

```
test <- read.csv(file = "C:/Users/gytjd/Desktop/QUESTNAIR.csv", header = T )
```

자료 정리

```
x <- na.omit(test)
dim(x)
```

```
## [1] 101 18
```

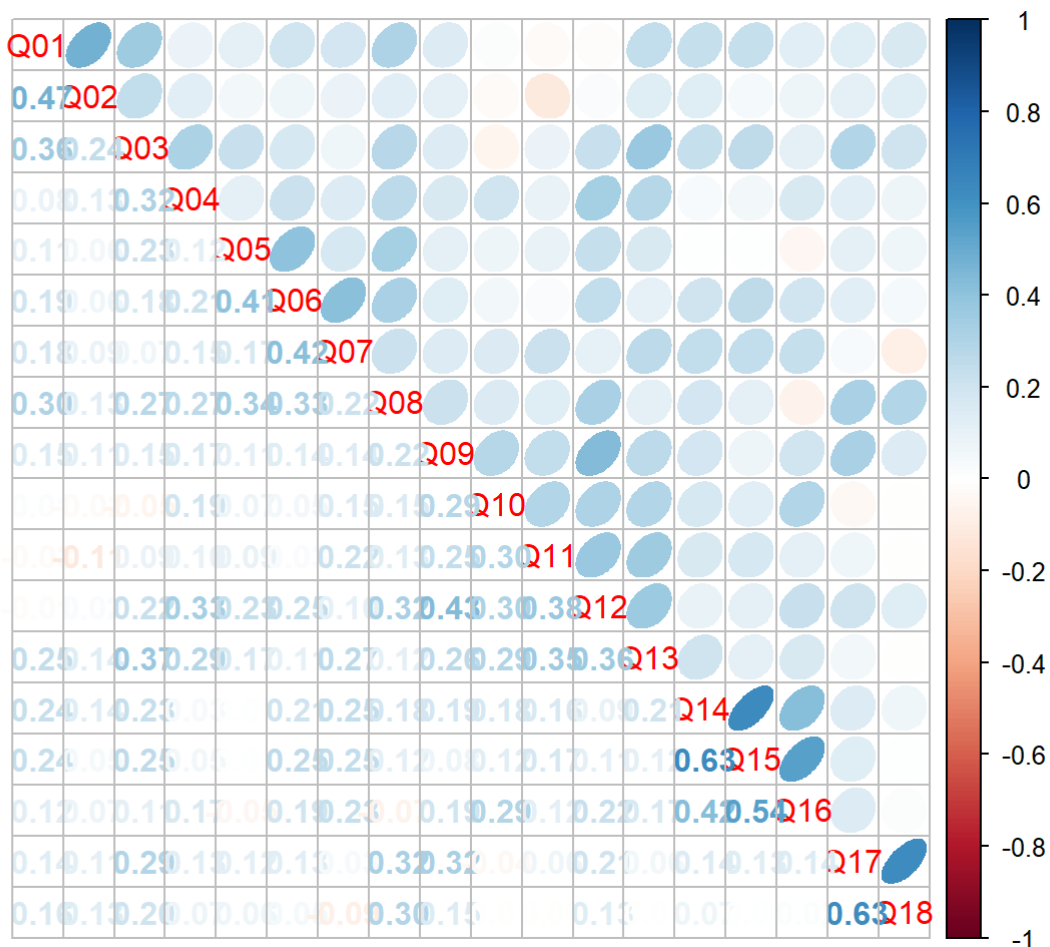
자료 탐색/요인 분석 적절성

```
# 상관행렬 계산 및 시각화
R <- cor(x)
library(corrplot)
```

```
## corrplot 0.91 loaded
```

```
corrplot.mixed(R,upper="ellipse")
```

```
# KMO의 MSA:상관관계(행렬)가 요인분석하기에 적합한지 측정
## overall 0.70이며 0.5보다 크므로 요인분석에 적합한 수준
library(psych)
```



```
KMO(R)
```

```
## Kaiser-Meyer-Olkin factor adequacy
## Call: KMO(r = R)
## Overall MSA = 0.7
## MSA for each item =
##   Q01  Q02  Q03  Q04  Q05  Q06  Q07  Q08  Q09  Q10  Q11  Q12  Q13  Q14  Q15  Q16
## 0.65 0.65 0.76 0.75 0.72 0.71 0.71 0.69 0.75 0.69 0.73 0.72 0.72 0.74 0.67 0.68
##   Q17  Q18
## 0.63 0.61
```

```
#Bartlett 구형성 검정을 하고 요인분석 진행에 적합한지 측정
## 귀무가설 기각 => 요인분석 진행 가능
cortest.bartlett(R)
```

