BACS HW15

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```
library(readxl)
sdata<-read_excel("C:/Users/eva/Desktop/作業 上課資料(清大)/大四下/BACS/HW14 BACS/security_questions.xlsx","data")
sdata<-as.data.frame(sdata)
data_pca<-prcomp(sdata, scale. = T)
summary(data_pca)
```

```
## Importance of components:
##                           PC1     PC2     PC3     PC4     PC5     PC6     PC7
## Standard deviation     3.0514 1.26346 1.07217 0.87291 0.82167 0.78209 0.70921
## Proportion of Variance 0.5173 0.08869 0.06386 0.04233 0.03751 0.03398 0.02794
## Cumulative Proportion  0.5173 0.60596 0.66982 0.71216 0.74966 0.78365 0.81159
##                            PC8     PC9   PC10    PC11    PC12    PC13    PC14
## Standard deviation     0.68431 0.67229 0.6206 0.59572 0.54891 0.54063 0.51200
## Proportion of Variance 0.02602 0.02511 0.0214 0.01972 0.01674 0.01624 0.01456
## Cumulative Proportion  0.83760 0.86271 0.8841 0.90383 0.92057 0.93681 0.95137
##                           PC15   PC16   PC17   PC18
## Standard deviation     0.48433 0.4801 0.4569 0.4489
## Proportion of Variance 0.01303 0.0128 0.0116 0.0112
## Cumulative Proportion  0.96440 0.9772 0.9888 1.0000
```

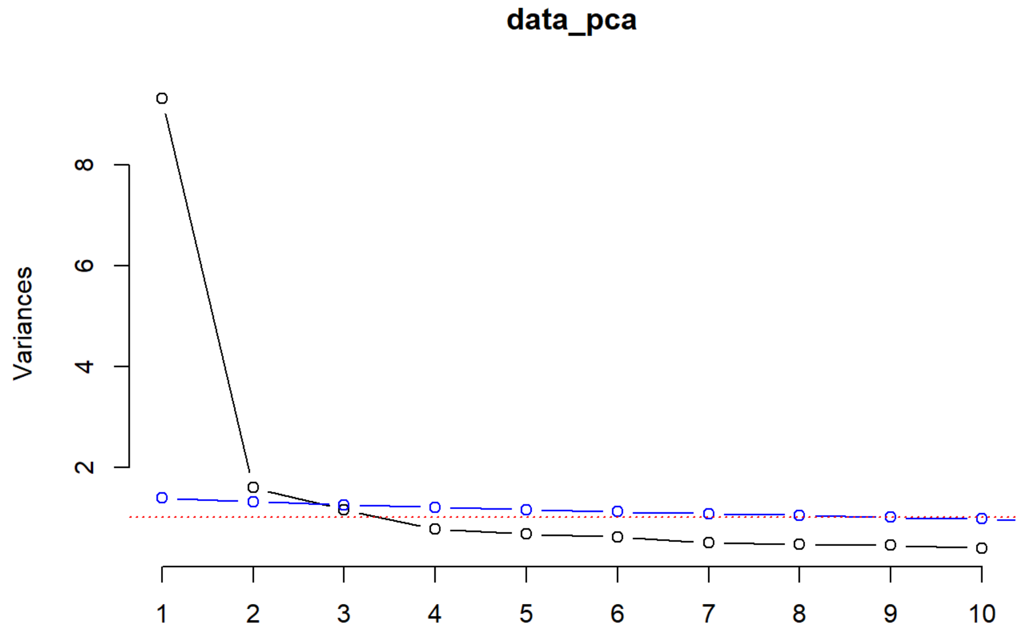
```
nrow(sdata)
```

```
## [1] 405
```

Question 1

(a) Show a single visualization with scree plot of data, scree plot of simulated noise, and a horizontal line showing the eigenvalue = 1 cutoff.

```
# Q1(a)
sim_noise_ev<-function(n, p) {
  noise<-data.frame(replicate(p,rnorm(n)))
  return( eigen(cor(noise))$values)
}
set.seed(42)
evalue_noise<-replicate(100, sim_noise_ev(405,18))
evalues_mean<-apply(evalue_noise,1, mean)
screeplot(data_pca, type='lines')
lines(evalues_mean, type='b', col='blue')
abline(h=1, lty='dotted', col='red')
```



(b) How many dimensions would you retain if we used Parallel Analysis?

> Only 2 dimension will be retained as Only two PCs have higher eignevalues than the"noise"

Question 2

(a)Looking at the loadings of the first 3 principal components, to which components does each item seem to best belong?

