True Intelligence in Finance

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Abstract

The growing popularity of artificial intelligence (AI), in modern day industry, has begun to spread to the financial sector. Due to this spread, the discussion has begun for what AI model can most accurately accomplish tasks such as financial predictions, risk assessment, and credit evaluation in the financial industry. Many of the AI models used today have various capabilities that make them better suited for certain jobs. The financial industry requires AI models with the capability of accurate prediction, even if most of the predictors for an outcome are usually unknown. Due to the fact that many of the predictors are unknown, it is important that the AI model be able to adjust the weights of known predictors to accommodate for the previously unknown predictor, a capability that neural networks have. Nevertheless, increasing reliance on AI has begun to raise questions on its viability, due to the possibility of discriminatory practices and other societal issues.

True Intelligence in Finance

**Introduction**

The financial sector is one of the cornerstone industries of our nation, and the growing efficiency of this industry could directly result in an increased standard of living. New artificial intelligence models have played a role in this industry since the early 80s and have helped revolutionize the way financial companies do business. With the increasing interest in AI models these days, there is a lot of debate over the direction the financial industry is taking. Many people have begun questioning whether it will be possible to replace the humans in finance with smarter and more efficient AI. The answer to these questions depend on the type of AI models the industry decides to implement. Artificial neural networks, created as a result of the growing interest in artificial intelligence and machine learning, will be more impactful in the financial industry than other AI models like linear regression models. Neural networks are superior when it comes to financial calculations in areas like credit evaluation, risk assessment, and financial prediction, resulting in an overall increase in industry productivity. However, there are many arguments against an increased reliance on AI which should be considered when implementing this technology, since this technology is extremely complex and controversial. In fact, AI models take months to prep in order to ensure they are functioning correctly.

**Background**

Functioning AI models for the financial industry are so difficult to make that there are only a dozen or so AI models operational throughout the various big name financial companies such as Wells Fargo, Citigroup, MetLife, etc. These models have been modified and replaced over the years in order improve them and allow them to handle larger amounts of data. One of the biggest improvements to these financial AI models was the implementation of neural networks instead of traditional linear regression models. The main strength of the neural network is that it is non-parametric, meaning that the AI model does not have a set number of inputted parameters but, rather, analyzes the data to come up with its own parameters. Linear regression models, on the other hand, have to have a specific set of parameters inputted (Burrell, Folarin, 1997, 194). Chase Manhattan Bank was one of the first banks to make this switch and was able to extract reliable data from financial statements, something that was not possible with the previous AI models (p.195). One of the issues with neural networks; however, is that there are no specific guidelines for when to use this AI model (Coakley, 2000, 120). Neural networks have been proven to be extremely useful in various areas of finance, such as credit evaluation, portfolio management, and financial prediction; however, various other fields have had very mixed results. (p.121). In order to understand why this model is so effective in these fields, some background must be provided.

Before implementing neural networks, most financial industries used financial marketing models such as efficient market hypothesis, statistical analysis, portfolio management theory, and financial ratios, in an attempt to predict the impact of unknown forces in finance; however, they were particularly weak and often were unreliable (Burrell,1997,194). Financial researchers quickly discovered that supplementing these models with neural networks yielded much more accurate results and these researchers have been using this AI model ever since. However, the wide application of this technology has a began to bring up many ethical questions over these various types of AI.

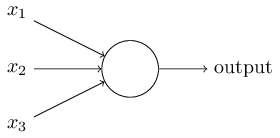
**Precedents and Related Works** As previously stated there are various different types of artificial intelligence models with various applications. One of the most popular models for machine learning is the linear regression model. This model revolves around one formula which is:  
 y = w1x1 + w2x2 + w3x3 ....

This model assumes that the output (y) is a linear combination of the various inputs (x1, x2,…)(Ho, 2012). The training phase of this model has one goal in mind which is learning the weights of each of these inputs. This is usually done with a gradient descent technique, which essentially adjusts with wait of each variable using the loss function, which is a function that shows how far off your results were from expected results. This model has been found to be extremely strong in both its predictions and in the learning phase, which are the reasons why it has been used since the 1990’s. As a result, this model has been found to be extremely effective in image recognition and speech recognition. Many other AI models have been implemented in various other industries as well, which has sparked debate over various ethical issues.

When factories began implementing machines to replace factory workers, the workers began to rebel, arguing that a machine could not do the work of a human simply because it could not put in the care and detail that humans could (Baase, 2013, 333). Machines evolved however, eventually resulting in their ability to mimic the work done by a human despite the machines’ inability to pay close attention to factors that might affect the final outcome of the product (p. 333). This technology has allowed for mass production and the automation of many jobs, advancements whose impact cannot be denied. These advancements have allowed society to focus on various different fields and advance significantly in the last few decades. The implementation of AI in the financial industry has raised many of the same questions that society had when automation began. Some of the questions raised were: whether a machine can do the work of a human, whether it can take into account the various factors that can affect the work that it is trying to do, and whether it is ethical to replace the jobs of thousands of workers. Tom Lin, from the University of Florida, proposes another issue altogether, the issue of regulation (2013, p.684). Regulation was also an issue that arose when it came to replacing factory workers. People believed that without regulation, companies would indiscriminately lay off workers, which would drive the American economy into the ground. However, all these changes did was allow for new innovation, leading to new jobs in different fields, all around keeping the unemployment rate at a steady percentage. Despite this controversy it seems that technology continues to evolve and profoundly impact societal change.

**Support**

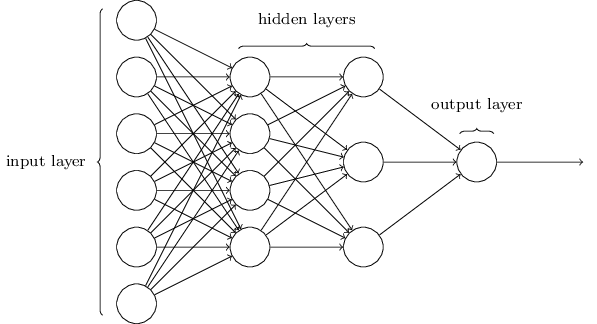
It is truly incredible how the minute difference between neural networks and linear regression models can create such diverse results. An artificial neural network has various different components. Neural networks are composed of layers of various interconnected units, neurons or perceptrons (Nielson, 2017, para. 8). Each neuron receives inputted connections from the neurons in the previous layer and outputs a single value, as seen in Figure 1 (Nielson, 2017).



*Figure 1*. Example of a perceptron

Neural networks use a web of these interconnected neurons to simplify large data sets into one simple output as seen in Figure 2 (Nielson, 2017).

*Figure 2*. Neural network model



Each neuron contains a specific value between 0 and 1, this is similar to the human brain where each neuron is either active or inactive, 0 or 1 (para.8). The value in each neuron is determined by adding up the values of the previous layer and adjusting the value of each of the inputs using a weight (Coakley, 2000, 120). This weighted sum is a linear combination of inputs from the previous layer (inputted layer). After applying weights to the inputs, a bias is applied to the weighted sum. Bias is a positive or negative number that is added to the weighted sum in order to adjust the value to be either more active or less active based on previous assumptions. The values of each neuron are then adjusted to ensure they are between 0 and 1 using a function known as the

*Figure 3*. Sigmoid function

sigmoid function (Wolfram, 2017). The sigmoid function, displayed in Figure 3, takes extremely large positive numbers and makes them close to one and very large negative numbers and brings them close to 0. This adjustment ensures that all neuron values are between 0 and 1. Recently however, researchers have been using a different the rectified linear unit function (ReLU) instead, which can be seen in Figure 4, seeing as that function results in shorter training times; however, for the sake of learning we will be using the sigmoid function (Sharma, 2017).



*Function 4*. Rectified Linear Unit Function

Now that we have the weighted sum which is adjusted for bias and which is adjusted using the sigmoid function, we now have the value of that one neuron. What we really need however is the values of the neurons in the output layer. We can determine this by using matrix multiplication, as displayed in Figure 5 (3Blue1Brown, 2017).

