

$$= \frac{1}{2} k(A^2 - y_2^2) \Rightarrow y_2 = A \frac{\sqrt{2}}{2} = \frac{4}{3} \cdot 10^{-1} \text{ V}$$

$$E_p = E_{p_{\max}} \Rightarrow \sin^2 \left( 3t_p + \frac{\pi}{3} \right) = 1 \Rightarrow \sin = \sin \left( \frac{\pi}{2} + n\pi \right); n = 0,1,2,\dots$$

$$\left[ \frac{1}{2} (x + y - xy + 1) \right] * z = -$$

$$+ xy - xyz + z + 1 \right] = \frac{1}{2} \left[ \frac{1}{2} (x + y -$$

$$y * z) = x * \left[ \frac{1}{2} (y + z - yz + 1) \right] =$$

$$I_R = \frac{U}{R} = \frac{220}{17,32} = 12,7 \text{ A},$$

$$\frac{I_R}{r_R^2 + I_L^2} = \frac{R}{\sqrt{R^2 + L^2 \omega^2}} = \frac{17,32}{34,64} = \frac{1}{2} \cdot \varphi =$$

$$(-1)^{n+1} \frac{1}{(n+2)^n} + (-1)^n \cdot \frac{n+3}{n+1} \cdot \frac{1}{n}.$$

$$\left[ \frac{1}{n+1} \right]^{n+1} - \frac{1 - \left( -\frac{1}{n+2} \right)^{n+1}}{n+3} \right] =$$

$$= sv_2(h_0)t_1 = \frac{v_2}{\sqrt{1 - \frac{v_2^2}{c^2}}} \sqrt{\frac{2h_0}{\rho}} \cdot \frac{v_2}{c} \cdot 40$$

$$Sh_0 = 2V_0 = C \cdot S \cdot \frac{1}{2} \cdot \frac{1}{\rho} \cdot \frac{1}{c} \cdot \frac{1}{40} \cdot \frac{m_{12}}{r_{12}^2},$$

$$t_{12} = -K \frac{m_{12}}{r_{12}^2},$$

$$t_{12} = -K \frac{m_{12}}{r_{12}^2},$$

$$E_p = E_{p_{\max}} \Rightarrow \sin^2 \left( 3t_p + \frac{\pi}{3} \right) = 1$$

$$= \sin \left( \frac{\pi}{2} + n\pi \right); n = 0,1,2,\dots$$

$$t_p = \frac{\pi}{3} \left( n + \frac{1}{6} \right); n = 0,1,2,\dots$$

# Uncertainty evaluation based on practical examples – Why we need numerical methods

S L R Ellison, LGC Limited, Teddington, UK

$$+ \frac{2}{a^2} \left[ \frac{1}{a} (e^{ax}) \Big|_0^0 \right] = -ae^{-a^2} - \frac{2}{a} e^{-a^2}$$

$$= \frac{1}{a^3 e^{a^2}} [2e^{a^2} - 2 - 2a^2 - a^4].$$

$$y \begin{pmatrix} -t & y \\ t & -x \end{pmatrix} = \begin{pmatrix} yz - xt & 0 \\ 0 & yz - tx \end{pmatrix} =$$

$$yz - xt) I_2 = -(xt - yz) I_2,$$

$$= p_2 V_2 \Rightarrow \frac{V_2}{V_1} = \frac{p_1}{p_2},$$

$$\left. \frac{d}{dx} \frac{-\frac{d}{dx}}{x^2} = - \int \frac{d}{dx} \left( \frac{1}{x} \right) = \right.$$

$$I = \sqrt{1 + x^2} - \ln \frac{\sqrt{1 + x^2} + x}{x},$$

$$J = \sqrt{1 + x^2} + x, \quad \left. \frac{d}{dx} \frac{d}{dx} \left( \frac{1}{x} \right) = \right.$$

$$O_1 = vCT(1 - e^{1/2}) + vC_1 T(\mathcal{Y} - 1)$$

# Introduction



- **Uncertainty from a measurement equation**
- **Gradient methods**
  - Finite difference and Kragten's method
- **Simulation methods**
  - Monte Carlo simulation (MCS)
  - Bayesian approach using Markov chain Monte Carlo (MCMC)



