

## Homework 0

Due Friday Feb 4th by 11:59pm **on Gradescope** (<https://www.gradescope.com>). Regrade requests should be sent via Gradescope.

Name:

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1. Normal distributions.

- (a) Suppose  $X_1 \sim N(1, 4)$ ,  $X_2 \sim N(3, 7)$  and  $X_1, X_2$  are independent. What is the distribution of  $X_1 + X_2$ ?
- (b) Suppose that  $X \sim N_k(\mu, \Sigma)$  and that  $A$  is a  $\ell \times k$  matrix with full rank. What is the distribution of the vector  $AX$ ? (Here  $N_k(\mu, \Sigma)$  is the  $k$ -dimensional Normal distribution with mean vector  $\mu \in \mathbb{R}^k$  and covariance matrix  $\Sigma \sim \mathbb{R}^{k \times k}$ .)
- (c) Suppose that  $y = X\beta + \epsilon$ , where  $\epsilon \sim N_n(\mathbf{0}, I)$  ( $\mathbf{0}$  is the all-zero vector and  $I$  denotes the  $n \times n$  identity matrix),  $\beta \in \mathbb{R}^k$  is a *fixed* vector,  $X \in \mathbb{R}^{n \times k}$  is a matrix with i.i.d. entries distributed as  $N(0, 1)$ , and  $\epsilon$  and  $X$  are independent of each other. What is the distribution of  $y$ ?

2. Mean and variance.

- (a) Express  $\text{Var}(X_1 + 2X_2)$  using the variances and covariance of  $X_1, X_2$  ( $X_1$  and  $X_2$  are *not* necessarily independent).
- (b) Suppose that  $X_1, \dots, X_n$  are i.i.d. real-valued random variables with finite variances. Show that

$$\text{Var}\left(\frac{1}{n} \sum_{i=1}^n X_i\right) = \frac{1}{n} \text{Var}(X_1).$$

- (c) Assume that  $X, Y$  are independent random variables with  $\mathbb{E}[X] = 0$ ,  $\mathbb{E}[Y] = 1$ ,  $\text{Var}(X) = 1$ ,  $\text{Var}(Y) = 3$ . Compute  $\mathbb{E}[(3X + Y)(6Y + 2X - 1)]$ .

3. Suppose that  $a$  is a fixed number and  $X$  is a random variable.

- (a) Prove that

$$\mathbb{E}[(X - a)^2] = (\mathbb{E}[X] - a)^2 + \text{Var}(X).$$

- (b) Find the (deterministic) value of  $a$  that minimizes the quantity  $\mathbb{E}[(X - a)^2]$ .

4. Suppose that  $Y, X_1, \dots, X_k$  are random variables, where  $Y$  takes values  $1, 2, 3, \dots, 10$ . If  $X_1, \dots, X_k$  are independent *conditioned on*  $Y$ , express the conditional probability  $\mathbb{P}(Y = 2 | X_1 = x_1, \dots, X_k = x_k)$  in terms of  $\mathbb{P}(Y = y)$  and  $\mathbb{P}(X_k = x_k | Y = y)$ ,  $y = 1, 2, \dots, 10$ .

5. For arbitrary numbers  $x_1, \dots, x_n, t_1, \dots, t_n \in \mathbb{R}$ , find the values of  $a$  and  $b$  that minimize the expression  $\sum_{i=1}^n (x_i - a - bt_i)^2$ .

6. For each number  $1 \leq q < \infty$ , the so-called  $\ell_q$  norm of a vector  $u \in \mathbb{R}^k$  is defined as  $\|u\|_q \triangleq \left( \sum_{i=1}^k |u_i|^q \right)^{1/q}$ . Prove that  $\|u\|_2 \leq \|u\|_1 \leq \sqrt{k} \|u\|_2$ .
7. True or false (capital letters denote matrices, which are assumed to be invertible; lower case letters denote column vectors):
- $AA^{-1} = A^{-1}A = I$ .
  - $(AB)^{-1} = A^{-1}B^{-1}$ .
  - $(AB)^\top = A^\top B^\top$ .
  - $(A^{-1})^\top = (A^\top)^{-1}$ .
  - $(A+B)^{-1} = A^{-1} + B^{-1}$ .
  - $\|u\|^2 = u^\top u = \text{trace}(uu^\top)$ .
8. Suppose that  $A \in \mathbb{R}^{p \times n}$  is a  $p$ -by- $n$  matrix. Prove that the matrix  $AA^\top$  is positive semidefinite.
9. Which of the following matrices has/have full rank? (An  $n$ -by- $m$  matrix  $Z$  is called full rank if  $\text{rank}(Z) = \min(n, m)$ .)  $A = \begin{pmatrix} 2 & 0 & 5 \\ 1 & 0 & 1 \end{pmatrix}$ ,  $B = \begin{pmatrix} 2 & 0 \\ 5 & 0 \end{pmatrix}$ ,  $C = \begin{pmatrix} 1 & 2 \\ 2 & 0 \end{pmatrix}$ .
10. Suppose that  $A \in \mathbb{R}^{p \times p}$  is a real symmetric and positive semidefinite matrix. Find a matrix  $Z \in \mathbb{R}^{p \times p}$  such that  $Z^2 = A$ . (Hint: Use the eigendecomposition of  $A$ .)
11. This is not a question, but it is very important that you are comfortable with the concepts and notations used in the following statement, and understand why the statement is true.

Suppose that  $X$  is a given  $n \times p$  matrix of the form

$$X = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1p} \\ X_{21} & X_{22} & \cdots & X_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ X_{n1} & X_{n2} & \cdots & X_{np} \end{bmatrix}$$

and  $y$  is a given  $n$ -dimensional column vector of the form

$$y = \begin{bmatrix} y_1 & y_2 & \cdots & y_n \end{bmatrix}^\top = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}.$$

If  $p > n$ , then:

- The matrix  $X^\top X$  is singular (that is, not invertible).
- In general there are infinitely many vectors  $\beta = \begin{bmatrix} \beta_1 & \beta_2 & \cdots & \beta_p \end{bmatrix}^\top$  that satisfy the linear equation system

$$X\beta = y.$$

To be rigorous, this is true when the matrix  $X$  has linearly independent rows, or equivalently, when  $X$  has full row rank.

These facts are useful when we discuss overfitting and model flexibility in linear regression.