

# Basic Concepts of Probability

## Basic Properties : Events

- ①  $(A \cap B)' = A' \cup B'$
- ②  $(A \cup B)' = A' \cap B'$
- ③  $A \cup (B \cap C) = (A \cup B) \cap (A \cup C)$
- ④  $A \cap (B \cup C) = (A \cap B) \cup (A \cap C)$
- ⑤  $A \cup B = A \cup (B \cap A')$
- ⑥  $A = (A \cap B) \cup (A \cap B')$

## De Morgan's Law

- ①  $(A_1 \cup A_2 \cup \dots \cup A_n)' = A_1' \cap A_2' \cap \dots \cap A_n'$
- ②  $(A_1 \cap A_2 \cap \dots \cap A_n)' = A_1' \cup A_2' \cup \dots \cup A_n'$

## Permutation and Combination

$$nPr = n(n-1)(n-2)\dots(n-(r-1)) = \frac{n!}{(n-r)!}$$

$$nCr = C_r^n = \binom{n}{r} = \frac{n!}{r!(n-r)!}$$

$$nCr \cdot r! = nPr$$

## Binomial Coefficient $\rightarrow (i)$

- ①  $\binom{n}{r} = \binom{n}{n-r}$  for  $r=0, 1, \dots, n$
- ②  $\binom{n}{r} = \binom{n-1}{r} + \binom{n-1}{r-1}$  for  $1 \leq r \leq n$
- ③  $\binom{n}{r} = 0$  for  $r < 0$  or  $r > n$

## Basic Properties : Probability

- ①  $Pr(A) = Pr(A \cap B) + Pr(A \cap B')$
- ②  $Pr(A_1 \cup A_2 \cup \dots \cup A_n) = \sum_{i=1}^n Pr(A_i) - \sum_{i=1}^{n-1} \sum_{j=i+1}^n Pr(A_i \cap A_j)$   
Inclusion-Exclusion Principle  
 $+ \dots + (-1)^{n+1} Pr(A_1 \cap A_2 \cap \dots \cap A_n)$

## Conditional Probability

$$Pr(A|B) = \frac{Pr(A \cap B)}{Pr(B)}$$

- ①  $Pr(S|A) = 1$
- ②  $B_1, B_2, \dots$  are mutually exclusive (disjoint) events  
 $\longrightarrow Pr(\bigcup_{i=1}^{\infty} B_i | A) = \sum_{i=1}^{\infty} Pr(B_i | A)$

## Multiplication Rule of Probability

$$Pr(A \cap B) = Pr(A) Pr(B|A) \\ = Pr(B) Pr(A|B), \text{ providing } Pr(A) > 0, Pr(B) > 0$$

In general,  $Pr(A_1 \cap A_2 \cap \dots \cap A_n) = Pr(A_1) Pr(A_2 | A_1) Pr(A_3 | A_1 \cap A_2) \dots Pr(A_n | A_1 \cap A_2 \cap \dots \cap A_{n-1})$ ,  
providing  $Pr(A_1 \cap A_2 \cap \dots \cap A_{n-1}) > 0$ .

## The Law of Total Probability

Let  $A_1, A_2, \dots, A_n$  be a partition of  $S$ . Then for any event  $B$ ,

$$Pr(B) = \sum_{i=1}^n Pr(B \cap A_i) = \sum_{i=1}^n Pr(A_i) Pr(B|A_i)$$

## Bayes' Theorem

Let  $A_1, A_2, \dots, A_n$  be a partition of  $S$ . Then

$$Pr(A_k|B) = \frac{Pr(A_k) Pr(B|A_k)}{\sum_{i=1}^n Pr(A_i) Pr(B|A_i)} \\ = \frac{Pr(A_k) Pr(B|A_k)}{Pr(B)}$$

## Random Variables

Discrete Random Variables	Continuous Random Variables
<p>probability (mass) function</p> <ul style="list-style-type: none"> <li>- Must satisfy:           <ul style="list-style-type: none"> <li>① <math>f(x_i) \geq 0 \quad \forall x_i</math></li> <li>② <math>\sum_{i=1}^{\infty} f(x_i) = 1</math></li> </ul> </li> </ul>	<p><math>f_x(x)</math> probability density function (p.d.f.)</p> <ul style="list-style-type: none"> <li>- Must satisfy:           <ul style="list-style-type: none"> <li>① <math>f(x) \geq 0 \quad \forall x \in R_x</math></li> <li>② <math>\int_{R_x} f(x) dx = 1 \quad \text{or} \quad \int_{-\infty}^{\infty} f(x) dx = 1</math></li> <li>③ <math>\forall c, d \text{ s.t. } c &lt; d, \Pr(c \leq X \leq d) = \int_c^d f(x) dx</math></li> </ul> </li> </ul>
<p>Cumulative Distribution Function (CDF)</p> $F(x) = \sum_{t \leq x} f(t) = \sum_{t \leq x} \Pr(X=t)$ <ul style="list-style-type: none"> <li>① <math>\Pr(a \leq X \leq b) = \Pr(X \leq b) - \Pr(X &lt; a)</math>  <math>= F(b) - F(a-1)</math></li> <li>② <math>a = b \rightarrow \Pr(X = a) = F(a) - F(a-1)</math></li> </ul>	<p><math>F_x(x)</math></p> $F(x) = \int_{-\infty}^x f(t) dt$ <ul style="list-style-type: none"> <li>① <math>\Pr(a \leq X \leq b) = \Pr(a &lt; X \leq b)</math>  <math>= F(b) - F(a)</math></li> <li>② <math>f(x) = \frac{d F(x)}{dx} \rightarrow \text{if the derivative exists}</math></li> </ul>
<p>Mean (Expectation) and Variance</p> $\mu_x = E(X) = \sum_i x_i f_x(x_i) = \sum_x x f_x(x)$ $E[g(x)] = \sum_x g(x) f_x(x)$ $\sigma_x^2 = V(x) = E[(X - \mu_x)^2] = \sum_x (x - \mu_x)^2 f_x(x)$	$\mu_x$ $\sigma_x^2$ $\mu_x = E(X) = \int_{-\infty}^{\infty} x f_x(x) dx$ $E[g(x)] = \int_{-\infty}^{\infty} g(x) f_x(x) dx$ $\sigma_x^2 = V(x) = E[(X - \mu_x)^2] = \int_{-\infty}^{\infty} (x - \mu_x)^2 f_x(x) dx$ <p><math>g(x) = x^k \rightarrow k\text{-th moment of } X</math></p> <ul style="list-style-type: none"> <li>① <math>E(aX + b) = aE(X) + b \rightarrow a, b \text{ are constants}</math></li> <li>② <math>V(x) = E(X^2) - [E(X)]^2</math></li> <li>③ <math>V(aX + b) = a^2 V(X)</math></li> </ul>

### Chebyshev's Inequality

$$\Pr(|X - \mu| \geq k\sigma) \leq \frac{1}{k^2}$$

$$\Pr(|X - \mu| < k\sigma) \geq 1 - \frac{1}{k^2}$$

## 2D RVs , Conditional Probability Distributions