NFL Exact Wins Model

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1 Abstract

Using available moneyline odds on each regular season NFL game, we can create a predictive model of an upcoming NFL season. By comparing the predictions of this model to the implied probabilities of available betting lines on each team's exact regular season win total, we can generate a list of bets with positive expectations.

2 Predictive Model

DraftKings is the only major US sportsbook to publish moneyline odds on every regular season NFL game prior to the season beginning. When you bet on a moneyline, you are wagering that the team you bet for will win the game outright. If said team wins, the payout you received is a multiple of your original bet. In the event of a tie, you receive your initial bet back with no additional payout.

In this paper, odds are presented in decimal format, where the payout of a bet will simply be the original bet amount multiplied by the decimal odds of the bet. The profit for a won bet will thus be the payout minus the original bet size

2.1 Basic properties of moneyline bets

For an arbitrary game between Team A and Team B:

$$\text{Let } d_a = \text{Decimal odds of Team A to win}$$

$$\text{Let } d_b = \text{Decimal odds of Team B to win}$$

Payout P of a successful arbitrary bet amount b placed on each team:

$$P_a = d_a b$$

$$P_b = d_b b$$

Profit π of a successful arbitrary bet amount b placed on either team:

$$\pi_a = (d_a - 1)b$$

$$\pi_b = (d_b - 1)b$$

When a bet loses, the payout is 0, and the profit is simply the negative bet amount b:

$$P_a = 0$$

$$P_b = 0$$

$$\pi_a = -b$$

$$\pi_b = -b$$

The moneyline odds of each outcome A or B imply a certain probability of those outcomes occurring. That is, d_a implies a probability $P(A)$ of team A to win, and d_b implies a probability $P(B)$ of team B to win. These probabilities can be derived quite easily from the decimal odds themselves:

$$P(A) = \frac{1}{d_a}$$

$$P(B) = \frac{1}{d_b}$$

2.1.1 Example

To demonstrate these principles, consider the game shown in **Figure 1**.

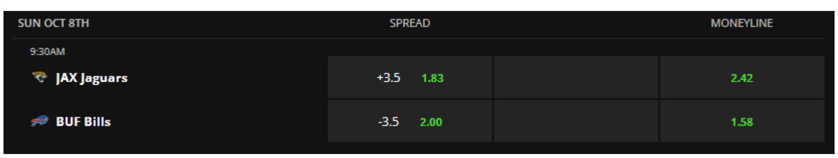

Figure 1: Odds on the 2023 week 5 JAX vs. BUF game

Let JAX be team A, and let BUF be team B. Then:

$$d_a = 2.42$$

$$d_b = 1.58$$

Using d_a and d_b, find payout, profit, and implied probabilites of each side of the game for an arbitrary bet size b:

$$P_a = d_a b = 2.42b$$

$$P_b = d_b b = 1.58b$$

$$\pi_a = (d_a - 1)b = 1.42b$$

$$\pi_b = (d_b - 1)b = 0.58b$$

$$P(A) = \frac{1}{d_a} = \frac{1}{2.42} \approx 0.4132$$

$$P(B) = \frac{1}{d_b} = \frac{1}{1.58} \approx 0.6329$$

This example leads to an important conclusion. Since outcome A and B are mutually exclusive events, we can find the probability of one or the other happening by summing $P(A)$ and $P(B)$:

$$P(A|B) = P(A) + P(B)$$

For the example values above:

$$P(A|B) = P(A) + P(B) = 0.4132 + 0.6329 \approx 1.0461$$

The extra 4.61% probability beyond 100% is the *house advantage* or *vig* that the sportsbook collects on all bets placed on this game. In order for our implied odds calculations to be accurate, we need to normalize $P(A)$ and $P(B)$ against $P(A|B)$:

$$P_{norm}(A) = \frac{P(A)}{P(A) + P(B)}, \; P_{norm}(B) = \frac{P(B)}{P(A) + P(B)} \tag{1}$$

For the JAX vs. BUF example, we can then find the true implied probabilities of each team winning:

$$P_{norm}(A) = \frac{P(A)}{P(A) + P(B)} = \frac{0.4132}{0.4132 + 0.6329} \approx 0.3950$$

$$P_{norm}(B) = \frac{P(B)}{P(A) + P(B)} = \frac{0.6329}{0.4132 + 0.6329} \approx 0.6050$$

These normalized implied probabilities will form the basis of our predictive model.

