



# DISCUS: Distributed Compression for Sensor Networks

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<http://basics.eecs.berkeley.edu/sensorwebs>

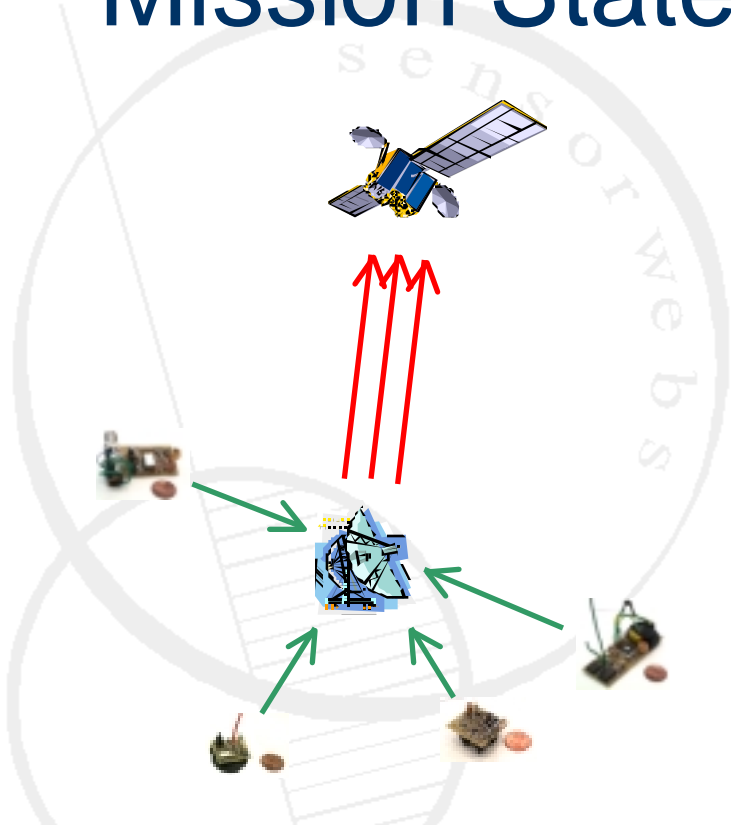
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# Motivations

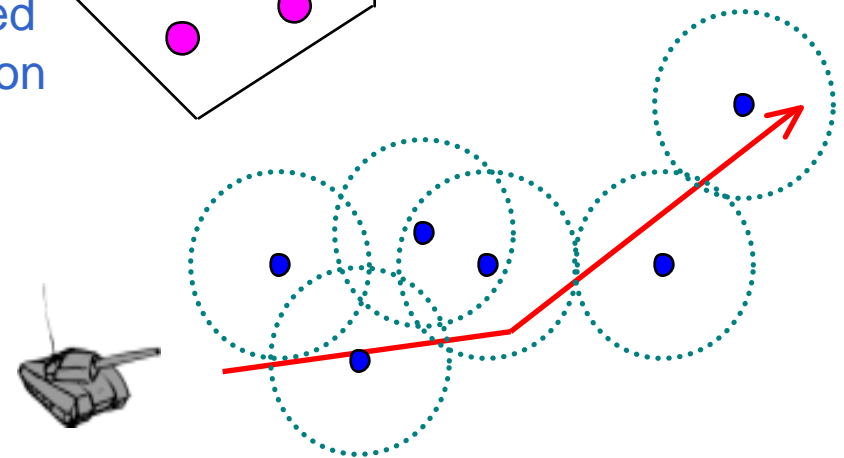
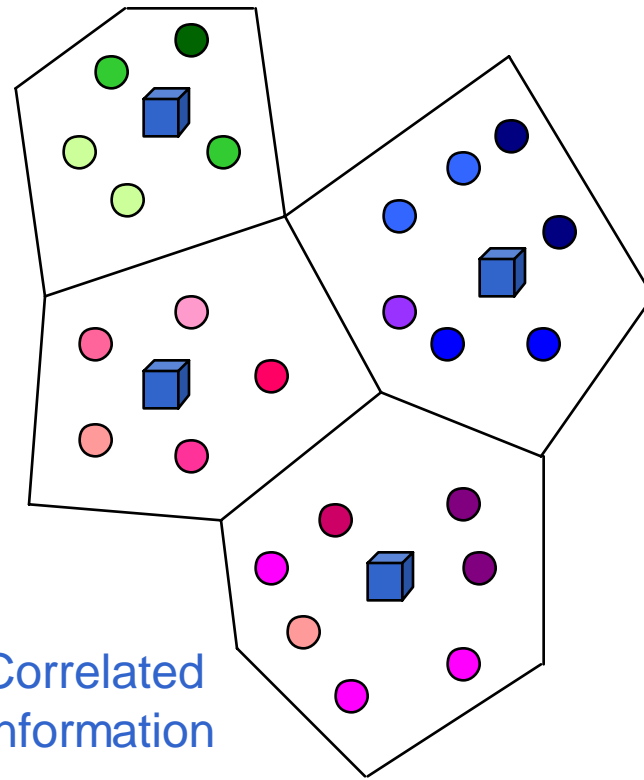
- SmartDust and MEMS: quantum leap in device and computing device technology
- Excellent platform for efficient, smart devices and collaborative, distributed theory and algorithms
- Bring unified theoretical approach to address specific scenarios
- Sensor networks -> correlated observations: want to **compress** in efficient and distributed manner

