

# Statistics

A pragmatic way in particle physics

## Lecture II

Xiaohu SUN, IHEP, 04-03-2014



# What is this lecture about?

- A fresh reminder of why we need statistics in particle physics
  - It helps to quantify our measurements, especially when the uncertainties are introduced
  - It helps to make decision “find or not a new particle?”
  - It helps to communicate physics results among experimentists as well as theorists
- Previously, I introduced the basics of probability: the definition,  $E[x]$ ,  $V[x]$ , error propagation and some important distributions
- This time, I discuss
  - The parameter estimation
  - The hypothesis testing

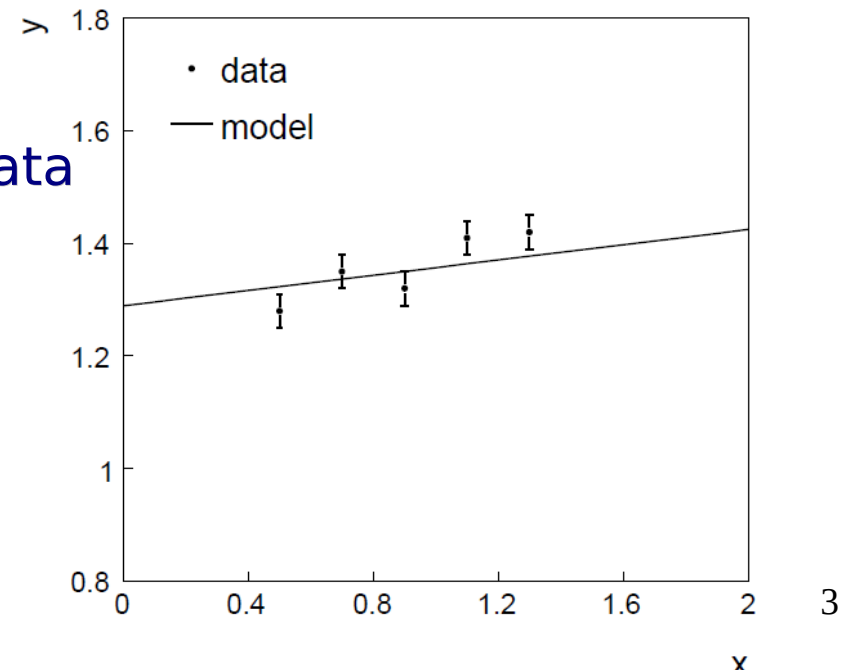
# Parameter estimation - intro

- Random variable  $y$  follows a Gaussian distribution with a known standard deviation and a mean value as a function of random variable  $x$

$$\mu(x; \theta_0, \theta_1) = \theta_0 + \theta_1 x$$

theoretical model

- where  $\theta_0$   $\theta_1$  are parameters to be fit
- suppose the real goal is to obtain  $\theta_0$  (i.e. **POI**)
- then  $\theta_1$  is treated as a **nuisance parameter**
- Data points  $y_{1,2,\dots,n}$ ,  $x_{1,2,\dots,n}$
- Find the optimal  $\theta_0$   $\theta_1$  according to data
- So we need a statistical model
  - to fit theoretical model to data



# Parameter estimation - L

- The pdf of  $y$  reads,

$$f(y_i; \theta) = \frac{1}{\sqrt{2\pi}\sigma_i} e^{-(y_i - \mu(x_i; \theta))^2 / 2\sigma_i^2}$$

- Construct a **likelihood function** that is a joint pdf of all  $y_i$  from data

$$L(\theta) = \prod_{i=1}^n f(y_i; \theta) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi}\sigma_i} e^{-(y_i - \mu(x_i; \theta))^2 / 2\sigma_i^2}$$

statistical model

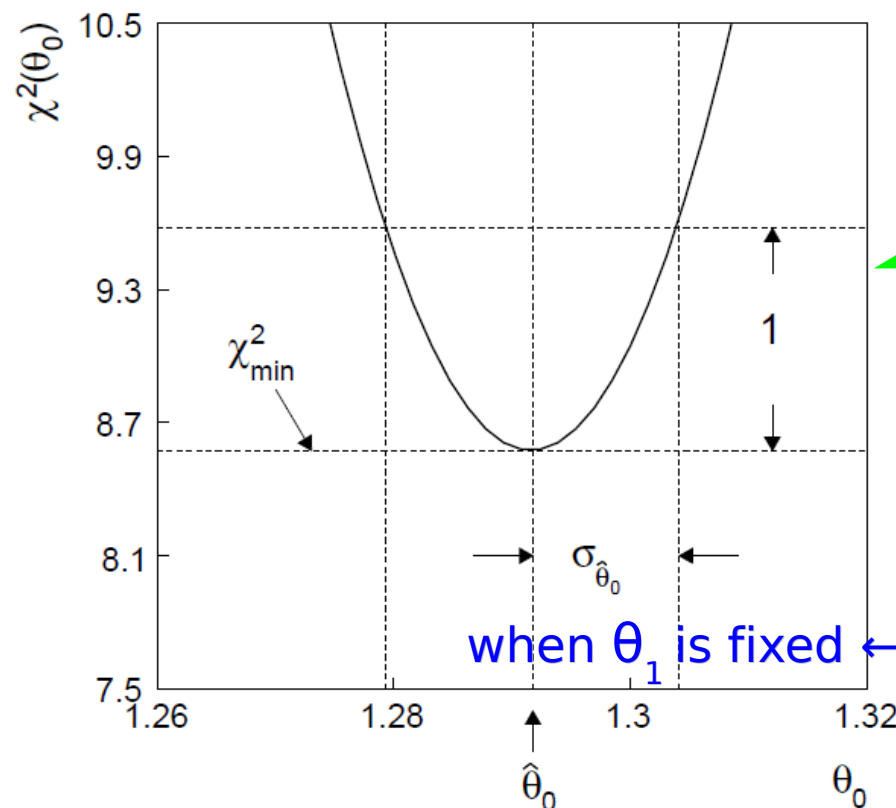
- $L$  contains our theoretical model with to-be-fit parameters as well as the data from experiments
- $L$  get maximized when the theoretical model describes well the data, in which case the parameters are optimal; otherwise,  $L$  value decreases
- The optimal (fitted) parameter is usually called estimator  $\hat{\theta}$
- Fit  $\rightarrow$  maximization/minimization

# Parameter estimation – NLL (LS)

- Maximize LL → Minimize NLL (negative LL)

$$\chi^2(\boldsymbol{\theta}) = \sum_{i=1}^n \frac{(y_i - \mu(x_i; \boldsymbol{\theta}))^2}{\sigma_i^2} = -2 \ln L(\boldsymbol{\theta}) + C$$

- The left equation is actually the method of **least square**
- In our case LS coincide with NLL (condition: Gaussian distribution)

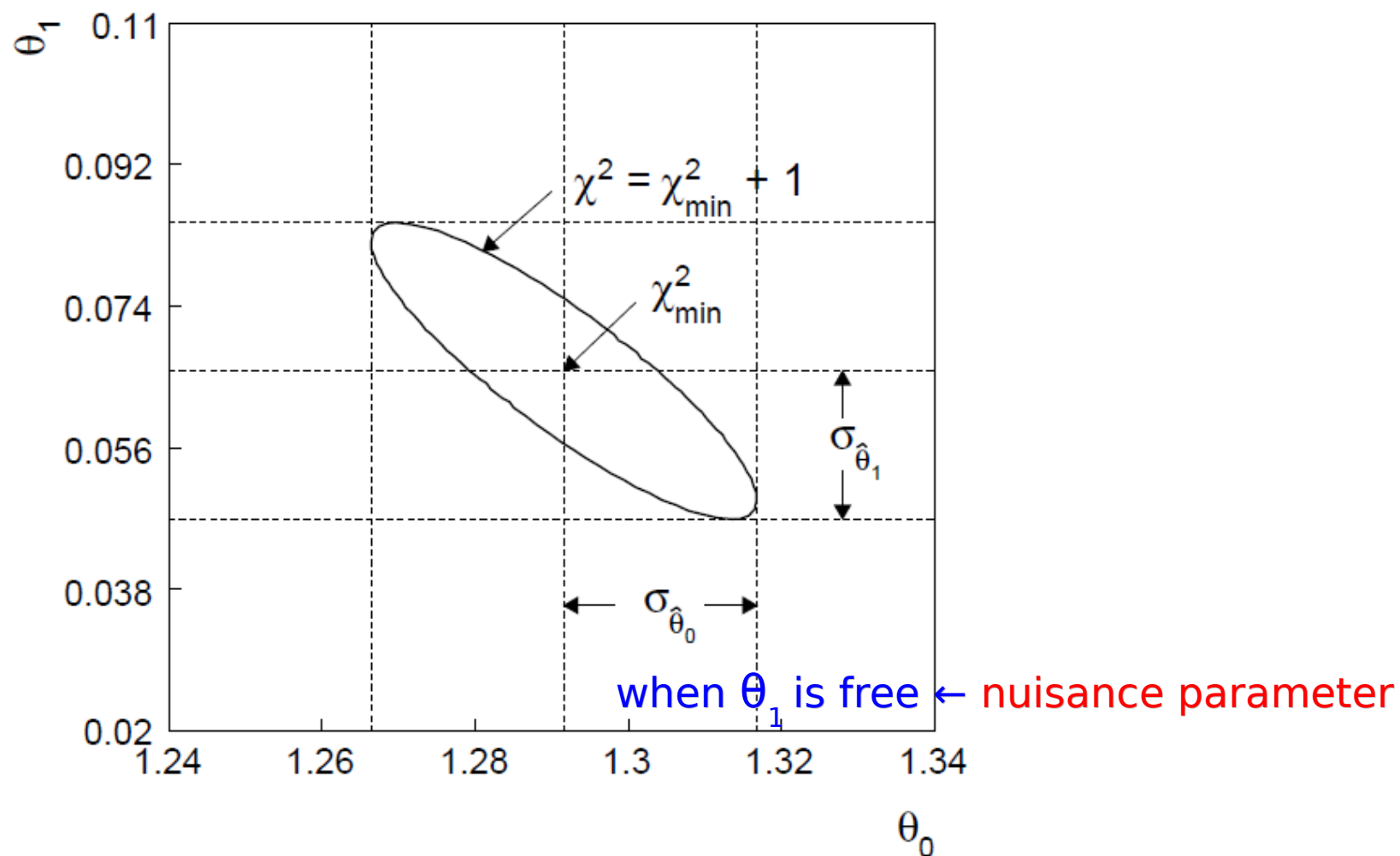


To find the error  
LS/NLL: +1.0  
LL: -0.5

when  $\theta_1$  is fixed ← NO nuisance parameter

# Parameter estimation – $\theta_1$ is free

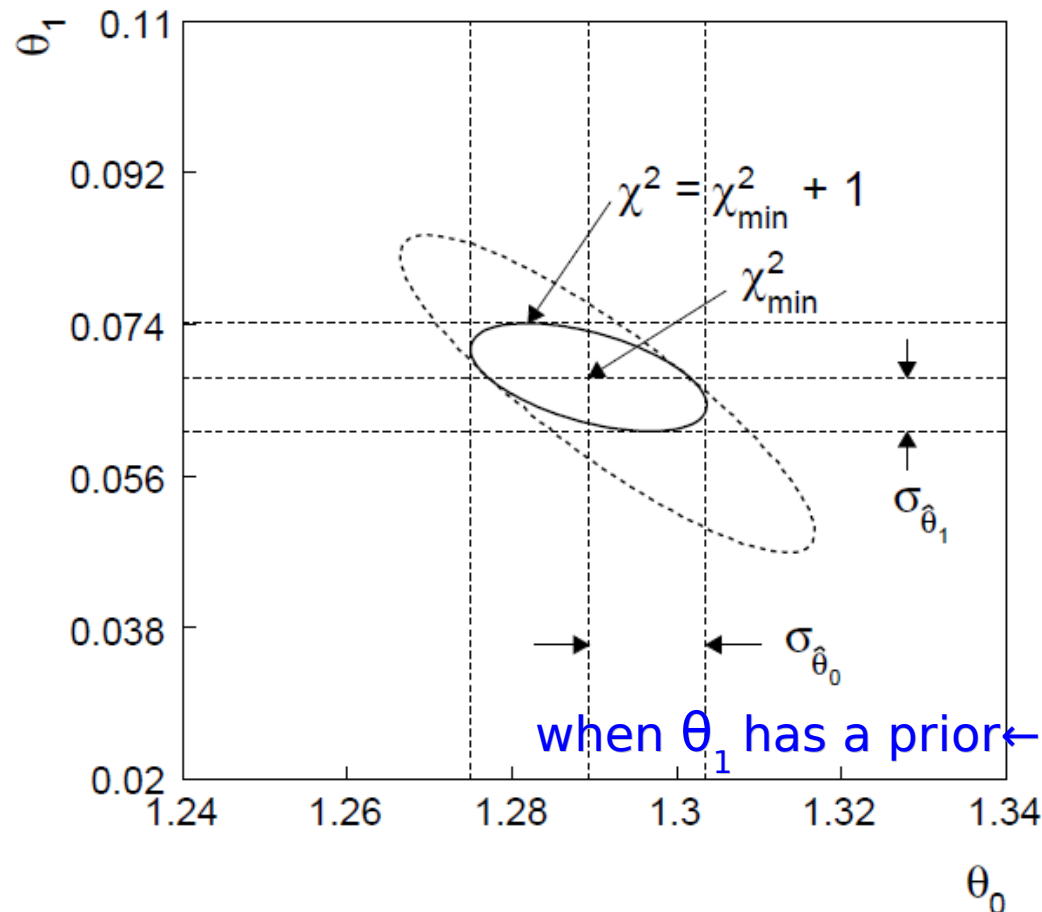
- By introducing one nuisance parameter, the error of POI is getting larger as a price



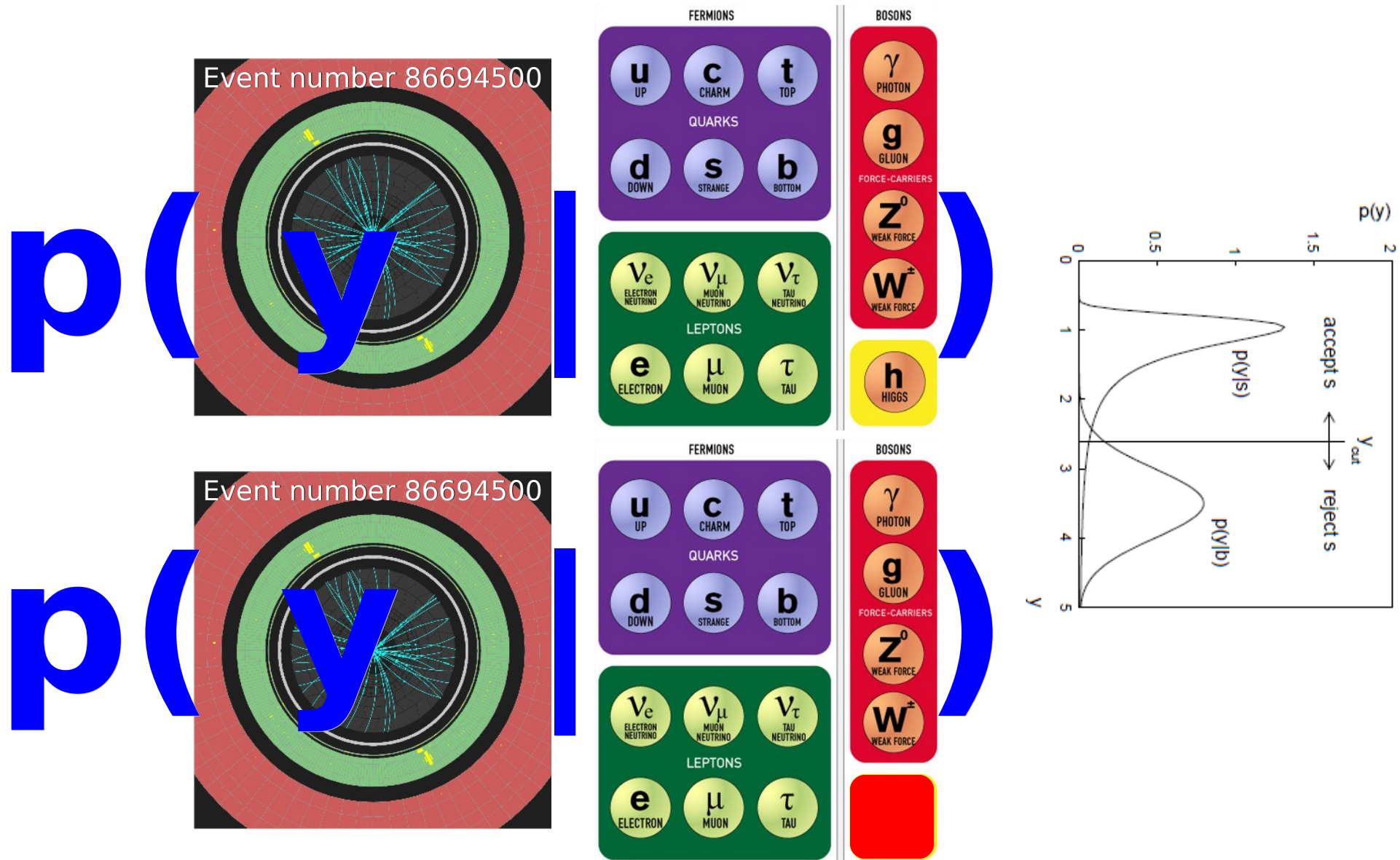
# Parameter estimation – $\theta_1$ has a prior

- To constrain the error of POI, one can introduce a prior of nuisance parameter (a knowledge on how nui behaves)

$$\chi^2(\boldsymbol{\theta}) = \sum_{i=1}^n \frac{(y_i - \mu(x_i; \boldsymbol{\theta}))^2}{\sigma_i^2} + \frac{(\theta_1 - t_1)^2}{\sigma_{t_1}^2}$$



