

Lecture 5: Parameter Estimation and Uncertainty



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Advanced Methods in Applied Statistics
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Oral Presentation and Report

- Now would be a good time to make sure you have:
 - Selected a topic
 - Selected a paper
 - Done some work on preparing the presentation and/or report

Outline

- Recap in 1D
- Extension to 2D
 - Likelihoods
 - Contours
 - Uncertainties
- If this lecture runs long, we'll use a portion of Thursday morning to finish it.

*Material derived from T. Petersen, D. R. Grant, and G. Cowan

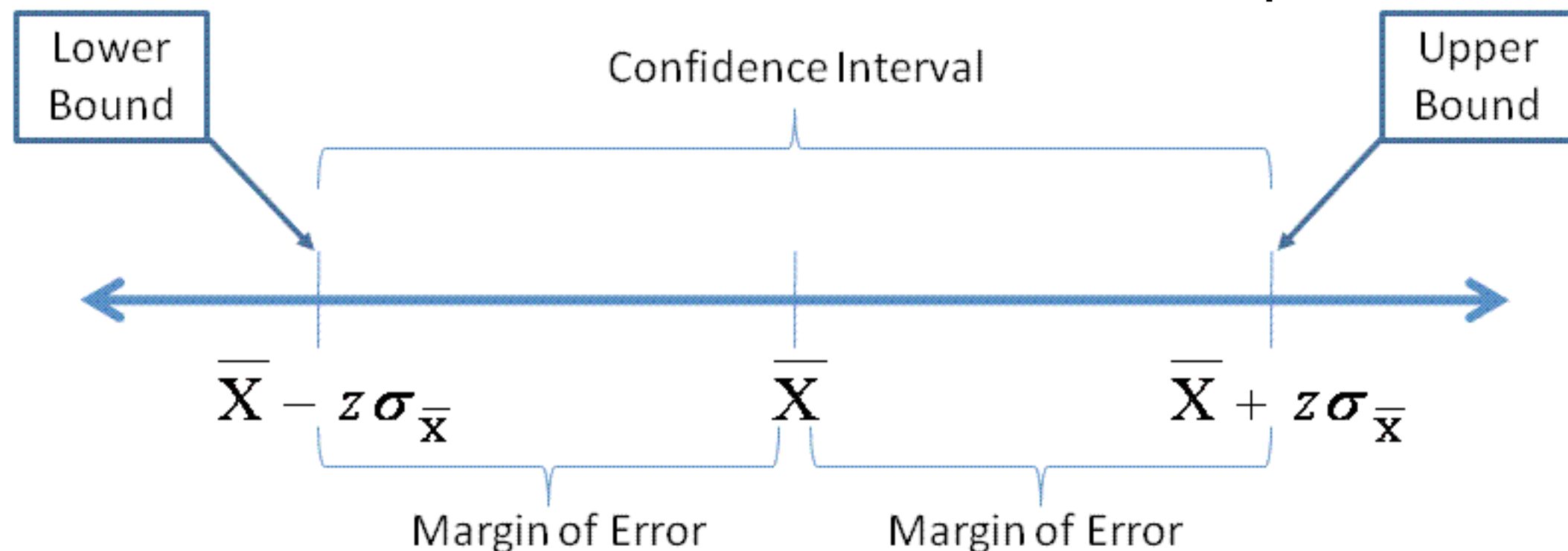
Confidence intervals

“Confidence intervals consist of a range of values (interval) that act as good estimates of the unknown population parameter.”

It is thus a way of giving a range where the true parameter value probably is.

A very simple confidence interval for a Gaussian distribution can be constructed as:
(z denotes the number of sigmas wanted)

$$\bar{x} \pm z \frac{s}{\sqrt{n}}$$



Confidence intervals

Confidence intervals are constructed with a certain **confidence level C**, which is roughly speaking the fraction of times (for many experiments) to have the true parameter fall inside the interval:

$$Prob(x_- \leq x \leq x_+) = \int_{x_-}^{x_+} P(x) dx = C$$

Often, C is in terms of σ or percent 50%, 90%, 95%, and 99%

There is a choice as follows:

1. Require symmetric interval (x_+ and x_- are equidistant from μ).
2. Require the shortest interval (x_+ to x_- is a minimum).
3. Require a central interval (integral from x_- to μ is the same as from μ to x_+).

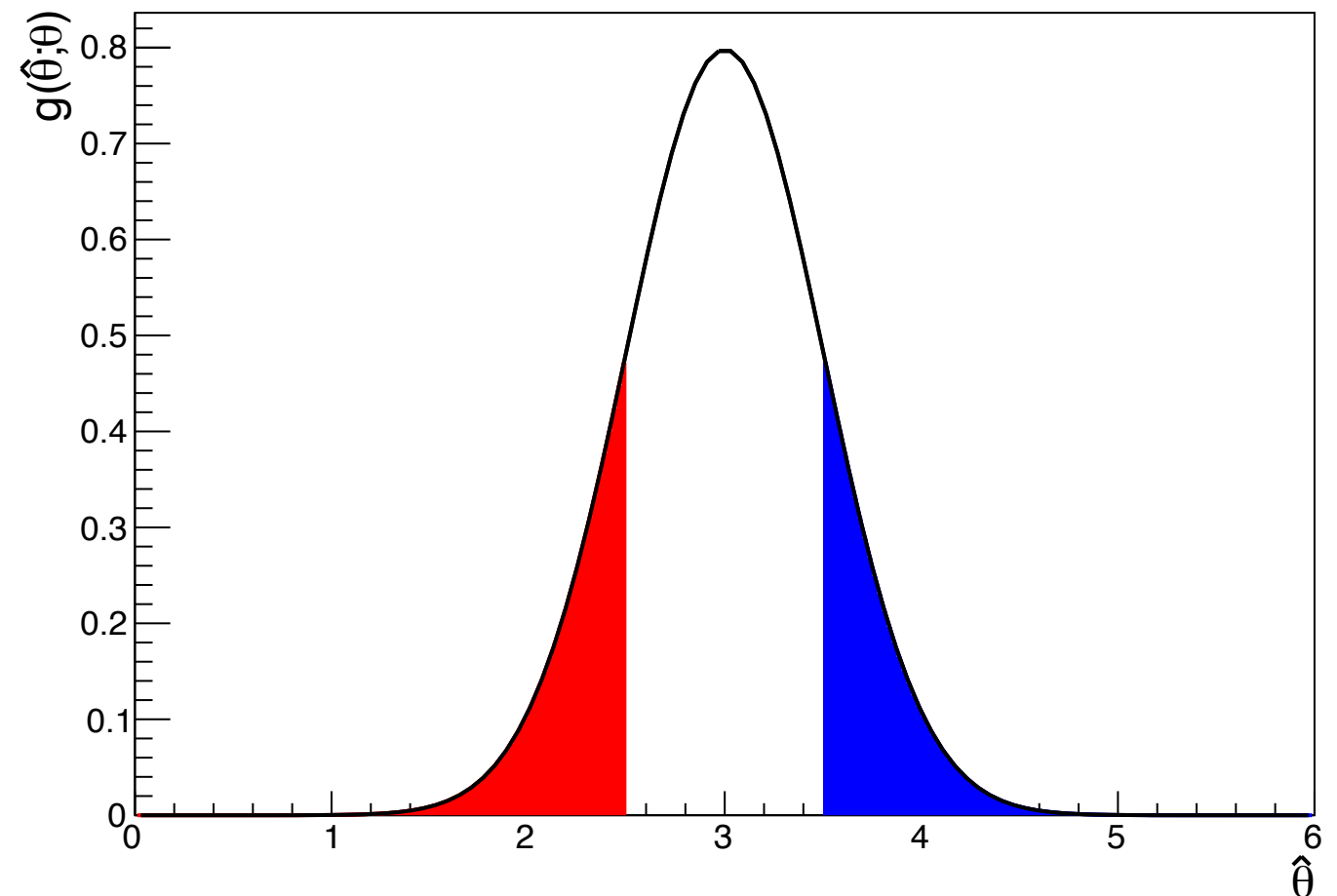
For the Gaussian, the three are equivalent!

Otherwise, 3) is usually used.

Confidence Intervals

- Confidence intervals are often denoted as C.L. or “Confidence Limits/Levels”
- Central limits are different than upper/lower limits
- We can establish uncertainties on our extracted best-fit parameters using likelihoods (hooray!)

