The Impact of Play Clock Timing on NFL Play Outcomes

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January 6, 2025

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1 Introduction

One moment etched in the hearts of Minnesota Vikings fans is the 2018 NFL playoff game against the New Orleans Saints. With just 5 seconds left on the play clock, Case Keenum launches a high, spiraling pass to Stefon Diggs, who streaks down the right sideline. The crowd erupts as Diggs makes the catch and sprints into the end zone, completing one of the most iconic touchdowns in NFL history. This unforgettable play, now famously known as the Minneapolis Miracle, highlights the critical role of the play clock. In football, the play clock isn't just a countdown, it's a pressure cooker that influences decision making, timing, and ultimately, the outcome of a play.

The focus of this research is to examine how the play clock at the snap, along with other variables, impacts play success. By investigating this relationship, we aim to develop a predictive model that forecasts play outcomes based on the timing of the snap.

2 Exploratory Analysis:

2.1 Background and Variables

We analyze multiple datasets, including player statistics, play-by-play data, and game metadata, sourced from the 2024–2025 NFL season as part of the Big Data Bowl competition.

The data that was used for most of analysis came from the "plays.csv" data set, A number of exploratory variables were recorded:
- yardsToGo:Distance needed for a first down (numeric)
- gameClock:Time on clock of play (MM:SS)
- offenseFormation:Formation used by possession team (text)
- playClockAtSnap:What the play clock value was at time of snap (numeric)
- passResult:Dropback outcome of the play (C: Complete pass, I: Incomplete pass , S: Quarterback sack, IN: Intercepted pass, R: Scramble, text)
- yardsGained:Net yards gained by the offense, including penalty yardage (numeric)

and many more.

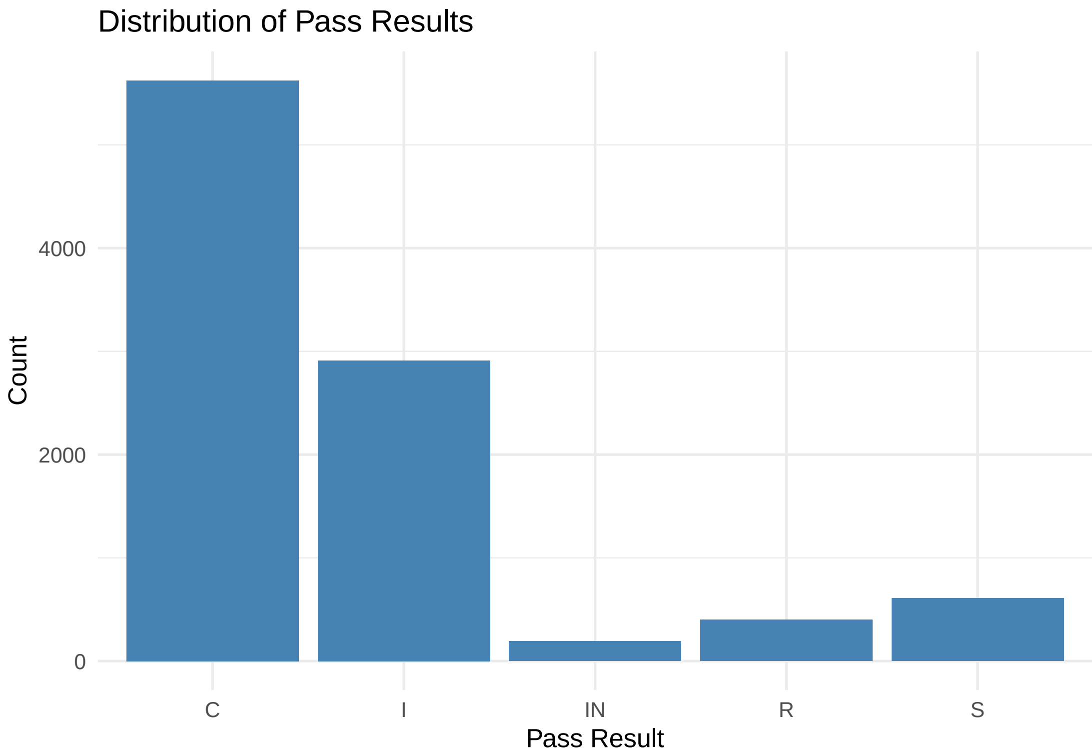
2.2 Some Exploratory Data Analysis with Play Clock at Snap

