

# MATH 542 Homework 4

Saket Choudhary  
skchoudh@usc.edu

February 4, 2016

## 1a. Problem 1

$$\begin{aligned} E[(X - a)(X - a)'] &= E[(X - a)(X' - a')] \\ &= E[XX' - Xa' - aX' + aa'] \\ &= E[XX'] - E[Xa'] - E[aX'] + E[aa'] \\ &= E[XX'] - E[X]a' - aE[X'] + E[aa'] \\ &= (Var[X] + E[X]E[X]') - E[X]a' - aE[X'] + aa' \\ &= Var[X] + E[X]E[X]' - E[X]a' - aE[X]' + aa' \text{ since } E[X'] = E[X]' \\ &= Var[X] + (E[X] - a)(E[X]' - a') \\ &= Var[X] + (E[X] - a)(E[X] - a)' \end{aligned}$$

$$Var[X] = \sum = (\sigma_{ij})$$

$$\|X - a\|_{1 \times 1}^2 = (X - a)'_{1 \times r} (X - a)_{1 \times r}$$

And hence(replace  $X$  with  $X'$  and  $a$  with  $a'$ ):

$$\begin{aligned} E[\|X - a\|^2] &= E[(X - a)'(X - a)] \\ &= E[X'X] - E[X']a - a'E[X] + a'a \\ &= \sum_i E[X_i^2] - E[X']a - a'E[X] + a'a \\ &= \sum_i (Var[X_i] + E[X_i]^2) - E[X']a - a'E[X] + a'a \\ &= \sum_i Var[X_i] + E[X']E[X] - E[X']a - a'E[X] + a'a \text{ since } \sum_i E[X_i]^2 = E[X'X] \\ &= \sum_i Var[X_i] + E[X]'E[X] - E[X]'a - a'E[X] + a'a \text{ since } \sum_i E[X_i]^2 = E[X'X] \\ &= \sum_i Var[X_i] + (E[X] - a)'(E[X] - a) \\ &= \sum_i \sigma_i + \|E[X] - a\|^2 \end{aligned}$$

## 1a. Problem 2

Fact:  $X - a - E[X - a] = X - E[X]$

$$\begin{aligned} \text{Cov}[X - a, Y - b] &= E[(X - a - E[X - a])(Y - b - E[Y - b])'] \\ &= E[(X - E[X])(Y - E[Y])'] \\ &= \text{Cov}[X, Y] \end{aligned}$$

## 1a. Problem 3

$$Y_i = X_i - X_{i-1}$$

$$\text{Cov}[Y_i, Y_j] = 0 \text{ for } i \neq j$$

Consider the vector  $(Y_1, Y_2, Y_3, \dots, Y_n)' = (X_1, X_2 - X_1, X_3 - X_2, \dots, X_n - X_{n-1})'$

We make use of  $\text{Var}(AX) = A\text{Var}(X)A'$ .

To find  $A$ , consider the vectors  $(Y_1, Y_2, Y_3, \dots, Y_n)' = (X_1, X_2 - X_1, X_3 - X_2, \dots, X_n - X_{n-1})'$

$$\begin{aligned} \begin{pmatrix} Y_1 \\ Y_2 \\ Y_3 \\ \vdots \\ Y_n \end{pmatrix} &= \begin{pmatrix} X_1 \\ X_2 - X_1 \\ X_3 - X_2 \\ \vdots \\ X_n - X_{n-1} \end{pmatrix} \\ &= \begin{pmatrix} 1 & 0 & 0 & \dots & 0 & 0 \\ -1 & 1 & 0 & \dots & 0 & 0 \\ 0 & -1 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & -1 & 1 \end{pmatrix} \times \begin{pmatrix} X_1 \\ X_2 \\ X_3 \\ \vdots \\ X_n \end{pmatrix} \end{aligned}$$

$$\text{Hence } A = \begin{pmatrix} 1 & 0 & 0 & \dots & 0 & 0 \\ -1 & 1 & 0 & \dots & 0 & 0 \\ 0 & -1 & 1 & \dots & 0 & 0 \\ \vdots & & & & & \\ 0 & 0 & 0 & \dots & -1 & 1 \end{pmatrix}$$

Now using  $\text{Var}(Y) = A\text{Var}(X)A'$  we get

$$\text{Var}(X) = A^{-1}\text{Var}(Y)A'^{-1}$$

$\text{Var}(Y) = I_{n \times n}$  and hence  $\text{Var}(X) = A^{-1}A'^{-1} = BB^T$  where  $B = A^{-1}$

## Problem 4

$X_{i+1} = \rho X_i$   
Consider:

$$\begin{aligned} \begin{pmatrix} X_1 \\ X_2 \\ X_3 \\ \vdots \\ X_n \end{pmatrix} &= \begin{pmatrix} X_1 \\ \rho X_1 \\ \rho X_2 \\ \vdots \\ \rho X_{n-1} \end{pmatrix} \\ &= \begin{pmatrix} 1 \\ \rho \\ \rho^2 \\ \vdots \\ \rho^{n-1} \end{pmatrix} X_1 \end{aligned}$$

