

Def: Let  $P$  be a prob. distribution on a discrete  $\Omega$ . The (Shannon) entropy

$$H(P) := \sum_{w \in \Omega} P(w) \log \frac{1}{P(w)}$$

For a discrete R.V.  $X: \Omega \rightarrow \mathcal{X}$

$$H(X) := H(P_X) = \sum_{x \in \mathcal{X}} P_X(x) \log \frac{1}{P_X(x)} = \mathbb{E} \left( \log \frac{1}{P_X(x)} \right)$$

$\log \frac{1}{P_X(x)}$ : the surprisal of  $X=x$  happens,  $H(X)$ : the uncertainty/<sup>↑</sup> randomness of  $P_X$ .  
 // 8 bits

Rem 1. Basis of log

$$\log_2 \longleftrightarrow \text{bits}$$

$$\log_{256} \longleftrightarrow \text{bytes}$$

2. We agree  $0 \log \frac{1}{0} = 0$  by  $\lim_{x \rightarrow 0} x \log \frac{1}{x} = 0$ .

Example (Bernoulli):  $X \in \{0, 1\}$ .  $P(X=1) = p$   $P(X=0) = 1-p$

$$H(X) = p \log \frac{1}{p} + (1-p) \log \frac{1}{1-p} := h(p)$$

where  $h(\cdot)$  is called binary entropy function

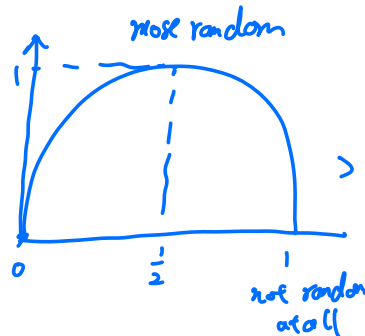
$$h\left(\frac{1}{2}\right) = 1$$

$$h(0) = h(1) = 0$$

In  $\log_2$  basis,

$$h(p) \leq 1 \text{ and}$$

$$h(p) = 1 \text{ iff } p = \frac{1}{2}$$



Example (Geometric):  $X \in \{0, 1, 2, \dots\}$   $P(X=i) = p(1-p)^i$   $i = 0, 1, 2, \dots$

$$H(X) = \sum_{i=0}^{\infty} p(1-p)^i \log \frac{1}{p(1-p)^i}$$

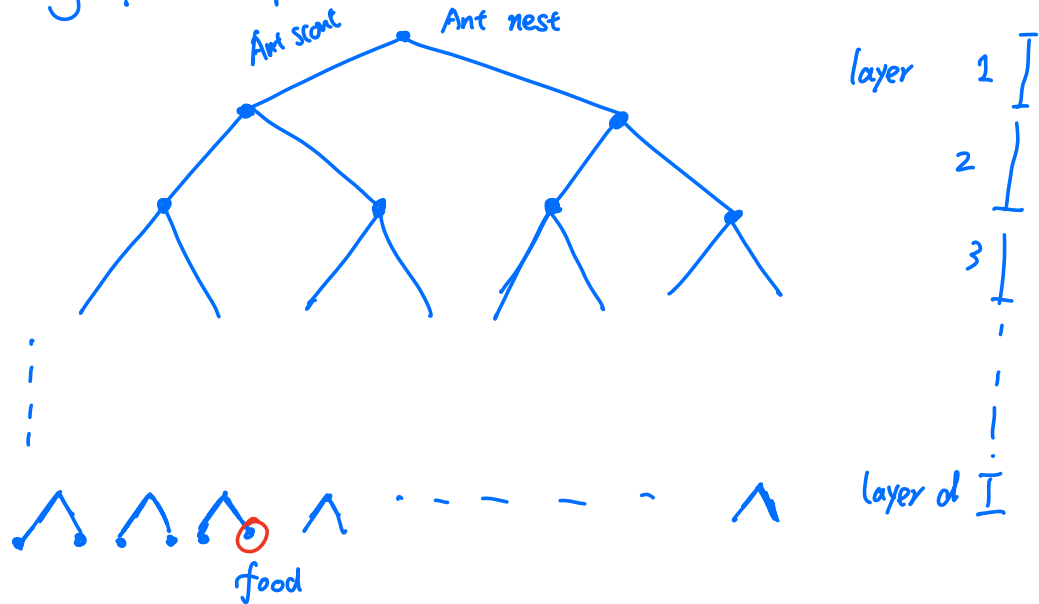
$$= \sum_{i=0}^{\infty} p(1-p)^i \left( \log \frac{1}{p} + i \log \frac{1}{1-p} \right)$$

$$= \log \frac{1}{p} \sum_{i=0}^{\infty} p(1-p)^i + p \log \frac{1}{1-p} \sum_{i=0}^{\infty} i p(1-p)^i$$

$$= \log \frac{1}{p} + p \log \frac{1}{1-p} \cdot \frac{1-p}{p^2} = \frac{h(p)}{p} \rightarrow +\infty \text{ as } p \rightarrow 0$$

Example ( $\infty$  entropy): Can  $H(X) = +\infty$ ? Yes,  $P(X=k) = \frac{c}{k \ln^2 k}$ ,  $k=2, 3, \dots$

Why "log": A experiment



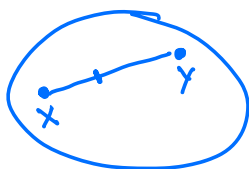
Time for ant scout to describe the location of food  $\sim \log_2 2^d = d$   
 left, right left . . . . . d binary digit  
 ant communication 0.7 - 1 bit/min

