

Sets

Set Identities

Union: $A \cup B : \{x \in \mathbb{S} : x \in A \text{ OR } x \in B\}$

Intersection: $A \cap B : \{x \in \mathbb{S} : x \in A \text{ AND } x \in B\}$

Complement: $A^c : \{x \in \mathbb{S} : x \notin A\}$

Difference: $A - B : \{x \in \mathbb{S} : x \in A, x \notin B\}$

Infinite Union: $\bigcup_{i=1}^{\infty} A_i : \{x \in \mathbb{S}, x \in A_i \exists A_i\}$

Infinite Intersection: $\bigcap_{i=1}^{\infty} A_i : \{x \in \mathbb{S}, x \in A_i \forall A_i\}$

Set Relationships

Containment: $A \subseteq B$ (A is a subset of B): $x \in A$ means $x \in B$

Equality: Two sets are equal if they contain each other: $A = B : A \subseteq B, B \subseteq A$

Disjoint: $A \cap B = \{\}$

Set Properties

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

Associativity: $A \cup (B \cup C) = (A \cup B) \cup C, A \cap (B \cap C) = (A \cap B) \cap C$

Distributive: $A \cap (B \cup C) = (A \cap B) \cup (A \cap C), A \cup (B \cap C) = (A \cup B) \cap (A \cup C)$

DeMorgan's Law: $(A \cup B)^c = A^c \cap B^c, (A \cap B)^c = A^c \cup B^c$

Sigma Algebras

Identity

A collection of subsets of S is a σ -algebra (\mathbb{B}) iff:

a. $\emptyset \in \mathbb{B}$

b. $A \in \mathbb{B} \implies A^c \in \mathbb{B}$

c. $A_1, A_2, \dots \in \mathbb{B} \implies \bigcup_{n=1}^{\infty} A_n \in \mathbb{B}$

Construction

S is finite/countable: $\mathbb{B} = \mathbb{P}(\mathbb{S})$ (Power Set of \mathbb{S} , all possible subsets of \mathbb{S})

S is infinite/uncountable: Use Borel sets: $\mathbb{B} = \{(a, b), [a, b), [a, b]\}$ for $a < b$ and all countable \cup and \cap of those

Probability Functions

Axioms

Given \mathbb{S} and σ -algebra, a probability function with domain \mathbb{B} satisfies:

a. $P(A) \geq 0$ for all $A \in \mathbb{B}$

b. $P(\mathbb{S}) = 1$

c. If A_1, A_2, \dots are pairwise disjoint, then $P(\bigcup_{n=1}^{\infty} A_n) = \sum_{n=1}^{\infty} P(A_n)$

Properties

1) $P(\emptyset) = 0$

2) $A \subseteq \mathbb{S} \implies P(A) \leq 1$

3) $P(A^c) = 1 - P(A)$

4) $P(B \cap A^c) = P(B) - P(A \cap B)$

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

6) $A \subseteq B \implies P(A) \leq P(B)$

7) Let c_1, c_2, \dots be a partition of \mathbb{S} (ie. $c_i \cap c_j = \emptyset$ for $i \neq j, \bigcup_{i=1}^{\infty} c_i = \mathbb{S}$)

- $P(A) = \sum_{i=1}^{\infty} P(A \cap c_i)$

8) For any A_1, A_2, \dots ; $P(\bigcup_{i=1}^{\infty} A_i) \leq \sum_{i=1}^{\infty} P(A_i)$

Counting

Sampling

	w/o Repl.	w/ Repl.
Ordered Perm.	$\frac{n!}{(n-1)!}$	n^r
Unordered Comb.	$\frac{n!}{(n-r)!r!} : \binom{n}{r}$	$\binom{n+r-1}{r}$

Axioms

Enumerating equally likely outcomes (assume large but finite $\mathbb{S}, |\mathbb{S}| = N$). Want $P(A)$ where $A \subset \mathbb{S}, A \in \mathbb{B}$

