MACHINE LEARNING FOR FUND SELECTION

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Overview

The use of quantitative techniques to analyse fund returns and support fund selection is as old as the first dataset that allowed conducting such analysis. Initial work assumed normally distributed fund returns and a linear relationship between these returns and market factors. These simple assumptions led to great insights and theories but faced a major issue. Linearity is not the norm, particularly for strategies relying on the heavy use of options, leverage, dynamic elements and other financial techniques that distort their return distribution and relationship to factors. Moreover, hedge funds have been the poster child of such non-linear behaviour.

In our analysis of hedge fund return predictability, we apply various quantitative methods from the realm of supervised machine learning in an attempt to capture this non-linear behaviour. While previous work on hedge fund performance attribution addressed non-linearities by means of benchmarks that incorporated market timing or option-like strategies, our focus is on prediction rather than performance attribution (Avramov, Barras and Kosowski (2013)). We forecast hedge fund returns by means of machine learning methodologies that allows us to directly capture interactions between predictors as well as conditioning them on time-series variables such as macroeconomic data. In our out-of-sample tests we use the novel SHAP methodology to explain which predictor helps to predict returns at a given point in time thus assisting with the economic interpretation of our results.

The past decade has seen Artificial Intelligence make its foray into finance, mostly through liquid markets, transforming the way investible instruments are analysed and selected. True to its philosophy, Unigestion puts collaborative intelligence and research of the most recent techniques, at the forefront. Building on our research in machine learning techniques in public and private equity (*A Quantitative Approach to Private Equity Fund Selection*), we apply similar techniques to analyse liquid alternative strategies to model the complex relationship and behaviour associated with them.

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Key Points

1. Artificial intelligence is increasingly being adopted in financial markets, transforming the way investible instruments are analysed and selected.
2. Integrating machine learning techniques in the quantitative due diligence process helps broaden the scope of the analysis and increases its quality, increasing its positive impact on portfolio returns.
3. Unigestion's 40 years of experience in liquid alternative investments leaves us well placed to add automation to our decision making process in fund selection.

Broadening the Technical Toolset

We use Unigestion's 40 years of experience in investing in alternative funds to identify the most relevant predictors (henceforth also referred to as features in the machine learning models' context) that could help forecast fund return statistics like Sharpe ratios. We then use these factors to train several machine learning algorithms for fund selection to forecast these statistics.

For each investment style category, we identify economically relevant predictors from fund data provided by Hedge Fund Research (HFR) in addition to our proprietary Nowcasters, which gauge economic and market conditions in terms of macro regimes. The goal of the selection model is to support the overall analysis of funds analysis by providing an investment recommendation in terms of the resulting forecasted quintile of some pre-defined output variables like the Sharpe ratio. In order to gauge which input factors impact the output variable most and in which direction, we employ the SHAP value framework.

The input features used are economically interpretable historical fund characteristics grouped into four main buckets: returns based (absolute and relative), qualitative, and macro based. Return based features are self-explanatory. The qualitative features bucket aims to capture 'operational quality' information by attributing a rank to the main financial intermediaries: auditors, administrators and prime brokers, as well as other information such as AUM and time since fund inception. Macro-based features aim to capture the risk-adjusted performance of each fund across periods in each of the following four macro-regimes: steady growth, recession, inflation, and market stress.

We then forecast several risk-adjusted fund performance metrics (Sharpe ratio, Sortino ratio, alpha and t-statistic of alpha).

Finally, we employ the framework of SHAP values to understand and confirm our intuition in terms of variable importance at the aggregate level, as well as to gauge, for a specific fund, which of its characteristics distinguished it within its peer group.

We test and calibrate the general model framework using a selection of machine learning and deep learning models that allow for performance forecasting, under the paradigm of 'Supervised Learning'. The models employed are ElasticNet, a regularised linear specification, Random Forest and XGBoost, two ensemble models based on decision trees, and fully connected neural networks from the deep learning literature.

We then order the forecasted outputs into quintiles of expected output outperformance with respect to the benchmark of each of the four investment styles: Dynamic Beta, Macro Directional, Alternative Income, and Market Neutral. Each quintile thus becomes a score complemented by the SHAP variable importance to support our decision of selection. The benchmark model forecasts the output variable to be the ex-post realised value of that same variable.

