Data-Driven Communications for Large Scale Sensor Networks

Presented by **Yao-Win Hong**

January 9, 2006

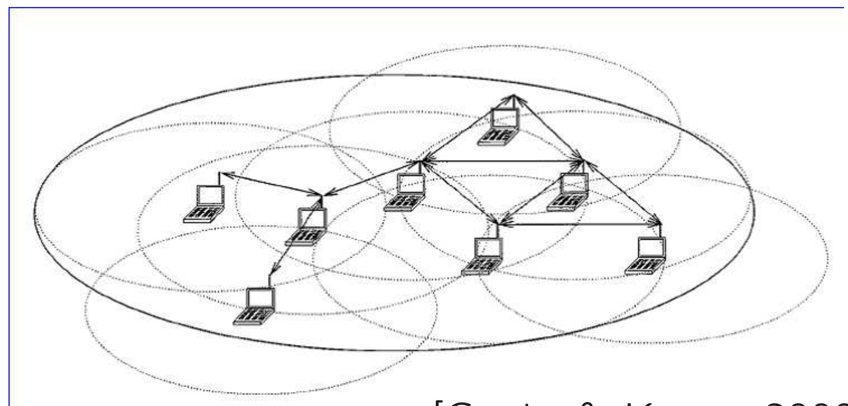
Joint work with Anna Scaglione and Pramod K. Varshney

Scalability of Wireless Communications

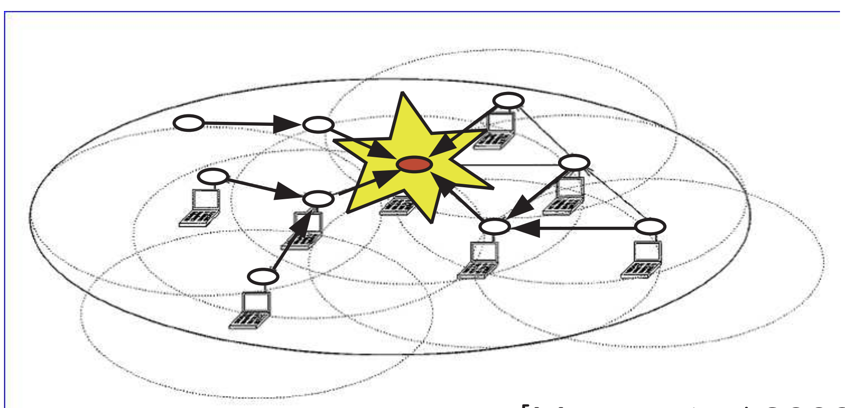
- Conventional communications systems assume independent and non-cooperative users.

⇒ Peer-to-peer per node throughput is $C_N = O(\frac{1}{\sqrt{N \log N}})$. ($N$: # of users) *i.e.* there exists a_1 and a_2 such that

$$\frac{a_1}{\sqrt{N \log N}} \leq C_N \leq \frac{a_2}{\sqrt{N \log N}}$$



[Gupta & Kumar 2000]



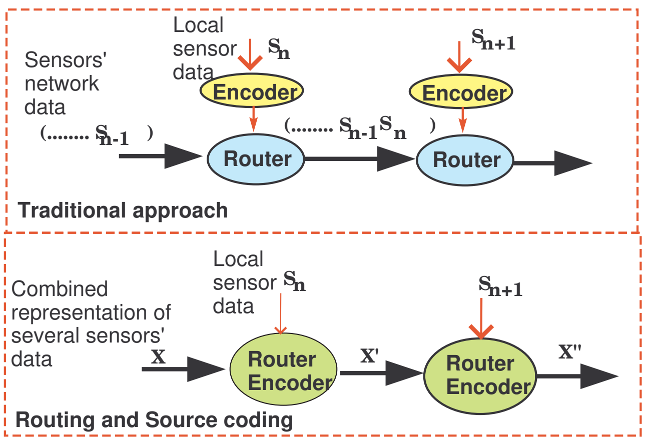
[Marco *et al* 2003]

⇒ Many-to-one per node throughput is $C_N = O(\frac{1}{N})$. (data-gathering structure)

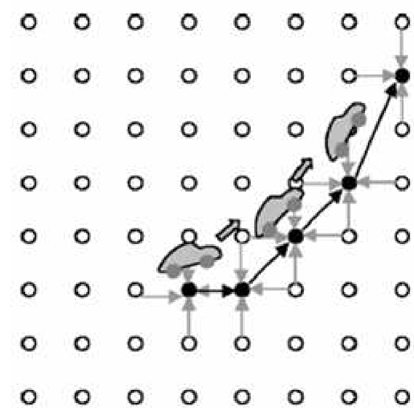
Data-Driven Communications

- Sensor systems measure dependent data with cooperative users.

▶ Joint routing and compression. [Scaglione & Servetto 2002]



▶ Route selection for detection [Sung, Tong & Ephremides], Tracking [Zhao *et al* 2003]

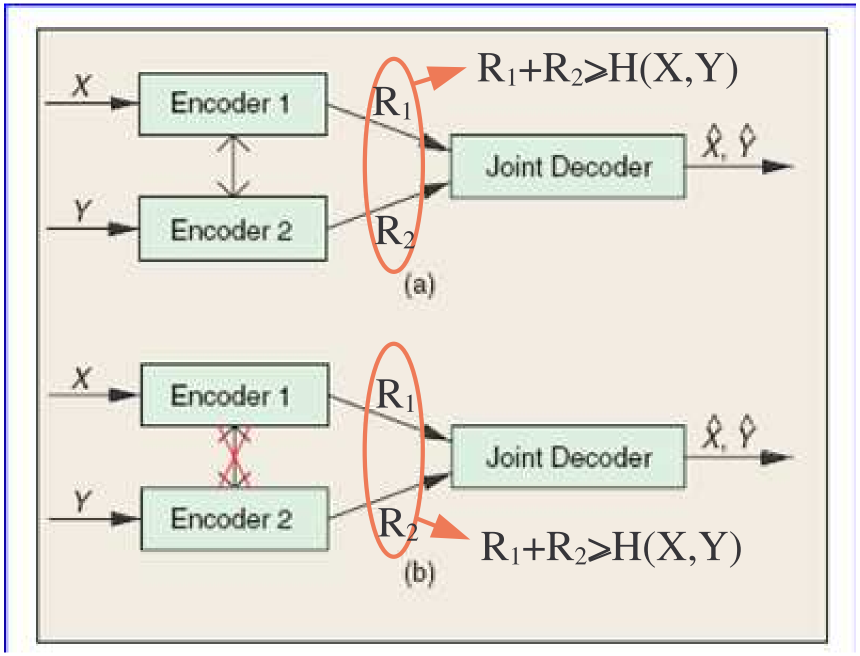


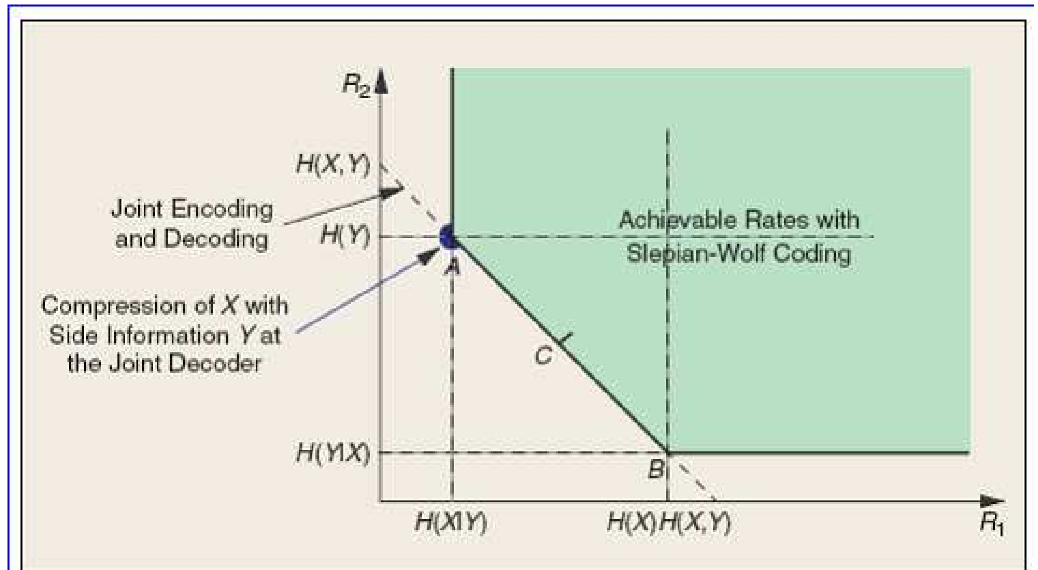
⇒ Belongs to the class of "Data Aggregation" Strategies

▶ Distributed Source Coding (compression without aggregation)

Distributed Source Coding

- Lossless Source Coding: Slepian-Wolf Theory [1973]



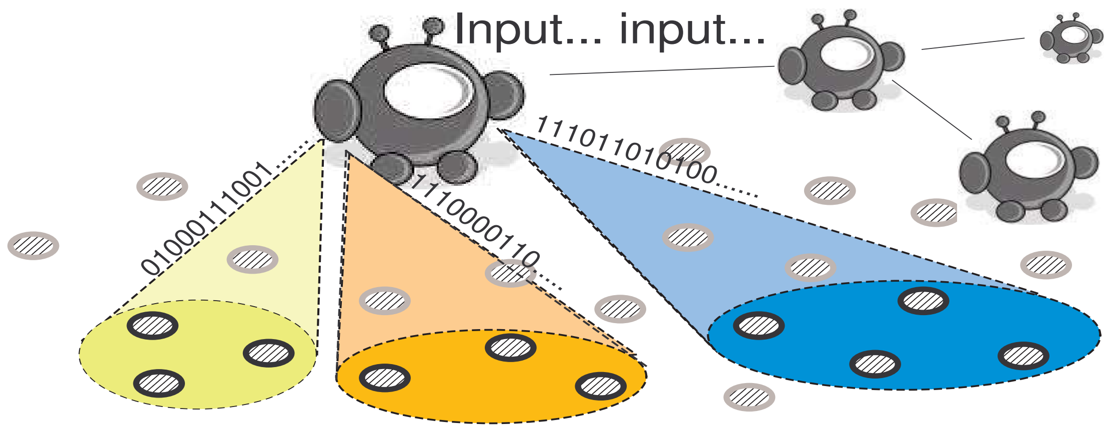


▲ 2. The Slepian-Wolf rate region for two sources.

► Lossy source coding (Wyner-Ziv Coding); Multiple Description Coding; Successive Refinement Coding.

Data Retrieval in Wireless Sensor Networks

- Consider a network of sensors $\mathcal{S} = \{s_0, s_1, \cdots, s_{N-1}\}$ and the observations $\mathbf{X} = [X_0, X_1, \cdots, X_{N-1}]$ made by the sensors.



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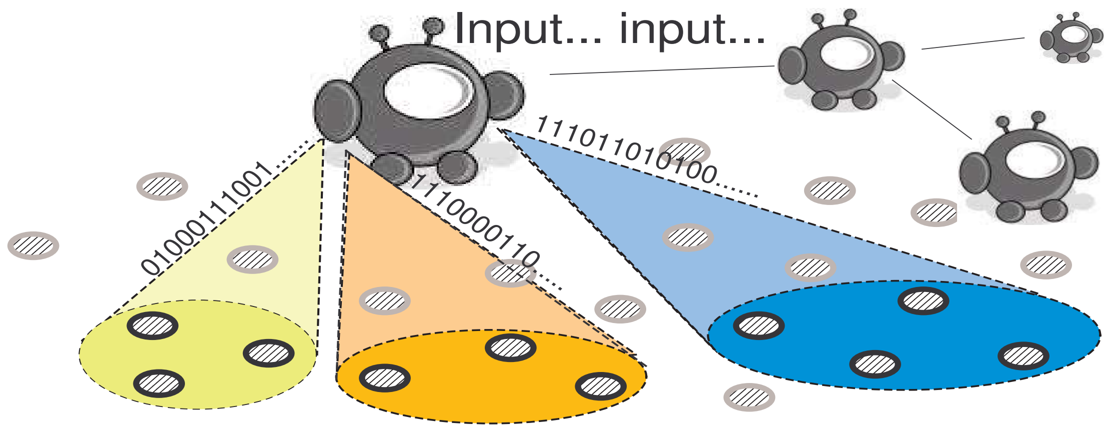

GOAL: Efficiently obtain a reconstruction of the observations $\mathbf{X}$ with the minimum number of channel accesses.

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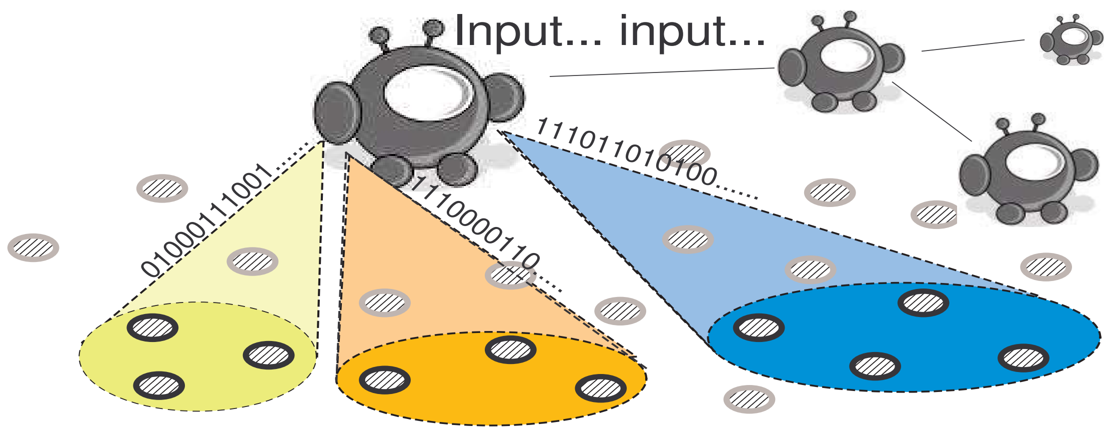

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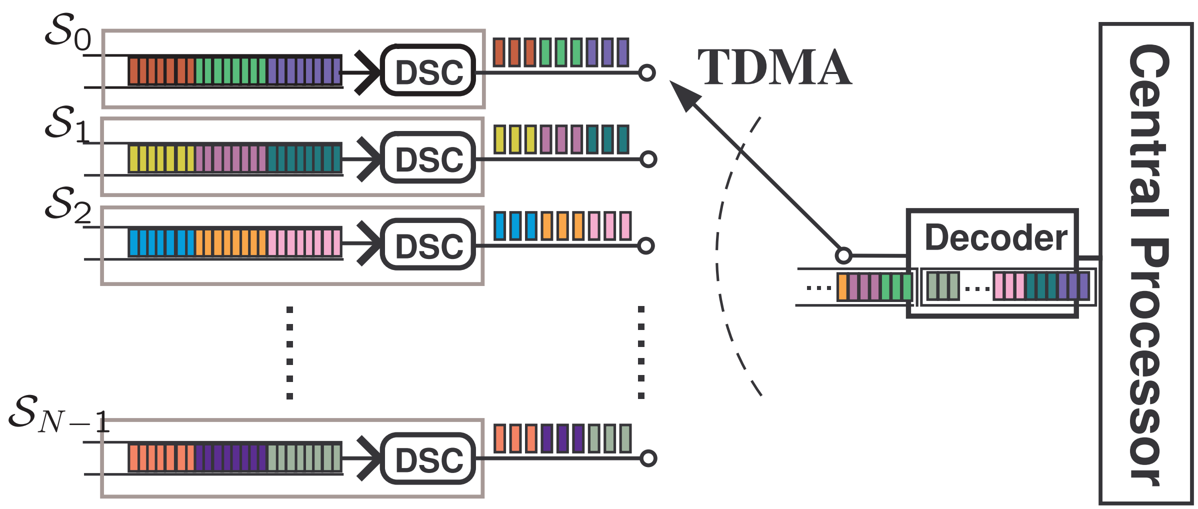
- Centralized query from a base-station;
- Multi-hop ad hoc network;
- Hierarchical sensor network.

State of the Art: Layered Solution

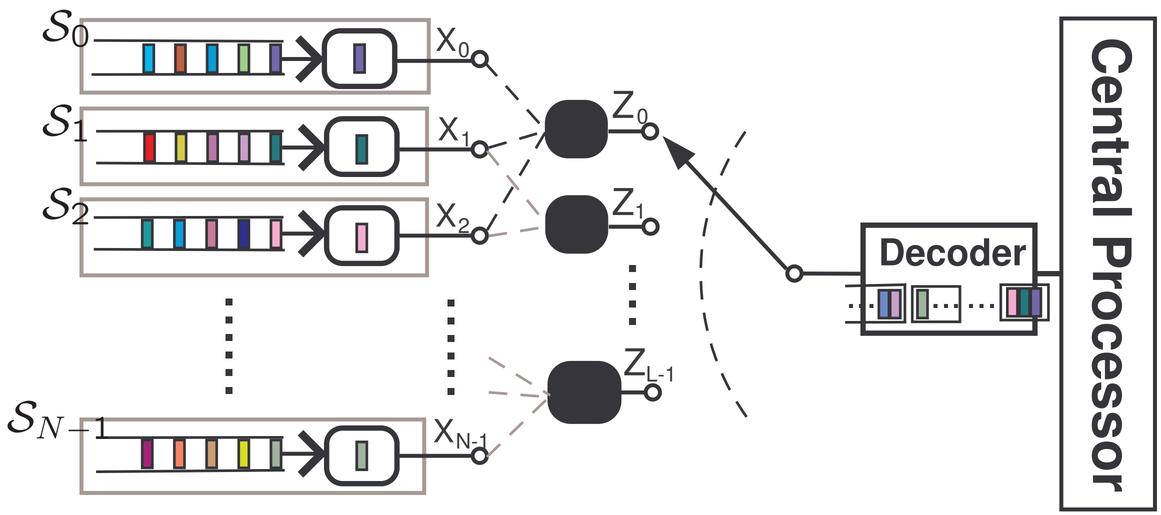
Distributed Source Coding + Point-to-point transmissions



- × **Encoding:** requires long blocks of data at each encoder/sensor.
- × **Transmission:** is point-to-point $\Rightarrow$ wireless is broadcast!!
- × **Decoding:** long latency due to joint decoding.

Key Intuition of Cooperative MAC

Key Intuition: Sensors with highly redundant data should cooperate to transmit through the same channel. [Hong, Scaglione 2004]



Similar ideas: Type-Based Multiple Access for Detection and Estimation problems [Mergen & Tong 2005], [Liu & Sayeed 2004]

Binary Markov Source Model

- Sensor network $\mathcal{S} = \{s_0, s_1, \cdots, s_{N-1}\}$.
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  $\Rightarrow$ $X_i \in \{0, 1\}$ is the observation of s_i.

