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INSIGHT INTO SA INVESTING FROM LEADING PROFESSIONALS

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Inside

HOW TECHNOLOGY IS IMPACTING ON FINANCIAL DECISION-MAKING

By David Kop

INTRODUCTION

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Navigating a technologically-shaped reality

Artificial intelligence and machine learning are radically reshaping our world, providing humans with great benefits. However, this shift can also have detrimental effects. Understanding these developments – and how they affect our daily lives – is important when making everyday decisions.

I am a self-confessed geek and love science-fiction movies. Being involved in a publication regarding technology, artificial intelligence (AI) and machine learning first had me scared. I have seen the movies and I know what happens when technology starts to think for itself. Humans end up with one of two careers: either a freedom fighter or a battery for the machines.

As I started reading through the various article contributions, and doing additional research, that fear has subsided a bit. It is clear that the march of technology is inevitable. And, in fact, it is when machine and human work together that the best results are achieved (at least for now).

Knowledge can do much to calm fears. This issue aims to share ideas on technology and how it is having an impact on investing and financial decision-making.

▶ The trust factor

As humans, we inevitably do not trust what we do not understand. In his article, Rudie Shepherd asks why it is a leap of faith for us to place the same trust in machines as we currently do in human financial advisers. Technology may be the answer to delivering the service – which human experts currently provide – at an affordable cost to a broader market.

▶ Terms of engagement

The question that remains is: What are the areas in which technology can be used to improve efficiencies in investing? Steven Sidley highlights three areas in which technology can be used. However, the use of technology comes with a warning – do your homework. While technologies can improve effectiveness, the plethora of options available make choosing a provider – human or automated – much more difficult than in the past. This decision should be approached with research and a healthy dose of scientism.

The rise of technology, taking us forward from carrier pigeons to newsletters and slide rules, introduces new terms. In today's world, the terms AI and machine learning are being thrown around. But what do they actually mean? Hywel George provides some insight into the different terminology and what AI means for investors.

Ainsley To does a deeper dive into machine learning. He provides some insight into its uses, but also its shortfalls, and advocates for pragmatism and intellectual honesty when using these new tools.

We must also not forget at this stage that technology analyses a set of data to provide a solution. Shazia Suliman argues that the quality of the model is based on accurate and complete datasets.

▶ Regulation and the human touch

Automation comes at a very human cost. Jobs once done by humans will be replaced by machines. Of course, technology creates new jobs, but if a person is not able to reskill, unemployment will increase. Hannes van den Berg and Terry Seaward provide a strong argument for the use of technology coupled with human insight to achieve better results.

Just as new technologies are employed in investing, so too do the regulations and supervision capabilities need to change. Unfortunately, it seems that the pace of change outstrips the pace of regulation. In some instances, innovation can be stifled due to archaic and outdated regulations and laws. A balance needs to be found to allow innovation, while at the same time protecting the consumer. Richard Rattue explores the rise of regulation and supervision technology alongside financial technology and the future role of the compliance officer.

▶ Ethics

Susan Spinner asks the question: Alexa, are you acting in my best interest? I recall an advert for one cellphone service provider where a child is wanting to learn a word and asks the virtual assistant for a definition. But what influence will these virtual assistants have on our children? Are

While technology can currently replace many of the repetitive tasks, it cannot yet replicate the very human characteristic of empathy. This calls for human oversight of AI, as well as complete transparency in technological development.

they programmed to act in their best interest? We have seen how googling a seemingly innocent phrase can bring up unintended search results. Susan provides examples of where AI has gone horribly wrong.

While technology can currently replace many of the repetitive tasks, it cannot yet replicate the very human characteristic of empathy. This calls for human oversight of AI, as well as complete transparency in technological development.

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Conclusion

The controlled use of fire by humans (widely believed to have begun about 300 000 years ago) was one of the most important technological advances in our history. It led to significant changes in human behaviour and diet. Activity no longer had to be restricted to daylight hours due to the light the fire provided. Fire offered protection from predators. The ability to cook food allowed us to expand our diet to meat and more starchy vegetables that led to an increased calorie intake.

For all the benefits of fire, it can also be deadly, destroying homes and animal habitats and releasing greenhouse gases into the atmosphere.

Likewise, the progression of AI can have significant benefits to humankind. However, we must proceed with caution, lest science-fiction movies depicting a dystopian future with machine overlords and human slaves become science fact. ■

David Kop is an executive director at the Financial Planning Institute of Southern Africa.

By Jessica Phalafala

TECHNOLOGY

Demystifying artificial intelligence

Financial markets are characterised by large volumes of data, making them highly suitable for the adoption of AI. In fact, the technological revolution has already resulted in highly efficient global financial markets.

Artificial intelligence (AI) has had a significant global impact by changing the way enterprises, markets and consumers define efficiency and innovation. Financial markets typically feature large volumes of noisy and dynamic data while utilising highly complex quantitative models. This, therefore, makes them a suitable area for the application of AI.

Put in the simplest terms, AI refers to the integration of intelligence in machines that imitates the natural intelligence humans possess. The combined development of high computing power, improved data generation and storage capacity, together with increased accessibility of affordable computing, has resulted in the rising adoption of AI in finance and investments.

Developments in this field are not limited to the devices and apps we use today. IBM's Deep Blue computer made history in 1997 by winning a chess match against the reigning world champion at the time, Garry Kasparov, showcasing the capability of AI to the world.

Machine learning is the subset of AI where algorithms and statistical models not only use data as an input, but recognise patterns in the data and make valid deductions with minimal human intervention. The learning process is enhanced if there is a larger dataset to "learn" from. This results in robust pattern recognition, inferences and findings that can be readily generalised. For example, the more shows an individual watches on Netflix – thereby generating usage data – the more suitable the suggestions made by the underlying recommender system employed by Netflix. Similarly, the more you use your credit card, the less the chance your purchase will be declined due to fraud detection.

The full advantage of the application of machine learning in investments is particularly realised in the development of quantitative models that are used to analyse the high volumes of data generated in markets. Deep learning is the specific subset of machine learning that deals with complex/dynamic structures in a manner inspired by the workings of neurons within the human brain. Deep learning algorithms analyse data iteratively by passing it through multiple layers.

The initial layers evaluate simple features of the data and latter layers identify the more complex features. For instance, Natural Language Processing – a deep learning algorithm – takes simple text data collected from tweets, newsfeeds and other media to perform sentiment analysis of market developments. This analysis can then be integrated into a larger quantitative model to inform an investment decision.

AI is no longer limited to the use of intelligence services and massive corporations like Google and Facebook. It is within our immediate reach. The fourth industrial revolution is driven by big data and high-performance computing.

