A Novel End-to-end Framework for A-share Stock Market Portfolio Optimization Considering Risk Measure and Feature Exposure

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Abstract
In the current financial markets, where portfolio optimization remains a significant challenge, the dynamic changes in market conditions and investment demands render the development of an effective portfolio optimization framework more crucial than ever. This study introduces an end-to-end portfolio optimization framework, termed Quality-Growth-Momentum-Sentiment-Bayesian Optimization Asset Portfolio (QBOAP), aimed at constructing robust and profitable asset portfolios within the A-share stock market. The framework enhances both portfolio performance and trading value. The QBOAP framework utilizes the Quality-Growth-Momentum-Sentiment (QGMS) feature set to capture a comprehensive array of market information, ensuring that feature combinations are both representative and explanatory. A novel loss function is employed within this framework, incorporating considerations of return curve stability and feature exposure, and is optimized using a Bayesian optimization algorithm to determine the optimal asset weights. Additionally, the framework integrates a weight rank-based trading strategy designed to minimize transaction costs and complexity, thereby improving overall trading value. Empirical validation through backtesting from 2017 to 2024 reveals that the QBOAP framework achieves a Compound Annual Growth Rate (CAGR) of 0.216, a Sharpe ratio of 1.46, and a Calmar ratio of 1.60. These metrics are superior to those of ten baseline models, demonstrating the framework's effectiveness and offering valuable insights for the construction and optimization of A-share portfolios.

CCS CONCEPTS • Information systems • Data management systems • Database management system engines

Additional Keywords and Phrases: Portfolio Optimization, Risk Measure, Regularization, Bayesian Optimization

1 INTRODUCTION

The preservation and appreciation of residents' wealth is an important driver of national economic growth. In China, the effectiveness of asset allocation is crucial to preserving and appreciating of wealth due to the large total amount of residents' wealth [1][2]. However, in recent years, with the proliferation of investable underlying assets and the explosion of information, traditional asset allocation strategies are faced with the dual challenges of the number of assets and the dimension of investment information. Under such circumstances, traditional asset allocation methods struggle to meet the needs of investors. Therefore, it becomes especially urgent and important to construct an asset allocation method that adapts to modern investment needs.

Classical asset allocation models (e.g., the Markowitz mean-variance model [3]) typically use a two-step strategy: first estimating the distribution of returns (including the mean and covariance matrices of the returns), and then deciding the portfolio weights based on these estimates [4][5]. However, this asset allocation strategy suffers from the following shortcomings: first, predicting asset returns is a very non-trivial task that may generate prediction errors that can affect the final portfolio decision, and the estimation of the covariance matrices becomes unstable when dealing with a large number of variables [6]. Second, this two-step strategy breaks the organic link between return distribution estimation and portfolio decision-making, and the return distribution estimation is merely an intermediate step in portfolio decision-making; and minimizing its estimation error, such as Mean Squared Error, does not necessarily lead to portfolio optimization [7].

To overcome the above two problems of traditional asset allocation models, an end-to-end model has been proposed to directly predict portfolio weights based on asset features. This approach allows for direct optimization of portfolio metrics by circumventing the estimation of the covariance matrix of expected means and returns [8][9]. However, the significant increase in asset features renders traditional regression models and portfolio ranking methods no longer applicable, making it difficult to extract the effective signals in high dimensional and massive data. Therefore, existing research methods are facing the challenge of "garbage in, garbage out" [10]. Determining a reasonable feature integration to identify the key factors affecting model performance remains a challenge. In addition to feature construction and selection, the formulation of optimization problem is equally important in effectively controlling portfolio risk while maintaining portfolio returns. Finally, the trading value and feasibility of the model are also significant aspects of evaluating the portfolio. Therefore, there are three main issues when using optimization algorithms to construct asset portfolio allocation models: (a) feature construction and selection (b) optimization problem formulation and (c) trading value of the model. These three issues are discussed in detail as follows.

(a) Feature construction and selection. Some studies [12][13][14] have considered only asset prices when performing portfolio optimization, ignoring other characteristics that may have significant explanatory power for asset returns. This approach may result in models that lack generalization ability due to insufficient sample information. In contrast, Park et al.[15] established a twin-system recurrent reinforcement learning with technical features related to historical prices up to the present and fundamental features related to macroeconomic factors and specific industry characteristics. Ma et al.[16] selected 13 financial indicators from value, profitability, operating status, growth and solvency to construct a three-level nested portfolio optimization model. These studies subjectively select fundamental and technical features to solve optimal weights for assets, but the features are not systematic enough to include comprehensive information in the stock market. Therefore, how to construct a combination of features that is both representative and explanatory is worth exploring in depth.

