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] 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.

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[1] An NFL season consists of 256 games, where each of the NFL's 32 teams plays 16 games during a 17-week period

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]. 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.

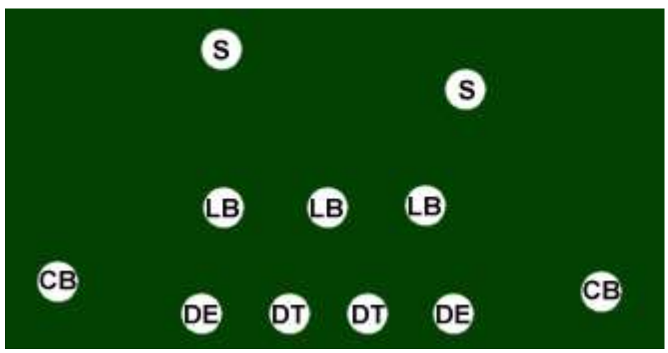

Figure 1: 4-3 Defense, a very popular defensive formation in the NFL. It uses four defensive linemen, three linebackers, two cornerbacks, and two safeties

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

[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

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 1: Neural network inputs and description

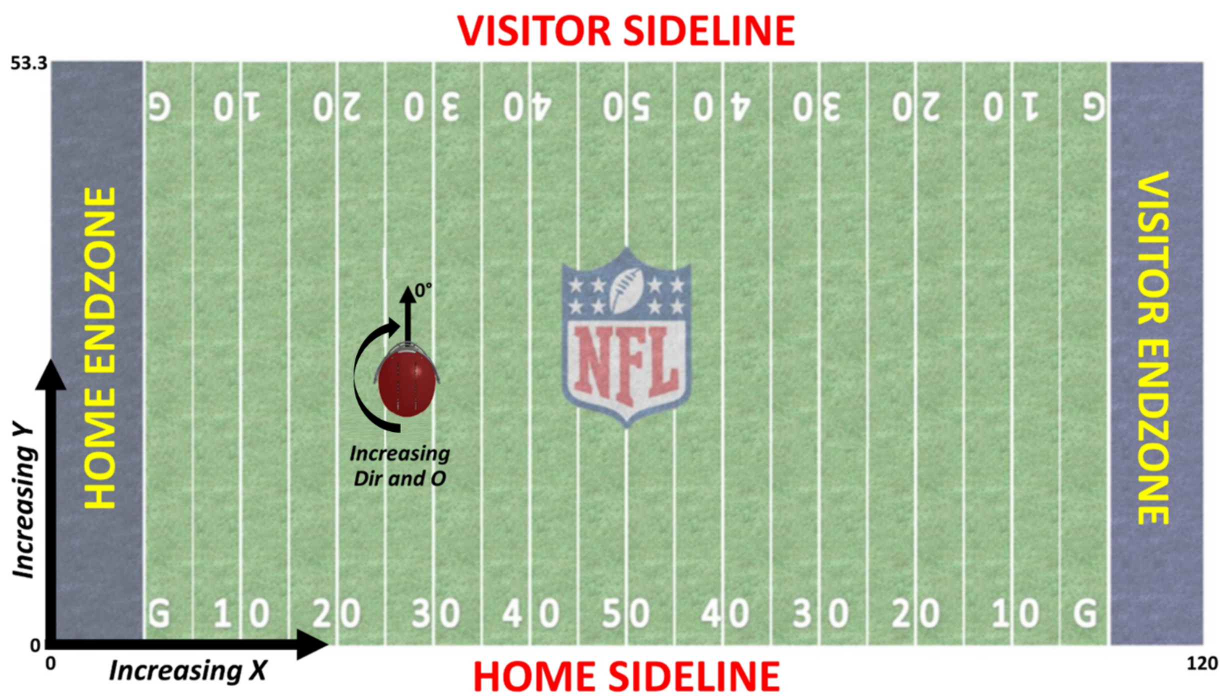

Figure 2: Visualization of positional tracking data (Source: Kaggle NFL Big Data Bowl 2021)

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.

```python
def closest_player(selected_player, other_players):
    other_players = np.asarray(other_players)
    delta = other_players - selected_player
    dist = np.einsum('ij,ij->i', delta, delta)
    return np.argmin(dist)
```

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] 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.

