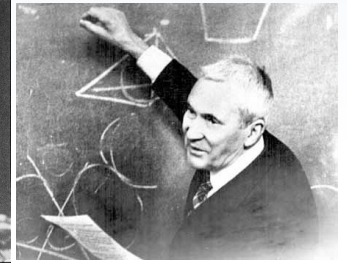
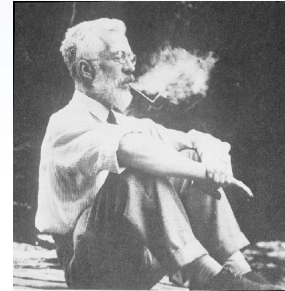
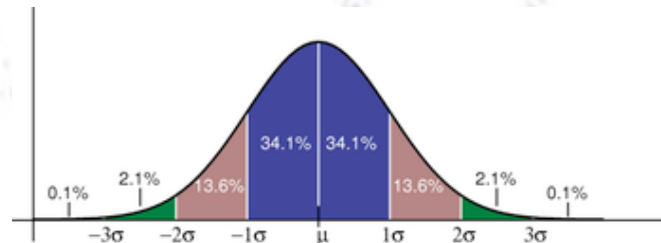


# Applied Statistics

## Error propagation



Troels C. Petersen (NBI)



*"Statistics is merely a quantisation of common sense"*

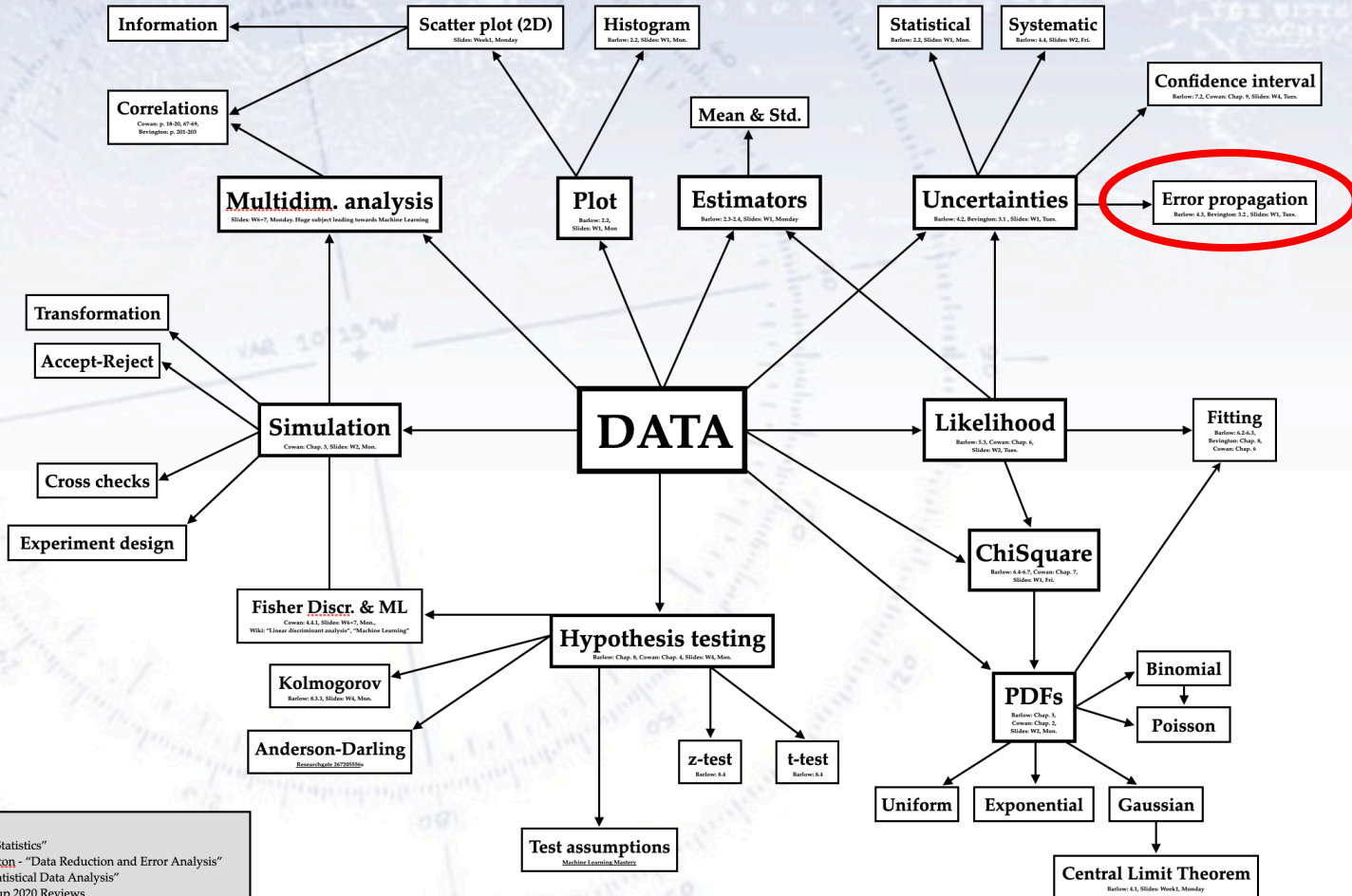
# Error propagation

Applied Statistics

Describe data (Quantify & Visualise)

Overview of subjects

Version 1.2, 6. Nov. 2020



Simulate data (Design & Cross Check)

Model data (Predict & Understand)

References:  
 Barlow: R. J. Barlow - "Statistics"  
 Bevington: P. H. Bevington - "Data Reduction and Error Analysis"  
