

Artificial Intelligence: The new frontier for hedge funds

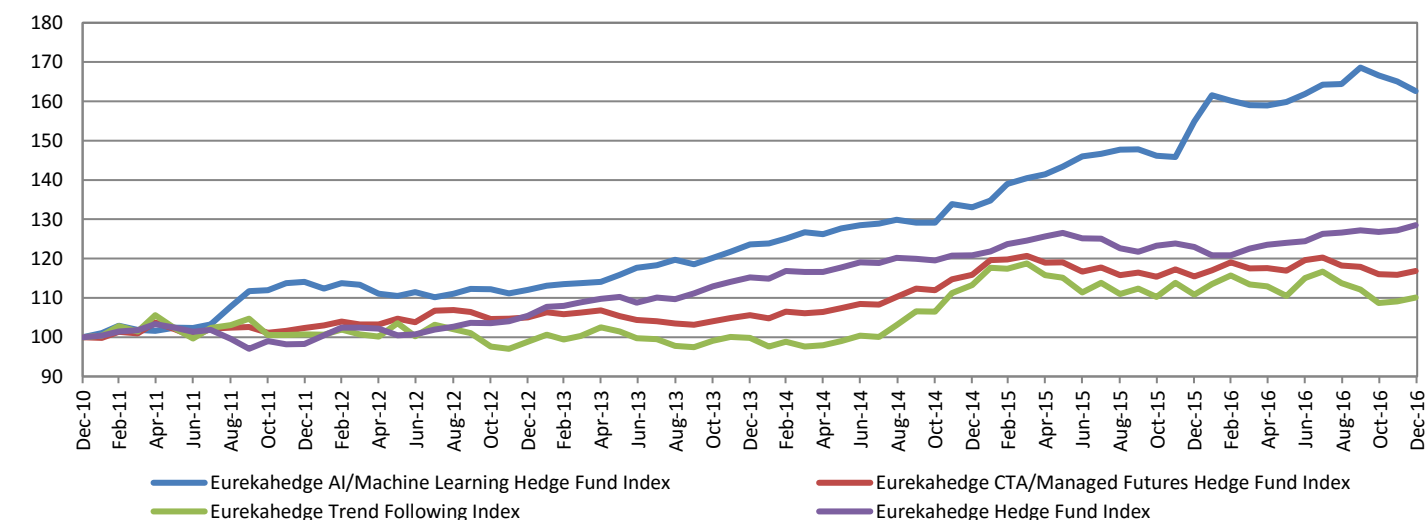
Quantitative hedge fund strategies have received considerable interest from investors over the last decade. The application of growing computing power and the availability of big data has enabled these systematic trading models to capitalise on market inefficiencies that were otherwise difficult to identify or harvest given the implied trading costs. However, this growth has met with some headwinds on two key accounts; firstly, trading models built using back-tests on historical data have often failed to deliver good returns in real time (as previously identified trends have broken down), and secondly, the diffusion of similar quant models which has led to crowding in the space and consequently depressed the returns from such strategies. The latter of the two problems is being addressed to some extent through the use of even faster processing machines (competition in the high frequency trading space) as funds race to place their trades ahead of the crowd. However, it is the developments on the first front that could transform the quant landscape as trading models upgrade from identifying trends (through back tests) to ‘predicting and adapting’ to the trends in real time (such as using walk forward tests) – i.e. the application of artificial intelligence (AI) and machine learning theory to hedge fund quants.

The application of AI in the hedge fund industry is still at an early stage – with some hedge fund managers utilising AI as a partial input into their trading process (retaining their discretionary control over investing and risk management) whilst others, what we call ‘pure AI hedge funds’, have outsourced both the trading and risk management aspect to the machine with minimal input from the fund manager. This variability in the application of AI in the hedge fund space mirrors its development in other industries as well; such as transport sector where a fully reliable self-driven car is yet to hit the roads. The challenge will lie in successfully showcasing the ability of the machine in meaningful learning, and in the context of hedge funds, consistently and profitably for their investors.

The piece below looks at the performance of hedge funds that utilise artificial intelligence and machine learning theory in their trading process and concludes with our interview with Mr. Yoshinori Nomura, Director at Simplex Asset Management who shares the nuts and bolts about his pure AI strategy and his views for the future of AI in the hedge fund industry.

