Group 13: Technical Write-Up
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Determining the Optimal Use of Aggressive Offensive Playing Strategies in College Football

Background Information and Question of Interest

The data for this project comes from Pro Football Focus (PFF) and consists of every single college football play that occured from 2015-2019. The data consists of over 100 variables and hundreds of thousands of observations, each containing all the offensive and defensive information for a particular play. For this research project, only the plays from the 2019 college football season are used.

Ultimately, the question of interest is to determine what type of offensive strategy (aggressive or non-aggressive) is most beneficial for teams when they are losing in the fourth quarter. More specifically, given a specific score differential, this project seeks to determine when in the fourth quarter it is optimal for teams to start employing an aggressive offensive strategy, if at all.

This question will be answered by building a Markov chain model using probability distributions approximated from the data in order to simulate the fourth quarter of a game with different combinations of score differential and offensive play strategy (the time in which a team begins playing aggressive). Monte Carlo simulations are then used to simulate each score/strategy combination many times, allowing us to calculate a win percentage for each combination and determine when teams should employ aggressive strategies.

Data Cleaning and Preparation: might not need this because we didn't really have to do much cleaning for our final question

Most of the details in the variables that were provided for each play were disregarded since they were not of relevance to our question of interest. In particular, we did not consider any defensive information.

The only variables that were necessary to answer our question of interest were:

- pff_FIELDPOSITION: the line of scrimmage at the start of the play; within the field of play, the two sides of the field are listed as "positive" and "negative" yardage lines with the "positive" yardage lines being on the away side of the midfield stripe while the home team defends the "negative" yardage lines
- pff_PLAYENDFIELDPOSITION: the field position at the play's ended, coded the same as the variable above
- pff_RUNPASS: coded as "P", "R" or NA to denote a pass, run or other play type

- pff_TRICKPLAY: coded as 1 if the offensive play was a trick play
- pff_DEEPPASS: coded as 1 to indicate a deep pass if the offensive play was a pass where the intended receiver was greater than 20 yards from the line of scrimmage
- pff_KICKDEPTH: distance of a punt between the line of scrimmage and its first point of contact with either the field or a player
- pff_DRIVEENDEVENT: the event that ended the drive (ex: field goal, touchdown, punt, interception)

We had to create a variable for YDS_GAINED because the field position variables were difficult to work with, as this is the main variable we looked at when determining the probability distributions for each play type. We used the logic below to transform the variable in terms of yards to the opposing team's end zone.

```
START_YDS_TO_END_ZONE = ifelse(pff_FIELDPOSITION < 0,
                               pff_FIELDPOSITION + 100,
                               pff_FIELDPOSITION),
END_YDS_TO_END_ZONE = ifelse(pff_PLAYENDFIELDPOSITION < 0,
                                     pff_PLAYENDFIELDPOSITION + 100,
                                     pff_PLAYENDFIELDPOSITION),
YDS_GAINED = START_YDS_TO_END_ZONE - END_YDS_TO_END_ZONE
```

Ultimately, the majority of our data preparation was using tools in R's dplyr package to create subsets of the data set for every offensive play situation we were interested in studying. These subsets included all runs, all passes, deep passes, trick play runs, punts, and field goal attempts. In the following sections, it will be explained how we used each of these subsets to build probability distributions and answer our question of interest.

Defining Aggressive vs. Non-Aggressive Strategies

Since there is no concrete standard for what constitutes aggressive and non-aggressive offensive strategies, we were tasked with specifically defining these two categories for the purpose of model building and analysis. We came to the following definitions:

Non-Aggressive Strategy:

- 52.8% of plays are passes and 47.2% are runs. These were the respective proportions of each play type from the 2019 college football season.
- If the team is within 30 yards of their opponent's end zone, they will kick a field goal on 4th down. If they are greater than 30 yards away, they will punt.
- Generally, a team playing non-aggressively will take longer to run plays (use more of the play clock), as they are trying to take as much time as possible off the clock.

Aggressive Strategy:

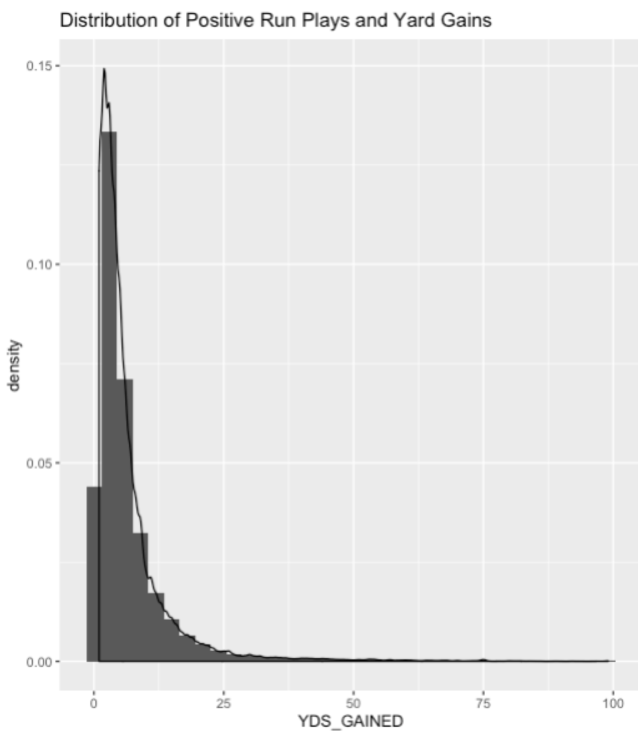
- 40% of plays are regular passes, 25% are regular runs, 25% are deep passes and 10% are running trick plays. These were the respective proportions of each play type when teams were losing in the 4th quarter, which is the specific situation we are seeking to understand.
- Regardless of field position, the team on offense will go for it on 4th down.
- An aggressive play strategy is also characterized by running plays quickly (using less of the play clock), in order to execute as many as possible in the time remaining and even attempt to run a play before the defensive team is ready.

