GRIP Task 4: Exploratory Data Analysis - Terrorism

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Importing libraries and visualising the data

We first load the libraries required for our work and then read the dataset.

```
#Fortunately, we do not need to load any other library for this work
df<-read.csv('D:\\Important Documents\\Internship\\Task-4\\globalterrorismdb_0718dist.csv',
                         header=T)#reading the dataset
dim(df)#dimensions of the dataset

## [1] 181691    135

length(is.na(df))#number of 'na' values

## [1] 24528285

names(df)

##   [1] "eventid"             "iyear"               "imonth"
##   [4] "iday"                "approxdate"          "extended"
##   [7] "resolution"          "country"             "country_txt"
##  [10] "region"              "region_txt"          "provstate"
##  [13] "city"                "latitude"            "longitude"
##  [16] "specificity"         "vicinity"            "location"
##  [19] "summary"             "crit1"               "crit2"
##  [22] "crit3"               "doubtterr"           "alternative"
##  [25] "alternative_txt"     "multiple"            "success"
##  [28] "suicide"             "attacktype1"         "attacktype1_txt"
##  [31] "attacktype2"         "attacktype2_txt"     "attacktype3"
##  [34] "attacktype3_txt"     "targtype1"           "targtype1_txt"
##  [37] "targsubtype1"        "targsubtype1_txt"    "corp1"
##  [40] "target1"             "natlty1"             "natlty1_txt"
##  [43] "targtype2"           "targtype2_txt"       "targsubtype2"
##  [46] "targsubtype2_txt"    "corp2"               "target2"
##  [49] "natlty2"             "natlty2_txt"         "targtype3"
```

```
##  [52] "targtype3_txt"      "targsubtype3"       "targsubtype3_txt"
##  [55] "corp3"              "target3"            "natlty3"
##  [58] "natlty3_txt"        "gname"              "gsubname"
##  [61] "gname2"             "gsubname2"          "gname3"
##  [64] "gsubname3"          "motive"             "guncertain1"
##  [67] "guncertain2"        "guncertain3"        "individual"
##  [70] "nperps"             "nperpcap"           "claimed"
##  [73] "claimmode"          "claimmode_txt"      "claim2"
##  [76] "claimmode2"         "claimmode2_txt"     "claim3"
##  [79] "claimmode3"         "claimmode3_txt"     "compclaim"
##  [82] "weaptype1"          "weaptype1_txt"      "weapsubtype1"
##  [85] "weapsubtype1_txt"   "weaptype2"          "weaptype2_txt"
##  [88] "weapsubtype2"       "weapsubtype2_txt"   "weaptype3"
##  [91] "weaptype3_txt"      "weapsubtype3"       "weapsubtype3_txt"
##  [94] "weaptype4"          "weaptype4_txt"      "weapsubtype4"
##  [97] "weapsubtype4_txt"   "weapdetail"         "nkill"
## [100] "nkillus"            "nkillter"           "nwound"
## [103] "nwoundus"           "nwoundte"           "property"
## [106] "propextent"         "propextent_txt"     "propvalue"
## [109] "propcomment"        "ishostkid"          "nhostkid"
## [112] "nhostkidus"         "nhours"             "ndays"
## [115] "divert"             "kidhijcountry"      "ransom"
## [118] "ransomamt"          "ransomamtus"        "ransompaid"
## [121] "ransompaidus"       "ransomnote"         "hostkidoutcome"
## [124] "hostkidoutcome_txt" "nreleased"          "addnotes"
## [127] "scite1"             "scite2"             "scite3"
## [130] "dbsource"           "INT_LOG"            "INT_IDEO"
## [133] "INT_MISC"           "INT_ANY"            "related"
```