# Mission Statement



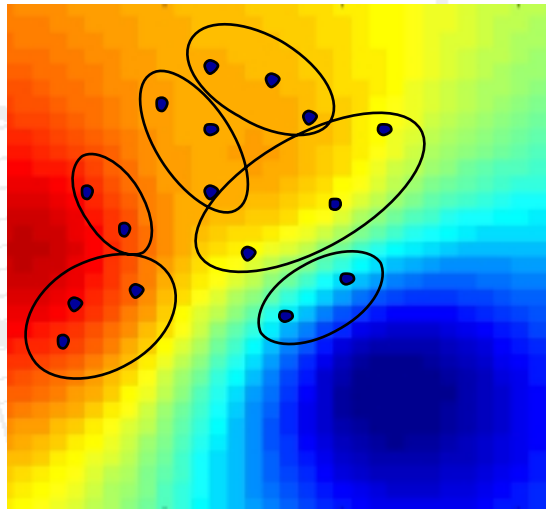
- Experimental testbed to leverage advances in SmartDust MEMS technology and demonstrate developed theories and algorithms -- the BCSN (Berkeley Campus Sensor Network).

Correlated information



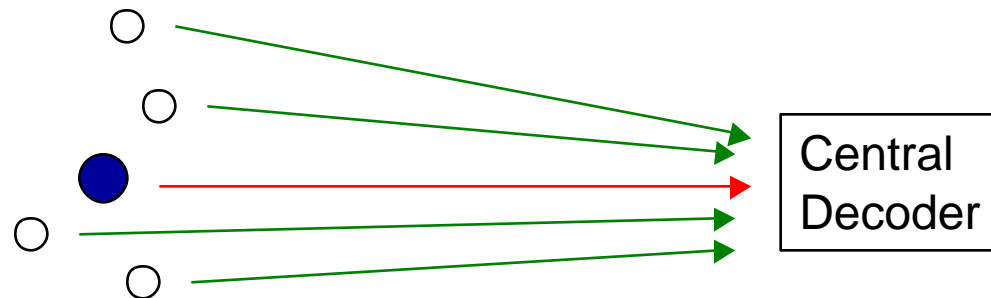
# Scenario: correlated observations

- Varying temperature field



