

## **BEYOND LEAST SQUARES**

V.Dose

Max Planck Institut  
für Plasmaphysik



## C. F. Gauss 1777 - 1855



1794 first use of quadratic distance measure

1798 probabilistic explanation

1821 quadratic measure ad hoc

first(?) mention of weights

1823 exact variances unknown

1826 data censoring unnecessary (?)



## Bayesian probability theory



$$P(\boldsymbol{\theta}|\mathbf{D},\mathbf{M},I) = P(\mathbf{D}|\boldsymbol{\theta},\mathbf{M},I) P(\boldsymbol{\theta}|\mathbf{M},I) / P(\mathbf{D}|\mathbf{M},I)$$

$$\int P(x|I) P(y|x,I) dx = \int P(x,y|I) dx = P(y|I)$$



## Sufficient statistic



$$\hat{G} = u^2(\hat{G}) \sum_i d_i / \sigma_i^2 \quad , \quad u^2(\hat{G}) = 1 / \sum_i 1 / \sigma_i^2$$

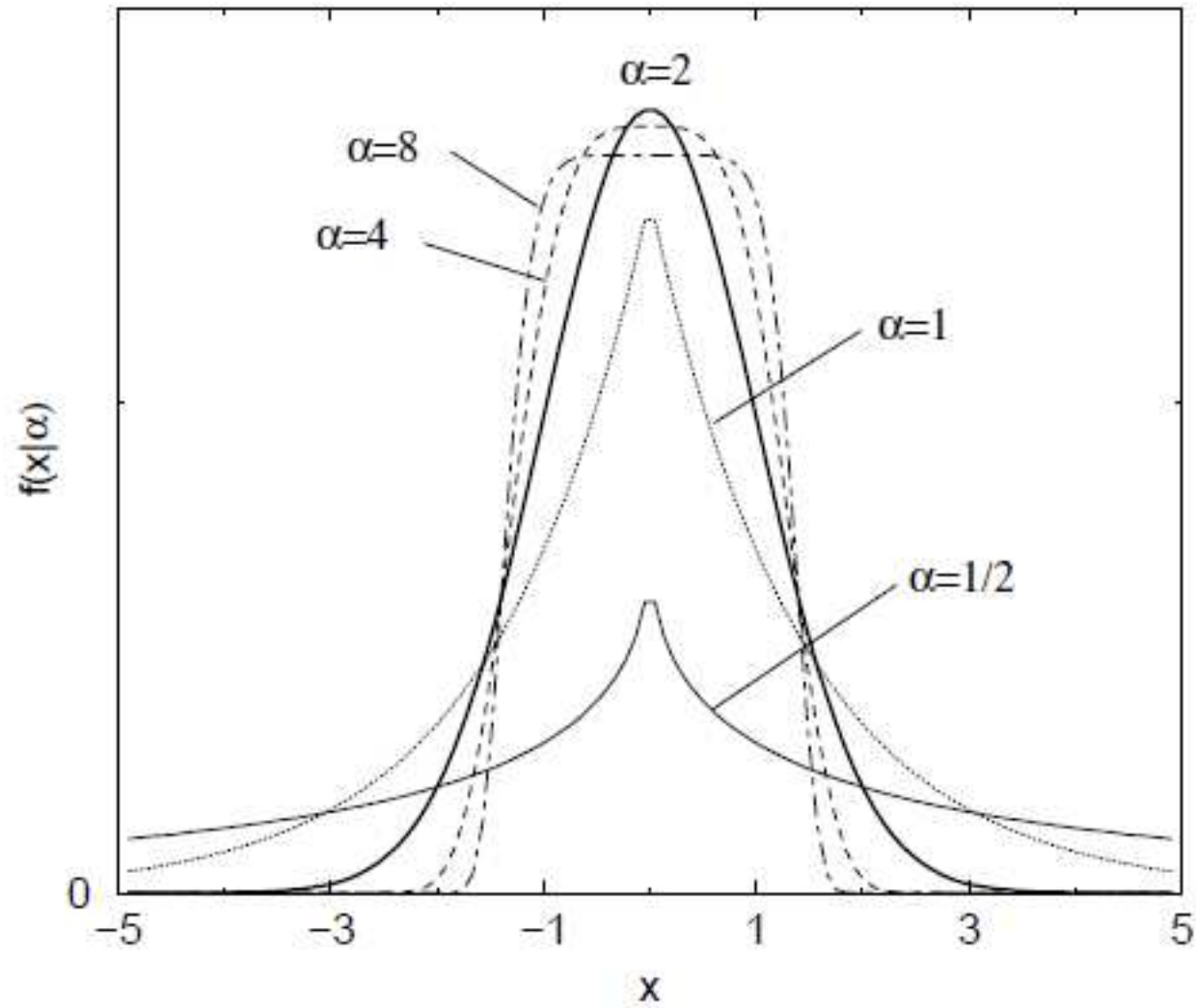
$$d_i \rightarrow d_i + \gamma(d_i - \hat{G}) \quad \text{invariance!}$$

generalised Gauss :

$$p(d|G, \sigma, \alpha) = \frac{1}{2\sigma\sqrt{2}\Gamma(1+1/\alpha)} \exp \left\{ - \left| \frac{d-G}{\sigma\sqrt{2}} \right|^\alpha \right\}$$



# generalised Gauss





$$p(\vec{d}|G, \vec{\sigma}, \alpha) = \frac{1}{\{\Gamma(1 + 1/\alpha)\}^N} \cdot \prod_i \frac{1}{2\sigma_i\sqrt{2}} \exp\left\{-\left|\frac{d_i - G}{\sigma_i\sqrt{2}}\right|^\alpha\right\}$$

$$p(\vec{d}|G, \vec{\sigma}) = \int_0^\infty d\alpha p(\alpha) p(\vec{d}|G, \vec{\sigma}, \alpha)$$



