

## 2. From random walk to probability distributions

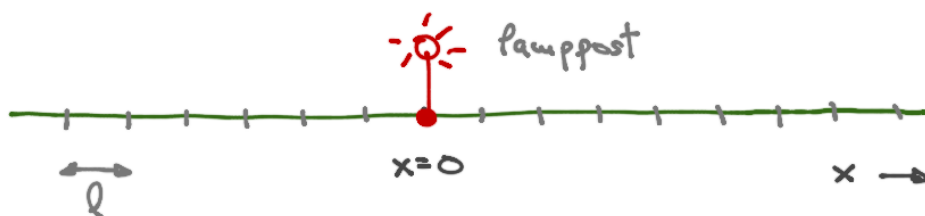
The aim of this chapter is to understand why the Gaussian probability distribution appears so often in Physics.

Statistical ensemble: It is an idealisation consisting of a large number of virtual copies of a system, considered all at once, each of which represents a possible state that the real system might be in. In other words, a statistical ensemble is a probability distribution for the state of the system.

### I. A simple probabilistic system: Random Walk

The problem is stated as follows:

- \* A drunk starts out from a lamppost ( $x=0$ ) and each step is of equal length  $l$ .
- \* Step to right with probability  $p$  and to left with probability  $q = 1-p$ . Each step is independent of the preceding step.



- \* After  $N$  steps the drunk will be at  $x = m l$
- \* Compute the probability (distribution)  $P_N(m)$  of finding the drunk at position  $x = m l$  after  $N$  steps.

Language: One can replace the drunk by a particle.

Denoting

$n_1 \equiv$  steps to the right

$n_2 \equiv$  steps to the left

one has

$$\begin{cases} N = n_1 + n_2 \\ m = n_1 - n_2 \end{cases} \Rightarrow \begin{cases} n_1 = \frac{1}{2}(N+m) \\ n_2 = \frac{1}{2}(N-m) \end{cases}$$

Notice that

$$m = n_1 - n_2 = 2n_1 - N \Rightarrow \begin{cases} N \text{ odd} \Rightarrow m \text{ odd} \\ N \text{ even} \Rightarrow m \text{ even} \end{cases}$$

Probability of a sequence: Since there is no memory, the probability of any one given sequence of  $n_1$  steps to the right and  $n_2$  steps to the left is

$$\underbrace{p \cdots p}_{n_1} \underbrace{q \cdots q}_{n_2} = p^{n_1} q^{n_2}$$

But a given pair  $(n_1, n_2)$  can have multiple realisations so that the particle ends up at the same  $x = m \ell$  after the  $N$  steps

$$\text{Multiplicity} = \frac{N!}{n_1! n_2!}$$

Ex:  $N=3$

		$n_1$	$n_2$	$m$	$\frac{N!}{n_1! n_2!}$
1)	→ → → }	3	0	3	1
2)	← → → }	2	1	1	3
3)	→ ← → }				
4)	→ → ← }				
5)	← ← → }	1	2	-1	3
6)	← → ← }				
7)	→ ← ← }				
8)	← ← ← }	0	3	-3	1

The probability of taking (in a total of  $N$  step)  $n_1$  steps to the right and  $n_2 = N - n_1$  steps to the left is

$$W_N(n_1) = \underbrace{\frac{N!}{n_1! (N-n_1)!}}_{\text{multiplicity}} p^{n_1} (1-p)^{N-n_1}$$

Using  $n_1 = \frac{1}{2}(N+m)$  yields

$$P_N(m) = W_N(n_1) = \frac{N!}{[\frac{1}{2}(N+m)]! [\frac{1}{2}(N-m)]!} p^{\frac{1}{2}(N+m)} (1-p)^{\frac{1}{2}(N-m)}$$

Ex: In the case  $N=3$  with  $p=q=1/2$  one finds

$$P_3(m) = W_3(n_1) = \frac{1}{8}, \frac{3}{8}, \frac{3}{8}, \frac{1}{8}$$

The probability distribution above is called "binomial dist" by virtue of the binomial expansion