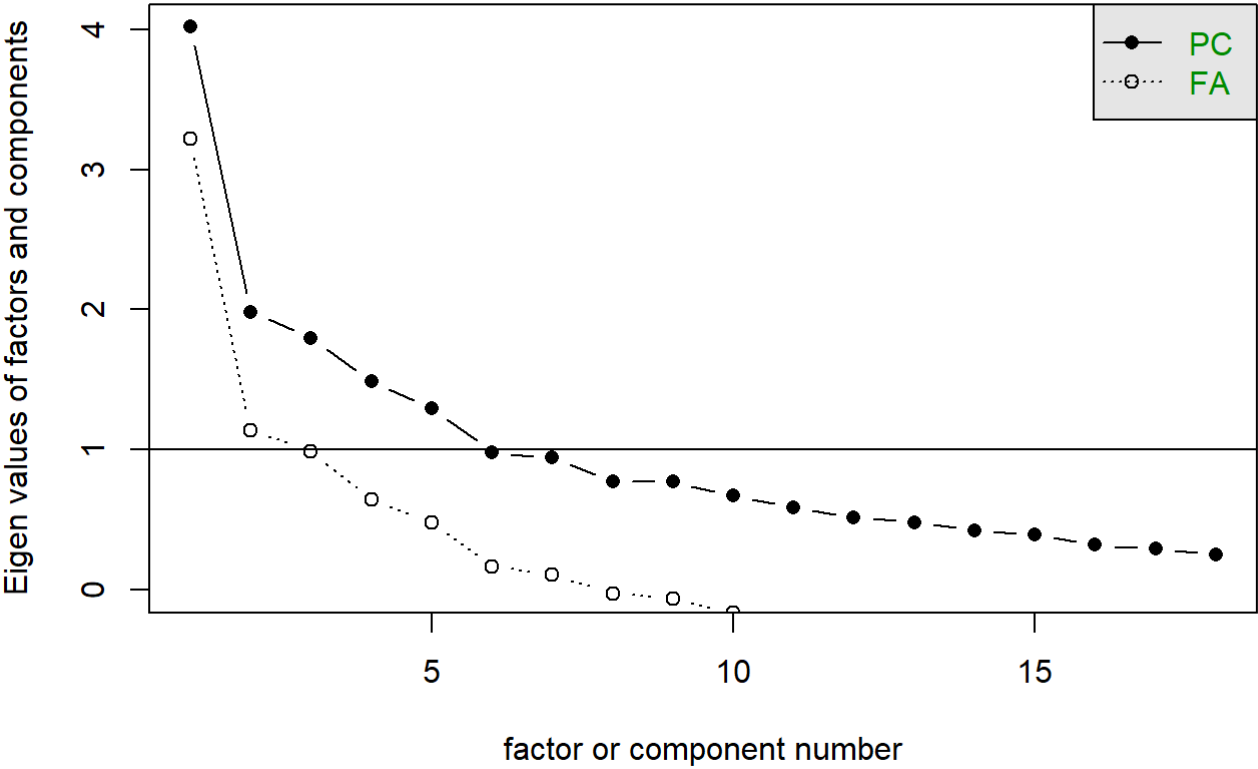
```
## Warning in cortest.bartlett(R): n not specified, 100 used
```

```
## $chisq
## [1] 472.1814
##
## $p.value
## [1] 2.926665e-34
##
## $df
## [1] 153
```

