

# Empirical Methods in Finance - Assignment 3

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Extract the portfolio and risk free data. Apply the date constraints and remove the invalid columns. Sample data is for excess returns is as below.

## Principal Component Analysis

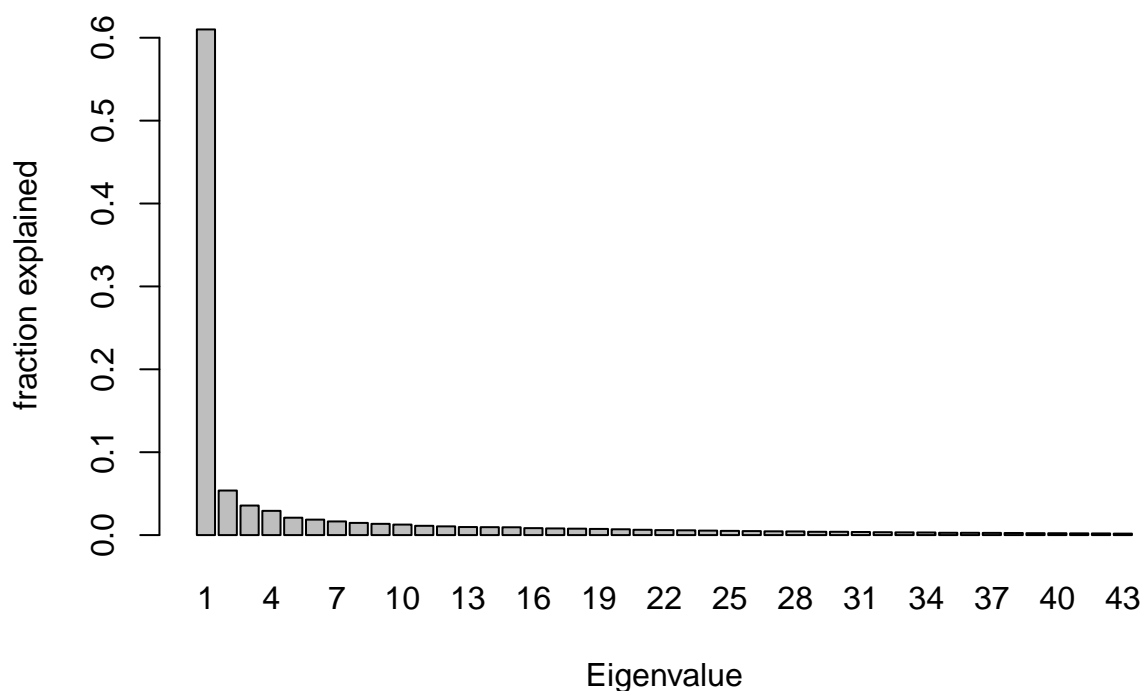
### 1

The eigenvalues of the variance-covariance matrix can be calculated using **eigen** R function

```
## [1] 1061.782182 93.547500 62.062228 50.913744 36.527472
## [6] 32.466362 28.690390 25.586583 23.620709 22.044200
## [11] 19.487297 18.334225 16.900536 16.642947 16.397853
## [16] 14.611519 13.972664 13.514532 12.933193 12.179409
## [21] 11.168473 10.452042 10.040775 9.384985 8.838352
## [26] 8.401733 7.902281 7.664925 6.961698 6.917135
## [31] 6.513456 6.059360 5.730276 5.475691 4.890513
## [36] 4.799644 4.637173 4.416646 4.031374 3.892260
## [41] 3.640982 3.481827 3.080961
```

The fraction explained by each eigen value can be seen in this graph.

**Plot of fraction of variance explained by each eigenvalue**



## 2a

The largest 3 Principal Components explain **69.94%** of the total variance

## 2b

The Principal Components can be calculated using this formula

$$y_{it} = e_i' r_t = \sum_{j=1}^N e_{ij} r_{jt}$$

where  $y_{it}$  is the  $i^{th}$  principal component at time  $t$ .

$e_{ij}$  is the weight of the  $j^{th}$  asset in the  $i^{th}$  eigenvector.

$r_{jt}$  is the return of the  $j^{th}$  asset at time  $t$ .

