Can Machine Learning enhance systematic incorporation of equity signals?

By Tarun Gupta, Ph.D., David Mischlich and Yifei Shea, Ph.D.

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In theory, an investor can achieve above-market performance by obtaining better information or having a better process to distill relevant information from the available data. We conduct an experiment to evaluate whether machine learning (ML) can enable better inference of future returns from stock characteristics such as earnings yield, profitability, and momentum. Our findings suggest that while employing a non-linear ML model may lead to improved signal processing, thoughtful transformation of raw signals potentially further enhances information extraction of the ML model.

In the world of systematic and factor investing, the quest for informational advantage has led to an increasing number of predictive stock characteristics being 'discovered'.[1] As such traditional signals become more commoditized, researchers are looking for alternative alpha, for example by analyzing earnings call transcripts or credit card transaction data.[2]

But how should the available signals be incorporated in an investment model? Machine learning (ML) techniques have drawn significant attention, as they are generally well suited for dimension reduction and signal combination.[3] Additionally, they may capture potential non-linear relationships between signals and future returns as well as interaction effects among the signals.

There are, however, caveats associated with applying ML methods for return forecasting. For instance, stock characteristics such as earnings yield are known to be weak predictors of future stock returns; in other words, the signal-to-noise ratio is rather low. This and the dynamic nature of markets are challenges for any statistical modeling technique, but with increased model complexity there is increased concern of overfitting. Allowing non-linearities also makes the results more difficult to interpret, necessitating additional tools for performance monitoring and attribution.

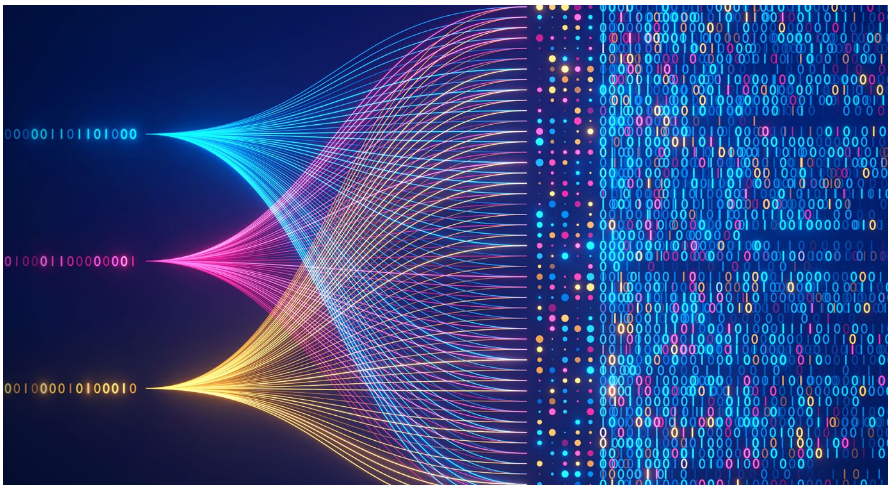

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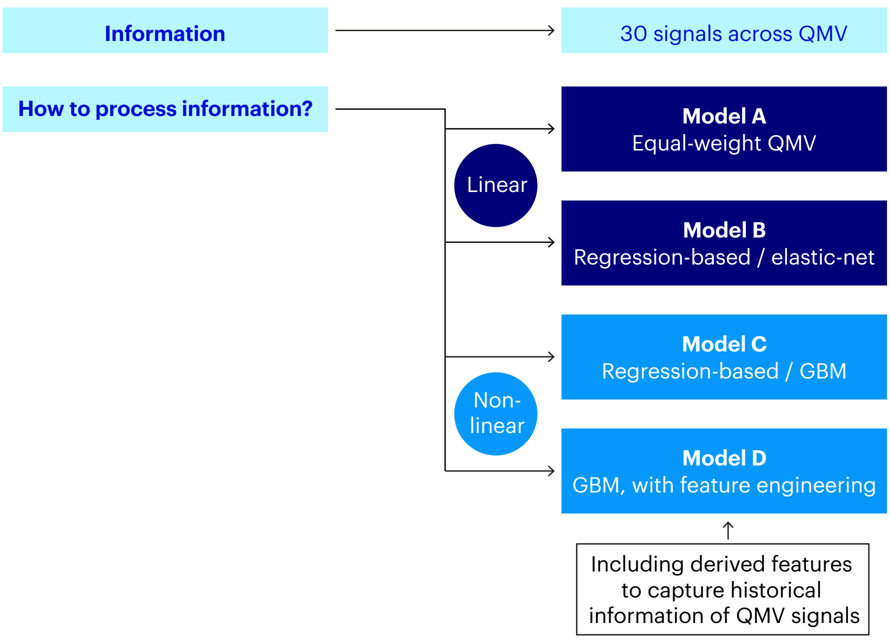
Figure 1
Four predictive models for extracting signal information