 Cowan: G. Cowan - "Statistical Data Analysis"  
 PDG: Particle Data Group 2020 Reviews  
 Slides: T. C. Petersen - "Applied Statistics 2020" course (W = Week)  
 Wiki: Good reference for ALL subjects (only specified when essential)  
 SciPy: SciPy Statistical Functions and (very brief) documentation

Test hypotheses on data (Decide)

# Error propagation

Imagine that  $y$  is a function of  $x_i$

$$y(x_i)$$

and that we wish to find the error on  $y$  from the errors on  $x_i$ .

$$\sigma(x_i) = 0.8$$

$$\sigma(y(x_i)) = ?$$

# Error propagation

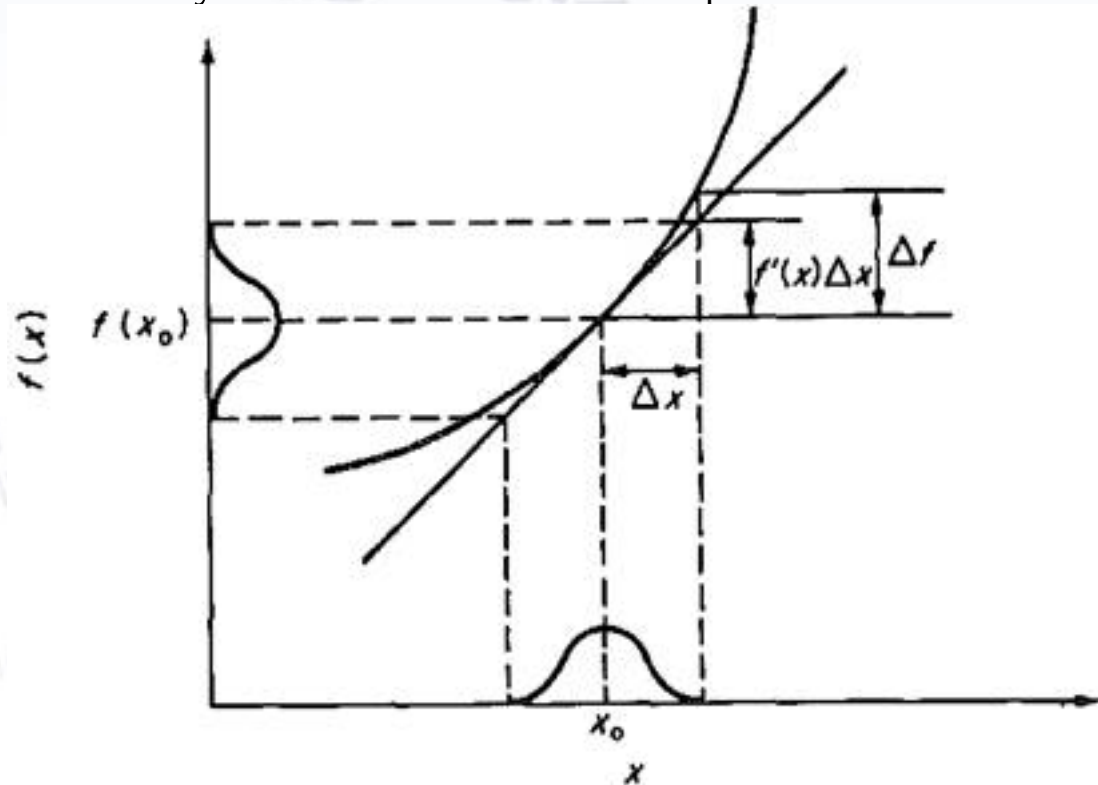
Imagine that  $y$  is a function of  $x_i$

