SAP - Project

Analysis of UFC fights

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Initial data analysis

```
total_fight_data = read.csv("../total_fight_data.csv", sep = ";")
dim(total_fight_data)
```

```
## [1] 6012   41
```

```
fighter_details = read.csv("../fighter_details.csv", sep = ",")
dim(fighter_details)
```

```
## [1] 3596   14
```

```
all <- merge(total_fight_data, fighter_details, by.x = "R_fighter", by.y = "fighter_name",
    all.x = TRUE)
all <- merge(all, fighter_details, by.x = "B_fighter", by.y = "fighter_name", all.x = TRUE,
    suffixes = c(".r", ".b"))
```

```
dim(all)
```

```
## [1] 6012   67
```

Task 1: Can we expect a fight to end by knockout depending on the difference in arm length between the fighters?

The initial step in solving this task was to convert the weight, height and reach of both fighters from the imperial system to the metric system. One conversion is shown here, the other 5 conversions were made in the same way. We ignored all datapoints with NA values.

```
# Conversion of inches to cm
all$Height_cm.b = sapply(strsplit(as.character(all$Height.b), "'|\""), function(x) {
    30.48 * as.numeric(x[1]) + 2.54 * as.numeric(x[2])
})
```

```
# Moving lines that have NA reach
all_without_na_in_reach <- subset(all, !is.na(Reach_cm.b))
all_without_na_in_reach <- subset(all_without_na_in_reach, !is.na(Reach_cm.r))
```

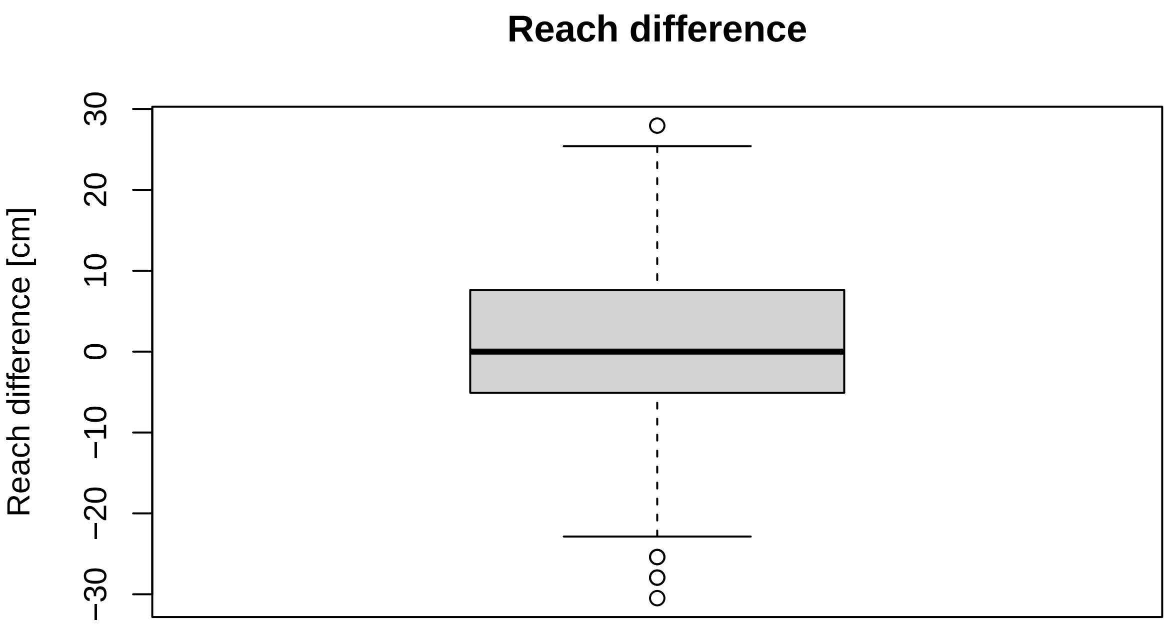
```
# Only fights that ended in a knockout
all_only_knockouts = subset(all_without_na_in_reach, all_without_na_in_reach$win_by ==
    "KO/TKO")
```

```
# Calculating the difference in the reach of winners and losers
d = c()
for (i in 1:nrow(all_only_knockouts)) {
```

```r
    row = all_only_knockouts[i, ]
    diff = row$Reach_cm.r - row$Reach_cm.b
    if (row$Winner == row$R_fighter) {
        d = append(d, diff)
    } else {
        d = append(d, -diff)
    }
}

summary(d)
```

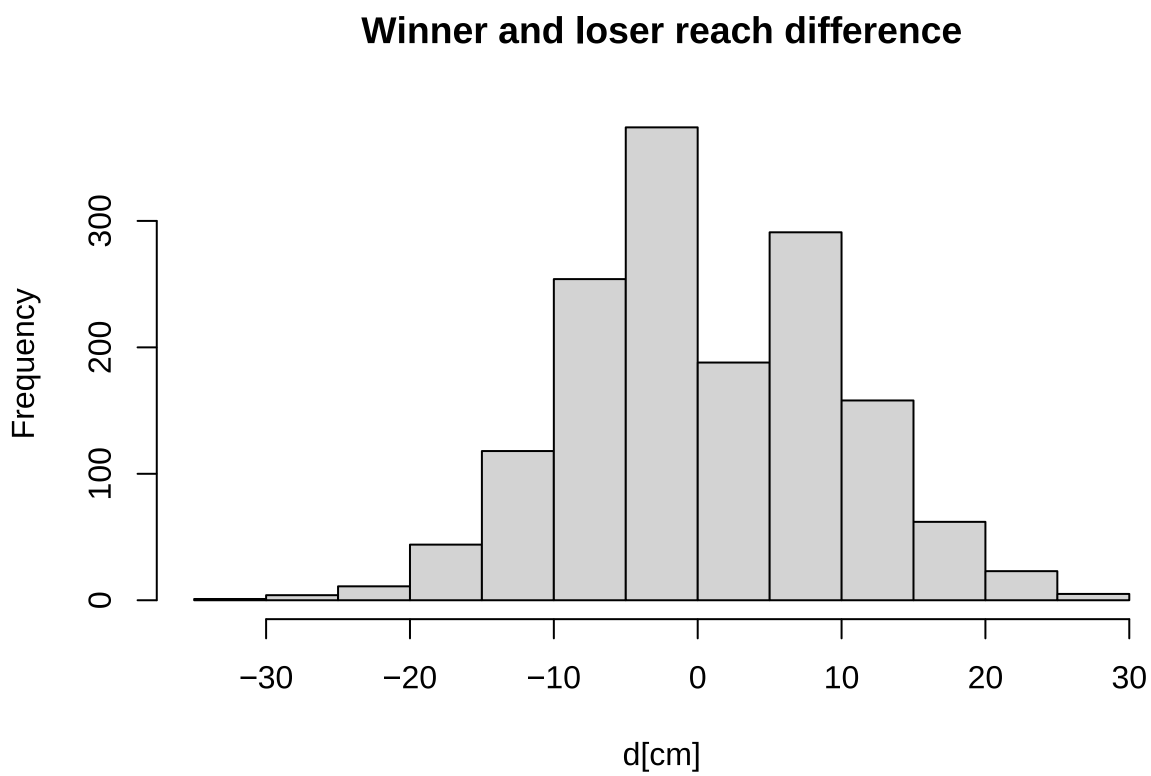
```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -30.4800  -5.0800   0.0000   0.8251   7.6200  27.9400
```

```r
boxplot(d, ylab = "Reach difference [cm]", main = "Reach difference")
```

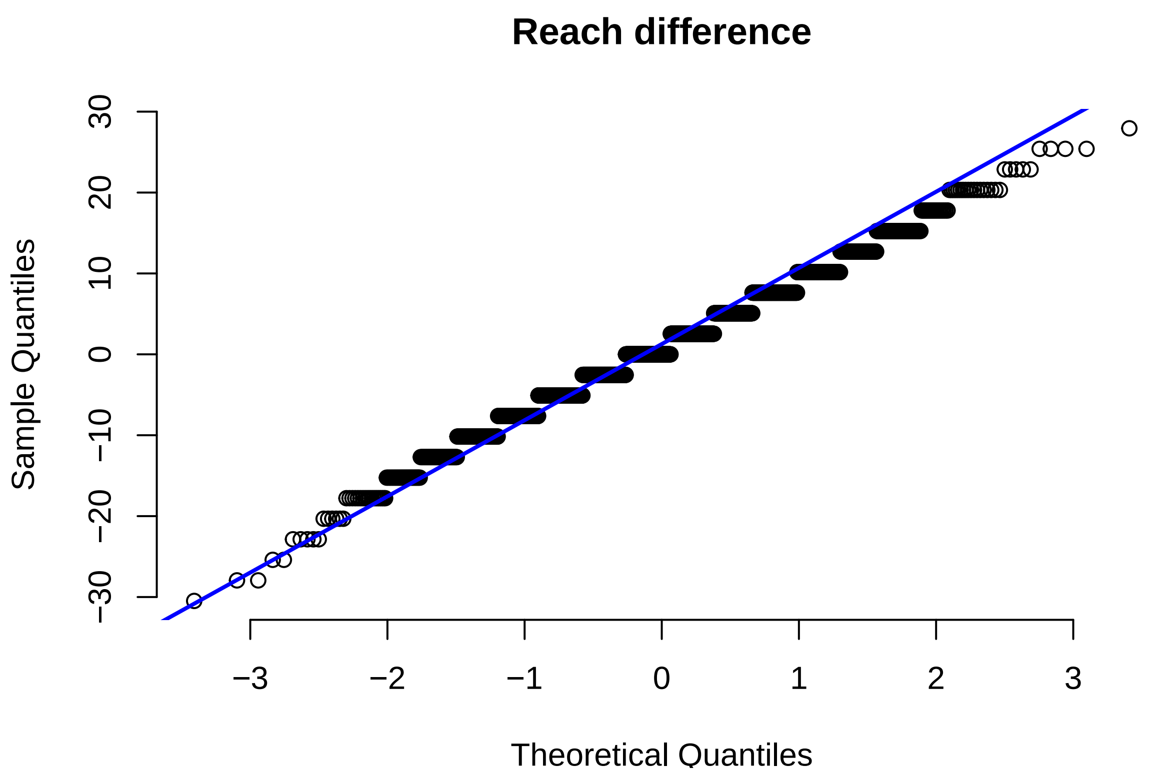


In order to be able to apply the t-test, it is first necessary to check the normality of the data distribution.

```r
hist(d, main = "Winner and loser reach difference", xlab = "d[cm]")
```




```r
qqnorm(d, pch = 1, frame = FALSE, main = "Reach difference")
qqline(d, col = "blue", lwd = 2)
```



From the histogram and Q-Q plot, we can conclude that the data is normally distributed, and we apply the t-test.