# Measurement equations

A simple example



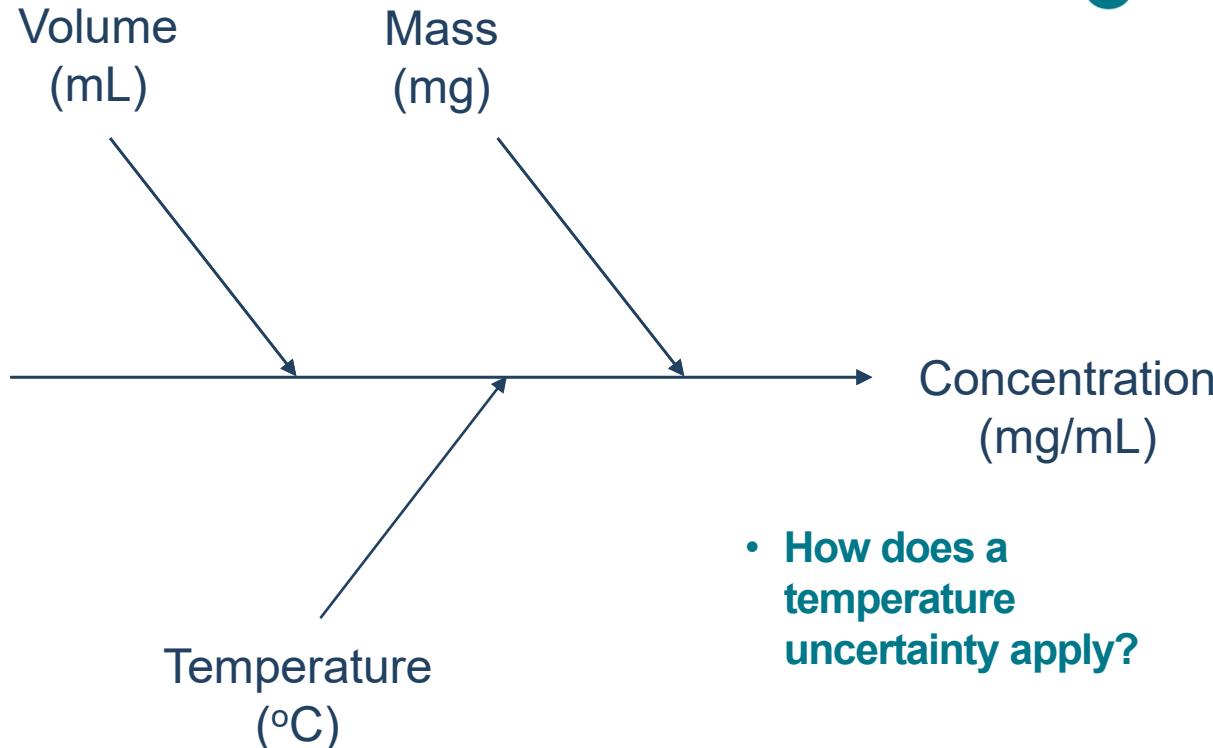
# A volumetric example



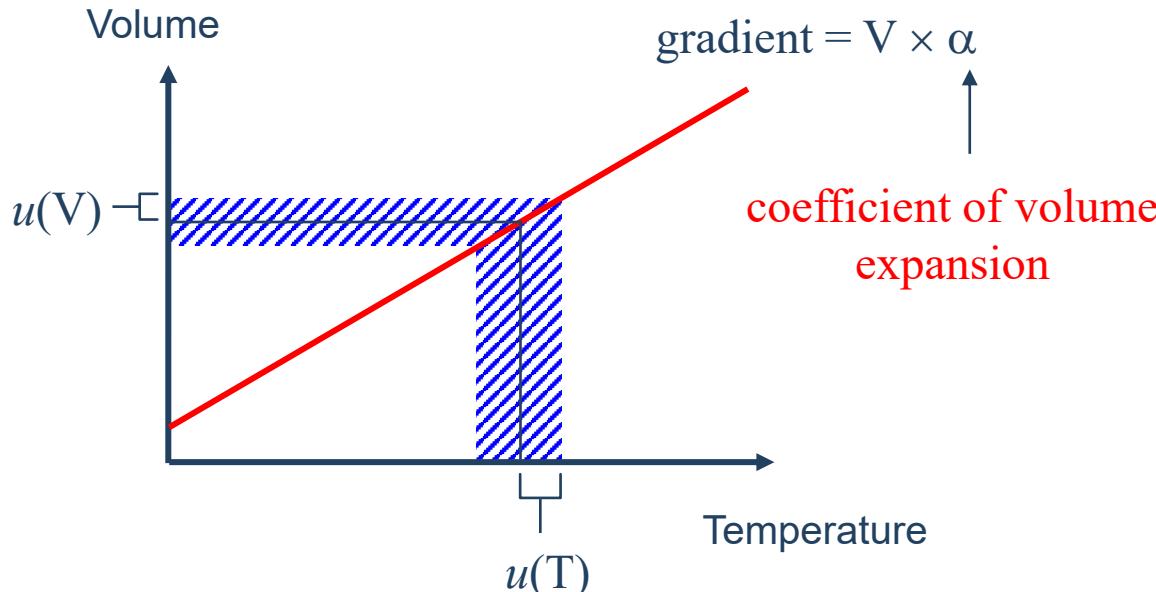
- Make up a 1 mg/ml solution
- in a 100ml volumetric flask ( $U = 0.2 \text{ ml}$ ,  $k=2$ )
- allowing for mass uncertainty ( $U = 4 \text{ mg}$ ,  $k=2$ )
- at a laboratory temperature  $25 \pm 2 \text{ }^{\circ}\text{C}$

Evaluate the uncertainty in concentration

# Example: The effect of temperature on concentration

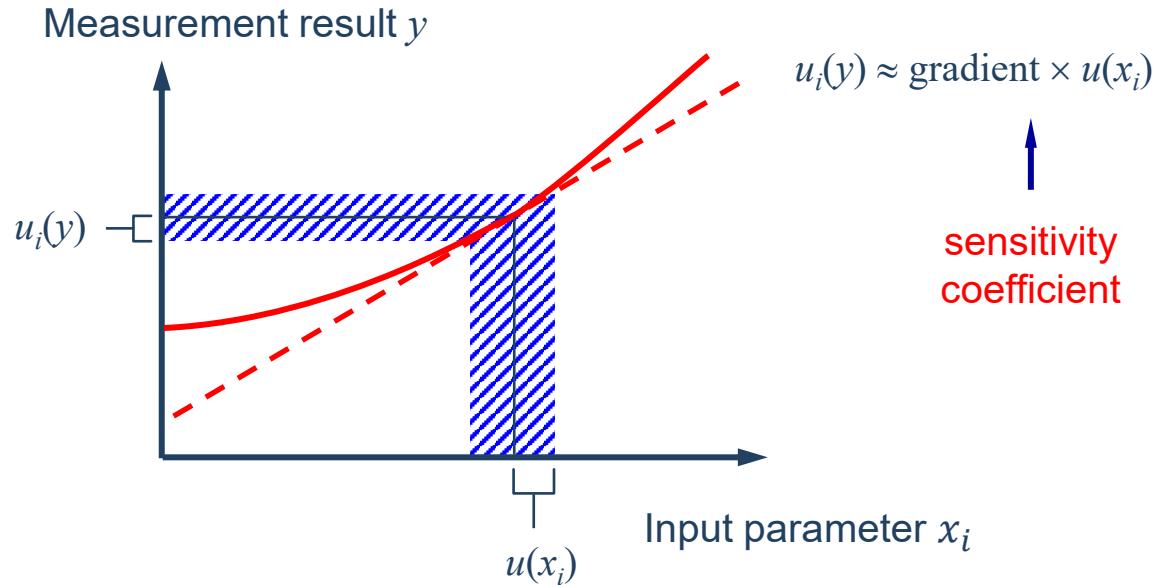


# Example: The effect of temperature on volume



$$u(V) = \text{gradient} \times u(T)$$

# Uncertainty propagation



# Mathematical form of uncertainty



- $x_i$  parameter affecting analytical result  $y$
- $u(x_i)$  uncertainty in  $x_i$
- $u_i(y)$  uncertainty in  $y$  due to uncertainty in  $x_i$

$$u_i(y) = \sqrt{\sum_i \left( \frac{\partial y}{\partial x_i} \right)^2 u(x_i)^2}$$

↑  
sensitivity  
coefficient

# The volume example

$$C_0 = \frac{m}{V_T} (1 + \alpha(T - T_0))$$

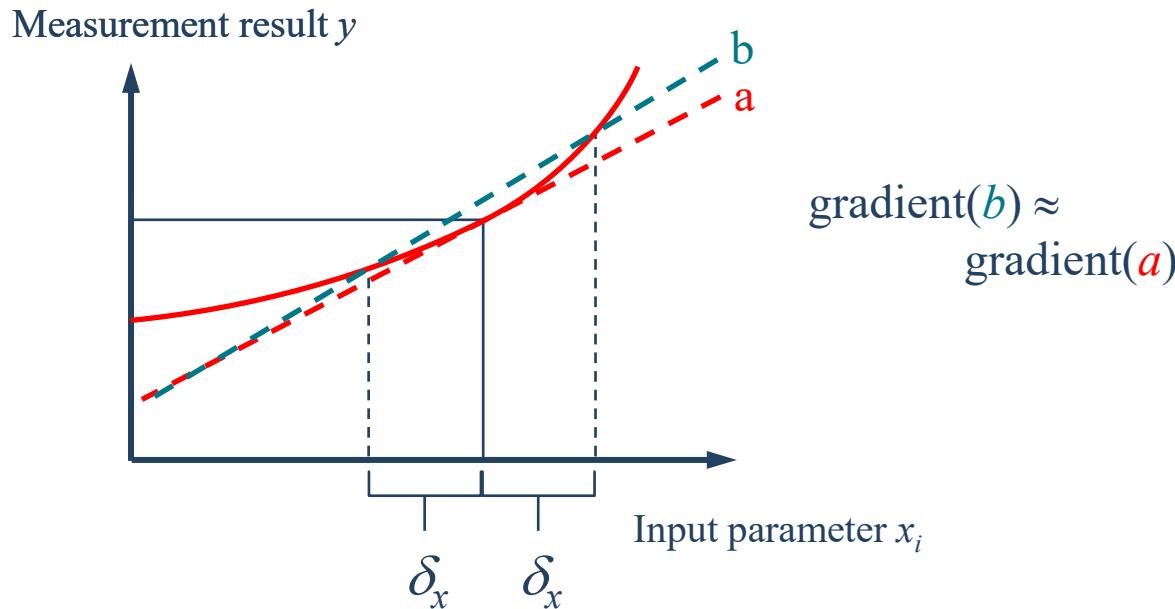
Quantity	Value $x$	Standard uncertainty $u_x$
Mass $m$	100 mg	2 mg
Volume $V_T$	100 ml	0.1 ml
Volume coefficient $\alpha$	$1 \times 10^{-3} \text{ K}^{-1}$	
Temperature $T$	25 °C	1.15 °C
Standard temperature $T_0$	25 °C	



