Wrangling Chess Tournament Data

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Setup

Load libraries

```
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --

## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.4     v dplyr   1.0.7
## v tidyr   1.1.3     v stringr 1.4.0
## v readr   2.0.1     v forcats 0.5.1

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(stringr)
library("RMySQL")
```

```
## Loading required package: DBI
```

Establish connection to SQL

After processing and formatting the input data as per assignment instructions, we will be saving the output in SQL. I've created two tables:

- players: a table of players
- scores: a table of player scores from tournaments played

```
mydb = dbConnect(MySQL(), user = 'root', dbname='data_607', host='localhost')
```

The below code will close all open SQL connections if run

```
lapply(dbListConnections(dbDriver(drv = "MySQL")), dbDisconnect)
```

And here is the code to create the tables

```
CREATE TABLE data_607.players (
  id int NOT NULL,
  player_name varchar(100) NOT NULL,
  player_state varchar(25) DEFAULT NULL,
  PRIMARY KEY (id)
) ENGINE=InnoDB DEFAULT CHARSET=utf8mb4 COLLATE=utf8mb4_0900_ai_ci;

CREATE TABLE data_607.scores (
  unique_id int AUTO_INCREMENT NOT NULL,
  tournament_id int NOT NULL,
  player_id int NOT NULL,
  number_of_games int DEFAULT NULL,
  total float DEFAULT NULL,
  expected_total float DEFAULT NULL,
  pre_score int DEFAULT NULL,
  avg_opponent_score int DEFAULT NULL,
  PRIMARY KEY (unique_id),
  FOREIGN KEY (player_id) REFERENCES players(id)
) ENGINE=InnoDB DEFAULT CHARSET=utf8mb4 COLLATE=utf8mb4_0900_ai_ci;
```

Convert [input data] –> [desired assignment format]

This assignment's input data is a "|" delimited .txt file containing information about players in a chess tournament. This project aims to wrangle the input data into a tabular format, with the following columns:

- Player's Name
- Player's State
- Total Number of Points
- Player's Pre-Rating
- Average Pre Chess Rating of Opponents

Import data and inspect

```
data = read.table("https://raw.githubusercontent.com/man-of-moose/masters_607/main/projects/project_1/cl
                  sep="|",
                  fill=TRUE
                  )
```

```
head(data)
```

```
##                                                                                                 V1
## 1 ---------------------------------------------------------------------------------------------------
## 2                                                                                              Pair
## 3                                                                                              Num
## 4 ---------------------------------------------------------------------------------------------------
## 5                                                                                                1
## 6                                                                                               ON
##                                 V2    V3    V4    V5    V6    V7    V8    V9
## 1
## 2  Player Name                    Total Round Round Round Round Round Round
## 3  USCF ID / Rtg (Pre->Post)       Pts    1     2     3     4     5     6
## 4
## 5  GARY HUA                       6.0   W  39 W  21 W  18 W  14 W   7 D  12
## 6  15445895 / R: 1794   ->1817    N:2   W     B     W     B     W     B
##     V10 V11
## 1        NA
## 2 Round  NA
## 3   7    NA
## 4        NA
## 5 D   4  NA
## 6 W      NA
```

Change column names

Rename columns to make analysis meaningful

```
column_names <- c("id","name","total","round_1","round_2","round_3","round_4",
                  "round_5","round_6","round_7","delete")

colnames(data) <- column_names
```

Remove "————-" rows

Following data import, there are some rows that serve no purpose for our assignment. Additionally, an unexpected column of NAs was created which we will want to delete. We will use dplyr::filer and dplyr::select to achieve this.

```
data<- data %>%
        filter(str_detect(id, "[a-zA-z\\d]")) %>%
        select(-delete)
```

Looking at our data now

Due to the structure of the input data, and the steps we've taken so far, our current dataframe is structured in an interesting way. Rows with a numeric "id" value contain information about a player's name, their total score, and the rounds they played. While rows with a character "id" contain information about a player's state and pre_score.

```
head(data)
```

```
##       id                              name total round_1 round_2 round_3
```

```
## 1  Pair   Player Name                        Total   Round   Round   Round
## 2  Num    USCF ID / Rtg (Pre->Post)          Pts       1       2       3
## 3     1   GARY HUA                          6.0     W  39   W  21   W  18
## 4    ON   15445895 / R: 1794   ->1817       N:2     W       B       W
## 5     2   DAKSHESH DARURI                   6.0     W  63   W  58   L   4
## 6    MI   14598900 / R: 1553   ->1663       N:2     B       W       B
##   round_4 round_5 round_6 round_7
## 1   Round   Round   Round   Round
## 2     4       5       6       7
## 3   W  14   W   7   D  12   D   4
## 4   B       W       B       W
## 5   W  17   W  16   W  20   W   7
## 6   W       B       W       B
```

