**Is Rushing in the Modern NFL a Viable Option?**

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## Introduction

The NFL is the premier sports league in the United States. Its revenue of 17 billion dollars tops even international leagues such as the Premier League in Britain.[1] Players and coaches earn huge contracts when winning, as that success brings in absurd amounts of money to the owners. To break it down to the most basic form, you win football by scoring points, and these points are scored by moving the ball up the field. Your two options for this are passing, where you throw the ball to someone up the field, and rushing, where someone runs the ball up the field. Passing and rushing have both been effective strategies at winning in the NFL, but rushing is continuously trending towards irrelevancy. Every year the top teams have a star quarterback who methodically puts points on the board. Every Super Bowl MVP going back to 1998 has either been a quarterback, wide receiver, or a star defender who repeatedly stops the opposing team's quarterback through sacks and interceptions. With rushing being such a forgotten aspect of the game for most of the league, I aim to see if there is merit to rushing being inferior in the modern NFL.

## Methodology

I will be doing this by looking at a variety of simple statistics such as yards gained on a play, as well as an advanced statistic known as Estimated Points Added (EPA).[2] This statistic looks at the average points scored by the league from a given position. If it is 3rd and 8 from your own 20-yard line, the expected points are very low. If it is 1st and goal from the opponent's 1-yard line, then the expected points are very high. This statistic takes the expected points after a play has finished and subtracts the expected points from before the play started. The difference is the EPA, which my data set refers to as Diff. This makes it so that a play has a quantifiable value beyond just yards gained or lost. It adds value to key plays that secure a first down or touchdown on 3rd down and short, while it takes away value from plays that do not accomplish anything

[1] https://www.statista.com/markets/409/topic/627/professional-sports/#statistic3

[2] https://www.nfeloapp.com/analysis/expected-points-added-epa-nfl/

meaningful, such as completing a pass for 10 yards on 3rd and 28. It is important to note that this statistic is not perfect and is not the end all be all of statistics in football. It is simply the one I chose of those available to me that does a decent job assigning value to any given play, which was my goal.

The data used for this project is from StatHead.com. They record every play from every game for the entire season. This data goes back almost 30 years, with a variety of options to filter plays. This allowed me to easily pull the specific data I want without having hundreds of plays that don't apply.

I ended up pulling from every play during 2022 regular season. I filtered plays by pass and by run to exclude plays such as punts which do not apply to my model. I filtered out plays that ended in no play, which means that penalties cancelled the outcome of the play. I also filtered out quarterback kneels as they are essentially not plays, instead they are tools to run the clock out. I made sure to use every team to avoid bias from only looking at a team with a particularly good quarterback or running back.

The source only allowed 500 records at a time, so I pulled the first 500 records from each team for pass and run each. The way I left data out was simply sorting by date ascending. This was my best option as it only eliminates one or two games at the end of the season. Most teams did not have 500 rushes all year, and some teams did not even have 500 passes, so little data was excluded in the overall sample.

The data source provided a column called detail, which was a simple description of the play. It had the same structure for every play, so I was able to pull out which direction of the field the play was targeting from this column. I was also able to pull out whether a pass was short or deep, whether a touchdown was scored or not, and whether there was a penalty on the play. It is important to note that the Direction and pass Depth do not have a clear methodology shown that determines the difference between these variables. This does leave some confusion as to how these were determined. If a player runs right, then after 5 yards cuts back across the field to the left, is it a left run or right run? If a pass is 5 yards in the air, then the receiver runs 30 more yards, is it deep or short?

