Brandon Mather DSC550-T301 - Final Project

Introduction:

In the current atmosphere, sports betting is on the rise. Everybody is looking for an edge into figuring out the best odds of winning including the people placing the bets, but also the companies. Through data we can try and figure out the best way to find out which teams are more likely to beat another to gain an edge. This analysis will be most useful to sports betting companies so that they know the best odds to put games at. I will be focusing on the NFL for this project, using data from the last three seasons, and will be proving that scoring is not the single thing that can make a team win, there are a lot of factors that go into a game. I will be using a logistic regression model to best determine which teams are most likely to win in a scenario. This will help sports betting companies get an even better edge on the bettor. I believe that this type of model would be useful in other leagues as well, but the statistics would have to change. The overall goal of the model will be to determine who would win in a head to head matchup based off wins in the last 3 seasons. All of the data has been collected from https://www.pro-football-reference.com/.

Data Preparation:

In [94]:

```
import pandas as pd
import matplotlib as mpl
import matplotlib.pyplot as plt
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
import seaborn as sns
```

In [2]:

```
standings_2020 = pd.read_csv('NFL_standings20.csv')
standings_2021 = pd.read_csv('NFL_standings21.csv')
standings_2022 = pd.read_csv('NFL_standings22.csv')
stats_2020 = pd.read_csv('NFL_stats2020.csv')
stats_2021 = pd.read_csv('NFL_stats2021.csv')
stats_2022 = pd.read_csv('NFL_stats2022.csv')
defense_2020 = pd.read_csv('NFL_defense2020.csv')
defense_2021 = pd.read_csv('NFL_defense2021.csv')
defense_2022 = pd.read_csv('NFL_defense2022.csv')
```

In [3]:

```
to_drop_standings = ['W-L%', 'PF', 'PA', 'SoS', 'SRS', 'OSRS', 'DSRS']
to_drop_defense = ['Rk', 'G', 'Ply', 'Y/P', 'FL', 'Cmp', 'Att', 'Yds', 'TD', 'Int', 'N
                   'Att','1stPy', 'TO%', 'EXP']
to_drop_stats = ['Rk', 'G', 'Ply', 'Y/P', 'FL', 'Cmp', 'PassAtt', 'PassYds', 'PassTD',
                 'RushYds', 'RushTD', 'Y/A', 'Rush1stD', 'PenYds', '1stPy', 'TO%', 'EX
```

In [4]:

```
stats_2020.drop(to_drop_stats, inplace=True, axis=1)
stats_2021.drop(to_drop_stats, inplace=True, axis=1)
stats_2022.drop(to_drop_stats, inplace=True, axis=1)
defense_2020.drop(to_drop_defense, inplace=True, axis=1)
defense_2021.drop(to_drop_defense, inplace=True, axis=1)
```

```
defense_2022.drop(to_drop_defense, inplace=True, axis=1)
standings_2020.drop(to_drop_standings, inplace=True, axis=1)
standings_2021.drop(to_drop_standings, inplace=True, axis=1)
standings_2022.drop(to_drop_standings, inplace=True, axis=1)
```

In [5]:

```
to_drop_defense2 = ['1stD.1', 'Att.1', 'Yds.1', 'TD.1', '1stD.2', 'Yds.2']
```

In [6]:

```
defense_2020.drop(to_drop_defense2, inplace=True, axis=1)
defense_2021.drop(to_drop_defense2, inplace=True, axis=1)
defense_2022.drop(to_drop_defense2, inplace=True, axis=1)
```

In [7]:

```
stats_Merged_data = pd.concat([stats_2020, stats_2021]).groupby(['Tm']).sum().reset_in
```

In [8]:

```
stats_Merged_data = pd.concat([stats_Merged_data, stats_2022]).groupby(['Tm']).sum().r
```

In [9]:

```
defense_Merged_data = pd.concat([defense_2020, defense_2021]).groupby(['Tm']).sum().re
```

In [10]:

```
defense_Merged_data = pd.concat([defense_Merged_data, defense_2022]).groupby(['Tm']).s
```

In [11]:

```
standings_Merged_data = pd.concat([standings_2020, standings_2021]).groupby(['Tm']).su
```

In [12]:

```
standings_Merged_data = pd.concat([standings_Merged_data, standings_2022]).groupby(['T
```