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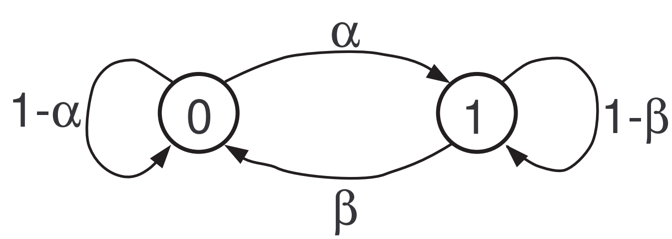
Two-state Markov Model:



Transition probabilities:

$$\alpha = \Pr\{X_{i+1} = 1 | X_i = 0\};$$
$$\beta = \Pr\{X_{i+1} = 0 | X_i = 1\}$$

$$\Rightarrow p = \Pr\{X_i = 1\} = \frac{\alpha}{\alpha + \beta}; \quad \rho = \frac{\mathrm{Cov}(X_i, X_{i+1})}{\sigma_{X_i}\sigma_{X_{i+1}}} = 1 - (\alpha + \beta)$$

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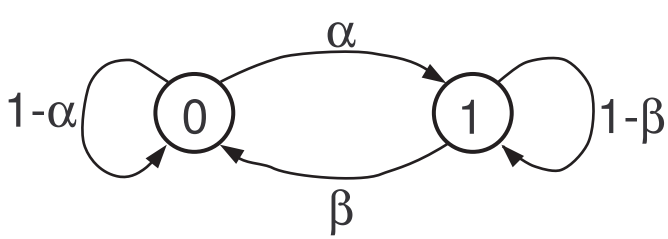

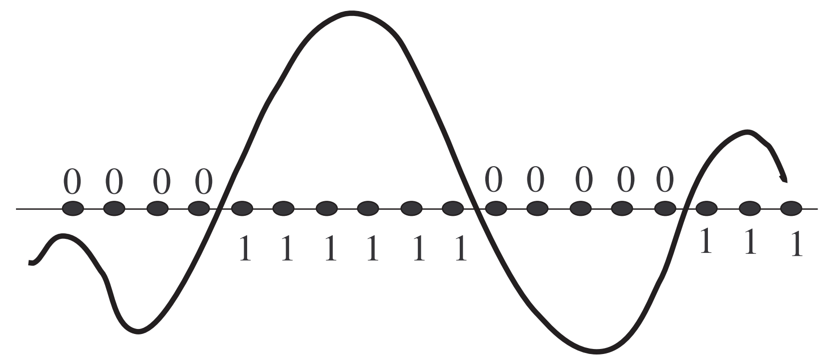

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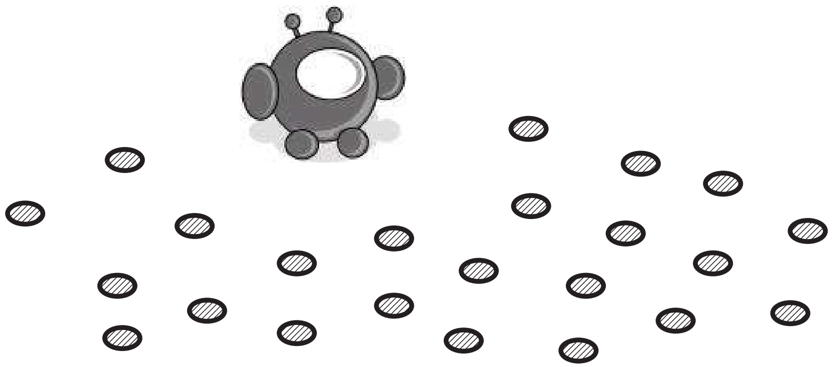
Cooperative Data Gathering



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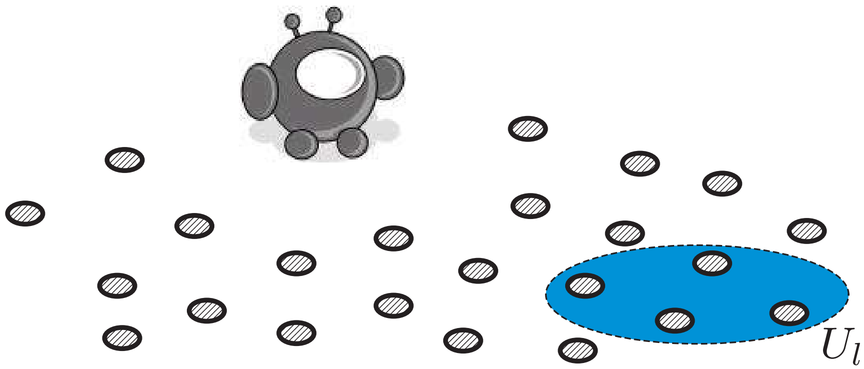

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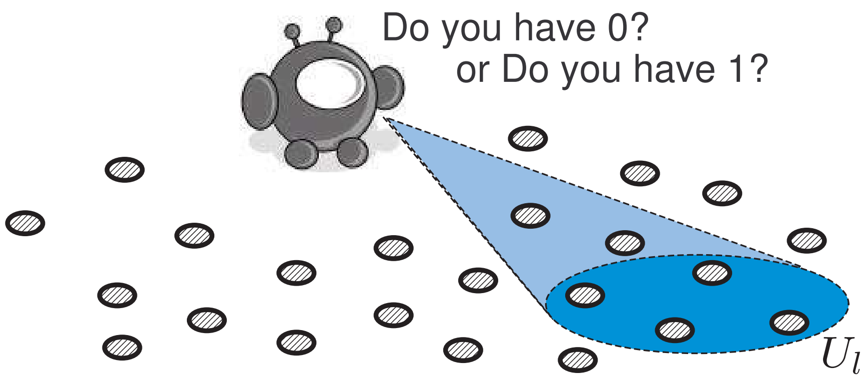

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- Binary OR Channel:

$$Z_{U_l} = \vee_{\{i : s_i \in U_l\}} \{X_i \neq 1\}$$

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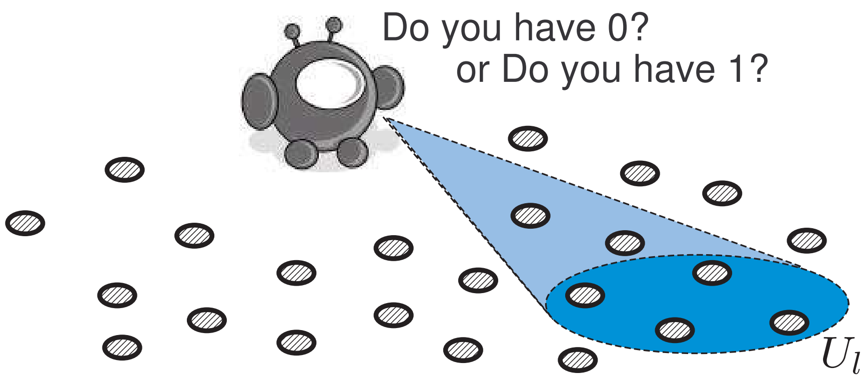

- $U_l \triangleq$ the l-th group queried.
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$$Z_{U_l} = \vee_{\{i: s_i \in U_l\}} f_i(X_i)$$

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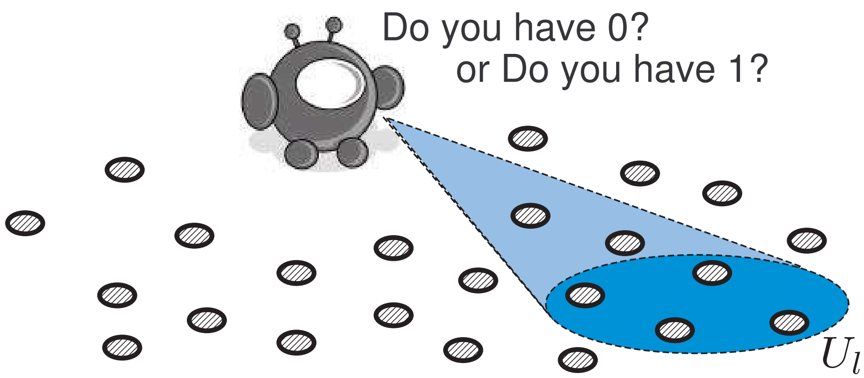

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The Physical Channel: $r(t) = \sum_i A_i \cdot f_i(X_i) \cdot p(t - \tau_i) + n(t)$

▶ Noiseless Energy Detector: $\|r(t)\|^2 = \|\sum_i A_i f_i(X_i) p(t - \tau_i)\|^2 > 0$

$\Rightarrow$ Equivalent source coding problem ($\mathbf{Z} = [Z^{(1)}, Z^{(2)}, ..., Z^{(L)}]$ represents $\mathbf{X} = [X_0, X_1, ..., X_{N-1}]$ where $\mathbf{E}[L] \leq N$).

$$\boxed{H(\mathbf{X}) \leq \mathbf{E}[L_{opt}]}$$

Scalability of the Cooperative Scheme

- Upper bound with suboptimal strategy,

$$H(\mathbf{X}) \leq \mathbf{E}[L_{opt}] \leq \min_{K} \mathbf{E}[L_{sub}]$$

Theorem: **Case I:** for fixed (p, ρ) where $(1-\rho) \ll 1$,

$$\mathbf{E}[L_{opt}] = O(N) = O(H(\mathbf{X}));$$

Case II: for fixed p and $1-\rho = c'/N$ for some $c' > 0$,

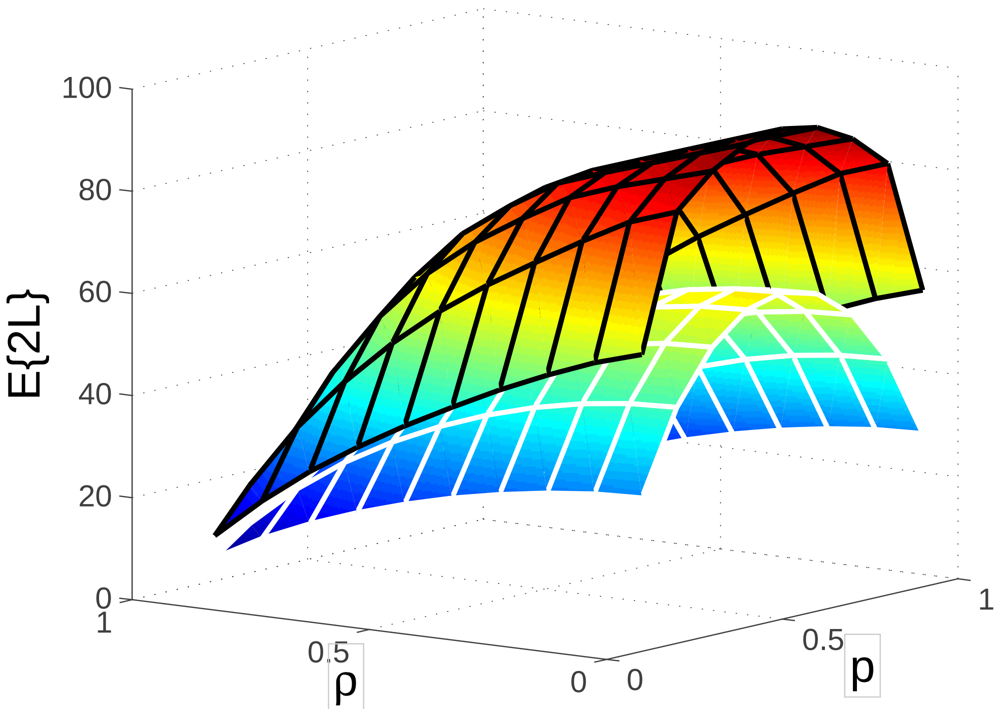
$$\mathbf{E}[L_{opt}] = O(\log(N)) = O(H(\mathbf{X})).$$

