

Design of LDPC Codes for Slepian-Wolf coding with uncertain knowledge of the correlation

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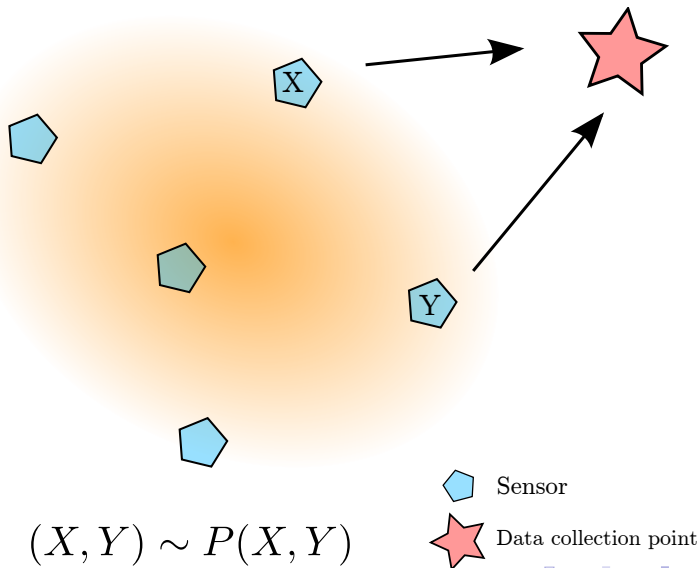
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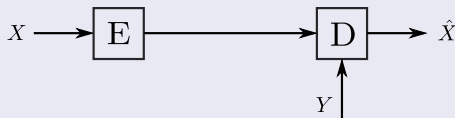
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Context



Context



- Theoretical performance [SW73]
- Coding schemes based on channel codes [LXG02, LXG03, MUM10, XLC04]

In general, **perfect knowledge of $P(X, Y)$**

- $P(X)$ unknown [JVW10]
- $P(Y|X)$ given at decoder, partly unknown at encoder [Sga77]

Practical solution

- Feedback channel [AZG02, EY05, VAG06]

Context

In this work

- $P(Y|X)$ partly unknown to both encoder and decoder
- No feedback

Objectives

- Design efficient coding/decoding schemes robust to uncertainty on $P(Y|X)$
- Solution based on non-binary LDPC codes

- 1 Context
- 2 Source Definition
- 3 Coding scheme
- 4 Experimental results
- 5 Conclusions

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Modeling the uncertainty

Four source models considered in [DRK12].

Here, focus on the **Static without Prior Source (SwP-Source)**

Definition (SwP-Source)

A *SwP-Source* (X, Y) , produces a sequence of *independent* discrete symbols $\{(X_n, Y_n)\}_{n=1}^{+\infty}$ drawn from a distribution belonging to

$$\{P(X, Y|\theta) = P(X)P(Y|X, \theta)\}_{\theta \in \mathcal{P}_\theta}$$

θ is fixed for $\{(X_n, Y_n)\}_{n=1}^{+\infty}$.

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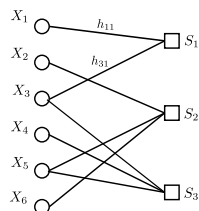
LDPC-based Encoder in $GF(q)$

Theoretical Performance [Csi82]

$$R = \sup_{\theta \in \mathcal{P}_\theta} H(X|Y, \theta).$$

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

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



Degree distributions $(\lambda(x), \rho(x))$ for H dimensional for the worst case, need to be optimized

Decoder

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

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

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

- Update of the $\theta^{(\ell)}$ by maximizing

$$\begin{aligned} Q(\theta, \theta^{(\ell)}) &= E_{\mathbf{X} | \mathbf{y}, \mathbf{s}, \theta^{(\ell)}} [\log P(\mathbf{y} | \mathbf{X}, \mathbf{s}, \theta)] \\ &= \sum_{n=1}^N \sum_{k=0}^{q-1} P(X_n = k | y_n, \mathbf{s}, \theta^{(\ell)}) \log P(y_n | X_n = k, \theta) \end{aligned}$$

Decoder

Two-step EM-based approach

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

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

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

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

Initialization of the EM algorithm (Additive Model)

Additive model: $Y = X \oplus Z$, $P(Z = k) = \theta_k$

- Compute

$$\mathbf{u} = \mathbf{s} \ominus H^T \mathbf{y} = H^T \mathbf{z}$$

Assumption: the U_m are obtained from *i.i.d.* R.V.s $Z_j^{(m)}$.

