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# Freezing the Kicker

## Introduction

Although kickers in football contribute many points per game, you often hear that kickers are not real football players. It is easy to assume that they should just make a kick regardless of the situation. But it is not unusual for a kicker to attempt a game-winning field goal with just a few seconds left on the game clock. At times like these, the opposing team's coach can make the decision to ice the kicker by calling a timeout. The theory behind icing the kicker is that the timeout will disrupt the kicker's routine and lower the odds of his making the field goal. The popular belief in the National Football League (NFL) is that coaches should freeze the opposing kicker to lower their chances of making a field goal.

To evaluate whether icing a kicker affects his odds of making a field goal, we analyzed field goals from the NFL between the years 2009 and 2015. We looked at whether a timeout before a kicker attempted a field goal affected his odds of success. We also looked at how the likelihood of making a field goal changed as the distance of the attempt increased. We hoped that the answers to these questions would allow us to answer the bigger question: Is it worth freezing the kicker?

**Methods**

The main question we were trying to answer was whether freezing the kicker changes the odds of successfully making a field goal. We first looked at the distance at which the field goal was attempted to see if it had an impact on a kicker's performance. We looked at the distances between 18 yards and 60 yards and fit a logistic regression model to it to see if there was a relationship between the distance of the field goal attempt and the odds of success. The table below shows the results of a Wald test. A Wald analysis tests whether a variable such as "FieldGoalDistance" is related to an outcome, such as whether a field goal attempt was successful or not successful.

```
#>                    Coef    S.E.   Wald Z Pr(>|Z|)
#>  Intercept          5.7204 0.1767  32.38 <0.0001
#>  FieldGoalDistance -0.1007 0.0040 -25.24 <0.0001
```

The coefficient of "FieldGoalDistance" is -0.1007, which is the slope of the log odds of making a field goal at different distances. The negative slope means that as the distance of the field goal attempt increases, the kicker has lower log odds of making the field goal. The P value associated with this coefficient is less than .05, implying that there is a significant relationship between a kicker's odds of making a field goal and the distance the field goal attempt.

For the next analysis, we repeated the previous analysis but only used field goal attempts for distances between 29 and 46 yards. These values correspond to the interquartile range (IQR). We believe that the IQR is probably a better representation of the relationship between a kicker's success and the distance of the attempt because at 18 yards, most of the field goals will be made, and at 60 yards, most of the field goals will be missed. The results of this analysis are shown below.

```
summary(FG.lrm.dist)
#>              Effects              Response : FieldGoalGood
#>
#>  Factor            Low High Diff. Effect   S.E.     Lower 0.95 Upper 0.95
#>  FieldGoalDistance 29  46   17    -1.71110 0.067788 -1.84400   -1.57820
#>   Odds Ratio       29  46   17     0.18067       NA  0.15819    0.20634
summary(FieldGoalDistance, na.rm = TRUE)
#>    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
#>   18.00   29.00   38.00   37.31   46.00   71.00       4
min(FieldGoalDistance, na.rm = TRUE)
```

The odds ratio is calculated by the probability of success over probability of failure at 29 yards, divided by the probability of success over the probability of failure at 40 yards. The odds ratio tells us that at 46 yards, the odds of a successful field goal are 0.18 times the odds of a successful field goal at 29 yards. Another way to think of this is that at 46 yards, the odds of missing a field goal are 5.5 times greater than the odds of missing a field goal at 29 yards. (The reciprocal of an odds ratio of 0.18 is 5.5.)