- H0: The difference in reach between winners and losers is zero.
- H1: Winners have a greater reach than losers.

```
t.test(d, alternatives = "greater", mu = 0, conf.level = 0.95)
```

```
##
##  One Sample t-test
##
## data:  d
## t = 3.8558, df = 1532, p-value = 0.0001201
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  0.4053728 1.2448816
## sample estimates:
## mean of x
## 0.8251272
```

With the significance level $\alpha = 0.05$, we can reject the hypothesis H0 in favor of the hypothesis H1.

Task 2: Does the duration of fights (s) differ between individual categories?

First, we calculated the overall duration of the fight from the record of the fight format and the duration of the last round.

```
# Calculation of the total duration of the fight
fight_length <- function(parsed_format, last_round, last_round_time) {
    if (parsed_format[1] == "No Time Limit") {
        return(convert_string_time_to_seconds(last_round_time))
    }
    if (last_round == 1) {
        return(convert_string_time_to_seconds(last_round_time))
    }
    total_time = 0
    for (i in 1:(last_round - 1)) {
        total_time = total_time + parsed_format[i] * 60
    }

    total_time = total_time + convert_string_time_to_seconds(last_round_time)
    return(total_time)
}

# Based on the row calculation of the total duration of the fight
time_from_row <- function(row) {
    parsed_format = parse_format(row$Format)
    last_round = row$last_round
    last_round_time = row$last_round_time
    return(fight_length(parsed_format, last_round, last_round_time))
}

# Calculation of the fight duration vector for each row of the table
dur = c()
for (i in 1:nrow(all)) {
    dur = append(dur, time_from_row(all[i, ]))
}

# Adding a column for the total duration of the fight in seconds
```

```r
all$Fight_duration_s <- dur
```

```r
# Grouping by category (separated by gender)
men_classes = c("Light Heavyweight", "Open Weight", "Lightweight", "Heavyweight",
    "Featherweight", "Bantamweight", "Welterweight", "Middleweight", "Flyweight")
women_classes = c("Women's Bantamweight", "Women's Strawweight", "Women's Featherweight",
    "Women's Flyweight")

# The function for string s returns TRUE if it contains one of the previously
# mentioned classes (men_classes, women_classes)
filter_not_in_classes <- function(s) {
    for (w in women_classes) {
        if (grepl(w, s)) {
            return(TRUE)
        }
    }
    for (m in men_classes) {
        if (grepl(m, s)) {
            return(TRUE)
        }
    }
    return(FALSE)
}

# Function for string s returns the category from men_classes or women_classes
# it contains
check_which_class <- function(s) {
    for (w in women_classes) {
        if (grepl(w, s)) {
            return(w)
        }
    }
    for (m in men_classes) {
        if (grepl(m, s)) {
            return(m)
        }
    }
}

# All types of fights that we do not know how to group into categories by
# weight and gender
ignore_fight_types = c()
categories = unique(all$Fight_type)
for (category in categories) {
    if (!filter_not_in_classes(category)) {
        ignore_fight_types = append(ignore_fight_types, category)
    }
}

ignore_fight_types
```

```
##  [1] "Catch Weight Bout"
##  [2] "UFC 4 Tournament Title Bout"
##  [3] "UFC Superfight Championship Bout"
```

```
##  [4] "UFC 5 Tournament Title Bout"
##  [5] "UFC 6 Tournament Title Bout"
##  [6] "Ultimate Ultimate '96 Tournament Title Bout"
##  [7] "UFC 10 Tournament Title Bout"
##  [8] "UFC 8 Tournament Title Bout"
##  [9] "UFC 3 Tournament Title Bout"
## [10] "Ultimate Ultimate '95 Tournament Title Bout"
## [11] "UFC 2 Tournament Title Bout"
## [12] "UFC 7 Tournament Title Bout"
```

Certain categories do not contain information about gender and weight, and therefore we do not take them into account during further analysis.

```
# From the entire data set, we move the fights whose fight_type is inside the
# ignore_fight_types vector
all_without_unknown_weight_classes = subset(all, !(Fight_type %in% ignore_fight_types))
```

The assumptions of the parametric ANOVA method are:

- independence of individual data in the samples
- normal data distribution
- homogeneity of variances among populations

1) We assume independence of the data in the samples, because the fights are mutually independent.
2) We continue with testing the normality of data distribution. We use the Lilliefors normality test.

- H0: The data belong to a normal distribution.
- H1: The data does not belong to a normal distribution.

3) If the data distribution is not normal, there is no point in checking for homoscedasticity. In the second case, we have to check homoscedasticity with Bartlett's test.

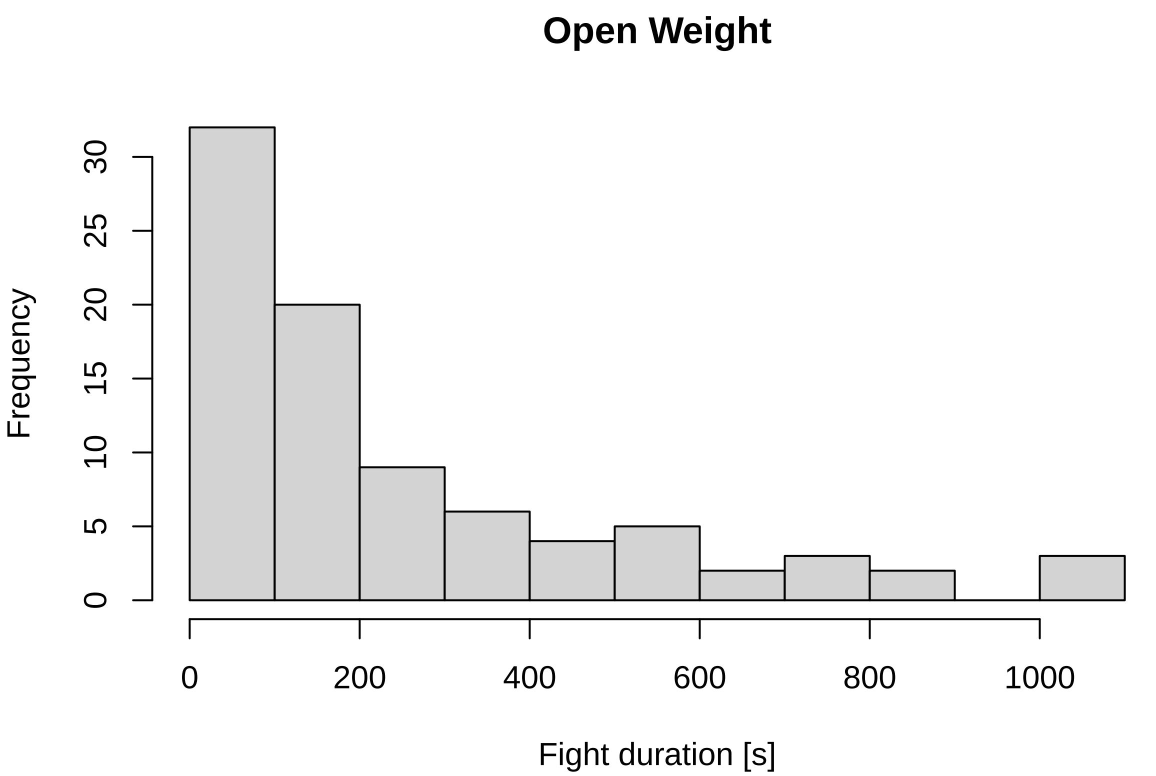
```
## Loading required package: nortest
```

```
lillie.test(all_without_unknown_weight_classes$Fight_duration_s[weight_class == "Open Weight"])
```

