

ECE 443: Turbo Codes

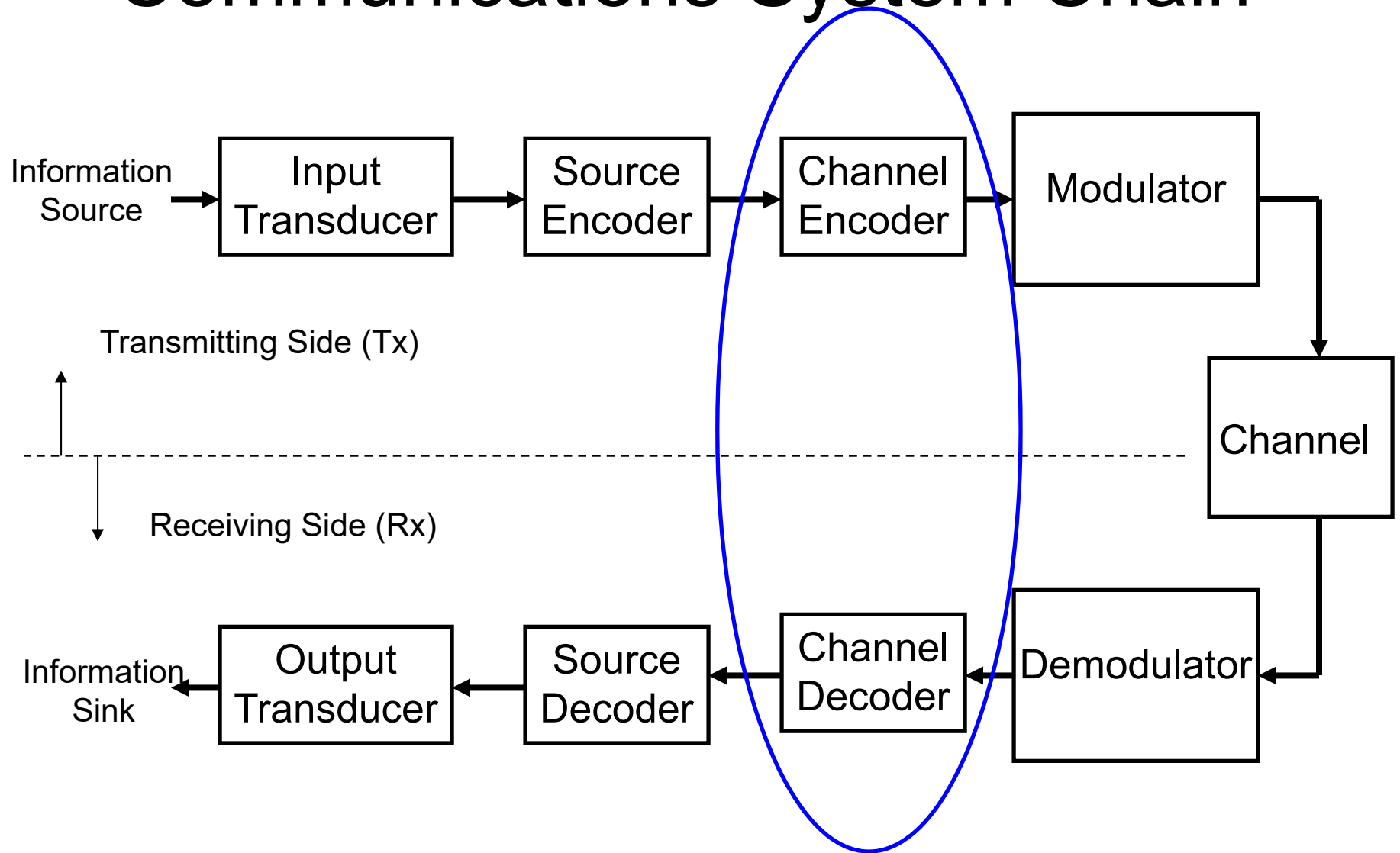
An Approximation Approach for Probabilistic Modeling

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Lecture Objectives

- So far, exact inference using probabilistic models
 - IID, Markov Models
 - HMMs and SCFGs
- Exact inference sometimes too hard
- Approx. often provides an excellent alternative
 - Example: Turbo Codes
 - Builds upon our example of Convolutional codes and HMM decoding

Channel Coding in the Communications System Chain



Recall: Convolutional Codes

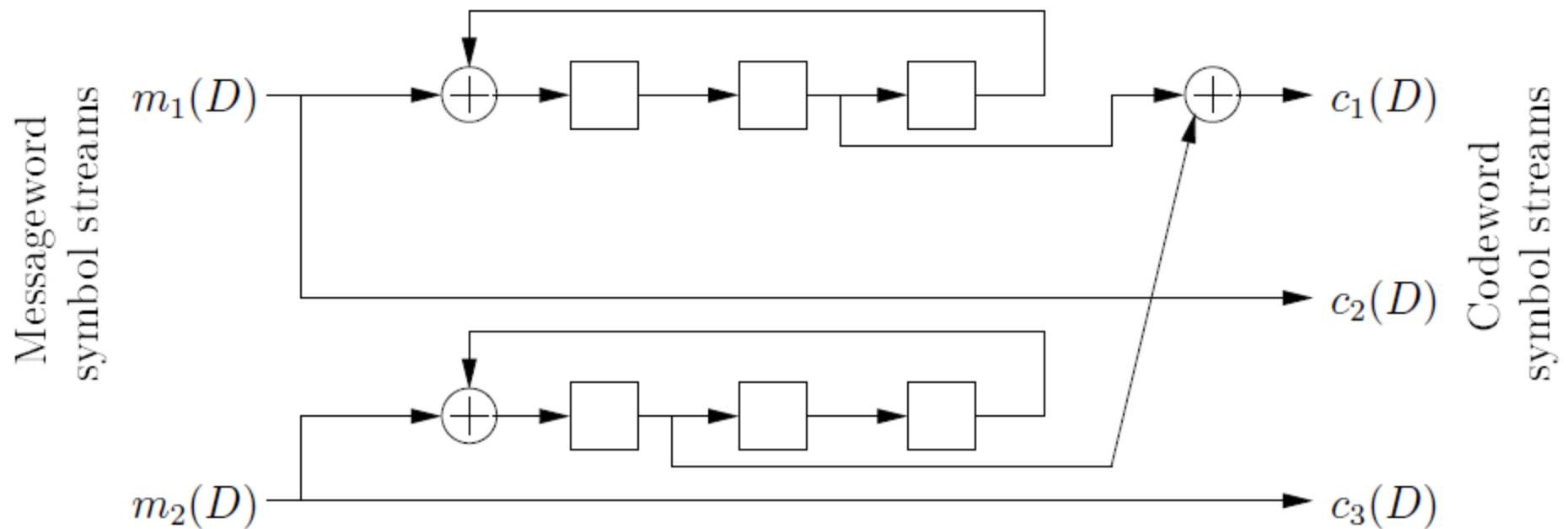
- Systems view
 - k-input, n-output, linear shift invariant system
- State space view
 - Finite state causal system
- Prior discussion emphasizes state space view and HMM based decoding
 - Viterbi (most likely state sequence)
 - Symbol-by-symbol MAP

