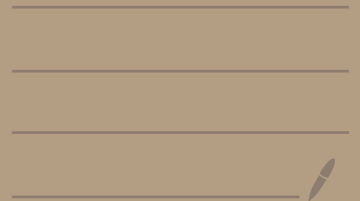


Information Theory & Coding

Oct 25th, 2020



Yesterday:

Channels



$$p(y=z | \text{input} = x) = \underline{\underline{p(z(x))}}$$

If the channel is stationary & memoryless,

if the channel is used without feedback

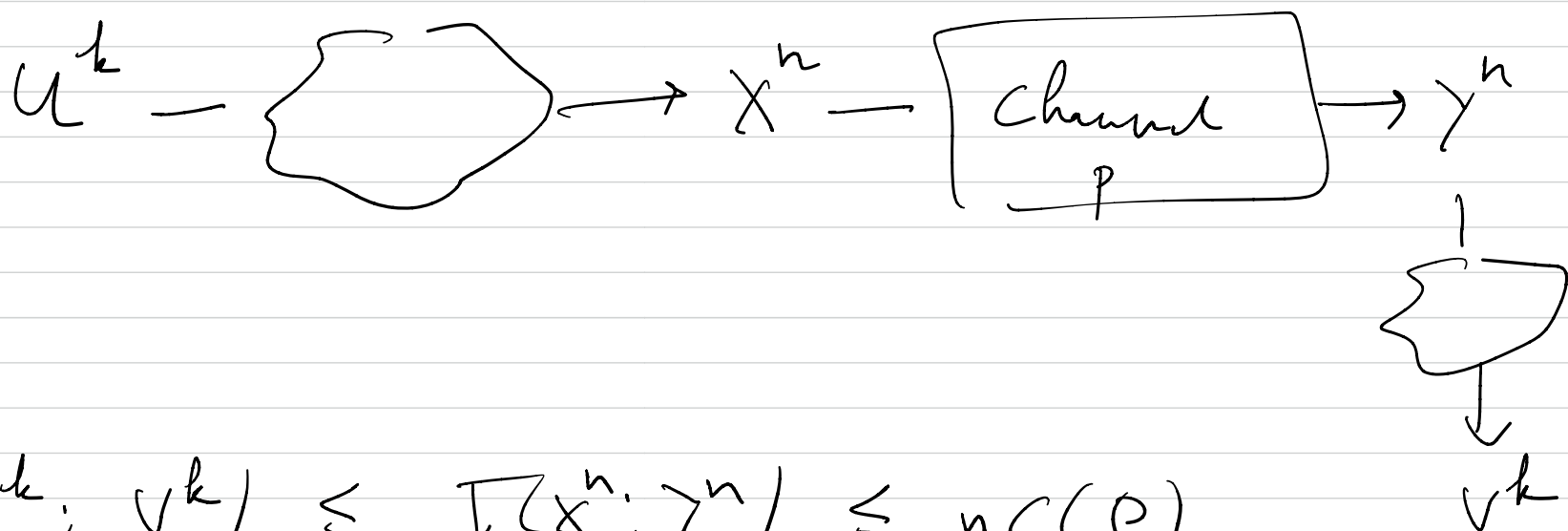
$$\text{then } p(y^n = z^n | X^n = x^n) = \prod_{i=1}^n p(y_i | x_i)$$

$$\Rightarrow H(y^n | X^n) = \sum H(y_i | x_i)$$

Given a channel $P = \{p(y|x)\}$ we define

$$C(P) = \max_{p_X} \underbrace{I(X; Y)}_{\text{function of } p_X} = f(p_X, P)$$

As a corollary:



