Goldman Sachs | Portfolio Strategy Research

12 September 2017 | 7:08PM EST

Australia

Machine Learning the Market

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- **"AI" adoption lagging given a more challenging prediction problem.** Machine learning has had a profound impact on many industries in recent years given advancements in cloud computing, 'big data' and computational speeds. Its application in investing poses a greater challenge given 'beating the market' requires not only quantifying current trends, but also assessing how much of what you know is already in the price. Access to rich data sets and better prediction models has greatly benefited many companies in being able to better target customers, but investors have a tougher problem to solve.
- **Advances are being made by short-horizon investors looking for trading signals among the large volumes of unstructured data.** Examples include using satellite images to count cars in shopping centers or analyze commodity stockpiles, tracking store footfall via smartphone locations, capturing consumer transactions from email providers, measuring sentiment from conference calls or analyst reports, web scraping for product pricing, or using a mixture of geo-location and social media to zero-in on market moving events in real-time.
- **A Machine Learning 101, demonstrating the benefit it can bring to timing factor exposures.** While adoption by traditional fund managers has been slower, interest in the field is rising along with the AUM in quantitative strategies. We provide an overview of some key techniques, illustrating how they can be used to time style exposures in a market where factor rotations are becoming more frequent and extreme. By identifying non-linear relationships that were able to better predict 'Value' crashes, our model added 15% p.a. above a simple long-short Value factor. Negative momentum and valuation dispersion were the most reliable predictors. Interestingly, in periods where 'Value' performed strongly, our model could manage no better than a 50% hit-rate.
- **Avoiding Artificial Stupidity.** While machine learning methods can uncover complex relationships, there is often limited ability to understand the drivers in these models. Their 'black box' nature will likely constrain their wide-adoption, at least in a fully automated sense (for example our model currently tells us to be long 'Value', but we don't know why). Investors are more likely to implement these algorithms in much the same way as the recommendation engines of

Netflix or Amazon, suggesting a menu of possible trades for a manager to research, and thus avoiding trading off the back of spurious relationships.

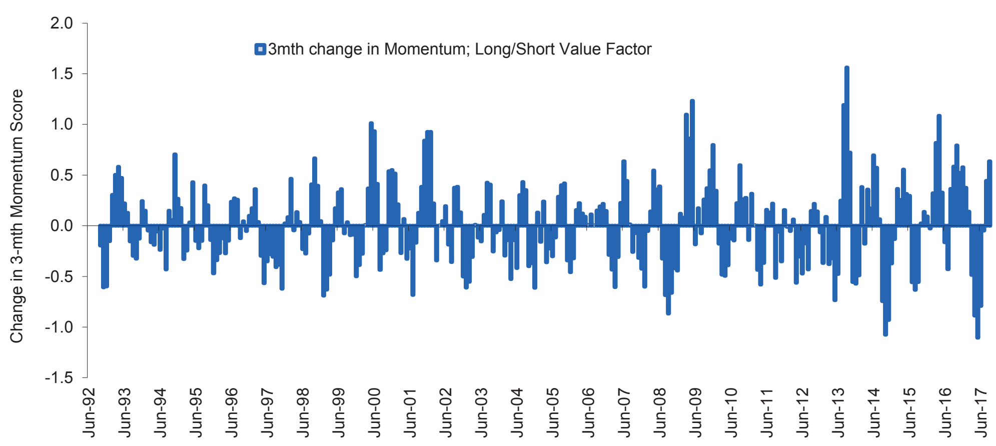
A Machine Learning 101

Machine learning (ML) methods make predictions by identifying patterns and trends from data. They have been shown to demonstrate superior predictive power compared to 'traditional' methods such as regressions, and can navigate through complex and unstructured relationships across a large number of variables - without the need for the researcher to explicitly define these relationships.

ML has been increasingly applied to equity market problems, although so far the focus has been on extracting signals from large volumes of unstructured data for a short-term information edge. Examples include using textual analysis to pick-up shifts in sentiment from analyst reports or company conference calls, web scraping for product pricing or using satellite imagery to count cars in shopping centers or to analyze commodity stockpiles.

