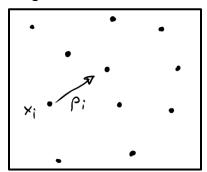
#### Lecture 1 – Probability & multiplicity

KEY CONCEPT: Microscopic vs. macroscopic states

- Microscopic state (or "microstate") = complete description of each particle or configuration in a system
- Macroscopic state (or "macrostate") = description of a system in terms of a few (e.g. 2) properties

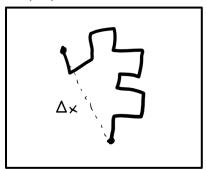
Ex: gas molecules in a box



Microstate = set  $\{x_i, p_i\}$  of all positions and momentum of all particles in the system

Macrostate = gas pressure p (for example)

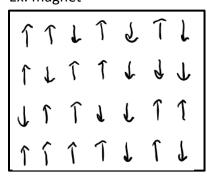
Ex: polymer



Microstate = configuration of every segment of the polymer

Macrostate = end-to-end extension  $\Delta x$ 

Ex: magnet



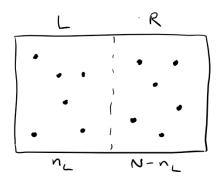
Microstate = configuration of every spin in the magnet

Macrostate = average magnetization *M* of the magnet

In general there are many more microstates than macrostates.

Note that the definition of microstate/macrostate is not rigid; it will depend on the system and the question being asked.

Ex: Imagine N identical particles in a box split in equal halves



Define macrostate & microstate as:

Macrostate = number of particles in left half,  $n_L$ 

Microstate = configuration of all *N* particles (i.e. a list of L/R state of each particle: LRRL...RL)

KEY CONCEPT: The <u>multiplicity</u>  $\Omega(n_L, N)$  – How many microstates (configurations of N particles) give the same macrostate ( $n_L$  particles in left half)?

For N = 1

Microstate	Multiplicity $\Omega(n_L, N)$	Macrostate n <sub>L</sub>
	1	0
•	1	1
Total	2 <sup>1</sup>	2

For N = 2

Microstate	Multiplicity $\Omega(n_L, N)$	Macrostate n <sub>L</sub>
2	1	0
2	2	1

2	1	2
Total	$2^2 = 4$	2+1 = 3

## Question 1: Complete table for N = 3

For N = 3

Microstate	Multiplicity $\Omega(n_L, N)$	Macrostate n <sub>L</sub>
2	1	0
• 3		
2 3	3	1
3 . 2		
2 1 3		
3 . 2	3	2
2 3		
2 3	1	3
Total	$2^3 = 8$	3+1 = 4

## These are called <u>statistical ensembles</u>

• Measurement repeated many times to get every possible configuration or microstate

#### Question 2: What is the total number of microstates and macrostates for arbitrary N?

Following the pattern:

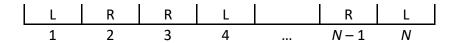
Total number of microstates =  $2^N$ 

Total number of macrostates = N+1

Huge difference for large N

There are  $\Omega(n_L, N)$  ways of configuring N particles so that  $n_L$  are to the left half How do we get  $\Omega(n_L, N)$  in general for arbitrary N?

- Take N slots, representing N particles
- Distribute  $n_L$  particles to the L,  $N n_L$  to the R
- Like so:



N choices for 1st L particles

N-1 choices for 2<sup>nd</sup> L particle

N-2 choices for  $3^{rd}$  L particle

:

 $N - n_L + 1$  choices for the  $n_L^{th}$  L particle

So, 
$$N(N-1)(N-2)\cdots(N-n_i+1)$$
 total choices

This actually overcounts the multiplicity. In the above example, we can interchange slots #1, #4, and #N to give the exact same configuration, so we need to divide this number by all the ways to interchange the L particles. For  $n_L$  particles there are  $n_L$ ! identical ways to arrange them.

