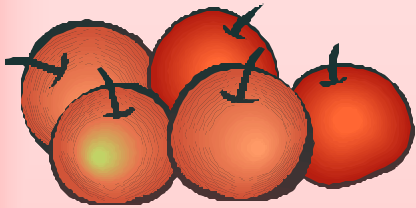


Statistics for HEP

Roger Barlow
Manchester University

Lecture 4: Confidence Intervals

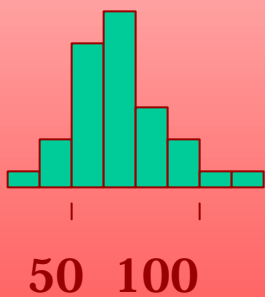
The Straightforward Example



Apples of different weights

Need to describe the distribution

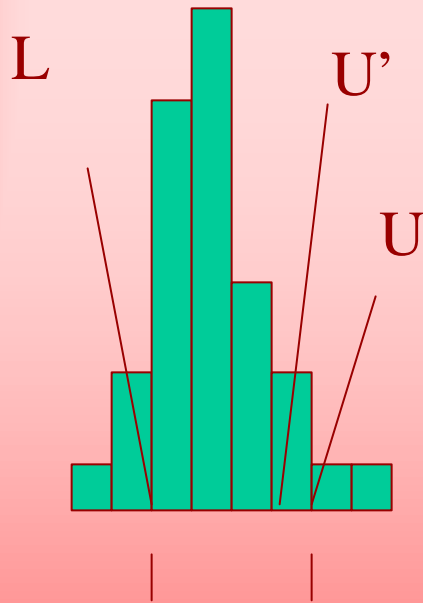
$$\mu = 68\text{g} \quad \sigma = 17\text{g}$$



All weights between 24 and 167 g (Tolerance)

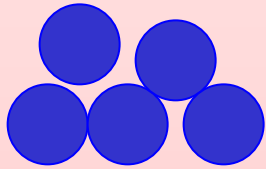
90% lie between 50 and 100 g } Confidence level statements
94% are less than 100 g }
96% are more than 50 g }

Confidence Levels



- Can quote at any level
(68%, 95%, 99%...)
- Upper or lower or twosided
($x < U$ $x < L$ $L < x < U$)
- Two-sided has further choice
(central, shortest...)

The Frequentist Twist



Particles of the same weight

Distribution spread by
measurement errors



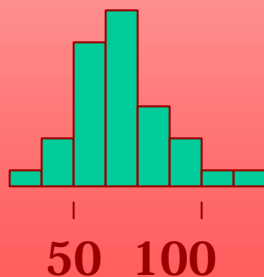
What can we say about M ?

$$\mu = 68 \quad \sigma = 17$$

" $M < 90$ " or " $M > 55$ " or " $60 < M < 85$ " @90% CL

These are each always true or always false

Solution: Refer to ensemble of statements



Frequentist CL in detail



You have a meter: no bias,

Gaussian error 0.1.

