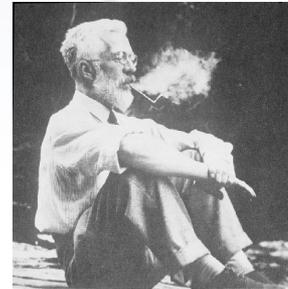
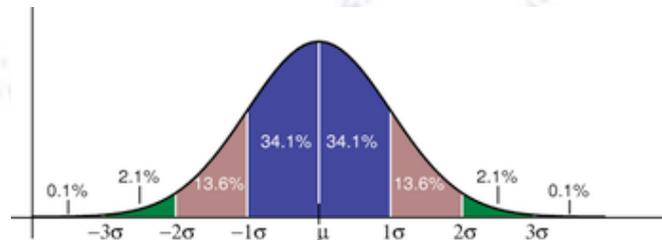


# Applied Statistics

## Mean and Width



Troels C. Petersen (NBI)

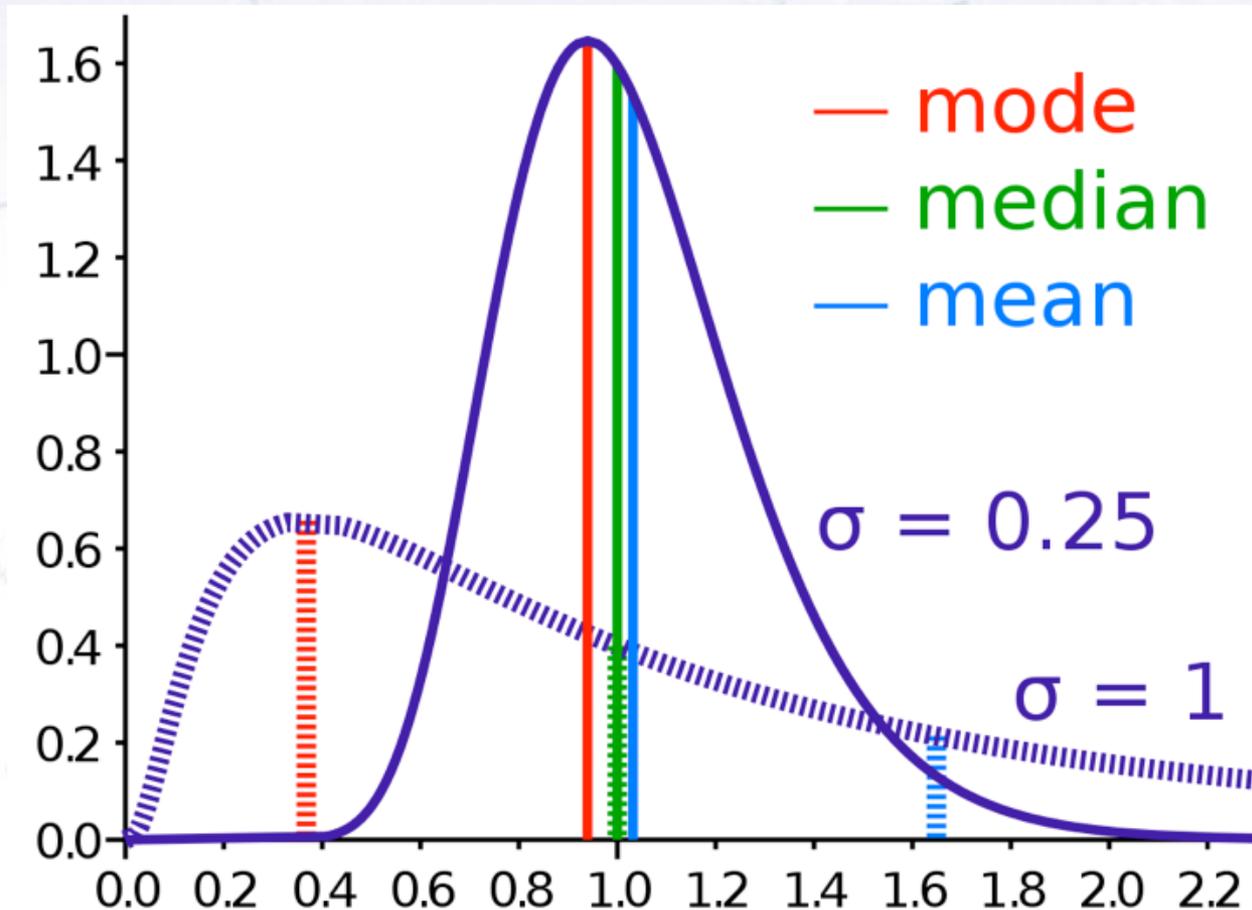


*"Statistics is merely a quantisation of common sense"*

# Defining the mean

There are several ways of defining “a typical” value from a dataset:

- a) Arithmetic mean   b) Mode (most probably)   c) Median (half below, half above)  
d) Geometric mean   e) Harmonic mean   f) Truncated mean (robustness)



# Mean and Width

It turns out, that the best estimator for the **mean** is (as you all know):

$$\hat{\mu} = \frac{1}{N} \sum_i x_i = \bar{x}$$

For the **width** of the distribution (a.k.a. **standard deviation** or **RMS**) it is:

$$\hat{\sigma} = \sqrt{\frac{1}{N} \sum_i (x_i - \mu)^2}$$

Note the “hat”, which means “estimator”. It is sometimes dropped...

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$$\hat{s} = \sqrt{\frac{1}{N-1} \sum_i (x_i - \bar{x})^2}$$

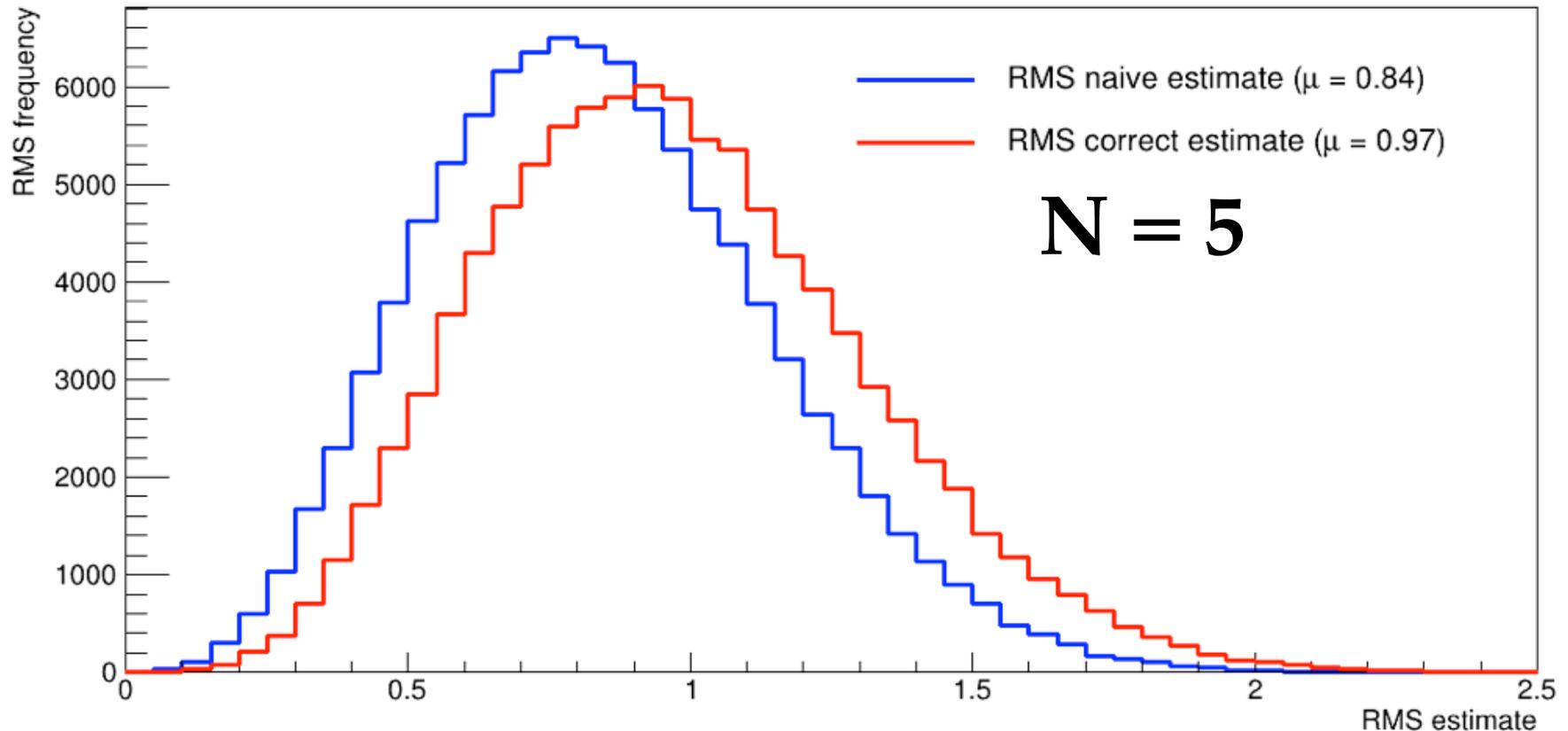
Note the “hat”, which means “estimator”. It is sometimes dropped...