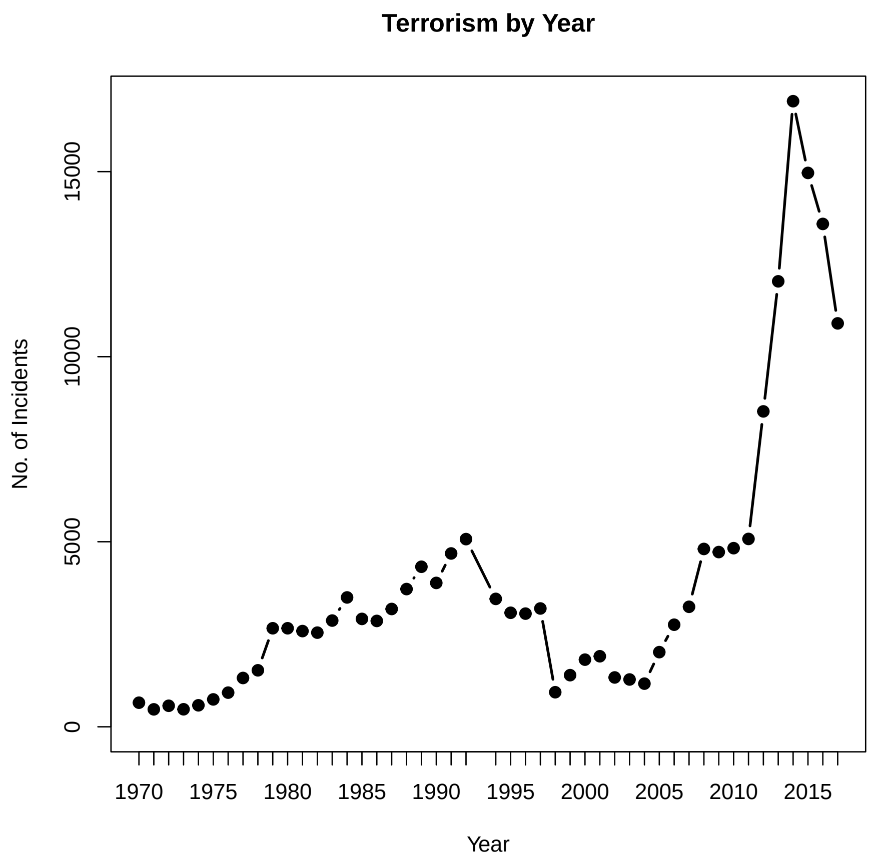
Exploratory Data Analysis

We now move forward to our Exploratory Data Analysis part.

Attacks by Year:

The below chart describes the number of attacks by year

```
attack_year<-table(df$iyear)
plot(attack_year,type='b',main='Terrorism by Year',
        xlab='Year',ylab='No. of Incidents',pch=19)
```



Conclusions

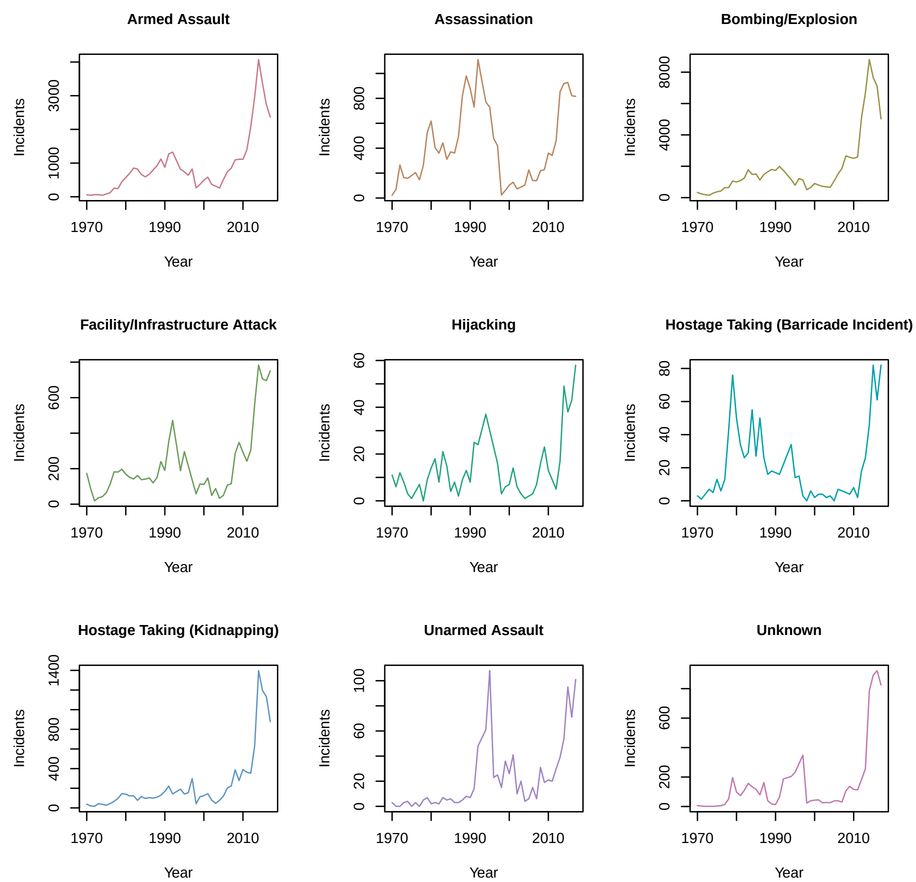
From the above chart, we observe that no. of attacks increased over the years since 1970 till the early 90s. However, there was a decline in the no. of attacks till the late 90s. Moving further, we obseve a steep incline in the no. of attacks since the late 90s till 2014(which also has the highest number of attacks in a calender year) and we note a decline in the no. of attacks since then.

