# E2 205 Error-Control Coding <br> Lecture 25 

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## 1 LDPC Code: Density Evolution

1.1 BP at a variable node


$$
\begin{equation*}
l_{d_{v}}=\sum_{j=0}^{d_{v}-1} l_{j} \tag{1}
\end{equation*}
$$

$l_{j}=P\left(x_{t} / E_{j}\right)$
$E_{0}=y_{t}$
$E_{i}=$ some disjoint subset of received symbols.

### 1.2 Density Evolution

Assume 1 was transmitted. The received symbols are all independent.This makes the $\left\{l_{j}\right\}_{j=0}^{d_{v}-1}$ independent.
Therefore the pdf of $l_{d_{v}}$ is the convolution of the pdfs of the $l_{j}, 0 \leqslant j \leqslant d_{v}-1$ Therefore,
$P_{l_{d_{v}}}=\mathbb{F}^{-1}\left\{\mathbb{F}\left\{P_{l_{0}}\right\} * \mathbb{F}\left\{P_{l_{j}}\right\}^{d_{v}-1}\right\}$ for some $j, 1 \leqslant j \leqslant d_{v}-1$

### 1.3 BP at a check node

We saw that here message passing takes on the form

$$
\begin{equation*}
\tanh \left(\frac{l_{d_{v}}}{2}\right)=\prod_{j=1}^{d_{c}-1} \tanh \left(\frac{l_{j}}{2}\right) \tag{2}
\end{equation*}
$$

Would like to take logs on both sides of equation 2 .


However, $\tanh \left(\frac{l}{2}\right)$ can take negative values. So we replace $\tanh \left(\frac{l}{2}\right)$ by $(X, Y)$ where:
$X=\operatorname{sgn}(l)$
$Y=-\ln \left|\tanh \left(\frac{l}{2}\right)\right|$
and

$$
\operatorname{sgn}(l)= \begin{cases}0 & \text { for } l \geqslant 0 \\ 1 & \text { for } l<0\end{cases}
$$

(Think of $(-1)^{\operatorname{sgn}(l)}$ as indicating the sign of l )

From equation 2 it follows that

$$
\begin{aligned}
& X_{d_{c}}=\sum_{j=1}^{d_{c}-1} X_{j} \bmod 2 \\
& Y_{d_{c}}=\sum_{j=1}^{d_{c}-1} Y_{j}
\end{aligned}
$$




Let $P_{j}(0, y)$ be such that $P_{j}(0, y+\Delta y)-P_{j}(0, y)$ is the probability $y \leqslant$ $Y \leqslant y+\Delta y$.
$Y=-\ln \left|\frac{\tanh (L)}{2}\right|=-\ln \left(\tanh \left(\frac{L}{2}\right)\right)$
( $Y=g(L), L \geqslant 0)$


## ASIDE: Change of variables

$Y=g(X)$
$f_{Y}(y)=\frac{f_{X}\left(g^{-1}(y)\right)}{\left|\frac{d y}{d x}\right|_{x=g^{-1}(y)}}$
Let $g^{-1}(y)=h(y)$
Then $\left|\frac{d y}{d x}\right|=\frac{1}{\left|\frac{d h}{d y}\right|}$
$e^{-Y}=\frac{e^{L}-1}{e^{L}+1}$
$e^{L}\left(1-e^{-Y}\right)=e^{-Y}+1$
$e^{L}=\frac{1+e^{-Y}}{1-e^{-Y}}$
$e^{-L}=\frac{1-e^{-Y}}{1+e^{-Y}}$
$=\frac{e^{Y}-1}{e^{Y}+1}$
Therefore,

$$
\begin{gathered}
L=-\ln \tanh \left(\frac{Y}{2}\right) \\
=h(Y) \\
\left|\frac{d h}{d y}\right|=\frac{1}{\tanh \frac{y}{2}} \frac{d}{d y}\left(\frac{e^{y}-1}{e^{y}+1}\right) \\
=\frac{1}{\tanh \frac{y}{2}} \frac{\left(e^{y}+1\right) e^{y}-\left(e^{y}-1\right) e^{y}}{\left(e^{y}+1\right)^{2}} \\
=\frac{e^{y}+1}{e^{y}-1} * \frac{2 e^{y}}{\left(e^{y}+1\right)^{2}} \\
=\frac{2 e^{y}}{e^{y}-1} \\
=\frac{1}{\sinh (y)}
\end{gathered}
$$

Therefore,

$$
P(0, y)=\frac{1}{\sinh (y)} P_{L}\left(-\ln \tanh \left(\frac{y}{2}\right)\right)
$$

Similarly,

$$
\begin{aligned}
P(1, y) & =\frac{1}{\sinh (y)} P_{L}\left(\ln \tanh \left(\frac{y}{2}\right)\right) \\
\sinh (y) & =\frac{e^{y}-e^{-y}}{2}
\end{aligned}
$$