Suboptimal strategy with **0, 1, e**

Sup-optimal Cooperative Transmission (0, 1, e):

$$(Z_{U_l}, \bar{Z}_{U_l}) = \left(\vee_{s_i \in U_l}\{X_i \neq 0\}, \vee_{s_i \in U_l}\{X_i \neq 1\}\right).$$

$E[2L]$ vs Entropy Lower Bound



- Number of nodes $N = 64$

(0): $(Z_{U_l}, \bar{Z}_{U_l}) = (0, 1)$
$\Rightarrow$ all have bit 0;

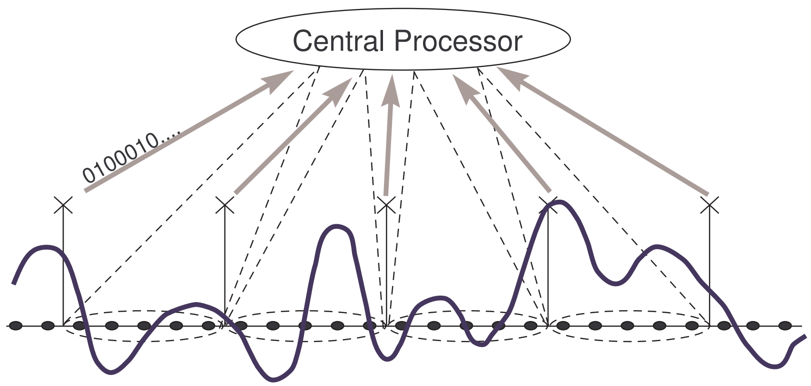
(1): $(Z_{U_l}, \bar{Z}_{U_l}) = (1, 0)$
$\Rightarrow$ all have bit 1;

(e): $(Z_{U_l}, \bar{Z}_{U_l}) = (1, 1)$
$\Rightarrow$ *Erasure*.

High or Low Density Sensor Networks

HDSN vs LDSN

⇒ Example: reconstruction of bandlimited sensor fields.



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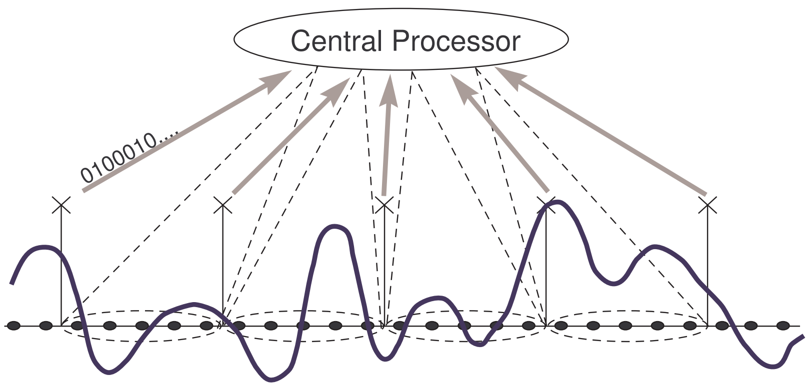
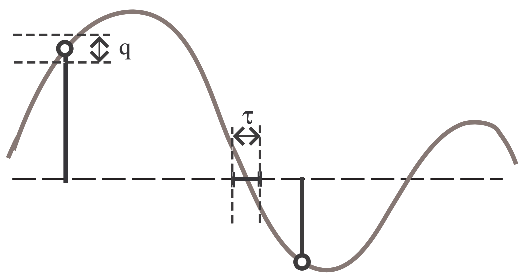


▶ **Reconstruction performance**

LDSN: Nyquist Sampling

HDSN: Zero Crossing Position



Distortion:
$D = O(q^2)$ (LDSN);
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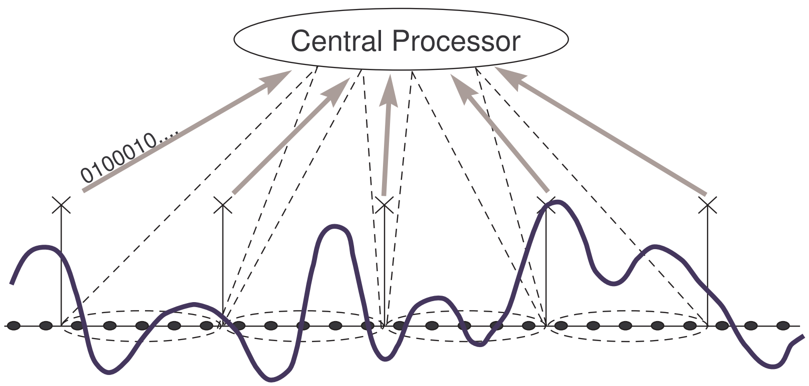

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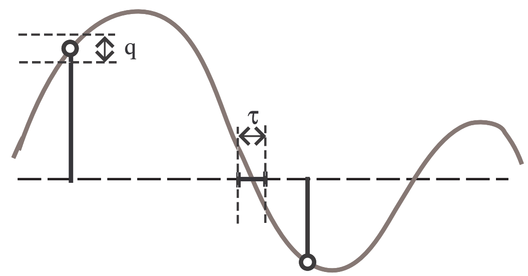

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▶ **Communication cost**

LDSN: Bits tx'ed $k = O(\log \frac{1}{q})$

HDSN: Using GTMA $k = O(\log \frac{1}{\tau})$

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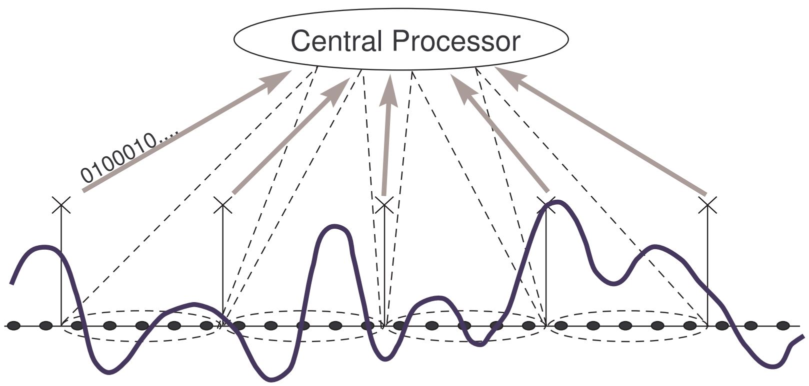

HDSN superior to LDSN

– Energy Efficiency

– Hardware Cost

– System Versatility

– Robustness

[See Hong *et al* 2005 MILCOM]

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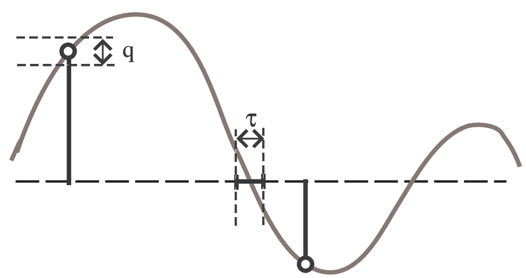

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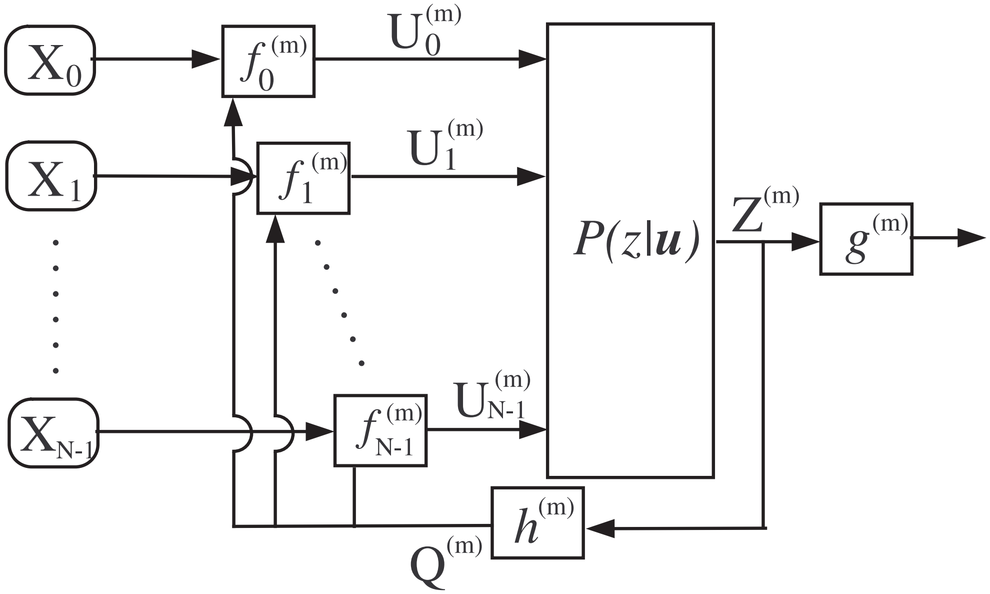
Data Gathering thru Sensor Queries



Encoder

$$f_i^{(m)} : \mathcal{X}_i \times \mathcal{Q}^{m-1} \to \mathcal{U}_i^{(m)},$$

Decoder

$$g^{(m)} : \mathcal{Z}^m \to \prod_{i=0}^{N-1} \mathcal{X}_i,$$

Feedback

$$h_i^{(m)} : \mathcal{Z}^{m-1} \to \mathcal{Q},$$

- Let $\hat{\mathbf{X}}^{(m)} = g^{(m)}(Z^{(1)}, \cdots, Z^{(m)})$ be the estimate after m queries. Let L be the number of queries used to acquire X.