Let  $A = (1 \ \rho \ \rho^2 \ \dots \ \rho^{n-1})'$  and hence variance  $Var[X] = AVar(X_1)A' = \sigma^2 AA'$

$$Var[X] = \begin{pmatrix} 1 & \rho & \rho^2 & \dots & \rho^{n-1} \\ \rho & \rho^2 & \rho^3 & \dots & \rho^n \\ \rho^2 & \rho^3 & \rho^4 & \dots & \rho^{n+1} \\ \vdots & \vdots & \vdots & \dots & \vdots \\ \rho^n & \rho^{n+1} & \rho^{n+2} & \dots & \rho^{2n-2} \end{pmatrix}$$

## 1b. Problem 1

$$\begin{aligned} X_1^2 + 2X_1X_2 - 4X_2X_3 + X_3^2 &= (X_1 + X_2)X_1 + (X_1 - 2X_3)X_2 + (-2X_2 + X_3)X_3 \\ &= (X_1 \ X_2 \ X_3) \begin{pmatrix} 1 & 1 & 0 \\ 1 & 0 & -2 \\ 0 & -2 & 1 \end{pmatrix} \begin{pmatrix} X_1 \\ X_2 \\ X_3 \end{pmatrix} \end{aligned}$$

$$X = (X_1 \ X_2 \ X_3)'$$

$$A = \begin{pmatrix} 1 & 1 & 0 \\ 1 & 0 & -2 \\ 0 & -2 & 1 \end{pmatrix}$$

$$A \Sigma = AVar[X] = \sigma^2 \begin{pmatrix} 1 & 1 & \frac{1}{4} \\ 1 & -\frac{1}{2} & -2 \\ 0 & -\frac{7}{4} & \frac{1}{2} \end{pmatrix}$$

Thus,

$$E[X'AX] = tr(A \Sigma) + \mu' A \mu = \sigma^2 + \mu' A \mu$$

## 1b. Problem 2

$$\begin{aligned}
 \sum_i (X_i - \bar{X})^2 &= \sum_i (X_i^2 - 2X_i\bar{X} + \bar{X}^2) \\
 &= \sum_i X_i^2 - 2 \sum_i X_i\bar{X} + \bar{X}^2 \\
 &= \sum_i X_i^2 - n\bar{X}^2
 \end{aligned}$$

Now  $\sum_i X_i^2 = X'X$  and  $\bar{X} = \frac{1}{n} \sum_i X_i = \frac{1}{n} \mathbf{1}'X = \frac{1}{n} X'\mathbf{1}$   
Hence,

$$\begin{aligned}
 \sum_i (X_i - \bar{X})^2 &= \sum_i X_i^2 - n\bar{X}^2 \\
 &= X'X - n \frac{1}{n^2} (X'\mathbf{1}\mathbf{1}'X) \\
 &= X'X - \frac{1}{n} (X'\mathbf{1}\mathbf{1}'X) \\
 &= X'(\mathbf{I} - \frac{1}{n} \mathbf{1}\mathbf{1}')X
 \end{aligned}$$

Let  $A = (\mathbf{I} - \frac{1}{n} \mathbf{1}\mathbf{1}')$

Now using  $E[X'AX] = \text{tr}(A\Sigma) + \mu'A\mu$  we have:

$$\begin{aligned}
 A\Sigma &= \begin{pmatrix} 1-1/n & -1/n & -1/n & \dots & -1/n \\ -1/n & 1-1/n & -1/n & \dots & -1/n \\ \vdots & & & & \\ -1/n & -1/n & -1/n & \dots & 1-1/n \end{pmatrix} \times \text{diag}(\sigma_1^2, \sigma_2^2, \dots, \sigma_n^2) \\
 &= (1 - \frac{1}{n}) \sum_i \sigma_i^2
 \end{aligned}$$

Also,

$$\mu'A = (\mu \quad \mu \quad \dots \quad \mu) \times \begin{pmatrix} 1-1/n & -1/n & -1/n & \dots & -1/n \\ -1/n & 1-1/n & -1/n & \dots & -1/n \\ \vdots & & & & \\ -1/n & -1/n & -1/n & \dots & 1-1/n \end{pmatrix} = 0$$

and hence  $\mu'A\mu = 0$

$$\begin{aligned}
 E[\sum_i (X_i - \bar{X})^2] &= (1 - \frac{1}{n}) \sum_i \sigma_i^2 \\
 E[\frac{1}{n(n-1)} \sum_i (X_i - \bar{X})^2] &= \frac{1}{n^2} \sum_i \sigma_i^2
 \end{aligned}$$

Finally,

$$\begin{aligned}
\text{var}(\bar{X}) &= \text{Var}\left(\frac{1}{n} \sum_i X_i\right) \\
&= \frac{1}{n^2} \sum_i \text{Var}(X_i) \\
&\text{since } X_i \text{ are mutually independent} \\
&= \frac{1}{n^2} \sum_i \sigma_i^2 \\
&= E\left[\frac{1}{n(n-1)} \sum_i (X_i - \bar{X})^2\right]
\end{aligned}$$

