

## **Statistical Data Analysis course**

**In-depth part : Profile Likelihood Ratio & MINOS interval**

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## Connection between Profile Likelihood Ratio & MINOS uncertainties

# Profile Likelihood

In the next slides this connection will be argued/explained.

Firstly, remember the difference between these two concepts:

- **POI(s)** = **parameter(s) of interest**: parameter(s) of theoretical model (we assume predicts distribution of observed variables)

- **NPs** = **nuisance parameters**: additional unknown parameters, appearing together with the POI(s), that represent the effect of the detector response (resolutions, miscalibrations, ...), the presence of background, ...

Typically they can represent systematic uncertainties & can be usually determined from simulation or data control samples.

Let's assume for simplicity to have a POI  $\mu$  and a set of NPs  $\vec{\theta}$  (i.e. all parameter are treated as NPs with exception of  $\mu$ ).

The **likelihood function** is written as:  $\mathcal{L}(\vec{x}; \mu, \vec{\theta})$ . To easy the notation we drop the  $\vec{x}$  and write simply  $\mathcal{L}(\mu, \vec{\theta})$ .

The so-called **profile likelihood** is constructed following this prescription:

- for a **given value of the POI**  $\bar{\mu}$  derive the **ML estimates**  $\hat{\hat{\theta}}(\bar{\mu})$  (it's a *conditional ML estimate*; fit with  $\mu$  fixed to a constant value  $\bar{\mu}$ )

- thus the maximum likelihood for a given value of  $\bar{\mu}$  is  $\mathcal{L}_{max}(\bar{\mu}, \hat{\hat{\theta}}(\bar{\mu}))$ ;

- recalculating (CPU expensive) for each value of  $\mu$  (scan of  $\mu$  values) we get a truly function of  $\mu$ :  $\mathcal{L}_{max}(\mu, \hat{\hat{\theta}}(\mu))$   
which is the **likelihood function maximized w.r.t. all the NPs and** is called **profile likelihood** !

# Profile Likelihood Ratio

On the other hand it is always possible to maximize the likelihood getting the best estimates (fit values) of  $\mu$  and  $\vec{\theta}$  corresponding to the observed data  $\vec{x}$ :  $\hat{\mu}$  and  $\hat{\vec{\theta}}$ . Thus the maximized likelihood is:  $\mathcal{L}_{max}(\hat{\mu}, \hat{\vec{\theta}})$

At this point we can consider the **Profile Likelihood ratio**:  $\lambda(\mu) = \frac{\mathcal{L}_{max}(\mu, \hat{\vec{\theta}}(\mu))}{\mathcal{L}_{max}(\hat{\mu}, \hat{\vec{\theta}})}$  (that does not depend on the NPs  $\vec{\theta}$ )

This ratio is used in the convenient test statistic  $t_\mu = -2 \ln \lambda(\mu)$ . Dropping the obvious “max” index:  $\lambda(\mu) = \frac{\mathcal{L}(\mu, \hat{\vec{\theta}}(\mu))}{\mathcal{L}(\hat{\mu}, \hat{\vec{\theta}})}$

In other words the **profile likelihood ratio substitutes the ordinary likelihood ratio**, in the test statistics  $t_\mu = -2 \ln \lambda(\mu)$ , **when** we have to deal with nuisance parameters:

$$\lambda(\mu) = \frac{\mathcal{L}(\mu)}{\mathcal{L}(\hat{\mu})} \quad \text{Maximum Likelihood} \quad \longrightarrow \quad \lambda(\mu) = \frac{\mathcal{L}(\mu, \hat{\vec{\theta}}(\mu))}{\mathcal{L}(\hat{\mu}, \hat{\vec{\theta}})} \quad \text{Maximum Likelihood}$$

