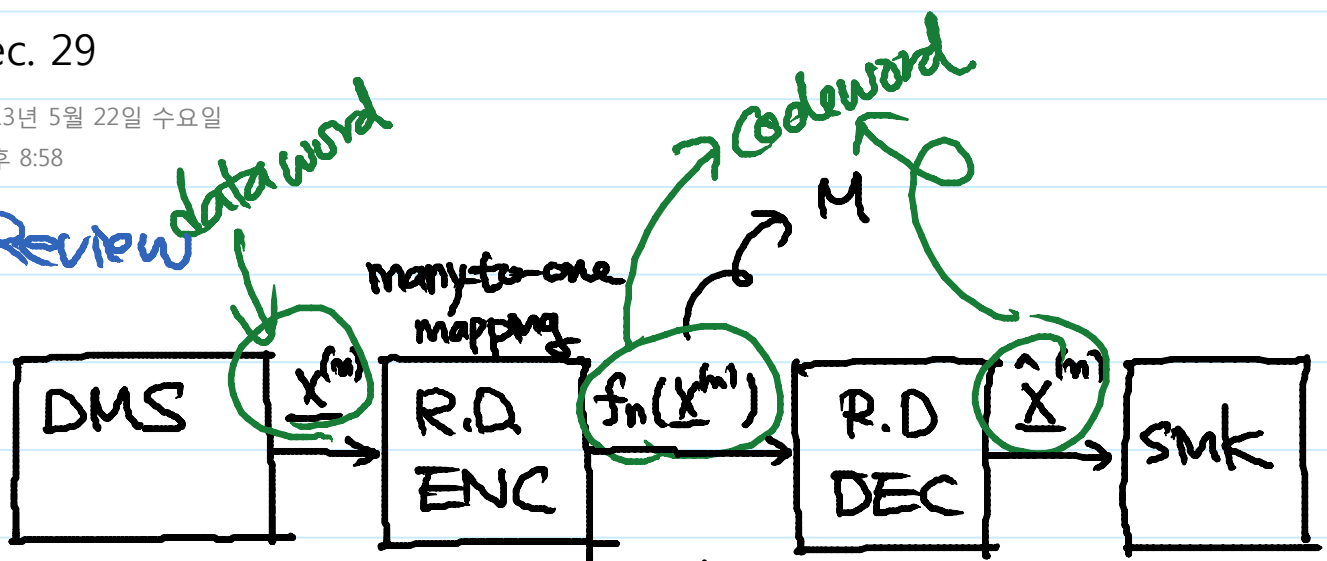


Review



X : source alphabet

$$E \{d(x^{(m)}, \hat{x}^{(m)})\} \leq D$$

$$\min \frac{\log_2 M}{n} \quad [\text{bits/source output}]$$

$$\text{s.t. } E \{d(x^{(m)}, \hat{x}^{(m)})\} \leq D$$

Def.

A rate distortion pair (R, D) is achievable if

there exists $(2^{nR}, n_k)$ rate distortion codes such that

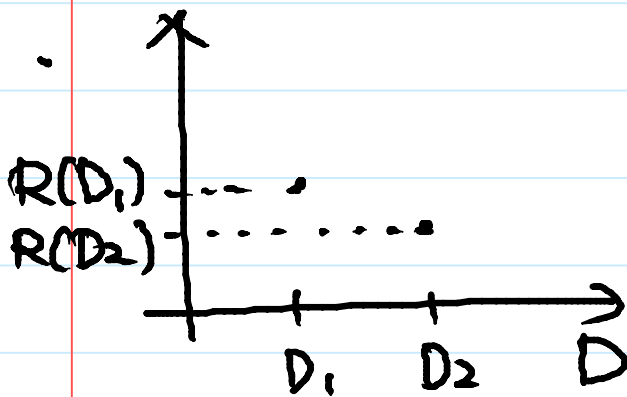
$$\lim_{k \rightarrow \infty} E \{d(x^{(n_k)}, \hat{x}^{(n_k)})\} \leq D.$$

an $(M(n))$ rate distortion code
 # of source outputs
 compression

To show, if $R < R_I(D) = \min_{\text{prx}} I(X; \hat{X})$
 s.t. $E \{d(x, \hat{x})\} \leq D$
 then (R, D) is achievable.

then (R.D) is achievable.

