Asset Allocation Technique for a Diversified Investment Portfolio Using Artificial Neural Networks

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This thesis titled
Asset Allocation Technique for a Diversified Investment Portfolio Using Artificial Neural Networks

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ABSTRACT

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As part of planning for the future and retirement, people typically build their investment portfolio. Investment portfolios are made up of four different asset classes, and typically managed by one of the major investment firms such as the Edward Jones Company. This research works with artificial neural networks (ANN) and closely with an advisor from the Edward Jones Company to provide a machine learning decision making aid for them to use when allocating the four main asset classes that make up a portfolio. The asset class prediction results and trends are then compared by the advisors consulted to decide if this methodology would be a useful aid during high volatility times in the stock market, such as the market crash of 2008. The use of this successful machine learning aid will benefit the investment portfolio that shows promise for yielding higher return on investment (ROI). This research was determined to be a successful machine learning aid to assist advisors with the asset allocation of an investment portfolio.
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1 INTRODUCTION

As part of planning for the future and their retirement, people typically build their investment portfolio. Investment portfolios are made up of mainly four different asset classes, and typically managed by one of the major investment firms, such as the Edward Jones Company.

1.1 What Does an Investment Portfolio Consist Of?

A typical Investment Portfolio is made up four main asset classes. The four main asset classes are U.S. Stocks, Bonds, International Stocks, and Hedge Positions. Those asset classes are made up of multiple stock indices.

U.S. Stocks consist of six different indices that cover the largest amount of U.S. traded stocks without any overlap, since a stock does not fit into multiple indices. The six indices that make up U.S. Stocks are: Large-Cap Growth, Large-Cap Value, Mid-Cap Growth, Mid-Cap Value, Small-Cap Growth, and Small-Cap Value.

The four major bond issuers that make up the Bond asset class are: Government, Corporate, International, and Municipal. These four bond issuers consist of ten different bond indices which include, but are not limited to, Government-Short Term, Government-Intermediate Term, Government-Long Term, Corporate-Short Term, Corporate-Intermediate Term, Corporate-Long Term, International, Municipal-Short Term, Municipal-Intermediate Term, and Municipal-Long Term.

Twenty-two developed countries--excluding Canada and the U.S.--make up the broadest selection of International Stock indices as well as the International Stock portion
of the investment portfolio. The three indices that cover the broadest of the international stocks are Value, Growth, and the Emerging Market Index.

The last of the four main asset classes that make up the investment portfolio are Hedge Positions. Hedge Positions consist of three major indices that make up the most significant portion of that asset class. Those indices are Real Estate, Cash, and Natural Resources (gold and other precious metals).

1.2 What Determines a Good or Bad Portfolio?

A good investment portfolio is determined by the total return on investment over the course of the portfolio. The investment portfolio can and will change depending upon the client and the stage of their life. An example of this would be a conservative client that has a 5% return; they may consider their portfolio to be good, yet an aggressive investor who has a 7% return may consider it to have performed poorly. The portfolio is an investment in the owner’s future; therefore, the return over a longer period of time is the better determination of a good or bad portfolio. The time period that is often used to determine a good or bad portfolio is a five year window. This is because the idea of investing in your future/retirement is a plan that is often done early in the life of a person, giving the portfolio years to grow.

Diversification of the investment portfolio is an important part of deciding if it is a good or bad investment. Although there are some cases in which one could argue that the portfolio returned more money by being less diverse, this is not an intelligent decision for the investor. When a portfolio has no diversification and the area of investment is doing well, the returns will parallel with the performance of that investment. On the
other hand, if all of the owner’s investments are in one area and the area does poorly, the owner’s returns will go down at the same rate. This can lead to quick gains, but also losses from which sometimes can’t be easily recovered from, especially in the later stages of a person’s life.

Most financial institutions will not let a client’s investment portfolio be under-diversified. Under-diversification happens generally because of individual investors, and typically happens because of one of several reasons. William N. Goetzmann stated in 2008 that, “U.S. individual investors hold under-diversified portfolios, where the level of under-diversification is greater among younger, low-income, less-educated, and less-sophisticated investors. The level of under-diversification is also correlated with investment choices that are consistent with over-confidence, trend-following behavior, and local bias” [1]. This is an example of why an under-diversified portfolio is generally considered to be a bad portfolio, even in the rare case where it has returned more than another, more diversified, portfolio.

Another determination of a successful portfolio is its variance/volatility. As was explained earlier, this will change depending on the owner of the portfolio, since everyone has a different tolerance for risk or volatility when it comes to their finances. If the variance in the portfolio is high, the risk is high, which means that there is a better chance that the return on investment will be minimal, or even become a loss, depending upon the life stage of the owner.

The volatility of the portfolio can also cause it to be deemed bad by the owner, even if the return on investment is positive. The owner may have a low tolerance for
risk, so even if the portfolio is growing in an overall positive direction, they may decide that the portfolio is unsuccessful. They may decide that a portfolio with overall positive returns, a lower variance, and lower returns would better fit their personality and life stage. Although most financial advisors would disagree and prefer a portfolio with higher returns, the final decision would be made by the owner of the portfolio.

1.3 Traditional Approach

The traditional approach to asset allocation for a diversified investment portfolio examined in this research comes from the Edward Jones Company. This approach consists of a risk-tolerance questionnaire, a life stage assessment, a portfolio objective guidance table/matrix, and finally, allocation judgments made by a financial advisor with the clients’ approval.

1.3.1 Risk Tolerance Questionnaire Introduction

A risk tolerance questionnaire is used by Edward Jones in order to question the client as to the risk they are willing to accept in regards to their portfolio and end goals. These questions help the client and advisor decide the best path for the client while keeping the risk at an acceptable level. It will help the advisor determine if the client is willing to accept a higher or lower risk/volatility of returns of their investment. The questionnaire is also used to document the answers of each of the six questions asked of them by the advisor, in case there is ever a discrepancy in the investment strategy/path the client is on.

The questionnaire is made up of six questions that are scored on a 0-17 scale for four of the six questions and a 0-16 scale for the remaining two questions. Questions one
and five offer four answers and are scored from 0-17; questions two and three offer three options and are scored from 0-16; and questions four and six have three answer options and are scored on a scale of 0-17.

After all the questions have been answered, the scores from each are added up to generate a final score. A score ranging from 80-100 results in a high tolerance for risk, 60-79 is a medium-to-high risk tolerance, 40-59 a medium tolerance, 19-39 a low-to-medium tolerance, and 0-18 equals a low tolerance for risk.

1.3.2 Life Stage Assessment (As Defined by the Edward Jones Co.)

After the client fills out the risk tolerance questionnaire, the financial advisor is able to quantify the tolerance for risk/variance the client has by using the resultant score from the six questions. Knowing this number, the advisor then needs to determine what life stage of investment the client is in. A life stage refers to where the client is in their life. Edward Jones breaks the investing life of a person into five stages.

1.4 Portfolio Objective Guidance Table/Matrix

The financial advisor then uses the number/classification of the risk tolerance of the client and the stage of their life investment to pick the most suitable portfolio objective for that client. This is done by using a portfolio objective guidance table/matrix. This was developed by the Edward Jones Co., and is what the advisor is expected to use to determine the portfolio that fits the client’s tolerance for risk and goals for their investment stage. This matrix can be seen in Figure 6.
1.5 Actual Investment Portfolio

Knowing the recommended portfolio objective based on the matrix, the advisor then enters information about the client from the risk tolerance questionnaire, life stage assessment, and matrix into an internal computer program that recommends a range in five subsets of the overall portfolio. The five subsets are used to diversify the client’s portfolio. Diversification, as mentioned earlier, is one determination regarding if a portfolio is successful or not. Investment portfolios are required to be diversified by Edward Jones; therefore, the advisor is expected to follow this diversification bar chart.

The diversification bar chart is broken down into five subsets, consisting of cash, income, growth and income, growth, and aggressive. Each subset has two bars that describe both the actual and recommended ranges for the advisor to make judgments. Across the bottom (x-axis) of the bar chart are the five subsets which are made up of many different indices of bonds, stocks, and hedge positions. Down the left side of the chart (y-axis) are the percentages from 0 to 100 that the bars recommend the advisor allocate in order to meet the portfolio objectives of the client and keep it diversified.

Figure 1 shows the bar chart of an actual portfolio with both the actual and recommended ranges. The bar to the right of each of the subsets has a white area, which is what percentage the program recommends the advisor should allocate to that subset. On top of the white section of the bar graph is a shaded area, where the advisor makes decisions as to the different percentages that he/she is willing to allocate to the client’s investment in addition to the recommendations from the computer system. The left bar of each column on the chart is a snapshot of where the portfolio is at on that day. The
market varies every day, so at any given point the actual percentage will vary from the recommended ranges based upon how the market performed. The advisor and client make the decision regarding if and when they should rebalance the portfolio based on how far the actual percentage is from the recommended. The advisor consulted in this research recommends a +/-5% change in any one subset of the recommendations to rebalance the portfolio. This can vary depending upon the advisor and client.

Figure 1. Diversification Bar Chart

The five subsets of the diversification bar chart are made up of many indices that were mentioned earlier in this paper. Table 1 shows the breakdown of the bar chart and the indices of which each consist.
1.6 Limitations of the “Traditional Approach”

Emotional investing is a major limitation of the Edward Jones investment model. Emotional investing is human error that leads to buying high and selling low, which can be very detrimental to the investment portfolio for both the client and advisor. If the advisor makes poor judgments for a client, the client’s investment portfolio returns will suffer, and less return on investments for clients can lead to poor client/advisor relationships. Emotional investing can happen because of over-confidence, following trends, and even local bias.

Client/advisor interaction and trust is another limitation of the approach. No matter what their education level, every client that is investing their money must trust that their advisor is giving them suitable advice and recommendations in regard to their asset allocation. Although the financial advisor is governed by the institution he/she works for, in order to not cheat the client or make decisions that are not in the best interest of the client and his/her objectives and end goals, there must be trust between the two individuals. If the client feels that the advisor is making investments to benefit themselves, he/she may want to change the brokerage firm or advisor.
The biggest limitation of the traditional approach is that stock indices are difficult to predict, due to volatile behavior and a very complex interaction of multiple variables. The stock market is a complex system and has non-linear behavior making it hard to predict.

