



# ENTROPY:

*Gaining Knowledge by Admitting Ignorance*

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with thanks to James Binney, who convinced me that  
it's better to gamble than to count

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Mean energy:  $U = \langle E_\alpha \rangle = \sum_{\alpha} p_\alpha E_\alpha$

Pressure:  $P = - \left\langle \frac{\partial E_\alpha}{\partial V} \right\rangle = - \sum_{\alpha} p_\alpha \frac{\partial E_\alpha}{\partial V}$

external parameter (volume)

An arrow points from the text 'external parameter (volume)' to the partial derivative term  $\frac{\partial E_\alpha}{\partial V}$  in the pressure equation.

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$$\text{More generally, Force} = - \sum_{\alpha} p_\alpha \frac{\partial E_\alpha}{\partial \text{Displacement}}$$



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$$\text{E.g., tension: } f = \sum_{\alpha} p_\alpha \frac{\partial E_\alpha}{\partial L}, \quad \text{magnetisation: } M = - \sum_{\alpha} p_\alpha \frac{\partial E_\alpha}{\partial B}$$

# What Do We Want to Know?



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# The Philosophy of Good-Enough-ism



How likely is it to happen?

This is what we want to determine.

We do not need to know the  $p_\alpha$ 's in any "true" sense.

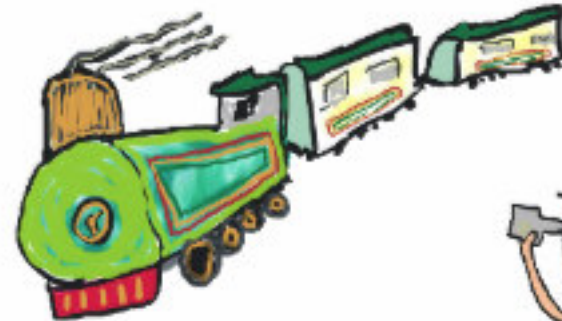
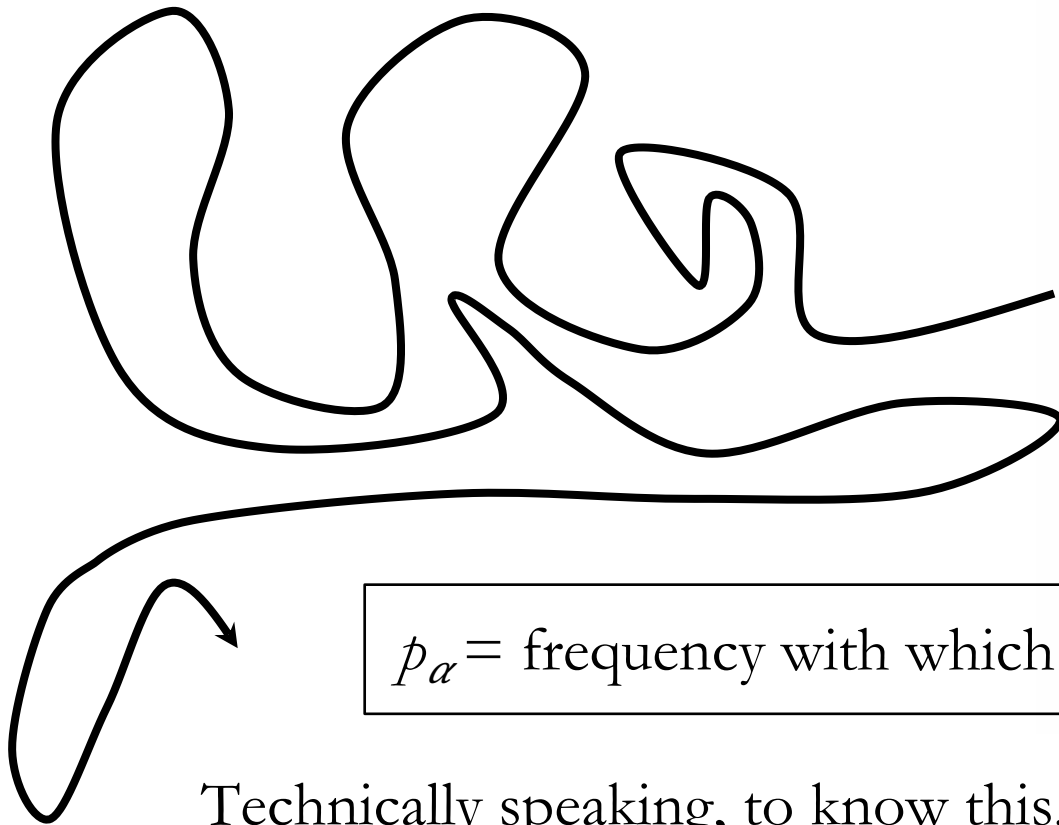
We just need to know such  $p_\alpha$ 's that the few macroscopic quantities that we are ever likely to measure come out right.

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# Trainspotter's Statistics



$p_\alpha$  = frequency with which system visits  $\alpha$ .

Technically speaking, to know this, we need to understand (or assume something about) the system's dynamics.

Also, we must believe that the time necessary for the system to visit all of its phase space is a reasonable time for us to wait.

This is not, however, how forecasting works...

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$p_\alpha =$  likelihood that the system is in  $\alpha$ .

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If we know nothing, the only adequate expectation is

$$p_\alpha = \frac{1}{\Omega}$$

(all states are equally probable)



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Ludwig  
Boltzmann  
(1844-1906)

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**isolated system  
in equilibrium**

**(Boltzmann's  
equal a priori probabilities  
postulate)**

# Gambler's Statistics



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A fair and adequate assignment of likelihoods must be based on some information about the system, however incomplete.

What if we know one thing, e.g., mean energy:

$$U = \langle E_\alpha \rangle = \sum_{\alpha} p_\alpha E_\alpha$$

This is one constraint on  $\Omega \gg \gg \gg 1$  likelihoods.

How do we work out  $p_\alpha$ 's using this and *only this* information?

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$$p_\alpha = \frac{N_\alpha}{N}$$



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The most likely outcome of this game is the one that can be obtained  
in the largest number of ways:

this maximum  
is very sharp  
at large  $N$

$$W = \frac{N!}{N_1! \cdots N_\Omega!} \rightarrow \max \text{ (subject to constraints)}$$

(thus, we determine  $p_\alpha$ 's by maximising  $W$  in this way)

# A Fair Game



Using Stirling's formula  $\ln \mathcal{N}! = \mathcal{N} \ln \mathcal{N} - \mathcal{N} + O(\ln \mathcal{N})$ , get:

$$\begin{aligned} \ln W &= \frac{\mathcal{N} \ln \mathcal{N} - \mathcal{N}}{\sum_{\alpha} (\mathcal{N}_{\alpha} \ln \mathcal{N} + \cancel{\mathcal{N}_{\alpha}})} + O(\ln \mathcal{N}) - \sum_{\alpha} [\mathcal{N}_{\alpha} \ln \mathcal{N}_{\alpha} - \cancel{\mathcal{N}_{\alpha}} + O(\ln \mathcal{N}_{\alpha})] \\ &= - \sum_{\alpha} \mathcal{N}_{\alpha} \ln \frac{\mathcal{N}_{\alpha}}{\mathcal{N}} + O(\ln \mathcal{N}) \\ &= -\mathcal{N} \left[ \sum_{\alpha} p_{\alpha} \ln p_{\alpha} + O\left(\frac{\ln \mathcal{N}}{\mathcal{N}}\right) \right]. \end{aligned}$$

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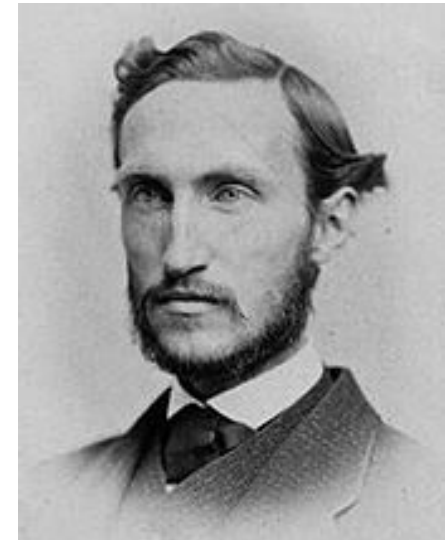
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I will call this **Gibbs entropy**



