



# Probability and Stochastic Processes

Joint MGF/CF, Probabilistic Inequalities–Markov’s Inequality,  
Chebyshev’s Inequality, Chernoff Bound, Jensen’s Inequality

**Karthik P. N.**

**Assistant Professor, Department of AI**

**Email: [pnkarthik@ai.iith.ac.in](mailto:pnkarthik@ai.iith.ac.in)**

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# Joint MGF/CF

## Joint MGF and Joint Characteristic Functions

Fix a probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ .

Let  $X_1, \dots, X_n$  be random variables w.r.t.  $\mathcal{F}$ .

### Joint MGF and Joint Characteristic Function

1. The joint MGF of  $X_1, \dots, X_n$  is a function  $M_{X_1, \dots, X_n} : \mathbb{R}^n \rightarrow [0, +\infty]$ , defined as

$$M_{X_1, \dots, X_n}(t_1, \dots, t_n) = \mathbb{E}[e^{t_1 X_1 + \dots + t_n X_n}] = \mathbb{E}[e^{\mathbf{t}^\top \mathbf{X}}],$$

where  $\mathbf{t} = [t_1 \ \dots \ t_n]^\top$  and  $\mathbf{X} = [X_1 \ \dots \ X_n]^\top$ .

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2. The joint characteristic function of  $X_1, \dots, X_n$  is a function  $C_{X_1, \dots, X_n} : \mathbb{R}^n \rightarrow \mathbb{C}$ , defined as

$$C_{X_1, \dots, X_n}(s_1, \dots, s_n) = \mathbb{E}[j(s_1 X_1 + \dots + s_n X_n)] = \mathbb{E}[e^{j \mathbf{s}^\top \mathbf{X}}],$$

where  $\mathbf{s} = [s_1 \ \dots \ s_n]^\top$ .

## Independence and Joint MGF/CF

Fix a probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ . Let  $X_1, \dots, X_n$  be random variables w.r.t.  $\mathcal{F}$ .

### Theorem (Independence and Joint MGF/CF)

1. Suppose that  $M_{X_1, \dots, X_n}(t_1, \dots, t_n) < +\infty$  for all  $(t_1, \dots, t_n) \in B(\mathbf{0}, \varepsilon)$  for some  $\varepsilon > 0$ , where  $B(\mathbf{0}, \varepsilon)$  denotes a ball in  $\mathbb{R}^n$  centered at the origin  $\mathbf{0}$  and having radius  $\varepsilon$ . Then, the random variables  $X_1, \dots, X_n$  are independent **if and only if**

$$M_{X_1, \dots, X_n}(t_1, \dots, t_n) = \prod_{i=1}^n M_{X_i}(t_i) \quad \forall (t_1, \dots, t_n) \in \mathbb{R}^n.$$

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2. The random variables  $X_1, \dots, X_n$  are independent **if and only if**

$$C_{X_1, \dots, X_n}(s_1, \dots, s_n) = \prod_{i=1}^n C_{X_i}(s_i) \quad \forall (s_1, \dots, s_n) \in \mathbb{R}^n.$$

## Caution

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To check that two random variables  $X$  and  $Y$  are independent, it **DOES NOT** suffice to check that

$$C_{X,Y}(s, s) = C_X(s) C_Y(s) \quad \forall s \in \mathbb{R}.$$

Example:

$$f_{X,Y}(x, y) = \begin{cases} \frac{1}{4}(1 + xy(x^2 - y^2)), & |x| < 1, |y| < 1, \\ 0, & \text{otherwise.} \end{cases}$$

# Probabilistic Inequalities



## Markov's Inequality

Fix a probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ .

Let  $X$  be a random variable w.r.t.  $\mathcal{F}$ .

### Theorem (Markov's Inequality)

Let  $X$  be a **non-negative** random variable with  $\mathbb{E}[X] < +\infty$ . Then,

$$\mathbb{P}(\{X > \alpha\}) \leq \frac{\mathbb{E}[X]}{\alpha}, \quad \forall \alpha > 0.$$

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Remarks:

- Markov's inequality only applies to non-negative random variables
- The inequality is useful only for  $\alpha > \mathbb{E}[X]$

## Example

The course AI5030 has a total registration of 88 students.

The class average in the midterm exam was evaluated to be 6.65 (out of 30).

What is the maximum number of students that could have scored more than 10 marks?

## Chebyshev's Inequality

Fix a probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ .

Let  $X$  be a random variable w.r.t.  $\mathcal{F}$ .

### Theorem (Chebyshev's Inequality)

Let  $X$  have mean  $\mathbb{E}[X] = \mu \in \mathbb{R}$  and variance  $\sigma^2 < +\infty$ . Then,

$$\mathbb{P}(\{|X - \mu| > \alpha\}) \leq \frac{\sigma^2}{\alpha^2}, \quad \forall \alpha > 0.$$

## Chernoff Bound

Fix a probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ .

Let  $X$  be a random variable w.r.t.  $\mathcal{F}$ .

### Theorem (Chernoff Bound)

Suppose that  $M_X(t) < +\infty$  for all  $t \in (-\varepsilon, \varepsilon)$  for some  $\varepsilon > 0$ . Then,

$$\mathbb{P}(\{X > \alpha\}) \leq \frac{M_X(t)}{e^{t\alpha}}, \quad \forall \alpha > 0, t > 0, t \in \text{ROC of } M_X.$$

Noting that the left-hand side of the above inequality is independent of  $t$ , we can optimise the right-hand side over  $t$  to get

$$\mathbb{P}(\{X > \alpha\}) \leq \inf_{\substack{t > 0, \\ t \in \text{ROC}}} \frac{M_X(t)}{e^{t\alpha}}, \quad \forall \alpha > 0.$$

## Jensen's Inequality

Fix a probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ .

### Theorem (Jensen's Inequality)

Let  $X : \Omega \rightarrow \mathbb{R}$  be a random variable w.r.t.  $\mathcal{F}$ .

Let  $g : \mathbb{R} \rightarrow \mathbb{R}$  be a **convex**, differentiable function, i.e.,

$$g(y) \geq g(x) + g'(x)(y - x) \quad \forall x, y \in \mathbb{R}.$$

If  $\left| \mathbb{E}[X] \right| < +\infty$  and  $\left| \mathbb{E}[g(X)] \right| < +\infty$ , then

$$\mathbb{E}[g(X)] \geq g(\mathbb{E}[X]).$$

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Corollary:

$$\mathbb{E}[X^2] \geq (\mathbb{E}[X])^2, \quad \mathbb{E}[|X|] \geq |\mathbb{E}[X]|, \quad \mathbb{E}[\log X] \leq \log \mathbb{E}[X].$$