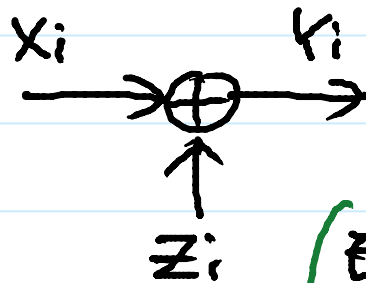


Review

- DT (discrete-time) **AWGN** channel



$$\begin{cases} E\{z_i\} = 0, \forall i \\ E\{z_i z_j\} = \sigma_z^2 \delta_{i,j} \end{cases}$$

independent of x_i

uncorrelatedness
 $\Rightarrow$ independence

- new problem $\begin{cases} \text{discover} \\ \text{given} \end{cases}$

search for a similar problem in your brain
similarities/commonalities, differences

simplify the problem keeping the essence
experience, lesson
increase the complexity
generalization

- Shannon's information measures

$$h(X) \triangleq E\left\{\log \frac{1}{p_X(x)}\right\}$$

- A.E.P. when $X_1, X_2, \dots, X_n$ are i.i.d.

continuous r.v.'s

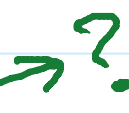
- Informational channel capacity for cond. $X \& Y$.

$$\tilde{C} \triangleq \max_{f_X(x)} I(X; Y)$$

W/o any constraint, $\tilde{C}$ could be $+\infty$.
 Thus, we impose a β -admissibility constraint

$$E\{c(X)\} \leq \beta$$

for some constraint function $c(\cdot)$.

ex/ $c(x) = x^2$. 

$$C = \sup_{f_X(x)} I(X; Y)$$

subject to $E\{c(X)\} \leq \beta$.

- $\Omega = \{f_X(x) : E\{c(X)\} \leq \beta\}$ may not be a convex set.
- $I(X; Y)$ may not be a concave ft of $f_X(x)$.

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

represent

$$\begin{aligned} I(X; Y) &= h(Y) - h(Y|X) \\ &= h(Y) - h(X+Z|X) \\ &= h(Y) - h(Z) \\ &= h(Y) - \frac{1}{2} \log 2\pi e \sigma_Z^2 \end{aligned}$$

where

$$\begin{aligned} E\{Y\} &= E\{X+Z\} = E\{X\} \triangleq m \\ \text{Var}\{Y\} &= \text{Var}\{X+Z\} = \text{Var}\{X\} + \sigma_Z^2 \end{aligned}$$

$$\leq \frac{1}{2} \log \left(2\pi e \left(\text{Var}\{X\} + \sigma_Z^2 \right) \right) - \frac{1}{2} \log 2\pi e \sigma_Z^2$$

where

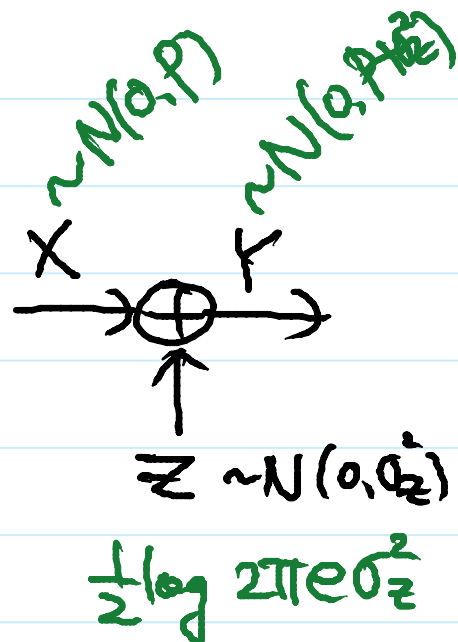
 X is Gaussian

$$E\{X^2\} = m^2 + \text{Var}\{X\} \leq P$$

$$\leq \frac{1}{2} \log \left\{ 2\pi e \left(P - m^2 + \sigma_Z^2 \right) \right\} - \frac{1}{2} \log 2\pi e \sigma_Z^2$$

