# UFC Statistics

Team #5

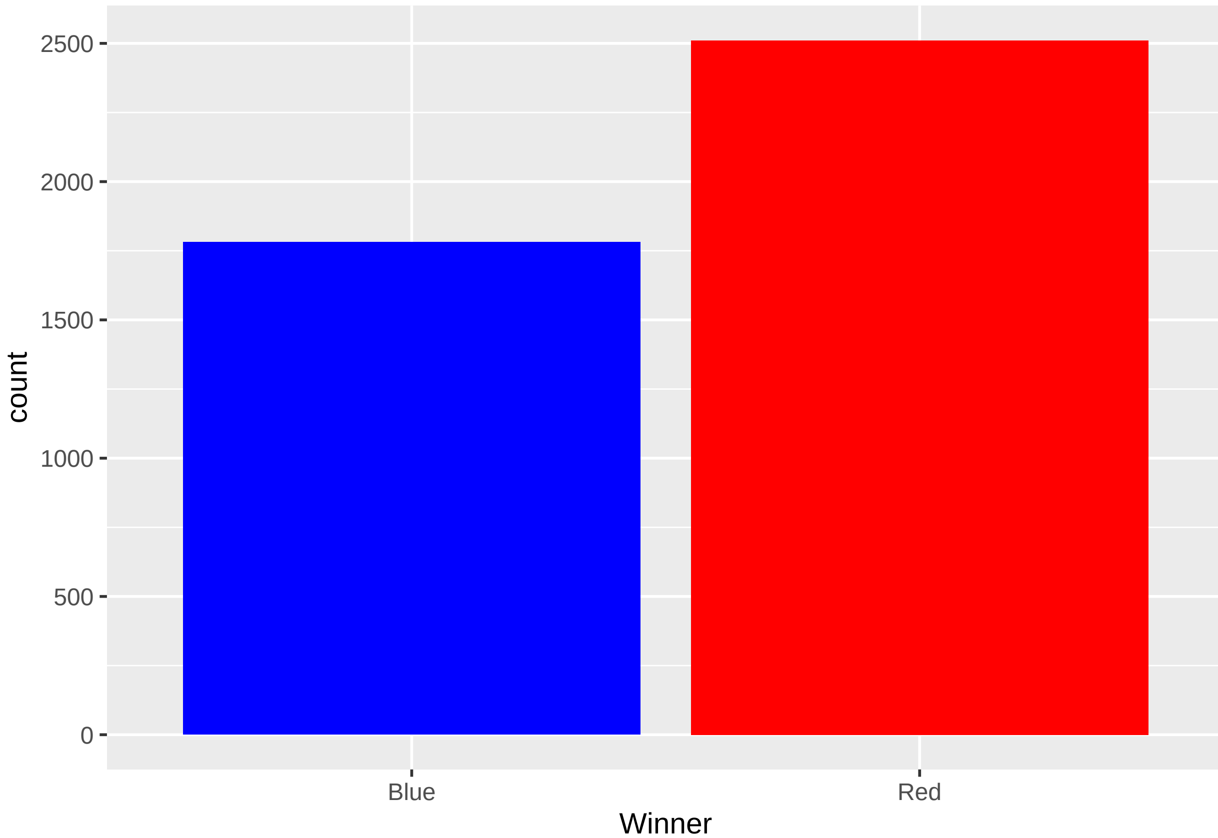
7/24/2020

Link to the data set: https://www.kaggle.com/mdabbert/ultimate-ufc-dataset?select=ufc-master.csv

```
df <- read.csv('ufc-master.csv')

# head(df)
# names(df)
# summary(df)
```

## Inquiry 1: Does one color have an advantage over the other? Does gender make a difference?

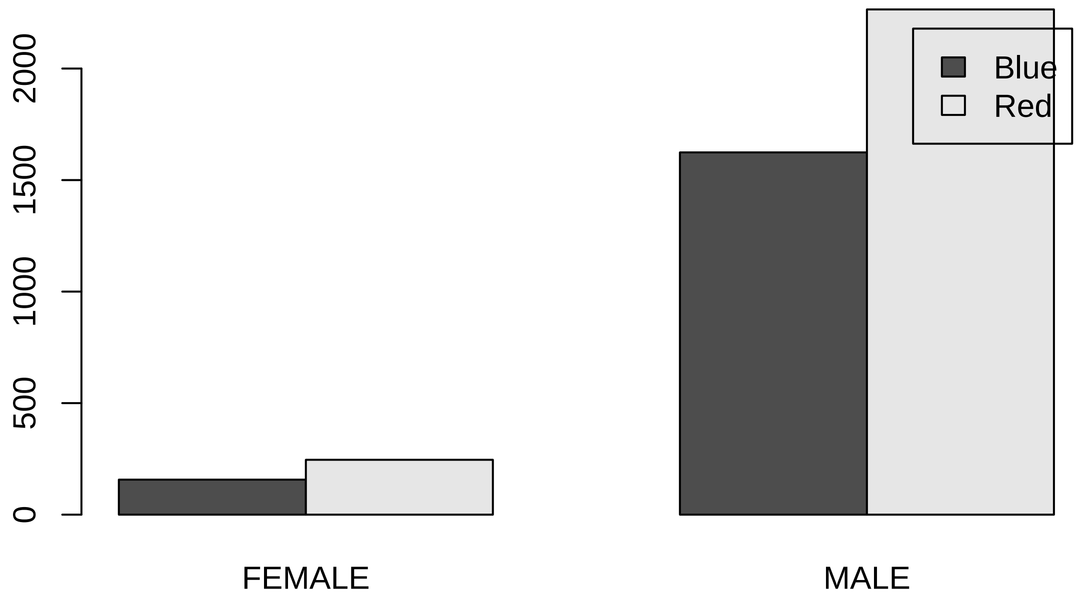
```
# Get the data
color <- df[,c('Winner', 'gender')]

# Plot the graph without gender
colorOnly.bar <- ggplot(color, aes(x = Winner))
colorOnly.bar +
  geom_bar(fill = c('Blue', 'Red'))
```




Based on the graph, it appears that red has a large advantage over blue. (Question: How are colors chosen? At random? Based on rank?)

