

## Recitation 5

9-22-2011

Today

1. BSC review
2. Overview of PDF, CDF - Random Processes
  - eg. Binomial Distr.
  - eg. Gaussian Distr.
3. Optimal Detection
  - Digitizing thresholds & Decision Rule
  - BER calculations and Packet Error Rate

Note: Independent vs. Disjoint

- (\*) Events  $E_1$  and  $E_2$  are disjoint (mutually exclusive) if
- $$P(E_1 \cup E_2) = P(E_1) + P(E_2)$$
- $$\text{if } P(E_1 \cap E_2) = \emptyset$$
- (\*) Events  $E_1$  and  $E_2$  are independent if
- $$P(E_1 \cap E_2) = P(E_1) \cdot P(E_2)$$

Model:

(\*) Consider source (sender)  $S$  producing symbols 0, 1 with marginal probabilities (a priori)  $P_0$  and  $P_1$ , respectively.

over a channel with error probability (crossover) of  $p$ .  
i.e.  $P(R=0|S=1) = P(R=1|S=0) = p$ .

Find:

$$(A) P(R=1) = ?$$

Soln: Total Probability Thm:

$$P(A) = \sum_{i=1}^n P(A|E_i) \cdot P(E_i)$$

↑  
 $i^{\text{th}}$  cond.-prob.  
marginal prob.

for collectively exclusive and disjoint events.

$$\text{So, } P(R=1) = \underbrace{P(R=1|S=0)}_{p} \cdot \underbrace{P(S=0)}_{P_0} + \underbrace{P(R=1|S=1)}_{(1-p)} \cdot \underbrace{P(S=1)}_{P_1}$$

$\sim$  i.e. sum of all probs into "1"

$$= pP_0 + (1-p)P_1 \quad \checkmark$$

$$(B) P(S=0|R=1) = ?$$

Soln: Bayes' Rule:

$$\text{So, that } P(S=0|R=1) = \frac{P(R=1|S=0) \cdot P(S=0)}{P(R=1)}$$

$$= \frac{p \cdot P_0}{pP_0 + (1-p)P_1} \quad \checkmark$$

$P(R=1) \sim$  from above, using total prob. thm.

$$P(E_i|A) = \frac{P(A|E_i) \cdot P(E_i)}{P(A)} = \frac{P(A|E_i) \cdot P(E_i)}{\sum_{i=1}^n [P(A|E_i) \cdot P(E_i)]}$$

## (2) Random Processes

- Good model for describing noise and communication generally.

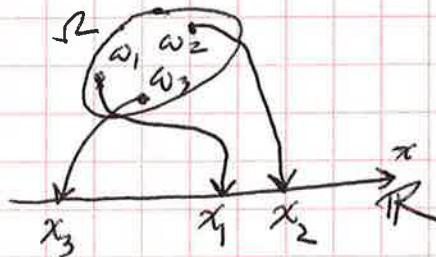
- Information is inherently random, ie. uncertainty!

~ cannot predict with certainty.

\* RP is RV with time as parameter.

What is RV? - RV is a mapping (function) of outcomes in  $\Omega$  to  $\mathbb{R}$  (set of real numbers)

$$\text{i.e. } \xrightarrow[\omega]{X} \xrightarrow{x} \quad X(\omega) = x$$



- RV's represented by capital X, Y, etc.

~ individual values of X denoted  $X(\omega) = x$ .

\* RV's characterized by the Probability Density Functions (pdf)  $f_x(x)$  defined as

$$\boxed{f_x(x) = \frac{d}{dx} F_x(x)}$$

where  $F_x(x)$  is the cumulative distribution function (cdf)

Generally,  $\int f_x(x) dx = P(X \in A)$

In particular,  $\int_{a^+}^{b^+} f_x(x) dx = P(a < X \leq b)$

with following properties:

① The cdf is a non-decreasing probability distribution that gives

$$\begin{aligned} F_x(x) &= P(X \leq x) \\ &= P\{\omega \in \Omega \mid X(\omega) = x\} \end{aligned}$$

②  $P(a < X \leq b) = F_x(b) - F_x(a)$

③  $0 \leq F_x(x) \leq 1$  ~ a probability func.

