

Homework 3

Applied Multivariate Analysis

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1 Workspace

1.1 Packages

```
library(car)
library(knitr)
library(psych)
library(kableExtra)
library(multcomp)
library(lme4)
library(plyr)
library(tidyverse)
library(MVN)
```

1.2 data

The file, Set.3.csv, contains the data from a study in which 500 high school students completed a measure of scholastic aptitude: Grammar, Paragraph Comprehension, Vocabulary, Sentence Completion, Geometry, Algebra, Numerical Puzzles, Series Completion, Practical Problem Solving, Symbol Manipulation, Analytical Ability, and Formal Logic.

```
wd <- "https://github.com/emoriebeck/homeworks/raw/master/multivariate/homeworks/homework3"

dat <- sprintf("%s/Set_3.csv", wd) %>%
  read.csv(., stringsAsFactors = F)

head(dat)
```

##	ID	Grammar	Paragraph_Comprehension	Vocabulary	Sentence_Completion
## 1	1	2.0298794	0.7009379	0.9224983	0.7783650
## 2	2	1.8460110	0.8176540	1.6230497	0.5595109
## 3	3	-0.5514456	0.1155194	-0.2451959	1.2206362
## 4	4	-1.3804105	0.2193181	0.5195521	0.3530657
## 5	5	0.4384477	1.5177577	0.4692875	1.4074032
## 6	6	-0.5984267	-0.8757810	-0.9889196	-1.4836151
##		Geometry	Algebra	Numerical_Puzzles	Series_Completion
## 1		0.7169340	0.649042462	0.1797594	0.521331792
## 2		-1.4336680	0.008714271	-0.2517458	0.000110179
## 3		-0.5504154	-0.776083508	0.8131658	-0.802679845
## 4		1.7218792	1.076026142	0.7711456	-0.381686114

```
## 5  0.7914582  1.541237112          0.4042484          0.825899485
## 6 -0.5157728 -0.441559349        -1.0049260        -2.612748945
##   Practical_Problem_Solving Symbol_Manipulation Analytical_Ability
## 1          1.3030926          1.3690616          1.5512126
## 2          0.9545397         -0.9592880          1.4883905
## 3         -1.5259042         -1.2038384         -0.7812775
## 4         -0.5231818          0.1203525         -0.3958278
## 5          1.2598039          2.6013012          0.9772288
## 6         -0.1936980         -0.1956773         -0.2486582
##   Formal_Logic
## 1    0.7546186
## 2   -0.3733971
## 3   -1.1192996
## 4    1.7353933
## 5    3.0419200
## 6   -0.8137567
```

Answer the following questions about these data:

2 Question 1

What evidence do you have that these data should be subjected to a principal components analysis?

```
R <- dat %>% select(-ID) %>% cor

(KMO1 <- KMO(R))

## Kaiser-Meyer-Olkin factor adequacy
## Call: KMO(r = R)
## Overall MSA = 0.82
## MSA for each item =
##           Grammar Paragraph_Comprehension
##           0.83          0.84
##           Vocabulary Sentence_Completion
##           0.83          0.82
##           Geometry Algebra
##           0.82          0.83
##           Numerical_Puzzles Series_Completion
##           0.77          0.84
## Practical_Problem_Solving Symbol_Manipulation
##           0.84          0.81
##           Analytical_Ability Formal_Logic
##           0.82          0.83

(CB_1 <- cortest.bartlett(R=R,n=nrow(dat)))

## $chisq
## [1] 1794.866
##
## $p.value
## [1] 0
##
## $df
## [1] 66
```

The overall MSA is .82, and all but one of the MSA values are .8 (1 (Numerical Puzzles) is .77), which indicates very strong evidence for conducting a PCA.

In addition, the χ^2 value of the Bartlett test ($\chi^2(66) = 1794.87$), which indicates that the correlation matrix departs significantly from an identity matrix (independence among indicators).

3 Question 2

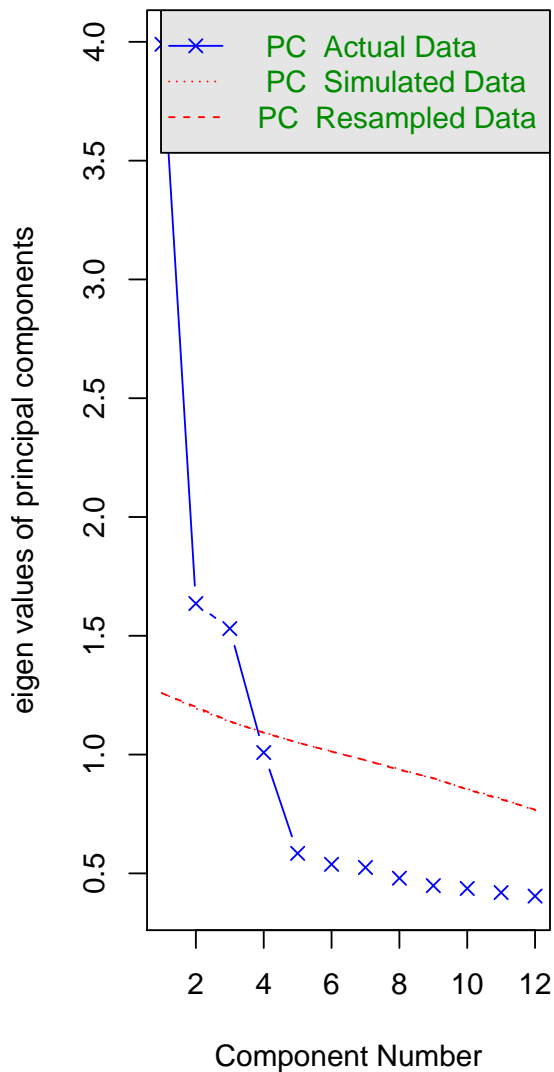
How many principal components should be extracted?

```
par(mfrow=c(1,2))
scree_1 <- fa.parallel(dat %>% select(-ID), fa="pc")

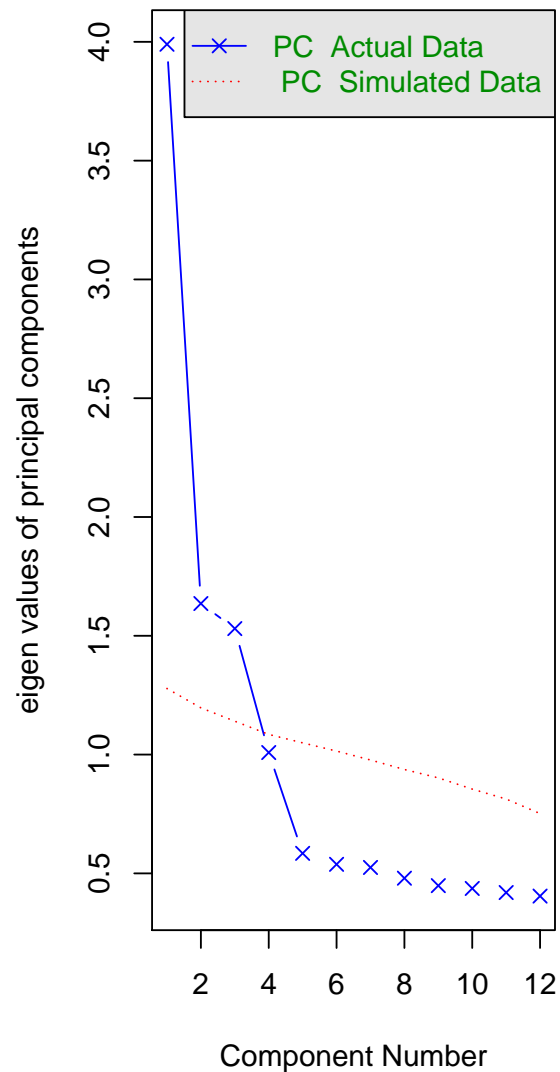
## Parallel analysis suggests that the number of factors = NA and the number of components = 3

scree_2 <- fa.parallel(R, fa = "pc", n.obs = nrow(dat))
```

Parallel Analysis Scree Plots



Parallel Analysis Scree Plots



```
## Parallel analysis suggests that the number of factors = NA and the number of components = 3
```

Parallel analysis suggests that 3 factors should be extracted from the data.

4 Question 3

How much variance do these extracted components account for in the original data?

```
pca_1 <- principal(R, nfactors = 3, rotate = "none", n.obs = nrow(dat), residuals = T)

pca_1$Vaccounted %>% data.frame %>% mutate(m = rownames(.)) %>%
  mutate_at(vars(PC1:PC3), funs(round(.,2))) %>%
  select(m, everything()) %>%
```

```
kable(., "latex", booktabs = T, escape = F)
```

m	PC1	PC2	PC3
SS loadings	3.99	1.64	1.53
Proportion Var	0.33	0.14	0.13
Cumulative Var	0.33	0.47	0.60
Proportion Explained	0.56	0.23	0.21
Cumulative Proportion	0.56	0.79	1.00

The three extracted components account for 60% of the variance.

5 Question 4

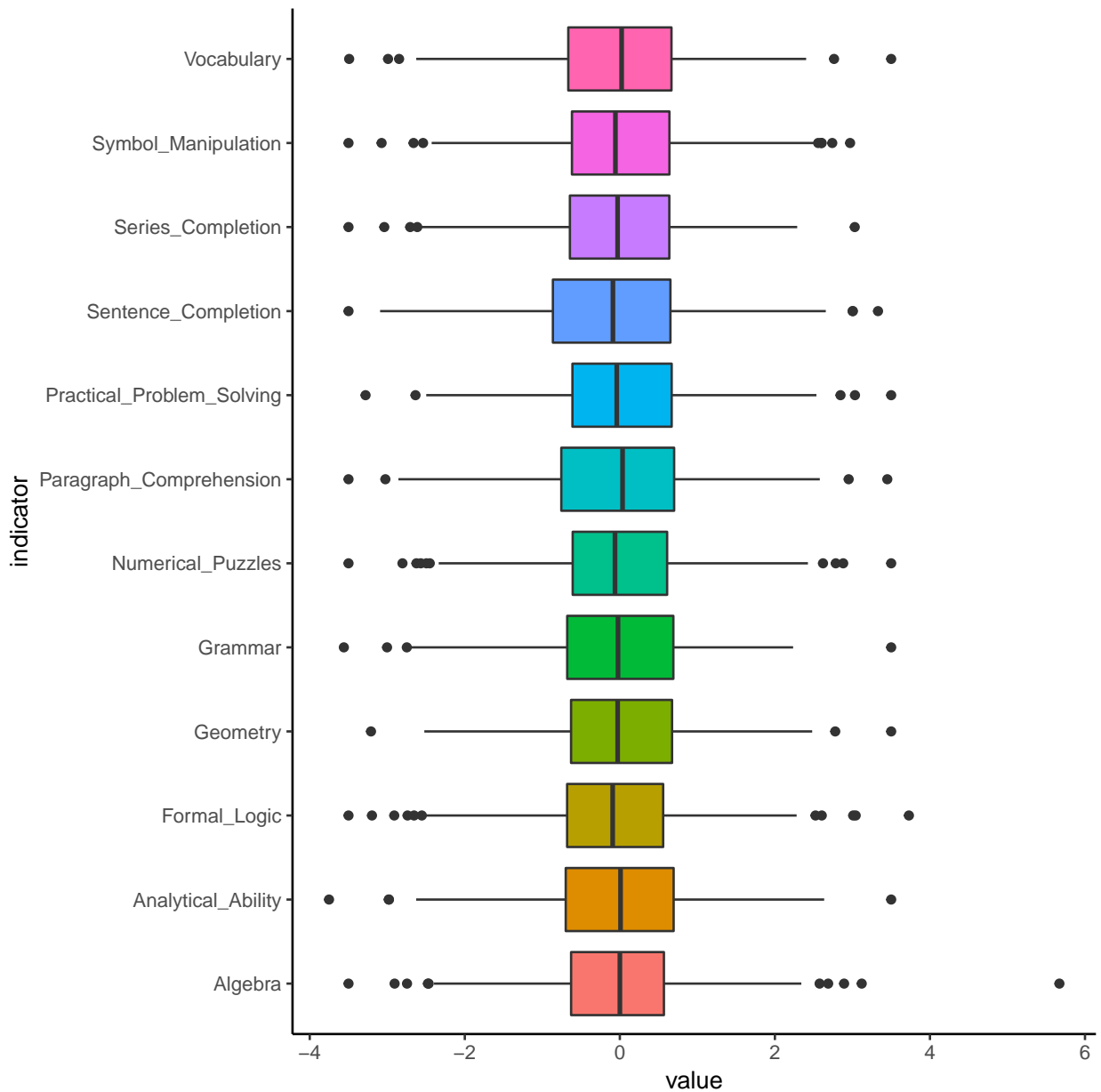
How much variance in the original Geometry variable is accounted for by these extracted components? The extracted components account for 57.85% of the variance in the original Geometry variable.