We can break this down and look at the gender splits.

```
# Plot the graph with gender
colorGender.table <- with(color, table(Winner, gender))
colorGender.bar <- barplot(colorGender.table, beside = TRUE, legend = TRUE)
```




```
# Calculate win percentages
print(paste('Overall Red Wins: ',
            nrow(subset(color, Winner == 'Red'))))
```

```
## [1] "Overall Red Wins:  2511"
```

```
print(paste('Overall Blue Wins: ',
            nrow(subset(color, Winner == 'Blue'))))
```

```
## [1] "Overall Blue Wins:  1781"
```

```
print(paste('Overall Red Win Pct: ',
            round( 100 * nrow(subset(color, Winner == 'Red')) / nrow(color), 2 )))
```

```
## [1] "Overall Red Win Pct:  58.5"
```

```
print(paste('Overall Blue Win Pct: ',
            round( 100 * nrow(subset(color, Winner == 'Blue')) / nrow(color), 2 )))
```

```
## [1] "Overall Blue Win Pct:  41.5"
```

```
print(paste('Overall Male Red Wins: ',
            nrow(subset(color, Winner == 'Red' & gender == 'MALE'))))
```

```
## [1] "Overall Male Red Wins:  2265"
```

```
print(paste('Overall Male Blue Wins: ',
            nrow(subset(color, Winner == 'Blue' & gender == 'MALE'))))
```

```
## [1] "Overall Male Blue Wins:  1624"
```

```r
print(paste('Overall Male Red Win Pct: ',
            round( 100 * nrow(subset(color, Winner == 'Red' & gender == 'FEMALE')) /
                     nrow(subset(color, gender == 'FEMALE')), 2)))
```

```
## [1] "Overall Male Red Win Pct:  61.04"
```

```r
print(paste('Overall Male Blue Win Pct: ',
            round( 100 * nrow(subset(color, Winner == 'Blue' & gender == 'FEMALE')) /
                     nrow(subset(color, gender == 'FEMALE')), 2 )))
```

```
## [1] "Overall Male Blue Win Pct:  38.96"
```

```r
print(paste('Overall Female Red Wins: ',
            nrow(subset(color, Winner == 'Red' & gender == 'FEMALE'))))
```

```
## [1] "Overall Female Red Wins:  246"
```

```r
print(paste('Overall Female Blue Wins: ',
            nrow(subset(color, Winner == 'Blue' & gender == 'FEMALE'))))
```

```
## [1] "Overall Female Blue Wins:  157"
```

```r
print(paste('Overall Female Red Win Pct: ',
            round( 100 * nrow(subset(color, Winner == 'Red' & gender == 'FEMALE')) /
                     nrow(subset(color, gender == 'FEMALE')), 2 )))
```

```
## [1] "Overall Female Red Win Pct:  61.04"
```

```r
print(paste('Overall Female Blue Win Pct: ',
            round( 100 * nrow(subset(color, Winner == 'Blue' & gender == 'FEMALE')) /
                     nrow(subset(color, gender == 'FEMALE')), 2 )))
```

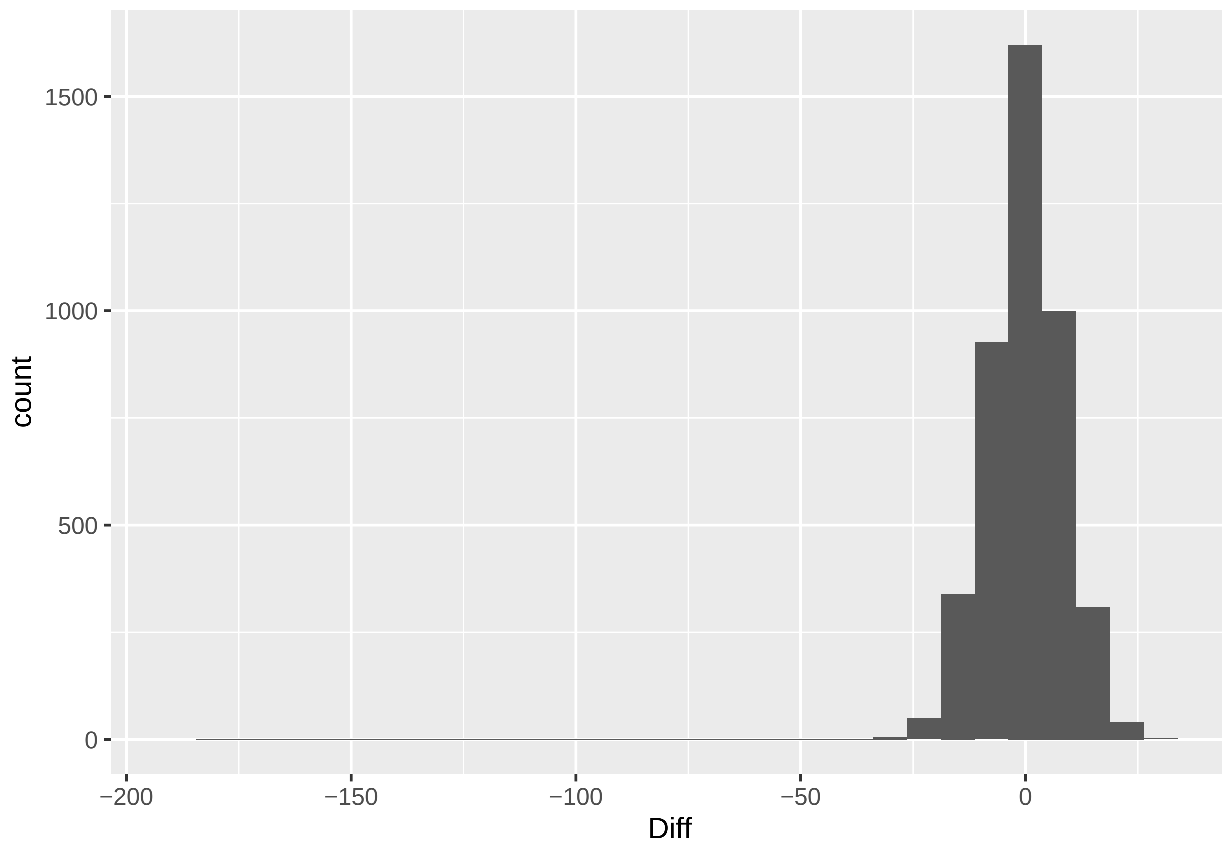
```
## [1] "Overall Female Blue Win Pct:  38.96"
```

