

~~2/20/2020~~

Note 1.

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## STA 200C: Hypothesis testing

Purpose and outline:

① Testing methods:

Likelihood ratio tests

Union-interaction / Interaction-union tests

Bayesian tests

② Basic concepts:

Power function

Size and level

P-values

Confidence intervals

③ Large-sample theory

④ Other topics:

Robustness

Nonparametric methods

Multiple testing and FDR.

Statistical model

$$X \sim f(x|\theta)$$

pdf / pmf

$$\theta \in \Theta$$

parametric space

$\mathbf{X} = (X_1, \dots, X_n)$  is called a random sample from  $f(x|\theta)$  - if all  $X_i$  have distribution given by  $f(x|\theta)$ , and the  $X_i$  are independent.

Statistical procedures aim to make inference about  $\theta$  based on  $\mathbf{X}$ .

- 1) Point estimation: find  $\hat{\theta}$  based on  $\mathbf{X}$ ;
- 2) Confidence interval: find  $[\hat{\theta}_L, \hat{\theta}_U]$  based on  $\mathbf{X}$ :
- 3) Hypothesis testing: make decision on  $\theta \in \Theta_0$  or  $\theta \in \Theta_1$ ,  
where  $\left| \begin{array}{l} \Theta_0 \cup \Theta_1 = \Theta \\ \Theta_0 \cap \Theta_1 = \emptyset \end{array} \right.$

In this course, we aim to establish generic methods, concepts and theory for hypothesis testing.

The following three examples will be used repeatedly throughout the course.

Example 1.  $X_1, \dots, X_n \stackrel{iid}{\sim} N(\theta - \theta^2), \sigma^2$  is known.

$$\text{pdf: } f(x|\theta) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\theta}{\sigma}\right)^2}$$

Shift family of normal distribution  
 $\theta \in \Theta = (-\infty, \infty)$

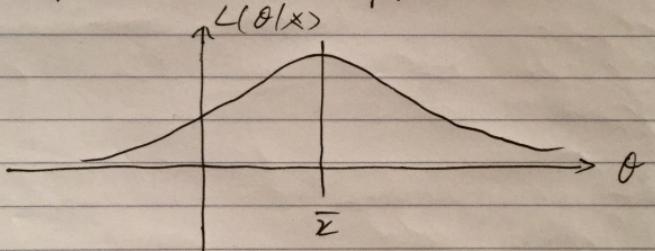
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Then

$$\begin{aligned}f(\mathbf{x} | \theta) &= \prod_{i=1}^n f(x_i | \theta) \\&= \left( \frac{1}{\sigma \sqrt{2\pi}} \right)^n \exp \left\{ -\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \theta)^2 \right\} \\&= \left( \frac{1}{\sigma \sqrt{2\pi}} \right)^n \exp \left\{ -\frac{1}{2\sigma^2} \sum_{i=1}^n x_i^2 \right\} \exp \left\{ \frac{1}{2\sigma^2} \left( n\theta^2 - n\bar{x}^2 \right) \right\}\end{aligned}$$

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

Sufficient statistic:  $T(\mathbf{x}) = \bar{x}$



$$\text{MLE: } \hat{\theta} = \bar{x}.$$

Example 2: Bernoulli family

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

$$\theta \in \Theta = (0, 1)$$

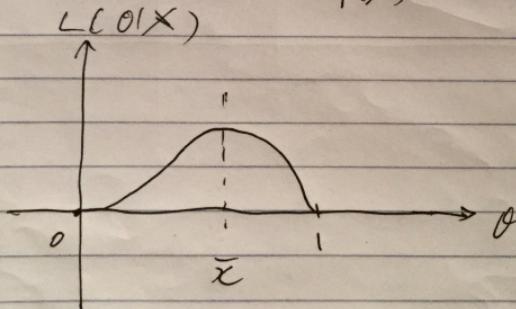
$$\begin{aligned}\text{pmf: } f(\mathbf{x} | \theta) &= \begin{cases} \theta^x (1-\theta)^{1-x} & \text{if } x=1 \\ 1-\theta & \text{if } x=0 \end{cases} \\&= \theta^x (1-\theta)^{1-x}\end{aligned}$$

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$$\begin{aligned} \text{Then } f(\mathbf{x} | \theta) &= \prod_{i=1}^n f(x_i | \theta) \\ &= \prod_{i=1}^n \theta^{x_i} (1-\theta)^{1-x_i} \\ &= \theta^{\sum_{i=1}^n x_i} (1-\theta)^{n - \sum_{i=1}^n x_i} \\ &= \theta^{n\bar{x}} (1-\theta)^{n(1-\bar{x})} \\ &= \exp \left\{ n\bar{x} \log \theta + n(1-\bar{x}) \log(1-\theta) \right\} \\ &= \exp \left\{ n\bar{x} (\log \theta - \log(1-\theta)) + n \log(1-\theta) \right\} \end{aligned}$$

The likelihood function:  $L(\theta | \mathbf{x}) = f(\mathbf{x} | \theta)$ .

Sufficient statistic:  $T(\mathbf{x}) = \bar{x}$ .



$$\text{mle: } \hat{\theta} = \bar{x}$$

Example 3: Shift family of exponential distribution

$X_1, \dots, X_n$  iid exponential with pdf

$$f(x|\theta) = \begin{cases} e^{-(x-\theta)} & x \geq \theta \\ 0 & x < \theta \end{cases}$$

$$\theta \in \Theta = (-\infty, \infty)$$

Then

$$\begin{aligned} f(\mathbf{x}|\theta) &= \prod_{i=1}^n f(x_i|\theta) \\ &= \begin{cases} e^{-\sum_{i=1}^n (x_i - \theta)} & x_{(1)} \geq \theta \\ 0 & x_{(1)} < \theta \end{cases} \end{aligned}$$

$$\text{where } x_{(1)} = \min_i x_i.$$

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

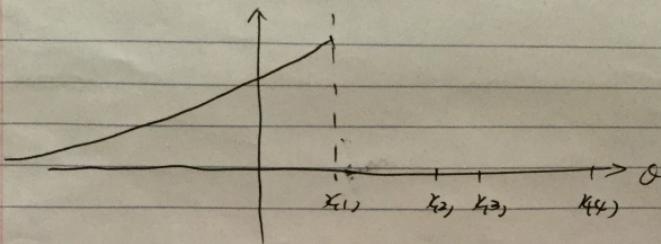
$$= \begin{cases} e^{-\sum_{i=1}^n (x_i - \theta)} & \theta \leq x_{(1)} \\ 0 & \theta > x_{(1)} \end{cases}$$

$$= e^{-n\bar{x}} e^{n\theta} \mathbb{1}_{\{\theta \leq x_{(1)}\}}$$

The sufficient statistic is  $T(\mathbf{x}) = x_{(1)}$

$L(\theta|x)$

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$$\text{mle : } \hat{\theta} = x_{11}$$