

$$\boxed{\sum_{i=1}^n x_i = N}$$

$$0 = N - \sum_{i=1}^n x_i$$

$$0 = (N - \sum_{i=1}^n x_i)$$

$$\text{only way } 0 = \frac{dP}{dx}$$

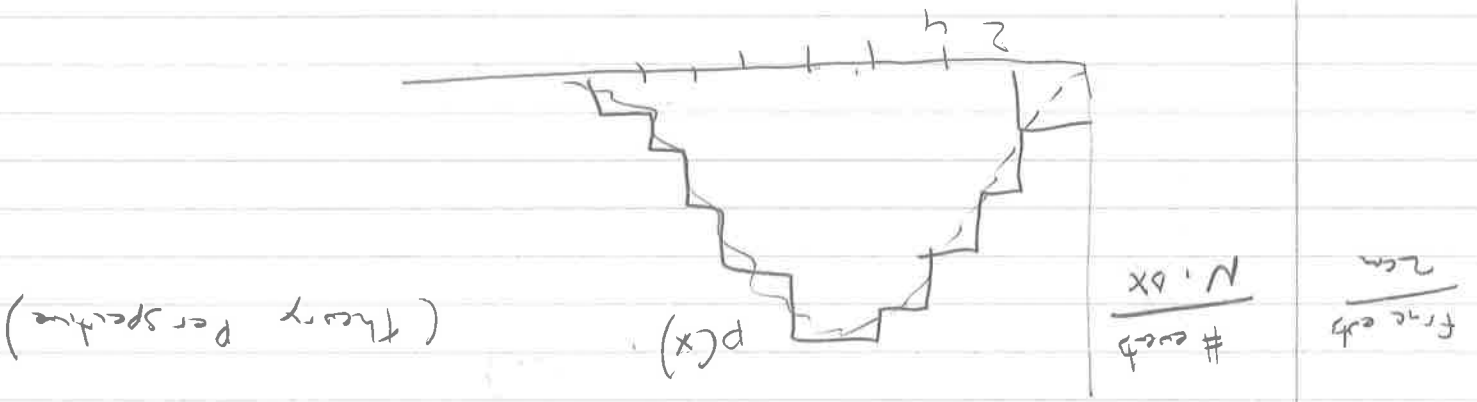
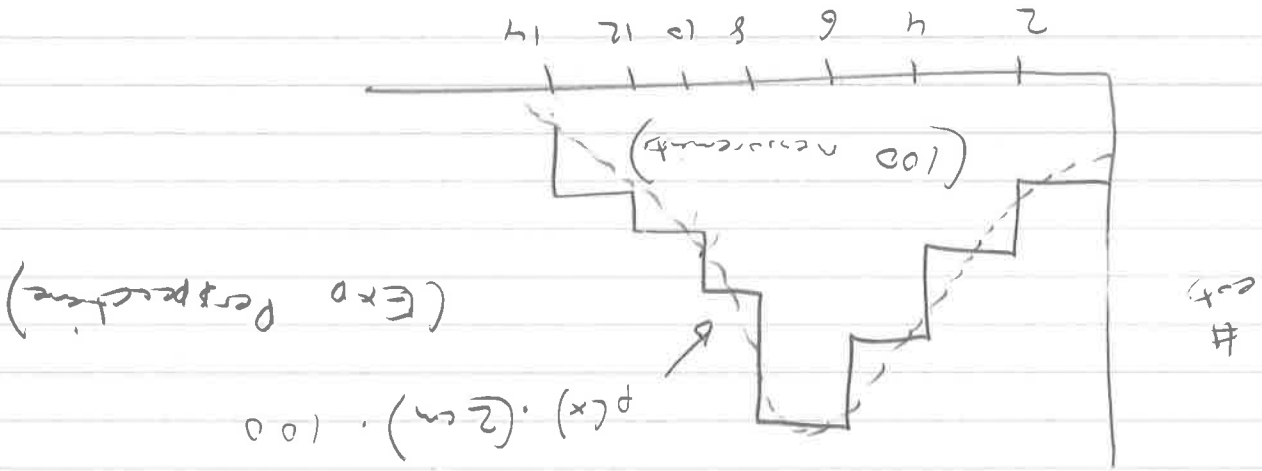
$$= - \frac{P}{\sum_{i=1}^n (x_i - x)}$$

$$\frac{dP}{dx} = P \cdot \frac{dx}{d} - \left(\frac{\sum_{i=1}^n (x_i - x)^2}{\sum_{i=1}^n (x_i - x)^2} \right)$$

$$\boxed{\frac{dP}{dx} = 0}$$

The main technique (not "trick" because we will use it many times) is to maximize probability by setting

