

Review

- NCCT for DT AWGN channel
 - Achievability: $R < \frac{1}{2} \log \left(1 + \frac{P}{\sigma_z^2} \right)$ is achievable
 - Converse: R is achievable then $R \leq \frac{1}{2} \log \left(1 + \frac{P}{\sigma_z^2} \right)$

$$\Rightarrow C_0 = \frac{1}{2} \log_2 \left(1 + \frac{P}{\sigma_z^2} \right) \text{ [bits/ch.use]}$$

- Difference

β -admissibility constraint

$$E\{b(x)\} \leq \beta, \quad E\{x^2\} \leq P$$

Achievability of R

$$\frac{1}{n} \sum_{i=1}^n b(x_{i,j}^{(n)}) \leq \beta, \quad \|x_i^{(n)}\|^2 \leq nP$$

$$C(\beta) = \sup_{\substack{f_X(x) \\ \text{s.t. } E[b(X)] \leq \beta}} I(X; Y)$$

Capacity-cost function.

$$\begin{aligned} H(W | \underline{Y}^{(n)}) &\stackrel{\text{continuous}}{=} \int_{\underline{y}^{(n)}} H(W | \underline{Y}^{(n)} = \underline{y}^{(n)}) f_{\underline{Y}^{(n)}}(\underline{y}^{(n)}) d\underline{y}^{(n)} \\ I(W; \underline{Y}^{(n)}) &\stackrel{\text{continuous}}{=} H(W) - H(W | \underline{Y}^{(n)}) \\ &\leq I(X^{(n)}; \underline{Y}^{(n)}) \end{aligned}$$

11b.pdf
i.i.d. $p_X(x)$

X_i 's look like

↑ optimal pmf.

Gaussian Codebook

"Converse: If R is achievable, then $R \leq C$."

(i) If we have a seq of codes that achieves $C - \epsilon$. By the converse, this seq. of codes satisfies

$$\begin{aligned} h(Y^{(n)}) - h(Y^{(n)} | X^{(n)}) \\ \leq \sum_{i=1}^n h(Y_i) - h(Y^{(n)} | X^{(n)}) \end{aligned}$$

where the equality holds iff Y_i 's are independent.

$\Rightarrow$ If Y_i 's & Z_i 's are all indep. then X_i 's are also indep.

$$(ii) \quad \sum_{i=1}^n I(X_i; Y_i) \leq \sum_{i=1}^n \frac{1}{2} \log \left(1 + \frac{P_i}{\sigma_z^2} \right)$$

$\Rightarrow$ If Y_i 's & Z_i 's are all indep. Gaussian, then X_i 's are also indep.

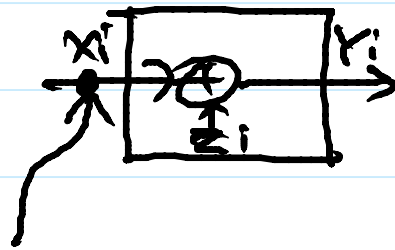
Gaussian

$$(iii) \quad \sum_{i=1}^n \frac{1}{2} \log \left(1 + \frac{P_i}{\sigma_z^2} \right) \leq \frac{n}{2} \log \left(1 + \frac{P - \epsilon}{\sigma_z^2} \right)$$

$$(iii) \sum_{i=1}^n \frac{1}{2} \log \left(1 + \frac{\mu_i^2}{\sigma_i^2} \right) \leq \frac{n}{2} \log \left(1 + \frac{\mu - \epsilon}{\sigma^2} \right)$$

$\Rightarrow p_i = p_i^* \forall i$, i.e., X_i 's are identical.

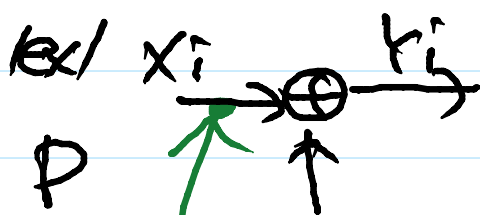
DT ACWEN



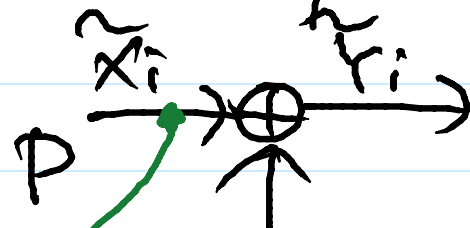
x_i 's look like i.i.d. Gaussian
cf. n variables

Thus, the near-optimal code
is called the Gaussian codebook.