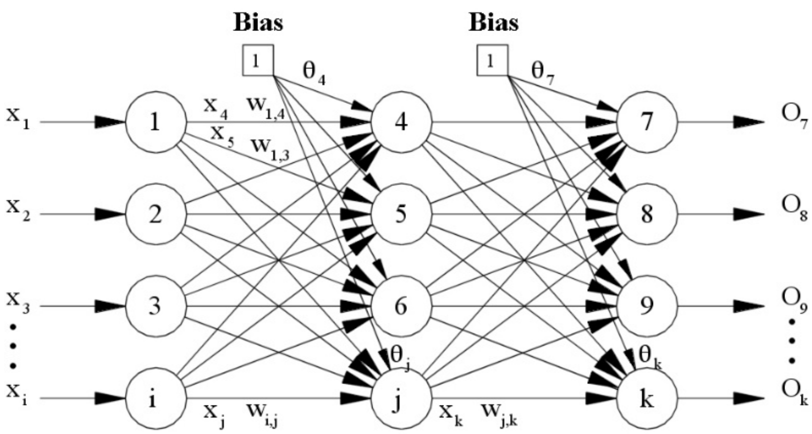

Figure 2: Backpropagation Neural Network with 1 hidden layer

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.

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[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

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.

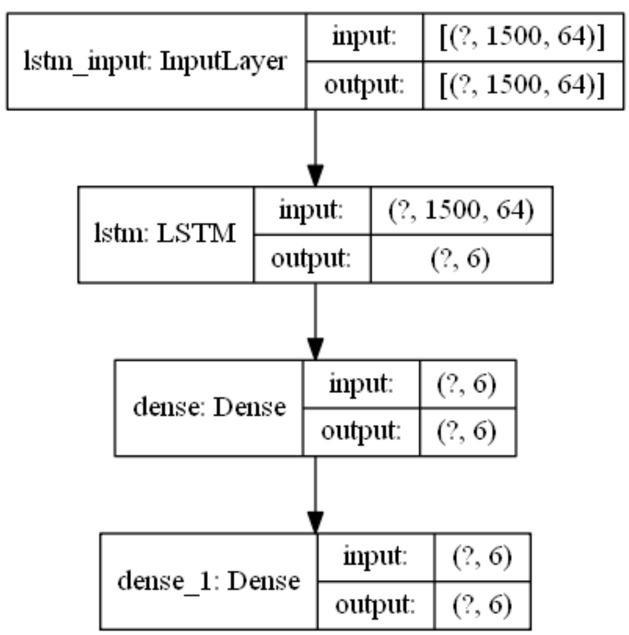

Figure 3: Final Neural Network Structure. All plays were padded to 1500 length

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. H_1: 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. H_1: sample mean = non-random mean

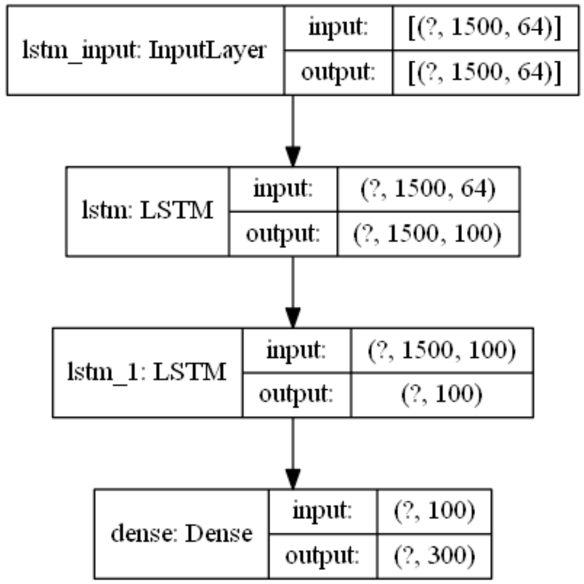

Figure 4: Model 2 Neural Network Structure

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.

References

Blaikie, Andrew D., et al. "NFL and NCAA Football Prediction using Artificial Neural Networks." Proceedings of the Midstates Conference for Undergraduate Research in Computer Science and Mathematics, Denison University, Granville, OH. 2011.

This study builds off the NFL neural network created in Kahn (2003) and also creates one for the NCAA. The NFL predictive model ranked in the top half compared to other prediction experts while their NCAA model was closer to the middle of the rankings

Bowley, Jennifer L., and Paul D. Berger. "Predicting National Football League (NFL) Stadium Attendance."

This study explores the factors that determine attendance at NFL games. The paper concludes through uses of single and multivariate models, that previous wins (which indicates potential for future wins) and the number of individual star players on a teams were the most important factors in determining attendance at an NFL regular season game.

Bradbury, John Charles. "Determinants of revenue in sports leagues: An empirical assessment." *Economic Inquiry* 57.1 (2019): 121-140.

Looking at determinants of revenue in North America's four major professional sports leagues, revenue is positively associated with on-field success in the MLB, NBA, NHL, but not the NFL

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.