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

## II. Random walk and mean values

\* Mean values in Mathematics: Let  $u$  be a variable that can take any of the  $M$  discrete values

$$u_1, u_2, \dots, u_M$$

with respective probabilities (stochastic variable)

$$P(u_1), P(u_2), \dots, P(u_M)$$

The mean or average value of  $u$  is defined by

$$\begin{aligned} \bar{u} &\equiv \frac{P(u_1)u_1 + P(u_2)u_2 + \dots + P(u_M)u_M}{P(u_1) + P(u_2) + \dots + P(u_M)} = \frac{\sum_{i=1}^M P(u_i)u_i}{\underbrace{\sum_{i=1}^M P(u_i)}_{=1 \text{ as } P(u_i) \text{ is defined as a probability "normalisation cond"}}} \\ &= \sum_{i=1}^M P(u_i)u_i \end{aligned}$$

More generically one has

$$\overline{f(u)} \equiv \sum_{i=1}^M P(u_i) f(u_i)$$

for a function  $f(u)$ .

• Property 1:  $\overline{f(u) + g(u)} = \sum_{i=1}^n P(u_i) [f(u_i) + g(u_i)]$   
 $= \sum_{i=1}^n P(u_i) f(u_i) + \sum_{i=1}^n P(u_i) g(u_i)$   
 $= \overline{f(u)} + \overline{g(u)}.$

• Property 2:  $\overline{cf(u)} = c \overline{f(u)}$  for  $c \equiv \text{cte.}$

There are some specific mean values which are particularly relevant in statistical physics

0) mean value  $\bar{u} = \sum_{i=1}^n P(u_i) u_i$

1) first moment of  $u$  about its mean:  $\overline{\Delta u} \equiv \overline{(u - \bar{u})} = \bar{u} - \bar{u} = 0$

2) second moment of  $u$  about its mean or "dispersion"

$$\overline{(\Delta u)^2} \equiv \sum_{i=1}^n P(u_i) (u_i - \bar{u})^2 \geq 0 \quad \text{~~~~~} \quad \Delta^* u \equiv \sqrt{\overline{(\Delta u)^2}} \equiv \text{"Standard deviation"}$$

Note that

$$\overline{(\Delta u)^2} = \overline{(u - \bar{u})^2} = \overline{(u^2 - 2u\bar{u} + \bar{u}^2)} = \overline{u^2} - 2\bar{u}^2 + \bar{u}^2 = \overline{u^2} - \bar{u}^2$$

$$\Rightarrow \overline{(\Delta u)^2} = \overline{u^2} - \bar{u}^2 \geq 0 \Rightarrow \overline{u^2} \geq \bar{u}^2$$

n)  $n^{\text{th}}$  moment of  $u$  about its mean:  $\overline{(\Delta u)^n}$

NOTE: Probability generating function  $\Rightarrow g(t, u) \equiv \overline{e^{t u}}$   
 $\Rightarrow \overline{u^k} = \left. \frac{d^k g}{dt^k} \right|_{t=0}$

\* Mean values for the random walk system: Let us focus on the binomial probability distribution

$$W(n_1) = \frac{N!}{n_1! (N-n_1)!} p^{n_1} q^{N-n_1}$$

• Normalisation:

$$\sum_{n_1=0}^N W(n_1) = \sum_{n_1=0}^N \frac{N!}{n_1! (N-n_1)!} p^{n_1} (1-p)^{N-n_1} = \underbrace{(p+q)^N}_{1} = 1^N = 1$$

o) Mean number of steps to the right:

$$\bar{n}_1 \equiv \sum_{n_1=0}^N W(n_1) n_1 = \sum_{n_1=0}^N \frac{N!}{n_1! (N-n_1)!} p^{n_1} q^{N-n_1} n_1 = (*)$$

NOTE:  $n_1 p^{n_1} = p \frac{d}{dp} (p^{n_1})$

$$(*) = \sum_{n_1=0}^N \frac{N!}{n_1! (N-n_1)!} q^{N-n_1} p \frac{d}{dp} (p^{n_1})$$

$$= p \frac{d}{dp} \left[ \sum_{n_1=0}^N \frac{N!}{n_1! (N-n_1)!} p^{n_1} q^{N-n_1} \right] = p \frac{d}{dp} [(p+q)^N]$$

$$= N p \underbrace{(p+q)^{N-1}}_1 = N p \Rightarrow \boxed{\bar{n}_1 = N p}$$

NOTE: Similarly one finds that  $\bar{n}_2 = N q \Rightarrow \bar{n}_1 + \bar{n}_2 = N \underbrace{(p+q)}_1 = N$ .

