

STAT547 Homework 1

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Problem 1

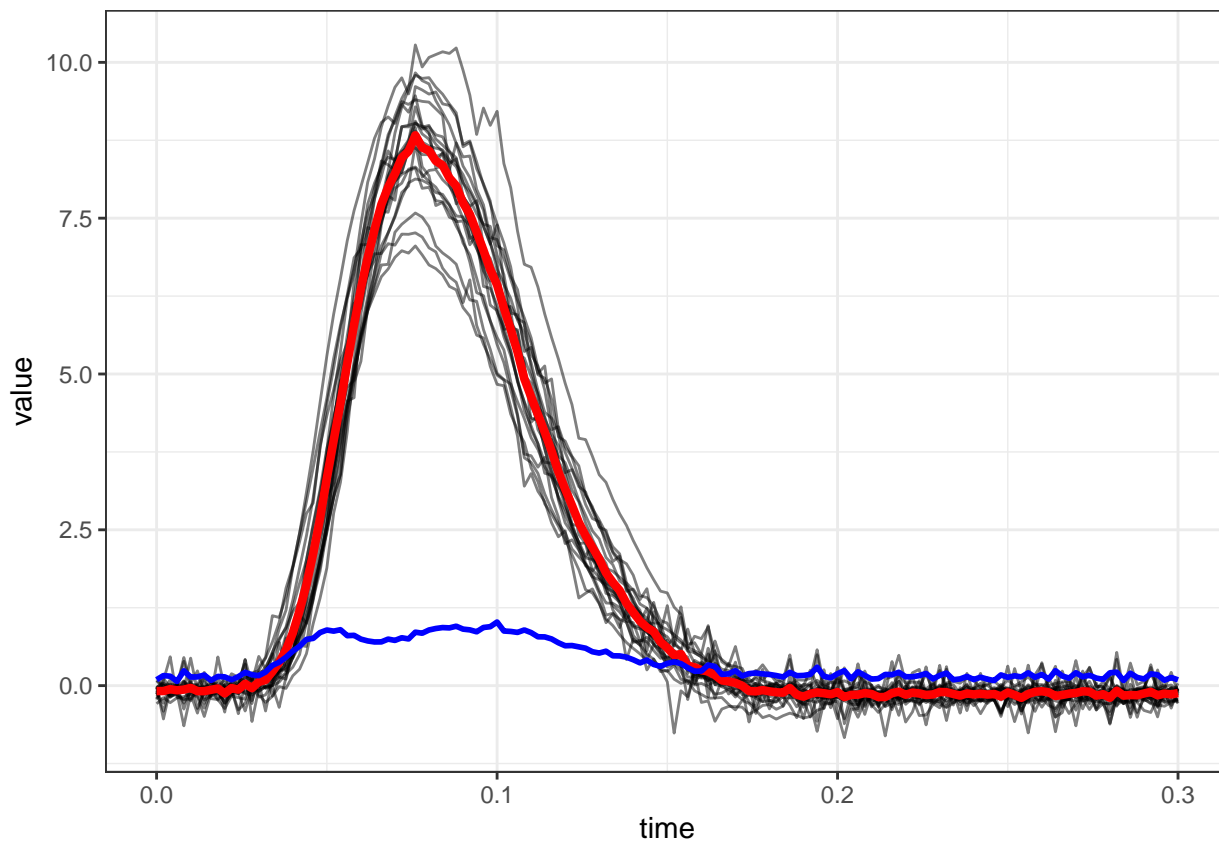
```
data(pinch)
dim(pinch)

## [1] 151 20

##### (b) #####
pinch_mu <- apply(pinch, 1, mean)
pinch_sd <- apply(pinch, 1, sd)

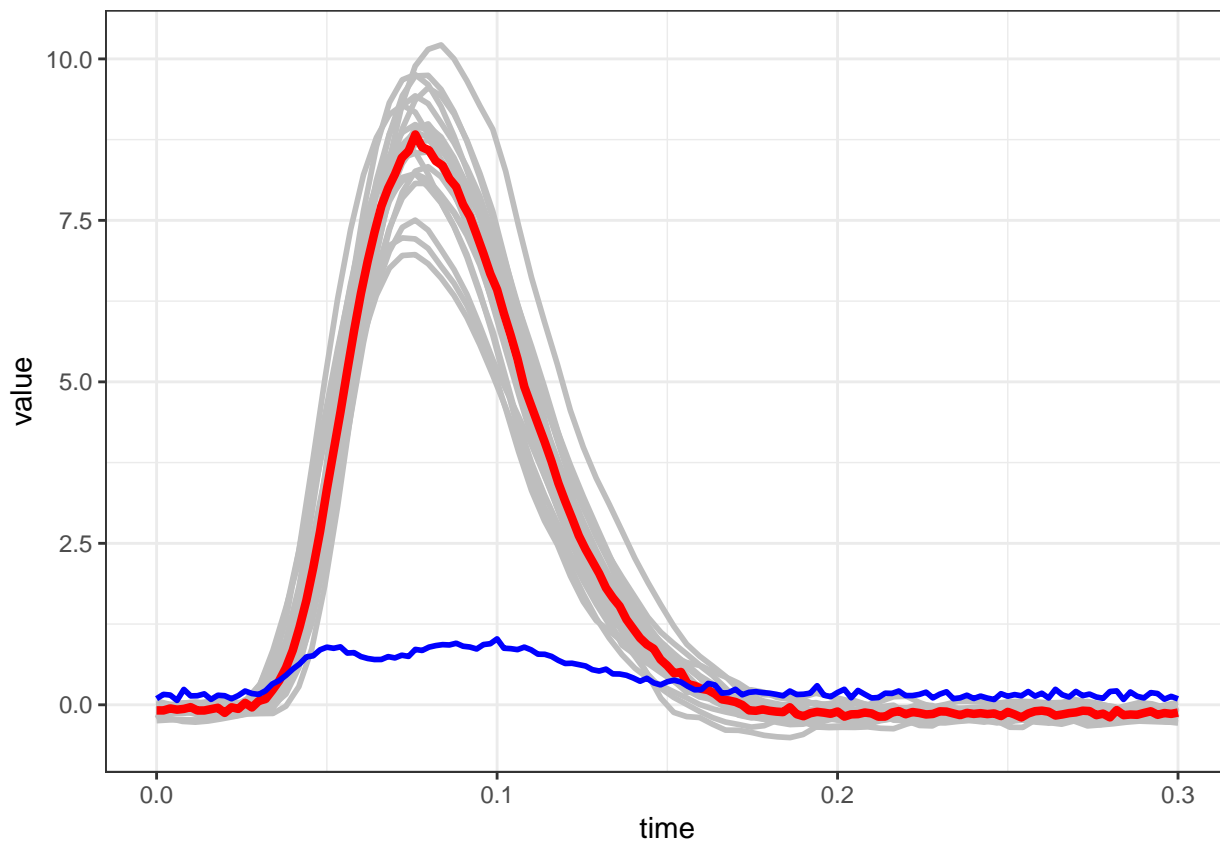
r_pinch <- melt(pinch)
names(r_pinch) <- c("time", "rep", "value")
r_pinch$time <- rep(pinchtime, 20)
r_pinch$rep <- as.factor(r_pinch$rep)

## raw
ggplot(data = r_pinch) +
  geom_line(aes(x = time, y = value, group = rep),
            alpha = 0.5) +
  geom_line(data = data.frame(x = pinchtime, y = pinch_mu),
            aes(x=x, y=y), colour = "red", size = 1.5) +
  geom_line(data = data.frame(x = pinchtime, y = pinch_sd),
            aes(x=x, y=y), colour = "blue", size = 1) +
  theme_bw()
```