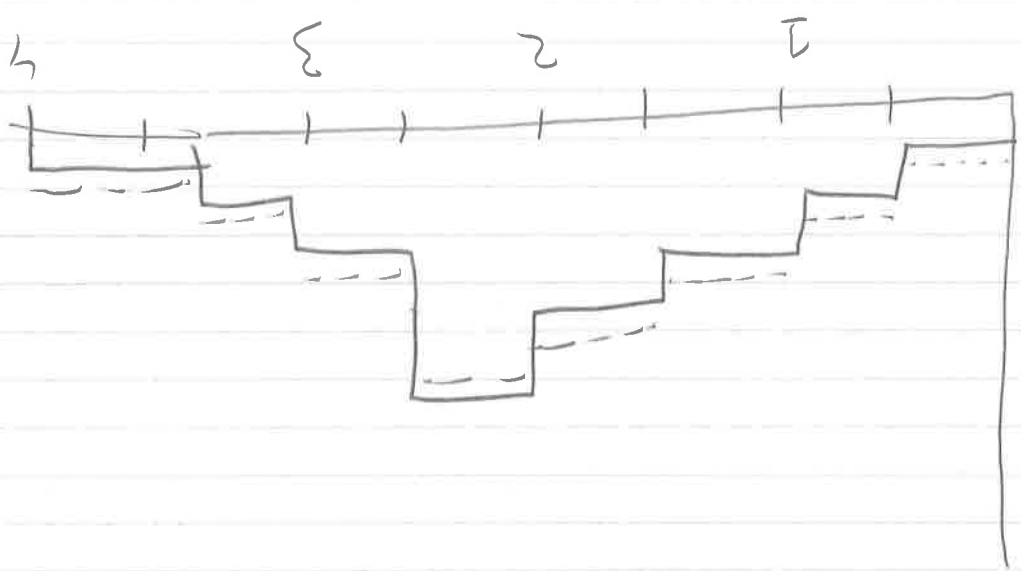
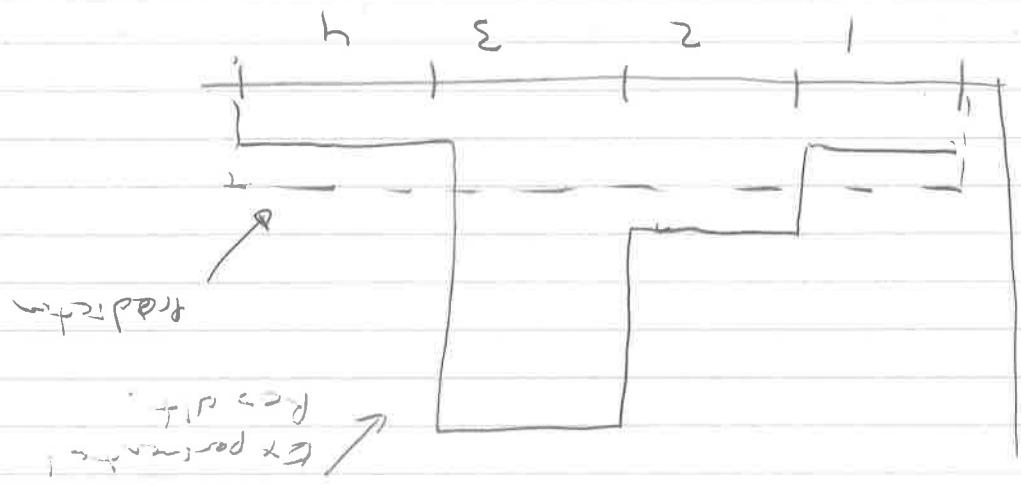
While it may seem like you think about it, you must consider to account for normalization of prediction to experiment.



Distributions!

Science has one and only one purpose: predicting the results of experiments!

If most experiments are this way (even without quantum mechanics!) with similar but non-identical results in well-performed experiments... what does a prediction look like



Prediction: # of events in a particular bin
 Result: # of events in a particular bin.

This would tend to mean our theory (which predicts outcomes of experiments) depends explicitly on our choice of bins. Also, it will depend on number of measurements. Not pretty! We get a bit from fixing this.

Our theory would better tell us what's going on!

$$p(x) = \text{probability to measure } x.$$

Except that doesn't work!

Q: What is probability to measure exactly the value "1.23576125312"?

A: 0.

Probabilities are only non-zero over non-infinitesimal ranges.

We can do a lot with our prediction
 $p(x)$ which is called a probability
 distribution function (PDF).

$$\text{I) } \int_{-\infty}^{\infty} p(x) dx = ?$$

$$\text{II) } \underline{\bar{x}} = \int x p(x) dx$$

is they predict for average value.

$$\text{III) RMS:}$$

$$\sigma_x^2 = \int_{-\infty}^{\infty} (x - \bar{x})^2 f(x) dx$$

(It will turn out σ_x is related to uncertainty)

\Rightarrow Now some specific

distributions.

INTRODUC, will prove later

There are lots of ways to think about what comes next...

