# Statistics and parameter estimation in cosmology

Observational Cosmology
NASSP course
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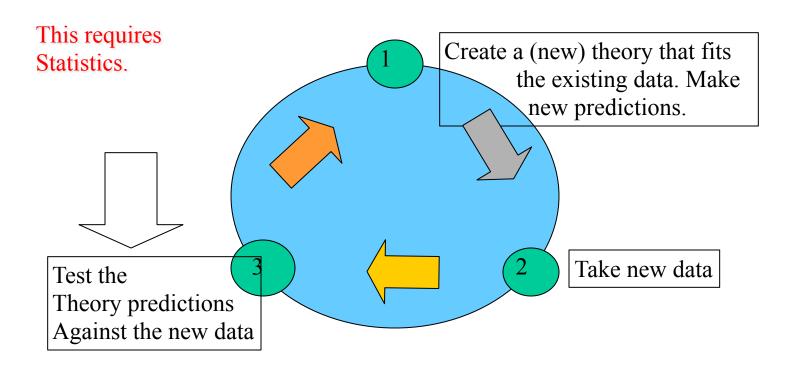
#### Resources

• Wikipeadia.com + lots on the web

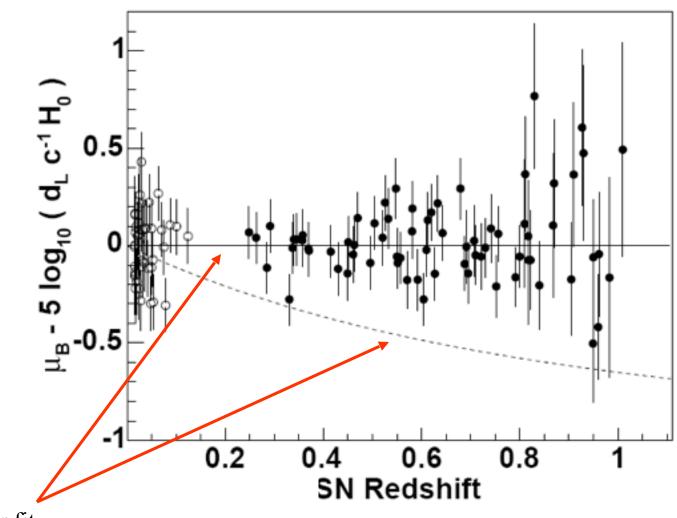
- D. J. C. MacKay, Information theory, inference, and learning algorithms Cambridge (2003). A good how-to book for MCMC, neural networks, data compression.
- Available on the web at: http://www.inference.phy.cam.ac.uk/mackay/itila/book.html

## What's the point?

• A crude characterisation of science is that it is the full circle:



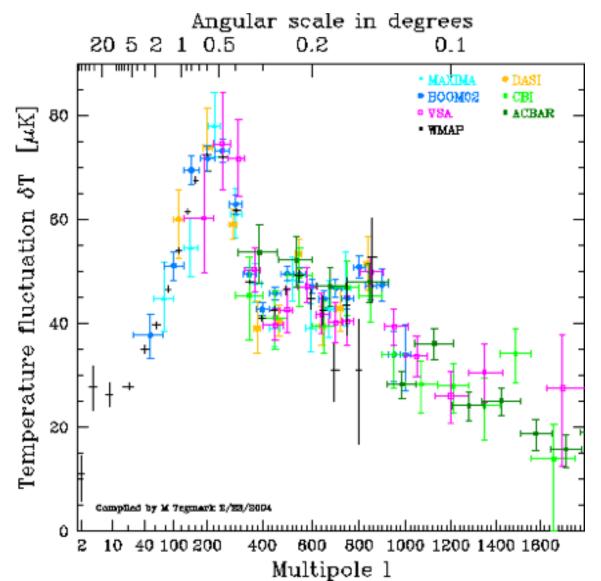
## The problem...



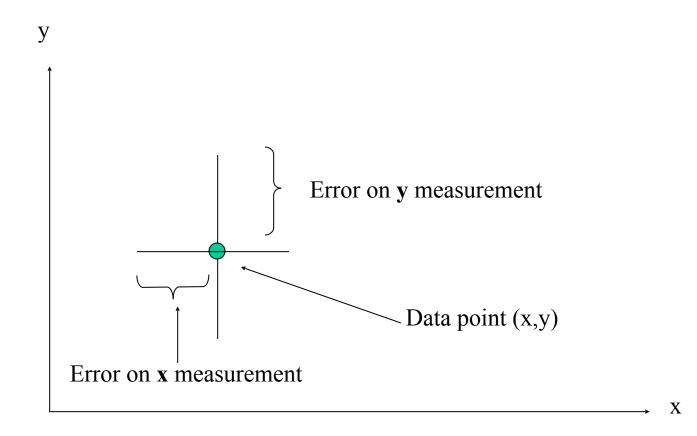
The solid line
Is clearly a better fit

To the data...but how do we quantify this belief?

## ...and how do we combine multiple datasets?



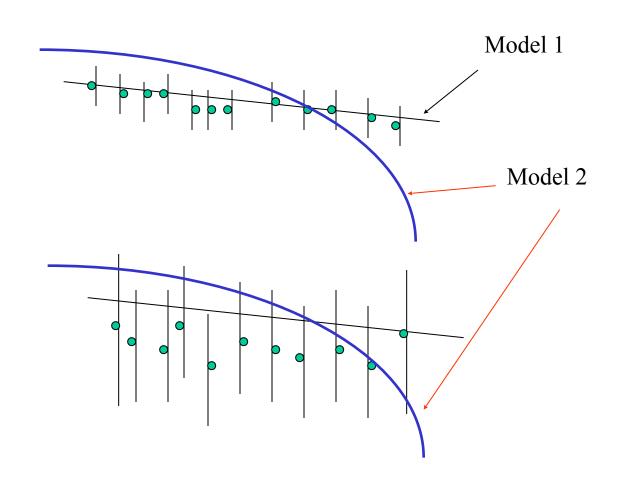
## What are error bars?



### error bar sizes

Here model 2 is ruled out by the data at high confidence.

Here model 2 is not ruled out by the data.



## The $\chi^2$ statistic

• A useful measure of how well data is fit by a theoretical curve (which may depend on some parameters,  $\theta_{i}$ ) is the quantity:

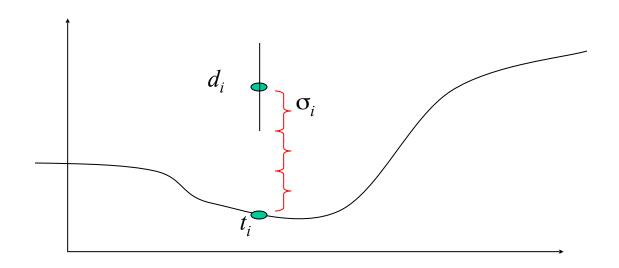
$$\chi^{2} = \sum_{i=1}^{2} \left( \frac{d_{i}(x_{i}) - t(x_{i}, \theta)}{\sigma_{i}} \right)^{2}$$

 $d_i$  is the data  $t_i$  is the theoretical prediction at that point. The sum is over data points.

• This is the sum of the number of standard deviations  $(\sigma_i)$  the data is away from the theoretical curve.

## What is the $\chi^2$ ?

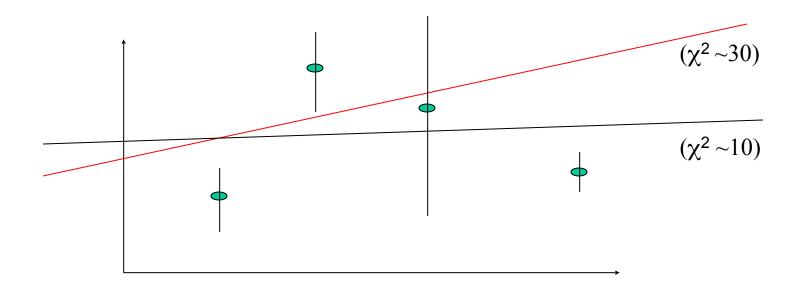
$$\chi^{2}(\theta_{\alpha}) \equiv \sum_{i} \frac{(d_{i} - t_{i}(\theta_{\alpha}))^{2}}{\sigma_{i}^{2}}$$



• This point has  $\chi^2 \sim 9$ 

$$\chi^{2}(\theta_{\alpha}) = \sum_{i} \frac{(d_{i} - t_{i}(\theta_{\alpha}))^{2}}{\sigma_{i}^{2}}$$

•  $\chi^2$  is just the sum over the data points, of the number of standard deviations the data is from the model:



## $\chi^2$ continued...

• Exercise 1: assuming a linear model:

$$t(\mathbf{x}, \mathbf{\theta}_i) = \mathbf{\theta}_1 \mathbf{x} + \mathbf{\theta}_2$$

Analytically compute the best-fit values of the parameters given a set of N data-points with given errors,  $\sigma_i$ , using the  $\chi^2$  statistic.

#### Parameter estimation - I

- A very common problem in science is that we want to find the parameter values that best fit given observational data.
- For example: what is the period of a binary star, the mass of the electron, the value of the Hubble constant or the size of the cosmological constant?

#### Parameter estimation - II

- How can we estimate the best-fitting parameters?
- Since any measurement has finite accuracy, this is always a statistical problem. We want the most-likely values of the parameters.
- We can estimate this by minimising  $\chi^2$  while we vary the parameters of the theory. We already did it in the case of a linear model.

To estimate parameters...

$$\frac{\partial \chi^2}{\partial \theta_{\alpha}} = 0...\alpha = 1...n$$

#### Parameter estimation - III

- If the model depends nonlinearly on the parameters we usually cannot solve it analytically and must use numerical methods.
- This is a well-studied branch of computational mathematics.
- We want to find the global minimum of  $\chi^2$  (there are often lots of local minima which we are not interested in)

#### Parameter estimation - IV

- One of the easiest ways to minimise  $\chi^2$  when there are few parameters (less than 4 or 5) is the *grid method*.
- Consider the case of a single parameter,  $\theta$ , for simplicity. We split up the allowed range of  $\theta$  into n equal regions, with grid points labeled  $\theta_i$ .
- We then compute  $\chi^2$  at each point in the region and then choose the smallest  $\chi^2_i$ . The corresponding  $\theta_i$  is approximately the best-fit parameter value. Obviously the method can be refined by increasing n.
- Grid method fails for large number of parameters (why?). Stochastic/Monte Carlo methods are much better in this case (e.g. MCMC, simulated annealing).