Machine Learning Approach for Systematic Global Macro Strategies

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See important disclosures at the end of this presentation.

Outline of the talk

Global Tactical Asset Allocation

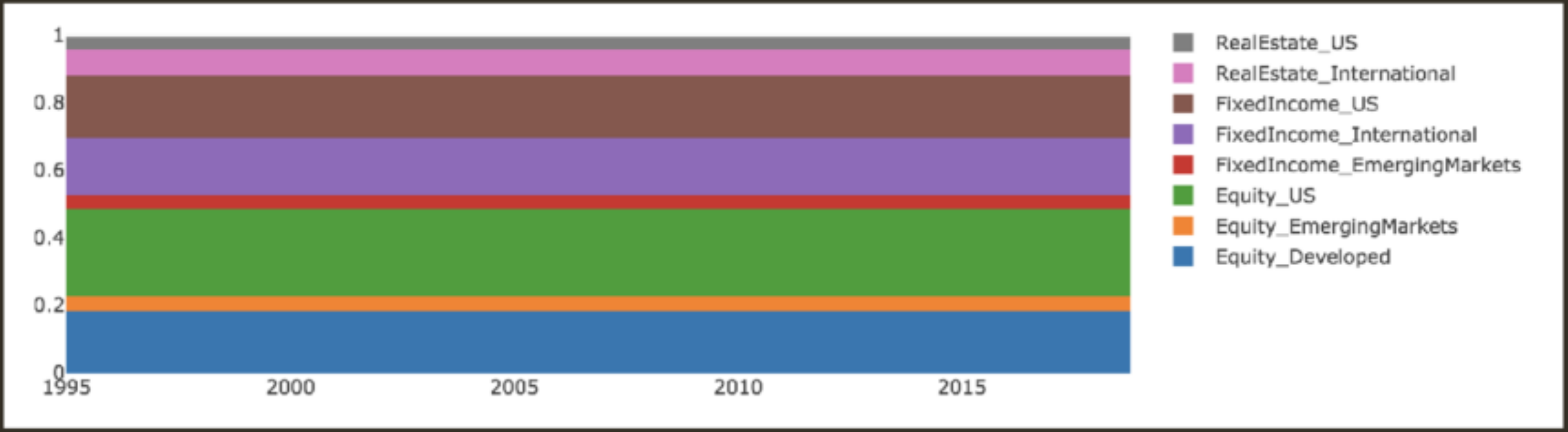
Why Asset Allocation

Macroeconomic Data

Why Deep Learning

Case Study

Global Strategic Asset Allocation



Source: Qplum Research

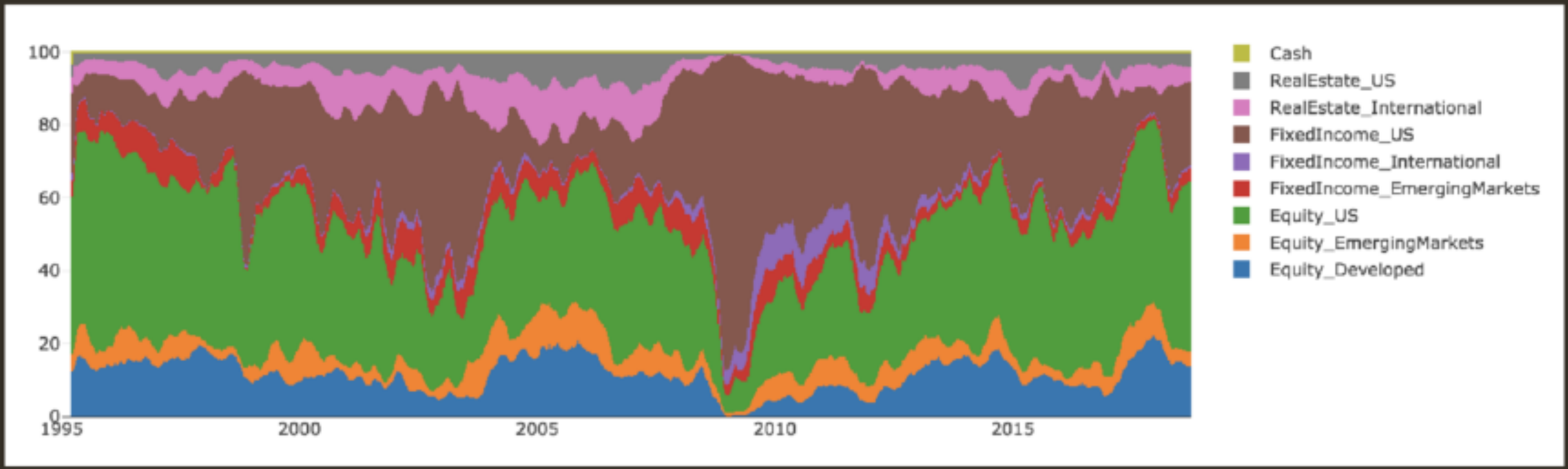
Salient Features

Based on Long Term Capital Market Assumptions

Incorporates Desired Risk and Return Profile

