

Data Analysis

Lecture 3: Confidence intervals

In this lecture

- Interval estimation
 - Errors on the fit parameters
- Confidence intervals

Reminder

- Example: histogram fitting

Physicists

1. Determining the “best fit” parameters of a curve

2. Determining the errors on the parameters

3. Judging the goodness of a fit

Statisticians

1. Point estimation

2. Confidence interval estimation

3. Goodness-of-fit (Hypothesis) testing

Adopted from [Baker, Cousins, 1984]

Confidence intervals⁷

For a Gaussian estimator the result of an experiment is usually expressed by

- The parameter’s estimated value, plus/minus an estimate of the **standard deviation**, $\hat{\theta} \pm \sigma_{\hat{\theta}}$

If the pdf is not Gaussian, or in the presence of physical boundaries

- One usually quotes instead an **interval**.

The quoted interval or limit should:

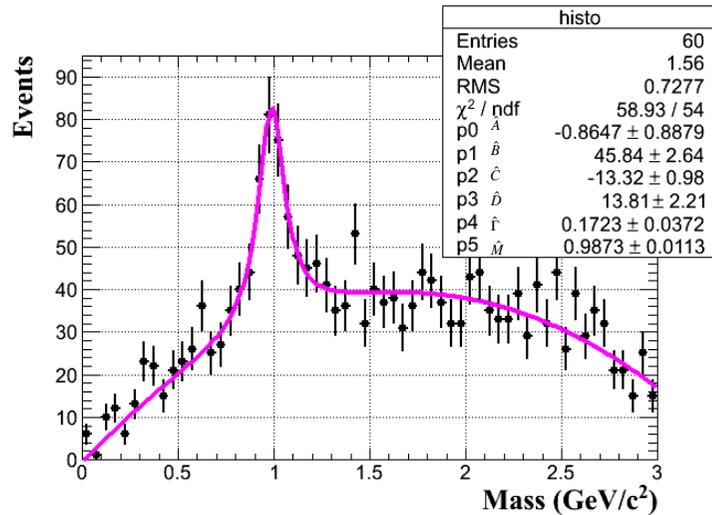
- Objectively communicate the result of the experiment,
- **Communicate incorporated prior beliefs** and relevant assumptions,
- Provide interval that covers the true value of the θ with specified probability,
- Make possible to draw conclusions about the parameter.

These goals are satisfied in **case of large data sample** by $\hat{\theta} \pm \sigma_{\hat{\theta}}$, and in the multi-parameter case by

- The parameter estimates and covariance matrix.

⁷Adapted from [Particle Data Group](#).

Example: results of the fit



Errors on the ML estimates (1/4)

- How to obtain errors on the parameters estimated by the ML?

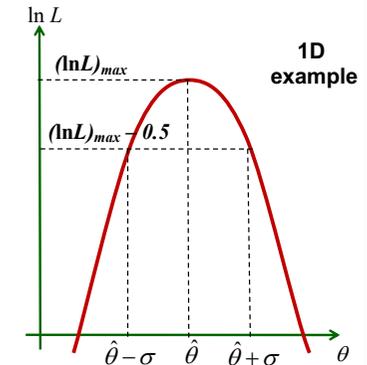
- Option 1: **Matrix inversion**

- Covariance matrix is minus the inverse of the matrix of second derivatives
- Done with MINUIT/HESSE in ROOT

$$\text{cov}^{-1}(\theta_i, \theta_j) = - \left. \frac{\partial^2 L}{\partial \theta_i \partial \theta_j} \right|_{\theta = \hat{\theta}}$$