6 Question 5

Now screen the data for unusual cases and determine if your conclusions change when any such cases are excluded from the analysis.

If you believe there is more than one outlier in the data, follow a sequential approach to determining how many to exclude. This means that you will identify the worst offender, exclude that case, and then repeat your diagnostics to determine if other outliers are present. If so, again exclude the worst one, and repeat the diagnostics to determine if an additional outlier is present. Keep cycling through these steps until you are satisfied you have all outliers identified and excluded. Then conduct the principal components analysis. This iterative approach is necessary for multivariate diagnostics such as Mahalanobis distance because the presence of one outlier can influence the apparent presence of others via their joint influence on the covariance matrix. Removing them one at a time insures you dont miss any or mistakenly remove cases that are not really outliers.

```
dat %>%
  gather(indicator, value, -ID) %>%
  ggplot(aes(x = indicator, y = value, fill = indicator)) +
    geom_boxplot() +
    coord_flip() +
    theme_classic() +
    theme(legend.position = "none")
```



Visual inspection of the boxplot suggests there is one outlier in the algebra indicator, but let's check multivariate normality before making a decision.

```
(pca_2 <- principal(
  dat %>% select(-ID)
  , nfactors = ncol(dat)-1
  , rotate = "none"
  , residuals = T
  , scores = TRUE)
)
```

Principal Components Analysis
 ## Call: principal(r = dat %>% select(-ID), nfactors = ncol(dat) - 1,
 ## residuals = T, rotate = "none", scores = TRUE)
 ## Standardized loadings (pattern matrix) based upon correlation matrix

```

##          PC1  PC2  PC3  PC4  PC5  PC6  PC7  PC8
## Grammar      0.62 -0.16 -0.46  0.27  0.04 -0.07  0.32 -0.20
## Paragraph_Comprehension 0.61 -0.09 -0.48 -0.30 -0.01 -0.24 -0.10  0.17
## Vocabulary    0.60 -0.18 -0.44  0.30 -0.25  0.36 -0.05 -0.04
## Sentence_Completion 0.60 -0.14 -0.50 -0.27  0.21 -0.04 -0.14  0.02
## Geometry      0.51  0.55  0.09  0.23  0.39  0.34 -0.23  0.02
## Algebra       0.56  0.46  0.10 -0.38 -0.21  0.19  0.27  0.34
## Numerical_Puzzles 0.48  0.60  0.09  0.32  0.11 -0.37  0.13  0.11
## Series_Completion 0.57  0.50  0.17 -0.20 -0.32 -0.08 -0.13 -0.46
## Practical_Problem_Solving 0.59 -0.31  0.34  0.30 -0.31 -0.09 -0.31  0.24
## Symbol_Manipulation 0.55 -0.35  0.44 -0.28  0.10  0.18  0.25 -0.08
## Analytical_Ability 0.60 -0.32  0.38  0.32  0.07 -0.07  0.20  0.00
## Formal_Logic   0.61 -0.33  0.37 -0.26  0.22 -0.09 -0.18 -0.09
##          PC9  PC10  PC11  PC12 h2      u2 com
## Grammar      -0.08  0.14 -0.04 -0.36  1 -1.3e-15 4.4
## Paragraph_Comprehension 0.22 -0.37 -0.14 -0.09  1  3.3e-16 4.5
## Vocabulary    0.07  0.04 -0.20  0.29  1  1.2e-15 4.9
## Sentence_Completion -0.14  0.18  0.38  0.18  1  1.3e-15 4.5
## Geometry      0.05 -0.12  0.02 -0.17  1 -4.4e-16 4.8
## Algebra       -0.22  0.05 -0.03 -0.05  1  4.4e-16 5.4
## Numerical_Puzzles 0.18  0.19 -0.07  0.22  1 -4.4e-16 4.6
## Series_Completion -0.02 -0.08  0.09  0.00  1  1.1e-16 4.4
## Practical_Problem_Solving 0.05  0.14  0.15 -0.20  1 -2.2e-16 5.6
## Symbol_Manipulation 0.42  0.07  0.11  0.01  1 -2.2e-16 5.4
## Analytical_Ability -0.25 -0.37  0.13  0.17  1 -2.2e-16 5.1
## Formal_Logic   -0.21  0.17 -0.38  0.03  1  4.4e-16 5.0
##
##          PC1  PC2  PC3  PC4  PC5  PC6  PC7  PC8  PC9  PC10
## SS loadings    3.99 1.64 1.53 1.01 0.58 0.54 0.52 0.48 0.45 0.44
## Proportion Var 0.33 0.14 0.13 0.08 0.05 0.04 0.04 0.04 0.04 0.04
## Cumulative Var 0.33 0.47 0.60 0.68 0.73 0.77 0.82 0.86 0.89 0.93
## Proportion Explained 0.33 0.14 0.13 0.08 0.05 0.04 0.04 0.04 0.04 0.04
## Cumulative Proportion 0.33 0.47 0.60 0.68 0.73 0.77 0.82 0.86 0.89 0.93
##          PC11  PC12
## SS loadings    0.42 0.40
## Proportion Var 0.03 0.03
## Cumulative Var 0.97 1.00
## Proportion Explained 0.03 0.03
## Cumulative Proportion 0.97 1.00
##
## Mean item complexity = 4.9
## Test of the hypothesis that 12 components are sufficient.
##
## The root mean square of the residuals (RMSR) is 0
## with the empirical chi square 0 with prob < NA
##
## Fit based upon off diagonal values = 1

scores_2 <- pca_2$scores %>% data.frame

describe(scores_2)

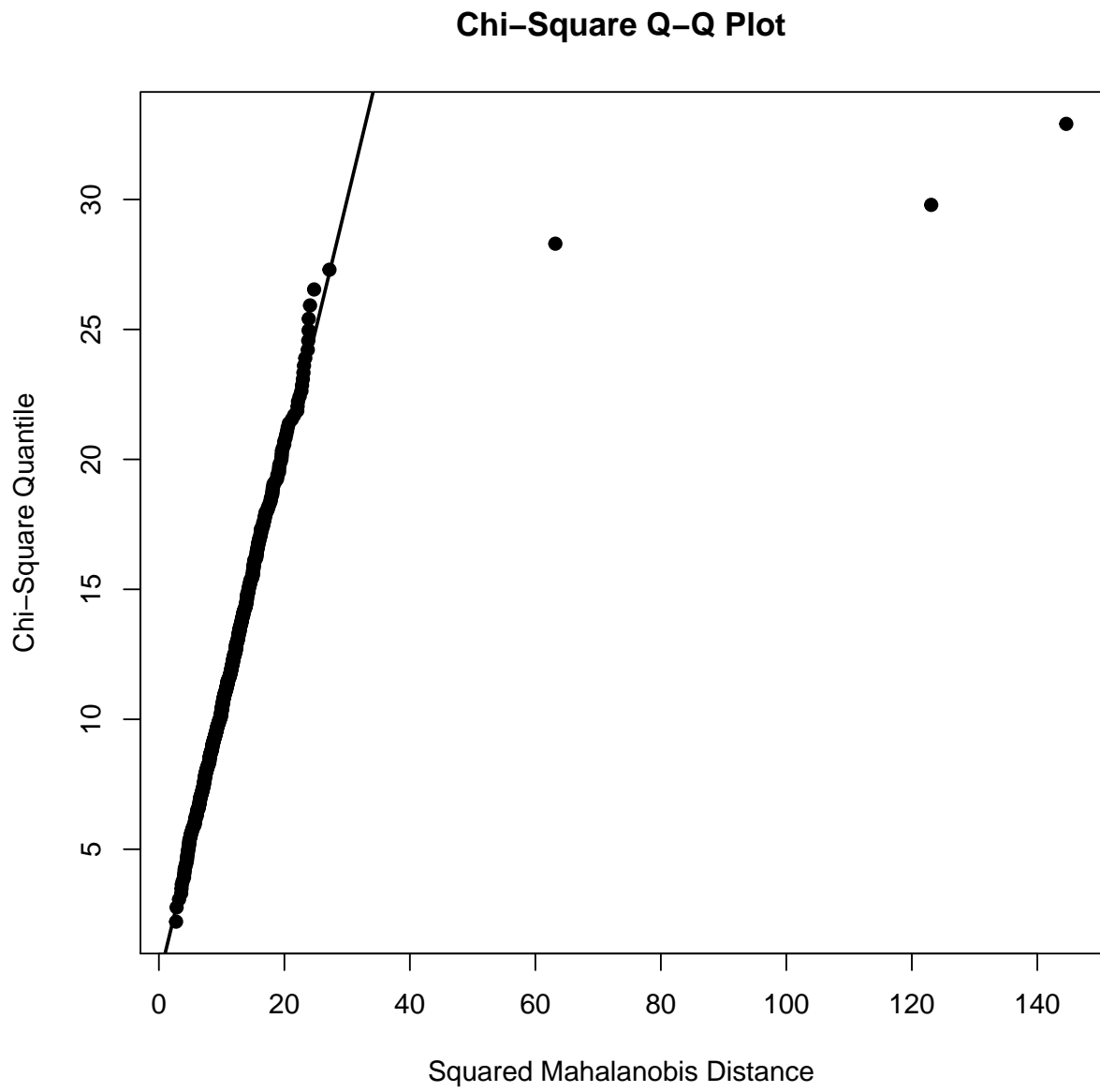
##      vars    n mean sd median trimmed  mad   min   max range  skew
## PC1      1 500    0  1   0.01    0.01 0.97  -3.03  2.72  5.75 -0.12

