

Last time:

Theorem [Shannon's noisy coding theorem]

$$C(N) = \max_{p(x)} I(X:Y)$$

How to prove this?

1. Direct coding – consider high-rate codes

Not easy -- instead, consider "random"  $(M,n)$  codes with rate  $= I(X:Y)$  and show  $\text{Prob}(EP_e \rightarrow 0) > 0$ .

Thus  $\exists$  code with small  $EP_e$  (our 2nd encounter with "existential proofs"). Extract a subcode with similar rate but  $P_e \rightarrow 0$ .

2. Converse – show that at higher rates,  $EP_e \not\rightarrow 0$ .

Plan: 2, then heuristic 1, then 1.

1. Direct coding:  $c_1 = x_{11}, x_{12}, \dots, x_{1n}$   
 $c_2 = x_{21}, x_{22}, \dots, x_{2n}$   $x_{ij}$  chosen iid  $\sim p(x)$

.

.

$c_M = x_{M1}, x_{M2}, \dots, x_{Mn}$

Better proof why  $P_e \rightarrow 0$ .

Long version (18 pages) available in homepage,  
here, a 6-page version skipping  $\varepsilon$ ,  $\delta$  & some details.

Recall:

**Def[typical sequence]:**

$x^n$   $\varepsilon$ -typical if  $|-1/n \log(p(x^n)) - H(X)| \leq \varepsilon$

It means  $2^{-n(H(X)+\varepsilon)} \leq p(x^n) \leq 2^{-n(H(X)-\varepsilon)}$ .

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\begin{General technical tool}

**Def[Jointly typical sequence]:**

$x^n y^n$   $\varepsilon$ -jointly-typical if

$|-1/n \log(p(x^n y^n)) - H(XY)| \leq \varepsilon$

where  $p(x^n y^n) = \prod_{i=1}^n p(x_i y_i)$ .

Need also: (a)  $|-1/n \log(p(x^n)) - H(X)| \leq \varepsilon$

[The strong typicality has (c)  $\Rightarrow$  (a,b),

(b)  $|-1/n \log(p(y^n)) - H(Y)| \leq \varepsilon$

but not for entropic typicality.]

**Def[Jointly-typical set]:**  $A_{n,\varepsilon} = \{x^n y^n \text{ } \varepsilon\text{-jointly typical}\}$

## Joint asymptotic equipartition (Joint AEP) theorem:

Let  $(X^n, Y^n)$  be sequences of length  $n$

drawn iid according to  $p(x^n y^n) = \prod_{i=1}^n p(x_i y_i)$ .

Then:

$$1. \Pr(X^n Y^n \in A_{n,\varepsilon}) \rightarrow 1$$

$$2. |A_{n,\varepsilon}| \approx 2^{nH(XY)}$$

$$3. \text{if we draw } X^n \text{ & } Y^n \text{ according to } q(x^n y^n) = p(x^n) p(y^n).$$

$$\Pr_q(\text{outcome} \in A_{n,\varepsilon}) \approx 2^{-nI(X:Y)}$$

Proved in the 18 page notes, similar to the proof for the asymptotic equipartition thm.

More observations:

Given  $y^n \in T_{n,\varepsilon}^Y$ , collect in a set  $S(y^n)$   
all those  $x^n \in T_{n,\varepsilon}^X$  s.t.  $x^n y^n \in A_{n,\varepsilon}$ .

$$(1) p(x^n|y^n) = p(x^n y^n) / p(y^n) \approx 2^{-n[H(XY)-H(Y)]} = 2^{-n[H(X|Y)]}$$

↑ since  $x^n y^n \in A_{n,\varepsilon}$  !!

$$(2) 1 = \sum_{x^n \in S} p(x^n|y^n) \approx |S(y^n)| 2^{-n[H(X|Y)]}$$

Hence,  $|S(y^n)| \approx 2^{nH(X|Y)}$ . Fraction of such  $x^n \approx 2^{-nI(X:Y)}$ .

Similarly, given  $x^n \in T_{n,\varepsilon}^X$ ,  $\approx 2^{nH(Y|X)}$   $y^n$ 's are jointly typical with it, and the fraction of such  $y^n \approx 2^{-nI(X:Y)}$ .

