

# Probability Theory

## Sets

### Definitions

Keyword	Definition
Sample space $S$	The set of all possible outcomes.
Event $A$	An event $A$ is a subset of $S$ .
$A \cap B$	$A$ and $B$ occurred.
$A \cup B$	$A$ or $B$ occurred.
$\overline{A}$	$A$ did not occur.

Properties of set operations.

**Commutative**       $A \cap B = B \cap A$   
 $A \cup B = B \cup A$

**Associative**       $(A \cap B) \cap C = A \cap (B \cap C)$   
 $(A \cup B) \cup C = A \cup (B \cup C)$

### Definition

$A$  and  $B$  are **mutually exclusive** iff  $A \cap B = \emptyset$

The following identities are true.

$$\begin{aligned} A \cap \overline{A} &= \emptyset \\ A \cup \overline{A} &= S \\ S - B &= \overline{B} \\ A - B &= A \cap \overline{B} \\ \overline{A \cup B} &= \overline{A} \cap \overline{B} \\ \overline{A \cap B} &= \overline{A} \cup \overline{B} \end{aligned}$$

## Probability

The probability  $P(A)$  of  $A$  happening is defined as

$$P(A) = \lim_{N \rightarrow \infty} \frac{N_A}{N}$$

Where  $N_A$  is the number of events in  $N$  experiments.

Properties of probabilities.

- $0 \leq P(A) \leq 1$
- $P(A \cap \overline{A}) = 0$
- $P(A \cup \overline{A}) = 1$
- $P(\overline{A}) = 1 - P(A)$

The union of two events  $P(A \cup B) = P(A) + P(B) - P(A \cap B)$

- If  $A$  and  $B$  are **mutually exclusive**, then  $P(A \cup B) = P(A) + P(B)$
- Extending for three events:

$$P(A \cup B \cup C) = P(A) + P(B) + P(C) - P(A \cap B) - P(B \cap C) - P(A \cap C) + P(A \cap B \cap C)$$

This can be proved using the rule for two events on  $P(A \cup (B \cup C))$

### Definition

**Conditional probability:**  $P(B|A)$  is the probability of  $B$  occurring given  $A$ .

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

Because  $P(A \cap B) = P(A)P(B|A)$ , we have

$$P(A)P(A|B)P(A|B \cap C) = P(A \cap B)P(A|B \cap C) = P(A \cap B \cap C)$$

### Bayes Theorem

It is obvious that

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

Provided  $P(B) \neq 0$

It is also true that

$$P(A|B) = \frac{P(A)P(B|A)}{P(A)P(B|A) + P(\bar{A})P(B|\bar{A})}$$

## Combinatorics

### Permutations and Combinations

- The number of permutations for choosing  $r$  elements from  $n$  elements is

$${}^n P_r = \frac{n!}{(n-r)!}$$

- The number of combinations (order doesn't matter) is therefore

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

${}^n C_r$  is called the **binomial coefficients**.

$$(p+q)^n = \sum_{r=0}^n {}^n C_r q^r p^{n-r}$$

From **Pascal's triangle** we have  ${}^n C_r = {}^{n-1} C_r + {}^{n-1} C_{r-1}$ , which we can also prove

$$\frac{(n-1)!}{r!(n-1-r)!} + \frac{(n-1)!}{(r-1)!(n-r)!} = \frac{(n-r)(n-1)! + r(n-1)!}{r!(n-r)!}$$

$$= \frac{n!}{r!(n-r)!}$$

### Arrangements

Suppose there are  $r$  identical objects  $R$ ,  $t$  of  $T$ ,  $s$  of  $S$ , then the number of distinguishable arrangement is

$$\frac{n!}{r!s!t!}$$

Where  $n = r + s + t$ , and  $r!$  is the number of (non-distinguishable) arrangements for  $R$ , etc.

### Balls in Boxes

How to put  $p$  balls into  $q$  boxes.

We can write the situation out in  $\square\square \mid \square \mid \mid \square \mid \dots$ , there are  $p$  balls and  $q - 1$  walls.

- Number of permutations of all objects is  $(p + q - 1)!$
- Number of distinguishable arrangement is

$$\frac{(p + q - 1)!}{p!(q - 1)!}$$

## Discrete Probability Distributions

### Definitions

Keyword	Definition
Random variable	A variable whose value is determined by the outcome of an experiment.
Discrete variable	The variable only takes discrete values.
Probability function	$f(x)$ is the probability that $X$ takes the value $x$ .

If there are only  $n$  values that  $f(x)$  can take, is true that

$$\sum_{i=0}^{n-1} f(x_i) = 1$$

The **cumulative probability function** is

$$F(x) = P(X \leq x) = \sum_{x_i \leq x} f(x_i)$$

$$P(a < x \leq b) = F(b) - F(a)$$

### Mean and Variance

#### Definition

**Mean** is also called the expected value, denoted  $E(X)$  or  $\langle X \rangle$

$$E(X) = \sum_{i=0}^{n-1} x_i f(x_i)$$

## Properties of Mean

$$E(aX) = aE(X)$$

$$E(X + Y) = E(X) + E(Y) \text{ where } X \text{ and } Y \text{ are independent}$$

$$E(g(X)) = \sum_{i=0}^{n-1} g(x_i) f(x_i)$$

### Definition

**Variance** measures how the results spread around the mean.

$$\sigma^2 = E((X - E(x))^2) = \overline{(X - \bar{X})^2}$$

The **standard deviation**  $\sigma = \sqrt{\sigma^2}$

An alternative way to calculate the variance is

$$\begin{aligned} \sigma^2 &= E((X - \mu)^2) \\ &= E(X^2 - 2X\mu + \mu^2) \\ &= E(X^2) - 2\mu E(X) + \mu^2 \\ &= E(X^2) - \mu^2 \end{aligned}$$

## Discrete Probability Distributions

### The Binomial Distribution

#### Note

The handout use a different way of calculating expected value and variance.