(b) Optimization problem formulation. The core of portfolio optimization and asset allocation lies in the construction of the optimization objective / loss function. Existing studies have explored the application of various optimization objectives in portfolio optimization. Lv et al. [17] formulated a five-objective optimization problem that incorporates mean, variance, skewness, kurtosis, and distance-to-default as key consideration. Bedoui et al. [12] investigated the potential benefits of using the Conditional Value at Risk (CVaR) portfolio optimization approach. Savaei et al. [13] measured risk based on the conditional drawdown-at-risk (CDaR) measure, which could prevent major declines in investment as a conservative investment strategy. However, few studies have considered optimizing the slope of return curve to ensure a stable increasing cumulative return. If the portfolio's drawdown can be minimized by optimizaing the curve's shape, portfolio returns can be amplified by increasing leverage while maintaining a reasonable return to risk ratio [18]. It is also important to control the portfolio's exposure to a particular feature [19]. There are differences in the explanatory power of different factors varies across different markets. If the portfolio's exposure to a particular characteristic is too high, it may cause the model to earn better returns in markets where that characteristic has stronger explanatory power and face losses in markets where the characteristic is less explanatory. However, most of the relevant studies consider controlling for asset-specific positions and do not control for the weights of the features. Therefore, balancing portfolio returns with maximum drawdown, as well as reasonably controlling the portfolio's exposure to each feature, are key issues that need to be studied in depth in portfolio optimization.

(c) Trading value of the model. The primary goal of portfolio optimization model is to provide valuable recommendation for real-world trading. However, existing portfolio optimization research suffers from two problems in terms of trading value. The first is selection bias. Wu et al. [20] selected a dataset of 55 stocks from the Chinese A-share market, training their model from 2018 to 2019 and testing it from 2020 to 2021. Wang and Aste [21] selected 100 stocks from NSDQ, FTSE and HS300 during the trading period between 2010 and 2020. Alzaman studied 100 stocks traded on the Toronto Stock Exchange (TSE) from 2015 to 2021 to train and test DeepRank model. These studies subjectively choose the asset pool for portfolio optimization and the backtesting period [22]. Chen and Huang [23] carried out empirical analysis on 122 cases of Taiwanese equity mutual funds from 2003 to 2006. This introduces selection bias, as the performance of the asset pool at a specific time cannot be known at the beginning of the backtesting period. Thus, the selection of the asset pool and backtesting time range should be more general to make the results more robust and credible. The second problem is trading difficulty. Some existing portfolio optimization studies are usually conducted for a larger stock pool containing many stocks [24][25]. However, trading a large number of stocks brings high commission and trading difficulty, which is unfavorable for real trading applications. Therefore, constructing a more stable portfolio with a more optimal number of assets based on the calculated optimal weights is a worthwhile research problem.

To address the above issues, this study aims to develop an optimization algorithm-driven end-to-end asset allocation model. The model is capable of capturing financial market returns while controlling portfolio risk with both trading value and trading feasibility. In this model, a stock market feature framework QGMS is first set up to construct a feature set with strong explanatory power for asset returns from four dimensions: quality, growth, momentum and sentiment. Based on the constructed features, this paper constructs an optimization framework that considers the tradeoff between portfolio return and maximum drawdown, while utilizing L1-regularization to control the weight of each feature. Furthermore, it adopts the Bayesian optimization algorithm to solve the optimization problem. Finally, a feasible and profitable trading strategy based on portfolio weights is developed to enhance its trading value. The proposed QGMS -- Bayesian Optimization -- Asset portfolio (QBOAP) model is compared with various models to verify its performance. The rest of this paper is organized as follows. Section 2 analyses and summarizes the research idea of this paper. Section 3 and 4 present the methodology adopted to set up the feature framework and optimization problem. Section 5 presents various comparative experimental results and discussions to demonstrate the effectiveness of the proposed approach. Section 6 provides conclusions and directions for future research.

2 MODEL FRAMEWORK

This section introduces the framework of the proposed QBOAP framework: Quality-Growth-Momentum-Sentiment-Bayesian-Optimization-Asset-Portfolio. The in-depth procedure is detailed below.

(1) Feature construction: This step aims at constructing a high-quality feature set for optimal weight solution. Four angles are taken into account: Quality, Growth, Momentum and Sentiment. Quality assesses the fundamental strength of the company, Growth evaluates its future expansion potential, Momentum looks at recent price trends, and Sentiment gauges market perception and investor attitudes. By integrating insights from these four angles, a more comprehensive and robust information set can be established. After calculating the factors, in order to solve the problem that the factor values contain outliers, and stocks with different market capitalization and industries cannot be compared under the same scale, this paper carries out MAD outlier treatment, Z-score standardization and market capitalization and industry neutralization on the factor values.

(2) Optimization problem setting: This step solves the optimal weight from the constructed feature set. A novel term considering the slope and maximum drawdown of the return curve is adopted to optimize the performance of the portfolio,

while a regularization term to control the exposure of feature on portfolio is used to make the portfolio more robust. Further, Bayesian Optimization Algorithm is utilized to solve the optimization problem.

(3) Trading strategy construction: Aimed at reducing the trading difficulty in order to enhance the trading value of the framework, a weight rank based trading strategy is proposed to construct the final investment portfolio. To evaluate the performance of strategy, eight metrics are adopted: CAGR, Sharpe, Calmar, Sortino, Omega, TailRatio, RankIC, ICIR. The larger the values of these metrics are, the better the performance of the constructed portfolio.

