

Recapulation:

$$X^n = (X_1, \dots, X_n) \in \mathcal{X}^n, X_1, \dots, X_n \text{ i.i.d. } \sim p(x)$$

$$X^n \rightarrow \boxed{\begin{array}{c} \text{encoder} \\ f_n \end{array}} \xrightarrow{f_n(X^n) \in \{1, \dots, 2^{nR}\}} \boxed{\begin{array}{c} \text{decoder} \\ g_n \end{array}} \rightarrow \hat{X}^n$$

$$\hat{X}^n = (\hat{X}_1, \dots, \hat{X}_n) \in \hat{\mathcal{X}}^n$$

Def. 5.3. Distortion measure

$$d(x^n, \hat{x}^n) = \frac{1}{n} \sum_{i=1}^n d(x_i, \hat{x}_i)$$

Def. 5.4. A  $(2^{nR}, n)$ -rate distortion code of rate  $R$  and block length  $n$  consists an encoder

$$f_n: \mathcal{X}^n \rightarrow \{1, 2, \dots, 2^{nR}\}$$

and a decoder

$$g_n: \{1, 2, \dots, 2^{nR}\} \rightarrow \hat{\mathcal{X}}^n.$$

The expected distortion of the  $(f_n, g_n)$  is

$$D = E d(X^n, \hat{X}^n) = E d(X^n, g_n(f_n(X^n))). \quad \lrcorner$$

Remarks.

a)  $\mathcal{X}, \hat{\mathcal{X}}$  are assumed to be finite.

b)  $2^{nR}$  means  $\lceil 2^{nR} \rceil$ , if it is not integer.

c)  $f_n$  yields  $2^{nR}$  different values.

We need  $\approx nR$  bits to represent each. Hence,

$R$  = no. of bits per source symbol needed to represent  $f_n(x^n)$ .

d)  $D = E d(x^n, \hat{x}^n)$

$= E d(x^n, g_n(f_n(x^n)))$

$= \sum_{x^n \in \mathcal{X}^n} p(x^n) d(x^n, g_n(f_n(x^n)))$

↓

e)  $\{g_n(1), \dots, g_n(2^{nR})\}$  is called codebook.

$f_n^{-1}(1), \dots, f_n^{-1}(2^{nR})$  are called assignment regions.

Ultimate goal of lossy source coding:

- minimize  $R$  for a given  $D$  or
- minimize  $D$  for a given  $R$ .

Def. 5.5. A rate distortion pair  $(R, D)$  is called achievable if there exists a sequence of  $(2^{nR}, n)$ -rate distortion codes such that

$$\lim_{n \rightarrow \infty} E d(X^n, g_n(f_n(X^n))) \leq D. \quad \perp$$

Def. 5.6. The rate distortion function is defined as

$$R(D) = \inf_{(R, D) \text{ is achievable}} R \quad \perp$$

Def. 5.7. The information ~~dist~~rate distortion function  $R_I(D)$  is defined as follows

$$\begin{aligned} R_I(D) &= \min_{p(\hat{x}|x) : \sum_{(x, \hat{x})} p(x, \hat{x}) d(x, \hat{x}) \leq D} I(X, \hat{X}) \\ &= \min_{p(\hat{x}|x) : E d(X, \hat{X}) \leq D} I(X, \hat{X}) \quad \perp \end{aligned}$$

Compare with capacity:

$C$ : given  $p(\hat{x}|x)$ , max  $I(X, \hat{X})$  over the input distr  
 $R_I(D)$ : given  $p(x)$ , min  $I(X, \hat{X})$  over "channels" s.t.  
the expected distortion does exceed  $D$ .



Theorem 5.8.

a)  $R_I(D)$  is a convex nonincreasing fct. of  $D$ .

b)  $R_I(D) = 0$ , if  $D > D^*$ ,  $D^* = \min_{\hat{x} \in \mathcal{X}} E d(X, \hat{x})$

c)  $R_I(0) \leq H(X)$   $\perp$

Proof. Yeung, p. 198 ff, Cover & Thomas p. 316 ff.

Theorem 5.9.  $X \sim \text{Bin}(1, p)$ ,  $P(X=0) = 1-p$ ,  $P(X=1) = p$ ,  $0 \leq p \leq 1$ ,

$d$ : Hamming distance.

$$R_I(D) = \begin{cases} H(p) - H(D), & 0 \leq D \leq \min\{p, 1-p\} \\ 0, & \text{otherwise} \end{cases}$$

Proof. W.l.o.g. assume  $p < \frac{1}{2}$ , otherwise interchange 0 and 1.

$$R_I(D) = \min_{p(\hat{x}|x) : E d(X, \hat{x}) \leq D} I(X; \hat{x})$$

Assume  $D \leq p < \frac{1}{2}$

$$I(X; \hat{x}) = H(X) - H(X| \hat{x})$$

$$= H(X) - H(X \oplus \hat{x} | \hat{x})$$

$$\geq H(X) - H(X \oplus \hat{x})$$

$$= H(p) - H(P(X \neq \hat{x}))$$

$$\geq H(p) - H(D)$$

$[X \oplus \hat{x}$  given  $\hat{x}$  has the same entropy as  $X$  given  $\hat{x}$

