**Introduction:**

**Thesis:**

Technology has had a large effect on the financial industry. This paper will provide a historical overview of technology used in modern finance, and how its success has culminated in AI being used in finance. The paper will then discuss the history and application of artificial intelligence. Finally, the last part will discuss how AI is being integrated in finance, and how the role of banker will go to an entirely technology driven one.

**Literature Review:**

* **Go through each of the sources**

**Argument/Analysis**

History of technology in finance:

* ATMs
* Computers
  + Automated trading
  + Supercomputers
  + Office computers and graphing
  + Credit rating and so forth
* Today they have exhausted human capability of using technology to optimizing performance, moving to AI

Go through different parts of artificial intelligence.

* What is AI
  + Where it is used, what is it going forward.
* Where is AI used in finance

**Given these details, the role of a banker will be more technical and develop systems which will efficiently evaluate market trends to give the optimal results to its clients. Artificial Intelligence is here to stay in banking, and this will cause some serious shakeups such as**

* **No more face-to-face banking**
  + **Pros**
    - **More efficient**
    - **Eliminates quackery**
  + **Cons**
    - **Relies on people to know their stuff especially mathematics.**
    - **Less human interaction**
* **Applying for loans will become instantaneous**
  + **Pros**
    - **Numerical and fair**
    - **Faster**
  + **Cons**
    - **Do not get to review as many options**
* **The Financial Advisor will go away**
  + **Pro**
    - **A loooot less deception**
    - **More efficient markets**
  + **Con**
    - **Algorithms will ignore what other algorithms forgot about**
    - **Only a few stocks will get chosen and is prone to bigger crashes**

1. **Introduction**

Artificial Intelligence (AI) has long been considered one of the final frontiers of human labor, and within the past few years we have finally seen its development in the workplace. Similar to how automobiles replaced the horse, light bulbs replaced the candle, and robots took over the assembly line, it is believed that the must innate part of humans–thought–is currently being replaced by AI systems. According to analysts at McKinsey, tech firms invested between $30 billion in AI in 2016 alone, and that number is supposed to double by 2020.

The finance industry is not unique to these developments. People like to follow the money, and no one likes money more than bankers. The thought of reducing the high price of human labor in the thought intensive financial industry with systems that can work 24/7 is extremely compelling to executives. As a result, nearly every large financial institutions has began investing in AI to stay competitive in a rapidly changing global workplace where the role of an educated worker is increasingly meant to create automation.

The purpose of this paper is to show the benefits that increasing Artificial Intelligence in finance will have on the marketplace, specifically the breadth of clients it is capable in assisting as well its role in creating a more efficient market. Additionally, it will focus on the transformation the banker from someone who qualitative and client focused worker who tries to get deals done to a quantitative and technically trained worker whose job it is to create AI systems that will interact with clients the banker will never meet.

Due to the technical depth of Artificial Intelligence as well as the Financial Technology (FinTech) this paper will have a plethora of background information. The first two sections of the analysis chapter will be dedicated to informing the reader the necessary knowledge they must know before they learn about the use of AI in finance. The first of these two sections will give a history FinTech starting with the introductions of computers in finance, and how its path lead to where the industry stands today. The second of these sections will give a brief overview on what Artificial Intelligence is. The implementation of AI is only a couple decades old, however, its history dates back to World War II, and the debate on what is considered AI continues to this day. This section will help clear up the misconceptions of AI as well give an understanding of how much work is being done currently to make it a part of our everyday life.

The final section of the paper will tell the reader all of the ways that AI is currently being used in finance and how each of these implementations is assisting to create an equality of opportunity in personal finance in addition to a more efficient market. Moreover, the final section will illustrate the future role of the banker as an architect of financial intelligence systems rather than a deal maker.

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Syver Johansen

December 2017

**III. Analysis**

**Section I: A history of technology in Financial Markets**

*Reporter: Why did you decide to rob banks?*

*Willie Sutton: Because that’s where the money is.*

**Introduction:**

Becoming rich in both time and money is an innate desire. As a result, people like to maximize the efficiency to create capital gain so that they make the most money for the least possible work. One of the greatest ways to exploit the inefficiencies in market in order to make capital gains is to create the means through the latest technology to maximize the number of transactions carried out in your favor. The practice of technology in finance and banking has lasted for nearly two thousand years, however, most of its investments have come in the last half century with the development of computers. This section will explain the history of technology in banking and will be organized in a timeline manner. Although technology has been used in finance as early 900 AD with the introduction of paper checks, for the sake of only considering modern technology, this section will begin in the 1950s with the beginning of computational finance as a discipline.

