

# Lecture 17

Note Title

3/7/2012

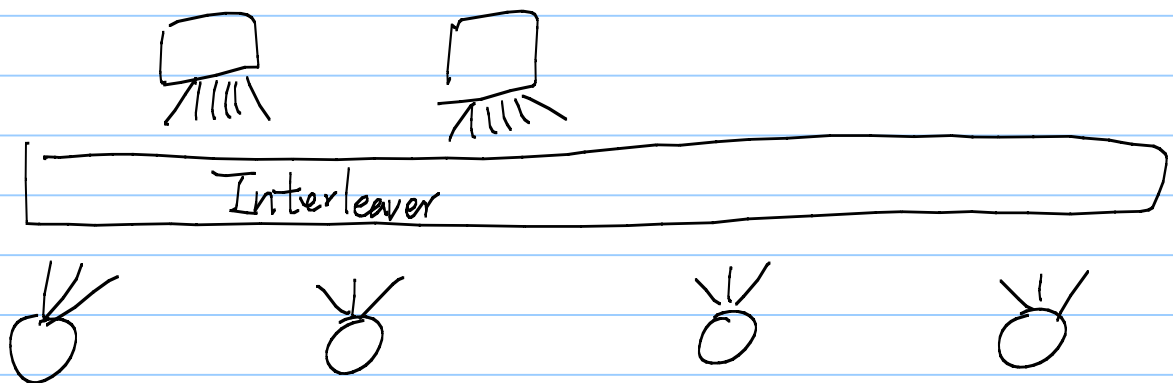
- \* Density Evolution Analysis for LDPC codes (Richardson Urbanke 01)
- \* It is generally very difficult to analyze individual codes, But it is easier to analyze the averaged behavior of a set of codes, also termed the code ensemble.
- \* DE focuses on the following special code ensemble.
- \* The regular bipartite-graph-based ensemble, which has three parameters
  - $N$ : the codeword length.
  - $d_v$ : the variable node degree
  - $d_c$ : the check node degree

The construction:

①  $n$  variable nodes,  $n = \frac{d_v}{d_c}$  check nodes.

② Each variable node has  $d_v$  sockets  
Each check node has  $d_c$  sockets

Ex:  $d_v = 3$   $d_c = 6$   $n = 4$



③ A uniform interleaver that maps the var. sockets to the check node sockets.

$$④ H = \begin{pmatrix} h_{j,i} \end{pmatrix}$$

Each

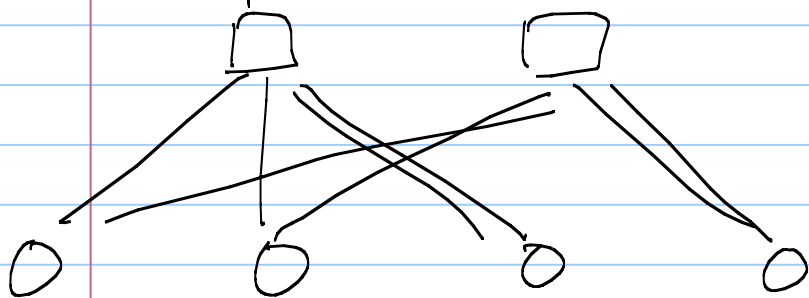
entry  $h_{j,i} = 1$  if there is an odd #  
of edges connecting  $X_i, C_j$   
 $= 0$  otherwise

Example

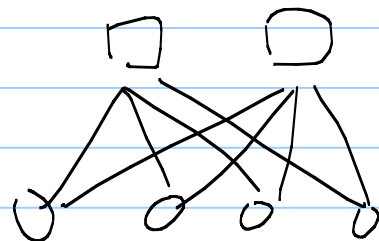
$d_v=2$

$d_c=4$

$N=4$



$$H = \begin{pmatrix} 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \end{pmatrix}$$



$$H = \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{pmatrix}$$

⑤ Any permutation / interleaver will lead to a new code.

There are  $(nd_v)!$  different permutations  $\Rightarrow (nd_v)!$  different codes.

⑥ We are interested in the bit error rate averaged over  $X_1, \dots, X_N$  and over all  $(nd_v)!$  codes, when we stop the LDPC decoder after a fixed # of  $T$  iterations.