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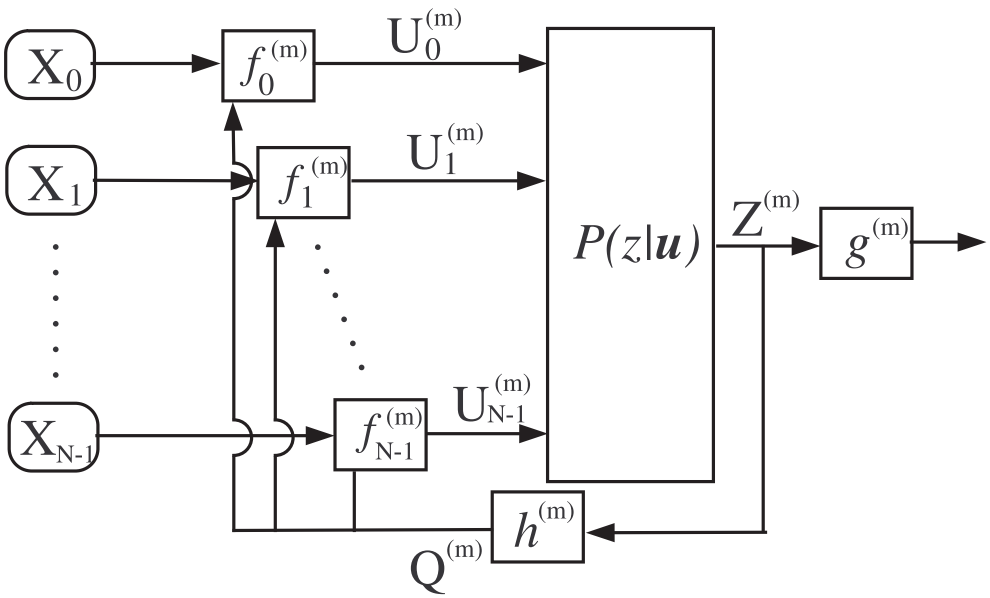

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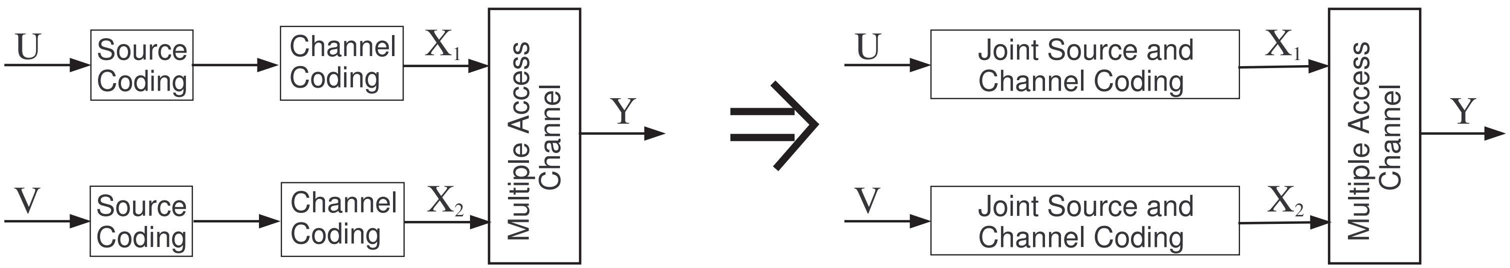
Let L be the number of queries used to acquire X.

Problem Description: Suppose $g^{(m)}$ is fixed and $Q^{(m)} = Z^{(m-1)}$, find $\{f_i^{(m)}\}$ that minimize $\mathbf{E}[L]$ subject to $\mathbf{E}[d(\mathbf{X}, \hat{\mathbf{X}}^{(L)})] \le D$ (where $d(\cdot,\cdot)$: distortion function; D: distortion constraint).

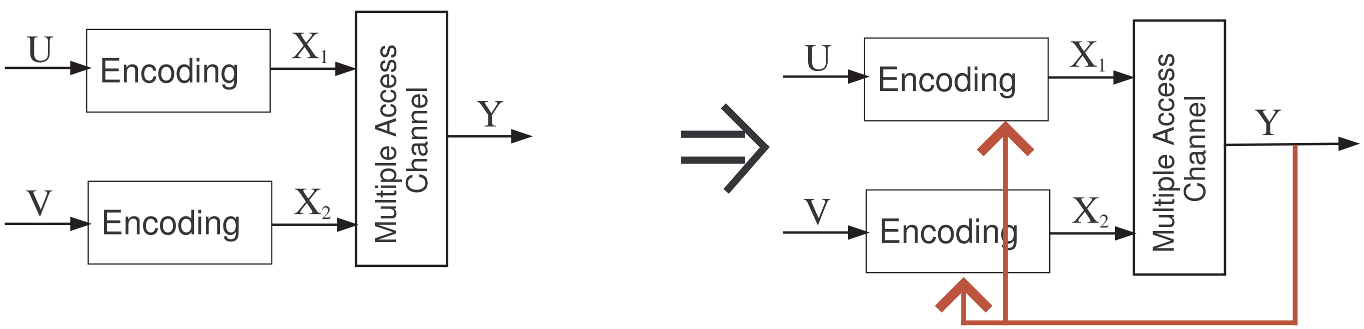
Improved Multiple Access Capacity

✗ In general, symbol-by-symbol encoding does NOT achieve maximum coding efficiency.

▶ Cooperation over correlated sources increases the capacity of the MAC channel.[Cover, El Gamal & Salehi 1980]



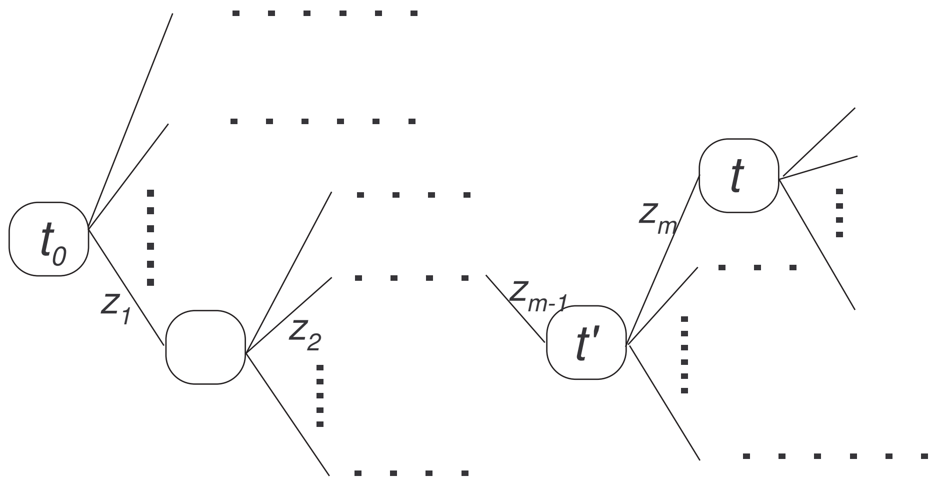
▶ Feedback increases the MAC capacity.[Gaarder & Wolf 1975]



Tree Representation

- For $|\mathcal{Z}|$ finite $\Rightarrow$ Sensor query is represented as a tree T.

▶ Let $(\Omega, \mathcal{B}, P)$ be the probability space.



▶ Each node represents an event, eg. $t_0 = \Omega$ and $t = \{\omega : Z^{(1)}(\omega) = z_1, \cdots, Z^{(m)}(\omega) = z_m\}$

Estimate:

$$\hat{\mathbf{x}}_t = g^{(m)}(z^{(1)}, \cdots, z^{(m)})$$

Distortion: $\mathbf{E}[d(\mathbf{X}, \hat{\mathbf{x}}_t)|t]$

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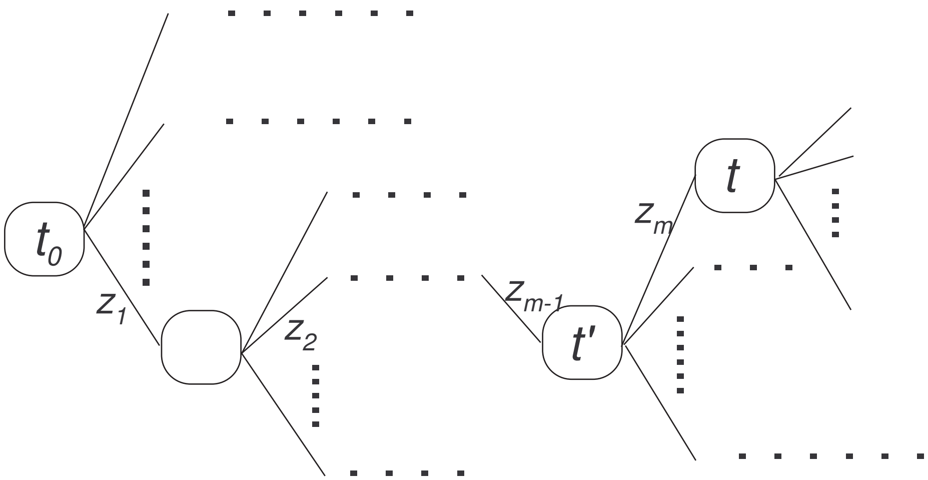

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- Let l_t be the depth of t and $\tilde{T}$ be the leaf of tree T.

(1) **Expected number of queries:** $\mathbf{E}[L] = \sum_{t \in \tilde{T}} l_t \cdot P(t)$

(2) **Average Distortion:** $\mathbf{E}[d(\mathbf{X}, \hat{\mathbf{X}}^{(L)})] = \sum_{t \in \tilde{T}} \mathbf{E}[d(\mathbf{X}, \hat{\mathbf{x}}_t)|t] \cdot P(t)$

Tree Construction

Special Case: Consider the trees T s.t. $\mathbf{E}[d(\mathbf{X}, \hat{\mathbf{x}}_t)|t] \leq D' < D$ for all $t \in \tilde{T}$, where D is the distortion constraint.

Information-Theoretic Criterion: Given $z^{(0)}, \cdots, z^{(m-1)}$, the functions $\mathbf{f}^{(m)} = \{f_i^{(m)}, \ \forall i\}$, is chosen such that

$$\mathbf{f}^{(m)} = \arg\max_{\mathbf{f}^{(m)}} \ I(\mathbf{X}; \bar{Z}^{(m)}|\bar{\mathbf{Z}}^{(1:m-1)} = \mathbf{z}^{(1:m-1)})$$

The dependence is as follows:

$$\Pr(Z^{(m)}|\mathbf{z}^{(1:m-1)}) = \sum_{\mathbf{x} \in \prod_i \mathcal{X}_i} \Pr(Z^{(m)}|\mathbf{f}^{(m)}(\mathbf{x}))\Pr(\mathbf{x}|\mathbf{z}^{(1:m-1)}).$$

Performance Bounds

Theorem 4 Let

$$\alpha = \sup\left\{k \geq 1 : P\left(\mathbf{E}[d(\mathbf{X}, \hat{\mathbf{X}}_{|\mathbf{Z}^{(1:k)}})|\mathbf{Z}^{(1:k)}] > D'\right) > 0\right\}.$$

For any tree T, $\mathbf{E}[L]$ can be bounded as

$$\boxed{I(\mathbf{X}; \bar{\mathbf{Z}}^{(1:\alpha+1)})/G_{\max} \leq \mathbf{E}[L] \leq I(\mathbf{X}; \bar{\mathbf{Z}}^{(1:\alpha+1)})/G_{\min}}$$

where

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and $I(\mathbf{X}; \bar{Z}^{(1)}|\bar{\mathbf{Z}}^{(1:0)}) = I(\mathbf{X}; \bar{Z}^{(1)})$.