We choose $m=0$

$$\leq \frac{1}{2} \log 2\pi e (P + \sigma_Z^2) - \frac{1}{2} \log 2\pi e \sigma_Z^2$$

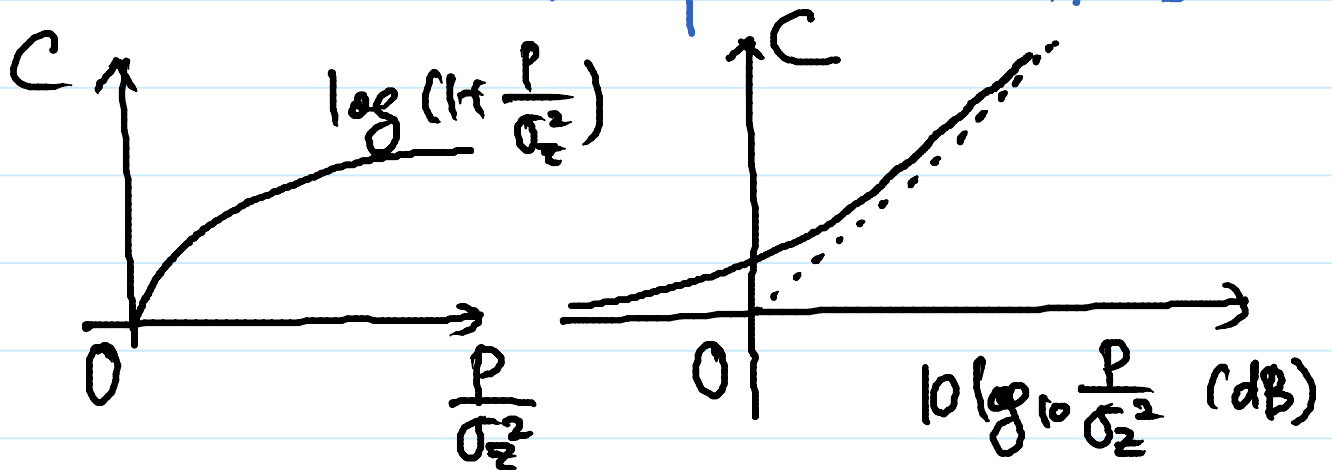


$$X \sim N(0, \bar{P}) \cdot \frac{1}{2} \log \left(1 + \frac{P}{\sigma_z^2} \right) \quad [\text{bits/c.u.}]$$

Informational Channel Capacity of power-constrained average DT AWGN channel

$$C = \frac{1}{2} \log \left(1 + \frac{P}{\sigma_z^2} \right) \text{ [bits/c.u.]}$$

Visualize! Which parameter affects how?



- NCCT for average-power constrained DT AWGN channel.

Def. A rate R is achievable over a ~~memoryless~~ channel if ^{channel} there exists a sequence of codes, $\{C_k\}_k$ such that

(i) $R_k \rightarrow R$ that satisfies the constraint

(ii) $\lambda_k \rightarrow 0$

Def. The operational channel capacity is defined as $\sup R$ where R is achievable.

Theorem. Operational = $\frac{1}{2} \log \left(1 + \frac{P}{\sigma_z^2} \right)$

$$\uparrow$$

$$\left(E\{X^2\} \leq P \right)$$

$$\leftarrow$$

For example, given a codeword $\underline{x}_1^{(n)}$
 $\underline{x}_1^{(n)} \triangleq (x_{1,1}, \dots, x_{1,n})$

