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Artificial Intelligence in Portfolio Management

With the introduction of ChatGPT, the field of artificial intelligence (AI) has entered a new era. Currently, AI techniques are being employed across various industries and markets to enhance existing capabilities and explore new opportunities. One of these markets is that of asset management and more specifically the underlying quantitative portfolio management that drives risk-return optimization and financial risk management. The goal of portfolio management is to establish an asset portfolio that can maximize a risk-return trade-off given the allowed investment world and relevant constraints.

One of classical portfolio management's hallmarks is that of the static mean-variance analysis based on Modern Portfolio Theory (Markowitz, 1952). In this framework, a portfolio is constructed such that the expected return is maximized given a targeted volatility. While the classic method is easy to implement, it also has many limitations such as the stability of the output, ignoring the skewness of return distributions, not discriminating between upside and downside risk, bias towards assets with high Sharpe ratio and many more. More advanced frameworks have been developed but these tend to be highly complex, non-robust to changing environments, or use-case specific. In recent years, techniques involving AI have rapidly been introduced for portfolio management and are gaining more ground.

Underlying almost all these techniques are so-called neural networks (NNs). NNs are computational models inspired by the human neuron and trained on large sets of data. Their main goal is to predict an output variable based on various inputs, e.g., predicting the optimal asset allocation based on the current economic and financial figures. For this purpose, the inputs are guided through a series of hidden layers and nodes to extract from it the relationship between the input and output variables (see Figure 1 for a graphical representation).

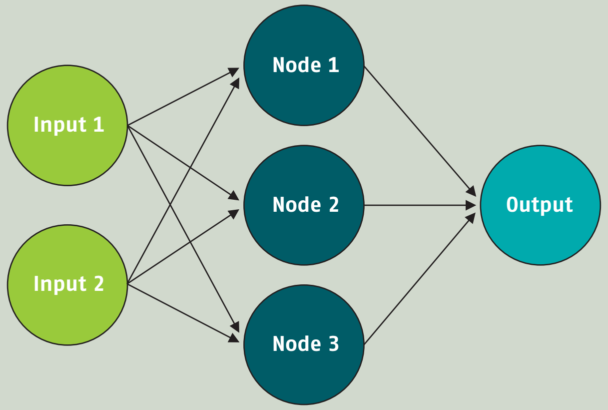

Figure 1. Graphical representation of a simple neural network with one hidden layer and three nodes

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One technique utilizing NNs for portfolio management was developed by Andersson and Oosterlee (2023), which can handle a wide array of elements such as transaction costs, option trading, future portfolio rebalancing, constraints, and alternative objectives. Note that while the method is highly flexible, it remains relatively easy to implement compared to the previously mentioned advanced frameworks. To show the flexibility and strength of the method, we will shortly set it out in the coming paragraphs and show some practical use cases.

MEAN-VARIANCE (MV)

On a high-level the method of Andersson and Oosterlee (2023) can be described as learning NNs to replicate the optimal investment strategy for a portfolio management problem. Optimality in a mean-variance setting means that we are maximizing the expected return while minimizing the variance corresponding to an investor's risk aversion. To replicate the optimal investment strategy the NNs take as input the asset prices at a specific time point and output an investment strategy. Training the NNs is an iterative procedure in which batches of simulated forecasts are provided to the NNs. After each forecast batch, the NNs adjust the underlying strategy in such a way that it comes closer to optimality in the mean-variance sense. In Figure 2, we made a visualization of the method.

To show the results of the method, we will consider a traditional setting in which an investor is maximizing a mean-variance objective and is able to invest semiyearly into a single risky asset and a risk-free money market account. For the sake of simplicity, we assume a Black-Scholes financial market with mean yearly return 7.1% and yearly volatility 17.8% estimated on daily AEX data from 01-01-2010 up until 01-09-2023. The investor has a starting capital of 1 euro.

The results of the method show in the left-hand side plot of Figure 3. In this plot, we represent the investor's final distribution of wealth using the NNs investment strategy, which is depicted in yellow. The wealth distribution follows a normal distribution pattern, which is a consequence of the underlying Black-Scholes assumption. The average return achieved by the investor is 6.7%, with a volatility of 14.8%. The initial investment allocation chosen by the NNs is 77% in the AEX and 23% in the money market account, which has a risk-free rate of 3%. It is important to note that adjusting the underlying risk aversion can impact the portfolio's return. However, such adjustments will also result in a linear change in return volatility.

