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Lecture 1

Plan

1. Randomness. Random numbers.
2. Probability and probability distributions.
3. The central limiting theorem.

Randomness is a lack of predictability in events, symbols, steps, etc.

A random sequence of events, ~~the~~ symbols, or steps has no order.

Individual random events are by definition unpredictable.

Examples:

Throwing a coin. Eagle or tail?

Eagle = 1, tail = 0

1, 0, 0, 1, 1, 1, 0, 0,

After  $N$  attempts, ~~the~~ the eagle appears

$N_e$  times and the tail appears  $N_t = N - N_e$  times.

$$N_e + N_t = N$$

We introduce the probability to find the eagle (tail).  
We define

$$P_e \equiv \frac{N_e}{N}, \quad P_t = \frac{N_t}{N}$$

Normalization

$$P_e + P_t = \frac{N_e}{N} + \frac{N_t}{N} = \frac{N_e + N_t}{N} = 1$$

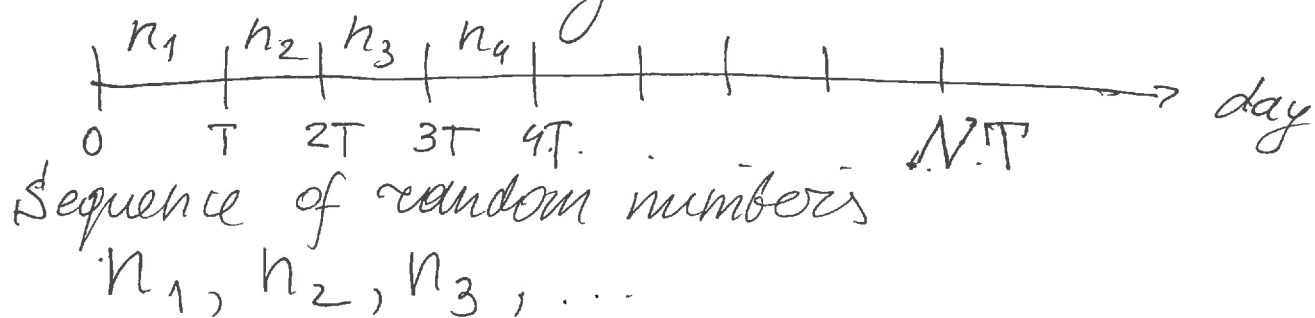
$$P_e + P_t = 1$$

Probability is defined only in the limit  $N \rightarrow \infty$

$$P_e = \lim_{N \rightarrow \infty} \frac{N_e}{N}, \quad P_t = \lim_{N \rightarrow \infty} \frac{N_t}{N}$$

Another example.

The number of cars that passed a street during an interval  $T$



$N(n)$  is the number of intervals when the number  $n$  (cars) appears

$$p(n) = \lim_{N \rightarrow \infty} \frac{N(n)}{N} = \text{the probability to find } n \text{ cars}$$

It is obvious that

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$$\sum_{n=0}^{\infty} N(n) = N$$

~~the~~ The normalization condition

$$\sum_{n=0}^{\infty} p(n) = \sum_n \frac{N(n)}{N} = \frac{\sum_n N(n)}{N} = 1$$

$$\boxed{\sum_{n \geq 0} p(n) = 1}$$

The mean value of random numbers

$$\frac{1}{N} \sum_{i=1}^N n_i \equiv \langle n \rangle \text{ (or } \bar{n})$$

We can write this equation in another form

$$\begin{aligned} \langle n \rangle &= \frac{1}{N} \sum_{i=1}^N n_i = \frac{1}{N} \sum_n N(n) n = \\ &= \sum_n \frac{N(n)}{N} n = \sum_{n \geq 0} p(n) n \end{aligned}$$

$$\langle n \rangle = \sum_{n \geq 0} p(n) n$$

Fluctuations. We define

$$\delta n_i \equiv n_i - \langle n \rangle$$

$\delta n_i$  shows a deviation of  $n_i$  from the mean value.

It is obvious that

$$\begin{aligned} \sum_{i=1}^N \delta n_i &= \sum_{i=1}^N (n_i - \langle n \rangle) = \\ &= \sum_{i=1}^N n_i - \sum_{i=1}^N \langle n \rangle = N \frac{1}{N} \sum_{i=1}^N n_i - N \langle n \rangle = \\ &= N \langle n \rangle - N \langle n \rangle = 0 \end{aligned}$$

Variance.