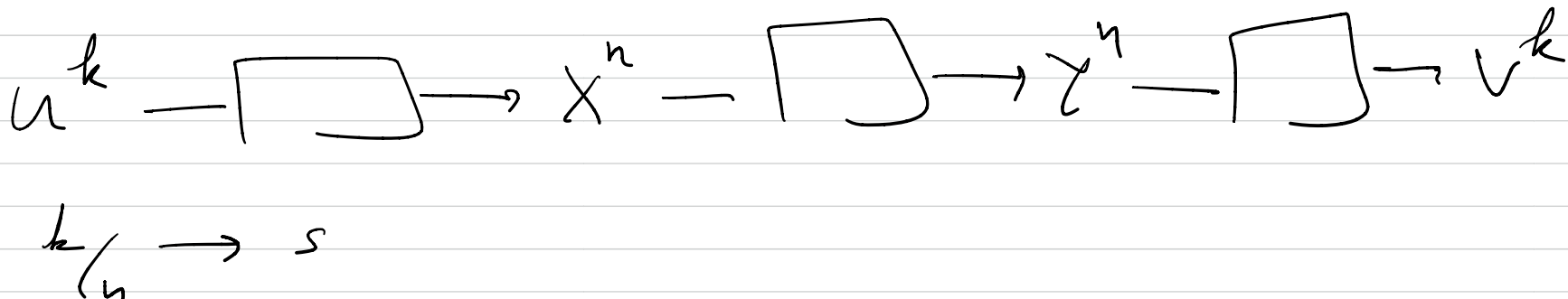
$$I(u^k; v^k) \leq I(X^n; y^n) \leq nC(P)$$

$$\Rightarrow H(u^k | v^k) \geq H(u^k) - nC(P)$$

Thm: Suppose $u, u_L, \dots$ is a stationary source with entropy rate $\mathcal{H}$. Suppose we have a communication system that sends s source letters per channel use. Then the "symbol error probability" $\bar{p}$ will satisfy

$$h_2(\bar{p}) + \bar{p} \log_2(u-1) \geq \mathcal{H} - \underbrace{C(P)/s}.$$

Pf:



$$\textcircled{1} \quad \underbrace{\frac{1}{k} H(u^k | v^k)} \geq \underbrace{\frac{1}{k} H(u^k)} - \underbrace{\left(\frac{1}{k} n\right) C} \geq \mathcal{H} - C/s$$

$\textcircled{2}$ By Fano's Ineq. we have

$$\underbrace{h_2(\bar{p}) + \bar{p} \log_2(u-1)} \geq \underbrace{\frac{1}{k} H(u^k | v^k)}$$

with $\bar{p} = \frac{1}{k} \sum_{i=1}^k \Pr(u_i \neq v_i)$

Put $\textcircled{1}$ & $\textcircled{2}$ together //

Ex: Suppose $u = \{0, 1\}$ $\mathcal{H} = 0.9$ bits

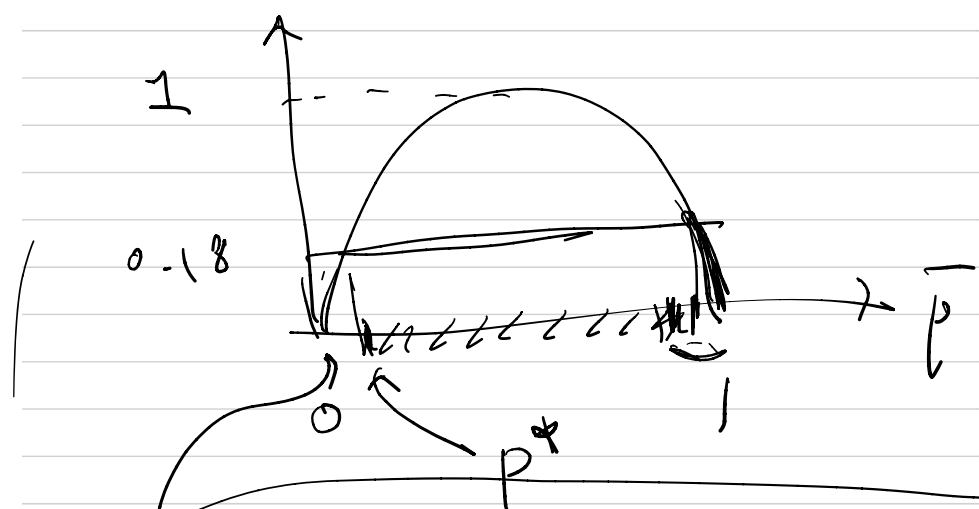
Suppose $C(P) = 0.5$

$s = 0.7$ source letters / channel use

Then will say $\bar{p}$ will satisfy

$$h_2(\bar{p}) + \bar{p} \log_2(2-p) \geq 0.9 - \frac{0.5}{0.7}$$

$$h_2(\bar{p}) = 0.18 \dots$$



$\bar{p} < p^*$ is impossible regardless of the design of



Consequence: Reliable systems (the systems that allow for small $\bar{p}$) are possible only when