### 1b. Problem 3

Given:  $\bar{X}_w = \sum_i w_i X_i$  and  $\sum w_i = 1$

$$\begin{aligned}
\text{Var}(\bar{X}_w) &= \text{Var}\left(\sum w_i X_i\right) \\
&= \sum w_i^2 \text{Var}(X_i) \text{ since } X_i \text{ are mutually independent} \\
&= \sum w_i^2 \sigma_i^2
\end{aligned}$$

Now consider,

$$\text{minimize } \sum w_i^2 \sigma_i^2 \text{ subject to } \sum_i w_i = 1$$

We consider the following lagrange formulation:

$$\text{min}_w f(\mathbf{w}) = \sum_i w_i^2 \sigma_i^2 + \lambda \left(\sum_i w_i - 1\right)$$

Now to find optimal  $\lambda$ , we solve  $\frac{\partial f(\mathbf{w})}{\partial w_i} = 0$

$$\begin{aligned}
\frac{\partial f(\mathbf{w})}{\partial w_i} &= 2w_i \sigma_i^2 + \lambda = 0 \\
\implies w_i &= -\frac{\lambda}{2\sigma_i^2}
\end{aligned}$$

Thus,  $w_i = -\frac{\lambda}{2\sigma_i^2}$  or  $w_i \propto \frac{1}{\sigma_i^2}$

Using  $\sum_i w_i = 1$  we get:

$$\begin{aligned}
\sum_i w_i &= 1 \\
\sum_i \frac{\lambda}{-2\sigma_i^2} &= 1 \\
\Rightarrow \lambda &= \frac{-2}{\sum_i 1/\sigma_i^2} \\
\Rightarrow w_i &= \frac{1}{\sigma_i^2 \sum_i (1/\sigma_i^2)} \\
\Rightarrow f_{min}(w) &= \sum_i \left( \frac{1}{\sigma_i^2 \sum_i (1/\sigma_i^2)} \right) \sigma_i^2 \\
v_{min} &= \frac{1}{\sum_i (1/\sigma_i^2)}
\end{aligned}$$

**Part b**

$$\begin{aligned}
\sum_i w_i (X_i - \bar{X}_w)^2 &= \sum_i w_i (X_i^2 - 2X_i \bar{X}_w + \bar{X}_w^2) \\
&= \sum_i w_i X_i^2 - 2\bar{X}_w \sum_i w_i X_i + \bar{X}_w^2 \\
&= \sum_i w_i X_i^2 - 2\bar{X}_w^2 + \bar{X}_w^2 \\
&= \sum_i w_i X_i^2 - \bar{X}_w^2
\end{aligned}$$

Now, we rewrite  $\sum_i w_i X_i^2 = X' \Lambda X$  where  $\Lambda = \text{diag}(w_1, w_2, \dots, w_n)$  and  $\bar{X}_w = \sum_i w_i X_i = X' w = w' X$

$$\begin{aligned}
\bar{X}_w^2 &= \left( \sum_i w_i X_i \right)^2 \\
&= X' w w' X
\end{aligned}$$

and hence  $\sum_i w_i (X_i - \bar{X}_w)^2 = X' (\Lambda - w w') X$

$$\text{Define } A = \Lambda - w w' = \begin{pmatrix} w_1 - w_1^2 & w_1 w_2 & w_1 w_3 & \dots & w_1 w_n \\ w_2 w_1 & w_2 - w_2^2 & w_2 w_3 & \dots & w_2 w_n \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ w_n w_1 & w_n w_2 & w_n w_3 & \dots & w_n - w_n^2 \end{pmatrix}$$

so that

$$E\left[\sum_i w_i (X_i - \bar{X}_w)^2\right] = E[X' A X] = \text{tr}(A \sum) + \mu' A \mu$$

$$\text{tr}(A \sum) = \sum_i (w_i - w_i^2) \sigma_i^2 = \sum_i w_i \sigma_i^2 - \sum_i w_i (w_i \sigma_i^2) = \sum_i (a - a w_i) = na - a$$

and the (1, 1) element of the matrix  $\mu' A$  is given by:

$$\begin{aligned}\mu' A_1 &= \mu(w_1 - w_1^2 - w_1 \sum_{i=2} w_i) \\ &= w_1 - w_1^2 - w_1(1 - w_1) \\ &= 0\end{aligned}$$

and hence it's essentially a zero matrix (other elements are zero similarly)

Also,

$$v_{min} = \frac{1}{\sum_i 1/\sigma_i^2} = \frac{1}{\sum_i \frac{w_i}{a}} = a$$

Thus,

$$\begin{aligned}E[S_w^2] &= \frac{1}{n-1} \text{tr}(A \sum) + \mu' A \mu \\ &= \frac{1}{n-1} (na - a) + 0 \\ &= a \\ &= v_{min}\end{aligned}$$