

# Homework 1: Due November 1 in class

Reading: Read chapter 1 of Lecture notes.

1. Let  $A \in \mathbb{R}^{m \times n}$ ,  $b \in \mathbb{R}^m$  and define  $\phi: \mathbb{R}^n \rightarrow \mathbb{R}^m$  by  $\phi(x) = Ax - b$ .

Prove that for every  $i \in \{1, 2, \dots, n\}$  one has that

$$\sum_{j=1}^m \frac{\partial \phi_j}{\partial x_i}(x) \phi_j(x) = a_i^T (Ax - b).$$

2. Let  $A \in \mathbb{R}^{m \times n}$ , where  $m \leq n$ , and assume that  $r(A) = m$ .

Prove that  $A^\dagger = A^T (AA^T)^{-1}$ .

3. Let  $A \in \mathbb{R}^{m \times n}$ .

Prove that, if  $A = U\Sigma V^T$  is a singular value decomposition for  $A$ , then  $A^\dagger = V\Sigma^{-1}U^T$ .

4. (a) Compute by hand a singular value decomposition and the pseudoinverse of  $A = \begin{bmatrix} 1 & -\frac{1}{2} \\ 0 & 0 \\ -2 & 1 \end{bmatrix}$ .

(b) Now try to do the same using Julia. Do you get what you expected? What happens if you compare the pseudoinverse obtained via the command `pinv` to the one obtained by taking  $V\Sigma^{-1}U^T$ ? Produce a jupyter notebook documenting your work, including your comments on the behavior above.

5. Let  $X \sim N(\mu, \sigma^2)$  for  $\mu \in \mathbb{R}$  and  $\sigma^2 > 0$ . Prove that  $\mathbb{E}X = \mu$  and  $\text{Var}(X) = \sigma^2$ .

Hint: it might be useful to recall that  $\int_{-\infty}^{+\infty} e^{-\frac{x^2}{2}} dx = \sqrt{2\pi}$ .

6. Let  $X$  and  $Y$  be two real random variables that are either:

both discrete; both continuous, have respective densities  $f_X, f_Y$  and finite expected values, i.e.,  $\mathbb{E}(X), \mathbb{E}(Y) < \infty$ .

Prove that for all  $a, b \in \mathbb{R}$  one has that  $\mathbb{E}(aX + bY) = a\mathbb{E}(X) + b\mathbb{E}(Y)$ .

Hint: use the transformation law (Lemma 1.25 in the notes) for  $g(X, Y) = X + Y$  and that for every random variable  $\mathbb{E}|X| < \infty$  if and only if  $\mathbb{E}X < \infty$  (see Eq. (3.1.7) in Ash's book). The concept of marginal density might also be useful.

7. Let  $\Omega := \{x_1, \dots, x_n\}$  and  $p_1, \dots, p_n \geq 0$  with  $p_1 + \dots + p_n = 1$ . Prove that the following algorithm generates a random variable  $X \in \Omega$  with  $P(X = x_i) = p_i$ :

define the numbers  $w_k := \sum_{i=1}^k p_i$ ,  $1 \leq k \leq n$ , and  $w_0 := 0$ ; draw  $Y \sim \text{Unif}([0, 1])$  (for instance, in **Julia** one can draw  $Y$  using the command `rand()`); let  $k$  be such that  $w_{k-1} \leq Y < w_k$ ; return  $x_k$ .

8. The element caesium-137 has a half-life of about 30,17 years. In other words, a single atom of caesium-137 has a 50 percent chance of surviving after 30,17 years, a 25 percent chance of surviving after 60,34 years, and so on.

(a) Determine the probability that a single atom of caesium-137 decays (i.e., does not survive) after a single day. How would you model the random variable  $X$  that takes the value 1 when the atom decays and 0 otherwise?

(b) Using **Julia**, simulate 1000 times the behaviour of a collection  $C$  of  $10^6$  caesium-137 atoms in a single day. How would you model the random variable  $Y = |\{\text{atoms in } C \text{ decaying after a single day}\}|$ ?

(c) The Poisson distribution with parameter  $\lambda$  is a discrete probability distribution that is used to "model rare events".

When  $Z \sim \text{Pois}(\lambda)$ , one has that  $P(Z = k) = \frac{\lambda^k e^{-\lambda}}{k!}$ . Plot the Poisson distribution with  $\lambda = 10^6 \cdot p$ , where  $p$  is the probability computed in part (a).

(d) Compare the empirical distribution in part (b) to the theoretical distribution in part (c).

Some **Julia** packages that might be useful: **Distributions**, **StatsPlots**.