There has been an exponential increase in the amount of data generated globally and at the average person's disposal. In fact, according to Forbes, by the middle of 2018, 90% of all the data in the world had been generated in the preceding two years. Technological advancements have contributed to this vast proliferation of data by introducing new datasets such as credit card usage, satellite images and social media posts. A new dataset that has the potential to significantly change the landscape for financial and banking services is the Internet of Things (IoT). The IoT refers to a system of devices, objects or living subjects that receive and send data over a network.

The International Data Corporation projects that global investment in big data will rise to

$203bn

in 2020, compared to the $130.1bn investment realised in 2016.

A bank can, for example, use the foot traffic data generated from a network of ATMs to determine the optimal number of ATMs to open in specific areas, as well as to determine the most suitable services for the customers at a particular location.

The International Data Corporation (IDC) projects that global investment in big data will rise to $203bn in 2020, compared to the $130.1bn investment realised in 2016.

Photo: Shutterstock

The technological revolution has also led to a transformation of market microstructure. Open outcry markets consisting of human floor traders are a relic of the past in this era of algorithmic and high-frequency trading (HFT).

HFT exploits extremely fast speeds to perform trading based on automated quantitative models. In the case of ultra-low latency HFT, the amount of time required to send orders through to their endpoint is measured in nanoseconds. This challenges the physical limitations of sending information through time and space. HFT combines these fast speeds with the ability of machines to gather vast amounts of data from various sources, such as web scraping, financial statements and newsfeeds, in order to execute trades swiftly with minimal market impact. This has led to highly efficient global financial markets with minimal arbitrage opportunities.

All market participants need to embrace these new technologies. AI is no longer a buzzword that is loosely used to describe futuristic technology. It is today's reality; something to be globally adopted like the use of electricity after the second industrial revolution. ■

Jessica Phalafala is a quantitative analyst at Prescient Investment Management.

By Rudie Shepherd

MACHINE LEARNING

How about a 'self-driving' financial plan?

Imagine a personal financial manager who focuses solely on your financial goals. Now imagine the costs related to such an agreement. And now imagine if AI could make such a service affordable to you.

I am fascinated by self-driving cars. Slightly horrified actually. That video of the guy fast asleep behind the wheel of his Tesla hurtling down a road at highway speed is enough to make anyone hold their breath just a little and go, "How stupid!" And then, after letting it sink in… "How amazing!"

If the video was about a guy fast asleep in the passenger seat of a taxi you would think nothing of it. He too is using a "self-driving car", isn't he?

We have grown accustomed to trusting strangers with our lives on the premise that they are human – and know what they are doing. Not only to drive us around but also with managing our money.

As humans we will entrust an investment manager with our life savings, with the confidence that, as a trained expert with years of experience, they too know what they are doing.

Trusting machines with the same responsibility is still a huge leap of faith for most people – but why should it be? Given the same training, trial, error and real-world experience as a human, why would the outcome be any less acceptable?

The building blocks of artificial intelligence

Let's consider the ordeal of getting to the airport in peak-hour traffic. Not a simple task, given the many obstacles and dangers along the highway. But after the umpteenth trip, an experienced taxicab driver can do this without having to "think" about it much, using their brain (a literal neural network), connected to their eyes and muscles (a sensor network), to steer a car (a driving algorithm in the sub-conscious).

Machine learning is similar. A sensor network (cameras, LIDAR, GPS) feeds an artificial neural network to process the data using algorithms, each with a specific purpose.

Unfortunately, the subject matter of data science is so convoluted with complex terminology that it becomes difficult to see the forest for the trees (if you pardon the pun referring to AdaBoosting using K-means clustering, assisted by a support vector machine with principle component analysis to isolate the occurrence of K nearest neighbour objects matching orientation of similar gradients in a homogeneous dataset of spatially related green and brown objects…).

Data science doesn't have to be rocket science. The basic capabilities of machine learning are the same as you would expect a human to have in the same situation. Expressed in simple human terms, the key algorithms in machine learning are responsible for:

- Detecting objects (e.g. potential obstacles in the area).
- Recognising distinct objects and patterns (like the minibus taxi ahead).
- Locating an object of interest in the scene (in the emergency lane where it doesn't belong).
- Predicting where the object is going to be next (90% confidence it will cut in in front of us in the next few seconds).
- Reinforcement through trial and error (that's the third one in ten minutes… Now 99% sure the next one will do the same).

The same capabilities and associated algorithms are as useful in personal financial management as they are in self-driving cars because **detecting risk, recognising patterns, tracking trends, predicting the future** and **learning from mistakes** is all in a day's work for a financial adviser.

If we can successfully apply these algorithms in financial services, we can indeed create autonomous personal financial management – or a self-driving financial plan, if you will.

In fact, maybe a machine can be better at retirement planning than a human? Consider the inherent human handicap of a short memory, limited pattern-recognition abilities and the tendency to follow popular trends over personal circumstances. Maybe an algorithm will do a better job?

For starters, the machine has an extremely large dataset to draw experience from – including experience from a network of connected "brains" exchanging trial and error data at the speed of light. With its near-perfect memory, it can see patterns over time and can predict what may be lying ahead.

It is objective and unbiased, and not fazed by small bumps in the road. It doesn't have a biological clock ticking, so it can make better long-term decisions. When the time comes to act fast, it can do many things in parallel, considering many courses of action to avert a catastrophe. It is dedicated to one master and that is you, serving your personal interests with infinite patience.

If we can successfully apply these algorithms in financial services, we can indeed create autonomous personal financial management – or a self-driving financial plan, if you will.

Imagine if your personal financial adviser was all that. Some humans are like that. The exceptional ones. As sophisticated as today's machine learning is, it still does not compare to a truly talented human with a mastery in their field. The machine can emulate but it cannot innovate – yet.

If I had the choice, and the financial means, I would, of course, prefer a human expert to dedicate 100% of their time to me and my goals. Who wouldn't want their own chauffeur or dedicated financial manager? But I don't have the means, and neither does the majority of society. So for me, the most exciting development in AI is the ability of machines to learn from the most capable humans on earth – and one day bring those once-exclusive capabilities to me at a price I can afford. If the progress with self-driving cars is anything to go by, that day for financial services is very near indeed. ■

Rudie Shepherd is head of digital innovation and platform management at Alexander Forbes Empower.

Photo: Shutterstock

By Steven Boykey Sidley

FUNDAMENTALS

Dear investor, do your homework

Technology has the potential to change the way we invest, what we invest in, and how we value our investments.

Many years ago, I lost a painful amount on a major European corporation which was part of a basket of equities that a high-priced money manager had assembled for me. The AAA-rated corporation suddenly went bankrupt and it was 10% of my portfolio.

Never again, I said. That was 1999.