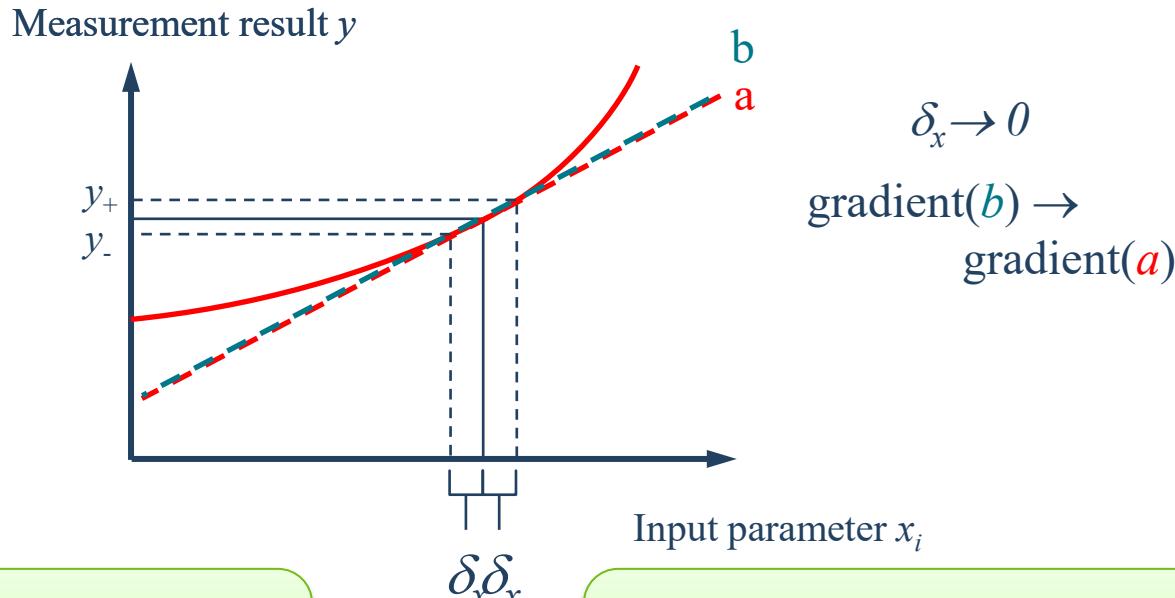
# Sensitivity coefficients from spreadsheets

1. Differentiation by finite difference

# Finite difference method



# Finite difference method



$$\frac{\partial y}{\partial x_i} \approx \frac{y_+ - y_-}{2\delta_{x_i}}$$

$$u_i(y) \approx \frac{y_+ - y_-}{2\delta_{x_i}} u(x_i)$$

# Compare finite difference with the GUM



## GUM first order

Uncertainty budget:

	x	u	c	u.c
$m$	100	2.0	0.01	0.02
$V_T$	100	0.10	-0.01	0.001
$T$	25	1.15	-0.001	0.00115

$$y: \quad 1$$

$$u(y): \quad 0.20$$

## Finite Difference ( $\delta = 0.01u$ )

Uncertainty budget:

	x	u	c	u.c
$m$	100	2.0	0.01	0.02
$V_T$	100	0.10	-0.01	0.001
$T$	25	1.15	-0.001	0.00115

$$y: \quad 1$$

$$u(y): \quad 0.20$$

# Disadvantages of the finite difference method



- **Two additions and a division**
  - Slightly tedious in a spreadsheet
- **No obvious choice of  $\delta$** 
  - Big enough to avoid internal round-off errors
  - Small enough for a ‘good’ approximation
  - Can take several trial runs to establish reliable difference



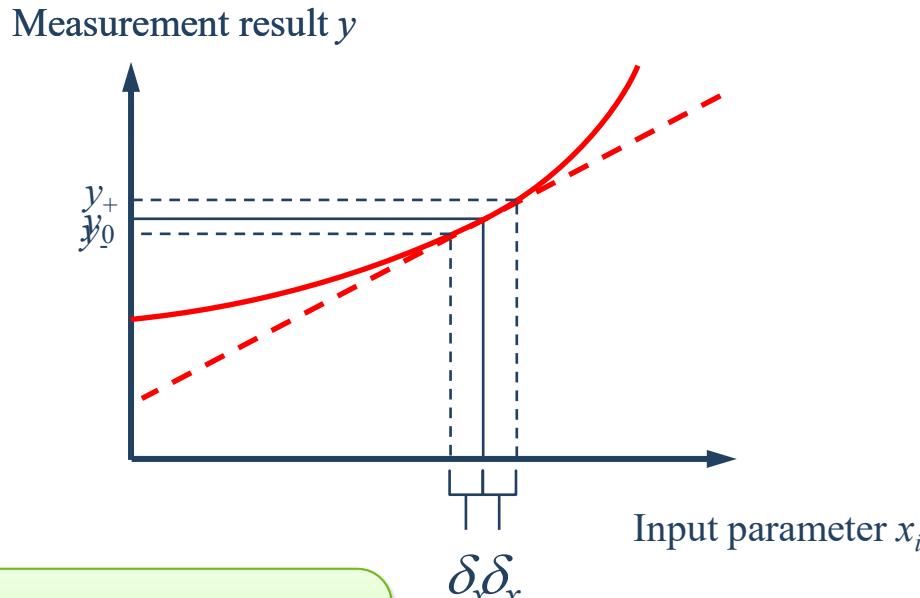
# Sensitivity coefficients from spreadsheets

2. Kragten's method

LGC

The LGC logo is located in the bottom right corner. It consists of the letters "LGC" in a bold, blue, sans-serif font, enclosed within a white circle.

