

HW 4 Solutions

Your name here

```
library(mosaic)
library(RCurl)
url <- getURL("https://raw.githubusercontent.com/statsbylopez/StatsSports/master/Kickers.csv")
nfl.kick <- read.csv(text = url)
```

For this homework, we will be using data provided in the `nfl.kick` data set, as was done during class. Our goals will be to confirm our knowledge of logistic regression, our interpretations of slopes, as well as kicker-specific analysis.

Part I: Exploratory data analysis

1. Use R to find the **kicker** with the best percentage of successful field goals. Why might one argue that this specific kicker may not be the most accurate, even though he has the highest percentage?

```
library(RCurl)
library(mosaic)
url <- getURL("https://raw.githubusercontent.com/statsbylopez/StatsSports/master/Kickers.csv")
nfl.kick <- read.csv(text = url)
tally(Success ~ Kicker, data = nfl.kick, format = "proportion")
```

```
##      Kicker
## Success Akers Andersen Andrus Bailey Barth Bironas
##      0 0.19940476 0.11764706 0.60000000 0.10493827 0.15060241 0.14487633
##      1 0.80059524 0.88235294 0.40000000 0.89506173 0.84939759 0.85512367
##      Kicker
## Success Boswell Brien Brindza Brown Bryant Buehler
##      0 0.07692308 0.75000000 0.50000000 0.17827869 0.13961039 0.25000000
##      1 0.92307692 0.25000000 0.50000000 0.82172131 0.86038961 0.75000000
##      Kicker
## Success Bullock Carney Carpenter Catanzaro Coons Cortez
##      0 0.19354839 0.15107914 0.15175097 0.10606061 0.12500000 0.29411765
##      1 0.80645161 0.84892086 0.84824903 0.89393939 0.87500000 0.70588235
##      Kicker
## Success Coutu Crosby Cundiff Dawson Edinger Elam
##      0 1.00000000 0.19314642 0.22471910 0.14156627 0.26470588 0.15753425
##      1 0.00000000 0.80685358 0.77528090 0.85843373 0.73529412 0.84246575
##      Kicker
## Success Elling Feely Folk Forbath France Franks
##      0 1.00000000 0.15248227 0.19475655 0.15853659 0.22222222 0.18750000
##      1 0.00000000 0.84751773 0.80524345 0.84146341 0.77777778 0.81250000
##      Kicker
## Success Freese Gano Gostkowski Gould Graham Gramatica
##      0 0.57142857 0.20100503 0.12280702 0.14285714 0.14285714 0.23076923
##      1 0.42857143 0.79899497 0.87719298 0.85714286 0.85714286 0.76923077
##      Kicker
## Success Hall Hanson Hartley Hauschka Henery Hocker
##      0 0.17857143 0.15384615 0.16964286 0.12626263 0.18279570 0.28571429
```

```

##      1 0.82142857 0.84615385 0.83035714 0.87373737 0.81720430 0.71428571
##      Kicker
## Success   Hopkins Janikowski   Kaeding   Kasay   Koenen   Lambo
##      0 0.10344828 0.20059880 0.15151515 0.15137615 0.69230769 0.18750000
##      1 0.89655172 0.79940120 0.84848485 0.84862385 0.30769231 0.81250000
##      Kicker
## Success   Lindell   Longwell   Mare   McManus   Medlock   Mehlhaff
##      0 0.16194332 0.15591398 0.19512195 0.15517241 0.33333333 0.25000000
##      1 0.83805668 0.84408602 0.80487805 0.84482759 0.66666667 0.75000000
##      Kicker
## Success   Murray   Myers   Nedney   Novak   Nugent   Parkey
##      0 0.16666667 0.13333333 0.13422819 0.18023256 0.18819188 0.12500000
##      1 0.83333333 0.86666667 0.86577181 0.81976744 0.81180812 0.87500000
##      Kicker
## Success   Peterson   Pettrey   Potter   Prater   Rackers   Rayner
##      0 0.08000000 0.50000000 0.25000000 0.17226891 0.16101695 0.27777778
##      1 0.92000000 0.50000000 0.75000000 0.82773109 0.83898305 0.72222222
##      Kicker
## Success   Reed   Santos   Schmitt   Scifres   Scobee   Stitser
##      0 0.16304348 0.16666667 0.33333333 0.00000000 0.19927536 0.12500000
##      1 0.83695652 0.83333333 0.66666667 1.00000000 0.80072464 0.87500000
##      Kicker
## Success   Stover   Sturgis   Succop   Suisham   Tucker   Tynes
##      0 0.13071895 0.21505376 0.17553191 0.16791045 0.11538462 0.18777293
##      1 0.86928105 0.78494624 0.82446809 0.83208955 0.88461538 0.81222707
##      Kicker
## Success Vanderjagt Vinatieri   Walsh   Wilkins   Zuerlein
##      0 0.17777778 0.13864307 0.14965986 0.17000000 0.21848739
##      1 0.82222222 0.86135693 0.85034014 0.83000000 0.78151261

