Final Project

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```r
library(dplyr)
```

```
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
```

```r
library(tidyverse)
```

```
-- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
v forcats   1.0.0     v readr     2.1.4
v ggplot2   3.4.3     v stringr   1.5.0
v lubridate 1.9.2     v tibble    3.2.1
v purrr     1.0.2     v tidyr     1.3.0

-- Conflicts ------------------------------------------ tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom
```

```r
library(tidymodels)
```

```
-- Attaching packages -------------------------------------- tidymodels 1.1.1 --
v broom        1.0.5     v rsample      1.2.0
v dials        1.2.0     v tune         1.1.2
v infer        1.0.5     v workflows    1.1.3
v modeldata    1.2.0     v workflowsets 1.0.1
v parsnip      1.1.1     v yardstick    1.2.0
v recipes      1.0.8
-- Conflicts ----------------------------------------- tidymodels_conflicts() --
x scales::discard() masks purrr::discard()
x dplyr::filter()   masks stats::filter()
x recipes::fixed()  masks stringr::fixed()
x dplyr::lag()      masks stats::lag()
x yardstick::spec() masks readr::spec()
x recipes::step()   masks stats::step()
* Dig deeper into tidy modeling with R at https://www.tmwr.org
```

```r
library(ggplot2)
library(Stat2Data)
tennis <- read.csv("data/wta_matches_qual_itf_2023.csv")
```

Introduction and Data

Research Question

Does the court type impact the duration of a women's single tennis match, considering the winner's height, age, and playing hand?

The data we chose was the Women's Tennis Association data set from Awesomedata's GitHub repository (https://github.com/JeffSackmann/tennis_wta/blob/master/wta_matches_qual_itf_2023.csv) The data was created in 2023 and was collected from the International Tennis Federation. The data contains 34,323 observations and 49 variables. The variables of interest in our research include surface, winner and loser height, winner and loser age, and winner and loser hand. These variables will help us answer the question of the court types impact on the duration of tennis matches. There are some NA variables corresponding to the players height. Since this is our variable of interest, we will be dropping all NA values corresponding to height. This will leave us with 1,256 obeservations. Additionally, since grand slams are played on either clay, grass, or hard courts, we will be dropping the matches that were played on carpet. This will then leave us with 1,239 observations. The motivation behind this project is to help Women's Tennis players better prepare for the length of their match based on the surface they will be playing on. With the Olympics coming up, this data will help the tennis player better prepare for a match.

```r
tennis <- tennis %>%
  filter(!is.na(winner_ht) & !is.na(loser_ht) & surface != "Carpet")
```

Variables of Interest

Surface: Surface the match was played on (clay, grass, or hard)

Winner_hand: Dominant playing hand of the winner (right, left, undecided)

Winner_ht: Height of the winner in centimeters (cm)

Winner_age: Age of the winner

loser_hand: Dominant playing hand of the loser (right, left, undecided)

loser_ht: Height of the loser in centimeters (cm)

loser_age: Age of the loser

Minutes: Duration of the tennis match in minutes

```r
winner_hand_counts <- tennis |>
  count(winner_hand)

loser_hand_counts <- tennis |>
  count(loser_hand)

print(winner_hand_counts)
```

```
  winner_hand    n
1           L  116
2           R 1110
3           U   13
```

```r
print(loser_hand_counts)
```

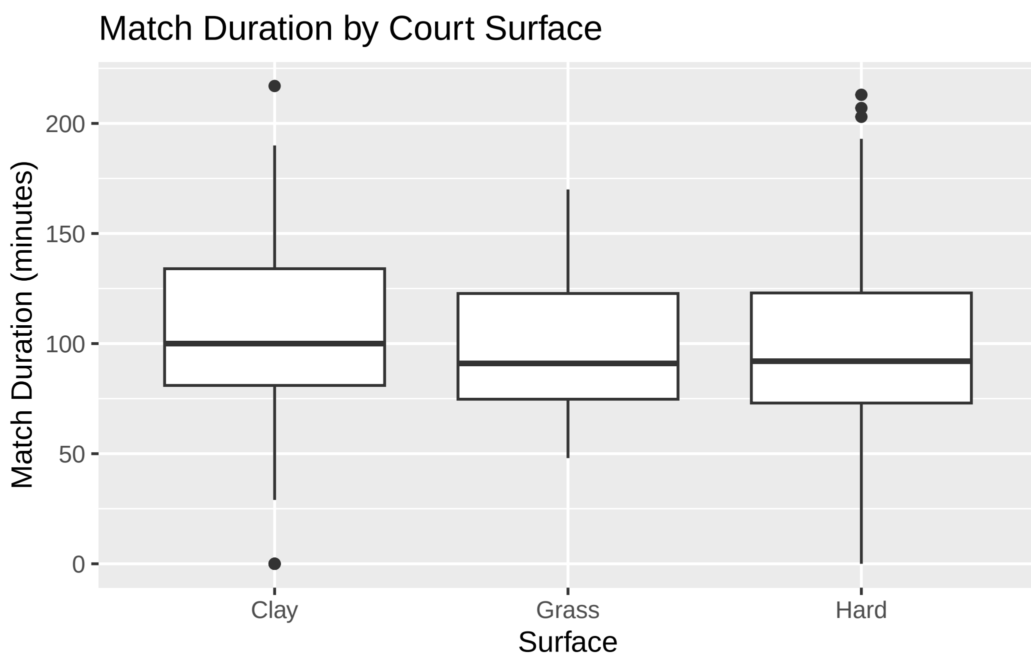
```
  loser_hand    n
1          L  107
2          R 1107
3          U   25
```

Methodology

First we wanted to visualize the relationship between the match duration and the surface that match was played on. We generated a box plot for each surface, clay, grass, and hard. The results indicated that the average match duration tends to be higher for matches played on clay.