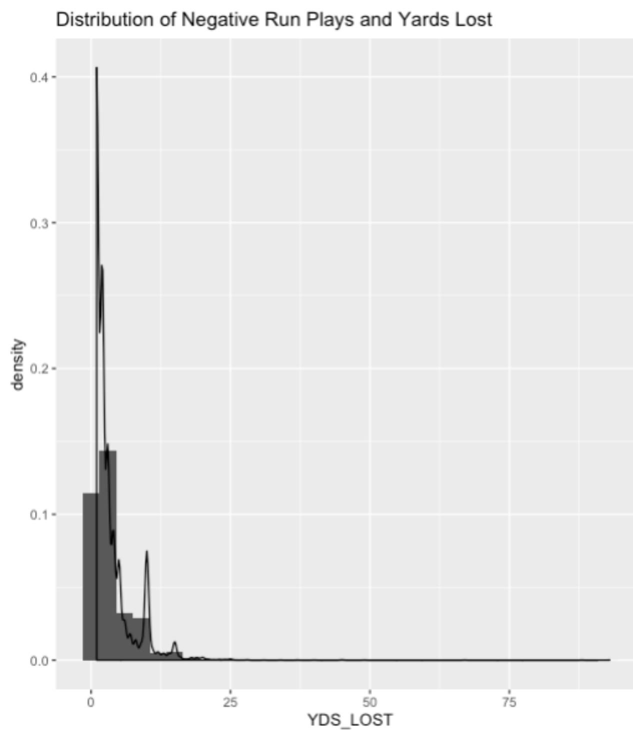
Building Markov Chain Model

Regular Run Plays

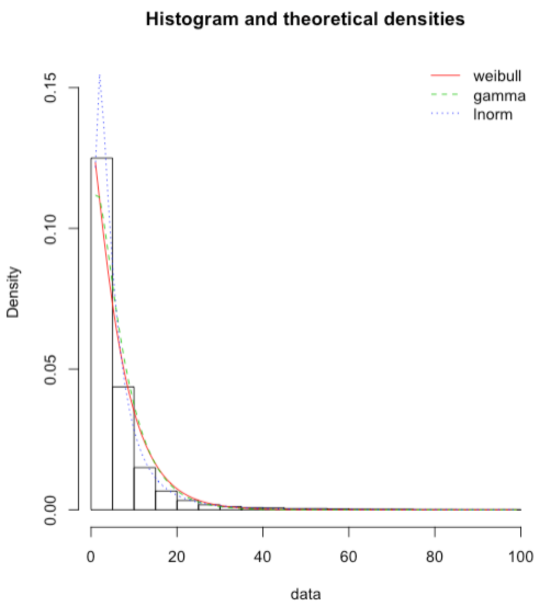
The regular runs play attempts were divided into two categories: positive yard gains and negative/zero yard gains. Through some data manipulation, we found that 78.9% of runs resulted in positive yard gains, while 21.1% resulted in no gain or a loss.

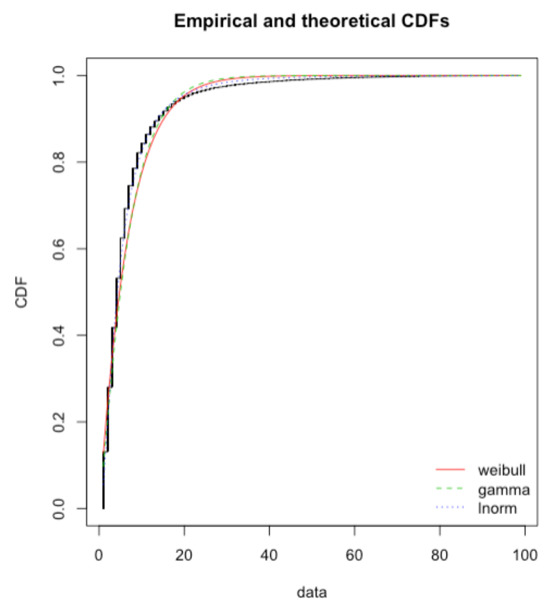
The distributions for these two groups of runs are graphed below:





We did some exploratory analysis to fit the empirical distributions to a known theoretical distribution by using the fitdistrplus R package. We fit the data to 3 distributions that were known to be very right-skewed. For positive plays, here are the initial analysis graphs:

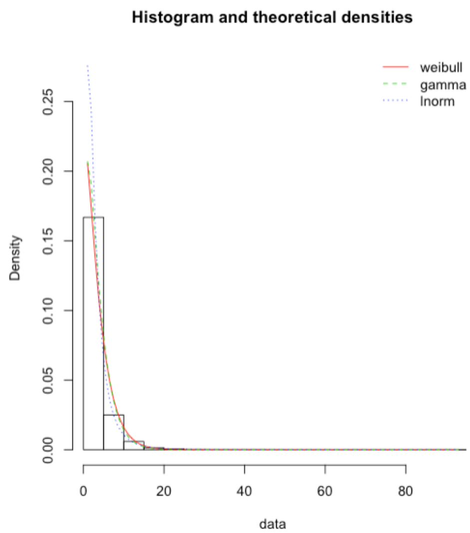


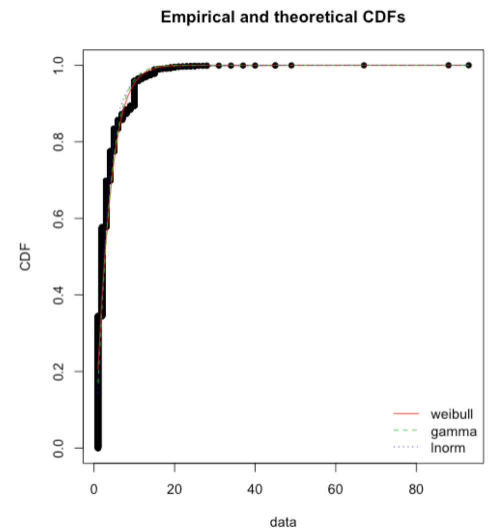


We found that the weibull, gamma and lognormal distribution all seem to fit to the data fairly well. However, the goodness of fit statistics below suggest that a lognormal is the best fit, and we get **Lognormal(meanlog = 1.454, sdlog = .907)** as the distribution.

```
> gofstat(list(runfit_w_p, runfit_g_p, runfit_ln_p), fitnames = c("weibull", "gamma", "lnormal"))
Goodness-of-fit statistics
                                weibull        gamma      lnormal
Kolmogorov-Smirnov statistic    0.1272068    0.1267382   0.07951737
Cramer-von Mises statistic    170.3470536  179.6053691  49.64783253
Anderson-Darling statistic   1142.5731520 1072.8179642 398.68109981
```

For negative runs, we went through the same process and again used the weibull, gamma and lognormal distributions for comparison. The graphs below suggest that they all fit the data fairly well.





The goodness of fit statistics once again suggested lognormal being the best fit for the distribution, and we get **Lognormal(meanlog = .874, sdlog = .822)** as the distribution.

```
> gofstat(list(fit_w, runfit_g, runfit_ln), fitnames = c("weibull", "gamma", "lnormal"))
Goodness-of-fit statistics
                              weibull       gamma     lnormal
Kolmogorov-Smirnov statistic  0.2062954   0.2062487   0.2007895
Cramer-von Mises statistic   64.7755485  70.2319518  48.5960389
Anderson-Darling statistic  400.6681613 426.2947523 337.8001343
```

Unfortunately, the data did not provide an easy way to estimate distributions for the time elapsed on a particular type of play in the same way it was possible to estimate the number of yards gained or lost. We determined that appropriate approximations for time elapsed for a run play are as follows:

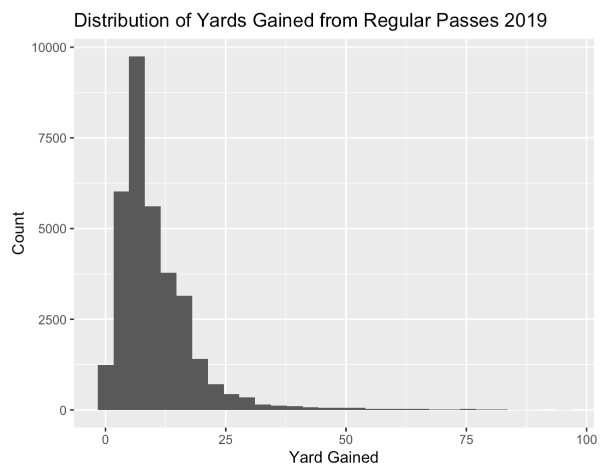
- The time elapsed on a run play in a non-aggressive setting is **Normal(mean = 18, sd = 4)**
- The time elapsed on a run play an aggressive setting is **Normal(mean = 12, sd = 3)**

This time is intended to account for the duration of the play itself, which is the time that elapses between the center snapping the quarterback and the play-end event (tackle, touchdown, interception, etc.), and time that runs between the end of a play and the start of the next play (which will always occur when there is more than 2 minutes left in the game, and the result of the play is not an incompletion or a tackle out-of-bounds).

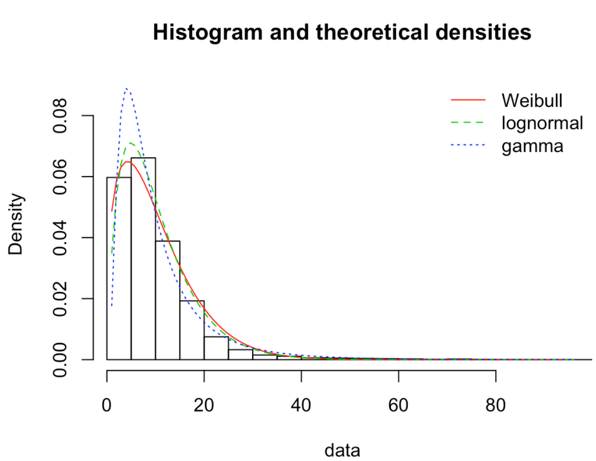
Regular Pass Plays

The pass play attempts are further subdivided into 3 categories: positive yard plays, negative yard plays, and 0 yard plays (incompletions). The data showed that positive yard plays account for 54.3% of the data, negative yard plays make up 8.5% of the data, and incomplete passes account for the remaining 37.2% of the data. In our game simulation, one of these three outcomes was randomly chosen based on their probabilities of occurrence. From the 2019 data, it was found that 4% of all passes resulted in an interception. Therefore, our Markov Chain model will also simulate an interception on 4% of passes.

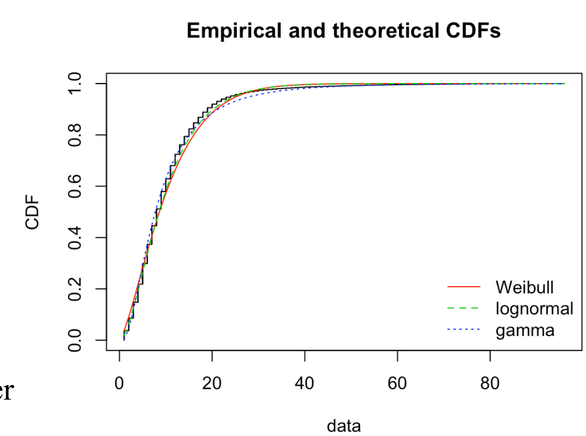
The next step was fitting the approximate distribution of yards gained for each of the three outcomes. Incomplete passes are always 0 yards, so that was already set. To find the distribution for positive pass plays, we first graphed a histogram of the distribution (shown below).



