Project 1: Olmypic History Trend Analytics

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```
#Importing Required packages
library(tidyverse)
library(reshape2)
library(dplyr)
library(knitr)
library(gridExtra)
library(ggplot2)
library(data.table)

## Uncomment below to set the working directory.
##setwd("C:/Users/Docs")
```

1. Data Acquisition

Importing the datasets

```
# Data of the athelets and countries
atheletes_df <- read.csv('athlete_events.csv', header = TRUE, sep = ',')
head(atheletes_df, 5) # structure of the dataset
```

```
##   ID                      Name Sex Age Height Weight           Team NOC
## 1  1                 A Dijiang   M  24    180     80          China CHN
## 2  2                  A Lamusi   M  23    170     60          China CHN
## 3  3       Gunnar Nielsen Aaby   M  24     NA     NA        Denmark DEN
## 4  4      Edgar Lindenau Aabye   M  34     NA     NA Denmark/Sweden DEN
## 5  5 Christine Jacoba Aaftink   F  21    185     82    Netherlands NED
##         Games Year Season      City          Sport
## 1 1992 Summer 1992 Summer Barcelona     Basketball
## 2 2012 Summer 2012 Summer    London           Judo
## 3 1920 Summer 1920 Summer Antwerpen       Football
## 4 1900 Summer 1900 Summer     Paris     Tug-Of-War
## 5 1988 Winter 1988 Winter   Calgary Speed Skating
##                              Event Medal
## 1      Basketball Men's Basketball  <NA>
## 2     Judo Men's Extra-Lightweight  <NA>
## 3          Football Men's Football  <NA>
## 4      Tug-Of-War Men's Tug-Of-War  Gold
## 5 Speed Skating Women's 500 metres  <NA>
```

```r
# Importing Data of the regions tied with the NOC code
regions_df <- read.csv('noc_regions.csv', header= TRUE, sep =',')
head(regions_df, 5)
```

```
##   NOC      region                notes
## 1 AFG Afghanistan
## 2 AHO     Curacao Netherlands Antilles
## 3 ALB     Albania
## 4 ALG     Algeria
## 5 AND     Andorra
```

2. Data Wrangling

2.1 Data Discovery

A. Summary Statistics

```r
summary(atheletes_df)
```

```
##        ID             Name               Sex                 Age
##  Min.   :     1   Length:271116      Length:271116      Min.   :10.00
##  1st Qu.: 34643   Class :character   Class :character   1st Qu.:21.00
##  Median : 68205   Mode  :character   Mode  :character   Median :24.00
##  Mean   : 68249                                        Mean   :25.56
##  3rd Qu.:102097                                        3rd Qu.:28.00
##  Max.   :135571                                        Max.   :97.00
##                                                        NA's   :9474
##      Height          Weight          Team               NOC
##  Min.   :127.0   Min.   : 25.0   Length:271116      Length:271116
##  1st Qu.:168.0   1st Qu.: 60.0   Class :character   Class :character
##  Median :175.0   Median : 70.0   Mode  :character   Mode  :character
##  Mean   :175.3   Mean   : 70.7
##  3rd Qu.:183.0   3rd Qu.: 79.0
##  Max.   :226.0   Max.   :214.0
##  NA's   :60171   NA's   :62875
##     Games                Year         Season              City
##  Length:271116      Min.   :1896   Length:271116      Length:271116
##  Class :character   1st Qu.:1960   Class :character   Class :character
##  Mode  :character   Median :1988   Mode  :character   Mode  :character
##                     Mean   :1978
##                     3rd Qu.:2002
##                     Max.   :2016
##
##     Sport              Event              Medal
##  Length:271116      Length:271116      Length:271116
##  Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character
##
##
##
##
```

We can see that there are NA's in the numerical fields of Age, Height, Weight which we will handle

```
summary(regions_df)
```

```
##      NOC                region             notes          
##  Length:230         Length:230         Length:230        
##  Class :character   Class :character   Class :character  
##  Mode  :character   Mode  :character   Mode  :character
```

B. Discovering Discrete Data

```
kable(
  atheletes_df %>%
    summarise(total_records=n()),
  caption = "Total Records for Athletes Dataframe"

)
```

Table 1: Total Records for Athletes Dataframe

total_records
271116

```
kable(
  regions_df %>%
    summarise(total_records=n()),
  caption = "Total Records in Regions Dataframe"

)
```

Table 2: Total Records in Regions Dataframe

total_records
230

Looking for NA's in all the columns

```
# Store the cols with missing values
list_na <- colnames(atheletes_df)[apply(atheletes_df, 2, anyNA)]
list_na
```

```
## [1] "Age"    "Height" "Weight" "Medal"
```

We have NA's for numerical data: Age, Height & Weight and for categorical data: Medal.

