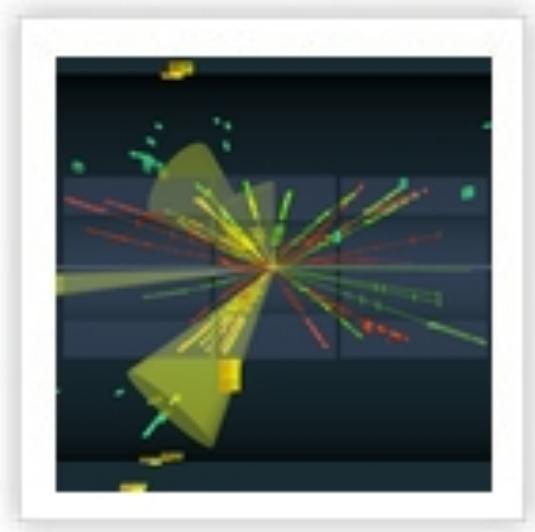


# Statistics in High Energy Physics



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# Outline

- I. Review of probability
- II. Review of parameter estimation
- III. Review of statistical tests
- IV. The Poisson counting experiment
  - Discovery
  - Limits
- V. Systematic uncertainties, nuisance parameters
  - Simple fit
  - More on Poisson counting exp.
- VI. Further examples

# Some statistics books, papers, etc.

J. Beringer *et al.* (Particle Data Group), *Review of Particle Physics*, Phys. Rev. D86, 010001 (2012); see also [pdg.lbl.gov](http://pdg.lbl.gov)  
sections on probability statistics, Monte Carlo

G. Cowan, *Statistical Data Analysis*, Clarendon, Oxford, 1998  
see also [www.pp.rhul.ac.uk/~cowan/sda](http://www.pp.rhul.ac.uk/~cowan/sda)

R.J. Barlow, Statistics: A Guide to the Use of Statistical Methods in the Physical Sciences, Wiley, 1989  
see also [hepwww.ph.man.ac.uk/~roger/book.html](http://hepwww.ph.man.ac.uk/~roger/book.html)

L. Lyons, *Statistics for Nuclear and Particle Physics*, CUP, 1986

F. James., *Statistical and Computational Methods in Experimental Physics*, 2nd ed., World Scientific, 2006

S. Brandt, *Statistical and Computational Methods in Data Analysis*, Springer, New York, 1998

# Quick review of probability

Frequentist ( $A$  = outcome of repeatable observation):

$$P(A) = \lim_{n \rightarrow \infty} \frac{\text{outcome is } A}{n}$$

Subjective ( $A$  = hypothesis):  $P(A)$  = degree of belief that  $A$  is true

Conditional probability:

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

Bayes' theorem:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} = \frac{P(B|A)P(A)}{\sum_i P(B|A_i)P(A_i)}$$

# Frequentist Statistics – general philosophy

In frequentist statistics, probabilities are associated only with the data, i.e., outcomes of repeatable observations.

Probability = limiting frequency

Probabilities such as

$P$  (WIMPs exist),

$P(0.298 < \Omega_m < 0.332)$ ,

etc. are either 0 or 1, but we don't know which.

The tools of frequentist statistics tell us what to expect, under the assumption of certain probabilities, about hypothetical repeated observations.

The preferred theories (models, hypotheses, ...) are those for which our observations would be considered ‘usual’.

# Bayesian Statistics – general philosophy

In Bayesian statistics, interpretation of probability extended to degree of belief (subjective probability). Use this for hypotheses:

probability of the data assuming hypothesis  $H$  (the likelihood)

prior probability, i.e., before seeing the data

$$P(H|\vec{x}) = \frac{P(\vec{x}|H)\pi(H)}{\int P(\vec{x}|H)\pi(H) dH}$$

posterior probability, i.e., after seeing the data

normalization involves sum over all possible hypotheses

Bayesian methods can provide more natural treatment of non-repeatable phenomena:

systematic uncertainties, probability that Higgs boson exists,...

No golden rule for priors (“if-then” character of Bayes’ thm.)

# Distribution, likelihood, model

Suppose the outcome of a measurement is  $x$ . (e.g., a number of events, a histogram, or some larger set of numbers).

The probability density (or mass) function or ‘distribution’ of  $x$ , which may depend on parameters  $\theta$ , is:

$$P(x|\theta) \quad (\text{Independent variable is } x; \theta \text{ is a constant.})$$

If we evaluate  $P(x|\theta)$  with the observed data and regard it as a function of the parameter(s), then this is the likelihood:

$$L(\theta) = P(x|\theta) \quad (\text{Data } x \text{ fixed; treat } L \text{ as function of } \theta.)$$

We will use the term ‘model’ to refer to the full function  $P(x|\theta)$  that contains the dependence both on  $x$  and  $\theta$ .

# Bayesian use of the term ‘likelihood’

We can write Bayes theorem as

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

where  $L(x|\theta)$  is the likelihood. It is the probability for  $x$  given  $\theta$ , evaluated with the observed  $x$ , and viewed as a function of  $\theta$ .

Bayes’ theorem only needs  $L(x|\theta)$  evaluated with a given data set (the ‘likelihood principle’).

For frequentist methods, in general one needs the full model.

For some approximate frequentist methods, the likelihood is enough.

# Quick review of frequentist parameter estimation

Suppose we have a pdf characterized by one or more parameters:

$$f(x; \theta) = \frac{1}{\theta} e^{-x/\theta}$$

random variable      parameter

Suppose we have a sample of observed values:  $\vec{x} = (x_1, \dots, x_n)$

We want to find some function of the data to estimate the parameter(s):

$$\hat{\theta}(\vec{x}) \quad \leftarrow \text{estimator written with a hat}$$

Sometimes we say ‘estimator’ for the function of  $x_1, \dots, x_n$ ;  
‘estimate’ for the value of the estimator with a particular data set.

# Maximum likelihood

The most important frequentist method for constructing estimators is to take the value of the parameter(s) that maximize the likelihood:

$$\hat{\theta} = \operatorname{argmax}_{\theta} L(x|\theta)$$

The resulting estimators are functions of the data and thus characterized by a sampling distribution with a given (co)variance:

$$V_{ij} = \operatorname{cov}[\hat{\theta}_i, \hat{\theta}_j]$$

In general they may have a nonzero bias:

$$b = E[\hat{\theta}] - \theta$$

Under conditions usually satisfied in practice, bias of ML estimators is zero in the large sample limit, and the variance is as small as possible for unbiased estimators.

ML estimator may not in some cases be regarded as the optimal trade-off between these criteria (cf. regularized unfolding).

## ML example: parameter of exponential pdf

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

and suppose we have i.i.d. data,  $t_1, \dots, t_n$

The likelihood function is  $L(\tau) = \prod_{i=1}^n \frac{1}{\tau} e^{-t_i/\tau}$

The value of  $\tau$  for which  $L(\tau)$  is maximum also gives the maximum value of its logarithm (the log-likelihood function):

$$\ln L(\tau) = \sum_{i=1}^n \ln f(t_i; \tau) = \sum_{i=1}^n \left( \ln \frac{1}{\tau} - \frac{t_i}{\tau} \right)$$

## ML example: parameter of exponential pdf (2)

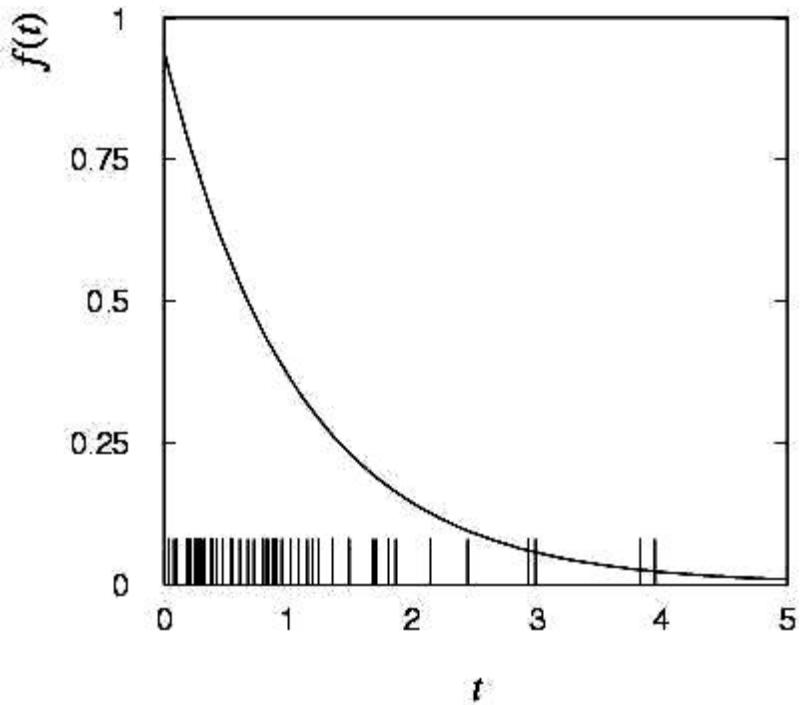
Find its maximum by setting  $\frac{\partial \ln L(\tau)}{\partial \tau} = 0$ ,

$$\rightarrow \hat{\tau} = \frac{1}{n} \sum_{i=1}^n t_i$$

Monte Carlo test:  
generate 50 values  
using  $\tau = 1$ :

We find the ML estimate:

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



# Variance of estimators: Monte Carlo method

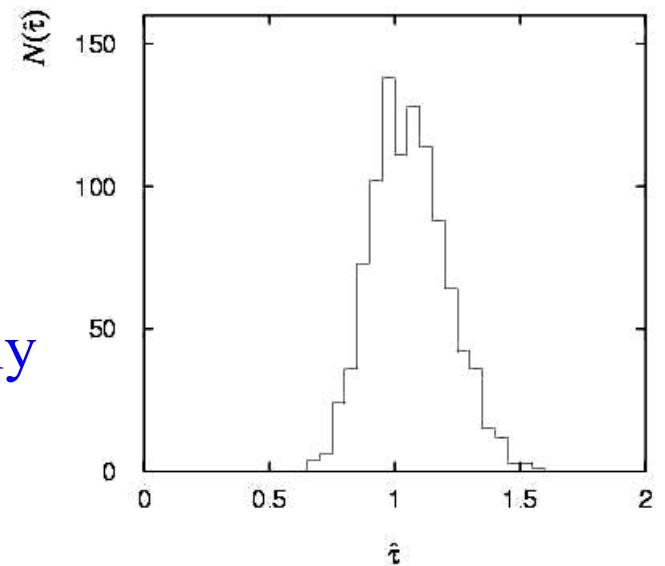
Having estimated our parameter we now need to report its ‘statistical error’, i.e., how widely distributed would estimates be if we were to repeat the entire measurement many times.

One way to do this would be to simulate the entire experiment many times with a Monte Carlo program (use ML estimate for MC).

For exponential example, from sample variance of estimates we find:

$$\hat{\sigma}_{\hat{\tau}} = 0.151$$

Note distribution of estimates is roughly Gaussian – (almost) always true for ML in large sample limit.



# Variance of estimators from information inequality

The information inequality (RCF) sets a lower bound on the variance of any estimator (not only ML):

$$V[\hat{\theta}] \geq \left(1 + \frac{\partial b}{\partial \theta}\right)^2 \Bigg/ E\left[-\frac{\partial^2 \ln L}{\partial \theta^2}\right]$$

Minimum Variance  
Bound (MVB)  
 $(b = E[\hat{\theta}] - \theta)$

Often the bias  $b$  is small, and equality either holds exactly or is a good approximation (e.g. large data sample limit). Then,

$$V[\hat{\theta}] \approx -1 \Bigg/ E\left[\frac{\partial^2 \ln L}{\partial \theta^2}\right]$$

Estimate this using the 2nd derivative of  $\ln L$  at its maximum:

$$\hat{V}[\hat{\theta}] = - \left(\frac{\partial^2 \ln L}{\partial \theta^2}\right)^{-1} \Bigg|_{\theta=\hat{\theta}}$$

# Variance of estimators: graphical method

Expand  $\ln L(\theta)$  about its maximum:

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

First term is  $\ln L_{\max}$ , second term is zero, for third term use information inequality (assume equality):

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

$$\text{i.e., } \ln L(\hat{\theta} \pm \hat{\sigma}_{\hat{\theta}}) \approx \ln L_{\max} - \frac{1}{2}$$

→ to get  $\hat{\sigma}_{\hat{\theta}}$ , change  $\theta$  away from  $\hat{\theta}$  until  $\ln L$  decreases by 1/2.

# Example of variance by graphical method

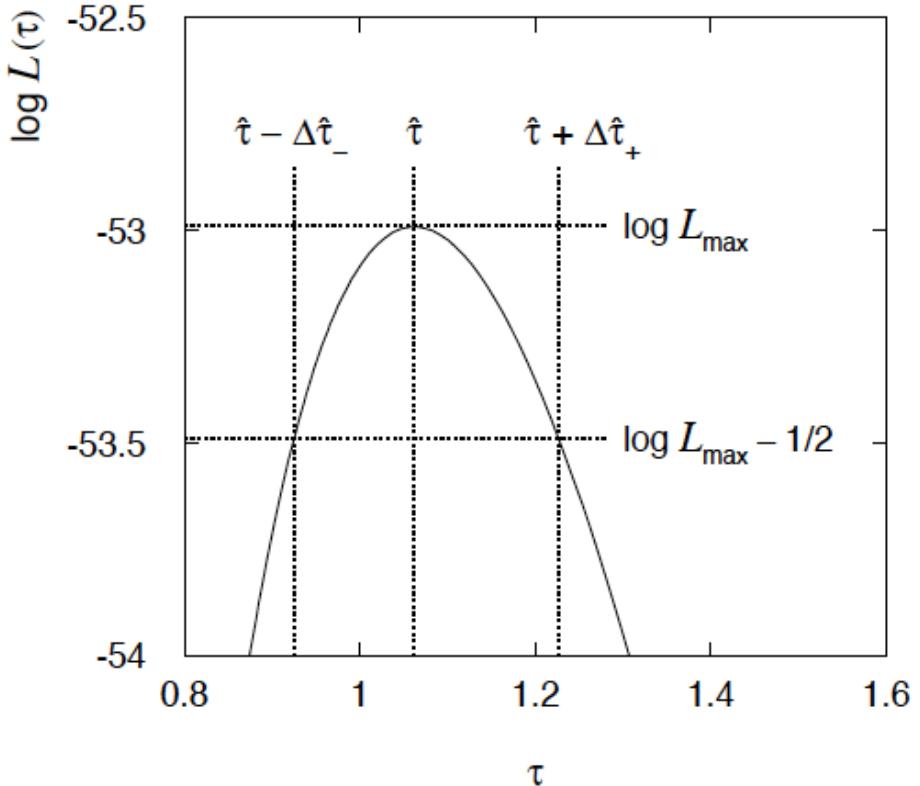
ML example with exponential:

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

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

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

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



Not quite parabolic  $\ln L$  since finite sample size ( $n = 50$ ).

# Information inequality for $n$ parameters

Suppose we have estimated  $n$  parameters  $\vec{\theta} = (\theta_1, \dots, \theta_n)$ .

The (inverse) minimum variance bound is given by the Fisher information matrix:

$$I_{ij} = E \left[ -\frac{\partial^2 \ln L}{\partial \theta_i \partial \theta_j} \right] = -n \int f(x; \vec{\theta}) \frac{\partial^2 \ln f(x; \vec{\theta})}{\partial \theta_i \partial \theta_j} dx$$

The information inequality then states that  $V - I^{-1}$  is a positive semi-definite matrix, where  $V_{ij} = \text{cov}[\hat{\theta}_i, \hat{\theta}_j]$ . Therefore

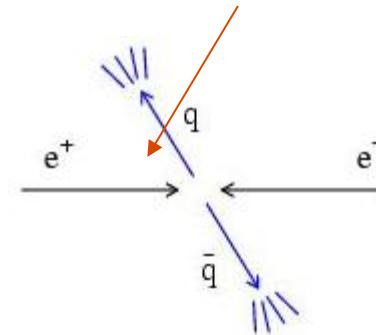
$$V[\hat{\theta}_i] \geq (I^{-1})_{ii}$$

Often use  $I^{-1}$  as an approximation for covariance matrix, estimate using e.g. matrix of 2nd derivatives at maximum of  $L$ .

## Two-parameter example of ML

Consider a scattering angle distribution with  $x = \cos \theta$ ,

$$f(x; \alpha, \beta) = \frac{1 + \alpha x + \beta x^2}{2 + 2\beta/3}$$



Data:  $x_1, \dots, x_n$ ,  $n = 2000$  events.

As test generate with MC using  $\alpha = 0.5$ ,  $\beta = 0.5$

From data compute log-likelihood:

$$\ln L(\alpha, \beta) = \sum_{i=1}^n \ln f(x_i; \alpha, \beta)$$

Maximize numerically (e.g., program MINUIT)

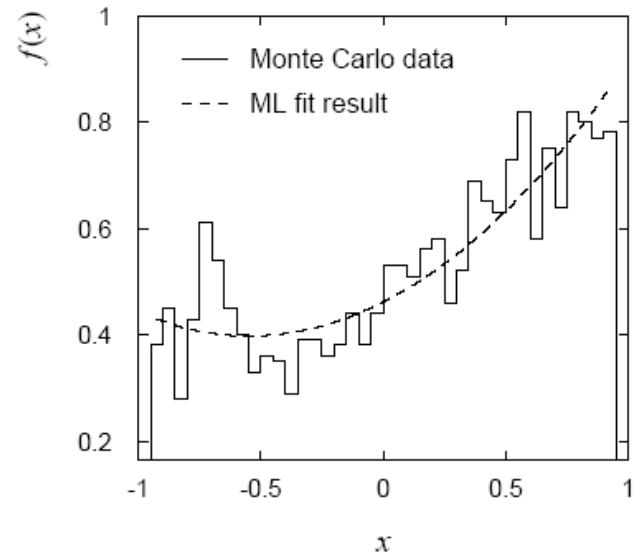
# Example of ML: fit result

Finding maximum of  $\ln L(\alpha, \beta)$  numerically (**MINUIT**) gives

$$\hat{\alpha} = 0.508$$

$$\hat{\beta} = 0.47$$

N.B. Here no binning of data for fit,  
but can compare to histogram for  
goodness-of-fit (e.g. ‘visual’ or  $\chi^2$ ).



(Co)variances from  $(\widehat{V^{-1}})_{ij} = -\frac{\partial^2 \ln L}{\partial \theta_i \partial \theta_j} \Big|_{\vec{\theta}=\widehat{\vec{\theta}}}$  **MINUIT routine HESSE**)

$$\hat{\sigma}_{\hat{\alpha}} = 0.052$$

$$\text{cov}[\hat{\alpha}, \hat{\beta}] = 0.0026$$

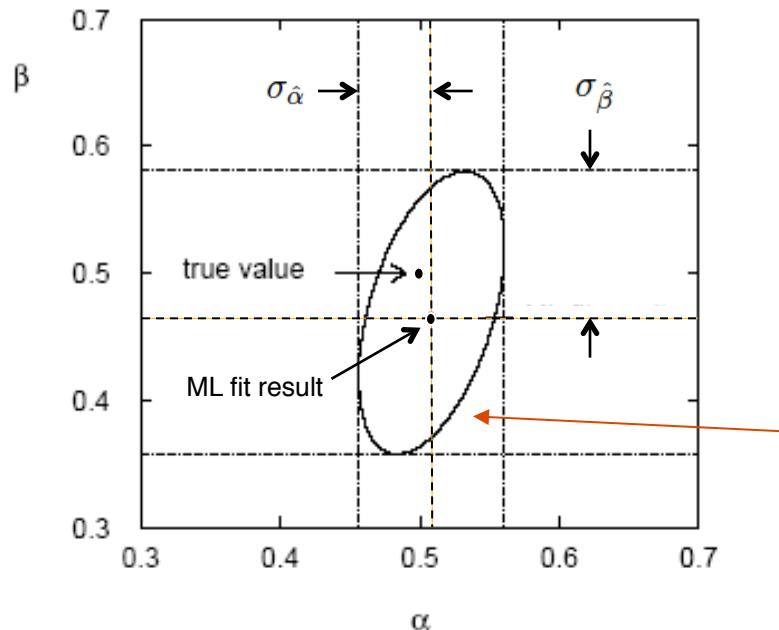
$$\hat{\sigma}_{\hat{\beta}} = 0.11$$

$$r = 0.46$$

# Variance of ML estimators: graphical method

Often (e.g., large sample case) one can approximate the covariances using only the likelihood  $L(\theta)$ :

$$\hat{V}_{ij}^{-1} \approx -\frac{\partial^2 \ln L}{\partial \theta_i \partial \theta_j} \Big|_{\theta=\hat{\theta}}$$



This translates into a simple graphical recipe:

$$\ln L(\alpha, \beta) = \ln L_{\max} - 1/2$$

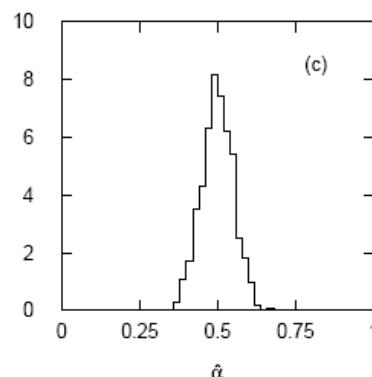
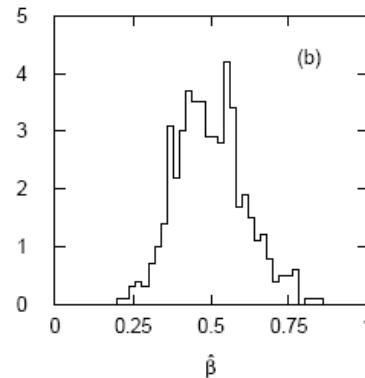
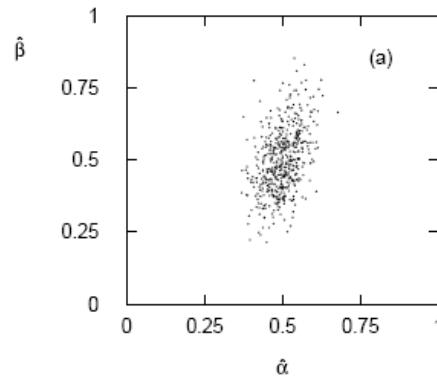
→ Tangent lines to contours give standard deviations.

