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# HOW TO BEAT THE MACHINES BEFORE THEY BEAT YOU

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*The use of "big" data, algorithms and machine learning is disrupting investment management. By carefully selecting domains where data is sparse and there is possibility of regime changes, a human investor can not only survive, but also thrive in a world of investment machines.*

Machine Learning and Artificial Intelligence have arrived, yet again, in investment management, and this time they come reinforced with even better data, faster speeds, better algorithms, and the benefits of a more comprehensive ecosystem.

So the question naturally arises how humans should adapt to not only survive but also excel in the investment and trading game against powerful investment machines. I take the view that algorithms are designed to respond quickly and automatically under a specific set of conditions, which creates both their superiority and limitations against human investors. The existence of large amount of data is required for algorithms to respond accurately under these conditions. But when a truly unknown event without parallel in the historical dataset occurs, human decision-making can indeed be superior. This is because human investors can evaluate scenarios and outcomes around extremely rare events, paying special attention to contrasts and differences that are not in the data. This ability to think outside the box using both rigorous logic and imagination in domains with sparse data allows humans to excel, especially when faced with regime changes. Today's investing environment, I believe, provides opportunities for human investors as a decade long regime of low volatility, central bank stimulus, and liquidity is being supplanted with higher volatility, central bank withdrawal and unpredictable politics that are in few recent data sets.

## 1 Where does investment edge come from?

Let us recall that the ability of human or machine to outperform in the inherently uncertain environment of investing arises from an edge in one or all of four main categories of expertise: (1) Information, (2) Analytical Process, (3) Execution and (4) Risk Management.

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Looking first at information as a source of investment edge, we can identify four main criteria for why certain pieces of information are superior to others. First, superior information is timely. Humans who interpret news by watching television, newspapers or even other private modes of communication are at a disadvantage to a well-programmed news scraping and text recognition algorithm. Machines can process the same information faster, and they can do it simultaneously on many channels at the same time. They also do it in a consistent manner. The same information and the same background produce the same interpretation and reaction by a machine, though this cannot be said for a human. Second, breadth of information is valuable. More high-quality information can assist in updating of priors, minimizing errors and improving forecasts through cross-validation. Third, the information has to be deep, so that a more robust logical process can be built through tests at different levels of fine-tuning. And finally, the information should be relevant to investments. Machines, I believe, have developed a distinct advantage in all four of these elements.

The second element behind investment edge, i.e. better estimation and forecasting methods, and "closed-form" analytical models, have led to rapid growth of the practice of financial theory in markets. While historically the need for good closed-form models was paramount due to relatively weak computational power, today the need for analytically tractable models is less critical. In a world of almost unlimited computational power, a pattern matching machine that can iterate across all possibilities rapidly while incorporating actual market imperfections can be as good as, or even better than, an elegant analytical model or recipe. For example, given a large number of training samples a machine learning algorithm can "learn" long division without having to learn the rules as taught traditionally in primary school. Notably, when the number of samples provided is small, the algorithm makes errors. But as the number of training samples increases, the machine learning algorithm becomes almost perfect, even for very large numbers. This example highlights the facts that the key to machine learning is data. As long as there is plentiful data on which an algorithm can train, a machine can begin to gain the type of rapid decision logic that is useful for it to make good predictions even with simple methods (see, e.g. Bishop, 2006; Alpaydin, 2014). Thus traditional tools excel when data is sparse, but they are slow. Machine-based tools excel when data is plentiful, and they are fast. This fact can be used in the investment world to advantage.

When it comes to the third component of investing edge, there are reasons to believe that machines have already acquired a substantial edge over humans. Machines do not fatigue like humans do, and machines do not change their minds based on a last minute whim, i.e. they are more disciplined in following an investment plan. Machines can also be optimized to minimize transactions costs, i.e. by splitting large orders into small orders, or waiting patiently round the clock on the bid or the offer, or sourcing liquidity from different venues. Thus, in trade execution, machines have already far surpassed their human counterparts, and this spread in capability will certainly widen with time.

Finally, risk management, which is key to long-term survival in investing, has developed standard tools, which are easily translatable into risk-based rebalancing algorithms. The plethora of volatility targeting strategies in the market today speaks for this evolution. As we know through experience, good risk management approaches (1) have good qualitative and quantitative underpinnings suited to the investment at hand, (2) are forward looking rather than just dictionaries of historical statistics and (3) allow the user to implement risk management actions in a clear and unambiguous way. Since measurement and monitoring is now easily done by a stack of servers running sophisticated risk management software, this again is a facet where the human risk monitor has a distinct disadvantage as long as the markets are stable and repeat known patterns. Less so when they can undergo regime changes that are not in the dataset.

