Bangladesh Data Analysis

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As before, first we import the data.

```
bangladesh=read.csv("bangladesh-data.csv", header=TRUE)
names(bangladesh)
```

```
## [1] "Arsenic"  "Chlorine" "Cobalt"
```

```
#accessing single columns
#bangladesh$Arsenic
attach(bangladesh)
Arsenic
```

```
##   [1] 2400    6  904  321 1280  151  141 1050  511  688   81    8   37    6   22
##  [16]   43   39   92  253  200  255 1150 1180    9  107    6  149    6   46   13
##  [31]    6  150    6  189  364   42  390    6  270  248  139    6   82   82  256
##  [46]  165    6  180   86    6   38  262  404    8   85   98    6   22    6    6
##  [61]    6   15  103   86    6   46   62   43    6    6   55    6  107   65  276
##  [76]  114    6    6    6   65  142  194    6   54  702    6  986  153   84   16
##  [91] 1460  306   49   36  106    6   41   84  278   41
##  [ reached 'max' / getOption("max.print") -- omitted 171 entries ]
```

```
mean(Arsenic)
```

```
## [1] 125.3199
```

```
var(Arsenic)
```

```
## [1] 88789.39
```

```
#hist(Arsenic)
#what are the dimensions of `bangladesh`
dim(bangladesh)
```

```
## [1] 271   3
```

```
#see if there are missing data
bangladesh=na.omit(bangladesh)
#what are the "new" dimensions of `bangladesh`
dim(bangladesh)
```

```
## [1] 268   3
```

```
attach(bangladesh)
```

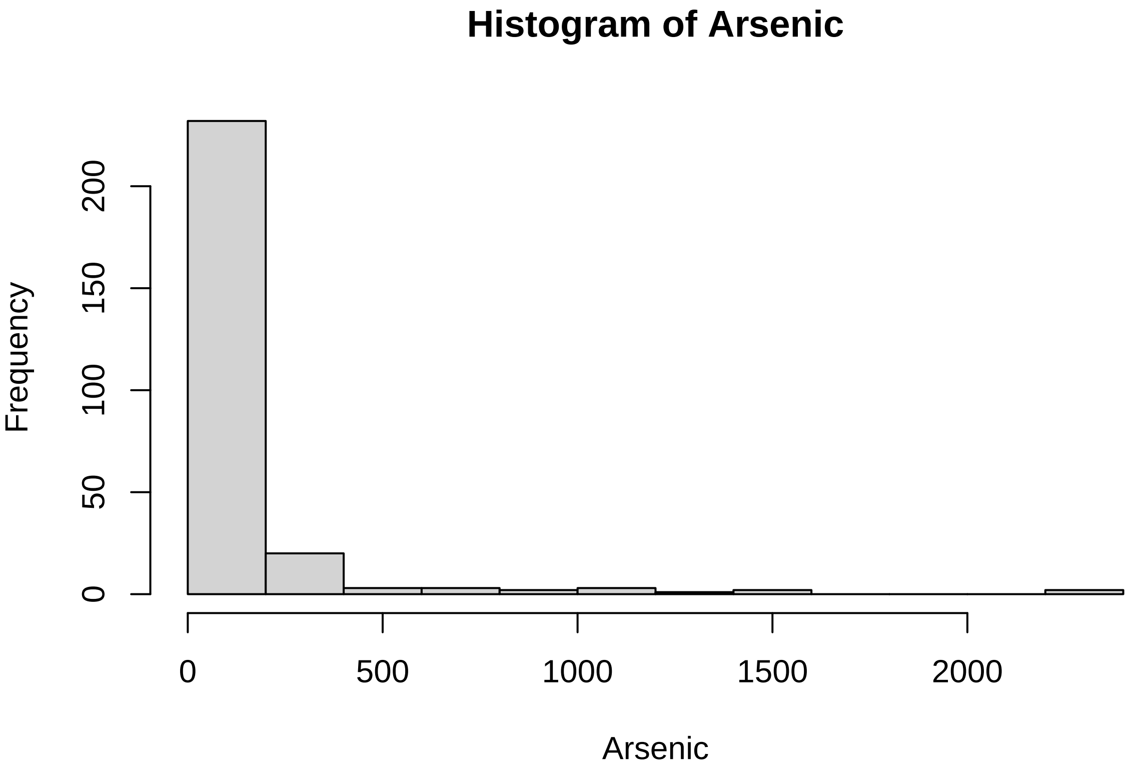
```
## The following objects are masked from bangladesh (pos = 3):
##
##     Arsenic, Chlorine, Cobalt
```

```
n=length(Arsenic)
n
```

