

# EE 5654 - Digital Communications Spring 2005



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Lecture #7 - Optimum Receiver Structures for Digital  
Modulation





# Modulation

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- Modulation is used to transmit digital data over a channel
- Gram-Schmidt procedure allows vector representation of any signal constellation
- Optimal receiver consists of a correlator, weighted to adjust for signal energy and a priori probabilities
- Receiver implementation can be simplified with reduced correlation and matched filter
- We now turn to calculating performance



# Problem Statement

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- We transmit a signal  $s(t) \in \{s_1(t), s_2(t), \dots, s_M(t)\}$  , where  $s(t)$  is nonzero only on  $t \in [0, T]$  .
- Let the various signals be transmitted with probability:  $p_1 = \Pr[s_1(t)], \dots, p_M = \Pr[s_M(t)]$
- The received signal is corrupted by noise:  
$$r(t) = s(t) + n(t)$$
- Given  $r(t)$  , the receiver forms an estimate  $\hat{s}(t)$  of the signal  $s(t)$  with the goal of minimizing symbol error probability  $P_s = \Pr[\hat{s}(t) \neq s(t)]$



# Final Form of MAP Receiver

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$$\begin{aligned}\hat{\mathbf{s}} &= \arg \max_{\{\mathbf{s}_1, \dots, \mathbf{s}_M\}} \left\{ p\{\mathbf{s}_m\} p\{\mathbf{r}|\mathbf{s}_m\} \right\} \\ &= \arg \max_{\{\mathbf{s}_1, \dots, \mathbf{s}_M\}} \left\{ \frac{N_0}{2} \ln[p_m] + \sum_{k=1}^K r_k s_{m,k} - \frac{1}{2} \sum_{k=1}^K s_{m,k}^2 \right\}\end{aligned}$$

# Interpreting This Result

- $\frac{N_0}{2} \ln[p_m]$  weights the a priori probabilities
  - If the noise is large,  $p_m$  counts a lot
  - If the noise is small, our received signal will be an accurate estimate and  $p_m$  counts less

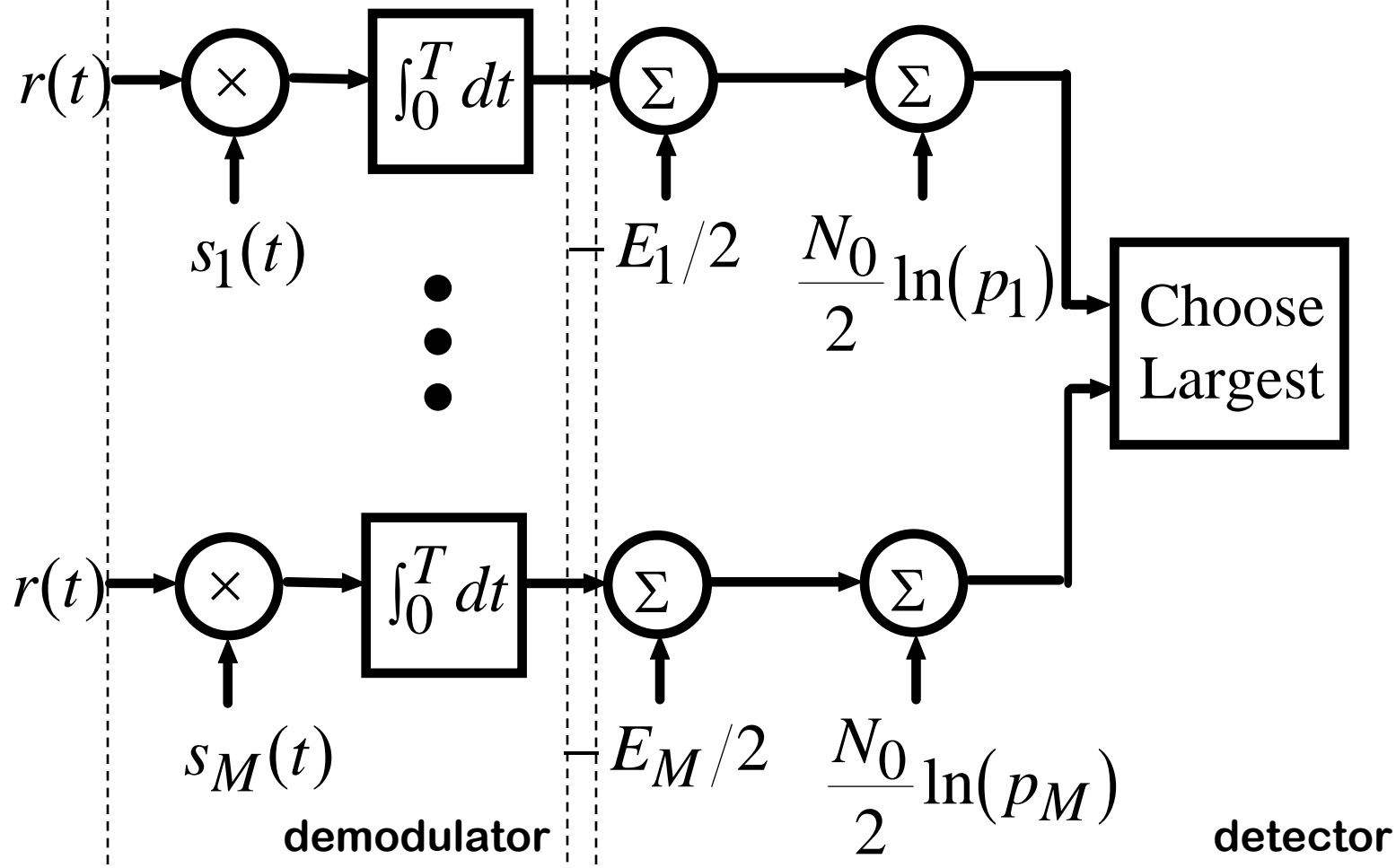
- $\sum_{k=1}^K r_k s_{m,k} = \int_0^T s_m(t) r(t) dt$  represents the

