# 2016 Summer Olympic and Total Olympic Medals by Country Analysis

```
# Yasamin Yazdani, yy8429
```

## Introduction

The title of this report is called “2016 Summer Olympic and Total Olympic Medals by Country Analysis”. This report includes two datasets. The first one, “data16”, is the number of gold, silver, and bronze medals won by country in the 2016 summer olympics as well as whether the countries are located in the Northern Hemisphere, the Southern Hemisphere, or both. The seconds one, “totaldata”, is the grand total of gold, silver, bronze, and toal olympic medals won by country from 1896 to the present. These datasets were acquired from online websites (total data- https://worldpopulationreview.com/country-rankings/olympic-medals-by-country (https://worldpopulationreview.com/country-rankings/olympic-medals-by-country) , 2016 data- https://www.insidethegames.biz/games/7/medals (https://www.insidethegames.biz/games/7/medals)) of world data reports on topics like sports. I also used maps to locate countries in the Northern and Southern hemispheres. With these resources, I made my own dataset. I found this data interesting because my grandfather was an olympic gold medalist from Iran. I do not anticipate any specific associations, but I do expect to see that the United States is the top producer of all the different medal cetegories since the start of the olympics and in 2016. I also expect the Northern Hemisphere to be the producer of most olympic medals.

## Importing the Datasets

```
# I will use the package "readxl" to import the two datasets.
library(readxl)
# Now I will import the datasets. The first one is the 2016 medals by country and the se
cond is the total medals by country.
data16 <- read_xlsx("2016olympic.xlsx")
totaldata <- read_excel("totalolympic.xlsx")
```

## Tidying the Dataset

The datasets that I have used for this project are already tidy because I have created the datasets, therefore I do not need to reshape them in any way. This means that I can move onto joining the two datasets.

## Joining The Datasets

```
# Now, I will merge the two datasets together into one dataset. First, I need to downloa
d the "dplyr" package to "left_join" the data. Here is this step:
library(dplyr)
```

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

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

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

```
# Now, I will join my data using the "left_join" function. I used this type of join beca
use both of the datasets have the same "country" variable. However, the dataset from 201
6 has less  rows/observations than the total olympic datset, so the "left_join" will be
 the best way to pair the variables on the basis of their country names while dropping o
ff the countries who did not compete in the 2016 summer olympics. Here is this joining b
elow (I have also saved it as a new dataset):
mydata1 <- left_join(data16, totaldata, by = c("country"))
# Now, I will take a look at the new dataset and compare it to the other two to see how
 many cases of each dataset were dropped.
glimpse(mydata1)
```

```
## Rows: 87
## Columns: 9
## $ country       <chr> "United States", "United Kingdom", "China", "Russia", "…
## $ gold.2016     <dbl> 46, 27, 26, 19, 17, 12, 10, 9, 8, 8, 8, 8, 7, 7, 6, 6, …
## $ silver.2016   <dbl> 37, 23, 18, 18, 10, 8, 18, 3, 12, 11, 7, 3, 6, 4, 6, 3,…
## $ bronze.2016   <dbl> 38, 17, 26, 19, 15, 21, 14, 9, 8, 10, 4, 4, 6, 6, 1, 2,…
## $ ns.hemisphere <chr> "northern", "northern", "northern", "northern", "northe…
## $ gold.total    <dbl> 1127, 274, 237, 195, 283, 156, 248, 121, 246, 152, 130,…
## $ silver.total  <dbl> 907, 299, 195, 163, 282, 158, 276, 112, 214, 168, 136, …
## $ bronze.total  <dbl> 793, 310, 176, 188, 290, 183, 316, 104, 241, 192, 149, …
## $ grand.total   <dbl> 2827, 883, 608, 546, 855, 497, 840, 337, 701, 512, 415,…
```

```
glimpse(data16)
```

```
## Rows: 87
## Columns: 5
## $ country       <chr> "United States", "United Kingdom", "China", "Russia", "…
## $ gold.2016     <dbl> 46, 27, 26, 19, 17, 12, 10, 9, 8, 8, 8, 8, 7, 7, 6, 6, …
## $ silver.2016   <dbl> 37, 23, 18, 18, 10, 8, 18, 3, 12, 11, 7, 3, 6, 4, 6, 3,…
## $ bronze.2016   <dbl> 38, 17, 26, 19, 15, 21, 14, 9, 8, 10, 4, 4, 6, 6, 1, 2,…
## $ ns.hemisphere <chr> "northern", "northern", "northern", "northern", "northe…
```

```
glimpse(totaldata)
```

```
## Rows: 135
## Columns: 5
## $ country      <chr> "United States", "United Kingdom", "Germany", "France", …
## $ gold.total   <dbl> 1127, 274, 283, 248, 246, 202, 237, 195, 188, 137, 176, …
## $ silver.total <dbl> 907, 299, 282, 276, 214, 216, 195, 163, 174, 166, 149, 1…
## $ bronze.total <dbl> 793, 310, 290, 316, 241, 234, 176, 188, 158, 198, 173, 1…
## $ grand.total  <dbl> 2827, 883, 855, 840, 701, 652, 608, 546, 520, 501, 498, …
```

It appears that the total olympic dataset had more cases than the 2016 one. As a result, all the countries from the 2016 data (87) were retained and all of the countries that were from the total data who did not compete in the olympics were dropped off on the merged dataset. I will do a simple calculation below to determine what that number is.

```
135-87
```

```
## [1] 48
```

A total of 48 cases/countries were dropped in the new, joined dataset. This means that out of the 135 total countries to have ever competed in the olympics, 87 of them were at the 2016 olympics.

## Exploring Summary Statistics

```
# Now I am going to do some exploring with the 6 core dplyr functions. First, I want to
 know the proportion of medals won in the Rio olympics to the total olympic medals won f
or that country. First, I will create a new dataset mutating the first one to have a col
umn called "rioproportion", where i divide the sum of the country's gold, silver, and br
onze medals at the 2016 olympics by the total number of medals ever won, and multiplied
 that number by 100.
project1 <- mydata1 %>% mutate(rioproportion = (gold.2016 + silver.2016 +bronze.2016)/gr
and.total * 100)
# Now, I used the "summarize" function on my new dataset to pick the variables "country"
and the new "rioproportion". I also had the table arranged in descending order by "riopr
oportion" using the "arrange" function.
project1  %>% summarize(rioproportion, country) %>% arrange(desc(rioproportion))
```

```
## # A tibble: 87 x 2
##    rioproportion country
##            <dbl> <chr>
##  1         100   Fiji
##  2         100   Kosovo
##  3         100   Jordan
##  4          66.7 Bahrain
##  5          66.7 Ivory Coast
##  6          53.3 Serbia
##  7          50   Vietnam
##  8          50   Grenada
##  9          50   Burundi
## 10          50   Niger
## # … with 77 more rows
```