## Zellner's maximum data information prior



$$-H(p) = \int p(\mathbf{d}, \alpha) \log p(\mathbf{d}, \alpha) d\mathbf{d} d\alpha,$$

$$p(\mathbf{d}, \alpha) = p(\alpha) p(\mathbf{d}|\alpha)$$

$$-H(p) = \int I(\alpha) p(\alpha) d\alpha + \int \cancel{p(\alpha) \log p(\alpha)} d\alpha$$

$$I(\alpha) = \int p(\mathbf{d}|\alpha) \log p(\mathbf{d}|\alpha) d\mathbf{d}$$



$$I(\alpha) = \int p(\mathbf{d}|\alpha) \log p(\mathbf{d}|\alpha) d\mathbf{d}$$

$$\Phi(p) = -\int p(\alpha) \log p(\alpha) d\alpha + \int I(\alpha) p(\alpha) d\alpha$$

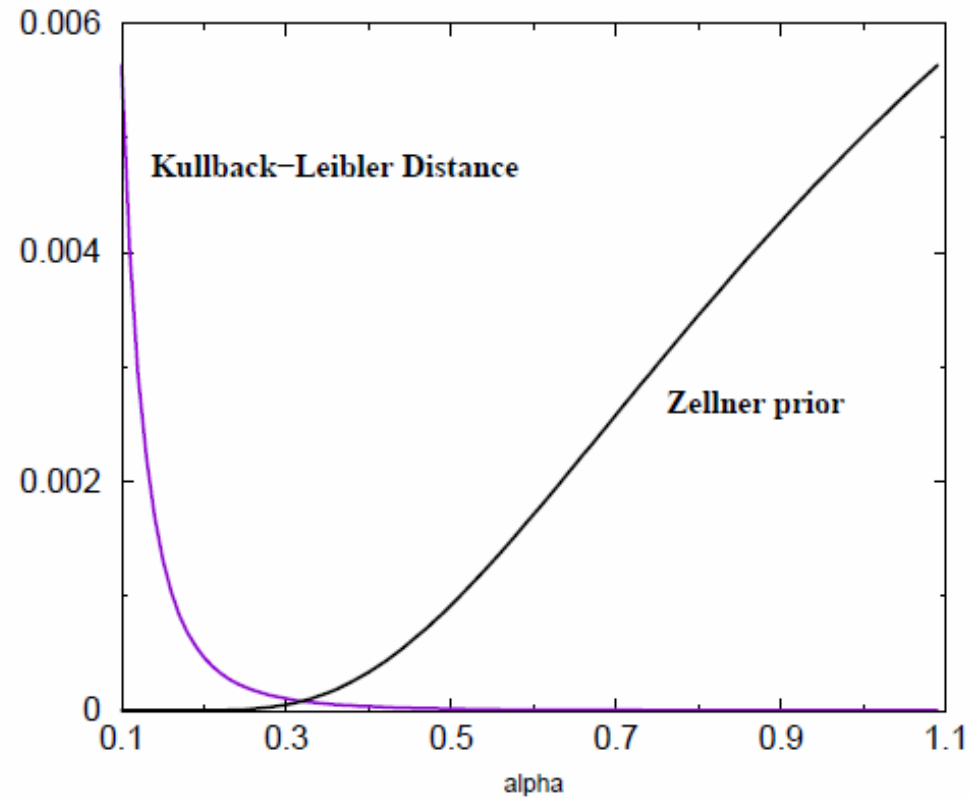
$$p(\alpha) = \exp( I(\alpha) ) / Z$$

$$p(\alpha) = \frac{\exp\{-1/\alpha\}}{\Gamma(1+1/\alpha)} \frac{1}{Z(\alpha_0)}, \quad 0 \leq \alpha \leq \alpha_0$$