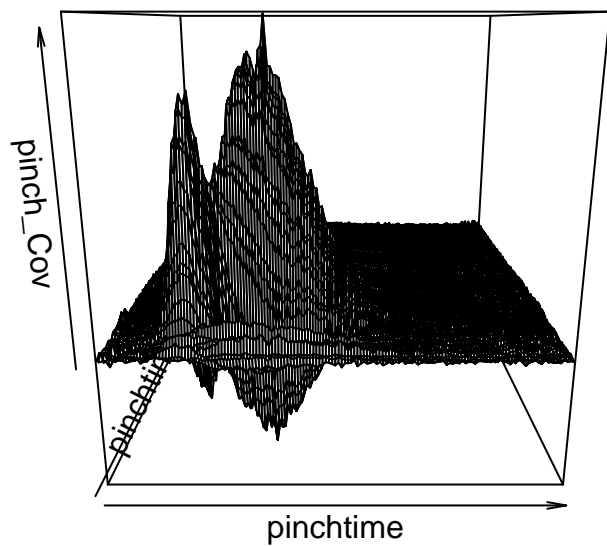


```
## smoothed
ggplot(data = r_pinch) +
  geom_smooth(aes(x = time, y = value, group = rep),
    alpha = 0.5, span = 0.1, se = FALSE, col = "gray") +
  geom_line(data = data.frame(x = pinchtime, y = pinch_mu),
    aes(x=x, y=y), colour = "red", size = 1.5) +
  geom_line(data = data.frame(x = pinchtime, y = pinch_sd),
    aes(x=x, y=y), colour = "blue", size = 1) +
  theme_bw()
```

