

Journal Watch

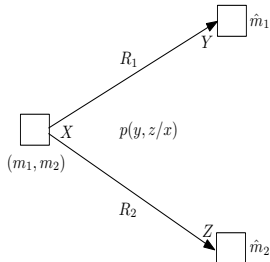
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On Marton's Inner Bound and Its Optimality for Classes of Product Broadcast Channels

Authors: Geng, Y. ; Gohari, A. ; Nair, C. ; Yu, Y.



Inner bound (Marton)

$$R_1 \leq I(U, W : Y)$$

$$R_2 \leq I(V, W : Z)$$

$$R_1 + R_2 \leq \min[I(W; Y), I(W; Z)] + I(U; Y|W)I(V; Z|W) - I(U; V|W)$$

$$(U, V, W) \rightarrow X \rightarrow (Y, Z)$$

$$|\mathcal{U}|, |\mathcal{V}| \leq |\mathcal{X}| \quad |\mathcal{W}| \leq |\mathcal{X}| + 4 \quad \longrightarrow \text{Recent result (Gohari, Ananthram)}$$

Outer bound (Nair, El-Gamal)

$$R_1 \leq I(U; Y)$$

$$R_2 \leq I(V; Z)$$

$$R_1 + R_2 \leq I(V; Z) + I(X; Y|V)$$

$$R_1 + R_2 \leq I(U; Y) + I(X; Z|U)$$

$$(U, V) \rightarrow X \rightarrow (Y, Z)$$

$$|\mathcal{U}|, |\mathcal{V}| \leq |\mathcal{X}| + 1 \quad \longrightarrow \text{Recent result (Nair, Gohari, Ananthram)}$$

Product BC

$$p(y_1, y_2, z_1, z_2 | x_1, x_2)$$

$$= q_1(y_1, z_1 | x_1) q_2(y_2, z_2 | x_2)$$

$$\mathcal{X} = (\mathcal{X}_1, \mathcal{X}_2) \quad \mathcal{Y} = (\mathcal{Y}_1, \mathcal{Y}_2) \quad \mathcal{Z} = (\mathcal{Z}_1, \mathcal{Z}_2)$$

Reversely semideterministic BC

$$q_1(y_1 | x_1), q_1(z_1 | x_1) \in \{0, 1\}$$

$$q_2(y_2 | x_2), q_2(z_2 | x_2) \in \{0, 1\}$$

Reversely more capable BC

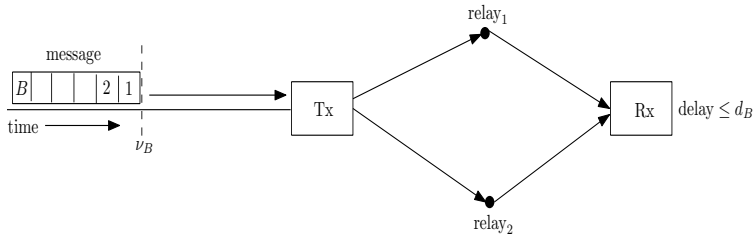
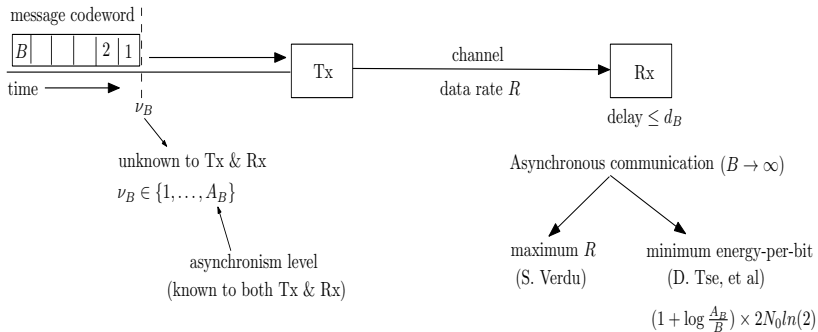
$$I(X_1; Y_1) \geq I(X_1; Z_1) \& I(X_2; Z_2) \geq I(X_2; Y_2)$$

$$I(X_1; Z_1) \geq I(X_1; Y_1) \& I(X_2; Y_2) \geq I(X_2; Z_2)$$

Bounds are tight

Diamond Networks With Bursty Traffic: Bounds on the Minimum Energy-Per-Bit

Authors: Shomorony, I. ; Etkin, R.H. ; Parvaresh, F. ; Avestimehr, A.S.