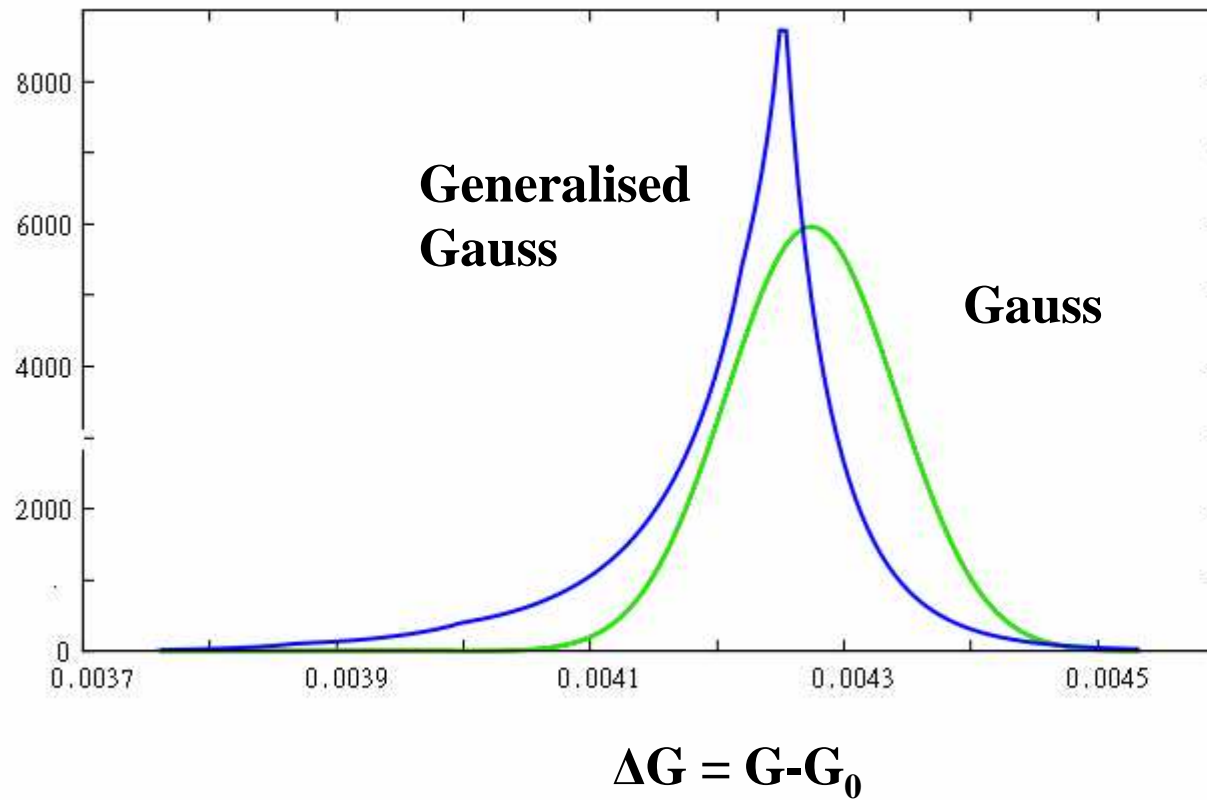
## Zellner prior and K/L-distance



$$K/L(\alpha) = \int dx f(x|\alpha+\varepsilon) \log f(x|\alpha), \varepsilon=0.001$$

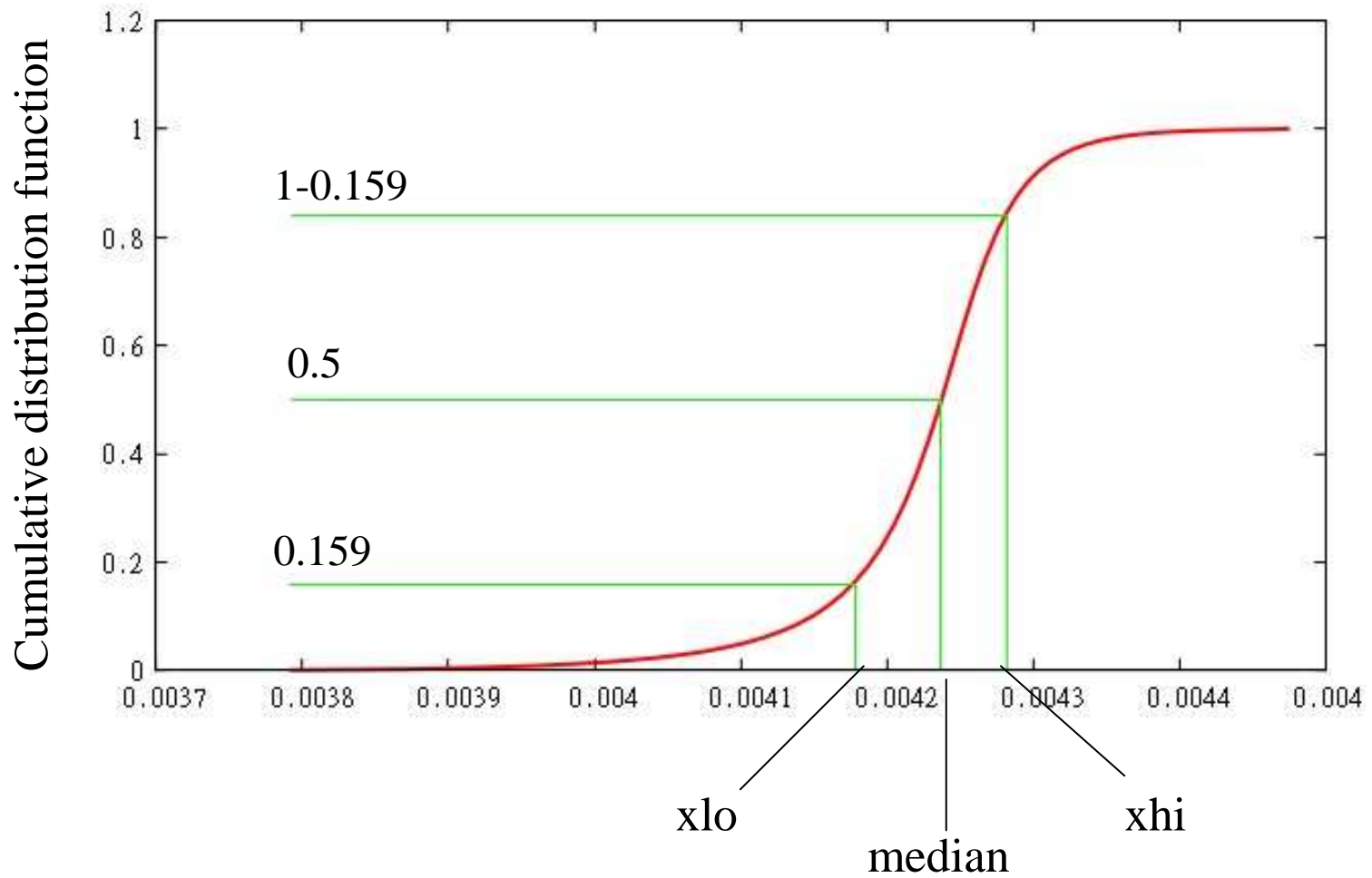


# Gauss and generalized Gauss





# asymmetric posterior (cdf)





## Comparison of evaluations



### Newtonian constant of gravitation

	point est.	uncertainty
least squares	6.674274	(+67, -67)
Gauss generalised	6.674200	(+71, -103)
CODATA 06	6.67428	(+670, -670)

