

# Lecture 16

Note Title

3/5/2012

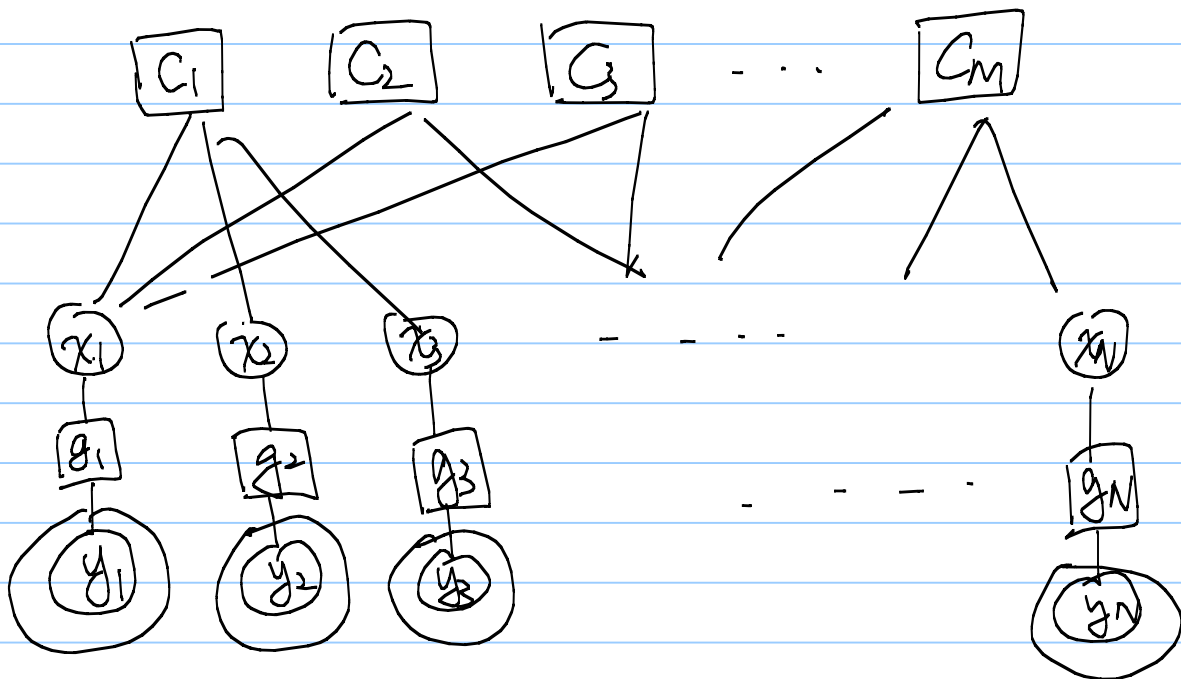
\* LDPC decoder

\* The factor graph representation of the likelihood function, assuming

that we have independent channel

$$P_{\vec{y}|\vec{x}}(\vec{y}|\vec{x}) = \prod_{i=1}^N P_{Y_i|X_i}(y_i|x_i)$$

$$\arg \max_{\vec{x}: H\vec{x}=\vec{0}} P_{\vec{y}|\vec{x}}(\vec{y}|\vec{x}) = \arg \max_{\vec{x}} \prod_{j=1}^M f_{C_j}(x_i \in \partial j) \cdot \prod_{i=1}^N P(y_i|x_i)$$



$$f_{C_j}(\cdot, \cdot, \dots, \cdot) = \begin{cases} 1 & \text{if the \# of 1s is even} \\ 0 & \text{otherwise} \end{cases}$$

## Terminology:

- ①  $(x_i)$ : the variable nodes
- ②  $[C_j]$ : the parity-check nodes
- ③ degree of nodes: the number of neighbor nodes

Observation: <sup>\*</sup>In the resulting factor graphs, there are many cycles.