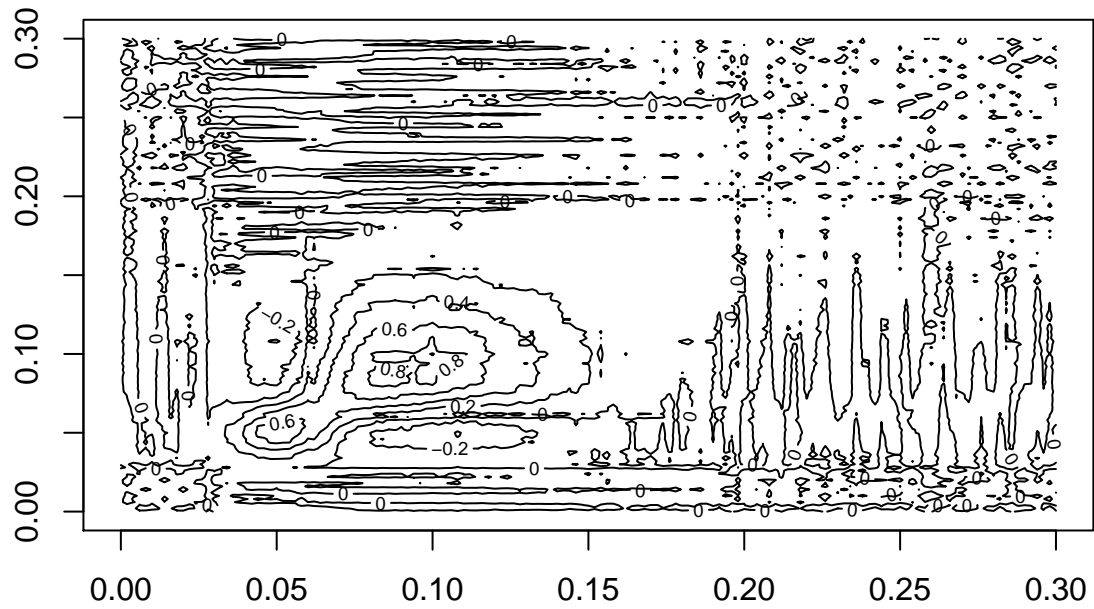
```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



```
##### (c) #####
pinch_Cov <- cov(t(pinch))
persp(x=pinchtime, y=pinchtime, z=pinch_Cov)
```



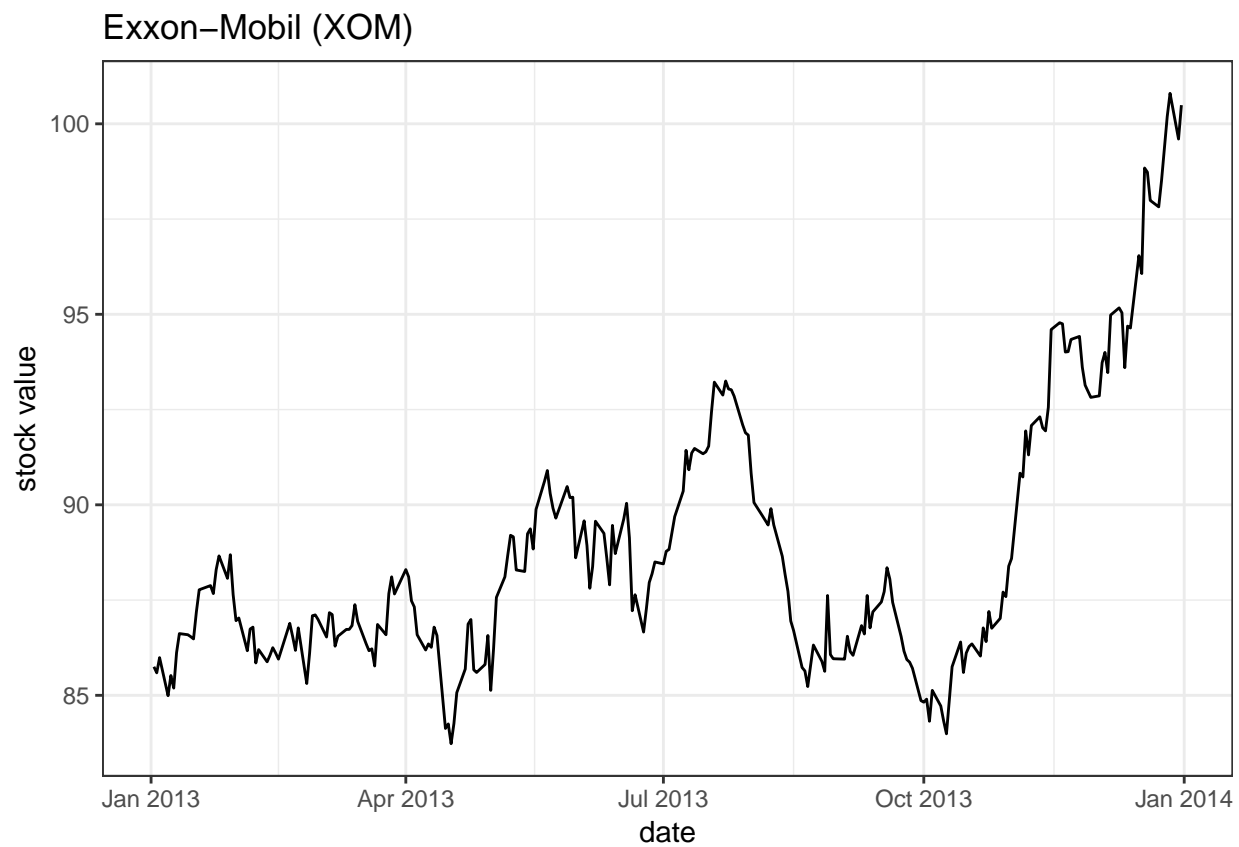
```
contour(x=pinchtime, y=pinchtime, z=pinch_Cov)
```



