

Syllabus

- Meeting Time: Tue, Thr 9:00 - 10:15am
- Pre-recommended: Mathematical Statistics and Regression Analysis (Undergraduate level)
- TEXTBOOK: Statistical Inference, 2nd edition; Casella and Berger, 2002.
- Homework 10%, Test I & II, 20% each, Midterm & Final 25%
- HOMEWORK: Approximately 10 homework assignments
- All exams are closed book and notes.

Ch 1. Probability Theory

Intro: Goal

The purpose of this chapter is to define probability and discuss some of its properties. Probability is the foundation upon which almost all statistics is built, and provides a means for modeling populations, experiments, sampling and almost anything that could be considered a random phenomenon. Just as statistics builds upon the foundation of probability theory, probability theory builds on set theory

1.1. Set Theory

- Probability of "SOMETHING"
- Basics
 - **Set:** A collection of objects (or elements). Use the uppercase letters for set (A, B, C, \dots) and the lowercase letters for the elements $(x, y, z \dots)$.
 - **Family or Class:** Set of sets. Elements are sets.
 - **Notations:**
 - Element: $x \in A$, $x \notin A$
 - Subset: $A \subset B$, $x \in A \rightarrow x \in B$
 - Equivalent sets: $A = B$, $A \subset B$ and $B \subset A$
 - Empty set: \emptyset , no element in the set
 - Universal set: Ω

1.1. Set Theory

Definition (Sample Space S)

The set, S , of all possible outcomes of a particular experiment.

Example:

Experiment	Sample Space
Tossing a coin	$S = \{H, T\}$
Measuring weights	$S = \{x : 0 \leq x \leq 500\}$

Definition (Event)

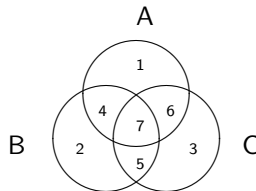
Any collection of possible outcomes of an experiment. That is, any subset of sample space S .

1.1. Set Theory

- Elementary Set Operations

- Union: $A \cup B = \{x : x \in A \text{ or } x \in B\}$.
- Intersection: $A \cap B = \{x : x \in A \text{ and } x \in B\}$.
- Compliment: $A^c = \{x : x \notin A\}$.
- Set difference:
 $A \setminus B = A - B = \{x : x \in A \text{ and } x \notin B\} = A \cap B^c$.

- Venn Diagram



1.1. Set Theory

Theorem

Idempotent Law:

$$A \cap A = A, A \cup A = A.$$

Commutative Law:

$$A \cap B = B \cap A, A \cup B = B \cup A$$

Distributive Law:

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

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

DeMorgan's Law:

$$(A \cap B)^c = A^c \cup B^c, (A \cup B)^c = A^c \cap B^c$$

Note: Set Operations of more than two sets

$$\bigcup_{i=1}^{\infty} A_i, \bigcap_{i=1}^{\infty} A_i, \bigcup_{a \in \Gamma} A_a, \bigcap_{a \in \Gamma} A_a.$$

1.1. Set Theory

Definition

Two events A and B are *mutually exclusive* if $A \cap B = \emptyset$.

Definition

$\{A_1, A_2, \dots\}$ is called a *partition* of a sample space if $A_i \cap A_j = \emptyset$ for all $i \neq j$ and $A_1 \cup A_2 \cup \dots = S$.

1.2. Probability Theory

Probability:

- Frequency of occurrence:
Experiment is performed a number of times. Check the frequency of outcomes of interest.
$$\text{Probability} = \text{number of outcomes of interest} / \text{number of experiments}$$
- Axiomatic Probability:
Set function that satisfies a certain axioms

1.2. Probability Theory

1.2.1. Axiomatic Foundation

Definition (Sigma Algebra, or σ -algebra, or σ -field, or Borel Field \mathcal{B})

A collection of subsets of S , \mathcal{B} , that satisfies

S1: $\emptyset \in \mathcal{B}$

S2: If $A \in \mathcal{B}$ then $A^c \in \mathcal{B}$

S3: If $A_1, A_2, \dots \in \mathcal{B}$ then $\cup_{i=1}^{\infty} A_i \in \mathcal{B}$

Note: S1-S3 also implies $S \in \mathcal{B}$ and it is closed under countable intersection.

