financial and non-financial indicators have been identified that have the most significant impact on the ranking of Mongolian joint-stock companies. The weight of decision-making factors is calculated using a critical method, which is advantageous because it allows the individual to avoid subjective judgments. K-means clustering method is used to cluster stock returns and risks. The stock weight within the optimal portfolio and portfolio return and risks were estimated using the Markowitz method. In addition to offering investors a portfolio of stocks issued by the system, investors can choose a portfolio that suits their behavior. The system is crucial because it allows investors to build the most profitable portfolio according to their economic situation, behavior, and risk tolerance. With the support of the system we have developed, investors will make non-intuitive decisions based on factual information and calculations.

As a result of the research work, creating a portfolio by clustering the stocks is the most efficient method. In future research, we plan to do the following:

- Using the Association analysis method, we will discover association rules on stock sales;
- Predict stock selection based on investor's behavior

- Discover the association between investors' decisions and joint-stock company information posted on social networks.
- Predict future stock prices from historical trading data

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