Lecture 5: Logistic regression & NFL kickers

Skidmore College

Preamble:

```
library(tidyverse)
nfl_kick <- read.csv("https://raw.githubusercontent.com/statsbylopez/StatsSport
head(nfl_kick)
```

```
##   Team Year GameMinute Kicker Distance ScoreDiff Grass Temp Success
## 1  PHI 2005          3  Akers       49         0 FALSE   72       0
## 2  PHI 2005         29  Akers       49        -7 FALSE   72       0
## 3  PHI 2005         51  Akers       44        -7 FALSE   72       1
## 4  PHI 2005         14  Akers       43        14  TRUE   82       0
## 5  PHI 2005         60  Akers       23         0  TRUE   75       1
## 6  PHI 2005         39  Akers       34        -3  TRUE   68       1
```

Warm-Ups 1/2

- Identify the longest field goal kicked by each kicker
- Identify the rate of successful field goals in each season

Warm ups 3/4

- Surfaces with Grass $==$ `FALSE` occur on turf. What is the rate of field goals made on each surface?
- Identify the rate of successful field goals kicked between 48 and 52 yards

Review: multivariate linear regression

Model:

$$y_i = \beta_0 + \beta_1 * x_{i1} + \beta_2 * x_{i2} + \ldots + \beta_{p-1} * x_{i,p-1} + \epsilon_i$$

Assumptions:

- $\epsilon_i \sim N(0, \sigma^2)$
- ϵ_i,$\epsilon_{i'}$ independent for all i, i'
- Linear relationship between y and x

Example: NFL kickers

```r
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```

```
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## 6  PHI 2005         39  Akers       34        -3  TRUE   68       1
```
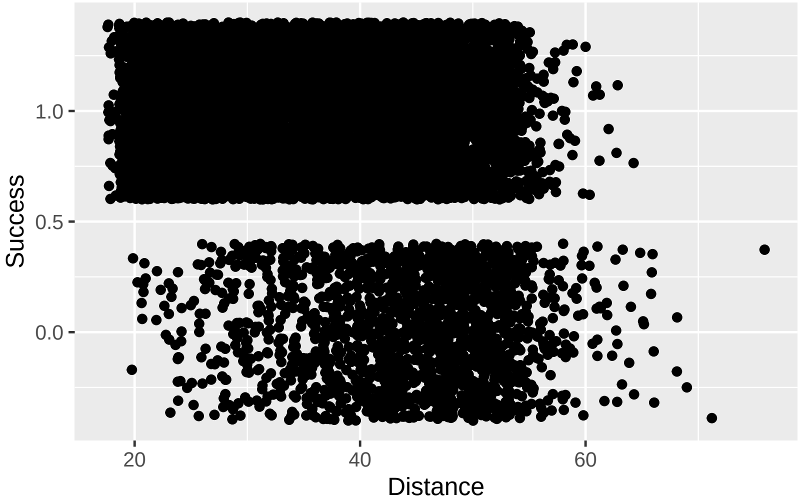
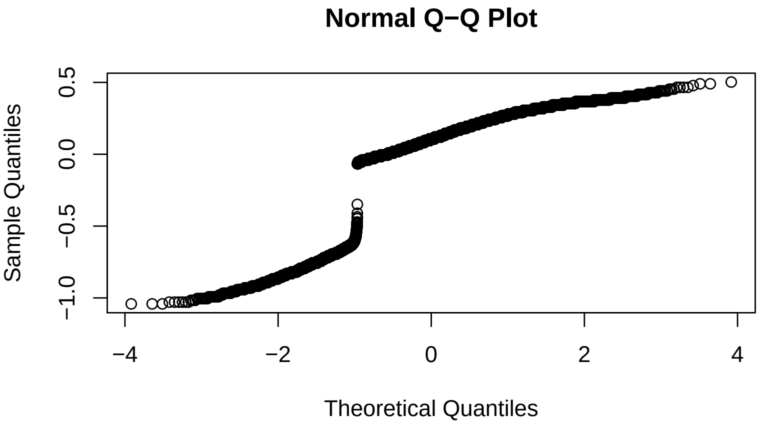

Example: NFL kickers

```
fit_0 <- lm(Success ~ Distance, data = nfl_kick)
ggplot(data = nfl_kick, aes(Distance, Success)) +
  geom_jitter()
```



Example: NFL kickers