Gaussian Estimator



Variance of Estimators - Gaussian Estimators

- Used for 1 or 2 parameters when the maximum likelihood estimate and variance cannot be found analytically. Expand $\ln L$ about its maximum via a Taylor series:

$$\ln L(\theta) = \ln L(\hat{\theta}) + \left(\frac{\partial \ln L}{\partial \theta}\right)_{\theta=\hat{\theta}}(\theta - \hat{\theta}) + \frac{1}{2!} \left(\frac{\partial^2 \ln L}{\partial \theta^2}\right)_{\theta=\hat{\theta}}(\theta - \hat{\theta})^2 + \dots$$

- First term is $\ln L_{\max}$, 2nd term is zero, third term can be used for information inequality (not covered here)

- For **1** parameter:

- Minimize, or scan, as a function of θ to get $\hat{\theta}$
- Uncertainty deduced from positions where $\ln L$ is reduced by 0.5. For a Gaussian likelihood function w/ **1** fit parameter:

$$\ln L(\theta) = \ln L_{\max} - \frac{(\theta - \hat{\theta})^2}{2\hat{\sigma}_{\hat{\theta}}^2}$$

$$\ln L(\hat{\theta} \pm \hat{\sigma}_{\hat{\theta}}) = \ln L_{\max} - \frac{1}{2} \quad \text{or} \quad \ln L(\hat{\theta} \pm N\hat{\sigma}_{\hat{\theta}}) = \ln L_{\max} - \frac{N^2}{2} \quad \text{For } N \text{ standard deviations}$$

$\ln(\text{Likelihood})$ and $2 \cdot \text{LLH}$

- A change of 1 standard deviation (σ) in the maximum likelihood estimator (MLE) of the parameter θ leads to a change in the $\ln(\text{likelihood})$ value of 0.5 for a **gaussian distributed estimator**
 - Even for a non-gaussian MLE, the 1σ region^a defined as $\text{LLH}-1/2$ can be an *okay* approximation
 - Because the regions^a defined with $\Delta\text{LLH}=1/2$ are consistent with common χ^2 distributions multiplied by 1/2, we often calculate the likelihoods as $(-)\cdot 2 \cdot \text{LLH}$
- Translates to >1 fit parameters too, with the appropriate change in $2 \cdot \text{LLH}$ confidence values
 - 1 fit parameter, $\Delta(2\text{LLH})=1$ for 68.3% C.L.
 - 2 fit parameter, $\Delta(2\text{LLH})=2.3$ for 68.3% C.L.

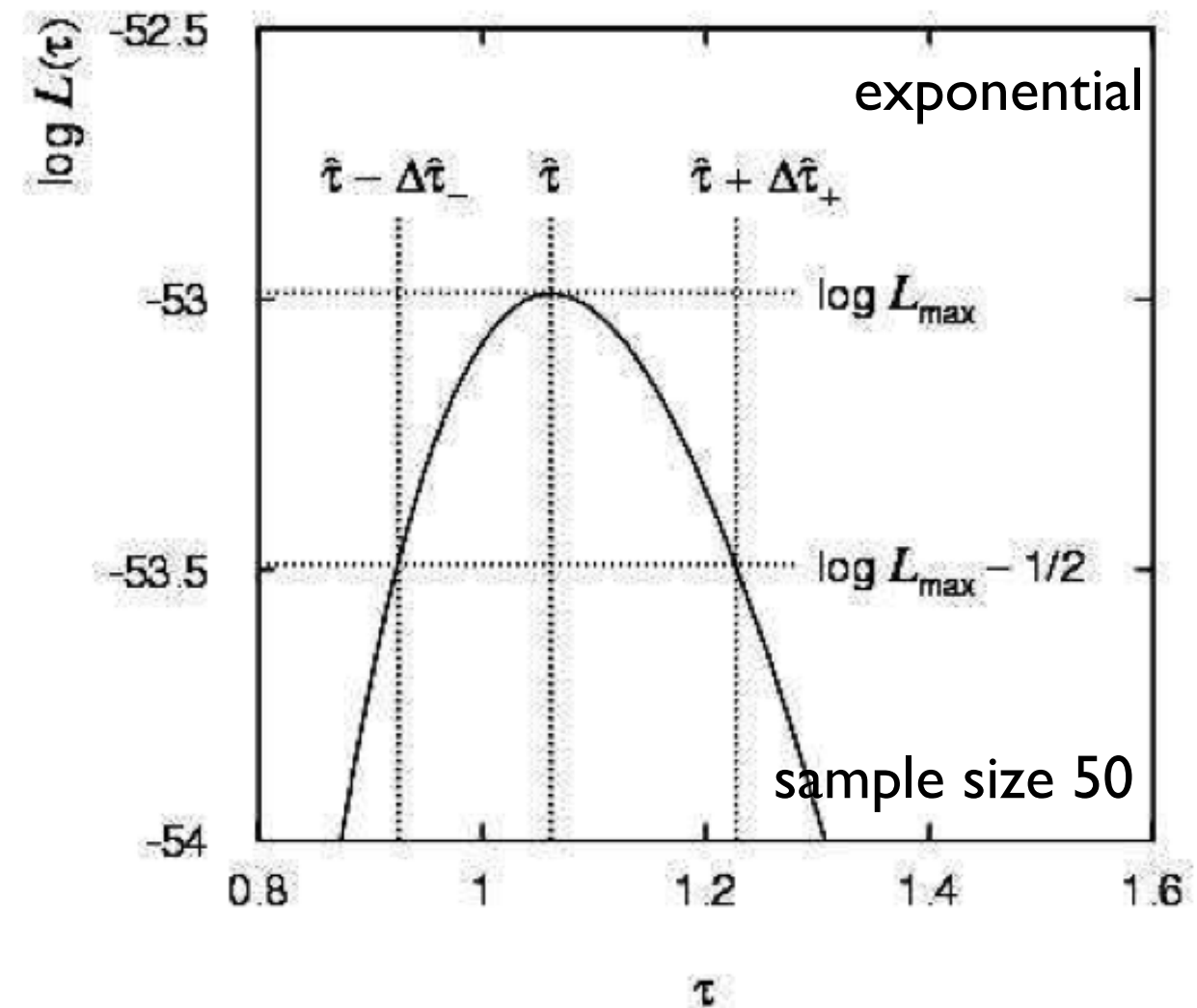
^afor a distribution w/ 1 fit parameter

Variance of Estimator

Likelihood is from Lecture 3 and is

$$f(t; \tau) = \frac{1}{\tau} e^{-t/\tau}$$

- First, we find the best-fit estimate of τ via our LLH minimization to get $\hat{\tau}_{\text{best}}$
 - Provides $\text{LLH}(\hat{\tau}_{\text{best}}) = -53.0$
 - We could scan to get $\hat{\tau}_{\text{best}}$, but it won't be as precise or fast as the minimizer
- We only have 1 fit parameter, so from slide 7 we know that values of $\hat{\tau}$ which cross $\text{LLH}(\tau_{\text{best}}) - 0.5$ are the 1σ ranges, i.e. when the LLH equals -53.5