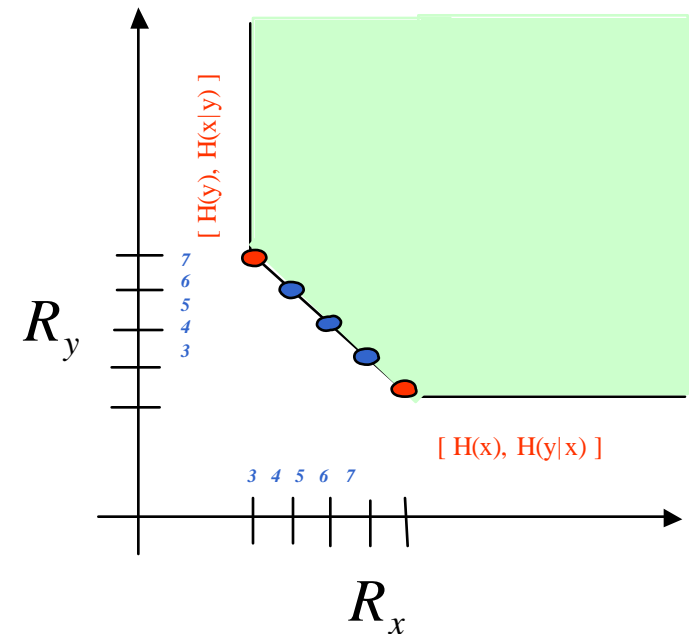
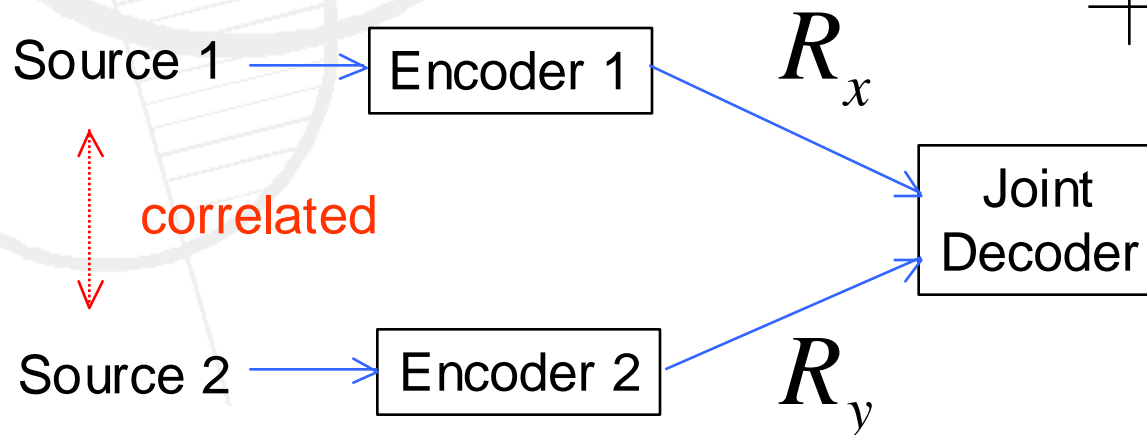
Information Theory: can gain performance boost thanks to correlation

DISCUS: constructive way of harnessing correlation for blind joint compression close to optimum



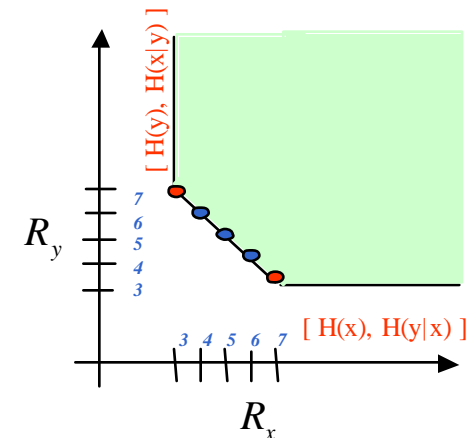
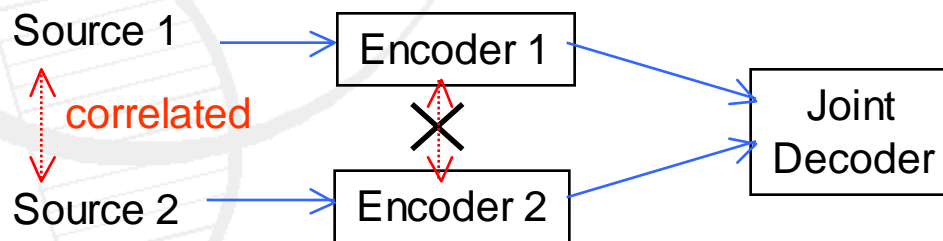
# At The End of The Day

