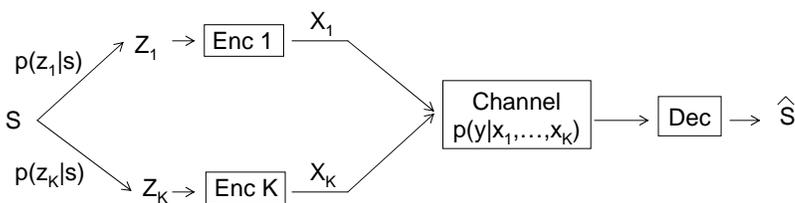


EE 8510: Sensor Network Notes

- Sensor Network Model
- Single Sensor Capacity
- Multi-terminal Source Coding
- CEO Problem

Sensor Network Model

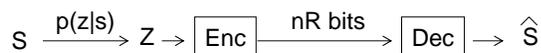


- S : source (random variable)
- Z_1, \dots, Z_k : sensor observations
- X_1, \dots, X_k : sensor transmissions
- Y : channel output
- \hat{S} : estimate of source

Simplified Models

1. Single sensor
 - Separation theorem holds
2. $\mathbf{S}=(S_1, \dots, S_k)$, $Z_i = S_i$
 - Multi-terminal source coding and MAC
3. No channel (sensors send bits to decoder)
 - CEO problem

Single Sensor, No Channel



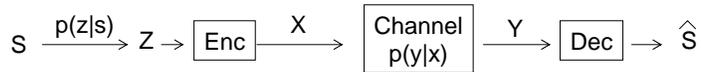
- Remove channel for simplicity
- Decoder transmits R bits per symbol
- Rate distortion with noisy observation [1]:

$$R(D) = \min_{p(\hat{s}|z)} I(Z; \hat{S})$$

$$\text{s.t. } E[d(s, \hat{s})] \leq D$$

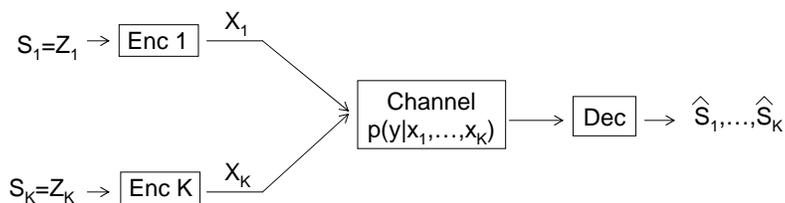
- Only difference is that must map from observation z to estimate of s, instead of from s to estimate of s (since s not known at encoder)

Single Sensor (# 1)



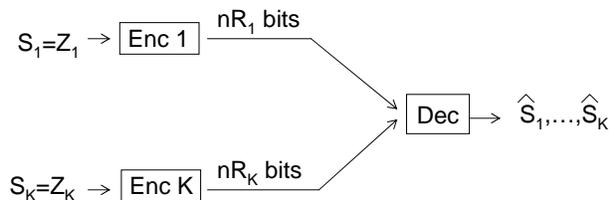
- Separation theorem holds: Can get estimate of S satisfying distortion D if and only if $R(D) < C$ [1]
- Implication:
 - First perform quantization of Z (to achieve $R(D)$)
 - Next perform channel coding treating quantization index as the message
 - Receiver decodes message (i.e. quantization index), and estimates using reconstruction codebook

Arbitrary Source (# 2)



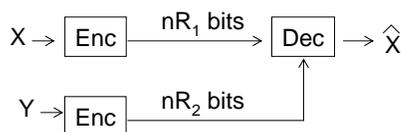
- Arbitrary source $S=(S_1, \dots, S_k)$
- $Z_i = S_i$ (no measurement noise)
- Question: What sources can be reconstructed at decoder?
- If require lossless coding of S , is MAC with correlated sources [2]
- Same conclusion for lossy coding
 - Capacity unknown, separation does not hold