Figure 1 compares the *Eurekahedge AI/Machine Learning Hedge Fund Index* with traditional quants (denoted by the *Eurekahedge CTA/Managed Futures Hedge Fund Index* and its sub-group of systematic trend followers) and traditional hedge funds as captured by the *Eurekahedge Hedge Fund Index*. The AI/Machine Learning Hedge Fund Index tracks 23 funds historically (including dead ones to account to offset any survivorship bias in index values) and as of present tracks the performance of 12 live actively trading funds. As can be seen in the figure, AI/machine learning hedge funds have outperformed both traditional quants and the average hedge fund since 2010, delivering annualised returns of 8.44% over this period compared with 2.62%, 1.62% and 4.27% for CTA’s, trend-followers and the average global hedge fund respectively. For the very volatile year ending 2016, AI/machine learning hedge funds are up 5.01%, ahead of the average global hedge fund which gained 4.48% and their peers as displayed in Table 1.

Figure 1: AI/Machine Learning Hedge Fund Index vs. quants and traditional hedge funds



Source: Eurekahedge

Table 1 summarises the key performance statistics for AI/machine learning hedge funds relative to their peers. Key takeaways include:

1. AI/machine learning hedge funds have outperformed the average global hedge fund for all years excluding 2012.
2. Barring 2011 and 2014, returns for AI/machine learning hedge funds have outpaced those for traditional CTA/managed futures strategies while underperforming systematic trend following strategies only for the year 2014 when the latter realised strong gains from short energy futures.
3. Over both the five, three and two year annualised period, AI/machine learning hedge funds have outperformed both traditional quants and the average global hedge fund delivering annualised gains of 7.35%, 9.57% and 10.56% respectively over these periods.
4. AI/machine learning hedge funds have also posted better risk-adjusted returns over the last two and three year annualised periods compared to all peers depicted in the table below, with Sharpe ratios of 1.51 and 1.53 over both periods respectively.
5. While returns have been more volatile compared to the average hedge fund (compare with *Eurekahedge Hedge Fund Index*), AI/machine learning funds have posted considerably lower annualised volatilities compared with systematic trend following strategies.

Table 1: Performance in numbers – AI/Machine Learning Hedge Fund Index vs. quants and traditional hedge funds

	Eurekahedge Event Driven Hedge Fund Index	Eurekahedge Distressed Debt Hedge Fund Index	S&P GSCI	Bank of America Merrill Lynch US High Yield Index
2011	14.10%	2.33%	0.71%	(1.75%)
2012	(1.80%)	2.66%	(1.86%)	7.34%
2013	10.34%	0.55%	1.02%	9.24%
2014	7.64%	9.66%	13.44%	4.89%
2015	16.40%	(0.31%)	(2.18%)	1.78%
2016	5.01%	1.15%	(0.62%)	4.48%
5 year annualised returns	7.35%	2.68%	1.80%	5.51%
5 year annualised volatility	4.95%	4.18%	7.13%	3.20%
5 year Sharpe Ratio (RFR=1%)	1.28	0.40	0.11	1.41
3 year annualised returns	9.57%	3.41%	3.31%	3.71%
3 year annualised volatility	5.61%	4.63%	7.78%	3.03%
3 year Sharpe Ratio (RFR=1%)	1.53	0.52	0.30	0.89
2 year annualised returns	10.56%	0.42%	(1.40%)	3.12%
2 year annualised volatility	6.31%	4.90%	8.07%	3.31%
2 year Sharpe Ratio (RFR=1%)	1.51	(0.12)	(0.30)	0.64