```
#plot_ly(x=pinchtime, y=pinchtime, z=pinch_Cov) %>% add_surface(  
#   contours = list(  
#     z = list(  
#       show=TRUE,  
#       usecolormap=TRUE,  
#       highlightcolor="#ff0000",  
#       project=list(z=TRUE)  
#     )  
#   )  
#)
```

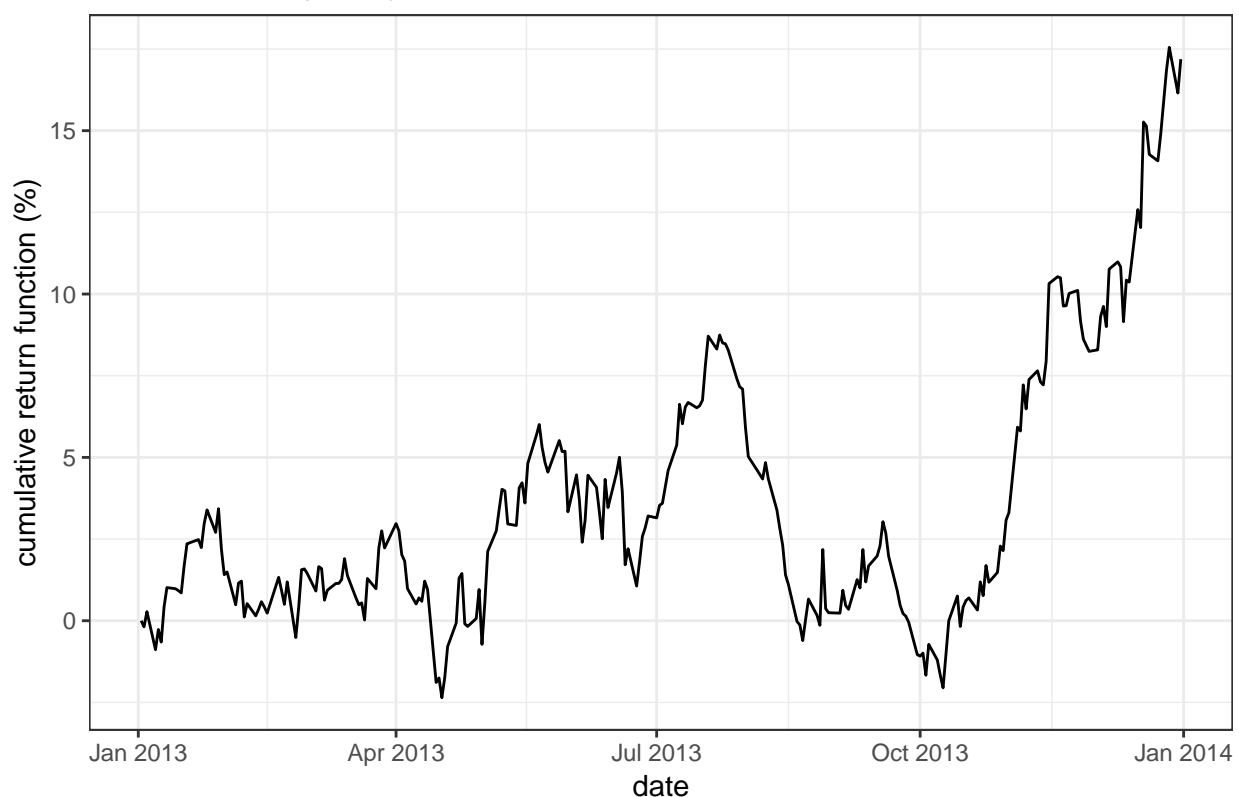
Problem 2

```
##### Problem 2 #####  
D2 <- read.csv("/Users/apple/Desktop/ISU 2019 fall/STAT547/data/DataSets/Dow_companies_data.csv")  
  
##### (a) #####  
P1 <- D2$XOM[1]  
date <- as.Date(as.character(D2$Date), format = "%m/%d/%y")  
  
D_XOM <- data.frame(date = date, v1 = D2$XOM,  
                    v2 = 100*((D2$XOM/P1)-1))  
  
ggplot(data = D_XOM) +  
  geom_line(aes(x = date, y = v1)) +  
  ylab("stock value") +  
  ggtitle("Exxon-Mobil (XOM)") + theme_bw()
```



```
ggplot(data = D_XOM) +  
  geom_line(aes(x = date, y = v2)) +  
  ylab("cumulative return function (%)") +  
  ggtitle("Exxon-Mobil (XOM)") + theme_bw()
```

Exxon-Mobil (XOM)