# Kragten's method

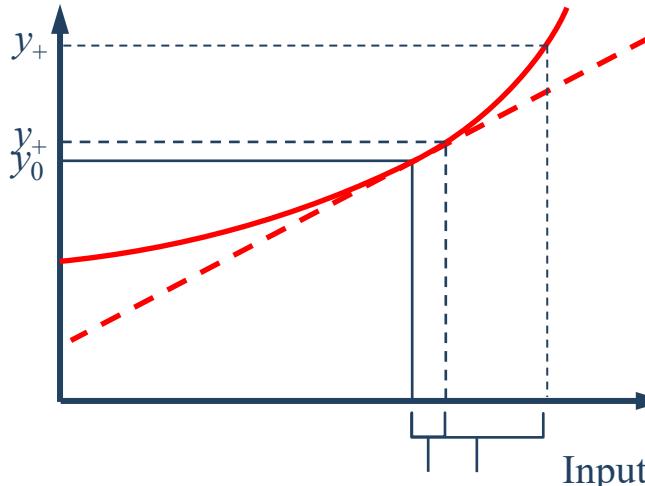


$$u_i(y) \approx \frac{y_+ - y_0}{\delta_{x_i}} u(x_i)$$

# Kragten's method



Measurement result  $y$



$$u_i(y) \approx \frac{y_+ - y_0}{u(x_i)} u(x_i)$$



$$u_i(y) \approx y_+ - y_0$$

# Kragten's method

## Spreadsheet implementation

	x	u						
m	100	2	102	100	100	100	100	
V <sub>T</sub>	100	0.1	100	100.1	100	100	100	
α	0.001		0.001	0.001	0.001	0.001	0.001	
T	25	1.15	25	25	25	26.15	25	$x+u(x)$
T <sub>0</sub>	25		25	25	25	25	25	
C	1	0.020	1.02	0.999001	1	1.00115	1	Recalculation
			0.02	-0.001	0	0.00115	0	Differences
			0.0004	9.98E-07	0	1.32E-06	0	Diff <sup>2</sup>

Combined uncertainty

Details in QUAM:2012

# WARNING

*Kragten is not exact for  
non-linear cases*



# Compare Kragten with FD



## Finite Difference

Expression:  $a/(b - c)$

### Uncertainty budget:

x	u	c	u.c
a	1	0.05	1.000000
b	3	0.15	-1.000002
c	2	0.10	1.000001

y: 1.0

u(y): 0.1870832

## Kragten

Expression:  $a/(b - c)$

### Uncertainty budget:

x	u	c	u.c
a	1	0.05	1.0000
b	3	0.15	-0.8695
c	2	0.10	1.1111

y: 1.0

u(y): 0.1784906

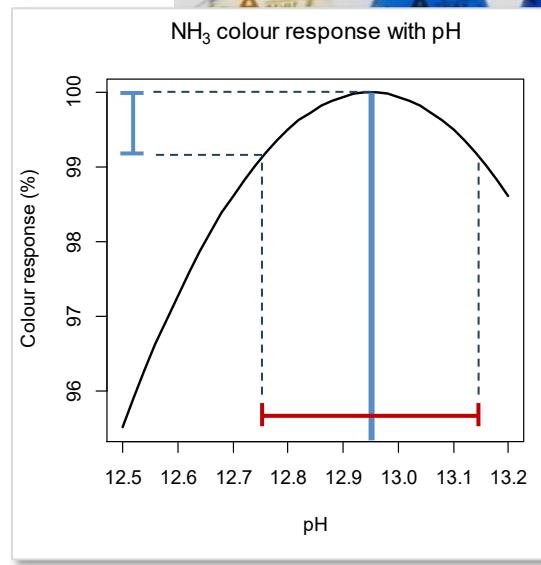
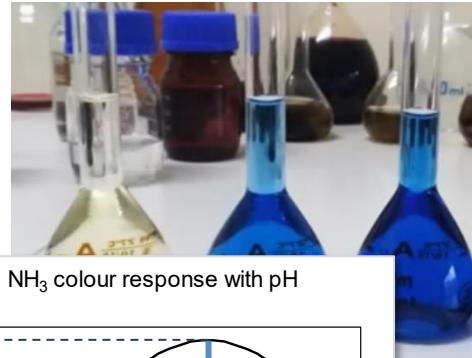
# Why would we use a less accurate algorithm?



# Example: Ammonia in water



- Spectrophotometric determination
- Phenol/hypochlorite forms indophenol blue; enhanced with sodium nitroprusside and measured photometrically
- Colour formation is pH-sensitive\*
- Analysis may be carried out close to maximum
- Require MU due to pH uncertainty



\* Pym, R. V. E., Milham, P. J.,  
Analytical Chemistry, 1976, 48, 9, 1413-1415

# $(\text{NH}_3)$ example: Kragten vs GUM



## GUM

Expression:  $a * \text{pH}^2 + b * \text{pH} + c$

### Uncertainty budget:

	x	u	c	u.c
pH	12.95	0.115	0.0000	0
a	-22.22	0.000	167.7025	0
b	575.56	0.000	12.9500	0
c	-3626.72	0.000	1.0000	0

y: 100

u(y): 0.0

## Kragten

Expression:  $a * \text{pH}^2 + b * \text{pH} + c$

### Uncertainty budget:

	x	u	c	u.c
pH	12.95	0.115	-2.57	-0.2963
a	-22.22	0.00	167.70	0.0
b	575.56	0.00	12.95	0.0
c	-3626.72	0.00	1.00	0.0

y: 100

u(y): 0.296

# Finite difference methods compared



## Finite difference 1<sup>st</sup> order

- Accurate gradient
  - Faithfully reproduces 1<sup>st</sup> order GUM uncertainty
  - Simple to calculate
- 
- 1<sup>st</sup> order GUM is insufficient for highly non-linear cases
    - Needs 2<sup>nd</sup> and higher order

## Kragten

- Exact only for linear examples
  - Does not reproduce 1<sup>st</sup> order GUM
  - Simple to calculate
- 
- Usually adequate for mild nonlinearity
  - May be better for highly non-linear cases