In this report, we provide an illustration of using ML methods for factor-timing, by identifying investment rules based on both fundamentals and market characteristics. Correctly timing factor exposures has become a bigger driver of portfolio returns in a market where these rotations are becoming more frequent and extreme (Exhibit 1).

Exhibit 1: Extreme factor rotations have become more common in recent years
The four largest rotations in the 25-year history of our long-short value factor have occurred in the past 4 years; 3-mth change in the momentum score of our long/short value factor



Source: Goldman Sachs Global Investment Research, FactSet

In the language of ML, this is known as a **'supervised learning'** problem, where the machine learns to classify observations into groups (e.g. the Value factor outperforms or underperforms) based on certain features of the data. In 'supervised learning' the groups are already identified by the researcher - i.e. the machine is given the 'right answers' and it learns to find the best rules to predict those groupings. Examples include spam detection, where the algorithm learns to flag an email trained on a database that has been pre-classified . Fraud detection has been one area where financial institutions have leaned heavily on ‘supervised learning’ techniques to limit losses.

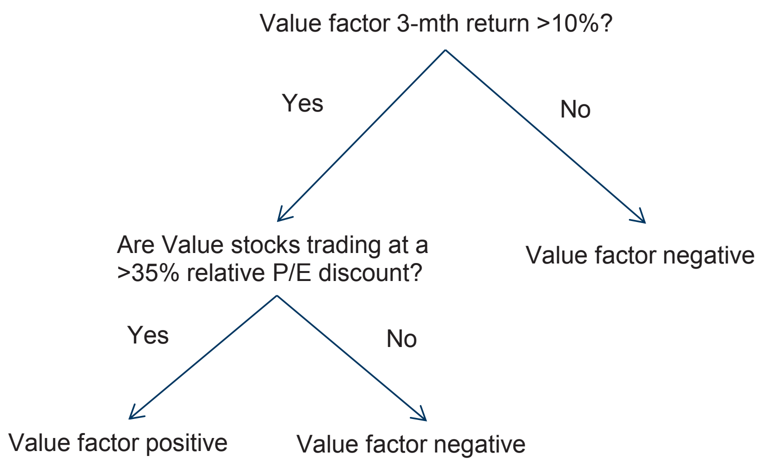
In contrast, in **‘unsupervised learning’** the machine is not given the ‘right answers’ - rather it is left on its own to discover common features in the data. Examples of this include principal component analysis, where common factors are extracted to identify underlying trends in the data - our economics team’s Current Activity Indicator is an illustration. Similar to recommendation systems used by the likes of Amazon, equity risk models often utilise these techniques to uncover the clusters of stocks that are highly correlated to each other.

For our factor-timing exercise, we use three related supervised learning techniques: Classification Trees, Random Forest, and Adaptive Boosting (AdaBoost) to predict the Value factor returns. The latter two methods can be viewed as extensions or enhancements of the standard classification tree approach.

A classification tree can be depicted by a set of decision rules (yes/no) on a set of explanatory variables, in the form of a decision tree – Exhibit 2 shows a simple example. Each ‘node’ of the tree represents an input variable (e.g. is the momentum of the long-short portfolio above 10%). There is a yes/no vote on a node that either leads to another decision rule, or a terminal ‘leaf’ of the tree which represents a predicted outcome – in this case whether the Value factor return will be positive or negative the next month. To make a new prediction, one has to simply put the testing observations through the tree and follow the nodes.

The classification tree is easily interpretable and fast to compute. However, because it uses all observations in the training dataset and is computed only once, it is prone to over-fitting the data and often has poor out-of-sample performance. In fact, in our factor-timing study we find a basic classification tree underperforms the simple long-short strategy. The model can also sometimes generate very different trees even for small changes in the underlying dataset – an undesirable property given the instability of predictions.

