

Why entropy represents information?

- * A source code C for a random variable X is a mapping from the range of X to the set of finite-length strings of symbols from a D -ary alphabet, denote D^* .

$C(x)$ — codeword correspond to x

$\ell(x)$ — length of $C(x)$

- Binary alphabet $\{0, 1\}$

- A code is called a prefix code or an instantaneous code if no codeword is a prefix of any other code-word.

| $P(x)$ | X | not instantaneous | instantaneous |
|---------------|-----|-------------------|---------------|
| $\frac{1}{2}$ | 1 | 10 | 0 |
| $\frac{1}{4}$ | 2 | 00 | 10 |
| $\frac{1}{8}$ | 3 | 11 | 110 |
| $\frac{1}{8}$ | 4 | 110 | 111 |

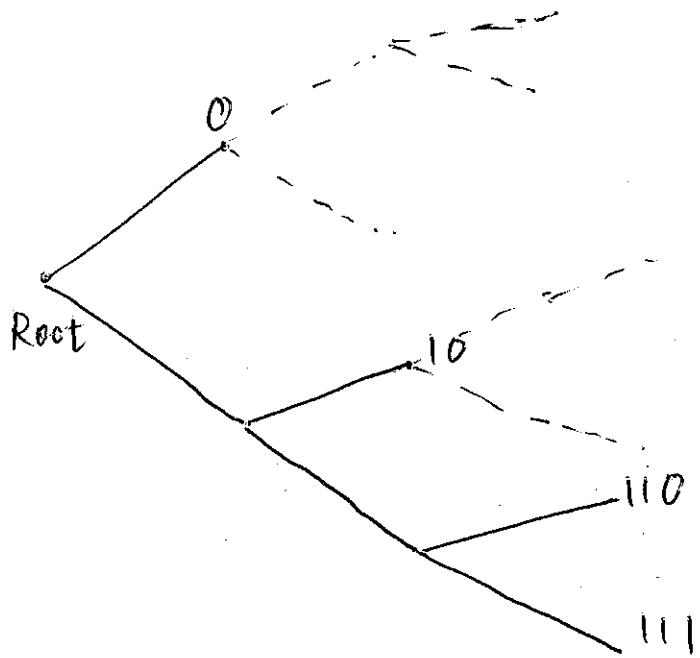
- Expected length of a source code $C(x)$ for a n.v. X with prob. mass $P(x)$ is

$$L(C) = \sum_x P(x) \ell(x)$$

- Kraft Inequality:

Instantaneous code
over alphabet of size D $\Leftrightarrow \sum_i D^{-\ell_i} \leq 1$

Let's look at an example for binary alphabet. The code tree ~~not~~ for an instantaneous code looks like



l_{\max} — the length of the longest code word.

A codeword at level ~~of~~ l_i has $D^{l_{\max}-l_i}$ descendants at level l_{\max} .

$$\sum_i D^{l_{\max}-l_i} \leq D^{l_{\max}}$$

$$\Rightarrow \sum_i D^{-l_i} \leq 1$$

Optimal Codes

$$\min L = \sum_i p_i l_i$$

$$\text{st. } \sum_i D^{-l_i} \leq 1$$

l_i integers

Let me go sloppy here.

Drop the integrality constraint, and assume that

$$\sum_i D^{-l_i} = 1 \text{ at optimal.}$$

Then, we have

$$G = \sum_i p_i l_i + \lambda (\sum D^{-l_i} - 1)$$

$$\frac{\partial G}{\partial l_i} = p_i - \lambda D^{-l_i} \cdot \log_e D = 0 \quad (D^{-l_i} = e^{-l_i \cdot \log_e D})$$

$$D^{-l_i} = \frac{p_i}{\lambda \log_e D}$$

$$\sum D^{-l_i} = 1 \Rightarrow \lambda = 1 / \log_e D$$

$$\Rightarrow p_i = D^{-l_i}$$

$$\Rightarrow l_i^* = -\log_D p_i$$

It can be verified that this is a global minimum for the LP relaxation. (Omit the proof here.)

$$\therefore L \geq \sum_i p_i l_i^* = -\sum_i p_i \log_D p_i = H_D(x)$$

for the optimal code.

Note that we can choose

$$l_i = \lceil \log_D \frac{1}{p_i} \rceil$$

This satisfies the Kraft inequality.

$$\sum D^{-\lceil \log_D \frac{1}{p_i} \rceil} \leq \sum D^{-\log \frac{1}{p_i}} = \sum p_i = 1$$

$$\log_D \frac{1}{p_i} \leq l_i < \log_D \frac{1}{p_i} + 1$$

$$\Rightarrow H_D(x) \leq L < H_D(x) + 1$$

This is the bound for optimal code length.

* differential entropy for continuous probability distribution.

$$h(x) = - \int_S f(x) \log f(x) dx \quad \text{where } S \text{ is the support of } X$$

Not all properties of entropy hold.

E.g. $f(x)$ can be greater than 1.

$$X \sim U(0, \frac{1}{2})$$

$$h(x) = - \int_0^{\frac{1}{2}} 2 \log 2 dx = -\log 2 < 0$$