Get state_data character vector

We need to capture the state data in a character vector, to later be used to represent the state column of our output. We can do this by filtering for rows that contain 2 capital letters, and saving the "id" column into a variable called state_data

```
state_data <- data$id
state_data <- state_data[grepl("[A-Z]{2}",state_data)]
state_data <- str_trim(state_data, side = c("both"))
```

Get pre_score data

We can extract the pre_score data in the same way we did state_data. Unlike state_data, the pre_score data will require more advanced regex to properly extract.

```
pre_score_data <- data$name

data$id <- data$id %>%
  str_trim(side=c("both"))

pre_score_data <- data %>%
  filter(str_detect(id,"[A-Z]{2}")) %>%
  .$name

pre_score_data <- pre_score_data %>%
              str_extract("R:[^\\d]*\\d*") %>%
              str_replace("R:","") %>%
              str_trim(side=c("both"))
```

Remove rows with non-numeric values

Now that we've extracted the state data and pre_score data, we can remove rows with non-numeric values.

```
data <- data %>%
        filter(str_detect(id,"\\d"))
```

Add state and pre_score columns

And now we can take state_data and pre_score_data and add them as new columns to the recently filtered dataframe.

```
data$state <- state_data
data$pre_score <- as.integer(pre_score_data)
```

Rearrange columns for clarity

Using dply::select and everything() we can easily re-arrange our column values for easier reading.

```
data <- data %>%
          select(name, state, pre_score, total, everything())
```

```
head(data)
```

```
##                                name state pre_score total id round_1 round_2
## 1  GARY HUA                           ON      1794 6.0    1   W  39   W  21
## 2  DAKSHESH DARURI                    MI      1553 6.0    2   W  63   W  58
## 3  ADITYA BAJAJ                       MI      1384 6.0    3   L   8   W  61
## 4  PATRICK H SCHILLING                MI      1716 5.5    4   W  23   D  28
## 5  HANSHI ZUO                         MI      1655 5.5    5   W  45   W  37
## 6  HANSEN SONG                        OH      1686 5.0    6   W  34   D  29
##   round_3 round_4 round_5 round_6 round_7
## 1   W  18   W  14   W   7   D  12   D   4
## 2   L   4   W  17   W  16   W  20   W   7
## 3   W  25   W  21   W  11   W  13   W  12
## 4   W   2   W  26   D   5   W  19   D   1
## 5   D  12   D  13   D   4   W  14   W  17
## 6   L  11   W  35   D  10   W  27   W  21
```

Convert total into double

The 'total' value was parsed as a character. since we will be applying math to this later, we need to convert to a double.

```
data$total <- as.double(data$total)
```

Create new column, "oppo_ids"

This new column will include vectors containing the opponent ids for each respective player. As an example, Gary Hua's value here would be:

c(39,21,18,14,7,12,4)

This is achieved by first concatenating each of the "round_" columns. Following this, we use stringr to parse out and collect the opponent ids.

```
data <- data %>% mutate(oppo_ids = str_c(round_1,round_2,round_3,round_4,round_5,round_6,round_7))

data$oppo_ids <- data$oppo_ids %>%
  str_replace_all("[A-Z]","") %>%
  str_trim(side=c("both")) %>%
  str_replace_all("\\s{2,}","|")

data$oppo_ids <- data$oppo_ids %>% str_split("\\|")
```

Create function to calculate average opponent score

This function will use the previously created "oppo_id" column values as input, in order to filter for and average the correct opponent pre_scores.

```
get_avg_oppo_score <- function(id_data) {
  temp_df <- data %>%
              filter(id %in% id_data) %>%
              summarise(pre_score_mean = mean(pre_score, na.rm=TRUE))

  return(temp_df[,1])
}
```

Test it out on the first example

```
get_avg_oppo_score(c(39,21,18,14,7,12,4))
```

```
## [1] 1605.286
```