```

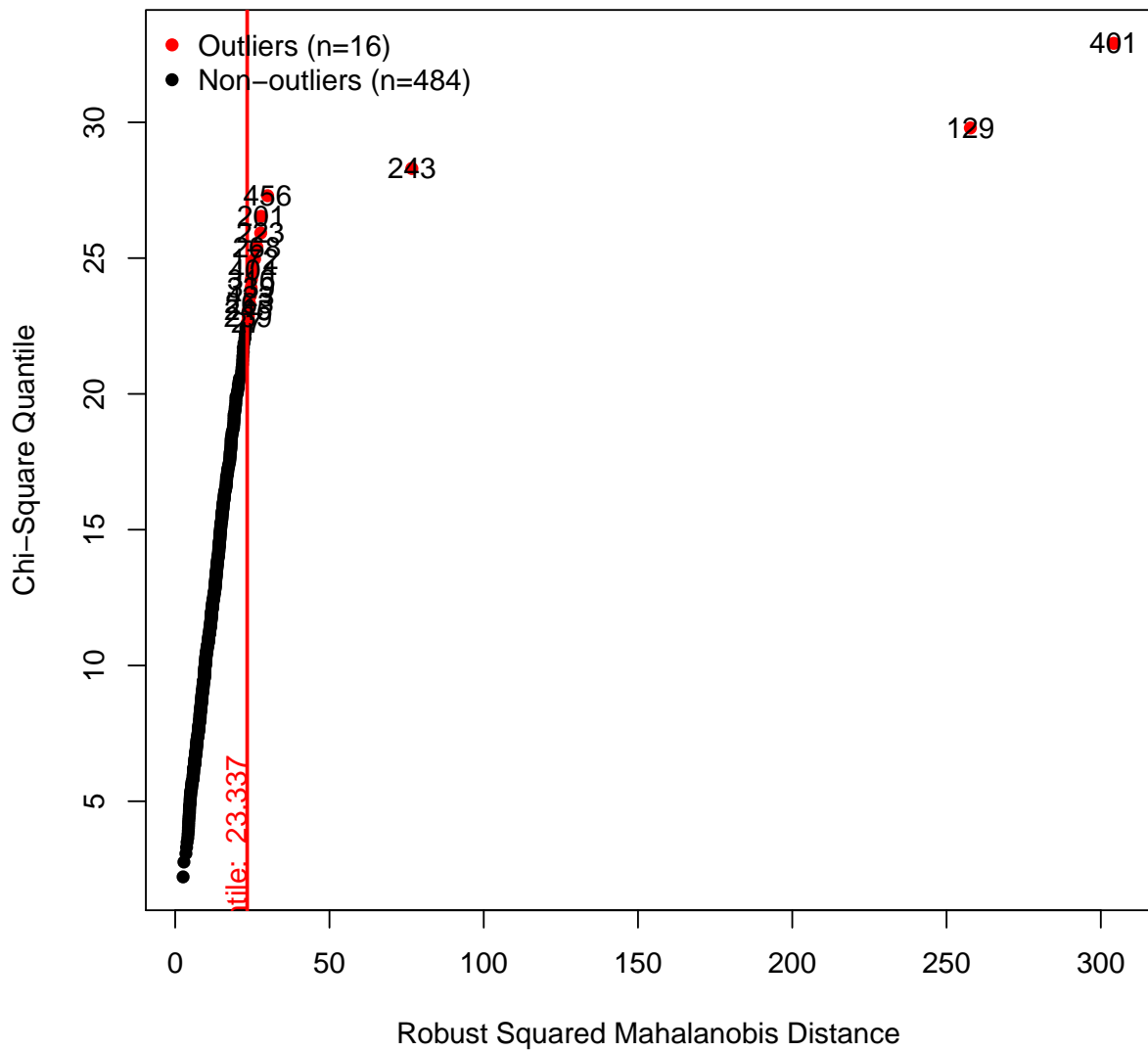
```
## PC2      2 500      0 1      0.00      -0.02 1.02      -2.93 3.00 5.93 0.15
## PC3      3 500      0 1      0.03      -0.01 0.97      -3.06 3.10 6.16 0.06
## PC4      4 500      0 1     -0.04      -0.01 0.67     -10.78 11.72 22.50 0.71
## PC5      5 500      0 1      0.02      0.00 1.01      -4.09 2.68 6.77 -0.11
## PC6      6 500      0 1      0.00      0.02 0.96      -2.74 3.11 5.85 -0.14
## PC7      7 500      0 1      0.05      0.03 0.96      -3.22 3.17 6.39 -0.31
## PC8      8 500      0 1     -0.04      -0.01 0.98      -2.54 3.59 6.13 0.13
## PC9      9 500      0 1      0.02      -0.01 1.07      -3.21 3.10 6.31 0.03
## PC10     10 500      0 1     -0.03      0.00 0.94      -3.44 3.34 6.77 0.04
## PC11     11 500      0 1      0.03      0.02 0.98      -3.00 3.33 6.33 -0.08
## PC12     12 500      0 1      0.01      0.01 1.00      -2.67 2.90 5.56 -0.03
##          kurtosis      se
## PC1         -0.26 0.04
## PC2          0.01 0.04
## PC3          0.14 0.04
## PC4         62.60 0.04
## PC5          0.17 0.04
## PC6         -0.04 0.04
## PC7          0.10 0.04
## PC8          0.06 0.04
## PC9         -0.17 0.04
## PC10         0.27 0.04
## PC11         0.09 0.04
## PC12        -0.20 0.04
```

Checking the PCA suggests that there is a multivariate outlier in PCA 4
But let's check multivariate normality

```
dat2 <- dat %>% select(-ID) %>% data.frame
rownames(dat2) <- 1:nrow(dat2)
(mv <- mvn(dat2,mvnTest="mardia", multivariatePlot="qq",multivariateOutlierMethod="quan",showOutliers=T
```

Chi-Square Q-Q Plot



```
## $multivariateNormality
##           Test           Statistic           p value Result
## 1  Mardia Skewness  468.99164354467 0.000162906731930752    NO
## 2  Mardia Kurtosis  37.8554992977048              0      NO
## 3              MVN              <NA>              <NA>      NO
##
## $univariateNormality
##           Test           Variable Statistic   p value Normality
## 1  Shapiro-Wilk           Grammar      0.9967  0.4074      YES
## 2  Shapiro-Wilk Paragraph_Comprehension  0.9989  0.9922      YES
## 3  Shapiro-Wilk           Vocabulary      0.9958  0.1996      YES
## 4  Shapiro-Wilk Sentence_Completion      0.9981  0.8464      YES
## 5  Shapiro-Wilk           Geometry      0.9978  0.7646      YES
## 6  Shapiro-Wilk           Algebra      0.9835 <0.001      NO
```

```

## 7  Shapiro-Wilk      Numerical_Puzzles      0.9968  0.4251      YES
## 8  Shapiro-Wilk      Series_Completion      0.9971  0.5203      YES
## 9  Shapiro-Wilk      Practical_Problem_Solving  0.9967  0.4047      YES
## 10 Shapiro-Wilk      Symbol_Manipulation    0.9956  0.1713      YES
## 11 Shapiro-Wilk      Analytical_Ability     0.9977  0.7187      YES
## 12 Shapiro-Wilk      Formal_Logic           0.9952  0.1221      YES
##
## $Descriptives
##              n              Mean      Std.Dev              Median
## Grammar              500 -0.0083641562  1.0016648 -0.0237048215
## Paragraph_Comprehension 500 -0.0070088967  1.0829739  0.0350785195
## Vocabulary            500 -0.0169538702  1.0169743  0.0232942325
## Sentence_Completion    500 -0.0903289108  1.1065777 -0.0893020655
## Geometry              500  0.0071552259  0.9973637 -0.0282354790
## Algebra              500 -0.0151778962  1.0149132  0.0003852515
## Numerical_Puzzles      500 -0.0153611723  1.0132508 -0.0624955155
## Series_Completion      500 -0.0077428597  0.9819436 -0.0291777090
## Practical_Problem_Solving 500 -0.0182512446  0.9584017 -0.0400207855
## Symbol_Manipulation    500 -0.0009142506  0.9922338 -0.0569430780
## Analytical_Ability     500 -0.0073984716  1.0009061  0.0090736190
## Formal_Logic           500 -0.0650934689  1.0367206 -0.0925315375
##              Min              Max              25th              75th
## Grammar              -3.560000  3.500000 -0.6789687  0.6903545
## Paragraph_Comprehension -3.500000  3.450000 -0.7551515  0.7002892
## Vocabulary            -3.491518  3.500000 -0.6651436  0.6660205
## Sentence_Completion    -3.500000  3.330000 -0.8637548  0.6525117
## Geometry              -3.210000  3.500000 -0.6294255  0.6737671
## Algebra              -3.500000  5.670000 -0.6288277  0.5685107
## Numerical_Puzzles      -3.500000  3.500000 -0.6082066  0.6101796
## Series_Completion      -3.500000  3.030000 -0.6444230  0.6380559
## Practical_Problem_Solving -3.280000  3.500000 -0.6115184  0.6685177
## Symbol_Manipulation    -3.500000  2.970000 -0.6179801  0.6397075
## Analytical_Ability     -3.751222  3.500000 -0.6981759  0.6938528
## Formal_Logic           -3.500000  3.728522 -0.6802409  0.5589411
##              Skew      Kurtosis
## Grammar              -0.05430769  0.13596613
## Paragraph_Comprehension -0.08800734  0.02507948
## Vocabulary            -0.20788125  0.16156136
## Sentence_Completion    0.02093275 -0.07335932
## Geometry              0.11181433  0.10313111
## Algebra              0.23409531  1.98559538
## Numerical_Puzzles      0.01651535  0.33457069
## Series_Completion      -0.13807654  0.07180595
## Practical_Problem_Solving 0.13693839  0.33690319
## Symbol_Manipulation    0.05168770  0.34049898
## Analytical_Ability     -0.11832265  0.22344750
## Formal_Logic           0.03731202  0.57661676
##
## $multivariateOutliers
##      Observation Mahalanobis Distance Outlier
## 401           401          304.171      TRUE
## 129           129          257.717      TRUE
## 243           243           76.697      TRUE

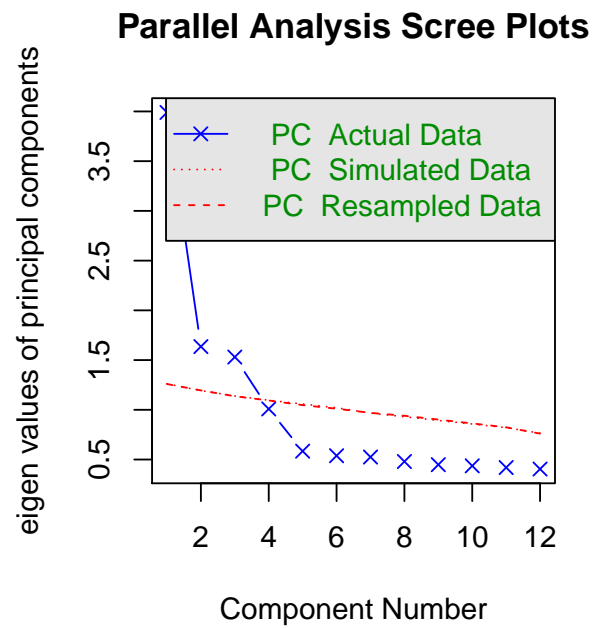
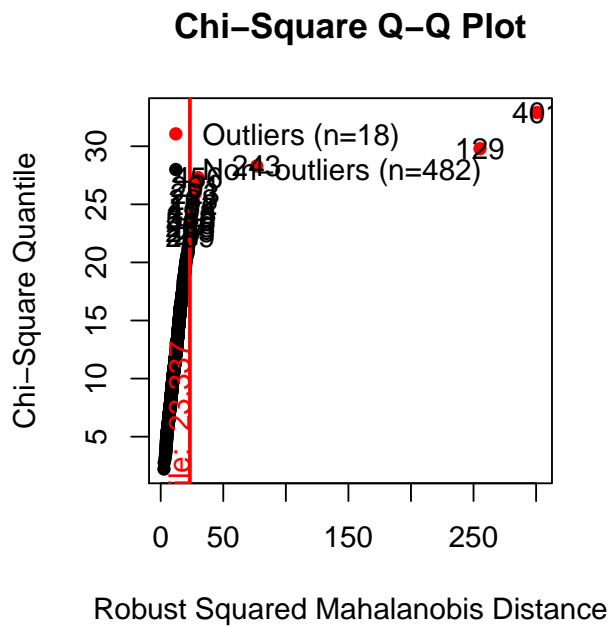
```