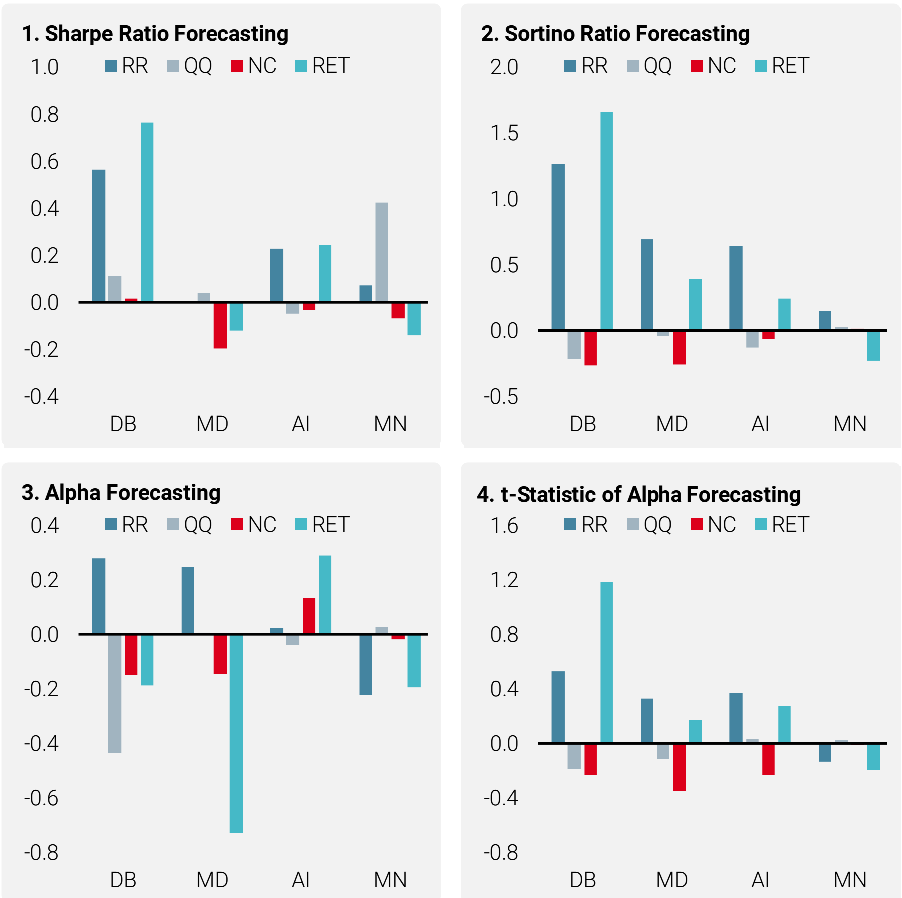
We find that the funds in the top and bottom quintile present typical behaviour, such as trend followers in the top quintile for Macro Directional, or long-biased equity manager in top quintile for Dynamic Beta. More importantly, this is consistent across machine learning models, showing that these models are able to leverage the information within the economically meaningful predictors to arrive at a consensus. We find a similar consensus using SHAP value analysis, which is a recent development in the field of explainable machine learning, whose goal is to explain the effect of each predictor. The analysis reveals that even when a high degree of non-linearity is present, the predictors that stand out are those that one would intuitively believe to impact future performance, as illustrated in Figure 1.

Figure 1: Most Consistently Important Predictors, per Predictor Category

Category	Qualitative	Abs. Return	Rel. Return	Nowcaster
Dynamic Beta	Prime Broker Score	Ret. Quartiles	Sharpe/Index	Stress
	Administrator Score	Max DD	Sharpe/RF	
	Auditor Score	Volatility	Sortino	
		Gainloss	Alpha t-Statistic	
Macro Directional	Prime Broker Score	Ret. Quartiles	Sharpe/Index	Recession
	Administrator Score	Volatility	Sharpe/RF	
	Auditor Score	Gainloss	Alpha t-Statistic	
	Regional Variables	Skew, Kurt	Sortino	
Alternative Income	Prime Broker Score	Gainloss	Sharpe/Index	Inflation
	Administrator Score	Max DD	Sharpe/RF	
	Auditor Score	Calmar	Alpha t-Statistic	
		Ret. Quartiles	UP RVA	
Market Neutral	Prime Broker Score	Gainloss	Sharpe/Index	Recession
	Regional Variables	Calmar	Sharpe/RF	
		Skew, Kurt		

Sources: Unigestion. Data as of September 2020.

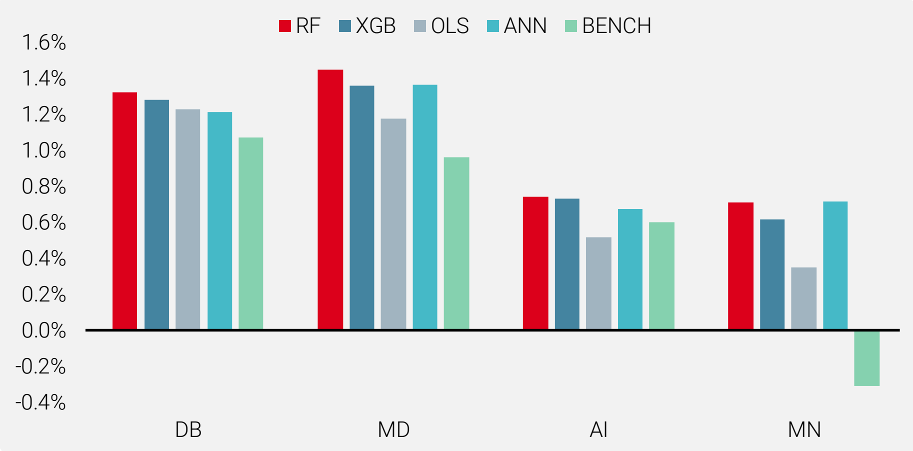
Figure 2: Predictor Category Average of Time-Series Average of SHAP Values, for Each Dependent Variable, Across Investment Categories



Sources: Unigestion. Data as of September 2020.

