

EXIT Charts: The Very Basics

Sarah Johnson

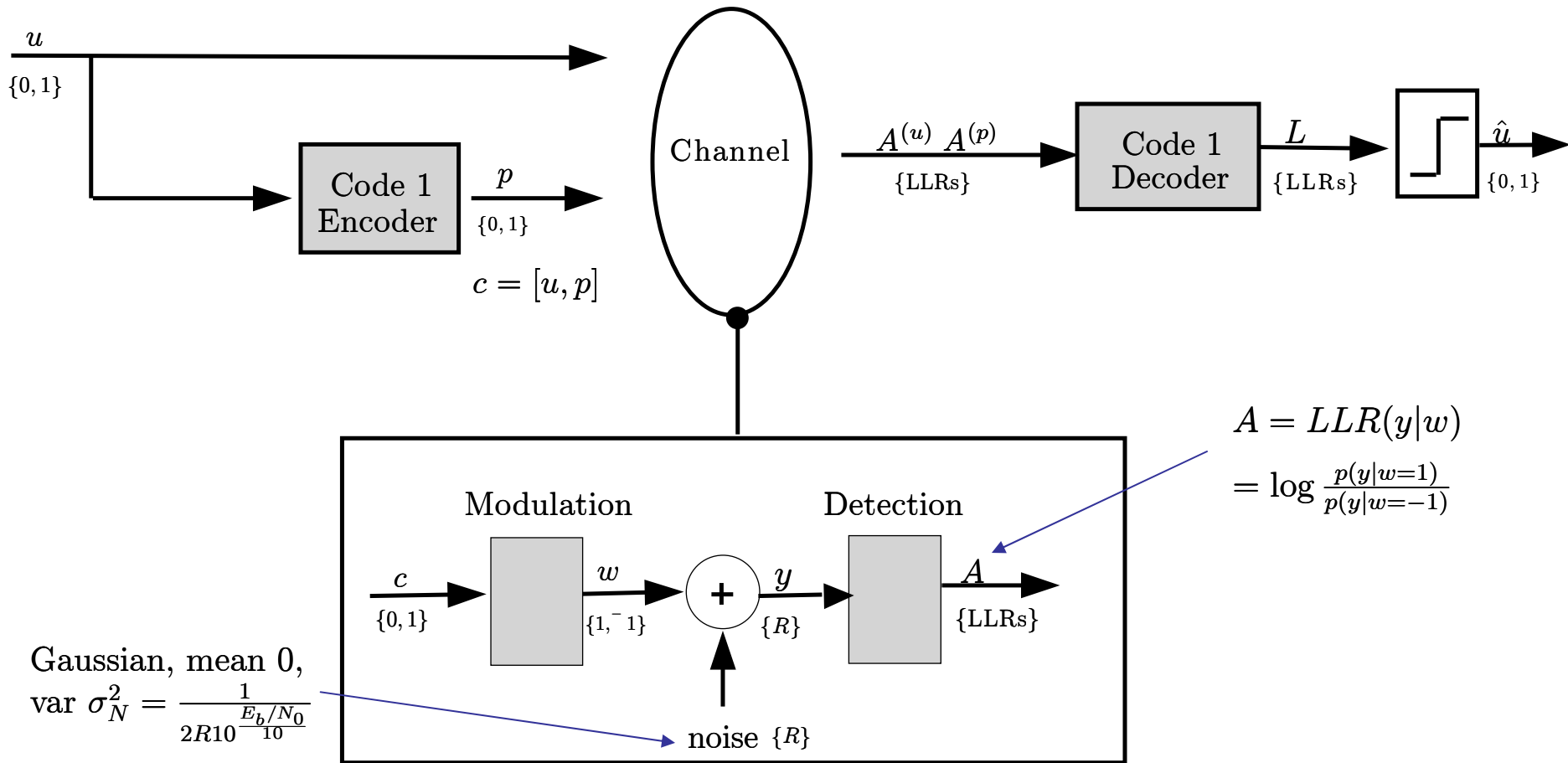


The UNIVERSITY
of NEWCASTLE
AUSTRALIA

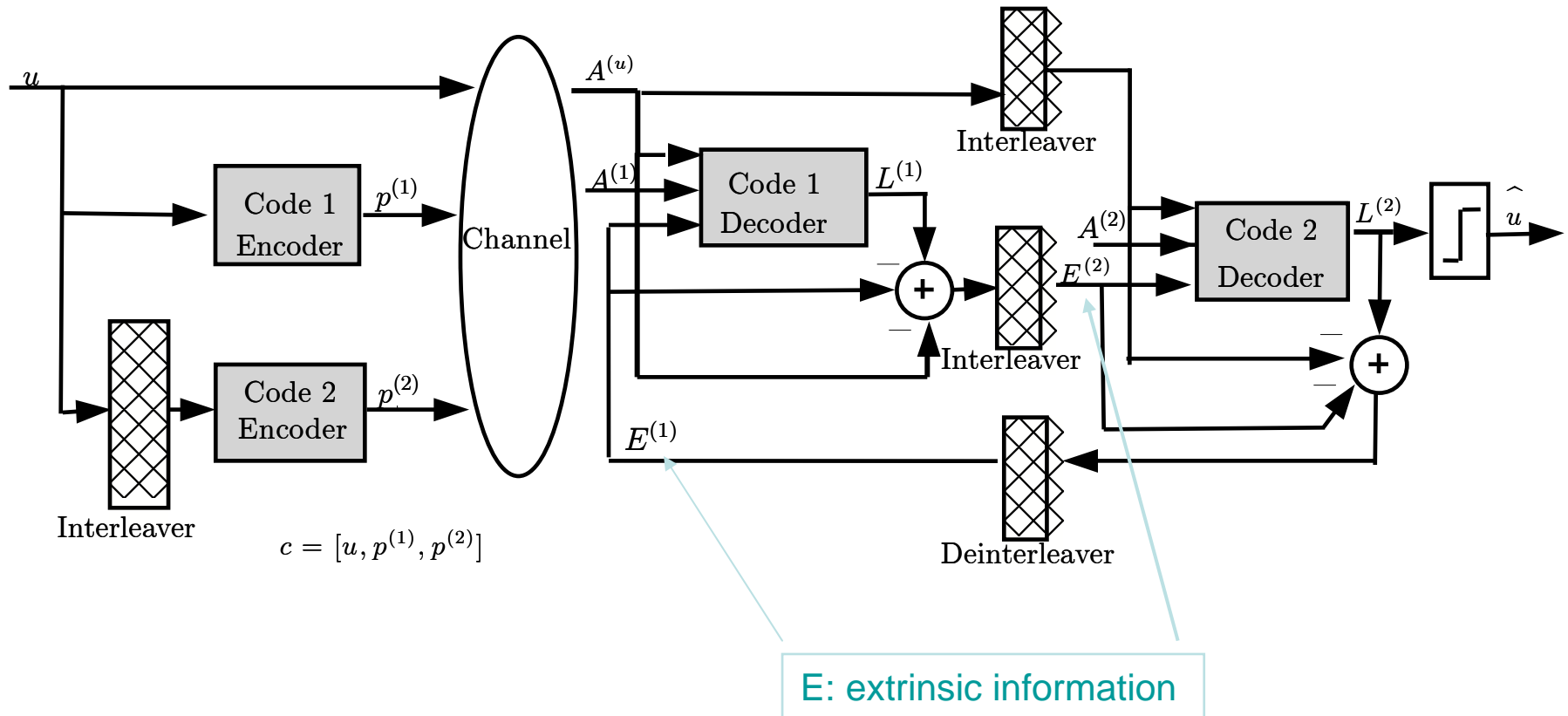
EXIT Charts: The Very Basics

- Convolutional codes and Turbo codes
- Mutual information transfer curves
- EXIT charts
- The benefits of EXIT charts

