

# RECAP LECTURE 4 + FRITS PAERELS

THERMAL LIMIT OF STOCHASTIC RADIATION PROCESSES

→  $h\nu \ll kT$  THERMAL LIMIT  $\overline{\Delta P^2}(\nu) = \bar{P}^2(\nu)$

PAERELS SHOWED THAT ONE DOESN'T ALWAYS GET THE EXACT POISSON QUANTUM NOISE AT  $h\nu \gg kT$

→ USE INCOMPLETE GAMMA FUNCTION TO CALCULATE POISSON AND GAUSS CUMULATIVE DISTRIBUTION FUNCTION

→ PROPAGATION OF ERRORS  
UNDER THE ASSUMPTION OF INDEPENDENT VARIABLES

$$\bar{f} = f(\bar{u}, \bar{v}, \dots)$$

$$\sigma_f^2 = \sigma_u^2 \left( \frac{\partial f}{\partial u} \right)^2 + \sigma_v^2 \left( \frac{\partial f}{\partial v} \right)^2 + \dots$$

TODAY:

COMPARING DATA WITH A MODEL:  
LEAST-SQUARES FITTING, MAXIMUM  
LIKELIHOOD METHOD: GAUSSIAN DATA

“REAL” MAXIMUM LIKELIHOOD  
METHOD: POISSONIAN DATA

OAF2 CHAPTER 5.3+5.4  
SEE ALSO NUM RES CHAPTER 15

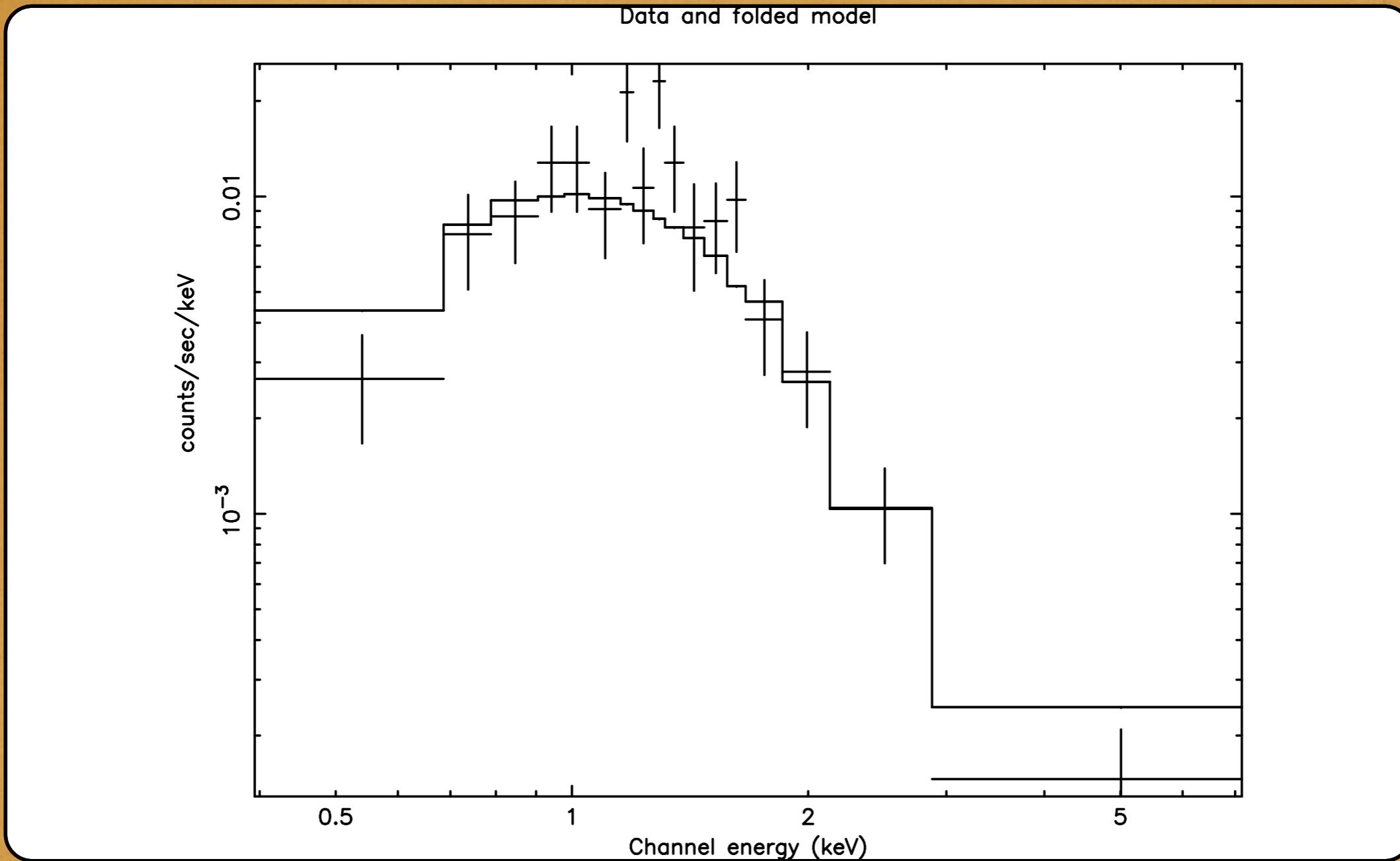
# COMPARE DATA WITH A MODEL

DESCRIBE DATA IN TERMS OF A CONTINUOUS  
FUNCTION

COMPARE OBSERVATIONS (DATA) WITH  
THEORETICAL MODEL PREDICTION

DESCRIBE THE DATA IN A FEW PARAMETERS

# EXAMPLE: CONTINUOUS MODEL THROUGH DISCRETE DATA & MODEL PREDICTION



X-RAY BINARY IN QUIESCEENCE NEUTRON STAR  
ATMOSPHERE MODEL

MAXIMUM LIKELIHOOD: MOST LIKELY  
OUTCOME IS ASSUMED TO BE THE  
‘CORRECT’ ONE

## METHOD OF LEAST SQUARES

$$dQ_i = P_i dx$$

PROBABILITY DENSITY FUNCTION  $\frac{dQ_i}{dx} = P_i$   
 $\hookrightarrow$  GAUSS, POISSON

$$P(y_i) \Delta y = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left(-\frac{1}{2} \frac{(y_i - y_m)^2}{\sigma_i^2}\right) \Delta y$$

NOTE:  $y_m$  = MODEL VALUE NOT MEAN HERE!