For a value X_T it gives a value X_M
according to a Gaussian Distribution

X_M is within 0.1 of X_T 68% of the time

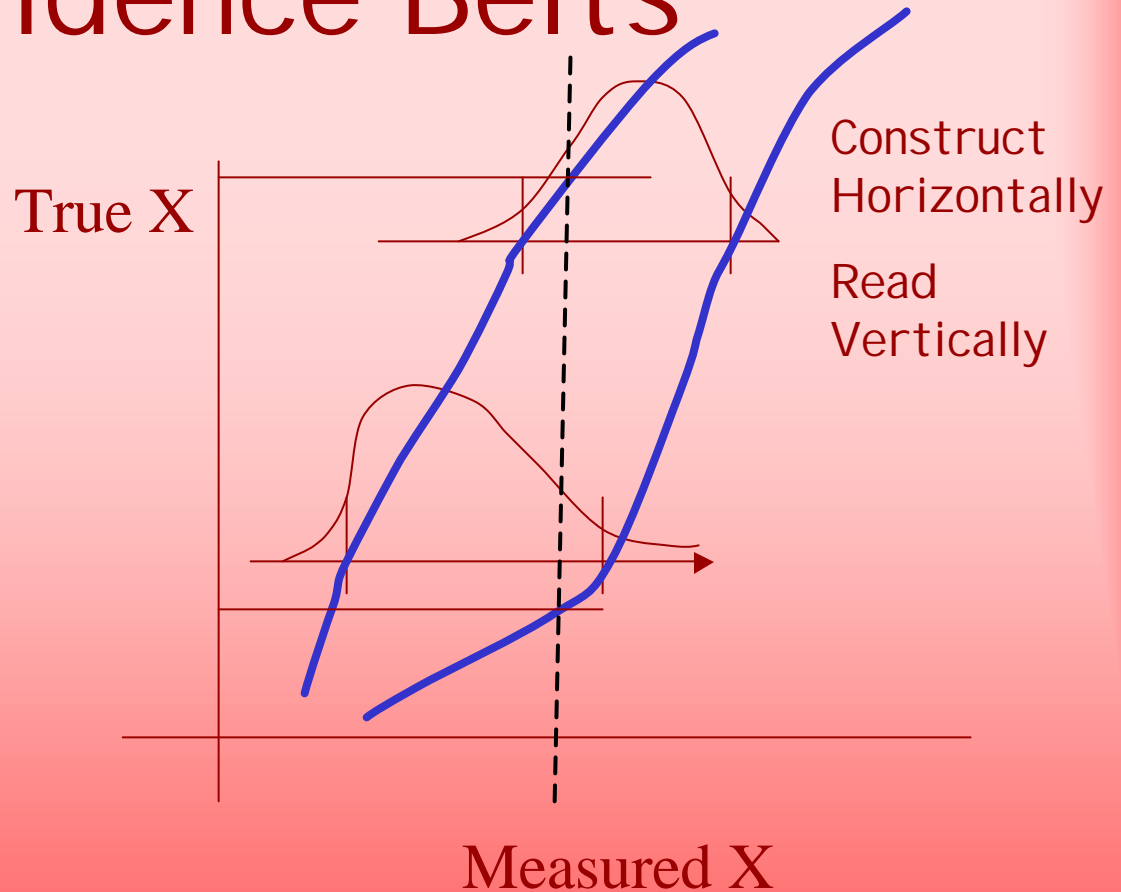
X_T is within 0.1 of X_M 68% of the time

Can state $X_M - 0.1 < X_T < X_M + 0.1$ @68% CL

Confidence Belts

For more complicated distributions it isn't quite so easy

But the principle is the same



Coverage



Think about: the difference between a 90% upper limit and the upper limit of a 90% central interval.

" $L < x < U$ " @ 95% confidence
(or " $x > L$ " or " $x < U$ ")

This statement belongs to an ensemble of similar statements of which at least* 95% are true