2.1.2 Expected profit

Now that we have calculated implied probabilities of each outcome of the game, we can easily find the expected value of a hypothetical bet placed on each team.

For an arbitrary bet size b and arbitrary odds $\{d_a, d_b\}$:

$$EV_a = \pi_a P_{norm}(A) - b(1 - P_{norm}(A))$$

$$= b(d_a - 1)P_{norm}(A) - b + bP_{norm}(A)$$

$$= b[(d_a - 1)P_{norm}(A) - 1 + P_{norm}(A)]$$

$$a = b(d_a P_{norm}(A) - 1)$$

$$EV_a = bd_a P_{norm}(A) - b \tag{2}$$

Similarly,

$$EV_b = bd_b P_{norm}(B) - b$$

Using the same JAX vs. BUF example:

$$EV_a = bd_a P_{norm}(A) - b$$

$$EV_a = (2.42)(0.3950)b - b = 0.9559b - b$$

$$EV_a = -0.0441b$$

$$EV_b = \ldots = -0.0441b$$

We can see that these bets both have negative expectations. Intuitively, this is a result of the *vig* that the sportsbook adds to the bets. This leads to the conclusion that it is impossible to find a positive expectation moneyline bet if you assume that the implied odds of the moneylines offered by the sportsbook are sufficiently near the *true odds* of the game, i.e. the odds that an all-knowing omniscient being would place on the game.

In past research I've done, the odds on major sportsbook historically appear to be quite close to the true odds of games, such that it is reasonable to assume the normalized implied odds of the moneylines are effectively the same as the true odds. This assumption will form the basis of our predictive model.

2.2 Basic properties of win total bets

Also offered at sportsbooks are odds on each team's season win total. You can bet on a team to get more or less than a certain win threshold - known as over/under bets, or bet on a team to finish with an exact win quantity.

Over/under bets are mostly irrelevant to this model, but will come into play in a small capacity. Sportsbook offer one *main line* per team. The main line is the win threshold closest to having 50/50 odds to go over or under. The odds for each side will therefore be near 2.0, but may vary slightly due to win totals only coming in half-game increments. If the "true" 50/50 point was 8.7 wins, The main line would likely be set at 8.5 wins, with slightly better odds on the under to account for the 0.2 win difference.

There are also *alt lines* offered, where several alternate over/under thresholds are offered with varying odds depending on location. Intuitively, the over odds will be significantly better than under odds for alternate lines above the main line - since it's less likely for a team to go over a higher win total compared to a lower one. Vice versa for alternate lines below the main line.

More important to this model are *exact win* bets, where you try to select the exact number of wins a team will finish with. These odds tend to be much higher than most over/under bets, since even the most likely outcome for a team is still relatively unlikely with so many different win outcomes possible.

Figure 2: Example of an exact win market on a single team

Probability, implied odds, and EV calculations are similar for these bets as for moneyline bets, e.g. implied probability is still inversely related to decimal odds.

Let W = Event of a team finishing with W wins and d_W = Decimal odds of W

$$\text{Implied probability } P(W) = \frac{1}{d_W}$$

I will not go over the calculations for the other properties at this point since they are not directly relevant to the predictive model.

2.3 Monte Carlo Simulation

There will be 272 regular season games played in the 2023 NFL season. DraftKings currently has moneyline odds published for each one of these games. Using the implied odds of those games' moneylines, we can repeatedly randomly simulate the outcome of a full season and observe the behavior of the win totals of each team over a sufficiently large set of season.

