PORTFOLIO OPTIMIZATION BASED ON DYNAMIC MULTIFACTOR STOCK SCORING

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Abstract

Current portfolio researches focus on the optimization model design and the risk measurement. Specifically, existing methods mainly utilize the return time series itself as an input, while factors describing various aspects of a stock's state are not fully explored. Moreover, most current multifactor scoring models are linear, and may not adapt the complex market changes in a timely manner. Then, based on the above considerations, this paper presents a comprehensive investment model that seamlessly integrates stock selection and portfolio management into a cohesive framework. By incorporating fundamental and momentum factors, along with the predicted factor derived from technical factors, a nonlinear dynamic stock scoring method is proposed. These scores are then combined together to construct a portfolio optimization model. In this way, the portfolio returns are significantly improved, and the proposed advantages are experimentally verified compared to some state-of-the-art works.

Introduction

We propose a comprehensive investment model that integrates stock prediction, selection, and portfolio optimization. It utilizes technical factors and LSTM to predict future returns and incorporates a dynamic stock scoring model with multifactors. The scores are converted to stock weights using a softmax function for gradient descent optimization. The key contributions of this paper are summarized as follows:

- A new portfolio optimization model incorporating stock selection is proposed. By designing the relationship between stock scores and weights, selection and portfolio are tightly integrated.
- A nonlinear term in the traditional linear scoring model is introduced and its effectiveness is experimentally verified.
- An application of multifactor including technical, fundamental and momentum factors is presented. It prevents the final returns from being solely reliant on the accuracy of the estimated return data.

Methodology

In this section, a portfolio optimization strategy combining multifactor stock scoring with stock prediction is proposed. Specifically, our approach involves developing a new dynamic portfolio model that aims to maximize returns and minimize risks. The model utilizes stock scores based on predicted returns, fundamental factors, and momentum factors to construct the optimal portfolio. The overall framework is illustrated in Fig. 1.

