

Variance

$$\sigma^2 = \langle x^2 \rangle - \langle x \rangle^2$$

for discrete variables

$$\sigma^2 = \langle i^2 \rangle - \langle i \rangle^2$$

$$\sigma^2 = \sum_{i=1}^t i^2 p(i) - \left[ \sum_{i=1}^t i p(i) \right]^2$$

for continuous variables

$$\sigma^2 = \langle x^2 \rangle - \langle x \rangle^2$$

$$\sigma^2 = \int_a^b x^2 p(x) dx - \left[ \int_a^b x p(x) dx \right]^2$$

the standard deviation is given by:

$$S_d = \sqrt{\sigma^2} \equiv \sigma$$

## Stirling's Approximation

$$N! \approx \left(\frac{N}{e}\right)^N \quad \left. \begin{array}{l} \text{get this from} \\ \text{a Taylor-McLaurin} \\ \text{series} \end{array} \right\}$$

$$\downarrow$$
$$\ln(N!) \approx \ln \left[ \frac{N}{e} \right]^N = \ln N^N - \ln e^N$$

$$\downarrow$$
$$\ln(N!) \approx N \ln N - N \ln e$$

$$\downarrow$$
$$\ln(N!) \approx N \ln N - N = N(\ln N - 1)$$

$\downarrow$  for very large  $N$   $\ln N \gg 1$

$$\ln(N!) \approx N \ln N$$

# Binomial Theorem

$$(x+y)^N = \sum_{n_1=0}^N \frac{N!}{n_1!(N-n_1)!} x^{N-n_1} y^{n_1}$$

↓ Let  $y=1$

$$(1+x)^N = \sum_{n_1=0}^N \frac{N!}{n_1!(N-n_1)!} x^{n_1}$$

We make use of the above equation to determine  $\langle n_1 \rangle$  and  $\langle n_1^2 \rangle$  for a binomial dist'n

Let  $n_1 = \#$  successes of a coin-flip ( $p = \frac{1}{2}$ ) with  $N$  trials

$$P_{n_1} = p^{n_1} p^{N-n_1} \frac{N!}{n_1!(N-n_1)!} = \left(\frac{1}{2}\right)^N \frac{N!}{n_1!(N-n_1)!}$$

note: 
$$\sum_{n_1=0}^N P_{n_1} = \sum_{n_1=0}^N \frac{1}{2^N} \frac{N!}{n_1!(N-n_1)!} = 1$$

$$\sum_{n_1=0}^N \frac{N!}{n_1!(N-n_1)!} = 2^N$$

just as if we set  $x=1$  in the equation above

Now, let's find  $\langle n_1 \rangle = \sum_{n_1=0}^N n_1 P_{n_1}$

$$\langle n_1 \rangle = \sum_{n_1=0}^N n_1 P^{n_1} (1-P)^{N-n_1} \frac{N!}{n_1! (N-n_1)!}$$

$$\downarrow P = \frac{1}{2}$$

$$\langle n_1 \rangle = \sum_{n_1=0}^N n_1 \left(\frac{1}{2}\right)^N \frac{N!}{n_1! (N-n_1)!}$$

$$= \frac{\sum_{n_1=0}^N n_1 \frac{N!}{n_1! (N-n_1)!}}{2^N}$$

From the binomial theorem

$$(1+x)^N = \sum_{n_1=0}^N \frac{N!}{n_1! (N-n_1)!} x^{n_1}$$

$$\frac{d(1+x)^N}{dx} = \frac{d}{dx} \left[ \sum_{n_1=0}^N \frac{N!}{n_1! (N-n_1)!} x^{n_1} \right]$$

$$N(1+x)^{N-1} = \sum_{n_1=0}^N \frac{N!}{n_1! (N-n_1)!} n_1 x^{n_1-1}$$

$$\downarrow \text{let } x=1$$

$$N 2^{N-1} = \sum_{n_1=0}^N \frac{N!}{n_1! (N-n_1)!} n_1$$

$$\therefore \langle n_1 \rangle = \frac{\sum_{n_1=0}^N n_1 \frac{N!}{n_1! (N-n_1)!}}{2^N}$$

$$= \frac{N 2^{N-1}}{2^N}$$

↓

$$\langle n_1 \rangle = \frac{N}{2}$$

Find  $\langle n_1^2 \rangle$  similarly  $\Rightarrow \langle n_1^2 \rangle = \frac{\sum_{n_1=0}^N n_1^2 \frac{N!}{n_1! (N-n_1)!}}{2^N}$

$$\frac{d^2}{dx^2} (1+x)^N = \frac{d}{dx} (N(N-1)(1+x)^{N-2})$$

$$= \frac{d^2}{dx^2} \left[ \sum_{n_1=0}^N \frac{N!}{n_1! (N-n_1)!} x^{n_1} \right]$$

$$= \sum_{n_1=0}^N n_1(n_1-1) \frac{N!}{n_1! (N-n_1)!} x^{n_1}$$

$$N(N-1) 2^{N-2} = \sum_{n_1=0}^N n_1^2 \frac{N!}{n_1! (N-n_1)!} - \sum_{n_1=0}^N n_1 \frac{N!}{n_1! (N-n_1)!}$$

↓

$$N(N-1) 2^{N-2} = 2^N \langle n_1^2 \rangle - 2^N \langle n_1 \rangle$$

$$\frac{N(N-1)}{4} = \langle n_i^2 \rangle - \langle n_i \rangle$$



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

$$\langle n_i^2 \rangle = \frac{N^2}{4} - \frac{N}{4} + \frac{2N}{4} = \frac{N^2}{4} + \frac{N}{4}$$

$$\langle n_i^2 \rangle - \langle n_i \rangle^2 = \frac{N^2}{4} + \frac{N}{4} - \frac{N^2}{4} = \frac{N}{4}$$



$$\sigma^2 = \frac{N}{4}$$

$$\sigma = \frac{\sqrt{N}}{2}$$

ratio



$$\lim_{N \rightarrow \infty} \frac{\sigma}{\langle n_i \rangle} = \lim_{N \rightarrow \infty} \frac{\frac{\sqrt{N}}{2}}{\frac{N}{2}} = \lim_{N \rightarrow \infty} \frac{1}{\sqrt{N}} \rightarrow 0$$

as  $N$  gets large only the mean (expected) value is observed

For binomial distribution

Let  $n_1 = \#$  successes,  $p = \frac{1}{2}$ ,  $N$  trials

$$P_{n_1} = \frac{N!}{n_1!(N-n_1)!} = \frac{W(n_1, N)}{2^N}$$

from a well-known theorem

$$(x+y)^N = \sum_{n_1=0}^N \frac{N! x^{(N-n_1)} y^{n_1}}{n_1!(N-n_1)!}$$

$N$  is an integer greater than 0

let  $x = 1$

$$(1+y)^N = \sum_{n_1=0}^N \frac{N!}{n_1!(N-n_1)!} y^{n_1}$$

↓

$$(1+y)^N = \sum_{n_1=0}^N W(n_1, N) y^{n_1}$$

let  $y = 1$

$$2^N = \sum_{n_1=0}^N W(n_1, N)$$

$$\therefore P_{n_1} = \frac{W(n_1, N)}{\sum_{n_1=0}^N W(n_1, N)}$$

we now determine  $\langle n_i \rangle$

$$\langle n_i \rangle = \sum_{n_i=0}^N n_i P_{n_i} = \frac{\sum_{n_i=0}^N n_i W(n_i, N)}{\sum_{n_i=0}^N W(n_i, N)}$$

examine more closely the term

$$n_i W(n_i, N) = \frac{n_i N!}{n_i! (N-n_i)!} = \frac{N!}{(n_i-1)! (N-n_i)!}$$

with a little manipulation we can make the right-hand side look like a binomial multiplicity

$$\frac{N!}{(n_i-1)! (N-n_i)!} = \frac{N(N-1)!}{(n_i-1)! [(N-1)-(n_i-1)]!} = N W(n_i-1, N-1)$$

the numerator in our expression for  $\langle n_i \rangle$  becomes

$$\begin{aligned} \sum_{i=1}^N N W(n_i-1, N-1) &= N \sum_{i=1}^N W(n_i-1, N-1) \\ &= N 2^{N-1} \end{aligned}$$

$$\therefore \langle n_1 \rangle = \frac{N 2^{N-1}}{2^N} = \frac{N}{2}$$

this means that for  $N$  flips of an unbiased coin the average # heads (or # tails)  $\equiv n_1$  is exactly half (i.e.  $\frac{N}{2}$ )

You will show in the HW that if you optimize  $W(n_1, N)$  with respect to  $n_1$  (same as optimizing  $\ln W(n_1, N)$ ), the value  $n_1^*$  that maximizes  $\ln W(n_1, N)$  is:

$$n_1^* = \langle n_1 \rangle$$

Highest Probability Outcomes  $\Rightarrow$  Highest Multiplicity

Ex: 4 coin flips

$n_H$	$W(n_H, 4)$	$P(n_H)$
0	1	$\frac{1}{16} = 0.0625$
1	4	$\frac{1}{4} = 0.2500$
2	6	$\frac{3}{8} = 0.3750$
3	4	$\frac{1}{4} = 0.2500$
4	1	$\frac{1}{16} = 0.0625$

$$W_{\text{total}} = 16 = 2^4$$

10 coin flips

$n_H$	$W(n_H, 10)$	$P(n_H)$
(10) 0	1	0.0009765625
(9) 1	10	0.009765625
(8) 2	45	0.0439453125
(7) 3	120	0.1171875
(6) 4	210	0.205078125
5	252	0.24609375

# Simple models for physical systems

- gases exert pressure on container walls  $\Rightarrow$  gases expand to fill volume
- model (in 1-D) for this system are 3 balls (gas particles) in boxes (total boxes = volume)
  - constraint on this system is that there (mode) can only be 1 ball per box

- smallest volume = 3 boxes and expand from here

- if we assume that the probability of filling any one box is the same as any other then we have Bernoulli trials with success = the ball in a box

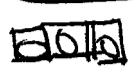

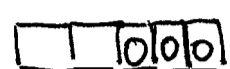
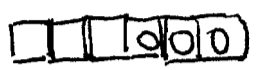
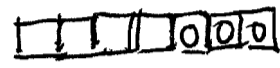
- $N = \# \text{ boxes} \Rightarrow \text{volume}$

- $3 = \# \text{ successes} = \text{filled boxes}$

- $N-3 = \# \text{ empty boxes} = \text{failures}$

- highest probability  $\Rightarrow$  highest multiplicity as we have seen with our coin flip example (also Bernoulli trials)

KAMPAN

$\frac{N}{}$	$\frac{W}{}$	# configurations w/3 ball clusters
3	1	 (1)
4	4	 (2)
5	10	 (3)
6	20	 (4)
7	35	 (5)
8	56	(6)
9	84	(7)
10	120	(8)

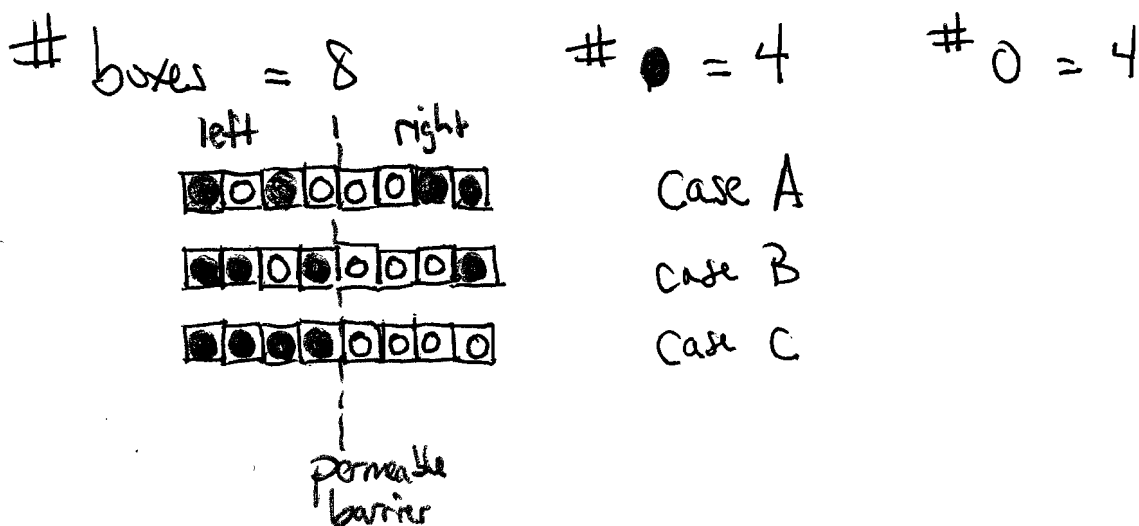
$$W = \frac{N!}{3! (N-3)!}$$

as  $N \uparrow$  so does  $W$ , and the probability of having 3-ball clusters goes down

Maximum multiplicity  $\Rightarrow$  balls spread out over all boxes

# boxes  $\Rightarrow$  volume

- materials diffuse and mix
- in this model we fix the volume (# boxes) and we have 2 colors of balls ● and ○
- we split the number of boxes with a "permeable" barrier that allows balls to move from one side of barrier to the other
- like previous model only 1 ball per box and probability of a ● filling a box is the same as a ○ filling a box (all boxes are filled)



- for this problem we partition the 8 boxes into 2 sets of 4 boxes left side and right side

- we now have 2 Bernoulli trial sets
- let a box with ● = success

∴ for case A

$$W(\text{left}) = \frac{4!}{2!2!} \quad W(\text{right}) = \frac{4!}{2!2!}$$

from the multiplication rule for probabilities  
(independent trials)

$$P(\text{left} \cdot \text{right}) = P(\text{left}) P(\text{right})$$



$$W(\text{left} \cdot \text{right}) = W(\text{left}) W(\text{right}) = W$$

Case

A

$$\frac{4!}{2!2!} \cdot \frac{4!}{2!2!} = 36$$

B

$$\frac{4!}{3!1!} \cdot \frac{4!}{1!3!} = 16$$

C

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