- Want to compress correlated observations
- Don't want communication between nodes



# Distributed Compression

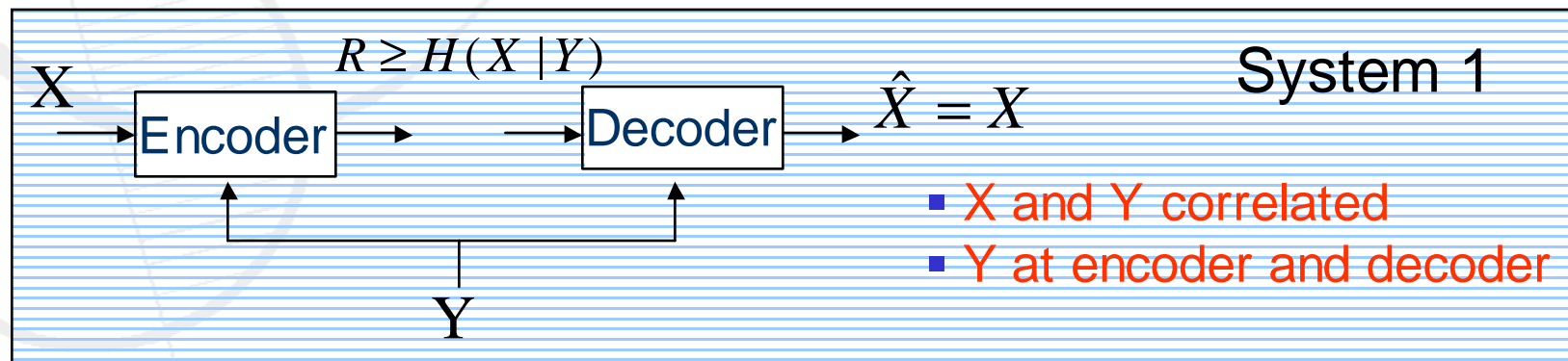
- Slepian-Wolf, Wyner-Ziv (ca. 70's): information-theoretically can jointly compress correlated observations, even with no communication between nodes.



- DISCUS: constructive framework, using **well-studied error-correcting codes** from coding theory.

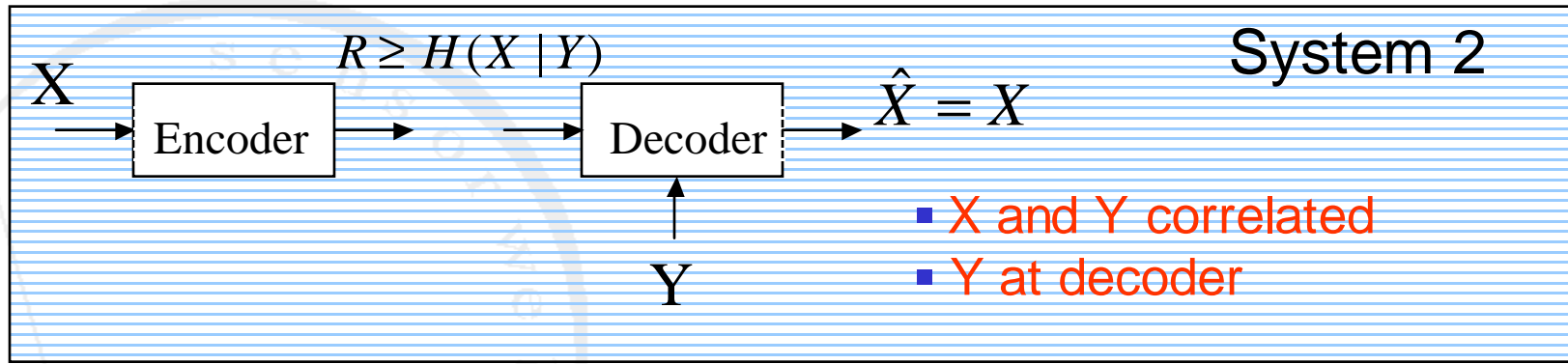
# Source Coding with Side Information – discrete alphabets

- $X$  and  $Y \Rightarrow$  length-3 binary data (equally likely),
- Correlation: Hamming distance between  $X$  and  $Y$  is at most 1.  
 Example: When  $X=[0\ 1\ 0]$ ,  
 $Y \Rightarrow [0\ 1\ 0], [0\ 1\ 1], [0\ 0\ 0], [1\ 1\ 0]$ .



