

Modern Channel Coding

Ingmar Land & Jossy Sayir

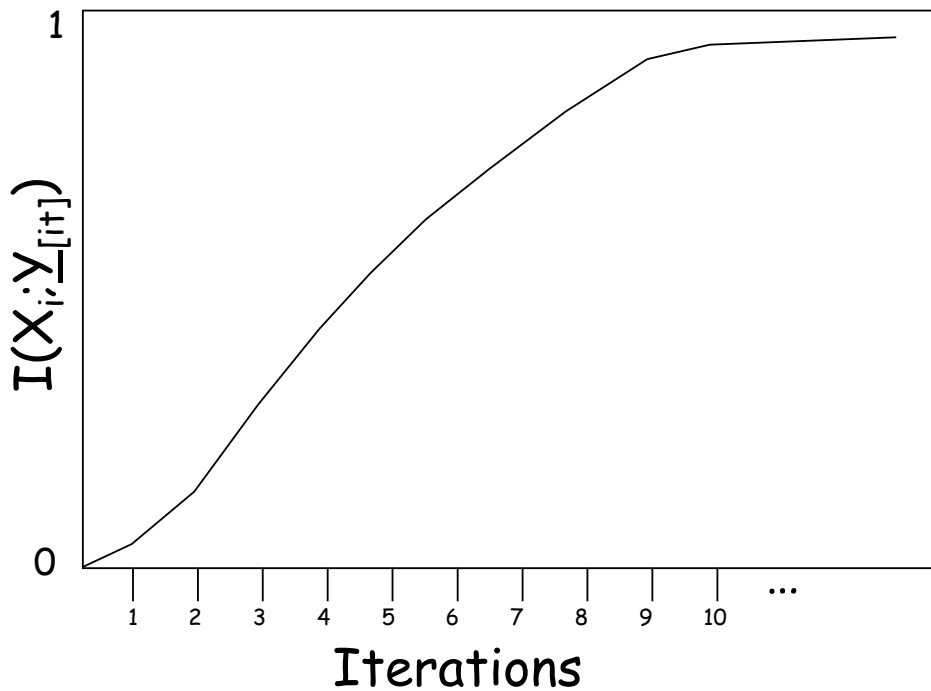
Lecture 4: EXIT Charts

ACoRN Summer School 2007

Iterative Decoding

- How does the **mutual information** evolve in an **iterative decoding** algorithm?
- We have learned that it is possible to **optimize** LDPC codes so as to **maximize their threshold**
- We will see that we can design **capacity-achieving, iteratively decodable** families of LDPC codes!!
(i.e., threshold \rightarrow capacity)
- What is the implication in terms of **mutual information**?

Mutual Information Trajectory



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Mutual Information Trajectory

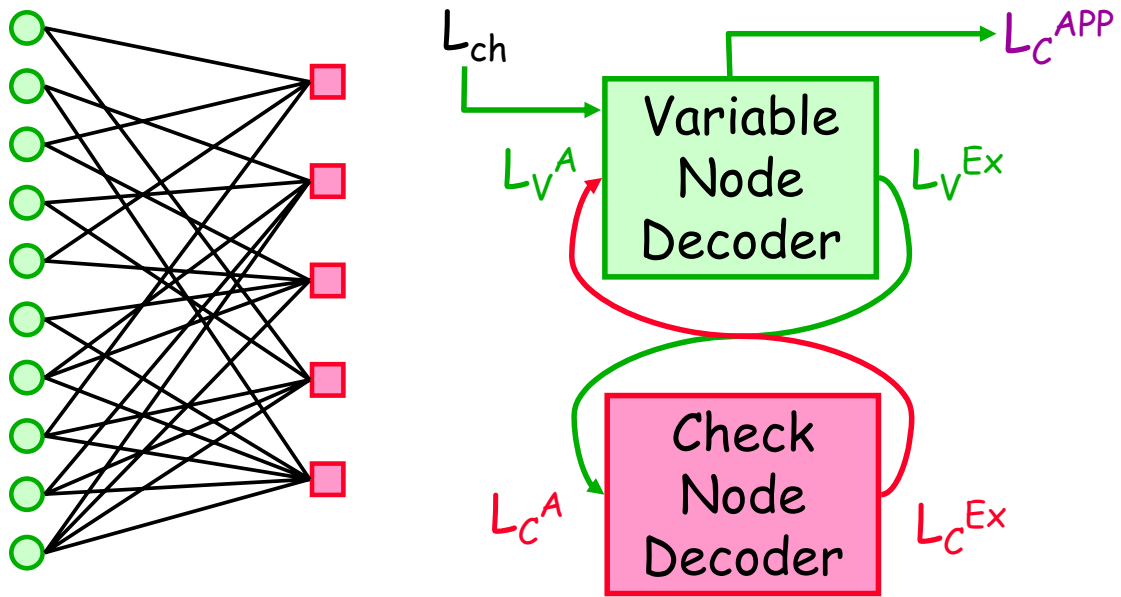
- The L-values calculated in the tree are optimal in the sense of a **MAP-calculator**, i.e., $L(X_i | \underline{Y}_{[i+]})$ is a sufficient statistic for $\underline{Y}_{[i+]}$:

$$I(X_i ; L(X_i | \underline{Y}_{[i+]})) = I(X_i ; \underline{Y}_{[i+]})$$

- We can also draw the trajectory at **half-iterations** (after variable nodes & after check nodes)
- **But:** the output messages of variable nodes and check nodes are **extrinsic** L-values, whereas the mutual information trajectory we consider now is for **a-posteriori** L-values

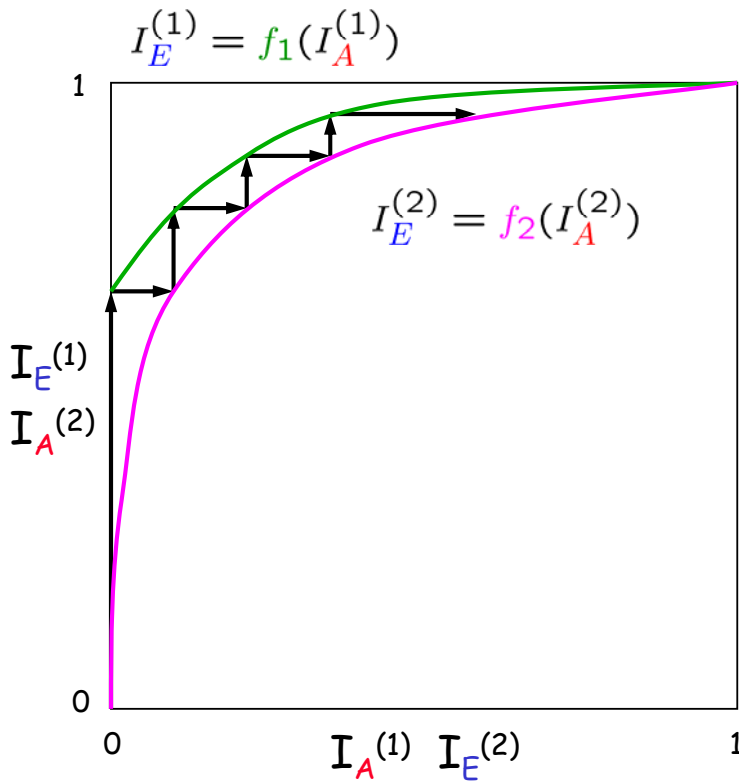
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Message Passing



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Tracking of Messages



This assumes that the decoder depends only on mutual information!

Problem: How to compute the "transfer functions" f_1 and f_2 ?

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Tracking of Messages

Tracking of messages would mean **tracking of pdfs**

(→ Density Evolution)

Instead of tracking the pdfs we reduce the problem to **tracking of mutual information** between the messages and the codeword which are scalar quantities

$$I_A = \frac{1}{N} \sum_{n=1}^N I(X_i; A_i)$$

$$I_E = \frac{1}{N} \sum_{n=1}^N I(X_i; E_i)$$

$$I_A^{(1)} = 0$$

$$\Rightarrow I_E^{(1)} \rightarrow I_A^{(2)}$$

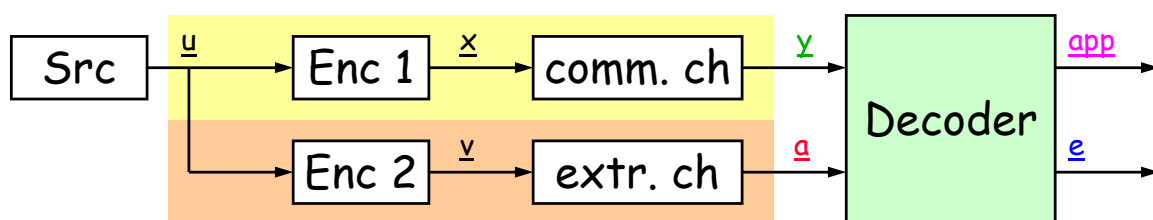
$$\Rightarrow I_E^{(2)} \rightarrow I_A^{(1)}$$

...

