homework 6

Sam Helms, Charles Wong, Woods Connell, and Hannah Knight

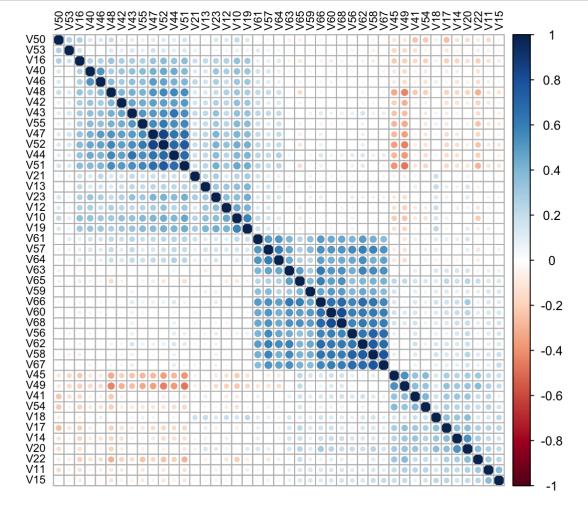
Problem 1

(nothing to turn in here)

Problem 2

```
library(corrplot)
```

```
## corrplot 0.84 loaded
```



Problem 3

Compute KMO or other measure (i.e. just look at matrix produced above) to comment on suitability of data for factor analysis.

Almost all of the KMO values are above 0.9, suggesting that the data is very suitable for factor analysis.

```
## Kaiser-Meyer-Olkin factor adequacy
## Call: KMO(r = c)
## Overall MSA = 0.91
## MSA for each item =
## V10 V11 V12 V13 V14 V15 V16 V17 V18 V19 V20 V21 V22 V23 V40
## 0.91 0.82 0.89 0.88 0.84 0.81 0.95 0.90 0.83 0.91 0.85 0.83 0.89 0.92 0.88
## V41 V42 V43 V44 V45 V46 V47 V48 V49 V50 V51 V52 V53 V54 V55
## 0.86 0.95 0.94 0.94 0.91 0.89 0.89 0.93 0.92 0.74 0.96 0.89 0.67 0.85 0.95
## V56 V57 V58 V59 V60 V61 V62 V63 V64 V65 V66 V67 V68
## 0.95 0.93 0.91 0.93 0.92 0.94 0.94 0.93 0.90 0.91 0.94 0.91 0.90
```

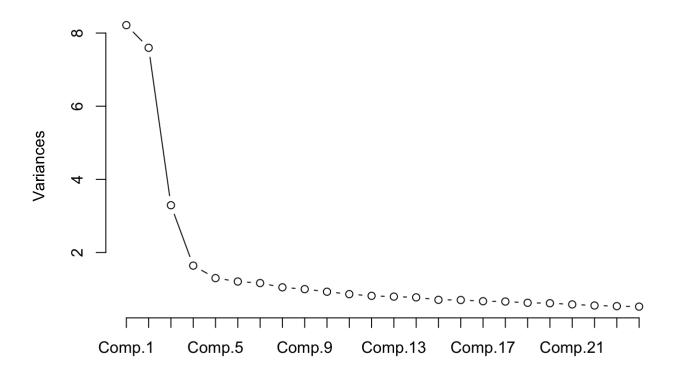
Problem 4

Use Principle Components (or appropriate option in Factor Analysis) to decide on a number of latent factors. You can use Scree Plot, eigenvalue>1, or parallel analysis.