Exhibit 2: An example of a classification tree for Value factor timing
This example tree has two inputs - 3-mth returns of the Value factor, and relative P/E of the Value leg. It makes a prediction of whether the Value factor will be positive or negative based on two decision rules.

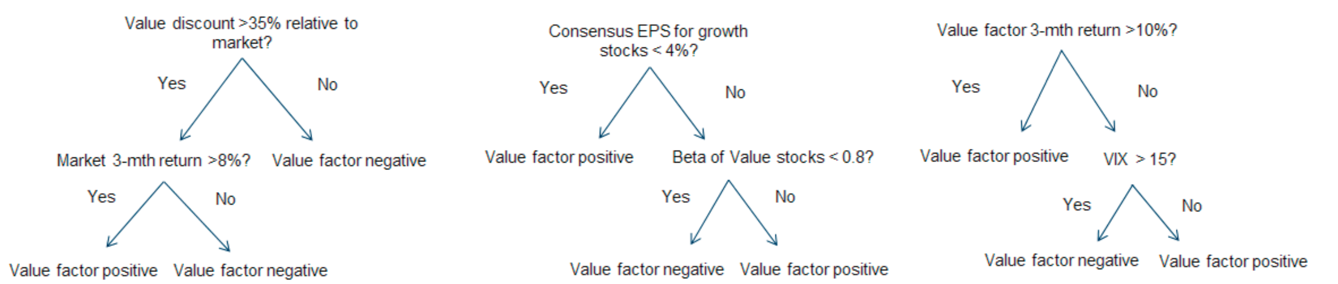


Source: Goldman Sachs Global Investment Research

A Random Forest (RF) grows many classification trees. However, instead of using all of the inputs and observations, each tree is grown using only a subset of randomly selected input variables, on a subset of randomly selected observations from the full dataset.

To make predictions, a new observation is put through each of the trees individually, and the 'most popular' prediction - i.e. the mode prediction - out of all the trees is voted as the model prediction.

Exhibit 3: An example of 3 trees in a Random Forest, each grown on a randomly selected subset of predictors and observations within the full sample.
To make a prediction, the observation is run through each tree in the forest. The outcome that receives the most votes is the final prediction of the RF.



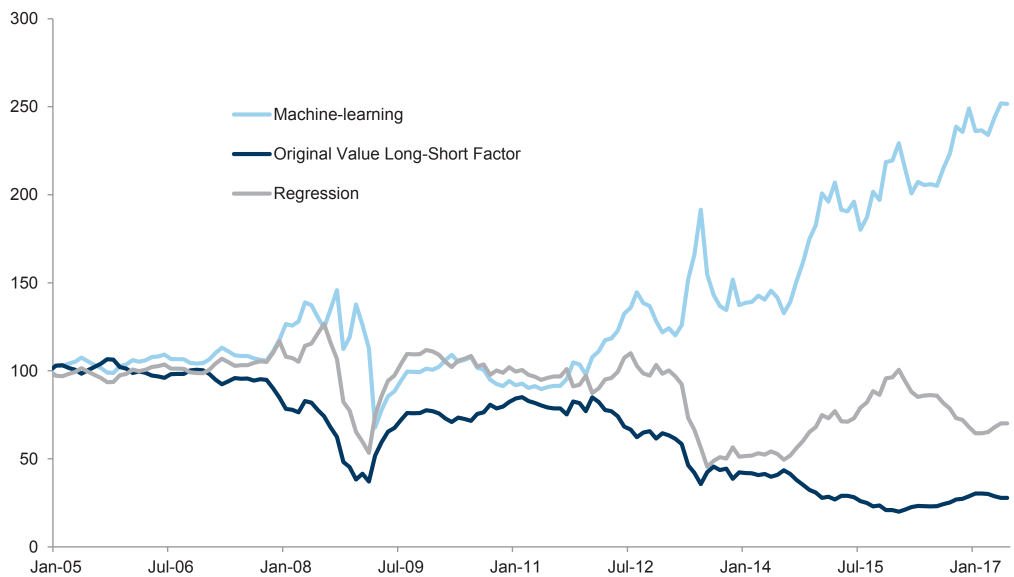
Source: Goldman Sachs Global Investment Research

The RF algorithm has much stronger out-of-sample predictive power than the standard classification tree and is less prone to over-fitting. It can be quickly computed even with large datasets and a large number of predictors, and is also more robust to changes in the input data. This is because RF only uses a subsample to estimate each tree, and many trees are estimated such that noises in the individual trees largely cancel out and the overall model prediction becomes more informative.