Asset allocation remains *unchanged* over time

Global Tactical Asset Allocation



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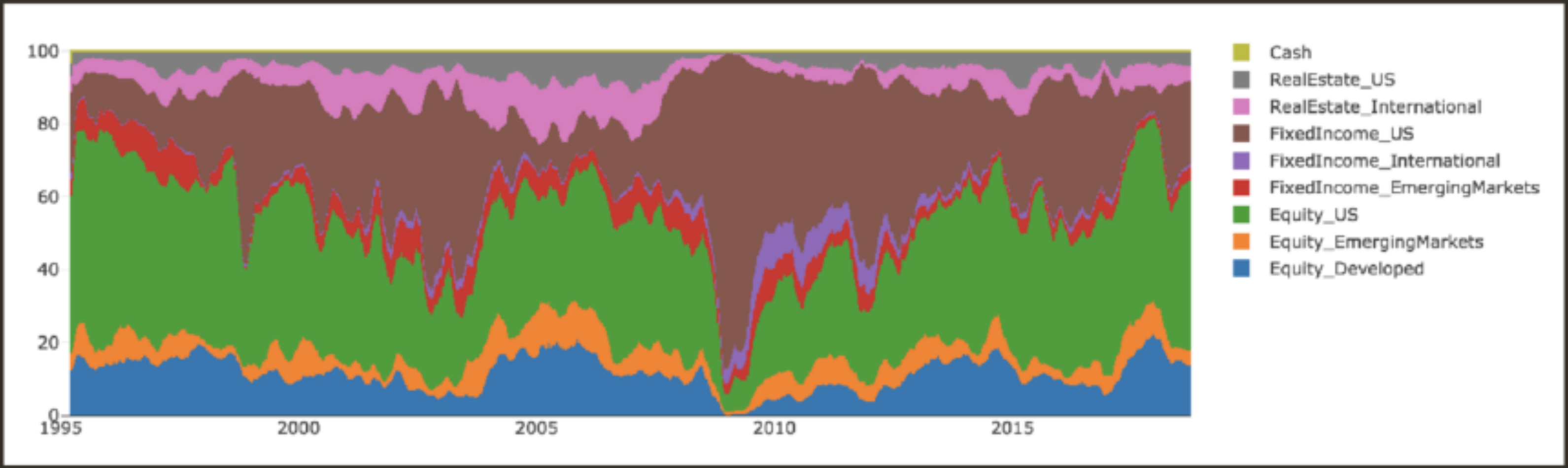
Global Tactical Asset Allocation



Source: Qplum Research

Salient Features

Based on *Long Term* and *Short Term* Capital Market Assumptions

Incorporates Desired Return and Risk Profile

Dynamic Asset Allocation

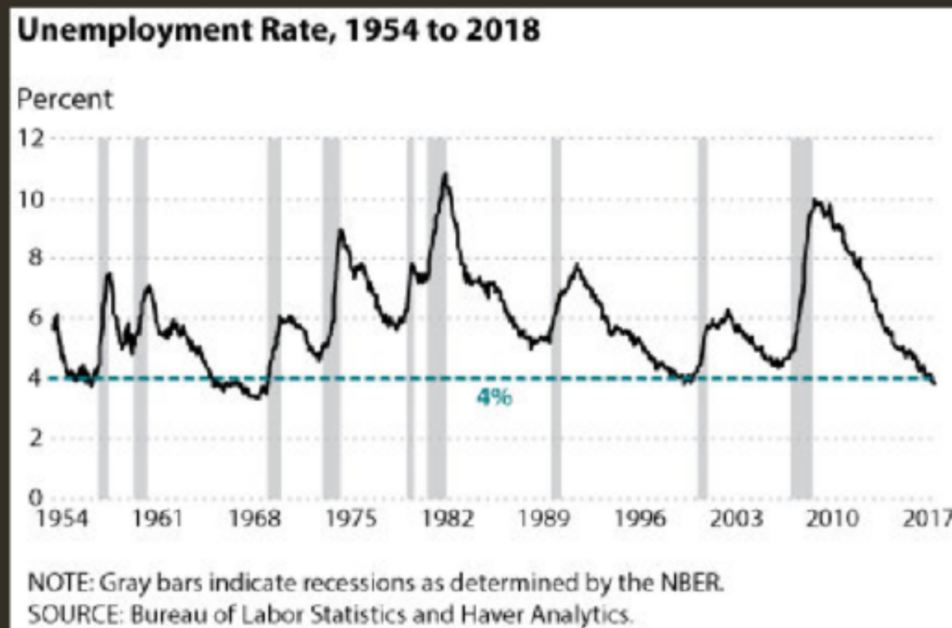
Average Asset Allocation over long periods is similar to strategic allocation

Why Asset Allocation ?

