

Tensor Train and Taylor methods for LDPC decoding

Daniil Polykovskiy, Alexander Novikov

Apr. 15, 2016

Channel model

- ▶ Transmits only 0 and 1
- ▶ Flips with low probability p
- ▶ Bit stream is split into messages of length n

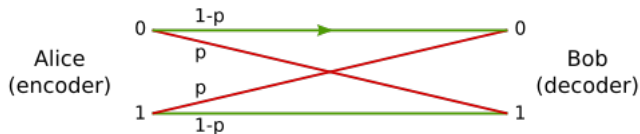
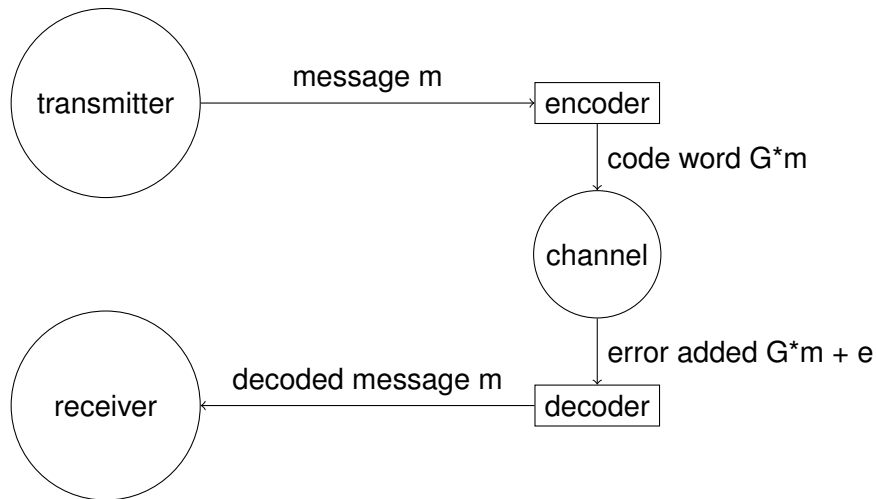


Figure: Binary symmetric channel

Communication system

- ▶ Redundancy is added at the encoder
- ▶ Error correction/detection at the receiver



LDPC codes

- ▶ Set of code words (C) is a subspace of $\{0, 1\}^N$
- ▶ Linear codes: $\forall c_1, c_2 \in C : c_1 + c_2 \in C$
- ▶ Parity check matrix $H \in \{0, 1\}^{K \times N}$: $H * c = 0 \quad \forall c \in C$
- ▶ Generator matrix $G \in \{0, 1\}^{N \times n}$: $G * m \in C \quad \forall m \in \{0, 1\}^n$
- ▶ Orthogonality property: $H * G = 0$
- ▶ LDPC codes: H is sparse

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

$$G = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 1 \\ 1 & 1 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Figure: An example of code-defining matrices

Examples

$$H * m = \begin{bmatrix} 1 & 1 & 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 & 1 & 1 \end{bmatrix} * \begin{bmatrix} 0 \\ 1 \\ 1 \\ 1 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

$$H * \hat{m} = \begin{bmatrix} 1 & 1 & 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 & 1 & 1 \end{bmatrix} * \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}$$

Decoding algorithms

- Optimal decoder
 - ▶ Find the closest code word
- Heuristics
 - ▶ Bit-flipping
 - ▶ Simulated annealing
- Linear programming
- Maximum a posteriori decoder
$$m = \operatorname{argmax}_{m \in C} P(m | \text{received_message})$$
 - ▶ Loopy BP
 - ? Tensor Train
 - ? Taylor

Tensor train

Tensor train and a bunch of formulas

- ▶ $m_i = \operatorname{argmax}_{m_i \in \{0,1\}} P(m_i|c)$
- ▶ $m_i = \operatorname{argmax}_{t \in \{0,1\}} \sum_{m:m_i=t} P(m|c)$
- ▶ $m_i = \operatorname{argmax}_{t \in \{0,1\}} \sum_{m:m_i=t} P(c|m)P(m)$

Tensor train and a bunch of formulas

- ▶ $m_i = \operatorname{argmax}_{m_i \in \{0,1\}} P(m_i|c)$
- ▶ $m_i = \operatorname{argmax}_{t \in \{0,1\}} \sum_{m:m_i=t} P(m|c)$
- ▶ $m_i = \operatorname{argmax}_{t \in \{0,1\}} \sum_{m:m_i=t} P(c|m)P(m)$
- ▶ $P(c|m) = \prod_{j=0}^N p^{m_j=c_j} (1-p)^{m_j \neq c_j}$
- ▶ $P(m) \propto 1\{H * m = 0\}(m)$
- ▶ $1\{H * m = 0\}[m_1, m_2, \dots, m_N] = \prod_{i=1}^K \psi_i[m_1, m_2, \dots, m_N]$
- ▶ $\psi_i[m_1, m_2, \dots, m_N]$ — is i^{th} constraint satisfied

TT cores

Invariant: after multiplying first k cores, an obtained value should be a vector $[0, 1]$ if partial parity sum is 0 and $[1, 0]$ otherwise

$$\psi_i[m_1, m_2, \dots, m_N] = [0, 1] * D_1^i[m_1] * D_2^i[m_2] * \dots * D_N^i[m_N] * [0, 1]^T$$

$$D_j^i[1] = \begin{cases} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, & H[i,j] = 0, \text{ no dependence on this bit} \\ \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, & H[i,j] = 1, \text{ parity should flip} \end{cases}$$

$$D_j^i[0] = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \text{ because 0 does not change parity}$$

Kronecker product

Kronecker product of an $M \times N$ matrix A and a $P \times Q$ matrix B is the following $MP \times NQ$ matrix C :

$$A \otimes B = C = \begin{bmatrix} a_{11}B & \dots & a_{1n}B \\ \vdots & \ddots & \vdots \\ a_{m1}B & \dots & a_{mn}B \end{bmatrix}$$

The Kronecker product is bilinear and associative. Also $(\mathbf{A} \otimes \mathbf{B})(\mathbf{C} \otimes \mathbf{D}) = (\mathbf{AC}) \otimes (\mathbf{BD})$.