Source: Eurekahedge

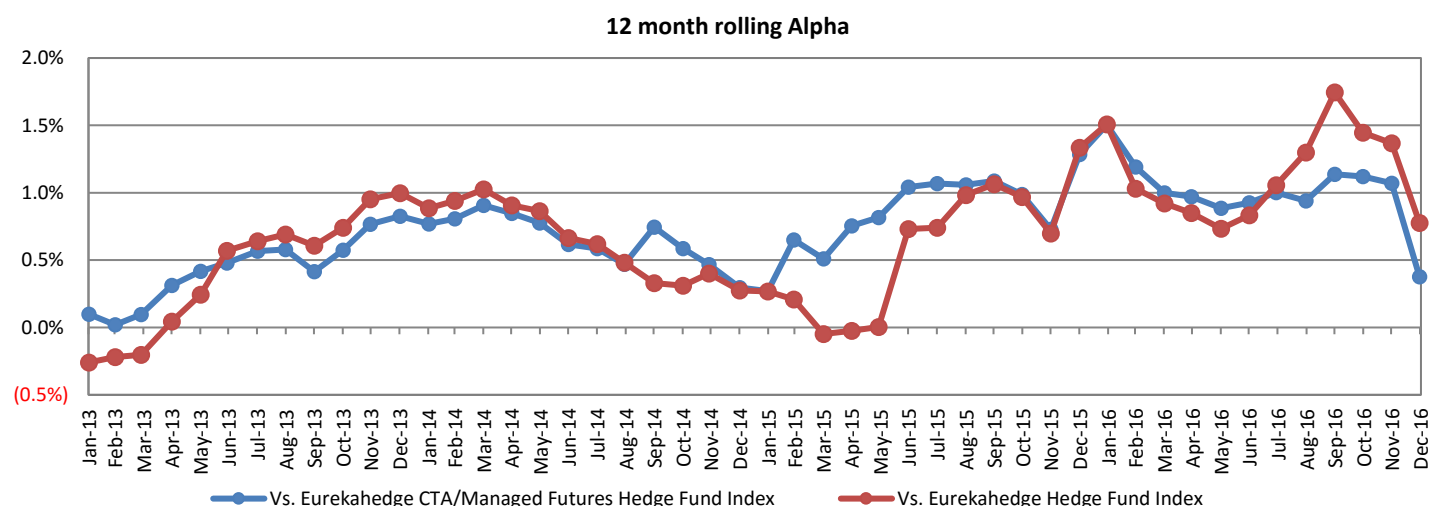
Table 2 shows the correlation matrix of AI/machine learning hedge funds with respect to their peers identified. It is interesting to note the strategy is negatively correlated to the average hedge fund (-0.267) and has zero-to-marginally positive correlation to CTA/managed futures and trend following strategies, highlighting the positive gains that can accrue to the overall portfolio from a potential diversification across this strategy.

Table 2: Correlation matrix

	Eurekahedge AI/ Machine Learning Hedge Fund Index	Eurekahedge CTA/Managed Futures Hedge Fund Index	Eurekahedge Trend Following Index	Eurekahedge Hedge Fund Index
Eurekahedge AI/Machine Learning Hedge Fund Index	1			
Eurekahedge CTA/Managed Futures Hedge Fund Index	0.014	1		
Eurekahedge Trend Following Index	0.062	0.938	1	
Eurekahedge Hedge Fund Index	(0.267)	0.284	0.178	1

Source: Eurekahedge

Figure 2 depicts the 12-month rolling alpha (excess returns assuming zero risk-free rate) of AI/machine learning hedge funds relative to CTA/managed futures strategy (approximating quants) and the average global hedge fund. Alpha has generally been positive with 12-month alpha for the year ending 2016 coming in at 0.38% and 0.78% relative to CTA/managed futures strategies and the average hedge fund respectively, pointing perhaps towards a combination of the improved capability of AI/machine learning models and the over-crowding (shrinking alpha) in comparable strategies.

Figure 2: 12-month rolling alpha relative to quants and traditional hedge funds


Source: Eurekahedge

To conclude, Table 3 looks at the performance of AI/machine learning hedge funds and their peers during periods of market stress in the recent past and gauges the ability of different strategies to deliver positive returns in volatile times. Key takeaways include:

1. AI/machine learning hedge funds have been in the red in three out of the 11 monthly risk events identified in the table below, the least among the group. In comparison, the average global hedge fund posted losses in seven out of these 11 months.
2. With regards to some of the idiosyncratic risk events identified in Table 3 such as the Trump win and Brexit, AI funds have posted a mixed record but have done relatively better compared to their peer group. An improvement in AI application and its learning capabilities could perhaps yield even better results in the future, but as their recent losses in November 2016 (Trump win) show, there are clear limits to predicting the future for the machines.