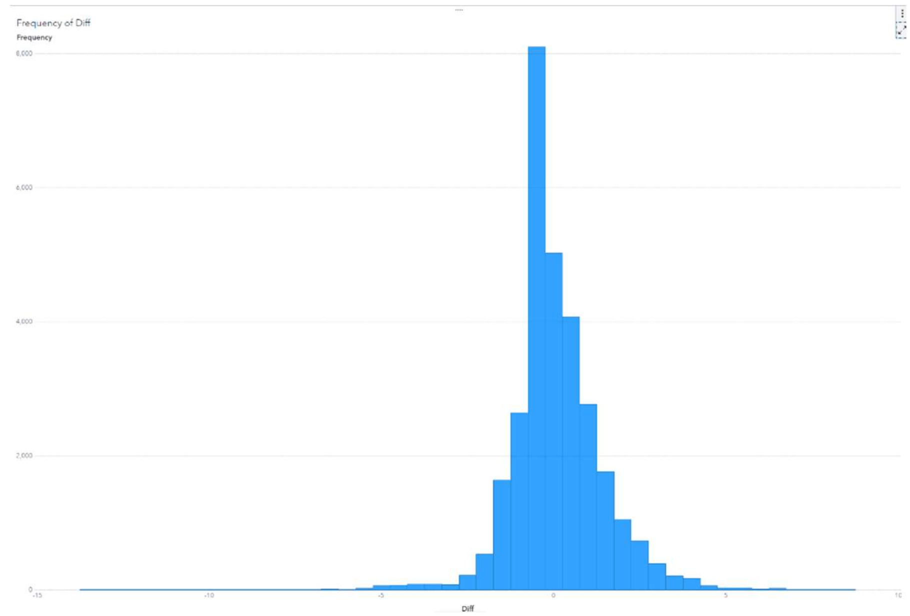
For short vs deep passes, there appears to be a clear answer. The data has thousands of records for deep passes with a 0 yard gain, which represents an incomplete pass. From there, there are a handful of different yardage gains leading up to 16, where there are 53 records. This seems to indicate that a deep pass is any pass that goes at least 16 yards in the air. The few records below 16 are when someone catches a deep pass for 16 yards, then tries to avoid defenders by running sideways/backwards and loses a few yards. Typically running backwards is not a good idea, which is why there are so few records for these.

For left, right, or middle of the field, the answer is more ambiguous. For rushes, the detail column clearly states where the rusher begins his run. It says "(NAME) (Part of the line he rushed towards) for X yards." This means that we can clearly tell if he ran up the middle near his Center, or to the left/right towards his guard or tackle. Passing is where an assumption needs to be made. Without watching hours of plays and cross-referencing them with my data, there does not appear to be an easy way to identify what direction the ball goes towards. Since Passing depth was determined by where the ball went in the air, I am going to have to assume that passing direction is also where the ball went in the air. As for what differentiates the edges of the middle from left and right, I am assuming it is inside the hash marks as middle, as every field has them standardized and they are a clear divide all the way up the field. With all this data gathered, cleaned, and expanded upon, my next step was to start building my model. I uploaded the data into SAS Viya for Learners and made sure that the variables had the correct types. I also made a 70/30 partition variable to train and validate my model.

While looking through the data in SAS Viya, I noticed some key issues. My attempts to pull play information from the details column were mostly successful, but there were still a few issues. When a quarterback got sacked, it assigned it null for direction. This also happened when a ball was spiked. Both of these outliers made direction disproportionately good at predicting Diff, because sacks are horrible plays for an offense, and spikes are essentially not plays at all. They are just a tool used for clock management that wastes an entire play.

Another key issue was with deep short and deep passes. The variable gave a null to all runs, sacks, and other types of plays mentioned here. I went back and added "run" to runs and "sack" to sacks. There were still a few rows with nulls for these columns, as football can get very strange sometimes. One simpler example is when a snap is fumbled. This is at the start of the play before anyone has done anything. If the ball is instantly fumbled, there is no great way to determine info for the play as chaos instantly unfolds. For these small amounts of records, I simply left them null and plan on adding a filter to remove them from any predictive analytics. This is the best way for me to proceed as these plays are essentially not plays, along with spikes and QB kneels. They are simply quirks of the game that don't translate well to a stat sheet.