And so I began a two decade-long excavation into how to use technology to give my investments an edge, both in growth and capital preservation. My idea was to apply statistics to stock price series (and to fundamentals) in order to extract patterns of predictability. I joined up with a scientist in Cincinnati and a programmer in Singapore (who I had met online) and we got started.

Millions (literally, millions) of lines of codes were written. Hundreds of systems were imagined, designed and coded and tested by us.

We never lost money, nor did we make money.

We were stumped by all manner of challenges. Like our order being received on Nasdaq a mere 50 microseconds too late (compared to someone with a server just metres from the exchange). Like being bested by people who understood fast-trading bid-ask spreads better than we did. Like dark pools (don't ask). Like being killed at the open auctions, where prices bounce wildly and without discernible direction for about 15 seconds.

No matter. I got into this so deeply and spent so much time reading and testing and coding that I can now speak with callused-knuckle experience about the tech-driven investment landscape.

Photo: Shutterstock

Here is the view:

The application of technology to investing happens in three broad areas. These are trading, company analysis and asset allocation. There are other related tech developments like cryptocurrencies, but that is a subset for another day.

1. Trading

Trading refers to the activity of taking a bid price for an asset from a buyer and matching it as closely as possible to an ask price from a seller. The transaction is handled by a broker – a human, historically, but increasingly via a computer algorithm. Trades are also assembled and codified and repackaged into a moving price chart, so familiar to all of us in stock market charts.

Over the last 20 years the advent of real-time ticker price feeds, powerful low-cost computing and fast fibre networks has given the ability to both the 16-year-old enthusiast and the PhDs of Goldman Sachs to ingest these charts and to feed them into algorithms with the hope of predicting where the price will go next.

This may be from the micro-second timeframe all the way to much larger frames – minutes, days, months, even years. And the algorithms? Design or buy, it really doesn't matter to the computer.

How well have these trading algorithms fared? In the early days of technical trading (around 1980s) it was indeed possible to find what is called "market inefficiencies" to gain an edge – sometimes a significant one. History is replete with sudden wealth fuelled by a smart trading algorithm.

But nothing lasts forever, and as new entrants started diving into algo-trading marketing, opportunities for an edge became harder to find, particularly with the advent of high-frequency trading and machine learning.

There are hundreds of books on technical trading (sometimes called technical analysis). I have read many. Oscillators, head-and-shoulders stochastics, cyclicals, candle patterns, moving average breaches, etc. A few seconds of analysis will reveal the obvious – if there was a way to beat a market with these published techniques, then it would be either quashed by hoards immediately, or everyone would be billionaires. In my view, it is all nonsense.

But lurking in the millions of times series charts (of which there are millions – stock prices, bond yields, futures, interest rates, unemployment, agricultural figures, weather forecasts) there may well be gold. Sooner or later someone (or an algorithm) who finds a short-to-long-term price predictor will get rich if they (or their algorithm) are lucky enough to move fast, ahead of the mob. Or at least faster than a competitive algorithm... For a short period before the window closes.

2. Company analysis

Compared to trading, the world of company analysis is more staid, and has been around for long before tech came on the scene. Ask Warren Buffett.

Take a company's published financial figures and apply some math to the various rows and columns in the income/balance sheet and cash flow statements. (This usually refers to public companies where such figures are publicly accessible.) It can obviously be done faster and deeper with tech now, and more companies and other variables (like sector analyses) can be cross-correlated as part of the analysis.

Also central to company analysis is valuation. How much is a company worth? Does the invisible hand of the market know? Or a clever human analyst in a corner office somewhere? Or a smarter piece of software in the cloud?

Take a look at the valuations of some of today's unicorns. Like WeWork (estimated at $4bn in August). I certainly gasp, failing to understand some of these valuations. But it is likely that various pieces of smart software disagree with me.

The analysis of a company's prospects has, of course, always been part art. Is the CEO a good enough leader? Will the marketing plans strike a nerve with customers? Are there unseen political risks in geographies of consumption? Is the IP defensible (remember MXit?).

These factors are currently beyond tech analysis. But then again: never say never.

3. Asset allocation

Asset allocation has also been around for a long time, both within an asset class (like, for example, property stocks vs tech stocks, agri stocks or manufacturing stocks), and across asset classes (like stocks vs bonds vs collectibles vs currencies, etc).

This is a massive area for tech investment right now. Companies like Betterment provide to the retail investor the ability to balance a portfolio according to the investor's needs – it could, for example, exclude stocks with exposure to alcohol or cigarettes, and increase exposure to renewables (with a little biotech on the side) at a fraction of the cost of a human analyst or broker.

> **Technology addressing this fecund ground can instantly repurpose a portfolio based on user-defined rules, instantaneously adjusting for risk and liquidity and other measures.**

Technology addressing this fecund ground can instantly repurpose a portfolio based on user-defined rules, instantaneously adjusting for risk and liquidity and other measures. While tech has been applied to allocation since before the days of Harry Markowitz's portfolio allocation theories of the 1970s, it has only recently become available to retail investors via low-cost investment applications, for which there is vicious competition.

The sea-change in investor tech has been driven by a single phenomenon – Moore's Law. While this originally was written to predict the density of transistors on a chip, it has been somewhat bastardised to extend to storage, communications speeds, saturation of smartphones, etc. It has had the effect of exploding out the black-box secrets living behind the doors of the grand old investment houses; and into the hands of the common investor.

And it is just started. In the chase for alpha (a real definable word which basically means outsize profits) in a world in which our old assumptions (like always increasing property prices, currency stability, the robustness of derivatives, predictable stock market volatility etc) are being shot down every few years, we can be sure that technology (and particularly the promise of AI and machine learning) will fuel an arms race for the smartest investment strategies.

It is not clear who will win, or whether it is winnable, or whether the underreported wisdom of simply investing in the S&P 500 will calmly take the prize.

Finally, what does this all mean for the average consumer, who simply wants the best return for his or her money? It means homework. Handing over cash for investment to an institution or software package or fund manager is a consequential decision, and is much more complex today than a generation ago. It means familiarising oneself with the latest in investment technologies, even on a superficial basis. It means a lot of Googling, and even more scepticism.

If the individual consumer is not prepared to do this, well, caveat emptor. ■

Steven Boykey Sidley is a director at Bridge Capital Future Advisory.

By Hywel George

INVESTMENT EFFICIENCY

Is AI all hype? Or the next revolution in asset management?

The question in the world of investment professionals should not be whether artificial intelligence will make them obsolete. Rather, it should be around how machines can be used to improve efficiencies.

2017 saw the advent of the first fully artificial intelligence-powered, daily traded exchange-traded funds (ETFs), with some viewing this as heralding a shift into a new investment paradigm of Autonomous Learning Investment Strategies (ALIS).

