

## Shannon Entropy

**Definition.** Let  $(X, p)$  be a discrete probability space. The *entropy* of  $X$  is

$$H(X) = - \sum_{x \in X} p(x) \log p(x).$$

The choice of logarithm base determines the unit: bits, digits, nats, etc. The *joint entropy* of spaces  $X$  and  $Y$  is then  $H(X, Y) = - \sum_{x, y} p(x, y) \log p(x, y)$ , and the *conditional entropy* of  $Y$  given  $X$  is

$$H(Y | X) = \mathbb{E}_X[H(Y)] = - \sum_{x, y} p(x, y) \log p(y | x).$$

We then have  $H(X, Y) = H(X) + H(Y | X)$ .

Consider a sequence of probability spaces  $X_1, \dots, X_k$  with common "alphabet"  $X$  and respective p.m.f.'s  $p_1, \dots, p_k$ . Denote the  $i$ th joint space  $(X_1, \dots, X_i)$  by  $Y_i$ . Then we have

$$H(Y_k) = H(X_1) + \sum_{i=2}^k H(X_i | Y_{i-1}).$$

The infinite joint space  $Y = (X_1, \dots)$  is then said to have per-symbol entropy

$$H(Y) = \lim_{k \rightarrow \infty} \frac{H(Y_k)}{k},$$

provided this limit exists. In the special case when all allowed words of length  $k$  are equiprobable, we know that  $H(Y_k) = \log |Y_k|$ , so the limit is

$$H(Y) = \lim_{k \rightarrow \infty} \frac{\log |Y_k|}{k}.$$

For a sequence of events satisfying certain properties

## Fractal Dimension

**Definition.** The *Box Dimension* (or Minkowski-Bouligand dimension) of a set  $S \in \mathbb{R}^2$  is the limit

$$D_{\text{box}}(S) = \lim_{\epsilon \rightarrow 0} \frac{-\log N(\epsilon)}{\log \epsilon},$$

(provided the limit exists) where  $N(\epsilon)$  is the number of square boxes of side length  $\epsilon$  required to cover the set. For any finite sequence  $\epsilon_0 > \dots > \epsilon_n$ , the slope of the best-fit line through the points  $(-\log \epsilon_k, \log N(\epsilon_k))$  is an approximation to  $D_{\text{box}}$ .

Notice in particular that, for any  $r > 0$ , we must have

$$D_{\text{box}}(S) = \lim_{k \rightarrow \infty} \frac{-\log N(r^{-k})}{\log r^{-k}} = \lim_{k \rightarrow \infty} \frac{\log_r N(r^{-k})}{k}.$$

Accordingly, we define the *entropy of a fractal* to be

$$H(S) = D_{\text{box}}(S) \text{ bits.}$$

This is the (limiting) amount of information produced each time we “zoom in” by a factor of two.

### Image Analysis

**Definition.** An *image* is a real-valued function defined on a region in  $\mathbb{R}^2$ .

Often, our information about an image is limited to its (perhaps approximate) values at a set of regularly spaced lattice points on a rectangular region of the domain. It is then convenient to represent this grid of values in a matrix, called the *image matrix* (or simply the image, if the meaning is clear).

**Definition.** The *fractal spectrum* of an image  $I$  over a set of threshold values,  $S \in \mathbb{R}$ , is the function  $\text{FS} : S \rightarrow \mathbb{R}$  such that, for  $t \in S$ ,

$$\text{FS}(t) = D_{\text{box}}(I_t^{-1}), \quad \text{where } I_t^{-1} = \{x : |I(x)| \leq t\}.$$

For an image matrix we take an approximation to  $D_{\text{box}}$ . If  $S = \{t_1, \dots, t_m\}$  is finite, we may write  $\text{FS}(I) = [D_{\text{box}}(t_1), \dots, D_{\text{box}}(t_m)]^T \in \mathbb{R}^m$ , where typically  $t_1 < \dots < t_m$ .

**Definition.** Let  $I$  be an image matrix and let  $I'$  be a copy of  $I$  with scrambled entries (the entries of  $I'$  are a uniform random permutation of the entries of  $I$ ). For  $t \in \mathbb{R}$ , the *fractal excess* of  $I$  at  $t$  is the expectation

$$\text{fe}(t) = \mathbb{E} [\text{FS}_{M'}(t) - \text{FS}_M(t)].$$

The fractal excess FE of  $I$  over a threshold set  $S$  is simply the restriction of  $\text{fe}$  to  $S$ ; again, for finite  $S$ , we may write FE as a vector in  $\mathbb{R}^m$ .