Type of Attack by Year:

We next look at the frequency of attacks over the years by their type

```
type_year<-cbind(unique(df$iyear),table(df$iyear,df$attacktype1_txt))
type_year<-type_year[order(type_year[,1]),]
par(mfrow=c(3,3))
```

```
for(i in 2:ncol(type_year))
{
        plot(x=type_year[,1],y=type_year[,i],main=colnames(type_year)[i],
                xlab='Year',ylab='Incidents',type='l',cex.main=0.95,
                col=hcl.colors(9,'dark 2')[i-1])
}
```



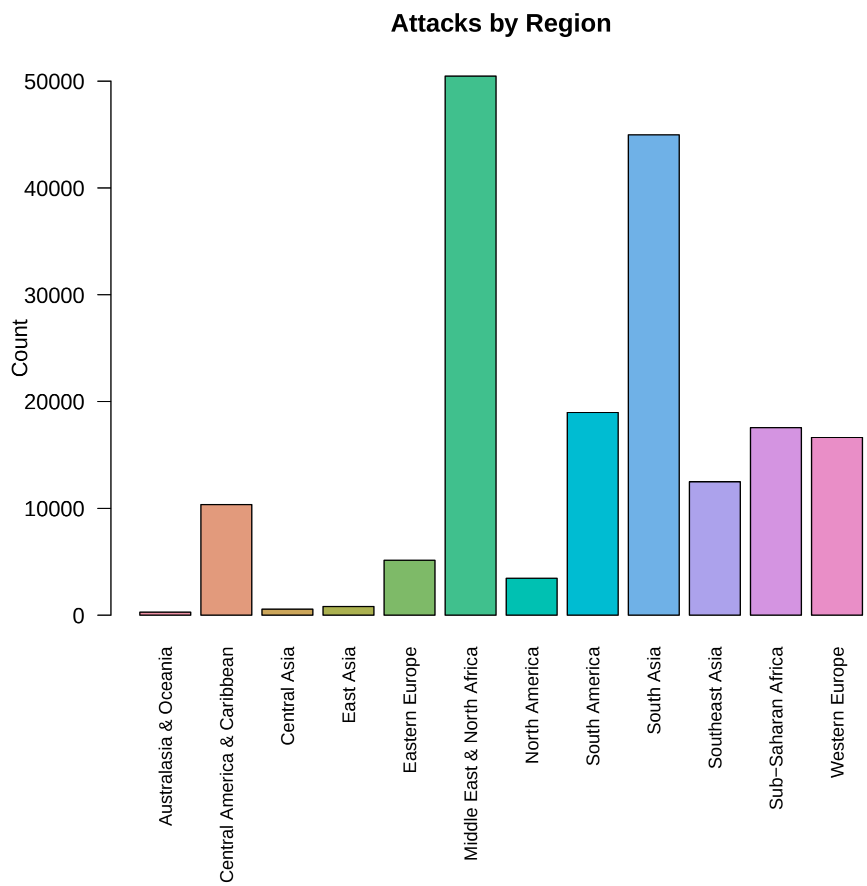
Conclusions

We notice some interesting patterns in the type of attacks over the years. **Armed Assault** saw an overall growth till the mid 90s with the no. of cases dipping before rising steeply from the mid 2000s till 2014 and then declining again. **Assassination** was very popular since the beginning with the no. of cases rising in the till the early 90s before this type of attack faced a drop. However, since the late 90s, the no. of cases corresponding to this type of attack increased (almost) exponentially till the mid 2010s. **Bombings/Explosions** were somewhat common till the mid 2000s before gaining popularity as the no. of cases soared up till the mid 2010s. It has seen a decline since then. **Facility/Infrastructure Attacks** gained popularity just before the 90s and then again since the mid 