Predicting NFL Wins from Previous Season Statistics

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November 27, 2024

1 Data Sources

The data was downloaded from https://www.pro-football-reference.com/ for the 2021, 2022, and 2023 NFL seasons. Specific offensive and defensive statistics for all 32 teams were selected and analyzed to remove highly correlated statistics. The data was preprocessed in python to join offense and defense statistics for a given season with the number of wins for the next season, for each of the 32 teams.

1.1 Correlation Analysis

There is multiple collinearity for all statistics, as expected. The model won't gain much information by including all of the data, more data will only slow the model down. 'points_for' and 'net_passing_yards_per_attempt' are the least correlated of the offensive stats, and 'points_for' is weakly inverse-correlated with 'points_against'. The inverse correlation between 'points_against' and 'points_for' makes sense in the context of well-rounded teams: if a team is "good" they will have an efficent offense and an efficient defense. This leads to more 'points_for' and less 'points_against.' Three statistics were selected as predictors after analysis: 'points for', 'net passing yards per attempt', and 'points against.' All statistics are calculated on a per-game basis. Pair plots for offensive and defensive statistics for the 2021 season are given below in Figs. 1 and 2.

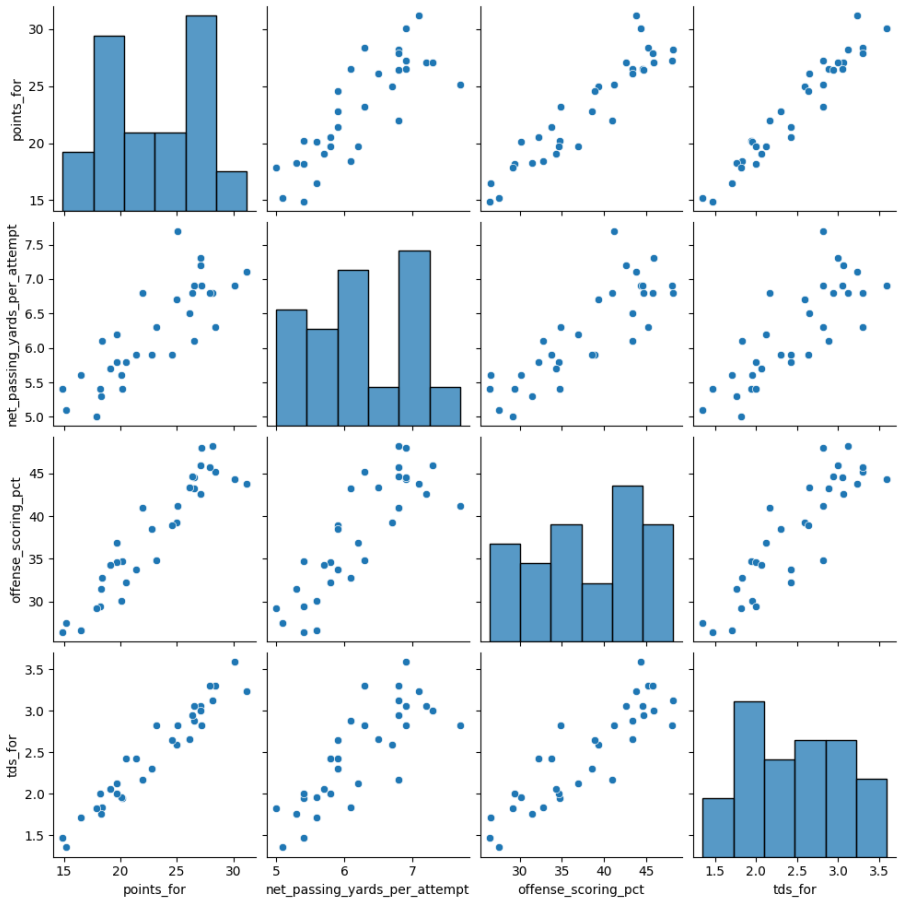

Figure 1: Pair plots for offensive statistics

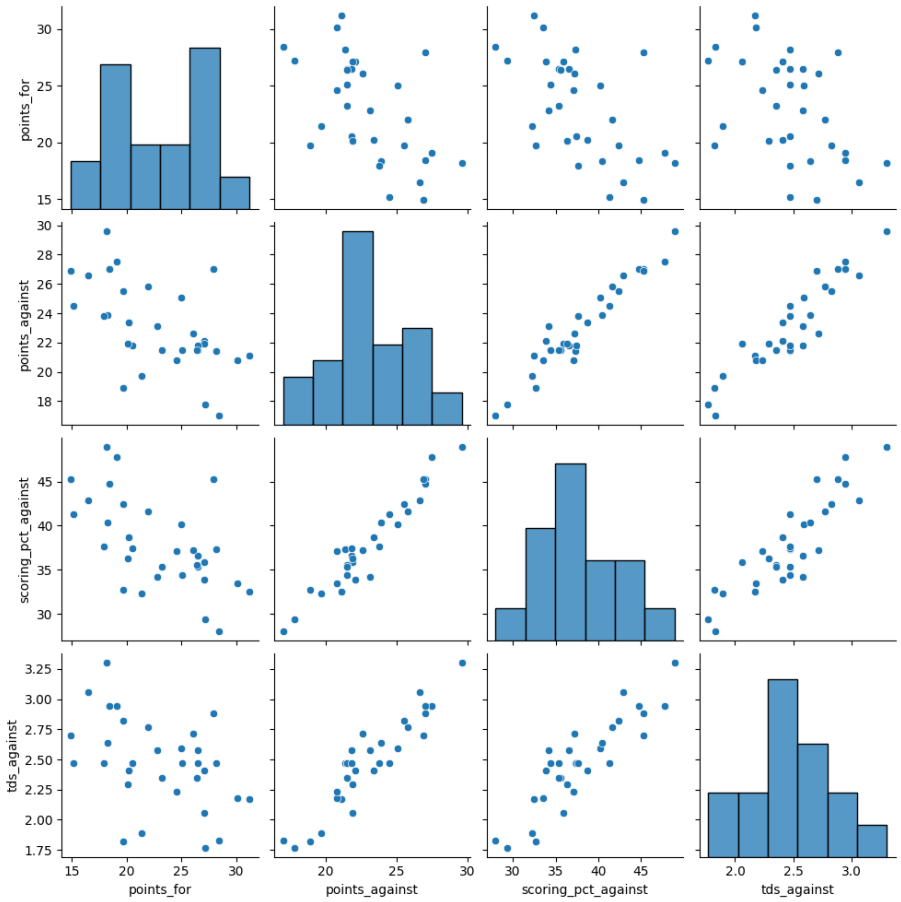

Figure 2: Pair plots for defensive statistics

2 Models

2.1 Model Type

The model selected was a Poisson Generalized Linear Model with log-link. Poisson was chosen since the response variable is an integer: number of wins in the next season (w). All predictors were given non-informative normal prior distributions.

$$\begin{aligned} w|\beta_0, \beta_1, \beta_2, \beta_3 &\sim \mathcal{P}oi(\lambda) \\ \lambda &= exp(\mathbf{X}\boldsymbol{\beta}) \\ \beta_i &= \mathcal{N}(0, \sigma^2 = 1000), i = 0, 1, 2, 3 \end{aligned}$$

2.2 Model Setup

The GLM was built using PyMC, and run for 5000 MCMC observations with 1000 burn-in. All data were standardized to allow faster model sampling.

2.3 2021 Model

The 2021 model was built using data from the 2021 season with the response variable being the number of wins in the 2022 season.

2.3.1 2021 Parameter Summary

Parameter	Mean	SD	$CI_{95\%}$
β_0 (intercept)	2.110	0.062	[1.987, 2.232]
β_1 (points_for)	0.321	0.243	[-0.146, 0.794]
β_2 (net_passing_yards_per_attempt)	0.035	0.218	[-0.394, 0.454]
β_3 (points_against)	0.087	0.150	[-0.204, 0.383]

