**Introduction**

**1.1 Statement of the Problem and Motivation:**

In the 2020 Season of the National Football League, the average franchise is worth $3.05 Billion. For comparison, the average MLB franchise value is worth $1.85 Billion and the average value of the top 20 premier league franchises is $1.75 Billion (*Ozanian, 2019; 2020*). The NFL has the lowest correlation between win percent and revenue. This is likely due to the revenue-sharing system which smooths out the revenue differences between teams (Miller, 2012). There is a significant literature on the connection between winning and attendance (Welki, 1999). Winning teams attract more attention. In a model for ticket prices, a team’s previous season[[1]](#footnote-1) win percentage was found to be positively correlated with ticket price (Brunkhorst, 2010). These relationships of stadium attendance, ticket prices and revenue with winning percentage create the foundation for the economic justification in studying how to win in the NFL.

The determinants of winning in the NFL is a highly studied topic, questions such as whether defense or offense is more important in winning is a topic debated not only among TV sportscasters but also among sport economists. The determinants of winning games in the National Football League (NFL) can be viewed as the on-field factors categorized as variables measuring the performance of the team’s offense, defense, and special teams; penalties per game; and net turnovers (Stair, 2008). There have been previous studies looking at the determinants of wins in the NFL using box office scores to model the success of an NFL team (Robst, 2011; Blaikie, 2001; Purucker, 1996). *Money Ball: The Art of Winning an Unfair Game* use the tools of statistical analysis to determine the factors in winning in the Major League Baseball (MLB) and shift spending towards promoting those factors. One major impact data analysis had in the MLB was convincing teams to stop giving away outs, strategies such as sacrifice bunts were less effective and did not make up for losing an out. A similar logic applied to the NFL, do everything possible to keep the ball. This strategy closely pertains to how plays should be run on different downs and especially with the play decisions on 4th down. *4th Down Bot* from the *New York Times* uses live analysis of every 4th down in the NFL to make the statistically best decision, showing what the coach’s decision was as well. The NFL has taken the necessary steps to begin a data analytics revolution within the sport.

**1.2 Main Research Question:**

Based on the evidence surrounding the benefit of winning in the NFL and previous studies on how to win in the NFL, this paper will address how to win in the NFL expanding off previous neural network studies (Robst, 2011; Blaikie, 2001; Purucker, 1996), utilizing tracking data, player data and game data as input to a neural network.

**1.3 Contribution:**

Next Gen Stats, the NFL’s advanced player-tracking data service, became a full-fledged initiative in 2013. By utilizing tracking chips in the player’s shoulder pads, the NFL can gather data on player position, orientation, speed and acceleration. These stats have allowed for data analysis beyond box office scores. The goal of this study is to utilize neural network modeling on NFL Next Gen Stats player tracking data to make broader conclusions into how NFL teams win. The conclusions and methodology of this paper will hopefully serve as reference to other economic studies looking to take advantage of the predictive capabilities of a neural network.

**Research Hypothesis**

This study is designed to assess the determinants of play-by-play success (yards-gained) and winning through the lens of a back propagation multilayer perception neural network[[2]](#footnote-2). Expanding off previous studies, the model will focus on maximizing previously determined win determinants. The study will utilize data from Next Gen Stats from the NFL analyzing player movements and field position to predict a play’s yardage gain, play success rate against certain set formations, and to look to confirm strategies developed by NFL data analysts. Expanding off existing win models (Robst, 2011; Stair, 2008; Blaikie, 2001; Purucker, 1996), this study will seek how to maximize the statistics important to winning a game in the NFL. It is hypothesized that play efficiency (expected yards gained) in the earlier downs in a possession will be favored, allowing for a team to garner more first downs and more time in possession. This hypothesis is based off the work of Warren Sharp, creator of the website *sharpfootballstats.com.* It is also hypothesized that certain matchups between defensive and offensive formations will be more successful.

To assess the determinants of play-by-play success, our study will analyze the expected yardage gain differences between types of offensive plays­­­— rushing, passing— against types of defensive positions. Figure 1 shows an overhead view of player positions in a 4-3 defense.



Figure : 4-3 Defense, a very popular defensive formation in the NFL. It uses four defensive linemen, three linebackers, two cornerbacks, and two safeties

**Literature Review**

The NFL has experienced much popularity and success and competitive balance is the most documented reason for the relative success of the NFL (Fenn, 2006). The NFL is unique in its revenue factors, unlike the MLB, NHL and NBA, on field-success was not positively associate with revenue (Bradbury, 2019). However, stadium attendance and pricing behavior for stadium ticket prices were shown to be affected by stadium novelty, star players and previous wins (Bowley, 2017) (Spenner, 2010). While winning may not be a determinant in a franchise’s revenue, winning does have a significant effect on stadium attendance and stadium ticket prices (Aju, 2010; Chang, 2016; Welki, 1999). The determinants of winning in the NFL is a highly studied topic, questions such as whether defense or offense is more important in winning is a topic debated not only among TV sportscasters but also among sport economists, the conclusions in these studies differ. In a study from 2011, *Defense Wins Championships?: Answer from the Gridiron* looking at the determinants of a team making the playoffs, it was found that the marginal benefit from improving the defense was similar to the marginal benefit from improving the offense (Robst, 2011). Alternatively, an older study using data from the 1997 NFL regular season which assessed components that best predicted success in a game found that points conceded on defense explained 73.5% of the variance in success vs 14.7% explained by points scored on offense (Onwuegbuzie, 1999).

Previous applications of machine learning to the NFL are focused on a model for predicting game outcomes. Utilizing a back propagation multilayer perceptron neural network, the model utilizes box scores and was 3% more accurate on average that eight sportscasters on ESPN (Kahn, 2003). Another older study utilized four statistical categories, yards gained, rushing yards gained, turnover margin and time of possession to compared relative strengths of NFL teams. Several neural network strategies were used to try and predict NFL games outcomes (Purucker, 1996). A separate study utilized the model built by *Khan, Joshua (2003*) to apply it to the NCAA and improve it for the NFL. The NFL model ranked in the top half of prediction experts while the NCAA model was in the middle of the rankings (Blaikie, 2001).

All previous research applying neural networks to the NFL were centered around using box office scores to predict who would win in a game. This research, while beneficial to people who bet on sports games, lacks the analysis to make conclusions about what helps teams win. Other studies that make conclusions on the determinants of wins in the NFL have yet to take advantage of the new data being released by NFL NextGenStats and the standard statistical regressions are difficult to utilize with positional tracking data. This study aims to bridge the gap on neural network analysis, to make conclusions if a neural network can utilize positional tracking data to predict success in NFL games and gain insight into how the model weighs the input data.

**Methodology**

The data used for this model is from NFL NextGenStats, available on *Kaggle.com.* To prepare the data and train the neural network model, Python in conjunction with libraries: keras, pandas, numpy, sklearn, and tensorflow were used.

**4. 1** **Data Preparation**

A full list of the inputs to the neural network model can be found in Table 1. Including dummy variables, 62 inputs were uses into the full neural network model. To train the model, the data was formatted into a 3-dimensional array, tracking data for an entire play is provided with a resulting offensive gain in order to train the model.

|  |  |
| --- | --- |
| Input | Description |
| x | X position of player on field |
| y | Y position of player on field |
| Closest Teammate | Distance to closest teammate |
| Closest Opponent | Distance to closest opponent |
| S | Speed of player (yards/sec) |
| A | Acceleration of player (yards/sec^2) |
| dis | Distance traveled from prior time point (yards) |
| o | Player orientation (deg) |
| dir | Angle of player motion (deg) |
| Player Information | Player height and weight (inches, lbs) |
| Position | Dummy Variables for play position (QB, WR, …) |
| team | Dummy Variables for player route (Flat, Post, …) |
| route | Dummy variables for route by player |

Table : Neural network inputs and description

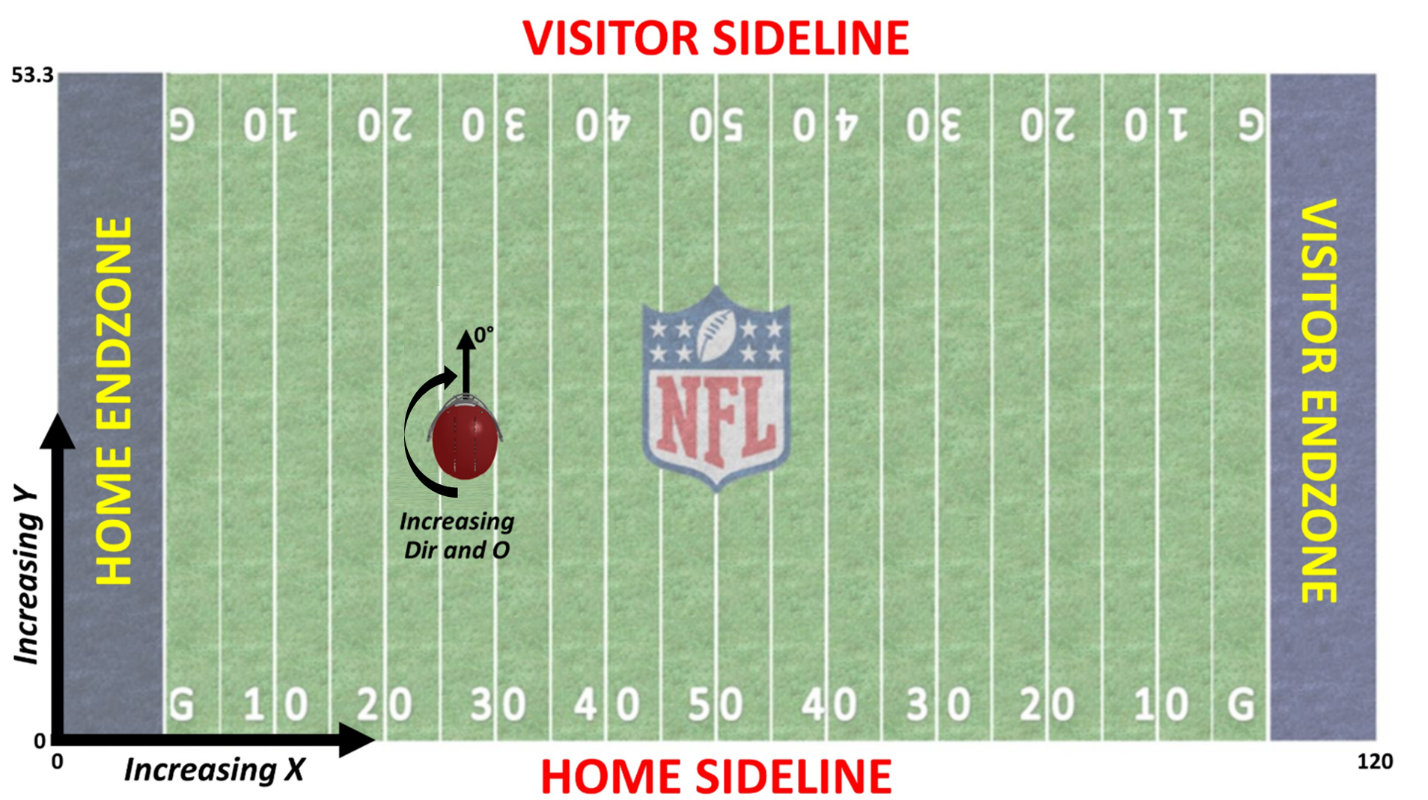


Figure 2: Visualization of positional tracking data (Source: Kaggle NFL Big Data Bowl 2021)

Prior to applying the model to the data, some data preprocessing was required. Certain games with incomplete data was were dropped and other data cleaning was needed. Inputs, closest teammate and closest opponent were calculated using an Einstein summation. Dummy variables for player positions, offensive and defensive formations, player running routes, player team (team football was used to specify a row as such) were generated as well. The data was then normalized for the training.