Table 3: AI/machine learning hedge fund returns during key market risk events

Date	Event	AI Hedge Funds	Eurekahedge CTA/Managed Futures Hedge Fund Index	Eurekahedge Trend Following Hedge Fund Index	Eurekahedge Hedge Fund Index
Nov 16	Trump Win	(0.94%)	(0.18%)	0.38%	0.31%
Jun 16	Brexit	1.29%	2.32%	4.18%	0.32%
Feb 16	Oil Price Dip/China growth concerns	(0.86%)	1.71%	1.92%	0.00%
Jan 16	Oil Price Dip/China growth concerns	4.33%	1.33%	2.42%	(1.74%)
Aug 15	China Equity Crash	0.72%	(1.72%)	(2.54%)	(1.92%)
Jul 15	China Equity Crash	0.43%	0.97%	2.25%	(0.06%)
Jun 15	Greek referendum	1.84%	(2.00%)	(3.28%)	(1.14%)
Jan 15	Swiss Franc De-pegging	1.30%	3.23%	3.87%	0.78%
Sep 14	Oil Price Dip	(0.57%)	1.98%	3.33%	(0.22%)
Jun 13	Taper Tantrum	1.56%	(0.93%)	(1.66%)	(1.31%)
May 13	Taper Tantrum	1.55%	(1.41%)	(1.07%)	0.45%
Nov 16	Trump Win	(0.94%)	(0.18%)	0.38%	0.31%

Source: Eurekahedge

Interview with Yoshinori Nomura, Director at Simplex Asset Management Co., Ltd.

Simplex Asset Management Co., Ltd. is an independent hedge fund and investment management firm in Japan founded in 1999. The AUM is JPY 507 billion as of September 2016.

1. Please share with our readers a bit about your background, and in particular what led you to starting a pure artificial intelligence (AI) driven hedge fund? When did you first conceive this idea?

I have a Master of Science in physics at Waseda University, and majored in Nonlinear Non-equilibrium Statistical Mechanics which served as the inspiration behind my investment strategy. After graduate school, I joined Nomura Research Institute, an affiliate of Nomura Securities group, where I conducted a lot of data mining projects and demand forecasting projects as a business consultant. I also worked for Accenture and Citigroup Global Markets, before I joined Simplex Asset Management (SAM) in 2008. In SAM, I took over a portfolio manager role of a quant driven market neutral strategy of Japan equities which used very traditional multi factor models and performed not as well as was originally expected. So, I started exploring why back tested simulations do not work and what should be done so that I can trust the result of simulation. My basic premises were as per the followings; 1) the model should be as simple as possible, 2) there should be some governing dynamics of pricing model just like physics, 3) the model must have some capability to learn and adjust to the changes in the market environment whilst maintaining its predictive capability. Creating a new mathematical model took many years of using physics theories, and in addition AI/Machine Learning methodologies were applied to implement learning and adjusting function. I believe that there are many people who are not completely satisfied with CAPM and multi factor models as scientific pricing models. So, I ambitiously tried to construct some sort of alternative to describe different aspect of real market dynamics. That's why I created this pure AI driven strategy.

2. How difficult was it to launch such a niche strategy that sits right at the frontiers of the fund management industry?

It took a few years to find a seed investor after I created the strategy. I guess it was partly because there were many investors who had lost money investing in quant strategies before and partly because the word 'AI' was too new for the institutional

investors such as banks to pass along to internal investment committee. Most importantly, there was neither a real track record nor a similar kind of AI strategy to compare with. Therefore, as I mention later again, demonstration of 'Walk Forward Test' was crucially important to convince investors about the merits of my pure AI offering.

3. Our research indicates that there are only a handful of pure AI hedge funds out there in the industry, with others who utilise limited aspects of machine learning theory to their investment models. What is the current nature of AI application to the hedge fund space and what are the key challenges complicating its adoption among systematic strategies?