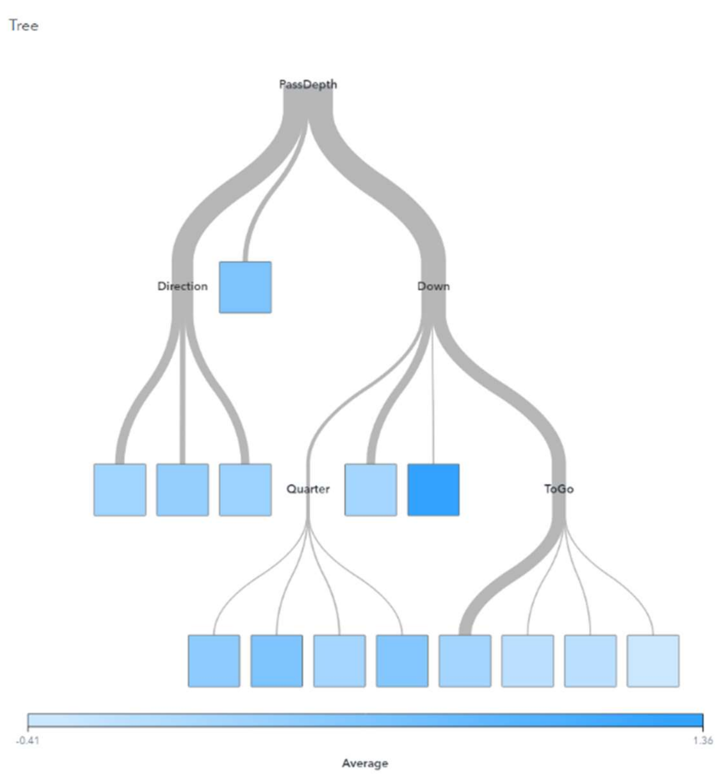
Before creating a decision tree, I did some exploratory data analysis on a few key variables. The most important of these was a simple histogram of the EPA values to check that it was somewhat normally distributed. The graph below shows that it was normal. I initially thought that the limit would be 7 which is the maximum points possible to score on a single play. It is interesting to note that there are plays that exceeded 7 points added, and ones that had -13 points added. These are cases where a team was expected to score such as 1$^{st}$ and one on the goal line, but threw an interception that the other team scored on. This led to an EPA of about -13. On the other hand, there were plays where it was 3$^{rd}$ and long on their own 1 yard line where they scored a 99 yard touchdown which resulted in an EPA of over 8. One other thing that stood out to me was how the peak was -0.25 to -0.75 points added. I would have assumed that it would be 0 or even slightly above 0 as the average is around 0.14 for all plays. This seems to indicate that the data is very mildly right skewed.



