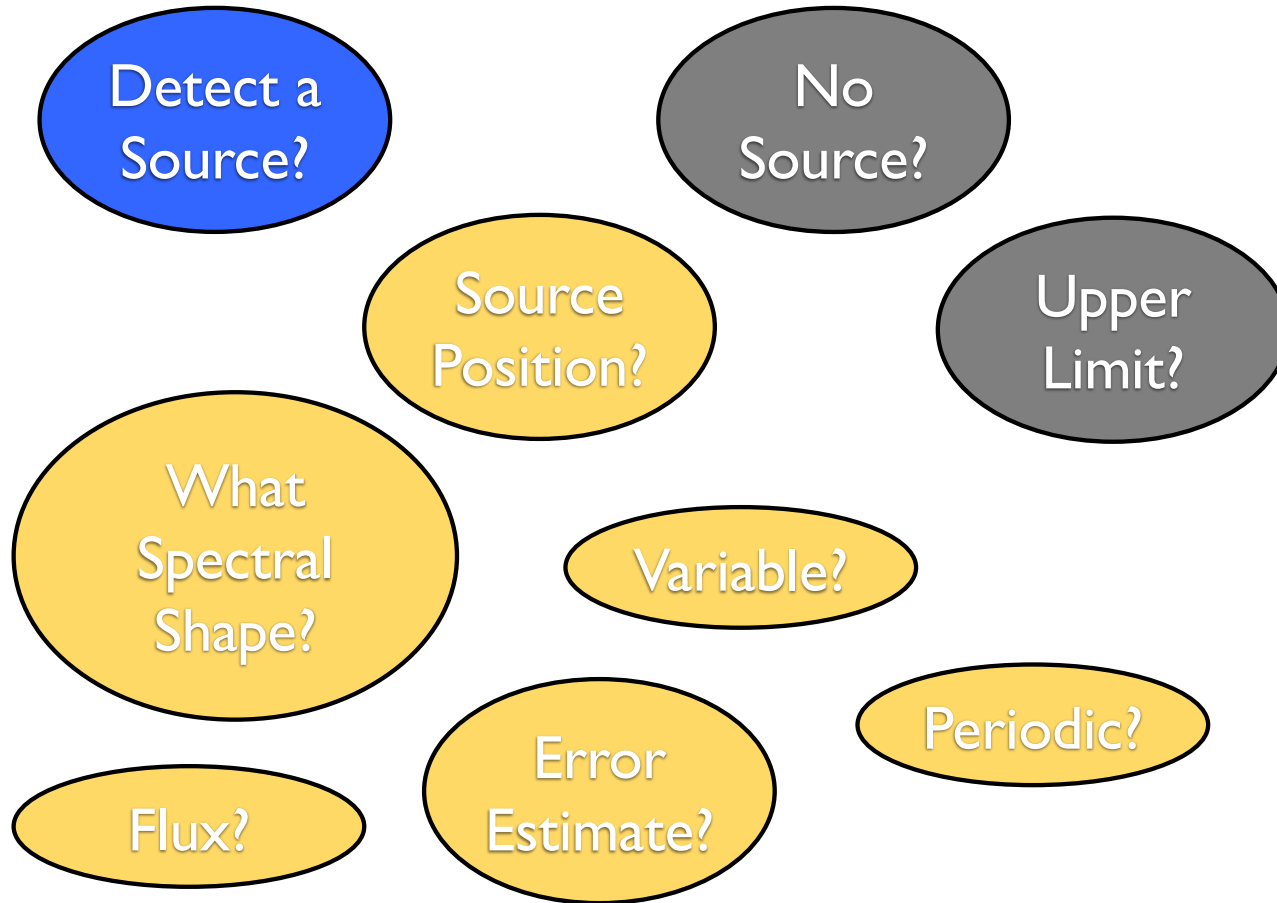


# Notes on Maximum Likelihood in LAT

What can I infer from my observation?



# Measurements in $\gamma$ -ray astronomy

Hypothesis testing

- Is a source significantly detected?