Josiah Willard Gibbs  
(1839-1903)

$$S_G = - \sum_{\alpha} p_{\alpha} \ln p_{\alpha} \rightarrow \max \text{ (subject to constraints)}$$

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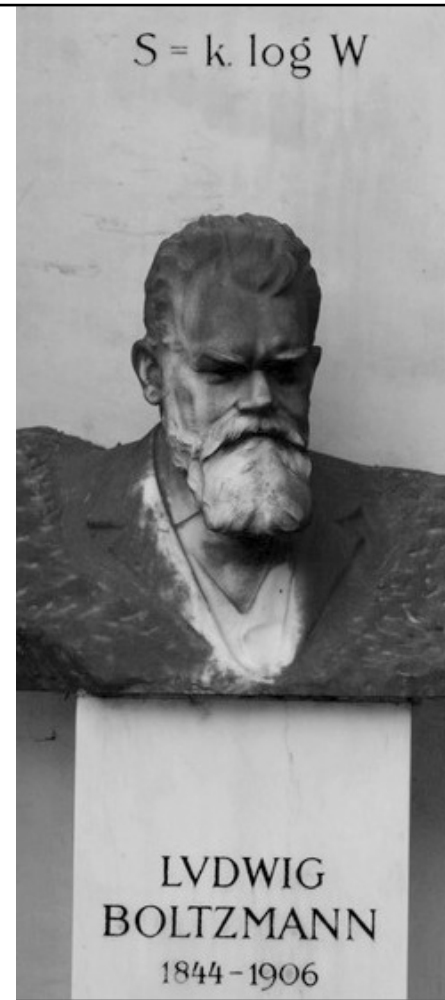
$$p_\alpha = \frac{1}{\Omega} \Rightarrow S_G = - \sum_\alpha \frac{1}{\Omega} \ln \frac{1}{\Omega} = \ln \Omega$$

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It corresponds to the number of all possible distributions of  $N$  units of probability between  $\Omega$  states:  $W_{\max} = \Omega^N$ , so

$$S_{G,\max} = \frac{1}{N} \ln W_{\max} = \ln \Omega$$

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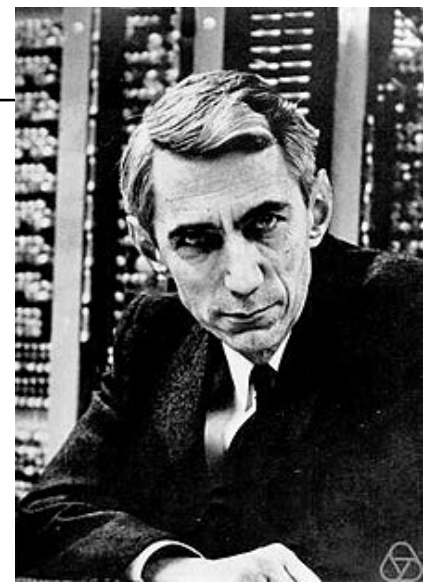
# Shannon's Theorem

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Was that the only possible fair game?

Shannon declared that a good measure of uncertainty of set of probabilities  $p_\alpha$  called  $H(p_1, \dots, p_\Omega)$ , must be

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- 5) additive and independent of counting scheme: if we split all states into subgroups with probabilities  $w_i$ , and calculate  $H_i$  for each subgroup (with conditional probabilities  $p_\alpha/w_i$ ), then

$$H(p_1, \dots, p_\Omega) = H(w_1, w_2, \dots) + \sum_i w_i H_i$$

total uncertainty      uncertainty in choosing subgroup      uncertainty within subgroup



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He then proved that the only function with these properties is

$$H(p_1, \dots, p_\Omega) = -k \sum_\alpha p_\alpha \ln p_\alpha = kS_G$$



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# How to Maximise Entropy (with strings attached)



$$\Lambda = S_G(p_1, \dots, p_\Omega) - \sum_i \lambda_i F_i(p_1, \dots, p_\Omega) \rightarrow \max$$

Entropy

$$- \sum_{\alpha} p_{\alpha} \ln p_{\alpha}$$

“Lagrange  
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Always:

$$\sum_{\alpha} p_{\alpha} - 1 = 0$$

Mean energy known:

$$\sum_{\alpha} p_{\alpha} E_{\alpha} - U = 0$$

...etc.

