

$$\underline{X} \sim N(0, I_n)$$

$$\Rightarrow \underline{X}' \underline{X} \sim \chi^2(n)$$

Proof: $\underline{X} = \begin{pmatrix} \bar{x}_1 \\ \vdots \\ \bar{x}_n \end{pmatrix} \quad x'x = \sum_{i=1}^n x_i^2$

$$A = (a_{ij})$$

$$\text{trace}(A) = \sum_{i=1}^n a_{ii}$$

$$\text{trace}(A+B) = \text{trace}(A) + \text{trace}(B)$$

$$\text{trace}(AB) = \text{trace}(BA)$$

(*) Prove this on your own.

Lemma: Suppose P is idempotent (ie. $P=P \cdot P$) and symmetric (ie. $P=P'$). Then all eigenvalues of P are either 0 or 1.

Proof: If λ is an eigenvalue, then $\exists x$ s.t. $Px = \lambda x$.

$$\text{Therefore } \lambda x = Px = (P \cdot P)x = P(Px) = P\lambda x = \lambda(Px) = \lambda^2 x$$

$$\text{And thus } \lambda = \lambda^2 \Rightarrow \lambda \in \{0, 1\}$$

Theorem: Suppose P is symmetric and idempotent. Suppose

$$\underline{X} \sim N(0, I_n). \quad \text{Then } \underline{X}' P \underline{X} \sim \chi^2(\text{trace}(P))$$

Proof: Define $\Delta = \begin{bmatrix} 1 & & & \\ & 1 & & \\ & & \ddots & \\ & & & 0 \end{bmatrix}$. Then $P = C' \Delta C$ with $C'C = C' = I_n$

Define $\underline{Y} = (C \underline{X}) \sim N(0, C'C) = N(0, I_n)$.

$$\underline{X}' P \underline{X} = \underline{X}' C' \Delta C \underline{X} = (C \underline{X})' \Delta (C \underline{X}) = \underline{Y}' \Delta \underline{Y}$$

Assume that $\text{trace}(\Delta) = m$. Then,

$$\underline{Y}' \Delta \underline{Y} = [\underline{Y}_1 \quad \underline{Y}_n] \begin{bmatrix} 1 & & & \\ & 1 & & \\ & & \ddots & \\ & & & 0 \end{bmatrix} \begin{bmatrix} \underline{Y}_1 \\ \vdots \\ \underline{Y}_n \end{bmatrix} = \sum_{i=1}^m \underline{Y}_i^2 \sim \chi^2(m).$$

Finally, $\text{trace}(P) = \text{trace}(C' \underbrace{\Delta}_{B} C) = \text{trace}(\Delta C') = \text{trace}(\Delta) = m. \quad \square$

The remainder of this course will be devoted to inverse probability. That is, statistics. (Prob - game of gods, Stats - game of human beings)

Suppose \mathcal{X} is a random vector $\mathcal{X} \sim \{f_{\mathcal{X}}(\bar{x}; \theta_0); \theta_0 \in \Theta\}$ = family of pdfs.
 Let $u(\mathcal{X})$ be a statistic. Note u cannot be a fn of θ .
 You want to find out θ_0 .

Defn: An estimator is said to be unbiased if
 $E[u(\mathcal{X})] = \int u(x) f(x; \theta) dx = \theta$ (arbitrary value of θ)

Notation: We will denote the "truth" with a zero subscript.
 You are "correct" if $E[u(\mathcal{X})] = \int u(x) f(x; \theta_0) dx = \theta_0$

There is a semantic difference b/t being "correct" and being "unbiased."

Consistent estimator.

If $\text{plim}_{n \rightarrow \infty} u(\mathcal{X}) = \theta$, then $u(\mathcal{X})$ is called a consistent estimator.

[Spce $\mathcal{X} = \begin{pmatrix} \bar{X}_1 \\ \vdots \\ \bar{X}_n \end{pmatrix}$. $u(\mathcal{X}) = \frac{1}{n} \sum_{i=1}^n \bar{X}_i$. Then if $\mathcal{X}' = \begin{pmatrix} \bar{X}_1 \\ \vdots \\ \bar{X}_{n+1} \end{pmatrix}$, we cannot use] the "same" estimator. The correct notation should be $u_n(\mathcal{X})$.]

Maximum likelihood estimator (MLE)

likelihood
 Spce $\bar{X}_1, \dots, \bar{X}_n \stackrel{iid}{\sim} f(x; \theta)$
 $\Rightarrow \prod_{i=1}^n f(x_i; \theta)$ ← function in x_i
 ← function in θ .
 Joint likelihood: $\prod_{i=1}^n f(\bar{X}_i; \theta)$

Suppose $\bar{X}_1, \bar{X}_2 \stackrel{iid}{\sim} N(\theta, 1)$

$$f(x_1, x_2; \theta) = \frac{1}{2\pi} \exp\left[-\frac{(x_1 - \theta)^2 + (x_2 - \theta)^2}{2}\right] = g(x_1, x_2)$$

Fix x_1^*, x_2^*

$$f(x_1^*, x_2^*; \theta) = \frac{1}{2\pi} \exp\left[-\frac{(x_1^* - \theta)^2 + (x_2^* - \theta)^2}{2}\right] = h(\theta)$$

MLE:

$$X \stackrel{\text{pdf}}{\sim} f(x; \theta)$$

$$L(\theta) = f(X; \theta)$$

$$\operatorname{argmax}_{\theta} L(\theta) = u(X) \leftarrow \text{MLE}$$

Proposition: Under "regularity conditions," MLE is consistent, although it may not be unbiased.

Example: Let $X_i \stackrel{\text{iid}}{\sim} N(\theta, 1)$ $i \in \{1, \dots, n\}$

$$L(\theta) = \frac{1}{(2\pi)^{n/2}} \exp \left[-\frac{\sum_{i=1}^n (X_i - \theta)^2}{2} \right]$$

$$\hat{\theta} = \operatorname{argmax}_{\theta} L(\theta) = \frac{1}{n} \sum_{i=1}^n X_i$$

(*) Know the derivation.

(Invariance principle)

$h(\theta)$ - you are interested in this. Spse $h(\theta)$ is 1-1.

$$h(\hat{\theta}) = h(\hat{\theta})$$

Suppose $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} N(\theta, 1) = N(\psi^3, 1)$ if $\theta = \psi^3$

$\hat{\psi} = \hat{\theta}^{1/3}$. We can find $\hat{\psi}$ by calculating $\hat{\theta}$. This is all the theorem says.

Method of Moments estimator

$$X_1, \dots, X_n \stackrel{\text{iid}}{\sim} N(\theta, 1)$$

$$\theta = E[X_i] \approx \frac{1}{n} \sum_{i=1}^n X_i = \hat{\theta}$$

Suppose $X_i \sim \text{Gamma}(\alpha, \beta)$,

$$E[X_i] = \alpha\beta$$

$$\text{Var}(X_i) = \alpha\beta^2$$

$$\Rightarrow E[X_i^2] = \alpha^2\beta^2 + \alpha\beta^2$$

Suppose we want to find α and β .

Solve for $\hat{\alpha}$, $\hat{\beta}$ solving:

$$\frac{1}{n} \sum_{i=1}^n X_i = \hat{\alpha} \hat{\beta}$$

$$\frac{1}{n} \sum_{i=1}^n X_i^2 = \hat{\alpha}^2 \hat{\beta}^2 + \hat{\alpha} \hat{\beta}^2$$