1. **Genesis of Computational Finance (1950s)**

Prior to the 20th century, banking was largely an elitist and qualitative industry that vastly ruled by kings, merchants, and industrialists needing to raise capital to start wars, fund trans-oceanic trade, and build factories, respectively. Although loan offering requires knowledge of a number of variables including inflation rates and present value that require mathematics, the industry was a lot more about making connections with deep pockets in order to get receive funds from M&A setups and large loan payments. The early capital markets in addition were exclusive to company owners who wanted to diversify their assets in case their business had a bad year. As a result of being a largely qualitative industry, and technological innovation being focused to material instead of data purposes, finance used little technology besides paper until telephones in 1920s when the world experienced a credit and stock boom.

After the Great Depression, the stock market did not go away and the worldwide focus on education, specifically in mathematics, from the World War II and the Cold War brought calculus and data analytics to Wall Street. With the increased focus on data, it became necessary to be able to process it in a meaningful manner. Luckily within the past decade people had figured out how to configure electric circuitry to process input in the forms of computers. Economist Harry Markowitz was the pioneer of the new discipline of computational finance when in 1952 he hypothesized that portfolio selection could be a mean-variance optimization problem for which he was later awarded a Nobel Prize. Although the computers he was working with at the time did not have nearly enough computational power to solve the optimizations. As a result, Markowitz used algorithms that were close enough to approximate the best portfolio possible. Markowitz discovery of using computers to handle large amounts of financial data sparked a revolution in the industry that is still happening to this day.

**2. Quantitative Analysis (1960-Present)**

WIth Markowitz’ new financial innovation, mathematicians entered the financial industry in droves to study portfolio theory. In the 1960s, fund managers Ed Thorp and Michael Goodkin joined Markowitz and economists Paul Samuelson and Robert Merton in developing computers to arbitrage trade. In doing so, there became an automated way for investors to take an advantage in the different prices between markets by making deals that capitalize the difference in prices. Arbitrage trading has become a staple in hedge fund trading ever since, and has contributed to an overall more efficient marketplace as differences in markets have been nullified by arbitrage traders attempting to maximize their profits.

In addition to the pioneering of arbitrage trading, Eugene Fama of the University of Chicago relied heavily on computers and Markowitz’ work on optimization to discover his efficient-market hypothesis (EMH). The EMH states that asset prices reflect all of the public information on the asset and thus any attempt to beat the market will be futile because the inefficiencies that do exist in the market are random and cannot be discovered with the available data. Fama’s theory has been heavily contested, and has even been blamed for the 2008 financial crisis. However, despite some inaccuracies in the theory, it has been proven to be a good rule-of-thumb to follow for most investors. The EMH eventually lead to an increase in index funds and thus passive asset management, which will be touched upon in the Section III discussion on robo-advisors.

In the 1970s and 80s, computational finance largely shifted towards options pricing with the invention of the Black-Scholes formula as the standard option pricing method. Due to the Black-Scholes equation becoming standard, many funds brought in their own quantitative analysts to make their own models that could outperform Black-Scholes in some areas to make money for the fund. The highly mathematical nature of this formula options pricing as well the reduction in defense spending from the Cold War ending brought in the “rocket scientists”–many from the Soviet Union– to Wall Street's. Many of these financial engineers had graduate degrees in Physics or Mathematics, and it wasn’t long before they started inventing their own derivative pricing models and asset classes.

In addition to the investment friendly economy brought on by the Reagan Revolution and introduction of personal computers, the plethora of asset classes and financial instruments that exploited inefficiencies in the market brought booms to Wall Street. At the beginning of 1980 the Dow Jones was at 867 points. By the start of new millennium that number grew to 11,722, an unprecedented 1252% increase spread out over 20 years. These new assets were credited with decreasing interest rates and increases in lending by financial institutions during this time period. However, among the thousands of derivative instruments that were created a few turned out to be poisonous. The housing industry in particular grew to astronomical levels as a result of shoddy credit keeping and the reckless belief that people could pay back mortgages that consisted of a large part of the recipient’s income. The result was an economic meltdown and a reconfiguration on how banks practice lending.