- To show, if (R, D) is achievable, then $R \geq R_I(D)$.



$$R_I(D_1) = \inf_{(R, D_1) \text{ is achievable}} R$$

$$R_I(D_2) = \inf_{(R, D_2) \text{ is achievable}} R$$

Q. $R(D)$

- Lemma.

$R_I(D)$ as a function of $D \geq 0$ is a monotonically decreasing convex function (proof)

Suppose that

$$D_1 < D_2$$

$$R_I(D_1) = \min_{P_X | Y} I(X; \hat{X})$$

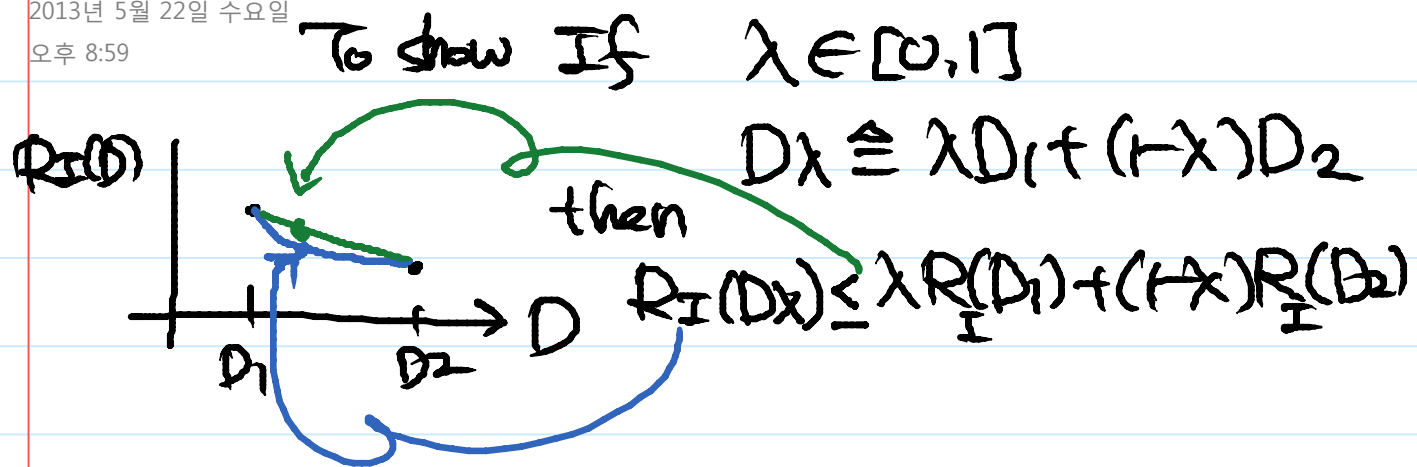
$$\text{s.t. } E\{d(X, \hat{X})\} \leq D_1$$

Ω_1

$$\geq R_I(D_2) = \min_{P_X | Y}$$

$$\text{s.t. } E\{d(X, \hat{X})\} \leq D_2$$

$$\Omega_1 < \Omega_2$$



A detour

$$R_I(D) = \min_{p(\hat{x}|x)} I(x; \hat{x})$$

s.t. $E\{d(x, \hat{x})\} \leq D$

To show, if $\lambda \in [0, 1]$

$$p_1(\hat{x}|x) p(x) = p_1(x, \hat{x}) \quad \text{s.t.} \quad E_1\{d(x, \hat{x})\} \leq D$$

$$p_2(\hat{x}|x) p(x) = p_2(x, \hat{x}) \quad \text{s.t.} \quad E_2\{d(x, \hat{x})\} \leq D$$

then

$$p_\lambda(\hat{x}|x) = \lambda p_1(\hat{x}|x) + (1-\lambda) p_2(\hat{x}|x)$$

$$\Leftrightarrow p_\lambda(x, \hat{x}) = \lambda p_1(x, \hat{x}) + (1-\lambda) p_2(x, \hat{x})$$

$$E_x\{d(x, \hat{x})\} = E_1\{d(x, \hat{x})\} \lambda + E_2\{d(x, \hat{x})\} (1-\lambda)$$

$$\leq \lambda D + (1-\lambda) D = D$$

$\therefore$ The constraint set is a convex set.