2.1 Feature Construction

This paper constructs a feature framework QGMS for equity portfolios that integrates multidimensional factors such as firm financial quality, growth, momentum, and market sentiment. More details for QGMS can be found as follows, separately:

Quality Factor: Factors that measure a company's financial condition and profitability.

Ratio of net cash flow from operating activities to enterprise value (cfo_to_ev): measures a company's ability to generate cash flow through the ratio of net cash flow from operating activities to enterprise value, where enterprise value is equal to the sum of the company's market capitalization and liabilities minus money funds, i.e.

$$\text{cfo\_to\_ev} = \frac{CFO_{TTM}}{EV} \tag{1}$$

Cash-to-current-liability ratio (cfo_to_li): A measure of a company's ability to utilize cash flow to pay off current liabilities, i.e.

$$\text{cfo\_to\_li} = \frac{CFO_{TTM}}{Total\ Current\ Liabilities} \tag{2}$$

Profitability Stability (margin_stability): Calculated using the mean and standard deviation of gross margins over 8 years to measure the stability of a company's profitability, i.e.

$$\text{margin\_stability} = \frac{\frac{1}{8}\sum_{i=t-7}^{t} GM_i}{\sqrt{\frac{1}{7}\sum_{i=t-7}^{t}\left(GM_i - \frac{1}{8}\sum_{i=t-7}^{t} GM_i\right)^2}} \tag{3}$$

where GM is the gross margin TTM over the last 8 years.

Return on invested capital (roic_ttm): A measure of a company's ability to generate net profit from invested capital, i.e.

$$\text{roic\_ttm} = \frac{NetIncome_{TTM}}{\frac{1}{4}\sum_{i=1}^{4} InvestmentCapital_i} \tag{4}$$

Operating Profit to Total Operating Revenue (ope_profit_to_ope_rev): Reflects the ratio of the company's operating profit to its total operating revenue to assess the company's profitability, i.e.

$$\text{ope\_profit\_to\_ope\_rev} = \frac{Operating\ Profit_{TTM}}{Operating\ Revenue_{TTM}} \tag{5}$$

Growth Factor: Factors that measure the company's development speed and growth potential.

Net cash flow growth rate from operating activities (cfo_gr): Measures the annual growth rate of the company's net cash flow from operating activities, i.e.

$$\text{cfo\_gr} = \frac{CFO_{TTM,t}}{CFO_{TTM,t-4}} - 1 \tag{6}$$

PEG: Assesses the growth of a stock through the ratio of the price-earnings ratio (PE) to the growth rate of net profit attributable to the parent company, i.e.

$$\text{PEG} = \frac{PE}{100 * NetIncome\ GrowthRate_{TTM}} \tag{7}$$

Total Assets Growth Rate: Measures the rate of expansion of a company's assets, i.e.

$$\text{ta\_gr} = \frac{TotalAsset_t}{TotalAsset_{t-4}} - 1 \tag{8}$$

Momentum Factor: Factors that are mainly based on the momentum and trend analysis of stock prices.

Money Flow Indicator (MFI_14): Assesses market momentum through typical price, volume and positive and negative money flows, i.e.

$$\text{MFI\_14} = 100 - \frac{100}{1 + MR_{14}} \tag{9}$$

Where:

$$\text{sgn(x, y, z)} = \begin{cases} 0, & x < y \\ z, & x \geq y \end{cases} \tag{10}$$

$$\text{MR\_14} = \frac{\sum_{i=t-13}^{t} sgn(CLOSE_i, CLOSE_{i-1}, VOLUME_i)}{\sum_{i=t-13}^{t} sgn(-CLOSE_i, -CLOSE_{i-1}, VOLUME_i)} \tag{11}$$

6 Day Closing Price to Date Linear Regression Coefficient (PLRC_6): Analyzes price trends using the linear regression coefficient of the 6-day closing price to the date sequence number. It is solved by fitting the following OLS function, i.e.

$$\frac{CLOSE_t}{\frac{1}{6}\sum_{i=t-5}^{t} CLOSE_i} = PLRC\_6 * t + \alpha \tag{12}$$

Bullish Power (bull_power): A measure of market long power by the ratio of the difference between the highest price and the 13-day exponential moving average to the closing price, i.e.

$$\text{bull\_power} = \frac{HIGH - EMA(CLOSE, 13)}{CLOSE} \tag{13}$$

Bollinger Bands Down (boll_down): Analyzes the range of price fluctuations through the ratio of the lower Bollinger Bands to today's closing price, i.e.

$$\text{boll\_down} = \frac{\frac{1}{20}\sum_{i=t-19}^{t} CLOSE_i - 2 * \sqrt{\frac{1}{19}\sum_{i=t-19}^{t}(CLOSE_i - \frac{1}{20}\sum_{i=t-19}^{t} CLOSE_i)^2}}{CLOSE} \tag{14}$$