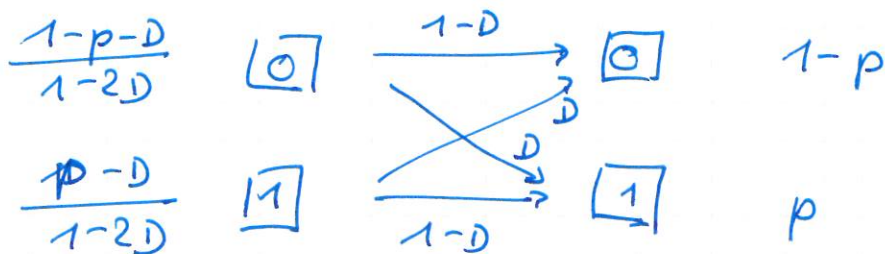
$$[P(X \oplus \hat{x} = 1) = P(X \neq \hat{x})$$

$$[P(X \neq \hat{x}) = E d(X, \hat{x}) \leq D < \frac{1}{2}$$

This lower bound is attained by the following joint distribution of  $(X, \hat{X})$

$X \backslash \hat{X}$	0	1	
0	$\frac{(1-D)(1-p-D)}{1-2D}$	$\frac{D(p-D)}{1-2D}$	$1-p$
1	$\frac{D(1-p-D)}{1-2D}$	$\frac{1-D(p-D)}{1-2D}$	$p$
	$\frac{1-p-D}{1-2D}$	$\frac{p-D}{1-2D}$	1

Corresponds to a BSC



It follows that

$$\begin{aligned}
 P(X \neq \hat{X}) &= E d(X, \hat{X}) \\
 &= \frac{D(p-D)}{1-2D} + \frac{D(1-p-D)}{1-2D} = D
 \end{aligned}$$

Further

$$\begin{aligned}
 I(X; \hat{X}) &= H(X) - H(X|\hat{X}) \\
 &= H(p) - \left[ \underbrace{H(X|\hat{X}=0)}_{=H(D)} P(\hat{X}=0) + \underbrace{H(X|\hat{X}=1)}_{=H(1-D)=H(D)} P(\hat{X}=1) \right] \\
 &= H(p) - H(D)
 \end{aligned}$$

such that the lower bound is attained.

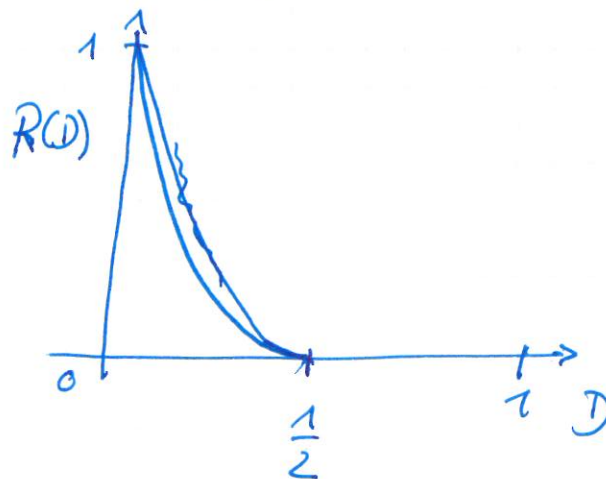
If  $D \geq p$  set  $P(\hat{X}=0) = 1$  and get

$X \backslash \hat{X}$	0	1	
0	$1-p$	0	$1-p$
1	$p$	0	$p$
	1	0	

Then  $E d(X, \hat{X}) = P(X \neq \hat{X}) = P(X=1) = p \leq D$

$$\begin{aligned} \text{and } I(X; \hat{X}) &= H(X) - H(X|\hat{X}) \\ &= H(p) - H(X|\hat{X}=0) \cdot 1 \\ &= H(p) - H(p) = 0 \end{aligned}$$

Plot for  $\text{Bin}(1, \frac{1}{2})$ :



Theorem 5.10. (Converse to the rate distortion theorem)

$$R(D) \geq R_I(D) \quad \square$$

Proof.

Recall the general situation:  $X_1, \dots, X_n$  i.i.d.  $\sim X \sim p(x), x \in \mathcal{X}$ .

$\hat{X}^n = g_n(f_n(X^n))$  has at most  $2^{nR}$  values. Hence

$$H(\hat{X}^n) \leq \log 2^{nR} \leq nR$$

We first show:  $(R, D)$  achievable  $\Rightarrow R \geq R_I(D)$

Suppose  $(R, D)$  is achievable. Then

$$nR \geq H(\hat{X}^n)$$

$$\geq H(\hat{X}^n) - H(\hat{X}^n | X^n)$$

$$= I(\hat{X}^n; X^n) = I(X^n; \hat{X}^n)$$

$$= H(X^n) - H(X^n | \hat{X}^n)$$

$$= \sum_{i=1}^n H(X_i) - \sum_{i=1}^n H(X_i | \hat{X}^n, X_1, \dots, X_{i-1})$$

$$\geq \sum_{i=1}^n I(X_i; \hat{X}_i)$$

$$\geq \sum_{i=1}^n R_I(\text{Ed}(X_i, \hat{X}_i))$$

$$= n \sum_{i=1}^n \frac{1}{n} R_I(\text{Ed}(X_i, \hat{X}_i))$$

$$\geq n R_I\left(\frac{1}{n} \sum_{i=1}^n \text{Ed}(X_i, \hat{X}_i)\right) \quad (R_I \text{ convex})$$

$$= n R_I \text{Ed}(X^n, \hat{X}^n)$$

$$\text{Ed}(X^n, \hat{X}^n) \leq D$$

$$\geq n R_I(D)$$

$(R_I \text{ non-increasing})$

Hence,  $(R, D)$  achievable  $\implies R = R(D) \geq R_I(D) \quad \square$



The reverse inequality in Th. 5.10. also holds.

Th. 5.11. (The Rate Distortion Theorem)

$$R(D) = R_I(D). \quad \lrcorner$$

Proof.  ~~$R(D) \geq R_I(D)$~~   $\checkmark$  Th. 5.10.

$$R_I(D) \leq R(D)$$

Yeung: Section 9.5, p. 206-212

Cover & Thomas: Section 10.5, p. 318-324  $\lrcorner$