I_A, I_E average symbolwise mutual information

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Extrinsic Channel Model



A-priori messages are **modeled** as independent noisy observations of the encoded source.

Assumptions:

- **independent** observations
- **model** for extrinsic channel

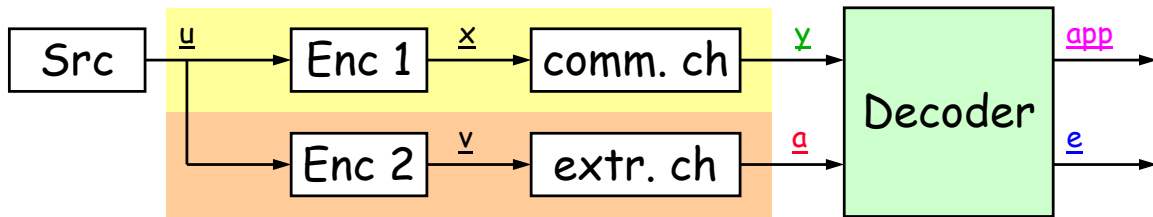
$$I_A = I(X_i; A_i) = I(V_i; A_i)$$

$$I_E = I(X_i; E_i) \leq I(X_i; Y_{A \setminus i})$$

with equality if the decoder is optimal

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Transfer Functions



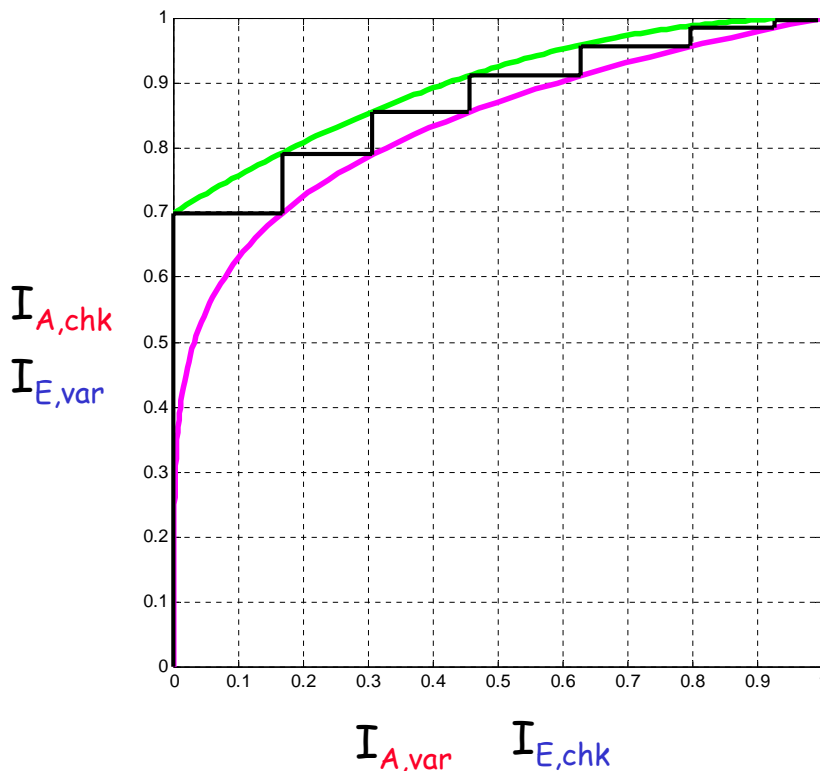
Assuming a model for the extrinsic channel we can vary I_A by varying the channel parameter.

At the output of the decoder we can measure/calculate $I_E \Rightarrow I_E = f(I_A)$

This is only exact if the model of the extrinsic channel is correct!

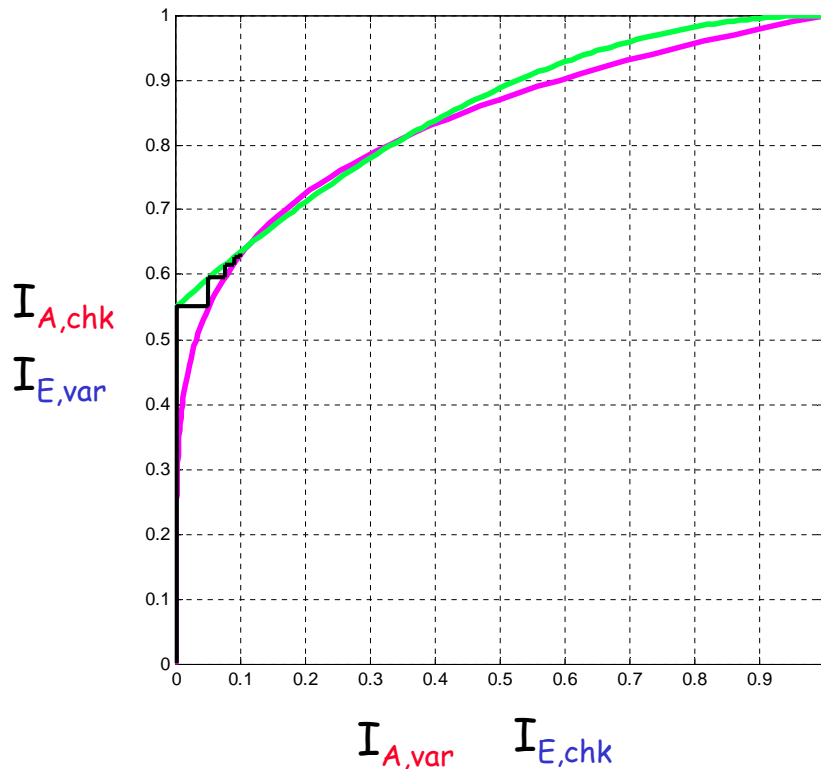
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EXIT Chart of LDPC Code



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Intersecting Curves



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Extrinsic Information Transfer Charts (Stephan ten Brink)



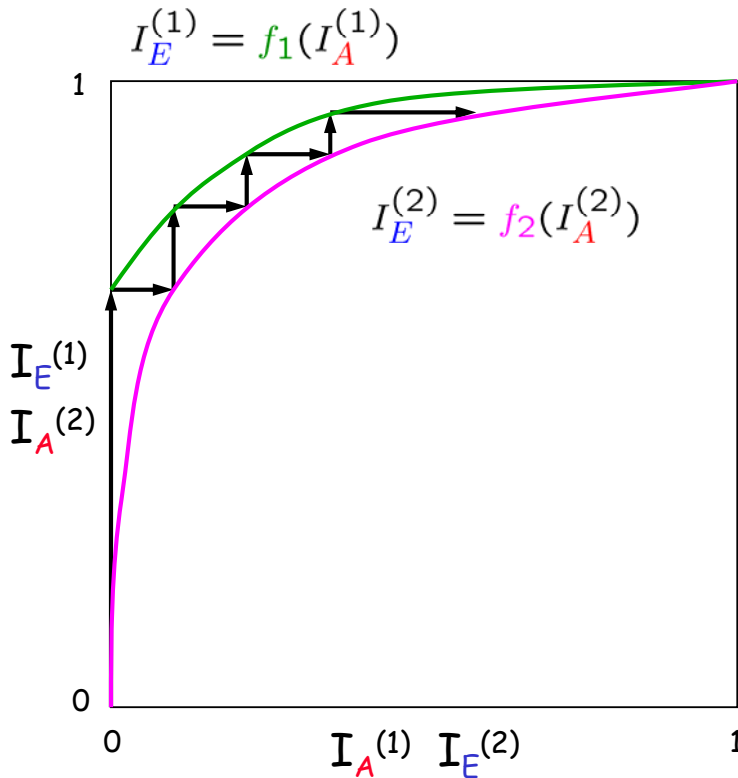
Photo by Jossy Sayir

Stephan did his PhD at the U of Stuttgart, then worked for Bell Labs in the U.K., then in New Jersey. He is currently with RealTek. He is a regular visitor of ftw. and TU Wien.