- Definition $\rightarrow$ Existence, Uniqueness



$$z_i \sim N(0, \sigma_1^2)$$



$$z_i \sim N(0, \sigma_2^2)$$

$$\sigma_1^2 < \sigma_2^2$$



Compare

$$C_1 = \frac{1}{2} \log \left(1 + \frac{p}{\sigma_1^2} \right)$$

x_i 's $\sim$ i.i.d.

$N(0, p)$

Rate of
Gaussian

Codebook #1

$$C_2 = \frac{1}{2} \log \left(1 + \frac{p}{\sigma_2^2} \right)$$

$\tilde{x}_i$'s $\sim$ i.i.d.

$N(0, p)$

Rate of
Gaussian

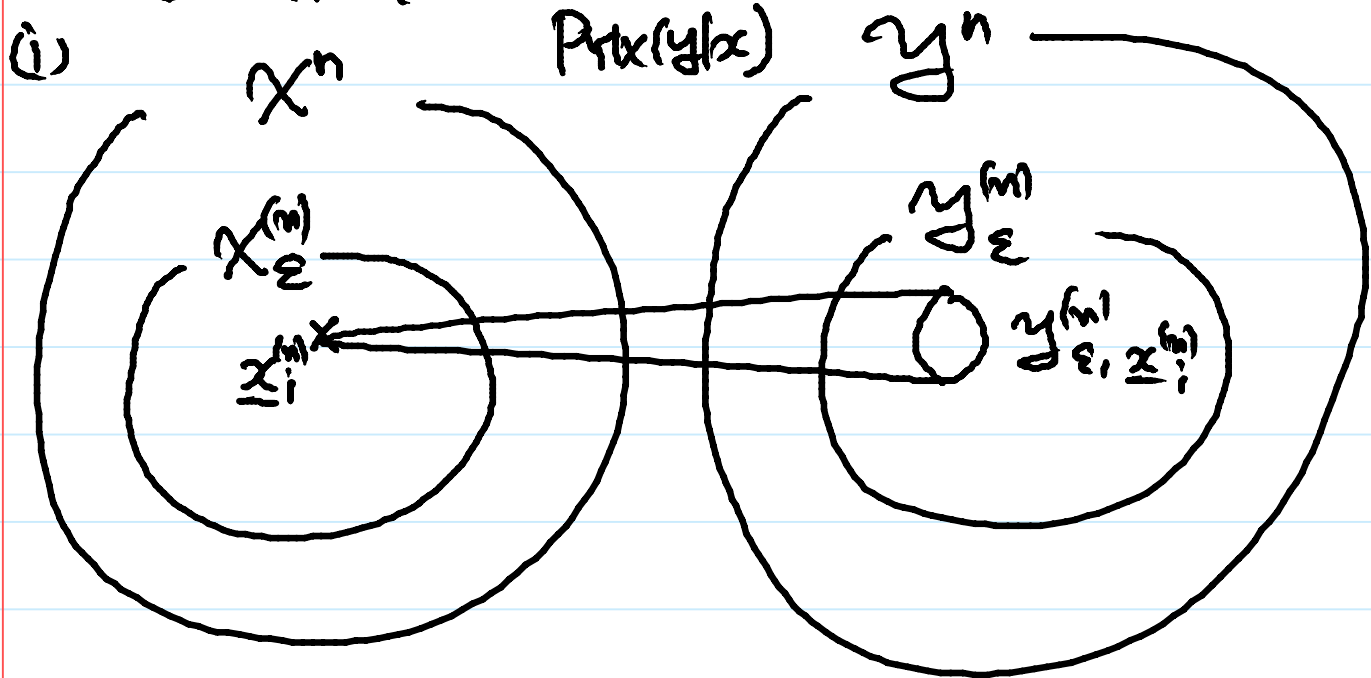
Codebook #2

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• Sphere Packing Argument

(i) DMC

(ii) DT AWGN



$$|y_{\epsilon}^{(n)}| \approx 2^{nH(Y)}$$

$$|y_{\epsilon, x_i^{(n)}}^{(n)}| \approx 2^{nH(Y|X)}$$

$$Y = X + Z$$