2000s. **Hijacking** has an uneven history with sometimes gaining popularity and sometimes not. **Hostage Taking (Barricade Incident)** was initially a very common form of attack until the mid 90s when these incidents were significantly reduced. However, since 2010, the no. or these events rose at an increasing rate. **Hostage Taking (Kidnapping)** was initially a not-so-common form of attack. However, it saw a steady increase and the no. of cases leaped at a tremendous pace since the early 2000s. **Unarmed Assault** was very common in the mid 90s before subsiding in the 2000s. However, since 2010, the no. of cases of this type is on the rise. **Unknown** attacks gained popularity since the 2010s and has been on the rise since then.

Attack by Region:

We next look at the frequency of attacks based on regions

```
attack_reg<-table(df$region_txt)
par(mar=c(10,4,4,1)+.1)
barplot(attack_reg,las=2,cex.names=0.8,
        col=hcl.colors(nrow(attack_reg),'set 2'),
        ylab='Count',main='Attacks by Region')
```



Conclusions

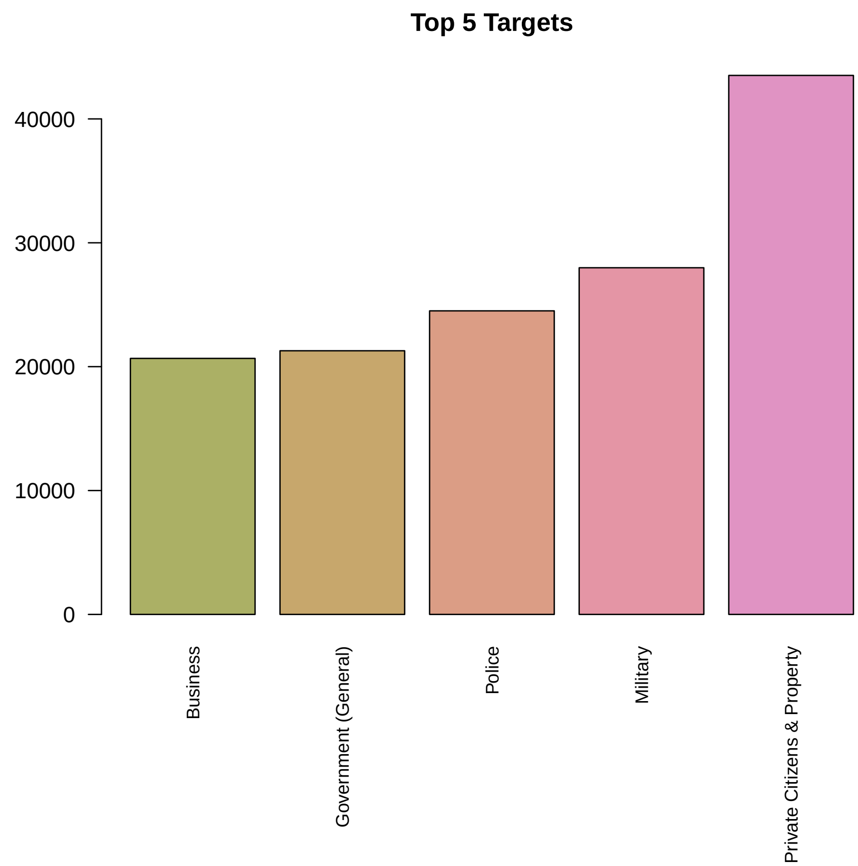
We find that the most affected region by terrorism in the world is **Middle East & North Africa** followed closely by **South Asia**. The third most affected region is **South America**, however, there's a big gap between the first second and the third.