To show, $I_\lambda(x; \hat{x}) \leq \lambda I_1(x; \hat{x}) +$

$$(1-\lambda)I_2(X;\tilde{X})$$

$$I_X(X;\hat{X}) = E \left\{ \log \frac{p_X(X, \hat{X})}{p(X)p_X(\hat{X})} \right\} \dots (*)$$

$$I_1(X;\hat{X}) = E \left\{ \log \frac{p_1(X, \hat{X})}{p(X)p_1(\hat{X})} \right\} \dots (**)$$

$$I_2(X;\hat{X}) = E \left\{ \log \frac{p_2(X, \hat{X})}{p(X)p_2(\hat{X})} \right\} \dots (***)$$

- Log-sum inequality

$$a_i > 0$$

$$b_i > 0$$

$$a_1 \log \frac{a_1}{b_1} + a_2 \log \frac{a_2}{b_2} \geq (a_1 + a_2) \log \frac{(a_1 + a_2)}{(b_1 + b_2)}$$

(sol)'' f is convex.

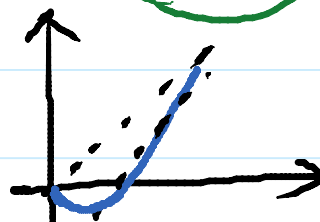
$$\Rightarrow E[f(x)] \geq f(E[x])''$$

$$\sum_i p_i f(x_i) \geq f\left(\sum_i p_i x_i\right)$$

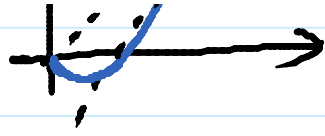
Choose

$$p_i = \frac{b_i}{\sum_{j=1}^n b_j}, \quad x_i = \frac{a_i}{b_i}$$

$$f(x) = x \log x$$



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$$\begin{aligned}
 & f(EG(x)) \\
 &= f\left(\sum_i p_i x_i\right) \\
 \sum_i \frac{a_i}{\sum_j b_j} \log \frac{a_i}{b_i} &\geq \frac{\sum_i a_i}{\sum_j b_j} \log \frac{\sum_i a_i}{\sum_j b_j}
 \end{aligned}$$

$$\Rightarrow \sum_i a_i \log \frac{a_i}{b_i} \geq \left(\sum_i a_i\right) \log \frac{\left(\sum_i a_i\right)}{\left(\sum_j b_j\right)}$$

- Back to the convexity of $R_I(D)$

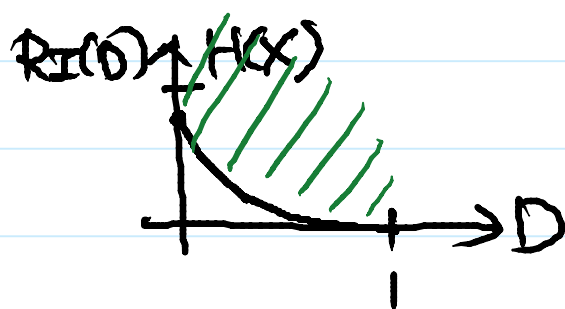
$$D_1 < D_2, \lambda$$

$$\lambda R_I(D_1) + (1-\lambda) R_I(D_2) \geq R_I(\lambda D_1 + (1-\lambda) D_2)$$

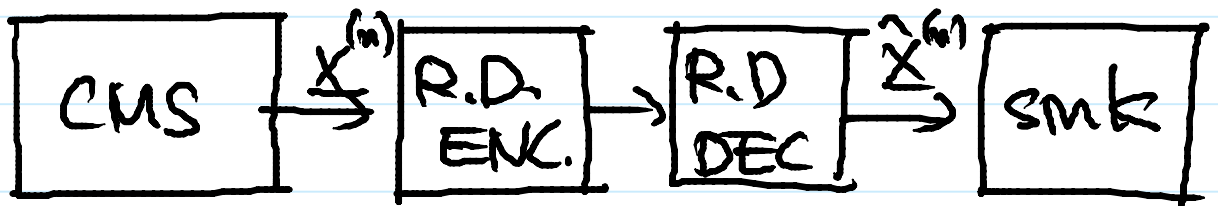
$$\lambda I_1(x; \hat{x}) + (1-\lambda) I_2(x; \hat{x}) \geq I_{\lambda}(x; \hat{x})$$

$$\begin{aligned}
 & \geq R_I(\lambda D_1 + (1-\lambda) D_2). \\
 & \quad \quad \quad \uparrow \\
 & \quad \quad \quad E[d(x, \hat{x})] \leq \lambda D_1 + (1-\lambda) D_2
 \end{aligned}$$