The financial advisor works with the portfolio diversification bar chart using the recommendations from the computer system, which are set and governed by the Edward Jones Investment Policy Committee (IPC). This is the subject area in which the ability to predict each of the four asset classes would help the advisor make better allocations with the client’s investment and increase their return on investment.

1.7 Purpose

This thesis has multiple objectives: first, to show that artificial neural networks can provide models that are capable of predicting real-world occurrences, and secondly, to provide a predictive aid to the Edward Jones Company Financial Advisors when diversifying a client’s investment portfolio. Edward Jones is one of the top financial firms in the nation, but due to the volatility of the financial market, they consider said market to be unpredictable. With that stated, they do not disregard data, and work to understand what the market may do in the future.

1.8 Organization

Six sections separate this thesis research: an introduction to investment portfolios, the Edward Jones Company, traditional approaches to asset allocation, and the limitations of those approaches. A literature review is in section 2, which includes more about the Edward Jones Company, Artificial Neural Networks, traditional and non-
traditional approaches to investing, and information about imbalanced datasets requiring a synthetic minority over-sampling technique (SMOTE). The third section of this thesis describes the methodology in this research, along with how the dataset was compiled. Section 4 contains the results of the ANNs for each of the four asset classes, as well as expert opinion on the prediction performance. The expert opinion also covers if this machine learning methodology would be useful. Discussion of the results is contained in section 5 of this paper. Finally, section 6 consists of the conclusions about the research and possible future directions.
2 LITERATURE REVIEW

In this section, I will describe the Edward Jones Company [2.1], Artificial Neural Networks [2.2], traditional approaches to investing [2.3], non-traditional approaches to investing [2.4], what SMOTE is and the imbalanced datasets requiring it [2.5], and finally, a section summary [2.6].

2.1 Edward D. Jones & Company

The Edward D. Jones & Company is an investment firm that was founded in 1922 and that prides itself in taking a personal, face-to-face approach to serving its nearly seven million clients [6]. It is a full-service firm that has remained a private partnership since its beginning, which the company feels gives them “the independence to make long-term decisions that are in the best interest of our clients and associates without the pressures publicly traded companies face to meet short-term earnings forecasts” [8]. The company has more than 13,000 financial advisors, 36,000 associates, and is approximately a $5 billion-plus business [7]. Edward Jones’ advisors do not focus on day trading, which is defined by Investapedia as “an investor who attempts to profit by making trades intraday” [23]. Instead, the company’s focus is on the long-term financial goals of its clients [8].

2.1.1 Edward Jones’ Competitors

Edward Jones is not the only company to advocate for a conservative investment strategy [9]. There are many investment firms that potential clients can look to for their investment needs. Firms such as The Charles Schwab Corporation, FMR LLC (better known as Fidelity Investments), and Raymond James & Associates, INC. [9] are three of
Edward Jones’ top competitors. This competition drives the companies to be diverse, provide many investment options, advisor availabilities, customer service—and most importantly, a high return on investment for their clients. Edward Jones thinks it can provide this by utilizing their four core values [7]:

1. Clients’ interests come first
2. Belief in a quality-oriented, long-term investment philosophy
3. There is an innate value working in partnerships
4. Individuals and their contributions are respected and valued

2.1.2 Edward Jones Short-Term vs Long-Term Approach/Client

Short-term investing can be thought of as day traders and those with a time horizon of less than five years, while long-term investing involves anything with a horizon over five years, according to the advisors questioned during this research. Edward Jones is not the company for the client who is looking for the “hot” investment of the day [10] for short-term success. They instead focus and work with only the clients that are looking for long-term investment success [7]. This approach by the firm eliminates errors made due to fads [10], speculation [7], and emotional investment, which results in low return on investments for clients.

Although long-term success is most important for their clients, there are stories of those who have had success with timing the market perfectly, resulting in a quick profit. Although this has happened, Edward Jones refuses to “offer options and futures because they are wagers on the short-term value of an underlying security” [7]. There are also taxes and commissions associated with these that can reduce the client’s profit [7] [10].
2.1.3 Edward Jones Investment Approach

The Edward Jones Co. focuses on clients who have long-term investing as their priority, not quick profits. Clients who are trying to make a quick dollar can almost be thought of as gamblers instead of investors. They are gambling on which investments they feel will be the strongest at any one given time. An example of this “gambling” was seen by the Initial Public Offering (IPO) of Facebook in 2012 [7]. Many people bought shares, expecting the value to rise, and most probably thought they could sell it almost immediately after the purchase to make a fast profit. Instead, the shares dropped steeply, proving the purchase was more of an emotional buy than an investment. Many agree with the thought that investors should steer clear of new listings, since it is easy to become more emotional than strategic.

With that said, Edward Jones Co. believes that a 65% investment in equities and a 35% investment in fixed income is the best portfolio allocation for long-term success [7]. Of course, this is the baseline recommendation, which is subject to change based upon the client’s situation. The investments that make up the 65% and 35% allocations should be closely monitored and rebalanced annually by the advisor [7].

Equities are thought of as ownership in an asset after all debts associated with the asset are paid off. In this context, stocks are equity because they are ownership in a particular company [11]. Fixed income is a type of investing or budgeting style where real return rates or periodic income is received at regular intervals at reasonably predictable levels [12]. Those investors who are majority-invested in fixed-income investments are typically retired individuals who are expecting a stable income [12].
The reason for a diversified portfolio is to perform well in both a bull and well in a bear market. A bull market is one in which prices are expected to rise [13]. A bear market is a declining market in excess of 20% [14]. A market decline of 10-20% is considered a “correction”. The investor usually acts differently in different markets. In a bull market, the investor is commonly purchasing securities and commodities in hopes of selling them later for profits. In a bear market, on the other hand, the investor commonly sells with the hopes that they can buy them back later at lower prices. In both markets there are always examples of clients looking to make a quick profit, but diversification has proven to be the best decision for the financial advisors at Edward Jones Co.

To put it more simply, the client can think of diversification as the principle that when bonds rise, stocks usually fall. If the investor has their investments in products that are declining in value, then their portfolio will drop steeply. On the other hand, if they have been lucky enough to invest in products that are increasing in value, then their portfolio would increase steeply due to the heavier-weighted decision based on the market. This is considered by many to be risky, and essentially is gambling, rather than investing [7].

2.1.4 Risk Tolerance

Clients can vary on their levels of comfort associated with risk and their investment portfolios. There are many ways to determine risk and how the investor should allocate their portfolios. A conventional way to decide how much the client should allocate toward stocks is to subtract their age from 100 [15]. One such chart based on this method is provided in Table 2 [15]. Generally speaking, the older the investor gets,
the less risk they should take with their portfolios, due to the declining number of possible years of generating income. This risk tolerance can only be decided based upon the person making the investment and their level of comfort in long-term goals.

Table 2.

*Conventional Asset Allocation by Age (Client’s Age Subtracted by 100)*

<table>
<thead>
<tr>
<th>Age</th>
<th>Stocks</th>
<th>Bonds</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-18</td>
<td>100%</td>
<td>0%</td>
</tr>
<tr>
<td>20</td>
<td>80%</td>
<td>20%</td>
</tr>
<tr>
<td>25</td>
<td>75%</td>
<td>25%</td>
</tr>
<tr>
<td>30</td>
<td>70%</td>
<td>30%</td>
</tr>
<tr>
<td>35</td>
<td>65%</td>
<td>35%</td>
</tr>
<tr>
<td>40</td>
<td>60%</td>
<td>40%</td>
</tr>
<tr>
<td>45</td>
<td>55%</td>
<td>45%</td>
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<tr>
<td>50</td>
<td>50%</td>
<td>50%</td>
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<tr>
<td>55</td>
<td>45%</td>
<td>55%</td>
</tr>
<tr>
<td>60</td>
<td>40%</td>
<td>60%</td>
</tr>
<tr>
<td>65</td>
<td>35%</td>
<td>65%</td>
</tr>
<tr>
<td>70</td>
<td>30%</td>
<td>70%</td>
</tr>
<tr>
<td>75+</td>
<td>25%</td>
<td>75%</td>
</tr>
</tbody>
</table>

*Source: FinancialSamurai.com 2015*

There are models associated with whatever different level of risk the client wants to choose. They can go with a nothing-to-lose type of mentality, such as what is shown in Table 3 [15], which is heavily focused on stocks until retirement age. Another way a
client can decide to allocate their portfolio is with more of a survival asset allocation model, such as what is shown in Table 4 [15], which equally invests in both stocks and bonds, even through the retirement years. Only the investor can decide what is right for them.

Table 3.

*Conventional Nothing-to-Lose Asset Allocation*

<table>
<thead>
<tr>
<th>Age</th>
<th>Stocks</th>
<th>Bonds</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-18</td>
<td>100%</td>
<td>0%</td>
</tr>
<tr>
<td>20</td>
<td>100%</td>
<td>0%</td>
</tr>
<tr>
<td>25</td>
<td>100%</td>
<td>0%</td>
</tr>
<tr>
<td>30</td>
<td>100%</td>
<td>0%</td>
</tr>
<tr>
<td>35</td>
<td>100%</td>
<td>0%</td>
</tr>
<tr>
<td>40</td>
<td>100%</td>
<td>0%</td>
</tr>
<tr>
<td>45</td>
<td>100%</td>
<td>0%</td>
</tr>
<tr>
<td>50</td>
<td>100%</td>
<td>0%</td>
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<tr>
<td>55</td>
<td>100%</td>
<td>0%</td>
</tr>
<tr>
<td>60</td>
<td>100%</td>
<td>0%</td>
</tr>
<tr>
<td>65</td>
<td>100%</td>
<td>0%</td>
</tr>
<tr>
<td>70</td>
<td>50%</td>
<td>50%</td>
</tr>
<tr>
<td>75+</td>
<td>50%</td>
<td>50%</td>
</tr>
</tbody>
</table>

*Source: FinancialSamurai.com 2015*
Like other firms, Edward Jones also performs a risk tolerance assessment on each client to help the advisor choose the proper asset allocation for that particular client. Each client is asked to complete a risk tolerance questionnaire to quantify the level of risk they are willing to accept in relation to their portfolio. This questionnaire allows for the advisor to understand what level of risk the client is comfortable with while also choosing the correct asset allocation to meet their financial needs and risk comfort. This is also
used to document the mutual decision between the client and advisor, in case there is ever a discrepancy in the future. The questionnaire is made up of six questions for the client to answer.