As a result of the housing crisis, banks are more than ever relying on quantitative models to correctly assess lending and investing practices so that such a crisis will not happen again, while their income can still satisfy shareholder’s demand. This comes with a large price as the cost for an analyst who is technically proficient to produce such modeling is more than just about any other type of employee. The result is banks and hedge funds are investing in large amounts so that the dynamic modeling required to keep up with market speeds can be fully automated and they can employ fewer traditional quants. This is where AI in modeling has begun and is the future in both the loan and investing divisions of banks and funds, respectively. Further discussion on what this entails can be found in Section III.

**3. Exchanges Go Electronic**

One the greatest outreach programs in terms of market accessibility that the stock exchanges performed was the implementation of electronic trading. Prior to the developed communication technology in the late 20th century, stock exchanges were centralized in location where buyers and sellers would engage in on the floor open outcry trading. This system relied on people to process trades and centralized traders to only a few places in the world.

The world of exchanges began its drastic change to a decentralized, global system with the opening of the NASDAQ stock market in 1971. Although at first it only quoted prices as the technology for e-trading did not exist yet, NASDAQ was crucial in eliminating the spread (difference between bid and ask prices) that was a barrier to many investors. By the NASDAQ began taking over-the-counter (OTC) trades and had listed stocks on its exchange. Throughout the 1980s, the NASDAQ expanded its outreach by adding automated trading systems and being able to execute trades via the Internet. The accessibility of the NASDAQ proved to be valuable to investors. In 1990 when it was still a relatively small exchange, the NASDAQ had a daily trading volume of around 200 million shares. In the next decade that number had grown to 2 billion shares per day. Within no time NASDAQ began passing well established exchanges in terms of size. Despite being an exchange for slightly over 30 years, the NASDAQ has the 2nd highest market cap in the world, only trailing the New York Stock Exchange.

The addition of NASDAQ to the marketplace brought its competitors to ditch the trading floor method for a more electronic one.

**4. Personal Computers Come to Wall Street!**

Part 2: What is Artificial Intelligence

**This section will be lengthened from what it currently is so it will be split up into the following categories:**

* **A description about what artificial intelligence is.**
* **History in the workplace**
* **History of AI**
* **Current state of AI**

*“Maybe the only significant difference between a really smart simulation and a human being was the noise they made when you punched them.”--Terry Pratchett*

**Introduction:**

Artificial intelligence is one of the buzzwords that has loomed over society for the past 50 plus years. As computers increased their capabilities, it has been a consistent fear that human labor and thought will be overcome by the cold-hearted and restless beings that are machines.

This section will explain what exactly Artificial Intelligence (AI) is, the history of AI, and what stage of AI we are in currently.

**What is Artificial Intelligence?**:

Artificial Intelligence is the study of intelligent agents that perceive their environment and act upon them. There are many different criteria for what constitutes Artificial Intelligence, however, they are mainly split up by being able to acting or thinking and whether the ideal performance is that of a human or an entirely rational being.

In order to be considered able to act like a human is the most traditional method of measuring Artificial Intelligence. The measurement of acting humanely is performed by the Turing Test whose namesake is based on its designer Alan Turing. A computer can be considered to be artificial intelligence if a human interrogator cannot tell whether or not the written responses it is getting is from a person or a computer. In order to have these traits a computer must have four specific abilities. The first is natural language processing or the ability to communicate successfully in English. The second is knowledge representation, or the ability to keep what it learns in some form of memory. The penultimate ability is to use automated reasoning which us using memory to answer questions and draw new conclusions. The final skill is machine learning which is adapting to new circumstances, and detect and extrapolate patterns.

Thinking humanly is less often used method of benchmarking Artificial Intelligence and there is no formal test that a computer must pass in order to be considered as “thinking humanly”. However, computers that are made in order to think similarly to humans requires knowledge of the human mind. One way that artificial intelligence has been set up to think humanly is through neural networks. Artificial neural networks is a set of machine learning where network nodes work together in clusters to solve problems using shared memory, much similar to how the human neural network works. The development of neural networking is growing rapidly in the AI field as search engines require them in their search algorithms to bring the most relevant information to the user.

Thinking rationally is a criteria that is difficult to define as it requires the computer to be able to perform the “correct” type of thinking. Belief in “rational thought” began its history with Aristotle whose syllogisms began the study of logical thinking where if A=B and B=C, then A=C. This logical type of thinking has been the backbone of computer programming, however, it has not been easy to make artificial intelligence to think in this way, especially when knowledge is not certain. The biggest obstacle for computers to think rationally is optimizing the data it is given. Some of the most powerful computers have problems making rational decisions based on only a few hundred variables.