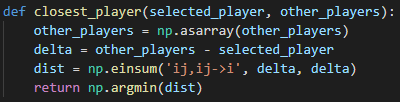


Figure 3: Code used to find closest distance between players

**4.2. Model**

Backpropagation neural network (Figure 4) training can be broken into two steps: feedforward and backpropagation. In feedforward, a pattern in applied to the input and going layer by layer, an output is produced from the network. The network’s output and the actual output are compared, and an error signal is computed from each of the output nodes. The error signal is then sent backwards to the previous layers to update the values of each node. The backpropagation step minimizes the value of the error using gradient descent[[3]](#footnote-3) adjusting node weights. The weights that minimize the error are then considered the solutions. In this study the model will be built in Python 3.8 using keras.

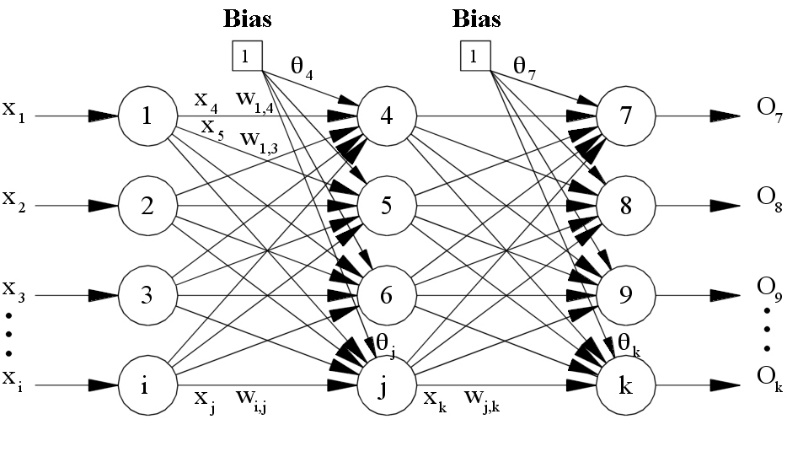


Figure : Backpropagation Neural Network with 1 hidden layer

An LSTM (Long Short Term Memory) layer and a dense layer were used in the initial neural network model. Using this base model, the number of nodes in the LSTM and dense layer were tested from one to ten nodes and their combinations over six trainings taking the average root mean squared error on the test data for each combination. Each model was trained with a fixed random seed with a batch size of 128 on five epochs. Table 2 shows the lowest average RMSE models with their different number of nodes. Further testing into the structure on the neural network tested one to three LSTM and one to two dense layers and their combinations. For this testing, two nodes combinations were tested, six – six and four – two (LSTM – dense Nodes respectively). The results of the structure testing are shown in Table 3. A finalized model of 6 LSTM nodes and 6 dense nodes with a 2 – 1 structure was chosen and used in the analysis.

|  |  |  |
| --- | --- | --- |
| LSTM Nodes | Dense Nodes | Avg RMSE |
| 6 | 6 | 11.3922 |
| 4 | 2 | 11.3934 |
| 7 | 5 | 11.3975 |
| 4 | 9 | 11.3979 |
| 7 | 8 | 11.3981 |

Table 2: Five models with lowest average RMSE on test data over 6 trainings

|  |  |  |  |
| --- | --- | --- | --- |
| LSTM Layers | Dense Layers | Node Number | Avg RMSE |
| 1 | 2 | 6-6 | 11.3379 |
| 2 | 2 | 4-2 | 11.3858 |
| 3 | 2 | 4-2 | 11.3949 |
| 2 | 2 | 6-6 | 11.3961 |
| 1 | 1 | 4-2 | 11.4091 |
| 2 | 1 | 6-6 | 11.4173 |
| 3 | 1 | 6-6 | 11.4223 |
| 3 | 1 | 4-2 | 11.4233 |
| 1 | 1 | 4-2 | 11.4276 |
| 2 | 1 | 4-2 | 11.4308 |
| 1 | 2 | 4-2 | 11.4328 |
| 3 | 2 | 6-6 | 11.456 |

Table 3: Neural Network Structure Optimization Results: Sorted by lowest average RMSE on test data over 6 trainings

As shown in Table 3, the model that had the minimum average root mean squared error had 6 nodes in the LSTM Layer, 6 in the dense Layer and used a 1 - 2 structure. A more detailed visual representation of the final model is show in Figure 3.

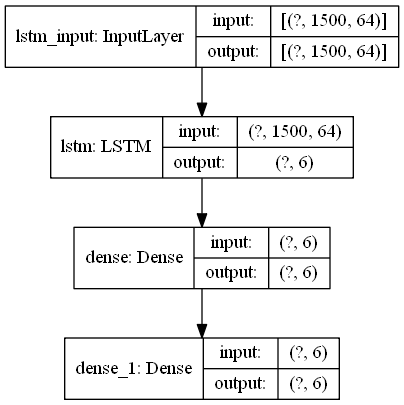


Figure : Final Neural Network Structure. All plays were padded to 1500 length

**4.3 Method of Analysis**

Neural networks are a black box such that while they can approximate any function, it is very difficult to gain insights into the structure of the function being approximated by studying the structure of the network. A method such as removing an input from the model and seeming the resulting changes in error is a good technique as error in the error function is a direct measure of predictive importance (Sarle, 2000). The downside of this method is that for each input removed, retraining the model is necessary. If the model is not retrained it is the same as setting the removed input to 0. In some cases, 0 may be a reasonable value for an input. Comparing weights can also be misleading in a neural network due to the hidden layers involved in the model. In this study an input randomization technique is used.

In order to gain insights into the significance of the inputs in the final model, inputs were systematically randomized. This gave information on the importance of the input to predicting offensive yardage gained. The results of this analysis are in Table 4. For the analysis, inputs were systematically randomized in groups and individually, each input randomization was averaged over sixteen tests. Confidence intervals and p values are calculated. The purpose of this analysis is to compare the RMSE of each test to see if randomizing certain inputs leads to greater error in the model. Since retraining of the model is not necessary with this method, the computation time needed is much less.

