The use of Deep Reinforcement Learning in Tactical Asset Allocation

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Group 01

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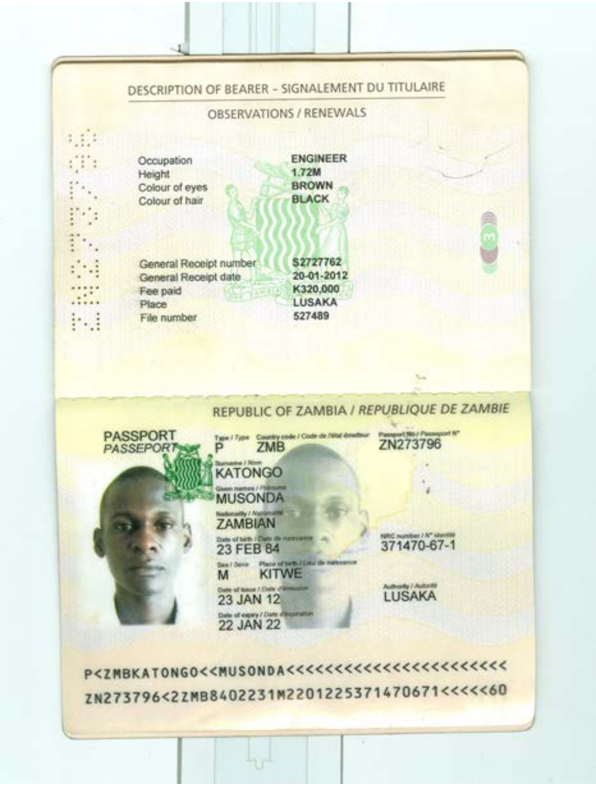


Project Goal and Importance

- Tactical Asset Allocation (TAA) is an active portfolio management strategy
- It aims at allocating the asset weights in a portfolio in order to take advantage of market trends
- The project aims at building a TTA model that is able to accurately capture short to medium term market trends
- Model should be able to maximize risk adjusted returns of the portfolio

Literature Review/Background

- The following are some of the related works which were reviewed for the study:

  - Yang, H., Liu, X., Zhong, S. and Walid, A., 2020. Deep Reinforcement Learning for Automated Stock Trading: An Ensemble Strategy. *SSRN Electronic Journal*.
  - Chakravorty, G., Awasthi, A., Da Silva, B. and Singhal, M., 2018. Deep learning based global tactical asset allocation. *SSRN Electronic Journal*
  - Neuneier, R., 1996. Optimal asset allocation using adaptive dynamic programming. In *Advances in Neural Information Processing Systems* (pp. 952-958).
  - Obeidat, S., Shapiro, D., Lemay, M., MacPherson, M.K. and Bolic, M., 2018. Adaptive portfolio asset allocation optimization with deep learning. *International Journal on Advances in Intelligent Systems*, *11*(1), pp.25-34.

Literature Review/Background Cont. . .

- The project contributes to the current research in the subject in the following ways:
  - Employees the use of Neural Network Autoencoders in the selection of stocks to be included in the portfolio for the period;
  - The research proposes the use of a number of features (technical indicators) in the implementation of a DRL model

Assumptions and Choice of Technology

- The following are the assumptions made in the implementation of the model:
  - The market is liquid and it is possible to trade at any time;
  - Transactions are small enough not to affect the market price of the assets
  - Transaction costs have been assumed at 0.1% of each trade total value.
- The models are developed and coded using python programming language
- GitHub Link: https://github.com/Musonda2day/Asset-Portfolio-Management-usingDeep-Reinforcement-Learning-

Peer Review Feedback

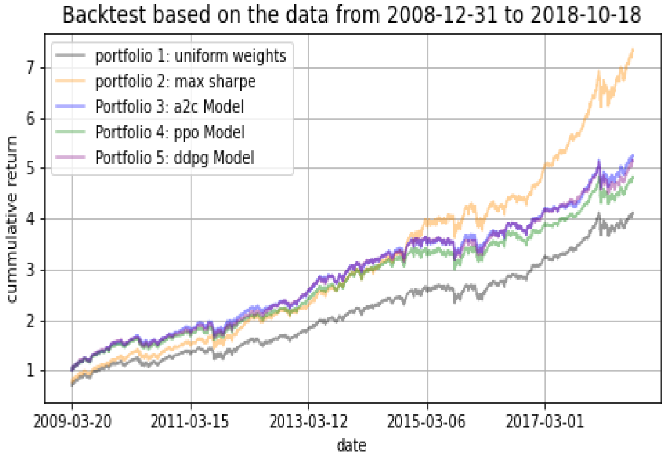
- From the peer review feedback, the researcher considered the following in the development of the project:
  - Clearly defining the benchmark portfolio strategies based on equal weights and mean-variance optimization;
  - The researcher used cumulative portfolio value as the object function. The use of risk adjusted returns (Differential Sharpe) has been proposed for future work;
  - Use of a wider space of asset class has also been proposed for future work in maximizing portfolio risk adjusted returns.