Both much simpler than manual differentiation

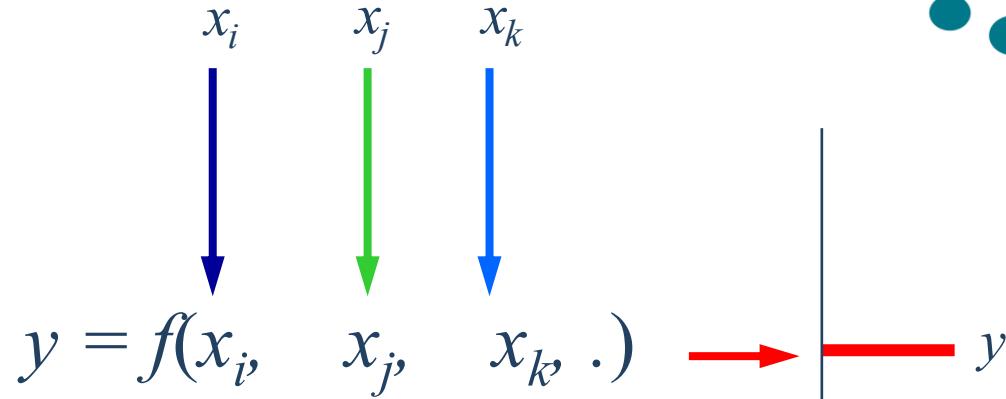


# Simulation methods

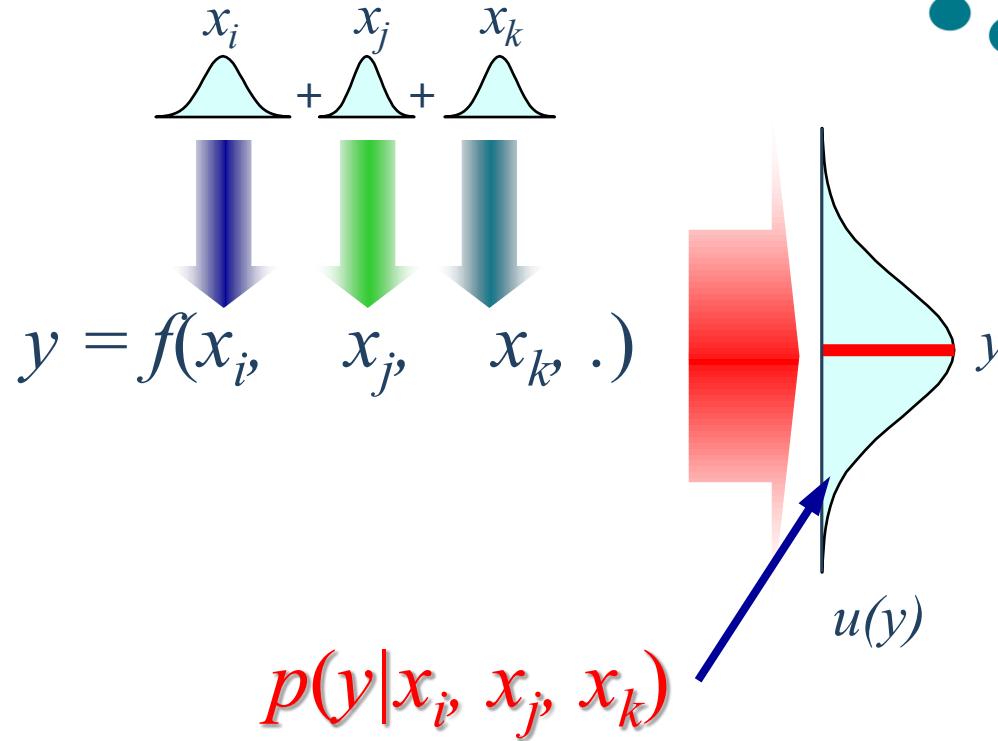
1. Monte Carlo Simulation  
(GUM Supplement 1)