Due to the insignificant results from the first model, a new model was created using 100 LSTM nodes, and 300 Dense nodes with a structure of two LSTM layers and one dense layer (Figure 4). This model was then tested using the same randomized input analysis. The results for this model are in Table 5.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Randomized Input** | **Offensive Formations** | **Tracking Data** | **Player Route** | **Player Position** | **Closest Opponent** | **Closest Teammate** | **Type Dropback** | **Defenders In Box** | **Pass Rushers** | **Down** |
| **1** | 11.0211 | 10.6264 | 9.8760 | 10.5700 | 10.1358 | 11.0211 | 9.4146 | 10.1687 | 10.3371 | 10.6511 |
| **2** | 10.2829 | 11.1351 | 10.9250 | 10.4158 | 11.4495 | 10.2829 | 10.9662 | 11.2128 | 11.2534 | 10.8403 |
| **3** | 9.8179 | 10.8560 | 10.7625 | 10.4039 | 10.7776 | 9.8179 | 11.1945 | 10.2871 | 10.6749 | 10.6268 |
| **4** | 11.3607 | 10.9469 | 10.6818 | 10.9333 | 11.0621 | 11.3607 | 10.4534 | 11.6681 | 10.7929 | 11.4445 |
| **5** | 10.8246 | 9.7881 | 10.6811 | 11.5921 | 10.9242 | 10.6264 | 11.2663 | 10.6238 | 10.8224 | 10.7196 |
| **6** | 10.9610 | 11.4780 | 11.5538 | 10.4853 | 10.5510 | 11.1351 | 11.3426 | 11.0671 | 10.6710 | 10.8917 |
| **7** | 10.8142 | 10.2815 | 10.2375 | 11.0460 | 10.4101 | 10.8560 | 10.8356 | 10.4041 | 10.8564 | 10.4948 |
| **8** | 11.0483 | 11.0042 | 11.3905 | 10.7102 | 10.8440 | 10.9469 | 10.6077 | 10.6892 | 10.7797 | 10.5092 |
| **9** | 10.6238 | 10.8224 | 10.7196 | 10.8364 | 10.7851 | 9.7881 | 10.8174 | 10.5406 | 10.6430 | 10.8909 |
| **10** | 11.0671 | 10.6710 | 10.8917 | 10.7990 | 11.4988 | 11.4780 | 9.8113 | 10.0358 | 10.3454 | 10.7874 |
| **11** | 10.4041 | 10.8564 | 10.4948 | 10.7858 | 10.7402 | 10.2815 | 10.6366 | 11.1279 | 10.8343 | 11.1156 |
| **12** | 10.6892 | 10.7797 | 10.5092 | 10.6830 | 10.6261 | 11.0042 | 10.2007 | 11.0619 | 11.0250 | 10.1578 |
| **13** | 10.1687 | 10.3371 | 10.6511 | 10.8588 | 10.5285 | 10.8246 | 11.6863 | 11.3270 | 11.4330 | 11.1002 |
| **14** | 11.2128 | 11.2534 | 10.8403 | 10.6091 | 10.2522 | 10.9610 | 10.7097 | 11.1533 | 10.6541 | 10.3116 |
| **15** | 10.2871 | 10.6749 | 10.6268 | 11.4536 | 10.6301 | 10.8142 | 11.3204 | 10.5458 | 10.5250 | 11.3118 |
| **16** | 11.6681 | 10.7929 | 11.4445 | 10.1433 | 11.1011 | 11.0483 | 10.9169 | 10.3489 | 10.7140 | 10.4807 |
| **Avg** | 10.7657 | 10.7690 | 10.7679 | 10.7703 | 10.7698 | 10.7654 | 10.7613 | 10.7664 | 10.7726 | 10.7709 |
| **95% CI** | 10.9956 | 10.9589 | 10.9720 | 10.9466 | 10.9500 | 10.9987 | 11.0403 | 10.9901 | 10.9086 | 10.9380 |
| 10.5358 | 10.5792 | 10.5637 | 10.5941 | 10.5895 | 10.5322 | 10.4822 | 10.5426 | 10.6366 | 10.6038 |
| **P(T<=t) two-tail** | 0.9968 | 0.9868 | 0.9911 | 0.9820 | 0.9754 | 0.9809 | 0.9808 | 0.9998 | 0.9601 | 0.9772 |