\* Let's look more closely @ one of the most useful pdfs in communication and statistics

① Binomial Distribution ??? (Not today)

✓ ② Gaussian (Normal) Distribution

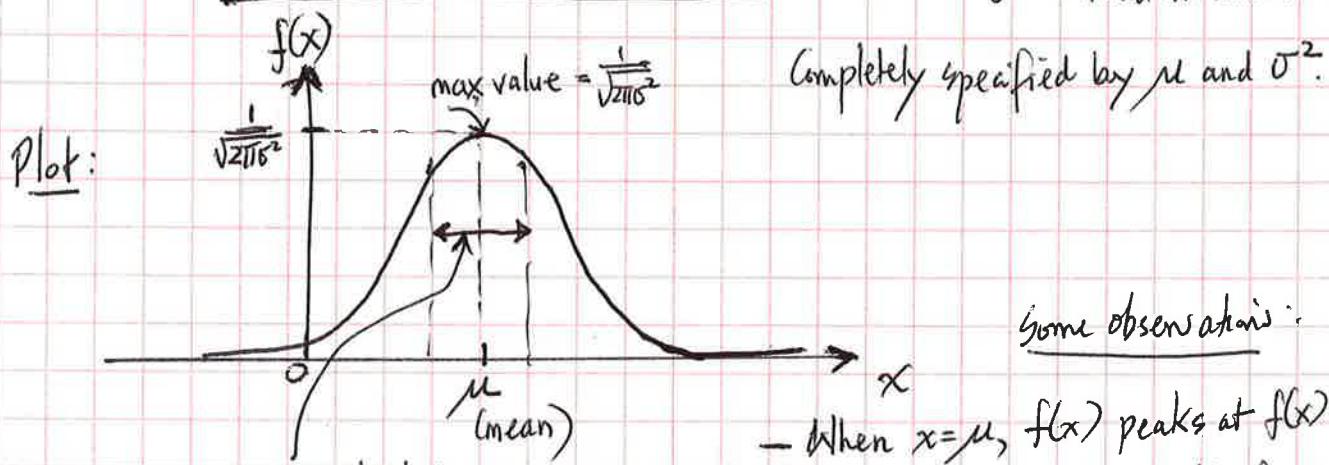
## Gaussian (Normal) Distribution — perhaps the most important distr. func. in communications!

PDF : 
$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

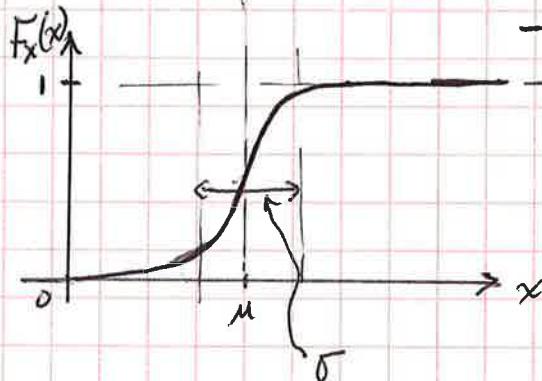
where  $\mu \sim \text{mean}$

$\sigma^2 \sim \text{variance, (standard deviation)}^2$

$\sigma \sim \text{standard deviation}$ .



Its corresponding cdf.



Some observations:

- When  $x=\mu$ ,  $f(x)$  peaks at  $f(x)=\frac{1}{\sqrt{2\pi\sigma^2}}$
- As  $\sigma \rightarrow 0$ ,  $f(x) \rightarrow$  delta func at  $x=\mu$ .
- As  $\sigma \rightarrow \text{large}$ , peak drops and  $f(x)$  spreads out.

$$\begin{aligned} F_x(a) &= P(X \leq a) = \int_{-\infty}^a f_x(x) dx \\ &= \int_{-\infty}^a \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx \\ &= \int_{-\infty}^{\frac{a-\mu}{\sigma}} \frac{1}{\sqrt{2\pi \cdot \sigma}} e^{-\frac{t^2}{2}} \sigma dt \\ &= \frac{1}{\sqrt{2\pi}} \int_{\frac{a-\mu}{\sigma}}^{\infty} e^{-\frac{t^2}{2}} dt = Q\left(\frac{a-\mu}{\sigma}\right) \end{aligned}$$

i) 
$$F_x(a) = Q\left(\frac{a-\mu}{\sigma}\right)$$

where  $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} e^{-\frac{t^2}{2}} dt$

(3)

### Optimum Detection

Consider binary PAM signals given by

$$s_1 = -s_0 = \sqrt{E_b}, \text{ where } E_b \sim \text{energy per bit.}$$

$$\text{Def } P(s_1) = P_1$$

$$P(s_0) = P_0$$



Problem

We wish to transmit these signals over an AWGN channel.

Goal: Find optimum decision rule when transmitted signal corrupted by AWGN noise!  
(for receiver)

Soln:

Received signal  $r = \pm\sqrt{E_b} + n$ , where  $n$  is a zero-mean Gaussian RV with variance  $\sigma^2 = \frac{N_0}{2}$

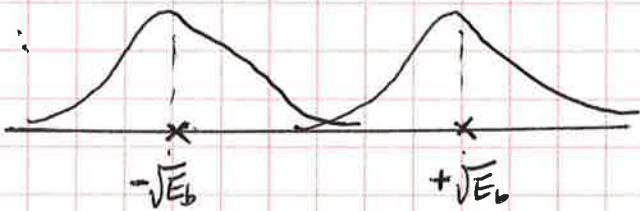
i.e.  $r$  will be a Gaussian distribution with mean  $\pm\sqrt{E_b}$ .

where  $N_0 \sim \text{power spectral density}$

-Cf. Central Limit Thm.