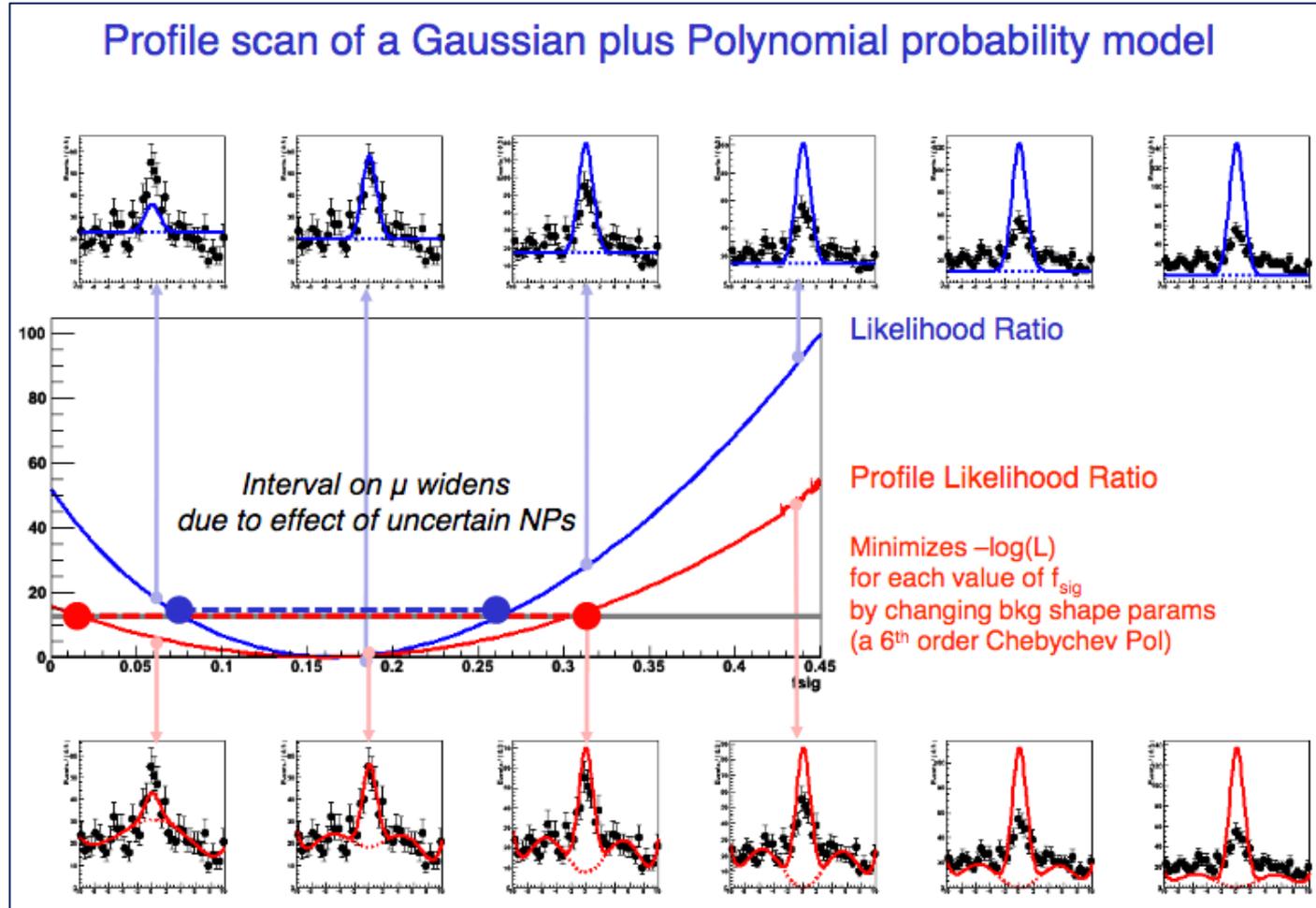
Maximum Likelihood for a given  $\mu$

Comments on the **Profile Likelihood approach**:

- it is **computationally challenging** because it requires to perform the minimization of the likelihood w.r.t. **all** the nuisance parameters for every point in the profile likelihood curve (see also next slide that illustrates this)
- the minimization can be difficult because of the possibly strong correlation among POIs and NPs or multiple/local minima

# How to obtain a Profile Likelihood

For visualization purposes have a look at this figure illustrating the scan of  $\mu$  values in order to obtain  $\mathcal{L}(\mu, \hat{\hat{\theta}}(\mu))$  :



# Profile Likelihood & Contours - I

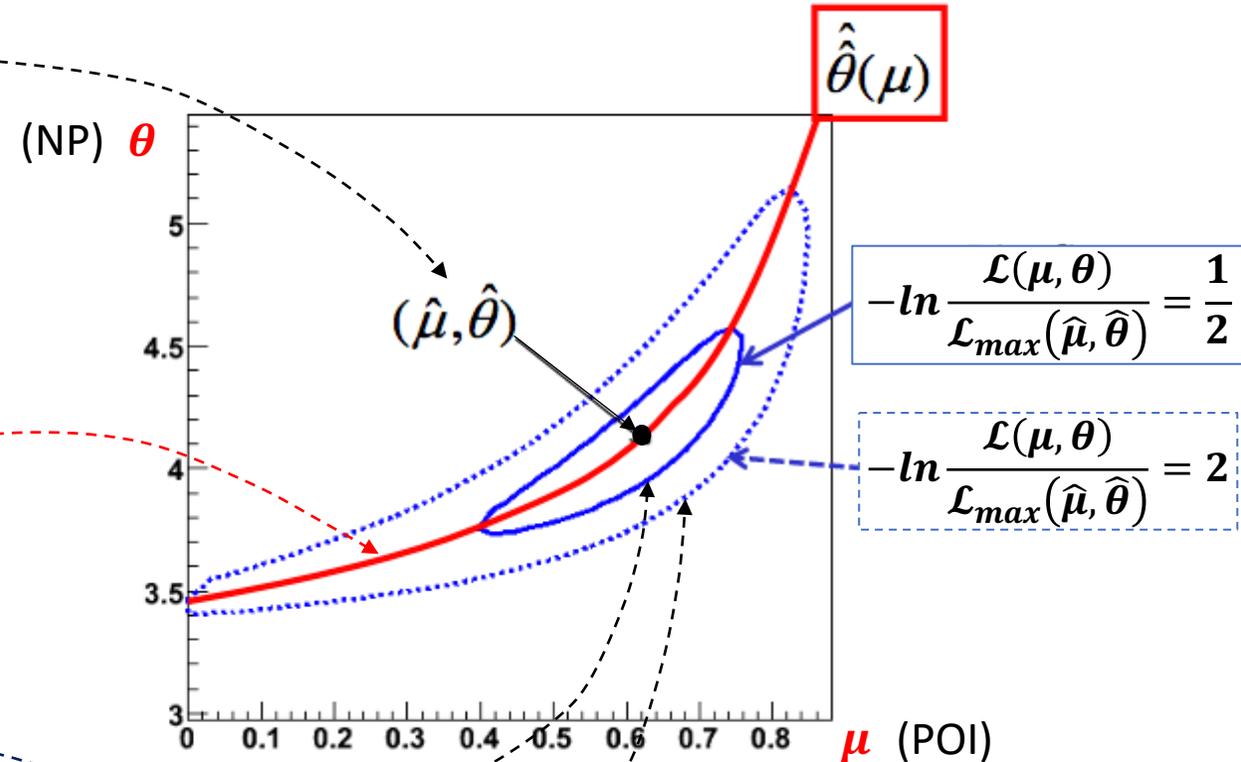
For illustration purposes let us consider one POI ( $\mu$ ) and one NP ( $\theta$ ) in order to visualize the profiling.

