Source coding with side information and uncertain correlation knowledge

Elsa Dupraz

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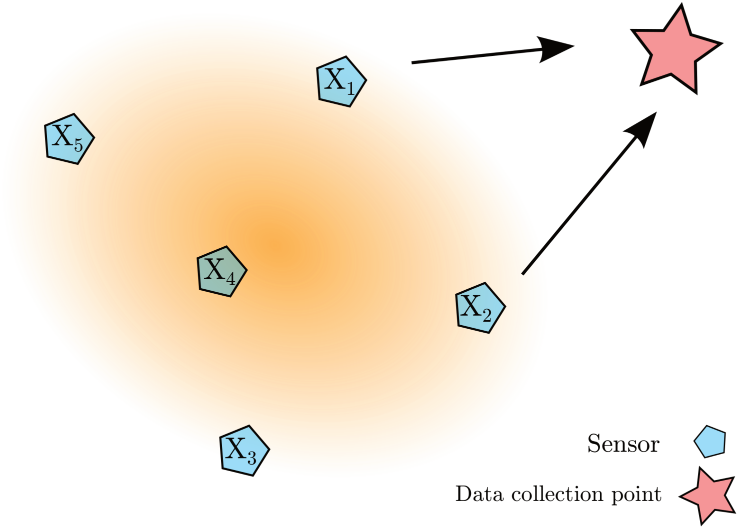
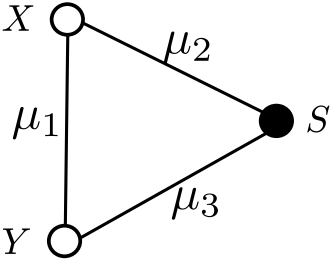
PhD defense 03/12/2012

Sensor networks



Two sensors, 1 collection point

Two sources: $(X, Y) \sim P(X, Y)$
Transmission cost of R on link i : $\mu_i R$ [CBLV05]



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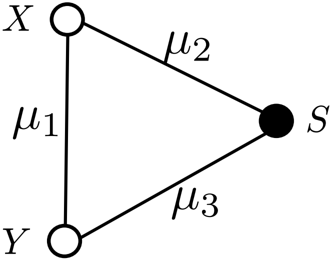
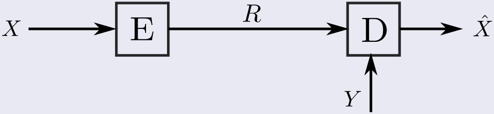


Context

$P(X, Y)$ not perfectly known

The source coding problem



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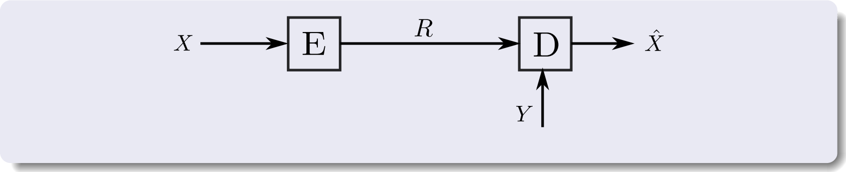


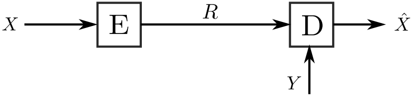
In this work

- $P(Y|X)$ partly unknown to both encoder and decoder
- No feedback [AZG02, YH10]

Objectives

- Performance analysis
- Efficient coding schemes robust to uncertainty on $P(Y|X)$

2. Non-binary LDPC codes
    - Non-binary LDPC codes for SW coding
    - Density evolution for SW coding



Coding scheme for the lossless case
$P(X, Y)$ perfectly known, X in GF(q)

Non-binary LDPC codes for SW coding [LFK09, LXG02]

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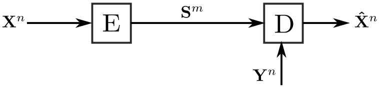

Encoding in GF(q) ($m < n$)

$$\mathbf{s}^m = H^T \mathbf{x}^n$$

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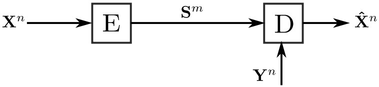