I'm not sure what test to run here to show that color is significant.

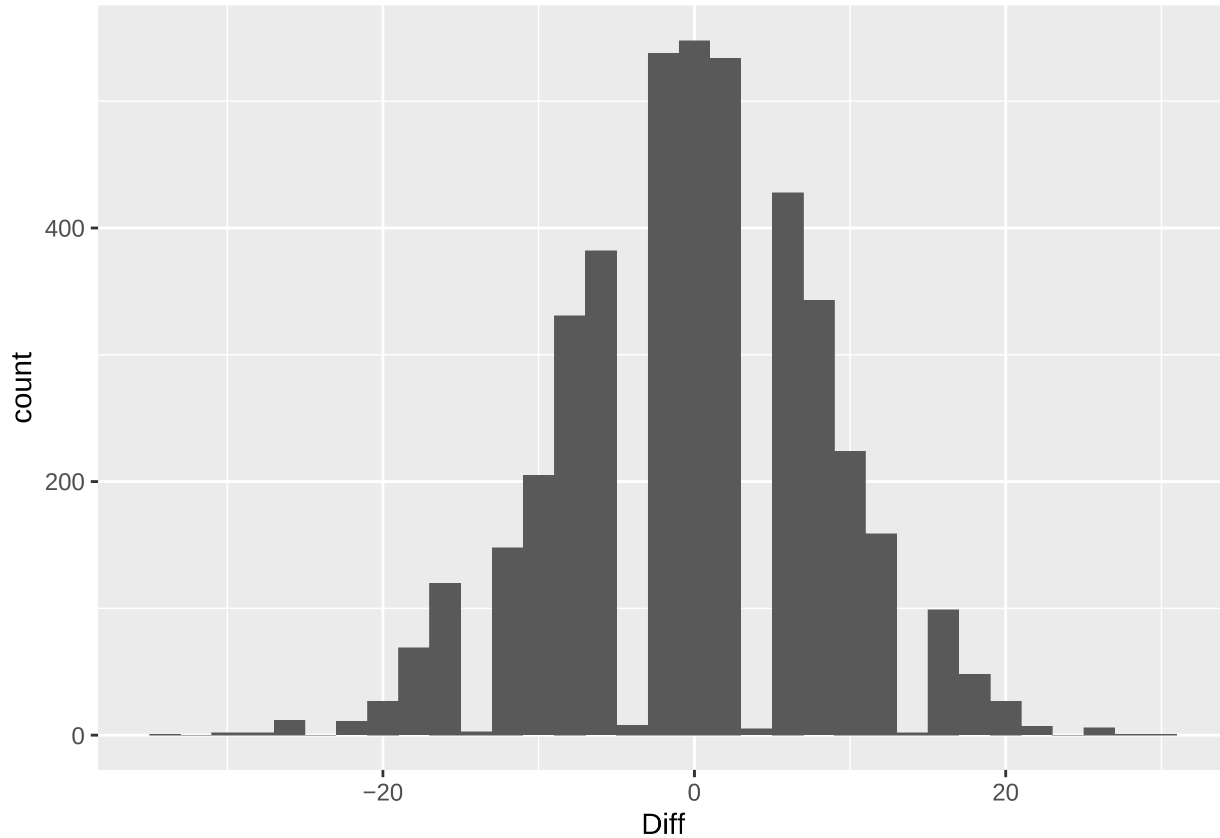
## Question 2: Does a reach advantage lead to more wins?

```r
# Create a smaller data frame
reach <- df[,c('Winner', 'gender', 'B_Reach_cms', 'R_Reach_cms')]

# Calculate the difference in reach (positive = blue advantage)
reach$Diff <- reach$B_Reach_cms - reach$R_Reach_cms

# Plot the reach differences
reach.plot <- ggplot(reach, aes(x = Diff))
reach.plot +
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

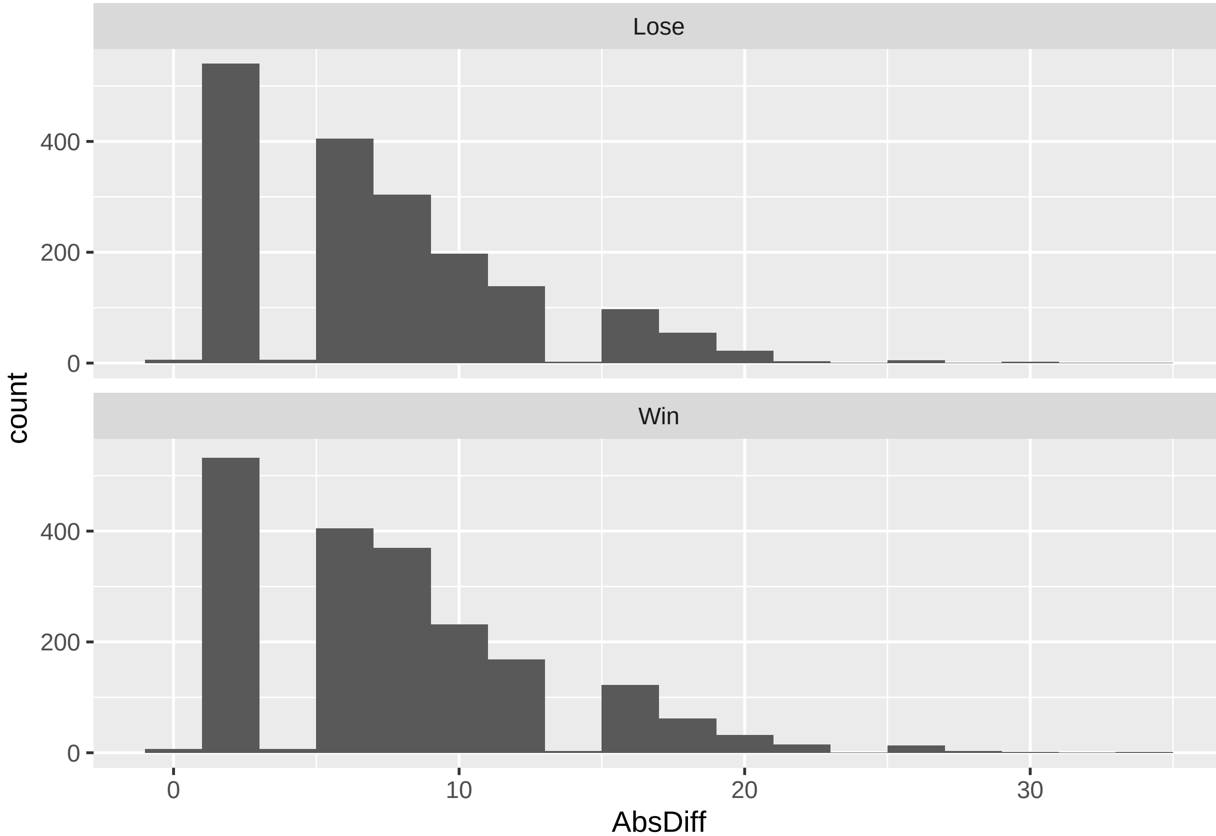