In this way one can find $P_{j}(0, y), 1 \leqslant j \leqslant d_{c}-1$
Define a transform on $\mathrm{P}(\mathrm{x}, \mathrm{y})$


$$
\begin{equation*}
\mathbb{E}\left[(-1)^{\lambda X} e^{-s Y}\right]=\sum_{x=0}^{1}(-1)^{\lambda x} \int_{0}^{\infty} e^{-s y} P(x, y) d y \tag{3}
\end{equation*}
$$

$$
\mathbb{E}\left[(-1)^{\lambda X_{d_{c}}} e^{-s Y_{d_{c}}}\right]=\mathbb{E}\left[\prod_{j=1}^{d_{c}-1}(-1)^{\lambda X_{j}} e^{-s Y_{j}}\right]
$$

$$
=\prod_{j=1}^{d_{c}-1} \mathbb{E}\left[(-1)^{\lambda X_{j}} e^{-s Y_{j}}\right]
$$

$$
=\prod_{j=1}^{d_{c}-1}\left[\hat{P}_{j}(0, s)+(-1)^{\lambda} \hat{P}_{j}(1, s)\right]
$$

where,
$X_{d_{c}}=\sum X_{j} \bmod 2$
$Y_{d_{c}}=\sum_{j} Y_{j}$
Setting $\lambda=0$ we get

$$
\begin{aligned}
& \hat{P_{d_{c}}}(0, s)+\hat{P_{d_{c}}}(1, s)=\prod_{j=1}^{d_{c}-1}\left[\hat{P}_{j}(0, s)+\hat{P}_{j}(1, s)\right] \\
& \hat{P_{d_{c}}}(0, s)-\hat{P_{d_{c}}}(1, s)=\prod_{j=1}^{d_{c}-1}\left[\hat{P}_{j}(0, s)-\hat{P}_{j}(1, s)\right]
\end{aligned}
$$

Thus we can recover $\hat{P_{d_{c}}}(0, s)$ and $\hat{P_{d_{c}}}(1, s)$
In the reverse direction, from $P(0, y)$ we can recover $P_{L}(l), l \geqslant 0$ and from $P(1, y)$ we can recover $P_{L}(l), l \leqslant 0$

Theorem: Over the probability space of all graphs $C\left(d_{v}, d_{c}\right)$ and channel realizations, let $Z$ be the number of incorrect messages among all $n_{d_{v}}$ variable to check node message passed at iteration $l$. Let $p$ be the expected number of incorrect messages passed along an edge with a tree-like directed neighborhood of depth at least $2 l$ at the $l^{\text {th }}$ iteration. Then there exists positive constants $\beta=\beta\left(d_{v}, d_{c}, l\right)$ and $\gamma=\gamma\left(d_{c}, d_{v}, l\right)$ such that:
i Concentration around the expected value.
For any $t>0$ we have:

$$
\operatorname{Pr}\left\{|Z-\mathbb{E}[Z]|>\frac{n d_{v} t}{2}\right\} \leqslant 2 e^{-\beta t^{2} n}
$$

ii Convergence to the cycle-free case:
For any $t>0$ and $n>\frac{2 \gamma}{t}$, we have

$$
\left|\mathbb{E}[Z]-n d_{v} p\right|<\frac{n d_{v} t}{2}
$$

iii Concentration around the cycle-free case:
For any $t>0$ and $n>\frac{2 \gamma}{t}$, we have

$$
\operatorname{Pr}\left\{\left|Z-n d_{v} p\right|>\frac{n d_{v} t}{2}\right\} \leqslant 2 e^{-\beta t^{2} n}
$$



## 2 Polar Codes

A coding scheme (polar coding) is presented that achieve the "symmetric capacity"(capacity assuming both inputs are equally likely) of the BIDMC(Binary Inout Discrete Memoryless Channel).

Equally likely inputs achieve capacity on large class of channels: BSC, BEC and others.

### 2.1 Basic Idea



$$
\begin{aligned}
I\left(U_{1} U_{2} ; Y_{1} Y_{2}\right) & =I\left(X_{1} X_{2} ; Y_{1} Y_{2}\right) \\
& =2 I(W)
\end{aligned}
$$

$$
\begin{aligned}
I\left(X_{1} X_{2} ; Y_{1} Y_{2}\right) & =H\left(Y_{1} Y_{2}\right)-H\left(Y_{1} Y_{2} / X_{1} X_{2}\right) \\
& =H\left(Y_{1}\right)+H\left(Y_{2}\right)-H\left(Y_{1} / X_{1} X_{2}\right)-H\left(Y_{2} / X_{1} X_{2} Y_{1}\right) \\
& =H\left(Y_{1}\right)+H\left(Y_{2}\right)-H\left(Y_{1} / X_{1}\right)-H\left(Y_{2} / X_{2}\right) \\
& =I\left(X_{1} ; Y_{1}\right)+I\left(X_{2} ; Y_{2}\right) \\
& =2 I(W) \\
I\left(U_{1} U_{2} ; Y_{1} Y_{2}\right) & =I\left(U_{1} ; Y_{1} Y_{2}\right)+I\left(U_{2} ; Y_{1} Y_{2} / U_{1}\right) \\
& =I\left(Y_{1} Y_{2} ; U_{1}\right)+I\left(Y_{1} Y_{2} U_{1} ; U_{2}\right) \\
& =I\left(W^{-}\right)+I\left(W^{+}\right)
\end{aligned}
$$

