

FIFA Player Assessment Model and Analytics

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Loading Data

```
fifa16 <- fread("~/Desktop/Northeastern-University/SML/FIFA-Player-Assessment-Model-and-Analytics/Datas/fifa16")
fifa16 <- as_tibble(fifa16)

fifa17 <- fread("~/Desktop/Northeastern-University/SML/FIFA-Player-Assessment-Model-and-Analytics/Datas/fifa17")
fifa17 <- as_tibble(fifa17)

fifa18 <- fread("~/Desktop/Northeastern-University/SML/FIFA-Player-Assessment-Model-and-Analytics/Datas/fifa18")
fifa18 <- as_tibble(fifa18)

fifa19 <- fread("~/Desktop/Northeastern-University/SML/FIFA-Player-Assessment-Model-and-Analytics/Datas/fifa19")
fifa19 <- as_tibble(fifa19)

fifa20 <- fread("~/Desktop/Northeastern-University/SML/FIFA-Player-Assessment-Model-and-Analytics/Datas/fifa20")
fifa20 <- as_tibble(fifa20)

fifa_datasets_list = list(fifa16, fifa17, fifa18, fifa19, fifa20)
years = list("2016", "2017", "2018", "2019", "2020")
```

Exploratory Data Analysis

Abstract Hypothesis EDA

1. There exists a positive correlation between player rating and value

```
# Correlation between player overall and value in euros
for (i in seq_along(fifa_datasets_list)) {
  ovr_val_wag <- fifa_datasets_list[[i]] %>% select(overall, value_eur, wage_eur)
  cor_ovr_val_wag <- cor(ovr_val_wag)
  print(paste("Year", years[[i]], ":"))
  print(round(cor_ovr_val_wag, 2))
}

## [1] "Year 2016 :"
##          overall value_eur wage_eur
## overall     1.00      0.60     0.73
## value_eur    0.60      1.00     0.91
```

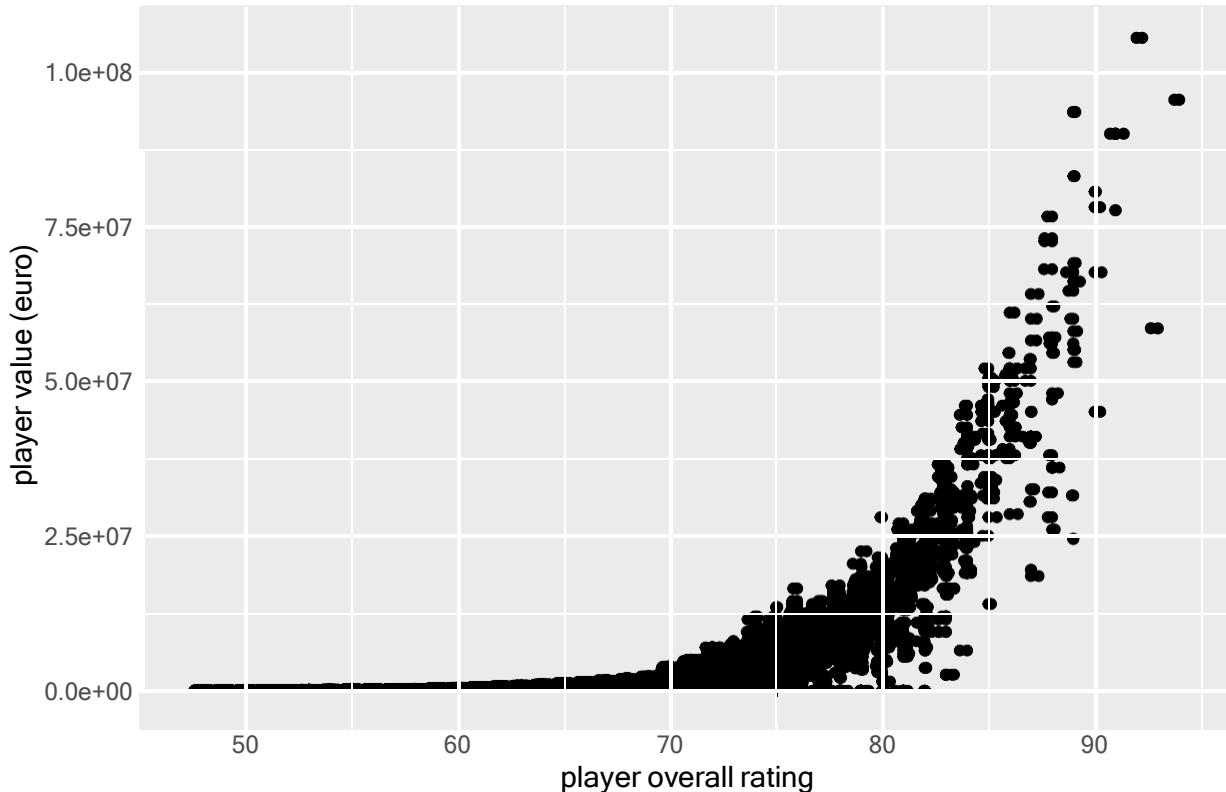
```

## wage_eur      0.73      0.91      1.00
## [1] "Year 2017 :"
##          overall value_eur wage_eur
## overall      1.00      0.60      0.62
## value_eur     0.60      1.00      0.88
## wage_eur     0.62      0.88      1.00
## [1] "Year 2018 :"
##          overall value_eur wage_eur
## overall      1.00      0.63      0.60
## value_eur     0.63      1.00      0.85
## wage_eur     0.60      0.85      1.00
## [1] "Year 2019 :"
##          overall value_eur wage_eur
## overall      1.00      0.63      0.57
## value_eur     0.63      1.00      0.86
## wage_eur     0.57      0.86      1.00
## [1] "Year 2020 :"
##          overall value_eur wage_eur
## overall      1.00      0.64      0.57
## value_eur     0.64      1.00      0.86
## wage_eur     0.57      0.86      1.00

fifa20 %>% ggplot(aes(x=overall,y=value_eur)) + geom_point() + geom_jitter() +
  labs(x = "player overall rating", y = "player value (euro)",
       title = "Year 2020: Plot of player rating vs player value")

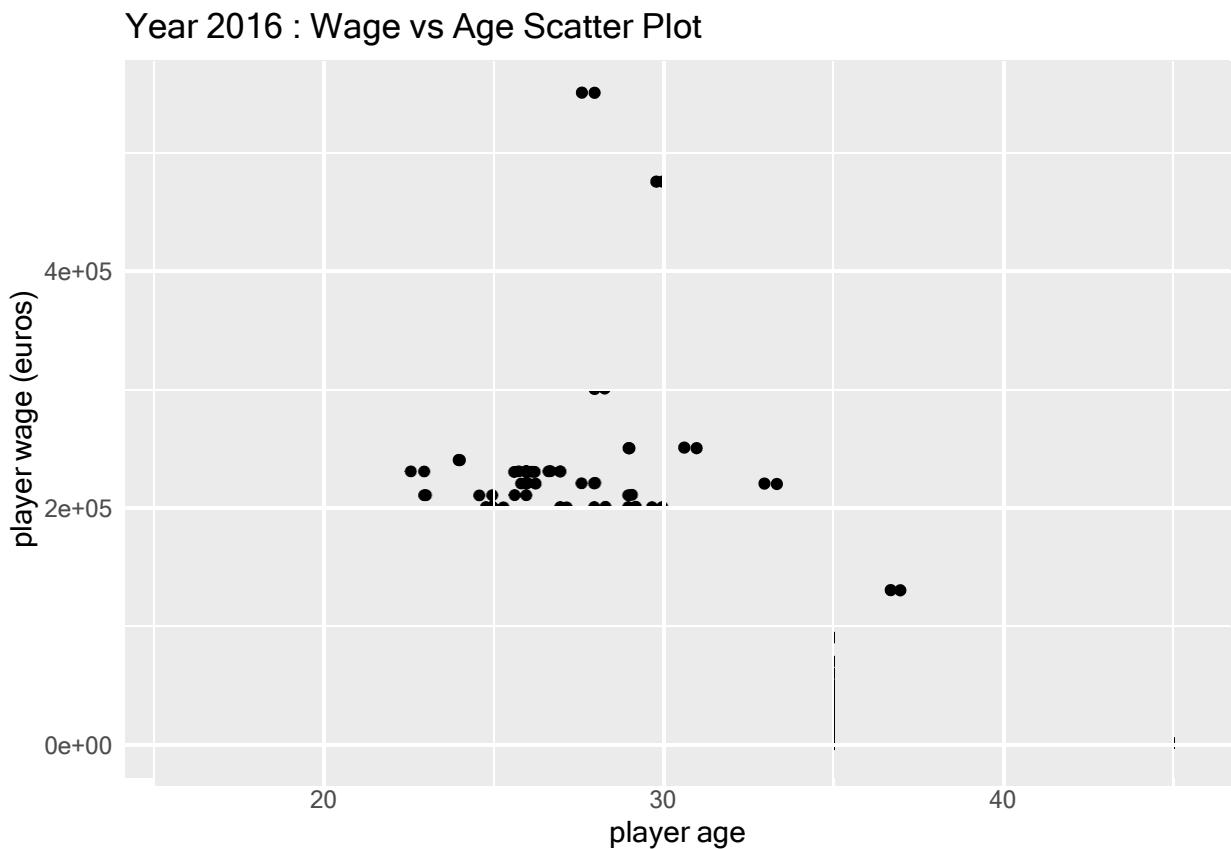
```

Year 2020: Plot of player rating vs player value

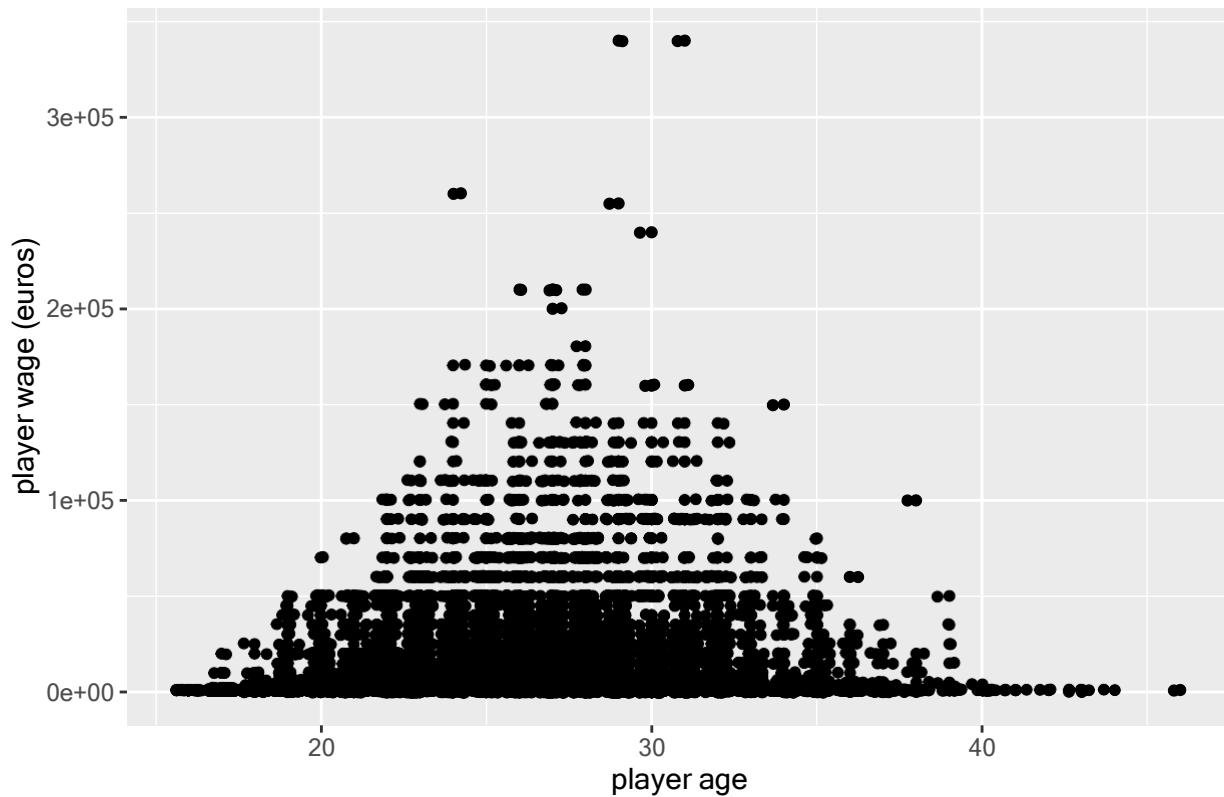


2. Player wage and age are positively correlated upto the age of 31 and negatively correlated after that

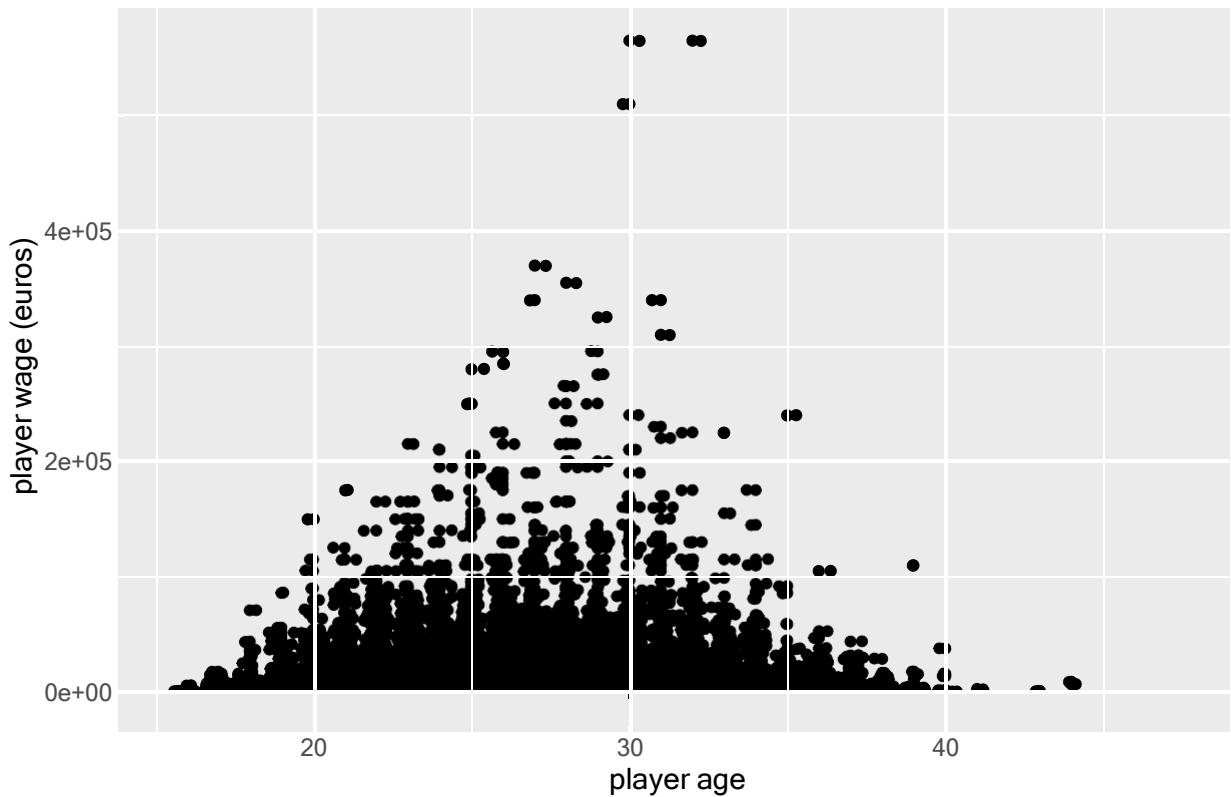
```
# WAGE AND AGE CORRELATION: scatter plot of wage and age
for (i in seq_along(fifa_datasets_list)) {
  wage_age_plt <- fifa_datasets_list[[i]] %>% ggplot(aes(age, wage_eur)) +
    geom_point() + geom_jitter()
  labs(x="player age", y="player wage (euros)",
       title= paste("Year", years[[i]], ":", "Wage vs Age Scatter Plot"))
  print(wage_age_plt)
}
```



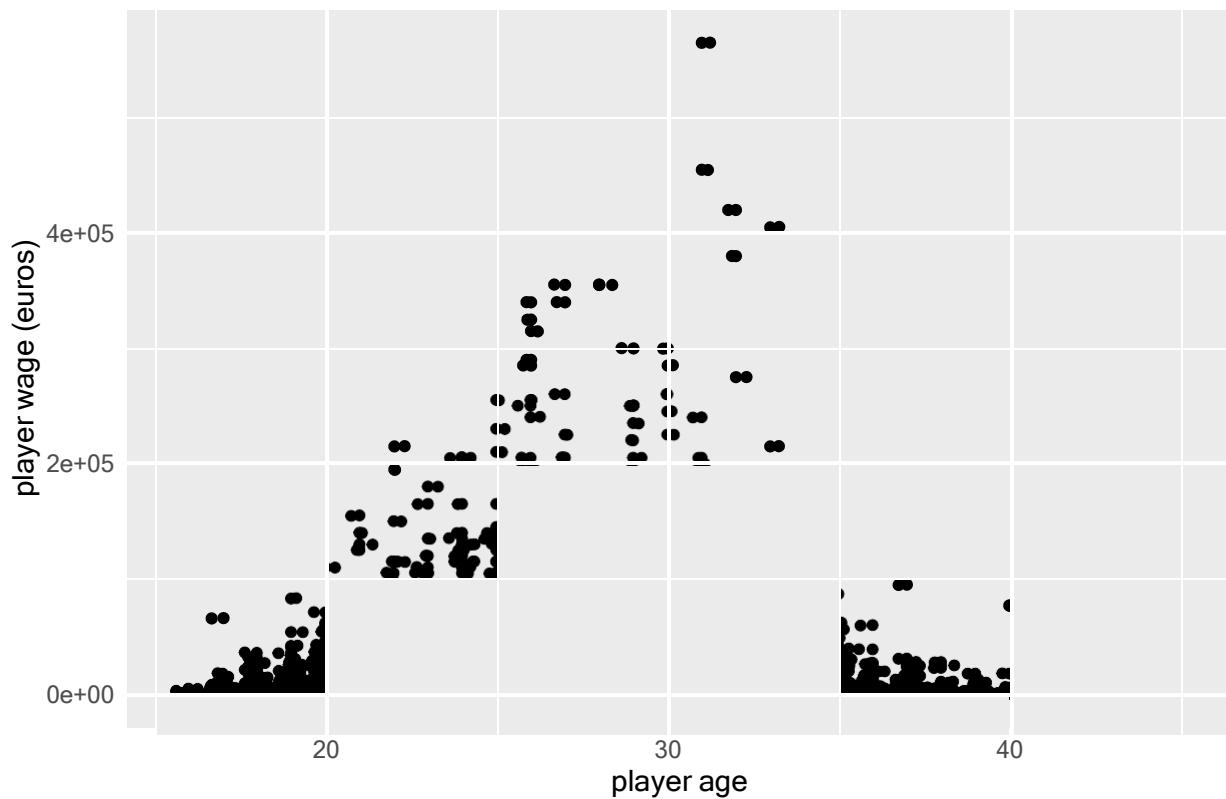
Year 4 : Wage vs Age Scatter Plot



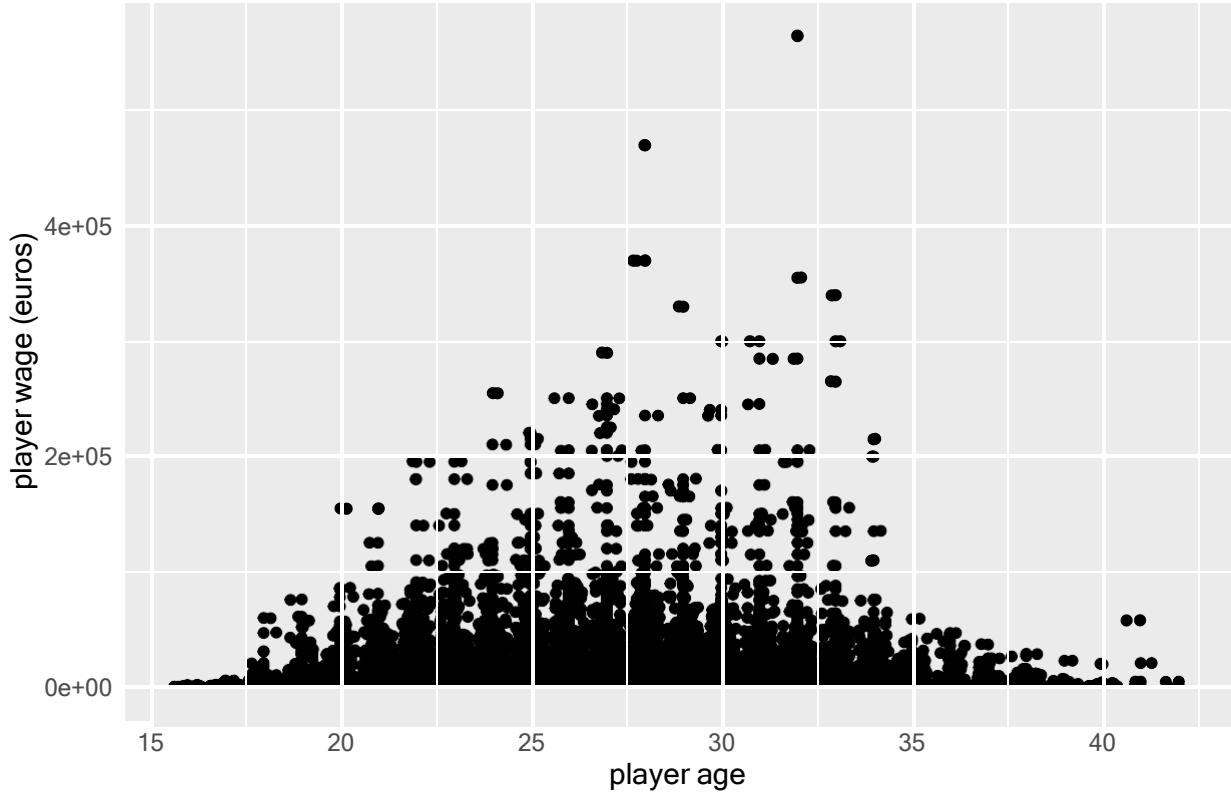
Year 5 : Wage vs Age Scatter Plot



Year 6 : Wage vs Age Scatter Plot



Year 7 : Wage vs Age Scatter Plot



```

for (i in seq_along(fifa_datasets_list)) {

  players31_andless <- fifa_datasets_list[[i]] %>%
    filter(age <= 31)%>% select(age, wage_eur, value_eur)
  players_over31 <- fifa_datasets_list[[i]] %>%
    filter(age > 31)%>% select(age, wage_eur, value_eur)

  cor_31andless_cor <- cor(players31_andless)
  print(paste("Year", years[[i]], ":", "Players <= 31"))
  print(round(cor_31andless_cor, 2))
  #age and wage are +vely correlated but the correlation is not very high.

  players_over31_cor <- cor(players_over31)
  print(paste("Year", years[[i]], ":", "Players > 31"))
  print(round(players_over31_cor, 2))
  #age and wage are -vely correlated but the correlation is not very high.
}

## [1] "Year 2016 : Players <= 31"
##           age wage_eur value_eur
## age      1.00    0.27     0.15
## wage_eur  0.27    1.00     0.91
## value_eur 0.15    0.91     1.00
## [1] "Year 2016 : Players > 31"
##           age wage_eur value_eur
## age      1.00   -0.08    -0.15

```

```

## wage_eur -0.08      1.00      0.87
## value_eur -0.15      0.87      1.00
## [1] "Year 2017 : Players <= 31"
##           age wage_eur value_eur
## age        1.00     0.23     0.15
## wage_eur   0.23     1.00     0.89
## value_eur  0.15     0.89     1.00
## [1] "Year 2017 : Players > 31"
##           age wage_eur value_eur
## age        1.00    -0.12    -0.17
## wage_eur  -0.12     1.00     0.81
## value_eur -0.17     0.81     1.00
## [1] "Year 2018 : Players <= 31"
##           age wage_eur value_eur
## age        1.00     0.20     0.16
## wage_eur   0.20     1.00     0.86
## value_eur  0.16     0.86     1.00
## [1] "Year 2018 : Players > 31"
##           age wage_eur value_eur
## age        1.00    -0.11    -0.17
## wage_eur  -0.11     1.00     0.86
## value_eur -0.17     0.86     1.00
## [1] "Year 2019 : Players <= 31"
##           age wage_eur value_eur
## age        1.00     0.19     0.16
## wage_eur   0.19     1.00     0.87
## value_eur  0.16     0.87     1.00
## [1] "Year 2019 : Players > 31"
##           age wage_eur value_eur
## age        1.00    -0.12    -0.18
## wage_eur  -0.12     1.00     0.88
## value_eur -0.18     0.88     1.00
## [1] "Year 2020 : Players <= 31"
##           age wage_eur value_eur
## age        1.00     0.19     0.15
## wage_eur   0.19     1.00     0.87
## value_eur  0.15     0.87     1.00
## [1] "Year 2020 : Players > 31"
##           age wage_eur value_eur
## age        1.00    -0.12    -0.18
## wage_eur  -0.12     1.00     0.92
## value_eur -0.18     0.92     1.00

```

3. Left footed players have a higher overall rating compared to right footed players

```

# Left footed players have a higher overall rating compared to right footed players
for (i in seq_along(fifa_datasets_list)) {
  left_foot <- fifa_datasets_list[[i]] %>% filter(preferred_foot=="Left") %>%
    summarise(avg_player_overall_left = mean(overall)) %>% mutate(year = years[[i]])

```

```

right_foot <- fifa_datasets_list[[i]] %>% filter(preferred_foot=="Right")%>%
  summarise(avg_player_overall_right = mean(overall)) %>% mutate(year = years[[i]])

foot_rating_year <- left_foot %>% left_join(right_foot)
print(foot_rating_year)
}

## Joining, by = "year"

## # A tibble: 1 x 3
##   avg_player_overall_left year avg_player_overall_right
##   <dbl> <chr>           <dbl>
## 1 66.2  2016             65.5

## Joining, by = "year"

##   avg_player_overall_left year avg_player_overall_right
##   <dbl> <chr>           <dbl>
## 1 66.73062 2017          66.06775

## Joining, by = "year"

## # A tibble: 1 x 3
##   avg_player_overall_left year avg_player_overall_right
##   <dbl> <chr>           <dbl>
## 1 66.7  2018             66.2

## Joining, by = "year"

## # A tibble: 1 x 3
##   avg_player_overall_left year avg_player_overall_right
##   <dbl> <chr>           <dbl>
## 1 66.8  2019             66.1

## Joining, by = "year"

## # A tibble: 1 x 3
##   avg_player_overall_left year avg_player_overall_right
##   <dbl> <chr>           <dbl>
## 1 66.7  2020             66.1

```

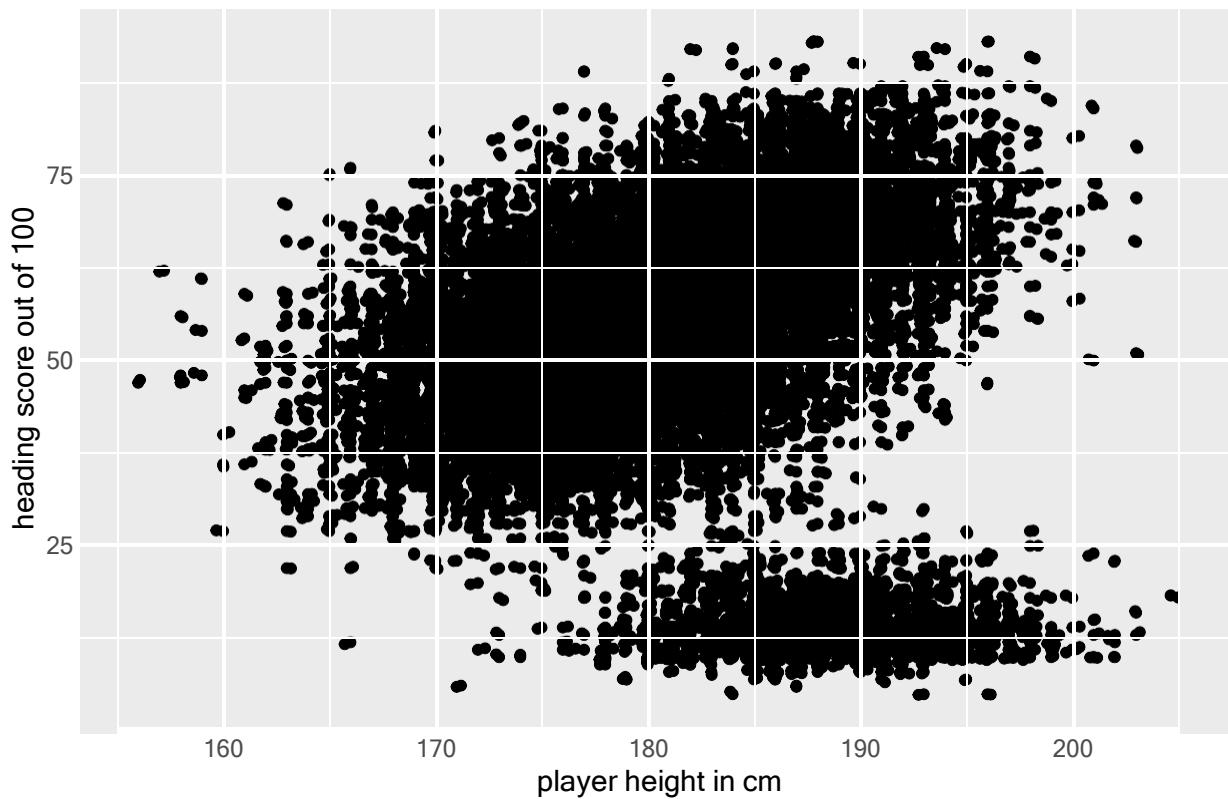
4. Tall, short and strong players are statistically good at heading, dribbling and tackling respectively

```

# Tall players and heading: scatter plot of height vs heading
fifa20 %>% ggplot(aes(height_cm, attacking_heading_accuracy)) +
  geom_point() + geom_jitter() +
  labs(x="player height in cm", y="heading score out of 100",
       title = "Plot of height vs heading score")

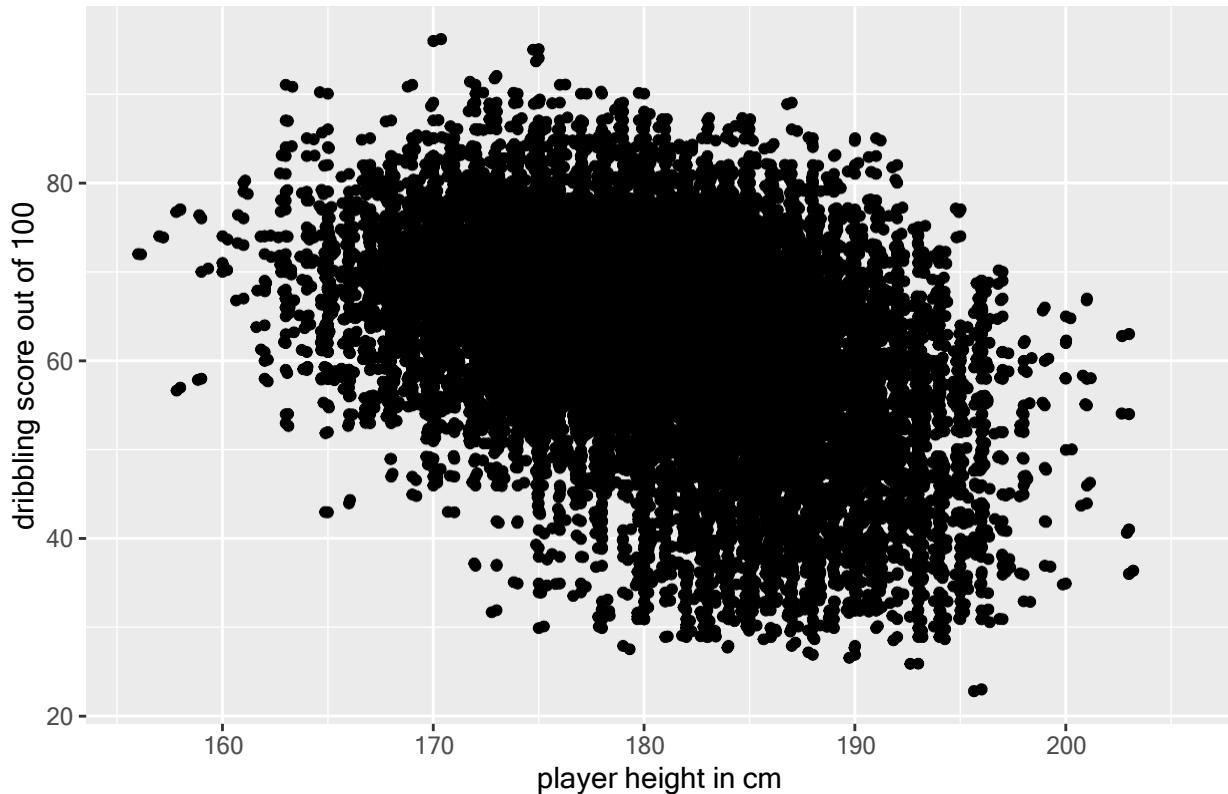
```

Plot of height vs heading score



```
# THIS IS A VERY INTERESTING FIND. WHY?  
cor(fifa20$height_cm, fifa20$attacking_heading_accuracy,  
    method = "spearman", use = "complete.obs")  
  
## [1] 0.2054838  
  
# There exists a weak positive correlation between height and heading.  
  
# Short players and dribbling: scatter plot of height vs dribbling  
fifa20 %>% ggplot(aes(height_cm, dribbling))+geom_point()  
  geom_jitter() + labs(x="player height in cm", y="dribbling score out of 100",  
    title = "Plot of height vs dribbling score")
```

Plot of height vs dribbling score



```
cor(fifa20$height_cm, fifa20$dribbling,  
    method = "spearman", use = "complete.obs")
```

```
## [1] -0.3946403
```

There is a weak negative correlation b/w height and dribbling ie short players are good at dribbling.

#Dribbling and movement attributes:

```
cor(fifa20$dribbling, fifa20$movement_agility,  
    method = "pearson", use = "complete.obs")
```

```
## [1] 0.7241454
```

#Dribbling and movement_agility are highly +vely correlated

```
cor(fifa20$dribbling, fifa20$movement_balance,  
    method = "pearson", use = "complete.obs")
```

```
## [1] 0.5581589
```

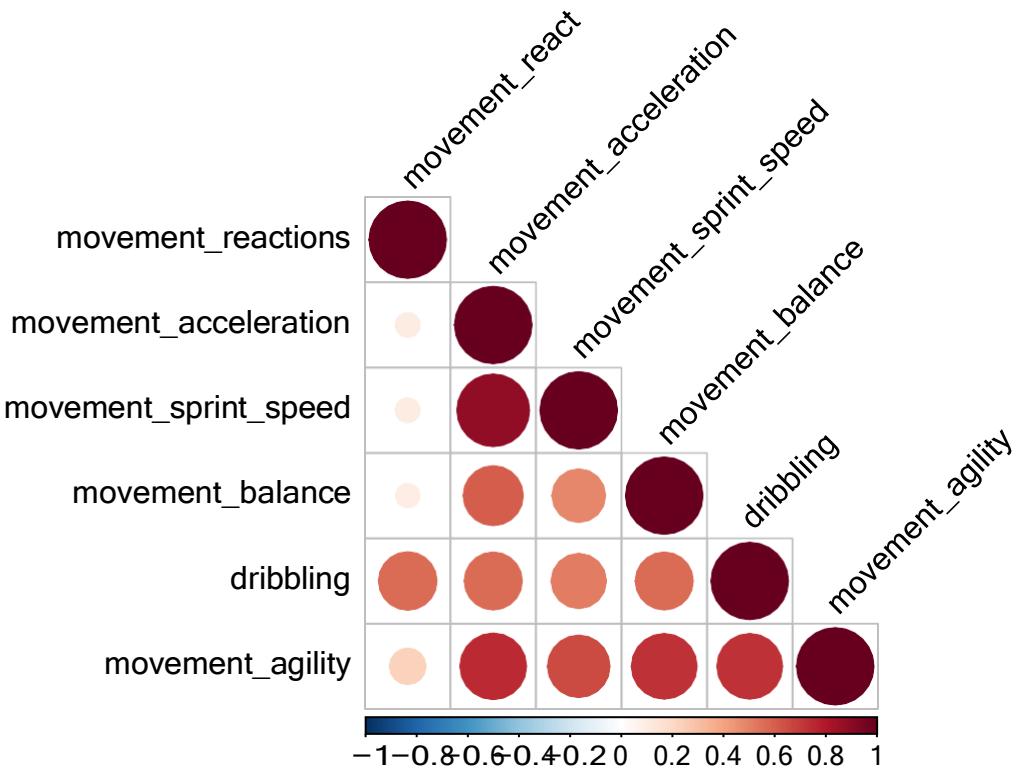
#Dribbling and movement_balance are moderately +vely correlated

Correlation matrix for dribbling and movement attributes:

```

drib_move <- fifa20 %>% select(dribbling,movement_acceleration,
                                    movement_sprint_speed, movement_agility,
                                    movement_reactions, movement_balance)
source("http://www.sthda.com/upload/rquery_cormat.r")
require("corrplot")
rquery.cormat(drib_move)

```



```

## $r
##           movement_reactions movement_acceleration
## movement_reactions          1
## movement_acceleration       0.1          1
## movement_sprint_speed       0.1          0.88
## movement_balance            0.096         0.6
## dribbling                   0.57          0.56
## movement_agility            0.22          0.74
##           movement_sprint_speed movement_balance dribbling
## movement_reactions
## movement_acceleration
## movement_sprint_speed          1
## movement_balance              0.48          1
## dribbling                     0.51          0.56
## movement_agility              0.65          0.72      1
##           movement_agility
## movement_reactions
## movement_acceleration

```

```

## movement_sprint_speed
## movement_balance
## dribbling
## movement_agility           1
##
## $p
##               movement_reactions movement_acceleration
## movement_reactions          0
## movement_acceleration      2.8e-151
## movement_sprint_speed      1.7e-155
## movement_balance            3.1e-97
## dribbling                   0
## movement_agility            5.89999999999934e-312
##               movement_sprint_speed movement_balance dribbling
## movement_reactions
## movement_acceleration
## movement_sprint_speed      0
## movement_balance            0
## dribbling                   0
## movement_agility            0
##               movement_agility
## movement_reactions
## movement_acceleration
## movement_sprint_speed
## movement_balance
## dribbling
## movement_agility           0
##
## $sym
##               movement_reactions movement_acceleration
## movement_reactions          1
## movement_acceleration
## movement_sprint_speed
## movement_balance
## dribbling
## movement_agility
##               movement_sprint_speed movement_balance dribbling
## movement_reactions
## movement_acceleration
## movement_sprint_speed      1
## movement_balance            .
## dribbling                   .
## movement_agility            ,
##               movement_agility
## movement_reactions
## movement_acceleration
## movement_sprint_speed
## movement_balance
## dribbling
## movement_agility           1
## attr(,"legend")
## [1] 0 ~ 0.3 ~ 0.6 ~ 0.8 ~ 0.9 ~ 0.95 "B" 1

```

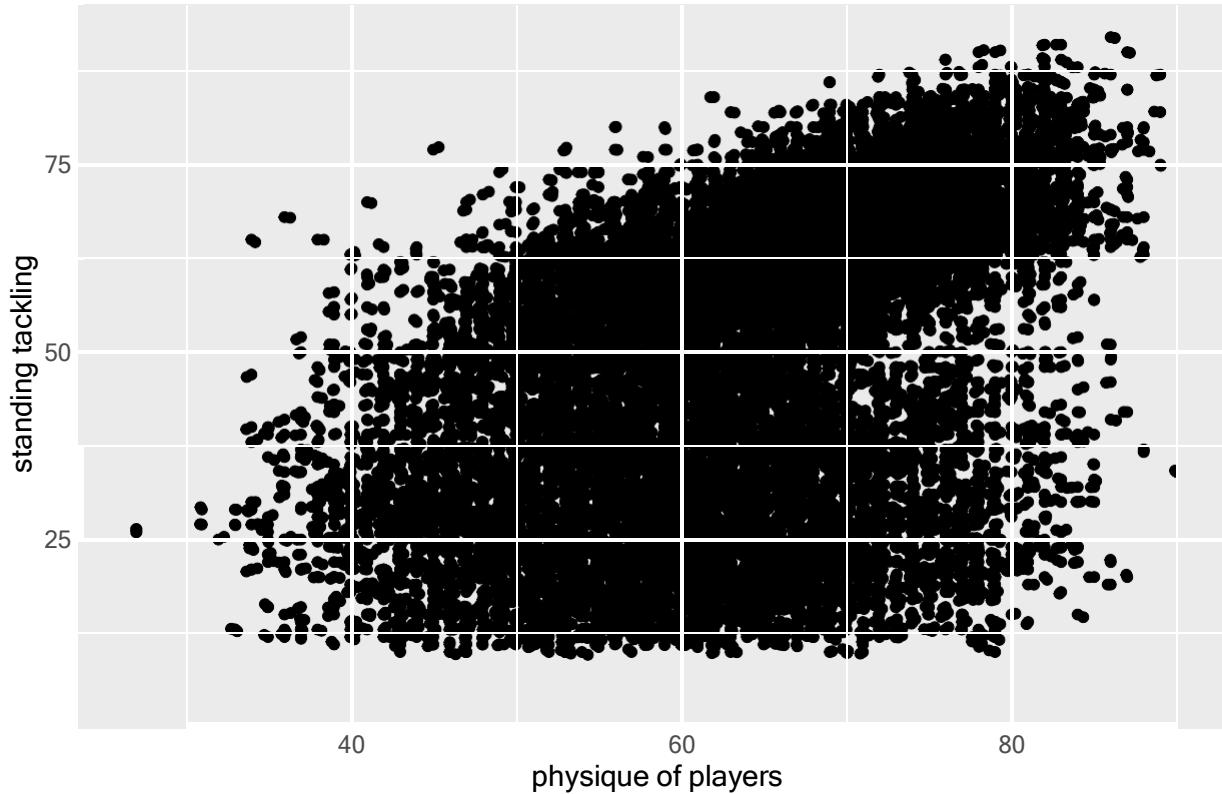
```

# We can see from the corrplot that dribbling is highly
# +vely correlated with the movement attributes.

# Strong players and tackling(both standing and sliding)
# scatter plot of physique vs standing tackling
fifa20 %>% ggplot(aes(physic, defending_standing_tackle)) +geom_point() +
  geom_jitter() +labs(x="physique of players", y="standing tackling",
  title = "physique vs standing tackling")

```

physique vs standing tackling



```

cor(fifa20$physic, fifa20$defending_standing_tackle,
  method = "pearson", use = "complete.obs")

```

```

## [1] 0.4896467

```

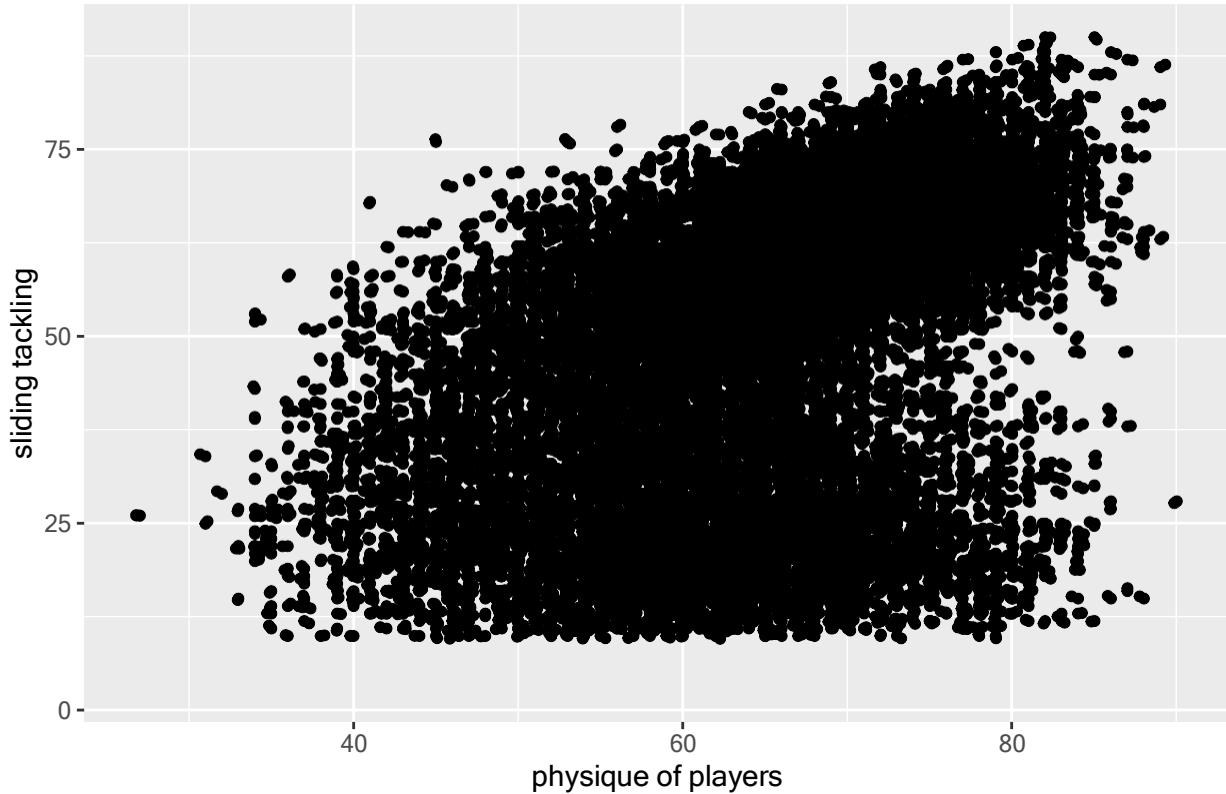
```

# Moderate +ve correlation

# Scatter plot of physique vs sliding tackling
fifa20 %>% ggplot(aes(physic, defending_sliding_tackle)) +geom_point() +
  geom_jitter() +labs(x="physique of players", y="sliding tackling",
  title = "physique vs sliding tackling")

```

physique vs sliding tackling



```
cor(fifa20$physic, fifa20$defending_sliding_tackle,
    method = "pearson", use = "complete.obs")
```

```
## [1] 0.4515019
```

Moderate +ve correlation

```
team_of_the_year <- function(year_data) {

  team_11 <- vector(mode = "list", length = 11)

  # STRIKER - positions to be considered: ST, CF, LS, RS, LF, RF
  striker <- year_data %>% filter(team_position %in% c("ST", "CF", "LS", "RS", "LF", "RF")) %>%
    arrange(desc(overall)) %>% select(short_name, team_position, overall) %>% top_n(1)
  team_11[[1]] = data.frame(striker)

  # Wingers: 2 wingers to be picked, one on the left and one on the right.
  # positions to be considered: RW, LW
  lw <- year_data %>% filter(team_position %in% c("LW")) %>%
    arrange(desc(overall)) %>% select(short_name, team_position, overall) %>% top_n(1)
  team_11[[2]] = data.frame(lw)

  rw <- year_data %>% filter(team_position %in% c("RW")) %>%
    arrange(desc(overall)) %>% select(short_name, team_position, overall) %>% top_n(1)
  team_11[[3]] = data.frame(rw)
```

```

# 1 AM, positions: CAM, LAM, RAM
am <- year_data %>% filter(team_position %in% c("CAM","LAM","RAM")) %>%
  arrange(desc(overall)) %>% select(short_name, team_position, overall) %>% top_n(1)
team_11[[4]] = data.frame(am)

# 2 midfielders, one on the right and one on the left:
# right midfielder: RCM, CDM, RDM, CM
rm <- year_data %>% filter(team_position %in% c("RCM","CDM","RDM","CM")) %>%
  arrange(desc(overall)) %>% select(short_name, team_position, overall) %>% top_n(1)
team_11[[5]] = data.frame(rm)

# left midfielder: LCM, CDM, LDM, CM
lm <- year_data %>% filter(team_position %in% c("LCM","CDM","LDM","CM")) %>%
  arrange(desc(overall)) %>% select(short_name, team_position, overall) %>% top_n(1)
team_11[[6]] = data.frame(lm)

# 2 wing backs, one on the right and one on the left:
# left back, positions to be considered: LB, LWB
lb <- year_data %>% filter(team_position %in% c("LWB","LB")) %>%
  arrange(desc(overall)) %>% select(short_name, team_position, overall) %>% top_n(1)
team_11[[7]] = data.frame(lb)

# right back, positions to be considered: RB, RWB
rb <- year_data %>% filter(team_position %in% c("RWB","RB")) %>%
  arrange(desc(overall)) %>% select(short_name, team_position, overall) %>% top_n(1)
team_11[[8]] = data.frame(rb)

# 2 centre backs:
# positions to be considered: LCB, RCB
lcb <- year_data %>% filter(team_position %in% c("LCB")) %>%
  arrange(desc(overall)) %>% select(short_name, team_position, overall) %>% top_n(1)
team_11[[9]] = data.frame(lcb)

rcb <- year_data %>% filter(team_position %in% c("RCB")) %>%
  arrange(desc(overall)) %>% select(short_name, team_position, overall) %>% top_n(1)
team_11[[10]] = data.frame(rcb)

gk <- year_data %>% filter(team_position %in% c("GK")) %>%
  arrange(desc(overall)) %>% select(short_name, team_position, overall) %>% top_n(1)
team_11[[11]] = data.frame(gk)

best11 <- do.call("rbind", team_11)
print(best11)
}