# How incorrect is the naive RMS?

Such questions can most easily be answered by a small simulation...

Produce  $N=5$  numbers from a unit Gaussian, and calculate the RMS estimate:

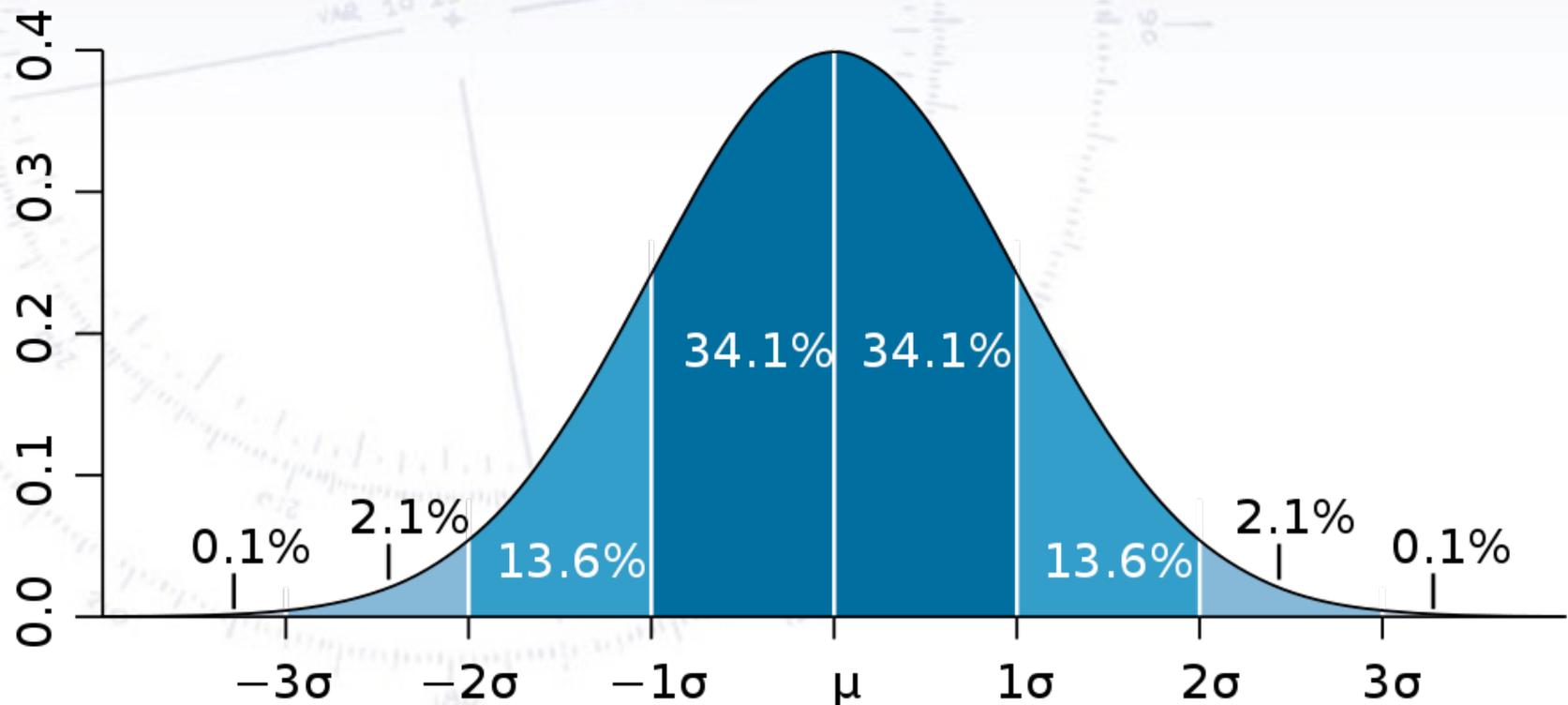
Distribution of RMS estimates on five unit Gaussian numbers