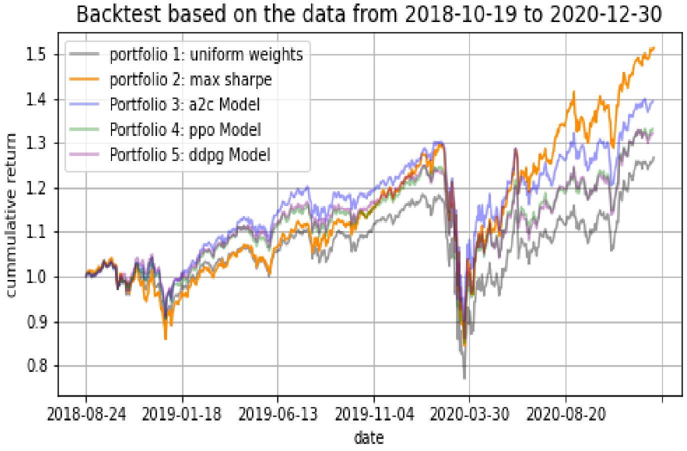
Methodology

- Select the constituent stocks or assets that will form the portfolio
- Feature selection and data pre-processing
- Perform Feature Reduction using Neural Network Autoencoders
- Split the data into train data and test data
- Construct benchmark portfolios
- Construct the DRL models based on the DDPG, PPO and A2C algorithms
- Backtesting the performance of the portfolios

Summary of Results

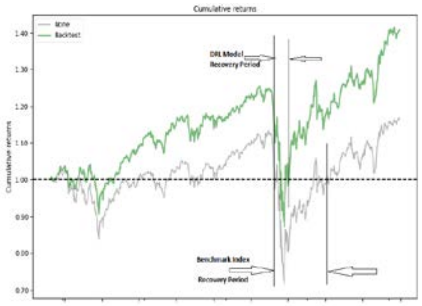
Backtest on train and test data





Summary of Results Cont. . .

	uniform_weights	maximum_sharpe	a2c Model	ppo Model	ddpg Model
Annual return	0.105787	0.192664	0.156780	0.122878	0.149199
Cumulative returns	0.266969	0.513771	0.407957	0.312931	0.386375
Annual volatility	0.260248	0.268582	0.237111	0.237551	0.229603
Sharpe ratio	0.517581	0.792533	0.733154	0.606988	0.721078
Calmar ratio	0.302289	0.552062	0.515068	0.413202	0.508426
Stability	0.291490	0.742925	0.665671	0.649122	0.674682
Max drawdown	-0.349952	-0.348990	-0.304388	-0.297381	-0.293452



- Mean-variance presents the highest Sharpe ratio followed by the A2C
- The equal weight allocation has the lowest Sharpe Ratio
- The DRL model outperforms the benchmark index in all market regimes

Summary of Results Cont. . .

- The project work contributes to the current research by combining the asset selection methods with DRL methods for asset allocation
- The model could not produce consistently better performance than the mean-variance optimization
- The model however, shows better performance than the benchmark index in all market regimes
- DRL models have a potential to perform better than the traditional allocations methods
- Rebalancing periods needs to be optimized to adjust for transaction costs

Conclusions

- The project aimed at developing a TAA model based on DRL
- DRL is used to perform asset allocation based on the reward function of cumulative portfolio value
- The developed model outperforms the mean-variance optimization in periods of less market uncertainties
- The model outperforms the benchmark index in all market regimes
- The performance of the model can be fine-tuned to ensure consistent performance in all market regimes

Future Scope of Work

- Explore the use of differential Sharpe ratio as the reward function for the DRL model
- Application of the DRL model on a bigger stock constituent and consider a wider space of assets
- Consideration of a number of technical indicators
- Consider using different portfolio initialization strategies apart from the equal weights initialization
- Optimize the rebalancing period

Thank you