→ Angle of ellipse  $\phi$  related to correlation:  $\tan 2\phi = \frac{2\rho\sigma_{\hat{\alpha}}\sigma_{\hat{\beta}}}{\sigma_{\hat{\alpha}}^2 - \sigma_{\hat{\beta}}^2}$

# Variance of ML estimators: MC

To find the ML estimate itself one only needs the likelihood  $L(\theta)$ .

In principle to find the covariance of the estimators, one requires the full model  $L(x|\theta)$ . E.g., simulate many times independent data sets and look at distribution of the resulting estimates:



$$\bar{\hat{\alpha}} = 0.499$$

$$s_{\hat{\alpha}} = 0.051$$

$$\bar{\hat{\beta}} = 0.498$$

$$s_{\hat{\beta}} = 0.111$$

$$\text{cov}[\hat{\alpha}, \hat{\beta}] = 0.0024$$

$$r = 0.42$$

# A quick review of frequentist statistical tests

Consider a hypothesis  $H_0$  and alternative  $H_1$ .

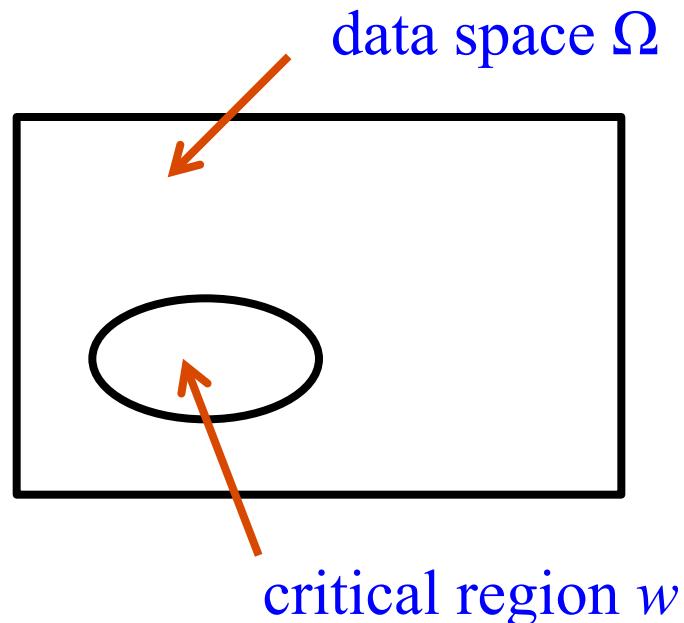
A test of  $H_0$  is defined by specifying a critical region  $w$  of the data space such that there is no more than some (small) probability  $\alpha$ , assuming  $H_0$  is correct, to observe the data there, i.e.,

$$P(x \in w \mid H_0) \leq \alpha$$

Need inequality if data are discrete.

$\alpha$  is called the size or significance level of the test.

If  $x$  is observed in the critical region, reject  $H_0$ .

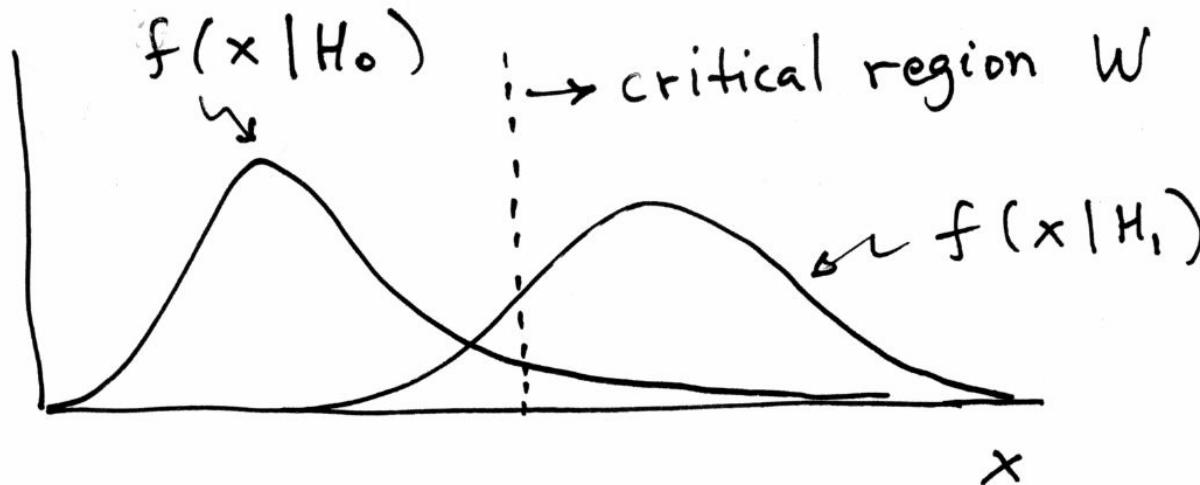


## Definition of a test (2)

But in general there are an infinite number of possible critical regions that give the same significance level  $\alpha$ .

So the choice of the critical region for a test of  $H_0$  needs to take into account the alternative hypothesis  $H_1$ .

Roughly speaking, place the critical region where there is a low probability to be found if  $H_0$  is true, but high if  $H_1$  is true:



## Type-I, Type-II errors

Rejecting the hypothesis  $H_0$  when it is true is a Type-I error.

The maximum probability for this is the size of the test:

$$P(x \in W | H_0) \leq \alpha$$

But we might also accept  $H_0$  when it is false, and an alternative  $H_1$  is true.

This is called a Type-II error, and occurs with probability

$$P(x \in S - W | H_1) = \beta$$

One minus this is called the power of the test with respect to the alternative  $H_1$ :

$$\text{Power} = 1 - \beta$$

# Rejecting a hypothesis

Note that rejecting  $H_0$  is not necessarily equivalent to the statement that we believe it is false and  $H_1$  true. In frequentist statistics only associate probability with outcomes of repeatable observations (the data).

In Bayesian statistics, probability of the hypothesis (degree of belief) would be found using Bayes' theorem:

$$P(H|x) = \frac{P(x|H)\pi(H)}{\int P(x|H)\pi(H) dH}$$

which depends on the prior probability  $\pi(H)$ .

What makes a frequentist test useful is that we can compute the probability to accept/reject a hypothesis assuming that it is true, or assuming some alternative is true.

# Defining a multivariate critical region

For each event, measure, e.g.,

$x_1 = \text{missing energy}, x_2 = \text{electron } p_T, x_3 = \dots$

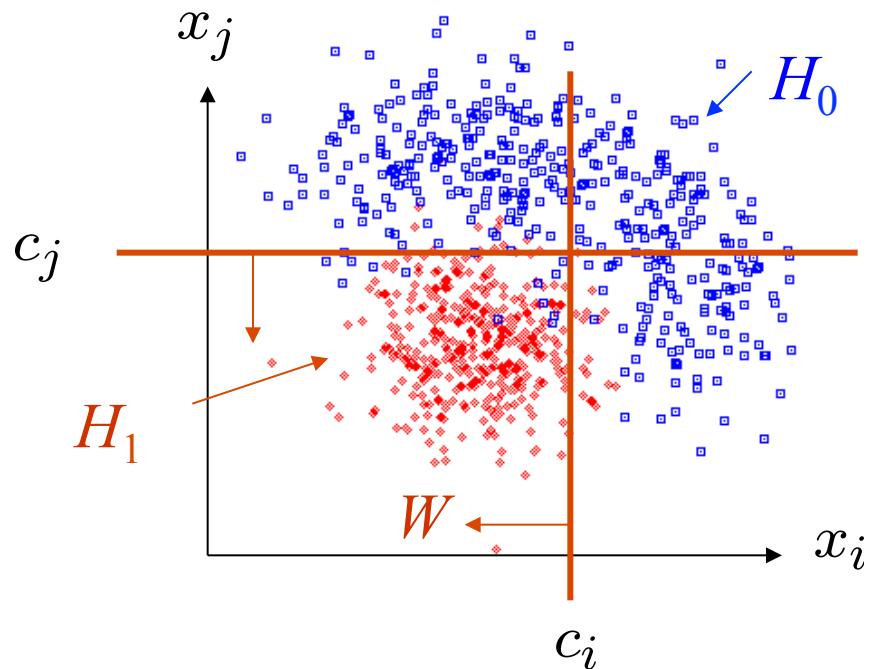
Each event is a point in  $n$ -dimensional  $x$ -space; critical region is now defined by a ‘decision boundary’ in this space.

What is best way to determine the boundary?

Perhaps with ‘cuts’:

$$x_i < c_i$$

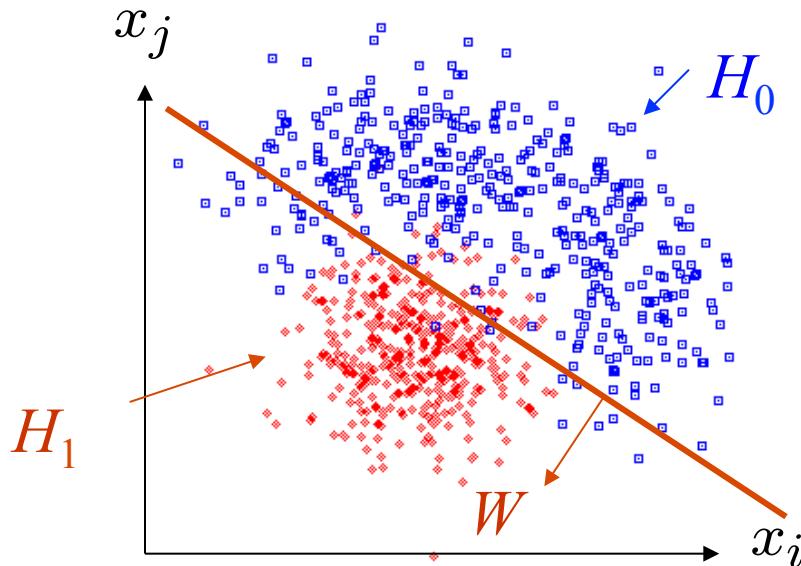
$$x_j < c_j$$



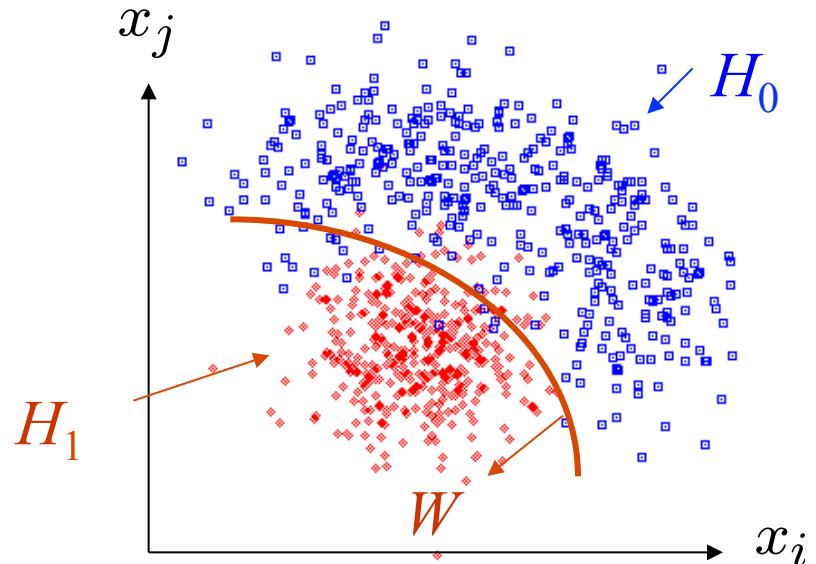
# Other multivariate decision boundaries

Or maybe use some other sort of decision boundary:

linear



or nonlinear



Multivariate methods for finding optimal critical region have become a Big Industry (neural networks, boosted decision trees,...).

No time here to cover these but see, e.g., slides and resources on  
[http://www.pp.rhul.ac.uk/~cowan/stat\\_valencia.html](http://www.pp.rhul.ac.uk/~cowan/stat_valencia.html)

# Test statistics

The boundary of the critical region for an  $n$ -dimensional data space  $\mathbf{x} = (x_1, \dots, x_n)$  can be defined by an equation of the form

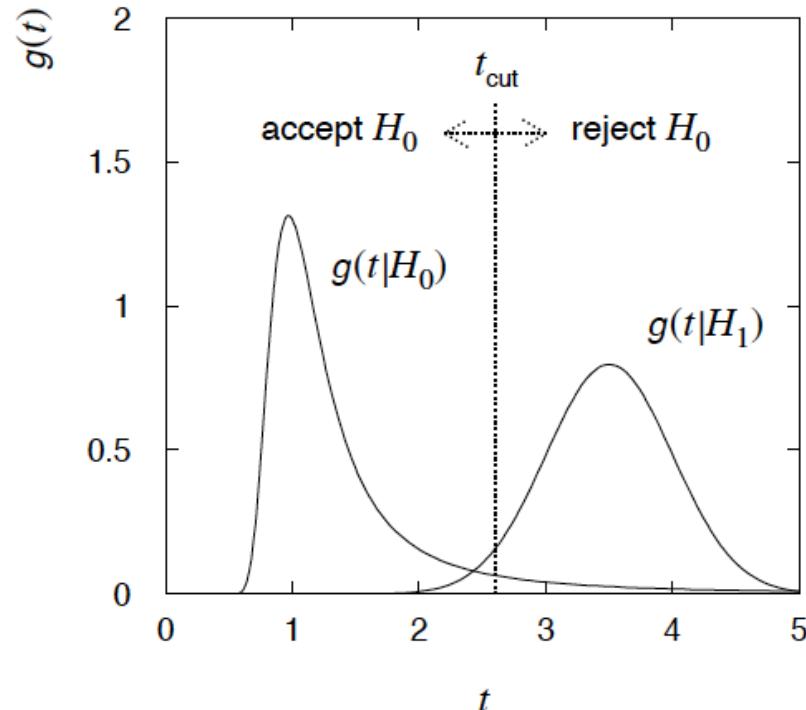
$$t(x_1, \dots, x_n) = t_{\text{cut}}$$

where  $t(x_1, \dots, x_n)$  is a scalar test statistic.

We can work out the pdfs  $g(t|H_0)$ ,  $g(t|H_1)$ , ...

Decision boundary is now a single ‘cut’ on  $t$ , defining the critical region.

So for an  $n$ -dimensional problem we have a corresponding 1-d problem.



# Test statistic based on likelihood ratio

How can we choose a test's critical region in an ‘optimal way’?

Neyman-Pearson lemma states:

To get the highest power for a given significance level in a test of  $H_0$ , (background) versus  $H_1$ , (signal) the critical region should have

$$\frac{P(\mathbf{x}|H_1)}{P(\mathbf{x}|H_0)} > c$$

inside the region, and  $\leq c$  outside, where  $c$  is a constant which determines the power.

Equivalently, optimal scalar test statistic is

$$t(\mathbf{x}) = \frac{P(\mathbf{x}|H_1)}{P(\mathbf{x}|H_0)}$$

N.B. any monotonic function of this leads to the same test.

## *p*-values

Suppose hypothesis  $H$  predicts pdf  $f(\vec{x}|H)$  for a set of observations  $\vec{x} = (x_1, \dots, x_n)$ .

We observe a single point in this space:  $\vec{x}_{\text{obs}}$

What can we say about the validity of  $H$  in light of the data?

Express level of compatibility by giving the *p*-value for  $H$ :

$p$  = probability, under assumption of  $H$ , to observe data with equal or lesser compatibility with  $H$  relative to the data we got.

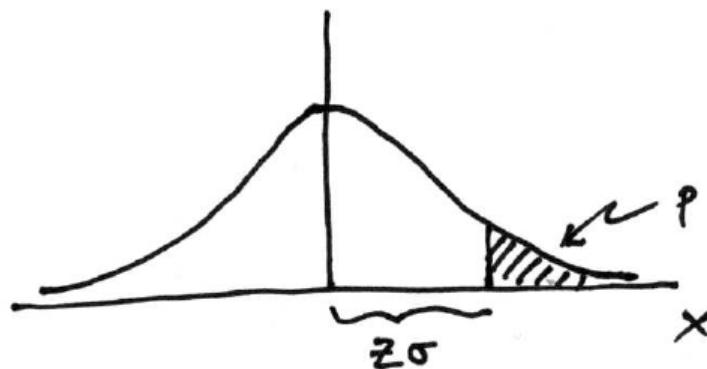


This is not the probability that  $H$  is true!

Requires one to say what part of data space constitutes lesser compatibility with  $H$  than the observed data (implicitly this means that region gives better agreement with some alternative).

# Significance from $p$ -value

Often define significance  $Z$  as the number of standard deviations that a Gaussian variable would fluctuate in one direction to give the same  $p$ -value.



$$p = \int_Z^\infty \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx = 1 - \Phi(Z) \quad 1 - \text{TMath::Freq}$$

$$Z = \Phi^{-1}(1 - p) \quad \text{TMath::NormQuantile}$$

E.g.  $Z = 5$  (a “5 sigma effect”) corresponds to  $p = 2.9 \times 10^{-7}$ .

## Using a $p$ -value to define test of $H_0$

One can show the distribution of the  $p$ -value of  $H$ , under assumption of  $H$ , is uniform in  $[0,1]$ .

So the probability to find the  $p$ -value of  $H_0$ ,  $p_0$ , less than  $\alpha$  is

$$P(p_0 \leq \alpha | H_0) = \alpha$$

We can define the critical region of a test of  $H_0$  with size  $\alpha$  as the set of data space where  $p_0 \leq \alpha$ .

Formally the  $p$ -value relates only to  $H_0$ , but the resulting test will have a given power with respect to a given alternative  $H_1$ .

# Confidence intervals by inverting a test

Confidence intervals for a parameter  $\theta$  can be found by defining a **test** of the hypothesized value  $\theta$  (do this for all  $\theta$ ):

Specify values of the data that are ‘disfavoured’ by  $\theta$  (critical region) such that  $P(\text{data in critical region}) \leq \alpha$  for a prespecified  $\alpha$ , e.g., 0.05 or 0.1.

If data observed in the critical region, reject the value  $\theta$ .

Now invert the test to define a **confidence interval** as:

set of  $\theta$  values that would **not** be rejected in a test of size  $\alpha$  (confidence level is  $1 - \alpha$ ).

The interval will cover the true value of  $\theta$  with probability  $\geq 1 - \alpha$ .

Equivalently, the parameter values in the confidence interval have *p*-values of at least  $\alpha$ .

# Ingredients for a frequentist test

In general to carry out a test we need to know the distribution of the test statistic  $t(x)$ , and this means we need the full model  $P(x|H)$ .

Often one can construct a test statistic whose distribution approaches a well-defined form (almost) independent of the distribution of the data, e.g., likelihood ratio to test a value of  $\theta$ :

$$t_\theta = -2 \ln \frac{L(\theta)}{L(\hat{\theta})}$$

In the large sample limit  $t_\theta$  follows a chi-square distribution with number of degrees of freedom = number of components in  $\theta$  (Wilks' theorem).

So here one doesn't need the full model  $P(x|\theta)$ , only the observed value of  $t_\theta$ .

# The Poisson counting experiment

Suppose we observe  $n$  events; these can consist of:

$n_b$  events from known processes (background)

$n_s$  events from a new process (signal)

If  $n_s, n_b$  are Poisson r.v.s with means  $s, b$ , then  $n = n_s + n_b$  is also Poisson, mean =  $s + b$ :

$$P(n; s, b) = \frac{(s + b)^n}{n!} e^{-(s+b)}$$

Suppose  $b = 0.5$ , and we observe  $n_{\text{obs}} = 5$ . Should we claim evidence for a new discovery?

Give  $p$ -value for hypothesis  $s = 0$ :

$$p\text{-value} = P(n \geq 5; b = 0.5, s = 0)$$

$$= 1.7 \times 10^{-4} \neq P(s = 0)!$$

# Frequentist upper limit on Poisson parameter

Consider again the case of observing  $n \sim \text{Poisson}(s + b)$ .

Suppose  $b = 4.5$ ,  $n_{\text{obs}} = 5$ . Find upper limit on  $s$  at 95% CL.

Relevant alternative is  $s = 0$  (critical region at low  $n$ )

$p$ -value of hypothesized  $s$  is  $P(n \leq n_{\text{obs}}; s, b)$

Upper limit  $s_{\text{up}}$  at CL =  $1 - \alpha$  found from

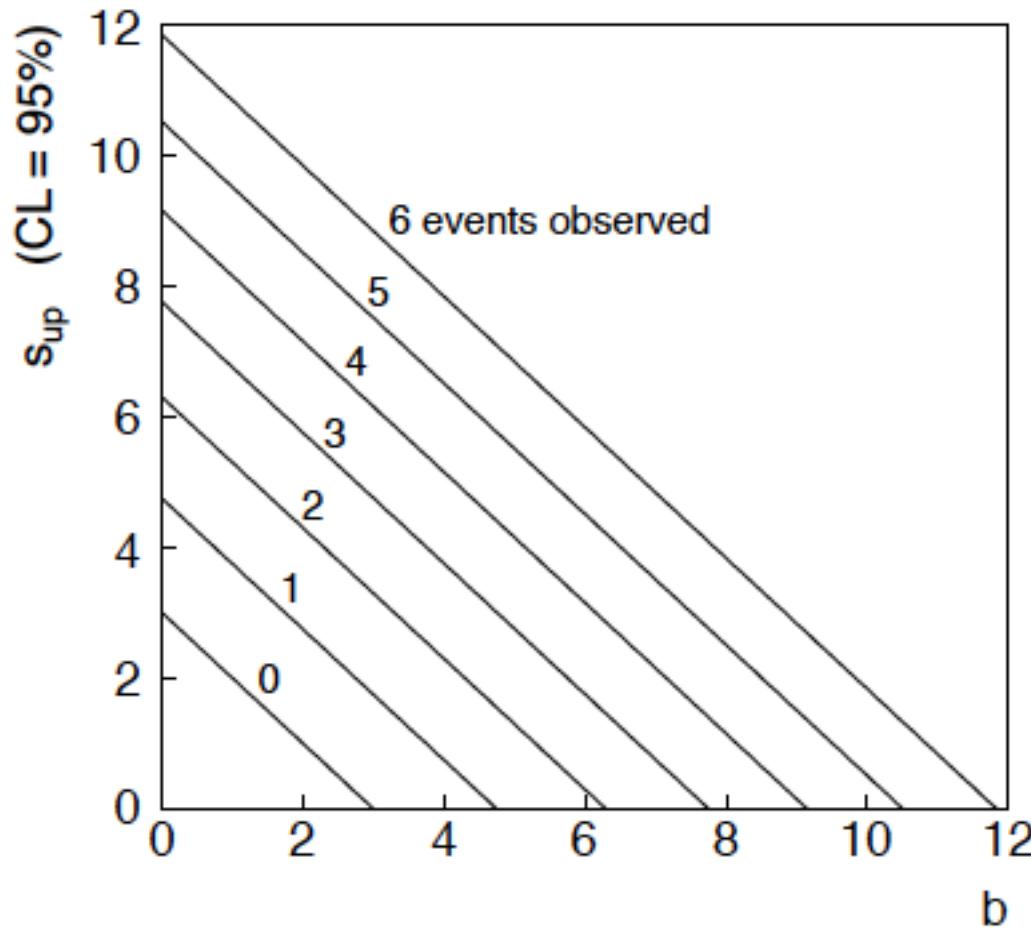
$$\alpha = P(n \leq n_{\text{obs}}; s_{\text{up}}, b) = \sum_{n=0}^{n_{\text{obs}}} \frac{(s_{\text{up}} + b)^n}{n!} e^{-(s_{\text{up}} + b)}$$

$$s_{\text{up}} = \frac{1}{2} F_{\chi^2}^{-1}(1 - \alpha; 2(n_{\text{obs}} + 1)) - b$$

$$= \frac{1}{2} F_{\chi^2}^{-1}(0.95; 2(5 + 1)) - 4.5 = 6.0$$

$n \sim \text{Poisson}(s+b)$ : frequentist upper limit on  $s$

For low fluctuation of  $n$  formula can give negative result for  $s_{\text{up}}$ ;  
i.e. confidence interval is empty.