Target type:

We next look at the most common targets of the terrorists by type

```
par(mar=c(10,4,4,1)+.1)
targ_type<-table(df$targtype1_txt)
max_targ_type<-tail(sort(targ_type),5)
barplot(max_targ_type,col=hcl.colors(5,'warm'),las=2,
```

```
        cex.names=0.8,main='Top 5 Targets')
```



Conclusions

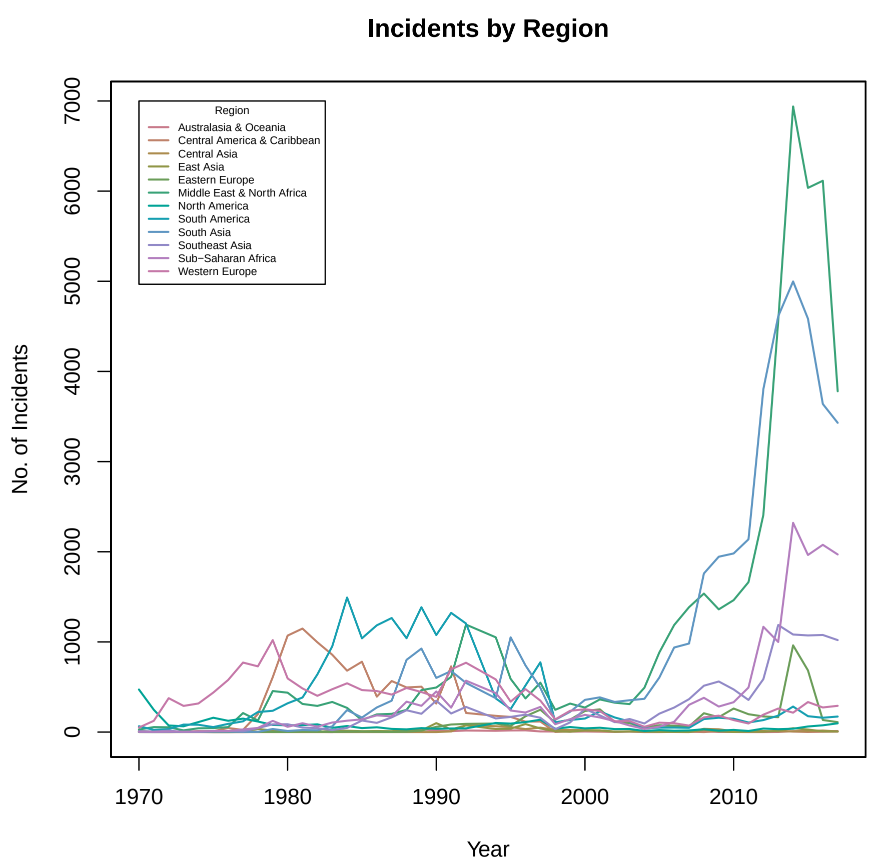
We observe that **Private Citizens & Properties** is the most popular target type for the terrorists. However, violence against **Military**, **Police**, **Government(General)** and **Business** are also not uncommon.