In order to find how strong are fluctuations we define the variance as follows

$$\sigma^2 \equiv \frac{1}{N} \sum_{i=1}^N \delta n_i^2$$

we have

$$\begin{aligned} \sigma^2 &= \frac{1}{N} \sum_{i=1}^N (n_i - \langle n \rangle)^2 = \frac{1}{N} \sum_{i=1}^N (n_i^2 - 2n_i \langle n \rangle + \\ &+ \langle n \rangle^2) = \frac{1}{N} \sum_{i=1}^N n_i^2 - \frac{2\langle n \rangle}{N} \sum_{i=1}^N n_i + \langle n \rangle^2 \\ &= \langle n^2 \rangle - 2\langle n \rangle \langle n \rangle + \langle n \rangle^2 \\ &= \langle n^2 \rangle - \langle n \rangle^2 \end{aligned}$$

where

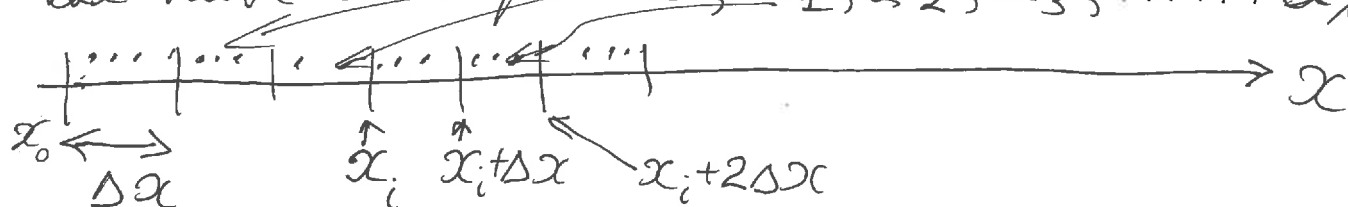
$$\langle n^2 \rangle = \frac{1}{N} \sum_{i=1}^N n_i^2$$

So, we get

$$\begin{aligned}\sigma^2 &= \langle (n - \langle n \rangle)^2 \rangle \\ &= \langle n^2 \rangle - \langle n \rangle^2\end{aligned}$$

## Probability density distributions

In a general case, random numbers  $\alpha_i$  can be ~~any~~ arbitrary real numbers. We have a sequence,  $\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_N$



We divide the axes into the intervals of the width  $\Delta x$ .

We define

$\Delta N(x_i, x_i + \Delta x)$  as the number of random numbers  $\alpha_i$  in the interval  $[x_i, x_i + \Delta x]$ , so

$$x_i < \alpha_i \leq x_i + \Delta x$$

## Probability density

$$\mathcal{P}(x_i) \equiv \lim_{\substack{\Delta x \rightarrow 0 \\ N \rightarrow \infty}} \frac{\Delta N(x_i, x_i + \Delta x)}{N \Delta x}$$

# Normalization

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$$\sum_i P(x_i) \stackrel{N}{=} \sum_i \frac{\Delta N(x_i, x_i + \Delta x)}{N \Delta x} \Delta x =$$

(all intervals)

$$= \frac{\sum_i \Delta N(x_i, x_i + \Delta x)}{N} = \frac{N}{N} = 1$$

Integral representation.

In the limit  $\Delta x \rightarrow 0$ ,  $N \rightarrow \infty$ ,  $\Delta N(x_i, x_i + \Delta) \gg 1$ , ~~we can write~~  
we can write

$$\sum_i P(x_i) \Delta x = \int_{-\infty}^{\infty} P(x) dx$$

Thus, the normalization condition is

$$\int_{-\infty}^{\infty} P(x) dx = 1$$

# The central limiting theorem.

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History: Moivre (1733), Laplace (1812),  
Lyapunov (1901).

We have a sequence of random numbers

$$\underbrace{a_1, a_2, a_3, \dots, a_N}_{\alpha=1} \mid \underbrace{a_{N+1}, a_{N+2}, a_{N+3}, \dots, a_{2N}}_{\alpha=2} \mid \dots$$
$$\dots \mid a_{\alpha N+1}, \dots, a_{\alpha N} \mid$$

We divide this sequence into groups of  $N$  numbers. The groups are numerated by the index  $\alpha=1, 2, \dots, M$ . The total number of numbers is  $NM$ .

We introduce a new variable

$$X_\alpha \equiv \frac{1}{N} \sum a_i$$

$$i \in [N(\alpha-1)+1, N\alpha]$$

So we have sequence  $X_1, X_2, X_3, \dots, X_M$

The mean value of  $a$

$$\langle a \rangle \equiv \frac{1}{NM} \sum_{i=1}^{NM} a_i$$

The variance

$$\sigma^2 = \langle (a - \langle a \rangle)^2 \rangle$$

Let us find the variance of random numbers  $X_\alpha$  and the mean value of  $X_\alpha$  /8

$$\langle X \rangle = \frac{1}{M} \sum_{\alpha=1}^M X_\alpha =$$

$$= \frac{1}{M} \sum_{\alpha=1}^M \frac{1}{N} \sum_{i \in [N(\alpha-1)+1, N\alpha]} a_i =$$