# Limits near a physical boundary

Suppose e.g.  $b = 2.5$  and we observe  $n = 0$ .

If we choose CL = 0.9, we find from the formula for  $s_{\text{up}}$

$$s_{\text{up}} = -0.197 \quad (\text{CL} = 0.90)$$

Physicist:

We already knew  $s \geq 0$  before we started; can't use negative upper limit to report result of expensive experiment!

Statistician:

The interval is designed to cover the true value only 90% of the time — this was clearly not one of those times.

Not uncommon dilemma when testing parameter values for which one has very little experimental sensitivity, e.g., very small  $s$ .

## Expected limit for $s = 0$

Physicist: I should have used  $CL = 0.95$  — then  $s_{\text{up}} = 0.496$

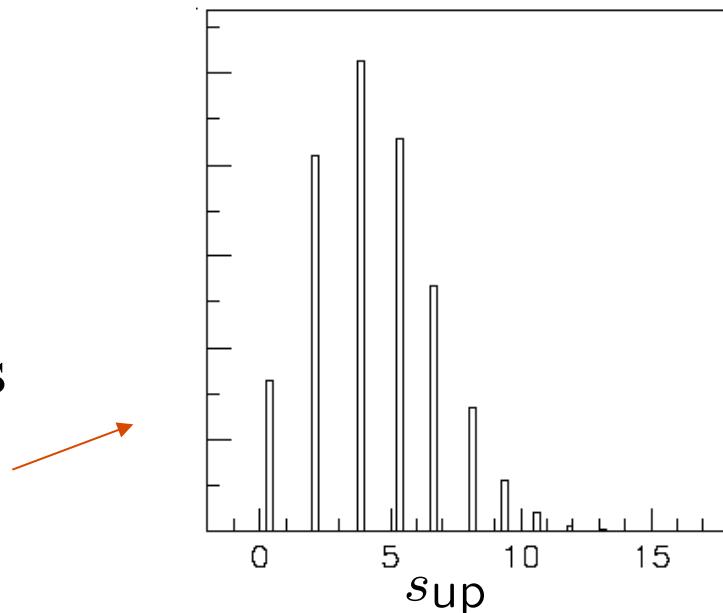
Even better: for  $CL = 0.917923$  we get  $s_{\text{up}} = 10^{-4}$  !

Reality check: with  $b = 2.5$ , typical Poisson fluctuation in  $n$  is at least  $\sqrt{2.5} = 1.6$ . How can the limit be so low?

Look at the mean limit for the no-signal hypothesis ( $s = 0$ ) (sensitivity).

Distribution of 95% CL limits with  $b = 2.5, s = 0$ .

Mean upper limit = 4.44



# The Bayesian approach to limits

In Bayesian statistics need to start with ‘prior pdf’  $\pi(\theta)$ , this reflects degree of belief about  $\theta$  before doing the experiment.

Bayes’ theorem tells how our beliefs should be updated in light of the data  $x$ :

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

Integrate posterior pdf  $p(\theta|x)$  to give interval with any desired probability content.

For e.g.  $n \sim \text{Poisson}(s+b)$ , 95% CL upper limit on  $s$  from

$$0.95 = \int_{-\infty}^{s_{\text{up}}} p(s|n) ds$$

# Bayesian prior for Poisson parameter

Include knowledge that  $s \geq 0$  by setting prior  $\pi(s) = 0$  for  $s < 0$ .

Could try to reflect ‘prior ignorance’ with e.g.

$$\pi(s) = \begin{cases} 1 & s \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

Not normalized but this is OK as long as  $L(s)$  dies off for large  $s$ .

Not invariant under change of parameter — if we had used instead a flat prior for, say, the mass of the Higgs boson, this would imply a non-flat prior for the expected number of Higgs events.

Doesn’t really reflect a reasonable degree of belief, but often used as a point of reference;

or viewed as a recipe for producing an interval whose frequentist properties can be studied (coverage will depend on true  $s$ ).

# Bayesian interval with flat prior for $s$

Solve to find limit  $s_{\text{up}}$ :

$$s_{\text{up}} = \frac{1}{2} F_{\chi^2}^{-1} [p, 2(n+1)] - b$$

where

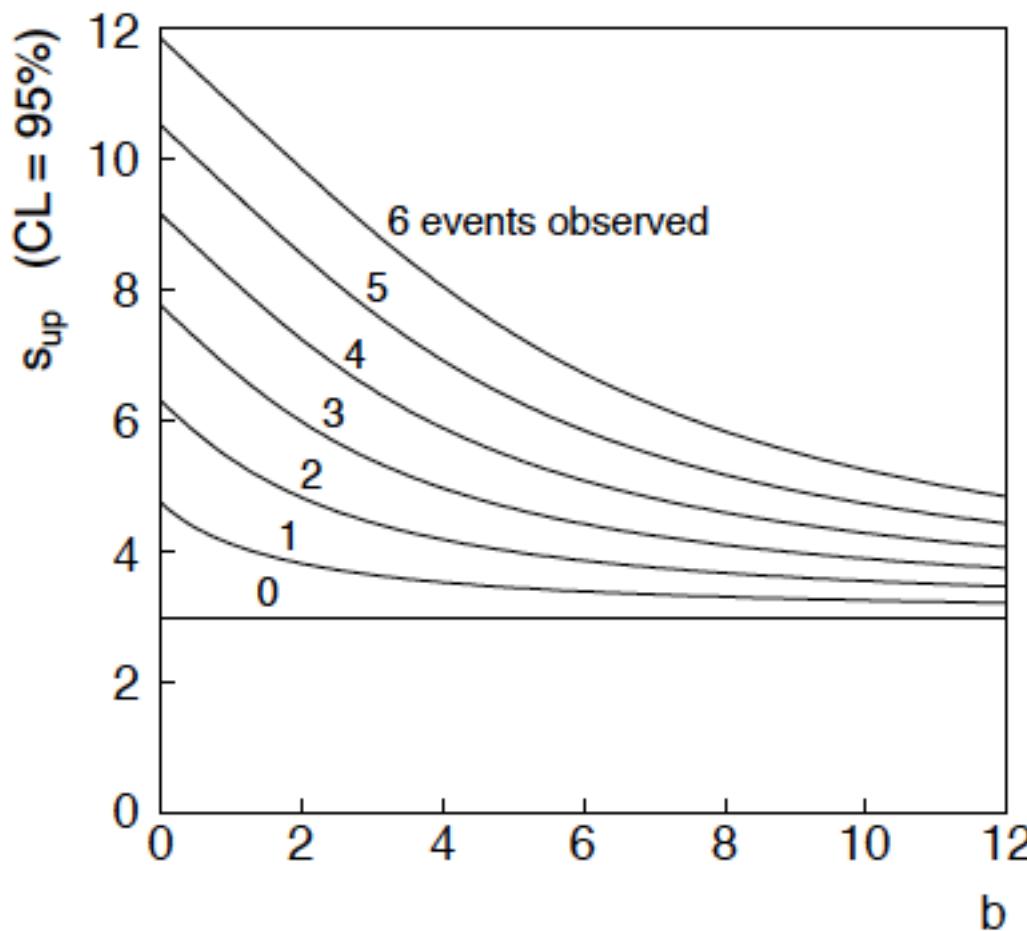
$$p = 1 - \alpha \left( 1 - F_{\chi^2} [2b, 2(n+1)] \right)$$

For special case  $b = 0$ , Bayesian upper limit with flat prior numerically same as one-sided frequentist case ('coincidence').

# Bayesian interval with flat prior for $s$

For  $b > 0$  Bayesian limit is everywhere greater than the (one sided) frequentist upper limit.

Never goes negative. Doesn't depend on  $b$  if  $n = 0$ .



# Priors from formal rules

Because of difficulties in encoding a vague degree of belief in a prior, one often attempts to derive the prior from formal rules, e.g., to satisfy certain invariance principles or to provide maximum information gain for a certain set of measurements.

Often called “objective priors”

Form basis of Objective Bayesian Statistics

The priors do not reflect a degree of belief (but might represent possible extreme cases).

In Objective Bayesian analysis, can use the intervals in a frequentist way, i.e., regard Bayes’ theorem as a recipe to produce an interval with certain coverage properties.

# Priors from formal rules (cont.)

For a review of priors obtained by formal rules see, e.g.,

Robert E. Kass and Larry Wasserman, *The Selection of Prior Distributions by Formal Rules*, J. Am. Stat. Assoc., Vol. 91, No. 435, pp. 1343-1370 (1996).

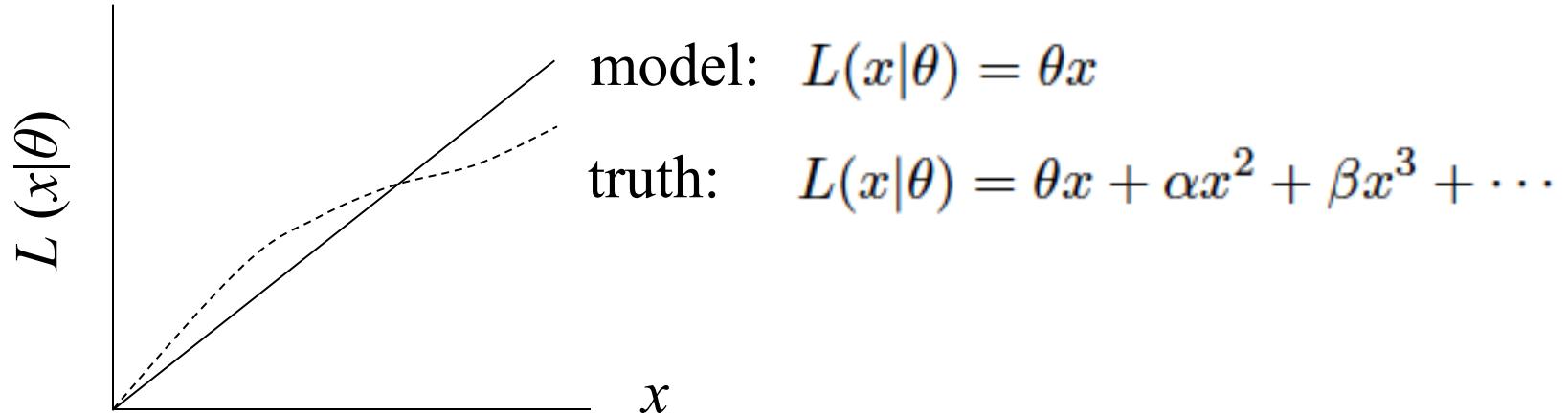
Formal priors have not been widely used in HEP, but there is recent interest in this direction, especially the reference priors of Bernardo and Berger; see e.g.

L. Demortier, S. Jain and H. Prosper, *Reference priors for high energy physics*, Phys. Rev. D 82 (2010) 034002, arXiv:1002.1111.

D. Casadei, *Reference analysis of the signal + background model in counting experiments*, JINST 7 (2012) 01012; arXiv:1108.4270.

# Systematic uncertainties and nuisance parameters

In general our model of the data is not perfect:



Can improve model by including additional adjustable parameters.

$$L(x|\theta) \rightarrow L(x|\theta, \nu)$$

Nuisance parameter  $\leftrightarrow$  systematic uncertainty. Some point in the parameter space of the enlarged model should be “true”.

Presence of nuisance parameter decreases sensitivity of analysis to the parameter of interest (e.g., increases variance of estimate).

# Example: fitting a straight line

Data:  $(x_i, y_i, \sigma_i)$ ,  $i = 1, \dots, n$ .

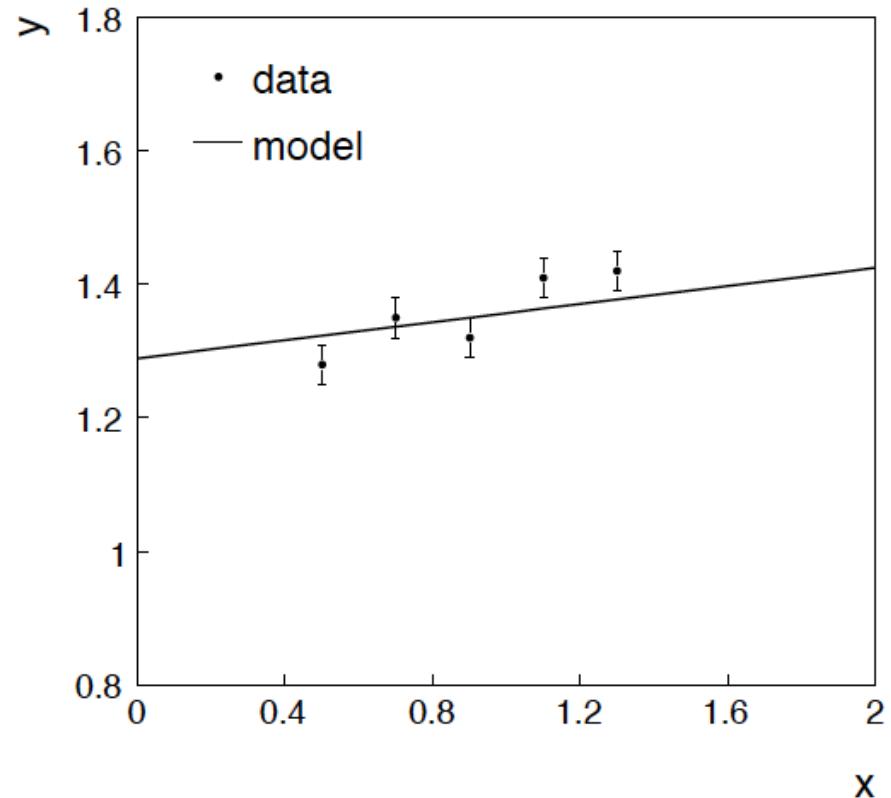
Model:  $y_i$  independent and all follow  $y_i \sim \text{Gauss}(\mu(x_i), \sigma_i)$

$$\mu(x; \theta_0, \theta_1) = \theta_0 + \theta_1 x,$$

assume  $x_i$  and  $\sigma_i$  known.

Goal: estimate  $\theta_0$

Here suppose we don't care about  $\theta_1$  (example of a “nuisance parameter”)



# Maximum likelihood fit with Gaussian data

In this example, the  $y_i$  are assumed independent, so the likelihood function is a product of Gaussians:

$$L(\theta_0, \theta_1) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi}\sigma_i} \exp \left[ -\frac{1}{2} \frac{(y_i - \mu(x_i; \theta_0, \theta_1))^2}{\sigma_i^2} \right],$$

Maximizing the likelihood is here equivalent to minimizing

$$\chi^2(\theta_0, \theta_1) = -2 \ln L(\theta_0, \theta_1) + \text{const} = \sum_{i=1}^n \frac{(y_i - \mu(x_i; \theta_0, \theta_1))^2}{\sigma_i^2}.$$

i.e., for Gaussian data, ML same as Method of Least Squares (LS)

# $\theta_1$ known a priori

$$L(\theta_0) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi}\sigma_i} \exp \left[ -\frac{1}{2} \frac{(y_i - \mu(x_i; \theta_0, \theta_1))^2}{\sigma_i^2} \right].$$

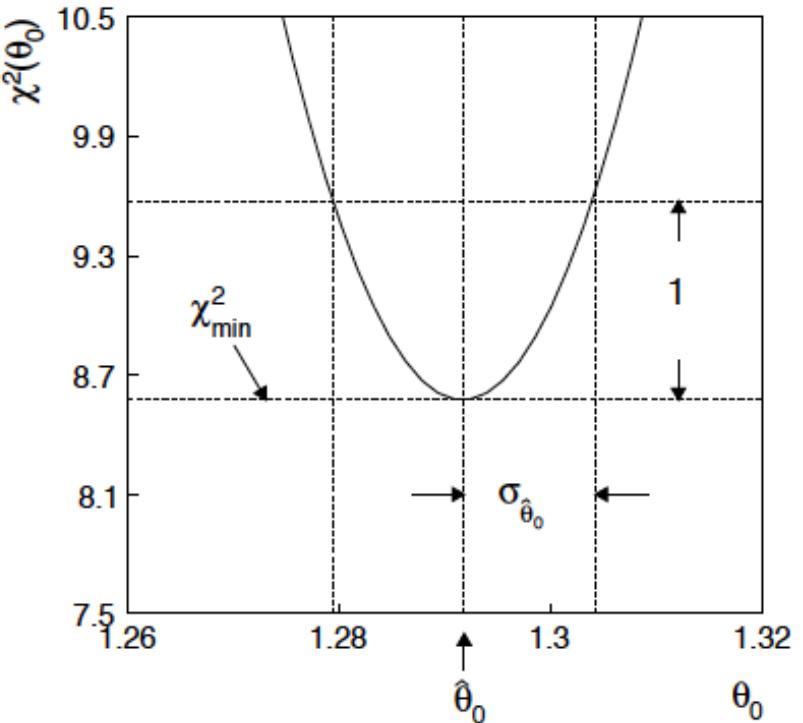
$$\chi^2(\theta_0) = -2 \ln L(\theta_0) + \text{const} = \sum_{i=1}^n \frac{(y_i - \mu(x_i; \theta_0, \theta_1))^2}{\sigma_i^2}.$$

For Gaussian  $y_i$ , ML same as LS

Minimize  $\chi^2 \rightarrow$  estimator  $\hat{\theta}_0$ .

Come up one unit from  $\chi^2_{\min}$

to find  $\sigma_{\hat{\theta}_0}$ .



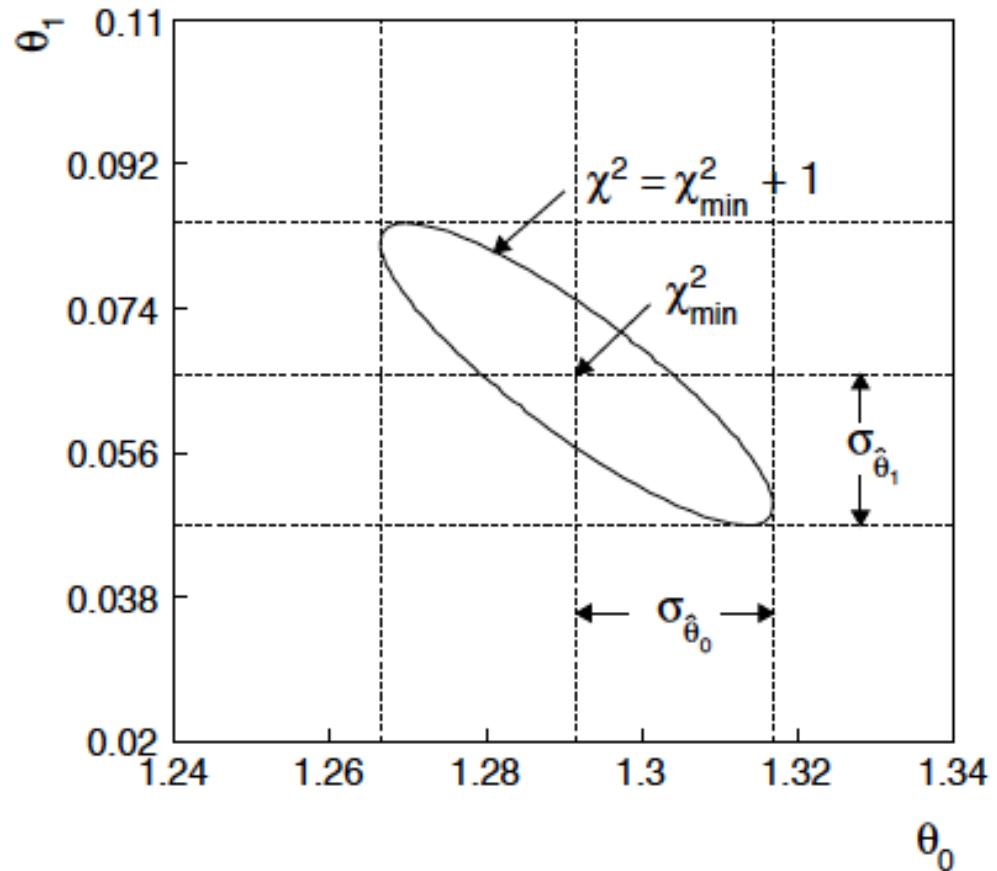
# ML (or LS) fit of $\theta_0$ and $\theta_1$

$$\chi^2(\theta_0, \theta_1) = -2 \ln L(\theta_0, \theta_1) + \text{const} = \sum_{i=1}^n \frac{(y_i - \mu(x_i; \theta_0, \theta_1))^2}{\sigma_i^2}.$$

Standard deviations from  
tangent lines to contour

$$\chi^2 = \chi^2_{\min} + 1.$$

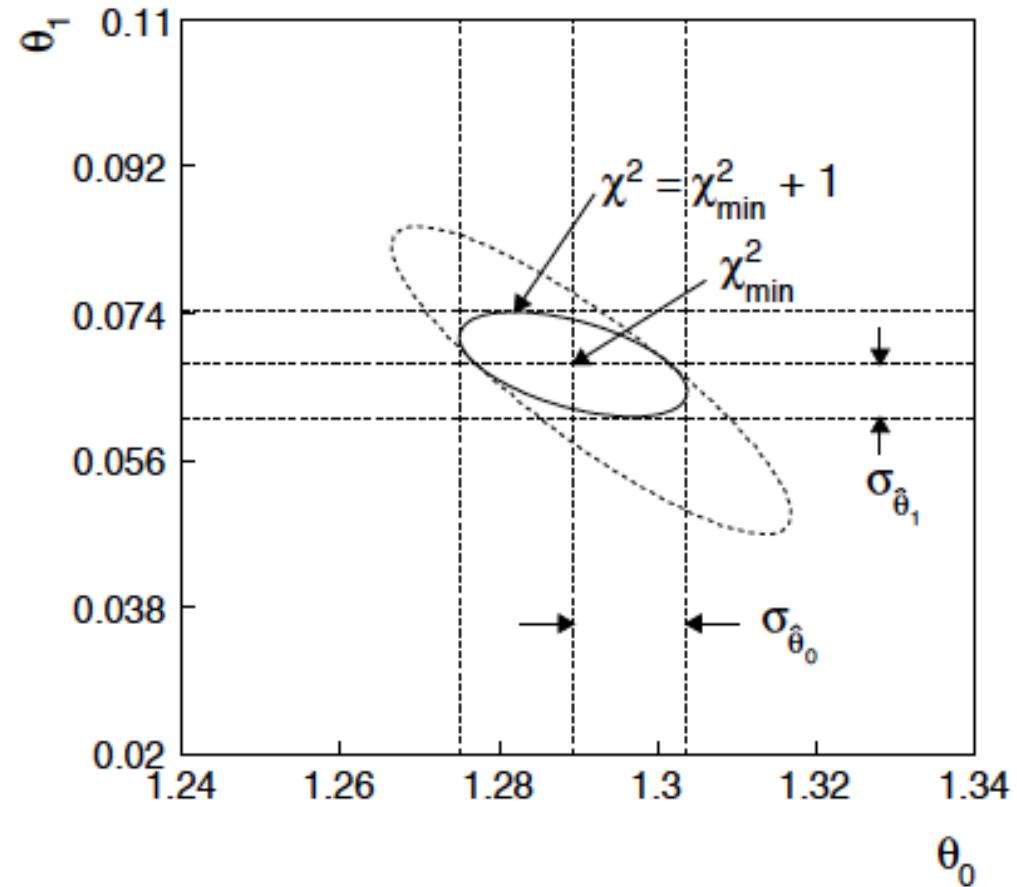
Correlation between  
 $\hat{\theta}_0, \hat{\theta}_1$  causes errors  
to increase.