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Height** | **Weight** | **Yardline** | **x** | **y** | **x & y** | **Orientation & Direction** | | **Team** | **None** | **All** |
| 10.8588 | 10.5285 | 11.6863 | 10.6264 | 9.8760 | 10.5700 | | 10.1358 | 9.4146 | 10.8246 | 11.0211 |
| 10.6091 | 10.2522 | 10.7097 | 11.1351 | 10.9250 | 10.4158 | | 11.4495 | 10.9662 | 10.9610 | 10.2829 |
| 11.4536 | 10.6301 | 11.3204 | 10.8560 | 10.7625 | 10.4039 | | 10.7776 | 11.1945 | 10.8142 | 9.8179 |
| 10.1433 | 11.1011 | 10.9169 | 10.9469 | 10.6818 | 10.9333 | | 11.0621 | 10.4534 | 11.0483 | 11.3607 |
| 10.8364 | 10.7851 | 10.8174 | 9.7881 | 10.6811 | 11.5921 | | 10.9242 | 11.2663 | 11.0211 | 11.0211 |
| 10.7990 | 11.4988 | 9.8113 | 11.4780 | 11.5538 | 10.4853 | | 10.5510 | 11.3426 | 10.2829 | 10.2829 |
| 10.7858 | 10.7402 | 10.6366 | 10.2815 | 10.2375 | 11.0460 | | 10.4101 | 10.8356 | 9.8179 | 9.8179 |
| 10.6830 | 10.6261 | 10.2007 | 11.0042 | 11.3905 | 10.7102 | | 10.8440 | 10.6077 | 11.3607 | 11.3607 |
| 10.8246 | 9.7881 | 10.6811 | 9.7881 | 10.6811 | 11.5921 | | 10.9242 | 11.2663 | 10.8246 | 10.8246 |
| 10.9610 | 11.4780 | 11.5538 | 11.4780 | 11.5538 | 10.4853 | | 10.5510 | 11.3426 | 10.9610 | 10.9610 |
| 10.8142 | 10.2815 | 10.2375 | 10.2815 | 10.2375 | 11.0460 | | 10.4101 | 10.8356 | 10.8142 | 10.8142 |
| 11.0483 | 11.0042 | 11.3905 | 11.0042 | 11.3905 | 10.7102 | | 10.8440 | 10.6077 | 11.0483 | 11.0483 |
| 11.0211 | 10.6264 | 9.8760 | 10.6264 | 9.8760 | 10.5700 | | 10.1358 | 9.4146 | 11.0211 | 10.8246 |
| 10.2829 | 11.1351 | 10.9250 | 11.1351 | 10.9250 | 10.4158 | | 11.4495 | 10.9662 | 10.2829 | 10.9610 |
| 9.8179 | 10.8560 | 10.7625 | 10.8560 | 10.7625 | 10.4039 | | 10.7776 | 11.1945 | 9.8179 | 10.8142 |
| 11.3607 | 10.9469 | 10.6818 | 10.9469 | 10.6818 | 10.9333 | | 11.0621 | 10.4534 | 11.3607 | 11.0483 |
| 10.7687 | 10.7674 | 10.7630 | 10.7645 | 10.7635 | 10.7696 | | 10.7693 | 10.7601 | 10.7663 | 10.7663 |
| 10.9656 | 10.9781 | 11.0243 | 11.0065 | 11.0159 | 10.9564 | | 10.9556 | 11.0479 | 10.9905 | 10.9905 |
| 10.5719 | 10.5566 | 10.5016 | 10.5225 | 10.5112 | 10.5828 | | 10.5830 | 10.4723 | 10.5422 | 10.5422 |
| 0.9834 | 0.9953 | 0.9848 | 0.9917 | 0.9870 | 0.9817 | | 0.9839 | 0.9777 | 1.0000 | 1.0000 |

Table 4: Model 1 input significance tests. H1: sample mean = non-random mean

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Randomized Input** | **Offensive Formations** | **Tracking Data** | **Player Route** | **Player Position** | **Closest Opponent** | **Closest Teammate** | **Type Dropback** | **Defenders In Box** | **Pass Rushers** | **Down** |
| **1** | 10.3933 | 10.4519 | 10.3117 | 10.5014 | 9.7566 | 10.4920 | 10.4129 | 9.9939 | 10.2457 | 10.2684 |
| **2** | 10.4755 | 10.2931 | 10.5752 | 10.4842 | 10.9814 | 11.1010 | 9.1815 | 9.6661 | 9.7570 | 10.5964 |
| **3** | 10.0868 | 10.2561 | 9.9852 | 10.4084 | 9.7092 | 10.2888 | 10.1039 | 10.7135 | 10.2654 | 10.8010 |
| **4** | 10.2247 | 10.4058 | 10.0855 | 10.3490 | 9.1468 | 10.1390 | 9.9142 | 10.6213 | 10.9083 | 9.5552 |
| **5** | 9.6986 | 9.9217 | 10.2742 | 10.6217 | 11.2890 | 9.9965 | 11.5204 | 10.9738 | 11.2218 | 10.6906 |
| **6** | 10.9147 | 10.8319 | 10.3557 | 9.8980 | 10.2754 | 9.8847 | 10.2749 | 10.8275 | 10.2417 | 9.9478 |
| **7** | 9.8446 | 10.3994 | 10.2998 | 11.1808 | 9.6210 | 10.3748 | 11.0469 | 10.2068 | 10.0920 | 11.0445 |
| **8** | 11.3022 | 10.4573 | 11.1108 | 9.5162 | 10.7145 | 10.7080 | 10.4200 | 9.9598 | 10.2340 | 10.0527 |
| **9** | 10.3933 | 10.4519 | 10.3117 | 10.5014 | 10.8818 | 10.4920 | 10.4129 | 9.9939 | 10.2457 | 10.2684 |
| **10** | 10.4755 | 10.2931 | 10.5752 | 10.4842 | 9.8367 | 11.1010 | 9.1815 | 9.6661 | 9.7570 | 10.5964 |
| **11** | 10.0868 | 10.2561 | 9.9852 | 10.4084 | 10.8336 | 10.2887 | 10.1039 | 10.7135 | 10.2654 | 10.8010 |
| **12** | 10.2247 | 10.4058 | 10.0855 | 10.3490 | 11.6471 | 10.1390 | 9.9142 | 10.6213 | 10.9083 | 9.5552 |
| **13** | 9.6986 | 9.9217 | 10.2742 | 10.6217 | 10.6778 | 9.9965 | 11.5204 | 10.9738 | 11.2219 | 10.6905 |
| **14** | 10.9147 | 10.8319 | 10.3557 | 9.8980 | 9.1634 | 9.8847 | 10.2749 | 10.8275 | 10.2417 | 9.9478 |
| **15** | 9.8446 | 10.3993 | 10.2997 | 11.1808 | 10.8010 | 10.3748 | 11.0469 | 10.2068 | 10.0920 | 11.0445 |
| **16** | 11.3022 | 10.4573 | 11.1108 | 9.5162 | 10.3404 | 10.7080 | 10.4200 | 9.9597 | 10.2340 | 10.0527 |
| **Avg** | 10.3676 | 10.3771 | 10.3748 | 10.3700 | 10.3547 | 10.3731 | 10.3593 | 10.3703 | 10.3707 | 10.3696 |
| **95% CI** | 10.6129 | 10.4933 | 10.5333 | 10.5962 | 10.7085 | 10.5546 | 10.6827 | 10.5886 | 10.5850 | 10.5986 |
| 10.1222 | 10.2610 | 10.2162 | 10.1438 | 10.0009 | 10.1915 | 10.0359 | 10.1521 | 10.1565 | 10.1405 |
| **P(T<=t) two-tail** | 0.9925 | 0.9561 | 0.9695 | 0.9967 | 0.9447 | 0.9805 | 0.9610 | 0.9946 | 0.9923 | 0.9984 |