More than 90% of the variance in returns
can be attributed to
Asset Allocation vs Security Selection

Source : CFA Institute Blog

Macro Data for Business Cycle Detection



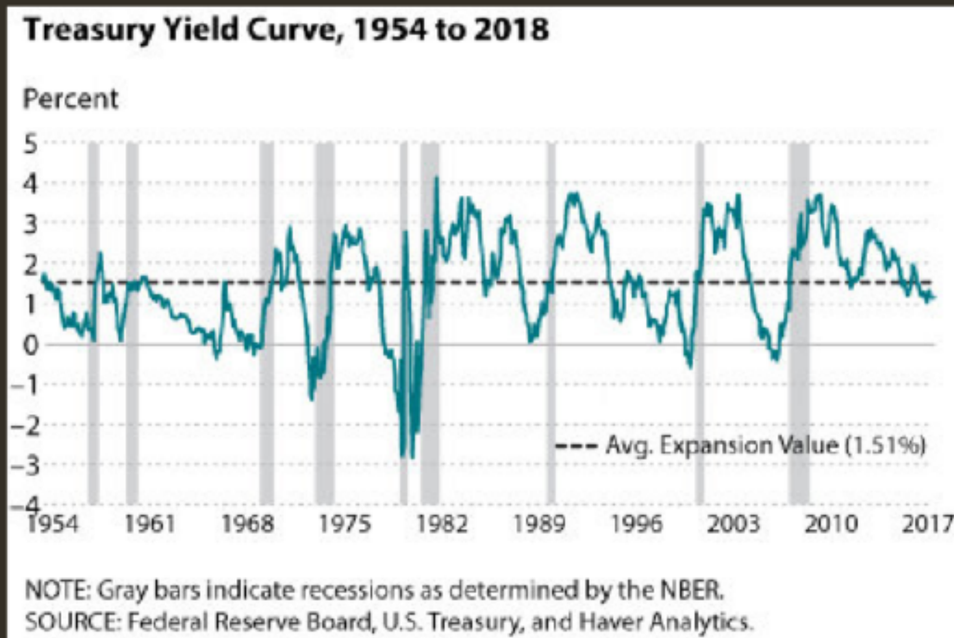
Plot of Unemployment Rate OverTime

Troughs of Unemployment Rate turn out to be fairly robust predictors of recession.

Current unemployment rate is 3.7% which is the lowest since 1969.

Source : Federal Reserve Bank of St. Louis

Macro Data for Business Cycle Detection



Plot of difference of 10 year yields - 3 month yields over time

Yield Curve Inversion is another variable which has successfully predicted recessions.

Current unemployment rate is 3.7% which is the lowest since 1969.

Source : Federal Reserve Bank of St. Louis

Why Deep Learning ?

Deep learning models excel at...

Capturing highly non-linear relationships

Combining disparate sources of information

Bayesian Deep Learning

Signal to Noise ratio is high in financial time series data

Point estimates of expected returns can have significant errors

Important to estimate model uncertainty along with expected returns

Dropout as a bayesian approximation

Source : Yarin Gal et. al. 2016

Case Study

The model or backtested portfolio and performance data provided in this presentation is theoretical and is not based on the performance of actual portfolios. It does not reflect trading in actual accounts; actual results may significantly differ from the theoretical returns being presented It is provided for informational purposes to illustrate use of deep learning only. Any interpretation of the results should take into consideration the limitations inherent in the results of the model. Backtested performance is developed with the benefit of hindsight, including the ability to adjust the method for selecting securities until returns for the past period are maximized, and has inherent limitations. Actual performance may differ significantly from backtested performance.

Macro-economic Indicators

10 Year - 2 Year Yield Spread	JPY	S&P500
2 Year - 3Month Yield Spread	10 Year Yield	US Inflation
Copper / Gold Ratio	Gold	US Non-farm Payroll
S&P 500/ Dow Jones Ratio	Copper	US GDP Growth
S&P 500/ Russell 2000 Ratio	Oil	

Sample List of macro-economic indicators

Traded Securities

ETF	Description	Expense Ratio	Asset Class
BND	Vanguard Total Bond Market ETF	0.05	US Fixed Income
BNDX	Vanguard Total International Bond ETF	0.11	International Fixed Income
VWOB	Vanguard Emerging Markets Govt Bond ETF	0.32	Emerging Fixed Income
VTI	Vanguard Total Stock Market ETF	0.04	US Equities
VGK	Vanguard FTSE Europe ETF	0.10	Europe Equities
VWO	Vanguard FTSE Emerging Markets ETF	0.14	Emerging Equities
VNQ	Vanguard Real Estate ETF	0.12	US Real Estate
VNQI	Vanguard Global Ex-US Real Estate ETF	0.14	Ex-US Real Estate