5-Day Ultimate Indicator (TRIX_5): Calculates the composite movement of the 5-, 10-, and 5-day exponential moving averages to analyze trend reversal signals, i.e.

$$\text{MTR} = EMA(EMA(EMA(CLOSE, 5), 10), 5) \tag{15}$$

$$\text{TRIX\_5} = \frac{MTR_t - MTR_{t-1}}{MTR_{t-1}} * 100 \tag{16}$$

60-Day Moving Average (mac_60): The ratio of the 60-day moving average to today's closing price, which is used to assess long-term trends, i.e.

$$\text{mac\_60} = \frac{\sum_{i=t-59}^{t} CLOSE_t}{CLOSE_t} \tag{17}$$

Sentiment Factor: Factors that represent the confidence and sentiment of market participants.

Standard deviation of 6-day turnover (amstd_6): Measures the volatility of the market through the standard deviation of turnover, i.e.

$$\text{amstd\_6} = \sqrt{\frac{1}{5}\sum_{i=t-5}^{t}\left(VOLUME_i - \frac{1}{6}\sum_{i=t-5}^{t} VOLUME_i\right)^2} \tag{18}$$

Turnover relative volatility (turn_vol): Analyzes changes in market sentiment through the standard deviation of turnover of individual stocks over 20 trading days, i.e.

$$\text{turn\_vol} = \sqrt{\frac{1}{19}\sum_{i=t-19}^{t}\left(TurnoverRate_i - \frac{1}{20}\sum_{i=t-19}^{t} TurnoverRate_i\right)^2} \tag{19}$$

5-day average turnover ratio to 120-day average turnover ratio (turn_5_120): Measures the difference between short-term and long-term trading activities through the ratio of 5-day average turnover ratio to 120-day average turnover ratio, i.e.

$$\text{turn\_5\_120} = \frac{\frac{1}{5}\sum_{i=t-4}^{t} TurnoverRate_i}{\frac{1}{120}\sum_{i=t-119}^{t} TurnoverRate_i} \tag{20}$$

To sum up, this QGMS feature framework is constructed with the aim of capturing the multiple attribute characteristics of stocks through a comprehensive multi-dimensional and multi-frequency factor analysis, which in turn provides more effective explanatory variables for the solution of asset weights.

2.2 Feature Preprocessing

The preprocessing of factor incorporates four parts: Standardization, Outlier processing, Size neuralization and Industry neuralization. Through these steps, the final factors are cleansed of outlier, size, and industry influences, providing a clearer view of the inner relationships with the future return and proper weight they are meant to measure.

2.2.1 Outlier processing

The first step involves identifying and handling outliers using the Median Absolute Deviation (MAD) method. Outliers can significantly skew results, so it's essential to address them. The MAD is calculated as follows:

$$MAD = median(|X_i - X_{median}|) \tag{21}$$

$$X_i' = \begin{cases} X_{median} + n * MAD & if\ X_i > X_{median} + n * MAD \\ X_{median} - n * MAD & if\ X_i < X_{median} - n * MAD \\ X_i & if\ X_{median} - n * MAD \ \le\ X_i \le X_{median} + n * MAD \end{cases} \tag{22}$$

where X_i represents the factor value and median(X) is the median of these values. Values that exceed a certain multiple of the MAD (typically 3) are considered outliers and can be handled by capping them to a threshold value or removing them from the dataset.

2.2.2 Standardization

After outlier treating, the next step is to standardize the factors. This process involves transforming the factor values so they have a mean of zero and a standard deviation of one. The standardization is performed using the Z-score method:

$$Z_i = \frac{X_i - \mu}{\sigma} \tag{23}$$

where Z_i is the standardized factor value, X_i is the original factor value, μ is the mean of the factor, and σ is the standard deviation. This transformation ensures that all factors are on a comparable scale, making it easier to analyze them collectively.

2.2.3 Market size neuralization

Factors are often influenced by the size of the company, measured by its market capitalization. To neutralize this effect, a regression is performed with the standardized factor values as the dependent variable and market capitalization as the independent variable:

$$X_i = \alpha + \beta * MV_i + \epsilon_i \tag{24}$$

where, X_i denotes the standardized factor value, MV_i is the market capitalization, α and β are the regression coefficients, and ϵ_i is the residual. The size-neutralized factor value is then obtained by subtracting the effect of market capitalization:

$$X_i' = X_i - \beta * MV_i \tag{25}$$

2.2.4 Industry neuralization

Finally, the factors are neutralized for industry effects, which can significantly impact factor behavior. This is done by regressing the size-neutralized factor values against industry dummy variables:

$$X_i' = \alpha + \sum_{j=1}^{k} \gamma_j I_{ij} + \epsilon_i \tag{26}$$

where X'_i is the size-neutralized factor value, I_{ij} represents dummy variables for the k industries, and γ_j are the industry-specific coefficients. The residuals ϵ_i from this regression represent the industry-neutralized factor values:

$$X_i'' = \epsilon_i \tag{27}$$

2.3 Optimization Problem Formulating

In financial research, asset characteristics can be used to predict expected returns [26][27][28], i.e., expected returns can be expressed as a function of asset features:

$$\mu_{t+1} = \mu(X_t), \tag{28}$$

where X_t denotes the asset characteristics at time t, and μ_t denotes the expected return of the asset at time $t+1$. Asset features can also be used to estimate the covariance matrix[29][30], i.e., the covariance matrix can be expressed as a function of asset features:

$$\sigma_{t+1} = \sigma(X_t), \tag{29}$$

where σ_{t+1} denotes the covariance matrix of the asset at time $t+1$.

