

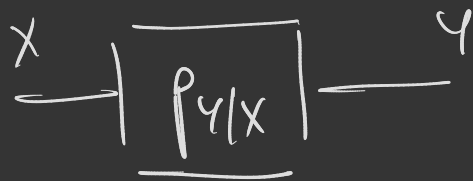
Basic properties

$$H(X) = \sum_{x \in \mathcal{X}} p_X(x) \log_2 \frac{1}{p_X(x)}$$

$\log_2 \frac{1}{p_X(x)}$
Average randomness in
X

$$I(X; Y) = \sum_{\substack{x \in \mathcal{X} \\ y \in \mathcal{Y}}} p_{X,Y}(x,y) \log_2 \frac{p_{X,Y}(x,y)}{p_X(x) p_Y(y)}$$

Amount of information
Y gives about X



$$\frac{k}{n} \approx I(X; Y)$$

$$P_e \approx 0$$

$$I(Y; X) = I(X; Y)$$

$$k \approx n I(X; Y)$$

Conditional entropy

$H(X)$: Uncertainty / randomness in X

$X \rightarrow p_X(\cdot) = 1$ deterministic

$H(X) \geq 0$ bits

$H(X)$ is max when X is uniform

all outcomes eq. likely

$(X, Y) \sim p_{X,Y}$ conditional entropy of Y given X

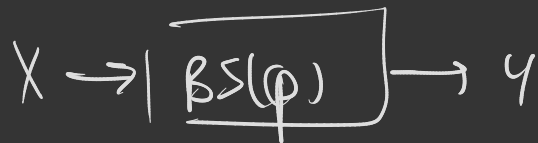
$$H(Y|X) = \sum_{x \in \mathcal{X}} \underline{H(Y|X=x)} p_X(x)$$

$$= \sum_{x \in \mathcal{X}} \left[\sum_Y \left(p_{Y|X}(y|x) \log_2 \frac{1}{p_{Y|X}(y|x)} \right) \right] p_X(x)$$

$$= \sum_x \sum_y p_{XY}(x, y) \log_2 \frac{1}{p_{Y|X}(y|x)}$$

$H(Y|X)$ is the ^{avg} amt of uncertainty left in Y after observing X .

$$X=0$$



$$X \sim \text{Ber}(1/2)$$

$$p_{Y|X}(0|0) = 1-p$$

$$p_{Y|X}(1|1) = 1-p$$

$$p_{Y|X}(0|1) = p$$

$$p_{Y|X}(1|0) = p$$

$$H(X) = \sum_x p_X(x) \log_2 \frac{1}{p_X(x)} = 0.5 \log_2 \frac{1}{0.5} + 0.5 \log_2 \frac{1}{0.5} = 1 \text{ bit}$$

$$p_Y(0) = \sum_x p_{Y|X}(0|x) p_X(x)$$

$$p_Y(1) = \frac{1}{2}$$

$$= p(0|0) p_X(0) + p(0|1) p_X(1)$$

$$= (1-p) \frac{1}{2} + p \times \frac{1}{2}$$

$$Y \sim \text{Ber}(1/2)$$

$$= \frac{1}{2}$$

$$\Rightarrow H(Y) = 1 \text{ bit}$$

$$H(Y|X=0) = \sum_y p_{Y|X}(y|0) \log_2 \frac{1}{p_{Y|X}(y|0)} = p(0|0) \log_2 \frac{1}{p(0|0)} + p(1|0) \log_2 \frac{1}{p(1|0)}$$

$$= H_2(p)$$

$$H(Y|X=1) = H_2(p)$$

$$H(Y|X) = \sum_x H(Y|X=x) p_X(x)$$

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

$$= H_2(p) \frac{1}{2} + H_2(p) \frac{1}{2}$$

$$= H_2(p) \text{ bits} < 1$$

$$\text{if } p < \frac{1}{2}$$

$$\text{or } p > \frac{1}{2}$$

$$H(Y|X) < H(Y)$$

Relation between entropy and mutual information

$$I(X; Y) = \sum_{x, y} p_{xy}(x, y) \log_2 \frac{p_{xy}(x, y)}{p_x(x) p_y(y)}$$

$$= \sum_{x, y} p_{xy}(x, y) \left[\log_2 \frac{1}{p_y(y)} + \log_2 p_{y|x}(y|x) \right]$$

$$= \sum_{x, y} p_{xy}(x, y) \log_2 \frac{1}{p_y(y)} + \sum_{x, y} p_{xy}(x, y) \log_2 p_{y|x}(y|x)$$

$$= \sum_y \left(p_y(y) \log_2 \frac{1}{p_y(y)} \right) \left(\sum_x p_{x|y}(x|y) \right) - \sum_{x, y} p_{xy}(x, y) \log_2 \frac{1}{p_{y|x}(y|x)}$$

