

#### Overview of activities

#### Day 1

- Introduction, overview
- Obtaining and exploring LAT data
- Inspecting the data: count map



#### Day 2

- Basics of modeling
- Likelihood analysis of a blazar
- Create a SED
- Produce a light curve

#### Structure of this talk

Basic theory of likelihood analysis



- Likelihood fit → Characterize spectra of a source
- obtain spectral energy distribution (SED)
- o build a light curve

hands-on

# Fundamental questions of science statistics

Model fitting: given this model, what parameters best fit my data?

Model selection: given two potential models, which better describes my data?

## Model fitting

given this model, what parameters best fit my data?

**Frequentist** 

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P(data | scientific model)

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likelihood

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### P(data | scientific model)

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likelihood

$$\frac{\partial \mathcal{L}}{\partial \theta} = 0$$

**Frequentist** 

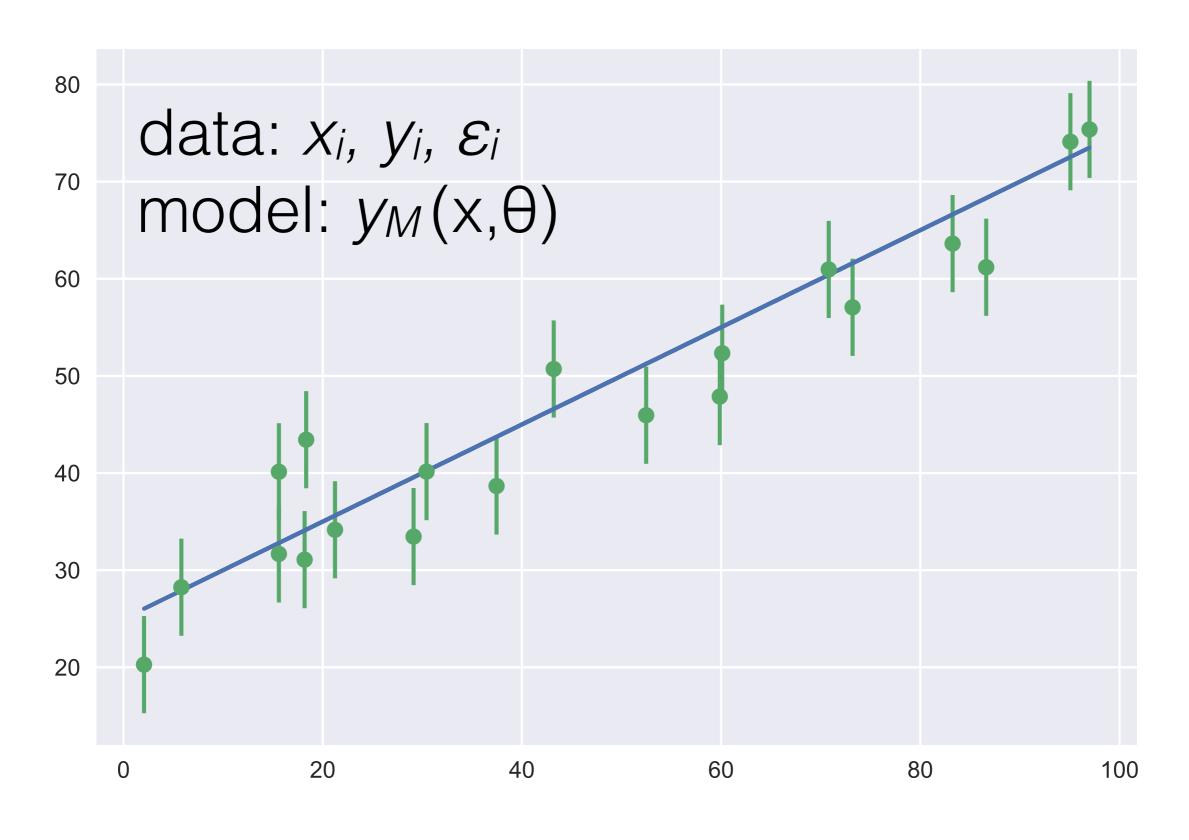
## P(data | scientific model)

$$\mathcal{L} \equiv P(D \mid \theta)$$

likelihood

$$\frac{\partial \mathcal{L}}{\partial \theta} = 0 \Rightarrow \{\theta_{\text{best-fit}}\}$$