```
library(psych)
library(dplyr)
s_principal<-principal(sdata, nfactor=10, rotate="none", scores=TRUE)
lpc1<-as.data.frame(s_principal$loadings[,1])
lpc1_i<-filter(.data=lpc1, lpc1$`s_principal$loadings[, 1]` >=0.7)
lpc1_i
```

```
##     s_principal$loadings[, 1]
## Q1                  0.8169846
## Q3                  0.7655215
## Q8                  0.7861054
## Q9                  0.7230295
## Q11                 0.7529735
## Q13                 0.7119085
## Q14                 0.8114677
## Q15                 0.7040428
## Q16                 0.7575616
## Q18                 0.8067284
```

```
lpc2<-as.data.frame(s_principal$loadings[,2])
lpc2_i<-filter(.data=lpc2, lpc2$`s_principal$loadings[, 2]` >=0.7)
lpc2_i
```

```
## [1] s_principal$loadings[, 2]
## <0 rows> (or 0-length row.names)
```

```
sort(s_principal$loadings[,2], decreasing = T)
```

```
##         Q17         Q4         Q12          Q8         Q15          Q2
##  0.66426051  0.64307826  0.63753124  0.04235983  0.01057936 -0.01375526
##          Q5          Q3         Q13         Q10         Q14          Q6
## -0.03126466 -0.03269651 -0.06463837 -0.09868038 -0.09970016 -0.10462094
##         Q18          Q1         Q16          Q9         Q11          Q7
## -0.11360432 -0.13941235 -0.20281591 -0.23164618 -0.26100673 -0.31763196
```

```
lpc3<-as.data.frame(s_principal$loadings[,3])
lpc3_i<-filter(.data=lpc3, lpc3$`s_principal$loadings[, 3]` >=0.7)
lpc3_i
```

```
## [1] s_principal$loadings[, 3]
## <0 rows> (or 0-length row.names)
```

```
sort(s_principal$loadings[,3], decreasing = T)
```

```
##           Q7           Q6           Q9          Q16          Q11          Q14
##  0.324176779  0.207232000  0.203556038  0.183170175  0.172516196  0.156787046
##          Q12          Q17           Q4           Q3           Q2          Q13
##  0.121522834  0.110061160  0.108031860  0.089686106  0.089174403  0.084335919
##           Q1          Q18          Q15           Q8          Q10           Q5
## -0.002115927 -0.065189145 -0.332546876 -0.343212951 -0.532678749 -0.542354570
```

(b)How much of the total variance of the security dataset do the first 3 PCs capture?