# Total Ignorance (Isolated System)



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$$\frac{\partial \Lambda}{\partial \lambda} = \sum_{\alpha} p_{\alpha} - 1 = 0 \quad \Rightarrow \quad p_{\alpha} = \frac{1}{\Omega} \quad \text{method works!}$$

# Gibbs' Ensemble



$$\Lambda = - \sum_{\alpha} p_{\alpha} \ln p_{\alpha} - \lambda \left( \sum_{\alpha} p_{\alpha} - 1 \right) - \beta \left( \sum_{\alpha} p_{\alpha} E_{\alpha} - U \right) \rightarrow \max$$

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= Z( $\beta$ )  
"partition function"

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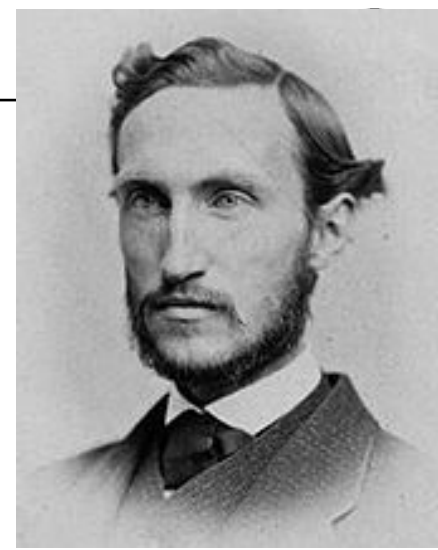
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$$p_{\alpha} = \frac{e^{-\beta E_{\alpha}}}{Z(\beta)}$$

likelihoods based on knowledge of  $U$

$$Z(\beta) = \sum_{\alpha} e^{-\beta E_{\alpha}} \quad \text{normalisation constant}$$

$$U = -\frac{1}{Z} \frac{\partial Z}{\partial \beta} \quad \text{implicit equation for mysterious } \beta$$



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It looks like we have calculated something, but what does it mean?

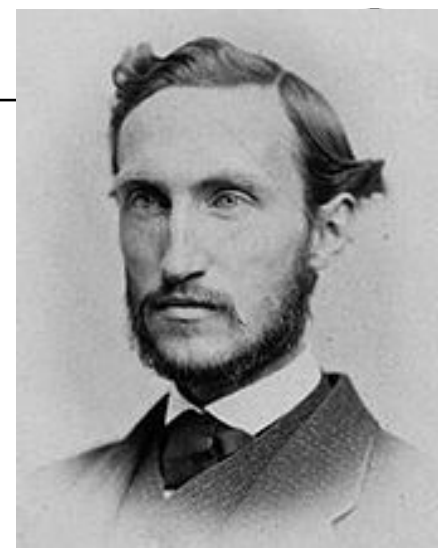
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(1839-1903)

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$$S_G = -\sum_{\alpha} p_{\alpha} \ln p_{\alpha} = -\sum_{\alpha} p_{\alpha} (-\beta E_{\alpha} - \ln Z) = \beta U + \ln Z.$$