Sample list of ETFs used as proxies for different asset classes

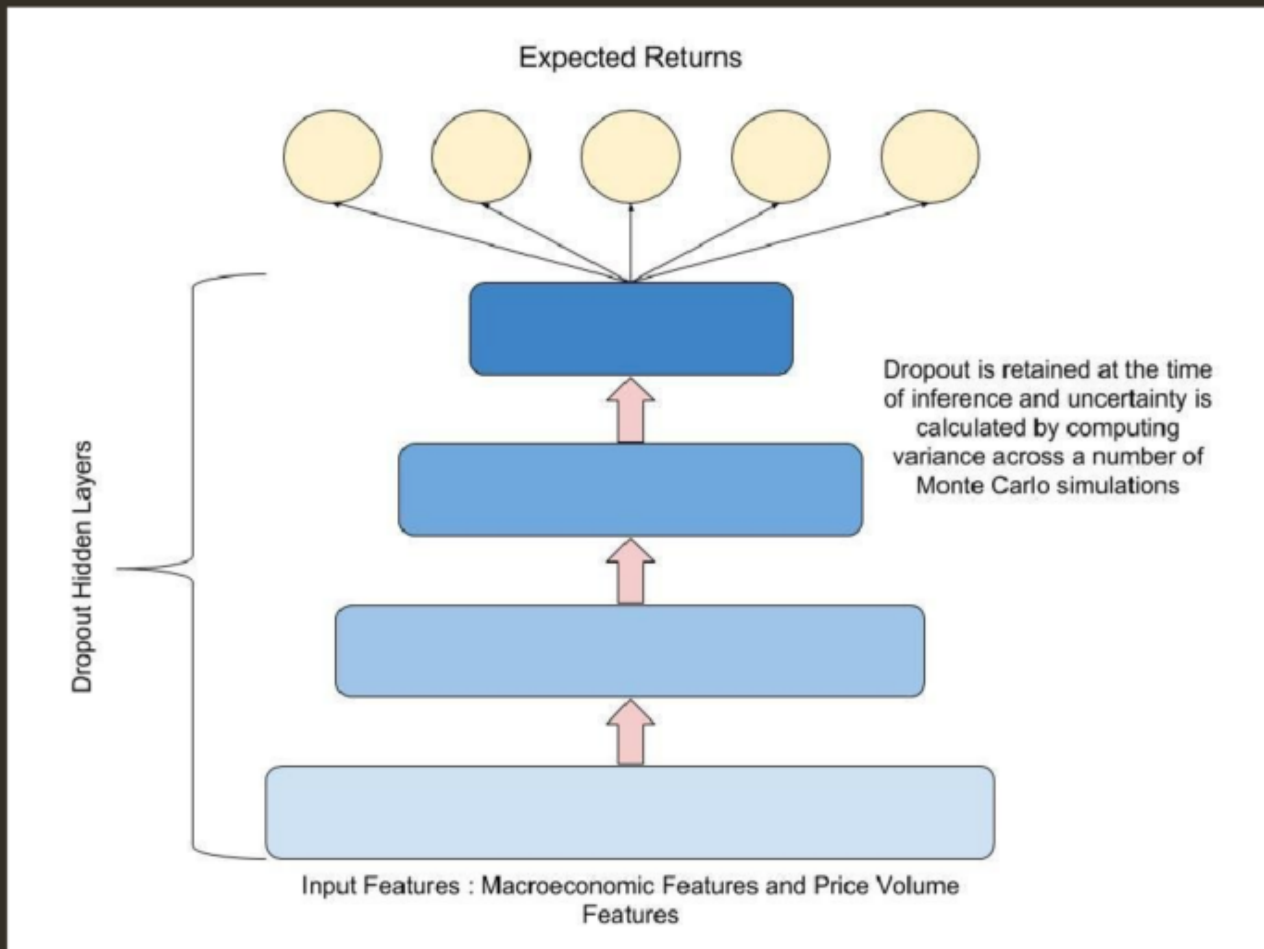
ETFs chosen such that the...