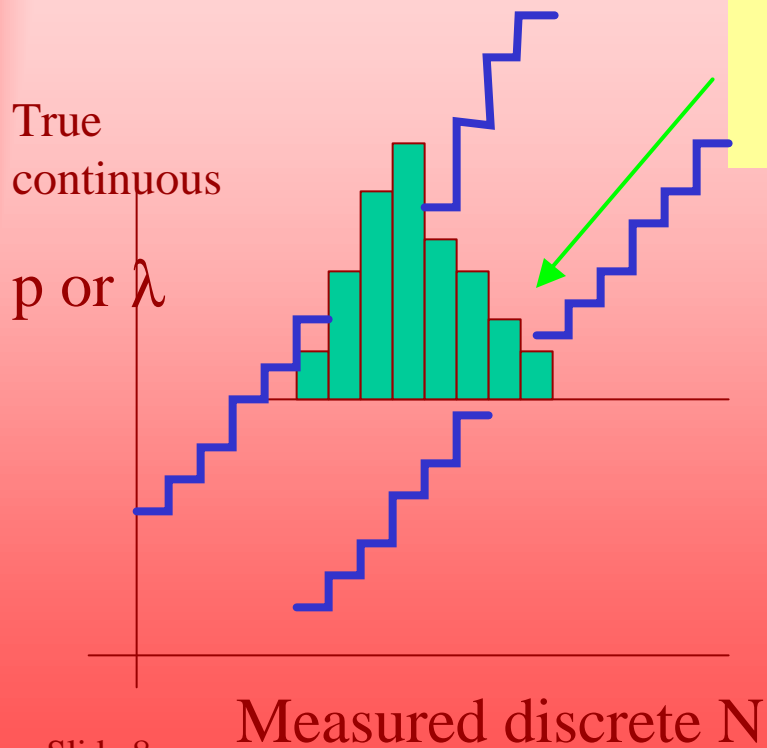
95% is the *coverage*

This is a statement about U and L , not about x .

*Maybe more. Overcoverage
EG composite hypotheses.
Meter with resolution ≤ 0.1

Discrete Distributions

CL belt edges
become steps



May be unable
to select (say)
5% region

Play safe.

Gives
overcoverage

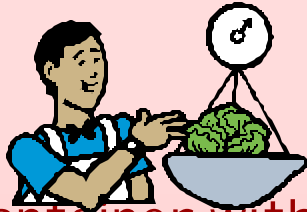
Binomial: see tables

Poisson

	Upper			Lower		
	90	95	99	90	95	99
0	2.3	3	4.61			
1	3.89	4.74	6.64	0.11	0.05	0.01
2	5.32	6.3	8.41	0.53	0.36	0.15
3	6.68	7.75	10.05	1.1	0.82	0.44

*Given 2 events, if the true mean is 6.3 (or more)
then the chance of getting a fluctuation this low
(or lower) is only 5% (or less)*

Problems for Frequentists



Weigh
object+container with some
Gaussian precision

Get reading R

$$R - \sigma < M + C < R + \sigma \text{ @68\%}$$

$$R - C - \sigma < M < R - C + \sigma \text{ @68\%}$$

E.g. $C=50$, $R=141$, $\sigma=10$

$$81 < M < 101 \text{ @68\%}$$

E.g. $C=50$, $R=55$, $\sigma=10$

$$-5 < M < 5 \text{ @68\%}$$

E.g. $C=50$, $R=31$, $\sigma=10$

$$-29 < M < -9 \text{ @68\%}$$

Poisson: Signal + Background

Background mean 2.50

Detect 3 events:

$$\text{Total} < 6.68 \text{ @ 95\%}$$

$$\text{Signal} < 4.18 \text{ @95\%}$$

Detect 0 events

$$\text{Total} < 2.30 \text{ @ 95\%}$$

$$\text{Signal} < -0.20 \text{ @ 95\%}$$

These statements are OK.
We are allowed to get 32% / 5% wrong.
But they are stupid

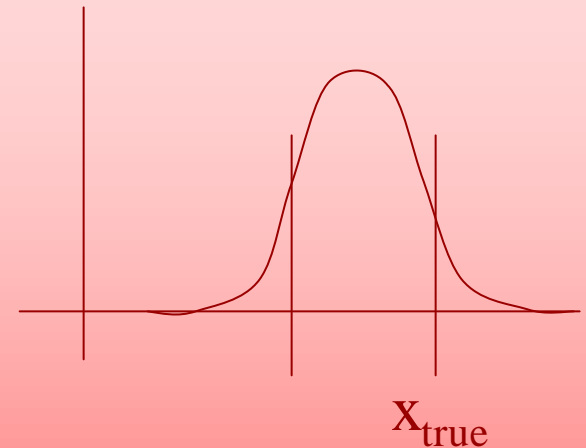
Bayes to the rescue

$$P(\text{Theory} | \text{Data}) = \frac{P(\text{Data} | \text{Theory})}{P(\text{Data})} P(\text{Theory})$$