## 456	456	29.946	TRUE
## 201	201	27.842	TRUE
## 223	223	27.716	TRUE
## 268	268	26.481	TRUE
## 172	172	25.730	TRUE
## 404	404	25.203	TRUE
## 316	316	24.710	TRUE
## 339	339	24.606	TRUE
## 423	423	24.315	TRUE
## 263	263	24.070	TRUE
## 245	245	23.736	TRUE
## 239	239	23.673	TRUE
## 27	27	23.408	TRUE

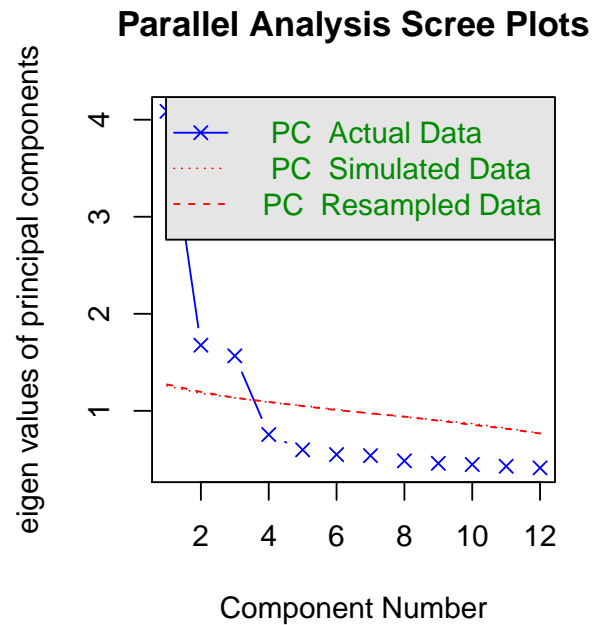
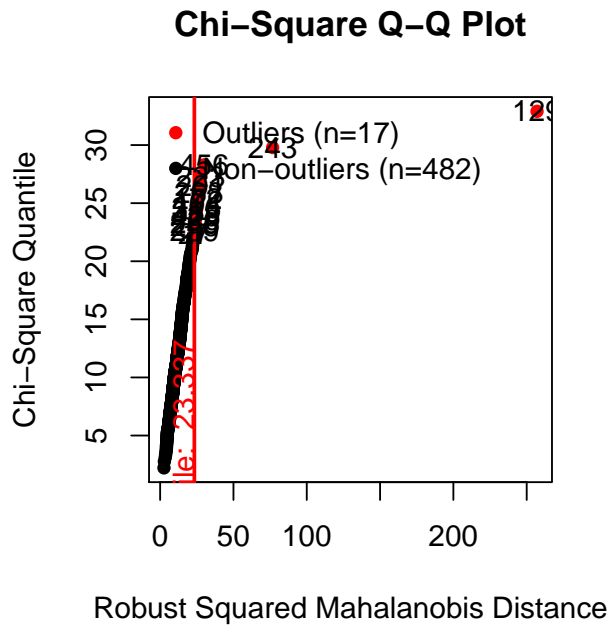
Based on the test of multivariate normality, there are 16(!) outliers. Let's remove the outlier and check again.

I'm going to use a while loop to do this rather than copying and pasting the code.

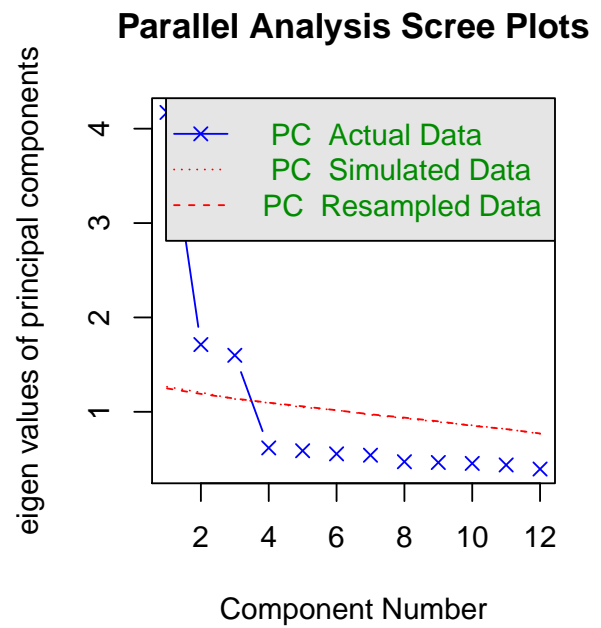
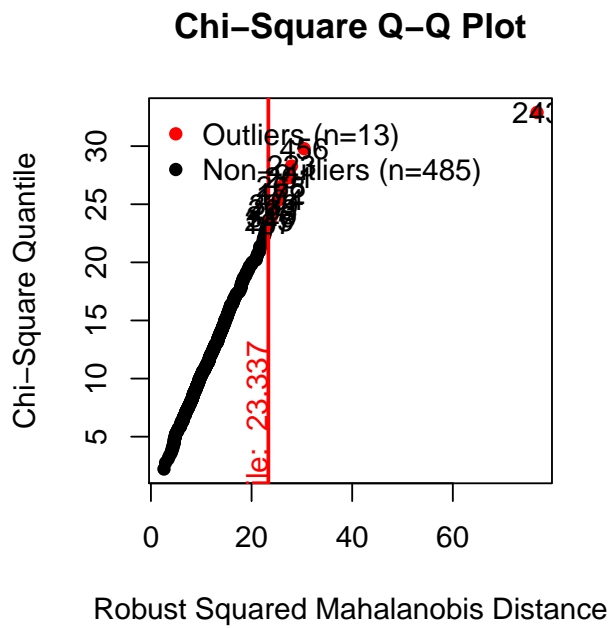
```
k <- 1
remove <- c()
par(mfrow = c(1,2))
while(nrow(mv$multivariateOutliers) > 0){
  if(k!=1){tmp <- dat2[-remove,]} else{tmp <- dat2}
  mv <- mvn(tmp, mvnTest="mardia", multivariatePlot="none",multivariateOutlierMethod="quan",showOutlier=TRUE)
  mv$multivariateOutliers
  remove <- c(remove, as.numeric(as.character(mv$multivariateOutliers$Observation[1])))
  sink("/dev/null")
  scree <- fa.parallel(tmp, fa="pc")
  sink()
  print(sprintf("Case %s removed. %s factors remain. This is the %s round", remove[k], scree$ncomp, k))
  if(nrow(mv$multivariateOutliers) == 0){break}
  k <- k + 1
}
```



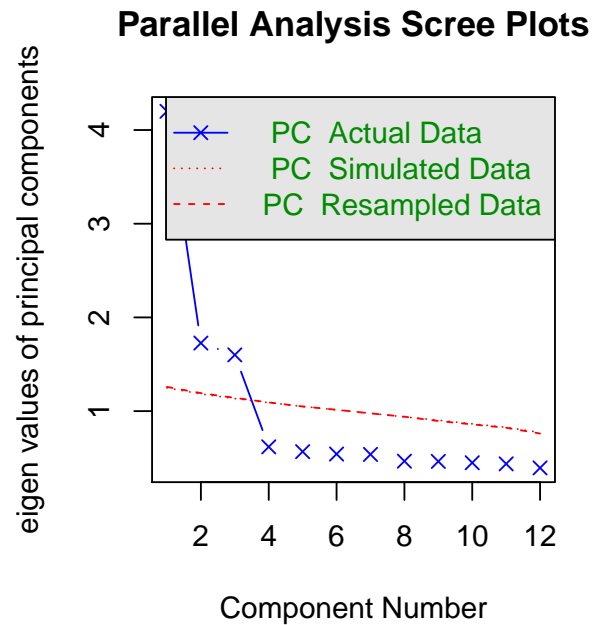
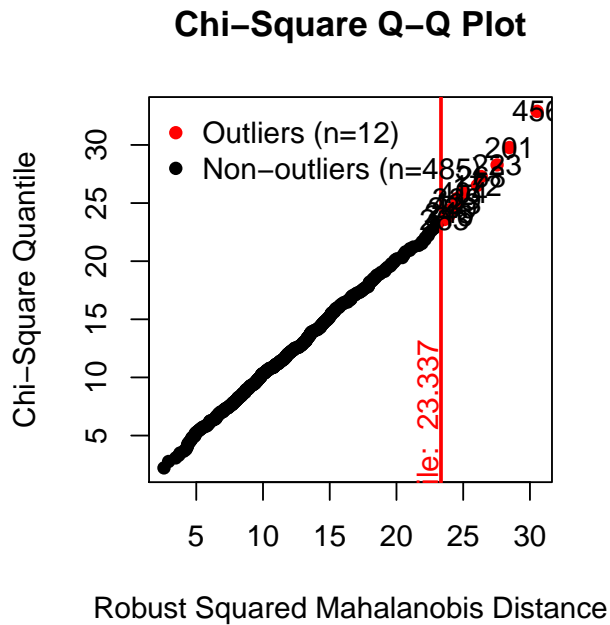
```
## [1] "Case 401 removed. 3 factors remain. This is the 1 round"
```



```
## [1] "Case 129 removed. 3 factors remain. This is the 2 round"
```

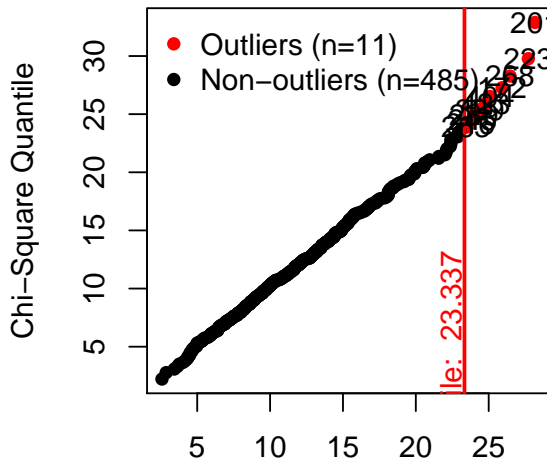


```
## [1] "Case 243 removed. 3 factors remain. This is the 3 round"
```