Central Limit Thm: Sum of independent RVs yield PDF  $\approx$  Gaussian generally!

So: Received  $r$ :



conditional pdfs:

$$f(r|s_1) = \frac{1}{\sqrt{\pi N_0}} e^{-(r-\sqrt{E_b})^2/N_0}$$

likelihood ~

$$f(r|s_0) = \frac{1}{\sqrt{\pi N_0}} e^{-(r+\sqrt{E_b})^2/N_0}$$

$$2\sigma^2 = N_0$$

power spectral density

The optimum detector seeks to maximize

$$PM(r, s) = f(r|s) \cdot p(s)$$

$$\left. \begin{aligned} i.e. \quad PM(r, s_1) &= f(r|s_1) \cdot P_1 \\ PM(r, s_0) &= f(r|s_0) \cdot P_0 \end{aligned} \right\} \quad \begin{cases} \text{If } PM(r, s_1) > PM(r, s_0) \text{ we pick } s_1 \\ \text{else pick } s_0. \end{cases}$$

$$\text{i.e. } \frac{PM(r, s_1)}{PM(r, s_0)} \stackrel{s_1}{\underset{s_0}{\geqslant}} 1$$

Substituting expressions for  $PM(r, s_1)$  and  $PM(r, s_0)$ ,

$$\frac{PM(r, s_1)}{PM(r, s_0)} = \frac{P_1}{P_0} e^{\frac{[(r+\sqrt{E_b})^2 - (r-\sqrt{E_b})^2]}{N_0}} \stackrel{s_1}{\underset{s_0}{\geqslant}} 1$$

Taking logs of both sides,

$$\ln \frac{P_1}{P_0} + \frac{(r+\sqrt{E_b})^2 - (r-\sqrt{E_b})^2}{N_0} \stackrel{s_1}{\underset{s_0}{\geqslant}} 0$$

$$\text{i.e. } \frac{4r\sqrt{E_b}}{N_0} \stackrel{s_1}{\underset{s_0}{\geqslant}} \ln \left( \frac{P_0}{P_1} \right)$$

OR

$$\boxed{r\sqrt{E_b} \stackrel{s_1}{\underset{s_0}{\geqslant}} \frac{N_0}{4} \ln \left( \frac{P_0}{P_1} \right)}$$

Correlation metric      threshold

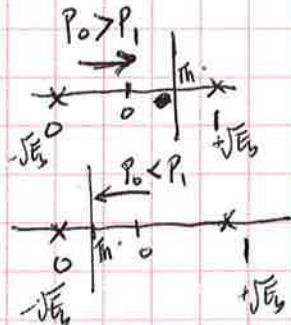
The optimum detector calculates the correlation metric and compares with a threshold.

Special Case: If  $P_0 = P_1 = \frac{1}{2}$ ,  $\ln \left( \frac{P_0}{P_1} \right) = 0$

and  $r \stackrel{s_1}{\underset{s_0}{\geqslant}} 0$  — which is the case we examined in class for equiprobable a priori probs!

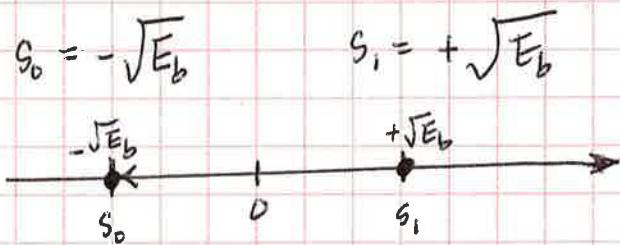
Q If  $P_0 > P_1$ , where does threshold move to?

If  $P_0 < P_1$ , where does threshold move to?



(4) P(error) For Binary Signalling

Consider binary antipodal signals  $s_0$  and  $s_1$ , with energy  $E_b$  each, whose geometric representations are the one-dimensional vector (respectively)



Signal pts for binary antipodal signals.