Source : Invesco.

In this article we evaluate whether a non-linear ML model performs better than a linear combination of stock selection signals, and if feature engineering – the thoughtful transformation of raw inputs – can further improve the ML model's performance. To this end, we present our experiment set-up, backtest results and examples of the application of Interpretable Machine Learning (IML) tools.

The predictive models and their rationale

We construct and compare four predictive models (figure 1) based on a global developed market large cap stock universe.[4] Our information set includes 30 well-established Quality, Momentum and Value (QMV) equity signals with good economic intuition.[5] To keep signal selection parsimonious, we restrict data to non-financial sectors, given certain fundamental signals are less applicable to financial stocks. Our sample includes monthly signals and one-month forward returns from December 31, 1997 to December 31, 2020. On average, there are 2,490 stocks each month during this period.

For processing the inputs, Model A applies equal weighting of the signals within each of the three buckets: Quality, Momentum and Value and then equal weights the three factors. In comparison, Model B is based on the estimated statistical relationship between the current month's signals and next month's stock returns. We use a regularized linear regression model called elastic-net (or e-net for short), often used to reduce overfitting and to make the model easier to interpret.

Both Models A and B are linear combination of the 30 signals; they serve as benchmarks for evaluating Models C and D, which apply a non-linear ML algorithm (Gradient Boosting Machine, or GBM). GBM is a well-performing tree-based model which efficiently combines a large number of weak predictors into a strong one. It has also been applied and discussed in Leung et al. (2021).

In ML, better information extraction does not only happen at the modeling stage but can also be achieved by transforming raw signals before supplying them to the model. This process is called feature engineering, since signals are called 'features' in ML. Thus, while Model C uses the same inputs as Models A and B, in Model D, we extract 48 additional features based on the 30 QMV signals to capture their historical evolution and use all original and derived features as GBM inputs. An example of a derived feature is the trailing percentile of the earnings yield (figure 2).[6] Whereas earnings yield is one of the most popular Value factors, and useful for gauging the 'cheapness' of a stock relative to its peers, its trailing percentile provides incremental information regarding whether a stock is cheap relative to own history.

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What is GBM?

GBM (Gradient Boosting Machine) is a popular machine learning technique to create a strong learner from multiple weak learners using shallow regression trees. It builds the model recursively by adding regression trees sequentially to an ensemble, with each one correcting its predecessor. In each stage, the model attempts to correct the errors of the previous stage by fitting a new tree to the residual error. More specifically, we apply stochastic gradient boosting (Friedman, 2002) which selects random subsamples of the training data to fit each tree in the ensemble. The use of subsamples allows for faster training and can improve the model's ability to generalize to new data. In contrast, traditional gradient boosting trains each tree on the full training set.

Figure 2
An example of a derived feature: trailing 3-year percentile of analyst forecast earnings yield

3-year trailing percentile calculation based on a 38-month look-back window to account for potential reporting lag.
Source: Invesco. For illustrative purposes only.

