

tags: distributionrelationships dist

NOTE:

field: ₅₄

field: $X \sim Gamma(a, b)$ $P(X \leq x) = P(Y \geq a)$ Where $Y \sim$

field: $X \sim Gamma(a, b)$ $P(X \leq x) = P(Y \geq a)$ Where $Y \sim Pois(x/b)$

NOTE:

field: ₅₅

field:

$$X_1, \dots, X_n \sim iidN(0, 1)$$
$$\sum X_i \overset{?}{\sim}$$

field:

$$X_1, \dots, X_n \sim iidN(0, 1)$$
$$\sum X_i \sim N(0, n)$$

NOTE:

field: ₅₆

field:

$$X_1, \dots, X_n \sim iidN(\mu_i, \sigma_i^2)$$
$$\sum X_i \overset{?}{\sim}$$

field:

$$X_1, \dots, X_n \sim iid N(\mu_i, \sigma_i^2)$$
$$\sum X_i \sim N(\sum \mu_i, \sum \sigma_i^2)$$

NOTE:

field: ₅₇

field:

$$X \sim N(\mu, \sigma^2)$$
$$aX + b \stackrel{?}{\sim}$$

field:

$$aX + Y \sim N(a\mu + b, a^2\sigma^2)$$

NOTE:

field: ₅₈

field: $X \sim Binom(1, p) \stackrel{?}{\sim}$

field: $X \sim Bern(p)$

NOTE:

field: ₅₉

field: $X \sim NegBinom(1, p) \stackrel{?}{\sim}$

field: $X \sim Geom(p)$

NOTE:

field: ₆₀

field: $X \sim Gamma(1, \theta) \overset{?}{\sim}$

field: $X \sim Exp(\theta)$

NOTE:

field: ₆₁

field: $X \sim Exp(\theta) \overset{?}{\sim}$

field: $X \sim Gamma(1, \theta)$

NOTE:

field: ₆₂

field: $X \sim Gamma(v/2, 1/2) \overset{?}{\sim}$

field: $X \sim \chi^2(v)$

NOTE:

field: ₆₃

field:

$$X \sim \chi^2(v) \overset{?}{\sim}$$

field:

$$X \sim Gamma(v/2, 2)$$

NOTE:

field: ₆₄

field:

$$X \sim \chi^2(2) \stackrel{?}{\sim}$$

field:

$$X \sim \exp(2)$$

NOTE:

field: ₆₅

field:

$$X \sim Weibull(1, \beta) \stackrel{?}{\sim}$$

field:

$$X \sim \text{Exp}(\beta)$$

NOTE:

field: ₆₆

field: $X_1, X_2 \sim \chi^2(v_i)$ independent $\frac{X_1/v_1}{X_2/v_2}$

field:

$$\frac{(X_1/v_1)}{(X_2/v_2)} \sim F(v_1, v_2)$$

NOTE:

field: ⁶⁷

field:

$$X \sim beta(1, 1) \stackrel{?}{\sim}$$

field:

$$X \sim Unif(0, 1)$$

NOTE:

field: ⁶⁸

field:

$$X \sim Unif(0, 1) \stackrel{?}{\sim}$$

field:

$$X \sim beta(1, 1)$$

NOTE:

field: ⁶⁹

field: Special case of t

$$X \sim t_1 \stackrel{?}{\sim}$$

field:

$$X \sim Cauchy(0, 1)$$

NOTE:

field: ₇₀

field: Scaled Gamma

$$X \sim Gamma(\alpha, \beta), Y = aX \stackrel{?}{\sim}$$

field:

$$Y \sim Gamma(\alpha, a\beta)$$

NOTE:

field: ₇₁

field: Scaled Exponential

$$X \sim Exp(\lambda), Y = aX \stackrel{?}{\sim}$$

field:

$$Y \sim Exp(a\lambda)$$

NOTE:

field: ₇₂

field: Sum of Exponential, equal rate $X_i \sim \text{Exp}(\lambda), Y = \sum X_i$

field:

$$Y \sim \text{Gamma}(n, \lambda)$$

NOTE:

field: ₇₃

field:

$$X \sim \text{Exp}(\lambda), Y = e^{-x}$$

field:

$$Y \sim \text{Beta}(\lambda, 1)$$

NOTE:

field: ₇₄

field: Min of Exponential (using λ parametrization)

$$X_1, \dots, X_n \sim \text{Exp}(\lambda_i), Y = \min(X_i) \stackrel{?}{\sim}$$

field: $Y \sim \text{exp}(\sum \lambda_i)$

NOTE:

field: ₇₅

field: Min of Uniform

$$X_i \sim Unif(0, 1), Y = \lim n \min(X_i) \stackrel{?}{\sim}$$

field:

$$Y \sim Exp(1)$$

NOTE:

field: ₇₆

field:

$$X \sim Beta(\alpha, \beta), Y = (1 - X)$$

field:

$$Y \sim Beta(\beta, \alpha)$$

NOTE:

field: ₇₇

field: $X \sim F_X(X), Y = F_X^{-1}(X)$

field: $Y \sim Unif(0, 1)$

NOTE:

field: ₇₈

field: $X \sim N(\mu, \sigma^2), Y = e^X$

field: $Y \sim \text{lognormal}(\mu, \sigma^2)$

NOTE:

field: ₇₉

field: $X \sim \exp(\beta), Y = X^{1/z}$

field: $Y \sim \text{Weibull}(z, \beta)$

NOTE:

field: ₈₀

field: Square of Normal $X \sim N(0, 1), Y = X^2$

field: $Y \sim \chi^2(1)$

NOTE:

field: ₈₁

field: Square of t $X \sim t(v), Y = X^2$

field: $Y \sim F(1, v)$

NOTE:

field: ₈₂

field: Sum of Poisson $X_i \sim \text{Poisson}(\mu_i) Y = \sum X_i$

field: $Y \sim \text{Poisson}(\sum \mu_i)$

NOTE:

field: ₈₃

field: Sum of Gamma $X_i \sim \text{Gamma}(\alpha_i, \beta), Y = \sum X_i$

field: $Y \sim \text{Gamma}(\sum \alpha_i, \beta)$

NOTE:

field: ₈₄

field: Sum of independent Chi-squared $X_i \sim \chi^2(v_i) Y = \sum X_i$

field: $Y \sim \chi^2(\sum v_i)$

NOTE:

field: ₈₅

field: X, Y independent $X, Y \sim N(0, 1), X/Y$

field: $X/Y \sim \text{Cauchy}(0, 1)$

NOTE:

field: ₈₆

field: $X_1, X_2 \sim \text{gamma}(\alpha_i, 1)$ independent, $\frac{X_1}{X_1 + X_2}$

field:

$$\frac{X_1}{X_1 + X_2} \sim \text{beta}(\alpha_1, \alpha_2)$$

NOTE:

field: ₈₇

field: $X_1, X_2 \sim \text{gamma}(\alpha_i, \beta_i)$ independent, $\frac{\beta_2 X_1}{\beta_2 X_1 + \beta_1 X_2}$

field:

$$\frac{\beta_2 X_1}{\beta_2 X_1 + \beta_1 X_2} \sim \text{beta}(\alpha_1, \alpha_2)$$

NOTE:

field: ₈₈

field: X, Y independent $\exp(\mu)$ $X - Y$

field: $X - Y \sim \text{double exponential}(0, \mu)$

NOTE:

field: ₈₉

field: $X \sim \text{Gamma}(\alpha, \beta)$ $Y = 1/X$

field: Inverted Gamma

NOTE:

field: ₉₀

field: Bernoulli(p), $E(X) =$, $V(X) =$

field: Bernoulli(p), $E(X) = p$, $V(X) = p(1 - p)$

NOTE:

field: ₉₁

field: Discrete Uniform N , $E(X) =$, $V(X) =$

field: Discrete Uniform $N, E(X) = \frac{N+1}{2}, V(X) = \frac{(N+1)(N-1)}{12}$

NOTE:

field: ₉₂

field: Cauchy(θ, σ), $E(X) =, V(X) =$

field: Cauchy(θ, σ), $E(X) = na, V(X) = na$

NOTE:

field: ₉₃

field: Double Exponential(μ, σ), $E(X) =, V(X) =$

field: Double Exponential(μ, σ), $E(X) = \mu, V(X) = 2\sigma^2$

NOTE:

field: ₉₄

field: $F(v_1, v_2), E(X) =, V(X) =$

field: $F(v_1, v_2), E(X) = \frac{v_1}{v_2-2}, V(X) = 2\left(\frac{v_2}{v_2-2}\right)^2 \frac{(v_1+v_2-2)}{v_1(v_2-4)}$

NOTE:

field: ₉₅

field: Mean and Variance for Distributions not on bible (but in CB)

- Double Exponential(μ, σ), $E(X) =$, $V(X) =$
- $F(v_1, v_2)$, $E(X) =$, $V(X) =$
- Logistic(μ, β), $E(X) =$, $V(X) =$
- Lognormal(μ, σ^2), $E(X) =$, $V(X) =$
- Pareto(α, β), $E(X) =$, $V(X) =$
- $t(v)$, $E(X) =$, $V(X) =$
- Weibull(γ, β), $E(X) =$, $V(X) =$

field: Mean and Variance. for Distributions not on bible (but in CB)

- Logistic(μ, β), $E(X) = \mu$, $V(X) = \frac{\pi^2 \beta^2}{3}$
- Lognormal(μ, σ^2), $E(X) = e^{\mu + (\sigma^2/2)}$, $V(X) = e^{2(\mu + \sigma^2)} - e^{2\mu + \sigma^2}$
- Pareto(α, β), $E(X) = \frac{\beta \alpha}{\beta - 1}$, $V(X) = \frac{\beta \alpha^2}{(\beta - 1)^2 (\beta - 2)}$
- $t(v)$, $E(X) = 0$, $V(X) = \frac{v}{v - 2}$
- Weibull(γ, β), $E(X) = \beta^{1/\gamma} \Gamma(1 + 1/\gamma)$, $V(X) = \beta^{2/\gamma} (\Gamma(1 + 2/\gamma) - \Gamma^2(1 + 1/\gamma))$

tags: Calculus calc

NOTE:

field: ₉₆

field: $\int_0^\infty e^{-x^2/2} =$

field: $\int_0^\infty e^{-x^2/2} = \sqrt{\pi/2}$

NOTE:

field: ₉₇

field: $\int_0^\infty x^{a-1} e^{-x/b} =$

field: $\int_0^\infty x^{a-1} e^{-x/b} = \Gamma(a) b^a$

NOTE:

field: ₉₈

field: $\int_0^1 x^{a-1} (1-x)^{b-1} =$

field: $\int_0^1 x^{a-1} (1-x)^{b-1} = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}$

NOTE:

field: ₉₉

field: $\log(x) = y, x =$

field: $\log(x) = y, x = e^y$

NOTE:

field: ₁₀₀

field: $\lim_{x \rightarrow \infty} (1 + \frac{a}{x})^x =$

field: $\lim_{x \rightarrow \infty} (1 + \frac{a}{x})^x = e^a$

NOTE:

field: ₁₀₁

field: $\lim_{x \rightarrow \infty} (1 + \frac{a}{x})^x =$

field: $\lim_{x \rightarrow \infty} (1 + \frac{a}{x})^x = e^a$

NOTE:

field: ₁₀₂

field: $\frac{d}{dx} f(g(x)) =$

field: $\frac{d}{dx} f(g(x)) = f'(g(x))g'(x)$ (Chain rule)

NOTE:

field: ₁₀₃

field: $\frac{d}{dx} \int_a^x f(t)dt =$

field: $\frac{d}{dx} \int_a^x f(t)dt = f(x)$ (fundamental theorem of calculus)

NOTE:

field: ₁₀₄

field: $\int_a^b u dv =$
ex: $\int x e^{-x}$

field: $\int_a^b u dv = uv|_a^b - \int_a^b v du$
ex: $u = x, dv = e^{-x}, du = dx, v = -e^{-x}$

$$\begin{aligned} \int x e^{-x} &= -x e^{-x} + \int e^{-x} \\ &= -x e^{-x} - e^{-x} + c \end{aligned}$$

NOTE:

field: ₁₀₅

field: $\sum_{k=0}^{\infty} \frac{x^k}{k!} =$

field: $\sum_{k=0}^{\infty} \frac{x^k}{k!} = e^x$

NOTE:

field: ₁₀₆

field: $e^x =$

field: $e^x = \sum_{k=0}^{\infty} \frac{x^k}{k!}$

NOTE:

field: ₁₀₇

field: $\sum_{k=0}^{\infty} x^k =$

field: $\sum_{k=0}^{\infty} x^k = \frac{1}{1-x}$ for $|x| < 1$

NOTE:

field: ₁₀₈

field: $\sum_{k=0}^n x^k =$

field: $\sum_{k=0}^n x^k = \frac{1-x^{n+1}}{1-x}$ for $x \neq 1$

NOTE:

field: ₁₀₉

field: $\lim_{x \rightarrow -\infty} e^{-x} =$

field: $\lim_{x \rightarrow -\infty} e^{-x} = \infty$

NOTE:

field: ₁₁₀

field: $\lim_{x \rightarrow \infty} e^{-x} =$

field: $\lim_{x \rightarrow -\infty} e^{-x} = 0$

NOTE:

field: ₁₁₁

field:

$$(fg)' =$$

field:

$$(fg)' = f'g + g'f$$

(product rule)

NOTE:

field: ₁₁₂

field: $\frac{d}{dx} x^n =$

field: $\frac{d}{dx} x^n = nx^{n-1}$

NOTE:

field: ₁₁₃

field: $\frac{d}{dx} a^x =$

field: $\frac{d}{dx}a^x = a^x \ln(a)$

NOTE:

field: $_{114}$

field: $\frac{d}{dx} \ln(x) =$

field: $\frac{d}{dx} \ln(x) = \frac{1}{x}$

NOTE:

field: $_{115}$

field: $\frac{d}{dx}(f(x))^n =$

field: $\frac{d}{dx}(f(x))^n = n(f(x))^{n-1}f'(x)$

NOTE:

field: $_{116}$

field: $\frac{d}{dx} \ln(f(x)) =$

field: $\frac{d}{dx} \ln(f(x)) = \frac{f'(x)}{f(x)}$

NOTE:

field: $_{117}$

field: $\frac{d}{dx} e^{f(x)} =$

field: $\frac{d}{dx} e^{f(x)} = f'(x)e^{f(x)}$

NOTE:

field: ₁₁₈

field: $\int x^n =$

field: $\int x^n = \frac{1}{n+1}x^{n+1}$

NOTE:

field: ₁₁₉

field: $\int \frac{1}{x} =$

field: $\int \frac{1}{x} = \ln(|x|)$

NOTE:

field: ₁₂₀

field: $\int \frac{1}{ax+b} =$

field: $\int \frac{1}{ax+b} = \frac{1}{a}\ln(|ax+b|)$

NOTE:

field: ₁₂₁

field: $\int e^{cx} =$

field: $\int e^{cx} = \frac{1}{c}e^{cx}$

NOTE:

field: ₁₂₂

field: $\int xe^{-cx^2} =$

field: $\int x e^{-cx^2} = -\frac{1}{2c} e^{-cx^2}$

NOTE:

field: ₁₂₃

field: U substitution:
example; $\int_1^2 5x^2 \cos(x^3)$

field: $\int_a^b f(g(x))g'(x) = \int_{g(a)}^g(b)f(u)du$
Where $u = g(x), du = g'dx$
Ex: $u = x^3, du = 3x^2, x^2du = 1/3du$ $\int_1^2 5x^2 \cos(x^3) = \int_1^8 5/3 \cos(u)du$

NOTE:

field: ₁₂₄

field: $\Gamma(a) =$

field: $\int_0^\infty t^{a-1} e^{-t} dt$

NOTE:

field: ₁₂₅

field: $\int_0^\infty t^{a-1} e^{-t} dt$

field: $= \Gamma(a)$

NOTE:

field: ₁₂₆

field: $\Gamma(a+1) =$

field: $\Gamma(a + 1) = a\Gamma(a)$

NOTE:

field: ₁₂₇

field: $\Gamma(n) =$

field: $\Gamma(n) = (n - 1)!$ (for n an integer)

NOTE:

field: ₁₂₈

field: $\Gamma(1/2) =$

field: $\Gamma(1/2) = \sqrt{\pi}$

NOTE:

field: ₁₂₉

field: $\Gamma(1) =$

field: $\Gamma(1) = 1$

tags: Theory1

NOTE:

field: ₁₃₀

field:	number of trials	replace	no replacement
	Draw till nth success		

field:		replace	no replacement
	number of trials	Binom	Hypergeometric
	Draw till nth success	Nbinom	Negative hypergeometric

NOTE:

field: ¹³¹

field: Plug uniform into inverse CDF

field: Get cdf

NOTE:

field: ¹³²

field: Sample Space

field: The set, S , of all possible outcomes of a particular experiment is called the *sample space* for the experiment.

NOTE:

field: ¹³³

field: Event

field: An *event* is any collection of possible outcomes of an experiment, that is, any subset of S (including S itself).

NOTE:

field: ¹³⁴

field: Union

field: $A \cup B = \{x : x \in A \text{ or } x \in B\}$

NOTE:

field: ₁₃₅

field: Intersection

field: $A \cap B = \{x : x \in A \text{ and } x \in B\}$

NOTE:

field: ₁₃₆

field: Complementation

field: $A^c = \{x : x \notin A\}$

NOTE:

field: ₁₃₇

field: Commutativity

$$A \cup B =$$

$$A \cap B =$$

field: Commutativity

$$A \cup B = B \cup A$$

$$A \cap B = B \cap A$$

NOTE:

field: ₁₃₈

field: Associativity

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

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

field: Associativity

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

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

NOTE:

field: ₁₃₉

field: Distributive Laws

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

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

field: Distributive Laws

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

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

NOTE:

field: ₁₄₀

field: DeMorgan's Laws

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

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

field: DeMorgan's Laws

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

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

NOTE:

field: ₁₄₁

field: Disjoint

field: Disjoint: Two events A and B are disjoint (or mutually exclusive) if $A \cap B = \emptyset$

NOTE:

field: ₁₄₂

field:

$$P(A_1 \cap A_2 \cap \cdots \cap A_n) =$$

field:

$$P(A_1)P(A_2|A_1)P(A_3|A_1A_2) \cdots P(A_n|A_1 \cdots A_{n-1})$$

NOTE:

field: ¹⁴³

field:

$$P(A, B, C) =$$

field:

$$P(A, B, C) = P(A)P(B|A)P(C|A, B)$$

NOTE:

field: ¹⁴⁴

field:

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

field:

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

NOTE:

field: ¹⁴⁵

field: Pairwise disjoint

field: Two Events A_1, A_2 are pairwise disjoint (or mutually exclusive) if $A_i \cap A_j = \emptyset$ for all $i \neq j$

NOTE:

field: ¹⁴⁶

field: Partition

field: If A_1, A_2, \dots are pairwise disjoint and $\cup_{i=1}^{\infty} A_i = S$, then the collection A_1, A_2, \dots forms a partition of S .

