

CHAPTER 5 – ENTROPY

$$S = k \ln W, \quad k = 1.38 \times 10^{-23} \text{ J / K}$$

Why this functional form?

Recall
$$W = \frac{N!}{n_1! n_2! \dots n_t!}$$

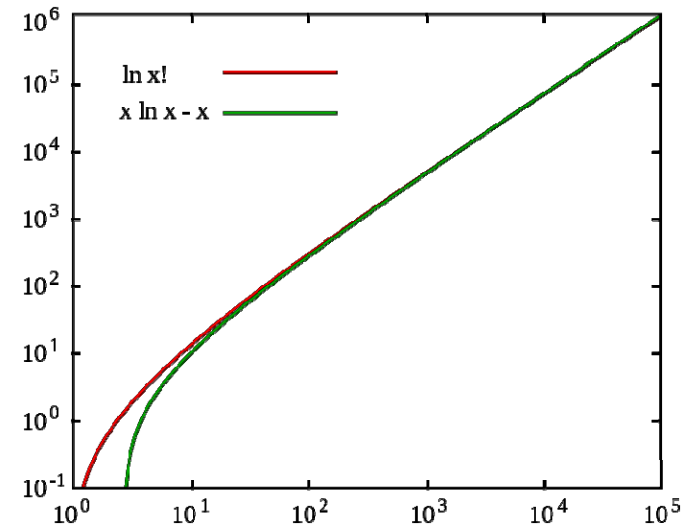
Stirling's approximation $x! \approx \left(\frac{x}{e}\right)^x$ for large x

Then

$$\begin{aligned} W &\approx \frac{(N/e)^N}{(n_1/e)^{n_1} (n_2/e)^{n_2} \dots (n_t/e)^{n_t}} \\ &= \frac{N^N}{(n_1)^{n_1} (n_2)^{n_2} \dots (n_t)^{n_t}} = \frac{1}{\left(\frac{n_1}{N}\right)^{n_1} \left(\frac{n_2}{N}\right)^{n_2} \dots \left(\frac{n_t}{N}\right)^{n_t}} \\ &= \frac{1}{(p_1)^{n_1} (p_2)^{n_2} \dots (p_t)^{n_t}} \end{aligned}$$

$$\Gamma(n) = (n-1)! = \int_0^\infty x^{n-1} e^{-x} dx$$

The gamma function



$$\begin{aligned} \ln W &\approx -\ln(p_1)^{n_1} - \ln(p_2)^{n_2} - \dots - \ln(p_t)^{n_t} \\ &= -n_1 \ln p_1 - n_2 \ln p_2 - \dots - n_t \ln p_t = -\sum_{i=1}^t n_i \ln p_i \end{aligned}$$

$$\frac{1}{N} \ln W = -\sum_{i=1}^t p_i \ln p_i = \frac{S_N}{Nk} = -\sum_{i=1}^t n_i \ln p_i$$

$$S = k \ln W = -k \sum p_i \ln p_i$$

S_N = total entropy,

$$S = \frac{S_N}{N} = \text{entropy per trial}$$

perfectly ordered state: $S = 0$
 most random state: highest entropy

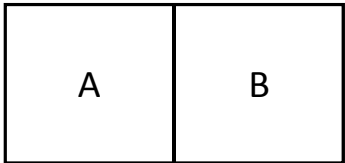
k = entropy per particle

$$S = R \ln W, \quad R = \eta k$$

↑
entropy per mole

↑
Avogadro's constant

Consider a system that we divide into two parts, A and B



Whatever definition we use for Entropy, it has to obey $S_{tot} = S_A + S_B$

We already know that $W_{tot} = W_A W_B$

If we define $S = k \ln W$

$$\begin{aligned} \ln W_{tot} &= \ln W_A W_B = \ln W_A + \ln W_B \\ \Rightarrow S_{tot} &= S_A + S_B \end{aligned}$$

Biased vs. nonbiased (flat) distributions

many rolls of die expect avg to be $\frac{1+2+3+4+5+6}{6} = 3.5$

If you measure 3.5, the distribution could be flat (but it is not necessarily so)

If you get an average $\neq 3.5$, it is **not** flat

If there are no constraints **other than normalization**, max entropy \Rightarrow flat distribution

$$\sum_{i=1}^t p_i = 1 \rightarrow \sum dp_i = 0 \quad \leftarrow \text{Normalization}$$

$$\begin{aligned} S &= -k \sum p_i \ln p_i \\ \Lambda &= -\sum p_i \ln p_i - \alpha \left(\sum p_i - 1 \right) \end{aligned} \quad \left| \begin{array}{l} \text{for simplicity, set } k = 1 \\ \alpha \text{ is the Lagrange multiplier} \end{array} \right.$$

$$\frac{d\Lambda}{dp_i} = 0 = -\ln p_i - 1 - \alpha \quad \forall i$$

$$\ln p_i^* = -1 - \alpha \quad p_i^* = e^{(-1-\alpha)}$$

$$\sum p_i^* = t e^{(-1-\alpha)} \Rightarrow \frac{p_i^*}{\sum p_i^*} = \frac{1}{t} \quad \left| \begin{array}{l} \text{all } p_i^* \text{ equally} \\ \text{probable} \Rightarrow \text{flat distribution} \end{array} \right.$$