(Stephan is the guy on the right, not the clown on the left)

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Tracking of Messages



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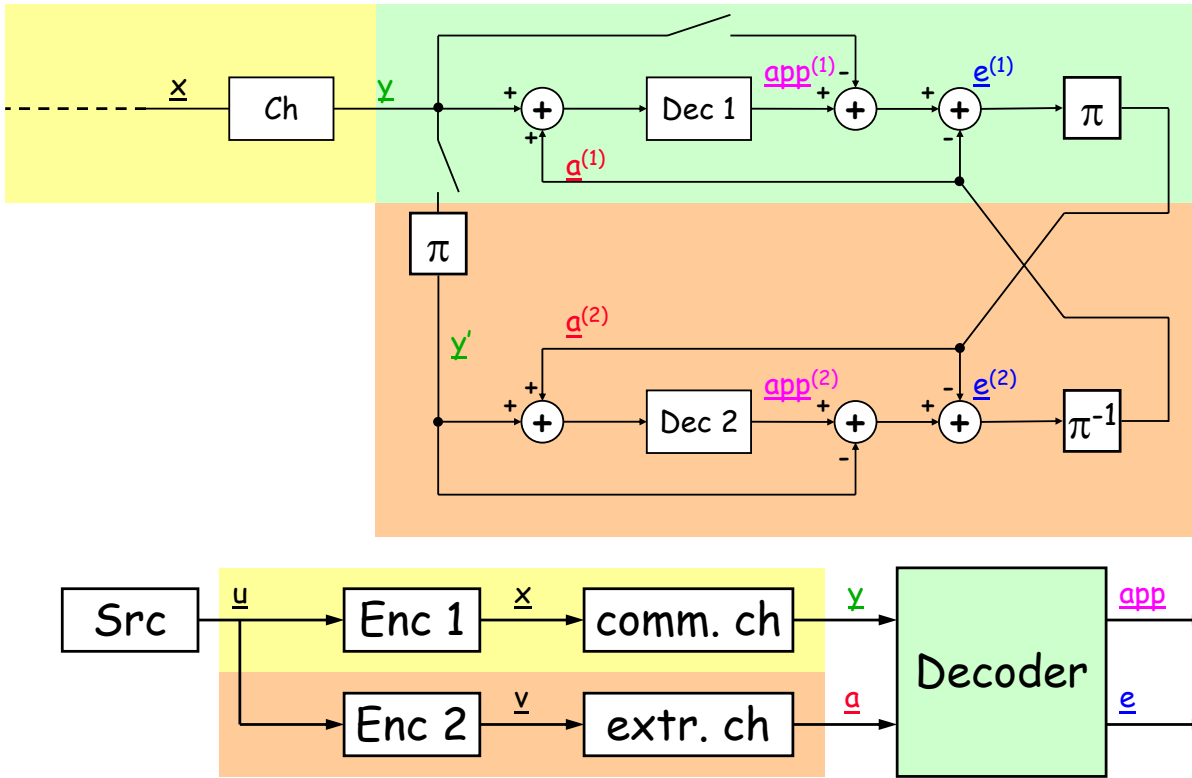
$$\Rightarrow I_E^{(2)} \rightarrow I_A^{(3)}$$

...

I_A, I_E average symbolwise mutual information

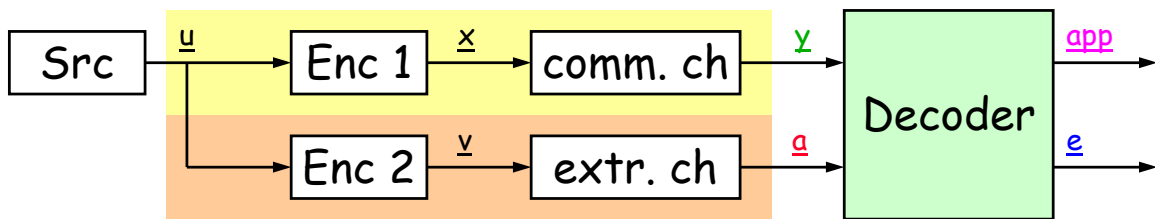
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Extrinsic Channel Model



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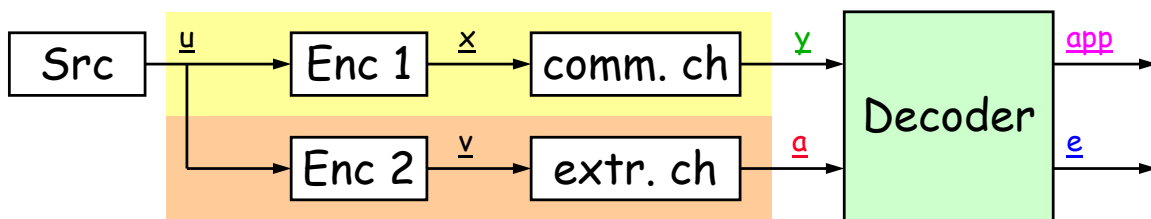
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Transfer Functions



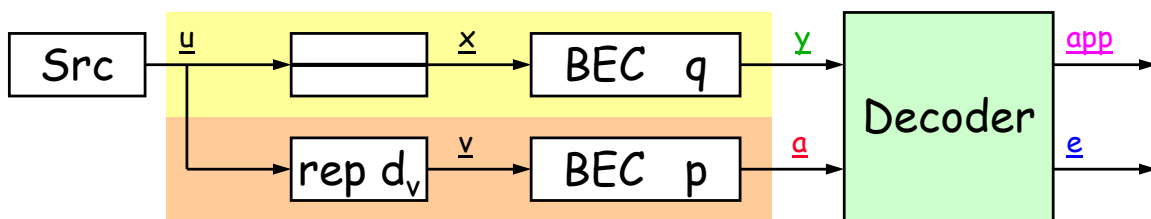
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Variable Nodes and BEC

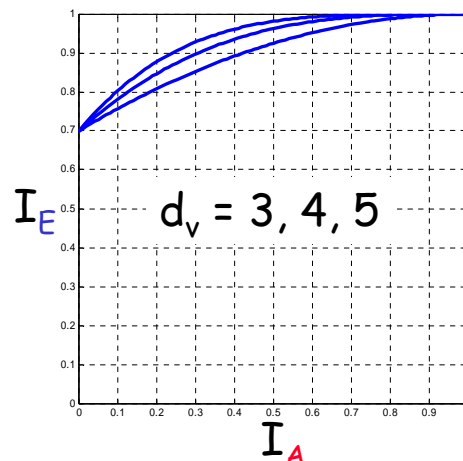


Extrinsic channel is modeled as BEC (exact).

$$I_A = I(X_i; A_i) = I(V_i; A_i) = 1 - p$$

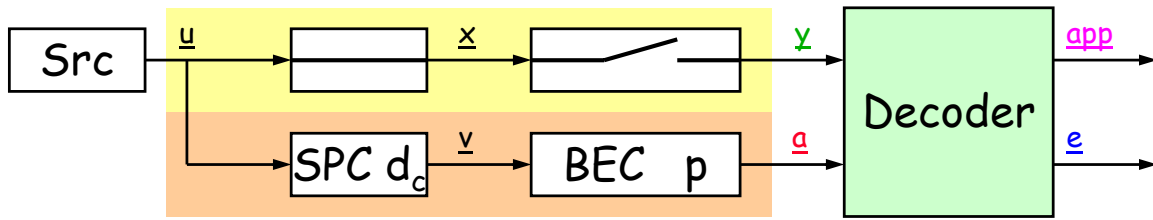
$$I_E = I(X_i; \underline{Y} A \setminus i) = 1 - qp^{d_v-1}$$