$$dS_G = \beta dU + U d\beta + \frac{dZ}{Z}$$

“d” here means we are varying some parameter of the equilibrium, say  $V$

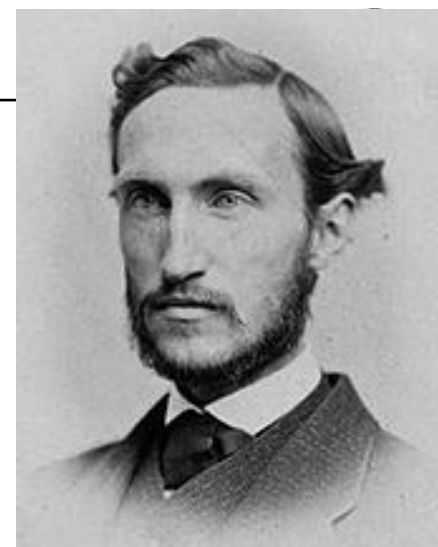
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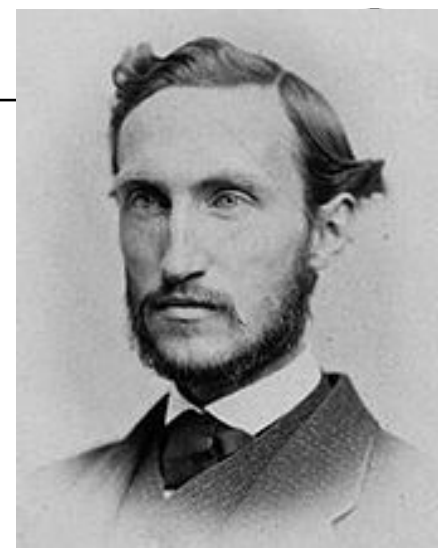
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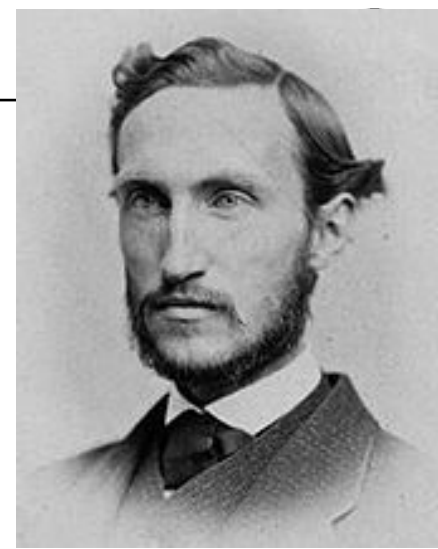
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$$= \beta(dU + PdV)$$

$$dE_\alpha = \frac{\partial E_\alpha}{\partial V} dV$$

pressure

$$P = -\sum_{\alpha} p_\alpha \frac{\partial E_\alpha}{\partial V}$$

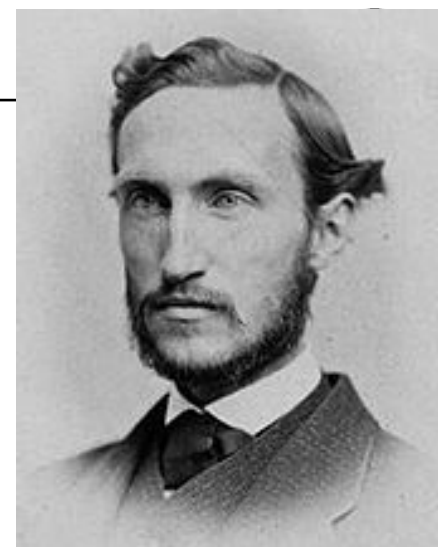
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$$= \beta(dU + PdV) = \beta(dU - dW) = \beta dQ_{\text{rev}} \quad \begin{array}{l} \text{heat in a reversible process} \\ = \text{energy} - \text{work} \end{array}$$

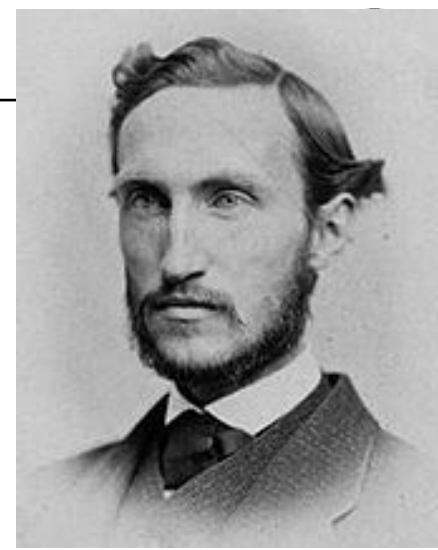
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Thus, change of entropy is proportional to reversible heat, and the constant of proportionality is  $\beta$ .



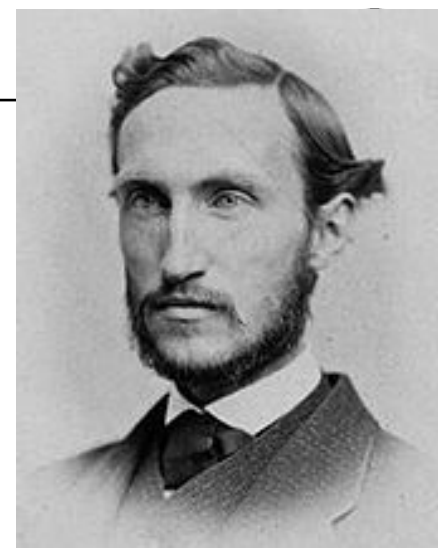
# Entropy Is “Real”!