Question one asks the client how concerned they are about inflation. The four answer options for this question allow the client to decide if they want to minimize volatility even if their growth doesn’t keep up with inflation, with options up to trying to grow significantly more than inflation while accepting the larger variances in portfolio values. The client chooses between the four options (A, B, C, or D), and that answer is then assigned a numerical score. An answer of A will equal a score of 0, an answer of B will equal a score of 5, an answer of C will equal a score of 12, and an answer of D will equal a score of 17. The question offers the client a brief description as to the difference in expectations between stocks which have a high volatility but offer a better chance of keeping up with inflation, and bonds which have less variance but offer less of an opportunity to keep up with inflation.

Question two asks the client to state their goals for their investment portfolio by choosing one of the three provided statements that best describes their end goal. Option A would result in a score of 0, option B would score 8, and option C would be a score of 16. Option A describes an end goal that primarily worries about income, with the lowest level of risk of loss and volatility. Option B is a statement that describes an end goal with modest amounts of both volatility and risk of loss over time. Finally, option C describes an end goal that is willing to accept higher rates of volatility and risk of loss in exchange for a higher potential for bigger returns over the time period of the portfolio.
The third question asks the client to choose between three different hypothetical portfolios, with the varying ranges of volatility and potential returns based upon an initial investment of $100,000. An answer of A is scored at a value of 0, B equals a score of 8, and an answer of C gives a score of 16. The hypothetical A scenario shows a portfolio with low volatility and lower potential return, while B shows moderate returns and moderate volatility. The hypothetical C portfolio shows higher volatility and higher potential returns. The hypothetical portfolios are based upon an initial investment of $100,000, and the ranges of the examples showing low-to-high volatility are as follows: A- $87,000-$119,000, B- $81,000-$125,000, and C- $70,000-$135,000.

The fourth of the six questions on the questionnaire asks the client to choose between three statements that best describe thoughts regarding the trade-off between returns and volatility. An answer of A would score a 0, answer B would equal 8, and an answer of C would equal 17. The answers vary from the client being more worried about the portfolio losing value and the return being secondary, to focusing on the return potential, with the potential losses being of secondary importance.

Question five asks how the client would react if the value of their portfolio dropped 25% or more in a year. For example, how would the client react if the value fell from $200,000 to $150,000 in a year? There are four options for the client to choose between, with answers varying from moving their investments to different places to reduce further losses, to leaving their money where it is and possibly investing more. An answer of A for this question would equal a score of 0, B a score of 6, C a score of 12, and D a score of 17.
The last question on the questionnaire asks the client to choose between three portfolios with a long-term average return and their potential yearly gains or losses. The first option has an average return of six percent, the second option an average return of seven-and-a-half percent, and the last portfolio with an average nine percent return. As the average return of each portfolio goes up, the variance also goes up. If the client is able to tolerate higher volatility/risk, then the potential average return hoes higher. Choosing A scores 0, B scores 8 points, and C equals a score of 17.

Once the questions are answered, the numbers are then summed, which generates the score for risk tolerance. A high tolerance for risk is a score from 80-100, a medium-to-high tolerance for risk is 60-79, a 40-59 score is a medium tolerance, 19-39 is a low-to-medium tolerance, and a 0-18 score defines a low tolerance for risk.

2.1.5 Life Stage Assessment (As Defined by Edward Jones)

Life stage assessment is performed by the financial advisor on the client. They break this assessment into five different stages.

The first life stage of investing as defined by Edward Jones is considered to be the “early investing years”. This stage is considered to be the first job for a client who has yet to start a family. This investment stage of a client’s life is generally when they are more risky with their investments and are able to accept higher volatility. This is due to the time they are able to take to recover potential losses caused by a market crash or poor investment choice.

The “good earning years” are the second of the five life stages. This investment stage is when the client is considered to have a stable job and a growing family. The
client in this stage will be someone who is working a job that is considered their career, rather than “just a job”. They usually have a child or children and/or are married, meaning that they have more to consider when making decisions about their future than just themselves.

The “higher income and savings years” are the third of the five life stages. This stage is when the client is at their peak in terms of their career advancement and earnings. Children of a client in this stage would be in or approaching college. The client would typically be advanced in their career field and approaching the peak of their salary. Since the client in this stage is peaking in their career, they are typically able to save more as well.

The “early retirement years” are the fourth of the five life stages. This life stage is considered to be the first 10-15 years of retirement. During this investment stage, the client typically starts to change their investment strategies to less risky, more conservative options. Large losses caused by poor decisions or market crashes are hard to recover from in this stage of life. The client is now on a fixed income from retirement and previous investments, rather than the earnings from the peak of their career.

The “late retirement years” are considered the last stage of the five life stages. This stage is when the client has been retired for more than 10-15 years. At this stage, the investor will typically be the most conservative they have been at any stage in their life. A client in this stage is not able to recover from losses, since they are on a fixed income based upon previous investments and salary. A typical advisor strategy would be to put the investor in very conservative, low-variance investments.
2.1.6 Portfolio Objective Guidance Table/Matrix

The portfolio objective guidance table/matrix consists of the five investment stages of the client across the x-axis of the matrix, as well as the five risk tolerance classifications down the y-axis. Following the classification across to the column of the life stage the investor is currently in will be the recommended portfolio objective that best fits the client in question. The different objectives that are classified in the matrix are growth focus, balanced toward growth, balanced growth and income, balanced toward income, and income focus. Figure 2 shows the matrix that the advisor uses to determine the portfolio objective for the client.

<table>
<thead>
<tr>
<th>RISK TOLERANCE</th>
<th>Early Investing Years</th>
<th>Good Earnings Years</th>
<th>Higher Income &amp; Savings Years</th>
<th>Early Retirement Years</th>
<th>Late Retirement Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>Growth Focus</td>
<td>Growth Focus</td>
<td>Growth Focus</td>
<td>Balanced toward Growth</td>
<td>Balanced toward Growth</td>
</tr>
<tr>
<td>Medium to High</td>
<td>Growth Focus</td>
<td>Growth Focus</td>
<td>Growth Focus</td>
<td>Balanced toward Growth</td>
<td>Balanced – Growth &amp; Income</td>
</tr>
<tr>
<td>Medium</td>
<td>Growth Focus</td>
<td>Growth Focus</td>
<td>Balanced toward Growth</td>
<td>Balanced – Growth &amp; Income</td>
<td>Balanced toward Income</td>
</tr>
<tr>
<td>Medium to Low</td>
<td>Growth Focus</td>
<td>Balanced toward Growth</td>
<td>Balanced toward Growth</td>
<td>Balanced – Growth &amp; Income</td>
<td>Balanced toward Income</td>
</tr>
<tr>
<td>Low</td>
<td>Balanced toward Growth</td>
<td>Balanced – Growth &amp; Income</td>
<td>Balanced – Growth &amp; Income</td>
<td>Balanced toward Income</td>
<td>Income Focus</td>
</tr>
</tbody>
</table>

*Figure 2. Portfolio Objective Guidance Table/Matrix*

2.2 Artificial Neural Networks

Artificial Neural Networks are nonlinear models made up of combinations of simple nonlinear functions that are similar to biological neural networks such as the human brain. This enables them to provide some human problem-solving characteristics that other linear and non-linear models do not. They are trained with expert knowledge from data that is run through different learning algorithms and transfer functions to create
a model that can replicate the outputs based upon the data inputs. They are said to be “universal approximators” [2] that can learn any model, given enough data and processing elements. This is done with very few formal assumptions about data. The exceptional structure of the information processing system is a very important property of an ANN model and something that is unique to them [36].

A trained ANN can predict output/s based upon the inputs of a dataset, along with being able to extract knowledge from the data by using a sensitivity analysis about the mean in order to examine complex relationships between the inputs and outputs. This analysis helps to determine the most important inputs that most significantly affect the output/s.

ANNs are trained from data which can use experts to help build the dataset, but it is not required; the ANNs will learn and adapt to changing conditions [37], such as the stock market. Although expert knowledge is not required for ANN’s, the data collection process must be done precisely; otherwise, unwanted variances can be accidentally introduced into the model [38]. Since the neural networks’ processing time is not a concern, they have the ability to model complex systems with very large datasets; in general, the more data to train the model, the better.

2.2.1 Topologies/Architectures

There are many ways for synapses to connect to the processing elements of an artificial neural network. Multi-layered perceptrons (MLP) are feed-forward networks that are usually trained with back propagation and are layered. The architecture of a typical MLP is shown in Figure 3. The generalized feed forward (GFF) is an MLP
network where synapses are allowed to skip over one or more hidden layers in an attempt to become more efficient during the training process; this is shown in Figure 4. There are other types of ANNs such as modular neural networks, Figure 5, radial basis function networks, Figure 6, and recurrent neural networks, Figure 7. Each of the figures shown should be read from left to right; the left is the input layer, followed by varying numbers of hidden layers, and on the right is the output layer.

Figure 3. MLP ANN

Figure 4. GFF ANN
Figure 5. Modular ANN

Figure 6. RBF ANN

Figure 7. Recurrent ANN
There are also special types of MLPs called modular NNs that are made up of a number of MLPs in parallel, creating organization inside the topology; then, the results are combined. MLPs usually use the sigmoidal transfer function, while radial basis function networks utilize the Gaussian transfer functions, and are hybrid in nature [39]. Finally, a network that allows data from previously processed instances to be kept in the memory of the network for a specific amount of time is called a recurrent neural network [40].