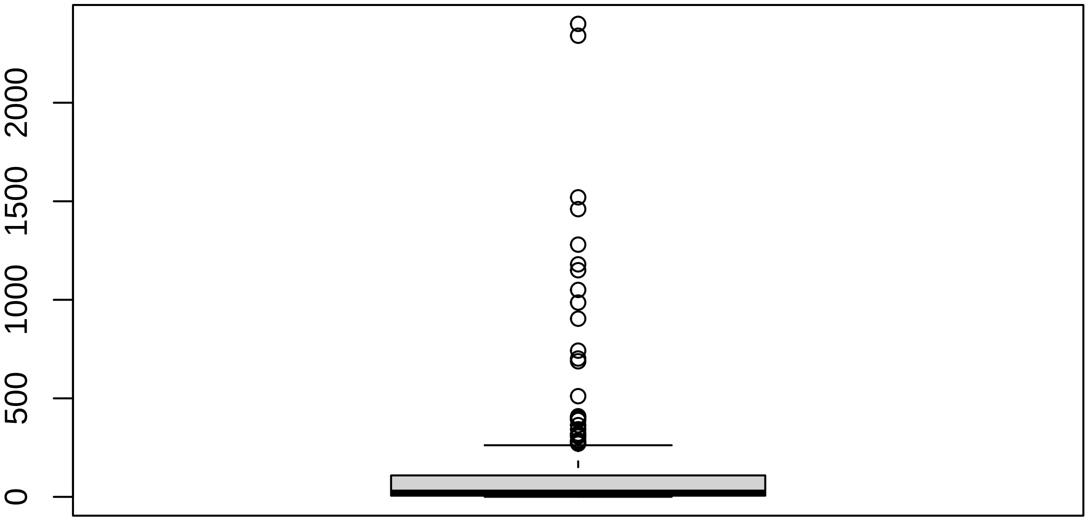
```
## [1] 268
```

Again, we undertake a rudimentary exploratory data analysis.