Based on this analysis, it looks like three countries, Fiji, Kosovo, and Jordan, won all of their olympic medals at the 2016 summer olympics in Rio.

```
# Now, lets look at the average of the total medals won when grouped by the hemisphere t
he country comes from. In order to do this, I wll first create a new dataset where I tak
e the original, merged data ('mydata1') and I apply the "group_by" command and specified
that I would like to group by my categorical variable stating whether the country is in
 the nothern, southern, or both hemispheres (variable- 'ns.hemisphere'). Then, I summari
zed to get the mean of the grand total of the medals won by country. Additionally, I use
d the 'arrange' command to arrange the average medals by hemisphere by highest to lowes
t.
Project2 <- mydata1 %>% group_by(ns.hemisphere) %>% summarise(hemisphere.avg = mean(gran
d.total)) %>% arrange(desc(hemisphere.avg))
# Now I will take a look at the table by simply typing the name of the dataset and runni
ng the code.
Project2
```

```
## # A tibble: 3 x 2
##   ns.hemisphere hemisphere.avg
##   <chr>                  <dbl>
## 1 northern                194.
## 2 southern                132.
## 3 both                     63
```

As you can see, the northern hemisphere has more olympic medals than the southern hemisphere and countries in both hemispheres. This may be because most of the world's countries are located in the northern hemisphere, thus leading to more opportunities and people to win olympic medals.

```
# Now, I will explore the standard deviation of silver medals won in 2016 for countries
 located in the southern hemisphere only. To do this, I will also create a new dataset w
hich takes the merged data and applies the 'filter' command to pick the countries from t
he variable 'ns.hemisphere' that only say 'southern'. Then, I will use the 'mutate' comm
and to apply the 'sd' command and get the standard deviation of the variable 'silver.201
6' for these countries in the southern hemisphere. I will then use the 'summarize' comma
nd to pick the new mutated variable and the 'country' variable. Finally, I will look at
 the new dataset.
Project3 <- mydata1 %>% filter(ns.hemisphere == "southern") %>% mutate(sd.silver.16 = sd
(silver.2016)) %>% summarize(sd.silver.16, country)
Project3
```

```
## # A tibble: 6 x 2
##   sd.silver.16 country
##          <dbl> <chr>
## 1         4.68 Australia
## 2         4.68 New Zealand
## 3         4.68 Argentina
## 4         4.68 South Africa
## 5         4.68 Fiji
## 6         4.68 Burundi
```

There are six sounthern hemisphere countries in the 2016 olympics, and the standard deviation of silver medals for the 2016 olympics is about 4.7 medals.

```
# Lets look at the variance in the bronze medals of 2016. This is done by creating a new
dataset taking the merged data and using 'summarize' to get the 'var' of the 'bronze.201
6' variable. Then, let's look at the dataset.
project4 <- mydata1 %>% summarize(var.bronze.16 = var(bronze.2016))
project4
```

```
## # A tibble: 1 x 1
##   var.bronze.16
##           <dbl>
## 1          39.3
```

The variance in bronze medals for the 2016 olympics is 39.27453 square medals.

```
# Let's now see how many distinct values there are for the total gold medals in all the
 olympics. This is done by creating a new dataset taking the merged data and using 'summ
arize' to get the 'n_distinct' of the 'gold.total' variable. Then, we will take a look a
t the dataset.
project5 <- mydata1 %>% summarize(distinct.gold = n_distinct(gold.total))
project5
```

```
## # A tibble: 1 x 1
##   distinct.gold
##           <int>
## 1            50
```

There are 50 unique values for total gold medals. This means that for 37 of the countries (87-50), their number of gold medals overlaps with at least one other country.

```
# Now we will look at the 95th percentile of silver medals in all of the olympics. This
 is done by creating a new dataset with the merged data and using 'summarize' to apply t
he 'quantile' function to 'silver.total'. We will also specify that we are looking for t
he 95th percentile by applying 'probs=c(0.95)'. Then, we will look at the data.
project6 <- mydata1 %>% summarize(silver.95th = quantile(silver.total, probs = c(0.95)))
project6
```

```
## # A tibble: 1 x 1
##   silver.95th
##         <dbl>
## 1        215.
```

It looks like the 95th percentile of total silver medals is 215.4 medals.

```
# Now, we will look at the minimum number of total bronze medals. To do this, I will tak
e the merged data, use 'select' to pick the 'bronze.total' variable, and use 'summarize'
to see the 'min' of the bronze medals to make a new dataset. Then, I will look at the da
ta.
project7 <- mydata1 %>% select(country, bronze.total) %>% summarize(bronze.min = min(bro
nze.total))
project7
```

```
## # A tibble: 1 x 1
##   bronze.min
##        <dbl>
## 1          0
```

```
# It looks like zero medals was the minimum for bronze medals. Let's see what countries
 have zero bronze medals. First, I will apply the 'filter' to select values equal to zer
o in the 'bronze.total' variable. Then, I will 'select' for the 'country' and 'bronze.to
tal' variables.
mydata1 %>% filter(bronze.total == "0") %>% select(country, bronze.total)
```

```
## # A tibble: 7 x 2
##   country bronze.total
##   <chr>          <dbl>
## 1 Bahrain            0
## 2 Vietnam            0
## 3 Fiji               0
## 4 Kosovo             0
## 5 Jordan             0
## 6 Grenada            0
## 7 Burundi            0
```

The seven countries with zero bronze medals are Bahrain, Vietnam, Fiji, Kosovo, Jordan, Grenada, and Burundi.

```
# Now, we will look at the maximum total number of medals. To do this, I will take the m
erged data, use 'select' to pick the 'grand.total' variable, and use 'summarize' to see
 the 'max' of the total medals to make a new dataset. Then, I will look at the data.
project8 <- mydata1 %>% select(country, grand.total) %>% summarize(total.max = max(gran
d.total))
project8
```

```
## # A tibble: 1 x 1
##   total.max
##       <dbl>
## 1      2827
```

```
# It looks like 2827 medals was the maximum for total medals won in all the olympics by
 a country. Let's see what country has 2827 total medals. First, I will apply the 'filte
r' to select values equal to 2827 in the 'grand.total' variable. Then, I will 'select' f
or the 'country' and 'grand.total' variables.
mydata1 %>% filter(grand.total == "2827") %>% select(country, grand.total)
```

```
## # A tibble: 1 x 2
##   country       grand.total
##   <chr>               <dbl>
## 1 United States         2827
```

