In [1]:
```
library('outliers')
suppressWarnings(suppressMessages(library('ggpubr')))
```

In [2]:
```
data <- read.table('./uscrime.txt', header = T)
```

In [3]:
```
head(data)
```

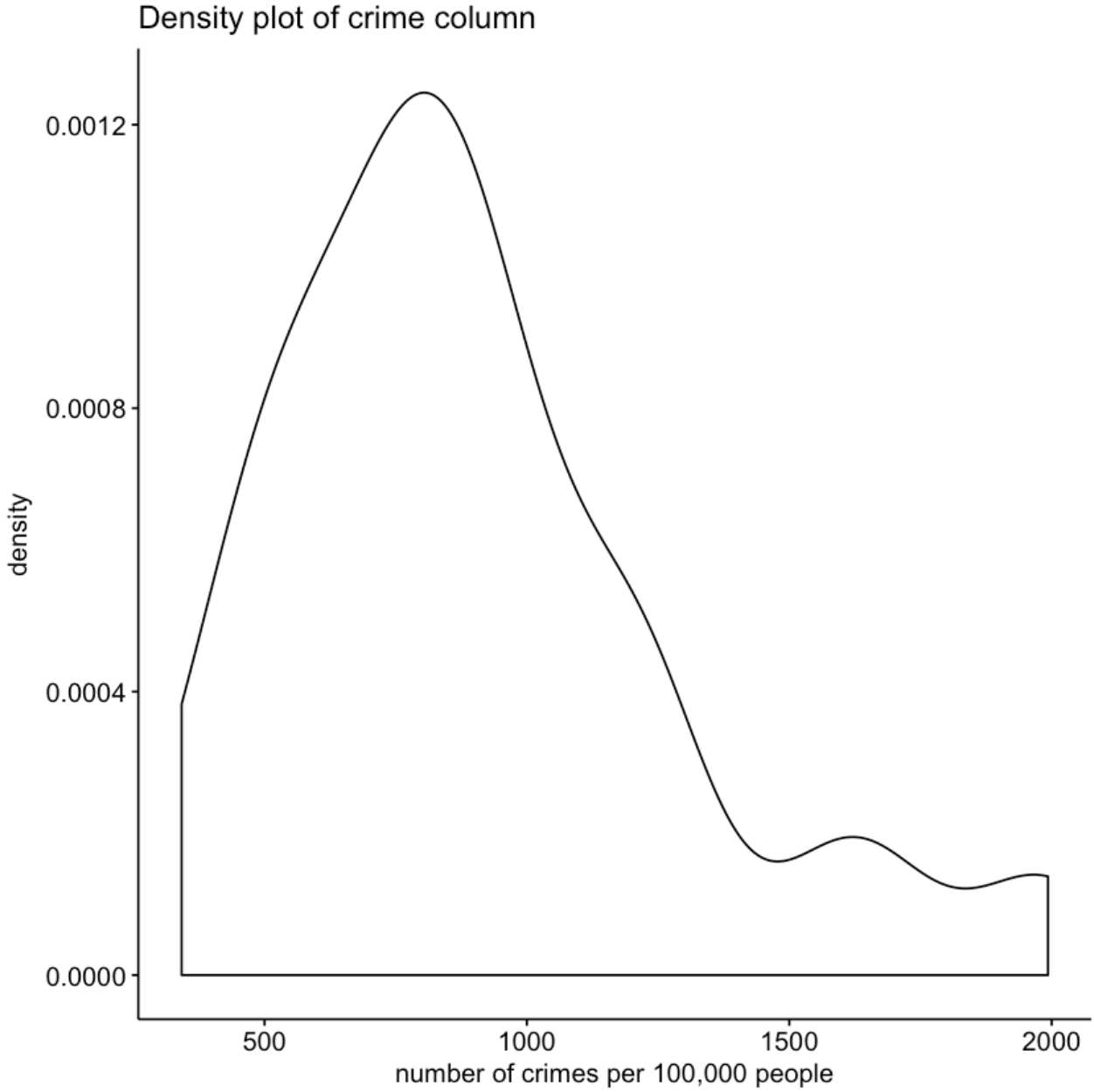
M	So	Ed	Po1	Po2	LF	M.F	Pop	NW	U1	U2	Wealth	Ineq	Prob	Time
15.1	1	9.1	5.8	5.6	0.510	95.0	33	30.1	0.108	4.1	3940	26.1	0.084602	26.2011
14.3	0	11.3	10.3	9.5	0.583	101.2	13	10.2	0.096	3.6	5570	19.4	0.029599	25.2999
14.2	1	8.9	4.5	4.4	0.533	96.9	18	21.9	0.094	3.3	3180	25.0	0.083401	24.3006
13.6	0	12.1	14.9	14.1	0.577	99.4	157	8.0	0.102	3.9	6730	16.7	0.015801	29.9012
14.1	0	12.1	10.9	10.1	0.591	98.5	18	3.0	0.091	2.0	5780	17.4	0.041399	21.2998
12.1	0	11.0	11.8	11.5	0.547	96.4	25	4.4	0.084	2.9	6890	12.6	0.034201	20.9995

