Deep Learning-Driven Portfolio Construction under PolyModel Theory

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Introduction

When constructing portfolios, a key problem is that a lot of financial time series data are sparse, making it challenging to apply machine learning methods. Polymodel theory can solve this issue and demonstrate superiority in portfolio construction from various aspects. To implement the PolyModel theory for constructing a hedge fund portfolio, we begin by identifying an asset pool, utilizing over 10,000 hedge funds for the past 29 years' data. PolyModel theory also involves choosing a wide-ranging set of risk factors, which includes various financial indices, currencies and commodity prices. This comprehensive selection mirrors the complexities of the real-world environment. Leveraging on the PolyModel theory, we create quantitative measures such as Long-term Alpha, Long-term Ratio, and SVaR. We also use more classical measures like the Sharpe ratio or Morningstar's MRAR. To enhance the performance of the constructed portfolio, we also employ the latest deep learning techniques (iTransformer) to capture the upward trend, while efficiently controlling the downside, using all the features. The iTransformer model is specifically designed to address the challenges in high-dimensional time series forecasting and could largely improve our strategies. More precisely, our strategies achieve a better Sharpe ratio and annualized return. The above process enables us to create multiple portfolio strategies aiming for high returns and low risks when compared to various benchmarks. The integration of PolyModel theory with machine learning methods facilitates a nuanced and precise understanding of hedge fund returns. This amalgamation enables us to overcome challenges related to hedge fund data, offering a more robust methodology for analyzing hedge fund performance and guiding investment decisions. This is a very meaningful attempt to combine fundamental statistical analysis with the latest machine learning techniques.

PolyModel Theory

PolyModel theory is more a framework rather than a single statistical analysis tool, after its first introduction, quite a few extensions and applications have been proposed and studied. For a nice overview of more applications and the history of this theory, more concise mathematical description and its implementation, one can consult [2]. The core idea of PolyModel theory is to combine a large enough collection of valid descriptions of one aspect of the same target or reality in order to get a as close as possible full understanding of the target's nature. In the financial industry, the target is usually the return of some assets on which one wants to invest.

If we imagine that the target is alive, like an animal, then PolyModel theory can be regarded as a methodology to observe how this animal reacts to the outside environment, especially, to each single environment factor. If we can capture and understand all its reactions, then we can fully characterize this animal. This idea is, surprisingly, like a Python terminology called "Duck Typing": "when an object quacks like a duck, swims like a duck, eats like a duck or simply acts like a duck, that object is a duck." Though coming from very different fields, the two ideas introduced above can both be viewed as a variant of

Phenomenology [3]: "Literally, phenomenology is the study of 'phenomena': appearances of things, or things as they appear in our experience, or the ways we experience things, thus the meanings things have in our experience. “

Briefly speaking, the basic idea of PolyModel can be summarized as follows: In PolyModel theory, we have a target asset pool (hedge fund) and a risk factor pool (environment element). First, we use Hermitian polynomial to do the regression between environment elements and hedge funds for a certain look back period. We add ridge regularization term to prevent over-fitting and minimize the mean square error to fit the model and then get original R^2. Then, we use causal inference to get an estimation of empirical distribution of R^2. Based on the location of the original R^2 in the empirical distribution, construct a significance indicator between each environment element and target asset. Based on significance indicator and other statistical indicator from PolyModel, we use machine learning method to construct an innovative portfolio strategy for hedge funds.

Feature Construction

In our research, to achieve the final good performance, various features based on PolyModel theory are proposed and tested. In this section, we only discuss some representative ones here to illustrate the idea.

Long-Term Alpha(LTA):

For the given hedge fund and risk factor pair (Y_i, X_j), assume we already fitted the regression polynomial $\Phi_{ij}(x)$. Assume that $\theta_{j,q}$ represents the q-quantile of the empirical distribution of X_j where q = 1%, 16%, 50%, 84%, 99%. They are calculated using the very long history of the factor. The extremes 1% and 99% are computed by fitting a Pareto distribution on the tails. Then we define

$$LTA(Y_i, X_j) = \sum_{\mathrm{q=1\%}}^{99\%} w_q \Phi_{ij}(\theta_{j,q}),$$

subject to $E(X_j) = \sum_{\mathrm{q=1\%}}^{99\%} w_q \theta_{j,q}$, where w_q corresponds to Lagrange method of interpolating an integral and are hyper-parameters. We use more features like Long-Term Ratio (LTR), SVaR and LTS etc. For more feature details, please refer to [1] and [3].

iTransformer

The iTransformer, an advanced variant of the Transformer model, excels in time series prediction due to several technical advantages. One key feature is its self-attention mechanism, which allows the model to weigh the importance of different time steps, capturing long-range dependencies more effectively than traditional recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) networks. This mechanism enables the iTransformer to handle temporal correlations over extended periods without the vanishing gradient problem often encountered in RNNs.