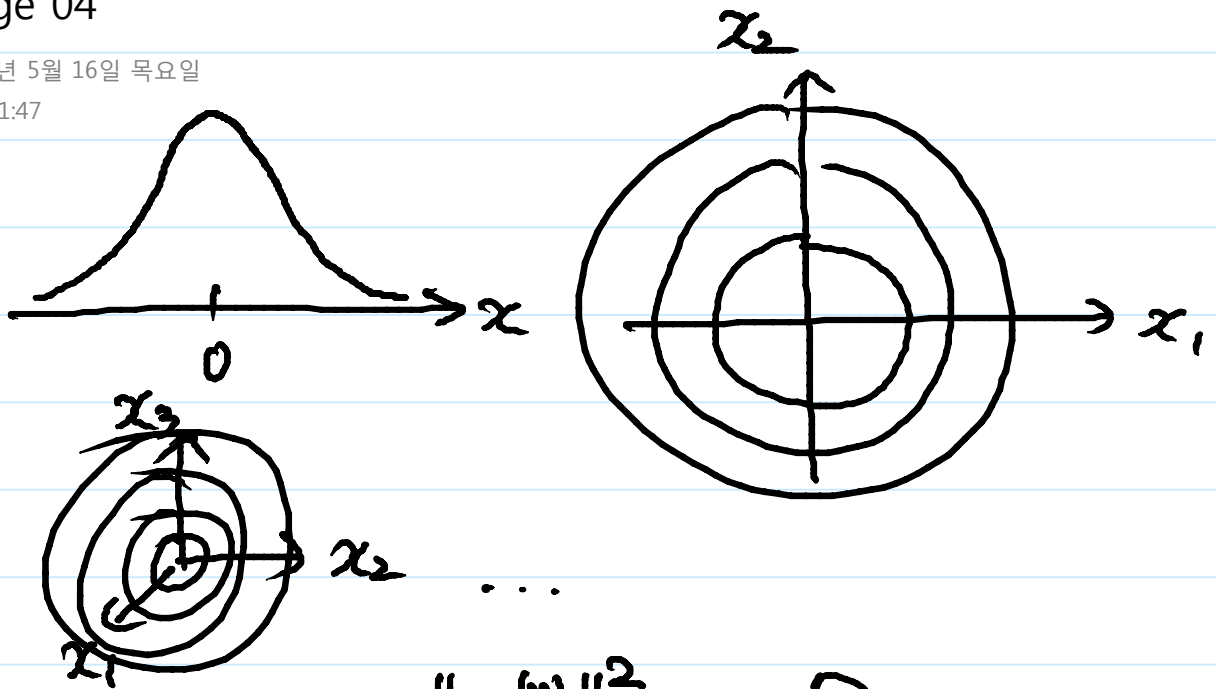
$\nearrow \quad \uparrow$
 $N(0, P) \quad N(0, \sigma_z^2)$

$$\Rightarrow \frac{\log_2 2^{nI(X;Y)}}{n} = I(X;Y)$$

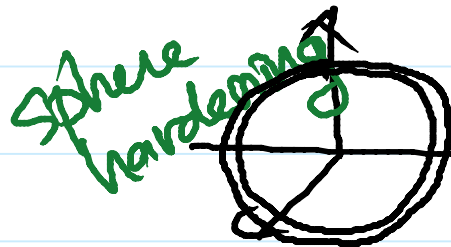
(ii) $\text{Vol}(y_{\epsilon}^{(n)}) \approx 2^{nh(Y)}$

$$\text{Vol}(y_{\epsilon, x_i^{(n)}}^{(n)}) \approx 2^{nh(Y|X)}$$

$$\Rightarrow \frac{\log_2 2^{nI(X;Y)}}{n} = I(X;Y) \leq \frac{1}{2} \left(1 + \frac{P}{\sigma_z^2} \right)$$



$$\|\underline{x}^{(n)}\|^2 \rightarrow nP$$



$$\|\underline{x}\| = 1$$

$$\underline{x}_1^2 + \underline{x}_2^2 = 1$$

$$(ii) \quad \underline{y}^{(n)} = \underline{x}_i + \underline{z}^{(n)} \quad \|\underline{y}^{(n)} - \underline{x}_i\|_2^2 \simeq n\sigma_z^2 \sqrt{n\sigma_z^2}$$