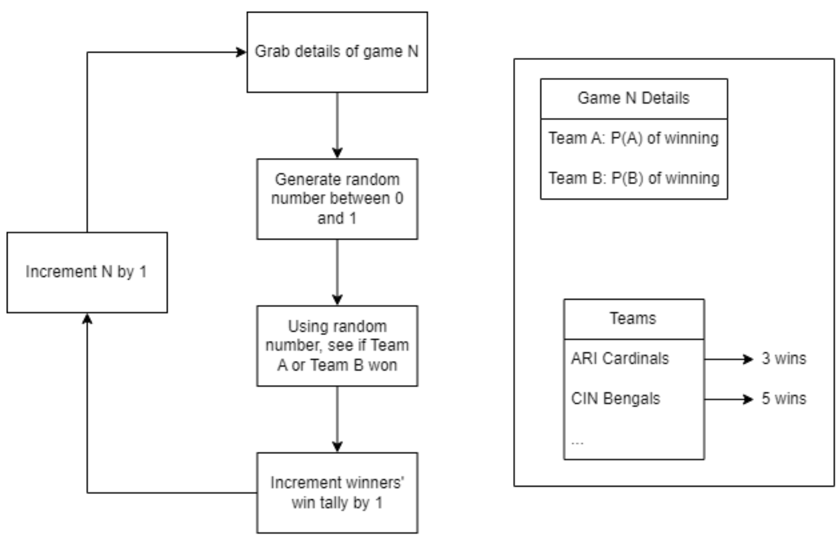

Figure 3: Basic illustration of simulation of a season

Figure 3 demonstrates the basic flow of how one season is randomly simulated. At the end, we're left with a tally of how many games each team won in that simulated season. By repeating this process for many seasons, we can start to observe the probability distribution of a team's win totals.

2.3.1 Evolving odds

The above depiction of a Monte Carlo simulation is only reliable if each game is a completely isolated event from the others, i.e. the outcome of one game doesn't influence the outcome of a future game. Unfortunately, this isn't the case. If a team wins their first game, it should be slightly more likely than expected that they will win their next, as they demonstrated a higher level of skill than was expected. In order to resolve this, we need a mechanism to modify the probabilities of a game's outcomes based on the outcomes of the games before it. I accomplish this by *evolving* the odds of each game based on each team's performance up to that point.

Begin by assigning every team an initial rating, equal to the value of their *main over/under threshold*. For example:

$$\{R_{0,ari} = 4.5,\ R_{0,atl} = 8.5,\ \ldots,\ R_{0,was} = 7.5\}$$

For each game, calculate the ratio between each team's current rating and their initial rating as a way to measure the difference between their projected and actual performance.

$$r_{cur,ari} = \frac{R_{cur,ari}}{R_{0,ari}}$$

If the team has been outperforming their project performance so far, $r_{cur} > 1$. If a team is underperforming, $r_{cur} < 1$. Once we have r_{cur} for both teams, we will recalculate the probability of each outcome of the game using r_{cur}. For example, for a hypothetical matchup between ARI and ATL:

$$P_{adj}(ARI) = r_{cur,ari} * P_{norm}(ARI)$$
$$P_{adj}(ATL) = r_{cur,ari} * P_{norm}(ATL)$$

Now renormalize each P_adj against the other:

$$P_{adj,norm}(ARI) = \frac{P_{adj}(ARI)}{P_{adj}(ARI) + P_{adj}(ATL)}$$
$$P_{adj,norm}(ATL) = \frac{P_{adj}(ATL)}{P_{adj}(ARI) + P_{adj}(ATL)}$$

Finally, in general for teams A and B:

$$P_{adj,norm}(A) = \frac{r_{cur,a} * P_{norm}(A)}{r_{cur,a} * P_{norm}(A) + r_{cur,b} * P_{norm}(B)} \tag{3}$$