Apply function to entire dataframe

```
data$avg_oppo_score <- lapply(data$oppo_ids,FUN=get_avg_oppo_score)
```

Calculate total number of games played

We will need this later on for extra credit. Here we are counting how many games each player participated in.

```
data$number_of_games <- as.integer(
  lapply(
    lapply(data$oppo_ids,FUN=lengths),
    FUN=sum
    )
  )
```

Select only interesting columns

There are a few columns we don't need anymore such as all of the "round_" columns, the "oppo_ids" column, and others. We can use dplyr::select to select only what's interesting.

```
final_data <- data %>%
                select(name,
                       state,
                       total,
                       number_of_games,
                       pre_score,
                       avg_oppo_score
                       )
```

Round avg_oppo_score (Average Opponent Score) and inspect

Based on the description of this project, we will be rounding the values of avg_oppo_score with the round() function.

```
final_data$avg_oppo_score <- as.integer(
  lapply(final_data$avg_oppo_score,FUN=round)
  )
```

```
final_data
```

```
##                              name state total number_of_games pre_score
## 1   GARY HUA                   ON   6.0               7      1794
## 2   DAKSHESH DARURI            MI   6.0               7      1553
## 3   ADITYA BAJAJ               MI   6.0               7      1384
## 4   PATRICK H SCHILLING        MI   5.5               7      1716
## 5   HANSHI ZUO                 MI   5.5               7      1655
## 6   HANSEN SONG                OH   5.0               7      1686
## 7   GARY DEE SWATHELL          MI   5.0               7      1649
## 8   EZEKIEL HOUGHTON           MI   5.0               7      1641
## 9   STEFANO LEE                ON   5.0               7      1411
## 10  ANVIT RAO                  MI   5.0               7      1365
## 11  CAMERON WILLIAM MC LEMAN   MI   4.5               7      1712
## 12  KENNETH J TACK             MI   4.5               6      1663
## 13  TORRANCE HENRY JR          MI   4.5               7      1666
## 14  BRADLEY SHAW               MI   4.5               7      1610
## 15  ZACHARY JAMES HOUGHTON     MI   4.5               7      1220
## 16  MIKE NIKITIN               MI   4.0               5      1604
## 17  RONALD GRZEGORCZYK         MI   4.0               7      1629
## 18  DAVID SUNDEEN              MI   4.0               7      1600
## 19  DIPANKAR ROY               MI   4.0               7      1564
## 20  JASON ZHENG                MI   4.0               7      1595
## 21  DINH DANG BUI              ON   4.0               7      1563
## 22  EUGENE L MCCLURE           MI   4.0               6      1555
## 23  ALAN BUI                   ON   4.0               7      1363
## 24  MICHAEL R ALDRICH          MI   4.0               7      1229
## 25  LOREN SCHWIEBERT           MI   3.5               7      1745
## 26  MAX ZHU                    ON   3.5               7      1579
```

```
## 27  GAURAV GIDWANI                    MI   3.5              6      1552
## 28  SOFIA ADINA STANESCU-BELLU         MI   3.5              7      1507
## 29  CHIEDOZIE OKORIE                  MI   3.5              6      1602
## 30  GEORGE AVERY JONES                ON   3.5              7      1522
## 31  RISHI SHETTY                      MI   3.5              7      1494
## 32  JOSHUA PHILIP MATHEWS             ON   3.5              7      1441
## 33  JADE GE                           MI   3.5              7      1449
## 34  MICHAEL JEFFERY THOMAS            MI   3.5              7      1399
## 35  JOSHUA DAVID LEE                  MI   3.5              7      1438
## 36  SIDDHARTH JHA                     MI   3.5              6      1355
## 37  AMIYATOSH PWNANANDAM              MI   3.5              5       980
## 38  BRIAN LIU                         MI   3.0              6      1423
## 39  JOEL R HENDON                     MI   3.0              7      1436
## 40  FOREST ZHANG                      MI   3.0              7      1348
## 41  KYLE WILLIAM MURPHY               MI   3.0              4      1403
## 42  JARED GE                          MI   3.0              7      1332
## 43  ROBERT GLEN VASEY                 MI   3.0              7      1283
## 44  JUSTIN D SCHILLING                MI   3.0              6      1199
## 45  DEREK YAN                         MI   3.0              7      1242
## 46  JACOB ALEXANDER LAVALLEY          MI   3.0              7       377
## 47  ERIC WRIGHT                       MI   2.5              7      1362
## 48  DANIEL KHAIN                      MI   2.5              5      1382
## 49  MICHAEL J MARTIN                  MI   2.5              5      1291
## 50  SHIVAM JHA                        MI   2.5              6      1056
## 51  TEJAS AYYAGARI                    MI   2.5              7      1011
## 52  ETHAN GUO                         MI   2.5              7       935
## 53  JOSE C YBARRA                     MI   2.0              3      1393
## 54  LARRY HODGE                       MI   2.0              6      1270
## 55  ALEX KONG                         MI   2.0              6      1186
## 56  MARISA RICCI                      MI   2.0              5      1153
## 57  MICHAEL LU                        MI   2.0              6      1092
## 58  VIRAJ MOHILE                      MI   2.0              6       917
## 59  SEAN M MC CORMICK                 MI   2.0              6       853
## 60  JULIA SHEN                        MI   1.5              5       967
## 61  JEZZEL FARKAS                     ON   1.5              7       955
## 62  ASHWIN BALAJI                     MI   1.0              1      1530
## 63  THOMAS JOSEPH HOSMER              MI   1.0              5      1175
## 64  BEN LI                            MI   1.0              7      1163
##    avg_oppo_score
## 1            1605
## 2            1469
## 3            1564
## 4            1574
## 5            1501
## 6            1519
## 7            1372
## 8            1468
## 9            1523
## 10           1554
## 11           1468
## 12           1506
## 13           1498
## 14           1515
## 15           1484
```

```
## 16          1386
## 17          1499
## 18          1480
## 19          1426
## 20          1411
## 21          1470
## 22          1300
## 23          1214
## 24          1357
## 25          1363
## 26          1507
## 27          1222
## 28          1522
## 29          1314
## 30          1144
## 31          1260
## 32          1379
## 33          1277
## 34          1375
## 35          1150
## 36          1388
## 37          1385
## 38          1539
## 39          1430
## 40          1391
## 41          1248
## 42          1150
## 43          1107
## 44          1327
## 45          1152
## 46          1358
## 47          1392
## 48          1356
## 49          1286
## 50          1296
## 51          1356
## 52          1495
## 53          1345
## 54          1206
## 55          1406
## 56          1414
## 57          1363
## 58          1391
## 59          1319
## 60          1330
## 61          1327
## 62          1186
## 63          1350
## 64          1263
```

