

HW8

Yining Qu

2024-05-15

```
library(stats)
library(glmnet)
```

```
## Loading required package: Matrix
```

```
## Loaded glmnet 4.1-8
```

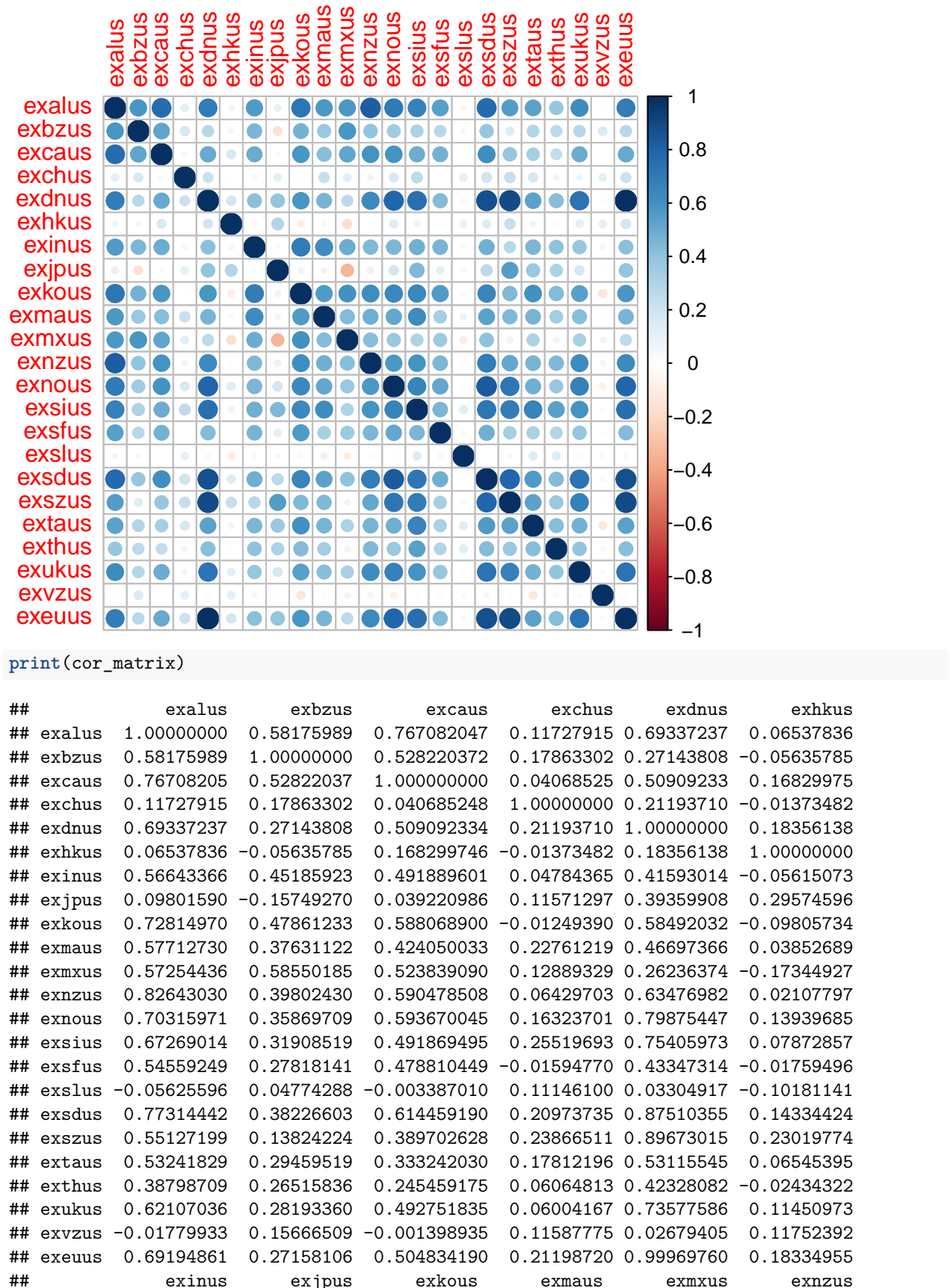
```
library(Rcpp)
library(ggplot2)
library(reshape2)
library(corrplot)
```

```
## corrplot 0.92 loaded
```

```
fx <- read.csv("FXmonthly.csv")
fx <- (fx[2:120,]-fx[1:119,])/(fx[1:119,])
sp500 <- read.csv("sp500.csv")
```