correlation with the received signal

- $\frac{1}{2} \sum_{k=1}^K s_{m,k}^2 = \frac{1}{2} \int_0^T s_m^2(t) dt = \frac{E_m}{2}$  represents signal

energy

# An Implementation of the Optimal Receiver - Correlation Receiver





# Simplifications for Special Cases

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- ML case: All signals are equally likely ( $p_1 = \dots = p_M$ ). A priori probabilities can be ignored.
- All signals have equal energy ( $E_1 = \dots = E_M$ ). Energy terms can be ignored.
- We can reduce the number of correlations by directly implementing:

$$\hat{\mathbf{s}} = \arg \max_{\{\mathbf{s}_1, \dots, \mathbf{s}_M\}} \frac{N_0}{2} \ln[p_m] + \sum_{k=1}^K r_k s_{m,k} - \frac{1}{2} \sum_{k=1}^K s_{m,k}^2$$



# Summary of Optimal Receiver Design

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- Optimal coherent receiver for AWGN has three parts:
  - Correlates the received signal with each possible transmitted signal
  - Normalizes the correlation to account for energy
  - Weights the a priori probabilities according to noise power
- This receiver is completely general for any signal set
- Simplifications are possible under many circumstances



## Example

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- **Problem:** Consider the case of binary PAM signals in which the two possible signal points are

$$s_1 = \sqrt{E_b} p(t)$$

$$s_2 = -\sqrt{E_b} p(t)$$

where  $E_b$  is the energy per bit and  $p(t)$  is the transmitted pulse shape normalized to unit energy. The *a priori* probabilities are  $P(s_1) = p$  and  $P(s_2) = 1-p$ . Let's determine the decision rule for the optimum MAP detector when the transmitted signal is corrupted with AWGN.



## Example (cont.)

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**Solution:** The received signal is one-dimensional and with basis function  $p(t)$

The received vector is then represented as

$$\mathbf{s}_1 = \sqrt{E_b}$$

$$\mathbf{s}_2 = -\sqrt{E_b}$$

$$\mathbf{r} = \pm\sqrt{E_b} + n$$



## Example (cont.)

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- $n$  is a Gaussian random variable with variance  $\sigma_n^2 = \frac{N_o}{2}$
- Thus the conditional pdf's of the two signals are

$$p(r|s_1) = \frac{1}{\sqrt{2\pi}\sigma_n} \exp\left[-\frac{(r - \sqrt{E_b})^2}{2\sigma_n^2}\right]$$

$$p(r|s_2) = \frac{1}{\sqrt{2\pi}\sigma_n} \exp\left[-\frac{(r + \sqrt{E_b})^2}{2\sigma_n^2}\right]$$



## Example (cont.)

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- If we define the metrics upon which we make a decision as  $pm(r, s_i)$

$$\hat{\mathbf{s}} = \arg \max_{\{\mathbf{s}_1, \dots, \mathbf{s}_M\}} \left\{ p\{\mathbf{s}_m\} p\{\mathbf{r}|\mathbf{s}_m\} \right\}$$

$$= \arg \max_{\{\mathbf{s}_1, \dots, \mathbf{s}_M\}} \left\{ pm(\mathbf{r}, \mathbf{s}_m) \right\}$$

$$pm(\mathbf{r}, \mathbf{s}_m) = p\{\mathbf{s}_m\} p\{\mathbf{r}|\mathbf{s}_m\}$$

**Note that these are scalars in this case since there is only one basis function.**



## Example (cont.)

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- The metrics for the two symbols are then

$$pm(r, s_1) = \frac{p}{\sqrt{2\pi}\sigma_n} \exp\left[-\frac{(r - \sqrt{E_b})^2}{2\sigma_n^2}\right]$$
$$pm(r, s_2) = \frac{(1-p)}{\sqrt{2\pi}\sigma_n} \exp\left[-\frac{(r + \sqrt{E_b})^2}{2\sigma_n^2}\right]$$

- If  $pm(r, s_1) > pm(r, s_2)$ , then we select  $s_1$  as the transmitted signal. Otherwise we select  $s_2$ .



## Example (cont.)

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- Since there are only two symbols, We may express the decision rule as

$$pm(r, s_1) \begin{matrix} < \\ > \end{matrix} pm(r, s_2)$$

$$\frac{pm(r, s_1)}{pm(r, s_2)} \begin{matrix} < \\ > \end{matrix} 1$$



# Example (cont.)

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- Substituting:

$$\frac{pm(r, s_1)}{pm(r, s_2)} < \frac{s_2}{s_1} > 1$$

$$\frac{\frac{p}{\sqrt{2\pi}\sigma_n} \exp\left[-\frac{(r - \sqrt{E_b})^2}{2\sigma_n^2}\right]}{\frac{(1-p)}{\sqrt{2\pi}\sigma_n} \exp\left[-\frac{(r + \sqrt{E_b})^2}{2\sigma_n^2}\right]} < \frac{s_2}{s_1} > 1$$

$$\frac{p}{1-p} \exp\left[\frac{(r + \sqrt{E_b})^2 - (r - \sqrt{E_b})^2}{2\sigma_n^2}\right] < \frac{s_2}{s_1} > 1$$



