

# Assignment 2

Ayush Jha

May 2024

## Problem 1

**Proof:**

(a)  $X^{-1}(\Phi) = \Phi$

Since  $A = \Phi$  (the empty set), therefore:

$$X^{-1}(\Phi) = \{\omega \in \Omega \mid X(\omega) \in \Phi\}$$

Since  $\Phi$  is the empty set, there are no elements in  $\Phi$ , so no  $\omega \in \Omega$  can satisfy  $X(\omega) \in \Phi$ . Thus,

$$X^{-1}(\Phi) = \Phi$$

(b)  $X^{-1}(\mathbb{R}) = \Omega$

If  $A = \mathbb{R}$  then:

$$X^{-1}(\mathbb{R}) = \{\omega \in \Omega \mid X(\omega) \in \mathbb{R}\}$$

Since  $X$  is a random variable, by definition, it maps every element  $\omega \in \Omega$  to some real number in  $\mathbb{R}$ . Therefore, every  $\omega \in \Omega$  satisfies  $X(\omega) \in \mathbb{R}$ , and:

$$X^{-1}(\mathbb{R}) = \Omega$$

## Problem 2

The support of a random variable  $X$  means probability density function  $f_X(x)$  is positive.

First, we find the probability density function  $f_X(x)$  by differentiating the cumulative distribution function  $F_X(x)$ .

For  $x < 0$ :

$$F_X(x) = 0 \implies f_X(x) = \frac{d}{dx} 0 = 0$$

For  $x \geq 0$ :

$$F_X(x) = 1 - e^{-\lambda x} \implies f_X(x) = \frac{d}{dx} (1 - e^{-\lambda x}) = \lambda e^{-\lambda x}$$

The probability density function  $f_X(x)$  is positive for all  $x \geq 0$ . Therefore, the support of the random variable  $X$  is:

$$\text{Support of } X = [0, \infty)$$

### Problem 3

The cost function is equal to:

$$J(m, c) = \frac{1}{N} \sum_{i=1}^N (y_i - mx_i - c)^2$$

The goal is to minimize  $J$  with respect to  $m$  and  $c$ , i.e.  $\frac{\partial J}{\partial Z} = 0$ , where  $Z$  can be  $m$  or  $c$ .

$$\frac{\partial J}{\partial c} = \frac{2}{N} \sum_{i=1}^N (mx_i + c - y_i)x_i = 0$$

$$\frac{\partial J}{\partial m} = \frac{2}{N} \sum_{i=1}^N (mx_i + c - y_i)x_i = 0$$

After solving for  $m$ (slope) and  $c$ (intercept) :

$$m = \frac{N(\sum_{i=1}^N x_i y_i) - (\sum_{i=1}^N x_i)(\sum_{i=1}^N y_i)}{N(\sum_{i=1}^N x_i^2) - (\sum_{i=1}^N x_i)^2}$$
$$c = \frac{(\sum_{i=1}^N y_i)(\sum_{i=1}^N x_i^2) - (\sum_{i=1}^N x_i)(\sum_{i=1}^N x_i y_i)}{N(\sum_{i=1}^N x_i^2) - (\sum_{i=1}^N x_i)^2}$$

Hence, proved.