What's new about these investment processes is that the technology learns and adapts as it goes along, based on the information and enormous datasets the algorithms have access to, and on which they are basing their investment decisions and problem solving. All with no human input.

As in other fields of artificial intelligence (AI), this has raised the spectre of Singularity – a much-vaunted future state when computers could potentially have superintelligence that surpasses our own and which could, it is feared by many, ultimately put humans out of business.

But have we truly crossed the AI Rubicon or is this all just a matter of hype?

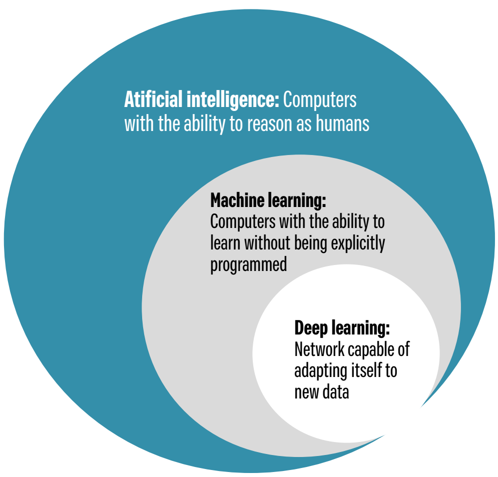
For many, the AI milestones that have been achieved over the last few years (see AI timeline) have set us up for the greatest technological revolution in history over the next decade – and the investment industry will undoubtedly be at the centre of this.

But AI and talk of technological revolution has been around for quite a while. It was first talked about in 1965 when a British mathematician and cryptologist brought up the concept of an intelligence explosion. Then in 1993, a sci-fi writer and computer scientist said that within 30 years we would have the means to create superhuman intelligence.

There are many definitions of AI, but *Forbes* magazine contributor David Thomas puts it most succinctly: AI is a branch of computer science which aims to create intelligent machines that teach themselves.

There are different levels of AI, with each level becoming more sophisticated and autonomous in the tasks computers can do without human intervention. There is machine learning (or structured learning), which is the ability of computers to learn and improve tasks with experience. Then there is deep (or unstructured) learning, when a computer uses algorithms that adapt to new data and thus trains itself to perform tasks. The best-known examples of deep learning are IBM Watson and driverless cars.

A DEEPER UNDERSTANDING OF AI



SOURCE: *Forbes* magazine

Inevitably, the advances in AI have spurred robust debate about what impact AI will have on the investment world. To get a balanced perspective, it's worth considering why AI is developing so rapidly.

AI advances have been made possible primarily by the sharp decline in the price of graphics processing units (GPUs) in recent years, driven by the rise and advancement of gaming. This has enabled AI to access immense amounts of data of all types (numerical, image, voice), which are being made available from tech giants such as Google, Facebook and Microsoft.

Cloud-based hosting has also provided access to extremely capable AI platforms. For instance, you can use IBM's or Google's AI platforms to take advantage of work they have already done and build on top of this.

Why is this important? Essentially, it allows for quick-to-market implementation when you have enough data to teach your algorithm. In addition, with so much data being made available, users don't even need to come up with a hypothesis to code in; they can simply throw mountains of data at the AI

Considerations around the use of data

By Shazia Suliman

Peter Sondergaard from Gartner Inc. once said: "Information is the oil of the 21st century and analytics is the combustion engine." Industry leaders are investing in data scientists, data architects and engineers, as well as data governance specialists, to work together to map out and build data lakes. Data lakes consist of information internally available in a database (structured data), as well as unstructured data (third-party information which enriches their knowledge of clients' needs and behaviours). The specialist data team mines the data and ensures the authenticity of the data, and that all legal and regulatory requirements are met. To be machine learning-ready, firms need high-quality structured and unstructured data which ranges from pricing data to news sentiment as well as social media and mobile phone provider data. Getting this type of data can be challenging – from dealing with incomplete or missing records to identifying accurate information about the coverage, history and population of the data. Ultimately, the accuracy of the models is based on accurate and complete data sets. Junk In – Junk Out! ■

Shazia Suliman is head of analytical tools at Alexander Forbes.

An algorithm learns as time goes by, but it cannot determine an upcoming black swan event unless it has a previous black swan event to base its learnings on.

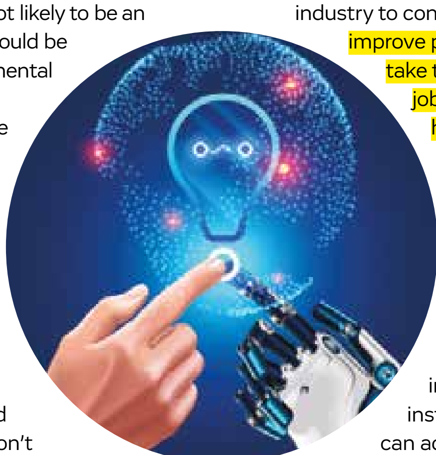
TIMELINE OF AI MILETONES

1956	The first Dartmouth College summer AI conference is organised by John McCarthy, Marvin Minsky, Nathan Rochester of IBM and Claude Shannon.
1965	Joseph Weizenbaum (MIT) builds ELIZA, an interactive program that carries on a dialogue in English language on any topic.
1978	Herbert A. Simon wins the Nobel Prize in Economics for his theory of bounded rationality, one of the cornerstones of AI known as "satisficing".
1993	Vernor Vinge publishes *The Coming Technological Singularity*, predicting that, within the next 30 years, humankind would have the ability to create superhuman intelligence.
1997	The Deep Blue chess machine (IBM) defeats the (then) world chess champion, Garry Kasparov.
2009	Google builds a self-driving car.
2011	IBM's Watson computer defeated television game show *Jeopardy!* champions Rutter and Jennings.
2016	Google DeepMind's AlphaGo defeats 3x European Go champion Fan Hui by 5 games to 0.
2017	Google's AlphaGo Zero – an improved version of AlphaGo – learns by playing only against itself and beat its predecessor 89:11 after only 40 days.

SOURCE: Wikipedia; Old Mutual Investment Group

and, through deep learning, the system will figure out the pattern. Platforms are also cheap – or even free – so the barriers to entry are low. The main barrier to entry is access to enough rich data.

Notwithstanding the increasingly fast-paced innovation we've seen and the growing excitement about the potential of AI, it is not likely to be an investment panacea – and it would be premature to think that fundamental qualitative investment professionals will no longer have jobs as a result of AI.



Instead, some of the things the investment industry needs to be thinking about include the issue of using poor, or incorrect, data, resulting in a spurious or incorrect result (which might appear to be a correct result, but as it is based on the wrong information, it won't be). Also worth considering is the fact that an algorithm learns as time goes by, but it cannot determine an upcoming black swan event unless it has a previous black swan event to base its learnings on.