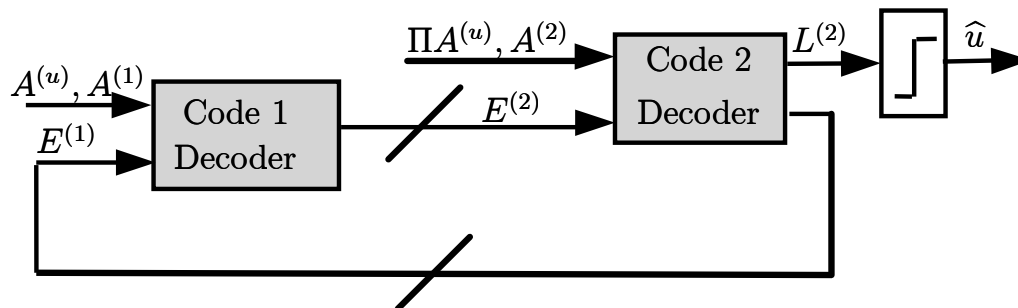
Convolutional Coding



Turbo Coding



Mutual information transfer



- We want to quantify the ‘improvement’ over each iteration
- Do this by measuring the mutual information between E and W

$$\mathcal{I}(X; Y) = \int \int p(x, y) \log_2 \frac{p(x, y)}{p(x)p(y)} dx dy$$

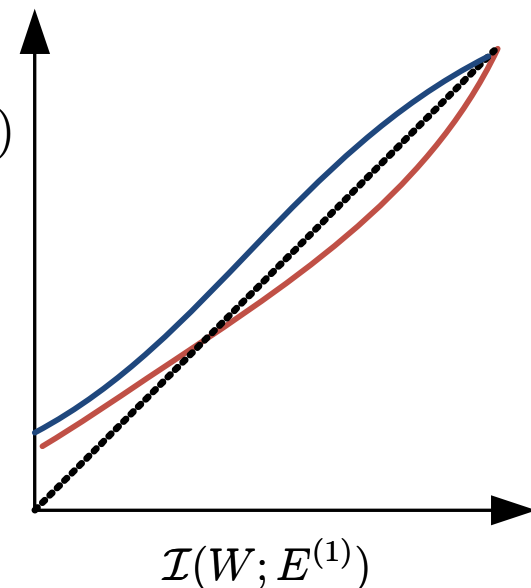
$$\mathcal{I}(W; E) = \int_{y \in E} \sum_{w \in \pm 1} p(w, y) \log_2 \frac{p(w, y)}{p(w)p(y)} dy$$

$$\mathcal{I}(W; E) = \frac{1}{2} \int_{y \in E} \sum_{w \in \pm 1} p(y|w) \log_2 \frac{p(y|w)}{\frac{1}{2}(p(y|1) + p(y|-1))} dy$$