According to mean-variance theory, the portfolio weights are a function of the expected returns and the covariance matrix[3][31], which can be determined by combining equations (28) and (29):

$$W_{t+1} = f\big(\mu(X_t), \sigma(X_t)\big), \tag{30}$$

where f (•) denotes the functional relationship between the expected return and covariance matrices and W_{t+1} denotes the portfolio weights at time $t+1$. If the expected return and covariance matrices are first estimated through the asset characteristics and then used to estimate the portfolio weights, the intermediate steps are inevitably subject to prediction errors, making the estimation process cumbersome. Since equation (30) can also be interpreted as the portfolio weights W_{t+1} being a function of asset characteristic X_t, further simplify Eq. (30) to:

$$W_{t+1} = f_m(x_t; \theta), \tag{31}$$

The portfolio weights W_{t+1} are directly estimated through the asset characteristics X_t , where $f_m(\bullet)$ denotes a function of the asset characteristics X_t and θ is the parameter to be estimated. Based on Brandt [32] assumption, the optimal weight can be presented as a linear combination of asset features. Therefore, the $f_m(\bullet)$ can be further simplified as a linear combination of X_t and θ. Based on this, this paper employs convex optimization techniques to fit the complex underlying functional relationships, with the portfolio tilted towards stocks that contribute to increasing the investor's utility:

$$W_{t+1} = \overline{W_{t+1}} + f_m(x_t; \theta), \tag{32}$$

where $\overline{W_{t+1}}$ is the base weight in period $t+1$, representing an equal weight used to adjust the portfolio estimated from the asset characteristics. The resulting portfolio return in period t+1 is:

$$r_{p,t+1}(\theta) = \overline{W}_{t+1}^T r_{t+1} + f_m(x_t; \theta)^T r_{t+1}, \tag{33}$$

where r_{t+1} denotes the return vector of the asset in period $t+1$. To solve for θ, we maximize the utility function, i.e., the loss function, designed in this paper. The loss function consists of two parts: one based on the ratio of the portfolio's return multiplied by the the slope of cumulative return curve to the maximum drawdown, and the other controlling for the $L1$ regularization term of the individual feature weights. It is represented as follows:

First, given the return curve, fit the OLS function of cumulative return and time to solve the slope term, where n is the total time length of return curve:

$$cumret_t = slope * t + \epsilon, t = 1,2, \dots, n. \tag{34}$$

Then, based on the slope, the loss function is constructed as:

$$\hat{\theta} = arg \min_{\theta} J(\theta) = -\frac{TotalReturn * slope}{Max\ Drawdown} + \lambda * \sum_i |\theta_i| \tag{35}$$

Additionally, the optimal portfolio weights $\widehat{W_{t+1}}$ are obtained in an end-to-end manner using equation (32).

2.4 Construction of Weight-based Trading Strategy

Given that the total stock pool consists of over 5000 stocks, transferring all stocks according to their optimal weights would face substantial huge transaction costs. Therefore, after determining the stock weights, this paper designs an investment strategy based on factor cross-section ranking.

Specifically:

step1: Define the weight range. Suppose the i^{th} stock with weight of W_i, sort the weights in ascending order to obtain a list $\{W_1, W_2, W_3, \dots, W_n\}$, where $W_1 < W_2 < \dots < W_n$.

step2: Define the trading stock. For stocks in the top 10%, range of there weights are considered to have a higher probability of going up and the strategy is to go long on these stocks: $\{ W_{(n-[0.1n]+1)} , \dots , W_{(n)}\}$. For the bottom 10% stocks, the strategy will go short on them:$\{ W_{(1)} , \dots , W_{([0.1n])}\}$.