2.2.1 Distributions of Important Variables

There were a variety of possible variables that along with playClockAtSnap that would be important in our analysis. This section explores distributions of important variables and the relationships between them. Below are the different variables and their distributions that we looked at in our analysis:

passResult (Categorical): We have filtered out the NA values which indicate non-pass plays, as we are only trying to explore passing plays. (C: Complete pass, I: Incomplete pass , S: Quarterback sack, IN: Intercepted pass, R: Scramble)

```r
plays_filtered <- plays_raw_data %>%
  filter(!is.na(passResult))

ggplot(plays_filtered, aes(x = passResult)) +
  geom_bar(fill = "steelblue") +
  labs(
    title = "Distribution of Pass Results",
    x = "Pass Result",
    y = "Count"
  ) +
  theme_minimal()
```

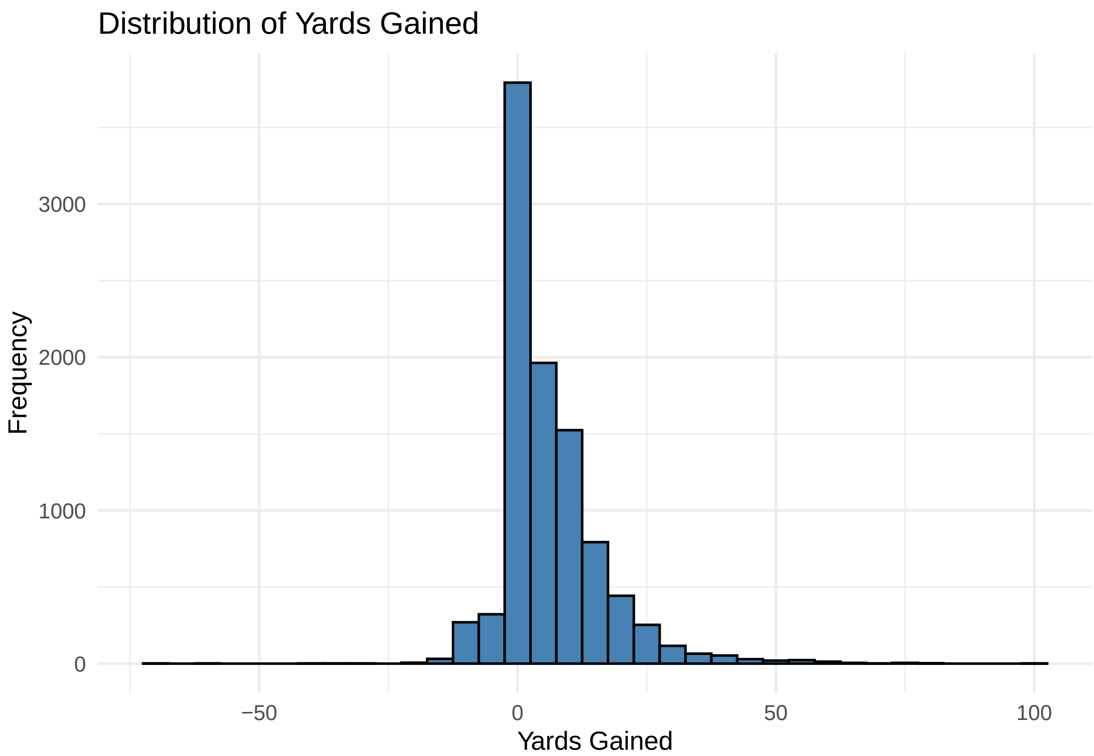


The most frequent pass result is C (completed pass). This makes sense as a lot of the time the quarterback will complete his pass to a receiver. The second most frequent category is I (incomplete pass), which is also expected. After that, the next most frequent categories are in order as follows: S (quarterback sack), R (scramble–quarterback improvised run), and IN (intercepted pass).

yardsGained (Quantitative):

```
ggplot(plays_filtered, aes(x = yardsGained)) +
  geom_histogram(binwidth = 5, fill = "steelblue", color = "black") +
  labs(
    title = "Distribution of Yards Gained",
    x = "Yards Gained",
    y = "Frequency"
  ) +
```

```
  theme_minimal()
```