These four elements that drive investment edge have influenced both discretionary and systematic investment styles.

The discretionary paradigm of investing is based on experts and expert knowledge. A popular example is global macro investing. A global macro investor collects and gleans all the information about macroeconomic variables, politics, positioning, etc. and makes a forecast of market direction in one or more asset classes. This approach, when successful, is based on superior expertise in obtaining information, converting that hopefully superior information into superior forecasts, and superior tactical timing of both entries and exits. As exemplified in Garry Kasparov's recent book "Deep Thinking" (Kasparov, 2017), the chess grandmaster, similar to a successful macro investor, wins by using both a deep ability of pattern recognition and by figuring out how specific types of events are likely to unfold to play well tactically, when pitted against other humans with the same tactical limitations. Anecdotally, since the advent of machines, the returns to global macro investing have suffered both because of better information processing and faster execution by algorithms. It is my guess that the more traditional type of tactical macro investing that relies on processing lower frequency economic data is going to quickly be supplanted by machines that can process the same information and execute trades more efficiently than human investors.

The second dominant approach to investing is algorithmic, or "quant". In such a style, the patterns of market inefficiency discovered by humans or machines are encapsulated into rules of some kind. One sub-style is "supervised algorithms" since humans design and update the rules which the machines implement. Trend following, risk-parity, volatility-targeting, etc. are examples of algorithmic trading styles that are supervised, but could easily arise from a machine "discovering" one of these strategies, given enough data. While parameters and specific parts of the algorithms may be different, the core ideas of systematic, rules-based investing are broadly similar across implementations. The other substyle of quant relies on "machine learning". In this approach machines are designed to find patterns in market and economic data without much human intervention. Techniques such as pattern recognition, neural networks and deep learning discover variables of interest in the data via a battery of statistical approaches, rather than by humans defining variables of interest for them.

This discussion paints a depressing picture of the future role of humans in investing. Is there any room for humans to be at par, or even excel, against their algorithmic counterparts? I believe there is. While recent history of artificial intelligence driven investing may be too short to be conclusive, the results of machine-based investing have broadly disappointed as the market environment has changed. I believe this is symptomatic. The disappointing period has coincided with a new regime of investing where politics, news surprises and the impact of global central banks have mattered much more than ever before. In other words, the data that we are obtaining today is very sparse, and this sparsity of data combined with the possibility of regime shifts creates unique opportunity for human investors.

## 2 How can humans beat machines in investment?

The central idea behind this paper is very simple: when there is little or no data, humans have the opportunity to do better than machines. Thus, when markets are near regime shifts or inflection points, human investors may be able to beat their mechanical opponents, at least until there is enough data so the machines can learn from it and level the playing field. To be able to take advantage of this small sphere of opportunity requires carefully selecting both the domain and style of investing.

1. *Look for opportunities where there is little or no data*: Since machine-based investing obtains its dominance from the ability to gather, process and even create large amounts of data, the most important avenue to gain superiority over a machine is to look for investment opportunities where there is little or no data. Note that the absence of data does not mean that probabilistic logic cannot be used. When data are sparse, probabilistic forecasts are less about statistics and more about expressing degrees of belief (see Jaynes, 2003). Using Bayes rule, humans can still make reasonable forecasts and guesses, admittedly with large errors. Machines are unlikely to even want to participate, and given the lack of data even try to form and test hypotheses and models. Examples of this unique human ability appear periodically whenever markets have a sharp change in regime and electronic market makers, who rely on algorithms, quit making markets, leaving the field wide open for human investors who can imagine and profit from outcomes that are not in the historical data. By following a decision tree, also known also as a "Bayesian net" or "graphs", where each node is dependent on previous nodes and inherits a conditional probability table, a "model" of probabilities can be built. The user forecasts probabilities of each node and the connections between the nodes that flow logic. This approach provides the ability to perform sensitivity tests, scenario analyses, and even backward induction. This approach also allows for counterfactuals to imagine events beyond the available dataset. The ability to ask "why", and think in counterfactuals is a unique innate strength of humans that machines have not been able to master, thus giving human investors a significant edge (Pearl, 2009, 2018).
2. *Invest in volatile markets*: When markets become illiquid and volatile, neither models nor statistics are dependable, even though there might be plenty of noisy data. A biased and parsimonious model can actually have lower prediction error than a fully specified explanatory model when: either the data are very noisy (i.e. high standard deviation of observations), the coefficients on the excluded variables are small, the predictors are highly correlated, sample size is small or the range of excluded variables is small (Wu *et al.*, 2007). Participating in volatile markets requires being extra careful in risk management. More volatility means a larger potential gains and losses, and exposure to the consequences of tactical mistakes. As discussed, machine-based systems usually do not participate as actively in markets that are volatility due to the perceived illiquidity and risks.
3. *Rely on strategy instead of tactics*: The cutoff of where strategy ends and tactics begin is hard to pinpoint, but with the incredibly large amount of high-frequency data that is being generated in the markets, it is not hard to see that at shorter time scales, humans have almost no edge over machines. Tactical trading requires persistence and patience in following rules, where the machine's intrinsic physical resilience is a substantial edge over humans.