$$= \frac{1}{MN} \sum_{i=1}^N a_i = \langle a \rangle$$

Thus

$$\langle X \rangle = \langle a \rangle$$

Then, the variance

$$\Delta^2 \equiv \langle (X - \langle X \rangle)^2 \rangle =$$

$$= \frac{1}{M} \sum_{\alpha=1}^M (X_\alpha - \langle X \rangle)^2 = \frac{1}{M} \sum_{\alpha=1}^M \left[ \frac{1}{N} \sum_{i \in [N(\alpha-1)+1, N\alpha]} (a_i - \langle a \rangle) \right]^2$$

$$= \frac{1}{MN} \sum_{\alpha=1}^M \left[ \sum_{i_\alpha} (a_{i_\alpha} - \langle a \rangle) \right]^2$$

where

$$\sum_{i_\alpha} \equiv \sum_{i \in [N(\alpha-1)+1, N\alpha]}$$

Thus

$$\Delta^2 = \frac{1}{MN} \sum_{\alpha=1}^M \sum_{i_\alpha} \sum_{j_\alpha} (a_{i_\alpha} - \langle a \rangle)(a_{j_\alpha} - \langle a \rangle)$$



Assuming that fluctuations  $\delta a = a - \langle a \rangle$  are uncorrelated we find that

$$\begin{aligned} \sum_{i\alpha} \sum_{j\alpha} (a_{i\alpha} - \langle a \rangle) (a_{j\alpha} - \langle a \rangle) &= \\ &= \sum_{i\alpha=j\alpha} (a_{i\alpha} - \langle a \rangle)^2 + \sum_{i\alpha \neq j\alpha} \delta a_{i\alpha} \delta a_{j\alpha} = 0 \\ &= \sum_{i\alpha} \delta a_{i\alpha}^2 \end{aligned}$$

Therefore

$$\begin{aligned} \Lambda^2 &= \frac{1}{MN^2} \sum_{\alpha=1}^M \sum_{i\alpha} \delta a_{i\alpha}^2 = \\ &= \frac{1}{MN} \sum_{\alpha=1}^M \left( \frac{1}{N} \sum_{i\alpha} \delta a_{i\alpha}^2 \right) \end{aligned}$$

In the limit  $M, N \rightarrow \infty$

$$\frac{1}{N} \sum_{i\alpha} \delta a_{i\alpha}^2 = \sigma^2$$

We get

$$\Lambda^2 = \frac{1}{MN} \sum_{\alpha=1}^M \sigma^2 = \frac{\sigma^2}{N}$$

The central limiting theorem states that

$$\boxed{\Lambda^2 = \frac{\sigma^2}{N}}$$

Applications of the central limiting theorem. (11)

Kinetic energy  $\epsilon_i$  of molecules in gases.  
The mean energy of a molecule

$$\langle \epsilon \rangle = \frac{1}{N} \sum_i \epsilon_i$$

The variance

$$\sigma^2 = \langle (\epsilon - \langle \epsilon \rangle)^2 \rangle$$

The total energy  $E$  of molecules per molecule

$$E(N) = \frac{1}{N} \sum_{i=1}^N \epsilon_i$$

$$\langle E(N) \rangle = \langle \epsilon \rangle$$

The variance

$$\begin{aligned} \Lambda^2 &= \langle (E(N) - \langle E(N) \rangle)^2 \rangle = \left\langle \left( \frac{1}{N} \sum_i (\epsilon_i - \langle \epsilon \rangle) \right)^2 \right\rangle \\ &= \frac{\langle \sigma^2 \rangle}{N} \end{aligned}$$

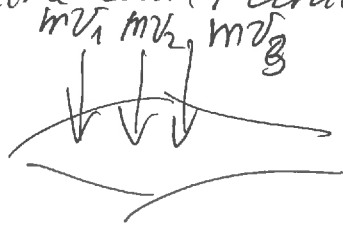
⚡ In the limit  $N \rightarrow \infty$  ( $N_A = 10^{23}$ )  
The variance of the total energy is very small

$$\Lambda^2 = \frac{\langle \sigma^2 \rangle}{N} \ll \langle \sigma^2 \rangle$$

The total energy is defined by the temperature  $T$ . The total energy defines all thermodynamic properties. A small

variance means stability of thermodynamic properties with respect to fluctuations. (1.)

The pressure of air on our skin is determined by the total momentum of molecules ~~that~~ that hit our skin per unit time and unit square



$$P = \frac{1}{N_{\Delta}} \sum_i m v_i$$

$$\langle (P - \langle P \rangle)^2 \rangle = \frac{\langle m v^2 \rangle}{N_{\Delta}} \ll \langle m v \rangle$$