Standard (Gaussian) measurement

- No prior knowledge of true value
- No prior knowledge of measurement result
- $P(\text{Data} | \text{Theory})$ is Gaussian
- $P(\text{Theory} | \text{Data})$ is Gaussian

Interpret this with Probability statements in any way you please



Gives same limits
as Frequentist
method for simple
Gaussian

Bayesian Confidence Intervals (contd)

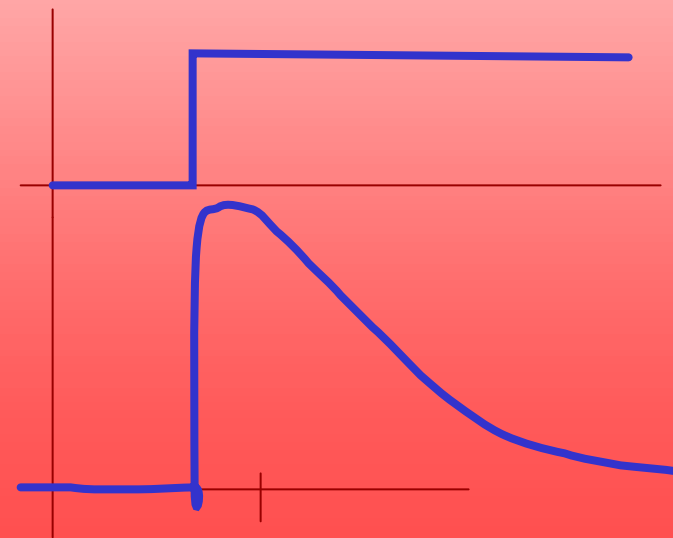
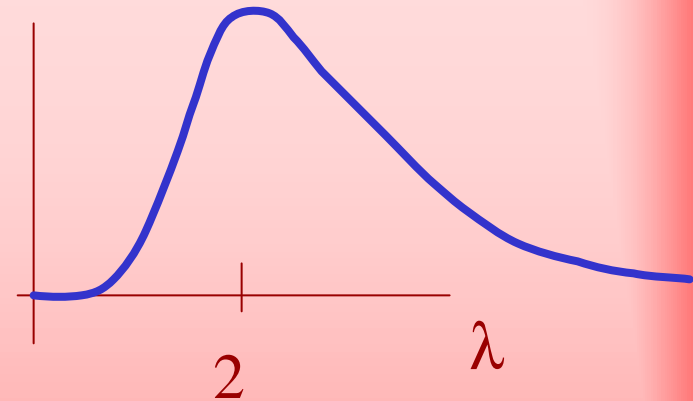
Observe (say) 2 events