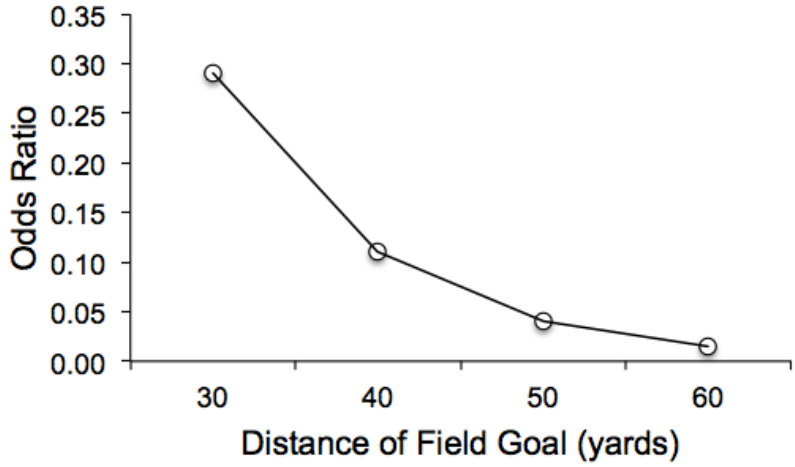
For the next analysis, we used the full range of distances, not just those of the IQR. We looked at how the odds of making a field goal changed as the distance of the attempt increased by 10 yards. We compared the odds of a kicker making a field goal at 30, 40, 50, and 60 yards to their odds of making a field goal at 18 yards, the baseline. The table below shows the results of these analyses.

```
#>              Effects              Response : FieldGoalGood
#>
#>  Factor            Low High Diff. Effect   S.E.    Lower 0.95 Upper 0.95
#>  FieldGoalDistance 18  30   12    -1.20780 0.04785 -1.30160   -1.11410
#>   Odds Ratio       18  30   12     0.29884      NA  0.27209    0.32823
summary(FG.lrm.dist, FieldGoalDistance = c(min(FieldGoalDistance, na.rm = TRU
E),
    40))
#>              Effects              Response : FieldGoalGood
#>
#>  Factor            Low High Diff. Effect   S.E.     Lower 0.95 Upper 0.95
#>  FieldGoalDistance 18  40   22    -2.21440 0.087725 -2.386300  -2.04240
#>   Odds Ratio       18  40   22     0.10922       NA  0.091969   0.12971
summary(FG.lrm.dist, FieldGoalDistance = c(min(FieldGoalDistance, na.rm = TRU
E),
    50))
#>              Effects              Response : FieldGoalGood
#>
#>  Factor            Low High Diff. Effect    S.E.   Lower 0.95 Upper 0.95
#>  FieldGoalDistance 18  50   32    -3.220900 0.1276 -3.471000  -2.970800
#>   Odds Ratio       18  50   32     0.039919     NA  0.031086   0.051262
summary(FG.lrm.dist, FieldGoalDistance = c(min(FieldGoalDistance, na.rm = TRU
E),
    60))
#>              Effects              Response : FieldGoalGood
#>
#>  Factor            Low High Diff. Effect   S.E.    Lower 0.95 Upper 0.95
#>  FieldGoalDistance 18  60   42    -4.22740 0.16748 -4.555700  -3.899200
#>   Odds Ratio       18  60   42     0.01459      NA  0.010507   0.020258
```