The idea that historical evolution of stock characteristics, such as earnings yield, is useful for future return prediction is supported in previous research. For instance, Pani and Fabozzi (2021) show that trend in various Value factors are potent return forecasting signals. A well-known Quality signal, Piotroski's F-score[7], also includes several components based on year-over-year change in selected financial metrics. Instead of devising an economic rationale for each signal, Avramov, Kaplanski and Subrahmanyam (2022) suggest that a neglection of historical fundamentals is a manifestation of 'anchoring',[8] and they utilize deviation of 93 stock fundamentals from historical mean to forecast drifts in prices. Similarly, our intuition is over-arching, such that we think there is a general under-utilization of historical signal information. This allows us to mitigate potential bias in feature selection yet only supply sensible inputs in Model D.

The backtest framework and results

When setting up the models, we use a ranking-based standardization for pre-processing of the input signals and returns to ensure industry and region neutrality. Accordingly, our model forecasts represent the outperformance or underperformance of a stock relative to its peers.

While Model A uses no statistical tools, we train return prediction models using an expanding window for Models B, C and D; the first estimation models are based

Table 1
Backtest results of different models and regions

Region	Model	Return p.a.	Standard deviation p.a.	Information ratio	Max. drawdown	Turnover
US (average number of stocks: 972)	A (Equal-weight QMV)	1.5%	4.2%	0.36	-30.0%	3.84
	B (Linear / elastic-net)	1.6%	4.2%	0.38	-29.6%	5.29
	C (Non-linear / GBM)	2.7%	3.8%	0.70	-22.6%	6.96
	D (GBM, with historical information)	3.8%	3.8%	0.98	-20.9%	8.10
Japan (average number of stocks: 568)	A (Equal-weight QMV)	3.0%	4.5%	0.67	-21.5%	4.25
	B (Linear / elastic-net)	3.7%	4.7%	0.78	-23.2%	5.66
	C (Non-linear / GBM)	4.9%	4.4%	1.12	-15.4%	7.39
	D (GBM, with historical information)	6.4%	4.4%	1.47	-10.1%	8.61
EU ex UK (average number of stocks: 394)	A (Equal-weight QMV)	4.4%	3.7%	1.20	-21.2%	4.46
	B (Linear / elastic-net)	4.4%	3.7%	1.19	-14.8%	5.76
	C (Non-linear / GBM)	4.0%	3.7%	1.07	-14.4%	7.72
	D (GBM, with historical information)	5.0%	3.6%	1.39	-11.4%	8.77
UK (average number of stocks: 213)	A (Equal-weight QMV)	3.8%	4.9%	0.77	-14.1%	4.22
	B (Linear / elastic-net)	4.3%	5.3%	0.81	-11.7%	5.70
	C (Non-linear / GBM)	3.8%	5.5%	0.70	-12.0%	7.63
	D (GBM, with historical information)	3.8%	4.9%	0.76	-11.9%	8.56

Results for large cap universes of main developed regions, excluding financials, December 2002 to January 2021. The signals from each model are transformed into market and industry-neutral portfolios within each investment region. All portfolios are rebalanced monthly from December 31, 2002 to December 31, 2020. Turnover figures are one-way, annualized. Model doesn't take into account fees.
Source: Invesco. Back-tested performance is not a guide to future returns.

on features and forward returns from December 31, 1997 to November 30, 2002, then applied on inputs as of December 31, 2002 to obtain following-month return predictions. In this manner, we generate out-of-sample following-month return forecasts based on each model from December 31, 2002 to December 31, 2020.[9]

Next, we transform the monthly forecasts of each model into dollar, market and industry-neutral long and short portfolios for every region.[10] Table 1 shows the backtest performance of the four models in key developed market regions. The main performance metric is Information Ratio (IR), which measures the risk and reward trade-off of a strategy. We find, using the original information set of 30 signals, that the performance of non-linear model C is mixed relative to the two linear models A and B, even though Model C outperforms in the two regions with larger cross-section of stocks, US and Japan.