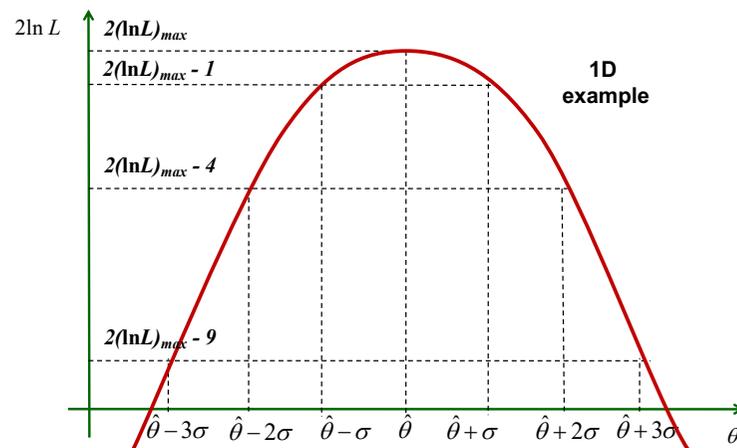
- Option 2: **Log - likelihood curve**

- In the large N limits the likelihood function is Gaussian and the log-likelihood is parabola
- By definition $(\ln L)_{\max} = \ln L(\hat{\theta})$
- $\pm 1\sigma$ limits on θ are those values of θ for which $\ln L$ falls by 0.5 from its maximum value L_{\max}
- For $\pm 2\sigma$ ($\pm 3\sigma$) limits $\ln L$ falls by 2 (4.5)
- Done with MINUIT/MINOS in ROOT



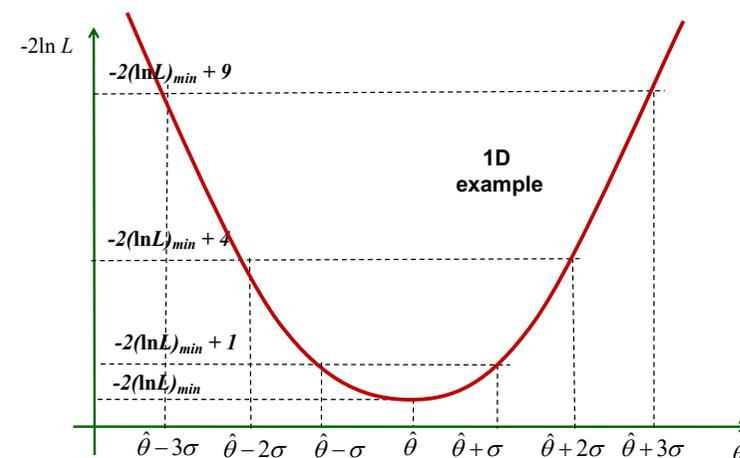
Errors on the ML estimates (2/4)

- The same, but now maximizing $2\ln L$



Maximisation \rightarrow Minimisation

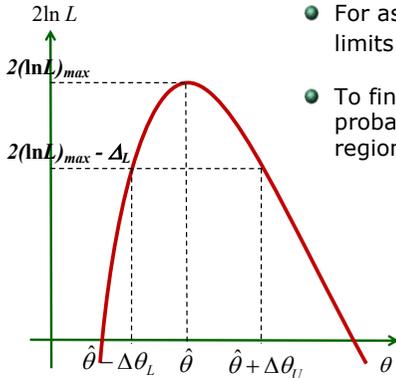
- In reality one is minimizing $-2\ln L$



Errors on the ML estimates (3/4)

Asymmetric example

- For finite samples and/or non-linear problems $\ln L$ is not necessarily parabolic nor symmetric
- Confidence intervals can still be extracted from the $\ln L$ curve



- For asymmetric $\ln L$ curve **upper** and **lower** limits on θ are not the same $\theta = \hat{\theta}^{+\Delta\theta_U}_{-\Delta\theta_L}$
- To find upper and lower limits with a certain probability content (β) of the confidence region \rightarrow use Δ_L from the table:

Δ_L	β (%)
1	68.27
4	95.45
9	99.73

- ROOT uses Minuit/MINOS to extract limits (errors) in this way

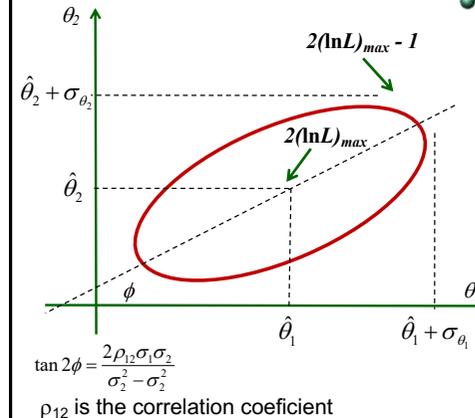
1D example

Errors on the ML estimates (4/4)