Acting rationally, the final qualification some define as Artificial Intelligence revolves around rational agents that acts to achieve an optimal outcome. In order to be considered a rational agent, one has to reason logically in order to decide on an action that will achieve the task at hand. However, sometimes rational outcome is not possible, so the agent must decide what action, if any, will result in the best possible outcome. The skills necessary to pass the Turing Test also apply to acting rationally, however, the rational agent method is slightly improved in that it is more responsive to scientific development. As artificial intelligence becomes a larger part of industry, a greater number of people use rational action as their barometer of AI.

**A History of Artificial Intelligence**

The first universally accepted introductory work of AI was performed in 1943 by Warren McCulloch and Walter Pitts. McCulloch and Pitts proposed a model of nuerons that would be characterized as on or off in response to stimulation from surrounding neurons. This proposition was based on the basic physiology of the human brain, propositional logic, and Turing’s theory of computation. McCulloch and Pitts believed that the network of neurons could learn by updating the strength in connection between neurons.

While McCulloch and Pitts may have been the first ones to theorize artificial intelligence, it was John McCarthy of Princeton would lead the first implementation of AI. In the Summer of 1956, McCarthy brought together some of the top minds in the study of computer science and intelligence to Dartmouth to “find out how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves”. At this retreat, Allen Newell and Herbert Simon of Carnegie Mellon developed the Logic Theorist program that is “capable of thinking non-numerically, and thereby solves the venerable mind-body problem.” In additional to Newell and Simon, researchers developed an AI programs where a computer could play a human in checkers. This was the first instance in a long series of programs where the mind of a computer could compete against a human in a board game.

Shortly after their Logic Theorist, Newell and Simon came out with another hit, the “General Problem Solver” (GPS). The GPS took humanlike approaches to solving puzzles in that it made subgoals and then aggregated the subgoals into completing the whole task. Not long after the camp at Dartmouth, John McCarthy moved to MIT where he developed the Lisp language which is the basis for most modern AI programming languages. McCarthy was joined by another founder of AI, Marvin Minsky, in 1958. Together they developed the Advice Taker, the first hypothetical AI system that is still used as a model today.

After the initial breakthroughs in Artificial Intelligence, the so-called “founding fathers”–McCarthy, Simon, Minsky, and Newell became overconfident in their predictions. In 1957 Simon was quoted as saying the ability of machines to learn and create would surpass humans in the visible future. Furthermore, he believed that by 1967 a computer would be a world chess champion. These beliefs were given a hard dose of reality as the early AI programs were simple and required few neuron connections to carry out the task. One of the noted difficulties occurred with language translation where computer interpretation of Russian to English was an utter disaster. Furthermore, early belief was that solely faster hardware would improve the scalability of Artificial Intelligence programs. This proved not to be the case as it turned out there was massive diseconomies to scale required in machine evolution. As a result, complex problems such as beating chess masters became impossible to solve given the current state of AI solutions and computer hardware.

The first breakthrough to tackle the issue of scalability came in 1969 with the development of the dendral program. Previously, AI problem solving had been performed with so-called “weak methods” which solely connected small steps to a complete solution. As they had learned the hard way, this did not work for specific complex issues such as playing chess. The dendral program was the first implementation of domain-specific knowledge which allowed for better handling of cases in an expertise. The dendral program was developed at a Stanford lab by a team of computer scientists and geneticists when trying to find a way to guess a molecular structure given data from a mass spectrometer. Originally, the program made all possible structures with the formula, and then guessed the mass which proved to be extremely inefficient. To solve the issue, consulted chemists gave the research team ways to seek known patterns in the molecules. The new program using the consulted methods turned out to be a tremendous success and a major breakthrough in domain-specific AI. Later the same team of researchers that developed the Dendral program also developed the Mycin program that could diagnose blood infections as well as blood experts. The success of the Dendral system did not stay at Stanford, however. Yale linguist Roger Schank developed a program to understand natural language and the issues of having the knowledge required for understanding language.

