

# ECE 7251: Signal Detection and Estimation

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Lecture 24, 3/11/01:  
Chernoff Bounds (Gaussian Examples)

## Material from Last Lecture

- Consider the *loglikelihood* ratio test

$$L \equiv \ln \Lambda = \ln \frac{p(y | H_1)}{p(y | H_0)} \underset{H_0}{\overset{H_1}{\geq}} \ln \mathbf{I} \equiv \mathbf{g}$$

- Main object of interest:  $\mathbf{m}(s) \equiv \ln \Phi_{L|H_0}(s)$

$$\begin{aligned} \Phi_{L|H_0}(s) &\equiv E[e^{sL} | H_0] = \int_{-\infty}^{\infty} e^{sl} p(l | H_0) dl \\ &= \int_y p(y | H_1)^s p(y | H_0)^{1-s} dy \end{aligned}$$

- Both representations will be useful
- Discussion based on Van Trees, pp. 126-129

### Ex. 1: Gaussian, Equal Variances

$$H_1 \sim N(m, \mathbf{s}^2), H_0 \sim N(0, \mathbf{s}^2)$$

$$\begin{aligned} \mathbf{m}(s) &= \ln \int_y p(y | H_1)^s p(y | H_0)^{1-s} dy \\ &= \ln \int_{-\infty}^{\infty} \dots \int_{-\infty}^{\infty} \left\{ \prod_{i=1}^n \frac{1}{\sqrt{2ps^2}} \exp \left[ \frac{(y_i - m)^2}{2s^2} \right] \right\}^s \\ &\quad \times \left\{ \prod_{i=1}^n \frac{1}{\sqrt{2ps^2}} \exp \left[ \frac{y_i^2}{2s^2} \right] \right\}^{1-s} dy_1 \dots dy_n \\ &= n \ln \int_{-\infty}^{\infty} \frac{1}{\sqrt{2ps^2}} \exp \left[ \frac{(y-m)^2 s + y^2 (1-s)}{2s^2} \right] dy \end{aligned}$$

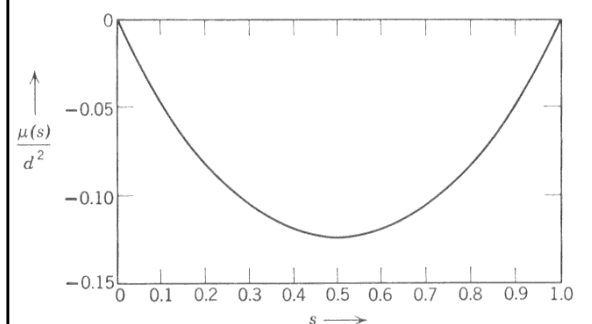
### Ex. 1: Completing the Square

$$\begin{aligned} &\int_{-\infty}^{\infty} \frac{1}{\sqrt{2ps^2}} \exp \left[ \frac{(y-m)^2 s + y^2 (1-s)}{2s^2} \right] dy \\ &= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2ps^2}} \exp \left[ -\frac{(y^2 - 2my + m^2)s + y^2 (1-s)}{2s^2} \right] dy \\ &= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2ps^2}} \exp \left[ \frac{y^2 - 2msy + m^2 s + m^2 s^2 - m^2 s^2}{2s^2} \right] dy \\ &= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2ps^2}} \exp \left[ \frac{(y^2 - 2msy + m^2 s^2) - m^2 s^2 + m^2 s}{2s^2} \right] dy \end{aligned}$$

### Ex. 1: Finish Computing the Mu

$$\begin{aligned} &\int_{-\infty}^{\infty} \frac{1}{\sqrt{2ps^2}} \exp \left[ \frac{(y^2 - 2msy + m^2 s^2) - m^2 s^2 + m^2 s}{2s^2} \right] dy \\ &= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2ps^2}} \exp \left[ -\frac{(y-ms)^2}{2s^2} \right] \exp \left[ -\frac{m^2 s(1-s)}{2s^2} \right] dy \\ &= \exp \left[ \frac{m^2 s(s-1)}{2s^2} \right] \\ &\quad \underbrace{\left\{ \int_{-\infty}^{\infty} \frac{1}{\sqrt{2ps^2}} \exp \left[ -\frac{(y-ms)^2}{2s^2} \right] dy \right\}}_{=1} \\ \mathbf{m}(s) &= n \ln \left\{ \frac{s(s-1)}{2} \frac{nm^2}{s^2} \right\} \equiv \frac{s(s-1)}{2} d^2 \end{aligned}$$