$\therefore R_I(D)$ is a convex function of D



Example.



$$X \sim N(0, \sigma^2)$$

Q. Find $R_I(D)$ when $d(x, \hat{x}) = (x - \hat{x})^2$
 $\min I(X; \hat{X})$ $\quad D < \sigma^2$.

$p_{\hat{X}|X}$

$$\text{s.t. } E\{d(X, \hat{X})\} \leq D$$

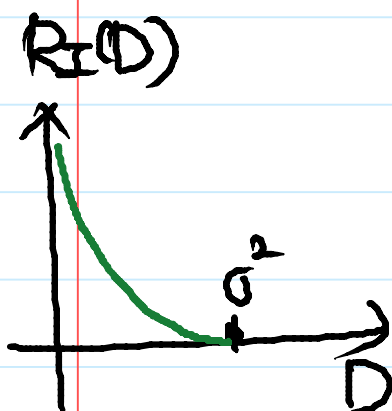
$$I(X; \hat{X}) = h(X) - h(X|\hat{X})$$

$$\begin{matrix} p_{\hat{X}|X} & p_X \\ f_{\hat{X}|X} & f_X \end{matrix}$$

~~$$= h(\hat{X}) - h(\hat{X}|X)$$~~

$$= \frac{1}{2} \log(2\pi e \sigma^2) - \int_{\hat{x}} h(X|\hat{X}=\hat{x}) f(\hat{x})$$

$$\begin{array}{c} \hat{X} \xrightarrow{\quad} \oplus \xrightarrow{\quad} X \sim N(0, \sigma^2) \\ \uparrow \\ \sim N(0, \sigma^2 - D) \\ \uparrow \\ Z \sim N(0, D) \end{array}$$



$$\geq \frac{1}{2} \log(2\pi e \sigma^2) - \frac{1}{2} \log(2\pi e D)$$

$$= \frac{1}{2} \log \frac{\sigma^2}{D}, \quad D < \sigma^2$$

- To show the rate-distortion theorem in the next meeting.

★ achievability : If $R > R_I(D)$, then (R, D) is achievable
 ★ converse : If (R, D) is achievable, then $R \geq R_I(D)$.

- (R, D) is achievable.
- $R_I(D)$ is a monotone decreasing convex function of D .

($\because I(X; \hat{X})$ is a convex function of $P_{\hat{X}|X}$).

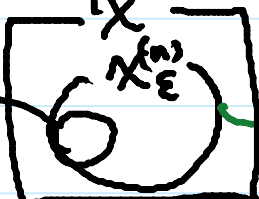
$(R_I(D) = \min_{P_{\hat{X}|X} \text{ s.t. } E[d(X, \hat{X})] \leq D} I(X; \hat{X}))$ is obtained from the sphere covering argument.)

Example.

Gaussian
 σ^2 / σ^2

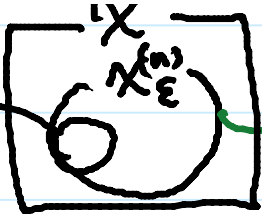
$$\rightarrow \frac{1}{2} \log \frac{\sigma^2}{D} \text{ [bits/s.o.]}$$

Vol
 $\approx 2^{-n \frac{1}{2} \log \frac{\sigma^2}{2\pi e D}}$



$$\rightarrow \text{Vol}(X^n_\epsilon) \approx 2^{-nh(X)} = 2^{-n \cdot \frac{1}{2} \log 2\pi e \sigma^2 / D}$$

$\text{Vol} \approx 2^{-n \frac{1}{2} \log 2 \pi e \sigma^2}$



$\text{Vol}(X_{\epsilon}^{(n)}) \approx 2^{-nh(x)} = 2^{-n \cdot \frac{1}{2} \log 2 \pi e \sigma^2}$