

# Information Theory: Entropy

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# Definition

Let  $X$  be a discrete random variable with probability distribution  $p(x)$ .

## Entropy $H_X$

$$H_X = - \sum_{x \in X} p(x) \log_2 p(x) = \mathbb{E} \log_2 \left[ \frac{1}{p(X)} \right].$$

Here we define  $0 \log_2 0 = 0$ .

In a sense, the entropy of a random variable shows how “surprising” the event is.

# Examples

## Entropy of a fair coin

A fair coin has entropy  $\frac{1}{2} \log_2(2) + \frac{1}{2} \log_2(2) = 1$ .

## Entropy of a fair $m$ -sided die

A  $m$ -sided die has entropy  $\log_2(m)$ .

## Entropy of $n$ fair coin flips

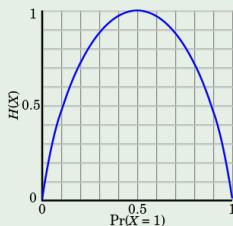
Flipping  $n$  coins produce  $2^n$  uniformly distributed possibilities, and hence, the entropy is  $n$ .

# Examples

## Entropy of a Bernoulli trial

If  $X$  is a random variable taking values between 0 and 1, where  $p(0) = p$  and  $p(1) = 1 - p$ , its entropy is

$$H_p = -p \log_2 p - (1 - p) \log_2 (1 - p).$$



# Example

## Entropy of an unfair dice

An unfair dice with four faces and

$$p(1) = 1/2, p(2) = 1/4, p(3) = 1/8, p(4) = 1/8$$

has entropy  $7/4$ , smaller than the one of the corresponding fair dice 2. (This dice is less surprising than the fair dice.)

# Motivation [TODO]

Define a function  $H$  that takes in a random variable and outputs an integer, such that:

- If a random variable  $X$  takes  $n$  values, then  $H(X)$  is maximized if  $X$  is uniform.
- Entropy is additive, in the sense that: if  $X$  takes  $x_i$  with probability  $p_i$ ,  $Y$  takes  $x_i$  with probability  $q_i$ , and  $Z$  takes  $x_i$  with probability  $\alpha p_i + \beta q_i$  for all  $i$ , then

$$H(Z) = \alpha H(X) + \beta H(Y).$$

Then  $H(X) = -\sum p_i \log p_i$  is the only possible function (up to the base of the logarithm).

# Properties (TPM 15.7.1)

- 1  $H(X) \leq \log |S|.$
- 2  $H(X) \leq H(X, Y) \leq H(X) + H(Y).$
- 3  $H(X|Y, Z) \leq H(X|Y).$

## Entropy is subadditive (TPM 15.7.2)

Let  $X = (X_1, \dots, X_n)$  be a random variable taking values in the set  $S = S_1 \times S_2 \times \dots \times S_n$ , where each of the coordinates  $X_i$  of  $X$  is a random variable taking values in  $S_i$ . Then

$$H(X) \leq \sum_{i=1}^n H(X_i).$$

(This is just induction on the property  $H(X, Y) \leq H(X) + H(Y).$ )

## TPM 15.7.3

Let  $\mathcal{F}$  be a family of subsets of  $\{1, 2, \dots, n\}$  and let  $p_i$  denote the fraction of sets in  $\mathcal{F}$  that contain  $i$ . Then

$$|\mathcal{F}| \leq 2^{\sum H(p_i)}.$$

### Proof

Let  $X = (X_1, \dots, X_n)$  taking  $F \in \mathcal{F}$  with equal probability. Then  $H(X) \leq \sum H(X_i)$  implies  $\log |\mathcal{F}| \leq \sum H(p_i)$ .



## TPM 15.7.4

Let  $X = (X_1, \dots, X_n)$  taking values in  $S = S_1 \times \dots \times S_n$ , where each  $X_i$  takes values in  $S_i$ . For an index set  $I \subseteq \{1, 2, \dots, n\}$  let  $X(I)$  denote  $(X_i)_{i \in I}$ . If  $\mathcal{G}$  is a family of subsets of  $\{1, \dots, n\}$  and each  $i \in \{1, \dots, n\}$  belongs to at least  $k$  members of  $\mathcal{G}$ , then

$$kH(X) \leq \sum_{G \in \mathcal{G}} H(X(G)).$$

### Proof

Use induction. If there is  $G \in \mathcal{G}$  where  $G = \{1, \dots, n\}$  we are done. Otherwise, we prove

$$H(X(G \cup G')) + H(X(G \cap G')) \leq H(X(G)) + H(X(G')).$$

## TPM 15.7.5

Let  $\mathcal{F}$  be a family of vectors in  $S_1 \times S_2 \times \cdots \times S_n$ . Let  $\mathcal{G} = \{G_1, G_2, \dots, G_m\}$  be a collection of subsets of  $N = \{1, 2, \dots, n\}$ , and suppose that each element  $i \in N$  belongs to at least  $k$  members of  $\mathcal{G}$ . For each  $1 \leq i \leq m$  let  $\mathcal{F}_i$  be the set of all projections of the members of  $\mathcal{F}$  on  $G_i$ . Then

$$|\mathcal{F}|^k \leq \prod_{i=1}^m |\mathcal{F}_i|.$$

### Proof

Let  $X = (X_1, \dots, X_n)$  taking  $F \in \mathcal{F}$  with equal probability. Then  $kH(X) \leq \sum H(X(G_i))$  implies  $k \log |\mathcal{F}| \leq \sum \log |\mathcal{F}_i|$ .