Tactical Asset Allocation with Ensemble Learning Using Walk-Forward Optimization

Renjie Pan, Tianyu Zhang, Liang Zou

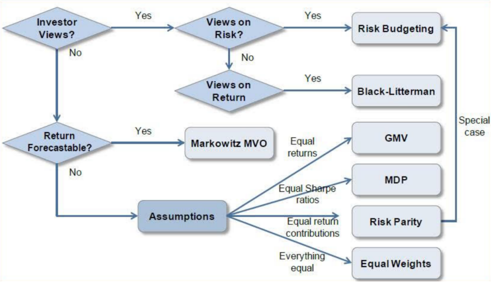
Courant Institute, New York University

Advisor: Dan Singleman, BNP Paribas Asset Management

December 12, 2019

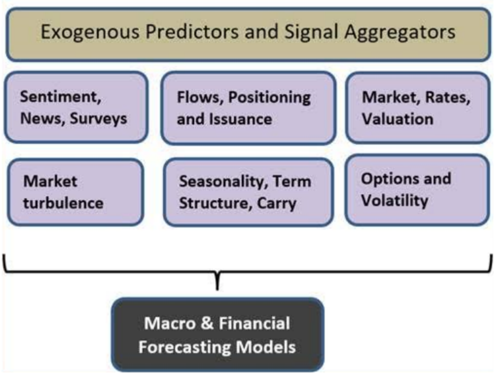
Introduction

- The goal of this project is to generate investor views by applying ensemble learning algorithms to predict direction signals of monthly returns of 14 assets.
- We use walk-forward optimization to tune the hyper-parameters of different models across various time periods.
- We generate the portfolio weights using Black Litterman based on our directional predictions and compare the performance of different benchmark portfolios, including equal weights, risk parity and mean-variance optimization.



Data Sources and Features

- Source: The dataset consists of monthly price data of 14 asset classes (Equities, Oil, Gold, etc.) and different monthly factors (Macro, Sentiment, and Market).
- Features: For each factor, we compute the percentage change, absolute change, monthly moving average, z-score for feature transformation. After transformation, we get 871 features.

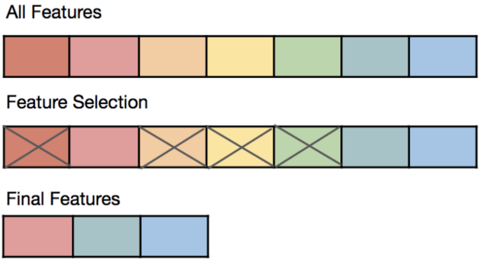


Feature Selection and Feature Importance

- Ensemble Feature Importance: Random Forest Feature Importance, XGBoost Feature Importance
- A Nonlinear Dependency Metric: Absolute Co-moment Score

$$absComoment(X_i, Y, dim) = \frac{E[|X|^{dim-1}|Y|]}{(E[|X|^{dim}]^{dim-1}E[|Y|^{dim}])^{\frac{1}{dim}}}$$

- The score can be any linear combinations of the absComoment for different dimensions

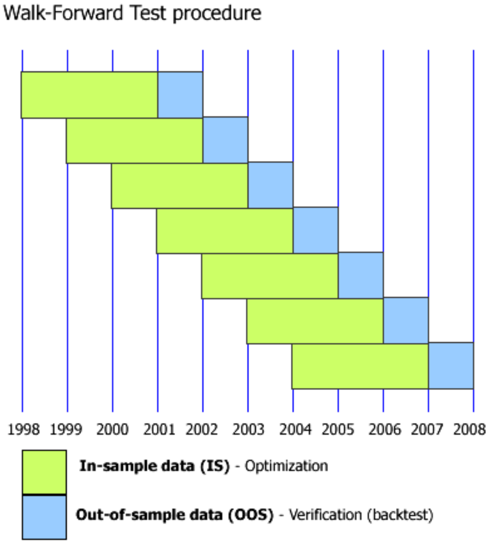


Classification Models

- Support Vector Machines
- Random Forest
- Extreme Gradient Boost
- Extreme Gradient Boost - Random Forest

Walk-Forward Optimization and Hyper-parameter Tuning

For time series data model, we use Walk-Forward optimization instead of cross-validation.