Parameter estimation

- If so, what is its flux?

Hypothesis testing

- If not, what upper limit on the flux?

Hypothesis testing

- What kind of spectrum does it have?

Parameter estimation

- What is its spectral index?

Parameter estimation

- What is its location in the sky?

Hypothesis testing

- What are the errors on these values?

Hypothesis testing

- Is the source variable?

# ~~Good things about maximum likelihood~~ Cautions

- General framework for statistical questions.
  - Unbiased, minimum variance estimate as sample size increases.
  - Asymptotically Gaussian: allows evaluation of confidence bounds & hypothesis testing.
  - Well studied in the literature.
  - Starting point for Bayesian analysis.
- Only answers the question asked.
  - Be aware of small number regimes and departure from Gaussian assumption for confidence bounds and hypothesis testing
  - Starting point for Bayesian analysis.

# Maximum likelihood technique

Given a set of observed data

- produce a model that *accurately* describes the data, including parameters that we wish to estimate,
- derive the probability (density) for the data given the model (probability density function, PDF),
- treat this as a function of the model parameters (likelihood function), and
- maximize the likelihood with respect to the parameters - ML estimation.



**Data**

**Model**

**PDF**

**Likelihood  
Function**

## ML estimation (MLE)

- Parameters can be estimated by maximizing likelihood. Easier to work with log-likelihood:

$$\ln \mathcal{L}(\Theta) = \ln \mathcal{L}(\Theta|X) = \sum_i \ln P(x_i|\Theta)$$

- Estimates of parameters  $\{\hat{\theta}_k\}$  from solving simultaneous equations:  $\left. \frac{\partial \ln \mathcal{L}}{\partial \theta_j} \right|_{\{\hat{\theta}_k\}} = 0$

- For one parameter, if we have:  $\mathcal{L}(\theta) \sim e^{-\frac{(\theta-\hat{\theta})^2}{2\sigma_\theta^2}}$

then:  $\left. \frac{\partial^2 \ln \mathcal{L}}{\partial \theta^2} \right|_{\hat{\theta}} = -\frac{1}{\sigma_\theta^2}$

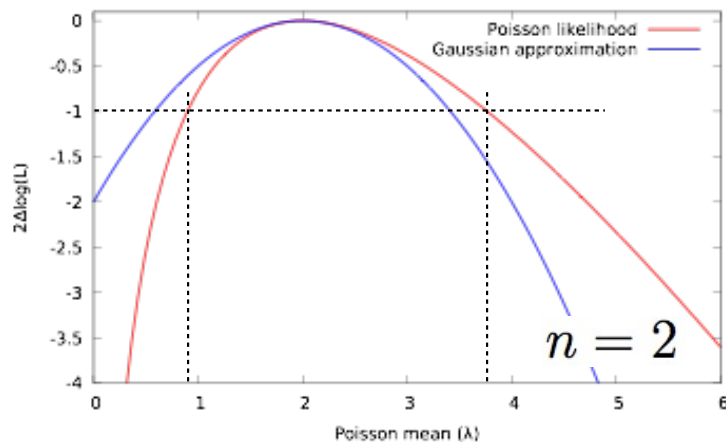
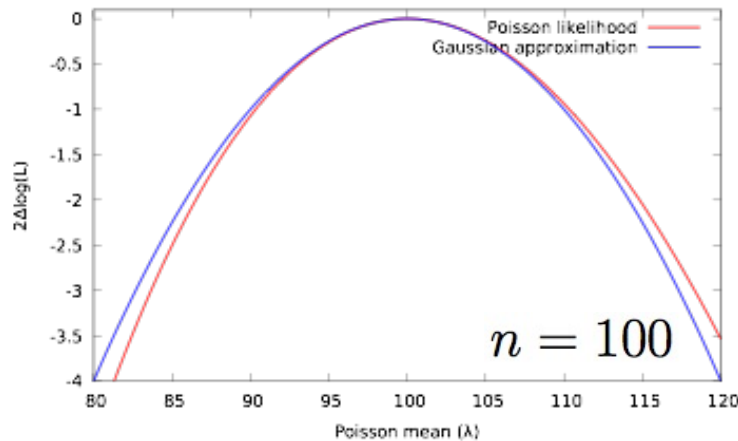
**Gaussian approximation**

