# PEER REVIEW

MScFE Capstone Project

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## Introduction:

The use of Deep Reinforcement Learning in Tactical Asset Allocation – This paper tries to use Neural Networks to decide whether to rebalance a portfolio. The goal of the model is to increase risk adjusted returns over and above a naïve rebalancing strategy.

## SWOT ANALYSIS

## Strength

Selecting Neural Networks over other ML algorithms does seem to be a worthwhile option because of its manoeuvrability and wide usage. Besides, many researchers like Andrew Ng have proved that Neural Networks, when used properly, consistently generates better predictions than any other ML algorithms.

Using machine generated rebalancing decisions removes human error and improves consistency of decisions.

There can be many spin-offs of this model. The internal methodology to predict market movements and capture market micro-structure can be used in a plethora of other exercises.

## Weakness

Since financial market structures and regimes change all the time, any model that predicts market movements needs constant supervision and updating. The old adage stands – "Past performance is no indicator of future results."

It seems that this project will only use equities in its portfolios. However, rebalancing decisions are also often between equities, bonds and cash. While maximising risk adjusted returns seems to be a good objective function, it is often not possible to reduce portfolio risk beyond a certain point by only using equities. Also, a bigger solution space is being lost by assuming only one asset class.

The construction of the naïve case for comparison is not very clear. Most naïve rebalancing strategies implement a buffer for periodic rebalancing. For example: If an asset has to be assigned 50% weight, there may be a buffer which says "do not rebalance between 48 and 52". Rebalancing in the naïve case for extreme low precisions may be impractical and may lead to inflated outcomes.

## Opportunity

Machine Learning in Finance is still relatively new. While the number of research papers on usage of ML in finance is increasing by the day, financial institutions are yet to leverage the full power of ML to make trading decisions. Many fund houses and brokerages which provide portfolio management services face the dilemma of whether or not to rebalance constantly. It has been proved by many researchers that frequent rebalancing or naïve periodic rebalancing often reduces the alpha capture by a lot, especially when a portfolio is held long term. This problem is thus a very practical one to solve and any progress towards a smart system that automates the process will be well received in the industry.

## Threat

Usually, portfolio clients have strict risk profiles. This may add additional constraints to the model and prevent it from reaching the global maxima. Besides, rebalancing is often done to realign the portfolio risk to client's risk appetite, irrespective of whether that decision can prove harmful in the long term.

In addition to that, regulatory and fiduciary obligations often force firms to rebalance portfolios irrespective of its impact.

Many financial institutions and RIAs earn through periodic rebalancing. And as such, this model may pose a conflict of interest.

Neural Networks are costly to implement due to the IT infrastructure it requires. This makes it less scalable for firms with large number of clients.

There has been recent shift towards passive investing with more and more investors moving away from active management practices. This stems from the realization that "on an average, no investor can beat the market."

## Summary

As mentioned above, this is a very practical research topic. Any success in it will be highly appreciated. A comparison of performance of various ML algorithms vis-à-vis Neural Network can be done, If other algorithms are able to achieve similar results, then they may be preferred since the cost of running a Neural Network is very high.

Variable attribution analysis to see which variable has the most explanatory power seems like a good appendage to the model building. We may be able to find market structure relations that the variable is able to explain by studying it.

This project may be extended by doing a holding period analysis. Questions like what is the optimum holding period when at 90% confidence, alpha is positive may be answered. Another interesting thing to analyse would be the standard deviation of alphas generated in each period. This would tell us about the consistency of the model in out-of-sample data.