- Maximize

$$L(\theta) = \log P(\mathbf{u}|\theta) = \sum_{m=1}^M \log \mathcal{F}_{u_m}^{-1} \left(\prod_{j=1}^{dc} \mathcal{F}(W[h_j^{(m)}]\theta) \right)$$

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Experimental framework

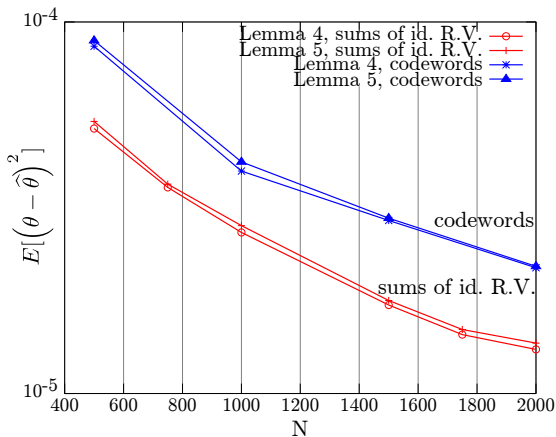
Symbols in $\text{GF}(4)$, $Y = X \oplus Z$,
 $\theta = [\theta_0, \dots, \theta_3]$ and $\text{Pr}(Z = k) = \theta_k$.
 \mathcal{P}_θ s.t. $\forall \theta \in \mathcal{P}_\theta, \theta_0 \geq 0.76$.

Code tuned for the **worst case** $\theta = [0.76, 0.08, 0.08, 0.08]$

- $\lambda(x) = 0.413x + 0.375x^2 + 0.012x^4$
- $\rho(x) = x$
- $R = 1.6$ bit/symbol

Initialization of the EM algorithm

MSE of the estimators



Global scheme

1000 source vectors of length 1000 are generated.
For each vector, θ selected uniformly at random in \mathcal{P}_θ .

Setup	Err	Time (s)	Rate (bit/symb.)
Genie-aided	$< 10^{-5}$	5.4	1.6
Learn. Seq.	$< 10^{-5}$	4.2	1.7
EM	$< 10^{-5}$	9.1	1.6
EM random	7.2×10^{-3}	47.0	1.6

Conclusions

Summary

- Practical coding scheme based on **non-binary** LDPC codes when the correlation is **uncertain**

Future works

- Extension to the lossy case
- Design of good degree distributions
- Correlation model selection

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- [AZG02] A. Aaron, R. Zhang, and B. Girod.
Wyner-Ziv coding of motion video.
In *Conference Record of the Thirty-Sixth Asilomar Conference on Signals, Systems and Computers*, volume 1, pages 240–244, 2002.
- [Csi82] I. Csiszar.
Linear codes for sources and source networks: Error exponents, universal coding.
IEEE Transactions on Information Theory, 28(4):585–592, 1982.
- [DRK12] E. Dupraz, A. Roumy, and M. Kieffer.
Source coding with side information at the decoder: Models with uncertainty, performance Bounds, and practical coding schemes.
In *Proceedings of the International Symposium on Information Theory and its Applications 2012*, pages 1–5, October 2012.
- [EY05] A.W. Eckford and W. Yu.
Rateless Slepian-Wolf Codes.
In *Conference Record of the Thirty-Sixth Asilomar Conference on Signals, Systems and Computers*, pages 1757 – 1761, 2005.
- [JVW10] S. Jalali, S. Verdú, and T. Weissman.
A universal scheme for Wyner-Ziv coding of discrete sources.
IEEE Transactions on Information Theory, 56(4):1737–1750, 2010.
- [LXG02] A. Liveris, Z. Xiong, and C. Georghiades.
Compression of binary sources with side information at the decoder using LDPC codes.
IEEE Communications Letters, 6:440–442, 2002.
- [LXG03] A.D. Liveris, Zixiang Xiong, and C.N. Georghiades.
Distributed compression of binary sources using conventional parallel and serial concatenated convolutional codes.
In *Data Compression Conference, 2003. Proceedings. DCC 2003*, pages 193 – 202, march 2003.

- [MUM10] T. Matsuta, T. Uyematsu, and R. Matsumoto.
Universal Slepian-Wolf source codes using Low-Density Parity-Check matrices.
In *IEEE International Symposium on Information Theory, Proceedings.*, pages 186–190, june 2010.
- [Sga77] A. Sgarro.
Source coding with side information at several decoders.
IEEE Transactions on Information Theory, 23(2):179–182, 1977.
- [SW73] D. Slepian and J. Wolf.
Noiseless coding of correlated information sources.
IEEE Transactions on Information Theory, 19(4):471–480, July 1973.
- [VAG06] D. Varodayan, A. Aaron, and B. Girod.
Rate-adaptive codes for distributed source coding.
EURASIP Signal Processing, 86(11):3123–3130, 2006.
- [XLC04] Z. Xiong, A.D. Liveris, and S. Cheng.
Distributed source coding for sensor networks.
IEEE Signal Processing Magazine, 21(5):80–94, Sep 2004.