$$H_0 \leq C.$$

Bad news

Given a channel P ; input alphabet $\mathcal{X}$
output " $\mathcal{Y}$

Def: an encoder is

a mapping: $\text{enc}: \{1, \dots, M\} \rightarrow \mathcal{X}^n$

M : # of different messages the encoder accepts

n : block length of the encoder

$\frac{\log_2 M}{n}$: rate of the encoder bits/channel use

Def: a decoder for the same channel is a

$$\text{map: } \text{dec}: \mathcal{Y}^n \rightarrow \{1, \dots, M\}$$

$$\text{let } P_{e,m} = \Pr(\text{dec}(\mathcal{Y}^n) \neq m \mid \underbrace{X^n = \text{enc}(m)}).$$

$$P_e(\text{enc}, P, \text{dec}) = \frac{1}{M} \sum_{m=1}^M P_{e,m}$$

$$\hat{P}_e(\text{enc}, P, \text{dec}) = \max_m P_{e,m}.$$

Def: given a channel P , a rate R is said to be achievable if $\forall \underline{\underline{\varepsilon > 0}} \exists \text{ an enc, dec s.t.}$

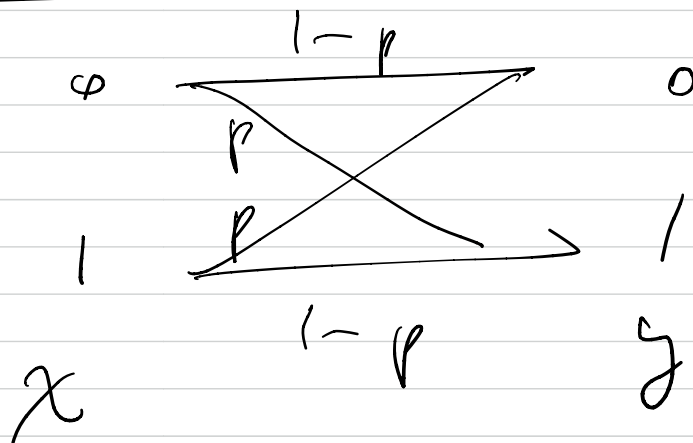
$$\hat{P}_e(\text{enc}, P, \text{dec}) < \varepsilon$$

$$\text{rate}(\text{enc}) \geq R.$$

Thm: given a channel P any $R \leq C(P)$ is achievable.

Examples for $C(P)$.

BSC(p):



$$I(X; Y) = H(Y) - \underbrace{H(Y|X)}$$

$$H(Y|X) = H(Y|X=0) P_X(0) + H(Y|X=1) P_X(1)$$

$$\left. \begin{aligned} H(Y|X=0) &= h_2(p) \\ H(Y|X=1) &= h_2(p) \end{aligned} \right\} \Rightarrow H(Y|X) = h_2(p).$$

$$\max_{p_X} I(X; Y) = \max_{p_X} \underbrace{H(Y)} - h_2(p)$$

$$\text{Since } \mathcal{Y} = \{0, 1\} \quad \underline{H(Y) \leq \log_2 |\mathcal{Y}| = 1}$$