\* But there is only a small # of short cycles when  $n$ , the codeword length is large

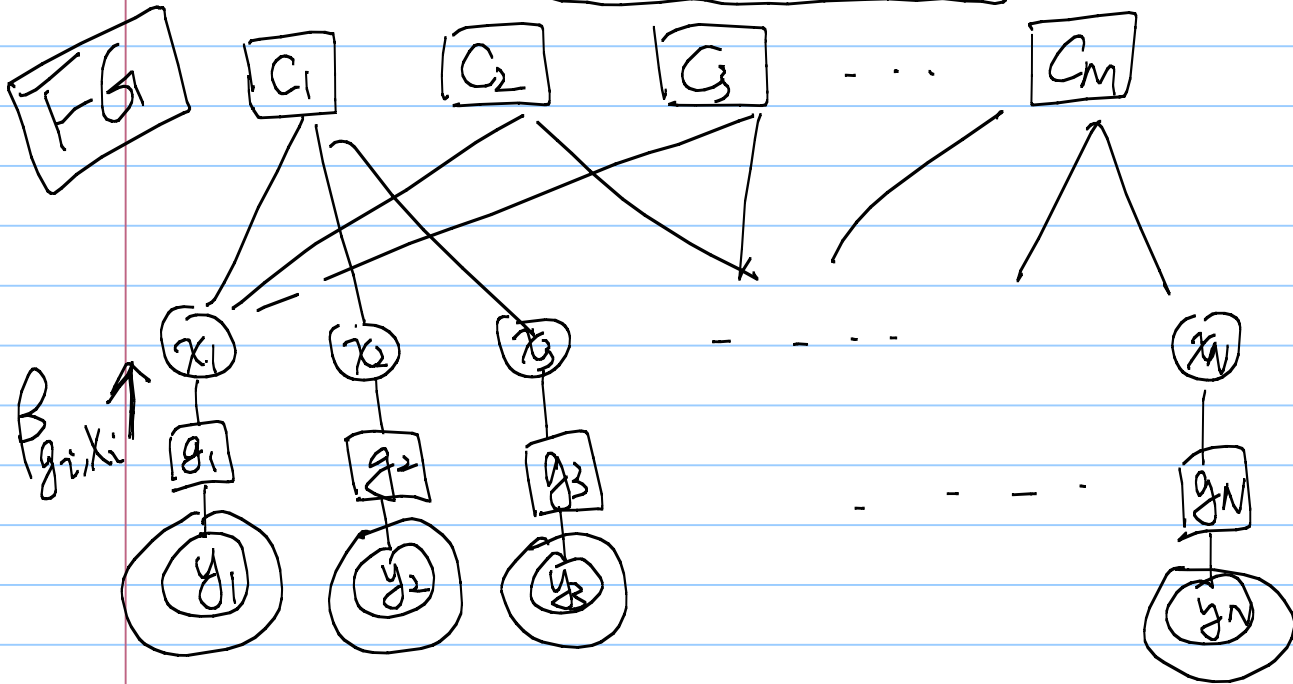
We can thus apply the sub-optimal min-sum or sum-product algorithms.

In particular, their parallel version.

## Comparison of LDPC & turbo codes

- ① LDPC codes are generally easier to analyze
- ② LDPC codes have slightly better performance  
∴ With a carefully chosen  $t_1$ , the performance of LDPC codes can be made extremely close to the capacity ( $\leq 0.01$  dB away from cap)
- ③ LDPC codes have potentially fully parallel structure.
- ④ LDPC codes were ignored for 40 yrs because it generally needs very long codeword length, 500 bits to 10k bits before the performance becomes competitive. It's hard to simulate a long code in the 60s.

# LDPC decoder



Parallel BCJR, the sum-product algorithm

Initialization:

Given the observation  $y_i$ ,  $\beta_{g_i, x_i}^{[0]}(x_i) = P(y_i | x_i)$

time index

$\beta_{c_j, x_i}^{[0]}(x_i) = 1$  for all  $x_i$

Each iteration

$$\alpha_{x_i, c_j}^{[t]}(x_i) = \beta_{g_i, x_i}^{[0]}(x_i) \prod_{k \in \partial(i) \setminus j} \beta_{c_k, x_i}^{[t-1]}(x_i)$$