NOTE:

field: ¹⁴⁷

field: Sigma Algebra

field: A collection of subsets of S is called a sigma algebra (or Borel field), denoted by \mathcal{B} , if it satisfies the following three properties:

1. $\emptyset \in \mathcal{B}$ (the empty set is an element of \mathcal{B})
2. If $A \in \mathcal{B}$, then $A^c \in \mathcal{B}$ (\mathcal{B} is closed under complementation)
3. If $A_1, A_2, \dots \in \mathcal{B}$, then $\cup_{i=1}^{\infty} A_i \in \mathcal{B}$ (\mathcal{B} is closed under countable unions)

NOTE:

field: ¹⁴⁸

field: Probability Function / Kolmogorov Axioms

field: Given a sample space S and an associated sigma algebra \mathcal{B} , a probability function is a function P with domain \mathcal{B} that satisfies:

1. $P(A) \geq 0$ for all $A \in \mathcal{B}$
2. $P(S) = 1$
3. If $A_1, A_2, \dots \in \mathcal{B}$ are pairwise disjoint, then $P(\cup_{i=1}^{\infty} A_i) = \sum_{i=1}^{\infty} P(A_i)$
(Axiom of Countable Additivity)

NOTE:

field: ₁₄₉

field: If $A \in \mathcal{B}$ and $B \in \mathcal{B}$ are disjoint, then

$$P(A \cup B) = P(A) + P(B)$$

Axiom of Finite Additivity

field: If $A \in \mathcal{B}$ and $B \in \mathcal{B}$ are disjoint, then

$$P(A \cup B) = P(A) + P(B)$$

NOTE:

field: ₁₅₀

field: Properties of probability functions

1. $P(\emptyset) =$
2. $P(A)$
3. $P(A^c) =$

field: Properties of probability functions

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

NOTE:

field: ₁₅₁

field: If P is a probability function and A and B are any sets in \mathcal{B} , then

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

field: If P is a probability function and A and B are any sets in \mathcal{B} , then

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

NOTE:

field: ₁₅₂

field: If P is a probability function and A and B are any sets in \mathcal{B} , then

$$P(A \cup B) =$$

field: If P is a probability function and A and B are any sets in \mathcal{B} , then

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

NOTE:

field: ₁₅₃

field: If P is a probability function and A and B are any sets in \mathcal{B} , then if $A \subset B$ then

field: If P is a probability function and A and B are any sets in \mathcal{B} , then if $A \subset B$ then $P(A) \leq P(B)$

NOTE:

field: 154

field: Bonferroni's Inequality

$$P(A \cap B)$$

field: Bonferroni's Inequality:

$$P(A \cap B) \geq P(A) + P(B) - 1$$

NOTE:

field: 155

field: If P is a probability function, then for any partition C_1, C_2, \dots $P(A) =$

field: If P is a probability function, then for any partition C_1, C_2, \dots $P(A) = \sum_{i=1}^{\infty} P(A \cap C_i)$

NOTE:

field: 156

field: Boole's Inequality

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

field: If P is a probability function,

$$P(\cup_{i=1}^{\infty} A_i) \leq \sum_{i=1}^{\infty} P(A_i) \text{ for any sets } A_1, A_2, \dots$$

NOTE:

field: 157

field: Fundamental Theorem of Counting

field: If a job consists 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 $n_1 \times n_2 \times \dots \times n_k$ ways.

NOTE:

field: 158

field: Ordered without replacement: number of arrangements of size r from n objects

field:

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

eg lottery with $n = 44$ choices for $r = 6$ values, cant use same number twice, order matters

NOTE:

field: 159

field: Unordered without replacement: number of arrangements of size r from n objects

field:

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

eg lottery with $n = 44$ choices for $r = 6$ values, cant use same number twice, order does not matter (Use ordered without replacement and divide by redundant orderings)

NOTE:

field: ₁₆₀

field: Ordered with replacement: number of arrangements of size r from n objects

field: Ordered with replacement: number of arrangements of size r from n objects

$$n^r$$

eg lottery with $n = 44$ choices for $r = 6$ values, can use same number twice, order matters

NOTE:

field: ₁₆₁

field: Unordered with replacement: number of arrangements of size r from n objects

field: Unordered with replacement: number of arrangements of size r from n objects

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

eg lottery with $n = 44$ choices for $r = 6$ values, can use same number twice, order does not matters

NOTE:

field: ₁₆₂

field: Number of arrangements of size r from n objects

	Without Replacement	With replacement
Ordered		
Unordered		

field: Number of arrangements of size r from n objects

	Without Replacement	With replacement
Ordered	$\frac{n!}{(n-r)!}$	n^r
Unordered	$\binom{n}{r}$	$\binom{n+r-1}{r}$

NOTE:

field: ₁₆₃

field: Binomial Coefficient $\binom{n}{r}$

field: Binomial Coefficient

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

NOTE:

field: ₁₆₄

field:

$$P(A|B) =$$

field:

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

NOTE:

field: 165

field: Statistically independent $P(A \cap B) =$

field: Statistically independent $P(A \cap B) = P(A)P(B)$

NOTE:

field: 166

field: If A and B are independent events, what else is independent?

field:

- A and B^c
- A^c and B
- A^c and B^c

NOTE:

field: 167

field: Mutually independent

field: A collection of events A_1, \dots, A_n are mutually independent for any subcollection A_{i_1}, \dots, A_{i_k} , we have

$$P((\cap_{j=1}^k A_{ij})) = \prod_{j=1}^k P(A_{ij})$$

NOTE:

field: 168

field: Random variable

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

NOTE:

field: 169

field: Definition of a pdf

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

1. $f_X(x) \geq 0$ for all x
2. $\sum_x f_X(x) = 1$ or $\int_{-\infty}^{\infty} f_X(x) dx = 1$

NOTE:

field: 170

field: (Theorem) Let X have cdf $F_X(x)$, let $Y = g(X)$

1. If g is an increasing function on X , $F_Y(y) = F_X(g^{-1}(y))$ for $y \in Y$
2. If g is a decreasing function on X and X is a continuous random variable, $F_Y(y) = 1 - F_X(g^{-1}(y))$ for $y \in Y$

field: (Theorem) Let X have cdf $F_X(x)$, let $Y = g(X)$

1. If g is an increasing function on X , $F_Y(y) = F_X(g^{-1}(y))$ for $y \in Y$
2. If g is a decreasing function on X and X is a continuous random variable, $F_Y(y) = 1 - F_X(g^{-1}(y))$ for $y \in Y$

NOTE:

field: 171

field: Method of pdf + conditions

field: Conditions:

1. g is a monotone function
2. $f_X(x)$ is continuous on X
3. $g^{-1}(y)$ has a continuous derivative

Let X have pdf $f_X(x)$ and let $Y = g(X)$

$$f_Y(y) = f_X(g^{-1}(y)) \left| \frac{d}{dy} g^{-1}(y) \right|$$

NOTE:

field: 172

field: (Theorem) Let X have cdf $F_X(x)$, let $Y = g(X)$

- If g is an increasing function, $F_Y(y) =$
- If g is a decreasing function, and X is a continuous random variable, $F_Y(y) =$

field: (Theorem) Let X have cdf $F_X(x)$, let $Y = g(X)$

- If g is an increasing function, $F_Y(y) = F_X(g^{-1}(y))$
- If g is a decreasing function, and X is a continuous random variable, $F_Y(y) = 1 - F_X(g^{-1}(y))$

NOTE:

field: ₁₇₃

field: eg: $X \sim Unif(0, 1)$, $Y = -\log(X)$ $F_Y(y) =$

field: $F_Y(y) = 1 - F_x(g^{-1}(y)) = 1 - F_X(e^{-y}) = 1 - e^{-y}$

NOTE:

field: _{173x}

field: X is a continuous random variable. For $y > 0$, $Y = X^2$ $F_Y(y) =$

field:

$$\begin{aligned} F_Y(y) &= P(Y \leq y) \\ &= P(X^2 \leq y) \\ &= P(-\sqrt{y} \leq X \leq \sqrt{y}) \\ &= P(X \leq \sqrt{y}) - P(X \leq -\sqrt{y}) \\ &= F_X(\sqrt{y}) - F_X(-\sqrt{y}) \end{aligned}$$

NOTE:

field: ₁₇₄

field: Pdf of $F_X(g(X))$, where $Y = g(X)$

field: Chain rule: $f_Y(y) = g'(y)f(g(y))$

NOTE:

field: ₁₇₅

field: Method of pdf if g is not monotone all entire domain

field: $f_Y = \sum f_x(g_i^{-1}(y)) \left| \frac{d}{dy} g_i^{-1}(y) \right|$ $y \in Y$, 0 otherwise
 eg: $Y = X^2$,

NOTE:

field: ₁₇₆

field: $P(Y \leq y)$ when $Y = F_X(x)$

field:

$$\begin{aligned} P(Y \leq y) &= P(X \leq F_x^{-1}(y)) \\ &= F_X(F_X^{-1}(y)) \\ &= y \end{aligned}$$

Y is uniformly distributed

NOTE:

field: ₁₇₇

field: $M_x(t) = (\text{discrete})$

field: $M_x(t) = E(e^{tX}) = \sum_x e^{tX} P(X)$ (discrete)

NOTE:

field: ₁₇₈

field: $M_x(t) = (\text{continuous})$

field: $M_x(t) = E(e^{tX}) = \int_{-\infty}^{\infty} e^{tX} f_x(x) dx$ (continuous)

NOTE:

field: ₁₇₉

field: $E(X^n) =$

field: $E(X^n) = M_x^n(0) = \frac{d^n}{dt^n} M_x(t)|_{t=0}$

NOTE:

field: ₁₈₀

field: $M(aX + b)(t) =$

field: $M(aX + b)(t) = e^{bt} M_x(at)$

NOTE:

field: ₁₈₁

field: If $E(X^n)$ exists then...

field: If $E(X^n)$ exists then $E(X^m)$ exists for $m \leq n$

NOTE:

field: ₁₈₂

field: If X_i are independent and $Y = a_1X_1 + \dots + a_nX_n + b$, then $M_Y(t) =$

field: If X_i are independent and $Y = a_1X_1 + \dots + a_nX_n$, then $M_Y(t) = e^{bt} \prod_{i=1}^n M_{X_i}(a_it)$

NOTE:

field: ₁₈₃

field: Example of using MGF for finding expected value: MGF gamma: $(\frac{1}{1-\beta t})^\alpha$: $E(X) =$

field: $E(X) = \frac{\alpha\beta}{(1-\beta t)^{\alpha+1}}|_{t=0} = \alpha\beta$

NOTE:

field: 184

field: Using MGF to relate distributions: MGF exp = $(1 - \beta t)^{-1}$

field: $Y = \sum X_i$ is gamma as MGF gamma is $(1 - \beta t)^{-\alpha}$

NOTE:

field: 185

field: First step in transforming a RV

field: Determine support

NOTE:

field: 186

field: n th Moment of X

field: $E(X^n)$

NOTE:

field: 187

field: n th central moment of X

field: $E[(X - \mu)^n]$

NOTE:

field: ₁₈₈

field: $(a + b)^n =$

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

NOTE:

field: ₁₈₉

field: $\sum_{x=0}^n \binom{n}{x} a^x b^{n-x} =$

field: $(a + b)^n$

NOTE:

field: ₁₉₀

field: N balls r red $N - r$ green. Select n balls. Probability that y are red?

field: Hypergeometric distribution(N, r, n)

NOTE:

field: ₁₉₁

field: Hypergeometric distribution description (N, r, n)

field: N is total balls, r is number red balls, n is number balls selected.

NOTE:

field: ₁₉₂

field: Negative binomial description

field: Number of Bernoulli trials required to get a fixed number of successes.
 r being the r th success

NOTE:

field: ₁₉₃

field: Geometric description

field: Modeling waiting time. X is the trial at which the first success occurs.

NOTE:

field: ₁₉₄

field: Location-scale family for $f(x)$

field: $\frac{1}{\sigma} f\left(\frac{x-\mu}{\sigma}\right)$

NOTE:

field: ₁₉₅

field: Given X give the mean and variance for the location-scale random
 $Y = 1/\sigma f((y - \mu)/\sigma)$ variable

field: $E(Y) = \sigma E(X) + \mu, V(Y) = \sigma^2 V(X)$

NOTE:

field: ₁₉₆

field: $X \sim Pois(\lambda) \ P(X = x + 1) =$

field: $X \sim Pois(\lambda) \ P(X = x + 1) = \frac{\lambda}{x+1} P(X = x)$

NOTE:

field: ₁₉₇

field: $f(y|x) =$ (definition of conditional)

field: $f(y|x) = \frac{f(x,y)}{f_x(x)}$

NOTE:

field: ₁₉₈

field: $E(g(Y)|x) =$

field: $E(g(Y)|x) = \int_{-\infty}^{\infty} g(y) f(y|x) dy$

NOTE:

field: ₁₉₉

field: Example of calculating conditional pdfs $f(x, y) = e^{-y}, 0 < x < y < \infty$. $f(y|x) =$

field:

$$\begin{aligned} f_x(x) &= \int_{-\infty}^{\infty} f(x, y) dy \\ &= e^{-x} \end{aligned}$$

$$\begin{aligned} f(y|x) &= \frac{f(x, y)}{f_x(x)} \\ &= \frac{e^{-y}}{e^{-x}} \text{ if } y > x \\ &= \frac{0}{e^{-x}} \text{ if } y \leq x \end{aligned}$$

NOTE:

field: 200

field: Let (X, Y) be given as $f(x, y)$. Then X and Y are independent if

field: Let (X, Y) be given as $f(x, y)$. Then X and Y are independent if there exist functions $g(x), h(y)$ such that $f(x, y) = g(x)h(y)$ (factorization - don't need to compute marginals)

NOTE:

field: 201

field: Let X, Y be independent. Then $E(g(X)h(Y)) =$

field: $E(g(X)h(Y)) = (E(g(X)))(E(h(Y)))$
example: $E(X^2Y) = E(X^2)E(Y)$

NOTE:

field: 202

field: X, Y independent

$$Z = X + Y$$

$$M_Z(t) =$$

$$\text{field: } M_Z(t) = M_X(t)M_Y(t)$$

NOTE:

field: ₂₀₃

field: Method of pdf bivariate

$$\text{field: } f_{u,v}(u, v) = f_{x,y}(h_1(u, v), h_2(u, v))|J|$$

$$\text{Where } |J| = \begin{vmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{vmatrix} = \frac{\partial x}{\partial u} \frac{\partial y}{\partial v} - \frac{\partial y}{\partial u} \frac{\partial x}{\partial v}$$

$$\text{and } u = g_1(x, y), v = g_2(x, y) \text{ and } x = h_1(x, y), y = h_2(x, y)$$

NOTE:

field: ₂₀₄

field: X, Y independent, $g(X)$ a function only of X and $h(Y)$ a function only of Y . Then

field: $g(X)$ and $g(Y)$ are independent.

NOTE:

field: ₂₀₅

field: Correlation

$$\text{field: } \rho_{XY} = \frac{Cov(X, Y)}{\sigma_X \sigma_Y}$$

NOTE:

field: 206

field: m independent trials, each trial resulting in one of n outcomes, with probabilities p_1, \dots, p_n . X_i is the count of the number of times the i th outcome occurred in the m trials.

field: Multinomial distribution $f(x_1, \dots, x_n) = \frac{m!}{x_1! \dots x_n!} p_1^{x_1} \dots p_n^{x_n}$

NOTE:

field: 207

field: $|E(XY)|$

field: $|E(XY)| \leq E(|XY|) \leq (E(|X|^2))^{1/2} (E(|Y|^2))^{1/2}$ (Cauchy-Schwartz)

NOTE:

field: 208

field: $E(g(X))$ where g is a convex function

field: $E(g(X)) \geq g(E(X))$ where g is a convex function (Jensen's inequality)

NOTE:

field: 209

field: Ranking of types of means

field: $\mu_{\text{harmonic}} \leq \mu_{\text{geometric}} \leq \mu_{\text{arithmetic}}$ By Jensen's inequality (using logs)

NOTE:

field: ₂₁₀

field: Linear transformations of multivariate normal $X \sim N(\vec{\mu}, \Sigma)$
 $A\vec{X} + \vec{b}$

field: $A\vec{X} + \vec{b} \sim N(A\vec{\mu} + \vec{v}, A\Sigma A^t)$

NOTE:

field: ₂₁₁

field: $X \sim N(\vec{\mu}, \Sigma)$

$$\vec{X}_a | \vec{X}_b \sim$$

field: $\vec{X}_a | \vec{X}_b \sim N(\vec{\mu}_a + \Sigma_{ab}\Sigma_{bb}^{-1}(\vec{x}_b - \vec{\mu}_b), \Sigma_{ba} - \Sigma_{ab}\Sigma_{bb}^{-1}\Sigma_{ba})$

$$\text{ex: } (X_1, X_2, X_3), \vec{\mu} = (1, 2, 3)^t, \Sigma = \begin{pmatrix} 3 & 1 & 0 \\ 1 & 3 & 1 \\ 0 & 1 & 3 \end{pmatrix} \quad X_1, X_3 | X_2 = 1$$

$$a = \{1, 3\}, b = \{2\}$$

$$\mu_a = (1, 3)^t, \mu_b = 1$$

$$\Sigma_{aa} = \begin{pmatrix} 3 & 0 \\ 0 & 3 \end{pmatrix}, \Sigma_{ab} = (1, 1)^t$$

NOTE:

field: ₂₁₂

field: (X, Y) multinomial
 $aX + bY \sim$

field: $aX + bY \sim N(a\mu_x + b\mu_y, a^2\sigma_x^2 + b^2\sigma_y^2 + 2ab\rho\sigma_x\sigma_y)$

NOTE:

field: ₂₁₃

field: (X, Y) multinomial
 $Y|X \sim$

field: $Y|X \sim N(\mu_y + \rho \frac{\sigma_y}{\sigma_x}(x - \mu_x), \sigma_Y^2(1 - \rho^2))$

NOTE:

field: ₂₁₄

field: CDF for Max order statistic

field: $(F(x))^n$

NOTE:

field: ₂₁₅

field: PDF for Max order statistic

field: $nf(x)(F(x))^{n-1}$

NOTE:

field: ₂₁₆

field: CDF for Min order statistic

field: $1 - (1 - F(x))^n$

NOTE:

field: ₂₁₇

field: PDF for Min order statistic

field: $n(1 - F(x))^{n-1}f(x)$

NOTE:

field: ₂₁₈

field: CDF for k th order statistic

field: $F_{(k)}(x) = \sum_{j=k}^n \binom{n}{j} (F(x))^j (1 - F(x))^{n-j}$

NOTE:

field: ₂₁₉

field: PDF for k th order statistic

field: $f_{(k)}(x) = k \binom{n}{k} f(x) F(x)^{k-1} (1 - F(x))^{n-k}$

NOTE:

field: ₁

field: CDF of Geometric (p)

field: $1 - (1 - p)^x$

NOTE:

field: ₂

field: CDF of Exponential(β)

field: $1 - e^{-\frac{x}{\beta}}$

NOTE:

field: ₃

field:

- $B = \Omega \cap B = (A \cup A^c) \cap B =$
- $P(A^c) =$
- $P(B) =$
- $P(\Omega) = \quad P(\emptyset) =$
- $(\bigcup_n A_n) = \quad (\bigcap_n A_n) = \quad \text{DEMORGAN}$

field:

- $B = \Omega \cap B = (A \cup A^c) \cap B = (A \cap B) \cup (A^c \cap B)$
- $P(A^c) = 1 - P(A)$
- $P(B) = P(A \cap B) + P(A^c \cap B)$
- $P(\Omega) = 1 \quad P(\emptyset) = 0$
- $(\bigcup_n A_n) = \bigcap_n A_n \quad (\bigcap_n A_n) = \bigcup_n A_n \quad \text{DEMORGAN}$

NOTE:

field: ₄

field: Probability Set intersection

- $P(\bigcup_n A_n) =$
- $P(A \cup B) = \implies$
- $P(A \cup B) =$
- $P(A \cap B^c) =$

field: Probability Set intersection

- $P(\bigcup_n A_n) = 1 - P(\bigcap_n A_n)$
- $P(A \cup B) = P(A) + P(B) - P(A \cap B)$
 $\implies P(A \cup B) \leq P(A) + P(B)$
- $P(A \cup B) = P(A \cap B^c) + P(A^c \cap B) + P(A \cap B)$
- $P(A \cap B^c) = P(A) - P(A \cap B)$

NOTE:

field: ₅

field: $P(A \cap B) =$ when A and B independent

field: $P(A \cap B) = P(A)P(B)$ when A and B independent

NOTE:

field: ₆

field:

$$P(A|B) =$$

field:

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

NOTE:

field: ₇

field: Law of total probability

field: Law of total probability

$$P(B) = \sum_{i=1}^n P(B|A_i)P(A_i) \quad \Omega = \cap_{i=1}^n A_i$$

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

NOTE:

field: 8

field: Bayes Theorem $P(A_i|B) =$

field: Bayes Theorem

$$P(A_i|B) = \frac{P(B|A_i)P(A_i)}{\sum_{j=1}^n P(B|A_j)P(A_j)} \quad \Omega = \cup_{i=1}^n A_i$$

NOTE:

field: 9

field: CDF Laws

field: CDF Laws

1. Nondecreasing: $x_1 < x_2 \implies F(x_1) \leq F(x_2)$
2. Limits: $\lim_{x \rightarrow -\infty} F(x) = 0$ and $\lim_{x \rightarrow \infty} F(x) = 1$
3. Right-Continuous $\lim_{y \rightarrow x^+} F(y) = F(x)$

NOTE:

field: 10

field:

$$f_{y|x}(y|x) =$$

field:

$$f_{y|x}(y|x) = \frac{f(x, y)}{f_x(x)}$$

NOTE:

field: ₁₁

field: X, Y independent

- $P(X \leq x, Y \leq y) =$
- $f_{x,y}(x, y) =$

field: X, Y independent

- $P(X \leq x, Y \leq y) = P(X \leq x)P(Y \leq y)$
- $f_{x,y}(x, y) = f_x(x)f_y(y)$

NOTE:

field: ₁₂

field: Transformations $Z = \phi(X)$

- Discrete: $f_Z(z) =$
- Continuous: $F_Z(z) =$
- Cont, ϕ strictly monotone: $f_z(z)$

field: Transformations $Z = \phi(X)$

- Discrete:

$$f_Z(z) = P(\phi(X) = z) = P(X \in \phi^{-1}(z)) = \sum_{x \in \phi^{-1}(z)} f_x(x)$$

- Continuous (Method of CDF):

$$F_Z(z) = P(\phi(X) \leq z) = \int_{x: \phi(x) \leq z} f(x) dx$$

- Cont, ϕ strictly monotone: (Method of PDF) $f_z(z) = f_x(\phi^{-1}(z)) \left| \frac{d}{dz} \phi^{-1}(z) \right|$

NOTE:

field: ₁₃

field: Rule of the Lazy Statistician: $E[g(x)] =$

field: Rule of the Lazy Statistician: $E[g(x)] = \int g(x) f_x(x) dx$

NOTE:

field: ₁₄

field: Expectation rules

- $E(c) =$
- $E(cX) =$
- $E(X + Y) =$
- $E(\phi(X)) =$

field: Expectation rules

- $E(c) = c$
- $E(cX) = cE(X)$
- $E(X + Y) = E(X) + E(Y)$
- $E(\phi(X)) \neq \phi(E(X))$

NOTE:

field: ₁₅

field: Conditional expectation

- $E(Y|X = x) =$
- $E(X) =$
- $E(Y + Z|X) =$
- $E(Y|X) = c \implies$

field: Conditional expectation

- $E(Y|X = x) = \int yf(y|x)dy$
- $E(X) = E(E(X|Y))$
- $E(Y + Z|X) = E(Y|X) + E(Z|X)$
- $E(Y|X) = c \implies Cov(X, Y) = 0$

NOTE:

field: ₁₆

field: Variance

- $V(X) = \sigma_x^2 =$
- $V(X + Y) =$
- $V\left[\sum_{i=1}^n X_i\right] =$

field: Variance

- $V(X) = \sigma_x^2 = E[(X - E(X))^2] = E(X^2) - E(X)^2$
- $V(X + Y) = V(X) + V(Y) + Cov(X, Y)$
- $V\left[\sum_{i=1}^n X_i\right] = \sum_{i=1}^n V(X_i) + \sum_{i \neq j} Cov(X_i, X_j)$

NOTE:

field: ₁₇

field: Covariance

- $Cov(X, Y) =$
- $Cov(X, c) =$
- $Cov(Y, X) =$
- $Cov(aX, bY) =$
- $Cov(X + a, Y + b) =$
- $Cov\left(\sum_{i=1}^n X_i, \sum_{j=1}^m Y_j\right) =$

field: Covariance

- $Cov(X, Y) = E[(X - E(X))(Y - E(Y)))] = E(XY) - E(X)E(Y)$
- $Cov(X, c) = 0$
- $Cov(Y, X) = Cov(X, Y)$
- $Cov(aX, bY) = abCov(X, Y)$
- $Cov(X + a, Y + b) = Cov(X, Y)$
- $Cov\left(\sum_{i=1}^n X_i, \sum_{j=1}^m Y_j\right) = \sum_{i=1}^n \sum_{j=1}^m Cov(X_i, Y_j)$

NOTE:

field: ₁₈

field: Correlation: $\rho(X, Y)$

field: Correlation: $\rho(X, Y) = \frac{Cov(X, Y)}{\sqrt{V(X)V(Y)}}$

NOTE:

field: ₁₉

field: Conditional Variance

- $V(Y|X) =$
- $V(Y) =$

field: Conditional Variance

- $V(Y|X) = E[(Y - E(Y|X))^2|X] = E(Y^2|X) - E(Y|X)^2$
- $V(Y) = E(V(Y|X)) + V(E(Y|X))$

NOTE:

field: ₂₀

field: Law of total probability $k = 2$ (using conditional probability)

field: $P(A) = P(A|B)P(B) + P(A|B^c)P(B^c)$

NOTE:

field: ₂₁

field: Bayes formula in terms of law of total probability,

field: $P(B|A) = \frac{P(A|B)P(B)}{P(A|B)P(B) + P(A|B^c)P(B^c)}$

NOTE:

field: ₂₂

field: $P(A \text{ and } B) = P(A, B) =$

field: $P(A \text{ and } B) = P(A|B)P(B) = P(B|A)P(A)$

NOTE:

field: ₂₃

field: Events A and B are independent if

field: $P(A|B) = P(A)$ equivalently $P(A \text{ and } B) = P(A)P(B)$

NOTE:

field: ₂₄

field: Poisson setting

field: The Poisson setting arises in the context of discrete counts of events that occur over space or time with the small probability and where successive events are independent

Eg: 2 on average calls a minute, X is number of calls a minute, $X \sim Pois$

NOTE:

field: ₂₅

field: Poisson approximation of binomial distribution

field: Suppose $X \sim Binom(n, p)$, $Y \sim Pois(\lambda)$. If $n \rightarrow \infty$, and $p \rightarrow 0$, in such a way that $np \rightarrow \lambda > 0$, then for all k , $P(X = k) \rightarrow P(Y = k)$. The Poisson distribution with parameter $\lambda = np$ serves as a good approximation for the binomial distribution when n is large and p is small.

NOTE:

field: ₂₆

field: $E(f(X, Y))$ when X, Y are discrete

field: $E(f(X, Y)) = \sum_x \sum_y f(x, y)P(X = x, Y = y)$

NOTE:

field: ₂₇

field: If X, Y are independent, then $f(X), g(Y)$

field: are also independent

NOTE:

field: ₂₈

field: If X, Y independent, $E(XY) = E(f(X)g(Y)) =$

field: If X, Y independent, $E(XY) = E(X)E(Y), E(f(X)g(Y)) = E(f(X))E(g(Y))$

NOTE:

field: ₂₉

field: Sum of independent discrete random variables X, Y : $P(X + Y = k)$

field: $P(X + Y = k) = \sum_i P(X = i)P(Y = k - i)$

NOTE:

field: ₃₀

field: $V(X) = 0$

field: If and only if X is a constant

NOTE:

field: ₃₁

field: $E(I_A) =, V(I_A)$ Where I_A is an indicator function

field: $E(I_A) = P(A), V(I_A) = P(A)P(A^c)$

NOTE:

field: ₃₂

field: For discrete jointly distributed random variables,

$$P(X = y|X = x) =$$

field: For discrete jointly distributed random variables,

$$P(X = y|X = x) = \frac{P(X = x, Y = y)}{P(X = x)}$$

NOTE:

field: ₃₃

field: For discrete random variables $E(Y|X = x) =$

field: For discrete random variables $E(Y|X = x) = \sum_y yP(Y = y|X = x)$

NOTE:

field: ₃₄

field: Problem solving strategy for expected value of counting

field: Use indicator functions for each trial , where $X = \sum I$ and use linearity of expectation

NOTE:

field: ₃₅

field: $P(X > s + t|X > t)$ for geometric, exponential

field: $P(X > s + t|X > t) = P(X > s)$

NOTE:

field: ₃₆

field: Distribution for: A bag of N balls which contains r red balls and $N - r$ blue balls, X is number of red balls in a sample of size n taken without replacement.

field: Hypergeometric.

NOTE:

field: ₃₇

field: Distribution for modeling arrival time

field: Exponential

NOTE:

field: ₃₈

field: $E(g(X, Y)) = (\text{continuous})$

field: $E(g(X, Y)) = \int_{y=-\infty}^{\infty} \int_{x=-\infty}^{\infty} g(x, y) f(x, y) dx dy$

NOTE:

field: ₃₉

field: $Cov(X, Y) = (\text{integration})$

field: $Cov(X, Y) = \int_{y=-\infty}^{\infty} \int_{x=-\infty}^{\infty} (x - E(X))(y - E(Y)) dx dy$

NOTE:

field: ₄₀

field: Problem solving strategies for functions of random variables

field:

- Methods of cdf: $Y = g(X)$, find cdf $P(Y \leq y) = P(g(X) \leq y) = P(X \leq g^{-1}(y))$
- For finding $P(X < Y)$, set up integrals that cover
- For finding probabilities of independent uniform random variables, use geometric (area) properties

NOTE:

field: ₄₁

field: Quantile

field: If X is a continuous random variable, then the p th quantile is the number q that satisfies $P(X \leq q) = p/100$

NOTE:

field: ₄₂

field: Poisson process

field: Times between arrivals are modeled as iid exponential random variables with parameter $\lambda = 1/\beta$. Let N_t be the number of arrivals up to time t . Then $N_t \sim Pois(\lambda t)$

NOTE:

field: ₄₃

field: Conditional density function $f_{Y|X}(y|x) =$

field: $f_{Y|X}(y|x) = \frac{f(x,y)}{f_x(x)}$

NOTE:

field: ₄₄

field: Continuous bayes formula

field: $f_{X|Y}(x|y) = \frac{f_{Y|X}(y|x)f_x(x)}{\int_{t=-\infty}^{\infty} f_{Y|X}(y|t)f_x(t)dt}$

NOTE:

field: ₄₅

field: Conditional expectation for continuous random variables $E(Y|X = x)$

field: $E(Y|X = x) = \int_y y f_{Y|X}(y|x) dy$

NOTE:

field: ₄₆

field: Law of total expectation

field: $E(Y) = E(E(Y|X))$

NOTE:

field: ₄₇

field: Properties of conditional expectation

- $E(aY + bZ|X) =$
- $E(g(Y)|X = x) =$
- If X, Y independent, $E(Y|X) =$
- If $Y = g(X)$, then $E(Y|X) =$

field: Properties of conditional expectation

- $E(aY + bZ|X) = aE(Y|X) + bE(Z|X)$
- $E(g(Y)|X = x) = \int_y g(y)f_{Y|X}(y|x)dy$
- If X, Y independent, $E(Y|X) = E(Y)$
- If $Y = g(X)$, then $E(Y|X) = Y$

NOTE:

field: ₄₉

field: Conditional variance $V(Y|X = x)$

field:

$$V(Y|X = x) = \sum_y (y - E(Y|X = x))^2 P(Y = y|X = x)$$

discrete

$$V(Y|X = x) = \int_y (y - E(Y|X = x))^2 f_{Y|X}(y|x)dy$$

continuous

NOTE:

field: ₅₀

field: Properties of conditional variance

- $V(Y|X = x) =$
- $V(aY + b|X = x) =$
- If Y, Z independent, $V(Y + Z|X = x) =$

field: Properties of conditional variance

- $V(Y|X = x) = E(Y^2|X = x) - (E(Y|X = x))^2$
- $V(aY + b|X = x) = a^2V(Y|X = x)$
- If Y, Z independent, $V(Y + Z|X = x) = V(Y|X = x) + V(Z|X = x)$

NOTE:

field: ₅₁

field: $P(X \geq \epsilon)$

field: $P(X \geq \epsilon) \leq E(X)/\epsilon$ (Markov's Inequality)

NOTE:

field: ₅₂

field: $P(|X - \mu| \geq \epsilon)$

field: $P(|X - \mu| \geq \epsilon) \leq \sigma^2/\epsilon^2$ (Chebyshev's inequality, if mean and variance finite)

NOTE:

field: ₅₃

field: $P(\lim_{n \rightarrow \infty} S_n/n = \mu) =$

field: $P(\lim_{n \rightarrow \infty} S_n/n = \mu) = 1$ (Strong law of large numbers)

tags: TheoryTwo t2

NOTE:

field: 220

field: Definition of Convergence

field: A sequence $\{a_n\}_{n>1}$ of real numbers is said to **converge** to a point $a \in \mathbb{R}$ if for any $\epsilon > 0$ there exists $N \in \mathbb{N}$ such that for all $m > N$ we have $|a_m - a| < \epsilon$

NOTE:

field: 221

field: Example of convergence: $a_n = \frac{1}{n}$

field: For any $\epsilon > 0$, choose N such that $\frac{1}{N} < \epsilon$. Then for any $m > N$ we have that

$$a_n = \frac{1}{n} < \frac{1}{N} < \epsilon$$

and therefore $|a_m - 0| = \frac{1}{n} < \epsilon$

NOTE:

field: 222

field: Given two convergent sequences $\{a_n\}$ and $\{b_m\}$ such that $a_m \rightarrow a$ and $b_m \rightarrow b$
 $\lim_{n \rightarrow \infty} a_n b_n =$

field: Given two convergent sequences $\{a_n\}$ and $\{b_n\}$ such that $a_n \rightarrow a$ and $b_n \rightarrow b$
 $\lim_{n \rightarrow \infty} a_n b_n = (\lim_{n \rightarrow \infty} a_n)(\lim_{n \rightarrow \infty} b_n) = ab$

NOTE:

field: 223

field: Definition: Convergence in probability

field: A sequence of random variables $\{X_n\}_{n \geq 1}$ **converges in probability** to a random variable X , if for every $\epsilon > 0$,

$$\lim_{n \rightarrow \infty} P(|X_n - X| \geq \epsilon) = 0$$

We write $X_n \xrightarrow{p} X$

Equivalently, $x_n \xrightarrow{p} x$ if $\lim_{n \rightarrow \infty} P(|x_n - x| < \epsilon) = 1$

NOTE:

field: 224

field: Convergence in probability example: Let $\{x_n\}$ be a sequence of random variables such that $x_n \sim N(0, 1/n^2)$

Show that $x_n \xrightarrow{p} 0$:

field: Let $\epsilon > 0$. We obtain $P(|x_n - 0|) = P(x_n > \epsilon) + P(x_n < -\epsilon)$. ie we are looking at the tail probabilities.

Now,

$$\begin{aligned} P(X_n < -\epsilon) + P(x_n > \epsilon) &= P(nx_n < n\epsilon) + P(nx_n > n\epsilon) \\ &= \Phi(n\epsilon) + 1 - \Phi(n\epsilon) \\ &= 2\Phi(-n\epsilon) \xrightarrow[n \rightarrow \infty]{} 0 \end{aligned}$$

Therefore $x_n \xrightarrow{p} 0$

NOTE:

field: 225

field: Example convergence in probability Let $W \sim N(0, 1)$ and $U \sim Unif(0, 1)$, and define the sequence $\{x_n\}_{n \geq 1}$ as $x_n = W$ with prob $1 - 1/n$, U with prob $1/n$

Show that $x_n \xrightarrow{p} W$

field: Let $\epsilon > 0$ Then.

$$\begin{aligned} P(|X_n - W| > \epsilon) &= P(|X_n - W| > \epsilon | X_n = W)P(X_n = W) \\ &\quad + P(|X_n - W| > \epsilon | X_n = U)P(X_n = U) \\ &= 0 \cdot (1 - 1/n) + p_n(1/n) \end{aligned}$$

Where p_n is a probability, and therefore $0 \leq p_n \leq 1$

It follows that $p_n \frac{1}{n} \xrightarrow{n \rightarrow \infty} 0$, and therefore $P(|X_n - W| > \epsilon) \xrightarrow{n \rightarrow \infty} 0$, for all $\epsilon > 0$, so that $X_n \xrightarrow{p} W$.

NOTE:

field: 226

field: Does $X_n \xrightarrow{p} c$ imply $E(X_n) \rightarrow c$?

field: No

Let $X_n = 0$ with probability $1 - 1/n$, n^2 with probability $1/n$ Then $P(|X_n - 0| > \epsilon) \leq P(X_n = n^2) = 1/n \xrightarrow{n \rightarrow \infty} 0$ On the other hand, $E(X_n) = 0 \cdot P(X_n = 0) + n^2 P(X_n = n^2) = 0 + n^2 \frac{1}{n} = n \xrightarrow{n \rightarrow \infty} \infty$. Therefore $X_n \xrightarrow{p} c$ does not imply $E(X_n) \rightarrow c$

NOTE:

field: 227

field: Does $E(X_n) \rightarrow c$ imply $X_n \xrightarrow{p} c$?

field: No.