Expense ratio is low

Cover important asset classes

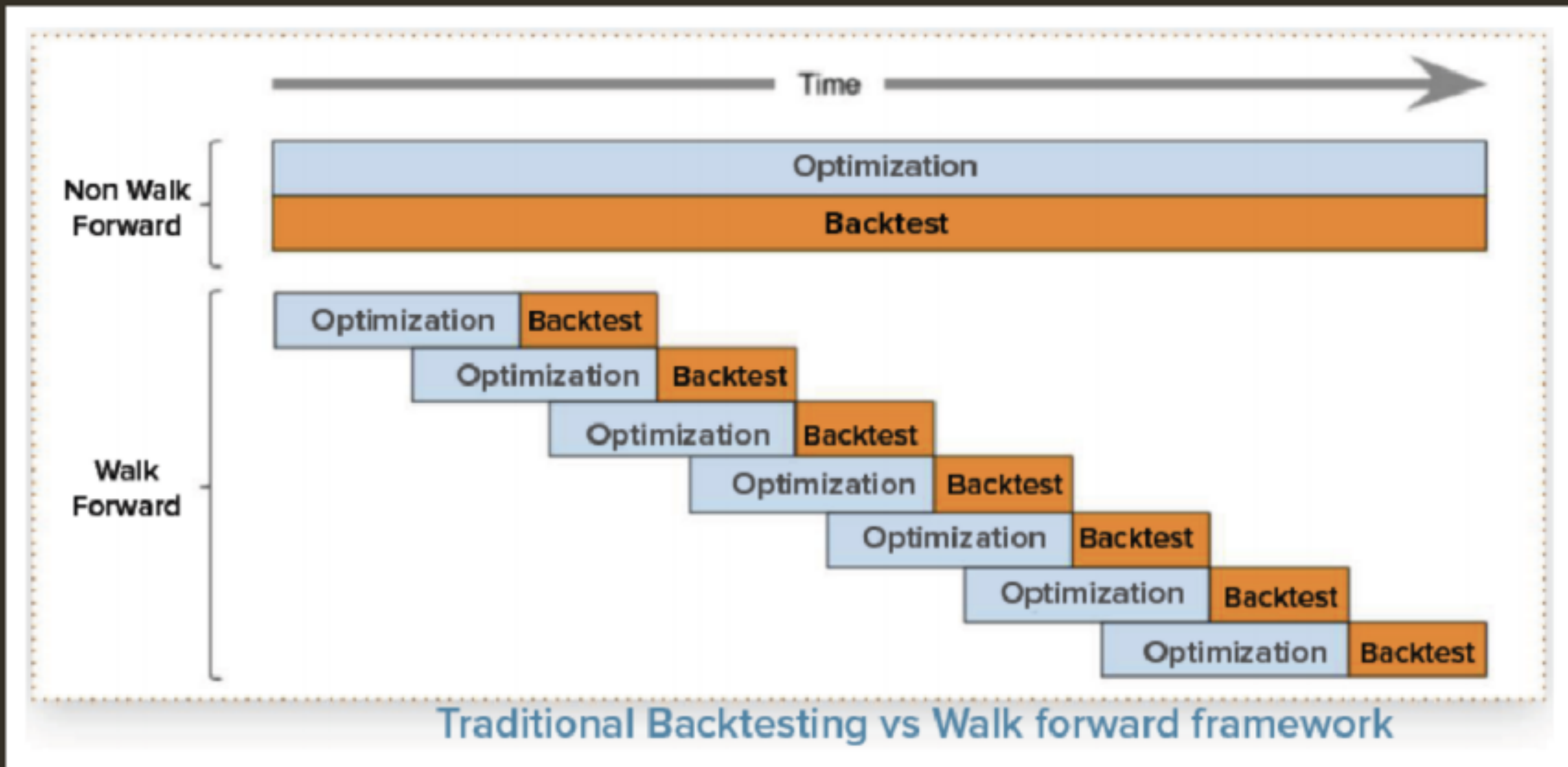
AUM is high

Expected Returns Model



Architecture for the feed-forward neural network for computed expected returns and expected model uncertainty