This resampling aspect and the associated flexibility of RF make it particularly well-suited to problems that are highly non-linear and conditional in nature - such as market-timing value exposures. The ability to use multiple subsamples allows RF to better capture interaction effects between the many predictors, including momentum and valuation spreads, during extreme market regimes. Traditional techniques such as regressions can have difficulties capturing such complex relationships, in part due to the limited occurrence of these events and the need for the modeler to explicitly specify these conditions. This advantage of ML allows our strategy to significantly outperform both a simple long-short factor strategy as well as a factor-timing model based on a regression approach (Exhibit 4), and becomes particularly useful when there is more variation in the Value factor towards the latter half of the sample.

Exhibit 4: Our machine-learning strategy significantly outperforms the long-short Value factor, as well as a regression-based market-timing strategy.

For the regression strategy, we run a rolling Probit model estimated monthly using the same set of predictors as the ML strategy. The strategy trades long Value & short Growth when the predicted probability of Value outperformance >50%, and vice versa.



Source: Goldman Sachs Global Investment Research, FactSet

For the rest of this report, we focus on the RF algorithm as our preferred approach. In the Appendix we describe a third and related method, AdaBoost, and show that it achieves similar performances as our RF model in factor-timing. However, RF has the advantage of faster computation on larger datasets (3 times faster than AdaBoost in our example), and is more intuitive to understand in our context.

By better predicting 'Value' crashes, machine learning generates a large alpha from market timing

Our ML strategy takes a range of fundamental and market variables shown in Exhibit 5 as predictors, and applies the Random Forest algorithm to predict the direction of next month's 'Value' returns to be either 'Positive' or 'Negative'. Our 'Value' strategy is an equally weighted long-short portfolio that is long the 40 stocks from the ASX 200 that are trading on the lowest forward valuations (average of 12-mth forward P/E, P/B and EV/EBITDA) and short the 40 most expensive names. The portfolio is rebalanced monthly.

Our 'ML Strategy' goes long Value & short Growth when the algorithm predicts a 'Positive' factor return, and long Growth & short Value when it predicts 'Negative'. Our backtest starts in January 2005 with the previous 5-years of data history forming the models initial training dataset. Each month we move forward we add another month of data to our training set and we re-estimate the model to determine a prediction for the performance of our 'Value' factor next month. As such the strategy is implemented in 'real-time' and there is no look-ahead bias. We compare the performance of this ML strategy against the simple long-short Value factor.

Exhibit 5: Variables used in our ML strategy

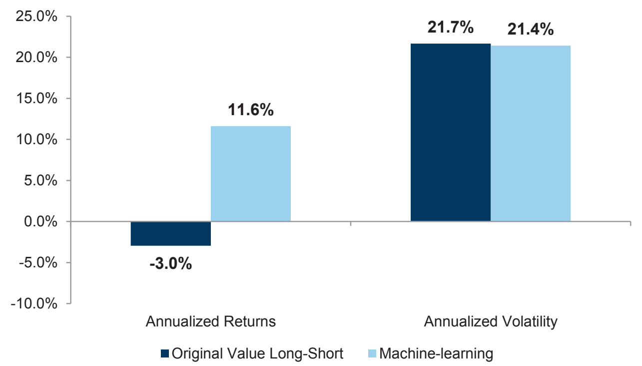
Variable	Definition
Beta (Value & Growth separately)	4-year market beta, estimated using monthly portfolio returns
Debt to Equity ratio (Value & Growth separately)	Average debt-equity for stocks in the portfolio
Dividend yield (market relative, Value & Growth separately)	Market relative consensus NTM dividend yield
Fwd EPS Growth (Value & Growth separately)	Average 2yr forward consensus EPS growth for stocks in the portfolio
Volatility (Long-Short factor)	Prior 3-month volatility of the long-short Value factor
Relative PE (Value & Growth separately)	Market relative NTM PE
Market Return Momentum	Prior 3-month returns of the market portfolio
Long-short Factor Return Momentum	Prior 3-month returns of the long-short Value factor
Portfolio Turnover (Value & Growth separately)	Monthly turnover of the two portfolios
VIX	S&P500 VIX