Now consider introducing a bias

suppose the six sides of the die have numbers

$\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4, \varepsilon_5, \varepsilon_6$

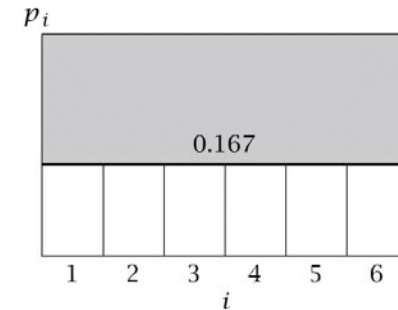
$$E = \sum_{i=1}^t \varepsilon_i n_i = \text{total \#}$$

$$p_i = \frac{n_i}{N}$$

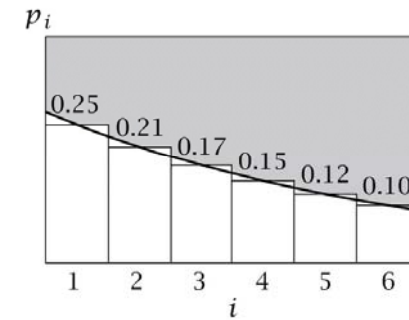
$$\frac{E}{N} = \sum \varepsilon_i p_i = \langle \varepsilon \rangle$$

Also $\sum p_i = 1$

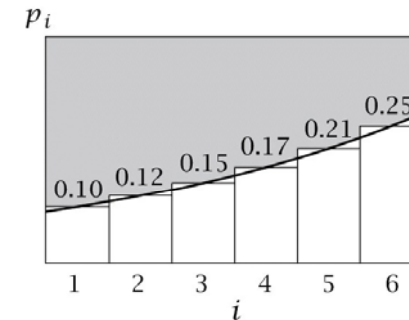
(a) $\langle \varepsilon \rangle = 3.5$



(b) $\langle \varepsilon \rangle = 3.0$



(c) $\langle \varepsilon \rangle = 4.0$



$$\Lambda = -\sum p_i \ln p_i - \alpha [\sum p_i - 1] - \beta [\sum \varepsilon_i p_i - \langle \varepsilon \rangle]$$

Now have two constraints

$$\frac{d\Lambda}{dp_i} = -\ln p_i - 1 - \alpha [1] - \beta [\varepsilon_i] = 0$$

$$\ln p_i^* = -1 - \alpha - \beta \varepsilon_i$$

$$p_i^* = e^{-1 - \alpha - \beta \varepsilon_i}$$

$$\sum p_i^* = \sum e^{-1 - \alpha - \beta \varepsilon_i}$$

$$\frac{p_i^*}{\sum p_i^*} = \frac{e^{-1 - \alpha - \beta \varepsilon_i}}{\sum e^{-1 - \alpha - \beta \varepsilon_i}}$$

$$p_i^* = \frac{e^{-\beta \varepsilon_i}}{\sum e^{-\beta \varepsilon_i}}$$

define $q = \sum e^{-\beta \varepsilon_i}$

$$p_i^* = e^{-\beta \varepsilon_i} / q$$

Note: β must have units that are the inverse of the units of ε_i . If ε_i has units of energy, $\beta = 1/kT$

$$p_i^* = \frac{e^{-\varepsilon_i/kT}}{q}$$

$$\langle \varepsilon \rangle = \sum \varepsilon_i p_i^* = \frac{1}{q} \sum \varepsilon_i e^{-\beta \varepsilon_i}$$

Now consider some examples

suppose $\varepsilon_i = i$ (standard die)

$$p_i^* = \frac{e^{-\beta \varepsilon_i}}{\sum e^{-\beta \varepsilon_i}} = \frac{e^{-i\beta}}{e^{-1\beta} + e^{-2\beta} + e^{-3\beta} + e^{-4\beta} + e^{-5\beta} + e^{-6\beta}}$$

Let $x = e^{-\beta}$

$$p_i^* = \frac{x^i}{x + x^2 + x^3 + x^4 + x^5 + x^6}$$

$$\langle \varepsilon \rangle = \frac{x + 2x^2 + 3x^3 + 4x^4 + 5x^5 + 6x^6}{x + x^2 + x^3 + x^4 + x^5 + x^6}$$

$$\varepsilon(x + x^2 + x^3 + x^4 + x^5 + x^6) = (x + 2x^2 + 3x^3 + 4x^4 + 5x^5 + 6x^6)$$

if $\langle \varepsilon \rangle = 3.5 \Rightarrow x = 1$

$\Rightarrow p_1 = p_2 = p_3 = p_4 = p_5 = p_6 = 1/6$, result for unbiased die

Two ways of getting a flat distribution

(1) $\langle e \rangle =$ value expected from uniform distribution

(2) you have no information at all

if $\varepsilon = 3$, $x = 0.84$

if $\varepsilon = 4$, $x = 1.19$