$$\hat{\tau} = 1.062$$

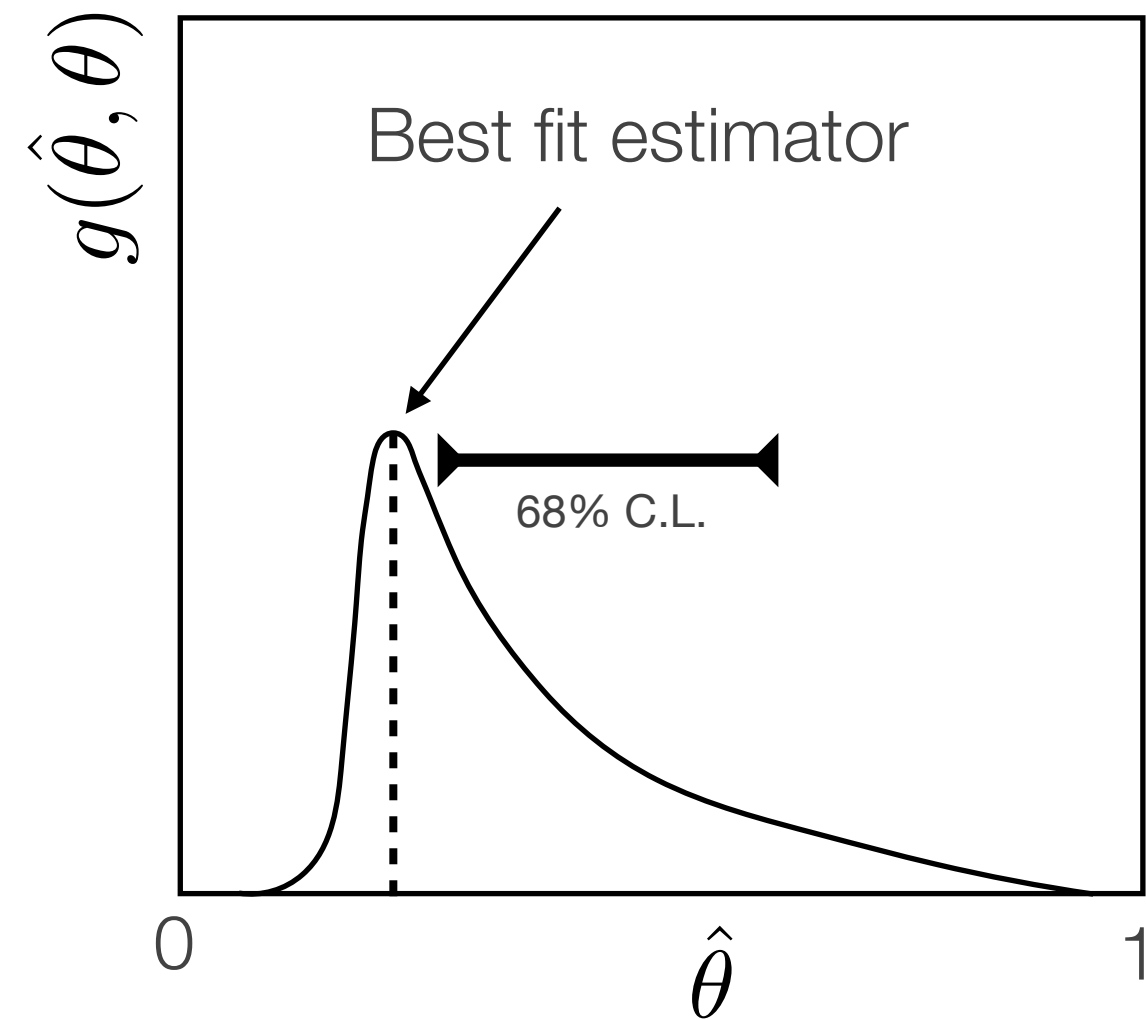
$$\Delta\hat{\tau}_- = 0.137$$

$$\Delta\hat{\tau}_+ = 0.165$$

$$\hat{\sigma}_{\hat{\tau}} \approx \Delta\hat{\tau}_- \approx \Delta\hat{\tau}_+ \approx 0.15$$

Reporting Very Asymmetric Central Limits

- Central limits are often reported as $\hat{\theta} \pm \sigma_{\theta}$ or $\hat{\theta}_{-\sigma_{\theta_2}}^{+\sigma_{\theta_1}}$ if the error bars are asymmetric
- What happens when upper or lower range away from the best-fit value(s) does not have the right coverage? E.g. for 68% coverage, the lower 17% of the distribution includes the best fit point.
 - Quote the best-fit estimator of θ and the limit ranges separately. "Best fit is $\theta=0.21$ and the 90% central confidence region is 0.17-0.77"



Exercise #1

- Before we use the LLH values to determine the uncertainties for α and β , let's do it via Monte Carlo first
- Similar to the exercises 2-3 from Lecture 3, we will use the theoretical prediction:

$$f(x; \alpha, \beta) = 1 + \alpha x + \beta x^2$$

- For $\alpha=0.5$ and $\beta=0.5$, generate 2000 Monte Carlo data points using the above function transformed into a PDF over the range $-0.95 \leq x \leq 0.95$
 - Remember to **normalize** the function properly to convert it to a proper PDF
 - Fit the MLE parameters $\hat{\alpha}$ and $\hat{\beta}$ using a minimizer/maximizer
 - Repeat 100 to 500 times plotting the distributions of $\hat{\alpha}$ and $\hat{\beta}$ as well as $\hat{\alpha}$ vs. $\hat{\beta}$

Exercise #1

- Shown are 500 Monte Carlo pseudo-experiments
- The estimates average to approximately the true values, the variances are close to initial estimates from earlier slides and the estimator distributions are approximately Gaussian

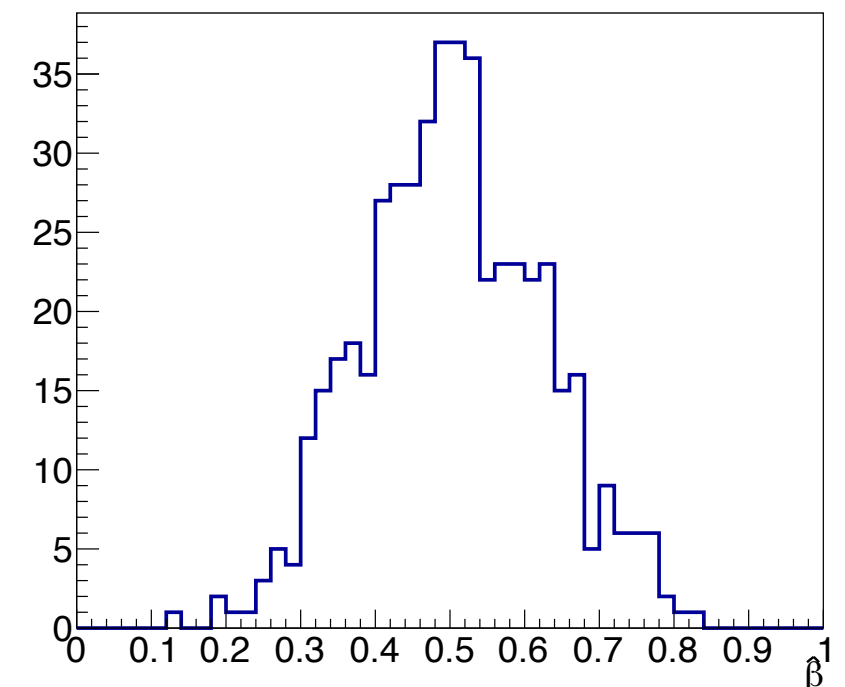
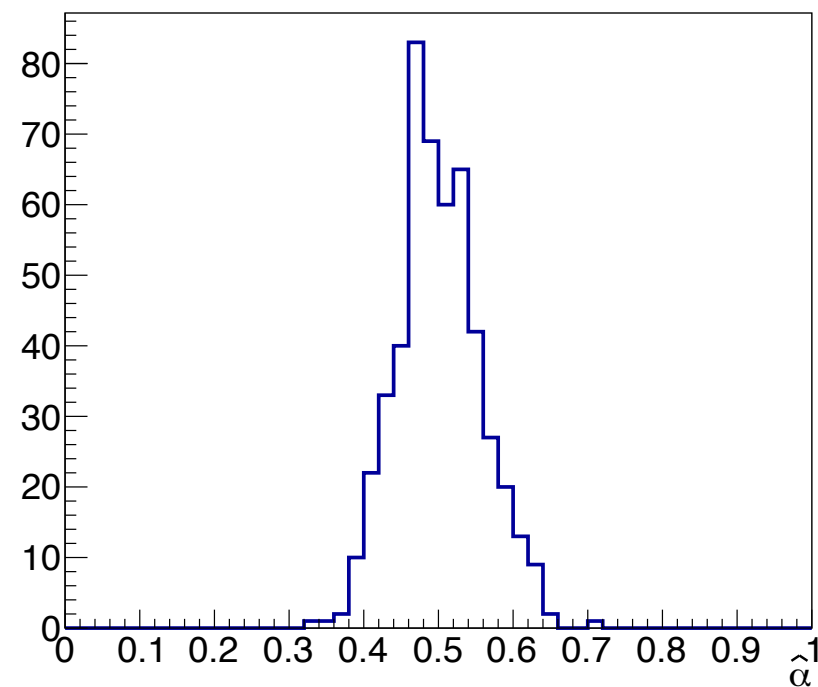
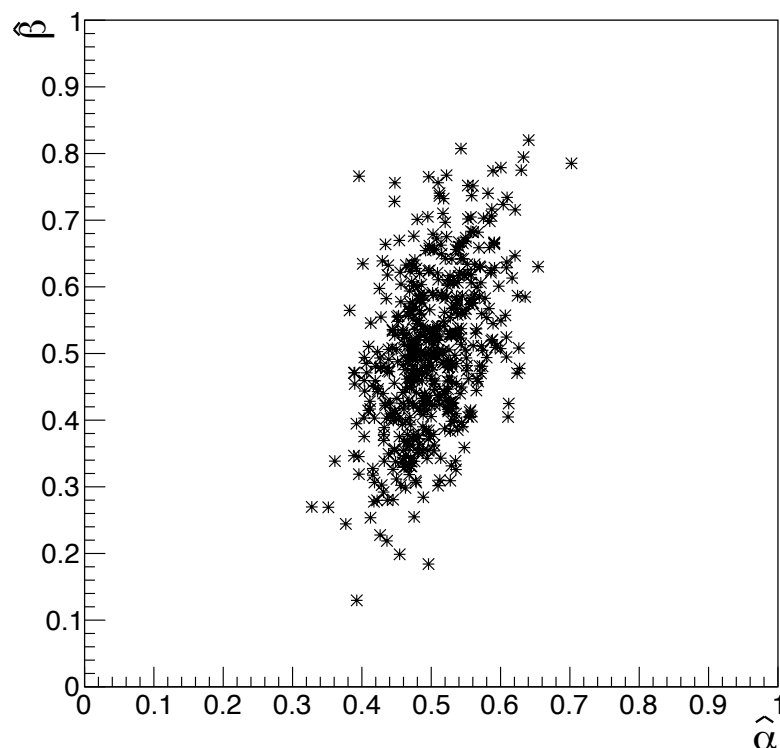
$$\bar{\hat{\alpha}} = 0.5005$$

$$\hat{\alpha}_{RMS} = 0.0557$$

$$\bar{\hat{\beta}} = 0.5044$$

$$\hat{\beta}_{RMS} = 0.1197$$

RMS = Root Mean Squared, i.e. $\sqrt{\text{variance}}$



Comments

- After finding the best-fit values via $\ln(\text{likelihood})$ maximization/minimization from data, one of **THE** best and most robust calculations for the parameter uncertainties is to run numerous pseudo-experiments using the best-fit values for the Monte Carlo 'true' values and find out the spread in pseudo-experiment best-fit values
 - MLEs don't have to be gaussian. Thus, the uncertainty is accurate even if the Central Limit Theorem is invalid for your data/parameters
 - The routine of 'Monte Carlo plus fitting' will take care of many parameter correlations
 - The problem is that it can be slow and gets exponentially slower with each dimension