In [13]:

```
defense_Merged_data = defense_Merged_data.rename(columns = {'TO':'DeffenseTO'})
```

In [14]:

```
stats_Merged_data = stats_Merged_data.rename(columns = {'TO':'OffenseTO'})
```

In [15]:

```
final_merged_data = pd.merge(stats_Merged_data, defense_Merged_data, on='Tm')
```

In [16]:

```
final_merged_data = pd.merge(final_merged_data, standings_Merged_data, on='Tm')
```

In [17]:

```
final_merged_data.drop('Tm', inplace=True, axis=1)
```

In [18]:

```
final_merged_data
```

Out[18]:

	PF	Ydsgained	OffenseTO	total1stD	OffPen	Sc%offense	PA	Ydsallowed	DeffenseTO	DefF
0	1199	18004	61	1074	345	117.0	1182	17159	68	2
1	1074	16476	65	1002	243	117.1	1259	18724	58	3
2	1205	18010	65	1058	288	122.7	1010	16967	62	2
3	1439	19197	71	1162	307	139.6	950	15383	83	2
4	1001	15879	71	938	306	104.8	1180	16915	55	2
5	1009	15760	76	946	274	104.7	1240	17293	57	2
6	1189	17029	63	1012	236	117.1	1122	17562	62	3
7	1118	17638	59	1047	314	107.4	1171	16662	60	2
8	1392	18902	69	1108	327	125.9	1173	17763	90	3
9	945	16514	74	939	277	98.5	1127	16871	58	3
10	1155	17547	59	1055	290	116.0	1413	19842	53	2
11	1329	18184	46	1067	242	130.4	1111	16644	68	2
12	953	15551	68	869	282	98.3	1336	19655	61	2
13	1191	17248	68	1028	259	116.9	1154	16826	79	2
14	963	16484	76	966	301	96.0	1299	18691	53	2
15	1449	20431	64	1224	303	142.5	1095	17584	71	3
16	1203	18310	71	1051	335	131.3	1335	18173	43	2
17	1249	18855	57	1126	282	122.1	1269	17501	64	2
18	1139	17126	71	1000	223	113.6	1052	16172	69	2
19	1142	16840	67	1012	290	110.3	1110	17367	69	2
20	1279	18605	59	1097	281	115.1	1328	19422	71	2
21	1152	16592	65	982	261	117.7	1003	16418	82	2
22	1176	16874	60	979	295	110.9	1017	15736	65	2
23	903	15354	68	948	275	98.3	1144	17710	63	3
24	849	15096	69	873	295	85.6	1277	18249	49	2
25	1255	18087	64	1073	304	113.8	1147	16525	62	2
26	1067	16199	57	990	281	106.9	1056	16649	72	3
27	1253	18525	72	1058	281	118.9	1032	15410	70	2
28	1261	17394	54	1004	287	119.8	1138	18683	65	2
29	1316	18940	58	1114	280	124.1	1066	16382	74	2
30	1208	17210	60	1020	300	114.7	1152	17957	65	3
31	991	16193	74	1006	261	97.3	1106	16159	60	2

Graphical Analysis:

In [19]:

```
wins = final_merged_data["W"]
offensive_scoring = final_merged_data["PF"]
defensive_scoring_allowed = final_merged_data["PA"]
offensive_yrds = final_merged_data["Ydsgained"]
defensive_yrds = final_merged_data["Ydsallowed"]
```

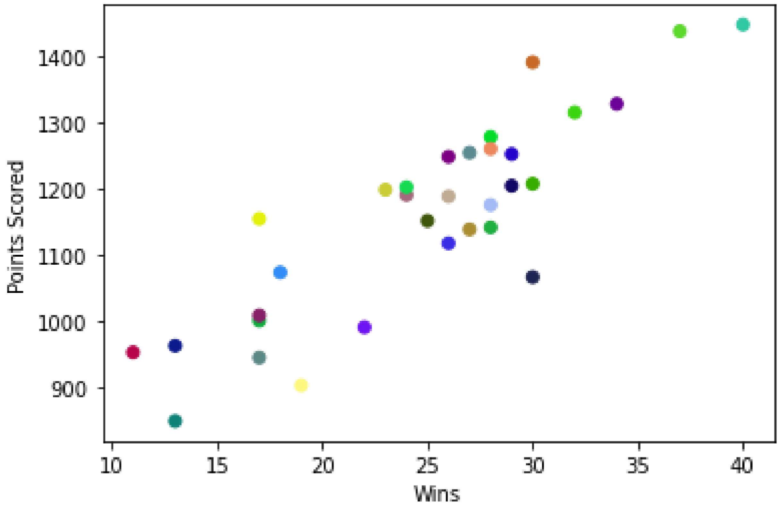
With this graphical analysis I want to compare the four statistics that I think will have the biggest impact on wins, these are Points Scored, Points Allowed, Yards Gained, and Yards allowed.