Trim names

While you can't tell from the above tibble, many of the player names actually have surrounding white spaces. We can remoe with stringr::str_trim

```
final_data$name <- str_trim(final_data$name, side=c("both"))
```

Calculate expected score for each player

In chess a player's "total score" for a game is determined by whether or not the player wins (+1), loses (+0), or draws (+0.5)

The "expected score" for a player in one game can be represented as a modified probability that they will win, based on their pre_score relative to their opponent's pre_score.

The following function can perform the required calculation:

```
1/(10^(({oppo_pre_score}-{pre_score})/400)+1)
```

Because have already computed averages for our opponent_pre_scores, we can modify the above equation as such:

```
1/(10^(({oppo_Pre_score}-{pre_score})/400)+1) * {number_of_games}
```

The function used above was identified from the following sources:

- http://www.uschess.org/index.php/Players-Ratings/Do-NOT-edit-CLOSE-immediately.html
- https://chess.stackexchange.com/questions/18209/how-do-you-calculate-your-tournament-performance-rating

```
final_data <- final_data %>%
                mutate(
  expected_total = 1/(10^((avg_oppo_score-pre_score)/400)+1) * number_of_games
  )
```

EXTRA CREDIT: which player scored the most points relative to their expected score?

Answer is Aditya Bajaj, who performed very well throughout this tournament. In fact, Adtiya's total was more than 4.16 points above his expected total. He won 6 out of 7 games, despite the fact that, on average, he was rated nearly 200 points below each of his opponents.

```
final_data %>%
  mutate(score_differential = total - expected_total) %>%
  arrange(desc(score_differential)) %>%
  .[1,c('name','pre_score','avg_oppo_score','total','expected_total','score_differential')]
```

```
##           name pre_score avg_oppo_score total expected_total score_differential
## 1 ADITYA BAJAJ      1384           1564     6       1.833237           4.166763
```

Generate a .CSV file and load values into SQL

Generate a .CSV file

```
write.table(final_data, sep=",", file = "/Users/alecmccabe/Desktop/Masters Program/DATA 607/masters_607
```

Create function to assign ids to players

The reason why I chose to include two tables in my SQL database was to allow for continued use of this script. When new tournaments happen, new players may participate.

