# EXTREME FINANCIAL RISK MEASUREMENT ASSIGNMENT

## GROUP 9

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## Required:

Fitting a suitable Generalized Extreme Value Distribution to a set of annual loss maxima data, calculate the 5 % Value at Risk and the return level.

We shall import our data from excel:

```
> head(LossData)
          Year   Loss
    1.    1971    7.4
    2.    1972    0.0
    3.    1973    0.6
    4.    1974    3.4
    5.    1975    0.0
    6.    1976    0.0
```

# Exploratory Data Analysis

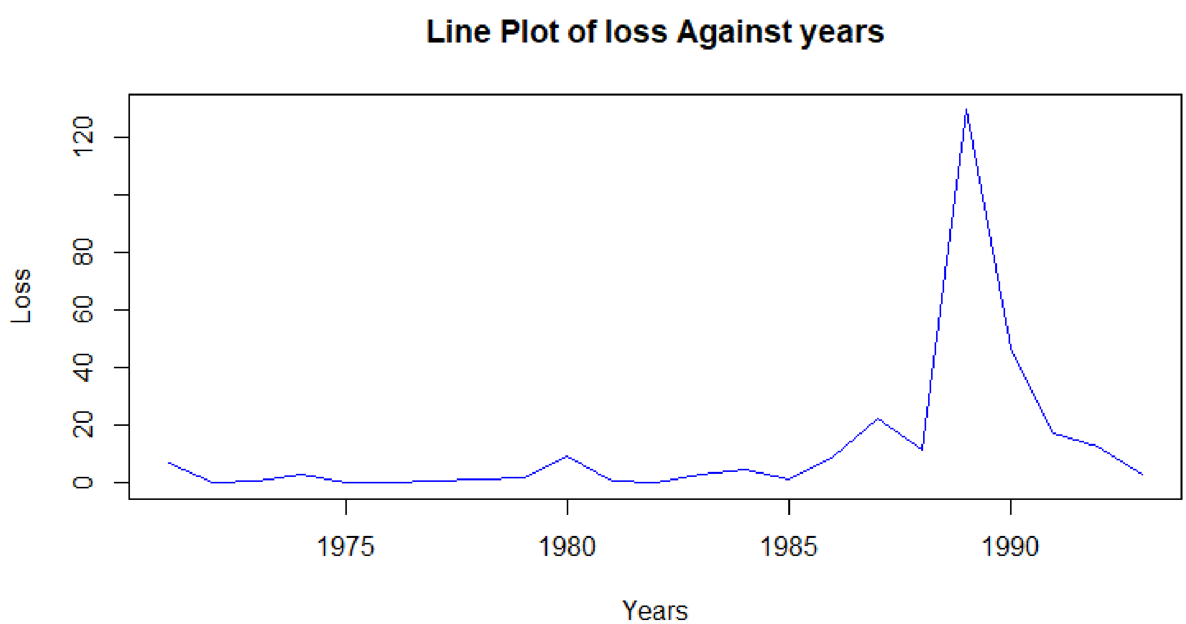
After we have imported our data, let us get a general overview:

```
#structure of the data
> str(LossData)
Classes 'tbl_df', 'tbl' and 'data.frame':    23 obs. of  2 variables:
 $ Year: num  1971 1972 1973 1974 1975 ...
 $ Loss: num  7.4 0 0.6 3.4 0 0 0.7 1.5 2.2 9.2 ...
> #class of object
> class(LossData)
[1] "tbl_df"     "tbl"       "data.frame"
> summary(LossData)
     Year          Loss
```

```
 Min.   :1971   Min.:  0.00
 1st Qu.:1976   1st Qu.:  0.80
 Median :1982   Median :  3.20
 Mean   :1982   Mean   : 12.55
 3rd Qu.:1988   3rd Qu.: 10.40
 Max.   :1993   Max.   :129.80
```

A line plot of Loss against Years

```
#Plot the Lossdata against the Years
> plot(Years, Loss)
> plot(Years, Loss, type = 'l', col = 'blue', xlab = 'Years', ylab = 'Loss',
+       main = 'Line Plot of loss Against years')
```



## Fitting the Model

We will fit the model and obtain the location, scale and shape MLE estimates as shown below:

```
gev_model$result$par
 location     scale     shape
0.4514559 2.4282843 5.3783726
```

The estimated parameters of the GEV distribution are as follows:

Location ($\mu$): 0.4514559

Scale ($\sigma$): 2.4282843

Shape($\xi$): 5.3783726

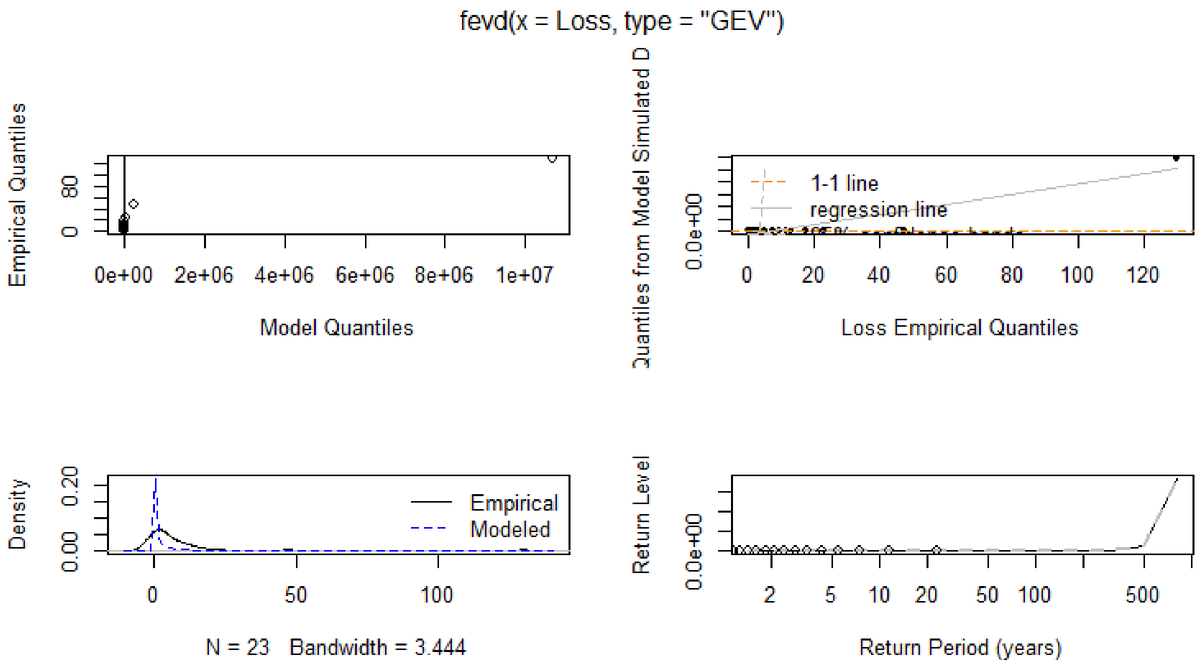
The location parameter ($\mu$) represents indicates the central tendency of the data.

The scale parameter ($\sigma$) measures the variability or dispersion of the data.

The shape parameter ($\xi$) determines the shape of the distribution and indicates whether it is heavy-tailed ($\xi > 0$), light-tailed ($\xi < 0$), or approximately exponential ($\xi = 0$).

Our shape parameter 5.3783726 > 0 thus it indicates a heavy tail, hence an indication that the data follows a **Fretchet** distribution.

```
> plot(gev_model)
```




As instrumental graphical tools, these diagnostic plots were used to assess the goodness-of-fit between the chosen model and the observed dataset. When determining if the selected distribution accurately captures the subtleties of the observed data, these diagnostic charts are essential.

## Empirical Quantiles against Model Quantiles

The quantiles of the fitted distribution are compared with the quantiles of the observed data. A deviation from the expected distribution could be indicated by a deviation from a straight line. The plots in the preceding image closely match along a straight line, indicating that the model's predictions and the actual distribution of the data are in good agreement. A satisfactory fit between the observed data and the GEV distribution model is indicated by this alignment.

## Quantiles from Model Simulated against Loss Empirical Quantiles

This plot displays the quantiles of the residuals, which were specially determined to evaluate the GEV model's suitability. By contrasting the expected (theoretical) quantiles under the GEV distribution with the quantiles derived from the residuals, these quantiles aid in assessing how well the GEV model represents the extreme values in the data.

## Density plot

Compares the estimated probability density function of the fitted distribution to the observed data's histogram. The values N=23 and bandwidth=3.444 in the context of a density plot typically refer to N=23: This represents the number of observations or data points in your dataset. Bandwidth=3.444:

## Return Level against Return Period

This plot shows the estimated return levels for different return periods. It helps visualize how extreme values are predicted by the fitted distribution.