Now that we have an expression for $P_{adj,norm}(A)$ and $P_{adj,norm}(B)$, we can use those new adjusted normalized probabilities to simulate the game instead of the original implied probabilities from before. The other requirement for this mechanism is to update each team's current rating after simulating a game they were involved in. If a team wins a game, they should see their rating increase, and vice versa for a loss. Additionally, their rating should increase more for winning games they were the underdog in, and decrease more for losing games they were the favorite in. This is similar to an elo rating system, and is quite easy to implement.

$$\Delta r = k(\frac{r_{cur,winner}}{r_{cur,loser}})^{-1} = k\frac{r_{cur,loser}}{r_{cur,winner}}$$

where k is a scalar coefficient. The new ratings of the teams then become:

$$r_{cur,winner} = r_{cur,winner} + \Delta r$$

and

$$r_{cur,loser} = r_{cur,loser} - \Delta r$$

$r_{cur,winner}$ and $r_{cur,loser}$ will then be used as the ratings for those two teams in their next game. At this point, continue iterating through each game, determining the outcome and updating ratings accordingly.

2.3.2 End result of a season simulation

At the end of a season simulation, we are left with a list of teams and how many wins they got in that simulation run.

Team	Wins
ARI	5
ATL	6
BAL	12
BUF	10
CAR	10
CHI	7
CIN	12
CLE	6
DAL	6
DEN	9
DET	10
GB	8
HOU	5
IND	6
JAX	8
KC	8
LA	5
LA	11
LV	13
MIA	6
MIN	8
NE	11
NO	10
NY	7
NY	11
PHI	10
PIT	3
SEA	9
SF	12
TB	10
TEN	9
WAS	9

Table 1: Artifact of season simulation

2.3.3 Many-season simulation

Next, we will repeat the season simulation process many ($n >= 100,000$) times and observe how the distribution of results compares to the implied odds of each exact win possibility for each team.
For simplicity, let's consider one possible bet as a numerical example. Consider the bet for the Arizona Cardinals to win 6 games in the season as seen in **Figure 2**. Then:

$$W = 6$$

$$d_W = 7.0$$

$$P(W) = \frac{1}{d_W} = \frac{1}{7} \approx 0.1429$$

We are interested in comparing the implied probability of W occurring according to the sportsbook with the probability of W occurring according to the results of the many-season simulation.

$$P_{sim}(W) = \frac{\text{Number of sims where W occurred}}{\text{Number of total sims}}$$

When $P_{sim}(W) > P(W)$, the bet in question has a positive expectation. When $P_{sim}(W) < P(W)$, the bet has a negative expectation. In general for arbitrary bet size b:

$$\begin{aligned} EV_W &= b(d_W - 1)P_{sim}(W) - b(1 - P_{sim}(W)) \\ EV_W &= bd_W P_{sim}(W) - b \end{aligned} \tag{4}$$

Now we can put it all together. For every team and exact win outcome W, calculate EV_W and compile a list of all combinations where $EV_W > 0$. This is a list of every bet we can make with a positive expectation:

team	win total	decimal odds	implied prob	Sportsbook	real prob	ev
ARI Cardinals	7	10	10.00%	DraftKings	14.94%	49.36%
KC Chiefs	10	8.5	11.76%	DraftKings	17.40%	47.87%
ARI Cardinals	8	15	6.67%	DraftKings	9.81%	47.09%
ARI Cardinals	6	8	12.50%	FanDuel	18.24%	45.88%
LV Raiders	9	11	9.09%	FanDuel	12.91%	42.05%
PHI Eagles	9	9.5	10.53%	DraftKings	14.62%	38.88%
KC Chiefs	9	11	9.09%	DraftKings	12.55%	38.09%
LV Raiders	8	8	12.50%	FanDuel	17.16%	37.30%
NO Saints	9	7.5	13.33%	FanDuel	18.25%	36.91%
WAS Command	8	8	12.50%	DraftKings	16.73%	33.82%
BAL Ravens	9	7.5	13.33%	FanDuel	17.80%	33.50%
LA Rams	8	8	12.50%	FanDuel	16.56%	32.45%
PIT Steelers	8	7.5	13.33%	FanDuel	17.54%	31.56%
DET Lions	9	7	14.29%	DraftKings	18.78%	31.45%
LA Chargers	9	7	14.29%	FanDuel	18.76%	31.31%
LA Chargers	8	8	12.50%	FanDuel	16.38%	31.05%
SF 49ers	10	7	14.29%	FanDuel	18.64%	30.46%
LA Rams	9	11	9.09%	FanDuel	11.84%	30.23%
NE Patriots	9	8.5	11.76%	FanDuel	15.30%	30.08%
IND Colts	8	7.5	13.33%	FanDuel	17.32%	29.88%
NY Jets	9	7	14.29%	FanDuel	18.55%	29.83%
LV Raiders	7	7	14.29%	FanDuel	18.54%	29.79%
HOU Texans	7	7	14.29%	FanDuel	18.53%	29.72%
PHI Eagles	10	7	14.29%	FanDuel	18.52%	29.67%
NO Saints	8	8	12.50%	DraftKings	16.18%	29.47%
CHI Bears	8	7	14.29%	DraftKings	18.48%	29.33%
ARI Cardinals	9	23	4.35%	DraftKings	5.62%	29.21%
TB Buccaneers	7	7	14.29%	FanDuel	18.44%	29.08%
NY Giants	8	7	14.29%	FanDuel	18.39%	28.70%
WAS Command	7	7	14.29%	FanDuel	18.38%	28.63%
JAX Jaguars	9	7	14.29%	FanDuel	18.34%	28.41%

Figure 4: Snapshot of a list of positive expectation bets, sorted by EV

3 Bet sizing and profit projection

Now that we have built a predictive model that can generate a set of positive expectation bets, we need to figure out how to split our total bankroll between each bet in the set, as well as build a model to see how our bet strategy performs against our simulated seasons.

3.1 Bet sizing

The basic principle of our bet sizing strategy is to maintain a constant ratio between a bet's total payout and EV across all bets. Specifically for N number of bets,

$$\frac{EV_n}{b_n d_n} = \frac{EV_{n+1}}{b_{n+1} d_{n+1}}$$

for all integer $n \in [0, N-1]$.

The easiest way to find all bet sizes b_n is to let $b_0 = 1$ and assign values to all other bets recursively. This will result in each bet being scaled appropriately with respect to all others, but the sum $\Sigma_{n=0}^{N-1} b_n$ will be arbitrary. In order to make the sum of our bet sizings equal to an arbitrary bankroll size B_{tot}, we can scale each bet up or down as needed:

$$b_{adj,n} = b_n \frac{B_{tot}}{\Sigma_{n=0}^{N-1} b_n} \tag{5}$$

The sum of all $b_{adj,n}$ will then be equal to our desired bankroll size B_{tot}. This methodology results in each bet having the following characteristic:

$$\frac{EV_n}{\Sigma_{m=0}^{N-1} EV_m} = \frac{P_n}{\Sigma_{m=0}^{N-1} P_m}$$

where P_n is the payout of bet n. Simply put, the ratio between a bet's EV and the sum of all bets' EVs is the same as the ratio between the same bet's payout and the sum of all bets' payouts.