$$\Rightarrow C(p) \leq 1 - h_2(p)$$

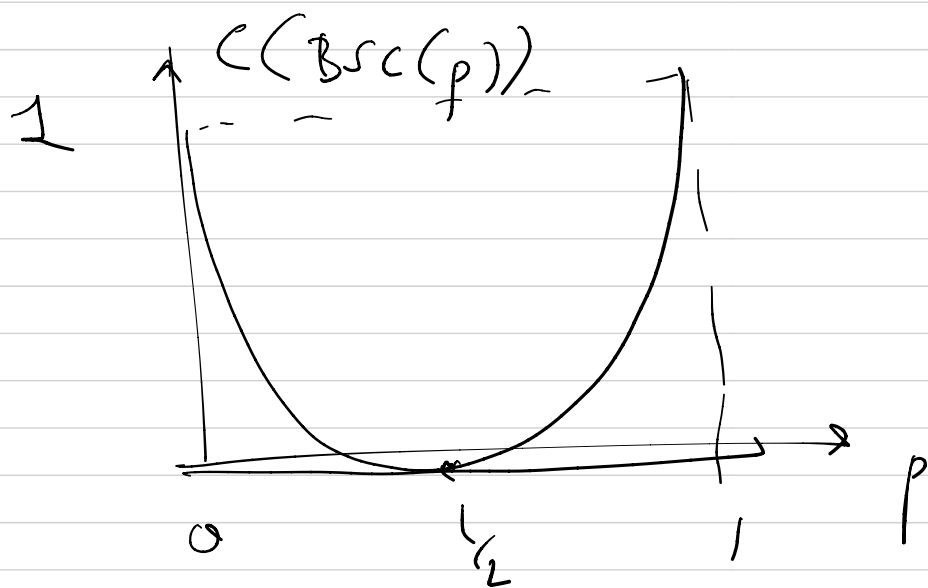
Q: can $H(Y)$ be made $= 1$ by some choice of p_X ?

$\equiv$ Can $P_Y(Y=0)$ be made $= \frac{1}{2}$ " " " " ?

$$P_Y(Y=0) = p_X(0)(1-p) + p_X(1)p$$

$$\text{If } p_X(0) = p_X(1) = \frac{1}{2} \Rightarrow P_Y(Y=0) = \frac{1}{2}$$

$$\text{So } C(p) = 1 - h_2(p).$$

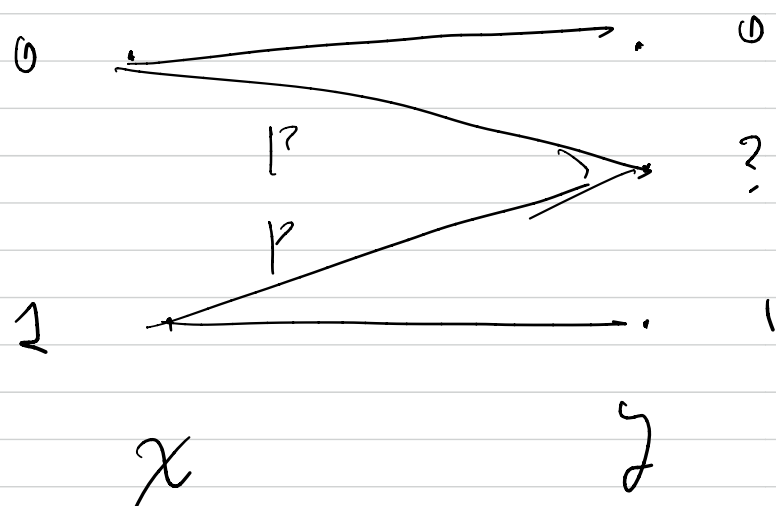


$$\text{Note: } C\left(\text{BSC}\left(\frac{1}{2}\right)\right) = 0$$

for a $\text{BSC}\left(\frac{1}{2}\right)$ Y is independent of X .

$$C(\text{BSC}(0)) = C(\text{BSC}(1)) = 1$$

Ex: BEC(p)



$$I(X; Y) = H(X) - H(X|Y)$$

observe $H(X|Y=0) = H(X|Y=1) = 0$

$$H(X|Y) = H(X|Y=?) \underbrace{\Pr(Y=?)}_p = \underline{p H(X|Y=?)}$$

$$\begin{aligned} \Pr(Y=?) &= \Pr(Y=?|X=0) \Pr(X=0) + \Pr(Y=?|X=1) \Pr(X=1) \\ &= p(p_X(0) + p_X(1)) = p \end{aligned}$$