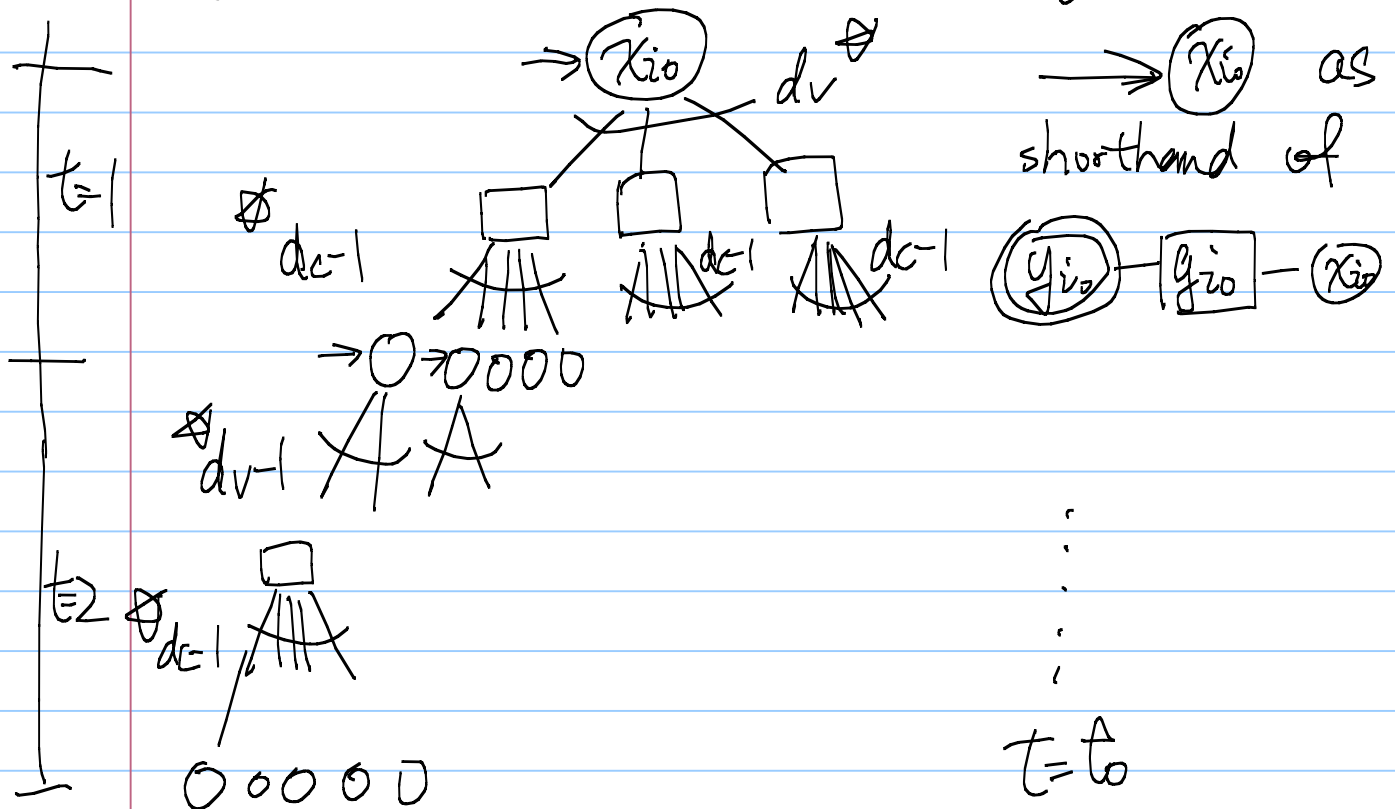
⑦ For finite  $N$ , the problem is still too hard. We let  $N \rightarrow \infty$  while keeping  $T, d_v, d_c$  fixed.

Recall our "free of short cycles" observation.

\* Thm 1: Fix  $i_0$  (focusing on a given bit  $X_{i_0}$ ) and fix  $t_0, d_v, d_c$

$$\lim_{n \rightarrow \infty} \text{Prob}(X_{i_0} \text{ is involved in a cycle of length } \leq 4t_0) = 1.$$

\* Thm 1 implies that the neighborhood of  $X_{i_0}$  within distance  $2t_0$  must be a tree.