The United States had the highest number of total olympic medals. Go USA!

```
# Now I want to see the number of observations for 'ns.hemisphere' after grouping by the
hemispheres. I am also looking for the correlation between 2016 gold medals and total go
ld medals grouped by hemisphere as well. First, I will use 'select' to select 'ns.hemisp
here', 'gold.2016', and 'gold.total'. Then, I will use 'group_by' to group be 'ns.hemisp
here'. Then, I will 'summarize' the 'ns.hemisphere' by 'n()', and also use 'cor' to see
 the pearson correlation coefficient between the variables "gold.2016' and 'gold.total'.
Then, I will look at the data.
project9 <- mydata1 %>% select(ns.hemisphere, gold.2016, gold.total) %>% group_by(ns.hem
isphere) %>% summarize(n(), gold.correlation = cor(gold.total, gold.2016, method = c("pe
arson")))
project9
```

```
## # A tibble: 3 x 3
##   ns.hemisphere `n()` gold.correlation
## * <chr>         <int>            <dbl>
## 1 both              3            0.919
## 2 northern         78            0.873
## 3 southern          6            0.964
```

There appears to be a strong, positive correlation (0.96) between the number of gold medals in 2016 and the number of gold medals total for the southern hemisphere countries. This correlation stays strong, but decreases going to the countries in both hemispheres and finally to northern hemisphere countries. There are 6 countries in the southern hemisphere, 78 in the northern hemisphere, and 3 countries in both.

## Making a Table of Summary Statistics Using Dashes and Vertical Bars

| Summary | Statistic | Value | Unit | Description |
|---|---|---|---|---|
| 1 | Proportion of 2016 medals to total medals | 0-100 | % | Findings- Fiji, Kosovo, and Jordan won their first olympic medal(s) in 2016. |
| 2 | Average of total medals won by hemisphere | 63-194 | medals | Findings- The northern hemisphere countries have the highest average (194 medals). |
| 3 | SD of 2016 silver medals (southern hemisphere) | 4.68 | silver medals | Findings- SD is 4.68 medals and there are 6 countries in the southern hemisphere. |
| 4 | Variance in bronze medals in 2016 | 39.27 | medals-squared | Findings- The variaence is 39.27 bronze medals-squared for the 2016 olympics. |
| 5 | Distinct gold medal values for total medals | 50 | distinct values | Findings- 50 unique gold medal values means there’re overlaps for 37 countries. |

| Summary | Statistic | Value | Unit | Description |
|---|---|---|---|---|
| 6 | 95th percentile of total silver medals | 215.4 | silver medals | Findings- The 95th percentile for total silver medals is 215.4 medals. |
| 7 | Minimum of total bronze medals | 0 | bronze medals | Findings- Bahrain, Vietnam, Fiji, Kosovo, Jordan, Greneda, & Burundi have 0 bronze medals |
| 8 | Maximum total number of medals | 2827 | total medals | Findings- The USA has the most medals (2827) out of all the olympic countries! |
| 9a | Number of observations/countries by hemisphere | 3-78 | countries | Findings- Only six countries are from the southern hemisphere in the dataset. |
| 9b/10 | Correlation-2016 gold/total gold by hemisphere | .87-.96 | n/a | Findings- There is a strong positive correlation in all three hemispheres. |

# Making Visualizations

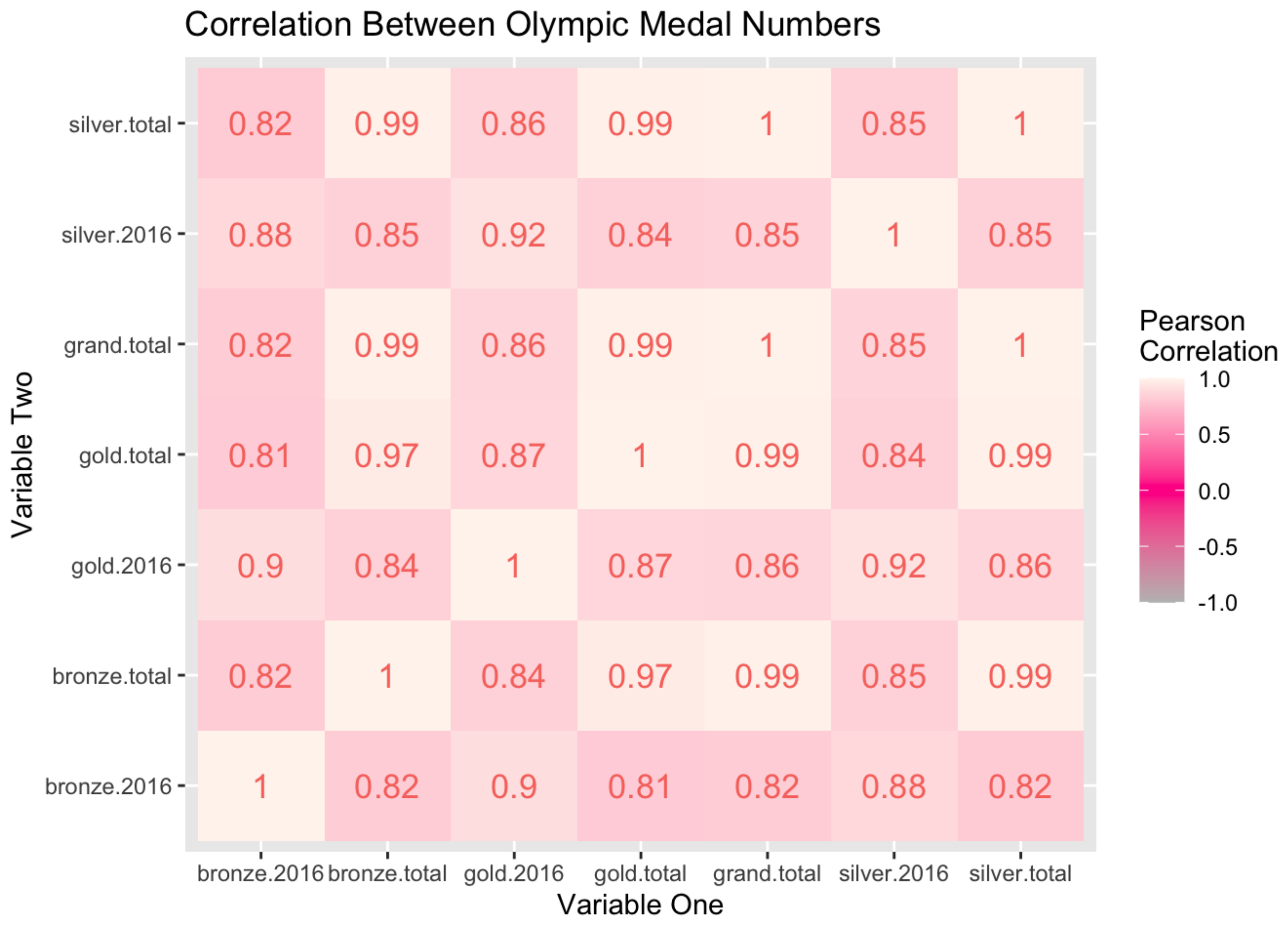
```
# To start making visualizations, I will need the "ggplot2" package. Additioanlly, to ma
ke a correlation matrix, I also need the 'tidyverse' package. I will get them from the
 'library' function below-
library(ggplot2)
library(tidyverse)
```

```
## ── Attaching packages ─────────────────────────────────────── tidyverse 1.3.0 ──
```

```
## ✓ tibble  3.0.5     ✓ purrr   0.3.3
## ✓ tidyr   1.1.2     ✓ stringr 1.4.0
## ✓ readr   1.3.1     ✓ forcats 0.5.0
```