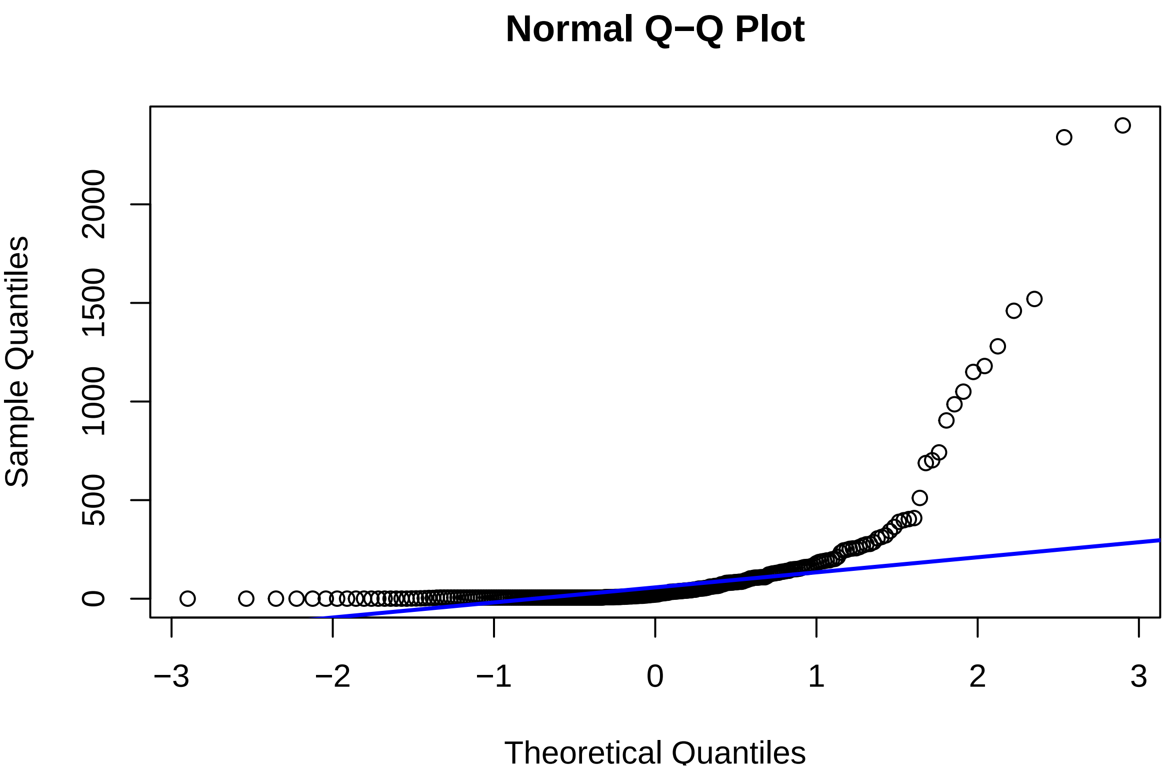
```r
hist(Arsenic)
```



```r
boxplot(Arsenic)
```



```r
qqnorm(Arsenic)
qqline(Arsenic, col="blue", lwd=2)
```



What does the test of normality tell us?

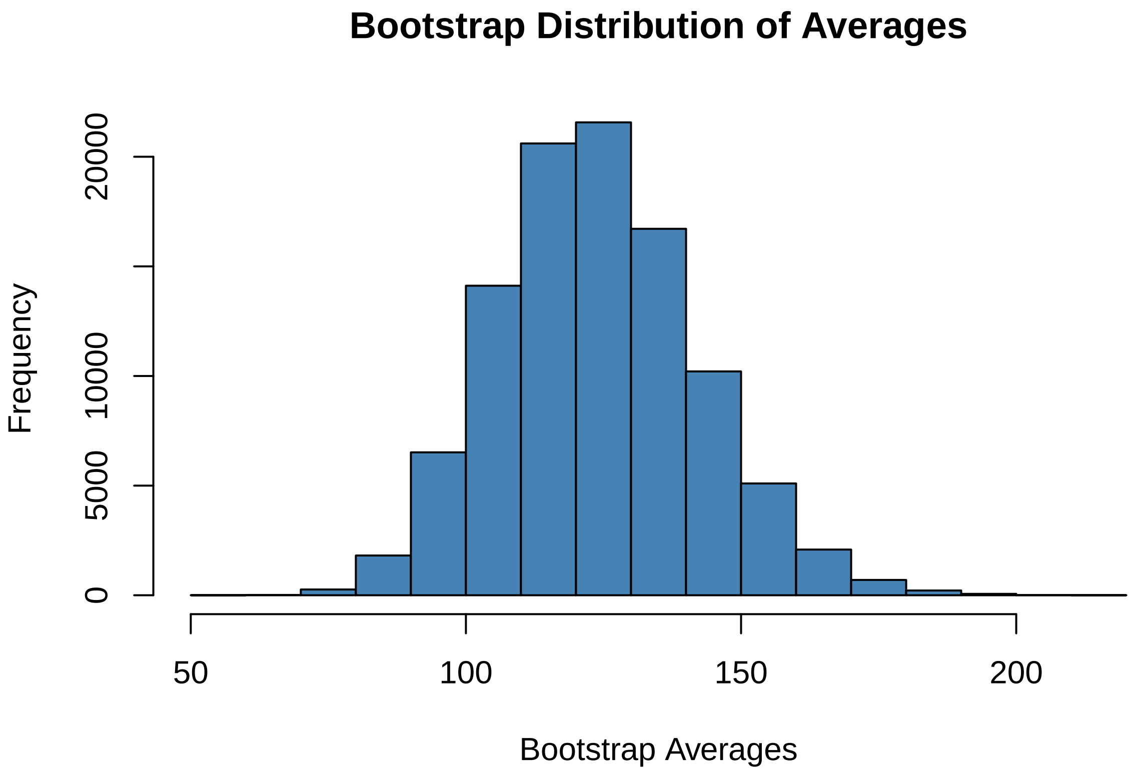
```
shapiro.test(Arsenic)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  Arsenic
## W = 0.42284, p-value < 2.2e-16
```

