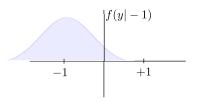
BP decoding of LDPC codes

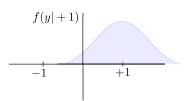
Introduction to Graphical Models and Inference for Communications ${\bf UC3M}$

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uc3m

Binary-input discrete AWGN (BIAWGN) channel





Assuming a uniform prior distribution $P(S=1)=P(S=-1)=\frac{1}{2}...$

$$P(S = 1|y) = \frac{f(y|1)}{f(y|1) + f(y|-1)}$$

Optimal decoder for the BIAWGN channel

LDPC codeword of n bits.

$$s = (s_1 \ s_2 \ \dots \ s_n)$$
 Vector of n encoded BPSK symbols.
 $y = (y_1 \ y_2 \ \dots \ y_n)$ Observation vector.

- Optimal LDPC decoder: bitwise-MAP decoder. For i = 1..., n,
 - Ompute

$$P(S_i = +1|\boldsymbol{y})$$

② If
$$P(S_i = +1|\mathbf{y}) > 0.5$$
, then $\hat{S}_i = 1$.

Baye's rule ...

$$P(\boldsymbol{S} = \boldsymbol{s}|\boldsymbol{y}) = \frac{f(\boldsymbol{y}|\boldsymbol{s})P(\boldsymbol{S} = \boldsymbol{s})}{f(\boldsymbol{y})}, \quad P(\boldsymbol{S} = \boldsymbol{s}) = \frac{1}{2^{\text{rn}}} \quad \forall \boldsymbol{s} \in \mathcal{C}, \qquad f(\boldsymbol{y}|\boldsymbol{s}) = \prod_{j=1}^{\text{n}} f(y_j|s_j)$$

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Therefore

$$P(S_i = 1|\mathbf{y}) = \sum_{\mathbf{s} \in C: s_i = 1} P(\mathbf{S} = \mathbf{s}|\mathbf{y})$$

$$= \frac{1}{f(\mathbf{y})} \frac{1}{2^{\text{rn}}} \sum_{\mathbf{s} \in C: s_i = 1} \prod_{j=1}^{n} f(y_j|s_j)$$

$$\propto \sum_{\mathbf{s} \in C: s_i = 1} \prod_{j=1}^{n} f(y_j|s_j)$$

Optimal decoder for the BIAWGN channel

$$P(S_i = 1|\boldsymbol{y}) \propto \sum_{\boldsymbol{s} \in \mathcal{C}: s_i = 1} \prod_{j=1}^n f(y_j|s_j) \qquad P(S_i = -1|\boldsymbol{y}) \propto \sum_{\boldsymbol{s} \in \mathcal{C}: s_i = -1} \prod_{j=1}^n f(y_j|s_j)$$

- The number of terms to be sum is roughly half of the codewords 2^{rn-1} .
- The decoding complexity grows exponentially fast with n.
- Prohibitive complexity for n ≥ 100!!

Approximate decoder for the BIAWGN channel

- Belief Propagation (BP) algorithm to approximate marginals!
- Message-Passing description.
- Complexity grows linearly with the code length n!
- At each iteration, variable nodes in the Tanner graph send a "belief" (estimated probability) to check nodes and check nodes recompute a belief for each variable node.
- We proceed in this way for a given number of iterations ℓ_{\max} .
- The associated factor graph is sparse, only contains very large cycles involving a large number of variables.
- BP estimates, based on local computations, are reasonably accurate.

Towards a BP formulation

$$P(S_i = 1|\mathbf{y}) \propto \sum_{\mathbf{s} \in \mathcal{C}: s_i = 1} \prod_{j=1}^n f(y_j|s_j)$$
$$= \sum_{\mathbf{s} \in \{0,1\}^n: s_i = 1} \prod_{j=1}^n f(y_j|s_j) \mathbb{1}[\mathbf{H}\mathbf{x} = \mathbf{0} \pmod{2}]$$

• $\mathbb{1}[Hx = 0 \pmod{2}]$ can be decomposed as follows

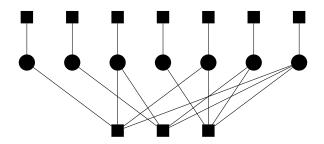
$$\prod_{q=1}^{k} \mathbb{1}[\boldsymbol{h}_q \boldsymbol{x} = 0]$$

where h_q is the q-th row of H and k is the number of rows.

$$P(S_i = 1|\mathbf{y}) \propto \sum_{\mathbf{s} \in \{0,1\}^n: s_i = 1} \prod_{j=1}^n f(y_j|s_j) \prod_{q=1}^k \mathbb{1}[\mathbf{h}_q \mathbf{x} = 0]$$

The LDPC Tanner graph

$$P(\boldsymbol{S} = \boldsymbol{s}|\boldsymbol{y}) \propto \prod_{j=1}^{n} f(y_j|s_j) \prod_{q=1}^{k} \mathbb{1}[\boldsymbol{h}_q \boldsymbol{x} = 0]$$



From here you already know how to implement a BP decoder.

Excersise

Show that the BP message passing rules for binary LDPC codes can be simplified to the following experessions.

Update rule at variable nodes

Variable with K+1 neighbours sends a message to neighbour K+1:

$$l_{K+1} = \sum_{k=1}^{K} l_k,$$

where l_j , j = 1, ..., K + 1 are real scalars.

Update rule at parity check nodes

Factor with J+1 neighbours sends a message to neighbour J+1:

$$l_{J+1} = 2\tanh^{-1}\left(\prod_{j=1}^{J}\tanh(l_j/2)\right)$$

where l_i , j = 1, ..., J + 1 are real scalars.