```
principal(sdata, nfactor=10, rotate="none", scores=TRUE)
```

```
## Principal Components Analysis
## Call: principal(r = sdata, nfactors = 10, rotate = "none", scores = TRUE)
## Standardized loadings (pattern matrix) based upon correlation matrix
##      PC1   PC2   PC3   PC4   PC5   PC6   PC7   PC8   PC9  PC10   h2    u2 com
## Q1  0.82 -0.14  0.00  0.11 -0.04  0.14 -0.34 -0.01 -0.11 -0.02 0.85 0.153 1.6
## Q2  0.67 -0.01  0.09  0.23  0.08  0.62  0.07 -0.25  0.01  0.01 0.98 0.024 2.6
## Q3  0.77 -0.03  0.09 -0.35 -0.05  0.11  0.21  0.03  0.03 -0.39 0.93 0.071 2.3
## Q4  0.62  0.64  0.11  0.04 -0.06 -0.05  0.05  0.06  0.02 -0.08 0.83 0.165 2.2
## Q5  0.69 -0.03 -0.54  0.05 -0.16  0.12  0.14  0.13  0.15  0.06 0.87 0.127 2.4
## Q6  0.68 -0.10  0.21  0.00  0.50  0.04 -0.05  0.37  0.22 -0.03 0.96 0.037 3.0
## Q7  0.66 -0.32  0.32  0.29  0.01 -0.04  0.32  0.16 -0.16  0.20 0.91 0.088 3.7
## Q8  0.79  0.04 -0.34  0.07  0.17 -0.16 -0.05 -0.14 -0.16  0.05 0.84 0.155 1.8
## Q9  0.72 -0.23  0.20 -0.11  0.02 -0.21  0.09 -0.31  0.40  0.16 0.96 0.035 2.9
## Q10 0.69 -0.10 -0.53 -0.03 -0.20  0.02  0.11  0.17  0.09  0.06 0.86 0.138 2.4
## Q11 0.75 -0.26  0.17  0.23 -0.17 -0.15 -0.01  0.12 -0.19 -0.08 0.83 0.171 2.1
## Q12 0.63  0.64  0.12  0.05  0.04 -0.04 -0.02  0.00  0.01  0.10 0.84 0.164 2.2
## Q13 0.71 -0.06  0.08 -0.53 -0.02  0.07 -0.03  0.01 -0.19  0.30 0.93 0.070 2.5
## Q14 0.81 -0.10  0.16 -0.32 -0.07  0.00 -0.05 -0.02 -0.15 -0.08 0.83 0.170 1.5
## Q15 0.70  0.01 -0.33  0.06  0.42 -0.20  0.11 -0.21 -0.17 -0.12 0.93 0.072 2.9
## Q16 0.76 -0.20  0.18  0.18 -0.28 -0.17 -0.03 -0.13  0.09 -0.13 0.83 0.168 2.0
## Q17 0.62  0.66  0.11  0.07 -0.13 -0.04  0.02  0.03  0.02  0.06 0.86 0.137 2.2
## Q18 0.81 -0.11 -0.07  0.04 -0.02 -0.03 -0.41  0.05  0.12 -0.01 0.86 0.139 1.6
##
##                        PC1  PC2  PC3  PC4  PC5  PC6  PC7  PC8  PC9 PC10
## SS loadings           9.31 1.60 1.15 0.76 0.68 0.61 0.50 0.47 0.45 0.39
## Proportion Var        0.52 0.09 0.06 0.04 0.04 0.03 0.03 0.03 0.03 0.02
## Cumulative Var        0.52 0.61 0.67 0.71 0.75 0.78 0.81 0.84 0.86 0.88
## Proportion Explained  0.59 0.10 0.07 0.05 0.04 0.04 0.03 0.03 0.03 0.02
## Cumulative Proportion 0.59 0.69 0.76 0.81 0.85 0.89 0.92 0.95 0.98 1.00
##
## Mean item complexity =  2.3
## Test of the hypothesis that 10 components are sufficient.
##
## The root mean square of the residuals (RMSR) is  0.03
##  with the empirical chi square  111.53  with prob <  1.6e-15
##
## Fit based upon off diagonal values = 1
```

> The first 3 PCs capture 0.76 of the total variance of the security dataset.

(c)Looking at commonality and uniqueness, which items are less than adequately explained by the first 3 principal components?