Source: Goldman Sachs Global Investment Research

Exhibit 6 shows that over the 12 years of our testing sample, our ML strategy delivered an annualized return of 11.6% p.a. versus a loss of -3.0% p.a. for the simple long-short factor. The outperformance of ML has strengthened over the latter half of the sample (Exhibit 3), due to 1) the algorithm has more data points to learn from as the sample period extends, and 2) the long-short factor has had more variation post-GFC. Both of these aspects enhance the learning advantage of ML algorithms. When there is more variation in the data, there is more to be exploited.

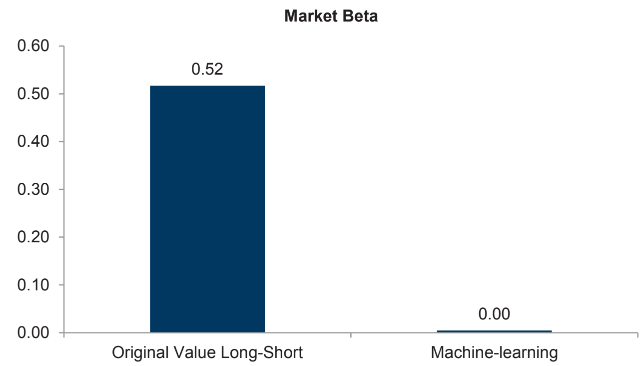
Interestingly, the ML strategy has managed to achieve this outperformance with near-identical return volatility as the simple long-short factor. However the composition of risk is vastly different between the two strategies, with the ML strategy having a much lower market risk exposure as measured by Beta (Exhibit 7).

Exhibit 6: Our ML strategy significantly outperforms the standard long-short strategy, with a similar-sized return volatility



Source: Goldman Sachs Global Investment Research, FactSet

Exhibit 7: While ML doesn't reduce total return volatility, the strategy achieves significantly lower systematic risk



Source: Goldman Sachs Global Investment Research, FactSet

To better understand the source of the ML strategy's outperformance, we can decompose the returns broadly into:

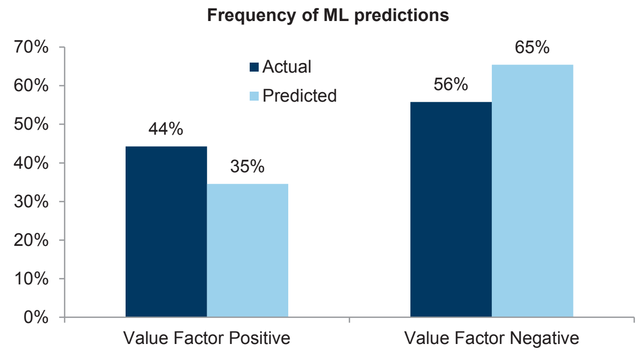
1. the composition of predictions (% of Positives vs Negatives predicted),
2. the accuracy of predictions, and
3. the returns from making the correct predictions

Over the whole sample, the ML strategy correctly predicts the direction of our value factor 58% of the time (Exhibit 8). Its hit-rate on the downside (71%) is much higher than on the upside (42%), but some of this comes form the fact that the model over-estimates the likelihood of a negative Value return (Exhibit 9). That said, it demonstrates a consistent ability to identify left-tail events, predicting 16 of the 20 largest negative moves (Exhibit 10).