AI is very good at doing one thing well, but not at integrating many things into a "super-solution". For instance, you can use AI to determine what the market may do using machine-readable news – an advanced service for automating the consumption and systematic analysis of news – as a factor in an investment portfolio, but you are not able to simply "ask AI to come up with a portfolio" and let it just figure it out.

More important issues for the investment industry to consider include: how we can use AI to improve portfolios; how we can we use AI to take the repetitive grudge work out of our jobs in order to focus more time on the hard-thinking work; and how can we use AI to augment what we do as opposed to worrying about it replacing what we do?

To embrace this area of development as an investment professional, upskill yourself in the proficiencies that the machines can't do – improve your ability to interpret the results, develop your instinct, refine your discernment. If you can add these skills to the benefits offered by the machines – automating repetitive tasks, accounting for human behavioural inefficiencies, instantaneously aggregating vast amounts of information from multiple sources – you will have the best of both worlds.

In other words, it is not a case of human versus machine; rather, it is human and machine together, which is better than human alone. ■

Hywel George is director of investments at Old Mutual Investment Group.

Photo: Shutterstock

By Hannes van den Berg and Terry Seaward

SMARTTECH

How clever tech is changing the game

Will intelligent technologies replace fundamental analysis by humans? It does not have to be either/or.

Businesses across the spectrum, from social media and entertainment to banking and investments, have recognised the benefits of harnessing big data.

Advances in intelligent technologies have resulted in data screening tools (quantitative analysis) gaining a strong foothold in the investment management industry.

When it comes to finding good companies to invest in, information and timing are key. This requires the ability to process huge volumes of information from multiple sources speedily.

A quantitative approach uses mathematical and statistical modelling that collects immense volumes of data at lightning speed to help identify good investment ideas and assess portfolio risks. More than 16m discrete pieces of information feed into constructing a portfolio from a 4 000-stock universe. (Quant analysts are therefore often described as data analysts working in finance, as they need to be highly skilled in maths, statistics, computer science and finance.)

Why human insight remains key

When it comes to big data and machine learning, public debate tends to pit humans against machines, reinforcing the stereotype of an "us versus them" scenario, rather than entertaining a "marriage of two minds".

Even within the asset management industry it's common that active equity managers only employ quantitative analysis as an initial screening tool to identify good investment ideas based on a specific set of criteria. Quants are often used as a filter to narrow a large investment universe, after which fundamental analysts do a deep dive on these stock ideas.

However, each approach (quantitative and fundamental analysis) has key strengths and weaknesses. The quant approach is "a mile wide, but an inch deep", while fundamental research is a "mile deep, but an inch wide". Investment managers can capitalise on the best attributes of both.

Idea generation – finding the right balance

Qualitative: Uses bottom-up fundamental research by investment analysts. For instance, an analyst would examine the market's earnings forecasts for a company in order to determine whether a company is likely to have higher (or lower) earnings than other market participants expect. When profit forecasts are revised upwards or downwards, this can have a material impact on a company's share price.

Quantitative: A stock screening process which identifies the best investment ideas, based on very specific data-driven, fundamental criteria. This screening includes finding companies based on fundamental investment data, with favourable dynamics (earnings/profit expectations) and reasonable valuations.

Some managers still prefer to use the two independently, but quantitative stock screening research and fundamental analysis can run parallel. Since these two research processes run independently, the one may identify a stock as a good or bad investment idea, but might not be supported by the other. For example:

■ Naspers* scores poorly on our quant-based metrics (valuation). But a more detailed fundamental analysis reveals reasonable value, when valuing each business within Naspers separately.

■ Some stocks might look attractive from a valuation perspective due to idiosyncratic risk or specific news flow, which a backward-looking stock screen will not know, but which requires human insight and further exploration. Tiger Brands (listeriosis), Old Mutual (dispute between the CEO and board) and Sasol (delay in results) are recent investment situations where human judgement was needed.

	STRENGTHS	WEAKNESSES
Quantitative research	Discipline, repeatability, objectivity and efficiency	Slow to adapt to changing trends
	Breadth: The ability to analyse a vast amount of data in a short period of time	Based on historical information
	Good at portfolio construction and risk management: The ability to optimise correlations and co-variances of all possible combinations of holdings	
Fundamental research	Judgement, insight and experience	Emotional bias
	Depth: The ability to assess many different aspects of a company in detail and to consider multiple angles using the same data	Inconsistent
	Ability to communicate, debate portfolio positioning and express a view	Slow – a finite amount of time to analyse available data
	Flexibility and the ability to adapt to new situations/breaking news	

SOURCE: Investec Asset Management

Both processes may fuel debate, highlighting the need for further analysis of an investment idea. However, the integrated approach has the potential benefit of reducing the risk of "over-confidence", which can be a pitfall where idea generation favours only one of these two research processes.

Managing risk together

While investments are generally quite risky and may lead to financial loss, having quant expertise can help with addressing some of these challenges. Quant models can help to identify securities that optimise the portfolio and/or diversify it further.

This is not to say that there is no room for human insight. Human insight and common sense remain crucial in risk management processes. Fundamental analysts are still best placed to interpret breaking company news, market dynamics, regulatory or tax changes, and environmental, social and governance (ESG) issues.

Geographies and companies are reacting differently to technology disruption and we are already seeing changes in the allocation of capital by businesses. Humans need to embrace the tech revolution. How we collect data (accurate and consistent), how we consume data and how we can do this in real time in order to make better decisions are important considerations.

Fundamental analysis and quantitative analysis have an important role to play in finding good stock ideas, as well as constructing a portfolio and managing risk. ■

*finweek *is a publication of Media24, a subsidiary of Naspers.*

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By Richard Rattue

COMPLIANCE

Getting it right in 'RegTech'

The disruptive age is here and has resulted in increased demand for technology-led financial products. But can regulation keep up?

The financial services industry may wonder about the way forward for compliance and risk functions as Regulatory Technology, or 'RegTech', undeniably becomes a factor for all.

In the past, compliance programmes were largely unprepared for the risks associated with a shift to technology, but as we face increasingly frequent and intricate rules, and the digital age further shapes financial services globally, the necessity for sustainable compliance is evident.

There have been at least 50 000 new regulations across the G20 since 2014 and various surveys reveal how technology is an essential ingredient of any future compliance function.

According to Citi Group, from 2014 to 2018, 9 000 people were hired globally for compliance and control positions, while according to Nasdaq, compliance spend in firms increased 56% from 2014 to 2017.