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

KL divergence

Kullback-Liebler divergence / Relative entropy

p_x, q_x pmf on \mathcal{X}

$$D(p_x \parallel q_x) = \sum_{x \in \mathcal{X}} p_x(x) \log_2 \frac{p_x(x)}{q_x(x)}$$

$$D(p_x \parallel p_x) = 0$$

$$D(p_x \parallel q_x) \geq 0$$

$$I(X; Y) = \sum_{x, y} p_{XY}(x, y) \log_2 \frac{p_{XY}(x, y)}{p_X(x) p_Y(y)}$$

$$D(p \parallel q) = \sum_n p(x) \log_2 \frac{p(x)}{q(x)}$$

$$I(X; Y) = D(p_{XY} \parallel p_X p_Y)$$

p_{XY} defined on $\mathcal{X} \times \mathcal{Y}$

$p_X p_Y$ — " — $\mathcal{X} \times \mathcal{Y}$

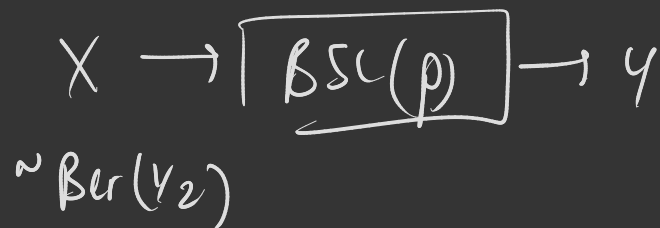
$$p_{XY}(x, y) \quad q_{XY}(x, y) = p_X(x) p_Y(y)$$

$$D(p_{XY} \parallel q_{XY})$$

$$(X, Y) \sim p_{XY}$$

$$(\tilde{X}, \tilde{Y}) \sim q_{XY} = p_X(x) p_Y(y)$$

$I(X; Y) = 0 \iff X, Y$ are independent



$p =$

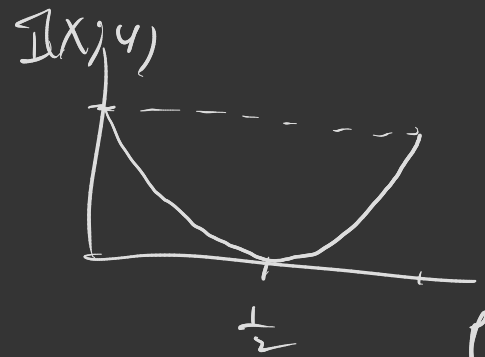
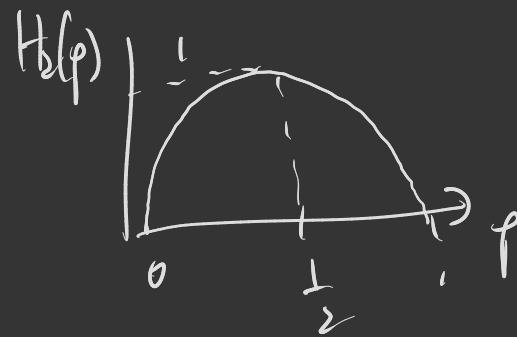
$$H(Y|X) = H_2(p)$$

$$H(Y) = 1 \text{ bit}$$

$$I(X; Y) = H(Y) - H(Y|X) = 1 - H_2(p)$$

If $p = \frac{1}{2}$, X & Y indep

$p < \frac{1}{2}$, $p > \frac{1}{2}$ X & Y NOT INDEP



$$H(X) = \sum_x p_X(x) \log_2 \frac{1}{p_X(x)}$$

$$H(X|Y) = \sum_{x,y} p_{X,Y}(x,y) \log_2 \frac{1}{p_{X|Y}(x|y)}$$

$$I(X;Y) = \sum_{x,y} p_{X,Y}(x,y) \log_2 \frac{p_{X,Y}(x,y)}{p_X(x) p_Y(y)}$$

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

$$D(p \parallel q) = \sum_x p(x) \log_2 \frac{p(x)}{q(x)} \neq D(q \parallel p)$$

$$I(X;Y) = D(p_{X,Y} \parallel p_X p_Y)$$

$$R = \frac{\mathbb{E}L}{n} \approx H(p_x) + D(p_x \parallel q_x)$$

$$X^n \sim p_x$$

Design based on q_x

$$X \sim \text{Ber}(p) \longrightarrow$$

$$X' \sim \text{Ber}(q)$$

$\{0, 1\} \rightarrow$ Support / alphabet.