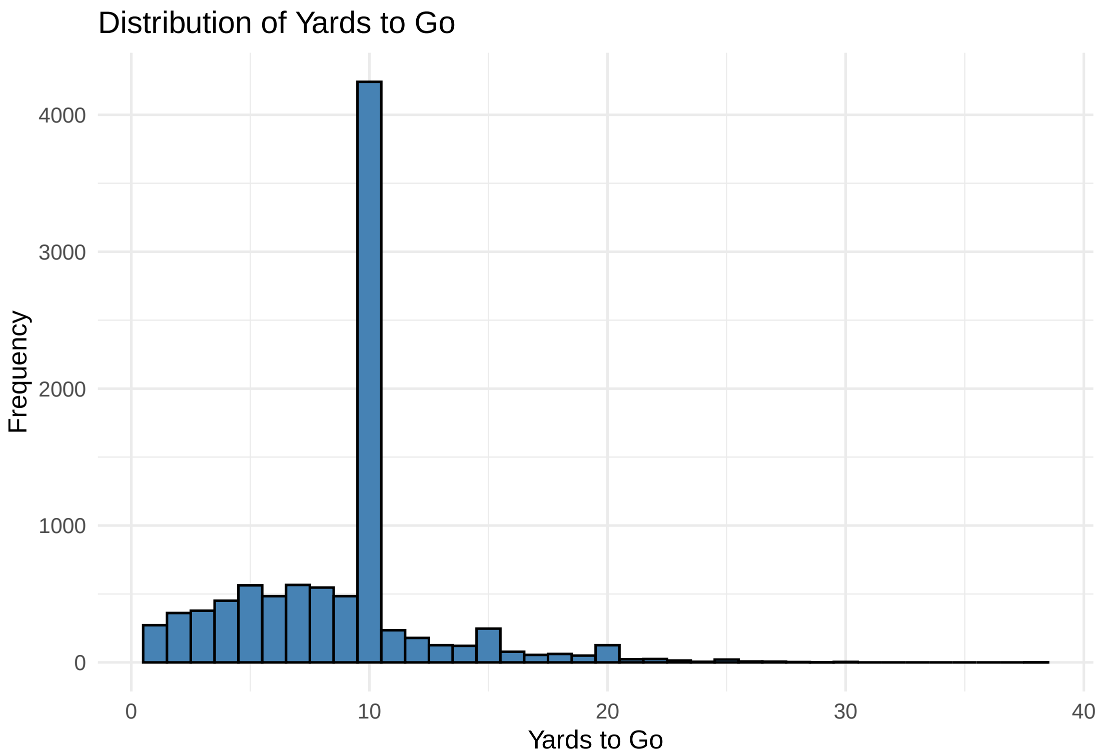


Yards gained looks like it is slightly normally distributed and is right skewed. The overwhelming majority of plays result in 0 yards gained according to the graphic. This makes sense as all incomplete passes result in 0 yards gained, assuming no penalties.

yardsToGo (Quantitative):

```
ggplot(plays_filtered, aes(x = yardsToGo)) +
  geom_histogram(binwidth = 1, fill = "steelblue", color = "black") +
  labs(
    title = "Distribution of Yards to Go",
    x = "Yards to Go",
    y = "Frequency"
```