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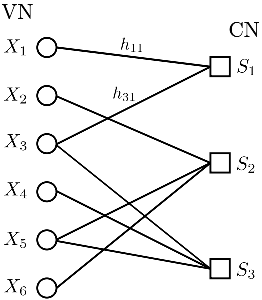
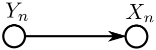


MAP decoding of $\mathbf{x}^n$ from $\mathbf{s}^m$ and $\mathbf{y}^n$

$$\hat{x}_n = \arg \max_{k \in \mathrm{GF}(q)} P(X_n = k | Y_n = y_n, \mathbf{s}^m)$$

LDPC decoding [LFK09, LXG02]

- Initial messages $\mathbf{m}_n^{(0)} \in \mathbb{R}^q$



$$m_{n,k}^{(0)} = \log \frac{P(X_n = 0 | Y_n = y_n)}{P(X_n = k | Y_n = y_n)}$$

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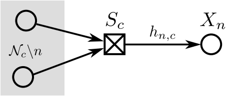
- Messages from CN to VN



$$\mathbf{m}_{c \to n}^{(\ell)} = \mathscr{A}[\overline{s}_c]\mathscr{F}^{-1}\left(\prod_{n' \in \mathcal{N}_c \backslash n} \mathscr{F}\left(W\left[\overline{h}_{n',c}\right]\mathbf{m}_{n' \to c}^{(\ell-1)}\right)\right)$$

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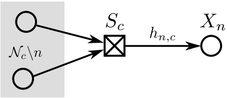

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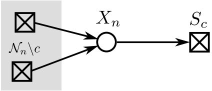
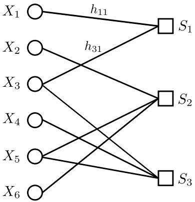


$$\mathbf{m}_{n\to c}^{(\ell)} = \sum_{c'\in\mathcal{N}_n\backslash c}\mathbf{m}_{c'\to n}^{(\ell)} + \mathbf{m}_n^{(0)}$$

Practical scheme

2 Non-binary LDPC codes
- Non-binary LDPC codes for SW coding
- Density evolution for SW coding

Code degree distributions [RSU01]



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Degree distributions for H

$\lambda(x) = \sum_{i\geq 2} \lambda_i x^{i-1}$,
$\rho(x) = \sum_{i\geq 2} \rho_i x^{i-1}$

$$r(\lambda, \rho) = \frac{\sum_{i\geq 2} \lambda_i / i}{\sum_{i\geq 2} \rho_j / j}$$

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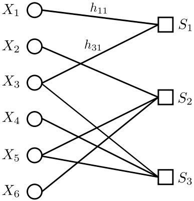

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$(\lambda(x), \rho(x))$ need to be optimized

Principle of density evolution [BB06, LFK09]

- Messages represented by random variables

$$(\mathbf{M}_n^{(0)}|X_n = k) \sim P_k{}^{(0)}, \;\; (\mathbf{M}_{c\to n}^{(\ell)}|X_n = k) \sim P_k{}^{(\ell)}, \;\; (\mathbf{M}_{n\to c}^{(\ell)}|X_n = k) \sim Q_k{}^{(\ell)}$$

cycle-free assumption: independent random variables

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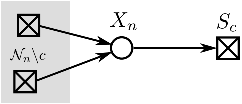
cycle-free assumption: independent random variables

Example: from VN to CN



$$\mathbf{m}_{n\to c}^{(\ell)}=\sum_{c'\in\mathcal{N}_n\backslash c}\mathbf{m}_{c'\to n}^{(\ell)}+\mathbf{m}_n^{(0)}$$

$${P_k}^{(\ell)}=\sum_{i\le 2}\lambda_i\left({P_k}^{(0)}\otimes\left({Q_k}^{(\ell-1)}\right)^{\otimes(i-1)}\right)$$

Then $P_e^{(\ell)}(\lambda,\rho)$ from $P_k^{(\ell)}$ and $Q_k^{(\ell)}$

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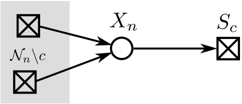

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Then $P_e^{(\ell)}(\lambda,\rho)$ from $P_k^{(\ell)}$ and $Q_k^{(\ell)}$

Problem: the probabilities depend on the input codeword

Symmetric channel

Symmetry (X, Y in GF(q))[1]

