

# Information Theory with Applications, Math6397

## Lecture Notes from October 9, 2014

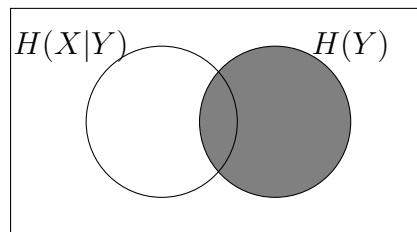
taken by Kedar Grama

### Warm Up: Binary erasure channel(BEC)

With  $Y = \gamma(X)$  and  $\mathbb{P}(\Delta) = \epsilon$

Last time we had observed

$$\begin{aligned} C &= \max_Y I(X = 0; Y) = \max_Y I(X = 1; Y) \\ &= \max_{X,Y} I(X; Y) \\ &= \max_{X,Y} (H(Y) - H(Y|X)) \\ &= \max_Y \left( H(Y) - \sum_{i=0}^1 \mathbb{P}_X(i) H(Y|X = i) \right) \\ &= \max_Y (H(Y) - h(\epsilon)) \end{aligned}$$



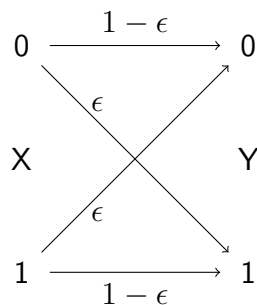
Maximality of  $H(Y)$  implies, by the fixed probability  $\mathbb{P}_Y(\Delta) = \epsilon$ , a uniform distribution on the other two outcomes,

$$\mathbb{P}_Y(0) = \mathbb{P}_Y(1) = \frac{1 - \epsilon}{2}.$$

We conclude the capacity is:

$$\begin{aligned} C &= -1 \frac{1}{2} (1 - \epsilon) \ln \frac{2 - 1}{2} - \epsilon \ln \epsilon + (1 - \epsilon) \ln(1 - \epsilon) \\ &= -(1 - \epsilon) \ln \frac{1}{2} = (1 - \epsilon) \ln 2 \end{aligned}$$

## Binary Symmetric Channel



To compute capacity, we compute

$$\begin{aligned}
 I(X; Y) &= H(Y) - H(Y|X) \\
 &= H(Y) - \sum_{i=0}^1 \mathbb{P}_X(i) H(Y|X=i) \\
 &= H(Y) - h(\epsilon)
 \end{aligned}$$

To achieve the max of  $I(X; Y)$  we need to maximize  $H(Y)$ . Entropy is maximized if  $\mathbb{P}_Y(0) = \mathbb{P}_Y(1) = \frac{1}{2}$ ,  $H(Y) = \ln 2$ . Hence, in this case, we transmit at a rate of  $R = \ln 2 - h(\epsilon)$ .

When  $\epsilon = 0$  we transmit as expected at a rate of  $\ln 2$ , corresponding to one bit per channel use, but the same holds if  $\epsilon = 1$ , because then the output only has to be inverted to get the input message. Finally, when  $\epsilon = 1/2$ , the transmission rate is 0 because the channel output is independent of the input.

In order to derive a (weak) converse to the channel coding theorem we use the following lemma.

**3.1.16 Lemma (Fano).** *Let  $S, Y$  be random variables with the finite alphabet  $\mathbb{A}$ , and*

$$E = \begin{cases} 0, & S = Y \\ 1, & S \neq Y \end{cases}$$

Then,

$$H(S|Y) \leq H(E) + H(S|E, Y) + \mathbb{P}(S \neq Y) \ln |\mathbb{A}| - 1$$

*Proof.* Express  $H(E, S|Y)$  in two ways using additivity

$$H(E, S|Y) = H(S|Y) + \underbrace{H(E|S, Y)}_{=0 \text{ because } S \text{ and } Y \text{ determine } E} = H(E|Y) + H(S|E, Y)$$

We estimate:

$$H(S|Y) \leq H(E) + H(S|E, Y)$$

Also, consider

$$\begin{aligned} H(S|E, Y) &= \mathbb{P}_E(0) \underbrace{H(S|Y, E=0)}_{=0} + \underbrace{\mathbb{P}_E}_{\mathbb{P}(S \neq Y)} \underbrace{H(S|Y, E=1)}_{\leq \ln(|\mathbb{A}|-1)} \\ &\leq \mathbb{P}(S \neq Y) \ln(|\mathbb{A}|-1) \end{aligned}$$

Then, collecting terms we get:

$$H(S|Y) \leq H(E) + \mathbb{P}(S \neq Y) \ln(|\mathbb{A}|-1)$$

□

Next, we state a (weak) converse to the channel coding theorem.