Attacks by Region over the years:

We now look at the attacks over the years on various regions

```
reg_year<-table(df$region_txt,df$iyear)
plot(x=colnames(reg_year),y=reg_year[1,],type='l',lwd=1.5,
        ylim=c(min(reg_year),max(reg_year)),xlim=c(1970,2017),
```

```
        col=hcl.colors(nrow(reg_year),'dark 2')[1],
        xlab='Year',ylab='No. of Incidents',
        main='Incidents by Region')
for(i in 2:nrow(reg_year))
{
        par(new=T)
        plot(x=colnames(reg_year),y=reg_year[i,],type='l',lwd=1.5,
                ylim=c(min(reg_year),max(reg_year)),xlim=c(1970,2017),
                xaxt='n',yaxt='n',xlab=NA,ylab=NA,
                col=hcl.colors(nrow(reg_year),'dark 2')[i])
}
legend(x=1970,y=7000,rownames(reg_year),lwd=1.5,
                col=hcl.colors(nrow(reg_year),'dark 2'),
                cex=0.5,title='Region')
```



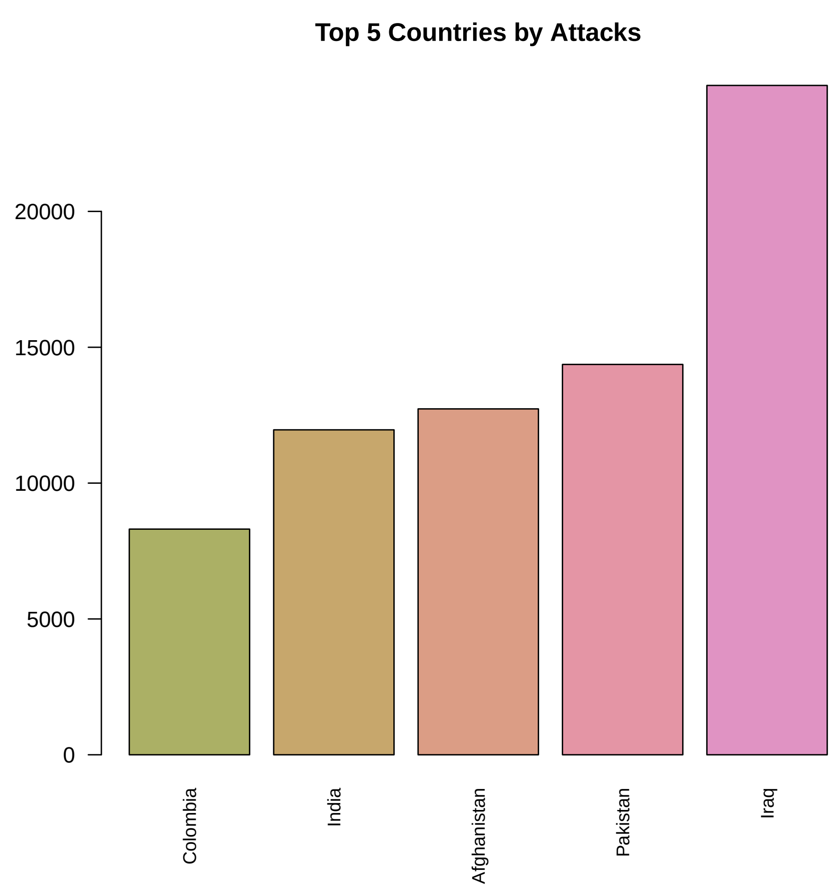
Conclusions

We notice an interesting trend of attacks in various regions over the years. While initially, **South America** saw more unrests in the period between 1980 to 2000, **South Asia** and **Middle East & North Africa** saw a huge rise in terror activities. We also notice that in the year 2014, there has been a global unrest, which cause every single region to have a spike in the annual uprisings.