```r
# There is an outlier that makes no sense, so remove it and replot
reach <- reach[reach$Diff > -50,]
reach.plot <- ggplot(reach, aes(x = Diff))
reach.plot +
  geom_histogram(binwidth = 2)
```




```
# Remove all cases where the players had equal reach
reach <- subset(reach, !(Diff == 0))

# Identify the fighter with the longer reach
reach$Advantage <-
  case_when(
    reach$Diff > 0 ~ 'Blue',
    reach$Diff < 0 ~ 'Red'
  )

# Identify if the advantaged fighter won
reach$AdWin <-
  case_when(
    reach$Advantage == reach$Winner ~ 'Win',
    reach$Advantage != reach$Winner ~ 'Lose'
  )

reach$AdWin <- as.factor(reach$AdWin)

# Take the absolute value of the difference
reach$AbsDiff <- abs(reach$Diff)

# Plot the data
reach.hist <- ggplot(reach, aes(x = AbsDiff))
reach.hist +
  geom_histogram(binwidth = 2) +
```

```r
  facet_wrap(~ AdWin, ncol = 1)
```




```r
# Create the logistic regression
reach.model <- glm(AdWin ~ AbsDiff, data = reach, family = binomial())

# Display summary
summary(reach.model)
```

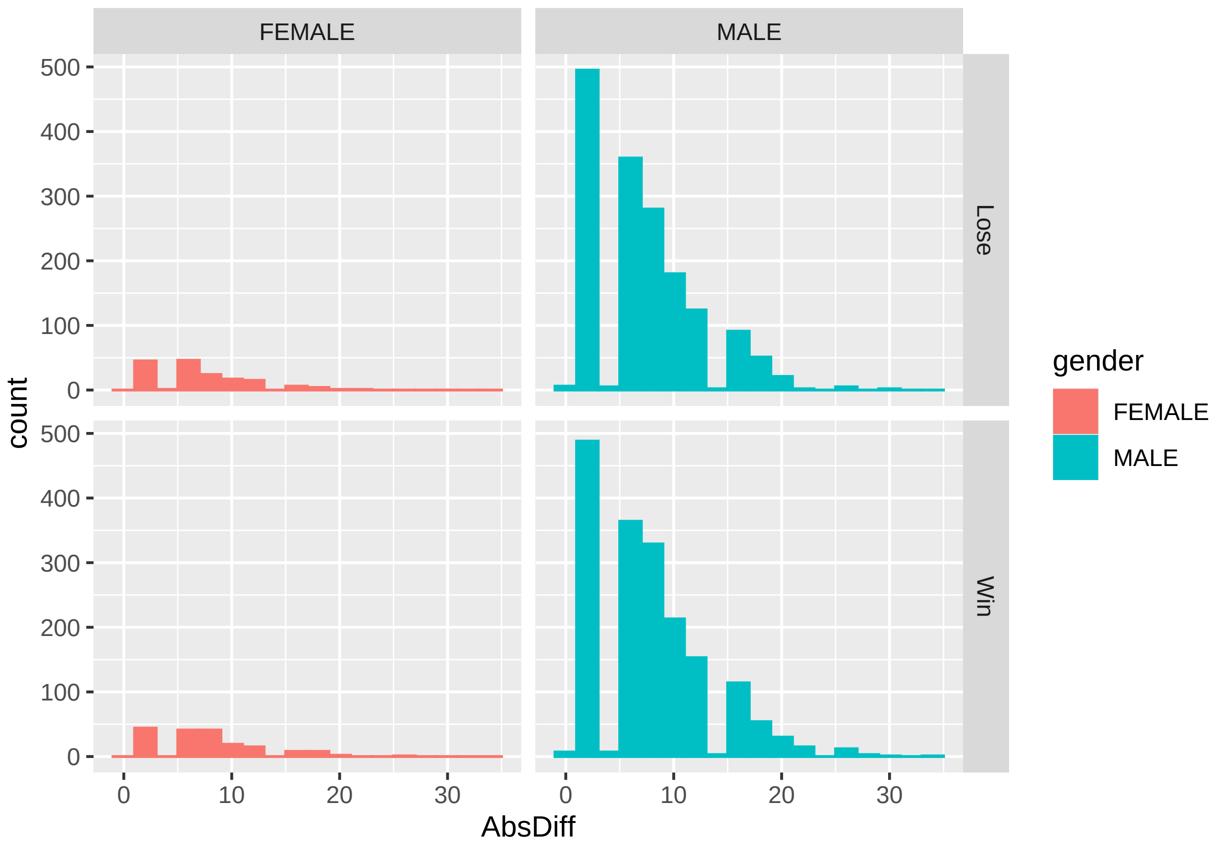
```
##
## Call:
## glm(formula = AdWin ~ AbsDiff, family = binomial(), data = reach)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -1.463  -1.197   1.034   1.158   1.209
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.075187   0.059314  -1.268 0.204937
## AbsDiff      0.023771   0.006688   3.554 0.000379 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5197.3  on 3755  degrees of freedom
```