**3.1.17 Theorem.** Let  $\gamma$  be a discrete memoryless channel with conditional probabilities  $\{\mathbb{W}(b|a)\}$ ,  $a \in \Delta$  and  $\{\mathcal{C}_n, \phi_n, \psi_n\}$  a transmission code sequence with the same size  $m_n = |\mathcal{C}_n|$ . If,

$$\liminf_{n \rightarrow \infty} \frac{1}{n} \ln m_n > C$$

Then, the averaged error probability  $P_e$  can be bounded away from zero for all sufficiently large  $n$ .

*Proof.* Without loss of generality, let  $\mathcal{C}_n = \{1, 2, \dots, m_n\}$ ,  $\Phi_n : \mathcal{C}_n \rightarrow \mathbb{A}^n$ . Assuming equally probable inputs, we have a uniform distribution  $\mathbb{Q}$  on  $\mathcal{C}_n$  with  $H(\mathbb{Q}) = \ln m_n$ . Let  $S$  be a random variable with values  $\mathcal{C}_m$  distributed according to  $\mathbb{Q}$ . Then, we have  $\{S, X = \Phi(S), Y\}$  forming a Markov chain, because

$$\begin{aligned} \mathbb{P}(Y = b) &= \frac{1}{m_n} \sum_{x \in \mathcal{C}_n} \mathbb{W}(b|\Phi_n(x)) \\ &= \sum_{a \in \mathbb{A}^n} \frac{|\Phi^{-1}(a)|}{m_n} \mathbb{W}(b|a) \end{aligned}$$

and  $X$  is a deterministic function of  $S$ . Now, by the data processing inequality for Markov chains,

$$I(S; Y) \leq I(X; Y)$$

and comparing with a discrete memoryless source as input

$$\begin{aligned} I(X; Y) &\leq \max_{\mathbb{P}_X, Y=\gamma(X)} I(X; Y) \\ &= \max_{\mathbb{P}_X, Y=\gamma(X)} \sum_{j=1}^n I(X_j; Y_j) \\ &\leq \max_{\mathbb{P}_X, Y_j=\gamma(X_j)} \sum_{j=1}^n \underbrace{I(X_j; Y_j)}_{\leq C} \\ &\leq nC \end{aligned}$$

Now, defining any  $\phi_n : \mathbb{B}^n \rightarrow \{1, 2, \dots, m_n\}$  we have for

$$E = \begin{cases} 1, & \psi_n(Y) \neq S \\ 0, & \text{else} \end{cases}$$

that

$$\begin{aligned} \ln m_n &= H(S) \\ &\stackrel{\text{additivity}}{=} H(S|Y) + I(S; Y) \\ &\stackrel{\text{Markov}}{\neq} H(S|Y) + I(X; Y) \end{aligned}$$

Next, using Fano's inequality

$$\begin{aligned} \ln m_n &= H(S) \\ &\leq H(E) + \mathbb{P}(E = 1) \ln(|\mathcal{C}_n| - 1) + nC \\ &\leq \ln 2 + \underbrace{\mathbb{P}(E = 1)}_{P_e} \ln(m_n - 1) + nC \end{aligned}$$

Solving for  $P_e$  gives

$$\begin{aligned} P_e &\geq \frac{\ln m_n - nC - \ln 2}{\ln(m_n - 1)} \\ &\geq \frac{\ln m_n - nC - \ln 2}{\ln m_n} \end{aligned}$$

So,

$$P_e \geq 1 - \frac{C}{\frac{1}{n} \ln m_n} - \frac{\ln 2}{\ln m_n}$$

If  $\liminf_{n \rightarrow \infty} \frac{1}{n} \ln m_n > C$  then there is a  $\delta > 0$  and  $N \in \mathbb{N}$  such that for all  $n > N$ ,  $\frac{1}{n} \ln m_n > C + \delta$

Assuming that  $N$  is such that  $n > N$  and  $\frac{\ln 2}{n} < \frac{\delta}{2}$ , then

$$\begin{aligned} P_e &\geq 1 - \underbrace{\frac{C}{C + \delta}}_{\frac{\delta}{C + \delta}} - \underbrace{\frac{\ln 2}{n(C + \delta)}}_{\frac{\delta}{2(C + \delta)}} \\ &\geq \frac{\delta}{2(C + \delta)} \\ &> 0 \end{aligned}$$

□

Wolfowitz shows that one can even prove  $P_e \rightarrow 1$ , see also Ahlswede's proof, but this requires a different type of typicality which we will not pursue here.