Affected Country:

The below graph shows the most attacked countries

```
country<-table(df$country_txt)
max_country<-tail(sort(country),5)
barplot(max_country,col=hcl.colors(5,'warm'),
                las=2,cex.names=0.8,main='Top 5 Countries by Attacks')
```



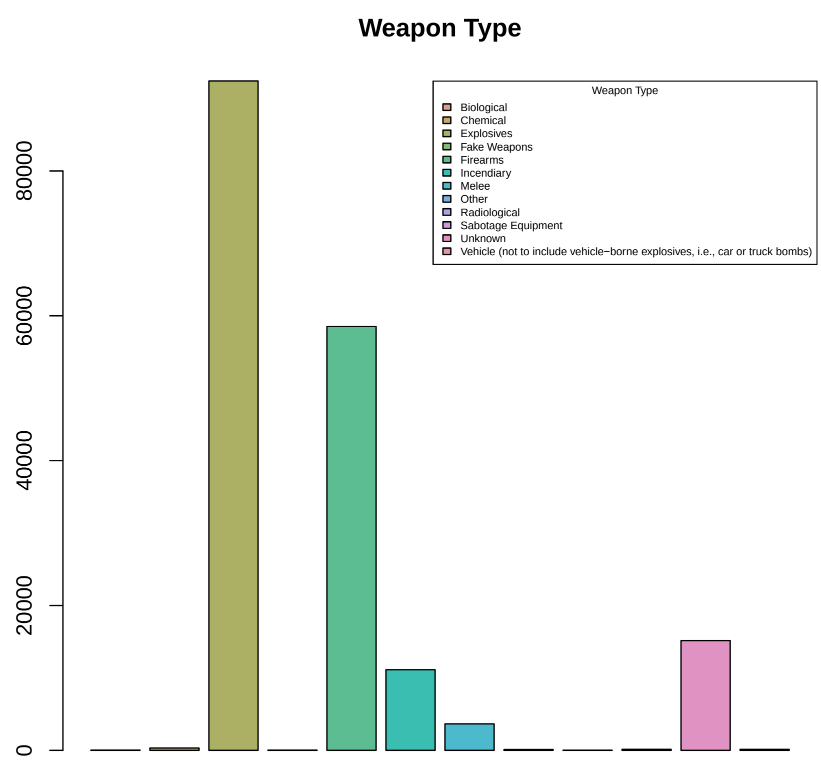
Conclusions

We find that **Iraq** is the most affected country in the world. It has a huge gap with **Pakistan** which is placed second in the list.

Weapons Used:

In the below given graph, we aim to look at the weapons used by the terrorists to carry out the attacks

```
weapon<-table(df$weaptype1_txt)
barplot(weapon,xaxt='n',col=hcl.colors(length(unique(df$weaptype1_txt)),'dynamic'),
                main='Weapon Type')
legend('topright',rownames(weapon),
                fill=hcl.colors(length(unique(df$weaptype1_txt)),'dynamic'),
                cex=0.5,title='Weapon Type')
```