In [4]:
```
crime <- data$Crime
```

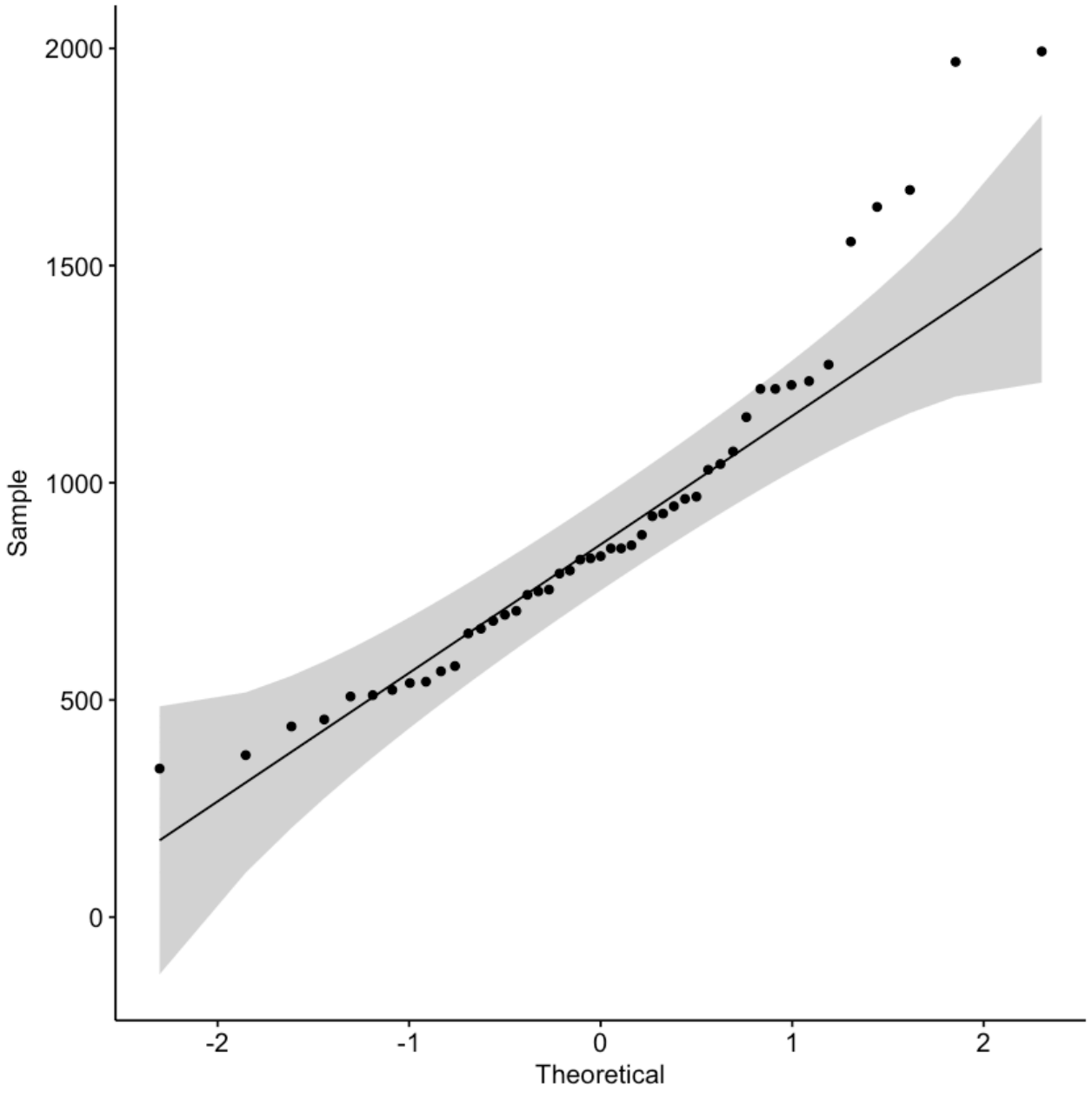
Wikipedia for Grubbs test states that --