Example: Let \mathcal{B} be a set of all subsets of $\{1, 2, 3\}$. That is

$$\mathcal{B} = \{\emptyset, \{1\}, \{2\}, \{3\}, \{1, 2\}, \{1, 3\}, \{2, 3\}, \{1, 2, 3\}\}.$$

Is this sigma algebra ? If S is finite or countable, then

$$\mathcal{B} = \{\text{all subset of } S, \text{ including } S\}$$

1.2. Probability Theory

1.2.1. Axiomatic Foundation (Axioms of Probability)

Axioms of Probability

Definition

Given S and associated sigma algebra \mathcal{B} , a *probability function* is a function P with domain \mathcal{B} that satisfies

A1: $P(A) \geq 0$ for all $A \in \mathcal{B}$

A2: $P(S) = 1$

A3: If $A_1, A_2, \dots \in \mathcal{B}$ and pairwise mutually exclusive then

$$P\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} P(A_i)$$

- Associated sigma algebra
- Probability Space: (S, \mathcal{B}, P) .

1.2. Probability Theory

1.2.1. Axiomatic Foundation

- Examples

1. Three-sided die with number 1, 2 and 3. $S = \{1, 2, 3\}$

$$\mathcal{B} = \{\emptyset, \{1\}, \{2\}, \{3\}, \{1, 2\}, \{1, 3\}, \{2, 3\}, \{1, 2, 3\}\}.$$

Define P as

$$P(\emptyset) = 0$$

$$P(\{1\}) = P(\{2\}) = P(\{3\}) = 1/3$$

$$P(\{1, 2\}) = P(\{1, 3\}) = P(\{2, 3\}) = 2/3$$

$$P(\{1, 2, 3\}) = P(S) = 1$$

2. $S = [0, \infty)$, $\mathcal{B} = ?$. Define P as, for $A \in \mathcal{B}$, $P(A) = \int_A e^{-x} dx$.
(See Example 1.2.3 for $S = (-\infty, \infty)$)

1.2. Probability Theory

1.2.2. The calculus of probability

Theorem

(See Theorem 1.2.8.) Given (S, \mathcal{B}, P) , for $A \in \mathcal{B}$,

- 1) $P(\emptyset) = 0$
- 2) $P(A) \leq 1$
- 3) $P(A^c) = 1 - P(A)$

Theorem

(See Theorem 1.2.9.) Given (S, \mathcal{B}, P) , for $A, B \in \mathcal{B}$,

- 1) $P(B \cap A^c) = P(B) - P(A \cap B)$
- 2) $P(A \cup B) = P(A) + P(B) - P(A \cap B)$
- 3) If $A \subset B$ then $P(A) \leq P(B)$
- 4) $P(A \cap B) \geq P(A) + P(B) - 1$
- 4) Bonferroni's inequality

1.2. Probability Theory

1.2.3. Counting

Consider the sample space with finite number of elements.

$$S = \{s_1, s_2, \dots, s_N\}.$$

Let all outcomes(elements) are equally likely, that is,
 $P(\{s_i\}) = 1/N$, for all i . Then, for $A \subset S$,

$$P(A) = \sum_{s_i \in A} P(\{s_i\}) = \sum_{s_i \in A} \frac{1}{N} = \frac{\# \text{ of elements in } A}{\# \text{ of elements in } S}$$

satisfies 3 axioms of probability.

1.2. Probability Theory

1.2.3. Counting

Theorem (Fundamental Theorem of Counting)

If a job consist of k separate tasks, the i -th of which can be done in n_i ways, $i = 1, \dots, k$, then the entire job can be done in $n_1 \times \dots \times n_k$ ways.

Definition

$$n! = n \cdot (n - 1) \cdot (n - 2) \cdots 2 \cdot 1$$

Definition (Binomial Coefficient)

$$\binom{n}{r} = \frac{n!}{r!(n-r)!} \quad , \quad n \geq r$$

1.3. Conditional Probability & Independence

- Probability that we have rain tomorrow: Probability of rain tomorrow given rain today.
 - Conditional probability is a probability defined on an updated sample space based on the available information.
- ▷ Example: Toss a fair die. $A = \{1\}$, $B = \{1, 3, 5\}$. What is the probability of throwing a 1 given that an odd number is thrown ?