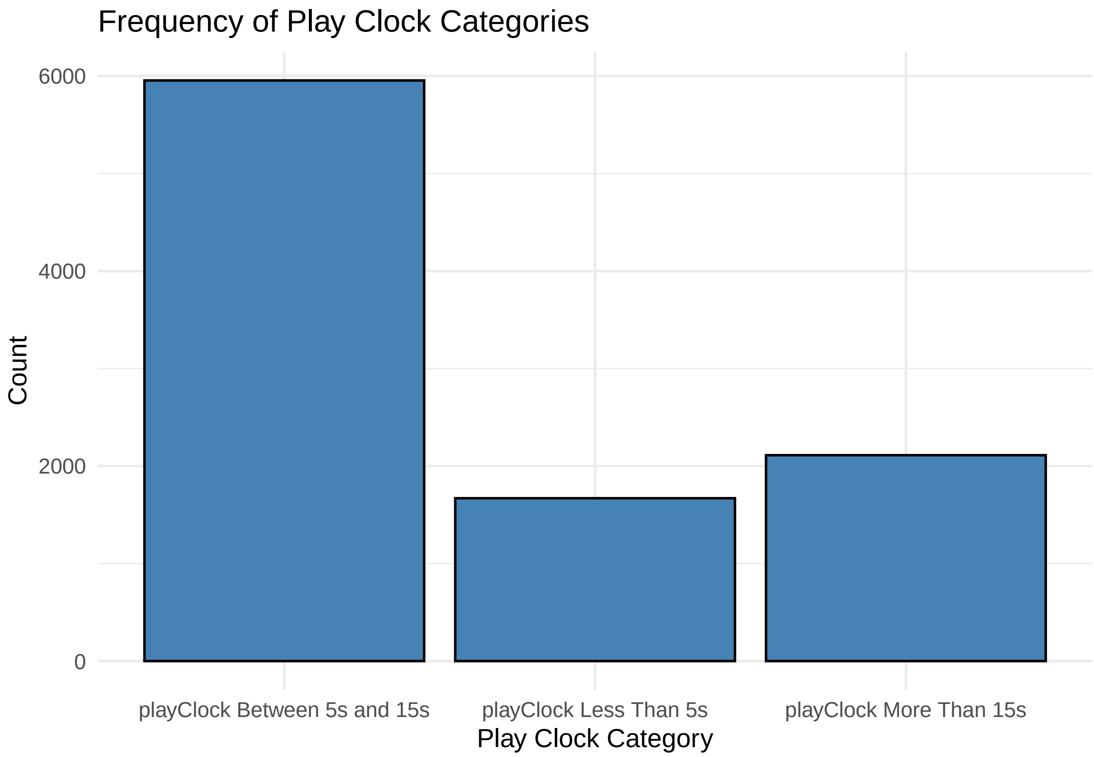
```
) +
  theme_minimal()
```



Yards to Go seems to be slightly normally distributed with a significant outlier with the vast majority of plays being at 10 yards to go. This makes sense as every play defaults to 10 yards to go for a first down. The distribution is slightly right skewed with more plays with less than 10 yards to go.

playClockAtSnap (Quantitative): For the play clock at snap, we split the quantitative variable into 3 buckets: High (>=15 seconds), Medium (5–15 seconds), and Low (<5 seconds). These thresholds were chosen to reflect typical game scenarios: early snaps, moderate decision-making time, and rushed snaps. In this case, we created a new variable called playClockCategory which is a categorical variable that has counts of plays in each of the 3 categories. Below is the distribution:

```
plays_raw_data <- plays_raw_data %>%
  mutate(playClockCategory =
           case_when(playClockAtSnap >= 15 ~ "playClock More Than 15s",
                      playClockAtSnap >= 5 &
                      playClockAtSnap < 15 ~ "playClock Between 5s and 15s",
                      playClockAtSnap < 5 ~ "playClock Less Than 5s",
    )
  )

plays_filtered <- plays_raw_data %>%
  filter(!is.na(playClockCategory), !is.na(passResult))

ggplot(plays_filtered, aes(x = playClockCategory)) +
  geom_bar(fill = "steelblue", color = "black") +
  labs(
    title = "Frequency of Play Clock Categories",
    x = "Play Clock Category",
    y = "Count"
  ) +
  theme_minimal()
```



Based on the above graph, we see that the vast majority of the time the ball is snapped in the moderate play clock zone with between 5 and 15 seconds left on the play clock. This makes sense as most of the time teams want to make sure they have time to huddle up, relay the play to everyone and get set before snapping the ball. The second most frequent category is when the play clock is greater than 15 seconds. This category expresses when teams may be in a hurry-up offense where they might need to get down the field quicker or just want to get the defense on their heels. The least frequent category is when the play clock is less than 5 seconds. This category includes plays where teams may take a little longer to get set. This can be for a variety of reasons; teams may be sending players in motion before the snap or the quarterback may be making audibles or adjustments at the line of scrimmage. The significant parts that are relevant in the analysis below will be the more extreme buckets of less than 5 seconds and more than 15 seconds.