Q1

```
# Calculate and visualize the correlation matrix
cor_matrix <- cor(fx)
corrplot::corrplot(cor_matrix, method = "circle")
```



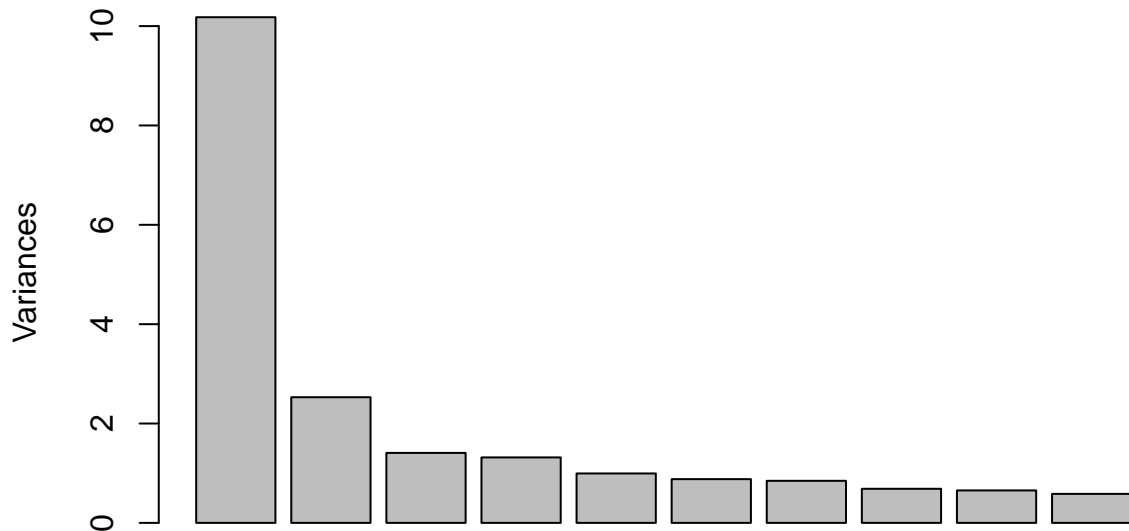
##	exalus	0.56643366	0.09801590	0.72814970	0.57712730	0.57254436	0.82643030
##	exbzus	0.45185923	-0.15749270	0.47861233	0.37631122	0.58550185	0.39802430
##	excaus	0.49188960	0.03922099	0.58806890	0.42405003	0.52383909	0.59047851
##	exchus	0.04784365	0.11571297	-0.01249390	0.22761219	0.12889329	0.06429703
##	exdnus	0.41593014	0.39359908	0.58492032	0.46697366	0.26236374	0.63476982
##	exhkus	-0.05615073	0.29574596	-0.09805734	0.03852689	-0.17344927	0.02107797
##	exinus	1.00000000	0.02629958	0.69868912	0.62858503	0.49929499	0.44375739
##	exjpus	0.02629958	1.00000000	0.07230273	0.06031551	-0.33065785	0.08599334
##	exkous	0.69868912	0.07230273	1.00000000	0.56874190	0.60836124	0.61913120
##	exmaus	0.62858503	0.06031551	0.56874190	1.00000000	0.43272821	0.48709449
##	exmxus	0.49929499	-0.33065785	0.60836124	0.43272821	1.00000000	0.42427106
##	exnzus	0.44375739	0.08599334	0.61913120	0.48709449	0.42427106	1.00000000
##	exnous	0.45568544	0.18986625	0.64859119	0.51163568	0.37117974	0.57617907
##	exsius	0.48821506	0.44334003	0.64944801	0.62731643	0.30814886	0.59447977
##	exsfus	0.46126593	0.11062863	0.56572912	0.33905995	0.36649642	0.45755149
##	exslus	0.03547963	0.04199605	-0.03763470	0.08669653	-0.09266344	-0.02565823
##	exsdus	0.48308539	0.26558951	0.65546644	0.53858563	0.40278409	0.69924506
##	exszus	0.27106252	0.55556312	0.44009345	0.44036337	0.07137343	0.51715164
##	extaus	0.45827196	0.37505875	0.60340968	0.46628391	0.31284204	0.46960797
##	exthus	0.40372659	0.31791591	0.43751317	0.34751629	0.06834804	0.44506296
##	exukus	0.38619538	0.17870941	0.54446050	0.42637156	0.32033512	0.62730344
##	exvzus	-0.05660536	-0.01543783	-0.13978309	-0.01630159	0.06837558	-0.06886414
##	exeuus	0.41482667	0.39230675	0.58340259	0.46725497	0.26173544	0.63450577
##	exnous	exsius	exsfus	exslus	exsdus		
##	exalus	0.70315971	0.67269014	0.54559249	-0.056255956	0.773144416	
##	exbzus	0.35869709	0.31908519	0.27818141	0.047742881	0.382266032	
##	excaus	0.59367004	0.49186949	0.47881045	-0.003387010	0.614459190	
##	exchus	0.16323701	0.25519693	-0.01594770	0.111461004	0.209737346	
##	exdnus	0.79875447	0.75405973	0.43347314	0.033049174	0.875103547	
##	exhkus	0.13939685	0.07872857	-0.01759496	-0.101811413	0.143344237	
##	exinus	0.45568544	0.48821506	0.46126593	0.035479633	0.483085389	
##	exjpus	0.18986625	0.44334003	0.11062863	0.041996048	0.265589507	
##	exkous	0.64859119	0.64944801	0.56572912	-0.037634701	0.655466435	
##	exmaus	0.51163568	0.62731643	0.33905995	0.086696532	0.538585629	
##	exmxus	0.37117974	0.30814886	0.36649642	