

Lecture 18

Note Title

3/19/2012

* Density Evolution (DE) analysis
of LDPC code ensembles.

* Tracing the prob density function
(pdf) of the messages $m^{[t]}$

More explicitly

$$P(m_{i_0}^{[t]} | \vec{X} = \vec{0})$$

$$P_{b,i_0}^{[t_0]} = P(m_{i_0}^{[t_0]} < 0 | \vec{X} = \vec{0}) \\ + \frac{1}{2} P(m_{i_0}^{[t_0]} = 0 | \vec{X} = \vec{0})$$

where

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

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

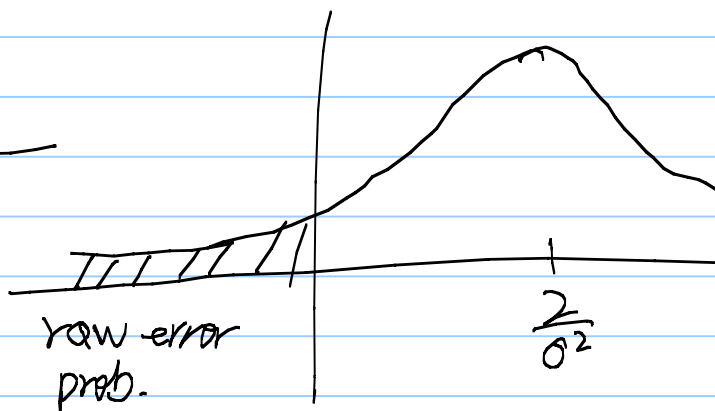
$$M_i^{(0)} = \log \left(\frac{P_{Y_i|X_i}(Y_i|0)}{P_{Y_i|X_i}(Y_i|1)} \right)$$

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

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

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

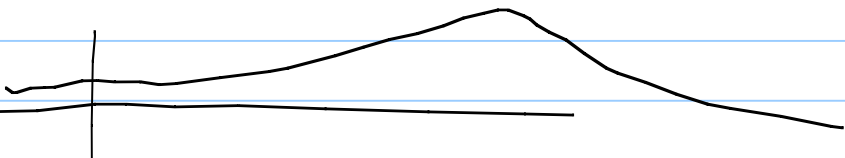
$$\Rightarrow P_{M_i^{(0)}|\vec{X}=\vec{0}} \sim \text{Gsn}\left(\frac{2}{\sigma^2}, \frac{4}{\sigma^2}\right)$$



row error
prob.

When $\sigma \rightarrow 0$
 $P_{M_i^{(0)}|\vec{X}=\vec{0}}$
keeps moving
to the right.

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



Example: The mismatch of the channel models.

Suppose the LDPC decoder is initialized / designed by assuming the channel being a GSN

will $Y_i = (-1)^{X_i} + \sigma N_i$ but the

true channel model being

$$Y_i = (-1)^{X_i} + \sqrt{2} \sigma N_i \quad (\text{underestimate the noise level})$$

Q: $P_{m_i^{(0)}} | X_i=0 = ?$

Ans: $m_i^{(0)} = \frac{2}{\sigma^2} y_i$

\therefore Given $X_i=0$ $Y_i \sim \mathcal{N}(1, 2\sigma^2)$

\therefore Given $X_i=0$

$$P_{m_i^{(0)}} | X_i=0 \sim \mathcal{N}\left(\frac{2}{\sigma^2}, \frac{8}{\sigma^2}\right)$$

The raw error prob

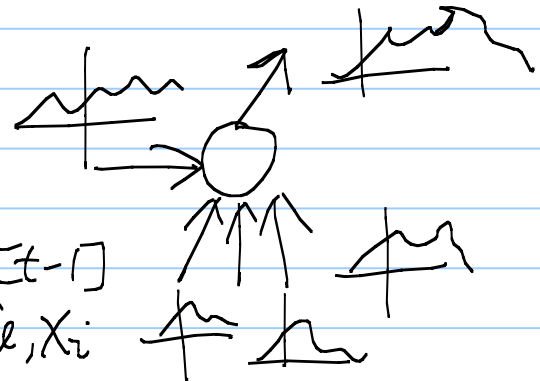
$$Q\left(\frac{\frac{2}{\sigma^2}}{\sqrt{\frac{8}{\sigma^2}}}\right) = Q\left(\frac{1}{\sqrt{2}\sigma}\right)$$

② Iterative compute the density of $P_m(\vec{x}=\vec{0})$ for the variable x check node map.

Recall

Variable node map

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



* All m 's are random variables.

* Moreover, ^{Given $\vec{x}=\vec{0}$,} each m depends on a disjoint set of independent observation (different sub-trees, no overlap by Thm 1)

* All m 's are independent R.V.

$$* P_{m_{x_i, g_j}}^{[t]} = P_{m_i^{(0)}} * \left(\prod_{l \in \partial i | j} P_{m_{C_l, X_i}}^{[t-1]} \right)$$

→ convolution

* Similarly, for the check node map

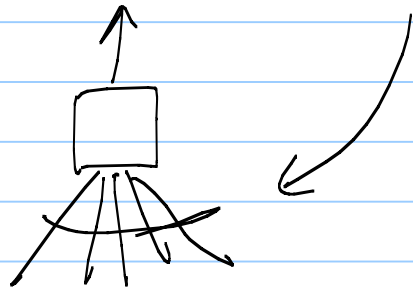
$$M_{C_j X_i}^{[t]} = \Phi_c (M_{X_k, C_j}^{[t]} : k \in \partial j \setminus i)$$

is a function of the input messages.