*Figure 5.* Equation for output layer

In Figure 5, the matrix on the left contains a matrix of all the weights for the inputs. The second matrix from the left contains the parameter values (originally inputted data from the outermost neural layer), and the final matrix is the bias. All of this is then plugged into the sigmoid function to produce an output matrix. Each entry in the output matrix corresponds with the value of the neurons in the final layer (3Blue1Brown, 2017). Finally, the output or prediction of the model then corresponds with the neuron with the highest value.

This is no easy process. These neural networks have to be trained for weeks, and sometimes months, in order to have the weights and biases adjusted correctly in order to have accurate results (3Blue1Brown, 2017). This is all done through backpropagation which essentially calculates the error of the model and then adjust the weights of inputs to ensure the results are more accurate. In some cases, the results are 99.8% accurate.

There are many things that make neural networks so successful. The main difference from linear regression models, and the strength of neural networks, is that neural networks can adjust the weights assigned to each individual neuron and does not simply assume a linear relation between inputs and outputs (Coakley, 2000, 120). The ability to adjust weights allows for neural networks to model non-linear processes, making them ideal in the financial industry where conditions are constantly changing (Burrell, 1997, 194).

The interesting thing about neural networks is that they are really not very different from linear regression models. In fact, in essence neural networks are more complex and layered linear regression models. Thinking back to the equation for the value of each neuron, each neuron contains a weighted sum of the inputs from the previous layer, which by definition is a linear combination. Linear regression models use this same linear combination except rather than apply it single neurons it attempts to find a linear relation between all the inputs through gradient descent. Simplified, neural networks and linear regression models both are attempting to adjust the weights and biases of their inputs, but neural networks are doing this on a smaller, neural, scale. This is what allows neural networks to make accurate predictions even if the inputs are non-linear.

The financial world is constantly changing and being impacted by unknown forces so being able to adjust your model for non-linear outside forces makes this model key for the financial industry. In fact, one of the first applications of neural networks in finance was by Lapedes and Farber, neural network researchers working in Los Alamos national laboratory, who used this model to predict chaotic times in the financial industry in 1987. While Lapedes and Farber’s model was not initially successful, recent research has revamped this model and is yielding increasingly positive predictions (p.194).

These small differences between linear regression models and neural networks allow for better performance in various aspects of financial calculations. Firstly, neural networks are extremely helpful for analyzing the success rate of smaller firms by interpreting the current success ratios of the company and by estimating the possible capital in the following couple of years (p.194). Furthermore, by combining past models with the neural network models, financial researchers have been able to simulate company expansions and failures with fairly accurate results (p.195). One of the most impressive feats achieved with the new neural network technologies was the implementation of accurate models that can predict banking failures (Ristolainen, 2017, 31). These models are known as early warning systems (EWS) and these systems use various models to help predict banking failures based on past failures as well as current international financial data (p.32). This was only made possible in the last decade by the ability to adjust the waits of unknown factors, something that economists have struggled with immensely since the Great Depression. Kim Ristolainen, a Scandinavian financial researcher who designed her own EWS, states that the difference between EWS systems with linear regression models and EWS systems with neural networks is that the linear regression models performed phenomenally with the in-sample results, meaning inputted past banking failures; however, they performed very poorly with out-of-sample results (p.34). The reasoning that Ristolainen gives is that the relation between the banking crisis probability and the indicators are not necessarily linear, and in fact most of them are non-linear, meaning that the linear regression model cannot handle the relation between indicators and probability correctly.

Arash Bahrammirzaee, an author for IEEE Spectrum, examines the various tasks which neural networks excel in and analyzed whether those same tasks are done in the financial industry. Some of the main tasks assigned to these AI models are decision making, forecasting, and complex problem solving. Having the best possible candidate do each of these tasks is essential for the financial industry, which is why most financial companies employ AI to do it. AI models excel in these tasks, and with good reason, they can make relations between non-linear factors, allowing for new technology and, in effect, new societal implications.

The financial institutions of America play a key role in the economic success of the nation as a whole. This means that a better functioning financial institution results in a more stable and successful economy, and ultimately happier and more comfortable citizens. There are actually arguments against whether a more successful economy leads to more happiness in a nation but that’s a separate argument all together, so for the sake of this argument we will assume that there is a direct correlation between economic success and general comfort and satisfaction in a nation (Dutt, 2008, 527).