2) Dispersion:

$$\overline{(\Delta n_1)^2} = \overline{n_1^2} - \overline{n_1}^2 = \overline{n_1^2} - (Np)^2$$

This is what we have to compute

$$\overline{n_1^2} \equiv \sum_{n_1=0}^N W(n_1) n_1^2 = \sum_{n_1=0}^N \frac{N!}{n_1! (N-n_1)!} p^{n_1} q^{N-n_1} n_1^2 = (*)$$

NOTE:  $n_1^2 p^{n_1} = \left[ p \frac{d}{dp} \right]^2 (p^{n_1})$

$$\begin{aligned} (*) &= \left( p \frac{d}{dp} \right)^2 \sum_{n_1=0}^N \frac{N!}{n_1! (N-n_1)!} p^{n_1} q^{N-n_1} = \\ &= \left( p \frac{d}{dp} \right)^2 (p+q)^N = p \frac{d}{dp} \left( p^N (p+q)^{N-1} \right) \\ &= p^N \underbrace{(p+q)^{N-1}}_1 + p^2 N(N-1) \underbrace{(p+q)^{N-2}}_1 \underbrace{q}_q \\ &= p^N [1 + p(N-1)] = p^N [(1-p) + pN] \\ &= Npq + (Np)^2. \end{aligned}$$

So one finds

$$\overline{(\Delta n_1)^2} = \overline{n_1^2} - (Np)^2 = Npq \Rightarrow \boxed{\overline{(\Delta n_1)^2} = Npq}$$

It is also meaningful to introduce the **relative standard deviation**

$$\frac{\Delta^* n_1}{\overline{n_1}} = \frac{\sqrt{\overline{(\Delta n_1)^2}}}{\overline{n_1}} = \frac{\sqrt{Npq}}{Np} = \sqrt{\frac{q}{p}} \frac{1}{\sqrt{N}} \quad \Rightarrow_{p=q} \frac{\Delta^* n_1}{\overline{n_1}} = \frac{1}{\sqrt{N}}$$

In terms of  $m = n_1 - n_2 = 2n_1 - N$  one has

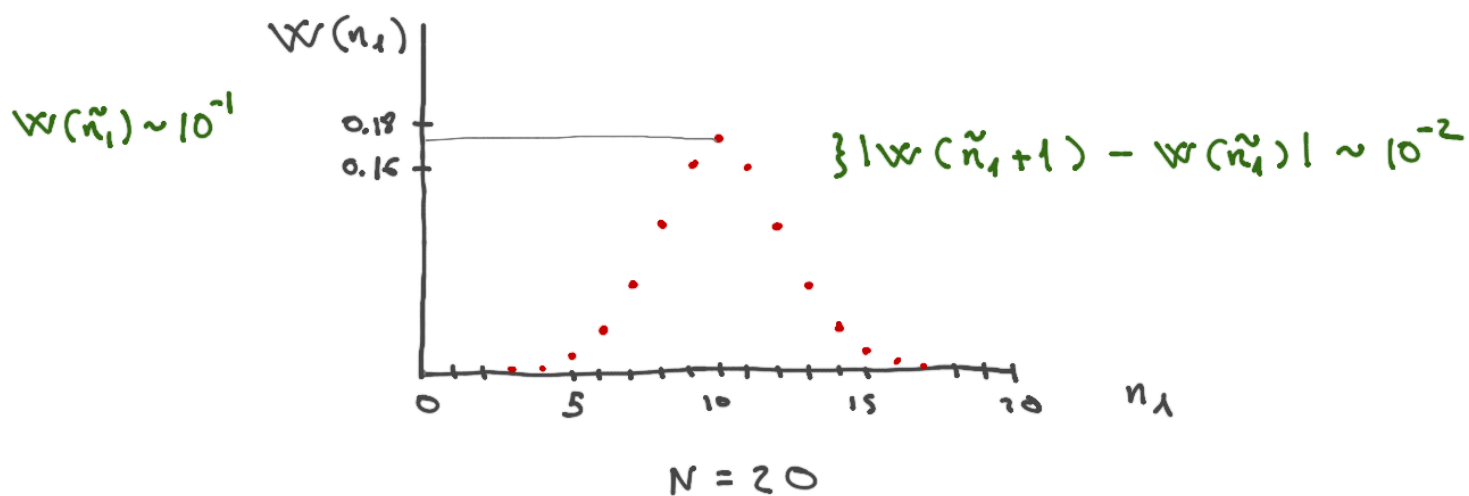
$$0) \bar{m} = 2\bar{n}_1 - N = 2Np - N = Np + N(p-1) = N(p-q)$$