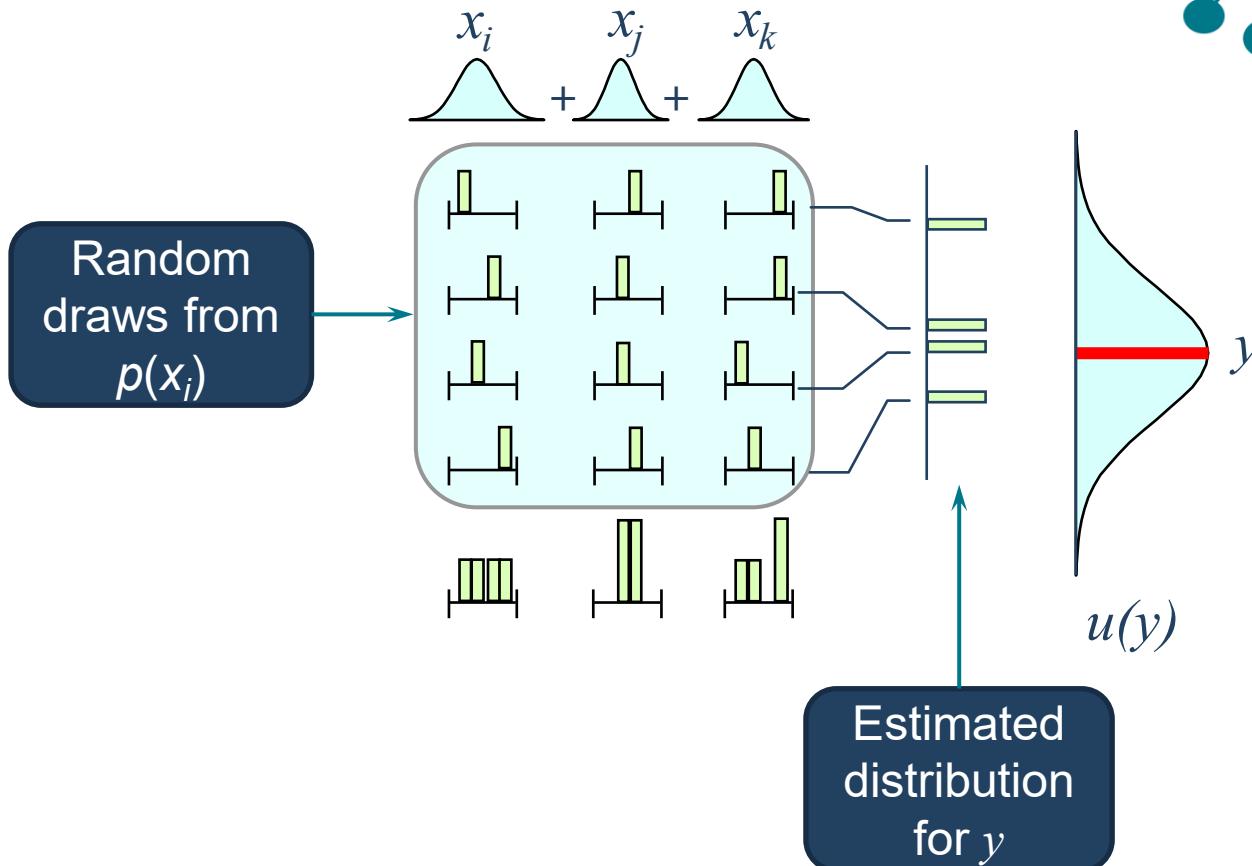
# Principle of simulation



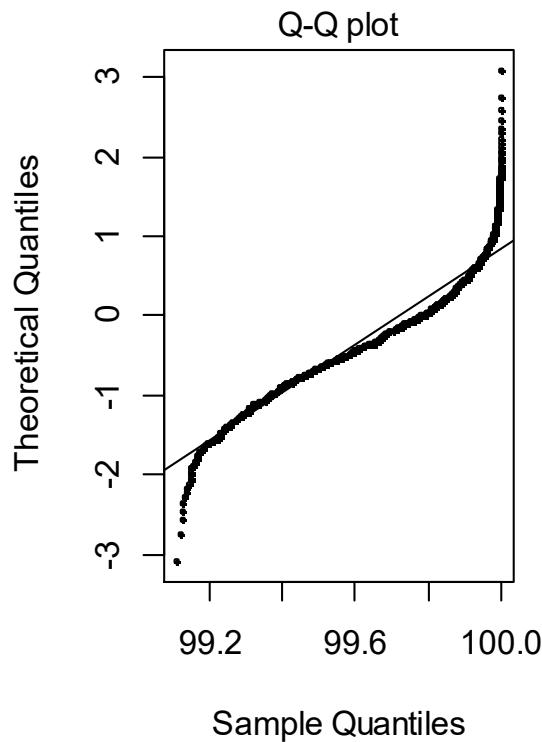
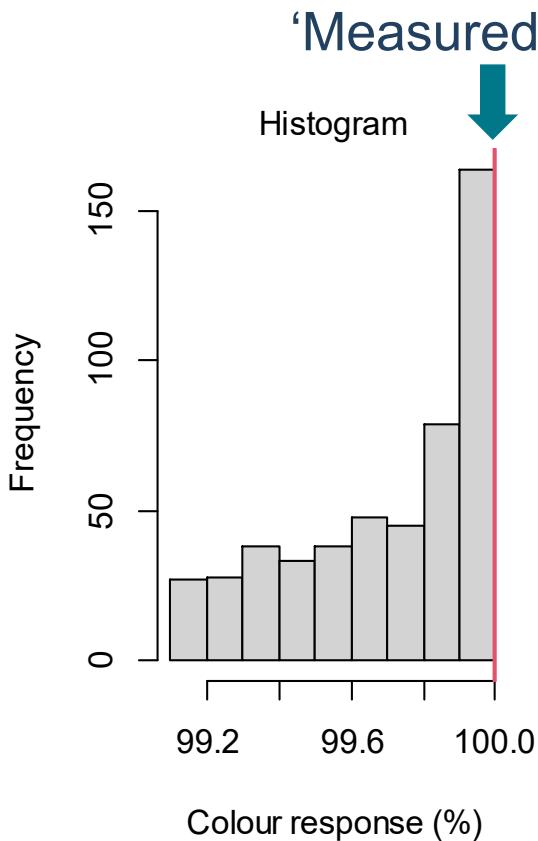
# Principle of simulation



# Principle of simulation



# NH<sub>3</sub> example: MCS, 500 replicates



# $(\text{NH}_3)$ example: MCS and Kragten



## MCS

Expression:  $a * \text{pH}^2 + b * \text{pH} + c$

### Uncertainty budget:

	x	u	c	u.c
pH	12.95	0.115	0.049	-0.0056

distrib distrib.pars

unif min=12.75, max=13.15

y: 100  
u(y): 0.265

## Kragten

Expression:  $a * \text{pH}^2 + b * \text{pH} + c$

### Uncertainty budget:

	x	u	c	u.c
pH	12.95	0.115	-2.57	-0.2963
a	-22.22	0.00	167.70	0.0
b	575.56	0.00	12.95	0.0
c	-3626.72	0.00	1.00	0.0

y: 100  
u(y): 0.296

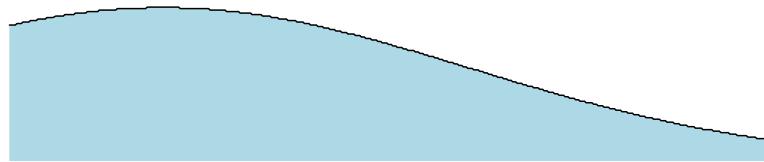


# Simulation methods

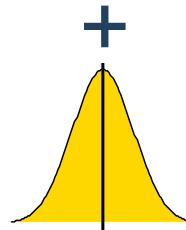
## 2. Bayesian methods using MCMC



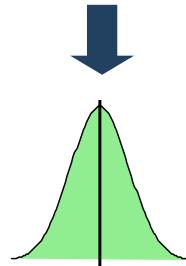
# Bayes applied to Measurement Uncertainty