$$I_E = 1 - q(1 - I_A)^{d_v-1}$$



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Check Nodes and BEC

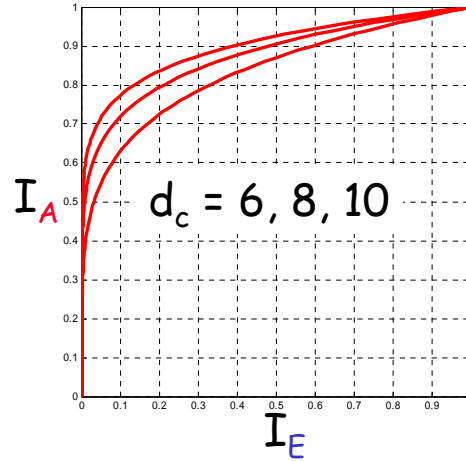


SPC ... single parity check

$$I_A = I(X_i; A_i) = I(V_i; A_i) = 1 - p$$

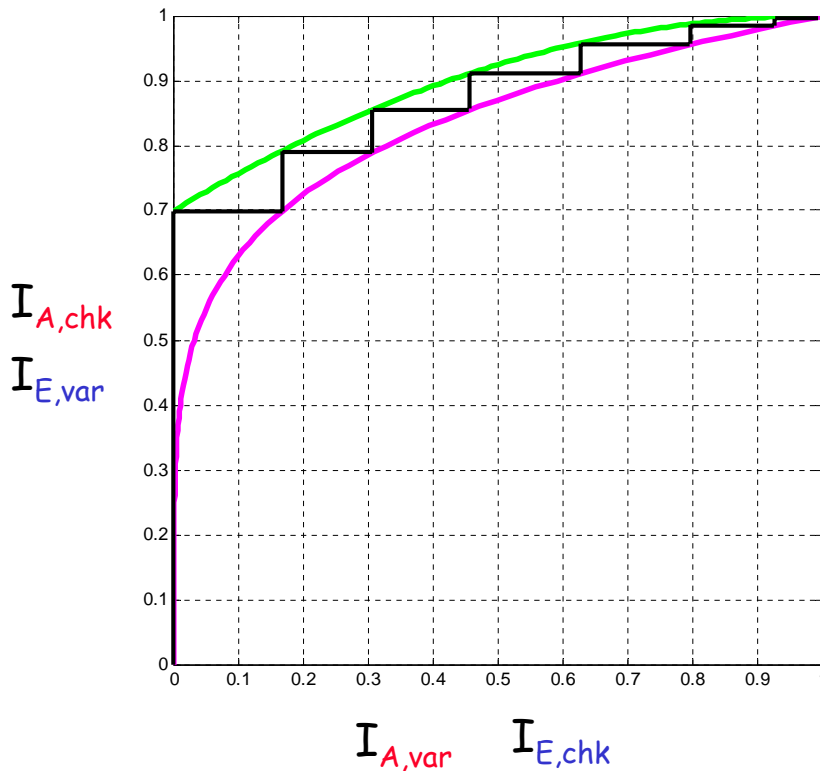
$$I_E = I(X_i; \underline{Y} A \setminus i) = (1 - p)^{d_c - 1}$$

$$I_E = (I_A)^{d_c - 1}$$



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EXIT Chart of LDPC Code



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Other Channels

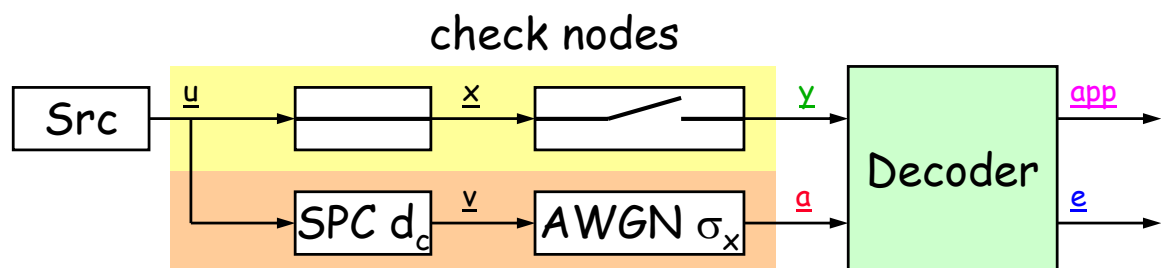
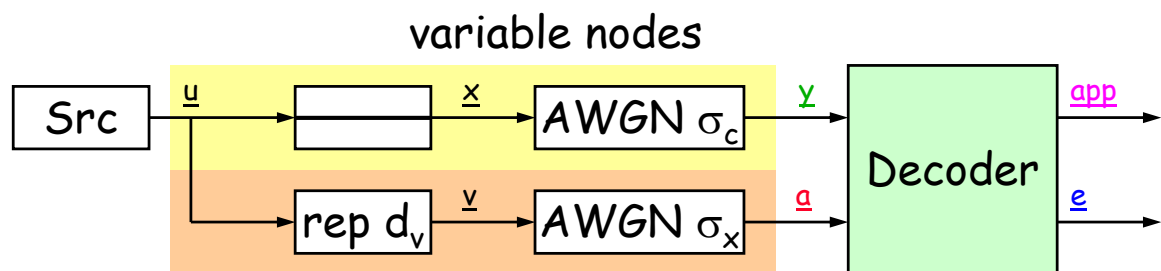
Modeling the extrinsic channel as a **BEC is exact** if the communication channel is a BEC.

For other communication channels, the assumption of the extrinsic channel is **in general an approximation**.

If the communication channel is an AWGN channel, we **model the extrinsic channel also as an AWGN**, but this is only an approximation!

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AWGN Channel



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Convolutional Codes

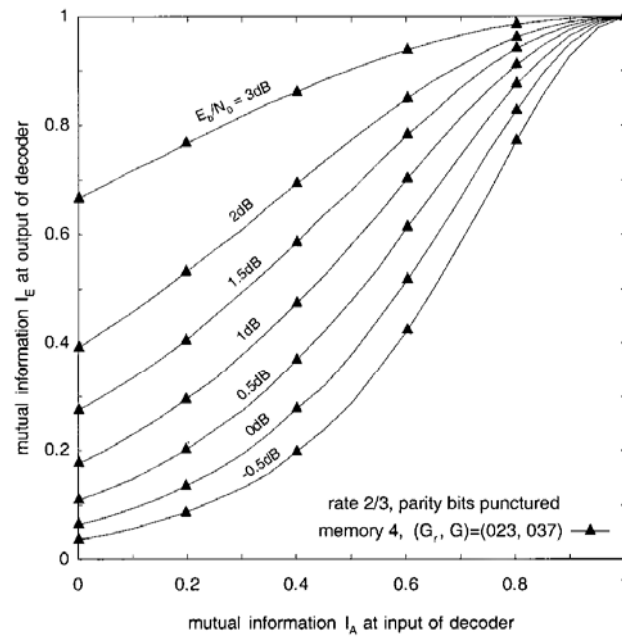
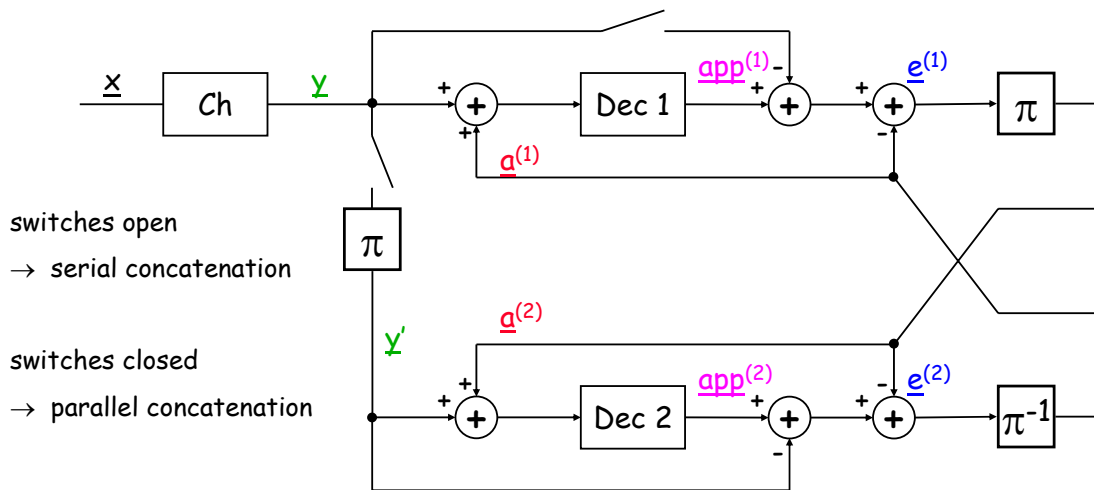


Fig. 2. Extrinsic information transfer characteristics of soft in/soft out decoder for rate 2/3 convolutional code; E_b/N_0 of channel observations serves as parameter to curves.