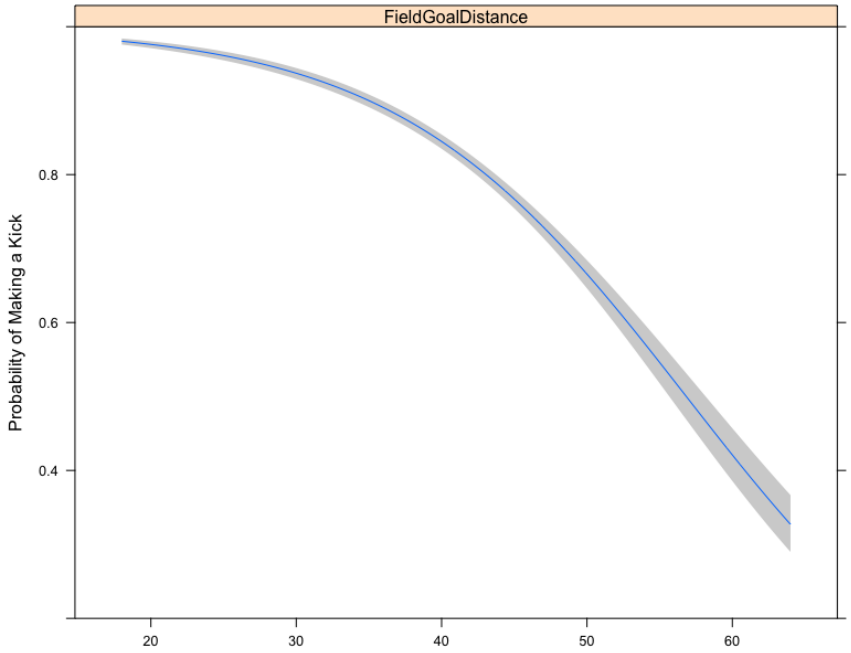
We can now compare the odds of making a field goal when the distance was 18 and 30 yards, 18 and 40 yards, 18 and 50 yards, and 18 and 60 yards. The analysis showed that the odds of making a field goal at 30 yards are 0.29 times the odds of making a field goal at 18 yards. Instead of thinking in terms of success, it is sometimes easier to think in terms of failure: The odds of missing a field goal at 30 yards are 3.45 times greater than the odds of missing a field goal at 18 yards. (The reciprocal of an odds ratio of 0.29 is 3.45.)

The odds ratio for the 18 yards to 40 yards comparison is 0.109. This tells us that at 40 yards, the odds of a successful field goal are 0.11 times the odds of a successful field goal at 18 yards. At 50 yards, the odds ratio is 0.0399. This means that at 50 yards the odds of a successful field goal are 0.0399 times the odds of a successful field goal at 18 yards. At 60 yards, the odds of a successful field goal are 0.015 times the odds of a successful field goal at 18 yards.

If you graph “Odds Ratio” versus “Distance of Field Goal” from the previous analysis, you can see that the odds ratio decreases as the distance of the field goal attempt increases.




The changes in the odds ratio is consist with the relationship between the probability of making a field goal and the distance of the attempt. Using the data from all of the kickers, we can see their probability of making a kick from various distances, which is shown in the graph below. Increasing the distance of the attempt lowers the probability of making the field goal.



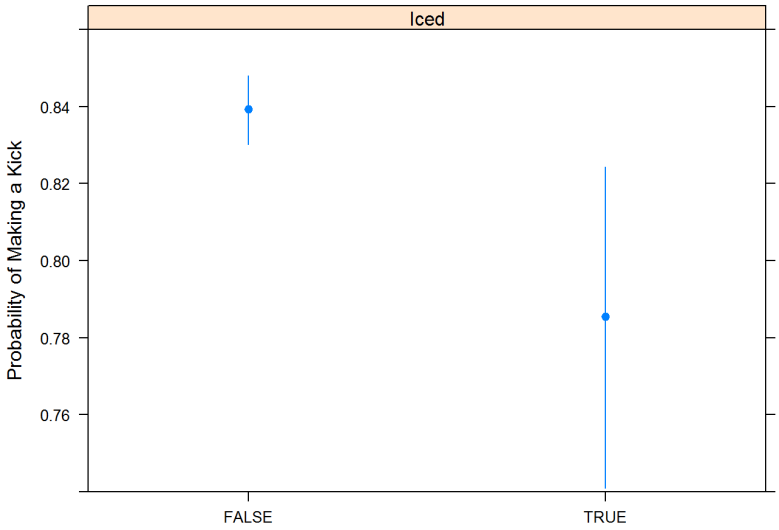
Based on our data, the distance at which a field goal is attempted has an impact on a kicker's success. After looking at the impact of distance on the odds and probability of making a field goal, we then looked at how being iced affects the odds of making a field goal. Icing is the process of taking a timeout just before a field goal attempt to disrupt a kicker's routine and lower his chances of making a field goal.