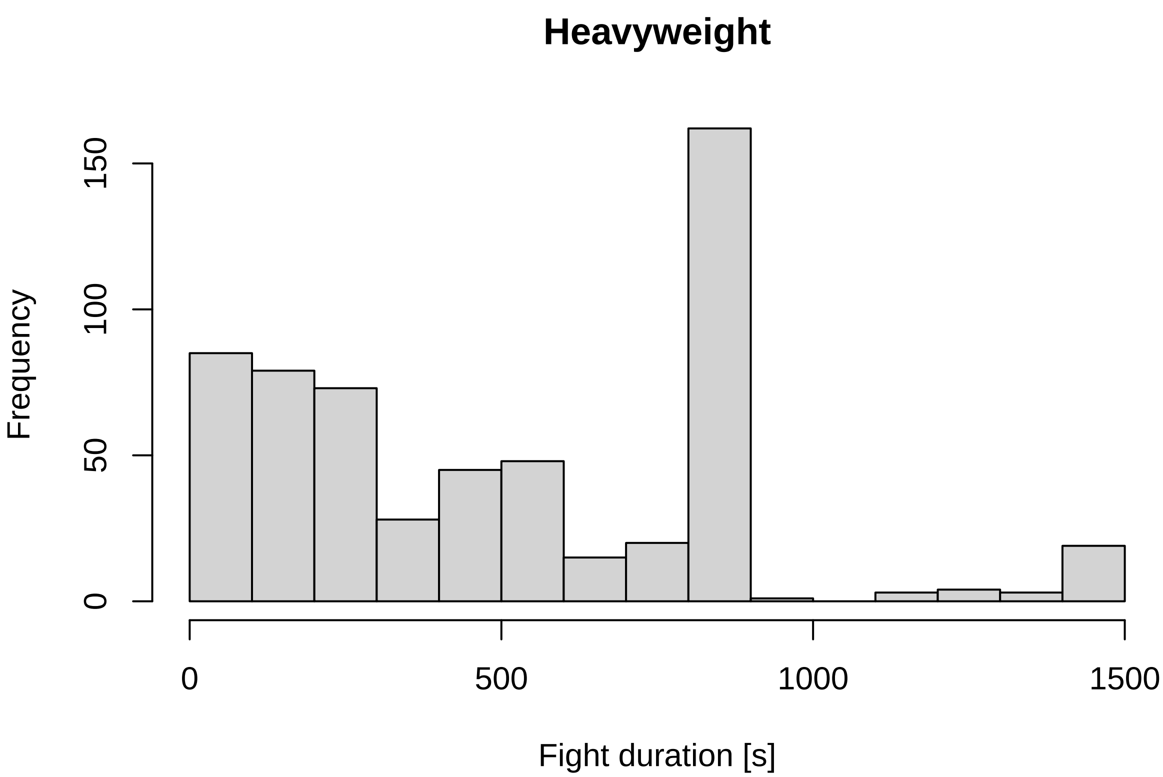
```
##
##  Lilliefors (Kolmogorov-Smirnov) normality test
##
## data:  all_without_unknown_weight_classes$Fight_duration_s[weight_class ==     "Open Weight"]
## D = 0.19826, p-value = 6.363e-09
```

Due to the very small p value, we reject H0 in favor of H1 and conclude that the data are not normally distributed. That's why we have to use the non-parametric version of the ANOVA test, the Kruskal-Wallis χ^2-test. Therefore, we do not test for homogeneity of variances across categories.

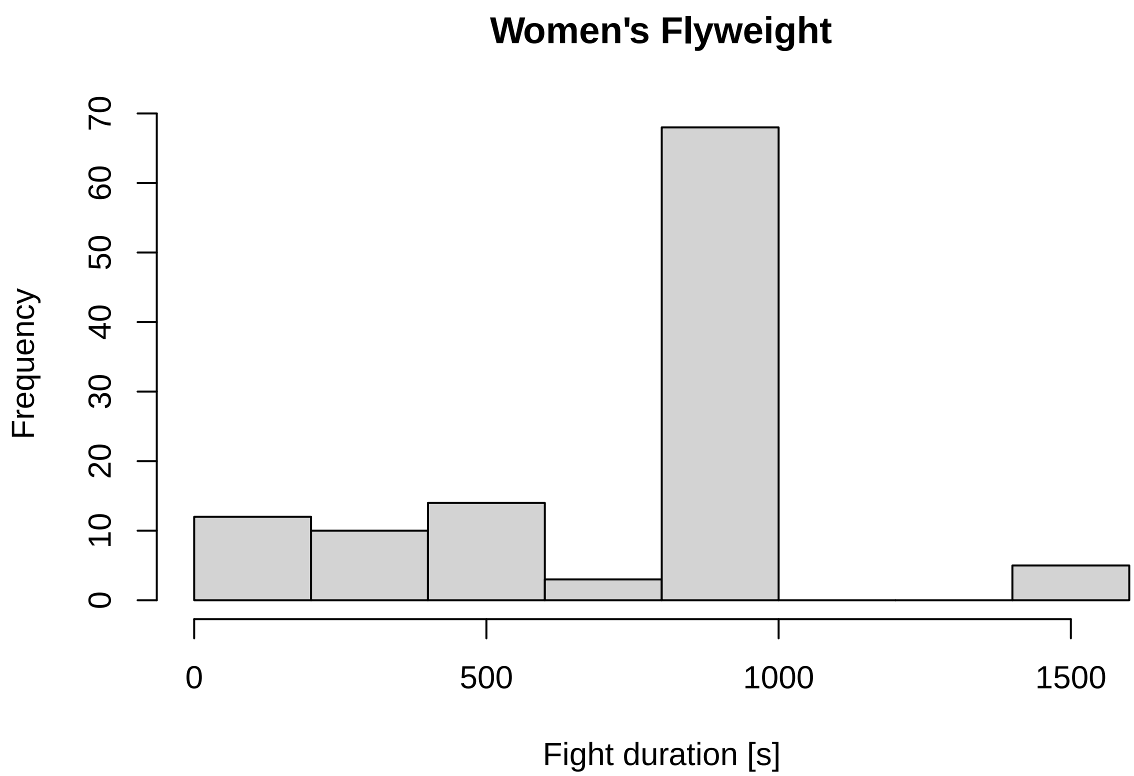
```
# weight_classes = c(men_classes, women_classes)
hist(all_without_unknown_weight_classes$Fight_duration_s[all_without_unknown_weight_classes$weight_class
    "Open Weight"], xlab = "Fight duration [s]", main = "Open Weight")
```




```r
hist(all_without_unknown_weight_classes$Fight_duration_s[all_without_unknown_weight_classes$weight_clas
    "Heavyweight"], xlab = "Fight duration [s]", main = "Heavyweight")
```




```r
hist(all_without_unknown_weight_classes$Fight_duration_s[all_without_unknown_weight_classes$weight_clas
    "Women's Flyweight"], xlab = "Fight duration [s]", main = "Women's Flyweight")
```



From the histograms shown, we can see that the fight times are consistent with the fight formats (most fights end in the 15th minute because they are 5+5+5 minutes).

In order to perform the Kruskal-Wallis test, we must have a minimum of 5 observations in each of the categories, which we can confirm from the following table:

```
table(all_without_unknown_weight_classes$weight_class)
```

```
##
##          Bantamweight         Featherweight             Flyweight
##                   475                   551                   230
##           Heavyweight      Light Heavyweight           Lightweight
##                   585                   573                  1091
##          Middleweight           Open Weight          Welterweight
##                   813                    86                  1083
##   Women's Bantamweight Women's Featherweight     Women's Flyweight
##                   151                    16                   112
##    Women's Strawweight
##                   192
```

We put forward hypotheses:

- H0: The duration of fights does not differ between categories.
- H1: Fight duration differs between at least two categories.

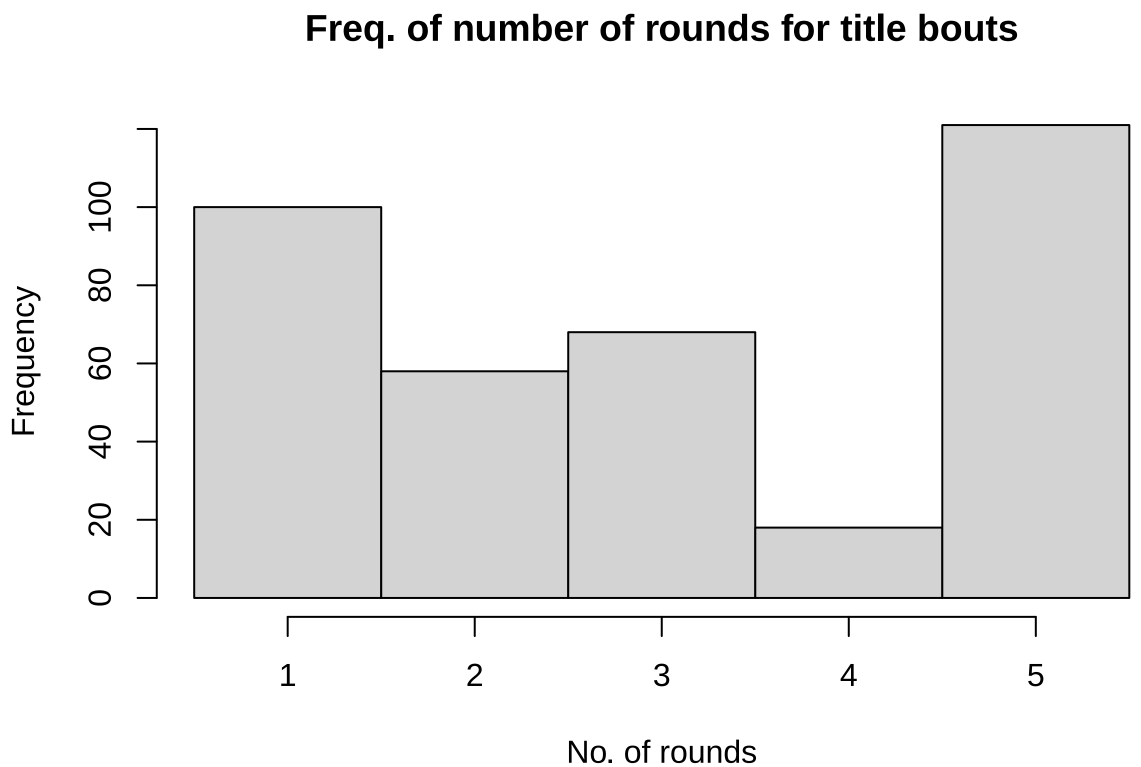
```
kruskal.test(Fight_duration_s ~ weight_class, data = all_without_unknown_weight_classes)
```

```
##
##  Kruskal-Wallis rank sum test
##
## data:  Fight_duration_s by weight_class
## Kruskal-Wallis chi-squared = 283.65, df = 12, p-value < 2.2e-16
```

