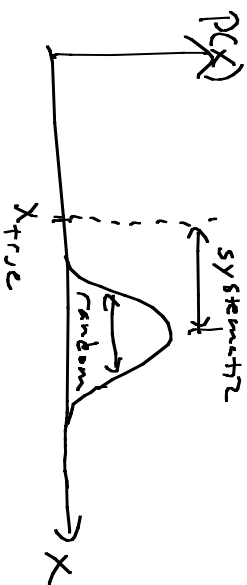


## Measurement Error

Systematic errors  $\rightarrow$  accuracy

Random errors  $\rightarrow$  precision



Properties of probability distribution functions:

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

"Moments":

1<sup>st</sup>:

$$\frac{\int_{-\infty}^{\infty} P(x) \cdot x dx}{\int_{-\infty}^{\infty} P(x) dx} = \bar{x}$$

"mean"

$$2^{\text{nd}} : \frac{\int_{-\infty}^{\infty} P(x) (x - \bar{x})^2 dx}{\int_{-\infty}^{\infty} P(x) dx} = \sigma^2 \quad \text{"Variance"}$$

$$\sigma \quad \text{"Standard deviation"}$$

$$3^{\text{rd}} : \frac{\int_{-\infty}^{\infty} P(x) (x - \bar{x})^3 dx}{\sigma^3 \int_{-\infty}^{\infty} P(x) dx}$$

"Skew" (asymmetry)

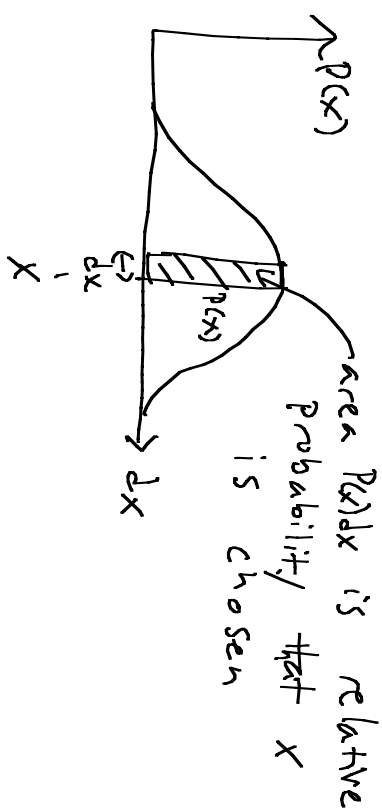
$$4^{\text{th}} : \frac{\int_{-\infty}^{\infty} P(x) (x - \bar{x})^4 dx}{\sigma^4 \int_{-\infty}^{\infty} P(x) dx} = 3 \quad \text{"Kurtosis" (peakedness)}$$

# Sampling

"Mean": 
$$\frac{\int_{-\infty}^{\infty} x \underbrace{P(x) dx}_{\text{included in measurement!}}}{\int_{-\infty}^{\infty} P(x) dx}$$

Sampling  $\Rightarrow$

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



"Variance": 
$$\frac{\int_{-\infty}^{\infty} (x - \bar{x})^2 P(x) dx}{\int_{-\infty}^{\infty} P(x) dx}$$

$$\Rightarrow \frac{\sum_{i=1}^N (x_i - \bar{x})^2}{N-1}$$

$\bar{x}$  not independent of  $x_i$

"mode": most common value(s)

"median": middle value  $\rightarrow$  half larger, half smaller

other ways to characterize lists of values

## Combining measurements

Lacking any other info, we assume that probability distribution function is

$$P(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\bar{x})^2}{2\sigma^2}}$$

This is convenient: Gaussian is a simple distribution w/o skew or kurtosis!

If two measurements of the same variable are made, each with result  $X_A$  and  $X_B$

$$P(X_A) = \frac{1}{\sigma_A\sqrt{2\pi}} e^{-\frac{(X_A-\bar{X})^2}{2\sigma_A^2}}$$

$$P(X_B) = \frac{1}{\sigma_B\sqrt{2\pi}} e^{-\frac{(X_B-\bar{X})^2}{2\sigma_B^2}}$$

$$P(X_A, X_B) = P(X_A)P(X_B) \propto e^{-\frac{1}{2} \left[ \frac{(X_A-\bar{X})^2}{\sigma_A^2} + \frac{(X_B-\bar{X})^2}{\sigma_B^2} \right]}$$