# Example (cont.)

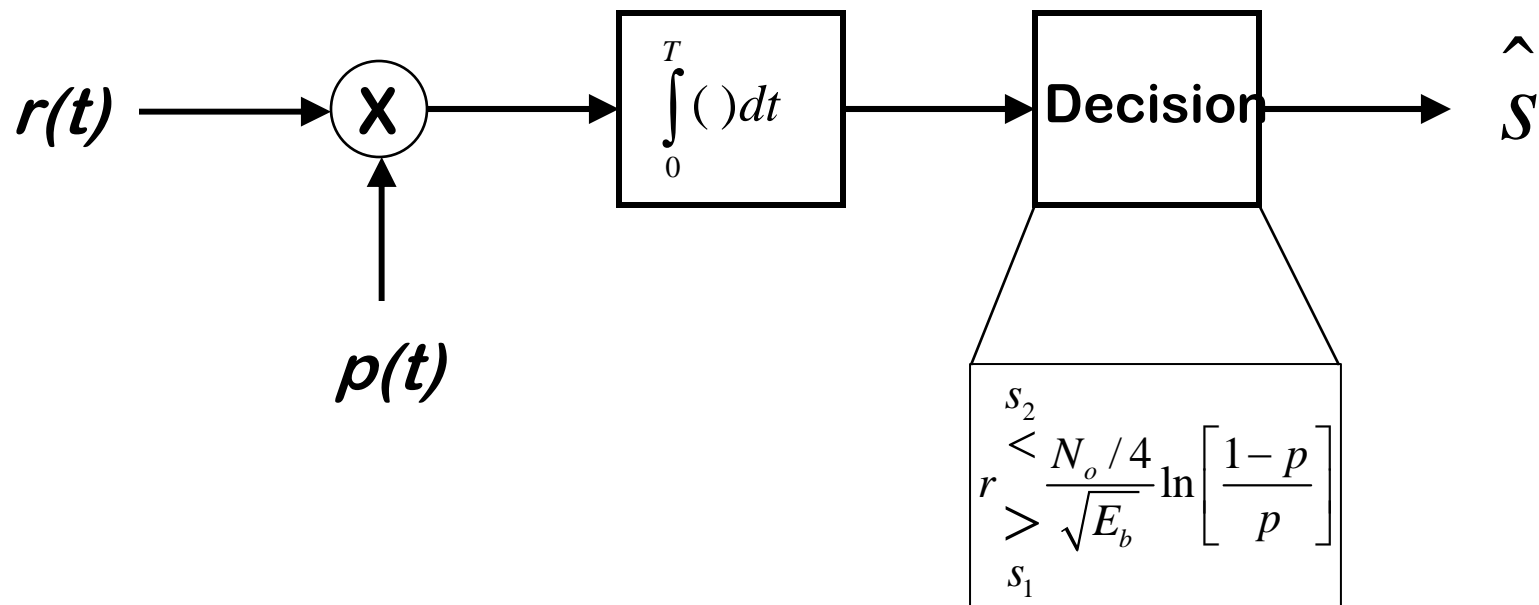
$$\frac{p}{1-p} \exp \left[ \frac{(r + \sqrt{E_b})^2 - (r - \sqrt{E_b})^2}{2\sigma_n^2} \right] \begin{matrix} < \\ > \end{matrix} \begin{matrix} s_2 \\ s_1 \end{matrix} \quad 1$$

$$\frac{(r + \sqrt{E_b})^2 - (r - \sqrt{E_b})^2}{2\sigma_n^2} \begin{matrix} < \\ > \end{matrix} \ln \left[ \frac{1-p}{p} \right] \begin{matrix} s_2 \\ s_1 \end{matrix}$$

$$\frac{2r\sqrt{E_b}}{\sigma_n^2} \begin{matrix} < \\ > \end{matrix} \ln \left[ \frac{1-p}{p} \right] \begin{matrix} s_2 \\ s_1 \end{matrix}$$

$$r \begin{matrix} < \\ > \end{matrix} \frac{N_o/4}{\sqrt{E_b}} \ln \left[ \frac{1-p}{p} \right] \begin{matrix} s_2 \\ s_1 \end{matrix} \xrightarrow{\text{If } p = 1/2} r \begin{matrix} < \\ > \end{matrix} 0 \begin{matrix} s_2 \\ s_1 \end{matrix}$$

## Example (cont.) – Optimal Receiver





# Decision Regions

- Optimal Decision Rule:

$$\hat{s} = \arg \max_{\{s_1, \dots, s_M\}} \frac{N_0}{2} \ln[p_m] + \sum_{k=1}^K r_k s_{m,k} - \frac{1}{2} \sum_{k=1}^K s_{m,k}^2$$

- Let  $R_i \subset \mathfrak{R}^K$  be the region in which

$$\frac{N_0}{2} \ln[p_i] + \sum_{k=1}^K r_k s_{i,k} - \frac{1}{2} \sum_{k=1}^K s_{i,k}^2$$

$$\geq \frac{N_0}{2} \ln[p_j] + \sum_{k=1}^K r_k s_{j,k} - \frac{1}{2} \sum_{k=1}^K s_{j,k}^2, \forall i \neq j$$

- Then  $R_i$  is the  $i$ th "Decision Region"