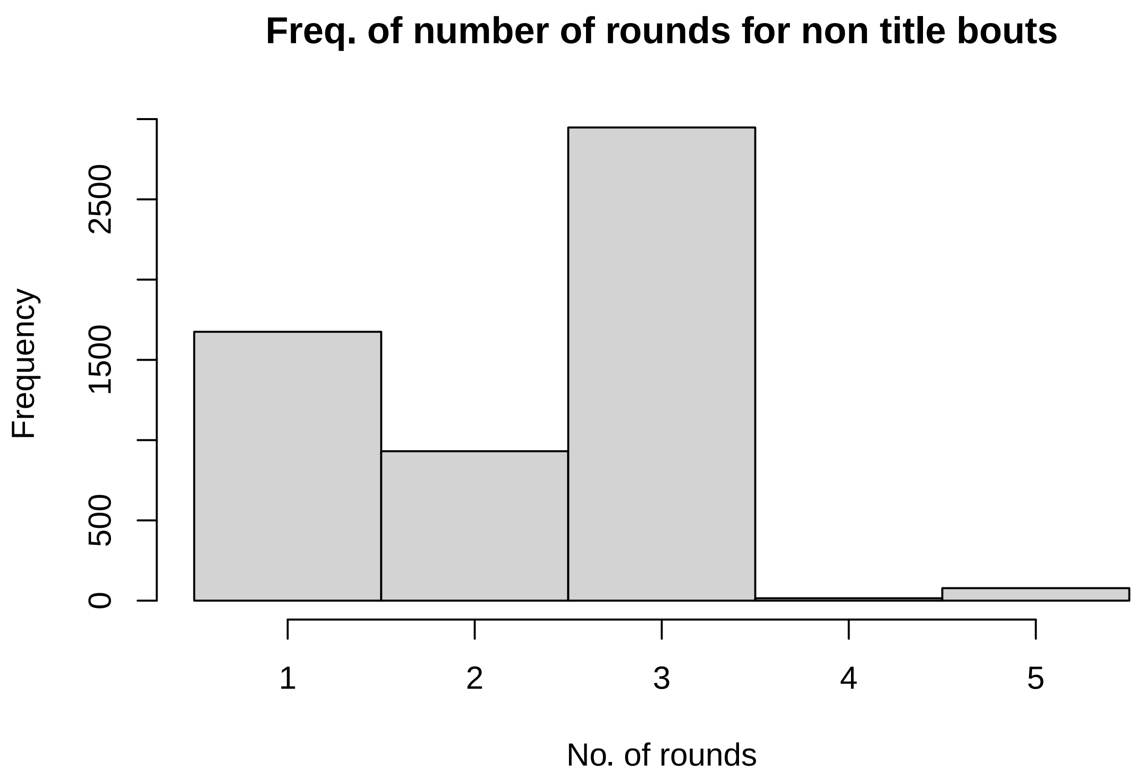
Due to the small p-value, we reject H0 in favor of H1 and conclude that the duration of fights is statistically significantly different between at least two weight categories.

Task 3: Do title fights last longer (in rounds) than other fights in the competition?

```
hist(title_bouts_last_round, breaks = seq(min(title_bouts_last_round) - 0.5, max(title_bouts_last_round)
    0.5, by = 1), main = "Freq. of number of rounds for title bouts", xlab = "No. of rounds")
```




```
hist(non_title_bouts_last_round, breaks = seq(min(non_title_bouts_last_round) - 0.5,
    max(non_title_bouts_last_round) + 0.5, by = 1), main = "Freq. of number of rounds for non title bou
    xlab = "No. of rounds")
```




```
lillie.test(non_title_bouts_last_round)
```

```
##
##  Lilliefors (Kolmogorov-Smirnov) normality test
##
## data:  non_title_bouts_last_round
## D = 0.31964, p-value < 2.2e-16
```

```
lillie.test(title_bouts_last_round)
```

```
##
##  Lilliefors (Kolmogorov-Smirnov) normality test
##
## data:  title_bouts_last_round
## D = 0.22181, p-value < 2.2e-16
```

From the histogram and the Lilliefors test, we see that the data are not normally distributed, so we apply the non-parametric version of the t-test, the Wilcoxon signed rank test. We hypothesize: - H0: Title fights do not last longer (in rounds) than other fights in the competition. - H1: Title fights last longer (in rounds) than other fights in the competition.

```
wilcox.test(title_bouts_last_round, non_title_bouts_last_round, alternatives = "greater",
    conf.level = 0.9)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  title_bouts_last_round and non_title_bouts_last_round
## W = 1264014, p-value = 2.6e-15
## alternative hypothesis: true location shift is not equal to 0
```

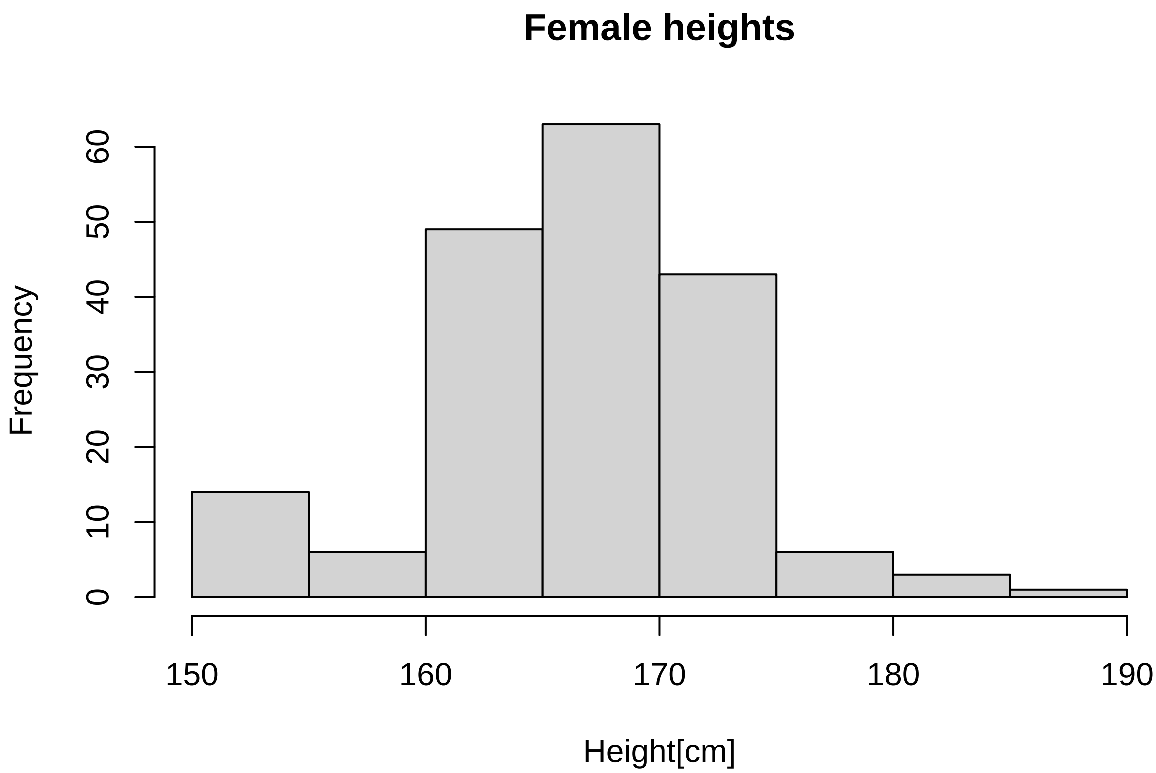
We chose the level of significance $\alpha = 0.1$ because we want greater robustness of the test. Due to the calculated p-value, we reject H0 in favor of H1 and conclude that title fights last longer (in rounds) than other fights in the competition.

Additional task 1. - Do shorter fighters win more often via submission?

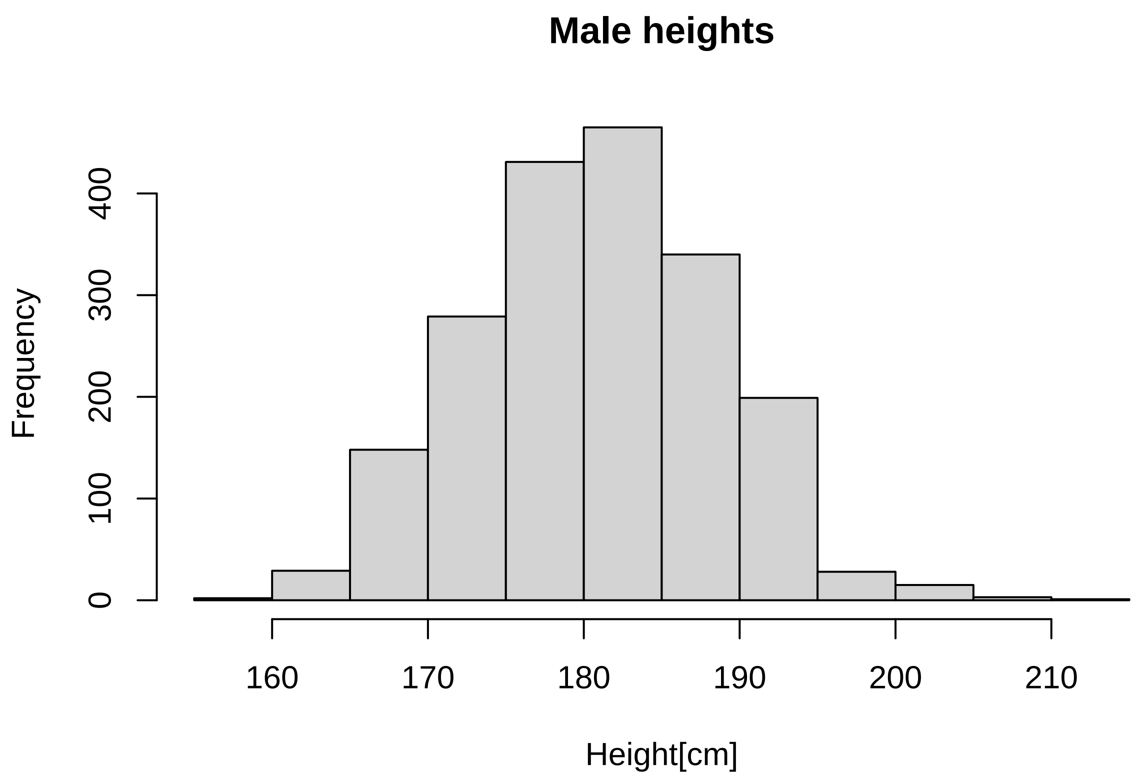
We have added a gender attribute to all fighters, which we have determined through the names of the fight categories in which that fighter fought.