## METHOD OF LEAST SQUARES

$$P \propto \prod_{i=1}^N \left\{ \exp \left[ -\frac{1}{2} \left( \frac{y_i - y_m}{\sigma_i} \right)^2 \right] \right\}$$

$$\propto \exp \left[ -\frac{1}{2} \sum_{i=1}^N \left( \frac{y_i - y_m}{\sigma_i} \right)^2 \right] \}$$

$$\text{MINIMISE: } \chi^2 \equiv \sum_{i=1}^N \left( \frac{y_i - y_m}{\sigma_i} \right)^2$$

## MINIMISATION: ROOT FINDING PROBLEM

$$1D: \quad \frac{\partial}{\partial y_i} \sum_{i=1}^N \left( \frac{y_i - y_m}{\sigma_i} \right)^2 = 0$$

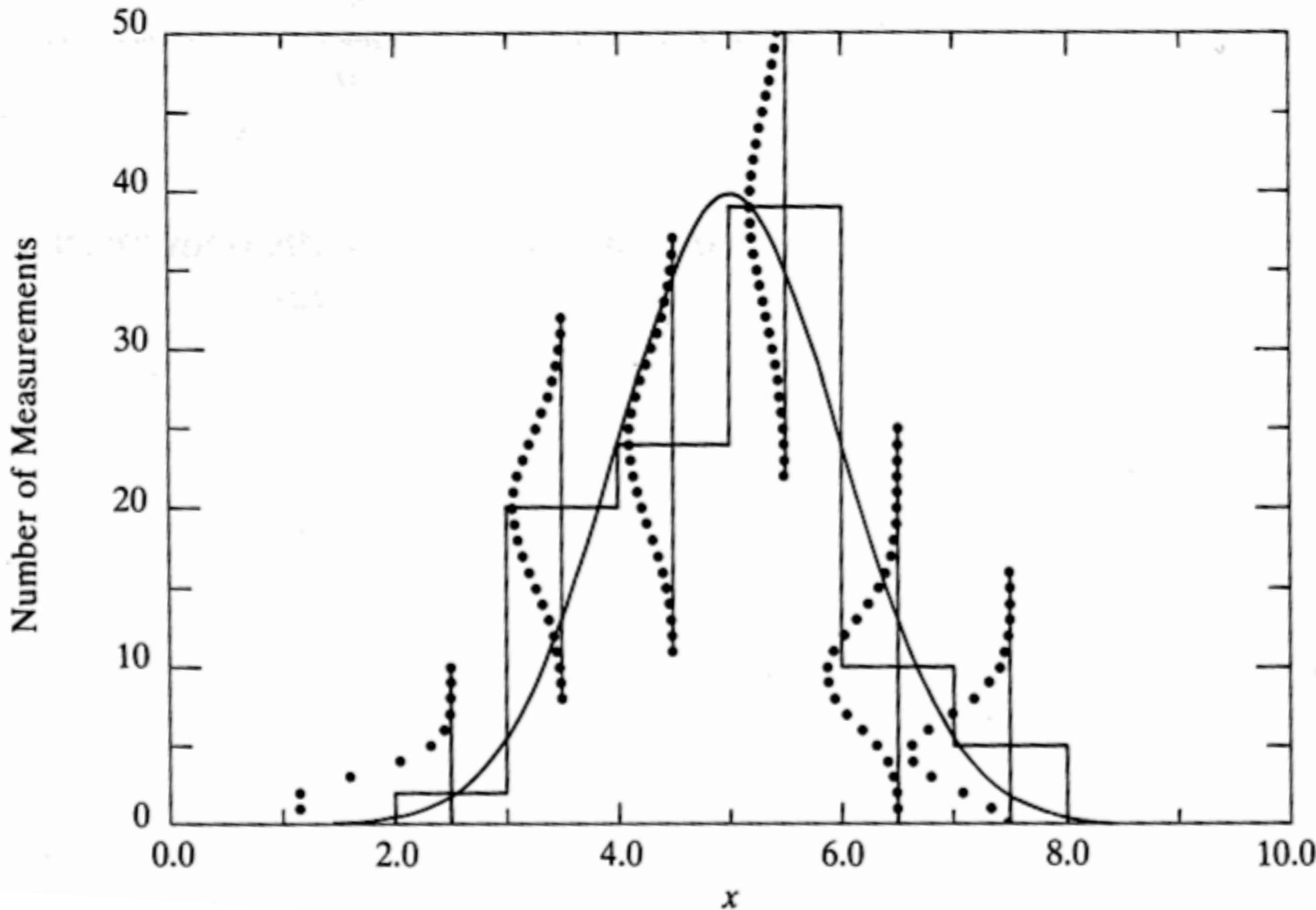
# MORE ABOUT $\chi^2$

DRAWN FROM NORMAL DISTRIBUTION  
DISTRIBUTION OF  $\chi_i^2$  IS A  $\chi^2$  DISTRIBUTION  
FOR N MEASUREMENTS DESCRIBED BY  
M VARIABLES, THERE ARE N-M  
DEGREES OF FREEDOM (D.O.F.)

PROBABILITY OF OBTAINING A  
CERTAIN  $\chi^2$

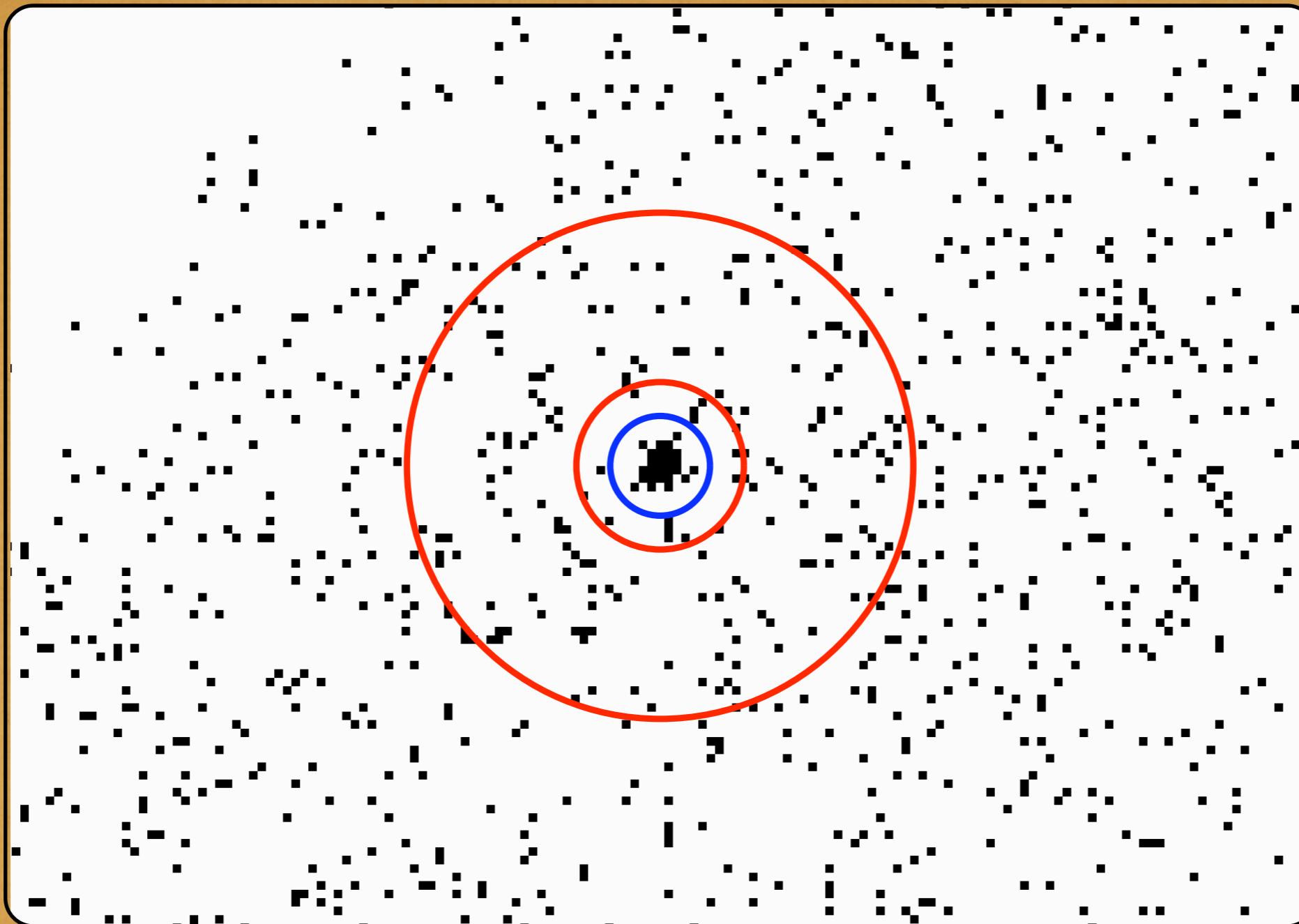
$$P(\chi_{obs}^2) = \text{gammq}\left(\frac{N - M}{2}, \frac{\chi_{obs}^2}{2}\right)$$

# VALUE AND POISSON ERRORS

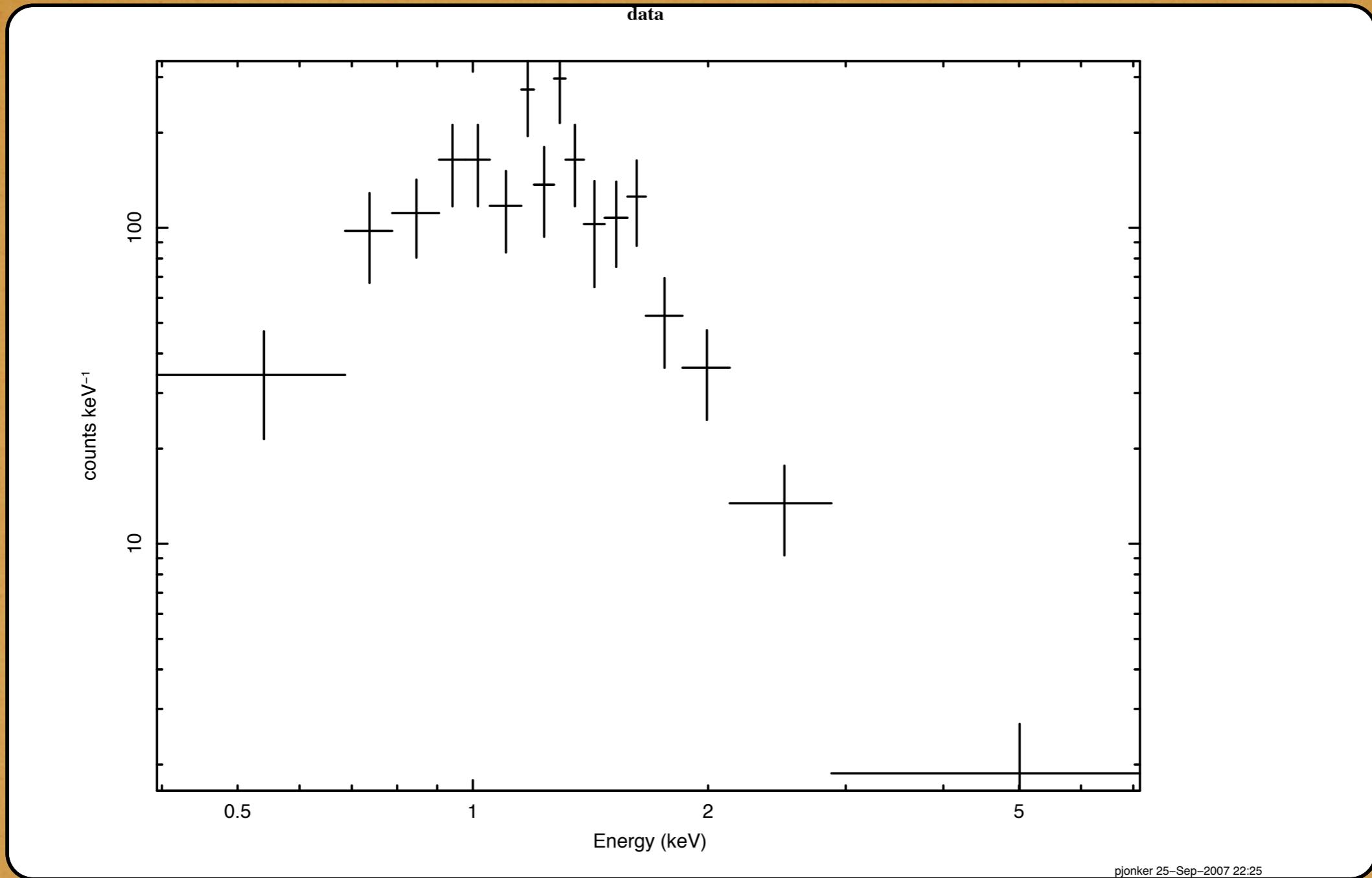


EXAMPLE FROM BEVINGTON & ROBERTSON 1992

# CHANDRA CCD (ACIS) OBSERVATION OF AN X-RAY BINARY



# SAME DATA AS BEFORE



GAUSSIAN APPROXIMATION FOR  
ERRORS BUT AT LOW COUNTS GAUSS  
AND POISSON ERRORS DIFFER

$\chi^2$  FITTING PROVIDES:

BEST-FITTING PARAMETERS

AN ERROR ESTIMATE OF THE  
UNCERTAINTY OF THE FITTED  
PARAMETERS

A PROBABILITY THAT THE DATA IS  
DRAWN FROM A PARENT POPULATION  
DESCRIBED BY THE MODEL  
PARAMETERS

# FITTING A STRAIGHT LINE TO THE DATA

(SEE ALSO EXERCISE)

$$y_m(x_i, a, b) = a + bx_i$$

MINIMISE  $\chi_i^2$  TO FIND BEST-FITTING PARAMETERS

$$\frac{\partial \sum_{i=1}^N \left( \frac{y_i - a - bx_i}{\sigma_i} \right)^2}{\partial a} = 0 \quad \rightarrow$$

$$\sum \frac{y_i}{\sigma_i^2} - a \sum \frac{1}{\sigma_i^2} - b \sum \frac{x_i}{\sigma_i^2} = 0$$

&

$$\sum \frac{x_i y_i}{\sigma_i^2} - a \sum \frac{x_i}{\sigma_i^2} - b \sum \frac{x_i^2}{\sigma_i^2} = 0$$

$$a = \frac{\sum_i \frac{x_i^2}{\sigma_i^2} \sum_i \frac{y_i}{\sigma_i^2} - \sum_i \frac{x_i}{\sigma_i^2} \sum_i \frac{x_i y_i}{\sigma_i^2}}{\sum_i \frac{1}{\sigma_i^2} \sum_i \frac{x_i^2}{\sigma_i^2} - (\sum_i \frac{x_i}{\sigma_i^2})^2}$$

# DETERMINE ERRORS ON THE BEST-FITTING PARAMETERS

REMEMBER

$$\sigma_f^2 = \sigma_u^2 \left( \frac{\partial f}{\partial u} \right)^2 + \sigma_v^2 \left( \frac{\partial f}{\partial v} \right)^2 + \dots$$

$$\sigma_a^2 = \sum_{i=1}^N \left[ \sigma_i^2 \frac{\partial a}{\partial y_i} \right]^2$$

$\partial u$  &  $\partial v$  etc are the different measurement values  $y_i$

$$\sigma_a^2 = \frac{\sum_i \frac{x_i^2}{\sigma_i^2}}{\sum_i \frac{1}{\sigma_i^2} \sum_i \frac{x_i^2}{\sigma_i^2} - \left( \sum_i \frac{x_i}{\sigma_i^2} \right)^2}$$

SIMILARLY

$$\sigma_b^2 = \frac{\sum_i \frac{1}{\sigma_i^2}}{\sum_i \frac{1}{\sigma_i^2} \sum_i \frac{x_i^2}{\sigma_i^2} - \left( \sum_i \frac{x_i}{\sigma_i^2} \right)^2}$$

FINALLY CALCULATE THE PROBABILITY  
OF OBTAINING THE  $\chi^2$   
BY CHANCE

$$P(\chi_{obs}^2) = \text{gammq}\left(\frac{N - M}{2}, \frac{\chi_{obs}^2}{2}\right)$$

FOR THE STRAIGHT LINE FIT  $M=2$

$\nu = N - M$  DEGREES OF FREEDOM

REDUCED  $\chi^2_\nu$

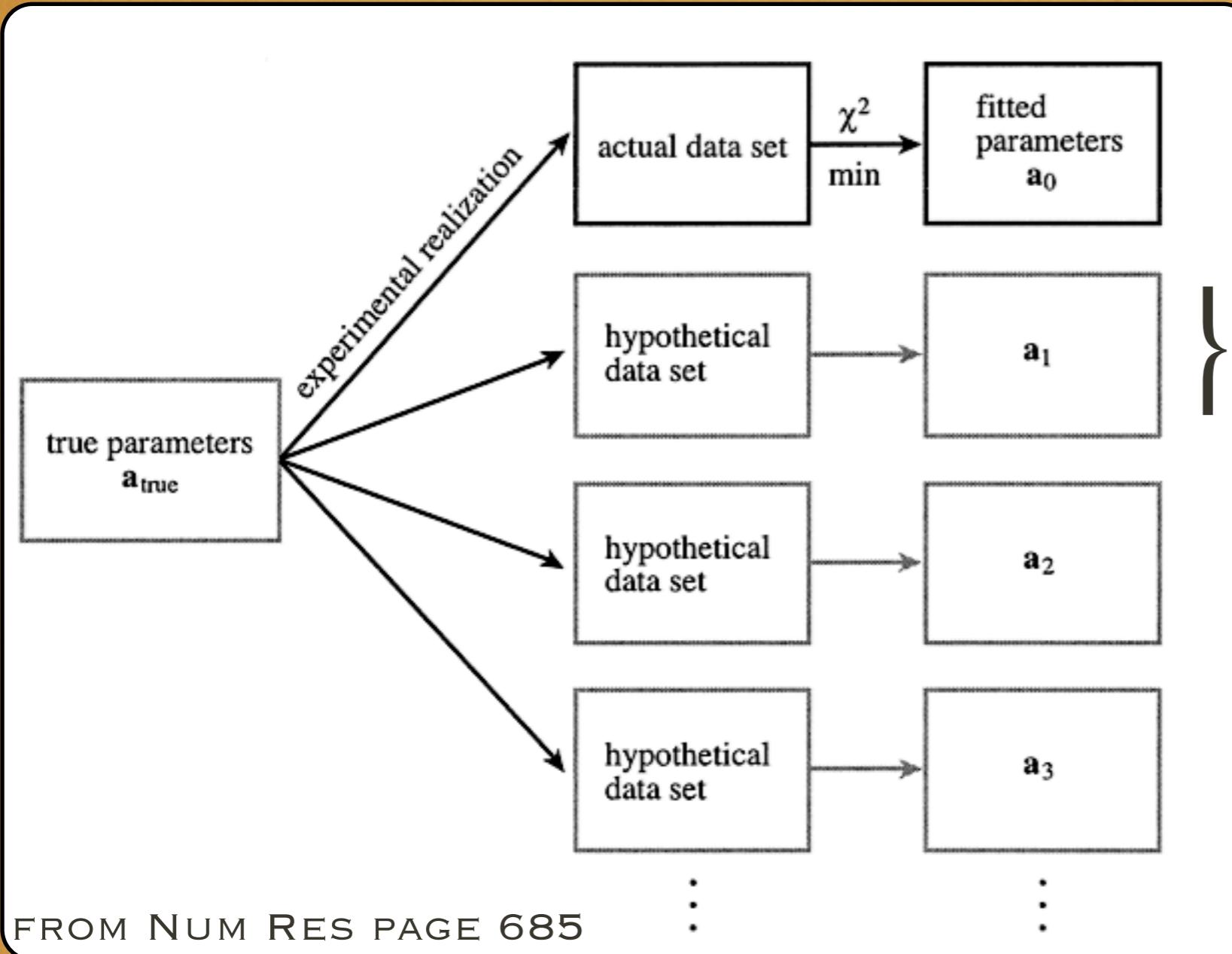
$$\chi^2_\nu \equiv \frac{\chi^2}{\nu}$$

FOR DATA FITTING:  $\chi^2_\nu \sim 1$      $\chi^2 \approx \nu$

$$\sigma_{\chi^2} = \sqrt{2\nu}$$

# ESTIMATING CONFIDENCE LIMITS

## MONTE CARLO SIMULATIONS

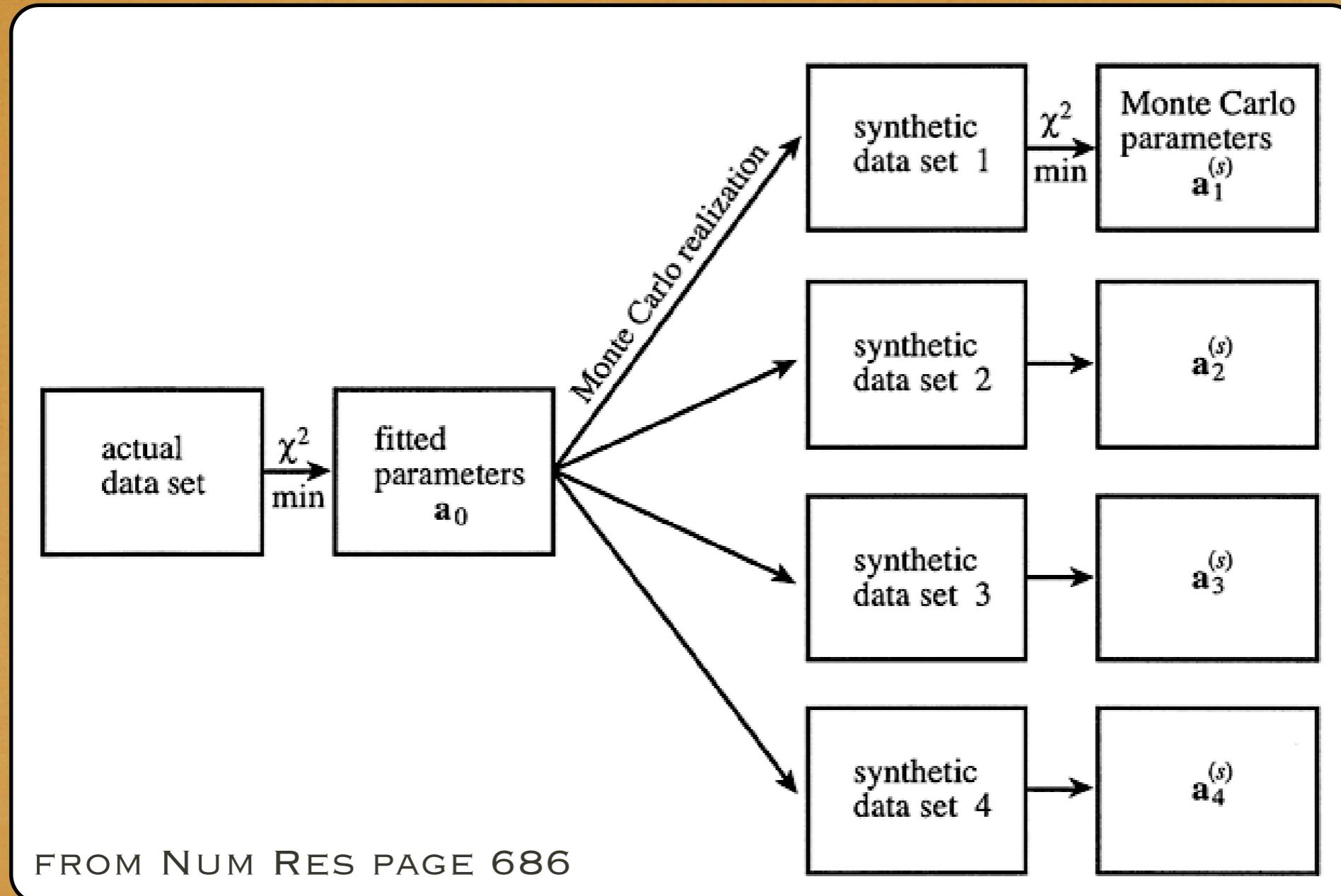


ASSUME THAT THE DISTRIBUTION OF  
 $a_i - a_0$

IS CLOSE TO THE PROBABILITY DISTRIBUTION

$a_i - a_{true}$

# MONTE CARLO SIMULATIONS



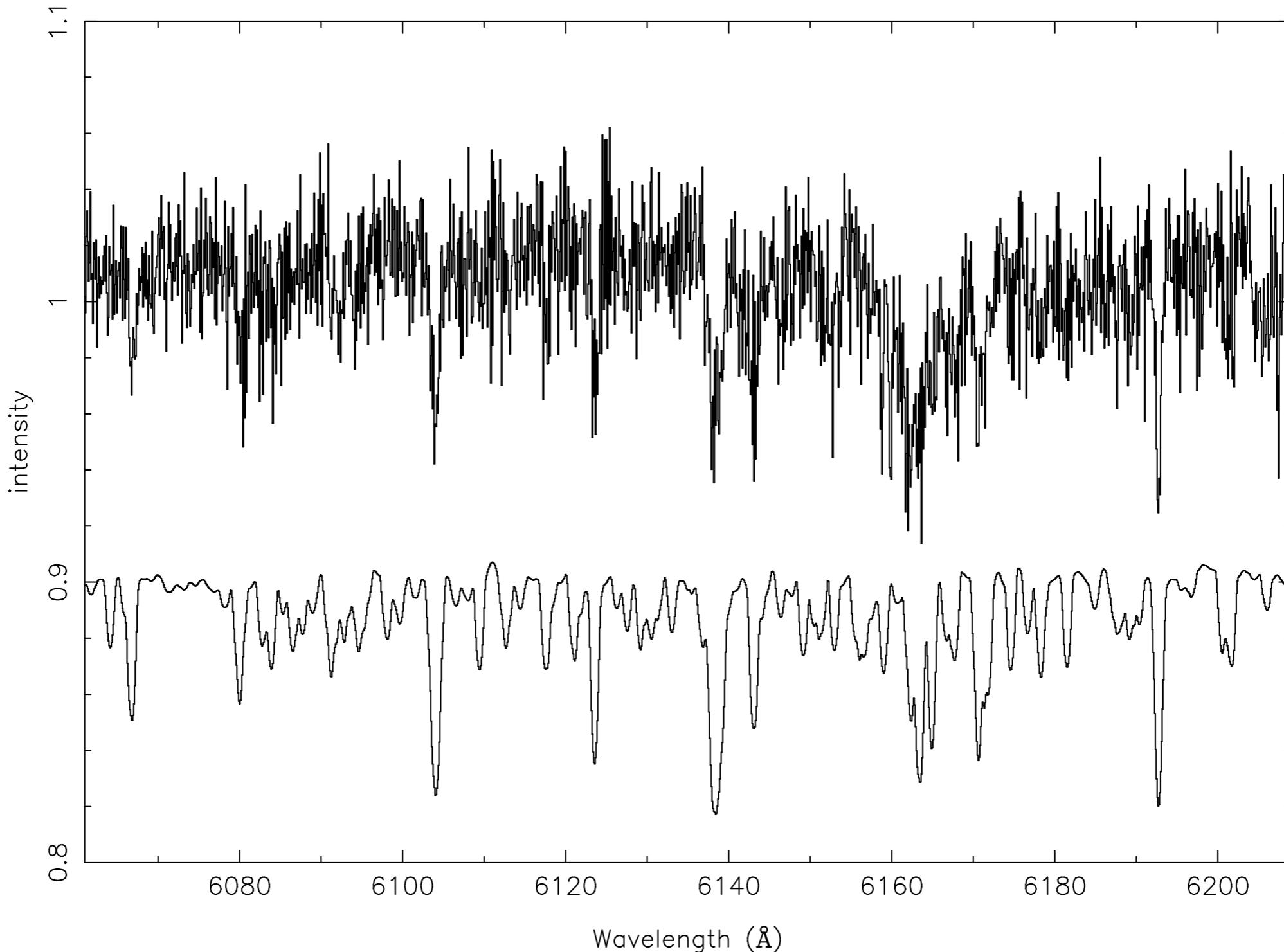
CALCULATE DISTRIBUTION OF  $a_i - a_0$

BY SIMULATING MANY SETS OF DATA AND  
USING  $\chi^2$  FITTING TO DETERMINE  $a_i$

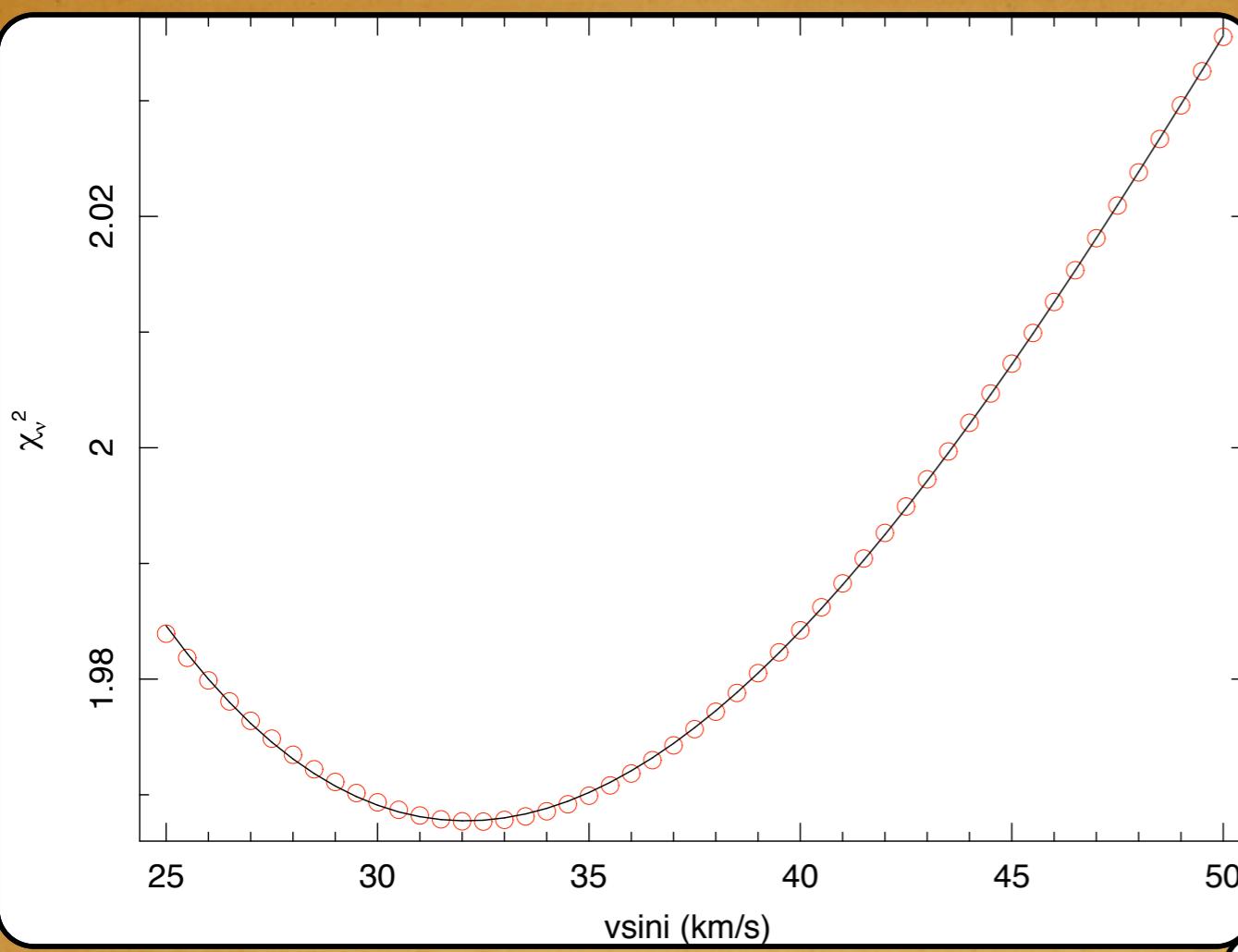
# BOOTSTRAP METHOD AND APPLICATION

## X-RAY BINARY V395 CAR

V395 Car / HD99322

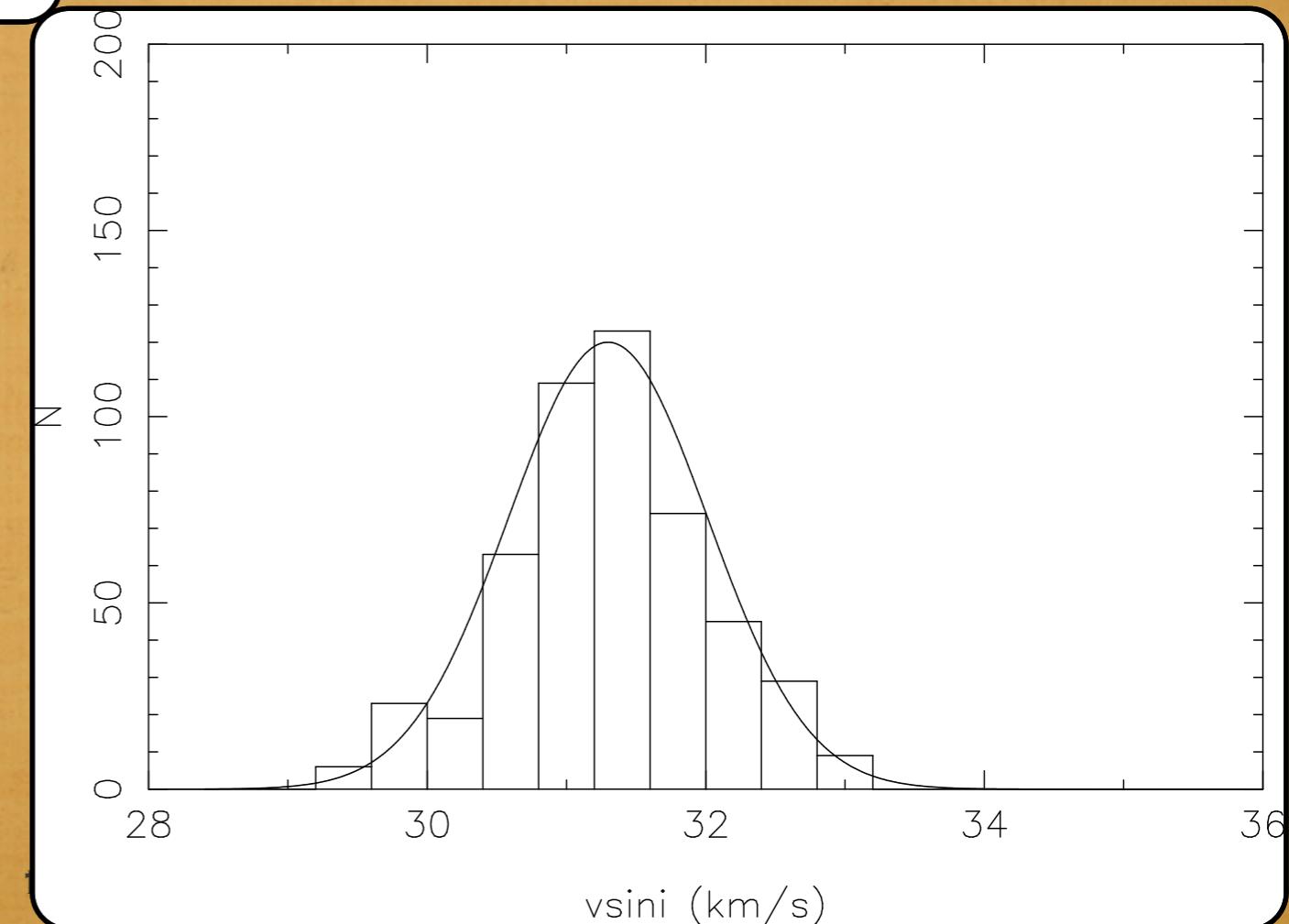


# BROADENING AND OPTIMAL SUBTRACTION

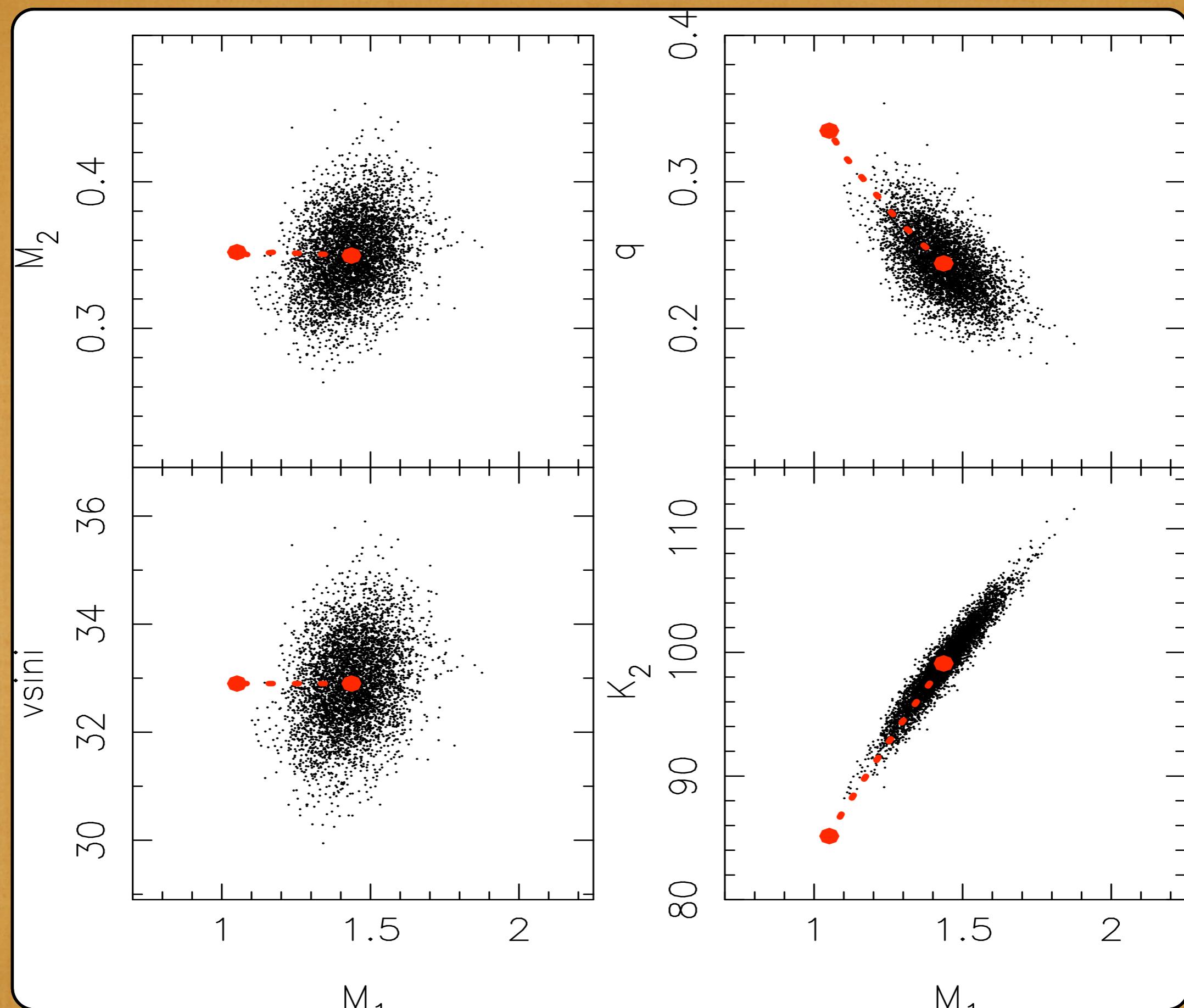


NOTE REDUCED  $\chi_{\nu}^2$

BOOTSTRAP DETERMINED  
ROTATIONAL VELOCITY

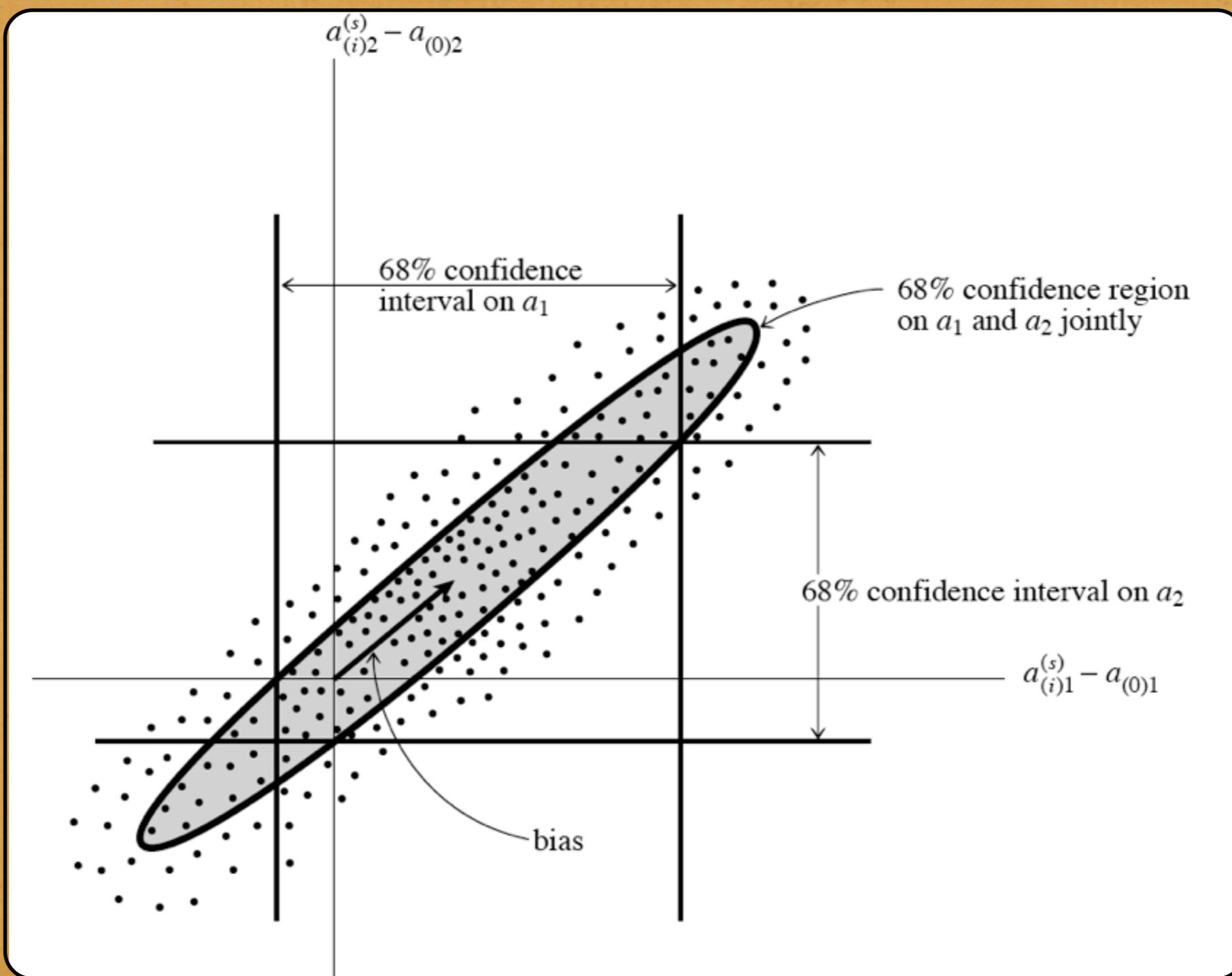


# BOOTSTRAP METHOD: AN APPLICATION



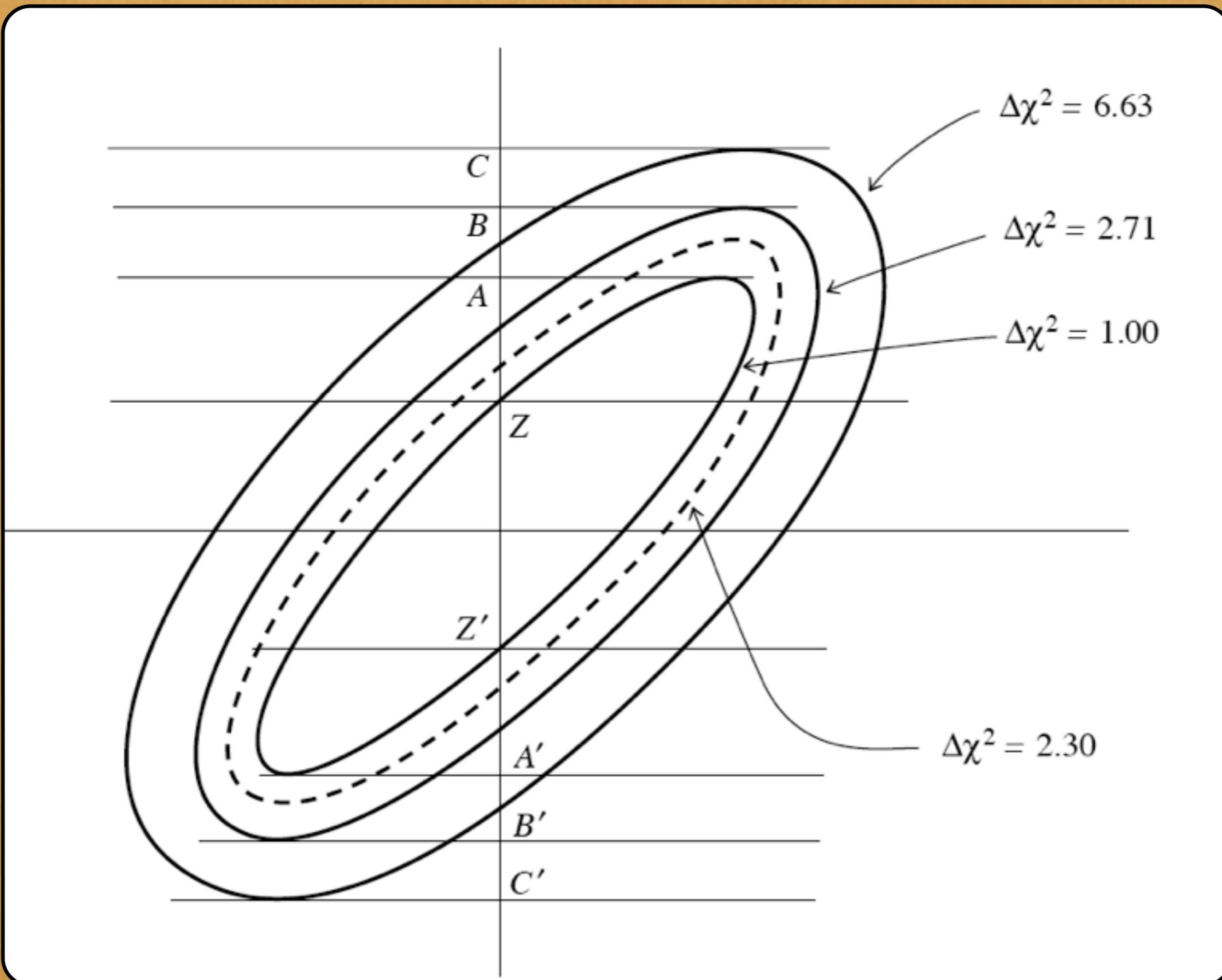
# CONFIDENCE LIMITS

## SINGLE VS. MULTIPLE PARAMETER CONFIDENCE REGION



FROM NUM RES PAGE 688

# PROJECTIONS



FROM NUM RES PAGE 689

# BE AWARE OF NON-GAUSSIAN DISTRIBUTIONS