Current popular utilisation of AI technology is a simple substitution of human routine tasks because AI is fast and accurate without fatigue. For example, estimation of stock price impact of news announcements by comparing precedential cases, reading financial results or analyst reports to find hidden causality between many companies' results, text mining of Twitter to find correlation between stock price and some words, etcetera. These are just pieces of convenient cutting edge technologies, a partial adoption of AI but cannot be integrated as a pure AI strategy.

On the other hand, traditional systematic players might use AI, too. They usually monitor many indices to predict market directionality and AI/machine learning methods might be applied to find the best combination of chart patterns of indices to predict the future. This approach is sometimes referred as 'Evidence Based Technical Analysis'. Here is the challenge. AI can easily find the best correlations between patterns but they can be false correlations which might lead to a big loss because 1) A machine does not learn any meaning of causality between indices, 2) A human might not be able to understand what a machine learned and evaluate if it is meaningful or not, and 3) There might not be any reason or evidence that some specific indices can predict the future in the first place. Therefore, it is not surprising at all if a pure AI driven systematic strategy does not work well. At least, I don't know that any academic research has solved this issue of 'meaningless learning'.

4. How has the AI-driven Simplex Equity Futures Strategy overcome these challenges? Could you share some details about your strategy, and an example of an AI-executed trade that highlights the superiority of machine learning based investment in relation to the traditional systematic strategies.

In order to avoid the aforementioned meaningless learning problem, I used physics theories which give a priori meaning to the model's answer. A motion equation of price describes the governing dynamics of a market such as the TOPIX. As physics always tries to be simple and universal, I focused on describing the simple and universal phenomena of financial markets, i.e. momentum and mean reversion which are naturally observed when many investors interact through their trading activities in the marketplace. Input data utilised for the model is a single time series of historical price which derives momentum index and mean reversion index. In order to adjust the motion equation to the current market environment, the AI/machine learning method is applied.

Generally speaking, CTAs tend to use trend following strategies which works well when there is strong momentum in the market but does not work well in mean reverting environment. Counter trend following strategies are just the opposite. Our strategy looks at momentum and mean reversion at the same time so that it can adapt to both market conditions.

In terms of the superiority of AI-based strategy to traditional systematic strategy, the AI model can have daily automatic learning and adjusting function which allows the strategy to maintain its predictive capability even if the market environment changes, whereas a traditional systematic strategy usually does not change inner parameters in the model so often because human analysts usually require at least a few months to find new parameter set, which might be too late to catch-up with quickly changing market.

5. What is the 'walk forward test' and how does it help maintain the predictive capabilities of your trading model?

'Walk Forward Test (WFT)' is a verification method of sustainable predictive capability of a quant strategy as an alternative to back test. New quant strategies will always suffer from a 'chicken and egg' problem, and have a tough time convincing investors that a good looking back tested result will not fail in real time and suffer from the classic 'betrayal of the back test' phenomenon. WFT avoids this 'betrayal of the back test' and directly evaluates the sustainability of the predictive capability of the new quant model. A good looking back test result might be dubious because the quant analyst knows the result of market at first place and can choose the best combination of trading strategies in the back test period of time to make it look the best, however this 'optimisation' does not usually lend predictive capability to the model. On the other hand, the result of WFT is based only on prediction by the model which does not use any future information in prediction. WFT uses historical time series (ex. 20years) and the model firstly looks back certain period of time (ex. 1 year look back from 19 years ago) to learn and adjust to the market condition of its present (ex. 19 years ago). Then, the model predicts the future and trades for a short period of

time (ex. a week). After the profit/loss of the trade is fixed, it looks back the same period of time again to refresh the model's predictive capability and repeats this process until the end of the historical data. If the model has no predictive capability, the result of WFT is miserable, but if the result shows stable returns over time, it is very difficult to say the model does not have any predictive capability since all the result are implemented only by the prediction. At least, if a human trader with a good track record can be considered to have sustainable predictive capability for some reason, an AI model with a good WFT result can be considered in the same way.

6. On average, how many trades are executed in a given day, and how large is the investment opportunity set for the model? Could you also detail the maximum/minimum gross exposure for the strategy?

