

# STA257: PROBABILITY AND STATISTICS I

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# 1 Probability and Counting

## 1.1 Introduction

**Experiments:** situations where outcome is random. eg. flipping a coin is an experiment.

**Sample space:** set of all possible outcomes, denoted  $S$  or  $\Omega$ . The number of elements in the sample space (cardinality) is denoted  $|\Omega|$ .

**Event:** a subset of a sample space.

**Outcome:** a particular element of a sample space  $s_1 \in \Omega$ .

## 1.2 Set Theory

### 1.2.1 Definitions

- **union:**  $A \cup B$ . Elements in either  $A$  or  $B$ .
- **intersection:**  $A \cap B$ . Elements in both  $A$  and  $B$ .
- **complement** of  $A$ :  $A^c$ . Elements not in  $A$ .
- **empty set:**  $\emptyset$ . Set with no elements in it.
- $A$  and  $B$  are **disjoint**:  $A \cap B = \emptyset$ . There are no elements in the intersection of  $A$  and  $B$ .

### 1.2.2 Laws of Set Theory

1. **commutativity:**  $A \cup B = B \cup A$ ,  $A \cap B = B \cap A$
2. **associativity:**  $(A \cup B) \cup C = A \cup (B \cup C)$ ,  $(A \cap B) \cap C = A \cap (B \cap C)$
3. **distributivity:**  $(A \cup B) \cap C = (A \cap C) \cup (B \cap C)$ ,  $(A \cap B) \cup C = (A \cup C) \cap (B \cup C)$

## 1.3 Probability Measures

**Probability measure:** a function which maps subsets of  $\Omega$ , which can be defined on any space, to real numbers  $\mathbb{R}$ .

### 1.3.1 Axioms of Probability Measures

- $P(\Omega) = 1$
- $\forall A \in \Omega, P(A) \geq 0$
- if  $A_1, A_2, \dots, A_n, \dots$  are mutually disjoint, then  $P(\bigcup_{i=1}^{\infty} A_i) = \sum_{i=1}^{\infty} P(A_i)$ .

### 1.3.2 Properties of Probability Measures

- $\forall A \in \Omega, P(A^c) = 1 - P(A)$

Proof:

$$\begin{aligned} 1 &= P(\Omega) && \text{by Axiom 1} \\ &= P(A \cup A^c) && \text{by definition of complement} \\ &= P(A) + P(A^c) && \text{by Axiom 3 (since } A, A^c \text{ are disjoint)} \end{aligned}$$

Rearrange this to see that  $P(A^c) = 1 - P(A)$ .

- $P(\emptyset) = 0$

Proof:

$$\begin{aligned} P(\Omega) &= P(\Omega \cup \emptyset) && \text{since } \Omega \cup \emptyset = \Omega \\ &= P(\Omega) + P(\emptyset) && \text{by Axiom 3 (since } \Omega, \emptyset \text{ are disjoint)} \end{aligned}$$

So  $P(\emptyset) = 0$ .

- For  $A, B \subseteq \Omega, A \subseteq B \implies P(A) \leq P(B)$

Proof:

$$\begin{aligned} P(B) &= P(A \cup (B \cap A^c)) \\ &= P(A) + P(B \cap A^c) \end{aligned} \quad \text{by Axiom 3 (since } A, A^c \text{ are disjoint)}$$

But note that  $P(B \cap A^c) \geq 0$  by Axiom 2.

Then  $P(B) = P(A) + P(B \cap A^c) \geq P(A)$ .

- For  $A, B \subseteq \Omega, P(A \cup B) = P(A) + P(B) - P(A \cap B)$

Proof:

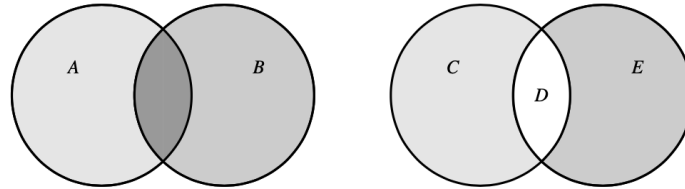
Case 1:  $A, B$  are disjoint. Then  $A \cap B = \emptyset \implies P(A \cap B) = 0$ .

$$\begin{aligned} P(A \cup B) &= P(A) + P(B) && \text{by Axiom 3 (since } A, B \text{ are disjoint)} \\ &= P(A) + P(B) + P(A \cap B) && \text{since we can add 0 wherever we want} \end{aligned}$$

Case 2:  $A, B$  not disjoint. Then  $A \cap B \neq \emptyset$ .