Walk-forward Training and Testing

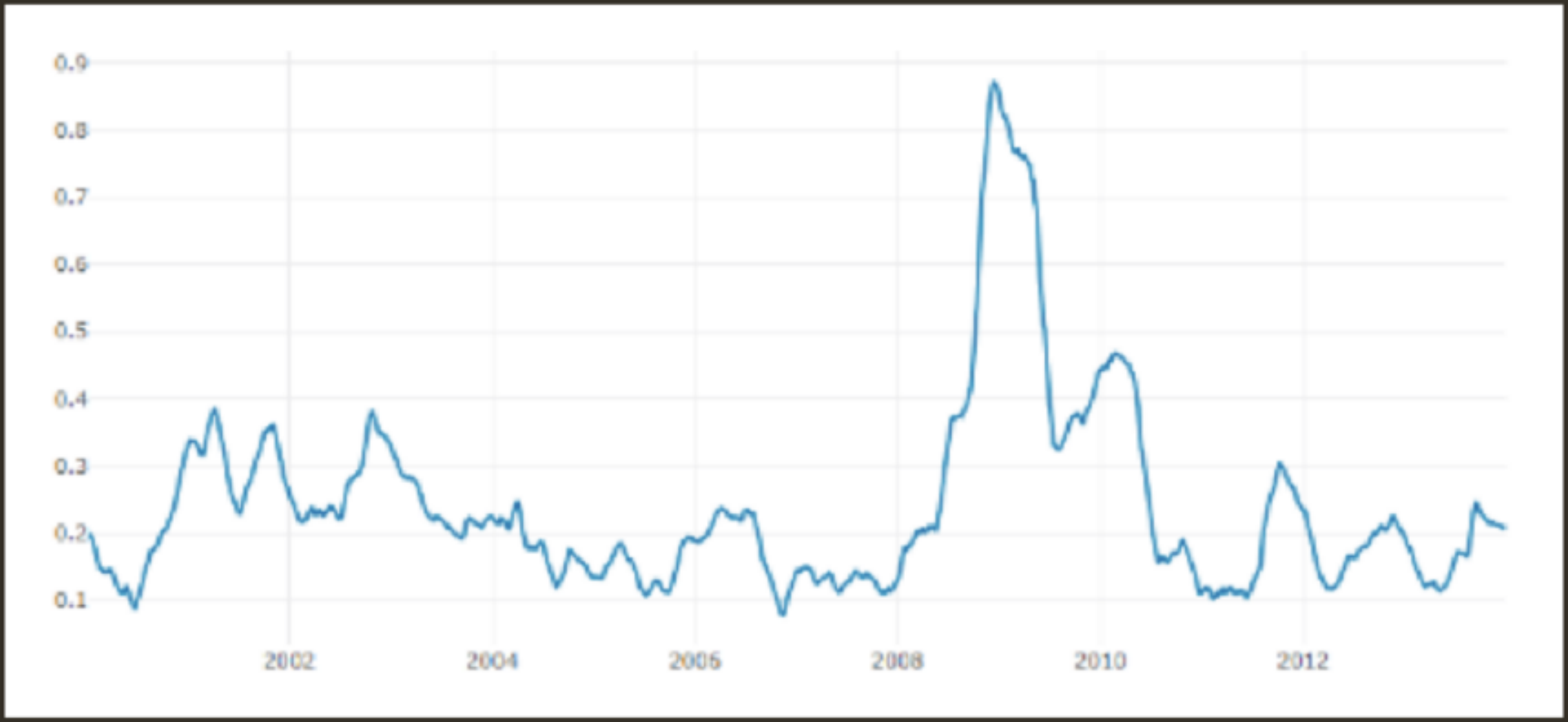


Walk-forward Optimization helps in....

Better performance in out of sample data

Higher conviction in backtested results

Expected Returns Model



Source: Qplum Research

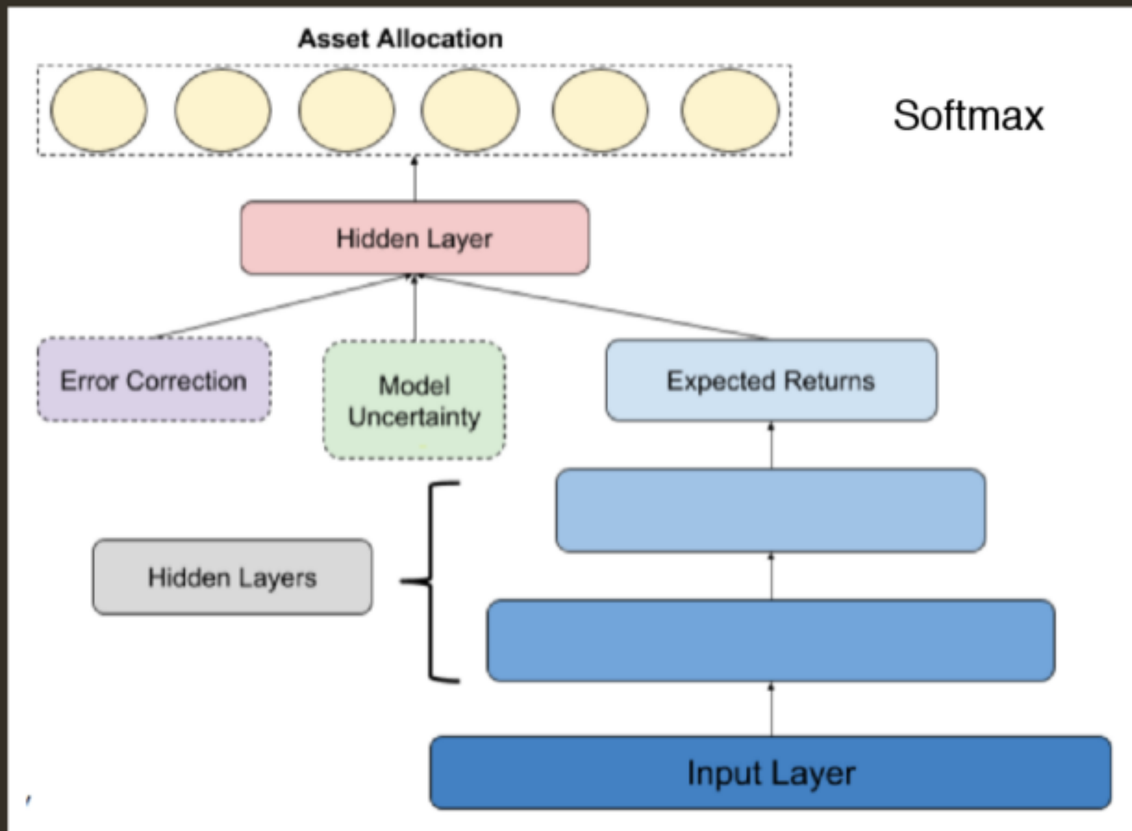
Mean exponentially weighted MAE (mean absolute error) across all assets (scaled between 0 and 1)