$P(Y|X)$ is symmetric if there exists a bijective function $h : GF(q) \rightarrow GF(q)$ s.t.

$$P(Y = y|X = x) = P(Y = h^{-1}(h(y) \oplus x)|X = 0)$$

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[1] Elsa Dupraz, Valentin Savin, Aline Roumy, Michel Kieffer *Density Evolution for the Design of Non-Binary Low Density Parity Check Codes for Slepian-Wolf Coding*, Technical report

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	$X = 0$	$X = 1$	$X = 2$	$\dots$
$Y = 0$	p_0	p_1	p_2	$\dots$
$\dots$	$\dots$	$\dots$	$\dots$	$\dots$
$Y = q-2$	p_{q-2}	p_{q-1}	p_0	$\dots$
$Y = q-1$	p_{q-1}	p_0	p_1	$\dots$

Examples: $Y = X \oplus Z$, any linear channel, BSC, q-ary sym., etc.

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All-zero codeword assumption [LFK09]

All-zero codeword assumption

If $P(X,Y)$ s.t.

- X distributed uniformly
- $P(Y|X)$ symmetric

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Problem: assumptions on $P(X,Y)$ not reasonable in SW coding

Source equivalence

Equivalent source ($X \in \mathrm{GF}(q)$, Y discrete)[1]

For every $P(X,Y)$ there exists a $P(U,W)$ such that

- U is distributed uniformly
- $P(W|U)$ is symmetric
- $P(X,Y)$ and $P(U,W)$ have the same DE equations

All-zero codeword assumption for $P(U,W)$

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Equivalent source construction[1]

Setting $W = (W_1, W_2)$, we get

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- $H(X|Y) = H(U|W)$

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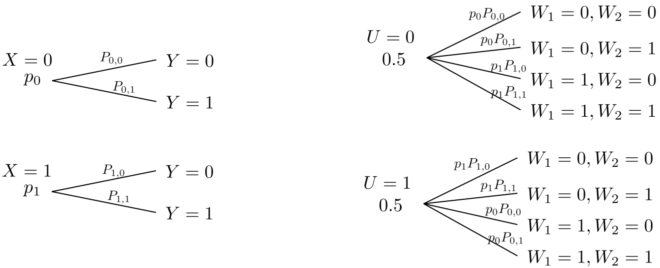

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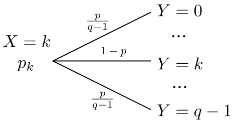
Numerical results

q-ary correlation channel



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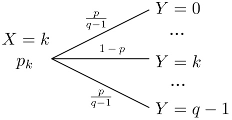


- GF(4), $X \sim [0.5, 0.25, 0.125, 0.125]$, $r = 1/2$, $\overline{p} = 0.225$

Max VN deg.	6	10	15	Reg
p	0.214	0.220	0.221	0.083
$H(p)$	0.483	0.492	0.494	0.246

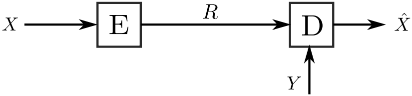
- GF(16), $X \sim [0.4, 0.04, \ldots, 0.04]$, $r = 1/2$, $\overline{p} = 0.367$

Max VN deg.	10	15	20	Reg
p	0.319	0.325	0.324	0.198
$H(p)$	0.452	0.458	0.457	0.32

Summary

- NB LDPC degree distribution design method for SW coding
- Degree distribution optimization using MCMC simulations

3. Slepian-Wolf coding with uncertainty
    - Performance
    - Practical scheme



Coding scheme for the lossless case, X in GF(q)
Uncertain knowledge of $P(X, Y)$

Performance when the joint distribution is known

$P(X,Y)$ perfectly known

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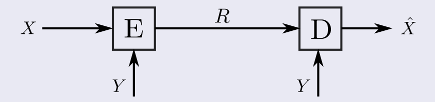
Conditional coding



To guarantee error probability asymptotically close to 0 :

$R \geq H(X|Y)$ bit/symb. [GL72]

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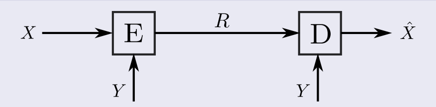
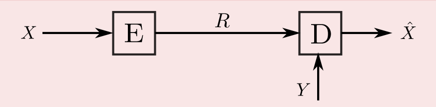