Mean sample returns for these 3 factor portfolios are

```
##          PCA1          PCA2          PCA3
## -3.7787500   0.2156532  -0.5140327
```

sample standard deviation for these 3 factor portfolios are

```
##          PCA1          PCA2          PCA3
## 32.584999   9.671996   7.877958
```

Correlation for these 3 factor portfolios are

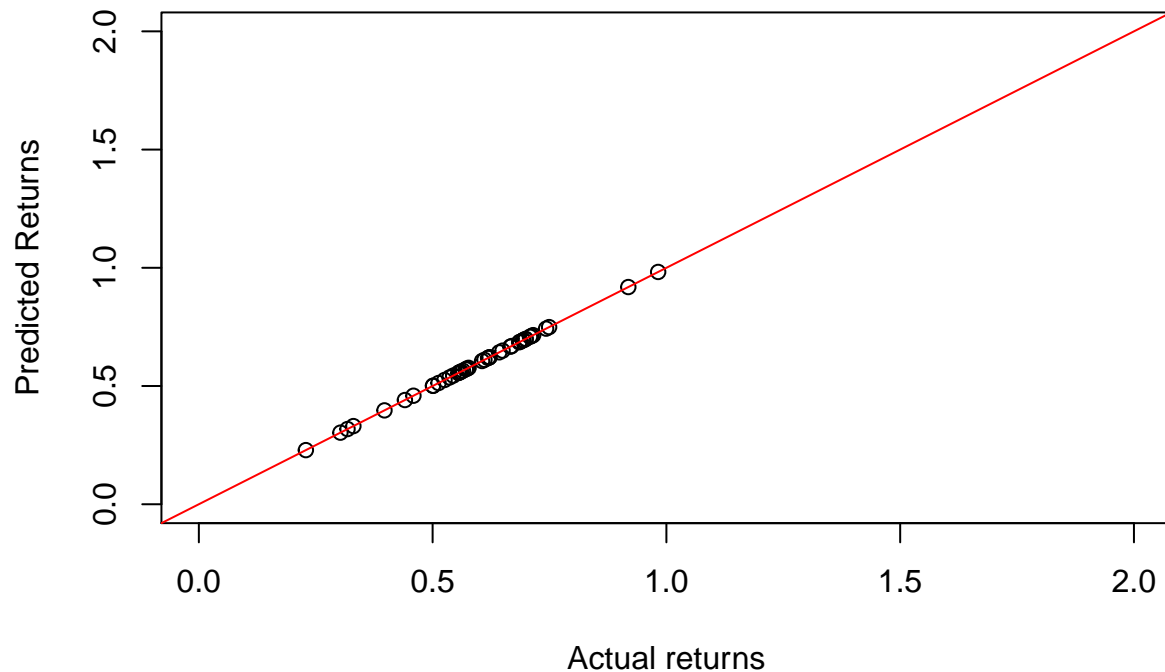
```
##          PCA1          PCA2          PCA3
## PCA1   1.000000e+00  2.412379e-16 -1.471233e-16
## PCA2   2.412379e-16  1.000000e+00  1.937757e-16
## PCA3  -1.471233e-16  1.937757e-16  1.000000e+00
```

## 2c

The loadings for each industry in the case will be equal to the weights of the industry in each of the eigen vectors. The formula  $\sqrt{\lambda_i} e_i$  ( $\lambda_i$  is the eigen value and  $e_i$  is the eigen vector weights) holds good only if the data is standardized (divided by standard deviation).

For calculating this predicted value, the demeaned value of actual data should be used to calculate the demeaned prediction. After that we need to add the mean of the actual data to get the final prediction. This prediction can be compared with the actual returns.

### Plot between actual portfolio returns and predicted returns from APT model



All the points are on the 45 degree line. On an average across the entire time period, we can see that the Principal components can predict the actual data with high accuracy.