Let $X_n = 0$, with prob $1 - 1/n$, n with prob $1/n$. Then $E(X_n) = 0 \cdot P(X_n = 0) + nP(X_n = n) = 0 + n1/n = 1$ for all n . But $P(|X_n - 0| > \epsilon) \leq P(X_n = n) = \frac{1}{n} \xrightarrow{n \rightarrow \infty} 0$. It follows, $X_n \xrightarrow{p} 0$, and therefore we have $E(X_n) \rightarrow c$ does not imply $X_n \xrightarrow{p} c$.

NOTE:

field: 228

field: Suppose $\{X_n\}_{n \geq 1}$ and $\{Y_n\}_{n \geq 1}$ be two sequences of random variables such that $X_n \xrightarrow{p} x_0$ and $Y_n \xrightarrow{p} y_0$ as $n \rightarrow \infty$, where $x_0, y_0 \in \mathbb{R}$.

What properties do we have?

field:

- $X_n \pm Y_n \xrightarrow{p} x_0 \pm y_0$ as n increases to ∞
- $X_n Y_n \xrightarrow{p} x_0 y_0$ as n increases to ∞
- $X_n / Y_n \xrightarrow{p} x_0 / y_0$ as n increases to infinity, provided that $P(Y_n = 0) = 0$ for all n and $y_0 \neq 0$

NOTE:

field: 229

field: Let $\{X_n\}_{n \geq 1}$ be a sequence of random variables such that $x_n \xrightarrow{p} x_0 \in \mathbb{R}$, as $n \rightarrow \infty$, and let $g : \mathbb{R} \rightarrow \mathbb{R}$ be a continuous function. Then

$$g(X_n) \xrightarrow{p} g(x_0) \text{ as } n \rightarrow \infty$$

field: Let $\{X_n\}_{n \geq 1}$ be a sequence of random variables such that $x_n \xrightarrow{p} x_0 \in \mathbb{R}$, as $n \rightarrow \infty$, and let $g : \mathbb{R} \rightarrow \mathbb{R}$ be a continuous function . Then

$$g(X_n) \xrightarrow{p} g(x_0) \text{ as } n \rightarrow \infty$$

NOTE:

field: 230

field: Proof of: Let $\{X_n\}_{n \geq 1}$ be a sequence of random variables such that $x_n \xrightarrow{p} x_0 \in \mathbb{R}$, as $n \rightarrow \infty$, and let $g : \mathbb{R} \rightarrow \mathbb{R}$ be a continuous function . Then

$$g(X_n) \xrightarrow{p} g(x_0) \text{ as } n \rightarrow \infty$$

field: Since g is continuous at $X = x_0$, we have that for any $\epsilon > 0$, there exists $\delta > 0$ such that $|g(x) - g(x_0)| > \epsilon$ implies $|x - x_0| > \delta$

We obtain

$$0 \leq P(|g(X_n) - g(x_0)| > \epsilon) \leq P(|X_n - x_0| > \delta) \xrightarrow{n \rightarrow \infty} 0$$

NOTE:

field: 231

field: Weak Law of Large numbers

field: Let $X_1, X_2, X_3 \dots$ Be a sequence of iid random variables with $E(X_1) = \mu$ (finite) and $V(X_1) = \sigma^2 < \infty$, and define $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$ (the sample mean).

Then

$$\bar{X}_n \xrightarrow{p} \mu \text{ as } n \rightarrow \infty$$

NOTE:

field: 232

field: Proof of Weak Law of Large Numbers

field:

$$\begin{aligned}P(|\bar{X}_n - \mu| > \epsilon) &= P((\bar{X}_n - \mu)^2 > \epsilon^2) \\&\leq \frac{E((\bar{X}_n - \mu)^2)}{\epsilon^2} \text{ by Chebyshev's Inequality} \\&= \frac{V(\bar{X}_n)}{\epsilon^2} \text{ by def of variance} \\&= \frac{\sigma^2}{n\epsilon^2} \xrightarrow{n \rightarrow \infty} 0\end{aligned}$$

Therefore $\bar{X}_n \xrightarrow{p} \mu$

NOTE:

field: 233

field: Consistency

field: If our estimate converges in probability to the value of the parameter of interest as the sample size n increases

NOTE:

field: 234

field: Consistency of S^2

field: Suppose X_1, X_2, \dots is a sequence of iid random variables with $E(X_1) = \mu$ finite and $V(X_1) = \sigma^2 < \infty$
and define

$$S_n^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X}_n)^2 \quad \text{The sample variance}$$

Can we show that S_n^2 is a consistent estimate of σ^2 ? In other words, can we show that $S_n^2 \xrightarrow{p} \sigma^2$ as $n \rightarrow \infty$

Using Chebychev's inequality, we obtain

$$\begin{aligned} P(|S_n^2 - \sigma^2| > \epsilon) &\leq \frac{E[(S_n^2 - \sigma^2)^2]}{\epsilon^2} \\ &= \frac{V(S_n^2)}{\epsilon^2} \end{aligned}$$

Therefore, a sufficient condition that S_n^2 converges in probability to σ^2 is that the variance of S_n^2 , $V(S_n^2) \rightarrow 0$, as $n \rightarrow \infty$

NOTE:

field: ²³⁵

field: $V(S_n^2) \rightarrow 0$ as long as

field: $V(S_n^2) \rightarrow 0$ as long as the fourth central moment $\mu_4 = E[(X_1 - \mu)^4]$ is finite.

NOTE:

field: ²³⁶

field: Khinchin's WLLN

field: Let X_1, X_2, \dots be a sequence of iid random variables with $E(X_1) = \mu$ (finite). Then, $\bar{X}_n \xrightarrow{p} \mu$ as $n \rightarrow \infty$

NOTE:

field: 237

field: Let X_1, X_2, \dots be a sequence of random variables, such that for some $r > 0$ and $c \in \mathbb{R}$, $E[|X_n - c|^r] \xrightarrow{n \rightarrow \infty} 0$. Then $X_n \xrightarrow{p} c$, as $n \rightarrow \infty$

field: (A general result to establish convergence in probability)

Let X_1, X_2, \dots be a sequence of random variables, such that for some $r > 0$ and $c \in \mathbb{R}$, $E[|X_n - c|^r] \xrightarrow{n \rightarrow \infty} 0$. Then $X_n \xrightarrow{p} c$, as $n \rightarrow \infty$

NOTE:

field: 238

field: Consistent estimator for $X_1, X_2, \dots, X_n \sim \text{iid Unif}(0, \theta)$, $\theta > 0$. (and sketch of proof)

field: $X_{(n)} = \max(X_1, \dots, X_n)$ (the largest order statistic)

Proof

First recall that the pdf of $X_{(n)}$ is given by

$$f(x) = nx^{n-1}\theta^{-n}, 0 < x < \theta, 0 \text{ otherwise}$$

We obtain

$$\begin{aligned}
E(X_{(n)}) &= \int_0^\theta x f(x) dx \\
&= n\theta^{-n} \int_0^\theta x^n dx \\
&= \frac{n}{n-1} \theta \\
E(X_{(n)}^2) &= \int_0^\theta x^2 f(x) dx \\
&= n\theta^{-n} \int_0^\theta x^{n+1} dx \\
&= \frac{n}{n+2} \theta^2
\end{aligned}$$

We have

$$\begin{aligned}
E[(X_{(n)} - \theta)^2] &= E(X_{(n)}^2) - 2\theta E(X_{(n)}) + \theta^2 \\
&= \frac{n}{n+2} \theta^2 - 2\theta \frac{n}{n+1} \theta + \theta^2 \\
&\dots \\
&= \frac{2\theta^2}{(n+1)(n+2)} \xrightarrow{n \rightarrow \infty} 0
\end{aligned}$$

Hence, taking $c = 0$ and $r = 2$, from the previous theorem, we obtain $X_{(n)} \xrightarrow{P} \theta$ as $n \rightarrow \infty$

NOTE:

field: 239

field: Definition Almost Sure Convergence

field: A sequence $\{X_n\}_{n \geq 1}$ of random variables is said to converge **Almost Surely** to a random variable X if for every $\epsilon > 0$,

$$P(\lim_{n \rightarrow \infty} |X_n - X| > \epsilon) = 0$$

We write $X_n \xrightarrow{a.s} X$ as $n \rightarrow \infty$

NOTE:

field: 240

field: Strong Law of Large Numbers

field: Let X_1, X_2, \dots be an iid sequence of random variables, with $E(X_1) = \mu$ (finite) and $V(X_1) = \sigma^2 < \infty$. Then,

$$\bar{X}_n \xrightarrow{a.s.} \mu \quad \text{as } \mu \rightarrow \infty$$

NOTE:

field: 241

field: Does convergence in probability imply convergence almost surely?

field: No. Let $\Omega = [0,1]$, with uniform probability distribution. Define the sequence $\{X_n\}_{n \geq 1}$ as:

$$\begin{aligned} X_1(\omega) &= \omega + \mathbb{I}_{[0,1]}(\omega) \\ X_2(\omega) &= \omega + \mathbb{I}_{[0,1/2]}(\omega) \\ X_3(\omega) &= \omega + \mathbb{I}_{[1/2,1]}(\omega) \\ X_4(\omega) &= \omega + \mathbb{I}_{[0,1/3]}(\omega) \\ X_5(\omega) &= \omega + \mathbb{I}_{[1/3,2/3]}(\omega) \\ &\vdots \end{aligned}$$

$$X_5(\omega) = \omega + 1$$

Let $X(\omega) = \omega$, then it is easy to show that $X_n \xrightarrow{P} X$ because $P(|X_n - X| \geq \epsilon) = P([a_n, b_n])$, where $l_n = \text{length}([a_n, b_n]) \xrightarrow{n \rightarrow \infty} 0$.

However X_n does not converge to X almost surely, because for every $\omega \in [0,1]$, alternates between ω and $\omega + 1$, infinitely often as $n \rightarrow \infty$

NOTE:

field: 242

field: Convergence in Distribution

field: A sequence $\{X_n\}_{n \geq 1}$ of random variables converges in distribution to a random variable X if,

$$\lim_{n \rightarrow \infty} F_{X_n}(x) = F_X(x)$$

at all points x where $F_X(x)$ is continuous

We write $X_n \xrightarrow{d} X$

NOTE:

field: 243

field: Example of convergence in distribution

Let $X_n \sim N(0, \frac{n+1}{n})$, and $X \sim N(0, 1)$. We want to show that $X_n \xrightarrow{d} X$.

field:

$$\begin{aligned} P(X_n \leq X) &= P\left(\sqrt{\frac{n}{n+1}} X_n \leq \sqrt{\frac{n}{n+1}} x\right) \\ &= \Phi\left(\sqrt{\frac{n}{n+1}} x\right) \xrightarrow{n \rightarrow \infty} \Phi(x) \end{aligned}$$

And we obtain that $F_{X_n} \rightarrow \Phi(x) = F_X(x), \forall x$, and therefore $X_n \xrightarrow{d} X$

NOTE:

field: 244

field: Does Convergence in probability imply convergence in distribution?

field: Yes

NOTE:

field: ²⁴⁵

field: Does Convergence in distribution imply convergence in probability?

field: No - unless converges in distribution to a constant

NOTE:

field: ²⁴⁶

field: A sequence $\{X_n\}_{n \geq 1}$ of random variables converges in probability to a constant $c \in \mathbb{R}$ if and only if

field: A sequence $\{X_n\}_{n \geq 1}$ of random variables converges in probability to a constant $c \in \mathbb{R}$ if and only if the sequence converges in distribution to c

NOTE:

field: ²⁴⁷

field: If $X_n \xrightarrow{d} X$ and $Y_n \xrightarrow{d} Y$ we have that

1. $X_n \pm Y_n$
2. $X_n Y_n$

field: In general it is not true that if $X_n \xrightarrow{d} X$ and $Y_n \xrightarrow{d} Y$ we have that

1. $X_n \pm Y_n \xrightarrow{d} X + Y$
2. $X_n Y_n \xrightarrow{d} XY$

NOTE:

field: ²⁴⁸

field: Let $\{X_n\}_{n \geq 1}$ be a sequence of random variables such that $X_n \xrightarrow{d} X$, for some random variable X (possibly a constant). Then for any continuous function $g : \mathbb{R} \rightarrow \mathbb{R}$, we have $g(X_n) \xrightarrow{d}$

field: Let $\{X_n\}_{n \geq 1}$ be a sequence of random variables such that $X_n \xrightarrow{d} X$, for some random variable X (possibly a constant). Then for any continuous function $g : \mathbb{R} \rightarrow \mathbb{R}$, we have $g(X_n) \xrightarrow{d} g(X)$

NOTE:

field: ²⁴⁹

field: Let $\{X_n\}_{n \geq 1}$ and $\{Y_n\}_{n \geq 1}$ be two sequences of random variables such that $X_n \xrightarrow{d} X$ for some random variable X (possibly a constant) and $Y_n \xrightarrow{p} c \in \mathbb{R}$

Then, as $n \rightarrow \infty$,

1. $X_n \pm Y_n \xrightarrow{d}$
2. $X_n Y_n \xrightarrow{d}$
3. $X_n / Y_n \xrightarrow{d}$ provided $P(Y_n = 0) = 0 \forall n$ and $c \neq 0$

field: Slutsky's Theorem Let $\{X_n\}_{n \geq 1}$ and $\{Y_n\}_{n \geq 1}$ be two sequences of random variables such that $X_n \xrightarrow{d} X$ for some random variable X (possibly a constant) and $Y_n \xrightarrow{p} c \in \mathbb{R}$

Then, as $n \rightarrow \infty$,

1. $X_n \pm Y_n \xrightarrow{d} X \pm c$
2. $X_n Y_n \xrightarrow{d} cX$
3. $X_n / Y_n \xrightarrow{d} X/c$ provided $P(Y_n = 0) = 0 \forall n$ and $c \neq 0$

NOTE:

field: 250

field: Central Limit Theorem

field: Let X_1, X_2, \dots be an iid sequence of random variables, with $E(X_1) = \mu$ (finite) and $V(X_1) = \sigma^2 < \infty$

Then, for $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$ (the sample mean), we have that

$$\frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma} \xrightarrow{d} N(0, 1) \quad \text{as } n \rightarrow \infty$$

NOTE:

field: 251

field: Equivalent results of CLT

field:

- $\frac{(\bar{X}_n - \mu)}{\frac{\sigma}{\sqrt{n}}} \xrightarrow{d} N(0, 1)$
- $\sqrt{n}(\bar{X}_n - \mu) \xrightarrow{d} N(0, \sigma^2)$
- $\frac{\sum_{i=1}^n X_i - n\mu}{\sqrt{n}\sigma} \xrightarrow{d} N(0, 1)$
- $\bar{X}_n \xrightarrow{d} N(\mu, \sigma^2/n)$

NOTE:

field: 252

field: Let $\{X_n\}_{n \geq 1}$ be a sequence of random variables such that the mgf $M_{X_n}(t)$ of X_n exists in a neighborhood of 0, for all n , and suppose that

$$\lim_{n \rightarrow \infty} M_{X_n}(t) = M_X(t) \quad \text{for all } t \text{ in a neighborhood of } 0$$

where $M_X(t)$ is the mgf for some random variable X . Then,

field: Let $\{X_n\}_{n \geq 1}$ be a sequence of random variables such that the mgf $M_{X_n}(t)$ of X_n exists in a neighborhood of 0, for all n , and suppose that

$$\lim_{n \rightarrow \infty} M_{X_n}(t) = M_X(t) \quad \text{for all } t \text{ in a neighborhood of } 0$$

where $M_X(t)$ is the mgf for some random variable X . Then, there exists a unique cdf $F_X(x)$ whose moments are determined by $M_X(t)$ and for all x , where $F_X(x)$ is continuous we have $\lim_{n \rightarrow \infty} F_{X_n}(x) = F_X(x)$

NOTE:

field: 253

field: $\frac{\sqrt{n}(\bar{X} - \mu)}{S_n} \xrightarrow{d}$

field: Using the CLT, and Slutsky's theorem, we have

$$\frac{\sqrt{n}(\bar{X} - \mu)}{S_n} = \frac{\sigma}{S_n} \cdot \frac{\sqrt{n}(\bar{X} - \mu)}{\sigma} \xrightarrow{d} N(0, 1)$$

NOTE:

field: 254

field: $g(X) \approx$
 $E(g(X)) \approx, V(g(X)) \approx$

field:

$$g(X) \approx g(\mu) + g'(\mu)(X - \mu)$$

Using a first order Taylor approximation $E(g(X)) \approx g(\mu), V(g(X)) \approx [g'(\mu)]^2 V(X)$

NOTE:

field: 255

field: Delta Method

field: Let $\{Y_n\}_{n \geq 1}$ be a sequence of random variables such that $\sqrt{n}(Y_n - \theta) \xrightarrow{d} N(0, \sigma^2)$ as $n \rightarrow \infty$. Suppose that for a given function g and a specific value of θ , $g'(\theta)$ exists and is not equal to zero. Then

$$\sqrt{n}(g(Y_n) - g(\theta)) \xrightarrow{d} N(0, \sigma^2[g'(\theta)]^2)$$

as $n \rightarrow \infty$

NOTE:

field: 256

field: Second Order delta method

field: Let $\{Y_n\}_{n \geq 1}$ be a sequence of random variables such that $\sqrt{n}(Y_n - \theta) \xrightarrow{d} N(0, \sigma^2)$ as $n \rightarrow \infty$. And that for a given function g as specific value of θ , we have $g'(\theta) = 0$, but $g''(\theta)$ exists and is not equal to 0. Then

$$\sqrt{n}(g(Y_n) - g(\theta)) \xrightarrow{d} \sigma^2 \frac{g''(\theta)}{2} \chi_1^2 \quad \text{as } n \rightarrow \infty$$

NOTE:

field: 257

field: $\chi_n^2 \sim$ for sufficiently large n

field: $\chi_n^2 \sim N(n, 2n)$

NOTE:

field: 258

field: Definition Statistic

field: Let X_1, \dots, X_n be a random sample from a given population. Then, any observable real-valued (or vector-valued) function $T(\mathbf{X}) = T(X_1, \dots, X_n)$ of the random variables X_1, \dots, X_n is called a **Statistic**

NOTE:

field: 259

field: Sampling Distribution

field: The probability distribution of the statistic $T(\mathbf{X})$ is called the **Sampling Distribution** of $T(\mathbf{X})$

NOTE:

field: 260

field: Sufficient Statistic

field: A statistic $T(\mathbf{X})$ is a **Sufficient Statistic** for θ , if the conditional distribution of the sample \mathbf{X} given the value of $T(\mathbf{X})$ does not depend on θ