$$p_x(x) = \begin{cases} p & x=1 \\ 1-p & x=0 \end{cases}$$

$$q_x(x) = \begin{cases} q & x=1 \\ 1-q & x=0 \end{cases}$$

Chain rule of entropy

$$(X, Y) \sim P_{XY}$$

$$H(X, Y) = \sum_{x, y} P_{XY}(x, y) \log_2 \frac{1}{P_{XY}(x, y)}$$

$$= \sum_{x, y} P_{XY}(x, y) \log \frac{1}{P_X(x) P_{Y|X}(y|x)}$$

$$= \sum_{x, y} P_{XY}(x, y) \left[\log_2 \frac{1}{P_X(x)} + \log_2 \frac{1}{P_{Y|X}(y|x)} \right]$$

$$= \sum_{x, y} P_{XY}(x, y) \log_2 \frac{1}{P_X(x)} + \sum_{x, y} \frac{P_{XY}(x, y)}{P_X(x)} \log_2 \frac{1}{P_{Y|X}(y|x)}$$

$$= \sum_x \left[\left(P_X(x) \log_2 \frac{1}{P_X(x)} \right) \left(\sum_y P_{Y|X}(y|x) \right) \right] + H(Y|X)$$

$$H(X, Y) = H(X) + H(Y|X)$$

$$\sum_y p(y|x) = 1$$

$$H(X, Y) = H(Y, X) = H(Y) + H(X|Y)$$

$$H(X_1, X_2, X_3) = H(X_1) + H(X_2|X_1) + H(X_3|X_1, X_2)$$

OPTIMAL JOINT

SEQUENTIAL (OPTIMAL)

$$\underline{H(X_1^n, X_2^n, X_3^n)}$$

n

$$H(X_1, \dots, X_n) = H(X_1) + H(X_2 | X_1) + H(X_3 | X_2, X_1) + \dots + H(X_n | X_{n-1}, \dots, X_1)$$

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

X_1, X_2, \dots, X_n

$$X_1, \dots, X_n \sim \text{indep.} \quad P_{X_i | X_1, \dots, X_{i-1}} \approx P_{X_i}$$

$$H(X_i | X_1, \dots, X_{i-1}) \approx H(X_i)$$

$$H(X^n) \approx H(X_1) + H(X_2) + \dots + H(X_n)$$

Chain rule of mutual information

$$I(X; Y, Z) = \sum_{x, y, z} p_{X, Y, Z}(x, y, z) \log_2 \left(\frac{p_{X, Y, Z}(x, y, z)}{p_X(x) p_{Y, Z}(y, z)} \right)$$

$$= \sum_{x, y, z} p_{X, Y, Z}(x, y, z) \log_2 \frac{p_{X|Y, Z}(x|y, z)}{p_X(x)}$$

$$= \sum_{x, y, z} p_{X, Y, Z}(x, y, z) \log_2 \left(\frac{p_{X|Y}(x|y) p_{Z|X, Y}(z|x, y)}{p_X(x) p_Y(y) p_{Z|Y}(z|y)} \right)$$

$$= \sum_{x, y, z} p(x, y, z) \left[\log_2 \left(\frac{p(x, y)}{p(x) p(y)} \right) + \log_2 \left(\frac{p_{Z|X, Y}(z|x, y)}{p(z|y)} \right) \right]$$

$$= \sum_{x,y,z} p(x,y,z) \log_2 \frac{p(x,y)}{p(x)p(y)} + \sum_{x,y,z} p(x,y,z) \times \log_2 \left(\frac{p(z|x,y)}{p(z|y)} \right)$$

$$= \sum_{x,y} \log_2 \frac{p(x,y)}{p(x)p(y)} \sum_z p(x,y,z)$$

$$+ \sum_{x,y,z} p(x,y,z) \log_2 \left(\frac{p(x,y)p(z|x,y)}{p(x,y)p(z|y)} \right)$$

$$= \sum_{x,y} p(x,y) \log_2 \frac{p(x,y)}{p(x)p(y)} + \sum_{x,y,z} p(x,y,z) \log_2 \left(\frac{p(x,z|y)}{p(x|y)p(z|y)} \right)$$