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Thus, change of entropy is proportional to reversible heat, and the constant of proportionality is  $\beta$ .  
Therefore,

$$dS_G = \beta dQ_{\text{rev}}$$

$$dS = \frac{dQ_{\text{rev}}}{T}$$

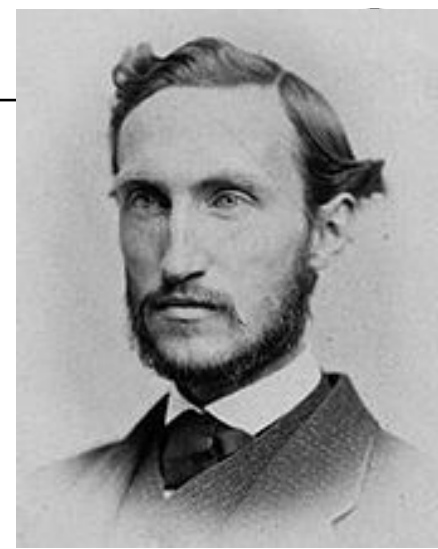
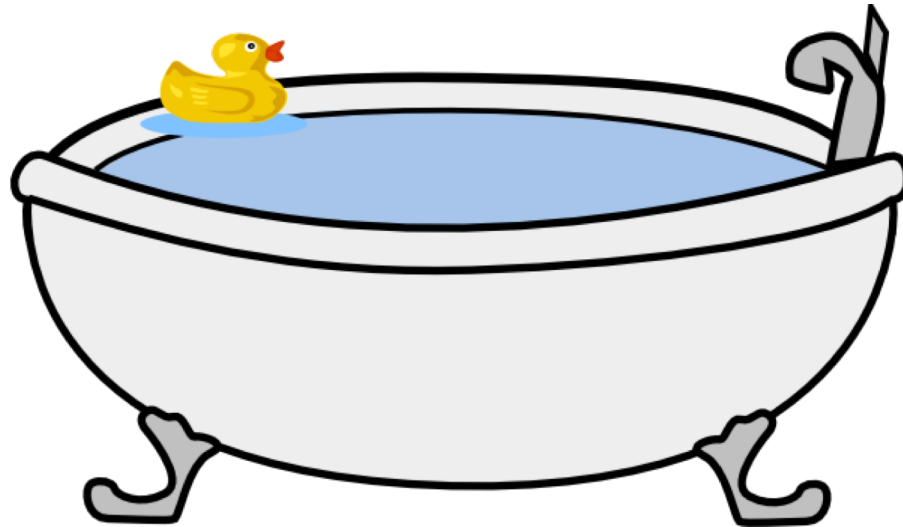
$$\beta = \frac{1}{k_B T} \quad \text{and} \quad S = k_B S_G$$

temperature

Gibbs entropy is  
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# System in a Bath

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Physically, a system at fixed temperature is a system embedded in a “thermal bath”,