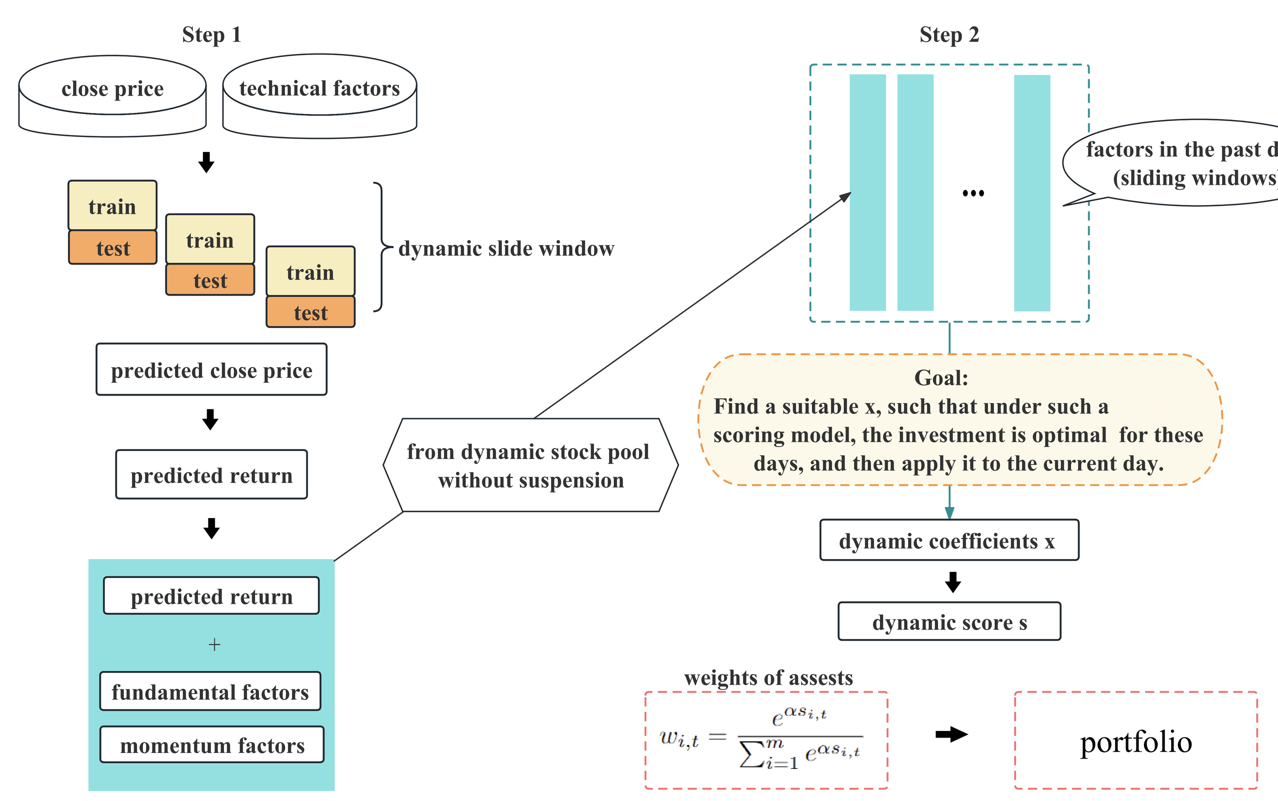

Figura 1: Overall framework of the proposed method.

Stock Prediction

The returns of all candidate stocks for the next period are predicted to reflect the future features of stock markets, thereby serving portfolio strategy. Based on LSTM and some technical factors as shown in Table **??** for the past ten days, the close price of stocks i for the day $t+1$ is predicted and denoted as $\widehat{P}_{i,t+1}$. Then, the daily return can be predicted as

$$\widehat{R}_{i,t+1} = \frac{\widehat{P}_{i,t+1} - P_{i,t}}{P_{i,t}} \tag{1}$$

where $P_{i,t}$ is the real close price on the day t. This prediction result will be then served as one of the inputs for the following portfolio model.

Portfolio Optimization based on Stock Scoring

A new portfolio model based on multifactor stock scoring selection is established. The portfolio is to maximize the following objective function which includes both returns measured by expectation and risks measured by variance

$$\max\ L(x) = E(\widetilde{R}_{t+1}) + \lambda Var(\widetilde{R}_{t+1}) \tag{2}$$

where $\widetilde{R}_{t+1}$ denotes the portfolio return at day $t+1$ with $t \in \{1, \dots, \tau\}$, and λ is a negative number controlling risks with different investment preferences. In other words, decisions are made on day $t+1$ using this model with a sliding window of past t days' inputs. Furthermore, λ is chosen in relation to order of magnitude of variance, and the calculation of $\widetilde{R}_{t+1}$ will be expanded in details below.

Empirical Study

To evaluate our method, we conduct experiments on two distinct markets and compare our results with several representative techniques separately for stock selection, portfolio optimization, and combination of both.

Dataset	Metrics	this paper	EGO	XgbCPP	HDE	MVF	MV
SSE	Final returns	**0.3350**	0.2582	0.0912	0.0520	0.1768	0.0396
	AR	**0.0057**	0.0036	0.0014	0.0013	0.0027	0.0009
	LR (%)	**201.3550**	140.3410	39.5406	21.3493	86.1601	15.9719
	Sharpe	1.7208	**3.5692**	1.8080	0.0926	1.7703	0.5583
SZSE	Final returns	**0.3072**	0.2050	0.2935	0.0584	0.0536	0.1341
	AR	**0.0054**	0.0031	0.0040	0.0009	0.0012	0.0022
	LR (%)	**178.0747**	103.8222	167.1577	24.2093	22.0469	61.7038
	Sharpe	1.6238	1.9386	**3.3721**	1.1557	0.6655	1.4360

Figura 2: Performance comparisons between the proposed method and baseline models. The best results are highlighted in bold.