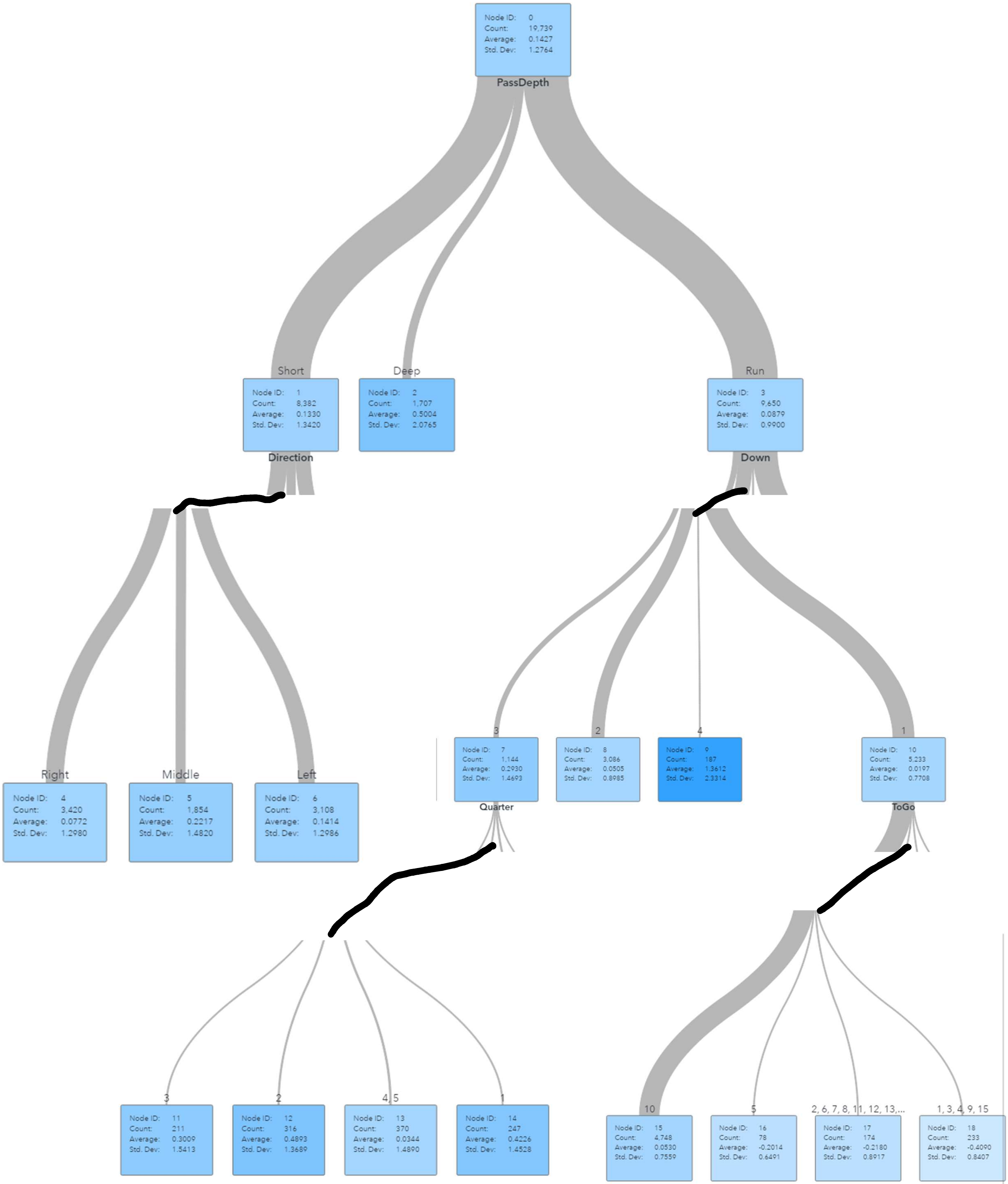

## **Results**

I created a decision tree within SAS Viya for Learners. I used the Diff variable which represents Expected Points Added as my Response variable. This will allow me to show what predictors truly have an impact on any given play and lead to success on the football field. The predictors I selected are Down, Pass Depth, Type of Play, Yards to Go, Play Direction, and Quarter. These were selected as they are all available to someone before the outcome of a play, so they can help indicate what plays may be best to run. I set the maximum branches to 4, which would allow the tree to divide by the 4 quarters, or 4 downs. I set the maximum levels to 4 to create a tree that is not overly complex. Last, I set the leaf size to 15, as it would allow for some interesting observations to be made without making them overly fit to the training sample.

I ran the model and the tree generated is shown below with some relevant statistics. I also show a breakdown of the tree on the next page