Even though we have ample evidence against the normality of the data, due to the large sample size, we could use the classical approach to the confidence interval.

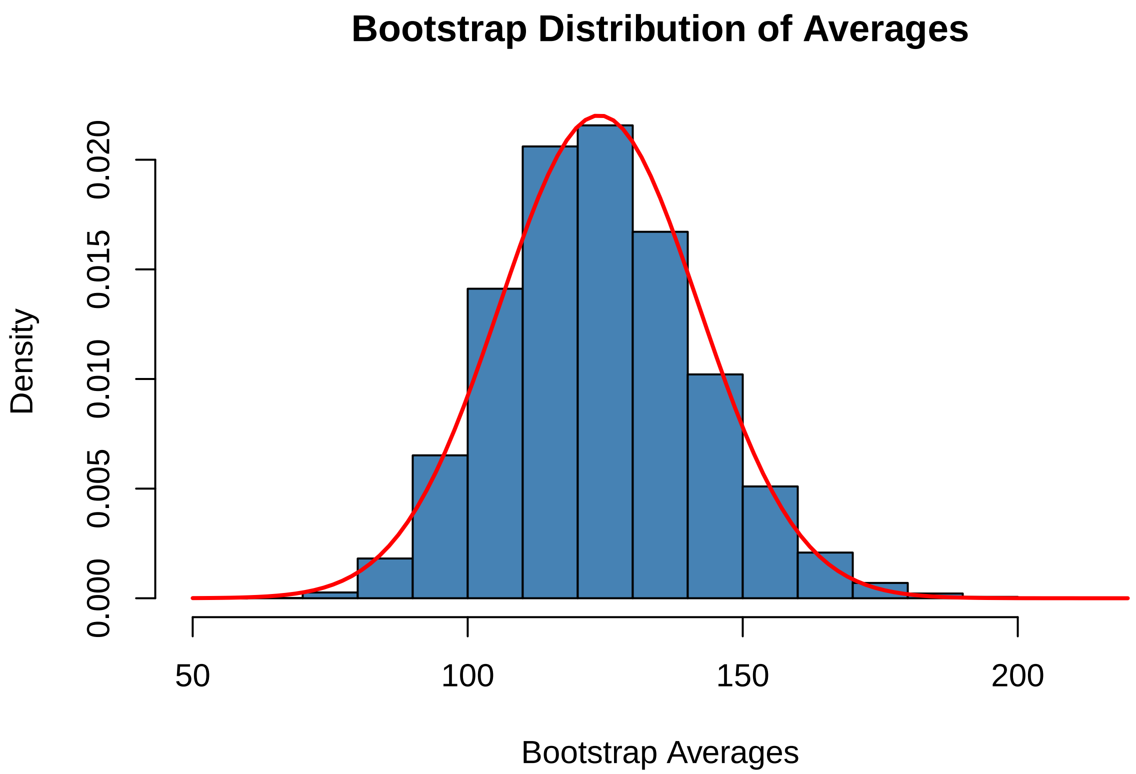
Now, what about bootstrap?

```
n.boot=10^5
arsenic.mean=replicate(n.boot, mean(sample(Arsenic, n, replace=TRUE)))
hist(arsenic.mean,
     main="Bootstrap Distribution of Averages",
     xlab="Bootstrap Averages",
     col="steelblue")
```