# Decision Regions

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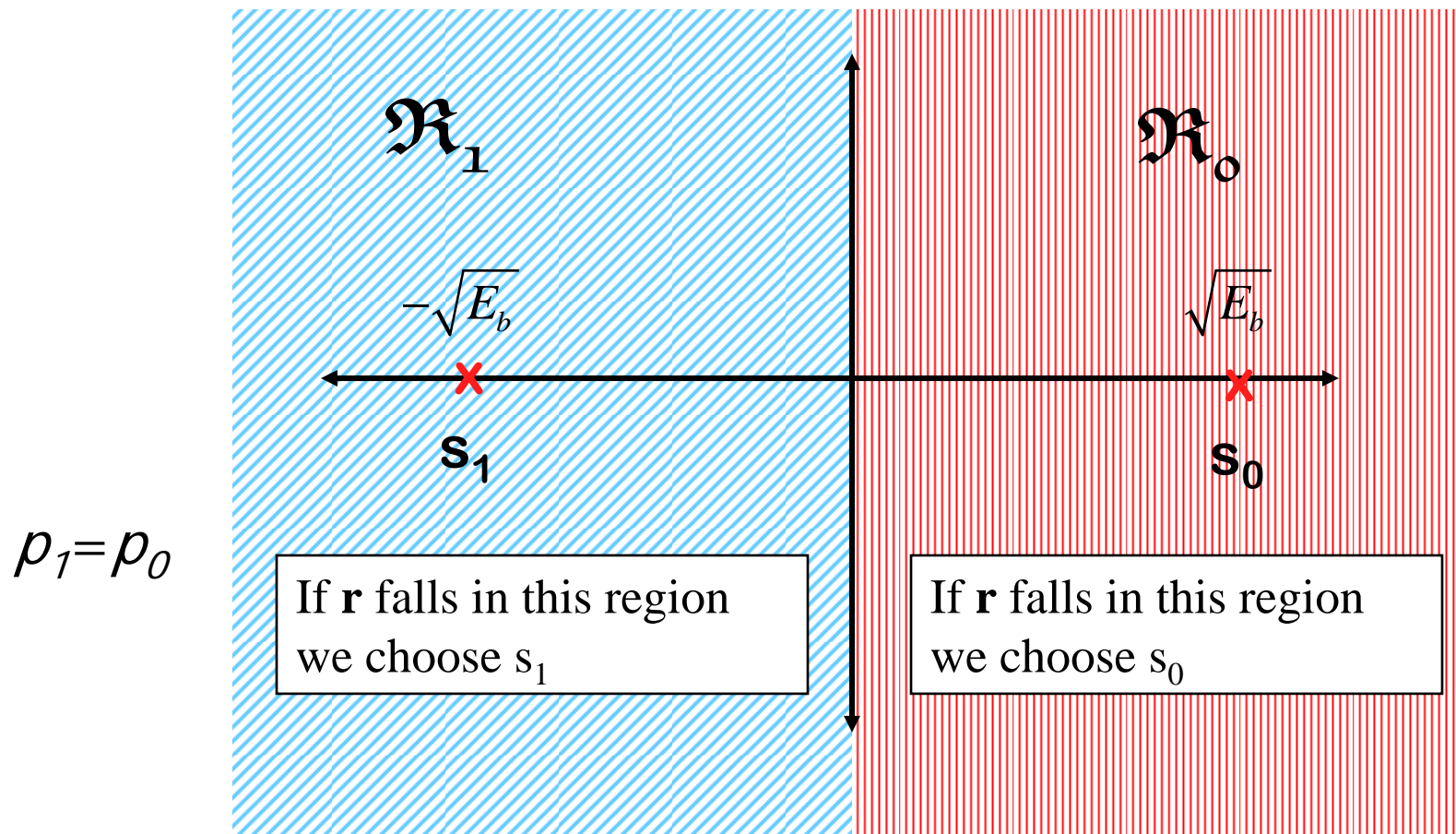
- Maximum Likelihood Case ( $p_1 = p_2 = \dots = p_M$ )

$$\begin{aligned}\hat{s} &= \arg \max_{\{s_1, \dots, s_M\}} \ln[p_m] - \frac{K}{2} \ln[\pi N_0] - \frac{1}{N_0} \sum_{k=1}^K (r_k - s_{m,k})^2 \\ &= \arg \max_{\{s_1, \dots, s_M\}} - \frac{1}{N_0} \sum_{k=1}^K (r_k - s_{m,k})^2\end{aligned}$$