$$1) \Delta m \equiv m - \bar{m} = (2n_1 - N) - (2\bar{n}_1 - N) = 2(n_1 - \bar{n}_1) = 2\Delta n_1 \Rightarrow (\Delta m)^2 = 4(\Delta n_1)^2$$

$$2) \overline{(\Delta m)^2} \equiv 4 \overline{(\Delta n_1)^2} = 4Npq$$

### III. Probability distribution at large $N$

When  $N \gg 1$  the probability distribution  $W(n_1)$  has a sharp maximum around a value  $n_1 = \tilde{n}_1$ .



If  $N$  is large and one considers regions around the maximum  $n_1 = \tilde{n}_1$ , one has that

$$|W(n_1+1) - W(n_1)| \ll W(n_1)$$

Idea:  $W$  can, to a good approximation, be considered as a continuous function of the continuous variable  $n_1$  although only  $n_1 \in \mathbb{N}$  are of physical relevance.



The maximum of  $W(n_1)$  is located at

$$\frac{dW}{dn_1} = 0 \quad \text{or equivalently} \quad \frac{d \ln W}{dn_1} = 0$$

NOTE:  $\ln W$  is a much more slowly varying function.

Taylor expanding around  $n_1 = \tilde{n}_1$  gives

$$\ln W(n_1) = \ln W(\tilde{n}_1) + B_1 (n_1 - \tilde{n}_1) + \frac{1}{2!} B_2 (n_1 - \tilde{n}_1)^2 + \dots$$

with

$$B_k = \left. \frac{d^k \ln W}{dn_1^k} \right|_{n_1 = \tilde{n}_1}$$

Since  $n_1 = \tilde{n}_1$  is a maximum then  $B_1 = 0$  and  $B_2 < 0$  so

$$\ln W = \ln W(\tilde{n}_1) - \frac{1}{2} |B_2| (n_1 - \tilde{n}_1)^2 + \text{higher-order terms}$$

To first approximation one finds

$$W = \underbrace{\tilde{W}}_{W(\tilde{n}_1)} \cdot e^{-\frac{|B_2|}{2} (n_1 - \tilde{n}_1)^2}$$

Math: Starting from  $W(n) = \frac{N!}{n! (N-n)!} p^n q^{N-n}$  then

$$\ln W = \ln N! - \ln n! - \ln (N-n)! + n \ln p + (N-n) \ln q$$

Trick: If  $n$  is a large integer  $n \gg 1$  then  $\ln n!$  can be considered an almost continuous function of  $n$  since  $\ln n!$  changes by a small fraction of itself if  $n$  is changed by a small integer. Hence

$$\frac{d \ln n!}{dn} \approx \frac{\ln(n+1)! - \ln n!}{1} = \ln \frac{(n+1)!}{n!} = \ln(n+1)$$

and for  $n \gg 1$

$$\frac{d \ln n!}{dn} \approx \ln n$$

Then one has that

$$\frac{d}{dn_1} \ln W = -\ln n_1 + \ln(N - n_1) + \ln p - \ln q = \ln \left[ \left( \frac{N - n_1}{n_1} \right) \frac{p}{q} \right]$$

NOTE 1:  $\frac{d \ln \overbrace{(N - n_1)!}^Y}{dn_1} = - \frac{d \ln Y!}{dY} \approx -\ln Y = -\ln(N - n_1)$