2D example: Standard error ellipse

- For more information see f.g. PDG

This is so called the plane tangent method



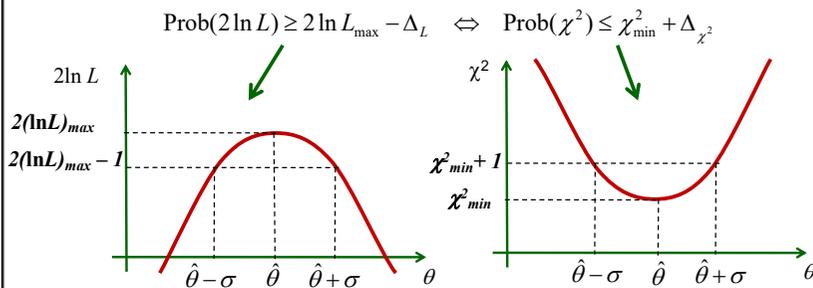
ROOT uses Minuit/MINOS

- Works well also with non-regular iso-probability curves
- Upper and lower limits for parameter θ_i are those values of θ_i for which $\max_{\theta_{j \neq i}} [2 \ln L] = 2(\ln L)_{\max} - \Delta_L$ with Δ_L from the table on the slide before
- This is OK when interested in errors for only **one** parameter, regardless all others
- Case of **simultaneous errors** estimate for more parameters \rightarrow later in this lecture

Chi-square: Finding errors

Errors (or limits) on parameters are found in the equivalent way as for the ML method

- Matrix inversion
- Shape of χ^2 around it's minimum value



Multiparameters errors

- When interested in simultaneous error estimation on more than one parameter, then the probability content (coverage probability) of the constant $-2\ln L$ or χ^2 contours is much smaller than in 1D case

- Example (recall 2D Gaussians probabilities):

	$\Delta_L / \Delta_{\chi^2}$	P_{1D}	P_{2D}
1σ	1	0.68	0.39
2σ	4	0.96	0.86

- Therefore, to increase the coverage probability we have to increase Δ_L or $\Delta_{\chi^2} \rightarrow$ see the values in the table (from PDG)

Table 32.2: $\Delta\chi^2$ or $2\Delta\ln L$ corresponding to a coverage probability $1 - \alpha$ in the large data sample limit, for joint estimation of m parameters.

$(1 - \alpha)$ (%)	$m = 1$	$m = 2$	$m = 3$
68.27	1.00	2.30	3.53
90.	2.71	4.61	6.25
95.	3.84	5.99	7.82
95.45	4.00	6.18	8.03
99.	6.63	9.21	11.34
99.73	9.00	11.83	14.16

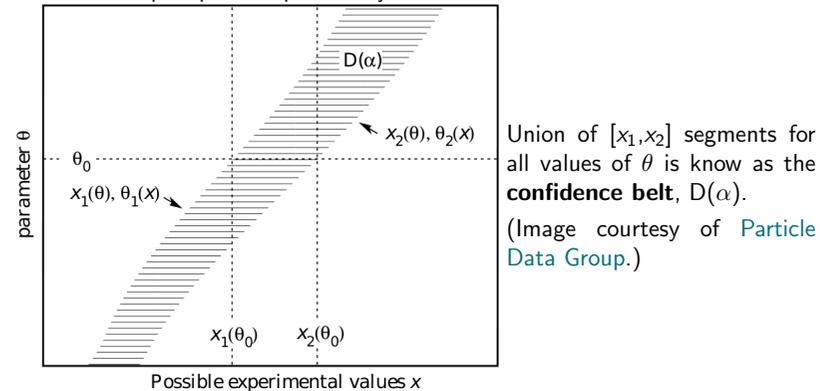
ROOT Tminuit::Contour draws contours of constant $-2\ln L$ or χ^2 with a given probability coverage

Neyman Confidence Interval (1/2)

Using frequentist approach Neyman defines confidence interval to unknown parameter θ :

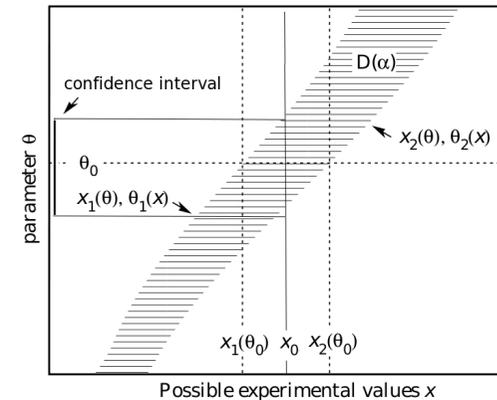
$$P(x_1 < x < x_2; \theta) = 1 - \alpha = \int_{x_1}^{x_2} f(x; \theta) dx,$$

where $1-\alpha$ is pre-specified probability and x is measurement.