Distributed coding



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Uncertain correlation knowledge

Definition: $(X, Y) \sim P(X, Y|\theta) = P(X)P(Y|X, \theta)$

- $\theta \in \mathscr{P}_\theta$: fixed but unknown parameter

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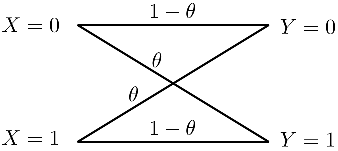
Example: i.i.d. binary sources



$$\theta \in [0, \overline{\theta}]$$
$$P(X=1) = 1/2$$

BSC(θ): $P(Y=1|X=0,\theta) = P(Y=0|X=1,\theta) = \theta$

Performance with uncertain correlation knowledge

Uncertain correlation knowledge $(X, Y) \sim P(X, Y|\theta)$[1]

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Performance with uncertain correlation knowledge

Uncertain correlation knowledge $(X, Y) \sim P(X, Y|\theta)^1$

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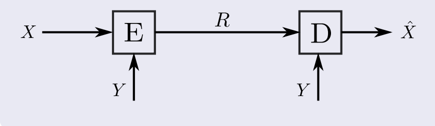

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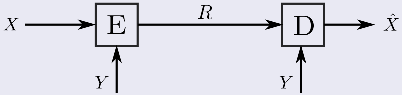

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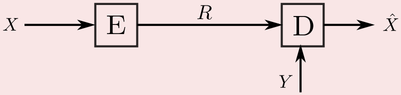

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$R \geq H(X|Y, \mathbf{\Theta} = \theta)$ bit/symb. $\quad$ $R \geq \sup_{\theta \in \mathscr{P}_\theta} H(X|Y, \mathbf{\Theta} = \theta)$ bit/symb.

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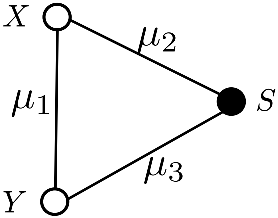
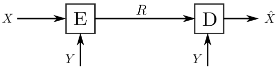
The three nodes network

Conditional or distributed coding?





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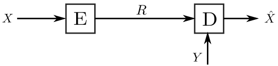

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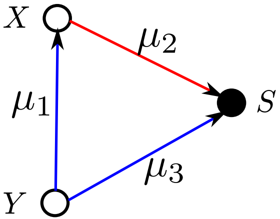

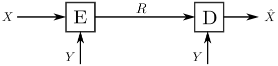

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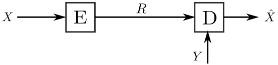

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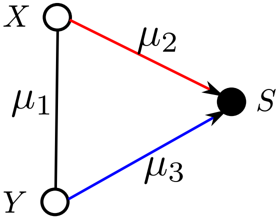
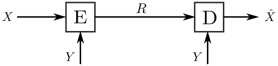
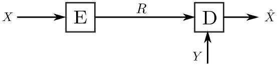




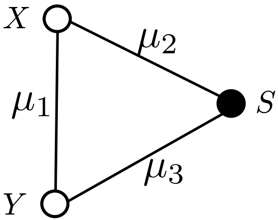
$$R \geq H(X|Y,\boldsymbol{\Theta}=\theta)$$

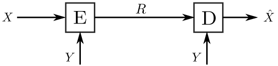


$$R \geq \sup_{\theta\in\mathscr{P}_\theta} H(X|Y,\boldsymbol{\Theta}=\theta)$$

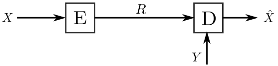
The three nodes network

Conditional or distributed coding?





$$R \geq H(X|Y, \mathbf{\Theta} = \theta)$$

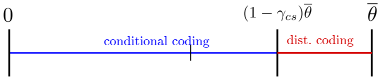


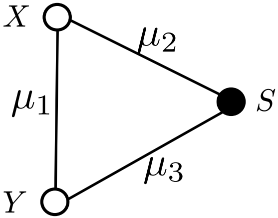
$$R \geq \sup_{\theta \in \mathscr{P}_\theta} H(X|Y, \mathbf{\Theta} = \theta)$$