So the maximum is located at

$$\left. \frac{d}{dn_1} \ln W \right|_{n_1 = \tilde{n}_1} = 0 \Rightarrow \frac{N - \tilde{n}_1}{\tilde{n}_1} = \frac{q}{p}$$

$$\Rightarrow (N - \tilde{n}_1) p = \tilde{n}_1 q$$

$$\Rightarrow N p = \tilde{n}_1 (p + q)$$

$$\Rightarrow \tilde{n}_1 = N p = \bar{n}_1 \Rightarrow \text{Maximum at the mean value}$$

Taking a further derivative

$$\frac{d^2}{dn_1} \ln W = \frac{n_1}{N-n_1} \frac{q}{p} \left( -\frac{N}{n_1^2} \frac{p}{q} \right) = -\frac{N}{n_1(N-n_1)}$$

and evaluating it at the maximum one gets

$$\begin{aligned} \left. \frac{d^2}{dn_1^2} \ln W \right|_{n_1 = \tilde{n}_1} &= -\frac{N}{\tilde{n}_1(N-\tilde{n}_1)} = -\frac{N}{Np(N-Np)} \\ &= -\frac{N}{N^2 p(1-p)} = -\frac{1}{Npq} \\ \Rightarrow B_2 &= -\frac{1}{Npq} < 0 \end{aligned}$$

Finally the factor  $\tilde{W} = W(\tilde{n}_1)$  can be determined from the normalisation condition

$$\sum_{n_1=0}^N W(n_1) \approx \int W(n_1) dn_1 = \int_{-\infty}^{\infty} W(\underbrace{\tilde{n}_1 + \eta}_{n_1}) d\eta \stackrel{!}{=} 1$$

NOTE: The integration over  $-\infty < \eta < \infty$  is an excellent approximation since the contribution far from  $\eta=0$  is negligible.

$$\int_{-\infty}^{\infty} W(n_1) d\eta \approx \int_{-\infty}^{\infty} \tilde{W} e^{-\frac{|B_2|}{2} \eta^2} d\eta = \tilde{W} \sqrt{\frac{2\pi}{|B_2|}} \stackrel{!}{=} 1$$

↳ see Math

$$\Rightarrow \tilde{\omega} = \sqrt{\frac{|B_2|}{2\pi}} = (2\pi N p q)^{-1/2}$$

Math: Relevant integrals:

$$\bullet \int_0^{\infty} e^{-\eta} \eta^p d\eta = \Gamma(p+1) = p!$$

$$\bullet \int_{-\infty}^{\infty} e^{-\eta^2} d\eta = \sqrt{\pi}$$

$$\bullet I(p) \equiv \int_0^{\infty} e^{-\alpha \eta^2} \eta^p d\eta = \frac{1}{2} \Gamma\left(\frac{p+1}{2}\right) \alpha^{-\frac{p+1}{2}}$$

so that

$$I(0) = \frac{1}{2} \sqrt{\pi} \alpha^{-1/2}$$

$$I(1) = \frac{1}{2} \alpha^{-1}$$

$$I(2) = \frac{1}{4} \sqrt{\pi} \alpha^{-3/2}$$

$$I(3) = \frac{1}{2} \alpha^{-2}$$

.....

Using these formulae we obtain

$$\int_{-\infty}^{\infty} e^{-\frac{1}{2}|B_2|\eta^2} d\eta = 2 \times I(0) = \sqrt{\pi} \frac{\sqrt{2}}{\sqrt{|B_2|}} = \sqrt{\frac{2\pi}{|B_2|}}$$

$\downarrow$   
 $\alpha = \frac{|B_2|}{2}$

The previous computations show that

$$W(n_1) = (2\pi N p q)^{-1/2} e^{-\frac{(n_1 - Np)^2}{2N p q}}$$

Recalling that  $\bar{n}_1 = \tilde{n}_1 = Np$  and  $\overline{(\Delta n_1)^2} = N p q$  then

$$W(n_1) = \left(2\pi \overline{(\Delta n_1)^2}\right)^{-1/2} e^{-\frac{(n_1 - \bar{n}_1)^2}{2 \overline{(\Delta n_1)^2}}}$$

