Eli Weissler Math189R SP19 Homework 1 Monday, February 03, 2019

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

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

First recall the definition of expectation value \mathbb{E} of a vector \mathbf{x}

$$\mathbb{E}[\mathbf{x}] = \begin{pmatrix} \mathbb{E}[x_1] \\ \mathbb{E}[x_2] \\ \cdots \\ \mathbb{E}[x_i] \\ \cdots \end{pmatrix} = \begin{pmatrix} \int x_1 f(x_1) dx_1 \\ \int x_2 f(x_2) dx_2 \\ \cdots \\ \int x_i f(x_i) dx_i \\ \cdots \end{pmatrix}$$

where $f(x_i)$ is some probability density function, and the integral is performed over the kernel. In this case, we assume that \mathbf{x} is a random vector with n continuous random variables, A is a constant matrix, and \mathbf{b} is a constant vector.

$$\mathbb{E}[A\mathbf{x} + \mathbf{b}] = \begin{pmatrix} \mathbb{E}[A_{1:} \cdot \mathbf{x} + b_{1}] \\ \mathbb{E}[A_{2:} \cdot \mathbf{x} + b_{2}] \\ \cdots \\ \mathbb{E}[A_{i:} \cdot \mathbf{x} + b_{i}] \\ \cdots \end{pmatrix}$$

Note that I am using A_i : to denote the row vector formed by all elements in row i of A. If we examine an arbitrary element, we see that

$$\mathbb{E}[A_{i:} \cdot \mathbf{x} + b_i] = \mathbb{E}[\sum_j A_{ij} x_k + b_i]$$

Now we use the formal definition of expectation value to convert to an integral. Although we have to integrate over all x_i , unless a term contains an x_i the integral goes to one.

$$\mathbb{E}\left[\sum_{j} A_{ij} x_{k} + b_{i}\right] = \int \int \dots \int f(x_{1}) dx_{1} f(x_{2}) dx_{2} \dots f(x_{n}) dx_{n} \left(\sum_{j} A_{ij} x_{j} f(x_{j}) + b_{i}\right)$$

$$= \sum_{j} \int A_{ij} x_{j} f(x_{j}) dx_{j} + b_{i} = \sum_{j} A_{ij} \int x_{j} f(x_{j}) dx_{j} + b_{i}$$

$$= \sum_{j} A_{ij} \mathbb{E}[x_{j}] + b_{i} = A_{i:} \cdot \mathbb{E}[\mathbf{x}] + b_{i}$$

Bringing this back together, we see that

$$\mathbb{E}[A\mathbf{x} + \mathbf{b}] = \begin{pmatrix} A_{1:} \cdot \mathbb{E}[\mathbf{x}] + b_1 \\ A_{2:} \cdot \mathbb{E}[\mathbf{x}] + b_2 \\ & \cdots \\ A_{i:} \cdot \mathbb{E}[\mathbf{x}] + b_i \\ & \cdots \end{pmatrix} = A\mathbb{E}[\mathbf{x}] + \mathbf{b}$$

as desired.

Now recall the definition of covariance

$$cov[\mathbf{x}]_{ij} = \mathbb{E}[(x_i - \mathbb{E}[x_i])(x_j - \mathbb{E}[x_j])]$$

If we make the same assumptions, i.e. that \mathbf{x} is a random vector with n continous variables, A is a constant matrix, and \mathbf{b} is a constant vector, then

$$cov[A\mathbf{x} + \mathbf{b}]_{ij} = \mathbb{E}[((A\mathbf{x} + \mathbf{b})_i - \mathbb{E}[(A\mathbf{x} + \mathbf{b})_i])((A\mathbf{x} + \mathbf{b})_j - \mathbb{E}[(A\mathbf{x} + \mathbf{b})_j])]$$

$$= \mathbb{E}[(A_{i:} \cdot \mathbf{x} + b_i - A_{i:} \cdot \mathbb{E}[x] - b_i)(A_{j:} \cdot \mathbf{x} + b_j - A_{j:} \cdot \mathbb{E}[x] - b_j)]$$

$$= \mathbb{E}[(A_{i:} \cdot \mathbf{x} - A_{i:} \cdot \mathbb{E}[x] -)(A_{j:} \cdot \mathbf{x} - A_{j:} \cdot \mathbb{E}[x])]$$

