

Feel free to work with other students, but make sure you write up the homework and code on your own (no copying homework *or* code; no pair programming). Feel free to ask students or instructors for help debugging code or whatever else, though. The starter code for problem 2 part c and d can be found under the Resource tab on course website.

*Note:* You need to create a Github account for submission of the coding part of the homework. Please create a repository on Github to hold all your code and include your Github account username as part of the answer to problem 2.

**1 (Linear Transformation)** Let  $\mathbf{y} = A\mathbf{x} + \mathbf{b}$  be a random vector. show that expectation is linear:

$$\mathbb{E}[\mathbf{y}] = \mathbb{E}[A\mathbf{x} + \mathbf{b}] = A\mathbb{E}[\mathbf{x}] + \mathbf{b}.$$

Also show that

$$\text{cov}[\mathbf{y}] = \text{cov}[A\mathbf{x} + \mathbf{b}] = A\text{cov}[\mathbf{x}]A^\top = A\Sigma A^\top.$$

a) To show that  $A\mathbb{E}[\mathbf{x}] + \mathbf{b}$  is linear, we first need to integrate the given statement  $\mathbb{E}[\mathbf{y}] = \mathbb{E}[A\mathbf{x} + \mathbf{b}]$  such that  $\mathbb{E}[\mathbf{y}] = \int_S \mathbf{y}P(\mathbf{x})d\mathbf{x}$ . Since  $\mathbf{y} = A\mathbf{x} + \mathbf{b}$ ,  $\mathbb{E}[\mathbf{y}] = \int_S (A\mathbf{x} + \mathbf{b})P(\mathbf{x})d\mathbf{x}$ .

Now, factor in the  $P(\mathbf{x})$ , then split the intergral across the addition, such that:

$$\int_S (A\mathbf{x})P(\mathbf{x})d\mathbf{x} + \int_S \mathbf{b}P(\mathbf{x})d\mathbf{x}$$

Next, factor out the constants  $A$  and  $\mathbf{b}$ , such that:

$$A \int_S (\mathbf{x})P(\mathbf{x})d\mathbf{x} + \mathbf{b} \int_S P(\mathbf{x})d\mathbf{x}$$

This simplifies to:  $A\mathbb{E}[\mathbf{x}] + \mathbf{b}$ , since the integral  $\int_S (\mathbf{x})P(\mathbf{x})d\mathbf{x} = \mathbb{E}[\mathbf{x}]$

b) Since  $\mathbf{y} = A\mathbf{x} + \mathbf{b}$ ,  $\text{cov}[\mathbf{y}] = \text{cov}[A\mathbf{x} + \mathbf{b}]$ .

Per the definition of covariance,  $\text{cov}[\mathbf{x}] = \mathbb{E}[(\mathbf{x} - \mathbb{E}[\mathbf{x}])(\mathbf{x} - \mathbb{E}[\mathbf{x}])^\top]$

Thus,  $\text{cov}[\mathbf{y}] = \text{cov}[A\mathbf{x} + \mathbf{b}] = \mathbb{E}[(A\mathbf{x} + \mathbf{b} - \mathbb{E}[A\mathbf{x} + \mathbf{b}])(A\mathbf{x} + \mathbf{b} - \mathbb{E}[A\mathbf{x} + \mathbf{b}])^\top]$

Per a), we can factor out the internal  $\mathbb{E}[A\mathbf{x} + \mathbf{b}]$ , such that:  $\mathbb{E}[(A\mathbf{x} + \mathbf{b} - A\mathbb{E}[\mathbf{x}] - \mathbf{b})(A\mathbf{x} + \mathbf{b} - A\mathbb{E}[\mathbf{x}] - \mathbf{b})^\top]$

Combine terms to get:  $\mathbb{E}[(A\mathbf{x} - A\mathbb{E}[\mathbf{x}])(A\mathbf{x} - A\mathbb{E}[\mathbf{x}])^\top]$

Factor out  $A$ :  $A\mathbb{E}[(\mathbf{x} - \mathbb{E}[\mathbf{x}])(\mathbf{x} - \mathbb{E}[\mathbf{x}])^\top]A^\top$

Per the definition of the covariance,  $\mathbb{E}[(\mathbf{x} - \mathbb{E}[\mathbf{x}])(\mathbf{x} - \mathbb{E}[\mathbf{x}])^\top] = \text{cov}[\mathbf{x}]$

Therefore, the above statement is equal to:  $A\text{cov}[\mathbf{x}]A^\top$

Which is equal to  $A\Sigma A^\top$ , per definition of the covariance. QED. ■

2 Given the dataset  $\mathcal{D} = \{(x, y)\} = \{(0, 1), (2, 3), (3, 6), (4, 8)\}$

- (a) Find the least squares estimate  $y = \theta^\top \mathbf{x}$  by hand using Cramer's Rule.
- (b) Use the normal equations to find the same solution and verify it is the same as part (a).
- (c) Plot the data and the optimal linear fit you found.
- (d) Find randomly generate 100 points near the line with white Gaussian noise and then compute the least squares estimate (using a computer). Verify that this new line is close to the original and plot the new dataset, the old line, and the new line.

a)  $X = \begin{pmatrix} 1 & 0 \\ 1 & 2 \\ 1 & 3 \\ 1 & 4 \end{pmatrix} \quad \mathbf{y} = \begin{pmatrix} 1 \\ 3 \\ 6 \\ 8 \end{pmatrix}$  Therefore,  $X^\top X = \begin{pmatrix} 4 & 9 \\ 9 & 29 \end{pmatrix}$  ■

and  $X^\top \mathbf{y} = \begin{pmatrix} 18 \\ 56 \end{pmatrix}$

Now, to find the 2x1  $\theta$  matrix, we need to use Cramer's rule, such that:

$$\theta_0 = \det[(18, 9)(56, 29)] / \det[(4, 9)(9, 29)] = 18/35$$
$$\theta_1 = \det[(4, 18)(9, 56)] / \det[(4, 9)(9, 29)] = 62/35$$

b) The normal equation, per the lecture notes, is  $\theta^* = \text{inv}((X^\top X))X^\top \mathbf{y}$

Using the matrices from part a, and plugging them into Matlab (sorry, linalg triggers me), we get that  $\theta^* = \begin{pmatrix} 18/35 \\ 62/35 \end{pmatrix}$ , as per part a.

For part c and d, I included the graphs as part of my submission to github.