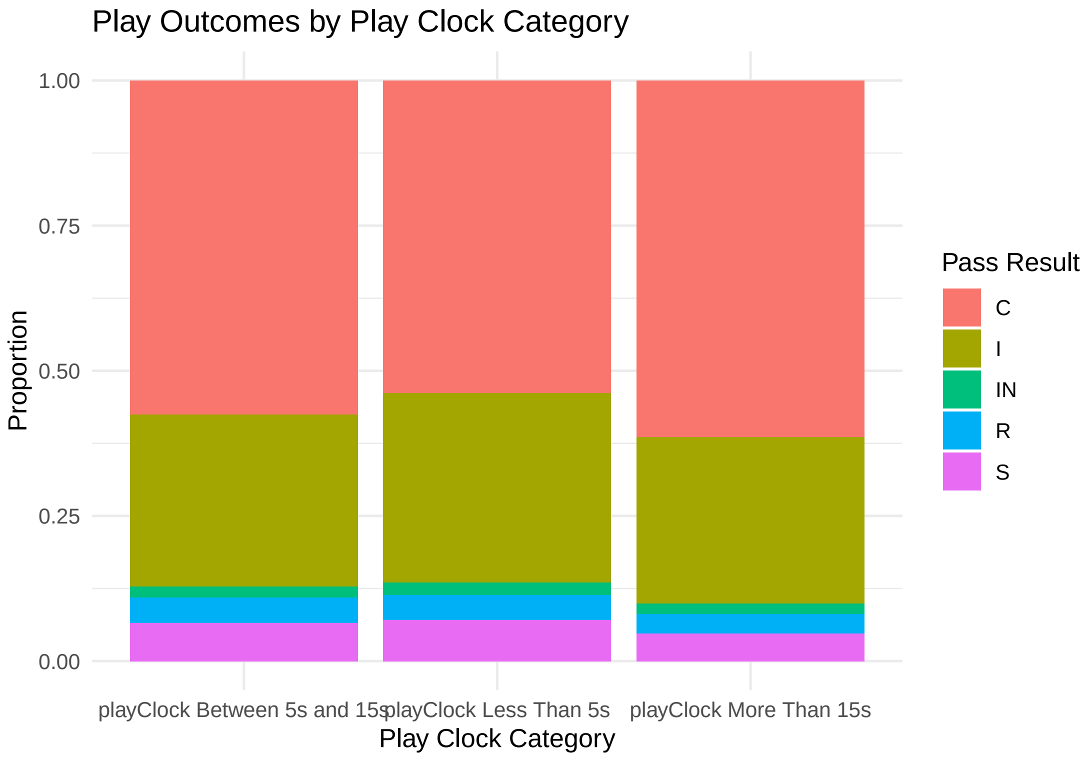
2.2.2 Relationships Between Variables

Before building predictive models, it's important to investigate potential relationships between variables that could impact play outcomes. In this section, we focus on the playClockAtSnap variable, which records the play clock value at the time of the snap, and explore its relationship with pass results and yards gained during a play.

The play clock is a critical element in football, as it dictates when a play must begin. A snap taken with a lower play clock may suggest hurried decision making, potentially leading to rushed plays or errors.

Below are some visuals and descriptions exploring the relationships between variables:

```r
ggplot(plays_filtered, aes(x = playClockCategory, fill = passResult)) +
  geom_bar(position = "fill") +
  labs(
    title = "Play Outcomes by Play Clock Category",
    x = "Play Clock Category",
    y = "Proportion",
    fill = "Pass Result"
  ) +
  theme_minimal()
```



We can see that when the playClock is less than or equal to 5s (lower), there is a more varied distribution of pass results, including incomplete passes, sacks, and interceptions. This suggests that rushed plays may increase the likelihood of unfavorable outcomes. On the other hand (higher), it looks like high play clock snaps tend to result in more complete passes, potentially indicating that the offense had more time to organize and execute a well prepared play.