If we have a measurement  $t_1 \sim \text{Gauss}(\theta_1, \sigma_{t1})$

$$\chi^2(\theta_0, \theta_1) = \sum_{i=1}^n \frac{(y_i - \mu(x_i; \theta_0, \theta_1))^2}{\sigma_i^2} + \frac{(\theta_1 - t_1)^2}{\sigma_{t1}^2}.$$

The information on  $\theta_1$   
improves accuracy of  $\hat{\theta}_0$ .



# Bayesian method

We need to associate prior probabilities with  $\theta_0$  and  $\theta_1$ , e.g.,

$$\pi(\theta_0, \theta_1) = \pi_0(\theta_0) \pi_1(\theta_1)$$

$$\pi_0(\theta_0) = \text{const.}$$

$$\pi_1(\theta_1) = \frac{1}{\sqrt{2\pi}\sigma_{t_1}} e^{-(\theta_1 - t_1)^2 / 2\sigma_{t_1}^2}$$

'non-informative', in any case much broader than  $L(\theta_0)$

← based on previous measurement

Putting this into Bayes' theorem gives:

$$p(\theta_0, \theta_1 | \vec{y}) \propto \prod_{i=1}^n \frac{1}{\sqrt{2\pi}\sigma_i} e^{-(y_i - \mu(x_i; \theta_0, \theta_1))^2 / 2\sigma_i^2} \pi_0 \frac{1}{\sqrt{2\pi}\sigma_{t_1}} e^{-(\theta_1 - t_1)^2 / 2\sigma_{t_1}^2}$$

posterior  $\propto$

likelihood  $\times$  prior

# Bayesian method (continued)

We then integrate (marginalize)  $p(\theta_0, \theta_1 | x)$  to find  $p(\theta_0 | x)$ :

$$p(\theta_0 | x) = \int p(\theta_0, \theta_1 | x) d\theta_1 .$$

In this example we can do the integral (rare). We find

$$p(\theta_0 | x) = \frac{1}{\sqrt{2\pi}\sigma_{\theta_0}} e^{-(\theta_0 - \hat{\theta}_0)^2 / 2\sigma_{\theta_0}^2} \quad \text{with}$$

$$\hat{\theta}_0 = \text{same as ML estimator}$$

$$\sigma_{\theta_0} = \sigma_{\hat{\theta}_0} \quad (\text{same as before})$$

Usually need numerical methods (e.g. Markov Chain Monte Carlo) to do integral.

# Digression: marginalization with MCMC

Bayesian computations involve integrals like

$$p(\theta_0|x) = \int p(\theta_0, \theta_1|x) d\theta_1 .$$

often high dimensionality and impossible in closed form,  
also impossible with ‘normal’ acceptance-rejection Monte Carlo.

Markov Chain Monte Carlo (MCMC) has revolutionized  
Bayesian computation.

MCMC (e.g., Metropolis-Hastings algorithm) generates  
correlated sequence of random numbers:

cannot use for many applications, e.g., detector MC;  
effective stat. error greater than if all values independent .

Basic idea: sample multidimensional  $\vec{\theta}$ ,  
look, e.g., only at distribution of parameters of interest.

# MCMC basics: Metropolis-Hastings algorithm

Goal: given an  $n$ -dimensional pdf  $p(\vec{\theta})$ ,  
generate a sequence of points  $\vec{\theta}_1, \vec{\theta}_2, \vec{\theta}_3, \dots$

1) Start at some point  $\vec{\theta}_0$

Proposal density  $q(\vec{\theta}; \vec{\theta}_0)$   
e.g. Gaussian centred  
about  $\vec{\theta}_0$

2) Generate  $\vec{\theta} \sim q(\vec{\theta}; \vec{\theta}_0)$

3) Form Hastings test ratio  $\alpha = \min \left[ 1, \frac{p(\vec{\theta})q(\vec{\theta}_0; \vec{\theta})}{p(\vec{\theta}_0)q(\vec{\theta}; \vec{\theta}_0)} \right]$

4) Generate  $u \sim \text{Uniform}[0, 1]$

5) If  $u \leq \alpha$ ,  $\vec{\theta}_1 = \vec{\theta}$ ,  $\leftarrow$  move to proposed point

else  $\vec{\theta}_1 = \vec{\theta}_0$   $\leftarrow$  old point repeated

6) Iterate

# Metropolis-Hastings (continued)

This rule produces a *correlated* sequence of points (note how each new point depends on the previous one).

For our purposes this correlation is not fatal, but statistical errors larger than if points were independent.

The proposal density can be (almost) anything, but choose so as to minimize autocorrelation. Often take proposal density symmetric:  $q(\vec{\theta}; \vec{\theta}_0) = q(\vec{\theta}_0; \vec{\theta})$

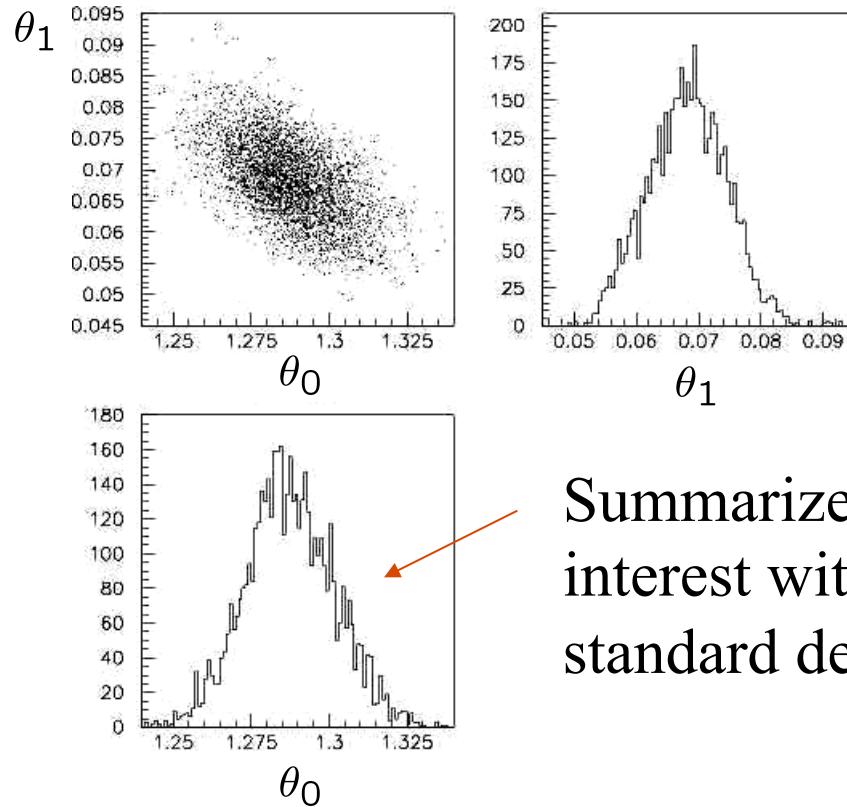
Test ratio is (*Metropolis-Hastings*):  $\alpha = \min \left[ 1, \frac{p(\vec{\theta})}{p(\vec{\theta}_0)} \right]$

I.e. if the proposed step is to a point of higher  $p(\vec{\theta})$ , take it; if not, only take the step with probability  $p(\vec{\theta})/p(\vec{\theta}_0)$ .

If proposed step rejected, hop in place.

# Example: posterior pdf from MCMC

Sample the posterior pdf from previous example with MCMC:



Summarize pdf of parameter of interest with, e.g., mean, median, standard deviation, etc.

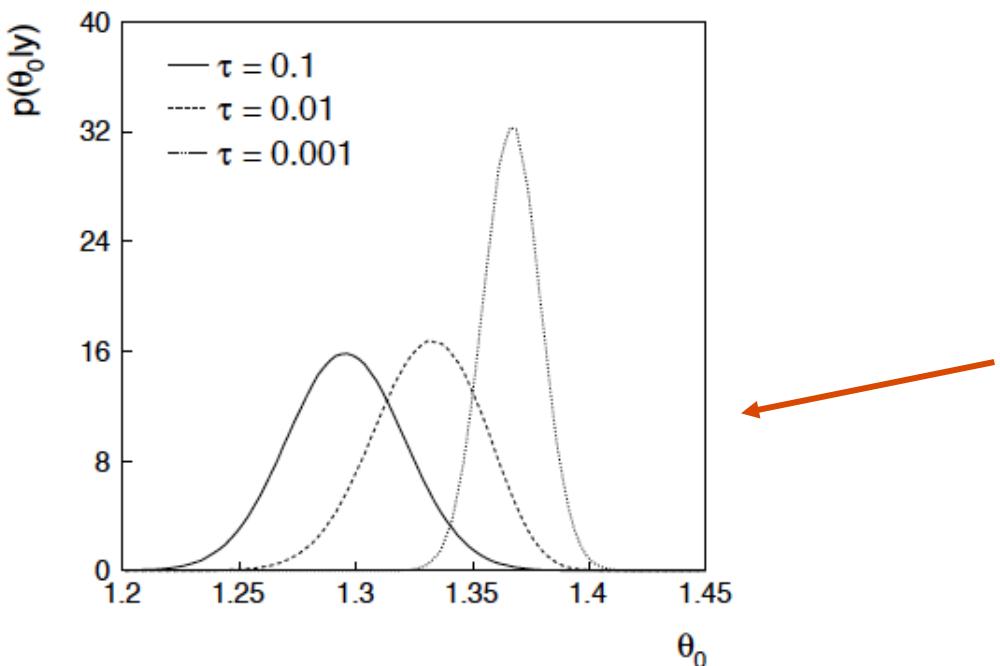
Although numerical values of answer here same as in frequentist case, interpretation is different (sometimes unimportant?)

# Bayesian method with alternative priors

Suppose we don't have a previous measurement of  $\theta_1$  but rather, e.g., a theorist says it should be positive and not too much greater than 0.1 "or so", i.e., something like

$$\pi_1(\theta_1) = \frac{1}{\tau} e^{-\theta_1/\tau}, \quad \theta_1 \geq 0, \quad \tau = 0.1.$$

From this we obtain (numerically) the posterior pdf for  $\theta_0$ :



This summarizes all knowledge about  $\theta_0$ .

Look also at result from variety of priors.

# Prototype search analysis

Search for signal in a region of phase space; result is histogram of some variable  $x$  giving numbers:

$$\mathbf{n} = (n_1, \dots, n_N)$$

Assume the  $n_i$  are Poisson distributed with expectation values

$$E[n_i] = \mu s_i + b_i$$

strength parameter

where

$$s_i = s_{\text{tot}} \int_{\text{bin } i} f_s(x; \boldsymbol{\theta}_s) dx, \quad b_i = b_{\text{tot}} \int_{\text{bin } i} f_b(x; \boldsymbol{\theta}_b) dx.$$

signal

background

## Prototype analysis (II)

Often also have a subsidiary measurement that constrains some of the background and/or shape parameters:

$$\mathbf{m} = (m_1, \dots, m_M)$$

Assume the  $m_i$  are Poisson distributed with expectation values

$$E[m_i] = u_i(\boldsymbol{\theta})$$



nuisance parameters ( $\boldsymbol{\theta}_s, \boldsymbol{\theta}_b, b_{\text{tot}}$ )

Likelihood function is

$$L(\mu, \boldsymbol{\theta}) = \prod_{j=1}^N \frac{(\mu s_j + b_j)^{n_j}}{n_j!} e^{-(\mu s_j + b_j)} \prod_{k=1}^M \frac{u_k^{m_k}}{m_k!} e^{-u_k}$$

# The profile likelihood ratio

Base significance test on the profile likelihood ratio:

$$\lambda(\mu) = \frac{L(\mu, \hat{\theta})}{L(\hat{\mu}, \hat{\theta})}$$

maximizes  $L$  for  
Specified  $\mu$

maximize  $L$

The likelihood ratio of point hypotheses gives optimum test (Neyman-Pearson lemma).

The profile LR should be near-optimal in present analysis with variable  $\mu$  and nuisance parameters  $\theta$ .

## Test statistic for discovery

Try to reject background-only ( $\mu = 0$ ) hypothesis using

$$q_0 = \begin{cases} -2 \ln \lambda(0) & \hat{\mu} \geq 0 \\ 0 & \hat{\mu} < 0 \end{cases}$$

i.e. here only regard upward fluctuation of data as evidence against the background-only hypothesis.

Note that even if physical models have  $\mu \geq 0$ , we allow  $\hat{\mu}$  to be negative. In large sample limit its distribution becomes Gaussian, and this will allow us to write down simple expressions for distributions of our test statistics.

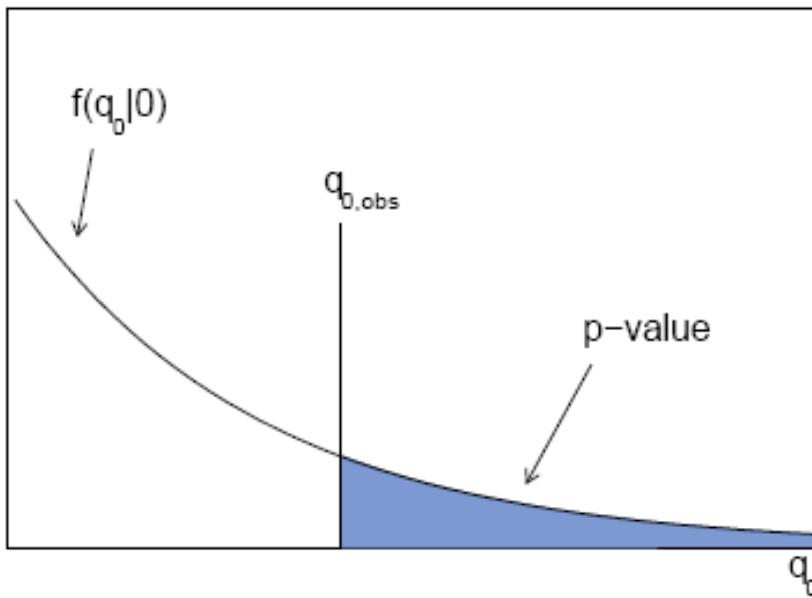
## *p*-value for discovery

Large  $q_0$  means increasing incompatibility between the data and hypothesis, therefore *p*-value for an observed  $q_{0,\text{obs}}$  is

$$p_0 = \int_{q_{0,\text{obs}}}^{\infty} f(q_0|0) dq_0$$



will get formula for this later

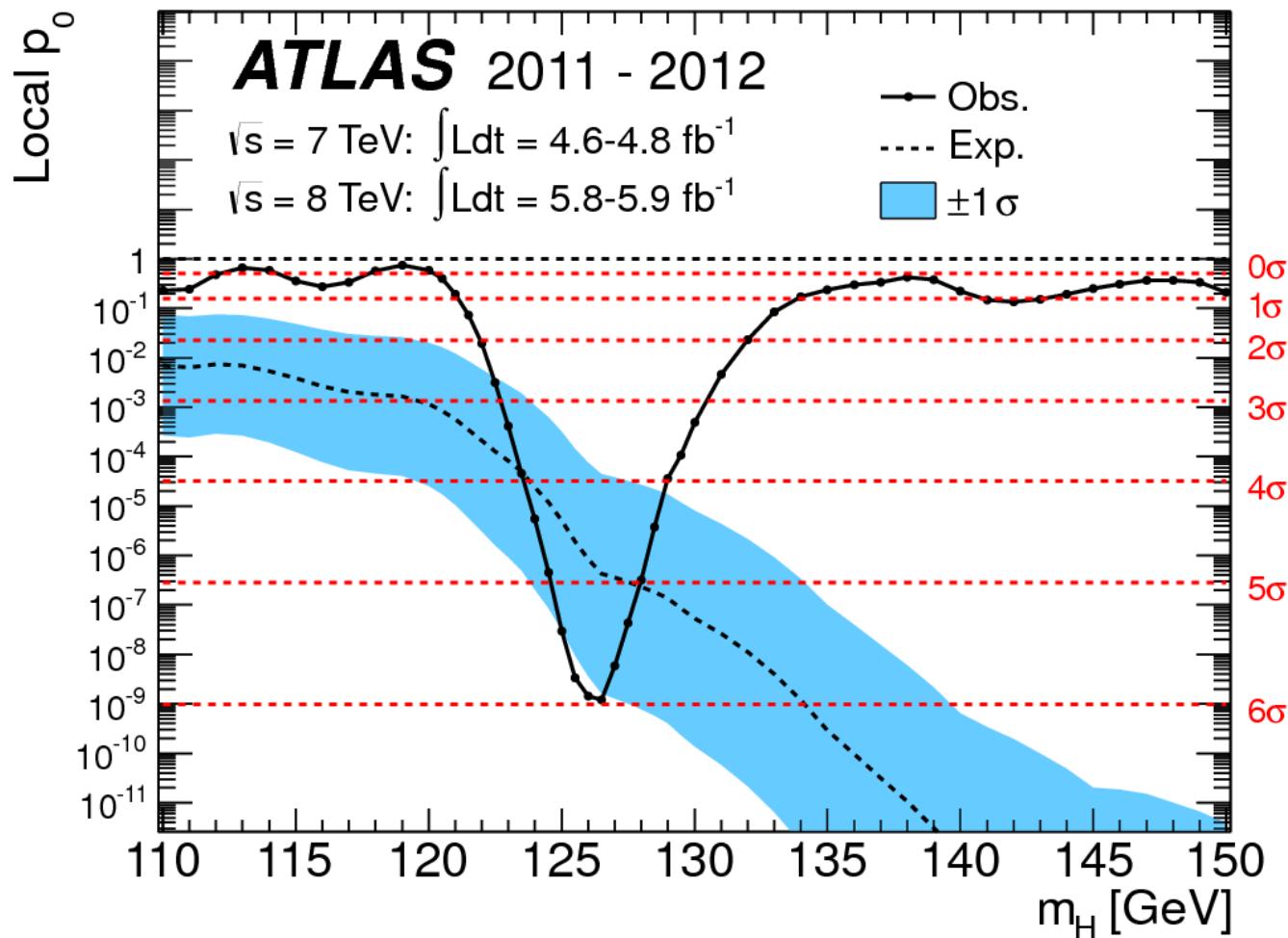


From *p*-value get equivalent significance,

$$Z = \Phi^{-1}(1 - p)$$

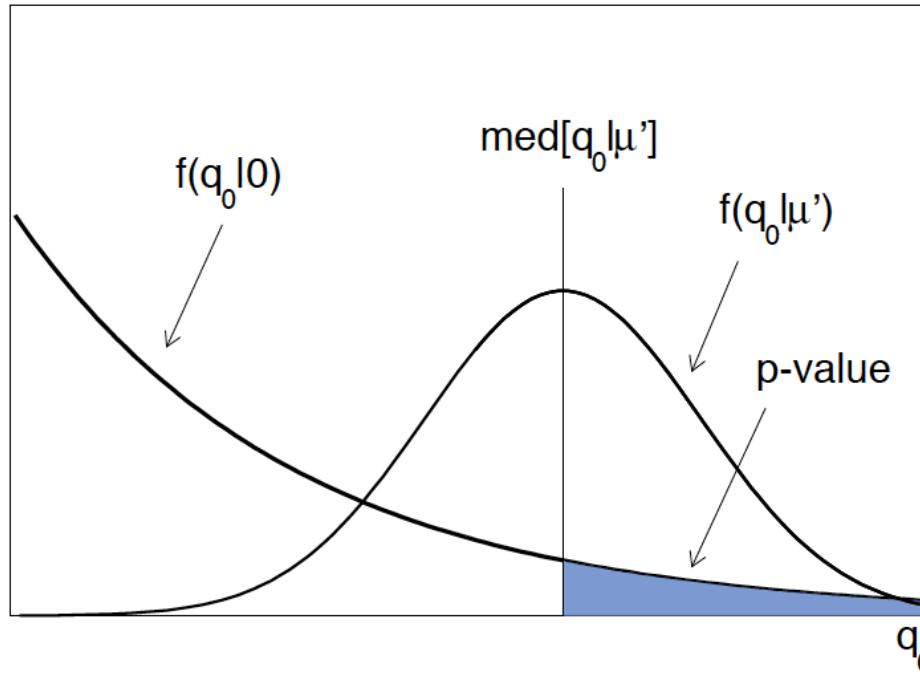
# Example of a $p$ -value

ATLAS, Phys. Lett. B 716 (2012) 1-29



# Expected (or median) significance / sensitivity

When planning the experiment, we want to quantify how sensitive we are to a potential discovery, e.g., by given median significance assuming some nonzero strength parameter  $\mu'$ .