"Gaussian distribution"

( $N \gg 1$ ,  $n_1 \gg 1$ )

#### IV. Gaussian probability distribution

Let us move to the more physical variable

$$x \equiv m \cdot l = (2n_1 - N) l \quad \Rightarrow \quad dx = l dm = 2l dn_1$$

$\hookrightarrow m = n_1 - n_2$

so that

$$W(x) = [2\pi N p q]^{-1/2} e^{-\frac{[\frac{x}{l} - N(p-q)]^2}{8N p q}}$$

NOTE:  $(n_1 - Np) = \frac{1}{2}(N+m - 2Np) = \frac{1}{2}[m - N \underbrace{(2p-1)}_{(p-q)}] = \frac{1}{2}[m - N(p-q)] = \frac{1}{2}[\frac{x}{l} - N(p-q)]$

Equating the cumulative probability  $\mathcal{P}(x) dx = W(n_i) dn_i = W(x) \frac{dx}{2l}$

$$\begin{aligned}\mathcal{P}(x) &= \frac{1}{2l} W(x) = \frac{1}{2l} [2\pi N p q]^{-1/2} e^{-\frac{[\frac{x}{l} - N(p-q)]^2}{8 N p q}} \\ &= \frac{1}{2l} [2\pi N p q]^{-1/2} e^{-\frac{[x - N(p-q)l]^2}{l^2 8 N p q}} \\ &= \frac{1}{\sqrt{2\pi} \sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} = P(\mu) \frac{dx}{2l}\end{aligned}$$

with  $\mu \equiv (p-q) N l$  and  $\sigma \equiv 2 \sqrt{N p q} l$ .

\* Normalisation :

$$\begin{aligned}\int_{-\infty}^{\infty} \mathcal{P}(x) dx &= \frac{1}{\sqrt{2\pi} \sigma} \int_{-\infty}^{\infty} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx \\ y = x - \mu \quad \leftarrow &= \frac{1}{\sqrt{2\pi} \sigma} \int_{-\infty}^{\infty} e^{-\frac{y^2}{2\sigma^2}} dy \\ dy = dx \\ 2 \times I(0) \quad \leftarrow &= \frac{1}{\sqrt{2\pi} \sigma} 2 \cdot \frac{1}{2} \sqrt{\pi} \sqrt{2} \sigma = 1 \quad \checkmark\end{aligned}$$

\* Mean value of  $x$  :

$$\bar{x} = \int_{-\infty}^{\infty} \mathcal{P}(x) x dx = \frac{1}{\sqrt{2\pi} \sigma} \int_{-\infty}^{\infty} x e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$$

$$\begin{aligned}
&= \frac{1}{\sqrt{\pi} \sigma} \int_{-\infty}^{\infty} (y+\mu) e^{-\frac{y^2}{2\sigma^2}} dy \\
&= \underbrace{\frac{1}{\sqrt{\pi} \sigma} \int_{-\infty}^{\infty} y e^{-\frac{y^2}{2\sigma^2}} dy}_{\text{zero} \equiv \text{odd function}} + \mu \underbrace{\frac{1}{\sqrt{\pi} \sigma} \int_{-\infty}^{\infty} e^{-\frac{y^2}{2\sigma^2}} dy}_{2 \times I(0)}
\end{aligned}$$

$$= \mu \frac{1}{\sqrt{\pi} \sigma} 2 \frac{1}{2} \sqrt{\pi} \sqrt{2} \sigma = \mu = (p-q) N l$$

\* Dispersion :

$$\overline{(\Delta x)^2} = \overline{(x-\mu)^2} = \int_{-\infty}^{\infty} (x-\mu)^2 P(x) dx$$

$$= \frac{1}{\sqrt{\pi} \sigma} \int_{-\infty}^{\infty} y^2 e^{-\frac{y^2}{2\sigma^2}} dy$$

$$2 \times I(2) \leftarrow = \frac{1}{\sqrt{\pi} \sigma} \underbrace{2 \frac{1}{4} \sqrt{\pi}}_{\frac{1}{2}} \underbrace{(\sqrt{2} \sigma)^{3/2}}_{\sqrt{2} \sigma \cdot \sqrt{2} \sigma} = \sigma^2 = 4 N p q l^2$$

TAKE HOME MESSAGE : Starting from the simplest probabilistic system (random walk) and taking  $N \gg 1$  and  $n_1 \gg 1$  limits we found that a Gaussian distribution emerges !!