By the time the 80s rolled around, commercial institutions began implementing artificial intelligence. The first system R1 was developed at Digital Equipment Corporation and arranged orders for computer systems. R1 was such a tremendous success that by 1988 they had 40 R1-esque systems deployed saving the company hundreds of millions of dollars a year. The success of DEC led an increase in AI research development from a few million dollars to over one billion dollars in less than a decade. Systems that were developed included vision systems to visualize data, and robots to act upon the sight. Once again the lofty goals of AI were too much for researchers to handle, and commercial AI went into a recession that lasted until the 21st century.

Despite the slump in AI following the 80s, people began to see a small resurgence in the late 1990s. One of these examples was with the acceptance of the intelligent agent. As discussed in the previous section, an intelligent agent acts based on what will maximize its success for a given goal. An intelligent agent is an economical way of thinking that deals with solving subproblems. Intelligent agents appeared with the explosion in internet popularity, specifically in reference to bots and search engines. Search engines in particular are dependent on intelligent agents as the results of a query are specifically tailored to a number of variables of the user including location, age, gender, and personal preferences. Intelligent agents have found most of their success in internet applications, however, as industry machinery has struggled with it due to sensory perception of machinery faltering. In addition to the internet breakthroughs of the 90s, Deep Blue, a computer developed by IBM defeated world chess champion Garry Kasparov in a six match competition.

Since the turn of the 21st century, AI has largely been about handling large datasets for help with analytics. This is largely due to the merging of AI with standard computer science algorithms. In modern computer science, people are becoming less worried about algorithms to apply for organizing data and more worried about gathering data so that AI itself can sort it out. One of the methods that was used to teach a computer to generate coherent and relatable sentences came from something called “bootstrapping”. Bootstrapping is a method that uses random sampling with replacements and constantly gets feedback in order to accurately represent the data. As the amount of text grows, the computer begins to formulate its own sentences better and better until it is fluent in language. Additionally, solutions to knowledge bottleneck–knowing what a system needs for a solution–have been introduced with the invention of these bootstrapping-type learning methods. These breakthroughs lead many to believe that we are on the verge of an AI revolution

Part 3: The AI Invasion in Finance

*“We are a technology company.”*

*--Lloyd Blankfein, CEO Goldman Sachs*

Similar to any other industry, finance has been affected by the development of artificial intelligence. This section will discuss the different types that currently in use or production by financial institutions as well their success and future. Finally, this section will provide insight on what the future role of the banker will look like.

**Robo-advisors**

Perhaps the most widespread use of AI in finance has come with the development of robo-advisors. Robo-advisors which typically use a more passive asset management system has shaken up the mutual fund industry immensely in the past few years. Although the industry started during the 2008 financial crisis, it has grown insurmountably with an expected $2 trillion in assets managed by robo-advisors by 2020. This section will provide an overview of the history to this point of robo-advisors, an explanation on their inner-workings and common strategies, and what the robo-advisor business will look like going forward.

The history of robo-advisors is not a lengthy one. The first robo-advisors were founded in 2008 amidst a global financial meltdown as a cheaper alternative for investors to receive advice on their holdings. Prior to 2008, many human financial advisors used software that gave advice on what to buy and sell based on preset algorithms that examined market movements. The first robo-advisors were essentially the same as the software used by financial advisors, except they eliminated the middleman and could be used by the consumers themselves. Silicon Valley took notice of the potential profit of automated advising and within no time, systems such as Betterment and kaChing were developed. This new wave of robo-advisors equipped newer features such as tax-loss harvesting. Betterment in particular caught on with investors and since it launched in 2010 it has gone from a startup to an investment company with $10 billion in assets under management (AUM). It did not take more than a few years for the large mutual funds to catch on with the competition. In 2015 both Charles Schwab and Vanguard launched their robo-advisors for clients with $50,000 and $5,000 in capital. The programs became an instant success with AUM being $65 billion and $16 billion as of present time.