$$P(\lambda; 2) \propto P(2; \lambda) = e^{-\lambda} \lambda^2$$

Normalise and interpret

If you know background mean is 1.7, then you know $\lambda > 1.7$

Multiply, normalise and interpret



Bayes: words of caution

Taking prior in λ as flat is not justified

Can argue for prior flat in $\ln \lambda$ or $1/\sqrt{\lambda}$
or whatever

Good practice to try a couple of priors
to see if it matters

Feldman-Cousins Unified Method

Physicists are human

Ideal Physicist

1. Choose Strategy
2. Examine data
3. Quote result



Real Physicist

1. Examine data
2. Choose Strategy
3. Quote Result



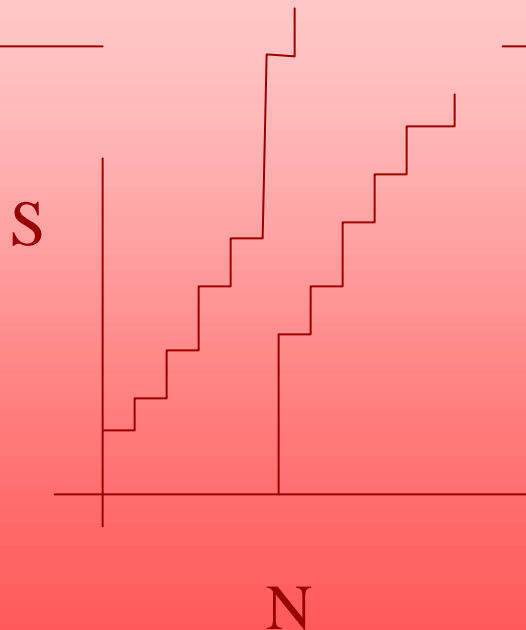
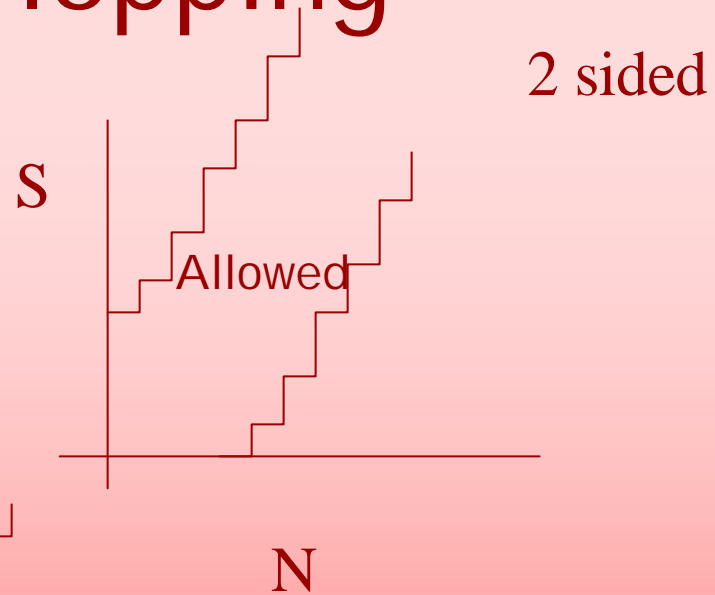
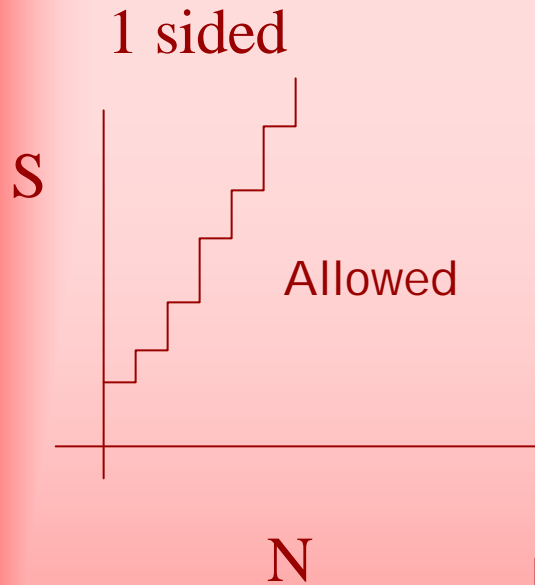
Example:

You have a background of 3.2

Observe 5 events? Quote one-sided upper limit (9.27-3.2 = 6.07@90%)