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

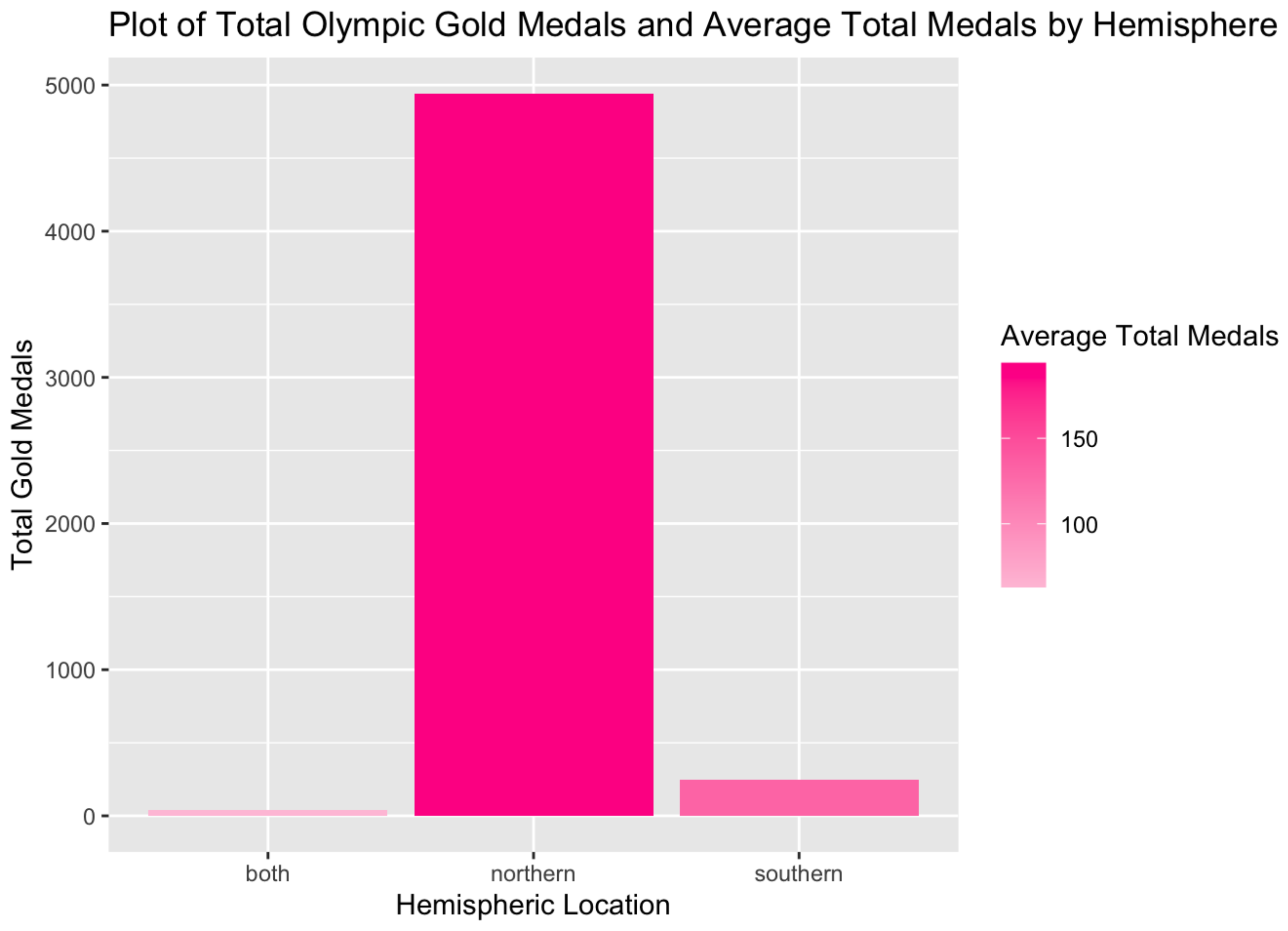
```
# Now, I will make a correlation heatmap. First, I need to remove my categorical variabl
e ('ns.hemisphere' and 'country'). I will make a new dataset and use 'select' to remove
 them.
projectcor1 <- mydata1 %>% select(-country, -ns.hemisphere)
# Then, I will use 'cor' to make a correlation matrix with pairwise observations in orde
r to find the correlation between any two of my numeric variables.
cor(projectcor1, use = "pairwise.complete.obs") %>%
# Now, I will save the matrix as a datarame with 'as.data.frame'.
  as.data.frame() %>%
# Now, I will convert my row names to explicit variables.
  rownames_to_column %>%
# Using 'pivot_longer', I will make every correlation appear in the same column.
  pivot_longer(-1, names_to = "other_var", values_to = "correlation") %>%
# Now, I will make the correlation heatmap using 'ggplot' and 'geom_tile'. My x and y ax
es are going to be the two variables, and the fill will be their correlation values. Thi
s will be filled within 'aes'
  ggplot(aes(rowname, other_var, fill = correlation)) +
  geom_tile() +
# To make the graph pretty, I will use 'scale_fill_gradient2', set the midpoint to zero,
the limits to one and negative one, and rename the color key. Additionally, I used 'ggti
tle' and 'labs' to add a title to the graph and rename the axes, respectively.
  scale_fill_gradient2(low = "gray", high = "seashell1", mid = "deeppink", midpoint = 0,
limit = c(-1,1), space = "Lab", name = "Pearson\nCorrelation") +
  ggtitle("Correlation Between Olympic Medal Numbers") +
  labs(x = "Variable One", y = "Variable Two") +
# Additionally, I added the correlation values to the heatmap with 'geom_text', rounded
 the values to two decimal places with 'round', colored the text, set the font size, and
removed the legend for the text.
  geom_text(aes(label = round(correlation, 2), color = "roseybrown4", size = 4), show.le
gend = FALSE)
```



One thing I found particularly unique is that there is a very strong correlation between any two variables. The lowest correlation value between two distinct variables is 0.81 and is between ‘gold.total’ and ‘’bronze.2016’, and the highest correlation between two distinct variables is 0.99. This value is for variables ‘grand.total’ and ‘bronze.total’, ‘grand.total’ and ‘gold.total’, ‘silver.total’ and ‘bronze.total’, and ‘silver.total’ and ‘gold.total’.