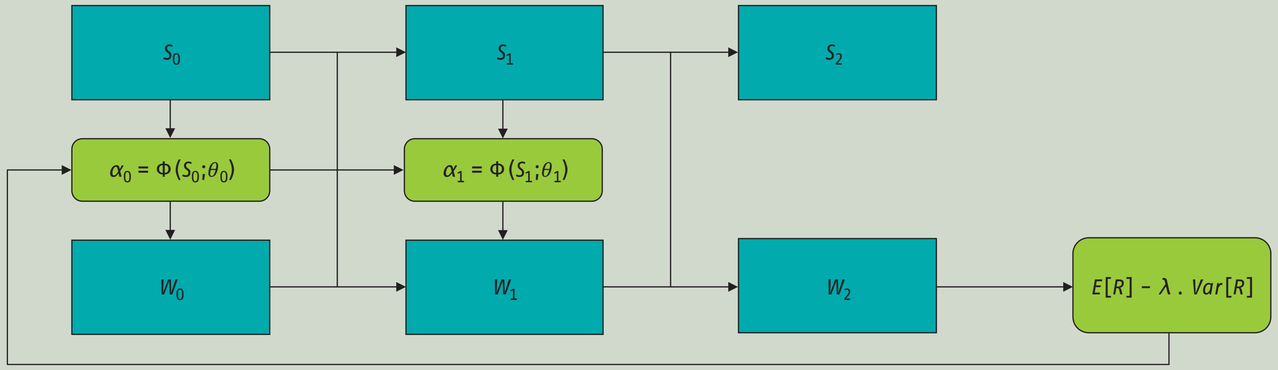
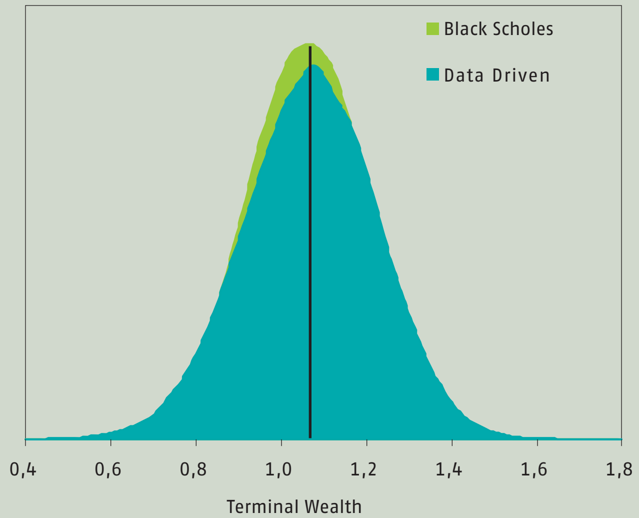


Figure 2. Visualization of the method. α is the investment strategy, S_t is the asset price, W_t is the invested wealth, Φ is the *NN*, R is the final return and λ is the risk aversion parameter. Note that the *MV* objective has a feedback loop to adjust the *NNs*.

DATA-DRIVEN APPROACH

The previous example demonstrated the power of the method, but it relied on the simplifying assumptions of a Black-Scholes financial market. Now, let's consider a more complex scenario where the asset price is forecasted using a data-driven approach. We forecast the AEX index based on empirical returns by applying a block bootstrap methodology, which allows for dependence over time.

In this new setting, the method is implemented similarly to before, and the investor's final distribution of wealth is represented with orange in the left-hand side plot of Figure 3. It can be observed that the distribution is like that of the Black-Scholes setting but has heavier tails. The average return is 6.7% with a volatility of 15.7%. This indicates that the data-driven approach reveals more volatility in the underlying empirical data compared to what is assumed by the Black-Scholes model. Consequently, the corresponding investment strategy also differs. Now, the NNs invest 86% in the risky asset and 14% in the money market account. The data-driven approach showcases that relying on mathematical models can result in less-than-optimal investment strategies and that the NNs method is able to handle these more data-driven approaches. Note that this was expected as stock returns tend to exhibit fatter tails than predicted by the normal distribution.