Chang, Y.-M., Potter, J.M. and Sanders, S. (2016), "Inelastic sports ticket pricing, marginal win revenue, and firm pricing strategy: A behavioral pricing model", Managerial Finance, Vol. 42 No. 9, pp. 922-927. https://doi.org/10.1108/MF-02-2016-0047

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

Kahn, Joshua. "Neural network prediction of NFL football games." World Wide Web electronic publication (2003): 9-15.

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.

M. C. Purucker, "Neural network quarterbacking," in IEEE Potentials, vol. 15, no. 3, pp. 9-15, Aug.-Sept. 1996, doi: 10.1109/45.535226.

This study uses four statistical categories, yards gained, rushing yards gained, turnover margin and time of possession to compare the relative strengths of NFL teams. Several neural network strategies are tried to predict winners in NFL games. Predictions are presented and the performance of each network is examined.

Miller P. (2012) An Overview of NFL Revenues and Costs. In: Quinn K. (eds) The Economics of the National Football League. Sports Economics, Management and Policy, vol 2. Springer, New York, NY. https://doi.org/10.1007/978-1-4419-6290-4_4
This study briefly discusses the connection between winning and revenue in the NFL. It also provides information on revenue sharing within the NFL.

Onwuegbuzie, Anthony J. "Defense or Offense? Which Is the Better Predictor of Success for Professional Football Teams?" Perceptual and Motor Skills, vol. 89, no. 1, Aug. 1999, pp. 151–159, doi:10.2466/pms.1999.89.1.151.
This study analyzes data from the 1997 NFL regular season to access whether components that best predict success (winning a game) tend to be more associated with offense or defense. Analysis concluded that points conceded by the defense in the regular season explained more variance in success (73.5%) than the points scored on offense (14.7%). The model introduced in this paper also included turnover differential and when included, explained 43.4% of the variance in success.

Ozanian, Mike. "The World's Most Valuable Soccer Teams 2019: Real Madrid Is Back On Top, At $4.24 Billion." Forbes, Forbes Magazine, 30 May 2019, www.forbes.com/sites/mikeozanian/2019/05/29/the-worlds-most-valuable-soccer-teams-2019/?sh=30cc492840d6.

Ozanian, Mike. "The NFL's Most Valuable Teams 2020: How Much Is Your Favorite Team Worth?" *Forbes*, Forbes Magazine, 25 Sept. 2020, www.forbes.com/sites/mikeozanian/2020/09/10/the-nfls-most-valuable-teams-2020-how-much-is-your-favorite-team-worth/?sh=78eb157b2ba4

Robst, John, et al. "'Defense Wins Championships?': The Answer from the Gridiron." *International Journal of Sport Finance* 6.1 (2011): 72.
In an effort to answer the question, Is offense or defense more important for making the playoffs and advancing in the playoffs, this study examines a variety of dependent variables and tests to determine whether offense or defense contribute more to making the playoffs and advancing in the playoffs. Examine the probability of advancing in the playoffs or a game-by-game analysis, no evidence was found that teams benefit from focusing on offense or defense. In a sense it provides evidence that the league is efficient. The marginal benefit from improving the offense is similar to the marginal benefit from improving the defense.

Sarle, Warren S. "How to Measure Importance of Inputs?" *SAS Institute Inc*, 23 June 2000
This study discusses various technique and misconceptions about neural network input importance.

Spenner, Erin LeAnne, Aju J. Fenn, and John R. Crooker. "The demand for NFL attendance: A rational addiction model." Journal of Business & Economics Research (JBER) 8.12 (2010).
This study analyzes the demand for attendance at NFL games using a rational addiction model. The hypothesis tested in the study is that professional football displays the properties of a habit-forming good. A model for pricing power is introduced in the paper to identify anticipated pricing behavior. The data includes statistics from each NFL team from 1983 to 2008 seasons. Current attendance is modeled as a functions of team specific variables including past and future attendance, ticket price, and team performance. It is found that past and future attendance, winning percentage, age of the stadium for a team, and own-price elasticity influence attendance.

Stair, Anthony. "April Day, Daniel Mizak, and John Neral,(2008)" The factors affecting team performance in the NFL: does off-field conduct matter?."." Economics Bulletin 26.2 (2008): 1-9.

Abstract: “This paper contains a statistical analysis of the factors that contribute to team wins in the NFL. The variables examined are divided into offensive, defensive, and special teams categories. In addition, net turnovers, penalties, and off-field conduct, as measured by team arrests, are also included as independent variables. The results show that the quarterback rating has the largest impact on team wins followed by field goal percentage, opponent’s passing yards per game, and opponent’s rushing yards per game. Team arrests were not found to have a statistically significant impact on team performance.”

Welki, A.M., Zlatoper, T.J. U.S. professional football game-day attendance. Atlantic Economic Journal 27, 285–298 (1999). https://doi.org/10.1007/BF02299579

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

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