```
principal(sdata, nfactor=3, rotate="none", scores=TRUE)
```

```
## Principal Components Analysis
## Call: principal(r = sdata, nfactors = 3, rotate = "none", scores = TRUE)
## Standardized loadings (pattern matrix) based upon correlation matrix
##      PC1   PC2   PC3   h2   u2 com
## Q1  0.82 -0.14  0.00 0.69 0.31 1.1
## Q2  0.67 -0.01  0.09 0.46 0.54 1.0
## Q3  0.77 -0.03  0.09 0.60 0.40 1.0
## Q4  0.62  0.64  0.11 0.81 0.19 2.1
## Q5  0.69 -0.03 -0.54 0.77 0.23 1.9
## Q6  0.68 -0.10  0.21 0.52 0.48 1.2
## Q7  0.66 -0.32  0.32 0.64 0.36 2.0
## Q8  0.79  0.04 -0.34 0.74 0.26 1.4
## Q9  0.72 -0.23  0.20 0.62 0.38 1.4
## Q10 0.69 -0.10 -0.53 0.76 0.24 1.9
## Q11 0.75 -0.26  0.17 0.66 0.34 1.4
## Q12 0.63  0.64  0.12 0.82 0.18 2.1
## Q13 0.71 -0.06  0.08 0.52 0.48 1.0
## Q14 0.81 -0.10  0.16 0.69 0.31 1.1
## Q15 0.70  0.01 -0.33 0.61 0.39 1.4
## Q16 0.76 -0.20  0.18 0.65 0.35 1.3
## Q17 0.62  0.66  0.11 0.83 0.17 2.0
## Q18 0.81 -0.11 -0.07 0.67 0.33 1.1
##
##                        PC1  PC2  PC3
## SS loadings           9.31 1.60 1.15
## Proportion Var        0.52 0.09 0.06
## Cumulative Var        0.52 0.61 0.67
## Proportion Explained  0.77 0.13 0.10
## Cumulative Proportion 0.77 0.90 1.00
##
## Mean item complexity =  1.5
## Test of the hypothesis that 3 components are sufficient.
##
## The root mean square of the residuals (RMSR) is  0.05
##  with the empirical chi square  258.65  with prob <  1.4e-15
##
## Fit based upon off diagonal values = 0.99
```

> - h2: communities, u2:uniqueness
> - Communalities refers to shared variance with the other items.
> - uniqueness is variance not explained by the other items.

- Column h2 refers to the component common factor variance, i.e., the degree of variance explained by the principal component for each variable. column u2 refers to component uniqueness, i.e., the proportion of variance that cannot be explained by the principal component.
- Q2 is less than adequately explained by the first 3 principal components, as it got the lowest h2 and highest u2.

(d)How many measurement items share similar loadings between 2 or more components?

```
principal(sdata, nfactor=10, rotate="none", scores=TRUE)
```

```
## Principal Components Analysis
## Call: principal(r = sdata, nfactors = 10, rotate = "none", scores = TRUE)
## Standardized loadings (pattern matrix) based upon correlation matrix
##      PC1   PC2   PC3   PC4   PC5   PC6   PC7   PC8   PC9  PC10   h2    u2 com
## Q1  0.82 -0.14  0.00  0.11 -0.04  0.14 -0.34 -0.01 -0.11 -0.02 0.85 0.153 1.6
## Q2  0.67 -0.01  0.09  0.23  0.08  0.62  0.07 -0.25  0.01  0.01 0.98 0.024 2.6
## Q3  0.77 -0.03  0.09 -0.35 -0.05  0.11  0.21  0.03  0.03 -0.39 0.93 0.071 2.3
## Q4  0.62  0.64  0.11  0.04 -0.06 -0.05  0.05  0.06  0.02 -0.08 0.83 0.165 2.2
## Q5  0.69 -0.03 -0.54  0.05 -0.16  0.12  0.14  0.13  0.15  0.06 0.87 0.127 2.4
## Q6  0.68 -0.10  0.21  0.00  0.50  0.04 -0.05  0.37  0.22 -0.03 0.96 0.037 3.0
## Q7  0.66 -0.32  0.32  0.29  0.01 -0.04  0.32  0.16 -0.16  0.20 0.91 0.088 3.7
## Q8  0.79  0.04 -0.34  0.07  0.17 -0.16 -0.05 -0.14 -0.16  0.05 0.84 0.155 1.8
## Q9  0.72 -0.23  0.20 -0.11  0.02 -0.21  0.09 -0.31  0.40  0.16 0.96 0.035 2.9
## Q10 0.69 -0.10 -0.53 -0.03 -0.20  0.02  0.11  0.17  0.09  0.06 0.86 0.138 2.4
## Q11 0.75 -0.26  0.17  0.23 -0.17 -0.15 -0.01  0.12 -0.19 -0.08 0.83 0.171 2.1
## Q12 0.63  0.64  0.12  0.05  0.04 -0.04 -0.02  0.00  0.01  0.10 0.84 0.164 2.2
## Q13 0.71 -0.06  0.08 -0.53 -0.02  0.07 -0.03  0.01 -0.19  0.30 0.93 0.070 2.5
## Q14 0.81 -0.10  0.16 -0.32 -0.07  0.00 -0.05 -0.02 -0.15 -0.08 0.83 0.170 1.5
## Q15 0.70  0.01 -0.33  0.06  0.42 -0.20  0.11 -0.21 -0.17 -0.12 0.93 0.072 2.9
## Q16 0.76 -0.20  0.18  0.18 -0.28 -0.17 -0.03 -0.13  0.09 -0.13 0.83 0.168 2.0
## Q17 0.62  0.66  0.11  0.07 -0.13 -0.04  0.02  0.03  0.02  0.06 0.86 0.137 2.2
## Q18 0.81 -0.11 -0.07  0.04 -0.02 -0.03 -0.41  0.05  0.12 -0.01 0.86 0.139 1.6
##
##                        PC1  PC2  PC3  PC4  PC5  PC6  PC7  PC8  PC9 PC10
## SS loadings           9.31 1.60 1.15 0.76 0.68 0.61 0.50 0.47 0.45 0.39
## Proportion Var        0.52 0.09 0.06 0.04 0.04 0.03 0.03 0.03 0.03 0.02
## Cumulative Var        0.52 0.61 0.67 0.71 0.75 0.78 0.81 0.84 0.86 0.88
## Proportion Explained  0.59 0.10 0.07 0.05 0.04 0.04 0.03 0.03 0.03 0.02
## Cumulative Proportion 0.59 0.69 0.76 0.81 0.85 0.89 0.92 0.95 0.98 1.00
##
## Mean item complexity =  2.3
## Test of the hypothesis that 10 components are sufficient.
##
## The root mean square of the residuals (RMSR) is  0.03
##  with the empirical chi square  111.53  with prob <  1.6e-15
##
## Fit based upon off diagonal values = 1
```

> Except the Q13, measurement items share similar loadings between 2 or more components.

(e)Can you distinguish a ‘meaning’ behind the first principal component from the items that load best upon it? (see the wording of the questions of those items)

> The ‘meaning’ behind the first principal component is about security, confidentiality , protection of personal identity and safe transcation.

Question 3

(a)Individually, does each rotated component (RC) explain the same, or different, amount of variance than the corresponding principal components (PCs)?