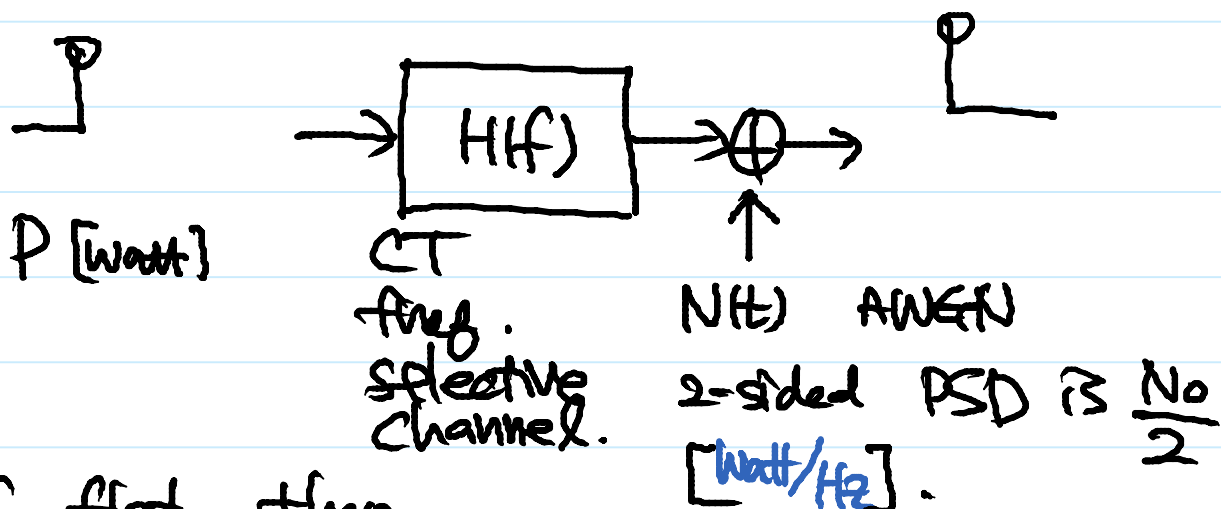
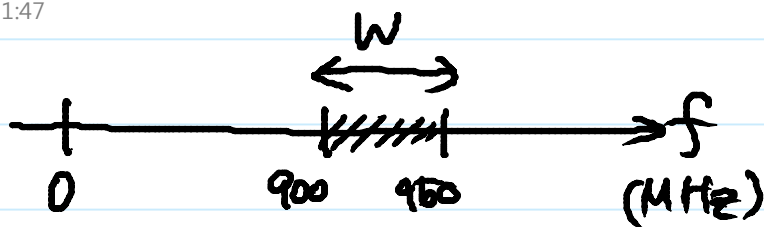
$$x_1^2 + x_2^2 + \dots + x_n^2 = n$$

$$(iii) \quad \underline{y}^{(n)} = \underline{x}^{(n)} + \underline{z}^{(n)} \quad \|\underline{y}^{(n)}\|^2 \simeq n(P + \sigma_z^2)$$

$$\sqrt{n(P + \sigma_z^2)}$$

$$(iv) \quad \frac{Vol}{Vol} \simeq \frac{\sqrt{n(P + \sigma_z^2)}^n}{\sqrt{n\sigma_z^2}^n}$$

$$\frac{\log \frac{\sqrt{n(P + \sigma_z^2)}^n}{\sqrt{n\sigma_z^2}^n}}{n} = \frac{1}{2} \log\left(1 + \frac{P}{\sigma_z^2}\right)$$