The best strategy depends on the true value of θ

The three nodes network

BSC(θ), $\theta \in [0, \overline{\theta}]$

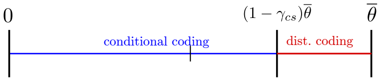


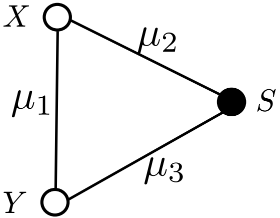


$\mu_2 = \mu_3 = 1$

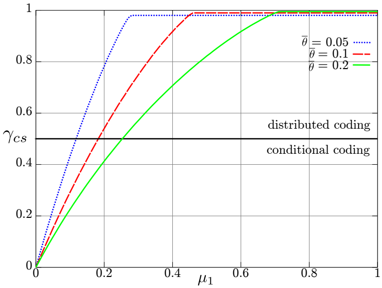
The three nodes network

$\mathrm{BSC}(\theta)$, $\theta \in [0, \overline{\theta}]$





$\mu_2 = \mu_3 = 1$



3 Slepian-Wolf coding with uncertainty
- Performance
- Practical scheme

Practical decoder[1]

Two-step EM-based approach: $(\mathbf{x}^{(\ell)}, \boldsymbol{\theta}^{(\ell)})$ at iteration ℓ

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[1] **Elsa Dupraz**, Aline Roumy, Michel Kieffer *Source coding with side information at the decoder and uncertain knowledge of the correlation* To appear in IEEE Transactions on Communications

Practical decoder[1]

Two-step EM-based approach: $(\mathbf{x}^{(\ell)}, \theta^{(\ell)})$ at iteration ℓ

- LDPC decoding with estimate $\theta^{(\ell-1)}$ to obtain

$$P(X_n = k | y_n, \mathbf{s}, \theta^{(\ell-1)})$$

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$$P(X_n = k | y_n, \mathbf{s}, \theta^{(\ell-1)})$$

- Update of the $\theta^{(\ell)}$ for $Y = X \oplus Z$, $P(Z = k) = \theta_k$

$$\theta_k^{(\ell)} = \frac{\sum_{n=1}^{N} P(X_n = y_n \ominus k | y_n, \mathbf{s}, \theta^{(\ell-1)})}{\sum_{n=1}^{N} \sum_{k'=0}^{q-1} P(X_n = y_n \ominus k' | y_n, \mathbf{s}, \theta^{(\ell-1)})}$$

---

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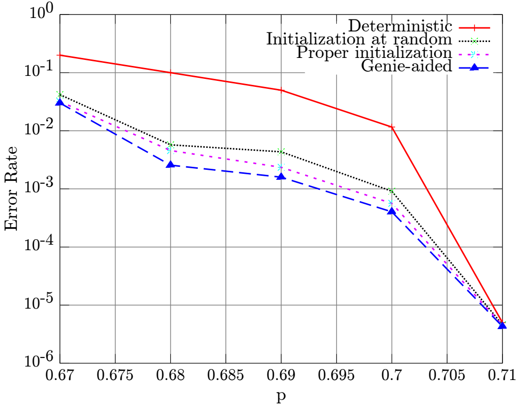
Numerical results

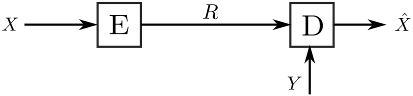
Symbols in GF(4), $r = 3/4$, $Y = X \oplus Z$,
$\theta = [\theta_0, \dots, \theta_3]$, $Pr(Z = k) = \theta_k$ and $\forall \theta \in \mathscr{P}_\theta$, $\theta_0 \geq p$



Summary

- Performance analysis
    - in the case with uncertainty
    - when estimated parameters are available
    - when an outage is authorized
- Coding scheme based on NB LDPC codes able to deal with the uncertainty

4. Wyner-Ziv coding with memory
   - Performance
   - Practical scheme



Coding scheme for the lossy case, X and Y continuous
Memory on the correlation channel