So for  $p$ -value, need  $f(q_0|0)$ , for sensitivity, will need  $f(q_0|\mu')$ ,

# Distribution of $q_0$ in large-sample limit

Assuming approximations valid in the large sample (asymptotic) limit, we can write down the full distribution of  $q_0$  as

$$f(q_0|\mu') = \left(1 - \Phi\left(\frac{\mu'}{\sigma}\right)\right) \delta(q_0) + \frac{1}{2} \frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{q_0}} \exp\left[-\frac{1}{2} \left(\sqrt{q_0} - \frac{\mu'}{\sigma}\right)^2\right]$$

The special case  $\mu' = 0$  is a “half chi-square” distribution:

$$f(q_0|0) = \frac{1}{2} \delta(q_0) + \frac{1}{2} \frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{q_0}} e^{-q_0/2}$$

In large sample limit,  $f(q_0|0)$  independent of nuisance parameters;  $f(q_0|\mu')$  depends on nuisance parameters through  $\sigma$ .

# Cumulative distribution of $q_0$ , significance

From the pdf, the cumulative distribution of  $q_0$  is found to be

$$F(q_0|\mu') = \Phi\left(\sqrt{q_0} - \frac{\mu'}{\sigma}\right)$$

The special case  $\mu' = 0$  is

$$F(q_0|0) = \Phi\left(\sqrt{q_0}\right)$$

The  $p$ -value of the  $\mu = 0$  hypothesis is

$$p_0 = 1 - F(q_0|0)$$

Therefore the discovery significance  $Z$  is simply

$$Z = \Phi^{-1}(1 - p_0) = \sqrt{q_0}$$

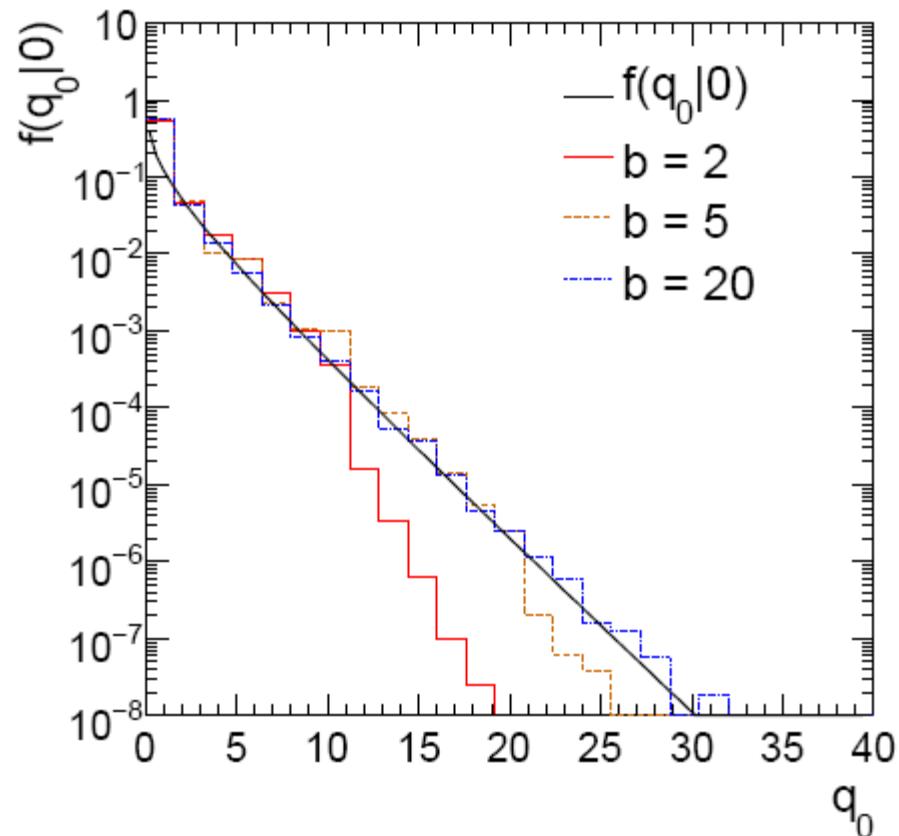
# Monte Carlo test of asymptotic formula

$$n \sim \text{Poisson}(\mu s + b)$$

$$m \sim \text{Poisson}(\tau b)$$

Here take  $\tau = 1$ .

Asymptotic formula is good approximation to  $5\sigma$  level ( $q_0 = 25$ ) already for  $b \sim 20$ .



# Back to Poisson counting experiment

$n \sim \text{Poisson}(s+b)$ , where

$s$  = expected number of events from signal,

$b$  = expected number of background events.

To test for discovery of signal compute  $p$ -value of  $s = 0$  hypothesis,

$$p = P(n \geq n_{\text{obs}} | b) = \sum_{n=n_{\text{obs}}}^{\infty} \frac{b^n}{n!} e^{-b} = 1 - F_{\chi^2}(2b; 2n_{\text{obs}})$$

Usually convert to equivalent significance:  $Z = \Phi^{-1}(1 - p)$   
where  $\Phi$  is the standard Gaussian cumulative distribution, e.g.,  
 $Z > 5$  (a 5 sigma effect) means  $p < 2.9 \times 10^{-7}$ .

To characterize sensitivity to discovery, give expected (mean or median)  $Z$  under assumption of a given  $s$ .

# $s/\sqrt{b}$ for expected discovery significance

For large  $s + b$ ,  $n \rightarrow x \sim \text{Gaussian}(\mu, \sigma)$ ,  $\mu = s + b$ ,  $\sigma = \sqrt{s + b}$ .

For observed value  $x_{\text{obs}}$ ,  $p$ -value of  $s = 0$  is  $\text{Prob}(x > x_{\text{obs}} \mid s = 0)$ :

$$p_0 = 1 - \Phi\left(\frac{x_{\text{obs}} - b}{\sqrt{b}}\right)$$

Significance for rejecting  $s = 0$  is therefore

$$Z_0 = \Phi^{-1}(1 - p_0) = \frac{x_{\text{obs}} - b}{\sqrt{b}}$$

Expected (median) significance assuming signal rate  $s$  is

$$\text{median}[Z_0 \mid s + b] = \frac{s}{\sqrt{b}}$$

# Better approximation for significance

Poisson likelihood for parameter  $s$  is

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

For now  
no nuisance  
params.

To test for discovery use profile likelihood ratio:

$$q_0 = \begin{cases} -2 \ln \lambda(0) & \hat{s} \geq 0 , \\ 0 & \hat{s} < 0 . \end{cases}$$

$$\lambda(s) = \frac{L(s, \hat{\theta}(s))}{L(\hat{s}, \hat{\theta})}$$

So the likelihood ratio statistic for testing  $s = 0$  is

$$q_0 = -2 \ln \frac{L(0)}{L(\hat{s})} = 2 \left( n \ln \frac{n}{b} + b - n \right) \quad \text{for } n > b, 0 \text{ otherwise}$$

# Approximate Poisson significance (continued)

For sufficiently large  $s + b$ , (use Wilks' theorem),

$$Z = \sqrt{2 \left( n \ln \frac{n}{b} + b - n \right)} \quad \text{for } n > b \text{ and } Z = 0 \text{ otherwise.}$$

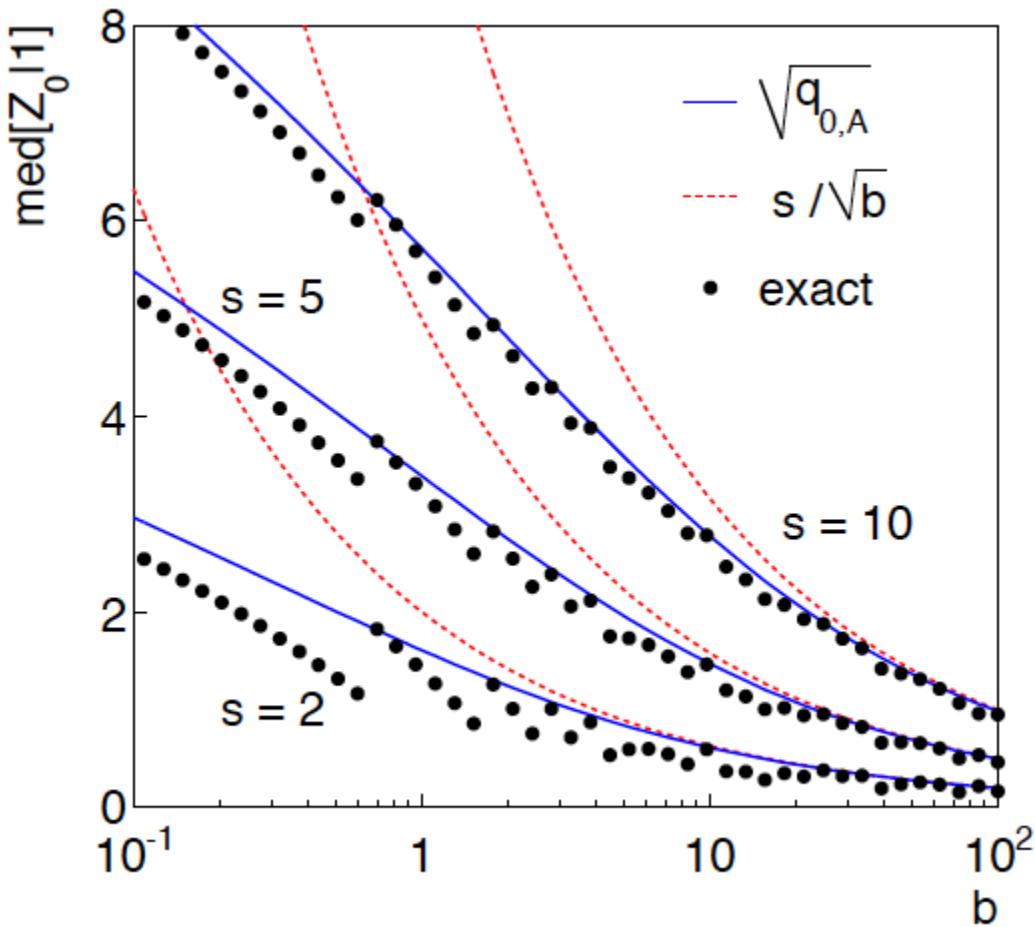
To find median[ $Z|s$ ], let  $n \rightarrow s + b$  (i.e., the Asimov data set):

$$Z_A = \sqrt{2 \left( (s + b) \ln \left( 1 + \frac{s}{b} \right) - s \right)}$$

This reduces to  $s/\sqrt{b}$  for  $s \ll b$ .

$n \sim \text{Poisson}(s+b)$ , median significance,  
assuming  $s$ , of the hypothesis  $s = 0$

CCGV, EPJC 71 (2011) 1554, arXiv:1007.1727



“Exact” values from MC,  
jumps due to discrete data.

Asimov  $\sqrt{q_{0,A}}$  good approx.  
for broad range of  $s, b$ .

$s/\sqrt{b}$  only good for  $s \ll b$ .

## Extending $s/\sqrt{b}$ to case where $b$ uncertain

The intuitive explanation of  $s/\sqrt{b}$  is that it compares the signal,  $s$ , to the standard deviation of  $n$  assuming no signal,  $\sqrt{b}$ .

Now suppose the value of  $b$  is uncertain, characterized by a standard deviation  $\sigma_b$ .

A reasonable guess is to replace  $\sqrt{b}$  by the quadratic sum of  $\sqrt{b}$  and  $\sigma_b$ , i.e.,

$$\text{med}[Z|s] = \frac{s}{\sqrt{b + \sigma_b^2}}$$

This has been used to optimize some analyses e.g. where  $\sigma_b$  cannot be neglected.

# Adding a control measurement for $b$

(The “on/off” problem: Cranmer 2005; Cousins, Linnemann, and Tucker 2008; Li and Ma 1983,...)

Measure two Poisson distributed values:

$$\begin{aligned} n &\sim \text{Poisson}(s+b) && \text{(primary or “search” measurement)} \\ m &\sim \text{Poisson}(\tau b) && \text{(control measurement, } \tau \text{ known)} \end{aligned}$$

The likelihood function is

$$L(s, b) = \frac{(s+b)^n}{n!} e^{-(s+b)} \frac{(\tau b)^m}{m!} e^{-\tau b}$$

Use this to construct profile likelihood ratio ( $b$  is nuisance parameter):

$$\lambda(0) = \frac{L(0, \hat{\hat{b}}(0))}{L(\hat{s}, \hat{b})}$$

# Ingredients for profile likelihood ratio

To construct profile likelihood ratio from this need estimators:

$$\hat{s} = n - m/\tau ,$$

$$\hat{b} = m/\tau ,$$

$$\hat{\hat{b}}(s) = \frac{n + m - (1 + \tau)s + \sqrt{(n + m - (1 + \tau)s)^2 + 4(1 + \tau)sm}}{2(1 + \tau)} .$$

and in particular to test for discovery ( $s = 0$ ),

$$\hat{\hat{b}}(0) = \frac{n + m}{1 + \tau}$$

# Asymptotic significance

Use profile likelihood ratio for  $q_0$ , and then from this get discovery significance using asymptotic approximation (Wilks' theorem):

$$Z = \sqrt{q_0} \\ = \left[ -2 \left( n \ln \left[ \frac{n+m}{(1+\tau)n} \right] + m \ln \left[ \frac{\tau(n+m)}{(1+\tau)m} \right] \right) \right]^{1/2}$$

for  $n > \hat{b}$  and  $Z = 0$  otherwise.

Essentially same as in:

Robert D. Cousins, James T. Linnemann and Jordan Tucker, NIM A 595 (2008) 480–501; arXiv:physics/0702156.

Tipei Li and Yuqian Ma, Astrophysical Journal 272 (1983) 317–324.

# Asimov approximation for median significance

To get median discovery significance, replace  $n, m$  by their expectation values assuming background-plus-signal model:

$$n \rightarrow s + b$$

$$m \rightarrow \tau b$$

$$Z_A = \left[ -2 \left( (s+b) \ln \left[ \frac{s + (1+\tau)b}{(1+\tau)(s+b)} \right] + \tau b \ln \left[ 1 + \frac{s}{(1+\tau)b} \right] \right) \right]^{1/2}$$

Or use the variance of  $\hat{b} = m/\tau$ ,  $V[\hat{b}] \equiv \sigma_b^2 = \frac{b}{\tau}$ , to eliminate  $\tau$ :

$$Z_A = \left[ 2 \left( (s+b) \ln \left[ \frac{(s+b)(b+\sigma_b^2)}{b^2 + (s+b)\sigma_b^2} \right] - \frac{b^2}{\sigma_b^2} \ln \left[ 1 + \frac{\sigma_b^2 s}{b(b+\sigma_b^2)} \right] \right) \right]^{1/2}$$

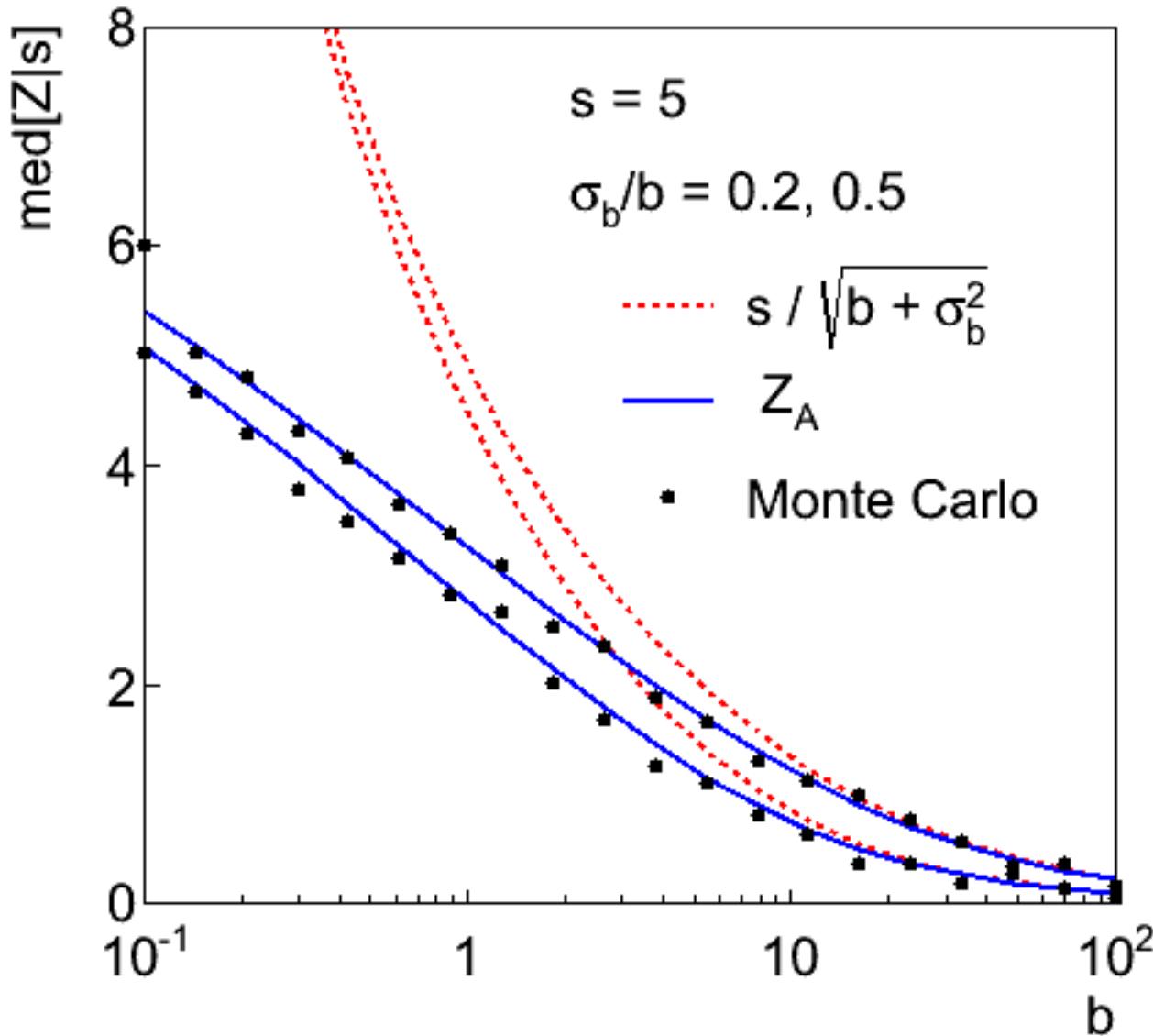
## Limiting cases

Expanding the Asimov formula in powers of  $s/b$  and  $\sigma_b^2/b$  ( $= 1/\tau$ ) gives

$$Z_A = \frac{s}{\sqrt{b + \sigma_b^2}} \left( 1 + \mathcal{O}(s/b) + \mathcal{O}(\sigma_b^2/b) \right)$$

So this “intuitive” formula can be justified as a limiting case of the significance from the profile likelihood ratio test evaluated with the Asimov data set.

## Testing the formulae: $s = 5$



# Using sensitivity to optimize a cut

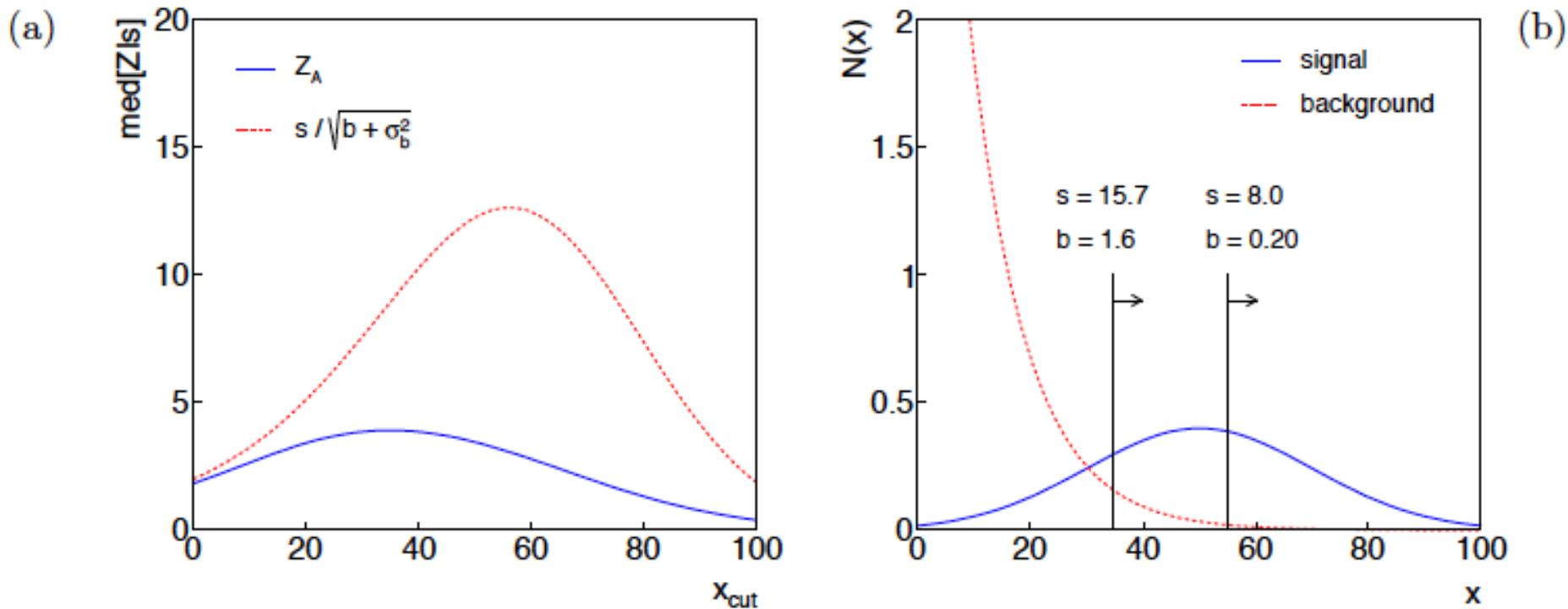


Figure 1: (a) The expected significance as a function of the cut value  $x_{\text{cut}}$ ; (b) the distributions of signal and background with the optimal cut value indicated.