NOTE:

field: 261

field: Determine if $T(\mathbf{X}) = \sum X_i$ where $X_i \sim \text{Bern}(p)$ is sufficient for p using definition of sufficiency

field:

$$\begin{aligned} P(\mathbf{X} = \mathbf{x} | T = t) &= \frac{P(\cap_{i=1}^n X_i = x_i)}{P(T = t)} \\ &= \prod_{i=1}^n \frac{P(X_i = x_i)}{P(T = t)} \quad \text{by independence} \\ &= \frac{p^{\sum_{i=1}^n x_i} (1-p)^{n-\sum_{i=1}^n x_i}}{\binom{n}{t} p^t (1-p)^{n-t}} \quad \text{Because } T \sim \text{Binom}(n, p) \\ &= \frac{p^t (1-p)^{n-t}}{\binom{n}{t} p^t (1-p)^{n-t}} \quad \text{because } t = \sum_{i=1}^n x_i \\ &= \frac{1}{\binom{n}{t}} \quad \text{which is free of } p \end{aligned}$$

NOTE:

field: 262

field: How to show sufficiency (not using factorization)

field: Let $p(\mathbf{X}|\theta)$ be the joint PDF or PMF of \mathbf{X} and $q(t|\theta)$ the PDF or PMF of the statistic $T(\mathbf{X})$. Then $T(\mathbf{X})$ is a sufficient statistic for θ if for every \mathbf{X} in the sample space, the ratio

$$\frac{p(\mathbf{x}|\theta)}{q(T(\mathbf{x})|\theta)}$$

is constant as a function of θ

NOTE:

field: 263

field: Suppose that X_1, \dots, X_n are iid $N(\mu, \sigma^2)$ where σ^2 is known. If the statistic $T(\mathbf{X}) = \bar{X}_n$ sufficient for μ ?

field:

$$\begin{aligned}\frac{f(\mathbf{x}|\mu)}{q(T(\mathbf{X})|\mu)} &= \frac{(2\pi\sigma^2)^{n/2}e^{-\frac{1}{2\sigma^2}[\sum_{i=1}^n(x_i-\bar{x})^2+n(\bar{x}-\mu)^2]}}{(2\pi\sigma/n)^{-1/2}e^{-\frac{1}{2\sigma^2}(\bar{x}-\mu)^2}} \\ &= n^{-1/2}(2\pi\sigma^2)^{-(n-1)/2}e^{-\frac{1}{2\sigma^2}\sum_{i=1}^n(x_i-\bar{x})^2}\end{aligned}$$

Which does not depend on μ , and therefore \bar{X}_n is sufficient for μ as long as σ^2 is known

NOTE:

field: 264

field: Find the joint pdf of the sample $\mathbf{X} = (X_1, X_2, \dots, X_n)$ given that X_1, \dots, X_n are iid $N(\mu, \sigma^2)$ where σ^2 is known.

field:

$$\begin{aligned}f(\mathbf{x}|\mu) &= \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x_i-\mu)^2} \\ &= (2\pi\sigma^2)^{n/2} e^{-1/2\sigma^2 \sum_{i=1}^n (x_i-\mu)^2} \\ &= (2\pi\sigma^2)^{n/2} e^{-1/2\sigma^2 \sum_{i=1}^n (x_i-\bar{x}+\bar{x}-\mu)^2} \\ &= (2\pi\sigma^2)^{n/2} e^{-1/2\sigma^2 \sum_{i=1}^n (x_i-\bar{x})^2 + 2(\bar{x}-\mu) \sum_{i=1}^n (x_i-\bar{x}) + n(\bar{x}-\mu)^2} \\ &= (2\pi\sigma^2)^{n/2} e^{-1/2\sigma^2 (\sum_{i=1}^n (x_i-\bar{x})^2 + n(\bar{x}-\mu)^2)}\end{aligned}$$

NOTE:

field: 265

field: Show a statistic $T(\mathbf{X})$ is sufficient

field: Neyman factorization theorem Let $f(\mathbf{x}|\theta)$ denote the joint pdf or pmf of the sample \mathbf{X} , A statistic $T(\mathbf{X})$ is a sufficient statistic for θ if and only if there exists functions $g(t|\theta)$ and $h(\mathbf{x})$ such that for all sample points \mathbf{x} and all values of θ we can write

$$f(\mathbf{x}|\theta) = g(T(\mathbf{x})|\theta)h(\mathbf{x})$$

Note, in the theorem

- The function $g(T(\mathbf{X})|\theta)$ depends on $\mathbf{x} = (x_1, \dots, x_n)$ only through the statistic $T(\mathbf{X})$.
- The function $h(\mathbf{X})$ does not depend on θ

NOTE:

field: 266

field: Exponential Family

field:

$$f(\mathbf{X}|\theta) = \mathbf{h}(\mathbf{x})\mathbf{c}(\theta)e^{\sum_{i=1}^n \mathbf{w}_i((\theta))\mathbf{t}_i(\mathbf{x})}$$

NOTE:

field: 267

field: Sufficiency in the exponential family

field: Let X_1, \dots, X_n be iid observations from a PDF or PMF, $f(x|\boldsymbol{\theta})$ that belongs to an exponential family of the form

$$f(x|\boldsymbol{\theta}) = h(x)c(\boldsymbol{\theta})e^{\sum_{i=1}^k w_i(\boldsymbol{\theta})t_i(x)}$$

Where $\boldsymbol{\theta} = (\theta_1, \dots, \theta_d)$, $d \leq k$. Then

$$T(\mathbf{X}) = \left(\sum_{j=1}^k t_1(x_j), \dots, \sum_{j=1}^k t_k(x_j) \right)$$

is sufficient

NOTE:

field: 268

field: Minimal Sufficient Statistic

field: A sufficient statistic $T(\mathbf{X})$ is called a **Minimal Sufficient Statistic** if for any other sufficient statistic $T'(\mathbf{X})$, $T(\mathbf{X})$ is a function of $T'(\mathbf{X})$

NOTE:

field: 269

field: Determining if a statistic is minimal sufficient

field: Let $f(x|\theta)$ be the PDF or PMF of a sample \mathbf{X} . Suppose there exists a function $T(x)$ such that, for every two sample points, \mathbf{x} and \mathbf{y} , the ratio $\frac{f(\mathbf{x}|\theta)}{f(\mathbf{y}|\theta)}$ is constant as a function of θ iff and only if $T(\mathbf{x}) = T(\mathbf{y})$. Then $T(\mathbf{x})$ is a minimal sufficient statistic for θ .

NOTE:

field: 270

field: Example of finding a minimal sufficient statistic: Suppose that X_1, \dots, X_n are iid Bernoulli(p). What is a minimal sufficient statistic for p ?

field:

$$\begin{aligned} f(\mathbf{x}|p) &= \prod_{i=1}^n p^{x_i} (1-p)^{1-x_i} \\ &= p^{\sum_{i=1}^n x_i} (1-p)^{n-\sum_{i=1}^n x_i} \end{aligned}$$

And therefore for any two sample points \mathbf{x} and \mathbf{y} , we obtain

$$\begin{aligned}\frac{f(\mathbf{x}|p)}{f(\mathbf{y}|p)} &= \frac{p^{\sum_{i=1}^n x_i} (1-p)^{n-\sum_{i=1}^n x_i}}{p^{\sum_{i=1}^n y_i} (1-p)^{n-\sum_{i=1}^n y_i}} \\ &= p^{\sum_{i=1}^n x_i - \sum_{i=1}^n y_i} (1-p)^{\sum_{i=1}^n y_i - \sum_{i=1}^n x_i}\end{aligned}$$

Which is constant as a function of p iff $\sum_{i=1}^n x_i = \sum_{i=1}^n y_i$

Hence it follows from Lehman-Sheffe that $T(\mathbf{x}) = \sum_{i=1}^n x_i$ is minimal sufficient for p

NOTE:

field: 271

field: Minimal sufficient statistic for μ, σ^2 , where the X s are $N(\mu, \sigma^2)$

field: $T(\mathbf{x}) = (\bar{x}, S_x^2)$ by Lehmann-Schaffe is minimal sufficient.

NOTE:

field: 272

field: Facts about sufficiency

field:

- The entire sample \mathbf{X} is always sufficeint.
- Any one-to-one funciton of a minimal sufficient statisitc is also a minimal sufficient statistic

NOTE:

field: 273

field: Ancillary Statistic

field: A statistic $S(\mathbf{X})$ whose distribution does not depend on the parameter θ is called an ancillary statistic for θ

NOTE:

field: ₂₇₄

field: Complete statistic

field: Let $f(t|\theta)$ be the family of pdf's or pmfs for a statistic $T = T(\mathbf{x})$.

The family of probability distributions is called **complete** (with respect to θ) if $E_\theta(g(t)) = 0$ for all θ , implies $P_\theta(g(T) = 0) = 1$ for all θ

Equivalently, we say that $T = T(\mathbf{X})$ is a complete statistic.

In short, a statistic $T = T(\mathbf{X})$ is complete, if $E_\theta(g(T)) = 0$ for all θ implies $g(t) = 0$ with probability 1

NOTE:

field: ₂₇₅

field: (Binomial complete sufficient statistic)

field: Suppose the statistic $T \sim \text{Binom}(n, p)$, $0 < p < 1$, and let g be a function such that $E_p(g(T)) = 0$ for all p .

Then, with $r = (\frac{p}{1-p})^t$

$$\begin{aligned}
0 &= E_p(g(T)) \\
&= \sum_{t=0}^n g(t) \binom{n}{t} p^t (1-p)^{n-t} \\
&= (1-p)^n \sum_{t=0}^n g(t) \binom{n}{t} \left(\frac{p}{1-p}\right)^t \\
&= (1-p)^n \sum_{t=0}^n g(t) \binom{n}{t} r^t \\
&\neq 0 \cdot \text{This is a polynomial of degree } n \text{ in } r \text{ with coefficients } g(t) \binom{n}{t}
\end{aligned}$$

For the polynomial to be 0 for all r (and consequently for all p) each coefficient must be zero and therefore it must be the case that $g(t) = 0$ for $t = 0, 1, 2, \dots, n$. Since $T \sim \text{Binom}(n, p)$, we have that T takes on the values $t = 0, 1, 2, \dots, n$ with probability 1 and therefore, we obtain $P_p(g(T) = 0) = 1$. Hence T is a complete statistic.

NOTE:

field: \mathbb{R}

field: $\text{Uniform}(0, \theta)$ complete sufficient statistic

field: $T(\mathbf{X}) = X_{(n)}$

Suppose that X_1, \dots, X_n are iid $\text{Uniform}(0, \theta)$, $\theta > 0$. We know that $T(\mathbf{X}) = X_{(n)}$ (the max order statistic) is sufficient for θ . Furthermore ,

$$f(t|\theta) = nt^{n-1}\theta^{-n} \quad 0 < t < \theta$$

Now suppose that $g(t)$ is a function satisfying $E_\theta(g(T)) = 0, \forall \theta$. Differentiating on both sides with respect to θ ,

$$\begin{aligned}
0 &= \frac{d}{d\theta} E_\theta(g(t)) \\
&= \frac{d}{d\theta} \int_0^\theta g(t) n t^{n-1} \theta^{-n} dt \\
&= \theta^{-n} \frac{d}{d\theta} \int_0^\theta g(t) n t^{n-1} dt + \left(\frac{d}{d\theta} \theta^{-n} \right) \int_0^\theta g(t) n t^{n-1} dt \\
&= \theta^{-n} g(\theta) n \theta^{n-1} + 0
\end{aligned}$$

Since $n\theta^{-1} \neq 0$, we must have that $g(\theta) = 0 \quad \forall \theta > 0$. And therefore T is complete.

NOTE:

field: 277

field: Does minimal sufficient imply complete?

field: No

Suppose that X_1, \dots, X_n are iid $N(\theta, \theta^2)$ where $\theta \in \mathbb{R}$ is the unknown parameter of interest.

We have

$$\begin{aligned}
\frac{f(\mathbf{x}|\theta)}{f(\mathbf{y}|\theta)} &= \frac{(2\phi\sigma^2)^{-n/2} e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \theta)^2}}{(2\phi\sigma^2)^{-n/2} e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (y_i - \theta)^2}} \\
&= \frac{e^{-\frac{1}{2\sigma^2} [\sum_{i=1}^n x_i^2 - 2\theta \sum_{i=1}^n x_i]}}{e^{-\frac{1}{2\sigma^2} [\sum_{i=1}^n y_i^2 - 2\theta \sum_{i=1}^n y_i]}}
\end{aligned}$$

Which is free of θ if $\sum_{i=1}^n x_i^2 = \sum_{i=1}^n y_i^2$ and $\sum_{i=1}^n x_i = \sum_{i=1}^n y_i$
It follows that $T(\mathbf{X}) = (\sum_{i=1}^n x_i, \sum_{i=1}^n x_i^2)$ is minimal sufficient for θ
Now observe that $T_1(\mathbf{X}) = \sum_{i=1}^n x_i \sim N(n\theta, n\theta^2)$ and therefore

$$\begin{aligned}
E(T_1^2) &= V(T_1) + [E(T_1)]^2 \\
&= n\theta^2 + n^2\theta^2 \\
&= n\theta^2(1 + n)
\end{aligned}$$

On the other hand, for $T_2 = \sum_{i=1}^n x_i^2$,

$$\begin{aligned} E(T_2) &= nE(X_1)^2 \\ &= n[V(X_1) + [E(X_1)]^2] \\ &= n\theta^2 + n\theta^2 \\ &= 2n\theta^2 \end{aligned}$$

Then, taking $h(t_1, t_2) = 2t_1^2 - (n+1)t_2$, we have

$$\begin{aligned} E_\theta[h(T_1, T_2)] &= E_\theta[2T_1^2 - (n+1)T_2] \\ &= 2E_\theta(T_1^2) - (n+1)E(T_2) \\ &= 2n(n+1)\theta^2 - 2n(n+1)\theta^2 \\ &= 0 \quad \forall \theta \end{aligned}$$

But because $h(\mathbf{t}) \neq 0 \quad \forall \theta$, we have that $T(\mathbf{X})$ is not complete.

NOTE:

field: 278

field: Complete statistics in the exponential family

field: Let X_1, \dots, X_n be iid observations from an exponential family. with PDF or PMF of the form

$$f(x|\theta) = h(x)c(\theta)e^{\sum_{j=1}^k \omega_j(\theta_j)t_j(x)}$$

Where $\boldsymbol{\theta} = (\theta_1, \dots, \theta_k)$

Then, the statistic $T(\mathbf{X}) = (\sum_{i=1}^n t_1(x_i), \sum_{i=1}^n t_2(x_i), \dots, \sum_{i=1}^n t_k(x_i))$ is complete, as long as the parameter space Θ contains an open set in \mathbb{R}^k

NOTE:

field: 279

field: Suppose that a statistic T is complete and let g be a one-to-one function. Is the statistic $U = g(T)$ also complete?

field: Yes

NOTE:

field: ₂₈₀

field: Does complete statistic imply minimal sufficient statistic?

field: If a minimal sufficient statistic exists, then any complete statistic is also a minimal sufficient statistic

NOTE:

field: ₂₈₁

field: Basu's Theorem

field: If $T(\mathbf{x})$ is a complete and minimal sufficient statistic, then $T(\mathbf{x})$ is an independent of every ancillary statistic.

NOTE:

field: ₂₈₂

field: Likelihood function

field: Let $f(\mathbf{x}|\theta)$ denote the joint pdf or pmf of the sample $\mathbf{X} = (X_1, \dots, X_n)$, then given that $\mathbf{X} = \mathbf{x}$ is observed, the function of θ defined as

$$L(\theta|\mathbf{x}) = f(\mathbf{x}|\theta)$$

is called the Likelihood Function

NOTE:

field: ₂₈₃

field: Idea of likelihood function

field: Suppose that \mathbf{X} is a discrete random vector (so we can interpret probabilities easier)

Then $L(\theta|\mathbf{x}) = P_\theta(\mathbf{X} = \mathbf{x})$. Now if we compare the likelihood function at two parameter values θ_1, θ_2 and we observe that

$$P_{\theta_1}(\mathbf{X} = \mathbf{x}) = L(\theta_1|\mathbf{x}) > L(\theta_2|\mathbf{x}) = P_{\theta_2}(\mathbf{X} = \mathbf{x})$$

Then, the sample point \mathbf{x} that we actually observed is more likely to have occurred if $\theta = \theta_1$, than if $\theta = \theta_2$, which can be interpreted as that θ_1 , is a more plausible value for the true value of θ than θ_2 is.