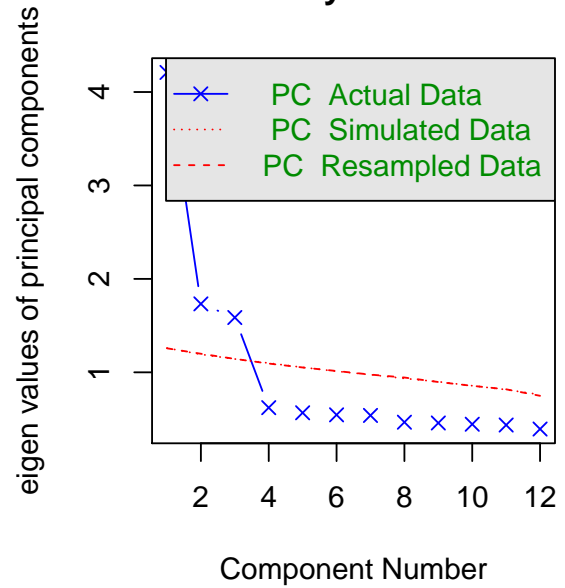


```
## [1] "Case 456 removed. 3 factors remain. This is the 4 round"
```

Chi-Square Q-Q Plot

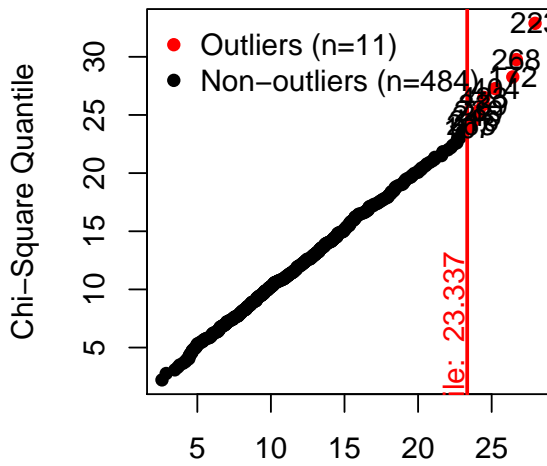


Parallel Analysis Scree Plots

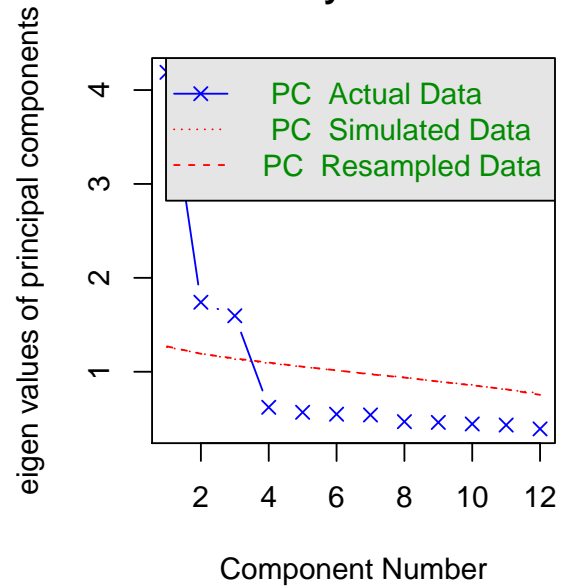


```
## [1] "Case 201 removed. 3 factors remain. This is the 5 round"
```

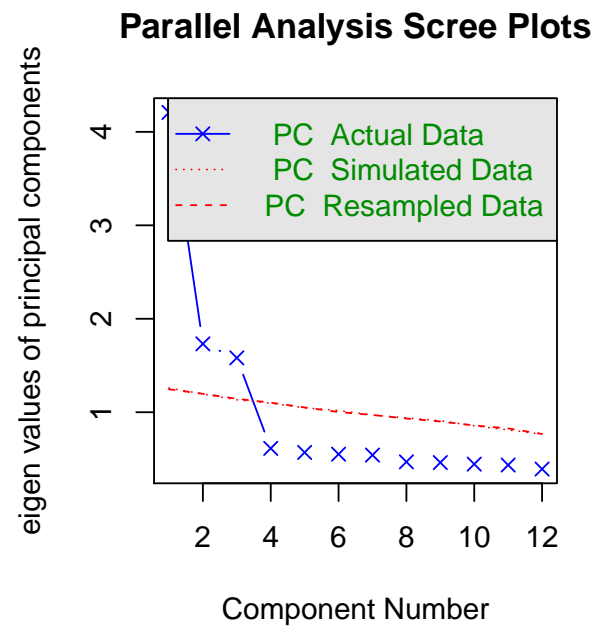
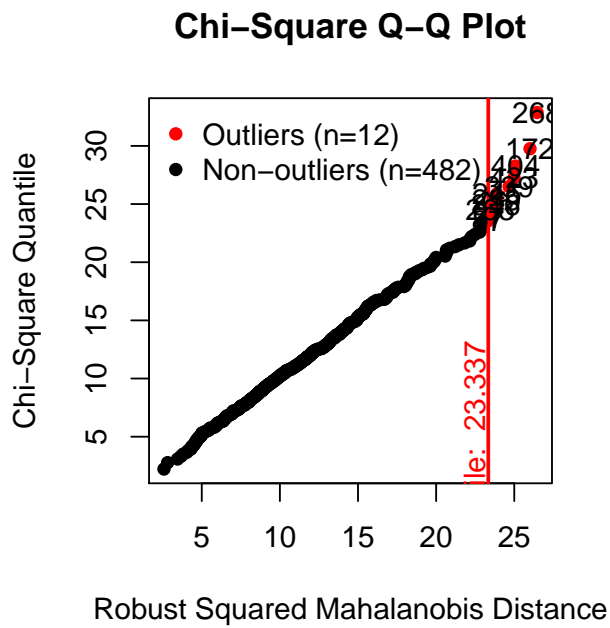
Chi-Square Q-Q Plot



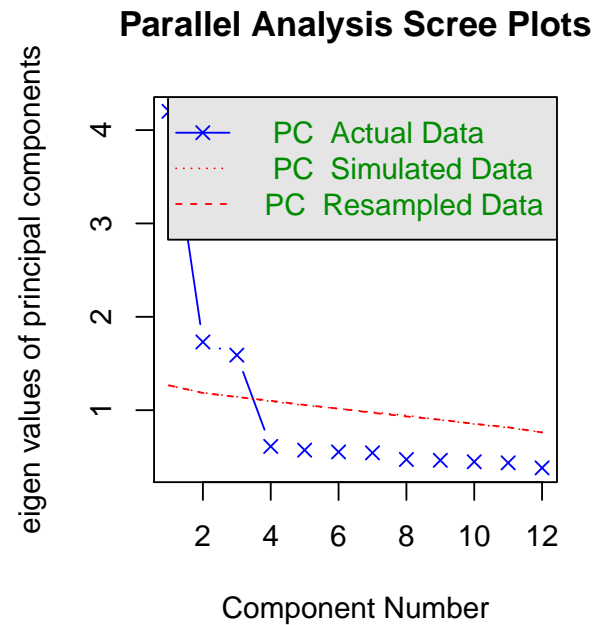
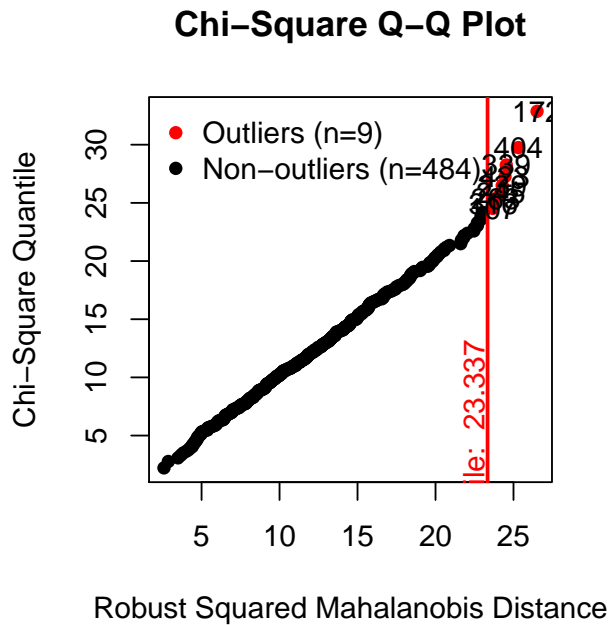
Parallel Analysis Scree Plots



```
## [1] "Case 223 removed. 3 factors remain. This is the 6 round"
```

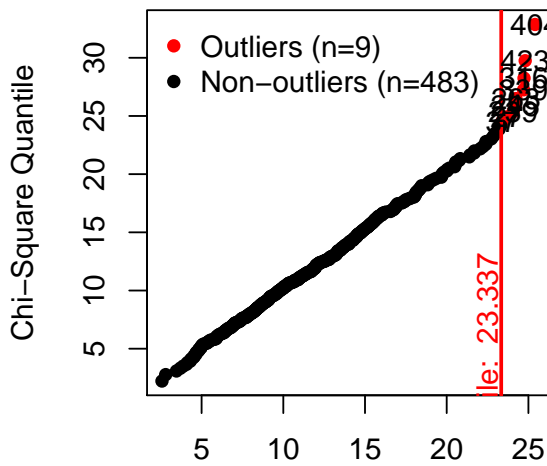


```
## [1] "Case 268 removed. 3 factors remain. This is the 7 round"
```

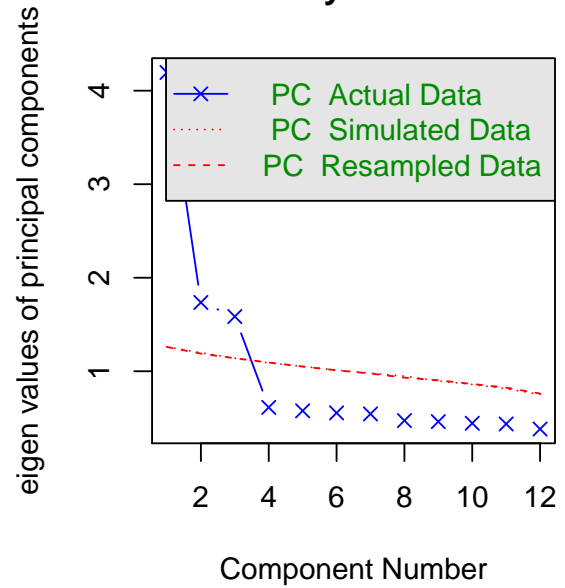


```
## [1] "Case 172 removed. 3 factors remain. This is the 8 round"
```