We trade twice a day, open and close of the Japan market. Current strategy allows approximately USD 500mn of capacity. The maximum gross exposure is 200% and the minimum is 0% of NAV and net exposure can vary from -100% to +100% of NAV.

7. In this process of drilling down and optimising to the best trades, how often has the machine got it right? Apart from the actual performance of the fund that an investor would look at, is there a performance indicator that evaluates the machines ability to zero-in on the best trades?

The WFT indicated monthly winning rate is 60% with +2% of return and 40% with -1% of return. The AI model has a conviction evaluator that indicates the degree of wining probability in every trade.

8. What kind of market environments are best and least suited to the performance of your strategy? Humans have a terrible record of learning from history, does the machine hold more promise or will it be equally susceptible to idiosyncratic events such as GPIF buying domestic equity ETFs, Brexit or a Trump win?

The model learns from historical time series of price. Therefore the model is expected to be effective if the market environment is consistent with the near past. Obviously, the model does not foresee any of idiosyncratic event such as natural disaster, referendum, or political change which are very difficult for humans too. The good point of AI is that AI has no cognitive bias which sometimes overwhelms people's mind especially in idiosyncratic big events such as Brexit and forces them to trade at undesired timing, but the AI without cognitive bias might be able to learn purely from the market reactions to the sudden chaos which sometimes happen in the market and react differently from humans in an idiosyncratic event.

9. Eurekahedge research shows that AI/machine learning hedge funds did better during the market turmoil of Brexit but posted losses in November following Trump's election win in the US. Based on your fund's experience during these two time periods and your research on walk-forward tests (WFT), how would you explain these contrasting results?

The similarity of Brexit and Trump's election was the investor's failure of optimistic expectation, but the difference was the investor's reaction after the events. I don't know what other hedge fund AIs thought and acted in the events, but I guess there are two possible reasons. If they are trend following type AIs, the short term trend looked downward before Brexit so it was reasonable to hold short position in Brexit. Whereas in the Trump's case, the short term trend looked upward. This opposite trend directionality might have lead different results in both events. Second reason is more complicated. The AIs might have learned former negatively shocking events which were usually followed by second dips including Brexit. Therefore the market movement seems to be more predictable for AIs in the Brexit case. Whereas in the Trump's case, second dip did not happen and the market started to climb up in one direction. I think AIs have not learned this kind of movement before. My AI had the same problem however, the WFT research shows the AI has learned the Trump's case and is now able to deal with the same situation in much better way. This is an example of AI's adaptive capability to the change in market environment.

10. How is risk managed and mitigated within the strategy? As the fund manager how often will you intervene, and is there ever a 'pull the plug on the machine' option under consideration if the AI comes to terms with a totally unexpected market environment?

The AI model includes risk management function. In the case of weak conviction of directionality, the model automatically unwinds target exposure. There is no fixed hard limit loss cut rule but the AI model automatically adjusts the target exposure in accordance with the market situation. I have never intervened in the AI model and there is no plan to do that because human judgement can be contaminated by cognitive bias especially in an unexpected situation. However, AI technology develops day by day. We will be able to upgrade the AI model to become more flexible to unexpected abrupt market changes.

11. How well has your unique offering been received by investors and what have been some of their common concerns regarding the strategy?

I think many investors show their interest in our simplified application such as only using one input time series with only two factors (momentum and mean reversion) to predict the future, and only twice trade a day. WFT also receives attention especially from quant experts who know well how difficult it is to create a model that can pass the WFT.

However, the fund was only incepted as of April 2016. So, this short real track record is the largest challenge for us because many investors have their internal rules about minimum period of real track record even if WFT shows a good result.

12. Lastly, what is the future of AI in the hedge fund industry? Could fund managers look forward to a stress free holiday in the distant future knowing their client investments are safe in the hands of the machine?

The role of AI will increase significantly in the hedge fund industry - an inevitable destiny. Most of the routine work will be taken over by AI or machines even if it requires difficult training for humans. Traditional quants strategies will be taken over by AI. Some part of the bottom up analyst work will be done by AI, too. Traders have already started to be taken over by AI or machines.

However, AI's master fund manager might not be able to enjoy holidays sleeping on the beach because in the future there might be stronger and smarter AIs trading in the marketplace at any given time.