

# $\mu S+B$ Fit

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## Process:

1. Determine the distribution of the signal and background.
2. Use these distribution to generate Asimov data.
3. Fit Asimov data.

$$\mu_{S+B}: \mu = \frac{N_{obs}}{N_{exp}}$$

# Likelihood Fit Principle:

## How to calculate?

Use likelihood model to quantify.

- Signal strength

$$\mu \equiv \frac{\sigma_{obs}}{\sigma_{exp}}$$

- For each bin,

$$E(n) = \mu * s_i + b_i$$

Poisson

- Basic form:

$$L(\mu) = \frac{(\mu s + b)^n}{n!} e^{-(\mu s + b)}$$

- Add nuisance parameters (NP) to model.
  - besides POI(parameter of interest, here is  $\mu$ )
  - describe uncertainty, bkg parameterization, ..... anything we need.



## Likelihood function: an example



$$\mathcal{L} = \prod_i \left\{ \frac{e^{-v_i}}{n_i!} \prod_j^{n_i} [v_i^{sig} \mathcal{F}_i^{sig}(m^j, \theta; m_H) + v_i^{bkg} \mathcal{F}_i^{bkg}(m^j)] \right\} \times \prod_l G_l(\theta)$$

- Function form:
 
$$f = N \cdot \begin{cases} e^{-\frac{1}{2}\alpha_L^2} \cdot \left[ \frac{\alpha_L}{n_L} \left( \frac{n_L}{\alpha_L} - [\alpha_L + x] \right) \right]^{-n_L}, & x < -\alpha_L \\ e^{-\frac{1}{2}x^2}, & -\alpha_L \leq x \leq \alpha_H \\ e^{-\frac{1}{2}\alpha_H^2} \cdot \left[ \frac{\alpha_H}{n_H} \left( \frac{n_H}{\alpha_H} - [\alpha_H - x] \right) \right]^{-n_H}, & x > \alpha_H \end{cases}$$
- $\mathcal{F}^{sig}$ : pdf(probability distribution function) of signal, describe the signal shape.
- $\mathcal{F}^{bkg}$ : pdf of background
- Function **minimizes the bias** observed in the extracted signal yield
- The bkg model with the **least parameters** is chosen
- $G_l$ : Uncertainties.

# Likelihood Fit Principle:

- Easy to do **combination** each channels/categories.

$$L(\mu, \theta) = \prod_i L_i(\mu, \theta_i)$$

Times the subpart directly!

- uniformed, simultaneous statistical procedure and framework
- can easily include necessary correlations      Share the same name
- Final model can be very complicated to consider all info from the analysis.

## Profile likelihood ratio



$$\lambda(\mu) \equiv \frac{L(\mu, \hat{\theta})}{L(\hat{\mu}, \hat{\theta})} \quad 0 \leq \lambda \leq 1$$

Maximize L for specified  $\mu$       Under NPs with  $\theta$

Maximize L

Larger  $\lambda$ , better agreement data & hypothesis

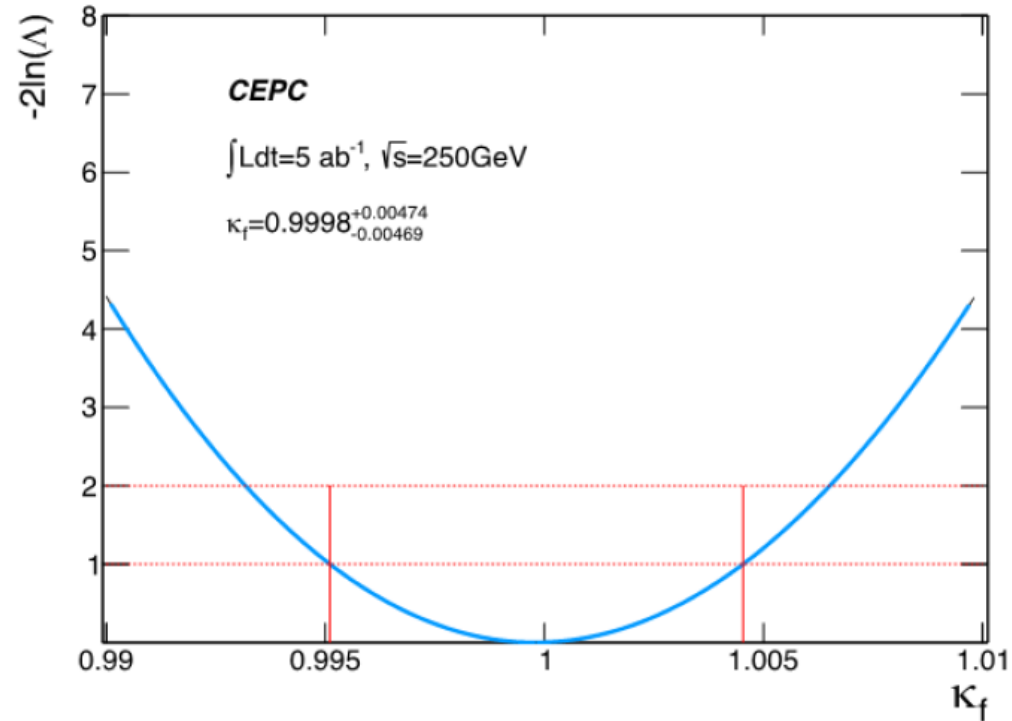
- Test statistics

$$q(\mu) \equiv -2 \ln \lambda(\mu) \quad \text{Higher } q, \text{ less incompatible.}$$

To reject background-only ( $\mu = 0$ ) hypothesis using

$$q_0 = \begin{cases} -2 \ln \lambda(0) & \hat{\mu} \geq 0 \\ 0 & \hat{\mu} < 0 \end{cases}$$

## Fit method: likelihood scan



Deviation at  $1\sigma$  : precision  $\Delta\mu$

Deviation at  $(1.95)\sigma$  : upper limit at 95% C.L.

## Fit result:

All fits done in 0.01 min (cpu), 0.02 min (real)

Fit Summary of POIs ( STATUS OK )

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RooRealVar::qz4v = 1.00003 +/- (-0.995064,0.997171) L(-5 - 5)

$\mu$

$\sigma$

At 95% Confidence level, the upper limit of Br is  $(\mu + 2\sigma)Br$ .  
Here, the value is 0.32%.

$\sigma$  is statistical error.