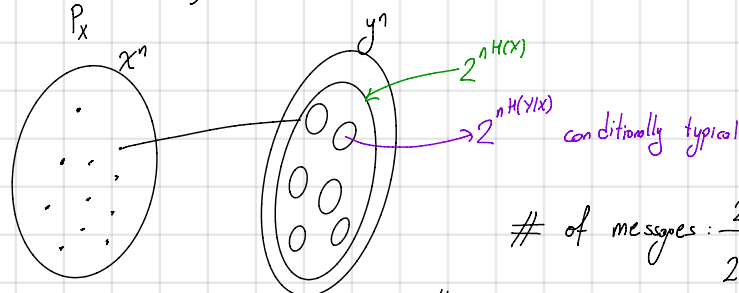


10/04/2016
Tuesday

$$C = \max_{P_X} I(X; Y)$$



$$\# \text{ of messages: } \frac{2^{nH(Y)}}{2^{nH(Y|X)}} = 2^{nI(X; Y)}$$

"Sphere Packing" idea.

Jointly typical:

$$A_{\epsilon}^{(n)}(P_{XY}) = \left\{ (x^n, y^n) : \left| \frac{1}{n} \log \frac{1}{P_{X^n Y^n}(x^n, y^n)} - H(X, Y) \right| \leq \epsilon, X^n \in A_{\epsilon}^{(n)}, Y^n \in A_{\epsilon}^{(n)} \right\}$$

Properties of $A_{\epsilon}^{(n)}(P_{XY})$:

1. If X^n, Y^n jointly i.i.d. $\sim P_{XY}$

$$P[(X^n, Y^n) \in A_{\epsilon}^{(n)}] \rightarrow 1 \text{ as } n \rightarrow \infty$$

Union bound $P(A \text{ or } B \text{ or } C) \leq P(A) + P(B) + P(C)$

$$2. |A_{\epsilon}^{(n)}| \in \left[(1-\epsilon) 2^{n(H(X, Y) - \epsilon)}, 2^{n(H(X, Y) + \epsilon)} \right]$$

lower bound is for n sufficiently large

3. If X^n i.i.d. $\sim P_X, Y^n$ i.i.d. $\sim P_Y, X^n \perp Y^n$

$$P[(X^n, Y^n) \in A_{\epsilon}^{(n)}] \in \left[(1-\epsilon) 2^{-n(I(X, Y) + 3\epsilon)}, 2^{-n(I(X, Y) - 3\epsilon)} \right]$$

lower bound is for large enough n .

proof

$$\begin{aligned} P[(X^n, Y^n) \in A_{\epsilon}^{(n)}] &= \sum_{X^n, Y^n \in A_{\epsilon}^{(n)}} P_{X^n Y^n}(x^n, y^n) = \sum_{X^n, Y^n \in A_{\epsilon}^{(n)}} P_{X^n}(x^n) P_{Y^n}(y^n) \\ &\leq |A_{\epsilon}^{(n)}| 2^{-n(H(X) + H(Y) - 2\epsilon)} \leq 2^{-n(H(X) + H(Y) - H(X, Y) - 3\epsilon)} \end{aligned}$$

$\rightarrow$ The lower bound is similar to prove!

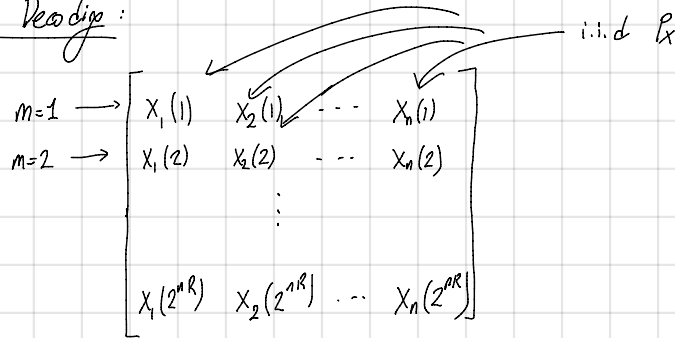
Channel Coding Theorem: Achievability proof.

Let $R < C$. Let $P_X = \arg\max_{P_X} I(X; Y)$

Random Codebook $\rightarrow C = \{X^n(m)\}_{m=1}^{2^{nR}}$

Joint Typicality Decoding:

(ϵ is specified)



Decoder: Maximum likelihood is optimal, but we'll use suboptimal decoder.