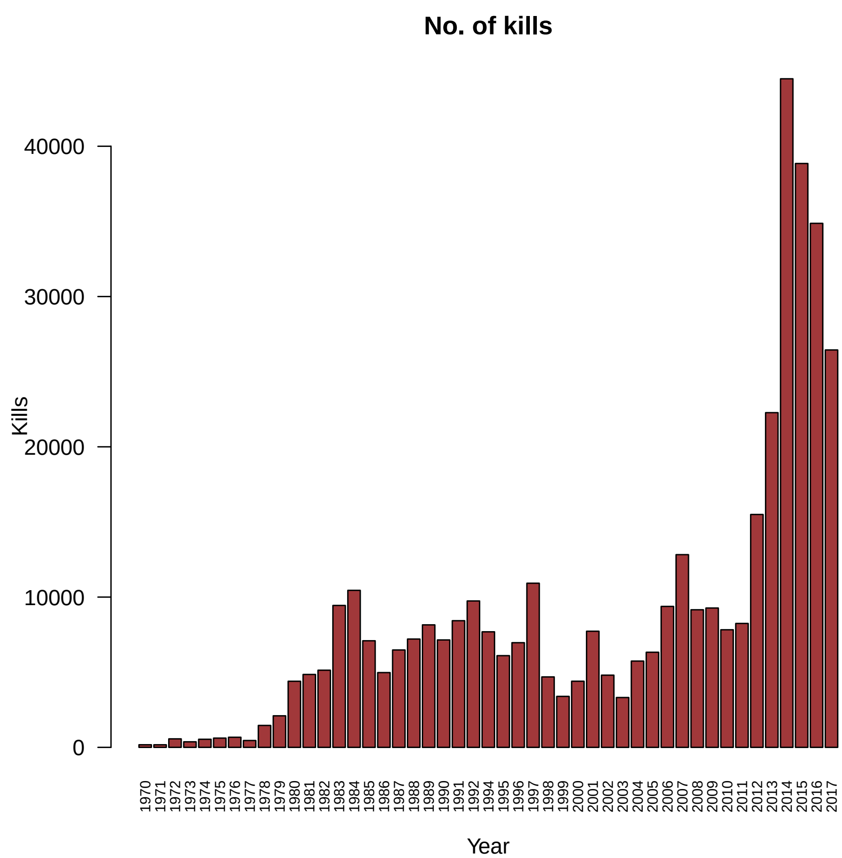
Conclusions

We note from the graph that the most common weapon used was **Explosives**, followed by **Firearms**. These two itself consisted of the max percentage of weapons used for the attacks.

Casualties by Year:

Finally, we look at the casualties by year globally

```
df[is.na(df$nkill),]$nkill<-0
year_kill<-tapply(df$nkill,df$iyear,sum)
year_kill<-as.table(year_kill)
barplot(year_kill,las=2,cex.names=0.7,main='No. of kills',
                xlab='Year',ylab='Kills',col='#a1383a')
```



Conclusions

We find that in the year 2014, maximum number of deaths occurred across the world. This is in keeping with the fact that there was an increase in global terrorism in that particular year.

Further, looking at this graph, we can relate it to the graph of the Attacks by Year. We proceed to further find a correlation between the number of deaths and the number of attacks in a calendar year.

Correlation:

We find the correlation coefficient between Casualties and No. of Attacks

```
attack_kill<-cbind(year_kill,attack_year)
atk_cor<-cor(attack_kill)
atk_cor

##             year_kill attack_year
## year_kill    1.000000    0.966005
## attack_year  0.966005    1.000000

atk_cor[lower.tri(atk_cor,diag=T)]<-0
max(atk_cor)

## [1] 0.966005
```

We observe that the correlation coefficient is pretty high, which implies that the there is a direct relation between the Casualties and No. of Attacks in a calendar year.

Database Source:

The below table lists the database source

```
source<-as.data.frame(table(df$dbsource))
colnames(source)<-c('Source','Freq')
source

##                                      Source  Freq
## 1                 Anti-Abortion Project 2010   186
## 2                           Armenian Website    40
## 3                                       CAIN  1588
## 4                      CBRN Global Chronology    46
## 5                                      CETIS 16163
## 6          Disorders and Terrorism Chronology     5
## 7                           Eco Project 2010   147
## 8                             Hewitt Project  1005
```

```
## 9                                 Hijacking DB    54
## 10                                         HSI    97
## 11                                      Hyland    71
## 12                                        ISVG 17207
## 13                    Leuprecht Canadian Data     6
## 14                                        PGIS 63740
## 15                                     Sageman     3
## 16                    START Primary Collection 78002
## 17              State Department 1997 Document    28
## 18                        UMD Algeria 2010-2012   848
## 19                  UMD Assassinations Project    18
## 20                        UMD Black Widows 2011     7
## 21 UMD Encyclopedia of World Terrorism 2012    48
## 22                          UMD JTMM Nepal 2012   104
## 23                           UMD Miscellaneous   259
## 24                             UMD Schmid 2012  1165
## 25                            UMD South Africa   449
## 26                           UMD Sri Lanka 2011   405
```

Inference

We draw the following conclusions from the Data Analysis:

- The **Middle East** region is the hot zone of terrorism in the world with **Iraq** being the most active one in this region (and across the globe).
- Since 2014, the overall terror activity across the globe has decreased significantly.