

Last Time: "Derivation" of Gaussian distribution.

$$\Rightarrow \text{Found } P_G = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

Prob. of a measurement falling between x_1 & x_2 is:

$$P(x_1, x_2) = \int_{x_1}^{x_2} P_G(x; \mu, \sigma) dx$$

68-95-99.7 Rule

Prob. of a measurement falling within one std. dev. of mean is:

$$\mu - \sigma < x < \mu + \sigma \Rightarrow 68\%$$

$$\mu - 2\sigma < x < \mu + 2\sigma \Rightarrow 95\%$$

$$\mu - 3\sigma < x < \mu + 3\sigma \Rightarrow 99.7\%$$

Summary of Prob. dist'n's:

Binomial:

$$P_B(x; n, p) = \frac{n!}{x!(n-x)!} p^x (1-p)^{n-x}$$

$$\mu = np \quad \sigma^2 = np(1-p)$$

Poisson:

$p \ll 1$ limit of
Binomial dist'n

(small prob. of
success in any
individual trial)

$$P_P(x; \mu) = \frac{\mu^x}{x!} e^{-\mu}$$

mean: μ

$$\sigma = \sqrt{\mu}$$

Relevant for counting experiments

Gaussian:

n large $\{ np \gg 1$ limit of
Binomial dist'n.

$$P_G(x; \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

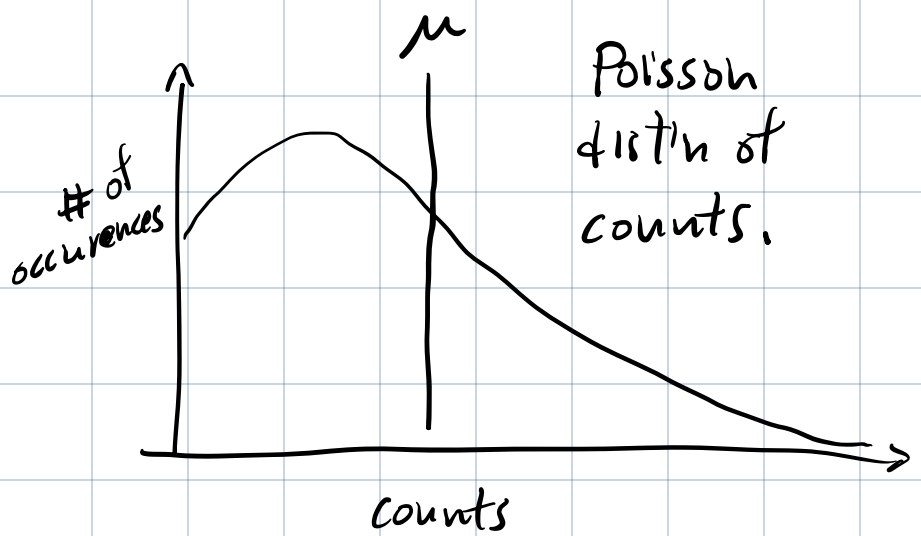
mean: μ std. dev.: σ

Uncertainty in Counting Exp'ts.

In principle can meas. no of events in a time interval w/ absolute certainty.

However, if repeat meas. many times will get statistical fluctuations in the no. of counts.

trial	counts
1	18
2	24
3	21
4	19
⋮	⋮



std. dev. of mean is $\sigma = \sqrt{\mu}$

In practice, often cannot make many repeated experiments to map out the full dist'n in order to properly estimate μ .

∴ in counting expts often do the meas. once
 & assume that our result is a reasonable est. of μ .

Assume that $\mu = N$ & $\sigma = \sqrt{N}$
 ↑
 no. of counts.

Propagation of Errors

Suppose we want to determine some quantity y that depends on meas. values

$$u \pm \sigma_u \quad \& \quad v \pm \sigma_v.$$

If $y = f(u, v)$, what is σ_y ?

Eg. In Boltzmann's Const.

$$\ln I \approx \ln I_0 + \left(\frac{e}{k_B T} \right) V$$

If you plot $\ln I$ vs V , slope is equal to

$$m = \frac{e}{k_B T}$$

Assume that you've determined $m \pm \sigma_m$ & $T \pm \sigma_T$.
Now, you want to calc. k_B (assume e is known)

$$k_B = \frac{e}{m T}$$

now $k_B(m, T)$

know $m \pm \sigma_m$ & $T \pm \sigma_T$

What is σ_{K_B} ?

$$y = f(u) \quad \text{know} \quad u \pm \sigma_u$$

Want to find σ_y .

Recall that if we have a fun of one variable, can approx $f(u)$ as a Taylor series

$$f(u) = f(\bar{u}) + (u - \bar{u}) f'(u) \Big|_{u=\bar{u}}$$

Taylor series expansion about $u = \bar{u}$.