Let  $C = A \cap B^c, D = A \cap B, E = A^c \cap B$ .

Then  $C, D, E$  are disjoint, and  $A = C \cup D, B = D \cup E$ , and  $A \cup B = C \cup D \cup E$ .



$$\begin{aligned} P(A) + P(B) - P(A \cap B) &= P(C \cup D) + P(D \cup E) - P(D) && \text{by how we defined } C, D, E \\ &= P(C) + P(D) + P(D) + P(E) - P(D) && \text{by Axiom 3 and disjointness of } C, D, E \\ &= P(C) + P(D) + P(E) \\ &= P(C \cup D \cup E) && \text{by Axiom 3 and disjointness of } C, D, E \\ &= P(A \cup B) \end{aligned}$$

## 1.4 Counting

**Multiplication principle:** if there are  $m$  ways to do one thing, and  $n$  ways to do another thing, then there are  $mn$  ways to do both things.

**Permutation:** ordered arrangement of objects.

- Sampling **with replacement** means that duplicate item selection is allowed. (can pick the same object twice). For a set of size  $n$  and a **sample size** (number of items selected)  $r$ , there are  $n^r$  possible selections.
- Sampling **without replacement** means that each item is selected once at most. For a set of size  $n$  and a sample size  $r$ , there are  $n(n-1) \dots (n-r+1) = \frac{n!}{(n-r)!}$  possible selections. In particular, there are  $n(n-1) \dots (1) = n!$  ways to order  $n$  elements.

**Combination:** arrangement of objects *without regard to order*. Think about this as the ways to select objects without replacement, divided by the ways that those objects can be ordered. For a set of size  $n$  and a sample size  $r$ , we express the combination as follows:

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

**Binomial expansion:**

$$(a+b)^n = \sum_{k=0}^n \binom{n}{k} a^k b^{n-k}$$

In particular, for  $a = b = 1$ ,

$$(1+1)^n = 2^n = \sum_{k=0}^n \binom{n}{k} (1)^k (1)^{n-k} = \sum_{k=0}^n \binom{n}{k}$$

The number of ways to group  $n$  objects into  $r$  classes, with  $n_i$  objects in the  $i$ th classes, where  $1 < i < r$ , is given by the following formula:

$$\binom{n}{n_1 n_2 \dots n_r} = \frac{n!}{n_1! n_2! \dots n_r!}$$

Proof: There are  $\binom{n}{n_1}$  ways to select the first class,  $\binom{n-n_1}{n_2}$  ways to select the second class, and so on. Repeat this for all  $r$  classes, and then apply the multiplication rule. Then we have that

$$\begin{aligned} \binom{n}{n_1} \binom{n-n_1}{n_2} \dots \binom{n-n_1-\dots-n_{r-1}}{n_r} &= \frac{n!}{n_1! (n-n_1)!} \frac{(n-n_1)!}{n_2! (n-n_1-n_2)!} \dots \frac{(n-n_1-\dots-n_{r-1})!}{n_r! 0!} \\ &= \frac{n!}{n_1! \cancel{(n-n_1)!}} \frac{\cancel{(n-n_1)!}}{n_2! \cancel{(n-n_1-n_2)!}} \dots \frac{\cancel{(n-n_1-\dots-n_{r-1})!}}{n_r! 0!} \\ &= \frac{n!}{n_1! n_2! \dots n_r!} \end{aligned}$$

## 1.5 Conditional Probability and Independence

**Conditional probability:** probability that some event will occur given that another event has occurred:

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

Two events are **independent** if knowing that one has occurred gives no information about the likelihood of the other occurring. Events  $A, B$  are independent if and only if any of the following hold:

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

From the definition of conditional probability, we can derive **Bayes' Rule**, which describes the probability of an event given prior knowledge of conditions related to the event:

$$\begin{aligned} P(A|B) P(B) &= P(A \cap B) = P(B \cap A) = P(B|A) P(A) \\ \implies P(A|B) P(B) &= P(B|A) P(A) \\ \implies P(A|B) &= \frac{P(B|A) P(A)}{P(B)} \end{aligned}$$