* Each input messages are independent R.V.

* The marginal input message distributions

$P_{M_{X_k, C_j}^{[t]}}$ \Rightarrow Joint distribution



\Rightarrow We can compute the marginal

of the output $P_{M_{C_j X_i}^{[t]}}$ from $P_{M_{X_k, C_j}^{[t]}} : k \in \partial j \setminus i$

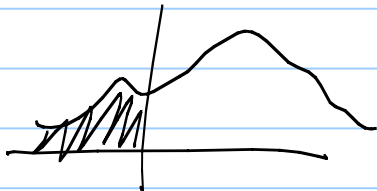
Summary: Given ① the message maps Φ_V , Φ_C of the variable & check nodes.

② the marginal of $m_i^{(0)}$ computed from the i.i.d. channel distribution

③ All incoming messages of the support tree are indep (by Thm 1)

\Rightarrow We can iteratively compute the "density" of the messages on the support tree

Once the density of the final LLR $m_i^{[t_0]}$ is computed, the final bit error rate after t_0 iterations is

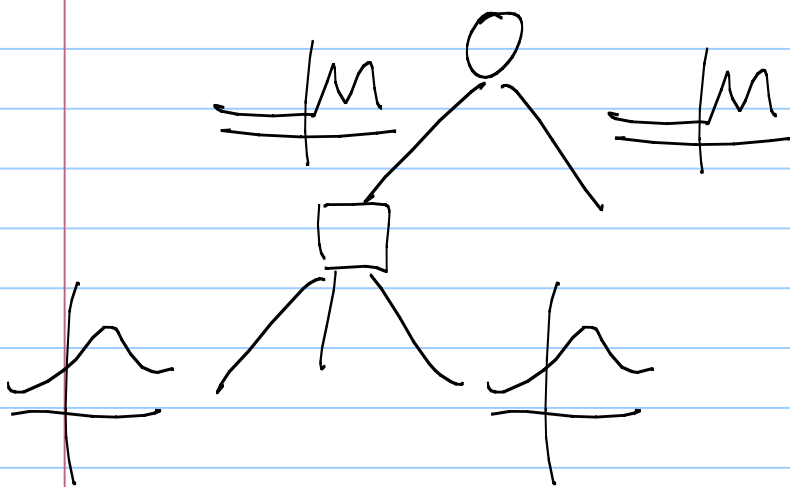
$$\text{ber} = P(m_{i_0}^{[t_0]} < 0 \mid \vec{X} = \vec{0}) + \frac{1}{2} P(m_{i_0}^{[t_0]} = 0 \mid \vec{X} = \vec{0})$$


Simplification

* Assume that the channel noise is not only memoryless (independent) but also identically distributed

⇒ There is no need to consider a fixed root X_{i_0} , All bits will have the same ber.

⇒ Moreover, there is no need to distinguish the incoming messages, all of them will have the same marginal distribution



As a result, we need only

$P^{(0)}$: The marginal of $M_i^{(0)}$

$P^{(t)}$: The marginal of $V \rightarrow C$ messages

$$M_{X_i, C_j}^{[t]}$$

$Q^{(t)}$: The marginal of $C \rightarrow V$ messages

$$M_{C_j, X_i}^{[t]}$$

$$\Rightarrow P^{(1)} = P^{(0)}$$

$$Q^{(t)} = F_{chk}(P^{(t)}, d_c)$$

$$P^{(t+1)} = F_{var}(Q^{(t)}, d_v, P^{(0)})$$

where F_{chk} , F_{var} are functionals that take densities as input & output a density.

a new

Even with the above simplification
 Usually, the "density evolution" does not admit
 any closed-form expression, except for the
 simple setting of BECs.

Example: the density evolution formula
 for BECs. $X=0$ $\sum_{x=1}^{x=0}$ "x", the erasure
 prob = ϵ

① Suppose the all-zero \vec{X} is transmitted

$$\textcircled{2} m_i^{(0)} = \log \left(\frac{P(y_i|0)}{P(y_i|1)} \right)$$

$$= \begin{cases} \infty & \text{if } y_i = 0 \\ 0 & \text{if } y_i = "x" \\ -\infty & \text{if } y_i = 1. \end{cases}$$