In [20]:

```
print("Wins Vs Points Scored")
plt.scatter(wins, offensive_scoring, c=np.random.rand(len(wins),3))

plt.xlabel("Wins")
plt.ylabel("Points Scored")
plt.show()
```

```
Wins Vs Points Scored
```

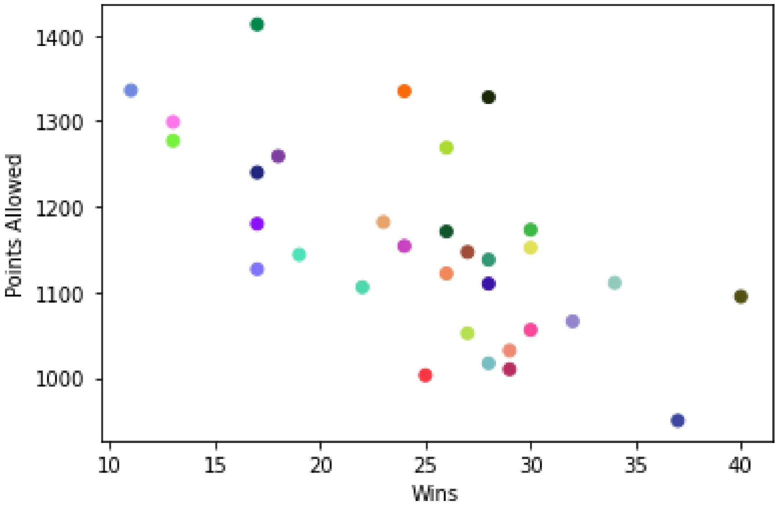


In [21]:

```
print("Wins Vs Points Allowed")
plt.scatter(wins, defensive_scoring_allowed, c=np.random.rand(len(wins),3))

plt.xlabel("Wins")
plt.ylabel("Points Allowed")
plt.show()
```

```
Wins Vs Points Allowed
```

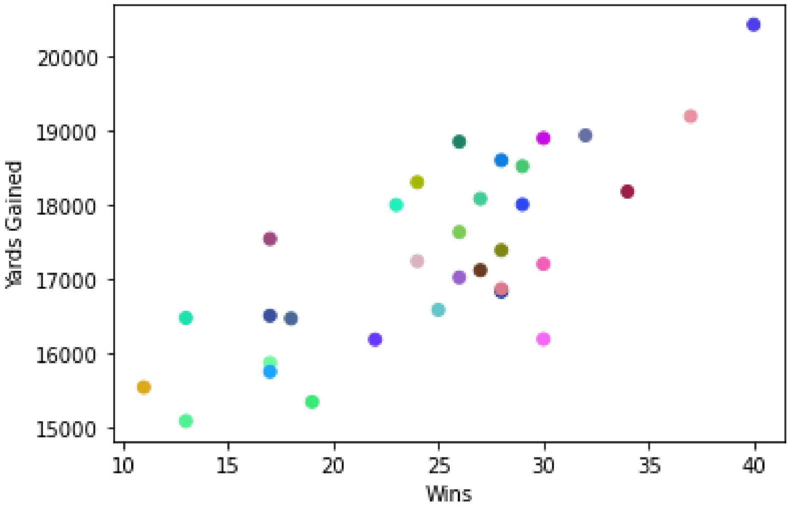


In [22]:

```
print("Wins Vs Yards Gained")
plt.scatter(wins, offensive_yrds, c=np.random.rand(len(wins),3))

plt.xlabel("Wins")
plt.ylabel("Yards Gained")
plt.show()
```

```
Wins Vs Yards Gained
```