```
D_XOM$v2[length(D_XOM$v2)]
```

```
## [1] 17.1895
```

```
##### (b) #####
```

```
D2_1 <- D2[, -1]
```

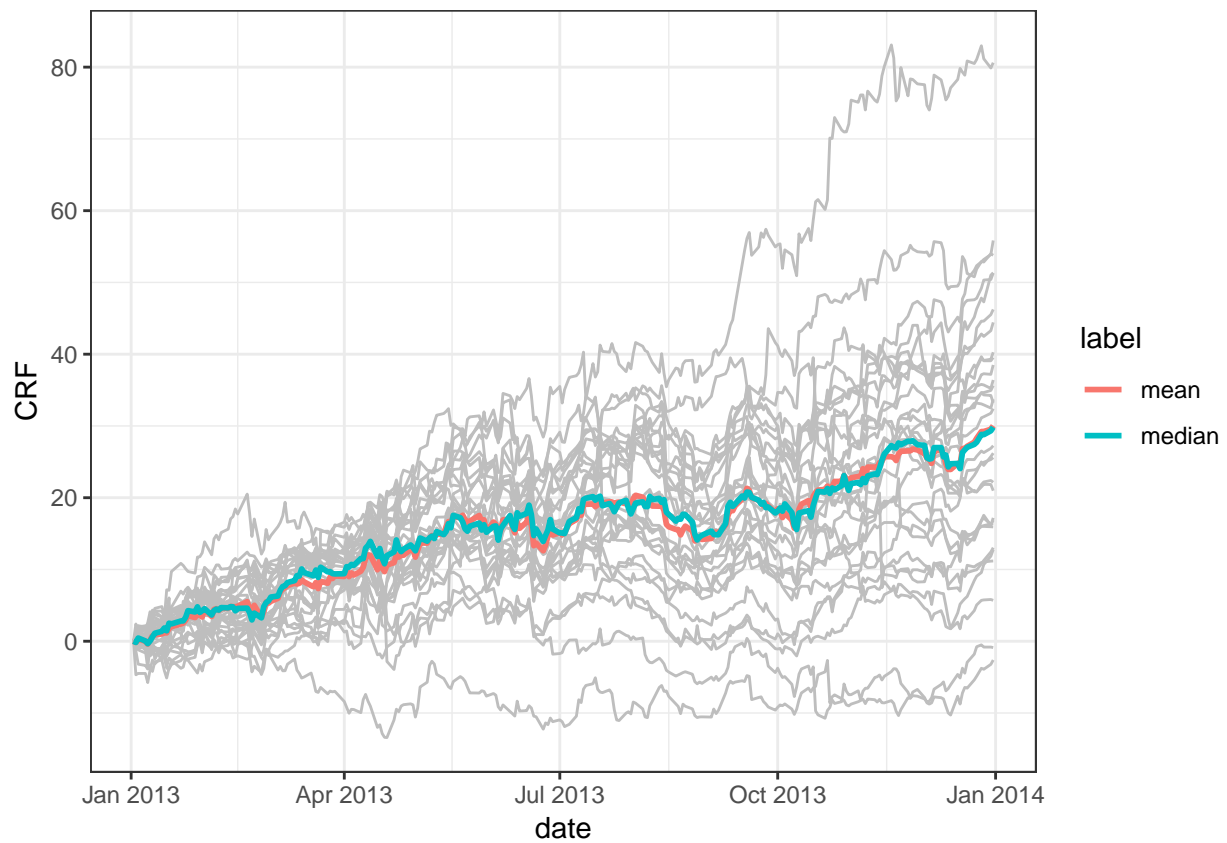
```
D2_2 <- apply(D2_1, 2, FUN = function(x){
  return( 100*(x - x[1])/x[1] )
})
```

```
r_D2_2 <- melt(D2_2)
names(r_D2_2) <- c("date", "stock", "CRF")
r_D2_2$date <- rep(date, 30)
```

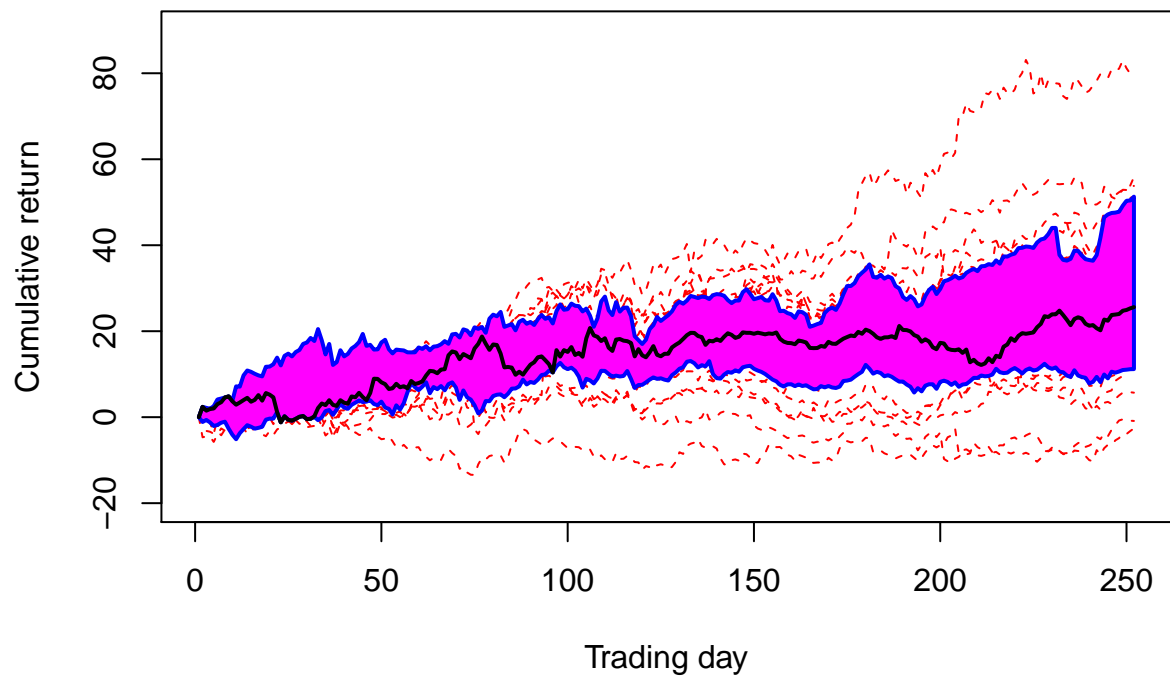
```
stock_mean <- apply(D2_2, 1, mean)
stock_med <- apply(D2_2, 1, median)
```