```

```
tally(Success ~ Kicker, data = nfl.kick)
```

```

##      Kicker
## Success Akers Andersen Andrus Bailey Barth Bironas Boswell Brien Brindza
##      0 67 6 3 17 25 41 3 3 6
##      1 269 45 2 145 141 242 36 1 6
##      Kicker
## Success Brown Bryant Buehler Bullock Carney Carpenter Catanzaro Coons
##      0 87 43 8 18 21 39 7 4
##      1 401 265 24 75 118 218 59 28
##      Kicker
## Success Cortez Coutu Crosby Cundiff Dawson Edinger Elam Elling Feely Folk
##      0 5 1 62 40 47 9 23 1 43 52
##      1 12 0 259 138 285 25 123 0 239 215
##      Kicker
## Success Forbath France Franks Freese Gano Gostkowski Gould Graham
##      0 13 2 3 4 40 42 47 37
##      1 69 7 13 3 159 300 282 222
##      Kicker
## Success Gramatica Hall Hanson Hartley Hauschka Henery Hocker Hopkins
##      0 6 5 34 19 25 17 4 3
##      1 20 23 187 93 173 76 10 26
##      Kicker
## Success Janikowski Kaeding Kasay Koenen Lambo Lindell Longwell Mare

```

```

##      0      67      30      33      9      6      40      29      40
##      1     267     168     185      4     26     207     157     165
##      Kicker
## Success McManus Medlock Mehlhaff Murray Myers Nedney Novak Nugent Parkey
##      0      9      4      1      4      4      20      31      51      5
##      1     49      8      3     20     26     129     141     220     35
##      Kicker
## Success Peterson Pettrey Potter Prater Rackers Rayner Reed Santos Schmitt
##      0      2      2      1     41     38     25     30     12      1
##      1     23      2      3    197    198     65    154     60      2
##      Kicker
## Success Scifres Scobee Stitser Stover Sturgis Succop Suisham Tucker Tynes
##      0      0     55      1     20     20     33     45     18     43
##      1      1    221      7    133     73    155    223    138    186
##      Kicker
## Success Vanderjagt Vinatieri Walsh Wilkins Zuerlein
##      0      8      47     22     17     26
##      1     37     292    125     83     93