```
fit_0 <- lm(Success ~ Distance, data = nfl_kick)
qqnorm(fit_0$resid)
```



What are the problems?

Logistic regression model

Model: $log(\frac{P(y=1)}{1-P(y=1)}) = \beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \ldots + \beta_{p-1} * x_{p-1}$

Comments:

- Dependent variable: log-odds
  - What are odds?
- Model checks more complex
- Uses z test statistics for parameters

Logistic regression model

Model: $log(\frac{P(y=1)}{1-P(y=1)}) = \beta_0 + \beta_1 * x_1$

Extract probabilities:

- $P(y = 1)$:

Estimated logistic regression model

Estimated model:
$log(\frac{P(y=1)}{1-P(y=1)}) = \hat{\beta}_0 + \hat{\beta}_1 * x_1 + \hat{\beta}_2 * x_2 + \ldots + \hat{\beta}_{p-1} * x_{p-1}$

Slope interpretation:

- $\hat{\beta}_1$:
- $e^{\hat{\beta}_1}$:

Ex: Field goal kicking by distance

Model: $log(\frac{P(Success=1)}{1-P(Success=1)}) = \beta_0 + \beta_1 * Distance$

```
library(broom)
fit_1 <- glm(Success ~ Distance, data = nfl_kick, family = "binomial")
tidy(fit_1)
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic   p.value
##   <chr>          <dbl>     <dbl>     <dbl>     <dbl>
## 1 (Intercept)    5.72    0.137        41.7 0.
## 2 Distance      -0.103   0.00314     -32.7 5.63e-235
```

Slope interpretation: $e^{\hat{\beta}_1}$

Ex: Field goal kicking by distance

```r
tidy(fit_1)
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic   p.value
##   <chr>          <dbl>     <dbl>     <dbl>     <dbl>
## 1 (Intercept)    5.72    0.137        41.7 0.
## 2 Distance      -0.103   0.00314     -32.7 5.63e-235
```

Estimate the probability of a successful 50-yard field goal:

Ex: Field goal kicking by distance

```
tidy(fit_1)
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic   p.value
##   <chr>          <dbl>     <dbl>     <dbl>     <dbl>
## 1 (Intercept)    5.72    0.137        41.7 0.
## 2 Distance      -0.103   0.00314     -32.7 5.63e-235
```

Estimate the probability of a successful 51-yard field goal:

Ex: Field goal kicking by distance

Use your answers on the previous slides to estimate the odds of a 51-yard field goal relative to the odds of a 50-yard field goal. Where else do you see this number?

Model checking

- Model checking for logistic regression relies on assessment of fit
  - Are the predicted probabilities accurate?
  - Ex: 48 to 52 yard field goals

```
long_FG <- filter(nfl_kick, Distance >= 48, Distance <= 52)
long_FG %>%
  summarise(ave_success = mean(Success))
```

```
##   ave_success
## 1   0.6510989
```

Categorical predictors

```
fit_2 <- glm(Success ~ Distance + Grass,
             data = nfl_kick, family = "binomial")
tidy(fit_2)
```

```
## # A tibble: 3 x 5
##   term        estimate std.error statistic   p.value
##   <chr>          <dbl>     <dbl>     <dbl>     <dbl>
## 1 (Intercept)    5.83    0.142        41.1  0.
## 2 Distance      -0.103   0.00314     -32.7  3.99e-235
## 3 GrassTRUE     -0.168   0.0547       -3.07 2.12e-  3
```

Estimated model

Categorical predictors

```r
tidy(fit_2)
```

```
## # A tibble: 3 x 5
##   term        estimate std.error statistic   p.value
##   <chr>          <dbl>     <dbl>     <dbl>     <dbl>
## 1 (Intercept)    5.83    0.142       41.1  0.
## 2 Distance      -0.103   0.00314    -32.7  3.99e-235
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```

Slope interpretation: $e^{\hat{\beta}_1}$

Categorical predictors

```r
tidy(fit_2)
```

```
## # A tibble: 3 x 5
##   term        estimate std.error statistic   p.value
##   <chr>          <dbl>     <dbl>     <dbl>     <dbl>
## 1 (Intercept)    5.83    0.142       41.1  0.
## 2 Distance      -0.103   0.00314    -32.7  3.99e-235
## 3 GrassTRUE     -0.168   0.0547      -3.07 2.12e-  3
```

Slope interpretation: $e^{\hat{\beta}_2}$