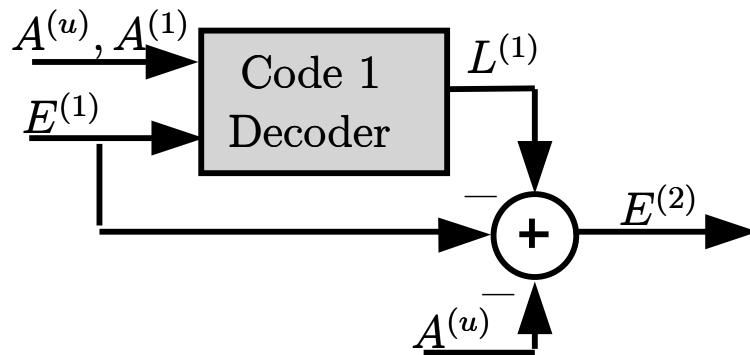
$\mathcal{I}(W; E^{(2)})$

$\mathcal{I}(W; E^{(1)})$

W: binary equiprobable source



Mutual information transfer



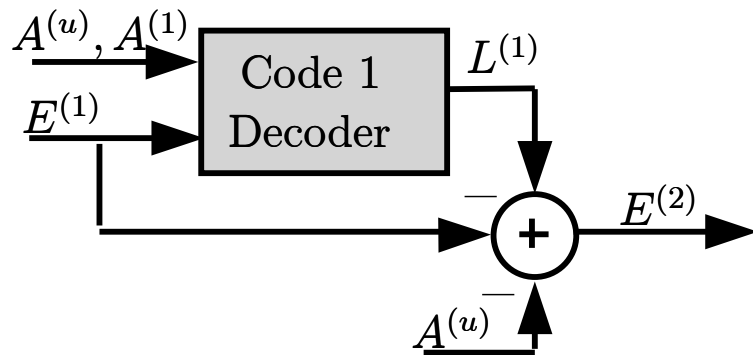
Gaussian, mean 0,
 $\text{var } \sigma_N^2 = \frac{1}{2R10^{\frac{E_b}{N_0}}}$

$$\begin{aligned}
 A &= \ln \frac{p(w = 1|y)}{p(w = -1|y)} \\
 &= \ln \frac{p(w = 1)p(y|w = 1)/p(y)}{p(w = -1)p(y|w = -1)/p(y)} \\
 &= \ln \frac{e^{\frac{-1}{2\sigma^2}(y-1)^2}}{e^{\frac{-1}{2\sigma^2}(y+1)^2}} = \frac{2y}{\sigma^2}
 \end{aligned}$$

Fix the channel noise and generate $A^{(u)}$ and $A^{(1)}$:

$$\mathbf{y} = \mathbf{w} + \mathbf{n}_A, \quad A = \frac{2}{\sigma_N^2} \mathbf{y}$$

Mutual information transfer



$$\mathcal{I}(W; E) = \frac{1}{2} \int_{y \in E^{(1)}} \sum_{w \in \pm 1} p(y|w) \log_2 \frac{p(y|w)}{\frac{1}{2} [p(y|1) + p(y|-1)]} dy$$

$$p(y|w) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2\sigma^2}(y-\mu w)^2}$$

Fix the channel noise and generate $A^{(u)}$ and $A^{(1)}$:

$$\mathbf{y} = \mathbf{w} + \mathbf{n}_A, \quad A = \frac{2}{\sigma_N^2} \mathbf{y}$$

For a few different values of $\mathcal{I}\{E^{(1)}\}$:

1. Generate $E^{(1)}$ with a gaussian pdf: $E^{(1)} = \mu_E \mathbf{w} + n_E$

then
$$\mathcal{I}(W; E^{(1)}) = 1 - \int_{y \in E^{(1)}} \frac{e^{-\frac{1}{2\sigma_E^2}(y-\mu_E)^2}}{\sqrt{2\pi}\sigma_E} \log_2(1 - e^{-y}) dy$$

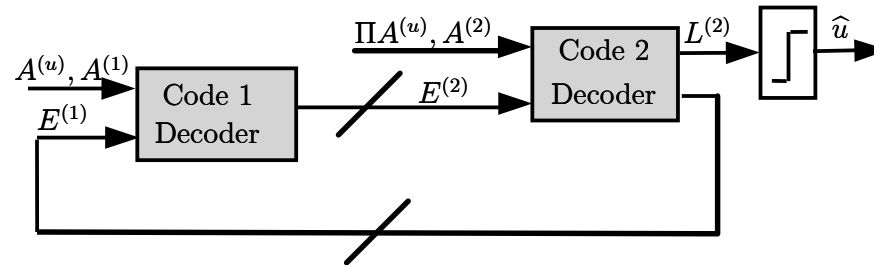
Gaussian, mean 0,
var $\sigma_E^2 = 2\mu_E$

Independent noisy observations of W

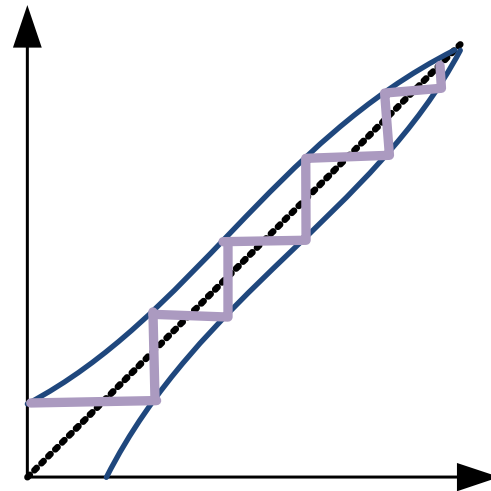
2. Run the BCJR decoder. Since $w = +1$ a histogram of $E^{(2)}$ values provides $p(E^{(2)}|w = 1)$, and since $p(E^{(2)}|w = -1) = p(-E^{(2)}|w = 1)$ we can calculate $\mathcal{I}(W : E^{(2)})$ numerically