Superimposing the normal bell curve.

```
hist(arsenic.mean,
     main="Bootstrap Distribution of Averages",
     xlab="Bootstrap Averages",
     col="steelblue",
     prob=TRUE)
curve(dnorm(x, mean=mean(arsenic.mean), sd=sd(arsenic.mean)), col="red", lwd=2, add=TRUE)
```



We could now construct a 2SE bootstrap confidence interval.

```
#bootstrap mean
mu.boot=mean(arsenic.mean)
mu.boot
```

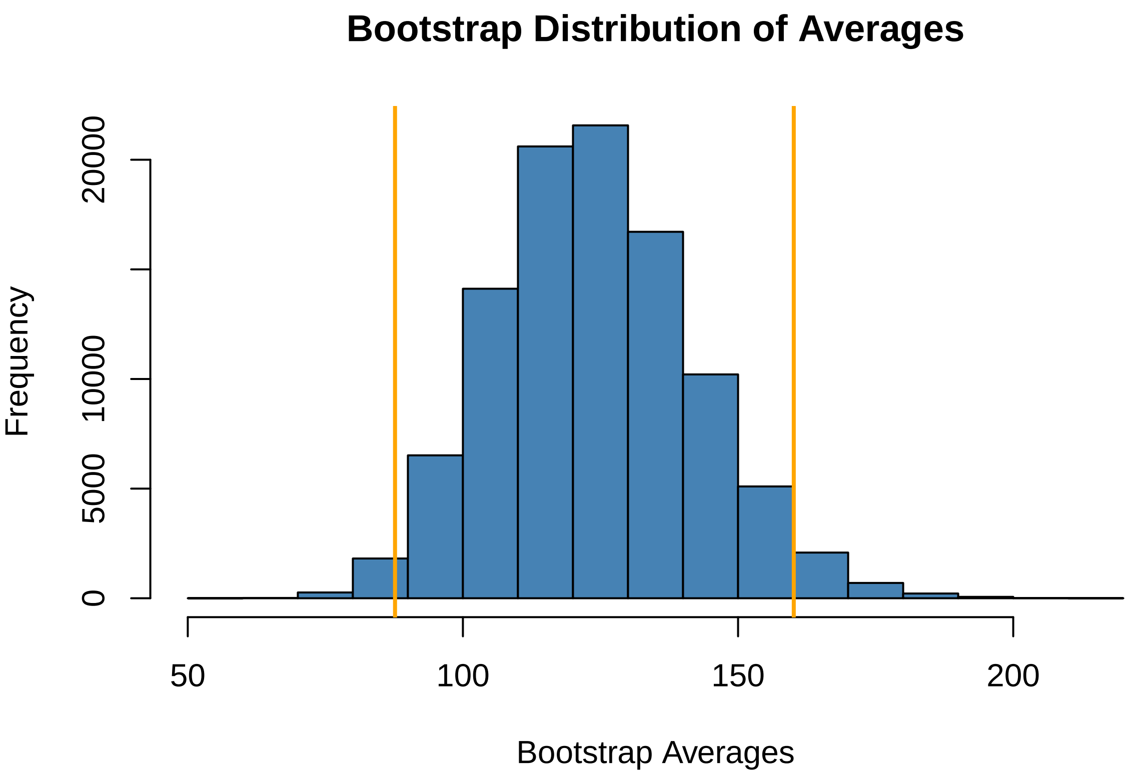
```
## [1] 123.8925
```

```
#bootstrap SE
se.boot=sd(arsenic.mean)

#lower bound
l.bd=mu.boot-2*se.boot
#upper bound
u.bd=mu.boot+2*se.boot

print(c(l.bd, u.bd))
```

```
## [1]  87.66321 160.12179
```