Some benefits of ANNs are that they typically outperform other linear and non-linear models. They produce excellent results for pattern recognition problems. They also have been shown to perform well with incomplete/noisy inputs. ANNs typically perform better than linear and other non-linear models in terms of predicting and classifying data because systems generally behave in non-linear ways. Principe also stated that they provide excellent results for problems across many different fields and categories [35]. These reasons are why ANNs, according to Qian in 2007, are “ideal for stock market prediction” [3].

2.3 Traditional Techniques

Technical trading and risk tolerance can take on multiple definitions, depending upon the source. Risk tolerance will vary from person to person, and is an important measure when tied to an investment portfolio. An investment portfolio is made up of a client’s investments, and is a crucial part of their future. Investments are money invested by the client, and therefore, quickly become important. Big swings or shifts in portfolio values can be hard for clients to handle; therefore, a measure of risk/variance is an important measure for the firm to do for every client.
Risk measurements have been done by many different firms, including Edward Jones. Niko Canner in 1997 examined how investors’ attitudes toward risk should influence the composition of their portfolios. His research first offered a simple answer to the question by using the mutual-fund separation theorem, which states that all investors should hold the same composition of risky assets [5]. Most financial advisors recommend that the more conservative investor’s portfolio should consist of a higher ratio of bonds-to-stocks, while a portfolio of a more aggressive investor should consist of a lower ratio of bonds-to-stocks.

In the Edward Jones Co., as well as in most other firms, the financial advisors are also responsible for aligning the client’s portfolio with how much to invest in the different asset classes. As Massimo Guidolin and Allan Timmermann state, “how much to invest in major asset classes such as cash, stocks and bonds—is a key determinant of their portfolio performance” [26]. They also state that there are four different regimes that effect asset returns; they are crash, slow growth, bull, and recovery. Which of the four is active will determine which asset allocation will be optimal [26]. With the market changing very quickly at times, the Advisor must remain active in each client’s portfolio in order to maintain the proper asset allocation.

These traditional approaches commonly mention the mutual-fund separation theorem, which states that all investors should hold the same composition of risky assets [28][27]. There are two advantages these traditionalists commonly refer to regarding this theorem; namely, that it usually is lower in regards to transaction costs to an investor, and
that if the theorem is practiced, “then the implications for the functioning of asset markets can be derived and tested” [27].

The mutual-fund separation theorem is common advice and can be found in most financial textbooks, but there are many people and advisors who challenge this method. Many of those advisors from some larger firms suggest that the more aggressive clients should hold a higher ratio of stocks-to-bonds than the more conservative clients [28]. This also leaves investors to decide if the advice given to them optimal in itself.

Advisors are trying to help their clients optimize their portfolios, but their advice often contradicts economic theory and is very hard to explain between firms and advisors [27]. With that said, this is why more and more nontraditional approaches are being developed and introduced, to help both clients and advisors alike.

2.4 Nontraditional Techniques

Although there are many brokerage firms that maintain traditional approaches, there are some that are utilizing newer technology and prediction methods. This section will describe some nontraditional approaches to asset allocation and identify one such company--Charles Schwab Corporation--that has begun utilizing models alongside experts for their customers. Artificial neural networks (ANNs) as aids in stock market predictions are also covered in this section. ANNs are primarily used only in academia because of their ability to model complex nonlinear systems, but some are beginning to use them for solving more problems in industry [41]. As Young [41] states, they are not commonly used in industry because they are hard to implement, usually not understood very well, and have a reputation of being “black-box” models. Although there are few
mathematical models that exist that can outperform ANNs, most industries have been reluctant to accept them for solving practical problems [41].

2.4.1 Charles Schwab Intelligent Portfolios

Charles Schwab is a brokerage and banking company that operates in four main divisions: investing, wealth management, banking, and trading [24]. The company is based out of San Francisco, California, and has been in business since 1971. Charles Schwab Corporation added an automated investment portfolio service in 2015 [25].

The automated investment portfolio is more than just an advisory service for their clients. It is a technology that will create, monitor, and then rebalance if needed, the customer’s portfolio automatically [25]. The technology will diversify the client’s portfolio across many different asset classes while experts monitor their performance. It also rebalances the portfolios so that they remain balanced and diversified appropriately in regards to the client’s risk profile.

2.4.2 Artificial Neural Networks Used in the Stock Market

ANNs and other machine learning techniques are not new when it comes to being used in the stock market to predict outcomes. Researchers have used them in trying to predict turns in individual stocks and bonds. One such example is the work of W-C Chiang and TL Urban, who use artificial neural network methods to forecast the end-of-year net asset value (NAV) of mutual funds. The method involves using back-propagation neural networks, and significantly outperforms regression models in situations with limited data availability. The NN is made up of one input layer of 15 inputs and one hidden layer of 20 neurons, with the output being the NAV of a mutual
fund at the year’s end. The method utilized a total of 101 datasets, and used stepwise regression in SAS to choose the most significant variables for each model. The datasets trained on a range from 1981 to 1985, and were tested on the actual data from 1986. The ANN performed 40% better than the linear regression models [4].

ANNs have been used to help predict many different things where correct predictions would improve performance and rate of return, including even the restaurant industry. One such example is found in Ronald Dravenstott’s thesis, where he used ANNs to forecast 1, 4, and 13 weeks into the future. His method was to accurately predict future stock price changes and trends in the restaurant industry. His use of ANNs was found to forecast better than his benchmarks and as high as 60% [29].

Like Dravenstott, K. S. Vaisla [30] used neural networks for stock market analysis and prediction. ANNs have been found to provide a good method for predicting outcomes in the financial market. Vaisla compared regression to Neural Network prediction, and found that the regression models significantly underperformed compared to the ANNs [30]. Akinwale [31] also utilized a back-propagation ANN compared to a regression analysis when predicting Nigeria stock market prices.

Many articles and conference papers have been written about ANNs regarding how to predict portions of the stock market. A majority of those are about predicting movement of the indices, which are composed of many individual stocks. Although this has been a popular use of ANNs, there are others that also take a broader approach to utilizing ANNs to predict those individual stock prices. Weckman [32] was one of those who has used an ANN model to predict individual stock prices; Lakshminarayanan [33]
and Hui [34] also used a neural network (which is supervised learning) and a Kohenen network (which is unsupervised learning) to do the same [29][34].

2.5 Imbalanced Datasets Requiring SMOTE and What SMOTE Is

The data for this project was an imbalanced dataset, which means that additional work was done to understand what how this could modify the prediction performance capabilities of the model. What makes a dataset imbalanced is when the categories associated to the dataset are not equally represented. In other words, it contains a larger amount of data of a certain type (majority class) and a smaller amount of data that is of another, opposite type (minority class) [20]. Time-series data, and data in general, is not always guaranteed to be balanced data.

A method to assist with an imbalanced dataset is described by Chawla as a synthetic minority over-sampling technique (SMOTE) [21] [22]. SMOTE was designed by Chawla, Hall, and Kegelmeyer in 2002 to combine random under-sampling of the majority class with informed over-sampling of the minority class [21]. This method oversamples the minority class by creating synthetic data examples along with the original data, rather than oversampling that minority class with replacement [22]. SMOTE commonly yields some of the best results when it comes to re-sampling and modifying probabilistic estimate techniques [21].

2.5.1 How SMOTE Works

SMOTE is not a method to just create data to help with the dataset in question. It is also a method to generate synthetic data examples from the original data in a less application -specific manner. This is done by operating in a “feature space” rather than a
“data space” [21]. It introduces synthetic data along the line segments joining any minority class to its nearest neighbor [21]. That difference is multiplied by a random number between 0 and 1; this sum is then added to the feature vector in question.

The SMOTE technique is essentially forming new minority class examples and synthetic data by interpolating between several minority class examples that are close to one another. It does this in a “feature space” rather than a “data space.” In each minority class, SMOTE introduces new/synthetic data examples along the line segments that join all the $k$ minority class nearest neighbors [21]. Depending on the amount of synthetic data needed, neighbors from the $k$ nearest neighbors are randomly chosen.

### 2.5.2 SMOTE’s Shortcomings/Limitations

Although SMOTE has been shown to be useful in evaluating imbalanced datasets, it is not a “miracle answer” for all of them. It blindly generalizes the minority set without considering the majority class, which is dangerous. Since the amount of data needed is fixed in advance, the method does not allow for a dynamic update or flexibility of the generated data in general.

Of course, other properties of SMOTE--such as optimizing the way that the nearest neighbors are selected--could also be considered limitations, although this is arguably the case in most situations. Another limitation/future work that Chawla stated was that focusing on the nearest neighbor examples that were classified incorrectly could potentially improve the SMOTE method and performance [21]. This example could be found or described as a minority class sample, in which the nearest neighbor is from the majority class rather than the minority class. This could cause the decision surfaces to be
recreated to favor the minority class, which would essentially contribute to overgeneralization [21].

2.6 Summary

ANNs have shown great promise in terms of learning non-linear behavior and applying that knowledge. This, along with the performance of the ANNs to predict the future of economic conditions, has the potential to be an aid to the Financial Advisors of the Edward D. Jones Company. By better predicting the performance and trends of the four asset classes that make up a diversified portfolio, the Advisor would have data to better support decisions made for their clients. This machine learning aid—along with expert knowledge--could potentially help identify more quickly instances such as the market crash of 2008. This will result in a better-performing portfolio, which would produce increased returns for both the client and the Advisor.
3 METHODOLOGY

3.1 Assign Matrix Percentages—Unchanged

A brokerage firm’s (Edward Jones Co.) risk tolerance and life stage assessment numbers in their portfolio objective matrix were used to generate the portfolio objective that best fits the client’s goals. That portfolio objective was then used in the computer system to assign a percentage of the investment to each of the four top level asset classes; namely, U.S. Stocks, International Stocks, Bonds, and Hedge Positions. The total investment from the client will be divided between these four asset classes to equal 100% of the investment total.

This process must remain consistent in order to meet the guidelines placed upon each investment portfolio strategy Edward Jones creates for its prospective clients. The risk of the individual and the life stage that they are in must be created with the advisor and client in mind in order for both to understand the end goal of the client. This process is also the best way to document the answers from the client, in case there is ever an issue or discrepancy between what the advisor and client originally put the client’s investment in and what the client was expecting.

