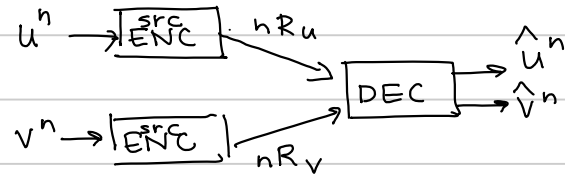


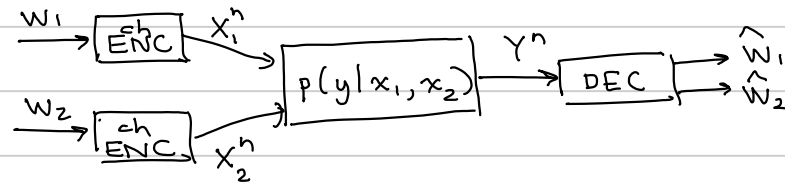
Network Information Theory: Lecture 3

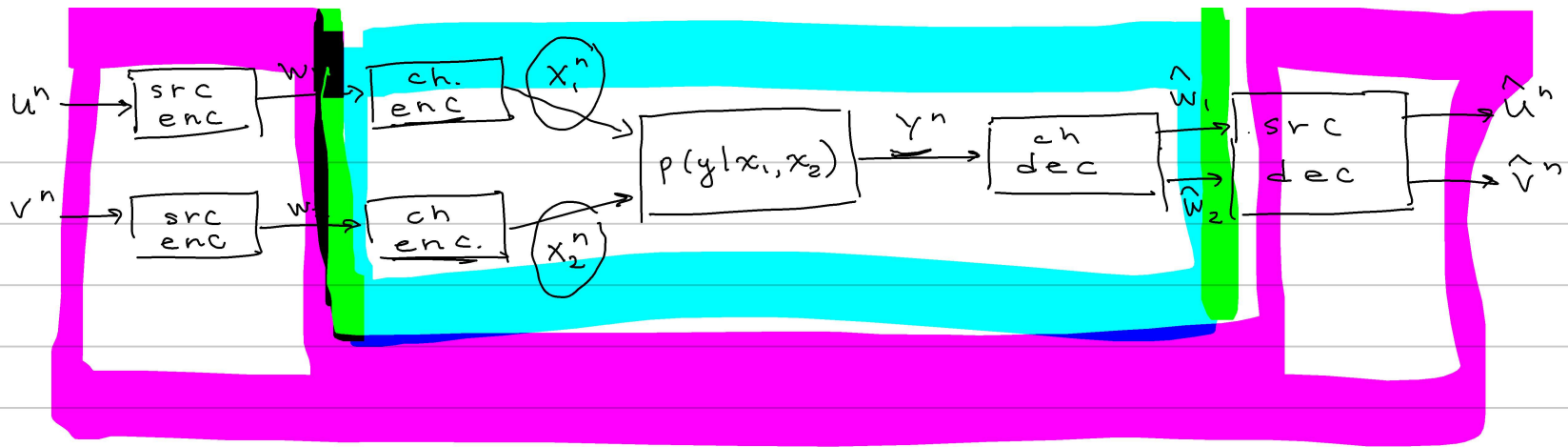
Last time: Multiple Access Source Coding



Today

Multiple Access Channel Coding





A $((2^{nR_1}, 2^{nR_2}), n)$ multiple access channel code is defined by
 a pair of encoders (MAC)

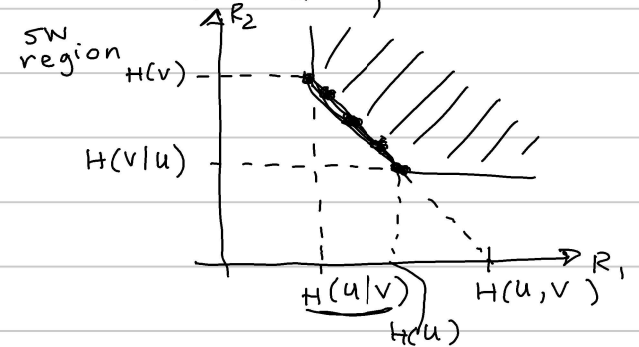
$$f_{1,n} : \{1, \dots, 2^{nR_1}\} \rightarrow \mathcal{X}_1^n$$

$$f_{2,n} : \{1, \dots, 2^{nR_2}\} \rightarrow \mathcal{X}_2^n$$

and a single decoder

$$g_n : y^n \rightarrow \{1, \dots, 2^{nR_1}\} \times \{1, \dots, 2^{nR_2}\}$$

We assume that the messages W_1 and W_2 are independent & uniformly distributed



The probability of error for this code is

$$P_e^{(n)} = \Pr(g_n(Y^n) \neq (w_1, w_2) \mid \underline{X}_1^n = f_{1,n}(w_1), \underline{X}_2^n = f_{2,n}(w_2)).$$

A rate vector $\underline{(R_1, R_2)}$ is achievable if \exists a seq. of $((2^{nR_1}, 2^{nR_2}), n)$ MAC codes $\{((f_{1,n}, f_{2,n}), g_n)\}_{n=1}^{\infty}$ with $\underline{P_e^{(n)}} \rightarrow 0$ as $n \rightarrow \infty$.