Assume that $f(\bar{u}) \approx \bar{f}$

$$f = \bar{f} + (u - \bar{u}) f'(\bar{u})$$

$$\therefore \underline{f - \bar{f}} = (u - \bar{u}) f'(\bar{u}) = (u - \bar{u}) \frac{df}{du} \Big|_{\bar{u}}$$

$$\sigma = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (x_i - \mu)^2} \quad \text{Definition of std. dev.}$$

In a similar way, we can find σ_f as:

$$\sigma_f^2 = \frac{1}{N-1} \sum_{i=1}^N (f_i - \bar{f})^2$$

$$\therefore \sigma_f^2 = \frac{1}{N-1} \sum_{i=1}^N \left((u_i - \bar{u}) \left. \frac{df}{du} \right|_{\bar{u}} \right)^2$$

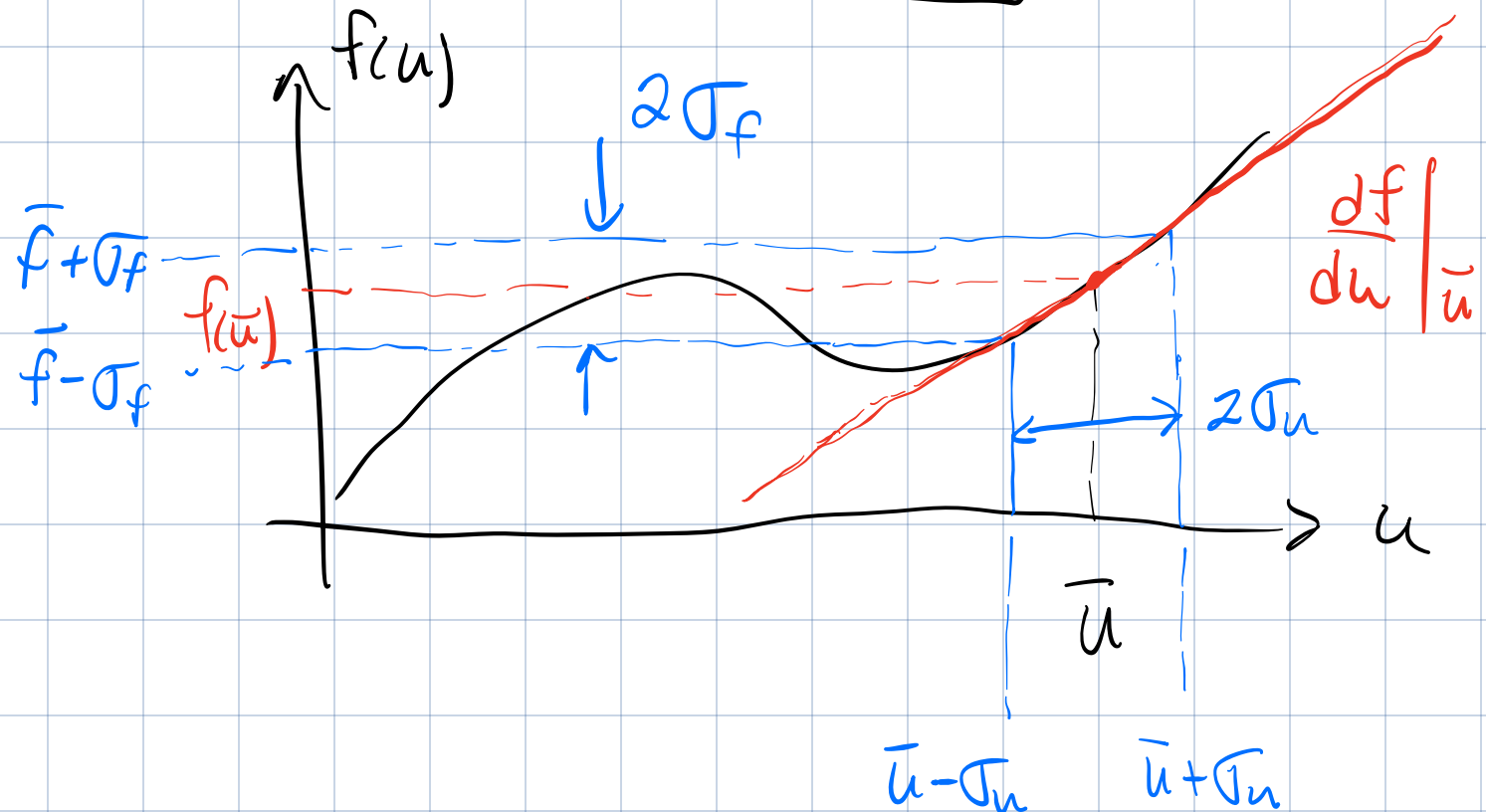
$$= \frac{1}{N-1} \sum_{i=1}^N \left[(u_i - \bar{u})^2 \underbrace{\left(\left. \frac{df}{du} \right|_{\bar{u}} \right)^2}_{\text{indep. of } i} \right]$$

$$\therefore \sigma_f^2 = \underbrace{\left(\frac{1}{N-1} \sum_{i=1}^N (u_i - \bar{u})^2 \right)}_{\sigma_u^2} \left(\left. \frac{df}{du} \right|_{\bar{u}} \right)^2$$

$$\therefore \sigma_f^2 = \sigma_u^2 \left(\frac{df}{du} \Big|_{\bar{u}} \right)^2$$

Prop. of errors for a function of one variable.

$$\sigma_f = \sigma_u \left| \frac{df}{du} \Big|_{\bar{u}} \right|$$



For the red line, slope is $\frac{\text{rise}}{\text{run}} = \frac{\cancel{2}\sigma_f}{\cancel{2}\sigma_u}$

\hat{v} must also equal $\left. \frac{df}{du} \right|_{\bar{u}}$

$$\frac{\sigma_f}{\sigma_u} = \left. \frac{df}{du} \right|_{\bar{u}} \Rightarrow \sigma_f = \sigma_u \left. \frac{df}{du} \right|_{\bar{u}}$$

For a fcn of more than one variable

$$y = f(u, v, \dots)$$

the first order Taylor series expansion is:

$$y = f(u, v, \dots) = f(\bar{u}, \bar{v}, \dots) + (u - \bar{u}) \left. \frac{\partial f}{\partial u} \right|_{\bar{u}} + (v - \bar{v}) \left. \frac{\partial f}{\partial v} \right|_{\bar{v}} + \dots$$

$$\text{Assume } f(\bar{u}, \bar{v}, \dots) \approx \bar{f}$$

$$\therefore f - \bar{f} \approx (u - \bar{u}) \left. \frac{\partial f}{\partial u} \right|_{\bar{u}} + (v - \bar{v}) \left. \frac{\partial f}{\partial v} \right|_{\bar{v}} + \dots$$

$$\sigma_f^2 \approx \frac{1}{N-1} \sum_{i=1}^N (f_i - \bar{f})^2$$

$$= \frac{1}{N-1} \sum_{i=1}^N \left[(u_i - \bar{u}) \left. \frac{\partial f}{\partial u} \right|_{\bar{u}} + (v_i - \bar{v}) \left. \frac{\partial f}{\partial v} \right|_{\bar{v}} + \dots \right]^2$$

$$\therefore \sigma_f^2 = \frac{1}{N-1} \sum_{i=1}^N \left[(u_i - \bar{u})^2 \left(\left. \frac{\partial f}{\partial u} \right|_{\bar{u}} \right)^2 + (v_i - \bar{v})^2 \left(\left. \frac{\partial f}{\partial v} \right|_{\bar{v}} \right)^2 + \dots \right.$$

$$\left. + 2 (u_i - \bar{u}) (v_i - \bar{v}) \left(\left. \frac{\partial f}{\partial u} \right|_{\bar{u}} \right) \left(\left. \frac{\partial f}{\partial v} \right|_{\bar{v}} \right) + \dots \right]$$

$$\frac{1}{N-1} \sum_{i=1}^N (u_i - \bar{u})^2 = \sigma_u^2$$

$$\frac{1}{N-1} \sum_{i=1}^N (v_i - \bar{v})^2 = \sigma_v^2$$

↑
"Variance" of u

Define the covariance σ_{uv}^2

$$\sigma_{uv}^2 = \frac{1}{N-1} \sum_{i=1}^N (u_i - \bar{u})(v_i - \bar{v})$$

$$\begin{aligned} \sigma_f^2 = & \sigma_u^2 \left(\frac{\partial f}{\partial u} \bigg|_{\bar{u}} \right)^2 + \sigma_v^2 \left(\frac{\partial f}{\partial v} \bigg|_{\bar{v}} \right)^2 + \dots \\ & + 2\sigma_{uv}^2 \left(\frac{\partial f}{\partial u} \bigg|_{\bar{u}} \right) \left(\frac{\partial f}{\partial v} \bigg|_{\bar{v}} \right) + \dots \end{aligned}$$

If the meas. of u & v follow Gaussian dist'n,
then

$$\sum (u_i - \bar{u}) = 0$$

$$\sum (v_i - \bar{v}) = 0$$

$$\sum (u_i - \bar{u})(v_i - \bar{v}) = 0$$

$$\Rightarrow \text{covariance } \sigma_{uv}^2 = 0.$$

$$\sigma_f^2 = \sigma_u^2 \left(\frac{\partial f}{\partial u} \Big|_{\bar{u}} \right)^2 + \sigma_v^2 \left(\frac{\partial f}{\partial v} \Big|_{\bar{v}} \right)^2 + \dots$$

Propagation of Errors.