

## Class 13.5 (0xD.8): Feldman-Cousins confidence regions

### How do we choose confidence intervals (Neyman construction)

(Following section 32.3.2.1 in [PDG-Stat].)

- Find intervals for each value of the parameter  $\theta$  such that

$$P(\hat{\theta}_1 < \hat{\theta} < \hat{\theta}_2) = 1 - \alpha = \int_{\hat{\theta}_1}^{\hat{\theta}_2} f(\hat{\theta}; \theta) d\hat{\theta}.$$

Here  $f(\hat{\theta}; \theta)$  is the p.d.f. of the estimator  $\hat{\theta}$ .

- $\hat{\theta}_1$  and  $\hat{\theta}_2$  should depend on  $\theta$  monotonically. The functions are invertible:  $\hat{\theta} = \hat{\theta}_1(\theta)$  implies  $\theta_1 = \theta_1(\hat{\theta})$ .
- Then (see figure)

$$1 - \alpha = P(\hat{\theta}_1 < \hat{\theta} < \hat{\theta}_2) = P(\theta_1(\hat{\theta}) < \hat{\theta} < \theta_2(\hat{\theta}))$$

### The “Feldman-Cousins” method for generating “unified” confidence intervals

(See section 32.3.2.2 in [PDG-Stat].)

- We pick the edges of the region to have a particular difference log-likelihood from the best fit point,  $\Delta \log L = \log(L(\theta)) - \log(L(\hat{\theta}))$ .
- The right  $\Delta \log L$  to use varies as a function of the best fit parameters. So you need a “map” of the correct  $\Delta \log L$  to use when checking whether each value of  $\theta$  should be in or out of the region.
- If the parameter space has a boundary, it’s no problem, the “map” adjusts the log-likelihood level to encompass enough space.

- Note that the “difference in log-likelihood” is simply the log of the Neyman-Pearson test statistic hypothesis test. The “Feldman-Cousins” technique is equivalent to doing a two-hypothesis test for each possible value of  $\theta$ , rejecting points where the hypothesis “the true value is  $\theta$ ” would be rejected at the  $\alpha$  significance level.
- In general, the p.d.f. of the log-likelihood is generated via MC for each setting of each parameter, just like the hypothesis test.

## The Feldman-Cousins procedure in detail

The procedure for building up the “map” of  $\Delta \log L$  cutoffs is simply to build the p.d.f.s for  $\Delta \log L$  on a grid of values of the parameters. For each point on the map, find the value  $(\Delta \log L)_\alpha$  below which a fraction  $(1 - \alpha)$  of the distribution lies.

Procedure for building up map of  $\Delta \log L$  cutoffs for all *theta*:

```

Make an array to store the results
Loop over values of  $\theta$ :
    build the p.d.f. of  $\Delta \log L$  for this parameter (see below)
    sum up the p.d.f. to find the  $(\Delta \log L)_\alpha$ 
    store  $(\Delta \log L)_\alpha$  for this parameter in the array

```

The procedure for building up a  $\Delta \log L$  p.d.f. is essentially identical to that for building up the p.d.f.s of the  $L_{\max}$  for a significance test, except for the quantity evaluated. (Contrast the steps below to Class 0x0B example 4.)

Procedure for building up p.d.f. of  $\Delta \log L$  :

```

loop M times:
    simulate a dataset using the hypothesis
    fit the dataset
    calculate  $\log L_{\max}$  at the best fit point
    calculate  $\log L$  at the true value
    “fill” histogram using  $\Delta \log L = \log L_{\max} - \log L$ 

```

Procedure for simulating a dataset:

```

Loop N times:
    generate random variable x according to the model p.d.f. for x
        (see class notes on MC simulation, use inverse distribution
        method)
    store x in vector of doubles to be used as dataset
        (instead of reading x from a file)

```

## Drawing the confidence region

This is simplicity itself:

given  $\log L_{\max}$  of the best fit point and your map from above,

loop over the points in the “map”:

    evaluate  $\log L$  for your real data at that parameter to find  $\Delta \log L$

    is  $\Delta \log L > (\Delta \log L)_\alpha$  at this point in the map?

        if yes, point is excluded -- clear pixel and/or print '.' on screen

        if no, point is included -- set pixel and/or print '\*' on screen

## Exercise/assignment

Build the 90%-CL and 99%-CL confidence regions for the same exponential + background of the assignment from class 11 (aka class 0x0B), with the restriction that the background parameter  $b$  must be in the range  $0 \leq b < 1$  and the mean  $\mu$  must be positive.

- Note this is a good example of where the full Feldman-Cousin's treatment is usually necessary: non-Gaussian model, limits on parameters.
- Just follow the Feldman-Cousins procedure.
- Initially, use a grid of 10 divisions from 0 to 1 for  $b$ , 10 divisions over the range  $(1 \pm 0.5)\hat{\mu}$  for  $\mu$ .
- Print out the map of  $\Delta \log L_\alpha$  to make sure it is reasonable. (Should be 2 for the 90% CL.)
- Print out or draw the confidence region.
- After getting this to work, make the grid finer if you like.

[KamLAND2008] KamLAND Collaboration, “Precision Measurement of Neutrino Oscillation Parameters with KamLAND”, Phys.Rev.Lett.100:221803,2008; [arXiv:0801.4589v3 \[hep-ex\]](#).

[DZero2010] D0 Collaboration, “Evidence for an anomalous like-sign dimuon charge asymmetry”, Submitted to Phys. Rev. D, 2010; Fermilab-Pub-10/114-E; [arXiv:1005.2757v1](https://arxiv.org/abs/1005.2757v1) [hep-ex].

[PDG-Stat] “Statistics”, G. Cowan, in *Review of Particle Physics*, C. Amsler et al., PL B667, 1 (2008) and 2009 partial update for the 2010 edition ( <http://pdg.lbl.gov/2009/reviews/rpp2009-rev-statistics.pdf> ).