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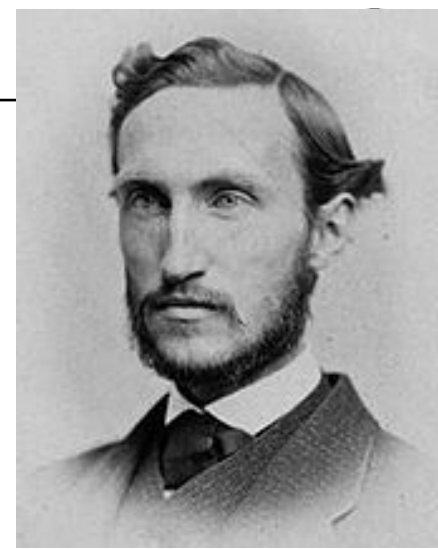
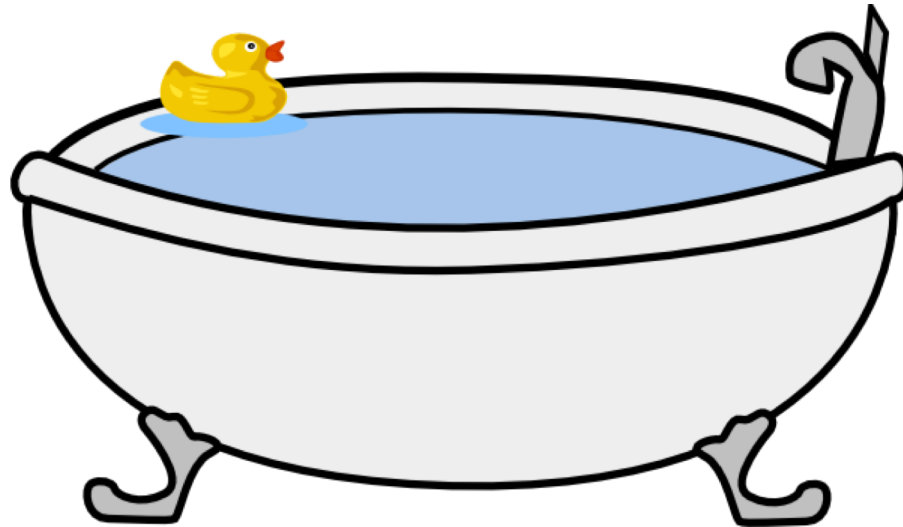
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more fun and games  
with thermodynamics  
in J. Chalker’s lecture

# The Second Law

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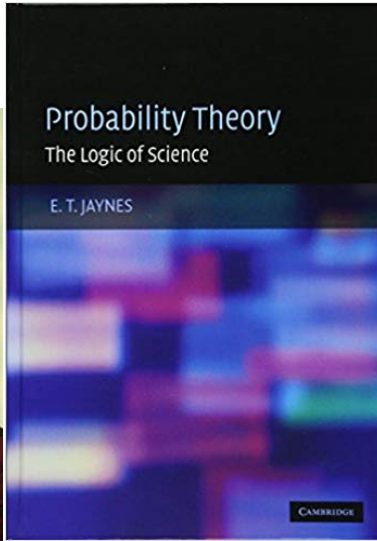
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Edwin Jaynes  
(1922-1998)



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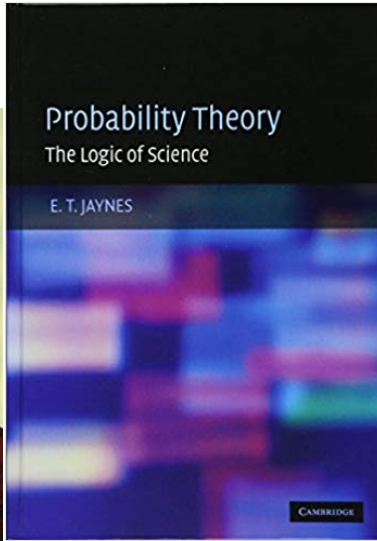


*The thermodynamic entropy of the world (closed system) increases with time.*

**Time  $t$ :** Measure something about some part of the world, maximise  $S_G$  subject to that info, get a set of  $p_\alpha$ 's and

$$S(t) = k_B S_{G,\max}(t)$$

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**Time  $t' > t$ :** Consider the evolution of the system since  $t$ : states evolve:  $\alpha(t) \rightarrow \alpha(t')$ , but their probabilities stay the same, so

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$$S(t') = \underbrace{k_B S_{G,\max}(t')}_{\substack{\text{the new } S_G, \\ \text{maximised at} \\ \text{time } t'}} \geq \underbrace{k_B S_G(t')}_{\substack{\text{the "true"} \\ S_G, \text{ evolved} \\ \text{from time } t}} = k_B S_G(t) = S(t)$$



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Thus,  $S(t') > S(t)$  at  $t' > t$ , q.e.d.

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*The increase of  $S$  reflects our insistence to forget the detailed knowledge that we possess as a result of evolving in time any earlier state (even if based on earlier statistical inference) and re-apply at every later time the rules of statistical inference based on knowledge obtained in new measurements.*

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