Composite Hypothesis Testing Approaches

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EECE 566

Introduction

$$H_0: \mathbf{x} \sim p(\mathbf{x}; \boldsymbol{\theta}_0)$$

 $H_1: \mathbf{x} \sim p(\mathbf{x}; \boldsymbol{\theta}_1)$

- $oldsymbol{ heta}$ $oldsymbol{ heta}_0$ (resp. $oldsymbol{ heta}_1$) is the vector parameter under H_0 (resp. under H_1)
- ullet $oldsymbol{ heta}_0$ and $oldsymbol{ heta}_1$ may be different parameters

Bayesian approach

- Assign prior pdf's to the parameters under both H_0 and H_1 : $p({m heta}_0)$ and $p({m heta}_1)$
- Convert to simple HT by finding

$$p(\mathbf{x}|H_0) = \int p(\mathbf{x}|\boldsymbol{\theta}_0, H_0) p(\boldsymbol{\theta}_0) d\boldsymbol{\theta}_0$$

$$p(\mathbf{x}|H_1) = \int p(\mathbf{x}|\boldsymbol{\theta}_1, H_1) p(\boldsymbol{\theta}_1) d\boldsymbol{\theta}_1$$
(LRT):
$$\frac{p(\mathbf{x}|H_1)}{p(\mathbf{x}|H_0)} = \frac{\int p(\mathbf{x}|\boldsymbol{\theta}_1, H_1) p(\boldsymbol{\theta}_1) d\boldsymbol{\theta}_1}{\int p(\mathbf{x}|\boldsymbol{\theta}_0, H_0) p(\boldsymbol{\theta}_0) d\boldsymbol{\theta}_0}$$

Bayesian approach

- $p(\boldsymbol{\theta}_0)$ and $p(\boldsymbol{\theta}_1)$ may be difficult to assign
- In absence of knowledge, use non-informative priors, e.g. uniform pdf
- Unknown DC level problem
 - lacktriangle Range of $m{ heta}_1=A$ is infinite \implies cannot be uniform on $\mathbb R$
 - \blacksquare We can choose $A \sim \mathcal{N}(0, \sigma_A^2)$ and let $\sigma_A^2 \to \infty$

$$\begin{split} H_0: \quad x_i &= \xi_i \\ H_1: \quad x_i &= A + \xi_i \end{split}$$

$$\xi_i \sim \mathcal{N}(0, \sigma^2), \text{ with known } \sigma^2 \\ A \text{ is unknown. } A \sim \mathcal{N}(0, \sigma_A^2) \end{split}$$

$$(\text{LRT}): \frac{p(\mathbf{x}|H_1)}{p(\mathbf{x}|H_0)} \ = \ \frac{\int p(\mathbf{x}|A, H_1) p(A) \mathrm{d}A}{p(\mathbf{x}|H_0)} \overset{0}{\lessgtr} \gamma \end{split}$$

$$p(\mathbf{x}|H_1) = \int_{-\infty}^{+\infty} (2\pi\sigma^2)^{-n/2} \exp\left(\frac{-1}{2\sigma^2} \sum_{i=1}^n (x_i - A)^2\right) \cdot (2\pi\sigma_A^2)^{-1/2} \exp\left(\frac{-A^2}{2\sigma_A^2}\right) dA$$

$$= (2\pi\sigma^2)^{-n/2} (2\pi\sigma_A^2)^{-1/2} \cdot \int_{-\infty}^{+\infty} \exp\left(\frac{-1}{2\sigma^2} \sum_{i=1}^n (x_i - A)^2 - \frac{A^2}{2\sigma_A^2}\right) dA$$

$$-\frac{1}{2}F(A) = -\frac{1}{2} \left[\frac{1}{\triangle^2} (A - \heartsuit)^2 + \diamondsuit\right]$$