The more consistent performance improvement is observed once we additionally include features derived from original signals to capture their historical information, as manifested in the higher IRs from Model D compared to Model C. In unreported results, we find that Model D generally provides alphas beyond traditional QMV factors, mainly due to the derived features. In addition, table 1 shows lower or similar drawdown for the non-linear vs. the linear models.

However, one of the caveats of the non-linear models is the higher portfolio turnover. In the backtest period, the average turnover across regions is twice as high for Model D as for the equal-weight Model A. Smoothing the investment signals from Model D would result in reduced turnover while incurring decay in signal efficacy.[11] Therefore, net of transaction costs, it may be difficult to translate Model D signals into a profitable strategy, especially in the presence of various portfolio constraints such as long-only.

Next we examine the backtest performance through time for the four models. Figure 3 shows the cumulative returns in US Large Cap universe, excluding financials. The annualized return differential between Models D and B per annum is 2.1%, which can be further broken down to 1.1% from including derived features to capture historical signal information (proxied by the return differential between Models D and C), and 1% from allowing non-linearity (proxied by the return differential between Models C and B). In addition, we note the return contribution from including signal evolution information is more stable over time and across regions, compared to the contribution from purely adopting GBM instead of linear regression. This seems to confirm that, although the non-linear modeling technique may help, information can potentially be more reliably extracted in the feature engineering stage of ML – though caution is required, as our observations are essentially based on one historical realization.

To avoid the pitfall of 'research through backtesting', we spend much time building and employing Interpretable ML tools for all estimated models. Our aim is to ensure a good understanding of the relationship between input features and model forecasts before evaluation of performance. In the next section, we show examples of such IML applications.

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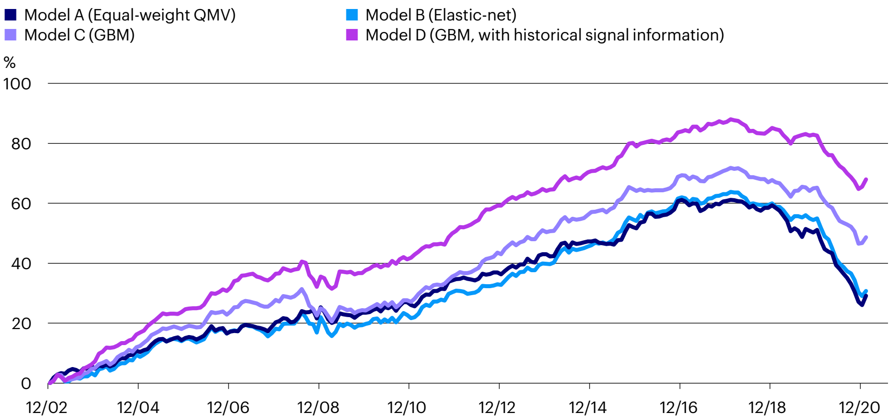
Illuminating the black box

One of the most popular statistics used to shed light on non-linear ML models is called variable importance, which measures to the relative importance of each feature in the model.[12] Figure 4 shows the variable importance of feature groups over time based on Model D. We can see the relative importance of each feature group remains stable over time; on average, the importance of Value, Quality, Momentum and derived features is 24%, 12%, 34% and 29%, respectively.

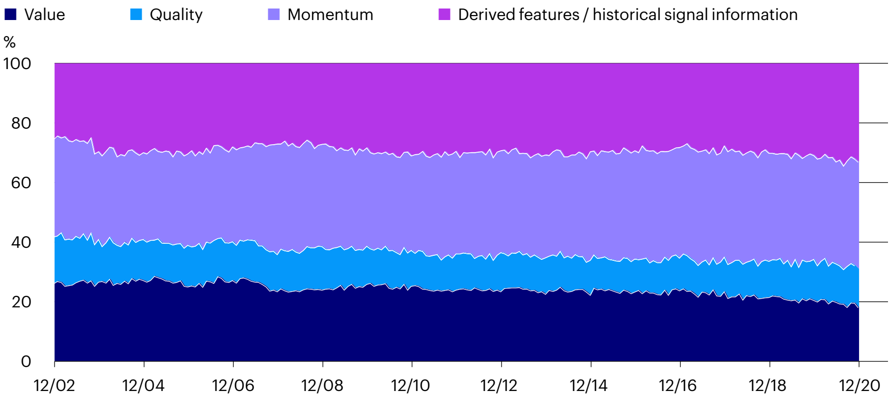
On the individual feature level, share turnover[13] emerges as highly important in non-linear models C and D, but does not rank high when measured by its correlation with return forecasts (a metric to capture