Moreover, the iTransformer's architecture supports parallelization, unlike the sequential nature of RNNs, leading to significantly faster training times and scalability for large datasets. The use of positional encoding in the iTransformer allows it to maintain the order of time series data, ensuring the temporal context is preserved. Additionally, the iTransformer can incorporate external covariates and multivariate time series data seamlessly, making it highly adaptable to complex real-world scenarios.

These technical enhancements collectively make the iTransformer a powerful tool for time series prediction, offering superior accuracy, efficiency, and flexibility compared to traditional methods. For more details, please consult [4].

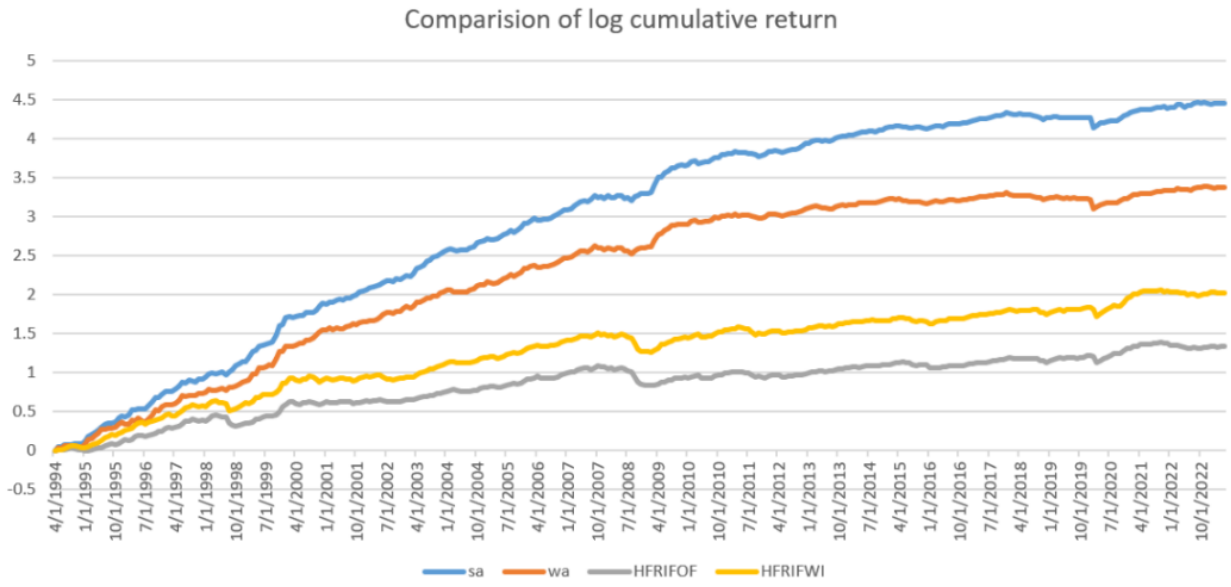
Methodology

For every hedge fund Y_i, at any time stamp, we have 5 features: LTS_i, $MRaR_i$, Sharpe Ratio, Monthly Return , AUM. We use them to train the deep learning models such as iTransformer to predict the return of next month. We choose to predict the trend of return instead of the numerical result itself. This is because in real world applications, usually the correct trend is more useful than an accurate predicted return but moving in the opposite direction against the market, especially for risk management.

Now, at any time, for each hedge fund Y_i, the trained iTransformer model will return a probability on whether the return of the hedge fund of the next month is positive, let's denote it as pi. Then we regard LTS_i, $MRaR_i$, Sharpe Ratio and pi as four major features of hedge funds and set some criteria based on them to select the hedge funds and only keep those which are believed to have strong performance in the next month to invest.

Performance

Below is the performance comparison of our proposed portfolio against some usual benchmarks. Specially, we considered 2 benchmarks: average return for the selected funds (sa) and AUM weighted average return (wa). We can see that our best portfolio (blue curve) is much better.



Reference

[1] Rapheal. Douady., Siqiao Zhao, Dan Wang, 2003, Using machine learning techniques to enhance the portfolio construction based on PolyModel theory, RiO 2003.

[2] Raphael. Douady., Thomas Barrau, 2022, Artificial intelligence for financial markets the polymodal approach, Springer.

[3] Siqiao Zhao, Zhikang Dong, Zeyu Cao, 2024, Hedge Fund Portfolio Construction Using PolyModel Theory and iTransformer, on-working paper.

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