So, the “naive” RMS underestimates the uncertainty a bit...

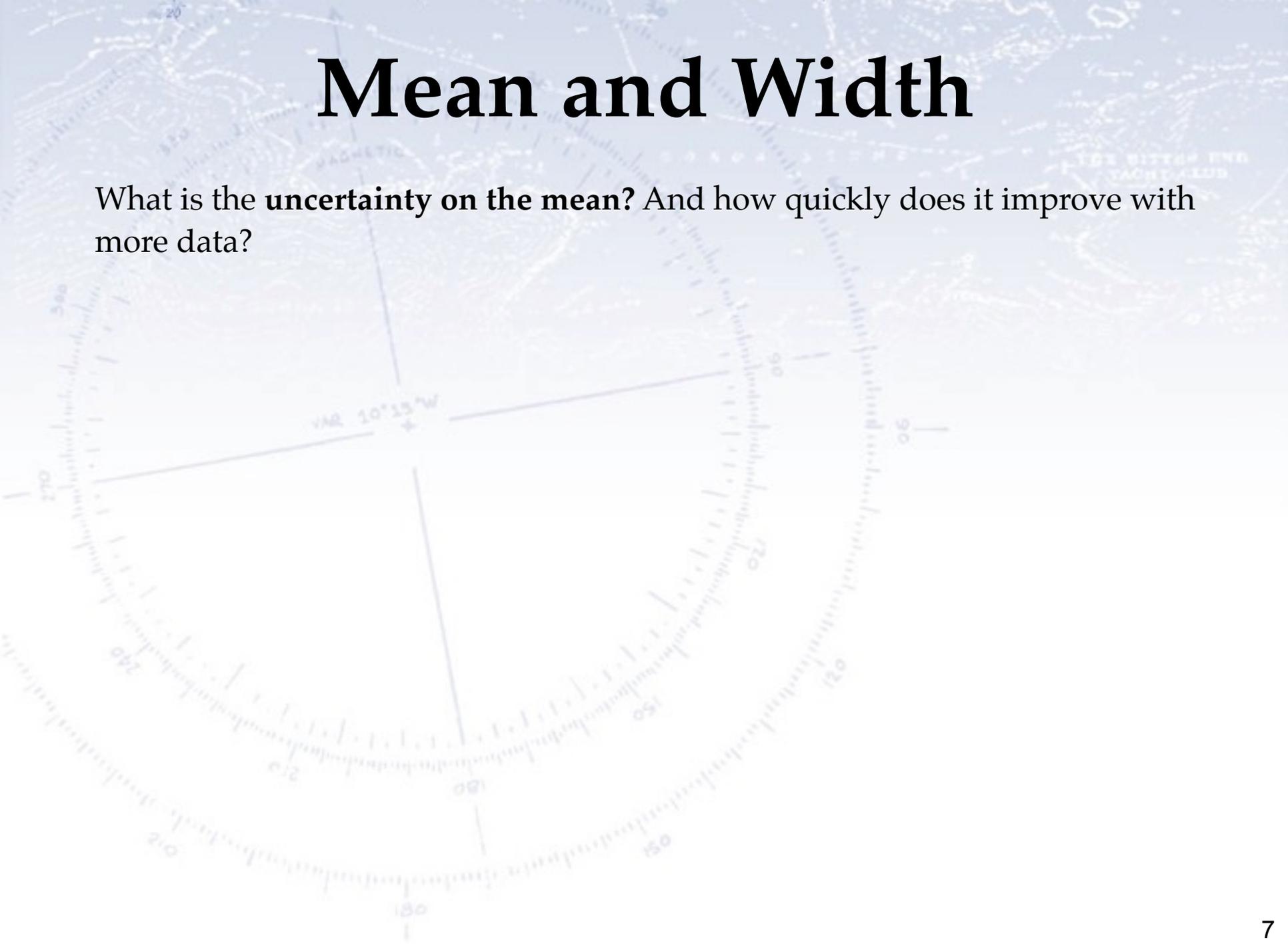
# Relation between RMS and Gaussian width...