-0.092663441	0.402784092	
##	exnzus	0.57617907	0.59447977	0.45755149	-0.025658225	0.699245061	
##	exnous	1.00000000	0.66737540	0.51236031	0.022308998	0.834378993	
##	exsius	0.66737540	1.00000000	0.45356322	0.139018508	0.721657909	
##	exsfus	0.51236031	0.45356322	1.00000000	-0.036317889	0.488569655	
##	exslus	0.02230900	0.13901851	-0.03631789	1.000000000	-0.001847732	
##	exsdus	0.83437899	0.72165791	0.48856965	-0.001847732	1.000000000	
##	exszus	0.72799036	0.69781934	0.33353238	0.043268845	0.797027907	
##	extaus	0.48710314	0.66451614	0.32376293	0.137020618	0.566664748	
##	exthus	0.37097575	0.54304525	0.29471735	0.135590097	0.431078059	
##	exukus	0.67703722	0.59904549	0.38843005	0.023796836	0.736155303	
##	exvzus	-0.08760748	-0.02065454	-0.02102668	-0.032644674	-0.040674882	
##	exeuus	0.79573687	0.75407025	0.43231367	0.036629370	0.873324184	
##	exszus	extaus	exthus	exukus	exvzus	exeuus	
##	exalus	0.55127199	0.53241829	0.38798709	0.62107036	-0.017799328	0.69194861
##	exbzus	0.13824224	0.29459519	0.26515836	0.28193360	0.156665087	0.27158106
##	excaus	0.38970263	0.33324203	0.24545917	0.49275184	-0.001398935	0.50483419
##	exchus	0.23866511	0.17812196	0.06064813	0.06004167	0.115877754	0.21198720
##	exdnus	0.89673015	0.53115545	0.42328082	0.73577586	0.026794054	0.99969760
##	exhkus	0.23019774	0.06545395	-0.02434322	0.11450973	0.117523924	0.18334955

```
## exinus 0.27106252 0.45827196 0.40372659 0.38619538 -0.056605363 0.41482667
## exjpus 0.55556312 0.37505875 0.31791591 0.17870941 -0.015437827 0.39230675
## exkous 0.44009345 0.60340968 0.43751317 0.54446050 -0.139783095 0.58340259
## exmaus 0.44036337 0.46628391 0.34751629 0.42637156 -0.016301594 0.46725497
## exmxus 0.07137343 0.31284204 0.06834804 0.32033512 0.068375579 0.26173544
## exnzus 0.51715164 0.46960797 0.44506296 0.62730344 -0.068864136 0.63450577
## exnous 0.72799036 0.48710314 0.37097575 0.67703722 -0.087607476 0.79573687
## exsius 0.69781934 0.66451614 0.54304525 0.59904549 -0.020654537 0.75407025
## exsfus 0.33353238 0.32376293 0.29471735 0.38843005 -0.021026679 0.43231367
## exslus 0.04326884 0.13702062 0.13559010 0.02379684 -0.032644674 0.03662937
## exsdus 0.79702791 0.56666475 0.43107806 0.73615530 -0.040674882 0.87332418
## exszus 1.00000000 0.53815259 0.37443024 0.67677862 -0.018493536 0.89445029
## extaus 0.53815259 1.00000000 0.42588984 0.47378345 -0.126804225 0.53134140
## exthus 0.37443024 0.42588984 1.00000000 0.39123809 -0.039137403 0.42120387
## exukus 0.67677862 0.47378345 0.39123809 1.00000000 -0.027253590 0.73354533
## exvzus -0.01849354 -0.12680422 -0.03913740 -0.02725359 1.000000000 0.02657169
## exeuus 0.89445029 0.53134140 0.42120387 0.73354533 0.026571689 1.00000000
```

