

- 1) Normal distributions - PDFs & the Gaussian
- 2) SDOM - standard deviation of the mean
- 3) ~~weighted averages~~

3) Lab 2 Brownian Motion

- 1) typically ^{plan for} ~~with~~ N measurements of same thing for an experiment.
Often we might change an variable and go again, that's later

$$x_1, x_2, x_3, \dots, x_N$$

→ Our goal, then, is to develop a "best estimate" & "best width estimate" from these N

We start our statistical analysis process by assuming our distribution of measures x_i has a well-defined mean & standard deviation \bar{x} & σ .

Thus the central limit theorem says that M sets of these N measures would be "normal", \Rightarrow

Look at suboutline & 2 results

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sp 16
L3.2

Assumption:
Dist. is normal

that its probability density fctn
could be Gaussian.

$$\text{Prob}[x_i, x_i + dx] = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x_i - \bar{x})^2}{2\sigma^2}} dx$$

So now we can estimate the ^(joint) probability
of observing our original N x 's.

$$\text{Prob}_{x, \sigma}(x_1, x_2, \dots, x_N) = \text{Prob}_{x, \sigma}(x_1) \cdot \text{Prob}_{x, \sigma}(x_2) \cdot \dots \cdot \text{Prob}_{x, \sigma}(x_N)$$

and
point:
if probabilities
are multiplicative

Each of
these is a Gaussian



Note $e^x \cdot e^y = e^{x+y}$

3rd point:
JPs mult.
=> Σ of exponents

So joint probability =>

$$\text{Prob}_{x, \sigma}(x_1, x_2, \dots, x_N) \propto \frac{1}{\sigma^N} e^{-\frac{\sum (x_i - \bar{x})^2}{2\sigma^2}}$$

Q assumptions? - all σ 's are same, and \bar{x} 's

fine, but we don't ^{really} know $\bar{x} + \sigma$

to
maximize
JP

to pursue this, we'll use the "principle of
Maximum likelihood" eg. find $\bar{x} + \sigma$ that maximize
JP

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Q?: how to minimize SP?

4th step
≡
minimize
exp.

- minimize the (negative) exponent -

Q: how to do this?

$\frac{\partial}{\partial x}$ of $\sum_{i=1}^N \frac{(x_i - \bar{x})^2}{2\sigma^2}$, set to 0
(a min or max)

$$\Rightarrow \sum (x_i - \bar{x}) = 0 \Rightarrow$$

$$\bar{x} = \frac{\sum x_i}{N} = \bar{x}$$

So the sample average is the best estimate
assuming normal distribution, well-defined mean
& std. dev (σ)

to find σ_b , set $\frac{\partial}{\partial \sigma} [SP \text{ exp.}] = 0$ and solve
[thw 5.26]

$$\Rightarrow \sigma_b = \sqrt{\frac{1}{N} \sum (x_i - \bar{x})^2} = \text{our defn } \sigma_x$$

← sometimes $\frac{1}{N-1}$

2) SDom

have established, given certain (reasonable) assumptions, $\bar{X} = \bar{x}$ and $b_0 = b$

Still working w/ N x_i , what is "reliability" of $\bar{X} = \bar{x}$?

to consider, take data at $\bar{X}_k = \frac{\sum_{i=1}^N x_{i,k}}{N}$ $k=1, \dots, M$ (sets)
dist. of \bar{x}_k over M "sets"

we note that if x_1, x_2, \dots, x_N is normally distributed then \bar{x} is normally distributed (simple fn of x_i)

2nd, each x_i has the same true value \bar{X}

$$\text{so } \bar{X} = \frac{\bar{x}_1 + \bar{x}_2 + \bar{x}_3 \dots}{N} = \text{true value}$$

(New look at stability 2 results)

So measuring M sets doesn't change $\bar{X} = \bar{x}$ (of all)

Q: What is width estimate of \bar{x} ?

(add error in \bar{x} in quadrature)

$$\sigma_{\bar{x}} = \sqrt{\left(\frac{\partial \bar{x}}{\partial x_1} \Delta x_1\right)^2 + \left(\frac{\partial \bar{x}}{\partial x_2} \Delta x_2\right)^2 + \dots + \left(\frac{\partial \bar{x}}{\partial x_N} \Delta x_N\right)^2}$$

but

$$\Delta x_1 = \Delta x_2 = \Delta x_N = \Delta x$$

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and: $\frac{\partial \bar{x}}{\partial x_1} = \frac{\partial \bar{x}}{\partial x_2} = \dots = \frac{\partial \bar{x}}{\partial x_N} = \frac{1}{N}$

$$\Rightarrow \sigma_{\bar{x}} = \sqrt{\left(\frac{1}{N} \sigma_x\right)^2 + \dots + \left(\frac{1}{N} \sigma_x\right)^2}$$
$$= \frac{\sigma_x}{\sqrt{N}} \quad \text{SDOM}$$

(What we see in reporting error)

3) Brownian Motion

- Say we put 25 micron sphere in deionized water at room temp

- what would we see? (under)

" " " " with 40x mag.? (still under)

- what would we see if made movies with 40x digital microscope

(still under)
(depends on frame rate)

- lets make frame rate 0.25 fps (ask for what the news)

- (show movie)

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L3.6

we note: (ask for this)

- spheres appear to move
- "motion" is called Brownian Motion
- there may be other factors affecting their motion (query)

Why do this?

$$\overline{\Delta x^2} = 2 D_{ax} \Delta t$$

(also $\overline{\Delta y^2} = 2 D_{ay} \Delta t$
 $\overline{\Delta r^2} = 4 D_{ar} \Delta t$)

- first, why $\underline{\Delta x}$ ($\underline{\Delta y}$, or)?

- next what does $\overline{\Delta x^2}$ mean?

- note that $\sigma_{\Delta x}^2 = \overline{\Delta x^2} - (\overline{\Delta x})^2$

what do expect $\overline{\Delta x}$ to be for BM?

[mention it should be 0, but this might be 'experimental zero' \Rightarrow

$$\text{then } \overline{\Delta x^2} \approx \sigma_{\Delta x}^2$$

- what is $\sigma_{\Delta x}^2$? could we vary it?
 how is that useful?

\$1M question, what is D ?
(the 'diffusion-constant' first
hypothesized by Einstein

with $D = k_B T$ $T = ?$, units?

and $f = 6\pi\eta R$ (drag factor, calculable)

\Rightarrow If we can estimate D + its error (δD) \Leftarrow
then we can " k_B + its error

In the lab we will:

- 1) make movies of spheres undergoing BM
- 2) analyze these, first using Logger Pro
- 3) get LP data \Rightarrow python (or MC)
- 4) ? calc Δx , $\overline{\Delta x^2}$ vs $\overline{\Delta t^2}$
 \uparrow random (data quality)
- 5) ? do statistics
- 6) ? est D + δD
- 7) calc k_B + δk_B
- 8) 'Time Evolution'

ask
students
to
complete
last