```

```
tally(Success ~ Team, data = nfl.kick, format = "proportion")
```

```

##      Team
## Success      ARI      ATL      BAL      BUF      CAR      CHI
##      0 0.1485714 0.1560694 0.1460396 0.1522388 0.1622419 0.1536232
##      1 0.8514286 0.8439306 0.8539604 0.8477612 0.8377581 0.8463768
##      Team
## Success      CIN      CLE      DAL      DEN      DET      GB
##      0 0.1618497 0.1529052 0.1783626 0.1555556 0.1753846 0.2036554
##      1 0.8381503 0.8470948 0.8216374 0.8444444 0.8246154 0.7963446
##      Team
## Success      HOU      IND      JAC      KC      MIA      MIN
##      0 0.1857923 0.1340782 0.1856678 0.2023810 0.1970588 0.1558824
##      1 0.8142077 0.8659218 0.8143322 0.7976190 0.8029412 0.8441176
##      Team
## Success      NE      NO      NYG      NYJ      OAK      PHI
##      0 0.1250000 0.2056075 0.1412742 0.1830601 0.2005988 0.1721311
##      1 0.8750000 0.7943925 0.8587258 0.8169399 0.7994012 0.8278689
##      Team
## Success      PIT      SD      SEA      SF      STL      TB
##      0 0.1466667 0.1468927 0.1389646 0.1639785 0.1902017 0.1945289
##      1 0.8533333 0.8531073 0.8610354 0.8360215 0.8097983 0.8054711
##      Team
## Success      TEN      WAS
##      0 0.1433022 0.2111437
##      1 0.8566978 0.7888563

```

```
tally(Grass ~ Team, data = nfl.kick, format = "proportion")
```

```

##      Team
## Grass      ARI      ATL      BAL      BUF      CAR      CHI
## TRUE  0.7428571 0.3005780 0.3836634 0.2805970 0.7433628 0.7130435
## FALSE 0.2571429 0.6994220 0.6163366 0.7194030 0.2566372 0.2869565
##      Team

```

```

## Grass      CIN      CLE      DAL      DEN      DET      GB
##  TRUE  0.3034682  0.7553517  0.2777778  0.8750000  0.2584615  0.2845953
##  FALSE 0.6965318  0.2446483  0.7222222  0.1250000  0.7415385  0.7154047
##      Team
## Grass      HOU      IND      JAC      KC      MIA      MIN
##  TRUE  0.7841530  0.3631285  0.7719870  0.8422619  0.7588235  0.2617647
##  FALSE 0.2158470  0.6368715  0.2280130  0.1577381  0.2411765  0.7382353
##      Team
## Grass      NE      NO      NYG      NYJ      OAK      PHI
##  TRUE  0.2994792  0.3489097  0.2853186  0.2377049  0.8712575  0.7240437
##  FALSE 0.7005208  0.6510903  0.7146814  0.7622951  0.1287425  0.2759563
##      Team
## Grass      PIT      SD      SEA      SF      STL      TB
##  TRUE  0.7546667  0.8615819  0.2915531  0.7231183  0.2968300  0.7325228
##  FALSE 0.2453333  0.1384181  0.7084469  0.2768817  0.7031700  0.2674772
##      Team
## Grass      TEN      WAS
##  TRUE  0.8286604  0.6950147
##  FALSE 0.1713396  0.3049853

```

Scifres hit 100% of his field goals, but this is a silly measurement as he only attempted one field goal! Also, some kickers may take FGs from different distances.

2. Use R to find the **team** with the best percentage of successful field goals. Why might one argue that this team may not have had the best kickers even though they've posted the highest overall percentage?

New England hit the most FG's: because we don't know about distances and surfaces, they may not have the best kickers (for example, the Patriots could attempt shorter field goals)

3. Identify the teams that have kicked the highest percentage of their field goals on grass (recall: the **Grass** variable is a TRUE/FALSE indicator for whether or not each kick was kicked on a grass surface.).

Denver's attempted 87.5% of FGs on grass.

Part II: Logistic regression

4. There are several variables in this data set. Using the AIC criteria, identify the logistic regression model that is the best fit for our **Success** outcome.

```
fit1 <- glm(Success ~ Grass + ScoreDiff + Distance +
           GameMinute+Year, family = binomial(), data= nfl.kick)
```

```
fit2 <- glm(Success ~ Grass + Distance +
           Year, family = binomial(), data= nfl.kick)
```

```
AIC(fit1)
```

```
## [1] 8710.012
```

```
AIC(fit2)
```

```
## [1] 8706.263
```

I get the lowest AIC when using `Success`, `Distance` and `Year`, but answers can vary.