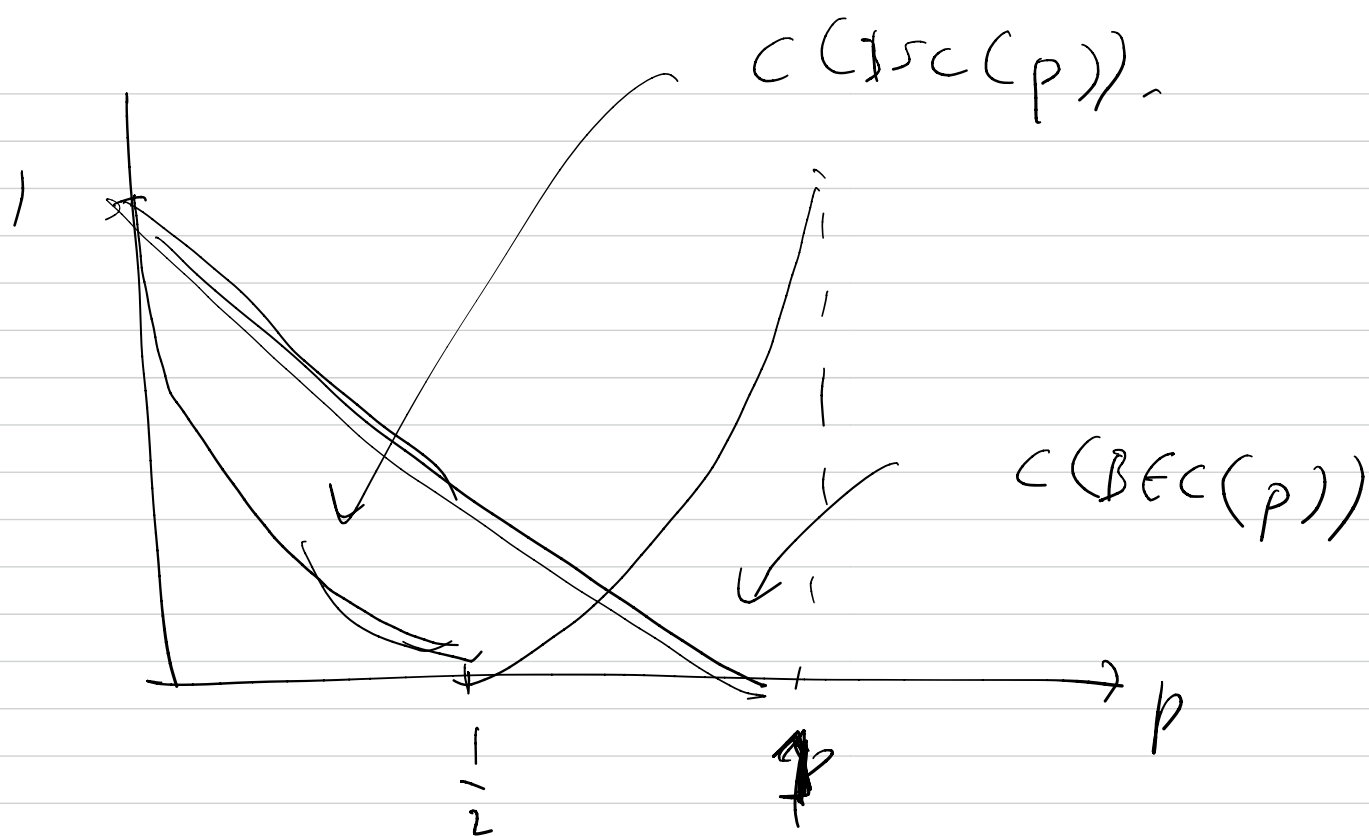
$$\begin{aligned} \Pr(X=0|Y=?) &= \frac{\Pr(X=0, Y=?)}{\Pr(Y=?)} \\ &= \frac{\Pr(X=0) \Pr(Y=?|X=0)}{p} = \Pr(X=0) \end{aligned}$$

$\Rightarrow H(X|Y=?) = H(X)$ so

$$I(X; Y) = (1-p) H(X)$$

$$C(\text{BEC}(p)) = \max_{p_X} (1-p) H(X) = (1-p)$$

with p_X uniform on $\{0, 1\}$



on the nature of how to compute $C(p)$.

