Week 4 - EDA

Exploratory Data Analysis on the Armed Conflict Dataset

Loading in libraries and reading in the final dataset

```
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
```

```
library(corrplot)
```

```
corrplot 0.94 loaded
```

```
library(FactoMineR)
library(factoextra)
```

```
Loading required package: ggplot2

Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
```

```r
library(here)
```

```
here() starts at C:/Users/victo/OneDrive/Documents/MSc Biostatistics - UofT/CHL 8010 - Statis
```

```r
# Read in the data
data <- read.csv(here("original","analytical", "finaldata.csv"),header=TRUE)

# View first few rows of dataset
head(data)
```

```
  country_name ISO        region year   gdp1000 OECD OECD2023  popdens    urban
1  Afghanistan AFG Southern Asia 2000        NA    0        0 14.13654 16.25324
2  Afghanistan AFG Southern Asia 2001        NA    0        0 14.23156 16.25661
3  Afghanistan AFG Southern Asia 2002 0.1835328    0        0 14.32270 16.42654
4  Afghanistan AFG Southern Asia 2003 0.2004626    0        0 14.40691 16.60701
5  Afghanistan AFG Southern Asia 2004 0.2216576    0        0 15.21947 16.71367
6  Afghanistan AFG Southern Asia 2005 0.2550551    0        0 15.33619 16.85096
    agedep male_edu     temp rainfall1000 matmor infmor neomor un5mor totdeath
1 108.3466 2.762086 12.69959    0.2763704   1450   90.5   60.9  129.2     5065
2 108.9899 2.856936 12.85570    0.2793079   1390   87.9   59.7  125.2     5394
3 109.3472 2.954241 12.71081    0.3805710   1300   85.3   58.5  121.1     5553
4 109.4475 3.054121 12.16592    0.4288939   1240   82.7   57.2  116.9     1157
5 109.2868 3.156706 13.04643    0.3754336   1180   80.0   55.9  112.6      944
6 107.9646 3.262133 12.23141    0.4415680   1140   77.3   54.6  108.4      817
  conflict drought earthquake
1        1       1          0
2        1       0          1
3        1       0          1
4        1       0          1
5        1       0          1
6        1       0          1
```

We will generate summary statistics of the data to see the general distribution of the data. We will also remove any rows with missing values.

```r
# Summary statistics
summary(data)
```

```
 country_name           ISO              region              year
 Length:3720        Length:3720        Length:3720        Min.   :2000
```