Grubbs' test is based on the assumption of normality. That is, one should first verify that the data can be reasonably approximated by a normal distribution before applying the Grubbs' test.

In [5]:
```
#so let's check for normality first.
ggdensity(crime,
          main = "Density plot of crime column",
          xlab = "number of crimes per 100,000 people")
```



In [6]:
```
ggqqplot(crime)
```



In [7]:
```
shapiro.test(crime)
```

```
        Shapiro-Wilk normality test

data:  crime
W = 0.91273, p-value = 0.001882
```

It is evident from the density plot, qq plot and shapiro test that the data isn't normal. For shapiro test, since the p-value < 0.05 -- we can reject the null hypothesis that the data is normal. Hence, Grubbs test wouldn't hold any meaning. However, we will proceed and see what results we get.

In [8]:
```
grubbs.test(crime, type = 10, opposite = T)
```

```
        Grubbs test for one outlier

data:  crime
G = 1.45590, U = 0.95292, p-value = 1
alternative hypothesis: lowest value 342 is an outlier
```

In [9]:
```
grubbs.test(crime, type = 10, opposite = F)
```

```
        Grubbs test for one outlier

data:  crime
G = 2.81290, U = 0.82426, p-value = 0.07887
alternative hypothesis: highest value 1993 is an outlier
```

In [10]:
```
grubbs.test(crime, type = 10, opposite = T, two.sided = T)
```

```
        Grubbs test for one outlier

data:  crime
G = 1.45590, U = 0.95292, p-value < 2.2e-16
alternative hypothesis: lowest value 342 is an outlier
```

In [11]:
```
grubbs.test(crime, type = 11, opposite = T)
```

```
        Grubbs test for two opposite outliers

data:  crime
G = 4.26880, U = 0.78103, p-value = 1
alternative hypothesis: 342 and 1993 are outliers
```

In [12]:
```
grubbs.test(crime, type = 11, opposite = F)
```

```
        Grubbs test for two opposite outliers

data:  crime
G = 4.26880, U = 0.78103, p-value = 1
alternative hypothesis: 342 and 1993 are outliers
```

In [13]:
```
grubbs.test(crime, type = 11, opposite = T, two.sided = T)
```

```
        Grubbs test for two opposite outliers

data:  crime
G = 4.26880, U = 0.78103, p-value < 2.2e-16
alternative hypothesis: 342 and 1993 are outliers
```

In [14]:
```
grubbs.test(crime, type = 11, opposite = F, two.sided = T)
```

```
        Grubbs test for two opposite outliers

data:  crime
G = 4.26880, U = 0.78103, p-value < 2.2e-16
alternative hypothesis: 342 and 1993 are outliers
```

In [15]:
```
#it can be seen that Grubbs test gives quite off results. And as per the
#are outliers.
```

5.1

I work for a small business lender. We recently got on board brokers to refer us premium quality applicants. We could use a CUSUM approach to detect a change in FICO score of the applicant, annual revenue of the business, profitability, etc. Threshold and critical value would be decided by trial and error. Since we already know when the brokers were on boarded, we could verify that our results are not off by comparing the time a change is detected -- it should not be too far/different from the time brokers were on boarded.

Exercise 6.2

Summer ends each year around the same period i.e last week of August to first week of September. Shown by conditional formatting on the excel sheet.

In [ ]: