



1 AXIOMS OF PROBABILITY

1.1 Definitions

1. For any event A , $0 \leq \Pr(A) \leq 1$.
2. $A \cup B \triangleq A + B$.
3. $A \cap B \triangleq AB$.
4. The null and complete event are $\phi = 0, S = 1$.
5. If $AB = 0$, $\Pr(A + B) = \Pr(A) + \Pr(B)$.
6. $(A + B)' = A'B'$

1.2 Problems

Prove the following:

1.

$$A = AB + AB' \quad (1.2.1.1)$$

2.

$$\Pr(A) = \Pr(AB) + \Pr(AB') \quad (1.2.2.1)$$

3.

$$A + B = B + AB' \quad (1.2.3.1)$$

4.

$$\Pr(A + B) = \Pr(A) + \Pr(B) - \Pr(AB) \quad (1.2.4.1)$$

2 DISTRIBUTION OF THE SUM OF RANDOM VARIABLES

2.1 Definitions

1. The mean of X is defined as

$$E(X) = \sum_k k p_X(k) \quad (2.1.1.1)$$

2. The Z transform of X is defined as

$$M_X(z) = E(z^{-X}) = \sum_{k=-\infty}^{\infty} z^{-k} p_X(k) \quad (2.1.2.1)$$

3. There is a one to one relationship between the pmf and its Z transform.
4. If X_1 and X_2 are independent,

$$E[f(X_1)g(X_2)] = E[f(X_1)]E[g(X_2)] \quad (2.1.4.1)$$

5. For a Bernoulli random variable X , the pmf is

$$p_X(n) = \begin{cases} p & k = 1 \\ 1 - p & k = 0 \\ 0 & \text{otherwise} \end{cases} \quad (2.1.5.1)$$

6. X_i are said to be i.i.d (independent and identically distributed) if they are independent and have the same pmf.

2.2 Problem

1. Find the Z-transform for X , given that X is a Bernoulli random variable with parameter p .
2. If X_1 and X_2 are independent, and

$$Y = X_1 + X_2, \quad (2.2.2.1)$$

show that

$$M_Y(z) = M_{X_1}(z)M_{X_2}(z) \quad (2.2.2.2)$$

3. Find the Z-transform of Y , given that X_i are i.i.d Bernoulli random variables with parameter p .
4. Find the pmf of Y .
5. Find the pmf of

$$Y = \sum_{i=1}^N X_i, \quad (2.2.5.1)$$

where X_i are i.i.d.

3 MOMENTS AND VARIANCE

3.1 Definitions

1. The variance of X is defined as:

$$\text{Var}(X) = E(X - E(X))^2 \quad (3.1.1.1)$$

2. The Z transform of X is defined as

$$M_X(z) = E(z^{-X}) = \sum_{k=-\infty}^{\infty} z^{-k} p_X(k) \quad (3.1.2.1)$$

3. Let X be a random variable with pmf.

$$p_X(k) = \begin{cases} 1/6 & 1 \leq k \leq 6 \\ 0 & \text{otherwise} \end{cases} \quad (3.1.3.1)$$

X is said to be Discrete Uniform Random Variable

4. The n^{th} moment of X is defined as:

$$E(X^n) = \sum_{k=-\infty}^{\infty} k^n p_X(k) \quad (3.1.4.1)$$

3.2 Problems

1. Show that $Var(X) = E(X^2) - [E(X)]^2$
2. Find $M_X(z)$
3. Show that $E(X) = \frac{d}{dz} M_X(z^{-1}) \big|_{z=1}$
4. Find $E(X^2)$
5. Find $Var(X)$.

4 CONVOLUTION

4.1 Definitions

1. The Z transform of X is defined as

$$M_X(z) = E(z^{-X}) = \sum_{k=-\infty}^{\infty} z^{-k} p_X(k) \quad (4.1.1.1)$$

2. Let X be a random variable with pmf.

$$p_X(k) = \begin{cases} 1/6 & 1 \leq k \leq 6 \\ 0 & \text{otherwise} \end{cases} \quad (4.1.2.1)$$

X is said to be Discrete Uniform Random Variable

3. Convolution of two sequences using Toeplitz matrices

$$\mathbf{y} = \mathbf{x} \otimes \mathbf{h} \quad (4.1.3.1)$$

$$\mathbf{y} = \begin{pmatrix} h_1 & 0 & \cdot & \cdot & \cdot & 0 \\ h_2 & h_1 & \cdot & \cdot & \cdot & 0 \\ h_3 & h_2 & h_3 & \cdot & \cdot & 0 \\ h_{m-1} & \cdot & \cdot & \cdot & h_2 & h_1 \\ h_m & h_{m-1} & \cdot & \cdot & \cdot & h_2 \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & \cdot & \cdot & \cdot & h_m \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ x_n \end{pmatrix} \quad (4.1.3.2)$$

4.2 Problems

1. If $\mathbf{x} = \mathbf{h} = \frac{1}{2} \begin{pmatrix} 1 \\ 1 \end{pmatrix}$, find \mathbf{y} .
2. Find $p_{X_1}(k) \otimes p_{X_2}(k)$ using toeplitz matrices.
3. Find $M_Y(z)$, such that $Y = X_1 + X_2$
4. Find $p_Y(k)$

5 Z-TRANSFORM APPLICATIONS

5.1 Definitions

1.

$$u(n) = \begin{cases} 1 & n \geq 0 \\ 0 & n < 0 \end{cases} \quad (5.1.1.1)$$

2. The Z transform of X is defined as

$$M_X(z) = E(z^{-X}) = \sum_{k=-\infty}^{\infty} z^{-k} p_X(k) \quad (5.1.2.1)$$

5.2 Problems

1. If

$$p_Y(n) \xleftrightarrow{Z} M_Y(z), \quad (5.2.1.1)$$

show that

$$p_Y(n-k) \xleftrightarrow{Z} M_Y(z) z^{-k}, \quad (5.2.1.2)$$

2. Show that

$$u(n) \xleftrightarrow{z} \frac{1}{(1 - z^{-1})}, \quad |z| > 1 \quad (5.2.2.1)$$

3. Show that

$$nu(n) \xleftrightarrow{z} \frac{z^{-1}}{(1 - z^{-1})^2}, \quad |z| > 1 \quad (5.2.3.1)$$

4. Let

$$M_Y(z) = \left\{ \frac{z^{-1}(1 - z^{-6})}{6(1 - z^{-1})} \right\}^2, \quad |z| > 1 \quad (5.2.4.1)$$

Show that

$$p_Y(n) = \frac{(n-1)u(n-1) - 2(n-7)u(n-7) + (n-13)u(n-13)}{36} \quad (5.2.4.2)$$

6 MARKOV CHAIN

6.1 Definitions

1. Fig. 6.1.1.1 shows a Markovs chain with 5 states. Transition from one state to another happens over time. s_0 and s_4 are absorbing states.

$$p + q = 1 \quad (6.1.1.1)$$

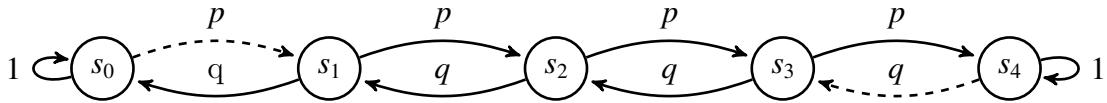


Fig. 6.1.1.1

2. At time instant n ,

$$\mathbf{p}^{(n)} = \begin{pmatrix} P_0^{(n)} \\ P_1^{(n)} \\ P_2^{(n)} \\ P_3^{(n)} \\ P_4^{(n)} \end{pmatrix} \quad (6.1.2.1)$$

where $P_i^{(n)}$ are defined to be the *stationary* probabilities.

3. P_{ij} is defined as the *transition* probability of going to state i from state j .

4. For a matrix \mathbf{A} , let

$$\mathbf{Ax} = \lambda \mathbf{x}. \quad (6.1.4.1)$$

Then λ is a scalar defined to be the eigenvalue of \mathbf{A} and \mathbf{x} is the corresponding eigenvector.

6.2 Problems

1. Let

$$P_0^{(n+1)} = P_0^{(n)} \quad (6.2.1.1)$$

$$P_1^{(n+1)} = pP_0^{(n)} + qP_2^{(n)} \quad (6.2.1.2)$$

$$P_2^{(n+1)} = pP_1^{(n)} + qP_3^{(n)} \quad (6.2.1.3)$$

$$P_3^{(n+1)} = pP_2^{(n)} + qP_4^{(n)} \quad (6.2.1.4)$$

$$P_4^{(n+1)} = P_4^{(n)} \quad (6.2.1.5)$$

Find the matrix \mathbf{P} such that $\mathbf{p}^{(n+1)} = \mathbf{P}\mathbf{p}^{(n)}$

2. Show that 1 is an eigen value of \mathbf{P} .
3. Show that

$$P_2^{(n+1)} = pP_1^{(n)} + qP_3^{(n)} \quad (6.2.3.1)$$

4. If $P_0 = 1, P_N = 0$ and

$$P_i = pP_{i-1} + qP_{i+1} \quad (6.2.4.1)$$

show that

$$P_i = \frac{\left(\frac{p}{q}\right)^i - \left(\frac{p}{q}\right)^N}{1 - \left(\frac{p}{q}\right)^N}, 0 \leq i \leq N \quad (6.2.4.2)$$

7 GAUSSIAN DISTRIBUTION

7.1 Definitions

1. The CDF of X is defined as,

$$F_X(x) = \Pr(X \leq x) \quad (7.1.1.1)$$

2. The PDF of X is defined as,

$$p_X(x) = \frac{d}{dx} F_X(x) \quad (7.1.2.1)$$

3. Let $X \sim \mathcal{N}(\mu, \sigma^2)$. Then the Q function is defined as,

$$Q(x) = \Pr(X > x), \quad x \geq 0 \quad (7.1.3.1)$$

7.2 Problems

1. Find

$$\Pr(|X - \mu| \leq k\sigma) \quad (7.2.1.1)$$

in terms of Q function.

2. Find

$$\Pr(X \leq x, |X - \mu| \leq k\sigma) \quad (7.2.2.1)$$

in terms of $F_X(x)$

3. Find

$$F_X(x|X - \mu| \leq k\sigma) \quad (7.2.3.1)$$

4. Find

$$p_X(x|X - \mu| \leq k\sigma) \quad (7.2.4.1)$$

8 BIVARIATE GAUSSIAN

8.1 Definitions

1. Let

$$\mathbf{X} = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}, \boldsymbol{\mu} = E(\mathbf{X}) \quad (8.1.1.1)$$

$$\boldsymbol{\Sigma}_{\mathbf{x}} = E[(\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^\top] \quad (8.1.1.2)$$

Then $\boldsymbol{\Sigma}_{\mathbf{x}}$ is defined to be the *covariance* matrix of \mathbf{x} .

2. For $\mathbf{x} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma}_{\mathbf{x}})$,

$$f_{\mathbf{X}}(\mathbf{x}) = \frac{1}{2\pi \sqrt{|\boldsymbol{\Sigma}_{\mathbf{x}}|}} \exp -\frac{1}{2} \left((\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}_{\mathbf{x}}^{-1} (\mathbf{x} - \boldsymbol{\mu}) \right) \quad (8.1.2.1)$$

3. The *correlation coefficient* is defined as

$$\rho = \frac{E[(x_1 - \mu_1)(x_2 - \mu_2)]}{\sigma_1 \sigma_2} \quad (8.1.3.1)$$

where μ_i, σ_i^2 are the mean and variance of x_i .

8.2 Problems

1. Show that

$$E[(\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^\top] = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix} \quad (8.2.1.1)$$

2. Prove that $\boldsymbol{\Sigma}_{\mathbf{x}}$ is a diagonal matrix when x_1 and x_2 are independent.
3. Let

$$z_1 = x_1 + x_2 \quad (8.2.3.1)$$

$$z_2 = x_1 - x_2 \quad (8.2.3.2)$$

Find \mathbf{P} such that

$$\mathbf{z} = \begin{pmatrix} z_1 \\ z_2 \end{pmatrix} = \mathbf{P}\mathbf{x} \quad (8.2.3.3)$$

4. Show that

$$\boldsymbol{\Sigma}_{\mathbf{z}} = \mathbf{P}\boldsymbol{\Sigma}_{\mathbf{x}}\mathbf{P}^\top \quad (8.2.4.1)$$

5. Check the independence of z_1 and z_2 given that $\sigma_1 = \sigma_2$.
6. Show that columns of \mathbf{P} are eigenvectors of $\boldsymbol{\Sigma}_{\mathbf{z}}$.
7. Show that the eigenvectors of $\boldsymbol{\Sigma}_{\mathbf{z}}$ are orthogonal to each other.
8. Summarize your conclusion in one line.