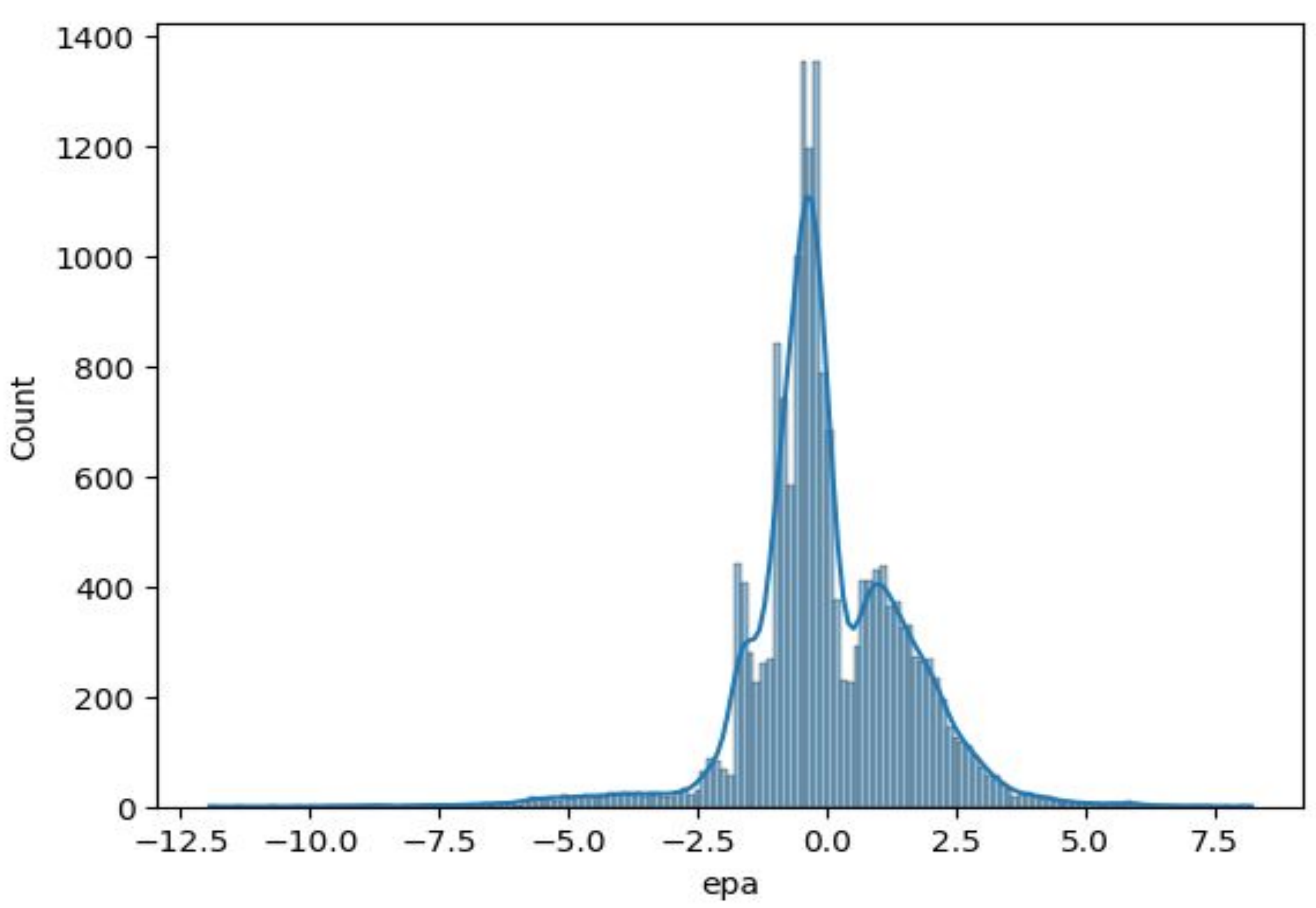
How to Score More Points in NFL Games?

Rhett Lavender, Blake Bridges, Nate Lai-Quong, Shane Faberman

What is our problem and how do we measure success?

We chose to investigate the factors that contribute to passing plays in the National Football League (NFL) resulting in positive expected points added (EPA), to identify which factors ultimately impact EPA the most. Expected points (EP) is a metric used in the NFL that represents the number of points a team is expected to score on the current drive. The expected points added metric measures how a team's expected points value changes on an individual play. Each play in an NFL game has many different moving parts, such as offensive and defensive formation, personnel, down, and distance to the first down marker. We were interested in developing a method to determine which factors on the football field are most important to determining a successful passing play, using EPA as our measure of success.



