

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

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

Suppose the cumulative distribution function of the  $N$ -dimensional random vector  $\mathbf{y}$  admits a density  $\mathbb{F}$ . Then

$$\mathbb{E}[\mathbf{y}] = \int_{\mathbb{R}} (A\mathbf{x} + \mathbf{b}) \mathbb{F}(x) dx = A \int_{\mathbb{R}} \mathbf{x} \mathbb{F}(x) dx + \mathbf{b} \int_{\mathbb{R}} \mathbb{F}(x) dx$$

by linearity of the Lebesgue integral. Because

$$\int_{\mathbb{R}} \mathbb{F}(x) dx = 1,$$

the claim is proven true.

Observe that by matrix transpose properties and the linearity of the expectation,

$$\begin{aligned} \text{cov}[\mathbf{y}] &= \mathbb{E}\left[ (A\mathbf{x} + \mathbf{b} - \mathbb{E}[A\mathbf{x} + \mathbf{b}]) (A\mathbf{x} + \mathbf{b} - \mathbb{E}[A\mathbf{x} + \mathbf{b}])^T \right] \\ &= \mathbb{E}\left[ (A\mathbf{x} - A\mathbb{E}[\mathbf{x}]) (A\mathbf{x} - A\mathbb{E}[\mathbf{x}])^T \right] \\ &= A\mathbb{E}\left[ (\mathbf{x} - \mathbb{E}[\mathbf{x}]) (\mathbf{x} - \mathbb{E}[\mathbf{x}])^T \right] A^T \\ &= A\text{cov}[\mathbf{x}]A^T. \end{aligned}$$

Then,

$$\begin{aligned}
\text{cov}[\mathbf{x}] &= \mathbb{E} \left[ (\mathbf{x} - \mathbb{E}[\mathbf{x}]) (\mathbf{x} - \mathbb{E}[\mathbf{x}])^T \right] \\
&= \mathbb{E} \left[ \begin{bmatrix} X_1 - \mu_1 \\ \dots \\ X_N - \mu_N \end{bmatrix} \cdot \begin{bmatrix} X_1 - \mu_1 \\ \dots \\ X_N - \mu_N \end{bmatrix}^T \right] \\
&= \mathbb{E} \left[ \begin{bmatrix} (X_1 - \mu_1)(X_1 - \mu_1) & (X_1 - \mu_1)(X_2 - \mu_2) & \dots & (X_1 - \mu_1)(X_N - \mu_N) \\ (X_2 - \mu_2)(X_1 - \mu_1) & (X_2 - \mu_2)(X_2 - \mu_2) & \dots & (X_2 - \mu_2)(X_N - \mu_N) \\ \vdots & \vdots & \ddots & \vdots \\ (X_N - \mu_N)(X_1 - \mu_1) & (X_N - \mu_N)(X_2 - \mu_2) & \dots & (X_N - \mu_N)(X_N - \mu_N) \end{bmatrix} \right] \\
&= \begin{bmatrix} E[(X_1 - \mu_1)(X_1 - \mu_1)] & E[(X_1 - \mu_1)(X_2 - \mu_2)] & \dots & E[(X_1 - \mu_1)(X_N - \mu_N)] \\ E[(X_2 - \mu_2)(X_1 - \mu_1)] & E[(X_2 - \mu_2)(X_2 - \mu_2)] & \dots & E[(X_2 - \mu_2)(X_N - \mu_N)] \\ \vdots & \vdots & \ddots & \vdots \\ E[(X_N - \mu_N)(X_1 - \mu_1)] & E[(X_N - \mu_N)(X_2 - \mu_2)] & \dots & E[(X_N - \mu_N)(X_N - \mu_N)] \end{bmatrix} \\
&= \boldsymbol{\Sigma}
\end{aligned}$$

as desired. ■

**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) We wish to find  $\theta_0$  and  $\theta_1$  such that

$$y^{(i)} = \theta_0 + \theta_1 x^{(i)} \quad (1)$$

for all  $i = 1, \dots, 4$ , where  $(x^{(i)}, y^{(i)}) \in \mathcal{D}$ . We can express equation (1) given dataset  $\mathcal{D}$  in matrix notation as

$$\begin{bmatrix} 1 \\ 3 \\ 6 \\ 8 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 2 \\ 1 & 3 \\ 1 & 4 \end{bmatrix} \begin{bmatrix} \theta_0 \\ \theta_1 \end{bmatrix}. \quad (2)$$

Let

$$\mathbf{x} \triangleq \begin{bmatrix} 1 & 0 \\ 1 & 2 \\ 1 & 3 \\ 1 & 4 \end{bmatrix}, \quad (3)$$

To use Cramer's Rule, we need square matrices. Let's left-multiply both sides by  $\mathbf{x}^T$ :

$$\begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 2 & 3 & 4 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \\ 6 \\ 8 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 2 & 3 & 4 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 1 & 2 \\ 1 & 3 \\ 1 & 4 \end{bmatrix} \begin{bmatrix} \theta_0 \\ \theta_1 \end{bmatrix}. \quad (4)$$

Evaluating,

$$\begin{bmatrix} 18 \\ 56 \end{bmatrix} = \begin{bmatrix} 4 & 9 \\ 9 & 29 \end{bmatrix} \begin{bmatrix} \theta_0 \\ \theta_1 \end{bmatrix}. \quad (5)$$

Thus,

$$\theta_0 = \frac{\det \begin{bmatrix} 18 & 9 \\ 56 & 29 \end{bmatrix}}{\det \begin{bmatrix} 4 & 9 \\ 9 & 29 \end{bmatrix}} = \frac{18}{35} \quad \text{and} \quad \theta_1 = \frac{\det \begin{bmatrix} 4 & 18 \\ 9 & 56 \end{bmatrix}}{\det \begin{bmatrix} 4 & 9 \\ 9 & 29 \end{bmatrix}} = \frac{62}{35}, \quad (6)$$

via Cramer's Rule.

(b) According to the normal equations:

$$\boldsymbol{\theta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}. \quad (7)$$

See that

$$(\mathbf{X}^T \mathbf{X})^{-1} = \begin{bmatrix} 4 & 9 \\ 9 & 29 \end{bmatrix}^{-1} = \begin{bmatrix} 4 & 9 \\ 9 & 29 \end{bmatrix}^{-1} = \frac{1}{35} \begin{bmatrix} 29 & -9 \\ -9 & 4 \end{bmatrix}. \quad (8)$$

So

$$(\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T = \frac{1}{35} \begin{bmatrix} 29 & -9 \\ -9 & 4 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 2 & 3 & 4 \end{bmatrix} = \frac{1}{35} \begin{bmatrix} 29 & 11 & 2 & -7 \\ -9 & -1 & 3 & 7 \end{bmatrix}. \quad (9)$$

Which means that

$$\boldsymbol{\theta} = \frac{1}{35} \begin{bmatrix} 29 & 11 & 2 & -7 \\ -9 & -1 & 3 & 7 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \\ 6 \\ 8 \end{bmatrix} = \frac{1}{35} \begin{bmatrix} 18 \\ 62 \end{bmatrix}, \quad (10)$$

as shown in part (a).

(c)

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