Figure 3
Backtest performance: Cumulative returns of four models in US large cap universe, excluding financials



The portfolios are rebalanced monthly from December 31, 2002 to December 31, 2020.
Source: Invesco. Backtested performance is not a guide to future returns.

Figure 4
Variable importance through time by feature group



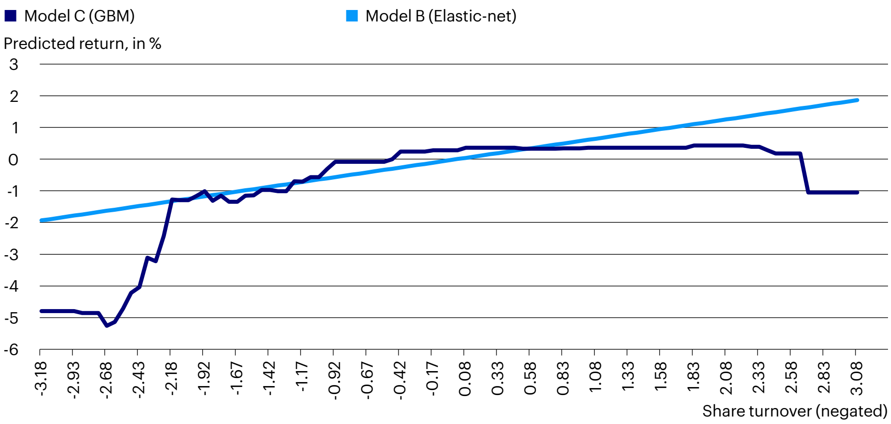
Relative variable importance is computed on signal level then aggregated by group. On December 31, 2002, the variable importance is based on GBM estimated using signals and 1-month forward returns from December 31, 1997 to November 30, 2002. An expanding window is used for each subsequent month of estimation.
Source: Invesco.

linear relationship). Thus, it is interesting to inspect how the predicted returns change with share turnover (holding values of other model features constant) based on either a linear or a non-linear model.

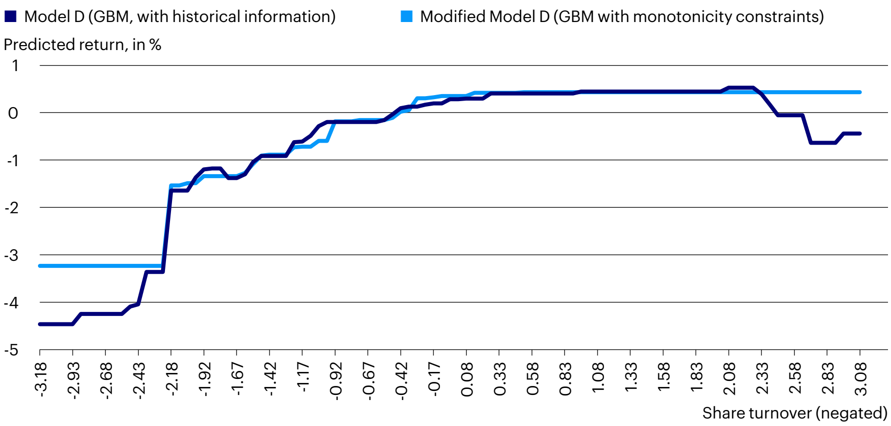
We use Partial Dependence Plots (PDPs)[14] to visualize such marginal effects and give an example for share turnover in figure 5. As shown in panel A, the non-linear Model C can detect certain non-linearities a linear model cannot. More specifically, for assets with a high turnover, it predicts lower forward returns compared to the linear model while suggesting little difference for assets with below average turnover. This is consistent with our intuition that high turnover can be an indication for stock underperformance, whereas low turnover does not necessarily precede better returns.