There is no repeated appearance of any variable node  $x_i$

\* The above subgraph is termed the "support tree" of the message passing decoder after  $t_0$  iterations.

Namely, the decision of  $x_i$  after  $t_0$  iterations depends only on the observation  $y_i$  for those  $x_i$  in the support tree

\* Theorem 2: <sup>①</sup> The structure of a linear code is symmetric. (No special preference between 0 & 1)

② The sumproduct, or belief propagation decoder is symmetric. (No special preference between 0, 1)

③ If the channel is also symmetric

ex: BSC,  $X = \begin{matrix} 1 \\ -1 \end{matrix} \xrightarrow{\quad} \oplus \xrightarrow{\quad} Y$

BiAWGNC

## BER/FER

then the performances of sending any two codewords  $\vec{x}_1, \vec{x}_2$  are identical

Corollary: to evaluate the performance of an LDPC code, we can assume the all-zero  $\vec{x} = 00000 \dots 0$  is sent.

The bit error rate after  $t_0$  iteration

$$\begin{aligned} P_{b, i_0}^{[t_0]} &= P(\hat{X}_{i_0}^{[t_0]} \neq X_{i_0}) \\ &= P(\hat{X}_{i_0}^{[t_0]} \neq X_{i_0} \mid \vec{X} = \vec{0}) \\ &= P(\hat{X}_{i_0}^{[t_0]} \neq 0 \mid \vec{X} = \vec{0}) \\ &= P(m_{i_0}^{[t_0]} < 0 \mid \vec{X} = \vec{0}) \\ &\quad + \frac{1}{2} P(m_{i_0}^{[t_0]} = 0 \mid \vec{X} = \vec{0}) \end{aligned}$$

For the following, we focus only on symmetric channels

\* Observation 3:  $M_{i_0}^{[t_0]}$  is a random variable, since it depends on the random observation  $y_i$  within the support tree. Exercise: how many observation bits  $y_i$  are involved in the  $t_0$ -level support tree of  $X_{i_0}$ ?

\* Let us trace the prob "density" function (pdf) of the LLR messages. In particular, the  $P_{M|\vec{X}=\vec{0}}(dm)$

$\Rightarrow$  Density evolution

①

Density of the initial message  $M_i^{(0)}$

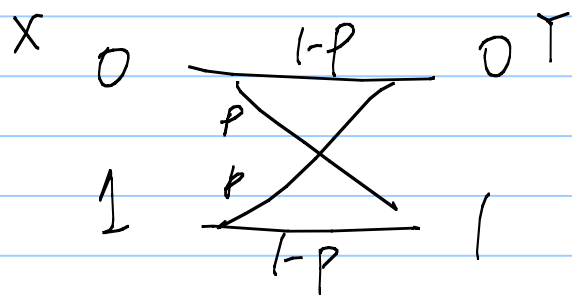
Recall

$$M_i^{(0)} = \log \left( \frac{P_{Y_i|X_i}(y_i|0)}{P_{Y_i|X_i}(y_i|1)} \right)$$

$= f(y_i)$  a function of observation  $y_i$

$\Rightarrow$  Given the  $P_{Y_i|X_i}(\cdot|0)$ , we can derive  $P_{M_i^{(0)}|X_i}(\cdot|0)$

Example: BSC w. cross-over prob  $p$ .

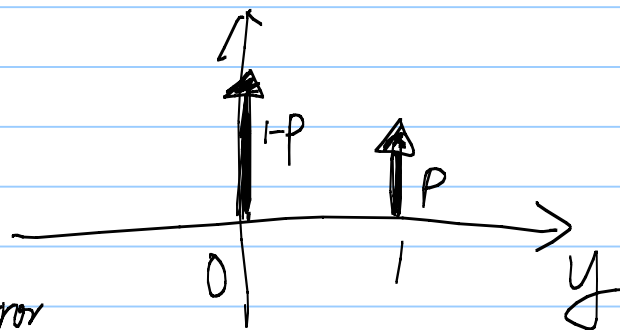


$$m_i^{(0)} = \log \left( \frac{P_{Y_i|X_i}(y_i|0)}{P_{Y_i|X_i}(y_i|1)} \right)$$

$$= \begin{cases} \log \left( \frac{1-p}{p} \right) & \text{if } y_i=0 \\ \log \left( \frac{p}{1-p} \right) & \text{if } y_i=1 \end{cases}$$