Definition

If A and B are events in S , and $P(B) > 0$, then the *conditional probability* of A given B is

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

1.3. Conditional Probability & Independence

- Note: Conditional probability also satisfies 3 axioms. That is,

A1: $P(A|B) \geq 0$ for all $A \in \mathcal{B}$

A2: $P(S|B) = 1$

A3: If $A_1, A_2, \dots \in \mathcal{B}$ and pairwise mutually exclusive then

$$P(\cup_{i=1}^{\infty} A_i | B) = \sum_{i=1}^{\infty} P(A_i | B)$$

▷ Example: Medical Test

In case of disease: test will fail to detect on 10% of cases

In case of no-disease: test will produce a false positive in 20% of cases.

We have 30% of individuals tested actually have disease.

1.3. Conditional Probability & Independence

▷ Example: Medical Test - Continued

Want to know (i) lab's overall error rate and (ii) the likelihood of having disease if lab return a positive result (+).

$$P(+|D) = 0.9, \quad P(-|D) = 0.1,$$

$$P(+|N.D.) = 0.2, \quad P(-|N.D.) = 0.8, \quad P(D) = 0.3.$$

Prob	Positive	Negative
Disease	0.27(=0.9·0.3)	0.1×0.3
No Disease	0.2×0.7	0.8×0.7

$$P(\text{overall error}) = 0.03 + 0.14$$

$$P(\text{Disease} \mid +) = 27/41 \text{ by Bayes' rule.}$$

1.3. Conditional Probability & Independence

Theorem

Let $\{A_1, A_2, \dots\}$ be a partition of the sample space S and B be any subset of \mathcal{B} . Then

$$P(B) = \sum_{j=1}^{\infty} P(A_j \cap B) = \sum_{j=1}^{\infty} P(B|A_j)P(A_j) \quad ,$$

*(law of the total probability)
and for each $i = 1, 2, \dots$*

$$P(A_i|B) = \frac{P(B|A_i)P(A_i)}{\sum_{j=1}^{\infty} P(B|A_j)P(A_j)}.$$

(Bayes' Rule)

1.3. Conditional Probability & Independence

▷ Example:

There are three rental agencies A , B and C . Probability of having unsafe car from these agencies are 0.1, 0.08 and 0.125 respectively. An agency is chosen randomly and a car tested is found to be unsafe. What is the conditional probability that the car came from agency A , B or C ?

$$P(Unsafe) =$$

$$P(A|Unsafe) =$$

$$P(B|Unsafe) =$$

$$P(C|Unsafe) =$$

1.3. Conditional Probability & Independence

Definition

Events A_1, A_2, \dots, A_n are called *mutually independent* provided the probability of the intersection of any sub-collection of events is the product of the probabilities of the events in the sub-collection. That is, if for any sub-collection $A_{i_1}, A_{i_2}, \dots, A_{i_k}$,

$$P\left(\bigcap_{j=1}^k A_{i_j}\right) = \prod_{j=1}^k P(A_{i_j}).$$

1.4. Random Variables

In most cases, we have interest in probabilities of certain event or function of elements of the sample space.

$$(S, \mathcal{B}, P) \xrightarrow{R.V. (X)} (\mathcal{R}, \mathcal{B}^1, P_X)$$

\mathcal{R} : Real Number , \mathcal{B}^1 : σ -field generated by R

P_X : Induced probability from P

Definition

A random variable is a function from a sample space S into the real numbers.

1.4. Random Variables

▷ Example: Toss a fair coin 3 times

$$S = \{hhh, hht, hth, htt, thh, tht, tth, ttt\}$$

\mathcal{B} = Collection of all subsets of S

Let X be a number of heads. Then

s	$P(s)$	$X(s) = x$
hhh	1/8	3
hht	1/8	2
hth	1/8	2
htt	1/8	1
thh	1/8	2
tht	1/8	1
tth	1/8	1
ttt	1/8	0

1.4. Random Variables

▷ Example - Continued

$X = x$	$P(X = x) = P_X(x)$
0	
1	
2	
3	

$$P(X = 1) = P_X(1) = P(s \in S : X(s) = 1) = \frac{3}{8}$$

◁ Note:

Random variable: Uppercase letter (X, Y, \dots)

Values of RV: Lowercase letter (x, y, \dots)

Subscript X is often deleted

1.5. Distribution Functions

Most general tool to specify the distribution (probability structure) of a random variable.