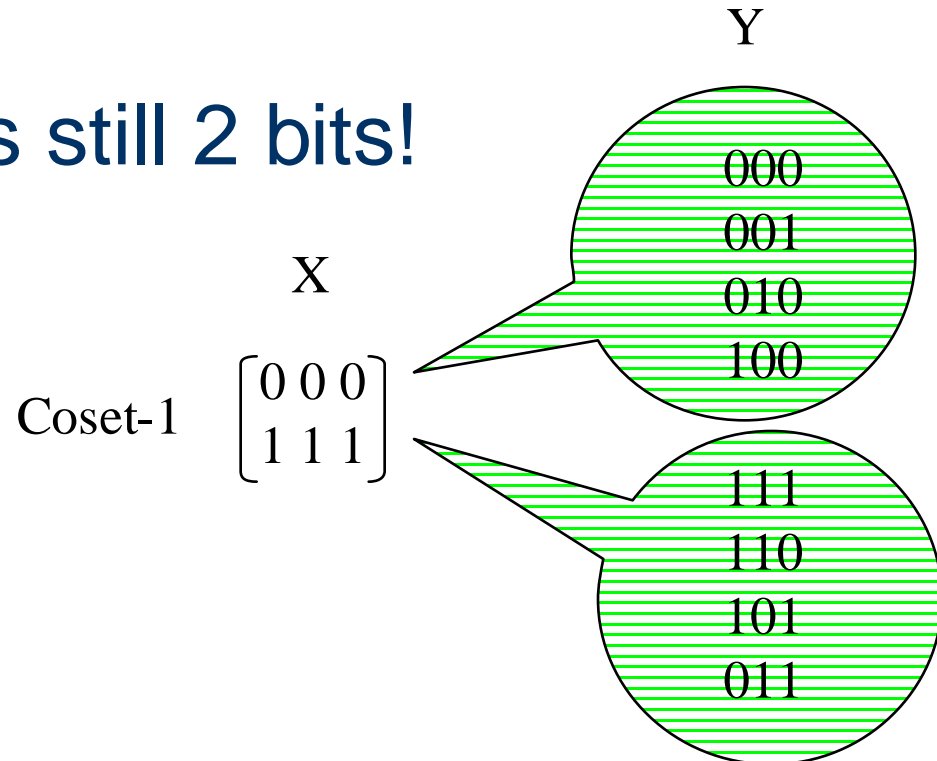
$$X+Y = \begin{cases} 000 \\ 001 \\ 010 \\ 100 \end{cases}$$

Need 2 bits to index this.



- What is the best that one can do?
- **The answer is still 2 bits!**

**How?**





$$\text{Coset-1} \begin{bmatrix} 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$

$$\text{Coset-2} \begin{bmatrix} 0 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix}$$

$$\text{Coset-3} \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix}$$

$$\text{Coset-4} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \end{bmatrix}$$

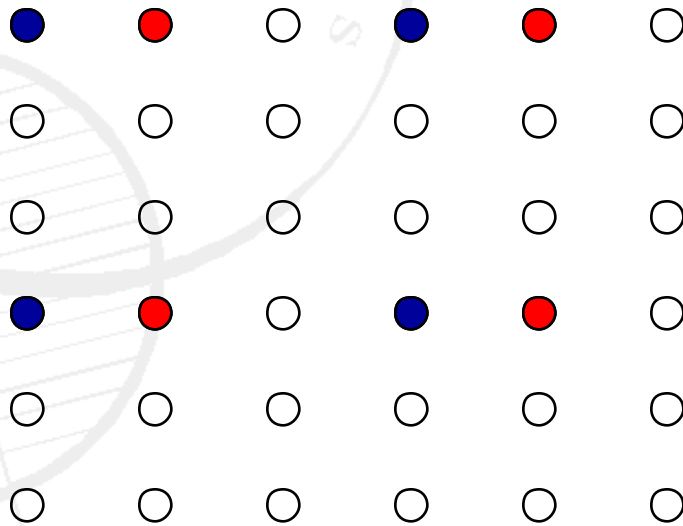
- Encoder  $\rightarrow$  index of the coset containing  $X$ .
- Decoder  $\rightarrow X$  in given coset.