Convexity

$V$  a vector space ( $V \cong \mathbb{R}^n$ ),

A subset  $S \subseteq V$  is convex if

$$\forall x, y \in S, \quad \lambda x + (1-\lambda)y \in S \text{ for } \lambda \in [0, 1]$$

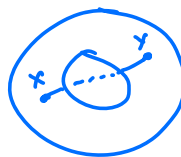


convex

convex combination



not convex



Example: ①  $\mathbb{R}^n$  is convex

$$[0,1] \subseteq \mathbb{R}, \quad (a,b) \subseteq \mathbb{R}$$

②  $\mathcal{P}(X) = \{ \text{prob. distribution on } X \}$

③  $\mathcal{P}_0(\mathbb{R}) = \{ P_X \mid \mathbb{E}(X) = 0 \} \subseteq \mathcal{P}(\mathbb{R})$

$$\mathbb{E}(\lambda X + (1-\lambda)Y) = \lambda \mathbb{E}X + (1-\lambda)\mathbb{E}Y = 0$$

A function  $f: S \rightarrow \mathbb{R}$  is

(i) convex if  $f(\lambda x + (1-\lambda)y) \leq \lambda f(x) + (1-\lambda)f(y)$ ,  $\forall x, y \in S, \lambda \in [0,1]$

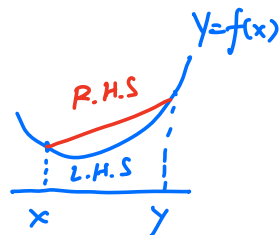
(ii) strictly convex if  $f(\lambda x + (1-\lambda)y) < \lambda f(x) + (1-\lambda)f(y)$ ,  $\forall x \neq y \in S, \lambda \in (0,1)$

(iii) (strictly) concave if  $-f$  is (strictly) convex

Example: ①  $x \mapsto x \log x$  convex strictly

$x \mapsto \log x$  concave strictly

②  $X \mapsto \mathbb{E}X$  convex but not strictly (proof?)



Jensen inequality:  $\forall X: \Omega \rightarrow S \subseteq \mathbb{R}^n$  vector valued R.V.

$$f \text{ convex} \Rightarrow f(\mathbb{E}X) \leq \mathbb{E}f(X)$$

If strictly convex, then  $f(\mathbb{E}X) = \mathbb{E}f(X)$  iff  $X = \mathbb{E}X$  a.s.  
constant R.V.

Pf: Convexity  $\Rightarrow f(\lambda_1 x_1 + \lambda_2 x_2 + \dots + \lambda_n x_n)$   
 $\leq \lambda_1 f(x_1) + \lambda_2 f(x_2) + \dots + \lambda_n f(x_n)$   
 $\lambda_i \geq 0 \quad \sum_{i=1}^n \lambda_i = 1$   
 $f(\mathbb{E}X) = f\left(\sum_{\omega} p(\omega) X(\omega)\right) \leq \sum_{\omega} p(\omega) f(X(\omega))$   
 $p(\omega) \geq 0 \quad \sum p(\omega) = 1 \quad = \mathbb{E} f(X)$

Properties of  $H$

- ①  $H(X) \geq 0$ .  $H(X) = 0$  iff  $X$  is constant
- ② If  $X$  is finite,  $H(X) \leq \log |X|$  with equality iff  $P_X$  is uniform on  $X$
- ③ For any bijective  $f$ ,  $H(X) = H(f(X))$
- ④  $P \mapsto H(P)$  is strictly concave

Pf: ①  $H(X) = \mathbb{E} \left[ \log \frac{1}{P_X} \right] \geq 0$   $P_X(x) \leq 1, \log \frac{1}{P_X(x)} \geq 0$

②  $H(X) = \mathbb{E} \left[ \log \frac{1}{P_X} \right] \leq \log \mathbb{E} \left( \frac{1}{P_X} \right)$   
 $= \log \sum_x P(x) \frac{1}{P(x)} = \log |X|$

equality iff  $\log \frac{1}{P_X}$  is constant

$\Leftrightarrow P_X$  constant

$\sum_{x \in X} P_X(x) = 1 \Rightarrow P_X(x) = \frac{1}{|X|}$

③  $P_X(x) = P(\{\omega \mid X(\omega) = x\}) = P(\{\omega \mid f \circ X(\omega) = f(x)\}) = P_{f(X)}(f(x))$   
 $H(X) = \sum_x P_X(x) \log \frac{1}{P_X(x)} = \sum_x P_{f(X)}(f(x)) \log \frac{1}{P_{f(X)}(f(x))} = H(f(X))$

$$\begin{aligned}
(4): \quad H(\lambda P_1 + (1-\lambda)P_2) &= \sum_{\omega} f(\lambda P_1(\omega) + (1-\lambda)P_2(\omega)) & f(t) &= t \log \frac{1}{t} \\
&\geq \sum_{\omega} \lambda f(P_1(\omega)) + (1-\lambda)f(P_2(\omega)) & &= -t \log t \text{ concave} \\
&= \lambda \sum_{\omega} f(P_1(\omega)) + (1-\lambda) \sum_{\omega} f(P_2(\omega)) \\
&= \lambda H(P_1) + (1-\lambda) H(P_2)
\end{aligned}$$