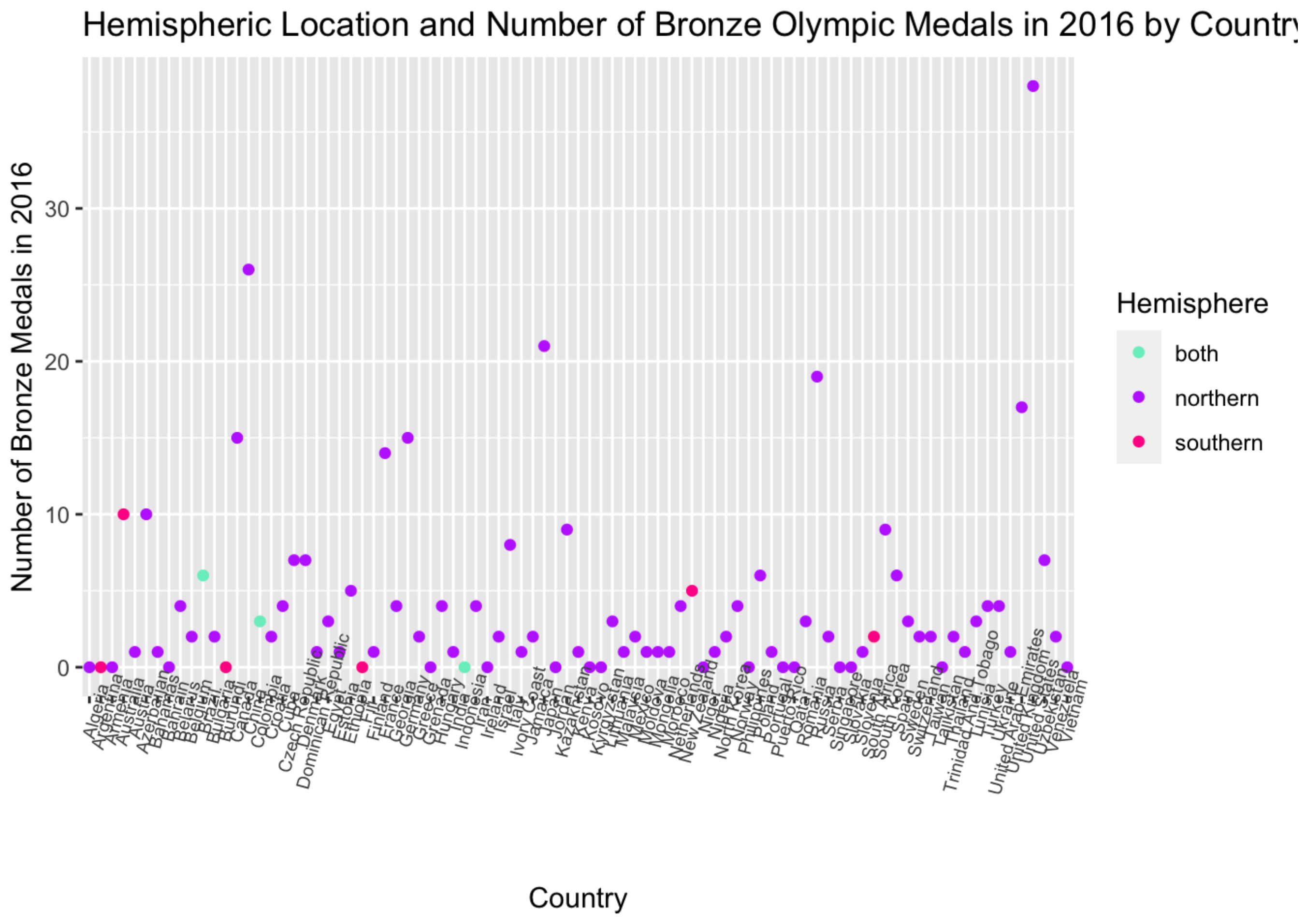
```
# Now I want to make a barchart. First, I will create a new dataset with three variables
- 'ns.hemisphere', the sum of 'gold.total', and the mean of 'grand.total'. All of these
 variables will be grouped by 'ns.hemisphere'. First, I deselected all of the variables
 irrelevant to the bar chart. Then, i grouped by 'ns.hemisphere'. Then, I used 'summariz
e' to get the mean of 'grand.total' and the sum of 'gold.total' by hemisphere.
projectplot1 <- mydata1 %>% select(-country, -silver.2016, -silver.total, -bronze.total,
-gold.2016, -bronze.2016) %>% group_by(ns.hemisphere) %>% summarize(averagetotal = mean
(grand.total), totalgold = sum(gold.total))

# Now, I will use 'ggplot' to make a bar chart. I will use the dataset I just created an
d use 'aes' to have my x-axis as the hemispheres, my y-axis as the sum of gold medals by
hemisphere, and the fill of the barchart as the average total gold medals by hemisphere.
ggplot(projectplot1, aes(x = ns.hemisphere, y = totalgold, fill = averagetotal)) +
  # Now I will use 'geom_col' to make a bar chart.
  geom_col() +
  # To make the graph pretty, I used 'scale_fill_gradient2' to have the lower values of
 average total medals be white, and the higher averages as a neon pink color. I also ren
amed the color key. Additionally, I used 'ggtitle' and 'labs' to add a title to the grap
h and rename the axes, respectively.
  scale_fill_gradient2(low = "white", high = "deeppink", name = "Average Total Medals")
 +
  ggtitle("Plot of Total Olympic Gold Medals and Average Total Medals by Hemisphere") +
  labs(x = "Hemispheric Location", y = "Total Gold Medals")
```