This function will work by looking at the total list of tournament participants, and cross-reference that list against the existing SQL table data_607.players

This ensures that if a participant has already been counted in previous tournaments, they will be assigned the same player_id.

Alternatively, if there is a new participant, this function will ensure that their generated player_id does not match any existing ones.

```
assign_player_ids <- function(insert_data, mydb) {
  names <- insert_data$name
  players_string <- str_c('"',str_trim(names,side=c("both")),'"',collapse=",")
  insert_data$id <- NA
  query <- str_interp("SELECT player_name, id FROM data_607.players WHERE player_name in (${players_str

  select_data <- dbGetQuery(mydb, query)

  for (row in 1:nrow(select_data)) {
    select_name <- select_data[row,"player_name"]
    select_id <- select_data[row,"id"]

    insert_data <- within(insert_data, id[name == select_name] <- select_id)
  }

  for (row in 1:nrow(insert_data)){
    if (is.na(insert_data[row,]$id)) {
      if (sum(!is.na(insert_data$id))>0) {
        max_id <- max(insert_data$id, na.rm=TRUE) +1
      } else {
        max_id <- 1
      }
      insert_data[row,]$id <- max_id
    }
  }

  return(insert_data)
}
```

Running id assignment

Because data_607.players is currently empty, each of the participants in this tournament will be provided with incremental ids, starting with 1 and ending at 64.

```
final_data <-assign_player_ids(final_data,mydb)
```

Create insert function to load into data_607.players

This function will load any new players, and their associated player_ids and state information into the data_607.players table.

```
insert_players <- function(data, mydb){

  names <- final_data$name
  players_string <- str_c('"',str_trim(names,side=c("both")),'"',collapse=",")
  query <- str_interp("SELECT player_name, id FROM data_607.players WHERE player_name in (${players_str

  select_data <- dbGetQuery(mydb, query)

  for (row in 1:nrow(final_data)){
    id <- as.integer(final_data[row, "id"])
    name <- str_trim(final_data[row, "name"], side=c("both"))
    state <- str_trim(final_data[row, "state"], side=c("both"))
    total <- final_data[row, "total"]
    pre_score <- final_data[row, "pre_score"]
    avg_opponent_score <- final_data[row, "avg_oppo_score"]

    insert_query <- str_interp('insert into data_607.players VALUES (${id},"${name}", "${state}")')

    if (name %in% select_data$player_name) {
      next
    } else {
      print(name)
      dbGetQuery(mydb, insert_query)
    }

  }
}
```

Create a function to insert into the data_607.scores table

This function will load a player's performance data and metrics into the data_607.scores table. This function takes 'tournament_id' variable as input in addition to data and db_connection.

```
insert_scores <- function(data, tournament_id, mydb){

  for (row in 1:nrow(final_data)){
    id <- as.integer(final_data[row, "id"])
    name <- str_trim(final_data[row, "name"], side=c("both"))
    total <- final_data[row, "total"]
    pre_score <- final_data[row, "pre_score"]
    avg_opponent_score <- final_data[row, "avg_oppo_score"]
    number_of_games <- final_data[row, "number_of_games"]
    expected_total <- final_data[row, "expected_total"]
```

```
    insert_query <- str_interp('insert into scores VALUES (DEFAULT,${tournament_id},${id},${number_of_g

    dbGetQuery(mydb, insert_query)
  }
}
```

Insert into SQL tables The insert_players function prints to the console each player's name that is added to the SQL data ("new players"). As we see below, everyone is added.

```
insert_players(final_data, mydb)
```

```
insert_scores(final_data,1, mydb)
```