# Test statistic – mapping into 1-D

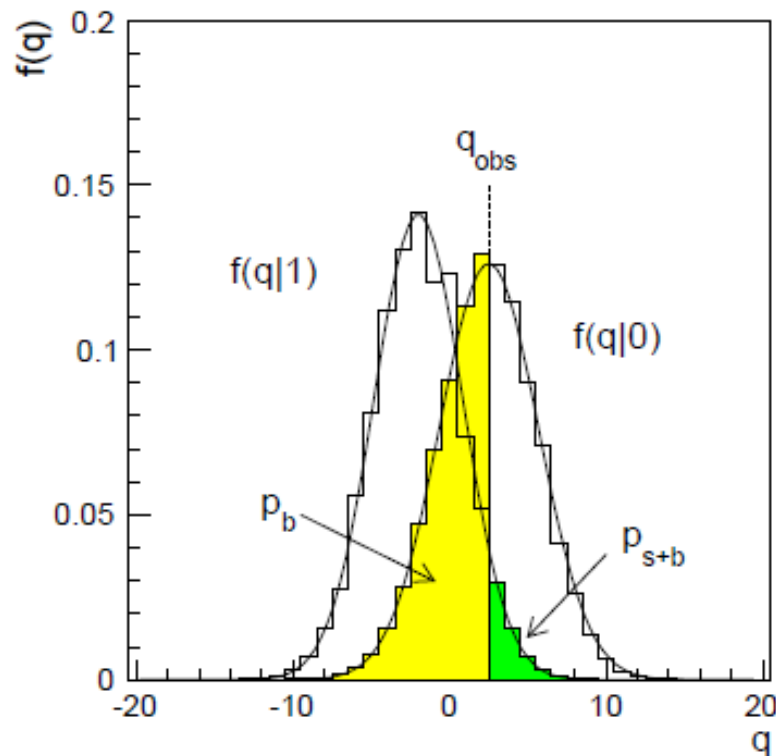


Data is mapped into a 1-d variable (**test statistics**) with two pdfs for S+B and B-only hypotheses



# Test statistic

- Pdfs  $f(q|1)$   $f(q|0)$  correspond to S+B and B hypo
- I leave the discussion on how to construct  $q$  in the future



$q_{\text{obs}}$  is the test statistics  
calculated from the data

The p-value of S+B is the prob to find  $q$   
greater than or equal to  $q_{\text{obs}}$  under the  
assumption of S+B

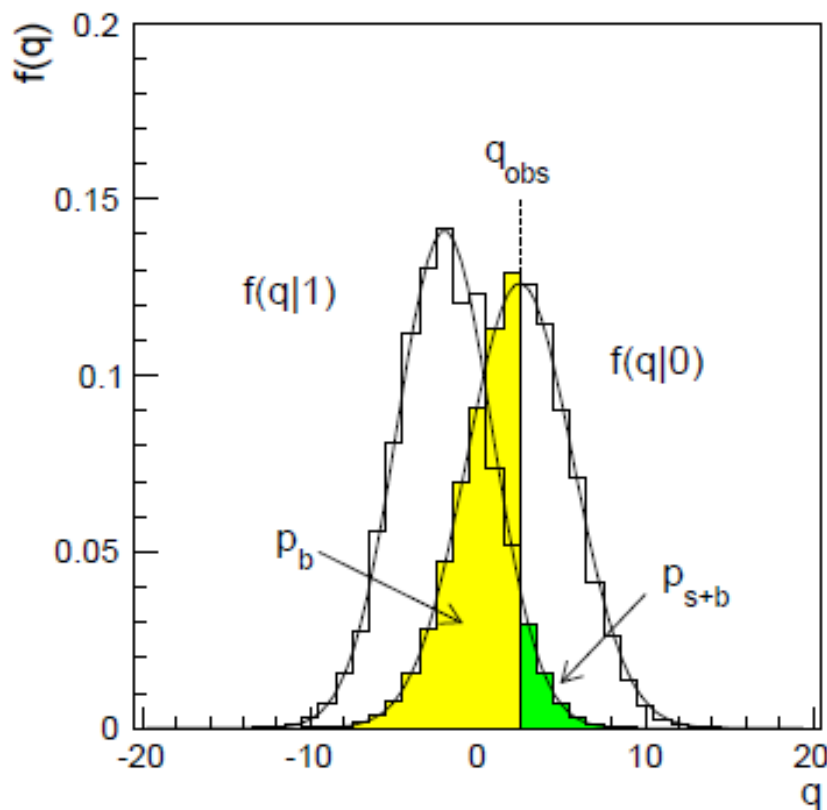
$$p_{s+b} = P(q \geq q_{\text{obs}} | s + b) = \int_{q_{\text{obs}}}^{\infty} f(q | s + b) dq$$

Similarly

$$p_b = P(q \leq q_{\text{obs}} | b) = \int_{-\infty}^{q_{\text{obs}}} f(q | b) dq$$