The single biggest cause of the great depression was the banking system’s ability to provide its clients with the proper amount of liquidity, forcing large chains of banks to go under. By being able to better predict the need for liquidity it would better allow financial institutions to prepare for these potentially disastrous events and combine their efforts to better deal with them.

By allowing financial institutions like banks to make more accurate predictions it allows for more stable loans and more flexibility on these loans. The stability of these loans would allow for a healthier banking system and a more stable economy. However, this also presents a very possible issue which is the issue of discrimination.

One of the main ethical issues that is often brought up when talking about the increased prominence of artificial intelligence in industry, is the issue of perpetuating discrimination. As stated, programmers are the ones who decide on bias in neural network models, meaning that if the programmer introduces bias towards a certain group of individuals in his neural network then it would result in further discrimination. Additionally, there is another type of bias that could feed into these neural networks which is bias in the inputted data. There is still discrimination in society today meaning that the data on these groups of individuals may also be impacted and may result in a biased model which would discriminate against minorities, further resulting in a sort of feedback loop. This is a valid concern; however, there are ways to deal with this without denouncing the technology as a whole.

One of the main ways to deal with this issue would be to make the assumptions and inputted biases of these AI models transparent. This transparency would allow others to critique these models and decide whether they are may be discriminating. Unfortunately, simply making these assumptions transparent is does not get at the root of the problem, which is technology perpetuating discrimination in society. While reforms can be made to attempt to regulate this discrimination in technology, there is no real solution simply because programmers are building their models with their own bias. Even with a regulated technology, minorities would still be discriminated against and this technology could potentially lead to them having higher insurance rates and loan interest rates, or even be declined for much needed loans. Overall, if this issue is left unsolved this technology could have drastic repercussions on the minorities, and according to John Rawls’ veil of ignorance, we cannot utilize this technology for financial purposes until we decide how to deal with machine bias so as to avoid hurting minorities.

Another issue that often comes up, which Jeff Hawkins, founder of Palm Technologies and founder of Redwood Center for Theoretical Neuroscience, discussed in an article he wrote is the issue of AI replacing human workers. Hawkins believes that there is no way for AI to replace us in finance (2007, 3). He believes that when making decisions, AI often tends to simplify the data in order to make it easier to process because the system either does not have the processing power or it would simply take too long to come to a proper conclusion (p.3). He believes this simplification makes the results invalid and would mean that humans are the only candidate possible for dealing with issues in finance.

The one flaw in this argument is that it assumes that the human brain is more successful than these AI models. As explained with the early warning system models, machines are much more capable of predicting behavior than humans are when given objective data. Perhaps when it comes to race, gender, and social standing, people are more biased than machines, and in turn humans should let machines do the decision making for them. Machines cannot take into account the stereotypes and past discrimination but rather they simply take in real time data making them biased as a result of their creator’s bias, meaning they are not inherently biased, and so they can accomplish tasks which are not prone to discrimination.

**Conclusion**

After considering the differences between neural networks and the other types of AI models, it seems that neural networks are the much more appropriate AI models for the financial industry due to their ability to adapt to previously unknown predictors. This minute difference between models can make for a tremendous impact on the American economy as a whole and have an incredible impact on the way its citizens live. This new AI model could result in a more reliable banking system, a more accurate credit evaluation system, and improved systems to predict financial instability. However, the implementation of this technology could easily cause various social issues, such as the issue of unemployment and minority discrimination. Overall society seems to have come to a cross road where it must decide whether it is accepting of technology and it allows AI to make decisions on its behalf. Many people are skeptical of this idea; however, based on the results of various AI models, in relation to the results of humans, it seems possible that AI has and will continue to have tremendous impacts on both society and industry. New technology is vastly increasing the modern comfort society experiences today, neural networks being the next step in this development. These comforts also come with costs, so, it is important that every person, especially computing professionals, reflect on the possible risks that come with newly developed technologies, in order to protect minorities from technology that may do them harm.

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