```
ggplot(data = tennis, aes(x = surface, y = minutes)) +
  geom_boxplot() +
  labs(title = "Match Duration by Court Surface",
       x = "Surface",
       y = "Match Duration (minutes)")
```

```
Warning: Removed 620 rows containing non-finite values (`stat_boxplot()`).
```



We are using a logistic regression model to evaluate whether the length of a tennis match is influenced by the surface the match is played on, the age of the player, the height of the player, and the playing hand of the player. This seems to be an appropriate model for our data given that it satisfies the independence and linearity assumptions in the log odds. Each observation in the dataset represents a different tennis match making this assumption hold since each tennis match is independent of each other. The outcome of one match doesn't not influence the outcome of the other. In addition, there is independence within each player. The characteristics of one player do not directly influence the characteristics of the other. For the outcome variable, we chose to use the binary version of whether a match was above or below the average minutes of all the matches. This binary outcome generates a simpler model that makes it easier to observe and interpret.

```r
library(MASS)
```

```

Attaching package: 'MASS'

The following object is masked from 'package:dplyr':

    select
```

```r
tennis_binary <- tennis |>
  mutate(minutes = case_when(minutes >= 101.3 ~ 1,
                             minutes <= 101.3 ~ 0),
         minutes = as.factor(minutes))

winner_mins <- glm(minutes ~ surface + winner_age +
                    as.numeric(winner_ht) + winner_hand, data = tennis_binary,
                   family = "binomial")
summary(winner_mins)
```

```

Call:
glm(formula = minutes ~ surface + winner_age + as.numeric(winner_ht) +
    winner_hand, family = "binomial", data = tennis_binary)

Coefficients:
                        Estimate Std. Error z value Pr(>|z|)
(Intercept)            -3.051243   2.321364  -1.314   0.1887
surfaceGrass           -0.246180   0.296445  -0.830   0.4063
surfaceHard            -0.198074   0.179377  -1.104   0.2695
winner_age              0.047255   0.019366   2.440   0.0147 *
as.numeric(winner_ht)   0.008849   0.012878   0.687   0.4920
winner_handR            0.121194   0.291980   0.415   0.6781
winner_handU          -12.810120 535.411309  -0.024   0.9809
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 849.49  on 618  degrees of freedom
Residual deviance: 840.17  on 612  degrees of freedom
  (620 observations deleted due to missingness)
AIC: 854.17

Number of Fisher Scoring iterations: 12
```

```
loser_mins <- glm(minutes ~ surface + loser_age +
                    as.numeric(loser_ht) + loser_hand, data = tennis_binary,
                    famil = "binomial")
summary(loser_mins)
```

```
Call:
glm(formula = minutes ~ surface + loser_age + as.numeric(loser_ht) +
    loser_hand, family = "binomial", data = tennis_binary)

Coefficients:
                      Estimate Std. Error z value Pr(>|z|)
(Intercept)          -6.106356   2.286333  -2.671  0.00757 **
surfaceGrass         -0.211784   0.298861  -0.709  0.47855
surfaceHard          -0.201920   0.180160  -1.121  0.26238
loser_age             0.009084   0.019564   0.464  0.64240
as.numeric(loser_ht)  0.030503   0.012685   2.405  0.01618 *
loser_handR           0.537760   0.308438   1.743  0.08125 .
loser_handU          -0.434522   0.873335  -0.498  0.61881
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 849.49  on 618  degrees of freedom
Residual deviance: 837.20  on 612  degrees of freedom
  (620 observations deleted due to missingness)
AIC: 851.2

Number of Fisher Scoring iterations: 4
```

```r
exp(coef(loser_mins))
```

```
  (Intercept)        surfaceGrass          surfaceHard 
  0.002228658         0.809139613          0.817160408 
    loser_age as.numeric(loser_ht)          loser_handR 
  1.009125753         1.030972719          1.712166551 
  loser_handU 
  0.647574123 
```