주성분 요인분석 1

```
# psych::scree(상관행렬 또는 X)로 적절한 요인수를 결정
a <- scree(R)
```

Scree plot



```
#회전없이 주성분 요인분석
Mfapc <- principal(x,nfactors = 5,rotate = 'none')
print(Mfapc,digits=4)
```

```
## Principal Components Analysis
## Call: principal(r = x, nfactors = 5, rotate = "none")
## Standardized loadings (pattern matrix) based upon correlation matrix
##      PC1      PC2      PC3      PC4      PC5      h2      u2      com
## Q01 0.4583  0.2763  0.4452 -0.2162  0.3427  0.6489  0.3511  4.001
## Q02 0.2943  0.3259  0.3618 -0.1613  0.4979  0.5976  0.4024  3.643
## Q03 0.5530  0.3057  0.1481 -0.0687  0.2719  0.4999  0.5001  2.309
## Q04 0.4564  0.0694 -0.2532 -0.1355  0.2056  0.3378  0.6622  2.299
## Q05 0.3759  0.2330 -0.2490 -0.4773 -0.2934  0.5715  0.4285  3.795
## Q06 0.5095  0.0244  0.0545 -0.4593 -0.4838  0.7081  0.2919  3.009
## Q07 0.4627 -0.2763  0.0834 -0.3979 -0.2055  0.4980  0.5020  3.156
## Q08 0.5569  0.3819 -0.1473 -0.1566 -0.2351  0.5575  0.4425  2.556
## Q09 0.5235  0.0026 -0.2895  0.2787  0.0888  0.4434  0.5566  2.229
## Q10 0.3818 -0.4171 -0.3319  0.1395  0.1207  0.4639  0.5361  3.350
## Q11 0.3944 -0.3556 -0.4043  0.1458  0.0569  0.4700  0.5300  3.278
## Q12 0.5806 -0.0645 -0.5173  0.1211  0.0094  0.6236  0.3764  2.097
## Q13 0.5546 -0.1757 -0.2198 -0.1226  0.4776  0.6299  0.3701  2.643
## Q14 0.5382 -0.3165  0.4837  0.1736 -0.1039  0.6647  0.3353  2.951
## Q15 0.5101 -0.3837  0.5323  0.1525 -0.2057  0.7563  0.2437  3.326
## Q16 0.4707 -0.4650  0.3147  0.2779 -0.0636  0.6181  0.3819  3.423
## Q17 0.4464  0.5117  0.0187  0.4976 -0.2426  0.7680  0.2320  3.408
## Q18 0.2998  0.6048  0.0131  0.4937 -0.1712  0.7289  0.2711  2.628
##
##
##      PC1      PC2      PC3      PC4      PC5
## SS loadings      4.0164  1.9848  1.7990  1.4876  1.2984
## Proportion Var      0.2231  0.1103  0.0999  0.0826  0.0721
## Cumulative Var      0.2231  0.3334  0.4333  0.5160  0.5881
## Proportion Explained 0.3794  0.1875  0.1699  0.1405  0.1226
## Cumulative Proportion 0.3794  0.5669  0.7368  0.8774  1.0000
##
## Mean item complexity = 3
## Test of the hypothesis that 5 components are sufficient.
##
## The root mean square of the residuals (RMSR) is 0.0732
## with the empirical chi square 165.7622 with prob < 3.597e-09
##
## Fit based upon off diagonal values = 0.8839
```

#공통성과 특수성

고품질 공통성=0.485, 특수성=0.515

분석시, 고품질의 변동성 중 공통요인으로 48.5%, 고품질의 특수성이 51.5% 설명
data.frame('공통성'=Mfapc\$communality, '특수성'=Mfapc\$uniqueness)

```
##          공통성    특수성
## Q01 0.6488538 0.3511462
## Q02 0.5976495 0.4023505
## Q03 0.4998979 0.5001021
## Q04 0.3377943 0.6622057
## Q05 0.5714675 0.4285325
## Q06 0.7081332 0.2918668
## Q07 0.4979755 0.5020245
## Q08 0.5575247 0.4424753
## Q09 0.4433895 0.5566105
## Q10 0.4639151 0.5360849
## Q11 0.4699719 0.5300281
## Q12 0.6236277 0.3763723
## Q13 0.6299203 0.3700797
## Q14 0.6646909 0.3353091
## Q15 0.7562745 0.2437255
## Q16 0.6181127 0.3818873
## Q17 0.7679798 0.2320202
## Q18 0.7289215 0.2710785
```

```
data.frame('초기고유값'=Mfapc$values, '비율분산'=Mfapc$values/sum(Mfapc$values)*100, '누적분산'=cumsum(Mfapc$values/sum(Mfapc$values))*100)
```

```
##      초기고유값  비율분산  누적분산
## 1    4.0164205 22.313447 22.31345
## 2    1.9847681 11.026490 33.33994
## 3    1.7989658  9.994255 43.33419
## 4    1.4875795  8.264331 51.59852
## 5    1.2983664  7.213147 58.81167
## 6    0.9819655  5.455364 64.26703
## 7    0.9420398  5.233555 69.50059
## 8    0.7746346  4.303525 73.80411
## 9    0.7731717  4.295398 78.09951
## 10   0.6699534  3.721963 81.82147
## 11   0.5893456  3.274142 85.09562
## 12   0.5178818  2.877121 87.97274
## 13   0.4821021  2.678345 90.65108
## 14   0.4260390  2.366883 93.01797
## 15   0.3931125  2.183959 95.20192
## 16   0.3206782  1.781545 96.98347
## 17   0.2910174  1.616763 98.60023
## 18   0.2519581  1.399767 100.00000
```

