

Review

Shannon's Information measures

$$H(X) \triangleq E\left\{\log \frac{1}{p_X(x)}\right\} = \sum_{i=1}^{\infty} p_i \log \frac{1}{p_i}$$

$$H(X, Y) = E\left\{\log \frac{1}{p_{X,Y}(X, Y)}\right\}$$

$$\vdots$$

$$H(X_1, X_2, \dots, X_N) = E\left\{\log \frac{1}{p_{X_1, X_2, \dots, X_N}(X_1, X_2, \dots, X_N)}\right\}$$

$$H(X|Y=y) = E\left\{\log \frac{1}{p_{X|Y}(X|Y)} \mid Y=y\right\}$$

$$H(X|Y) = E\left[E\left\{\log \frac{1}{p_{X|Y}(X|Y)} \mid Y\right\}\right]$$

(f) $E[X|Y=y]$ $\uparrow$ deterministic

$E[X|Y]$ $\uparrow$ f.e. $\neq$

$\uparrow$ r.v.

$$= E\left\{\log \frac{1}{p_{X|Y}(X|Y)}\right\}$$

$$\begin{aligned} H(X, Y) &= H(X) + H(Y|X) \\ &= H(Y) + H(X|Y) \end{aligned}$$

$$\begin{aligned} H(X_1, \dots, X_N) &= H(X_1) + H(X_2|X_1) + H(X_3|X_1, X_2) \\ &\quad + \dots + H(X_N|X_1, X_2, \dots, X_{N-1}) \end{aligned}$$

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

$$\begin{aligned} \cdot \quad I(X;Y) &= H(X) - H(X|Y) = E \left\{ \log \frac{P_{X|Y}(X|Y)}{P_X(X)} \right\} \\ &\parallel \\ I(Y;X) &= H(Y) - H(Y|X) = E \left\{ \log \frac{P_{Y|X}(Y|X)}{P_Y(Y)} \right\} \end{aligned}$$

representation.

$$= H(X) + H(Y) - H(X,Y) = E \left\{ \log \frac{P_{X,Y}(X,Y)}{P_X(X)P_Y(Y)} \right\}$$

Q1. $I(X;X) = H(X)$

Q2. $I(X;Y) = 0$ iff X & Y are independent.

$$\begin{aligned} \cdot \quad I(X,Y;Z) &\triangleq H(X,Y) - H(X,Y|Z) \\ &\triangleq H(Z) - H(Z|X,Y) \\ &\triangleq H(X,Y) + H(Z) - H(X,Y,Z) \\ &= E \left\{ \log \frac{P_{X,Y,Z}(X,Y,Z)}{P_{X,Y}(X,Y)P_Z(Z)} \right\} \end{aligned}$$

$$\cdot \quad I(X;Y|Z=z) = E \left\{ \log \frac{P_{X,Y|Z}(X,Y|z)}{P_{X|Z}(X|z)P_{Y|Z}(Y|z)} \mid Z=z \right\}$$

$$\cdot \quad I(X;Y|Z) \triangleq E \left\{ \log \frac{P_{X,Y|Z}(X,Y|Z)}{P_{X|Z}(X|Z)P_{Y|Z}(Y|Z)} \right\}$$

$$= E \left\{ \log \frac{P_{X|Y,Z}(X|Y,Z)}{P_{X|Z}(X|Z)} \right\}$$

$$\begin{aligned} \bullet \quad I(X;Y|Z) &= H(X|Z) - H(X|Y,Z) \\ &= H(Y|Z) - H(Y|X,Z) \\ &= E \left\{ \log \frac{P_{Y|X,Z}(Y|X,Z)}{P_{Y|Z}(Y|Z)} \right\} \end{aligned}$$

$$\begin{aligned} \bullet \quad I(X_1, X_2, \dots, X_N; Y) &= H(X_1, X_2, \dots, X_N) \\ &\quad - H(X_1, X_2, \dots, X_N | Y) \\ &= H(X_1) + H(X_2|X_1) + \dots + H(X_N|X_1, X_2, \dots, X_{N-1}) \\ &\quad - H(X_1|Y) - H(X_2|X_1, Y) - H(X_N|X_1, \dots, X_{N-1}, Y) \\ &= I(X_1; Y) + I(X_2; Y|X_1) + \dots + I(X_N; Y|X_1, \dots, X_{N-1}) \end{aligned}$$

where the equality holds

- $I(X;Y) \geq 0$ ✓ iff X & Y are independent.
 $I(X;Y|Z) \geq 0$ iff X & Y "conditionally" given $\{Z=z\}$

