## Lecture 16 Channel Coding Theorem

### Textbook 7.6-7.7, 7.9

### October 28th and November 4th, 2022

Lecture 17-18 Channel Coding Theorem

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# Outline





3 The converse part of the channel coding theorem

Lecture 17-18 Channel Coding Theorem

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### Definition

The set  $A_{\epsilon}^{(n)}$  of joint typical sequences  $\{(x^n, y^n)\}$  with respect to the distribution p(x, y) is the set of *n*-sequences with empirical entropies  $\epsilon$ -close to the true entropies:

$$\begin{aligned} A_{\epsilon}^{(n)} &= \{ (x^n, y^n) \in \mathcal{X}^n \times \mathcal{Y}^n : | -\frac{1}{n} \log p(x^n) - H(X) | < \epsilon, \\ &| -\frac{1}{n} \log p(y^n) - H(Y) | < \epsilon, \ | -\frac{1}{n} \log p(x^n, y^n) - H(X, Y) | < \epsilon \} \end{aligned}$$

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### Theorem (Joint AEP)

Let  $(X^n, Y^n)$  be sequences of length n drawn i.i.d. according to  $p(x^n, y^n) = \prod_{i=1}^n p(x_i, y_i)$ . Then: 1.  $\Pr((X^n, Y^n) \in A_{\epsilon}^{(n)}) \to 1$  as  $n \to \infty$ . 2.  $|A_{\epsilon}^{(n)}| \leq 2^{n(H(X,Y)+\epsilon)}$ . 3. If  $(\tilde{X}^n, \tilde{Y}^n) \sim p(x^n)p(y^n)$  [i.e.,  $\tilde{X}^n$  and  $\tilde{Y}^n$  are independent with the same marginals as  $p(x^n, y^n)$ ], then

$$\Pr((\tilde{X}^n, \tilde{Y}^n) \in A_{\epsilon}^{(n)}) \leq 2^{-n(I(X;Y) - 3\epsilon)}$$

Also, for sufficient large n,

$$\Pr((\tilde{X}^n, \tilde{Y}^n) \in A_{\epsilon}^{(n)}) \ge (1-\epsilon)2^{-n(I(X;Y)+3\epsilon)}$$

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#### Lecture 17-18 Channel Coding Theorem

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# Ideas

Shannon used a number of new ideas to prove that information can be sent reliably over a channel at all rates up to the channel capacity. These ideas include:

- Allowing an arbitrarily small but nonzero probability of error.
- Using the channel many times in succession, so that the law of large numbers comes into effect.
- Calculating the average of the probability of error over a random choice of codebooks, which symmetrizes the probability, and which can then be used to show the existence of at least one good code.

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# Channel coding theorem

### Theorem

For a discrete channel, all rates below capacity C are achievable. Specifically, for every rate R < C, there exists a sequence of  $(2^{nR}, n)$  codes with maximum probability of error  $\lambda^{(n)} \rightarrow 0$ . Conversely, any sequence of  $(2^{nR}, n)$  codes with  $\lambda^{(n)} \rightarrow 0$  must have  $R \leq C$ .

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# Achievability

Fix p(x). Generate a  $(2^{nR}, n)$  code at random according to the distribution p(x). Specifically, we generate  $2^{nR}$  codewords independently according to the distribution  $p(x^n) = \pi_{i=1}^n p(x_i)$ . We exhibit the  $2^{nR}$  codewords as the rows of a matrix:

$$C = \begin{pmatrix} x_1(1) & x_2(1) & \cdots & x_n(1) \\ \vdots & \vdots & \ddots & \vdots \\ x_1(2^{nR}) & x_2(2^{nR}) & \cdots & x_n(2^{nR}) \end{pmatrix}$$

Each entry in this matrix is generated i.i.d. according to p(x). Thus, the probability that we generate a particular code C is

$$\mathsf{Pr}(\mathcal{C}) = \prod_{w=1}^{2^{nR}} \prod_{i=1}^{n} p(x_i(w)).$$

- 1. A random code  ${\mathcal C}$  is generated as described above according to p(x).
- 2. The code C is then revealed to both sender and receiver. Both sender and receiver are also assumed to know the channel transition matrix p(y|x) for the channel.
- 3. A message  $\boldsymbol{W}$  is chosen according to a uniform distribution

$$P(W = w) = 2^{-nR}, w = 1, 2, \cdots, 2^{nR}.$$

4. The wth codeword  $X^n(w)$ , corresponding to the wth row of  $\mathcal{C}$ , is sent over the channel.

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5. The receiver receives a sequence  $Y^n$  according to the distribution

$$p(y^{n}|x^{n}(w)) = \prod_{i=1}^{n} p(y_{i}|x_{i}(w)).$$

- 6. The receiver guesses which message was sent. We will use jointly typical decoding: the receiver declares that the index  $\hat{W}$  was sent if the following conditions are satisfied:
  - $(X(\hat{W}), Y^n)$  is jointly typical.
  - There is no other index  $W' \neq \hat{W}$  such that  $(X^n(W'),Y^n) \in A_{\epsilon}^{(n)}.$

If no such  $\hat{W}$  exists or if there is more than one such, an error is declared.