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# Error propagation

Imagine that  $y$  is a function of  $x_i$

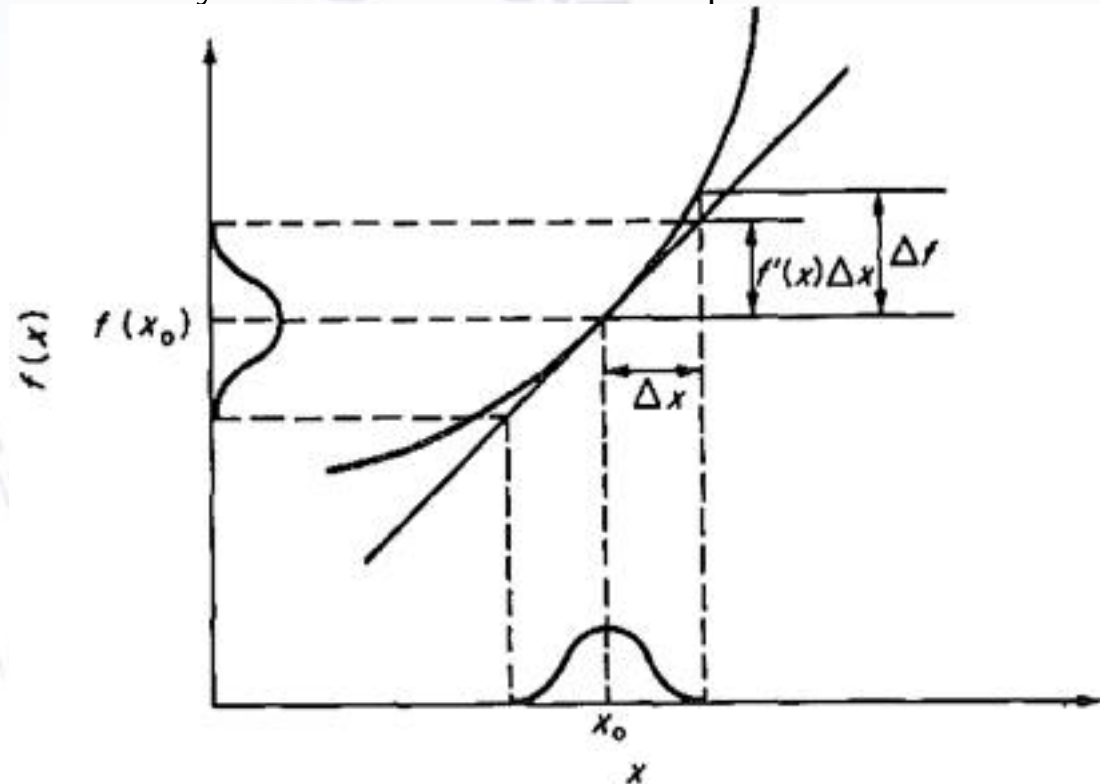
$$y(x_i)$$

and that we wish to find the error on  $y$  from the errors on  $x_i$ .