# Return to interval estimation

Suppose a model contains a parameter  $\mu$ ; we want to know which values are consistent with the data and which are disfavoured.

Carry out a test of size  $\alpha$  for all values of  $\mu$ .

The values that are not rejected constitute a *confidence interval* for  $\mu$  at confidence level  $CL = 1 - \alpha$ .

The probability that the true value of  $\mu$  will be rejected is not greater than  $\alpha$ , so by construction the confidence interval will contain the true value of  $\mu$  with probability  $\geq 1 - \alpha$ .

The interval depends on the choice of the test (critical region).

If the test is formulated in terms of a *p*-value,  $p_\mu$ , then the confidence interval represents those values of  $\mu$  for which  $p_\mu > \alpha$ .

To find the end points of the interval, set  $p_\mu = \alpha$  and solve for  $\mu$ .

# Test statistic for upper limits

cf. Cowan, Cranmer, Gross, Vitells, arXiv:1007.1727, EPJC 71 (2011) 1554.

For purposes of setting an upper limit on  $\mu$  one can use

$$q_\mu = \begin{cases} -2 \ln \lambda(\mu) & \hat{\mu} \leq \mu \\ 0 & \hat{\mu} > \mu \end{cases} \quad \text{where} \quad \lambda(\mu) = \frac{L(\mu, \hat{\theta})}{L(\hat{\mu}, \hat{\theta})}$$

I.e. when setting an upper limit, an upwards fluctuation of the data is not taken to mean incompatibility with the hypothesized  $\mu$ :

From observed  $q_\mu$  find  $p$ -value:  $p_\mu = \int_{q_{\mu,\text{obs}}}^{\infty} f(q_\mu | \mu) dq_\mu$

Large sample approximation:

$$p_\mu = 1 - \Phi\left(\sqrt{q_\mu}\right)$$

95% CL upper limit on  $\mu$  is highest value for which  $p$ -value is not less than 0.05.

# Monte Carlo test of asymptotic formulae

Consider again  $n \sim \text{Poisson}(\mu s + b)$ ,  $m \sim \text{Poisson}(\tau b)$

Use  $q_\mu$  to find  $p$ -value of hypothesized  $\mu$  values.

E.g.  $f(q_1|1)$  for  $p$ -value of  $\mu = 1$ .

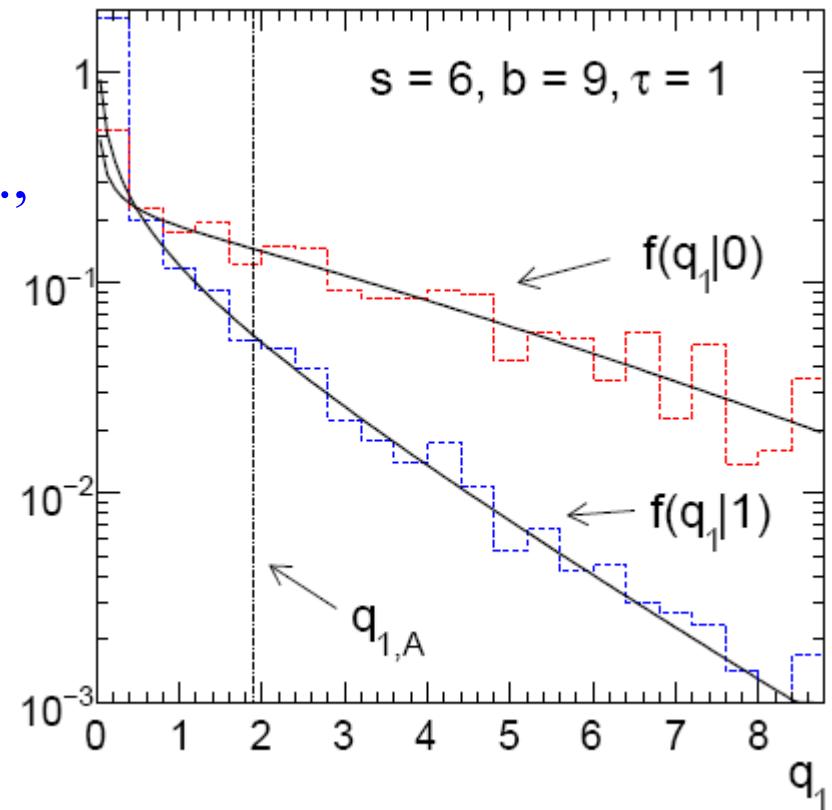
Typically interested in 95% CL, i.e.,

$p$ -value threshold = 0.05, i.e.,

$q_1 = 2.69$  or  $Z_1 = \sqrt{q_1} = 1.64$ .

Median[ $q_1|0$ ] gives “exclusion sensitivity”.

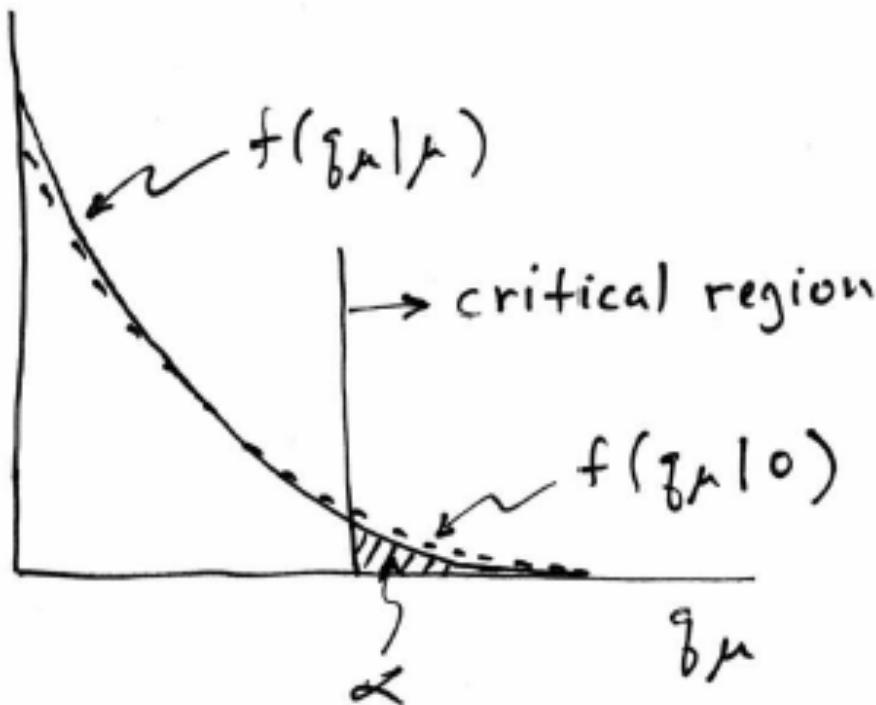
Here asymptotic formulae good for  $s = 6, b = 9$ .



## Low sensitivity to $\mu$

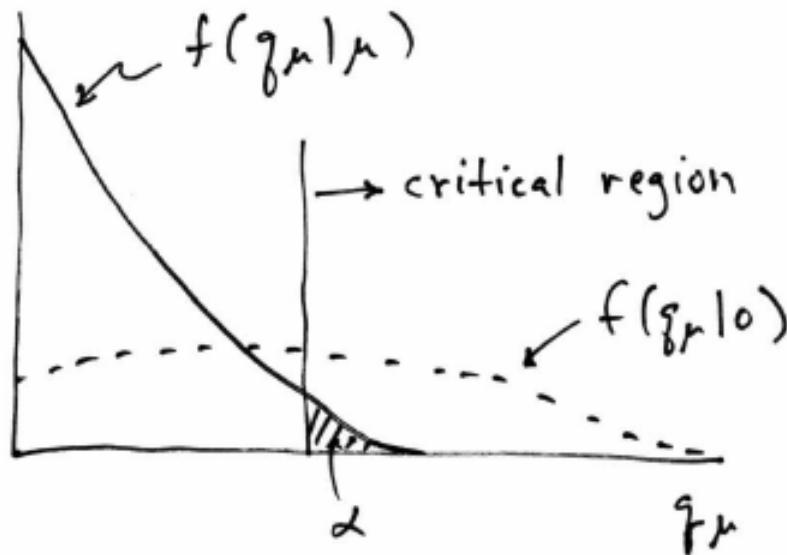
It can be that the effect of a given hypothesized  $\mu$  is very small relative to the background-only ( $\mu = 0$ ) prediction.

This means that the distributions  $f(q_\mu|\mu)$  and  $f(q_\mu|0)$  will be almost the same:



# Having sufficient sensitivity

In contrast, having sensitivity to  $\mu$  means that the distributions  $f(q_\mu|\mu)$  and  $f(q_\mu|0)$  are more separated:

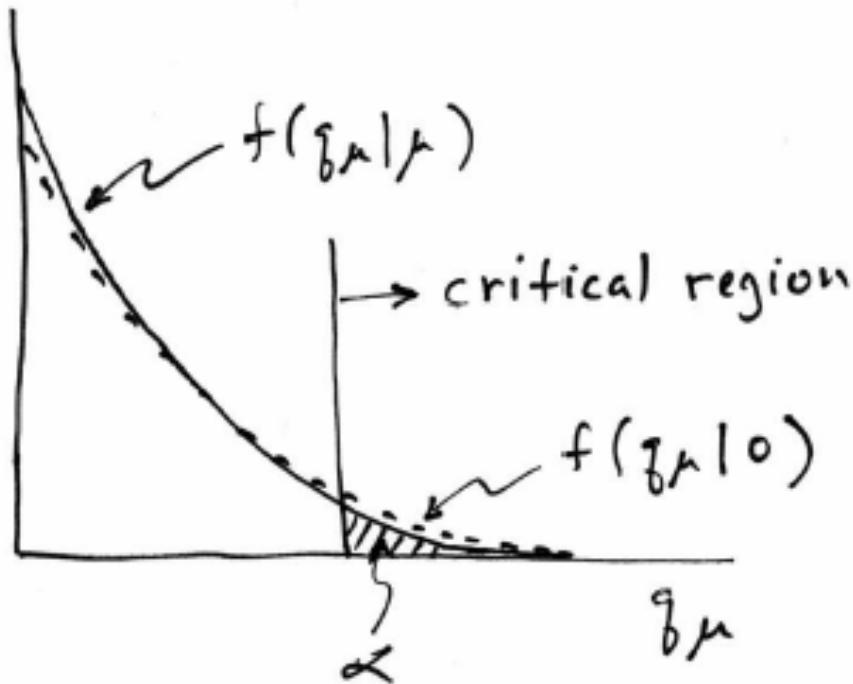


That is, the power (probability to reject  $\mu$  if  $\mu = 0$ ) is substantially higher than  $\alpha$ . Use this power as a measure of the sensitivity.

## Spurious exclusion

Consider again the case of low sensitivity. By construction the probability to reject  $\mu$  if  $\mu$  is true is  $\alpha$  (e.g., 5%).

And the probability to reject  $\mu = 0$  (the power) is only slightly greater than  $\alpha$ .



This means that with probability of around  $\alpha = 5\%$  (slightly higher), one excludes hypotheses to which one has essentially no sensitivity (e.g.,  $m_H = 1000$  TeV).

“Spurious exclusion”

# Ways of addressing spurious exclusion

The problem of excluding parameter values to which one has no sensitivity known for a long time; see e.g.,

Virgil L. Highland, *Estimation of Upper Limits from Experimental Data*, July 1986,  
Revised February 1987, Temple University Report C00-3539-38.

In the 1990s this was re-examined for the LEP Higgs search by Alex Read and others

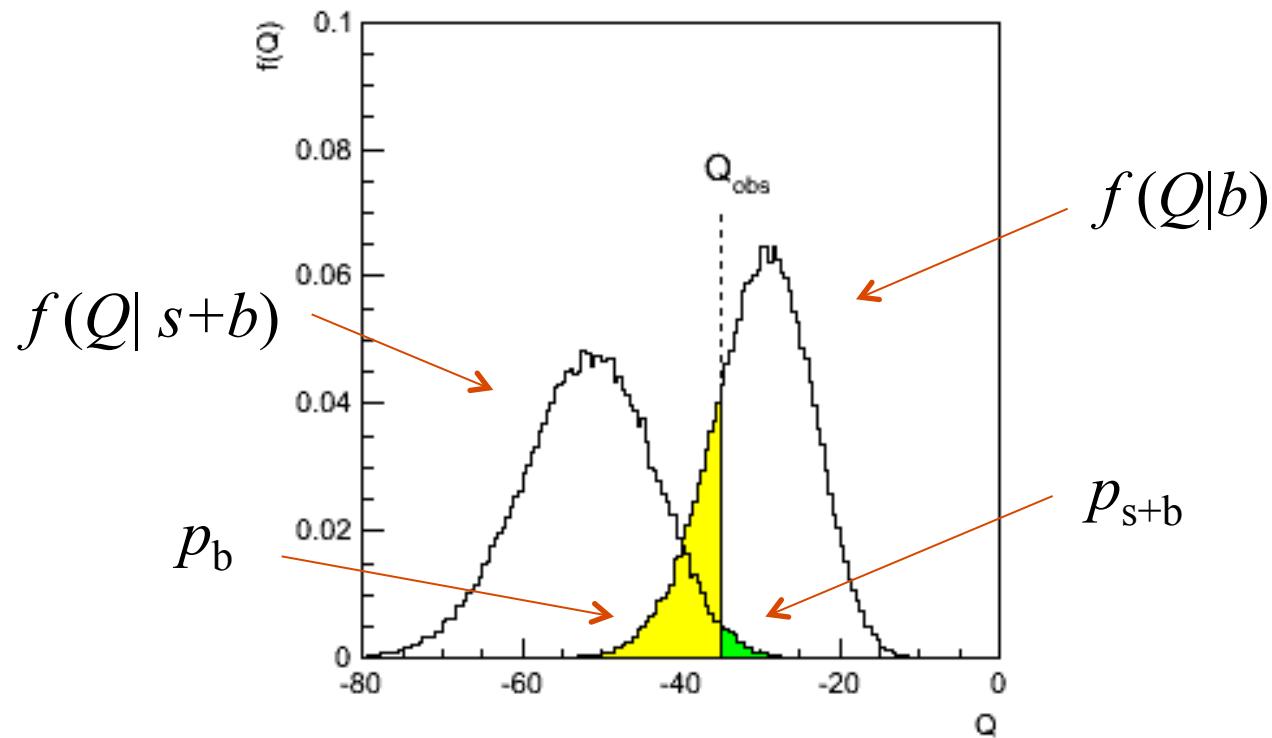
T. Junk, Nucl. Instrum. Methods Phys. Res., Sec. A **434**, 435 (1999); A.L. Read, J. Phys. G **28**, 2693 (2002).

and led to the “ $CL_s$ ” procedure for upper limits.

Unified intervals also effectively reduce spurious exclusion by the particular choice of critical region.

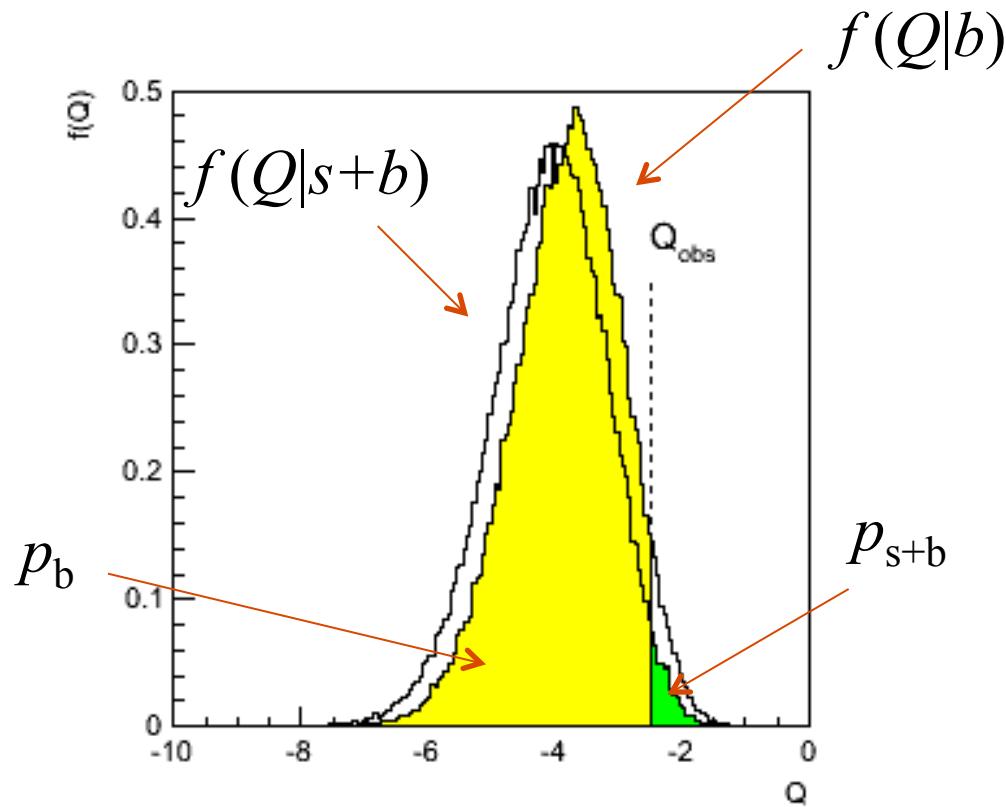
# The $\text{CL}_s$ procedure

In the usual formulation of  $\text{CL}_s$ , one tests both the  $\mu = 0$  ( $b$ ) and  $\mu > 0$  ( $\mu s+b$ ) hypotheses with the same statistic  $Q = -2\ln L_{s+b}/L_b$ :



## The CL<sub>s</sub> procedure (2)

As before, “low sensitivity” means the distributions of  $Q$  under  $b$  and  $s+b$  are very close:



## The $\text{CL}_s$ procedure (3)

The  $\text{CL}_s$  solution (A. Read et al.) is to base the test not on the usual  $p$ -value ( $\text{CL}_{s+b}$ ), but rather to divide this by  $\text{CL}_b$  ( $\sim$  one minus the  $p$ -value of the  $b$ -only hypothesis), i.e.,

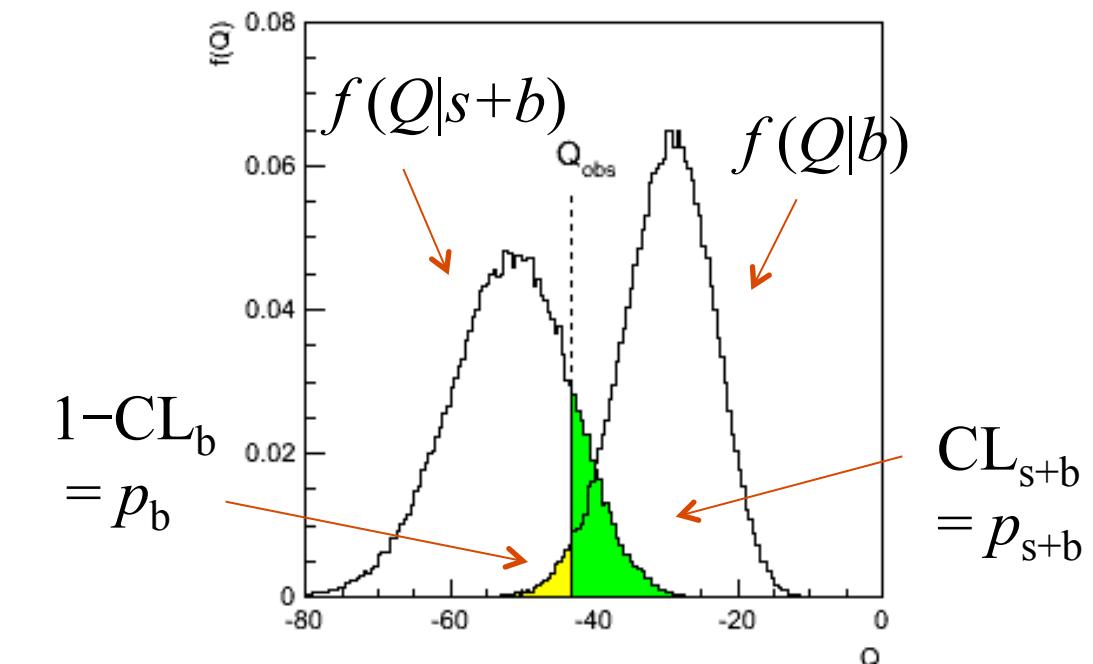
Define:

$$\text{CL}_s = \frac{\text{CL}_{s+b}}{\text{CL}_b}$$

$$= \frac{p_{s+b}}{1 - p_b}$$

Reject  $s+b$   
hypothesis if:

$$\text{CL}_s \leq \alpha$$



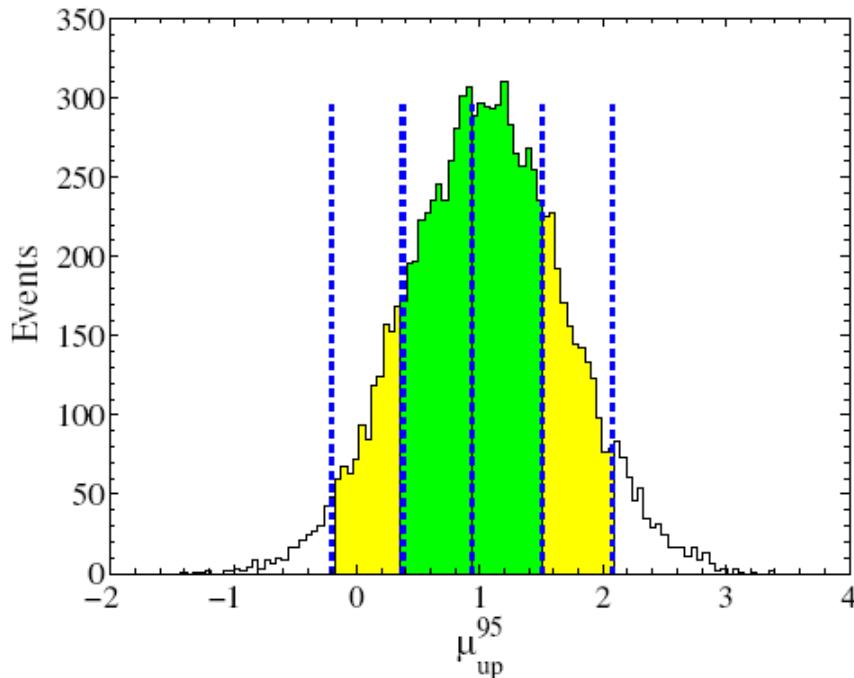
Reduces “effective”  $p$ -value when the two distributions become close (prevents exclusion if sensitivity is low).

