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Course 565/665 Lecture Number _____ Date 2/20/03

Lecturer Dr. Silvia Cavagnero Note Taker Eric Fulmer

Last Time

We used the maximum S principle to derive

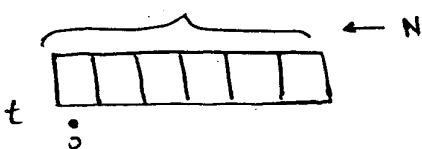
$$\frac{p_i^*}{\sum_{i=1}^t p_i^*} = \frac{1}{t} \quad \Leftarrow \text{Flat distribution}$$

in the absence of constraints (with the exception that the p_i 's are normalized).

t is the number of outcomes.

In real life, we typically gain knowledge about averages. Since we know the average of the quantity, we can use this as a constraint. [Implicit assumptions: events have an associate score.]

$\epsilon_i \equiv$ individual score per event.



$N = \#$ of 1D lattice points (boxes).

$$E = \sum_{i=1}^t \epsilon_i n_i$$

↑
total score

n_i is the number of outcomes of a particular energy level (of a particular ϵ_i score).

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Q: Expected Distribution that satisfies the following

$$\langle \epsilon \rangle = \frac{E}{N} = \frac{1}{N} \sum_{i=1}^t n_i \epsilon_i = \sum_{i=1}^t \frac{n_i}{N} \epsilon_i = \sum_{i=1}^t p_i \epsilon_i$$

AND it satisfies the SMAX principle?

ie, what is $\{p_1^*, p_2^*, \dots, p_t^*\}$ that maximizes S ?

$$g(p_1, p_2, \dots, p_t) = \sum_{i=1}^t p_i = 1$$

$$\Rightarrow \textcircled{1} \quad \boxed{\sum_{i=1}^t dp_i = 0}$$

$$h(p_1, p_2, \dots, p_t) = \langle \epsilon \rangle = \sum_{i=1}^t p_i \epsilon_i$$

$$\Rightarrow \textcircled{2} \quad \boxed{\sum_{i=1}^t \epsilon_i dp_i = 0}$$

Also, we want $\boxed{dS = 0}$ (3)

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Thus, we set up our equation:

$$\left(\frac{\partial S}{\partial p_i}\right) \text{ minus (A Lagrange Multiplier)} \left(\frac{d(\text{constraint})}{d p_i}\right) = 0$$

to find the set of p_i 's that maximizes S .

$$\boxed{\underbrace{\left(\frac{\partial S}{\partial p_i}\right)}_A - \alpha \underbrace{\left(\frac{\partial g}{\partial p_i}\right)}_B - \beta \underbrace{\left(\frac{\partial h}{\partial p_i}\right)}_C = 0}$$

Key Equation to set up.

$$\frac{S}{k} = -\sum p_i \ln p_i$$

let $k=1$ in this problem.

$$\underline{A} = -\ln p_i - 1$$

$$\underline{B} = 1$$

$$\underline{C} = \epsilon_i$$

Rewrite the Key Equation from above:

$$\boxed{-\ln p_i - 1 - \alpha - \beta \epsilon_i = 0}$$

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We would like to solve for the p_i that satisfies the three constraints and thus maximizes the S (entropy) with respect to that probability. Let this p_i be p_i^* .

$$-1 - \ln p_i^* - \alpha - \beta \epsilon_i = 0$$

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

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

Normalizing p_i ,

$$p_i^* = \frac{p_i^*}{\sum_{i=1}^t p_i^*} = \frac{e^{-1 - \alpha} e^{-\beta \epsilon_i}}{\sum_{i=1}^t e^{-1 - \alpha} e^{-\beta \epsilon_i}}$$

Thus,
$$p_i^* = \frac{e^{-\beta \epsilon_i}}{\sum_{i=1}^t e^{-\beta \epsilon_i}} = \frac{e^{-\beta \epsilon_i}}{Q} \quad [\text{Boltzmann Distribution}]$$

Where
$$Q = \sum_{i=1}^t e^{-\beta \epsilon_i} \quad [\text{The Partition Function}]$$

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The partition function is an enigmatic quantity, but its essence is much much less elusive than it would seem. Q [partition function] is only a Normalization Factor for the $e^{-\beta \epsilon_i}$ statistical weight. It is only the sum of all of the statistical weights, and it ensures that the sum of all of the p_i 's equals one. Remember, Q is only a constant, and it normalizes the weights. But the power of Q will be demonstrated later, as important quantities can be extracted from it (such as the free energy, etc).

$$p_i^* = \frac{e^{-\beta \epsilon_i}}{\sum_{i=1}^{\infty} e^{-\beta \epsilon_i}}$$

$$\begin{aligned} \langle \epsilon \rangle &= \sum_{i=1}^{\infty} p_i^* \epsilon_i \\ &= \frac{1}{Q} \sum_{i=1}^{\infty} \epsilon_i e^{-\beta \epsilon_i} \end{aligned}$$

Course SOS/605 Lecture Number _____ Date 2/20/03Lecturer Caragnero Note Taker FulmerExample | Rolling a Die.1) $t=6$ (faces of a die)2) $\varepsilon_i \equiv i$ [possible scores $i = \{1, 2, 3, 4, 5, 6\}$]3) $e^{-\beta} \equiv x$

$$\text{Thus, } e^{-\beta \varepsilon_i} = (e^{-\beta})^{\varepsilon_i} = x^{\varepsilon_i} = x^i \quad [\text{from above}]$$

Defining the Partition Function:

$$Q = \sum_{i=1}^6 e^{-\beta \varepsilon_i} = \sum_{i=1}^6 x^i = x + x^2 + x^3 + x^4 + x^5 + x^6$$

$$P_i^* = \frac{x^i}{\sum_{i=1}^6 x^i} = \frac{x^i}{x + x^2 + x^3 + x^4 + x^5 + x^6}$$

$$\langle \varepsilon \rangle = \sum_{i=1}^6 \varepsilon_i P_i^* = \sum_{i=1}^6 i P_i^* = \frac{x + 2x^2 + 3x^3 + 4x^4 + 5x^5 + 6x^6}{x + x^2 + x^3 + x^4 + x^5 + x^6}$$

Remember, $\langle \varepsilon \rangle$ is only a number.

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If $e^{-\beta} = x = 1$, then there is not a weighting factor depending on the state of the system (or the energy level). Each state would be equally likely.

$$\langle \epsilon \rangle = \frac{1 + 2 + 3 + 4 + 5 + 6}{1 + 1 + 1 + 1 + 1 + 1} = 3.5$$

We know this because

$$\langle \epsilon \rangle = 3.5 = \frac{x + 2x^2 + 3x^3 + 4x^4 + 5x^5 + 6x^6}{x + x^2 + x^3 + x^4 + x^5 + x^6}$$

Solving, $x = 1$.

$$P_i^* = \frac{1}{6} = \frac{1}{\epsilon} \quad \text{flat distribution.}$$

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If the average were weighted differently,

$$\langle \xi \rangle = 3.0 \quad \text{biased}$$

Solve for x ,

$$x = 0.84 \quad (\neq 1)$$

$$p_i = 0.25, 0.21, 0.17, \dots$$