BEHAVIOURAL INVESTMENT AND ARTIFICIAL INTELLIGENCE

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ABSTRACT

Owing to the transformation in the technology, machines have become increasingly capable which has led to a lot of mental facilities earlier assumed to entail intelligence being removed from the definition of artificial intelligence. Driven by this fact, it becomes imperative for us to explore frequently what are the capabilities currently classified as artificial intelligence. The research study by Accenture projects that, by the year 2035, artificial intelligence could spectacularly boost economic growth and productivity by as far as 40% which indicates the wide potential of Artificial Intelligence across variety of industries like trade, commerce, manufacturing, retail analytics, healthcare, space exploration as well financial decision making i.e. Financial analytics or also known as Fintech.

Key Words: *Artificial Intelligence, Technology, Fintech, Behavioural Finance, Decision Making, Biases, Heuristics, Irrational investment behaviour*

Behavioural Finance

Behavioural finance studies the psychology of financial decision-making. People acknowledge the effect of emotions on investment decisions. People in the industry commonly talk about the role greed and fear play in driving stock markets. Behavioural finance extends this analysis to the role of biases in decision making, such as the use of simple rules of thumb for making complex investment decisions. Hence, behavioural finance takes the insights from psychology and applies them to financial decision-making. Over the past fifty years established finance theory has assumed that investors have little difficulty making financial decisions and are well-informed, careful and consistent. Traditional theory posits that investors are not confused by how information is presented, nor swayed by emotions. But clearly reality does not match these assumptions. Behavioural finance has been growing over the last twenty years specifically

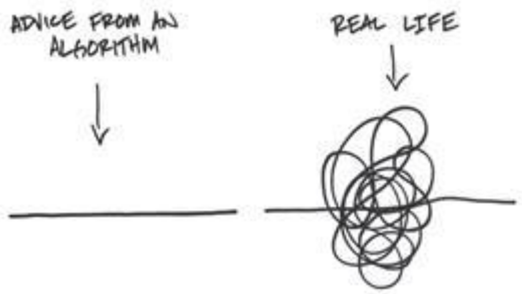

Figure 1: Traditional economic theory does not address human irrationality

because of the observation that investors rarely behave according to the assumptions made in traditional finance theory. Behavioural researchers have taken the view that finance theory should take account of observed human behavior. They use research from psychology to develop an understanding of financial decision-making and create the discipline of behavioural finance.

Overview of Heuristics and Biases Framework and Investment Behaviour

Research in psychology has recognized a number of behaviors known as biases. These biases can affect all types of decision-making, but have particular implications in relation to money and investing. The biases relate to how we process information to reach decisions and the preferences we have (Shefrin, 2000). In spite of the considerable funds that are at stake, financial decision-making i.e. investment activity is one of many domains of human activity to be affected by cognitive biases. What investors believe are valid judgements may in fact be the results of effort-saving mechanisms by the brain. It can be argued that supposedly rational decisions may be the result of mental shortcuts that disregard selective information, which then has a significant impact. Heuristics referred to rule of thumb, are means of reducing the search necessary to find solution to a problem. They are shortcuts that simplify the complex method of assessing probabilities and values ordinarily require making judgments, and eliminating the need for extensive calculations. A heuristics and biases framework can be envisioned as a counterpart to standard finance theory's asset pricing model. When decision maker faced with huge amounts of data and information and an array of decision problems, people are incapable of doing the complex optimization calculations that are fundamental assumption under standard finance theory. Instead, they rely on a limited number of cognitive strategies or heuristics that simplify the complex events in making decisions.

Confirmation bias - The confirmation bias refers to the phenomenon of seeking selective information to support one's own opinions or to interpret the facts in a way that suits our own world view. They avoid critical opinions and reports, reading only those articles that put their point of view in a positive light.

Availability bias - The attention bias states that products, companies, and issuers that are more frequently highlighted in the media will be remembered more quickly by investors when they look for a suitable investment. Negative or scarcely accessible information is not considered.

Home bias - Statistics show that most investors tend to buy stocks from companies in their home country. These stocks seem more trustworthy, as investors grew up with these company names. They are also mentioned more frequently in the local media.

Anchoring - When making decisions, investors do not rely on fundamental factors. Rather, they tend to base their decision on the price at which the stock was purchased. This point of purchase behaves as the anchor and causes irrational decisions. When making decisions, people are influenced by random data; this data may have no informational value or may be outrageously high or low.

Myopic loss aversion - Most investors fear losses more than the appreciation of profits. If stock performance is checked often, they tend to focus on short term loss money and sell everything off. A long-term view would be better. The more they can keep their curiosity at bay, the more likely they are to turn a profit with their investments, provided that their portfolio is broadly diversified.

Mental accounting - Many private investors make distinctions in their head that do not exist financially. Often, losses incurred are viewed separately from paper losses. This means that people are too quick to sell stocks when they earn a profit and too slow to sell when they sustain a loss.

Disposition effect - With the disposition effect, gains are realized too early and losses too late. Turning a paper profit into real profits makes us happy, while we tend to shy away from turning a paper loss into a real loss. One possible explanation for this is mental accounting.