2.5 Strategy Evaluation

After constructing the long-short asset portfolio based on optimal weights, this paper further analyzes and evaluates the portfolio's performance in a comprehensive manner. The following eight key metrics are adopted to measure the model results: Compound Annual Growth Rate (CAGR), Sharpe Ratio, Calmar Ratio, Sortino Ratio, Omega Ratio, Tail Ratio, Rank Information Coefficient (RankIC), and Information Coefficient Information Ratio (ICIR). Compound Annual Growth Rate (CAGR) assesses the average annual growth rate of an investment over a specific time period, accounting for the compounding effect of returns, thus providing a clear picture of long-term return performance. Sharpe Ratio measures excess return per unit of risk and reveals risk-adjusted investment performance by comparing the difference between the investment return and the risk-free rate. Calmar Ratio focuses on maximum drawdown-adjusted return, reflecting an investment's ability to recover from a significant loss. Sortino Ratio is similar to the Sharpe Ratio, but emphasizes downside risk, evaluating risk-adjusted returns by considering only negative volatility. Omega Ratio takes into account the full range of probabilities of gains and losses, providing a comprehensive measure of risk-return. Tail Ratio measures the risk of extreme gains or losses by comparing the tail behavior of a portfolio's return distribution. Rank Information Coefficient (RankIC) assesses the correlation between a model's predictive rankings and its actual return rankings, reflecting the model's predictive power. Information Coefficient Information Ratio (ICIR), measures the stability of RankIC, reflecting the reliability of the model's predictive accuracy over time. By using these metrics together, we can comprehensively assess the performance of investment models in terms of return, risk and forecast accuracy.

3 RESULT AND DISCUSSION

3.1 Results of Proposed Model

3.1.1 Experiment setting

Dataset: This experiment incorporates all A-share data from January 1, 2010 to May 31, 2024, and with 20 features introduced by the QGMS framework. All features are pre-processed as described in Section 2 before being input into the model.

Backtest: We conduct a backtest of the strategy on the entire A-share stock pool using a rolling backtesting approach. The training set spans 5 years, the validation set covers 2 years, and the test set lasts 1 year, with the model re-trained every 12 months. The training objective is to minimize the loss function and the optimal hyperparameter are determined using the validation set. Backtesting is performed on a monthly basis, excluding stocks that are suspended on trading days and stocks that hit the upper or lower price limits. The strategy involves taking long positions in the top 10% of stocks based on predicted returns and short positions in the bottom 10% of stocks. Stock positions are equally weighted. Backtested returns are calculated using compounding, and excess returns are calculated as the ratio of the strategy return to the benchmark return (All A-Share Return). The backtest does not account for slippage, fees, or the cost of financing short positions. Since an equal number of stocks are used for shorting and longing, the strategy effectively employs double leverage, using the initial capital for the long positions and disregarding the capital needed to finance the short position.

Baseline: To demonstrate the performance of our proposed model, we compare the loss function used in this paper with other loss functions proposed. Specifically, (1) for performance optimization of the return curve, we compare model performance using Sharpe, Calmar, Mean-Variance, VaR, CVaR, and CDaR as loss function (2) for model sparsification, we compare model performance using the L2 norm, elastic net norm, and the L1 and L2 norms for singal asset positions.

Backtest metrics: We use the following eight indicators to measure the model results: CAGR, Sharpe, Calmar, Sortino,Omega, TailRatio, RankIC and ICIR. The definitions of each indicator are provided in Section 2.5.

Experiment detail: The experiment is conducted using an Apple M3 Pro with an 18GB CPU. The hyperparameter lambda optimization range is [0,0.1], with a search step is 0.01. The feature weight optimization range is [1e-5,1e-2]. The number of training rounds is set to 100 trials. The training set, validation set and test set cover 5 years, 2 years and 1 year, respectively.

3.1.2 *Result Analysis*

In this section, we first examine the result of our proposed QBOAP framework. To provide a comprehensive analysis of the determined weight, we rank the weight into ten quantiles and compared the returns of each quantile. Then, we construct a long-short portfolio using the first quantile and the last quantile based on the weight-ranking rule. The results are shown in Fig. 1.

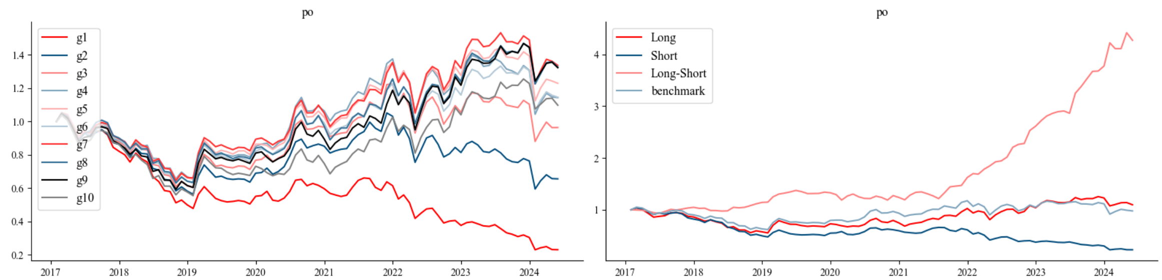

Fig. 1. **Quantile Return of Optimal Weight (left); Long-short Portfolio Return(right)**

The solved weights are divided into ten quantile, with g1 representing the smallest and g10 representing the largest. As show Fig. 1. on the left, assets in the lowest weight group exhibit a significant tendency to lose money, while the returns of the asset portfolio increase as the weights increase, reflecting the effectiveness of the weights in predicting the future asset returns. However, the monotonicity between weight values and returns gradually disappears in the highest-weighted portfolios. This is due to the loss function is designed to minimize drawdown and therefore it does not assign larger weights to the tail samples with more extreme returns. The return profile of the long-short portfolio, constructed based on the weight values is shown on the right. It significantly outperforms the benchmark returns, demonstrating the effectiveness of the strategy. On the right, the cumulative returns of long, short, long-short and benchmark portfolio are represented by quantile group 10, quantile group 1, the long group 10, the short group 1 and the overall A-share market return, respectively. It can be concluded that the long-short group achieves a relatively stable and high return, indicating the effectiveness of the weight-rank strategy. Moreover, from 2022 to 2024, profit were significantly larger due to the pronounced bear trend in the A-share market, where the quantile group 1 could earn stable return by short stock with a high probability of losing money. This also suggests that our strategy has greater exposure to short-side returns, which aligns with the previous analysis.