If we look at the chart, we can see that countries located in both hemispheres have the lowest gold medal count and the lowest average total medals. The southern hemispheric countries are not too far behind the countries in both hemispheres, and the northern hemisphere has an overwhelming advantage over all the other countries in terms of total gold medals and average total medals. Go team USA!

```
# Now I want to use 'ggplot' on my original merged 'mydata1' dataset and use 'aes' to se
t x to 'country', y to 'bronze.2016' and color the graph by 'ns.hemisphere'. I will make
a scatterplot using 'geom_point'.
ggplot(mydata1, aes(x = country, y = bronze.2016, color = ns.hemisphere)) +
  geom_point() +
# Now, I need to change the alignment and size of the x-axis text using 'theme'. Within
 that, i will use 'axis.text.x' to set the angle of the tex to 75 degrees and the font s
ize to 7 with 'element_text'.
  theme(axis.text.x = element_text(angle = 75, size = 7)) +
# To make the graph pretty, I used 'scale_color_manual' to manually fill the hemisphere
 category dots with colors that I have selected. I also renamed the color key. Additiona
lly, I used 'ggtitle' and 'labs' to add a title to the graph and rename the axes, respec
tively.
  scale_color_manual(values = c("aquamarine2", "darkorchid1", "deeppink"), name = "Hemis
phere") +
  ggtitle("Hemispheric Location and Number of Bronze Olympic Medals in 2016 by Country")
+
  labs(x = "Country", y = "Number of Bronze Medals in 2016")
```



One thing that surprised me in this graph is that most of the bronze medals are won by northern hemisphere countries. This may be because there is a disproportional amount of them relative to the other two categories, but I still expected to maybe see a southern hemisphere country mixed in at the top of the scatterplot with the northern hemisphere countries.

## Performing PCA

```
# Last but not least, I will perform a PCA of the dataset. I will use the dataset that I
manipulated for the correlation matrix where the categorical variables have been removed
('projectcor1'). First, I will need the 'cluster' and 'factoextra' packages which I will
get using 'library'
library(cluster)
library(factoextra)
```

```
## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WB
a
```

```
# Now, I will start the PCA. I will also use 'scale' to scale the data to zero mean and
 unit variance. Then, I will use 'prcomp' to run the PCA.
pca1 <- projectcor1 %>%
  scale() %>%
  prcomp()
```

```
# Now, let's take a look at the results of the PCA using 'names'.
names(pca1)
```

```
## [1] "sdev"     "rotation" "center"   "scale"    "x"
```

It looks like we have a list of standard deviations on each principal component (sdev) as well as the rotated data (x) amongst other things.

```
# Now, we will start to visualize the results by simply showing the PCA that we saved as
'pca1'
pca1
```

```
## Standard deviations (1, .., p=7):
## [1] 2.521520e+00 6.368481e-01 3.572325e-01 2.837612e-01 1.597018e-01
## [6] 5.215940e-02 3.345029e-16
##
## Rotation (n x k) = (7 x 7):
##                     PC1        PC2         PC3         PC4         PC5
## gold.2016    -0.3717343 -0.4065963 -0.27105032 -0.72747863  0.30417422
## silver.2016  -0.3673712 -0.4218391 -0.57793068  0.57375791 -0.15364697
## bronze.2016  -0.3590301 -0.5076085  0.76230398  0.13219134 -0.11854171
## gold.total   -0.3858101  0.3039427 -0.03100003 -0.22396378 -0.67366155
## silver.total -0.3876367  0.3246470  0.01163857 -0.01060899  0.04102990
## bronze.total -0.3846741  0.3177671  0.09910151  0.27167688  0.64216742
## grand.total  -0.3884116  0.3167208  0.02242596 -0.00463742 -0.04400202
##                      PC6           PC7
## gold.2016     0.03574510  2.642315e-16
## silver.2016  -0.01675529  3.925464e-18
## bronze.2016  -0.02823007 -1.762236e-16
## gold.total    0.38444931 -3.256186e-01
## silver.total -0.81524385 -2.789052e-01
## bronze.total  0.43016261 -2.645782e-01
## grand.total   0.01345157  8.638187e-01
```

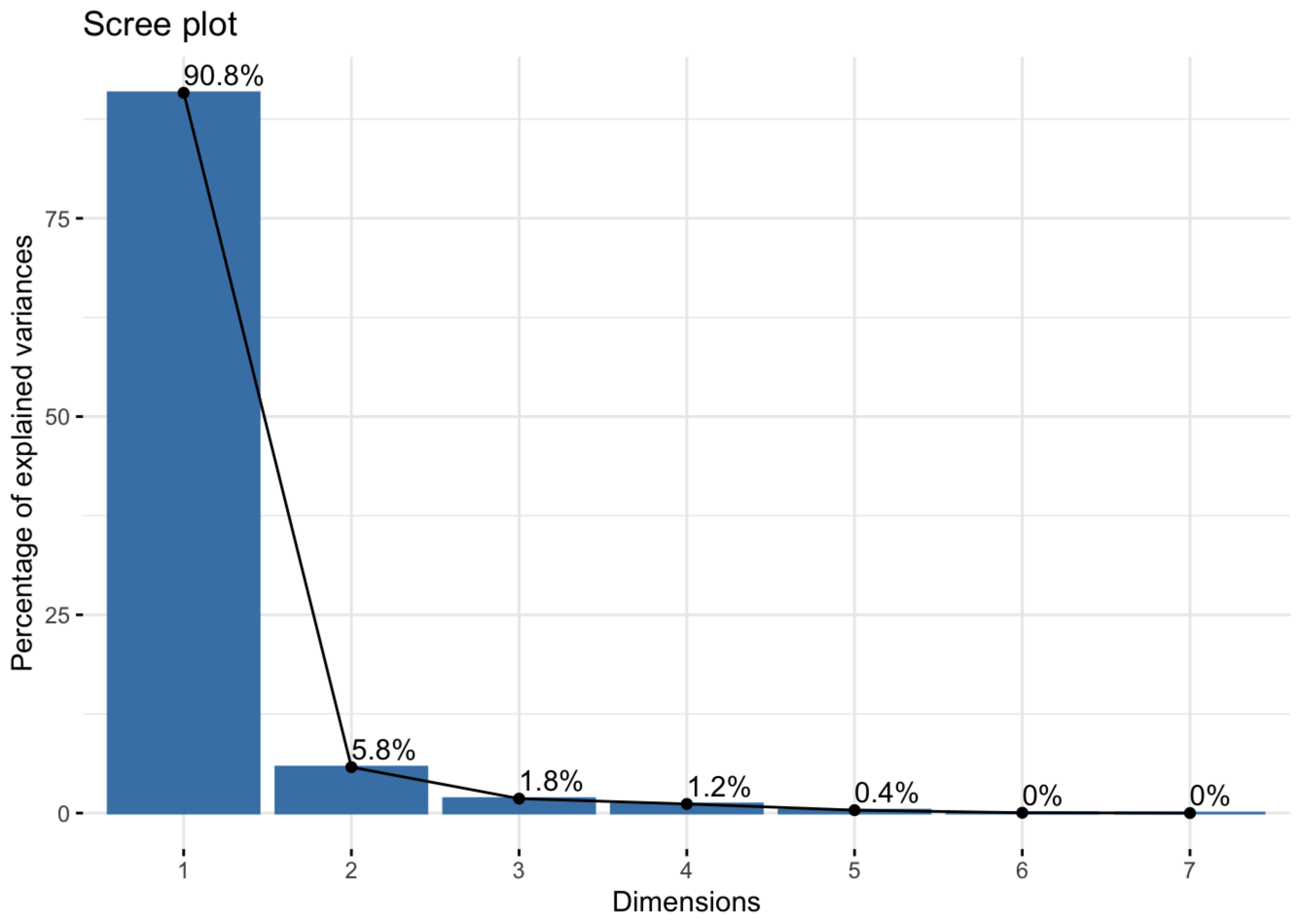
This gives us a better look at the standard deviations on each principal component.

```
# Now we can start to add the 'ns.hemisphere' variable abck to the PCA data 'pca1$x' and
take a quick look using the function 'head'.
pca2 <- data.frame(pca1$x, country = mydata1$country, hemisphere = mydata1$ns.hemispher
e)
head(pca2)
```

```
##          PC1        PC2        PC3         PC4         PC5          PC6
## 1 -17.522979  1.3847117 -0.2628060 -0.52300229 -0.72521187 -0.008559626
## 2  -6.236359 -1.4151737 -1.0792590 -0.05500434  0.63657781 -0.080174121
## 3  -5.173262 -2.7110057  0.4188144 -0.51163422 -0.03890958 -0.020599523
## 4  -4.144673 -1.9314758 -0.1433790  0.18339216  0.05590058  0.123142063
## 5  -4.620993  0.1828435  0.3542387 -0.39651128  0.41663737 -0.020247663
## 6  -3.046085 -1.1036676  1.3811752  0.02214475  0.14246674  0.010945528
##             PC7        country hemisphere
## 1 -1.154632e-14  United States   northern
## 2 -1.332268e-15 United Kingdom   northern
## 3 -2.220446e-15          China   northern
## 4 -8.881784e-16         Russia   northern
## 5 -1.998401e-15        Germany   northern
## 6 -6.661338e-16          Japan   northern
```