```
## Residual deviance: 5184.6  on 3754  degrees of freedom
## AIC: 5188.6
##
## Number of Fisher Scoring iterations: 3
```

There is a statistically significant correlation between the winner and having a reach advantage. (Note: Need to determine how to interpret the 0.02 coefficient. Is that a 2% increase in winning percentage per 1 cm of reach? That seems like a lot.)

### Check to see how gender affects this

```r
# Plot the data
reach_gender.hist <- ggplot(reach, aes(x = AbsDiff, color = gender))
reach_gender.hist +
  geom_histogram(binwidth = 2, aes(fill = gender)) +
  facet_grid(AdWin ~ gender)
```




```r
# Create the logistic regression
reach_diff.model <- glm(AdWin ~ AbsDiff, data = reach, family = binomial())
reach_gender.model <- update(reach_diff.model, .~. + gender)

# Display summary
summary(reach_diff.model)
```

```
##
## Call:
## glm(formula = AdWin ~ AbsDiff, family = binomial(), data = reach)
```

```
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -1.463  -1.197   1.034   1.158   1.209
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.075187   0.059314  -1.268 0.204937
## AbsDiff      0.023771   0.006688   3.554 0.000379 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5197.3  on 3755  degrees of freedom
## Residual deviance: 5184.6  on 3754  degrees of freedom
## AIC: 5188.6
##
## Number of Fisher Scoring iterations: 3
```

```r
summary(reach_gender.model)
```

```
##
## Call:
## glm(formula = AdWin ~ AbsDiff + gender, family = binomial(),
##     data = reach)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -1.462  -1.196   1.034   1.151   1.210
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.059510   0.119113  -0.500 0.617352
## AbsDiff      0.023784   0.006689   3.556 0.000377 ***
## genderMALE  -0.017338   0.114236  -0.152 0.879368
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5197.3  on 3755  degrees of freedom
## Residual deviance: 5184.5  on 3753  degrees of freedom
## AIC: 5190.5
##
## Number of Fisher Scoring iterations: 3
```

```r
anova(reach_diff.model, reach_gender.model)
```

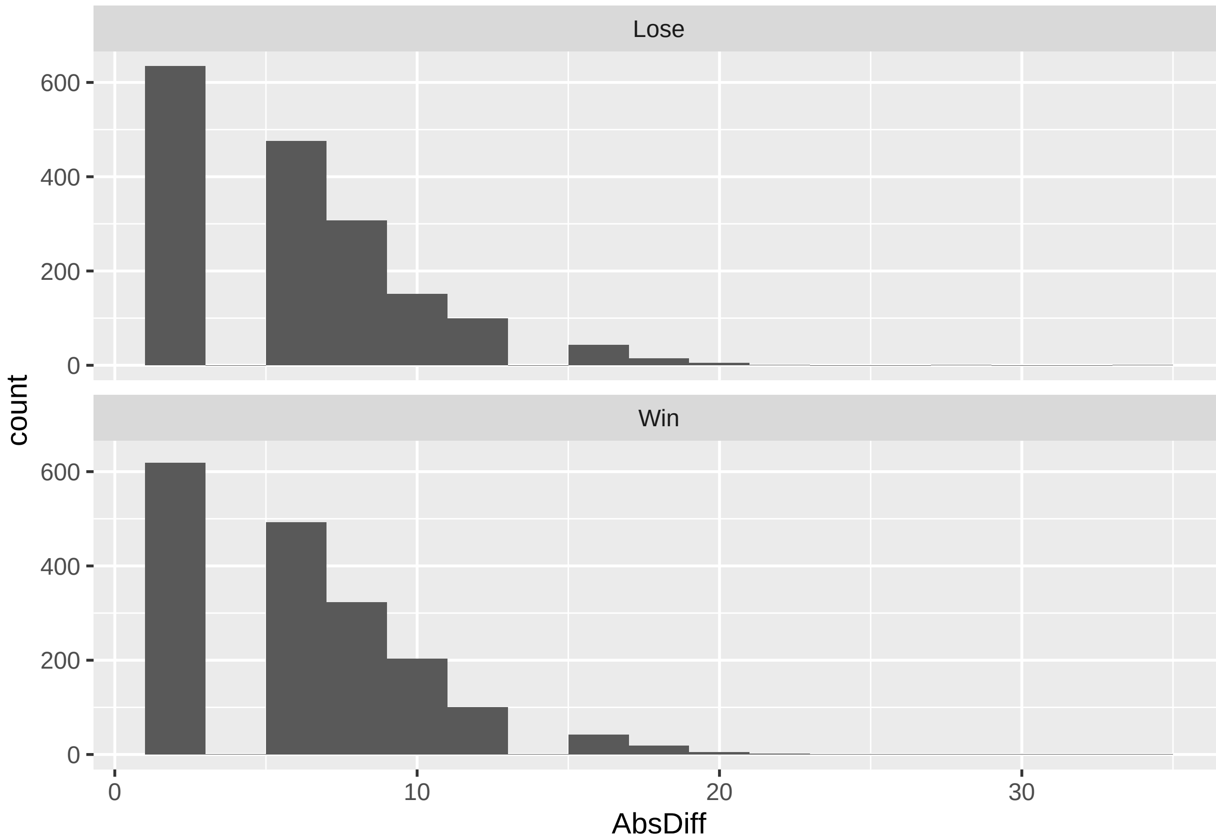
```
## Analysis of Deviance Table
##
## Model 1: AdWin ~ AbsDiff
## Model 2: AdWin ~ AbsDiff + gender
##   Resid. Df Resid. Dev Df Deviance
## 1      3754     5184.6
```