- $P(A) = \frac{\# \text{ things in } A}{N}$

Product Rule:

- If a job consists of k separate experiments, the i^{th} of which can be done in n_i ways, then the job can be done in $n_1 * n_2 * \dots * n_k$ ways

Sum Rule:

- If there are k events, the i^{th} of which can occur in n_i ways, then there are $n_1 + n_2 + \dots + n_k$ to complete exactly 1 event

Inclusion/Exclusion: want to enumerate elements in A : $N_A = |A|$, sometimes easier to find:

- $N_{A^c} = |A^c| \therefore N_A = N - N_{A^c}$

Continuous

Consider $\mathbb{S} \subset \mathbb{R}^d$ with uniform probability

Then for $A \subseteq \mathbb{S}$, $P(A) = \frac{\int_A ds}{\int_{\mathbb{S}} ds}$

Conditional Probability

If $A, B \subseteq \mathbb{S}$ and $P(B) > 0$:

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

Often use the law of total probability ($c_i \cap c_j = \emptyset$ for $i \neq j$, $\bigcup_{i=1}^{\infty} c_i = \mathbb{S}$):

$$P(B) = \sum_{i=1}^n P(B|c_i)P(c_i)$$

Independence

$A \perp\!\!\!\perp B$ iff $P(A|B) = P(A)$

$A \perp\!\!\!\perp B \implies A \perp\!\!\!\perp B^c, A^c \perp\!\!\!\perp B, A^c \perp\!\!\!\perp B^c$

Mutual Independence:

A collection of events A_1, \dots, A_n are mut. ind. if, for any subcollection of A_{i_1}, \dots, A_{i_k} we have:

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

Conditional Independence

A and B are conditionally independent given C if:

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

Random Variables

Definition

A random variable (vector) is a function that maps from the sample space \mathbb{S} to the real numbers \mathbb{R}

Formally: $X : \mathbb{S} \Rightarrow \mathbb{R}$, $\tilde{X} : \mathbb{S} \Rightarrow \mathbb{R}$

Cumulative Distribution Function

The CDF of a random variable ($F_X(x)$) is defined as: $P(X \leq x)$ for all $x \in \mathbb{R}$

$$a. \lim_{x \rightarrow -\infty} F_X(x) = 0, \lim_{x \rightarrow \infty} F_X(x) = 1$$

b. $F_X(x)$ is non-decreasing ie. for $x_i \leq x_2, F(x_1) \leq F(x_2)$

c. $F_X(x)$ is right-continuous ie. $\lim_{x \downarrow x_0} F_X(x) = F_X(x_0)$

Probability Density/Mass Function

A PMF is given by $f_X(x) = P(X = x)$

A PDF of a continuous random variable satisfies the following:

$$- \int_{-\infty}^x f_x(t)dt \text{ for all } x \therefore f(X) = \frac{dF_x}{dx}$$

$$- P(a \leq x \leq b) = \int_a^b f_X(x)dx = P(a < x < b) = F(b) - F(a)$$

A function is a valid PMF/PDF iff:

- a) $f_X(x) \geq 0, \forall x$
- b) $\sum_{x \in X} f_X(x) = 1$ -OR- $\int_X f_X(x)dx = 1$

Kernel

Any non-negative function with a finite integral or sum can be made into a PDF or PMF

- $h(x) \geq 0 \forall x$
- $\int_{x \in X} h(x)dx = k, 0 < k < \infty$
- $f_X(x) = \frac{1}{k}h(x)I_X(x)$

Common PDFs

Besides those given in the book:

- Survival Function: $S_X(x) = P(X > x) = 1 - F_X(x)$
- Hazard Function: $H_X(x) = \frac{f_X(x)}{S_X(x)}$
- Gamma Function: $\Gamma(\alpha) = \int_0^\infty t^{\alpha-1} e^{-t} dt$
- If α is an integer: $\Gamma(\alpha) = (\alpha - 1)!$
- For general α : $\Gamma(\alpha + 1) = \alpha\Gamma(\alpha)$
- Also: $\Gamma(\frac{1}{2}) = \sqrt{\pi}$