The capacity region for the MAC is the closure of the set of all achievable rates.

To derive the capacity, we again use an argument in 2 parts:

Achievability

Converse

Achievability

Random code Design: Fix $p_1(x_1)$ on alphabet \mathcal{X}_1 , $p_2(x_2)$ on alphabet \mathcal{X}_2 .

Draw the codewords $f_{1,n}(1), f_{1,n}(2), \dots, f_{1,n}(2^{nR_1}) \sim \text{iid } \prod_{i=1}^n p_1(x_i)$
 $f_{2,n}(1), f_{2,n}(2), \dots, f_{2,n}(2^{nR_2}) \sim \text{iid } \prod_{i=1}^n p_2(x_{2i})$.

Design the decoder: For each $y^n \in \mathcal{Y}^n$

$$g_n(y^n) = \begin{cases} (w_1, w_2) & \text{if } (f_{1,n}(w_1), f_{2,n}(w_2), y^n) \in A_\varepsilon^{(n)} \\ & \text{and } \nexists (\hat{w}_1, \hat{w}_2) \neq (w_1, w_2) \text{ s.t.} \\ & (f_{1,n}(\hat{w}_1), f_{2,n}(\hat{w}_2), y^n) \in A_\varepsilon^{(n)} \\ \text{"error"} & \text{otherwise} \end{cases}$$

$$\begin{aligned} E[P_e^{(n)}] &= E \left[\frac{1}{2^{nR_1}} \cdot \frac{1}{2^{nR_2}} \sum_{(w_1, w_2) \in \{1, \dots, 2^{nR_1}\} \times \{1, \dots, 2^{nR_2}\}} \Pr(g_n(Y^n) \neq (w_1, w_2) \mid X_1^n = f_{1,n}(w_1), X_2^n = f_{2,n}(w_2)) \right] \\ &= \frac{1}{2^{nR_1}} \frac{1}{2^{nR_2}} \sum_{(w_1, w_2)} E \left[\Pr(g_n(Y^n) \neq (w_1, w_2) \mid X_1^n = f_{1,n}(w_1), X_2^n = f_{2,n}(w_2)) \right] \\ & \quad \text{the same } \forall w_1, w_2 \text{ by symmetry of code design} \\ &= E \left[\Pr(g_n(Y^n) \neq (1, 1) \mid X_1^n = f_{1,n}(1), X_2^n = f_{2,n}(1)) \right] \end{aligned}$$

Events of interest: $E_{ij} = \{(f_{1,n}(i), f_{2,n}(j)), Y^n \in A_\epsilon^{(n)}\}$

Error events: E_{ii}^c : codewords transmitted are not jointly typical with Y^n received
 $(i,j) \neq (1,1)$ E_{ij} : codewords (i,j) are jointly typical with Y^n but (i,j) was not the message pair sent.

$$\begin{aligned}
 E[Pe^{(n)}] &= E[\Pr(g_n(Y^n) \neq (1,1) \mid (x_1^n, x_2^n) = (f_{1,n}(1), f_{2,n}(1)))] \\
 &= \Pr(E_{ii}^c \cup \bigcup_{(i,j) \neq (1,1)} E_{ij} \mid (x_1^n, x_2^n) = (f_{1,n}(1), f_{2,n}(1))) \quad \text{"(1,1) sent"} \\
 &\leq \Pr(E_{ii}^c \mid (1,1) \text{ sent}) + \sum_{j \neq 1} \Pr(E_{1j} \mid (1,1) \text{ sent}) + \sum_{i \neq 1} \Pr(E_{i1} \mid (1,1) \text{ sent}) \\
 &\quad + \sum_{i \neq 1} \sum_{j \neq 1} \Pr(E_{ij} \mid (1,1) \text{ sent}) \quad \text{by union bound}
 \end{aligned}$$