Banks, according to Thompson Reuters' *Cost of Compliance Survey*, which surveys over 800 financial services firms globally, reported a 67% increase in compliance spend in 2017. These trends point towards growing awareness of RegTech, particularly as cryptocurrencies become the norm for many, despite regulation still developing.

A big launch

Compliance and risk functions are, of course, not immune to disruption and for those who "fail to launch" the consequences could be dire. The disruptive age is here, whether you are ready or not.

Consumers are fast-tracking demand for technology-led financial products, which encourages exciting change, but also makes way for heightened risk. RegTech will undoubtedly align with the burgeoning "treating customers fairly" regulatory regime, using the underlying data as a force multiplier.

Big data and its interpretation are significant. It is increasingly becoming a real aid for compliance officers to try and spot the smoke before fires break out. They sometimes can't spot the smoke because they are under-resourced, and their field of view is just too great, but RegTech will help to solve compliance challenges in a smarter and faster way.

It will assist in meeting enhanced regulatory reporting standards, reduce barriers to entry, and automate routine compliance tasks where possible.

Heating up

As is often the case with change, there can be heat, and RegTech is no exception. Hot elements I anticipate coming to the fore include verification of identity, data capture aggregation, regulatory risk analysis and accuracy of reporting.

Supervisory Technology, aka SupTech (another key term), enables regulators to use technology to spot smoke too. It allows for analytics on market participants, provides proactive, intelligent analysis of data and trends in the marketplace, and paves the way for the growing interest in handbooks that are readable by machines, as well as enabling the development of Supervision Bots.

There are roadblocks and challenges, with regulatory acceptance key among them. The outdated market rules, stakeholder resistance and legacy infrastructure already in place indicate slow adoption to change by the top level, as well as skills or system shortages. It will be interesting to see how the regulator takes it on locally.

Consumer-driven times

If other parts of the world are anything to go by, technology is changing the game and empowering consumers. Smart regulations will pioneer a way forward in delivering financial services. While for many this threatens the status quo, failing to adapt in the end could mean fading away altogether.

RegTech comes with a number of advantages – from a quicker turnaround of services to increased transparency – as it provides enhanced fraud and behaviour detection. It is adaptable and scalable and the evolution of the RegTech ecosystem will see the continued integration of smart solutions.

Machine-readable handbooks and rules will improve processes and reduce human input required for routine oversight tasks. Regulators have adopted the "sandbox concept", which facilitates the rapid growth of the fintech industry, but in a calculated way where businesses are able to test various innovations in a controlled environment.

Despite challenges, RegTech will enable smoother and faster processes and makes way for upskilling of staff, including compliance officers, and paves the way for regulation primarily suited to the digital space.

Ultimately, the RegTech wave should benefit the man in the street when engaging with financial services since the enhanced oversight abilities should make it harder for persons of ill repute to peddle their wares to the public.

The role of the compliance officer in 2025

In the coming years, the role of the compliance officer will look quite different to today. Machines can review entire datasets, negating the need for sampling, and improving the risk of human error.

Financial services, I believe, is transitioning into a "digital first" era and we all need to board the train and navigate as best we can. The most sophisticated technology, however, is largely useless if the culture of evading the rules remains rooted in a firm. If you can get the culture right, the rest should follow. ■

Richard Rattue is managing director of Compli-Serve SA.

Photo: Shutterstock

By Susan Spinner

INNOVATION

Alexa, are you acting in my best interest?

Let's consider the ethical implications of using artificial intelligence in finance.

Recently, I attended a conference where one of the points of discussion was the disruption within the world of finance through new breakthroughs in artificial intelligence, or AI. One of the panellists said she worries about the influence that Amazon's (in)famous virtual assistant, Alexa, might have on her children. She questioned whether we can actually know what motives and morals 'she' has been programmed with. Can we trust the voice-controlled device sitting on our kitchen counter to keep our best interests at heart?

Alexa is an example of natural language processing, which is one form of AI. Although the exact definition of AI is still a point of contention, it usually involves the use of self-learning systems to mine big data, recognise patterns and process natural language. The aim is to copy how the brain works while processing information and making better decisions more quickly.

> **A study from early 2019 showed financial industry leaders identifying the growth in AI and machine learning as the greatest source of disruption for investment professionals in the next five to ten years.**

What does all this have to do with finance and investment, you might ask. While most financial services companies have not yet introduced voice-assisted technology, many do offer online financial advice and make computer-based investment recommendations. In fact, it was not long ago that so-called 'robo-advisers' were touted as a major threat to established investment firms.

But instead they have proven to be more complementary, rather than disruptive, with large firms simply buying up the most promising fintech startups and adding the new technology to their own services.

A robo-adviser is a computer-automated platform that responds to your queries online similarly to a human adviser, but is in fact a software program driven by AI and can be offered to clients at a lower cost.

The advantages of this type of service are clear for individuals who do not want to pay the higher fees of a financial adviser, who do not have large sums to invest, or who like to invest their funds independently, but with the support of an automated solution.

As a client, that means you are making a conscious choice to opt for the computer rather than the human adviser. Naturally, a human can make a mistake, give misleading advice or simply be bad at their job. In the same way, a robo-adviser is entirely dependent on the soundness of the algorithms and data that power it.

However, even if you have shied away from such a model thus far, there is every chance that you are already affected by the deployment of AI and machine learning technology somewhere in your financial affairs – whether you realise it or not.

In a global survey of investment professionals conducted by the CFA Institute in early 2018, 51% of respondents stated that their firm's top tech priority is the use of technology for client engagement, and a further 21% said it was the employment of machine learning in portfolio construction (i.e. using machines to make automated and instantaneous investment decisions depending on market movements and new data flowing in).

A more recent study from early 2019 showed financial industry leaders identifying the growth in AI and machine learning as the greatest source of disruption for investment professionals in the next five to ten years.

This development has the potential to bring significant advances and improvements to the world of finance. Imagine submitting a mortgage request (perhaps including a unique digital ID, so you don't even need to fill out lengthy forms) and immediately knowing whether and at which rate a bank will grant you a loan.

Photo: Shutterstock

Imagine supervisory authorities employing AI systems to detect fraudulent transactions, money laundering or tax evasion. Or a program tracking, comparing and evaluating company reports in real time, automatically highlighting the most relevant indicators to help investors make smarter choices. Already, today, a virtual assistant called Jasmine helps people in Singapore navigate the tax system and file returns. Computer-based technology is also infinitely better and more efficient at repetitive tasks, while remaining accurate.

So, what's not to like? The pace, for a start. It is apparent that AI is evolving much faster than our legal frameworks, regulatory oversight and popular understanding of these technologies can.

We know that both conscious and unconscious biases affect all of us – whether we are plumbers, bankers, portfolio managers or computer programmers. We have not yet established guidelines and frameworks that will reliably prevent such biases from infiltrating the datasets and code that shape an algorithm.