It might be interesting to superimpose it on the histogram.

```
hist(arsenic.mean,
     main="Bootstrap Distribution of Averages",
     xlab="Bootstrap Averages",
     col="steelblue")
abline(v=l.bd, col="orange", lwd=2)
abline(v=u.bd, col="orange", lwd=2)
```



We can also construct a bootstrap 95%-percentile confidence interval.

```
median(arsenic.mean)
```

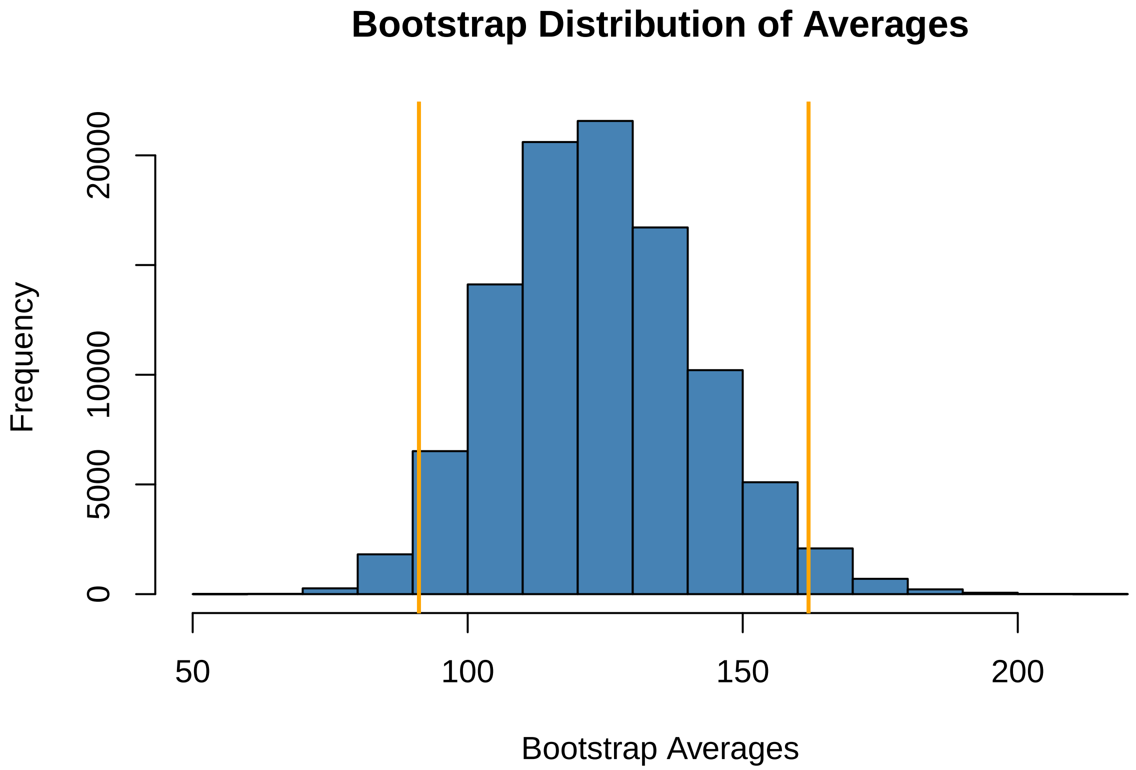
```
## [1] 122.9554
```

```
bds=quantile(arsenic.mean, c(0.025, 0.975))
bds
```

```
##      2.5%     97.5%
##  91.13395 161.96346
```

An analogous plot.

```
hist(arsenic.mean,
     main="Bootstrap Distribution of Averages",
     xlab="Bootstrap Averages",
     col="steelblue")
abline(v=bds, col="orange", lwd=2)
```


Bootstrap Distribution of Averages
Frequency
0
5000
10000
20000
50
100
150
200
Bootstrap Averages