To find the distribution of positive yard pass plays, weibull, gamma, lognormal and densities were fit to the histogram of positive pass plays, as seen in the figure below. Based on the two charts, both lognormal and weibull seemed to fit the distribution of regular pass plays fairly well.



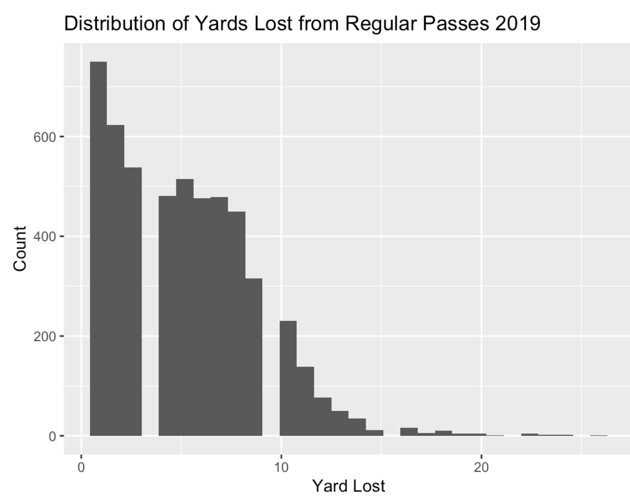
In order



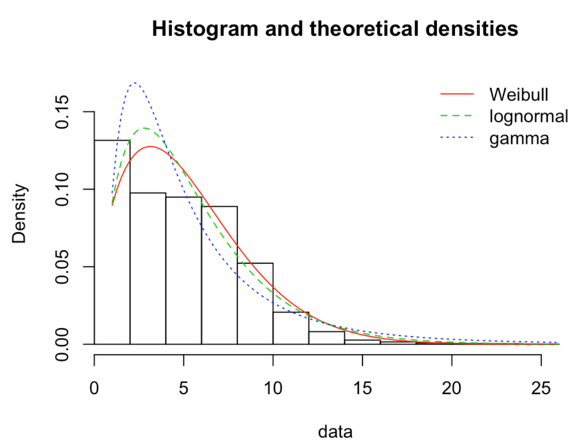
to determine which of the two was better suited, goodness of fit tests were run as well, and the statistics are shown below. The lognormal distribution was eventually chosen because it had the lowest goodness of fit statistics out of the three. Finally, we used the bootstrapping method to determine the unknown parameter values for the lognormal distribution, and the results are shown below as well. The final distribution used for the simulation was
Lognormal(meanlog = 2.044, sdlog = 0.790).

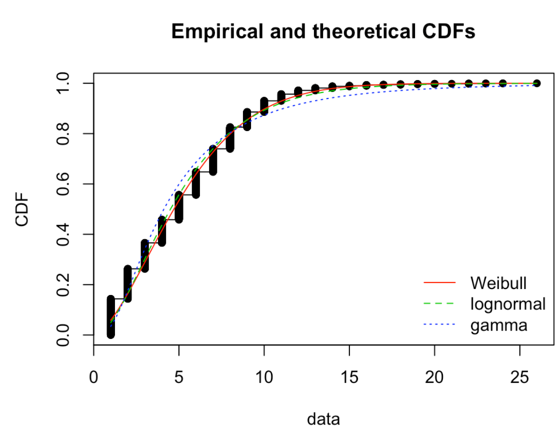
```
Goodness-of-fit statistics
                                Weibull    lognormal        gamma
Kolmogorov-Smirnov statistic  0.06882354   0.05241871   0.07691599
Cramer-von Mises statistic   34.47588570  16.16399374  30.62441661
Anderson-Darling statistic  243.79130035 110.49120769 210.13225804
```

The process for negative yard pass plays was almost identical to the positive pass plays, except the absolute value of the YARDS_GAINED variable had to be taken in order to fit the distribution of negative pass plays. The histogram is shown below:



Once again, weibull, gamma and lognormal densities were fit to the histogram of negative pass plays, as seen in the figures below. It seemed as if weibull and lognormal also fit the negative distribution best from the graphs, so goodness of fit tests were conducted to further evaluate.





The results from the goodness of fit test (displayed below) illustrate that unlike the positive pass plays, the Weibull distribution is the best fit as opposed to the lognormal distribution. The bootstrapping method was used to determine the unknown parameter values for the Weibull distribution, and the results are shown below as well. The final distribution used for the simulation was **Weibull(shape = 1.577, scale = 5.937)**.

Goodness-of-fit statistics

	Weibull	lognormal	gamma
Kolmogorov-Smirnov statistic	0.09827064	0.1015168	0.1407118
Cramer-von Mises statistic	7.44978650	10.2200975	19.3835202
Anderson-Darling statistic	57.05552246	74.4986417	135.8921142

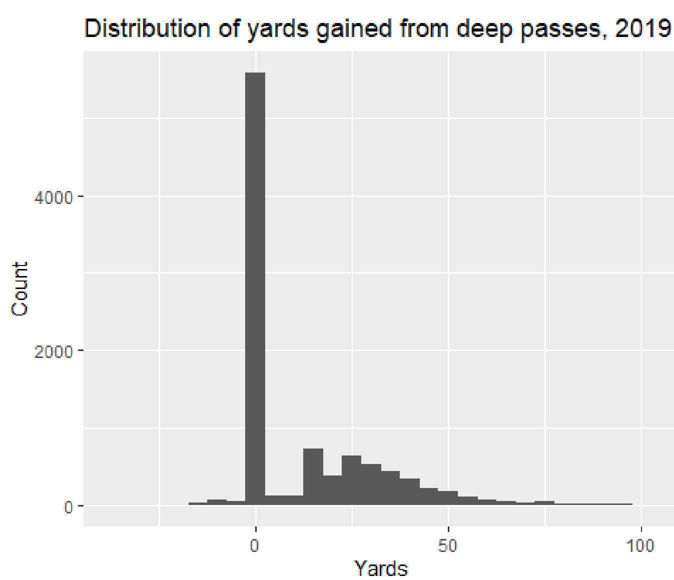
We determined that appropriate approximations for time elapsed for a pass play are as follows:

- The time elapsed on a pass play in a non-aggressive setting is **Normal(mean = 22, sd = 4)**
- The time elapsed on a pass play an aggressive setting is **Normal(mean = 17, sd = 3)**

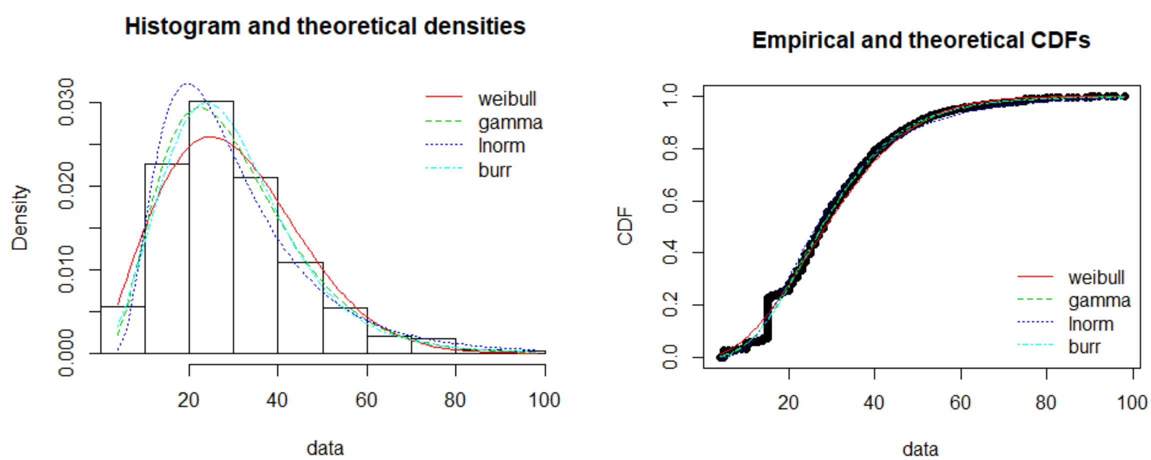
Deep Pass Plays

The deep pass play attempts are further subdivided into 3 categories: positive yard plays, negative yard plays, and 0 yard plays (incompletions). Using the data, it was easily found that positive yard plays make up 42.4% of deep pass attempts, negative yard plays make up 1.6% of deep pass attempts, and incompletions make up a majority of deep pass attempts at 56%. To decide which of the three options is executed, a random sample is performed with those three percentages. Like the regular passes, we wanted to account for the possibility of throwing an interception. In 2019, 10.5% of deep passes resulted in an interception. Thus, our simulation will result in an interception on 10.5% of all the deep passes that are completed.

The distribution of yards gained from deep passes is shown below.

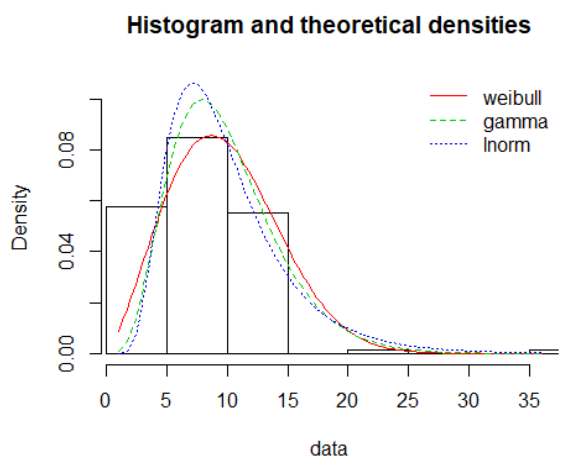


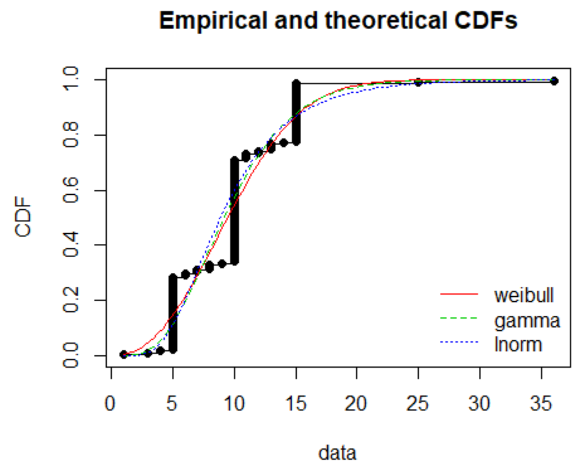
To find the distribution of positive yard deep pass plays, weibull, gamma, lognormal, and burr densities were fit to the histogram of positive deep pass plays, as seen in the figure below. Just looking at the histograms and theoretical CDF's, it appears that all the distributions fit the data fairly well. To determine which of the four density curves best fit the data, goodness of fit statistics were taken. From the goodness of fit test, the gamma and burr distributions had very similar numbers, both of which were overall lower than the weibull or lognormal distributions. The burr distribution was chosen because the statistics for this distribution were slightly lower, and upon close examination at the theoretical densities, it appears to match the histogram better. Lastly, a bootstrap was applied to estimate the uncertainty in the parameters for the burr distribution, and the results are shown below. The distribution that is used for the simulation is:
Burr(shape1 = 2.7031, shape2 = 2.6202, rate = .0225)




```
Goodness-of-fit statistics
                              weibull       gamma       lnorm        burr
Kolmogorov-Smirnov statistic  0.09357677  0.08079181  0.07989398  0.08560369
Cramer-von Mises statistic    3.54284464  1.97997497  4.40911113  1.87314853
Anderson-Darling statistic   26.41982223 16.63893897 32.63808004 15.63514363
```