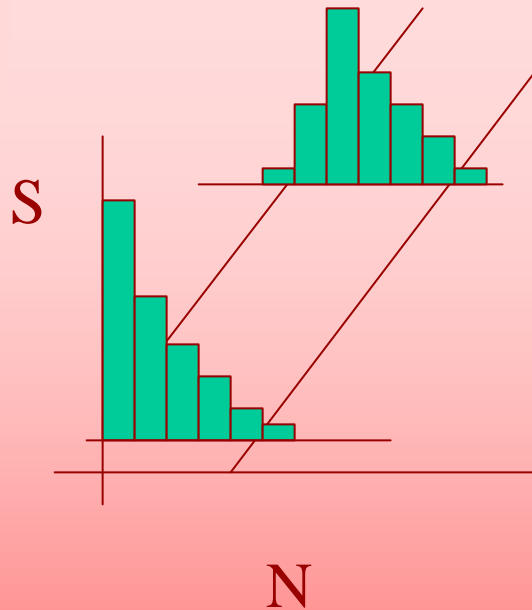
Observe 25 events? Quote two-sided limits

"Flip-Flopping"



This is not a true confidence belt!
Coverage varies.

Solution: Construct belt that does the flip-flopping



For 90% CL

For every S select set of N -values in belt

Total probability must sum to 90% (or more): there are many strategies for doing this

Crow & Gardner strategy (almost right):

Select N -values with highest probability
→ shortest interval

Better Strategy

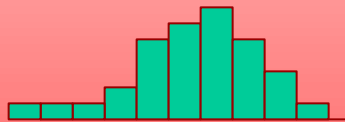
N is Poisson from S+B

B known, may be large

E.g. B=9.2, S=0 and N=1

P=.1% - not in C-G band

But any S>0 will be worse



Fair comparison of P is with
best P for this N

To construct band for a
given S:

For all N:

Find $P(N; S+B)$ and

$$P_{\text{best}} = P(N; N) \text{ if } (N > B) \\ \text{else } P(N; B)$$

Rank on P/P_{best}

Accept N into band until

$$\sum P(N; S+B) \geq 90\%$$

Feldman and Cousins Summary

- Makes us more honest (a bit)
- Avoids forbidden regions in a Frequentist way
- Not easy to calculate
- Has to be done separately for each value of B
- Can lead to 2-tailed limits where you don't want to claim a discovery
- Weird effects for $N=0$; larger B gives lower (=better) upper limit

Maximum Likelihood and Confidence Levels

ML estimator (large N) has variance given by MVB

$$\mathbf{s}_{\hat{a}}^2 = V(\hat{a}) = \frac{-1}{\left\langle \frac{d^2 \ln L}{da^2} \right\rangle}$$

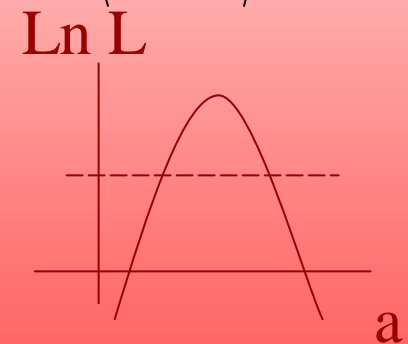
At peak $\ln L \approx L_{\max} + \frac{(a - \hat{a})^2}{2} \frac{d^2 \ln L}{da^2} \Big|_{a=\hat{a}}$ For large N $\left\langle \frac{d^2 \ln L}{da^2} \right\rangle = \frac{d^2 \ln L}{da^2} \Big|_{a=\hat{a}}$

Ln L is a parabola (L is a Gaussian)

$$\ln L = L_{\max} - \frac{(a - \hat{a})^2}{2\mathbf{s}_{\hat{a}}^2}$$

Falls by 1/2 at $a = \hat{a} \pm \mathbf{s}_{\hat{a}}$

Falls by 2 at $a = \hat{a} \pm 2\mathbf{s}_{\hat{a}}$



MVB example

N Gaussian measurements: estimate μ

$$P(x_i; \mathbf{m}) = \frac{1}{\mathbf{s} \sqrt{2\mathbf{p}}} e^{-(x_i - \mathbf{m})^2 / 2\mathbf{s}^2}$$

Ln L given by $-\sum_i \frac{(x_i - \mathbf{m})^2}{2\mathbf{s}^2} - N \ln(\mathbf{s} \sqrt{2\mathbf{p}})$