It looks like there is an elbow around component 5. We will use 5 latent factors.

```
fit <- princomp(covmat = c)
screeplot(fit, main='Scree Plot', npcs = 24, type = "lines")</pre>
```

Scree Plot



Problem 5

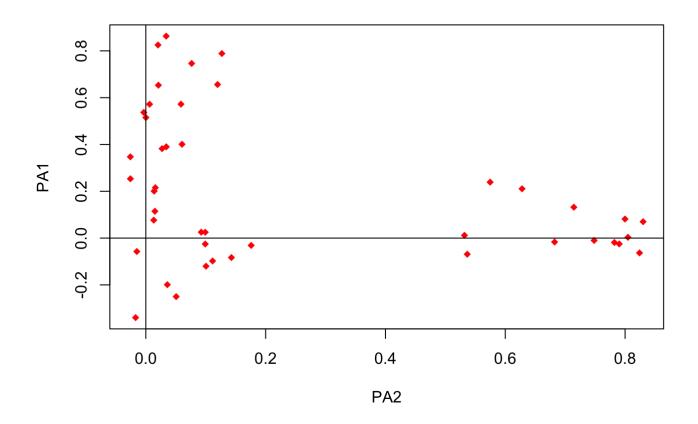
Perform a series of factor analyses using orthogonal models. First, try at least two extraction methods (choose from Principle Components, Principle Axis Factoring, Iterative Principle Components, Maximum Likelihood). Use some method for comparing extraction methods to choose a 'best' method (i.e. RMSR or # residuals greater than .05).

According to the RMSR and the # residuals greater than .05, the iterative PCA does a better job extracting latent factors (both are lower).

Iterative PCA

```
library(psych)
NFACTS <- 5
clean_data <- df[complete.cases(df)]
fact3=fa(df, nfactors=NFACTS, rotate="varimax", SMC=FALSE, fm="pa")

#get loading plot for first two factors
plot(fact3$loadings, pch=18, col='red')
abline(h=0)
abline(v=0)
text(fact3$loadings, labels=names(df))</pre>
```



```
#get reproduced correlation matrix
repro3=fact3$loadings%*%t(fact3$loadings)
#residual correlation matrix
resid3=c-repro3

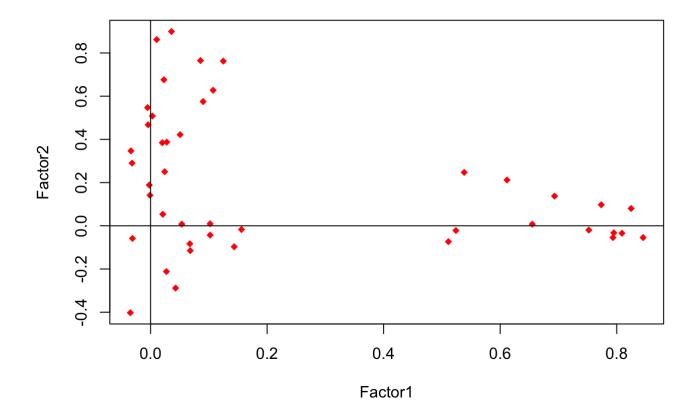
#get root-mean squared residuals
len=length(resid3[upper.tri(resid3)])
RMSR3=sqrt(sum(resid3[upper.tri(resid3)]^2)/len)
RMSR3
```

```
## [1] 0.03241084
```

```
#get proportion of residuals greater than 0.05 in absolute value
sum(rep(1,len)[abs(resid3[upper.tri(resid3)])>0.05])/len
```

```
## [1] 0.09745293
```

Principal axis factoring



```
#get reproduced correlation matrix
reprol=fact1$loadings%*%t(fact1$loadings)
#residual correlation matrix
resid1=fact1$cor-reprol
#get root-mean squared residuals
len=length(resid1[upper.tri(resid1)])
RMSR1=sqrt(sum(resid1[upper.tri(resid1)]^2)/len)
RMSR1
```

```
#get proportion of residuals greater than 0.05 in absolute value
sum(rep(1,len)[abs(resid1[upper.tri(resid1)])>0.05])/len
```

```
## [1] 0.1162791
```

Problem 6

The below plot suggests that the first principal axis is widely varying in how much influence it has on the variables, while the second principal axis has a very strong influence on a small subset (about a third) of the variables.

```
fit <- fa(df, fm="pa", nfactors=5, rotate="varimax")
load <- fit$loadings[,1:2]
plot(load, type="p", pch=16, col="purple")
abline(h=0)
abline(v=0)
text(load, labels = names(df))</pre>
```