Stephan ten Brink, "Convergence Behavior of Iteratively Decoded Parallel Concatenated Codes", IEEE Trans. Comm. October 2001

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Serial / Parallel Concatenation



Serial concatenation:

$$\underline{e} = \underline{app} - \underline{a}$$

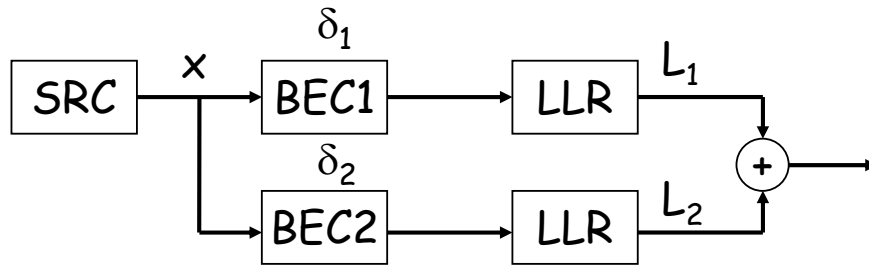
Parallel concatenation:

$$\underline{e} = \underline{app} - \underline{a} - \underline{y}$$

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Information Combining BEC

What is the effect on mutual information when we add L-values?



$$I_1 = I(X;L_1) = 1 - \delta_1$$

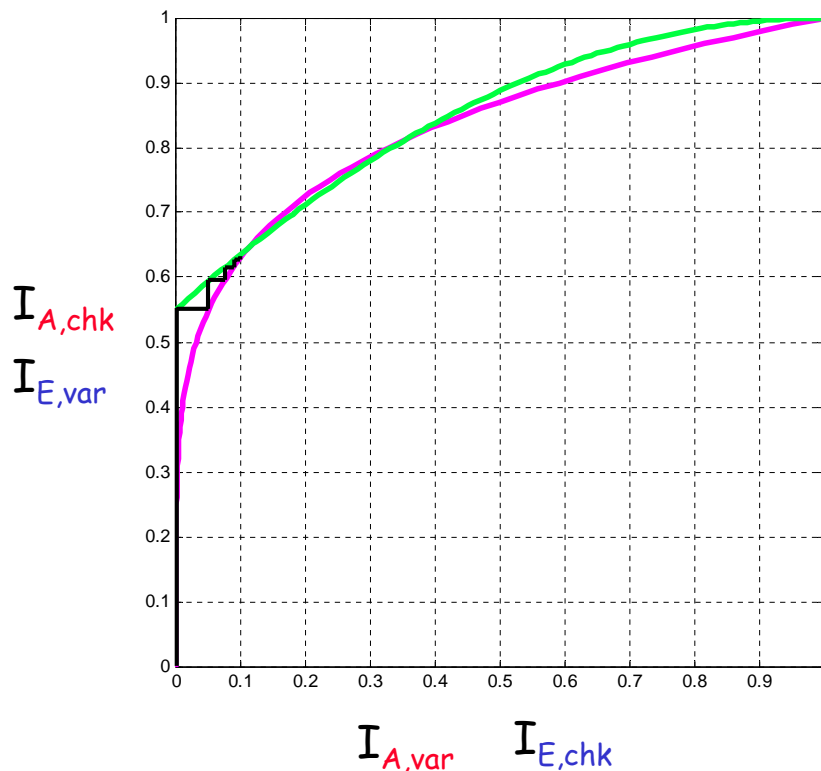
$$I(X;L_1L_2) = 1 - \delta_1\delta_2$$

$$I_2 = I(X;L_2) = 1 - \delta_2$$

$$= 1 - (1-I_1)(1-I_2)$$

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Intersecting Curves

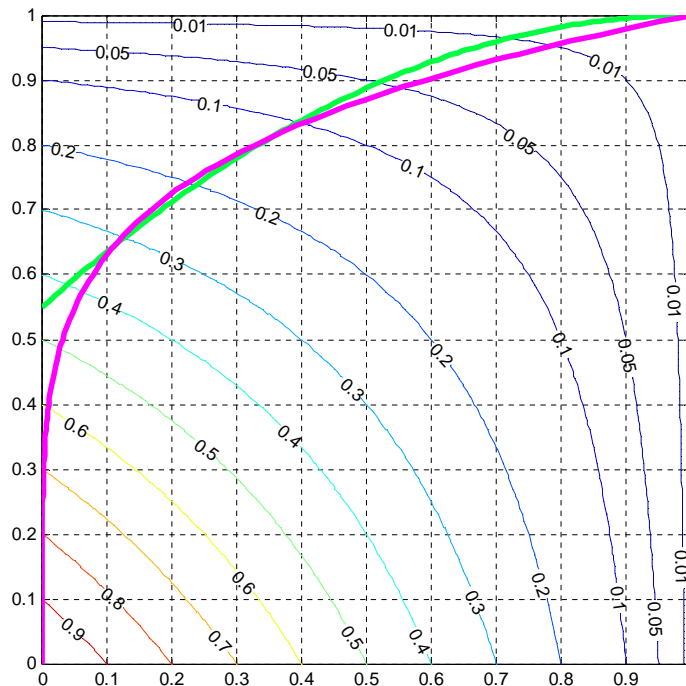


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BER from EXIT Chart (BEC)

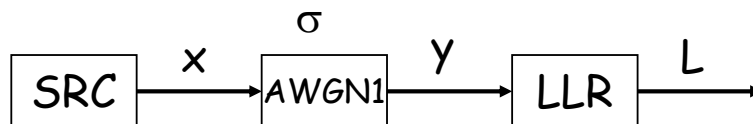
$$\text{app} = \underline{a} + \underline{e}$$

$$I(X; \text{APP}) = 1 - P_b = 1 - (1 - I_A)(1 - I_E)$$



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Information Combining AWGN

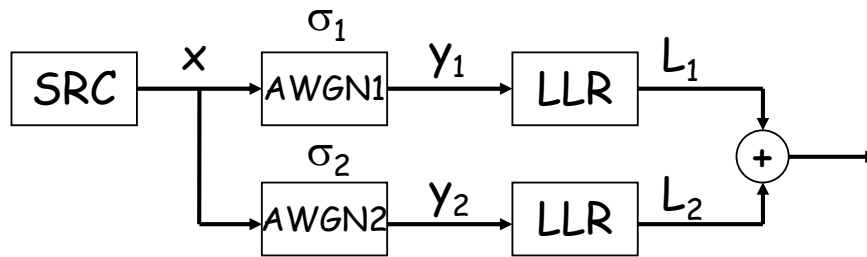


$$L = \frac{2y}{\sigma^2} \quad \Rightarrow \quad L \sim \mathcal{N}\left(\frac{2}{\sigma^2}, \frac{4}{\sigma^2}\right) = \mathcal{N}\left(\frac{\sigma_L^2}{2}, \sigma_L^2\right)$$

$$I(X; L) = 1 - \underbrace{\int_{-\infty}^{\infty} \frac{e^{-\frac{(\zeta - \sigma_L/2)^2}{2\sigma_L^2}}}{\sqrt{2\pi\sigma_L}} \log_2(1 + e^{-\zeta}) d\zeta}_{J(\sigma_L)}$$

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Information Combining AWGN



$$I_1 = I(X; L_1) = J(\sigma_{L1})$$

$$I_2 = I(X; L_2) = J(\sigma_{L2})$$

$$I(X; L_1 L_2) = J\left(\sqrt{\sigma_{L1}^2 + \sigma_{L2}^2}\right)$$

$$= J\left(\sqrt{J^{-1}(I_1)^2 + J^{-1}(I_2)^2}\right)$$

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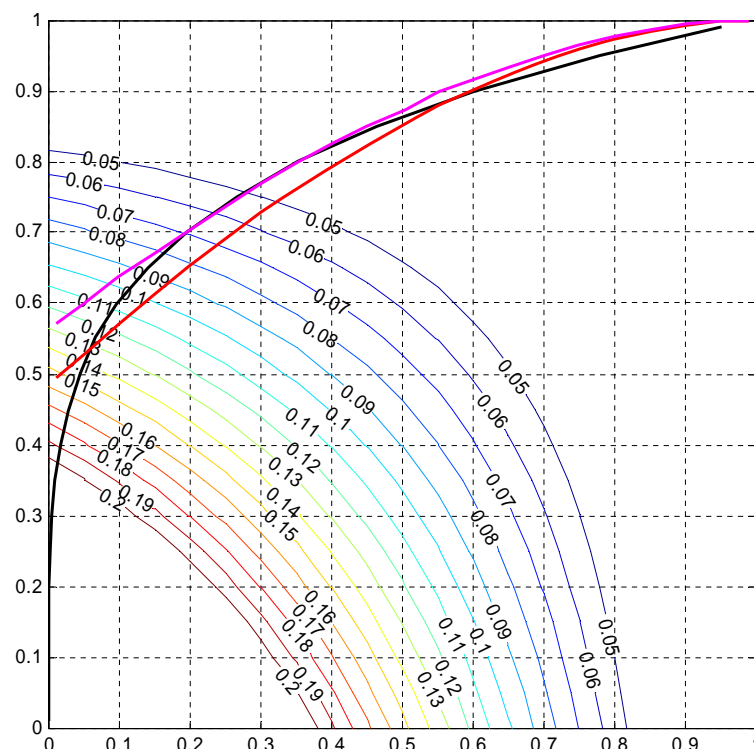
BER from EXIT Chart (AWGN)

$E_b/N_0 = 0.0\text{dB}$

$P_b = 0.13$

$E_b/N_0 = 1.0\text{dB}$

$P_b = 0.07$



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Independent Observations

Messages received from the extrinsic channel are **independent observations**, which is only fulfilled if $N \rightarrow \infty$