```

5. The starting eleven with the highest overall rating for a given year wins the champions league that year


```
## 13          L. Bonucci      RCB    88  
## 14          M. Neuer        GK    92  
## [1] "Year 2019 :"
```

```

##                short_name team_position overall
## 1            L. Suárez      ST    91
## 2 Cristiano Ronaldo     LW    94
## 3            L. Messi      RW    94
## 4          Neymar Jr     CAM   92
## 5        K. De Bruyne     RCM   91
## 6          L. Modrić     RCM   91
## 7            T. Kroos     LCM   90
## 8          Marcelo       LB    88
## 9        Azpilicueta     RB    86
## 10        Sergio Ramos   LCB   91
## 11          Piqué       RCB   87
## 12        De Gea         GK   91
## [1] "Year 2020 :"

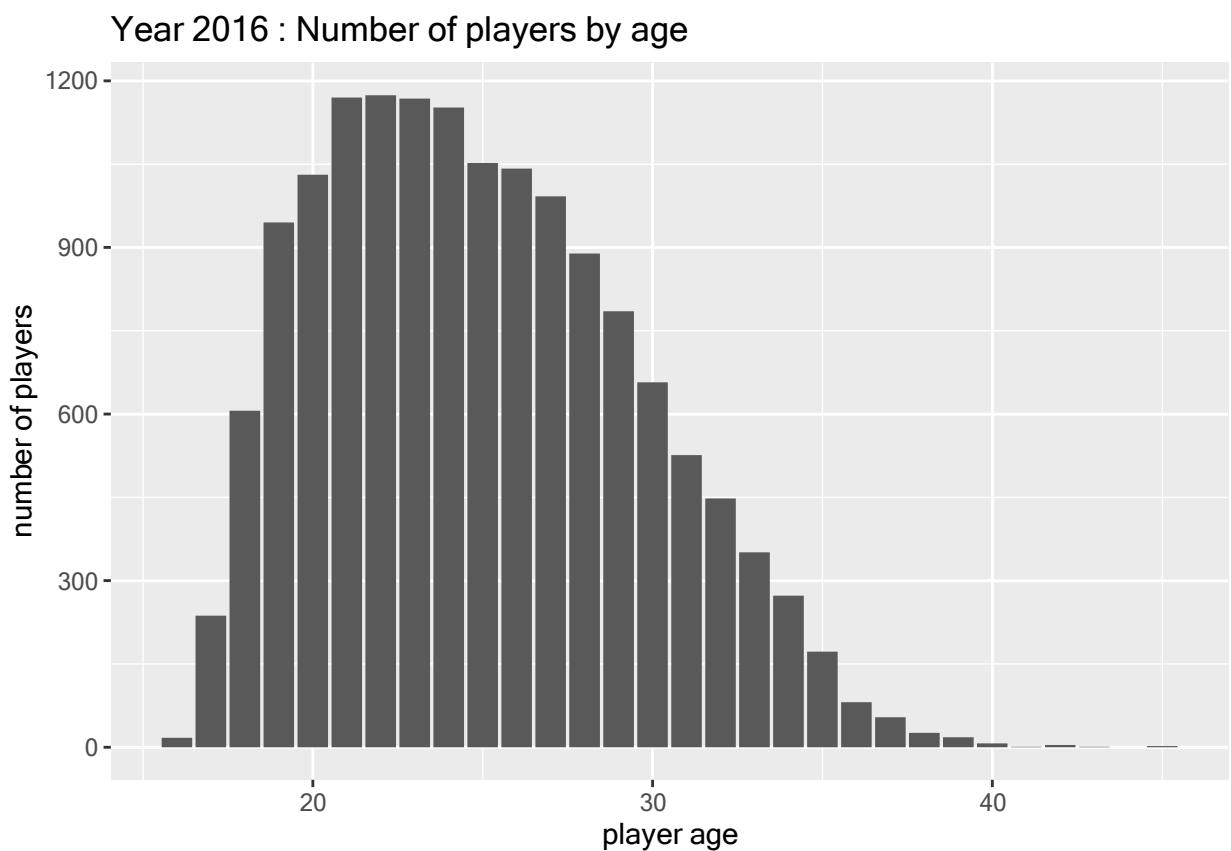
```

##	short_name	team_position	overall
## 1	H. Kane	ST	89
## 2	S. Agüero	ST	89
## 3	L. Suárez	ST	89
## 4	R. Lewandowski	ST	89
## 5	Cristiano Ronaldo	LW	93
## 6	L. Messi	RW	94
## 7	Neymar Jr	CAM	92
## 8	K. De Bruyne	RCM	91
## 9	Sergio Busquets	CDM	89

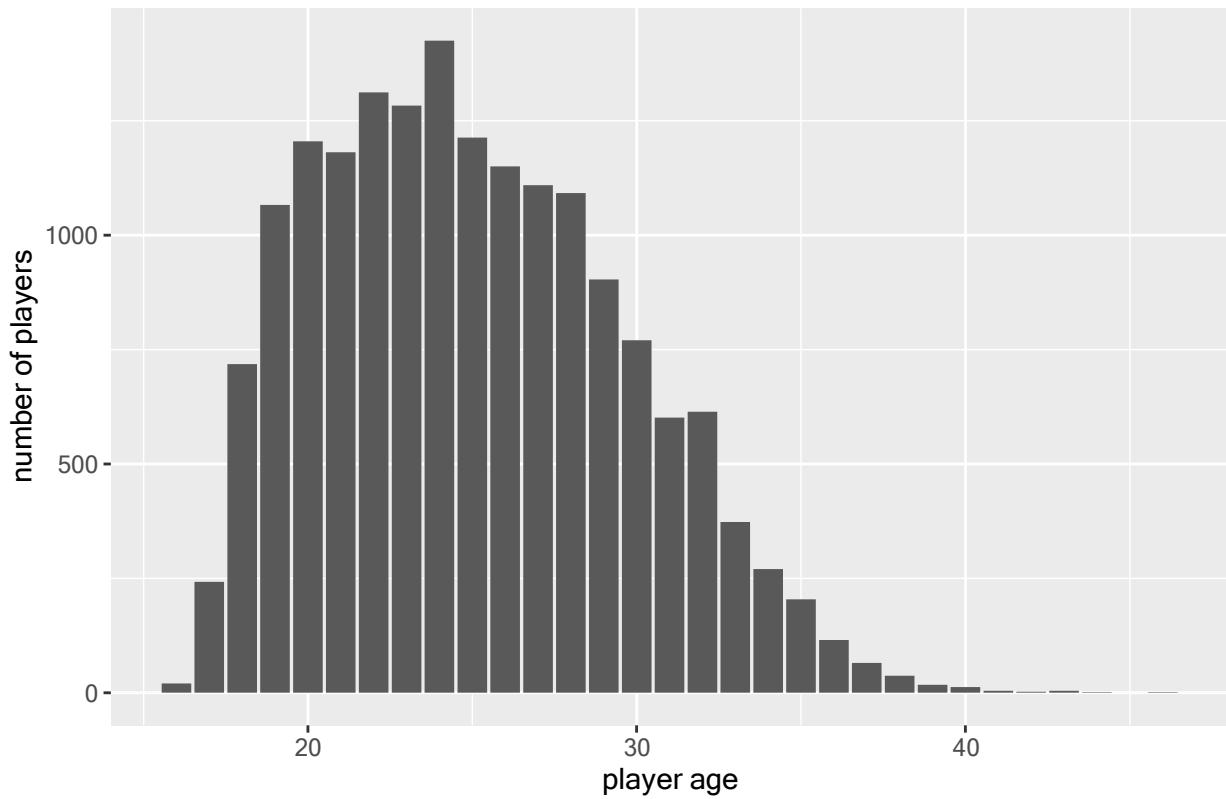
## 10	Jordi Alba	LB	87
## 11	J. Kimmich	RB	86
## 12	V. van Dijk	LCB	90
## 13	Piqué	RCB	88
## 14	D. Godín	RCB	88
## 15	J. Oblak	GK	91

Other Supplementary EDA

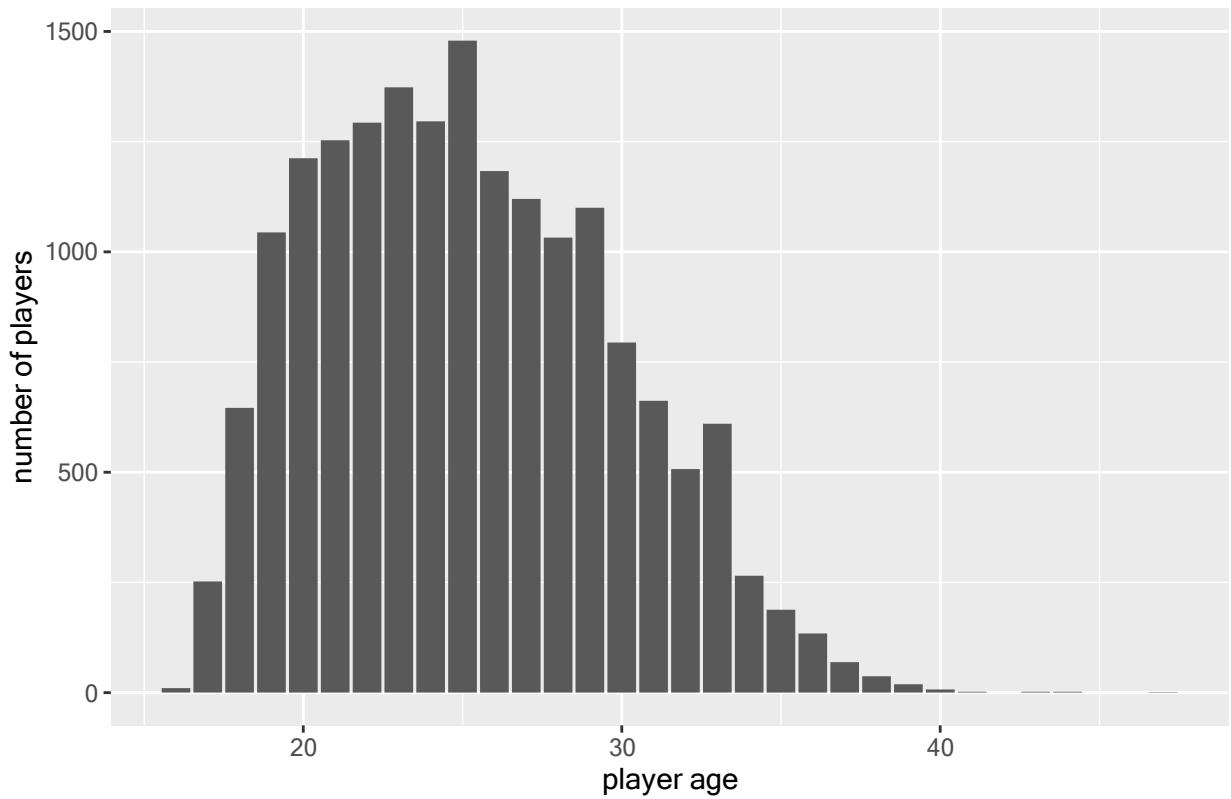
```
# Histogram of player age by year
for (i in seq_along(fifa_datasets_list)) {
  player_age_by_year <- fifa_datasets_list[[i]] %>% ggplot(aes(age)) +
    geom_bar() +
    labs(x="player age", y="number of players",
         title=paste("Year", years[[i]], ":", "Number of players by age"))
  print(player_age_by_year)
}
```



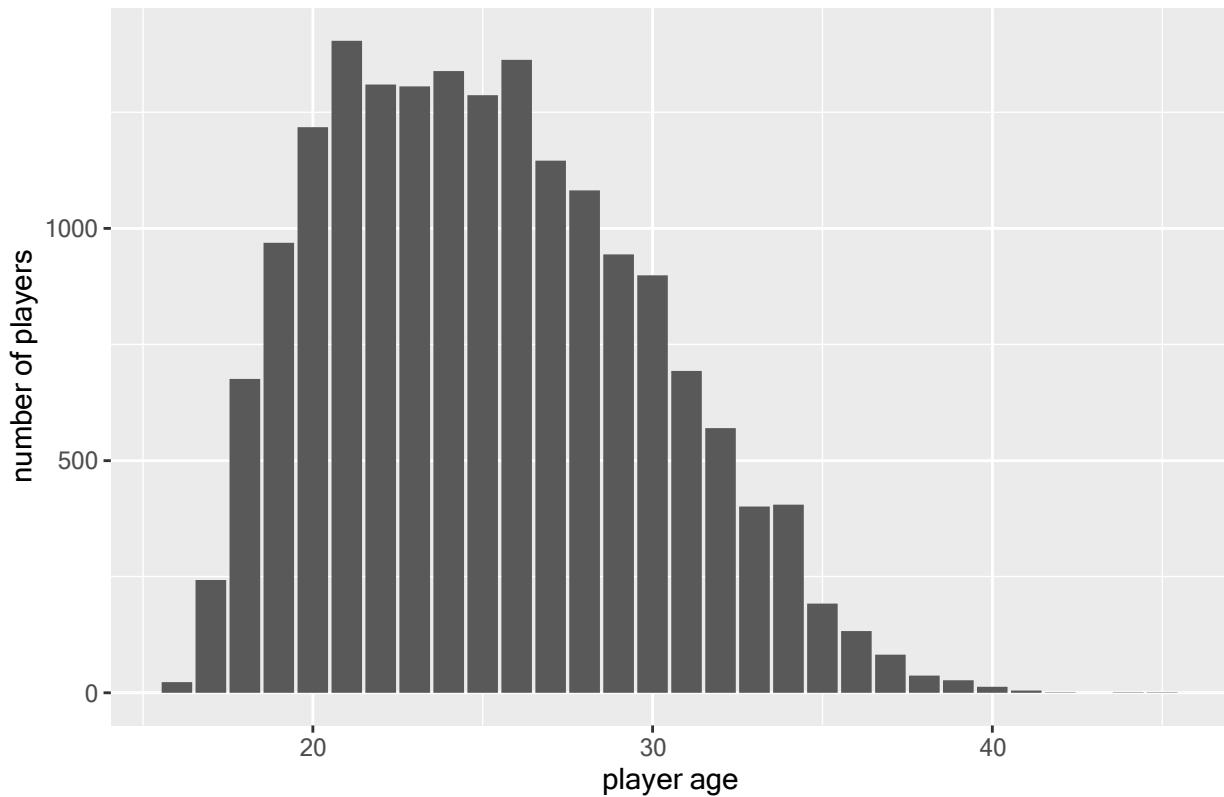
Year 21 : Number of players by age

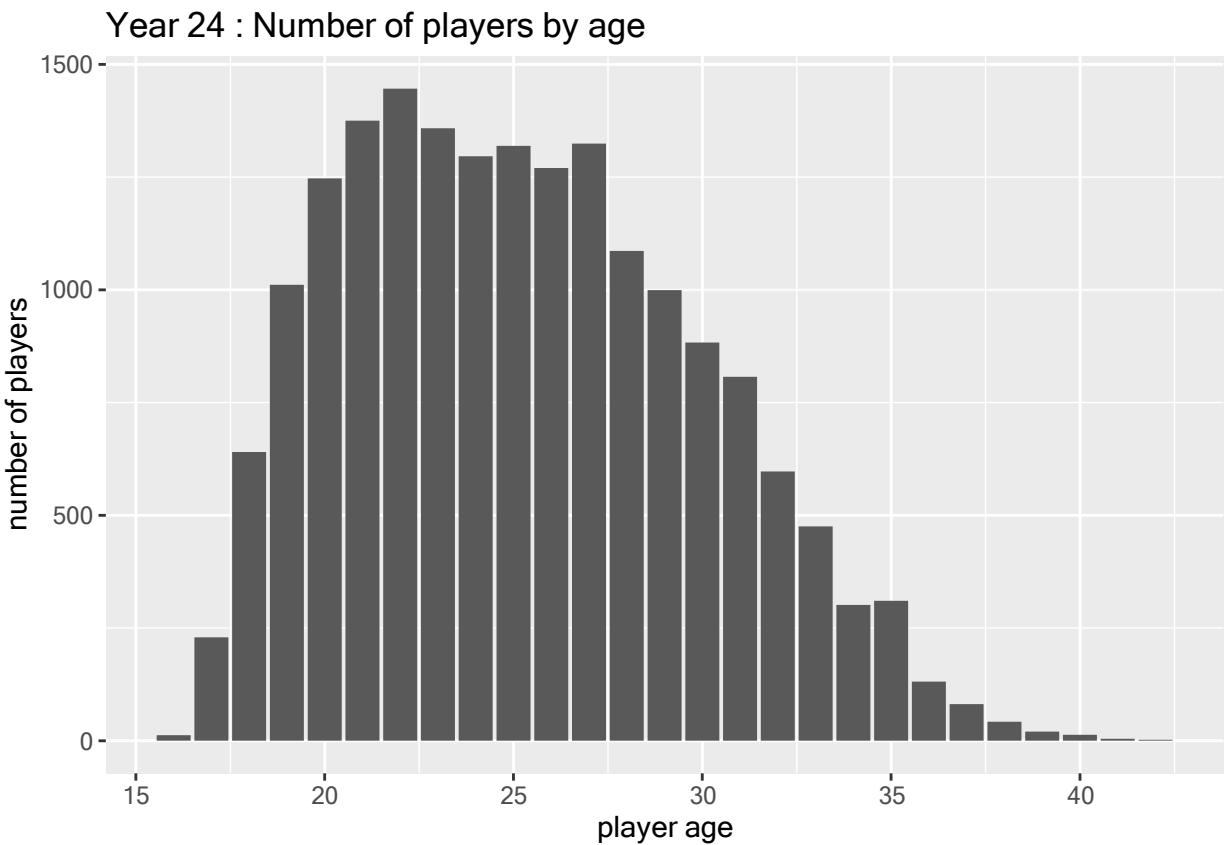


Year 22 : Number of players by age



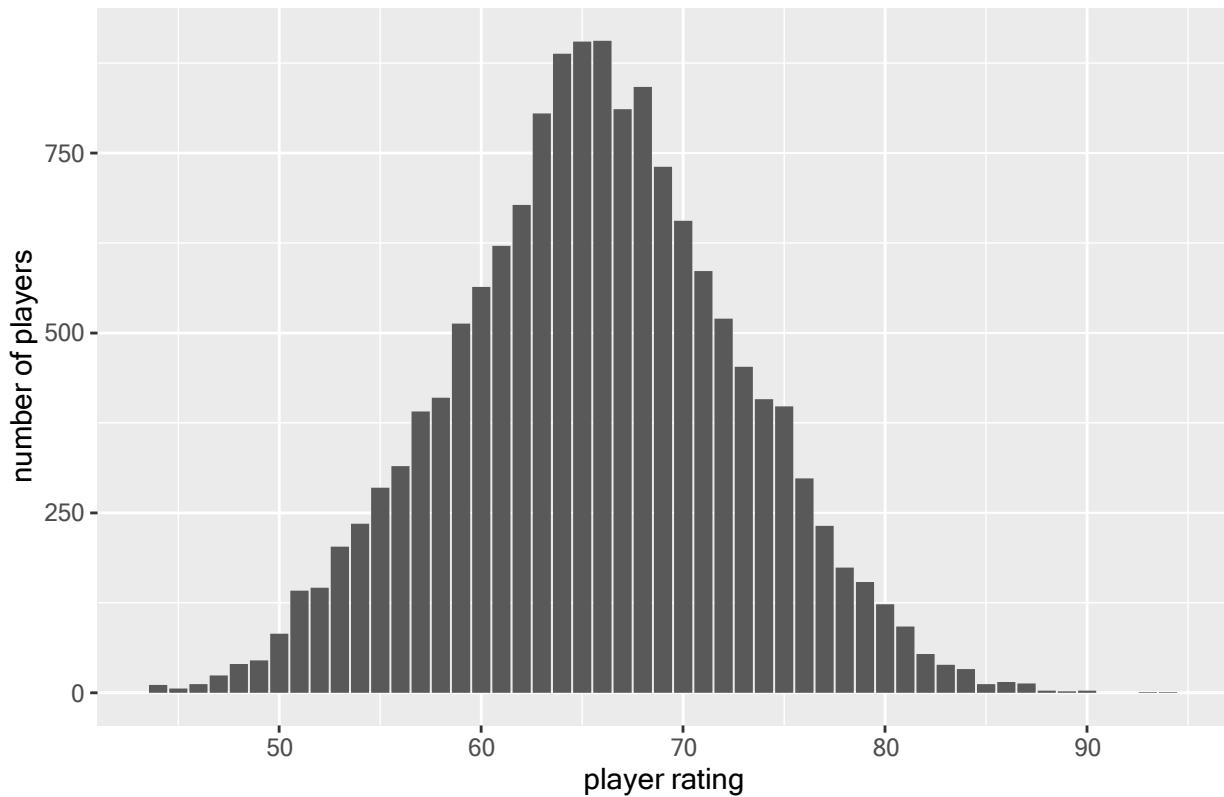
Year 23 : Number of players by age



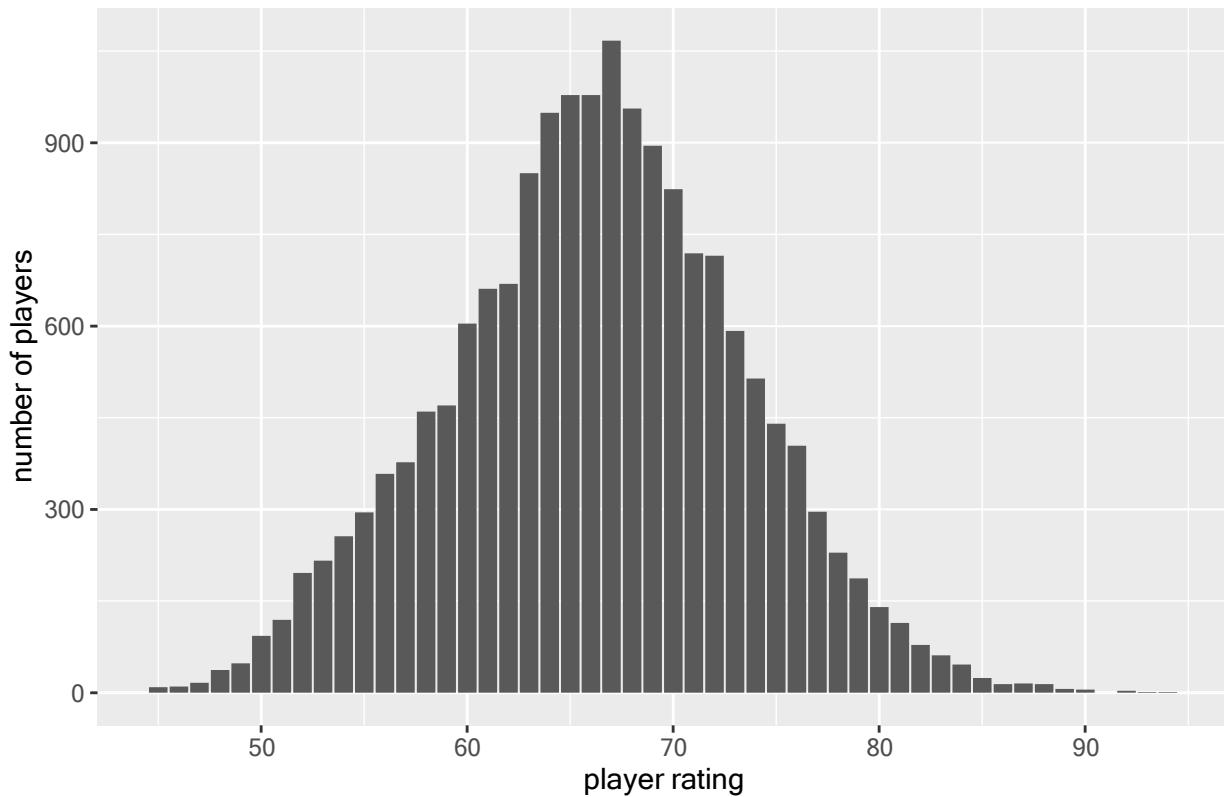


```
# Histogram of player rating by year
for (i in seq_along(fifa_datasets_list)) {
  player_rating_by_year <- fifa_datasets_list[[i]] %>% ggplot(aes(overall)) +
    geom_bar() +
    labs(x="player rating", y="number of players",
         title=paste("Year", years[[i]], ":", "Number of players by rating"))
  print(player_rating_by_year)
}
```

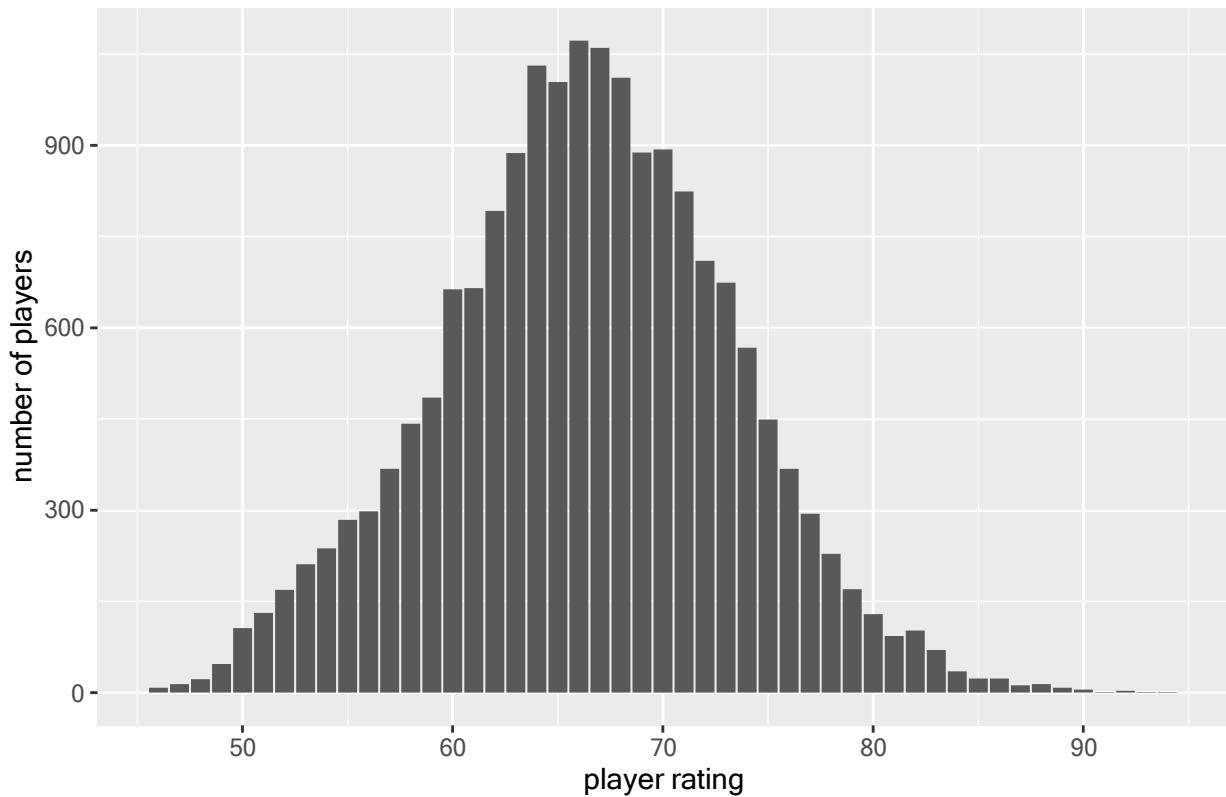
Year 25 : Number of players by rating



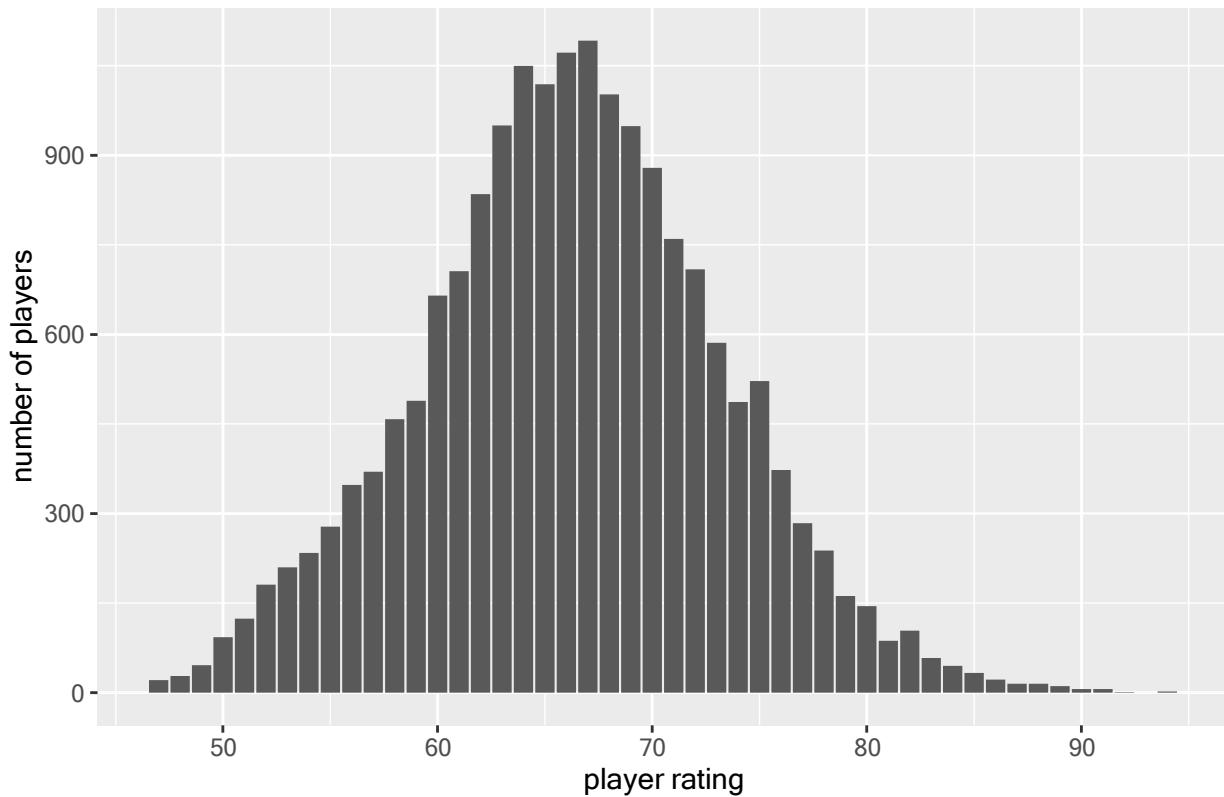
Year 26 : Number of players by rating



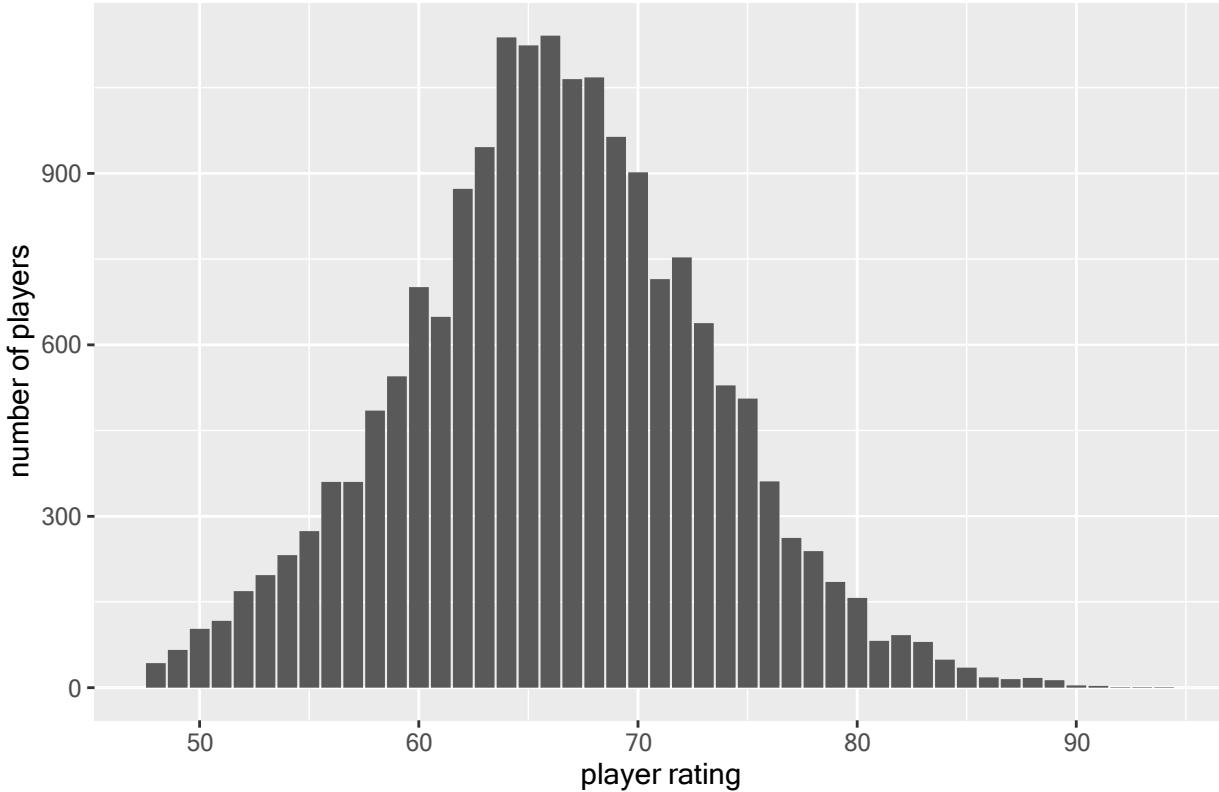
Year 27 : Number of players by rating



Year 28 : Number of players by rating



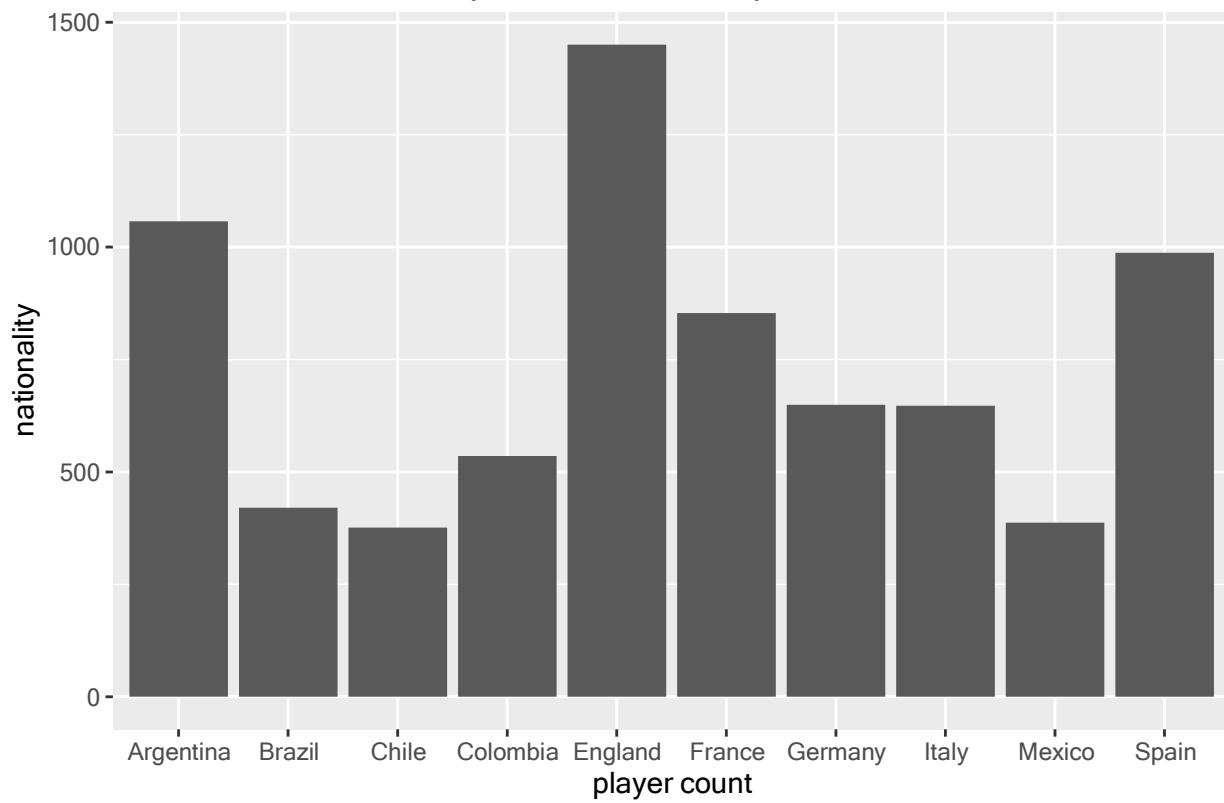
Year 29 : Number of players by rating



```
# Which country has the most players by year
for (i in seq_along(fifa_datasets_list)) {
  country_by_players_count <- fifa_datasets_list[[i]] %>% group_by(nationality) %>%
    summarise(count=n()) %>% arrange(desc(count)) %>% top_n(10) %>%
    ggplot(aes(x=nationality,y=count)) + geom_bar(stat = "identity") +
    labs(x="player count", y="nationality",
         title=paste("Year", years[[i]], ":", "Which Country has the most Players?"))
  print(country_by_players_count)
}
```

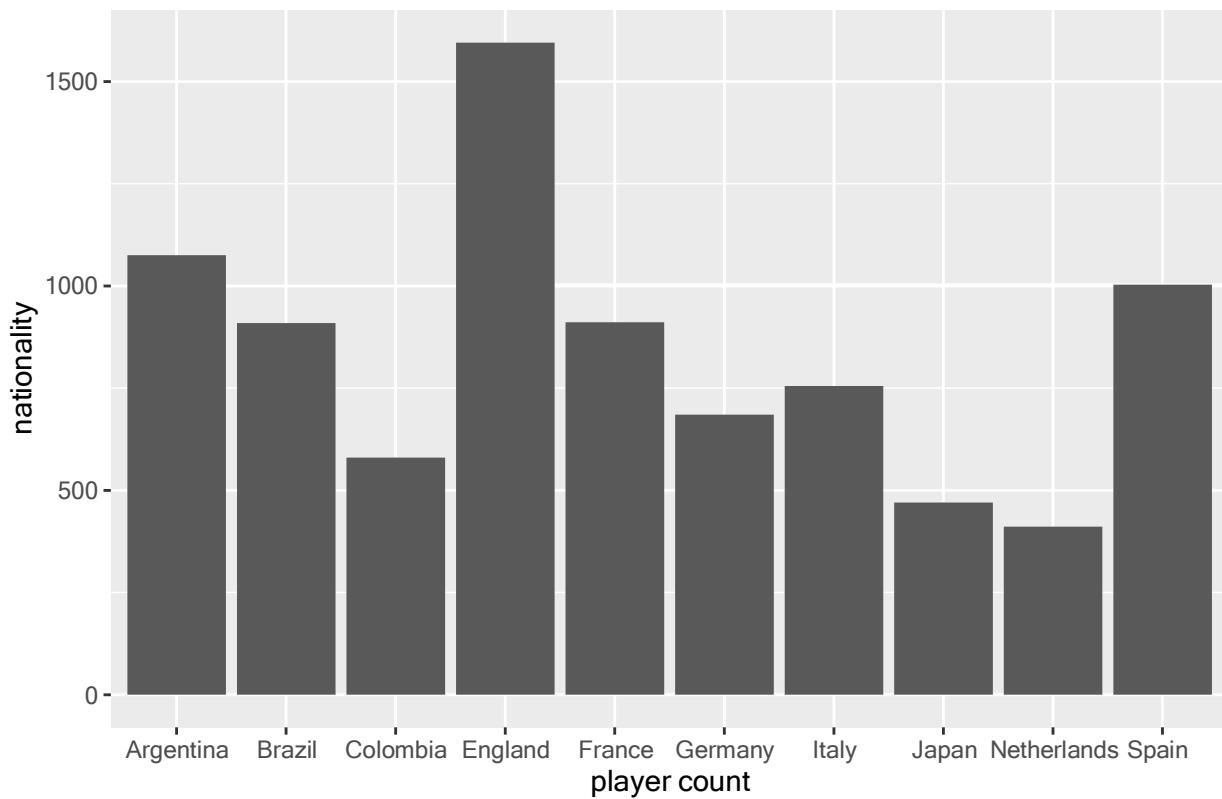
```
## Selecting by count
## Selecting by count
```

Year 30 : Which Country has the most Players?



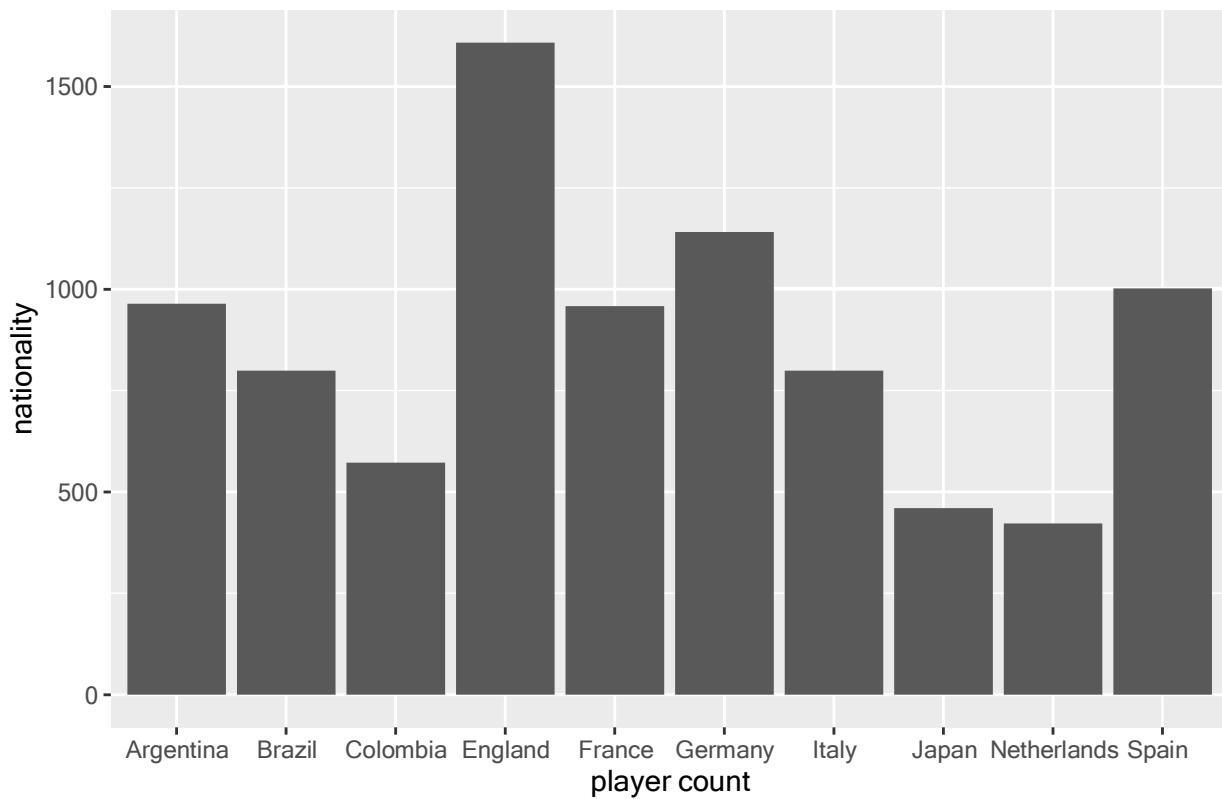
Selecting by count

Year 31 : Which Country has the most Players?



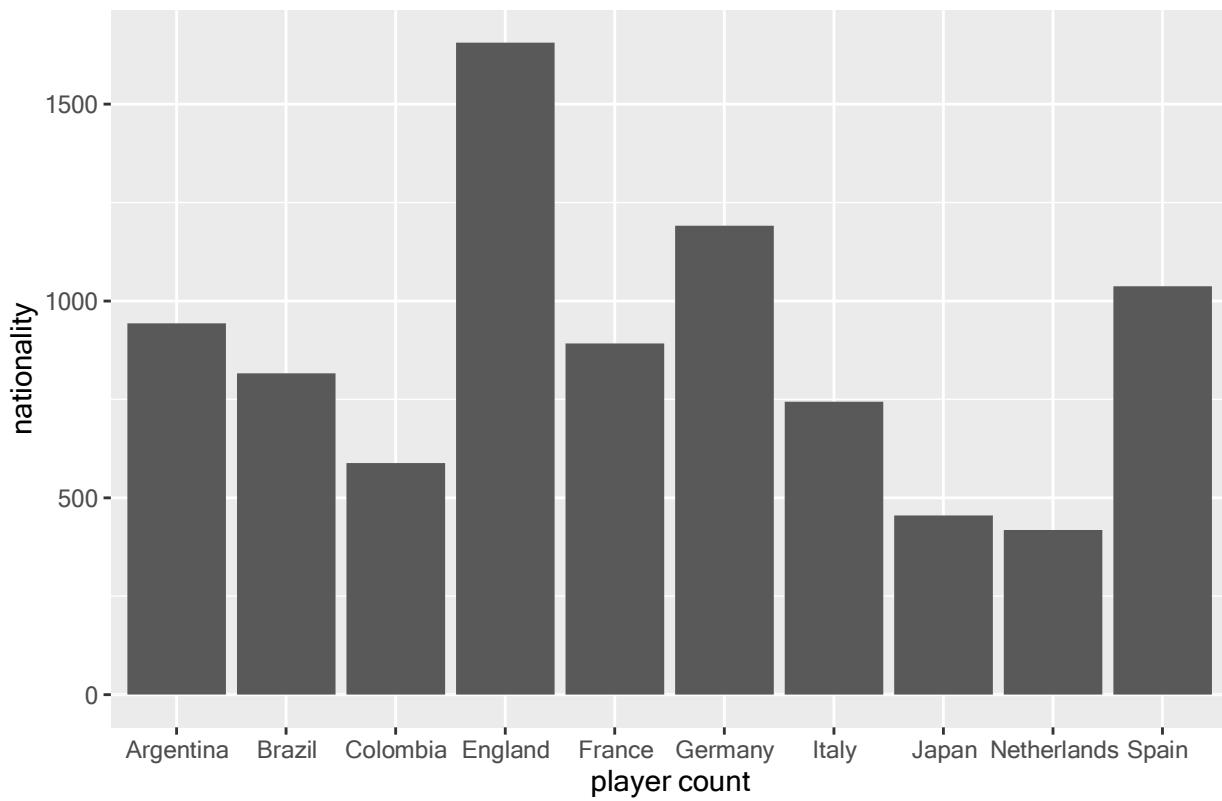
Selecting by count

Year 32 : Which Country has the most Players?