Model Uncertainty vs Volatility

Asset Class	Security	Correlation b/w Dropout Uncertainty and Volatility Uncertainty
US Fixed Income	BND	0.08
International Fixed Income	BNDX	-0.16
Emerging Markets Fixed Income	VWOB	-0.17
US Equities	VTI	0.36
EU Equities	VGK	0.30
Emerging Markets Equities	VWO	0.15
US Real Estate	VNQ	0.50
International Real Estate	VNQI	0.54

Correlation between uncertainties obtained from the model using dropout approximation and uncertainty obtained using volatility in different asset classes.

Utility Function based Position Sizing



Architecture for position sizing based on the utility function. *The basic idea is to learn the allocations directly based on the performance metric such as sharpe ratio.* It uses the expected returns model, an error correcting feedback and the uncertainty of the expected returns model

Utility Function

Sharpe Ratio (net of all trading and slippage assumptions)

+

Entropy of allocations to different asset classes

Easy to extend to other objective functions
capturing different investor preferences

Uncertainty estimate based on realized volatility

Source: Qplum Research

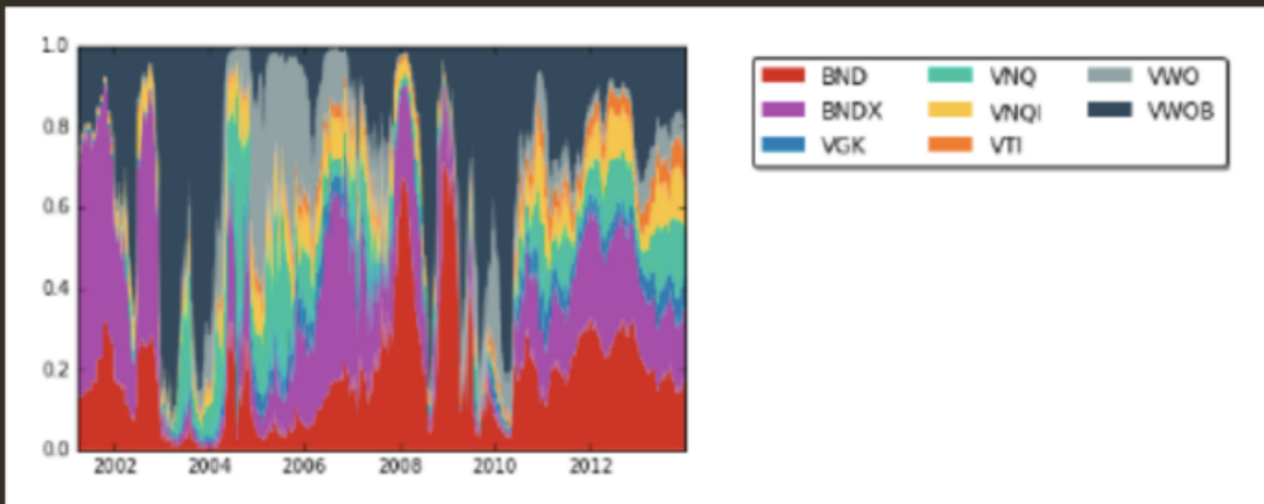
Backtested cumulative returns of the strategy across different runs against risk parity in the observation period. The variation in performance comes from different initializations of the neural network

	CAGR	Worst Drawdown	Sharpe Ratio	Sortino Ratio
Run 1	8.4	23.8	0.95	1.30
Run 2	8.4	25.2	0.89	1.22
Run 3	8.8	27.0	0.99	1.35
Run 4	8.9	26.3	0.98	1.36
Run 5	7.2	29.9	0.79	1.07
Risk Parity	8.9	27.8	0.87	1.20