The computer system also creates the recommended diversification bar chart breakdown. This breakdown will recommend the percent of each of the five subsets, which consist of multiple indices that should be allocated from the total investment. The area that this proposed methodology examined and attempted to improve is the shaded area above the white recommendation bar in each column shown in Figure 1.
3.2 Data Collection

Data is needed to train the Artificial Neural Networks (ANNs), in order to predict the different asset classes’ performances and trends. The data that was used in the creation of the dataset consisted of economic data that was used to predict the percent return of each of the four main asset classes for an investment portfolio. This data includes that which affects the economy, such as the unemployment rate, gross domestic product (GDP), political party in house, Senate, and President, just to name a few.

3.2.1 Example Data/Index that Was Used

A typical example of one of the indices that was examined in this methodology is shown in Table 5. Table 5 shows the Large Cap Growth Index and the percent return for the years 1995 to 2009. It is easy to see that the index varies significantly; during the market crash of 2008, the percent return was -38.44%.

Table 5.

Large Cap Growth Index Example Data

<table>
<thead>
<tr>
<th>Index Name</th>
<th>Year</th>
<th>Return</th>
<th>Index Style</th>
</tr>
</thead>
<tbody>
<tr>
<td>Russell 1000® Growth Index</td>
<td>1995</td>
<td>37.18</td>
<td>Large-Cap Indexes</td>
</tr>
<tr>
<td>Russell 1000® Growth Index</td>
<td>1996</td>
<td>23.12</td>
<td>Large-Cap Indexes</td>
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<tr>
<td>Russell 1000® Growth Index</td>
<td>1997</td>
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<td>Large-Cap Indexes</td>
</tr>
<tr>
<td>Russell 1000® Growth Index</td>
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<tr>
<td>Russell 1000® Growth Index</td>
<td>1999</td>
<td>33.16</td>
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</tr>
<tr>
<td>Russell 1000® Growth Index</td>
<td>2000</td>
<td>-22.42</td>
<td>Large-Cap Indexes</td>
</tr>
<tr>
<td>Russell 1000® Growth Index</td>
<td>2001</td>
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<td>Large-Cap Indexes</td>
</tr>
<tr>
<td>Russell 1000® Growth Index</td>
<td>2002</td>
<td>-27.88</td>
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<td>Russell 1000® Growth Index</td>
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<td>Russell 1000® Growth Index</td>
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<td>Russell 1000® Growth Index</td>
<td>2006</td>
<td>9.07</td>
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<td>Russell 1000® Growth Index</td>
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<tr>
<td>Russell 1000® Growth Index</td>
<td>2008</td>
<td>-38.44</td>
<td>Large-Cap Indexes</td>
</tr>
<tr>
<td>Russell 1000® Growth Index</td>
<td>2009</td>
<td>37.21</td>
<td>Large-Cap Indexes</td>
</tr>
</tbody>
</table>
3.2.2 Issues Obtaining Financial Data

The data associated to the financial market seems to be everywhere, but the data that actually affects how the market acts is more difficult to obtain. In the daily news we often hear about how each of the indices is performing, but rarely about the performance of the four different asset classes--U.S. Stocks, International Stocks, Hedges, and Bonds. The data that was needed to predict the performance of the asset classes that make up a portfolio became very difficult to collect and compile for this research.

The first attempt to get the data was via common routes, such as general internet searches and compiling the datasets in Excel. Many sites were visited, which led to little success. Data for the different indices’ high-level performance seemed to be the only performance data that was easy to collect. With that effort providing little success, research was done to find other means of collecting and compiling the data.

3.2.3 Morningstar Principia Software

Morningstar Principia software version 5.6 Build 158 ™ 2011 Morningstar Inc. [17] was purchased in order to get the data that was needed. This software provided historical month-to-month performance data for each of the four different asset classes and the indices that make them up [18]. Morningstar Principia has “been a trusted resource for financial professionals for more than 15 years” [18]. The software was purchased for approximately 200 dollars.

3.2.4 Outputs (Dependent Variables)

This software was utilized to get performance data for the four asset allocations and their individual components. They were as follows:
Bonds:
- Corporate Short Term
- Government Short Term
- Government Intermediate
- Government Long Term
- High Yield Corporate
- International
- Municipal Intermediate
- Municipal Long Term
- Municipal Short Term

Hedges:
- Cash
- Commodities
- Precious Metals
- Real Estate

International Stocks:
- Emerging Markets
- Growth
- Value

U.S. Stocks:
- Large Cap Growth
- Large Cap Value
- Mid Cap Growth
- Mid Cap Value
- Small Cap Growth
- Small Cap Value

The better the Financial Advisor and the models can predict the outputs/performance, the more the portfolio will be based on return-on-investment (ROI).

The output of the ANNs will be a percent return and variance of the prediction. The percent return will be the numerical output of the ANNs, and the variance of the predictions will be help to determine if the model is good or bad. This is due to the fact that one determination of a good investment portfolio is low volatility.
3.2.5 Inputs (Independent Variables)

The inputs that were needed to predict those different asset classes were based upon expert opinion. Expert Financial Advisors, all with more than five years’ experience and who make their living by being advisors to clients, were questioned to collect the list of economic inputs. The inputs to the models included both economic factors and political party, and as the models progressed, the data was compiled up to the point that was being predicted. The inputs were as follows:

- Political Party
- Effective Federal Funds Rate (%)
- Corporate Profits After Tax ($B)
- Consumer Price Index-Urban Wage Earners and Clerical Workers
- Industrial Production Index 2007=100
- Consumer Sentiment Index 1966=100
- Unemployment Rate (%)
- Civilian Unemployment Rate
- Consumer Price Index for All Urban Consumers: All Items
- Crude Oil Prices: West Texas Intermediate (WTI)-Cushing, Oklahoma
- Gross Federal Debt
- Housing Starts: Total: New Privately Owned Housing Units Started
- ISM Manufacturing: PMI Composite Index
- M2 Money Stock
- 30-Year Conventional Mortgage Rate
- Producer Price Index: All Commodities
- Real Retail and Food Services Sales
- Total Construction Spending
- Total Vehicle Sales
- Trade Balance: Goods and Services, Balance of Payments Basis
- University of Michigan: Consumer Sentiment
- Real Gross Domestic Product
- S&P/Case-Shiller U.S. National Home Price Index
- Gross Domestic Product
- New Privately Owned Housing Units Started
- Initial Claims
- Trade Weighted U.S. Dollar Index: Broad
The internet searches and the Principia [17] software did not provide all of the needed data required to complete the dataset for this research. Since there was still missing data, a new method was needed to complete the dataset to predict the outcomes that would potentially serve as an aid to the Financial Advisor in making the correct asset allocation for a diversified portfolio and a high ROI.

3.2.6 Federal Reserve Bank of St. Louis Economic Research

To complete the dataset, the Federal Reserve Bank of St. Louis’ Economic Research site [19] was utilized to gather additional data for both the inputs and outputs. The site allowed downloading of data from “246K U.S. and international time series from 77 sources” [19]. A person must first become a member on the site in order to download data. After becoming a member of the site, the data was then accessible and downloadable for free. The rest of the data needed to complete the dataset was available from this site.

3.2.7 Compiling Internet, Principia, the St. Louis Site Data

The data that was downloaded from the site was then added to the internet searched data and the Principia data to complete the dataset needed to predict performance. The complete dataset is made up of a combination of general internet search data, the purchased Principia software data, and the additional data downloaded from the Federal Reserve Bank of St. Louis’ Economic Research site. The performance predictions would then be used as a machine-learning decision making aid by the Financial Advisor in order to weight diversified portfolios for their customers.
3.3 Forecast Time Period

The data that created the set for each asset class was made up of 20 years of information that was then used to train the ANN to predict a six-month moving average forecast. This was decided by performing analysis on which type of forecast would most benefit the financial advisors.

The dataset included data from some of the indices that make up the different asset classes as far back as 1954, but not all inputs or outputs could be obtained back to that year. With the three different methods used for obtaining the data, there were mixed years of data across the different asset classes. With any prediction method, more data is usually preferred, but unfortunately for this research, there was only 20 years of data that was complete.

This methodology is made up of two methods to forecast performance for each of the four asset classes. A three-month moving window forecast was made using ANNs, as well as a six-month moving window forecast. Both methods utilized the same dataset and predicted the same outcomes. The data that was used to predict both moving windows consisted of 20 years of data, starting in 1991.

3.3.1 Determining what to Forecast as a Time Series

Research has shown that moving averages have been successfully predicted using artificial neural networks. With this known, three-month and six-month moving averages were created using Excel for the relevant data. Those moving averages were then added to the database in order to predict the performance of the different asset allocations. Moving averages are a “succession of averages of data from a time series, where each
average is calculated by successively shifting the interval by the same period of time” [42].

The first attempt in this research was to predict only the average of the four asset classes. ANNs were created and run on all four of the asset classes and then examined based upon their performance. An example of the variation of values for U.S. Stocks is shown in Figure 8. Also shown in Figure 8 is the training and cross-validation data, where the variation was considered too extreme to be used for this research.

![US Stock (Average)](image)

*Figure 8. U.S. Stock Training and Cross-Validation Variation*

Since predicting the average of each of the asset classes became unsuccessful because of too much variance, a three-month moving average was examined. The three-month moving average was then calculated and added as a new column in the dataset. The ANNs were then run again to predict the three-month moving average. The variation of values shown in Figure 9 shows that for the U.S. Stocks, the three-month moving
average prediction was much better than the average for each of the asset class predictions.

Although the three-month moving average did outperform the overall average, the change was not significant enough. A six-month moving average was then considered. The six-month moving average was calculated like the three-month moving average was and added to the dataset. Models were again run to determine which was best to forecast. This six-month moving average was determined to be the best of the three, as shown in Figure 10.

Figure 9. U.S. Stock 3-Month Moving Average ANN
The final decision for a six-month moving average was made based upon the performance between the three prediction periods and upon the experts consulted during the research. This forecasted time series was favored particularly by the experts, since long-term performance tends to be their main focus.