Source model

Hidden Markov model with Gaussian emissions

$Y = X + Z, \qquad X \sim \mathcal{N}(0, \sigma_x^2)$

Z : HMM of hidden state S

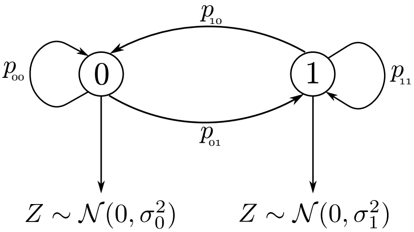
Source model

Hidden Markov model with Gaussian emissions

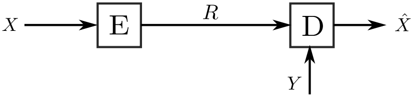
$Y = X + Z, \qquad X \sim \mathcal{N}(0, \sigma_x^2)$

Z : HMM of hidden state S

$P(S_k = j | S_{k-1} = i) = P_{i,j}$, $(Z|S = s) \sim \mathcal{N}(0, \sigma_s^2)$

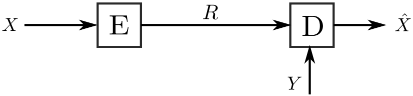


Rate-distortion performance [Iwa02]



- Distortion measure $d(\mathbf{X}^n, \hat{\mathbf{X}}^n) = \|\mathbf{X}^n - \hat{\mathbf{X}}^n\|^2$

Rate-distortion performance [Iwa02]

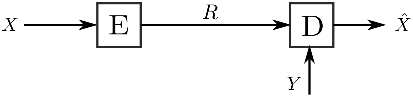


- Distortion measure $d(\mathbf{X}^n, \hat{\mathbf{X}}^n) = \|\mathbf{X}^n - \hat{\mathbf{X}}^n\|^2$
- Rate-distortion function

$$R_{X|Y}(D) = \lim_{n \to \infty} \inf \frac{1}{n} I(\mathbf{X}^n; \mathbf{U}^n | \mathbf{Y}^n)$$

inf on $\mathbf{U}^n$ s.t. $\mathbf{U}^n \leftrightarrow \mathbf{X}^n \leftrightarrow \mathbf{Y}^n$ and $\exists\, f_n : \mathscr{U}^n \times \mathscr{Y}^n \to \mathscr{X}^n$ s.t. $E\left[\frac{1}{n} d(\mathbf{X}^n, f_n(\mathbf{U}^n, \mathbf{Y}^n))\right] \leq D$

Rate-distortion performance [Iwa02]



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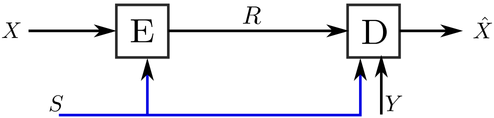
Problem: difficult to obtain in closed-form expression

Genie-aided setup[1]



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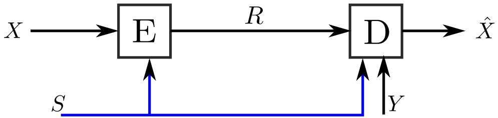
[1] **Elsa Dupraz**, Francesca Bassi, Thomas Rodet, Michel Kieffer *Distributed coding of sources with bursty correlation.* ICASSP 2012 : 2973-2976, Kyoto, Japan

Genie-aided setup[1]



$$R_{X|Y,S}(D) = \sum_{s \in \mathscr{S}} p_s \max\left(0, \frac{1}{2}\log_2 \frac{\sigma^2_{X|Y,s}}{D'}\right)$$

D' s.t. $\sum_{s \in \mathscr{S}} p_s \min(D', \sigma^2_{X|Y,s}) \leq D$.

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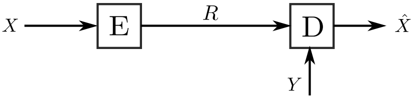
Bounds on the rate-distortion function[1]



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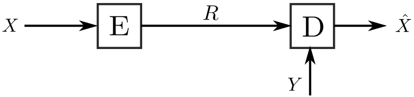
Bounds on the rate-distortion function[1]



$$R_{X|Y,S}(D) \leq R_{X|Y}(D) \leq R_{X|Y,S}(D) + L_{X|Y}(D) + \Lambda_{X|Y}$$

$$L_{X|Y}(D) = \frac{1}{2}\log_2\left(1 + \frac{D}{\sigma^2_{X|Y,0}}\right)$$

$$\Lambda_{X|Y} = \min\left(\lim_{k\to\infty} H(S_k|S_{k-1}),\ \ \mathrm{h}(\mathscr{Z}) - \lim_{k\to\infty} h(Z_k|S_k)\right)$$

