Annotated Bibliography

1. Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. *European Journal of Operational Research*, *270*(2), 654-669. doi: 10.1016/j.ejor.2017.11.054

In this article Fischer and Krauss analyses the influence of different deep learning models in respect to daily returns and the Sharpe Ratio. The authors used deep learning to predict the trajectory of the S&P 500's constituent stocks from 1992 to 2015, to try and identify which model presents the highest results. Their research focuses on assessing the performance of Long-Short Term Memory, Random Forest, deep neural networks, and a regression classifier in predicting future trends in the stock market. This article is useful to my research topic as the authors mention that there are various time-series prediction models out there and depending on the type of analysis the predictions can vary, even though the used data frame is the same. The main limitation to this study is that depth of analysis stops at the technical stage, as the use of sentimental analysis can improve the predictions. However, the authors fail to include this in their conclusion. This article is an approach to the Modern Portfolio Theory which is useful when deciding on which deep learning method to study, but it does not do deep analysis of stocks' information.

2. Lin, C., Huang, J., Gen, M., & Tzeng, G. (2006). Recurrent neural network for dynamic portfolio selection. *Applied Mathematics and Computation*, *175*(2), 1139-1146. doi: 10.1016/j.amc.2005.08.031

In this study Lin et al. review the influence of developing an Elman neural network -a type of Recurrent NN- to forecast future stock prices, and then comparing their results to the vector autoregression model. They assess the risk using a covariance matrix and the expected return rate. The researchers noted that, the RNN model showed a significant improvement in the prediction accuracy when compared to the VAR model. The main limitation of this article is that the risk could have been assessed using different risk measures such as L1 norm, etc. In addition, the researchers failed to introduce the data used throughout their study, which could've improved the understanding of this paper. This article will not form the basis of my research; however, it provides an in-depth understanding for the mean-variance and covariance methods, as well as; how RNN models could be implemented in time-series analysis.

3. Alizadeh, M., Rada, R., Jolai, F., & Fotoohi, E. (2010). An adaptive neuro-fuzzy system for stock portfolio analysis. *International Journal of Intelligent Systems*, *26*(2), 99-114. doi: 10.1002/int.20456

In this article Fotoohi et al. used an adaptive neuro-fuzzy inference called ANFIS which is available from Mathworks in its Fuzzy Logic Toolbox approach for portfolio return prediction and a variance index for risk assessment. The authors' input data consists of expected risk and returns estimated using a computational formula applied to the Tehran Stock Exchange historical data. The researchers use a noise-rejection fuzzy clustering algorithm for clustering the output space, this is done to determine the initial number of rules. Followed by tuning the parameters of antecedent and consequent part of fuzzy rules. The model present in this study point to a fruitful direction for merging market return prediction and portfolio optimization models, enabling us to completely exploit the advantages of stock forecasts in the growth of portfolio optimization models. This article is useful to my research topic, as Fotoohi et al. suggest that using deep learning time series analysis is better than traditional financial time series analysis. The main limitation of this paper is that the authors could test their models with different stock markets and a comparison could be made. This article will not form the basis of my research; however, it will be useful supplementary information for my research on whether machine learning helps in improving the value of investment portfolios.

4. Lee, S., & Yoo, S. (2018). Threshold-based portfolio: the role of the threshold and its applications. *The Journal of Supercomputing*, *76*(10), 8040-8057. doi: 10.1007/s11227-018-2577-1

In this study Seong and Sang develop and analyze three types of recurrent neural networks in time series analysis: Long-Short Term Memory, Gated Recurrent Unit, and Simple Recurrent Neural Network in respect of performance, and prediction accuracy. The authors apply the models to an investment universe consisting of 10 stocks in the S&P 500 (Open, High, Low, Close, and Volume) market index to build a data-driven portfolio featuring a target risk-return. The article is useful to my research topic, as previous studies highlight the strength of RNNs when it comes to time series analysis, this study carries further financial series analysis such as monthly rebalancing of portfolios to fit the constantly changing stock market, as well as the use of an equally weighted portfolio which plays the role of the lower bound of the threshold-based portfolios (TBPs). The authors make full use of financial and computing terms which makes this paper more insightful for researchers in both fields, and they provide illustrations on how to manage TBPs over multiple-periods and how to incorporate them into an MPT optimization portfolio. To conclude, Seong and Sang provided a simple and straightforward way to build portfolios with target risk-returns, using the RNN predictions only. This article will form the basis of my research as it proves that the insight provided could be used as a benchmark for future researches in the topic of machine learning and portfolio optimization.