A study on the efficacy of an attention mechanism-based strategy planning method for stock trading portfolios

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Abstract. In order to take full advantage of the fact that there is a large amount of information and data available in the field of stock trading, this paper develops a new type of stock trading strategy, which reduces investment risk. A stock trading portfolio strategy planning method based on an attention mechanism, as disclosed in the present invention, relates to the field of stock trading technology. The introduction of an attention mechanism allows the strategy to focus on those stocks with higher evaluation coefficients, thereby improving the selectivity and accuracy of the strategy and thus the effectiveness of the portfolio strategy. Furthermore, based on the prediction results of the deep spatio-temporal neural network model, it is possible to determine the stock's short-term trends and identify the optimal trading points. This information can be utilized as a reference for investors, assisting them in making more informed decisions regarding the timing of buying and selling, improving the success rate and yield of trading, enabling them to swiftly and accurately assess the performance of each stock, facilitating timely adjustments to their portfolios, and enabling them to devise the optimal trading strategy and timing for each stock, enhancing the accuracy and efficiency of their trading decisions.

Keywords: Attention Mechanism, Risk Control, Stock Trading.

1. Introduction

China's stock industry has developed and expanded rapidly against the backdrop of reform, opening up and marketization. Under the guidance and supervision of the government, the stock market has been gradually standardized and matured, providing important support for China's sustained economic growth and corporate financing. From the share system reform that gave birth to the first stock issuance to the full promotion of the registration system A-share market, in just forty years, the domestic capital market has experienced rapid development from scratch and from regional to national[1]. At present, China's capital market has entered the stage of high-quality development, its structure is gradually approaching the international mature market, the overall operation of the market is stable, attracting more and more small and medium-sized investors to pour into the financial market. Under the trend of economic globalization, the economic and financial exchanges between countries have become closer, and the risk of the stock market has also increased significantly. In this case, how to maximize the avoidance of trading risks, from the stock market to obtain the maximum benefit, has become the common wish of every investor. The traditional stock trading strategy is more one-sided in data analysis, unable to comprehensively consider the investment value of stocks, resulting in higher investment risk[2]. Attention mechanism-based stock trading portfolio strategy planning method refers to the use of attention mechanism to select and weigh the stock portfolio to achieve the purpose of optimizing the investment portfolio[3]. This method is usually based on a deep learning model, which analyzes and learns from market data to better identify potential investment opportunities. Compared with traditional methods, it is able to better explore the correlations and features in market data, which is expected to improve the effectiveness of the investment portfolio and risk control ability[4].

China's stock industry continues to develop, in deepening the supply-side structural reform, support the country's economic development, maintain social stability and promote the common wealth and so on plays an important role, but in the development of the problem still exists: the stock market is affected by external factors, in recent years, China's stock market long-term performance downturn in the Russian-Ukrainian conflict and the new crown of the epidemic of the double impact of the Shanghai Stock Exchange index fell below 3,000 points[5]. Under the trend of economic and financial globalization, the economic ties between countries are getting closer and closer, for example, there is a significant cross-correlation between the series of daily measures of economic policy uncertainty in the United States and the series of returns in various financial markets in China, and all the cross-correlations have obvious multi-fractal characteristics[6]. China's stock market is vulnerable to external shocks from developed economies in Europe and the United States, and the external spillovers have a clear dependence on regional organizations[7]. The lagged short-term economic policy uncertainty shock has a significant negative impact on stock market returns, and the negative impact gradually tends to zero as the lag period grows; stock market volatility has a stable positive impact on short-term economic policy uncertainty; the impact of economic policy uncertainty on the stock market shows a trend of divergence at the time point of different major events. The stock market is vulnerable to external shocks from developed economies in Europe and the United States, and the external spillovers have obvious regional organization dependence[8]. Convergence of investor opinions can generate buying crowded trading behavior and raise asset prices. Specifically, bullish convergence leads to sustained positive returns, while bearish convergence leads to short-term negative shocks; at the same time, investor convergence also leads to potential market risks such as trading volume contraction, price jumps, and herding behavior[9].

Thus, it can be seen that there are various risks in stock trading, coupled with the inability of retail investors to fully grasp the data, it is much more difficult for retail investors to benefit from stocks. In this paper, the attention mechanism based stock trading portfolio strategy planning method can help investors avoid their own problems such as incomplete data grasp, and improve the ability to deal with risks[10].

2. Case study analysis

On January 2, 2018, Xinhua released information showing that more than 60% of A-shareholders lost money and nearly 70% of stocks fell in the whole year of 2017.In 2018, the Shanghai Stock Exchange Statistical Yearbook (Volume 2018) released by the SSE showed that as of December 31, 2017, in terms of the number of shareholding accounts, the number of investors in the Shanghai market was 195 million, of which 194 million were natural person investors which accounted for more than 99%. However, from the market value of stock holdings, the vast majority of investors among natural persons held positions with a market value of less than 500,000 yuan, and the market value of stock holdings was 5.94 trillion, accounting for only 21.17% of the total market value.

In June 2019, the Shenzhen Stock Exchange released a survey showing that in 2018, the per capita loss of A-shareholders was as high as 94,000 yuan. The survey covered a total of 24,074 active shareholders in Shanghai and Shenzhen, aged between 18 and 60, covering 331 cities across the country.

From December 30, 2019 to January 17, 2020, CIIF organized and carried out the "2019 National Stock Market Investor Status Survey". A total of 198,000 valid questionnaires were returned, covering natural person investors (197,658), general institutional investors (613), and professional institutional investors (188), all of which are active investors in the market, and the statistical distribution is in line with the overall characteristics.

The results show that it was a rare year in many years when the percentage of investors' profits exceeded the percentage of losses. As of December 31, 2019, the number of stock investors nationwide reached 159,752,400, an increase of 9.04% over the same period of the previous year, of which 99.76% were natural person investors.In 2019, the combined percentage of surveyed investors who made a profit in stock investment was 55.2%, the percentage of those who had a flat profit/loss was 17.6%, and the percentage of those who had a loss was 27.2%. From the perspective of the proportion of investors in each profit and loss range, the largest number of investors with "profit of 10% to 30%" accounted for 23.6%, followed by investors with "flat profit and loss", accounting for 17.6%, and investors with "profit of 10% or less" accounted for 17.6%. The proportion of investors with "profit within 10%" is the second highest, at 16.6%. Compared to the previous year, the proportion of profitable investors increased from 24.9% to 55.2%.

January 14, 2021, Xinhua published "China's shareholders behavior annual report" shows that China's 1/4 of the family out of more than 50% of the family stocks speculation in the first half of 2023, the Oriental Wealth Network, a survey shows that 58% of the shareholders said that the first half of this year's losses, and another 9% of the shareholders have a slight floating loss. According to statistics, the number of A-share listed companies in 2023 increased from the old eight shares to more than 5,200 today, an increase of more than 600 times. From this, we can see that China's shareholders in urgent need of a scientific and effective stock trading portfolio strategy planning method.

Attention mechanism-based stock trading portfolio strategy is a method that utilizes the attention mechanism in deep learning to mine key information in stock market data to make more accurate trading decisions. The methodology includes data collection and preprocessing, feature extraction, modeling the attention mechanism, training the model, and formulating trading strategies and risk control.

3. Analytical steps

Existing techniques are unable to accurately assess the benefits of individual stocks because it may only consider a single metric or fail to consider the importance weighting of different metrics. This leads to less accurate trading strategies and may lead to wrong trading decisions. It is clear that this planning method has at least the following problems: 1. There is a large amount of information and data available to analyze in the existing stock market, and it is difficult for investors to sift out valuable information from it without an effective strategy methodology, and they can easily be overwhelmed by information overload, which leads to difficulty in decision making, and in the absence of a clear evaluation system and strategy methodology, investors are easily influenced by factors such as emotions, personal preferences or blindly following the trend and make subjective judgments, resulting in inaccurate and unstable investment decisions. Existing technology does not have effective indicators and methods to assess the technical trend and fundamental performance of stocks, making it difficult for investors to accurately judge the value and future performance of stocks, which can easily lead to blindness and risk in investment decisions, and making it difficult for investors to grasp the best time to buy or sell, which can easily lead to poor trading results and missed profit opportunities; at the same time, investors tend to focus only on certain indicators or specific stocks, making it difficult to grasp the overall global trends and opportunities in the stock market, limiting the diversity and diversification of investment portfolios.

Currently there are a variety of stock trading strategy planning methods on the market, Markowitz's mean-variance model, although it has created a precedent for quantitative investment and has been widely used in practice for its excellent performance, still has some shortcomings: poor interactivity and inability to make continuous investment decisions; unscientific risk measurement, the variance treats both positive and negative deviations equally; and excessive micro-weighting, leading to a decrease in operability and an increase in trading costs. decreased operability and increased transaction costs. The prediction effect of MI-LSTM model on the stock price prediction task is closely related to the information contained in the input features, and the selection of inappropriate input features may lead to poorer prediction effect of the model.The prediction errors of LSTM and MI-LSTM models on different stock price prediction tasks are different, and the prediction effect is worse on the stock price series with more violent price fluctuations. Traditional stock trading strategy planning methods are often based on historical data and empirical judgment, and although they can provide guidance to investors to a certain extent, their drawbacks are becoming increasingly apparent. These include over-reliance on historical data, excessive subjectivity, lack of flexibility and neglect of market microstructure, and with the continuous development of financial markets and technological advances, it has become imperative to find new stock trading strategy planning methods. Its necessity is mainly reflected in the following aspects: adapting to market changes, improving decision-making science, enhancing flexibility, and mining market micro information. Therefore, it is necessary to adopt a new model for the stock trading strategy planning method, i.e., the stock trading portfolio strategy planning method based on the attention mechanism mentioned herein.