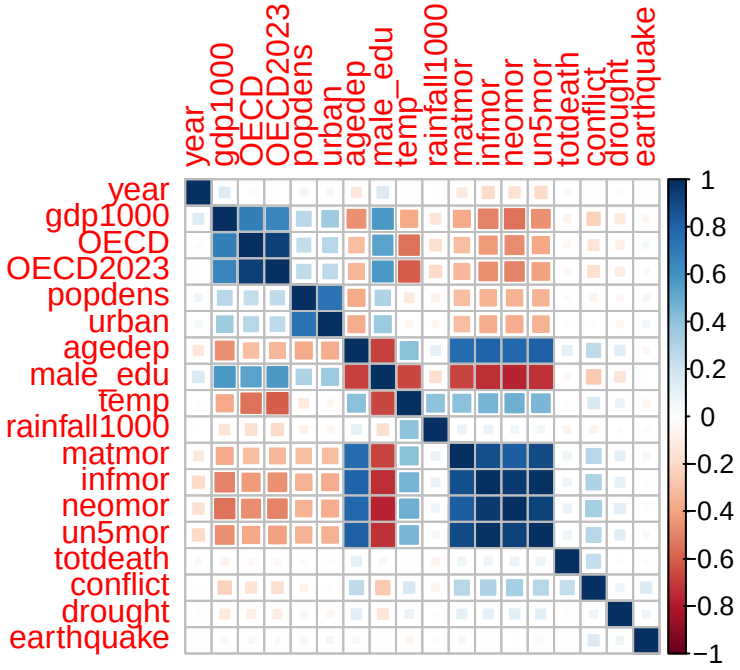
```
Class :character   Class :character   Class :character   1st Qu.:2005
Mode  :character   Mode  :character   Mode  :character   Median :2010
                                                         Mean   :2010
                                                         3rd Qu.:2014
                                                         Max.   :2019

   gdp1000             OECD          OECD2023         popdens
Min.   :  0.1105   Min.   :0.000   Min.   :0.0000   Min.   : 0.00
1st Qu.:  1.2383   1st Qu.:0.000   1st Qu.:0.0000   1st Qu.:14.79
Median :  4.0719   Median :0.000   Median :0.0000   Median :27.52
Mean   : 11.4917   Mean   :0.171   Mean   :0.1882   Mean   :30.57
3rd Qu.: 13.1531   3rd Qu.:0.000   3rd Qu.:0.0000   3rd Qu.:40.72
Max.   :123.6787   Max.   :1.000   Max.   :1.0000   Max.   :99.86
NA's   :62                                          NA's   :20
    urban             agedep          male_edu          temp
Min.   : 0.1025   Min.   : 16.17   Min.   : 1.067   Min.   :-2.405
1st Qu.:17.2872   1st Qu.: 47.94   1st Qu.: 5.904   1st Qu.:12.928
Median :30.2535   Median : 55.51   Median : 8.368   Median :21.958
Mean   :30.6948   Mean   : 61.94   Mean   : 8.258   Mean   :19.625
3rd Qu.:41.6558   3rd Qu.: 77.11   3rd Qu.:10.849   3rd Qu.:25.869
Max.   :93.4135   Max.   :111.48   Max.   :14.441   Max.   :29.676
NA's   :20                         NA's   :20       NA's   :20
 rainfall1000         matmor          infmor          neomor
Min.   :0.01993   Min.   :   2.0   Min.   :  1.60   Min.   : 0.80
1st Qu.:0.59146   1st Qu.:  17.0   1st Qu.:  7.60   1st Qu.: 4.90
Median :1.01288   Median :  66.0   Median : 18.90   Median :12.10
Mean   :1.20216   Mean   : 210.6   Mean   : 28.90   Mean   :16.18
3rd Qu.:1.68706   3rd Qu.: 299.8   3rd Qu.: 44.52   3rd Qu.:25.32
Max.   :4.71081   Max.   :2480.0   Max.   :138.10   Max.   :60.90
NA's   :20        NA's   :426      NA's   :20       NA's   :20
    un5mor          totdeath         conflict         drought
Min.   :  2.00   Min.   :    0.0   Min.   :0.0000   Min.   :0.00000
1st Qu.:  9.00   1st Qu.:    0.0   1st Qu.:0.0000   1st Qu.:0.00000
Median : 22.20   Median :    0.0   Median :0.0000   Median :0.00000
Mean   : 40.50   Mean   :  361.1   Mean   :0.1892   Mean   :0.08737
3rd Qu.: 61.33   3rd Qu.:    2.0   3rd Qu.:0.0000   3rd Qu.:0.00000
Max.   :224.90   Max.   :78644.0   Max.   :1.0000   Max.   :1.00000
NA's   :20
  earthquake
Min.   :0.00000
1st Qu.:0.00000
Median :0.00000
Mean   :0.08333
```

```
 3rd Qu.:0.00000
 Max.   :1.00000
```

```
# Remove missing rows
clean_data <- na.omit(data)
```

A correlation matrix will be used to explore the relationships between numeric variables within the dataset. One observation is that there is a negative correlation between mortality and urbanization, which could be due to better healthcare infrastructure in urban areas.