Then we converted the sum of all the fighters' heights from the imperial system of measurement units to the metric system.

```
female_heights = subset(fighter_details, gender == "female")$Height_cm
male_heights = subset(fighter_details, gender == "male")$Height_cm
hist(female_heights, main = "Female heights", xlab = "Height[cm]")
```




```
hist(male_heights, main = "Male heights", xlab = "Height[cm]")
```



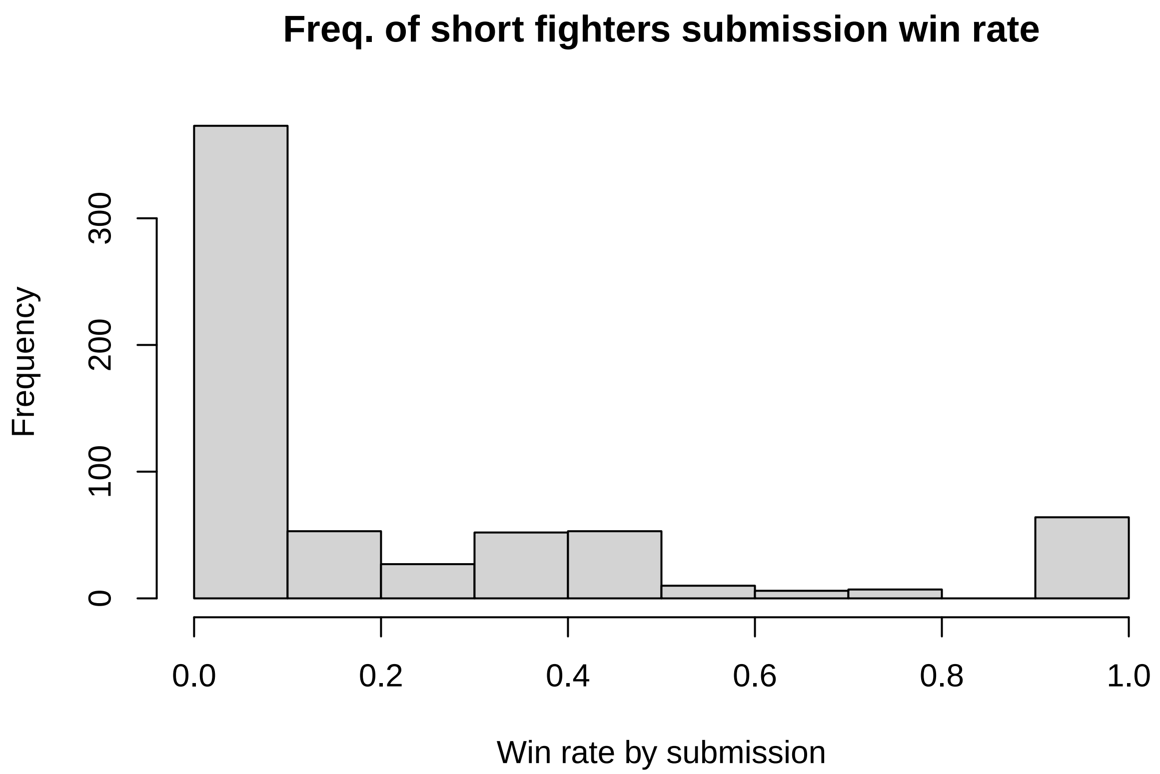
Based on the median of all male and female heights, we divided the fighters into shorter and taller fighters, with regard to gender.

```
# Determining the median height for the male and female population
male_median_height = median(male_heights, na.rm = TRUE)
female_median_height = median(female_heights, na.rm = TRUE)

# Determination of height category by gender (short for heights below the
# median, tall for heights above the median)
height_category = c()
for (i in 1:nrow(fighter_details)) {
    if (is.na(fighter_details[i, ]$Height_cm) | is.na(fighter_details[i, ]$gender)) {
        height_category = append(height_category, NA)
        next
    } else {
        if (fighter_details[i, ]$gender == "male") {
            if (fighter_details[i, ]$Height_cm >= male_median_height) {
                height_category = append(height_category, "tall")
            } else {
                height_category = append(height_category, "short")
            }
        } else {
            if (fighter_details[i, ]$Height_cm >= female_median_height) {
                height_category = append(height_category, "tall")
            } else {
                height_category = append(height_category, "short")
            }
        }
    }
}
```

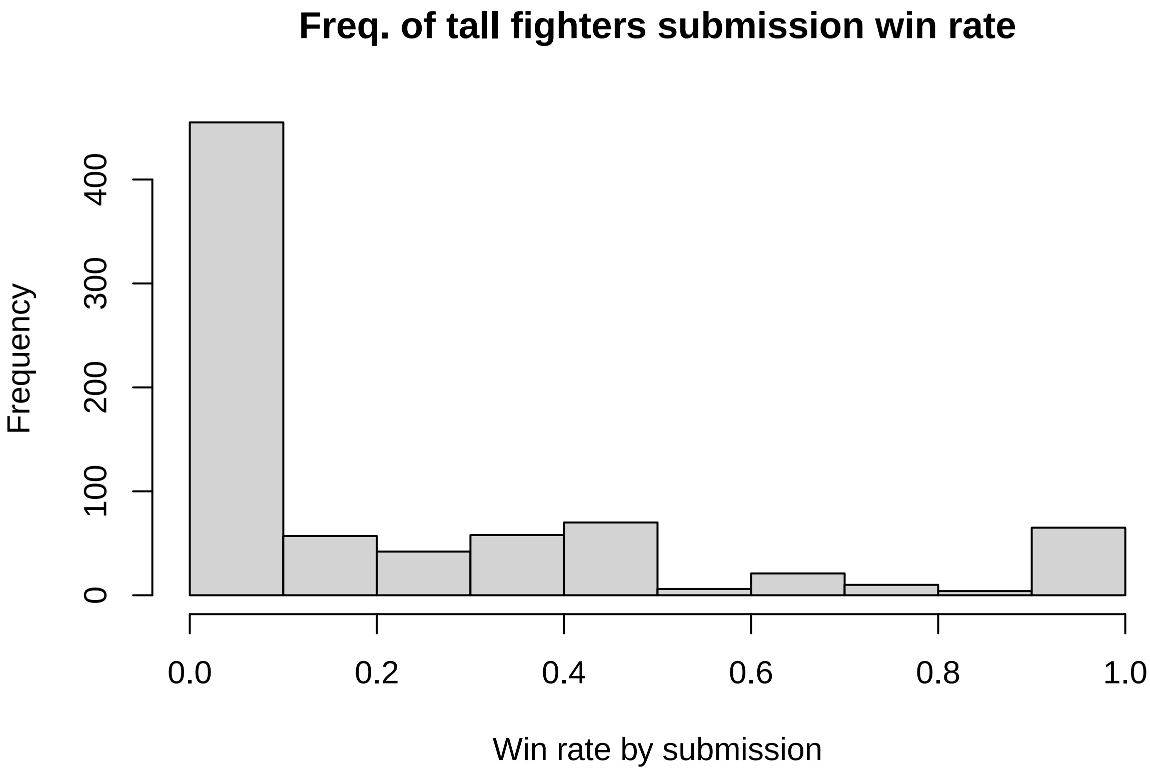
```r
# Adding a height category column
fighter_details$height_category = height_category
```

For each fighter, we determined the percentage of his victories through submission of the opposing fighter. If the fighter did not have a single victory, we marked the percentage of victories by submission of the opponent with NA.

```r
# Vector of submission win percentages for low fighters
short_winners = subset(fighter_details, height_category == "short" & !is.na(win_rate_by_submission))$wi
# Vectors of submission win percentages for tall fighters
tall_winners = subset(fighter_details, height_category == "tall" & !is.na(win_rate_by_submission))$win_

hist(short_winners, main = "Freq. of short fighters submission win rate", xlab = "Win rate by submissio
```




```r
hist(tall_winners, main = "Freq. of tall fighters submission win rate", xlab = "Win rate by submission")
```



We propose the following hypotheses:

- H0: Percentages of submission wins are the same for tall and short fighters.
- H1: The percentage of submission wins is lower for tall fighters.