$$F(A) = \frac{1}{\sigma^2} \sum_{i=1}^n x_i^2 - \frac{2An}{\sigma^2} \overline{\mathbf{x}} + \frac{nA^2}{\sigma^2} + \frac{A^2}{\sigma_A^2}$$

$$= \underbrace{\left(\frac{n}{\sigma^2} + \frac{1}{\sigma_A^2}\right)}_{1/\sigma_{A|\mathbf{x}}^2} A^2 - \frac{2An}{\sigma^2} \overline{\mathbf{x}} + \frac{1}{\sigma^2} \sum_{i=1}^n x_i^2$$

$$= \frac{A^2}{\sigma_{A|\mathbf{x}}^2} - \frac{2An\sigma_{A|\mathbf{x}}^2}{\sigma^2\sigma_{A|\mathbf{x}}^2} \overline{\mathbf{x}} + \frac{1}{\sigma^2} \sum_{i=1}^n x_i^2$$

$$F(A) = \frac{1}{\sigma_{A|\mathbf{x}}^2} \left(A - \frac{n\sigma_{A|\mathbf{x}}^2 \overline{\mathbf{x}}}{\sigma^2}\right)^2 - \frac{n^2 \overline{\mathbf{x}}^2 \sigma_{A|\mathbf{x}}^2}{\sigma^4} + \frac{1}{\sigma^2} \sum_{i=1}^n x_i^2$$

$$F(A) = \frac{1}{\sigma_{A/\mathbf{x}}^2} \left(A - \frac{n\sigma_{A|\mathbf{x}}^2 \overline{\mathbf{x}}}{\sigma^2} \right)^2 - \frac{n^2 \overline{\mathbf{x}}^2 \sigma_{A|\mathbf{x}}^2}{\sigma^4}$$

$$+ \frac{1}{\sigma^2} \sum_{i=1}^n x_i^2$$

$$\int \exp(-\frac{1}{2} F(A)) \mathrm{d}A = \exp\left(\frac{-1}{2\sigma^2} \sum_{i=1}^n x_i^2 \right) \exp\left(\frac{n^2 \overline{\mathbf{x}}^2 \sigma_{A|\mathbf{x}}^2}{2\sigma^4} \right)$$

$$\cdot \int_{-\infty}^{+\infty} \exp\left(\frac{-1}{2\sigma_{A|\mathbf{x}}^2} \left(A - \frac{n\sigma_{A|\mathbf{x}}^2 \overline{\mathbf{x}}}{\sigma^2} \right)^2 \right) \mathrm{d}A$$
Gaussian integral = $\sqrt{2\pi\sigma_{A|\mathbf{x}}^2}$

$$\frac{p(\mathbf{x}|H_1)}{p(\mathbf{x}|H_0)} = \frac{(2\pi\sigma^2)^{-n/2}(2\pi\sigma_A^2)^{-1/2}\exp\left(\frac{-1}{2\sigma^2}\sum_{i=1}^n x_i^2\right)}{(2\pi\sigma^2)^{-n/2}\exp\left(\frac{-1}{2\sigma^2}\sum_{i=1}^n x_i^2\right)} \cdot \exp\left(\frac{n^2\overline{\mathbf{x}}^2\sigma_{A|\mathbf{x}}^2}{2\sigma^4}\right)\sqrt{2\pi\sigma_{A|\mathbf{x}}^2}$$

$$\frac{p(\mathbf{x}|H_1)}{p(\mathbf{x}|H_0)} = \left(\frac{2\pi\sigma_{A|\mathbf{x}}^2}{2\pi\sigma_A^2}\right)^{1/2}\exp\left(\frac{n^2\overline{\mathbf{x}}^2\sigma_{A|\mathbf{x}}^2}{2\sigma^4}\right)$$

$$\frac{p(\mathbf{x}|H_1)}{p(\mathbf{x}|H_0)} = \left(\frac{2\pi\sigma_{A|\mathbf{x}}^2}{2\pi\sigma_A^2}\right)^{1/2} \exp\left(\frac{n^2\overline{\mathbf{x}}^2\sigma_{A|\mathbf{x}}^2}{2\sigma^4}\right)$$