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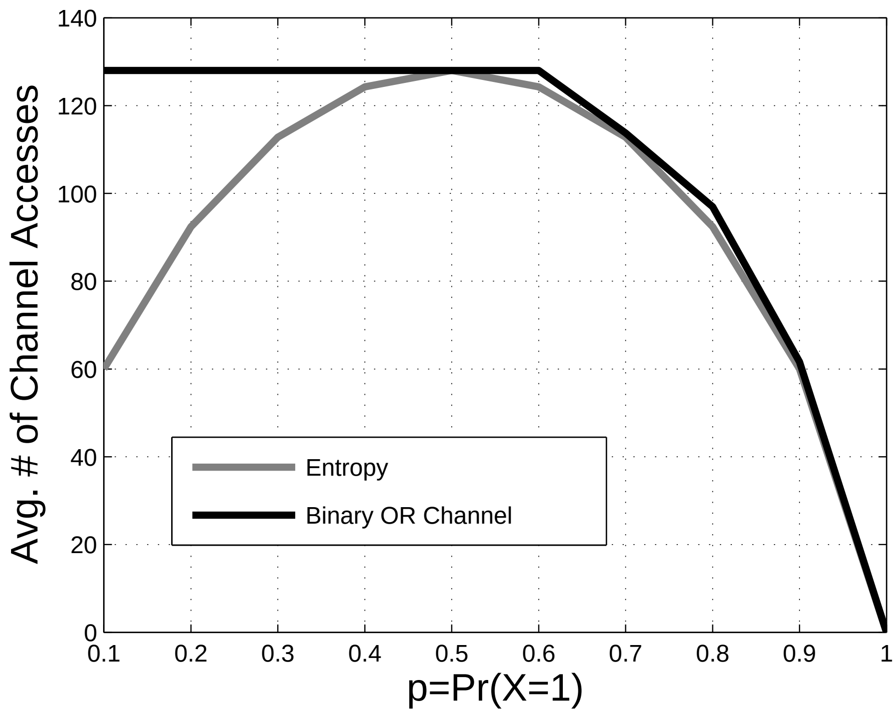
Performance of the Design Criterion



Blood Testing Example:

$\{X_j\}_{j=0}^{N-1}$ are *i.i.d.* Bernoulli with probability $p = Pr\{X_j = 1\}$.

For the m^{th} query, select $\mathcal{G}_m$ and
$$f_i^{(m)}(X_i) = \mathbf{1}_{\{i \in \mathcal{G}_m, X_i \neq 1\}}.$$
Response: (Binary OR Channel)

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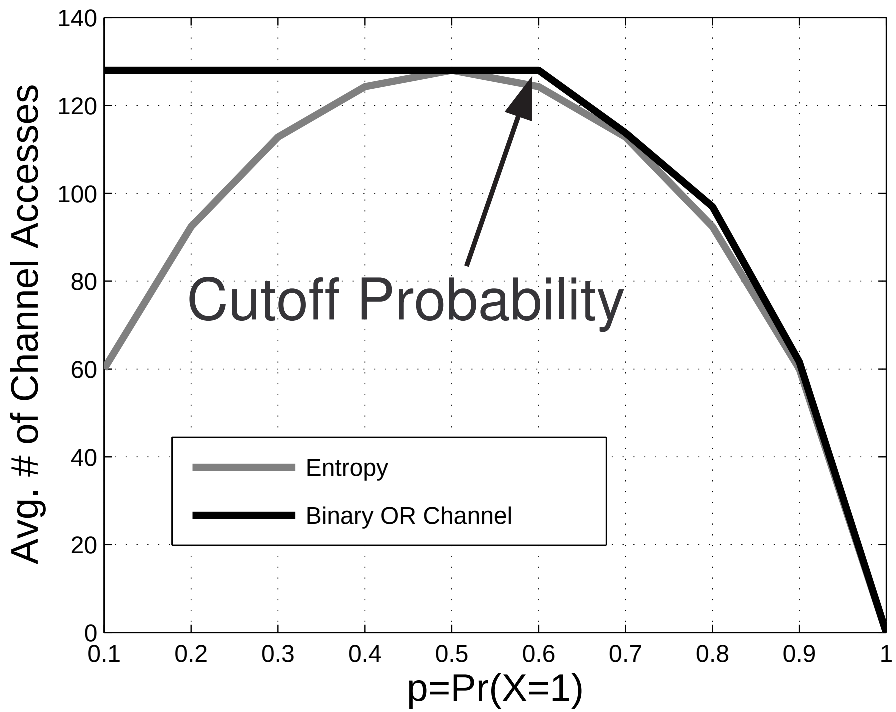

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Cutoff Probability: The value of p below which TDMA is optimal.

Rate-Distortion Tradeoff

- Construct a tree with

  Design Criterion: $I(\mathbf{X}; \bar{Z}^{(m)} | \bar{\mathbf{Z}}^{(1:m-1)} = \mathbf{z}^{(1:m-1)})$

  Stopping Rule: $L = \inf \left\{ l : \mathbf{E}[d(\mathbf{X}, \hat{\mathbf{X}}^{(l)}) | Z^{(1)}, \cdots, Z^{(l)}] \leq D' \right\}.$

$\Rightarrow$ The achieved distortion is $\mathbf{E}[d(\mathbf{X}, \hat{\mathbf{X}}^{(l)})] \leq D'$.

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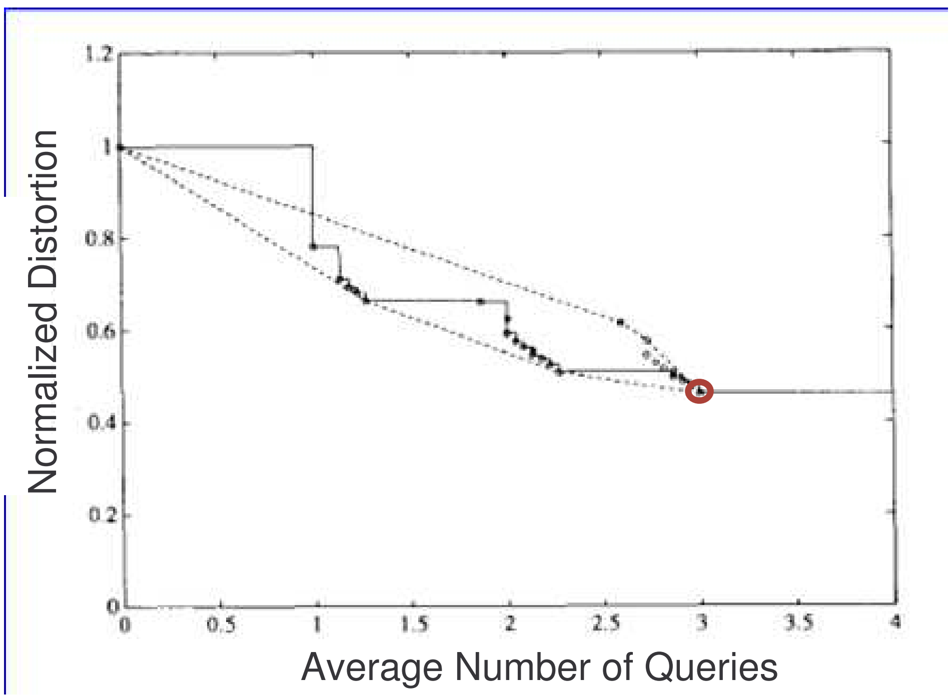

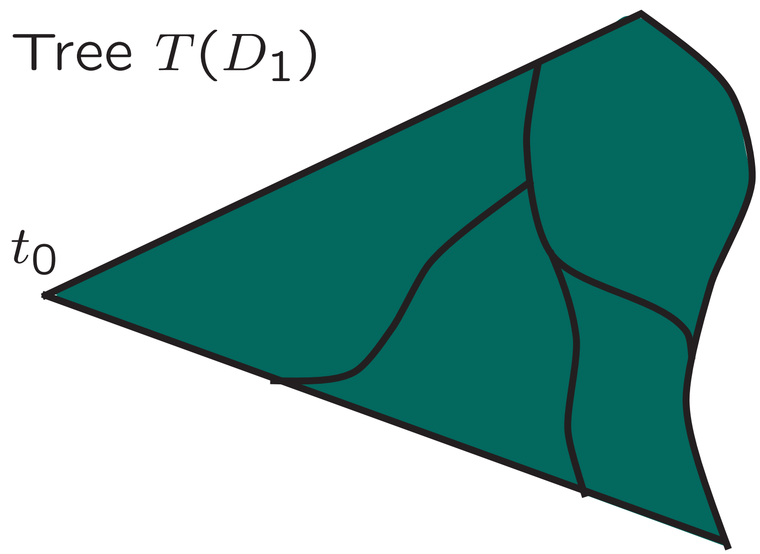

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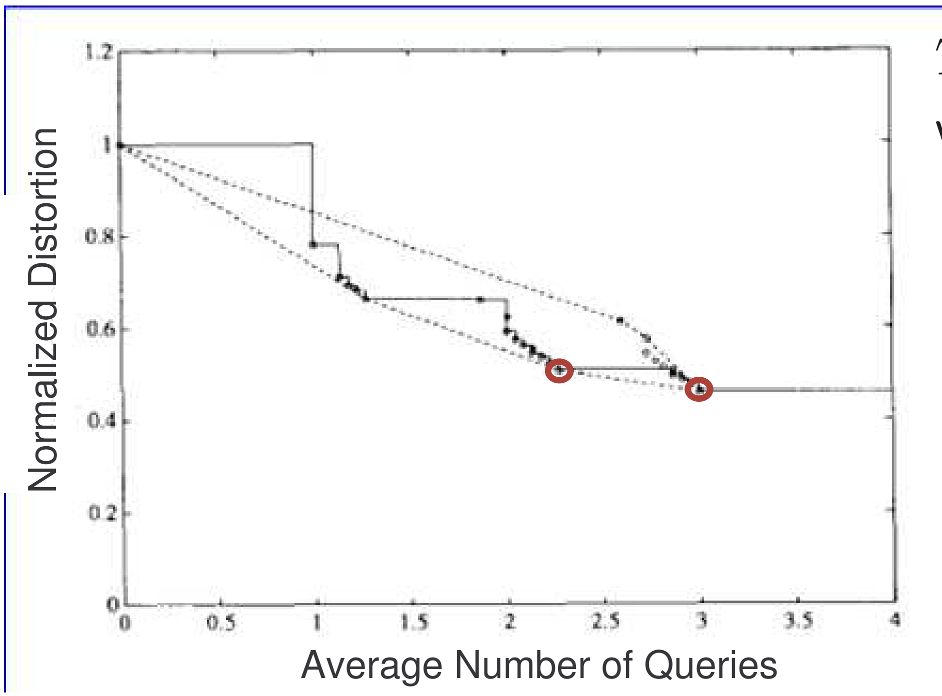