7. There is a decoding error if  $\hat{W} \neq W$ . Let  $\mathcal{E}$  be the event  $\{\hat{W} \neq W\}.$ 

We let W be drawn according to a uniform distribution over  $\{1, 2, \ldots, 2^{nR}\}$  and use jointly typical decoding  $\hat{W}$  as described in step 6. Let  $\mathcal{E} = \{\hat{W}(Y^n) \neq W\}$  be the error event. We will calculate the average probability of error. averaged over all codebooks; that is, we calculate

$$Pr(\mathcal{E}) = \sum_{\mathcal{C}} P(\mathcal{C}) P_e^{(n)}(\mathcal{C})$$
$$= \sum_{\mathcal{C}} P(\mathcal{C}) \frac{1}{2^{nR}} \sum_{w=1}^{2^{nR}} \lambda_w(\mathcal{C})$$
$$= \frac{1}{2^{nR}} \sum_{w=1}^{2^{nR}} \sum_{\mathcal{C}} P(\mathcal{C}) \lambda_w(\mathcal{C}).$$

For every codebook C, exchanging the 1st and wth row, we get a new codebook C'. Note P(C) = P(C'), and  $\lambda_1(C) = \lambda_w(C')$ . And the operation that exchange the 1st and wth row is a bijection over the set of all codebooks. So

$$\sum_{\mathcal{C}} P(\mathcal{C})\lambda_1(\mathcal{C}) = \sum_{\mathcal{C}'} P(\mathcal{C}')\lambda_w(\mathcal{C}'),$$

and

$$P(\mathcal{E}) = \sum_{\mathcal{C}} P(\mathcal{C})\lambda_1(\mathcal{C}) = P(\mathcal{E}|W=1).$$

Define the following events:

$$E_i = \{ (X^n(i), Y^n) \text{ is in } A_{\epsilon}^{(n)} \}, \ i \in \{1, 2, \cdots, 2^{nR} \}.$$

Recall that  $Y^n$  is the result of sending the first codeword  $X^n(1)$  over the channel.

Then an error occurs in the decoding scheme if and only if either  $E_1^c$  occurs (when the transmitted codeword and the received sequence are not jointly typical) or  $E_2 \cup E_3 \cup \cdots \cup E_{2^{nR}}$  occurs (when a wrong codeword is jointly typical with the received sequence).

Letting  $P(\mathcal{E})$  denote  $P(\mathcal{E}|W=1)$ , we have

$$P(\mathcal{E}) = P(\mathcal{E}|W = 1) = P(E_1^c \cup E_2 \cup E_3 \cup \dots \cup E_{2^{nR}}|W = 1) \leq P(E_1^c|W = 1) + \sum_{i=2}^{2^{nR}} P(E_i|W = 1).$$

by the union of events bound for probabilities.

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Now by the joint AEP, for n sufficiently large,

 $P(E_1^c|W=1) \le \epsilon.$ 

Since by the code generation process,  $X^n(1)$  and  $X^n(i)$  are independent for  $i \neq 1$ , so are  $Y^n$  and  $X^n(i)$ . Hence, the probability that  $X^n(i)$  and  $Y^n$  are jointly typical is  $\leq 2^{-nI(X;Y)-3\epsilon}$  by the joint AEP. Consequently,

$$P(\mathcal{E}) = P(\mathcal{E}|W=1) \le P(E_1^c|W=1) + \sum_{i=2}^{2^{nR}} P(E_i|W=1)$$

$$\leq \epsilon + \sum_{i=2}^{2^{nR}} 2^{-n(I(X;Y)-3\epsilon)}$$
  
=  $\epsilon + (2^{nR} - 1)2^{-n(I(X;Y)-3\epsilon)}$   
 $\leq \epsilon + 2^{3n\epsilon}2^{-n(I(X;Y)-R)}$   
 $\leq 2\epsilon,$ 

if n is sufficiently large and  $R < I(X;Y) - 3\epsilon$ . Hence, if R < I(X;Y), we can choose  $\epsilon$  and n so that the average probability of error, averaged over codebooks and codewords, is less than  $2\epsilon$ .

To finish the proof, we will strengthen the conclusion by a series of code selections.