**Note:**

- Coset-1  $\rightarrow$  repetition code.
- Each coset  $\rightarrow$  unique “syndrome”
- Distributed Source Coding Using Syndromes

# Discrete case – handwaving argument

- Consider abstraction using lattices
- Correlation structure translates to distance between  $X$  and  $Y$

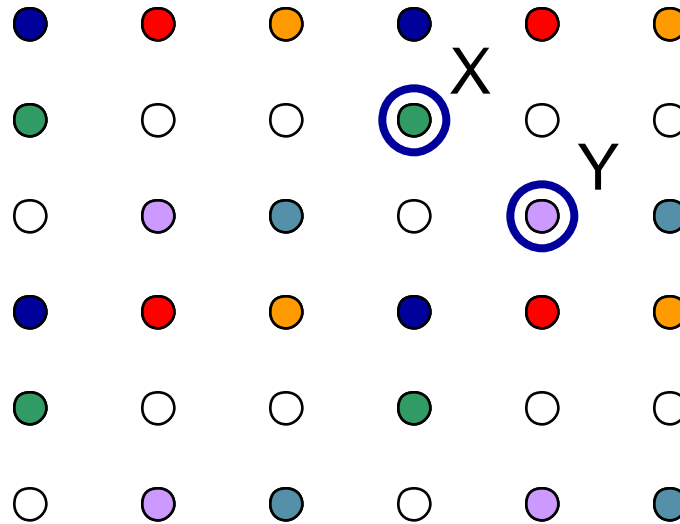


- Suppose  $X$  and  $Y$  have distance at most 1
- How to compress  $X$  if we know that  $Y$  is close to  $X$ ?

- Use cosets!
- Partition lattice space into cosets and send coset index!

# A little accounting

- How much have we compressed?
- Without compression:  $\log_2 36$  bits
- With compression:  $\log_2 9$  bits

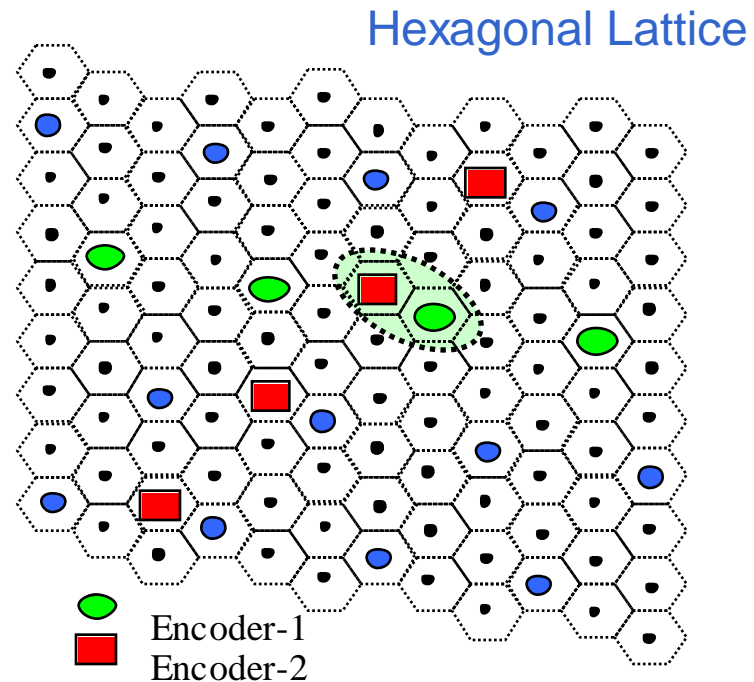


# And now the math cleanup!

- Can use well-studied channel codes to build codes on euclidean space!
- Basic idea: want to select points as far apart as possible (i.e. cosets) – done using channel codes
- Send ambiguous information, side information will disambiguate information!
- Can use Hamming, TCM, RS, etc. codes