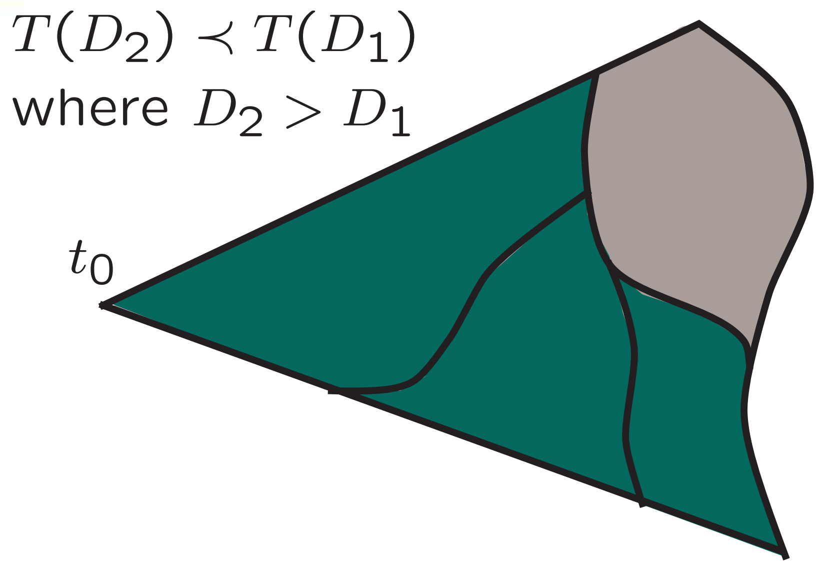

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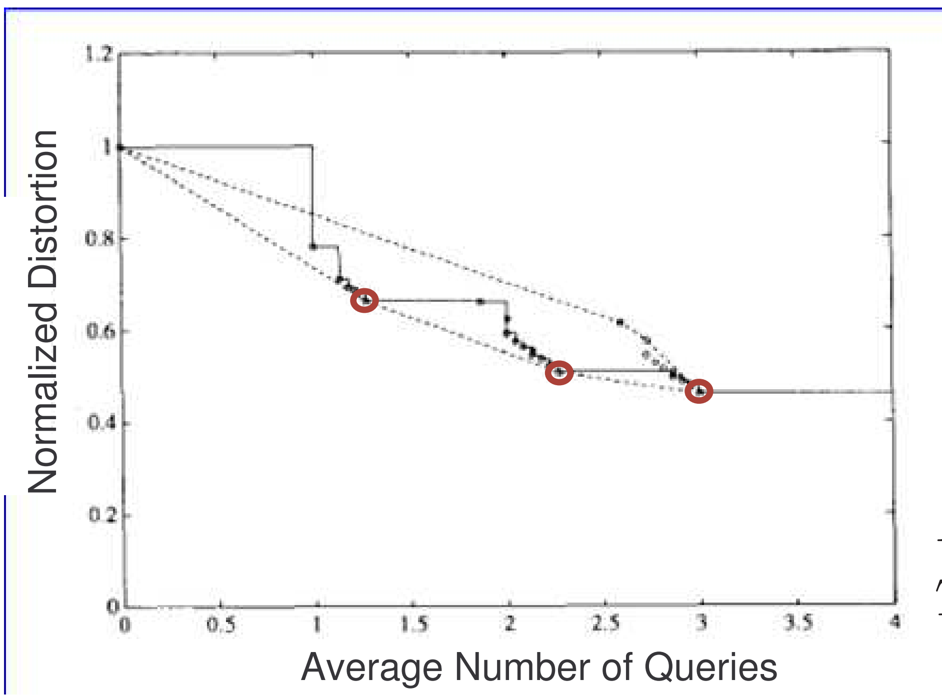

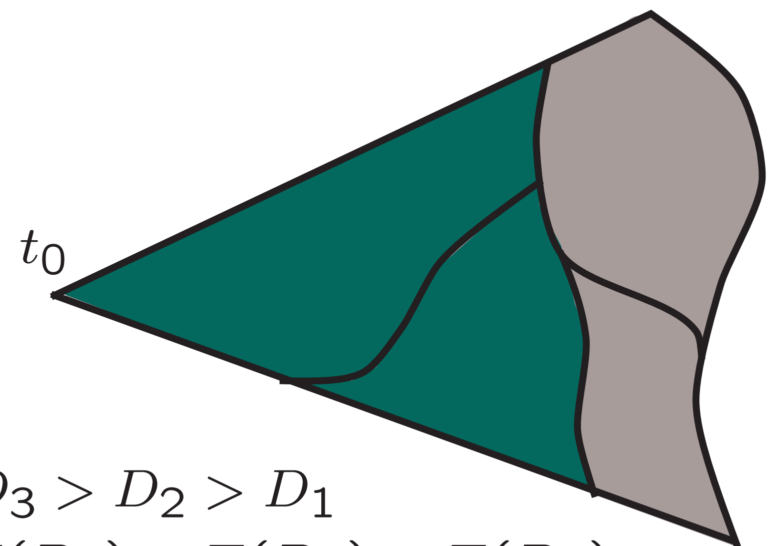

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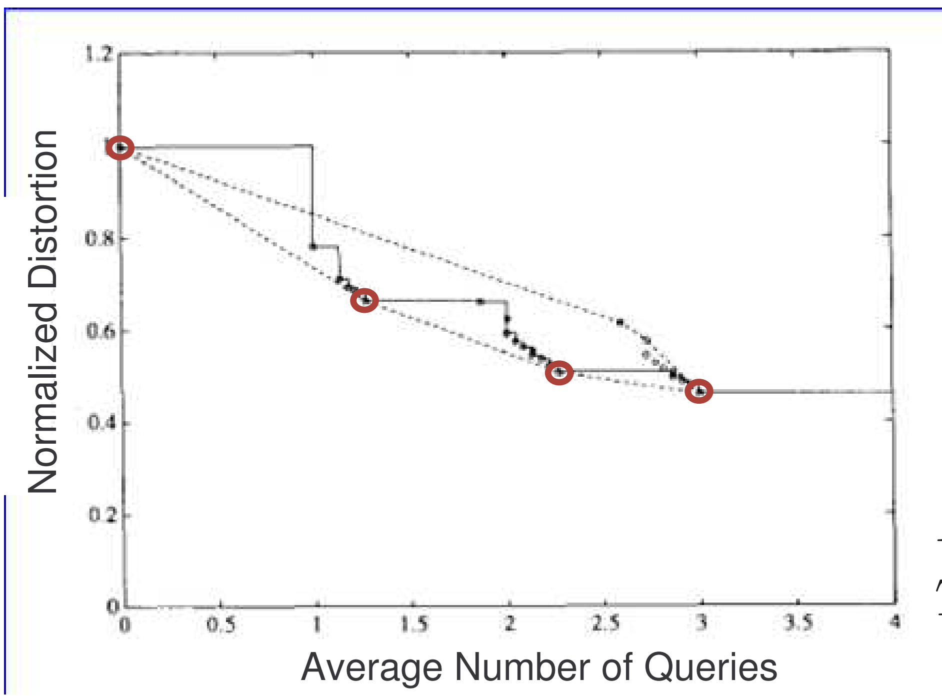

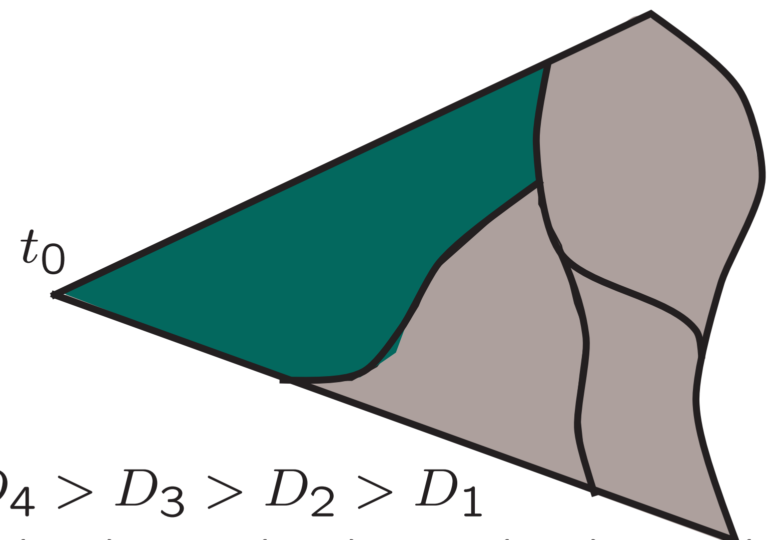

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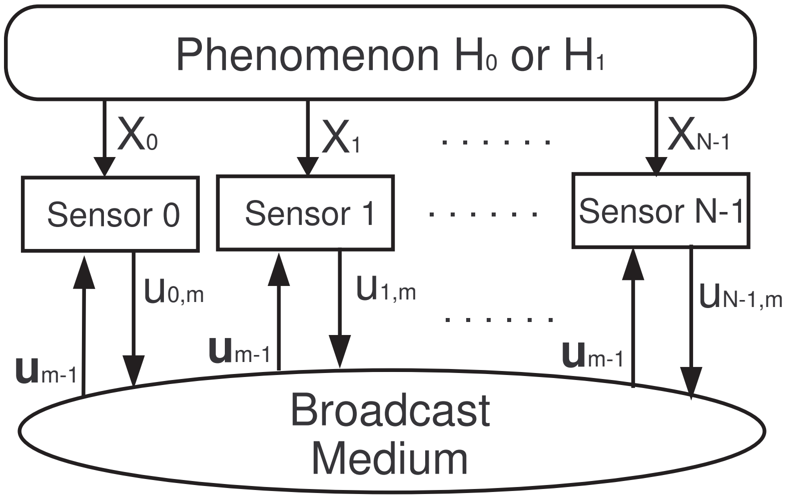
Consensus in Decentralized Decisions