Some unfortunate examples have become infamous: Microsoft's chatbot "Tay" began to spew antisemitic vitriol; a computer program used by US courts to assess the likelihood that defendants will become repeat offenders flags up black defendants at twice the rate of their white counterparts, and three different AI systems by IBM, Microsoft and Megvii have been found to identify a person's gender from a photo correctly at a rate of 99% – but only if that person is a white male. In other cases, such as for women of colour, the accuracy of facial recognition drops significantly.

If these kinds of issues persist, how can we be certain that race, religion, gender and other factors will not have adverse effects on how a software ranks an individual's credit quality, insurance premiums or similar issues?

Even leaving these unwanted and, one may hope, unintended results to one side, how can consumers know whether a financial product that is marketed to them by an algorithm really is in their best interest and not the company's?

The same can be true of a human adviser, one could argue. And that is undeniably true. However, AI brings with it the matter of scale, potentially misinforming hundreds of thousands of savers and investors, rather than the few hundred a bad adviser might. There is also a common notion that programs are more neutral and fairer than humans would be – a misconception that may easily lull consumers into a false sense of security.

What we need, then, is a fruitful interaction of artificial and human intelligence: AI + HI, ensuring that algorithms and datasets are adequately tested, screened for quality and regularly reviewed. There are already companies popping up to specialise in performing such "Algorithm Audits".

> What we need, then, is a fruitful interaction of artificial and human intelligence: AI + HI.

With technology taking over the more repetitive, basic tasks, the value of uniquely human characteristics such as empathy, ethical orientation, tacit knowledge and face-to-face communication rises. This is why we are increasingly emphasising the growing importance of soft skills to investment professionals.

In addition, we need regulatory bodies to move quickly and establish standard rules of play. The European Union earlier this year took a notable first step in this direction by publishing its *Ethics Guidelines for Trustworthy AI*, which include the need to maintain human agency and oversight as well as accountability, transparency and privacy. However, these guidelines are not yet legally binding.

And as long as the big players in technological innovation, China and the US, do not take similar steps, we will continue to play catch-up with the speed of development.

Because, at the end, we all want to be certain that all the "Alexas", "Siris" and "Jasmines" that we are dealing with will truly have our best interests at heart. ■

Susan Spinner (CFA) is the CEO of CFA Society Germany.

By Ainsley To

DIGGING DEEPER

Machine learning and investing: the cautious seldom err or write great poetry

Machine learning brings many advantages to the investment world. It may be complex, but that's no reason to discard it.

Machine learning (ML) is the nebulous intersection of computer science and statistics. But is it a new reality for investors or just hype that will fade into a new "AI winter"?

My old rule of thumb to differentiate substance from marketing, was simple: If it was mainly written in Python, it was of potential substance. If it was mainly written in PowerPoint, it was likely "Artificial Intelligence" (aka marketing skulduggery).

After conceding that this was not a robust approach, and spending some time re-educating myself (getting my hands dirty and building the models from scratch), my position has slowly evolved from outright cynic to sceptical enthusiast.

I should emphasise that there is no substitute for putting in the time and effort to learn the details (Robert Tibshirani's *Elements of Statistical Learning*, first published in 2001, would be a great starting point).

Going through individual ML algorithms is beyond the scope of this article. My goal, instead, is to provide (in the simplest terms possible) some explication for investors, using investing analogies and concepts familiar to those in finance. Or, failing that, perhaps to help mildly improve your cocktail party soundbites on the topic.

To paraphrase George Box's quote on models: "All analogies are wrong, but some are useful."

We can contrast an ML approach with that of traditional equity investors using a toy example:

■ **Investor A** is a traditional value investor who believes that there is a relationship between valuation and expected returns – the lower the valuation of a stock, the higher its expected return.

■ **Investor B** also believes that there is a non-linear relationship between valuation and expected returns – the lower the valuation, the higher the expected return, until a certain point beyond which low valuations are a sign of financial distress (and thus have lower expected returns). Thus, she wants to buy cheap companies but avoid the very cheapest companies.

■ **Investor C** believes in using multiple metrics to forecast returns. In addition to value, she believes that measuring the quality of a company can be used to avoid value traps. Her view is that expensive companies that are low-quality will have low returns in the future.

Consider each investor's models of expected returns stylised in these charts. For Investor A, returns are linearly related to a single variable – a straight line between valuation and returns. Investor B also considers only valuation but in a non-linear manner – a curve with expected returns peaking and declining for the extremely cheap valuations. Investor C is the most complex to visualise since she is concerned with the interaction between value and quality, which requires a 3D chart – expected returns are low for expensive companies of low quality.

This example points to two patterns that ML can improve over linear models. It has the flexibility to capture non-linear relationships (such as in B's case) as well as interactions between variables (as with Investor C).

However, an ML process gets there in a different way than in our example – while our investors make assumptions about expected returns, an ML algorithm instead learns the relationships directly from the data.

ML can find non-linear interactions between as many variables as it is given, in whatever combinations best fit the data. The difficulty is that the patterns the algorithms learn are rarely interpretable for a human investor and increasingly difficult the more features you give it to train on – we can see in only three dimensions and additional inputs beyond our example will be in higher-dimensional space.

This is one of the main trade-offs in using ML – performance (making the best predictions) versus interpretability (understanding why they made those predictions). The broad church of ML models all vary along this spectrum, but the two that are known to have the best performance (random forests and neural networks) are also among the hardest to interpret.

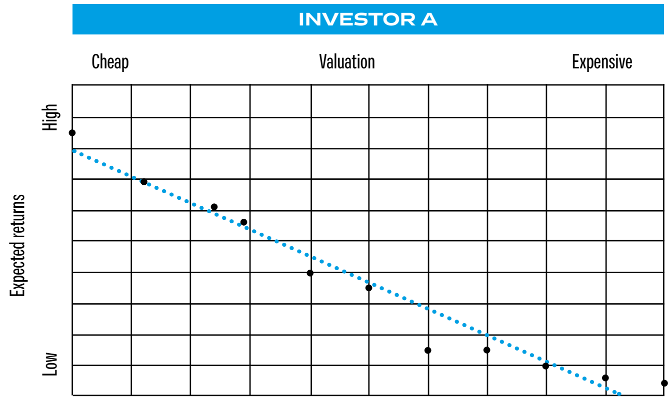
How do ML algorithms find patterns?

Every ML algorithm will at some stage involve numerical optimisation – a sophisticated form of trial and improvement. Running the same algorithm on the same data can give different results – it depends on what values are trialled and in what order, which are often randomly chosen.