Systematic Convolutional Encoders

- Analogous to systematic encoders for block codes
 - Input bits occur directly in the encoded stream
- Advantages:
 - Decoder can output hard decision symbol values when decoding fails
 - Useful in iterative decoding/concatenated coding (have reliability estimates for the message symbols)

A Recursive Systematic Convolutional Encoder

- A (2,3) Recursive Systematic Convolutional Encoder



$$\mathbf{G} = \begin{bmatrix} \frac{D^2}{1+D^3} & 1 & 0 \\ \frac{D}{1+D^3} & 0 & 1 \end{bmatrix}$$

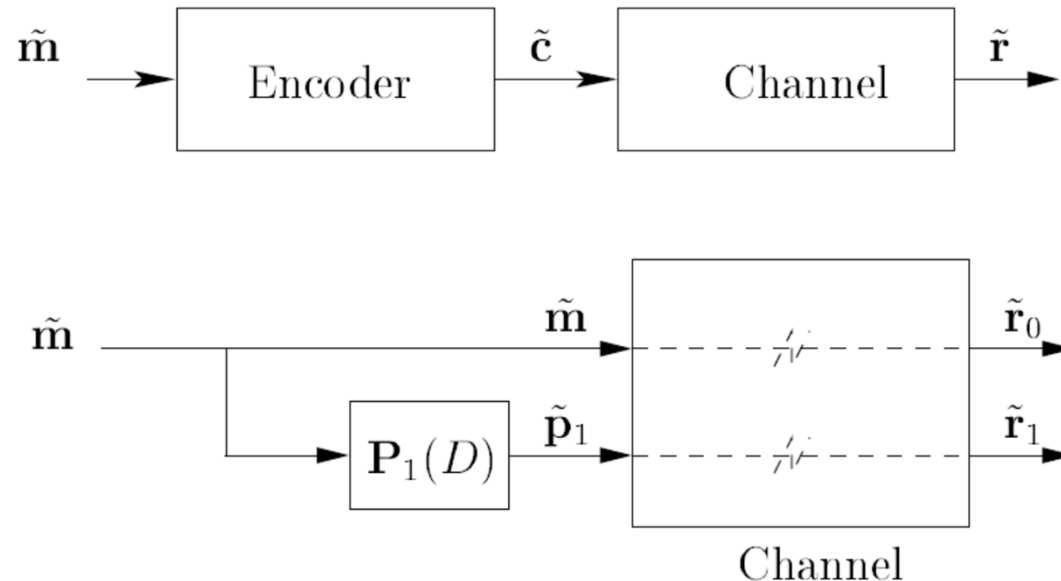
Convolutional Codes: Decoding Context

- Receiver seeks to estimate transmitted message stream based on received stream



Recursive Systematic Convolutional Codes: Decoding Context

- Receiver seeks to estimate transmitted message stream based on received stream



MAP Decoding of Convolutional Codes: Formulation

- Start with initial state 00
- L successive messageword frames

$$= \mathbf{m}^{(0)}, \mathbf{m}^{(1)}, \dots, \mathbf{m}^{(L-1)}$$

- Corresponding codeword frames

$$= \mathbf{c}^{(0)}, \mathbf{c}^{(1)}, \dots, \mathbf{c}^{(L-1)}$$

- and receivedword frames

$$\tilde{\mathbf{r}}_{(0)}^{(L-1)} = \mathbf{r}^{(0)}, \mathbf{r}^{(1)}, \dots, \mathbf{r}^{(L-1)}$$

$$\hat{\mathbf{m}}^{(l)} = \arg \max_{\mathbf{m}} p \left(\mathbf{m}^{(l)} = \mathbf{m} \mid \tilde{\mathbf{r}}_{(0)}^{(L-1)} \right)$$

