

## Lecture 17 : Multi-terminal Distributed Source Coding

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**1 Example:**

- Temperatures measured at Palace road meteorological centre and at IISc. Call them  $X, Y$ .
- Temperatures  $X$  and  $Y$  to be sent to New Delhi.
- IISc and Palace road centre, being geographically separated, have to do separate encoding.
- The simplest method is  $R_1 = H(X)$  and  $R_2 = H(Y)$ .
- When  $X$  and  $Y$  are independent, one can not do any better than the above, since even if they cooperate, to obtain  $\hat{X}\hat{Y}$  with high reliability  $R_1 + R_2 \geq H(XY) = H(X) + H(Y)$ .
- $R_1 = H(X), R_2 = H(Y)$  achieves it with no need for cooperation.
- Suppose

$$Y = \begin{cases} X & w.p.1/2 \\ X - 1 & w.p.1/2 \end{cases}$$

IISc can send just one bit; odd or even. 1 bit =  $H(Y|X)$ , achievable even if  $X$  is unknown.

- Key: universal source compression.

**2 Definitions**

**Definition 1 (DMS).** A (two user) discrete memoryless source (DMS) denoted by  $(\mathcal{X}_1, \mathcal{X}_2)$ , consists of two finite sets  $\mathcal{X}_1$  and  $\mathcal{X}_2$ , with the interpretation that  $X_k$  is the input to encoder  $k$ ,  $k = 1, 2$  and for  $n \in \mathbb{N}$ , with  $X_k^n = (X_{k1}, X_{k2}, \dots, X_{kn})$ ,  $k = 1, 2$  has a pmf

$$p_{X_{[2]}^n}(x_{[2]}^n) = \prod_{i=1}^n p_{X_{[2]}}(x_{[2]i}) \quad (1)$$

Note: The successive output symbols of the source are independently drawn from  $\mathcal{X}_{[2]}$  where as there could be a correlation between the components of  $X_{[2],i}$ .

**Definition 2 (Code).** An  $(n, M_1, M_2)$  distributed source code for the DMS  $(\mathcal{X}_1, \mathcal{X}_2)$  consists of the following:

1. An index set of messages for each user  $k$ ,  $\mathbb{W}_k = [M_k]$ .
2. An encoder  $f_k$  for each user  $k$ ,  $f_k : \mathbb{X}_k^n \rightarrow \mathbb{W}_k, k = 1, 2$ . Note that  $\mathbb{X}_k^n \ni X_k^n \mapsto f_k(X_k^n) \in \mathbb{W}_k$ .
3. A decoding rule,  $g : \mathbb{W}_1 \times \mathbb{W}_2 \rightarrow \phi \cup \left( \mathbb{X}_1^n \times \mathbb{X}_2^n \right)$ , i.e.,  $W_{[2]} \mapsto g(W_{[2]}) = \hat{X}_{[2]}^n \in \phi \cup \left( \mathbb{X}_1^n \times \mathbb{X}_2^n \right)$ .

**Definition 3 (Probability of error).** Let  $W_{[2]}^n$  be the message transmitted. The probability of error for the distributed source code  $c$  (when the symbols  $X_{[2]}^n$  come from a DMS) is given by

$$P_e^{(n)}(c) = \Pr \left\{ g \left( f_1(X_1^n), f_2(X_2^n) \right) \neq X_1^n X_2^n \right\}.$$

**Definition 4 (Achievability).** The rate pair  $(R_1, R_2)$  is achievable, if for every  $\eta > 0, \lambda \in (0, 1)$ , there exists a sequence of  $(n, M_1, M_2)$  distributed source codes that satisfy

1.  $P_e^{(n)} \leq \lambda$ , and
2.  $\frac{\log_2 M_k}{n} \leq R_k + \eta$ .

**Definition 5 (Achievable rate region).** The achievable rate region is the set of all achievable rate pairs.

**Lemma 1.** The achievable rate region is a closed convex set.

*Proof.* Exercise. □

**Theorem 2. (Slepian–Wolf)** The achievable rate region is

$$\left\{ (R_1, R_2) \in \mathbb{R}_+^2 \left| \begin{array}{l} R_1 \geq H(X_1|X_2) \\ R_2 \geq H(X_2|X_1) \\ R_1 + R_2 \geq H(X_1X_2) \end{array} \right. \right\}$$