# Test statistic $\rightarrow$ exclusion or upper limit

- Calculate the test statistic of S+B hypo based on its p-value
- The signal model is regarded as excluded at a confidence level of  $1 - \alpha = 95\%$  if one finds



$$p_{s+b} < \alpha$$

$$1 - \alpha = 95\%$$

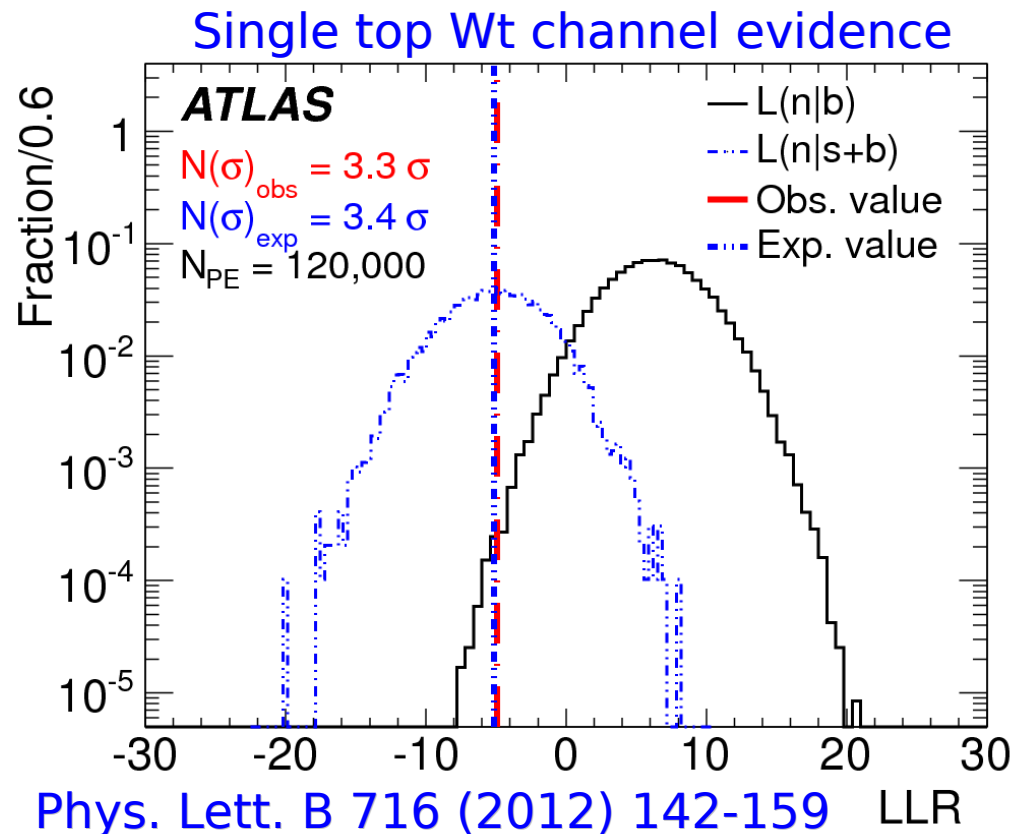
$$\text{confidence level CL} = 1 - \alpha$$

NOTE: in another word, the signal rate  $s$  under which the 5%  $p_{s+b}$  reaches, can be regarded as a upper limit  $s_{up}$ , for which signal is not excluded.

So the interval  $[0, s_{up}]$  covers  $s$  with a probability of at least 95%

# Test statistic $\rightarrow$ discovery

- Calculate the test statistic of B hypo based on its p-value:  $p_b$
- Convert p-value into standard deviation (XX sigma)
- 3 sigma  $\rightarrow$  evidence; 5 sigma  $\rightarrow$  discovery
- The background-only model is regarded as rejected if 5 sigma



# Summary

- In this lecture, the basics of probability is introduced
  - The parameter estimation
  - The L/NLL, the least square LS
  - The test statistic
  - The exclusion, upper limit, discovery
- In the following lectures, more interesting topics on statistics will be covered
  - How ATLAS usually defines the statistical model
  - How ATLAS usually defines the test statistic
  - Confidence level (optional)



A man with glasses and a black coat stands in the foreground, looking towards the right. Behind him is a body of water and a dense city skyline featuring several prominent skyscrapers, including the Chrysler Building. The scene is set on a grassy area with a concrete barrier in the immediate foreground.

Stay tuned  
for the next episode

P.O.I.