Recall: MAP Decoding of Convolutional Codes

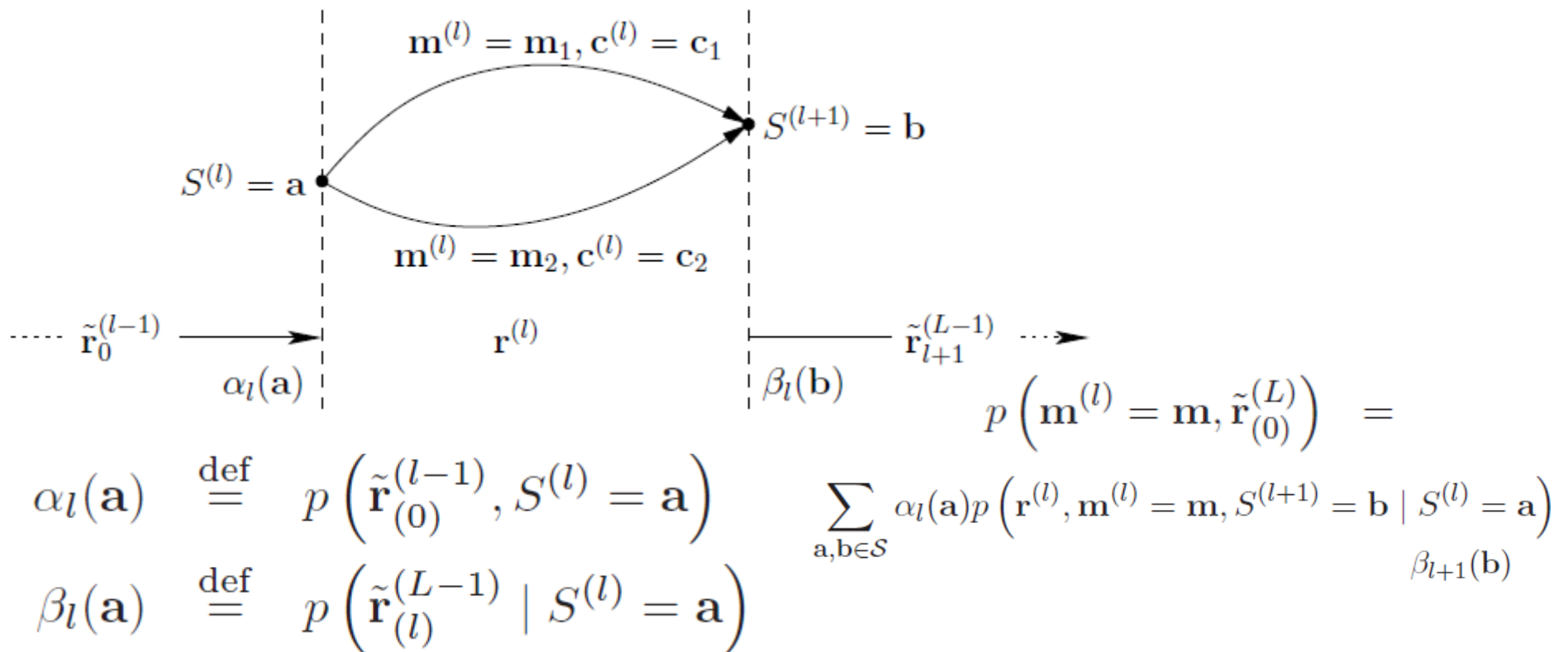
- MAP Decoding requires posterior probabilities

$$p\left(\mathbf{m}^{(l)} = \mathbf{a}, \tilde{\mathbf{r}}_{(0)}^{(L-1)}\right)$$

- Computed efficiently using forward-backward algorithm on code trellis
 - Can also incorporate prior probabilities for independent message words

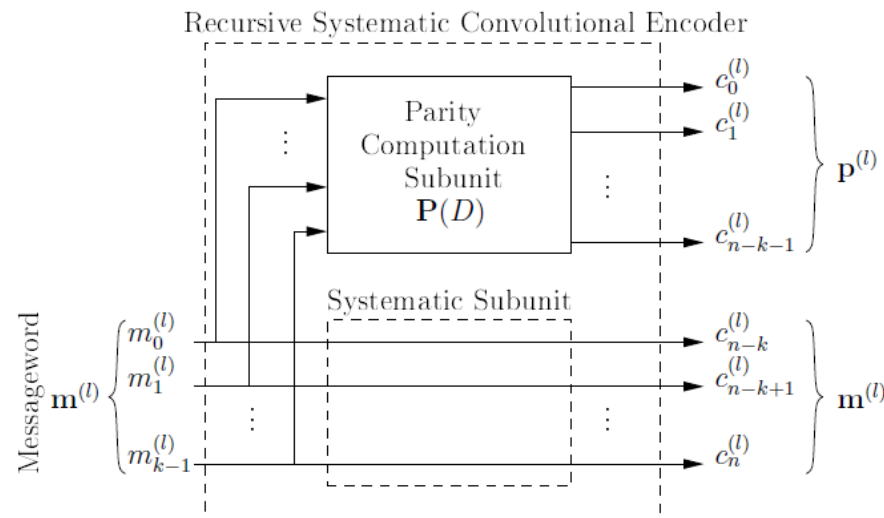
MAP Decoding

- Dynamic programming analogous to ML decoding: forward-backward/BCJR Algo

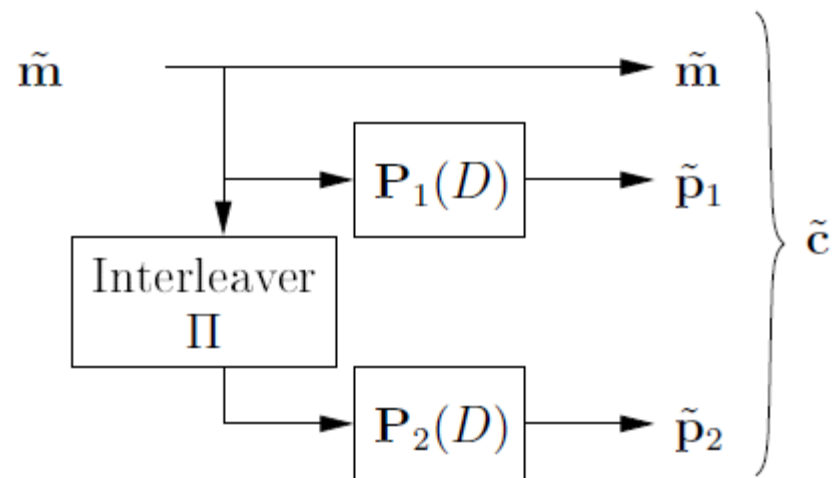
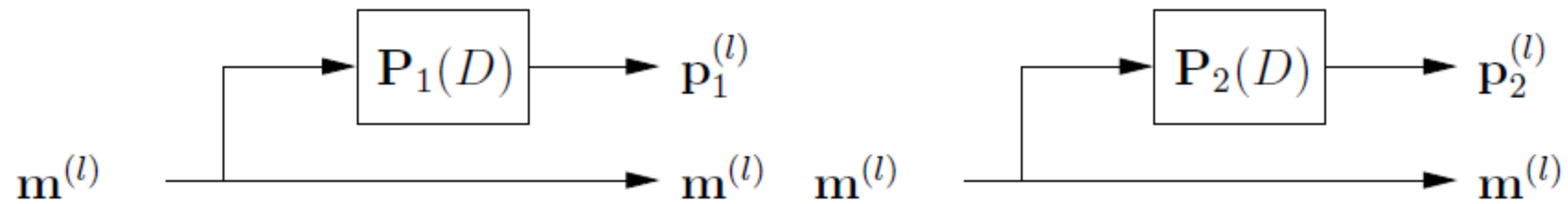