### Ex. 1: What Does Mu Look Like?



(Graph from p. 126 of Van Trees Vol. 1)

Ex. 1: Basic Bound on  $P_{FA}$

$$\mathbf{m}(s) = \frac{s(s-1)}{2} d^2, \quad \dot{\mathbf{m}}(s) = \frac{2s-1}{2} d^2$$

$$P_{FA} \leq \exp[\mathbf{m}(s) - s\dot{\mathbf{m}}(s)] \text{ for } 0 \leq s \leq 1$$

$$= \exp\left[\frac{s(s-1)}{2} d^2 - s \frac{(2s-1)}{2} d^2\right] = \exp\left[-\frac{s^2}{2} d^2\right]$$

where  $\mathbf{g} = \dot{\mathbf{m}}(s)$

$$\mathbf{g} = \frac{2s-1}{2} d^2$$

$$s = \frac{\mathbf{g}}{d^2} + \frac{1}{2}$$

Ex. 1: Basic Bound on  $P_m$

$$P_m \leq \exp[\mathbf{m}(s) + (1-s)\dot{\mathbf{m}}(s)]$$

$$= \exp\left[\frac{s(s-1)}{2} d^2 + (1-s) \frac{(2s-1)}{2} d^2\right]$$

$$= \exp\left[\frac{s^2-s}{2} d^2 + \frac{2s-1-2s^2+s}{2} d^2\right]$$

$$= \exp\left[\frac{2s-1-s^2}{2} d^2\right] = \exp\left[-\frac{(1-s)^2}{2} d^2\right]$$

Ex. 1: Where are the Bounds Meaningful?

- Recall we need

$$E[L | H_0] \leq \mathbf{g} \leq E[L | H_1]$$

$$\dot{\mathbf{m}}(0) \leq \mathbf{g} \leq \dot{\mathbf{m}}(1)$$

$$\frac{2 \cdot 0 - 1}{2} d^2 \leq \mathbf{g} \leq \frac{2 \cdot 1 - 1}{2} d^2$$

$$-\frac{d^2}{2} \leq \mathbf{g} \leq \frac{d^2}{2}$$

Ex. 1: The Refined Bound for  $P_{FA}$

- Recall the refined asymptotic bound:

$$P_{FA} \approx \exp[\mathbf{m}(s) - s\dot{\mathbf{m}}(s)] \exp\left[\frac{s^2 \ddot{\mathbf{m}}(s)}{2}\right] Q(s\sqrt{\dot{\mathbf{m}}(s)})$$

$$\dot{\mathbf{m}}(s) = \frac{2s-1}{2} d^2, \quad \ddot{\mathbf{m}}(s) = d^2$$

- In this case, since  $L$  is a sum of Gaussian random variables, the expression is exact:

$$P_{FA} = \exp\left[-\frac{s^2}{2} d^2\right] \exp\left[\frac{s^2 d^2}{2}\right] Q(sd) = Q(sd)$$

Ex. 1: The Refined Bound for  $P_M$

$$P_M \approx e^{\mathbf{m}(s) + (1-s)\dot{\mathbf{m}}(s)} \exp\left[\frac{(s-1)^2 \ddot{\mathbf{m}}(s)}{2}\right] Q((1-s)\sqrt{\dot{\mathbf{m}}(s)})$$

$$= \exp\left[-\frac{(1-s)^2}{2} d^2\right] \exp\left[\frac{(s-1)^2 d^2}{2}\right] Q((1-s)d)$$

- Again, since  $L$  is Gaussian, the expression is exact:

$$P_M = Q((1-s)d)$$

**Exercise:** Using MATLAB, plot basic Chernoff bound and true probs. of false alarm on the same graph vs.  $d$  for various choices of  $\mathbf{g}$