Q2

```
# Fit PCA
pcfx <- prcomp(fx, scale = TRUE)

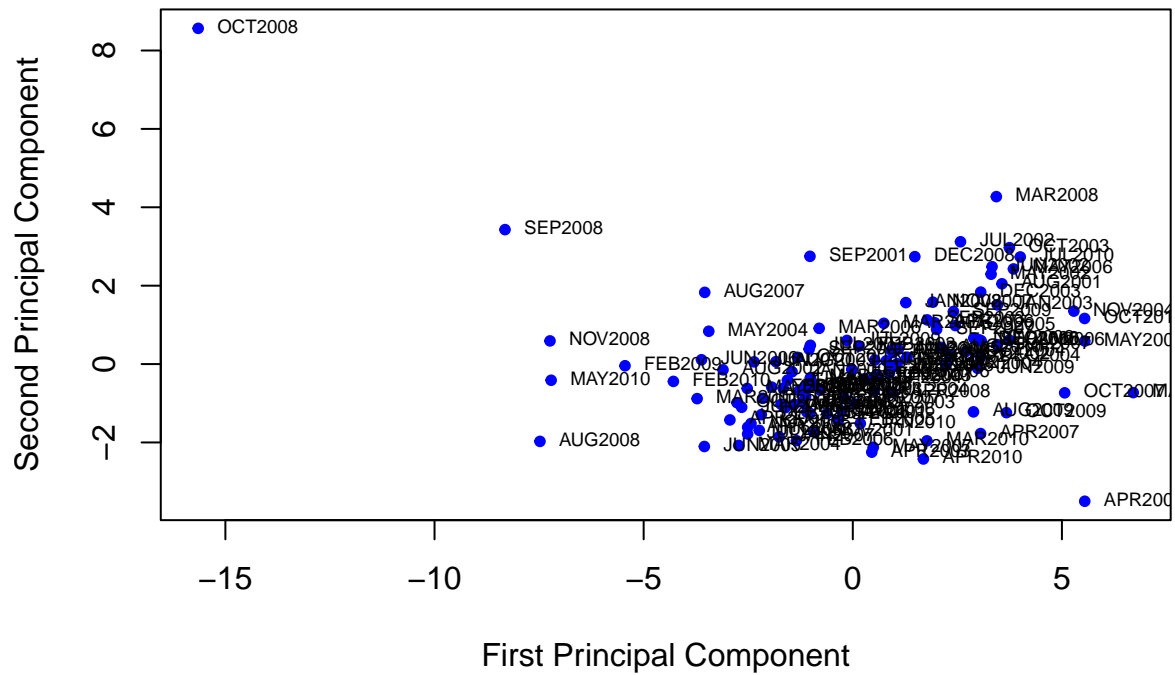
plot(pcfx, main="")
```



```
pcs <- predict(pcfx)

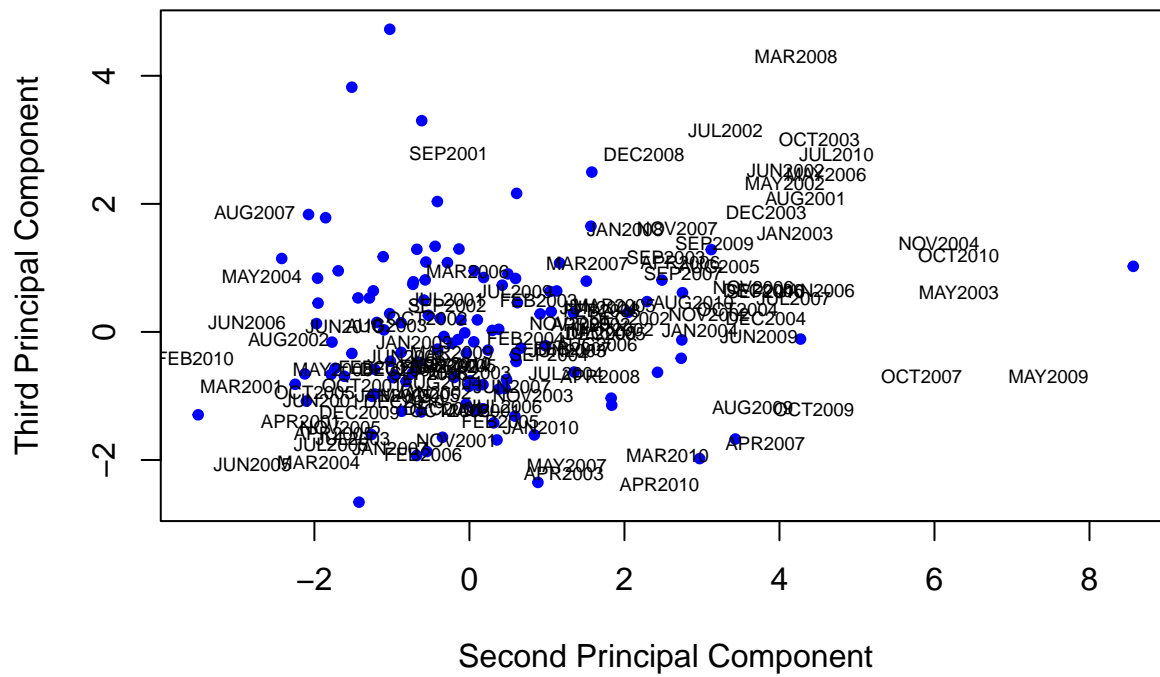
plot(pcs[,1], pcs[,2], xlab = "First Principal Component", ylab = "Second Principal Component", main = "PCA Plot")
text(pcs[,1], pcs[,2], labels = rownames(pcs), pos = 4, cex = 0.6)
```