We set the significance level α to 0.1 because we want to be less sensitive to not rejecting H0.

```
wilcox.test(tall_winners, short_winners, alternatives = "less", conf.level = 0.9)
```

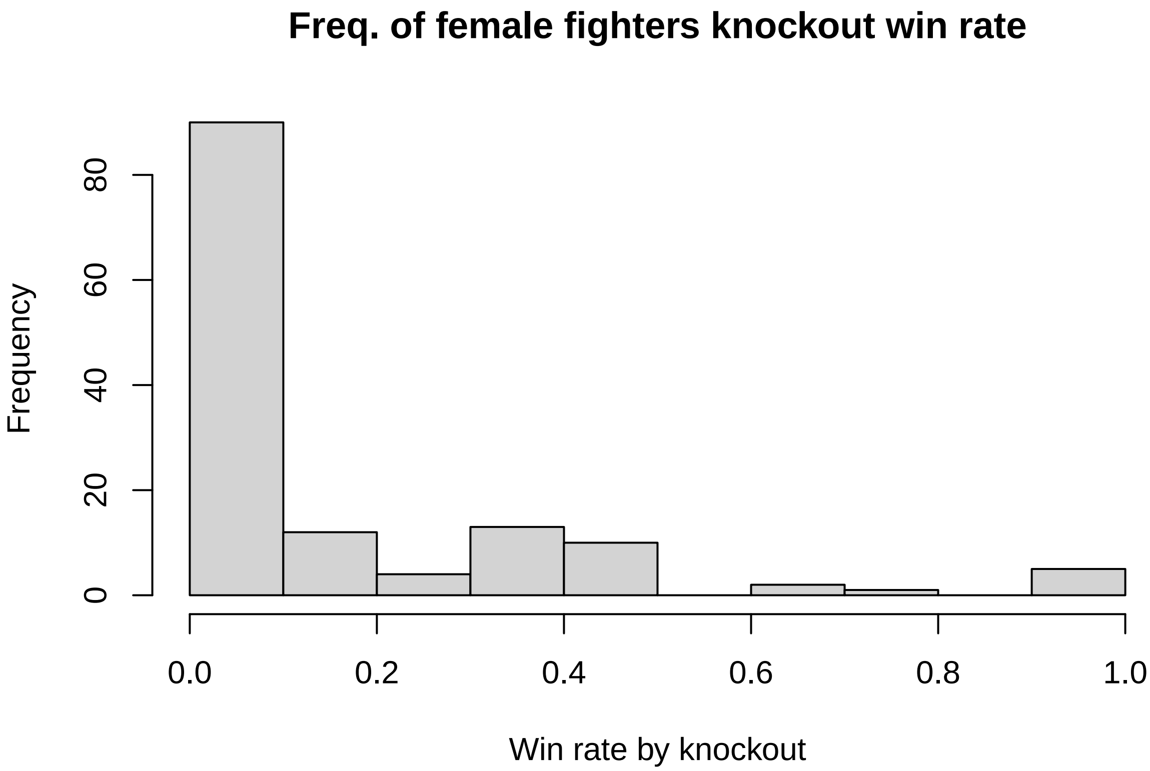
```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  tall_winners and short_winners
## W = 254820, p-value = 0.922
## alternative hypothesis: true location shift is not equal to 0
```

At the level of significance $\alpha = 0.1$ and the p value obtained from the Wilcoxon rank sum test, we conclude that we cannot reject H0 in favor of H1 (we cannot reject the hypothesis that the percentages of submission wins are the same for high and low fighters).

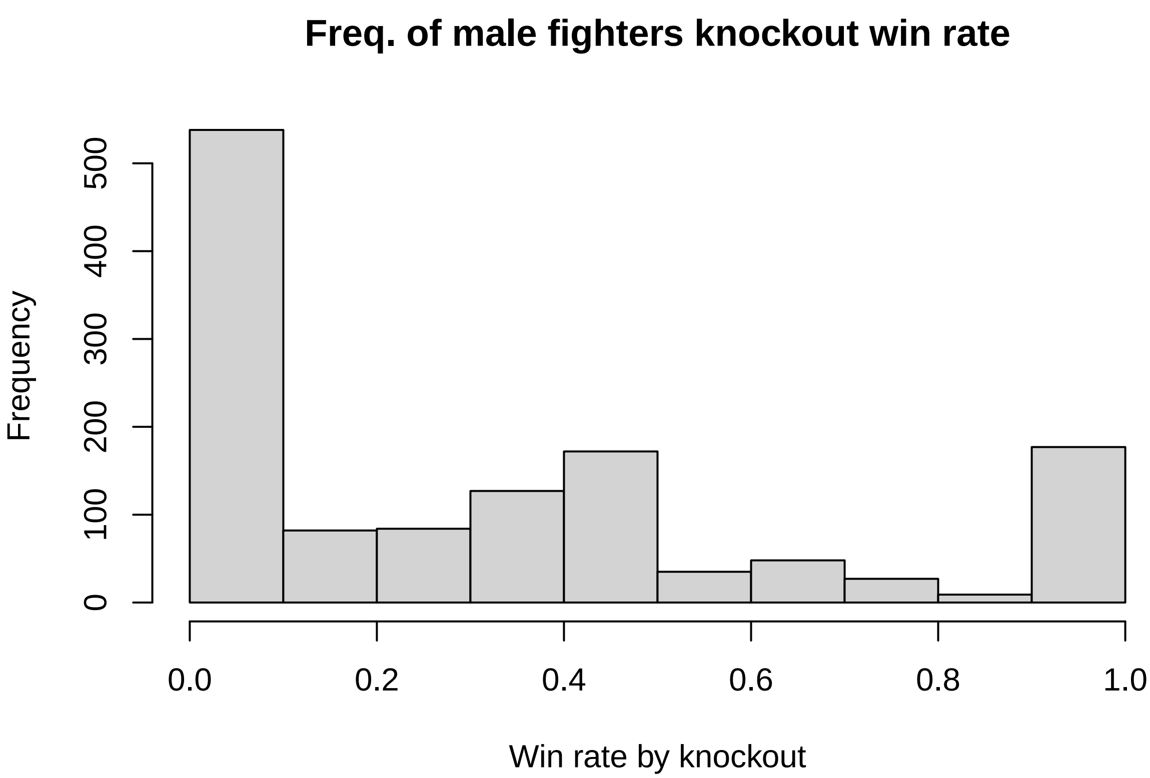
Additional task 2. - Do men's fights end more often with a knockout?

As with the previous task, we first determined each fighter's knockout percentage. For a fighter without a win, we recorded the percentage of wins by knockout with NA.

```
female_ko_winners = subset(fighter_details, gender == "female" & !is.na(win_rate_by_ko))$win_rate_by_ko
male_ko_winners = subset(fighter_details, gender == "male" & !is.na(win_rate_by_ko))$win_rate_by_ko

hist(female_ko_winners, main = "Freq. of female fighters knockout win rate", xlab = "Win rate by knocko
```




```
hist(male_ko_winners, main = "Freq. of male fighters knockout win rate", xlab = "Win rate by knockout")
```



We hypothesize:

- H0: The percentages of victories by knockout are equal for men and women.
- H1: The percentage of victories by knockout is higher for men.

We set the significance level α to 0.1, as in the previous tests.

```
wilcox.test(male_ko_winners, female_ko_winners, alternatives = "greater", conf.level = 0.9)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  male_ko_winners and female_ko_winners
## W = 116214, p-value = 7.468e-10
## alternative hypothesis: true location shift is not equal to 0
```

At the significance level $\alpha = 0.1$, we can reject H0 in favor of H1 (the percentage of victories by knockout is higher for men).

Additional task 3. - Does the number of victories and victories by knockout differ depending on the attitude of the fighter (stance)?

```
# Determination of the number of victories and the number of victories by
# knockout for fighters
total_wins = c()
total_wins_by_ko = c()
for (i in (1:nrow(fighter_details))) {
    fn = fighter_details[i, ]$fighter_name
    wins = subset(all, Winner == fn)
    wins_by_ko = subset(wins, win_by == "KO/TKO")
    total_wins = append(total_wins, nrow(wins))
    total_wins_by_ko = append(total_wins_by_ko, nrow(wins_by_ko))
}

# Adding total wins, total wins by knockout and total wins without knockout
# columns
fighter_details$total_wins = total_wins
fighter_details$total_wins_by_ko = total_wins_by_ko
fighter_details$total_wins_without_ko = total_wins - total_wins_by_ko

table(fighter_details$Stance)
```

```
##
##             Open Stance    Orthodox    Sideways    Southpaw      Switch
##         804           7        2163           3         493         126
```

We ignore fighters with an unknown attitude. We also ignore fighters with "Open Stance" and "Sideways" due to low frequency. If he is a fighter of the "Orthodox" position, then he is right-handed. If the stance is "Southpaw", then he is left-handed. If it's "Switch", then it's ambidextrous.

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

##
```

```
## Attaching package: 'data.table'

## The following objects are masked from 'package:dplyr':
##
##     between, first, last
```

```
stance_table
```

```
##      Stance total_wins_by_ko total_wins_without_ko
## 1: Orthodox             1408                  2999
## 2: Southpaw              384                   856
## 3:   Switch              100                   125
```

```
# We have to remove Stance because in the table it is represented as a
# dependent variable, but in fact it is an independent variable
stance_table = select(stance_table, -Stance)
```

The expected frequencies are greater than 5 in each cell of the table. Therefore, we can apply the homogeneity test. We hypothesize:

- H0: The percentage of victories by knockout is the same for each category of fighters according to stance (left-handed, right-handed and ambidextrous).
- H1: The percentage of victories by knockout is not equal for at least two of the categories of fighters according to stance (left-handed, right-handed and ambidextrous).

No conf_level argument is available for chisq.test, so we do not set any significance level as a test argument. However, we choose a significance level of $\alpha = 0.05$.