## Calculating VaR:

After fitting the GEV distribution and the obtained MLE parameter estimates, the 5% VaR shall be calculated as shown below:

```
var_5_percent <- qgev(0.95, gev_model$results$par[1],
gev_model$results$par[2], gev_model$results$par[3])
print(var_5_percent)
##    scale
## 36.05418
## attr(,"control")
##          xi        mu      beta                  lower.tail
##  0.4514559 2.428284 5.378373        TRUE
```

## Calculation of return level:

Return level for the 23 years is calculated as shown below:

```
> return_level_23_years<-return.level(gev_model, return.period = 23)
> print(return_level_23_years)
fevd(x = Loss, type = "GEV")
get(paste("return.level.fevd.", newcl, sep = ""))(x = x,
    return.period = return.period)
 GEV model fitted to  Loss
Data are assumed to be  stationary
[1] "Return Levels for period units in years"
23-year level
      8449002
```

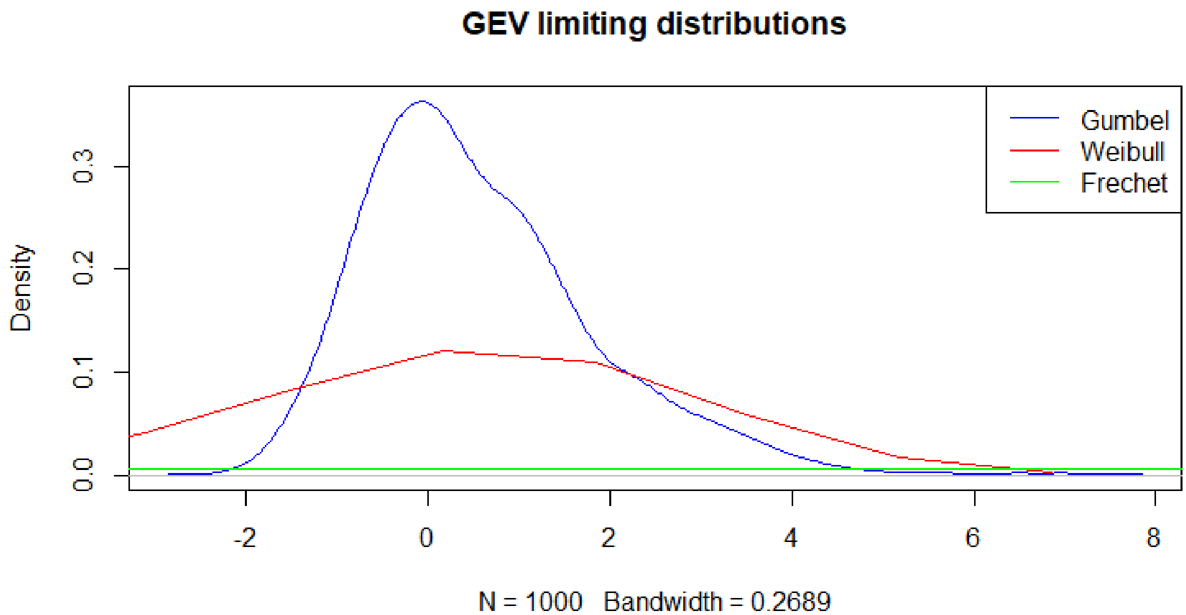
## Conclusion

The 5% VaR is 36.05418 that is at 95% confidence interval, there is a one chance in twenty or a 5% probability of a maximum loss of 36.05418 in a year will occur. The return level represents the threshold value that an extreme event is expected to exceed with a certain probability over a specified time period. The estimated return level for this study from the output given above is 8,449,002. Since the period level is provided as 23 years (As shown above), the interpretation of this is that an extreme event of this magnitude is expected to occur once in every 23 years.

## Simulating GEV Distributions:

```
#simulations from packages fEtremes
library(fExtremes)

my_Weibull<-gevSim(model = list(xi=-5.378726,mu=0.4514559 ,beta=2.4282843),
                n=100,seed=NULL)
my_Fretchet<-gevSim(model = list(xi=5.378726,mu=0.4514559 ,beta=2.4282843),
                n=100,seed=NULL)
my_gumbell<-gevSim(model = list(mu=0.4514559,beta=2.4282843),
                n=100,seed=NULL)
gum<-gevSim(model=list(xi=0,mu=0.4514559,beta=2.4282843),
          n=100,seed=NULL)
G<-density(my_gumbell)
W<-density(my_Weibull)
F<-density(my_Fretchet)
plot(G,col="blue",main='GEV limiting distributions')
lines(W,col="red")
lines(F,col="green")
legend(x="topright", legend=c("Gumbel", "Weibull", "Frechet"),
      col=c("blue", "red", "green"), lty=1, cex=1)
```


GEV limiting distributions
Gumbel
Weibull
Frechet
Density
0.0
0.1
0.2
0.3
-2
0
2
4
6
8
N = 1000   Bandwidth = 0.2689