NOTE:

field: 284

field: Fisher information - one parameter case

field: Let X be a random variable with pdf or pmf $f(x|\theta)$ where $\theta \in \Theta \subseteq \mathbb{R}$ (Fisher) information about θ contained in X is

$$I_X(\theta) = E_\theta\left[\left(\frac{\partial}{\partial\theta} \log f(x|\theta)\right)^2\right]$$

NOTE:

field: 285

field: Example of one parameter case Fisher information Suppose that $X \sim \text{Bern}(p)$ What is the information that X contains about the parameter p ?

field: We have that $f(x|p) = p^x(1-p)^{1-x}$. Then

$$\log f(x|p) = x \log p + (1-x) \log(1-p)$$

$$\frac{\partial}{\partial p} \log f(x|p) = \frac{x}{p} - \frac{1-x}{1-p}$$

We obtain

$$\begin{aligned} \left(\frac{\partial}{\partial p} \log f(x|p)\right)^2 &= \left(\frac{x}{p} - \frac{1-x}{1-p}\right)^2 \\ &= \frac{x^2}{p^2} - \frac{2x(1-x)}{p(1-p)} + \frac{(1-x)^2}{(1-p)^2} \\ &= \frac{x^2}{p^2} - \frac{2(x-x^2)}{p(1-p)} + \frac{(1-2x+x^2)}{(1-p)^2} \end{aligned}$$

Therefore,

$$\begin{aligned} I_x(p) &= E_p\left[\left(\frac{\partial}{\partial p} \log f(x|p)\right)^2\right] \\ &= \frac{p}{p^2} - \frac{2(p-p)}{p(1-p)} + \frac{1-2p+p}{(1-p)^2} \\ &= \frac{1}{p} + \frac{1}{1-p} \\ &= \frac{1}{p(1-p)} \end{aligned}$$

NOTE:

field: 286

field:

$$I_x(\theta) = E_\theta\left[\left(\frac{\partial}{\partial \theta} \log f(x|\theta)\right)^2\right] =$$

field: If $f(x|\theta)$ satisfies

$$\frac{\partial}{\partial \theta} E_{\theta} \left(\frac{\partial}{\partial \theta} \log f(x|\theta) \right) = \int \frac{\partial}{\partial \theta} \left[\frac{\partial}{\partial \theta} \log f(x|\theta) \right] f(x|\theta) dx$$

$$I_x(\theta) = E_{\theta} \left[\left(\frac{\partial}{\partial \theta} \log f(x|\theta) \right)^2 \right] = -E_{\theta} \left(\frac{\partial^2}{\partial \theta^2} \log f(x|\theta) \right)$$

NOTE:

field: 287

field: Suppose that X_1, \dots, X_n are iid observations with common pdf or pmf $f(x|\theta)$. Then, the information about θ contained in the sample $\mathbf{X} = (X_1, \dots, X_n)$ is

field:

$$I_{\mathbf{X}}(\theta) = nI_{X_1}(\theta)$$

NOTE:

field: 288

field: Fisher Information - multiparameter case

field: Let X be a random variable with pdf or pmf $f(x|\boldsymbol{\theta})$, where $\boldsymbol{\theta} = (\theta_1, \theta_2) \in \Theta \subseteq \mathbb{R}^2$. Denote by

$$I_{ij}(\boldsymbol{\theta}) = E_{\boldsymbol{\theta}} \left[\left(\frac{\partial}{\partial \theta_i} \log f(x|\boldsymbol{\theta}) \right) \left(\frac{\partial}{\partial \theta_j} \log f(x|\boldsymbol{\theta}) \right) \right] = -E_{\boldsymbol{\theta}} \left[\frac{\partial^2}{\partial \theta_i \partial \theta_j} \log f(x|\boldsymbol{\theta}) \right]$$

For $i, j = 1, 2$. Then the (fisher) information matrix about $\boldsymbol{\theta}$ is

$$I_x(\boldsymbol{\theta}) = \begin{pmatrix} I_{11}(\boldsymbol{\theta}) & I_{12}(\boldsymbol{\theta}) \\ I_{21}(\boldsymbol{\theta}) & I_{22}(\boldsymbol{\theta}) \end{pmatrix}$$

NOTE:

field: 289

field: Find Fisher information matrix for Normal RVs

field: We have that $\boldsymbol{\theta} = (\mu, \sigma^2)$ and $f(x|\boldsymbol{\theta}) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x-\mu)^2}$ Then,

$$\frac{\partial}{\partial \mu} \log f(x|\boldsymbol{\theta}) = \frac{\partial}{\partial \mu} \left[-\frac{1}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2}(x-\mu)^2 \right] = \frac{(x-\mu)}{\sigma^2}$$

$$\frac{\partial}{\partial \sigma^2} = \frac{1}{2\sigma^2} \left[\frac{(x-\mu)^2}{\sigma^2} - 1 \right]$$

$$\text{Therefore } I_{11} = E_{\theta} \left[\left(\frac{\partial}{\partial \mu} \log f(x|\boldsymbol{\theta}) \right)^2 \right] = E_{\theta} \left[\frac{(x-\mu)^2}{\sigma^4} \right] = \frac{1}{\sigma^4} \sigma^2 = \frac{1}{\sigma^2}$$

$$\begin{aligned} I_{22}(\boldsymbol{\theta}) &= E_{\theta} \left[\frac{\partial}{\partial \sigma^2} \log f(x|\boldsymbol{\theta})^2 \right] \\ &= E_{\theta} \left\{ \left[\frac{1}{2\sigma^2} \left(\frac{(x-\mu)^2}{\sigma^2} - 1 \right) \right]^2 \right\} \\ &= \frac{1}{4\sigma^4} E_{\theta} \left[\left(\frac{(x-\mu)^2}{\sigma^2} - 1 \right)^2 \right] \\ &= \frac{1}{4\sigma^4 \cdot 2} \\ &= \frac{1}{2\sigma^4} \quad \text{Since } = V(\chi_1^2) \end{aligned}$$

Now for the off diagonal elements,

$$\begin{aligned} I_{12}(\boldsymbol{\theta}) &= I_{21}(\boldsymbol{\theta}) = E_{\theta} \left[\left(\frac{\partial}{\partial \mu} \log f(x|\boldsymbol{\theta}) \right) \left(\frac{\partial}{\partial \sigma^2} \log f(x|\boldsymbol{\theta}) \right) \right] \\ &= E_{\theta} \left[\frac{(x-\mu)}{\sigma^2} \cdot \frac{1}{2\sigma^2} \left[\frac{(x-\mu)^2}{\sigma^2} - 1 \right] \right] \\ &= \frac{1}{2\sigma^4} E_{\theta} \left[\frac{(x-\mu)^3}{\sigma^3} - (x-\mu) \right] \end{aligned}$$

But $E_\theta[(x - \mu)^3] = E_\theta[(x - \mu)] = 0$, because X is symmetric around μ , and we obtain $I_{12}(\boldsymbol{\theta}) = I_{21}(\boldsymbol{\theta}) = 0$ We obtain that

$$\begin{aligned} I_{x_1}(\boldsymbol{\theta}) &= \begin{pmatrix} I_{11}(\boldsymbol{\theta}) & I_{12}(\boldsymbol{\theta}) \\ I_{21}(\boldsymbol{\theta}) & I_{22}(\boldsymbol{\theta}) \end{pmatrix} \\ &= \begin{pmatrix} \frac{1}{\sigma^2} & 0 \\ 0 & \frac{1}{2\sigma^4} \end{pmatrix} \end{aligned}$$

And hence

$$I_{\mathbf{x}}(\boldsymbol{\theta}) = nI_{X_1}(\boldsymbol{\theta}) = \begin{pmatrix} \frac{n}{\sigma^2} & 0 \\ 0 & \frac{n}{2\sigma^4} \end{pmatrix}$$

NOTE:

field: 290

field: $I_T(\theta) \leq$

field: $I_T(\theta) \leq I_{\mathbf{X}}(\theta)$ (The information of the statistic is less than or equal to the information of the sample)

NOTE:

field: 291

field: Let $\mathbf{X} = X_1, \dots, X_n$ denote the entire data, and let $T = T(\mathbf{X})$ be some statistic. Then, for all $\theta \in \Theta \subseteq \mathbb{R}$, $I_{\mathbf{X}}(\theta) \geq I_t(\theta)$ Where the equality is attained...

field: Let $\mathbf{X} = X_1, \dots, X_n$ denote the entire data, and let $T = T(\mathbf{X})$ be some statistic. Then, for all $\theta \in \Theta \subseteq \mathbb{R}$, $I_{\mathbf{X}}(\theta) \geq I_t(\theta)$ Where the equality is attained if and only iff $T(\mathbf{X})$ is sufficient for θ

NOTE:

field: 292

field: Let $\mathbf{X} = (X_1, \dots, X_n)$, denote a sample of iid observations and suppose the statistic $T(\mathbf{X}) = (T_1(\mathbf{X}), T_2(\mathbf{X}))$ is such that T_1 and T_2 are independent. Then

$$I_T(\boldsymbol{\theta}) =$$

field: Let $\mathbf{X} = (X_1, \dots, X_n)$, denote a sample of iid observations and suppose the statistic $T(\mathbf{X}) = (T_1(\mathbf{X}), T_2(\mathbf{X}))$ is such that T_1 and T_2 are independent. Then

$$I_T(\boldsymbol{\theta}) = I_{T_1}(\boldsymbol{\theta}) + I_{T_2}(\boldsymbol{\theta})$$

NOTE:

field: ₂₉₃

field: Point estimator

field: Any statistic $T(\mathbf{X})$ that is used to estimate the value of a parameter is called a point estimator of θ . We write $\hat{\theta} = T(\mathbf{X})$

NOTE:

field: ₂₉₄

field: Method of moments

field:

$$\begin{aligned} m_1 &= \frac{1}{n} \sum_{i=1}^n X_i^1, & \mu_1 &= E(X^1) \\ m_2 &= \frac{1}{n} \sum_{i=1}^n X_i^2, & \mu_2 &= E(X^2) \\ &\vdots \\ m_k &= \frac{1}{n} \sum_{i=1}^n X_i^k & \mu_k &= E(X^k) \end{aligned}$$

Equating and solving for θ gives the MoM estimators

NOTE:

field: 295

field: Example Method of Moments Suppose that X_1, \dots, X_n are iid Binomial(k, p), where both k and p are unknown.

field: We have that

$$P(X_i = x|k, p) = \binom{k}{x} p^x (1-p)^{k-x}, x = 0, 1, \dots, k$$

and we obtain $E(X_1) = kp$, $E(X_1^2) = kp(1-p) + k^2p^2$

Solving the sytem of equations we obtain

$$\begin{aligned} m_1 &= \frac{1}{n} \sum_{i=1}^n X_i = kp \\ m_2 &= \frac{1}{n} \sum_{i=1}^n X_i^2 = kp(1-p) + k^2p^2 \end{aligned}$$

Sovling the system of equations:

$$\tilde{p} = \frac{\bar{x}}{\tilde{k}}$$

$$\tilde{k} = \frac{\bar{x}^2}{\bar{x} - \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2}$$

Possible problems: k has to be an integer, and not negative. (Estimates of parameters that are outside of the parameter space.)

NOTE:

field: 296

field: Maximum Likelihood Estimator

field: In this context, we define the **Maximum Likelihood Estimator (MLE)** of θ as the parameter value $\hat{\theta}_{ML} = \hat{\theta}(\mathbf{x})$ that satisfies

$$L(\hat{\theta}_{ML}|\mathbf{x}) = \sup_{\theta \in \Theta} L(\theta|\mathbf{x})$$

Note this often proceeds as taking the derivative of the log likelihood function and setting to zero to solve for parameters - not always

NOTE:

field: 297

field: Example of MLE Suppose that X_1, \dots, X_n are iid Exponential(λ). Find the MLE $\hat{\lambda}_{ML}$ of λ

field: Suppose that X_1, \dots, X_n are iid Exponential(λ). Find the MLE $\hat{\lambda}_{ML}$ of λ

We have that $f(x|\lambda) = \frac{1}{\lambda}e^{-x/\lambda}$, $x > 0$, and therefore

$$L(\lambda|x) = \prod_{i=1}^n \frac{1}{\lambda} e^{-x_i/\lambda} = \lambda^{-n} e^{-\frac{1}{\lambda} \sum_{i=1}^n x_i}$$

Since $\log(\cdot)$ is a strictly monotone (one-to-one) and increasing, we consider instead the maximization of the log-likelihood

$$l(\lambda|\mathbf{x}) = \log L(\lambda|\mathbf{x}) = -n \log \lambda - \frac{1}{\lambda} \sum_{i=1}^n x_i$$

$$\frac{\partial}{\partial \lambda} l(\lambda|\mathbf{x}) = \frac{-n}{\lambda} + \frac{1}{\lambda^2} \sum_{i=1}^n x_i$$

Solving $\frac{\partial}{\partial \lambda} l(\lambda|\mathbf{x}) = 0$, we obtain

$$\frac{-n}{\lambda} + \frac{1}{\lambda^2} \sum_{i=1}^n x_i = 0$$

$$-n\lambda + n\bar{x} = 0$$

$$\lambda = \bar{x}$$

NOTE:

field: 298

field: Example of MLE when can't differentiate

Suppose that X_1, \dots, X_n are iid Uniform($0, \theta$), $\theta > 0$. Find the MLE of θ

field: We have that $f(x|\theta) = \frac{1}{\theta} I(0 < x < \theta)$

And therefore

$$\begin{aligned} L(\theta|\mathbf{x}) &= \prod_{i=1}^n \frac{1}{\theta} I(0 < x_i < \theta) \\ &= \frac{1}{\theta^n} I(X_{(1)} > 0) I(X_{(n)} < \theta) \end{aligned}$$

In this case, the support of X depends on θ and the maximization problem only makes sense whenever $L(\theta|\mathbf{x}) > 0$. We cannot simply approach the problem by taking partial derivatives, but assuming the likelihood is positive, we notice that $L(\theta|\mathbf{x})$ is decreasing as a function of θ , for $\theta > X_{(n)}$

Picture with $L(\theta)$ as zero until $X_{(n)}$ on x axis, goes up to $1/X_{(n)}$ there and decreases with $\frac{1}{\theta^n}$

It follows the MLE of θ is $\hat{\theta}_{ML} = X_{(n)}$

NOTE:

field: 299

field: If $\hat{\theta}_{ML}$ is the MLE of θ , then for any function $\tau(\theta)$, the MLE of $\eta = \tau(\theta)$ is $\hat{\eta}_{ML} =$

field: If $\hat{\theta}_{ML}$ is the MLE of θ , then for any function $\tau(\theta)$, the MLE of $\eta = \tau(\theta)$ is $\hat{\eta}_{ML} = \tau(\hat{\theta}_{ML})$

NOTE:

field: 300

field: Bias

field: Let $\hat{\theta} = T(\mathbf{X})$ be an estimator of θ . Then the Bias of $\hat{\theta}$ as an estimator of θ is defined as

$$B_{\theta}(\hat{\theta}) = E_{\theta}(\hat{\theta} - \theta) = E_{\theta}(\hat{\theta}) - \theta$$

That is the difference between the expected value of $\hat{\theta}$ and θ .

An estimator $\hat{\theta}$ of θ is said to be unbiased if $B_{\theta}(\hat{\theta}) = 0 \quad \forall \theta$

NOTE:

field: 301

field: Mean Squared Error

field: Let $\hat{\theta} = T(\mathbf{X})$ be an estimate of θ . Then, the **Mean Squared Error** (MSE) of $\hat{\theta}$ as an estimator of θ is defined as:

$$MSE(\hat{\theta}) = E_{\theta}[(\hat{\theta} - \theta)^2] = V_{\theta}(\hat{\theta}) + [B_{\theta}(\hat{\theta})]^2$$

NOTE:

field: 302

field: Do unbiased estimators always exist?

field: No, Suppose that $X \sim \text{Binomial}(n, p)$ and let $\theta = 1/p$ be the parameter of interest. Can we find an unbiased estimator for θ ?- No

NOTE:

field: 303

field: UMVUE

field: An estimator W^* is called a best unbiased estimator of $\tau(\theta)$ if it satisfies $E_{\theta}(W^*) = \tau(\theta)$, for all θ , and for any other estimator W with $E_{\theta}(W) = \tau(\theta)$, we have $V_{\theta}(W^*) \leq V_{\theta}(W), \forall \theta$. Equivalently W^* is also called a **Uniform Minimal Variance Unbiased Estimator** (UMVUE) of $\tau(\theta)$

NOTE:

field: 304

field: Finding a UMVUE

field: Start with a complete statistic, (find min suff statistic, prove completeness), Find bias (ie $E(T(\mathbf{X}))$). Then adjust $T(\mathbf{X})$ to be unbiased. (ie center or scale)

NOTE:

field: 305

field: Cramer-Rao Inequality

field: Let X_1, \dots, X_n be a sample with joint pdf or pmf $f(\mathbf{x}|\theta)$ and let $W(\mathbf{X}) = W(X_1, \dots, X_n)$ be any estimator satisfying

$$\frac{d}{d\theta} E_\theta(W(\mathbf{X})) = \int \frac{d}{d\theta} [W(\mathbf{X})f(\mathbf{x}|\theta)] d\mathbf{x}$$

and $V_\theta(W(\mathbf{X})) < \infty$

Then,

$$V_\theta(W(\mathbf{X})) \geq \frac{(\frac{d}{d\theta} E_\theta(W(\mathbf{X})))^2}{E_\theta[(\frac{\partial}{\partial \theta} \log f(\mathbf{x}|\theta))^2]}$$

Observe that if the sample X_1, \dots, X_n is iid with common pdf or pmf $f(x|\theta)$, we obtain

$$V_\theta(W(\mathbf{X})) \geq \frac{[\frac{d}{d\theta} E_\theta(W(\mathbf{X}))]^2}{nE_\theta[(\log f(\mathbf{x}|\theta))^2]}$$

The denominator is the information in the sample about θ

We have that as the information number gets bigger we have a smaller bound for the variance. of the best unbiased estimator and therefore more information is available.

NOTE:

field: 306

field: Cramer-Rao and UMVUE example UMVUE of λ for Poisson

field: Poisson example, we have $\tau(\lambda) = \lambda$, so $\frac{d}{d\lambda} \tau(\lambda) = 1$

On the other hand,

$$\begin{aligned}
nE_\lambda\left[\left(\frac{d}{d\lambda}\log f(x|\lambda)\right)^2\right] &= -nE_\lambda\left(\frac{\partial^2}{\partial\lambda^2}\log f(x|\lambda)\right) \\
&= -nE_\lambda\left(\frac{\partial^2}{\partial\lambda^2}\log\left(\frac{e^{-\lambda}\lambda^x}{x!}\right)\right) \\
&= -nE_\lambda\left[\frac{\partial^2}{\partial\lambda^2}(-\lambda + x\log\lambda - \log(x!))\right] \\
&= -nE_\lambda\left(\frac{-x}{\lambda^2}\right) \\
&= \frac{n}{\lambda}
\end{aligned}$$

Therefore, for any unbiased estimator W of λ , we must have $V_\lambda(W) \geq \lambda/n$. Since $V_\lambda(\bar{X}) = \frac{\lambda}{n}$, we have that \bar{X} is an UMVUE of λ

NOTE:

field: 307

field: Does S^2 for Normal attain cramer rao?

field: No - Suppose that X_1, \dots, X_n are iid $N(\mu, \sigma^2)$ and consider the estimation of σ^2 when μ is unknown.

We have that

$$\frac{\partial^2}{\partial(\sigma^2)^2} \log\left[\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x-\mu)^2}\right] = \frac{1}{2\sigma^4} - \frac{(x-\mu)^2}{\sigma^6}$$

and

$$\begin{aligned}
-E\left[\frac{\partial^2}{\partial(\sigma^2)^2} \log f(x|\mu, \sigma^2)\right] &= -E\left(\frac{1}{2\sigma^4} - \frac{(x-\mu)^2}{\sigma^6}\right) \\
&= -\frac{1}{2\sigma^4} + \frac{\sigma^2}{\sigma^6} \\
&= \frac{1}{2\sigma^4}
\end{aligned}$$

and therefore, any unbiased estimator W of σ^2 must satisfy $V(W) \geq \frac{2\sigma^4}{n}$. Recall that for S^2 we have

$$V(S^2) = \frac{2\sigma^4}{n-1} > \frac{2\sigma^4}{n}$$

and therefore S^2 does not attain the cramer-rao lower bound.