If flat, then

$$C = W \log \left(1 + \frac{P}{N_0 W} \right) \text{ [bits/sec]}$$

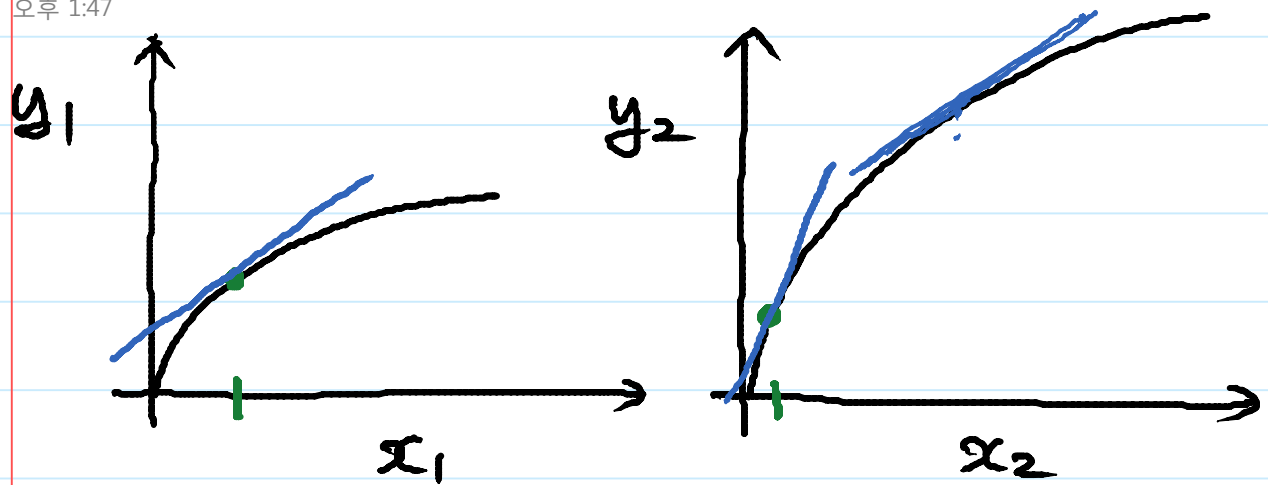
- Simplification
 - DT flat — vector
 - DT selective
 - CT flat

$$\begin{aligned} \underline{X}_i &\rightarrow \oplus \rightarrow \underline{Y}_i \equiv \begin{array}{c} \underline{X}_{i,1} \quad \underline{Y}_{i,1} \\ \oplus \\ \uparrow \\ \underline{Z}_{i,1} \end{array} \\ \vdots & \\ \underline{X}_{i,M} \quad \underline{Y}_{i,M} & \oplus \\ \uparrow & \underline{Z}_{i,M} \end{aligned}$$

$E[\|\underline{X}_i\|^2] \leq P$

$\underline{Z}_i \sim N(\underline{0}, \underline{R})$
i.i.d. ~~$\sigma_z^2 \mathbf{I}$~~
 $\text{diag}(\sigma_1^2, \sigma_2^2, \dots, \sigma_M^2)$

< Parallel Gaussian Channel
Gaussian product channel



→ Slopes should be equal!

$$C_I = \max_{f_X(x)} I(X; Y) \\ \text{s.t. } \mathbb{E}\{\|X\|^2\} \leq P$$

where $Y = X + Z$ &
 $Z \sim N(0, \text{diag}(\sigma_1^2, \sigma_2^2, \dots, \sigma_K^2))$

$$I(X; Y) = h(Y) - h(Y|X) \\ \stackrel{(\Rightarrow)}{=} \sum_{i=1}^K h(Y_i) - h(Z)$$

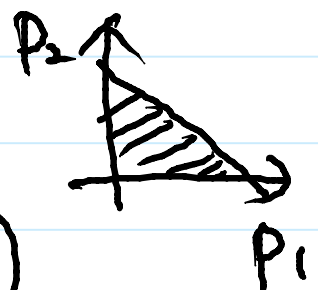
Y_i 's are independent.

$\Rightarrow X_i$'s are independent.

$$= \sum_{i=1}^K h(Y_i) - h(Y_i|X_i) \\ = \sum_{i=1}^K I(X_i; Y_i)$$

X_i 's are Gaussian w/ variance P_i

$$\stackrel{(\Rightarrow)}{=} \sum_{i=1}^K \frac{1}{2} \log \left(1 + \frac{P_i}{\sigma_i^2} \right)$$



$$C_I = \max_{(P_i)_i} \sum_{i=1}^K \frac{1}{2} \log \left(1 + \frac{P_i}{\sigma_i^2} \right) \\ \text{s.t. } 0 \leq P_i, \forall i, \sum_{i=1}^K P_i \leq P$$