Make a table of typical  $x^n$ 's and  $y^n$ 's, and for jointly typical  $x^ny^n$ , put a 1, else, put a 0.

	$y^{n(1)}$	$\dots$	$y^{n( )}$	$\leftarrow \approx 2^{nH(Y)}$ entries
$x^{n(1)}$				
$x^{n(2)}$				
.				
.				
$x^{n( )}$				

$\approx 2^{nH(X)}$  entries

each row has  $\approx 2^{nH(Y|X)}$  1's  
each column  $\approx 2^{nH(X|Y)}$  1's  
total:  $\approx 2^{nH(XY)}$  1's

$\backslash \text{end}\{ \text{General technical tool} \}$

Our random code corresponds to  $M$  randomly chosen rows.

Back to the direct coding proof:

$D_n$ : typical set decoding

Given  $y^n$ :

If there is a unique  $x^n \in S(y^n)$  output  $m'$  s.t.  $c_{m'} = x^n$ .  
Else, output  $W=M+1$  (error symbol).

How will this fail for input message  $m$ ?

Either - no such  $m'$

$\text{Err}_0$  unlikely-only when  $x^n y^n$  not jointly typical

- or  $\exists m'' \neq m$  with  $c_{m''} y^n \in A_{\varepsilon, n}$

$\text{Err}_{m''}$

For the random code  $C_n$ , let  $\text{EP}_e(C_n)$  be the average error (over all messages), by symmetry, same as error for  $m=1$ .

Averaging over the choice of  $C_n$ :

$$\Pr_{C_n} \text{EP}_e(C_n) = \Pr_{C_n} (W \neq 1 | m=1) = \Pr_{C_n} (\text{Err}_0 \cup \underbrace{\text{Err}_2 \dots \cup \text{Err}_M}_{\text{equiprobable}} | m=1)$$

union bdd 

$$\leq M \Pr_{C_n} (\text{Err}_2 | m=1)$$

unlikely ↑

Bounding  $\Pr_{C_n}(\text{Err}_2 | m=1) = \Pr_{C_n}(c_2 y^n \in A_{n, \varepsilon_n})$  :

But  $c_2$  and  $y^n = N^{\otimes n}(x_1)$  independent.

By joint AEP (3),  $\Pr_{C_n}(c_2 y^n \in A_{n, \varepsilon_n}) \approx 2^{-nI(X:Y)}$

If  $M = 2^{n(I(X:Y) - \delta_n)}$  and  $n\delta_n$  grows with  $n$  but  $\delta_n \rightarrow 0$

$\Pr_{C_n} EP_e(C_n) \leq M \Pr_{C_n}(\text{Err}_2 | m=1) \rightarrow 0$

Some code  $C_n$  (in fact most codes) has vanishing  $EP_e(C_n)$ .

Fix a code  $C_n$  that has vanishing  $EP_e(C_n)$ .

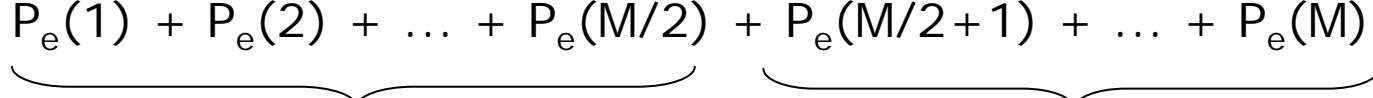
Claim:

Expunging the worse half of the codewords from  $C_n$ , we get a new code  $C'_n$  with  $P_e(C'_n) \leq 2 EP_e(C_n)$ .

Proof:

Reorder  $m$ 's so that  $P_e(m)$  is increasing.

$$P_e(1) + P_e(2) + \dots + P_e(M/2) + P_e(M/2+1) + \dots + P_e(M) = M EP_e(C_n)$$



replace each by zero      replace each by  $P_e(M/2)$

So,  $M/2 P_e(M/2) \leq M EP_e(C_n)$ ,  $P_e(M/2) \leq 2 EP_e(C_n)$ .

Keeping only codewords for  $m=1, \dots, M/2$ , worse case prob error =  $P_e(M/2) \leq 2 EP_e(C_n)$ . Rate decreases only by  $1/n$ .