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Height** | **Weight** | **Yardline** | **x** | **y** | **x & y** | **Orientation & Direction** | | **Team** | **None** | **All** |
| 10.5244 | 9.7566 | 11.2890 | 9.3621 | 10.3360 | 11.3064 | | 10.5230 | 10.9424 | 10.5244 | 10.4258 |
| 10.6335 | 10.9814 | 10.2754 | 11.1195 | 11.2430 | 10.1992 | | 10.1170 | 11.0169 | 10.6335 | 10.4949 |
| 10.4096 | 9.7092 | 9.6209 | 9.6693 | 9.6802 | 10.6266 | | 9.9989 | 10.6082 | 10.4096 | 9.9344 |
| 10.6333 | 9.1469 | 10.7145 | 10.6805 | 11.0005 | 10.3971 | | 10.5688 | 10.1155 | 10.6333 | 10.4396 |
| 10.5885 | 10.8818 | 10.6778 | 10.2360 | 9.2182 | 10.1337 | | 9.5155 | 8.8182 | 10.5884 | 10.5016 |
| 9.7480 | 9.8367 | 9.1634 | 10.7171 | 10.6162 | 9.8207 | | 11.2830 | 10.5859 | 9.7480 | 10.0924 |
| 9.3054 | 10.8336 | 10.8010 | 10.5960 | 10.4017 | 10.0079 | | 10.3815 | 10.7331 | 9.3052 | 10.2815 |
| 11.0863 | 11.6471 | 10.3404 | 10.5404 | 10.3934 | 10.4776 | | 10.5592 | 10.0465 | 11.0863 | 10.8429 |
| 10.5244 | 10.4258 | 10.6192 | 9.3621 | 10.3360 | 11.3064 | | 10.5229 | 10.9426 | 10.6191 | 10.5243 |
| 10.6335 | 10.4938 | 9.7289 | 11.1195 | 11.2431 | 10.1992 | | 10.1171 | 11.0169 | 9.7289 | 10.6335 |
| 10.4097 | 9.9348 | 10.5731 | 9.6693 | 9.6803 | 10.6268 | | 9.9989 | 10.6082 | 10.5731 | 10.4095 |
| 10.6333 | 10.4396 | 9.9407 | 10.6805 | 11.0006 | 10.3971 | | 10.5688 | 10.1155 | 9.9408 | 10.6331 |
| 10.5886 | 10.5019 | 10.4197 | 10.2359 | 9.2182 | 10.1337 | | 9.5155 | 8.8182 | 10.4197 | 10.5896 |
| 9.7479 | 10.0924 | 10.7230 | 10.7171 | 10.6162 | 9.8207 | | 11.2830 | 10.5859 | 10.7230 | 9.7477 |
| 9.3054 | 10.2815 | 10.9486 | 10.5960 | 10.4017 | 10.0079 | | 10.3816 | 10.7331 | 10.9486 | 9.3065 |
| 11.0863 | 10.8419 | 10.0255 | 10.5405 | 10.3934 | 10.4776 | | 10.5592 | 10.0466 | 10.0254 | 11.0863 |
| 10.3661 | 10.3628 | 10.3663 | 10.3651 | 10.3612 | 10.3711 | | 10.3684 | 10.3584 | 10.3692 | 10.3715 |
| 10.6257 | 10.6530 | 10.6276 | 10.6326 | 10.6625 | 10.5814 | | 10.6049 | 10.6851 | 10.5992 | 10.5758 |
| 10.1065 | 10.0726 | 10.1050 | 10.0976 | 10.0599 | 10.1609 | | 10.1318 | 10.0316 | 10.1392 | 10.1671 |
| 0.9849 | 0.9740 | 0.9834 | 0.9845 | 0.9713 | 0.9893 | | 0.9964 | 0.9619 | 1.0000 | 0.9900 |

Table 5: Model 2 input significance tests. H1: sample mean = non-random mean

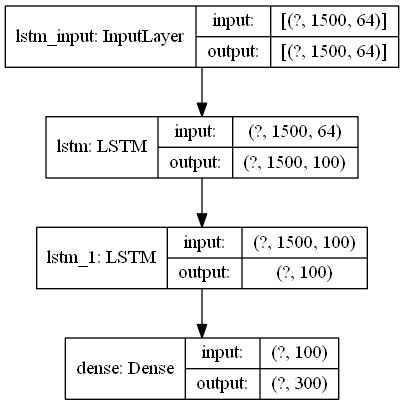
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Figure : Model 2 Neural Network Structure

**Analysis**

As shown in the analysis results, none of the inputs to the neural network model were significant for either model. The error when using random numbers to all the inputs of the model were within the confidence interval of the baseline model error. The same conclusion is made for every input and combination of inputs tested. It is hypothesized that a different neural network paired with more meta data on the tracking data would provide better predictive capabilities. Particularly a more complex neural network may be able to find a fit to the data. In this study a simple model was chosen due to computation power and time limitations as well as the extra computation power and time needed for analysis. The second model that was tested was more complex but still could not find a fit in the data. While the model’s goal was simply to derive conclusions about the inputs to the model, the analysis provided does not give any conclusions that can be made. In the future this study can be used as a reference for how simple neural networks can lack the complexity to fit some functions and the importance of providing descriptive data to the network. The results show that the model could not find a significant fit for the data provided to yards gained. More descriptive statistics on the tracking data and on the players could help a neural network find a fit and will require further testing and development.

One use this study has is in its method of analysis, for this study we used a similar methodology for optimizing our model as *Purucker, 1996.* The results of this study show the necessity in picking a wider range of node numbers. While the tests we ran to optimize the model certainly took in many combinations of node numbers, the model was not complex enough to fit the objective function. It is possible that a higher range of node numbers would deliver a better result. However even when a relatively more complex model was tried, the inputs were still insignificant. This result leads the author to believe that further efforts into additional descriptive statistics on the tracking and player data being passed into a neural network would see a better fitting model.