Neyman Confidence Interval (2/2)

Determining **confidence interval** for θ :



- Draw a vertical line through a measurement x_0 .
- Inspect where the confidence belt is intercepted by the line.

Bayesian Confidence Intervals

In Bayesian statistics, all knowledge about parameter θ is summarized by the posterior pdf $p(\theta|\mathbf{x})$,

$$p(\theta|\mathbf{x}) = \frac{L(\mathbf{x}|\theta)\pi(\theta)}{\int L(\mathbf{x}|\theta')\pi(\theta')d\theta'}$$

which gives the degree of belief for θ to have values in a certain region given the data \mathbf{x} .

- $\pi(\theta)$ is the prior pdf for θ , reflecting experimenter's subjective degree of belief about θ before the measurement.
- $L(\mathbf{x}|\theta)$ is the likelihood function, i.e. the joint pdf for the data given a certain value of θ .
 - $L(\mathbf{x}|\theta)$ should be published whenever possible, to enable readers to calculate their own posterior pdf.
- The denominator simply normalizes the posterior pdf to unity.

Example: Non-negative constraint of a Poisson variable

Consider Poisson variable n which counts known background event with mean b , and unknown signal events with mean s constrained to be non-negative using the prior pdf

$$\pi(s) = \begin{cases} 0 & \text{if } s \leq 0 \\ 1 & \text{if } s > 0. \end{cases}$$

The likelihood function for Poisson distributed n is

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

An upper limit s_+ at **credibility level** $1-\alpha$ can be obtained by requiring

$$1 - \alpha = \int_{-\infty}^{s_+} p(s|n) ds = \frac{\int_{-\infty}^{s_+} L(n|s)\pi(s) ds}{\int_{-\infty}^{\infty} L(n|s)\pi(s) ds}$$

If $b = 0$ the equation reduces to the quantile of the χ^2 distribution

$$s_+ = \frac{1}{2} F_{\chi^2}^{-1}(1 - \alpha; n_d),$$

where $n_d = 2(n+1)$ is the number of degrees of freedom.
(e.g. `0.5*TMath::ChisquareQuantile(0.95, 2*(10+1))` ≈ 17.0 .)

Uncertainty in physics

The sources of uncertainty in measurement⁹:

- **Incomplete definition** of the measurand; or its imperfect realization
- **Non-representative sampling**
- inadequate knowledge of the effects of environmental conditions; or imperfect measurements of these conditions
- **Personal bias** in reading instruments
- **Finite instrument resolution**
- Inexact values of measurement standards and reference materials
- **Inexact values of constants** and other parameters obtained from external sources and used in the data-reduction algorithm
- **Approximations and assumptions** incorporated in the measurement procedure
- **Variations of repeated observations** of the measurand under apparently identical conditions

⁹Adapted from the The International Organization for Standardization (ISO) Guide to the Expression of Uncertainty in Measurement.

Optimal presentation of search results

Optimal presentation of search results has some desired properties¹⁰:

- **Uncertainties due to systematic effects should be included in a clear and consistent way.**
 - Often it is useful to quote the statistical and systematic error separately, e.g. $\sigma = 45 \pm 4 \pm 1 \text{ mb}$.
- The result should summarize completely the experiment; so that no extra information should be required for further analysis.
- Results should be easily turned into probabilistic statements.
- Analysis should be transparent, and result should be stated in such a way that it cannot be misleading. The presentation of the result should not depend on the particular application.
- **If possible full pdf-distributions and even data sets can be attached into analysis results.**
- In **unified approach to data analysis**, the transitions between exclusion, observation, discovery, and measurement are kept as small as possible.

¹⁰Adapted from F. James, *Workshop on Confidence Limits*, CERN-2000-005, 2000.