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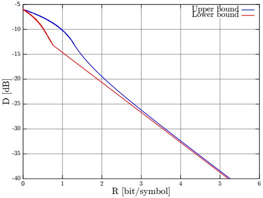
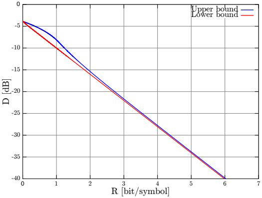
[1] Elsa Dupraz, Francesca Bassi, Thomas Rodet, Michel Kieffer *Distributed coding of sources with bursty correlation.* ICASSP 2012 : 2973-2976, Kyoto, Japan

Examples

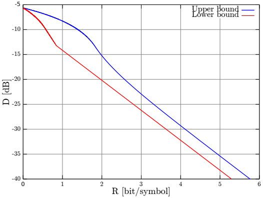
2 states, $\sigma_x^2 = 1,\ p_0 = 0.5$



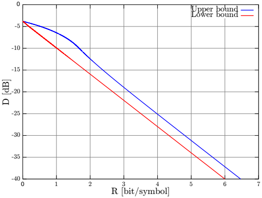
$\mu = 0.99,\ \sigma_0^2 = 0.05,\ \sigma_1^2 = 1$



$\mu = 0.99,\ \sigma_0^2 = 0.5,\ \sigma_1^2 = 1$



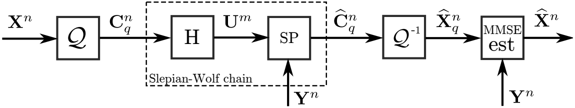
$\mu = 0.8,\ \sigma_0^2 = 0.05,\ \sigma_1^2 = 1$



$\mu = 0.8,\ \sigma_0^2 = 0.5,\ \sigma_1^2 = 1$

4. Wyner-Ziv coding with memory
   - Performance
   - Practical scheme

Practical scheme[1]



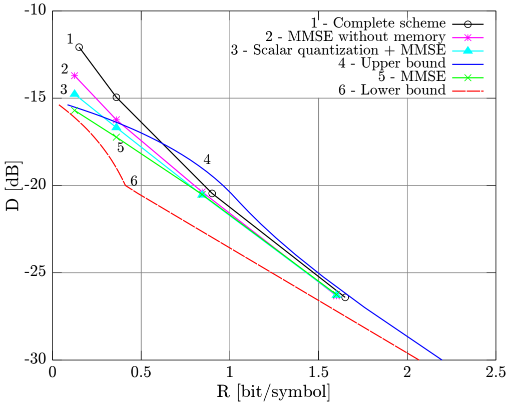
- Uniform Scalar Quantizer
- SW chain based on NB LDPC codes
- MMSE reconstruction based on a sampling method

---

[1] **Elsa Dupraz**, Francesca Bassi, Thomas Rodet, Aline Roumy, Michel Kieffer *Wyner-Ziv coding for Gaussian sources with Hidden State Markovian Correlation* Technical report

Numerical results

$$\mu = 1 - p_{01} - p_{10} = 0.98,\ \sigma_x^2 = 1,$$
$$\sigma_0^2 = 0.1,\ \sigma_1^2 = 0.01,\ p_0 = 0.9844,\ N = 10000$$



Summary

- Bounds on the rate-distortion function
- Practical coding scheme able to exploit the memory on the sources

Summary

- NB LDPC code design
  - Deg. distrib. design method for NB LDPC codes in SW coding
- SW coding with uncertainty
  - Performance analysis for SW coding in the case with uncertainty
  - Practical coding scheme for SW coding able to deal with the uncertainty
- WZ coding with memory
  - Performance analysis for WZ coding in the case with memory
  - Practical coding scheme for WZ coding able to deal with the memory

Perspectives

- SW coding
  - min-sum decoding for the SW setup
  - Density evolution in the case with uncertainty
- Model uncertainty
  - More complex models
  - Other coding situations
- Generalization to more complex networks
  - Performance analysis
  - Code construction
  - Other coding strategies

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