Taking logarithms, putting data independent terms to the r.h.s.

$$\frac{n^{2}\sigma_{A|\mathbf{x}}^{2}}{2\sigma^{4}}\overline{\mathbf{x}}^{2} \quad \stackrel{0}{\underset{1}{\leqslant}} \quad \ln \gamma \frac{\sigma_{A|\mathbf{x}}}{\sigma_{A}^{2}}$$

$$\overline{\mathbf{x}}^{2} \quad \stackrel{0}{\underset{1}{\leqslant}} \quad \gamma'$$

$$|\overline{\mathbf{x}}| \quad \stackrel{0}{\underset{1}{\leqslant}} \quad \sqrt{\gamma'}$$

$$\begin{split} H_0: \quad & x_i = \xi_i \qquad \overline{\mathbf{x}} \sim \mathcal{N}(0, \sigma^2/n) \\ H_1: \quad & x_i = A + \xi_i \quad \overline{\mathbf{x}} \sim \mathcal{N}(0, \sigma_A^2 + \sigma^2/n) \\ |\overline{\mathbf{x}}| \quad & \lessapprox_1 \quad \gamma \\ P_{\mathsf{FA}} \quad & = \quad \Pr\{|\overline{\mathbf{x}}| > \gamma | H_0\} = 2 \cdot \Pr\{\overline{\mathbf{x}} > \gamma | H_0\} \\ P_{\mathsf{FA}} \quad & = \quad 2Q \left(\frac{\gamma}{\sqrt{\sigma^2/n}}\right) \\ & \gamma \quad & = \quad \sqrt{\sigma^2/n} \, Q^{-1}(P_{\mathsf{FA}}/2) \end{split}$$

- ullet We do not need σ_A^2 to set a threshold for a given P_{FA}
- ullet But P_{D} will require the knowledge of σ_A^2

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$$H_0: \quad x_i = \xi_i \qquad \overline{\mathbf{x}} \sim \mathcal{N}(0, \sigma^2/n)$$

$$H_1: \quad x_i = A + \xi_i \quad \overline{\mathbf{x}} \sim \mathcal{N}(0, \sigma_A^2 + \sigma^2/n)$$

$$|\overline{\mathbf{x}}| \quad \lessapprox_1 \quad \gamma$$

$$P_{\mathsf{D}} = \Pr\{|\overline{\mathbf{x}}| > \gamma | H_1\} = 2 \cdot \Pr\{\overline{\mathbf{x}} > \gamma | H_1\}$$

$$P_{\mathsf{D}} = 2Q \left(\frac{\gamma}{\sqrt{\sigma_A^2 + \sigma^2/n}}\right)$$

$$P_{\mathsf{D}} = 2Q \left(\frac{\sqrt{\sigma^2/n}Q^{-1}(P_{\mathsf{FA}}/2)}{\sqrt{\sigma_A^2 + \sigma^2/n}}\right)$$

$$H_0: x_i = \xi_i \quad \overline{\mathbf{x}} \sim \mathcal{N}(0, \sigma^2/n)$$

 $H_1: x_i = A + \xi_i \quad \overline{\mathbf{x}} \sim \mathcal{N}(0, \sigma_A^2 + \sigma^2/n)$

$$P_{\mathsf{D}} = 2Q \left(\frac{\sqrt{\sigma^2/n} Q^{-1} (P_{\mathsf{FA}}/2)}{\sqrt{\sigma_A^2 + \sigma^2/n}} \right)$$

- $\sigma_A^2 = 0 \Rightarrow P_D = P_{FA}$: Random guesser because $H_0 = H_1$
- $\sigma_A^2 \to \infty \Rightarrow P_{\rm D} \to 1$: Perfect detection. A will be large enough with high probability

$$n = 10, \, \sigma^2 = 1$$