Scatter Plot of the First Two Principal Components



```
plot(pcs[,2], pcs[,3], xlab = "Second Principal Component", ylab = "Third Principal Component", main = "Scatter Plot of the Second versus the Third Principal Components")
text(pcs[,1], pcs[,2], labels = rownames(pcs), pos = 4, cex = 0.6)
```

Scatter Plot of the Second versus the Third Principal Components



```
# far right
smallest_pcs <- sort(pcs[,1])[1:5]
smallest_pcs
```

```
##      OCT2008      SEP2008      AUG2008      NOV2008      MAY2010
## -15.650761  -8.314062  -7.479007  -7.239428  -7.212144
```

```
# far left
largest_pcs <- sort(pcs[,1], decreasing = TRUE)[1:5]
largest_pcs
```

```
##      MAY2009      MAY2003      APR2009      OCT2010      NOV2004
##  6.706182  5.548390  5.545457  5.542401  5.286064
```

```
t(round(pcfx$rotation[,1:2],2))
```

```
##      exalus exbzus excaus exchus exdnus exhkus exinus exjpus exkous exmaus
## PC1  -0.28  -0.16  -0.22  -0.06  -0.28  -0.03  -0.20  -0.09  -0.25  -0.21
## PC2   0.14   0.33   0.18  -0.08  -0.21  -0.26   0.23  -0.46   0.20   0.11
##      exmxus exnzus exnous exsius exsfus exslus exsdus exszus extaus exthus
## PC1  -0.16  -0.25  -0.27  -0.26  -0.19  -0.01  -0.29  -0.24  -0.21  -0.17
## PC2   0.43   0.08  -0.05  -0.12   0.12  -0.06  -0.08  -0.33  -0.07  -0.08
##      exukus exvzus exeuus
## PC1  -0.24   0.01  -0.28
## PC2  -0.08   0.01  -0.21
```

PC1 Loadings: - Mostly negative across many currencies, indicating a general pattern where an increase in the principal component score corresponds to a decrease in these currency values against their pair. - The magnitude of the loadings (e.g., -0.28 for exdnus) signifies how much a unit change in the principal component affects the currency. Larger absolute values mean greater sensitivity to changes in this component.

PC2 Loadings: - Mixed signs across different currencies indicate diverse influences captured by this component. For instance, a positive loading for exbzus (0.33) against a negative for exjpus (-0.46) highlights how different economic or market conditions might be driving movements in these currencies.