```
## 2      3753     5184.5  1  0.02304
```

It appears that adding gender does not add much to the model.

## Question 3: Does height have an advantage?

```r
# Create a smaller data frame
height <- df[,c('Winner', 'B_Height_cms', 'R_Height_cms')]

# Calculate the difference in reach (positive = blue advantage)
height$Diff <- height$B_Height_cms - height$R_Height_cms

# Remove all cases where the players had equal reach
height <- subset(height, !(Diff == 0))

# Identify the fighter with the longer reach
height$Advantage <-
  case_when(
    height$Diff > 0 ~ 'Blue',
    height$Diff < 0 ~ 'Red'
  )

# Identify if the advantaged fighter won
height$AdWin <-
  case_when(
    height$Advantage == height$Winner ~ 'Win',
    height$Advantage != height$Winner ~ 'Lose'
  )

height$AdWin <- as.factor(height$AdWin)

# Take the absolute value of the difference
height$AbsDiff <- abs(height$Diff)

# Plot the data
height.hist <- ggplot(height, aes(x = AbsDiff))
height.hist +
  geom_histogram(binwidth = 2) +
  facet_wrap(~ AdWin, ncol = 1)
```




```r
# Create the logistic regression
height.model <- glm(AdWin ~ AbsDiff, data = height, family = binomial())