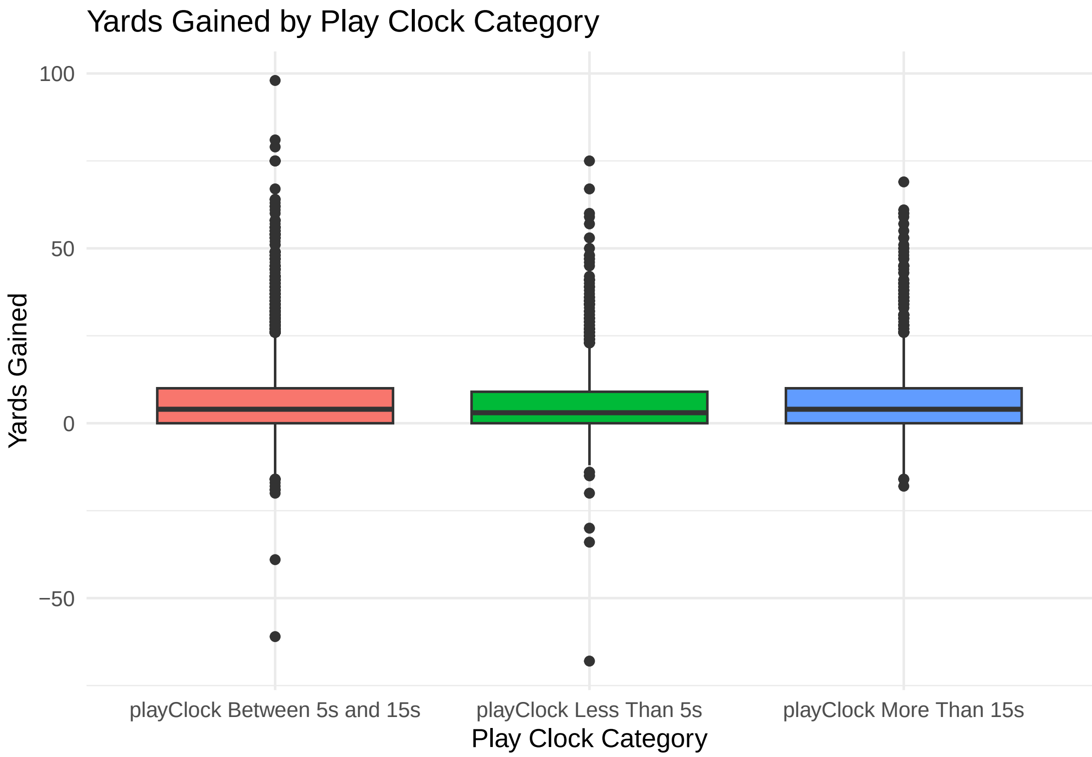
```
contingency_table <- table(plays_filtered$playClockCategory,
                           plays_filtered$passResult)


chi_sq_test <- chisq.test(contingency_table)
print(chi_sq_test)
```

```
##
```

```
##  Pearson's Chi-squared test
##
## data:  contingency_table
## X-squared = 29.539, df = 8, p-value = 0.0002549
```

And we can see here, the playClock is indeed statistically significant with a value of $0.0002549 < 0.05$. The next step would be to find a model to potentially predict results.

```r
ggplot(plays_filtered, aes(x = playClockCategory, y = yardsGained,
                           fill = playClockCategory)) +
  geom_boxplot() +
  labs(
    title = "Yards Gained by Play Clock Category",
    x = "Play Clock Category",
    y = "Yards Gained"
  ) +
  theme_minimal() +
  theme(legend.position = "none")
```