(In the example above, the 3 particles #1, #4, #N can be rearranged into the following ways: 14N, 1N4, 4N1, N14, N41, or 6 = 3x2x1 = 3! ways)

Therefore

$$\Omega(n_{L},N) = \frac{N(N-1)(N-2)\cdots(N-n_{L}+1)}{n_{L}!} = \frac{N!}{n_{L}!(N-n_{L})!} \equiv \binom{N}{n_{L}}$$
 "N choose  $n_{L}$ "

This is called the binomial coefficient

Comes from the binomial identity:

$$(p+q)^{N} = \sum_{n=0}^{N} \binom{N}{n} p^{n} q^{N-n}$$

Note that, setting p = q = 1,  $2^N = \sum_{n_l=0}^{N} \Omega(n_L, N)$ , as expected.

KEY CONCEPT: The <u>fundamental assumption</u> – in a closed or isolated system (not interacting with surroundings) each microstate in system is equally likely:

Prob. of 1 particular microstate = 
$$\frac{1}{2^N}$$

(Same as saying each particle has a prob. ½ of being to the left. For N particles, prob. is  $\frac{1}{2^N}$ )

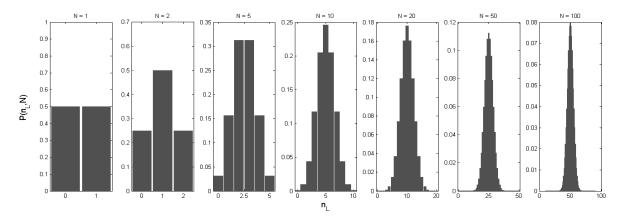
Although each <u>microstate</u> is equally likely, some <u>macrostates</u> are more likely than others (ex: N = 3,  $n_L = 1$  is 3x more likely then N = 3,  $n_L = 0$ )

Prob. that  $n_L$  out of N particles are to the left =

$$P(n_{L},N) = \frac{\Omega(n_{L},N)}{\Omega(0,N) + \Omega(1,N) + \cdots \Omega(N,N)}$$
$$= \frac{\Omega(n_{L},N)}{2^{N}} = \frac{N!}{n_{L}!(N-n_{L})!} \left(\frac{1}{2}\right)^{N}$$

This is an example of the binomial distribution

What does  $P(n_i, N)$  look like?



 $P(n_L, N)$  is peaked at  $n_L = N/2$ , gets sharper as N >> 1

Therefore, the most likely macrostate is with ½ the particles in L, ½ in R, because most microstates have  $n_L = N/2$ .

Properties of probabilities

Normalization:

Prob. of being in any one macrostate = 
$$\sum_{n_{L}=0}^{N} P(n_{L}, N) = 1$$

Check using binomial identity, setting p = q = 1/2:

$$\left(\frac{1}{2} + \frac{1}{2}\right)^{N} = \sum_{n_{L}=0}^{N} \frac{N!}{n_{L}!(N - n_{L})!} \left(\frac{1}{2}\right)^{n_{L}} \left(\frac{1}{2}\right)^{N - n_{L}} = \sum_{n_{L}=0}^{N} \frac{N!}{n_{L}!(N - n_{L})!} \left(\frac{1}{2}\right)^{N}$$

$$1 = \sum_{n_{L}=0}^{N} P(n_{L}, N)$$

Expectation (or mean) values:

For some function  $f(n_L)$ :  $\langle f(n_L) \rangle = \sum_{n_L=0}^{N} f(n_L) P(n_L, N)$ 

$$\langle n_L \rangle = \sum_{n_L=0}^{N} n_L P(n_L, N)$$
, and  $\langle n_L^2 \rangle = \sum_{n_L=0}^{N} n_L^2 P(n_L, N)$ , etc.