## v. Poisson probability distribution

It appears also as a limit of the binomial distribution

$$N \gg 1, \quad p \ll 1 \quad \text{so} \quad n_1 \ll N$$

Starting from

$$W(n_1) = \frac{N!}{n_1! (N-n_1)!} p^{n_1} q^{N-n_1} \approx \frac{N^{n_1}}{n_1!} p^{n_1} e^{-Np} = \frac{\lambda^{n_1}}{n_1!} e^{-\lambda}$$

$\underbrace{\hspace{10em}}_{\text{Poisson distribution}}$

$$\frac{N(N-1)(N-2)\dots(N-n_1+1)}{n_1!} \approx \frac{N^{n_1}}{n_1!}$$

with  $\lambda \equiv Np$ .

$$\begin{aligned} N &\gg n_1 \\ N &\gg 1 \end{aligned}$$

NOTE:  $\log q^{N-n_1} = (N-n_1) \log q = (N-n_1) \log(1-p)$

$$= N(-p + \text{higher order}) = -Np$$

$$\begin{aligned} p &\ll 1 \\ N &\gg n_1 \end{aligned}$$

$$\Rightarrow q^{N-n_1} = e^{-Np}$$

NOTE:  $\log(1+x) = x - \frac{x^2}{2} + \frac{x^3}{3} + \dots$

\* Normalisation :  $\sum_{n_1=0}^N \frac{\lambda^{n_1}}{n_1!} e^{-\lambda} = e^{-\lambda} \sum_{n_1=0}^{\infty} \frac{\lambda^{n_1}}{n_1!} = e^{-\lambda} e^{\lambda} = 1 \quad \checkmark$



\* Mean value of  $n_1$ :

$$\begin{aligned} \bar{n}_1 &= \sum_{n_1=0}^N n_1 \frac{\lambda^{n_1}}{n_1!} e^{-\lambda} = \sum_{n_1=1}^N n_1 \frac{\lambda^{n_1}}{n_1!} e^{-\lambda} \\ &= e^{-\lambda} \lambda \sum_{n_1=1}^N \frac{\lambda^{(n_1-1)}}{(n_1-1)!} = e^{-\lambda} \lambda \sum_{m=0}^{\infty} \frac{\lambda^m}{m!} = \lambda \end{aligned}$$

$$n_1 - 1 = m$$

$$N \gg 1$$

\* Dispersion:

$$\overline{(\Delta n_1)^2} = \overbrace{n_1^2}^{(*)} - \bar{n}_1^2 = \lambda(\lambda+1) - \lambda^2 = \lambda$$

$$\begin{aligned} (*) \overline{n_1^2} &= \sum_{n_1=0}^N n_1^2 \frac{\lambda^{n_1}}{n_1!} e^{-\lambda} = e^{-\lambda} \sum_{n_1=1}^N n_1 \frac{\lambda^{n_1}}{(n_1-1)!} \\ &= e^{-\lambda} \lambda \frac{d}{d\lambda} \sum_{n_1=1}^N \frac{1}{(n_1-1)!} \lambda^{n_1-1} \cdot \lambda = e^{-\lambda} \lambda \frac{d}{d\lambda} (e^{\lambda} \cdot \lambda) \end{aligned}$$

$$n_1 - 1 = m$$

$$N \gg 1$$

NOTE:  $\lambda \frac{d\lambda^{n_1}}{d\lambda} = n_1 \lambda^{n_1}$

$$= e^{-\lambda} \lambda (e^{\lambda} \lambda + e^{\lambda}) = \lambda(\lambda+1)$$

**TAKE HOME MESSAGE:** The Poisson distribution has to do with very unlikely ( $p \ll 1$ ) events that happen to occur because of a very large population ( $N \gg 1$ ).