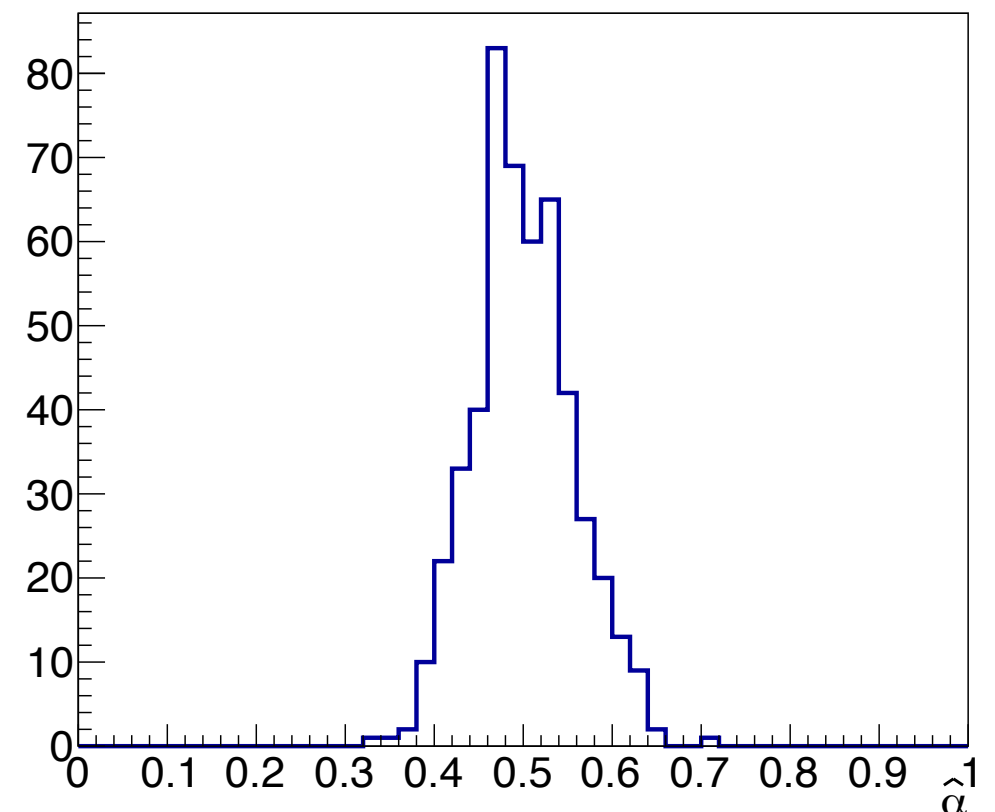
Brute Force

- If we either did not know, or did not trust, that our estimator(s) are nicely analytic PDFs (gaussian, binomial, poisson, etc.) we can use our pseudo-experiments to establish the uncertainty on our best-fit values
 - Using original PDF, sample from original PDF with injected values of $\hat{\alpha}_{obs}$ and $\hat{\beta}_{obs}$ that were found from our original 'fit'
 - Fit each pseudo-experiment
 - Repeat
 - Integrate ensuing estimator PDF

To get $\pm 1\sigma$ central interval

$$\frac{100\% - 68.27\%}{2} = \int_{C_+}^{\infty} g(\hat{\alpha}; \hat{\alpha}_{obs}) d\hat{\alpha}$$

$$\frac{100\% - 68.27\%}{2} = \int_{-\infty}^{C_-} g(\hat{\alpha}; \hat{\alpha}_{obs}) d\hat{\alpha}$$



Brute Force cont.

- The previous method is known as a **parametric bootstrap**
 - Overkill for the previous example
 - Useful for estimators which are complicated
- Finding the uncertainty using the integration of the tails works for bayesian posteriors in same way as for likelihoods

Exercise 1b

- Continuing from Exercise 1 and using the same procedure for the 100 or 500 values from the pseudo-experiments, i.e. parametric bootstrapping
 - Find the central 1σ confidence interval(s) for $\hat{\alpha}$ as well as $\hat{\beta}$ using bootstrapping
- Repeat, but now:
 - **Fix** $\alpha=0.5$, and only fit for β , i.e. α is now a constant
 - What is the new 1σ central confidence interval for $\hat{\beta}$?
- Repeat with a new range of the $-0.9 \leq x \leq 0.85$
 - Again, **fix** $\alpha=0.5$
 - 2000 Monte Carlo 'data' points

Exercise 1c

- Using the range of $-0.9 \leq x \leq 0.85$, use the likelihood value to calculate the uncertainty for β , i.e. σ_β
 - 2000 Monte Carlo 'data' points
 - **Fix** $\alpha=0.5$
 - Since α is fixed, the function $f(x; \alpha, \beta)$ is a 1 parameter equation, and the PDF of $f(x; \alpha, \beta)$ is also only dependent on 1 parameter. So the 1σ uncertainty is where $|\mathcal{L}(x : \alpha, \beta_{best-fit}) - \mathcal{L}(x : \alpha, \beta_\sigma)| = 0.5$, and $\sigma_\beta = \beta_{best-fit} - \beta_\sigma$
- [optional] Check to see if σ_β is asymmetric, i.e. $+\sigma_\beta \neq -\sigma_\beta$, for this problem when using the likelihood prescription to estimate the uncertainty.

Good?

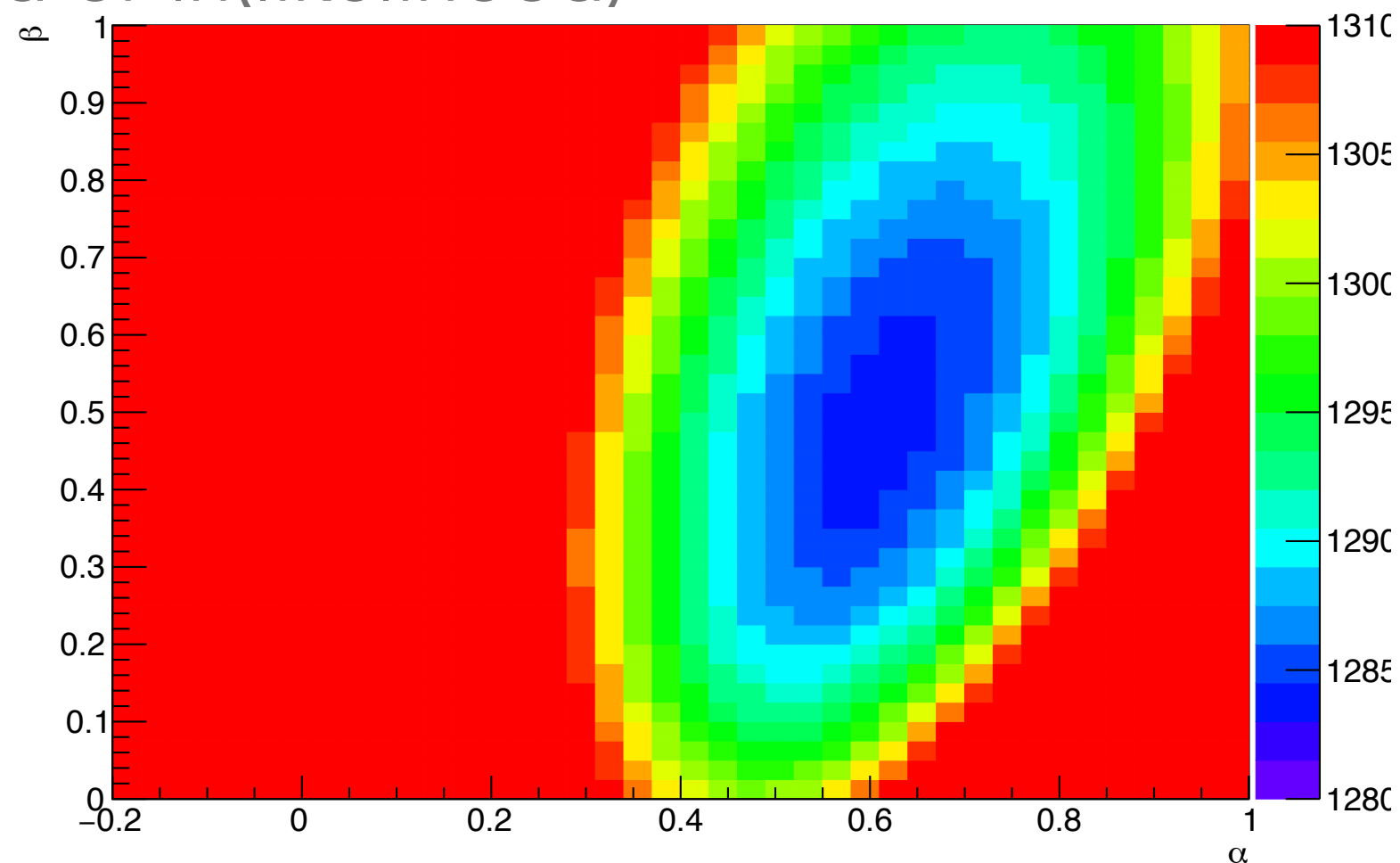
- The LLH minimization will give the best-fit values and often the uncertainty on the estimators. But, likelihood fits do not tell whether the data and the prediction agree
 - Remember that the likelihood has a form (PDF) that is provided by you and may not be correct
 - The PDF may be okay, but there may be some measurement systematic uncertainty that is unknown or at least unaccounted for which creates disagreement between the data and the best-fit prediction
 - Likelihood *ratios* between two hypotheses are a good way to exclude models, and we'll cover hypothesis testing next week