Expected Value

Definition

Given a random variable $g(x)$:

$$\mathbb{E}[g(x)] = \begin{cases} \int_{-\infty}^{\infty} g(x)f_X(x)dx, & \text{Continuous} \\ \sum_{x \in X} g(x)f_X(x), & \text{Discrete} \end{cases}$$

Law of Unconscious Statistician: Let $Y = g(x)$

$$- \mathbb{E}[g(x)] = \int_{-\infty}^{\infty} g(x)f_X(x)dx = \int_{-\infty}^{\infty} Yf_Y(y)dy = \mathbb{E}[Y]$$

Probability as an Expectation:

$$P(x \in A) = \int_A f_X(x)dx = \int_{-\infty}^{\infty} I_A(x)f_X(x)dx = \mathbb{E}[I_A(x)]$$

Properties of Expected Values

- 1) $\mathbb{E}[ax + b] = a\mathbb{E}[x] + b, \mathbb{E}[ag_1(x) + bg_2(x)] = a\mathbb{E}[g_1(x)] + b\mathbb{E}[g_2(x)]$
- 2) If $g(x) \geq 0, \forall x \in X$, then $\mathbb{E}[g(x)] \geq 0$
- 3) If $g_1(x) \geq g_2(x), \forall x \in X$, then $\mathbb{E}[g_1(x)] \geq \mathbb{E}[g_2(x)]$
- 4) If $a \leq g(x) \leq b, \forall x \in X$, then $a \leq \mathbb{E}[g(x)] \leq b$

Moments

Definition

For each integer n , the n^{th} moment of X is $\mathbb{E}[X^n]$

The n^{th} central moment is: $\mathbb{E}[X - \mathbb{E}[X]]^n$

Expected value is the first moment, Variance is the second central moment

Properties of Variance:

- $\text{Var}(aX + b) = a^2 \text{Var}(X)$
- $\text{Var}(X) = \mathbb{E}[X^2] - (\mathbb{E}[X])^2$

Jensen's Inequality

Want to compare $\mathbb{E}[X]$ vs. $\mathbb{E}[Y]$ where $Y = g(X)$. Often can't directly compare.

$$JE : \begin{cases} \mathbb{E}[g(X)] \geq g(\mathbb{E}[X]), & g(x) \text{ is convex} \\ \mathbb{E}[g(X)] \leq g(\mathbb{E}[X]), & g(x) \text{ is concave} \end{cases}$$

How to tell if $g(x)$ is convex:

- Draw it (convex is bowl-shaped)
- Second Derivative: $g''(x) > 0 \implies$ convex

Moment Generating Function (MGF)

$$M_X(t) = \mathbb{E}[e^{tx}] = \begin{cases} \int_{-\infty}^{\infty} e^{tx} f_X(x) dx, & X \text{ is continuous} \\ \sum_{x \in X} e^{tx} f_X(x), & X \text{ is discrete} \end{cases}$$

This holds if the expectation exists for t in the neighborhood of 0. That is, there exists an $h > 0$ such that $\mathbb{E}(e^{tx})$ exists for all $-h < t < h$

$$\mathbb{E}[X^n] = M_X^{(n)}(0) = \frac{d^n}{dt^n} M_X(t)|_{t=0}$$

Characterizing Distributions

- a) If X and Y have bounded support, $F_X(u) = F_Y(u)$ for all u iff $\mathbb{E}[X^r] = \mathbb{E}[Y^r]$, $r = 0, 1, 2, 3, \dots$ (all moments are equal)
- b) If MGF exists $M_X(t) = M_Y(t)$ for some t in neighborhood of 0, then $F_X(u) = F_Y(u)$ for all u

A sequence of random variables, $X_i, i = 1, 2, 3, \dots$ each with an MGF $M_{X_i}(t)$. Further suppose $\lim_{i \rightarrow \infty} M_{X_i}(t) = M_x(t)$ for t in neighborhood of 0, and $M_x(t)$ is also an MGF