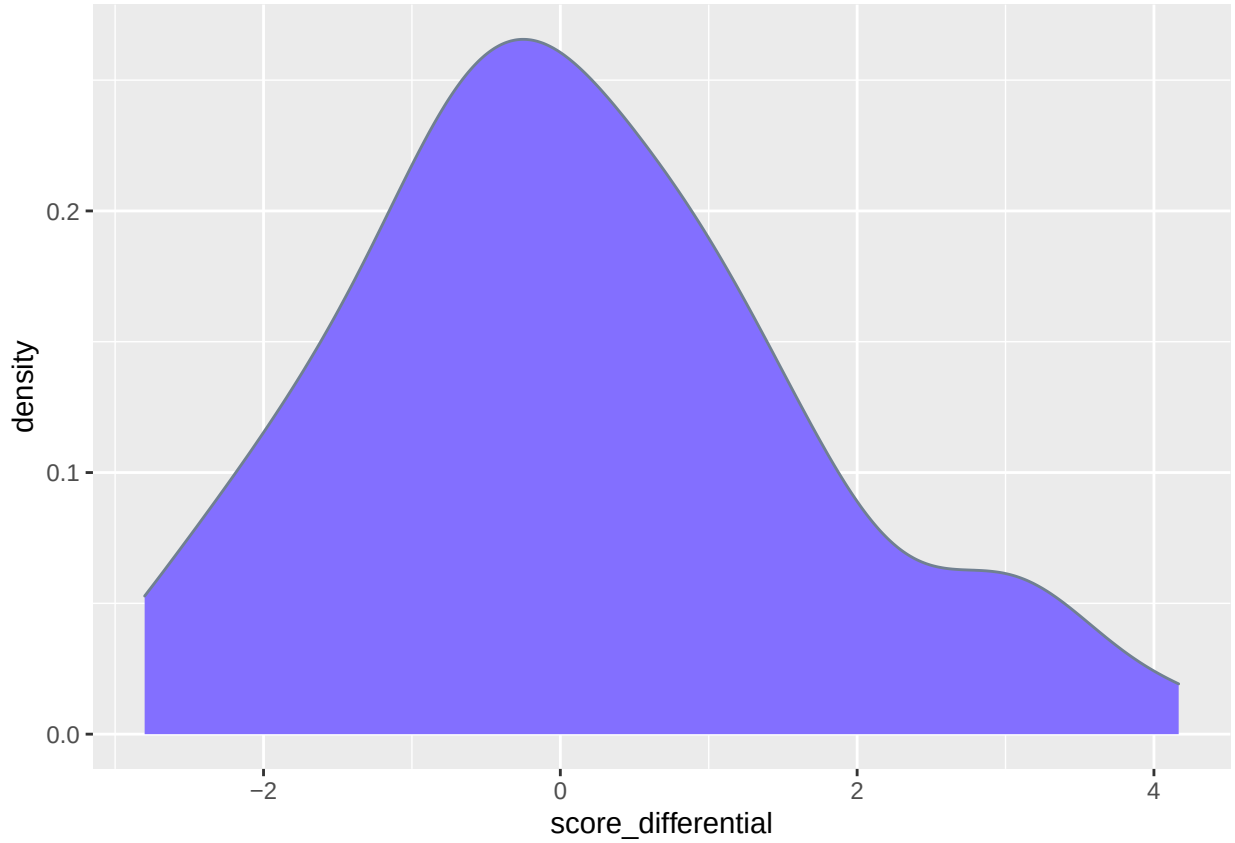
Visualize the distribution of 'score_differential' for players

'score_differential' will be defined as the difference between a player's expected total, and their actual total points.

```
final_data <- final_data %>%
  mutate(score_differential = total - expected_total)
```

The density plot below suggests that the score_difference distribution is nearly gaussian, with a mean centered around zero and only a slight right skew.

```
final_data %>%
  ggplot(aes(x=score_differential)) +
  geom_density(
    fill = "slateblue1",
    color = "slategrey"
    ) +
  theme_grey()
```