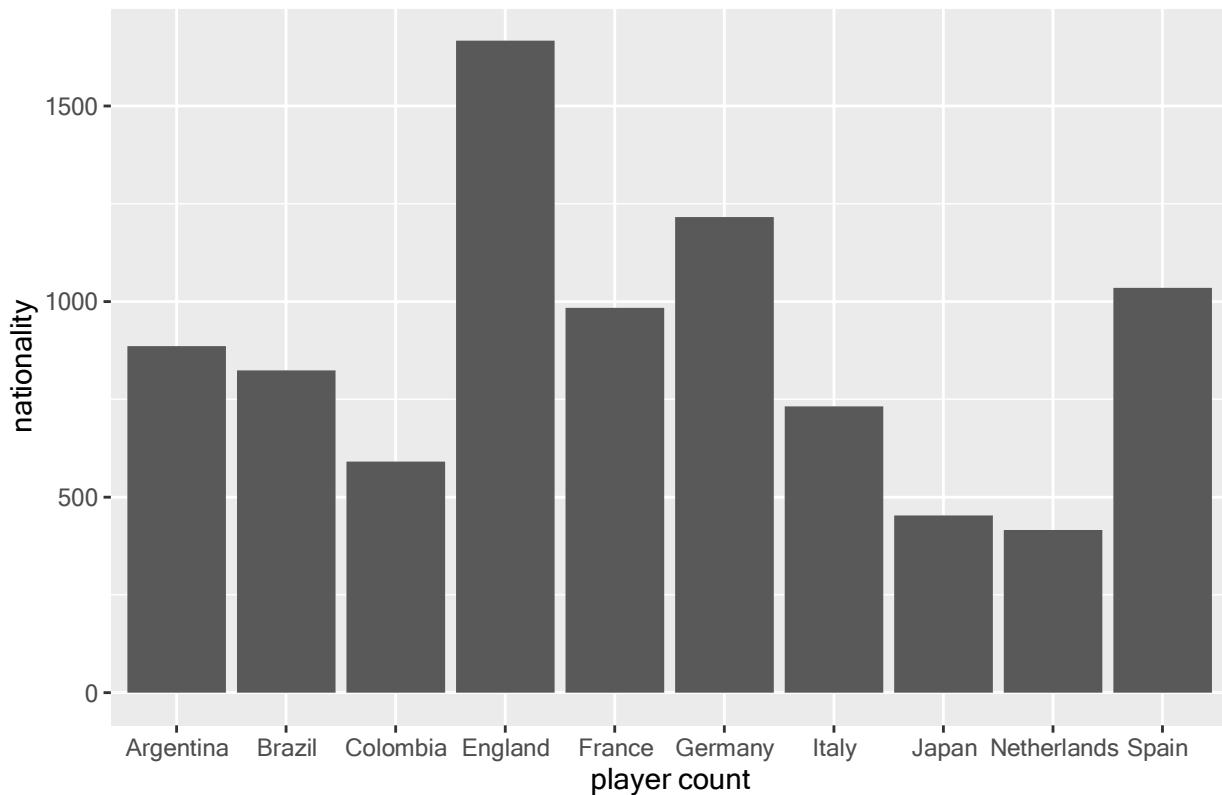


Selecting by count

Year 33 : Which Country has the most Players?

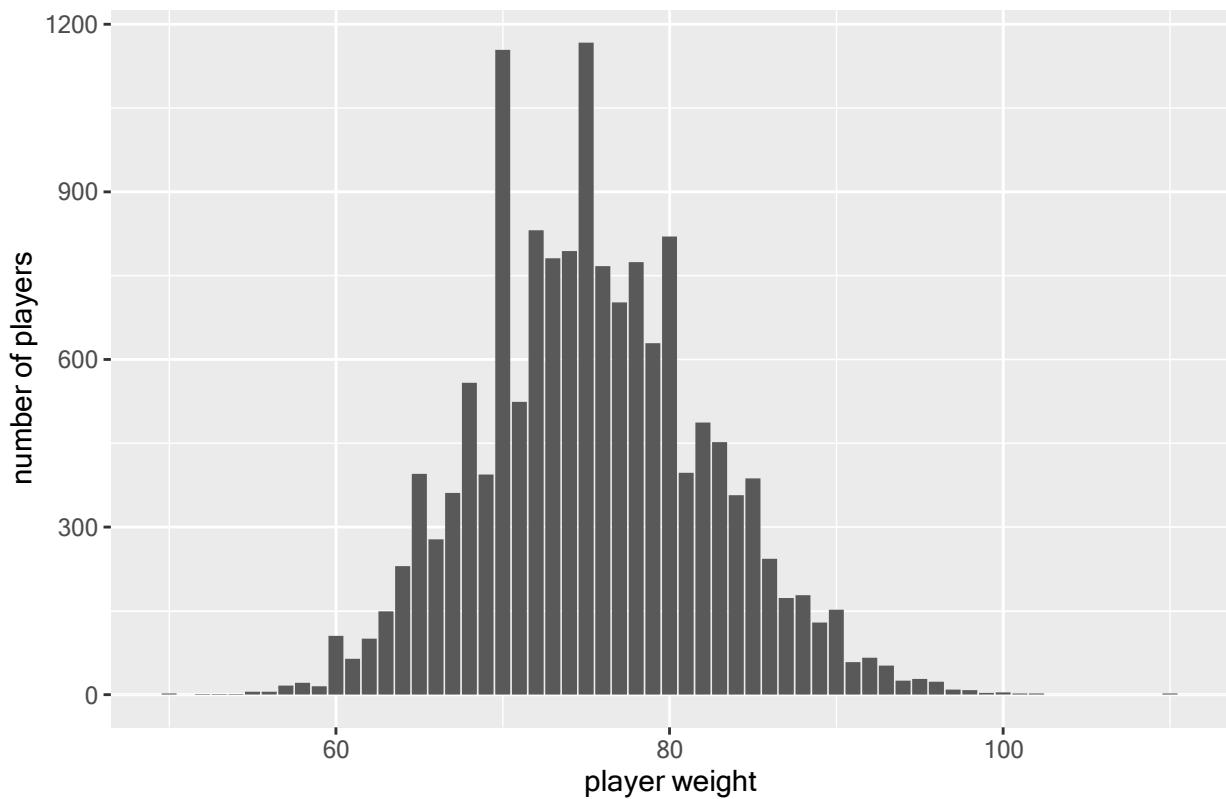


Year 34 : Which Country has the most Players?

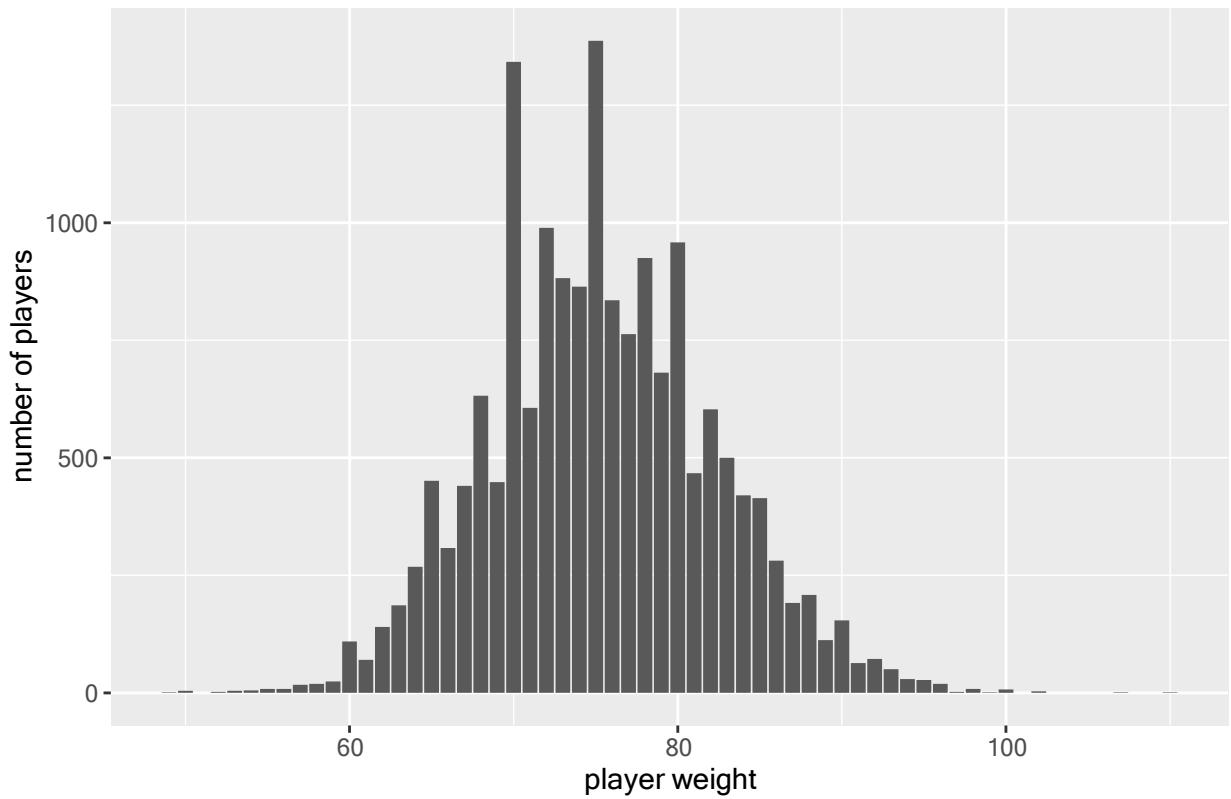


```
# Histogram of weight in kgs by year
for (i in seq_along(fifa_datasets_list)) {
  player_weight_by_year <- fifa_datasets_list[[i]] %>%
    ggplot(aes(weight_kg)) +
    geom_bar() +
    labs(x="player weight", y="number of players",
         title=paste("Year", years[[i]], ":", "Number of players by weight in kgs" ))
  print(player_weight_by_year)
}
```

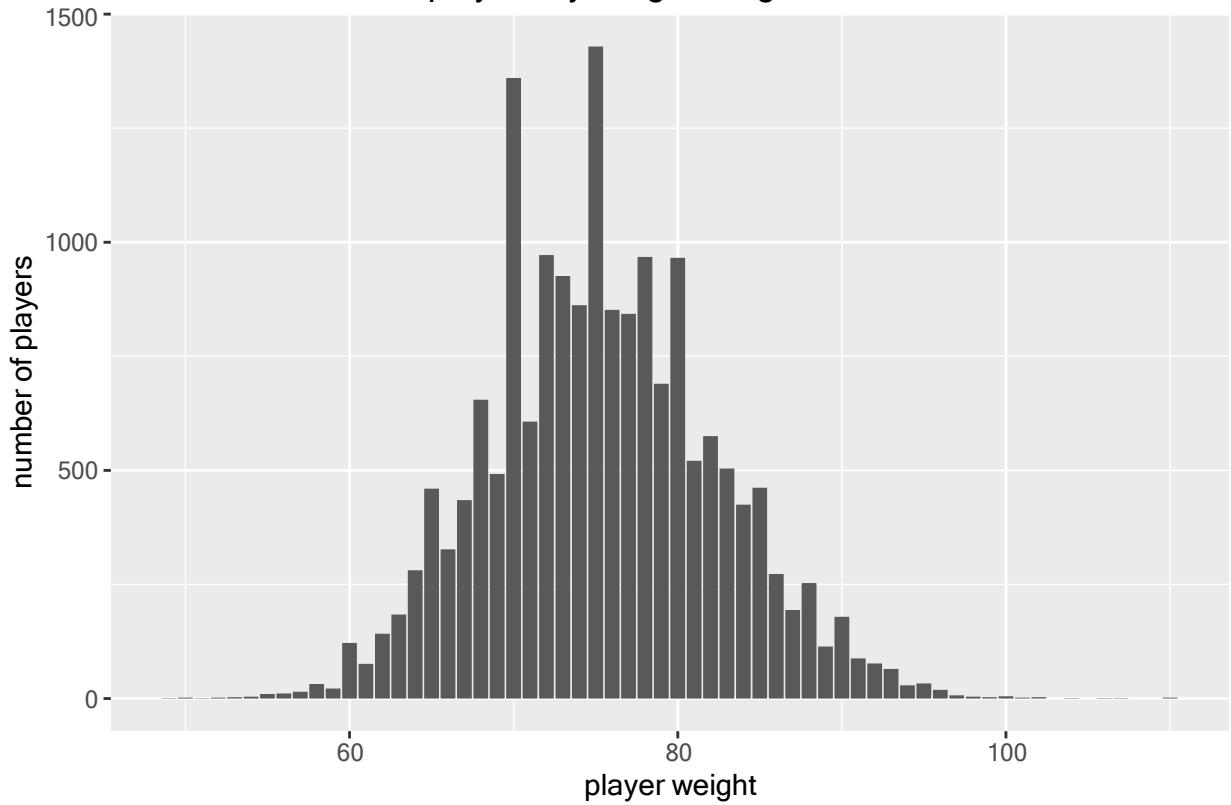
Year 35 : Number of players by weight in kgs



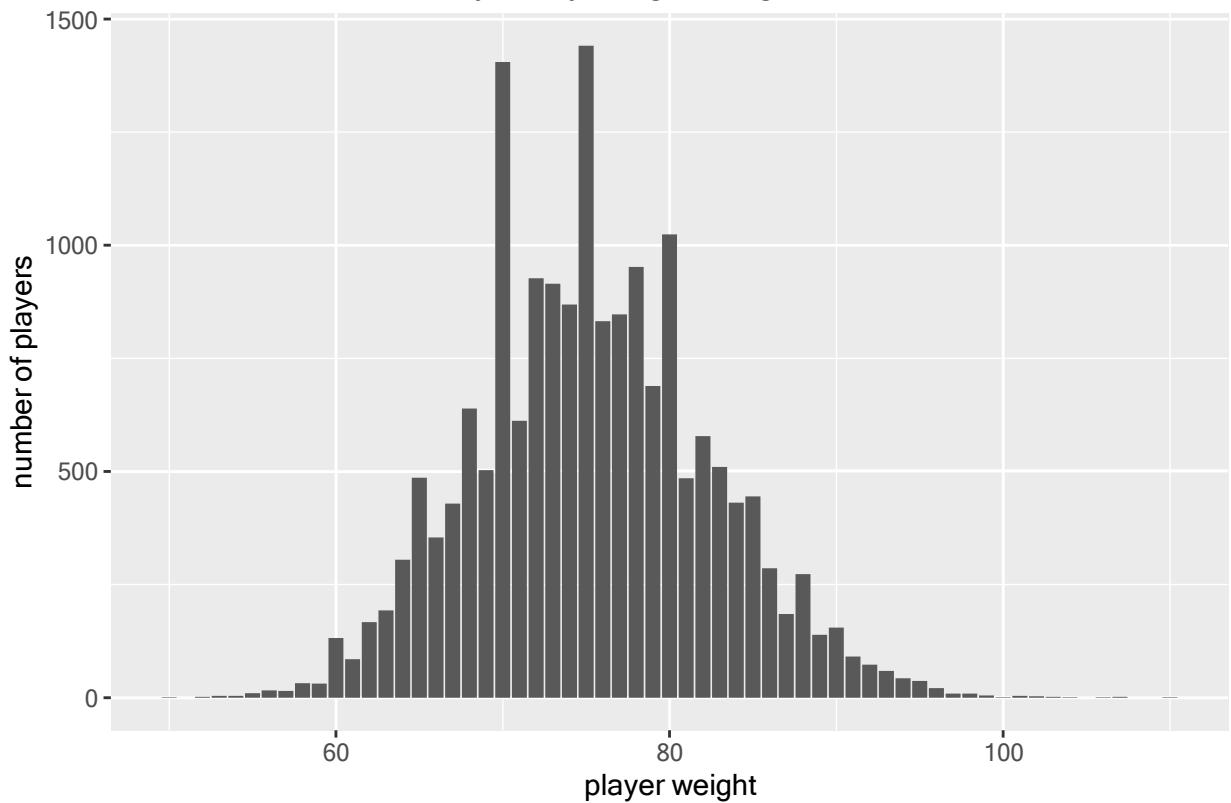
Year 36 : Number of players by weight in kgs



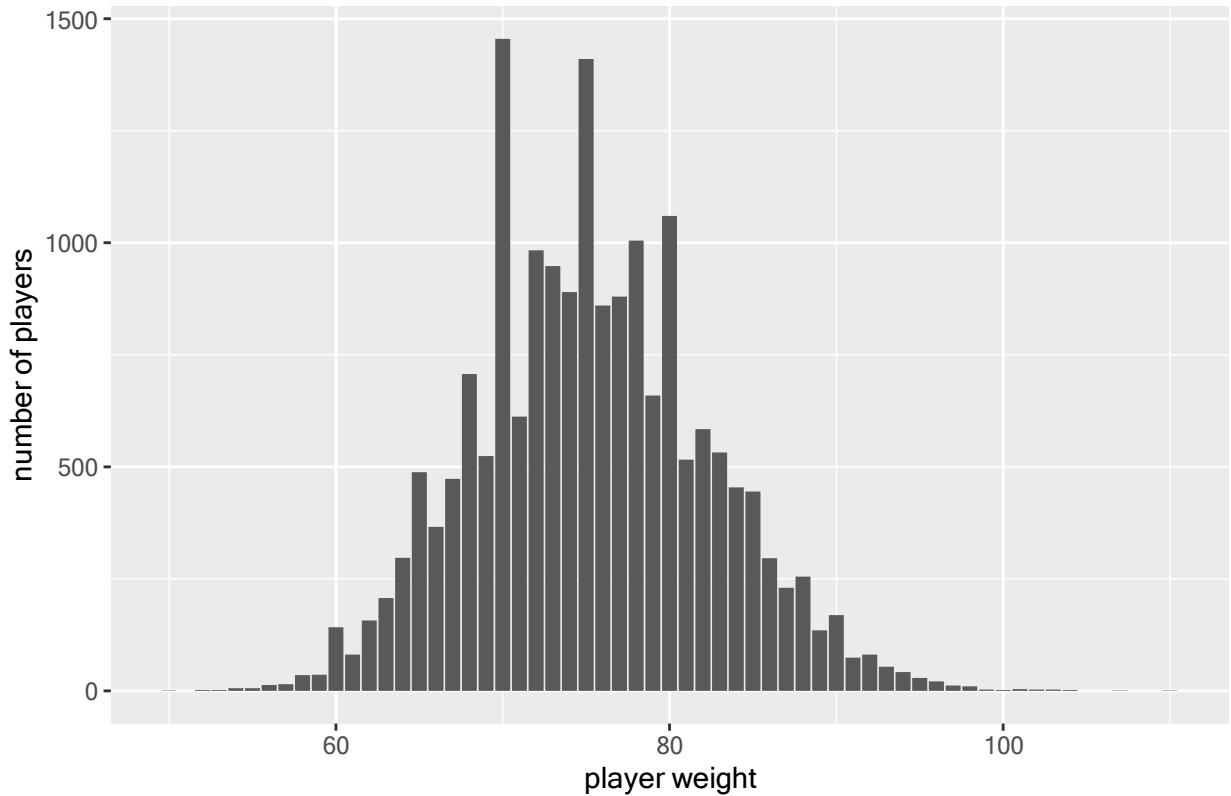
Year 37 : Number of players by weight in kgs



Year 38 : Number of players by weight in kgs

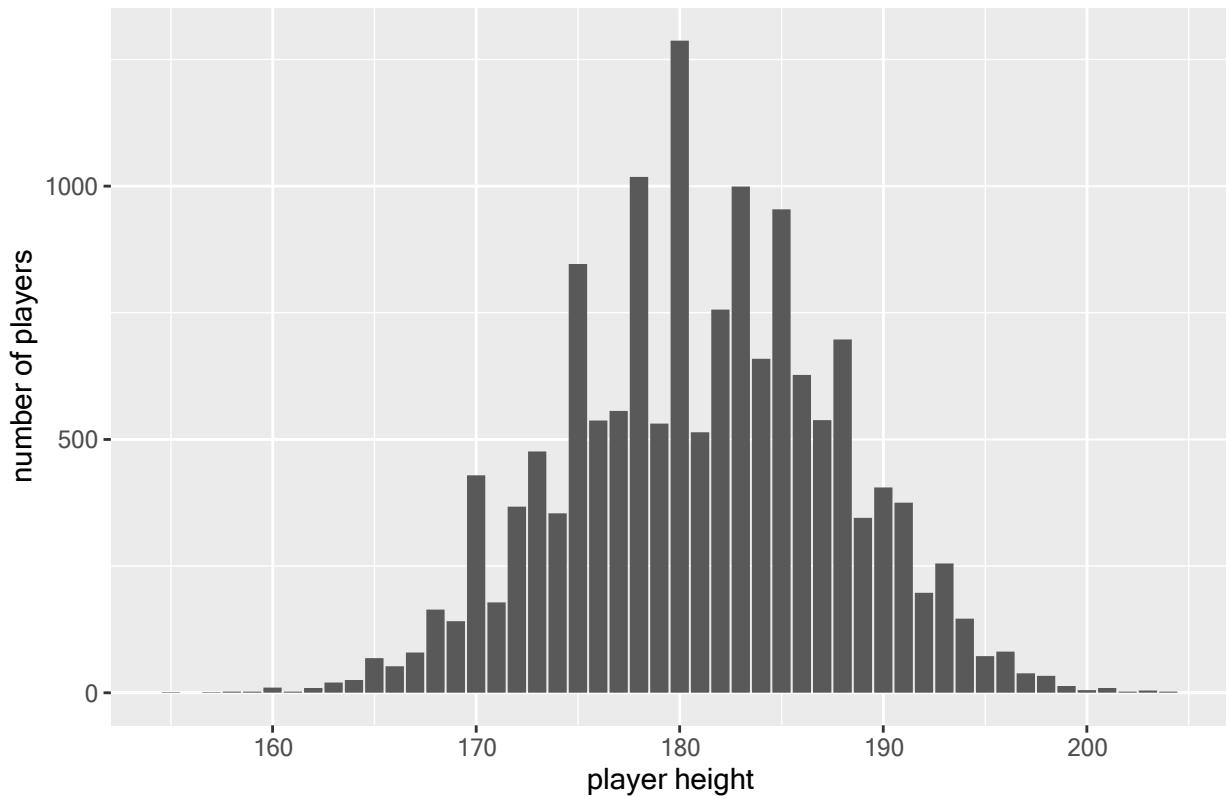


Year 39 : Number of players by weight in kgs

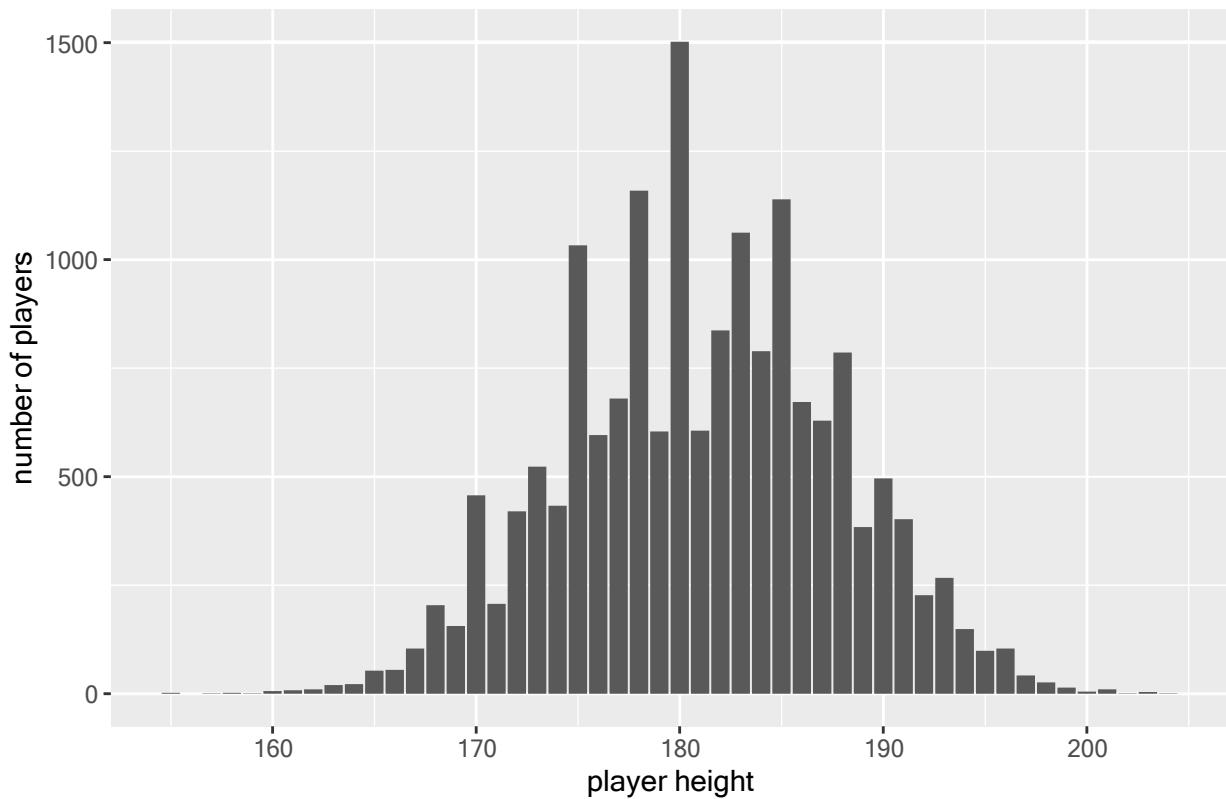


```
# Histogram of height in cms by year
for (i in seq_along(fifa_datasets_list)) {
  player_height_by_year <- fifa_datasets_list[[i]] %>%
    ggplot(aes(height_cm)) +
    geom_bar() +
    labs(x="player height", y="number of players",
         title=paste("Year", years[[i]], ":", "Number of players by height in cms" ))
  print(player_height_by_year)
}
```

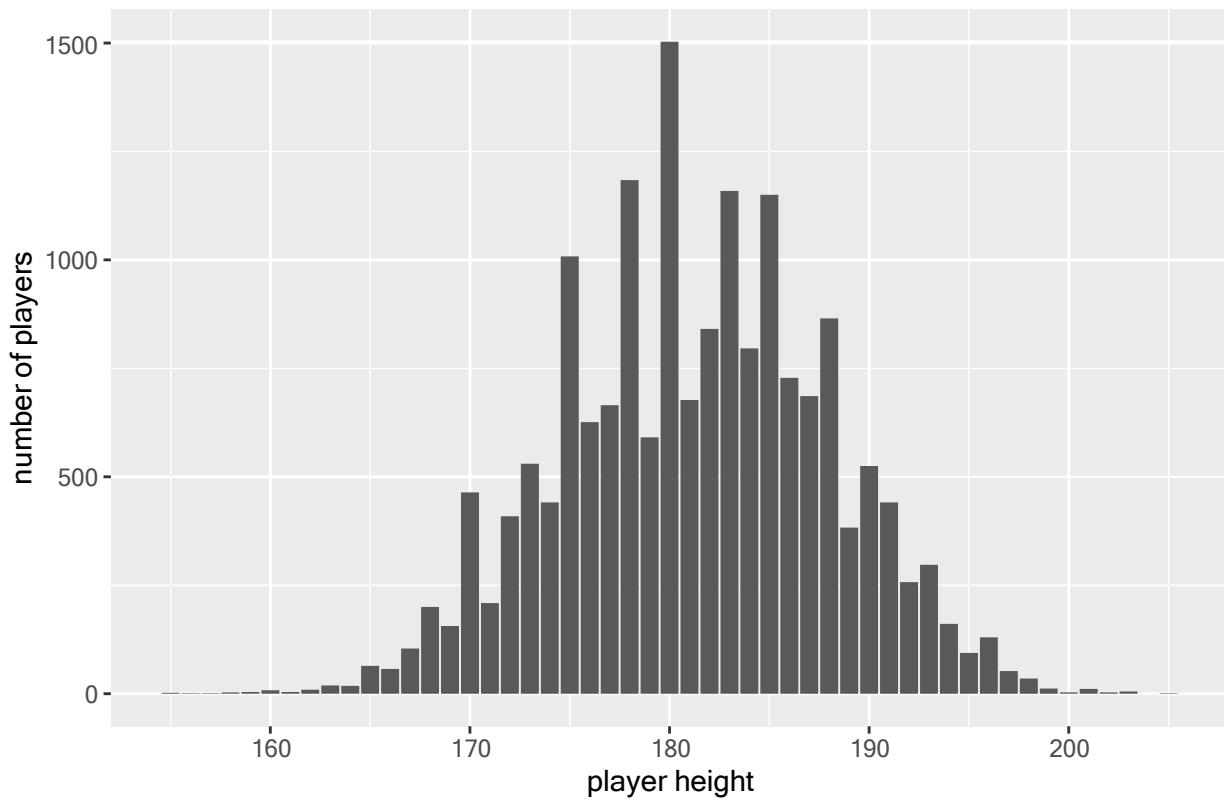
Year 40 : Number of players by height in cms



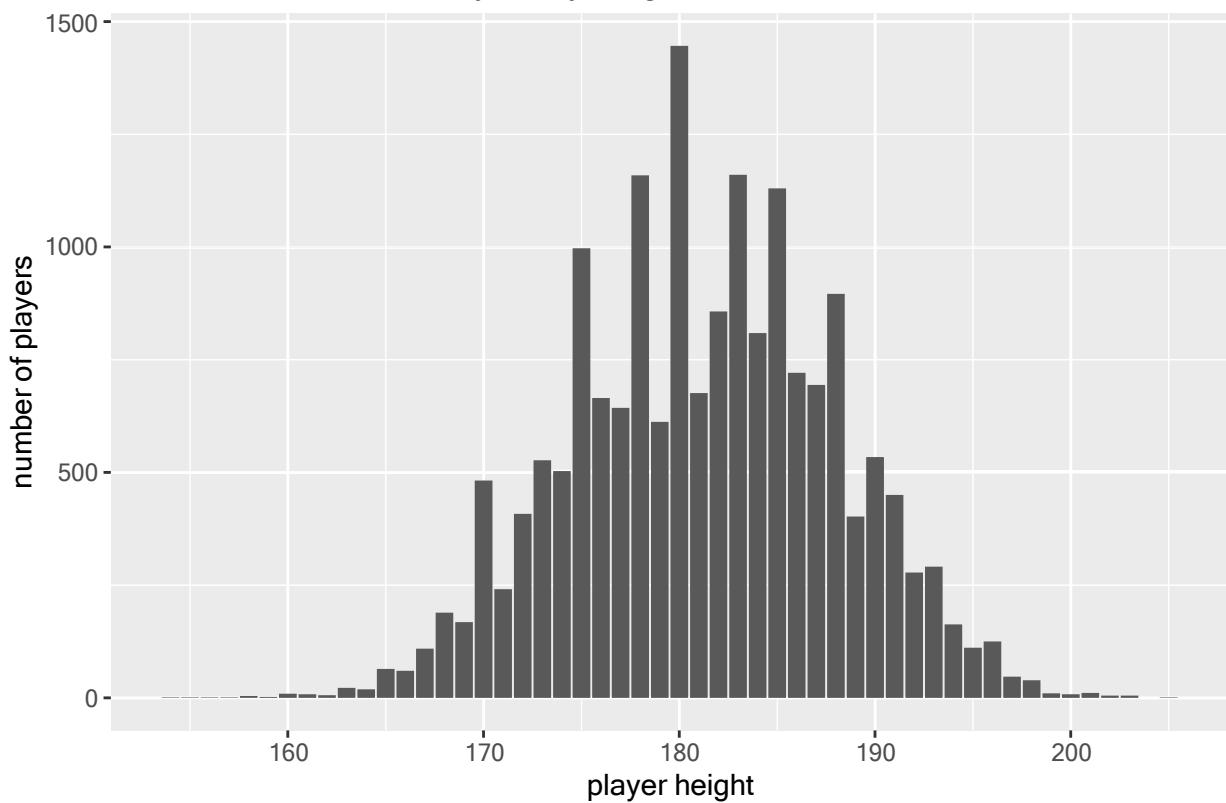
Year 41 : Number of players by height in cms



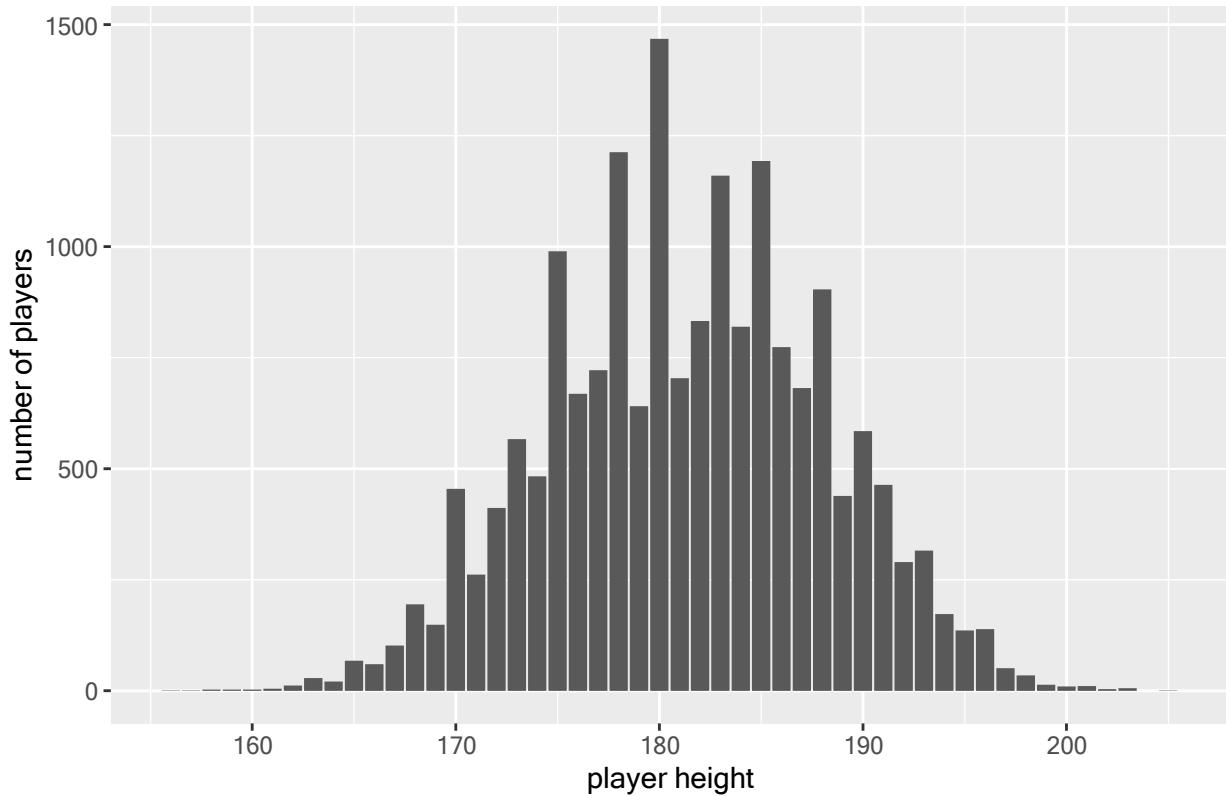
Year 42 : Number of players by height in cms



Year 43 : Number of players by height in cms



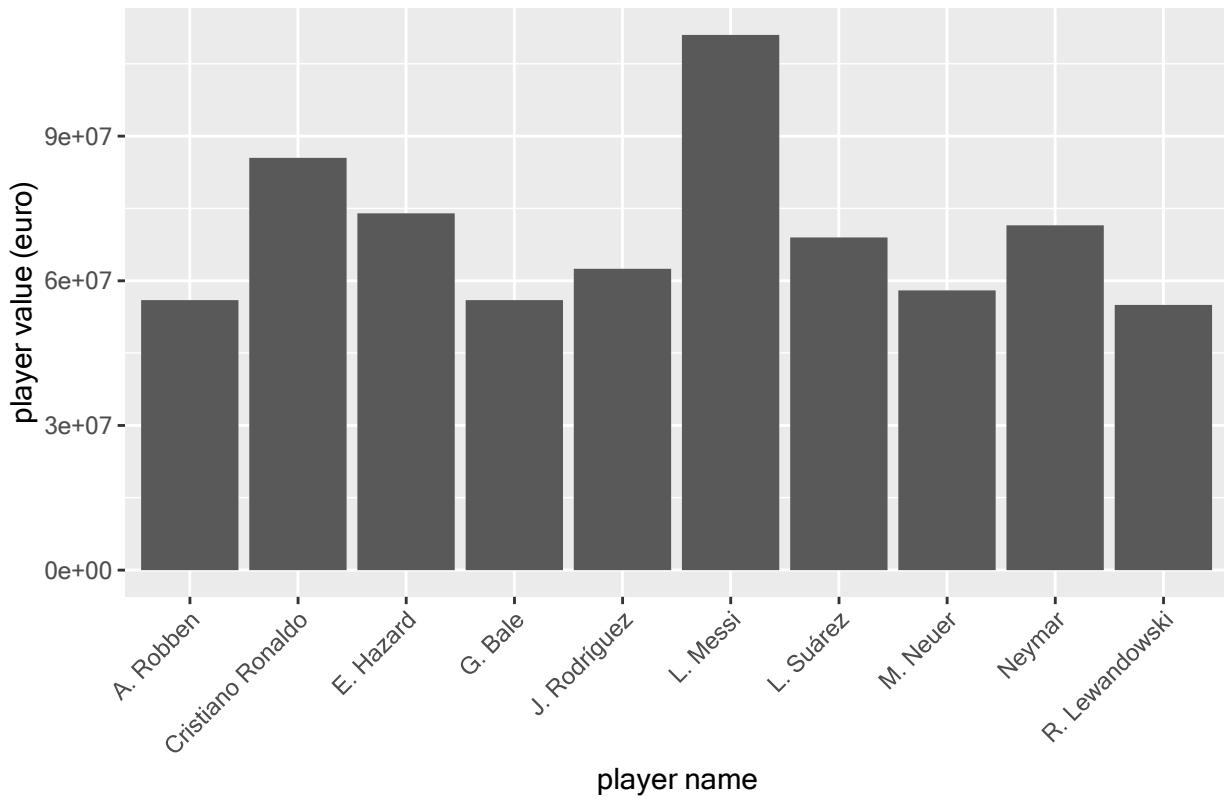
Year 44 : Number of players by height in cms



```
# Top 10 players with highest value in euros
for (i in seq_along(fifa_datasets_list)) {
  top10_value_players <- fifa_datasets_list[[i]] %>% arrange(desc(value_eur)) %>%
    select(short_name, club, nationality, overall, value_eur) %>% top_n(10) %>%
    ggplot(aes(x=short_name, y=value_eur)) + geom_bar(stat = "identity") +
    labs(x="player name", y="player value (euro)",
         title=paste("Year", years[[i]], ":", "Top 10 players highest value in euros" )) +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))
  print(top10_value_players)
}

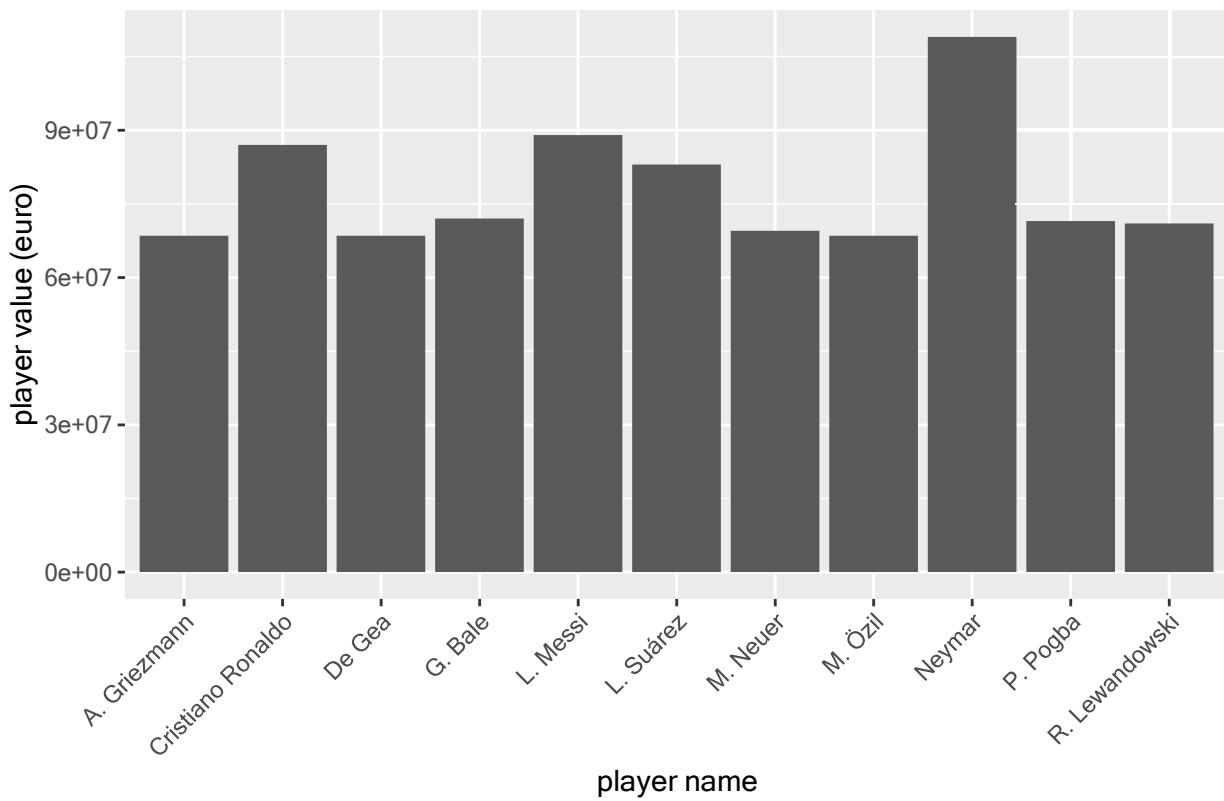
## Selecting by value_eur
## Selecting by value_eur
```