2<sup>nd</sup> derivative is related to “errors”

# Binned Likelihood

- Ideally, we would look up the exact response for each individual photon and add up each individual log likelihood
- That can add up to a lot of calculation for longer intervals. Instead group photons in similar bins in inclination angle and energy
  - The spatial and energy bins have to be small enough that the response is not very different for photons in the bin
- Numbers of total photons may be large, but numbers in any bin may be small

# Log-likelihood profile and errors



Large number of events – Gaussian approximation reasonably accurate

$$\sigma_{\lambda}^2 = n$$

Log-likelihood profile provides a more accurate estimate for small number of events

$$2 \ln \mathcal{L}(\lambda) = 2 \ln \mathcal{L}(\hat{\lambda}) - 1$$

$$n = 100; \quad \hat{\lambda} = 100.0^{+10.33}_{-9.67}$$

Log-likelihood profile provides a better error estimate

$$n = 2; \quad \hat{\lambda} = 2.0^{+1.77}_{-1.10}$$



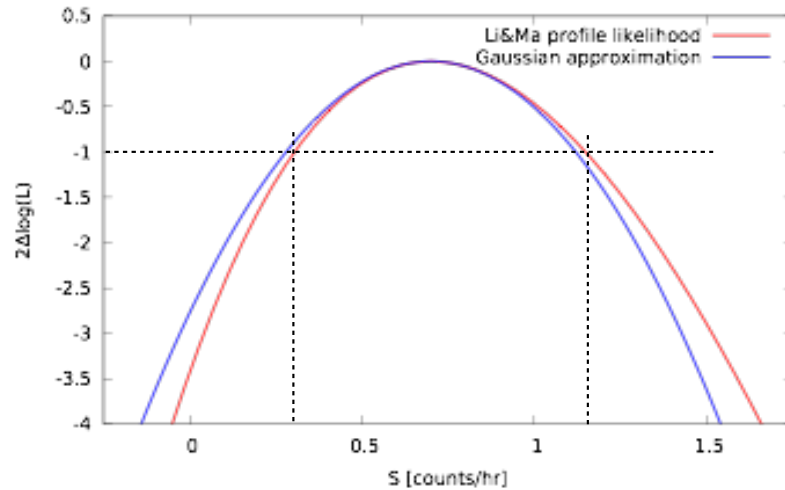
# Profile likelihood

Confidence regions with nuisance parameters

[Rolke, et al., NIM A, 551, 493 \(2005\)](#)

- Often we are either concerned only with the one parameter, or wish to treat the multiple parameters separately (ignore covariance).
- Produce “profile log-likelihood” curve, a function of only one parameter (at a time), maximized over all others.
- LRT says this should behave as  $\chi^2(1)$ .
- Define confidence region using this function exactly as before.

# Example of profile likelihood



Rate  $\hat{S} = 0.7_{-0.39}^{+0.45} \text{ hr}^{-1}$

This is not a significant result, so we would usually not claim a detection. Provide an upper limit instead.

- Use simple On/Off counting example

$$n_{off} = 24$$

$$n_{on} = 15$$

$$\alpha = 1/3$$

$$T = 10.0 \text{ hr}$$

- Giving:

$$\hat{S} = 0.7 \text{ hr}^{-1}$$

$$\sigma_S = 0.42 \text{ hr}^{-1}$$

$$TS = 3.43$$

$$\sigma = 1.85$$

# For next time

- Homework
  - Pick a source or topic you want to explore this summer. [Google form here](#).
  - Try making a profile log likelihood plot for a parameter in the 3C 279 example analysis.
  - Bonus example on source finding will be posted later today. We will come to this next week and discuss hypothesis testing.
- Next time
  - Special case: Light curves , or running a series of likelihood analyses