Turbo Codes

- Actually, “Turbo-Decoding” is the innovation rather than the code
- Built out of (parallel) concatenation of convolutional encoders with interleaver

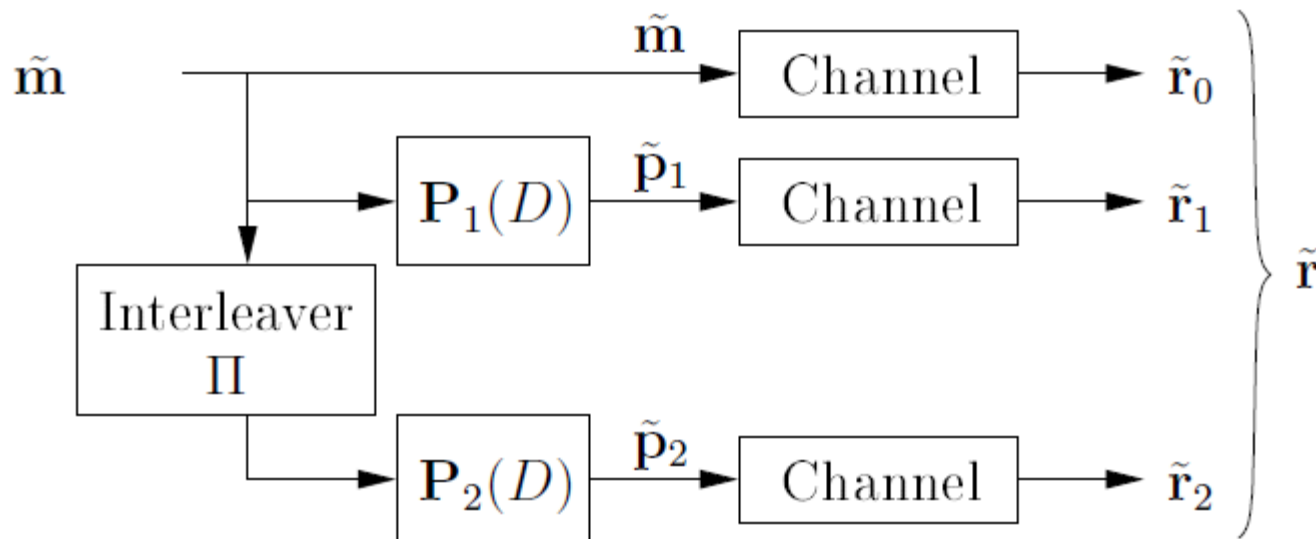


Turbo Codes: Encoding



Turbo Code: Decoding

- Joint decoding gives benefit of amortizing redundancy over large interleaver block length
 - Computationally horrendous



Exact MAP Decoding

- MAP Value of a symbol

$$\hat{\mathbf{m}}^{(l)} = \arg \max_{\mathbf{m}} p \left(\mathbf{m}^{(l)} = \mathbf{m} \mid \tilde{\mathbf{r}} \right)$$

- Baye's Rule

$$\begin{aligned} \hat{\mathbf{m}}^{(l)} &= \arg \max_{\mathbf{m}} \frac{p \left(\mathbf{m}^{(l)} = \mathbf{m}, \tilde{\mathbf{r}} \right)}{p \left(\tilde{\mathbf{r}} \right)} \\ &= \arg \max_{\mathbf{m}} p \left(\mathbf{m}^{(l)} = \mathbf{m}, \tilde{\mathbf{r}} \right) \end{aligned}$$

Exact MAP Decoding

- MAP Probabilities
 - Recall Trellis HMM for convolutional codes

$$\begin{aligned} p\left(\mathbf{m}^{(l)} = \mathbf{m}, \tilde{\mathbf{r}}\right) &= \sum_{\{\tilde{\mathbf{m}}: \mathbf{m}^{(l)} = \mathbf{m}\}} p(\tilde{\mathbf{m}}, \tilde{\mathbf{r}}) \\ &= \sum_{\{\tilde{\mathbf{m}}: \mathbf{m}^{(l)} = \mathbf{m}\}} p(\tilde{\mathbf{r}} \mid \tilde{\mathbf{m}}) p(\tilde{\mathbf{m}}) \\ &= \sum_{\{\tilde{\mathbf{m}}: \mathbf{m}^{(l)} = \mathbf{m}\}} p(\tilde{\mathbf{r}}_0, \tilde{\mathbf{r}}_1, \tilde{\mathbf{r}}_2 \mid \tilde{\mathbf{m}}) p(\tilde{\mathbf{m}}) \\ &= \sum_{\{\tilde{\mathbf{m}}: \mathbf{m}^{(l)} = \mathbf{m}\}} p(\tilde{\mathbf{r}}_0 \mid \tilde{\mathbf{m}}) p(\tilde{\mathbf{r}}_1 \mid \tilde{\mathbf{m}}) p(\tilde{\mathbf{r}}_2 \mid \tilde{\mathbf{m}}) p(\tilde{\mathbf{m}}) \end{aligned}$$

Exact MAP Decoding

- IID message symbols

$$p(\mathbf{m}^{(l)} = \mathbf{m}, \tilde{\mathbf{r}}) = \sum_{\{\tilde{\mathbf{m}}: \mathbf{m}^{(l)} = \mathbf{m}\}} p(\tilde{\mathbf{r}}_0 | \tilde{\mathbf{m}}) p(\tilde{\mathbf{r}}_1 | \tilde{\mathbf{m}}) p(\tilde{\mathbf{r}}_2 | \tilde{\mathbf{m}}) \prod_{i=0}^{L-1} p(\mathbf{m}^{(i)})$$