Multi-parameter

- Getting back to LLH confidence intervals
- In one dimension fairly straightforward
 - Confidence intervals, i.e. uncertainty, can be deduced from the LLH difference(s) to the best-fit point(s)
 - Brute force option is rarely a bad choice, and parametric bootstrapping is nice
- Both strategies work in multi-dimensions too
 - Often produce 2D contours of $\hat{\theta}$ vs. $\hat{\phi}$
 - There are some common mistakes to avoid

Likelihood Contour/Surface

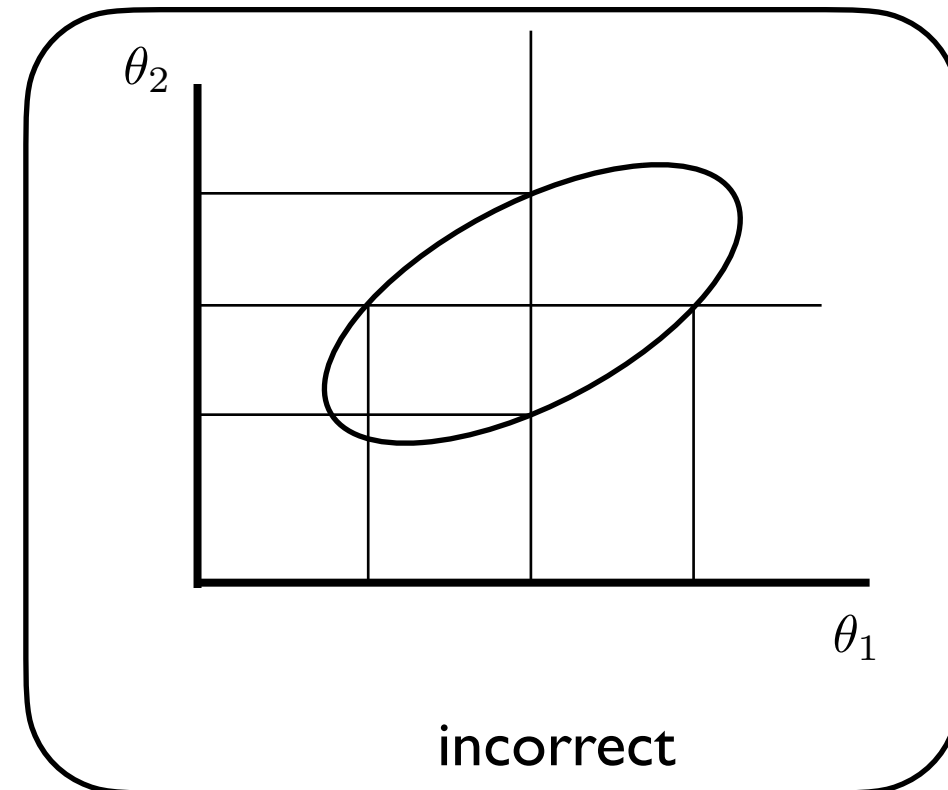
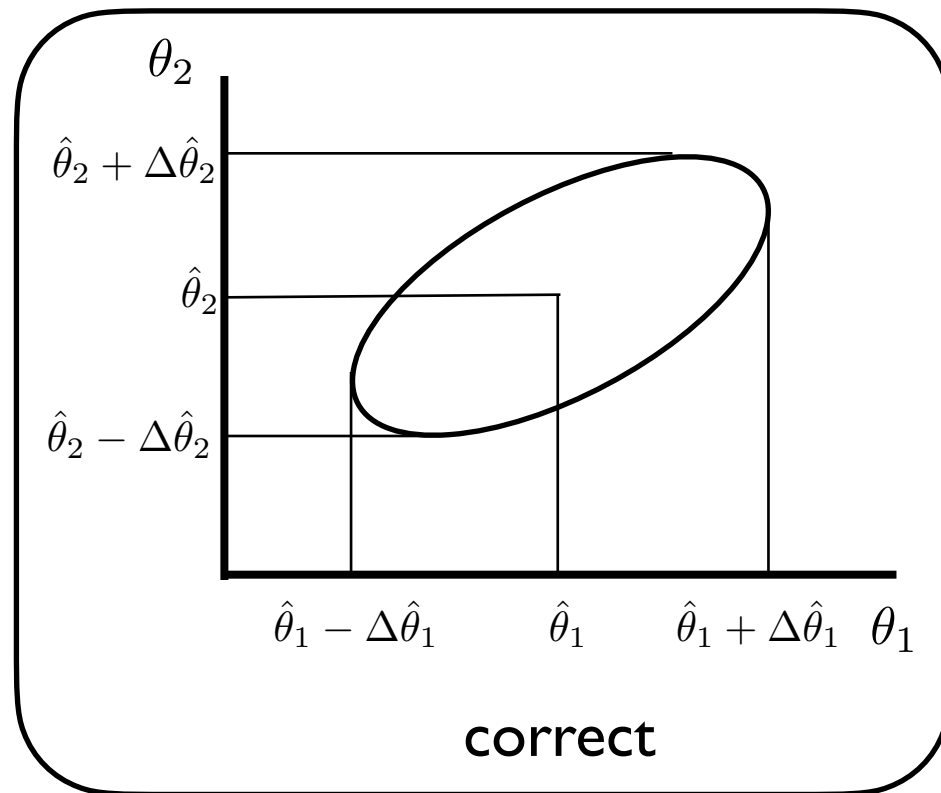
- For 2 dimensions, i.e. 2-parameter fits, we can produce likelihood landscapes. In 3 dimensions a surface, and in 3+ dimensions a likelihood hypersurface.
- The contours are then lines of with a constant value of likelihood or $\ln(\text{likelihood})$