$$I(X; YZ) = I(X; Y) + I(X; Z|Y)$$

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

Chain rule of entropy

$$= H(Y) + H(Z|Y) - (H(Y|X) + H(Z|XY))$$

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

$$= I(X; Y) + I(X; Z|Y)$$

$$I(XY; UV|W) = H(XY|W) - H(XY|UVW)$$

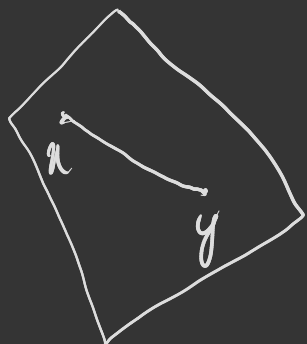
$$= H(UV|W) - H(UV|XYW)$$

$$H(AB|C) = H(A|C) + H(B|AC)$$

$$I(X; Y_1, \dots, Y_n | W) = \sum_{i=1}^n I(X; Y_i | Y_1, \dots, Y_{i-1}, W)$$

$$= I(X; Y_1 | W) + I(X; Y_2 | Y_1, W) + I(X; Y_3 | Y_1, Y_2, W) \\ + \dots$$

Convex sets



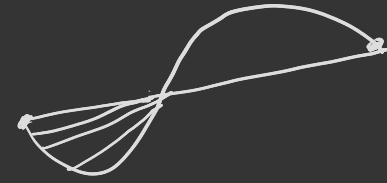
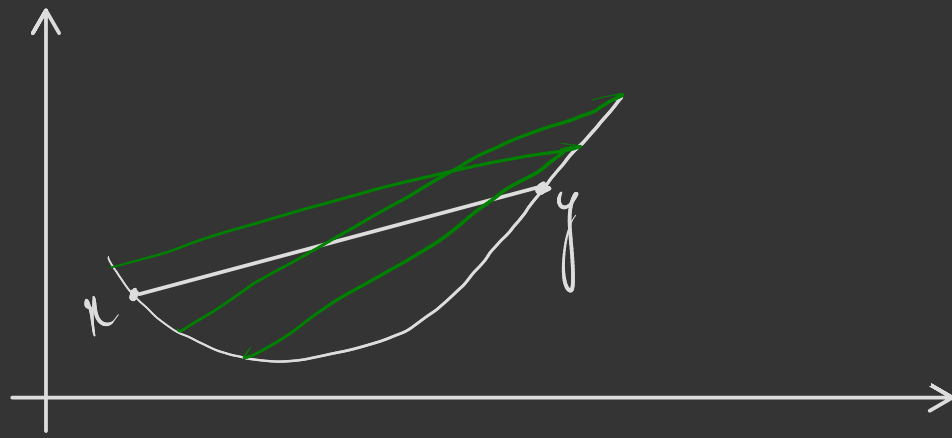
$A \subseteq \mathbb{R}^n$ is convex if $\forall \alpha \in [0, 1]$, $x, y \in A$

$$\alpha x + (1 - \alpha)y \in A$$

$$\alpha = 0$$

$$\alpha = 1$$

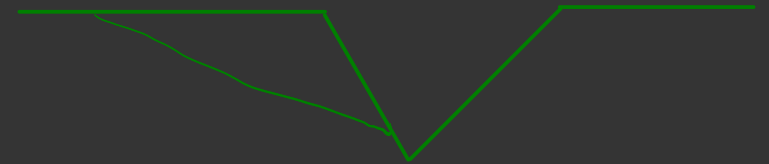
$$\alpha x + (1 - \alpha)y = y$$
$$\alpha x + (1 - \alpha)y = x$$



Convex functions: $f: \mathbb{R} \rightarrow \mathbb{R}$ is convex in $[a, b]$ if

$$f(\alpha x + (1-\alpha)y) \leq \alpha f(x) + (1-\alpha)f(y) \quad \forall x, y \in [a, b]$$

Strictly convex:



$f: \mathbb{R} \rightarrow \mathbb{R}$ is concave if $-f$ is convex.

Theorem: $f: \mathbb{R} \rightarrow \mathbb{R}$ is convex in $[a, b]$ if & only if (assuming f'' exists)

$$f''(x) \geq 0 \quad \forall x \in [a, b]$$

Strictly convex: > 0

Are these convex:

① $\log x$

② x^2

$$\textcircled{3} \quad n \log n$$

Jensen's inequality

If f is a convex function over \mathbb{R} & X any rv,

$$E f(X) \geq f(E X)$$

① $f(x) = x^2$

② $f(x) = \log x$

Important consequence: the log-sum inequality

Let $(\alpha_1, \dots, \alpha_m)$ & $(\beta_1, \dots, \beta_m)$ be non-negative real nos
st $\beta_i > 0 \Rightarrow \alpha_i > 0$

Then,

$$\sum_{i=1}^m \alpha_i \log_p \frac{\alpha_i}{\beta_i} \geq \left(\sum_{i=1}^m \alpha_i \right) \log_p \frac{\sum_{i=1}^m \alpha_i}{\sum_{i=1}^m \beta_i}$$

Proof: $y \log y$ is convex.

$$D(p \parallel q) = \sum_x p(x) \log_2 \frac{p(x)}{q(x)}$$

Apply log-sum inequality