$$\sigma(x_i) = 0.8$$

$$\sigma(y(x_i)) =$$

$$\frac{\partial y}{\partial x_i} \times 0.8$$



# Error propagation

Note, the approximation here:

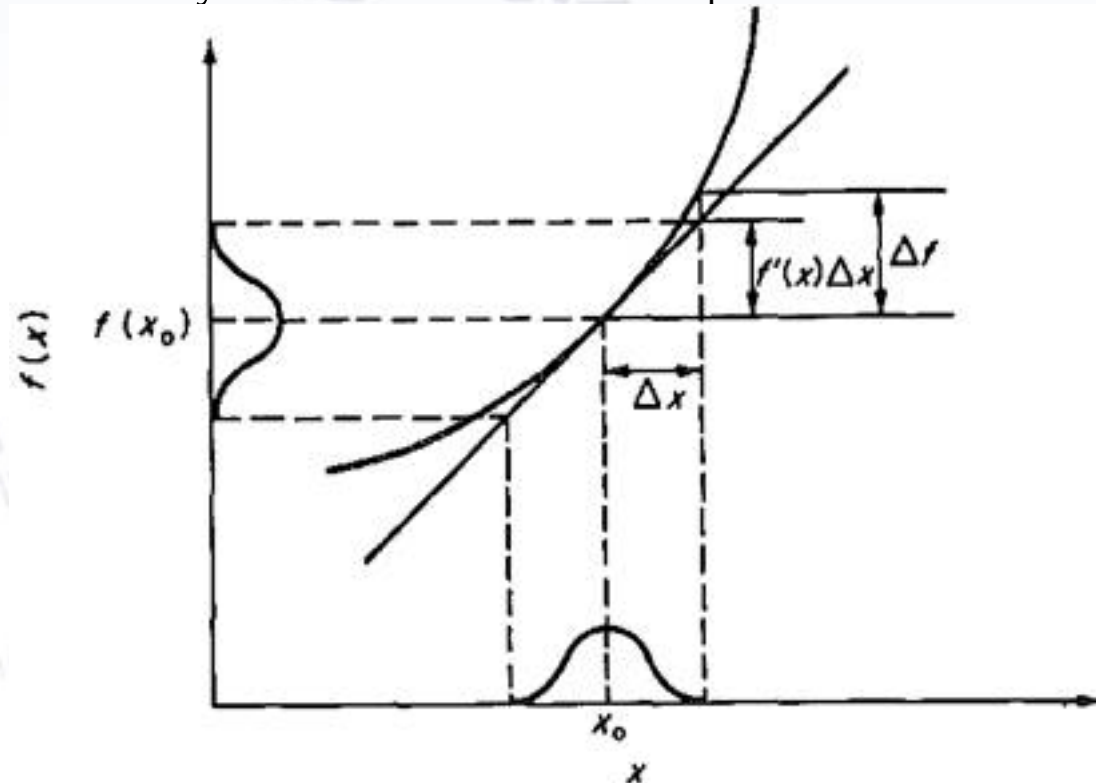
The derivative of  $y - dy / dx_i$  - should be relatively constant.  
If not, the error propagation formula breaks down.

and that we wish to find the error on  $y$  from the errors on  $x_i$ .

$$\sigma(x_i) = 0.8$$

$$\sigma(y(x_i)) =$$

$$\frac{\partial y}{\partial x_i} \times 0.8$$



# Error propagation

Imagine that  $y$  is a function of  $x_i$ , and that we wish to find the error on  $y$  from the errors on  $x_i$ . Making a Taylor expansion of the function  $y$  gives:

$$y(\bar{x}) \simeq y(\bar{\mu}) + \sum_i^n \frac{\partial y}{\partial x_i} (x_i - \mu_i)$$