The same process was used to find the distribution of negative yard deep pass plays. However, the absolute value of these plays need to be taken since most of the distributions that are explored are only applicable with positive integer values. Looking at the histogram and the theoretical CDFs in the figures below, it is clear that the distributions do not fit the data as well as it did for positive yard values. This makes sense because there are far fewer negative yard plays. Most negative yard plays off deep passes stem from penalties, which is why the frequent negative yardage losses are 5,10, or 15 yard losses, as reflected in the empirical and theoretical CDFs figure. To find the distribution of negative yard deep pass plays, weibull, gamma, and lognormal densities were fit to the histogram of negative deep pass plays, as seen below. The goodness of fit statistics were taken for these three distributions to determine the best distribution, and the weibull distribution yielded the lowest numbers, and thus was the best density curve. A bootstrap was applied to estimate the uncertainty of the parameters, and the distribution that is used for this simulation for negative yard deep pass plays is: **Weibull(shape = 2.3326, scale = 11.1046)**.

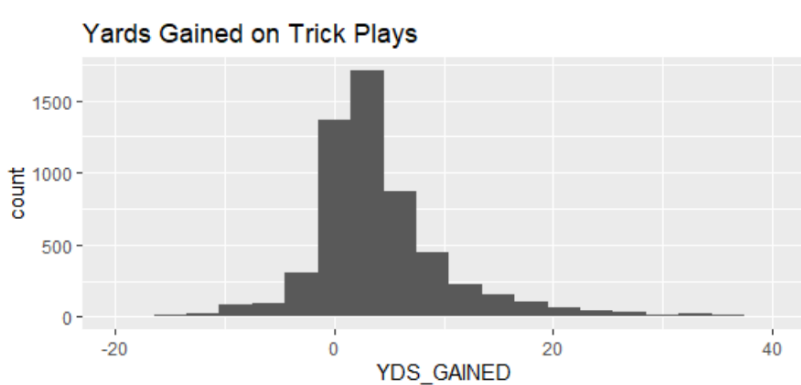





```
Goodness-of-fit statistics
                              weibull    gamma     lnorm
Kolmogorov-Smirnov statistic 0.2060507 0.234983 0.2605078
Cramer-von Mises statistic   1.1999736 1.376824 1.5823646
Anderson-Darling statistic   7.1051309 8.056597 8.9407862
```

We determined that the appropriate approximation for time elapsed for a deep pass play is as follows: the time elapsed on a trick run play in an aggressive setting is **Normal(mean = 22, sd = 4).** This time is slightly longer than the time for a regular pass play in an aggressive setting, as a deep pass requires that the intended receiver is at least 20 years from the line of scrimmage. Deep pass plays are not executed in a non-aggressive setting.

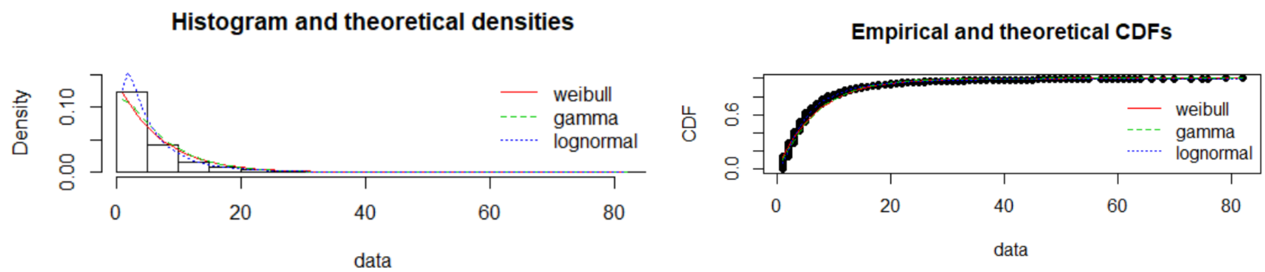
Run Trick Plays



It was determined that 85.33% of trick plays resulted in a yard gain, while 14.67% resulted in a yard loss.

To determine the distributions for both positive and negative running trick plays, we compared the fit of the Weibull, Gamma and Lognormal distributions.

The following figures display the theoretical probability density curves of each of these distributions relative to the histogram of the actual distribution of the data, as well as their cumulative density curves, and 3 different goodness of fit statistics for the positive plays. The statistics measure the extent to which the actual data differs from the theoretical distributions.

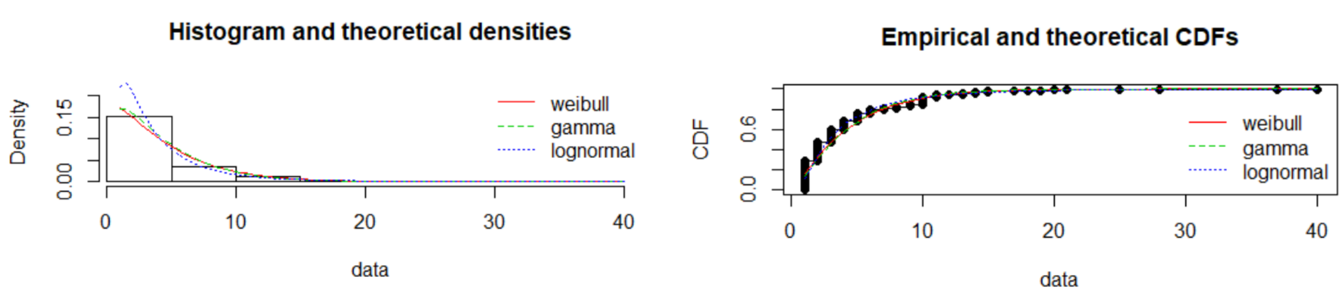


Goodness-of-fit statistics

	weibull	gamma	lognormal
Kolmogorov-Smirnov statistic	0.1290136	0.1283692	0.08571372
Cramer-von Mises statistic	13.7455908	15.8081237	4.37467691
Anderson-Darling statistic	93.6500684	95.4146647	36.98523096

The two plots do not show much of a difference among the three distributions - each distribution seems to fit relatively well to the data. It is easier to compare the distributions by looking at the goodness-of-fit statistics, from which it can be seen that the lognormal distribution is the best fit for this particular data.