```
DD <- data.frame(date = rep(date, 2),
  CRF = c(stock_mean, stock_med),
  label = rep(c("mean", "median"), each = 252))
```

```
ggplot(data = r_D2_2) +
  geom_line(aes(x = date, y = CRF, group = stock), colour = "gray") +
  geom_line(data = DD, aes(x = date, y = CRF, colour = label), size = 1) +
  theme_bw()
```



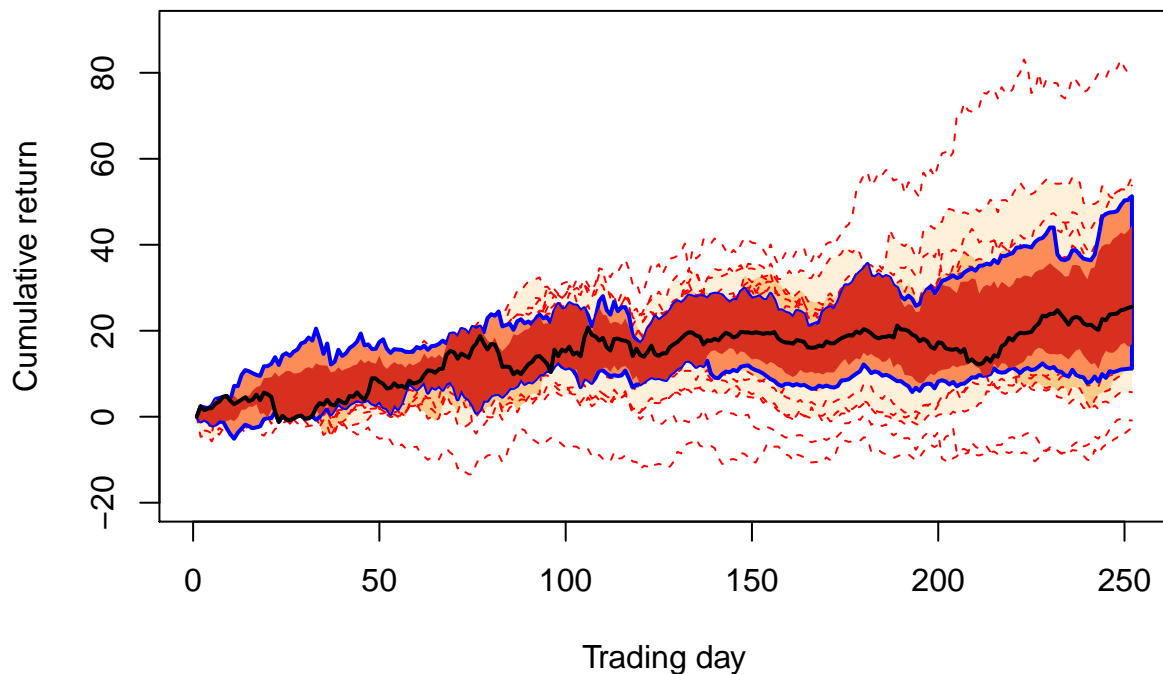
```
##### (c) #####
fbplot(fit = D2_2, ylim = c(-20,90), xlab="Trading day",
       ylab = "Cumulative return")
```



```
## $depth
##      MMM      AXP      T      BA      CAT      CVX      CSCD
```

```
## 0.4152915 0.3129926 0.2976852 0.1558498 0.1287926 0.4631477 0.4010787
##      KO      DD      XOM      GE      GS      HD      INTC
## 0.3526204 0.3906062 0.2521096 0.4612320 0.4046730 0.4735837 0.3979771
##      IBM      JNJ      JPM      MCD      MRK      MSFT      NKE
## 0.2310368 0.3479132 0.4568167 0.4265850 0.4872856 0.3478768 0.3127919
##      PFE      PG      TRV      UNH      UTX      VZ      V
## 0.4678366 0.4624726 0.4250160 0.3453772 0.4552842 0.4319308 0.4645525
##      WMT      DIS
## 0.4375319 0.3458881
##
## $outpoint
## [1] 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
## [24] 24 25 26 27 28 29 30
##
## $medcurve
## MRK
## 19
```