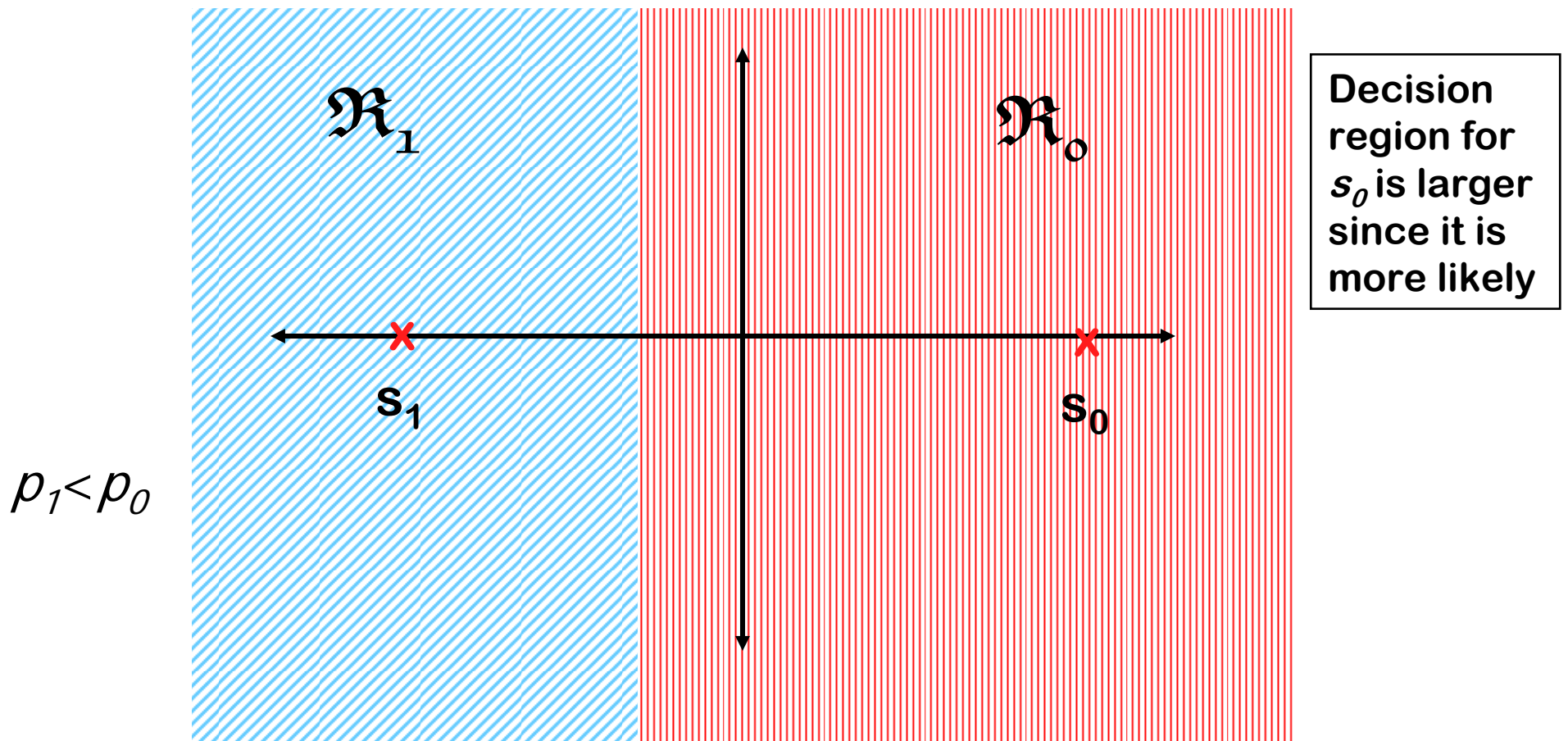
- Thus, we for maximum likelihood we choose the symbol that is closest to the received signal in  $K$ -dimensional space



# Example: BPSK



# Example: BPSK





# A Matlab Function for Visualizing Decision Regions

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- The Matlab Script File “sigspace.m” (on course web page) can be used to visualize two dimensional signal spaces and decision regions
- The function is called with the following syntax:  
 $\text{sigspace}([x_1 \ y_1 \ p_1; x_2 \ y_2 \ p_2; \dots; x_M \ y_M \ p_M], E_b/N_0)$ 
  - $x_i$  and  $y_i$  are the coordinates of the  $i$ th signal point
  - $p_i$  is the probability of the  $i$ th signal (omitting gives ML)
  - $E_b/N_0$  is the signal to noise ratio of digital system in dB



# Average Energy Per Bit: $E_b$

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- $E_i = \sum_{k=1}^K s_{i,k}^2$  is the energy of the  $i$ th signal
- $E_s = \frac{1}{M} \sum_{i=1}^M E_i$  is the average energy per symbol
- $\log_2 M$  is the number of bits transmitted per symbol
- $E_b = \frac{E_s}{\log_2 M}$  is the average energy per bit
  - allows fair comparisons of the energy requirements of different sized signal constellations



# Signal to Noise Ratio for Digital Systems

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- $N_0/2$  is the (two-sided) power spectral density of the background noise
- The ratio  $E_b/N_0$  measures the relative strength of signal and noise at the receiver
- $E_b$  has units of Joules = Watts \*sec
- $N_0$  has units of Watts/Hz = Watts\*sec
- The unitless quantity  $E_b/N_0$  is frequently expressed in dB



# Example: QPSK

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- symbols

$$s_i(t) = \cos\left(2\pi ft + (i-1)\frac{\pi}{4}\right) \quad 0 \leq t \leq T_s$$