```
kable(
  atheletes_df %>%
    group_by(Medal) %>%
    summarise(total_records=n())
    ,caption="Records by Medal Count"

)
```

Table 3: Records by Medal Count

Medal	total_records
Bronze	13295
Gold	13372
Silver	13116
NA	231333

There are 231333 NA's for Medals which is categorical data and we need to handle this in the cleaning part

```
#looking for NA's in regions_df
kable(
  regions_df %>%
    filter(is.na(region)) %>%
    group_by(NOC,region,notes) %>%
  summarise(Total_records=n()),
  caption="Records grouped by categories"
)
```

```
## `summarise()` has grouped output by 'NOC', 'region'. You can override using the `.groups` argument.
```

Table 4: Records grouped by categories

NOC	region	notes	Total_records
ROT	NA	Refugee Olympic Team	1
TUV	NA	Tuvalu	1
UNK	NA	Unknown	1

No NA's in region_df

2.2 Structuring

```
head(atheletes_df,5)
```

```
##   ID                    Name Sex Age Height Weight           Team NOC
## 1  1               A Dijiang   M  24    180     80          China CHN
## 2  2                A Lamusi   M  23    170     60          China CHN
```

```
## 3  3      Gunnar Nielsen Aaby   M  24     NA     NA        Denmark DEN
## 4  4     Edgar Lindenau Aabye   M  34     NA     NA Denmark/Sweden DEN
## 5  5 Christine Jacoba Aaftink   F  21    185     82    Netherlands NED
##         Games Year Season      City         Sport
## 1 1992 Summer 1992 Summer Barcelona    Basketball
## 2 2012 Summer 2012 Summer    London          Judo
## 3 1920 Summer 1920 Summer Antwerpen      Football
## 4 1900 Summer 1900 Summer     Paris    Tug-Of-War
## 5 1988 Winter 1988 Winter   Calgary Speed Skating
##                              Event Medal
## 1      Basketball Men's Basketball  <NA>
## 2     Judo Men's Extra-Lightweight  <NA>
## 3          Football Men's Football  <NA>
## 4      Tug-Of-War Men's Tug-Of-War  Gold
## 5 Speed Skating Women's 500 metres  <NA>
```

We can see that we don't need to do additional restructuring as columns like "Games" is already split and available as Year and Season

2.3 Cleaning

A. Handling Missing Data

We can't filter out the NA values since the columns that exhibit them are required for our analysis. We will be filling the NA values for numerical columns like Age, Height, Weight with the **median** values since we require whole numbers. The Medals are filled with **'None'** which would signify that the athletes simply didn't win any of the categories of Medals (Gold, Silver, Bronze).

We didn't filter out the NA records in Age, Height and Weight because that would mean that crucial data would be dropped leading to data skewness, we are using the Median values since we require whole numbers and to reduce the degree of skewness while maintaining data integrity.

```
atheletes_df$Medal <- atheletes_df$Medal %>%
  replace_na("None") # It is assumed tha the athlete participated in the sport but didn't win a medal
```

B. Replacing NA's in Medals Calculating Missing Median for the missing values for Age, Height and Weight

```
list_na <- list_na[ list_na !="Medal"]

# Calculate median for the missing values
missing_median <- apply(atheletes_df[,colnames(atheletes_df) %in% list_na],
      2, # 2 is for Columns
      median,
      na.rm =  TRUE)
missing_median
```

```
##    Age Height Weight
##     24    175     70
```

```
# Replace the missing values with median
atheletes_df <- atheletes_df %>%
   mutate(
     Age  = ifelse(is.na(Age), missing_median[1], Age),
     Height = ifelse(is.na(Height), missing_median[2], Height),
     Weight = ifelse(is.na(Weight), missing_median[3], Weight)
   )
```

```
# Replacing Na's with the respective region/notes for the NOC's
regions_df$region <- ifelse(is.na(regions_df$region), regions_df$notes, regions_df$region)
```

```
kable(
  regions_df %>%
    filter(is.na(region)) %>%
    group_by(region) %>%
    summarise(total_records=n())
  ,caption = "Number of NA's in Region after fix"

)
```

C. Handling Missing data in Regions

Table 5: Number of NA's in Region after fix

region	total_records

2.4 Enriching

A. Adding Attribute region

We will join regions_df and atheletes_df based on the NOC code to get the Region for enriching the data.