Plot $\mathcal{I}(W; E^{(2)})$ Vs $\mathcal{I}(W; E^{(1)})$

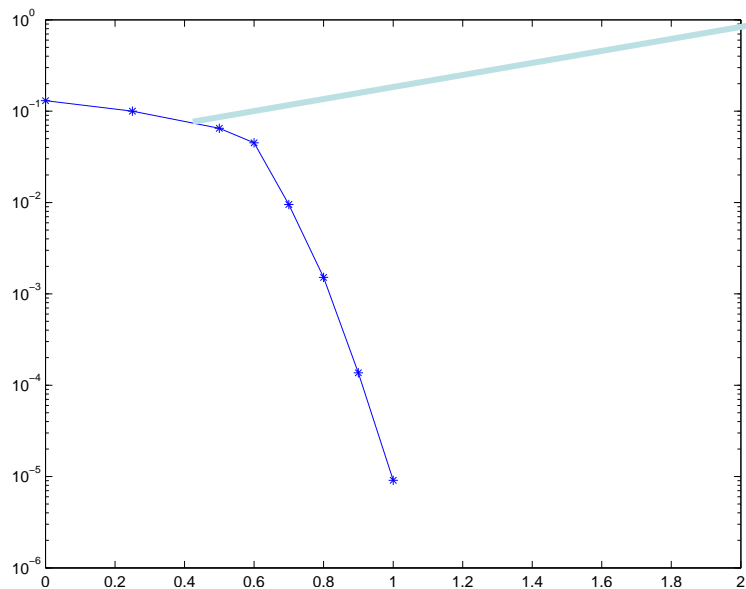
EXIT Charts



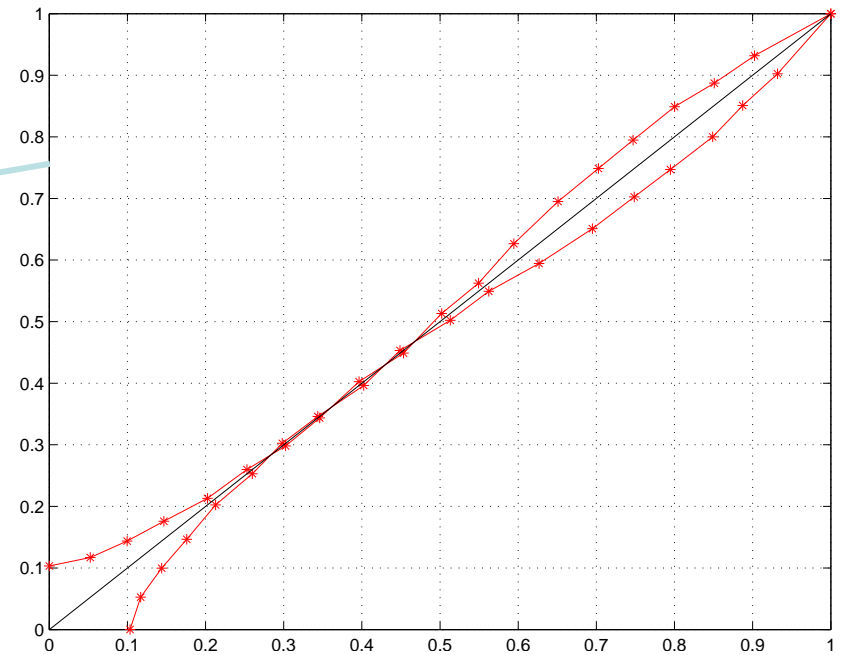
Plot $\mathcal{I}(W; E^{(2)})$ Vs $\mathcal{I}(W; E^{(1)})$ and $\mathcal{I}(W; E^{(1)})$ Vs $\mathcal{I}(W; E^{(2)})$