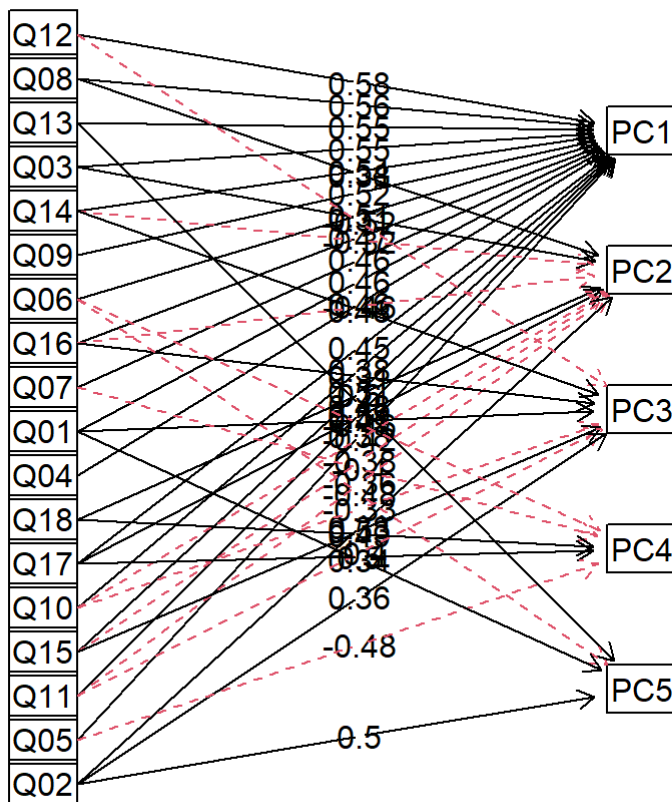
```
#회전 전 요인행렬: R의 아이겐벡터 SPSS는 요인
#요인1의 변수에 대한 적재량 = sqrt(아이겐값1) * 아이겐벡터1
#(R분석시) 요인과 변수간 상관계수 Cov[x, fT]=Cor[x, fT]=Λ
# 요인1: 모든 문항의 적재량이 0.3 이상. 전반적인 만족도
# 요인2~요인5: 전반적인 만족도 낮다.
```

```
#fa.sort로 요인적재량 높은 순으로 출력
fa.sort(Mfapc$loadings)
```

```
##
## Loadings:
##      PC1    PC2    PC3    PC4    PC5
## Q12  0.581          -0.517  0.121
## Q08  0.557  0.382 -0.147 -0.157 -0.235
## Q13  0.555 -0.176 -0.220 -0.123  0.478
## Q03  0.553  0.306  0.148          0.272
## Q14  0.538 -0.316  0.484  0.174 -0.104
## Q09  0.523          -0.289  0.279
## Q06  0.509          -0.459 -0.484
## Q16  0.471 -0.465  0.315  0.278
## Q07  0.463 -0.276          -0.398 -0.205
## Q01  0.458  0.276  0.445 -0.216  0.343
## Q04  0.456          -0.253 -0.136  0.206
## Q18  0.300  0.605          0.494 -0.171
## Q17  0.446  0.512          0.498 -0.243
## Q10  0.382 -0.417 -0.332  0.140  0.121
## Q15  0.510 -0.384  0.532  0.153 -0.206
## Q11  0.394 -0.356 -0.404  0.146
## Q05  0.376  0.233 -0.249 -0.477 -0.293
## Q02  0.294  0.326  0.362 -0.161  0.498
##
##              PC1    PC2    PC3    PC4    PC5
## SS loadings  4.016 1.985 1.799 1.488 1.298
## Proportion Var 0.223 0.110 0.100 0.083 0.072
## Cumulative Var 0.223 0.333 0.433 0.516 0.588
```

```
#fa.diagram을 이용하여 요인 적재량 시각화
fa.diagram(Mfapc,simple=FALSE,cut = 0.3,digits = 2)
```