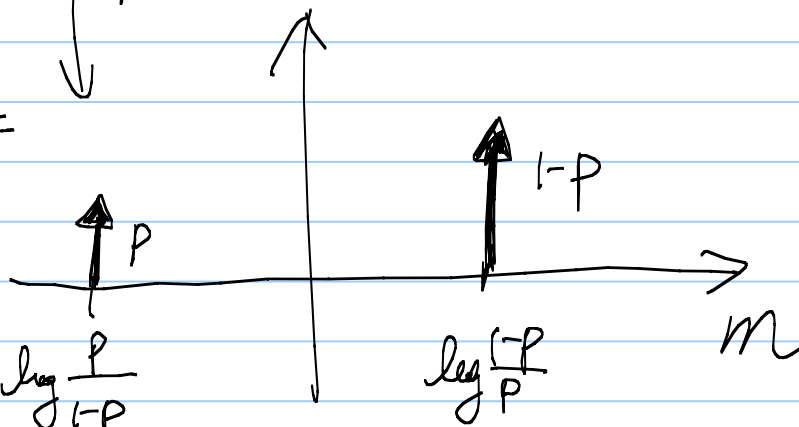
$$= \begin{cases} \log \left( \frac{1-p}{p} \right) & \text{if } y_i=0 \\ \log \left( \frac{p}{1-p} \right) & \text{if } y_i=1 \end{cases}$$

$$P_{Y_i|\vec{X}=\vec{0}}(\cdot|\vec{0}) =$$



row error prob.

$$P_{m_i^{(0)}|\vec{X}=\vec{0}} =$$



The density of our interest.

Remark: The confusion between the " $P_{Y_i|X_i}$ " inspired  $f_C(y_i)$  and the governing density  $P_{Y_i|X_i=\vec{0}}$



Example  $Y_i = (-1)^{X_i} + \sigma N_i$ ,  $N_i =$   
standard Gsn

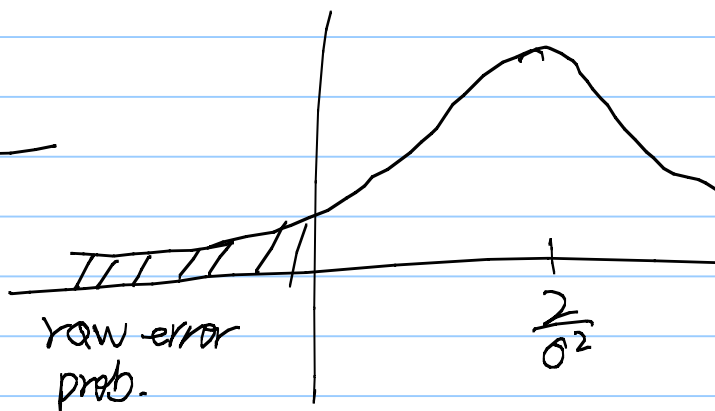
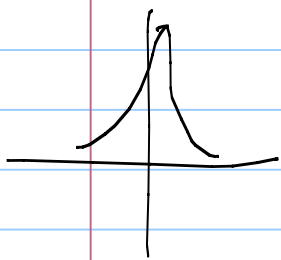
$$M_i^{(0)} = \log \left( \frac{P_{Y_i|X_i}(Y_i|0)}{P_{Y_i|X_i}(Y_i|1)} \right)$$

$$= \log \left( \frac{\frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{(Y_i-1)^2}{2\sigma^2}}}{\frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{(Y_i+1)^2}{2\sigma^2}}} \right)$$

$$= \frac{2}{\sigma^2} Y_i$$

$$P_{Y_i|\vec{X}=\vec{0}} \sim \text{Gsn}(1, \sigma^2)$$

$$\Rightarrow P_{M_i^{(0)}|\vec{X}=\vec{0}} \sim \text{Gsn}\left(\frac{2}{\sigma^2}, \frac{4}{\sigma^2}\right)$$



When  $\sigma \rightarrow 0$

$P_{M_i^{(0)}|\vec{X}=\vec{0}}$

keeps moving

to the right.

$$Q\left(\frac{2}{\sqrt{\frac{4}{\sigma^2}}}\right) = Q\left(\frac{1}{\sigma}\right)$$