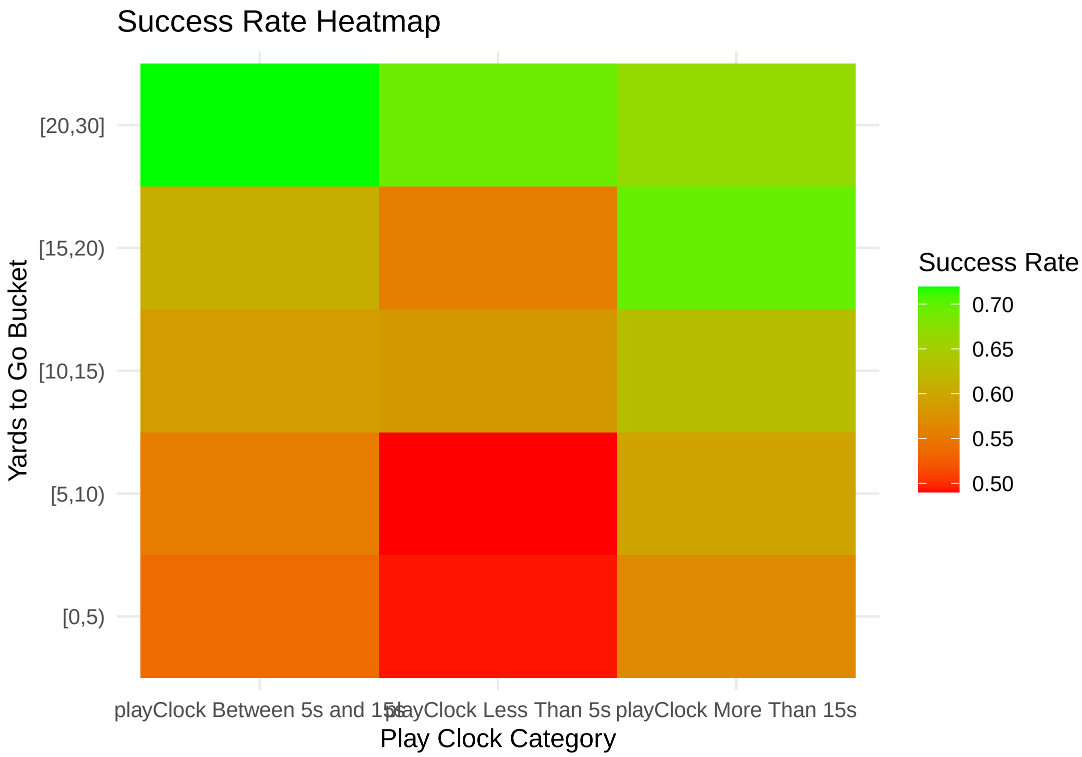


We also investigated the relationship that the play block at snap might have with the yards gained that play. However, as we can see the above visualization, there is no clear correlation between the two.

Further exploration of how the play clock affects other variables yields the following heat map. This heat map illustrates the play success rate based on the play clock and yards to go during that play.

```
heatmap_data <- plays_filtered %>%
  filter(!is.na(playClockCategory), !is.na(yardsToGo), yardsToGo >= 0, yardsToGo <
  mutate(
    yardsToGoBucket = cut(
      yardsToGo, breaks = c(0, 5, 10, 15, 20, 30),
      right = FALSE, include.lowest = TRUE
    )
```

```
  ) %>%
  group_by(playClockCategory, yardsToGoBucket) %>%
  summarize(success_rate = mean(passResult == "C", na.rm = TRUE), .groups = "drop"

ggplot(heatmap_data, aes(x = playClockCategory, y = yardsToGoBucket, fill = succes
  geom_tile() +
  labs(
    title = "Success Rate Heatmap",
    x = "Play Clock Category",
    y = "Yards to Go Bucket",
    fill = "Success Rate"
  ) +
  theme_minimal() +
  scale_fill_gradient(low = "red", high = "green")
```



The heatmap above shows the success rate of plays based on whether the pass was complete (passResult == "C"), categorized by play clock and yards-to-go buckets. Notably, the highest success rate occurs when the play clock exceeds 15 seconds, especially in long-yardage situations (20 to 30 yards), where the success rate is over 70%. This suggests that more time on the clock leads to better play execution, even when facing tougher distances.

Interestingly, short-yardage situations (0 to 10 yards) do not yield higher success rates. In fact, success rates in the [0, 5] and [5, 10] yards buckets are lower than longer-yardage plays, indicating that defensive anticipation may play a role. Additionally, when the play clock is less than 5 seconds, success rates drop across all yardage buckets, likely due to rushed decision-making by the offense. Overall, this heatmap shows a positive relationship between longer play clock times and higher play success, particularly in longer-yardage situations.

3 Modeling

Here for the predictive model I used a multinomial regression model because the prediction outcome is nominal with multiple categories which is perfect for this kind of model. The code block below makes the model and puts the predicted probabilities of the model back into the filtered plays dataframe as its own column.

```
library(nnet)

plays_filtered <- plays_filtered %>%
  mutate(
    playClockCategory = factor(playClockCategory),
    passResult = factor(passResult)
  ) |>
  filter(!is.na(passResult), !is.na(playClockAtSnap))

multinom_model <- multinom(passResult ~ playClockAtSnap, data = plays_filtered)
```

```
## # weights:  15 (8 variable)
## initial  value 15667.878078
## iter  10 value 10546.466417
## iter  20 value 10303.646910
## final  value 10303.627223
## converged
```

```
summary(multinom_model)
```

```
## Call:
```

```
## multinom(formula = passResult ~ playClockAtSnap, data = plays_filtered)
##
## Coefficients:
##    (Intercept) playClockAtSnap
## I   -0.5919611    -0.006360061
## IN  -3.2412784    -0.013173404
## R   -2.4540657    -0.018526994
## S   -1.9070770    -0.031906983
##
## Std. Errors:
##    (Intercept) playClockAtSnap
## I   0.04296130     0.003490795
## IN  0.13745234     0.011541819
## R   0.09674842     0.008267758
## S   0.07957039     0.007104210
##
## Residual Deviance: 20607.25
## AIC: 20623.25
```

```r
predictions <- predict(multinom_model, type = "probs")


nrow(plays_filtered)
```

```
## [1] 9735
```

```r
nrow(predictions)
```

```
## [1] 9735
```