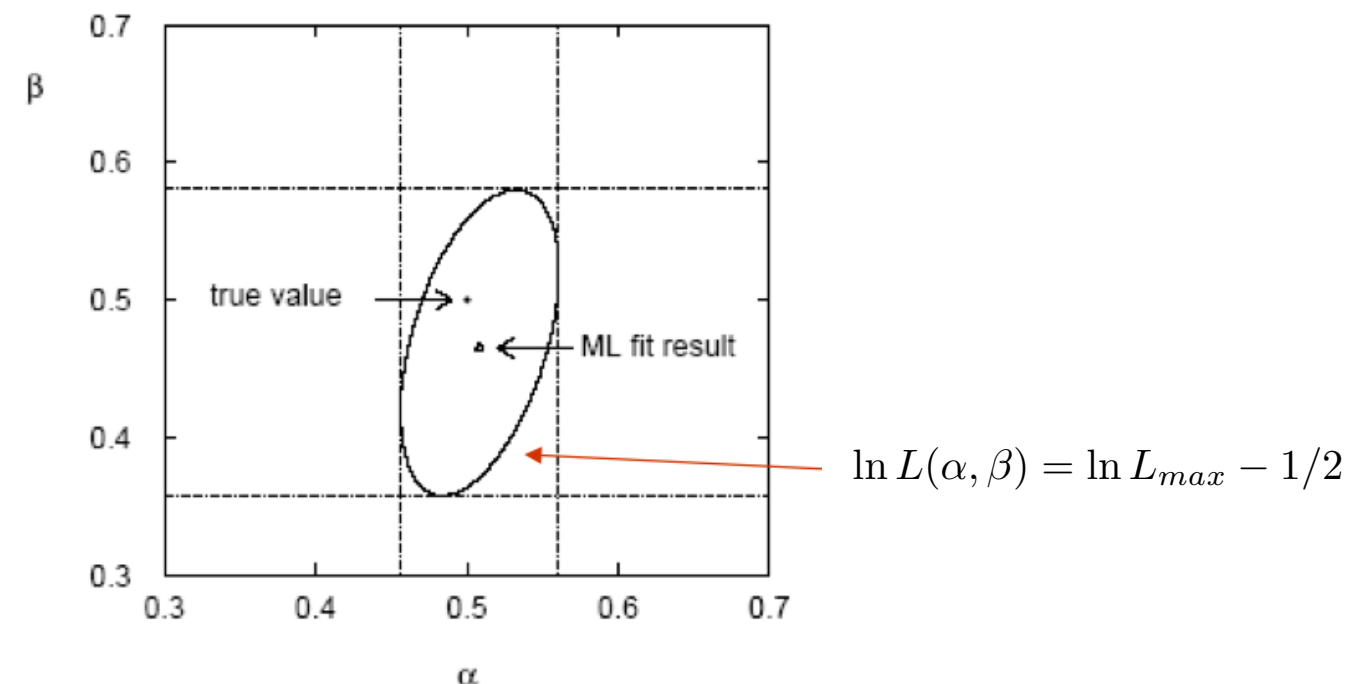
*LLH landscape is from
Lecture 3

Variance of Estimators - Graphical Method

- Two Parameter Contours

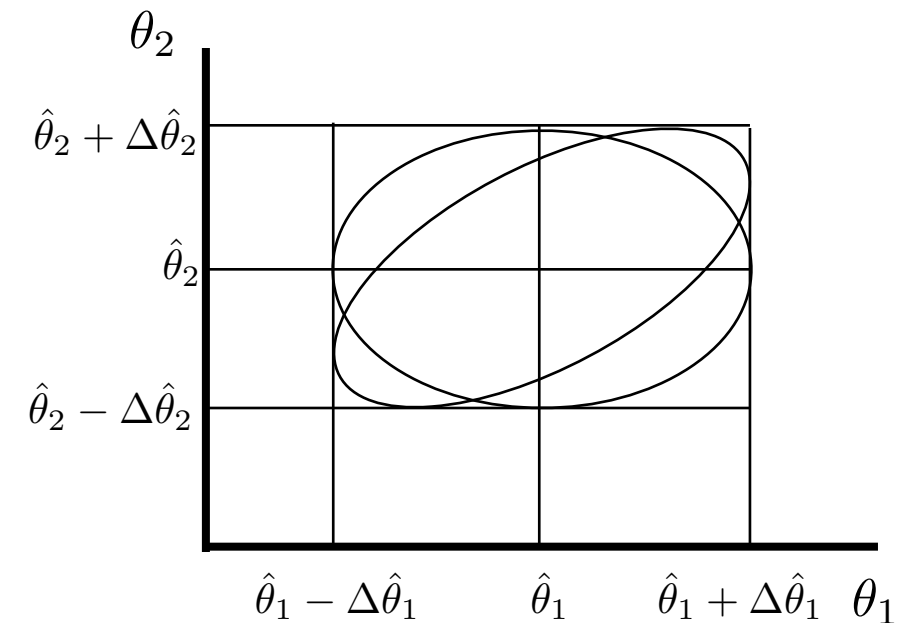


- Tangent lines to the contours give the standard deviations



Variance of Estimators - Graphical Method

- When the correct, tangential, method is used and the uncertainties are not dependent on the correlation of the variables.
- The probability the ellipses of constant $\ln L = \ln L_{max} - a$ contains the true point, θ_1 and θ_2 , is:



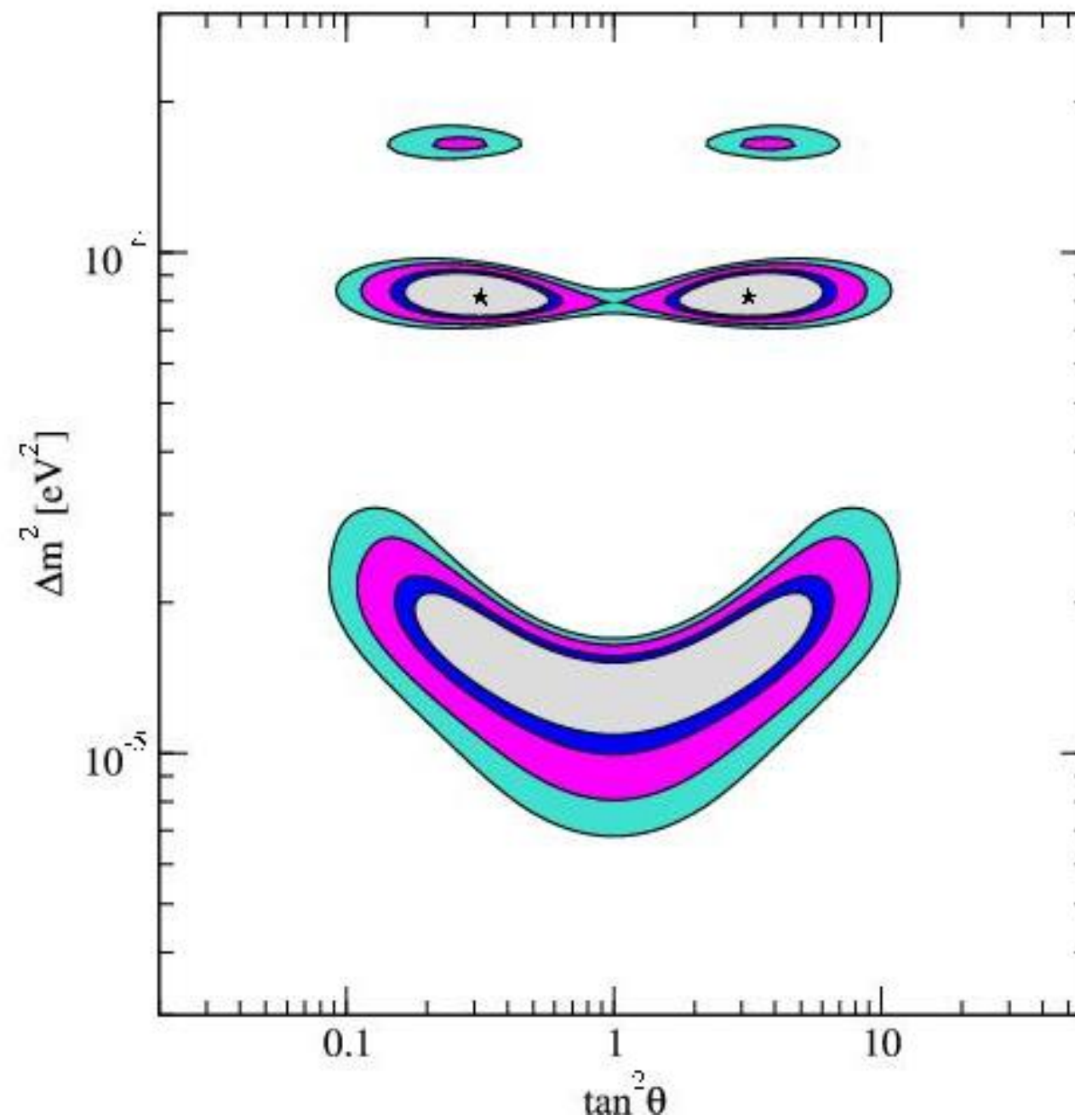
correct

a (1 DoF)	a (2 DoF)	σ
0.5	1.15	1
2.0	3.09	2
4.5	5.92	3

*DoF = Degree of freedom. Here it equates to the number of fit parameters in the likelihood.

Best Result Plot?