$\Pr(E_{ii}^c \mid (1,1) \text{ sent}) \rightarrow 0$ as $n \rightarrow \infty$ by AEP (WLLN)

$$\sum_{j \neq 1} \Pr(E_{i,j} | (1,1) \text{ sent}) = (2^{nR_2} - 1) \Pr(E_{1,2} | (1,1) \text{ sent}) \text{ by symmetry of code design}$$

$$\leq 2^{nR_2} \sum_{(x_1^n, \hat{x}_2^n, y^n) \in A_\varepsilon^{(n)}} \underbrace{p_1(x_1^n)}_{p_1(x_1^n)} \underbrace{p_2(\hat{x}_2^n)}_{p_2(\hat{x}_2^n)} \underbrace{p(y^n | x_1^n)}_{p(y^n | x_1^n)}$$

$$\leq 2^{nR_2} \sum_{(x_1^n, \hat{x}_2^n, y^n) \in A_\varepsilon^{(n)}} \underbrace{p_2(\hat{x}_2^n)}_{p_2(\hat{x}_2^n)} \underbrace{p(x_1^n, y^n)}_{p(x_1^n, y^n)}$$

$$\leq 2^{nR_2} |A_\varepsilon^{(n)}| \frac{2^{-n(H(x_2) - \varepsilon)}}{2} \frac{2^{-n(H(x_1, Y) - \varepsilon)}}{2}$$

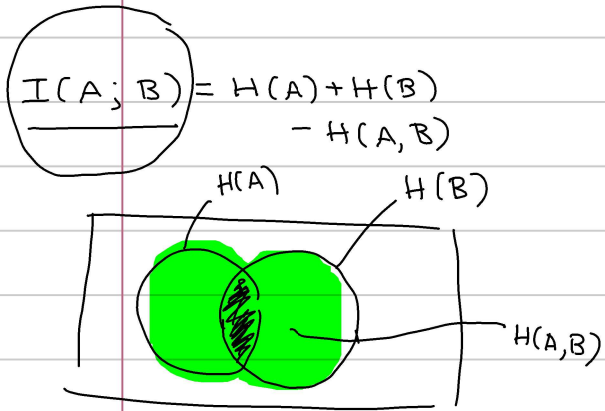
$$\leq 2^{nR_2} 2^{n(H(x_1, x_2, Y) + \varepsilon)} \frac{2^{-n(H(x_2) - \varepsilon)}}{2} \frac{2^{-n(H(x_1, Y) - \varepsilon)}}{2}$$

$$= 2^{-n(I(x_1, Y; x_2) - 3\varepsilon - R_2)}$$

$$\xrightarrow[n \rightarrow \infty]{} 0 \text{ provided } R_2 < \underbrace{I(x_1, Y; x_2)}_{I(x_1, Y; x_2)} - 3\varepsilon$$

$$= \underbrace{I(x_1; x_2)}_{=0 \text{ since } x_1 \perp x_2} + \underbrace{I(Y; x_2 | x_1)}_{= I(x_2; Y | x_1)}$$

$$\boxed{R_2 < I(x_2; Y | x_1)}$$



Similarly $\sum_{i \neq 1} \Pr(E_{i1} | (1,1) \text{ sent}) \rightarrow 0$ as $n \rightarrow \infty$ provided

$$\boxed{R_1 < I(x_1; Y | x_2)}$$

Finally $\sum_{i \neq 1} \sum_{j \neq 1} \Pr(E_{ij} | (1,1) \text{ sent}) \leq \underbrace{2^{nR_1} 2^{nR_2}}_{\substack{(\hat{x}_1^n, \hat{x}_2^n, y^n) \in A_\epsilon^{(n)}}} \underbrace{p_1(\hat{x}_1^n)}_{2^{-n(H(x_1) - \epsilon)}} \underbrace{p_2(\hat{x}_2^n)}_{2^{-n(H(x_2) - \epsilon)}} \underbrace{p(y^n)}_{2^{-n(H(Y) - \epsilon)}}$

$$\leq 2^{n(R_1 + R_2)} \frac{|A_\epsilon^{(n)}|}{2^{n(H(x_1, x_2, Y) + \epsilon)}} 2^{-n(H(x_1) + H(x_2) + H(Y) - 3\epsilon)}$$

$$= 2^{-n(H(x_1, x_2) + H(Y) - H(x_1, x_2, Y) - 4\epsilon - \underbrace{H(x_1, x_2)}_{\text{since } x_1 \perp\!\!\!\perp x_2} - (R_1 + R_2))}$$

$$= 2^{-n(I(x_1, x_2; Y) - 4\epsilon - (R_1 + R_2))}$$

$\rightarrow 0$ as $n \rightarrow \infty$ provided $\boxed{R_1 + R_2 < I(x_1, x_2; Y)}$

$E[P_e^{(n)}] \rightarrow 0$ as $n \rightarrow \infty$ provided

$$\begin{aligned} R_1 &< I(x_1; Y | x_2) \\ R_2 &< I(x_2; Y | x_1) \\ R_1 + R_2 &< I(x_1, x_2; Y) \end{aligned}$$

taking the union over all $p(x_1)p(x_2)$
and then the convex hull
and the closure turns out to give
the complete capacity region for MAC.