# Display summary
summary(height.model)
```

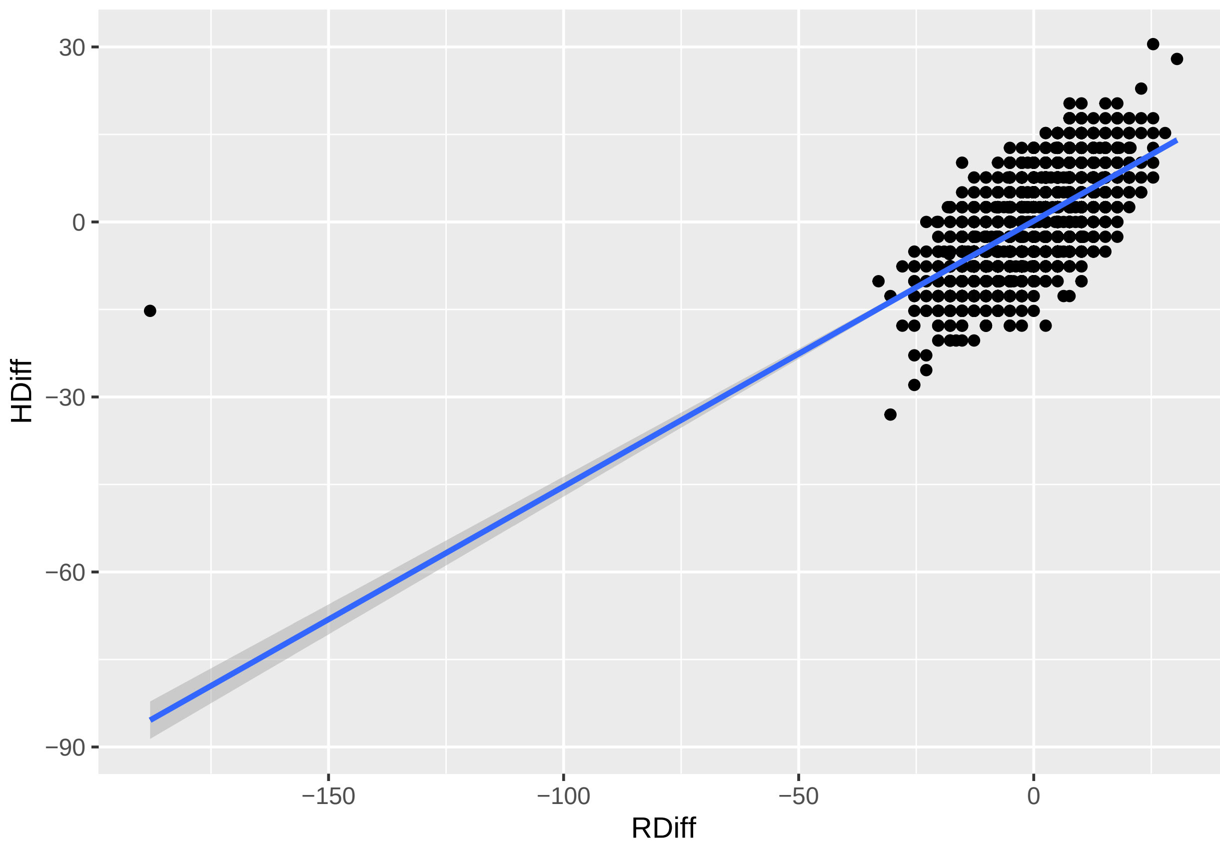
```
##
## Call:
## glm(formula = AdWin ~ AbsDiff, family = binomial(), data = height)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -1.369  -1.190   1.102   1.165   1.181
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.045048   0.063632  -0.708    0.479
## AbsDiff      0.014712   0.008979   1.638    0.101
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 4904.4  on 3538  degrees of freedom
## Residual deviance: 4901.7  on 3537  degrees of freedom
## AIC: 4905.7
##
## Number of Fisher Scoring iterations: 3
```

There is no significant advantage.

## Question 4: What about comining height and reach?

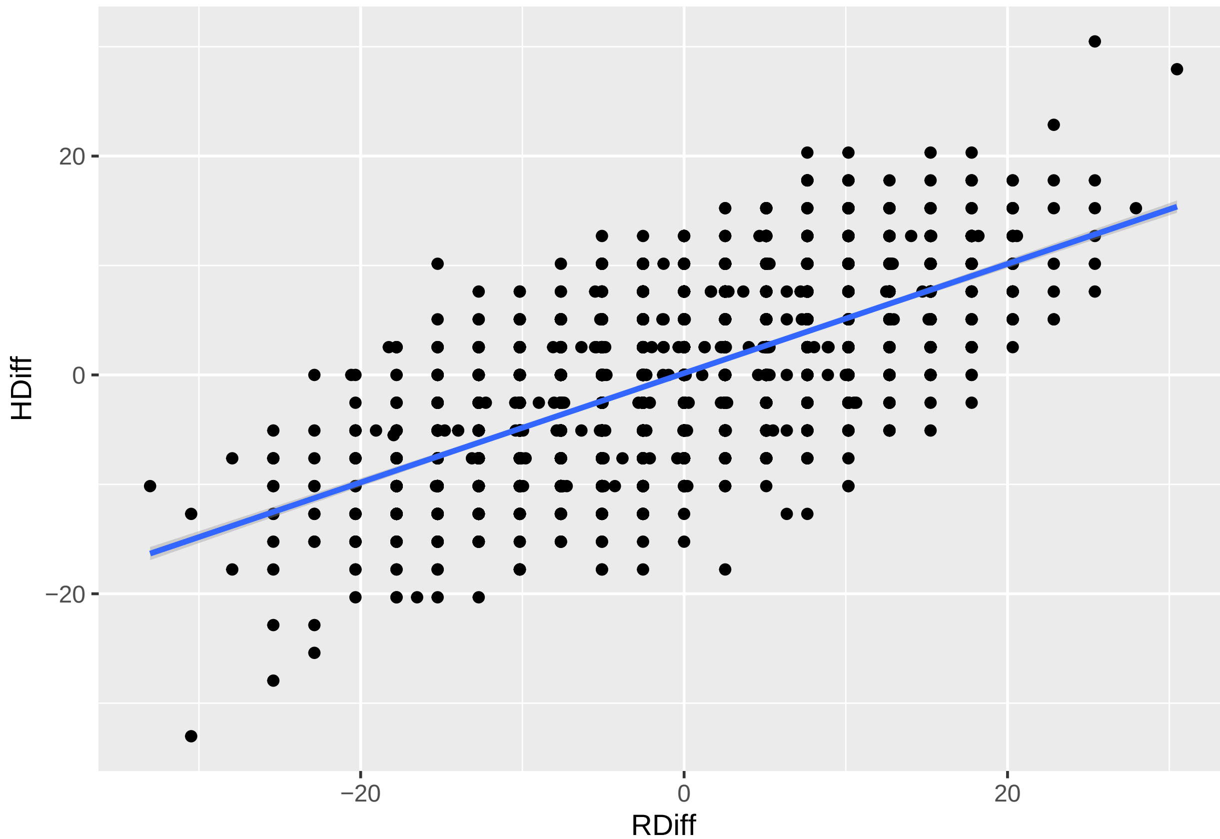
```
# Create a smaller data frame
height_reach <- df[,c('Winner', 'B_Reach_cms', 'R_Reach_cms', 'B_Height_cms', 'R_Height_cms')]

# Calculate the difference in height and reach relative to Blue
height_reach$HDiff <- height_reach$B_Height_cms - height_reach$R_Height_cms
height_reach$RDiff <- height_reach$B_Reach_cms - height_reach$R_Reach_cms

# Draw a scatterplot of the differences
height_reach.scatter <- ggplot(height_reach, aes(x = RDiff, y = HDiff))
height_reach.scatter +
  geom_point() +
  geom_smooth(method = 'lm')
```

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




```
# Remove bad data point and replot
height_reach <- height_reach[abs(height_reach$RDiff) < 50,]
height_reach.scatter <- ggplot(height_reach, aes(x = RDiff, y = HDiff))
height_reach.scatter +
  geom_point() +
  geom_smooth(method = 'lm')
```

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




This scatterplot only shows that the height and reach advantages have a correlation with each other, but it does not say anything about wins and losses.