1)

Jump to answer:

$$N_{pred} = p(x) \cdot \Delta x \cdot N$$

predicted
for particular
experience

frequency
prediction

bin size
and number
of measurements

made (exp dependent)

Q: Suppose x is a measurement of "cm"

What are dimensions of $p(x)$?

A) $\frac{1}{cm}$ "general" $[p(x)] = \left[\frac{1}{x} \right]$

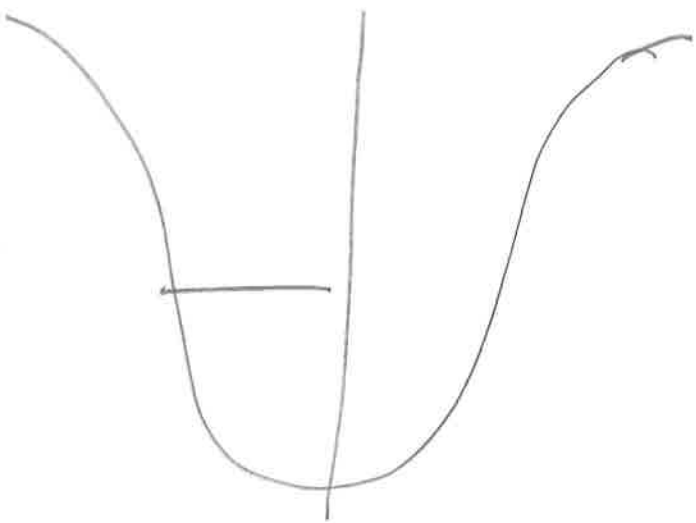
2) $P(x, x_0) = \int_{x_0}^x p(x) dx$

$\rightarrow p(x) = \frac{d}{dx} P(x, x_0)$

$\rightarrow p(x) = \frac{d}{dx} P(x, x_0)$

3) Book writes: $p(x) dx = \text{prob (x to } x+dx)$

Standard Interpretation of Errors



We know how to handle $\int_a^{-a} g(x)$

What if, say $\neq 0$

$$\frac{1}{\sqrt{2\pi}\sigma} \int_0^{\infty} \exp\left(-\frac{x^2}{2\sigma^2}\right) dx \quad ?$$

Not analytically possible

$$\text{erf}(x) = \frac{\sqrt{\pi}}{2} \int_0^x e^{-t^2} dt$$

(Interpretation $\sigma^2 = \frac{1}{2}$, $P[-x, x]$)

$$P = \frac{1}{\sqrt{\pi}} \int_x^{-x} \exp(-x^2) dx$$

$$= \frac{\sqrt{\pi}}{2} \int_x^{\infty} \exp(-x^2) dx \equiv \text{erf}(x)$$

16	$\text{erf}\left(\frac{1}{\sqrt{2}}\right) =$	68.3%
20	$\text{erf}\left(\frac{2}{\sqrt{2}}\right) =$	95.4%
30	$\text{erf}\left(\frac{3}{\sqrt{2}}\right) =$	98.5%
40	$\text{erf}\left(\frac{4}{\sqrt{2}}\right) =$	99.5%
50	$\text{erf}\left(\frac{5}{\sqrt{2}}\right) =$	99.9%

Standard Deviation of the Mean

Suppose we make N measurements of a quantity x each with uncertainty σ .

We calculate the mean:

$$\bar{x} = \frac{x_1 + x_2 + \dots + x_n}{N}$$

Note that as each x_i is centered on the true value x , our \bar{x} will also be centered on x , but with better uncertainty!

Just use error propagation

$$\sigma_{\bar{x}} = \sqrt{\left(\frac{\partial \bar{x}}{\partial x_1} \cdot \sigma\right)^2 + \dots + \left(\frac{\partial \bar{x}}{\partial x_n} \cdot \sigma\right)^2}$$

But each $\frac{\partial \bar{x}}{\partial x_i} = \frac{1}{N}$, so we have

$$\sigma_{\bar{x}} = \sqrt{\left(\frac{1}{N} \sigma\right)^2 + \dots + \left(\frac{1}{N} \sigma\right)^2}$$

$$= \sigma \cdot \sqrt{N \cdot \frac{1}{N^2}} = \sigma \cdot \frac{1}{\sqrt{N}}$$

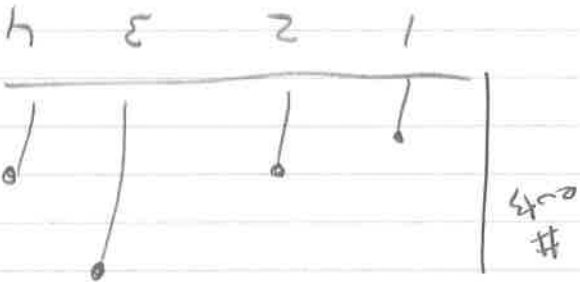
Repeating Measurement N times reduces uncertainty by a factor

$$\frac{1}{\sqrt{N}}$$

Histograms + uncertainty

Histograms

Have students pick numbers from 1 to 4
Tally the results and build a histogram

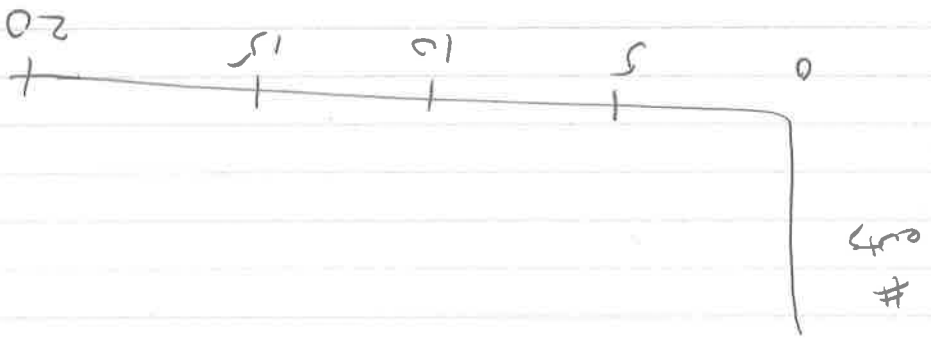


(Probably will be biased toward 3!)

Bias: Can mention (as motivation) statistics / uncertainty of \sqrt{N} to check for bias.

Q: How to handle data like:

15.4, 11.3, 12.1, 6.5, 10.1, 17.3



Note: Now each bin has a width and a number of entries

(2 things to keep track of)

Well assume (for now) all have same width (even spaced).

Maybe?

(Continued)

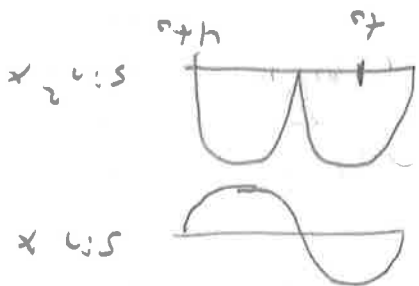
Johnson Noise

Last time, showed

(Actually, both "thermal" and "shot" noise)

$$\langle V^2 \rangle_{t_0} = R k T \frac{1}{t_0}$$

We need to convert this to frequency domain. think of which frequencies are contributing to this RMS



If we calculate RMS of a function with frequency $\nu = \frac{1}{4 t_0}$ for the interval

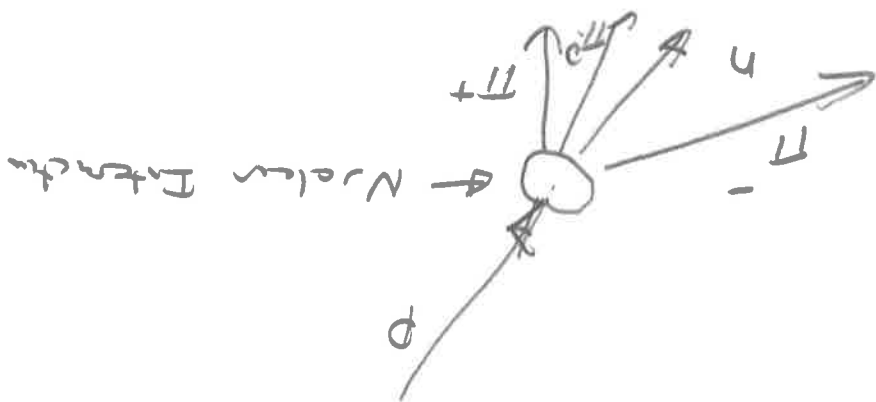
$$\langle V^2 \rangle_{\nu t_0} = 4 R k T \nu t_0$$

If we want to find RMS for frequencies in range ν_1 to ν_2

$$\langle V^2 \rangle_{\nu_1 \nu_2} - \langle V^2 \rangle_{\nu_1} = 4 R k T (\nu_2 - \nu_1)$$

$$\langle V^2 \rangle_{d\nu} = 4 R k T d\nu$$

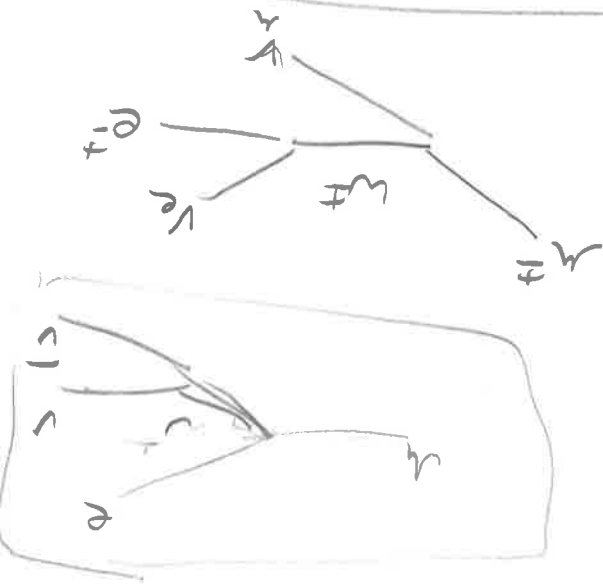
Meson Production Theory



$$\pi^\pm \rightarrow \mu^\pm \nu_\mu$$

$$\pi^0 \rightarrow \gamma\gamma$$

$$\mu^\pm \rightarrow e^\pm$$



$$1/\text{minute} \cdot \text{cm}^2 \text{ at } E \sim 4 \text{ GeV}$$

→ prof of reality

Muon Lab Lecture

Decay Rate:

μ is fundamental particle
 → discussed "radioactive decay", it
 has no "age" and therefore
 decays at a fixed rate

$$dN = -N(t) \lambda dt$$

$$\Rightarrow N(t) = N_0 \exp(-t/\tau)$$

$$\tau \equiv \text{lifetime} = \frac{1}{\lambda}$$

(Relate to half-life):

$$N(t_{1/2}) = \frac{1}{2} N_0 = N_0 \exp(-t_{1/2}/\tau)$$

$$\tau \cdot \log(2) = t_{1/2}$$

Plan:

① muon

Count rest



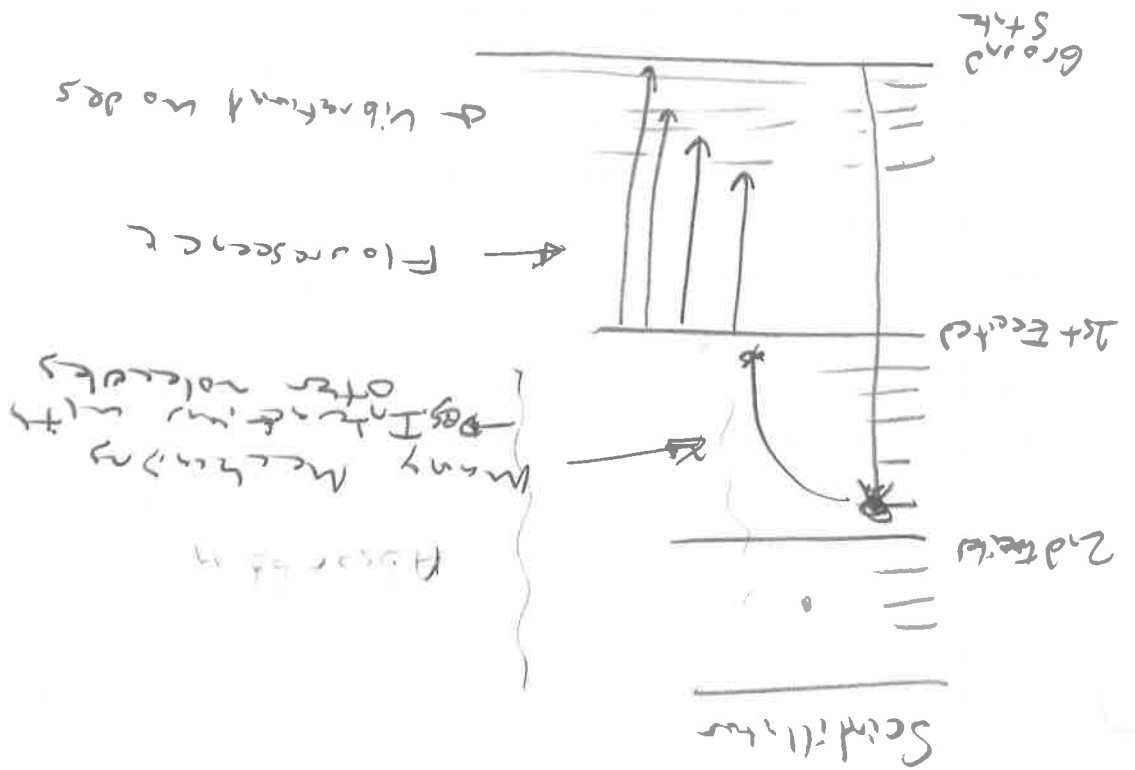
② Don't know
 how long
 muon took
 to ~~there~~
 Does it matter?

(prob of sink
 $N_0 = 1$)

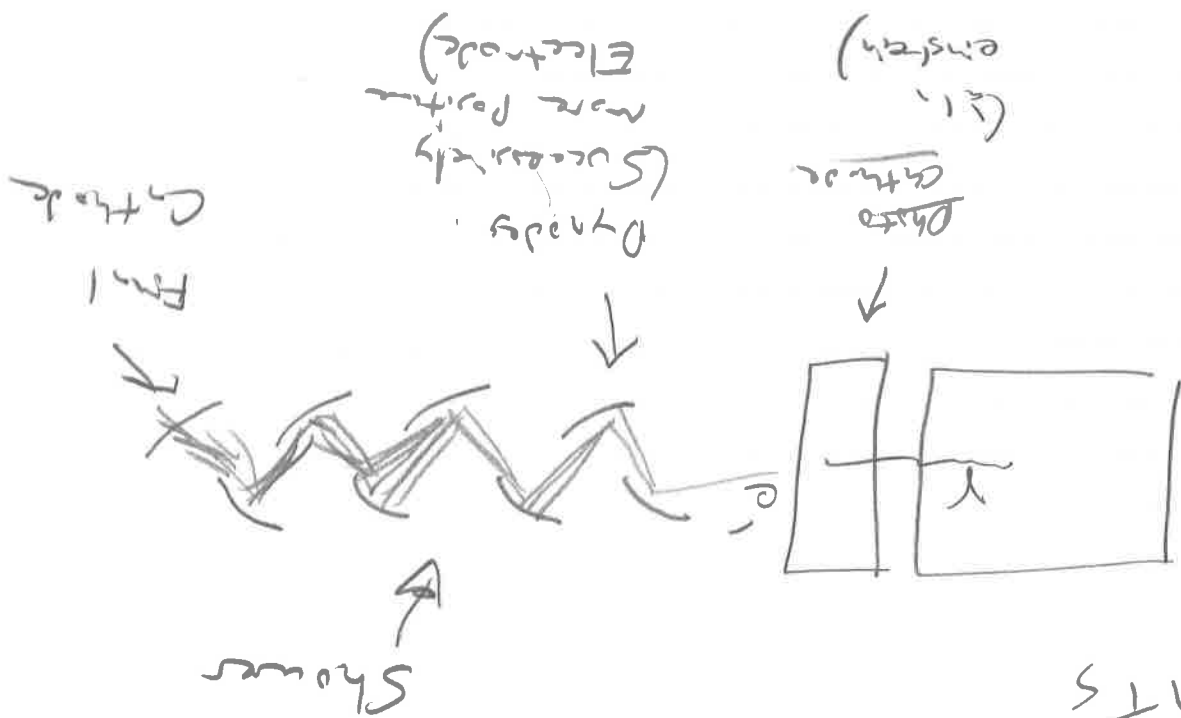
$$dN = -\lambda N_0 \exp(-\lambda t)$$

$$dW = -\lambda \exp(-\lambda t)$$

Only function of Enzyme is



PMTs



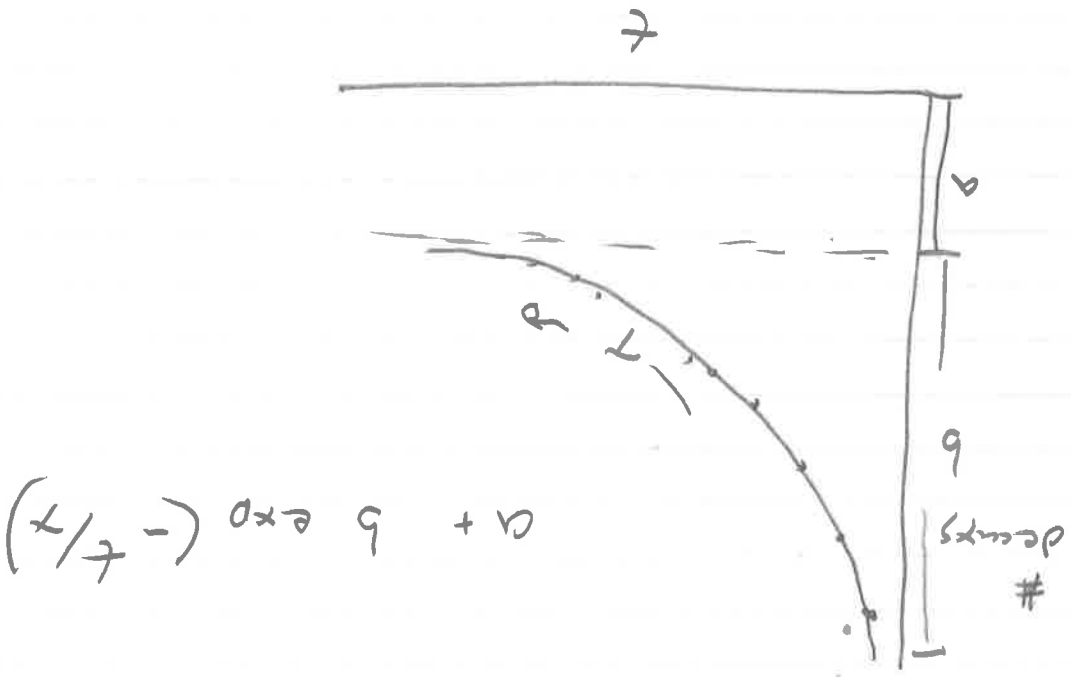
Gain is voltage dependent, but typically 100,000 to 1 million.

(Tuned to application)

Backsights:



Key points: An additional mean is likely to arise in any given interval. FLAT



μ^+ / μ^- differences



μ^- can occupy same orbital as an electron. Then decay via



This process is additional decay for μ^- not possible for μ^+

s. two decay rates:

λ^+ and λ^-

We measure λ^+ and λ^- average

Solve for ρ

$$\langle \lambda \rangle = (0+1) \frac{\lambda^0 + \lambda^1}{\lambda^0 + \lambda^1} = \lambda$$

$$\langle \frac{\lambda}{1} \rangle = \frac{0 + 1}{\frac{\lambda}{1} + \frac{\lambda}{1}}$$

Def: $\rho = w_+ / N_-$ $\lambda = \frac{w}{1}$

$$\langle \lambda \rangle = \frac{w_+ + w_-}{w_+ + w_-}$$

$$= - \frac{L}{L+} \left(\frac{L - L_{0.5}}{L - L_{0.5}} \right)$$

$$= \frac{L_{0.5} L - L + L}{L_{0.5} L - L + L}$$

$$0 \left(L + L - L_{0.5} L - L + L \right) = L_{0.5} L - L + L$$

$$(L + L + L) \cdot L_{0.5} = L + L + L$$

Covariance:

$$q_i = q(x_i, y_i)$$

$$\begin{matrix} x_i & \rightarrow & \bar{x} \\ y_i & \rightarrow & \bar{y} \end{matrix}$$

Now $x = \bar{x}, y = \bar{y}$

$$q_i = q(x_i, y_i) \approx q(\bar{x}, \bar{y}) + \frac{\partial q}{\partial x}(\bar{x}, \bar{y})(x_i - \bar{x}) + \frac{\partial q}{\partial y}(\bar{x}, \bar{y})(y_i - \bar{y})$$

$$q_i = q(\bar{x}, \bar{y})$$

$$q_i^2 = \frac{1}{n} \sum_{i=1}^n (q_i - \bar{q})^2$$

$$= \frac{1}{n} \sum_{i=1}^n \left(\frac{\partial q}{\partial x}(\bar{x}, \bar{y})(x_i - \bar{x}) + \frac{\partial q}{\partial y}(\bar{x}, \bar{y})(y_i - \bar{y}) \right)^2$$

$$= \left(\frac{\partial q}{\partial x}(\bar{x}, \bar{y}) \right)^2 \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 + \left(\frac{\partial q}{\partial y}(\bar{x}, \bar{y}) \right)^2 \frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2 + 2 \left(\frac{\partial q}{\partial x}(\bar{x}, \bar{y}) \frac{\partial q}{\partial y}(\bar{x}, \bar{y}) \right) \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})$$

$$= \left(\frac{\partial q}{\partial x}(\bar{x}, \bar{y}) \right)^2 s_x^2 + \left(\frac{\partial q}{\partial y}(\bar{x}, \bar{y}) \right)^2 s_y^2 + 2 \frac{\partial q}{\partial x}(\bar{x}, \bar{y}) \frac{\partial q}{\partial y}(\bar{x}, \bar{y}) s_{xy}$$

$$s_{xy} \equiv \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})$$

s_{xy} is the covariance of x and y .

Corresponding PDF:
Multivariate Normal

$$\frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2} (x - x_0)^T \Sigma^{-1} (x - x_0)\right)$$

$$\rightarrow \frac{1}{(2\pi)^k |\Sigma|} \exp\left(-\frac{1}{2} (x - x_0)^T \Sigma^{-1} (x - x_0)\right)$$

$$\Sigma = \begin{bmatrix} \sigma_x^2 & \sigma_{xy} \\ \sigma_{xy} & \sigma_y^2 \end{bmatrix}$$

In 2-D

$$\rho = \frac{\sigma_{xy}}{\sigma_x \sigma_y}$$

(Correlation between x and y)

$$\Sigma = \begin{bmatrix} \sigma_x^2 & \rho \sigma_x \sigma_y \\ \rho \sigma_x \sigma_y & \sigma_y^2 \end{bmatrix}$$

$$\Sigma^{-1} = \begin{bmatrix} \sigma_y^2 & -\rho \sigma_x \sigma_y \\ -\rho \sigma_x \sigma_y & \sigma_x^2 \end{bmatrix}$$

$$= \frac{1}{1 - \rho^2} \begin{bmatrix} \sigma_y^2 & -\rho \sigma_x \sigma_y \\ -\rho \sigma_x \sigma_y & \sigma_x^2 \end{bmatrix}$$

$$= \frac{1}{\sigma_x^2 \sigma_y^2 - \rho^2 \sigma_x^2 \sigma_y^2} \begin{bmatrix} \sigma_y^2 & -\rho \sigma_x \sigma_y \\ -\rho \sigma_x \sigma_y & \sigma_x^2 \end{bmatrix}$$