- basis functions

$$f_1(t) = \cos(2\pi ft) \quad 0 \leq t \leq T_s$$

$$f_2(t) = \sin(2\pi ft) \quad 0 \leq t \leq T_s$$

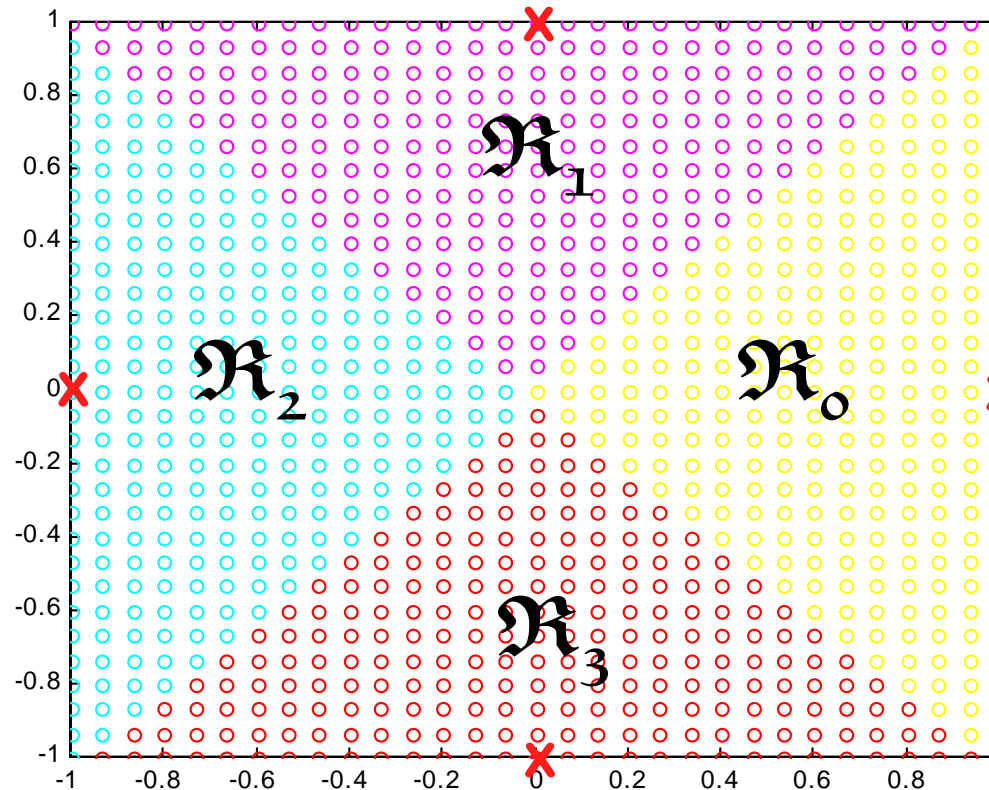
- symbol vectors

$$\mathbf{s}_1 = \begin{bmatrix} \sqrt{E_s} \\ 0 \end{bmatrix} \quad \mathbf{s}_2 = \begin{bmatrix} 0 \\ \sqrt{E_s} \end{bmatrix}$$

$$\mathbf{s}_3 = \begin{bmatrix} -\sqrt{E_s} \\ 0 \end{bmatrix} \quad \mathbf{s}_4 = \begin{bmatrix} 0 \\ -\sqrt{E_s} \end{bmatrix}$$

# Examples of Decision Regions - QPSK

- sigspace( [1 0; 0 1; -1 0; 0 -1], 20)



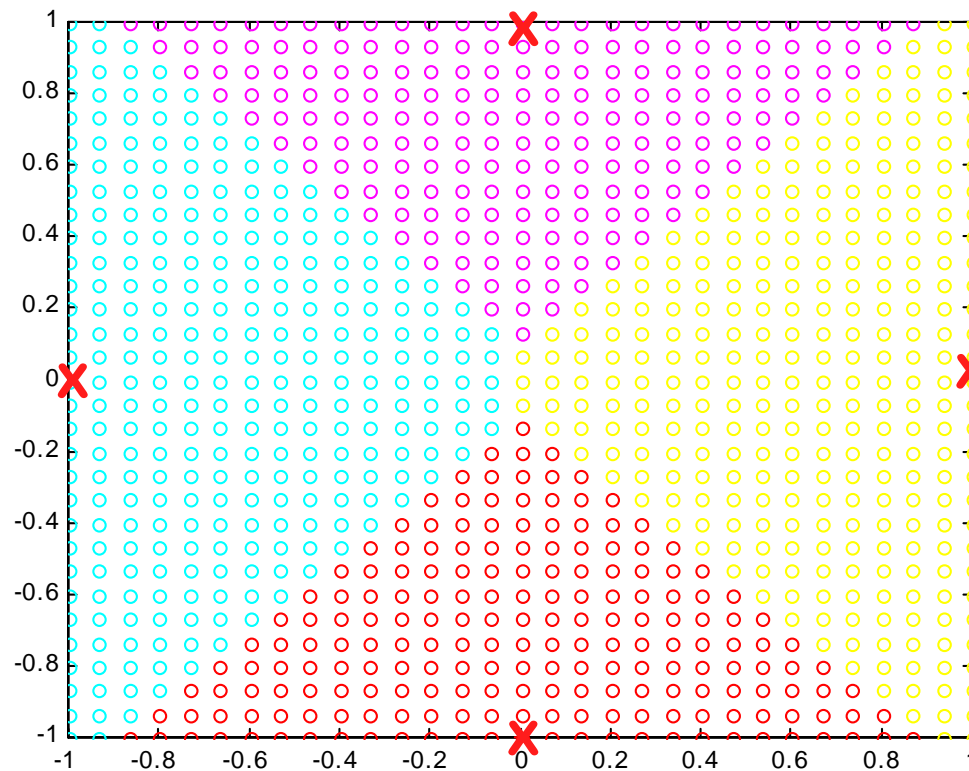
$E_b/N_0 = 20\text{dB}$   
But is irrelevant  
in this case

$$\hat{s} = \arg \max_{\{s_1, \dots, s_M\}} \ln [p_m] - \frac{1}{N_0} \sum_{k=1}^K (r_k - s_{m,k})^2$$