What is  $\langle n_{\scriptscriptstyle L} \rangle$  for  $P(n_{\scriptscriptstyle L},N)$  we derived?

$$\langle n_{L} \rangle = \sum_{n_{L}=0}^{N} n_{L} \frac{N!}{n_{L}!(N-n_{L})!} \left(\frac{1}{2}\right)^{N} = \left(\frac{1}{2}\right)^{N} N \sum_{n_{L}=1}^{N} \frac{(N-1)!}{(n_{L}-1)!(N-n_{L})!}, \qquad \text{let } n = n_{L}-1$$

$$= \left(\frac{1}{2}\right)^{N} N \sum_{n_{L}=0}^{N-1} \frac{(N-1)!}{n!(N-n-1)!} = \frac{N}{2}$$
 as expected

Note: Here is an alternate method of deriving this result using a math trick (we'll use this type of trick many times over the semester):

Consider the binomial identity  $(p+q)^N = \sum_{n=0}^N \binom{N}{n_i} p^{n_i} q^{N-n_i}$ .

Since  $\left(p\frac{\partial}{\partial p}\right)p^{n_l} = n_l p^{n_l}$  it follows that

$$\sum_{n=0}^{N} {N \choose n_{L}} n_{L} p^{n_{L}} q^{N-n_{L}} = p \frac{\partial}{\partial p} \sum_{n=0}^{N} {N \choose n_{L}} p^{n_{L}} q^{N-n_{L}} = p \frac{\partial}{\partial p} (p+q)^{N}$$
$$= Np(p+q)^{N-1}$$

Setting p = q = 1/2:

$$\langle n_L \rangle = \sum_{n=0}^{N} {N \choose n_L} n_L \left(\frac{1}{2}\right)^N = \frac{N}{2}$$

# Question 3: Calculate $\langle n_L^2 \rangle$

Apply the same operator twice:  $\left(p\frac{\partial}{\partial p}\right)^2 p^{n_l} = n_l^2 p^{n_l}$ 

$$\sum_{n=0}^{N} {N \choose n_{L}} n_{L}^{2} p^{n_{L}} q^{N-n_{L}} = \left(p \frac{\partial}{\partial p}\right)^{2} \sum_{n=0}^{N} {N \choose n_{L}} p^{n_{L}} q^{N-n_{L}} = \left(p \frac{\partial}{\partial p}\right)^{2} (p+q)^{N}$$

$$= p \frac{\partial}{\partial p} N p (p+q)^{N-1} = N p (p+q)^{N-1} + N(N-1) p^{2} (p+q)^{N-2}$$

Setting p = q = 1/2:

$$\langle n_L^2 \rangle = \sum_{n=0}^N \binom{N}{n_L} n_L^2 \left( \frac{1}{2} \right)^N = \frac{N}{2} + \frac{N(N-1)}{4} = \frac{N(N+1)}{4}$$

From these we can determine the variance in  $n_L$ :

$$\sigma_{n_{L}}^{2} \equiv \left\langle \left( n_{L} - \left\langle n_{L} \right\rangle \right)^{2} \right\rangle = \left\langle n_{L}^{2} \right\rangle - 2 \left\langle n_{L} \right\rangle \left\langle n_{L} \right\rangle + \left\langle n_{L} \right\rangle^{2} = \left\langle n_{L}^{2} \right\rangle - \left\langle n_{L} \right\rangle^{2}$$

$$= \frac{N(N+1)}{4} - \frac{N^{2}}{4} = \frac{N}{4}$$

So the standard deviation, or the half width of the probability  $P(n_L, N)$ ,  $\sigma_{n_L} = \sqrt{N}/2$  and the fractional deviation is:

$$\frac{\sigma_{n_l}}{\langle n_l \rangle} = \frac{1}{\sqrt{N}}$$

For a large system  $N \sim 10^{20}$ , this is  $10^{-10}$ , i.e. the width of the probability distribution is  $10^{-10}$  of the total range of the graph! This is extremely sharp.

In sum:

- The most likely macrostate has N/2 particles to the L and N/2 particles to the R. This is because there are the <u>most microstates</u> with this number, i.e.  $\Omega(n_i, N)$  is <u>maximum</u>.
- When N >> 1 any other macrostate is extremely unlikely to occur, due to sharpness of  $P(n_l, N)$ .
- This applies to all binary systems (see K & K, Chapter 1)