team	win total	decimal odds	implied prob	Sportsbook	real prob	ev	bet amount ($1000 total)	payout if hit (incl initial bet)
ARI Cardinals	7	10	10.00%	DraftKings	14.94%	49.36%	$14.37	$143.68
ARI Cardinals	8	15	6.67%	DraftKings	9.81%	47.09%	$9.14	$137.07
ARI Cardinals	6	8	12.50%	FanDuel	18.24%	45.88%	$16.69	$133.55
ARI Cardinals	9	23	4.35%	DraftKings	5.62%	29.21%	$3.70	$85.04
ARI Cardinals	5	6	16.67%	FanDuel	18.40%	10.38%	$5.04	$30.22
ATL Falcons	8	7	14.29%	FanDuel	18.22%	27.53%	$11.45	$80.14
ATL Falcons	9	7	14.29%	FanDuel	17.87%	25.10%	$10.44	$73.05
ATL Falcons	7	8	12.50%	DraftKings	15.25%	21.98%	$8.00	$63.99
ATL Falcons	10	7.5	13.33%	FanDuel	13.74%	3.07%	$1.19	$8.94
BAL Ravens	9	7.5	13.33%	FanDuel	17.80%	33.50%	$13.00	$97.51
BAL Ravens	8	8.5	11.76%	DraftKings	13.48%	14.61%	$5.00	$42.54
BAL Ravens	10	6	16.67%	DraftKings	18.93%	13.57%	$6.59	$39.51
BAL Ravens	11	6.5	15.38%	DraftKings	16.16%	5.05%	$2.26	$14.71
BUF Bills	9	8	12.50%	DraftKings	16.03%	28.26%	$10.28	$82.25
BUF Bills	10	6.5	15.38%	DraftKings	19.08%	23.99%	$10.74	$69.84
BUF Bills	11	6	16.67%	DraftKings	18.12%	8.73%	$4.23	$25.40
BUF Bills	8	10	10.00%	FanDuel	10.75%	7.46%	$2.17	$21.71
CAR Panthers	8	7	14.29%	DraftKings	17.96%	25.69%	$10.68	$74.78
CAR Panthers	7	7	14.29%	FanDuel	17.78%	24.43%	$10.16	$71.12
CAR Panthers	9	8	12.50%	DraftKings	14.69%	17.54%	$6.38	$51.04
CAR Panthers	6	7.5	13.33%	FanDuel	14.53%	8.98%	$3.49	$26.15
CHI Bears	8	7	14.29%	DraftKings	18.48%	29.33%	$12.19	$85.36
CHI Bears	9	7.5	13.33%	FanDuel	15.86%	18.98%	$7.37	$55.25
CHI Bears	7	6.5	15.38%	FanDuel	17.39%	13.00%	$5.82	$37.85
CHI Bears	10	9.5	10.53%	DraftKings	11.03%	4.79%	$1.47	$13.96
CIN Bengals	9	8	12.50%	DraftKings	15.49%	23.92%	$8.70	$69.63
CIN Bengals	10	6.5	15.38%	DraftKings	18.79%	22.12%	$9.90	$64.37
CIN Bengals	11	6	16.67%	DraftKings	18.48%	10.87%	$5.28	$31.65
CLE Browns	8	7.5	13.33%	FanDuel	16.66%	24.96%	$9.69	$72.65
CLE Browns	9	6.5	15.38%	FanDuel	18.50%	20.25%	$9.07	$58.94
CLE Browns	10	7	14.29%	DraftKings	16.93%	18.53%	$7.71	$53.94

Figure 5: Example bet amounts - notice that the ratio of payout:ev is the same for all bets

3.2 Profit projection

Now that we have a methodology for assigning sizes to each bet, let's project the distribution of profit outcomes for the season. Using the same Monte Carlo simulation method as before to determine game outcomes, we can imagine placing the bets with their respective sizes and observe how the bets cumulatively perform across many simulations ($N > 100,000$). For an initial bet of $1,000, this results in the distribution seen in **Table 2** and **Figure 6**.