```
athletes <- left_join(atheletes_df, regions_df, by="NOC")

# Replacing Region with Country to make the data more meaningful
colnames(athletes)[which(names(athletes) == "region")] <- "Region"
# Removing notes since it's not relevant to our analysis anymore
athletes <- athletes[,-17]
head(athletes,5)
```

```
##   ID                      Name Sex Age Height Weight           Team NOC
## 1  1                 A Dijiang   M  24    180     80          China CHN
## 2  2                  A Lamusi   M  23    170     60          China CHN
## 3  3       Gunnar Nielsen Aaby   M  24    175     70        Denmark DEN
## 4  4      Edgar Lindenau Aabye   M  34    175     70 Denmark/Sweden DEN
## 5  5 Christine Jacoba Aaftink   F  21    185     82    Netherlands NED
```

```
##         Games Year Season      City         Sport
## 1 1992 Summer 1992 Summer Barcelona    Basketball
## 2 2012 Summer 2012 Summer    London          Judo
## 3 1920 Summer 1920 Summer Antwerpen      Football
## 4 1900 Summer 1900 Summer     Paris    Tug-Of-War
## 5 1988 Winter 1988 Winter   Calgary Speed Skating
##                              Event Medal      Region
## 1      Basketball Men's Basketball  None       China
## 2     Judo Men's Extra-Lightweight  None       China
## 3          Football Men's Football  None     Denmark
## 4      Tug-Of-War Men's Tug-Of-War  Gold     Denmark
## 5 Speed Skating Women's 500 metres  None Netherlands
```

We don't have any other attribute to split or to create a new category since we believe that we have all the required columns for our analysis

2.5 Validating

A. Check for any missing values

```
# Counting the number of NA's for all the columns
colnames(athletes)[apply(athletes, 2, anyNA)]
```

```
## [1] "Region"
```

```
kable(
  athletes %>%
    select(NOC,Region)  %>%
    filter(is.na(Region)) %>%
    group_by(NOC,Region) %>%
    summarise(total_records=n())
    ,caption="Null Records check by Medal Count"

)
```

```
## `summarise()` has grouped output by 'NOC'. You can override using the `.groups` argument.
```

Table 6: Null Records check by Medal Count

NOC	Region	total_records
SGP	NA	349

For NOC SGP, there are no records in our regions_df but is present in atheltes_df, as a result we are getting NA values after the join. We will add Singapore Region to the NOC in the joined data

```
athletes$Region <- ifelse((is.na(athletes$Region) & athletes$NOC=='SGP'), "Singapore", athletes$Region)


kable(
  athletes %>%
    select(Region)  %>%
    filter(is.na(Region)) %>%
    group_by(Region) %>%
    summarise(total_records=n())
    ,caption="Checking for NA records in Region after change"

)
```

Table 7: Checking for NA records in Region after change

Region	total_records

B. Check for Duplicates

```
sum(duplicated(athletes))
```

```
## [1] 1385
```

There 1385 duplicate records on the whole data set

```
# Removing the duplicates
athletes <- unique(athletes)
```

C. Checking boundary cases

```
kable (
athletes %>%
summarise(max_age=max(Age), min_age=min(Age), Average_Age=mean(Age)),
caption="Age boundary cases"

)
```

Table 8: Age boundary cases

max_age	min_age	Average_Age
97	10	25.40454

```
kable (
athletes %>%
summarise(max_height=max(Height), min_height=min(Height), Average_height=mean(Height)),
caption="Height boundary cases"

)
```

Table 9: Height boundary cases

max_height	min_height	Average_height
226	127	175.265

```
kable (
athletes %>%
summarise(max_weight=max(Weight), min_weigt=min(Weight), Average_weight=mean(Weight)),
caption="Weight boundary cases"