## How to write the likelihood function for the problem below?



$$P_i = \frac{1}{\sqrt{2\pi\epsilon_i^2}} e^{-\frac{(y_i - y_M)^2}{2\epsilon_i^2}}$$

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Log-likelihood:

$$\log \mathcal{L} = -\frac{1}{2} \sum_{i=1}^{N} \left\{ \log(2\pi\varepsilon_i^2) + \frac{\left[y_i - y_M(x_i; \theta)\right]^2}{\varepsilon_i^2} \right\}$$

# What about Fermi LAT data?

#### **Poisson distribution**

## Experiment counting events during a fixed interval: Poisson distribution

**n**: number of detected events

**m**: expected number (model)

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Probability of observing **n** events

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$$\frac{\text{Standard}}{\text{deviation}} = \sqrt{n}$$

#### **Poisson distribution**

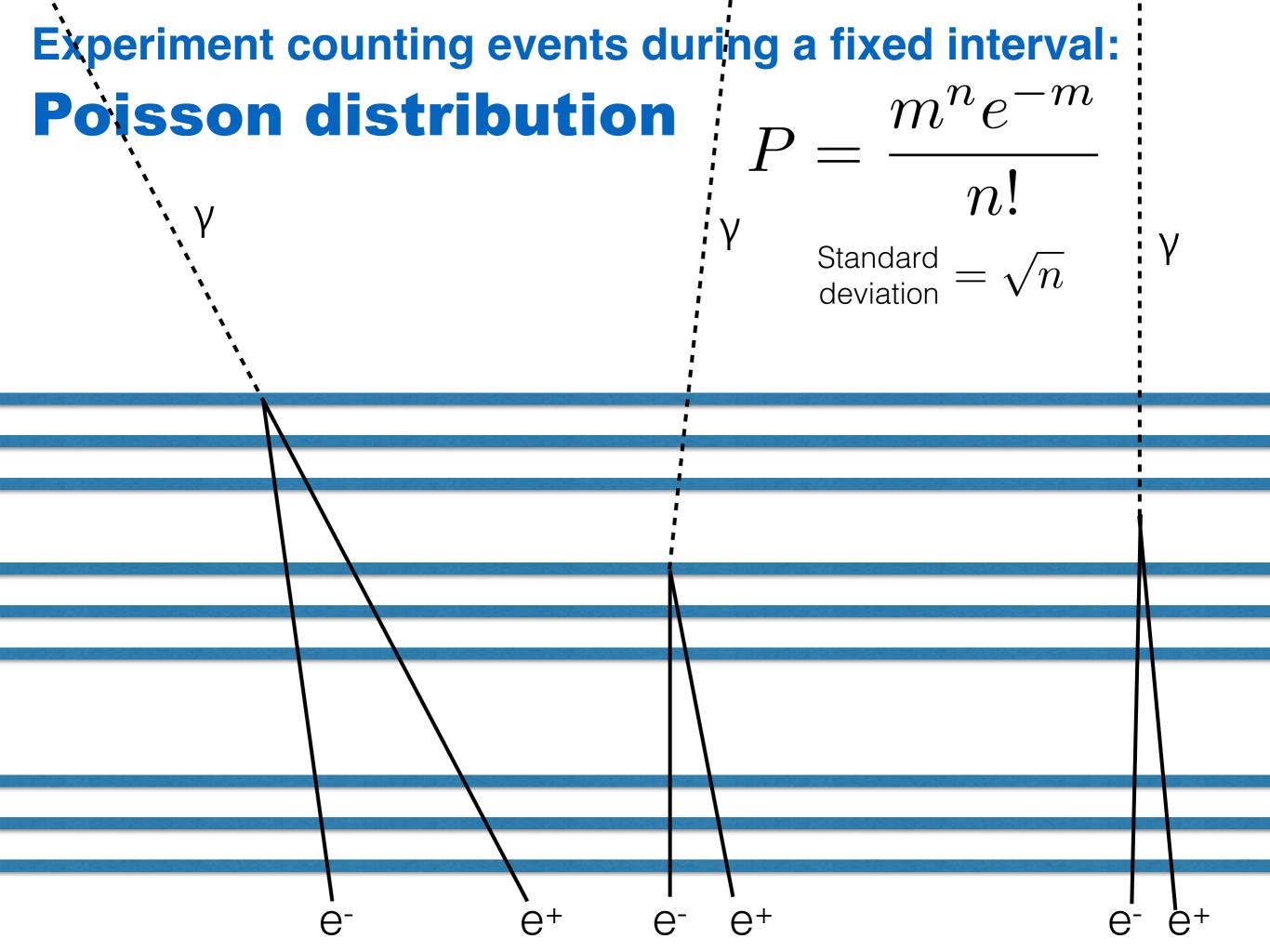
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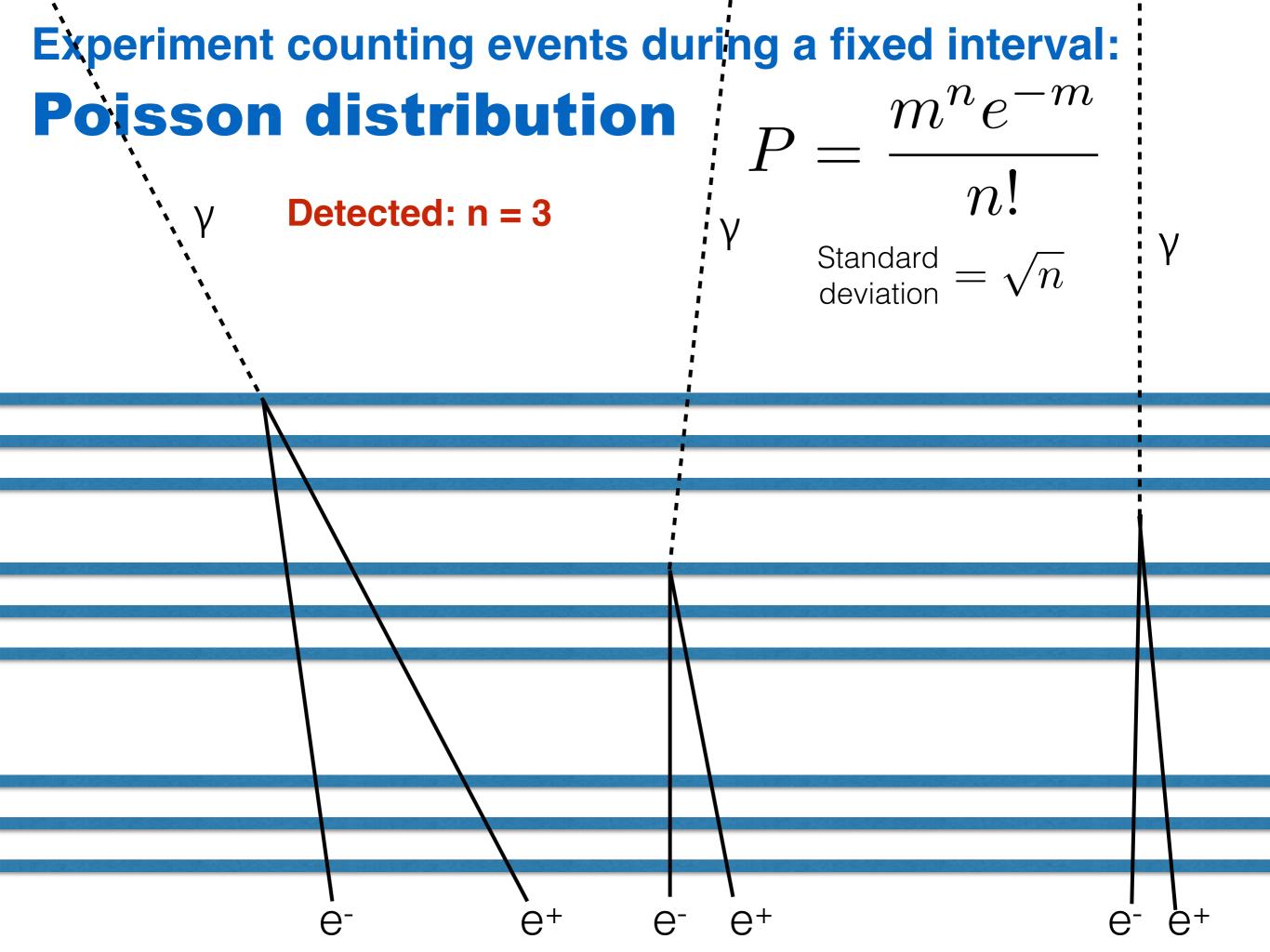
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Standard \_\_\_\_\_\_

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 Unbinned likelihood

Log-likelihood

$$\log \mathcal{L} = \sum_{i} \log m_i - N_{\text{pred}}$$

## We need to maximize this likelihood function numerically

$$\log \mathcal{L} = \sum_{i} \log m_i - N_{ ext{pred}}$$
 total predicted number of counts  $dE \, d\mathbf{p} \, dt$  function  $dE \, d\mathbf{p} \, dt$  source model  $dE \, d\mathbf{p} \, dt$  sources + other sources + stuff

### Model selection

given two potential models, which better describes my data?

## Is there a source in a given position of the sky?

maximum likelihood: model without an additional source (the "null hypothesis")

$$TS = -2\log\left(\frac{\mathcal{L}_{\max,0}}{\mathcal{L}_{\max,1}}\right)$$

maximum likelihood: model with additional source

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maximum likelihood: model

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source

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Rule of thumb:

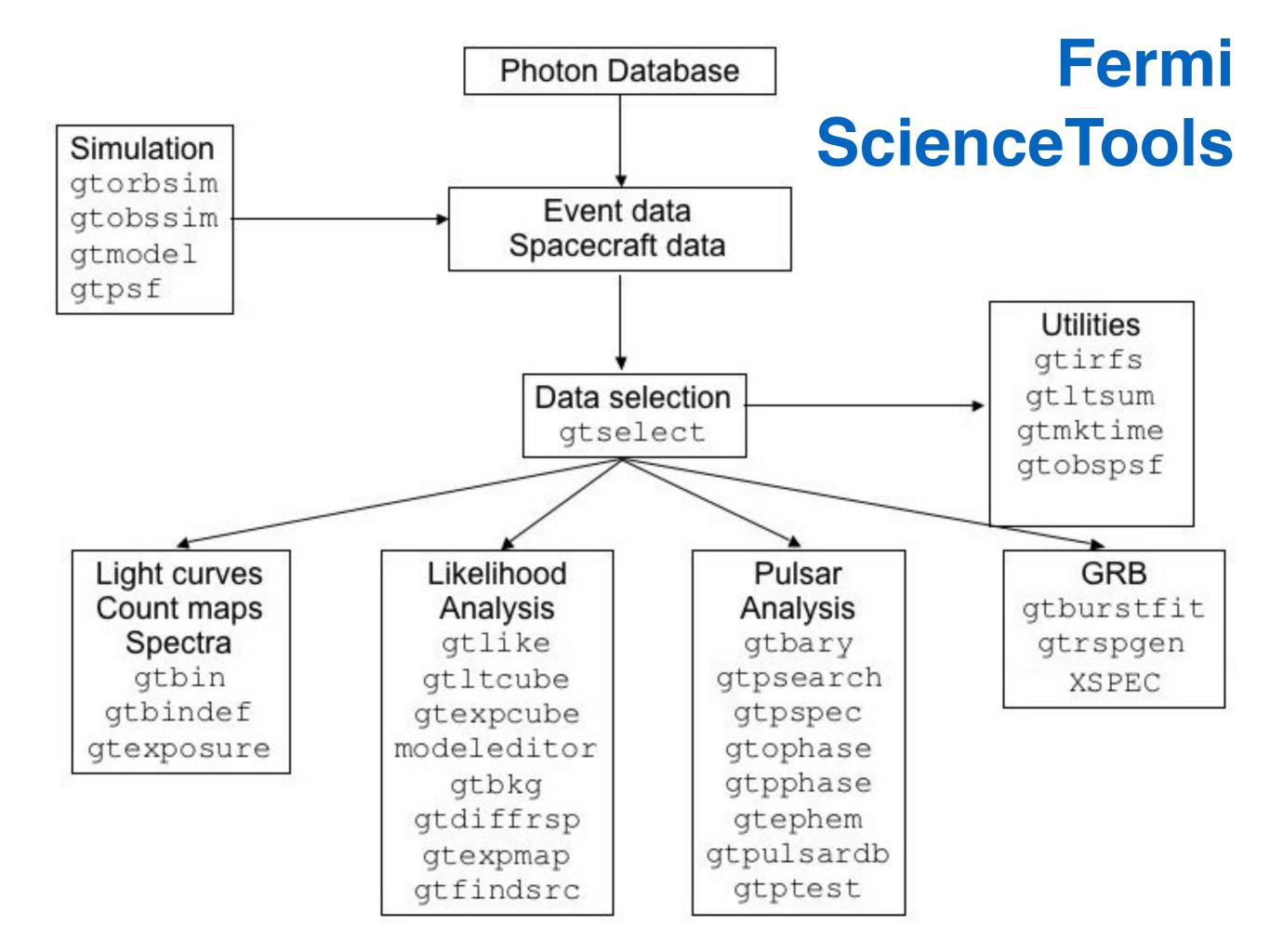
$$TS = 100 \Rightarrow \approx 10\sigma$$

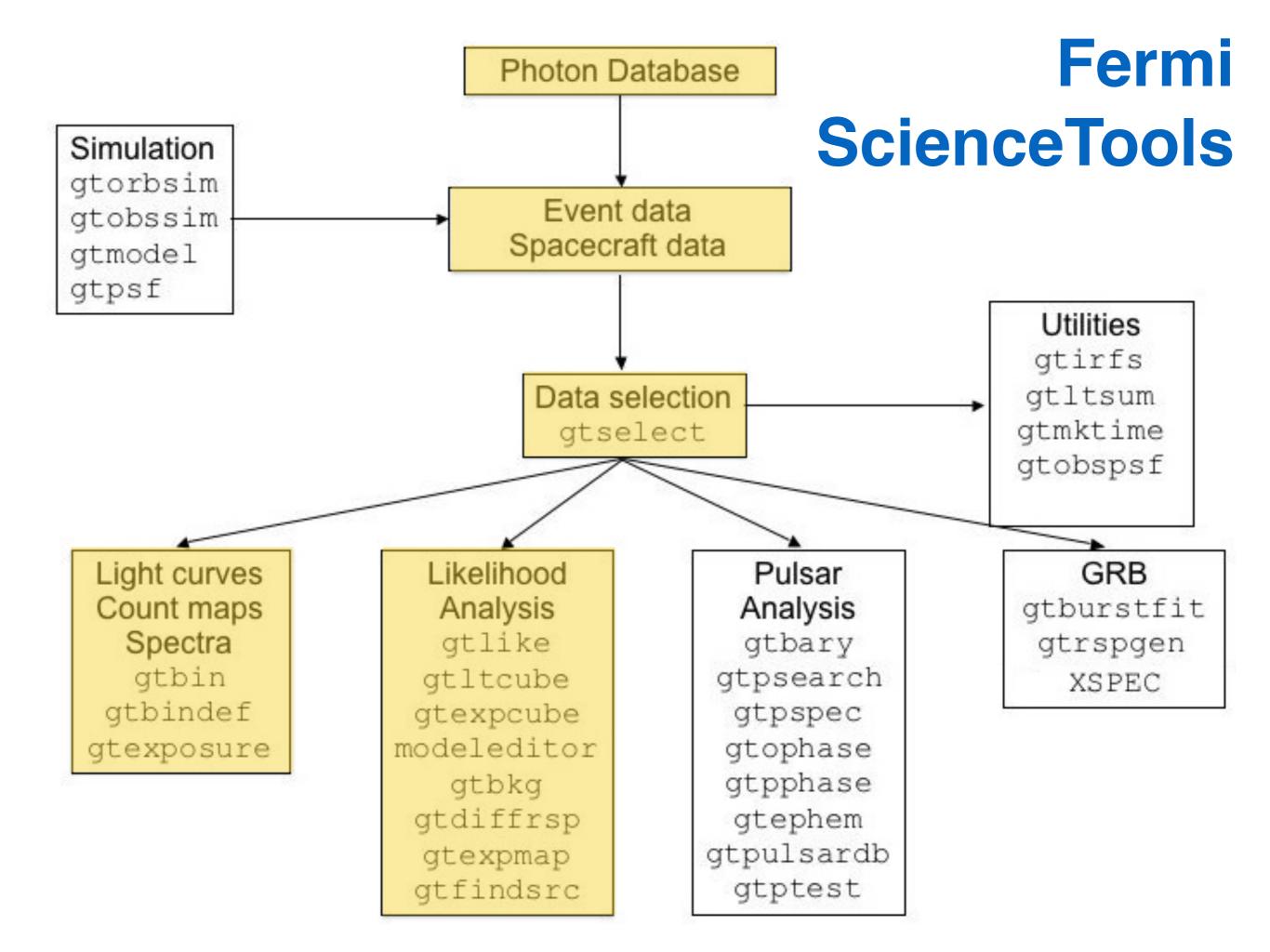
$$TS = 25 \Rightarrow \approx 5\sigma$$

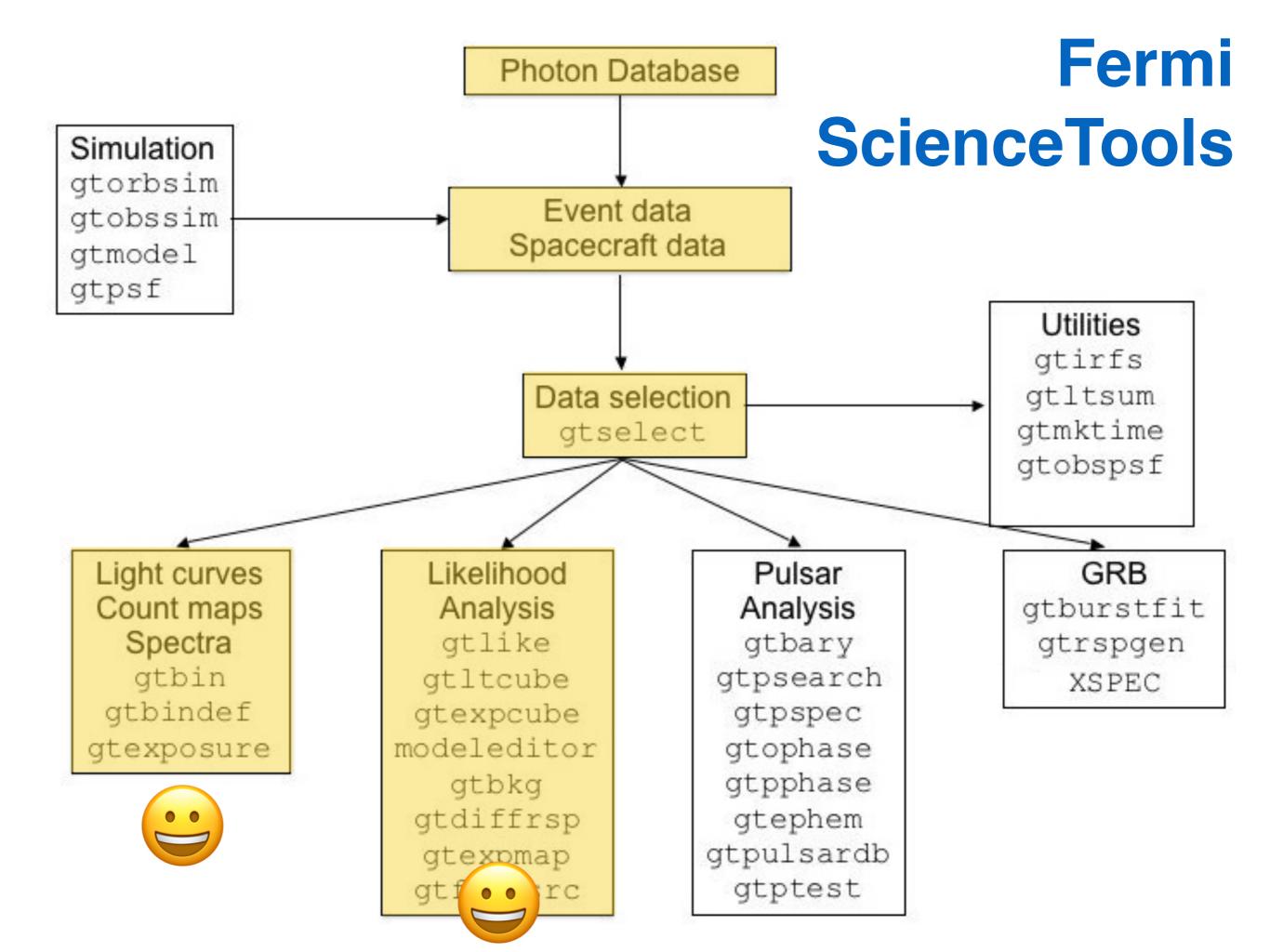
## Hands-on activity

#### Steps for modeling of Fermi LAT data

- 1 Define your source model
- 2 Select data + ROI cuts gtselect
- 3 Select good time intervals (GTI) gtmktime
- 4 Bin data, create a count map gtbin
- 5 Compute useful quantities: live time cube, binned exposure cube gtltcube, gtexpcube2
- 6 Maximize likelihood numerically, get initial estimate of parameters gtlike
- 7 Optimize fit: improve parameter estimate







## Python wrappers make analysis of Fermi data much easier: Enrico and fermipy

We will use Enrico:

http://enrico.readthedocs.io/en/latest/



https://github.com/rsnemmen/Fermi-LAT-tutorial

#### **Tutorials**

#### Day one

- 4:30-5:00: Introduction, overview of activities and tools (slides)
- 5:00-5:30: Obtaining and preparing LAT data for your favorite source
- 5:30-6:30: Exploring LAT data: Plotting the counts map

#### Day two

- 4:30-5:00: Overview of activity, basic theory of spectral modeling: slides, jupyter notebook
- 5:00-5:30: Getting a flux: Likelihood analysis
- 5:30-6:30: Creating a spectrum (SED)
- Bonus: Producing a light-curve







# Please do not download large files during the tutorial or the WIFI network will *overload*

## We will distribute the software and data you need via USB sticks





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