Differentiate twice wrt μ $-\frac{N}{\mathbf{s}^2}$

Take expectation value – but it's a constant

Invert and negate: $V(\hat{\mathbf{m}}) = \frac{\mathbf{s}^2}{N}$

Another MVB example

N Gaussian measurements: estimate σ

Ln L still given by $-\sum_i \frac{(x_i - \mathbf{m})^2}{2\mathbf{s}^2} - N \ln(\mathbf{s} \sqrt{2\mathbf{p}})$

Differentiate twice wrt σ

$$-\sum_i \frac{3(x_i - \mathbf{m})^2}{\mathbf{s}^4} + \frac{N}{\mathbf{s}^2}$$

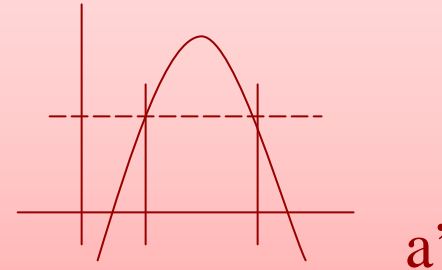
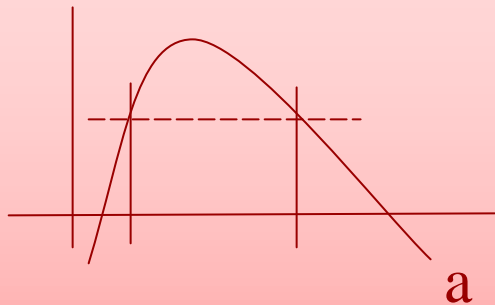
Take expectation value $\langle (x_i - \mu)^2 \rangle = \sigma^2 \forall i$

Gives $-\frac{2N}{\mathbf{s}^2}$

Invert and negate: $V(\hat{\mathbf{S}}) = \frac{\mathbf{s}^2}{2N}$

ML for small N

In L is not a parabola



Argue: we could (invariance) transform to some a' for which it is a parabola

We could/should then get limits on a' using standard $L_{\max}^{-1/2}$ technique

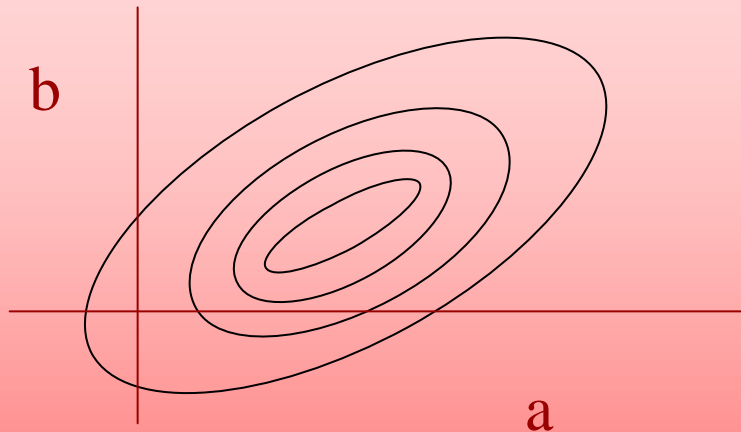
These would translate to limits on a

These limits would be at the values of a for which $L = L_{\max}^{-1/2}$

So just do it directly

Multidimensional ML

- L is multidimensional Gaussian



For 2-d 39.3% lies within 1σ
i.e. within region bounded by

$$L=L_{\max}^{-1/2}$$

For 68% need $L=L_{\max}^{-1.15}$

Construct region(s) to taste
using numbers from
integrated χ^2 distribution

Confidence Intervals

- Descriptive
- Frequentist
 - Feldman-Cousins technique
- Bayesian
- Maximum Likelihood
 - Standard
 - Asymmetric
 - Multidimensional