- Two interpretations:

- First code term $p(\tilde{\mathbf{r}}_0 | \tilde{\mathbf{m}}) p(\tilde{\mathbf{r}}_1 | \tilde{\mathbf{m}}) \prod_{i=0}^{L-1} p(\mathbf{m}^{(i)})$
 - Multiplied by additional $p(\tilde{\mathbf{r}}_2 | \tilde{\mathbf{m}})$
- Vice versa

Approximation I

- For first decoder approximate

$$p(\tilde{\mathbf{r}}_2 \mid \tilde{\mathbf{m}}) \approx \prod_{j=0}^{L-1} T_j(\mathbf{m}^{(j)})$$

- For second decoder approximate

$$p(\tilde{\mathbf{r}}_1 \mid \tilde{\mathbf{m}}) \approx \prod_{j=0}^{L-1} U_j(\mathbf{m}^{(j)})$$

Approximation II

- Two alternate expansions for $p(\mathbf{m}^{(l)} = \mathbf{m}, \tilde{\mathbf{r}})$

$$\begin{aligned}
 p(\mathbf{m}^{(l)} = \mathbf{m}, \tilde{\mathbf{r}}) &= \sum_{\{\tilde{\mathbf{m}}: \mathbf{m}^{(l)} = \mathbf{m}\}} p(\tilde{\mathbf{r}}_0 | \tilde{\mathbf{m}}) p(\tilde{\mathbf{r}}_1 | \tilde{\mathbf{m}}) \prod_{j=0}^{L-1} T_j(\mathbf{m}^{(j)}) \prod_{i=0}^{L-1} p(\mathbf{m}^{(i)}) \\
 &= \sum_{\{\tilde{\mathbf{m}}: \mathbf{m}^{(l)} = \mathbf{m}\}} p(\tilde{\mathbf{r}}_0 | \tilde{\mathbf{m}}) p(\tilde{\mathbf{r}}_1 | \tilde{\mathbf{m}}) \prod_{i=0}^{L-1} (T_i(\mathbf{m}^{(i)}) p(\mathbf{m}^{(i)})) \\
 p(\mathbf{m}^{(l)} = \mathbf{m}, \tilde{\mathbf{r}}) &= \sum_{\{\tilde{\mathbf{m}}: \mathbf{m}^{(l)} = \mathbf{m}\}} p(\tilde{\mathbf{r}}_0 | \tilde{\mathbf{m}}) p(\tilde{\mathbf{r}}_2 | \tilde{\mathbf{m}}) \prod_{j=0}^{L-1} U_j(\mathbf{m}^{(j)}) \prod_{i=0}^{L-1} p(\mathbf{m}^{(i)}) \\
 &= \sum_{\{\tilde{\mathbf{m}}: \mathbf{m}^{(l)} = \mathbf{m}\}} p(\tilde{\mathbf{r}}_0 | \tilde{\mathbf{m}}) p(\tilde{\mathbf{r}}_2 | \tilde{\mathbf{m}}) \prod_{i=0}^{L-1} (U_i(\mathbf{m}^{(i)}) p(\mathbf{m}^{(i)}))
 \end{aligned}$$

Approximation III

- Rearrangement of alternate expansions

$$\begin{aligned}
 p\left(\mathbf{m}^{(l)} = \mathbf{m}, \tilde{\mathbf{r}}\right) &= \sum_{\{\tilde{\mathbf{m}}: \mathbf{m}^{(l)} = \mathbf{m}\}} p\left(\tilde{\mathbf{r}}_1 \mid \tilde{\mathbf{m}}\right) \prod_{i=0}^{L-1} \left(p\left(\mathbf{r}_0^{(i)} \mid \mathbf{m}^{(i)}\right) T_i\left(\mathbf{m}^{(i)}\right) p\left(\mathbf{m}^{(i)}\right) \right) \\
 &= p\left(\mathbf{r}_0^{(l)} \mid \mathbf{m}^{(l)} = \mathbf{m}\right) T_l(\mathbf{m}) \mathcal{P}\left(\mathbf{m}^{(l)} = \mathbf{m}\right) \times \\
 &\quad \left[\sum_{\{\tilde{\mathbf{m}}: \mathbf{m}^{(l)} = \mathbf{m}\}} p\left(\tilde{\mathbf{r}}_1 \mid \tilde{\mathbf{m}}\right) \prod_{\substack{i=0 \\ i \neq l}}^{L-1} \left(p\left(\mathbf{r}_0^{(i)} \mid \mathbf{m}^{(i)}\right) T_i\left(\mathbf{m}^{(i)}\right) p\left(\mathbf{m}^{(i)}\right) \right) \right] \\
 p\left(\mathbf{m}^{(l)} = \mathbf{m}, \tilde{\mathbf{r}}\right) &= \sum_{\{\tilde{\mathbf{m}}: \mathbf{m}^{(l)} = \mathbf{m}\}} \prod_{j=0}^{L-1} p\left(\mathbf{r}_0^{(j)} \mid \mathbf{m}^{(j)}\right) p\left(\tilde{\mathbf{r}}_2 \mid \tilde{\mathbf{m}}\right) \prod_{i=0}^{L-1} \left(U_i\left(\mathbf{m}^{(i)}\right) p\left(\mathbf{m}^{(i)}\right) \right) \\
 &= p\left(\mathbf{r}_0^{(l)} \mid \mathbf{m}^{(l)} = \mathbf{m}\right) U_l(\mathbf{m}) \mathcal{P}\left(\mathbf{m}^{(l)} = \mathbf{m}\right) \times \\
 &\quad \left[\sum_{\{\tilde{\mathbf{m}}: \mathbf{m}^{(l)} = \mathbf{m}\}} p\left(\tilde{\mathbf{r}}_2 \mid \tilde{\mathbf{m}}\right) \prod_{\substack{i=0 \\ i \neq l}}^{L-1} \left(p\left(\mathbf{r}_0^{(i)} \mid \mathbf{m}^{(i)}\right) U_i\left(\mathbf{m}^{(i)}\right) p\left(\mathbf{m}^{(i)}\right) \right) \right].
 \end{aligned}$$