Distribution of EPA in our dataset

Data Preparation

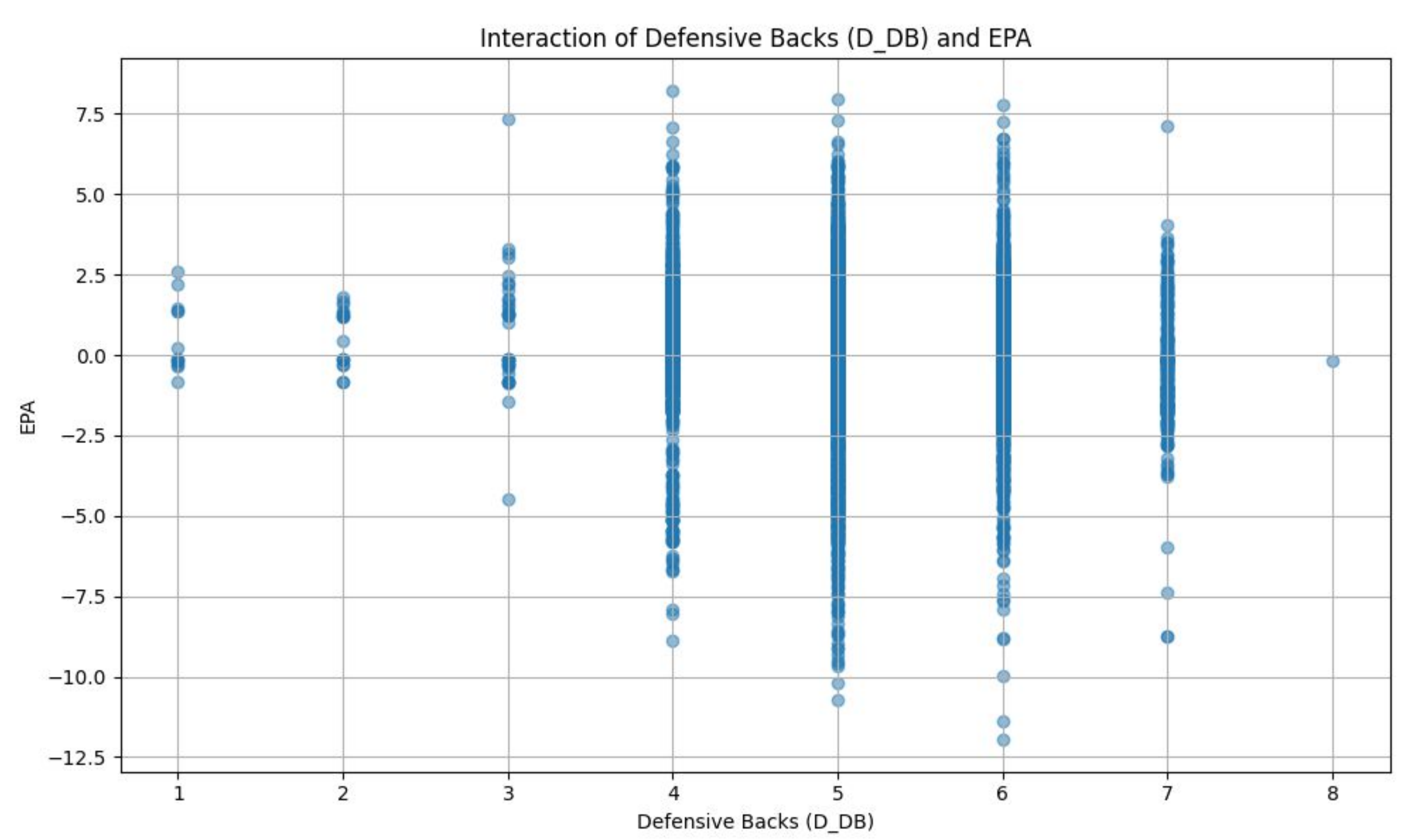
Some important steps we took during our research:

- Filtered out penalties because it isn't always the case that the offense causes the defense to commit a penalty
- Split categorical variables like offensive formation, personnel, down, etc into new numerical variables so we could incorporate them into our model
- Dropped rows with NA values
- Normalized all of our variables to the same scale

Model Building

Since we wanted to predict EPA values, we chose to use a regression model rather than a classification model. We chose to use a multiple linear regression because football is a complicated sport and many variables have an impact on each play, as our model ended up having 37 variables. Some key variables in our data:

- **offensePlayResult:** This variable refers to the yards gained on a play, which would make sense to be highly correlated with EPA.
- **yardsToGo, down_1, down_2, down_3, down_4, absoluteYardlineNumber:** We used these variable because, together, they extremely important in determining the likelihood of a plays success. For example, converting a 2nd & 1 on a team's own 41 yard-line is going to result in a much lower EPA than converting a 3rd & 13 on an opponents 49 yard-line because the former is far more probable and a successful conversion has far less of an effect on a team's win probability.
- **O_RB, O_WR, O_TE, D_DB, D_LB, D_DL:** These variables track positions that vary in numbers based on the personnel and play call, so these are relevant to track. For example, defenses are likely to play more DBs when they expect offenses to pass and offenses are likely to play more WRs in obvious passing downs. Offenses also want to catch defenses by surprise and pass in personnel groupings that would lead defenses to expect run, so we figured these variables would be important to our model.