We began by analyzing the results of every kicker in our dataset who has been iced. We wanted to see if icing affected the odds of making a field goal. The results of our analysis are shown below.

```
#>
#>             Coef    S.E.   Wald Z Pr(>|Z|)
#>  Intercept  1.6533 0.0337 49.01  <0.0001
#>  Iced=Yes  -0.3552 0.1306 -2.72  0.0065
#>
anova(FG.lrm.Iced)
#>                 Wald Statistics          Response: FieldGoalGood
#>
#>  Factor     Chi-Square d.f. P
#>  Iced       7.4        1    0.0065
#>  TOTAL      7.4        1    0.0065
summary(FG.lrm.Iced, Iced = c("No"))
#>              Effects              Response : FieldGoalGood
#>
#>  Factor        Low High Diff. Effect   S.E.    Lower 0.95 Upper 0.95
#>  Iced - Yes:No 1   2    NA    -0.35520 0.13058 -0.61113   -0.099273
#>   Odds Ratio   1   2    NA     0.70103      NA  0.54274    0.905500
summary(FG.lrm.Iced, Iced = c("Yes"))
```

The coefficient of "Iced=Yes" is -0.3552, which is the slope of the log odds of making a field goal as it relates to being iced. The negative slope means that icing a kicker has a negative impact on his log odds of making a field goal. The P value associated with this coefficient is less than .05, implying that there is a significant relationship between a kicker's odds of making a field goal and being iced.

The graph below shows the probability of making a field goal depending on whether the kicker was iced. "TRUE" means that the kicker was iced and "FALSE" means that the kicker was not iced. The vertical lines show the confidence intervals.




It looks like being iced does have an impact on the kickers' performance. Even with the confidence interval being fairly large when kickers were iced, we can still infer that icing does affect a kicker's success.

We then filtered our data to use only kickers who have been iced more than 4 times and have kicked more than 20 field goals. The results of this analysis are shown in the table below.

```
#>            Coef    S.E.   Wald Z Pr(>|Z|)
#>  Intercept  1.6798 0.0382 44.03  <0.0001
#>  Iced=Yes  -0.3711 0.1429 -2.60  0.0094
#>
anova(FG.lrm.Iced)
#>                 Wald Statistics          Response: FieldGoalGood
#>
#>  Factor     Chi-Square d.f. P
#>  Iced       6.74       1    0.0094
#>  TOTAL      6.74       1    0.0094
summary(FG.lrm.Iced, Iced = c("No"))
#>              Effects              Response : FieldGoalGood
#>
#>  Factor        Low High Diff. Effect   S.E.    Lower 0.95 Upper 0.95
#>  Iced - Yes:No 1   2    NA    -0.37105 0.14288 -0.65108   -0.091021
#>   Odds Ratio   1   2    NA     0.69001      NA  0.52148    0.913000
summary(FG.lrm.Iced, Iced = c("Yes"))
#>              Effects              Response : FieldGoalGood
#>
#>  Factor        Low High Diff. Effect  S.E.    Lower 0.95 Upper 0.95
#>  Iced - No:Yes 2   1    NA    0.37105 0.14288 0.091021   0.65108
#>   Odds Ratio   2   1    NA    1.44930      NA 1.095300   1.91760
plot(Predict(FG.lrm.Iced, fun = plogis), ylab = "Probability of Making a Kick
")
```

The P value for “Iced-Yes” is 0.0094. This implies that being iced is a significant factor in a kicker’s success. The log odds associated with this P value is -0.3711. This negative value means that the log odds of success decrease when a kicker is iced.

