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Tactical Asset Allocation with Ensemble Learning Using Walk-Forward Optimization*

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Tactical asset allocation is a dynamic investment strategy that actively adjusts a portfolio's asset allocation to improve the risk-adjusted returns of passive management investing. One of the most traditional ways to implement tactical asset allocation is to apply mean variance optimization to expected return and covariance matrix and get the optimal weight for each asset. One can also use equal weights and risk parity to construct optimal portfolios. Among these different methods, one of the common steps is to estimate the expected return and covariance matrix. Many previous works have been done to predict expected returns based on different factors, and in recent years, machine learning is widely used to make predictions.

Ensemble learning algorithms combine multiple weak learners to obtain better prediction performance, which are used in both classification and regression tasks. The overall performance of an ensemble learner is much better than a single weak learner. When we want to estimate the expected returns of different assets, we can consider it as a regression problem and predict the future returns directly. Alternatively, one can apply classification algorithms to predict the future directions of asset prices. Despite the less information provided by the direction, classification algorithms are commonly used in the financial markets since it is still important to express a bullish view or a bearish view when we don't have adequate information.

In this project, we analyze the effectiveness of ensemble learning in tactical asset allocation. We use monthly price data of 15 asset classes and monthly data of 68 factors. We

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transform the original data to get more features. We then use feature selection techniques to choose factors that have large contributions to our prediction. After feature selection, we retain the top 10 features for each asset during each time period. We formulate a binary classification problem by predicting the future directions of asset prices. We create a pool of ensemble learning classifiers and use walk-forward optimization to tune the hyper-parameters. We use the classification results given by our optimal models to generate qualitative views and incorporate them into the Black-Litterman model to get the posterior expected returns and covariance matrix. For backtest, we construct 7 portfolios including both passive portfolios and active portfolios. We compare the performance of Black Litterman portfolio and other benchmark portfolios with 1-month and 3-month holding period.

Overall, we conclude that feature quality is very important in classification tasks, and our absolute co-moment metric performs an efficient way of measuring both linear and non-linear dependency between features and responses. Ensemble learning is very powerful in combining various weak learners into strong learners to achieve better performance, and making the majority vote or computing weighted average of different model outputs can effectively reduce the variance of predictions. Incorporating our machine learning forecasts into Black Litterman improves our portfolio performance compared with other portfolios, since it produces higher Sharpe Ratio and annualized return in both 1-month and 3-month backtests. As a result, machine learning models actually provide some guidance on investments that can help asset managers make better decisions.