Prior for  
 $\mu$

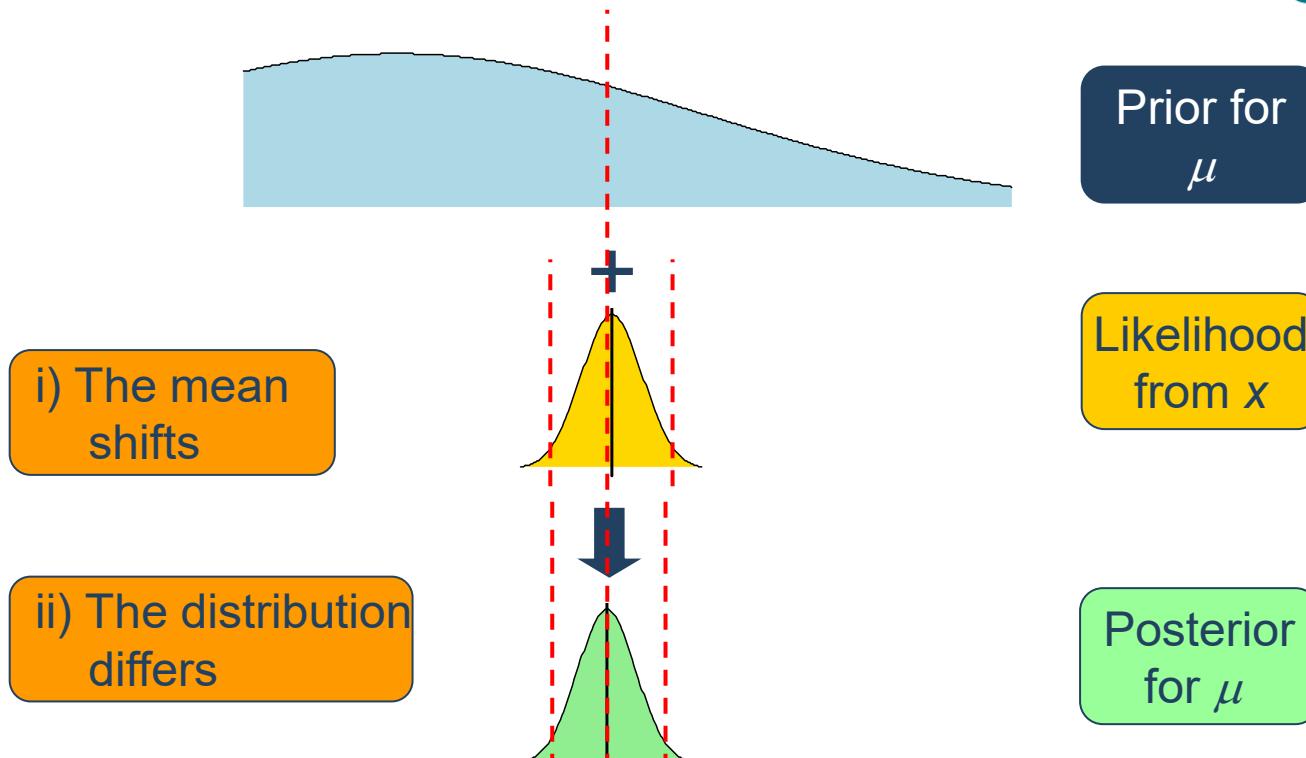


Likelihood  
from  $x$

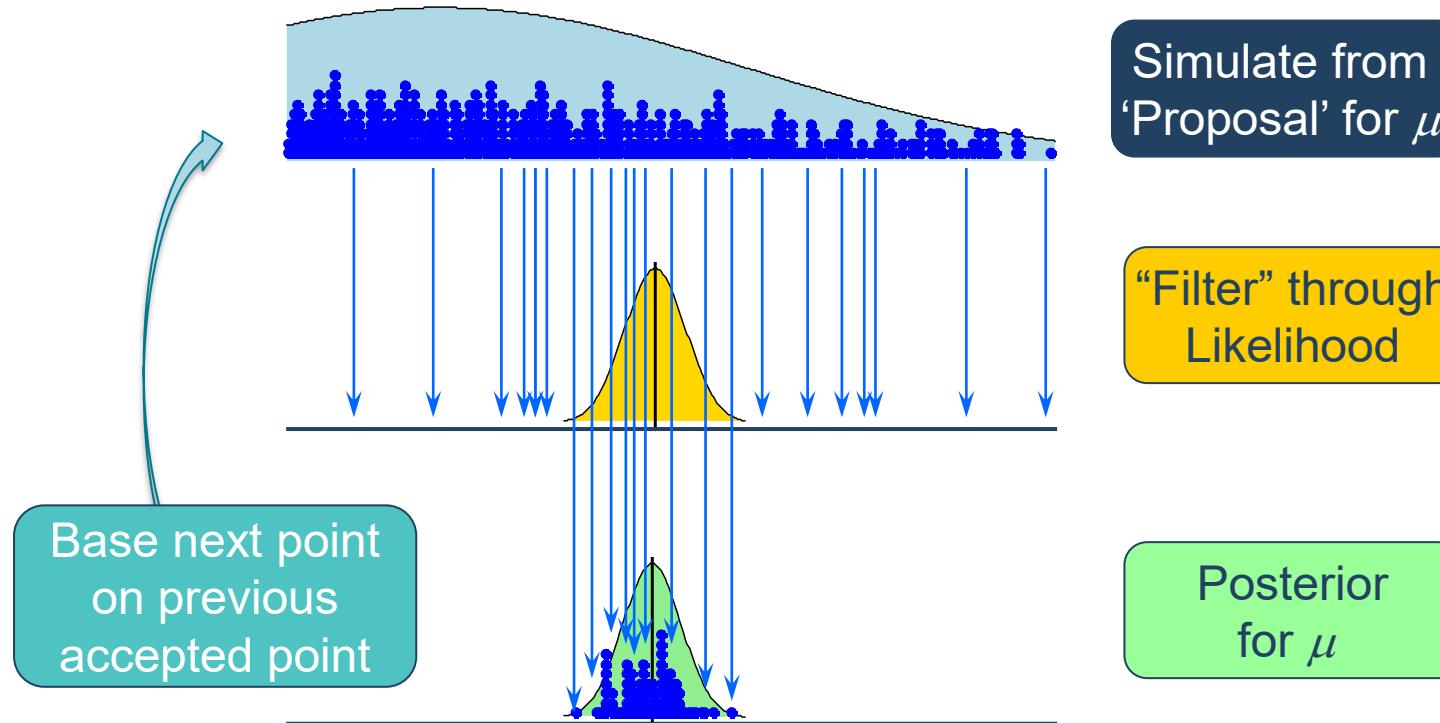


Posterior  
for  $\mu$

# Bayes applied to Measurement Uncertainty



# Bayes via Markov Chain Monte Carlo (MCMC)

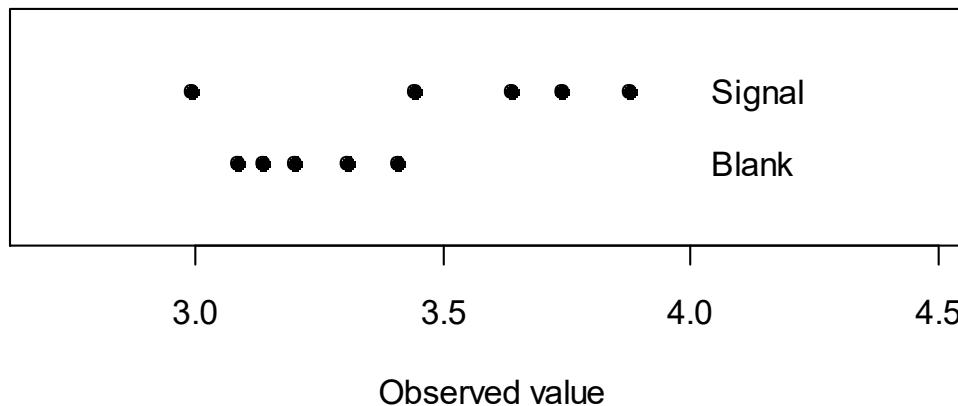


# MCMC example



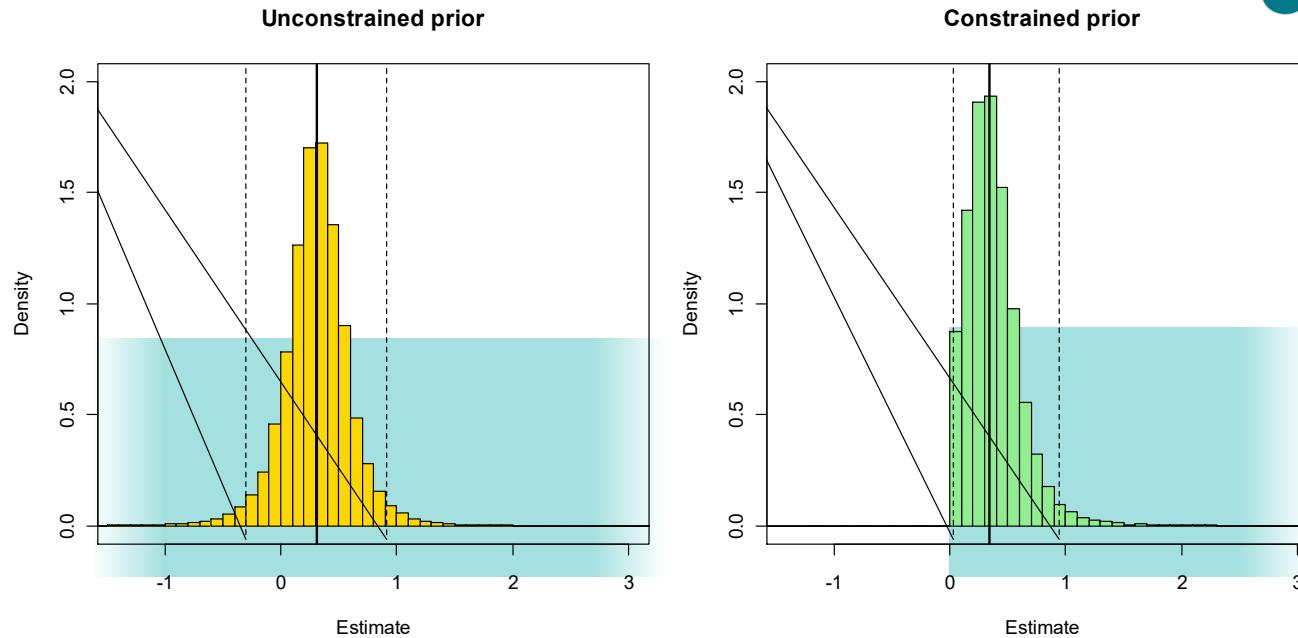
- **y is a concentration calculated from a signal minus a blank value**

Example data



- **True concentration cannot be below zero**

# MCMC example - results



Uniform priors assumed for  $y$  and for both variances; error distributions assumed normal.