3.3.2 Lagged Data

In addition to moving averages, the data was also lagged in order to predict a three-month (i.e., one quarter) window. To better describe this for this example, the data was trained so that the December 1991 output was used to predict March of 1992, then the January 1992 output was used for April 1992, and so on. This process is shown with Table 6.
The training and cross-validation data was then run through the SMOTE software. SMOTE created additional synthetic data to add to the original dataset in order to improve the learning of the ANN. Table 7 shows this.
The full dataset that included both the original data and the additional synthetic data was then trained using Neurosolutions 6.5. In the example shown in Table 8, the data that led up to the September 2006 outputs was used to train and cross-validate in the ANN model, in order to forecast the three-month lag of the six-month moving average between January 2007 and December 2007.

Table 8.

3-Month Lag of 6-Month Moving Average

The following figures (11-17) are outputs of the model; the training output is shown in Figure 11 and Figure 12. Figure 12 shows that the model’s output compared to the desired output performed very well, which is shown by the “tightness” of 45-degree plot.
**Figure 11.** Training Output

<table>
<thead>
<tr>
<th>Best Networks</th>
<th>Training</th>
<th>Cross Validation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Run #</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Epoch #</td>
<td>20823</td>
<td>20823</td>
</tr>
<tr>
<td>Minimum MSE</td>
<td>0.000948885</td>
<td>0.002809042</td>
</tr>
<tr>
<td>Final MSE</td>
<td>0.000948885</td>
<td>0.002809042</td>
</tr>
</tbody>
</table>

**Performance**  

<table>
<thead>
<tr>
<th>F S6ma</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE</td>
<td>0.03840831</td>
</tr>
<tr>
<td>NMSE</td>
<td>0.021607577</td>
</tr>
<tr>
<td>MAE</td>
<td>0.138600312</td>
</tr>
<tr>
<td>Min Abs Error</td>
<td>0.000100341</td>
</tr>
<tr>
<td>Max Abs Error</td>
<td>1.193739843</td>
</tr>
<tr>
<td>r</td>
<td>0.989225196</td>
</tr>
</tbody>
</table>

*Figure 12. Training 45 Degree Plot*
The cross-validation results are shown in Figure 13. It shows that the cross-validation also performed well, resulting in a .947 r-squared value.

![Output vs. Desired](image)

<table>
<thead>
<tr>
<th>Performance</th>
<th>F S6ma</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE</td>
<td>0.113713191</td>
</tr>
<tr>
<td>NMSE</td>
<td>0.05282374</td>
</tr>
<tr>
<td>MAE</td>
<td>0.211299046</td>
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<tr>
<td>Min Abs Error</td>
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</tr>
<tr>
<td>Max Abs Error</td>
<td>1.758044457</td>
</tr>
<tr>
<td>r</td>
<td>0.973589889</td>
</tr>
</tbody>
</table>

*Figure 13. Cross-Validation Results*

The results of the test data are shown in Figure 14.
The r-squared for the first three months (first quarter) forecasted was 0.318. This less-than-ideal performance can be seen in Figure 15.
Figures 11 through 15 describe the output of the first forecasted values of the moving window. The process identified earlier was then repeated as shown in figures 16 through 17, including Tables 9 and 10. With this process, the three months of training data was added, then the synthetic data was created, and lastly, the model was trained with the newer dataset. The additional forecast data was also incremented by adding three months of new data while the first three months’ worth of data was removed.

Notice in Table 9 and Table 10 the three-month shift in dates in the test data and the additional training records.

Table 9.

3-Month Shift of Training Data
Table 10.

3-Month Shift of Testing Data

![Table 10](image)

This is repeated until the data is used for the last three months, as shown in Figure 16.

![Figure 16](image)
The performance of the forecasted six-month moving average with the additional synthetic data resulted in an R-value of 0.752258588. This is shown in Figure 17.

3.4 Construction of ANNs

ANN model development is made up of many different types of architectures, learning algorithms, training percentages, cross validation percentages, testing percentages, transfer functions, and hidden layers. Multiple models were run on all four asset classes in order to find the best combination for each. Table 11 shows the key characteristics that went into constructing the multiple models during this research.
Table 11.

*ANN Key Characteristics*

<table>
<thead>
<tr>
<th>Architecture</th>
<th>Layers</th>
<th>Processing Elements</th>
<th>Activation Function</th>
<th>Learning Algorithms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multilayer Perceptron, General Feed</td>
<td>2-3</td>
<td>10-300</td>
<td>Hyperbolic Tangent, Sigmoid, Linear</td>
<td>Momentum, Levenberg-Marquardt, Gradient descent</td>
</tr>
<tr>
<td>Modular and Probabilistic</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 18 [43] shows a summary and flow of the method that was utilized to create the best ANN. It shows three phases, which are made up of pre-processing, training, and testing [43]. Utilizing the key characteristics in Table 11 and the flow chart, the ANNs were initialized and trained in order to make a final decision on the best model.
3.4.1 Determining the Best ANN Model(s)

An ANN model was developed for each of the four asset classes in order to predict the performance of each. Using the dataset mentioned earlier for each of the asset classes, multiple ANNs were trained and tested for each, based upon the six-month moving average. The ANN models varied in architectures, randomization, learning algorithms, cross-validation and testing percentages, and hidden layers.

Example architectures that were varied for each class include Generalized Feed Forward Networks (GFF), typical Multi-layered Perceptrons (MLP), and Modular Networks. All ANNs utilized many of the different learning algorithms, including momentum, delta bar delta, and conjugate gradient. The different architectures also
utilized different transfer functions, such as tanh axon, sigmoid, linear tanh, and linear sigmoid.

The number of hidden layers also changed for each of the different combinations of architectures, learning algorithms, and transfer functions. The number of hidden layers ranged from one hidden layer to three hidden layers for each of the different combinations. These combinations can also be seen in Table 11.

After numerous tests based upon all the characteristics mentioned above were run, there were four models that seemed to be the most promising. Table 12 shows the four models that showed the best performance, which was measured by the highest r-squared values of each model.
Table 12.

*Four Best Performing Models*

<table>
<thead>
<tr>
<th>Model #</th>
<th>Architecture</th>
<th>Layers</th>
<th>Processing Elements</th>
<th>Activation Function</th>
<th>Learning Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Multilayer Perceptron</td>
<td>3</td>
<td>100, 75, 50</td>
<td>Hyperbolic Tangent, Hyperbolic Tangent, Linear</td>
<td>Momentum</td>
</tr>
<tr>
<td>2</td>
<td>Multilayer Perceptron</td>
<td>3</td>
<td>100, 75, 50</td>
<td>Sigmoid, Sigmoid, Linear</td>
<td>Momentum</td>
</tr>
<tr>
<td>3</td>
<td>Multilayer Perceptron</td>
<td>3</td>
<td>30, 20, 10</td>
<td>Hyperbolic Tangent, Hyperbolic Tangent, Linear</td>
<td>Levenberg-Marquardt</td>
</tr>
<tr>
<td>4</td>
<td>Multilayer Perceptron</td>
<td>3</td>
<td>30, 20, 10</td>
<td>Sigmoid, Sigmoid, Linear</td>
<td>Levenberg-Marquardt</td>
</tr>
</tbody>
</table>
Training, cross validation, and testing percentages were examined during the creation of the ANN’s forecasting process. These were changed in very small increments from the default used in the NN software. This is because the changes made in the NN key characteristic combinations were more beneficial to work with when creating an ANN that predicted the long term outcome more accurately.

3.5 Determining SMOTE and Time Series Forecast

The original data that was available began on 12/1/1991 and ran through 10/1/2006 when it came to forecasting the next 12 months. This resulted in a total of 178 records, and of those 20% (36) were used for cross-validation. The remaining 142 were then used for the training of the ANN. For example, Bonds were trained and tested with the results in Figure 19. Figure 19 shows that the model was not learning from the data because the Epoch values were too low for training (376) as well as cross-validation (19).
This poor understanding of the data can then be seen from the testing results in Figure 20. The R-value of this test was only .008704613, meaning that the r-squared value was only .00007577028.

Viewing this test data in a 45-degree plot would align perfectly if the model was 100% accurate, but as shown in Figure 21, it was not even close.
Plotting the training data on a 45-degree plot is shown in Figure 22, which shows that there is a lot of variation. As stated above for the test data, for this to be considered to be accurate, the data points should fit along the 45-degree line. This variation in the training data helps to explain why, when the test data was plotted in Figure 21, it performed so poorly.

Figure 22. 45 Degree Plot of Bonds Training Data (142 Records)

To complete the picture, the same 45-degree plot method was used for cross-validation, which resulted in an even worse fit to the line. This can be seen in Figure 23.
The dataset that was compiled for this research--although it was made up of data from several different places--was not a dataset that consisted of many records. This was because research was done via a method called SMOTE, which is a method, used to generate synthetic data examples from the original data in a less application–specific manner [21]. This method was used to generate synthetic data for improved ANN performance.

SMOTE was applied to the original dataset in order to increase the number of records available to train and cross-validate against, which would better help predict the next 12 months. This synthetic data, along with the original data, now equaled 890 records. An example of the same Bonds and time periods from above are shown in Figure 24, but with the addition of synthetic data, which demonstrates that the ANN can now learn.
Figure 24. Bonds Training and Cross-Validation Results (Synthetic Data)

The model is still learning at 15000 Epochs, versus the earlier method with no synthetic data, which only had 19. Also, Figure 25 and Figure 26 show 45-degree plots that show the “tightness” of the training and cross-validation. Figure 25 is the plot for the training data, which follows the 45-degree line very well. Figure 26 is the plot of the cross-validation, which does not do as well as the training, but significantly outperforms the earlier cross-validation plot that did not include the synthetic data from SMOTE.
This synthetic data creation method, SMOTE, resulted in a better-performing ANN. This performance was a direct result of using SMOTE and the SMOTE generated synthetic data. The SMOTE data used throughout this research was based upon the results shown above.
4 RESULTS

This section describes the results of the ANN models and how well this methodology would be accepted as an aid to the Edward Jones Company financial advisors. It includes a correlation analysis, the results of the different asset class predictions, including trends associated to each as predicted by the ANNs.