Chi-Square Q-Q Plot

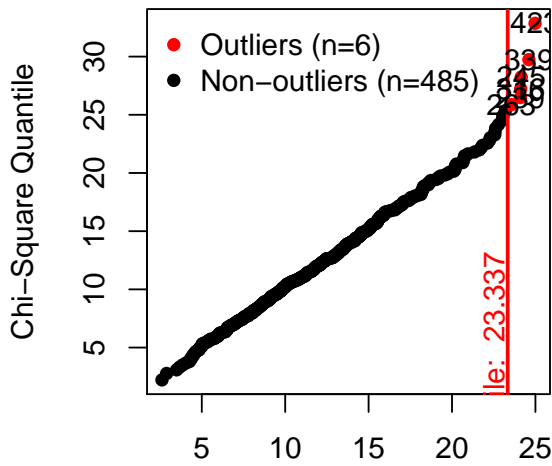


Parallel Analysis Scree Plots

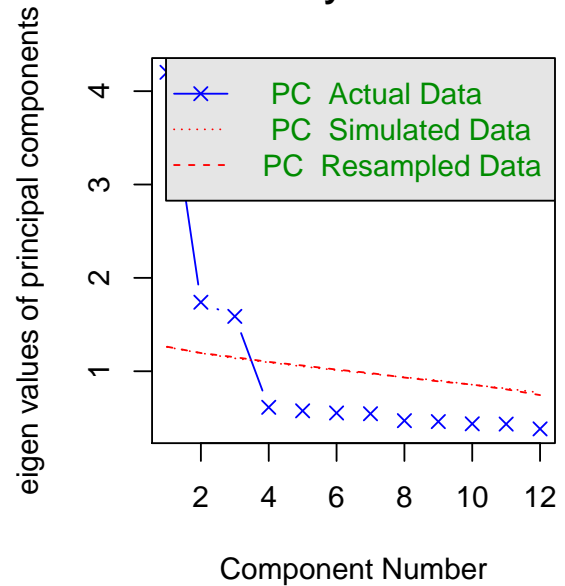


```
## [1] "Case 404 removed. 3 factors remain. This is the 9 round"
```

Chi-Square Q-Q Plot

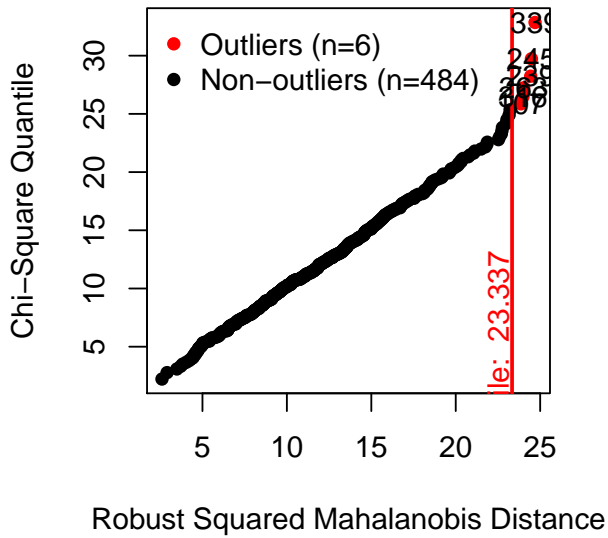


Parallel Analysis Scree Plots

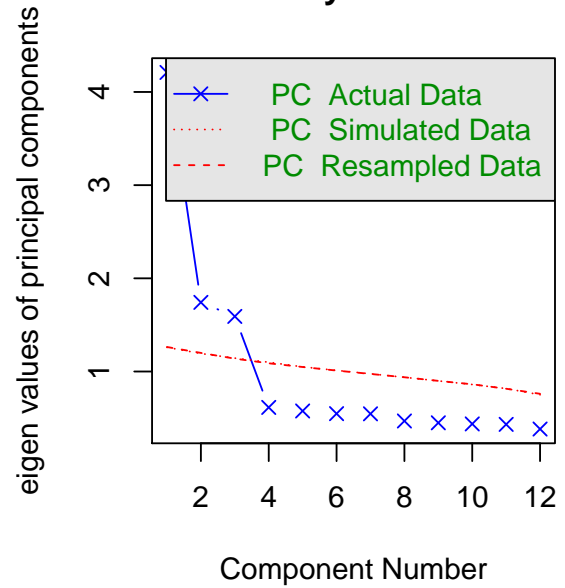


```
## [1] "Case 423 removed. 3 factors remain. This is the 10 round"
```

Chi-Square Q-Q Plot

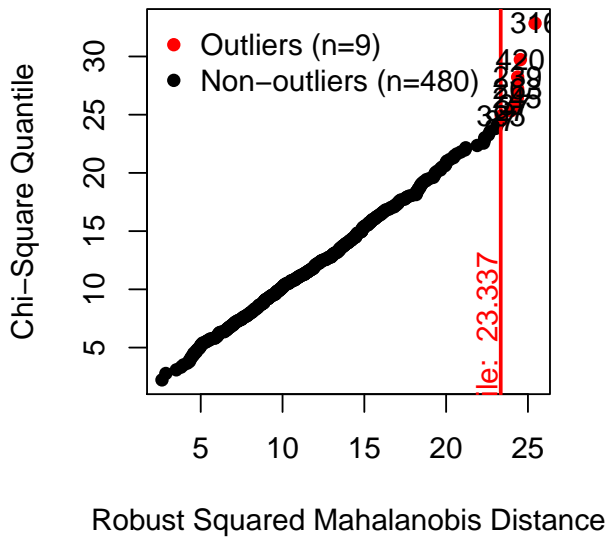


Parallel Analysis Scree Plots

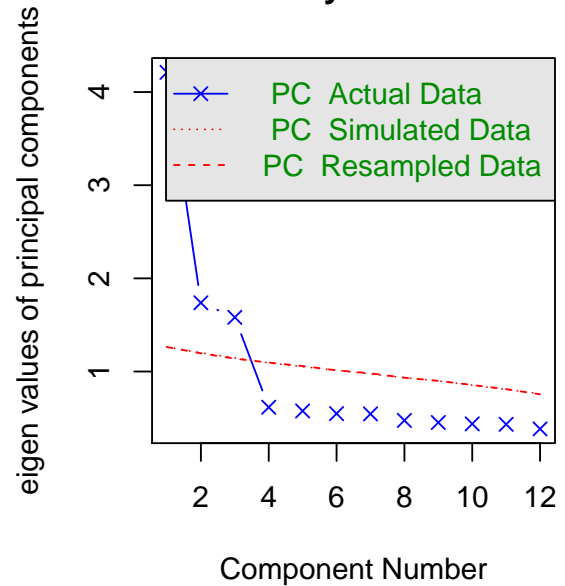


```
## [1] "Case 339 removed. 3 factors remain. This is the 11 round"
```

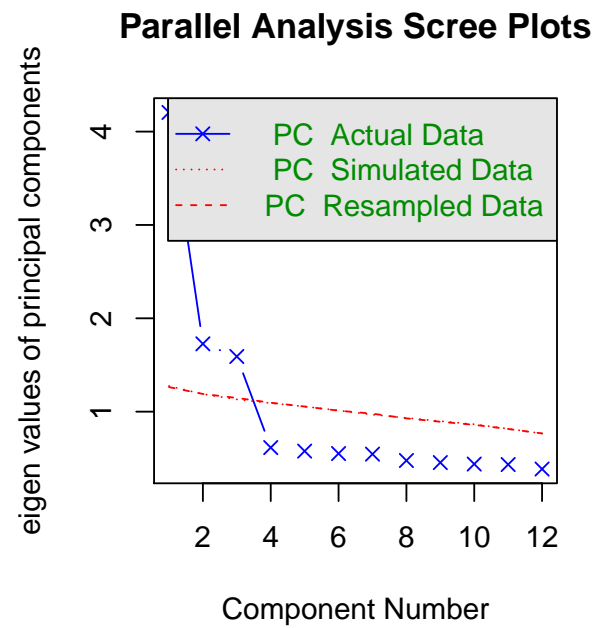
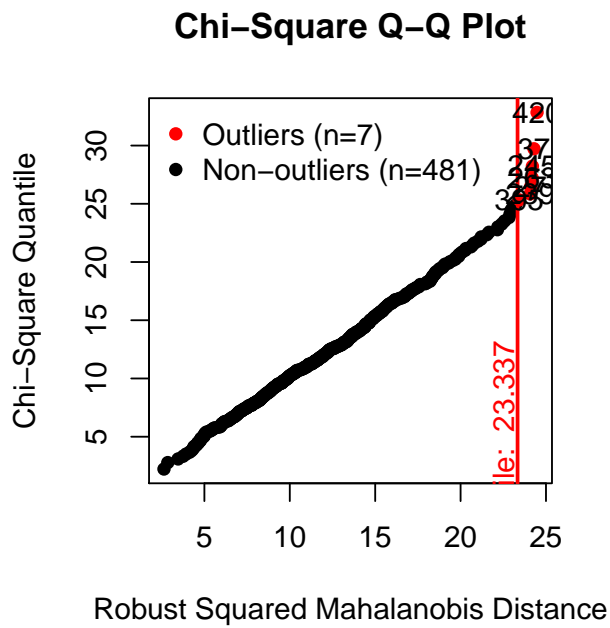
Chi-Square Q-Q Plot



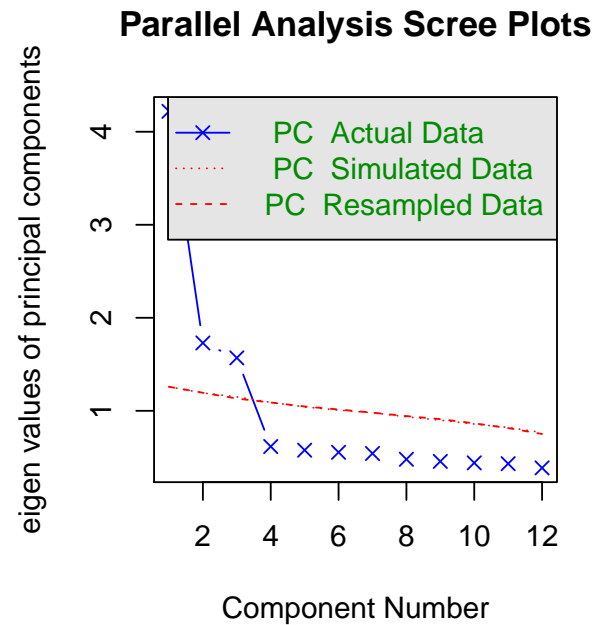
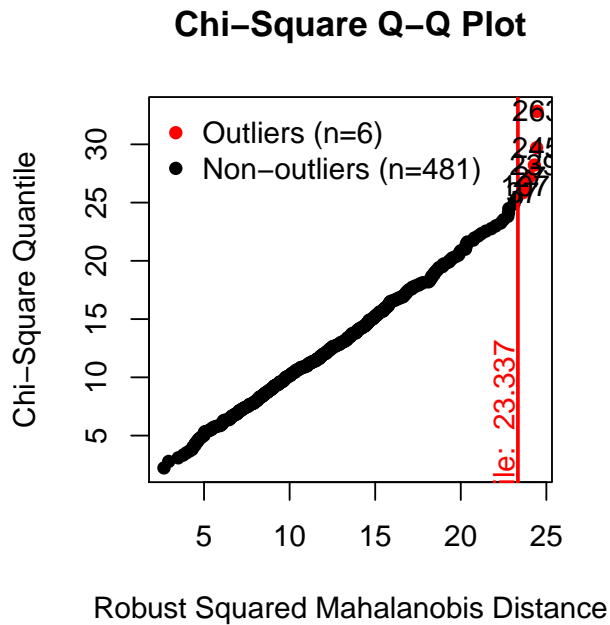
Parallel Analysis Scree Plots