To further analyze the performance of our proposed QBOAP model, we examine the metrics of each quantile and long-short portfolio, more details could be founded in Table 1.

Table 1: **Comparison of Quantile Return in QBOAP model**

quantile	CAGR	SR	CR	Sortino	Omega	TR
1	-0.180	-0.77	-0.23	-0.92	0.56	3.49
2	-0.055	-0.16	-0.12	-0.22	0.88	1.61
3	-0.005	0.08	-0.01	0.12	1.07	1.72
4	-0.005	0.19	-0.01	0.28	1.16	1.88
5	0.028	0.24	0.08	0.36	1.21	1.96
6	0.018	0.19	0.05	0.29	1.16	1.90
7	0.040	0.29	0.10	0.45	1.25	2.08
8	0.039	0.28	0.10	0.45	1.25	2.03
9	0.038	0.28	0.09	0.45	1.24	2.18

10	0.013	0.16	0.03	0.26	1.13	1.98
Long-Short	0.216	1.46	1.60	3.61	3.20	4.06

From the quantile analysis in Table 1, the monotonicity between weight values and returns gradually disappears in the high-weighted portfolios. Specifically, the returns for quantiles 7-9 hover around 0.039, while the return for quantile 10 drops to 0.013. Moreover, the return of long-short group has more exposure to short-side return, which produces a 0.18 CAGR with a Sharpe Ratio 0.77.

Furthermore, we compare the performance of our proposed model with the baseline, as Pnl curve shown in Fig 2 and evaluation metrics shown in Table 2.

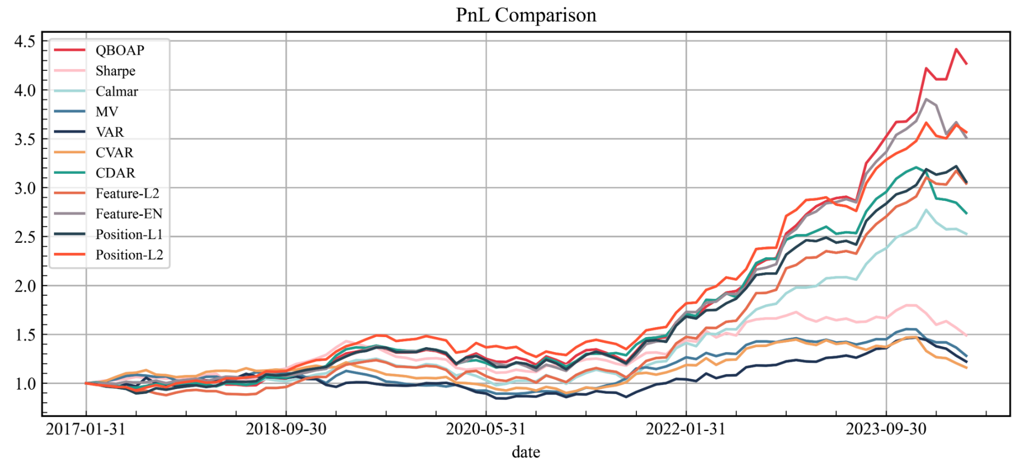

Fig. 2. **Pnl Comparison of QBOAP framework and Baseline**

Table 2: Comparison of QBOAP framework and Baseline

Term	Model	CAGR	SR	CR	Sortino	Omega	TR	RankIC	ICIR
Opt Term	QBOAP	0.216	1.46	1.60	3.61	3.20	4.06	0.040	0.409
	Sharpe	0.055	0.55	0.25	0.91	1.53	1.65	0.013	0.177
	Calmar	0.133	1.12	0.61	2.26	2.35	2.58	0.028	0.350
	MV	0.033	0.39	0.16	0.65	1.35	1.60	0.005	0.074
	VaR	0.027	0.31	0.12	0.49	1.27	1.58	0.003	0.043
	CVaR	0.020	0.24	0.08	0.37	1.20	1.52	0.004	0.050
	CDaR	0.146	1.14	0.90	2.41	2.54	3.00	0.029	0.324
Sparse Term	Feature-L2	0.162	1.19	0.87	2.64	2.55	3.34	0.030	0.318
	Feature-EN	0.185	1.33	1.02	2.88	2.84	3.57	0.037	0.400
	Position-L1	0.163	1.24	1.00	2.61	2.59	3.20	0.032	0.348
	Position-L2	0.187	1.45	1.28	3.03	2.77	3.85	0.035	0.411