$$\Delta \chi^2 = 1$$

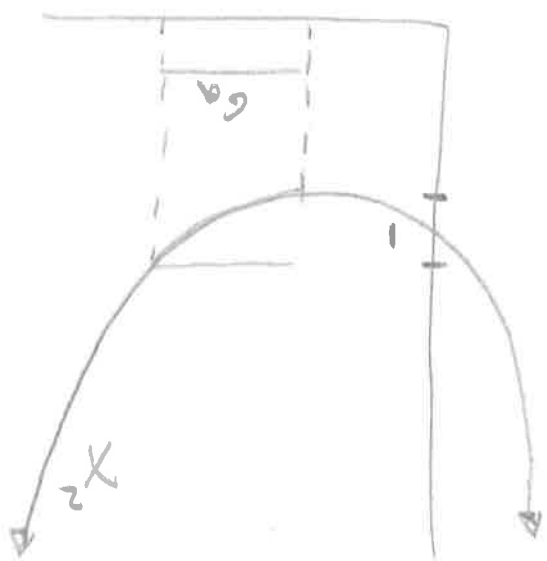
One approach to determining uncertainties

$$\begin{aligned}
 & \Delta \chi^2 = 1 \Rightarrow \Delta \chi^2 = 1 \\
 & -2 \log \mathcal{L} = \text{const} + \frac{\chi^2}{\sigma_x^2} \\
 & \mathcal{L} = \frac{1}{\sqrt{2\pi} \sigma} \exp\left(-\frac{1}{2} \frac{x^2}{\sigma^2}\right) \\
 & \text{Interpretation of } \Delta \chi^2
 \end{aligned}$$

$$(\Delta \chi^2 = \chi^2(\Delta x) - \chi^2(0))$$

We can use this to determine prices
uncertainties:

Picture:



$$X_2 = X_2(a^*) + \frac{\partial X_2}{\partial a} \bigg|_{a^*} (a - a^*) + \frac{1}{2} \frac{\partial^2 X_2}{\partial a^2} \bigg|_{a^*} (a - a^*)^2$$

$$0 = a^* + a^*$$

$$X_2 = X_2(a^*) + \frac{1}{2} \frac{\partial^2 X_2}{\partial a^2} \bigg|_{a^*} (a - a^*)^2 + \dots \quad (\text{Non Gaussian HOTS})$$

$$\Delta X_2 = 1 \quad \text{when} \quad a - a^* = a$$

$$1 = \frac{1}{2} \frac{\partial^2 X_2}{\partial a^2} \bigg|_{a^*} a^2$$

$$\Rightarrow a^2 = \frac{2}{\frac{\partial^2 X_2}{\partial a^2} \bigg|_{a^*}}$$

$$\int_C \frac{2\pi \times 6 \times 6 \sqrt{1-\rho^2}}{1} = G(x, y)$$

$$\cdot \exp \left(-\frac{1}{2} \frac{(1-\rho^2)}{2} \right) \left[\frac{6x^2}{(x-x_0)^2} + \frac{6y^2}{(y-y_0)^2} - \frac{6xy}{2\rho(x-x_0)(y-y_0)} \right]$$

$$\begin{pmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{pmatrix} \cdot \mathbf{z} = \begin{bmatrix} \frac{\partial \log L}{\partial \mu_1} \\ \frac{\partial \log L}{\partial \mu_2} \\ \frac{\partial \log L}{\partial \mu_3} \end{bmatrix}$$

$$\mathbf{z} = \mathbf{D}^{-1/2} \mathbf{y}$$

$$\Rightarrow \frac{1}{2} \mathbf{z}^T \mathbf{z} = \text{const}$$

$$-2 \log \mathcal{L} = \text{const} + \mathbf{z}^T \mathbf{z}$$

Convert to Multivariate Gaussian
 $\mathcal{L} = N(\mathbf{z} | \mathbf{0}, \mathbf{I})$

$$\chi^2 \sim \chi^2(a, b) + \frac{1}{2} \begin{bmatrix} \frac{\partial^2 \log L}{\partial \mu_1^2} & \frac{\partial^2 \log L}{\partial \mu_1 \partial \mu_2} \\ \frac{\partial^2 \log L}{\partial \mu_2 \partial \mu_1} & \frac{\partial^2 \log L}{\partial \mu_2^2} \end{bmatrix} \begin{pmatrix} \mu_1 - a \\ \mu_2 - b \end{pmatrix}$$

$$+ \frac{1}{2} \left[\frac{\partial^2 \log L}{\partial \mu_1^2} (\mu_1 - a)^2 + 2 \frac{\partial^2 \log L}{\partial \mu_1 \partial \mu_2} (\mu_1 - a)(\mu_2 - b) + \frac{\partial^2 \log L}{\partial \mu_2^2} (\mu_2 - b)^2 \right]$$

$$\chi^2 = \chi^2(a, b) + \frac{\partial \log L}{\partial \mu_1} (\mu_1 - a) + \frac{\partial \log L}{\partial \mu_2} (\mu_2 - b)$$