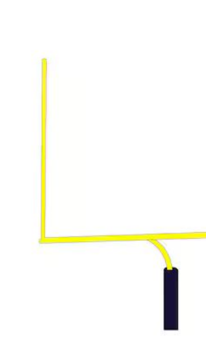
We can see how offenses have found success passing when defenses have unbalanced personnel on the field. Looking at when defenses are in quarter personnel (7 DBs) compared to dime (6 DBs), nickel (5 DBs), and base (4 DBs), we can see some noticeable differences in the EPA trends. Around half of the plays with quarter personnel go for positive EPA, compared to slightly less than half for dime and nickel.

Results

For our research question, we looked at many variables and how they affect Expected Points Added on passing plays. Looking at the results of our model, we can see a few observations. First of all, our model performed decently but was overall unspectacular. The training dataset had an R^2 value of .584 and the test data had an R^2 value of .575. This means that our model has some predictive value but has its share of flaws. Looking at the coefficient values, we can see that playResult is by far the most predictive of EPA, which matches what we'd expect, as the more yards a play results in, the more expected points a play should be worth. Looking at other variables that displayed larger magnitudes, we can see defensive personnel seem to have a major impact on EPA. All of D_DL, D_LB, and D_DB have coefficients of a high magnitude relative to the rest of the variables. This suggests that if defenses put unbalanced personnel groupings on the field, with a lot of DL for example, offenses tend to take advantage of it and generally have more successful EPA. 3rd and 4th downs tend to have a relatively high effect relative to other variables in this model, which makes sense considering how much a successful conversion could impact a team's win probability. One trend we found surprising was that the different offensive formations tended to be near the bottom in terms of coefficient magnitude, suggesting a relatively small effect on EPA for passes.

```
Train R-squared score: 0.584
Test R-squared score: 0.575
```

	Coefficient vals
offensePlayResult	1.169477
D_DL	0.631079
D_LB	0.628016
D_DB	0.446312
passResult	-0.229165
yardsToGo	-0.198190
typeDropback_TRADITIONAL	0.098195
down_4	-0.059278
typeDropback_SCRAMBLE	0.059215
typeDropback_DESIGNED_ROLLOUT_RIGHT	0.056223
typeDropback_SCRAMBLE_ROLLOUT_RIGHT	0.052986
typeDropback_DESIGNED_ROLLOUT_LEFT	0.045486
down_1	0.042824
down_3	-0.037953
defendersInTheBox	0.030754
typeDropback_SCRAMBLE_ROLLOUT_LEFT	0.030078
O_TE	0.027072
secondsRemaining	-0.022801
offenseFormation_JUMBO	0.022221
quarter_1	-0.020785
numberOfPassRushers	-0.020535
offenseFormation_SINGLEBACK	-0.017864
quarter_2	0.017842
offenseFormation_WILDCAT	0.015976
preSnapVisitorScore	-0.015949
quarter_5	0.015559
offenseFormation_I_FORM	-0.014986
offenseFormation_PISTOL	0.013714
O_RB	0.013224
O_WR	0.011561
offenseFormation_EMPTY	0.008852
down_2	0.007550
offenseFormation_SHOTGUN	0.006828
quarter_3	-0.006512
preSnapHomeScore	0.004922
quarter_4	0.003725
absoluteYardlineNumber	0.000019



Importance/Potential Problems

This model could be used to help teams game plan and improve their passing schemes by examining what specific factors have the most weight on an individual play's success. Some of the risks regarding the deployment of the model relate to the context needed to understand the impact of the model's results. For example, offenses pass out of formations like the shotgun far more often than out of jumbo, and when teams do pass out of run-heavy formations like jumbo, they can catch the defense off-guard with play-action because the defense is expecting a run. Even though our model suggests pass plays out of jumbo lead to more success than out of the shotgun, an offense can't just implement a lot more of these passing concepts out of run-heavy formations because defenses will be less fooled by play-action if an offense continues to pass out of those formations. This model also classifies variables generally and doesn't factor in player alignment or other important factors resulting in play success such as pre-snap motion.