Firstly let us design/locate the **(black) point** representing their best estimates that maximize the likelihood:  $(\hat{\mu}, \hat{\theta})$

$$(\mu, \theta) \equiv (\hat{\mu}, \hat{\theta}) \Rightarrow \mathcal{L} \equiv \mathcal{L}_{max}(\hat{\mu}, \hat{\theta})$$

Secondly let's design the **red curve** that represents those points  $(\mu, \hat{\theta}(\mu))$  for which  $\mathcal{L} \equiv \mathcal{L}_{max}(\mu, \hat{\theta}(\mu))$

...corresponding to a subset of subsequently given/fixed values of  $\mu$  which includes also the special value  $\bar{\mu} \equiv \hat{\mu}$ .



Finally we can design the contour curves at  $1\sigma$  and  $2\sigma$  with respect to  $(\hat{\mu}, \hat{\theta})$  the maximum (minimum) of the (negative) likelihood. This is discussed in detail in the next slide.

## Profile Likelihood & Contours - II

In particular the first contour corresponds to a set of parameters such that:  $-2\ln\mathcal{L}(\mu, \theta) = -2\ln\mathcal{L}_{max}(\hat{\mu}, \hat{\theta}) + 1$

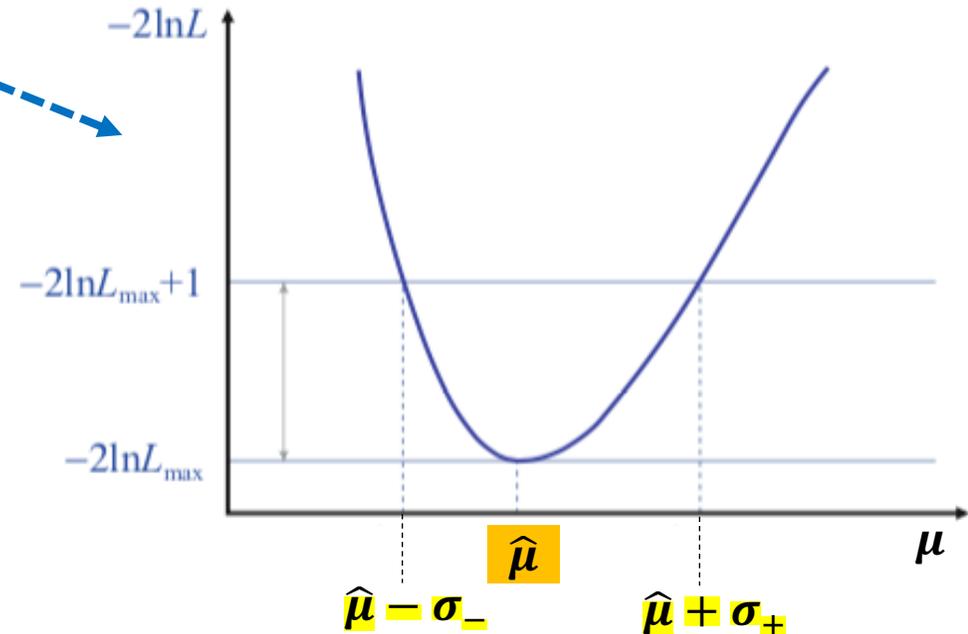
Indeed in the simplest case (only one POI & no NPs) one has:

$$-2\ln\mathcal{L}(\mu) \equiv -2\ln\mathcal{L}_{max}(\hat{\mu}) + 1$$

$$\iff 2\ln\mathcal{L}(\mu) - 2\ln\mathcal{L}_{max}(\hat{\mu}) = -1$$

$$\iff 2\ln\frac{\mathcal{L}(\mu)}{\mathcal{L}_{max}(\hat{\mu})} = -1 \iff -\ln\frac{\mathcal{L}(\mu)}{\mathcal{L}_{max}(\hat{\mu})} = +\frac{1}{2}$$

Note that in general **the uncertainty** (and thus the  $1\sigma$  interval) can be **asymmetric** (as depicted).