Strategy requires planning, and humans so far have superior ability to play out dominant or high-probability scenarios and their preferred reactions to contingencies. Machines have been limited in how much strategic thinking they can do, since accounting for each logical possibility requires a very large amount of computation and storage, and thus the computational horizon creates intrinsic limits (though these limits are likely to become more achievable as better algorithms are developed, as the success of Alpha Go and its successors has demonstrated). In practice, emphasizing strategy instead of tactics means dilating the time scale of investing. At longer time scales, investment is more about harvesting premiums rather than capturing bid–offer spreads, so returns are a compensation for risk transfer. Tactical decision-making required at smaller time horizons is predominantly an exercise in pattern recognition, speed and capturing the bid–offer spread. Machines are better at pattern recognition at shorter time scales and certainly faster at executing rapidly. By trading at shorter time scales, humans are pitting themselves against a much stronger opponent, who is guaranteed to win as the number of games increases. As described vividly in Kasparov's book, even before Deep Blue's victory, there was a lesser known event where the machine beat the world champion in a game of "blitz chess", where each player plays in a very limited amount of time. Thus human investors should replace trading with "investing", which means a longer holding time and little pressing need to make quick decisions.

4. *Anticipate regime changes*: A number of algorithmic strategies popular in the investment industry today can be traced to common drivers and overcrowding. The democratization of machine-based trading has resulted in many of these strategies being exposed to bouts of illiquidity. The common element of these three strategies is that as volatility rises, the algorithm de-risks, and as volatility falls, the algorithm re-risks. For example, Risk Parity is an investment strategy that essentially normalizes the risks of various asset classes and equally weights according to their volatility contribution to the portfolio. At the most basic level, as the volatility of an asset class falls, it's weighting in the portfolio increases proportionately. Another strategy that approaches portfolio construction from the angle of controlling risk is "volatility targeting". The volatility targeting algorithm simply buys or sells derivative contracts (predominantly equity index futures) in response to a target risk contribution. As volatility of the equity asset class falls, the weight to equity markets via derivatives increases. As volatility rises, the weight to equity futures is reduced or might even become negative. Yet another example is from trend following which implicitly targets volatility. As the volatility of an asset class falls, the weight of that asset (contingent on it being in trend) increases relative to other asset classes. There are also other systematic volatility selling strategies that target a certain amount of "income" by selling options, which increase position sizing as volatility falls and decrease position sizing as volatility rises. Many human investors were able to correctly measure and anticipate the unwind of many of these strategies in February of 2018. Further discussion of possible regime changes exposed to "volatility contingent strategies" is discussed in Bhansali and Harris (2018).
5. *If you can't fight them, join them*: Ultimately, the age of machines has come to the financial industry, whether one likes it or not. The history of development in any field is replete with examples of a resistance to innovation, which proves to be ultimately futile, as better technology ends up dominating the field

in due course. Today's financial marketplace is at the same inflection point. It might very well turn out that the best approach to beating machines is to work with the machines so that both the human and the machine-based investor can use the best of their individual skill sets that the other does not possess, i.e. the human's better ability to visualize and imagine, and the machine's ability to process and execute much more efficiently. In the meantime, being selective with domains, horizons and styles of investing provide the best chance for human investors to succeed.

## 3 Conclusion

Data in its various forms is the lifeblood of the superiority of machines over human investors. Whether it is the availability of data, the computational power to turn the data into usable inferences, or to use the data to create speed of execution, machine-based investment strategies rely on the availability of data. When there is the possibility of large regime shifts, rare events and tail events, it is simply not possible for machines to confidently anticipate the behavior of a large number of investors since there is usually not enough data on which to base forecasts. Human investors then have an edge that they are able to use the methods of self-consistent forward logic coupled with imagination to do relatively better. In the final analysis, the combination of speed and tactics from machines, and strategy and creativity from humans will be the unbeatable combination in investing as it has already become in many other fields.

## Important Disclosures



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