Approximation IV

- Two representations coincide when

$$T_l(\mathbf{m}) = \sum_{\{\tilde{\mathbf{m}}: \mathbf{m}^{(l)} = \mathbf{m}\}} p(\tilde{\mathbf{r}}_2 | \tilde{\mathbf{m}}) \prod_{\substack{i=0 \\ i \neq l}}^{L-1} p(\mathbf{r}_0^{(i)} | \mathbf{m}^{(i)}) U_i(\mathbf{m}^{(i)}) p(\mathbf{m}^{(i)})$$

$$U_l(\mathbf{m}) = \sum_{\{\tilde{\mathbf{m}}: \mathbf{m}^{(l)} = \mathbf{m}\}} p(\tilde{\mathbf{r}}_1 | \tilde{\mathbf{m}}) \prod_{\substack{i=0 \\ i \neq l}}^{L-1} p(\mathbf{r}_0^{(i)} | \mathbf{m}^{(j)}) T_i(\mathbf{m}^{(i)}) p(\mathbf{m}^{(i)})$$

- Want joint solutions to these systems of equations: Iterative method – Turbo iteration

Iterative Solution on Trellises

- The “extrinsic information” terms

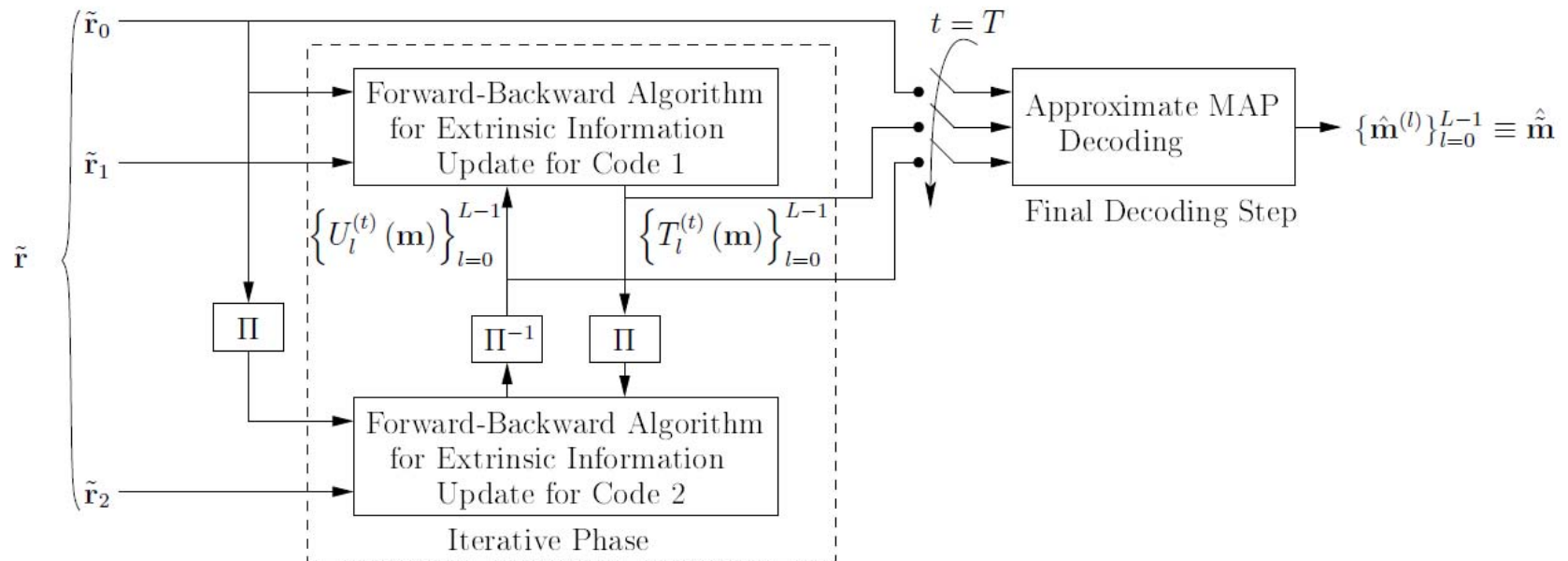
$$T_l(\mathbf{m}) = \sum_{\{\tilde{\mathbf{m}}: \mathbf{m}^{(l)} = \mathbf{m}\}} p(\tilde{\mathbf{r}}_2 | \tilde{\mathbf{m}}) \prod_{\substack{i=0 \\ i \neq l}}^{L-1} p(\mathbf{r}_0^{(i)} | \mathbf{m}^{(i)}) U_i(\mathbf{m}^{(i)}) p(\mathbf{m}^{(i)})$$

$$U_l(\mathbf{m}) = \sum_{\{\tilde{\mathbf{m}}: \mathbf{m}^{(l)} = \mathbf{m}\}} p(\tilde{\mathbf{r}}_1 | \tilde{\mathbf{m}}) \prod_{\substack{i=0 \\ i \neq l}}^{L-1} p(\mathbf{r}_0^{(i)} | \mathbf{m}^{(i)}) T_i(\mathbf{m}^{(i)}) p(\mathbf{m}^{(i)})$$

- Efficiently computed on individual code trellises
 - Modified BCJR (pseudo prior extrinsic information and exclusion of $i=l$ term)

Turbo Code: Decoding

- Approx. MAP decoding: Iterate individual decodings with feedback
 - Per iteration complexity = BCJR
 - Performance close to joint decoding



Turbo Decoding as an Approximation

- A posterior probabilities

$$p\left(\mathbf{m}^{(l)} = \mathbf{m}, \tilde{\mathbf{r}}\right) = \sum_{\{\tilde{\mathbf{m}}: \mathbf{m}^{(l)} = \mathbf{m}\}} p(\tilde{\mathbf{r}}_0 | \tilde{\mathbf{m}}) p(\tilde{\mathbf{r}}_1 | \tilde{\mathbf{m}}) p(\tilde{\mathbf{r}}_2 | \tilde{\mathbf{m}}) p(\tilde{\mathbf{m}})$$