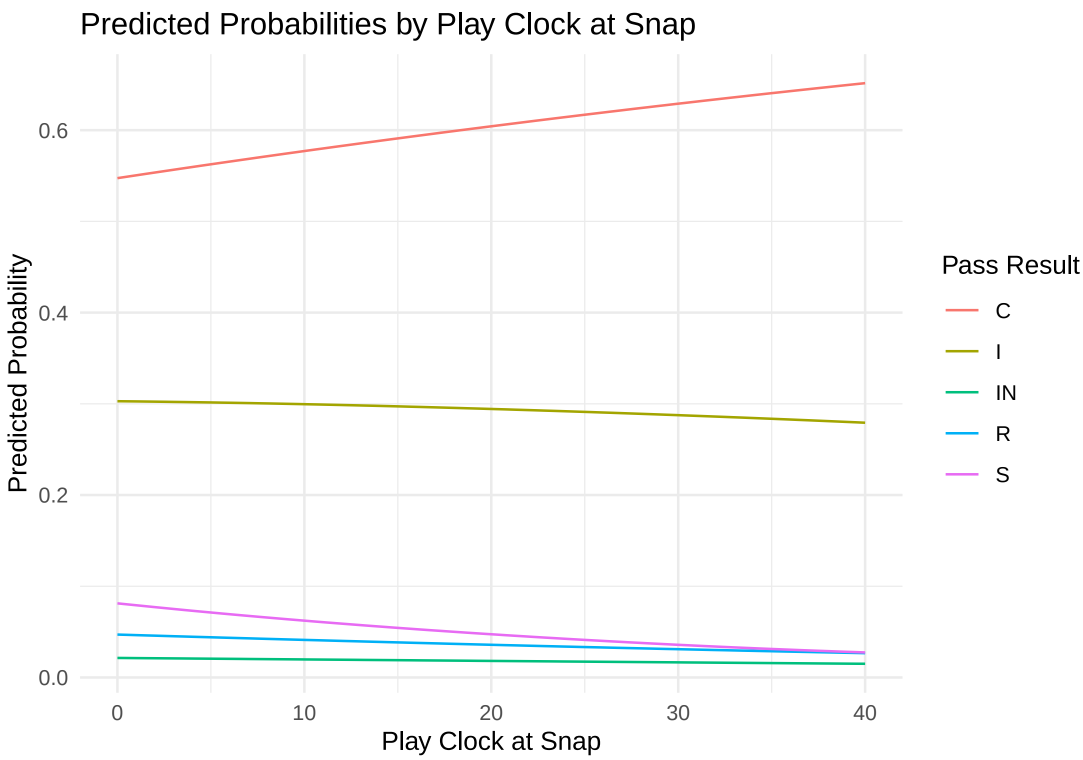
```r
plays_filtered <- cbind(plays_filtered, predictions)
```

Here I plotted the predicted probabilities to visualize the model. As we can see, as the play clock at snap increases, the probability of completing a pass also increases from the prediction of the model. This is reinforcing what we saw before on the exploratory data histogram of more completions when the play clock is higher. We can also see that the probabilities of the other categories are decreasing which is also parallel to what we saw before we fitted the model. Next we should discuss that this predictor may not be the best predictor and model for pass results due to the low explanation of variance from the model.

```r
predicted_probs_df <- plays_filtered %>%
  select(playClockAtSnap, passResult, C, I, IN, R, S) %>%
  pivot_longer(
    cols = C:S,
    names_to = "Predicted_Class",
    values_to = "Probability"
  )

ggplot(predicted_probs_df, aes(x = playClockAtSnap, y = Probability, color =
                                 Predicted_Class)) +
  geom_line(stat = "smooth", method = "loess") +
  labs(
    title = "Predicted Probabilities by Play Clock at Snap",
    x = "Play Clock at Snap",
    y = "Predicted Probability",
    color = "Pass Result"
```

```
  ) +
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



4 Discussion