```r
exp(coef(winner_mins))
```

```
   (Intercept)          surfaceGrass            surfaceHard 
  4.730011e-02          7.817814e-01           8.203089e-01 
    winner_age as.numeric(winner_ht)           winner_handR 
  1.048390e+00          1.008888e+00           1.128843e+00 
  winner_handU 
  2.732973e-06 
```

Loser For the loser of a match on a court with a surface of grass is predicted to have 0.810 times the odds of the match running over 101.3 minutes compared to a surface of clay while adjusting for age, height, and playing hand.

For the loser of a match on a court with a surface of hard is predicted to have 0.817 times the odds of the match running over 101.3 minutes compared to a surface of clay while adjusting for age, height, and playing hand.

For the loser of a match on a court with an age one year older than another is predicted to have 1.00913 times the odds of the match running over 101.3 minutes while adjusting for playing surface, height, and playing hand.

For the loser of a match on a court with a height 1 cm taller than another is predicted to have 1.031 times the odds of the match running over 101.3 minutes while adjusting for playing surface, age, and playing hand.

For the loser of a match on a court who plays with their right hand is predicted to have 1.712 times the odds of the match running over 101.3 minutes, compared to that of a left handed player while adjusting for playing surface, age, and height.

For the loser of a match on a court who plays with either hand is predicted to have 0.648 times the odds of the match running over 101.3 minutes, compared to that of a left handed player while adjusting for playing surface, age, and height.

Winner For the winner of a match on a court with a surface of grass is predicted to have 0.0782 times the odds of the match running over 101.3 minutes compared to a surface of clay while adjusting for age, height, and playing hand.

For the winner of a match on a court with a surface of hard is predicted to have 0.0820 times the odds of the match running over 101.3 minutes compared to a surface of clay while adjusting for age, height, and playing hand.

For the winner of a match on a court with an age one year older than another is predicted to have 1.0484 times the odds of the match running over 101.3 minutes while adjusting for playing surface, height, and playing hand.

For the winner of a match on a court with a height 1 cm taller than another is predicted to have 1.00889 times the odds of the match running over 101.3 minutes while adjusting for playing surface, age, and playing hand.

For the winner of a match on a court who plays with their right hand is predicted to have 1.129 times the odds of the match running over 101.3 minutes, compared to that of a left handed player while adjusting for playing surface, age, and height.

For the winner of a match on a court who plays with either hand is predicted to have 0.00000273 times the odds of the match running over 101.3 minutes, compared to that of a left handed player while adjusting for playing surface, age, and height.

We then checked to see if the linearity condition was met for the continuous predictors that we used on our variables. Our plots indicated that the winner age and loser age passed the linearity assumption. The linearity condition was not met for the predictors winner_ht and loser_ht. To address this violation of the linearity assumption, we used a log transformation on these variables.

We produced two models as seen below:

p(1-p) = the odds of the match duration being above 101.3 minutes.

$$log(p/(1-p)) = \beta_0 + \beta_1(surface) + \beta_2(winner\_age) + \beta_3(log(winner\_ht)) + \beta_4(winner\_hand)$$

$$log(p/(1-p)) = \beta_0 + \beta_1(surface) + \beta_2(log(loser\_age)) + \beta_3(log(loser\_ht)) + \beta_4(loser\_hand)$$

```
winner_mins <- glm(minutes ~ surface + winner_age +
                    log(as.numeric(winner_ht)) + winner_hand, data = tennis_binary,
                   family = "binomial")
summary(winner_mins)
```

```
Call:
glm(formula = minutes ~ surface + winner_age + log(as.numeric(winner_ht)) +
    winner_hand, family = "binomial", data = tennis_binary)

Coefficients:
                            Estimate Std. Error z value Pr(>|z|)
(Intercept)                 -9.07179   11.46850  -0.791   0.4289
surfaceGrass                -0.24619    0.29645  -0.830   0.4063
surfaceHard                 -0.19786    0.17937  -1.103   0.2700
winner_age                   0.04722    0.01937   2.438   0.0148 *
log(as.numeric(winner_ht))   1.46557    2.22021   0.660   0.5092
winner_handR                 0.12186    0.29193   0.417   0.6764
winner_handU               -12.80678  535.41132  -0.024   0.9809
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 849.49  on 618  degrees of freedom
Residual deviance: 840.20  on 612  degrees of freedom
  (620 observations deleted due to missingness)
AIC: 854.2

Number of Fisher Scoring iterations: 12
```

```r
loser_mins <- glm(minutes ~ surface + loser_age +
                  log(as.numeric(loser_ht)) + loser_hand, data = tennis_binary,
                  famil = "binomial")
summary(loser_mins)
```

```
Call:
glm(formula = minutes ~ surface + loser_age + log(as.numeric(loser_ht)) +
    loser_hand, family = "binomial", data = tennis_binary)

Coefficients:
                            Estimate Std. Error z value Pr(>|z|)
(Intercept)               -28.530883  11.347591  -2.514   0.0119 *
surfaceGrass               -0.210907   0.298914  -0.706   0.4805
surfaceHard                -0.201553   0.180189  -1.119   0.2633
```

```
loser_age                    0.009225   0.019566   0.471   0.6373
log(as.numeric(loser_ht))    5.375154   2.197977   2.446   0.0145 *
loser_handR                  0.539225   0.308468   1.748   0.0805 .
loser_handU                 -0.434222   0.873307  -0.497   0.6190
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 849.49  on 618  degrees of freedom
Residual deviance: 836.99  on 612  degrees of freedom
  (620 observations deleted due to missingness)
AIC: 850.99

Number of Fisher Scoring iterations: 4
```