In order to get the uncertainty of  $y$  as a function of the variables  $x_i$  we calculate:

$$\sigma_x^2 = \overline{x^2} - \bar{x}^2 = E[x^2] - E^2[x]$$

$$E[y(\bar{x})] \simeq y(\bar{\mu})$$

$$E[y^2(\bar{x})] \simeq y^2(\bar{\mu}) + \sum_{i,j}^n \left[ \frac{\partial y}{\partial x_i} \frac{\partial y}{\partial x_j} \right] V_{ij}$$

# Error propagation formula

Subtracting the two formulae, we obtain:

$$\sigma_y^2 = \sum_{i,j}^n \left[ \frac{\partial y}{\partial x_i} \frac{\partial y}{\partial x_j} \right]_{\bar{x}=\bar{y}} V_{ij}$$

If there are no correlations, only the diagonal (individual errors) enter:

$$\sigma_y^2 = \sum_i^n \left[ \frac{\partial y}{\partial x_i} \right]_{\bar{x}=\bar{y}}^2 \sigma_i^2$$



# Error propagation formula

Subtracting the two formulae, we obtain:

$$\sigma_y^2 = \sum_{i,j} \left[ \frac{\partial y}{\partial x_i} \frac{\partial y}{\partial x_j} \right]_{x=\bar{y}} \sigma_{x_i} \sigma_{x_j}$$

Note, that **each term** represents the **individual contributions** of  $x_i$  to the uncertainty on  $y$ .

If there are no correlations, only the diagonal (individual errors) enter:

$$\sigma_y^2 = \sum_i \left[ \frac{\partial y}{\partial x_i} \right]_{\bar{x}=\bar{y}}^2 \sigma_i^2$$

# Specific error propagation formula

## Addition

Specific formula:

$$x = u + v$$

$$\sigma_x^2 = \sigma_u^2 + \sigma_v^2 + 2V_{uv}$$

General formula:

$$x = au + bv$$

$$\sigma_x^2 = a^2\sigma_u^2 + b^2\sigma_v^2 + 2abV_{uv}$$

*“When adding numbers, their errors add in quadrature”*

# Specific error propagation formula

## Multiplication

$$x = uv$$

$$\sigma_x^2 = (v\sigma_u)^2 + (u\sigma_v)^2 + 2uvV_{uv}$$

Dividing by  $x^2$  to get relative terms, we obtain:

$$\frac{\sigma_x^2}{x^2} = \frac{\sigma_u^2}{u^2} + \frac{\sigma_v^2}{v^2} + 2\frac{V_{uv}}{uv}$$