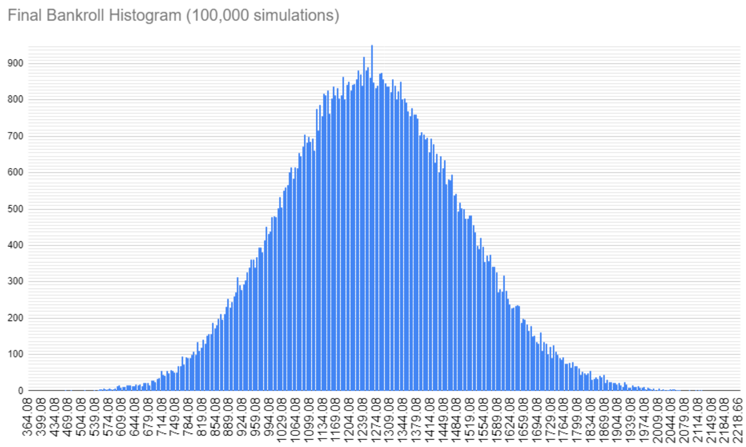

Figure 6: Histogram of final bankroll amounts for a starting bankroll of $1,000

Average Net Result	$262.57
Std. Dev.	$227.22
25th Percentile	$106.18
75th Percentile	$415.57
P(Profitable)	0.8765

Table 2: Statistics of final bankroll amounts for a starting bankroll of $1,000

4 Back testing

In order to verify that this model and accompanying strategy are profitable in practice, I attempted to back test them on previous years' data. Unfortunately, this would require access to every regular season game's preseason lines from that year, and the exact win total lines from that year. I have been unable to find either, and cannot use the final game lines for regular season games as that would introduce extremely large biases into the testing. Instead, I attempted to find patterns in the results of my model, and generalized it to work with only the main over/under win total lines for a given season, which are much more freely available. This methodology is unfortunately not as reliable as it would be if I had access to all the historical data I need, but nonetheless appears to have generated useful results.

4.1 Lower and upper bounds

The first pattern I noticed in my model's output is that it tends to find multiple profitable bets for each team, which are usually a window of 3-5 win sequential win totals. For example, the model generated bets for the Arizona Cardinals to win one of $5, 6, 7, 8, 9$ games, and the Cleveland Browns to win one of $8 - 10$ games. This seems to imply that some of the likelier outcomes for each team are generally under priced, and therefore are profitable bets.
I also noticed that the window of win totals for a given team appears to have its lower and upper bounds somewhat correlated to the main over/under win total line for that team. I found the line of best fit for this data so I can use a team's main over/under win total line in an arbitrary season to roughly predict my model's output for that team.

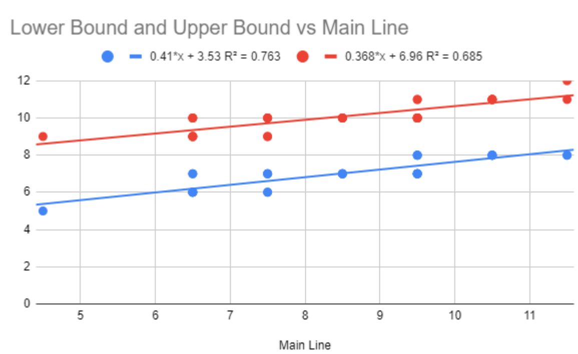

Figure 7: Linearly fitting main over/under threshold to lower and upper bound of the win total window

I also found a few other important statistics of my model:

$$\text{Average successful bet decimal odds} = 7.68$$

$$\text{Average normalized bet amount of a successful bet} = 0.0079$$

$$\text{Average normalized bet amount of a faied bet} = 0.0075$$

4.2 2022 Results

Using these statistics, I can roughly guess what my model would have chosen to bet on, how much each bet would've paid, and how the bets were sized relative to each other. Then, by looking at the actual results of the season, I can approximate the annual returns of the model. An example of backtesting against 2022 can be seen in **Tables 3/4**.

