



# Discover a particle for fun and profit

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# Let's do this!

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A 4.5 hours class

Cover few relevant cases for statistical analysis in HEP

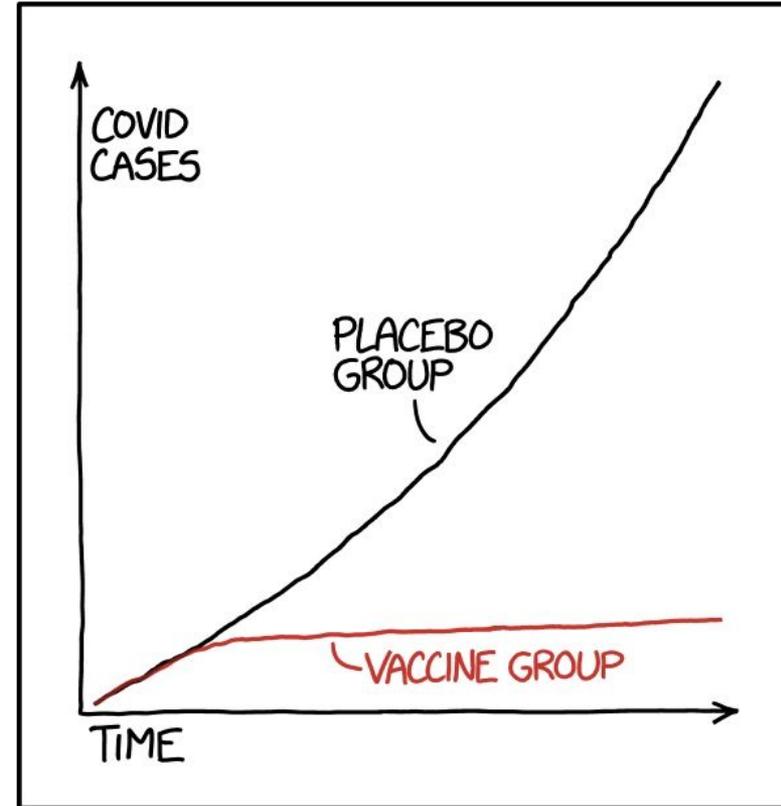
→ Using RooFit and RooStats as main tools

You can use your laptop for this (provided you installed ROOT and python)

→ Exercises will be in PyROOT

CERN/other labs central clusters usually work too

I will flash a few introductory slides for each topic



STATISTICS TIP: ALWAYS TRY TO GET DATA THAT'S GOOD ENOUGH THAT YOU DON'T NEED TO DO STATISTICS ON IT

# Disclaimer

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The point of this class is to introduce you to some libraries that let you use different statistical tools

I'll try to present as many different approaches as I can

These are not the best (or most appropriate) ways to approach **any** statistical problem

It's your responsibility to find (or build) the best tool for the job!

# RooFit, RooStats and friends

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**RooFit:** a ROOT library containing classes that allow to perform multi-dimensional (un)binned maximum likelihood/chi2 fits, toy-MC generation, plotting, etc

**RooStats:** a ROOT library that uses RooFit and provides classes to perform statistical interpretation of your results

**Combine:** an interface to RooFit+RooStats (with some very nifty tools!) created by and for the ATLAS and CMS collaborations

# Documentation

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For most of what I do, I refer to the ROOT reference guide:

<https://root.cern.ch/doc/master/classes.html>

This includes RooFit and RooStats reference

RooFit manual (a bit outdated):

[https://root.cern.ch/download/doc/RooFit\\_Users\\_Manual\\_2.91-33.pdf](https://root.cern.ch/download/doc/RooFit_Users_Manual_2.91-33.pdf)