- Prior probabilities

$$p(\tilde{\mathbf{m}}) = \prod_{i=0}^{L-1} p(\mathbf{m}^{(i)})$$

- Separable approximations (long interleaver)
 - Incorporated in BCJR as “pseudo-prior” probs.

$$p(\tilde{\mathbf{r}}_2 | \tilde{\mathbf{m}}) \approx \prod_{j=0}^{L-1} T_j(\mathbf{m}^{(j)}) \quad p(\tilde{\mathbf{r}}_1 | \tilde{\mathbf{m}}) \approx \prod_{j=0}^{L-1} U_j(\mathbf{m}^{(j)})$$

Turbo Decoding Algo. Overview

- Use modified BCJR to update extrinsic information for each component convolutional code
 - Use output extrinsic information from other decoder as “pseudo-prior” probabilities
- Iterate between the two decoders
 - Interleave/de-interleave as required
- Once iterations done, compute approximate *a posteriori* probabilities and decode

Turbo Decoding Algorithm

- Inputs: Received-word streams $\tilde{\mathbf{r}} = (\tilde{\mathbf{r}}_0, \tilde{\mathbf{r}}_1, \tilde{\mathbf{r}}_2)$
 – Messageword prior probabilities $\mathcal{P}(\mathbf{m}^{(l)} = \mathbf{m})$

- Initialization: $t = 0$

$$T_l^{(t)}(\mathbf{m}) = 1, \quad l = 0, 2, \dots (L-1), \forall \mathbf{m} \in F^k$$

- Extrinsic information updates (Modif. BCJR)

$$U_l^{(t)}(\mathbf{m}) = \sum_{\{\tilde{\mathbf{m}}: \mathbf{m}^{(l)} = \mathbf{m}\}} p(\tilde{\mathbf{r}}_1 | \tilde{\mathbf{m}}) \prod_{\substack{i=0 \\ i \neq l}}^{L-1} p(\mathbf{r}_0^{(i)} | \mathbf{m}^{(i)}) T_i^{(t-1)}(\mathbf{m}^{(i)}) p(\mathbf{m}^{(i)})$$

$$T_l^{(t)}(\mathbf{m}) = \sum_{\{\tilde{\mathbf{m}}: \mathbf{m}^{(l)} = \mathbf{m}\}} p(\tilde{\mathbf{r}}_2 | \tilde{\mathbf{m}}) \prod_{\substack{i=0 \\ i \neq l}}^{L-1} p(\mathbf{r}_0^{(i)} | \mathbf{m}^{(i)}) U_i^{(t)}(\mathbf{m}^{(i)}) p(\mathbf{m}^{(i)})$$

Turbo Decoding Algorithm (Contd.)

- Symbol-by-symbol decoding
 - Compute approximate posterior probabilities

$$\hat{p}(\mathbf{m}^{(l)} = \mathbf{m}, \tilde{\mathbf{r}}) = p(\mathbf{r}_0^{(l)} | \mathbf{m}^{(l)} = \mathbf{m}) T_l^{(T)}(\mathbf{m}) \mathcal{P}(\mathbf{m}^{(l)} = \mathbf{m}) U_l^{(T)}(\mathbf{m})$$

- Max approx. a posteriori prob decoding

$$\begin{aligned} \hat{\mathbf{m}}^{(l)} &= \arg \max_{\mathbf{m}} \hat{p}(\mathbf{m}^{(l)} = \mathbf{m}, \tilde{\mathbf{r}}) \\ &= \arg \max_{\mathbf{m}} p(\mathbf{r}_0^{(l)} | \mathbf{m}^{(l)} = \mathbf{m}) \mathcal{P}(\mathbf{m}^{(l)} = \mathbf{m}) T_l^{(T)}(\mathbf{m}) U_l^{(T)}(\mathbf{m}) \end{aligned}$$

Turbo Decoding: Observations

- Approximate Decomposition of problem of inference on complete data into
 - Two problems that are “loosely” coupled together by the exchange of “extrinsic” information: **local probabilistic information**
 - Individual problems are tightly coupled (trellis computation)
- Computation of local probabilistic information via (modified) BCJR (forward-backward) is critical
 - Not immediately obvious for Viterbi decoding