Ex. 1: Minimum Prob. of Error

- For minimum prob. of error test,  $\mathbf{g} = 0$

$$s_M = \frac{\mathbf{g}}{d^2} + \frac{1}{2} = \frac{1}{2}$$

- Recall approximate expression for  $P_e$  from last slide of last lecture

$$P_e \approx \frac{1}{2s_m(1-s_m)\sqrt{2\pi\dot{\mathbf{m}}(s_m)}} \exp[\mathbf{m}(s_m)]$$

$$= \frac{1}{2s_m(1-s_m)\sqrt{2\pi d^2}} \exp\left[\frac{s_m(s_m-1)}{2} d^2\right]$$

### Ex. 1: Min. Prob. of Error Con't

$$P_e \approx \frac{2}{\sqrt{2pd^2}} \exp\left[-\frac{d^2}{8}\right]$$

- Recall the exact expression is:

$$P_e = Q(d/2)$$

- Van Trees' rule of thumb: "approximation is very good for  $d > 6$ "

### The Bhattacharyya Distance

- If the criterion is the minimum prob. of error and  $\mathbf{m}(s)$  is symmetric about  $s=1/2$ , then

$$\mathbf{m}(s) = \ln \int_y \sqrt{p(y|H_1)} \sqrt{p(y|H_0)} dy$$

- $-\mathbf{m}(s)$  is called the Bhattacharyya distance

### Ex. 2: Gaussian, Equal Means

$$H_1 \sim N(0, \mathbf{s}_1^2), H_0 \sim N(0, \mathbf{s}_0^2)$$

**Exercise:** Verify that

$$\mathbf{m}(s) = \frac{n}{2} \ln \frac{(\mathbf{s}_0^2)^s (\mathbf{s}_1^2)^{1-s}}{s \mathbf{s}_0^2 + (1-s) \mathbf{s}_1^2}$$

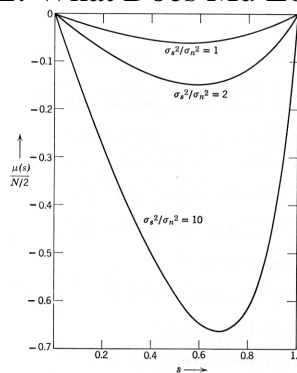
- A common special case:

$$\mathbf{s}_1^2 = \mathbf{s}_s^2 + \mathbf{s}_n^2, \mathbf{s}_0^2 = \mathbf{s}_n^2$$

**Exercise:** Verify that

$$\mathbf{m}(s) = \frac{n}{2} \left\{ (1-s) \ln \left[ 1 + \frac{\mathbf{s}_s^2}{\mathbf{s}_n^2} \right] - \ln \left[ 1 + (1-s) \frac{\mathbf{s}_s^2}{\mathbf{s}_n^2} \right] \right\}$$

### Ex. 2: What Does Mu Look Like?



(Graph from p. 128 of Van Trees Vol. 1)

### Ex. 2: Gaussian, Equal Means

**Exercise:** Verify that

$$\dot{\mathbf{m}}(s) = \frac{n}{2} \left\{ -\ln \left[ 1 + \frac{\mathbf{s}_s^2}{\mathbf{s}_n^2} \right] + \frac{\mathbf{s}_s^2 / \mathbf{s}_n^2}{1 + (1-s) \mathbf{s}_s^2 / \mathbf{s}_n^2} \right\}$$

$$\ddot{\mathbf{m}}(s) = \frac{n}{2} \left\{ \frac{\mathbf{s}_s^2 / \mathbf{s}_n^2}{1 + (1-s) \mathbf{s}_s^2 / \mathbf{s}_n^2} \right\}^2$$

**Exercise:** Find an expression for the  $s$  which gives the tightest bound in terms of  $g$

### Ex. 2: Gaussian, Equal Means

**Exercise:** Using MATLAB, plot four different ROC curves on the same graph:

- The true curve, computed using expressions from Lecture 21 and built in MATLAB commands like `chi2pdf`, etc.
  - The curve given by the basic Chernoff upper bound (this gives an upper bound ROC curve)
  - The curve given by the asymptotic Chernoff expression using the  $Q$  functions
  - The curve given by the asymptotic Chernoff expression using the approximation to  $Q$
- Try it for different values of  $n$  and  $\mathbf{s}_s^2 / \mathbf{s}_n^2$

## Ex. 2: ROC Curve Comparison