And for the negative plays:



Goodness-of-fit statistics

	weibull	gamma	lnorm
Kolmogorov-Smirnov statistic	0.1671257	0.1647411	0.1712876
Cramer-von Mises statistic	3.6314410	4.0557044	2.7795093
Anderson-Darling statistic	24.0906171	26.0527573	21.4872624

Again, each of the three distributions appears to fit the data relatively well. A close look at the plot of the CDFs suggests that the lognormal distribution is a slightly better fit, with the gamma and weibull distributions slightly underapproximating a large portion of the left side of the data (particularly values between 0 and 10). The goodness-of-fit statistics confirm that the lognormal distribution is likely the best.

Ultimately, we found that the exact best distribution for running trick plays with yards gained is:
Lognormal(meanlog = 1.4656, sdlog = .9465),
And for running trick plays with yards lost is:
Lognormal(meanlog = 1.0617, sdlog = .8847)

We determined that the appropriate approximation for time elapsed for a running trick play is as follows: the time elapsed on a trick run play in an aggressive setting is **Normal(mean = 14, sd = 4).** This time is slightly longer than the time for a regular run in an aggressive setting, as a trick play often involves another player first touching the ball before the running back does. Trick plays are not executed in a non-aggressive setting.

Special Teams

Punting:

In order to estimate the average yards kicked per punt, we subsetted the data to only include fourth downs, and then found a histogram to represent the kickyards. The histogram was approximately **Normal(mean = 40.5, sd = 9.7).** In order to simplify the process, we assumed that all punts ended in either a fair catch of a touchback.

We approximated the time that elapses for a punt play with **Normal(mean = 14, sd = 3).**

Field Goal Kicking:

Using the 2019 college football data, we built a logistic regression model to calculate the probability of making a field goal from a particular yard line. Here is the model:

P(Making a Field Goal) = $\dfrac{e^{2.4103 - 0.0649(YTG)}}{1 + e^{2.4193 - 0.0649(YTG)}}$, where the variable YTG represents the distance from the line of scrimmage to the opponent's end zone.

We approximated the time that elapses for a field goal play with **Normal(mean = 8, sd = 3).** This average time is lower than other plays to account for the fact that many field goals are taken after time outs, which stop the clock from the previous play.

<u>Using Monte Carlo Methods to Simulate 4th Quarter with Markov Chains</u>

Markov Chains are based on the principle of the conditional probability of moving from one state to another. For this analysis, a state is defined as follows:

State = S = (A, B, C, D, E, F), where
A = Starting field position of play (coded as yards to opponent's end zone)
B = Time remaining
C = Yards to first down
D = Down #
E = Starting score differential (coded as a negative number when team is losing)
F = Aggressive play indicator (0 if team is non-aggressive, 1 if aggressive)

Based on the following probability model:
P(St+1|St) = P(At+1, Bt+1, Ct+1, Dt+1, Et+1|At, Bt, Ct, Dt, Et)
And the Law of Total Probability:
P(A|B,W) = ΣP(A|Ci, BW)P(Ci|BW), where W is an indicator variable that is 1 for aggressive play calling, and 0 for conservative,
We can use the probability distributions derived above to simulate a football game, where the starting conditions of each play make up a state.

We used a total of 3 functions to run our simulations:
run_full_drive
This function takes the starting state of the drive (A-F) as its arguments, and it runs until one of the following drive ending events: touchdown, field goal/missed field goal, interception, punt or turnover on downs. The function returns the amount of time remaining, the ending field position and the number of points associated with the drive end event. One of the latter two will always be NA, because a team will either score or end the drive somewhere on the field.

game_simulator
This function takes the starting state of the game (A-F) as its arguments, plus an optional "t" argument that allows us to specify a specific period of time to change "F" from non-aggressive to aggressive for our team. For every game, the starting state is as follows:

- A is randomly sampled from a normal distribution with mean 60 and sd 10
- B is 15 (beginning of 4th quarter)
- C is 10 and D is 1 (we assume it is first down for simplicity)
- E is determined by the score differential range we are interested in studying. For example, if we are simulating games where we started down by 4-7 points, a number between 4 and 7 will be randomly selected

- F is 1 if we want to play aggressive the whole game. Otherwise, F is 0 and we can specify a time for t when we wish to start playing aggressive

The function allows us to keep track of the score of the game and transition from drive to drive by running *run_full_drive* until time runs out. After a drive ends, this function creates the starting state for the next drive, which are then the new arguments in *run_full_drive*. “A” will either become the field position where the previous drive ended, or the team’s own 25 yard-line if the previous drive ended in a scoring play (for simplicity, we simulate every kickoff as a touchback). “B” will be the time remaining when the previous drive ended for a non-scoring drive end event, or the time remaining minus 12 seconds (to account for a kickoff), when there was a scoring drive end event. “C” and “D” will always become 10 and 1, respectively. “E” does not change because it is not used in the Markov Chains, as this function stores each team’s score as separate variables. “F” is a little more complicated. We assume the opposing team always plays non-aggressively, so it is always set to 0 at the beginning of an opponent’s drive. If “F” is initially 1, it will remain 1 for our team. If “F” is initially 0, it will change to 1 at time=t, when t is specified. Once time has run out, the function returns the final score.

field_goal_probability

This function runs within *run_full_drive* and simply uses the logistic regression probability model shown above to determine the probability of a successful field goal given A (the starting field position of the play), and subsequently determines if the field goal was successful using the determined probability.