Q3

```
set.seed(4)

if (!requireNamespace("AICcmodavg", quietly = TRUE)) {
  install.packages("AICcmodavg")
}

# Load the AICcmodavg package
library(AICcmodavg)

# Convert the principal components to a data frame for modeling
zdf <- as.data.frame(pcs)

# Perform regression using the first two principal components
summary(fxglm <- glm(sp500$sp500 ~ ., data=zdf[, 1:2]))
```

```
##
## Call:
## glm(formula = sp500$sp500 ~ ., data = zdf[, 1:2])
##
```

```
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.0004431  0.0036555   0.121   0.904
## PC1          0.0059741  0.0011506   5.192 8.97e-07 ***
## PC2         -0.0111795  0.0023081  -4.844 3.98e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.001590122)
##
##      Null deviance: 0.26463  on 118  degrees of freedom
## Residual deviance: 0.18445  on 116  degrees of freedom
## AIC: -424.16
##
## Number of Fisher Scoring iterations: 2
# Function to calculate AICc for a glm model
calculateAICc <- function(model) {
  AICc(model)
}

# Perform GLM fits on 1:20 factors and calculate AICc for each
kfits <- lapply(1:20, function(K) {
  glm(sp500$sp500 ~ ., data = zdf[, 1:K, drop = FALSE])
})

aicc <- sapply(kfits, calculateAICc) # Apply AICc calculation to each fit
which.min(aicc) # Determine which model size (number of factors) is preferred by AICc

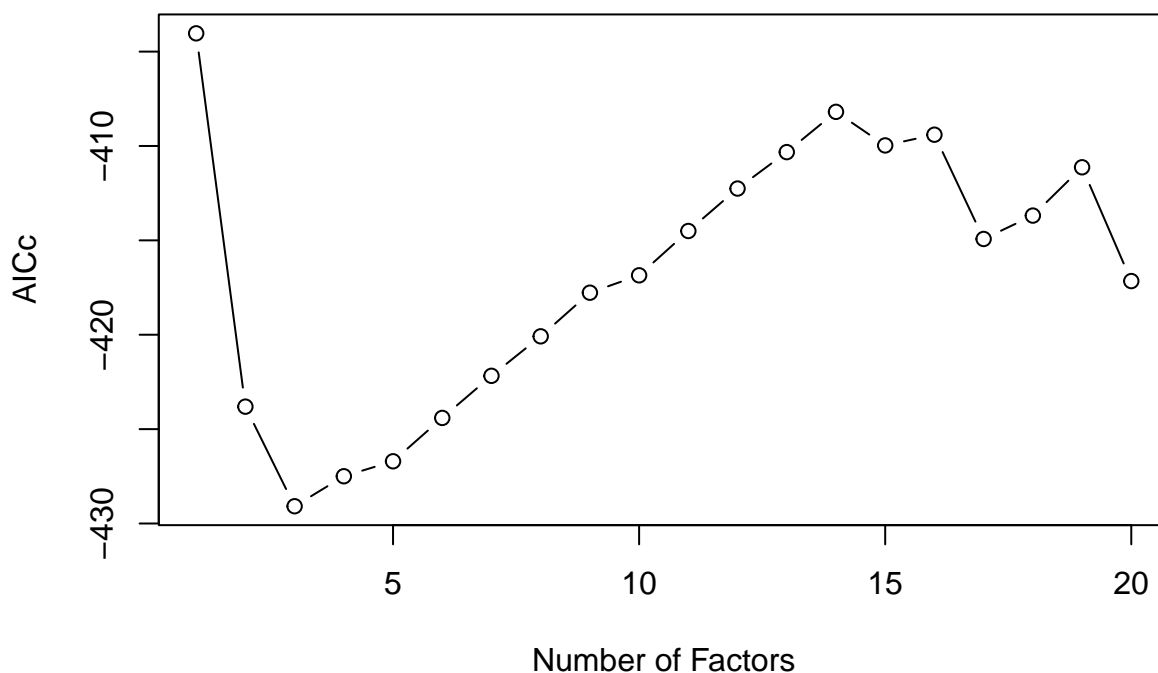
## [1] 3

# Optionally, also calculate BIC for comparison
bic <- sapply(kfits, BIC)
which.min(bic) # Determine which model size (number of factors) is preferred by BIC

## [1] 3

# Plot the AICc values
plot(aicc, type = 'b', xlab = "Number of Factors", ylab = "AICc", main = "AICc by Number of Factors")
```

AICc by Number of Factors



```
best_aicc_index <- which.min(aicc)
print(coef(kfits[[best_aicc_index]]))
```

```
##      (Intercept)          PC1          PC2          PC3
## 0.0004430924 0.0059741190 -0.0111794596 -0.0082100077
```

```
# Ensure the glmnet package is installed and loaded
```

```
if (!requireNamespace("glmnet", quietly = TRUE)) {
  install.packages("glmnet")
}
```

```
library(glmnet)
```

```
# Assuming 'pcs' is a data frame or matrix of principal components
# and 'sp500$sp500' is a vector of your response variable
```

```
# Convert 'pcs' to matrix if it is not already
```

```
pcs_matrix <- as.matrix(pcs)
```

```
# Set seed for reproducibility
```

```
# Perform Lasso regression with cross-validation
```

```
lassoPCR <- cv.glmnet(x = pcs_matrix, y = sp500$sp500, family = "gaussian", nfolds = 20, alpha = 1)
```

```
# Coefficients at the best lambda (lambda that gives minimum mean cross-validated error)
```

```
lasso_coef <- coef(lassoPCR, s = "lambda.min")
```

```
# Plotting the results
```