```
r_principal<-principal(sdata,nfactor=3,rotate="varimax",scores=TRUE)
r_principal
```

```
## Principal Components Analysis
## Call: principal(r = sdata, nfactors = 3, rotate = "varimax", scores = TRUE)
## Standardized loadings (pattern matrix) based upon correlation matrix
##      RC1  RC3  RC2   h2   u2 com
## Q1  0.66 0.45 0.22 0.69 0.31 2.0
## Q2  0.54 0.29 0.29 0.46 0.54 2.1
## Q3  0.62 0.34 0.31 0.60 0.40 2.1
## Q4  0.22 0.19 0.85 0.81 0.19 1.2
## Q5  0.24 0.83 0.16 0.77 0.23 1.3
## Q6  0.65 0.20 0.23 0.52 0.48 1.5
## Q7  0.79 0.10 0.06 0.64 0.36 1.0
## Q8  0.38 0.71 0.30 0.74 0.26 2.0
## Q9  0.74 0.23 0.14 0.62 0.38 1.3
## Q10 0.28 0.82 0.10 0.76 0.24 1.3
## Q11 0.76 0.28 0.12 0.66 0.34 1.3
## Q12 0.23 0.19 0.85 0.82 0.18 1.2
## Q13 0.59 0.32 0.26 0.52 0.48 1.9
## Q14 0.72 0.31 0.28 0.69 0.31 1.7
## Q15 0.34 0.66 0.24 0.61 0.39 1.8
## Q16 0.74 0.27 0.17 0.65 0.35 1.4
## Q17 0.21 0.19 0.87 0.83 0.17 1.2
## Q18 0.61 0.50 0.23 0.67 0.33 2.2
##
##                        RC1  RC3  RC2
## SS loadings           5.61 3.49 2.95
## Proportion Var        0.31 0.19 0.16
## Cumulative Var        0.31 0.51 0.67
## Proportion Explained  0.47 0.29 0.24
## Cumulative Proportion 0.47 0.76 1.00
##
## Mean item complexity =  1.6
## Test of the hypothesis that 3 components are sufficient.
##
## The root mean square of the residuals (RMSR) is  0.05
##  with the empirical chi square  258.65  with prob <  1.4e-15
##
## Fit based upon off diagonal values = 0.99
```