$$C(p) = \max_{P_X} \underbrace{I(X; Y)}_{\text{func}(P_X, \underline{P})}$$

$I(X; Y)$ as a function of P_X .

$$= H(Y) - \underbrace{H(Y|X)}$$

$$\sum_x P_X(x) \underbrace{H(Y|X=x)}_{\text{func}(P)}$$

linear function of P_X

$$\underbrace{P_Y(Y=g)} = \sum_x \underbrace{P(Y=g|x)}_{\text{func}(P_X)} P_X(x)$$

$\Rightarrow P_Y$ is a linear function of P_X .

* $H(Y)$ is a concave function of P_Y .

Proving that $H(u)$ is a concave function of P_U .

Let $H(P_U)$ denote the entropy of a random variable U

$$\underbrace{H(\lambda p + (1-\lambda)q)}_{\text{dist. of } U} \geq \underbrace{\lambda H(p) + (1-\lambda)H(q)}_{0 \leq \lambda \leq 1}$$

Let V be binary $\{1, 2\}$
w.p. $\lambda, 1-\lambda$

$$\left. \begin{aligned} P_U(U=u|V=1) &= p(u) \\ P_U(U=u|V=2) &= q(u) \end{aligned} \right\} P_U(U=u) = \lambda p(u) + (1-\lambda)q(u)$$

$$H(\lambda p + (1-\lambda)q) = H(U)$$

$$\left. \begin{aligned} H(p) &= H(U|V=1) \\ H(q) &= H(U|V=2) \end{aligned} \right\} \lambda H(p) + (1-\lambda)H(q) = H(U|V)$$

Since $H(U) \geq H(U|V)$ we find that

$$H(\lambda p + (1-\lambda)q) \geq \lambda H(p) + (1-\lambda)H(q)$$

thus $p \mapsto H(p)$ is a concave.

$$I(X; Y) = H(Y) - \underbrace{H(Y|X)}$$

linear in P_X

Concave funct

of a lin. funct of P_X

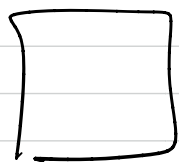
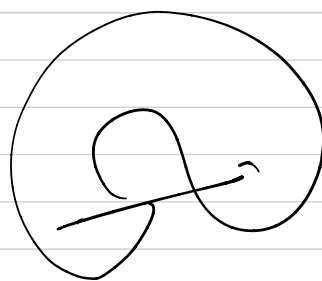
$\therefore$ a concave function of P_X

Division to concave / convex functions:

Recall: a set $S \subseteq \mathbb{R}^n$ is called convex if

$\forall x, y \in S \ \& \ 0 \leq \lambda \leq 1$ we have

$$\lambda x + (1-\lambda)y \in S.$$



A function $f: S \rightarrow \mathbb{R}$ is said to be convex

$$\text{if } \underbrace{f(\lambda x + (1-\lambda)y)}_{0 \leq \lambda \leq 1} \leq \underbrace{\lambda f(x) + (1-\lambda)f(y)}$$

f is concave if $(-f)$ is convex.

Lemma: if $f: (a, b) \rightarrow \mathbb{R}$ is ^{cont.} twice differentiable,

and if $f'' \geq 0$ then f is convex.

Given x, y , $0 \leq \lambda \leq 1$ let

$$z = \lambda x + (1-\lambda)y.$$

$$f(x) = \underbrace{f(z) + f'(z)(x-z)}_{\text{Taylor expansion}} + \frac{1}{2} \overbrace{f''(\xi)}^{\text{Taylor expansion}} (x-z)^2$$

$$f(y) = \underbrace{f(z) + f'(z)(y-z)}_{\text{Taylor expansion}} + \frac{1}{2} f''(\xi) (y-z)^2$$

$$\Rightarrow \boxed{\lambda f(x) + (1-\lambda)f(y)} \geq f(z) + f'(z) \underbrace{(\lambda x - \lambda z + (1-\lambda)y - (1-\lambda)z)}_{=0} //$$