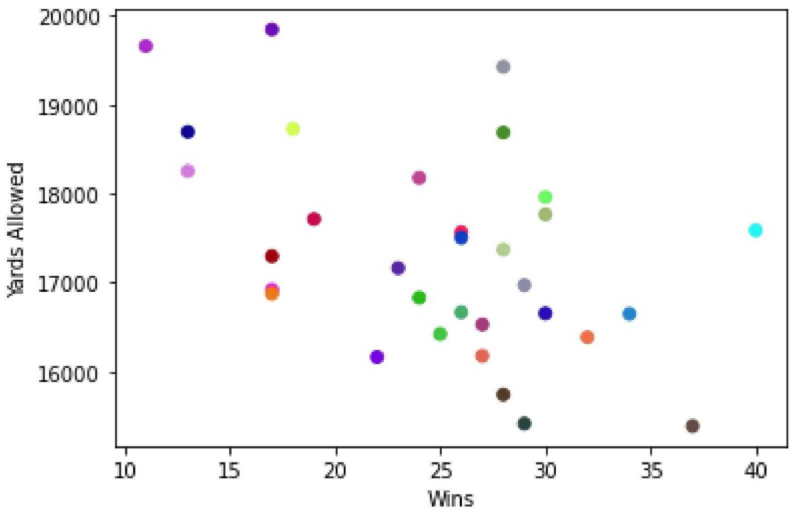


In [23]:

```
print("Wins Vs Yards Allowed")
plt.scatter(wins, defensive_yrds, c=np.random.rand(len(wins),3))

plt.xlabel("Wins")
plt.ylabel("Yards Allowed")
plt.show()
```

```
Wins Vs Yards Allowed
```



Model Building:

Here I will build a logistic regression model with the statistics. The target will be Wins and the test/train split will be 75% to 25%

```
In [24]: Y = final_merged_data.W
         X = final_merged_data.drop('W',axis=1)
```

```
In [25]: x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.25, random_state
```

```
In [26]: pipe = make_pipeline(StandardScaler(), LogisticRegression())
```

```
In [27]: pipe.fit(x_train, y_train)
```

```
Out[27]: Pipeline(steps=[('standardscaler', StandardScaler()),
                         ('logisticregression', LogisticRegression())])
```

Model Evaluation:

For the model evaluation I will be showing the accuracy of my model and finding which statistics had the most importance to the model as well.

```
In [28]: pipe.score(x_test, y_test)
```

```
Out[28]: 0.375
```

```
In [89]: feature_names = x_train.columns
```

```
In [90]: coefs = pipe.named_steps["logisticregression"].coef_.flatten()
```

```
In [91]: zipped = zip(feature_names, coefs)
```

```
In [92]: df = pd.DataFrame(zipped, columns=["feature", "value"])
```

In [93]:

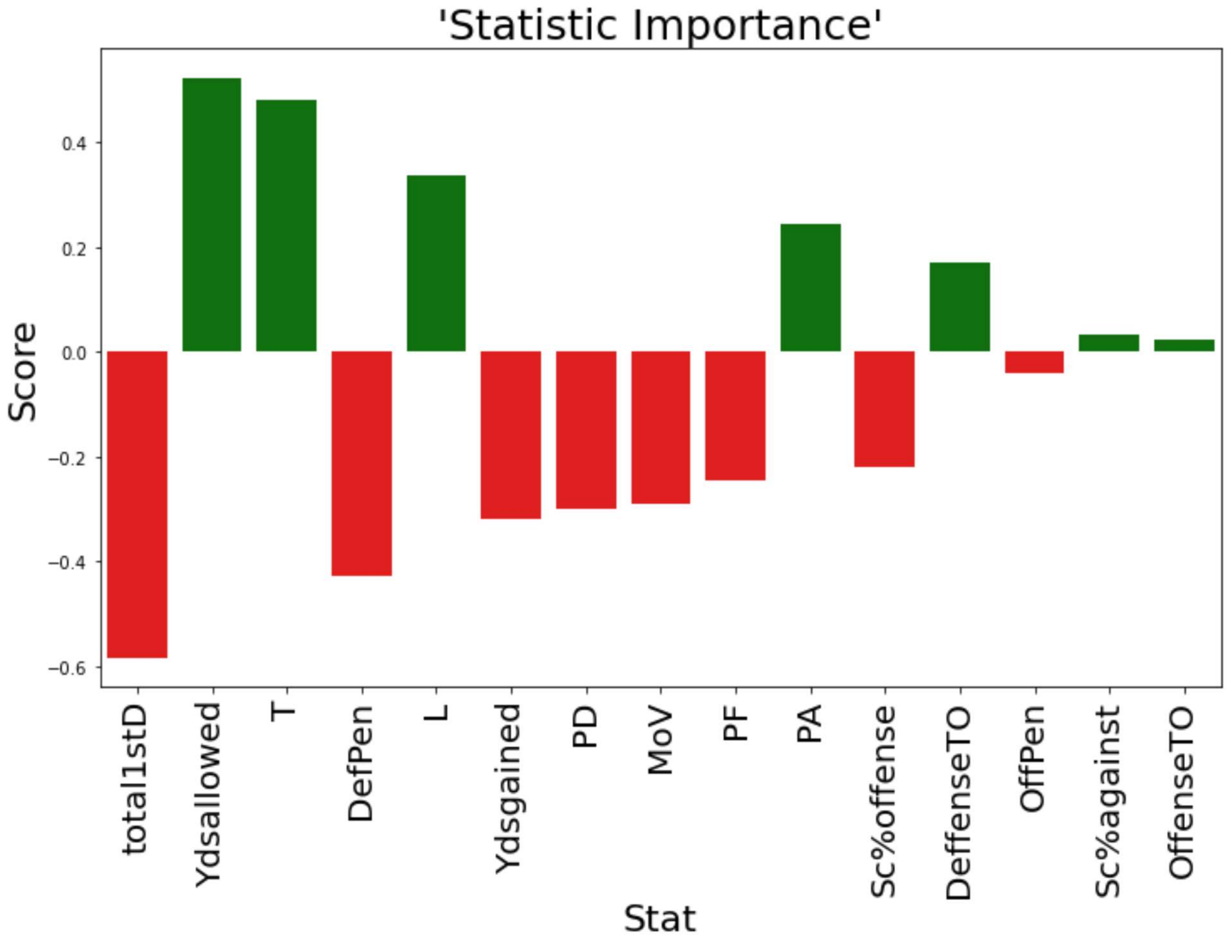
```
df["abs_value"] = df["value"].apply(lambda x: abs(x))
df["colors"] = df["value"].apply(lambda x: "green" if x > 0 else "red")
df = df.sort_values("abs_value", ascending=False)
```

In [98]:

```
fig, ax = plt.subplots(1, 1, figsize=(12, 7))
sns.barplot(x="feature",
            y="value",
            data=df,
           palette=df["colors"])
ax.set_xticklabels(ax.get_xticklabels(), rotation=90, fontsize=20)
ax.set_title("'Statistic Importance'", fontsize=25)
ax.set_ylabel("Score", fontsize=22)
ax.set_xlabel("Stat", fontsize=22)
```

Out[98]:

```
Text(0.5, 0, 'Stat')
```



Conclusion:

My model is telling me that the most important statistics that effect wins is Losses, Ties (which makes sense since if it's not a win then it's on of those) Yards allowed, Points against, Defensive Turnovers, Scoring % against, and offensive turnovers. This can tell a football team that defense could potentially have a bigger impact on winning then offense, since most of the positive importance stats are on the defensive side of the ball. I believe this model is ready to be deployed but could use some imporovements beforehand to make sure things are relevant. I think taking out Losses and Ties and replacing them with two other statistics would make it better and tell a coach more. I think another additional opportunity that would improve this model is to use even more statistics, you could use a longer period of time so the model has more data to work with which could make it even more accurate and show more of a representation of the league. You could even break up the last 20 years into 5 year blocks to see if there is a trend in the way football is played. Maybe 20 years ago offense mattered but now it's trending towards defense, and continuing to make these models may allow a coach to see when offense becomes a bigger part of winning.

In [ ]:

```
What does the analysis/model building tell you?
Is this model ready to be deployed?
What are your recommendations?
What are some of the potential challenges or additional opportunities that still need
```