This outperformance of ML during Value drawdowns is due to the algorithm's resampling process and its flexibility. Because the RF resamples the data over and over again and makes predictions based on many trees, it can better capture the interaction relationship between the predictors such as momentum, valuation spreads and market risk during extreme market conditions. These dynamics are harder to detect in a traditional regression framework, because there is a limited number of occurrence of these events in the data and the relationships would need to be explicitly specified by the modeler.

Exhibit 8: ML is more likely to over-estimate the likelihood of a negative Value return, compared to actual data.

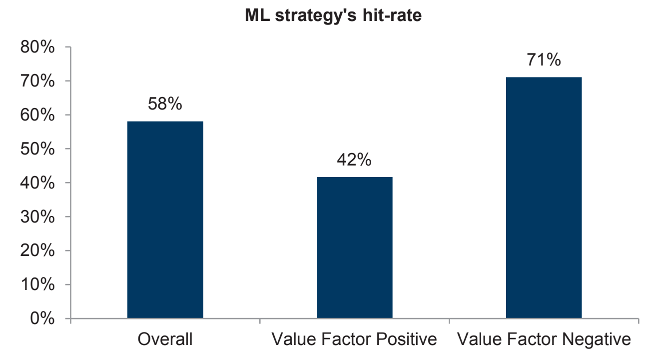
The frequency of ML predictions compared to actual data, split by the performance of the Value factor.



Source: Goldman Sachs Global Investment Research, FactSet

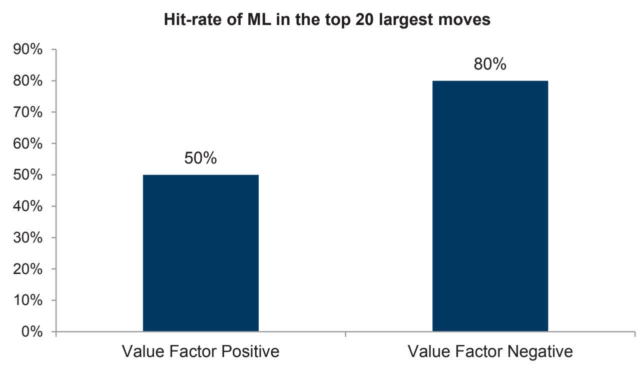
Exhibit 9: ML is more likely to get it right when Value underperforms.

The percentage of times with correct ML predictions.



Source: Goldman Sachs Global Investment Research, FactSet

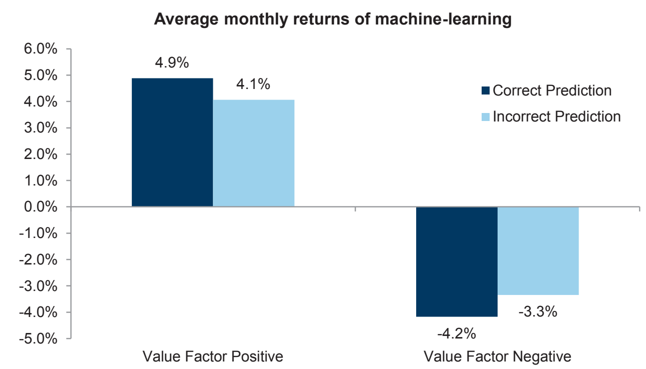
Exhibit 10: The ML strategy is more successful during extreme Value drawdowns



Source: Goldman Sachs Global Investment Research, FactSet

Exhibit 11: The gains are larger when ML makes a correct prediction - both on the upside and the downside.