Year 45 : Top 10 players highest value in euros



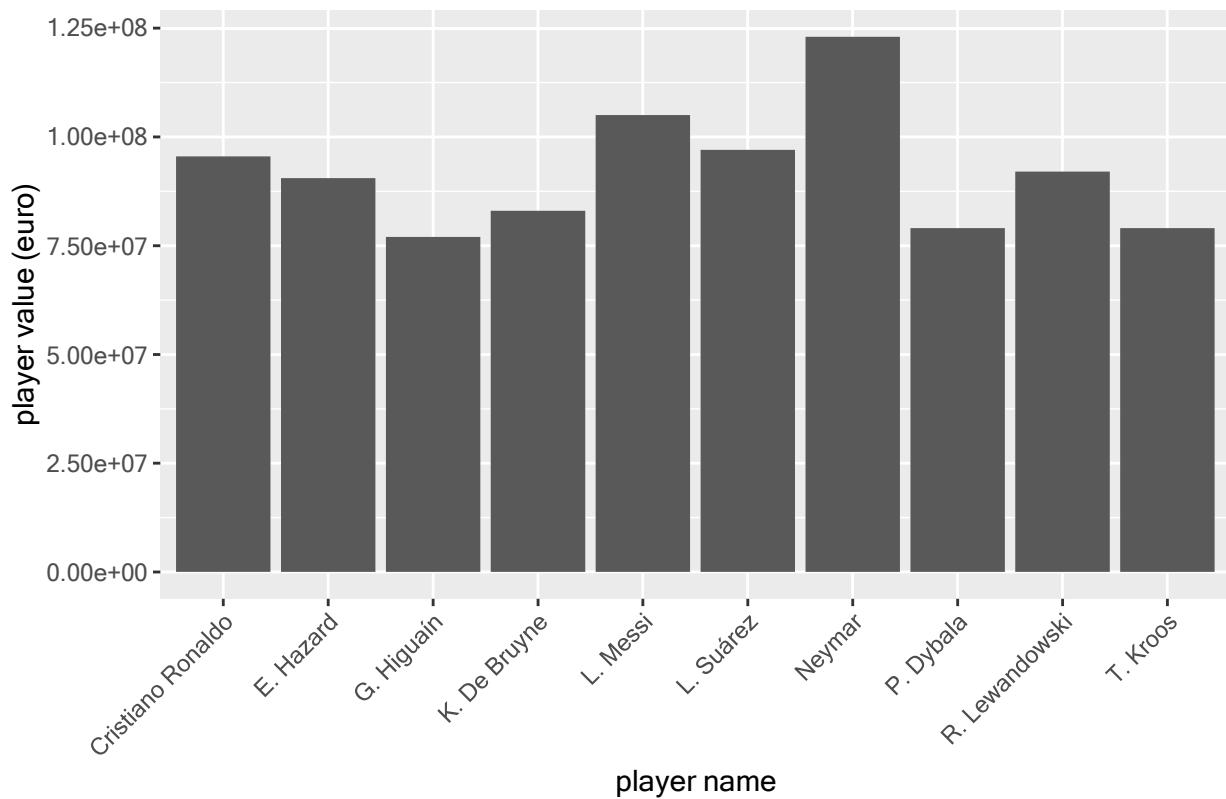
```
## Selecting by value_eur
```

Year 46 : Top 10 players highest value in euros



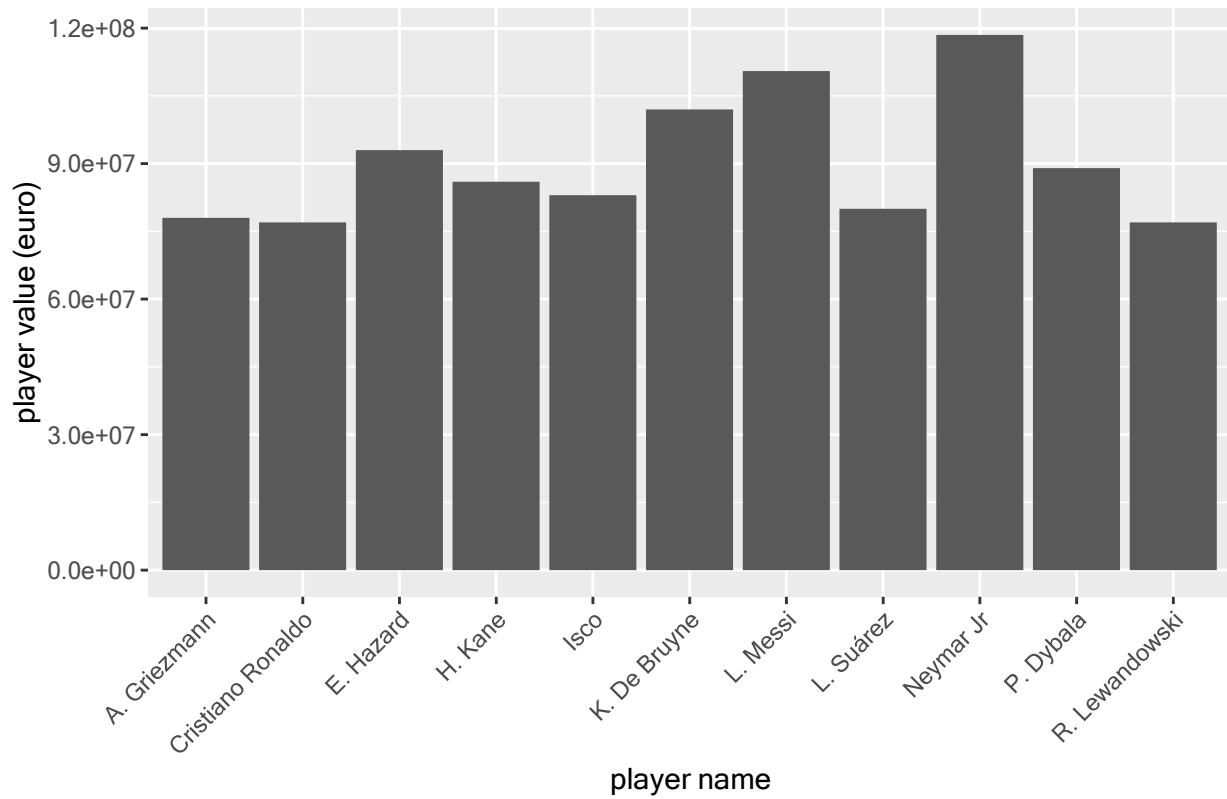
```
## Selecting by value_eur
```

Year 47 : Top 10 players highest value in euros

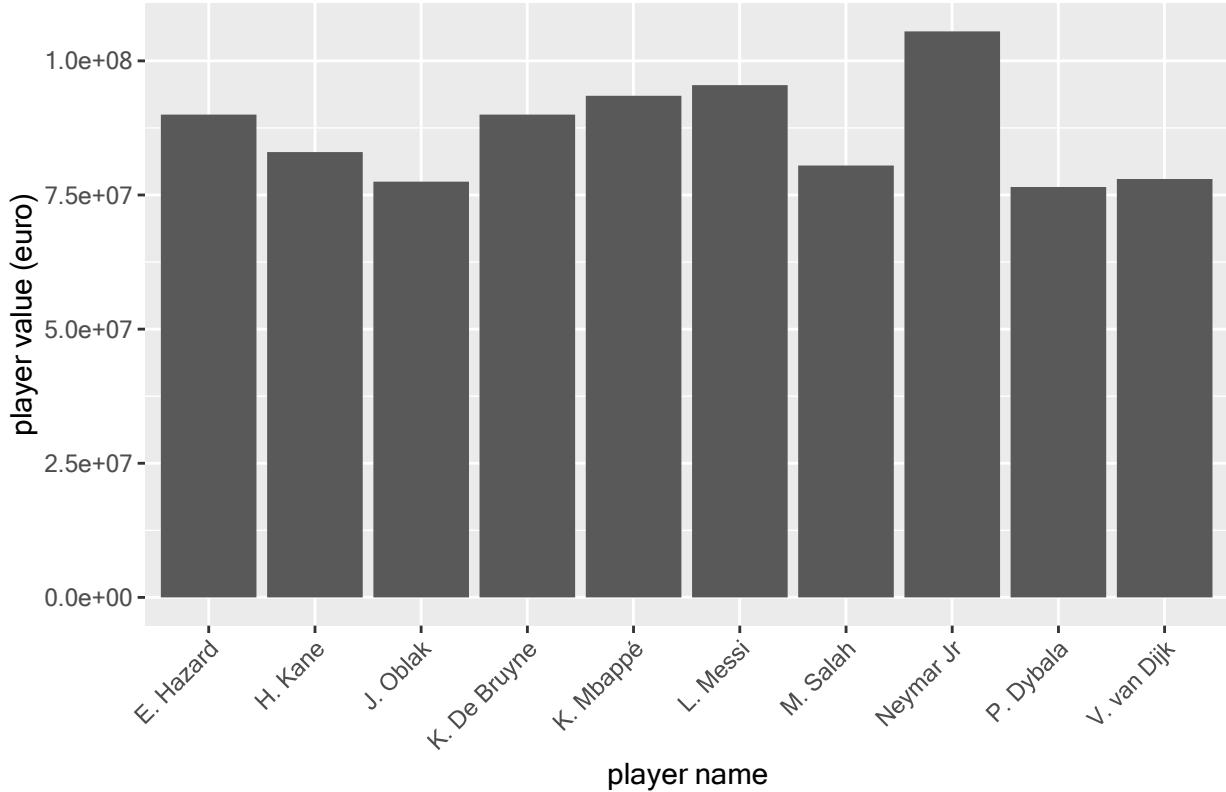


```
## Selecting by value_eur
```

Year 48 : Top 10 players highest value in euros



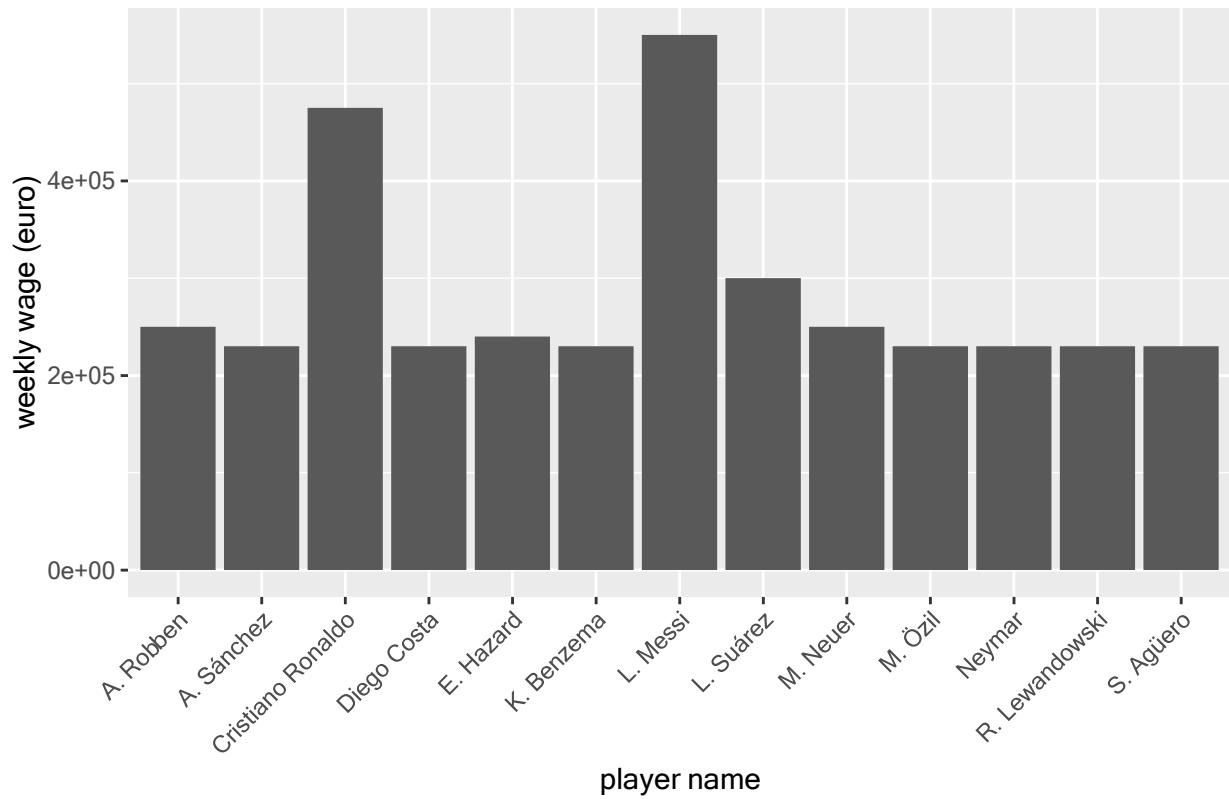
Year 49 : Top 10 players highest value in euros



```
# Top 10 players with highest weekly wage in euros
for (i in seq_along(fifa_datasets_list)) {
  top10_weekly_wage_players <- fifa_datasets_list[[i]] %>% arrange(desc(wage_eur)) %>%
    select(short_name, club, nationality, overall, wage_eur) %>% top_n(10) %>%
    ggplot(aes(x=short_name, y=wage_eur)) + geom_bar(stat = "identity") +
    labs(x="player name", y="weekly wage (euro)",
         title=paste("Year", years[[i]], ":", "Top 10 players weekly wage in euros" )) +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))
  print(top10_weekly_wage_players)
}

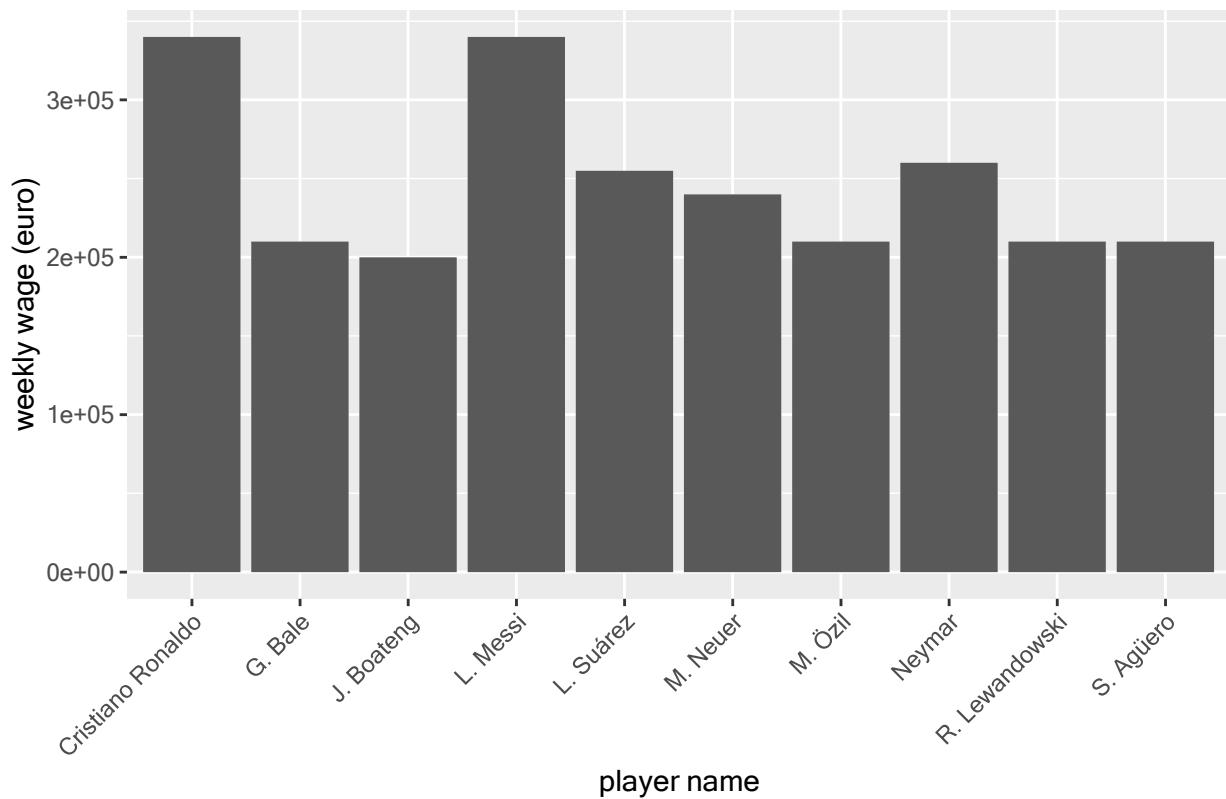
## Selecting by wage_eur
## Selecting by wage_eur
```

Year 50 : Top 10 players weekly wage in euros



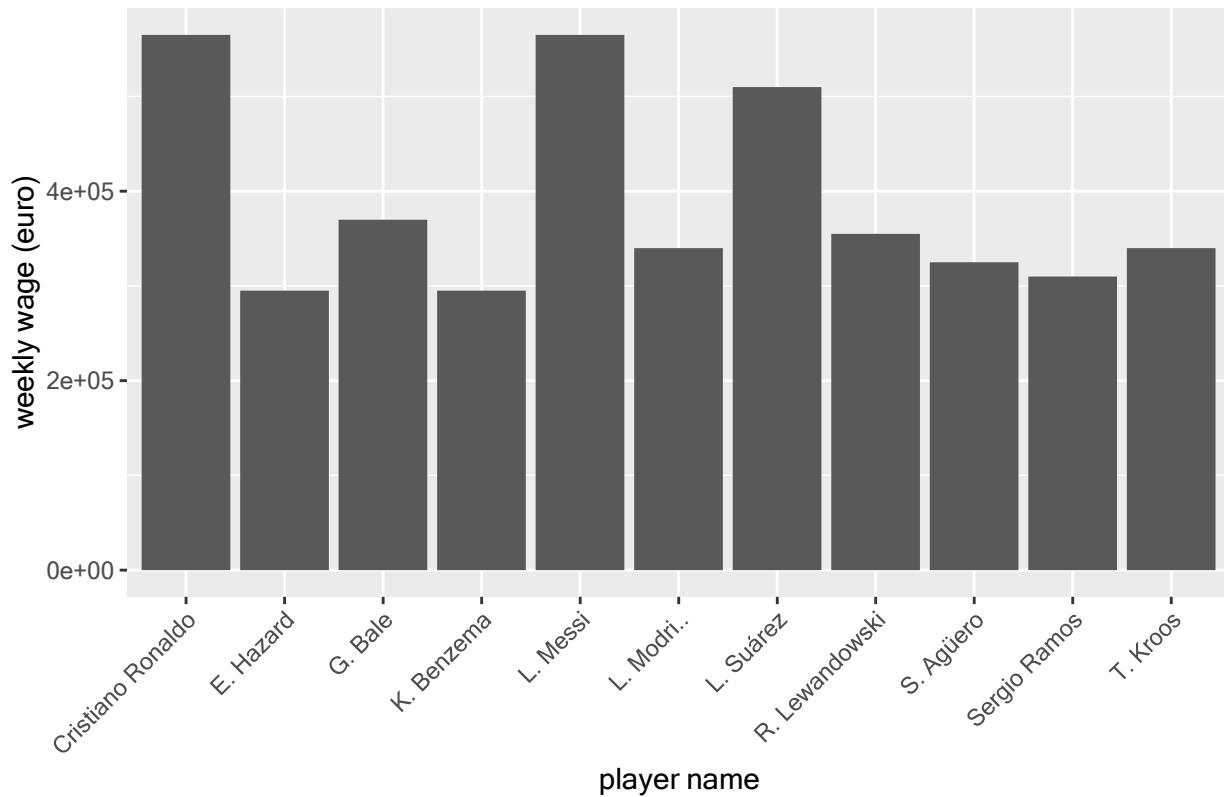
```
## Selecting by wage_eur
```

Year 51 : Top 10 players weekly wage in euros



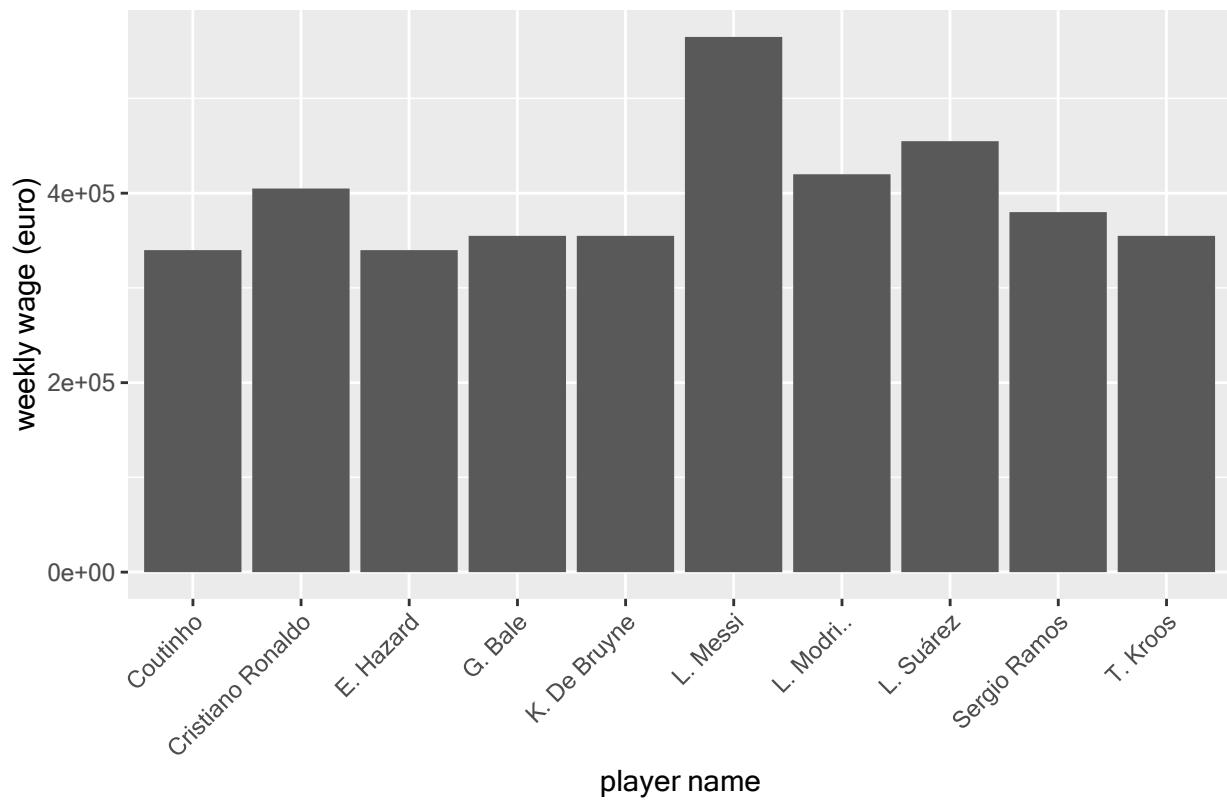
```
## Selecting by wage_eur
```

Year 52 : Top 10 players weekly wage in euros

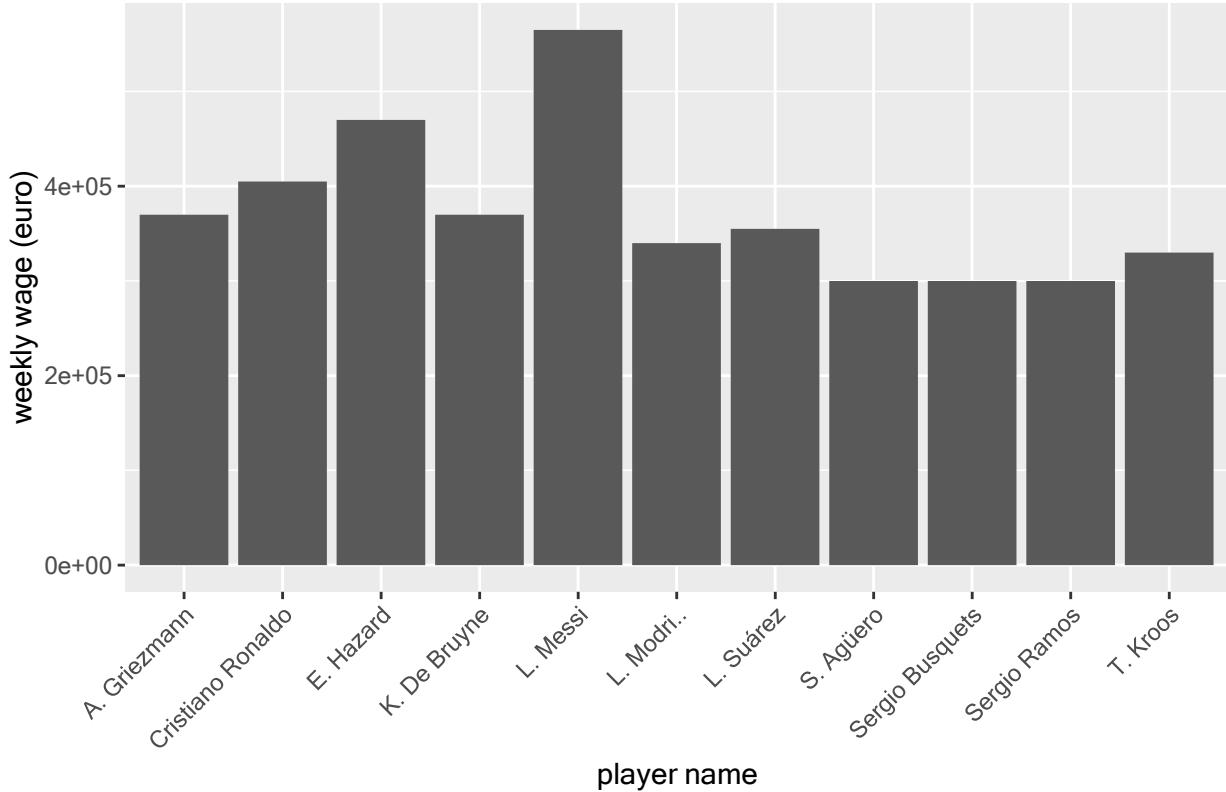


```
## Selecting by wage_eur
```

Year 53 : Top 10 players weekly wage in euros



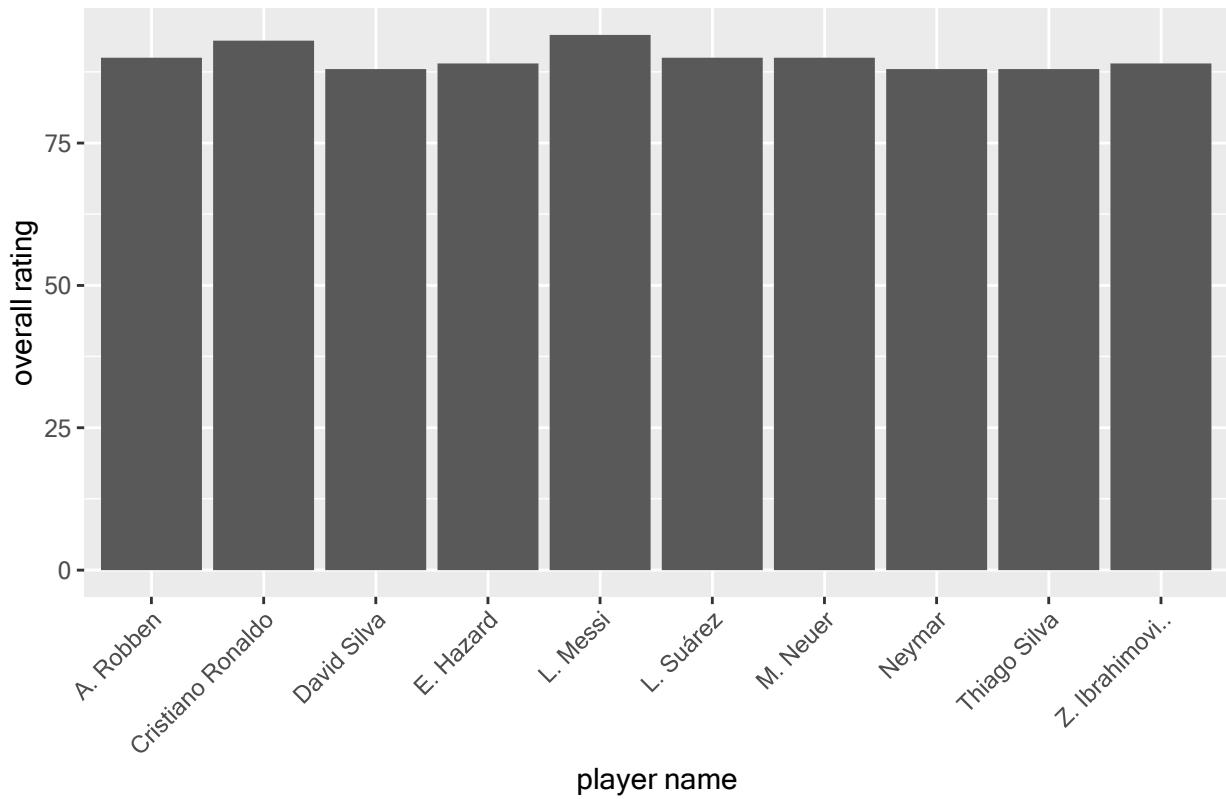
Year 54 : Top 10 players weekly wage in euros



```
# TTop 10 players with best rating
for (i in seq_along(fifa_datasets_list)) {
  top10_players <- fifa_datasets_list[[i]] %>% arrange(desc(overall)) %>%
    select(short_name, club, nationality, overall, overall) %>% top_n(10) %>%
    ggplot(aes(x=short_name, y=overall)) + geom_bar(stat = "identity") +
    labs(x="player name", y="overall rating",
         title=paste("Year", years[[i]], ":", "Top 10 Players with highest rating" )) +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))
  print(top10_players)
}

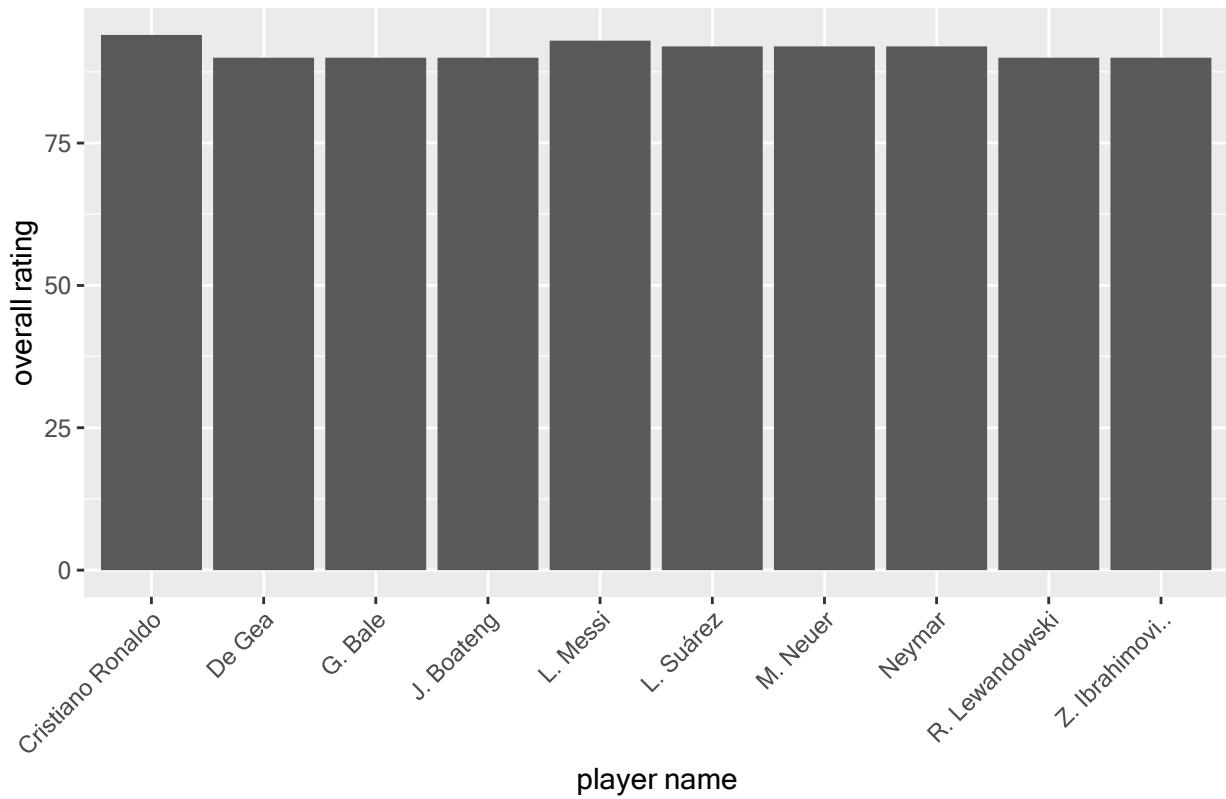
## Selecting by overall
## Selecting by overall
```

Year 55 : Top 10 Players with highest rating



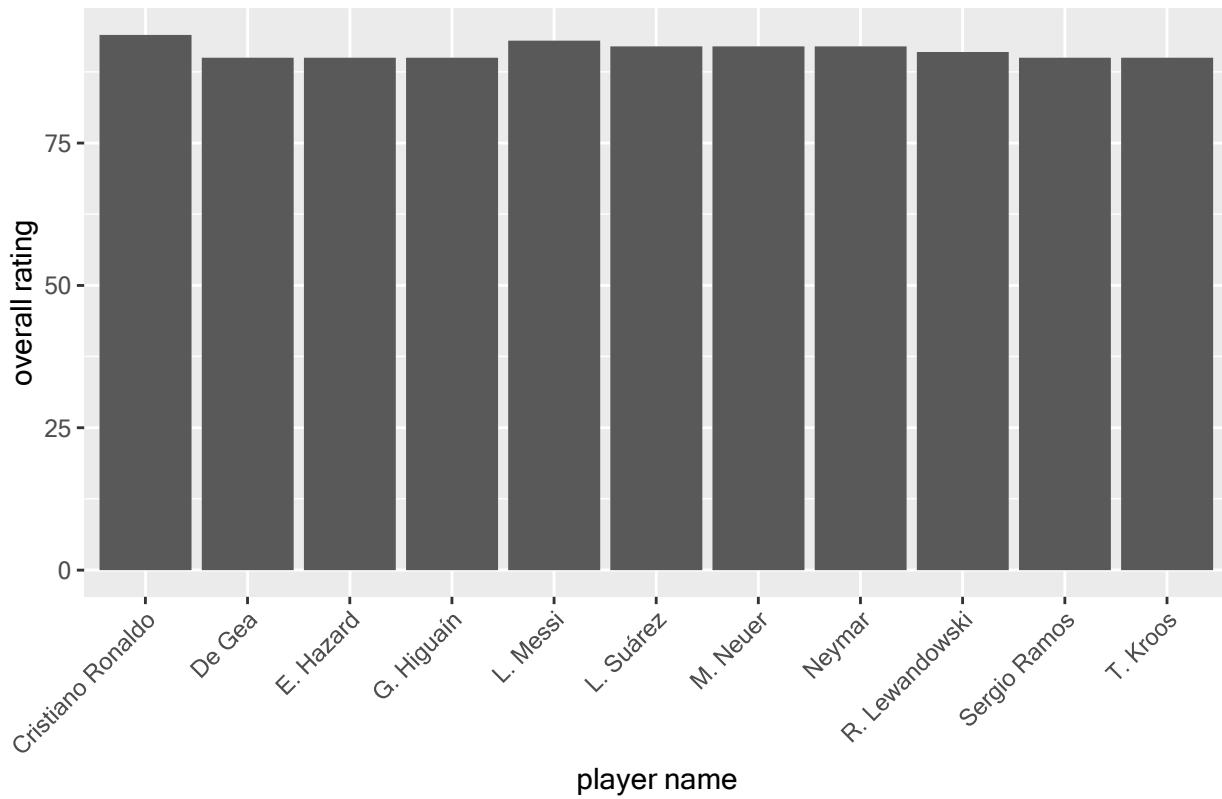
Selecting by overall

Year 56 : Top 10 Players with highest rating



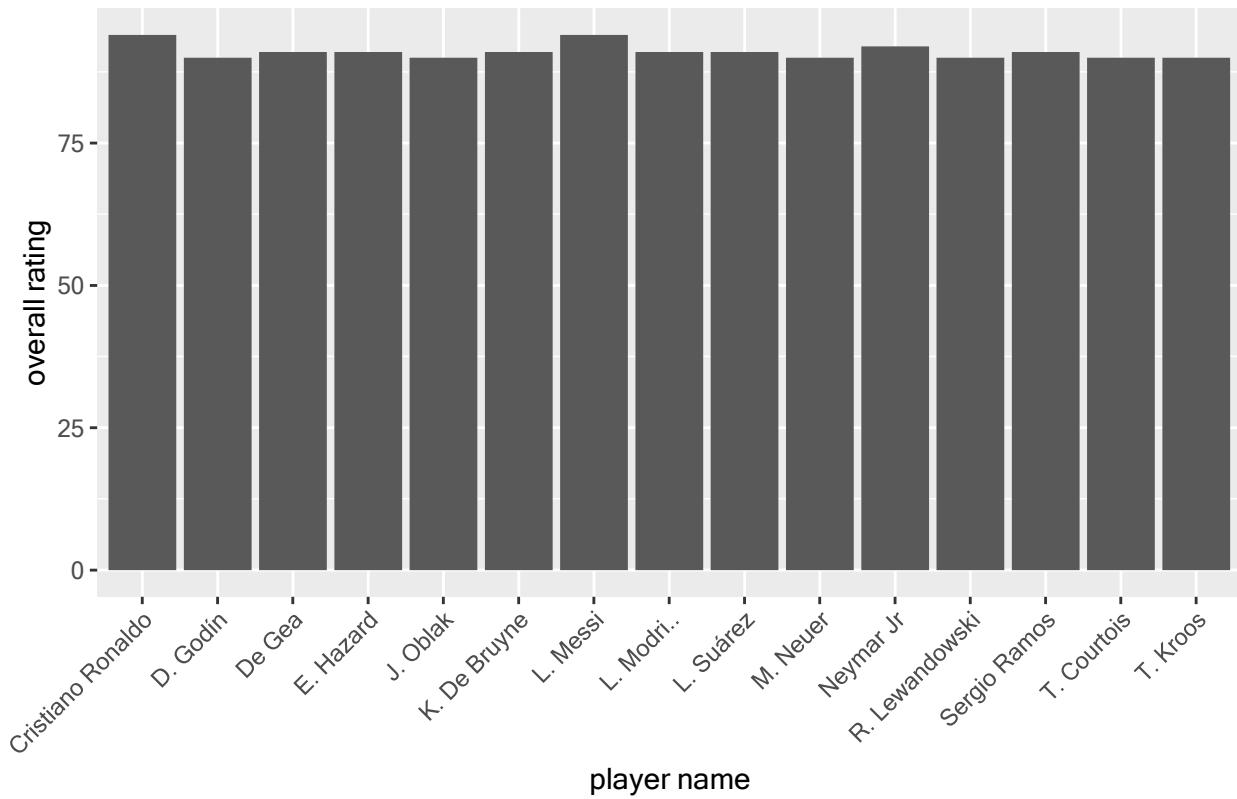
Selecting by overall

Year 57 : Top 10 Players with highest rating

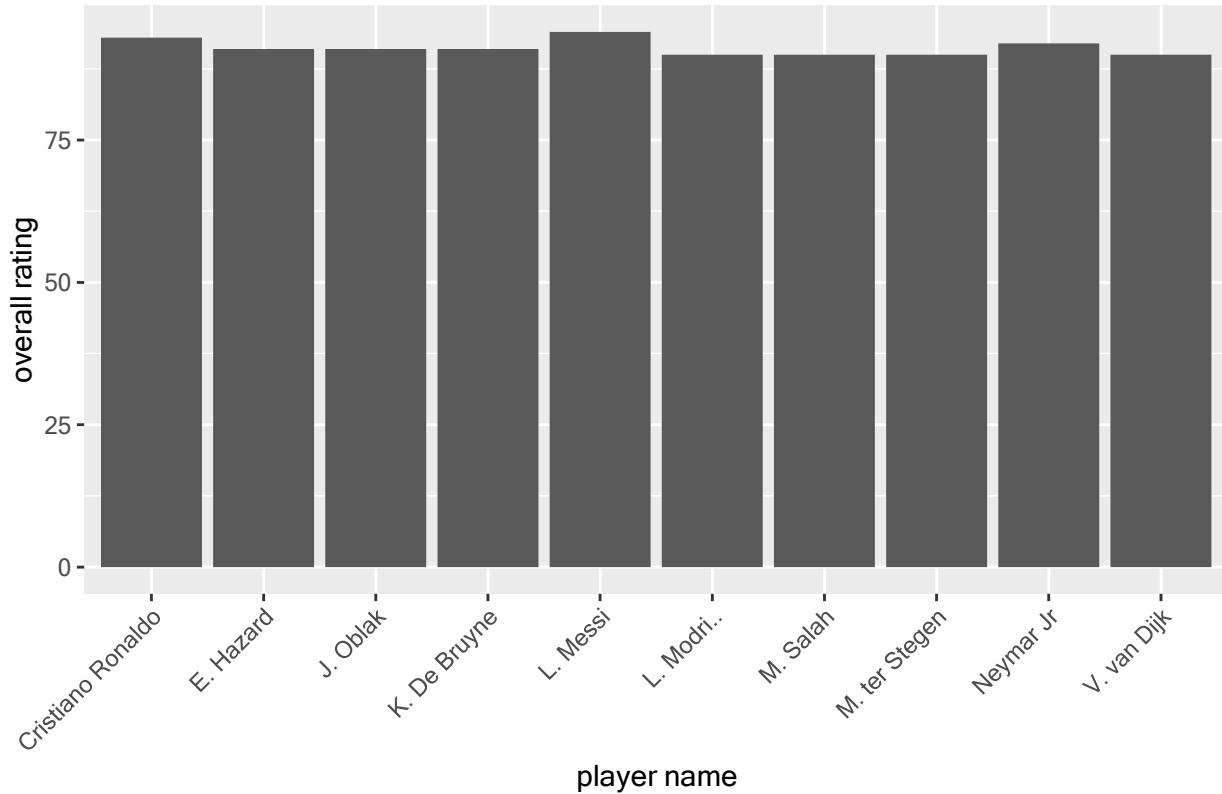


Selecting by overall

Year 58 : Top 10 Players with highest rating



Year 59 : Top 10 Players with highest rating



```
# Top 10 players with the best potential overall
for (i in seq_along(fifa_datasets_list)) {
  top10_best_potential <- fifa_datasets_list[[i]] %>% arrange(desc(potential)) %>%
    select(short_name, club, nationality, overall, potential) %>% top_n(10)
  print(top10_best_potential)
}
```

Selecting by potential

	short_name	club	nationality	overall	potential
	<chr>	<chr>	<chr>	<int>	<int>
## 1	L. Messi	FC Barcelona	Argentina	94	95
## 2	Cristiano Ronaldo	Real Madrid	Portugal	93	93
## 3	Neymar	FC Barcelona	Brazil	88	93
## 4	J. Rodríguez	Real Madrid	Colombia	87	93
## 5	P. Pogba	Juventus	France	86	92
## 6	E. Hazard	Chelsea	Belgium	89	91
## 7	G. Bale	Real Madrid	Wales	87	91
## 8	A. Robben	FC Bayern München	Netherlands	90	90
## 9	M. Neuer	FC Bayern München	Germany	90	90
## 10	L. Suárez	FC Barcelona	Uruguay	90	90
## 11	T. Kroos	Real Madrid	Germany	87	90
## 12	T. Courtois	Chelsea	Belgium	86	90
## 13	A. Halilović	Real Sporting de Gijón	Croatia	76	90
## 14	Y. Tielemans	RSC Anderlecht	Belgium	76	90

```
## Selecting by potential
```

```
##      short_name      club nationality overall potential
## 1       Neymar   FC Barcelona     Brazil      92      95
## 2 Cristiano Ronaldo  Real Madrid  Portugal      94      94
## 3       P. Pogba Manchester United France       88      94
## 4       L. Messi   FC Barcelona Argentina      93      93
## 5      T. Courtois    Chelsea Belgium       89      93
## 6       M. Neuer FC Bayern München Germany      92      92
## 7       L. Suárez   FC Barcelona Uruguay      92      92
## 8       De Gea Manchester United Spain       90      92
## 9      A. Griezmann Atlético Madrid France       88      92
## 10      J. Rodríguez  Real Madrid Colombia      87      92
## 11      P. Dybala    Juventus Argentina      85      92
```

```
## Selecting by potential
```

```
## # A tibble: 17 x 5
##   short_name      club      nationality overall potential
##   <chr>        <chr>        <chr>        <int>        <int>
## 1 Cristiano Ronaldo Real Madrid Portugal      94      94
## 2 Neymar          Paris Saint-Germain Brazil       92      94
## 3 K. Mbappé       Paris Saint-Germain France      83      94
## 4 G. Donnarumma   Milan          Italy       82      94
## 5 L. Messi        FC Barcelona Argentina      93      93
## 6 J. Oblak        Atlético Madrid Slovenia      88      93
## 7 P. Dybala       Juventus        Argentina      88      93
## 8 M. Neuer        FC Bayern München Germany      92      92
## 9 L. Suárez       FC Barcelona Uruguay      92      92
## 10 De Gea         Manchester United Spain       90      92
## 11 T. Courtois   Chelsea          Belgium      89      92
## 12 K. De Bruyne   Manchester City Belgium      89      92
## 13 P. Pogba       Manchester United France      87      92
## 14 R. Varane      Real Madrid        France      85      92
## 15 Marco Asensio Real Madrid        Spain       84      92
## 16 O. Dembélé    FC Barcelona        France      83      92
## 17 Gabriel Jesus Manchester City Brazil        81      92
```

```
## Selecting by potential
```

```
## # A tibble: 10 x 5
##   short_name      club      nationality overall potential
##   <chr>        <chr>        <chr>        <int>        <int>
## 1 K. Mbappé       Paris Saint-Germain France      87      95
## 2 Cristiano Ronaldo Juventus Portugal      94      94
## 3 L. Messi        FC Barcelona Argentina      94      94
## 4 P. Dybala       Juventus          Argentina      89      94
## 5 Neymar Jr      Paris Saint-Germain Brazil       92      93
## 6 De Gea          Manchester United Spain       91      93
## 7 J. Oblak        Atlético Madrid Slovenia      90      93
## 8 L. Sané         Manchester City Germany      86      93
## 9 Marco Asensio  Real Madrid        Spain       85      93
## 10 G. Donnarumma  Milan          Italy        82      93
```

```

## Selecting by potential

## # A tibble: 14 × 5
##   short_name     club      nationality overall potential
##   <chr>        <chr>      <chr>       <int>      <int>
## 1 K. Mbappé    Paris Saint-Germain France        89        95
## 2 L. Messi     FC Barcelona Argentina      94        94
## 3 Cristiano Ronaldo Juventus Portugal       93        93
## 4 J. Oblak     Atlético Madrid Slovenia      91        93
## 5 M. ter Stegen FC Barcelona Germany       90        93
## 6 M. de Ligt    Juventus Netherlands     85        93
## 7 João Félix   Atlético Madrid Portugal      80        93
## 8 Neymar Jr    Paris Saint-Germain Brazil       92        92
## 9 P. Dybala    Juventus Argentina      88        92
## 10 L. Sané     Manchester City Germany       86        92
## 11 G. Donnarumma Milan          Italy         85        92
## 12 J. Sancho   Borussia Dortmund England      84        92
## 13 K. Havertz   Bayer 04 Leverkusen Germany     84        92
## 14 Vinícius Jr. Real Madrid Brazil         79        92

```

```

# Players aged 25 or less with best potential:
for (i in seq_along(fifa_datasets_list)) {
  top_potential_below_25 <- fifa_datasets_list[[i]] %>% filter(age <= 25) %>%
    arrange(desc(potential)) %>% top_n(50) %>%
    select(short_name, club, nationality, overall, potential)
  print(top_potential_below_25)
}

```

```

## Selecting by rb

```

```

## # A tibble: 57 × 5
##   short_name     club      nationality overall potential
##   <chr>        <chr>      <chr>       <int>      <int>
## 1 P. Pogba      Juventus France        86        92
## 2 M. Verratti   Paris Saint-Germain Italy       84        89
## 3 L. Shaw       Manchester United England      78        89
## 4 D. Alaba      FC Bayern München Austria      85        88
## 5 William Carvalho Sporting CP Portugal      81        88
## 6 L. Kurzawa    Paris Saint-Germain France      80        88
## 7 R. Rodriguez  VfL Wolfsburg Switzerland    83        87
## 8 M. Musacchio  Villarreal CF Argentina     81        87
## 9 Marquinhos   Paris Saint-Germain Brazil       81        87
## 10 Gayà        Valencia CF Spain          80        87
## # ... with 47 more rows

```

```

## Selecting by rb

```

	short_name	club	nationality	overall
## 1	P. Pogba	Manchester United	France	88
## 2	R. Varane	Real Madrid	France	84
## 3	D. Alaba	FC Bayern München	Austria	87
## 4	M. Verratti	Paris Saint-Germain	Italy	85

## 5	E. Bailly	Manchester United	Ivory Coast	82
## 6	L. Shaw	Manchester United	England	81
## 7	A. Laporte	Athletic Club de Bilbao	France	84
## 8	S. Mustafi	Arsenal	Germany	83
## 9	S. Aurier	Paris Saint-Germain	Ivory Coast	83
## 10	Marquinhos	Paris Saint-Germain	Brazil	82
## 11	L. Kurzawa	Paris Saint-Germain	France	81
## 12	Saúl	Atlético Madrid	Spain	80
## 13	J. Stones	Manchester City	England	78
## 14	Alex Sandro	Juventus	Brazil	84
## 15	M. Musacchio	Villarreal CF	Argentina	83
## 16	Danilo Pereira	FC Porto	Portugal	82
## 17	S. Umtiti	FC Barcelona	France	82
## 18	Héctor Bellerín	Arsenal	Spain	79
## 19	Fabinho	AS Monaco	Brazil	79
## 20	João Cancelo	Valencia CF	Portugal	79
## 21	V. Koziello	OGC Nice	France	79
## 22	J. Kimmich	FC Bayern München	Germany	78
## 23	R. Rodríguez	VfL Wolfsburg	Switzerland	83
## 24	Carvajal	Real Madrid	Spain	83
## 25	T. Kolodziejczak	Sevilla FC	France	80
## 26	E. Can	Liverpool	Germany	80
## 27	J. Willems	PSV	Netherlands	79
## 28	L. Goretzka	FC Schalke 04	Germany	79
## 29	Danilo	SL Benfica	Brazil	79
## 30	A. Florenzi	Roma	Italy	82
## 31	N. Clyne	Liverpool	England	81
## 32	N. Kanté	Chelsea	France	81
## 33	Hugo Mallo	RC Celta	Spain	80
## 34	Gayà	Valencia CF	Spain	80
## 35	A. Baba	FC Schalke 04	Ghana	78
## 36	Ricardo Pereira	OGC Nice	Portugal	78
## 37	Wendell	Bayer 04 Leverkusen	Brazil	78
## 38	J. Matip	Liverpool	Cameroon	82
## 39	J. McCarthy	Everton	Republic of Ireland	81
## 40	F. Coquelin	Arsenal	France	81
## 41	Marc Bartra	Borussia Dortmund	Spain	81
## 42	Mario Gaspar	Villarreal CF	Spain	80
## 43	L. Digne	FC Barcelona	France	79
## 44	D. Sidibé	AS Monaco	France	79
## 45	N. Mendy	Leicester City	France	78
## 46	Allan	Napoli	Brazil	81
## 47	Mário Fernandes	PFC CSKA Moscow	Brazil	80
## 48	Danilo	Real Madrid	Brazil	80
## 49	S. Vrsaljko	Atlético Madrid	Croatia	79
## 50	Bernat	FC Bayern München	Spain	79
## 51	E. Hysaj	Napoli	Albania	79
## 52	A. Mandi	Real Betis	Algeria	78
## 53	D. Rose	Tottenham Hotspur	England	80
## 54	J. Guilavogui	VfL Wolfsburg	France	80
## 55	S. Rode	Borussia Dortmund	Germany	80
## 56	Montoya	Valencia CF	Spain	79
## 57	F. Ghoulam	Napoli	Algeria	79
## 58	Cédric	Southampton	Portugal	78

## 59	B. Davies	Tottenham Hotspur	Wales	78
## 60	Alberto Moreno	Liverpool	Spain	77
## 61	Alex Telles	FC Porto	Brazil	77
## 62	Mário Rui	Roma	Portugal	78
## 63	S. Arias	PSV	Colombia	77
## 64	Rafael	Olympique Lyonnais	Brazil	78
## 65	S. Corchia	LOSC Lille	France	77
## 66	Marcos Alonso	Chelsea	Spain	77
## 67	T. Meunier	Paris Saint-Germain	Belgium	77
## potential				
## 1	94			
## 2	91			
## 3	90			
## 4	90			
## 5	90			
## 6	89			
## 7	88			
## 8	88			
## 9	88			
## 10	88			
## 11	88			
## 12	88			
## 13	88			
## 14	87			
## 15	87			
## 16	87			
## 17	87			
## 18	87			
## 19	87			
## 20	87			
## 21	87			
## 22	87			
## 23	86			
## 24	86			
## 25	86			
## 26	86			
## 27	86			
## 28	86			
## 29	86			
## 30	85			
## 31	85			
## 32	85			
## 33	85			
## 34	85			
## 35	85			
## 36	85			
## 37	85			
## 38	84			
## 39	84			
## 40	84			
## 41	84			
## 42	84			
## 43	84			
## 44	84			

```

## 45      84
## 46      83
## 47      83
## 48      83
## 49      83
## 50      83
## 51      83
## 52      83
## 53      82
## 54      82
## 55      82
## 56      82
## 57      82
## 58      82
## 59      82
## 60      82
## 61      82
## 62      81
## 63      81
## 64      80
## 65      80
## 66      80
## 67      80

```

`## Selecting by rb`

```

## # A tibble: 64 x 5
##   short_name club          nationality overall potential
##   <chr>     <chr>        <chr>       <int>     <int>
## 1 R. Varane Real Madrid France        85      92
## 2 M. Verratti Paris Saint-Germain Italy        87      91
## 3 Saúl       Atlético Madrid Spain        82      90
## 4 Casemiro   Real Madrid Brazil        85      89
## 5 A. Laporte Athletic Club de Bilbao France       84      89
## 6 E. Bailly  Manchester United Ivory Coast    84      89
## 7 Marquinhos Paris Saint-Germain Brazil        83      89
## 8 C. Tolisso FC Bayern München France        82      89
## 9 D. Alaba   FC Bayern München Austria      86      88
## 10 S. Umtiti FC Barcelona France        83      88
## # ... with 54 more rows

```

`## Selecting by rb`

```

## # A tibble: 70 x 5
##   short_name club          nationality overall potential
##   <chr>     <chr>        <chr>       <int>     <int>
## 1 S. Umtiti FC Barcelona France        87      92
## 2 R. Varane Real Madrid France        86      92
## 3 M. Škriniar Inter Slovakia        85      92
## 4 Saúl       Atlético Madrid Spain        85      91
## 5 S. Milinković-Savić Lazio Serbia        85      90
## 6 M. Verratti Paris Saint-Germain Italy        86      89
## 7 Fabinho   Liverpool Brazil        85      89

```

```

## 8 Marquinhos          Paris Saint-Germain Brazil      84      89
## 9 D. Sánchez         Tottenham Hotspur Colombia  84      89
## 10 P. Kimpembe        Paris Saint-Germain France   83      89
## # ... with 60 more rows

```

```
## Selecting by rb
```

```

## # A tibble: 54 x 5
##   short_name club      nationality overall potential
##   <chr>     <chr>      <chr>       <int>    <int>
## 1 F. de Jong FC Barcelona Netherlands  85      91
## 2 A. Laporte Manchester City France    87      90
## 3 Marquinhos Paris Saint-Germain Brazil   86      90
## 4 Rodri      Manchester City Spain     85      90
## 5 S. Umtiti  FC Barcelona France    86      89
## 6 Saúl       Atlético Madrid Spain    85      89
## 7 Fabinho    Liverpool      Brazil   85      89
## 8 A. Robertson Liverpool      Scotland 85      89
## 9 C. Lenglet FC Barcelona France   85      89
## 10 João Cancelo Manchester City Portugal 84      89
## # ... with 44 more rows

```

Players aged 21 or less with best potential:

```

for (i in seq_along(fifa_datasets_list)) {
  top_potential_below_21 <- fifa_datasets_list[[i]] %>% filter(age <= 21) %>%
    arrange(desc(potential)) %>% top_n(50) %>%
    select(short_name, club, nationality, overall, potential)
  print(top_potential_below_21)
}

```

```
## Selecting by rb
```

```

## # A tibble: 71 x 5
##   short_name club      nationality overall potential
##   <chr>     <chr>      <chr>       <int>    <int>
## 1 L. Shaw   Manchester United England   78      89
## 2 D. Rugani Juventus      Italy     78      88
## 3 R. Bazoer Ajax          Netherlands 75      88
## 4 A. Laporte Athletic Club de Bilbao France  83      87
## 5 Marquinhos Paris Saint-Germain Brazil   81      87
## 6 Gayà      Valencia CF Spain    80      87
## 7 J. Stones Everton      England   77      87
## 8 K. Zouma   Chelsea      France   77      87
## 9 J. Geis    FC Schalke 04 Germany   79      86
## 10 J. Willems PSV          Netherlands 78      86
## # ... with 61 more rows