*Calculations carried out using WinBUGS 1.4*

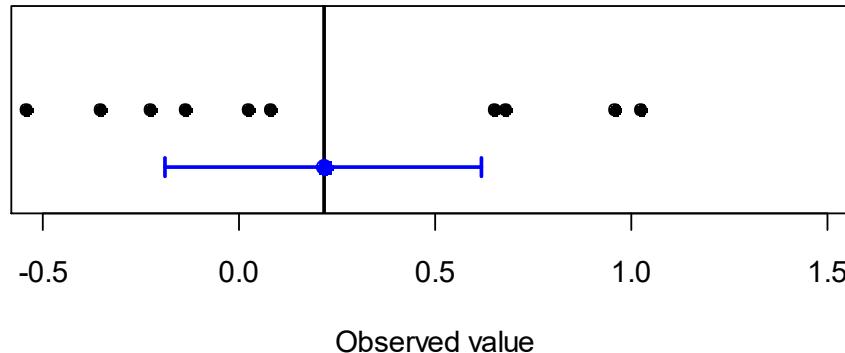
**Bayes is useful  
with  
informative prior  
information**



# MCMC example 2: Constant RSD - SD proportional to $\mu$



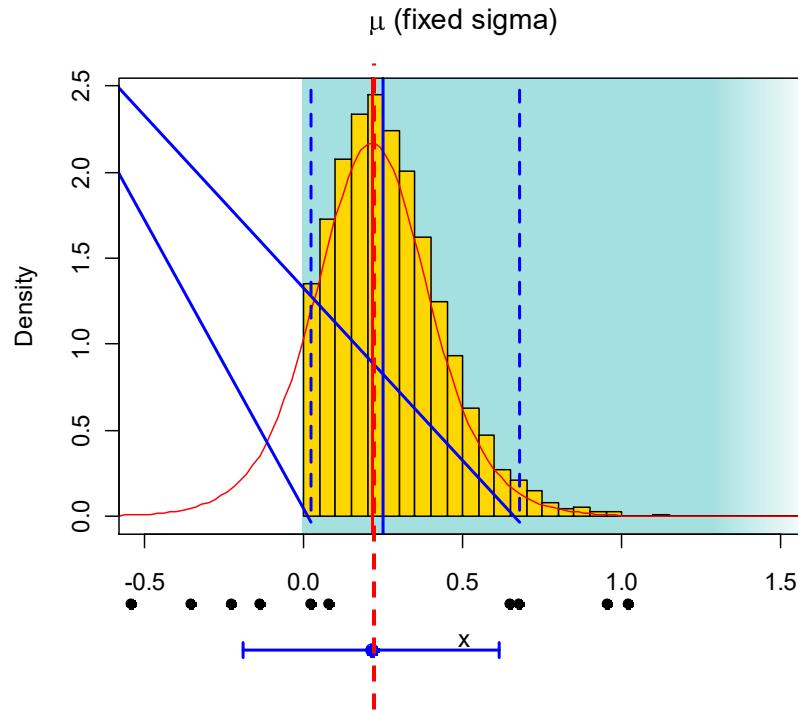
Example data



- Concentration: not below zero
- Common observation: standard deviation proportional to true value

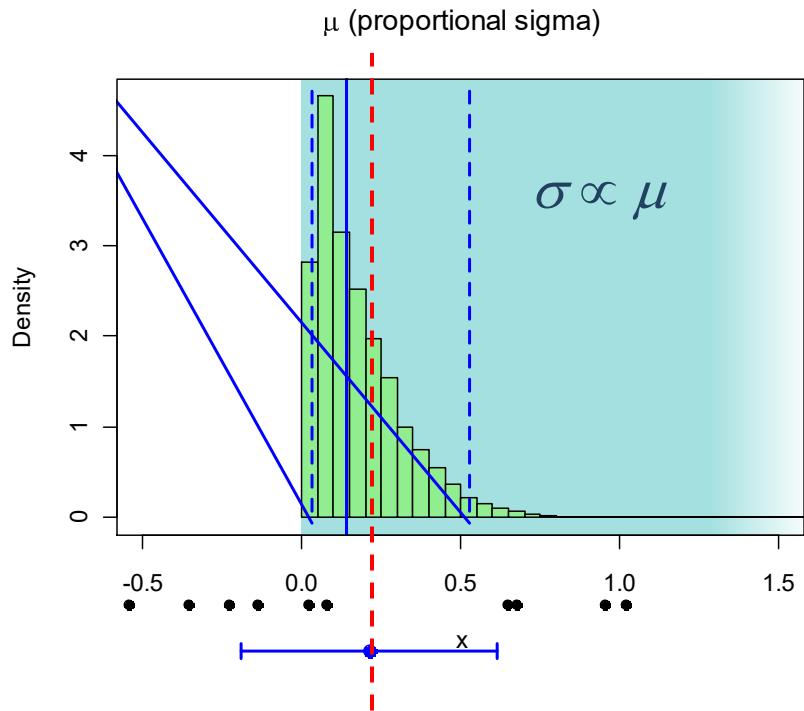
# MCMC results:

## i) Fixed standard deviation



## MCMC results

### ii) Proportional standard deviation



**Bayes respects the  
underlying statistical  
model**



# Bayes and measurement uncertainty: Avoiding controversy



## Rule 1: The default: Use an uninformative prior

- typically wide Normal or Uniform

## Rule 2: There are no truly uninformative priors

- And some ‘uninformative’ priors can be unexpectedly informative

## Rule 3: If an uninformative prior works for measurement uncertainty, there's probably an easier way

Bayes theorem is most  
useful for  
*uncontroversial,*  
*informative* priors

# Summary



- Numerical methods work
  - when used with care
- Finite difference and Kragten methods are simple to calculate and usually reliable
  - Kragten's method less like 1<sup>st</sup> order – but this is often good!
- Simulation methods show distributions
  - Not just standard uncertainties
- MCS (GS1) simple but computer intensive
- MCMC more appropriate for constraints and x distribution dependent on y (eg proportional sd) .. BUT:
  - Much more difficult – specialist software only
  - Interpretation needs care

# Software



- **Simple MCS, Kragten and Finite Difference**
  - metRology version 0.9-4 running under R version 2.12
  - <http://sourceforge.net/projects/metrology>

- **Bayesian MCMC calculation**
  - WinBUGS  
<http://www.mrc-bsu.cam.ac.uk/bugs/winbugs/contents.shtml>
  - Stan  
<https://mc-stan.org/>

- **See also**
  - JAGS<sup>1</sup>  
<https://mcmc-jags.sourceforge.io/>