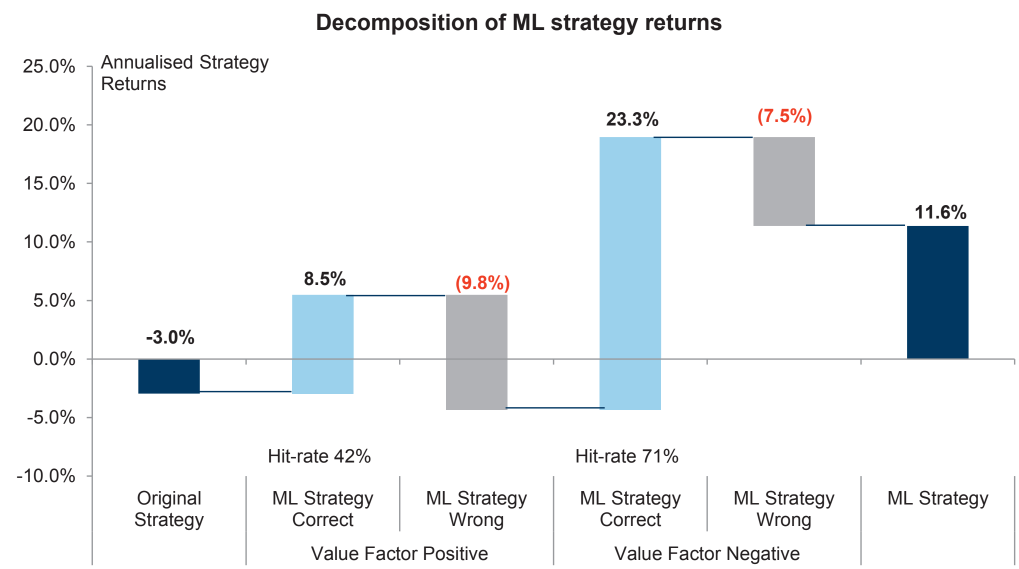
Average monthly returns of the ML strategy split by 1) whether the Value factor return was positive or negative, and 2) whether the ML strategy had the correct prediction.



Source: Goldman Sachs Global Investment Research

Exhibit 12 breaks down the ML strategy's performance improvement over the buy-and-hold factor into four subcomponents – the gains and losses from market-timing the positive Value performance, versus the gains and losses from market-timing the negative Value performance.

Exhibit 12: The vast majority of performance improvement comes from correctly predicting the negative Value returns.



Source: Goldman Sachs Global Investment Research, FactSet

Although the ML strategy has a lower hit-rate when 'Value' outperforms, this is somewhat compensated by the higher returns in the months when the model gets it correct (Exhibit 11). In the months when the 'Value' factor is negative, the ML strategy benefits from both the much higher hit-rate (71%) as well as the larger return when getting the prediction right. As a result, it makes a much larger gain from correctly predicting the negative outcomes and shorting the 'Value' factor (+23.3%) than the losses it generates from getting it wrong (7.5%).

Which predictors are the most useful?

Because of the resampling aspect of the RF approach, we can assess the relative importance of each predictive variable by looking at the change in error rates when we exclude each variable from the algorithm. If a variable has a high predictive power, including it in the sampling process will result in a larger decrease in the average error rate (known as the 'out-of-bag (OOB) error rate').

Exhibit 13 shows the prediction variables ranked by their relative importance. The variable of the 'highest importance' is the return momentum of the long-short Value portfolio – including it in the forecasting algorithm reduces the average prediction error across the trees in the forest by c.1.0%, a sizable improvement considering an overall hit-rate of the strategy of 58% (Exhibit 9). The next important variables are the Beta of the Value leg, as well as market relative PE ratios of the Value and Growth legs, respectively.

Exhibit 13: Momentum, beta and value spreads are the most powerful predictors.
The average reduction in prediction error (i.e. the out-of-bag error rate) in the RF strategy when each variable is excluded from the testing

Source: Goldman Sachs Global Investment Research

What are the drawbacks of machine learning?

Notwithstanding their superior predictive power in uncovering complex, non-linear relationships, ML techniques are not without flaws.