When a distribution is Gaussian, the RMS corresponds to the Gaussian width  $\sigma$ :



# Mean and Width

What is the **uncertainty on the mean**? And how quickly does it improve with more data?



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Example:

## Cavendish Experiment

(measurement of Earth's density)

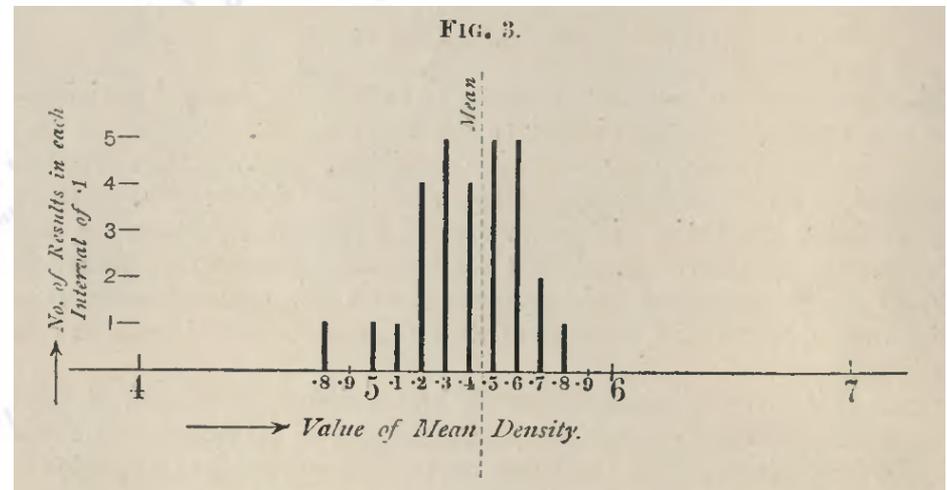
$N = 29$

$\mu = 5.42$

$\sigma = 0.333$

$\sigma(\mu) = 0.06$

**Earth density =  $5.42 \pm 0.06$**



# Mean and Width

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Cavendish Experiment  
(measurement of Earth's density)