)
```

Table 10: Weight boundary cases

max_weight	min_weigt	Average_weight
214	25	70.5417

All our boundary cases looks reasonable and accurate.

2.6 Publishing

The data is cleaned & wrangled and made available for the team to develop business cases.

3. Analytical Questions

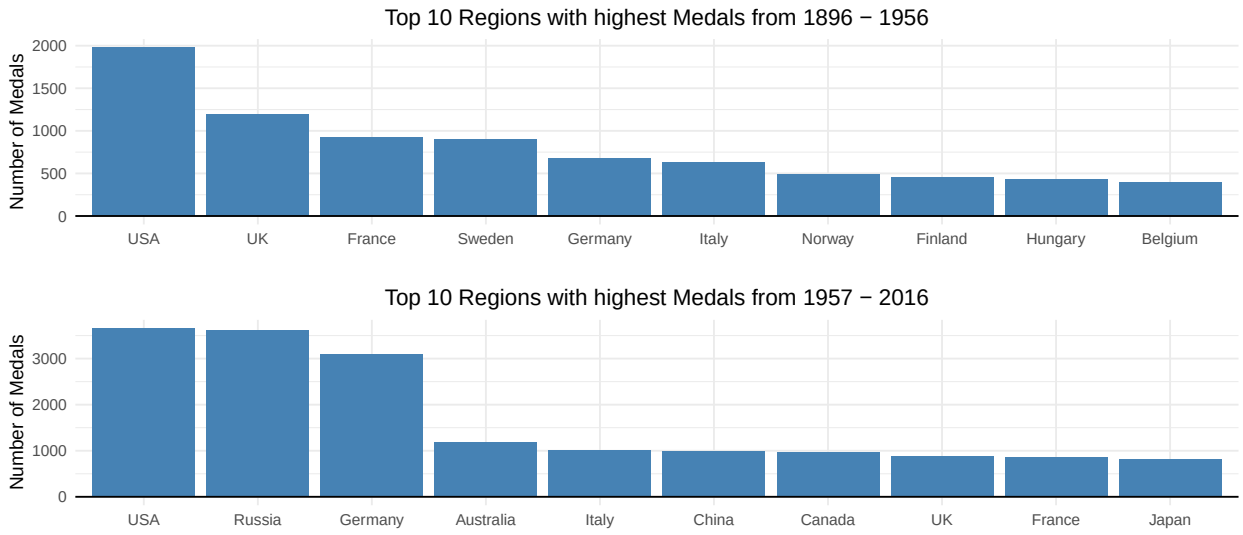
1. Trend analysis of Top 10 regions with the highest number of medals between 1896 - 1956 & 1957 - 2016

```
p1 <-
athletes %>%
    filter(Medal!='None' & Year<=1956) %>%
    group_by(Region) %>%
    summarize(total_medals=n()) %>%
    arrange(desc(total_medals))  %>%
    mutate(Region=factor(Region, levels=Region)) %>%
    slice(1:10) %>%
    ggplot( aes(x=Region, y=total_medals))+
    geom_col(fill="steelblue") +
    theme_minimal()+
    labs(y="Number of Medals")+
    xlab("")+
    theme(plot.title = element_text(hjust = 0.5)) +
    ggtitle("Top 10 Regions with highest Medals from 1896 - 1956")+
    geom_vline(xintercept = 0)+
    geom_hline(yintercept = 0)

p2 <-
```

```
athletes %>%
    filter(Medal!='None' & Year>1956) %>%
    group_by(Region) %>%
    summarize(total_medals=n()) %>%
    arrange(desc(total_medals))  %>%
    mutate(Region=factor(Region, levels=Region)) %>%
    slice(1:10) %>%
    ggplot( aes(x=Region, y=total_medals))+
    geom_col(fill="steelblue") +
    theme_minimal()+
    labs(y="Number of Medals")+
    xlab("")+
    theme(plot.title = element_text(hjust = 0.5)) +
    ggtitle("Top 10 Regions with highest Medals from 1957 - 2016")+
    geom_vline(xintercept = 0)+
    geom_hline(yintercept = 0)

grid.arrange(p1, p2, ncol=1)
```



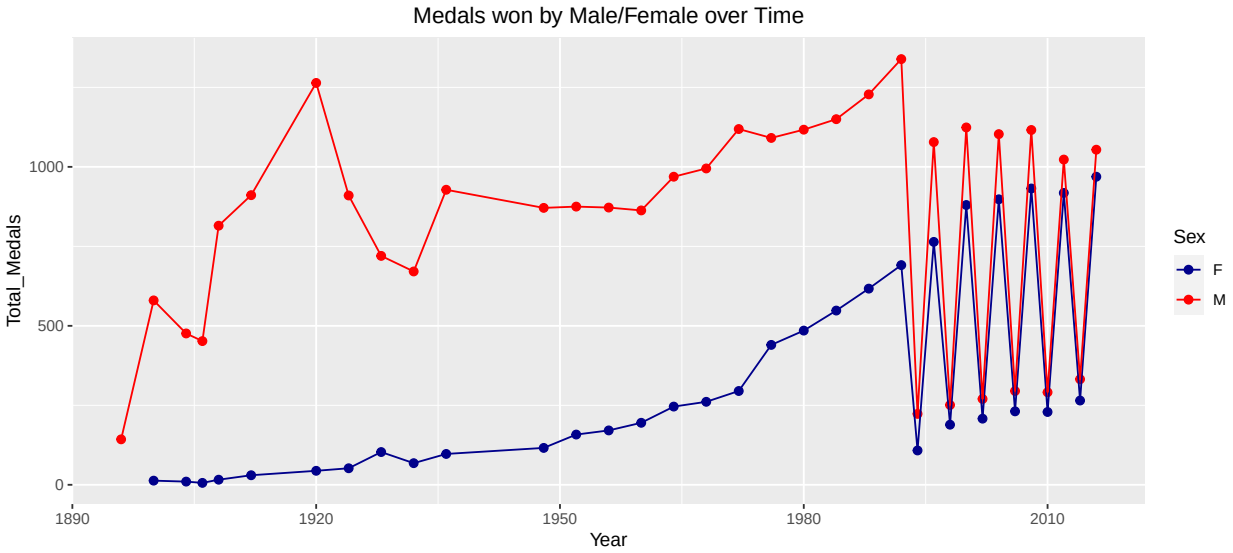
Observation: USA remains the region with the highest number of Medals in the combined history of 120 years in Olympics. Russia, a new inclusion in the top 10 took 2nd position in the later half.Germany moved into the 3rd position in the second half while UK and France slipped from 2nd and 3rd to 8th and 9th position. There are new countries in the later half such as Australia, Canada and Japan which where not in the top 10 for the earlier history of Olympics.

2. Medals won by Males/Females over Time