```
fbplot(fit = D2_2, ylim = c(-20,90), prob = c(0.9, 0.6, 0.5, 0.3),
       color = brewer.pal(4, "OrRd"),
       xlab="Trading day",
       ylab = "Cumulative return")
```



```
## $depth
##      MMM      AXP      T      BA      CAT      CVX      CSCD
## 0.4152915 0.3129926 0.2976852 0.1558498 0.1287926 0.4631477 0.4010787
##      KO      DD      XOM      GE      GS      HD      INTC
## 0.3526204 0.3906062 0.2521096 0.4612320 0.4046730 0.4735837 0.3979771
##      IBM      JNJ      JPM      MCD      MRK      MSFT      NKE
## 0.2310368 0.3479132 0.4568167 0.4265850 0.4872856 0.3478768 0.3127919
##      PFE      PG      TRV      UNH      UTX      VZ      V
## 0.4678366 0.4624726 0.4250160 0.3453772 0.4552842 0.4319308 0.4645525
##      WMT      DIS
```



```
## 0.4375319 0.3458881
##
## $outpoint
## [1] 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
## [24] 24 25 26 27 28 29 30
##
## $medcurve
## MRK
## 19
```

Problem 3

Suppose $\text{Var}(\mathbf{x}) = \Sigma = P\Lambda P^T$, where Λ is the eigenvalue matrix such that $\lambda_1 \geq \lambda_2 \geq \dots \geq 0$, P is the corresponding eigenvector matrix, then $\text{Var}(\mathbf{l}_1^T \mathbf{x}) = \mathbf{l}_1^T \Sigma \mathbf{l}_1 = \mathbf{y}_1^T \Lambda \mathbf{y}_1$, where $\mathbf{y}_1 = P^T \mathbf{l}_1$, and $\mathbf{y}_1^T \mathbf{y}_1 = \mathbf{l}_1^T \mathbf{l}_1 = 1$. Note that:

$$\mathbf{y}_1^T \Lambda \mathbf{y}_1 = \sum_{i=1}^d \lambda_i y_{1i}^2 \geq \lambda_1,$$

equality holds iff $\mathbf{y}_1 = \mathbf{e}_1 = (1, 0, \dots, 0)^T$. Therefore, $\mathbf{v}_1 = P\mathbf{e}_1 = \mathbf{p}_1$, where \mathbf{p}_1 is the eigenvector corresponding to λ_1 .

Also note that $\mathbf{e}_1^T \mathbf{y}_2 = \mathbf{v}_1^T \mathbf{l}_2 = 0$, which means $y_{21} = 0$, therefore:

$$\mathbf{y}_2^T \Lambda \mathbf{y}_2 = \sum_{i=2}^d \lambda_i y_{2i}^2 = \lambda_2,$$

and $\mathbf{v}_2 = P\mathbf{e}_2 = \mathbf{p}_2$, where \mathbf{p}_2 is the eigenvector corresponding to λ_2 .

Thus, $V := (\mathbf{v}_1, \dots, \mathbf{v}_d) = P$.

Problem 4

(a)

$$\mathbb{E}(\xi_k) = \mathbb{E}(\mathbf{v}_k^T (\mathbf{x} - \boldsymbol{\mu})) = \mathbf{v}_k^T (\boldsymbol{\mu} - \boldsymbol{\mu}) = 0$$

(b)

$$\text{Var}(\xi_k) = \mathbf{v}_k^T \Sigma \mathbf{v}_k = \mathbf{e}_k^T P^T P \Lambda P^T P \mathbf{e}_k = \lambda_k$$

(c)

$$\text{Cov}(\xi_j, \xi_k) = \mathbf{v}_j^T \Sigma \mathbf{v}_k = \mathbf{e}_j^T \Lambda \mathbf{e}_k = \delta_{jk} \lambda_k$$

(d)

$$\text{Corr}(X_j, \xi_k) = \frac{\text{Cov}(X_j, \xi_k)}{\sigma_{jj} \sqrt{\lambda_k}} = \frac{\mathbf{e}_j^T \Sigma \mathbf{v}_k}{\sigma_{jj} \sqrt{\lambda_k}} = \frac{\mathbf{e}_j^T (\lambda_k \mathbf{v}_k)}{\sigma_{jj} \sqrt{\lambda_k}} = \frac{v_{jk} \sqrt{\lambda_k}}{\sigma_{jj}}$$

Problem 5

(a)

$$\|ax\| = \langle ax, ax \rangle^{1/2} = |a| \langle x, x \rangle^{1/2} = |a| \|x\|$$

(b)

$$\begin{aligned} \because \langle x + ay, x + ay \rangle &\geq 0, \quad \forall a, \\ \therefore \langle y, y \rangle a^2 + 2\langle x, y \rangle a + \langle x, x \rangle &\geq 0, \quad \forall a, \\ \therefore 4\langle x, y \rangle^2 - 4\langle x, x \rangle \langle y, y \rangle &\leq 0, \\ \therefore |\langle x, y \rangle| &\leq \|x\| \|y\|. \end{aligned}$$