NOTE:

field: 308

field: Rao-Blackwell

field: Let W be any unbiased estimator $\tau(\theta)$ and let T be a sufficient statistic for θ . Define $\phi(T) = E(W|T)$. Then $E_\theta(\phi(T)) = \tau(\theta)$ and $V_\theta(\phi(T)) \leq V_\theta(W)$, for all θ . That is, $\phi(T)$ is a uniformly better unbiased estimator of $\tau(\theta)$

NOTE:

field: 309

field: Use of Rao-Blackwell

field: Estimators can be improved (their MSE) using sufficiency (already sufficient statistics, or functions of sufficient statistics cannot be improved)

NOTE:

field: 310

field: Are unbiased estimators based on complete sufficient statistics unique.

field: Unbiased estimators based on complete sufficient statistics are unique.

tags: Theory3

NOTE:

field: ₃₁₁

field: Data summaries vs Prediction vs Inference

field:

- Data summaries: descriptive statistics summarizing a dataset (ie sample mean)
- Prediction: Use patterns in a data-set to make predictions regarding values of new observations
 - Prediction setting is more flexible than inference setting, as we are not trying to make probabilistic inference, assumptions only matter if they affect prediction quality.
- Inference: Use observations in data set to infer information concerning population parameters

NOTE:

field: ₃₁₂

field: Parametric Inference

field: Inference (estimation and/or hypothesis testing performed under the assumption that the data come from a population distribution that belongs to some family of distributions $F(x; \theta)$) parametrized by a finite-dimensional parameter θ

Parameter space: The set Θ of all possible values of the parameter θ

Vs Nonparametric Inference - where no or limited assumptions or specifications of the form of the population distributions

NOTE:

field: 313

field: Are the following tests parametric, semiparametric, or nonparametric

- F-test
- Exact binomial test
- Fisher's exact test
- t-test
- Wilcoxon rank sum
- Permutation tests
- Sign test
- Mood's test
- KS test
- t-test

field:

- F-test - Parametric
- Exact binomial test
- Fisher's exact test
- t-test
- Wilcoxon rank sum: semiparametric
- Permutation tests
- Sign test: nonparametric
- Mood's test
- KS test
- t-test

NOTE:

field: 314

field: Definition: Simple hypothesis, composite hypothesis

field:

- Simple hypothesis: Completely specifies the parameter value and therefore the population distribution. Simple hypothesis have the form $H_0 : \theta = \theta_0$ and $H_1 : \theta = \theta_1$, for specified values of θ_0 and θ_1
- Composite hypothesis: Includes more than one possible parameter value. Composite hypotheses have the form $H_0 : \theta \in \Theta_0$ and $H_1 : \theta \in \Theta_1$

NOTE:

field: 315

field: Test procedure:

field:

- Random Sample (data): X_1, \dots, X_n
- Sample Space \mathcal{X} the set of all possible observed samples $X_1 = x_1, X_2 = x_2, \dots, X_n = x_n$
- Hypothesis $H_0 : \theta \in \Theta_0$ and $H_1 : \theta \in \Theta_1$ with $\Theta_0 \cap \Theta_1 = \emptyset$
- Rejection Region $\mathcal{R} \subset \mathcal{X}$:
 - If $(X_1, \dots, X_n \in \mathcal{R}, \text{Reject } H_0)$
 - If $X_1, \dots, X_n \notin \mathcal{R}, \text{Fail to reject } H_0$

Equivalently

- Random Sample (data): X_1, \dots, X_n

- Test statistic $T(X_1, \dots, X_n)$ is some function of the data, which is itself a random variable
- Test Statistic Sample Space \mathcal{T} the set of all possible observed samples $T = t$
- Rejection Region $\mathcal{R}_T \subset \mathcal{T}$:
 - If $T(X_1, \dots, X_n) \in \mathcal{R}_t$, Reject H_0)
 - If $T(X_1, \dots, X_n) \notin \mathcal{R}_t$, Fail to reject H_0

NOTE:

field: ₃₁₆

field: Power function (definition)

field: We can summarize the performance of a test procedure through the power function:

$$\begin{aligned}
 \text{Power}(\theta) &= \beta(\theta) = P_\theta(\text{Reject } H_0 \text{ when } \theta \text{ is the true value of the parameter of interest}) \\
 &= P_\theta((X_1, \dots, X_n) \in \mathcal{R}) \\
 &= P_\theta(T(X_1, \dots, X_n) \in \mathcal{R}_t)
 \end{aligned}$$

Equivalently, for a critical function ψ ,

$$\beta(\theta) = E_\theta(\psi(x_1, \dots, x_n))$$

NOTE:

field: ₃₁₇

field: Calculating Type I and Type II errors from the power function

field:

$$P(\text{Type I Error when } \theta = \theta_0 \in \Theta_0) = \beta(\theta_0)$$

$$P(\text{Type II Error when } \theta = \theta_1 \in \Theta_1) = 1 - \beta(\theta_1)$$

(Note these are for simple hypotheses), for complex hypothesis, we want to look at the maximum possible error

To work out these probabilities, we need to know the distribution of the test statistics under the null (For type I error) and alternative (For type II error)

NOTE:

field: 318

field: Size of a test procedure

field: The size of a test procedure for a null hypothesis $H_0 : \theta \in \Theta_0$ is the value

$$\sup_{\theta \in \Theta_0} P_{\theta}(\text{Reject } H_0) = \sup_{\theta \in \Theta_0} \beta(\theta)$$

That is, the size of a test procedure is the largest value of the probability of a Type I Error, across all values of θ in the null hypothesis set Θ_0

NOTE:

field: 319

field: Definition of a level α test

field: A hypothesis test procedure is said to be a level α test if

$$\sup_{\theta \in \Theta_0} P_{\theta}(\text{Reject } H_0) = \sup_{\theta \in \Theta_0} \beta(\theta) \leq \alpha$$

That is if the size of the test is less than or equal to α , the test is a level α test.

NOTE:

field: 320

field: most powerful level α test (definition)

field: Let \mathcal{C}_α be the set of all tests of $H_0 : \theta \in \Theta_0$ vs $H_1 : \theta \in \Theta_1$ where $\Theta_0 \cap \Theta_1 = \emptyset$ that have level α . A test belonging to \mathcal{C}_α is the most powerful level α test at $\theta_1 \in \Theta_1$ if

$$\beta(\theta_1) \geq \beta^*(\theta_1)$$

for any other test in \mathcal{C}_α with power function $\beta^*(\theta)$

NOTE:

field: 321

field: Uniformly most powerful level α test (definition)

field: A test belonging to \mathcal{C}_α with power function $\beta(\theta)$ is uniformly most powerful level α if it is the most powerful for every $\theta_1 \in \Theta_1$

NOTE:

field: 322

field: Critical Function / Test Function (definition)

field: A function $\psi : \mathcal{X} \rightarrow [0, 1]$ such that $\psi(x_1, \dots, x_n)$ is the probability of rejecting H_0 when the sample $(X_1 = x_1, \dots, X_n = x_n)$ is observed is called a critical function of a test procedure.

NOTE:

field: 323

field: Randomized Test (definition)

field: A test procedure with critical function ψ for which there are some points in the sample space such that $0 < \psi < 1$ is called a randomized test (often used in discrete cases)

NOTE:

field: 324

field: Finding the most powerful level α test of a simple null hypothesis vs a simple alternative hypothesis

field: (*Neyman – Pearson*) The most powerful level α test of a simple null hypothesis H_0 vs a simple alternative hypothesis H_1 based on data \mathbf{X} is given by the critical function

$$\psi(\mathbf{X}) = \begin{cases} 1 & \text{if } \frac{L(H_0:x)}{L(H_1:x)} < k \\ c & \text{if } \frac{L(H_0:x)}{L(H_1:x)} = k \\ 0 & \text{if } \frac{L(H_0:x)}{L(H_1:x)} > k \end{cases}$$

Where the constants k and c are chosen to ensure that $E_{H_0}(\psi(\mathbf{X})) = \alpha$

NOTE:

field: 325

field: Steps for using Neyman-Pearson to obtain most powerful tests for simple and alternative hypotheses:

field:

1. Identify the likelihood under the null $L(H_0 : x)$ and alternative $L(H_1 : x)$
2. Determine how the ratio of the likelihoods $\frac{L(H_0:x)}{L(H_1:x)}$ depends on the observed data \mathbf{x} (ie is it an increasing or decreasing function of $T(\mathbf{X})$)?
3. Identify the null distribution of the statistic $T(\mathbf{X})$

- (a) If $\frac{L(H_0:x)}{L(H_1:x)}$ is an increasing function of $T(\mathbf{x})$, rejecting for small values of $\frac{L(H_0:x)}{L(H_1:x)}$ is equivalent to rejecting for small values of $T(\mathbf{x})$, so find k such that

$$P_{H_0}(T(\mathbf{x}) < k) = \alpha$$

- (b) If $\frac{L(H_0:x)}{L(H_1:x)}$ is a decreasing function of $T(\mathbf{x})$, rejecting for large values of $\frac{L(H_0:x)}{L(H_1:x)}$ is equivalent to rejecting for large values of $T(\mathbf{x})$, so find k such that

$$P_{H_0}(T(\mathbf{x}) > k) = \alpha$$

NOTE:

field: 326

field: Uniformly most powerful (UMP) level α test procedure

field: Uniformly most powerful (UMP) level α test procedure for testing $H_0 : \theta \in \Theta_0$ vs $H_1 : \theta \in \Theta_1$ is one with power function $\beta(\theta)$ such that for every $\theta_1 \in \Theta_1$ we have

$$\beta(\theta) \geq \beta^*(\theta)$$

for any other level α test procedure with power function $\beta^*(\theta)$

NOTE:

field: 327

field: Monotone likelihood ratio

field: The family of distributions $\{F(x|\theta)\}$ indexed by parameter $\theta \in \Theta$ has monotone likelihood ratio if there is a statistic $T(\mathbf{X})$ such that for all $\theta^* > \theta \in \Theta$ and $\mathbf{x} \in \mathcal{X}$, the likelihood ratio

$$\frac{L(\theta^*|\mathbf{x})}{L(\theta|\mathbf{x})} \quad \text{is monotone nondecreasing in } T(\mathbf{x})$$

NOTE:

field: 328

field: How to find the UMP test of a simple null hypothesis vs a one sided complex alternative

field: See if the family has monotone likelihood ratio in $T(\mathbf{x})$ UMP tests of one sided alternative hypothesis exist and are given by the form in Neyman-Pearson (by Karlin Rubin)

NOTE:

field: 329

field: Karlin-Rubin Theorem

field: Suppose the family of distributions $\{F(x|\theta)\}$ indexed by parameter $\theta \in \Theta$ has monotone likelihood ratio Then to test

$$H_0 : \theta = \theta_0 \quad \text{vs} \quad H_1 : \theta > \theta_0$$

the test function

$$\phi(\mathbf{X}) = \begin{cases} 1 & \text{if } T(\mathbf{X}) > k \\ \gamma & \text{if } T(\mathbf{X}) = k \\ 0 & \text{if } T(\mathbf{X}) < k \end{cases}$$

Where k and γ are chosen so that $E_{\theta_0}(\phi(\mathbf{X})) = \alpha$ gives a uniformly most powerful (UMP) level α test.

(note if we have a one sided lower alternative, we flip the direction of the inequalities)

NOTE:

field: 330

field: Is there a UMP two sided test for X_1, \dots, X_n iid $\text{Exp}(\lambda)$ where $H_0 : \lambda = 2$ vs $H_1 \lambda \neq 2$?

field: No: For $\lambda_1 > \lambda_0 = 2$, the UMP test would have the form

$$\psi(\mathbf{X}) = \begin{cases} 1 & \text{if } T(\mathbf{x}) = \sum_{i=1}^n x_i > k_1 \\ 0 & \text{if } T(\mathbf{x}) = \sum_{i=1}^n x_i < k_1 \end{cases}$$

and for $\lambda_1 < \lambda_0 = 2$, the UMP test would have the form

$$\psi(\mathbf{X}) = \begin{cases} 1 & \text{if } T(\mathbf{x}) = \sum_{i=1}^n x_i < k_2 \\ 0 & \text{if } T(\mathbf{x}) = \sum_{i=1}^n x_i > k_2 \end{cases}$$

Since these forms are not the same, there is no UMP test.

NOTE:

field: ₃₃₁

field: Let $X \sim \text{Unif}(0, \theta)$. Is there a UMP test for testing two sided $H_0 : \theta = 1$ vs $H_1 : \theta \neq 1$

field: Yes:

$$\psi(\mathbf{x}) = \begin{cases} 1 & x < \alpha \text{ or } x > 1 \\ 0 & \alpha < x < 1 \end{cases}$$

NOTE:

field: ₃₃₂

field: Unbiased test (definition)

field: A test of $H_0 : \theta \in \Theta_0$ vs $H_1 : \theta \in \Theta_1$ is called unbiased if $\beta(\theta_1) \geq \beta(\theta_0)$ for all $\theta_1 \in \Theta_1$ and all $\theta_0 \in \Theta_0$

NOTE:

field: 333

field: Uniformly most powerful unbiased (UMPU) level α test (definition)

field: A level α test of $H_0 : \theta \in \Theta_0$ vs $H_1 : \theta \in \Theta_1$ with critical function $\psi(\mathbf{x})$ is called uniformly most powerful unbiased (UMPU) if it is unbiased level α and for any other unbiased test with critical function $\psi^*(\mathbf{x})$, we have

$$E_\theta(\psi(\mathbf{x})) \geq E_\theta(\psi^*(\mathbf{x})) \quad \text{for all } \theta \in \Theta_1$$

NOTE:

field: 334

field: Likelihood Ratio Test (definition)

field: Suppose we have the data $\mathbf{X} = X_1, \dots, X_n$, with joint density $f(x; \theta)$ for some parameter $\theta \in \Theta$, and we wish to perform a level α test of $H_0 : \theta \in \Theta_0$ vs $H_1 : \theta \in \Theta_1$, where $\Theta_1 \cup \Theta_0 = \Theta$. The likelihood ratio test statistic is given by

$$\lambda(\mathbf{x}) = \frac{\sup_{\theta \in \Theta_0} L(\theta|x)}{\sup_{\theta \in \Theta} L(\theta|x)} = \frac{L(\hat{\theta}_{0,MLE}; x)}{L(\hat{\theta}_{MLE}; x)}$$

and the null hypothesis is rejected for small values of λ (indicating that the null hypothesis is relatively 'unlikely')

We maximize by finding $\theta = \hat{\theta}_{MLE}$ and $\hat{\theta}_{0,MLE}$

NOTE:

field: 335

field: If $T(\mathbf{X})$ is a sufficient statistic for θ , then $\lambda(\mathbf{x})$ (the LRT statistic)...

field: If $T(\mathbf{X})$ is a sufficient statistic for θ , then $\lambda(\mathbf{x})$ will be a function of $T(\mathbf{x})$. In particular $\lambda(\mathbf{x})$ will be a function of the minimal sufficient statistic

NOTE:

field: 336

field: Frequentist Probability vs Bayesian probability (definition)

field:

- Frequentist: For an event E , in our outcome space, $P(E)$ is the long run proportion of experiments that have outcome E , the relative frequency with which an event happens is its probability
- Bayesian: For an event E in the outcome space, $P(E)$ is any number between zero and one that you want to assign it, as long as you are coherent about the rules of additivity etc.

NOTE:

field: 337

field: Treatment of population parameters, frequentist vs bayesian

field:

- Frequentist: A population parameter θ is some fixed (though generally unknown value) that belongs to some set of possible values Θ
- Bayesian: A population parameter θ is a random quantity that has a prior distribution

NOTE:

field: 338

field: Likelihood function (bayesian)

field: Given some value of the parameter θ , the distribution of the data \mathbf{x} is $f(\mathbf{x}; \theta)$ is the likelihood (a function of both the value θ and the data \mathbf{x}).

NOTE:

field: 339

field: Posterior Distribution (definition)

field: The posterior distribution of theta given the observed data \mathbf{x} is

$$k(\theta; \mathbf{x}) = \frac{f(\mathbf{x}; \theta)h(\theta)}{\int_{\theta} f(\mathbf{x}; \theta)h(\theta)d\theta}$$

Posterior probability \propto Likelihood \times prior probability

Note that the posterior distribution is proportional to the numerator.

NOTE:

field: 340

field: Conjugate Priors

field: If the prior $h(\theta)$ belongs to some (parametric) family of distributions \mathcal{P} and the likelihood $L(\theta; \mathbf{x})$ (the joint density of the data for any particular value of θ) is such that the posterior $k(\theta; \mathbf{x})$ belongs to the same family \mathcal{P} , then this family of priors is said to be conjugate for the likelihood $L(\theta; \mathbf{x})$ (ie the posterior family is the prior family if we choose a conjugate prior.)

NOTE:

field: 341

field: Non-informative Priors

field: A non-informative prior is intended to give as little information as possible about the value of the parameter of interest θ .

NOTE:

field: ³⁴²

field: Improper prior

field: an improper prior is a prior that does not integrate to one

NOTE:

field: ³⁴³ ©

field: Bayes Estimator

field: A Bayes estimator (with respect to the particular prior/likelihood) is the estimator that minimizes the Bayesian Risk

$$\delta^* = \operatorname{arginf}_{\delta \in D} \int_{\Theta} R(\theta, \delta) h(\theta) d\theta$$

Where D is the set of all possible estimators for θ

The Bayes Estimator equivalently minimizes the posterior risk, given the observed data.

For squared-error loss, the Bayes estimate is the mean of the posterior distribution $k\theta(\mathbf{x})$:

$$\delta^* = \int_{\Theta} \theta k(\theta|\mathbf{x}) d\theta$$

NOTE:

field: ³⁴⁴

field: Maximum A Posteriori (MAP)

field: A MAP test selects the hypothesis H_0 or H_1 that has the highest posterior probability. (Bayesian.)

NOTE:

field: 345

field: Definition of a p-value

field:

- For testing null hypothesis H_0 vs alternative hypothesis H_1 , the p-value $p(\mathbf{x})$ corresponding to the observed data, is the smallest value α for which H_0 would be rejected by a size α test
- Let $W(\mathbf{X})$ be a test statistic such that large values of W are evidence that H_1 is true, and therefore the null hypothesis H_0 is rejected for large $W(\mathbf{X})$ then a p-value can be defined as

$$p(\mathbf{x}) = \sup_{\theta \in \Theta} P_{\theta}(W(\mathbf{X}) \geq W(\mathbf{x}))$$

This says that the p-value is the (largest in the null space) probability of obtaining a test statistic at least as extreme as the observed test statistic value.

- A p-value is just a function of the observed data; a test statistic

NOTE:

field: 346

field: Validity of p-value

field: A p-value is valid (exact) if for every $\theta \in \Theta_0$ and every value of $\alpha \in [0, 1]$, we have

$$P_{\theta}(p(\mathbf{X}) \leq \alpha) \leq \alpha$$

NOTE:

field: 347

field: Confidence interval (definition)

field: Suppose we have data \mathbf{X} such that the (joint) density of our data give information about an unknown parameter θ . Then a $(1 - \alpha)100$ confidence interval for θ is a random interval $[L(\mathbf{X}), U(\mathbf{X})]$ such that

$$\inf_{\theta \in \Theta} P_{\theta}(L(\mathbf{X}) \leq \theta \leq U(\mathbf{X})) = 1 - \alpha$$

It is important to note that it is the limits of the interval $L(\mathbf{X}), U(\mathbf{X})$ that are the random quantities here.