Example: Propagation of errors/uncertainty

Your 16 GB **MicroSD** has package size (HxWxD) (mm) 15 x 11 x 1. Manufacturer claims 0.1 mm deviation from the nominal dimensions.

Estimate you cards volume $V = H W D$ and its uncertainty?

$$V = H W D = 15 \text{ mm } 11 \text{ mm } 1 \text{ mm} = 165 \text{ mm}^3.$$

Assuming uncorrelated variables we calculate

$$\left(\frac{\Delta V}{V}\right)^2 = \left(\frac{\Delta H}{H}\right)^2 + \left(\frac{\Delta W}{W}\right)^2 + \left(\frac{\Delta D}{D}\right)^2$$

$$\left(\frac{\Delta V}{165}\right)^2 = \left(\frac{0.1}{15}\right)^2 + \left(\frac{0.1}{11}\right)^2 + \left(\frac{0.1}{1}\right)^2 \approx 0.01.$$

$$V \pm \Delta V = 165 \pm 17 \text{ mm}^3.$$

Note: Commonly the error on a quantity, here ΔV , is given as the standard deviation, σ . If the statistical probability distribution of the variable is assumed to be a normal distribution, there is a 68% probability that the true value of volume lies in the region $V \pm \Delta V$.

Example: MC estimation of errors

ADVANCED

If Taylor series approximation (1) fails, errors can be estimated using Monte-Carlo simulation. A real life example from neutrino physics¹¹, where Data Handling

department at CERN had to estimate value of

$$R = \frac{a}{\frac{d}{ke}(b-c) - 2\left(1 - \frac{k^2 d}{ke}\right)a}$$

$$a = 3.84 \pm 1.33$$

$$b = 74 \pm 4$$

$$c = 9.5 \pm 3$$

$$d = 0.112 \pm 0.009$$

$$e = 0.320 \pm 0.002$$

$$k = 0.89$$

Using (1) one finds $\hat{R} = 0.191 \pm 0.073$.

What is the probability P that R is different from theoretical value $R_{th} = 0.42$?

If gaussian form is assumed

$$P = \int_{3.14}^{+\infty} e^{-x^2/2} \frac{dx}{\sqrt{2\pi}} = 8 \times 10^{-4}$$

`P=ROOT::Math::`

`gaussian_cdf_c(3.14)`

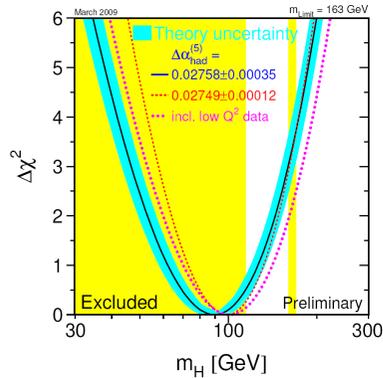
as introduced in `ProbFunc-MathCore.h`

$$(R_{th} - \hat{R})/\sigma_R = (0.42 - 0.191)/0.073 = \mathbf{3.14}$$

Monte-Carlo simulation gives a quite different result.

¹¹From B. Escoubès, *Probabilités et statistiques à l'usage des physiciens*, Ellipses, 1998.

Example Higgs boson mass constraints from Electroweak precision tests

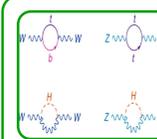


Method



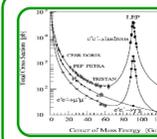
Step 1 – Very precise measurements of SM

- Measure SM parameters extremely well
- α , M_Z , G_F
- μ lifetime, $(g-2)_e$, LEP ...



Step 2 – Predictions (assuming Higgs boson)

- Calculate quantum corrections to other observables
- m_W , A_{LR} , $\sin^2\theta_W$...
- Depending on α , M_Z , G_F , but also on m_t , m_H ...



Step 3 – Precise electroweak measurements

- Measure very precisely observables from Step 2
- @ SLC, LEP, Tevatron ...