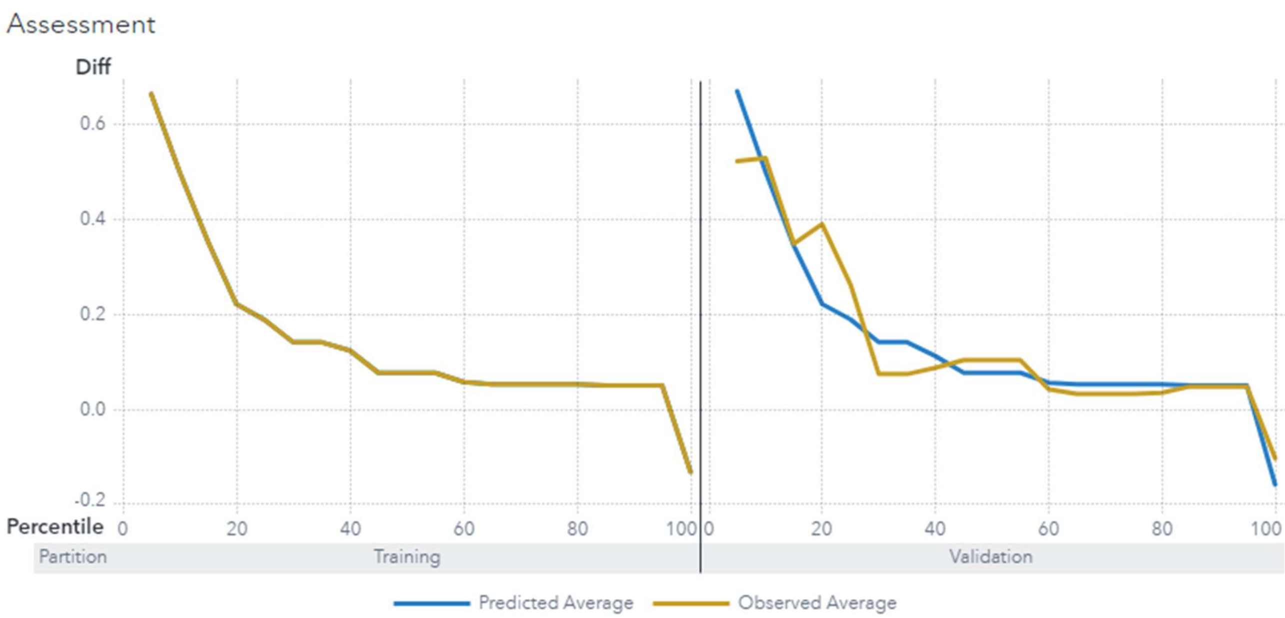



| Variable | Importance |
|---|---|
| Down | 380.0215 |
| PassDepth | 248.1936 |
| ToGo | 61.7472 |
| Quarter | 41.0976 |
| Direction | 25.4295 |
| Type | 0.0000 |



Node ID: 0
Count: 19,739
Average: 0.1427
Std. Dev: 1.2764
PassDepth
Short
Node ID: 1
Count: 8,382
Average: 0.1330
Std. Dev: 1.3420
Direction
Deep
Node ID: 2
Count: 1,707
Average: 0.5004
Std. Dev: 2.0765
Run
Node ID: 3
Count: 9,650
Average: 0.0879
Std. Dev: 0.9900
Down
Right
Node ID: 4
Count: 3,420
Average: 0.0772
Std. Dev: 1.2980
Middle
Node ID: 5
Count: 1,854
Average: 0.2217
Std. Dev: 1.4820
Left
Node ID: 6
Count: 3,108
Average: 0.1414
Std. Dev: 1.2986
3
Node ID: 7
Count: 1,144
Average: 0.2930
Std. Dev: 1.4693
Quarter
2
Node ID: 8
Count: 3,086
Average: 0.0505
Std. Dev: 0.8985
4
Node ID: 9
Count: 187
Average: 1.3612
Std. Dev: 2.3314
1
Node ID: 10
Count: 5,233
Average: 0.0197
Std. Dev: 0.7708
ToGo
3
Node ID: 11
Count: 211
Average: 0.3009
Std. Dev: 1.5413
2
Node ID: 12
Count: 316
Average: 0.4893
Std. Dev: 1.3689
4, 5
Node ID: 13
Count: 370
Average: 0.0344
Std. Dev: 1.4890
1
Node ID: 14
Count: 247
Average: 0.4226
Std. Dev: 1.4528
10
Node ID: 15
Count: 4,748
Average: 0.0530
Std. Dev: 0.7559
5
Node ID: 16
Count: 78
Average: -0.2014
Std. Dev: 0.6491
2, 6, 7, 8, 11, 12, 13,...
Node ID: 17
Count: 174
Average: -0.2180
Std. Dev: 0.8917
1, 3, 4, 9, 15
Node ID: 18
Count: 233
Average: -0.4090
Std. Dev: 0.8407

| Partition | ASE | Observed Average | SSE | Observations Used | Unused |
|---|---|---|---|---|---|
| Training | 1.5907 | 0.6635 | 31,399.4858 | 19,739 | 0 |
| Validation | 1.5809 | 0.5221 | 13,352.2140 | 8,446 | 0 |




**Conclusion**

The first thing my decision tree shows is that there is a major difference between passing and running the ball. The average run had almost half as much EPA as a short pass, and far less than a deep pass. It also highlighted that passing deep is by far the best option of the 3. The deep pass especially may be misleading which will be explained later, but the trend of passing being better than rushing is clear. Following the left branch, the short passes were then split up into three directions. What is most interesting is that passes to the right of the field have a low EPA of about 0.077. Passes to the left are almost double at 0.14 and passes to the middle are far better at 0.22. This seems to indicate that the most successful plays in a short passing attack target the middle of the field.

Looking at rushing, the next branch is what down it is. The instant standout is 4$^{th}$ down, which has a 1.36 EPA. This goes to show that teams going for it on fourth down have incredible success when rushing the ball. Part of this is explained by sample size, as most 4$^{th}$ down plays are short yardage, and most of those are rushes. Still, it is interesting to see how rushing on 4$^{th}$ down is still a very high value play.