These functions together simulate the 4th quarter of 1 game for a particular score differential and offensive playing strategy. In order to truly understand how differences in starting score differential and offensive playing strategy impact a team’s win probability, we used Monte Carlo simulations to simulate 10,000 games for a total of 24 different combinations, all of which can be seen in the results table in the next section. The snippet of code below shows how we ran a Monte Carlo simulation with a score differential between 1 and 3, and the strategy of starting to play aggressively when there are 10 minutes left in the quarter.

```
replicate(10000,
          game_simulator(A=floor(rnorm(1, 60, 10)),
                         B=15,
                         C=10,
                         D=1,
                         E=-sample(1:3, 1),
                         F=0,
                         t=10))
```

Results

The following table displays values for the proportion of games won out of 10,000. The rows represent the point in time of the quarter in which the team started employing aggressive offensive strategies, and the columns represent the starting score differential (how much "our team" was losing by when the 4th quarter began).

	1-3	4-7	8-14	>14
Non-Aggressive	.4675	.3091	.1139	.0239
Aggressive w/ 2.5 mins left	.4776	.3245	.1230	.0305
Aggressive w/ 5 mins left	.4881	.3551	.1359	.0389
Aggressive w/ 7.5 mins left	**.4911**	.3692	.1625	.0473
Aggressive w/ 10 mins left	.4711	**.3845**	.1800	.0606
Aggressive w/ 12.5 mins left	.4580	.3705	.1891	.0693
Whole Quarter Aggressive	.4565	.3624	**.2049**	**.0748**

In summary, when we started the 4th quarter down by 1 to 3 points, we won the most games by starting aggressive play at 7.5 minutes left in the quarter, with 5 minutes left being closely behind. When down 4 to 7 points, we won the most games by starting a bit earlier, at 10 minutes left. For both 8 to 13 points and greater than 14, it was most effective to start playing aggressively at the start of the 4th quarter.

The decision of whether or not to employ an aggressive offensive strategy seems to be most significant when down by 4-7 and 8-13 points, as the differences between the most and least effective playing strategies are 8-9 percentage points. Nevertheless, the other two score differential brackets still show evidence of a tangible difference among offensive strategies.

Conclusions, Limitations and Future Steps for Improvement

As mentioned in the previous section, a notable takeaway from our simulations suggest that starting to play aggressively too early can be detrimental at smaller score differentials (specifically when you would only need one offensive drive to tie or take the lead). This is expected, as it likely does not make sense to throw a 50 yard pass, or go for it on 4th and 10 at the beginning of the 4th quarter if you are only down by a field goal, as these plays can be very risky (the fact that the interception rate for deep passes is nearly triple the rate for regular passes is just one example of this). When only a field goal is needed, aggressive play should not start until more than halfway through the 4th quarter. When a touchdown is needed, starting just under 10 minutes makes sense.

In situations where it would require two scoring drives to tie or take the lead, teams should start playing aggressively early in the 4th quarter. Realistically, scoring twice can take 3 or more drives, and it will be nearly impossible to have this many drives unless the team is scoring quickly as quickly as possible through an aggressive playing strategy. The same logic applies when a team is down by more than 2 touchdowns at the start of the 4th quarter. In this scenario, however, 15 minutes of aggressive play is likely not enough to drastically increase the team's likelihood of a comeback (suggested by the win percentage of 7.48%). Though this study only focuses on the 4th quarter, our results suggest that it would be reasonable for a team down by more than 2 touchdowns to consider employing an aggressive playing strategy towards the end of the 3rd quarter.

It is very difficult to simulate all the intricacies of a football game, so making many underlying assumptions was necessary to conduct this analysis. For instance, we had to generalize that the opposing team would always employ a non-aggressive offensive strategy, that every punt resulted in a fair catch, every kickoff was a touchback, and that there were no penalties that significantly changed the outcome of the game. With more time, we could have attempted to incorporate these distributions from the data into our simulation in order to further improve the accuracy. Another limitation was the element of time, which obviously is a significant factor in determining a team's offensive strategy. With our data, there was not an intuitive way to build distributions for the time that elapses for each play type, requiring us to approximate these distributions based on logical thinking alone. Figuring out how to simulate time in the same way we simulated the yards gained would be a priority in improving this study with more time and resources.

The data we built our simulation from contains data from all teams, and therefore the winning percentages from the 10,000 games should be interpreted in the context of the "average" team. The strategies we defined as aggressive vs. non-aggressive were very concrete for the purpose of running a simulation, but they should be adapted to align with a team's identity and avoid being too predictable. As described above, a significant portion of an aggressive play strategy is deep passes. If a team has a quarterback who is particularly bad at passing, then it might not make sense to play aggressively at all if the team is only down by 1-3 points, since the difference in win percentages between the most effective and least effective strategies is only 3.5%. In other words, it is too risky to employ an aggressive strategy in this situation, because even a better quarterback would only increase their chance of winning by a small percentage. Another example would be the fact that our aggressive strategy never involves field goal kicking. If a team is choosing to adopt an aggressive strategy when down by only 3 points, and they face a 4th down situation at their opponent's 35 yard-line, it probably does make sense to kick a field goal if the team has a particularly strong field goal kicker and are content with tying the game, rather than taking the lead. Adopting an aggressive play strategy does not mean that every play has to be "aggressive," but there are general trends in play calling, as outlined above, that can be followed. Ultimately, the insight our research provides could be very useful to college football coaches in helping guide them in making the smartest decisions regarding the implementation of an aggressive playing strategy. However, each coach must analyze the implications with regard to their specific team, realizing that there are many other factors that must be considered outside of what our results provide, and there are certainly other steps that could be taken in the future to further improve the accuracy of our results.