We will use this later when making a scatter plot of the principal components.

```
# Then, we will determine how many principal components to consider using a screeplot an
d getting the eigenvvalues (functions- 'fviz_screeplot' and 'get_eigenvalue').
fviz_screeplot(pca1, addlabels = TRUE)
```

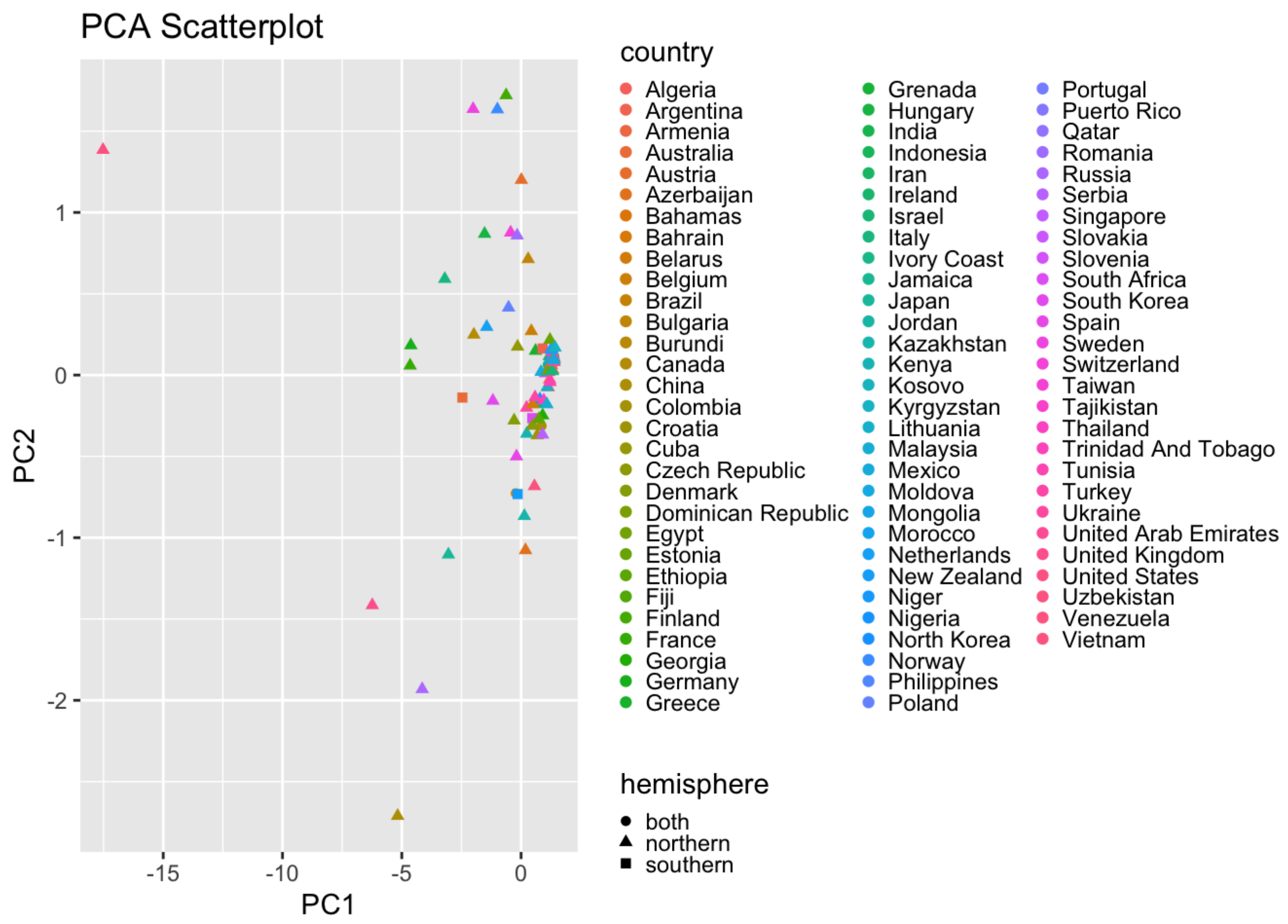


```
get_eigenvalue(pca1)
```

```
##         eigenvalue variance.percent cumulative.variance.percent
## Dim.1 6.358064e+00     9.082948e+01                    90.82948
## Dim.2 4.055755e-01     5.793935e+00                    96.62342
## Dim.3 1.276151e-01     1.823072e+00                    98.44649
## Dim.4 8.052043e-02     1.150292e+00                    99.59678
## Dim.5 2.550468e-02     3.643525e-01                    99.96113
## Dim.6 2.720603e-03     3.886575e-02                   100.00000
## Dim.7 1.118922e-31     1.598459e-30                   100.00000
```