Observe Y^n : Search for unique m such that

$$(X^n(m), Y^n) \in A_\epsilon^{(n)}$$

Choose n large enough s.t. $P(A_\epsilon^{(n)}) > 1 - \frac{\epsilon}{2}$

Let $\mathcal{E}$ be the error event

Choose $\epsilon < \frac{C-R}{4}$

$$P(\mathcal{E}) = \sum_c P_r(c) P_e^{(n)}(c)$$

$$\begin{aligned} P(\mathcal{E}) &= P[M \neq \hat{M}] = \sum_c P_r(c) P[M \neq \hat{M} | c] \\ &= \sum_c P_r(c) \cdot \frac{1}{2^{nR}} \sum_m P[M \neq \hat{M} | c, M=m] \\ &= \frac{1}{2^{nR}} \sum_m \sum_c P_r(c) P[M \neq \hat{M} | c, M=m] \\ &= \frac{1}{2^{nR}} \sum_m \sum_c P_r(c) P[M \neq \hat{M} | c, m=1] \\ &= P[M \neq \hat{M} | M=1] \end{aligned}$$

$$\text{Let } E_i = \{(X^n(i), Y^n) \in A_\epsilon^{(n)}\} \quad (X^n(1), Y^n) \sim P_{X^n Y^n}$$

$$X^n(j) \perp Y^n \quad \forall j \neq 1$$

$$\mathcal{E} = E_1^c \cup E_2 \cup \dots \cup E_{2^{nR}}$$

$$\begin{aligned}
 P(E|M=1) &\leq P[E_1^c] + \sum_{m=2}^{2^R} P[E_m] \\
 &\leq \frac{\epsilon}{2} + 2^{nR} \cdot 2^{-n(I(X;Y) - 3\epsilon)} = \frac{\epsilon}{2} + \underbrace{2^{-n(\frac{\epsilon}{4} - R)}}_{2^{-n(I(X;Y) - R - 3\epsilon)}} \\
 &\rightarrow 0 \text{ for small enough choice of } \epsilon.
 \end{aligned}$$

Channel Coding Theorem: Converse Proof

Let $\epsilon > 0$ be arbitrary, let n, f, p achieve $P[M \neq \hat{M}] < \epsilon$

$$\begin{aligned}
 nR &= H(M) \\
 &= I(M; \hat{M}) + \underbrace{H(M|\hat{M})}_{\text{we'll handle using Fano}}
 \end{aligned}$$

$$\text{Notice: } M = X^n = Y^n = \hat{M},$$

$$I(M; \hat{M}) \leq I(X^n; Y^n) \quad (\text{Data Proc. Ineq.})$$

$$= \sum_{i=1}^n I(X_i; Y_i | Y^{i-1})$$

$$\leq \sum_{i=1}^n I(X_i; Y_i | Y^{i-1}) + I(X^{i-1}, X_i; Y_i | X_i, Y^{i-1})$$

$$\leq \sum_{i=1}^n I(X_i; Y_i)$$

$$= nC$$

$$\begin{aligned}
 P_{Y^n|X^n} &= \prod P_{Y_i|X_i} \\
 (X^n, Y^{i-1}) &\rightarrow X_i = Y_i
 \end{aligned}$$

$$\Rightarrow R \leq C + \epsilon R + \frac{H(\epsilon)}{n}$$

How about continuous X, Y ? Then $H(X) = \infty$

$$\begin{aligned}
 I(X; Y) &= D(P_{XY} \| P_X P_Y) = \mathbb{E}_{P_{XY}} \left[\log \left(\frac{f_{XY}(X, Y)}{f_X(X) f_Y(Y)} \right) \right] \\
 &\neq H(X) - H(X|Y) \quad (\infty - \infty \text{ problem!})
 \end{aligned}$$

Define Differential Entropy: $h(X) = \mathbb{E} \left[\log \frac{1}{f_X(X)} \right]$

$$I(X; Y) = h(X) - h(X|Y)$$

$$A_\epsilon^{(n)} = \left\{ x^n : \left| \frac{1}{n} \log \frac{1}{f_{X^n}(x^n)} - h(X) \right| \leq \epsilon \right\} \quad \text{Vol}(A_\epsilon^{(n)}) \doteq 2^{n h(X)}$$

$$C = \frac{1}{2} \log \left(1 + \frac{P}{N} \right) \text{ for Gaussian Channel}$$