Downs 1 and 2 are around 0, while down 3 is at 0.3. This shows how in the current NFL, rushing it on early downs is not a great strategy, and is better utilized in short yardage situations on later downs to great effect. The model then broke down 3rd downs by quarter. What it seems to show is that in the first and second quarters, rushing on third down is quite effective, with EPAs both over 0.4. As the game goes later into the 3rd quarter, it is down to 0.3, and then an abysmal 0.03 for 4th quarter and overtime. This may be partly attributable to teams that are in the lead burning the clock by running the ball instead of playing to purely score points, but it is still an interesting point to note.

The last branch to look at is for first down when rushing. On plays where it is 1st and 10, rushing has a 0.05 EPA which is bad, but not a net negative. For every other situation outside of 1st and 10, running is a horrible option on first down. These plays result in EPA ranging from -.20 to -.40. This is the first place where a negative EPA shows up which shows just how poor a choice this is. If its 1st and 5, you are essentially given a free play to pass the ball deep and try to score, with a 2nd a 5 on incompletion still being a good situation. For longer yardage situations such as 1st and 20, you need to have some big gains to make up for a penalty, which rushing is less effective at.

In terms of overall importance of the variables, what down the current play is and the type of play called are the most important factors on EPA. The other factors that have some relevance are Yards to Go, what Quarter the game is in, and Direction of the play. The model overall had a 1.59 ASE for its training, and actually improved it to 1.58 for the validation dataset. This is a good sign that my model was not overly fit to just the data that was used to create it. It also applies to the rest of the data from the league.

Overall, what this decision tree seems to indicate is that rushing is incredibly effective at gaining a short amount of yards consistently. When this situation is required, rushing seems to be highly valuable, but otherwise is outclassed by both long and short passing.

## Further Considerations

The data available to me was somewhat limited. I was able to pull lots of valuable information out of it to develop my model, but there are still countless variables that could have an impact on a play's success. Weather is an important factor. Certain games have snow, rain, or excessive winds which makes passing a much worse option. If a team is at their home stadium or not, as fans make excessive noise which can impact communication on the field. The data could also be expanded upon to look at specific types of runs. Some runs are designed to fake a pass before running, some are designed to run one way then cut back the other, and others are designed specifically to gain one or two crucial yards. Being able to determine the type of run better would allow a more comprehensive look at what rushing strategies are successful.

One more limitation of the model is not knowing what play the initial plan was. The team could be having many receivers run deep routes, with one staying shallow for a small gain if nothing else is open. If nothing is open and they complete the short pass, then it would be registered as a short pass even though the goal was a deep pass. This is the biggest limitation in my mind, as teams are constantly reacting to what they see on the field, and changing the plan up to the last second before the play starts. There is a big difference between planning for a deep pass, and simply having a play break down leading to a deep pass. There is also a big difference between planning to run the ball, and having a quarterback scramble after no one is open for a long run.

There are so many variables and factors to consider that it makes quantifying sports an incredibly difficult task. Even if analysis shows that a certain play type is incredibly effective, in time teams will become aware of this and rework their entire defensive strategy to counter that play type. This in turn neutralizes the effectiveness of a play to an extent and gives rise to other play types that.

The broadest example of this is passing plays vs rushing plays historically in the NFL. Rushing was always seen as the dominant force of an offense. Passing was much less common and defenses focused on having big and bulky defenseman who stop the run. Over time, passing has become much more dominant.[3] Big bulky defenders are no match for a small fast player running past them and catching a ball. This has led to a transition back to more athletic and finesse focused defenders capable of stopping the pass, while being less effective vs the run.[4] There are obviously more factors at play than just one, but it is a noticeable trend throughout the league.

An analysis of what plays are most effective similar to the one shown in this paper could be done for each year or groups of years going back decades. This could be used to see in what ways types of plays are trending, and could potentially be used to predict future trends to allow a team to get ahead of the curve and gain an advantage.

[3] https://www.eldo.co/nfl-rushing-and-passing-in-four-charts.html
[4] https://www.pff.com/news/nfl-modern-football-transformed-linebacker-position