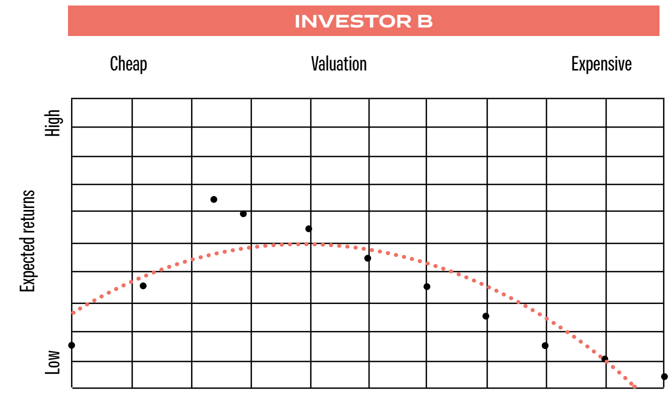
But, with the flexibility they are given, enough iterative trial and improvement will eventually get to an answer that looks good in sample (e.g. within the data used to train the algorithm). The problem in investing which we all know too well is that "past performance is not indicative of future performance". Overfitting is a significant risk in ML algorithms since they are trained to fit the past and they are given significant freedom to do so.

In contrast to traditional linear regression models that measure their goodness of fit on the whole dataset, the practice in ML is to optimise out of sample prediction – performance is measured using data that was not used to train the algorithm. Cross-validation is the process of withholding data from the algorithm for testing performance after training. For example, you can split ten years of data into two sets: from 2009 to 2017 and from 2018 to 2019.

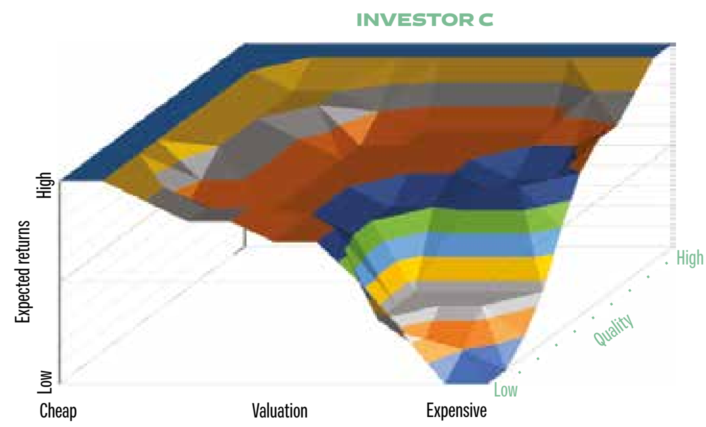
You create your strategy based on the training set (2009 to 2017), then see how it performs on the test set from 2017 to 2019 (data which was not involved in forming the strategy itself), providing a level of comfort that the algorithm is not simply overfitting noise in the training data. There are many other tools and techniques to constrain ML algorithms and avoid overfitting. The balancing act between overfitting (leading to variance in predictions) and constraining the algorithm (which increases bias in predictions) is another main consideration when using ML.



SOURCE: Credo Wealth



SOURCE: Credo Wealth



SOURCE: Credo Wealth

"If a method works, it should not be abandoned or dismissed just because theorists haven't yet figured out how to explain it."

Keep an open mind... but not so open that your brain falls out

Financial markets are extremely complex, with non-linear relationships and interactions between explanatory variables. It's therefore no surprise that simple linear models have difficulty capturing all the nuances.

However, the use of more complex tools is no guarantee of success due to properties that are unique to finance as a domain. The ratio of signal-to-noise in financial data is low by design. There are strong financial incentives to take advantage of any informational content in markets. When market participants act on this information, they drive prices and absorb the remaining amount of signal in the system – often to the point where it is too costly or risky to act on what is remaining.

This is why efficient markets can be approximated with random walks, since much of the movement in securities prices is due to news, which is by definition unpredictable.

Michael Brandt from Duke University gave an excellent illustration in his presentation, "We've got much less data than you think". The input data used for self-driving cars has a near-perfect signal and no noise. In stark contrast, the pictures show what the input into the algorithm would be if it had a similar signal-to-noise ratio of annual (1 to 3 signal to noise) and monthly financial data (1 to 10 signal to noise).

From a pure return forecasting perspective, it is unreasonable to expect that simply using the same algorithms from other domains will produce similar results in financial data.

Self-driving cars (Perfect signal-to-noise ratio)

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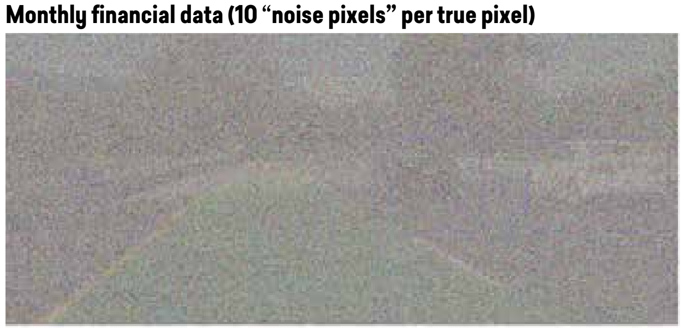
Annual financial data (3 "noise pixels" per true pixel)

Monthly financial data (10 "noise pixels" per true pixel)



SOURCE: Michael Brandt's presentation, "We've got much less data than you think"

Conclusion

ML generalises methods we already know to allow for non-linearity and interaction effects. Investors have been familiar with facets of ML for decades now – Bryan Kelly from Yale elegantly highlighted how sequential sorting in the famous Fama French factor portfolios are simple tree models (the building blocks for random forests).

Ensemble learning (combining ML models to produce an aggregate forecast) utilises the benefit of diversifying away uncorrelated errors, a concept that should be familiar to most portfolio managers. With some careful engineering, there are applications for ML across many parts of the investment process – not just the narrow return prediction context that I've focused on in this article.

There is credible concern over the dangers of overfitting. But this is not unique to ML – given the p-hacking (or selective reporting) epidemic in academic finance, one can argue we crossed the Rubicon of overfitting with traditional econometric models long ago.

A more difficult obstacle is the interpretability issue, which is particularly tangible for myself, as a practitioner who suffers the perpetual anxieties of alpha decay and understands the logistical realities of investment committees.

A pioneer in deep learning, Yann LeCun, once said: "There is a need for better theoretical understanding of deep learning. But if a method works, it should not be abandoned or dismissed just because theorists haven't yet figured out how to explain it."

My sentiment on ML in investing can be summarised by Yann LeCun's view and Einstein's famous quote to, "Keep things as simple as possible but no simpler."

Financial markets are one of the most complex puzzles human beings have ever encountered. To even stand a chance, we need to explore tools that are equal to the task. The aspiration is to do so with the appropriate level of pragmatism and intellectual honesty. ■

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