In order to solve the above technical problems, the present invention adopts the following technical solution: the present invention provides a stock trading portfolio strategy planning method based on an attention mechanism, comprising:

Step 1: Acquisition of Technical and Fundamental Indicators: Acquire the technical and fundamental indicators corresponding to each stock in each historical cycle of the target stock market, including the moving average index, relative strength index and volume index, and the fundamental indicators including the price-earnings ratio, dividend yield and net profit growth rate.

Step 2: Analysis of technical and fundamental indicators: Based on the technical and fundamental indicators corresponding to each stock in each historical cycle, analyze and obtain the evaluation coefficients of technical indicators and fundamental indicators corresponding to each stock in each historical cycle.

Step 3. Acquisition of comprehensive benefit assessment coefficients: Based on the assessment coefficients of the technical indicators and the assessment coefficients of the fundamental indicators corresponding to each stock in each historical cycle, analyze and obtain the comprehensive benefit assessment coefficients corresponding to each stock in each historical cycle.

Step 4: Market trend analysis module: for analyzing and obtaining the average operation assessment coefficient corresponding to each stock in each historical cycle based on the comprehensive benefit assessment coefficient corresponding to each stock in each historical cycle, so as to predict and analyze the market trend corresponding to each stock, and then obtain the trend assessment coefficient corresponding to each stock.

Step 5. Judgment of stock performance: Based on the trend assessment coefficient corresponding to each stock, the stock performance corresponding to each stock is then judged.

Step 6: Analysis of optimal trading strategies and trading points: Based on the trend assessment coefficients corresponding to each stock, the optimal trading strategies and optimal trading points corresponding to each stock are then analyzed.

The said analysis to obtain the evaluation coefficients of the technical indicators corresponding to each stock in each historical cycle is as follows: the moving average index, the relative strength index and the volume index corresponding to each stock in each historical cycle are denoted as t_{if} , y_{if} and p_{if} , respectively, wherein i denotes the number corresponding to each stock and $i = 1,2,...,n$, f denotes the number corresponding to each historical cycle, and $f = 1,2,...,m$, is substituted into the calculation formula.

$$\alpha_{if} = \frac{t'}{\left|t' - t_{if}\right| + 1} * \varpi_1 + \frac{y'}{\left|y' - y_{if}\right| + 1} * \varpi_2 + \frac{p'}{\left|p' - p_{if}\right| + 1} * \varpi_3 \qquad (1)$$

The evaluation coefficients α_{if} of the technical indicators corresponding to each stock in each historical cycle are obtained, where t' , y' and p' denote the standard moving average index, the standard relative strength index, and the standard volume index corresponding to the set stock, respectively, and ϖ_1, ϖ_2 and ϖ_3 denotes as the weight factor corresponding to the moving average index, the weight factor corresponding to the relative strength index, and the weight factor corresponding to the volume index of the set stock, respectively.

The said analysis to obtain the evaluation coefficients of the fundamental indicators corresponding to each stock in each historical cycle is as follows: the corresponding price-earnings ratios, dividend yields and net profit growth rates of each stock in each historical cycle are denoted as q_{if}, z_{if} and h_{if}, , respectively, and are substituted into the calculation formula .

$$\beta_{if} = \frac{q'}{\left|q' - q_{if}\right| + 1} * \theta_1 + \frac{z'}{\left|z' - z_{if}\right| + 1} * \theta_2 + \frac{h'}{\left|h' - h_{if}\right| + 1} * \theta_3 \tag{2}$$

The evaluation coefficients of fundamental indicators corresponding to each stock in each historical cycle are obtained β_{if}, where q', z' and h' denotes the standard price-earnings ratio, the standard dividend yield, and the standard net profit growth rate corresponding to the set stock, respectively, and θ_1, θ_2 and θ_3 denotes as the weighting factor corresponding to the price-earnings ratio, the weighting factor corresponding to the dividend yield, and the weighting factor corresponding to the net profit growth rate of the set stock, respectively.