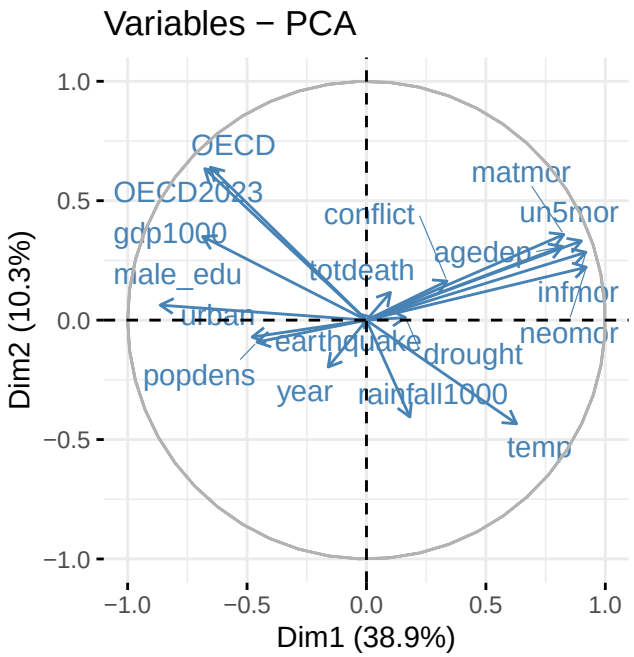
```
# Produce a correlation matrix
numeric_data <- clean_data %>% select_if(is.numeric)
cor_matrix <- cor(numeric_data, use = "complete.obs")
corrplot(cor_matrix, method = "square")
```



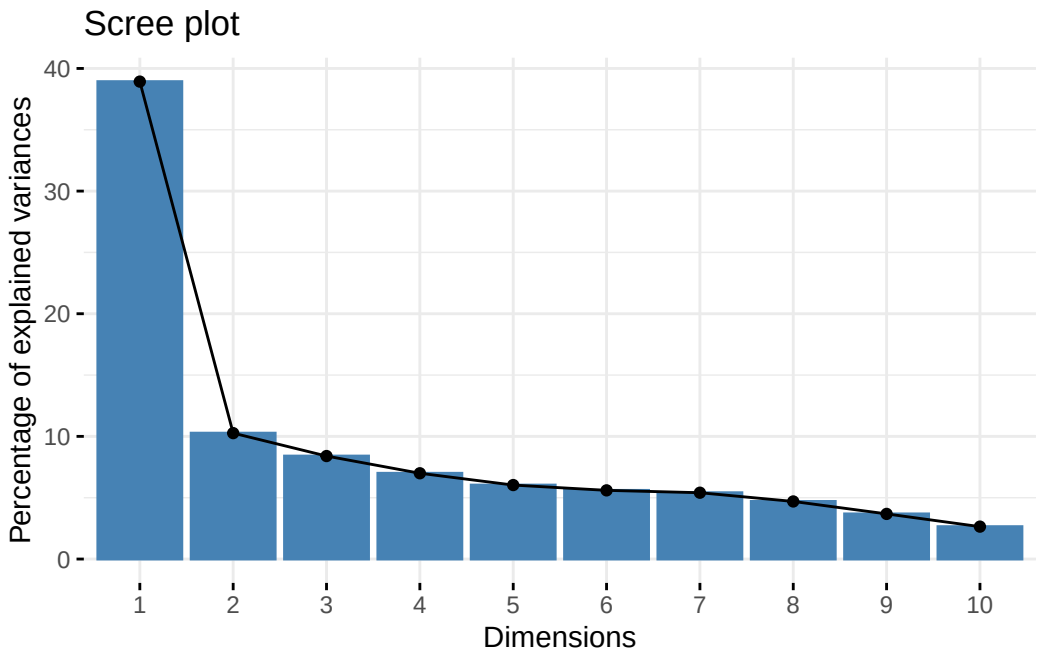
Performing PCA helps identify the most important components. A biplot allows us to observe how the original variables contirbute to the principal components and how the data points are distributed across the axes.

A scree plot can help visualize how much variability each component explains.

```r
# PCA - Principal Component Analysis
# Standardize the numeric data
scaled_data <- scale(numeric_data)

# Performing PCA
pca_result <- PCA(scaled_data, graph = FALSE)

# Create a biplot with only arrows (variables)
fviz_pca_var(pca_result,
             col.var = "steelblue",
             repel = TRUE,
             labelsize = 4)
```




```r
# Generate the scree plot
fviz_eig(pca_result)
```



The biplot shows that the first two components, Dim1 and Dim2, explain almost 50% of the total variance in the data. Variables like matmor (maternal mortality), un5mor (under-5 mortality), and infmor (infant mortality) have strong contributions to Dim1.

From the scree plot, the first principal component (PC1) accounts for about 40% of the variance, and second principal component (PC2) explains 10% of the variance. The elbow shows that the first two components account for a significant portion of the variance.