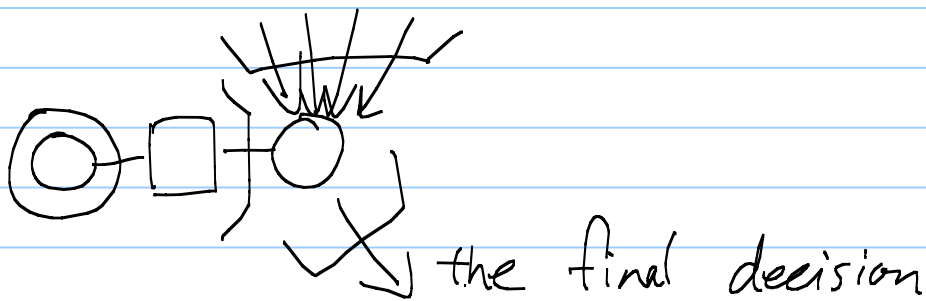
$$\beta_{c_j, x_i}^{[t]}(x_i) = \sum_{\left(\sum_k x_k\right) + x_i = 0} \prod_{k \in \partial(j) \setminus i} \alpha_{x_k, c_j}^{[t]}(x_k)$$

Repeat the above <sup>iterative</sup> update as if there is no need to worry about cycles

Terminate the iterative update after a fixed # of iterations, generally  $t=50-200$

Decision rule

$$\max_{x_i=0,1} \beta_{g_i, x_i}^{[0]}(x_i) \prod_{j \in \partial i} \beta_{g_j, x_i}(x_i)$$



\* An alternative description of the LDPC decoder — the log-likelihood-ratio-based decoder.

A high-level description

① We first notice that  $\alpha_{X_i G_j}(\cdot)$  &  $\beta_{G_j X_i}(\cdot)$  are functions taking only two input values  $X=0, 1$ .

② In a factor graph representation, everything is relative. Only the ratio

$$\frac{\alpha_{X_i G_j}(0)}{\alpha_{X_i G_j}(1)} \quad \& \quad \frac{\beta_{G_j X_i}(0)}{\beta_{G_j X_i}(1)} \quad \text{matter}$$

When trying to distinguish  $X=0$  from  $X=1$

$\Rightarrow$  instead of sending a "function"  $\alpha_{X_i G_j}(\cdot)$

or  $\beta_{G_j X_i}(\cdot)$ , we can send scalar

messages

$$M_{X_i, G_j} = \log \left( \frac{\alpha_{X_i G_j}(0)}{\alpha_{X_i G_j}(1)} \right)$$

$$\& \quad M_{G_j, X_i} = \log \left( \frac{\beta_{G_j X_i}(0)}{\beta_{G_j X_i}(1)} \right)$$

Detailed update rules based on <sup>the</sup> LLR.

\* Initialization

The channel observation LLR of the  $i$ -th

$$M_i^{(0)} \triangleq m_{g_i, X_i} = \log \left( \frac{\beta_{g_i X_i}(0)}{\beta_{g_i X_i}(1)} \right) \quad \text{bit}$$

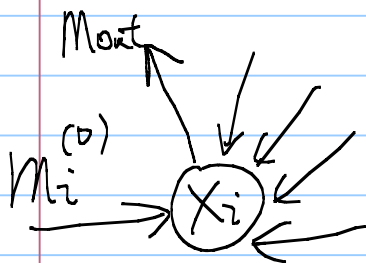
$$= \log \left( \frac{P_{Y_i | X_i}(y_i | 0)}{P_{Y_i | X_i}(y_i | 1)} \right)$$

\* Initial Check  $\rightarrow$  var. message

$$m_{C_j, X_i}^{[0]} = \log\left(\frac{\beta_{C_j, X_i}^{[0]}(0)}{\beta_{C_j, X_i}^{[1]}(1)}\right)$$

$$= \log\left(\frac{1}{1}\right) = 0$$

\* Variable node message map:



$$m_{X_i, C_j}^{[t]} \triangleq \log\left(\frac{\alpha_{X_i, C_j}^{[t]}(0)}{\alpha_{X_i, C_j}^{[t]}(1)}\right)$$

$$\therefore \alpha_{X_i, C_j}^{[t]}(x) = \beta_{C_j, X_i}(x) \cdot \prod_{l \in \partial(i) \setminus j} \beta_{C_l, X_i}^{[t-1]}(x)$$

$$\therefore = \log\left(\frac{\beta_{C_j, X_i}(0)}{\beta_{C_j, X_i}(1)}\right) + \sum_{l \in \partial(i) \setminus j} \log\left(\frac{\beta_{C_l, X_i}^{[t-1]}(0)}{\beta_{C_l, X_i}^{[t-1]}(1)}\right)$$

$$= m_i^{(0)} + \sum_{l \in \partial(i) \setminus j} m_{C_l, X_i}^{[t-1]}$$



Check node message map



$$m_{G_j X_i}^{[t]} = \log \left( \frac{\beta_{G_j X_i}^{[t]}(0)}{\beta_{G_j X_i}^{[t]}(1)} \right)$$