Overconfidence - In most cases, we overestimate our own abilities and think we are above average. Most experts overestimate themselves – frequently to a greater degree than laypersons do. Overconfidence is often seen when the markets are on the rise.

Hindsight bias - Hindsight is 20/20. The statement “I knew the whole time this would happen” shows that we have an explanation for everything after the fact. This hindsight bias keeps us from learning from our mistakes.

Representativeness bias - After even a brief period of positive returns on the financial markets, we may think the world has changed for the better. People tend to think in terms of schemes and stereotypes experienced in the past. They arrive at a result too quickly, based on imprecise information.

Gambler’s fallacy - Here, the effective probabilities are greatly underestimated or overestimated. For example, based on the false assumption that prices are about to drop, we sell too soon and vice versa assuming that the prices will recover soon, even though they are not yet doing so.

Framing bias - Decisions are based largely on how facts are depicted. For instance, we do not think that “Four out of ten are winners” and “Six out of ten are losers” mean the same thing. The statements are identical, but most people do not realize it (Hens & Meier, 2015).

Regret avoidance - If we invest in a blue chip stock and it does not perform as hoped, we call this bad luck. However, if we invest in a niche product that fails to perform well, we tend to regret this more than we do the failure of the blue chip stock. This is because many other people have made the same mistake and thus our decision to buy it does not seem so wrong.

Evolution of Artificial Intelligence

Artificial intelligence refers to the ability of a computer or a computer-enabled robotic system to process information and produce outcomes in a manner similar to the thought process of humans in learning, decision making and solving problems (Mitra, 2017). By extension, the goal of AI is to develop systems capable of tacking complex problems in ways similar to human logic and reasoning. Artificial intelligence has been one of the most debatable subjects in the discipline of computer science since its inception.

The field enjoyed an exponential growth rate in the last five years with highest funding of $2,388 million in 2016 (CB Insights, 2016). The terminology of artificial intelligence was coined by John McCarthy, who was one of the founders of the discipline or artificial intelligence in the mid-1950s (Peart, 2017). Artificial intelligence has been the branch of computer science concerned with making computers behave like humans.

Domains of Artificial Intelligence

Machine learning: Machine learning is a type of artificial intelligence which makes computer learn and evolve on its own without programming (Rouse, Machine Learning, 2017). For example, Facebook uses machine learning to personalize each member's news feed.

Deep learning is a subset of machine learning. It has facilitated object recognition in images, video labeling, and activity recognition, and is making progress in perception. For example, Facebook's deep learning application DeepFace has been trained to recognize people in photos.

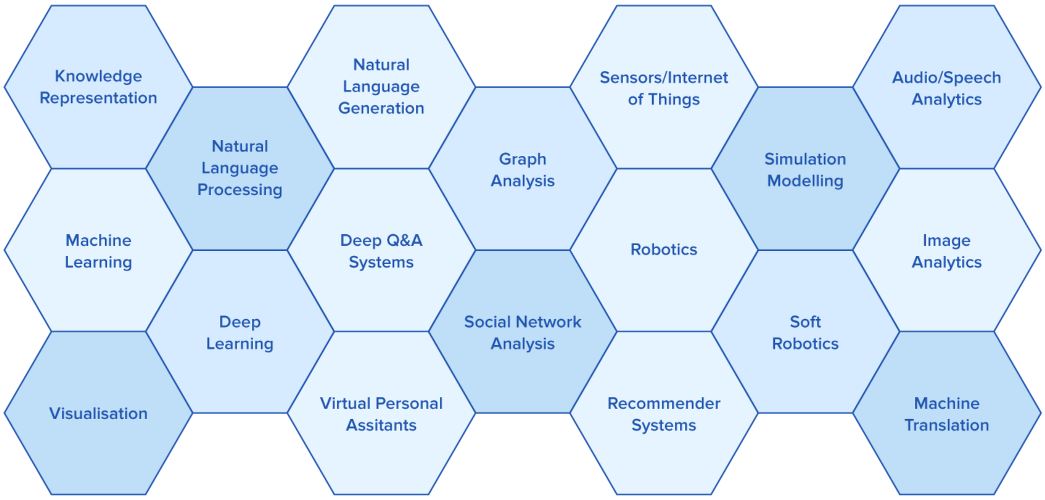

Figure 2: Pwc Report: AI and Robotics – 2017

Internet of things (IoT :) is devoted to the idea that a wide array of devices, including appliances, vehicles, and buildings can be interconnected.

Computer Vision: The aim of computer vision is to make machines capable of automatic extraction, analysis and understanding of useful information from one or more images. It has a variety of uses. For example, face recognition, gesture analysis, automated transportation etc. (BMVA).

Smart Robots: Smart robots are artificial intelligence systems which can learn from its surrounding as well as past experiences to perform tasks and build on it when necessary. There are currently around 65 companies that are into development of smart robots (Venture Scanner, 2018).

Intelligent personal assistant: Intelligent personal assistant is artificially intelligent assistance software that can finish tasks and provide services that a user needs. For example: Siri by Apple, and Cortana by Microsoft etc.