$$= \mathbb{E}[(A_{i:} \cdot \mathbf{x} - A_{i:} \cdot \mathbb{E}[x] -)(\mathbf{x}^T \cdot A_{:j}^T - \mathbb{E}[x]^T \cdot A_{:j}^T)] \quad \text{Rewriting the right parenthesis}$$

$$= \mathbb{E}[A_{i:} \cdot (\mathbf{x} - \mathbb{E}[\mathbf{x}])(\mathbf{x}^T - \mathbb{E}[\mathbf{x}]^T) \cdot A_{:j}]$$

$$= A_{i:} \cdot \mathbb{E}[(\mathbf{x} - \mathbb{E}[\mathbf{x}])(\mathbf{x}^T - \mathbb{E}[\mathbf{x}]^T)] \cdot A_{:j}$$

$$= (Acov[\mathbf{x}]A^T)_{ij}$$

Therefore $cov[A\mathbf{x} + \mathbf{b}] = Acov[\mathbf{x}]A^{\top}$ 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 are trying to minimize the cost function

$$J = \sum [y_i - (mx_i + b)]^2$$

We can do this by setting the partials with respect to *m*, *b* equal to zero.

$$\frac{\partial J}{\partial m} = \sum 2[y_i - (mx_i + b)](-x_i) = 0$$

$$\frac{\partial J}{\partial b} = \sum 2[y_i - (mx_i + b)](-1) = 0$$

$$\rightarrow \sum x_i y_i = m \sum x_i^2 + b \sum x_i$$

$$\rightarrow \sum y_i = m \sum x_i + bN$$

In this problem, this is equivalent to the matrix

$$\begin{pmatrix} \sum x_i y_i \\ \sum y_i \end{pmatrix} = \begin{pmatrix} \sum x_i^2 & \sum x_i \\ \sum x_i & N \end{pmatrix} \begin{pmatrix} m \\ b \end{pmatrix}$$
$$\begin{pmatrix} 56 \\ 18 \end{pmatrix} = \begin{pmatrix} 29 & 9 \\ 9 & 4 \end{pmatrix} \begin{pmatrix} m \\ b \end{pmatrix}$$

Using Cramer's rule from class, we get

$$m = \frac{62}{35}$$
$$b = \frac{18}{35}$$

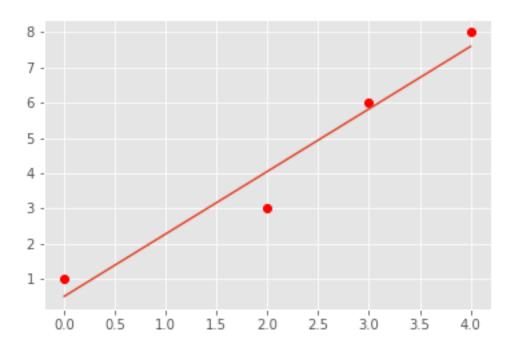
(b) Define our feature matrix and outcomes to be

$$X = \begin{pmatrix} 1 & 0 \\ 1 & 2 \\ 1 & 3 \\ 1 & 4 \end{pmatrix} \qquad Y = \begin{pmatrix} 1 \\ 3 \\ 6 \\ 8 \end{pmatrix}$$

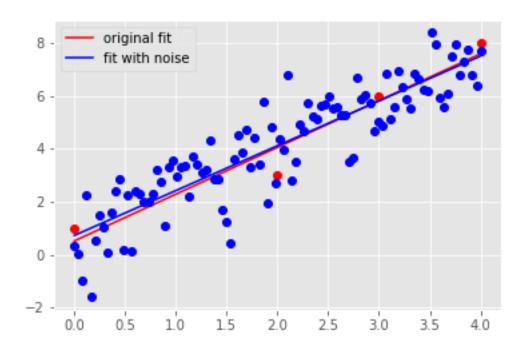
Which yields (I multiplied matrices using Mathematica)

$$\theta = (X^T X)^{-1} (X^T Y) = \begin{pmatrix} \frac{18}{35} \\ \frac{62}{35} \end{pmatrix}$$

Which agrees with the results from part (a), as $\theta_0 = b$ and $\theta_1 = m$.



(c)



(d)