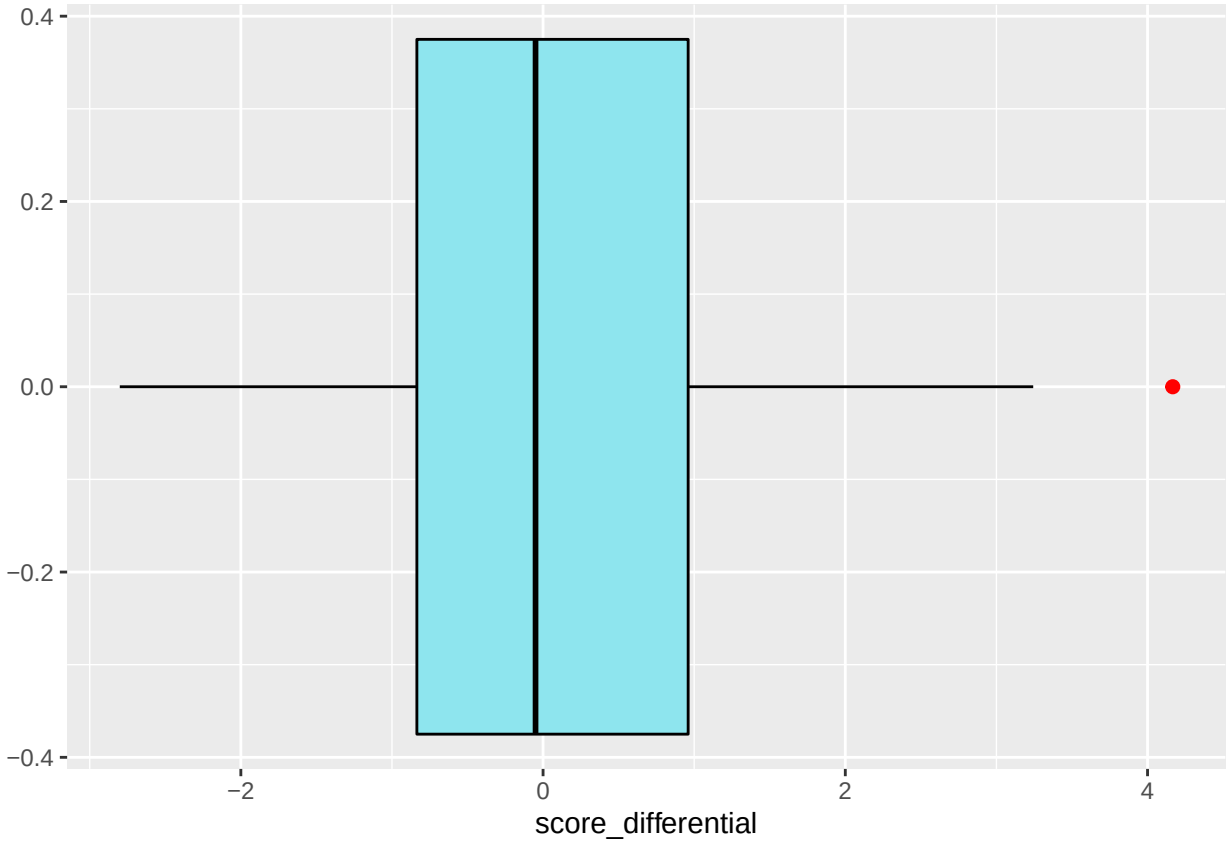


The below boxplot also shows that score_difference distribution is centered around zero, and seemingly normally distributed. Roughly 50% of the population's score_difference is between -1 and 1. Tail values stretch from -2.5 (performed much worse than expected) all the way to 2.5 (performed much better than expected).

There is also an outlier identified, with a score_differential of 4.166. As we discussed earlier, Aditya performed much better than expected.

Based on the data, one could make that claim that Aditya's performance was not a fluke, but rather a result of an "inaccurate" initial pre_score going into the tournament.

```
final_data %>%
  ggplot(aes(x=score_differential)) +
  geom_boxplot(
    color = "black",
    fill="cadetblue2",
    outlier.size=2,
    outlier.colour="red"
  ) +
  theme_grey()
```



The concept of an "innacurate" pre_score is interesting. Let's see if there is any correlation between the absolute score_differential and a player's pre_score.

```
final_data %>%
  mutate(
    score_differential = abs(score_differential)
  ) %>%
  select(pre_score, score_differential) %>%
  cor() %>%
  .[1,2]
```

```
## [1] -0.3396838
```