```
athletes %>%
  filter(Medal!='None') %>%
  group_by(Year, Sex) %>%
  summarize(Total_Medals = n()) %>%
```

```
  ggplot(., aes(x=Year, y=Total_Medals, group=Sex, color=Sex))+
  geom_point(size=2) +
  geom_line()  +
  scale_color_manual(values=c("darkblue","red")) +
  labs(title = "Medals won by Male/Female over Time") +
  theme(plot.title = element_text(hjust = 0.5))
```

```
## `summarise()` has grouped output by 'Year'. You can override using the `.groups` argument.
```



Observation: From the graph, we can see that there is a gradual increase in the number of medals won by female athletes over time. Male athletes tend to outnumber female athletes but their numbers also keep fluctuating over time. After the years 1994, the summer and winter Olympic games were split and held during seperate years, hence why the graph shows different points.

3. Finding the most participated sport in Olympics every year

```
q3<-
athletes %>%
  group_by(Year, Sport) %>%
  summarize(Participation = n()) %>%
  arrange(Year,desc(Participation))
```

```
## `summarise()` has grouped output by 'Year'. You can override using the `.groups` argument.
```

```
  q3 <- q3[!duplicated(q3$Year),] # Taking only the first record

  kable(
  q3,
  caption="Most participated Sport in Olympic Games every year"
  )
```

Table 11: Most participated Sport in Olympic Games every year

Year	Sport	Participation
1896	Athletics	106
1900	Fencing	317
1904	Gymnastics	458
1906	Athletics	470
1908	Athletics	778
1912	Athletics	962
1920	Athletics	849
1924	Athletics	1003
1928	Athletics	992
1932	Art Competitions	620
1936	Athletics	1007
1948	Gymnastics	1060
1952	Gymnastics	2391
1956	Athletics	1013
1960	Gymnastics	1746
1964	Gymnastics	1484
1968	Gymnastics	1496
1972	Athletics	1686
1976	Athletics	1297
1980	Athletics	1268
1984	Athletics	1674
1988	Athletics	2062
1992	Athletics	2054
1994	Cross Country Skiing	639
1996	Athletics	2386
1998	Cross Country Skiing	733
2000	Athletics	2468
2002	Cross Country Skiing	774
2004	Athletics	2175
2006	Cross Country Skiing	812
2008	Athletics	2244
2010	Cross Country Skiing	725
2012	Athletics	2278
2014	Cross Country Skiing	765
2016	Athletics	2508

Observation: This table shows that Athletics has remained the most contested sport in 120 years of Olympics. Art Competitions were the highest participated Olympic Sport in 1932 before it was removed from the Olympics. As the Olympic Winter and Summer games were seperated into different years from 1994, Cros Country Skiing emerged as the most participated game held during the Winters.

4. In which Olympic year did a particular country win a medal for the first time for a particular sport

```
Ans1 <-
athletes %>%
filter(Sport=="Football",Medal!="None") %>%
select(Region,Year) %>%
```

```
group_by(Region,Year) %>%
summarise(Year=min(Year))
```

```
## `summarise()` has grouped output by 'Region'. You can override using the `.groups` argument.
```