The received signal  $r$ , assuming  $s_1$  was transmitted, is given by

$$r = s_1 + n = \sqrt{E_b} + n, \text{ where } n \text{ is a zero-mean AWGN with variance } \sigma^2 = \frac{N_0}{2}.$$

The conditional pdf's of  $r$  are respectively

$$f(r|s_1) = \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{-(r-\sqrt{E_b})^2/2\sigma^2} \quad \text{and} \quad f(r|s_0) = \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{-(r+\sqrt{E_b})^2/2\sigma^2}$$

Given that  $s_1$  was transmitted, the prob. of error is the prob. that  $r < 0$  (assuming equally likely signals)

$$\text{i.e. } p(e|s_1) = \int_{-\infty}^0 f(r|s_1) dr = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^0 e^{-(r-\sqrt{E_b})^2/2\sigma^2} dr$$

$$\text{By substituting } x = \frac{(r-\sqrt{E_b})}{\sqrt{2\sigma}}, \ dr = -\sqrt{2}\sigma dx; \ x \rightarrow +\infty \text{ when } r \rightarrow -\infty \\ \text{and } x = \frac{\sqrt{E_b}}{\sqrt{2\sigma}} \text{ when } r = 0$$

The above expression becomes

$$p(e|s_1) = -\frac{1}{\sqrt{\pi}} \int_{\infty}^{\frac{\sqrt{E_b}/\sqrt{2\sigma}}{-\sqrt{2\sigma}}} e^{-x^2} dx = \frac{1}{\sqrt{\pi}} \int_{\frac{\sqrt{E_b}}{\sqrt{2\sigma}}}^{\infty} e^{-x^2} dx = \frac{1}{2} \operatorname{erfc}\left(\frac{\sqrt{E_b}}{\sqrt{2\sigma}}\right)$$

$$\text{where } \operatorname{erfc}(z) = \frac{2}{\sqrt{\pi}} \int_z^{\infty} e^{-x^2} dx.$$

Since  $\frac{N_0}{2} = \sigma^2$ , we obtain

p(e|s\_1) = \frac{1}{2} \operatorname{erfc}\left(\sqrt{\frac{E\_b}{N\_0}}\right)

(5)

## BER / PER Calculations

Example 1: Given  $\text{SNR} = 10 \text{ dB}$ , packet size = 1000 bits.

$$\text{(A) BER} = ?$$

$$\text{(B) Packet Error Rate (PER)} = ?$$

Soln: Recall  $\text{SNR}_{\text{dB}} = 10 \log_{10} \left( \frac{E_b}{N_0} \right)$

so that  $\frac{E_b}{N_0} = 10^{\frac{\text{SNR}}{10}}$

$$\text{Given SNR} = 10 \text{ dB}, \quad \frac{E_b}{N_0} = 10^{\frac{10}{10}} = 10$$

$$\begin{aligned} \text{(A) BER} &= \frac{1}{2} \operatorname{erfc} \left( \sqrt{\frac{E_b}{N_0}} \right) \\ &= \frac{1}{2} \operatorname{erfc} \left( \sqrt{10} \right) = \frac{1}{2} \operatorname{erfc} (3.16) = \underline{3 \times 10^{-6}} \end{aligned}$$

$$\text{(B) } P(\text{correct bit}) \hat{=} P_c = 1 - P(\text{bit in error})$$

i.e.  $P_c = 1 - \text{BER}$

A packet is correct when all 1000-bits in the packet are correct (for our example).

$$\text{i.e. } P(\text{Packet correct}) = [P(\text{Correct Bit})]^{1000} = [1 - \text{BER}]^{1000}$$

$$\text{Packet Error Rate} = 1 - P(\text{Packet correct}) = 1 - (1 - \text{BER})^{1000}$$

Recall that for  $|x| \ll 1$ ,  $(1-x)^N \approx 1 - Nx$ .

$$\text{So for very small BER, } (1 - \text{BER})^{1000} \approx 1 - 1000 \times \text{BER}.$$

$$\text{So that PER} \approx 1 - (1 - 1000 \times \text{BER}) = 1000 \times \text{BER} = 1000 \times (3 \times 10^{-6}) = \underline{3 \times 10^{-3}}$$

Example 2: Now consider the case where

$\text{SNR} = 0 \text{ dB}$ , for same packet size = 1000 bits.

(A)  $\text{BER} = ?$

(B)  $\text{PER} = ?$

Soln:  $\frac{E_b}{N_0} = 10^{\frac{\text{SNR}}{10}} = 10^0 = 1$

(A) So that  $\text{BER} = \frac{1}{2} \operatorname{erfc}\left(\sqrt{\frac{E_b}{N_0}}\right) = \frac{1}{2} \operatorname{erfc}(1) = 0.0787$

(B)  $\text{PER} = 1 - (1 - \text{BER})^{1000} = 1 - (1 - 0.0787)^{1000} \approx 1$  which is so unacceptable!

Note that we didn't use the approximation bcos the BER in this case is quite high!

Comparing Ex1 to Ex2, we see that changes in  $\text{SNR}$  can yield unacceptable changes in PER especially.