

Q1: Linear Algebra

From the hypothesis, we know that vector \hat{x} and \hat{y} are non-zero vectors. Thus, we get:

$$\|x\| \neq 0 \quad (1)$$

and

$$\|y\| \neq 0 \quad (2)$$

From the fact that \hat{x} and \hat{y} are orthogonal we have:

$$\vec{x} \cdot \vec{y} = 0 \implies \mathbf{x}^T \mathbf{y} = 0 \quad (3)$$

Let us assume we have the following class of matrices:

$$A = \mathbf{xy}^T + kI \text{ for } k \in \mathbb{Z} \quad (4)$$

Then we get:

$$\begin{aligned} (A\vec{x}) \cdot (A\vec{y}) &= (\mathbf{Ax})^T \mathbf{Ay} \\ &= \mathbf{x}^T A^T \mathbf{Ay} \\ &\stackrel{(4)}{=} \mathbf{x}^T (\mathbf{xy}^T + kI)^T (\mathbf{xy}^T + kI) \mathbf{y} \\ &= \mathbf{x}^T (\mathbf{yx}^T + kI) (\mathbf{xy}^T + kI) \mathbf{y} \\ &= (\mathbf{x}^T \mathbf{yx}^T + k\mathbf{x}^T) (\mathbf{xy}^T + kI) \mathbf{y} \\ &\stackrel{(3)}{=} k\mathbf{x}^T (\mathbf{xy}^T + kI) \mathbf{y} \\ &= (k\mathbf{x}^T \mathbf{xy}^T + k^2 \mathbf{x}^T) \mathbf{y} \\ &= k\|x\|^2 \mathbf{y}^T \mathbf{y} + k^2 \mathbf{x}^T \mathbf{y} \\ &\stackrel{(3)}{=} k\|x\|^2 \|y\|^2 \end{aligned}$$

Finally for $k \neq 0$ we have:

$$k\|x\|^2 \|y\|^2 \stackrel{(1,2)}{>} 0$$

Thus, for this class (4) of matrices A , $A\vec{x}$ and $A\vec{y}$ are not orthogonal.

NOTE: Many of you gave a specific example in this question by specifying x and y vectors. This is fine but we actually wanted you to find such a matrix A for all x and y vectors.

Q2: Partial Derivatives

We first calculate the first partial derivative:

$$\begin{aligned} \frac{\partial f(x_1, x_2, \dots, x_n)}{\partial x_i} &= \frac{\partial}{\partial x_i} \left[-\sum_{j=1}^n x_j \log(x_j) \right] \\ &= \frac{\partial}{\partial x_i} (-x_i \log(x_i)) \\ &= -\log(x_i) - x_i \frac{1}{x_i} \\ &= -\log(x_i) - 1 \end{aligned}$$

The partial derivative is defined for $x_i > 0$ (the same goes for the original function f).

For the second partial derivative there are two cases. If $j \neq i$ then it is 0. Otherwise, we have:

$$\begin{aligned}\frac{\partial^2 f(x_1, x_2, \dots, x_n)}{\partial x_i^2} &= \frac{\partial}{\partial x_i} \frac{\partial f(x_1, x_2, \dots, x_n)}{\partial x_i} \\ &= \frac{\partial}{\partial x_i} (-\log(x_i) - 1) \\ &= -\frac{1}{x_i}\end{aligned}$$

The second order partial derivative is defined for $x_i > 0$ (the same goes for the original function f).

Thus, the result is the following:

$$\frac{\partial^2 f(x_1, x_2, \dots, x_n)}{\partial x_i \partial x_j} = \begin{cases} -\frac{1}{x_i} & , \text{ if } i = j. \\ 0 & , \text{ otherwise.} \end{cases}$$

Q3: Conditional Probability

Let us define the following events:

$R \triangleq$ It rains in Ms. Y's neighborhood at any given day.

$S \triangleq$ The sprinkler is turned on next door.

$W \triangleq$ Ms. Y wears a poncho.

Then we need to calculate the probabilities of R given W and S given W . For the first one we have:

$$\begin{aligned}Pr[R/W] &= \frac{Pr[W/R] Pr[R]}{Pr[W]} \\ &= \frac{0.6 \times 0.1}{Pr[W]} \\ &= \frac{0.06}{Pr[W]}\end{aligned}$$

The first equality holds from "Probability Theory".

For the second one we have:

$$\begin{aligned}Pr[S/W] &= \frac{Pr[W/S] Pr[S]}{Pr[W]} \\ &= \frac{0.2 \times 0.3}{Pr[W]} \\ &= \frac{0.06}{Pr[W]}\end{aligned}$$

The first equality holds from "Probability Theory".

Thus, the first event (it rained at that day) and the second event (the sprinkler was on) are equally likely.

COMMON MISTAKE: Many of you tried to calculate $P[W]$ writing $Pr[W] = Pr[W/S] * Pr[S] + Pr[W/R] * Pr[R]$. You cannot calculate $Pr[W]$ this way because to be able to write this equation, you need to know that R and S do not intersect; however, this information is not given in the question.

Q4: Linearity of Expectation

Let us define the following events:

$F_i \triangleq \text{Fan } i \text{ is a baseball fan}$

$J_i \triangleq \text{Fan } i \text{ gets a baseball jersey}$

Let us suppose that we have a variable X_i defined as follows:

$$X_i = \begin{cases} 1 & , \text{ if } F_i \text{ and } J_i. \\ 0 & , \text{ otherwise.} \end{cases}$$

Then the expected number of baseball fans that will get a baseball shirt is the following:

$$\begin{aligned} E \left[\sum_{i=1}^{100} X_i \right] &= \sum_{i=1}^{100} E[X_i] \\ &= \sum_{i=1}^{100} \Pr[F_i \cap J_i] \\ &= \sum_{i=1}^{100} \Pr[F_i] \Pr[J_i] \\ &= \sum_{i=1}^{100} 0.1 \times 0.1 \\ &= \sum_{i=1}^{100} 0.01 = 1 \end{aligned}$$

The first equality holds from the "Linearity of Expectation" and the third one from the fact that F_i and J_i are completely independent of each other (random order from hypothesis).