



# Review of Mathematical Foundations – Part 3

# Objectives

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Objective

Review random variables &  
their distributions

# Discrete Random Variables

| Let  $x$  be a discrete random variable that can take any of the  $m$  different values in the set  $V = \{v_1, v_2, \dots, v_m\}$  with respective probabilities  $\{p_1, p_2, \dots, p_m\}$ , i.e.,  $p_i = \text{Prob}[x = v_i]$ .

$$- p_i \geq 0, \quad \sum_{j=1, \dots, m} p_j = 1.$$

| **Probability Mass Function**  $P(x)$  is used to represent the set of probabilities  $\{p_1, p_2, \dots, p_m\}$

$$P(x) \geq 0, \quad \sum_{x \text{ in } V} P(x) = 1$$

# Expected Value (Means) & Variance

| The **expected value** (mean) of  $x$ ,  $E[x]$ , often denoted  $\mu$

$$\mu = E[x] = \sum_{x \in \mathcal{V}} xP(x)$$

| The expected value of a function  $f(x)$ ,  $E[f(x)]$ ,

$$E[f(x)] = \sum_{x \in \mathcal{V}} f(x)P(x)$$

|  $E[\ ]$  is linear when viewed as an operator.

$$E[\alpha f(x) + \beta g(x)] =$$

| The **variance** of  $x$ ,  $\text{Var}[x]$ , often denoted  $\sigma^2$

$$\sigma^2 = \text{Var}(x) = E[(x-\mu)^2] = \sum_{x \in \mathcal{V}} (x-\mu)^2 P(x)$$

# Joint Distributions

- | Consider a pair of discrete random variables,  $x$  and  $y$ , taking values in  $V=\{v_1, v_2, \dots, v_m\}$  and  $W=\{w_1, w_2, \dots, w_n\}$  respectively.
  - $(x, y)$  to take a pair of values  $(v_i, w_j)$  with probability  $p_{ij}$
  - Or, we consider the **joint probability mass function**  $P(x, y)$

# Marginal Distributions



| Knowing  $P(x, y)$ , can we figure out  $P_x(x)$  or  $P_y(y)$  ?

➔ The concept of **marginal distribution** for  $x$  and  $y$  respectively.

# Statistical Independence



| Random variables  $x$  and  $y$  are said to be statistically independent if and only if  $P(x, y) = P_x(x) P_y(y)$

# Covariance

| Cov( $x, y$ ), often denoted  $\sigma_{xy}$

| **Covariance matrix**  $\Sigma$ ,  $\Sigma = E[(\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^t]$



# Conditional Density



|  $P(x|y) =$

| Similarly, we may write the Bayes Rule in terms of densities.

# How about continuous random variables?



- | Instead of  $P(x)$ , we have the **probability density function** (PDF)  $p(x)$
- | Some properties of  $p(x)$ :
- | The **cumulative distribution function** (CDF)  $F(x)$ :

# Continuous Random Variables

| Mean, variance, etc., are similarly defined, via integrals.

| Joint PDF  $p(x,y)$  of two variables

- Marginal PDFs for  $x$  and  $y$

- If  $x \sim p_x(x)$  and  $y \sim p_y(y)$  are independent  $p(x,y) =$

# Continuous Random Variables



| Conditional PDF  $p(x|y)$

| Bayes rule for PDF: