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Reminder of simple prob. things

- How to get estimates
- How to process uncertainty
- How to deal with Interval Uncertainty.

$$g(x) = \frac{1}{\sqrt{2\pi} \sigma} \exp\left(-\frac{(x-a)^2}{2\sigma^2}\right)$$

Prob. Density
for Gauss Distr.

$$\text{Prob} (x \leq \textcircled{S} \leq x + \Delta x) \approx g(x) \cdot \Delta x$$

random
variable

$$g(x) = \frac{\text{Prob} (x \leq \textcircled{S} \leq x + \Delta x)}{\Delta x}$$

Given: some measurements $x_1, \dots, x_n$

Solar: We know a, σ we simulate the distribution and predict the probability at dif points.

? How do we find a and σ ?

Idea is to select the most probable values a, σ
e.g.

$$H_1 = a=0, \sigma=1$$

$$H_2 = a=2.0, \sigma=1$$

$$\textcircled{x_i \approx 0}$$

If we use hypothesis 1 (H_1)

$$\frac{1}{\sqrt{2\pi} \cdot 1} \cdot \exp(-\sigma^2) = 0$$

If we use hypo 2 (H_2)

$$\frac{1}{\sqrt{2\pi} \cdot 1} \cdot \exp(-200)$$

↓
200

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1st observation

$$\frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x_1-a)^2}{2\sigma^2}\right) \Delta x$$

Depends accuracy
of the measured

2nd observation

$$\frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x_2-a)^2}{2\sigma^2}\right) \Delta x$$

⋮

nth observation

$$\frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x_n-a)^2}{2\sigma^2}\right) \Delta x$$

! We multiply

$$\left(\frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x_1-a)^2}{2\sigma^2}\right) \Delta x\right) \cdot \left(\frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x_2-a)^2}{2\sigma^2}\right) \Delta x\right) \cdots \left(\frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x_n-a)^2}{2\sigma^2}\right) \Delta x\right)$$

Max
a, σ

! Tricks!

$$a^b \cdot a^c = a^{(b+c)}$$

$$\frac{1}{\sqrt{2\pi}} \cdot \frac{1}{\sigma^n} \exp\left(-\frac{(x_1-a)^2}{2\sigma^2}\right) \exp\left(-\frac{(x_2-a)^2}{2\sigma^2}\right) \cdots \exp\left(-\frac{(x_n-a)^2}{2\sigma^2}\right)$$

$$\text{Const} \frac{1}{\sigma^n} \exp\left(-\frac{(x_1-a)^2}{2\sigma^2} - \frac{(x_2-a)^2}{2\sigma^2} - \cdots - \frac{(x_n-a)^2}{2\sigma^2}\right) \rightarrow \text{Max}_{a, \sigma}$$

Ex. Derive with respect to a

$$-\frac{(x_1 - a)^2}{2\sigma^2} - \frac{(x_2 - a)^2}{2\sigma^2} - \dots - \frac{(x_n - a)^2}{2\sigma^2} \rightarrow \text{Max}_{a, \sigma}$$

constant

$\frac{\partial x_i}{\partial a} = 0$ We can take the constants out $\left(\frac{1}{2\sigma^2}\right)$, then derivate the inner terms.

$$\frac{\partial a}{\partial a} = 1 \quad \frac{1}{2\sigma^2} \left(-2(x_1 - a)(-1) + 2(x_2 - a)(-1) + \dots + 2(x_n - a)(-1) \right) = 0$$

⚠ If we multiply both sides by some constant remains true
So we got:

$$(x_1 - a) + (x_2 - a) + \dots + (x_n - a) = 0$$

How we find σ ?

$$-\frac{(x_1 - a)^2}{2\sigma^2} - \dots - \frac{(x_n - a)^2}{2\sigma^2} - n \ln \sigma \rightarrow \text{Max } a, \sigma$$

$$\frac{(x_1 - a)^2}{2\sigma^2} + \dots + \frac{(x_n - a)^2}{2\sigma^2} + n \ln \sigma \rightarrow \text{min } a, \sigma$$

Now let's diff with respect σ

$$-\frac{(x_1-a)^2}{2\sigma^2} + \dots + \frac{(x_n-a)^2}{2\sigma^2} + n \ln \sigma \rightarrow \max_{a, \sigma}$$

$$(x_1-a)^2 \frac{\sigma^{-2}}{2} + \dots + (x_n-a)^2 \frac{\sigma^{-2}}{2} + n \ln \sigma \rightarrow \min_{a, \sigma}$$

$$= \frac{1}{2} \sigma^{-3} (x_1-a)^2 + \dots + \frac{1}{2} \sigma^{-3} (x_n-a)^2 + n \frac{1}{\sigma} = 0$$

$$-\sigma^{-3} (x_1-a)^2 + \dots - \sigma^{-3} (x_n-a)^2 + n \frac{1}{\sigma} = 0$$

$$n \frac{1}{\sigma} = \frac{(x_1-a)^2}{\sigma^3} + \dots + \frac{(x_n-a)^2}{\sigma^3}$$

$$n \frac{1}{\sigma} = \frac{1}{\sigma^3} \left[(x_1-a)^2 + \dots + (x_n-a)^2 \right]$$

$$n = \frac{1}{\sigma^2} \left[(x_1-a)^2 + \dots + (x_n-a)^2 \right]$$

$$\sigma^2 = \frac{(x_1-a)^2 + \dots + (x_n-a)^2}{n}$$

△ You choose something with the highest probability.

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- Data Fusion: If you have several measurements of a source, you merge them together.

x - same quantity.

$\tilde{x}_1, \tilde{x}_2$ - two results measuring the same quantity

$\Delta x_1 = \tilde{x}_1 - x$ - normally distr. w/0 mean and st. dev. σ_1

$\Delta x_2 = \tilde{x}_2 - x$ - normally distr.

$$\begin{array}{rcl} \tilde{x}_1 = 140 & \pm 30 & = \sigma_1 \\ \tilde{x}_2 = 110 & \pm 10 & = \sigma_2 \end{array}$$

Common Sense approach

choose a more accurate value

Ideally do not ignore

Combine

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Idea: Same idea:

We have two measurements:

$$\frac{1}{\sqrt{2\pi}\sigma_1} \exp\left(-\frac{(x-\tilde{x}_1)^2}{2\sigma_1^2}\right) \Delta x \cdot \frac{1}{\sqrt{2\pi}\sigma_2} \exp\left(-\frac{(x-\tilde{x}_2)^2}{2\sigma_2^2}\right) \Delta x \rightarrow \text{Max}$$

the prob.

for the 1st measurement

We got x_1

and second

We got x_2

△ We choose the one with highest probability.

△ How to deal with this?

We take logarithms.

We conclude:

$$\frac{-(x-\tilde{x}_1)^2}{2\sigma_1^2} - \frac{(x-\tilde{x}_2)^2}{2\sigma_2^2} \rightarrow \text{Max}$$

When is this the max?

a: When the reverse is the minimum.

This is what is called the least square Methods (LSM)

$$\frac{(x-\tilde{x}_1)^2}{2\sigma_1^2} + \frac{(x-\tilde{x}_2)^2}{2\sigma_2^2} \rightarrow \text{min}$$

$$2(x-\tilde{x}_1)$$

$$\frac{2(x-\tilde{x}_1)}{2\sigma_1^2} + \frac{2(x-\tilde{x}_2)}{2\sigma_2^2} = 0$$

$$x(\sigma_1^{-2} + \sigma_2^{-2}) = \tilde{x}_1\sigma_1^{-2} + \tilde{x}_2\sigma_2^{-2}$$

$$x = \frac{\tilde{x}_1\sigma_1^{-2} + \tilde{x}_2\sigma_2^{-2}}{\sigma_1^{-2} + \sigma_2^{-2}}$$

Case 1:

$$\tilde{x}_1 = 140 \quad \pm 10 = \sigma_1$$

$$x_2 = 110 \quad \pm 10 = \sigma_2$$

$$\frac{110 \cdot \frac{1}{100} + 140 \cdot \frac{1}{100}}{\frac{1}{100} + \frac{1}{100}} = \frac{110 + 140}{2} = \frac{250}{2} = 125$$

Case 2:

$$\tilde{x}_1 = 140 \quad \pm 30 = \sigma_1$$

$$\tilde{x}_2 = 110 \quad \pm 10 = \sigma_2$$

$$\frac{110 \cdot \frac{1}{9} + 140}{\frac{1}{9} + 1}$$

$$\frac{140 \cdot \frac{1}{900} + 110 \cdot \frac{1}{100}}{\frac{1}{900} + \frac{1}{100}}$$

$$\frac{40 \cdot \frac{1}{9} + 110}{\frac{1}{9} + 1} = \frac{140 + 9 \cdot 110}{1 + 9} = \frac{1130}{10} = 113$$

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Exercise Do the case of n measurement.

$$X \approx x_1 \sigma_1$$

$$X \approx x_2 \sigma_2$$

q3=∞.

$$X \approx x_n \sigma_n$$

$$\frac{1}{\sqrt{2\pi}\sigma_1} \exp\left(-\frac{(x-\tilde{x}_1)^2}{2\sigma_1^2}\right) \Delta x \cdot \dots \cdot \frac{1}{\sqrt{2\pi}\sigma_n} \exp\left(-\frac{(x-\tilde{x}_n)^2}{2\sigma_n^2}\right) \Delta x \rightarrow \text{Max}$$

must.

$$-\frac{(x-\tilde{x}_1)^2}{2\sigma_1^2} - \dots - \frac{(x-\tilde{x}_n)^2}{2\sigma_n^2} \rightarrow \text{Max}$$

$$\rightarrow \frac{(x-\tilde{x}_1)^2}{2\sigma_1^2} + \dots + \frac{(x-\tilde{x}_n)^2}{2\sigma_n^2} \rightarrow \text{min}$$

$$\frac{2(x-\tilde{x}_1)}{2\sigma_1^2} + \dots + \frac{2(x-\tilde{x}_n)}{2\sigma_n^2} = 0$$

$$x(\sigma_1^{-2} + \dots + \sigma_n^{-2}) = \tilde{x}_1 \sigma_1^{-2} + \dots + \tilde{x}_n \sigma_n^{-2}$$

$$x = \frac{\tilde{x}_1 \sigma_1^{-2} + \dots + \tilde{x}_n \sigma_n^{-2}}{\sigma_1^{-2} + \dots + \sigma_n^{-2}}$$

How accurate is it?

Same constant
... $\exp \left(-\frac{(x-\tilde{x}_1)^2}{2\sigma_1^2} - \frac{(x-\tilde{x}_2)^2}{2\sigma_2^2} \right)$

The normal distribution we have it
in this form.

If we can transform

$$\text{const} \cdot \exp \left(-\frac{(x-a)^2}{2\sigma^2} \right)$$

$$\frac{(x-\tilde{x}_1)^2}{2\sigma_1^2} + \frac{(x-\tilde{x}_2)^2}{2\sigma_2^2} \stackrel{?}{=} \frac{(x-a)^2}{2\sigma^2}$$

$$\frac{x^2 - 2x\tilde{x}_1 - \tilde{x}_1^2}{2\sigma_1^2} + \frac{x^2 - 2x\tilde{x}_2 - \tilde{x}_2^2}{2\sigma_2^2}$$

$$x^2 \left(\frac{1}{2\sigma_1^2} + \frac{1}{2\sigma_2^2} \right) - x \left(\frac{\tilde{x}_1}{\sigma_1^2} + \frac{\tilde{x}_2}{\sigma_2^2} \right) = \left(\frac{\tilde{x}_1^2}{\sigma_1^2} + \frac{\tilde{x}_2^2}{\sigma_2^2} \right)$$

$$\frac{1}{2\sigma^2} = \frac{1}{2\sigma_1^2} + \frac{1}{2\sigma_2^2}$$

$$\sigma^2 = \frac{1}{\frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2}} = \frac{1}{\frac{\sigma_1^2 + \sigma_2^2}{\sigma_1^2 \sigma_2^2}} = \frac{\sigma_1^2 \sigma_2^2}{\sigma_1^2 + \sigma_2^2}$$

$$\propto \exp \left(- \left(\frac{x - \tilde{x}_1}{2\sigma_1^2} \right)^2 + \dots + \frac{(x - \tilde{x}_n)^2}{2\sigma_n^2} \right)$$

$$\frac{1}{\sigma^2} = \frac{1}{\sigma_1^2} + \dots + \frac{1}{\sigma_n^2}$$

$$\sigma^2 = \frac{1}{\frac{1}{\sigma_1^2} + \dots + \frac{1}{\sigma_n^2}} = \frac{1}{n} = \frac{q_{\text{var}}}{n}$$

[HW]

Start with some value. (x) $\sigma_1, \dots, \sigma_n$ - input

① Simulate measurement errors

$$\begin{cases} \tilde{x}_1 = (x + \text{gauss}(\dots)) \cdot \sigma_1 \\ \vdots \\ \tilde{x}_n = (x + \text{gauss}(\dots)) \cdot \sigma_n \end{cases}$$

repeat

$$\sqrt{\frac{\sum (x_i - q)^2}{n}}$$

$$x_{\text{new}} = \frac{\tilde{x}_1 \cdot \sigma_1^{-2} + \dots + \tilde{x}_n \cdot \sigma_n^{-2}}{\sigma_1^{-2} + \dots + \sigma_n^{-2}}$$

$$\sqrt{\frac{1}{N} \sum (x_{\text{new}} - x)^2} \approx \frac{1}{\sigma_1^{-2} + \dots + \sigma_n^{-2}}$$