```
Ans1 <- Ans1[!duplicated(Ans1$Region),]

kable (
  Ans1,
  caption="First year in which countries won medal in Football"
)
```

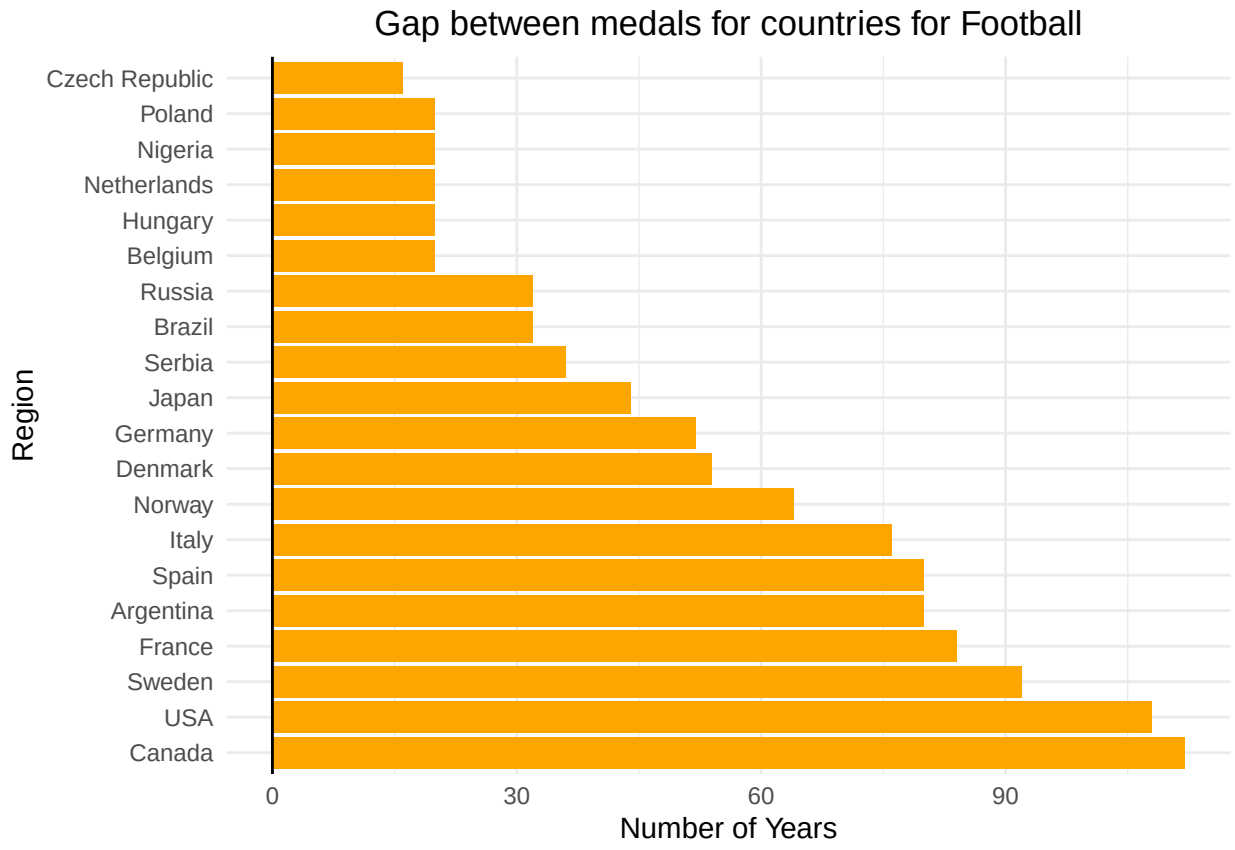
Table 12: First year in which countries won medal in Football

Region	Year
Argentina	1928
Austria	1936
Belgium	1900
Brazil	1984
Bulgaria	1956
Cameroon	2000
Canada	1904
Chile	2000
China	1996
Czech Republic	1964
Denmark	1906
France	1900
Germany	1964
Ghana	1992
Greece	1906
Hungary	1952
Italy	1928
Japan	1968
Mexico	2012
Netherlands	1900
Nigeria	1996
Norway	1936
Paraguay	2004
Poland	1972
Russia	1956
Serbia	1948
South Korea	2012
Spain	1920
Sweden	1924
Switzerland	1924
UK	1900
Uruguay	1924
USA	1904

Observation: From the above table we can see the first year in which each country won a medal for football. The first countries to win medals for football are UK,Belgium,France and Netherlands and all these countries are from Europe.

5. Trend analysis per sport per country for the gap between medals for Football