KamLAND: *"just smiling"*



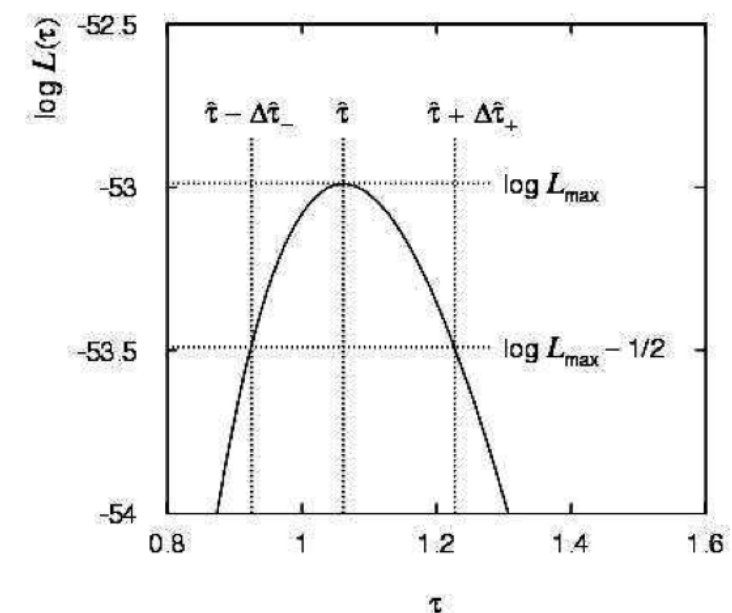
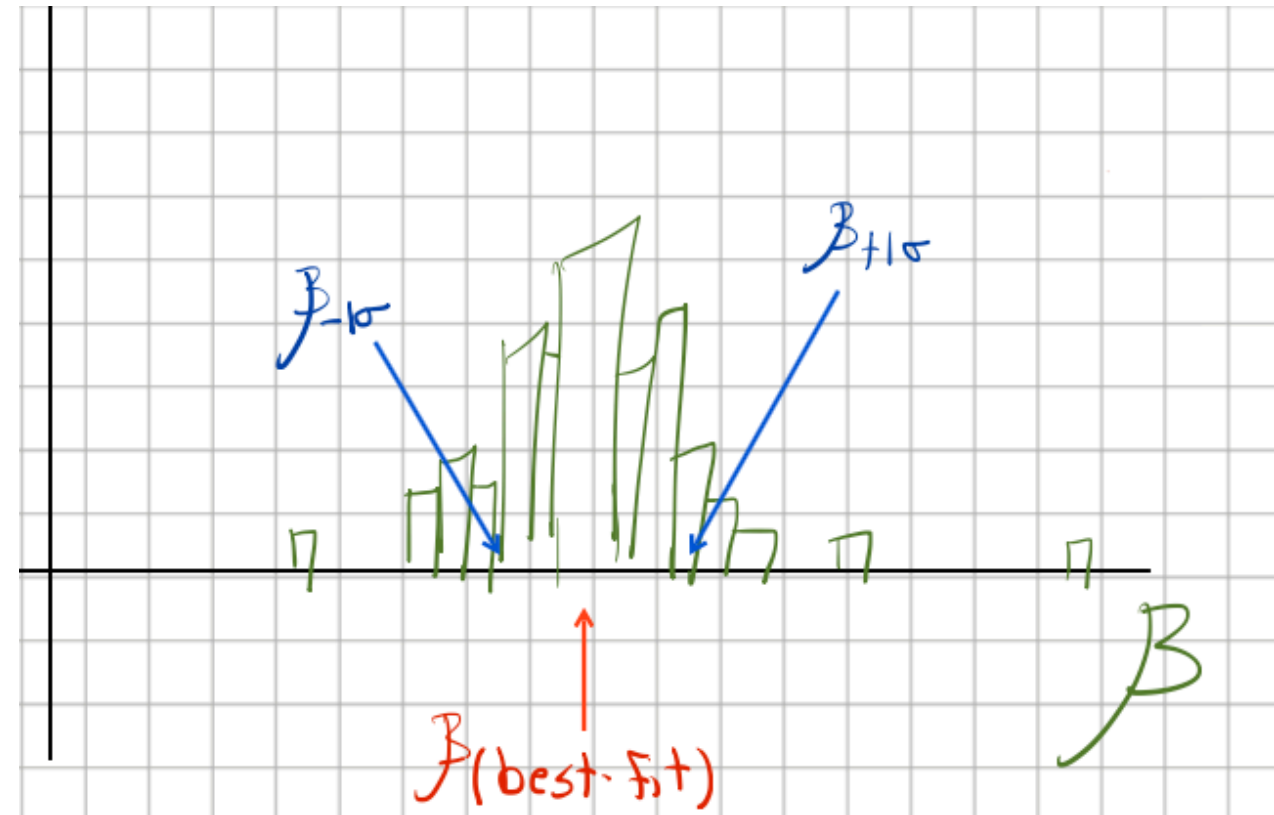
Variance/Uncertainty - Using LLH

Values

- The LLH (or $-2*LLH$) landscape provides the necessary information to construct 2+ dimensional confidence intervals
 - Provided the respective MLEs are gaussian or well-approximated as gaussian the intervals are 'easy' to calculate
 - For non-gaussian MLEs — which is not uncommon — a more rigorous approach is needed, e.g. parametric bootstrapping
- Some minimization programs will return the uncertainty on the parameter(s) after finding the best-fit values
 - The `.migrad()` call in `iminuit`
 - It is possible to write your own code to do this as well

Uncertainty from Bootstrapping vs. Likelihood

- The uncertainty estimate from bootstrapping: uses multiple Monte Carlo generated samples and the best-fit values of those samples to build a distribution. The 'width' of the ensuing best-fit values from the Monte Carlo constitutes the uncertainties.
- The uncertainty estimate from likelihood(s): get the best-fit of a parameter. Establish the value of the parameter where the LLH difference to the best-fit point is equal to the critical value for the number of fit parameters.
 - See critical values on slide 22, or find chi-square tables online for a more complete list

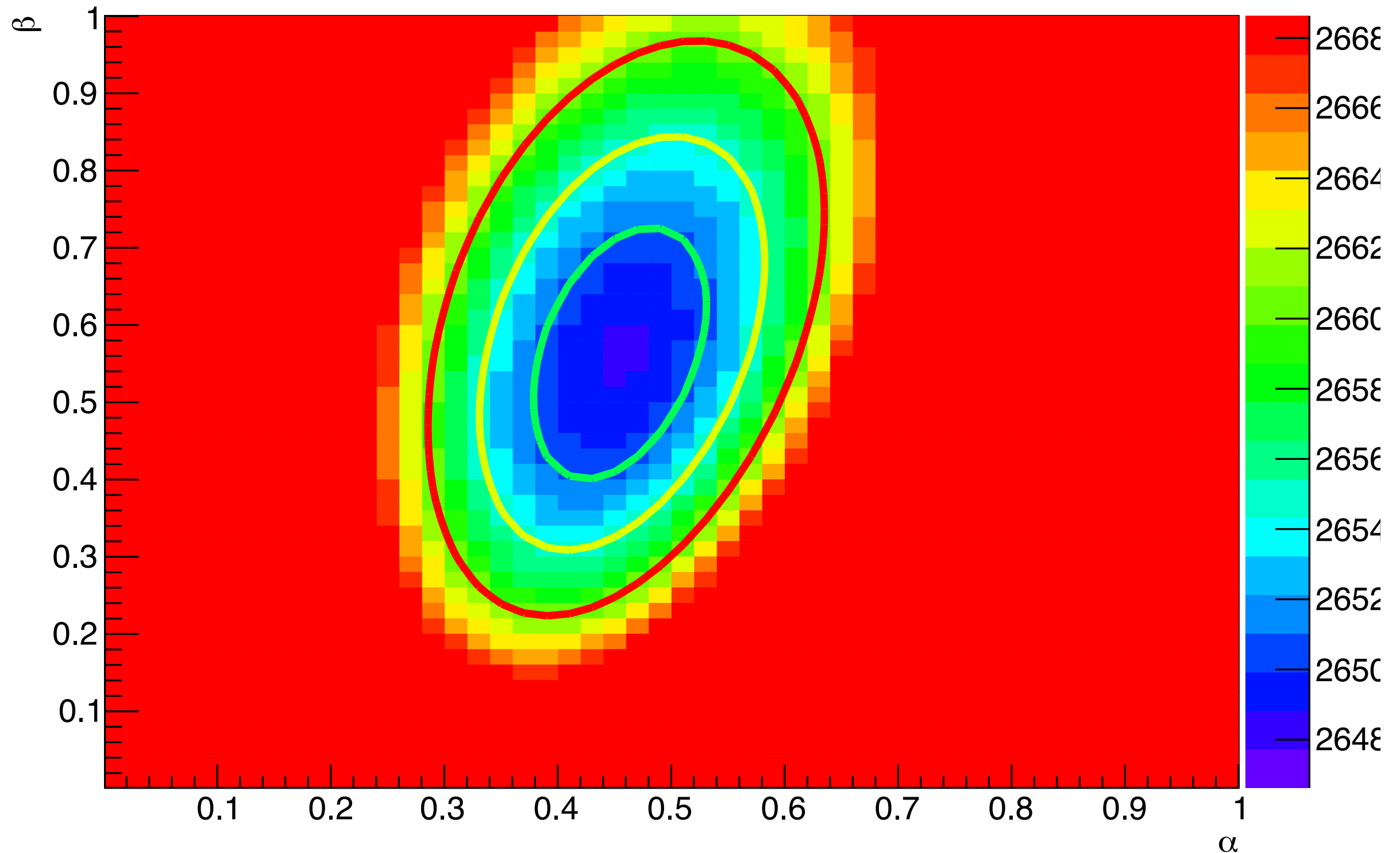


Exercise #2

- Using the same function and $\alpha=0.5$ and $\beta=0.5$ as Exercise #1, find the MLE values for a single Monte Carlo sample w/ 2000 points
- Plot the contours related to the 1σ , 2σ , and 3σ confidence regions
 - Remember that this function has 2 fit parameters
 - Because of different random number generators, your result is likely to vary from mine