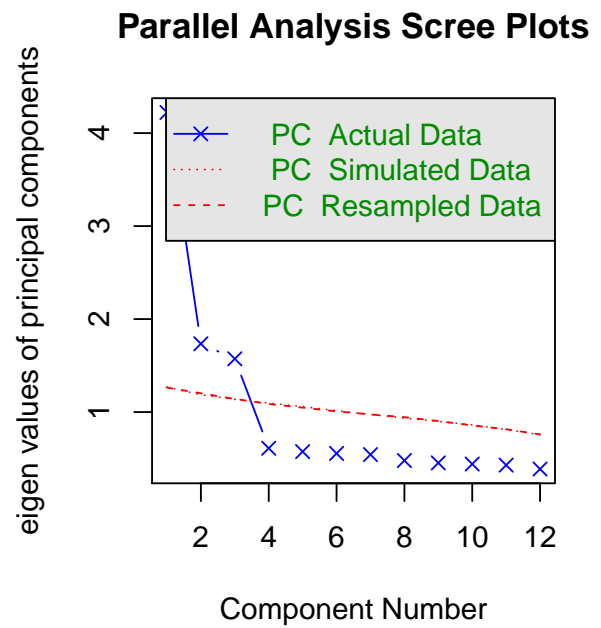
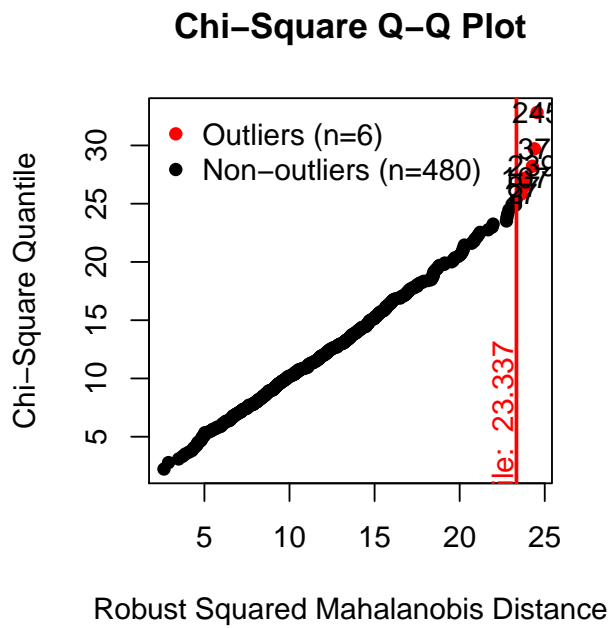
```
## [1] "Case 316 removed. 3 factors remain. This is the 12 round"
```



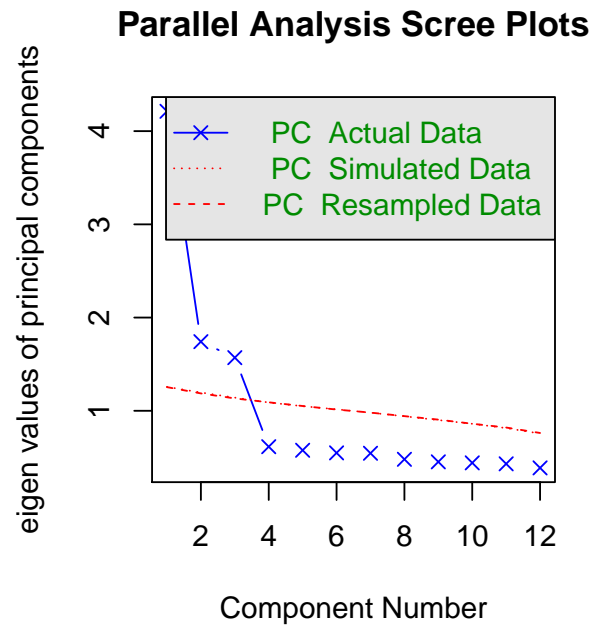
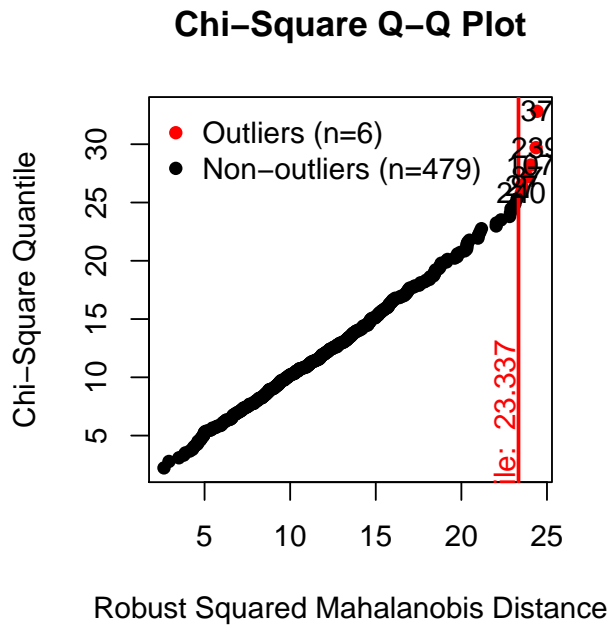
```
## [1] "Case 420 removed. 3 factors remain. This is the 13 round"
```



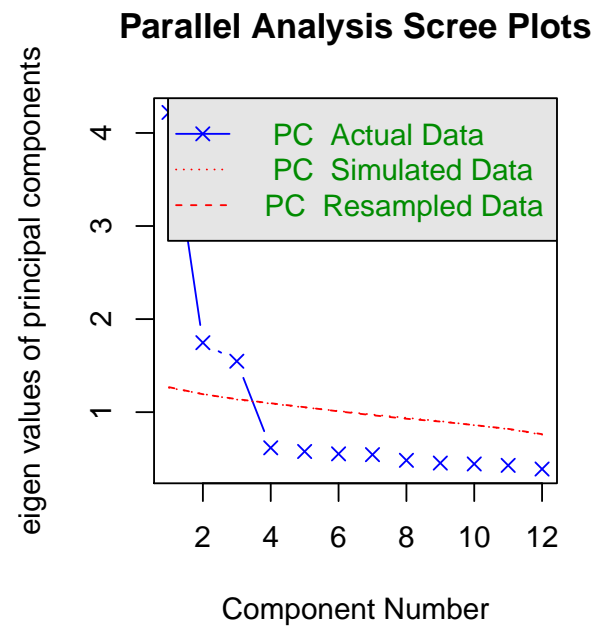
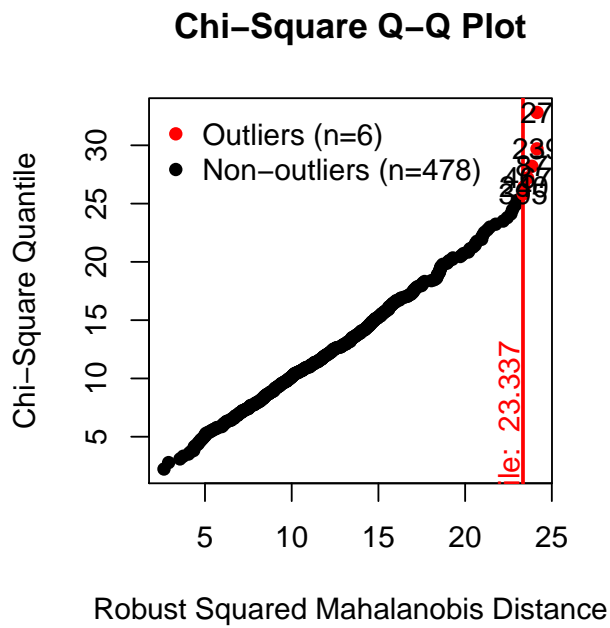
```
## [1] "Case 263 removed. 3 factors remain. This is the 14 round"
```



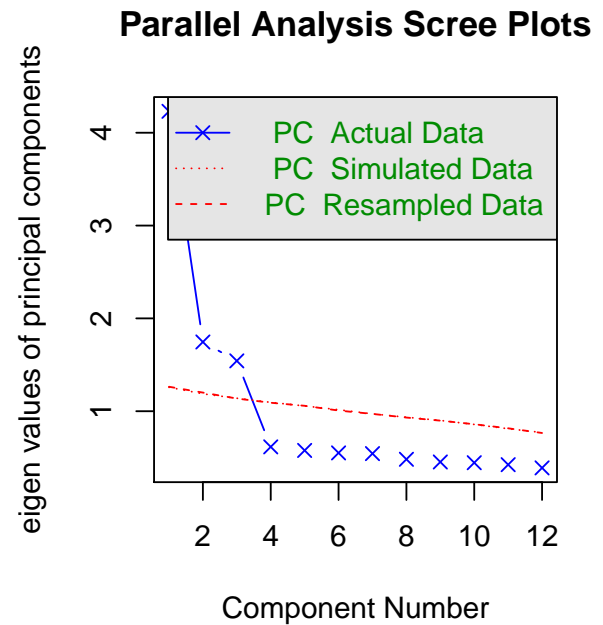
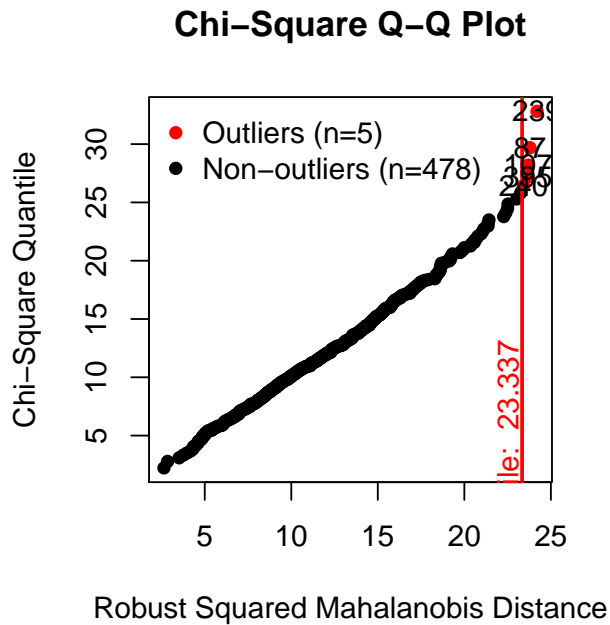
```
## [1] "Case 245 removed. 3 factors remain. This is the 15 round"
```



```
## [1] "Case 37 removed. 3 factors remain. This is the 16 round"
```

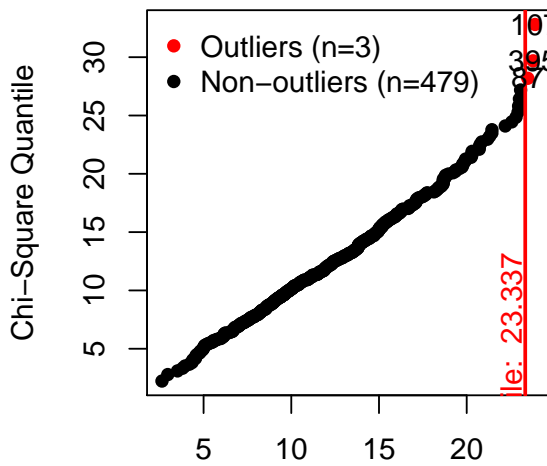


```
## [1] "Case 27 removed. 3 factors remain. This is the 17 round"
```