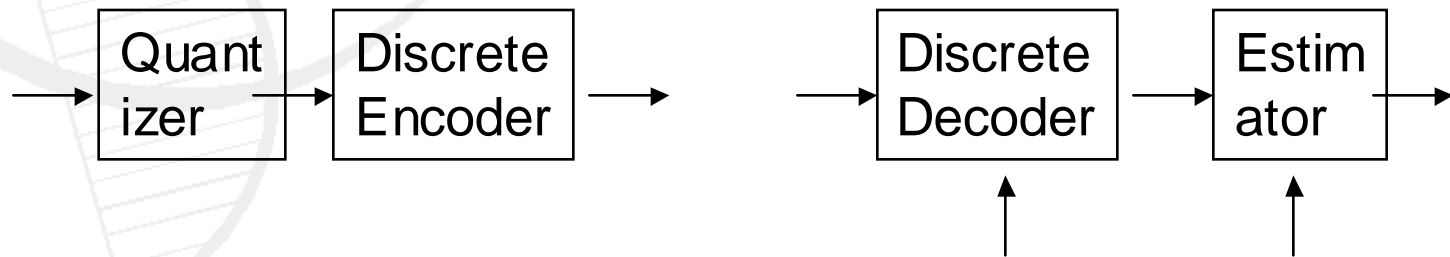
# Generalized coset codes: a/symmetric applications

- How to compress to arbitrary (but information-theoretically sound) rates?
- Use lattice idea again: 2 encoders send ambiguous information, but only one true answer that satisfy correlation constraint



# Continuous case – quantization and estimation

- Modular boxes:



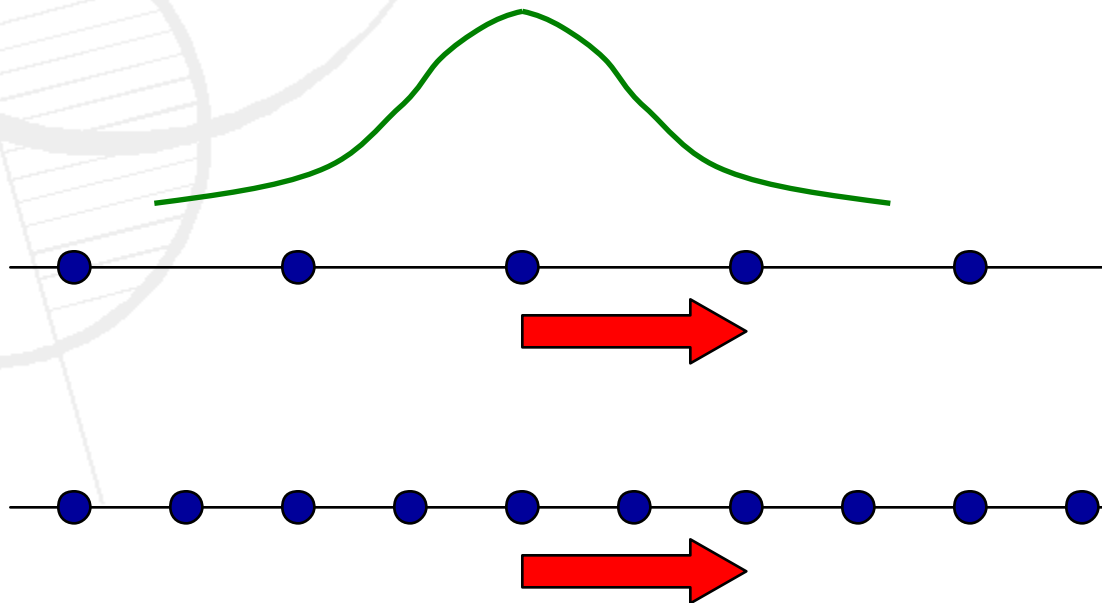
# Gaussian case example

- Estimation with side information:
  - First quantize sensor information
  - Use discrete DISCUS encoders / decoders
  - Estimate given decoder output and side information