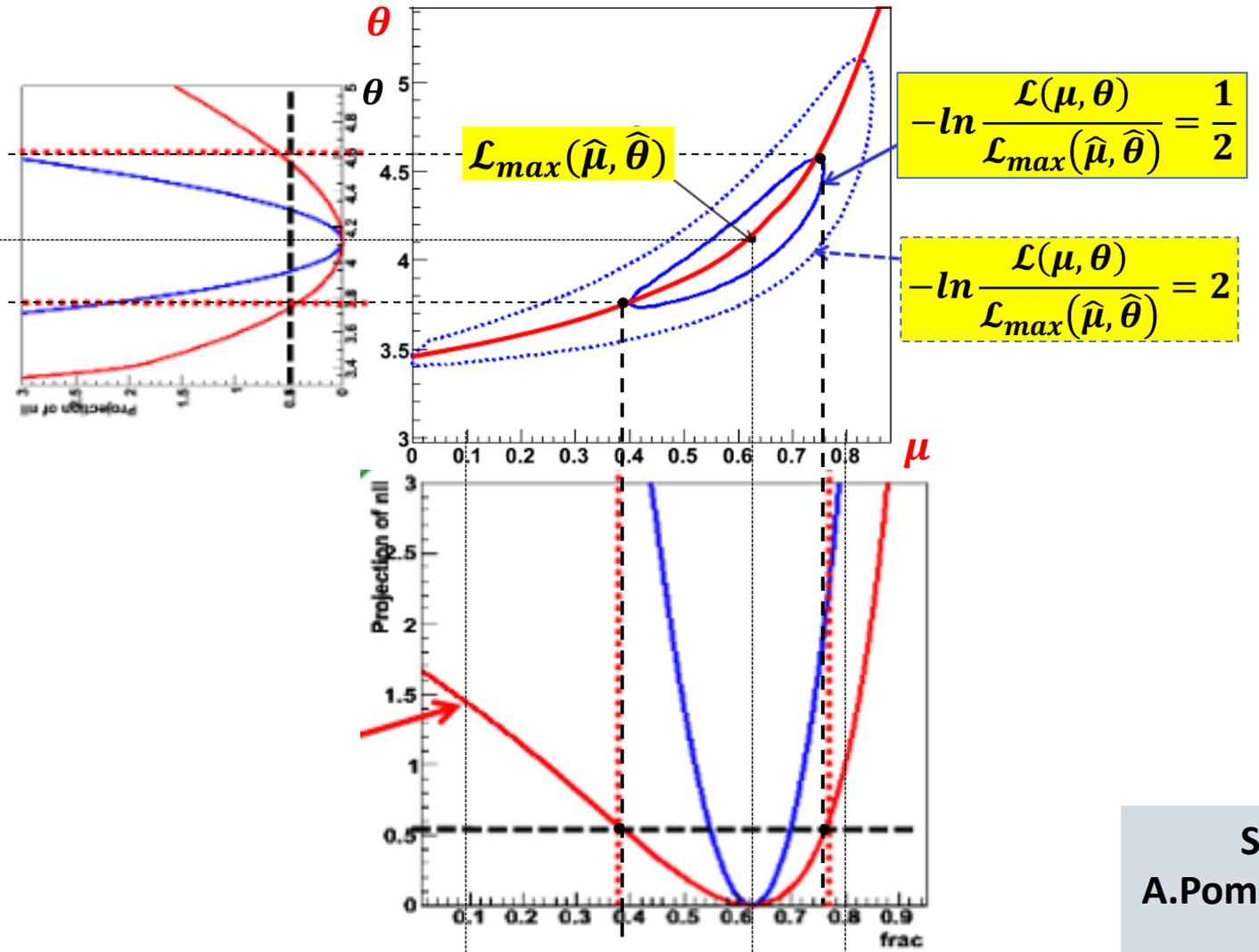
When there is also one NP one gets 2D contours (see next slide) and

$$-\ln\frac{\mathcal{L}(\mu)}{\mathcal{L}_{max}(\hat{\mu})} \quad \text{becomes} \quad -\ln\frac{\mathcal{L}(\mu, \theta)}{\mathcal{L}_{max}(\hat{\mu}, \hat{\theta})}$$

# Profile Likelihood & Contours - III

When there is also one POI and one NP one gets **2D contours**, here designed with the 2 projections:

Clearly **the correct  $1\sigma$  interval for the POI is given by the projection of the contour** (and not by the -marginalized - likelihood, that is the blue projection, which ignores the effect of the presence of the NP). It can be demonstrated that **this confidence interval provides the correct coverage in the frequentistic approach**.