Definition

The cumulative distribution function (cdf) for a random variable X is

$$F_X(x) = P(X \leq x) \quad , \quad \text{for all } x \in \mathcal{R}$$

◁ Note:

$$P(a < X \leq b) = P(X \leq b) - P(X \leq a) = F_X(b) - F_X(a).$$

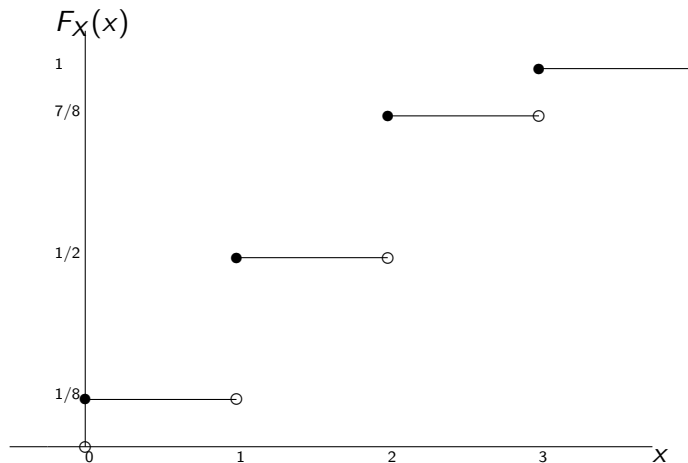
1.5. Distribution Functions

▷ Example: Tossing 3 coins. X = number of heads

$$F_X(x) = \begin{cases} 0, & x < 0, \\ \frac{1}{8}, & 0 \leq x < 1, \\ \frac{3}{8}, & 1 \leq x < 2, \\ \frac{6}{8}, & 2 \leq x < 3, \\ 1, & 3 \leq x. \end{cases}$$

Figure of the cdf of this RV X : Step function.

1.5. Distribution Functions



1.5. Distribution Functions

Theorem

The function $F_X(x)$ is a cdf if and only if the following 3 conditions hold:

- 1 $\lim_{x \rightarrow -\infty} F_X(x) = 0$ and $\lim_{x \rightarrow +\infty} F_X(x) = 1$
- 2 $F_X(x)$ is nondecreasing
- 3 $F_X(x)$ is right continuous, that is,

$$\lim_{x \downarrow x_0} F_X(x) = F_X(x_0) \quad , \quad \text{for all } x_0 \in \mathcal{R} \quad .$$

Definition

A random variable X is *continuous* if $F_X(x)$ is a (absolute) continuous function of x . A random variable X is *discrete* if $F_X(x)$ is a step function of x .

1.5. Distribution Functions

▷ Example: Geometric distribution (See Example 1.5.4)

Free draw success percentage of a basketball player = p . Under the independence assumption from shot to shot, let X be the number of shots required to get a hit. The *support* (collection of real numbers at which probability is positive) of X is $\{1, 2, 3, \dots\}$.

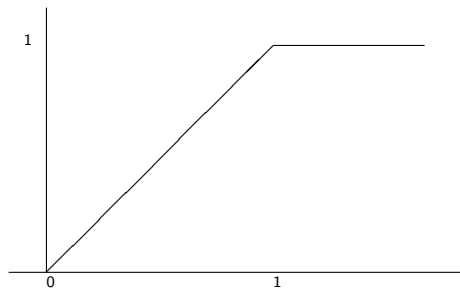
$$P(X = x) = P(\{MMM \dots H\}) =$$

$$\text{Thus, } F_X(x) =$$

1.5. Distribution Functions

▷ Example: Uniform distribution on $[0, 1]$, $X \sim (0, 1)$

$$F_X(x) = \begin{cases} 0, & x < 0, \\ x, & 0 \leq x \leq 1, \\ 1, & 1 < x. \end{cases}$$



1.5. Distribution Functions

Lemma

If the random variable X is continuous with cdf $F_X(x)$ then $P(X = a) = 0$ for all real number a

Proof) As $\{X = a\} \subset \{a - \epsilon < X \leq a\}$ for any $\epsilon > 0$, we have

$$\begin{aligned} P(X = a) &\leq P(a - \epsilon < X \leq a) \\ &= P(X \leq a) - P(X \leq a - \epsilon) \\ &= F_X(a) - F_X(a - \epsilon) \end{aligned}$$

Then, $0 \leq P(X = a) \leq \lim_{\epsilon \downarrow 0} [F_X(a) - F_X(a - \epsilon)] = 0$. as F_X is continuous. Thus $P(X = a) = 0$.