```
principal(sdata,nfactor=3,rotate="None",scores=TRUE)
```

```
## Specified rotation not found, rotate='none' used
```

```
## Principal Components Analysis
## Call: principal(r = sdata, nfactors = 3, rotate = "None", scores = TRUE)
## Standardized loadings (pattern matrix) based upon correlation matrix
##      PC1   PC2   PC3   h2   u2 com
## Q1  0.82 -0.14  0.00 0.69 0.31 1.1
## Q2  0.67 -0.01  0.09 0.46 0.54 1.0
## Q3  0.77 -0.03  0.09 0.60 0.40 1.0
## Q4  0.62  0.64  0.11 0.81 0.19 2.1
## Q5  0.69 -0.03 -0.54 0.77 0.23 1.9
## Q6  0.68 -0.10  0.21 0.52 0.48 1.2
## Q7  0.66 -0.32  0.32 0.64 0.36 2.0
## Q8  0.79  0.04 -0.34 0.74 0.26 1.4
## Q9  0.72 -0.23  0.20 0.62 0.38 1.4
## Q10 0.69 -0.10 -0.53 0.76 0.24 1.9
## Q11 0.75 -0.26  0.17 0.66 0.34 1.4
## Q12 0.63  0.64  0.12 0.82 0.18 2.1
## Q13 0.71 -0.06  0.08 0.52 0.48 1.0
## Q14 0.81 -0.10  0.16 0.69 0.31 1.1
## Q15 0.70  0.01 -0.33 0.61 0.39 1.4
## Q16 0.76 -0.20  0.18 0.65 0.35 1.3
## Q17 0.62  0.66  0.11 0.83 0.17 2.0
## Q18 0.81 -0.11 -0.07 0.67 0.33 1.1
##
##                        PC1  PC2  PC3
## SS loadings           9.31 1.60 1.15
## Proportion Var        0.52 0.09 0.06
## Cumulative Var        0.52 0.61 0.67
## Proportion Explained  0.77 0.13 0.10
## Cumulative Proportion 0.77 0.90 1.00
##
## Mean item complexity =  1.5
## Test of the hypothesis that 3 components are sufficient.
##
## The root mean square of the residuals (RMSR) is  0.05
##  with the empirical chi square  258.65  with prob <  1.4e-15
##
## Fit based upon off diagonal values = 0.99
```

> Each rotated component (RC) explain the different amount of variance than the corresponding principal components (PCs).

(b)Together, do the three rotated components explain the same, more, or less cumulative variance as the three principal components combined?

> The three rotated components explain the same cumulative variance as the three principal components combined.

(c)Looking back at the items that shared similar loadings with multiple principal components (#2d), do those items have more clearly differentiated loadings among rotated components?

> Yes, they do have more clearly differentiated loadings among rotated components.

(d)Can you now interpret the “meaning” of the 3 rotated components from the items that load best upon each of them? (see the wording of the questions of those items)

```
sort(r_principal$loadings[,1], decreasing = T)
```

```
##        Q7       Q11       Q16        Q9       Q14        Q1        Q6        Q3 
## 0.7895344 0.7573493 0.7396241 0.7378148 0.7187578 0.6602758 0.6524225 0.6206018 
##       Q18       Q13        Q2        Q8       Q15       Q10        Q5       Q12 
## 0.6090325 0.5931915 0.5437243 0.3819373 0.3417567 0.2768895 0.2441735 0.2327616 
##        Q4       Q17 
## 0.2182880 0.2054021
```

```
sort(r_principal$loadings[,2], decreasing = T)
```

```
##        Q5       Q10        Q8       Q15       Q18        Q1        Q3       Q13 
## 0.8279850 0.8229206 0.7062018 0.6557490 0.4953450 0.4497592 0.3367919 0.3150514 
##       Q14        Q2       Q11       Q16        Q9        Q6        Q4       Q17 
## 0.3100848 0.2860379 0.2779380 0.2669610 0.2335447 0.1991636 0.1933627 0.1869028 
##       Q12        Q7 
## 0.1861745 0.1031417
```