Then: there is a unique CDF $F_X(x)$ whose moments are determined by $M_x(t)$ and $\lim_{i \rightarrow \infty} F_{X_i}(x) = F_x(x)$

Basically, if the MGFs of RVs converge to an MGF, then the RVs themselves converge to the RV of the converged MGF

Lemma: Let a_1, a_2, a_3, \dots be a sequence of numbers such that $\lim_{n \rightarrow \infty} a_n = a$

$$\text{Then: } \lim_{n \rightarrow \infty} (1 + \frac{a_n}{n})^n = e^a$$

Theorem: Let $Y = aX + b \therefore M_Y(t) = e^{at} M_X(t)$

Transformations

Definition

X is a random variable, then $Y = g(X)$ is also a random variable. To find $P(Y)$ we need either $F_Y(y)$ or $f_Y(y)$

- $g(X)$ maps from \mathbb{X} to \mathbb{Y} , basically $\mathbb{S} \rightarrow \mathbb{X} \rightarrow \mathbb{Y}$
- $\forall A, P(Y \in A) = P(g(X) \in A) = P(\{x \in \mathbb{X} : g(x) \in A\}) = P(X \in g^{-1}(A))$

Discrete

$$f_Y(y) = \begin{cases} \sum_{X \in g^{-1}(y)} P(X = x), & Y \in \mathbb{Y} \\ 0, & \text{otherwise} \end{cases}$$

Steps:

- 1) Find \mathbb{Y}
- 2) Identify $g^{-1}(y)$
- 3) Sum over appropriate x (if $g^{-1}(y)$ is a set with one element, $f_Y(y) = f_X(g^{-1}(y))$)

Continuous

$$F_Y(y) = P(Y \leq y) = P(g(x) \leq y) = \int_{x \in \mathbb{X}: g(x) \leq y} f_X(x) dx$$

If $Y = g(X)$ is monotone, g^{-1} exists. If it's increasing, the inverse is as well (vice versa for decreasing)

If $g(X)$ is increasing, $F_Y(y) = F_X(g^{-1}(y))$. If $g(X)$ is decreasing, $F_Y(y) = -F_X(g^{-1}(y))$. In both:

$$f_Y(y) = \begin{cases} f_X(g^{-1}(y)) |\frac{d}{dy} g^{-1}(y)|, & y \in \mathbb{Y} \\ 0, & \text{otherwise} \end{cases}$$

Steps:

- 1) Find \mathbb{Y}
- 2) Find $g^{-1}(y)$
- 3) Find $\frac{d}{dy} g^{-1}(y)$
- 4) Plug into $f_X(g^{-1}) |\frac{d}{dy} g^{-1}(y)|$

If the transformation is non-monotonic, all you need to do is find the points of inflection and partition the transformation within each region of monotonicity

Probability Integral Transform

NOT SURE IF REALLY NEED (7 Oct 2025)

Location Scale Family

Let $f_X(x)$ be a PDF and $\mu \in \mathbb{R}, \sigma > 0$, then $g(x) = \frac{1}{\sigma} f_X(\frac{x-\mu}{\sigma})$

This is the case when there exists a Z such that $X = \mu + \sigma Z$

MonteCarlo Integration

Write an integral as an expectation:

$$I = \int_a^b h(x)dx = \int_a^b \frac{h(x)}{f_X(x)} f_X(x)dx = \mathbb{E}\left[\frac{h(x)}{f_X(x)} I_{(a,b)}(x)\right]$$

Steps:

- 1) Simulate x_1, \dots, x_n from $f_X(x)$
 - 2) Calculate $g(x_j) = \frac{h(x_j)}{f_X(x_j)} I_{(a,b)}^{(x_j)}$, $\forall j$
 - 3) $\mathbb{E}[g(x)] \approx \frac{1}{n} \sum_{j=1}^n g(x_j) \equiv \bar{g}$
- $$SE(\bar{g}_n) \approx \frac{1}{\sqrt{n}} s.d.(g(x_1), \dots, g(x_n))$$