$$p_1 = p_2 = p_3 = p_4$$

# QPSK with Unequal Signal Probabilities

- `sigspace( [1 0 0.4; 0 1 0.1; -1 0 0.4; 0 -1 0.1], 5)`



$$p_1 = 0.4$$

$$p_2 = 0.1$$

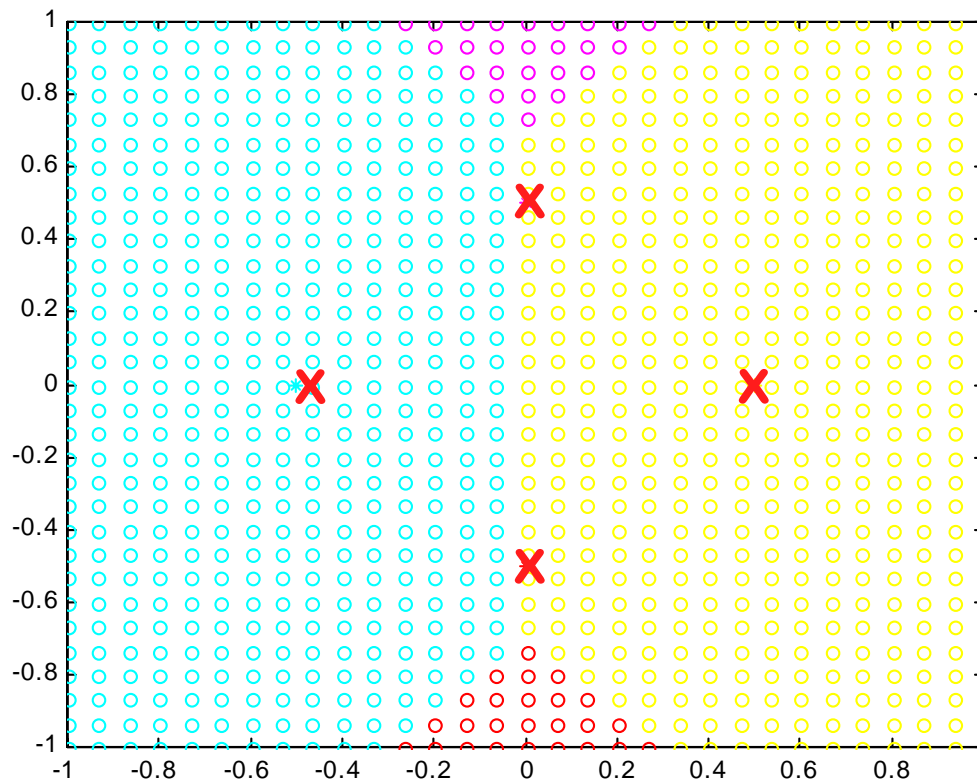
$$p_3 = 0.4$$

$$p_4 = 0.1$$

$$E_b/N_0 = 5dB$$

# QPSK with Unequal Signal Probabilities - Extreme Case

■ sigspace([0.5 0 0.4; 0 0.5 0.1; -0.5 0 0.4; 0 -0.5 0.1],-6)