NOTE:

field: ³⁴⁸

field: Construct a CI using a hypothesis test

field: A level $(1 - \alpha)100$ confidence interval can be constructed by inverting a level α hypothesis test. This fact is known as the duality of confidence intervals and hypothesis testing. The confidence region \mathcal{C} $\mathcal{C} = \{\theta_0 : H_0 : \theta = \theta_0 \text{ would not be rejected at level } \alpha\}$
(ie solve for θ_0 to be in the center)

NOTE:

field: ³⁴⁹

field: Pivot

field: Suppose X comes from some parametric family $F(\mathbf{x} : \theta)$ indexed by parameter θ . A pivot, or pivotal quantity is a random variable $U = g(\mathbf{X}, \theta)$ that depends upon both the sample \mathbf{X} and the unknown parameter θ for which the distribution of U does not depend on θ

NOTE:

field: ³⁵⁰

field: Finding a confidence interval for θ using the pivotal method

field:

1. Identify a pivotal quantity U and its distribution $F_U(u)$
2. Find a and b such that

$$P(a < U < b) = 1 - \alpha$$

Let $F_U(u)$ denote the cdf of the pivot U , so then we can set

$$\begin{aligned}a &= F_U^{-1}(c\alpha) \\ b &= F_U^{-1}(1 - (1 - c)\alpha)\end{aligned}$$

For any $c \in [0, 1]$ (usually .5 to split up area on the tails evenly)

3. Solve the inequality $a < U < b$ for θ in the middle.

NOTE:

field: ₃₅₁

field: Pivotal CI example: Let $Y \sim \exp(\theta)$.

field:

1. Let $U = Y/\theta$, so $U \sim \text{Exp}(1)$. which doesn't depend on θ , so U is a pivotal quantity.
2. We must find a, b , such that $P(a \leq U \leq b) = 1 - \alpha$. We then solve $P(U \leq a) = \alpha/2$ and $P(b \leq U) = \alpha/2$ Solve for θ

$$P(a \leq U \leq b) = P(Y/b \leq \theta \leq Y/a)$$

NOTE:

field: ₃₅₂

field: Finding a pivotal quantity

field:

- If θ is a location parameter, a possible pivot has the form $U = T(\mathbf{X}) - a(\theta)$
- If θ is a scale parameter, $U = T(\mathbf{X})/b(\theta)$ is a possible pivot
- If θ is a location-scale parameter, $U = (T(\mathbf{X}) - a(\theta))/b(\theta)$ is a possible pivot
- If neither, use how parameter is related to X , ie if $F_Y(y) = y^N$, use y^N as the pivot.

NOTE:

field: ₃₅₃

field: Confidence Interval optimality criteria

field:

- Length
 - Length can be a function of sample size and critical value choice (Normal mean with known variance), other cases a random quantity (Normal mean with unknown variance)
 - When length is random, we typically want confidence intervals with shortest mean length.
 - Ie for normal variance with known mean, the expected length of the confidence interval is $E(L) = c\sigma^2n$, so a shortest interval would be not using equal tails, but requires numerical computation.
- Convexity
 - In the case of a one-dimensional parameter, this means that the region should be a connected interval

- Agreement with a reasonable estimate and with a reasonable hypothesis test.
 - Example score test and wald CI
- Equal coverage probability for all θ

NOTE:

field: 354

field: $1 - \alpha$ credible interval

field: (Bayesian) A $1 - \alpha$ credible interval is an interval $[a, b]$ such that the credible probability of that interval is $1 - \alpha$, that is

$$\int_{\theta=a}^b k(\theta|\mathbf{x})d\theta = 1 - \alpha$$

Where the posterior distribution $k(\theta|\mathbf{x}) = \frac{f(\mathbf{x};\theta)h(\theta)}{\int_{\theta} f(\mathbf{x};\theta)h(\theta)} = \frac{p(\mathbf{x}|\theta)p(\theta)}{p(\mathbf{x})}$, where the posterior is proportional to the likelihood times the prior

In many cases, we can choose $c = .5$ and let $a =$ the $c \times \alpha$ quantile of the distribution, and $b =$ the $1 - (1 - c) \times \alpha$ quantile of the posterior distribution, but in cases when the posterior distribution is unimodal, we can obtain shorter intervals.

NOTE:

field: 355

field: Credible probability

field: (Bayesian) For any region $\mathcal{A} \subset \Theta$, the credible probability of the set \mathcal{A} is

$$P(\theta \in \mathcal{A}|\mathbf{x}) = \int_{\theta \in \mathcal{A}} k(\theta|\mathbf{x})d\theta$$

NOTE:

field: ₃₅₆

field: Highest posterior density $1 - \alpha$ credible interval

field: For a unimodal posterior distribution $k(\theta|\mathbf{x})$ Highest posterior density $1 - \alpha$ credible interval is the interval $[a, b]$ such that

1. $\int_{\theta=a}^b k(\theta|\mathbf{x})d\theta = 1 - \alpha$
2. $k(a|\theta) = k(b|\theta)$
3. $a < \theta^* < b$ where θ^* is the mode of the posterior distribution.

This credible interval will be the shortest. Note it might not contain the Bayes estimator for θ if the posterior distribution is very highly skewed and has a heavy tail.

NOTE:

field: ₃₅₇

field: Unimodal pdf

field: A pdf is unimodal if there exists some value x^* such that

1. For all $x \leq x^*$, $f(x)$ is non decreasing
2. For all $x \geq x^*$, $f(x)$ is non-increasing.

NOTE:

field: ₃₅₈

field: Confidence Intervals for functions of parameters: Obtain a confidence interval for $\tau = g(\theta)$, given a confidence interval for θ

field:

1. Invert a test of $H_0 : \tau = \tau_0$ vs $H_1 : \tau \neq \tau_0$
2. Create a pivot $U = h(\mathbf{X}, \tau)$, and construct a pivotal interval for τ
3. Transform the CI for θ into an interval for τ
 - Coverage of this interval: $C_\tau = \{\tau_0 : \tau_0 = g(\theta_0) \text{ for } \theta_0 \in C_\theta\}$
 - NOT the same as $(g(L_\theta(\mathbf{X})), g(U_\theta(\mathbf{X})))$ (unless strictly monotone, otherwise coverage not the same.)

NOTE:

field: 359

field: Joint Confidence Intervals for Multivariate parameters

field:

1. Construct $(1 - \alpha^*)$ CIs for each component θ_j separately
2. Define $\mathcal{C} = \{\theta_0 : \theta_{0,j} \in \mathcal{C}_j \text{ for all } j = 1, \dots, p\}$
3. Chose the univariate coverage levels $(1 - \alpha^*)$ to ensure that the coverage level of the joint confidence region is at least the desired level $(1 - \alpha)$
4. Often choose $\alpha^* = \alpha/p$, although this often gives larger CIs - over-coverage
5. If parameters independent, if we set $1 - \alpha = (1 - \alpha^{**})^p$

NOTE:

field: 360

field: Example: Construct a CI for

$$X_1, \dots, X_n \sim iidExp(\mu_x, \sigma)$$

$$Y_1, \dots, Y_n \sim iidExp(\mu_x, \sigma)$$

field: $\kappa(\theta) = \mu_x - \mu_y$

- Sufficient statistic for parameter (μ_x, μ_y, σ) is

$$(X_{(1)}, Y_{(1)}, W = \sum_{i=1}^n (X_i - X_{(1)}) + \sum_{i=1}^n (Y_i - Y_{(1)}))$$

- $X_{(1)} \sim \exp(\mu_x, \sigma/n)$
- $Y_{(1)} \sim \exp(\mu_y, \sigma/n)$
- $\frac{2W}{\sigma} \sim \chi_{4n-4}^2$
- Construct pivot: $U = \frac{|n(X_{(1)} - Y_{(1)} - \mu_x + \mu_y)|}{W/(2n-2)} \sim F_{2, 4n-4}$

NOTE:

field: ₃₆₁

field: Determinant of a square matrix

field: The determinant of a square matrix \mathbf{A} is denoted by $|\mathbf{A}|$ and is defined recursively

- For a (1×1) matrix $|\mathbf{A}| = a_{11}$
- For a $(p \times p)$ matrix $|\mathbf{A}| = \sum_{j=1}^p a_{ij}(-1)^{i+j}|\mathbf{A}_{-i, -j}|$
- Where $\mathbf{A}_{-i, -j}$ is the matrix obtained by removing the i th column and j th row from \mathbf{A}

NOTE:

field: ₃₆₂

field: Properties of the determinant

- $\det(\mathbf{I}_p)$
- $\det(\mathbf{A}^{-1})$
- \mathbf{A} is invertible iff
- $\det(AB)$
- $\det(\mathbf{A}^t)$
- $\det(\mathbf{XAX}^{-1}) =$
- Relationship to eigenvalues

field:

- $\det(\mathbf{I}_p) = 1$
- $\det(\mathbf{A}^{-1}) = (\det(\mathbf{A}))^{-1}$
- \mathbf{A} is invertible iff $\det(\mathbf{A}) \neq 0$
- $\det(\mathbf{AB}) = \det(\mathbf{A})\det(\mathbf{B})$
- $\det(\mathbf{A}^t) = \det(\mathbf{A})$
- $\det(\mathbf{XAX}^{-1}) = \det(\mathbf{A})$
- The determinant of \mathbf{A} is equal to the product of all eigen values of \mathbf{A}

NOTE:

field: ₃₆₃

field: Properties of the Multivariate Normal Distribution

field:

- If \mathbf{X} has a multivariate normal distribution, then each element has a marginal normal distribution
- Random variables X_1, \dots, X_p with marginal normal distributions DO NOT necessarily have a multivariate normal joint distribution
- All subsets of elements of \mathbf{X} have a multivariate normal distribution
- All linear combinations of the components of X are normally distributed
- $\mathbf{X} + c \sim MVN(\mu + c, \Sigma)$
- $\mathbf{A}\mathbf{X} \sim MVN(\mathbf{A}\mu, \mathbf{A}\Sigma\mathbf{A}^t)$, where each element of $\mathbf{A}\mathbf{X}$ is a linear combination of the random vector \mathbf{X}
- $Cov(X_j, X_k) = \sigma_{jk} = 0$ iff and only if X_j, X_k independent
- $Z = \Sigma^{-1/2}(\vec{X} - \vec{\mu}) \sim MVN(\vec{0}, I_p)$
- $Z^t Z \sim \chi_p^2$

NOTE:

field: ₃₆₄

field: Distribution of sample mean and variance from Multivariate normal

field:

- $\bar{\mathbf{X}} \sim MVN(\vec{\mu}, \frac{1}{n}\Sigma)$
- $\mathbf{S} = \frac{1}{n-1} \sum_{i=1}^n (\mathbf{X}_i - \bar{\mathbf{X}})(\mathbf{X}_i - \bar{\mathbf{X}})^t$

NOTE:

field: ₃₆₅

field: $X \sim \chi_{v_1}^2, Y \sim \chi_{v_2}^2, X + Y \sim$

field: $\chi_{v_1+v_2}^2$

NOTE:

field: 366

field: Definition of consistent sequence of estimators

field: Suppose we have random variables X_1, X_2, \dots , such that the collection $\{X_1, \dots, X_n\}$ gives information about a parameter θ . A sequence of estimators $W_n = W_n(X_1, \dots, X_n)$ is a consistent sequence of estimators of the parameter θ if FOR EVERY $\theta \in \Theta$,

$$W_n \xrightarrow{p} \theta$$

NOTE:

field: 367

field: Mean square error

field:

$$MSE(\hat{\theta}, \theta) = E[(\hat{\theta} - \theta)^2] = Bias^2 + V(\hat{\theta})$$

NOTE:

field: 368

field: If a sequence of estimators W_n for a parameter θ satisfies

- $\lim_{n \rightarrow \infty} V_\theta(W_n) \rightarrow 0$
- $\lim_{n \rightarrow \infty} E_\theta(W_n) \rightarrow \theta$
- Equivalently, if $MSE_\theta(W_n; \theta) \rightarrow 0$

for all $\theta \in \Theta$, then

field: W_n is a consistent sequence of estimators for the parameter θ

NOTE:

field: 369

field: How to prove consistency:

field: If a sequence of estimators W_n for a parameter θ satisfies

- $\lim_{n \rightarrow \infty} V_\theta(W_n) \rightarrow 0$
- $\lim_{n \rightarrow \infty} E_\theta(W_n) \rightarrow \theta$
- Equivalently, if $MSE_\theta(W_n; \theta) \rightarrow 0$

for all $\theta \in \Theta$, then W_n is consistent.

NOTE:

field: 370x

field: Definition of asymptotic distribution of Estimators

field: Suppose that a sequence of random variables W_n satisfies

$$k_n(W_n - \theta) \xrightarrow{d} F$$

- k_n is the stabilizing constant,
- F is the asymptotic distribution
- $\sigma^2(\theta)$ the asymptotic variance (which can't depend on n)

NOTE:

field: _{371x}

field: $X_i \sim \text{Exp}(\sigma), \sum X_i \sim$

field: $\sum X_i \sim \text{Gamma}(n, \sigma)$

NOTE:

field: ₃₇₂

field: Relationship between asymptotic variance and limiting variance

field: limiting variance \geq asymptotic variance, where the limiting variance is defined as $\lim_{n \rightarrow \infty} V(Y_n)$

NOTE:

field: ₃₇₃

field: Score function

field:

$$U(\theta) = \frac{\partial}{\partial \theta} l(\theta; \mathbf{x}) = \sum_{i=1}^n \frac{\frac{\partial}{\partial \theta} f(x_i; \theta)}{f(x_i; \theta)}$$

NOTE:

field: ₃₇₄

field: Notation and test construction X_1, \dots, X_n iid

- Density/Mass Function
- Likelihood
- Log likelihood
- Maximum likelihood estimator
- Score
- Information

field:

- Density/Mass Function : $f(x; \theta)$
- Likelihood : $L(\theta; \mathbf{x}) = \prod_{i=1}^n f(x_i; \theta)$
- Log likelihood $l(\theta; \mathbf{x}) = \log L(\theta; \mathbf{x}) = \sum_{i=1}^n \log f(x_i; \theta)$
- Maximum likelihood estimator $\hat{\theta}_n : \left. \frac{\partial}{\partial \theta} l(\theta; \mathbf{x}) \right|_{\theta=\hat{\theta}_n} = 0$ (except if support depends on parameter of interest)
- Score: $U(\theta) = \frac{\partial}{\partial \theta} l(\theta; \mathbf{x}) = \sum_{i=1}^n \frac{\frac{\partial}{\partial \theta} f(x_i; \theta)}{f(x_i; \theta)}$
- Information: $I_1(\theta) = E \left(- \frac{\partial^2}{\partial \theta^2} \log f(x; \theta) \right)$

NOTE:

field: ₃₇₅

field: Important Assumptions of Maximum Likelihood Estimators

field: Note these assumptions hold in exponential families, Binomial, Poisson, etc

- X_i iid with common density function
- Identifiability: for $\theta_1 \neq \theta_2$, $f(x; \theta_1) \neq f(x; \theta_2)$
- Common support (the one we need to verify) The set of possible values for X does not depend on the value of the parameter θ
- Open Parameter Space (ie cant include 0 or 1 in bernoulli case)

NOTE:

field: ³⁷⁶

field: Asymptotic Normality of MLE

field: Under the common assumptions, The MLE $\hat{\theta}_n$ for θ satisfies

$$\frac{\hat{\theta}_n - \theta}{\sqrt{\frac{1}{nI_1(\theta)}}} \xrightarrow{d} N(0, 1)$$

Equivalently, $\hat{\theta}_n \sim N(\theta, \frac{1}{nI_1(\theta)})$ This implies that the MLE is asymptotically the UMVUE (as $E(\hat{\theta}_n) \approx \theta$ and $Var(\hat{\theta}_n) \approx \frac{1}{nI_1(\theta)}$), the CRLB var of unbiased estimate of θ

NOTE:

field: ³⁷⁷

field: Mann-Wald Theorem (for MLE)

field: For any differentiable $g(\cdot)$ with non-zero first derivative: if $\sqrt{n}(\hat{\theta}_n - \theta) \xrightarrow{d} N(0, \frac{1}{I_1(\theta)})$, then

$$\sqrt{n}(g(\hat{\theta}_n) - g(\theta)) \xrightarrow{d} N(0, \frac{[g'(\theta)]^2}{I_1(\theta)})$$

NOTE:

field: 378

field: Wald Hypothesis Tests and Confidence intervals

field: Since θ is not known, we cannot find the value of $I(\theta)$ exactly, but we can use $\hat{I}(\theta) = I(\hat{\theta}_n) \xrightarrow{P} I(\theta)$, where $\hat{\theta}_n$ is the MLE

- Test statistic:

$$W(\theta_0) = \frac{\hat{\theta}_n - \theta_0}{\sqrt{\frac{1}{nI_1(\hat{\theta}_n)}}}$$

- Two sided alternative: Reject $H_0 : \theta = \theta_0$ vs $\theta \neq \theta_0$ if

$$|W(\theta_0)| > z_{\alpha/2}$$

- Confidence interval:

$$\left(\hat{\theta}_n - z_{\alpha/2} \sqrt{\frac{1}{nI_1(\hat{\theta}_n)}}, \hat{\theta}_n + z_{\alpha/2} \sqrt{\frac{1}{nI_1(\hat{\theta}_n)}} \right)$$

NOTE:

field: 379

field: Asymptotic Likelihood-Based Test Statistics

	Test	Test Statistic	Asymptotic Null Distribution
	Likelihood Ratio	$G(\theta_0) = 2(l(\hat{\theta}_n; \mathbf{x}) - l(\theta_0; \mathbf{x}))$	χ_1^2
field:	Wald	$W(\theta_0) = \frac{(\hat{\theta}_n - \theta_0)^2}{\frac{1}{nI_1(\hat{\theta}_n)}}$	χ_1^2
		$W^*(\theta_0) = \frac{\hat{\theta}_n - \theta_0}{\sqrt{\frac{1}{nI_1(\hat{\theta}_n)}}}$	
	Score	$S(\theta_0) = \frac{U(\theta_0)^2}{nI(\theta_0)}$ (no need to find MLE) $S^*(\theta_0) = \frac{U(\theta_0)}{\sqrt{nI(\theta_0)}}$	χ_1^2 $N(0, 1)$

NOTE:

field: 380

field: Comparison between Likelihood Ratio, Wald and Score tests and intervals

field:

1. Likelihood Ratio:

- Requires computation of $\sup_{\theta \in \Theta} L(\hat{\theta}; \mathbf{x})$ (likelihood of MLE) and $L(\theta_0; \mathbf{x})$ (likelihood of null hypothesis)
- Generally hardest to invert to form confidence intervals

2. Wald:

- Only requires computation of MLE and Information under MLE
- Tends to differ from the Score and LR tests more than they do from each other
- Easiest to invert to form confidence intervals

3. Score:

- Only requires computation of Information under Null
- Has best power of the three tests for alternatives close to null
- Typically similar in form to Wald, except variance is estimated under null instead of using MLE

All three tests are asymptotically equivalent under the null hypothesis when n is large. If the alternative is true, they may differ substantially, no matter the value of n

NOTE:

field: 381

field: Variance Stabilizing Transformation

field: To potentially improve confidence interval coverage in settings where there is a mean-variance relationship, we can try to find a function $g(\cdot)$ such that

$$(g'(\theta))^2 V(\hat{\theta}) = 1$$

That is the asymptotic variance of $g(\hat{\theta})$ does not depend on the value of θ . This function $g(\cdot)$ is called the variance stabilizing transformation for the estimate $\hat{\theta}$

NOTE:

field: ₃₈₂

field: Find the information in the sample $X_1, \dots, X_m, Y_1, \dots, Y_n$ where X_i iid and Y_j iid and X_i and Y_i are independent

field: $I_{X,Y}(\theta) = mI_{X_1}(\theta) + nI_{Y_1}(\theta)$