Table 1: Parameter means and 95% credible intervals

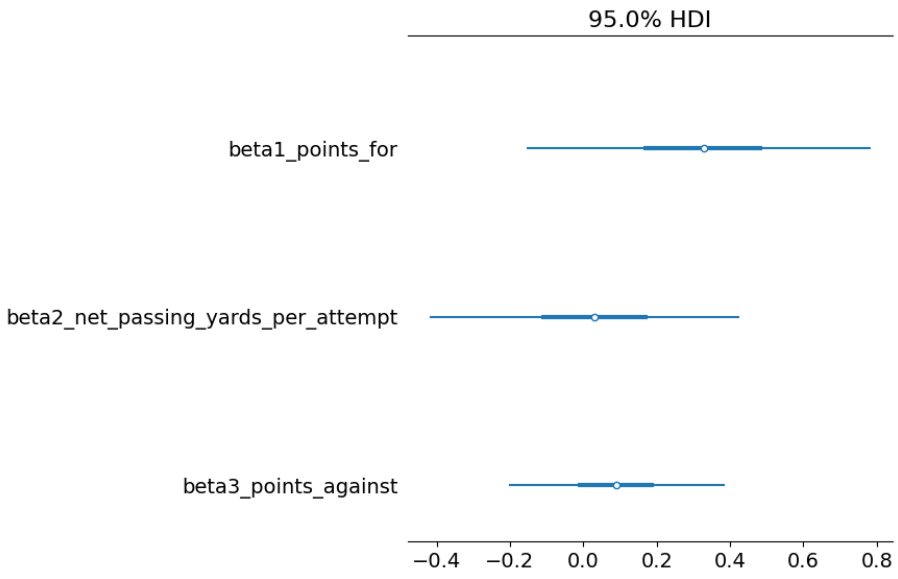

Figure 3: Forest plot for parameters with 95% credible intervals for 2021 model

From Table 1 and Fig. 3 above, it seems that points_for may be the only good predictor of the three as it has the largest magnitude mean. All three predictor's 95% credible intervals include 0, meaning there may be no predictive value of any predictor. This is not an extremely surprising result: the NFL is one of the most challenging sports to model and predict since there are an enormous amount of variables to account for and a lot of variation. Additionally, it would be expected for the coefficient for points_against (β_3) to be negative (not observed in model), since more points scored against a team would lower the likelihood of a win. It could also be the case that better teams have more points scored against as they are in higher scoring games in general.

2.3.2 Intercept

The intercept predicts the number of wins when all other predictors are 0, i.e. exactly at the 50th percentile for the case of standardized data.

$$\begin{aligned}
\beta_0 &= 2.110 \\
\lambda &= e^{\beta_0} = 8.121, \text{ for } \beta_1 = \beta_2 = \beta_3 = 0 \\
w &\sim \mathcal{P}oi(\lambda) \\
\mu &= E(w) = 8.121
\end{aligned}$$

This scenario makes sense: for a team that has exactly average statistics of points scored, passying yards per attempt, and points against, it would be expected that the team would go roughly .500 for the season: a record of around 8-9 or 9-8.

2.4 2022 Model

The same model was created on data from the 2022 season with the response variable being number of wins in the 2023 season. The parameter summary is shown below in Table 2 and Fig. 4.

Parameter	Mean	SD	$CI_{95\%}$
β_0 (intercept)	2.122	0.062	[2.001, 2.242]
β_1 (points_for)	0.095	0.210	[-0.298, 0.524]
β_2 (net_passing_yards_per_attempt)	0.175	0.218	[-0.248, 0.606]
β_3 (points_against)	-0.081	0.130	[-0.335, 0.171]

Table 2: Parameter means and 95% credible intervals for 2022 model

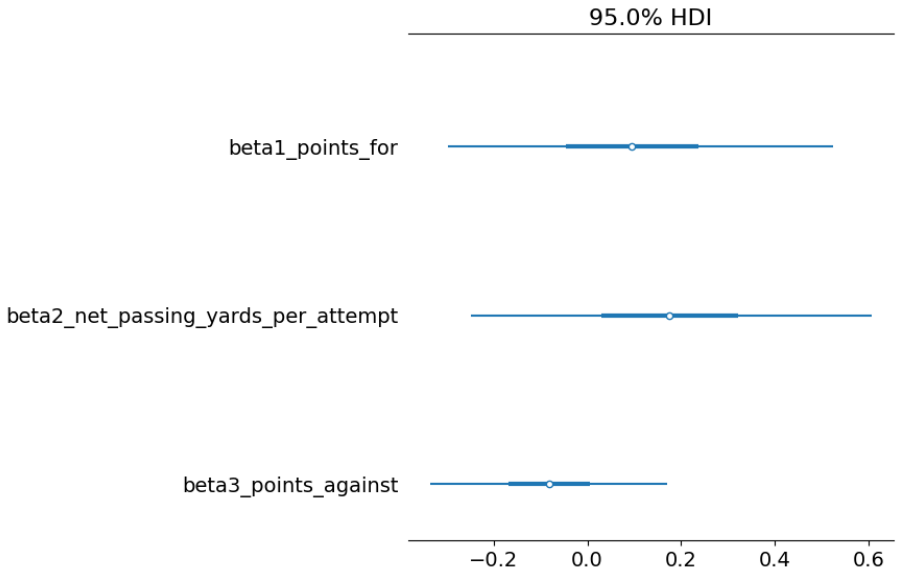

Figure 4: Forest plot for parameters with 95% credible intervals

Table 2 and Fig. 4 show similar parameter values for intercept and points against, but passing yards per attempt has a higher mean than points for. This indicates that passing yards per attempt may be a better predictor than points for in the 2022 season compared to the 2021 season.