```

```
## Selecting by rb
```

	short_name	club	nationality	overall
## 1	Renato Sanches	FC Bayern München	Portugal	78
## 2	L. Shaw	Manchester United	England	81

## 3	K. Zouma	Chelsea	France	80
## 4	J. Giménez	Atlético Madrid	Uruguay	83
## 5	Saúl	Atlético Madrid	Spain	80
## 6	M. Lemos	UD Las Palmas	Uruguay	80
## 7	J. Tah	Bayer 04 Leverkusen	Germany	79
## 8	N. Süle	TSG 1899 Hoffenheim	Germany	81
## 9	Héctor Bellerín	Arsenal	Spain	79
## 10	D. Rugani	Juventus	Italy	79
## 11	V. Koziello	OGC Nice	France	79
## 12	J. Kimmich	FC Bayern München	Germany	78
## 13	A. Christensen	Borussia Mönchengladbach	Denmark	78
## 14	T. Fosu-Mensah	Manchester United	Netherlands	71
## 15	L. Goretzka	FC Schalke 04	Germany	79
## 16	J. Weigl	Borussia Dortmund	Germany	79
## 17	Danilo	SL Benfica	Brazil	79
## 18	A. Romagnoli	Milan	Italy	78
## 19	C. Tolisso	Olympique Lyonnais	France	78
## 20	V. Nilsson Lindelöf	SL Benfica	Sweden	78
## 21	Grimaldo	SL Benfica	Spain	77
## 22	J. Riedewald	Ajax	Netherlands	76
## 23	Gayà	Valencia CF	Spain	80
## 24	A. Baba	FC Schalke 04	Ghana	78
## 25	A. Rabiot	Paris Saint-Germain	France	78
## 26	R. Bazoer	Ajax	Netherlands	77
## 27	T. Jedvaj	Bayer 04 Leverkusen	Croatia	75
## 28	G. Donsah	Bologna	Ghana	75
## 29	Rúben Neves	FC Porto	Portugal	75
## 30	M. Grujić	Liverpool	Serbia	71
## 31	M. Sansón	Montpellier HSC	France	78
## 32	C. Mbemba	Newcastle United	DR Congo	77
## 33	E. Gutiérrez	Pachuca	Mexico	76
## 34	D. Amartey	Leicester City	Ghana	75
## 35	K. Linetty	Sampdoria	Poland	74
## 36	N. Stark	Hertha BSC	Germany	74
## 37	J. Denayer	Sunderland	Belgium	74
## 38	A. Diawara	Napoli	Guinea	74
## 39	A. Cubas	Boca Juniors	Argentina	73
## 40	F. Mattiello	Juventus	Italy	72
## 41	E. Nabiullin	Rubin Kazan	Russia	72
## 42	L. Klostermann	RB Leipzig	Germany	72
## 43	A. Nagy	Bologna	Hungary	72
## 44	Rafa Soares	Rio Ave FC	Portugal	71
## 45	P. Galdames	Unión Española	Chile	71
## 46	S. Ascacíbar	Estudiantes de La Plata	Argentina	71
## 47	K. Tete	Ajax	Netherlands	77
## 48	L. Dendoncker	RSC Anderlecht	Belgium	76
## 49	J. Hendrix	PSV	Netherlands	76
## 50	S. Milinković-Savić	Lazio	Serbia	76
## 51	D. Cataldi	Lazio	Italy	75
## 52	J. Lerma	Levante UD	Colombia	75
## 53	O. Tufan	Fenerbahçe SK	Turkey	75
## 54	F. Ricca	Málaga CF	Uruguay	75
## 55	J. Gbamin	1. FSV Mainz 05	France	73
## 56	Marín	CD Leganés	Spain	73

## 57	O. Ndidi	KRC Genk	Nigeria	72
## 58	T. Vilhena	Feyenoord	Netherlands	76
## 59	R. Karsdorp	Feyenoord	Netherlands	76
## 60	C. Chambers	Middlesbrough	England	72
## 61	P. Højbjerg	Southampton	Denmark	74
## 62	T. Bakayoko	AS Monaco	France	74
## 63	N. Aké	Bournemouth	Netherlands	72
## 64	Varela	Real Oviedo	Spain	71
## 65	K. Diks	Fiorentina	Netherlands	71
## 66	T. Foket	KAA Gent	Belgium	73
## 67	Vigaray	Deportivo Alavés	Spain	71
## 68	B. Mendy	AS Monaco	France	75
## 69	J. Lukaku	Lazio	Belgium	73
## 70	J. Toljan	TSG 1899 Hoffenheim	Germany	73
## 71	S. Moreira	FC Lorient	France	72
## 72	C. Fiore	Standard de Liège	Belgium	72
## 73	Rubén Duarte	RCD Espanyol	Spain	72
## 74	R. Gosens	Heracles Almelo	Germany	71
## potential				
## 1	90			
## 2	89			
## 3	89			
## 4	88			
## 5	88			
## 6	88			
## 7	88			
## 8	87			
## 9	87			
## 10	87			
## 11	87			
## 12	87			
## 13	87			
## 14	87			
## 15	86			
## 16	86			
## 17	86			
## 18	86			
## 19	86			
## 20	86			
## 21	86			
## 22	86			
## 23	85			
## 24	85			
## 25	85			
## 26	85			
## 27	85			
## 28	85			
## 29	85			
## 30	85			
## 31	84			
## 32	84			
## 33	84			
## 34	84			
## 35	84			

```

## 36      84
## 37      84
## 38      84
## 39      84
## 40      84
## 41      84
## 42      84
## 43      84
## 44      84
## 45      84
## 46      84
## 47      83
## 48      83
## 49      83
## 50      83
## 51      83
## 52      83
## 53      83
## 54      83
## 55      83
## 56      83
## 57      83
## 58      82
## 59      82
## 60      82
## 61      81
## 62      81
## 63      81
## 64      81
## 65      81
## 66      80
## 67      80
## 68      79
## 69      79
## 70      79
## 71      79
## 72      79
## 73      79
## 74      75

```

`## Selecting by rb`

```

## # A tibble: 54 x 5
##   short_name    club      nationality overall potential
##   <chr>        <chr>      <chr>       <int>     <int>
## 1 T. Lemar    AS Monaco  France        83        91
## 2 D. Alli     Tottenham Hotspur England       84        90
## 3 N. Süle    FC Bayern München Germany      83        89
## 4 A. Christensen Chelsea  Denmark       81        89
## 5 J. Tah      Bayer 04 Leverkusen Germany      82        88
## 6 D. Sánchez  Tottenham Hotspur Colombia     81        88
## 7 Dani Ceballos Real Madrid Spain         78        88
## 8 M. Sarr     OGC Nice   France        75        88
## 9 J. Weigl    Borussia Dortmund Germany      81        87

```

```

## 10 Grimaldo      SL Benfica      Spain      80      87
## # ... with 44 more rows

## Selecting by rb

## # A tibble: 56 x 5
##   short_name     club    nationality overall potential
##   <chr>       <chr>       <chr>        <int>      <int>
## 1 M. de Ligt    Ajax    Netherlands     80        91
## 2 Arthur       FC Barcelona Brazil      82        90
## 3 T. Alexander-Arnold Liverpool England     78        88
## 4 N. Barella    Cagliari Italy      76        88
## 5 Rúben Neves  Wolverhampton Wanderers Portugal  79        87
## 6 Dani Ceballos Real Madrid Spain      78        87
## 7 F. Kessié      Milan    Ivory Coast 78        87
## 8 T. Ndombele   Olympique Lyonnais France     78        87
## 9 J. Gomez       Liverpool England     77        87
## 10 D. Calabria   Milan    Italy      77        87
## # ... with 46 more rows

```

```

## Selecting by rb

## # A tibble: 56 x 5
##   short_name     club    nationality overall potential
##   <chr>       <chr>       <chr>        <int>      <int>
## 1 M. de Ligt    Juventus Netherlands     85        93
## 2 T. Alexander-Arnold Liverpool England     83        89
## 3 H. Aouar       Olympique Lyonnais France     81        89
## 4 S. Tonali      Brescia   Italy      75        89
## 5 Éder Militão   Real Madrid Brazil      81        88
## 6 A. Wan-Bissaka Manchester United England     79        88
## 7 I. Konaté      RB Leipzig France      79        88
## 8 S. Berge       KRC Genk    Norway     79        87
## 9 D. Rice        West Ham United England     78        87
## 10 E. Palacios    River Plate Argentina 77        87
## # ... with 46 more rows

```

```

#Player with highest scope for increase in overall
for (i in seq_along(fifa_datasets_list)) {
  pot_inc <- fifa_datasets_list[[i]] %>%
    mutate(pot_increase = potential-overall) %>%
    arrange(desc(pot_increase)) %>%
    select(short_name, club, nationality, age, overall, potential, pot_increase)

#we see that young players have scope for highest increase in rating.
#so are pot_increase and age positively correlated?

pot_inc_age_pot_inc <- pot_inc %>% select(age, pot_increase)
cor_pot_inc_age_pot_inc <- cor(pot_inc_age_pot_inc)
print(paste("Year", years[[i]], ":"))
print(round(cor_pot_inc_age_pot_inc, 2))
}

```

```

## [1] "Year 2016 :"
##           age  pot_increase
## age      1.00     -0.87
## pot_increase -0.87      1.00
## [1] "Year 2017 :"
##           age  pot_increase
## age      1.00     -0.86
## pot_increase -0.86      1.00
## [1] "Year 2018 :"
##           age  pot_increase
## age      1.00     -0.86
## pot_increase -0.86      1.00
## [1] "Year 2019 :"
##           age  pot_increase
## age      1.00     -0.87
## pot_increase -0.87      1.00
## [1] "Year 2020 :"
##           age  pot_increase
## age      1.00     -0.87
## pot_increase -0.87      1.00

```

6 PHYSICAL ATTRIBUTES: pace, shooting, passing, dribbling, defending and physique

```

pace_dfs <- vector(mode = "list", length = 5)
shooting_dfs <- vector(mode = "list", length = 5)
passing_dfs <- vector(mode = "list", length = 5)
dribble_dfs <- vector(mode = "list", length = 5)
defend_dfs <- vector(mode = "list", length = 5)
physic_dfs <- vector(mode = "list", length = 5)

for (i in seq_along(fifa_datasets_list)) {

  # pace
  pace_ <- fifa_datasets_list[[i]] %>% arrange(desc(pace)) %>%
    select(short_name, club, nationality, overall, team_position, pace) %>% top_n(1)
  pace_ <- add_column(pace_, years[[i]], .before = "short_name")
  pace_dfs[[i]] <- data.frame(pace_)

  # shooting
  shooting_ <- fifa_datasets_list[[i]] %>% arrange(desc(shooting)) %>%
    select(short_name, club, nationality, overall, team_position, shooting) %>% top_n(1)
  shooting_ <- add_column(shooting_, years[[i]], .before = "short_name")
  shooting_dfs[[i]] <- data.frame(shooting_)

  # passing
  passing_ <- fifa_datasets_list[[i]] %>% arrange(desc(passing)) %>%
    select(short_name, club, nationality, overall, team_position, passing) %>% top_n(1)
  passing_ <- add_column(passing_, years[[i]], .before = "short_name")
  passing_dfs[[i]] <- data.frame(passing_)

  # dribble
  dribble_ <- fifa_datasets_list[[i]] %>% arrange(desc(dribbling)) %>%
    select(short_name, club, nationality, overall, team_position, dribbling) %>% top_n(1)
  dribble_ <- add_column(dribble_, years[[i]], .before = "short_name")
}

```

```

dribble_dfs[[i]] <- data.frame(dribble_)

# defending
defend_ <- fifa_datasets_list[[i]] %>% arrange(desc(defending)) %>%
  select(short_name, club, nationality, overall, team_position, defending) %>% top_n(1)
defend_ <- add_column(defend_, years[[i]], .before = "short_name")
defend_dfs[[i]] <- data.frame(defend_)

# physic
physic_ <- fifa_datasets_list[[i]] %>% arrange(desc(physic)) %>%
  select(short_name, club, nationality, overall, team_position, physic) %>% top_n(1)
physic_ <- add_column(physic_, years[[i]], .before = "short_name")
physic_dfs[[i]] <- data.frame(physic_)
}

## Selecting by pace
## Selecting by shooting##
Selecting by passing ##

Selecting by dribbling##
Selecting by defending##

Selecting by physic

## Selecting by pace
## Selecting by shooting##
Selecting by passing ##
Selecting by dribbling##
Selecting by defending##

Selecting by physic

## Selecting by pace
## Selecting by shooting##
Selecting by passing ##
Selecting by dribbling##
Selecting by defending

```

```

## Selecting by physic

## Selecting by pace

## Selecting by shooting##

Selecting by passing ##

Selecting by dribbling##

Selecting by defending##

Selecting by physic

## Selecting by pace

## Selecting by shooting##

Selecting by passing ##

Selecting by dribbling##

Selecting by defending##

Selecting by physic

pace_df <- do.call("rbind", pace_dfs)
shooting_df <- do.call("rbind", shooting_dfs)
passing_df <- do.call("rbind", passing_dfs)
dribble_df <- do.call("rbind", dribble_dfs)
defend_df <- do.call("rbind", defend_dfs)
physic_df <- do.call("rbind", physic_dfs)

print(pace_df)

##   years...i.    short_name          club nationality overall
## 1      2016     T. Walcott      Arsenal    England     81
## 2      2016     M. Bolly     Fortuna Düsseldorf Ivory Coast     67
## 3      2017 P. Aubameyang  Borussia Dortmund     Gabon     86
## 4      2017     M. Bolly     SpVgg Greuther Fürth Ivory Coast     67
## 5      2018 P. Aubameyang  Borussia Dortmund     Gabon     88
## 6      2018 J. Biabiany      Sparta Praha     France     75
## 7      2019     K. Mbappé    Paris Saint-Germain     France     87
## 8      2019     Adama Traoré Wolverhampton Wanderers     Spain     75
## 9      2020     K. Mbappé    Paris Saint-Germain     France     89
## 10     2020 Adama Traoré Wolverhampton Wanderers     Spain     74
##   team_position pace
## 1             ST  96
## 2            SUB  96
## 3             ST  96

```

```

## 4      SUB  96
## 5      ST   96
## 6      RM   96
## 7      RW   96
## 8      SUB  96
## 9      RW   96
## 10     SUB  96

```

```
print(shooting_df)
```

	years...i..	short_name	club	nationality	overall
## 1	2016	Cristiano Ronaldo	Real Madrid	Portugal	93
## 2	2017	Cristiano Ronaldo	Real Madrid	Portugal	94
## 3	2018	Cristiano Ronaldo	Real Madrid	Portugal	94
## 4	2019	Cristiano Ronaldo	Juventus	Portugal	94
## 5	2020	Cristiano Ronaldo	Juventus	Portugal	93
## team_position shooting					
## 1		LM	93		
## 2		LW	92		
## 3		LW	93		
## 4		LW	93		
## 5		LW	93		

```
print(passing_df)
```

	years...i..	short_name	club	nationality	overall
## 1	2016	A. Pirlo	New York City FC	Italy	84
## 2	2017	A. Pirlo	New York City FC	Italy	82
## 3	2018	T. Kroos	Real Madrid	Germany	90
## 4	2018	A. Pirlo	New York City FC	Italy	79
## 5	2019	K. De Bruyne	Manchester City	Belgium	91
## 6	2020	L. Messi	FC Barcelona	Argentina	94
## 7	2020	K. De Bruyne	Manchester City	Belgium	91
## team_position passing					
## 1		CDM	93		
## 2		LCM	91		
## 3		LCM	89		
## 4		SUB	89		
## 5		RCM	92		
## 6		RW	92		
## 7		RCM	92		

```
print(dribble_df)
```

	years...i..	short_name	club	nationality	overall	team_position
## 1	2016	L. Messi	FC Barcelona	Argentina	94	RW
## 2	2017	L. Messi	FC Barcelona	Argentina	93	RW
## 3	2018	L. Messi	FC Barcelona	Argentina	93	RW
## 4	2019	L. Messi	FC Barcelona	Argentina	94	RW
## 5	2020	L. Messi	FC Barcelona	Argentina	94	RW
## dribbling						
## 1	95					

```

## 2      96
## 3      96
## 4      96
## 5      96

```

```
print(defend_df)
```

	years...i...	short_name	club	nationality	overall
## 1	2016	Thiago Silva	Paris Saint-Germain	Brazil	88
## 2	2016	G. Chiellini	Juventus	Italy	87
## 3	2017	J. Boateng	FC Bayern München	Germany	90
## 4	2017	Thiago Silva	Paris Saint-Germain	Brazil	89
## 5	2017	G. Chiellini	Juventus	Italy	88
## 6	2018	G. Chiellini	Juventus	Italy	89
## 7	2019	Sergio Ramos	Real Madrid	Spain	91
## 8	2019	G. Chiellini	Juventus	Italy	89
## 9	2020	V. van Dijk	Liverpool	Netherlands	90
## 10	2020	G. Chiellini	Juventus	Italy	89
team_position defending					
## 1		RCB	90		
## 2		LCB	90		
## 3		RCB	90		
## 4		LCB	90		
## 5		LCB	90		
## 6		LCB	90		
## 7		LCB	91		
## 8		LCB	91		
## 9		LCB	90		
## 10		LCB	90		

```
print(physic_df)
```

	years...i...	short_name	club	nationality	overall
## 1	2016	G. Medel	Inter	Chile	81
## 2	2016	M. Fellaini	Manchester United	Belgium	78
## 3	2016	V. Wanyama	Southampton	Kenya	77
## 4	2016	J. Van Damme	Standard de Liège	Belgium	72
## 5	2016	C. Paterson	Heart of Midlothian	Scotland	65
## 6	2017	M. Fellaini	Manchester United	Belgium	78
## 7	2017	C. N'Doye	Angers SCO	Senegal	77
## 8	2017	C. Paterson	Heart of Midlothian	Scotland	68
## 9	2018	J. Van Damme	Royal Antwerp FC	Belgium	77
## 10	2019	S. Nzonzi	Roma	France	82
## 11	2019	D. Hediger	FC Thun	Switzerland	68
## 12	2020	M. Marega	FC Porto	Mali	80
team_position physic					
## 1		CDM	89		
## 2		SUB	89		
## 3		RDM	89		
## 4		LB	89		
## 5		RB	89		
## 6		RDM	90		
## 7		RCM	90		

```

## 8          RB    90
## 9          SUB   92
## 10         SUB   89
## 11         RDM   89
## 12         RS    90

# Goalkeeping stats
top_gks_dfs <- vector(mode = "list", length = 5)
gk_diving_dfs <- vector(mode = "list", length = 5)
gk_handling_dfs <- vector(mode = "list", length = 5)
gk_kicking_dfs <- vector(mode = "list", length = 5)
gk_reflex_dfs <- vector(mode = "list", length = 5)
gk_speed_dfs <- vector(mode = "list", length = 5)
gk_position_dfs <- vector(mode = "list", length = 5)

for (i in seq_along(fifa_datasets_list)) {

  # Top 5 best goalkeepers by year
  top_5_gk <- fifa_datasets_list[[i]] %>% filter(team_position=="GK") %>% arrange(desc(overall)) %>%
    select(short_name, club, nationality, overall) %>% top_n(5)
  top_5_gk <- add_column(top_5_gk, years[[i]], .before = "short_name")
  top_gks_dfs[[i]] <- data.frame(top_5_gk)

  # Top 5 best divers by year
  top_5_divers <- fifa_datasets_list[[i]] %>% filter(team_position=="GK") %>% arrange(desc(gk_diving)) %>%
    select(short_name, club, nationality, gk_diving) %>% top_n(5)
  top_5_divers <- add_column(top_5_divers, years[[i]], .before = "short_name")
  gk_diving_dfs[[i]] <- data.frame(top_5_divers)

  # Top 5 best handlers by year
  top_5_handlers <- fifa_datasets_list[[i]] %>% filter(team_position=="GK") %>%
    arrange(desc(gk_handling)) %>% select(short_name, club, nationality, gk_handling) %>% top_n(5)
  top_5_handlers <- add_column(top_5_handlers, years[[i]], .before = "short_name")
  gk_handling_dfs[[i]] <- data.frame(top_5_handlers)

  # Top 5 best kickers by year
  top_5_kickers <- fifa_datasets_list[[i]] %>% filter(team_position=="GK") %>%
    arrange(desc(gk_kicking)) %>% select(short_name, club, nationality, gk_kicking) %>% top_n(5)
  top_5_kickers <- add_column(top_5_kickers, years[[i]], .before = "short_name")
  gk_kicking_dfs[[i]] <- data.frame(top_5_kickers)

  # Top 5 best reflexes by year
  top_5_reflex <- fifa_datasets_list[[i]] %>% filter(team_position=="GK") %>%
    arrange(desc(gk_reflexes)) %>% select(short_name, club, nationality, gk_reflexes) %>% top_n(5)
  top_5_reflex <- add_column(top_5_reflex, years[[i]], .before = "short_name")
  gk_reflex_dfs[[i]] <- data.frame(top_5_reflex)

  # Top 5 best speed by year
  top_5_speed <- fifa_datasets_list[[i]] %>% filter(team_position=="GK") %>%
    arrange(desc(gk_speed)) %>% select(short_name, club, nationality, gk_speed) %>% top_n(5)
  top_5_speed <- add_column(top_5_speed, years[[i]], .before = "short_name")
  gk_speed_dfs[[i]] <- data.frame(top_5_speed)

  # Top 5 best position by year
}

```

```

top_5_position <- fifa_datasets_list[[i]] %>% filter(team_position=="GK") %>%
  arrange(desc(gk_positioning)) %>% select(short_name, club, nationality, gk_positioning) %>% top_n(5)
top_5_position <- add_column(top_5_position, years[[i]], .before = "short_name")
gk_position_dfs[[i]] <- data.frame(top_5_position)
}

## Selecting by overall

## Selecting by gk_diving

## Selecting by gk_handling

## Selecting by gk_kicking

## Selecting by gk_reflexes

## Selecting by gk_speed

## Selecting by gk_positioning

## Selecting by overall

## Selecting by gk_diving

## Selecting by gk_handling

## Selecting by gk_kicking

## Selecting by gk_reflexes

## Selecting by gk_speed

## Selecting by gk_positioning

## Selecting by overall

## Selecting by gk_diving

## Selecting by gk_handling

## Selecting by gk_kicking

## Selecting by gk_reflexes

## Selecting by gk_speed

## Selecting by gk_positioning

```

```

## Selecting by overall

## Selecting by gk_diving

## Selecting by gk_handling

## Selecting by gk_kicking

## Selecting by gk_reflexes

## Selecting by gk_speed

## Selecting by gk_positioning

## Selecting by overall

## Selecting by gk_diving

## Selecting by gk_handling

## Selecting by gk_kicking

## Selecting by gk_reflexes

## Selecting by gk_speed

## Selecting by gk_positioning

top_5_gks_yearly_df <- do.call("rbind", top_gks_dfs)
gk_diving_yearly_df <- do.call("rbind", gk_diving_dfs)
gk_handling_yearly_df <- do.call("rbind", gk_handling_dfs)
gk_kicking_yearly_df <- do.call("rbind", gk_kicking_dfs)
gk_reflexes_yearly_df <- do.call("rbind", gk_reflex_dfs)
gk_speed_yearly_df <- do.call("rbind", gk_speed_dfs)
gk_position_yearly_df <- do.call("rbind", gk_position_dfs)

print(top_5_gks_yearly_df )

```

	years..i..	short_name	club	nationality	overall
## 1	2016	M. Neuer	FC Bayern München	Germany	90
## 2	2016	De Gea	Manchester United	Spain	86
## 3	2016	P. Čech	Arsenal	Czech Republic	85
## 4	2016	H. Lloris	Tottenham Hotspur	France	85
## 5	2016	B. Leno	Bayer 04 Leverkusen	Germany	84
## 6	2016	G. Buffon	Juventus	Italy	84
## 7	2016	Casillas	FC Porto	Spain	84
## 8	2016	J. Hart	Manchester City	England	84
## 9	2017	M. Neuer	FC Bayern München	Germany	92
## 10	2017	De Gea	Manchester United	Spain	90
## 11	2017	T. Courtois	Chelsea	Belgium	89

## 12	2017	G. Buffon	Juventus	Italy	88
## 13	2017	P. Čech	Arsenal	Czech Republic	88
## 14	2017	H. Lloris	Tottenham Hotspur	France	88
## 15	2018	M. Neuer	FC Bayern München	Germany	92
## 16	2018	De Gea	Manchester United	Spain	90
## 17	2018	T. Courtois	Chelsea	Belgium	89
## 18	2018	G. Buffon	Juventus	Italy	89
## 19	2018	J. Oblak	Atlético Madrid	Slovenia	88
## 20	2018	H. Lloris	Tottenham Hotspur	France	88
## 21	2019	De Gea	Manchester United	Spain	91
## 22	2019	J. Oblak	Atlético Madrid	Slovenia	90
## 23	2019	T. Courtois	Real Madrid	Belgium	90
## 24	2019	M. Neuer	FC Bayern München	Germany	90
## 25	2019	M. ter Stegen	FC Barcelona	Germany	89
## 26	2020	J. Oblak	Atlético Madrid	Slovenia	91
## 27	2020	M. ter Stegen	FC Barcelona	Germany	90
## 28	2020	Alisson	Liverpool	Brazil	89
## 29	2020	De Gea	Manchester United	Spain	89
## 30	2020	Ederson	Manchester City	Brazil	88
## 31	2020	T. Courtois	Real Madrid	Belgium	88
## 32	2020	S. Handanovič	Inter	Slovenia	88
## 33	2020	M. Neuer	FC Bayern München	Germany	88
## 34	2020	H. Lloris	Tottenham Hotspur	France	88

```
print(gk_diving_yearly_df)
```

##	years...i..	short_name	club	nationality	gk_diving
## 1	2016	De Gea	Manchester United	Spain	88
## 2	2016	H. Lloris	Tottenham Hotspur	France	87
## 3	2016	Casillas	FC Porto	Spain	87
## 4	2016	S. Handanovič	Inter	Slovenia	87
## 5	2016	M. Neuer	FC Bayern München	Germany	85
## 6	2016	G. Buffon	Juventus	Italy	85
## 7	2016	J. Hart	Manchester City	England	85
## 8	2016	S. Mandanda	Olympique de Marseille	France	85
## 9	2016	A. Lopes	Olympique Lyonnais	Portugal	85
## 10	2017	M. Neuer	FC Bayern München	Germany	89
## 11	2017	De Gea	Manchester United	Spain	88
## 12	2017	Diego Alves	Valencia CF	Brazil	88
## 13	2017	G. Buffon	Juventus	Italy	87
## 14	2017	H. Lloris	Tottenham Hotspur	France	87
## 15	2017	K. Navas	Real Madrid	Costa Rica	87
## 16	2018	M. Neuer	FC Bayern München	Germany	91
## 17	2018	De Gea	Manchester United	Spain	90
## 18	2018	G. Buffon	Juventus	Italy	89
## 19	2018	H. Lloris	Tottenham Hotspur	France	88
## 20	2018	G. Donnarumma	Milan	Italy	88
## 21	2019	M. Neuer	FC Bayern München	Germany	91
## 22	2019	De Gea	Manchester United	Spain	90
## 23	2019	H. Lloris	Tottenham Hotspur	France	88
## 24	2019	G. Donnarumma	Milan	Italy	88
## 25	2019	T. Courtois	Real Madrid	Belgium	87
## 26	2019	M. ter Stegen	FC Barcelona	Germany	87
## 27	2019	S. Handanovič	Inter	Slovenia	87

## 28	2019	Casillas	FC Porto	Spain	87
## 29	2020	De Gea	Manchester United	Spain	90
## 30	2020	G. Donnarumma	Milan	Italy	90
## 31	2020	H. Lloris	Tottenham Hotspur	France	89
## 32	2020	M. ter Stegen	FC Barcelona	Germany	88
## 33	2020	S. Handanović	Inter	Slovenia	88

```
print(gk_handling_yearly_df)
```

##	years...i..	short_name	club	nationality
## 1	2016	M. Neuer	FC Bayern München	Germany
## 2	2016	P. Čech	Arsenal	Czech Republic
## 3	2016	B. Leno	Bayer 04 Leverkusen	Germany
## 4	2016	J. Cillessen	Ajax	Netherlands
## 5	2016	J. Oblak	Atlético Madrid	Slovenia
## 6	2017	T. Courtois	Chelsea	Belgium
## 7	2017	M. Neuer	FC Bayern München	Germany
## 8	2017	P. Čech	Arsenal	Czech Republic
## 9	2017	J. Oblak	Atlético Madrid	Slovenia
## 10	2017	S. Handanovič	Inter	Slovenia
## 11	2018	T. Courtois	Chelsea	Belgium
## 12	2018	M. Neuer	FC Bayern München	Germany
## 13	2018	J. Oblak	Atlético Madrid	Slovenia
## 14	2018	G. Buffon	Juventus	Italy
## 15	2018	P. Čech	Arsenal	Czech Republic
## 16	2019	J. Oblak	Atlético Madrid	Slovenia
## 17	2019	T. Courtois	Real Madrid	Belgium
## 18	2019	M. Neuer	FC Bayern München	Germany
## 19	2019	S. Handanovič	Inter	Slovenia
## 20	2019	De Gea	Manchester United	Spain
## 21	2019	M. ter Stegen	FC Barcelona	Germany
## 22	2020	J. Oblak	Atlético Madrid	Slovenia
## 23	2020	T. Courtois	Real Madrid	Belgium
## 24	2020	M. Neuer	FC Bayern München	Germany
## 25	2020	P. Gulácsi	RB Leipzig	Hungary
## 26	2020	M. ter Stegen	FC Barcelona	Germany
## 27	2020	S. Handanovič	Inter	Slovenia
## 28	2020	Y. Sommer	Borussia Mönchengladbach	Switzerland
##	gk_handling			
## 1		87		
## 2		84		
## 3		84		
## 4		84		
## 5		84		
## 6		91		
## 7		90		
## 8		90		
## 9		90		
## 10		89		
## 11		91		
## 12		90		
## 13		90		
## 14		88		
## 15		87		

```

## 16      92
## 17      91
## 18      88
## 19      86
## 20      85
## 21      85
## 22      92
## 23      89
## 24      87
## 25      86
## 26      85
## 27      85
## 28      85

```

```
print(gk_kicking_yearly_df)
```

##	years...i..	short_name	club	nationality
## 1	2016	M. Neuer	FC Bayern München	Germany
## 2	2016	C. Bravo	FC Barcelona	Chile
## 3	2016	De Gea	Manchester United	Spain
## 4	2016	I. Khune	Kaizer Chiefs	South Africa
## 5	2016	Y. Sommer	Borussia Mönchengladbach	Switzerland
## 6	2016	K. Schmeichel	Leicester City	Denmark
## 7	2017	M. Neuer	FC Bayern München	Germany
## 8	2017	I. Khune	Kaizer Chiefs	South Africa
## 9	2017	De Gea	Manchester United	Spain
## 10	2017	C. Bravo	Manchester City	Chile
## 11	2017	Y. Sommer	Borussia Mönchengladbach	Switzerland
## 12	2017	K. Schmeichel	Leicester City	Denmark
## 13	2018	M. Neuer	FC Bayern München	Germany
## 14	2018	M. Ryan	Brighton & Hove Albion	Australia
## 15	2018	De Gea	Manchester United	Spain
## 16	2018	M. ter Stegen	FC Barcelona	Germany
## 17	2018	J. Pickford	Everton	England
## 18	2019	M. Neuer	FC Bayern München	Germany
## 19	2019	Ederson	Manchester City	Brazil
## 20	2019	I. Khune	Kaizer Chiefs	South Africa
## 21	2019	M. ter Stegen	FC Barcelona	Germany
## 22	2019	J. Pickford	Everton	England
## 23	2020	Ederson	Manchester City	Brazil
## 24	2020	M. Neuer	FC Bayern München	Germany
## 25	2020	M. ter Stegen	FC Barcelona	Germany
## 26	2020	J. Pickford	Everton	England
## 27	2020	Kepa	Chelsea	Spain
## 28	2020	A. Onana	Ajax	Cameroon
##	gk_kicking			
## 1		91		
## 2		87		
## 3		86		
## 4		86		
## 5		85		
## 6		85		
## 7		95		
## 8		90		

```

## 9      87
## 10     87
## 11     85
## 12     85
## 13     95
## 14     90
## 15     87
## 16     87
## 17     85
## 18     91
## 19     90
## 20     90
## 21     88
## 22     88
## 23     93
## 24     91
## 25     88
## 26     87
## 27     86
## 28     86

```

```
print(gk_reflexes_yearly_df)
```

##	years...i..	short_name	club	nationality	gk_reflexes
## 1	2016	M. Perin	Genoa	Italy	90
## 2	2016	V. Enyeama	LOSC Lille	Nigeria	90
## 3	2016	De Gea	Manchester United	Spain	89
## 4	2016	H. Lloris	Tottenham Hotspur	France	88
## 5	2016	Casillas	FC Porto	Spain	88
## 6	2017	De Gea	Manchester United	Spain	90
## 7	2017	H. Lloris	Tottenham Hotspur	France	90
## 8	2017	V. Enyeama	LOSC Lille	Nigeria	90
## 9	2017	M. Neuer	FC Bayern München	Germany	89
## 10	2017	T. Courtois	Chelsea	Belgium	89
## 11	2018	De Gea	Manchester United	Spain	90
## 12	2018	H. Lloris	Tottenham Hotspur	France	90
## 13	2018	M. Perin	Genoa	Italy	90
## 14	2018	M. Neuer	FC Bayern München	Germany	89
## 15	2018	T. Courtois	Chelsea	Belgium	88
## 16	2018	G. Donnarumma	Milan	Italy	88
## 17	2019	De Gea	Manchester United	Spain	94
## 18	2019	H. Lloris	Tottenham Hotspur	France	92
## 19	2019	M. ter Stegen	FC Barcelona	Germany	90
## 20	2019	J. Oblak	Atlético Madrid	Slovenia	89
## 21	2019	S. Handanović	Inter	Slovenia	89
## 22	2020	De Gea	Manchester United	Spain	92
## 23	2020	H. Lloris	Tottenham Hotspur	France	91
## 24	2020	M. ter Stegen	FC Barcelona	Germany	90
## 25	2020	G. Donnarumma	Milan	Italy	90
## 26	2020	J. Oblak	Atlético Madrid	Slovenia	89
## 27	2020	Alisson	Liverpool	Brazil	89
## 28	2020	S. Handanović	Inter	Slovenia	89
## 29	2020	A. Lopes	Olympique Lyonnais	Portugal	89
## 30	2020	R. Bürki	Borussia Dortmund	Switzerland	89

```
print(gk_speed_yearly_df)
```

##	years...i..	short_name	club	nationality	gk_speed
## 1	2016	H. Lloris	Tottenham Hotspur	France	64
## 2	2016	Casillas	FC Porto	Spain	64
## 3	2016	F. Muslera	Galatasaray SK	Uruguay	62
## 4	2016	A. Lopes	Olympique Lyonnais	Portugal	62
## 5	2016	J. Orozco	Monterrey	Mexico	61
## 6	2016	J. Villalpando	Jaguares de Chiapas	Mexico	61
## 7	2017	Jairo Farnias	Joinville	Brazil	68
## 8	2017	G. Ochoa	Granada CF	Mexico	67
## 9	2017	O. Kivrak	Trabzonspor	Turkey	65
## 10	2017	H. Lloris	Tottenham Hotspur	France	64
## 11	2017	Casillas	FC Porto	Spain	64
## 12	2017	A. Belenov	FC Anzhi Makhachkala	Russia	64
## 13	2018	H. Lloris	Tottenham Hotspur	France	64
## 14	2018	Palatsí	Cultural Leonesa	Spain	64
## 15	2018	Ederson	Manchester City	Brazil	63
## 16	2018	A. Onana	Ajax	Cameroon	63
## 17	2018	Alberto	Rayo Vallecano	Spain	63
## 18	2019	A. Lopes	Olympique Lyonnais	Portugal	64
## 19	2019	H. Lloris	Tottenham Hotspur	France	63
## 20	2019	Ederson	Manchester City	Brazil	63
## 21	2019	A. Onana	Ajax	Cameroon	63
## 22	2019	Alberto	Rayo Vallecano	Spain	63
## 23	2019	Z. Zlámal	Heart of Midlothian	Czech Republic	63
## 24	2020	Jordi Masip	Real Valladolid CF	Spain	65
## 25	2020	A. Lopes	Olympique Lyonnais	Portugal	64
## 26	2020	Ederson	Manchester City	Brazil	63
## 27	2020	H. Lloris	Tottenham Hotspur	France	63
## 28	2020	A. Onana	Ajax	Cameroon	63
## 29	2020	Alberto	Rayo Vallecano	Spain	63

```
print(gk_position_yearly_df)
```

##	years...i..	short_name	club	nationality
## 1	2016	M. Neuer	FC Bayern München	Germany
## 2	2016	G. Buffon	Juventus	Italy
## 3	2016	Diego López	Milan	Spain
## 4	2016	S. Handanovič	Inter	Slovenia
## 5	2016	J. Hart	Manchester City	England
## 6	2016	Iraizoz	Athletic Club de Bilbao	Spain
## 7	2017	M. Neuer	FC Bayern München	Germany
## 8	2017	G. Buffon	Juventus	Italy
## 9	2017	J. Oblak	Atlético Madrid	Slovenia
## 10	2017	T. Courtois	Chelsea	Belgium
## 11	2017	S. Handanovič	Inter	Slovenia
## 12	2017	B. Leno	Bayer 04 Leverkusen	Germany
## 13	2018	M. Neuer	FC Bayern München	Germany
## 14	2018	G. Buffon	Juventus	Italy
## 15	2018	J. Oblak	Atlético Madrid	Slovenia
## 16	2018	S. Handanovič	Inter	Slovenia

```

## 17    2018 R. Jarstein      Hertha BSC      Norway
## 18    2019 S. Handanovič   Inter           Slovenia
## 19    2019 De Gea          Manchester United  Spain
## 20    2019 J. Oblak         Atlético Madrid  Slovenia
## 21    2019 M. Neuer        FC Bayern München Germany
## 22    2019 T. Courtois     Real Madrid      Belgium
## 23    2020 J. Oblak         Atlético Madrid  Slovenia
## 24    2020 Alisson         Liverpool       Brazil
## 25    2020 S. Handanovič   Inter           Slovenia
## 26    2020 M. ter Stegen   FC Barcelona     Germany
## 27    2020 Ederson         Manchester City  Brazil
## 28    2020 W. Szczęsny     Juventus       Poland
## 29    2020 R. Jarstein     Hertha BSC      Norway

## gk_positioning
## 1      90
## 2      89
## 3      87
## 4      86
## 5      84
## 6      84
## 7      91
## 8      90
## 9      87
## 10     86
## 11     86
## 12     86
## 13     91
## 14     90
## 15     87
## 16     87
## 17     87
## 18     89
## 19     88
## 20     88
## 21     88
## 22     87
## 23     90
## 24     90
## 25     89
## 26     88
## 27     86
## 28     86
## 29     86

# Attacking Stats: attacking_crossing, attacking_finishing and attacking_heading_accuracy
attack_crossing_dfs <- vector(mode = "list", length = 5)
attack_finish_dfs <- vector(mode = "list", length = 5)
attack_head_acc_dfs <- vector(mode = "list", length = 5)

for (i in seq_along(fifa_datasets_list)) {

  # Top 5 best crossers by year
  top_attack_crossing <- fifa_datasets_list[[i]] %>% arrange(desc(attacking_crossing)) %>%
    select(short_name, club, nationality, overall, attacking_crossing) %>% top_n(5)
}

```

```

top_attack_crossing <- add_column(top_attack_crossing, years[[i]], .before = "short_name")
attack_crossing_dfs[[i]] <- data.frame(top_attack_crossing)

# Top 5 best finishers by year
top_attack_finish <- fifa_datasets_list[[i]] %>% arrange(desc(attacking_finishing)) %>%
  select(short_name, club, nationality, overall, attacking_finishing) %>% top_n(5)
top_attack_finish <- add_column(top_attack_finish, years[[i]], .before = "short_name")
attack_finish_dfs[[i]] <- data.frame(top_attack_finish)
# ARE FINISHING AND SHOOTING CORRELATED?

# Top 5 players most likely to score a goal via a header each year
top_head_acc <- fifa_datasets_list[[i]] %>% arrange(desc(attacking_heading_accuracy)) %>%
  select(short_name, club, nationality, overall, attacking_heading_accuracy) %>% top_n(5)
top_head_acc <- add_column(top_head_acc, years[[i]], .before = "short_name")
attack_head_acc_dfs[[i]] <- data.frame(top_head_acc)
}

## Selecting by attacking_crossing

## Selecting by attacking_finishing

## Selecting by attacking_heading_accuracy

## Selecting by attacking_crossing

## Selecting by attacking_finishing

## Selecting by attacking_heading_accuracy

## Selecting by attacking_crossing

## Selecting by attacking_finishing

## Selecting by attacking_heading_accuracy

## Selecting by attacking_crossing

## Selecting by attacking_finishing

## Selecting by attacking_heading_accuracy

## Selecting by attacking_crossing

## Selecting by attacking_finishing

## Selecting by attacking_heading_accuracy

```

```
print(do.call("rbind", attack_crossing_dfs))
```

##	years...i..	short_name	club	nationality	overall
## 1	2016	A. Pirlo	New York City FC	Italy	84
## 2	2016	R. Rodriguez	VfL Wolfsburg	Switzerland	83
## 3	2016	L. Baines	Everton	England	83
## 4	2016	A. Kolarov	Manchester City	Serbia	79
## 5	2016	S. Larsson	Sunderland	Sweden	74
## 6	2017	L. Baines	Everton	England	83
## 7	2017	A. Pirlo	New York City FC	Italy	82
## 8	2017	R. Rodríguez	VfL Wolfsburg	Switzerland	83
## 9	2017	K. De Bruyne	Manchester City	Belgium	88
## 10	2017	A. Di María	Paris Saint-Germain	Argentina	87
## 11	2017	A. Kolarov	Manchester City	Serbia	79
## 12	2017	S. Larsson	Sunderland	Sweden	75
## 13	2018	A. Pirlo	New York City FC	Italy	79
## 14	2018	M. Plattenhardt	Hertha BSC	Germany	78
## 15	2018	Marcelo	Real Madrid	Brazil	87
## 16	2018	K. De Bruyne	Manchester City	Belgium	89
## 17	2018	Pedro León	SD Eibar	Spain	80
## 18	2019	K. De Bruyne	Manchester City	Belgium	91
## 19	2019	Quaresma	Beşiktaş JK	Portugal	84
## 20	2019	P. Max	FC Augsburg	Germany	78
## 21	2019	A. Kolarov	Roma	Serbia	82
## 22	2019	K. Trippier	Tottenham Hotspur	England	82
## 23	2019	Pedro León	SD Eibar	Spain	81
## 24	2020	K. De Bruyne	Manchester City	Belgium	91
## 25	2020	J. Kimmich	FC Bayern München	Germany	86
## 26	2020	Quaresma	Beşiktaş JK	Portugal	81
## 27	2020	Pedro León	SD Eibar	Spain	80
## 28	2020	J. Rodríguez	Real Madrid	Colombia	85
## 29	2020	A. Kolarov	Roma	Serbia	82
## attacking_crossing					
## 1		93+11			
## 2		92+4			
## 3		91+3			
## 4		90+5			
## 5		90+3			
## 6		91			
## 7		91			
## 8		90-2			
## 9		90			
## 10		90			
## 11		90			
## 12		90			
## 13		91			
## 14		90+4			
## 15		90+3			
## 16		90			
## 17		90			
## 18		93			
## 19		92			
## 20		91+1			

```

## 21          91
## 22          91
## 23          91
## 24          93
## 25          91
## 26          91
## 27          91
## 28          90
## 29          90

print(do.call("rbind", attack_finish_dfs))

##   years...i.. short_name      club nationality overall
## 1    2016 Cristiano Ronaldo Real Madrid Portugal    93
## 2    2016 L. Messi FC Barcelona Argentina    94
## 3    2016 L. Suárez FC Barcelona Uruguay     90
## 4    2016 Z. Ibrahimović Paris Saint-Germain Sweden     89
## 5    2016 S. Agüero Manchester City Argentina    87
## 6    2016 Diego Costa Chelsea Spain       86
## 7    2017 L. Messi FC Barcelona Argentina    93
## 8    2017 L. Suárez FC Barcelona Uruguay     92
## 9    2017 Cristiano Ronaldo Real Madrid Portugal    94
## 10   2017 R. Lewandowski FC Bayern München Poland      90
## 11   2017 G. Higuaín Juventus Argentina    88
## 12   2018 L. Messi FC Barcelona Argentina    93
## 13   2018 Cristiano Ronaldo Real Madrid Portugal    94
## 14   2018 L. Suárez FC Barcelona Uruguay     92
## 15   2018 G. Higuaín Juventus Argentina    90
## 16   2018 R. Lewandowski FC Bayern München Poland      91
## 17   2019 L. Messi FC Barcelona Argentina    94
## 18   2019 Cristiano Ronaldo Juventus Portugal    94
## 19   2019 L. Suárez FC Barcelona Uruguay     91
## 20   2019 H. Kane Tottenham Hotspur England      89
## 21   2019 S. Agüero Manchester City Argentina    89
## 22   2020 L. Messi FC Barcelona Argentina    94
## 23   2020 Cristiano Ronaldo Juventus Portugal    93
## 24   2020 H. Kane Tottenham Hotspur England      89
## 25   2020 S. Agüero Manchester City Argentina    89
## 26   2020 L. Suárez FC Barcelona Uruguay     89

##   attacking_finishing
## 1          95
## 2         93-1
## 3         90-1
## 4          90
## 5          90
## 6          90
## 7        95+2
## 8        94+4
## 9        93-2
## 10       91+2
## 11       91+1
## 12          95
## 13       94+1
## 14          94

```

```

## 15          91-1
## 16          91
## 17          95
## 18          94
## 19          94
## 20          94
## 21          93
## 22          95
## 23          94
## 24          94
## 25          93
## 26          91

print(do.call("rbind", attack_head_acc_dfs))

##   years...i. short_name      club nationality overall
## 1    2016   T. Cahill    Australia    Australia     73
## 2    2016   Aduriz      Athletic Club de Bilbao Spain        82
## 3    2016   Naldo       VfL Wolfsburg Brazil        85
## 4    2016   D. Godín    Atlético Madrid Uruguay       85
## 5    2016   L. de Jong   PSV Netherlands    Netherlands 79
## 6    2017   Aduriz      Athletic Club de Bilbao Spain        84
## 7    2017   T. Cahill    Melbourne City FC Australia     74
## 8    2017   Naldo       FC Schalke 04 Brazil        84
## 9    2017   D. Godín    Atlético Madrid Uruguay       88
## 10   2017   I. Slimani  Leicester City Algeria      83
## 11   2017   L. de Jong   PSV Netherlands    Netherlands 79
## 12   2018   Aduriz      Athletic Club de Bilbao Spain        84
## 13   2018   B. Dost     Sporting CP Netherlands 83
## 14   2018   T. Cahill    Melbourne City FC Australia     70
## 15   2018   D. Godín    Atlético Madrid Uruguay       88
## 16   2018   Sergio Ramos Real Madrid Spain        90
## 17   2019   Naldo       FC Schalke 04 Brazil        86
## 18   2019   Aduriz      Athletic Club de Bilbao Spain        83
## 19   2019   B. Dost     Sporting CP Netherlands 83
## 20   2019   M. Fellaini Manchester United Belgium      79
## 21   2019   D. Godín    Atlético Madrid Uruguay       90
## 22   2019   E. Adebayor Medipol Başakşehir FK Togo        79
## 23   2019   L. de Jong   PSV Netherlands    Netherlands 78
## 24   2020   B. Dost     Sporting CP Netherlands 82
## 25   2020   L. de Jong   Sevilla FC Netherlands 82
## 26   2020   L. Pavoletti Cagliari Italy        78
## 27   2020   Sergio Ramos Real Madrid Spain        89
## 28   2020   Aduriz      Athletic Club de Bilbao Spain        82
## 29   2020   M. Fellaini Shandong Luneng TaiShan FC Belgium      76

##   attacking_heading_accuracy
## 1                      95+1
## 2                      95
## 3                      93
## 4                      92+5
## 5                      92+4
## 6                      94-1
## 7                      93-2
## 8                      93