This selection effect is well illustrated below when we look at the top vs bottom quintile differences in alpha against the strategy benchmark, resulting from the fund selection for alpha. Machine learning models are capable of consistently finding a higher risk-adjusted top vs bottom quintile spread. These results are consistent across the projected metrics.

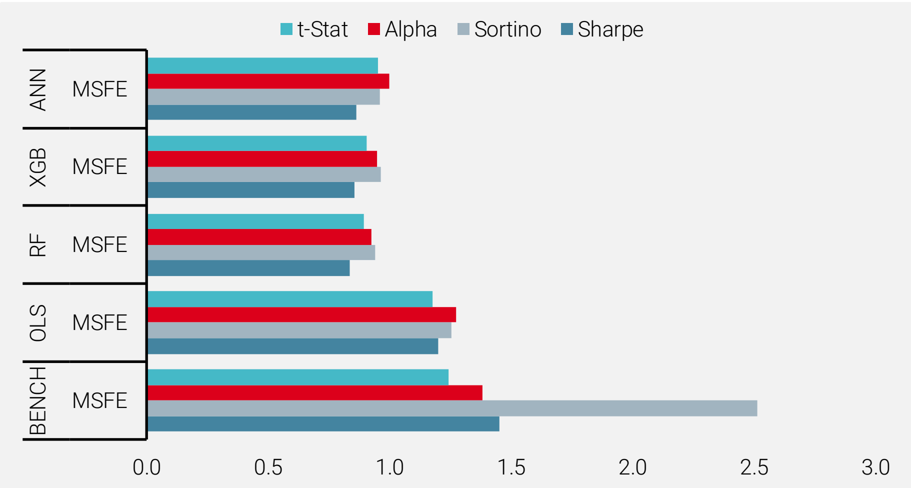
Figure 3: Alpha Forecasting – Top vs Bottom Quinitle Alpha Differences – 24 Months (Monthly)



Sources: Unigestion. Data as of September 2020.

We find that machine learning models have a considerably lower out of sample prediction error (Mean Squared Forecast Error, MSFE) when compared to the linear specification and the benchmark. The figure below is an average across investment styles and forecast horizons, presented for each forecast metric and for each model.

Figure 4: Mean of MSFE Across Models



Sources: Unigestion. Data as of September 2020.

Strengthening Due Diligence Process

Integrating machine learning techniques in the quantitative due diligence process improves analysis in several ways. First and foremost, it helps address the elephant in the room: financial market returns are not normally distributed and linear techniques are often ill-suited to explain their interactions. Broadening the scope of the analysis in a systematic fashion increases its quality, thereby impacting portfolio returns positively.

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In particular, identifying a predictive pattern within a strategy represents a strong appeal for portfolio construction. These best in class funds are also very representative of the common behaviour in their category and can therefore be used as core elements for each investment style within the allocation.

Applying machine learning techniques to liquid alternative funds is a natural step as they are well suited to identify non-linear relationships. It makes this approach potentially very powerful when generalised to other liquid strategies, thus fully integrating machine powered filters into current quantitative analysis.

Once we open the door to the addition of non-numeric information in the process, the possibilities becomes almost limitless. Other data science tools can be put to work to go through lengthy text documents to analyse and compile information, allowing humans to focus on value added decision making. Training the model is only possible if large amounts of historical data and the experience to choose the right factors are available. The 40 years of experience of Unigestion in liquid alternative investments provides a strong tailwind towards adding automation to our decision making process in fund selection.

Appendix

This appendix provides further detail on the data and some of the machine learning models employed in the study.

All input features and output forecast metrics are computed on a cross sectional basis, and all models are trained cross-sectionally, every three months, using the input – output pairs of feature and metric for all funds in a given cross section at the current forecast date. In order to allow the model training procedure to incorporate a maximal amount of diverse information, a multi-cross sectional approach is used, which consists of appending cross sections constructed at previous time periods; this allows for the model to be trained with more available data, as well as to learn persistent behaviour across the temporal span of included cross sections.

Recent research in the application of neural network models to returns forecasting in equities favours shallow networks to deep ones. We therefore employ a fully connected neural network with two hidden layers of 100 and 10 neurons respectively

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