```
athletes %>%
filter(Sport=="Football",Medal!="None") %>%
select(Region, Year) %>%
group_by(Region) %>%
summarise(Number_of_Years=max(Year)-min(Year)) %>%
arrange(desc(Number_of_Years)) %>%
mutate(Region=factor(Region, levels=Region)) %>%
slice(1:20) %>%
ggplot( aes(y=Region, x=Number_of_Years))+
geom_col(fill="orange") +
theme_minimal()+
#labs(y="Region")+
xlab("Number of Years")+
theme(plot.title = element_text(hjust = 0.5)) +
ggtitle("Gap between medals for countries for Football")+
geom_vline(xintercept = 0)+
geom_hline(yintercept = 0)
```



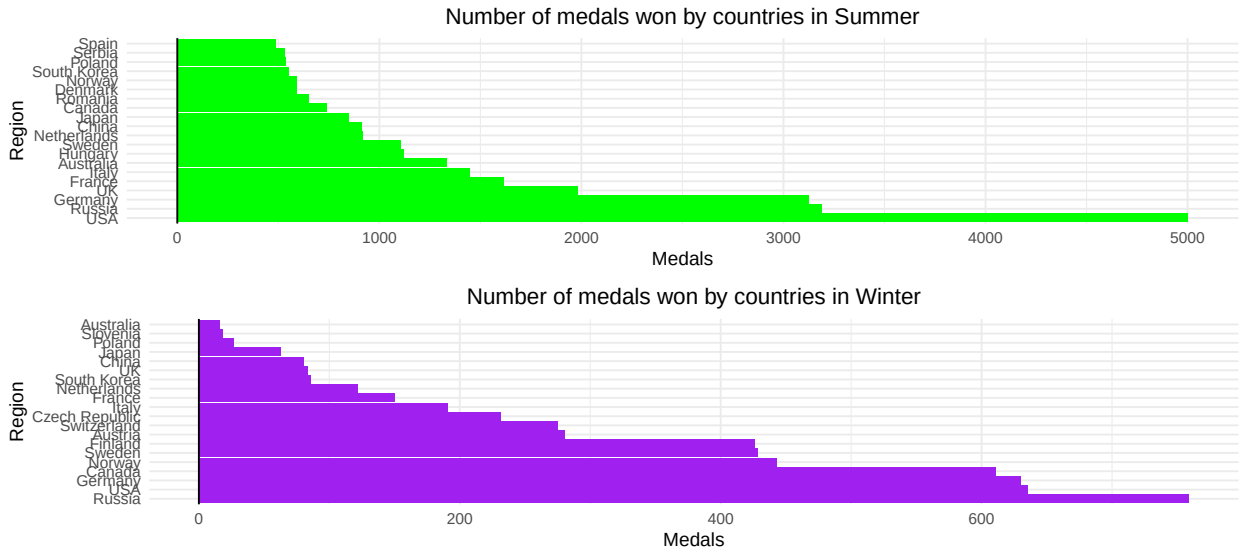
Observation: The gap between first and last medals for football for each country is displayed. Canada has the largest gap of 112 years while Czech Republic has the smallest gap of 16 years.

6. Comparison of medals won by regions in Summer & Winter.

```
Ans3.1 <-
athletes %>%
filter(Medal!='None',Season=="Summer") %>%
group_by(Region) %>%
summarize(number_of_medals=n()) %>%
arrange(desc(number_of_medals)) %>%
mutate(Region=factor(Region, levels=Region)) %>%
slice(1:20) %>%
ggplot( aes(y=Region, x=number_of_medals))+
geom_col(fill="green") +
theme_minimal()+
#labs(y="Region")+
xlab("Medals")+
theme(plot.title = element_text(hjust = 0.5)) +
ggtitle("Number of medals won by countries in Summer")+
geom_vline(xintercept = 0)+
geom_hline(yintercept = 0)

Ans3.2 <-
athletes %>%
filter(Medal!='None',Season=="Winter") %>%
group_by(Region) %>%
summarize(number_of_medals=n()) %>%
arrange(desc(number_of_medals)) %>%
mutate(Region=factor(Region, levels=Region)) %>%
slice(1:20) %>%
ggplot( aes(y=Region, x=number_of_medals))+
geom_col(fill="purple") +
theme_minimal()+
#labs(y="Region")+
xlab("Medals")+
theme(plot.title = element_text(hjust = 0.5)) +
ggtitle("Number of medals won by countries in Winter")+
geom_vline(xintercept = 0)+
geom_hline(yintercept = 0)

grid.arrange(Ans3.1,Ans3.2,ncol=1)
```



Observation: In Summer USA takes the top spot in the number of medals won and Russia stood second. When it comes to winter the positions are interchanged. Germany remains constant in both summer and winter. The graph has a uniform increase in the number of medals in summer but its not a uniform increase in winter, So this means that the winter games are more competitive while summer has a distinctive winner.

7. Top 10 Host cities with the highest participation.