**Conclusion**

The model developed in this study was a complete failure and was unable to offer any concrete conclusions about win determinants in the NFL. However, this study also provides insight into the feasibility and potential for neural network model applications to the NFL and other economic questions. Neural networks are traditionally treated as a ‘black box’ due to the complexity of the hidden layers. Any common technique used to gain insight in the structure of a regression does not work with a neural network. Instead techniques such as the one discussed from *Sarle, 2000,* or the one used in this paper must be utilized. Still the research into dissecting neural networks is incomplete. While there are many agreed upon techniques that do not work in analyzing a neural network, there is still no universally agreed upon technique for analyzing a neural network. Even in the optimization of model parameters and structure, the techniques involved are that of brute force and comparison instead of using a formula to find a solution.

Unfortunately, this study ended with a model that is useless in its predictive capabilities and had no conclusions to show for it. However, the outlined process of creating the model will be useful to anyone trying to apply a neural network model to any economic problem in the future. With the advancements in machine learning, the author believes that the innovations in data modeling will be extremely beneficial to the field of economics. AI allows for discovery untainted by human bias, conclusions that could only be reached through the help of an AI. Neural networks, while harder to analyze than your traditional regression, can estimate behaviors unseen to humans. This is a unique advantage to machine learning, unlike a human researcher who is subject to the bias from previous knowledge, machine learning can bring completely fresh outlooks to a problem. This happened most notably with AlphaGo, a Go (popular Chinese boardgame) AI. The AI through its own learning developed moves that a human player would have never thought of. This kind of discovery was one of the drivers in choosing to use a neural network. In a field such as economics where theoretical models are built to simplify real world situations, the potential of building a model within the complexity of the real-world situation seemed quite interesting to try.

Overall, this project was a bit too ambitious for an undergraduate thesis and to be done to completion, the model would need to be worked on for a much longer period. If anything was gained from this study, the author hopes that the potential of applying machine learning to the field of economics is recognized and pursued in the future.

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| Brunkhorst, John & Fenn, Aju. (2010). Profit Maximization In The National Football League. Journal of Applied Business Research. 26. 45-58. 10.19030/jabr.v26i1.276. |
| This study looks at whether NFL teams maximize profits with respect to ticket price. Modifying Ferguson et al’s (1991) NHL paper as it pertains to the NFL. A systems model is used as the estimation procedure to identify the determinants of ticket prices for NFL franchises. In their best fit model, previous year win percentage was found to be a significant determinant while current win percentage was not. Current win percentage was expectedly insignificant as that information is available when pricing tickets for the current season. |
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| This is the first model of sports ticket pricing to recognize the intertemporal nature of demand for a sports match. The authors construct a firm profit maximization problem in which a sports team considers both present and future revenue when pricing home games in the present period. Present game success was found to be positively related to attendance |
|  |
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| This study utilizes a neural network to predict NFL football games. Their model uses box scores and was 3% more accurate on average than eight sportscasters on ESPN. In the methodology section of the paper they review their choices for tweaking the neural network parameters for learning coefficient, momentum, number of hidden neurons, and network structure. For the final model they use a back-propagation multi-layer perceptron network. |
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| This study uses a Tobit analysis to estimate a model which explains game-day attendance at professional football games in the U.S. The study finds a positive relationship between team performance and attendance |

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**Appendix**

Full Dataset Variables with description

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| time | Time stamp of play (time, yyyy-mm-dd, hh:mm:ss) | | | |
| x | Player position along the long axis of the field, 0 - 120 yards. See Figure 1 below. (numeric) | | | |
| y | Player position along the short axis of the field, 0 - 53.3 yards. See Figure 1 below. (numeric) | | | |
| s | Speed in yards/second (numeric) | | |  |
| a | Acceleration in yards/second^2 (numeric) | | | |
| dis | Distance traveled from prior time point, in yards (numeric) | | | |
| o | Player orientation (deg), 0 - 360 degrees (numeric) | | | |
| dir | Angle of player motion (deg), 0 - 360 degrees (numeric) | | | |
| event | Tagged play details, including moment of ball snap, pass release, pass catch, tackle, etc (text) | | | |
| nflId | Player identification number, unique across players (numeric) | | | |
| displayName | Player name (text) |  |  |  |
| jerseyNumber | Jersey number of player (numeric) | | |  |
| position | Player position group (text) | |  |  |
| team | Team (away or home) of corresponding player (text) | | | |
| frameId | Frame identifier for each play, starting at 1 (numeric) | | | |
| gameId | Game identifier, unique (numeric) | | |  |
| playId | Play identifier, not unique across games (numeric) | | | |
| playDirection | Direction that the offense is moving (text, left or right) | | | |
| route | Route ran by offensive player (text) | | |  |
| gameId | Game identifier, unique (numeric) | | |  |
| playId | Play identifier, not unique across games (numeric) | | | |
| playDescription | Description of play (text) | |  |  |
| quarter | Game quarter (numeric) | |  |  |
| down | Down (numeric) |  |  |  |
| yardsToGo | Distance needed for a first down (numeric) | | | |
| possessionTeam | Team on offense (text) | |  |  |
| playType | Outcome of dropback: sack or pass (text) | | | |
| yardlineSide | 3-letter team code corresponding to line-of-scrimmage (text) | | | |
| yardlineNumber | Yard line at line-of-scrimmage (numeric) | | | |
| offenseFormation | Formation used by possession team (text) | | | |
| personnelO | Personnel used by offensive team (text) | | | |
| defendersInTheBox | Number of defenders in close proximity to line-of-scrimmage (numeric) | | | |
| numberOfPassRushers | Number of pass rushers (numeric) | | |  |
| personnelD | Personnel used by defensive team (text) | | | |
| typeDropback | Dropback categorization of quarterback (text) | | | |
| preSnapHomeScore | Home score prior to the play (numeric) | | |  |
| preSnapVisitorScore | Visiting team score prior to the play (numeric) | | | |
| gameClock | Time on clock of play (MM:SS) | |  |  |
| absoluteYardlineNumber | Distance from end zone for possession team (numeric) | | | |
| penaltyCodes | NFL categorization of the penalties that ocurred on the play. For purposes of this contest, the most important penalties are Defensive Pass Interference (DPI), Offensive Pass Interference (OPI), Illegal Contact (ICT), and Defensive Holding (DH). Multiple penalties on a play are separated by a ; (text) | | | |
| penaltyJerseyNumber | Jersey number and team code of the player commiting each penalty. Multiple penalties on a play are separated by a ; (text) | | | |
| passResult | Outcome of the passing play (C: Complete pass, I: Incomplete pass, S: Quarterback sack, IN: Intercepted pass, text) | | | |
| offensePlayResult | Yards gained by the offense, excluding penalty yardage (numeric) | | | |
| playResult | Net yards gained by the offense, including penalty yardage (numeric) | | | |
| epa | Expected points added on the play, relative to the offensive team. Expected points is a metric that estimates the average of every next scoring outcome given the play's down, distance, yardline, and time remaining (numeric) | | | |
| isDefensivePI | An indicator variable for whether or not a DPI penalty ocurred on a given play (TRUE/FALSE) | | | |
| nflId | Player identification number, unique across players (numeric) | | | |
| height | Player height (text) |  |  |  |
| weight | Player weight (numeric) | |  |  |
| birthDate | Date of birth (YYYY-MM-DD) | |  |  |
| collegeName | Player college (text) | |  |  |
| position | Player position (text) | |  |  |
| displayName | Player name (text) |  |  |  |
| gameId | Game identifier, unique (numeric) | | |  |
| gameDate | Game Date (time, mm/dd/yyyy) | | |  |
| gameTimeEastern | Start time of game (time, HH:MM:SS, EST) | | | |
| homeTeamAbbr | Home team three-letter code (text) | | |  |
| visitorTeamAbbr | Visiting team three-letter code (text) | | |  |
| week | Week of game (numeric) | |  |  |