One important drawback of this analysis is that we can only assess the relative importance of including each variable in the algorithm versus omitting it, rather than providing a directional inference – hence it is less useful if one wants to draw inferences such as "if momentum is positive, buy Value". This issue arises from the conditional nature of classification trees. The algorithm will often find optimal solutions such as "if relative PE is larger than X but smaller than Y, buy Value. But if it's even larger than Y, then sell Value".

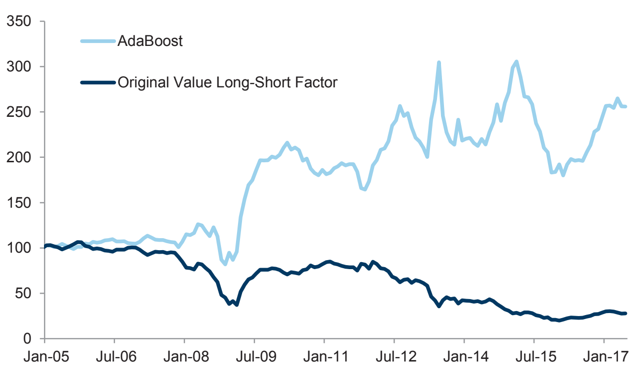
Another drawback is that many ML algorithms (including RF and AdaBoost) rely on resampling the data and randomly drawing of a subset of predictors each time the algorithm is iterated. While this process helps with reducing noise and makes the model less prone to over-fitting, it also introduces an additional degree of instability and uncertainty in the model. In our experience, even when using the same training dataset, running the same model several times could yield different backtesting results, particularly when the test-runs are making different predictions on the extreme outcomes (e.g. turning points in a cycle). While we do not find this to be a significant issue in our specific example and hence are comfortable with our key conclusions above, it is easy to imagine scenarios where different iterations of the same algorithm can generate vastly different performance depending on the underlying distribution of the data, particularly if the returns are heavily skewed and persistent.

Moreover, the limited ability to investigate the source of predictive power in terms of economic drivers makes many of these models essentially a 'black-box'. While there are more advanced techniques developed to deal with these issues, many of these tools are ultimately designed to 'predict' rather than 'understand'. In the investment world however, the latter is at least equally important, if not more important, than the former – hence this limitation will likely constrain the wide-adoption of these approaches as the dominant tool in investment processes, at least for now.

Appendix: AdaBoost as an alternative predictor

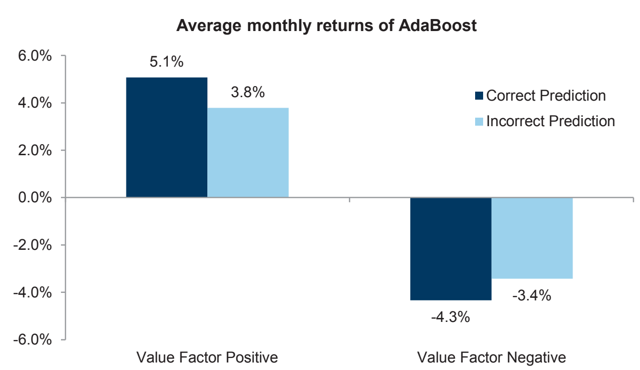
The Adaptive Boosting (AdaBoost) algorithm is another method that enhances the standard classification tree through sub-sampling and iterations. The algorithm starts by training a simple classification tree on a subsample of observations and evaluates its performance by looking at the prediction errors. In the next iteration, the model is re-estimated, now using an updated sample that over-weights the observations which the first model incorrectly predicted. The algorithm then repeats this process many times, each iteration improving on the previous version due to its increased weight on the previous errors. At the end, the overall model makes a prediction using all of the iterated models examined, and it has been shown that this process significantly improves the predictive power of the model above the standard classification tree.

Exhibit 14: The AdaBoost algorithm also shows superior performance relative to the simple long-short factor



Source: Goldman Sachs Global Investment Research, FactSet

Exhibit 15: The performance of AdaBoost has similar properties as the RF. In both cases, the reward to a correct prediction is larger when the algorithm gets it right.



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