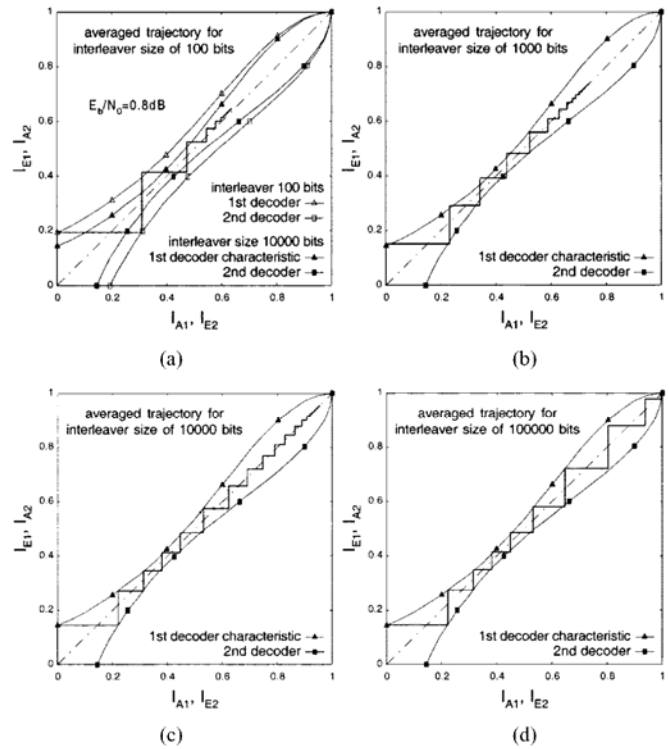


Fig. 8. Averaged decoding trajectories for different interleaver lengths; PCC rate 1/2 memory 4, $(G_r, G) = (023, 037)$; averaged over 10^8 information bits.

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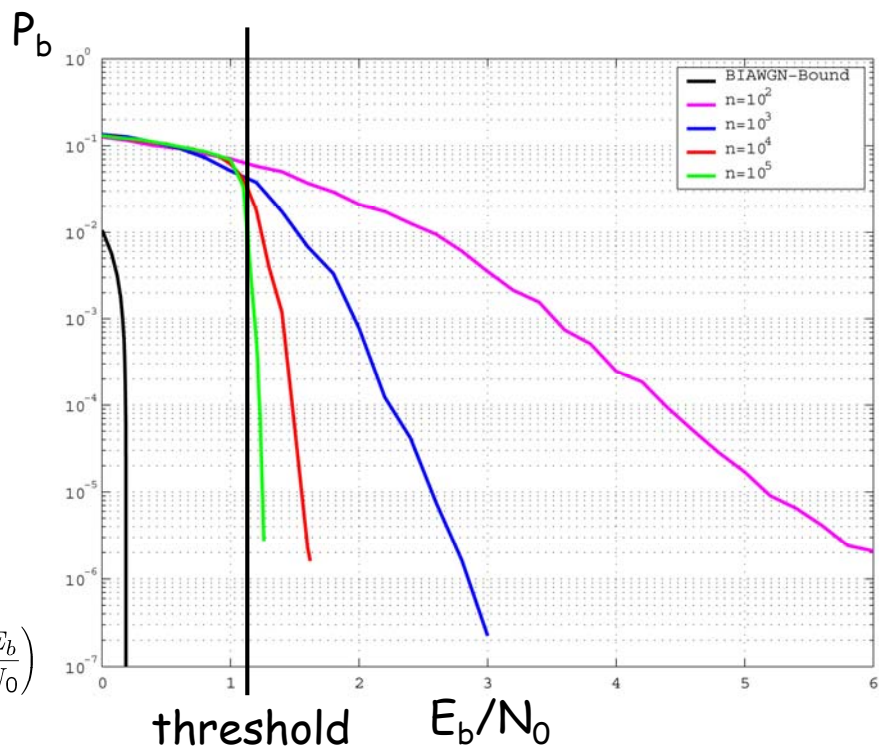
Statistics

We use **statistical quantities**, which are only correct if $N \rightarrow \infty$

$$E_s = R \cdot E_b \quad \sigma^2 = \frac{N_0}{2}$$

$$E_s := 1$$

$$\frac{E_b}{N_0} = \frac{E_s}{R2\sigma^2} \Rightarrow \sigma^2 = \frac{1}{2R} \cdot \left(\frac{E_b}{N_0} \right)$$



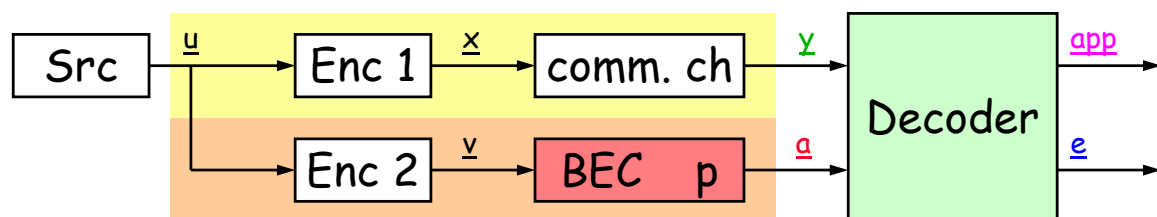
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Summary of Assumptions

- Messages received from the extrinsic channel are **independent observations**, which is only fulfilled if $N \rightarrow \infty$
- We use **statistical quantities**, which are only correct if $N \rightarrow \infty$
- We **model extrinsic messages** with an extrinsic channel. This can only be done exact for the BEC. The Gaussian assumption is an approximation.

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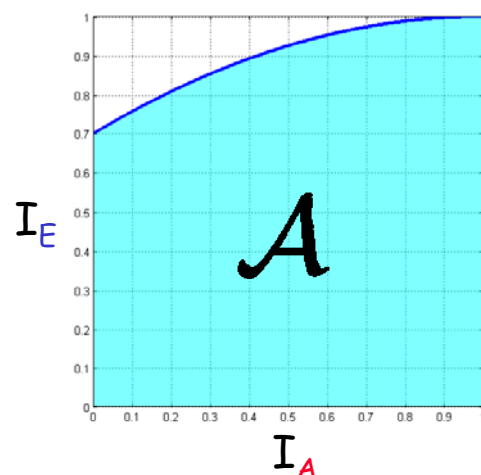
Area Property



$$m = |\underline{v}|$$

$$I_A = \frac{1}{m} \sum_{i=1}^m I(V_i; A_i) = 1 - p$$

$$\mathcal{A} = \int_0^1 I_E(I_A) dI_A = \int_0^1 I_E(p) dp$$



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Derivation of Area Property 1

$$\begin{aligned}
 I_E &= \frac{1}{m} \sum_{i=1}^m \underbrace{I(V_i; \underline{Y} A_{\setminus i})}_{\substack{H(V_i) - H(V_i | \underline{Y} A_{\setminus i}) \\ \uparrow \\ 1}} \\
 &= \frac{1}{m} \sum_{i=1}^m \sum_{\substack{\underline{a}_{\setminus i} \\ \mathcal{S} = \{b = 1 \dots m | b \neq i, A_b \neq \Delta\} \\ 0 \leq j = |\mathcal{S}| \leq m-1}} \underbrace{P(\underline{a}_{\setminus i}) \cdot H(V_i | \underline{Y}, A_{\setminus i} = \underline{a}_{\setminus i})}_{H(V_i | \underline{Y}, \underline{V}_{\mathcal{S}} = \underline{v}_{\mathcal{S}})} \\
 &= \frac{1}{m} \sum_{i=1}^m \sum_{j=0}^{m-1} (1-p)^j \cdot p^{m-1-j} \sum_{|\mathcal{S}|=j, i \notin \mathcal{S}} H(V_i | \underline{Y} \underline{V}_{\mathcal{S}}) \\
 I_E &= \frac{1}{m} \sum_{i=1}^m \left[1 - \sum_{j=0}^{m-1} (1-p)^j \cdot p^{m-1-j} \sum_{|\mathcal{S}|=j} H(V_i | \underline{Y} \underline{V}_{\mathcal{S}}) \right] \\
 I_E &= 1 - \frac{1}{m} \sum_{i=1}^m \sum_{j=0}^{m-1} (1-p)^j \cdot p^{m-1-j} \sum_{|\mathcal{S}|=j} H(V_i | \underline{Y} \underline{V}_{\mathcal{S}})
 \end{aligned}$$