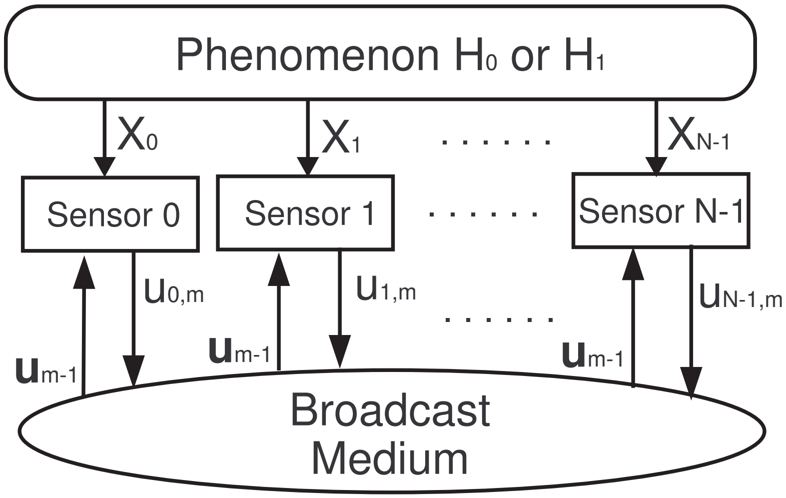


Local Binary Hypothesis Testing:

$$\mathcal{H}_0: \quad X_i \sim f_{0,i}$$
$$\mathcal{H}_1: \quad X_i \sim f_{1,i}$$

where $f_{0,i}$, $f_{1,i}$ are the density functions of X_i conditioned on $\mathcal{H}_0$,$\mathcal{H}_1$, respectively.

Consensus in Decentralized Decisions



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$f_{b,i}$: the density function of $X_i|\mathcal{H}_b$.

- Let $u_{i,m}$ be the local decision at s_i after $m-1$ iterations:

$$u_{i,m} = \mathcal{D}_i(X_i, \mathbf{u}_0, \mathbf{u}_1, \cdots, \mathbf{u}_{m-1})$$

where $\mathbf{u}_m = [u_{0,m}, u_{1,m}, \cdots, u_{N-1,m}]$.

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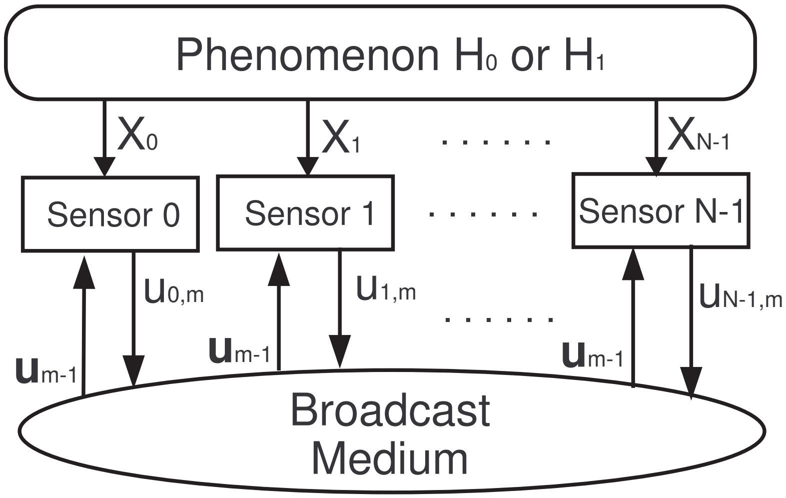

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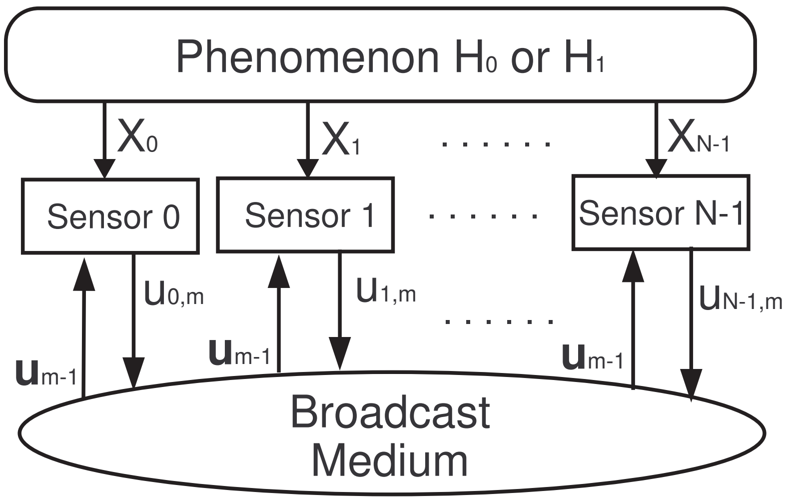

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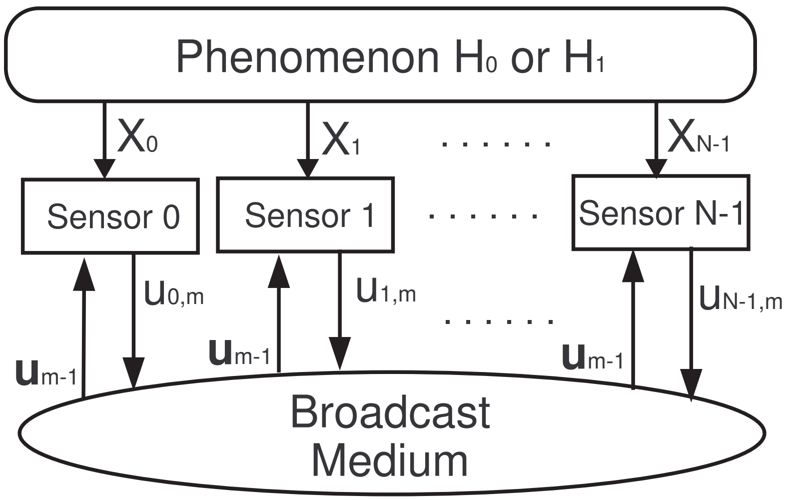

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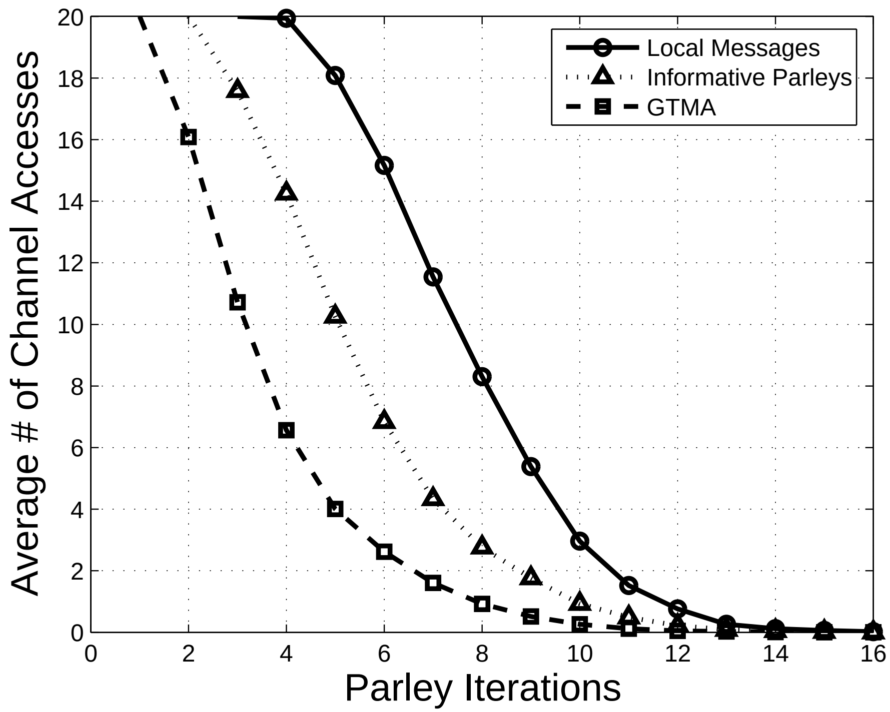
With Cooperation: $\mathbf{E}[L^{(m)}] \approx O(H(\mathbf{u}_m|\mathbf{u}_0^{m-1}))$.

Simulation: Gaussian Shift-in-mean



Gaussian Shift-in-Mean:

$$\mathcal{H}_0: \quad X_i \sim \mathcal{N}(\mu_0, \sigma^2)$$
$$\mathcal{H}_1: \quad X_i \sim \mathcal{N}(\mu_1, \sigma^2)$$

where $\mu_0 = -1$, $\mu_1 = 1$ and $\sigma = 2$.

Simulation Parameters:

– the number of nodes $N = 20$

– averaged over 1000 trials

– $\Pr(\mathcal{H}_0) = \Pr(\mathcal{H}_1) = 0.5$

Conclusions and Future Directions

- Importance of Data-Driven Communications: (1) Energy efficiency; (2) Bandwidth efficiency.

- We proposed Cooperative Transmissions through Group Queries as a method to achieve Data-Driven Communications.

Evolution of Sensor Network Communications:

Individual Query $\Rightarrow$ Group Query;
Node Centric $\Rightarrow$ Data Centric or Application Centric;
Point-to-point $\Rightarrow$ Connectionless Transmissions.

Future Directions

– Derive the fundamental limits of this strategy;
– Combine computation with communications.