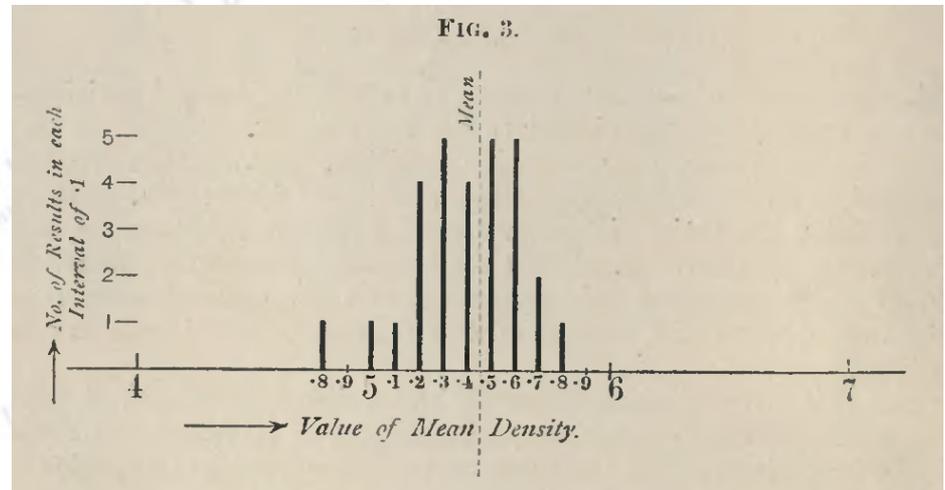
$N = 29$

$\mu = 5.42$

$\sigma = 0.333$

$\sigma(\mu) = 0.06$

Earth density =  $5.42 \pm 0.06$



# Weighted Mean

What if we are given data, which has different uncertainties?

How to average these, and what is the uncertainty on the average?

$$\hat{\mu} = \frac{\sum x_i / \sigma_i^2}{\sum 1 / \sigma_i^2}$$

For measurements with varying uncertainty, there is no meaningful RMS!

The uncertainty on the mean is:

$$\hat{\sigma}_{\mu} = \sqrt{\frac{1}{\sum 1 / \sigma_i^2}}$$

Can be understood intuitively, if two persons combine 1 vs. 4 measurements

# Resolution using InterQuantile Range

A useful measure of resolution is the InterQuantile Range (IQR), as this is not affected by long tails.

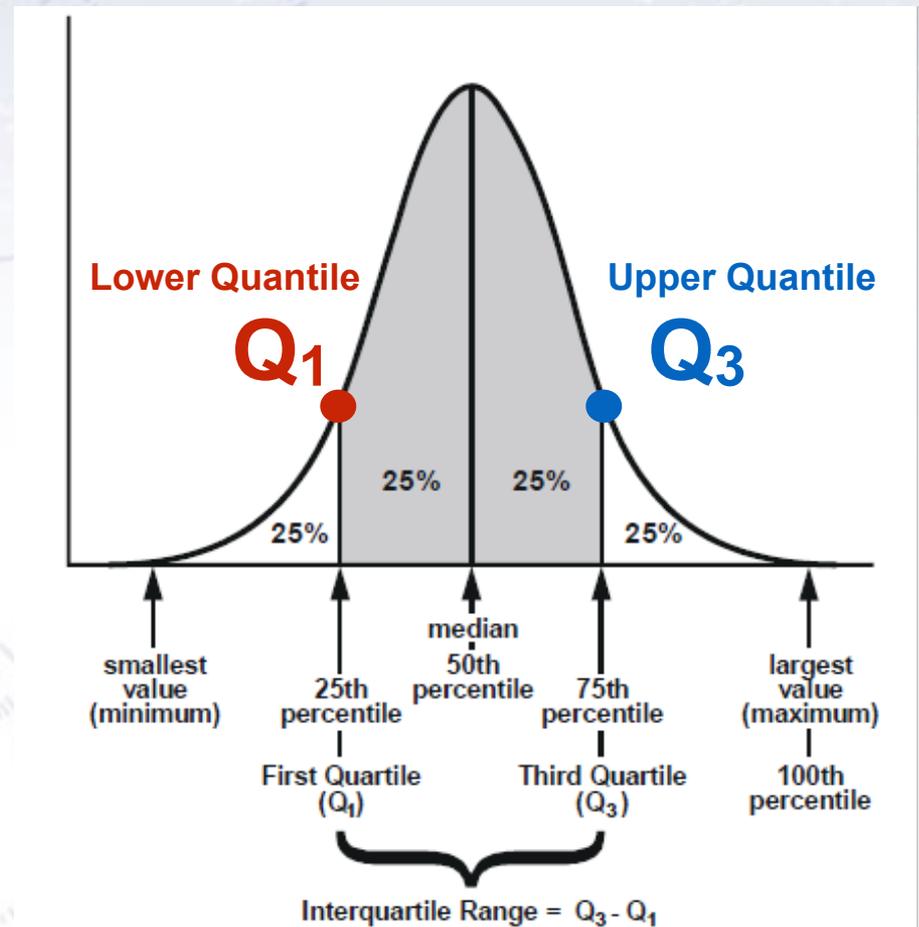
IQR measures **statistical dispersion**, calculated as the difference