```
sort(r_principal$loadings[,3], decreasing = T)
```

```
##        Q17        Q12         Q4         Q3         Q8         Q2        Q14 
## 0.87039101 0.85423462 0.85368376 0.31074186 0.30488390 0.28825252 0.28326088 
##        Q13        Q15         Q6        Q18         Q1        Q16         Q5 
## 0.25878712 0.24407206 0.23407080 0.22733033 0.22058261 0.17399181 0.16174750 
##         Q9        Q11        Q10         Q7 
## 0.13766953 0.11843957 0.10209878 0.05598322
```

> - PC1: Q7, Q11, Q16, Q9, Q14 : About the safety of personal information.
> - PC2: Q5, Q10, Q8 : About the safety of transaction information.
> - PC3: Q17, Q12, Q4 : Ensuring the transaction will not be denied.

(e)If we reduced the number of extracted and rotated components to 2, does the meaning of our rotated components change?

```
r_principal2<-principal(sdata,nfactor=2,rotate="varimax",scores=TRUE)
r_principal2
```

```
## Principal Components Analysis
## Call: principal(r = sdata, nfactors = 2, rotate = "varimax", scores = TRUE)
## Standardized loadings (pattern matrix) based upon correlation matrix
##      RC1  RC2   h2   u2 com
## Q1  0.78 0.27 0.69 0.31 1.2
## Q2  0.60 0.31 0.45 0.55 1.5
## Q3  0.69 0.34 0.59 0.41 1.5
## Q4  0.24 0.86 0.80 0.20 1.1
## Q5  0.62 0.31 0.48 0.52 1.5
## Q6  0.65 0.24 0.48 0.52 1.3
## Q7  0.73 0.04 0.53 0.47 1.0
## Q8  0.67 0.42 0.62 0.38 1.7
## Q9  0.75 0.15 0.58 0.42 1.1
## Q10 0.65 0.24 0.48 0.52 1.3
## Q11 0.79 0.13 0.64 0.36 1.1
## Q12 0.25 0.86 0.80 0.20 1.2
## Q13 0.65 0.29 0.51 0.49 1.4
## Q14 0.76 0.30 0.67 0.33 1.3
## Q15 0.61 0.35 0.50 0.50 1.6
## Q16 0.76 0.19 0.62 0.38 1.1
## Q17 0.22 0.88 0.82 0.18 1.1
## Q18 0.76 0.29 0.66 0.34 1.3
##
##                        RC1  RC2
## SS loadings           7.52 3.39
## Proportion Var        0.42 0.19
## Cumulative Var        0.42 0.61
## Proportion Explained  0.69 0.31
## Cumulative Proportion 0.69 1.00
##
## Mean item complexity =  1.3
## Test of the hypothesis that 2 components are sufficient.
##
## The root mean square of the residuals (RMSR) is  0.06
##  with the empirical chi square  439.68  with prob <  1.3e-38
##
## Fit based upon off diagonal values = 0.99
```

```
sort(r_principal2$loadings[,1], decreasing = T)
```

```
##       Q11        Q1       Q18       Q16       Q14        Q9        Q7        Q3
## 0.7855784 0.7830951 0.7616746 0.7615661 0.7591295 0.7451939 0.7284256 0.6865878
##        Q8       Q13       Q10        Q6        Q5       Q15        Q2       Q12
## 0.6684679 0.6549937 0.6488232 0.6487494 0.6197912 0.6118654 0.5960420 0.2452587
##        Q4       Q17
## 0.2364722 0.2211505
```

```
sort(r_principal2$loadings[,2], decreasing = T)
```

```
##        Q17         Q4        Q12         Q8        Q15         Q3         Q2
## 0.87959208 0.86384301 0.86234333 0.41582056 0.34843790 0.34013157 0.31196986
##         Q5        Q14        Q18        Q13         Q1        Q10         Q6
## 0.30504494 0.30354960 0.28908208 0.28631285 0.27140703 0.24407384 0.23725419
##        Q16         Q9        Q11         Q7
## 0.18721908 0.14531919 0.13401543 0.03797881
```

> - PC1: Q11, Q1, Q18, Q16, Q14, Q9, Q7: About the safety of personal information.
> - PC2: Q17, Q4, Q12 : Ensuring the transaction will not be denied.

(ungraded) Looking back at all our results and analyses of this dataset (from this week and previous), how many components (1-3) do you believe we should extract and analyze to understand the security dataset? Feel free to suggest different answers for different purposes.

I think 3 components should be extracted, as they all represent different meanings.