Table 3: 2022 Backtesting (part 1)

Team	Proj Win Total	Actual Win Total	Lower Bound	Upper Bound
ARI Cardinals	8.5	4	7	10
ATL Falcons	4.5	7	5	9
Baltimore Ravens	10.5	10	8	11
Buffalo Bills	12.0	13	8	11
Carolina Panthers	6.5	7	6	9
Chicago Bears	5.5	3	6	9
Cincinnati Bengals	9.5	12	7	10
Cleveland Browns	8.0	7	7	10
Dallas Cowboys	10.0	12	8	11
Denver Broncos	10.0	5	8	11
Detroit Lions	6.5	9	6	9
Green Bay Packers	11.0	8	8	11
Houston Texans	4.5	3	5	9
Indianapolis Colts	10.0	4	8	11
Jacksonville Jaguars	6.5	9	6	9
Kansas City Chiefs	10.5	14	8	11
Las Vegas Raiders	8.5	6	7	10
Los Angeles Chargers	10.5	10	8	11
Los Angeles Rams	10.5	5	8	11
Miami Dolphins	9.0	9	7	10
Minnesota Vikings	9.5	13	7	10
New England Patriots	8.5	8	7	10
New Orleans Saints	9.0	7	7	10
New York Giants	7.0	9	6	10
New York Jets	5.5	7	6	9
Philadelphia Eagles	10.0	14	8	11
Pittsburgh Steelers	7.5	9	7	10
San Francisco 49ers	10.0	13	8	11
Seattle Seahawks	5.5	9	6	9
Tampa Bay Buccaneers	11.0	8	8	11
Tennessee Titans	9.0	7	7	10
Washington Commanders	7.5	8	7	10

Table 4: 2022 Backtesting (part 2)

Num Bets	Did Win?	Decimal Odds	Bet Amount	Net Result
4	0	7.68	0.02625	-0.02625
5	1	7.68	0.03415	0.026522000000000004
4	1	7.68	0.02665	0.034022000000000004
4	0	7.68	0.02625	-0.02625
4	1	7.68	0.02665	0.034022000000000004
4	0	7.68	0.02625	-0.02625
4	0	7.68	0.02625	-0.02625
4	1	7.68	0.02665	0.034022000000000004
4	0	7.68	0.02625	-0.02625
4	0	7.68	0.02625	-0.02625
4	1	7.68	0.02665	0.034022000000000004
4	1	7.68	0.02665	0.034022000000000004
5	0	7.68	0.03375	-0.03375
4	0	7.68	0.02625	-0.02625
4	1	7.68	0.02665	0.034022000000000004
4	0	7.68	0.02625	-0.02625
4	0	7.68	0.02625	-0.02625
4	1	7.68	0.02665	0.034022000000000004
4	0	7.68	0.02625	-0.02625
4	1	7.68	0.02665	0.034022000000000004
4	0	7.68	0.02625	-0.02625
4	1	7.68	0.02665	0.034022000000000004
4	1	7.68	0.02665	0.034022000000000004
5	1	7.68	0.03415	0.026522000000000004
4	1	7.68	0.02665	0.034022000000000004
4	0	7.68	0.02625	-0.02625
4	1	7.68	0.02665	0.034022000000000004
4	0	7.68	0.02625	-0.02625
4	1	7.68	0.02665	0.034022000000000004
4	1	7.68	0.02665	0.034022000000000004
4	1	7.68	0.02665	0.034022000000000004
4	1	7.68	0.02665	0.034022000000000004

4.3 2000-2022 Results

I won't put the full tables for every year I back tested against, as it would take up way too much space, but here are the final statistics of this approach:

Annual Profits List (percent)		
25.57		
19.68		
-29.37		
11.72		
17.64		
6.63		
7.99		
7.57	Average Profit (percent)	6.75
-9.88	"Successful" Bets	355
-0.43	Total Bets	3035
3.89	Failed Bets	2680
25.57	Bet Success Rate	11.70%
-17.48		
8.90		
5.70		
17.64		
24.50		
-37.49		
13.68		
-21.66		
24.95		
24.95		
24.95		

Figure 8: Cumulative profit margin of each year, and other statistics

As seen in **Figure 8**, this methodology average 6.75% returns from 2000-2022. The lower value of this return rate compared to the profit projection of the live model makes sense when you consider that there is no intelligent simulation, modelling, etc. in the approach used in the back tests. Unfortunately, there doesn't appear to be a better way to verify this model due to lack of useful historical data.