The loading was also retrieved out of regression and compared with the loading out of eigen vectors and were found to be same (testing in the code appended at the end)

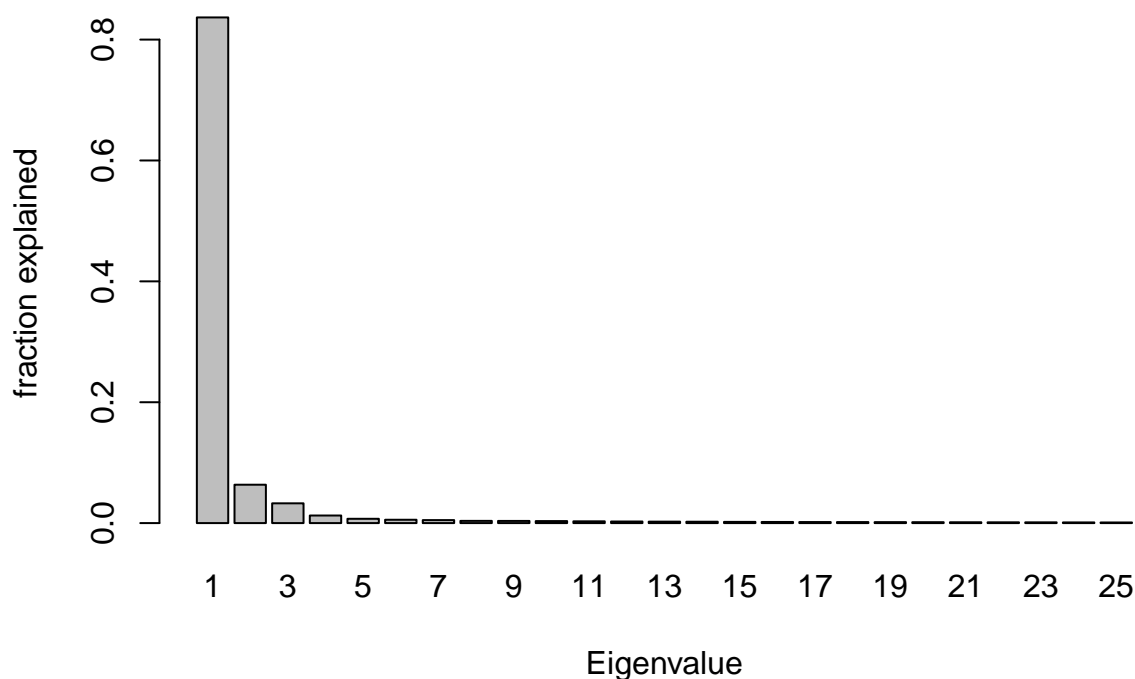
### 2d

Cross sectional  $R^2 = 1.0$ . As mentioned in previous question, as the model is able to completely explain the actual data on an average across time.

### 3a

The plot of variance explained by every eigen value for the 25 F-F portfolios is as below

### Plot of fraction of variance explained by each eigenvalue



3b

The first 5 PCA components explain as much as 95% of the data (information got out of the cumulative proportion in the summary view of princomp).

## Arbitrage Pricing in Factor Models

1a

The exposures of portfolio A involve 0.5 unit exposure to factor 1 and 0.75 unit exposure to factor 2. So to get the arbitrage opportunity,

We should go long the portfolio and short the assets which replicates the portfolio exposure (0.5 unit of factor 1 and 0.75 unit of factor 2).

By doing this we will get 1% extra return (profit) out of the portfolio.

1b

$\delta$  should be equal to -1% to avoid arbitrage opportunities.