Full Results of average RMSE node number optimization (sorted by lowest Avg RMSE)

|  |  |  |
| --- | --- | --- |
| LSTM Nodes | Dense Nodes | Avg RMSE |
| 6 | 6 | 11.3922 |
| 4 | 2 | 11.3934 |
| 7 | 5 | 11.3975 |
| 4 | 9 | 11.3979 |
| 7 | 8 | 11.3981 |
| 7 | 7 | 11.3987 |
| 9 | 6 | 11.3993 |
| 6 | 7 | 11.4006 |
| 2 | 5 | 11.4006 |
| 8 | 5 | 11.4007 |
| 4 | 1 | 11.402 |
| 8 | 9 | 11.404 |
| 1 | 4 | 11.4045 |
| 1 | 8 | 11.406 |
| 2 | 3 | 11.4061 |
| 8 | 3 | 11.4067 |
| 8 | 1 | 11.4074 |
| 4 | 4 | 11.4078 |
| 4 | 3 | 11.4084 |
| 7 | 3 | 11.4087 |
| 9 | 9 | 11.4087 |
| 8 | 6 | 11.4088 |
| 3 | 5 | 11.4091 |
| 5 | 5 | 11.4099 |
| 3 | 3 | 11.4101 |
| 9 | 7 | 11.4101 |
| 5 | 7 | 11.4104 |
| 5 | 6 | 11.411 |
| 2 | 6 | 11.411 |
| 8 | 7 | 11.4112 |
| 2 | 2 | 11.4112 |
| 2 | 7 | 11.4114 |
| 1 | 3 | 11.4117 |
| 9 | 5 | 11.4121 |
| 7 | 6 | 11.4126 |
| 7 | 9 | 11.4129 |
| 1 | 6 | 11.413 |
| 6 | 4 | 11.413 |
| 5 | 9 | 11.414 |
| 7 | 2 | 11.414 |
| 3 | 2 | 11.4143 |
| 4 | 8 | 11.4146 |
| 8 | 4 | 11.4147 |
| 8 | 8 | 11.4151 |
| 6 | 9 | 11.4154 |
| 4 | 7 | 11.4161 |
| 2 | 8 | 11.4167 |
| 1 | 9 | 11.4167 |
| 6 | 3 | 11.4171 |
| 2 | 9 | 11.4171 |
| 3 | 7 | 11.4173 |
| 8 | 2 | 11.4182 |
| 1 | 5 | 11.4182 |
| 2 | 4 | 11.4182 |
| 9 | 8 | 11.4188 |
| 6 | 1 | 11.4192 |
| 9 | 4 | 11.4212 |
| 1 | 7 | 11.4213 |
| 5 | 8 | 11.4216 |
| 3 | 1 | 11.4223 |
| 4 | 6 | 11.4227 |
| 5 | 3 | 11.4228 |
| 6 | 8 | 11.4233 |
| 3 | 9 | 11.4237 |
| 1 | 1 | 11.4239 |
| 6 | 5 | 11.4244 |
| 5 | 4 | 11.4246 |
| 9 | 2 | 11.4255 |
| 3 | 6 | 11.4257 |
| 1 | 2 | 11.4287 |
| 5 | 1 | 11.4287 |
| 6 | 2 | 11.4295 |
| 9 | 3 | 11.4317 |
| 4 | 5 | 11.4323 |
| 3 | 8 | 11.4326 |
| 7 | 4 | 11.4328 |
| 5 | 2 | 11.4349 |
| 3 | 4 | 11.4408 |
| 2 | 1 | 11.4421 |
| 7 | 1 | 11.4426 |
| 9 | 1 | 11.4474 |

1. An NFL season consists of 256 games, where each of the NFL's 32 teams plays 16 games during a 17-week period [↑](#footnote-ref-1)
2. One of the most general methods used for supervised training of multilayered neural networks. Backpropagation works by approximating the non-linear relationship between the input and the output by adjusting the weight values internally [↑](#footnote-ref-2)
3. The error is considered as a function of the weights, where there is a gradient for each weight. The weights that minimize the error are then found [↑](#footnote-ref-3)