- Using your model from (4), interpret the coefficient for `Distance` as an odds ratio.

```
exp(-0.104)
```

```
## [1] 0.9012253
```

Field goals that are a yard longer have about 10% lower odds of success, given our logistic regression model that adjusts for field type and year.

- Odds ratios are multiplicative. That is, if the odds of a successful outcome are e^{β_1} given a one-unit increase in x_1 , the odds of a successful outcome are $e^{c*\beta_1}$ given a c -unit increase in x_1 . Given your model in (4) what are the odds of making a field goal that is 10 yards longer?

```
exp(10*-0.1047)
```

```
## [1] 0.3509891
```

Odds drop by about 65%.

- Using the model below, estimate the probability of a successful 40-yard field goal, kicked on a non-grass surface in 2015.

```
fit.3 <- glm(Success ~ Distance + Grass + Year, data = nfl.kick, family = "binomial")
summary(fit.3)
```

Answer:

```
df <- data.frame(Distance = 40, Grass = FALSE, Year = 2015)
predict(fit.3, df, type = "response")
```

About 88%

Part III: Expected points

- Use your answer to Question (7) to estimate the expected points of a 40-yard field goal, kicked on a non-grass surface in 2015.

$0.88 * 3 = 2.64$ expected points

- Kicker A hits the field goal in Question (8) while Kicker B misses it. How many expected points has Kicker A added to his team given this single kick? How about Kicker B?

Kicker A was worth 0.36 over expectation, while Kicker B was worth -2.64 points.

- It is straightforward to estimate the value of kickers using expected points.

First, we generate predicted probabilities for each field goal using `fit.3`. Next, we use that to estimate the expected points for each field goal (`predict.points`). Finally, we use the result of the field goal (`Success = 0` or a `1`) and the value of the kick (3 points) to get an expected points added (EPA) for each kicker on each kick.

```
nfl.kick <- mutate(nfl.kick, predict.Success = predict(fit.3, nfl.kick, type = "response"),
                  predict.points = 3*predict.Success,
                  EPA = Success*3 - predict.points)
```

The first row corresponds to a David Akers kick in 2005. What was the predicted success rate for Akers on this kick? What relative worth (in terms of EPA) did Akers provide on this kick?

```
nfl.kick[1,]
```

```
## Team Year GameMinute Kicker Distance ScoreDiff Grass Success
## 1 PHI 2005 3 Akers 49 0 FALSE 0
```

Akers missed the field goal, costing his team 1.86 points.

- One metric we may be interested in is the relative worth, in terms of total EPA, among all kickers in our data set. The `dplyr` function makes it simple.

```
options(dplyr.print_max = 1e9)
kick.summary <- nfl.kick %>%
  group_by(Kicker) %>%
  summarize(percent.success = mean(Success), total.kicks = length(EPA), total.EPA = sum(EPA)) %>%
  arrange(total.EPA)
kick.summary
```

The above function calculates kicker-specific percentages, each kicker's total number of kicks, and each kickers total EPA.

Since 2005, who has been worth the most (and least) total EPA to their teams?

Rob Bironas (37.2 points) and Billy Cundiff (-41.8 points) have been worth the most and the least.

- Interpret the R-squared calculated below. What does it suggest about the fraction of unexplained variability when it comes to kicker EPA?

```
xyplot(total.EPA ~ percent.success, data = filter(kick.summary, total.kicks >=50 ))
cor(total.EPA ~ percent.success, data = filter(kick.summary, total.kicks >=50 ))^2
```

About half of the variability in `total.EPA` can be explained by a linear association with success rate. In other words, about half of how we judge kickers comes down to factors besides success rate.

- Given your readings, are there any other variables that you would want to account for when measuring field goal success that aren't in the current data set? How may it effect the ranking of kickers in Question Question (12)?

Yes! Temperature: it's more difficult to kick in the cold/wind. This would increase rankings of kickers who tend to kick in the cold.