Components Analysis



주성분 요인분석 2. Varimax회전

```
# Varimax 회전한 주성분 요인분석을 하시오
## 직교회전을 하면 공통성과 특수성은 그대로이나, 분산설명량은 바뀜
Mfapcvmx <- principal(x,nfactors = 5,rotate = 'varimax')
print(Mfapcvmx,digits=4)
```

```
## Principal Components Analysis
## Call: principal(r = x, nfactors = 5, rotate = "varimax")
## Standardized loadings (pattern matrix) based upon correlation matrix
##          RC1      RC3      RC4      RC5      RC2      h2      u2      com
## Q01 -0.0627  0.2018  0.1475  0.7599  0.0705  0.6489  0.3511  1.254
## Q02 -0.0598  0.0271 -0.0315  0.7684  0.0431  0.5976  0.4024  1.024
## Q03  0.1835  0.0986  0.1749  0.6063  0.2416  0.4999  0.5001  1.777
## Q04  0.4415 -0.0705  0.2267  0.2900  0.0486  0.3378  0.6622  2.390
## Q05  0.1239 -0.1643  0.7202  0.0769  0.0668  0.5715  0.4285  1.209
## Q06  0.0137  0.2456  0.8033  0.0378  0.0295  0.7081  0.2919  1.194
## Q07  0.1648  0.3544  0.5352  0.0847 -0.2273  0.4980  0.5020  2.449
## Q08  0.1855 -0.0292  0.5675  0.2029  0.3987  0.5575  0.4425  2.357
## Q09  0.5660  0.1072  0.0413  0.0884  0.3195  0.4434  0.5566  1.737
## Q10  0.6387  0.1975 -0.0091 -0.0905 -0.0933  0.4639  0.5361  1.281
## Q11  0.6550  0.1417  0.0470 -0.1347 -0.0239  0.4700  0.5300  1.196
## Q12  0.7190  0.0049  0.2349 -0.0152  0.2263  0.6236  0.3764  1.425
## Q13  0.6425  0.0659  0.0684  0.4288 -0.1556  0.6299  0.3701  1.937
## Q14  0.0907  0.7835  0.0756  0.1738  0.0821  0.6647  0.3353  1.169
## Q15  0.0302  0.8551  0.1166  0.0924  0.0451  0.7563  0.2437  1.069
## Q16  0.2455  0.7447 -0.0486  0.0212  0.0227  0.6181  0.3819  1.228
## Q17  0.0861  0.1255  0.0859  0.0932  0.8537  0.7680  0.2320  1.110
## Q18 -0.0035 -0.0118 -0.0026  0.1156  0.8458  0.7289  0.2711  1.038
##
##          RC1      RC3      RC4      RC5      RC2
## SS loadings      2.4771  2.2603  1.9702  1.9548  1.9237
## Proportion Var      0.1376  0.1256  0.1095  0.1086  0.1069
## Cumulative Var      0.1376  0.2632  0.3726  0.4812  0.5881
## Proportion Explained 0.2340  0.2135  0.1861  0.1847  0.1817
## Cumulative Proportion 0.2340  0.4475  0.6336  0.8183  1.0000
##
## Mean item complexity = 1.5
## Test of the hypothesis that 5 components are sufficient.
##
## The root mean square of the residuals (RMSR) is 0.0732
## with the empirical chi square 165.7622 with prob < 3.597e-09
##
## Fit based upon off diagonal values = 0.8839
```