```

```

## 9          92
## 10         92
## 11         92
## 12         94
## 13        93+1
## 14         93
## 15         92
## 16        91+1
## 17         94
## 18         94
## 19         94
## 20         93
## 21         92
## 22         92
## 23         92
## 24         93
## 25         93
## 26         93
## 27         92
## 28         92
## 29         92

# Movement Stats: movement_acceleration and movement_balance
mov_acc_dfs <- vector(mode = "list", length = 5)
mov_bal_dfs <- vector(mode = "list", length = 5)

for (i in seq_along(fifa_datasets_list)) {

  # Top 5 players with best acceleration
  top_acc <- fifa_datasets_list[[i]] %>% arrange(desc(movement_acceleration)) %>%
    select(short_name, club, nationality, overall, movement_acceleration) %>% top_n(5)
  top_acc <- add_column(top_acc, years[[i]], .before = "short_name")
  mov_acc_dfs[[i]] <- data.frame(top_acc)

  # Top 5 players with best balance
  top_bal <- fifa_datasets_list[[i]] %>% arrange(desc(movement_balance)) %>%
    select(short_name, club, nationality, overall, movement_balance) %>% top_n(5)
  top_bal <- add_column(top_bal, years[[i]], .before = "short_name")
  mov_bal_dfs[[i]] <- data.frame(top_bal)
  # ARE BALANCE AND DRIBBLING CORRELATED?
}

## Selecting by movement_acceleration
## Selecting by movement_balance
## Selecting by movement_acceleration
## Selecting by movement_balance
## Selecting by movement_acceleration
## Selecting by movement_balance

```

```

## Selecting by movement_acceleration

## Selecting by movement_balance

## Selecting by movement_acceleration

## Selecting by movement_balance

print(do.call("rbind", mov_acc_dfs))

##   years...i.    short_name      club    nationality
## 1     2016      M. Bolly Fortuna Düsseldorf Ivory Coast
## 2     2016      P. Aubameyang Borussia Dortmund Gabon
## 3     2016      J. Damm    Tigres U.A.N.L. Mexico
## 4     2016      T. Walcott    Arsenal England
## 5     2016      L. Messi FC Barcelona Argentina
## 6     2017      M. Bolly SpVgg Greuther Fürth Ivory Coast
## 7     2017 Douglas Costa FC Bayern München Brazil
## 8     2017 Héctor Bellerín    Arsenal Spain
## 9     2017      P. Aubameyang Borussia Dortmund Gabon
## 10    2017      Lucas Paris Saint-Germain Brazil
## 11    2017      A. Musa Leicester City Nigeria
## 12    2017      J. Damm    Tigres U.A.N.L. Mexico
## 13    2017      Cedrick Columbus Crew SC DR Congo
## 14    2018 Douglas Costa    Juventus Brazil
## 15    2018 Héctor Bellerín    Arsenal Spain
## 16    2018      K. Manneh Columbus Crew SC Gambia
## 17    2018 Gelson Martins Sporting CP Portugal
## 18    2018      J. Biabiány Sparta Praha France
## 19    2019 Douglas Costa    Juventus Brazil
## 20    2019      Adama Wolverhampton Wanderers Spain
## 21    2019      K. Mbappé Paris Saint-Germain France
## 22    2019      K. Manneh FC St. Gallen United States
## 23    2019      E. List Gillingham England
## 24    2020 Adama Traoré Wolverhampton Wanderers Spain
## 25    2020      K. Mbappé Paris Saint-Germain France
## 26    2020      R. Sterling Manchester City England
## 27    2020      S. Mané Liverpool Senegal
## 28    2020 Douglas Costa    Juventus Brazil
## 29    2020      Lucas Moura Tottenham Hotspur Brazil
## 30    2020 Gelson Martins AS Monaco Portugal
## 31    2020      I. Sarr Watford Senegal
## 32    2020      A. Musa Al Nassr Nigeria
## 33    2020      K. Nagai FC Tokyo Japan
## 34    2020      K. Manneh FC Cincinnati United States
## 35    2020      E. List Gillingham England

##   overall movement_acceleration
## 1       67             97
## 2       82             96
## 3       73            95+1
## 4       81            95-2
## 5       94            95-1
## 6       67             97

```

```

## 7    84    96
## 8    79    96
## 9    86    95
## 10   82    95
## 11   78    95
## 12   73    95
## 13   69    95
## 14   82    96
## 15   81    96
## 16   70    96
## 17   81    95+1
## 18   75    95+1
## 19   86    97
## 20   75    97
## 21   87    96
## 22   69    96
## 23   60    95+1
## 24   74    97
## 25   89    96
## 26   88    96
## 27   88    95
## 28   84    95
## 29   83    95
## 30   82    95
## 31   78    95
## 32   73    95
## 33   69    95
## 34   68    95
## 35   62    95

```

```
print(do.call("rbind", mov_bal_dfs))
```

##	years...i..	short_name	club	nationality
## 1	2016	G. Krebs	Karlsruher SC	France
## 2	2016	V. Hernández	Junior FC	Colombia
## 3	2016	Bernard	Shakhtar Donetsk	Brazil
## 4	2016	E. Oztumer	Peterborough United	England
## 5	2016	D. Villalva	Tiburones Rojos de Veracruz	Argentina
## 6	2017	E. Oztumer	Walsall	England
## 7	2017	Bernard	Shakhtar Donetsk	Brazil
## 8	2017	D. Buonanotte	Universidad Católica	Argentina
## 9	2017	D. Villalva	Tiburones Rojos de Veracruz	Argentina
## 10	2017	G. Krebs	Karlsruher SC	France
## 11	2017	Fer Cano	RCD Mallorca	Spain
## 12	2018	E. Oztumer	Walsall	England
## 13	2018	Bernard	Shakhtar Donetsk	Brazil
## 14	2018	S. Wharton	Blackburn Rovers	England
## 15	2018	K. Kadyrov	Terek Grozny	Russia
## 16	2018	L. Messi	FC Barcelona	Argentina
## 17	2018	P. De Blasis	1. FSV Mainz 05	Argentina
## 18	2018	M. Sau	Cagliari	Italy
## 19	2019	Ronald	Boavista FC	Brazil
## 20	2019	Bernard	Everton	Brazil
## 21	2019	T. Itō	Hamburger SV	Japan

## 22	2019	E. Oztumer	Bolton Wanderers	England
## 23	2019	T. Mizutani	Shimizu S-Pulse	Japan
## 24	2020	E. Oztumer	Charlton Athletic	England
## 25	2020	R. Fraser	Bournemouth	Scotland
## 26	2020	T. Itō	Hamburger SV	Japan
## 27	2020	L. Messi	FC Barcelona	Argentina
## 28	2020	Bernard	Everton	Brazil
## 29	2020	S. Kaneko	Shimizu S-Pulse	Japan
## 30	2020	Aridai	RCD Mallorca	Spain
## 31	2020	S. Horvath	SG Dynamo Dresden	Austria
## 32	2020	Isi Ros	AD Alcorcón	Spain
## 33	2020	K. Holzweiler	Viktoria Köln	Germany
## overall movement_balance				
## 1	66	96+4		
## 2	70	96+2		
## 3	78	96-1		
## 4	65	96-1		
## 5	70	96		
## 6	67	97+1		
## 7	79	96		
## 8	76	96		
## 9	73	96		
## 10	67	96		
## 11	64	96		
## 12	70	96-1		
## 13	79	96		
## 14	59	95+3		
## 15	58	95+3		
## 16	93	95		
## 17	77	95		
## 18	74	95		
## 19	60	99		
## 20	80	96		
## 21	71	96		
## 22	70	96		
## 23	56	96		
## 24	69	97		
## 25	81	96		
## 26	68	96		
## 27	94	95		
## 28	80	95		
## 29	70	95		
## 30	70	95		
## 31	67	95		
## 32	65	95		
## 33	64	95		

```
# Power Stats: power_shot_power, power_jumping, power_strength
shot_dfs <- vector(mode = "list", length = 5)
jump_dfs <- vector(mode = "list", length = 5)
strength_dfs <- vector(mode = "list", length = 5)

for (i in seq_along(fifa_datasets_list)) {
```

```

# Top 5 players with best shot power by year
top_shot <- fifa_datasets_list[[i]] %>% arrange(desc(power_shot_power)) %>%
  select(short_name, club, nationality, overall, power_shot_power) %>% top_n(5)
top_shot <- add_column(top_shot, years[[i]], .before = "short_name")
shot_dfs[[i]] <- data.frame(top_shot)
# ARE SHOOTING AND SHOT POWER CORRELATED?

# Top 5 players with best power jump by year
top_jump <- fifa_datasets_list[[i]] %>% arrange(desc(power_jumping)) %>%
  select(short_name, club, nationality, overall, power_jumping) %>% top_n(5)
top_jump <- add_column(top_jump, years[[i]], .before = "short_name")
jump_dfs[[i]] <- data.frame(top_jump)
# ARE JUMPING AND ATTACKING_HEADING_ACCURACY CORRELATED?

# Top 5 players with most power strength by year
top_strength <- fifa_datasets_list[[i]] %>% arrange(desc(power_strength)) %>%
  select(short_name, club, nationality, overall, power_strength) %>% top_n(5)
top_strength <- add_column(top_strength, years[[i]], .before = "short_name")
strength_dfs[[i]] <- data.frame(top_strength)

}

## Selecting by power_shot_power
## Selecting by power_jumping
## Selecting by power_strength
## Selecting by power_shot_power
## Selecting by power_jumping
## Selecting by power_strength
## Selecting by power_shot_power
## Selecting by power_jumping
## Selecting by power_strength
## Selecting by power_shot_power
## Selecting by power_jumping
## Selecting by power_strength
## Selecting by power_shot_power
## Selecting by power_jumping
## Selecting by power_strength

```

```
print(do.call("rbind", shot_dfs))
```

	years...i..	short_name	club	nationality
## 1	2016	Ronny	Hertha BSC	Brazil
## 2	2016	Cristiano Ronaldo	Real Madrid	Portugal
## 3	2016	Hulk	Zenit St. Petersburg	Brazil
## 4	2016	L. Podolski	Galatasaray SK	Germany
## 5	2016	Z. Ibrahimović	Paris Saint-Germain	Sweden
## 6	2017	Cristiano Ronaldo	Real Madrid	Portugal
## 7	2017	Z. Ibrahimović	Manchester United	Sweden
## 8	2017	L. Podolski	Galatasaray SK	Germany
## 9	2017	Naldo	FC Schalke 04	Brazil
## 10	2017	G. Bale	Real Madrid	Wales
## 11	2018	Cristiano Ronaldo	Real Madrid	Portugal
## 12	2018	Naldo	FC Schalke 04	Brazil
## 13	2018	L. Podolski	Vissel Kobe	Germany
## 14	2018	Z. Ibrahimović	Manchester United	Sweden
## 15	2018	G. Bale	Real Madrid	Wales
## 16	2018	A. Kolarov	Roma	Serbia
## 17	2019	Cristiano Ronaldo	Juventus	Portugal
## 18	2019	Hulk	Shanghai SIPG FC	Brazil
## 19	2019	F. Guarín	Shanghai Greenland Shenhua FC	Colombia
## 20	2019	V. Ayala	Gimnasia y Esgrima La Plata	Paraguay
## 21	2019	G. Bale	Real Madrid	Wales
## 22	2019	Naldo	FC Schalke 04	Brazil
## 23	2019	L. Podolski	Vissel Kobe	Germany
## 24	2020	Cristiano Ronaldo	Juventus	Portugal
## 25	2020	A. Kolarov	Roma	Serbia
## 26	2020	Hulk	Shanghai SIPG FC	Brazil
## 27	2020	G. Bale	Real Madrid	Wales
## 28	2020	K. De Bruyne	Manchester City	Belgium
##	overall power_shot_power			
## 1	72	95-1		
## 2	93	94		
## 3	84	94		
## 4	77	93+1		
## 5	89	93		
## 6	94	94		
## 7	90	93		
## 8	80	93		
## 9	84	92		
## 10	90	91+4		
## 11	94	94+2		
## 12	82	92		
## 13	80	92		
## 14	88	91-2		
## 15	89	91		
## 16	79	91		
## 17	94	95		
## 18	81	94		
## 19	76	93		
## 20	73	93		
## 21	88	92		

```

## 22      86        92
## 23      78        92
## 24      93        95
## 25      82        95
## 26      80        94
## 27      85        92
## 28      91        91

print(do.call("rbind", jump_dfs))

##   years...i.    short_name          club
## 1    2016       Aduriz    Athletic Club de Bilbao
## 2    2016       Rodri     Real Valladolid CF
## 3    2016      A. Caracciolo      Brescia
## 4    2016      C. Beauvue    Olympique Lyonnais
## 5    2016      M. Le Marchand      OGC Nice
## 6    2016      R. Azeez       UD Almería
## 7    2017      D. Mattocks    Portland Timbers
## 8    2017 Cristiano Ronaldo    Real Madrid
## 9    2017      A. Caracciolo    Hellas Verona
## 10   2017      K. Igboananike    DC United
## 11   2017      Regalón      CD Numancia
## 12   2018 Cristiano Ronaldo    Real Madrid
## 13   2018      A. Caracciolo    Hellas Verona
## 14   2018      Aduriz    Athletic Club de Bilbao
## 15   2018      D. Odoi       Fulham
## 16   2018      T. Cahill    Melbourne City FC
## 17   2018      J. Aidoo      KRC Genk
## 18   2018      J. Núñez      Club Tijuana
## 19   2018      D. Mattocks    Portland Timbers
## 20   2019 Cristiano Ronaldo    Juventus
## 21   2019      E. Sabbi      Hobro IK
## 22   2019      M. Icardi      Inter
## 23   2019      Aduriz    Athletic Club de Bilbao
## 24   2019      S. Aurier    Tottenham Hotspur
## 25   2019      S. Long       Southampton
## 26   2019      M. Barbieri    Rosario Central
## 27   2020 Cristiano Ronaldo    Juventus
## 28   2020      E. Sabbi      Hobro IK
## 29   2020      T. Hasegawa    Kawasaki Frontale
## 30   2020      M. Icardi      Inter
## 31   2020      O. Lewicki    Malmö FF
## 32   2020      M. Barbieri    Rosario Central
## 33   2020      T. Sugimoto    Matsumoto Yamaga
##   nationality overall power_jumping
## 1      Spain      82      96+1
## 2      Spain      71      95+3
## 3      Italy      67      95+3
## 4      France     79      95-1
## 5      France     73      94+3
## 6      Nigeria    71      94+3
## 7      Jamaica    66      97
## 8      Portugal    94      95+1
## 9      Italy       70      95

```

## 10	Nigeria	67	95
## 11	Spain	70	94+1
## 12	Portugal	94	95
## 13	Italy	71	95
## 14	Spain	84	94+1
## 15	Belgium	72	94
## 16	Australia	70	94
## 17	Ghana	67	94
## 18	Mexico	67	94
## 19	Jamaica	66	94
## 20	Portugal	94	95
## 21	United States	64	94+25
## 22	Argentina	87	94
## 23	Spain	83	94
## 24	Ivory Coast	81	94
## 25	Republic of Ireland	74	94
## 26	Argentina	70	94
## 27	Portugal	93	95
## 28	United States	68	95
## 29	Japan	66	95
## 30	Argentina	85	94
## 31	Sweden	72	94
## 32	Argentina	71	94
## 33	Japan	61	94

```
print(do.call("rbind", strength_dfs))
```

##	years...i..	short_name	club	nationality
## 1	2016	A. Akinfenwa	AFC Wimbledon	England
## 2	2016	C. Samba	Dinamo Moscow	Congo
## 3	2016	R. Torres	Seattle Sounders FC	Panama
## 4	2016	F. Baloy	Club Atlas	Panama
## 5	2016	J. Olave	Real Salt Lake	Colombia
## 6	2016	G. Elokobi	Colchester United	Cameroon
## 7	2016	A. Ba	Racing Club de Lens	Mauritania
## 8	2017	A. Akinfenwa	Wycombe Wanderers	England
## 9	2017	C. Samba	Panathinaikos FC	Congo
## 10	2017	R. Torres	Seattle Sounders FC	Panama
## 11	2017	A. Ba	Racing Club de Lens	Mauritania
## 12	2017	G. Elokobi	Colchester United	Cameroon
## 13	2018	A. Akinfenwa	Wycombe Wanderers	England
## 14	2018	C. Samba	Aston Villa	Congo
## 15	2018	O. Onyewu	Philadelphia Union	United States
## 16	2018	K. Sobieraj	Arka Gdynia	Poland
## 17	2018	K. Mbodj	RSC Anderlecht	Senegal
## 18	2019	A. Akinfenwa	Wycombe Wanderers	England
## 19	2019	Wesley	Club Brugge KV	Brazil
## 20	2019	T. Chorý	Viktoria Plzeň	Czech Republic
## 21	2019	K. Koulibaly	Napoli	Senegal
## 22	2019	R. Lukaku	Manchester United	Belgium
## 23	2019	N. Süle	FC Bayern München	Germany
## 24	2019	S. Coates	Sporting CP	Uruguay
## 25	2019	J. Vestergaard	Southampton	Denmark
## 26	2019	K. Mbodji	FC Nantes	Senegal

## 27	2019	R. Civelli	Club Atlético Banfield	Argentina
## 28	2019	A. Cerri	Cagliari	Italy
## 29	2019	M. Torsiglieri	Club Atlético Lanús	Argentina
## 30	2019	R. Torres	Seattle Sounders FC	Panama
## 31	2019	F. Ballas	SG Dynamo Dresden	Germany
## 32	2019	U. Ikpeazu	Heart of Midlothian	England
## 33	2019	F. Carvalho	Vålerenga Fotball	Uruguay
## 34	2019	M. Rhead	Lincoln City	England
## 35	2020	A. Akinfenwa	Wycombe Wanderers	England
## 36	2020	K. Koulibaly	Napoli	Senegal
## 37	2020	R. Lukaku	Inter	Belgium
## 38	2020	Wesley	Aston Villa	Brazil
## 39	2020	N. Süle	FC Bayern München	Germany
## 40	2020	S. Coates	Sporting CP	Uruguay
## 41	2020	D. Zapata	Atalanta	Colombia
## 42	2020	K. Waston	FC Cincinnati	Costa Rica
## 43	2020	A. Cerri	Cagliari	Italy
## 44	2020	O. Oularé	Standard de Liège	Belgium
## 45	2020	F. Ballas	SG Dynamo Dresden	Germany
## 46	2020	U. Ikpeazu	Heart of Midlothian	England
## 47	2020	I. Marega	La Berrichonne de Châteauroux	France
## 48	2020	T. Petrášek	Raków Częstochowa	Czech Republic
## overall power_strength				
## 1	64	98+1		
## 2	78	96+1		
## 3	71	95+2		
## 4	72	95		
## 5	71	95		
## 6	69	95		
## 7	64	95		
## 8	64	98		
## 9	78	96		
## 10	72	95		
## 11	65	95		
## 12	63	95		
## 13	64	98		
## 14	74	96		
## 15	69	96		
## 16	67	95+4		
## 17	78	94+6		
## 18	66	97		
## 19	76	95+3		
## 20	61	95		
## 21	87	94		
## 22	87	94		
## 23	84	94		
## 24	82	94		
## 25	80	94		
## 26	78	94		
## 27	76	94		
## 28	72	94		
## 29	72	94		
## 30	72	94		
## 31	70	94		

```

## 32      68      94
## 33      67      94
## 34      60      94
## 35      65      97
## 36      89      95
## 37      85      95
## 38      79      95
## 39      85      94
## 40      82      94
## 41      82      94
## 42      73      94
## 43      72      94
## 44      71      94
## 45      70      94
## 46      67      94
## 47      65      94
## 48      65      94

# Mentality Stats: mentality_positioning, mentality_penalties and mentality_vision
position_dfs <- vector(mode = "list", length = 5)
penalty_dfs <- vector(mode = "list", length = 5)
vision_dfs <- vector(mode = "list", length = 5)

for (i in seq_along(fifa_datasets_list)) {

  # Top 5 players with best position sense by year
  top_posit <- fifa_datasets_list[[i]] %>% arrange(desc(mentality_positioning)) %>%
    select(short_name, club, nationality, overall, team_position, mentality_positioning) %>% top_n(5)
  top_posit <- add_column(top_posit, years[[i]], .before = "short_name")
  position_dfs[[i]] <- data.frame(top_posit)

  # Top 5 best penalty takers by year
  top_penalty <- fifa_datasets_list[[i]] %>% arrange(desc(mentality_penalties)) %>%
    select(short_name, club, nationality, overall, mentality_penalties) %>% top_n(5)
  top_penalty <- add_column(top_penalty, years[[i]], .before = "short_name")
  penalty_dfs[[i]] <- data.frame(top_penalty)
  # ARE ATTACKING FINISHING AND PENALTIES CORRELATED?

  # Top 5 players with best vision by year
  top_vision <- fifa_datasets_list[[i]] %>% arrange(desc(mentality_vision)) %>%
    select(short_name, club, nationality, overall, mentality_vision) %>% top_n(5)
  top_vision <- add_column(top_vision, years[[i]], .before = "short_name")
  vision_dfs[[i]] <- data.frame(top_vision)
  # ARE VISION AND PASSING CORRELATED?

}

## Selecting by mentality_positioning
## Selecting by mentality_penalties
## Selecting by mentality_vision
## Selecting by mentality_positioning

```



```

##   team_position mentality_positioning
## 1          CF              94
## 2          LM             93+2
## 3          ST             91+3
## 4         CAM             91+1
## 5          RW             90-2
## 6          RW             96+2
## 7          LW             94+1
## 8          RW             93+3
## 9          LS             92+2
## 10         ST             92+1
## 11         LW             95+1
## 12         RW              93
## 13         RM              93
## 14         ST             92+3
## 15         ST              92
## 16         ST              92
## 17         LW              95
## 18         RW              94
## 19         ST              93
## 20         ST              93
## 21        RCM              93
## 22         LW              95
## 23         RW              94
## 24         ST              93
## 25         ST              93
## 26         ST              93

```

```
print(do.call("rbind", penalty_dfs))
```

	years...i..	short_name	club	nationality	overall
## 1	2016	R. Lambert	West Bromwich Albion	England	75
## 2	2016	M. Balotelli	Milan	Italy	80
## 3	2016	David Villa	New York City FC	Spain	80
## 4	2016	N. Ortigoza	San Lorenzo de Almagro	Paraguay	72
## 5	2016	Z. Ibrahimović	Paris Saint-Germain	Sweden	89
## 6	2017	R. Lambert	Cardiff City	England	75
## 7	2017	M. Balotelli	OGC Nice	Italy	79
## 8	2017	Z. Ibrahimović	Manchester United	Sweden	90
## 9	2017	N. Ortigoza	San Lorenzo de Almagro	Paraguay	75
## 10	2017	L. Baines	Everton	England	83
## 11	2017	T. Simons	Club Brugge KV	Belgium	74
## 12	2018	M. Balotelli	OGC Nice	Italy	82
## 13	2018	Fabinho	AS Monaco	Brazil	83
## 14	2018	Z. Ibrahimović	Manchester United	Sweden	88
## 15	2018	P. Verhaegh	VfL Wolfsburg	Netherlands	77
## 16	2018	D. Perotti	Roma	Argentina	81
## 17	2019	M. Balotelli	OGC Nice	Italy	83
## 18	2019	Fabinho	Liverpool	Brazil	85
## 19	2019	H. Kane	Tottenham Hotspur	England	89
## 20	2019	D. Perotti	Roma	Argentina	81
## 21	2019	R. Boudebouz	Real Betis	Algeria	80
## 22	2019	R. Jiménez	Wolverhampton Wanderers	Mexico	78
## 23	2019	L. Baines	Everton	England	78

```

## 24      2020      M. Kruse      Fenerbahçe SK      Germany      83
## 25      2020      Fabinho      Liverpool      Brazil       85
## 26      2020      S. Haller      West Ham United      France       83
## 27      2020      M. Balotelli      Brescia      Italy        82
## 28      2020      L. Milivojević      Crystal Palace      Serbia       81
##   mentality_penalties
## 1          96+1
## 2          92
## 3          92
## 4          91+1
## 5          91
## 6          96
## 7          92
## 8          91
## 9          91
## 10         90
## 11         90
## 12         92
## 13         91+3
## 14         91
## 15         90+4
## 16         90+2
## 17         92
## 18         91
## 19         90
## 20         90
## 21         90
## 22         90
## 23         90
## 24         92
## 25         91
## 26         91
## 27         91
## 28         91

```

```
print(do.call("rbind", vision_dfs))
```

	years...i..	short_name	club	nationality	overall
## 1	2016	A. Pirlo	New York City FC	Italy	84
## 2	2016	David Silva	Manchester City	Spain	88
## 3	2016	Cesc Fàbregas	Chelsea	Spain	87
## 4	2016	M. Özil	Arsenal	Germany	87
## 5	2016	L. Messi	FC Barcelona	Argentina	94
## 6	2016	F. Totti	Roma	Italy	80
## 7	2017	A. Pirlo	New York City FC	Italy	82
## 8	2017	M. Özil	Arsenal	Germany	89
## 9	2017	David Silva	Manchester City	Spain	87
## 10	2017	F. Totti	Roma	Italy	80
## 11	2017	Cesc Fàbregas	Chelsea	Spain	86
## 12	2018	M. Özil	Arsenal	Germany	88
## 13	2018	David Silva	Manchester City	Spain	87
## 14	2018	Cesc Fàbregas	Chelsea	Spain	86
## 15	2018	K. De Bruyne	Manchester City	Belgium	89
## 16	2018	C. Eriksen	Tottenham Hotspur	Denmark	87

```

## 17      2019    L. Messi    FC Barcelona  Argentina   94
## 18      2019    K. De Bruyne  Manchester City  Belgium    91
## 19      2019    L. Modrić    Real Madrid    Croatia    91
## 20      2019    David Silva  Manchester City    Spain     89
## 21      2019    C. Eriksen  Tottenham Hotspur  Denmark    88
## 22      2019    M. Özil      Arsenal        Germany    86
## 23      2019    Cesc Fàbregas  Chelsea        Spain     84
## 24      2020    L. Messi    FC Barcelona  Argentina   94
## 25      2020    K. De Bruyne  Manchester City  Belgium    91
## 26      2020    C. Eriksen  Tottenham Hotspur  Denmark    88
## 27      2020    L. Modrić    Real Madrid    Croatia    90
## 28      2020    David Silva  Manchester City    Spain     88
##   mentality_vision
## 1          94
## 2          93+3
## 3          93
## 4          92
## 5          90
## 6          90
## 7          94
## 8          93
## 9          92-1
## 10         91+1
## 11         91-1
## 12         92-1
## 13         92
## 14         91
## 15         90+2
## 16         90+1
## 17         94
## 18         94
## 19         92
## 20         92
## 21         91
## 22         91
## 23         91
## 24         94
## 25         94
## 26         92
## 27         91
## 28         91

```

```

# Defending Stats: defending_marking, defending_standing_tackle, defending_sliding_tackle
marking_dfs <- vector(mode = "list", length = 5)
stand_tackle_dfs <- vector(mode = "list", length = 5)
slide_tackle_dfs <- vector(mode = "list", length = 5)

for (i in seq_along(fifa_datasets_list)) {

  # Top 5 players best markers by year
  top_mark <- fifa_datasets_list[[i]] %>% arrange(desc(defending_marking)) %>%
    select(short_name, club, nationality, overall, defending_marking) %>% top_n(5)
  top_mark <- add_column(top_mark, years[[i]], .before = "short_name")
  marking_dfs[[i]] <- data.frame(top_mark)
}

```

```

# Top 5 best players at standing tackle by year
top_stand_t <- fifa_datasets_list[[i]] %>% arrange(desc(defending_standing_tackle)) %>%
  select(short_name, club, nationality, overall, defending_standing_tackle) %>% top_n(5)
top_stand_t <- add_column(top_stand_t, years[[i]], .before = "short_name")
stand_tackle_dfs[[i]] <- data.frame(top_stand_t)

# Top 5 best players at sliding tackle by year
top_slide_t <- fifa_datasets_list[[i]] %>% arrange(desc(defending_sliding_tackle)) %>%
  select(short_name, club, nationality, overall, defending_sliding_tackle) %>% top_n(5)
top_slide_t <- add_column(top_slide_t, years[[i]], .before = "short_name")
slide_tackle_dfs[[i]] <- data.frame(top_slide_t)

}

## Selecting by defending_marking

## Selecting by defending_standing_tackle

## Selecting by defending_sliding_tackle

## Selecting by defending_marking

## Selecting by defending_standing_tackle

## Selecting by defending_sliding_tackle

## Selecting by defending_marking

## Selecting by defending_standing_tackle

## Selecting by defending_sliding_tackle

## Selecting by defending_marking

## Selecting by defending_standing_tackle

## Selecting by defending_sliding_tackle

## Selecting by defending_marking

## Selecting by defending_standing_tackle

## Selecting by defending_sliding_tackle

print(do.call("rbind", marking_dfs))

```

##	years...i..	short_name	club
## 1	2016	G. Chiellini	Juventus
## 2	2016	Thiago Silva	Paris Saint-Germain
## 3	2016	F. Wiedwald	SV Werder Bremen
## 4	2016	Ederson	SL Benfica
## 5	2016	S. Viera	Junior FC
## 6	2016	B. Khuzwayo	Kaizer Chiefs
## 7	2016	J. Wiland	Malmö FF
## 8	2016	M. Müller	1. FC Kaiserslautern
## 9	2016	A. Weis	FSV Frankfurt
## 10	2016	E. Lobos	CD Cobresal
## 11	2016	R. Cierznik	Wisła Kraków
## 12	2016	B. Samba	AS Nancy Lorraine
## 13	2016	M. McGovern	Hamilton Academical FC
## 14	2016	A. Stoltz	TSG 1899 Hoffenheim
## 15	2016	G. Vailati	FC Basel 1893
## 16	2016	S. Radlinger	Hannover 96
## 17	2016	S. Bain	Dundee FC
## 18	2016	C. Day	Stevenage
## 19	2016	Kim Min Sik	Jeonnam Dragons
## 20	2016	H. Bonmann	Borussia Dortmund
## 21	2016	P. Camara	FC Sochaux-Montbéliard
## 22	2016	A. Favre	FC Zürich
## 23	2016	M. Herzog	FC St. Gallen
## 24	2016	R. Mandanda	AC Ajaccio
## 25	2016	C. Abella	Atlético Huila
## 26	2016	G. Sava	Dundalk
## 27	2016	J. Hall	Adelaide United
## 28	2017	G. Chiellini	Juventus
## 29	2017	J. Boateng	FC Bayern München
## 30	2017	Thiago Silva	Paris Saint-Germain
## 31	2017	A. Barzagli	Juventus
## 32	2017	P. Klandt	SC Freiburg
## 33	2018	G. Chiellini	Juventus
## 34	2018	Thiago Silva	Paris Saint-Germain
## 35	2018	A. Barzagli	Juventus
## 36	2018	M. Böcskör	SV Mattersburg
## 37	2018	Ederson	Manchester City
## 38	2018	Sergio	RC Celta
## 39	2018	D. Boyko	Beşiktaş JK
## 40	2018	F. Wiedwald	Leeds United
## 41	2018	M. Dmitrović	SD Eibar
## 42	2018	Edgar Badía	CF Reus Deportiu
## 43	2018	J. Wiland	Hammarby IF
## 44	2018	M. Higashiguchi	Gamba Osaka
## 45	2018	Y. Sanpian	CD O'Higgins
## 46	2018	S. Viera	Junior FC
## 47	2018	André Milazisco	Ponte Preta
## 48	2018	F. Nita	Romania
## 49	2018	K. Müller	1. FC Heidenheim 1846
## 50	2018	A. Weis	SSV Jahn Regensburg
## 51	2018	B. Khuzwayo	Kaizer Chiefs
## 52	2018	P. Klandt	SC Freiburg
## 53	2018	D. Bernhardt	VfR Aalen

## 54	2018	J. Contreras	Venezuela
## 55	2018	M. Müller	1. FC Kaiserslautern
## 56	2018	E. Mendy	Stade de Reims
## 57	2018	A. Camura	CD Huachipato
## 58	2018	M. McGovern	Norwich City
## 59	2018	Márcio Velinha	Palmeiras
## 60	2018	R. Mandanda	AC Ajaccio
## 61	2018	L. Bostyn	SV Zulte-Waregem
## 62	2018	B. Uphoff	Karlsruher SC
## 63	2018	H. Koffi	LOSC Lille
## 64	2018	K. Broll	SG Sonnenhof Großaspach
## 65	2018	S. Şahin-Radlinger	Hannover 96
## 66	2018	A. Stoltz	TSG 1899 Hoffenheim
## 67	2018	P. Dahlberg	IFK Göteborg
## 68	2018	S. Bain	Dundee FC
## 69	2018	B. Samba	Stade Malherbe Caen
## 70	2018	C. Merville	Valenciennes FC
## 71	2018	A. Poggenborg	SC Fortuna Köln
## 72	2018	S. Arai	Kawasaki Frontale
## 73	2018	Adrián López	RCD Espanyol
## 74	2018	G. Vailati	FC Basel 1893
## 75	2018	N. Kato	Omiya Ardija
## 76	2018	Ricardo Moura	CD Tondela
## 77	2018	D. Sappa	Estudiantes de La Plata
## 78	2018	J. Castillo	U.N.A.M.
## 79	2018	R. Martínez	Godoy Cruz
## 80	2018	Y. van Osch	PSV
## 81	2018	Quique Cebriá	SD Eibar
## 82	2018	K. Shimura	Júbilo Iwata
## 83	2018	V. Vorel	Sparta Praha
## 84	2018	E. Zelazny	ESTAC Troyes
## 85	2018	S. Anchoverrí	Club Olimpo
## 86	2018	Rafael Broetto	Clube Sport Marítimo
## 87	2018	F. Lončarić	Tromsø IL
## 88	2018	M. Cavallotti	Argentinos Juniors
## 89	2018	M. van de Meulenhof	PSV
## 90	2018	T. Nobile	FC Pro Vercelli 1892
## 91	2018	T. Casali	SV Mattersburg
## 92	2018	T. Aupic	Paris FC
## 93	2018	B. Gaye	DSC Arminia Bielefeld
## 94	2018	Sergio García	Real Zaragoza
## 95	2018	G. Gómez	Racing Club
## 96	2018	M. Funk	SpVgg Greuther Fürth
## 97	2018	F. Stritzel	SV Darmstadt 98
## 98	2018	M. Bruhn	FC Helsingør
## 99	2018	T. Okubo	FC Tokyo
## 100	2018	F. Dmitrovic	SCR Altach
## 101	2018	E. Dahlin	IFK Göteborg
## 102	2018	R. Hironaga	Sanfrecce Hiroshima
## 103	2018	C. Day	Stevenage
## 104	2018	L. Radliński	Sandecja Nowy Sącz
## 105	2018	J. Albrecht	SV Wehen Wiesbaden
## 106	2018	Lee Jae Hyeong	Jeonbuk Hyundai Motors
## 107	2018	Gorka Giralt	Real Oviedo

## 108	2018	B. Derksen	Roda JC Kerkrade
## 109	2018	S. Cleveland	Chicago Fire
## 110	2018	L. Chiappero	Defensa y Justicia
## 111	2018	V. Karakuş	Kayserispor
## 112	2018	S. Custers	VVV-Venlo
## 113	2018	G. Banaziak	Amiens SC
## 114	2018	R. Jendrusch	FC Erzgebirge Aue
## 115	2018	A. García	Atlético Huila
## 116	2018	F. Due	Randers FC
## 117	2018	G. Sava	Dundalk
## 118	2018	K. Martin	FC Lausanne-Sport
## 119	2018	N. Berchtold	FC Sion
## 120	2018	K. Chorążka	Wisła Kraków
## 121	2018	J. Holmes	Bournemouth
## 122	2018	J. Bruhns	SC Fortuna Köln
## 123	2018	R. Lovett	Cheltenham Town
## 124	2018	R. Piscitelli	Benevento
## 125	2018	J. Turner	Bolton Wanderers
## 126	2018	S. George	Carlisle United
## 127	2018	B. Gómez	Rionegro Águilas
## 128	2018	H. Acevedo	Deportivo Cali
## 129	2018	P. Ovchinnikov	PFC CSKA Moscow
## 130	2018	M. Bleve	Ternana
## 131	2018	E. Benedettini	Novara
## 132	2018	A. Yiğiter	Fenerbahçe SK
## 133	2018	V. Cabezas	Deportivo Pasto
## 134	2018	G. Coudert	Tours FC
## 135	2018	M. Nilsson	Malmö FF
## 136	2018	P. Burke	Finn Harps
## 137	2018	B. Petersen	Kaizer Chiefs
## 138	2018	R. Díaz	Querétaro
## 139	2018	Lee Hyun Woo	Daegu FC
## 140	2018	J. Caicedo	Deportivo Pasto
## 141	2018	T. Brinkmann	SC Paderborn 07
## 142	2018	D. Thürkau	SV Werder Bremen II
## 143	2018	H. Hawsawi	Al Fayha
## 144	2018	S. Schmidt	FC Carl Zeiss Jena
## 145	2018	K. Humeler	Club Atlético Talleres
## 146	2018	J. Muñoz	Club León
## 147	2018	G. Nyberg	AIK
## 148	2018	A. André Jr	Bristol Rovers
## 149	2018	K. Nasurov	Terek Grozny
## 150	2018	S. Tsuji	Sagan Tosu
## 151	2018	J. García	Santos Laguna
## 152	2018	D. Adamov	FC Krasnodar
## 153	2018	L. Wackerle	SKN St. Pölten
## 154	2018	Park Hyeong Min	GwangJu FC
## 155	2018	S. Więckowicz	Arka Gdynia
## 156	2018	W. Henry	Swindon Town
## 157	2018	M. Cerofolini	Fiorentina
## 158	2018	A. Kelsey	Scunthorpe United
## 159	2019	A. Barzagli	Juventus
## 160	2019	G. Chiellini	Juventus
## 161	2019	M. Škriniar	Inter

## 162	2019	K. Koulibaly	Napoli
## 163	2019	Piqué	FC Barcelona
## 164	2020	G. Chiellini	Juventus
## 165	2020	M. Škriniar	Inter
## 166	2020	V. van Dijk	Liverpool
## 167	2020	K. Koulibaly	Napoli
## 168	2020	N. Kanté	Chelsea
## 169	2020	Sergio Busquets	FC Barcelona
## 170	2020	D. Godín	Inter
## 171	2020	M. Hummels	Borussia Dortmund
## 172	2020	T. Alderweireld	Tottenham Hotspur
## 173	2020	L. Bonucci	Juventus
## 174	2020	C. Lenglet	FC Barcelona
## 175	2020	D. De Rossi	Boca Juniors
##		nationality	overall
		defending	marking
## 1		Italy	91+1
## 2		Brazil	90+2
## 3		Germany	9-16
## 4		Brazil	9-16
## 5		Uruguay	9-16
## 6		South Africa	9-16
## 7		Sweden	9-16
## 8		Germany	9-16
## 9		Germany	9-16
## 10		Chile	9-16
## 11		Poland	9-16
## 12		Congo	9-16
## 13	Northern Ireland	Ireland	9-16
## 14		Germany	9-16
## 15		Switzerland	9-16
## 16		Austria	9-16
## 17		Scotland	9-16
## 18		England	9-16
## 19	Korea Republic	Korea Republic	9-16
## 20		Germany	9-16
## 21		Senegal	9-16
## 22		Switzerland	9-16
## 23		Switzerland	9-16
## 24		France	9-16
## 25		Colombia	9-16
## 26		Italy	9-16
## 27		Australia	9-16
## 28		Italy	92+2
## 29		Germany	91+7
## 30		Brazil	90
## 31		Italy	90
## 32		Germany	9-5
## 33		Italy	92
## 34		Brazil	90
## 35		Italy	90
## 36		Austria	9-13
## 37		Brazil	9
## 38		Spain	9
## 39		Ukraine	9

## 40	Germany	76	9
## 41	Serbia	74	9
## 42	Spain	72	9
## 43	Sweden	72	9
## 44	Japan	72	9
## 45	Chile	71	9
## 46	Uruguay	71	9
## 47	Brazil	71	9
## 48	Romania	70	9
## 49	Germany	69	9
## 50	Germany	69	9
## 51	South Africa	69	9
## 52	Germany	69	9
## 53	Germany	69	9
## 54	Venezuela	68	9
## 55	Germany	68	9
## 56	France	68	9
## 57	Chile	68	9
## 58	Northern Ireland	68	9
## 59	Brazil	68	9
## 60	DR Congo	67	9
## 61	Belgium	67	9
## 62	Germany	67	9
## 63	Burkina Faso	66	9
## 64	Germany	66	9
## 65	Austria	66	9
## 66	Germany	66	9
## 67	Sweden	65	9
## 68	Scotland	65	9
## 69	Congo	65	9
## 70	France	65	9
## 71	Germany	65	9
## 72	Japan	65	9
## 73	Spain	64	9
## 74	Switzerland	64	9
## 75	Japan	64	9
## 76	Portugal	64	9
## 77	Argentina	63	9
## 78	Mexico	63	9
## 79	Argentina	63	9
## 80	Netherlands	62	9
## 81	Spain	62	9
## 82	Japan	62	9
## 83	Czech Republic	62	9
## 84	France	62	9
## 85	Argentina	62	9
## 86	Brazil	62	9
## 87	Croatia	62	9
## 88	Argentina	62	9
## 89	Netherlands	61	9
## 90	Italy	61	9
## 91	Austria	61	9
## 92	France	61	9
## 93	Germany	60	9

## 94	Spain	60	9
## 95	Argentina	60	9
## 96	Germany	60	9
## 97	Germany	60	9
## 98	Denmark	60	9
## 99	Japan	60	9
## 100	Serbia	59	9
## 101	Sweden	59	9
## 102	Japan	59	9
## 103	England	59	9
## 104	Poland	59	9
## 105	Germany	58	9
## 106	Korea Republic	58	9
## 107	Spain	58	9
## 108	Netherlands	58	9
## 109	United States	58	9
## 110	Argentina	58	9
## 111	Turkey	57	9
## 112	Netherlands	57	9
## 113	France	57	9
## 114	Germany	57	9
## 115	Colombia	57	9
## 116	Denmark	57	9
## 117	Romania	57	9
## 118	Switzerland	56	9
## 119	Switzerland	55	9
## 120	Poland	55	9
## 121	Australia	55	9
## 122	Germany	55	9
## 123	England	55	9
## 124	Italy	55	9
## 125	England	54	9
## 126	England	54	9
## 127	Colombia	54	9
## 128	Colombia	54	9
## 129	Russia	54	9
## 130	Italy	54	9
## 131	San Marino	54	9
## 132	Turkey	53	9
## 133	Colombia	53	9
## 134	France	53	9
## 135	Sweden	53	9
## 136	Republic of Ireland	53	9
## 137	South Africa	53	9
## 138	Mexico	53	9
## 139	Korea Republic	53	9
## 140	Colombia	53	9
## 141	Germany	53	9
## 142	Switzerland	52	9
## 143	Saudi Arabia	52	9
## 144	Germany	52	9
## 145	Argentina	52	9
## 146	Mexico	52	9
## 147	Sweden	52	9

```

## 148      France    52      9
## 149      Russia    51      9
## 150      Japan     51      9
## 151      Mexico    50      9
## 152      Russia    50      9
## 153      Austria   50      9
## 154      Korea Republic 50      9
## 155      Poland    49      9
## 156      England   49      9
## 157      Italy     48      9
## 158      England   46      9
## 159      Italy     84     94
## 160      Italy     89     93
## 161      Slovakia  85     92
## 162      Senegal   87     91
## 163      Spain     87     91
## 164      Italy     89     94
## 165      Slovakia  86     92
## 166      Netherlands 90     91
## 167      Senegal   89     91
## 168      France    89     90
## 169      Spain     89     90
## 170      Uruguay   88     90
## 171      Germany   87     90
## 172      Belgium   87     90
## 173      Italy     86     90
## 174      France    85     90
## 175      Italy     82     90

```

```
print(do.call("rbind", stand_tackle_dfs))
```

##	years...i..	short_name	club	nationality
## 1	2016	Thiago Silva	Paris Saint-Germain	Brazil
## 2	2016	G. Chiellini	Juventus	Italy
## 3	2016	J. Boateng	FC Bayern München	Germany
## 4	2016	V. Kompany	Manchester City	Belgium
## 5	2016	A. Pyatov	Shakhtar Donetsk	Ukraine
## 6	2016	G. Curci	1. FSV Mainz 05	Italy
## 7	2016	P. Garcés	Colo-Colo	Chile
## 8	2016	H. Lindner	Eintracht Frankfurt	Austria
## 9	2016	S. Viera	Junior FC	Uruguay
## 10	2016	B. Khuzwayo	Kaizer Chiefs	South Africa
## 11	2016	S. Kotsolis	Panathinaikos FC	Greece
## 12	2016	N. Mäenpää	Brighton & Hove Albion	Finland
## 13	2016	O. Werner	FC Sochaux-Montbéliard	Belgium
## 14	2016	Z. MacMath	Colorado Rapids	United States
## 15	2016	J. Carrasco	FC Metz	France
## 16	2016	D. Davari	DSC Arminia Bielefeld	Iran
## 17	2016	L. Hirschfeld	Vålerenga Fotball	Canada
## 18	2016	K. Stamatopoulos	AIK	Canada
## 19	2016	R. Pillot	KV Kortrijk	France
## 20	2016	R. Vollath	Karlsruher SC	Germany
## 21	2016	L. Staw	FK Bodø/Glimt	Norway
## 22	2016	E. Horvath	Molde FK	United States

## 23	2016	A. Favre	FC Zürich	Switzerland
## 24	2016	C. Abella	Atlético Huila	Colombia
## 25	2016	G. Sava	Dundalk	Italy
## 26	2016	E. Balayev	Eintracht Frankfurt	Azerbaijan
## 27	2017	J. Boateng	FC Bayern München	Germany
## 28	2017	G. Chiellini	Juventus	Italy
## 29	2017	M. Hummels	FC Bayern München	Germany
## 30	2017	Thiago Silva	Paris Saint-Germain	Brazil
## 31	2017	A. Barzagli	Juventus	Italy
## 32	2017	V. Kompany	Manchester City	Belgium
## 33	2017	Miranda	Inter	Brazil
## 34	2018	G. Chiellini	Juventus	Italy
## 35	2018	M. Hummels	FC Bayern München	Germany
## 36	2018	J. Boateng	FC Bayern München	Germany
## 37	2018	T. Alderweireld	Tottenham Hotspur	Belgium
## 38	2018	Sokratis	Borussia Dortmund	Greece
## 39	2019	G. Chiellini	Juventus	Italy
## 40	2019	Sergio Ramos	Real Madrid	Spain
## 41	2019	M. Hummels	FC Bayern München	Germany
## 42	2019	N. Kanté	Chelsea	France
## 43	2019	T. Alderweireld	Tottenham Hotspur	Belgium
## 44	2020	V. van Dijk	Liverpool	Netherlands
## 45	2020	N. Kanté	Chelsea	France
## 46	2020	G. Chiellini	Juventus	Italy
## 47	2020	K. Koulibaly	Napoli	Senegal
## 48	2020	T. Alderweireld	Tottenham Hotspur	Belgium
## 49	2020	I. Gueye	Paris Saint-Germain	Senegal
## overall_defending_standing_tackle				
## 1	88		91+1	
## 2	87		91+1	
## 3	87		90+2	
## 4	85		90+2	
## 5	79		9-16	
## 6	72		9-16	
## 7	72		9-16	
## 8	70		9-16	
## 9	70		9-16	
## 10	68		9-16	
## 11	68		9-16	
## 12	67		9-16	
## 13	67		9-16	
## 14	66		9-16	
## 15	66		9-16	
## 16	65		9-16	
## 17	63		9-16	
## 18	63		9-16	
## 19	62		9-16	
## 20	61		9-16	
## 21	61		9-16	
## 22	60		9-16	
## 23	60		9-16	
## 24	57		9-16	
## 25	56		9-16	
## 26	55		9-16	

```

## 27      90          94+4
## 28      88          92+2
## 29      87          91+4
## 30      89          91
## 31      86          90
## 32      86          90
## 33      86          90
## 34      89          92
## 35      88          92
## 36      88          91-1
## 37      86          90+2
## 38      86          90+1
## 39      89          93
## 40      91          92
## 41      89          92
## 42      89          91
## 43      85          91
## 44      90          92
## 45      89          91
## 46      89          91
## 47      89          90
## 48      87          90
## 49      83          90

```

```
print(do.call("rbind", slide_tackle_dfs))
```

##	years...i..	short_name	club
## 1	2016	P. Lahm	FC Bayern München
## 2	2016	G. Chiellini	Juventus
## 3	2016	J. Boateng	FC Bayern München
## 4	2016	Sergio Ramos	Real Madrid
## 5	2016	Pepe	Real Madrid
## 6	2017	P. Lahm	FC Bayern München
## 7	2017	J. Boateng	FC Bayern München
## 8	2017	A. Barzagli	Juventus
## 9	2017	Sergio Ramos	Real Madrid
## 10	2017	Pepe	Real Madrid
## 11	2017	G. Chiellini	Juventus
## 12	2018	Sergio Ramos	Real Madrid
## 13	2018	M. Hummels	FC Bayern München
## 14	2018	J. Boateng	FC Bayern München
## 15	2018	G. Chiellini	Juventus
## 16	2018	A. Schwołek	SC Freiburg
## 17	2018	Dani Hernández	CD Tenerife
## 18	2018	V. Acerval	Colo-Colo
## 19	2018	Victorino Magela	Palmeiras
## 20	2018	A. El-Shenawy	Egypt
## 21	2018	H. Donadelli	Universidad de Chile
## 22	2018	Nivo Serpinho	Grêmio
## 23	2018	Joel Pereira	Manchester United
## 24	2018	Mika	Sunderland
## 25	2018	S. Viera	Junior FC
## 26	2018	A. Adanuy	CD Huachipato
## 27	2018	P. Leciejewski	SK Brann