Units of  $10^{11} \text{ kg}^{-1} \text{ s}^{-2} \text{ m}^3$



## posterior alpha distribution

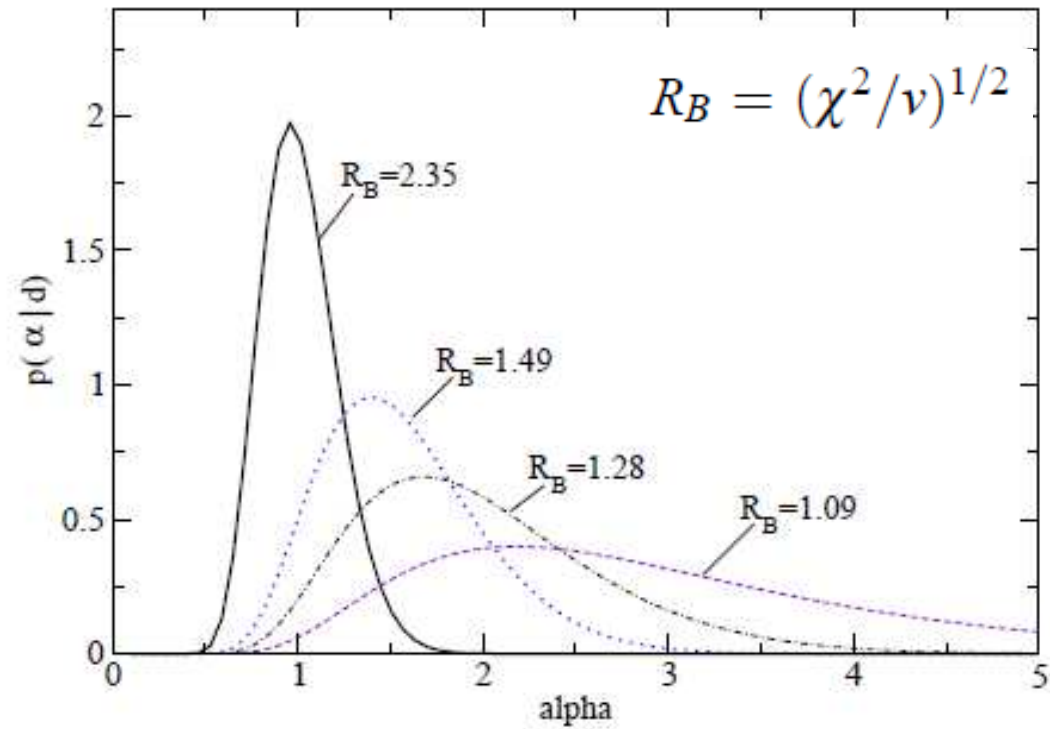


$$p(\mathbf{d}|\alpha, \boldsymbol{\sigma}) = \int dG p(G) p(\mathbf{d}|G, \alpha, \boldsymbol{\sigma})$$

$$p(\alpha|\mathbf{d}, \boldsymbol{\sigma}) = p(\alpha) p(\mathbf{d}|\alpha, \boldsymbol{\sigma}) / p(\mathbf{d}|\boldsymbol{\sigma})$$



# alpha distributions, real data





### uncertainties:

generate  $r_i(0,1]$ , scale by  $\lambda = \frac{1}{u^2(\hat{G}) \sum_i r_i}$       $\tilde{\sigma}_i = 1/\sqrt{\lambda r_i}$

### data:

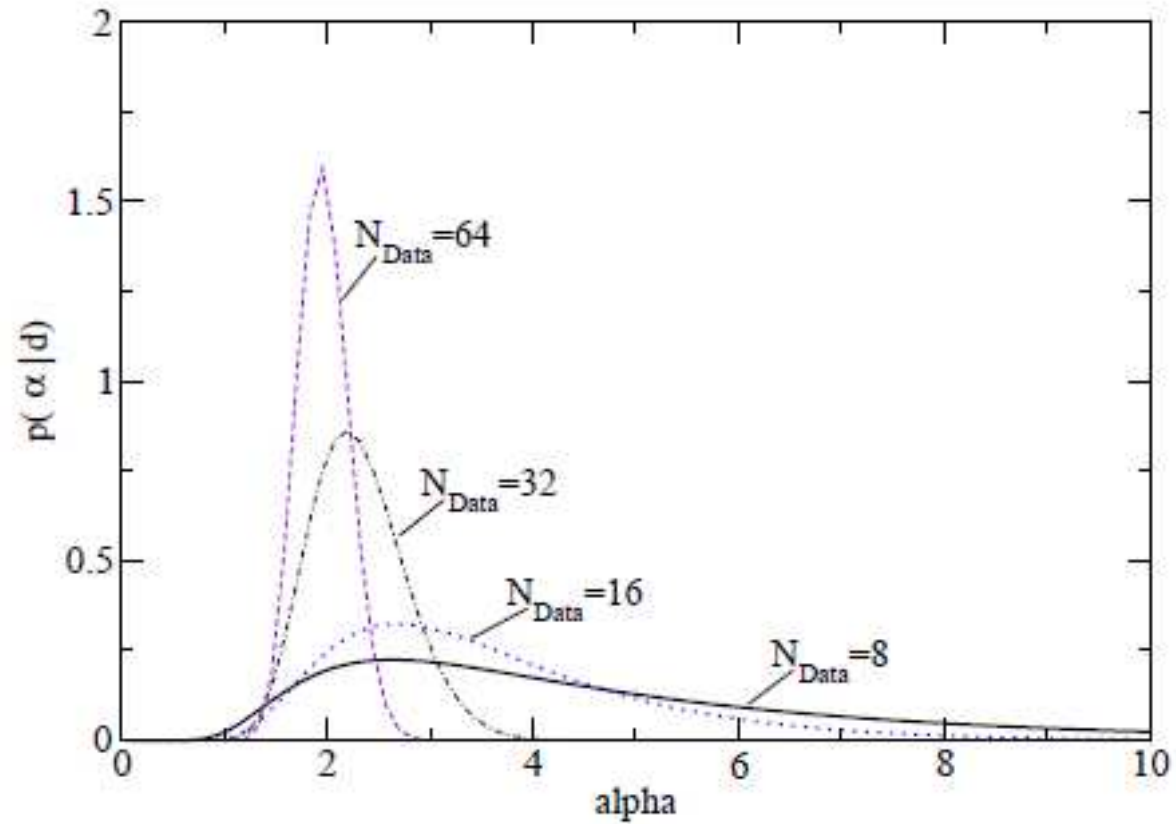
generate  $\text{rnd}_G(\hat{G}, u^2(\hat{G}))$

adjust scatter      $d_i \rightarrow d_i + \gamma(d_i - \hat{G})$

impose  $R_\gamma = 1$ ,      $R_\gamma = R_0(1 + \gamma)$



## alpha distributions, surrogate data







## Gauss 1823:



*„.....the variances of the measurement  $\sigma_i^2$  are practically never exactly known.....“*



## Precision of errors unknown



$$p(\sigma_i | s_i, \omega_i) = \delta \left( \sigma_i - \frac{s_i}{\omega_i} \right)$$

$$\langle \omega_i \rangle = 1 \text{ for all } i \longrightarrow p(\vec{\omega}) = \exp \left\{ - \sum_i \omega_i \right\}$$

$$p(\vec{d} | G, \vec{s}) = \int d\vec{\omega} p(\vec{\omega}) \int d\vec{\sigma} \prod_i \delta \left( \sigma_i - \frac{s_i}{\omega_i} \right) p(d_i | G, \sigma_i)$$

$$x_i = (d_i - G) / s_i \sqrt{2}$$

$$p(\vec{d} | G, \vec{s}) = \prod_i \frac{1}{s_i \sqrt{2\pi}} \int_0^\infty d\omega_i \omega_i \exp \{ -\omega_i - \omega_i^2 x_i^2 \}$$



## error marginalisation ctd



$$x_i = (d_i - G) / s_i \sqrt{2}$$

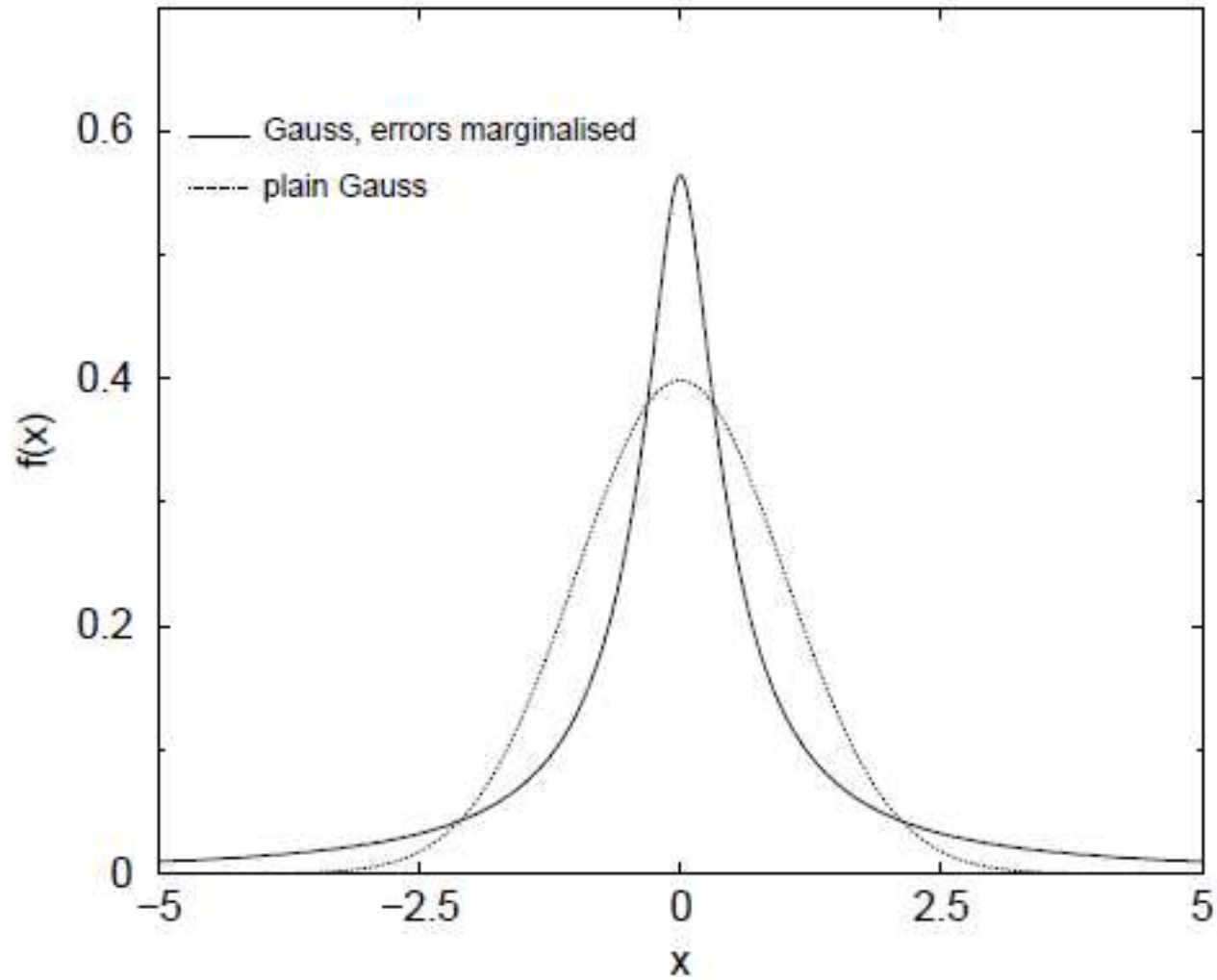
$$p(\vec{d} | G, \vec{s}) = \prod_i \frac{1}{s_i \sqrt{2\pi}} \frac{1}{2x_i^2} \left[ 1 - \frac{\sqrt{\pi}}{2x_i} e^{\frac{1}{4x_i^2}} \operatorname{erfc} \left\{ \frac{1}{2x_i} \right\} \right]$$

$$z = 1/2x \quad \operatorname{erfc}(z) = 1 - \operatorname{erf}(z)$$

$$\sqrt{\pi} \cdot z \cdot e^{z^2} \operatorname{erfc} \{z\} \sim 1 - \frac{1}{2z^2} + \frac{1 \cdot 3}{(2z^2)^2} - \frac{1 \cdot 3 \cdot 5}{(2z^2)^3} + \dots$$

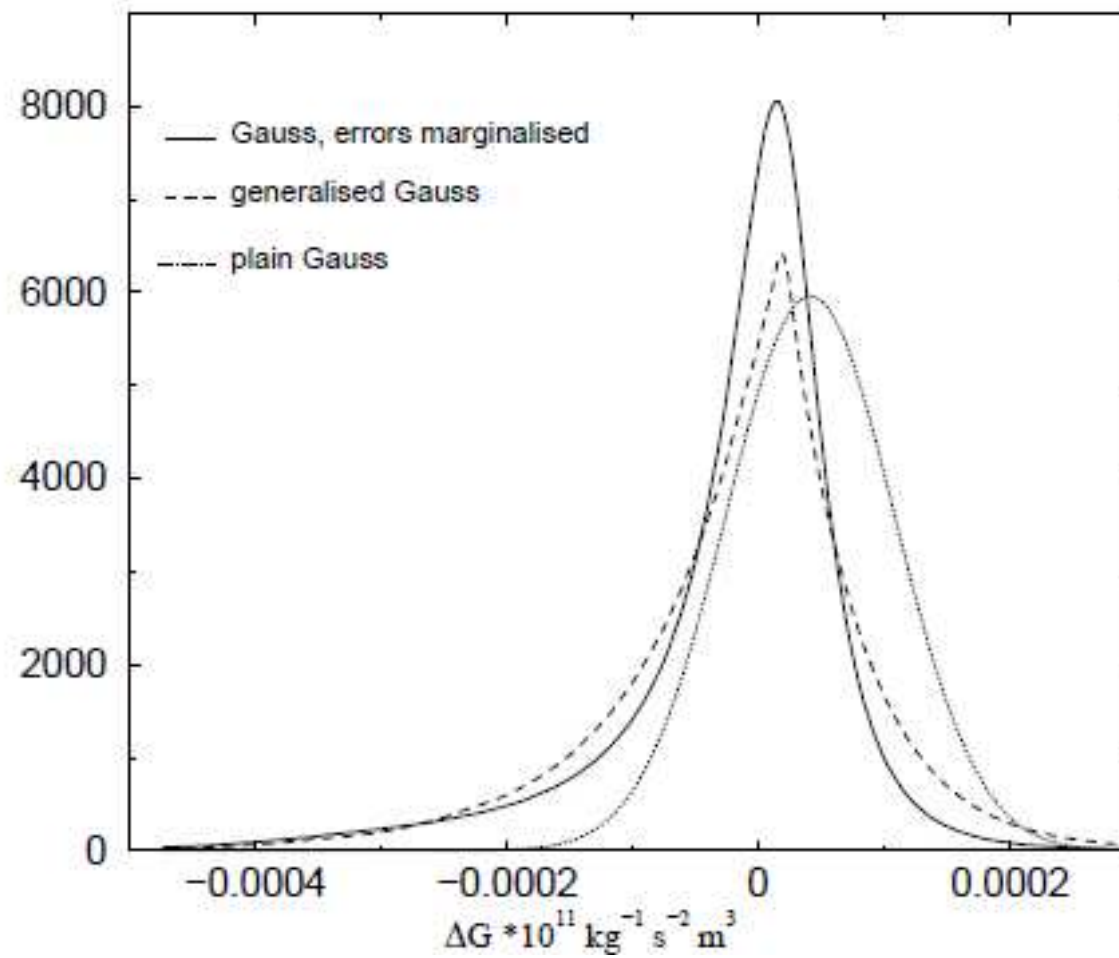


# Gauss & marginalised Gauss





## posterior distributions of $G$





## comparison of evaluations



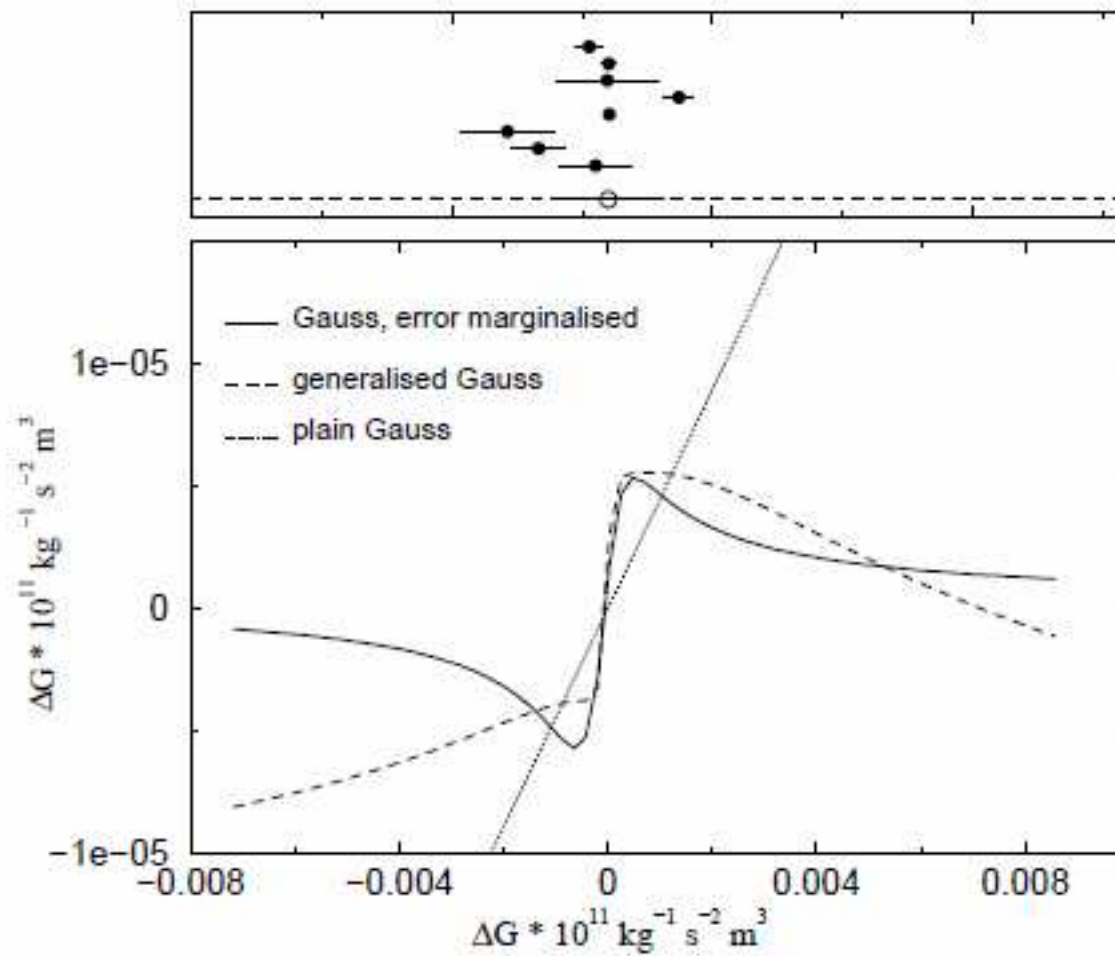
### Newtonian constant of gravitation

	point est.	uncertainty
least squares	6.674274	(+67, -67)
Gauss generalised	6.674200	(+71, -103)
Gauss marginalised	6.674233	(+49, -88)
CODATA 06	6.67428	(+670, -670) !!

**Units of  $10^{11} \text{ kg}^{-1} \text{ s}^{-2} \text{ m}^3$**



# robustness in G-estimation





## electron charge $e$ and Planck's constant $h$



CODATA 2006:  $e_0 = 1.602\,176\,487 \cdot 10^{-19} \text{ C}$  ,  $h_0 = 6.626\,068\,96 \cdot 10^{-34} \text{ Js}$

Josephson constant  $K_J = 2e/h = 2(e_0 + \Delta e)/(h_0 + \Delta h)$

$$\approx 2(e_0/h_0)(1 + \Delta e/e_0 - \Delta h/h_0)$$

v.Klitzing constant  $R_K = h/e^2 = (h_0 + \Delta h)/(e_0 + \Delta e)^2$

$$\approx (h_0/e_0^2)(1 + 2 \Delta e/e_0)$$

Product  $K_J^2 R_K = 4/h = 4/(h_0 + \Delta h) \approx (4/h_0)(1 - \Delta h/h_0)$





# Likelihood



$$L_1(e,h) = p(d_{R_K}|e,h)$$

$$L_2(e,h) = p(d_{K_J}|e,h)$$

$$L_3(e,h) = p(d_{K_J^2 R_K}|e,h)$$

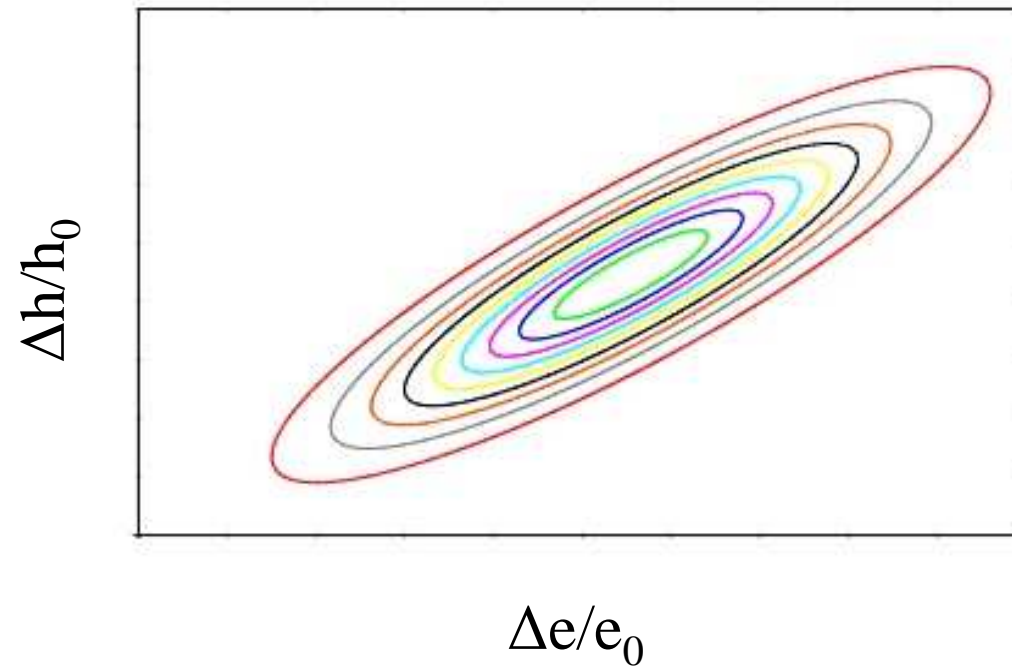
$$L(e,h) = L_1(e,h) * L_2(e,h) * L_3(e,h)$$



## 2-D Gaussian posterior

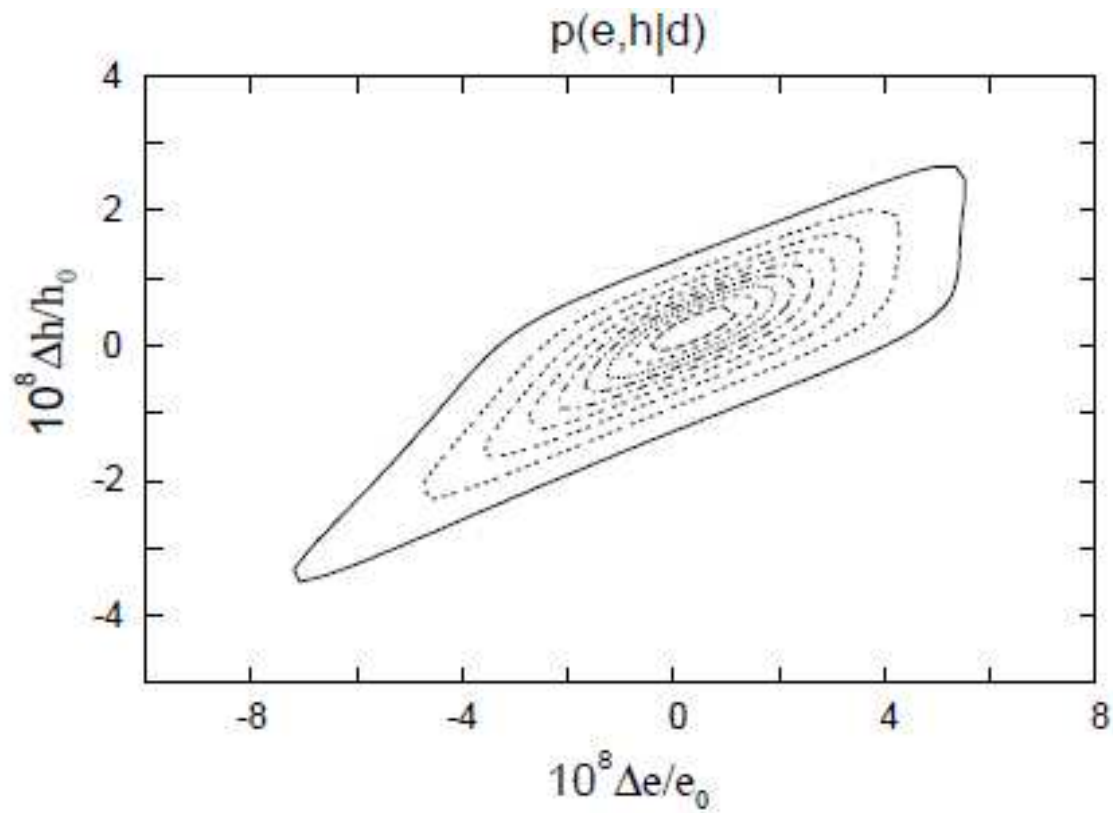


$P(e, h | \mathbf{d})$





# e/h posterior





## marginal distributions



Bayesian result :  $P(e,h|D)$

Marginals :  $P(e|D) = \int P(e,h|D) dh$

$P(h|D) = \int P(e,h|D) de$

Summaries : mean & variance

median & tails



## results on $e$ and $h$



**TABLE 3.** Estimates of  $e$  and  $h$  using traditional least squares and marginalised Gauss (16). CODATA-06 adjustments are shown for comparison.

	$e \cdot 10^{19} / C$
least squares	1.602 176 459 (+30, -30)
marg. Gauss	1.602 176 454 (+27, -33)
CODATA-06	1.602 176 487 (+40, -40)
	$h \cdot 10^{34} / J_s$
least squares	6.626 068 88 (+22,-22)
marg. Gauss	6.626 068 86 (+16,-25)
CODATA-06	6.626 068 96 (+33,-33)



*This talk is based on a paper by V.Dose and U.von Toussaint*



# THE END

**Thank you for your attention,  
the talk is open for discussion**