Based on this analysis, we should consider one principal componenet. This is because the second through seventh principal components do not greatly contribute to the variance of the data, while the first principal component contributes to about 91% of the variance (eigenvalue = 6.36).

```
# Now, I will plot the data according to principle component considered from above (as w
ell as the second one) using 'ggplot' and 'geom_point', coloring by 'country' and shapin
g by 'hemisphere' in 'aes'. This will tell us how many clusters of similarity the princi
pal components puts the data into.
ggplot(pca2, aes(x = PC1, y = PC2, color = country)) +
  geom_point(aes(shape = hemisphere)) +
# This original plot can barely be seen because the legend is so large and extensive. We
will fix this using 'theme'. 'element_blank' gets rid of the legend borders and 'legend.
key.size' ensures that the size is set to just one point.
  theme(legend.key = element_blank(), legend.key.size = unit(1, "point")) +
# To continue making the legend smaller, we will assign 30 countries (which the points a
re colored by) to each row of the legend with 'guides' and 'guide_legend'. Fianlly, we w
ill add a title.
  guides(color = guide_legend(nrow = 30)) +
  ggtitle("PCA Scatterplot")
```



As we can see, the principal components puts the dataframe into clusters of observations within the dataset according to based on their similarity. Although the second PC was not nearly as contribtive to the variance in data, I have included it in the visualization as well.

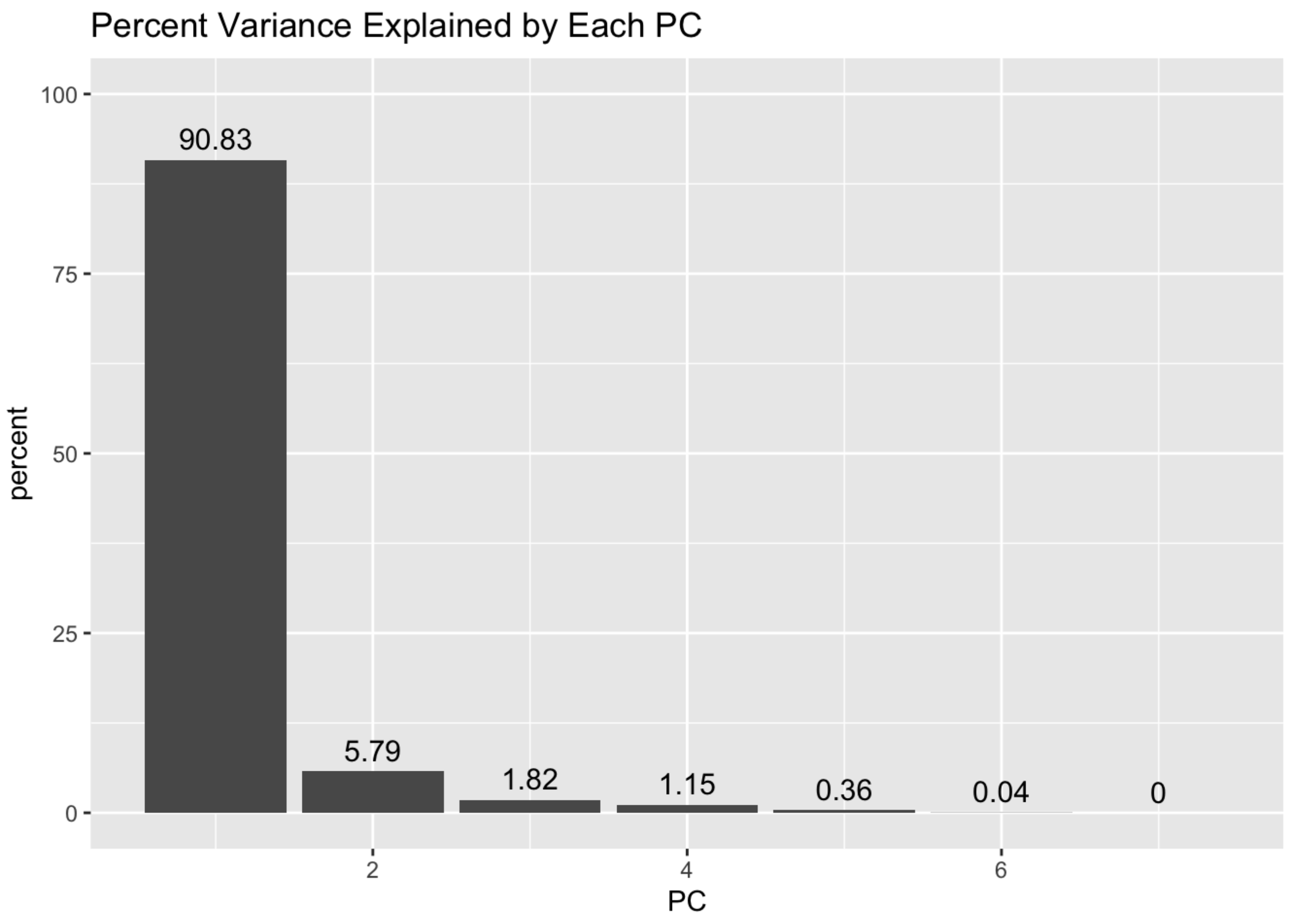
```
# We cen then do some calculations to see how much variance is caused by each of the com
ponents. This can be done by squaring the standard deviations of the PCA, dividing by th
e sum of all the squared standard deviations, and multiplying by 100%.
pca3 <- 100* (pca1$sdev^2 / sum(pca1$sdev^2))
pca3
```

```
## [1] 9.082948e+01 5.793935e+00 1.823072e+00 1.150292e+00 3.643525e-01
## [6] 3.886575e-02 1.598459e-30
```

Do these values look familiar? That is because it is shown as ‘variance.percent’ when we used ‘get_eigenvalue’ earlier.

```
# Now, we will save these percentages as a dataframe with 'data.frame'.
pca4 <- data.frame(percent = pca3, PC = 1:length(pca3))
```

```
# Now, we will use these percentages to see how they compare to one-another across each
 PC through a visualization. We will use 'ggplot' to make a 'geom_col' (bar chart).
ggplot(pca4, aes(x = PC, y = percent)) +
  geom_col() +
# Now I will label the graphs with their percentages with 'geom.text', rouding the value
s to two decimal points with 'round', and adjusting the size and position of the values.
  geom_text(aes(label = round(percent, 2)), size = 4, vjust = -0.5) +
# Finally, I will set a limit to the y-axis of 100 to ensure all of the variances are gr
aphed out with 'ylim', and add a title with 'ggtitle'.
  ylim(0, 100) +
  ggtitle("Percent Variance Explained by Each PC")
```



As we can see, the first PC contributes far greater to the variance of the data than all the other PCs. It contributes to 90.83% of the variance.