Expected value of  $R_{A,t}^e = 0.5E(R_{f1,t}) + 0.75E(R_{f2,t})$

$$= (0.5)(6\%) + (0.75)(-2\%) = \mathbf{1.5\%}$$

## R Code

```
#Data Retrieval
suppressMessages(library(xts))
portfolio.data <- read.csv("48_Industry_Portfolios.csv",header=TRUE,sep = ",",
                           ,stringsAsFactors = FALSE,skip = 11,nrows = 1086)
portfolio.data$X <- as.yearmon(as.character(portfolio.data$X),format="%Y%m")
portfolio.data <- xts(portfolio.data[,-1],order.by = portfolio.data$X)
factors.data <- read.csv("F-F_Research_Data_Factors.csv",header=TRUE,sep = ",",
                        ,stringsAsFactors = FALSE,skip = 3,nrows=1086)
factors.data$X <- as.yearmon(as.character(factors.data$X),format="%Y%m")
factors.data <- xts(factors.data[,-1],order.by = factors.data$X)

#Date and 99 constraints
portfolio.data <- portfolio.data[index(portfolio.data)>="1960-01-01" &
                                   index(portfolio.data)<="2015-12-31",]
portfolio.invalidColumns <- apply(portfolio.data,2
                                ,function(x){sum(x %in% -99.99) > 0})
portfolio.data <- portfolio.data[,!portfolio.invalidColumns]
factors.data <- factors.data[index(factors.data)>="1960-01-01"
                             & index(factors.data)<="2015-12-31",]

#Calculate Excess Returns
portfolio.excessReturns <- apply(portfolio.data,2,function(x){t(x - factors.data$RF)})

#1A
eigen.info <- eigen(cov(portfolio.excessReturns))
eigen.info$values

#1B
eigen.fractionExplained <- sapply(eigen.info$values,
                                function(x){x/sum(eigen.info$values)})
barplot(eigen.fractionExplained,names.arg = 1:length(eigen.fractionExplained)
        ,main = "Plot of fraction of variance explained by each eigenvalue",
        xlab = "Eigenvalue",ylab="fraction explained")

#2A
#Take top 3 eigen vectors
eigen.significantPcVector <- eigen.info$vectors[,c(1,2,3)]
eigen.significantfraction <- eigen.fractionExplained[c(1,2,3)]
sum(eigen.significantfraction)

#2B

#multiply weights by the corresponding industry returns
pcas <- apply(eigen.significantPcVector,2,function(eigenVec)
             {apply(portfolio.excessReturns,1,function(returnsTime){returnsTime%*%eigenVec})})
colnames(pcas) <- c("PCA1","PCA2","PCA3")

pcas.mean <- apply(pcas,2,mean)
pcas.sd <- apply(pcas,2,sd)
pcas.cor <- cor(pcas)

#2C
```

```

#Test to check if regression coefficients match the eigen loadings
##(in this case it is the weights itself)
LmOutput <- lm(portfolio.excessReturns[,1] ~ pcas[,1] + pcas[,2] + pcas[,3])
EigenOutput <- eigen.significantPcVector[1,]
##LmOutput$coefficients[-1] == EigenOutput

#calculate predicted returns by using top 3 PCA loadings and values
portfolio.meanreturns <- apply(portfolio.excessReturns,2,mean)
portfolio.indPredictedreturns <- sapply(1:dim(eigen.significantPcVector)[2],function(pc){
  eigen.significantPcVector[,pc]*pcas.mean[pc]
})
portfolio.predictedreturns <- apply(portfolio.indPredictedreturns,1,sum)
plot(portfolio.meanreturns,portfolio.predictedreturns,ylim=c(0,1),xlim=c(0,1)
     ,xlab="Actual returns", ylab="Predicted Returns")
abline(0,1,col="red")

#2D
#RCross section calculation
numerator <- var(portfolio.meanreturns - portfolio.predictedreturns)
Rcrosssection <- 1 - (numerator/var(portfolio.meanreturns))
Rcrosssection

#3A
#25 FF portfolios
portfolio.25.data <- read.csv("25_Portfolios_5x5.csv",header=TRUE,sep = ",",
                             ,stringsAsFactors = FALSE,skip = 19,nrows = 1086)
portfolio.25.data$X <- as.yearmon(as.character(portfolio.25.data$X),format="%Y%m")
portfolio.25.data <- xts(portfolio.25.data[,-1],order.by = portfolio.25.data$X)

#Date and 99 constraints
portfolio.25.data <- portfolio.25.data[index(portfolio.25.data)>="1960-01-01"
     & index(portfolio.25.data)<="2015-12-31",]
portfolio.25.invalidColumns <- apply(portfolio.25.data,2,
     function(x){sum(x %in% -99.99) > 0})
portfolio.25.data <- portfolio.25.data[,!portfolio.25.invalidColumns]
portfolio.25.excessReturns <- apply(portfolio.25.data,2
     ,function(x){t(x - factors.data$RF)})

eigen.25.Info <- eigen(cov(portfolio.25.excessReturns))
eigen.25.fractionExplained <- sapply(eigen.25.Info$values
     ,function(x){x/sum(eigen.25.Info$values)})
barplot(eigen.25.fractionExplained,names.arg = 1:length(eigen.25.fractionExplained)
     ,main = "Plot of fraction of variance explained by each eigenvalue"
     ,xlab = "Eigenvalue",ylab="fraction explained")

#3B
eigen.25.pcaInfo <- princomp(portfolio.25.excessReturns)
sum <- summary(eigen.25.pcaInfo)

```