RooStats documentation

<https://twiki.cern.ch/twiki/bin/view/RooStats/WebHome>

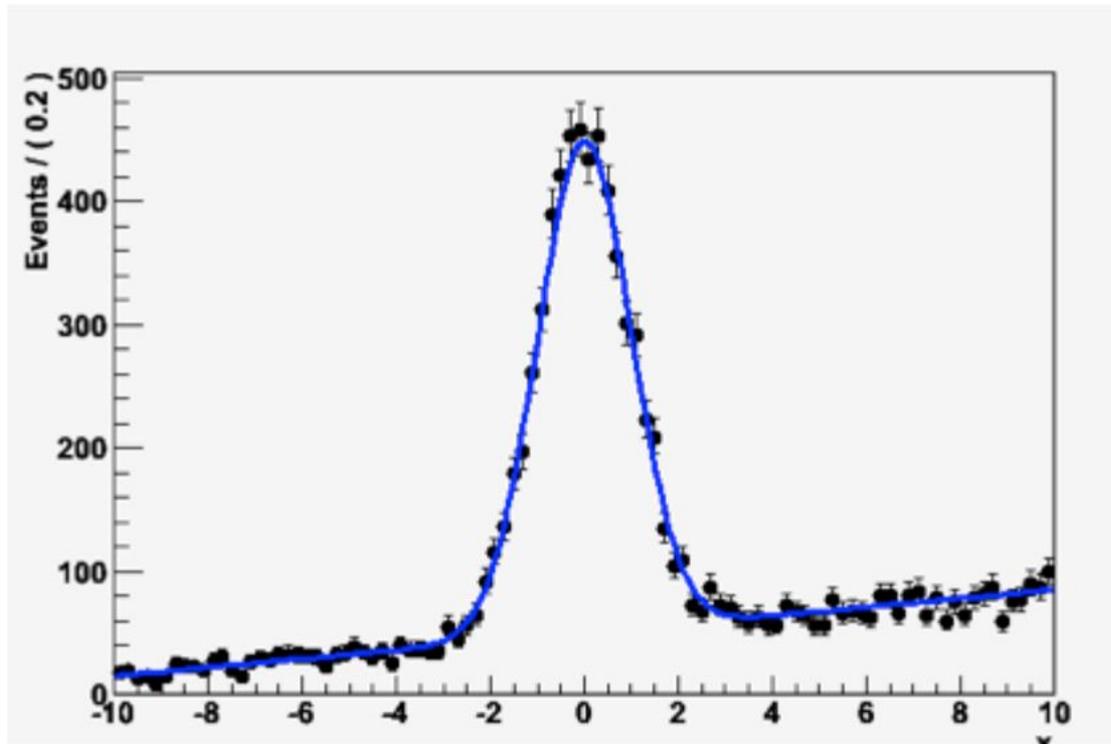
More RooFit/RooStats examples

[https://github.com/pellicci/UserCode/tree/master/RooFitStat\\_class](https://github.com/pellicci/UserCode/tree/master/RooFitStat_class) (C++ based)

[https://github.com/pellicci/UserCode/tree/master/RooFitStat\\_class\\_python](https://github.com/pellicci/UserCode/tree/master/RooFitStat_class_python)

# Why do we need RooFit?

- Focus on one practical aspect of many data analysis in HEP: **How do you formulate your p.d.f. in ROOT**
  - For 'simple' problems (gauss, polynomial) this is easy



- But if you want to do unbinned ML fits, use non-trivial functions, or work with multidimensional functions you quickly find that you need some tools to help you

# The origins

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- **BaBar experiment at SLAC:** Extract  $\sin(2\beta)$  from time-dependent CP violation of B decay:  $e^+e^- \rightarrow Y(4s) \rightarrow BB$ 
  - Reconstruct both Bs, measure decay time difference
  - Physics of interest is in decay time dependent oscillation

$$f_{sig} \cdot \left[ \text{SigSel}(m; \bar{p}_{sig}) \cdot \left( \text{SigDecay}(t; q_{sig}, \sin(2\beta)) \otimes \text{SigResol}(t \mid dt; r_{sig}) \right) \right] + (1 - f_{sig}) \left[ \text{BkgSel}(m; \bar{p}_{bkg}) \cdot \left( \text{BkgDecay}(t; q_{bkg}) \otimes \text{BkgResol}(t \mid dt; r_{bkg}) \right) \right]$$