- 1. Choose p(x) in the proof to be  $p^*(x)$ , the distribution on X that achieves capacity. Then the condition R < I(X;Y) can be replaced by the achievability condition R < C.
- 2. Get rid of the average over codebooks. Since the average probability of error over codebooks is small ( $\leq 2\epsilon$ ), there exists at least one codebook  $C^*$  with a small average probability of error. Thus,  $\Pr(\mathcal{E}|\mathcal{C}^*) \leq 2\epsilon$ .

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3. Throw away the worst half of the codewords in the best codebook  $C^*$ . Since the arithmetic average probability of error  $P_e^{(n)}([c]^*)$  for this code is less than  $2\epsilon$ , we

$$P(\mathcal{E}|\mathcal{C}^*) = \frac{1}{2^{nR}} \sum_{i=1}^{2^{nR}} \lambda_i(\mathcal{C}^*).$$

which implies that at least half the indices i and their associated codewords  $X^n(i)$  must have conditional probability of error  $\lambda_i$  less than  $4\epsilon$ . Hence the best half of the codewords have a maximal probability of error less than  $4\epsilon$ . If we reindex these codewords, we have  $2^{nR-1}$  codewords. Throwing out half the codewords has changed the rate from R to  $R-\frac{1}{n}$ , which is negligible for large n.

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Combining all these improvements, we have constructed a code of rate  $R' = R - \frac{1}{n}$ , with maximal probability of error  $\lambda^{(n)} \leq 4\epsilon$ . This proves the achievability of any rate below capacity.

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## Outline







#### Lecture 17-18 Channel Coding Theorem

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Let us define the setup under consideration. The index W is uniformly distributed on the set  $W = \{1, 2, \cdots, 2^{nR}\}$ , and the sequence  $Y^n$  is realted probabilistically to W. From  $Y^n$ , we estimate the index W that was sent. Let the estimate be  $\hat{W} = g(Y^n)$ . Thus,  $W \to X^n(W) \to Y^n \to \hat{W}$  forms a Markov chain. Note that the probability of error is

$$\Pr(\hat{W} \neq W) = \frac{1}{2^{nR}} \sum_{i} \lambda_i = P_e^{(n)}.$$

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### Lemma (Fano's inequality)

For a discrete memoryless channel with a codebook C the input message W uniformly distributed over  $2^{nR}$ , we have

 $H(W|\hat{W}) \le 1 + P_e^{(n)} nR.$ 

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#### Lemma

Let  $Y^n$  be the result of passing  $X^n$  through a discrete memoryless channel of capacity C. Then for all  $p(x^n)$ ,

 $I(X^n; Y^n) \le nC.$ 

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### Proof.

$$I(X^{n}; Y^{n}) = H(Y^{n}) - H(Y^{n}|X^{n})$$
  
=  $H(Y^{n}) - \sum_{i=1}^{n} H(Y_{i}|Y_{1}, \cdots, Y_{i-1}, X^{n})$   
=  $H(Y^{n}) - \sum_{i=1}^{n} H(Y_{i}|X_{i})$   
 $\leq \sum_{i=1}^{n} H(Y_{i}) - \sum_{i=1}^{n} H(Y_{i}|X_{i})$   
=  $\sum_{i=1}^{n} I(X_{i}; Y_{i})$   
 $\leq nC. \square$ 

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# Converse part of the channel coding theorem

We have to show that any sequence of  $(2^{nR}, n)$  codes with  $\lambda^{(n)} \to 0$  must have  $R \leq C$ . Note that  $P_e^{(n)} \to 0$ .

For a fixed encoding rule  $X^n(\cdot)$  and fixed decoding rule  $\hat{W} = g(Y^n)$ , we have  $W \to X^n(W) \to Y^n \to \hat{W}$ . For each n, let W drawn according to a uniform distribution over  $\{1, 2, \ldots, 2^{nR}\}$ . Since W has a uniform distribution,

$$\Pr(\hat{W} \neq W) = P_e^{(n)} = \frac{1}{2^{nR}} \sum_i \lambda_i.$$

### Hence,

$$\begin{split} nR &= H(W) \\ &= H(W|\hat{W}) + I(W;\hat{W}) \\ &\leq 1 + P_e^{(n)}nR + I(W;\hat{W}) \\ &\leq 1 + P_e^{(n)}nR + I(X^n;Y^n) \\ &\leq 1 + P_e^{(n)}nR + nC. \end{split}$$

Dividing by n, we obtain

$$R \le P_e^{(n)}R + \frac{1}{n} + C.$$

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Now letting  $n \to \infty,$  we see that the first two terms on the right-hand side tend to 0, and hence

$$R \leq C.$$

Note

$$P_e^{(n)} \ge 1 - \frac{C}{R} - \frac{1}{nR}.$$

This equation shows that if R > C, the probability of error is bounded away from 0 for sufficiently large n (and hence for all n). Hence, we cannot achieve an arbitrarily low probability of error at rates above capacity.

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