The said analysis to obtain the evaluation coefficients of comprehensive benefits corresponding to each stock in each historical cycle is as follows: the evaluation coefficients of technical indicators and the evaluation coefficients of fundamental indicators corresponding to each stock in each historical cycle are. Substitute them into the calculation formula.

$$\chi_{if} = \frac{\ln(\alpha_{if} * \tau_1 + \beta_{if} * \tau_2) * \mathrm{e}}{\tau_1 + \tau_2} \tag{3}$$

Obtain the comprehensive benefit assessment coefficients corresponding to each stock in each historical cycle χ_{if}, where τ_1 and τ_2 is the weight factor corresponding to the set technical indicator assessment coefficients and the weight factor corresponding to the fundamental indicator assessment coefficients, respectively.

The said analysis to obtain the average operating assessment coefficients corresponding to each stock is carried out as follows: the comprehensive benefit assessment coefficients corresponding to each stock in each historical cycle, are substituted into the calculation formula.

$$\Delta\chi_i = \frac{\sum_{f=2}^{m}\left(\chi_{if} - \chi_{i(f-1)}\right)}{f-1} \tag{4}$$

The average operating assessment coefficient $\Delta\chi_i$ corresponding to each stock is obtained, where $\chi_{i(f-1)}$ is denoted as the i comprehensive benefit assessment coefficient corresponding to the operating information of the $f-1$ dth historical cycle in the cth stock.

Preferably, said obtaining the trend assessment coefficients corresponding to each stock is obtained as follows: the average operating assessment coefficients corresponding to each stock, are substituted into the calculation formula.

$$\phi_i = \frac{\left(\sum_{g=1}^{u} \chi_{ig} - \chi_{im}\right)}{\Delta\chi_i} * \kappa_1 + \sum_{f=2}^{m} \frac{\left(\chi_{if} - \chi_{i(f-1)}\right)}{\Delta\chi_i} * \kappa_f \tag{5}$$

The corresponding trend assessment coefficients ϕ_i are obtained for each stock, where χ_{im} denotes the average operating assessment coefficient corresponding to the m historical cycle in the i stock, and κ_1 and κ_f denotes the weighting factor corresponding to the current historical cycle, and the f historical cycle for the setup, respectively.

The specific judgment process for judging the stock performance corresponding to each stock is as follows: comparing the trend assessment coefficient corresponding to each stock with the trend assessment coefficient corresponding to a set standard stock, if the trend assessment coefficient corresponding to a stock is smaller than the trend assessment coefficient corresponding to the set standard stock, then it is judged that the stock of that stock is underperforming, and if the trend assessment coefficient corresponding to a stock is greater than or equal to the trend assessment coefficient corresponding to the set trend assessment coefficient corresponding to a standard stock, then it is determined that the stock of the stock has a good stock performance, and in this manner, the stock performance of the stock corresponding to each stock is judged.

Said analyzing the best trading strategy corresponding to each stock, the specific analyzing process is as follows: comparing the trend assessment coefficient corresponding to each stock with the trend assessment coefficient corresponding to each trading strategy in the database, and if the trend assessment coefficient corresponding to a stock is the same as the trend assessment coefficient corresponding to a certain trading strategy in the database, then that trading strategy in the database is taken as the best trading strategy corresponding to the stock, and analyzing the optimal trading strategy corresponding to each stock in this manner. analyzing the best trading strategy corresponding to each stock.

Said analyzing the best trading point corresponding to each stock, the specific analyzing process is as follows: comparing the trend assessment coefficient corresponding to each stock with the trend assessment coefficient corresponding to each trading point in the database, if the trend assessment coefficient corresponding to a stock is the same as the trend assessment coefficient corresponding to a trading point in the database, then the trading point in the database will be taken as the best trading point corresponding to the stock, and in this manner analyzing the best trading point corresponding to each stock. If the trend evaluation coefficient of a stock is the same as the trend evaluation coefficient of a trading point in the database, the trading point in the database will be taken as the best trading point of that stock.

4. Conclusion

From the above, it can be seen that the stock trading portfolio strategy based on the attention mechanism can help to improve the assessment of stock benefits and improve the accuracy of trading strategies; help traders effectively capture the correlation between such information and improve the ability to understand market changes; adaptively learn and adjust the weights according to different situations to better adapt to the changes and fluctuations of different stock markets, and automatically learn and pay attention to the important features Reduce the impact of human Reduce the influence of human interference and subjective judgment on trading decisions Improve the objectivity and scientificity of trading; Process large-scale stock market data in real time Make predictions and decisions in a short period of time to improve the efficiency and timeliness of trading; Help investors to better control trading risks and safeguard the safety of their investments by taking risk factors into account.

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