1.5. Distribution Functions

▷ Example - Distribution of waiting time: Exponential distribution, $X \sim \exp(\lambda)$

$$F_X(x) = \begin{cases} 0, & x < 0, \\ 1 - \exp(-\lambda x), & 0 \leq x, \end{cases}$$

for some $\lambda > 0$

◁ Note:

- 1 Probability at least t_1 min
- 2 Memoryless property: probability of waiting additional t_1 min after waiting t_0 min.

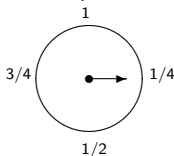
1.5. Distribution Functions

▷ Q - Is there a distribution that is neither discrete nor continuous? (Example 1.5.6)

1.

$$F_Y(y) = \begin{cases} \frac{1-\epsilon}{1+e^{-y}}, & y < 0, \\ \epsilon + \frac{1-\epsilon}{1+e^{-y}}, & y \geq 0. \end{cases}$$

2. Consider an experiment composed of 2 steps. At the first step, a fair coin tossed. If we tail then define a random variable $X = 0$. If we have head, spin a fair spinnes marked $(0,1]$ and let X =ending position of spinnes.



1.5. Distribution Functions

2. - Continued

$$F_X(x) = \begin{cases} 0, & x < 0, \\ 1/2, & x = 0, \\ (x + 1)/2, & 0 < x < 1, \\ 1, & 1 \leq x. \end{cases}$$

Definition

The random variables X and Y are *identically distributed* if for every set $A \in \mathcal{B}^1$,

$$P(X \in A) = P(Y \in A)$$

Note that this does not imply $X = Y$.

1.6. Density & Mass Functions

The cdf is the most general, but not necessarily most appealing mean of specifying a probability on \mathcal{R} . Now let us consider the probability concerned with *point probability*.

Definition

The *probability mass function* (pmf) associated with a discrete distribution with cdf F_X is the function

$$f_X(x) = F_X(x) - \lim_{y \rightarrow x^-} F_X(y), \quad (\text{size of jump at point } x)$$

or

$$f_X(x) = P(X = x) \quad , \quad \text{for all } x \in \mathcal{R} .$$

1.6. Density & Mass Functions

▷ Example: A four sided die that has different numbers (1, 2, 3, 4) affixed to each side. On a given roll each of 4 number is equally likely to occur. Roll the die twice. Define X = maximum of two numbers.

pmf of X is then

x	1	2	3	4
$f(x)$	1/16	3/16	5/16	7/16

$$P(1 \leq X \leq 3) = P(X \leq 3) =$$

1.6. Density & Mass Functions

Definition

The *probability density function* (pdf), $f_X(x)$, of a (absolute) continuous random variable with (absolute) continuous cdf F_X is the function that satisfies

$$F_X(x) = \int_{-\infty}^x f_X(t) dt, \quad \text{for all } x \in \mathcal{R}.$$

Note: By the fundamental theorem of calculus,

$$\frac{dF_X(x)}{dx} = f_X(x).$$

▷ Example: Uniform distribution

1.6. Density & Mass Functions

Theorem

A function $f_X(x)$ is a pdf (or pmf) of a random variable X if and only if (iff)

- ① $f_X(x) \geq 0$ for all x
- ② $\sum_x f_X(x) = 1$ (pmf), $\int_x f_X(x) = 1$ (pdf)

Note: The probability of $A \in \mathcal{R}$, then, is

$$P(X \in A) = \begin{cases} \sum_{x \in A} f_X(x), & \text{if discrete} \\ \int_A f_X(x), & \text{if continuous} \end{cases}$$

1.6. Density & Mass Functions

▷ Example: A 12 sided die that has different numbers (1, 2, \dots , 12) affixed to each side. On a given roll each of 12 number is equally likely to occur. Roll the die twice. Define X = maximum of two numbers.
pmf of X is then

x	1	2	\dots	12
$f(x)$				

$$P(X = x) = c(2x - 1) \quad , \quad x = 1, 2, \dots, 12 \quad .$$

Find a value for c .