**The overall uncertainty is in general asymmetric!**

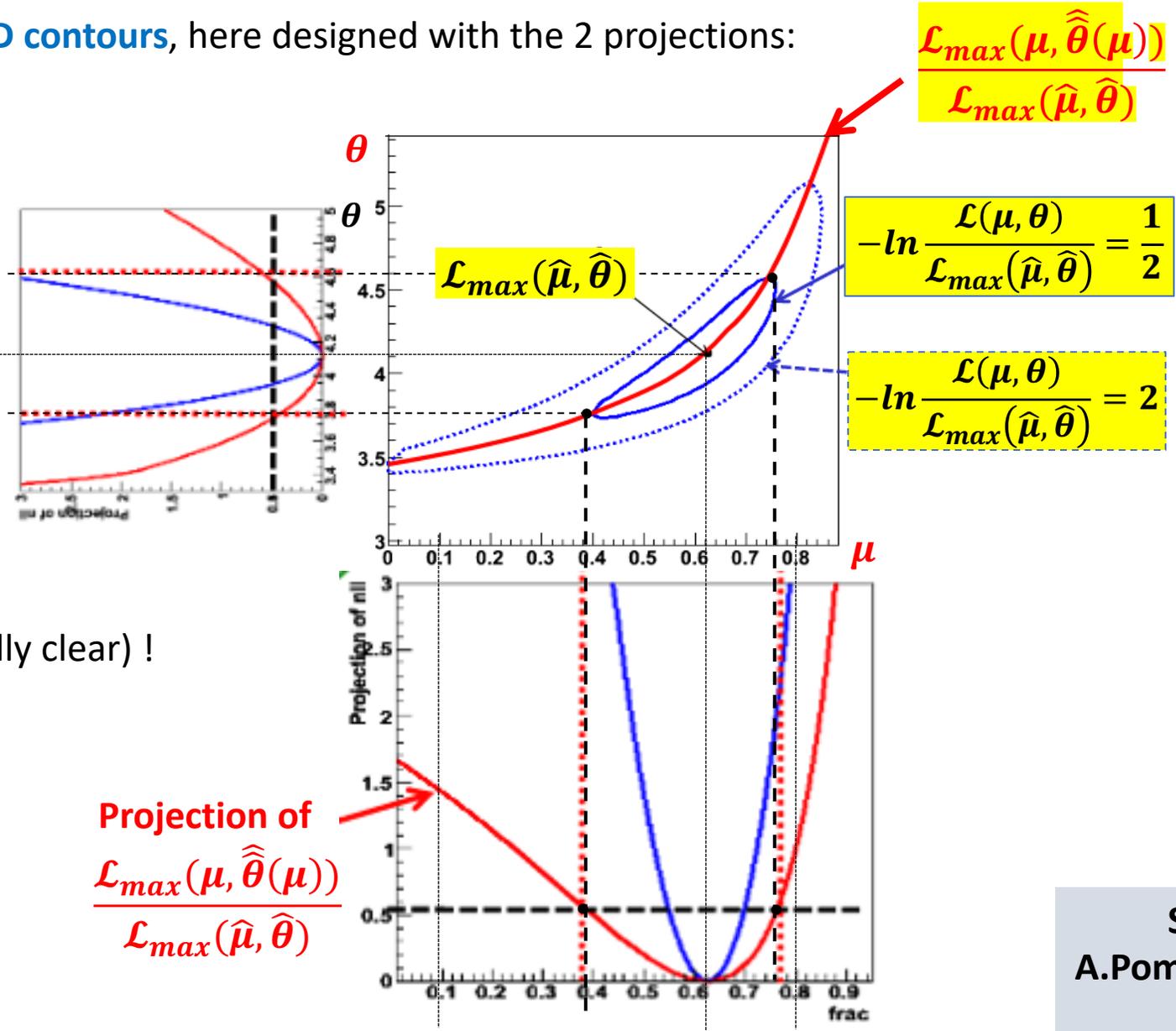
# Same confidence interval provided by Profile Likelihood & Contours

When there is also one POI and one NP one gets **2D contours**, here designed with the 2 projections:

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It is also crucial to know that **this interval is the same provided by (the projection of) the Profile Likelihood ratio** based on  $\mathcal{L}_{max}(\mu, \hat{\theta}(\mu))$  (as visually clear) !