$$p_1 = 0.4$$

$$p_2 = 0.1$$

$$p_3 = 0.4$$

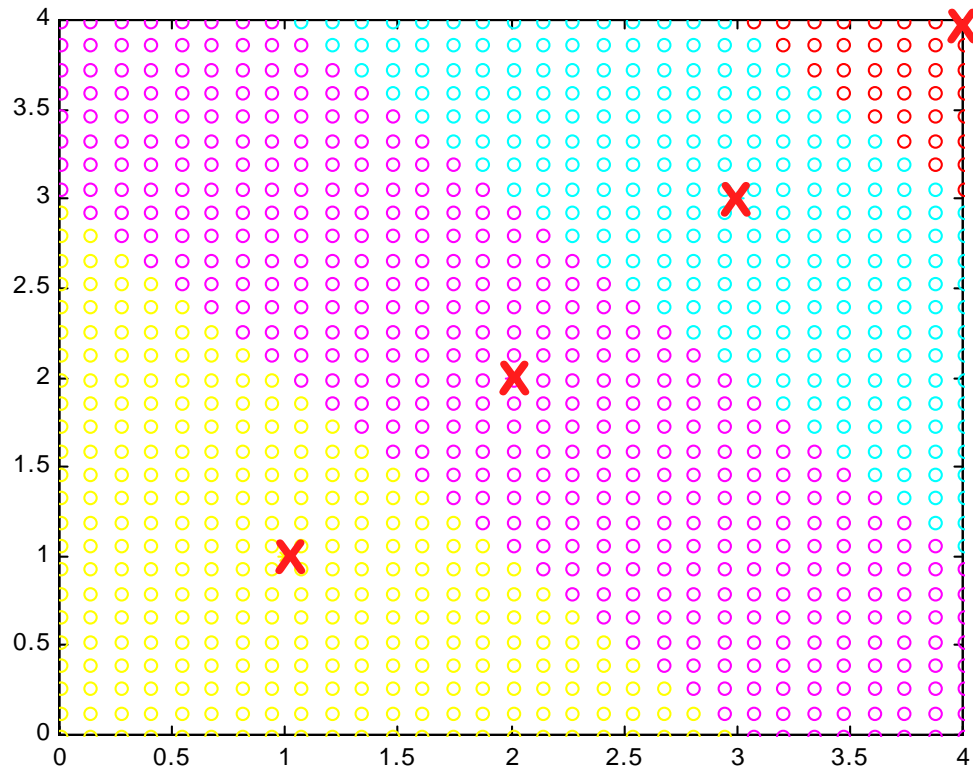
$$p_4 = 0.1$$

$$E_b/N_0 = -6dB$$

Low SNR gives heavy weighting to *a priori* probabilities

# Unequal Signal Powers

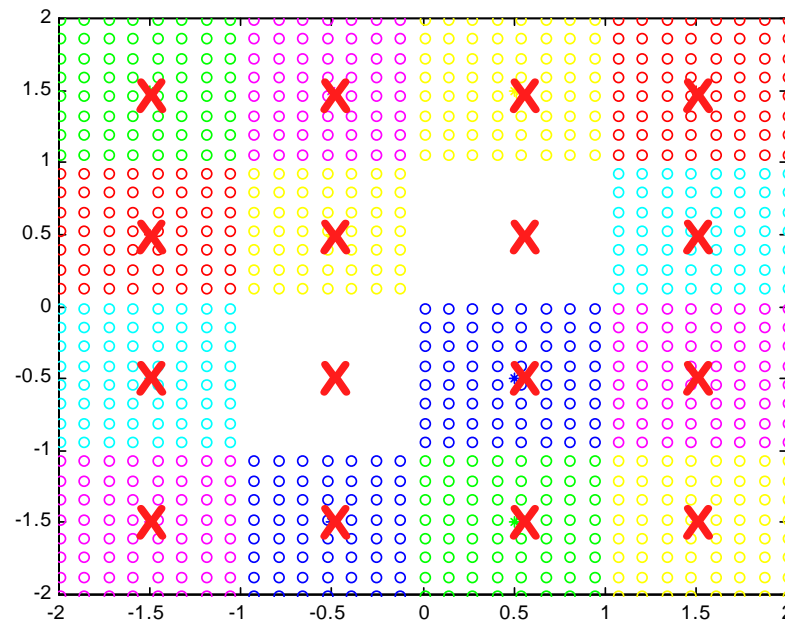
■ `sigspace( [1 1 ; 2 2; 3 3; 4 4], 10)`



**ASK scheme  
Could use  
single  
dimension**

# Signal Constellation for 16-ary QAM

- `sigspace([1.5 -1.5; 1.5 -0.5; 1.5 0.5; 1.5 1.5; 0.5 -1.5; 0.5 -0.5; 0.5 0.5; 0.5 1.5; -1.5 -1.5; -1.5 -0.5; -1.5 0.5; -1.5 1.5; -0.5 -1.5; -0.5 -0.5; -0.5 0.5; -0.5 1.5],10)`





# Notes on Decision Regions

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- Boundaries are perpendicular to a line drawn between two signal points
- If signal probabilities are equal, decision boundaries lie exactly halfway in between signal points
- If signal probabilities are unequal, the region of the less probable signal will shrink.
- Signal points need not lie within their decision regions for case of low  $E_b/N_0$  and unequal probabilities.



# Receiver Operations

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- What we have been discussing so far is the *optimum detector*. That is given the observed vector

$$\mathbf{r} = \mathbf{s} + \mathbf{n}$$

we have determined the optimal detection or decision rule.

- However, we haven't shown whether the creation of the vector  $\mathbf{r}$  is from the received signal is optimal. That is, we haven't shown that the *demodulator* is optimal.



# Optimal Demodulation

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- We have described the *correlation demodulator* and the equivalent *matched filter demodulator*.
- Consider a general correlator demodulator where the received signal is correlated with a function  $h(t)$

$$\begin{aligned}r_k &= \int_0^T r(t)h(t)dt \\ &= \int_0^T (s(t) + n(t))h(t)dt \\ &= \int_0^T s(t)h(t)dt + \int_0^T n(t)h(t)dt\end{aligned}$$

# Optimal Demodulation (cont.)

- Consider a general correlator demodulator where the received signal is correlated with a function  $h(t)$

**Desired  
Component**

$$r_k = \int_0^T s(t)h(t)dt + \int_0^T n(t)h(t)dt$$

**Noise  
Component**

$$SNR = \frac{\left[ \int_0^T s(t)h(t)dt \right]^2}{E \left[ \left( \int_0^T n(t)h(t)dt \right)^2 \right]}$$



# Optimal Demodulator (cont.)

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- The noise power can be determined as

$$\begin{aligned} E \left\{ \left[ \int_0^T n(t)h(t)dt \right]^2 \right\} &= \int_0^T \int_0^T E \{ n(t)n(\tau) \} h(t)h(\tau)dt d\tau \\ &= \frac{N_o}{2} \int_0^T \int_0^T \delta(t - \tau) h(t)h(\tau)dt d\tau \\ &= \frac{N_o}{2} \int_0^T h^2(t)dt \end{aligned}$$



# Optimal Demodulator - SNR

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- From the Cauchy-Schwarz Inequality we know

$$SNR = \frac{\left[ \int_0^T s(t)h(t)dt \right]^2}{\frac{N_o}{2} \int_0^T h^2(t)dt} \leq \frac{\int_0^T s^2(t)dt \int_0^T h^2(t)dt}{\frac{N_o}{2} \int_0^T h^2(t)dt}$$

where the equality is obtained when  $h(t) = s(t)$ . Thus, the demodulator that maximizes SNR at the output is the demodulator correlator where  $h(t) = s(t)$  or equivalently a matched filter with an impulse response equal to  $s(T-t)$ .



# Optimal Demodulator

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- Thus, the demodulator which correlates with the symbol waveform or which uses a matched filter matched to the symbol waveform *maximizes SNR*.
- Thus, the demodulator is optimal in that it provides the max SNR. The detector is optimal in that given r it minimizes probability of error.
- Further the SNR obtained is

$$\begin{aligned} SNR &= \frac{\int_0^T s^2(t) dt \int_0^T s^2(t) dt}{\frac{N_o}{2} \int_0^T s^2(t) dt} \\ &= \frac{\int_0^T s^2(t) dt}{\frac{N_o}{2}} \\ &= \frac{2E}{N_o} \end{aligned}$$