**Remark 1.** • Joint decoding with  $X_1^n$  supplied to encoder 2 and vice versa will also yield this rate region.

- SW theorem says we can do this without the knowledge of encoder 2's observation (and similarly encoder 1's observation is not known at encoder 2).
- Consider Example 1. Palace road compresses  $H(X)$  bits. IISc compresses to  $H(Y|X) = 1$  bit. Code: IISc indicates odd/even.
- Since  $H(X_2|X_1)$  is known, we have a non-stationary but independent (over time) source  $\prod_{i=1}^n p(y_i|x_{1i})$ , given  $x_1^n$ . Of course  $x_1^n$  is not observed. We have a universal code to compress this independent non-stationary source at its average entropy  $H(X_2|X_1)$ . Someone who knows  $X_1^n$  now reconstructs  $X_2^n$ .
- Not too surprising, since we know of the existence of universal codes for stationary and ergodic sources (Lempel-Ziv, fixed rate universal code, refer ITC-2 course notes).
- Universal compression at rate  $R = H(X)$ . Consider  $\lfloor 2^{n(R+\eta)} \rfloor = M$  bins.
- For each  $x^n \in \mathbb{X}^n$ , assign a bin among  $[M]$  uniformly.  $f(x^n) = \text{bin}\#$ . Reveal  $f$  to both encoder and decoder.
- Encoding is transmission of index  $f(x^n)$  with  $\frac{\log M}{n} < R + \eta$  bits/sample. Decoding: Look for a unique typical  $\hat{x}^n$  in bin  $f(x^n)$ . If none or more than 1, map to  $\phi$ .

- **Error analysis:**  $\mathbb{E}_c Pr\{g(f(X^n) \neq X^n)\} \leq Pr\{X^n \notin T_\delta^n(X)\} + Pr\{E_{21}\}$ , where  $E_{21}$  is the event that another of the  $T_\delta^n(X) - 1$  elements in  $T_\delta^n(X)$  falls in the bin  $f(x^n)$ .

$$\begin{aligned} Pr\{E_{21}\} &\leq (T_\delta^n(X) - 1) \frac{1}{M^n} \leq 2^{nH(X)+2n\delta} \cdot 2^{-nR-n\eta} \cdot 2^{n\eta/2} \\ &= 2^{-n(\eta/2-2\delta)} \downarrow 0 \text{ if } \eta > 4\delta. \end{aligned}$$

- Any source with  $H(X) \leq R$  can be compressed to rate  $R$  without knowledge of source. Of course, this i.i.d. property is lost in SW problem.

We now extend this to multi-terminal systems.

*Proof.* (Achievability.)

$$M_k = \lfloor 2^{n(R_k+\eta)} \rfloor, \quad k = 1, 2$$

$(R_1, R_2) \in$  region in the SW theorem.

**Random code:** Assign  $x_k^n$  to one of bins  $1, 2, \dots, M_k$ , independent of the sequence chosen and uniformly in the bins.

- $f_k(x_k^n) = \text{bin\#}$ .
- Reveal  $f_1, f_2$  to both encoders and decoder.
- Encoding is clear. Send  $f_k(x_k^n)$  using  $\frac{\log M_k}{n} < R_k + \eta$  bits/sample.

**Decoding:** Given bins  $f_k(x_k^n), k = 1, 2$ , look for a jointly typical  $\hat{x}_1^n \hat{x}_2^n$  in the joint bin. Moreover, they should satisfy  $\hat{x}_k^n \in T_{\frac{\delta}{2}}^{(n)}(X_k)$ .

- $\mathbb{E}_c P_e^{(n)}$ :

$$\begin{aligned} \text{Error} &\Leftrightarrow E_0 && X_{[2]}^n \notin T_\delta^{(n)}(X_{[2]}) \text{ or } X_k^n \notin T_{\frac{\delta}{2}}^{(n)}(X_k) \\ &\cup E_1 && \exists \hat{x}_1^n \neq x_1^n \text{ s.t. } (\hat{x}_1^n, x_2^n) \in T_\delta^{(n)}(X_{[2]}) \\ &\cup E_2 && \exists \hat{x}_2^n \neq x_2^n \text{ s.t. } (x_1^n, \hat{x}_2^n) \in T_\delta^{(n)}(X_{[2]}) \\ &\cup E_{12} && \exists \hat{x}_1^n \neq x_1^n, \hat{x}_2^n \neq x_2^n, \text{ s.t. } (\hat{x}_1^n, \hat{x}_2^n) \in T_\delta^{(n)}(X_{[2]}) \end{aligned}$$

$$\begin{aligned} \mathbb{E} P_e^{(n)} &\leq Pr\{E_0\} + Pr\{E_1|E_0^c\} + Pr\{E_2|E_0^c\} + Pr\{E_{12}|E_0^c\} \\ Pr\{E_0\} &\leq \frac{1}{n} 3\delta \\ Pr\{E_1|E_0^c\} &\leq |T_\delta^{(n)}(X_1|x_2^n)| \frac{1}{M_1} \\ &\leq 2^{nH(X_1|X_2)+n\delta} \cdot 2^{-nR_1-n\eta} \cdot 2^{n\eta/2} \\ &\leq 2^{-n(\eta/2-\delta)} \downarrow 0, \text{ if } \eta > 2\delta. \\ \text{similarly, } Pr\{E_2|E_0^c\} &\leq 2^{-n(\eta/2-\delta)} \downarrow 0. \\ Pr\{E_{12}|E_0^c\} = Pr\{E_{12}\} &\leq |T_\delta^{(n)}(X_1X_2)| \frac{1}{M_1M_2} \leq 2^{nH(X_1X_2)+n\delta} \cdot 2^{-n(R_1+R_2+\eta+\eta)} \cdot 2^{n\eta/2} \\ &\leq 2^{-n(3\eta/2-\delta)} \downarrow 0 \text{ if } \eta > 2\delta/3. \end{aligned}$$

□