Portfolio Construction

We use a window size of 5 years to calculate expected returns and covariance matrix, and we rebalance our portfolios every one month or every three months. The portfolios we construct are as follows:

- Equal Weights
- Mean-Variance Optimization
- Risk Parity
- Equal Weights with ML
- Mean-Variance Optimization with ML
- Risk Parity with ML
- Black Litterman

Black Litterman

Posterior mean returns

$$E_{BL}(R) = [(\tau\Sigma)^{-1} + P^T\Omega^{-1}P]^{-1}[(\tau\Sigma)^{-1}\pi + P^T\Omega^{-1}q]$$

Posterior covariance matrix

$$\Sigma_{BL}(R) = \Sigma + [(\tau\Sigma)^{-1} + P^T\Omega^{-1}P]^{-1}$$

- τ: Uncertainty in equilibrium
- π: Equilibrium, the prior mean returns
- Σ: Prior covariance matrix
- P: Descriptions of views
- q: Vector of views
- Ω: Uncertainty in views

Incorporating Classification Signals

For each asset, our ensemble learning models predict whether the return will be positive or negative. To incorporate bullish and bearish views in Black Litterman, we set the P matrix as a diagonal matrix, $\text{diag}(p_i)$, $p_i = 1$ if it's a bullish view, $p_i = -1$ if it's a bearish view.

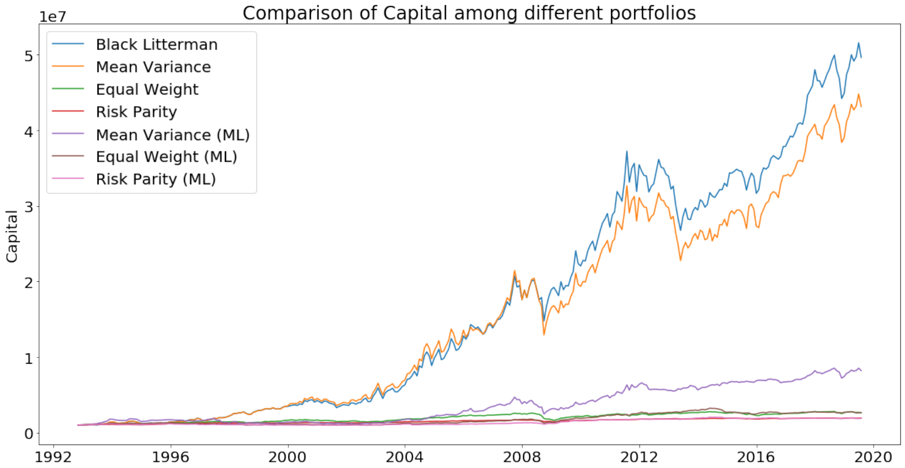
To illustrate that, if we only have 3 assets: oil, equities and gold, and our models predict that oil and equities prices will go up, while gold price will go down, we construct the P matrix as:

$$P = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -1 \end{pmatrix}$$

Model Performance

	1 month			3 month		
	Accuracy	Precision	AUC-ROC	Accuracy	Precision	AUC-ROC
MSCI EM	0.6528	0.7255	0.6234	0.6472	0.7731	0.6690
SPX 500 Price Return	0.6472	0.7073	0.5966	0.7028	0.8005	0.6798
Eurostoxx 600	0.6361	0.7006	0.6040	0.7111	0.8154	0.6749
MSCI Japan	0.6056	0.6786	0.6527	0.5778	0.6982	0.6409
MSCI World	0.6417	0.7131	0.6082	0.7194	0.7796	0.6499
Russell 2000	0.6695	0.7373	0.6407	0.6833	0.8096	0.7047
Crude Oil Total Return	0.5833	0.6556	0.6230	0.6083	0.6865	0.5908
CRB Metals	0.5833	0.6144	0.6020	0.6071	0.6809	0.6556
Gold Price	0.6222	0.6372	0.5951	0.6445	0.6758	0.6109
S&P GSCI Total Return Index	0.6083	0.6788	0.5975	0.6055	0.7355	0.6428
UST 7-10yr	0.5750	0.6543	0.5836	0.5778	0.6928	0.6323
German 7-10yr	0.6250	0.7560	0.6520	0.6305	0.7553	0.6692
US IG Corps	0.5861	0.6645	0.5993	0.5639	0.6766	0.6503
US HY Corp	0.6611	0.7269	0.6742	0.7139	0.7124	0.6701
US Mortgages	0.5889	0.6637	0.6025	0.6444	0.7169	0.6644