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Derivation of Area Property 2

$$\begin{aligned}
 I_E &= 1 - \frac{1}{m} \sum_{i=1}^m \sum_{j=0}^{m-1} (1-p)^j \cdot p^{m-1-j} \sum_{|\mathcal{S}|=j} H(V_i | \underline{Y} \underline{V}_{\mathcal{S}}) \\
 \mathcal{A} &= \int_0^1 1 - \frac{1}{m} \sum_{i=1}^m \sum_{j=0}^{m-1} (1-p)^j \cdot p^{m-1-j} \sum_{|\mathcal{S}|=j} H(V_i | \underline{Y} \underline{V}_{\mathcal{S}}) dp \\
 \mathcal{A} &= 1 - \frac{1}{m} \sum_{i=1}^m \sum_{j=0}^{m-1} \int_0^1 (1-p)^j \cdot p^{m-1-j} dp \sum_{|\mathcal{S}|=j} H(V_i | \underline{Y} \underline{V}_{\mathcal{S}}) \\
 \mathcal{A} &= 1 - \frac{1}{m} \sum_{i=1}^m \sum_{j=0}^{m-1} \frac{1}{m \binom{m-1}{j}} \sum_{|\mathcal{S}|=j} H(V_i | \underline{Y} \underline{V}_{\mathcal{S}}) \\
 &= 1 - \frac{1}{m} H(\underline{V} | \underline{Y})
 \end{aligned}$$

$$\mathcal{A} = 1 - \frac{1}{m} H(\underline{V} | \underline{Y}) = 1 - \frac{1}{m} H(\underline{X} | \underline{Y})$$

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Derivation of $H(\underline{V}|\underline{Y})$

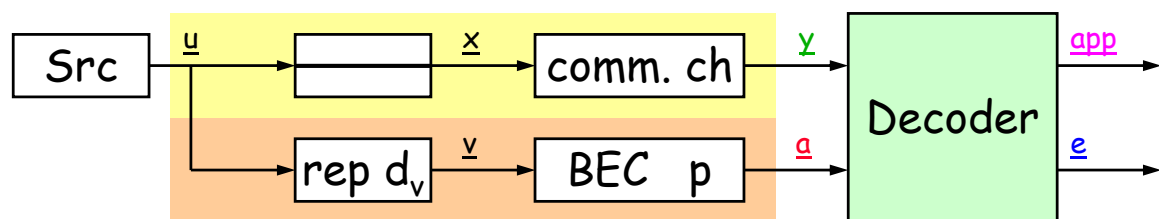
$$\begin{aligned}
 H(\underline{V}) &= H(V_1) + H(V_2|V_1) + H(V_3|V_1V_2) \\
 &= H(V_1) + H(V_3|V_1) + H(V_2|V_1V_3) \\
 &= H(V_2) + H(V_1|V_2) + H(V_3|V_1V_2) \\
 &= H(V_2) + H(V_3|V_2) + H(V_1|V_2V_3) \\
 &= H(V_3) + H(V_1|V_3) + H(V_2|V_1V_3) \\
 &= H(V_3) + H(V_2|V_3) + H(V_1|V_2V_3)
 \end{aligned}$$

$$\begin{aligned}
 3! \cdot H(\underline{V}) &= 2 \cdot (H(V_1) + H(V_2) + H(V_3)) + \\
 &+ H(V_1|V_2) + H(V_1|V_3) + H(V_2|V_1) + H(V_2|V_3) + H(V_3|V_1) + H(V_3|V_2) \\
 &+ 2 \cdot (H(V_1|V_2V_3) + H(V_2|V_1V_3) + H(V_3|V_1V_2))
 \end{aligned}$$

$$\sum_{i=1}^m \sum_{j=0}^{m-1} \frac{1}{m \binom{m-1}{j}} \sum_{|\mathcal{S}|=j} H(V_i|\underline{Y}_{\mathcal{S}})$$

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Variable Nodes

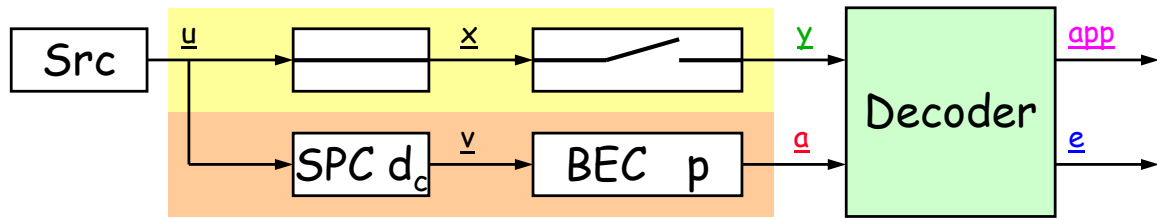


$$\begin{aligned}
 |\underline{u}| &= k & m &= |\underline{v}| = k \cdot d_v \\
 |\underline{x}| &= k
 \end{aligned}$$

$$\begin{aligned}
 \mathcal{A}_v &= 1 - \frac{1}{m} H(\underline{X}|\underline{Y}) = 1 - \frac{H(\underline{X}) - I(\underline{X}; \underline{Y})}{k \cdot d_v} \\
 &= 1 - \frac{k - k \cdot I(X_1; Y_1)}{k \cdot d_v} = 1 - \frac{1 - C}{d_v}
 \end{aligned}$$

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Check Nodes



$$\begin{aligned} |\underline{u}| &= k & m &= |\underline{v}| = k \cdot \frac{d_c}{d_c - 1} \\ |\underline{x}| &= k \end{aligned}$$

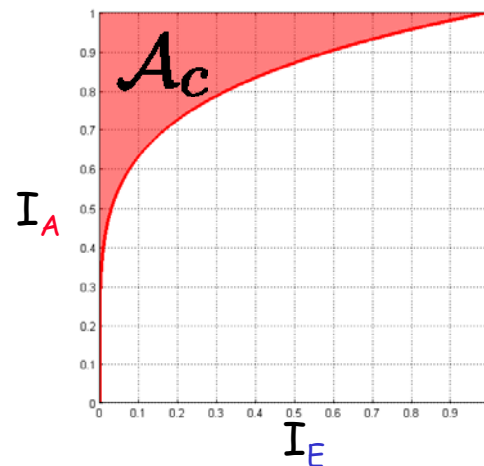
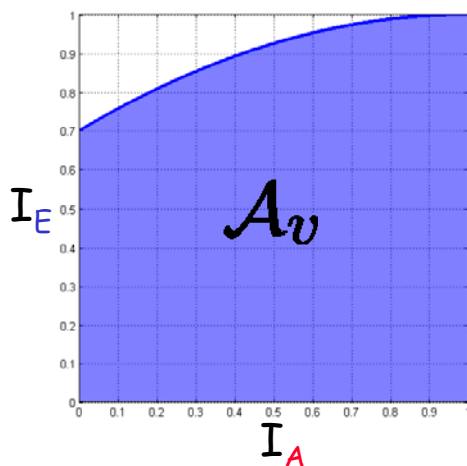
$$\begin{aligned} \mathcal{A}_c &= 1 - \frac{1}{m} H(\underline{V}|\underline{Y}) = 1 - \frac{H(\underline{V}) - I(\underline{V}; \underline{Y})}{m} \\ &= 1 - \frac{k \cdot (d_c - 1)}{k \cdot d_c} = \frac{1}{d_c} \end{aligned}$$

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Area of LDPC Component Codes

$$\mathcal{A}_v = 1 - \frac{1 - C}{d_v}$$

$$\mathcal{A}_c = \frac{1}{d_c}$$



Necessary condition for successful decoding:

$$1 - \mathcal{A}_v < \mathcal{A}_c$$

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Consequences of Area Property

$$1 - \mathcal{A}_v < \mathcal{A}_c$$

$$1 - 1 + \frac{1 - C}{d_v} < \frac{1}{d_c}$$

$$1 - C < \frac{d_v}{d_c}$$

$$C > 1 - \frac{d_v}{d_c} = R$$

"Surprising" result:

The area property tells us that the decoder can only converge if the rate is smaller than capacity!

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More Consequences...

Suppose the condition for convergence is fulfilled

$$1 - \mathcal{A}_v = \gamma \cdot \mathcal{A}_c < \mathcal{A}_c \quad 0 \leq \gamma < 1$$

$$\mathcal{A}_c = \frac{1}{d_c}$$

$$1 - \mathcal{A}_v = \gamma \cdot \mathcal{A}_c = \frac{1 - C}{d_v}$$

$$R = 1 - \frac{d_v}{d_c} = 1 - \frac{1 - C}{\gamma} = \frac{C - (1 - \gamma)}{\gamma} < C$$

What is the result of this inequality?

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Area and Rate Loss

$$R = 1 - \frac{d_v}{d_c} = 1 - \frac{1 - C}{\gamma} = \frac{C - (1 - \gamma)}{\gamma} < C$$

If $\gamma \rightarrow 1$ we can transmit at rates that approach capacity.
If $\gamma < 1$ we are bounded from capacity.

$$\gamma \rightarrow 1 \text{ means that } 1 - A_v = A_c$$

Furthermore, the curves must not intersect.

\Rightarrow The curves have to be matched.