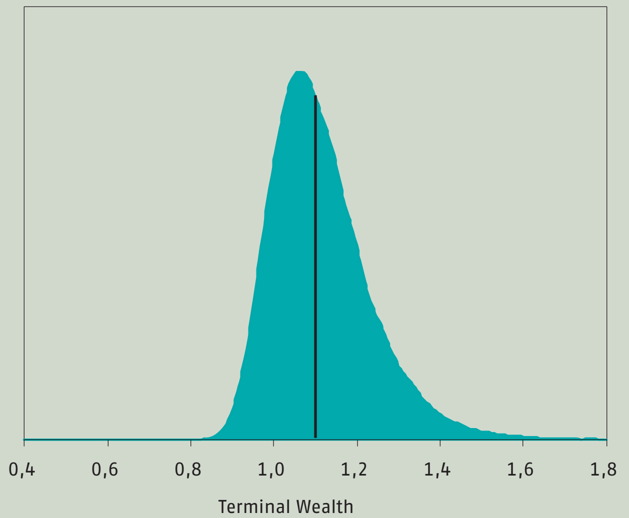


Figure 3. Distribution of terminal wealth under various configurations of the portfolio management problem.

EXTENDED APPROACH

We will now expand upon the previous setting in several ways. Firstly, we allow the investor to rebalance the portfolio more frequently, specifically each month over a one-year period. Additionally, we increase the number of assets to include five stocks from the AEX index: Ahold, ING, ASML, Unilever, and Heineken. These stocks will also be forecasted using a block bootstrap approach. Furthermore, we modify the investment objective to include control over the tails of the final distribution. This is achieved by the conditional value-at-risk (CVaR), which represents the expectation in the tail of the distribution. By incorporating these terms, we can differentiate between upside and downside risk.

The results obtained using the NN method are displayed in the plot on the right-hand side of Figure 3. From the plot, it is evident that the distribution has undergone significant changes compared to the mean-variance case. Specifically, the left tail of the distribution has decreased in size, while the right tail has remained relatively unchanged. In addition, the mean return has increased to 11.4% due to the wider selection of assets with varying risk-return levels. It is important to note that in this analysis, we have not considered transaction costs, which could impact portfolio rebalancing and the risk-return optimization.

PRACTICALITIES

While the above examples illustrate the power of NNs for portfolio management, we do want to consider some more practical considerations when one chooses to implement such techniques:

- The hyperparameters need to be tuned for the NNs and this is not straightforward. For instance, the batch size, number of hidden layers and the learning rate of the NNs need to be chosen such that the optimal strategy can be approximated.
- The number of assets and asset classes can be chosen relatively large; however, increasing the number will of course have implication for the computation times and memory usage.

CONCLUSION

To conclude, we have demonstrated the wide range of possibilities created by NNs for portfolio management such as alternative investor objectives, complex asset price forecasts, frequent portfolio rebalancing, multiple assets, etc. While this is already an impressive list of extensions compared to the classical mean-variance setting, one can even go further with the following extensions:

- Option trading can be included in the modelling framework to allow for more complex financial products with nonlinear payoff structures.
- Transaction costs for rebalancing to depict real world markets more accurately.
- Include more assets to widen the array of options and further optimize the risk-return tradeoff. Note that the NNs method can take on problems with up to 100 assets, but at the cost of increased computational burden.
- Include other asset classes such as fixed income, real estate, commodities, futures, and many more.
  Include other constraints such as non-bankruptcy or leverage (non-shortage) constraints.

In short, AI in portfolio management can handle a wide range of complexities with relative ease and the possibilities will most likely only grow. Leveraging these techniques for risk-return optimization is therefore a must in the new world of AI. ■

References:

- Andersson, K., & Oosterlee, C. W. (2023). D-TIPO: Deep time-inconsistent portfolio optimization with stocks and options. arXiv:2308.10556.
- Markowitz, H. (1952). Portfolio Selection. The Journal of Finance, 7, 77-91.