## 1.6 Law of Total Probability

Let  $B_1, B_2, \dots, B_n$  be sets satisfying the following conditions:

1.  $B_1 \cup B_2 \cup \dots \cup B_n = \Omega$  (the  $B_i$ 's are a **partition** of  $\Omega$ )
2.  $\forall i, j \in [1, n] \subseteq \mathbb{N}, i \neq j \implies B_i \cap B_j = \emptyset$  (pairwise disjoint)
3.  $\forall i \in [1, n] \subseteq \mathbb{N}, P(B_i) > 0$  (strictly positive probability),

we can conclude that for any event  $A$ , we have that

$$P(A) = \sum_{i=1}^n P(A|B_i) P(B_i)$$

Proof: Since all  $B_i$ 's are pairwise disjoint, all  $A \cap B_i$ 's must also be pairwise disjoint. Then

$$\begin{aligned}
P(A) &= P(A \cap \Omega) \\
&= P\left(A \cap \left(\bigcup_{i=1}^n B_i\right)\right) && \text{by condition 1} \\
&= P\left(\bigcup_{i=1}^n (A \cap B_i)\right) \\
&= \sum_{i=1}^n P(A \cap B_i) && \text{by Axiom 3 of probability measures} \\
&= \sum_{i=1}^n P(A|B_i) P(B_i) && \text{by definition of conditional probability}
\end{aligned}$$

Under the same conditions, we can also conclude an alternate form of Bayes' Rule:

$$P(B_j|A) = \frac{P(A|B_j) P(B_j)}{\sum_{i=1}^n P(A|B_i) P(B_i)}$$

## 1.7 Equations

Axioms	$P(\Omega) = 1$ $(A) \geq 0$ for mutually disjoint sets, $P(\bigcup_{i=1}^{\infty} A_i) = \sum_{i=1}^{\infty} P(A_i)$
Properties	$P(A^c) = 1 - P(A)$ $P(\emptyset) = 0, P(\Omega) = 1$ $A \subseteq B \implies P(A) \leq P(B)$ $P(A \cup B) = P(A) + P(B) - P(A \cap B)$
Permutations	with replacement: $n^r$ without replacement: $\frac{n!}{(n-r)!}$
Combinations	$\binom{n}{r} = \frac{n!}{(n-r)! r!}$
Binomial Expansion	$(a + b)^n = \sum_{i=1}^n \binom{n}{i} a^i b^{n-i}$
Grouping $n$ objects into $r$ classes	$\binom{n}{n_1 n_2 \dots n_r} = \frac{n!}{n_1! n_2! \dots n_r!}$
Conditional probability	$P(A B) = \frac{P(A \cap B)}{P(B)}$
Bayes' Rule	$P(A B) = \frac{P(B A) P(A)}{P(B)}$ $P(B_j A) = \frac{P(A B_j) P(B_j)}{\sum_{i=1}^n P(A B_i) P(B_i)}$
Law of Total Probability	$P(A) = \sum_{i=1}^n P(A B_i) P(B_i)$

## 2 Random Variables

### 2.1 Discrete Random Variables

#### 2.1.1 Bernoulli

#### 2.1.2 Binomial

#### 2.1.3 Geometric

#### 2.1.4 Negative Binomial

#### 2.1.5 Hypergeometric

#### 2.1.6 Poisson

### 2.2 Continuous Random Variables

#### 2.2.1 Uniform

#### 2.2.2 Exponential

#### 2.2.3 Gamma

#### 2.2.4 Beta

#### 2.2.5 Uniform

#### 2.2.6 Standard Normal

#### 2.2.7 General Normal

### 2.3 Transformations of Random Variables

### **3 Expected Values**

#### **3.1 Mean and Variance**

##### **3.1.1 LOTUS**

##### **3.1.2 Inequalities**

#### **3.2 Moment Generating Functions**

## 4 Joint Distributions

### 4.1 Joint and Marginal Distributions

#### 4.1.1 Discrete

#### 4.1.2 Continuous

### 4.2 Independence in Joint Distributions

### 4.3 Conditional Distributions

#### 4.3.1 Discrete

#### 4.3.2 Continuous

### 4.4 Functions of Joint Distributions

### 4.5 Order Statistics