3 Predicting Division Standings

Using the 2021 GLM, the performance of the model can be tested on data from the 2022 season to predict how many wins each team will have during the 2023 season. The posterior distribution can be sampled after passing a new data point of 2022 standardized data for an individual team. PyMC will return samples from each chain, which then can be used to calculate a mode for the number of wins.

3.1 2023 Predictions

NFC					
East			West		
Rank	Model	Actual	Rank	Model	Actual
1	Eagles (10)	Cowboys (12)	1	49ers (9)	49ers (12)
2	Cowboys (10)	Eagles (11)	2	Seahawks (9)	Rams (10)
3	Giants (7)	Giants (6)	3	Cardinals (7)	Seahawks (9)
4	Commanders (6)	Commanders (4)	4	Rams (6)	Cardinals (4)
North			South		
Rank	Model	Actual	Rank	Model	Actual
1	Lions (10)	Lions (12)	1	Falcons (8)	Buccaneers (9)
2	Vikings (9)	Packers (9)	2	Saints (7)	Saints (9)
3	Packers (8)	Vikings (7)	3	Panthers (7)	Falcons (7)
4	Bears (7)	Bears (7)	4	Buccaneers (6)	Panthers (2)

Table 3: 2023 NFC divisional rankings from model compared to actual rankings

AFC					
East			West		
Rank	Model	Actual	Rank	Model	Actual
1	Bills (10)	Bills (11)	1	Chiefs (11)	Chiefs (11)
2	Dolphins (9)	Dolphins (11)	2	Raiders (9)	Raiders (8)
3	Patriots (7)	Jets (7)	3	Chargers (8)	Broncos (8)
4	Jets (6)	Patriots (4)	4	Broncos (6)	Chargers (5)
North			South		
Rank	Model	Actual	Rank	Model	Actual
1	Bengals (9)	Ravens (13)	1	Jaguars (8)	Texans (10)
2	Browns (8)	Browns (11)	2	Texans (6)	Jaguars (9)
3	Ravens (7)	Steelers (10)	3	Colts (6)	Colts (9)
4	Steelers (6)	Bengals (9)	4	Titans (6)	Titans (6)

Table 4: 2023 AFC divisional rankings from model compared to actual rankings

From Tables 3 and 4 above, it can be seen that the model has some accuracy in divisions where there is a large disparity between team performance (i.e. large SD of wins within the division). The model predicted the winner correctly, or as tied for first, in 5 out of 8 divisions.

3.2 2024 Predictions

East			West		
Rank	NFC	AFC	Rank	NFC	AFC
1	Cowboys (10)	Bills (10)	1	49ers (11)	Chiefs (9)
2	Eagles (8)	Dolphins (10)	2	Rams (9)	Raiders (7)
3	Commanders (6)	Jets (6)	3	Seahawks (8)	Broncos (7)
4	Giants (6)	Patriots (6)	4	Cardinals (6)	Chargers (7)
North			South		
Rank	NFC	AFC	Rank	NFC	AFC
1	Lions (9)	Ravens (10)	1	Falcons (8)	Texans (8)
2	Packers (8)	Bengals (8)	2	Buccaneers (8)	Colts (8)
3	Vikings (8)	Steelers (7)	3	Saints (8)	Jaguars (9)
4	Bears (7)	Browns (7)	4	Panthers (6)	Titans (7)

Table 5: 2024 NFC & AFC divisional rankings preditions

Table 5 above shows the predicted divisional rankings for the 2024 season using the 2022 model with 2023 data.

4 Conclusions

Though the NFL is notoriously difficult to predict, the Bayesian GLM with only 3 predictors was able to predict 5/8 divisional winners for the 2023 season.

4.1 Improvements

Additional predictors that add information about off-season trades, drafts and changes to offensive / defensive efficiency could allow the model to predict more accurately. There was no limitation placed on number of wins per team (can't be more than 17), and there was no constraint that the sum of all wins should be 172 (16 games per week for 17 weeks). The constraint on sum of wins could display skill disparity between teams within divisions more effectively.