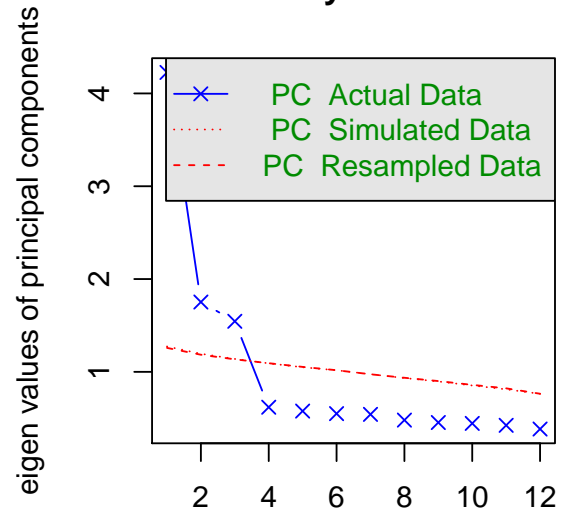
```
## [1] "Case 239 removed. 3 factors remain. This is the 18 round"
```

Chi-Square Q-Q Plot



Robust Squared Mahalanobis Distance

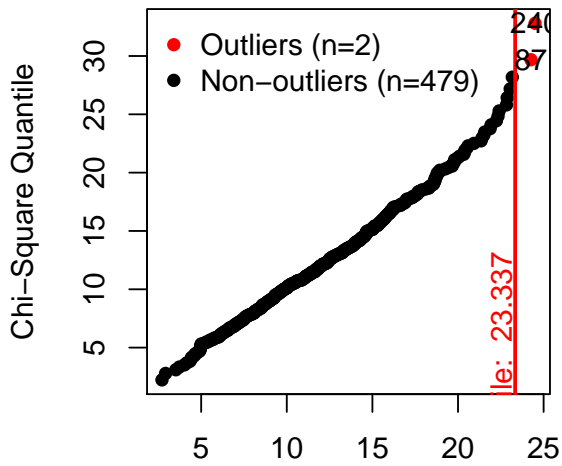
Parallel Analysis Scree Plots



Component Number

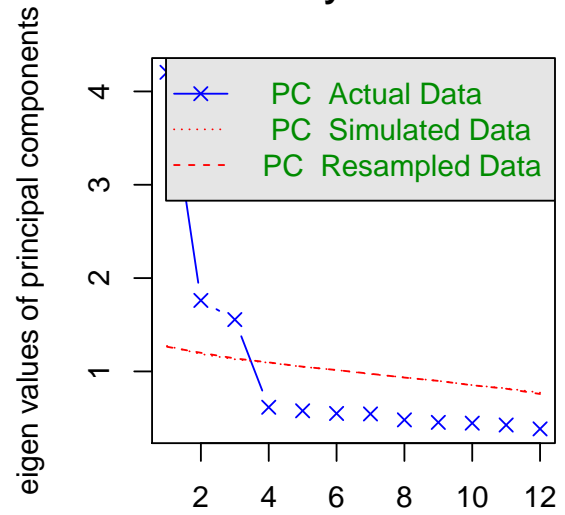
```
## [1] "Case 107 removed. 3 factors remain. This is the 19 round"
```

Chi-Square Q-Q Plot



Robust Squared Mahalanobis Distance

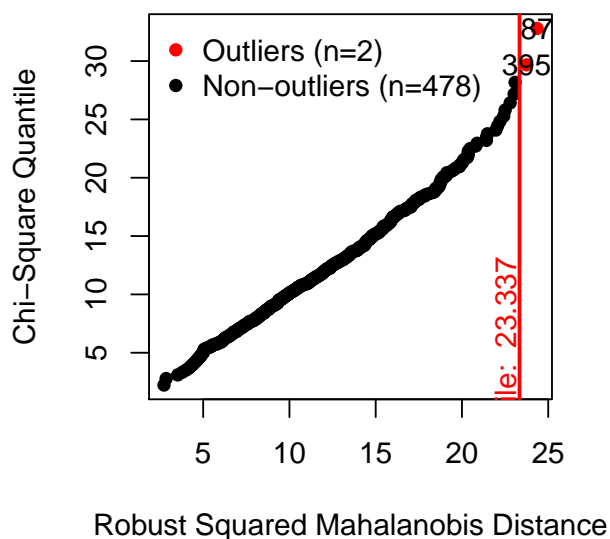
Parallel Analysis Scree Plots



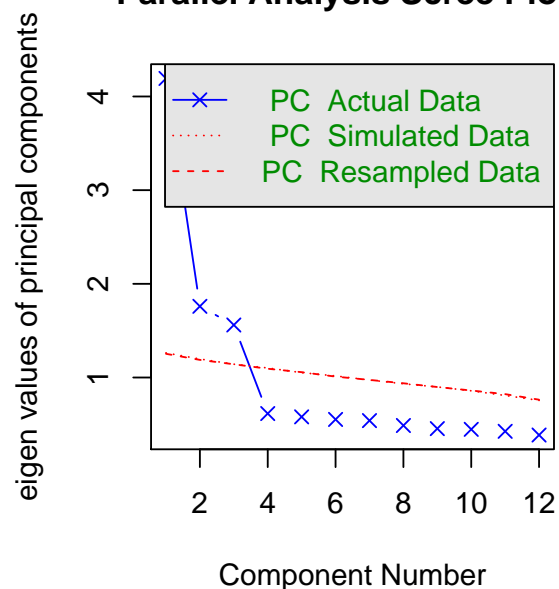
Component Number

```
## [1] "Case 240 removed. 3 factors remain. This is the 20 round"
```

Chi-Square Q-Q Plot

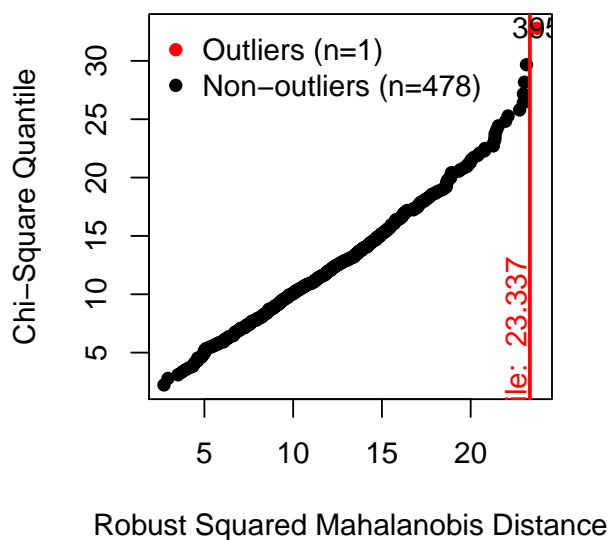


Parallel Analysis Scree Plots

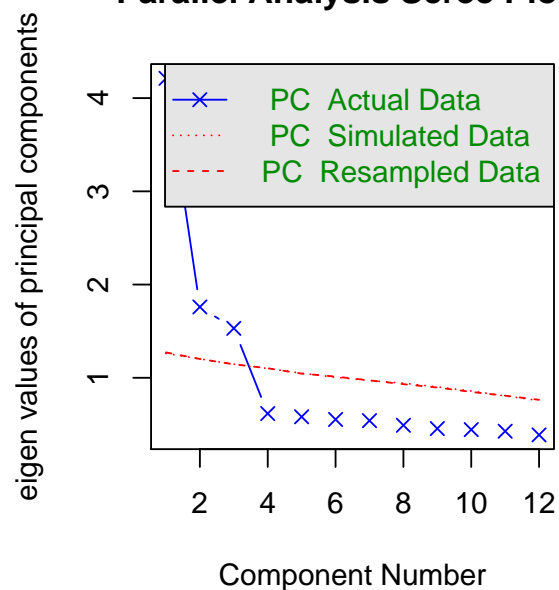


```
## [1] "Case 87 removed. 3 factors remain. This is the 21 round"
```

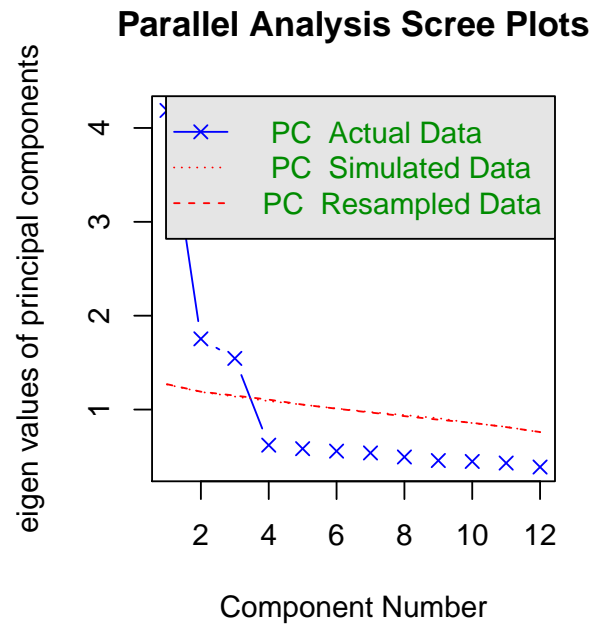
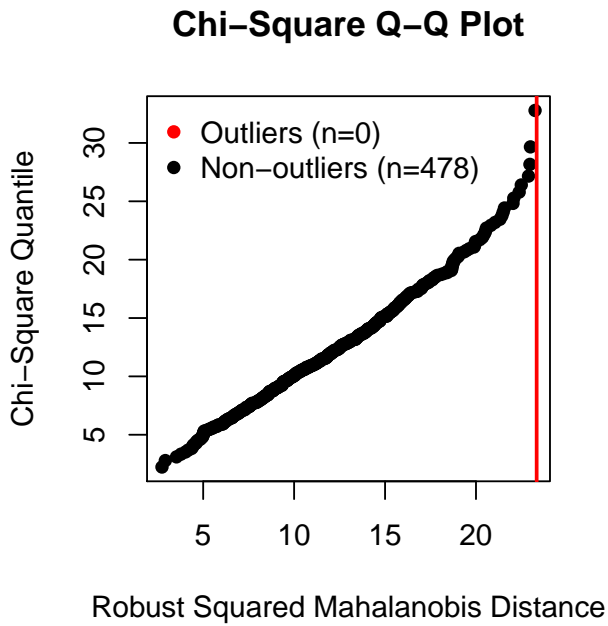
Chi-Square Q-Q Plot



Parallel Analysis Scree Plots



```
## [1] "Case 395 removed. 3 factors remain. This is the 22 round"
```



```
## [1] "Case NA removed. 3 factors remain. This is the 23 round"

pca_final <- principal(
  tmp
  , nfactors = scree$ncomp
  , rotate = "none"
  , residuals = T
  , scores = TRUE)

```

In total, using the mardia test, it took 23 rounds to remove the following outliers: cases .

Our conclusions do not change. We would still extract 3 components. However, the percentage of variance changes (see below):

```
pca_final$Vaccounted %>% data.frame %>% mutate(m = rownames(.)) %>%
  mutate_at(vars(PC1:PC3), funs(round(.,2))) %>%
  select(m, everything()) %>%
  kable(., "latex", booktabs = T, escape = F)

```

m	PC1	PC2	PC3
SS loadings	4.19	1.75	1.55
Proportion Var	0.35	0.15	0.13
Cumulative Var	0.35	0.49	0.62
Proportion Explained	0.56	0.23	0.21
Cumulative Proportion	0.56	0.79	1.00

The extracted components account for 61.56% of the variance in the original Geometry variable, while it accounted for 61.56% in the original model.