```
# Calculate the mean advantages for the winner
stat.desc(cbind(height_reach$HDiff, height_reach$RDiff))
```

```
##                      V1           V2
## nbr.val      4291.0000000 4291.00000000
## nbr.null      753.0000000  535.00000000
## nbr.na          0.0000000    0.00000000
## min           -33.0200000  -33.02000000
## max            30.4800000   30.48000000
## range          63.5000000   63.50000000
## sum           484.7200000 -399.16000000
## median          0.0000000    0.00000000
## mean            0.1129620   -0.09302261
## SE.mean         0.0983535    0.12757212
## CI.mean.0.95    0.1928237    0.25010732
## var            41.5086044   69.83450422
## std.dev         6.4427172    8.35670415
## coef.var       57.0343690  -89.83519766
```

Blue does not appear to have any average advantage/disadvantage with respect to height and reach.

```
# Create a column that indicates whether blue wins/loses
height_reach$BlueWin <-
```

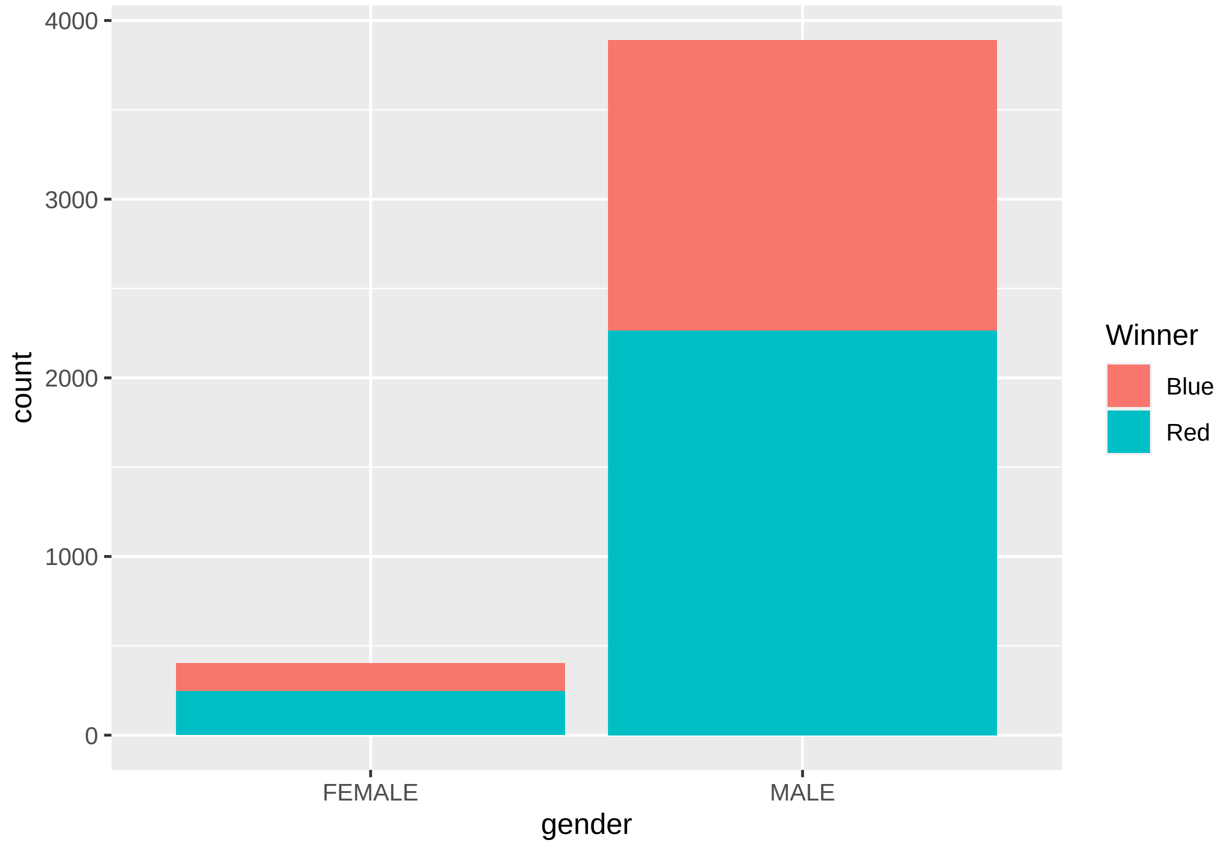
```r
  case_when(
    height_reach$Winner == 'Blue' ~ 'Yes',
    height_reach$Winner == 'Red' ~ 'No'
  )
height_reach$BlueWin <- as.factor(height_reach$BlueWin)

# Create a logistic regression
height_reach.model <- glm(BlueWin ~ HDiff * RDiff, data = height_reach, family = binomial())

summary(height_reach.model)
```

```
##
## Call:
## glm(formula = BlueWin ~ HDiff * RDiff, family = binomial(), data = height_reach)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.2685  -1.0422  -0.9697   1.3072   1.5112
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.3474431  0.0347860  -9.988  < 2e-16 ***
## HDiff       -0.0062342  0.0063319  -0.985    0.325
## RDiff        0.0199174  0.0049033   4.062 4.86e-05 ***
## HDiff:RDiff  0.0001482  0.0004509   0.329    0.742
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5824.1  on 4290  degrees of freedom
## Residual deviance: 5802.8  on 4287  degrees of freedom
## AIC: 5810.8
##
## Number of Fisher Scoring iterations: 4
```

As before, height does not appear to have an impact, but reach does.

```r
# Height, Weight, Age, Experience (# of matches), Wins, Stance
```

```r
ggplot(df, aes(x = gender, fill = Winner)) +
  geom_bar()
```




```
df %>%
  select(gender, Winner) %>%
  dplyr::summarise(`% Win` = n())
```

```
##   % Win
## 1  4292
```