We assume the maximum probability event has occurred, so maximize  $P(X_A, X_B)$  w.r.t  $\bar{X}$ . This is equivalent to minimizing the exponent:

$$\frac{d}{d\bar{X}} \left[ \frac{(X_A-\bar{X})^2}{\sigma_A^2} + \frac{(X_B-\bar{X})^2}{\sigma_B^2} \right] = 0$$

$$\frac{-2(X_A-\bar{X})}{\sigma_A^2} + \frac{-2(X_B-\bar{X})}{\sigma_B^2} = 0$$

$$\text{If } w_A \equiv \frac{1}{\sigma_A^2}, \quad w_B \equiv \frac{1}{\sigma_B^2},$$

$$w_A (x_A - \bar{x}) + w_B (x_B - \bar{x}) = 0$$

$$w_A x_A + w_B x_B - \bar{x} (w_A + w_B) = 0$$

$$\bar{x} = \frac{w_A x_A + w_B x_B}{w_A + w_B}$$

in general,

$$\bar{x} = \frac{\sum_i w_i x_i}{\sum_i w_i}$$

So measurements with large  $\sigma$  count less toward  $\bar{x}$ !

## Standard deviation of the mean

If you make  $N$  measurements, what is the uncertainty in  $\bar{x}$ ?

$$\begin{aligned} \prod_{i=1}^N P_i(x_i) &= e^{-\frac{(x-\bar{x})^2}{2\sigma_1^2}} e^{-\frac{(x-\bar{x})^2}{2\sigma_2^2}} e^{-\frac{(x-\bar{x})^2}{2\sigma_3^2}} \dots e^{-\frac{(x-\bar{x})^2}{2\sigma_N^2}} \\ &= e^{-\sum_{i=1}^N \frac{1}{\sigma_i^2} \frac{(x-\bar{x})^2}{2}} \longrightarrow \frac{1}{\sigma_{\bar{x}}^2} = \sum_{i=1}^N \frac{1}{\sigma_i^2} \end{aligned}$$

So  $\sigma_{\bar{x}}$  always decreases with more measurements (even ones w/ large  $\sigma$ )

If all  $\sigma_i^2$  are same,  $\frac{1}{\sigma_{\bar{x}}^2} = \frac{N}{\sigma^2}$ , so  $\sigma_{\bar{x}} = \frac{\sigma}{\sqrt{N}}$

## Propagation of errors

you want to calculate  $f(x, y)$  using sampled data  $x_i$  and  $y_i$ , with uncertainties  $\sigma_x$  and  $\sigma_y$ . What is  $\sigma_f$ ?

$$\sigma_f^2 = \frac{1}{N} \sum_i^N (f(x_i, y_i) - f(\bar{x}, \bar{y}))^2$$

If we Taylor expand  $f(x, y)$  to first order,

$$f(x_i, y_i) \sim f(\bar{x}, \bar{y}) + \frac{df}{dx}(x_i - \bar{x}) + \frac{df}{dy}(y_i - \bar{y})$$

So

$$\sigma_f^2 = \frac{1}{N} \sum_i^N (f(x_i, y_i) - f(\bar{x}, \bar{y}))^2 + \frac{df}{dx}(x_i - \bar{x}) + \frac{df}{dy}(y_i - \bar{y}) - f(\bar{x}, \bar{y})^2$$

$$\sigma_f^2 = \frac{1}{N} \sum_i \left[ \left( \frac{df}{dx} \right)^2 (x_i - \bar{x})^2 + \left( \frac{df}{dy} \right)^2 (y_i - \bar{y})^2 + 2 \frac{df}{dx} \frac{df}{dy} (x_i - \bar{x})(y_i - \bar{y}) \right]$$

$$= \frac{1}{N} \left[ \underbrace{\left( \frac{df}{dx} \right)^2 \sum_i (x_i - \bar{x})^2}_{\rightarrow \sigma_x^2} + \left( \frac{df}{dy} \right)^2 \sum_i (y_i - \bar{y})^2 + 2 \frac{df}{dx} \frac{df}{dy} \underbrace{\sum_i (x_i - \bar{x})(y_i - \bar{y})}_{\rightarrow \sigma_{xy}^2} \right]$$

for independent  
 $x, y$   
 $= 0$

$$\sigma_f^2 = \left( \frac{df}{dx} \right)^2 \sigma_x^2 + \left( \frac{df}{dy} \right)^2 \sigma_y^2$$

$$\sigma_f = \sqrt{\left( \frac{df}{dx} \right)^2 \sigma_x^2 + \left( \frac{df}{dy} \right)^2 \sigma_y^2}$$

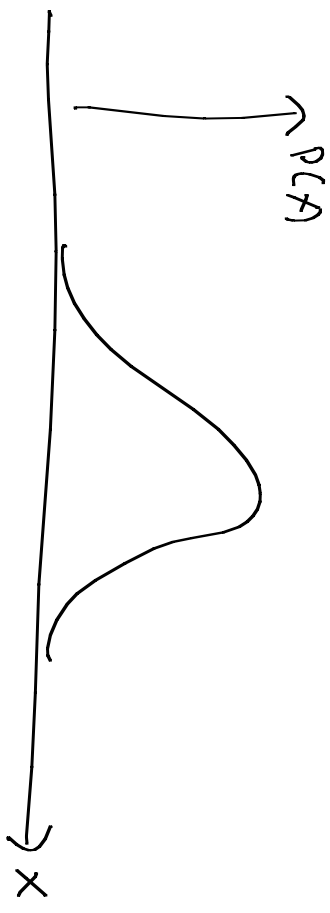
$$\rightarrow \sigma_f = \sqrt{\sum_i \left( \frac{df}{dx_i} \right)^2 \sigma_{x_i}^2}$$

for arbitrary number  
of variables.