Table reports the overall performance of our model and the benchmark algorithms from several perspectives on two datasets. As shown in Fig. 3, our model consistently outperforms other models in terms of daily market value, which is particularly evident in SSE where our market capitalization consistently exceeds that of the other models.

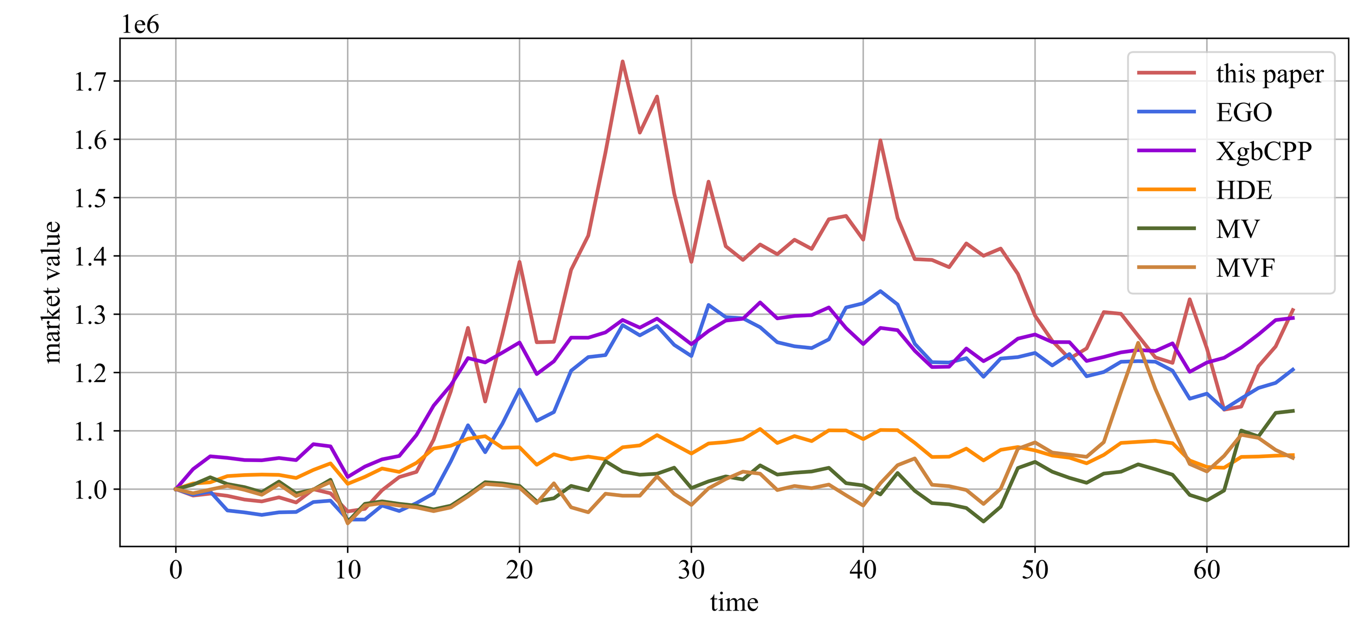

Figura 3: The daily market value of different models in SZSE.

In the linear term, in addition to the expected great role of predicted factor, the factor *evd_v*, which measures the speed of changes in the stock price, has the highest weight and plays the largest role for the scoring model. In the quadratic term, the *pb*, *ps*, and *total_share* factors have the largest weights and play a larger role than their linear forms.

Conclusion

In prior researches, although accurate predicted results provide valuable insights for decision-making, a robust portfolio strategy should not be constrained by estimation errors of the input data or ignore the combination with the stock selection process. To address this, we propose a portfolio strategy model tailored for real markets, which effectively integrates the three aspects of prediction, stock selection, and portfolio management by establishing a cohesive algorithm that defines the relationship between stock scores and weights.