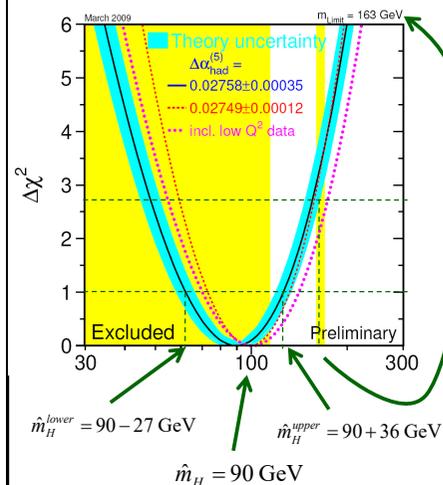
Results from step 2 and 3

Measurement	Fit	$ \sigma_{meas} - O_{fit} / \sigma_{meas}$
$\Delta\alpha_{had}^{(5)}(m_Z)$	0.02758 ± 0.00035	0.02767
m_Z [GeV]	91.1875 ± 0.0021	91.1874
Γ_Z [GeV]	2.4952 ± 0.0023	2.4959
σ_{had}^0 [nb]	41.540 ± 0.037	41.478
R_b	20.767 ± 0.025	20.742
$A_{FB}^{0,b}$	0.01714 ± 0.00095	0.01643
$A_l(P_e)$	0.1465 ± 0.0032	0.1480
R_b	0.21629 ± 0.00066	0.21579
R_c	0.1721 ± 0.0030	0.1723
$A_{FB}^{c,b}$	0.0992 ± 0.0016	0.1038
$A_{FB}^{b,c}$	0.0707 ± 0.0035	0.0742
A_b	0.923 ± 0.020	0.935
A_c	0.670 ± 0.027	0.668
$A_l(\text{SLD})$	0.1513 ± 0.0021	0.1480
$\sin^2\theta_{eff}^{lep}(Q_{fb})$	0.2324 ± 0.0012	0.2314
m_W [GeV]	80.399 ± 0.025	80.378
Γ_W [GeV]	2.098 ± 0.048	2.092
m_t [GeV]	173.1 ± 1.3	173.2

March 2009

The best fit

Adopted from <http://lepewwg.web.cern.ch/LEPEWWG/>



From the LEP Electroweak Working group:

- “The preferred value for its mass, corresponding to the minimum of the curve, is at 90 GeV, with an experimental uncertainty of +36 and -27 GeV (at 68 percent confidence level derived from Delta chi2 = 1 for the black line, thus not taking the theoretical uncertainty shown as the blue band into account).”
- “The precision electroweak measurements tell us that the mass of the Standard-Model Higgs boson is lower than about 163 GeV (one-sided 95 percent confidence level upper limit derived from Delta chi2 = 2.7 for the blue band, thus including both the experimental and the theoretical uncertainty).”

Mass of a new boson

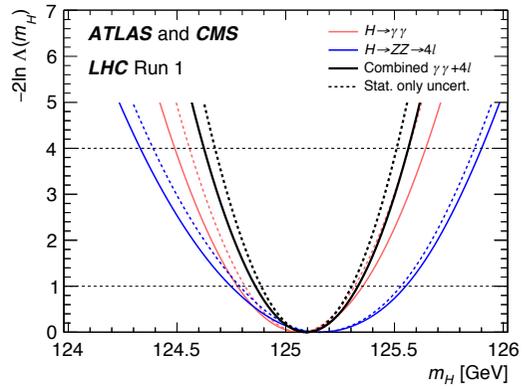


Figure 1: Scans of twice the negative log-likelihood ratio $-2 \ln \Lambda(m_H)$ as functions of the Higgs boson mass m_H for the ATLAS and CMS combination of the $H \rightarrow \gamma\gamma$ (red), $H \rightarrow ZZ \rightarrow 4\ell$ (blue), and combined (black) channels. The dashed curves show the results accounting for statistical uncertainties only, with all nuisance parameters associated with systematic uncertainties fixed to their best-fit values. The 1 and 2 standard deviation limits are indicated by the intersections of the horizontal lines at 1 and 4, respectively, with the log-likelihood scan curves.

$$\begin{aligned}
 m_H &= 125.09 \pm 0.24 \text{ GeV} \\
 &= 125.09 \pm 0.21 \text{ (stat.)} \pm 0.11 \text{ (syst.) GeV,}
 \end{aligned}$$

arXiv:1503.07589v1 [hep-ex] 26 Mar 2015