Figure 5
Partial dependence plots (PDPs) of share turnover

Panel A: PDPs of linear and non-linear models



Panel B: PDPs of GBM models with or without monotonicity constraints



Based on models estimated using standardized signal and one-month forward returns from December 31, 1997 to November 30, 2020.
Source: Invesco.

Thoughtful transformation of input signals to capture their historical evolution, coupled with using GBM to efficiently incorporate such information, may be advantageous.

Additionally, PDPs can be useful to visualize constraints in the ML model. To alleviate overfitting concerns, in one of our robustness studies, each input to Model D had to have a monotonic relationship with forward returns consistent with our prior. Panel B of figure 5 shows the impact of such monotonicity constraints.

Summary

We have designed experimental models to test whether non-linear ML models, when applied for systematic equity investing, improve the distillation of signal information compared to traditional linear models. Broadly, the answer is yes: According to our results, thoughtful transformation of input signals to capture their historical evolution, coupled with using GBM to efficiently incorporate such information, may be advantageous.

However, we need to be aware of the hurdles, as we show in backtesting. First, non-linear ML models have a high turnover, so the net gain will depend on portfolio constraints and implementation. Also, using non-linear technique makes the model harder to interpret. We think work towards illuminating interactions among signals and their historical evolution, as well as linking ML forecasts with stock fundamentals, could bring additional insights.

Notes

1 E.g. Cochrane (2011), and more recently, Bartram, Lohre, Pope and Ranganathan (2021).
2 E.g. Gupta and Shea (2022); Gupta, Leung and Roscovan (2022).
3 E.g. Rasekhschaffe and Jones (2019); Avramov, Cheng and Metzker (2022); Leung, Lohre, Mischlich, Shea and Stroh (2021); Nagel (2021).
4 The universe includes stocks from global and regional equity indexes: MSCI, FTSE, S&P, and STOXX. To alleviate investability concerns, we exclude stocks with very small free-float market capitalization, applying a 95% free-float market-capitalization percentile threshold per region and date.
5 There are 10 signals in the Quality bucket, including metrics to measure accrual and profitability; 11 signals in the Momentum bucket, including various price and earnings momentum signals; and 9 signals in the Value bucket, such as earnings yield and free-cash-flow yield.
6 Earning yield is defined as the ratio of consensus analyst forecast of next year EPS and stock price.
7 Piotroski (2000).
8 Tversky and Kahneman (1974).
9 The elastic-net and GBM models are implemented using the open-source ML platform H2O-3 including its pre-set of default hyperparameters. We also tested hyperparameter tuning following the training, validation and testing framework outlined in Leung et al. (2021), and noted limited added value given our sample size.
10 We use own industry definitions which closely follow GICS classifications, as well as predicted betas based on own calculations.
11 Another route for reducing turnover is to use longer horizon such as 6 -month forward returns in the estimation models, as discussed in Leung et al. (2021).
12 Hastie, Tibshirani and Friedman (2017). While we have constructed multiple measures of variable importance, in this section we use the definition from H2O for GBM (see https://docs.h2o.ai/h2o/latest-stable/h2o-docs/variable-importance.html#variable-importance-calculation-gbm-drf), such that the importance of a feature is determined by whether it was selected to split on during the tree building process, and how the squared error (over all trees) improved (decreased) as a result.
13 Share turnover is defined as the median of standardized industry-neutral trade dollar volume per shares outstanding (monthly) over last 12 months. The values are then negated so that higher scores represent lower share turnover.
14 Hastie et al. (2017).

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