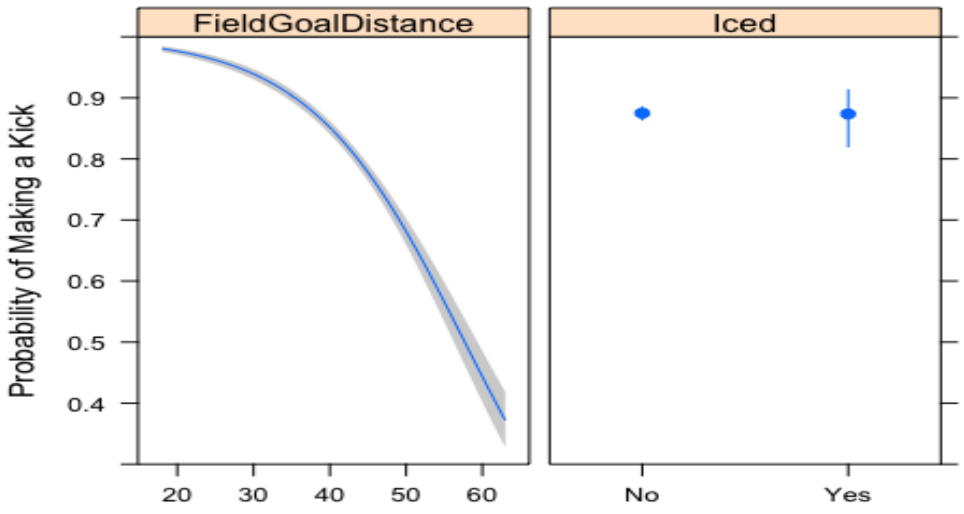
For our last analysis, we put both factors (“FieldGoalDistance” and “Iced=Yes”) in a logistic regression model to determine whether these factors interact to affect the odds of making a field goal. The results of this analysis are shown below.

```
#>                                  Coef    S.E.   Wald Z Pr(>|Z|)
#>  Intercept                        5.6971 0.2058  27.69 <0.0001
#>  Iced=Yes                         0.5832 0.9052   0.64 0.5194
#>  FieldGoalDistance               -0.0987 0.0046 -21.32 <0.0001
#>  Iced=Yes * FieldGoalDistance    -0.0157 0.0195  -0.80 0.4212
```

```
#>  Factor           Low High Diff. Effect    S.E.     Lower 0.95 Upper 0.95
#>  FieldGoalDistance 29  46   17    -1.678700 0.078742 -1.83300   -1.52440
#>   Odds Ratio       29  46   17     0.186620       NA  0.15993    0.21776
#>  Iced - Yes:No      1   2   NA    -0.011972 0.217400 -0.43808    0.41413
#>   Odds Ratio        1   2   NA     0.988100       NA  0.64528    1.51310
```

To determine if the factors relate to kicking success we look at the P values for each factor and their interaction. Since the P value for "Iced=Yes" (0.5194) is above .05 and the P value for "FieldGoalDistance" is below 0.05, we can infer than icing does not make a significant contribution to whether a kicker makes a field goal, but the distance of the attempt does. The P value for the interaction between "FieldGoalDistance" and "Iced=Yes" (0.4212) is greater than .05, which means that the combination of these factors does not contribute significantly to whether a field goal is made or not.

This analysis suggests that icing does not have an impact on a kicker's odds of success. In our previous analysis, icing seemed to have an effect on the kicker's success. This difference might have occurred because kickers can be frozen for field goal attempts at any distance. It could be that a kicker is more likely to be frozen when the distance is farther away, which means that if they miss the field goal, it is because of the distance and not that they were iced. If we factor in distance, the probability of making a field goal is not affected by icing. This is shown in the graph below.



**Conclusion**

We conclude that icing does not have an impact on a kicker's performance, but the distance of the field goal attempt does. The greater the distance, the lower the odds of making a field goal. Initially, when we looked at how distance effects a kicker and receive the result that as a kicker moves farther away their probability of making the field goal decreases. Next, we see how icing effects a kicker and discover that icing does in fact have an impact. Finally, we looked at icing and field goal distance combined, we find that by looking at the P value that they are not interacting and conclude that distance has the main impact on whether a kicker makes or miss a field goal.

References:

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