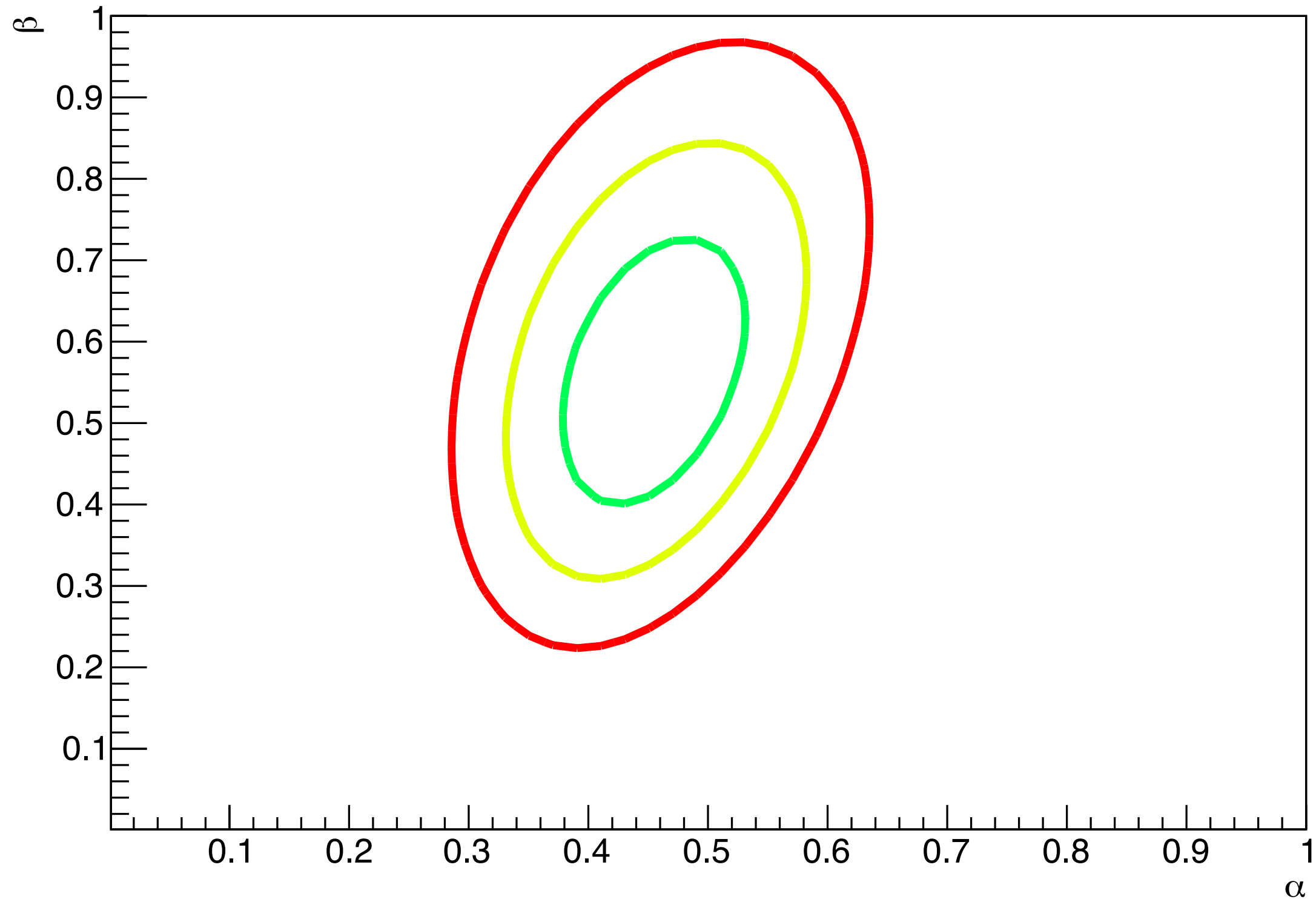
Contours on Top of the LLH Space

$-2*LLH$



Just the Contours

Contours from $-2*LLH$

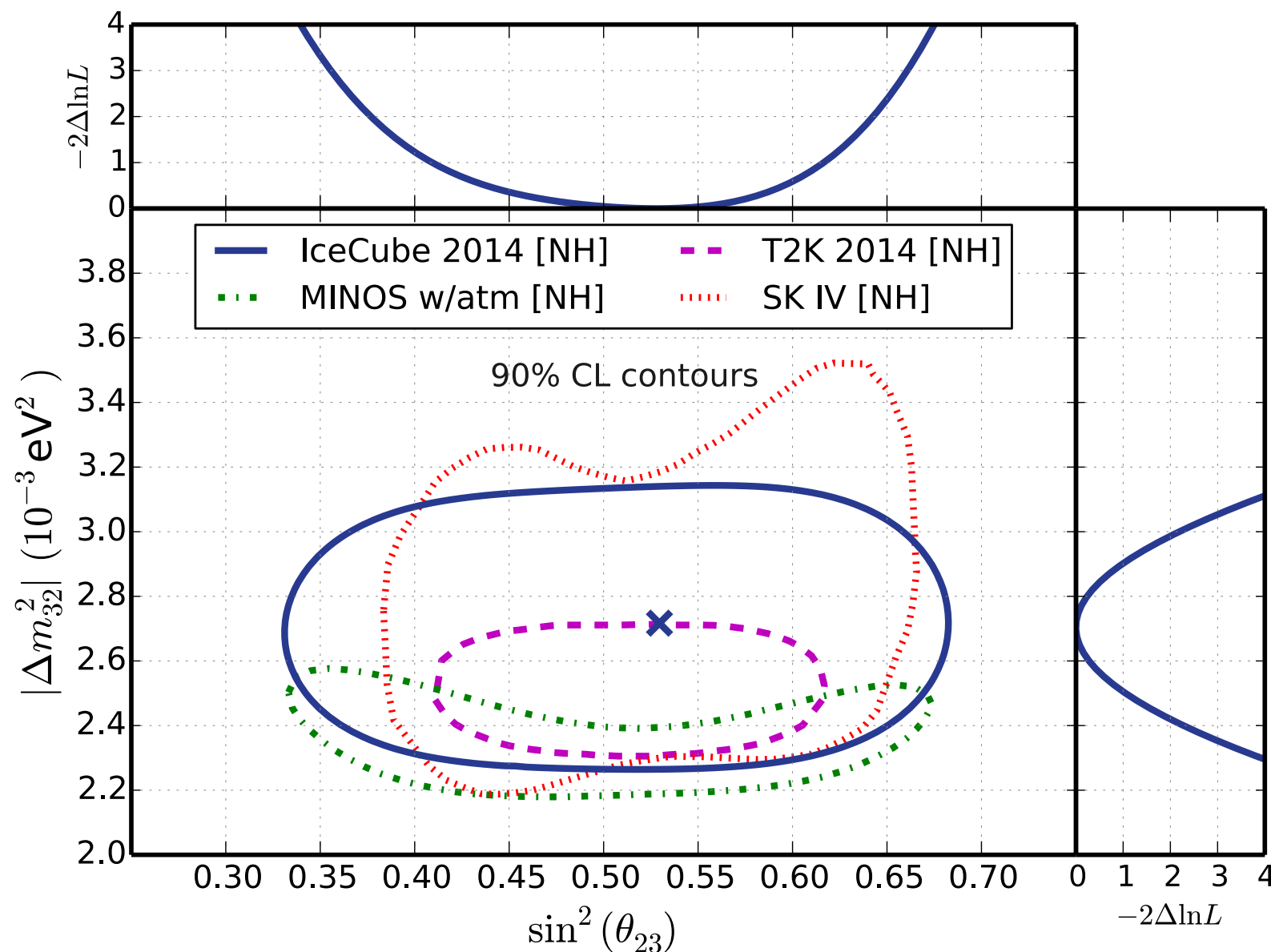


Real Data

- 1D projections of the 2D contour in order to give the best-fit values and their uncertainties

$$\sin^2 \theta_{23} = 0.53^{+0.09}_{-0.12}$$

$$\Delta m_{32}^2 = 2.72^{+0.19}_{-0.20} \times 10^{-3} \text{eV}^2$$



Remember, even though they are 1D projections the ΔLLH conversion to σ must use the degrees-of-freedom from the actual fitting routine

*arXiv:1410.7227

Exercise #3

- There is a file posted on the class webpage which has two columns of x numbers (not x and y , *just* x for 2 pseudo-experiments) corresponding to x over the range $-1 \leq x \leq 1$
- Using the function:

$$f(x; \alpha, \beta) = 1 + \alpha x + \beta x^2$$

- Find the best-fit for the unknown α and β
- [Optional] Using a chi-squared test statistic, calculate the goodness-of-fit (p-value) by histogramming the data. The choice of bin width can be important
 - Too narrow and there are not enough events in each bin for the statistical comparison
 - Too wide and any difference between the 'shape' of the data and prediction histogram will be washed out, leaving the result uninformative and possibly misleading

Extra

- Use a 3-dimensional function for $\alpha=0.5$, $\beta=0.5$, and $\gamma=0.9$ generate 2000 Monte Carlo data points using the function transformed into a PDF over the range $-1 \leq x \leq 1$

$$f(x; \alpha, \beta, \gamma) = 1 + \alpha x + \beta x^2 + \gamma x^5$$

- Find the best-fit values and uncertainties on α , β , and γ
- Similar to exercise #1, show that Monte Carlo re-sampling produces similar uncertainties as the Δ LLH prescription for the 3D hypersurface
 - In 3D, are 500 Monte Carlo pseudo-experiments enough?
 - Are 2000 Monte Carlo data points per pseudo-experiment enough?
 - Write a profiler to project the 2D contour onto 1D, properly