Note that

$$\beta_{G_j X_i}^{[t]}(x) = \sum_{k \in \partial j^i} \prod_{k \in \partial j^i} \alpha_{X_k G_j}^{[t]}(x_k)$$

$$\sum_k x_k = x$$

$$= \frac{1}{2} \left[ \prod_{k \in \partial j^i} \left( \alpha_{X_k, G_j}^{[t]}(0) + \alpha_{X_k, G_j}^{[t]}(1) \right) \right.$$

$$\left. + (-1)^x \prod_{k \in \partial j^i} \left( \alpha_{X_k, G_j}^{[t]}(0) - \alpha_{X_k, G_j}^{[t]}(1) \right) \right]$$

$$= \log \frac{\prod_{k \in \partial j^i} \left( \frac{\alpha_{X_k, G_j}^{[t]}(0)}{\alpha_{X_k, G_j}^{[t]}(1)} + 1 \right) + \prod_{k \in \partial j^i} \left( \frac{\alpha_{X_k, G_j}^{[t]}(0)}{\alpha_{X_k, G_j}^{[t]}(1)} - 1 \right)}{\prod_{k \in \partial j^i} \left( \frac{\alpha_{X_k, G_j}^{[t]}(0)}{\alpha_{X_k, G_j}^{[t]}(1)} + 1 \right) - \prod_{k \in \partial j^i} \left( \frac{\alpha_{X_k, G_j}^{[t]}(0)}{\alpha_{X_k, G_j}^{[t]}(1)} - 1 \right)}$$

$$= \log \frac{\prod_k (e^{m_k} + 1) + \prod_k (e^{m_k} - 1)}{\prod_k (e^{m_k} + 1) - \prod_k (e^{m_k} - 1)}$$

$$= \log \frac{1 + \prod_k \frac{e^{m_k} - 1}{e^{m_k} + 1}}{1 - \prod_k \frac{e^{m_k} - 1}{e^{m_k} + 1}}$$

By noting that

$$\tanh(t) = \frac{e^t - e^{-t}}{e^t + e^{-t}} = x$$

$$\tanh^{-1}(x) = \frac{1}{2} \log \left( \frac{1+x}{1-x} \right)$$

$$\Rightarrow \underline{\underline{m_{G_j X_i}^{[t]} = 2 \tanh^{-1} \left( \prod_{k \in \mathcal{J}_i} \tanh \left( \frac{m_{X_k, G_j}^{[t]}}{2} \right) \right)}}$$

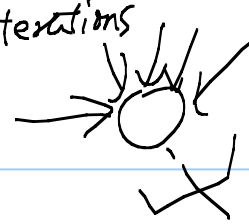
output ↙

Equivalently

$$\Leftrightarrow \tanh \left( \frac{m_{G_j X_i}^{[t]}}{2} \right) = \prod_{k \in \mathcal{J}_i} \tanh \left( \frac{m_{X_k, G_j}^{[t]}}{2} \right)$$

After a fixed # of iterations, say  $T$  iterations

Final decision:



$$\max_{x_i=0,1} \beta_{g_i, x_i}^{[0]}(x_i) \prod_{j \in \partial i} \beta_{g_j, x_i}^{[T]}(x_i)$$

$$\Leftrightarrow m_i^{[T]} = m_i^{[0]} + \sum_{j \in \partial i} m_{g_j, x_i}^{[T]} \begin{matrix} \hat{x}_i=0 \\ \geq 0 \\ \leq 0 \\ \hat{x}_i=1 \end{matrix}$$

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Summary: Given a turbo / LDPC code, we have learned how to construct its factor graph representation & design the corresponding (suboptimal due to cycles) sum-product algorithm

Question: How to analyze the code performance for memoryless channels without resorting to brute-force simulations

Q: How to optimize the code structure?