Arbitrary Source, No Channel



- Multi-terminal source coding: What rates required to reconstruct S according to certain fidelity?
- Lossless
 - Capacity region known (Slepian-Wolf) [3]
 - No sum rate loss relative to cooperative coding: $H(S_1, \dots, S_K)$
- Lossy
 - Capacity region unknown
 - Inner/Outer bounds (Berger-Tung) [4] (similar to Wyner-Ziv)
 - Generally rate loss relative to cooperative coding

Source Coding with Side Info



- Want to decode X losslessly using Y only as side information
- (R_1, R_2) achievable iff (Wyner) [5]:

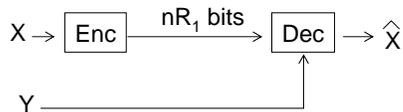
$$R_1 \geq H(X | U)$$

$$R_2 \geq I(Y; U)$$

for some $p(u|y)$

- Achievability: Cover Y with reconstruction r.v. U , use random binning on X and Markov lemma to find typical (X^n, U^n) pair in bin
- Markov Lemma: If $X \rightarrow Y \rightarrow Z$, (x^n, y^n) typical, and z^n chosen iid $p(z^n | y^n)$, then (x^n, y^n, z^n) typical with nearly probability one
 - By definition $X \rightarrow Y \rightarrow U$. Since (x^n, y^n) typical with high probability, also have (x^n, y^n, u^n) typical, which implies (x^n, u^n) typical

Rate-Distortion with Side Info



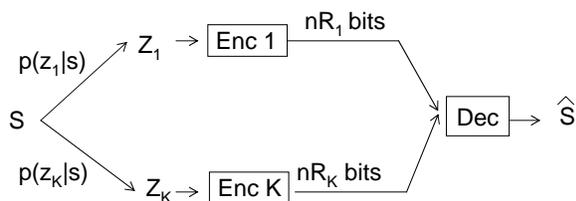
- Want to lossy decoding of X using Y as side information (Wyner-Ziv) [6]

$$R_Y(D) = \min_{p(u|x), f(y,u)} I(X;U) - I(Y;U)$$

$$E[d(x, f(y,u))] \leq D$$

- Generally is strict rate loss relative to cooperative encoder (i.e. encoder who knows \hat{X} and Y)
- Achievability: Generate $2^{nI(X;U)}$ codewords iid $p(u)$ and randomly place in 2^{nR} bins. Choose codeword typical with x^n and send bin index. Decoder finds (u^n, y^n) typical (Markov lemma) in correct bin. Given correct u^n , computes $f(u,y)$ to estimate X.

CEO Problem (# 3)



- Sensors (agents) observe source S, transmit quantized measurements to decoder (CEO) [7]
- Decoder estimates S according to distortion criteria (lossless or lossy reconstruction)
- Question: What rates R_1, \dots, R_K are required to achieve certain distortion?
 - Region not known in general

Lossless Coding of S

- Discrete source S must be reconstructed losslessly ($P_e \rightarrow 0$) at decoder
- Conditionally (on S) iid observations
- Fix sum of rates to be R
- If K goes to infinity and sensors could cooperate, could pool observations to recover S perfectly and if $R > H(S)$ could losslessly transmit S
- Non-cooperative sensors cannot achieve perfect reconstruction at decoder for any finite R [7]

Quadratic CEO Problem

- $Z_i = S + N_i$
- $S \sim N(0, P_S)$, $N_i \sim N(0, P_N)$ (independent)
- $D(S, \hat{S}) = (S - \hat{S})^2$
- Berger-Tung achievable region achieves capacity [8,9,10]
- Achievability:
 - Sensors perform single-user quantization on observation Z_i
 - Decoder recovers each quantized observation, which add additional Gaussian noise to Z_i
 - Decoder estimates S (via MMSE) based on quantized observations, which are jointly Gaussian with S

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