(c)

$$\begin{aligned} \because \|x + y\|^2 &= \langle x + y, x + y \rangle = \langle x, x \rangle + \langle y, y \rangle + 2\langle x, y \rangle \leq \|x\|^2 + \|y\|^2 + 2\|x\| \|y\| = (\|x\| + \|y\|)^2, \\ \therefore \|x + y\| &\leq \|x\| + \|y\|. \end{aligned}$$

(d)

$$\begin{aligned} d(x, y) &= \|x - y\| = \langle x - y, x - y \rangle^{1/2} = \langle y - x, y - x \rangle^{1/2} = \|y - x\| = d(y, x) > 0, \quad \text{iff } x \neq y, \\ d(x, x) &= \|x - x\| = 0 \\ d(x, y) &= \|x - y\| = \|(x - z) + (z - y)\| \leq \|x - z\| + \|z - y\| = d(x, z) + d(z, y). \end{aligned}$$

Problem 6

It's easy to find that l_2 space is a valid inner product space, we only need to verify that this space is complete. \forall Cauchy sequence $\{x^{(n)}\}_{n=1}^{\infty}$, we have:

$$\lim_{n, m \rightarrow \infty} \|x^{(n)} - x^{(m)}\| = 0,$$

therefore, for large n_k , $\exists n_{k+1} > n_k$, such that:

$$\begin{aligned} \|x^{(n_{k+1})} - x^{(n_k)}\| &\leq \frac{1}{k^2} \\ \therefore \sum_{k=1}^{\infty} \|x^{(n_{k+1})} - x^{(n_k)}\| &< \infty \end{aligned}$$

Define $x = \liminf_{k \rightarrow \infty} x^{(n_k)}$, we only need to prove (i). $\|x\|^2 < \infty$, and (ii). $\lim_{n \rightarrow \infty} \|x - x^{(n)}\| = 0$. First note that:

$$\|x\|^2 = \sum_{i=1}^{\infty} |x_i|^2 = \sum_{i=1}^{\infty} \liminf_k |x_i^{(n_k)}|^2 \leq \liminf_k \sum_{i=1}^{\infty} |x_i^{(n_k)}|^2 = \liminf_k \|x^{(n_k)}\|^2,$$

The inequality comes from Fatou's lemma, also:

$$\liminf_K \|x^{(n_K)}\| \leq \|x^{(n_1)}\| + \liminf_K \sum_{k=1}^{K-1} \|x^{(n_{k+1})} - x^{(n_k)}\| < \infty,$$

therefore $\|x\|^2 < \infty$.

Again, by Fatou's lemma:

$$\lim_{n \rightarrow \infty} \|x - x^{(n)}\|^2 = \lim_{n \rightarrow \infty} \sum_{i=1}^{\infty} |x_i - x_i^{(n)}|^2 = \lim_{n \rightarrow \infty} \sum_{i=1}^{\infty} \liminf_k |x_i^{(n_k)} - x_i^{(n)}|^2 \leq \lim_{n, k \rightarrow \infty} \sum_{i=1}^{\infty} |x_i^{(n_k)} - x_i^{(n)}|^2$$

By the property of Cauchy sequence:

$$\lim_{n \rightarrow \infty} \|x - x^{(n)}\|^2 \leq \lim_{n, k \rightarrow \infty} \|x^{(n_k)} - x^{(n)}\|^2 = 0,$$

hence, $\lim_{n \rightarrow \infty} \|x - x^{(n)}\| = 0$. Thus, l_2 space to that end is an Hilbert Space.

Problem 7

$$\begin{aligned} \mathbb{E} \|X - \sum_{k=1}^K \langle X, e_k \rangle e_k\|^2 &= \mathbb{E} \int X^2(t) dt - 2 \sum_{k=1}^K \mathbb{E} \langle X, e_k \rangle^2 + \sum_{k=1}^K \sum_{j=1}^K \mathbb{E} \langle X, e_j \rangle \langle X, e_k \rangle \delta_{jk} \\ &= \int \mathbb{E} X^2(t) dt - \sum_{k=1}^K \mathbb{E} \langle X, e_k \rangle^2 \\ &= \int G(t, t) dt - \sum_{k=1}^K \int \int e_k(s) e_k(t) G(s, t) ds dt. \end{aligned}$$

Thus, minimize $\mathbb{E} \|X - \sum_{k=1}^K \langle X, e_k \rangle e_k\|^2$ is equivalent to maximize $\sum_{k=1}^K \int \int e_k(s) e_k(t) G(s, t) ds dt$. By the theorem, for K orthonormal basis $\{e_k\}_{k=1}^K$, we have:

$$\max_{\{e_k\}_{k=1}^K} \sum_{k=1}^K \int \int e_k(s) e_k(t) G(s, t) ds dt = \sum_{k=1}^K \lambda_k,$$

and

$$\arg \max_{\{e_k\}_{k=1}^K} \sum_{k=1}^K \int \int e_k(s) e_k(t) G(s, t) ds dt = \{\phi_k\}_{k=1}^K,$$

where (λ_k, ϕ_k) is the k th eigenvalue-eigenfunction pairs for NND function $G(s, t)$.