```
chisq.test(stance_table, correct = FALSE)
```

```
##
##  Pearson's Chi-squared test
##
## data:  stance_table
## X-squared = 16.434, df = 2, p-value = 0.00027
```

At the selected significance level, we can reject H0 in favor of H1 (the proportion of wins by KO and wins by other means is not the same for all Stance categories). From the *stance_table* we can guess that fighters who are ambidextrous have a higher proportion of victories by KO.

Task 4: Can we predict the winner from the given characteristics?

For each fight, we calculated the age of both fighters (Red and Blue) on the day of the fight.

```
## Loading required package: timechange

##
## Attaching package: 'lubridate'

## The following objects are masked from 'package:data.table':
##
##     hour, isoweek, mday, minute, month, quarter, second, wday, week,
##     yday, year

## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union
```

Certain columns within the table of all fights are in the form “x of y” because they tell how many punches the fighter saved, received, etc. For a subset of those columns, we only considered the first number x, because it gives us information about the blows exchanged during the fight. Another subset of those columns describes the fighter's overall accuracy, and for that subset of columns we calculated the x/y ratio (percentage).

Nakon toga smo odredili regresorske varijable. Zavisna varijabla je indikatorska varijabla u obliku vektora (označava pobjedu crvenog borca).

```
# Odabrane regresorske varijable i zavisna varijabla
selected_columns = c("R_KD", "B_KD", "R_SUB_ATT", "B_SUB_ATT", "R_REV", "B_REV",
    "TD_Avg.r", "SLpM.r", "SApM.r", "Sub_Avg.r", "TD_Avg.b", "SLpM.b", "SApM.b",
    "Sub_Avg.b", "Height_cm.b", "Height_cm.r", "Reach_cm.b", "Reach_cm.r", "Weight_kg.b",
    "Weight_kg.r", "red_age", "blue_age", "r_sig_str", "b_sig_str", "r_total_str",
    "b_total_str", "r_td", "b_td", "r_head", "b_head", "r_body", "b_body", "r_leg",
    "b_leg", "r_distance", "b_distance", "r_clinch", "b_clinch", "r_ground", "b_ground",
    "str_def.r", "str_acc.r", "td_acc.r", "td_def.r", "str_def.b", "str_acc.b", "td_acc.b",
    "td_def.b", "red_is_winner", "is_b_southpaw", "is_b_orthodox", "is_r_southpaw",
    "is_r_orthodox")
variables = selected_columns[selected_columns != "red_is_winner"]
```

```
library(tidyr)
# Iz seta podataka uzimamo samo odabrane regresorske varijable i zavisnu
# varijablu
logreg_data = subset(all_for_logreg, select = selected_columns)
# Uzimamo samo retke koji nemaju NA vrijednosti unutar odabranih varijabli
logreg_data = logreg_data %>%
    drop_na()
```

Koristimo model logističke regresije jer je zavisna varijabla indikatorska.

```
require(caret)
```

```
## Loading required package: caret
```

```
## Loading required package: ggplot2
```

```
## Loading required package: lattice
```

```
# b je formula varijabla_1 + varijabla_2 + ..., pri čemu je varijabla_i unutar
# skupa odabranih regresorskih varijabli
b <- paste(variables, collapse = " + ")
logreg_mdl = glm(as.formula(paste("red_is_winner ~ ", b)), data = logreg_data, family = binomial())
summary(logreg_mdl)
```

```
##
## Call:
## glm(formula = as.formula(paste("red_is_winner ~ ", b)), family = binomial(),
##     data = logreg_data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.7502  -0.4115   0.1432   0.4793   3.9856
##
## Coefficients: (4 not defined because of singularities)
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -2.315747   2.083947  -1.111 0.266469
## R_KD          1.615162   0.129801  12.443  < 2e-16 ***
## B_KD         -1.497188   0.116559 -12.845  < 2e-16 ***
## R_SUB_ATT     0.846789   0.074988  11.292  < 2e-16 ***
## B_SUB_ATT    -0.570666   0.068959  -8.275  < 2e-16 ***
```

```
## R_REV          0.332944   0.120130   2.772 0.005579 **
## B_REV         -0.584883   0.120491  -4.854 1.21e-06 ***
## TD_Avg.r      -0.165656   0.050094  -3.307 0.000943 ***
## SLpM.r        -0.242986   0.059511  -4.083 4.45e-05 ***
## SApM.r         0.109205   0.059600   1.832 0.066906 .
## Sub_Avg.r      0.042456   0.076657   0.554 0.579686
## TD_Avg.b       0.059693   0.051272   1.164 0.244326
## SLpM.b         0.080281   0.058936   1.362 0.173141
## SApM.b        -0.039535   0.056360  -0.701 0.483002
## Sub_Avg.b      0.118123   0.075815   1.558 0.119220
## Height_cm.b   -0.011844   0.013229  -0.895 0.370655
## Height_cm.r    0.008308   0.012877   0.645 0.518828
## Reach_cm.b     0.001010   0.010314   0.098 0.922021
## Reach_cm.r     0.012004   0.010020   1.198 0.230929
## Weight_kg.b    0.010779   0.010546   1.022 0.306725
## Weight_kg.r   -0.006530   0.010316  -0.633 0.526739
## red_age       -0.042532   0.012143  -3.503 0.000461 ***
## blue_age       0.017983   0.012749   1.410 0.158396
## r_sig_str      0.086270   0.013324   6.475 9.51e-11 ***
## b_sig_str     -0.093908   0.013507  -6.952 3.59e-12 ***
## r_total_str    0.013798   0.002766   4.988 6.11e-07 ***
## b_total_str   -0.002868   0.002696  -1.064 0.287503
## r_td           0.350693   0.042225   8.305  < 2e-16 ***
## b_td          -0.388208   0.041210  -9.420  < 2e-16 ***
## r_head         0.014486   0.007965   1.819 0.068955 .
## b_head        -0.025500   0.008057  -3.165 0.001551 **
## r_body        -0.015307   0.011333  -1.351 0.176814
## b_body        -0.014322   0.011892  -1.204 0.228449
## r_leg                NA         NA      NA       NA
## b_leg                NA         NA      NA       NA
## r_distance    -0.039667   0.010012  -3.962 7.44e-05 ***
## b_distance     0.050576   0.010486   4.823 1.41e-06 ***
## r_clinch      -0.035021   0.012530  -2.795 0.005189 **
## b_clinch       0.055289   0.013084   4.226 2.38e-05 ***
## r_ground             NA         NA      NA       NA
## b_ground             NA         NA      NA       NA
## str_def.r      1.026442   0.884551   1.160 0.245882
## str_acc.r      1.025007   0.822912   1.246 0.212917
## td_acc.r       0.436551   0.278385   1.568 0.116845
## td_def.r      -0.135485   0.276350  -0.490 0.623945
## str_def.b      0.898371   0.805421   1.115 0.264677
## str_acc.b     -0.525559   0.770376  -0.682 0.495106
## td_acc.b       0.527283   0.270049   1.953 0.050873 .
## td_def.b      -0.352784   0.240572  -1.466 0.142529
## is_b_southpaw  0.110691   0.246610   0.449 0.653539
## is_b_orthodox  0.011043   0.231438   0.048 0.961944
## is_r_southpaw  0.215440   0.277156   0.777 0.436968
## is_r_orthodox  0.064542   0.262283   0.246 0.805621
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6505.0  on 4894  degrees of freedom
```

```
## Residual deviance: 3154.8  on 4846  degrees of freedom
## AIC: 3252.8
##
## Number of Fisher Scoring iterations: 6
```

Iz ispisa uočavamo da su neki od regresora međusobno zavisni (NA vrijednosti). U ispisu su označeni statistički signifikantni regresori.

Na tri različita načina evaluirat ćemo kvalitetu dobivenog modela.

Računamo R^2 koji govori o tome koliko je procjenjeni model blizu ili daleko od nul-modela (što je R^2 bliži 1, to je model bolji).

```
# Računanje Rsq
Rsq = 1 - logreg_mdl$deviance/logreg_mdl$null.deviance
Rsq
```

```
## [1] 0.5150178
```

Izrađujemo matricu zabune.

```
# Izrada confusion matrix-a
yhat <- logreg_mdl$fitted.values >= 0.5
tab <- table(logreg_data$red_is_winner, yhat)

tab
```

```
##    yhat
##     FALSE TRUE
##   0  1527  337
##   1   273 2758
```

Iz matrice zabune možemo zaključiti da model dobro predviđa ishod borbe (borbe u kojima crveni borac nije pobjednik su označene kao takve, i obrnuto).