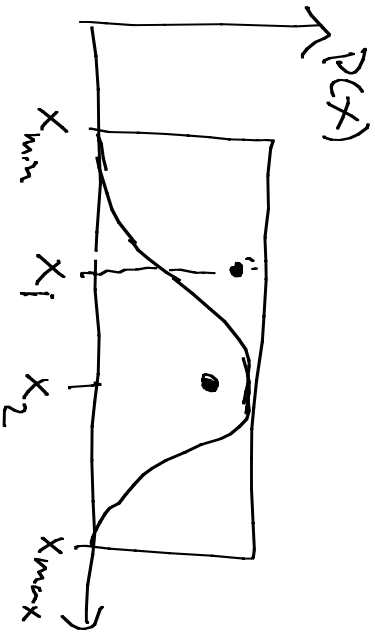


## Modeling sampling

given a PDF  $P(x)$ , how should we randomly sample values such that the histogram of  $X_i$ 's  $\rightarrow P(x)$  for large  $N$ ?



Von Neumann Sampling:



1. Pick random value of  $x = x'$ ,  $x_{\min} < x' < x_{\max}$
2. Pick random value  $y$  between 0 and  $\max(P(x))$  within the range  $x_{\min} < x < x_{\max}$
3. If  $y < P(x')$  then  $x'$  is a valid random sample of  $P(x)$ . Otherwise, repeat.

# Reflection and Refraction

Wave equation in matter:

$$\mu = \mu_r \mu_0$$
$$\epsilon = \epsilon_r \epsilon_0$$

$$\frac{\partial^2 E}{\partial z^2} = \mu_r \mu_0 \epsilon_r \epsilon_0 \frac{\partial^2 E}{\partial t^2}$$

$$\text{Velocity} = \frac{1}{\sqrt{\mu_r \epsilon_r \sqrt{\mu_0 \epsilon_0}}} = \frac{1}{\sqrt{\mu_r \epsilon_r}} \quad c \equiv \frac{c}{n}$$

Plane wave:  $E = E_0 e^{i(kz - \omega t)} = E_0 e^{ik(z - \frac{\omega}{k}t)}$

$$\text{Velocity} = \frac{\omega}{k} = \frac{c}{n}$$

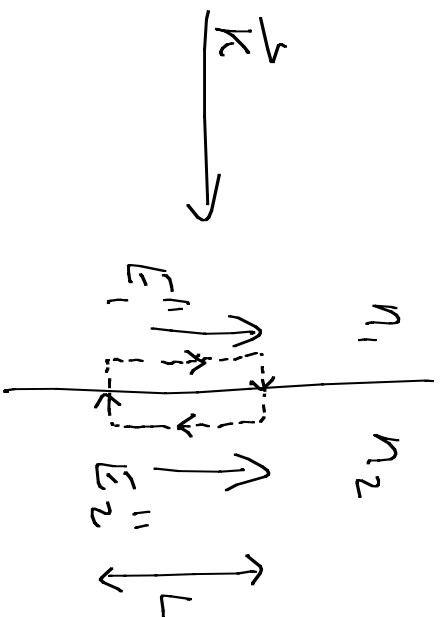
$$\omega \rightarrow \frac{\omega_0}{n} ?$$

$$k \rightarrow k_0 n ?$$

$\omega_0, k_0 \equiv$  free space values

# Boundary Conditions on $\vec{E}$ at interfaces

Faraday's Law:



$$\oint \vec{E} \cdot d\vec{l} = -\frac{d\Phi_B}{dt}$$

for path w)  
negligible area

$$E_1'' L - E_2'' L \rightarrow 0$$

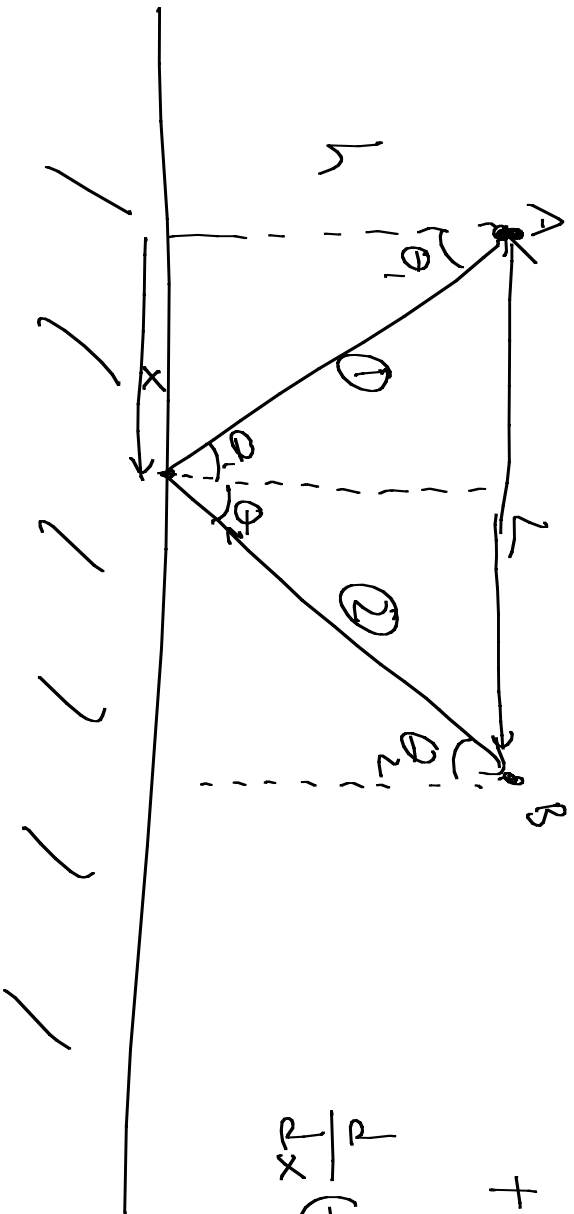
$$E_1'' = E_2''$$

So  $\vec{E}$  must have same freq. of oscillation on both sides

$$\implies \omega_1 = \omega_2$$

$$\text{So } k \rightarrow k_{0n}$$

# Obllique reflection



Fermat's Principle:

Light follows paths through space  
 a transit time that is a  
 local extrema (minimum or maximum!)

$$\text{time} = \frac{n\sqrt{h^2+x^2}}{c} + \frac{n\sqrt{h^2+(L-x)^2}}{c}$$

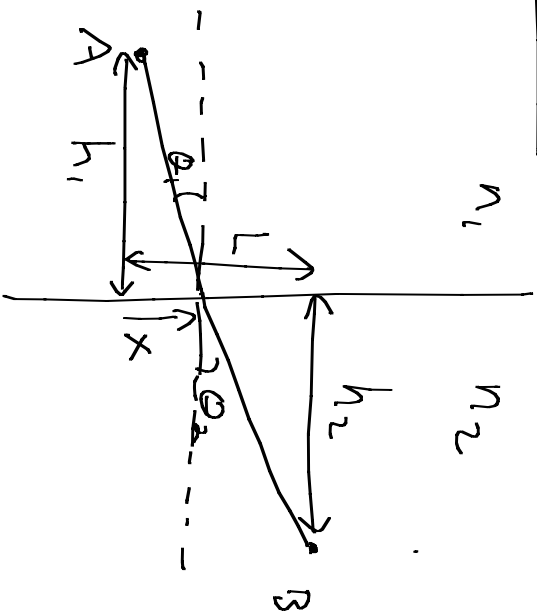
$$\frac{d}{dx}(\text{time}) = \frac{2nx}{2c\sqrt{h^2+x^2}} - \frac{2n(L-x)}{2c\sqrt{h^2+(L-x)^2}} = 0$$

$$\frac{x}{\sqrt{h^2+x^2}} = \frac{(L-x)}{\sqrt{h^2+(L-x)^2}}$$

$$\sin \theta_1 = \sin \theta_2$$

$$\theta_1 = \theta_2$$

# Refraction



$$\text{time} = \frac{n_1 \sqrt{h_1^2 + x^2}}{c} + \frac{n_2 \sqrt{h_2^2 + (L-x)^2}}{c}$$

"Stationäre" time

$$n_1 \frac{x}{\sqrt{h_1^2 + x^2}} = n_2 \frac{L-x}{\sqrt{h_2^2 + (L-x)^2}}$$

"Snell's Law"  $n_1 \sin \theta_1 = n_2 \sin \theta_2$

Note: for  $n_1 > n_2$

$$\theta_2 = \sin^{-1} \left( \frac{n_1}{n_2} \sin \theta_1 \right)$$

IF  $\sin \theta_1 > \frac{n_2}{n_1}$ ,  $\theta_2$  is undefined!

"total internal reflection"