As shown in Fig. 2., the proposed QBOAP framework achieves the highest return and maintains moderate volatility compared to other baseline methods. And as presented in Table 2, the combined strengths of the QBOAP model are particularly evident across several key financial metrics. First, the Compound Annual Growth Rate (CAGR) is a core metric for assessing long-term investment growth. The QBOAP model's CAGR of 0.216 is significantly higher than that of other models, indicating that it achieves substantial average annualized return growth over the investment duration. This high growth rate means that the QBOAP model not only performs strongly in terms of returns, but also consistently delivers stable income. The QBOAP model also outperforms other models in various ratios. For example, the Sharpe ratio, which measures return per unit of risk, is higher in the QBOAP model, indicating a better risk-adjusted return for the investment strategy, and the QBOAP model's high Sharpe ratio suggests that it can provide higher returns than other models for the same amount of risk. For example, the Sharpe ratios of Feature-EN and Position-L2 in the Sparse model are 1.33 and 1.45, respectively, which are close but still not as good as the QBOAP model. This reflects QBOAP's superior ability to optimize the balance between risk and return.

Overall, the QBOAP model outperforms in several key metrics, including CAGR, Sharpe Ratio, Calmar Ratio, Sortino Ratio, Omega Ratio, Total Return, and Forecasting Accuracy, demonstrating its overall superiority in terms of high returns and risk management. The leadership across these metrics demonstrates that the QBOAP model not only delivers high returns, but also manages risk effectively, making it the investment strategy.

3.2 Effective Analysis of the Proposed Model

We conduct ablation tests to verify the utility of individual models and algorithms for investment strategies. We consider six ablation methods and evaluate the results of each strategy. The specific variants are explained below:

(1) **w/o-Feature:** We remove all the features and use only the CLOSE price as the asset features.

(2) **w/o-slope:** We remove the slope term from the loss function.

(3) **w/o-return:** We remove the return term from the loss function.

(4) **w/o-drawdown:** We remove the max drawdown term from the loss function.

(5) **w/o-regularization:** We remove the regularization applied to features.

(6) **w/o-strategy:** We remove the trading strategy based on weight rank.

Table 3: Ablation Experiment for QBOAP

w/o term	CAGR	SR	CR	Sortino	Omega	TR	RankIC	ICIR
QBOAP	0.216	1.46	1.60	3.61	3.20	4.06	0.040	0.409
w/o Feature	0.045	0.31	0.11	0.48	1.27	1.62	0.008	0.052
w/o slope	0.152	1.17	1.27	2.58	2.52	3.00	0.031	0.339
w/o return	0.171	1.21	1.21	2.64	2.65	3.63	0.033	0.330
w/o drawdown	0.189	1.28	1.02	3.03	2.77	3.85	0.034	0.338
w/o regularization	0.147	1.04	0.69	2.31	2.38	2.90	0.031	0.318
w/o strategy	0.072	1.18	1.44	2.70	2.75	1.71	NA	NA

Table 3 demonstrates the effect of gradually removing different factors on the performance of the QBOAP model. Overall, the QBOAP model performs well on the metrics, with a CAGR of 0.216 and a Sharpe ratio of 1.46 for the benchmark model. However, removing the features significantly decreases the model's CAGR to 0.045, highlighting the key role of features in the model's ability to generate returns. The removal of factors such as retracement and slope, while leading to decreased model performance, suggests that these factors significantly contribute to the stability and risk control of the model. Overall, the experimental results show that the components work together to ensure the combined benefits of the QBOAP model in terms of returns, risk control and forecast accuracy.

4 CONCLUSION

To address the challenges of feature construction, optimization setting and trading value in financial asset portfolio optimization, a novel end-to-end model that incorporates risk measure and feature exposure for constructing portfolio in the A-share stock market. In this framework, the QGMS feature framework is first proposed to provide comprehensive and systematic information in the stock market. Then the Bayesian Optimization algorithm along with a loss function considering risk measure and feature exposure are adopted to determine the optimal weight. Finally, to enhance the trading value of the proposed model, a weight rank-based strategy is proposed and demonstrates superior performance in comparison to others. The main findings are summarized as follows:

(1) The QGMS feature framework play an important role in explaining the future returns of the underlying asset, significantly improving the CAGR from 0.045 to 0.216 by introducing a comprehensive and representative set of features into portfolio optimization.

(2) Optimizing the shape and stability of payoff curves, as well as imposing restrictions on feature weights can enhance the performance of portfolio optimization models, achieving the highest CAGR of 0.216 and highest sharpe ratio of 1.46.

(3) Cross-section long-short strategies based on optimal portfolio weights can achieve better performance while reducing trading complexity, improving the CAGR from 0.072 to 0.216 and the Sharpe ratio from 1.18 to 1.46.

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DATA AVAILABILITY

All data generated during the study are included in the article.

DECLARATIONS CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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