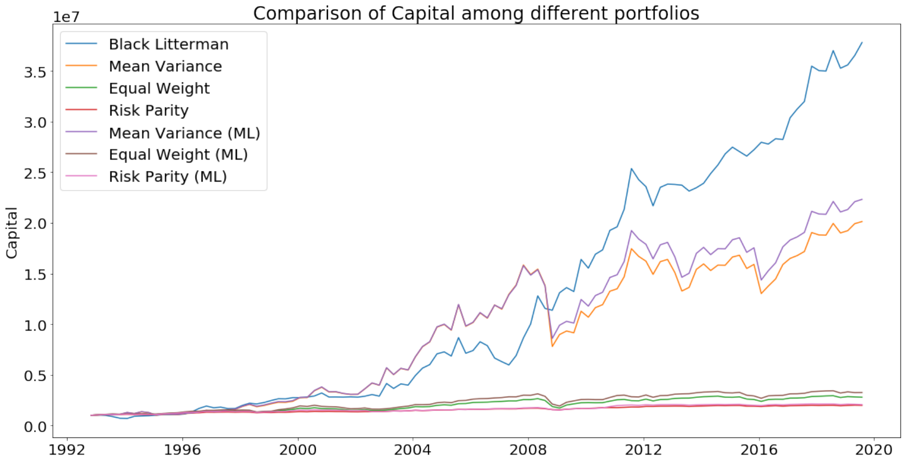
Backtest Results (1 Month)



Summary Statistics (1 Month)

	Sharpe Ratio	Max Drawdown(%)	Annualized Return(%)
Black Litterman	3.0156	-29.95	16.44
Mean Variance	2.8068	-34.48	16.08
Equal Weight	1.6224	-21.21	4.08
Risk Parity	2.1168	-9.66	2.52
Mean Variance (ML)	1.9464	-37.74	9.24
Equal Weight (ML)	1.5636	-19.54	4.08
Risk Parity (ML)	1.5396	-12.82	2.52

Backtest Results (3 Months)



Summary Statistics (3 Months)

	Sharpe Ratio	Max Drawdown(%)	Annualized Return(%)
Black Litterman	1.5324	-42.71	15.76
Mean Variance	1.2540	-60.74	13.84
Equal Weight	0.9028	-29.77	4.32
Risk Parity	1.3596	-9.90	2.64
Mean Variance (ML)	1.3064	-56.53	14.08
Equal Weight (ML)	0.9228	-34.13	5.04
Risk Parity (ML)	1.0700	-13.38	2.84

Conclusions

- Absolute Co-moment Score provides an effective way to select features.
- Using ensemble learning, we are able to get high precision and accuracy classification results.
- Combined with directional views, Black Litterman works better than other benchmark portfolios.

References and Special Thanks

- Friedman, Jerome, Trevor Hastie, and Robert Tibshirani. The elements of statistical learning. Vol. 1. No. 10. New York: Springer series in statistics, 2001.
- Inkinen, Manicardi, Panigirtzoglou, and John Normand. Can Machine Learning help with Tactical Asset Allocation? Global Markets Strategy, 2018.
- Kirkpatrick II, Charles D., and Julie A. Dahlquist. Technical analysis: the complete resource for financial market technicians. FT press, 2010.

- Special Thanks: Petter Kolm and Dan Singleman

The End

Thank you!