TT meets Leopold Kronecker

$$\begin{aligned} 1\{H * m = 0\}[m_1, m_2, \dots, m_N] &= \prod_{i=1}^K \psi_i[m_1, \dots, m_N] \\ &= \otimes_{i=1}^K \psi_i[m_1, \dots, m_N] \\ &= \otimes_{i=1}^K \left(\prod_{j=1}^N D_j^i[m_j] \right) \\ &= \prod_{j=1}^N \left(\otimes_{i=1}^K D_j^i[m_j] \right) \end{aligned}$$

$$P(c|m) 1\{H * m = 0\}(m) = \prod_{j=1}^N \left(\otimes_{i=1}^K D_j^i[m_j] \right) \cdot \prod_{i=1}^N P(c_i|m_i) = \prod_{j=1}^N A_j[m_j]$$

$$A_j[m_j] = \left(\otimes_{i=1}^K D_j^i[m_j] \right) \cdot P(m_j|c_j) \in \{0, 1\}^{2^K \times 2^K}$$

TT formulas. The final

► $m_i = \operatorname{argmax}_{t \in \{0,1\}} \sum_{m:m_i=t} P(c|m) 1\{H * m = 0\}(m)$

$$m_i = \operatorname{argmax}_{m_i \in \{0,1\}} \sum_{m_1, \dots, m_{i-1}, m_{i+1}, \dots, m_N} \prod_{j=1}^N A_j[m_j]$$

$$m_i = \operatorname{argmax}_{m_i \in \{0,1\}} \prod_{j=1}^{i-1} (A_j[0] + A_j[1]) \cdot A_i[m_i] \cdot \prod_{j=i+1}^N (A_j[0] + A_j[1])$$

- Values of $A_1[m_1] * \dots * A_j[m_j]$ are stored in TT format with some upper bound on the maximum rank
- Final complexity: $O(N^2 r_{\max}^4)$

TT experiments

Errors before decoding:	0	1	2	3	4	5	6
$r_{\max} = 2$	0	11	19	9	17	13	17
$r_{\max} = 5$	0	4	10	15	11	17	15
$r_{\max} = 10$	0	0	10	21	16	13	17
$r_{\max} = 100$	0	0	0	0	0	8	11
$r_{\max} = 500$	0	0	0	0	0	2	7
$r_{\max} = 1000$	0	0	0	0	0	0	5

Code: $n = 9, N = 30$

Taylor

Taylor basics

- ▶ Energy $E(m) = -\log P(c|m) + \text{const} =$
$$\begin{cases} -\sum_{i=1}^N [(m_i \neq c_i) \log p + (m_i = c_i) \log(1 - p)], & \text{if } H^*m=0 \\ +\infty, & \text{otherwise} \end{cases}$$
- ▶ Interpret E as a variable ξ (m is random)
- ▶ $\xi_{i,t}$ in a similar way, but for E defined only on code words with $m_i = t$, $t \in \{0, 1\}$.

Characteristic function computation

$$1 \quad m_i = \operatorname{argmax}_{t \in \{0,1\}} \sum_{m:m_i=t, H*m=0} \exp\{-E(m)\} = \operatorname{argmax}_{t \in \{0,1\}} \mathbb{E} \exp\{-E(m)\} = \operatorname{argmax}_{t \in \{0,1\}} \phi_{\xi,t}(j)$$

▶ $\phi_{\xi}(j) = \mathbb{E} \exp(j^2 \xi) = \sum_{k=0}^{\infty} \frac{(-1)^k}{k!} \mathbb{E}[\xi^k]$

▶ Approximate by first T moments

$$2 \quad m_i = \log[\operatorname{argmax}_{t \in \{0,1\}} \sum_{m:m_i=t, H*m=0} \exp\{-E(m)\}] = \operatorname{argmax}_{t \in \{0,1\}} \log \phi_{\xi,t}(j)$$

▶ $\log \phi_{\xi}(j) = \sum_{k=0}^{\infty} \frac{(-1)^k}{k!} \kappa_k$

▶ Approximate by first T cumulants (analytically computed from moments)

Complexity of both variants: $O(N^T T)$

Taylor experiments (1)

Approximation by T moments

Errors before decoding:	0	1	2	3	4	5	6
T=1	0	1	2	3	4	5	6
T=2	0	1	2	3	4	5	6
T=3	0	1	2	3	4	5	6
T=4	0	1	2	3	4	5	6
T=5	0	0	0	0	0	0	0
T=6	0	0	0	0	0	0	0

Code: $n = 9, N = 30$

Taylor experiments (2)

Approximation by T cumulants

Errors before decoding:	0	1	2	3	4	5	6
T=1	0	1	2	3	4	5	6
T=2	0	1	2	3	4	5	6
T=3	0	1	2	3	4	5	6
T=4	0	0	0	0	3	3	2
T=5	0	0	0	0	0	0	0
T=6	0	0	0	0	0	0	0

Code: $n = 9, N = 30$

Conclusion

- ▶ Asymptotic convergence to MAP decoder
- ▶ Taylor is parallelizable
- ▶ Possible use of Taylor in pipeline of decoders
- ▶ No complexity dependence on sparsity