# Setting upper limits on $\mu = \sigma/\sigma_{\text{SM}}$

Carry out the CLs procedure for the parameter  $\mu = \sigma/\sigma_{\text{SM}}$ , resulting in an upper limit  $\mu_{\text{up}}$ .

In, e.g., a Higgs search, this is done for each value of  $m_H$ .

At a given value of  $m_H$ , we have an observed value of  $\mu_{\text{up}}$ , and we can also find the distribution  $f(\mu_{\text{up}}|0)$ :



$\pm 1\sigma$  (green) and  $\pm 2\sigma$  (yellow) bands from toy MC;

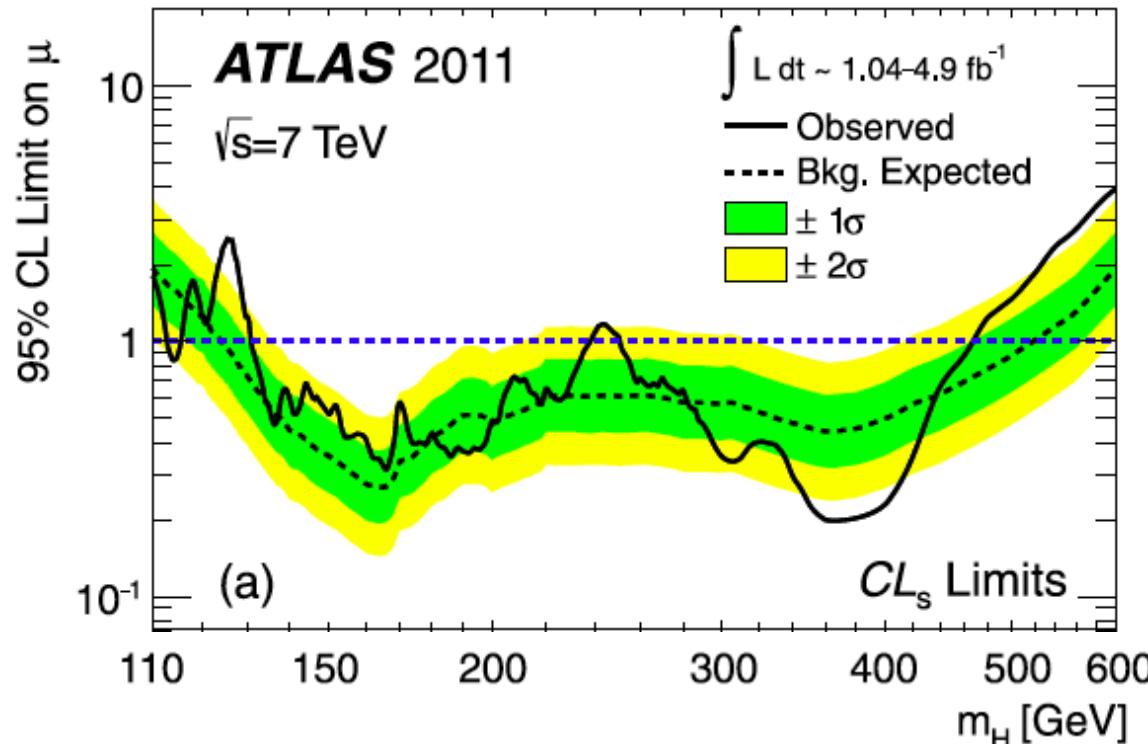
Vertical lines from asymptotic formulae.

# How to read the green and yellow limit plots

For every value of  $m_H$ , find the CLs upper limit on  $\mu$ .

Also for each  $m_H$ , determine the distribution of upper limits  $\mu_{\text{up}}$  one would obtain under the hypothesis of  $\mu = 0$ .

The dashed curve is the median  $\mu_{\text{up}}$ , and the green (yellow) bands give the  $\pm 1\sigma$  ( $2\sigma$ ) regions of this distribution.



ATLAS, Phys. Lett.  
B 710 (2012) 49-66

## Choice of test for limits (2)

In some cases  $\mu = 0$  is no longer a relevant alternative and we want to try to exclude  $\mu$  on the grounds that some other measure of incompatibility between it and the data exceeds some threshold.

If the measure of incompatibility is taken to be the likelihood ratio with respect to a two-sided alternative, then the critical region can contain both high and low data values.

→ unified intervals, G. Feldman, R. Cousins,  
Phys. Rev. D 57, 3873–3889 (1998)

The Big Debate is whether to use one-sided or unified intervals in cases where small (or zero) values of the parameter are relevant alternatives. Professional statisticians have voiced support on both sides of the debate.

# Unified (Feldman-Cousins) intervals

We can use directly

$$t_\mu = -2 \ln \lambda(\mu) \quad \text{where} \quad \lambda(\mu) = \frac{L(\mu, \hat{\theta})}{L(\hat{\mu}, \hat{\theta})}$$

as a test statistic for a hypothesized  $\mu$ .

Large discrepancy between data and hypothesis can correspond either to the estimate for  $\mu$  being observed high or low relative to  $\mu$ .

This is essentially the statistic used for Feldman-Cousins intervals (here also treats nuisance parameters).

G. Feldman and R.D. Cousins, Phys. Rev. D 57 (1998) 3873.

Lower edge of interval can be at  $\mu = 0$ , depending on data.

## Distribution of $t_\mu$

Using Wald approximation,  $f(t_\mu|\mu')$  is noncentral chi-square for one degree of freedom:

$$f(t_\mu|\mu') = \frac{1}{2\sqrt{t_\mu}} \frac{1}{\sqrt{2\pi}} \left[ \exp\left(-\frac{1}{2} \left( \sqrt{t_\mu} + \frac{\mu - \mu'}{\sigma} \right)^2\right) + \exp\left(-\frac{1}{2} \left( \sqrt{t_\mu} - \frac{\mu - \mu'}{\sigma} \right)^2\right) \right]$$

Special case of  $\mu = \mu'$  is chi-square for one d.o.f. (Wilks).

The  $p$ -value for an observed value of  $t_\mu$  is

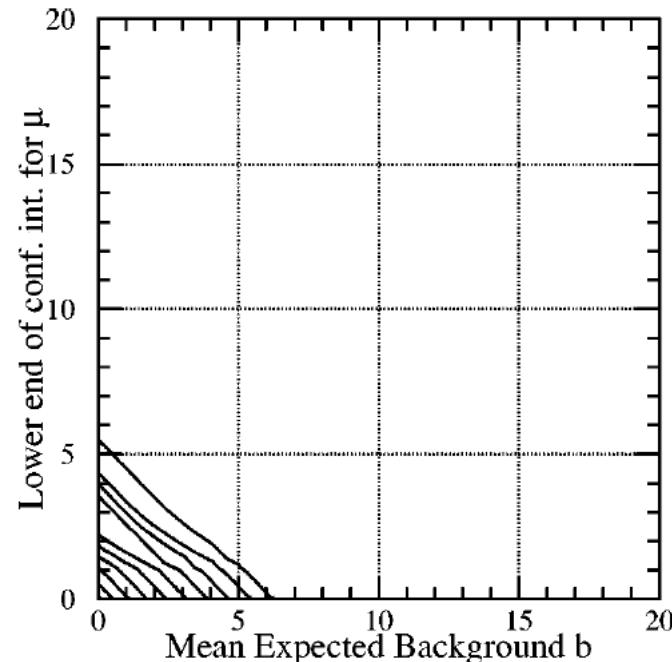
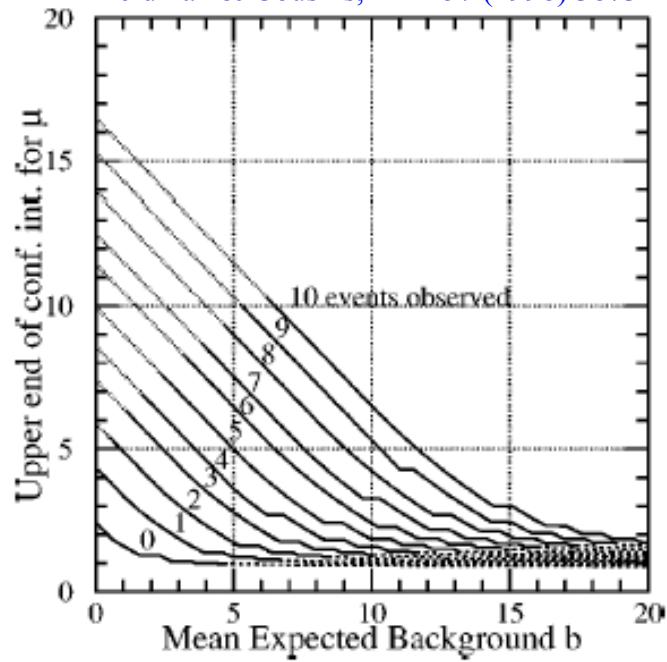
$$p_\mu = 1 - F(t_\mu|\mu) = 2 \left( 1 - \Phi(\sqrt{t_\mu}) \right)$$

and the corresponding significance is

$$Z_\mu = \Phi^{-1}(1 - p_\mu) = \Phi^{-1} \left( 2\Phi(\sqrt{t_\mu}) - 1 \right)$$

# Upper/lower edges of F-C interval for $\mu$ versus $b$ for $n \sim \text{Poisson}(\mu+b)$

Feldman & Cousins, PRD 57 (1998) 3873



Lower edge may be at zero, depending on data.

For  $n = 0$ , upper edge has (weak) dependence on  $b$ .

# Feldman-Cousins discussion

The initial motivation for Feldman-Cousins (unified) confidence intervals was to eliminate null intervals.

The F-C limits are based on a likelihood ratio for a test of  $\mu$  with respect to the alternative consisting of all other allowed values of  $\mu$  (not just, say, lower values).

The interval's upper edge is higher than the limit from the one-sided test, and lower values of  $\mu$  may be excluded as well. A substantial downward fluctuation in the data gives a low (but nonzero) limit.

This means that when a value of  $\mu$  is excluded, it is because there is a probability  $\alpha$  for the data to fluctuate either high or low in a manner corresponding to less compatibility as measured by the likelihood ratio.

## A toy example

For each event we measure two variables,  $\mathbf{x} = (x_1, x_2)$ .

Suppose that for background events (hypothesis  $H_0$ ),

$$f(\mathbf{x}|H_0) = \frac{1}{\xi_1} e^{-x_1/\xi_1} \frac{1}{\xi_2} e^{-x_2/\xi_2}$$

and for a certain signal model (hypothesis  $H_1$ ) they follow

$$f(\mathbf{x}|H_1) = C \frac{1}{\sqrt{2\pi}\sigma_1} e^{-(x_1-\mu_1)^2/2\sigma_1^2} \frac{1}{\sqrt{2\pi}\sigma_2} e^{-(x_2-\mu_2)^2/2\sigma_2^2}$$

where  $x_1, x_2 \geq 0$  and  $C$  is a normalization constant.

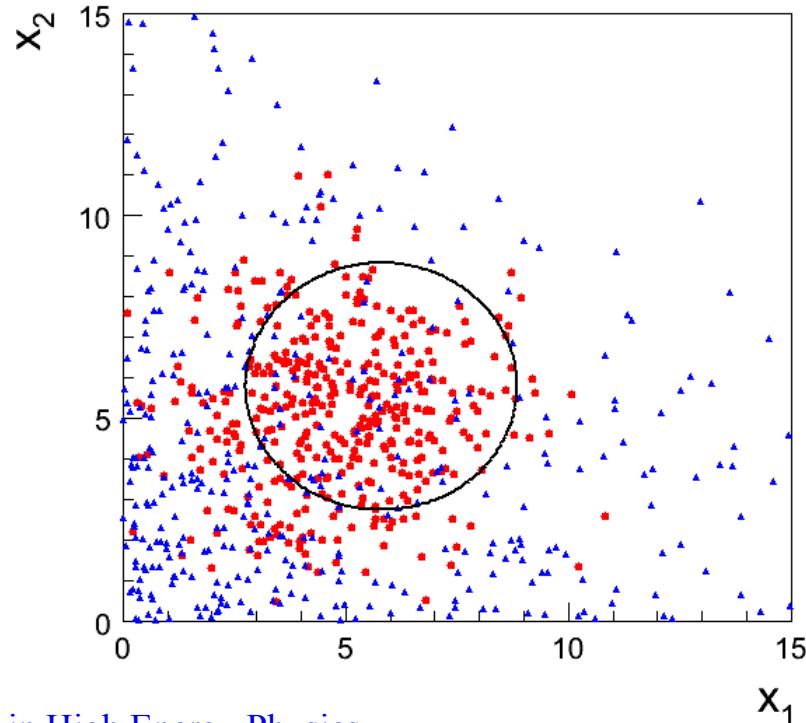
# Likelihood ratio as test statistic

In a real-world problem we usually wouldn't have the pdfs  $f(\mathbf{x}|H_0)$  and  $f(\mathbf{x}|H_1)$ , so we wouldn't be able to evaluate the likelihood ratio

$$t(\mathbf{x}) = \frac{f(\mathbf{x}|H_1)}{f(\mathbf{x}|H_0)}$$

for a given observed  $\mathbf{x}$ , hence the need for multivariate methods to approximate this with some other function.

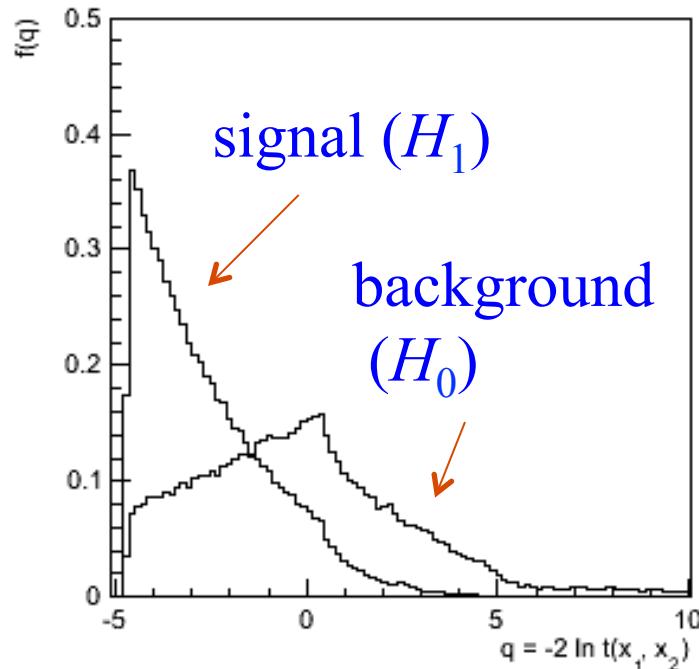
But in this example we can find contours of constant likelihood ratio such as:



# Event selection using the LR

Using Monte Carlo, we can find the distribution of the likelihood ratio or equivalently of

$$q = \left( \frac{x_1 - \mu_1}{\sigma_1} \right)^2 + \left( \frac{x_2 - \mu_2}{\sigma_2} \right)^2 - \frac{2x_1}{\xi_1} - \frac{2x_2}{\xi_2} = -2 \ln t(\mathbf{x}) + C$$



From the Neyman-Pearson lemma we know that by cutting on this variable we would select a signal sample with the highest signal efficiency (test power) for a given background efficiency.

# Search for the signal process

But what if the signal process is not known to exist and we want to search for it. The relevant hypotheses are therefore

$H_0$ : all events are of the background type

$H_1$ : the events are a mixture of signal and background

Rejecting  $H_0$  with  $Z > 5$  constitutes “discovering” new physics.

Suppose that for a given integrated luminosity, the expected number of signal events is  $s$ , and for background  $b$ .

The observed number of events  $n$  will follow a Poisson distribution:

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

# Likelihoods for full experiment

We observe  $n$  events, and thus measure  $n$  instances of  $\mathbf{x} = (x_1, x_2)$ .

The likelihood function for the entire experiment assuming the background-only hypothesis ( $H_0$ ) is

$$L_b = \frac{b^n}{n!} e^{-b} \prod_{i=1}^n f(\mathbf{x}_i | b)$$

and for the “signal plus background” hypothesis ( $H_1$ ) it is

$$L_{s+b} = \frac{(s+b)^n}{n!} e^{-(s+b)} \prod_{i=1}^n (\pi_s f(\mathbf{x}_i | s) + \pi_b f(\mathbf{x}_i | b))$$

where  $\pi_s$  and  $\pi_b$  are the (prior) probabilities for an event to be signal or background, respectively.

# Likelihood ratio for full experiment

We can define a test statistic  $Q$  monotonic in the likelihood ratio as

$$Q = -2 \ln \frac{L_{s+b}}{L_b} = 2s - 2 \sum_{i=1}^n \ln \left[ 1 + \frac{s}{b} \frac{f(\mathbf{x}_i|s)}{f(\mathbf{x}_i|b)} \right]$$

To compute  $p$ -values for the  $b$  and  $s+b$  hypotheses given an observed value of  $Q$  we need the distributions  $f(Q|b)$  and  $f(Q|s+b)$ .

Note that the term  $2s$  in front is a constant and can be dropped.

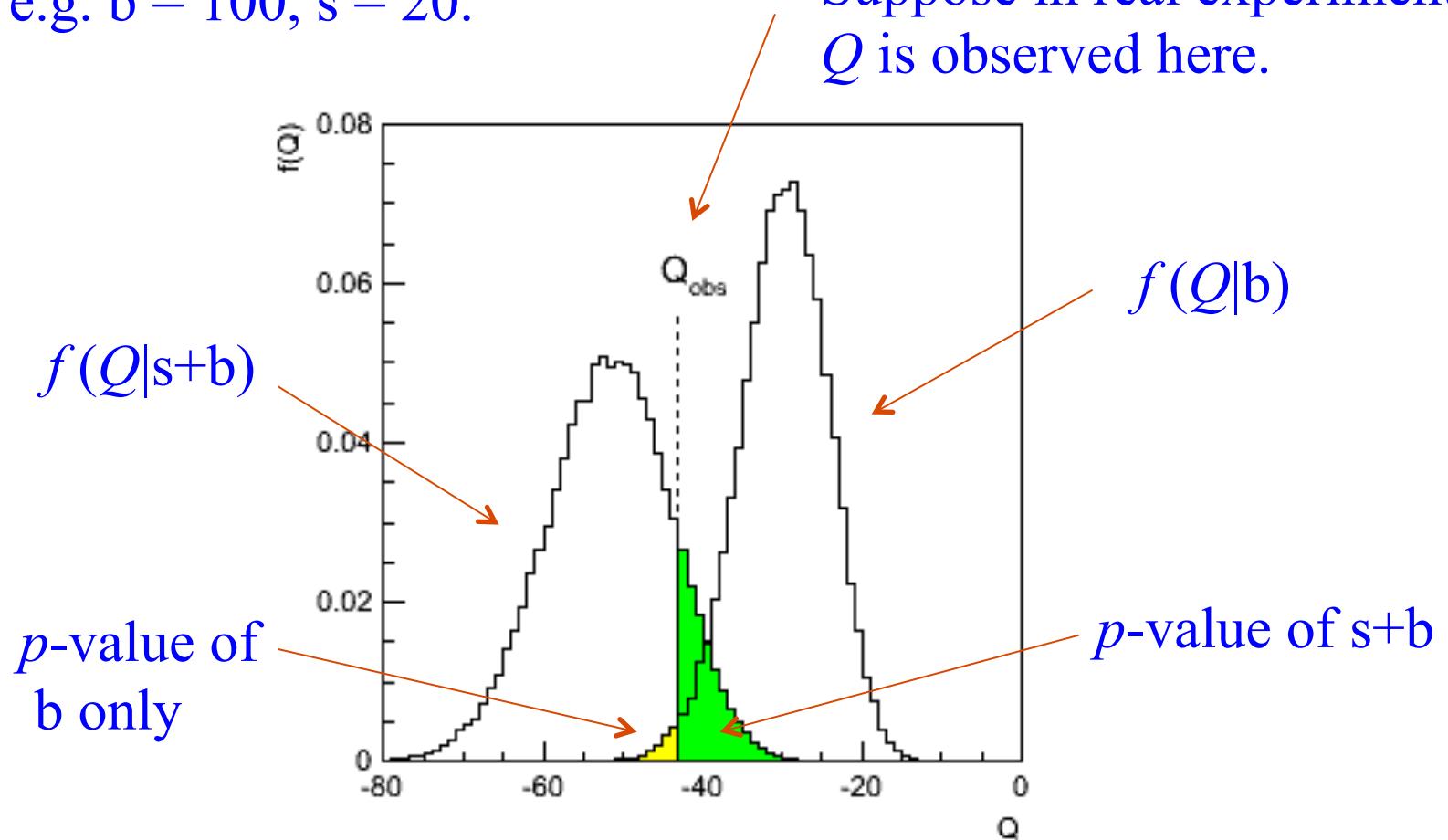
The rest is a sum of contributions for each event, and each term in the sum has the same distribution.

Can exploit this to relate distribution of  $Q$  to that of single event terms using (Fast) Fourier Transforms (Hu and Nielsen, physics/9906010).

# Distribution of $Q$

Take e.g.  $b = 100$ ,  $s = 20$ .

Suppose in real experiment  
 $Q$  is observed here.



If  $p_{s+b} < \alpha$ , reject signal model  $s$  at confidence level  $1 - \alpha$ .

If  $p_b < 2.9 \times 10^{-7}$ , reject background-only model (signif.  $Z = 5$ ).

# Systematic uncertainties

Previous example assumed all parameters were known exactly.

In practice they have some (systematic) uncertainty.

Suppose e.g. uncertainty in expected number of background events  $b$  is characterized by a (Bayesian) pdf  $\pi(b)$ .

Maybe take a Gaussian, i.e.,

$$\pi(b) = \frac{1}{\sqrt{2\pi}\sigma_b} e^{-(b-b_0)^2/2\sigma_b^2}$$

where  $b_0$  is the nominal (measured) value and  $\sigma_b$  is the estimated uncertainty.

In fact for many systematics a Gaussian pdf is hard to defend – can use instead e.g. log-normal, gamma,...

# Distribution of $Q$ with systematics

To get the desired  $p$ -values we need the pdf  $f(Q)$ , but this depends on  $b$ , which we don't know exactly.

But we can obtain the prior predictive (marginal) model:

$$f(Q) = \int f(Q|b)\pi(b) db$$

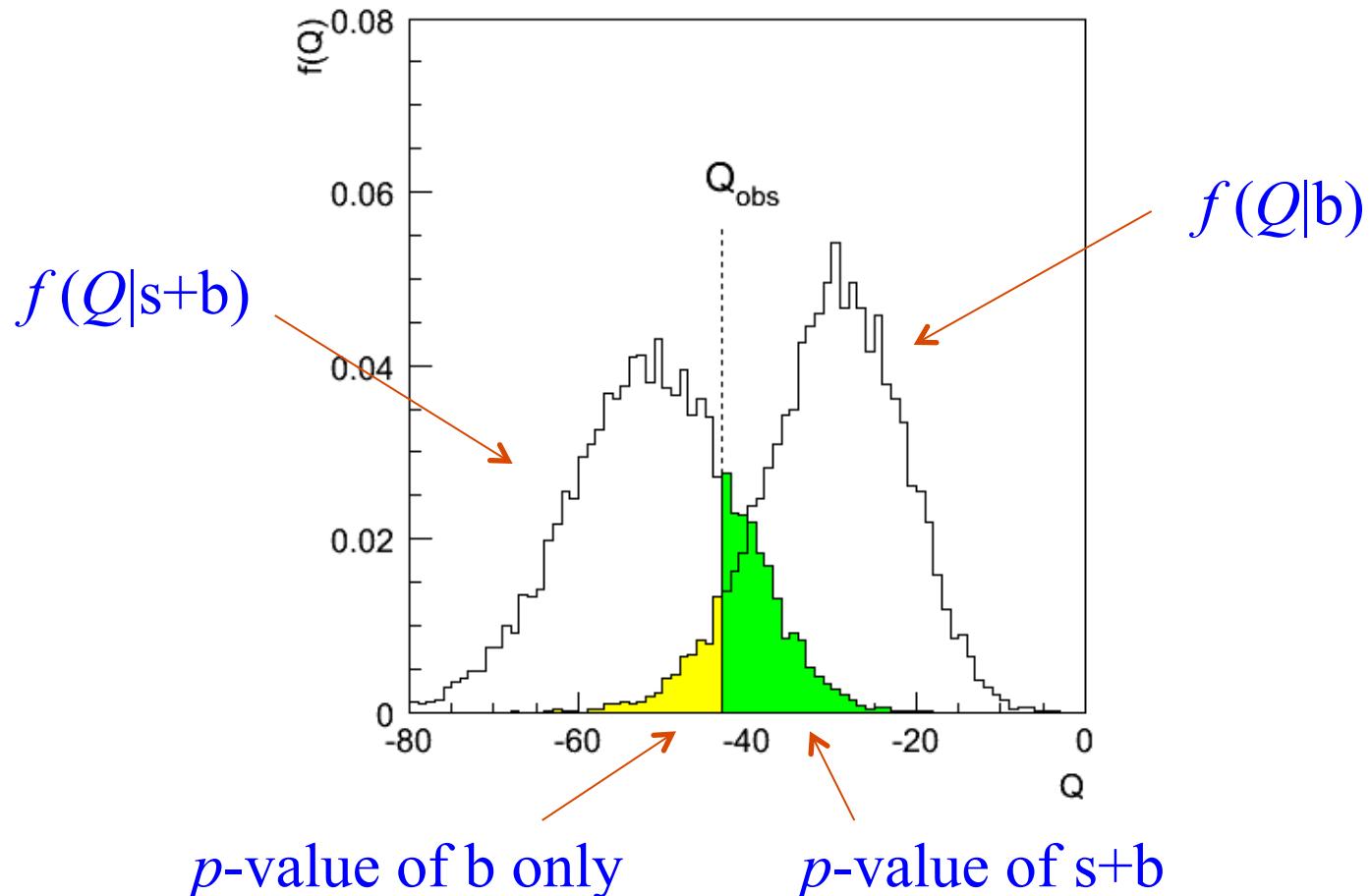
With Monte Carlo, sample  $b$  from  $\pi(b)$ , then use this to generate  $Q$  from  $f(Q|b)$ , i.e., a new value of  $b$  is used to generate the data for every simulation of the experiment.

This broadens the distributions of  $Q$  and thus increases the  $p$ -value (decreases significance  $Z$ ) for a given  $Q_{\text{obs}}$ .

The model we are testing is not a “physical” model with fixed  $b$ , but rather a model averaged over  $b$  with respect to  $\pi(b)$ ).

## Distribution of $Q$ with systematics (2)

For  $s = 20$ ,  $b_0 = 100$ ,  $\sigma_b = 20$  this gives



# Summary

## Parameter estimation:

Maximize likelihood function → ML estimator.

Bayesian estimator based on posterior pdf.

Confidence interval: set of parameter values not rejected in a test of size  $\alpha = 1 - \text{CL}$ .

## Statistical tests:

Divide data spaced into two regions; depending on where data are then observed, accept or reject hypothesis.

## Use in searches:

Design experiment with maximum probability to reject no-signal hypothesis if signal is present.

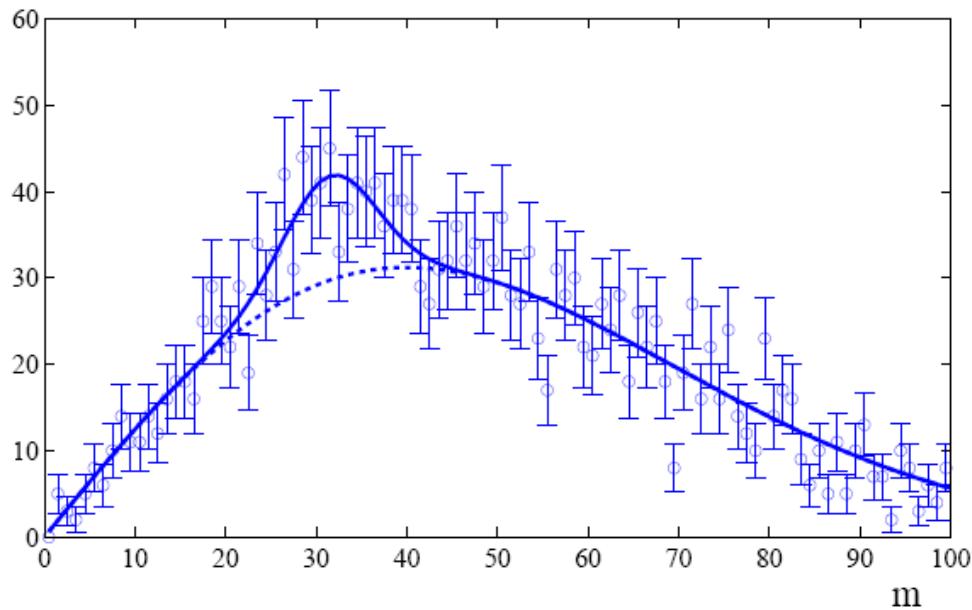
Nuisance parameters needed to cover systematics; lead to decrease in sensitivity.

# Extra slides

# The Look-Elsewhere Effect

Suppose a model for a mass distribution allows for a peak at a mass  $m$  with amplitude  $\mu$ .

The data show a bump at a mass  $m_0$ .



How consistent is this with the no-bump ( $\mu = 0$ ) hypothesis?

## Local $p$ -value

First, suppose the mass  $m_0$  of the peak was specified a priori.

Test consistency of bump with the no-signal ( $\mu = 0$ ) hypothesis with e.g. likelihood ratio

$$t_{\text{fix}} = -2 \ln \frac{L(0, m_0)}{L(\hat{\mu}, m_0)}$$

where “fix” indicates that the mass of the peak is fixed to  $m_0$ .

The resulting  $p$ -value

$$p_{\text{local}} = \int_{t_{\text{fix,obs}}}^{\infty} f(t_{\text{fix}}|0) dt_{\text{fix}}$$

gives the probability to find a value of  $t_{\text{fix}}$  at least as great as observed at the specific mass  $m_0$  and is called the local  $p$ -value.

# Global $p$ -value

But suppose we did not know where in the distribution to expect a peak.

What we want is the probability to find a peak at least as significant as the one observed **anywhere** in the distribution.

Include the mass as an adjustable parameter in the fit, test significance of peak using

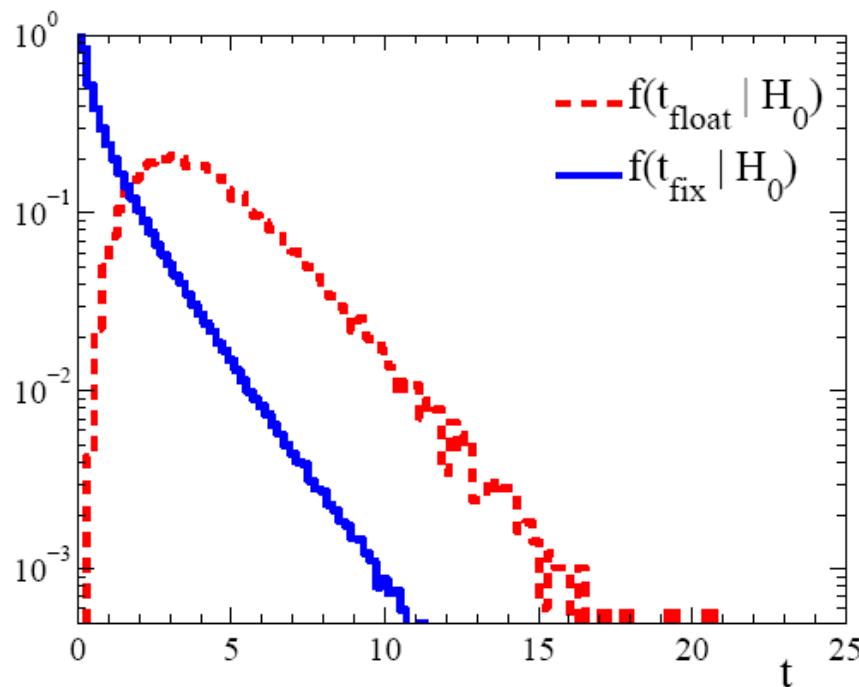
$$t_{\text{float}} = -2 \ln \frac{L(0)}{L(\hat{\mu}, \hat{m})} \quad (\text{Note } m \text{ does not appear in the } \mu = 0 \text{ model.})$$

$$p_{\text{global}} = \int_{t_{\text{float,obs}}}^{\infty} f(t_{\text{float}} | 0) dt_{\text{float}}$$

# Distributions of $t_{\text{fix}}$ , $t_{\text{float}}$

For a sufficiently large data sample,  $t_{\text{fix}} \sim \text{chi-square}$  for 1 degree of freedom (Wilks' theorem).

For  $t_{\text{float}}$  there are two adjustable parameters,  $\mu$  and  $m$ , and naively Wilks theorem says  $t_{\text{float}} \sim \text{chi-square}$  for 2 d.o.f.



In fact Wilks' theorem does not hold in the floating mass case because one of the parameters ( $m$ ) is not-defined in the  $\mu = 0$  model.

So getting  $t_{\text{float}}$  distribution is more difficult.

## Approximate correction for LEE

We would like to be able to relate the  $p$ -values for the fixed and floating mass analyses (at least approximately).

Gross and Vitells show the  $p$ -values are approximately related by

$$p_{\text{global}} \approx p_{\text{local}} + \langle N(c) \rangle$$

where  $\langle N(c) \rangle$  is the mean number “upcrossings” of  $t_{\text{fix}} = -2\ln \lambda$  in the fit range based on a threshold

$$c = t_{\text{fix,obs}} = Z_{\text{local}}^2$$

and where  $Z_{\text{local}} = \Phi^{-1}(1 - p_{\text{local}})$  is the local significance.

So we can either carry out the full floating-mass analysis (e.g. use MC to get  $p$ -value), or do fixed mass analysis and apply a correction factor (much faster than MC).

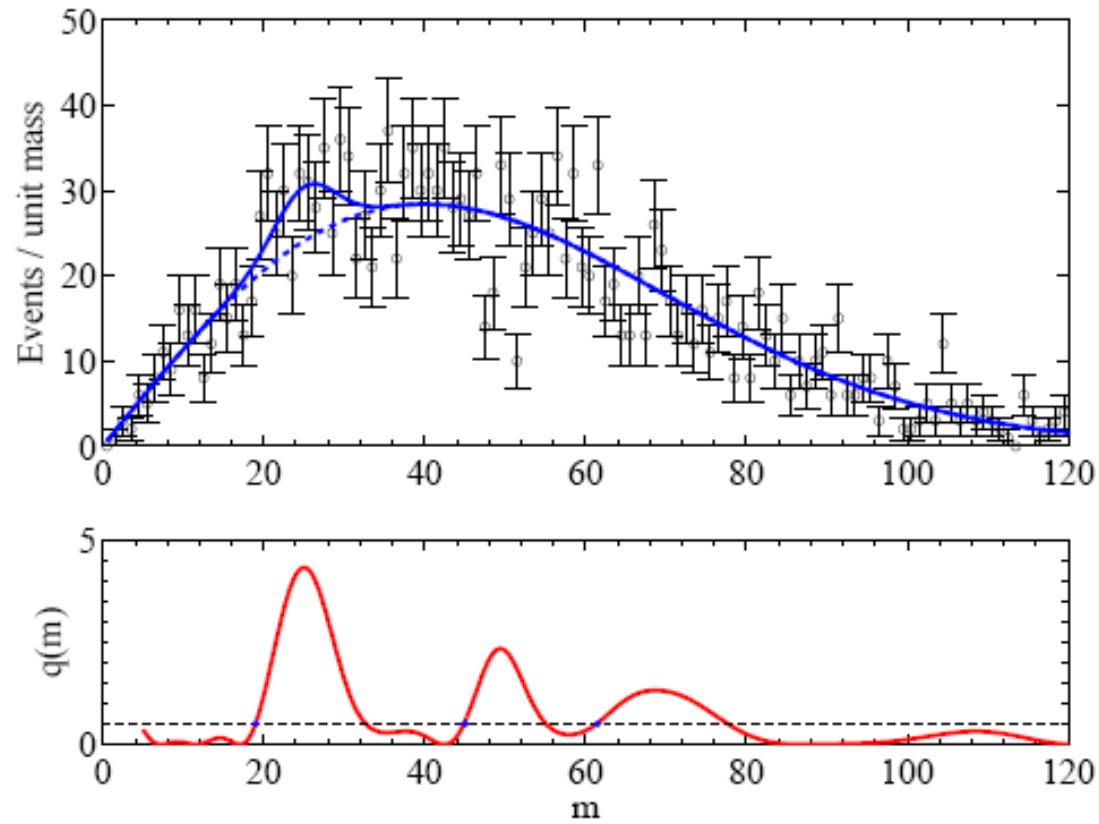
# Upcrossings of $-2\ln L$

The Gross-Vitells formula for the trials factor requires  $\langle N(c) \rangle$ , the mean number “upcrossings” of  $t_{\text{fix}} = -2\ln \lambda$  in the fit range based on a threshold  $c = t_{\text{fix}} = Z_{\text{fix}}^2$ .

$\langle N(c) \rangle$  can be estimated from MC (or the real data) using a much lower threshold  $c_0$ :

$$\langle N(c) \rangle \approx \langle N(c_0) \rangle e^{-(c-c_0)/2}$$

In this way  $\langle N(c) \rangle$  can be estimated without need of large MC samples, even if the the threshold  $c$  is quite high.

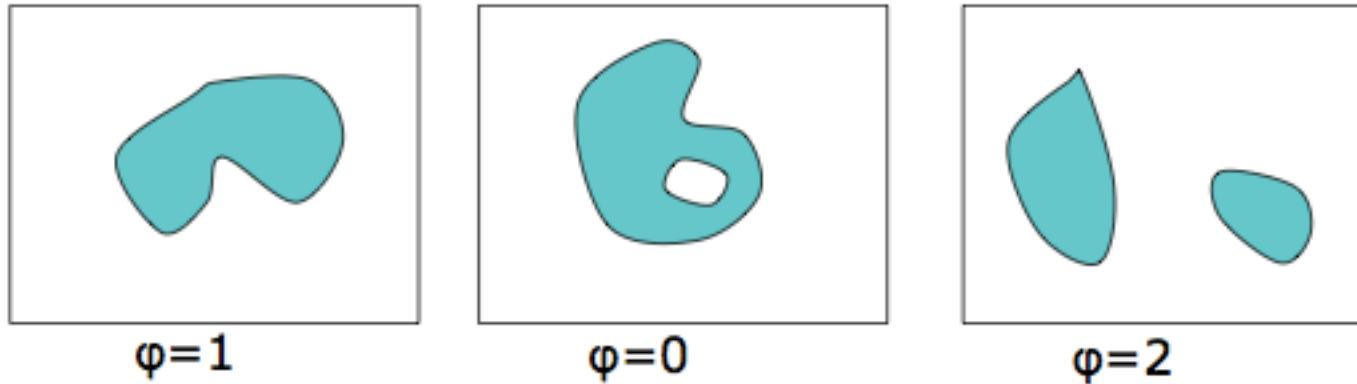


# Multidimensional look-elsewhere effect

Generalization to multiple dimensions: number of upcrossings replaced by expectation of Euler characteristic:

$$E[\varphi(A_u)] = \sum_{d=0}^n N_d \rho_d(u)$$

- Number of disconnected components minus number of 'holes'



Applications: astrophysics (coordinates on sky), search for resonance of unknown mass and width, ...

## Summary on Look-Elsewhere Effect

Remember the Look-Elsewhere Effect is when we test a single model (e.g., SM) with multiple observations, i.e, in multiple places.

Note there is no look-elsewhere effect when considering exclusion limits. There we test specific signal models (typically once) and say whether each is excluded.

With exclusion there is, however, the analogous issue of testing many signal models (or parameter values) and thus excluding some even in the absence of signal (“spurious exclusion”)

Approximate correction for LEE should be sufficient, and one should also report the uncorrected significance.

“There's no sense in being precise when you don't even know what you're talking about.” — John von Neumann

# Why 5 sigma?

Common practice in HEP has been to claim a discovery if the  $p$ -value of the no-signal hypothesis is below  $2.9 \times 10^{-7}$ , corresponding to a significance  $Z = \Phi^{-1}(1 - p) = 5$  (a  $5\sigma$  effect).

There are a number of reasons why one may want to require such a high threshold for discovery:

The “cost” of announcing a false discovery is high.

Unsure about systematics.

Unsure about look-elsewhere effect.

The implied signal may be a priori highly improbable (e.g., violation of Lorentz invariance).

## Why 5 sigma (cont.)?

But the primary role of the  $p$ -value is to quantify the probability that the background-only model gives a statistical fluctuation as big as the one seen or bigger.

It is not intended as a means to protect against hidden systematics or the high standard required for a claim of an important discovery.

In the processes of establishing a discovery there comes a point where it is clear that the observation is not simply a fluctuation, but an “effect”, and the focus shifts to whether this is new physics or a systematic.

Providing LEE is dealt with, that threshold is probably closer to  $3\sigma$  than  $5\sigma$ .

# More on treatment of nuisance parameters

Suppose we test a value of  $\theta$   
with the profile likelihood ratio:

$$t_\theta = -2 \ln \frac{L(\theta, \hat{\nu}(\theta))}{L(\hat{\theta}, \hat{\nu})}$$

We want a  $p$ -value of  $\theta$ :

$$p_\theta = \int_{t_{\theta,\text{obs}}}^{\infty} f(t_\theta | \theta, \nu) dt_\theta$$

Wilks' theorem says in the large sample limit (and under some additional conditions)  $f(t_\theta | \theta, \nu)$  is a chi-square distribution with number of degrees of freedom equal to number of parameters of interest (number of components in  $\theta$ ).

Simple recipe for  $p$ -value; holds regardless of the values of the nuisance parameters!

## Frequentist treatment of nuisance parameters in a test (2)

But for a finite data sample,  $f(t_\theta|\theta, v)$  still depends on  $v$ .

So what is the rule for saying whether we reject  $\theta$ ?

Exact approach is to reject  $\theta$  only if  $p_\theta < \alpha$  (5%) for all possible  $v$ .

This can make it very hard to reject some values of  $\theta$ ; they might not be excluded for value of  $v$  known to be highly disfavoured.

Resulting confidence level too large (“over-coverage”).

# Profile construction (“hybrid resampling”)

K. Cranmer, PHYSTAT-LHC Workshop on Statistical Issues for LHC Physics, 2008.  
oai:cds.cern.ch:1021125, cdsweb.cern.ch/record/1099969.

Compromise procedure is to reject  $\theta$  if  $p_\theta \leq \alpha$  where the  $p$ -value is computed assuming the value of the nuisance parameter that best fits the data for the specified  $\theta$  (the profiled values):

$$\hat{\nu}(\theta) = \operatorname{argmax}_{\nu} L(\theta, \nu)$$

The resulting confidence interval will have the correct coverage for the points  $(\theta, \hat{\nu}(\theta))$

Elsewhere it may under- or over-cover, but this is usually as good as we can do (check with MC if crucial or small sample problem).