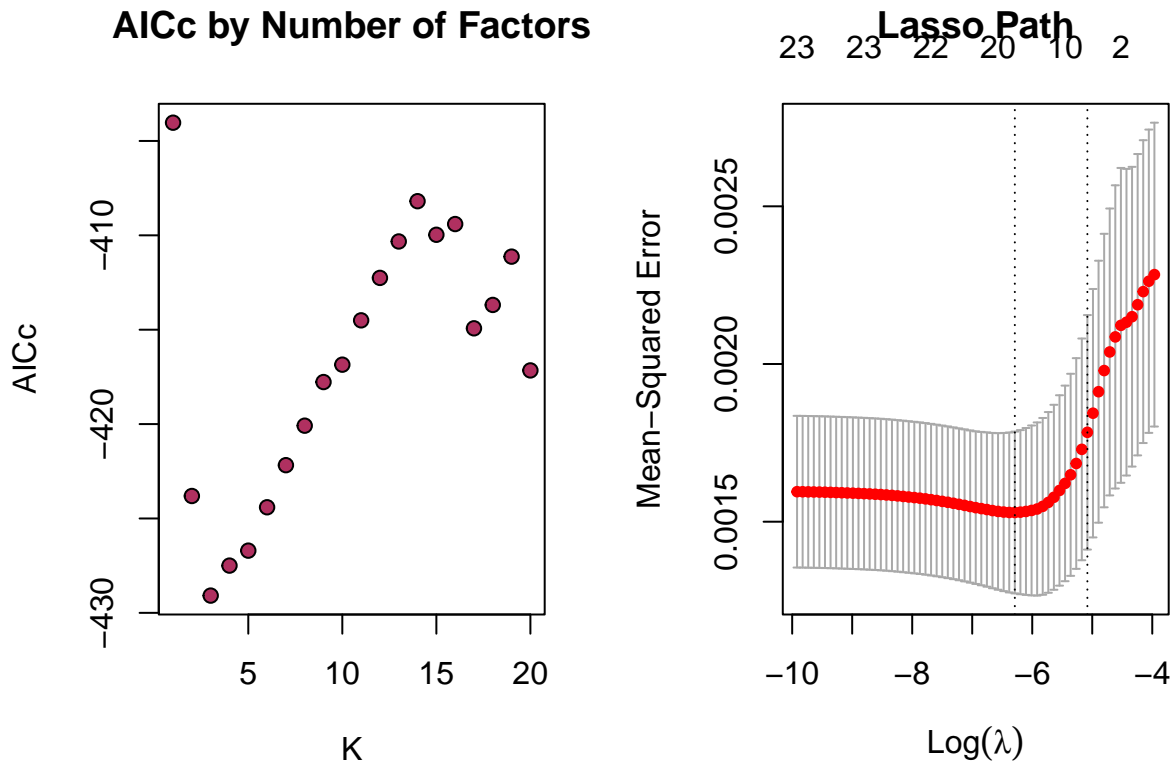
```
par(mfrow=c(1,2)) # Set up the plotting area to have 1 row and 2 columns
```

```
# Plot AICc
```



```
plot(aicc, pch=21, bg="maroon", xlab="K", ylab="AICc", main="AICc by Number of Factors")

# Plot Lasso path
plot(lassoPCR)
title("Lasso Path")
```



```
lambda_min <- lassoPCR$lambda.min
lasso_model_min <- glmnet(pcs_matrix, sp500$sp500, lambda = lambda_min)
coefficients_min <- coef(lassoPCR, s = "lambda.min")
print(coefficients_min)
```

```
## 24 x 1 sparse Matrix of class "dgCMatrix"
##              s1
## (Intercept)  4.430924e-04
## PC1          5.390442e-03
## PC2         -1.000862e-02
## PC3         -6.640944e-03
## PC4          8.040491e-04
## PC5         -2.372076e-03
## PC6          .
## PC7          .
## PC8          2.511257e-05
## PC9          .
## PC10        -3.216481e-03
## PC11         .
## PC12         1.455595e-04
## PC13        -1.719840e-03
## PC14         1.176683e-03
## PC15        -9.666570e-03
## PC16         6.210347e-03
```

## PC17	-1.703749e-02
## PC18	-5.406683e-03
## PC19	-3.719735e-04
## PC20	-2.238073e-02
## PC21	-1.476752e-02
## PC22	.
## PC23	4.434570e-01

Q4