- The KL distance $D(p \parallel q)$
 Kullback Leibler $\equiv$ the information divergence
 $\equiv$ the relative entropy

- A distance metric $d(x,y)$
 (i) non-negativity
 $d(x,y) \geq 0$ where equality holds iff $x=y$

(ii) commutativity

$$d(x,y) = d(y,x)$$

(iii) triangle inequality

$$d(x,y) \leq d(x,z) + d(z,y)$$

- Given two random variables

$$X \sim p_X(x)$$

$$Y \sim p_Y(y)$$

we call

$$D(p_X \parallel p_Y) \triangleq E \left\{ \log \frac{p_X(x)}{p_Y(x)} \right\}$$

the KL distance from p_X to p_Y .

- Since

$$D(p_X \parallel p_Y) = \sum_{x \in \mathcal{X}} p_X(x) \log \frac{p_X(x)}{p_Y(x)}$$

$$= \sum_{x \in \mathcal{X}} p_X(x) \log \frac{1}{p_Y(x)} \quad \text{mismatched.}$$

$$- \sum_{x \in \mathcal{X}} p_X(x) \log \frac{1}{p_X(x)} \quad \text{matched}$$

- Physical meaning : mismatched codebook.
- matched " .

Too good to be true!

$D(p_X \parallel p_Y) \geq 0$ where the equality holds iff $p_X(x) = p_Y(x), \forall x$

$$\bullet D(p_X || p_Y) = E \left\{ \log \frac{p_X(X)}{p_Y(X)} \right\}$$

$$= \sum_{x \in X} p_X(x) \log \frac{p_X(x)}{p_Y(x)}$$

$$= \log e \sum_{x \in X} p_X(x) \ln \frac{p_X(x)}{p_Y(x)}$$

$$\log_a b = \frac{\log_c b}{\log_c a}$$

$$\log_a e = \ln b$$

$$= \log_a b$$

$$\geq \log e \sum_{x \in X} p_X(x) \left(1 - \frac{p_Y(x)}{p_X(x)} \right)$$

$$= \log e \left(\sum_{x \in X} p_X(x) - \sum_{x \in X} p_Y(x) \right)$$

$$\geq \log e (1 - 1) = 0$$

$$= \text{iff } p_X(x) = p_Y(x) \text{ for all } x$$

$$= 0$$

$$\bullet D(p_X || p_Y) = E \left\{ \log \frac{p_X(X)}{p_Y(X)} \right\}$$

$$= \sum_{x \in X} p_X(x) \log \frac{p_X(x)}{p_Y(x)}$$

in general.

$$\bullet D(p_Y || p_X) = E \left\{ \log \frac{p_Y(Y)}{p_X(Y)} \right\}$$

$$= \sum_{y \in Y} p_Y(y) \log \frac{p_Y(y)}{p_X(y)}$$

$$\bullet D(p_{x,y} \parallel p_{z,w}) = E \left\{ \log \frac{p_{x,y}(x,y)}{p_{z,w}(x,y)} \right\}$$

$$= E \left\{ \log \frac{p_x(x) p_{Y|X}(Y|X)}{p_z(x) p_{W|Z}(Y|X)} \right\}$$

$$= E \left\{ \log \frac{p_x(x)}{p_z(x)} \right\} + E \left\{ \log \frac{p_{Y|X}(Y|X)}{p_{W|Z}(Y|X)} \right\}$$

$$\triangleq D(p_x \parallel p_z) + D(p_{Y|X} \parallel p_{W|Z})$$

$$\bullet I(X;Y) = H(X) + H(Y) - H(X,Y)$$

$$= E \left\{ \log \frac{p_{X,Y}(X,Y)}{p_X(X) p_Y(Y)} \right\}$$

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

$$\geq 0$$

where $=$ holds iff X & Y are independent.

upper bound

$$\bullet H(X) \geq H(X|Y), \quad H(Y) \geq H(Y|X)$$

$$\bullet H(X_1, X_2, \dots, X_N) \leq \sum_{n=1}^N H(X_n) \quad \text{Independence}$$