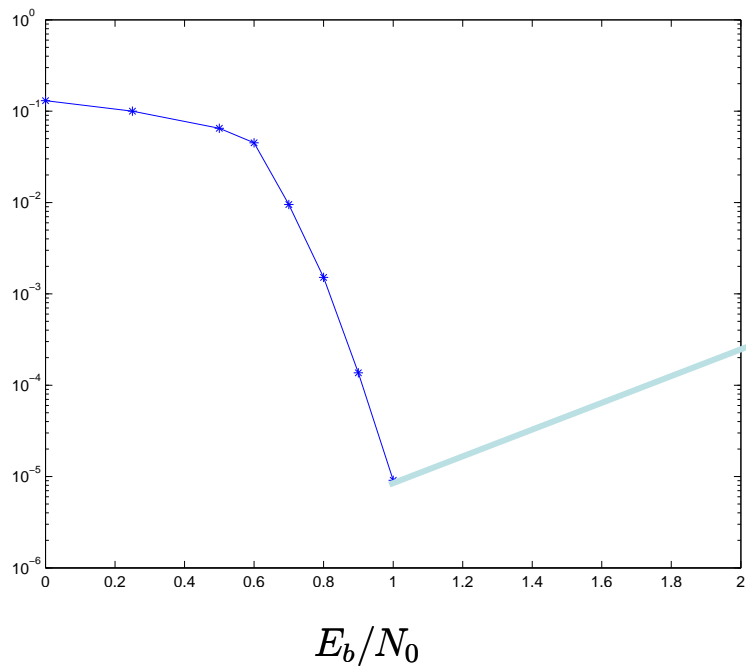
EXIT Charts



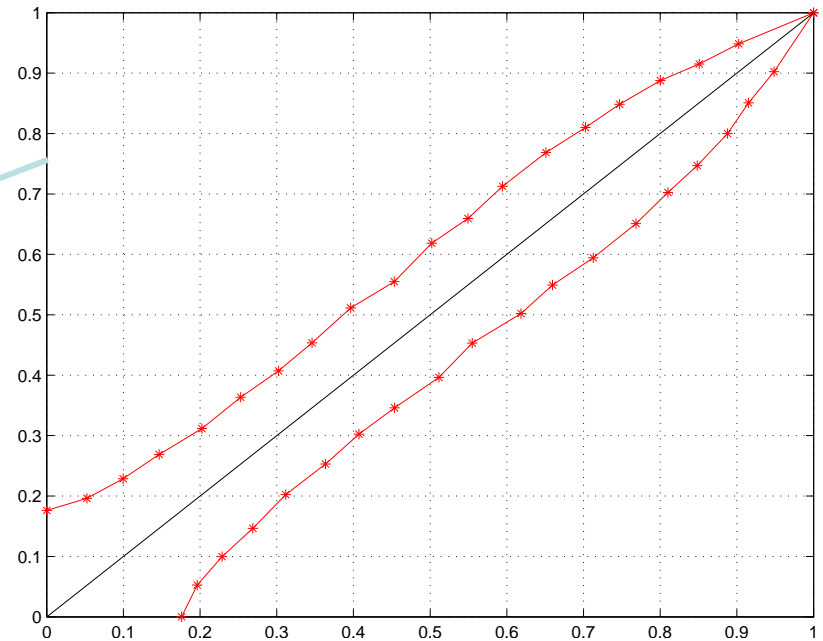
BER



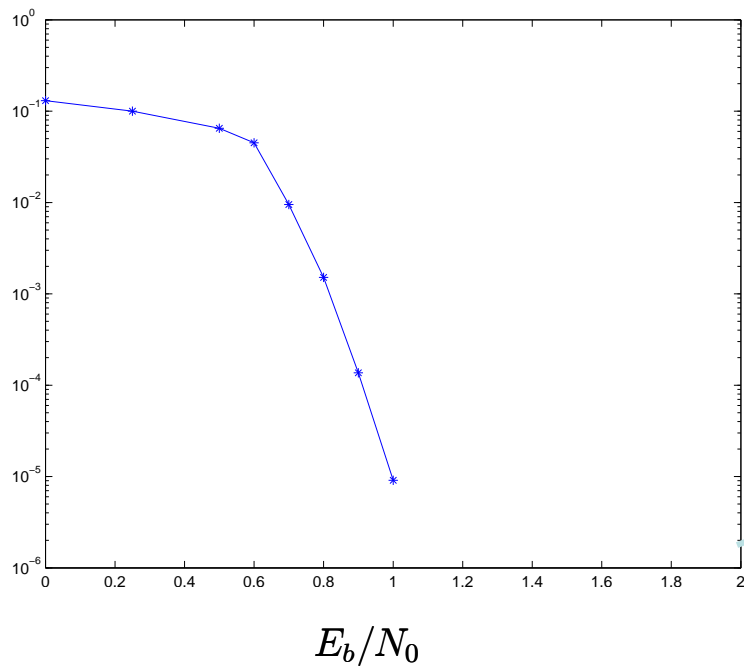
EXIT Charts



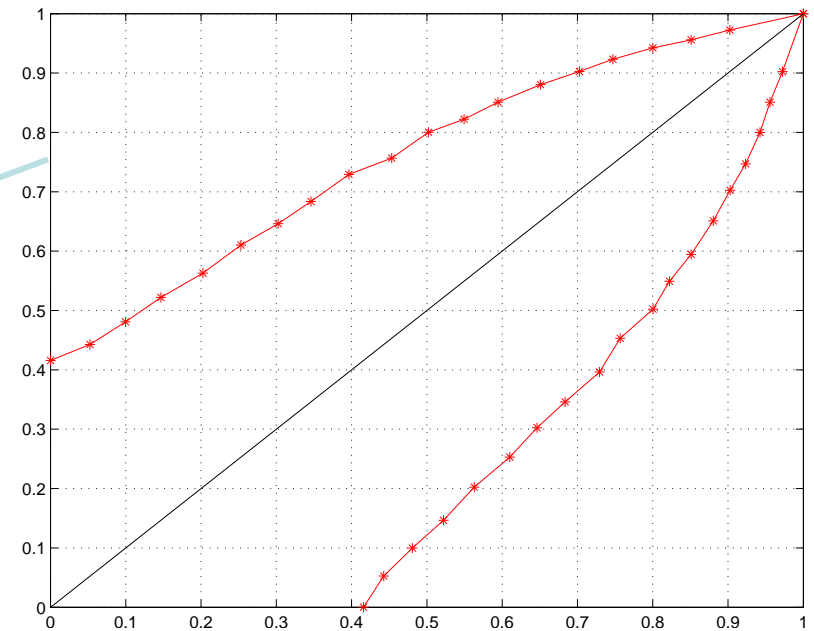
BER



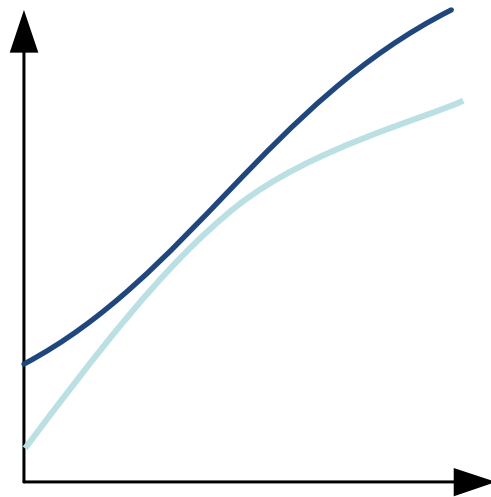
EXIT Charts



BER



- Understand the performance of iterative ‘turbo’ schemes
- Predict the decoder’s ‘threshold’ without having to simulate the whole decoder
- As a tool for designing the component codes



- Ignores the impact of the interleaver – assumes it is ideal