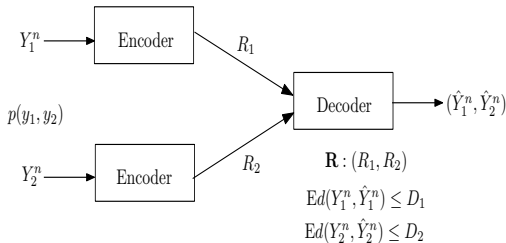


Main results

- ▶ $(1 + \log \frac{A_B}{B}) \times 2N_0 \ln(2)$ can be achieved by *separating synchronization and communication*:
 - ▶ As soon as the message arrives at time ν_B , Tx informs the Rx that a message bit is about to be transmitted.
 - ▶ If synchronization is successful, communication proceeds under the synchronous setting.
- ▶ For the diamond network:
 - ▶ Separation coding is optimal. Inference: employ relay₁, or relay₂, or both relay₁ and relay₂. This is in contrast to the synchronous case, where the optimal scheme is to employ as many relays as possible.
 - ▶ In the highly asynchronous regime, the separation-based scheme achieves the minimum energy-per-bit to within a constant fraction of 1 bit.
- ▶ Applicable for scenarios where communications is bursty.

Multiterminal Source Coding Under Logarithmic Loss

Authors: Courtade, T.A. ; Weissman, T.



Settled problems

$D_1 = D_2 = 0$ (Slepian, Wolf)

$D_1 = 0, D_2 = D_{\max}$ (Ahlswede, Korner)

Y_2 at decoder (Wyner, Ziv)

D_1 arbitrary, $D_2 = 0$ (Yeung, Berger)

$p(y_1, y_2)$ Gaussian; (D_1, D_2) arbitrary
(Wagner, Viswanath)

$$d(y_i, \hat{y}_i) = \log\left(\frac{1}{\hat{y}_i(y_i)}\right), i = 1, 2$$

$$d(y_i, \hat{y}_i) = D(\{Y_i = y_i\} | \hat{y}_i), i = 1, 2$$

$p(y_1, y_2)$ arbitrary

Inner bound

$$R_1 \geq I(Y_1; U_1 | U_2, Q)$$

$$R_2 \geq I(Y_2; U_2 | U_1, Q)$$

$$R_1 + R_2 \geq I(U_1, U_2; Y_1, Y_2 | Q)$$

$$D \geq H(X | U_1, U_2, Q)$$

Outer bound

$$R_1 \geq H(Y_1 | Y_2) - D$$

$$R_2 \geq H(Y_2 | Y_1) - D$$

$$R_1 + R_2 \geq H(Y_1, Y_2) - D$$

$$D \geq H(Y_1, Y_2 | U_1, U_2, Q)$$

$X \sim \text{Bernoulli}(\frac{1}{2})$

$$P(Y_i = X) = 1 - \alpha, \alpha > 0$$

Open problems

Characterize \mathbf{R}

D_1 arbitrary, $D_2 = D_{\max}$

$p(y_1, y_2)$ arbitrary

Characterize \mathbf{R}

$p(y_1, y_2)$ arbitrary

D arbitrary

Signal Estimation With Additive Error Metrics in Compressed Sensing

Authors: Tan, J; Carmon, D; Baron, D.

- ▶ $\mathbf{w} = \Phi \mathbf{x}$; $\mathbf{x} \in \mathbb{R}^N$ and i.i.d.; $\Phi \in \mathbb{R}^{M \times N}$ ($M < N$) is sparse and known.
- ▶ \mathbf{w} is passed through a channel $f(\mathbf{y}|\mathbf{w}) = \prod_{i=1}^M f(y_i|w_i)$; $f(y_i|w_i)$ is not restricted to follow a particular distribution.
- ▶ Estimate \mathbf{x} from Φ and \mathbf{y} .
- ▶ Error function: $D(\hat{\mathbf{x}}, \mathbf{x}) = \sum_{j=1}^N d(\hat{x}_j, x_j)$.
- ▶ Contributions:
 - ▶ A Bayesian estimation algorithm that minimizes the error metric is shown to be optimal;
 - ▶ Information-theoretic performance limits of estimation given an error metric (mean absolute error, mean support error, mean weighted-support error).
- ▶ $\hat{\mathbf{x}}_{\text{opt}} = \arg \min_{\hat{\mathbf{x}}} \mathbb{E}[D(\hat{\mathbf{x}}, \mathbf{x})|\mathbf{q}]$; $\mathbf{q} = \mathbf{x} + \mathbf{v}$, where $v_j \sim \mathcal{N}(0, \mu_j)$, $j = 1, \dots, N$.
- ▶ $D(\hat{\mathbf{x}}_{\text{opt}}, \mathbf{x})$ is the fundamental information-theoretic performance limit of an algorithm, i.e., no estimation algorithm can outperform this algorithm.

- ▶ Nir Lev, Ron Peled, and Yuval Peres, “Separating signal from noise”, <http://arxiv.org/pdf/1312.6843.pdf>
- ▶ Omer Melih Gul, and Elif Uysal-Biyikoglu, “UROP: A Simple, Near-Optimal Scheduling Policy for Energy Harvesting Sensors”, <http://arxiv.org/pdf/1401.0437.pdf>
- ▶ Ritesh Kolte, Urs Niesen, and Piyush Gupta, “Energy-Efficient Communication over the Unsynchronized Gaussian Diamond Network”, <http://arxiv.org/pdf/1401.1711.pdf>