4.1 Correlation Analysis

A correlation was done on the inputs that were used in the analysis to help identify any relationships present in the data. This was done between inputs, as well as from inputs to outputs. This was useful in that it showed that the Bonds had no significant correlation from the inputs to the outputs; that Hedge had some small correlations when considering government inputs such as cash; but that no correlations occurred regarding the other inputs compared to the outputs. In U.S. and International Stocks, there were no real correlations found from inputs to outputs, either. Therefore, looking at the overall correlation of inputs to outputs, it can be said that there were no real correlations for the overall four asset classes that make up an investment portfolio.

Although there were no significant correlations between inputs to outputs, there was a very high correlation between the inputs themselves. All inputs that were considered in this research seem to be highly correlated. In the discussion portion, there is mention of the need to re-evaluate the inputs of the model as a future work in order to improve the methodology and results.
4.2 Comparison to Moving Averages/Windows

The first comparison that was done was to compare the two methods--three-month and six-month moving windows--with predictions of the four asset classes that included expert opinion. The better of the two methods was the six-month moving average, which the financial advisor then reviewed. Although there are constraints the advisor and this methodology are held to, they are soft constraints, and as long as the decision is justified, they can be altered.

A comparison regarding times of high volatility--such as the market crash of 2008 or the tragic events of September 11th, 2001--were also examined to see how the proposed methodology would have helped the financial advisor perform or recover, compared to how the market performed during those same periods. Times of high market returns will also be looked at, but it was more interesting to see how well this machine-learning, decision-making aid would have helped the advisors during times of higher volatility. Priority was placed upon the market crash of 2008 for a final expert decision regarding the overall results and performance of this methodology.

4.3 Final Moving Window Results

The results of this methodology are included beginning with Figure 27. The results are included for average Bonds, Hedge funds, International Stocks, and U.S. Stocks. The example below is for U.S. Stocks with a Sigmoid transfer function, as well as three hidden layers made up of 100, 75, and 50 processing elements, respectively. Figure 27 shows the first forecast moving window, Figure 28 displays the second forecast
moving window, Figure 29 the third forecast moving window, and finally, Figure 30 shows the totals.

**Figure 27.** First Forecast Moving Window

**Figure 28.** Second Forecast Moving Window

**Figure 29.** Third Forecast Moving Window
4.4 Asset Class Final Results

A closer look at each of the asset classes was then done to better understand how well each performed. The Bond asset class performance is shown in Figure 31. The overall performance of this asset class resulted in an r-squared of .231. This low r-squared value shows that the ANN understood approximately 23% of the variation that was in the Bond asset class.

As described earlier, an emphasis was placed upon the data around the market crash of 2008. In Figure 31 the notation of “BC” represents before the crash while the notation of “AC” means after the crash. The r-squared value before the crash shows that the ANN essentially did not understand any of the variation in this asset class. After the crash in 2008, the model began learning from the inputs and did begin to perform better—it could understand approximately 29% of the variation. More on why this may have happened is covered in the discussion part of this thesis.
Figure 31. Final Bond Performance

The Hedge class was then examined closer. In Figure 32, the results from the Hedge asset class are shown. This asset class performance was very similar to the Bond asset class. The overall performance of the model on this class was an r-squared value of .249. This low r-squared value shows that the ANN only understood approximately 25% of the variation in this asset class.

The same notations—“BC” and “AC”—are used to describe the performance before the crash and after the crash. The results of this class are very similar to the Bond class in that before the crash, the model understood approximately 0% of the variation, but after the crash, it improved. In the discussion section of this paper, there is more detailed discussion as to why this may have happened.
The International Stock class was then examined. In Figure 33, the results are shown including the r-squared value overall, as well as before and after the crash. The r-squared value for the overall International Stock asset class was .651. Unlike the Bond and Hedge classes, the model performed just as well both before and after the crash. The value of .651 shows that the ANN model was capable of understanding approximately 65% of the variation in this asset class.

The BC and AC values were very similar in this model. Although the r-squared value before the crash and after the crash were very close to each other, it is interesting to note that after the crash, the model again seemed to perform better. The values were not significantly different, but it was noted for later discussion with experts.
Finally, the U.S. Stock class was examined. In Figure 34, the results are shown, which include the overall r-squared value, as well as the values before and after the crash. The U.S. Stock r-squared value was not as high as the International Stock class, but higher than the Hedge and Bond classes. The r-squared value was .446 for U.S. Stocks, which shows that approximately 45% of the variation in this class was understood by the ANN model.

Unlike the other classes, the model did not improve after the crash compared to before the crash performance. Before the crash, the r-squared value was around .638, while after the crash, it went down to .220. A reason that this may have happened was discussed with the experts and is in section 5.5-- the emotional decision making and predictions of this research.

*Figure 33. Final International Stock Performance*
The overall performance of the ANN model for each of the four asset classes is shown in Table 13. This was shown and discussed with the experts before they made the final judgment on the research methodology validity as a machine-learning decision-making aid.

**Table 13.**

*ANN Performance for Each Asset Class*

<table>
<thead>
<tr>
<th></th>
<th>Bonds</th>
<th>Hedge</th>
<th>Intl Stocks</th>
<th>US Stocks</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>RSQ</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>BC</strong></td>
<td>0.00</td>
<td>0.00</td>
<td>0.68</td>
<td>0.64</td>
</tr>
<tr>
<td><strong>AC</strong></td>
<td>0.29</td>
<td>0.04</td>
<td>0.69</td>
<td>0.22</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>0.23</td>
<td>0.25</td>
<td>0.65</td>
<td>0.45</td>
</tr>
</tbody>
</table>
4.5 Predicting Trends for the Asset Classes

Along with the performance of the ANN model regarding each of the asset classes, the experts also requested results on how well the models were able to predict trends. Trends are important to understand for the advisors as well as the performance quarterly and yearly. The quarterly average was calculated based upon the actual and model data. An example from U.S. Stocks is shown in Table 14 to better explain how the trends were provided to the advisors. After the averages were calculated, the trend was defined as either going down (D), or going up (U).
Table 14.

*U.S. Stock Trend Prediction*

<table>
<thead>
<tr>
<th>Date</th>
<th>F S6ma Actual</th>
<th>Actual Quarterly Average</th>
<th>Actual Trend</th>
<th>F S6ma Model</th>
<th>Model Quarterly Average</th>
<th>Model Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/1/2007</td>
<td>2.388</td>
<td></td>
<td></td>
<td>1.743</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2/1/2007</td>
<td>1.820</td>
<td></td>
<td></td>
<td>1.808</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3/1/2007</td>
<td>1.707</td>
<td>1.972</td>
<td>D</td>
<td>1.079</td>
<td>1.543</td>
<td></td>
</tr>
<tr>
<td>4/1/2007</td>
<td>1.522</td>
<td></td>
<td></td>
<td>2.224</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5/1/2007</td>
<td>1.696</td>
<td></td>
<td></td>
<td>1.978</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6/1/2007</td>
<td>1.289</td>
<td>1.502</td>
<td>D</td>
<td>2.052</td>
<td>2.085</td>
<td>U</td>
</tr>
<tr>
<td>7/1/2007</td>
<td>0.133</td>
<td></td>
<td></td>
<td>1.898</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8/1/2007</td>
<td>0.468</td>
<td></td>
<td></td>
<td>2.303</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9/1/2007</td>
<td>0.788</td>
<td>0.463</td>
<td>D</td>
<td>2.320</td>
<td>2.174</td>
<td>U</td>
</tr>
<tr>
<td>10/1/2007</td>
<td>0.575</td>
<td></td>
<td></td>
<td>1.192</td>
<td></td>
<td></td>
</tr>
<tr>
<td>11/1/2007</td>
<td>-0.969</td>
<td></td>
<td></td>
<td>0.732</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12/1/2007</td>
<td>-0.721</td>
<td>-0.372</td>
<td>D</td>
<td>0.782</td>
<td>0.902</td>
<td>D</td>
</tr>
</tbody>
</table>

Assuming that each quarter the Actual was the same as the Model, the overall accuracy results would be as shown in Table 15. This was done for the time period of 1/1/2007 through 6/1/2011.
Table 15.

*Trend Prediction Accuracy for Each Asset Class*

<table>
<thead>
<tr>
<th></th>
<th>Bonds</th>
<th>Hedge</th>
<th>Intl Stocks</th>
<th>US Stocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>64.7%</td>
<td>64.7%</td>
<td>70.6%</td>
<td>64.7%</td>
</tr>
</tbody>
</table>
5 DISCUSSION

This section regards the discussion of barriers and information that came up during this research. This section also includes information learned about the inputs and outputs, as well as feedback from a financial advisor from the Edward Jones Company.

5.1 Inputs to the Models

During the correlation analysis of inputs to outputs, as well as other times during this research, there were questions as to if the correct inputs were collected to accurately model and predict the outputs. The inputs to the models were compiled by researching economic metrics that could affect the stock market, as well as input from financial advisors. The final decision on the list on inputs was made by the advisors, since this research and methodology was to provide an aid to these advisors at the Edward Jones Company.

Future work to expand on this methodology and to potentially improve this method would look at re-evaluating the list of inputs used in the ANN models. The list of inputs that were used in this method were approved by the experts, but adding to or changing this list based upon more research or more advisors, could improve the accuracy of the models. It would be interesting to see if advisors from other firms would agree with the list of inputs that was used in this research as well.

5.2 Hedge Prediction Issues

This research methodology was shown to understand approximately 25% of the variation seen in the Hedge asset class. As stated by Ronald Lynch from Edward Jones, the advisors consulted agreed with the methodology and understood after reviewing the
results why the models did not perform as well as they had hoped. The reason he described as to why the models for the Hedge asset class did not perform to a high degree of accuracy is because “cash will certainly perform differently from Real Estate and Gold in various markets”.

After further discussion with the financial advisors, one suggestion for future work was to improve the Hedge prediction accuracy by splitting out the Hedge asset class and using ANN models to compile an overall Hedge asset class prediction. More details about this can be found under “Future Research” in section 6.4 of this thesis.