One of the unique features of robo-advisors is that they all adhere to a passive indexing strategy which is investing in market-weighted index or portfolio. Passive indexing has been shown as a beneficial strategy due to higher diversification, and low management and transaction fees. Furthermore, empirical evidence has shown that a mutual fund’s ability to pick stocks stocks that outperform market averages is largely a fallacy. This has been illustrated thoroughly in three major works in the past 50 years. The first was by Princeton Economist Burton Malkiel in his 1973 book *A Random Walk Down Wall Street* where he wrote that a company’s returns versus markets averages tends to follow a random walk and thus past prices do not contain enough information to hypothesize future stock predictions through technical or fundamental analysis. This research was updated by Yale’s David Swensen in his 2005 book *Unconventional Success*. By examining the largest active mutual funds, Swensen found that after fees and taxes, the largest funds underperformed market averages 86% to 96% of the time. Furthermore, he discovered that the average gains of a mutual fund that does outperform the market was less than the absolute value of the average losses of a mutual fund that does not outperform the market. Lastly, in 1998 investment analyst Charles Ellis wrote *Winning the Loser’s Game* which spoke of the effect mutual funds had on the efficient market hypothesis. Ellis wrote that active institutional investors were involved in a prisoner’s dilemma scenario where they each spend so much effort in beating the market that in doing so they create the market they are trying to beat. The more they try to beat the market, the more they rack up in transaction fees which in the long run puts them in an even deeper hole.

Robo-advisors still follow the same steps in investment as all institutional investors of: asset allocation, implementation, and monitoring and rebalancing. There is, however, differences in how these steps are enacted. In terms of asset allocation, robo-advisors tend to allow its clients to withdraw leaving them to liquid assets such as stocks, bonds, and tax harvesting. After figuring out the asset classes they can invest in, robo-advisors will then estimate make market assumptions about the expected returns and risks of potential asset classes. This is performed with built in algorithms that figure out the efficient frontier of the different assets using Markowitz’ mean-variance analysis. The robo-advisor will measure correlations between the assets as well to minimize systemic risk and make well diversified portfolios. The amount of risk is typically based on the investing needs of the client. If the client is older, they will not need as much risk in their assets and thus they will typically be heavily invested in bonds. In terms of implementation, robo-advisors select the assets (specific indices) that meet the criteria of the clients needs. In addition to picking assets, newer robo-advisors will also tax-loss harvest. What this means is that they will sell securities for a loss and use the proceeds to buy correlated assets to substitute. This takes advantage of capital losses and the portfolio return increases with the tax rate arbitrage that is obtained. The final step of robo-advising is monitoring and rebalancing the assets. Passive investing calls for threshold reinvesting as opposed to time reinvesting. This means that once returns are a specific percentage away from the target, the advisor will automatically performs the necessary trades to rebalance the account to the correct mean-variance levels.

The main difference between robo-advising and traditional financial advising is that financial advisors are human and thus have biases that are faulty to investing. This can be scene in the different steps of investing listed above. With asset allocation, traditional advisors typically do not use mean-variance analysis or proper portfolio when selecting assets to invest. Additionally, advisors are largely incapable of performing the same level demographic analysis as robo-advisors when considering age, income, wealth status, and often incorrectly take gender into consideration. In terms of implementation, monitoring, and rebalancing, human advisors are subpar at balancing the tradeoff between high performing assets and transaction fees. This balance is not hard to figure out for robo-advisors that focus on selecting ETFs that minimize expense ratios and maximize tax efficiency. In addition to improved investment methodology, robo-advisors also have more clarity when it comes to investment advice. A large part of how human advisors keep clients is by complicating their advice so that it appears that the layman cannot understand. Robo-advisors have nothing to lose by telling the truth, so they explain their exact strategies and asset allocation.

In addition to the benefit of better returns from passive management in comparison to active management, there has been empirical evidence of success of robo-advisors reducing fees and inefficiencies in its trading. An in-house study by robo-advising company, Betterment found that their expense ratio was was 0.15%, much lower than the fund’s industry average of 0.43%. Furthermore, the transparency of robo-advisors has been shown to be much improved. A study by Sendhil Mullainathan from Harvard found that 30% percent of advisors refused to offer their trading strategy before their clients transferred funds. Furthermore, despite robo-advisers being criticized for lacking a personal touch, they have been shown to be better at personalizing portfolios to the investor’s needs. A study of Canadian financial firms in 2015 showed that human advisors only covered 12% of the cross-section variance of the demographics while robo-advisors covered 30%.

Robo-advising has theoretical benefits to the markets as well in the same way that automated trading does.

* Better at timing markets and rebalancing
* Diversification through ETFs

Robo-advising has its detractors

* In the same way the proponents of robo-advising admire the humanless investing, its detractors believe that they are not as humanless as you think.

* + **Wealth managers and Market Analysis**
    - Blackrock is king here with Aladdin
  + **Underwriting**
* **The future role of the banker**

The banker of the future is who more resembles your Silicon Valley startup hero rather than