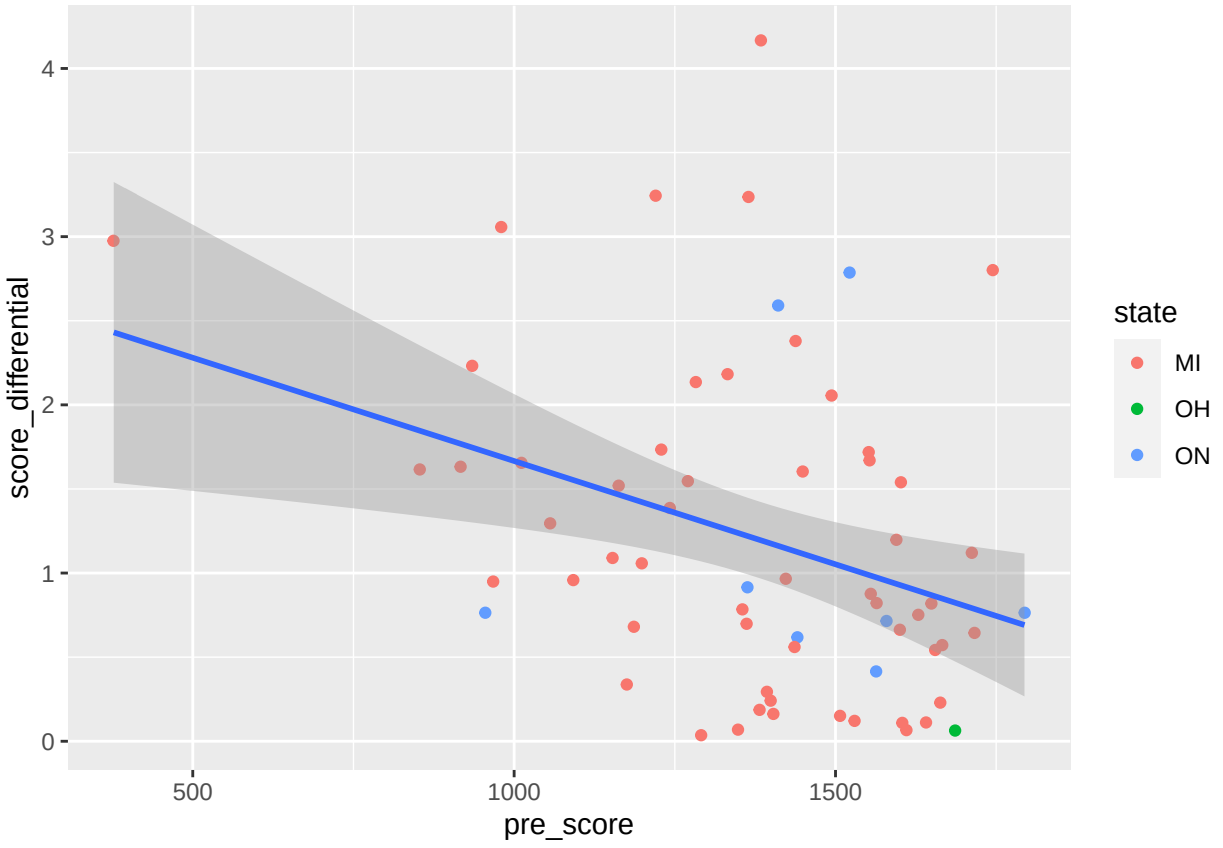
There is a small but not insignificant correlation. The below graph illustrates the correlation between pre_score and score_differential. As pre_score goes up, the absolute score_differential goes down. This implies that players with higher pre_scores can place more faith in their expected_totals than players with low pre_scores.

And intuitively, this makes sense. Many players have low pre_scores simply because they don't have as many tournament games played. Even Magnus Carlson was once lowly rated (though I doubt that lasted long).

head(final_data)

```
final_data %>%
  mutate(
```

```
  score_differential = abs(score_differential)
) %>%
ggplot() +
geom_point(aes(x=pre_score, y=score_differential, color=state),
           position="jitter") +
geom_smooth(aes(x=pre_score, y=score_differential),method='lm', formula=y~x)+
theme_grey()
```



Test functions "assign_player_ids" and "insert_players"

Here we will make sure that the above functions work as expected when presented with new player data.

As an example, imagine that a second tournament includes all of the members of this tournament, plus one new member: Johnny Apple.

If our functions work as expected, then the assign_player_id function will provide Johnny with the id 65, and the insert_players function will only insert Johhny (since the previous players are already contained in the SQL table)

```
final_data <- add_row(final_data,
        name="Johnny Apple",
        state="OH",
        total=5,
        number_of_games = 7,
```

```
        pre_score=1111,
        avg_oppo_score=1245,
        expected_total = 4,
        id=NA)
```

```
final_data <-assign_player_ids(final_data,mydb)
```

```
final_data[final_data$name=="Johnny Apple",c('name','id')]
```

```
##            name id
## 65 Johnny Apple 65
```

```
insert_players(final_data, mydb)
```