Indeed the addition of NP(s) broadens the shape of the Profile Likelihood as a function of the POI compared with the case where NP(s) are not added. As a consequence, **the uncertainty on the POI increases when NPs - that usually model sources of systematic uncertainties - are included.** **The overall uncertainty is in general asymmetric!**

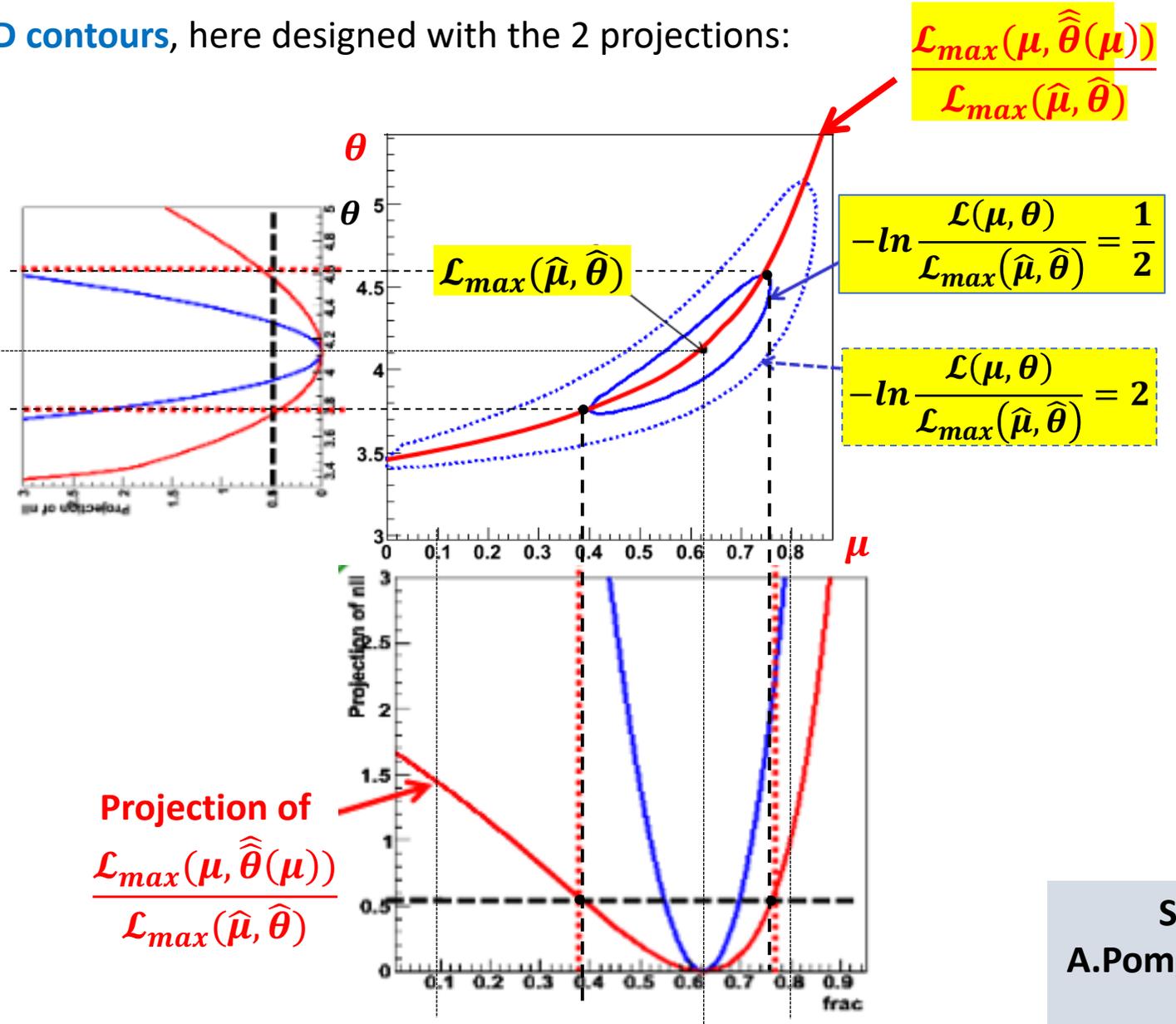


# MINOS uncertainties by likelihood scan

When there is also one POI and one NP one gets **2D contours**, here designed with the 2 projections:

Moreover :

The MINOS method (called by MINUIT) determines the overall uncertainties (in general asymmetric) based on the *likelihood scan* namely on the  $-2\ln\mathcal{L}(\mu)$  scan used to determine the  $1\sigma$  contour.



# MINOS uncertainties by likelihood scan

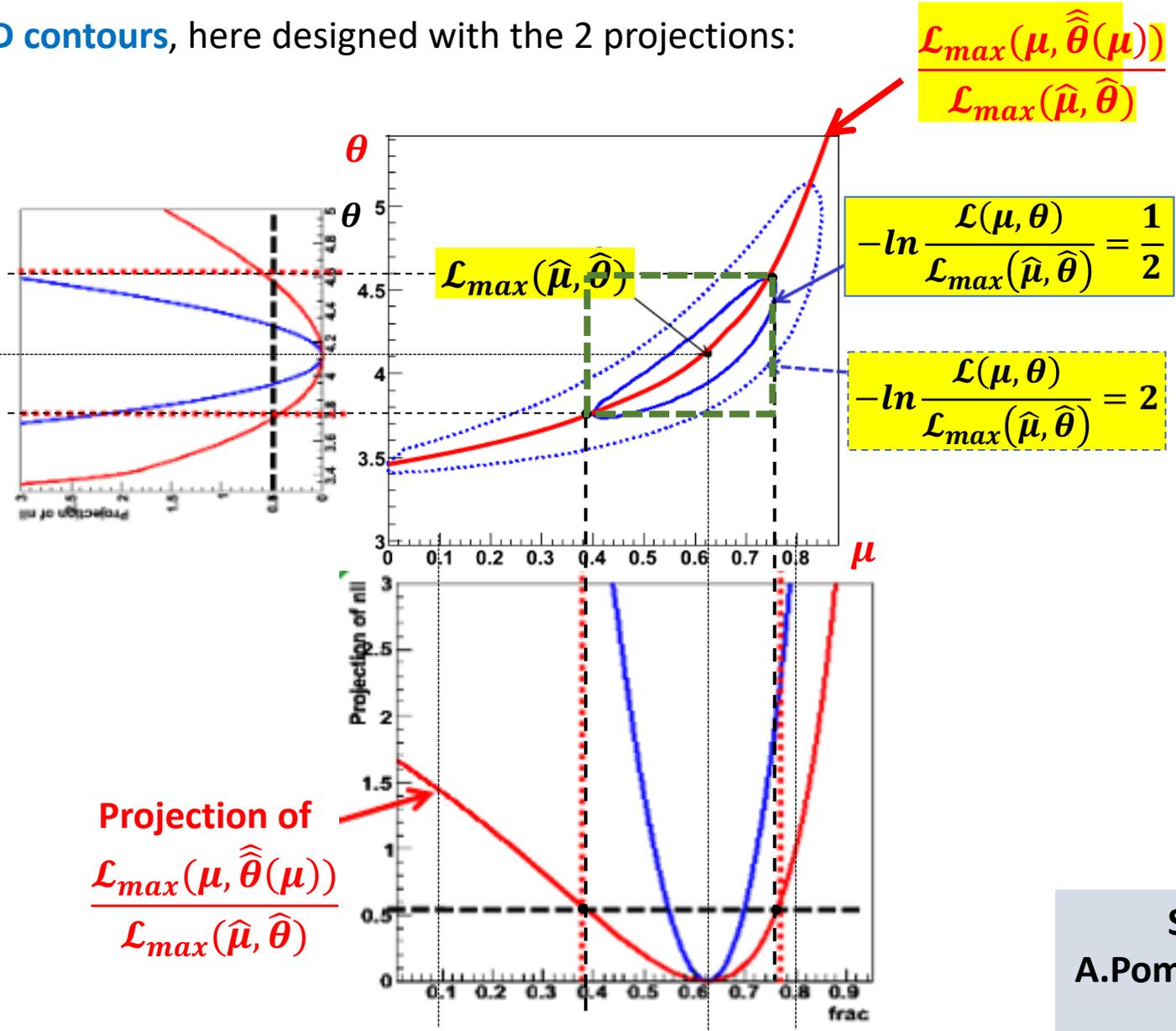
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The MINOS errors can be visualized with the size of the green bounding box around the contour

given by 
$$-\ln \frac{\mathcal{L}(\mu, \theta)}{\mathcal{L}_{max}(\hat{\mu}, \hat{\theta})} = \frac{1}{2} !$$



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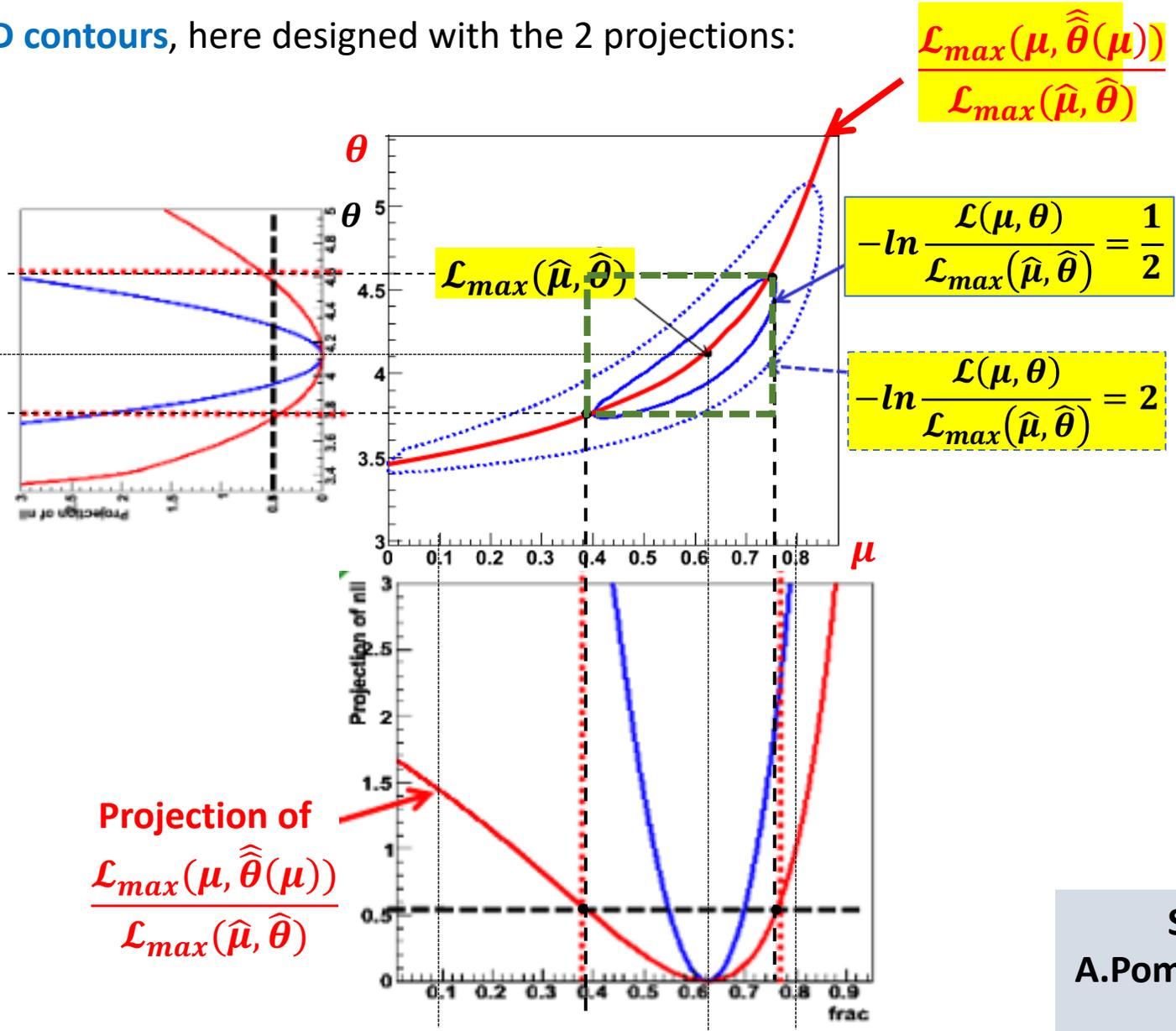
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$$-\ln \frac{\mathcal{L}(\mu, \theta)}{\mathcal{L}_{max}(\hat{\mu}, \hat{\theta})} = \frac{1}{2} !$$

In the gaussian case/regime  $-2\ln\mathcal{L}(\mu)$  can have a parabolic shape and the uncertainty of the POI is symmetric, or “close to symmetric” if parabolic approximation is good and contour is an ellipsis. However - in general - the coverage is usually improved performing the likelihood scan instead of the parabolic approximation (given by HESSE).



# Correspondence between MINOS uncertainties & Profile Likelihood intervals

Summarizing : the MINOS algorithm (\*) provides the same (asymmetric) uncertainties given by the Profile Likelihood ratio

For both ... the resulting confidence interval is satisfactorily "covered".

(\*) The MINOS algorithm will be studied next year in the Laboratory Course (*Statistical Data Analysis Lab.*)

Let us remind that in the frequentist approach:

For a large fraction of repeated experiments - usually 68.27% - the unknown true value of  $\mu$  is contained in the confidence interval  $[\hat{\mu} - \sigma, \hat{\mu} + \sigma]$ . The fraction is meant in the limit of infinitely large number of repetitions of the experiment, and  $\hat{\mu}$  &  $\sigma$  may vary from one experiment to the other, being the result of a measurement in each experiment.

- **Coverage**: property of the estimated interval to contain the true value in 68.27% of the experiments.
- **Confidence level** : the reference *probability level* usually taken as 68.27%.

Interval estimates that have a larger (or smaller) probability of containing the true value, compared to the desired confidence level, are said to **overcover** (or **undercover**).

It is important to know that the resulting confidence interval from the Profile Likelihood construction will have exact coverage for the points  $(\mu, \hat{\theta}(\mu))$ ; elsewhere it might be over- or under- covering.

We conclude stating: in the asymptotic regime (very large number of experiments) the MINOS algorithm (in ROOT) provides the (asymmetric) uncertainties used in the definition of the frequentist confidence intervals !

## Frequentist confidence intervals when NP are present

Exact confidence intervals are difficult when nuisance parameters are present:

- intervals should cover for any value of NPs (technically difficult)
- typically there can be a significant over-coverage

The approach to use the Profile Likelihood ratio guarantees the coverage at the measured values of NPs (only !)

- technically replace Likelihood ratio with Profile Likelihood ratio
- computationally more intensive but still very tractable

Asymptotically confidence intervals constructed with Profile Likelihood ratio correspond to MINOS likelihood ratios intervals

- as the distribution of the Profile Likelihood becomes asymptotically independent of  $\theta$  the coverage for all values of  $\theta$  is restored !