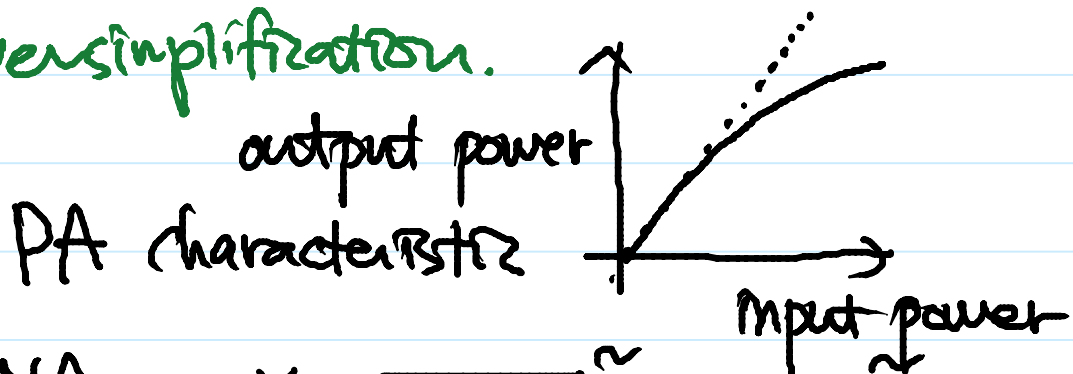
$$\underline{x}^{(n)} \equiv (x_1, \dots, x_n)$$

- Given $c(x)$,
 $E\{c(x)\} \leq \beta$ is translated to

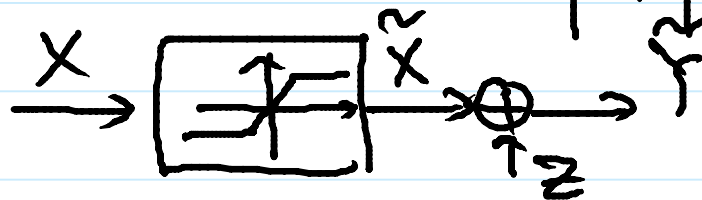
$$\frac{1}{n} \sum_{i=1}^n c(x_{j,i}^{(n)}) \leq \beta, \forall j$$

where $x_j^{(n)}$ is the j -th codeword

However, this translation is an oversimplification.



cf) LNA



$$\bullet \quad E\{x^2\} \leq P \quad \rightarrow \quad \underbrace{\|x_i^{(n)}\|^2}_{\substack{\uparrow \\ i\text{-th code word of} \\ \text{length } n.}} \leq nP$$

• Achievability

Choose $f_X(x) = \frac{1}{\sqrt{2\pi(P-\epsilon')}} \exp\left(-\frac{x^2}{2(P-\epsilon)}\right)$

Generate a random $(2^{nR}, n)$ code $\mathcal{C}_n$

Perform a ^{modified} typical set decoding

Given $\{y^{(n)} = y^{(n)*}\}$,

✓ The decoder output $\hat{w}$ is given by

$\hat{w} = m_i$ if

★ $(i) \quad \|x_i^{(n)}\|^2 \leq nP \quad \text{and}$

$(ii) \quad (x_i^{(n)}, y^{(n)}) \in A_\epsilon^{(n)}$

$(x_j^{(n)}, y^{(n)}) \notin A_\epsilon^{(n)}, \quad \forall j \neq i$

Otherwise declare error.

$$\mathcal{S}_n \rightarrow \Pr(\hat{W} \neq W | W = m_1, \mathcal{S}_n)$$

$$\vdots$$

$$\Pr(\hat{W} \neq W | W = m_{2^{n\epsilon}}, \mathcal{S}_n)$$

$$\Pr(\hat{W} \neq W | W = m_i) = \Pr(\hat{W} \neq m_i | W = m_i)$$

$$\leq \Pr(\|X^{(n)}\|^2 > nP)$$

$$+ \Pr((X^{(n)}, Y^{(n)}) \notin A_\epsilon^{(n)})$$

$$+ (2^{nR} - 1) \Pr((\hat{X}^{(n)}, Y^{(n)}) \in A_\epsilon^{(n)})$$

$$\leq \epsilon + \epsilon + 2^{-n(I(X;Y) - R - 3\epsilon)}$$

$$R < I(X;Y) - 3\epsilon$$

$$\Rightarrow \text{upper bound} \rightarrow 0 \text{ as } n \rightarrow \infty.$$