Code design reduces to curve fitting!

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Curve Fitting – Code Mixture

We only considered regular codes, where every symbol has the same properties. Therefore, averaging over all symbols is equivalent to the mutual information of an arbitrarily symbol.

$$I_E = \frac{1}{m} \sum_{i=1}^m I(V_i; E_i) = I(V_1; E_1)$$

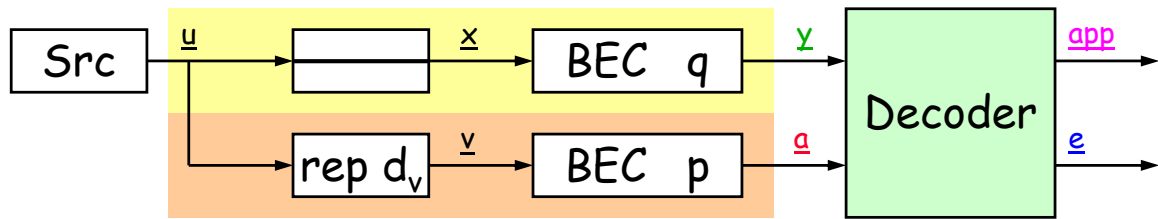
If we partition m into n_u groups $j=1\dots n_u$ each with length l_j , we can write I_E as

$$I_E = \sum_{j=1}^{n_u} \frac{l_j}{m} \left[\frac{1}{l_j} \sum_{i=1}^{l_j} I(V_{ji}; E_{ji}) \right] = \sum_{j=1}^{n_u} \gamma_j I_{E_j} \quad \gamma_j = \frac{l_j}{m} = \frac{l_j}{\sum_{j=1}^{n_u} l_j}$$

The resulting EXIT function is the weighted average of the EXIT functions of the groups.

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Example – Variable Mixture



70% of the variable nodes have $d_v=2$
 30% of the variable nodes have $d_v=5$

$$\gamma_1 = \frac{0.7 \cdot k \cdot 2}{0.7 \cdot k \cdot 2 + 0.3 \cdot k \cdot 5} = 0.48$$

$$\gamma_2 = \frac{0.3 \cdot k \cdot 5}{0.7 \cdot k \cdot 2 + 0.3 \cdot k \cdot 5} = 0.52$$

$$I_{E_j} = 1 - qp^{d_{vj}-1}$$

$$I_E = \gamma_1 \cdot [1 - qp^{d_{v1}-1}] + \gamma_2 \cdot [1 - qp^{d_{v2}-1}]$$

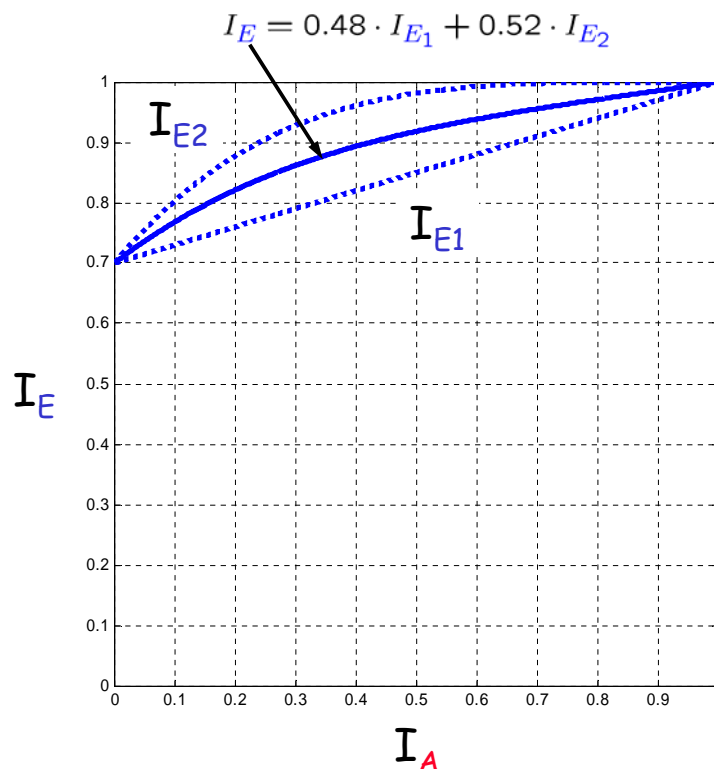
$$I_E(p) = 1 - q \cdot \sum_{j=1}^{n_u} \gamma_j \cdot p^{d_{vj}-1}$$

This is a polynomial in p

Note that $\sum \gamma_j = 1$

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Example – Variable Mixture



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Curve Fitting

Lets fix the EXIT function of the check node decoder.

$$I_{Ec} = (I_{Ac})^{d_c-1}$$

For curve fitting, we can exchange the following quantities

$$I_{Ec} = I_{Av} \quad I_{Ev} = I_{Ac}$$

Therefore, we can write the EXIT function of the variable node decoder as the inverse EXIT function of the check node decoder.

$$I_{Av} = (I_{Ev})^{d_c-1}$$

$$I_{Ev} = (I_{Av})^{\frac{1}{d_c-1}} = (1-p)^{\frac{1}{d_c-1}}$$

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Taylor Series Expansion

$$I_{Ev} = (I_{Av})^{\frac{1}{d_c-1}} = (1-p)^{\frac{1}{d_c-1}}$$

Assuming for example $d_c=5$ we can expand I_{Ev} as a Taylor series

$$I_{Ev} = 1 - \left[\frac{1}{4}p + \frac{3}{32}p^2 + \frac{7}{128}p^3 + \dots \right]$$

Truncating the Taylor series and normalizing the coefficients to 1 results in

$$I_{Ev} = 1 - \frac{51}{128} \left[\frac{32}{51}p + \frac{12}{51}p^2 + \frac{7}{51}p^3 \right]$$

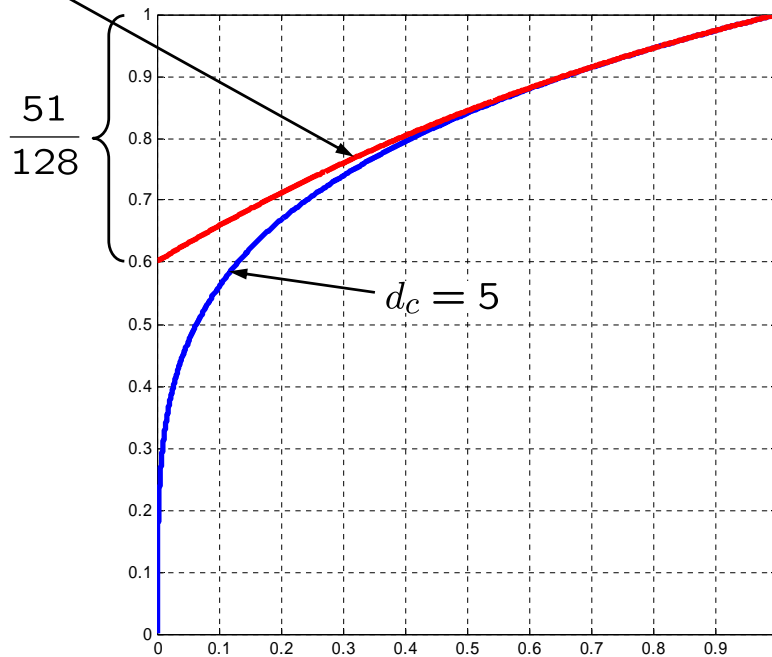
Compare this with the transfer function of the mixture of variable nodes...

$$I_E(p) = 1 - q \cdot \sum_{j=1}^{n_u} \gamma_j \cdot p^{d_{vj}-1}$$

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Curve Fitting

$$I_{Ev} = 1 - \frac{51}{128} \left[\frac{32}{51}(1 - I_{Av}) + \frac{12}{51}(1 - I_{Av})^2 + \frac{7}{51}(1 - I_{Av})^3 \right]$$



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Even more Consequences...

Using the same model as for the variable and check node decoder, it can be shown that the areas for a **serial concatenated** code with an outer code $R_{out} = k_{out}/n_{out}$ and an inner code $R_{in} = k_{in}/n_{in}$ are given by

$$A_{out} = 1 - R_{out} \qquad A_{in} = \frac{I(\underline{X}; \underline{Y})}{n_{in} \cdot R_{in}}$$

The same necessary condition $1 - A_{out} < A_{in}$ leads to

$$R_{out} \cdot R_{in} < \frac{I(\underline{X}; \underline{Y})}{n_{in}} \leq C$$

If the inner code has rate < 1 , i.e. $I(\underline{X}; \underline{Y})/n_{in} < C$ then we can not achieve capacity with serial concatenated codes!

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