Performance statistics for different runs and risk parity

Asset Allocation

Uncertainty estimate based on realized volatility



Source: Qplum Research

Asset allocation over time for utility based position sizing logic over time

Uncertainty estimate based on model uncertainty

Source: Qplum Research

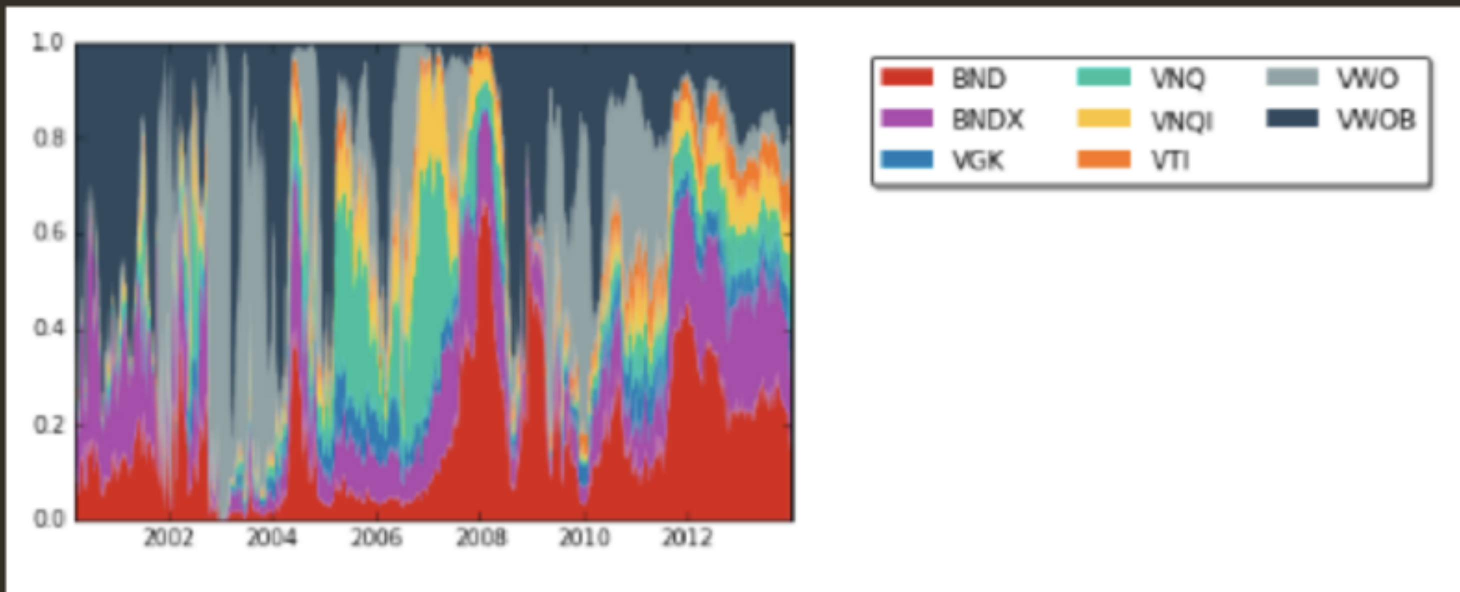
Backtested cumulative returns of the strategy across different runs against risk parity in the observation period. The variation in performance comes from different initializations of the neural network

	CAGR	Worst Drawdown	Sharpe Ratio	Sortino Ratio
Run 1	9.3	30.7	0.74	1.03
Run 2	10.6	29.9	0.87	1.23
Run 3	10.3	28.9	0.84	1.19
Run 4	9.9	26.3	0.84	1.18
Run 5	10.5	32.0	0.87	1.22
Risk Parity	8.9	27.8	0.87	1.20

Performance statistics for different runs and risk parity

Asset Allocation

Uncertainty estimate based on model uncertainty



Source: Qplum Research

Asset allocation over time for utility based position sizing logic over time

Source: Qplum Research

Performance of different formulations against risk parity in out of sample period

Strategy	CAGR	Worst Drawdown	Sharpe Ratio	Sortino Ratio
Utility Function (MC)	4.3	17.2	0.44	0.58
Utility Function (Vol)	5.2	12.9	0.62	0.82
Expected Returns	2.0	8.3	0.37	0.50
Risk Parity	4.6	9.3	0.76	1.03

Performance stats of different formulations against risk parity in out of sample period

Future Improvements

Increase the coverage of macro-economic variables

Better estimates of model uncertainty

Use hypothetical data to learn price-volume features

Explore other neural network architectures

Key Takeaways

Systematic walk-forward training of deep neural networks for financial time series data

Bayesian deep learning could be helpful in applications where signal to noise ratio is low such as capital markets

Utility function as an objective function for training to directly determine allocation

Deep neural networks are a flexible and powerful framework to do tactical asset allocation

Questions?

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