5.3 Bond Prediction Issues

The ANN models also did not perform as well as anticipated in the Bond asset class. This was at first a concern, because Bonds typically do not fluctuate as much as stocks do. With that general thinking, it was assumed that the prediction and understanding of the variance would be much higher in terms of its accuracy. Unfortunately, the models were only capable of understanding approximately 23% of the variation within that class.

After the crash of 2008, the model did seem to begin understanding the variation better than before the crash. The model had virtually no understanding before the crash based upon the inputs that were provided, while after the crash it understood around 29%.

The advisors were not as concerned with this poor performance of the model. Their feedback on this was that a prediction model for a Fixed Income bond would not really be needed, compared to the other classes for their typical clients. More details about this can be found under “Future Research” in section 6.4 of this thesis.
5.4 Competing with Intelligent Portfolios

Another important point that was mentioned earlier in this research was the example of portfolios that have several names, such as robo-advising and intelligent portfolios. Some firms have adopted the idea of using some type of machine learning to help improve their traditional approach to advising clients. Although this has not been in practice long enough to determine if this is the way of the future, it does show that this method should at least be considered.

Since this methodology was compiled for the Edward Jones Company, only they can determine if results such as those shown in this research are of accurate enough that they should consider having a group of forecasting professionals. Should they experiment more with machine-learning decision-making methods such as this one? Will their clients demand these intelligent-type portfolios? These are all questions that are interesting to discuss, yet only they can answer.

5.5 Emotional Decision Making and Predicting

Emotional decisions are one last factor in this research that is interesting to discuss. During this research, a metric or input for emotion was not used nor found. This emotional decision making can drive a lot of volatility into the stock market, which can significantly affect the prediction accuracy--this was seen throughout this research. One example regarding emotional decision making was brought up during the analysis of the U.S. Stock asset class results. The three other classes seemed to perform at least slightly better after the crash, except for the U.S. Stock class. It is also discussed in more detail in the “Future Research” section of this thesis whether the Hedge class could be used to
help quantify or create such an input that could help with understanding the emotions involved in the stock market, and ultimately, some of the variation due to it.
6 CONCLUSION

This section provides an overall methodology conclusion, in conjunction with an expert financial advisor’s feedback, to determine if the methodology is considered a success. Expert opinion is provided in this section to describe if this methodology would be helpful, and what those consulted considered the performance to be. This section also includes recommendations for future work that could be done to further enhance this research methodology.

6.1 Methodology Validation

Expert opinion was used to validate this methodology and its ability to be a successful machine learning aid to assist with the asset allocation of an investment portfolio. Due to the availability and privacy of investment portfolios and competitiveness in the financial field, actual portfolios and the Edward Jones Co. data were not directly available for this research. The results from the ANN’s prediction--as well as an analysis of how well the models predicted the trends--were given to the financial advisors at Edward Jones that were consulted during this research. All of the same information that was provided in the results section of this thesis was provided to the advisors for their feedback.

They used the results, trends, charts, and graphs--as well as the r-squared of each of the predictions--to compare with the market and their performance during times of higher market volatility, such as the crash in 2008. They were asked to consider the results and trend prediction capability of the ANNs to determine if this methodology would be useful to them and their co-workers.
6.2 Comparison Breakdown by Edward Jones Advisors

After reviewing the results, trend prediction of the classes, and comparisons with their actual results and market performance, the advisors provided feedback on how well this methodology performed. This research seems to show that ANNs can accurately predict real-world, high-variation time-series data—such as the stock market—and would have been useful during times of high volatility, such as the crash in 2008.

Ronald B. Lynch, one of the Edward Jones advisors consulted during this research, was one that originally questioned if ANNs could accurately forecast the stock market. He stated in his response, “Obviously, at the beginning of this project I seriously had my doubts about any and all forecasting models.” As the research continued, he slowly began to change his opinion on forecasting models and ANNs. He later stated, “…This certainly seems to have some merit. When I compare the forecasting models and the actual returns, the models seem to obviously understand at least parts of the financial markets.”

He then went on to discuss the performance of each of the different asset classes that were forecasted by the ANNs. The feedback he provided shows that this methodology would serve as a useful aid to him and other advisors for both International Stocks and U.S. Stocks. The example he provided was that if the advisor was able “…to more accurately ‘predict’ that International Stocks appear to be headed to the upside, [they] would most certainly assist financial advisors when having discussions with our clients as to whether they should be on the low or high end of our (hypothetically speaking) 25%-35% allowable range for International Stocks. Likewise for U.S. Stocks.”
He also compared the classes that had lower r-squared values and were said to have not performed well. These were the Hedge and Bond asset classes. After more discussions about the results and his review, he stated that they could “…see and fully understand as to why the models did not, with a high degree of accuracy, predict the ‘hedge positions’ mentioned in the paper. The reason I say this is understandable is because Cash, for example, will certainly perform differently from Real Estate and Gold in various markets. I do believe, from looking into the other asset classes that if those were peeled apart from one lump sum asset class like ‘hedge positions’, the models, it seems, could do a better job of forecasting. However, the usefulness of doing so would provide only a minimal amount of benefit to me at my firm, given our very small allocation to such asset classes (aside from cash, which is predictable in and of itself).”

He then described his perspective on the last of the four asset classes, Bonds. Bonds, like Hedges, did not perform as well as the International Stocks and U.S. Stocks. His response was that they, “…are not as concerned, nor would we need such models for Fixed Income bonds for our typical clients. The reason being is that bonds are not purchased, in most cases, for capital appreciation, but more so for preservation of principal and a reliable income stream. We can understand quite easily what it is that affects bond prices, but are primarily concerned with their ability to pay reliable interest payments. Therefore, the fact that the model doesn't seem to understand what's ‘...going on with bonds’ is of no concern to me, nor would it discourage the use of the forecasting model for the equity asset classes.”
6.3 Would this Methodology be a Useful Aid to Financial Advisors?

When asked if this would be an aid to him, Ronald stated that “…considering our firm’s conservative nature and our typical client, these models do appear to me to be of use as an aide.” Due to this analysis and feedback, this research can be considered a success, since it met the original goal of successfully utilizing an ANN to accurately predict asset class performance in order to provide the Edward Jones Company financial advisors a machine-learning decision-making aid which would better allocate the four different asset classes that make up an investment portfolio.

He then went on to provide an overall summary of the research that was done in this thesis. His final conclusion agrees with the earlier mentioned conclusion that this methodology would be useful as an aid to financial advisors of the Edward Jones Company during asset allocation of an investment portfolio. In his summary he states that, “All in all, I can see and understand the few spots where the models seem to have their limitations, but those areas are those in which we would have limited use for forecasting anyway. However, the models seem to truly understand--with relatively high accuracy--the asset classes that have a great impact on our clients, and those in which we would have the most use for an aide like your forecasting models.”

6.4 Future Research

Although this research was considered a success for the reasons mentioned above, there are still areas that could be considered for future research and improvement of the methodology. This section describes a few areas where future research could be initially directed in order to make the biggest enhancements.
One of the quickest areas where future research could benefit this methodology is in the list of inputs. As mentioned earlier, there were questions as to what the correct list should be, and therefore, more research into what should be used could ultimately improve the results. In addition to researching these inputs, expert opinion from other firms’ advisors could be interesting to utilize in the ANN models as well.

One specific input would be to research and work with a larger team, in order to be able to quantify emotional investing and decision making to better improve upon this study. This future research could either create such a metric, or include it if it does exist, so that it could be used as an input for this methodology. If that becomes too difficult to create or find, potentially the Hedge asset class could be utilized to help identify those emotional-type decisions and their effects.

One other task that could be done to improve this methodology would be to follow the advice from the advisors consulted in this research and split out the Hedge asset class. One could create ANN models to model and predict the performance of the indices which make up the asset class, and then compile those to provide a prediction for the class. Doing this could potentially result in a better understanding of the Hedge class.

One last suggestion for future work would be to optimize the traditional approach that is done by the advisors at the Edward Jones Co. This would be the hardest of the suggestions to implement, as it would require much more time and effort to complete. This would include both ANN models, as well as the use of Excel Solver, to optimize and accurately weight the percentage of each of the asset classes to be invested in.
Utilizing the ANN for each of the asset classes that performed the best in terms of forecasting the outcome, one could create an Excel Solver to optimize the percentages of allocation of the client’s investment in this area, similar to what the financial advisor currently does with the bar chart described earlier in this research. Solver could be used to minimize the variance of the system and optimize the return on investment for the client. Minimizing risk is done by minimizing variance in the system, and is part of determining if a portfolio is good or bad. The percentages could be held to the constraints placed upon the advisor by the Edward Jones Company, in order to enable the advisor to utilize this as a complete methodology in the future.

Multiple scenarios with varying weights (profit and variance) could be considered in this methodology. After each of the scenarios and models utilizing Solver were created, a determination of the best method could then be made. The best method must generate the greatest total return while minimizing variance. This could then be done for all five of the portfolio objectives that Edward Jones defines.

6.5 Limitations

Although this methodology was considered to be a success by those consulted, there are some limitations to this work. One of the first limitations of this methodology is that the risk tolerance and life stage assessments used in this research are from the Edward Jones Company; therefore, for this methodology to be used in other firms, something more appropriate for that firm would need to be either created or used.

This method was also created to be a machine-learning, decision making aid to the financial advisors, and not a replacement for that financial advisor. It was not created
to make the decisions and weighting alone, and therefore it does require expert interpretation in order to be useful in the industry. With that stated, their support of this methodology could be expanded from the four asset classes to the individual indices that make up each of those asset classes.

The biggest limitation to this methodology is its ability to predict emotional decisions that affect the asset classes. This was seen and explained earlier in this document when it was seen that the r-squared values for Hedges and Bonds were not very high. This limitation could be because there is no input for emotion in this research, nor was a metric found that was available to quantify it.

Keeping these limitations in mind, this methodology could be utilized by any financial firm as an aid to help improve their asset allocation process. This machine-learning decision making aid to asset allocation could be used in other areas, or even in other countries, for time-series imbalanced datasets. This includes asset classes as well as the indices that make up those classes.
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