Turbo Code Performance Example

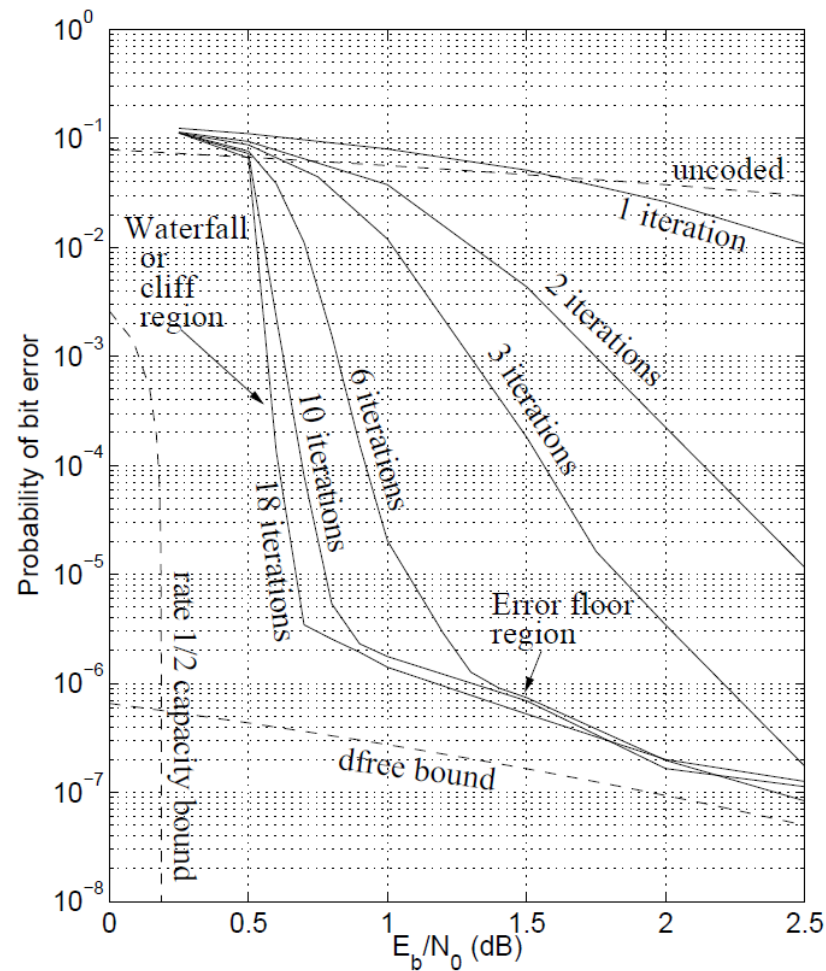


Figure 14.1: Decoding results for a (37,21,65536) code

From ECC, Todd Moon

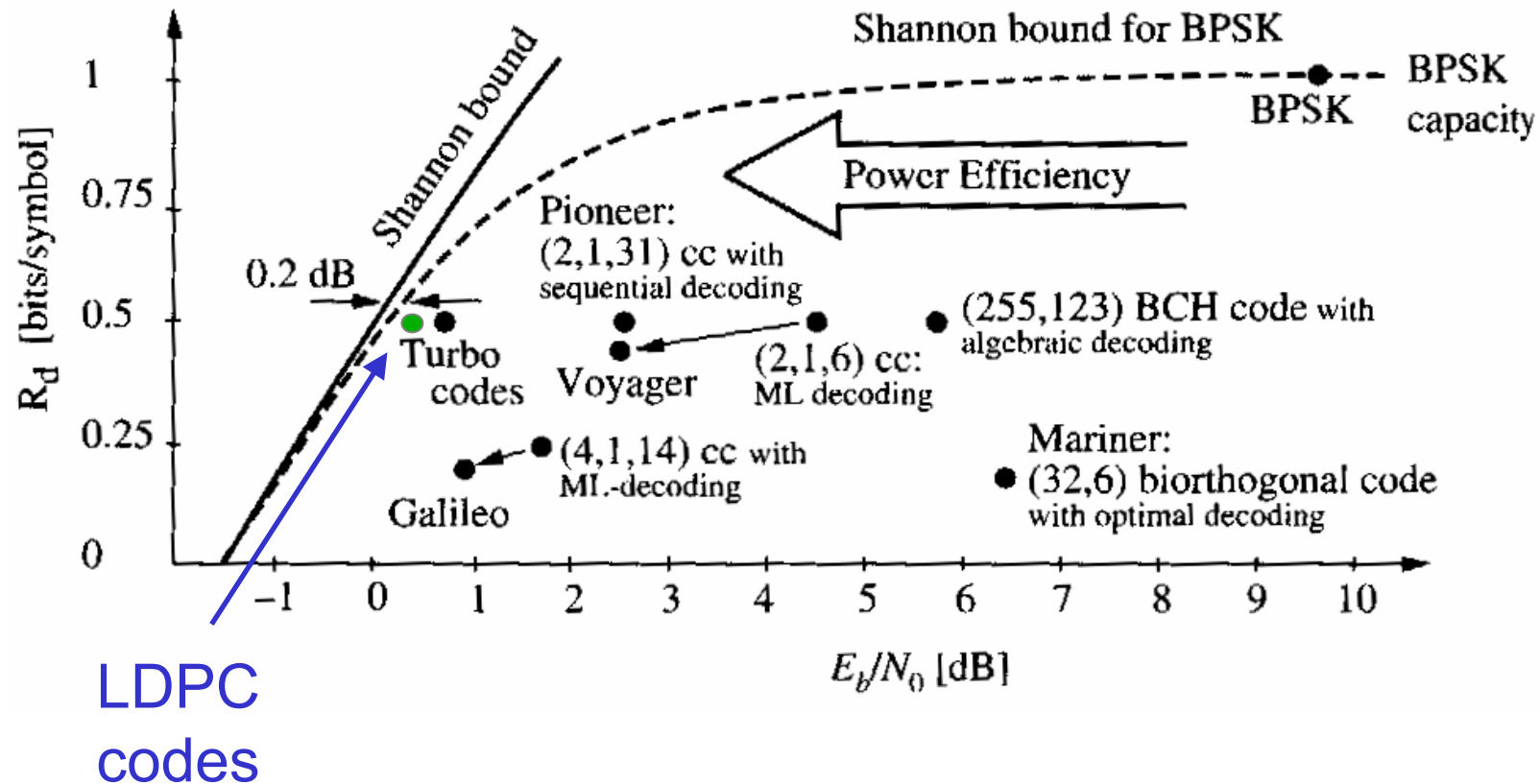
Turbo Code Performance

- Performance within a fraction of a dB of the capacity is achievable using turbo codes
 - Long interleaver lengths
 - Large number of iterations
 - Methods for determining when to terminate (e.g. cross-entropy)
- Practical applications pose restrictions
- Often concatenated with an outer algebraic code to correct residual error floors

Turbo Code Use

- Space
 - Mars Orbiter, Cassini (launched 1997), ...
- 3G/4G Mobile Telephony Standards
 - HSPA, EV-DO and LTE
- IEEE Wireless Standards
 - IEEE 802.16 (WiMAX)
- Digital Video Broadcasting - Return Channel via Satellite (DVB-RCS)

Coding in the Power-limited Domain



Source: Trellis and Turbo Coding, Schlegel and Perez, IEEE Press, 2004

Summary

- Example of Approximate Inference using Probabilistic Models
 - Turbo Codes
 - Exact MAP estimation would be exponential in interleaver length and is computationally infeasible
 - Approximation saves the day
 - “Linear complexity”
 - Rather small performance compromise
 - Performance quite close to theoretical limit (capacity)