# 28	2018	A. Lukse	SCR Altach
# 29	2018	Victor Fachinhas	Atlético Mineiro
# 30	2018	R. Zapata	Independiente Santa Fe
# 31	2018	T. Kirschbaum	1. FC Nürnberg
# 32	2018	T. Wellenreuther	Willem II
# 33	2018	S. Bruzzese	KV Kortrijk
# 34	2018	K. Kronholm	Holstein Kiel
# 35	2018	J. Mall	SV Darmstadt 98
# 36	2018	Y. Thuram	Le Havre AC
# 37	2018	D. Albil	Independiente
# 38	2018	T. Boss	SC Fortuna Köln
# 39	2018	M. Caillard	En Avant de Guingamp
# 40	2018	E. Redoga	San Luis de Quillota
# 41	2018	Alminho Boas	Vitória
# 42	2018	K. Eisele	FC Hansa Rostock
# 43	2018	A. Meyer	VfB Stuttgart
# 44	2018	A. Horwath	SK Brann
# 45	2018	T. Königsmann	SpVgg Greuther Fürth
# 46	2018	D. Reimann	Borussia Dortmund
# 47	2018	G. Doherty	Derry City
# 48	2018	E. Gründemann	FC Hansa Rostock
# 49	2018	F. Sollacaro	AC Ajaccio
# 50	2018	K. Martin	FC Lausanne-Sport
# 51	2018	R. Coulter	Bray Wanderers
# 52	2018	F. Kraft	VfL Bochum 1848
# 53	2019	Sergio Ramos	Real Madrid
# 54	2019	G. Chiellini	Juventus
# 55	2019	M. Hummels	FC Bayern München
# 56	2019	R. Nainggolan	Inter
# 57	2019	A. Schwolow	SC Freiburg
# 58	2019	M. Kozáčik	Viktoria Plzeň
# 59	2019	Victorino Magela	Bahia
# 60	2019	Nivo Serpinho	Chapecoense
# 61	2019	S. Viera	Junior FC
# 62	2019	Dani Hernández	CD Tenerife
# 63	2019	Joel Pereira	Vitória de Setúbal
# 64	2019	K. Kronholm	Holstein Kiel
# 65	2019	Victor Fachinhas	Ceará Sporting Club
# 66	2019	Mika	Os Belenenses
# 67	2019	R. Zapata	Independiente Santa Fe
# 68	2019	Cheng Yuelei	Guangzhou R&F FC
# 69	2019	T. Kirschbaum	Bayer 04 Leverkusen
# 70	2019	Kaíque Mutto	Atlético Mineiro
# 71	2019	Y. Thuram	Le Havre AC
# 72	2019	T. Boss	SG Dynamo Dresden
# 73	2019	S. Bruzzese	KV Kortrijk
# 74	2019	A. Lukse	SCR Altach
# 75	2019	T. Wellenreuther	Willem II
# 76	2019	P. Leciejewski	Zagłębie Lubin
# 77	2019	Z. Laaroubi	Ohod Club
# 78	2019	B. Maubleu	Grenoble Foot 38
# 79	2019	J. Deumeland	IK Start
# 80	2019	C. Patterson-Sewell	Toronto FC
# 81	2019	D. Reimann	Holstein Kiel

## 82	2019	K. Eisele	Hallescher FC
## 83	2019	M. Caillard	En Avant de Guingamp
## 84	2019	A. Meyer	VfB Stuttgart
## 85	2019	P. Gori	Benevento
## 86	2019	Yang Jun	Tianjin Quanjian FC
## 87	2019	A. Horwath	Real Salt Lake
## 88	2019	T. Königsmann	SpVgg Greuther Fürth
## 89	2019	G. Doherty	Derry City
## 90	2019	L. Weinkauf	Hannover 96
## 91	2019	E. Gründemann	FC Hansa Rostock
## 92	2019	N. Quindt	VfL Sportfreunde Lotte
## 93	2019	F. Maddaloni	Chamois Niortais Football Club
## 94	2019	F. Sollacaro	AC Ajaccio
## 95	2019	F. Kraft	VfL Bochum 1848
## 96	2019	K. Yoshimaru	Vissel Kobe
## 97	2019	N. Stephan	FC Würzburger Kickers
## 98	2020	Sergio Ramos	Real Madrid
## 99	2020	R. Nainggolan	Cagliari
## 100	2020	G. Chiellini	Juventus
## 101	2020	K. Manolas	Napoli
## 102	2020	A. Laporte	Manchester City
## 103	2020	J. Vertonghen	Tottenham Hotspur
## 104	2020	A. Vidal	FC Barcelona
## 105	2020	T. Delaney	Borussia Dortmund
##		nationality	overall
		defending	sliding_tackle
## 1		Germany	87
## 2		Italy	87
## 3		Germany	87
## 4		Spain	87
## 5		Portugal	84
## 6		Germany	88
## 7		Germany	90
## 8		Italy	86
## 9		Spain	89
## 10		Portugal	88
## 11		Italy	88
## 12		Spain	90
## 13		Germany	88
## 14		Germany	88
## 15		Italy	89
## 16		Germany	75
## 17		Venezuela	75
## 18		Chile	74
## 19		Brazil	74
## 20		Egypt	73
## 21		Chile	73
## 22		Brazil	73
## 23		Portugal	71
## 24		Portugal	71
## 25		Uruguay	71
## 26		Chile	70
## 27		Poland	70
## 28		Austria	70
## 29		Brazil	70

## 30	Colombia	69	9
## 31	Germany	69	9
## 32	Germany	68	9
## 33	Belgium	68	9
## 34	United States	68	9
## 35	Switzerland	67	9
## 36	France	66	9
## 37	Argentina	64	9
## 38	Germany	63	9
## 39	France	63	9
## 40	Chile	63	9
## 41	Brazil	63	9
## 42	Germany	62	9
## 43	Germany	62	9
## 44	United States	62	9
## 45	Germany	61	9
## 46	Germany	60	9
## 47	Northern Ireland	60	9
## 48	Germany	58	9
## 49	France	57	9
## 50	Switzerland	56	9
## 51	Republic of Ireland	54	9
## 52	Germany	52	9
## 53	Spain	91	91
## 54	Italy	89	90
## 55	Germany	89	90
## 56	Belgium	85	90
## 57	Germany	77	9
## 58	Slovakia	75	9
## 59	Brazil	74	9
## 60	Brazil	73	9
## 61	Uruguay	72	9
## 62	Venezuela	72	9
## 63	Portugal	71	9
## 64	United States	70	9
## 65	Brazil	70	9
## 66	Portugal	69	9
## 67	Colombia	69	9
## 68	China PR	69	9
## 69	Germany	69	9
## 70	Brazil	69	9
## 71	France	68	9
## 72	Germany	67	9
## 73	Belgium	67	9
## 74	Austria	67	9
## 75	Germany	66	9
## 76	Poland	66	9
## 77	Morocco	66	9
## 78	France	64	9
## 79	Germany	64	9
## 80	United States	64	9
## 81	Germany	63	9
## 82	Germany	63	9
## 83	France	63	9

## 84	Germany	63	9
## 85	Italy	63	9
## 86	China PR	62	9
## 87	United States	62	9
## 88	Germany	61	9
## 89	Northern Ireland	60	9
## 90	Germany	59	9
## 91	Germany	58	9
## 92	Germany	58	9
## 93	France	58	9
## 94	France	57	9
## 95	Germany	55	9
## 96	Japan	54	9
## 97	Germany	49	9
## 98	Spain	89	90
## 99	Belgium	83	90
## 100	Italy	89	89
## 101	Greece	85	89
## 102	France	87	88
## 103	Belgium	87	88
## 104	Chile	84	88
## 105	Denmark	82	88

```
# Team Stats
```

```
for (i in seq_along(fifa_datasets_list)) {

  # Top 10 teams with highest average player overall
  top_10_teams <- fifa_datasets_list[[i]] %>%
    filter(!club %in% c("Uruguay", "Colombia", "Mexico", "Netherlands")) %>%
    group_by(club) %>% summarise(avg_player_ovr = mean(overall)) %>%
    arrange(desc(avg_player_ovr)) %>% top_n(10)
  print(paste("Year", years[[i]], ":"))

  print(top_10_teams)

  # Top 10 teams with highest average player overall in
  # the starting 11 excluding subs and reserves
  top_10_special <- fifa_datasets_list[[i]] %>%
    filter(!club %in% c("Uruguay", "Colombia", "Mexico", "Netherlands")) %>%
    filter(!team_position %in% c("SUB", "RES")) %>%
    group_by(club) %>% summarise(avg_player_ovr = mean(overall)) %>%
    arrange(desc(avg_player_ovr)) %>% top_n(10)
  print(paste("Year", years[[i]], ":", "excluding reserves and substitute players"))
  print(top_10_special)

  # Worst 10 teams:
  worst_teams <- fifa_datasets_list[[i]] %>%
    filter(!club %in% c("Uruguay", "Colombia", "Mexico", "Netherlands", "India")) %>%
    filter(!team_position %in% c("SUB", "RES")) %>%
    group_by(club) %>%
    summarise(avg_player_ovr = mean(overall)) %>%
    arrange(avg_player_ovr) %>% top_n(10)
  print(paste("Year", years[[i]], ":", "worst 10 teams"))
  print(worst_teams)
}
```

```

# Top 10 most valuable squads:
most_val_team <- fifa_datasets_list[[i]] %>% group_by(club)%>%
  summarise(squad_value_eur = sum(value_eur)) %>% arrange(desc(squad_value_eur)) %>% top_n(10)
print(paste("Year", years[[i]], ":", "most valuable squads"))
print(most_val_team)

# Top 10 high weekly wage teams:
most_wage_team <- fifa_datasets_list[[i]] %>% group_by(club)%>%
  summarise(wage_value_eur = sum(wage_eur)) %>% arrange(desc(wage_value_eur)) %>% top_n(10)
print(paste("Year", years[[i]], ":", "high weekly wage"))
print(most_wage_team)
}

## Selecting by avg_player_ovr

## [1] "Year 2016 :"
## # A tibble: 10 x 2
##   club           avg_player_ovr
##   <chr>          <dbl>
## 1 Brazil          81
## 2 Juventus       79.3
## 3 FC Bayern München 78.7
## 4 FC Barcelona    78.6
## 5 Austria          78
## 6 Manchester City 77.2
## 7 Real Madrid      77.1
## 8 Atlético Madrid   76.9
## 9 Paris Saint-Germain 76.8
## 10 Napoli          76.7

## Selecting by avg_player_ovr

## [1] "Year 2016 : excluding reserves ans substitute players"
## # A tibble: 10 x 2
##   club           avg_player_ovr
##   <chr>          <dbl>
## 1 FC Barcelona    86.1
## 2 Real Madrid     85.5
## 3 FC Bayern München 84.9
## 4 Paris Saint-Germain 83.6
## 5 Chelsea          83.4
## 6 Manchester City 82.4
## 7 Juventus          82
## 8 Manchester United 82
## 9 Arsenal            81.7
## 10 Atlético Madrid   81.5

## Selecting by avg_player_ovr

## [1] "Year 2016 : worst 10 teams"
## # A tibble: 10 x 2

```

```

##   club           avg_player_ovr
##   <chr>          <dbl>
## 1 Atlético Madrid      81.5
## 2 Arsenal              81.7
## 3 Juventus             82
## 4 Manchester United    82
## 5 Manchester City      82.4
## 6 Chelsea               83.4
## 7 Paris Saint-Germain  83.6
## 8 FC Bayern München    84.9
## 9 Real Madrid           85.5
## 10 FC Barcelona          86.1

```

`## Selecting by squad_value_eur`

```

## [1] "Year 2016 : most valuable squads"
## # A tibble: 10 x 2
##   club           squad_value_eur
##   <chr>          <int>
## 1 FC Bayern München 615490000
## 2 Real Madrid       610475000
## 3 FC Barcelona       584950000
## 4 Chelsea            484850000
## 5 Paris Saint-Germain 441390000
## 6 Manchester City    434150000
## 7 Arsenal             401890000
## 8 Juventus            390100000
## 9 Manchester United   366715000
## 10 Borussia Dortmund  349365000

```

`## Selecting by wage_value_eur`

```

## [1] "Year 2016 : high weekly wage"
## # A tibble: 10 x 2
##   club           wage_value_eur
##   <chr>          <int>
## 1 FC Barcelona     3501000
## 2 FC Bayern München 3472000
## 3 Real Madrid      3304000
## 4 Chelsea           2880000
## 5 Manchester City   2814000
## 6 Paris Saint-Germain 2759000
## 7 Juventus           2656000
## 8 Arsenal             2635000
## 9 Borussia Dortmund  2398000
## 10 Manchester United 2250000

```

`## Selecting by avg_player_ovr`

```

## [1] "Year 2017 :"
## # A tibble: 10 x 2
##   club           avg_player_ovr
##   <chr>          <dbl>
## 1 Atlético Madrid      81.5
## 2 Arsenal              81.7
## 3 Juventus             82
## 4 Manchester United    82
## 5 Manchester City      82.4
## 6 Chelsea               83.4
## 7 Paris Saint-Germain  83.6
## 8 FC Bayern München    84.9
## 9 Real Madrid           85.5
## 10 FC Barcelona          86.1

```

```

##      <chr>                <dbl>
## 1 Juventus                  81
## 2 Argentina                 80
## 3 Italy                     80
## 4 Brazil                    79.7
## 5 FC Bayern München          79.5
## 6 Portugal                  79
## 7 Turkey                    79
## 8 Real Madrid                78.5
## 9 Manchester United          77.9
## 10 FC Barcelona               77.8

## Selecting by avg_player_ovr

## [1] "Year 2017 : excluding reserves ans substitute players"
## # A tibble: 10 x 2
##   club           avg_player_ovr
##   <chr>            <dbl>
## 1 Real Madrid             87.8
## 2 FC Bayern München        87.5
## 3 FC Barcelona              87
## 4 Juventus                 85.4
## 5 Arsenal                  84.5
## 6 Chelsea                  84.5
## 7 Atlético Madrid            83.9
## 8 Paris Saint-Germain       83.9
## 9 Manchester City            83.6
## 10 Manchester United          82.9

## Selecting by avg_player_ovr

## [1] "Year 2017 : worst 10 teams"
## # A tibble: 10 x 2
##   club           avg_player_ovr
##   <chr>            <dbl>
## 1 Manchester United          82.9
## 2 Manchester City             83.6
## 3 Atlético Madrid             83.9
## 4 Paris Saint-Germain         83.9
## 5 Arsenal                   84.5
## 6 Chelsea                    84.5
## 7 Juventus                   85.4
## 8 FC Barcelona                  87
## 9 FC Bayern München            87.5
## 10 Real Madrid                  87.8

## Selecting by squad_value_eur

## [1] "Year 2017 : most valuable squads"
## # A tibble: 10 x 2
##   club           squad_value_eur
##   <chr>            <int>

```

```

## 1 Real Madrid           772175000
## 2 FC Barcelona          702575000
## 3 FC Bayern München     651890000
## 4 Manchester United     565235000
## 5 Chelsea                 519480000
## 6 Arsenal                  512225000
## 7 Atlético Madrid         493245000
## 8 Paris Saint-Germain    492475000
## 9 Juventus                 485125000
## 10 Manchester City        483045000

```

Selecting by wage_value_eur

```

## [1] "Year 2017 : high weekly wage"
## # A tibble: 10 x 2
##   club             wage_value_eur
##   <chr>            <int>
## 1 Real Madrid      2734000
## 2 FC Barcelona     2550000
## 3 FC Bayern München 2484000
## 4 Manchester United 2225000
## 5 Juventus        2177000
## 6 Chelsea          2090000
## 7 Arsenal          2064000
## 8 Manchester City  1958000
## 9 Borussia Dortmund 1897000
## 10 Paris Saint-Germain 1872000

```

Selecting by avg_player_ovr

```

## [1] "Year 2018 :"
## # A tibble: 11 x 2
##   club             avg_player_ovr
##   <chr>            <dbl>
## 1 Portugal          83
## 2 FC Barcelona      82.4
## 3 Belgium           82
## 4 Juventus          81.7
## 5 Real Madrid       81.0
## 6 Brazil             80
## 7 Sweden             80
## 8 FC Bayern München 79.4
## 9 Paris Saint-Germain 78.0
## 10 Manchester United 77.7
## 11 Napoli            77.7

```

Selecting by avg_player_ovr

```

## [1] "Year 2018 : excluding reserves ans substitute players"
## # A tibble: 10 x 2
##   club             avg_player_ovr
##   <chr>            <dbl>
## 1 Portugal          83
## 2 FC Barcelona      82.4
## 3 Belgium           82
## 4 Juventus          81.7
## 5 Real Madrid       81.0
## 6 Brazil             80
## 7 Sweden             80
## 8 FC Bayern München 79.4
## 9 Paris Saint-Germain 78.0
## 10 Manchester United 77.7

```

```

## 1 Real Madrid           87.6
## 2 FC Bayern München    87.2
## 3 FC Barcelona          86.2
## 4 Juventus              85.6
## 5 Chelsea                84.6
## 6 Atlético Madrid        84.5
## 7 Paris Saint-Germain   84.1
## 8 Tottenham Hotspur      83.8
## 9 Arsenal                 83.7
## 10 Manchester United     83.7

```

`## Selecting by avg_player_ovr`

```

## [1] "Year 2018 : worst 10 teams"
## # A tibble: 10 x 2
##   club           avg_player_ovr
##   <chr>            <dbl>
## 1 Arsenal           83.7
## 2 Manchester United 83.7
## 3 Tottenham Hotspur 83.8
## 4 Paris Saint-Germain 84.1
## 5 Atlético Madrid   84.5
## 6 Chelsea            84.6
## 7 Juventus           85.6
## 8 FC Barcelona        86.2
## 9 FC Bayern München   87.2
## 10 Real Madrid         87.6

```

`## Selecting by squad_value_eur`

```

## [1] "Year 2018 : most valuable squads"
## # A tibble: 10 x 2
##   club           squad_value_eur
##   <chr>            <int>
## 1 Real Madrid       826750000
## 2 FC Bayern München 748825000
## 3 FC Barcelona       715000000
## 4 Chelsea            671910000
## 5 Paris Saint-Germain 631750000
## 6 Juventus           617100000
## 7 Manchester United   610625000
## 8 Manchester City      578715000
## 9 Atlético Madrid      566150000
## 10 Tottenham Hotspur     525955000

```

`## Selecting by wage_value_eur`

```

## [1] "Year 2018 : high weekly wage"
## # A tibble: 10 x 2
##   club           wage_value_eur
##   <chr>            <int>
## 1 Real Madrid        4751000

```

```

## 2 FC Barcelona          4532000
## 3 Manchester United    3557000
## 4 Chelsea                3545000
## 5 FC Bayern München      3273000
## 6 Juventus               3165000
## 7 Manchester City        3157000
## 8 Arsenal                 3007000
## 9 Liverpool               2752000
## 10 Everton                2499000

## Selecting by avg_player_ovr

## [1] "Year 2019 :"
## # A tibble: 10 x 2
##   club           avg_player_ovr
##   <chr>            <dbl>
## 1 Juventus          82.2
## 2 FC Barcelona       80.3
## 3 Argentina          80
## 4 Napoli              79.8
## 5 Inter               79.7
## 6 FC Bayern München  78.5
## 7 Milan               78.0
## 8 Real Madrid         77.8
## 9 Sweden              77.7
## 10 Manchester United 77.5

## Selecting by avg_player_ovr

## [1] "Year 2019 : excluding reserves and substitute players"
## # A tibble: 10 x 2
##   club           avg_player_ovr
##   <chr>            <dbl>
## 1 Real Madrid        87.7
## 2 FC Barcelona        87.6
## 3 FC Bayern München  86.4
## 4 Juventus            86.3
## 5 Manchester City     86.2
## 6 Atlético Madrid     85.3
## 7 Paris Saint-Germain 84.7
## 8 Tottenham Hotspur    84.7
## 9 Chelsea              84.4
## 10 Manchester United   84.1

## Selecting by avg_player_ovr

## [1] "Year 2019 : worst 10 teams"
## # A tibble: 10 x 2
##   club           avg_player_ovr
##   <chr>            <dbl>
## 1 Manchester United    84.1
## 2 Chelsea                84.4

```

```

## 3 Paris Saint-Germain      84.7
## 4 Tottenham Hotspur       84.7
## 5 Atlético Madrid         85.3
## 6 Manchester City         86.2
## 7 Juventus                 86.3
## 8 FC Bayern München        86.4
## 9 FC Barcelona              87.6
## 10 Real Madrid             87.7

```

`## Selecting by squad_value_eur`

```

## [1] "Year 2019 : most valuable squads"
## # A tibble: 10 x 2
##   club           squad_value_eur
##   <chr>          <int>
## 1 Real Madrid     880075000
## 2 FC Barcelona    837925000
## 3 Manchester City 757395000
## 4 FC Bayern München 715310000
## 5 Juventus        691975000
## 6 Atlético Madrid 641280000
## 7 Manchester United 627550000
## 8 Chelsea          620360000
## 9 Paris Saint-Germain 612725000
## 10 Tottenham Hotspur 600710000

```

`## Selecting by wage_value_eur`

```

## [1] "Year 2019 : high weekly wage"
## # A tibble: 10 x 2
##   club           wage_value_eur
##   <chr>          <int>
## 1 Real Madrid     4961000
## 2 FC Barcelona    4747000
## 3 Manchester City 3721000
## 4 Manchester United 3522000
## 5 Juventus        3271000
## 6 Chelsea          3266000
## 7 Liverpool        2911000
## 8 Tottenham Hotspur 2528000
## 9 Arsenal          2514000
## 10 FC Bayern München 2413000

```

`## Selecting by avg_player_ovr`

```

## [1] "Year 2020 :"
## # A tibble: 10 x 2
##   club           avg_player_ovr
##   <chr>          <dbl>
## 1 FC Bayern München 81.3
## 2 Real Madrid      80.1
## 3 Juventus          80.1

```

```

## 4 FC Barcelona          78.4
## 5 Bayer 04 Leverkusen   77.3
## 6 Chelsea                77.1
## 7 Manchester City        77
## 8 Napoli                  76.9
## 9 Manchester United      76.8
## 10 Tottenham Hotspur     76.5

```

Selecting by avg_player_ovr

```

## [1] "Year 2020 : excluding reserves ans substitute players"
## # A tibble: 10 x 2
##   club           avg_player_ovr
##   <chr>            <dbl>
## 1 FC Barcelona      87.6
## 2 Real Madrid       86.7
## 3 Manchester City   86.4
## 4 Liverpool          85.7
## 5 FC Bayern München  85.5
## 6 Juventus           85.3
## 7 Paris Saint-Germain 85.2
## 8 Tottenham Hotspur    84.1
## 9 Borussia Dortmund   83.6
## 10 Atlético Madrid     83.2

```

Selecting by avg_player_ovr

```

## [1] "Year 2020 : worst 10 teams"
## # A tibble: 10 x 2
##   club           avg_player_ovr
##   <chr>            <dbl>
## 1 Atlético Madrid     83.2
## 2 Borussia Dortmund   83.6
## 3 Tottenham Hotspur    84.1
## 4 Paris Saint-Germain 85.2
## 5 Juventus           85.3
## 6 FC Bayern München   85.5
## 7 Liverpool          85.7
## 8 Manchester City      86.4
## 9 Real Madrid          86.7
## 10 FC Barcelona        87.6

```

Selecting by squad_value_eur

```

## [1] "Year 2020 : most valuable squads"
## # A tibble: 10 x 2
##   club           squad_value_eur
##   <chr>            <int>
## 1 Real Madrid      897850000
## 2 FC Barcelona      869300000
## 3 Manchester City   845745000
## 4 Juventus          735475000

```

```

## 5 Liverpool          693265000
## 6 FC Bayern München 688775000
## 7 Paris Saint-Germain 687550000
## 8 Tottenham Hotspur   649850000
## 9 Atlético Madrid     590375000
## 10 Borussia Dortmund    532325000

## Selecting by wage_value_eur

## [1] "Year 2020 : high weekly wage"
## # A tibble: 10 x 2
##   club           wage_value_eur
##   <chr>            <int>
## 1 Real Madrid      5354000
## 2 FC Barcelona     4950000
## 3 Manchester City  3984000
## 4 Juventus         3750000
## 5 Manchester United 2874000
## 6 Chelsea          2806000
## 7 Liverpool         2667000
## 8 Tottenham Hotspur 2603000
## 9 FC Bayern München 2516000
## 10 Paris Saint-Germain 2396000

# FIFA World 11 - AGED 23 OR LESS

unique(fifa20$team_position)

## [1] "RW"   "LW"   "CAM"  "GK"   "RCM"  "LCB"  "ST"   "CDM"  "LDM"  "RM"   "RCB"
## [12] "LCM"  "LM"   "CF"   "SUB"  "LB"   "LS"   "RB"   "RDM"  "RES"  "RAM"  "RS"
## [23] "RF"   "CM"   "CB"   "LF"   "LAM"  "RWB"  "LWB"

# Assuming a 4231 formation, we come up with the best team for each year.

for (i in seq_along(fifa_datasets_list)) {
  print(paste("Year", years[[i]], ":"))
  fifa_team_leq_23 <- fifa_datasets_list[[i]] %>% filter(age <= 23)
  team_of_the_year(fifa_team_leq_23)
}

## [1] "Year 2016 :"

## Selecting by overall
```

	short_name	team_position	overall
## 1	Morata	LS	81
## 2	Neymar	LW	88
## 3	M. Salah	RW	80
## 4	D. Berardi	RW	80
## 5	J. Rodríguez	CAM	87
## 6	M. Verratti	RCM	84
## 7	P. Pogba	LCM	86
## 8	R. Rodriguez	LB	83
## 9	Carvajal	RB	81
## 10	D. Alaba	LCB	85
## 11	S. Mustafi	RCB	82
## 12	B. Leno	GK	84
## [1] "Year 2017 :"			

```

##          short_name team_position overall
## 1      P. Dybala        RS     85
## 2      Lucas         LW     82
## 3    R. Sterling       RW     82
## 4    D. Berardi       RW     82
## 5    R. Barkley      CAM     81
## 6 Bernardo Silva     RAM     81
## 7    M. Verratti     RCM     85
## 8    P. Pogba        LDM     88
## 9    R. Rodríguez      LB     83
## 10   S. Aurier        RB     83
## 11   A. Laporte       LCB     84
## 12   E. Bailly        RCB     82
## 13 Marquinhos        RCB     82
## 14   J. Oblak          GK     87
## [1] "Year 2018 :"

```

```

## Selecting by overall
## Selecting by overall

##           short_name team_position overall
## 1          H. Kane            ST    86
## 2        O. Dembélé          LW    83
## 3       K. Mbappé          RW    83
## 4        P. Dybala         CAM    88
## 5       Fabinho          RDM    83
## 6        N. Keïta          RDM    83
## 7         Saúl            LCM    82
## 8      T. Bakayoko         LCM    82
## 9         Gayà             LB    79
## 10     Héctor Bellerín        RWB    81
## 11      J. Kimmich            RB    81
## 12      A. Laporte           LCB    84
## 13      E. Bailly            RCB    84
## 14     Ederson              GK    83
## [1] "Year 2019 :"

```

	short_name	team_position	overall
## 1	T. Werner	LS	83
## 2	L. Sané	LW	86
## 3	K. Mbappé	RW	87
## 4	D. Alli	CAM	84
## 5	S. Milinković-Savić	CM	85
## 6	Saul	LCM	85
## 7	S. Milinković-Savić	CM	85
## 8	Grimaldo	LB	81
## 9	B. Mendy	LB	81
## 10	J. Kimmich	RB	85
## 11	V. Lindelöf	LCB	79
## 12	N. Aké	LCB	79
## 13	K. Rekik	LCB	79
## 14	M. Škriniar	RCB	85
## 15	Kepa	GK	83
## [1]	"Year 2020 :"		

```
## Selecting by overall  
## Selecting by overall  
## Selecting by overall
```

ONLY for Year 2020

```
# HIGHEST RATED PLAYERS FOR FAMOUS JERSEY NUMBERS: 1,2,3,4,5,6,7,8,9,10,11  
  
fifa20 %>% filter(team_jersey_number==1) %>%  
  arrange(desc(overall))%>%  
  select(short_name, team_jersey_number, overall) %>% top_n(1)
```

```
## Selecting by overall  
## # A tibble: 1 x 3  
##   short_name  team_jersey_number overall  
##   <chr>          <int>     <int>  
## 1 M. ter Stegen           1       90
```

```
#Ter Stegen  
fifa20 %>% filter(team_jersey_number==2) %>%  
  arrange(desc(overall))%>%  
  select(short_name, team_jersey_number, overall) %>% top n(1)
```

```
## Selecting by overall  
## # A tibble: 1 x 3  
##   short_name team_jersey_number overall  
##   <chr>          <int>     <int>  
## 1 D. Godín        ?     88
```

#Godin

```
fifa20 %>% filter(team_jersey_number==3) %>%
  arrange(desc(overall))%>%
  select(short_name, team_jersey_number, overall) %>% top_n(1)
```

Selecting by overall

```
## # A tibble: 1 x 3
##   short_name  team_jersey_number overall
##   <chr>           <int>      <int>
## 1 G. Chiellini            3        89
```

#Chiellini

```
fifa20 %>% filter(team_jersey_number==4) %>%
  arrange(desc(overall))%>%
  select(short_name, team_jersey_number, overall) %>% top_n(1)
```

Selecting by overall

```
## # A tibble: 1 x 3
##   short_name  team_jersey_number overall
##   <chr>           <int>      <int>
## 1 V. van Dijk            4        90
```

#Van Dijk

```
fifa20 %>% filter(team_jersey_number==5) %>%
  arrange(desc(overall))%>%
  select(short_name, team_jersey_number, overall) %>% top_n(1)
```

Selecting by overall

```
## # A tibble: 1 x 3
##   short_name  team_jersey_number overall
##   <chr>           <int>      <int>
## 1 Sergio Busquets          5        89
```

#Busquets

```
fifa20 %>% filter(team_jersey_number==6) %>%
  arrange(desc(overall))%>%
  select(short_name, team_jersey_number, overall) %>% top_n(1)
```

Selecting by overall

```
## # A tibble: 1 x 3
##   short_name  team_jersey_number overall
##   <chr>           <int>      <int>
## 1 P. Pogba            6        88
```

```
#Pogba
```

```
fifa20 %>% filter(team_jersey_number==7) %>%
  arrange(desc(overall))%>%
  select(short_name, team_jersey_number, overall) %>% top_n(1)
```

```
## Selecting by overall
```

```
## # A tibble: 1 x 3
##   short_name      team_jersey_number overall
##   <chr>                <int>     <int>
## 1 Cristiano Ronaldo            7         93
```

```
#Ronaldo
```

```
fifa20 %>% filter(team_jersey_number==8) %>%
  arrange(desc(overall))%>%
  select(short_name, team_jersey_number, overall) %>% top_n(1)
```

```
## Selecting by overall
```

```
## # A tibble: 1 x 3
##   short_name      team_jersey_number overall
##   <chr>                <int>     <int>
## 1 T. Kroos                  8         88
```

```
#Toni Kroos
```

```
fifa20 %>% filter(team_jersey_number==9) %>%
  arrange(desc(overall))%>%
  select(short_name, team_jersey_number, overall) %>% top_n(1)
```

```
## Selecting by overall
```

```
## # A tibble: 2 x 3
##   short_name      team_jersey_number overall
##   <chr>                <int>     <int>
## 1 L. Suárez                  9         89
## 2 R. Lewandowski              9         89
```

```
#Lewandowski
```

```
fifa20 %>% filter(team_jersey_number==10) %>%
  arrange(desc(overall))%>%
  select(short_name, team_jersey_number, overall) %>% top_n(1)
```

```
## Selecting by overall
```

```
## # A tibble: 1 x 3
##   short_name      team_jersey_number overall
##   <chr>                <int>     <int>
## 1 L. Messi                  10        94
```

#Messi

```
fifa20 %>% filter(team_jersey_number==11) %>%
  arrange(desc(overall))%>%
  select(short_name, team_jersey_number, overall) %>% top_n(1)
```

Selecting by overall

```
## # A tibble: 1 x 3
##   short_name team_jersey_number overall
##   <chr>           <int>      <int>
## 1 M. Salah            11        90
```

#Salah

```
# PLAYERS WITH THE BEST SKILL MOVES WITH OVERALL >=85
fifa20 %>% filter(overall>=85,skill_moves==5)%>%arrange(desc(skill_moves)) %>%
  select(short_name, club, nationality, team_position,overall,skill_moves) %>%
  group_by(skill_moves) %>% top_n(1) %>% ungroup()
```

Selecting by skill_moves

```
## # A tibble: 9 x 6
##   short_name   club     nationality team_position overall skill_moves
##   <chr>       <chr>    <chr>       <chr>      <int>      <int>
## 1 Cristiano Ron- Juventus Portugal    LW          93        5
## 2 Neymar Jr    Paris Saint- Brazil     CAM         92        5
## 3 K. Mbappé    Paris Saint- France    RW          89        5
## 4 P. Pogba     Manchester ~ France  LDM         88        5
## 5 Thiago       FC Bayern M- Spain    CDM         87        5
## 6 A. Di María  Paris Saint- Argentina LW          86        5
## 7 Coutinho      FC Bayern M- Brazil   LCM         86        5
## 8 Z. Ibrahimović LA Galaxy Sweden    ST          85        5
## 9 Marcelo      Real Madrid Brazil    LB          85        5
```

PLAYERS WITH BEST WEAK FOOT WITH OVERALL >=85

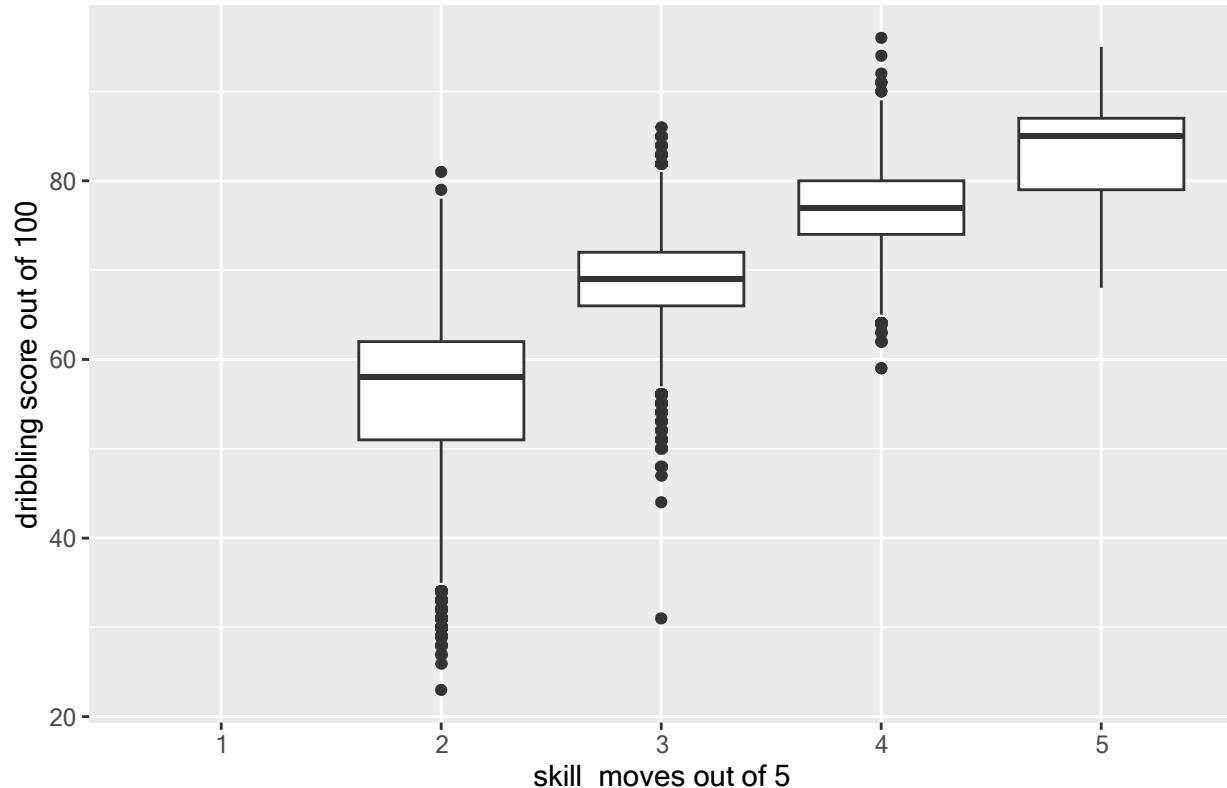
```
fifa20 %>% filter(overall>=85,weak_foot==5)%>%arrange(desc(weak_foot)) %>%
  select(short_name, club, nationality, team_position,overall,weak_foot) %>%
  group_by(weak_foot) %>% top_n(1) %>% ungroup()
```

Selecting by weak_foot

```
## # A tibble: 5 x 6
##   short_name   club     nationality team_position overall weak_foot
##   <chr>       <chr>    <chr>       <chr>      <int>      <int>
## 1 Neymar Jr    Paris Saint-G- Brazil    CAM         92        5
## 2 K. De Bruyne Manchester Ci- Belgium  RCM         91        5
## 3 C. Eriksen    Tottenham Hot- Denmark  RM          88        5
## 4 T. Kroos      Real Madrid Germany   LCM         88        5
## 5 H. Son        Tottenham Hot- Korea Republ- LM          87        5
```

```
# Boxplot of skill_moves vs dribbling
fifa20 %>% ggplot(aes(as.factor(skill_moves),dribbling))+geom_boxplot()+
  labs(x="skill_moves out of 5",y="dribbling score out of 100",
       title = "Boxplot of skill_moves vs dribbling")
```

Boxplot of skill_moves vs dribbling



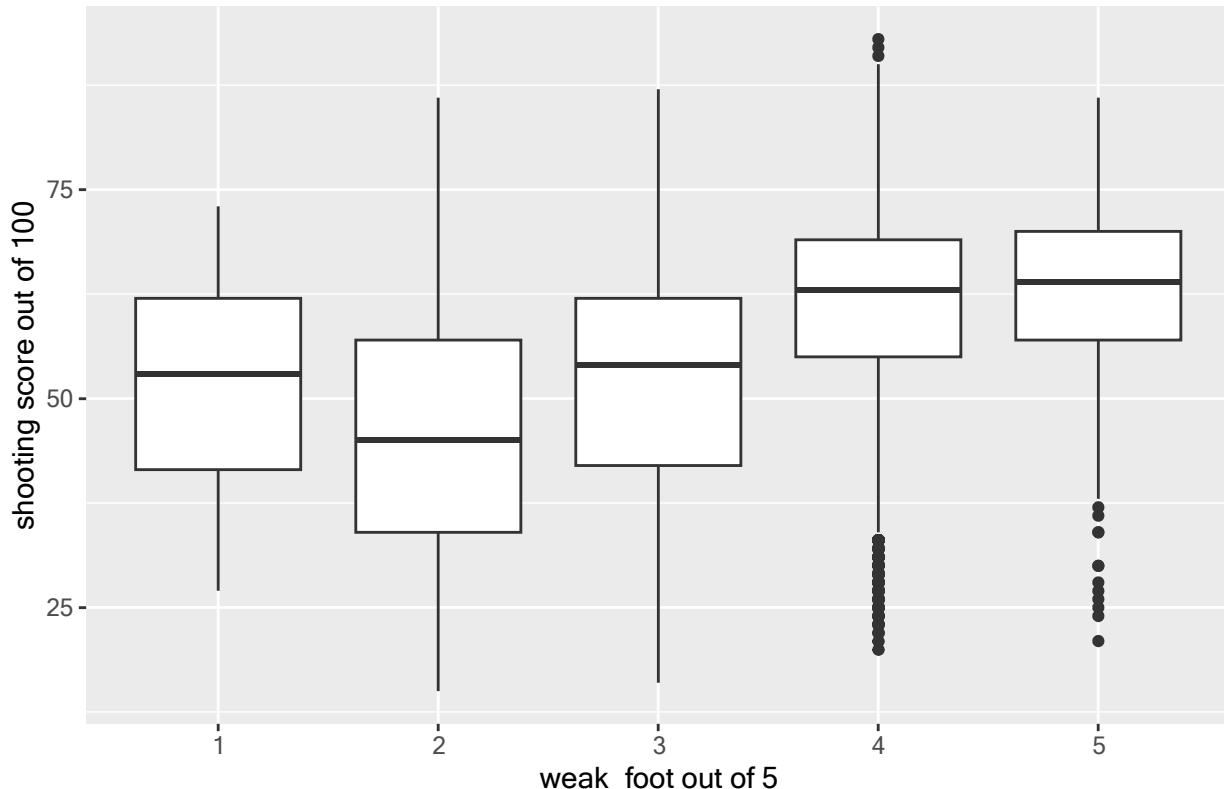
```
#They are positively correlated
#Strength of correlation:
cor(fifa20$skill_moves, fifa20$dribbling, method = "spearman",
     use = "complete.obs")
```

```
## [1] 0.7873962
```

```
# High positive correlation.
```

```
# Are players with a strong weak foot good at shooting?
# Boxplot of weak foot vs shooting
fifa20 %>% ggplot(aes(as.factor(weak_foot),shooting))+geom_boxplot()+
  labs(x="weak_foot out of 5",y="shooting score out of 100",
       title = "Boxplot of weak foot vs shooting")
```

Boxplot of weak foot vs shooting



```
# Strength of correlation:
cor(fifa20$weak_foot, fifa20$shooting, method = "spearman",
    use = "complete.obs")
```

```
## [1] 0.3237961
```

```
# Weak positive correlation
```

```
# Split work rate into 2 columns: attack and defence work rate:
fifa20 <- separate(fifa20, work_rate, into = c("attack_workrate","defence_workrate"),
                     sep = "/")
```

```
# Good players with high attack and defence workrates:
fifa20 %>% filter(overall >= 85, attack_workrate == "High", defence_workrate == "High") %>%
  arrange(desc(overall)) %>%
  select(short_name, club, nationality, team_position,
         attack_workrate, defence_workrate, overall) %>% group_by(overall) %>%
  top_n(1) %>% ungroup()
```

```
## Selecting by overall
```

```
## # A tibble: 18 x 7
##   short_name club  nationality team_position attack_workrate
##   <chr>      <chr>  <chr>        <chr>          <chr>
## 1 K. De Bru- Manc- Belgium     RCM          High
```

```

## 2 L. Modrić Real- Croatia RCM High
## 3 H. Kane Tott- England ST High
## 4 A. Griezm- FC B- France LW High
## 5 C. Eriksen Tott- Denmark RM High
## 6 E. Cavani Pari- Uruguay ST High
## 7 Bernardo ~ Manc- Portugal RW High
## 8 H. Son Tott- Korea Repu- LM High
## 9 J. Verton- Tott- Belgium LCB High
## 10 Roberto F- Live- Brazil CF High
## 11 T. Müller FC B- Germany SUB High
## 12 A. Lacaze- Arse- France ST High
## 13 Saúl Atlé- Spain LCM High
## 14 A. Robert- Live- Scotland LB High
## 15 Bruno Fer- Spor- Portugal RCM High
## 16 Carvajal Real- Spain RB High
## 17 Iago Aspas RC C- Spain RS High
## 18 Koke Atlé- Spain RM High
## # ... with 2 more variables: defence_workrate <chr>, overall <int>

```

```

# Laziest players on fifa20
fifa20 %>% filter(attack_workrate == "Low", defence_workrate == "Low") %>%
  arrange(desc(overall)) %>%
  select(short_name, club, nationality, team_position,
         attack_workrate, defence_workrate, overall) %>% group_by(overall) %>%
  top_n(1) %>% ungroup()

```

```
## Selecting by overall
```

```

## # A tibble: 35 x 7
##   short_name club  nationality team_position attack_workrate
##   <chr>      <chr> <chr>        <chr>          <chr>
## 1 C. Strand- Öreb- Sweden       LS            Low
## 2 M. Kramer  ADO ~ Netherlands SUB           Low
## 3 A. Fink    Karl- Germany     SUB           Low
## 4 S. Ameobi  Nott- England    SUB           Low
## 5 P. Forsell HJK ~ Finland   RES           Low
## 6 C. Kazim-- Tibu- Turkey    RS            Low
## 7 N. Schmidt VfL ~ Germany   SUB           Low
## 8 A. Ba      AJ A- Mauritania SUB           Low
## 9 Abraham G- Tibu- Spain     LDM           Low
## 10 E. Kujović Djur- Sweden   RES           Low
## # ... with 25 more rows, and 2 more variables: defence_workrate <chr>,
## #   overall <int>

```

```

# SUMMARIES OF FEW COLUMNS
sum_stats <- fifa20 %>% select(overall, potential, value_eur, wage_eur,
                                 release_clause_eur,
                                 pace, shooting, passing,
                                 dribbling, physic, defending)
summary(sum_stats)

```

```
##   overall      potential      value_eur      wage_eur
```

```

## Min. :48.00  Min. :49.00  Min. :      0  Min. :      0
## 1st Qu.:62.00 1st Qu.:67.00 1st Qu.: 325000 1st Qu.: 1000
## Median :66.00 Median :71.00 Median : 700000 Median : 3000
## Mean   :66.24 Mean   :71.55 Mean   :2484038 Mean   : 9457
## 3rd Qu.:71.00 3rd Qu.:75.00 3rd Qu.:2100000 3rd Qu.: 8000
## Max.  :94.00  Max.  :95.00  Max. :105500000 Max.  :565000
##
## release_clause_eur      pace      shooting      passing
## Min.   :13000  Min.   :24.0  Min.   :15.0  Min.   :24.00
## 1st Qu.: 563000 1st Qu.:61.0 1st Qu.:42.0 1st Qu.:50.00
## Median :1200000 Median :69.0  Median :54.0  Median :58.00
## Mean   :4740717 Mean   :67.7  Mean   :52.3  Mean   :57.23
## 3rd Qu.:3700000 3rd Qu.:75.0 3rd Qu.:63.0 3rd Qu.:64.00
## Max.  :195800000 Max.  :96.0  Max.  :93.0  Max.  :92.00
## NA's   :1298    NA's   :2036  NA's   :2036  NA's   :2036
## dribbling      physic      defending
## Min.   :23.00  Min.   :27.00  Min.   :15.00
## 1st Qu.:57.00 1st Qu.:59.00 1st Qu.:36.00
## Median :64.00  Median :66.00  Median :56.00
## Mean   :62.53  Mean   :64.88  Mean   :51.55
## 3rd Qu.:69.00 3rd Qu.:72.00 3rd Qu.:65.00
## Max.  :96.00  Max.  :90.00  Max.  :90.00
## NA's   :2036  NA's   :2036  NA's   :2036

```

#release_clause_eur is NA for 1298 players, this is because these players do not have a release clause included in their current contract.

#pace, shooting, passing, dribbling, defending and physic is NA for 2036 players, lets find out why

```

pace_na <- fifa20 %>% filter(is.na(pace),is.na(dribbling),is.na(shooting),
                                is.na(passing),is.na(defending),is.na(phsic)) %>%
  select(short_name, club, nationality, team_position, overall)
dim(pace_na) #2036 players with NAs.