$$\hat{X} = E[X | Y, X \in \Gamma_i]$$

# No Such Thing as Free Lunch

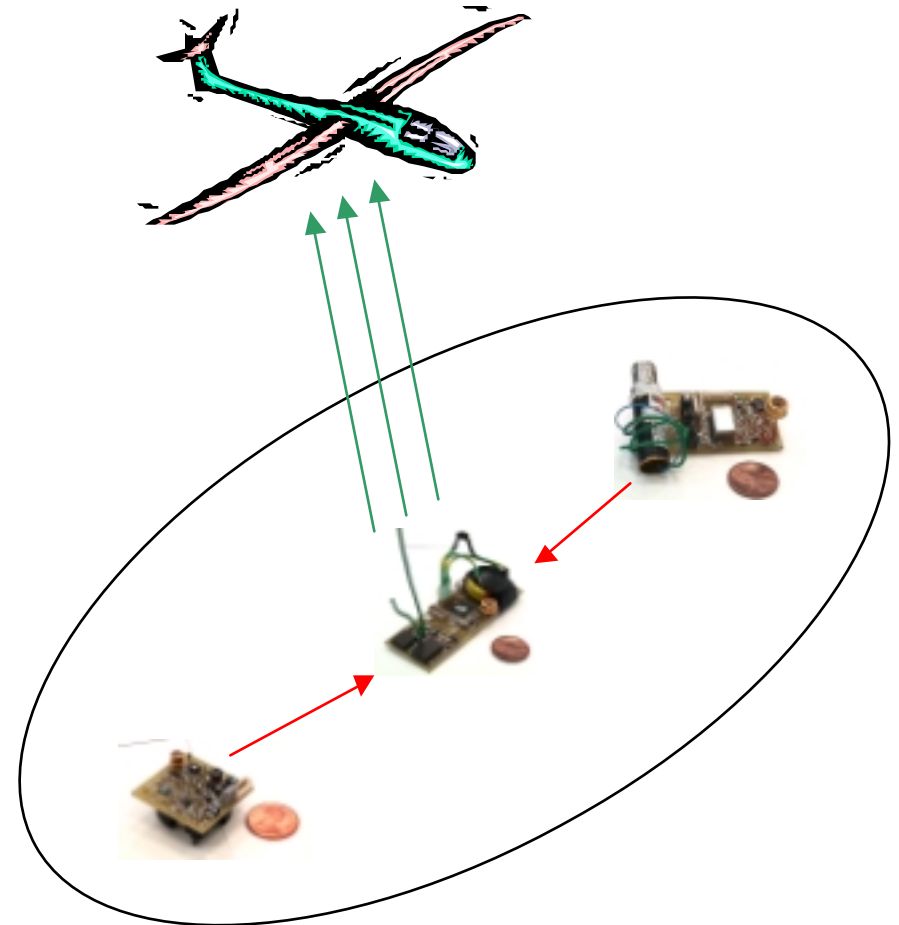
- **Big issue:** finer quantization means larger error distances – need stronger code to enable finer quantization!!!





# Deployment Scenario

- Observe readings:  
learn correlation
- Use clustering  
algorithm
- Assign codebooks  
to different motes
- Can rotate “centroid”  
mote in each group
- Centroid mote report  
to central decoder



# Dynamic Tracking Scenario

- Wish to dynamically update clustering
- Good news: **no need for child nodes to be aware!!!**  
Codebook assignment not an issue!
- Only central decoder needs to be aware of clustering
- Can also rotate centroid node within each cluster:  
can detect correlation changes

# Conclusions

- Can use efficient error-correcting codes to enable distributed compression
- Power/bandwidth/quality tradeoff through quantization and codebook selection
- Very little work for encoders!
- Tremendous gains in a sensor network