

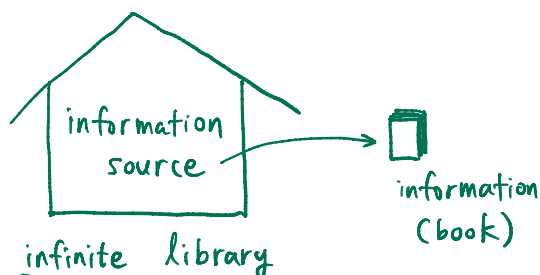
1-2 Shannon Entropy

Shannon theory

- noiseless channel coding theorem – data compression
- noisy channel coding theorem – channel capacity

You'll learn why entropy is defined so.

Model



why infinite?

set of alphabets $\chi = \{a, b, c, \dots\}$

random variable $X = x$ with probability $p(x)$, $x \in \chi$

information source \rightarrow a sequence of random variables of length n

$X^n \equiv X_1 X_2 \dots X_n$ (n : length)

X_i 's are i.i.d. (independent and identically distributed)

$X^n = x^n \equiv x_1 x_2 \dots x_n$ with probability $p(x^n)$

ex) $\chi = \{a, b\}$, $p(a) = 2/3$, $p(b) = 1/3$, $n = 2$

Result

As $n \rightarrow \infty$, you can encode the message into $\boxed{nH(X)}$ bits.

$$H(X) \equiv - \sum_x p(x) \log p(x) \quad \text{Shannon entropy}$$

ex) $\chi = \{a, b, c, d\}$

$p(a) = 1/2$, $p(b) = 1/8$, $p(c) = 1/4$, $p(d) = 1/8$

method 1: $a \rightarrow 00$, $b \rightarrow 01$, $c \rightarrow 10$, $d \rightarrow 11$

You need $2n$ bits.

method 2: $a \rightarrow 0$, $c \rightarrow 10$, $b \rightarrow 110$, $d \rightarrow 111$

$abcd \rightarrow 011010111$ (there is no ambiguity!)

of bits per character $= \frac{1}{2} \cdot 1 + \frac{1}{4} \cdot 2 + \frac{1}{8} \cdot 3 \cdot 2 = \frac{7}{4}$

You need $\frac{7}{4}n$ bits.

Sketch of the proof

$$x^n = x_1 x_2 \cdots x_n, \quad n \rightarrow \infty$$

$$x_i \in \{c_1, c_2, \dots, c_\alpha, \dots\}, \quad p_\alpha \equiv p(c_\alpha)$$

typical vs atypical sequences

typical x^n : # of $c_1 \approx np_1$, # of $c_2 \approx np_2$, ...

ex) coin tossing

asymptotic equipartition theorem

Almost all x^n 's are typical! (as $n \rightarrow \infty$)

$$p(\text{typical } x^n) \approx p_1^{np_1} p_2^{np_2} \cdots \text{ (all identical)}$$

$$\# \text{ of typical sequences} \approx \frac{1}{p(\text{typical } x^n)}$$

You encode only typical sequences into nR bits.

R : compression rate

$$p(\text{error}) \rightarrow 0 \text{ as } n \rightarrow \infty$$

$$nR \approx \log(\# \text{ of typical sequences})$$

$$= -\log(p_1^{np_1} p_2^{np_2} \cdots)$$

$$\approx -np_1 \log p_1 - np_2 \log p_2 - \cdots$$

$$= n \left(-\sum_{\alpha} p_{\alpha} \log p_{\alpha} \right)$$

$$= nH(X)$$

Q) Is this optimal? converse theorem