Natural language processing: The process of natural language processing is of making computers understand natural languages. The major challenge here is to clear the ambiguity in human languages. The computers must be able to understand both the context as well as meaning of words.

Speech to speech translation: Speech to speech translation talks about the process of catching a spoken phrase and translating and speaking it simultaneously in a different language. This has many real time applications. For example, Skype has enabled people from different countries to communicate without worrying about the language barrier (Lawler, 2014).

Context aware systems: Context aware computing is related to a type of mobile systems that are sensible when it comes to their environment and adapt to it accordingly (Robles & Tai-hoon , 2010). Context awareness means a computer can sense as well as react according to changes in its environment. For example, a phone that can set the brightness of the screen based on the climate around it.

Gesture recognition: Gesture recognition is simply a computer devise recognising a human motion and interpreting it in mathematical terms (Rouse, 2015). There are many industries benefiting from it such as automotive industry, gaming industry as well as consumer electronics industry.

Recommendation engine: Recommendation engines are simple algorithms which mean a very explicit step-by-step process used to solve problems mostly by computers. The objective is to provide the user with the most relevant items for them by filtering through a heap of data.

Artificial Intelligence and Investment

Data science is the discipline that allows us to analyse the unseen and with machine learning, it facilitates computing of large data sets and surface patterns, categorizing past performance for indicative future results. It’s been some time since professional traders first started using computers to assist or even replace them in the increasingly complex global financial markets. Algorithmic Investment Services now accounts for nearly 90 percent of the market (Glantz & Kissell , 2014). While high-frequency trading tools are designed to buy and sell financial instruments in fractions of a second, artificial intelligence based models look for the best trades hours, days, weeks or even months into the future.

As per a study by Accenture by 2035, using artificial intelligence economic growth and productivity could improve by 40%. For years, investment management companies have relied on computers to make trades. In 2000, Goldman Sachs’ US cash equities trading desk in its New York headquarters 600 traders. Today, it has two equity traders, with machines doing the rest. For investors, robo-advice can offer up to 70 percent in cost savings in certain services. In the investment management business, it is now the time of the Robo-Advisors. The term “robo-advisor” was essentially unheard-of just five years ago, but it is now commonplace in the financial landscape. These are algorithms built to calibrate a financial portfolio to the goals and risk tolerance of the user. Users enter their goals, age, income, and current financial assets. The advisor then spreads investments across asset classes and financial instruments in order to reach the user’s goals. Some established investment firms are buying existing robo-advisors while others are even creating their own robo-advisors.

The Financial Technology industry has drastically advanced because of the innovations in Artificial Intelligence. Advancements in technology have increased the power and speed with which data is computed, hence reducing cost. This results in better access to big data and innovative algorithms capable of transforming the fintech sector. Large amounts of data makes it is possible to predict financial behavior, preferences and have insights on investment possibilities. The surge in the use of technology has led to the development of a large number of companies in the Fintech industry, simply because of the capabilities of Artificial Intelligence. Many funds are now moving towards true machine learning. Just some of the pioneers in this field are Bridgewater Associates, Renaissance Technologies and the Medallion Fund at Renaissance (Nanalyze, 2016). Furthermore, a host of start-ups such as Alpaca, Binatix, Sentient, and Walnut Algorithms have made AI available to retail investors, whose operations are more influenced by cognitive biases than those of professional teams. A precise function provides investors with bespoke content based on specific behavioural analysis. This function helps users identify common trading biases and behavioural patterns, and provides them with relevant educational content whenever these biases are detected. It can also make financial calculations based on available data and provide educational materials to fix the biases. Thus, users can avoid the mental traps that humans tend to fall into while trading, and make more rational investment decisions. AI can be efficient in trading because of the large volumes of well-structured data available.

Conclusion

AI is now embarking on a new boom phase, the third in its history. Artificial intelligence is being utilized in various forms in the financial sector among many others. Financial institutions must optimize the use artificial intelligence more aggressively through open innovation. As an extension of market analysis, artificial intelligence could be employed with the aim of formulating optimal behavioural investment strategies. Moreover, companies now offer robo-advisory services that use artificial intelligence to recommend behavioral portfolios tailored to investors' investment style with the benefit of understanding the pertinent behavioural bias. Deep learning's competitiveness hinges on the quality of available training data and data processing speed. Financial institutions have been amassing large data archives and utilizing various algorithms since before deep learning's advent. Going forward, financial institutions will likely apply deep learning more broadly, capitalizing on their data archives. Utilization of deep learning requires a larger investment in computing power than most companies can afford on their own. Cloud vendors such as Google, Microsoft, IBM and Amazon offer artificial intelligence platforms. Utilizing such platforms to reap the benefits of deep learning will likely become the mainstream approach if affordability can be factored. Moreover, there are restrictions to individual as well as institutional capability to research and exploit artificial intelligence. As awareness in open innovation is growing in recent years even in the financial sector, artificial intelligence research and utilization could become a major sphere of AI led Fintech revolution.

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