Since the all-zero codeword is transmitted

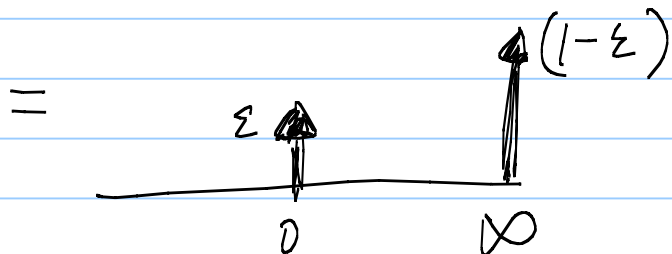
$$p^{(0)} \triangleq P_{m_i}^{(0)} = \epsilon \delta(m_i) + (1-\epsilon) \cdot \delta(m_i - \infty)$$

$$m_{C_j X_i}^{(0)} = 0$$

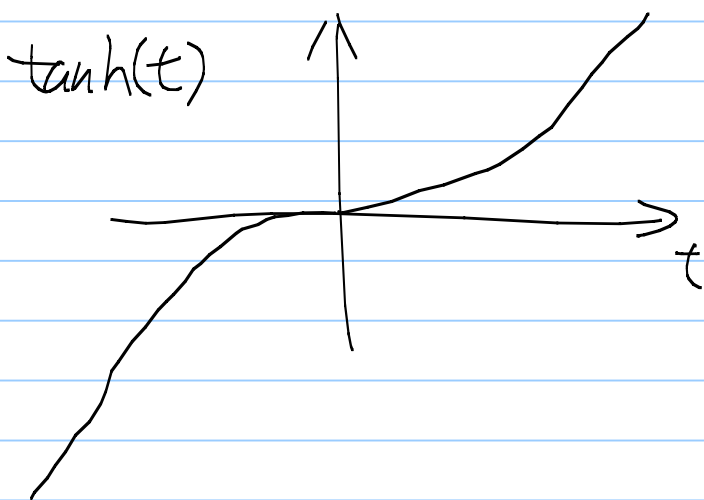
$$Q^{(0)} \triangleq Q_{m_{C_j X_i}^{(0)}} = \delta(m)$$

$$m_{X_i(j)}^{(1)} = m^{(0)} + \sum_{k \in \partial i | j} m_{C_k X_i}^{(0)}$$

$$P^{(1)} = P^{(0)} * (* Q^{(0)})$$



$$m_{C_j X_i}^{[\pm]} = 2 \tanh^{-1} \left(\prod_{k \in \partial j | i} \tanh \left(\frac{m_{X_k C_j}^{[\pm]}}{2} \right) \right)$$



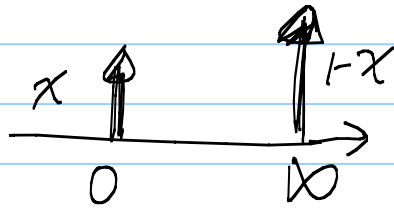
\Rightarrow any one of incoming edge is 0

\Rightarrow the outgoing message is zero.

otherwise the outgoing message is ∞

$$\Rightarrow Q^{(1)} = \begin{matrix} \uparrow & \uparrow \\ 1 - (1-\epsilon)^{d_c-1} & (1-\epsilon)^{d_c-1} \end{matrix}$$

Notice that P, Q are of the form



we thus need

to only trace the scalar ξ . (or $P \cdot Q$)

$$P^{(0)} = \varepsilon \quad Q^{(0)} = 1.$$

$$P^{(1)} = \varepsilon \quad Q^{(1)} = 1 - (1 - \varepsilon)^{d_c - 1}$$

$$P^{(2)} = ?$$

$$M_{X_i G_j}^{(2)} = M^{(0)} + \sum_{l \in \partial i \setminus j} M_{C_l X_i}^{(2)}$$

Note that any one of $M_{C_l X_i}^{(1)}$ is ∞

$$\Rightarrow M_{X_i G_j}^{(2)} = \infty.$$

otherwise

$$M_{X_i G_j}^{(2)} = 0$$

$$\Rightarrow P^{(2)} = P^{(1)} \cdot \left(Q^{(0)} \right)^{d_v - 1}$$

$$Q^{(2)} = 1 - (1 - P^{(0)})^{d_c - 1}$$

The final answer

$$\begin{cases} p^{(0)} = \varepsilon & q^{(0)} = 1. \\ p^{(t)} = p^{(0)} \cdot (q^{(t-1)})^{d_v-1} \\ q^{(t)} = 1 - (1 - p^{(t)})^{d_c-1} \end{cases}$$

The error prob after t_0 iterations becomes

$$\begin{aligned} & P(m_{i_0}^{(t_0)} < 0 \mid X_{i_0} = 0) \\ & + \frac{1}{2} P(m_{i_0}^{(t_0)} = 0 \mid X_{i_0} = 0) \\ & = \frac{1}{2} \left(p^{(0)} (q^{(t_0)})^{d_v} \right) \end{aligned}$$

Observation of the results of the DE for BECs & for all other channels.

* Experiencing a threshold behavior, Ex: for BECs
 $\text{If } \epsilon < 0.4293, \Rightarrow$
converges to zero.

$\epsilon > 0.4994 \Rightarrow$

bounded away from zero.

The threshold behavior is provable for BECs.

* Thm: for any i.i.d. symmetric channel, the error prob $P_{\text{ber}}^{(t)}$ is non-increasing function with respect to t .

Pf: The density evolution is actually computing the error of a "support tree code". When the support tree is larger, the $P_{\text{ber}}^{(t)}$ decreases.