```
accuracy = sum(diag(tab))/sum(tab)
precision = tab[2, 2]/sum(tab[, 2])
recall = tab[2, 2]/sum(tab[2, ])
specificity = tab[1, 1]/sum(tab[, 1])

accuracy
```

```
## [1] 0.875383
```

```
precision
```

```
## [1] 0.8911147
```

```
recall
```

```
## [1] 0.9099307
```

```
specificity
```

```
## [1] 0.8483333
```

Due to the high values of the calculated variables (accuracy, precision, response and specificity), we conclude that the model is of high quality.

Model without linearly dependent and insignificant regressors

```r
# Dropping non-significant variables
significant_variables = c("R_KD", "B_KD", "R_SUB_ATT", "B_SUB_ATT", "R_REV", "B_REV",
    "TD_Avg.r", "red_age", "r_sig_str", "b_sig_str", "r_total_str", "r_td", "b_td",
    "r_head", "b_head", "r_distance", "b_distance", "r_clinch", "b_clinch", "td_acc.b")

b <- paste(significant_variables, collapse = " + ")
logreg_mdl_reduced = glm(as.formula(paste("red_is_winner ~ ", b)), data = logreg_data,
    family = binomial())
summary(logreg_mdl_reduced)
```

```
##
## Call:
## glm(formula = as.formula(paste("red_is_winner ~ ", b)), family = binomial(),
##     data = logreg_data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.6433  -0.4280   0.1465   0.4861   4.0328
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.962231   0.368571   2.611  0.00904 **
## R_KD         1.607436   0.128391  12.520  < 2e-16 ***
## B_KD        -1.508489   0.112876 -13.364  < 2e-16 ***
## R_SUB_ATT    0.862154   0.068966  12.501  < 2e-16 ***
## B_SUB_ATT   -0.542844   0.061487  -8.829  < 2e-16 ***
## R_REV        0.345064   0.118854   2.903  0.00369 **
## B_REV       -0.604762   0.118980  -5.083 3.72e-07 ***
## TD_Avg.r    -0.120331   0.043399  -2.773  0.00556 **
## red_age     -0.026947   0.011107  -2.426  0.01526 *
## r_sig_str    0.072030   0.011583   6.219 5.01e-10 ***
## b_sig_str   -0.101973   0.010755  -9.482  < 2e-16 ***
## r_total_str  0.012599   0.002618   4.812 1.49e-06 ***
## r_td         0.340061   0.040379   8.422  < 2e-16 ***
## b_td        -0.376136   0.035837 -10.496  < 2e-16 ***
## r_head       0.025316   0.006281   4.031 5.56e-05 ***
## b_head      -0.020417   0.006350  -3.215  0.00130 **
## r_distance  -0.038536   0.009728  -3.961 7.46e-05 ***
## b_distance   0.051120   0.009804   5.214 1.85e-07 ***
## r_clinch    -0.037243   0.012331  -3.020  0.00253 **
## b_clinch     0.053164   0.012694   4.188 2.81e-05 ***
## td_acc.b     0.680129   0.242015   2.810  0.00495 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6505  on 4894  degrees of freedom
## Residual deviance: 3210  on 4874  degrees of freedom
## AIC: 3252
##
## Number of Fisher Scoring iterations: 6
```

As for the previous model, we calculate the same quality measures (R^2, accuracy, precision, response and specificity).

```
Rsq = 1 - logreg_mdl_reduced$deviance/logreg_mdl_reduced$null.deviance
Rsq
```

```
## [1] 0.5065386
```

```
yhat <- logreg_mdl_reduced$fitted.values >= 0.5
tab <- table(logreg_data$red_is_winner, yhat)

tab
```

```
##    yhat
##     FALSE TRUE
##   0  1519  345
##   1   268 2763
```

```
accuracy = sum(diag(tab))/sum(tab)
precision = tab[2, 2]/sum(tab[, 2])
recall = tab[2, 2]/sum(tab[2, ])
specificity = tab[1, 1]/sum(tab[, 1])

accuracy
```

```
## [1] 0.8747702
```

```
precision
```

```
## [1] 0.8889961
```

```
recall
```

```
## [1] 0.9115803
```

```
specificity
```

```
## [1] 0.850028
```

Comparison of original and reduced model

We will use ANOVA to compare the models. We hypothesize:

- H0: The models are of equal quality
- H1: The original model is better than the reduced one

```
# Comparison of two models
anova(logreg_mdl, logreg_mdl_reduced, test = "LRT")
```

```
## Analysis of Deviance Table
##
## Model 1: red_is_winner ~ R_KD + B_KD + R_SUB_ATT + B_SUB_ATT + R_REV +
##     B_REV + TD_Avg.r + SLpM.r + SApM.r + Sub_Avg.r + TD_Avg.b +
##     SLpM.b + SApM.b + Sub_Avg.b + Height_cm.b + Height_cm.r +
##     Reach_cm.b + Reach_cm.r + Weight_kg.b + Weight_kg.r + red_age +
##     blue_age + r_sig_str + b_sig_str + r_total_str + b_total_str +
##     r_td + b_td + r_head + b_head + r_body + b_body + r_leg +
##     b_leg + r_distance + b_distance + r_clinch + b_clinch + r_ground +
##     b_ground + str_def.r + str_acc.r + td_acc.r + td_def.r +
##     str_def.b + str_acc.b + td_acc.b + td_def.b + is_b_southpaw +
```

```
##     is_b_orthodox + is_r_southpaw + is_r_orthodox
## Model 2: red_is_winner ~ R_KD + B_KD + R_SUB_ATT + B_SUB_ATT + R_REV +
##     B_REV + TD_Avg.r + red_age + r_sig_str + b_sig_str + r_total_str +
##     r_td + b_td + r_head + b_head + r_distance + b_distance +
##     r_clinch + b_clinch + td_acc.b
##   Resid. Df Resid. Dev  Df Deviance Pr(>Chi)
## 1      4846     3154.8
## 2      4874     3210.0 -28  -55.157 0.001627 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

With the significance level $\alpha = 0.05$, we conclude that we can reject H0 in favor of H1 (the original model is better than the reduced one).

Model with a priori data

An interesting question arises whether we can determine the winner based only on the features available before the fight (previous statistics of each fighter).

We select only the variables available before the fight for each fighter, and use them as regressors in the new logistic model.

```r
fighter_details_variables = c("TD_Avg.r", "SLpM.r", "SApM.r", "Sub_Avg.r", "TD_Avg.b",
    "SLpM.b", "SApM.b", "Sub_Avg.b", "Height_cm.b", "Height_cm.r", "Reach_cm.b",
    "Reach_cm.r", "Weight_kg.b", "Weight_kg.r", "red_age", "blue_age", "str_def.r",
    "str_acc.r", "td_acc.r", "td_def.r", "str_def.b", "str_acc.b", "td_acc.b", "td_def.b",
    "red_is_winner", "is_b_southpaw", "is_b_orthodox", "is_r_southpaw", "is_r_orthodox")
logreg_fighters_data = subset(logreg_data, select = fighter_details_variables)
fighter_details_variables = fighter_details_variables[fighter_details_variables !=
    "red_is_winner"]

b <- paste(fighter_details_variables, collapse = " + ")
logreg_mdl_fighter_details = glm(as.formula(paste("red_is_winner ~ ", b)), data = logreg_fighters_data,
    family = binomial())
summary(logreg_mdl_fighter_details)
```

```
##
## Call:
## glm(formula = as.formula(paste("red_is_winner ~ ", b)), family = binomial(),
##     data = logreg_fighters_data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.5911  -1.1276   0.6372   0.9376   2.5427
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)    0.362263   1.470762   0.246 0.805442
## TD_Avg.r       0.082014   0.031043   2.642 0.008243 **
## SLpM.r         0.193547   0.041759   4.635 3.57e-06 ***
## SApM.r        -0.236117   0.046166  -5.115 3.15e-07 ***
## Sub_Avg.r      0.228914   0.053854   4.251 2.13e-05 ***
## TD_Avg.b      -0.135603   0.030649  -4.424 9.67e-06 ***
## SLpM.b        -0.393796   0.040807  -9.650  < 2e-16 ***
## SApM.b         0.290459   0.042341   6.860 6.89e-12 ***
## Sub_Avg.b     -0.020913   0.050196  -0.417 0.676955
```

```
## Height_cm.b    0.003686   0.009000   0.410 0.682136
## Height_cm.r   -0.018386   0.008944  -2.056 0.039817 *
## Reach_cm.b    -0.010076   0.006999  -1.440 0.149995
## Reach_cm.r     0.015135   0.007032   2.152 0.031382 *
## Weight_kg.b   -0.006954   0.007143  -0.973 0.330337
## Weight_kg.r    0.018584   0.007034   2.642 0.008240 **
## red_age       -0.070837   0.008392  -8.441  < 2e-16 ***
## blue_age       0.035646   0.008532   4.178 2.94e-05 ***
## str_def.r      2.573977   0.627867   4.100 4.14e-05 ***
## str_acc.r      1.311565   0.568228   2.308 0.020990 *
## td_acc.r       0.246586   0.199762   1.234 0.217052
## td_def.r       0.642828   0.193815   3.317 0.000911 ***
## str_def.b      0.009585   0.573514   0.017 0.986666
## str_acc.b     -0.089157   0.533090  -0.167 0.867177
## td_acc.b       0.727728   0.185291   3.927 8.58e-05 ***
## td_def.b      -0.958857   0.174279  -5.502 3.76e-08 ***
## is_b_southpaw  0.131983   0.173821   0.759 0.447669
## is_b_orthodox  0.201698   0.163164   1.236 0.216397
## is_r_southpaw  0.214007   0.196056   1.092 0.275027
## is_r_orthodox  0.035178   0.186356   0.189 0.850274
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6505.0  on 4894  degrees of freedom
## Residual deviance: 5812.6  on 4866  degrees of freedom
## AIC: 5870.6
##
## Number of Fisher Scoring iterations: 4
```

We calculate measures of model quality.

```r
# Calculation of Rsq
Rsq = 1 - logreg_mdl_fighter_details$deviance/logreg_mdl_fighter_details$null.deviance
Rsq
```

```
## [1] 0.1064381
```

```r
yhat <- logreg_mdl_fighter_details$fitted.values >= 0.5
tab <- table(logreg_fighters_data$red_is_winner, yhat)

tab
```

```
##    yhat
##     FALSE TRUE
##   0   754 1110
##   1   437 2594
```

```r
accuracy = sum(diag(tab))/sum(tab)
precision = tab[2, 2]/sum(tab[, 2])
recall = tab[2, 2]/sum(tab[2, ])
specificity = tab[1, 1]/sum(tab[, 1])

accuracy
```

```
## [1] 0.6839632
```

```
precision
```

```
## [1] 0.700324
```

```
recall
```

```
## [1] 0.8558232
```

```
specificity
```

```
## [1] 0.6330814
```

From the calculated quality measures, we infer that the model is worse than the previous ones, but also that it is better than ordinary guessing.