$$\text{IQR} = Q_3 - Q_1$$

The InterQuantile Efficiency (IQE) is defined as:

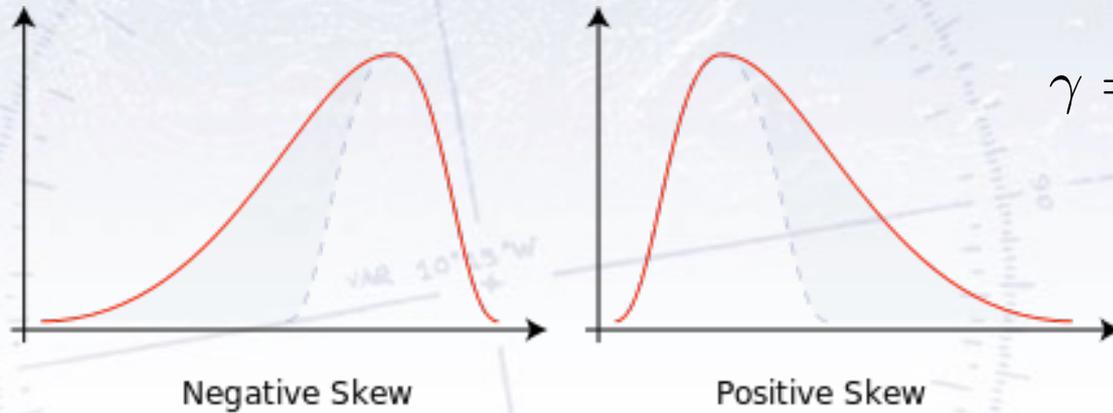
$$\text{IQE} = \text{IQR} / 1.349$$

The factor  $1.349 = 2 \Phi^{-1}(0.75)$  ensures that  $\text{IQR} = 1$  for a unit Gaussian.



# Skewness and Kurtosis

Higher moments reveal something about a distributions asymmetry and tails:



$$\gamma = \frac{\frac{1}{N} \sum_i (x_i - \bar{x})^3}{\left(\frac{1}{N} \sum_i (x_i - \bar{x})^2\right)^{3/2}}$$

$$\kappa = \frac{\frac{1}{N} \sum_i (x_i - \bar{x})^4}{\left(\frac{1}{N} \sum_i (x_i - \bar{x})^2\right)^2} - 3$$

**LEPTOKURTIC**  
(thicker tails)

**MESOKURTIC**  
(normal tails)

**PLATYKURTIC**  
(thinner tails)