*“When multiplying numbers, their RELATIVE errors add in quadrature”*



# Error propagation at work...

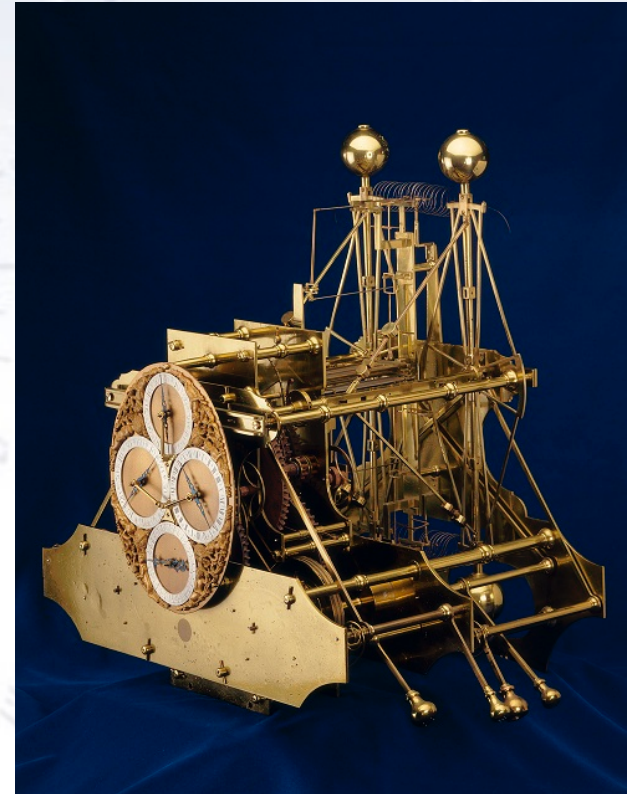


**John Harrison** (24 March 1693 – 24 March 1776)

British clockmaker extraordinaire

“Won” the Longitude Act prize (3 sec/day).

Harrison's first sea clock (H1)



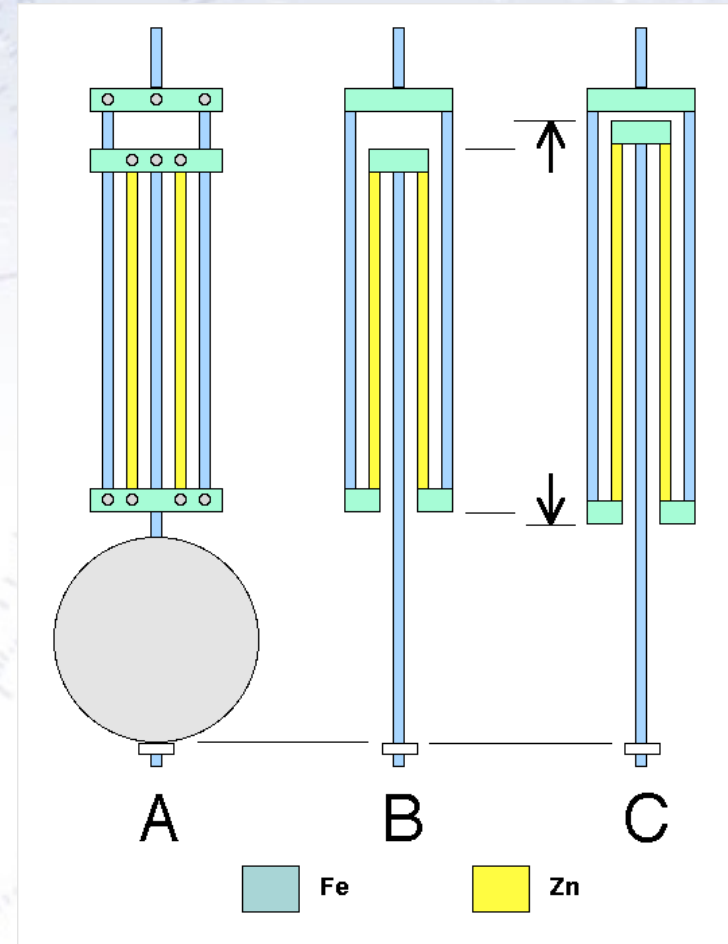
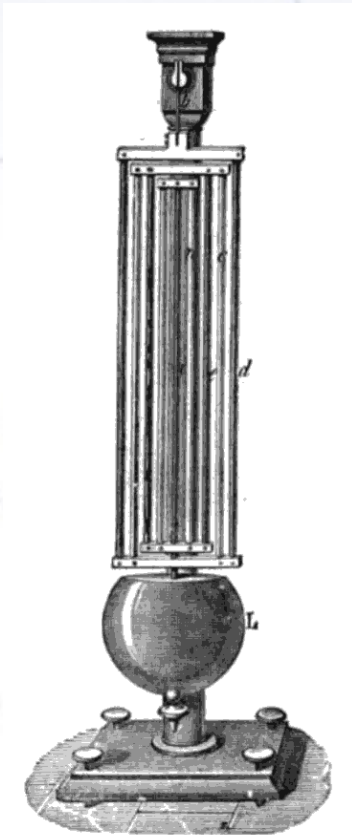
**Harrison build H1-H5.**

K1 (Copy of H4) was used by James Cook.