```
## Top 10 Host cities with highest participation.
Top10 <-
  athletes %>%
    select(Year,City) %>%
    group_by(Year,City) %>%
    summarize(number=n()) %>%
    arrange(desc(number))
```

```
## `summarise()` has grouped output by 'Year'. You can override using the `.groups` argument.
```

```
kable(
  head(Top10, 10)
  ,caption=("Host cities with highest participation")
)
```

Table 13: Host cities with highest participation

Year	City	number
2000	Sydney	13821
1996	Atlanta	13780
2016	Rio de Janeiro	13688
2008	Beijing	13602
2004	Athina	13443
1992	Barcelona	12977
2012	London	12920

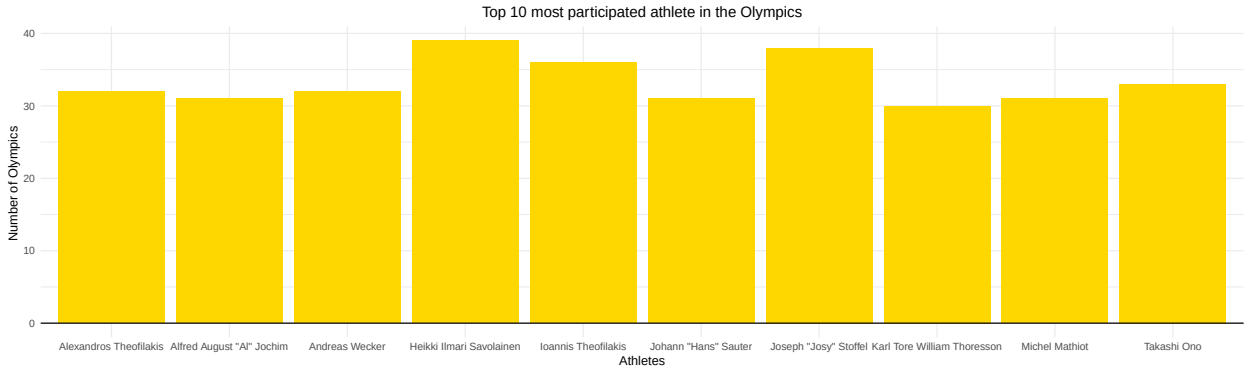
Year	City	number
1988	Seoul	12037
1972	Munich	10304
1984	Los Angeles	9454

Observation: The top ten cities with the highest participation are Sydney(2000), Atlanta(1996), Rio de Janeiro(2016),Beijing(2008), Athina(2004), Barcelona(1992), London(2012),Seoul(1988),Munich(1972),Los Angeles(1984)

8. Top 10 athletes with the highest participation in the Olympics

```
##
Top10a <-
    athletes %>%
    select(Name) %>%
    group_by(Name) %>%
    summarize(number=n())  %>%
    arrange(desc(number)) %>%
    slice(0:10)

ggplot(Top10a, aes(x=Name, y=number))+
geom_col(fill="gold") +
theme_minimal()+
labs(y="Number of Olympics ")+
xlab("Athletes")+
theme(plot.title = element_text(hjust = 0.5)) +
ggtitle("Top 10 most participated athlete in the Olympics")+
geom_vline(xintercept = 0)+
geom_hline(yintercept = 0)
```



Observation: As we can see nearly all the top 10 athletes participated in the Olympics more than 30 times and the one with the most is Heikki Ilmari Savolainen with 39 times

9. Athletes with the most number of medals in each sport

```r
###Athlete with the most number of medals per sport
df <-
   athletes %>%
   filter( Medal != 'None') %>%
   select(Name,Sport)%>%
   group_by(Name,Sport) %>%
   summarize(number=n())  %>%
   arrange(desc(number))
```

```
## `summarise()` has grouped output by 'Name'. You can override using the `.groups` argument.
```

```r
dfuevent <- df[!duplicated(df$Sport),]

kable(
  head(dfuevent,11)
  ,caption=("Athlete with the most number of medals per sport")
  )
```

Table 14: Athlete with the most number of medals per sport

Name	Sport	number
Michael Fred Phelps, II	Swimming	28
Larysa Semenivna Latynina (Diriy-)	Gymnastics	18
Edoardo Mangiarotti	Fencing	13
Ole Einar Bjrndalen	Biathlon	13
Birgit Fischer-Schmidt	Canoeing	12
Paavo Johannes Nurmi	Athletics	12
Carl Townsend Osburn	Shooting	11
Gerard Theodor Hubert Van Innis	Archery	10
Isabelle Regina Werth	Equestrianism	10
Marit Bjrgen	Cross Country Skiing	10
Yang Yang	Short Track Speed Skating	10

Observation: For Swimming, Michael Fred Phelps, II won the most number of medals(28) and there are 11 players with the number of medals equal or more than 10 in different sports.