Expection of value of  $X$

$$\begin{aligned} E(X) &= \sum_{k=0}^m k \binom{m}{k} p^k (1-p)^{m-k} \\ &= \sum_{k=0}^m q \times \binom{m}{k} \left( \frac{d}{dq} q^k \right) (1-p)^{m-k} \text{ where } p = q \\ &= q \times \frac{d}{dq} \sum_{k=0}^m \binom{m}{k} q^k (1-p)^{m-k} \\ &= q \times \frac{d}{dq} (q + 1 - p)^m \text{ by binomial theorem} \\ &= mq(q + 1 - p)^m \\ &= mp \end{aligned}$$

Variance of  $X$

$$\begin{aligned}
 E(X^2) &= \sum_{k=0}^m k^2 \binom{m}{k} q^k (1-p)^{n-k} \\
 &= \sum_{k=0}^m (k(k-1) + k) \binom{m}{k} q^k (1-p)^{n-k} \\
 &= mp + \sum_{k=0}^m k(k-1) \binom{m}{k} q^k (1-p)^{n-k} \text{ by previous result} \\
 &= mp + \sum_{k=0}^m k(k-1) \binom{m}{k} q^k (1-p)^{n-k} \\
 &= mp + q^2 \times \frac{d^2}{dq^2} \sum_{k=0}^m \binom{m}{k} q^k (1-p)^{n-k} \\
 &= mp + q^2 \times \frac{d^2}{dq^2} (q+1-p)^m \\
 &= mp + p^2 \times m(m-1) \\
 E(X^2) - E(X)^2 &= mp(1-p)
 \end{aligned}$$

### The Poisson Distribution

For binomial distribution where  $p \ll 1$  and  $np = \lambda$ , as  $n \rightarrow \infty$ , we have another well defined distribution

$$\begin{aligned}
 \mu &= np = \lambda \\
 \sigma^2 &= np(1-p) \\
 &= \lambda
 \end{aligned}$$

When  $n$  is large and  $p$  is small, the poisson distribution is a good approximation for the binomial distribution.

#### Note

Missing notes because the camera in the recording pointing towards the sheet of paper is off.

$$\begin{aligned}
 P(X = r) &= \frac{\lambda^r e^{-\lambda}}{r!} \\
 \sum_{r=0}^{\infty} P(X = r) &= e^{-\lambda} \sum_{r=0}^{\infty} \frac{\lambda^r}{r!} \\
 &= 1
 \end{aligned}$$

The poisson distribution is useful for events that happens in time:

- Probability of something happening at a time is very small.
- **Over a unit time**, the probability is  $\lambda^r e^{-\lambda} / r!$

### Continuous Probability Distribution

The normal distribution is a **continuous probability distribution** given by the **probability density function**, which gives the *probability per unit length*.

$$P(x \leq X \leq x + dx) = f(x)dx$$

The probability for any individual  $P(X = x)$  is zero. For a fixed range  $\alpha \leq X \leq \beta$

$$P(\alpha \leq X \leq \beta) = \int_{\alpha}^{\beta} f(x)dx$$

$f(x)$  obeys properties:

- $0 \leq f(x) < \infty$  for all  $x$
- $\int_{-\infty}^{\infty} f(x)dx = 1$

### Definition

The **cumulative probability function** is defined as

$$F(x) = P(X \leq x) = \int_{-\infty}^x f(x)dx$$

Which has property  $F'(x) = f(x)$ .

And also these equations are true.

$$P(\alpha \leq X \leq \beta) = F(\beta) - F(\alpha)$$

$$\mu = E(X) = \int_{-\infty}^{\infty} xf(x)dx$$

$$\sigma^2 = E(X^2) - E(X)^2 = \int_{-\infty}^{\infty} x^2 f(x)dx - \mu^2$$

### Uniform Probability Distribution

$$f(x) = \begin{cases} \frac{1}{\beta-\alpha} & \text{when } \alpha \leq x \leq \beta \\ 0 & \text{otherwise} \end{cases}$$

$$F(x) = \begin{cases} 0 & \text{when } x < \alpha \\ \frac{x-\alpha}{\beta-\alpha} & \text{when } \alpha \leq x \leq \beta \\ 1 & \text{when } x > \beta \end{cases}$$

$$\mu = \frac{\alpha + \beta}{2}$$

$$\sigma^2 = \frac{(\beta - \alpha)^2}{12}$$

This makes sense because  $\sigma^2$  should only depend on the difference between  $\alpha$  and  $\beta$ , not their individual values.

### The Normal Distribution

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\left(\frac{x-\mu}{\sqrt{2}\sigma}\right)^2\right)$$

$$F(x) = \frac{1}{2} + \frac{1}{2} \exp\left(\frac{x-\mu}{\sqrt{2}\sigma}\right)$$

You are required to know how to prove the result for  $F(x)$  and the mean, variance of the normal distribution from definition, not included here.

**Central Limit Theorem**

If  $x$  are samples taken from a distribution, then the arithmetic mean over  $n$  samples is normally distributed as  $n$  becomes large.

$$\bar{x} = \frac{1}{n} \sum_{i=0}^{n-1} x_i$$