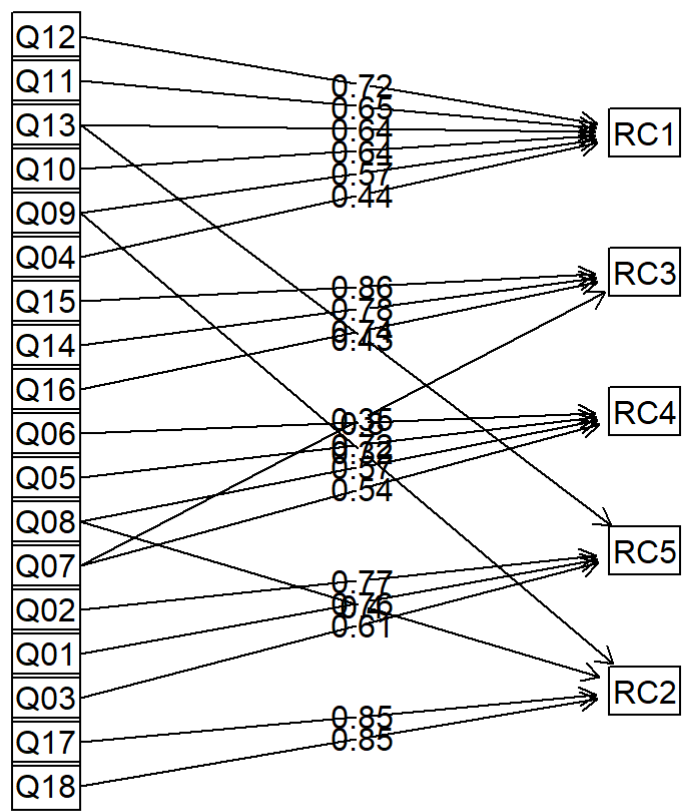
```
#회전 후 요인행렬:R의 아이겐벡터 SPSS는 요인
# 위와 동일
```

```
# fa.sort로 요인 적재량 높은 순으로 출력
print(fa.sort(Mfapcvmx),cut=0.3,digits=4)
```

```
## Principal Components Analysis
## Call: principal(r = x, nfactors = 5, rotate = "varimax")
## Standardized loadings (pattern matrix) based upon correlation matrix
##          RC1      RC3      RC4      RC5      RC2      h2      u2      com
## Q12  0.7190
## Q11  0.6550
## Q13  0.6425          0.4288
## Q10  0.6387
## Q09  0.5660          0.3195  0.4434  0.5566  1.737
## Q04  0.4415
## Q15          0.8551
## Q14          0.7835
## Q16          0.7447
## Q06          0.8033
## Q05          0.7202
## Q08          0.5675          0.3987  0.5575  0.4425  2.357
## Q07          0.3544  0.5352
## Q02          0.7684
## Q01          0.7599
## Q03          0.6063
## Q17          0.8537  0.7680  0.2320  1.110
## Q18          0.8458  0.7289  0.2711  1.038
##
##          RC1      RC3      RC4      RC5      RC2
## SS loadings      2.4771  2.2603  1.9702  1.9548  1.9237
## Proportion Var    0.1376  0.1256  0.1095  0.1086  0.1069
## Cumulative Var    0.1376  0.2632  0.3726  0.4812  0.5881
## Proportion Explained 0.2340  0.2135  0.1861  0.1847  0.1817
## Cumulative Proportion 0.2340  0.4475  0.6336  0.8183  1.0000
##
## Mean item complexity = 1.5
## Test of the hypothesis that 5 components are sufficient.
##
## The root mean square of the residuals (RMSR) is 0.0732
## with the empirical chi square 165.7622 with prob < 3.597e-09
##
## Fit based upon off diagonal values = 0.8839
```

```
#fa.diagram을 이용하여 요인 적재량 시각화
fa.diagram(Mfapcvmx,simple=FALSE,cut = 0.3,digits = 2)
```


Components Analysis



```
#biplot으로회전이 적절한지 확인
biplot(Mfapcvmx)
```

```
## Warning in arrows(0, 0, loadings[, 1L] * 0.8, loadings[, 2L] * 0.8, col =
## col[2L], : zero-length arrow is of indeterminate angle and so skipped
```