Importance Sampling

FILL IN STUFF

Oct 30

Ex: $X|Z \sim N(Z, \sigma^2)$, $Y|Z \sim N(Z, \sigma^2)$, $(X \perp Y)|Z$

We can say: $X = Z + \epsilon_X$, $Y = Z + \epsilon_Y$: $\epsilon_x, \epsilon_Y \sim N(0, \sigma^2)$, $Z \sim N(\mu, \tau^2)$

$Cov(X, Y) = Cov(Z + \epsilon_X, Z + \epsilon_Y) = Cov(Z, Z) = Var(Z) = \tau^2$

For the correlation we need:

$$Var(Y) = Var(Z) + Var(\epsilon_Y) = \tau^2 + \sigma^2$$

$$Var(X) = Var(Z) + Var(\epsilon_X) = \tau^2 + \sigma^2$$

$$Corr(X, Y) = \frac{Cov(X, Y)}{\sqrt{Var(X)}\sqrt{Var(Y)}} = \frac{\tau^2}{\tau^2 + \sigma^2}$$

Law of Total Covariance

For random variables X, Y, Z, with hierarchy as $(X|Y, Z), (Y|Z)$, and Z;

$$Cov(X, Y) = \mathbb{E}[Cov(X, Y|Z)] + Cov(\mathbb{E}[X|Z], \mathbb{E}[Y|Z])$$

Random Samples and Sums of Random Variables

Definition

The random variables X_1, \dots, X_n are a random sample of size n from population $f_X(x)$ if $X_i \stackrel{iid}{\sim} f_X(\cdot)$, $i = 1, \dots, n$

Joint PDF/PMF

X_1, \dots, X_n is a random sample. Since they are iid,

$$f(x_1, \dots, x_n) = \prod_{i=1}^n f_X(x_i)$$

Ex. Let X_1, \dots, X_n be the failure times in years of the i^{th} identical circuit components.

Assume $X_i \stackrel{iid}{\sim} Exp(\beta)$

$$\text{Thus: } f(x_1, \dots, x_n) = \prod_{i=1}^n \frac{1}{\beta} e^{-x_i/\beta} = \frac{1}{\beta^n} e^{\frac{1}{\beta} \sum X_i}$$

Use this to find:

$$P(X_1 > 2, X_2 > 2, \dots, X_n > 2) = [P(X_1 > 2)]^n = [1 - P(X_1 < 2)]^n = [1 - 1 + e^{\frac{-2}{\beta}}]^n = e^{\frac{-2n}{\beta}}$$

Definition: Sampling Distribution - Let X_1, \dots, X_n be a random sample of size n. Let $T(X_1, \dots, X_n)$ be a real-valued, real-vector function whose domain includes \mathbb{X} .

Then $T(X_1, \dots, X_n)$ is a statistic and its distribution is a sampling distribution.

Common Statistics

$$\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i$$

$$s^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$$

Order statistics: media, range, etc.

Theorem: Let x_1, \dots, x_n be any numbers and $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$ then:

a. $\min_a \sum_{i=1}^n (x_i - a)^2 = \sum_{i=1}^n (x_i - \bar{x})^2$ -or- $\bar{x} = \operatorname{argmin}_a \sum_i i = 1^n (x_i - a)^2$

b. $(n-1)s^2 = \sum_{i=1}^n (x_i - \bar{x})^2 = \sum_{i=1}^n x_i^2 - n\bar{x}^2$

Theorem: Let Z_1, \dots, Z_n be a random sample with population mean and variance μ, σ^2 , then:

1) $\mathbb{E}(\bar{X}) = \mu$

2) $Var(\bar{X}) = \frac{\sigma^2}{n}$

3) $\mathbb{E}(s^2) = \sigma^2$