```

```
## [1] 2036     5
```

#team positions of these players:

```
unique(pace_na$team_position)
```

```
## [1] "GK"  "SUB" "RES" ""
```

#We can see that goalkeepers, subs and reserve team players do not have values for these 6 attributes.

```
pace_na %>% filter(team_position=="")
```

```

## # A tibble: 40 x 5
##   short_name   club   nationality team_position overall
##   <chr>        <chr>  <chr>       <chr>      <int>
## 1 J. Serendero Uruguay Uruguay     ...          80
## 2 A. Lunev      Russia Russia     ...          79
## 3 L. Sáreda     Uruguay Uruguay     ...          79
## 4 P. Dárenas    Uruguay Uruguay     ...          75

```

```

## 5 H. Lindner Austria Austria .... 74
## 6 M. Borjan Canada Canada .... 74
## 7 J. Santigaro Ecuador Ecuador .... 74
## 8 A. El-Shenawy Egypt Egypt .... 73
## 9 A. Shunin Russia Russia .... 73
## 10 V. Belec Slovenia Slovenia .... 72
## # ... with 30 more rows

```

#There are 40 rows in this dataframe where the position is "". These players are fictional and do not belong to any club.

```

# RELEASE CLAUSE EDA
# Players with the highest release clauses in euros:
fifa20 %>% arrange(desc(release_clause_eur)) %>%
  select(short_name, club, nationality, overall, wage_eur,
         value_eur, release_clause_eur)

```

```

## # A tibble: 18,278 x 7
##   short_name club  nationality overall wage_eur value_eur release_clause_-
##   <chr>      <chr> <chr>       <int>    <int>    <int>        <int>
## 1 L. Messi  FC B- Argentina     94  565000  95500000 195800000
## 2 Neymar Jr Pari- Brazil       92  290000 105500000 195200000
## 3 K. Mbappé Pari- France      89  155000  93500000 191700000
## 4 E. Hazard Real- Belgium     91  470000  90000000 184500000
## 5 K. De Bru- Manc- Belgium     91  370000  90000000 166500000
## 6 J. Oblak  Atlé- Slovenia     91  125000  77500000 164700000
## 7 H. Kane   Tott- England      89  220000  83000000 159800000
## 8 V. van Di- Live- Netherlands 90  200000  78000000 150200000
## 9 M. Salah   Live- Egypt       90  240000  80500000 148900000
## 10 M. ter St- FC B- Germany    90  250000  67500000 143400000
## # ... with 18,268 more rows

```

Messi and Neymar have the highest release clauses in euros

```

# Are value and release clause correlated?
cor(fifa20$value_eur, fifa20$release_clause_eur, method = "pearson",
  use = "complete.obs")

```

```
## [1] 0.9937346
```

We see that value and release clause have very high positive correlation, correlation coefficient almost equal to 1.

```

# Are wage and release clause correlated?
cor(fifa20$wage_eur, fifa20$release_clause_eur, method = "pearson",
  use = "complete.obs")

```

```
## [1] 0.8538087
```

We also see that wage and release clause have high positive correlation.

```

# Do talented young players have high release clauses?
elite_young <- fifa20 %>% filter(age <= 23)%>%
  mutate(elite_pot_inc = potential-overall)%>%
  select(short_name, club, nationality, overall, potential,
         elite_pot_inc, release_clause_eur) %>%
  arrange(desc(elite_pot_inc))
elite_young

## # A tibble: 7,318 x 7
##   short_name club  nationality overall potential elite_pot_inc#
##   <chr>      <chr> <chr>       <int>     <int>        <int>
## 1 G. Bazunu Manc- Republic o-      59       84        25
## 2 S. Ramos ~ Boca- Argentina      56       81        25
## 3 B. Mumba Sund- England          55       80        25
## 4 S. Spasov Oxfo- Bulgaria        49       74        25
## 5 Tao Qiang- Hebe- China PR      48       73        25
## 6 B. McPher- Grim- England        48       73        25
## 7 K. Bafoun- Boru- France         59       83        24
## 8 L. Cheval- LOSC- France         58       82        24
## 9 J. García Cruz- Mexico         55       79        24
## 10 H. Mnoga Port- England        53       77        24
## # ... with 7,308 more rows, and 1 more variable: release_clause_eur <int>

```

```

# Check if 'elite_pot_inc' and 'release_clause_eur' are correlated
cor(elite_young$elite_pot_inc, elite_young$release_clause_eur,
    method = "pearson", use = "complete.obs")

```

```
## [1] -0.2187238
```

```

# They have a low negative correlation. One would expect, higher possibility of
# increase in overall would result in the player having a bigger release clause
# but that is not the case here.

```

```

# Do older players have smaller release clauses?
cor(fifa20$age, fifa20$release_clause_eur, method = "pearson",
    use = "complete.obs")

```

```
## [1] 0.06574811
```

```
# There is negligable correlation between these 2 variables which is surprising.
```

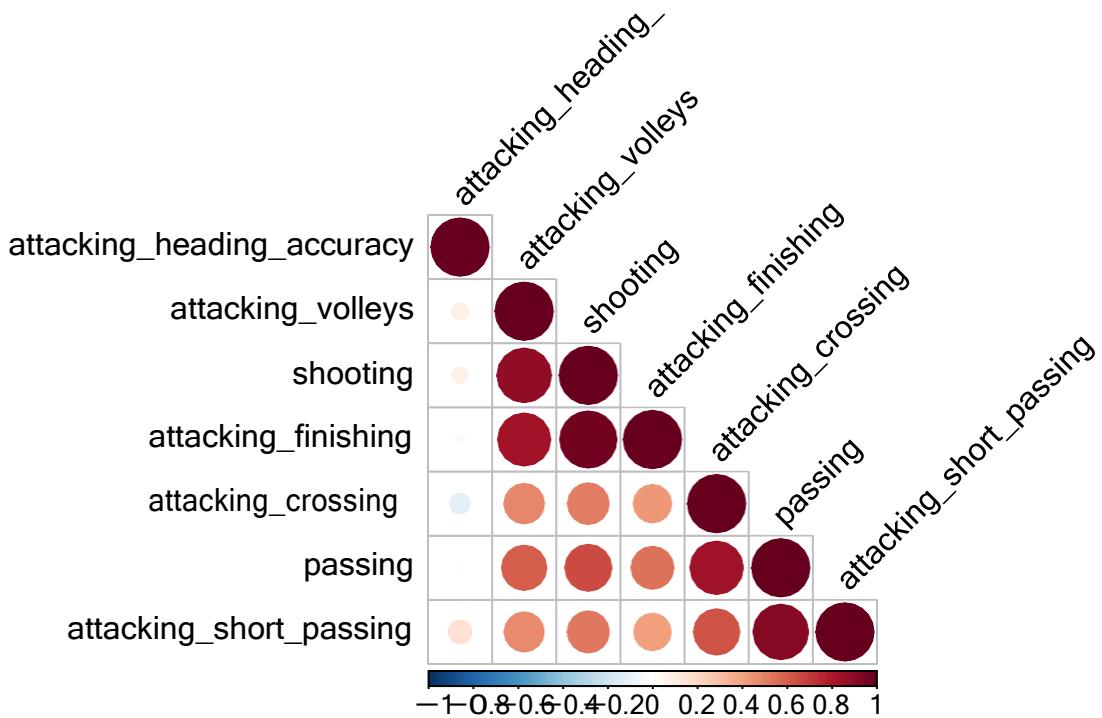
```
# Correlation for attack, goalkeeping, defending and power stats
```

```
# ATTACK STATS:
```

```

attack_stats <- fifa20%>% select(shooting, passing, attacking_crossing,
                                      attacking_finishing, attacking_heading_accuracy,
                                      attacking_short_passing, attacking_volleys)
source("http://www.sthda.com/upload/rquery_cormat.r")
require("corrplot")
rquery.cormat(attack_stats)

```



```

## $r
##                                     attacking_heading_accuracy attacking_volleys
## attacking_heading_accuracy                               1
## attacking_volleys                                0.081          1
## shooting                                         0.071          0.88
## attacking_finishing                            0.021          0.83
## attacking_crossing                           -0.12          0.48
## passing                                         0.0092         0.6
## attacking_short_passing                         0.16          0.47
##                                     shooting attacking_finishing attacking_crossing
## attacking_heading_accuracy
## attacking_volleys
## shooting                                         1
## attacking_finishing                            0.96          1
## attacking_crossing                           0.51          0.43
## passing                                         0.65          0.54
## attacking_short_passing                        0.52          0.41
##                                     passing attacking_short_passing
## attacking_heading_accuracy
## attacking_volleys
## shooting
## attacking_finishing
## attacking_crossing
## passing                                         1
## attacking_short_passing                      0.91          1
## 
```

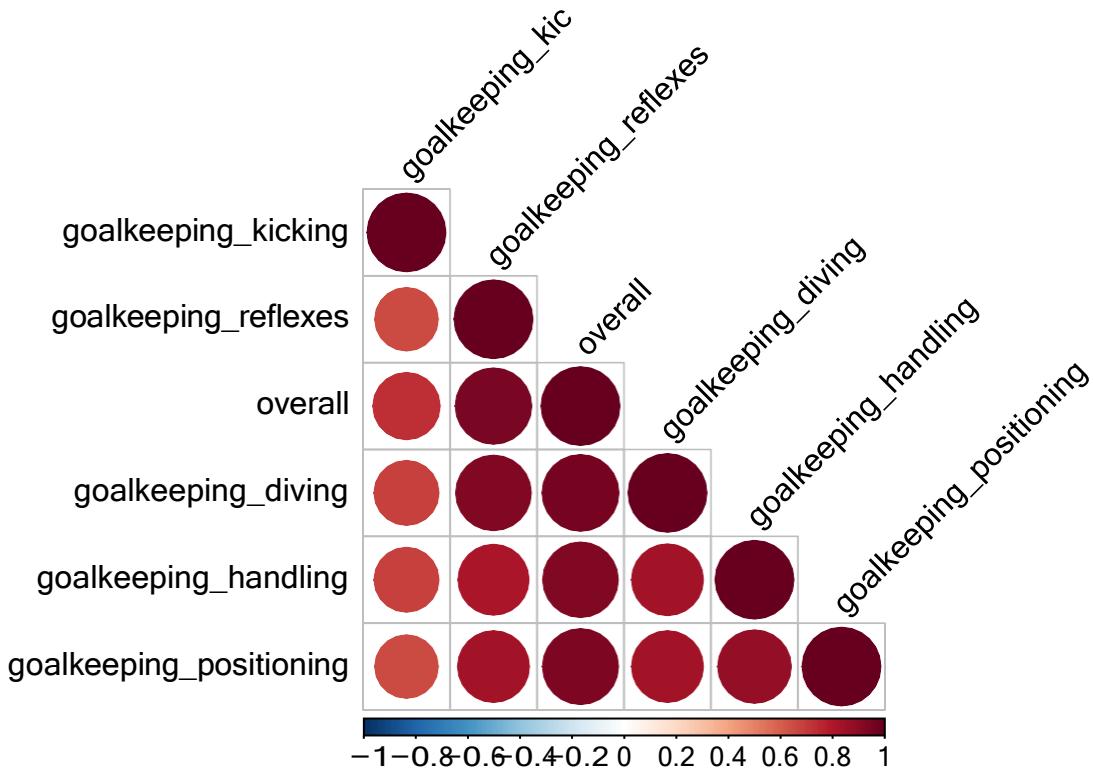
```

## $p
##                                     attacking_heading_accuracy attacking_volleys
## attacking_heading_accuracy                      0
## attacking_volleys                           0          0
## shooting                                2e-19      0
## attacking_finishing                      0          0
## attacking_crossing                      0          0
## passing                                 0.24      0
## attacking_short_passing                  0          0
##                                     shooting attacking_finishing attacking_crossing
## attacking_heading_accuracy
## attacking_volleys
## shooting                               0
## attacking_finishing                   0          0
## attacking_crossing                   0          0          0
## passing                                0          0          0
## attacking_short_passing                0          0          0
##                                     passing attacking_short_passing
## attacking_heading_accuracy
## attacking_volleys
## shooting
## attacking_finishing
## attacking_crossing
## passing                               0
## attacking_short_passing                0          0
##
## $sym
##                                     attacking_heading_accuracy attacking_volleys
## attacking_heading_accuracy 1
## attacking_volleys                     1
## shooting                            +
## attacking_finishing                 +
## attacking_crossing                  .
## passing                             .
## attacking_short_passing              .
##                                     shooting attacking_finishing attacking_crossing
## attacking_heading_accuracy
## attacking_volleys
## shooting                               1
## attacking_finishing                  B     1
## attacking_crossing                  .     .
## passing                            ,
## attacking_short_passing             .     .
##                                     passing attacking_short_passing
## attacking_heading_accuracy
## attacking_volleys
## shooting
## attacking_finishing
## attacking_crossing
## passing                               1
## attacking_short_passing             *     1
## attr(,"legend")
## [1] 0 `` 0.3 `` 0.6 `` 0.8 ``+`` 0.9 ``*`` 0.95 ``B`` 1

```

```
#Almost all pairs are positively correlated to each other.
#One exception is the correlation b/w heading and crossing. There is a -ve
#correlation b/w these 2 variables and it makes sense since a good crosser of the
#ball is the one delivering the crosses to the player whos good at heading.
```

```
# GOALKEEPING STATS:
gk_stats <- fifa20 %>% filter(team_position=="GK") %>%
  select(overall, goalkeeping_diving, goalkeeping_handling, goalkeeping_kicking,
         goalkeeping_positioning, goalkeeping_reflexes)
source("http://www.sthda.com/upload/rquery_cormat.r")
require("corrplot")
rquery.cormat(gk_stats)
```



```
## $r
##           goalkeeping_kicking goalkeeping_reflexes overall
## goalkeeping_kicking          1
## goalkeeping_reflexes        0.65          1
## overall                      0.73        0.94      1
## goalkeeping_diving          0.68          0.92      0.95
## goalkeeping_handling         0.68          0.81      0.92
## goalkeeping_positioning     0.65          0.83      0.93
##           goalkeeping_diving goalkeeping_handling
## goalkeeping_kicking
## goalkeeping_reflexes
```

```

## overall
## goalkeeping_diving           1
## goalkeeping_handling          0.83
## goalkeeping_positioning      0.83
## overall
## goalkeeping_diving           1
## goalkeeping_handling          0.87
## goalkeeping_positioning      0.87
## goalkeeping_kicking
## goalkeeping_reflexes
## overall
## goalkeeping_diving
## goalkeeping_handling
## goalkeeping_positioning      1
## $p
## goalkeeping_kicking          0
## goalkeeping_reflexes          2.8e-82
## overall                         2.3e-111 1.50000000019285e-315 0
## goalkeeping_diving            1.1e-89
## goalkeeping_handling           2.9e-90
## goalkeeping_positioning       1e-81
## goalkeeping_kicking          0
## goalkeeping_reflexes          2.9e-168
## overall                         1.9e-168 1e-204
## goalkeeping_positioning      0
## goalkeeping_kicking          0
## goalkeeping_reflexes          1
## overall                         1
## goalkeeping_diving            1
## goalkeeping_handling           1
## goalkeeping_positioning       1
## overall
## goalkeeping_kicking          1
## goalkeeping_reflexes          1
## overall                         1
## goalkeeping_diving            1
## goalkeeping_handling           1
## goalkeeping_positioning       1
## goalkeeping_kicking          1
## goalkeeping_reflexes          1
## overall                         1
## goalkeeping_positioning      1
## goalkeeping_kicking          1
## goalkeeping_reflexes          1
## overall                         1

```

```

## goalkeeping_diving
## goalkeeping_handling
## goalkeeping_positioning 1
## attr(,"legend")
## [1] 0 0.3 0.6 0.8 0.9 0.95 1

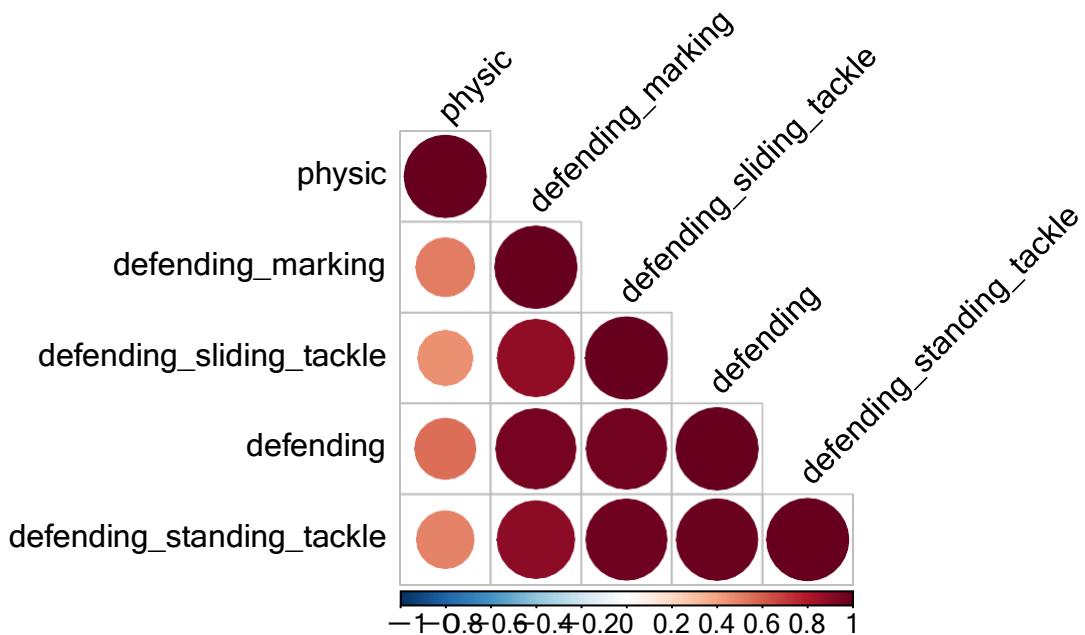
```

#kicking is not as highly correlated to GK overall when compared to other goalkeeping attributes.

```

# DEFENDING STATS:
defence_stats <- fifa20 %>% select(defending, defending_marking,
                                         defending_standing_tackle, defending_sliding_tackle,
                                         physic)
source("http://www.sthda.com/upload/rquery_cormat.r")
require("corrplot")
rquery.cormat(defence_stats)

```



```

## $r
##          physic  defending_marking
## physic      1
## defending_marking  0.51      1
## defending_sliding_tackle  0.45    0.88
## defending      0.55    0.95
## defending_standing_tackle  0.49    0.89

```

```

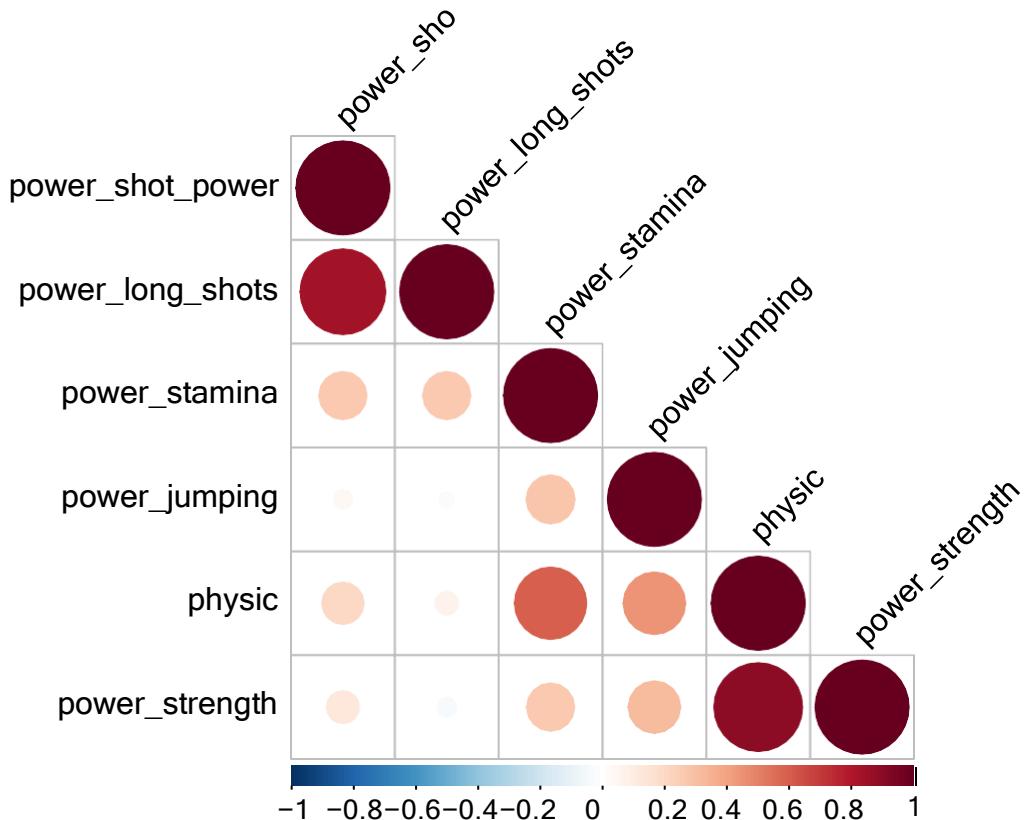
##                               defending_sliding_tackle defending
## physic
## defending_marking
## defending_sliding_tackle          1
## defending                      0.96      1
## defending_standing_tackle        0.97      0.98
##                               defending_standing_tackle
## physic
## defending_marking
## defending_sliding_tackle
## defending
## defending_standing_tackle          1
##
## $p
##                               physic defending_marking
## physic                  0
## defending_marking          0
## defending_sliding_tackle    0
## defending                      0
## defending_standing_tackle    0
##                               defending_sliding_tackle defending
## physic
## defending_marking
## defending_sliding_tackle          0
## defending                      0      0
## defending_standing_tackle        0      0
##                               defending_standing_tackle
## physic
## defending_marking
## defending_sliding_tackle
## defending
## defending_standing_tackle          0
##                               defending_standing_tackle
## $sym
##                               physic defending_marking
## physic                  1
## defending_marking          .
## defending_sliding_tackle    .
## defending                      .
## defending_standing_tackle    .
##                               defending_sliding_tackle defending
## physic
## defending_marking
## defending_sliding_tackle    1
## defending                      B      1
## defending_standing_tackle    B      B
##                               defending_standing_tackle
## physic
## defending_marking
## defending_sliding_tackle
## defending
## defending_standing_tackle 1
## attr(,"legend")
## [1] 0 0.3 0.6 0.8 0.9 0.95 B 1

```

```
#Though physique is not highly correlated to defence stats, having a high
#physique rating out of 100 implies that the player is good at defending.
```

POWER STATS:

```
power_stats <- fifa20%>%select(physic, power_shot_power, power_jumping,
                                 power_stamina, power_strength, power_long_shots)
source("http://www.sthda.com/upload/rquery_cormat.r")
require("corrplot")
rquery.cormat(power_stats)
```



```
## $r
```

```
## power_shot_power power_snot_power power_long_snots power_stamina
## power_long_shots          0.83           1
## power_stamina          0.26           0.26           1
## power_jumping          0.2            -0.038          0.59
## physic                  0.12           0.06           0.26
## power_strength          0.12           -0.038          0.26
##                               power_jumping physic power_strength
## power_shot_power
## power_long_shots
## power_stamina
## power_jumping          1
## physic                 0.44           1
```

```

## power_strength      0.31   0.89      1
##
## $p
##          power_shot_power power_long_shots      power_stamina
## power_shot_power      0
## power_long_shots      0      0
## power_stamina         0      0      0
## power_jumping        2.3e-56   9.8e-72      0
## physic              4.3e-152   1.5e-14      0
## power_strength       6e-110    5.1e-17 1.6999999988919e-314
##          power_jumping physic power_strength
## power_shot_power
## power_long_shots
## power_stamina
## power_jumping        0
## physic              0      0
## power_strength       0      0      0
##
## $sym
##          power_shot_power power_long_shots power_stamina
## power_shot_power  1
## power_long_shots +      1
## power_stamina      1
## power_jumping
## physic
## power_strength     .
##          power_jumping physic power_strength
## power_shot_power
## power_long_shots
## power_stamina
## power_jumping      1
## physic            .      1
## power_strength    .      +      1
## attr(,"legend")
## [1] 0 ~ 0.3 ~ 0.6 ~ 0.8 ~ 0.9 ~ 0.95 ~ B ~ 1

```

*#long shots and shot power have high +ve correlation which makes sense
#power strength and physique have high +ve correlation too which makes sense.*

```

# INTERCEPTIONS AND DEFENDING:
cor(fifa20$defending, fifa20$mentality_interceptions, method = "pearson",
use = "complete.obs")

```

```
## [1] 0.961099
```

Very high +ve correlation

INTERCEPTIONS FOR DEFENSIVE MIDS, WING BACKS AND CENTRE BACKS:

```

# DEFENSIVE MIDS:
mid_int_def <- fifa20 %>% filter(team_position %in% c("CDM","LDM","RCM","LCM","CM"))
cor(mid_int_def$defending, mid_int_def$mentality_interceptions)

```

```

## [1] 0.9254998

# Very high positive correlation(.93)

# WING BACKS:
wb_int_def <- fifa20%>%filter(team_position %in% c("LB","RB","LWB","RWB"))
cor(wb_int_def$defending, wb_int_def$mentality_interceptions)

## [1] 0.9085694

# CENTRE BACKS:
cb_int_def <- fifa20%>%filter(team_position %in% c("LCB","RCB"))
cor(cb_int_def$defending, cb_int_def$mentality_interceptions)

## [1] 0.9202419

# Mid way between defensive mids and wingbacks

# POSITIONING AND FINISHING:
cor(fifa20$mentality_positioning, fifa20$attacking_finishing, method = "pearson",
  use = "complete.obs")

## [1] 0.895442

# Very high positive correlation.

# STANDING TACKLING AND DEFENDING

# STANDING TACKLING FOR DEFENSIVE MIDS, WING BACKS AND CENTRE BACKS:

# DEFENSIVE MIDS:
mid_sttack_def <- fifa20%>%filter(team_position %in% c("CDM","LDM","RCM","LCM","CM"))
cor(mid_sttack_def$defending, mid_sttack_def$defending_standing_tackle)

## [1] 0.9506021

# Very high positive correlation(.95)

# WING BACKS:
wb_sttack_def <- fifa20%>%filter(team_position %in% c("LB","RB","LWB","RWB"))
cor(wb_sttack_def$defending, wb_sttack_def$defending_standing_tackle)

## [1] 0.9444266

# CENTRE BACKS:
cb_sttack_def <- fifa20%>%filter(team_position %in% c("LCB","RCB"))
cor(cb_sttack_def$defending, cb_sttack_def$defending_standing_tackle)

## [1] 0.9554827

```

```

cor(fifa20$passing, fifa20$mentality_vision, method = "pearson",
  use = "complete.obs")

## [1] 0.8792501

# Very high +ve correlation.

# FINISHING AND PENALTIES:
cor(fifa20$attacking_finishing, fifa20$mentality_penalties, method = "pearson",
  use = "complete.obs")

## [1] 0.8471015

# Very high +ve correlation.

```

DIFFERENCES BETWEEN FORWARD LINE, MIDFIELD AND DEFENCE:

```

# PACE

# Wingers:
fifa20 %>% filter(team_position %in% c("RW","LW")) %>%
  summarise(avg_pace = mean(pace)) #78.6

## # A tibble: 1 x 1
##   avg_pace
##       <dbl>
## 1     78.6

# Strikers and forwards:
fifa20 %>% filter(team_position %in% c("ST","CF","LS","RS","RF","LF")) %>%
  summarise(avg_pace = mean(pace)) #70.4

## # A tibble: 1 x 1
##   avg_pace
##       <dbl>
## 1     70.4

# Attacking mids:
fifa20 %>% filter(team_position %in% c("CAM","RM","LM","RAM","LAM")) %>%
  summarise(avg_pace = mean(pace)) #75.9

## # A tibble: 1 x 1
##   avg_pace
##       <dbl>
## 1     75.9

```

```
fifa20 %>% filter(team_position %in% c("RCM","CDM","LDM","LCM","RDM","CM")) %>%
  summarise(avg_pace = mean(pace)) #64.7
```

```
## # A tibble: 1 x 1
##   avg_pace
##       <dbl>
## 1     64.7
```

Wing backs:

```
fifa20 %>% filter(team_position %in% c("RB","LB","LWB","RWB")) %>%
  summarise(avg_pace = mean(pace)) #73.7
```

```
## # A tibble: 1 x 1
##   avg_pace
##       <dbl>
## 1     73.7
```

Centre backs:

```
fifa20 %>% filter(team_position %in% c("RCB","LCB","CB")) %>%
  summarise(avg_pace = mean(pace)) #57.5
```

```
## # A tibble: 1 x 1
##   avg_pace
##       <dbl>
## 1     57.5
```

Wingers are the fastest and cbs are the slowest.

SHOOTING:

Wingers:

```
fifa20 %>% filter(team_position %in% c("RW","LW")) %>%
  summarise(avg_shooting = mean(shooting)) #65.7
```

```
## # A tibble: 1 x 1
##   avg_shooting
##       <dbl>
## 1     65.7
```

#Strikers and forwards:

```
fifa20 %>% filter(team_position %in% c("ST","CF","LS","RS","RF","LF")) %>%
  summarise(avg_shooting = mean(shooting)) #68.6
```

```
## # A tibble: 1 x 1
##   avg_shooting
##       <dbl>
## 1     68.6
```

```

fifa20 %>% filter(team_position %in% c("CAM","RM","LM","RAM","LAM")) %>%
  summarise(avg_shooting = mean(shooting)) #63.1

## # A tibble: 1 x 1
##   avg_shooting
##       <dbl>
## 1      63.1

#Defensive mids:
fifa20 %>% filter(team_position %in% c("RCM","CDM","LDM","LCM","RDM","CM")) %>%
  summarise(avg_shooting = mean(shooting)) #57.8

## # A tibble: 1 x 1
##   avg_shooting
##       <dbl>
## 1      57.8

#Wing backs:
fifa20 %>% filter(team_position %in% c("RB","LB","LWB","RWB")) %>%
  summarise(avg_shooting = mean(shooting)) #47.8

## # A tibble: 1 x 1
##   avg_shooting
##       <dbl>
## 1      47.8

#Centre backs:
fifa20 %>% filter(team_position %in% c("RCB","LCB","CB")) %>%
  summarise(avg_shooting = mean(shooting)) #38.3

## # A tibble: 1 x 1
##   avg_shooting
##       <dbl>
## 1      38.3

# Strikers have the best shooting and centre backs have the worst shooting.

# PASSING

# Wingers:
fifa20 %>% filter(team_position %in% c("RW","LW")) %>%
  summarise(avg_passing = mean(passing)) #63.8

## # A tibble: 1 x 1
##   avg_passing
##       <dbl>
## 1      63.8

```

```
fifa20 %>% filter(team_position %in% c("ST", "CF", "LS", "RS", "RF", "LF")) %>%
  summarise(avg_passing = mean(passing)) #57.6
```

```
## # A tibble: 1 x 1
##   avg_passing
##       <dbl>
## 1      57.6
```

Attacking mids:

```
fifa20 %>% filter(team_position %in% c("CAM", "RM", "LM", "RAM", "LAM")) %>%
  summarise(avg_passing = mean(passing)) #64.9
```

```
## # A tibble: 1 x 1
##   avg_passing
##       <dbl>
## 1      64.9
```

Defensive mids:

```
fifa20 %>% filter(team_position %in% c("RCM", "CDM", "LDM", "LCM", "RDM", "CM")) %>%
  summarise(avg_passing = mean(passing)) #65.5
```

```
## # A tibble: 1 x 1
##   avg_passing
##       <dbl>
## 1      65.5
```

Wing backs:

```
fifa20 %>% filter(team_position %in% c("RB", "LB", "LWB", "RWB")) %>%
  summarise(avg_passing = mean(passing)) #60.6
```

```
## # A tibble: 1 x 1
##   avg_passing
##       <dbl>
## 1      60.6
```

Centre backs:

```
fifa20 %>% filter(team_position %in% c("RCB", "LCB", "CB")) %>%
  summarise(avg_passing = mean(passing)) #50.8
```

```
## # A tibble: 1 x 1
##   avg_passing
##       <dbl>
## 1      50.8
```

Defensive mids have the best passing and centre backs have the worst passing.

DRIBBLING

Wingers

```
fifa20 %>% filter(team_position %in% c("RW", "LW")) %>%
  summarise(avg_dribbling = mean(dribbling)) #72.3
```

```
## # A tibble: 1 x 1
##   avg_dribbling ##
##   <dbl>
## 1      72.3
```

Strikers and forwards:

```
fifa20 %>% filter(team_position %in% c("ST", "CF", "LS", "RS", "RF", "LF")) %>%
  summarise(avg_dribbling = mean(dribbling))    #67.7
```

```
## # A tibble: 1 x 1
##   avg_dribbling ##
##   <dbl>
## 1      67.7
```

Attacking mids:

```
fifa20 %>% filter(team_position %in% c("CAM", "RM", "LM", "RAM", "LAM")) %>%
  summarise(avg_dribbling = mean(dribbling))    #71.1
```

```
## # A tibble: 1 x 1
##   avg_dribbling ##
##   <dbl>
## 1      71.1
```

Defensive mids:

```
fifa20 %>% filter(team_position %in% c("RCM", "CDM", "LDM", "LCM", "RDM", "CM")) %>%
  summarise(avg_dribbling = mean(dribbling))    #67.3
```

```
## # A tibble: 1 x 1
##   avg_dribbling ##
##   <dbl>
## 1      67.3
```

Wing backs:

```
fifa20 %>% filter(team_position %in% c("RB", "LB", "LWB", "RWB")) %>%
  summarise(avg_dribbling = mean(dribbling))    #65.3
```

```
## # A tibble: 1 x 1
##   avg_dribbling ##
##   <dbl>
## 1      65.3
```

Centre backs:

```
fifa20 %>% filter(team_position %in% c("RCB", "LCB", "CB")) %>%
  summarise(avg_dribbling = mean(dribbling))    #51.9
```

```
## # A tibble: 1 x 1
##   avg_dribbling ##
##   <dbl>
## 1      51.9
```

#Wingers have the best dribbling and centre backs have the worst dribbling.

```
# DEFENDING
```

Wingers

```
fifa20 %>% filter(team_position %in% c("RW","LW")) %>%
  summarise(avg_defending = mean(defending)) #37.0
```

```
## # A tibble: 1 x 1
##   avg_defending
##       <dbl>
## 1      37.0
```

Strikers and forwards:

```
fifa20 %>% filter(team_position %in% c("ST","CF","LS","RS","RF","LF")) %>%
  summarise(avg_defending = mean(defending)) #33.4
```

```
## # A tibble: 1 x 1
##   avg_defending
##       <dbl>
## 1      33.4
```

Attacking mids:

```
fifa20 %>% filter(team_position %in% c("CAM","RM","LM","RAM","LAM")) %>%
  summarise(avg_defending = mean(defending)) #42.6
```

```
## # A tibble: 1 x 1
##   avg_defending
##       <dbl>
## 1      42.6
```

Defensive mids:

```
fifa20 %>% filter(team_position %in% c("RCM","CDM","LDM","LCM","RDM","CM")) %>%
  summarise(avg_defending = mean(defending)) #61.8
```

```
## # A tibble: 1 x 1
##   avg_defending
##       <dbl>
## 1      61.8
```

Wing backs:

```
fifa20 %>% filter(team_position %in% c("RB","LB","LWB","RWB")) %>%
  summarise(avg_defending = mean(defending)) #64.3
```

```
## # A tibble: 1 x 1
##   avg_defending
##       <dbl>
## 1      64.3
```

```
fifa20 %>% filter(team_position %in% c("RCB","LCB","CB")) %>%
  summarise(avg_defending = mean(defending)) #68.4
```

```
## # A tibble: 1 x 1
##   avg_defending
##       <dbl>
## 1      68.4
```

Centre backs have the best defense and forwards/strikers have the worst defense.

```
# PHYSIC
```

Wingers

```
fifa20 %>% filter(team_position %in% c("RW","LW")) %>%
  summarise(avg_physic = mean(phsic)) #61.5
```

```
## # A tibble: 1 x 1
##   avg_physic
##       <dbl>
## 1      61.5
```

Strikers and forwards:

```
fifa20 %>% filter(team_position %in% c("ST","CF","LS","RS","RF","LF")) %>%
  summarise(avg_physic = mean(phsic)) #68.9
```

```
## # A tibble: 1 x 1
##   avg_physic
##       <dbl>
## 1      68.9
```

Attacking mids:

```
fifa20 %>% filter(team_position %in% c("CAM","RM","LM","RAM","LAM")) %>%
  summarise(avg_physic = mean(phsic)) #61.6
```

```
## # A tibble: 1 x 1
##   avg_physic
##       <dbl>
## 1      61.6
```

Defensive mids:

```
fifa20 %>% filter(team_position %in% c("RCM","CDM","LDM","LCM","RDM","CM")) %>%
  summarise(avg_physic = mean(phsic)) #69.4
```

```
## # A tibble: 1 x 1
##   avg_physic
##       <dbl>
## 1      69.4
```

```
fifa20 %>% filter(team_position %in% c("RB", "LB", "LWB", "RWB")) %>%
  summarise(avg_physic = mean(physic)) #68.5
```

```
## # A tibble: 1 x 1
##   avg_physic
##       <dbl>
## 1     68.5
```

Centre backs:

```
fifa20 %>% filter(team_position %in% c("RCB", "LCB", "CB")) %>%
  summarise(avg_physic = mean(physic)) #73.6
```

```
## # A tibble: 1 x 1
##   avg_physic
##       <dbl>
## 1     73.6
```

Centre backs have the best physic and wingers/attacking mids have the worst physic.

Very good players who are slow:

```
good_slow <- fifa20 %>% filter(overall >= 85) %>%
  arrange(pace) %>%
  select(short_name, club, team_position, overall, pace)
head(good_slow, 5)
```

```
## # A tibble: 5 x 5
##   short_name    club      team_position overall  pace
##   <chr>        <chr>      <chr>        <int>  <int>
## 1 Parejo        Valencia CF RCM            86    41
## 2 Sergio Busquets FC Barcelona CDM            89    42
## 3 T. Kroos      Real Madrid  LCM            88    45
## 4 M. Hummels    Borussia Dortmund LCB            87    51
## 5 J. Rodríguez Real Madrid   SUB            85    55
```

Very fast players who are bad overall

```
fast_bad <- fifa20 %>% filter(overall <= 70) %>%
  arrange(desc(pace))%>%
  select(short_name, club, team_position, overall, pace)
head(fast_bad, 5)
```

```
## # A tibble: 5 x 5
##   short_name club      team_position overall  pace
##   <chr>        <chr>      <chr>        <int>  <int>
## 1 K. Nagai    FC Tokyo    LS             69    95
## 2 A. Chalá    Deportivo Toluca LWB            66    95
## 3 K. Manneh   FC Cincinnati SUB            68    94
## 4 C. Bărbuț Universitatea Craiova RW             68    94
## 5 J. Aguirre  Rosario Central  SUB            68    94
```

```

# Good players who are physically weak:
good_weak <- fifa20 %>% filter(overall >= 85) %>%
  arrange(phasic)%>%
  select(short_name, club, team_position, overall, physic)
head(good_weak, 5)

## # A tibble: 5 x 5
##   short_name   club      team_position  overall  physic
##   <chr>        <chr>      <chr>          <int>    <int>
## 1 L. Insigne Napoli       LS            87      47
## 2 D. Mertens Napoli      SUB           87      53
## 3 A. Gómez  Atalanta     CAM           85      55
## 4 R. Sterling Manchester City LW            88      57
## 5 David Silva Manchester City LCM          88      57

# Strong players who are bad overall:
strong_bad <- fifa20 %>% filter(overall <= 70) %>%
  arrange(desc(phasic))%>%
  select(short_name, club, team_position, overall, physic)
head(strong_bad, 5)

## # A tibble: 5 x 5
##   short_name   club      team_position  overall  physic
##   <chr>        <chr>      <chr>          <int>    <int>
## 1 M. Bostwick Lincoln City   RCB           68      88
## 2 B. Fofana   Gaz Metan Mediaş  SUB           68      88
## 3 A. Coly     Kristiansund BK   RB            65      88
## 4 Fali        Cádiz CF        SUB           70      87
## 5 J. Marquis  Portsmouth     ST             69      87

# Centre backs attack the goal during set pieces to chip in with headers

# Which centre backs are good at attacking the goal with their heads?
fifa20 %>% filter(team_position %in% c("LCB", "RCB", "CB"))%>%
  arrange(desc(attacking_heading_accuracy)) %>%
  select(short_name, club, overall, attacking_heading_accuracy) %>% top_n(1)

## Selecting by attacking_heading_accuracy

## # A tibble: 1 x 4
##   short_name   club      overall attacking_heading_accuracy
##   <chr>        <chr>      <int>                  <int>
## 1 Sergio Ramos Real Madrid     89                      92

# Sergio Ramos expected.

# Wing backs overlap with the wingers while attacking to deliver key crosses into the box

# Which wing/full backs are the best crossers?
fifa20 %>% filter(team_position %in% c("RB", "RWB", "LWB", "LB")) %>%
  arrange(desc(attacking_crossing)) %>%
  select(short_name, club, overall, attacking_crossing) %>% top_n(1)

```

```

## Selecting by attacking_crossing

## # A tibble: 1 x 4
##   short_name club           overall  attacking_crossing
##   <chr>      <chr>          <int>            <int>
## 1 J. Kimmich FC Bayern München     86                91

```

#Joshua Kimmich expected.

```

# Wingers who are very good crossers:
fifa20 %>% filter(team_position %in% c("RW","LW")) %>%
  arrange(desc(attacking_crossing)) %>%
  select(short_name, club, overall, attacking_crossing) %>% top_n(5)

```

```

## Selecting by attacking_crossing

## # A tibble: 7 x 4
##   short_name club           overall  attacking_crossing
##   <chr>      <chr>          <int>            <int>
## 1 L. Messi    FC Barcelona    94                88
## 2 M. Acuña    Sporting CP     81                87
## 3 A. Di María Paris Saint-Germain  86                86
## 4 Bernardo Silva Manchester City  87                85
## 5 Cristiano Ronaldo Juventus     93                84
## 6 D. Payet     Olympique de Marseille 81                84
## 7 P. Groß     Brighton & Hove Albion    78                84

```

#Target men are strikers who are tall, strong and good at heading.

```

# Best target men:
fifa20 %>% filter(height_cm >= 180, physic >= 75) %>%
  filter(team_position %in% c("ST","CF","LS","RS","RF","LF","SUB")) %>%
  arrange(desc(attacking_heading_accuracy)) %>%
  select(short_name, club, overall, attacking_heading_accuracy) %>% top_n(5)

```

```

## Selecting by attacking_heading_accuracy

## # A tibble: 5 x 4
##   short_name club           overall attacking_heading_accuracy
##   <chr>      <chr>          <int>                  <int>
## 1 B. Dost    Sporting CP     82                    93
## 2 L. de Jong Sevilla FC     82                    93
## 3 L. Pavoletti Cagliari    78                    93
## 4 O. Giroud   Chelsea       82                    91
## 5 M. Smith    Millwall      68                    91

```

*# Very good players who are poor at penalties: excluding fbs, wbs, cbs, gks and subs
since they dont generally take penalties*

```

fifa20 %>% filter(overall >=85) %>%
  filter(!team_position %in% c("RB","RWB","LWB","LB","GK","LCB","RCB","CB","SUB")) %>%
  arrange(mentality_penalties) %>%
  select(short_name, club, overall, mentality_penalties) %>% top_n(5)

```

```

## Selecting by mentality_penalties

## # A tibble: 5 x 4
##   short_name   club      overall  mentality_penalties
##   <chr>        <chr>     <int>            <int>
## 1 Z. Ibrahimović LA Galaxy       85             89
## 2 Neymar Jr    Paris Saint-Germain 92             90
## 3 H. Kane      Tottenham Hotspur   89             90
## 4 M. Reus      Borussia Dortmund  88             90
## 5 Fabinho     Liverpool          85             91

```

Wingers who cut in and shoot to score goals:

They are false wingers: right wingers with preferred foot as
left and have good shooting and vice versa

```
fifa20 %>% filter(team_position=="RW", preferred_foot=="Left")%>%
  arrange(desc(shooting))%>%
  select(short_name, club, shooting, overall) %>% top_n(1)
```

Selecting by overall

```

## # A tibble: 1 x 4
##   short_name   club      shooting  overall
##   <chr>        <chr>     <int>     <int>
## 1 L. Messi    FC Barcelona     92       94

```

```
fifa20 %>% filter(team_position=="LW", preferred_foot=="Right")%>%
  arrange(desc(shooting))%>%
  select(short_name, club, shooting, overall) %>% top_n(1)
```

Selecting by overall

```

## # A tibble: 1 x 4
##   short_name   club      shooting  overall
##   <chr>        <chr>     <int>     <int>
## 1 Cristiano Ronaldo Juventus     93       93

```

COMPARISON BETWEEN MESSI AND RONALDO: MAJOR STATS OUT OF 100

```

#BASIC STATS:
messi_ronaldo_basic <- fifa20 %>%
  filter(short_name == "L. Messi" | short_name == "Cristiano Ronaldo") %>%
  select(age, height_cm, weight_kg, overall, value_eur, wage_eur, release_clause_eur,
         international_reputation, weak_foot, skill_moves)

```

6 MAIN ATTRIBUTES:

```

messi_ronaldo_6main <- fifa20 %>%
  filter(short_name == "L. Messi" | short_name == "Cristiano Ronaldo") %>%
  select(pace, shooting, passing, dribbling, defending, physic)

# ATTACK ATTRIBUTES:
messi_ronaldo_attack <- fifa20 %>%
  filter(short_name == "L. Messi" | short_name == "Cristiano Ronaldo") %>%
  select(attacking_crossing, attacking_finishing, attacking_heading_accuracy,
         attacking_short_passing, attacking_volleys)

# MOVEMENT ATTRIBUTES:
messi_ronaldo_move <- fifa20 %>%
  filter(short_name == "L. Messi" | short_name == "Cristiano Ronaldo") %>%
  select(movement_acceleration, movement_sprint_speed, movement_agility,
         movement_reactions, movement_balance)

# POWER ATTRIBUTES:
messi_ronaldo_power <- fifa20 %>%
  filter(short_name == "L. Messi" | short_name == "Cristiano Ronaldo") %>%
  select(power_shot_power, power_jumping, power_stamina,
         power_strength, power_long_shots)

# DEFENSE ATTRIBUTES:
messi_ronaldo_def <- fifa20 %>%
  filter(short_name == "L. Messi" | short_name == "Cristiano Ronaldo") %>%
  select(defending_marking, defending_standing_tackle, defending_sliding_tackle)

# MENTALITY ATTRIBUTES:
messi_ronaldo_ment <- fifa20 %>%
  filter(short_name == "L. Messi" | short_name == "Cristiano Ronaldo") %>%
  select(mentality_aggression, mentality_interceptions, mentality_positioning,
         mentality_penalties, mentality_vision, mentality_composure)

```

```

# Difference in basic stats:
diff_basic <- data.frame(diff(as.matrix(messi_ronaldo_basic)))
diff_basic

```

```

##   age height_cm weight_kg overall value_eur wage_eur release_clause_eur
## 1    2        17       11      -1 -37000000  -160000      -99300000
##   international_reputation weak_foot skill_moves
## 1                      0          0           1

```

```

# Difference in 6 main attributes:
diff_6main <- data.frame(diff(as.matrix(messi_ronaldo_6main)))
diff_6main

```

```

##   pace shooting passing dribbling defending physic
## 1    3        1     -10       -7       -4      12

```

```

# Difference in attack attributes:
diff_attack <- data.frame(diff(as.matrix(messi_ronaldo_attack)))
diff_attack

```

```

##   attacking_crossing  attacking_finishing  attacking_heading_accuracy
## 1                 -4                      -1                         19
##   attacking_short_passing attacking_volleys
## 1                  -9                      -1

# Difference in movement attributes:
diff_move <- data.frame(diff(as.matrix(messi_ronaldo_move)))
diff_move

##   movement_acceleration movement_sprint_speed movement_agility
## 1                  -2                      7                      -6
##   movement_reactions movement_balance
## 1                   1                     -24

# Difference in defence attributes:
diff_def <- data.frame(diff(as.matrix(messi_ronaldo_def)))
diff_def

##   defending_marking defending_standing_tackle defending_sliding_tackle
## 1                  -5                      -5                      -2

# Difference in power attributes:
diff_power <- data.frame(diff(as.matrix(messi_ronaldo_power)))
diff_power

##   power_shot_power power_jumping power_stamina power_strength
## 1                  9                      27                     10                     10
##   power_long_shots
## 1                  -1

# Difference in mentality attributes:
diff_ment <- data.frame(diff(as.matrix(messi_ronaldo_ment)))
diff_ment

##   mentality_aggression mentality_interceptions mentality_positioning
## 1                  15                      -11                      1
##   mentality_penalties mentality_vision mentality_composure
## 1                  10                      -12                      -1

# These are the differences between messi and ronaldo.
# Who has got the best overall stats?

total_diff <- bind_cols(diff_6main, diff_attack, diff_def, diff_ment,
                        diff_move, diff_power)
total_diff

##   pace shooting passing dribbling defending physic attacking_crossing
## 1     3        1      -10       -7       -4      12        -4
##   attacking_finishing attacking_heading_accuracy attacking_short_passing
## 1                  -1                         19                      -9
##   attacking_volleys defending_marking defending_standing_tackle

```

```

## 1      -1      -5      -5
## defending_sliding_tackle mentality_aggression mentality_interceptions
## 1      -2      15     -11
## mentality_positioning mentality_penalties mentality_vision
## 1      1      10     -12
## mentality_composure movement_acceleration movement_sprint_speed
## 1      -1      -2      7
## movement_agility movement_reactions movement_balance power_shot_power
## 1      -6      1     -24      9
## power_jumping power_stamina power_strength power_long_shots
## 1      27      10      10     -1

```

```

# Adding values across columns:
sum <- 0
for (i in 1:length(total_diff))
{
  sum <- sum + total_diff[[i]]
}
print(sum)

```

```

## [1] 20

```

```

# OVERALL RONALDO LEADS MESSI BY 20 POINTS IN NUMERIC STATS.

```