# Error propagation at work...

Harrison's Gridiron pendulum is designed to cancel the change in length (in fact moment of inertia) with temperature.



Coefficient of thermal expansion:  
Iron =  $11.8 \times 10^{-6} / C^{\circ}$  Zinc =  $30.2 \times 10^{-6} / C^{\circ}$

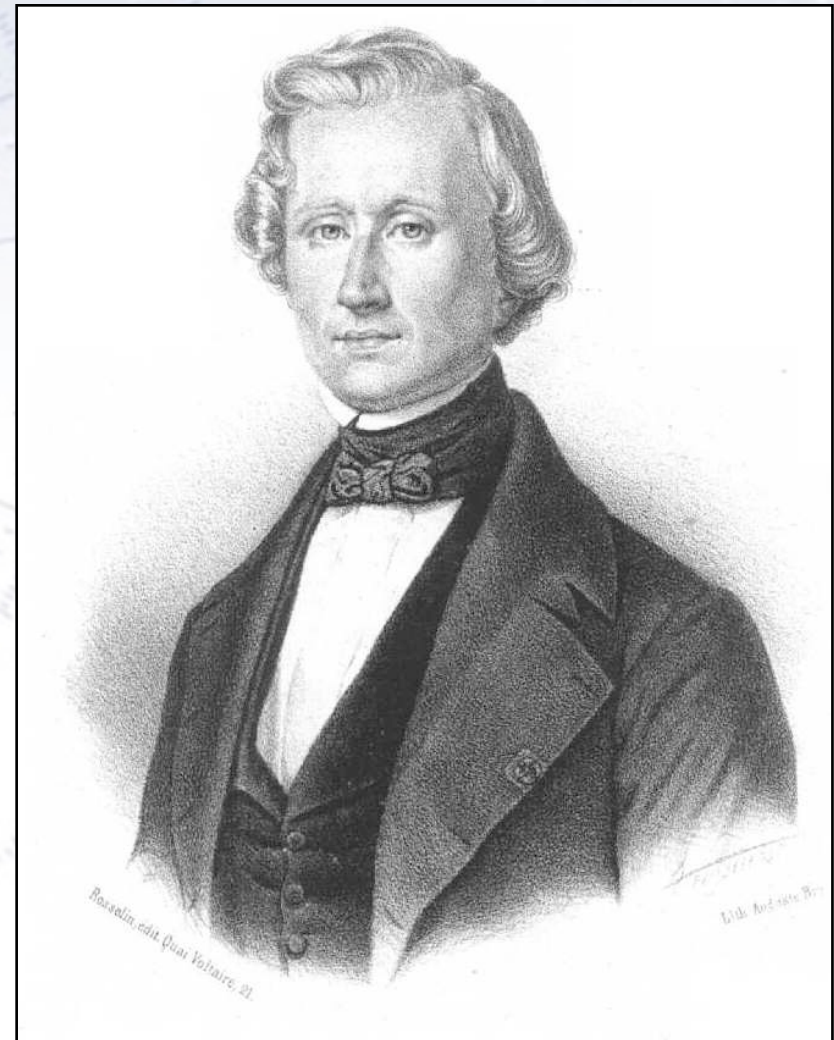
# Error propagation at more work...

Analysis of tiny differences in Uranus' orbit from Newtonian prediction led to the prediction and discovery of Neptune!

Continuing with Mercury...

TABLE II. Contributions to the motion of the perihelia of Mercury and the earth.

Cause	$m^{-1}$		Motion of perihelion	
			Mercury	Earth
Mercury	6 000 000	$\pm 1\ 000\ 000$	$0''.025 \pm 0''.00$	$-13''.75 \pm 2''.3$
Venus	408 000	$\pm 1\ 000$	$277.856 \pm 0.68$	$345.49 \pm 0.8$
Earth	329 390	$\pm 300$	$90.038 \pm 0.08$	
Mars	3 088 000	$\pm 3\ 000$	$2.536 \pm 0.00$	$97.69 \pm 0.1$
Jupiter	$1\ 047.39 \pm 0.03$		$153.584 \pm 0.00$	$696.85 \pm 0.0$
Saturn	3 499	$\pm 4$	$7.302 \pm 0.01$	$18.74 \pm 0.0$
Uranus	22 800	$\pm 300$	$0.141 \pm 0.00$	$0.57 \pm 0.0$
Neptune	19 500	$\pm 300$	$0.042 \pm 0.00$	$0.18 \pm 0.0$
Solar oblateness			$0.010 \pm 0.02$	$0.00 \pm 0.0$
Moon				$7.68 \pm 0.0$
General precession (Julian century, 1850)			$5025.645 \pm 0.50$	$5025.65 \pm 0.5$
Sum			$5557.18 \pm 0.85$	$6179.1 \pm 2.5$
Observed motion			$5599.74 \pm 0.41$	$6183.7 \pm 1.1$
Difference			$42.56 \pm 0.94$	$4.6 \pm 2.7$
Relativity effect			$43.03 \pm 0.03$	$3.8 \pm 0.0$



Urbain Le Verrier (1811-1877)

# Simulating error propagation

Imagine that  $y$  is a very complicated function of  $x_i$ , perhaps not even parametric (i.e. not a function, but rather a model).

A simple method is to use simulation:

- Choose random values of  $x_i$ , corresponding to mean and SD of each  $x$ .
- Calculate  $y(x_i)$  and record the resulting values.
- The standard deviation (and distribution) of  $y$  reflects the impact of  $x_i$ .

Note that the distribution of  $y$  may NOT be Gaussian, if the error propagation formula breaks down. It is then important to make this clear to the reader.

However, simulation exactly allows one to see to what degree the resulting distribution in  $y$  is Gaussian.



The background is a nautical chart with depth contours and magnetic variation information. A prominent feature is a magnetic variation line labeled "VAR 10°15' W" with a crosshair symbol. Other text on the chart includes "MAGNETIC" and "THE BOSTON YACHT CLUB".

# Error propagation exercise



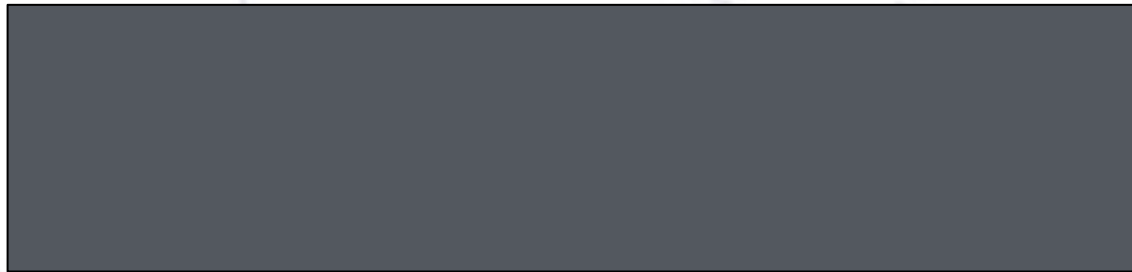
# Error propagation exercise

Imagine that you measure the Length (L) and Width (W) of a table:

$$L = 3.5 \pm 0.4 \text{ and } W = 0.8 \pm 0.2$$

Now you want to calculate the Perimeter (P), Area (A), and Diagonal (D), along with the uncertainty on these. This problem is an obvious case of applying the error propagation formula.

$$L = 3.5 \pm 0.4$$



$$W = 0.8 \pm 0.2$$

But imagine that you were asked to propagate the error through:

$$y1 = \log(\text{square}(L*\tan(W))+\text{sqrt}((L-W)/(\cos(W)+1.0+L)))$$

Use simulation... not even certain that error propagation formula holds!