- Many issues arise
  - Standard ROOT function framework clearly insufficient to handle such complicated functions  $\rightarrow$  **must develop new framework**
  - **Normalization of p.d.f. not always trivial to calculate**  $\rightarrow$  may need numeric integration techniques
  - Unbinned fit, >2 dimensions, many events  $\rightarrow$  computation performance important  $\rightarrow$  **must try optimize code** for acceptable performance
  - Simultaneous fit to control samples to account for detector performance

# “Dictionary”

- Mathematical objects are represented as C++ objects

Mathematical concept			RooFit class
variable	$x$	➔	<code>RooRealVar</code>
function	$f(x)$	➔	<code>RooAbsReal</code>
PDF	$f(x)$	➔	<code>RooAbsPdf</code>
space point	$\vec{x}$	➔	<code>RooArgSet</code>
integral	$\int_{x_{\min}}^{x_{\max}} f(x) dx$	➔	<code>RooRealIntegral</code>
list of space points		➔	<code>RooAbsData</code>

RooFit uses MINUIT for most of its work, it just provides an easy to use interface and optimizations

# Design philosophy

- Represent relations between variables and functions as client/server links between objects

Math	$f(x,y,z)$
RooFit diagram	<pre>graph TD; f[RooAbsReal f] --&gt; x[RooRealVar x]; f --&gt; y[RooRealVar y]; f --&gt; z[RooRealVar z];</pre>
RooFit code	<pre>RooRealVar x("x","x",5) ; RooRealVar y("y","y",5) ; RooRealVar z("z","z",5) ; RooBogusFunction f("f","f",x,y,z) ;</pre>

# Variables

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All variables ([observables](#) or [parameters](#)) are defined as **RooRealVar**

Several constructors available, depending on the needs:

```
var1 = ROOT.RooRealVar("var1", "My first var", 4.15)      #constant variable
var2 = ROOT.RooRealVar("var2", "My second var", 1., 10.); #range, no initial value
var3 = ROOT.RooRealVar("var3", "My third var", 3., 1., 10.); #valid range, initial value
```

You can also specify the unit (mostly for plotting purposes)

```
time = ROOT.RooRealVar("time", "Decay time", 0., 100., "[ps]");
```

You can change the properties of your RooRealVar later (setRange, setBins, etc.)

If you want to be 100% sure a variable will stay constant, use RooConstVar

For discrete variables, use RooCategory

# Probability Density Functions

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Each PDF in RooFit must inherit from RooAbsPdf

RooAbsPdf provides methods for numerical integration, events generation (hit & miss), fitting methods, etc.

RooFit provides extensive list of predefined functions (RooGaussian, RooPolynomial, RooCBSShape, RooExponential, RooLandau, etc...)

If possible, use a predefined function (if analytical integration or inversion method for generation available, will speed your computation)

You can define a custom function using RooGenericPdf

# Data Handling

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Two basic classes to handle data in RooFit:

- **RooDataSet**: an unbinned dataset (think of it as a TTree). An ntuple of data
- **RooDataHist**: a binned dataset (think of it as a TH1F)

Both types of data handlers can have multiple dimensions, contain discrete variables, weights, etc.

# The perfect container

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In order to “move” information among different RooFit/RooStats programs, one can use the RooWorkspace class

A **RooWorkspace** can contain:

- Variables
- PDFs
- DataSets

A RooWorkspace can be saved into a ROOT file

We'll see how to use it

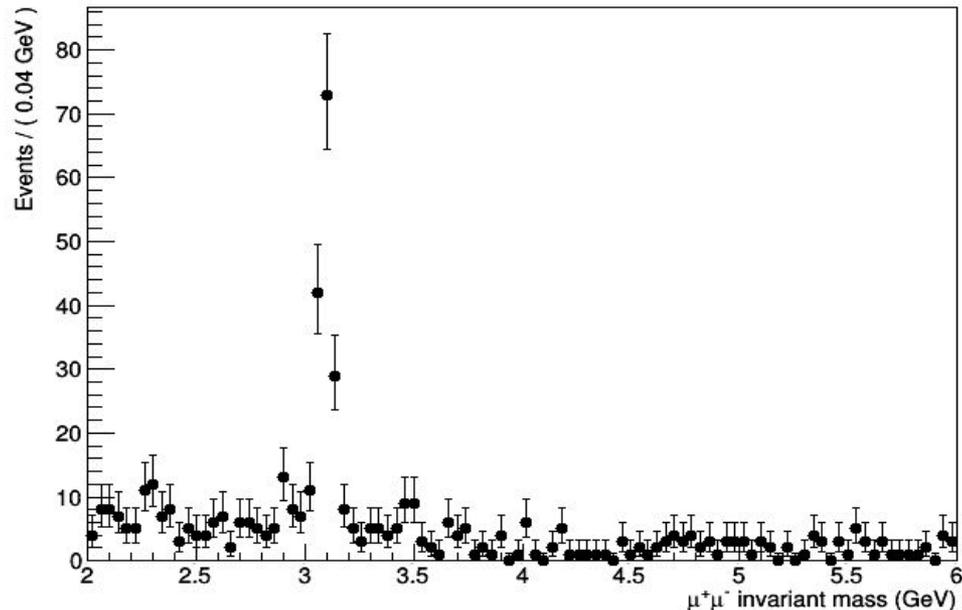
# The problem at hand

We'll be analyzing a sample from the 2010 CMS dataset

All CMS data from Run1-2 is public → [opendata.cern.ch](http://opendata.cern.ch)

- Events with two opposite sign muons
- Calculated the invariant mass of the system
- Saved it into a RooDataSet (a 1D ntuple containing “mass” variable)

A RooPlot of " $\mu^+\mu^-$  invariant mass"



First, let's look at the first three weeks of data taking (corresponds to about half a  $\text{pb}^{-1}$  of integrated lumi)

We'll be studying this distribution

# Exercise #0

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The first exercise involves RooFit only

- Construct a  $J/\psi$  and  $\psi(2S)$  + background PDF
  - $J/\psi$  with a Crystal Ball function
  - $\psi(2S)$  with a “similar” Crystal Ball
  - Background with a polynomial
- For now, the  $\psi(2S)$  will involve a very small amount of signal events
- Fit it, plot it, save it

We are going to use this program all the way through the exercises

# Parameter of interest

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→ a variable you want to know to the best precision and accuracy possible.  
Depends on problem

Number of  $\psi(2S)$  could be considered the POI

In reality, probably more interested in cross section of  $\psi(2S)$  production →  
real connection with theory

$$\sigma(pp \rightarrow \psi(2S)) * BR(\psi(2S) \rightarrow \mu\mu) = \frac{N_{\psi(2S)}}{\mathcal{L} * \epsilon_{\mu\mu}}$$

How do we express our problem in this way?

We'll assume:

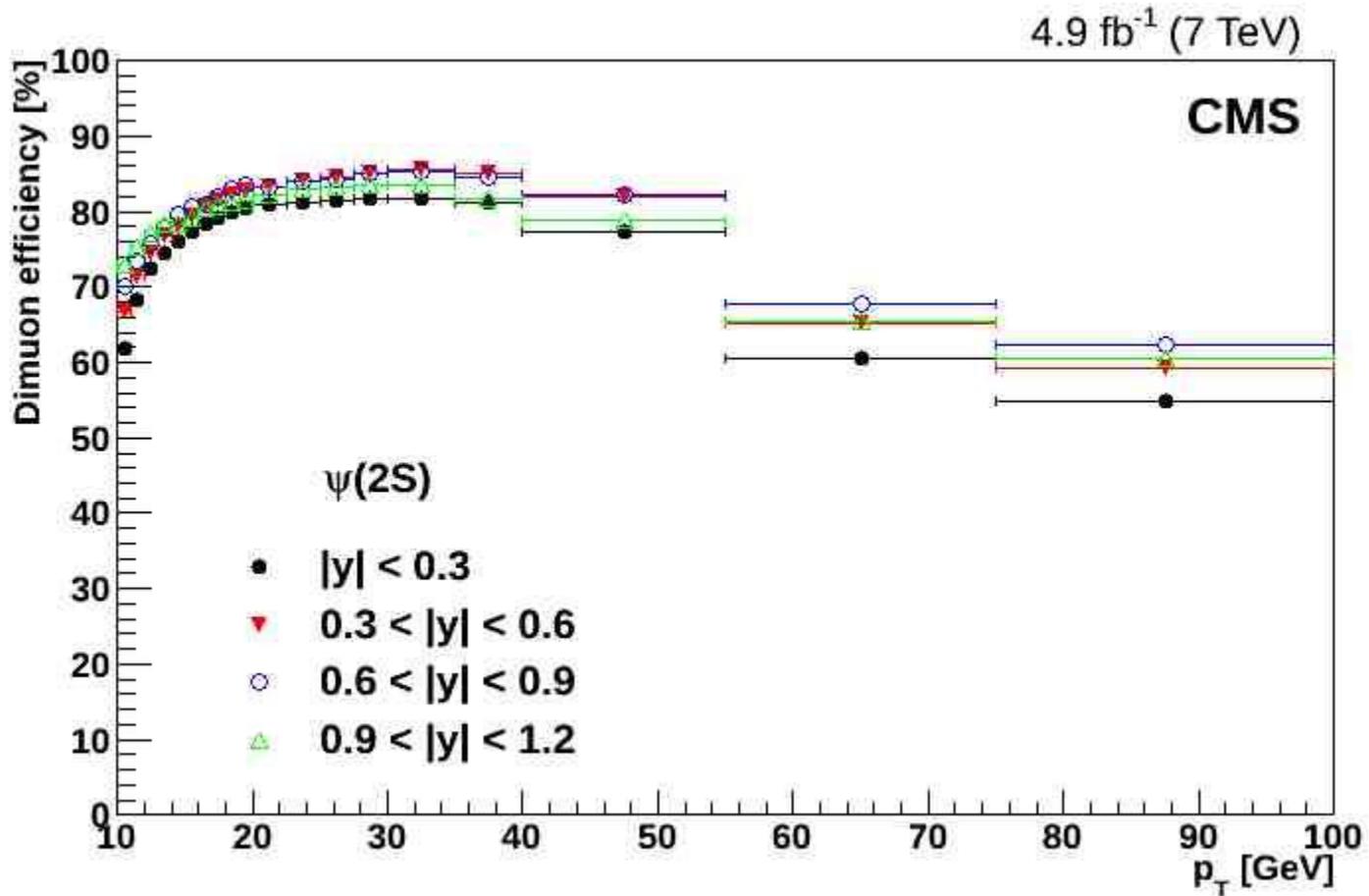
75% total efficiency

A luminosity of  $0.64 \text{ pb}^{-1}$

Both efficiency and luminosity uncertainties are negligible (for now!)

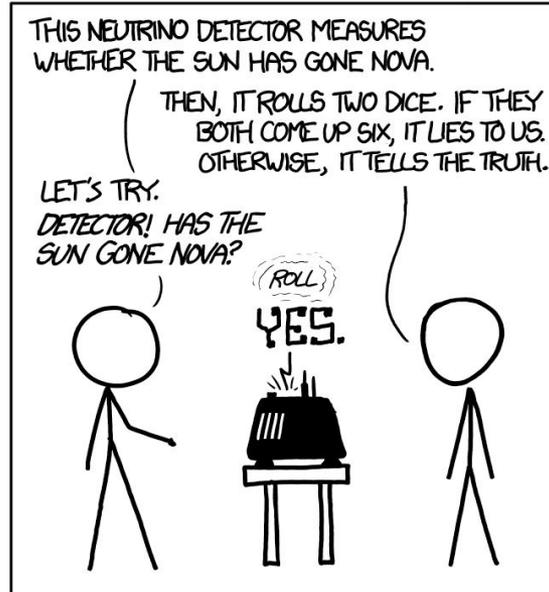
# Dimuon efficiency

From CMS-BPH-14-001

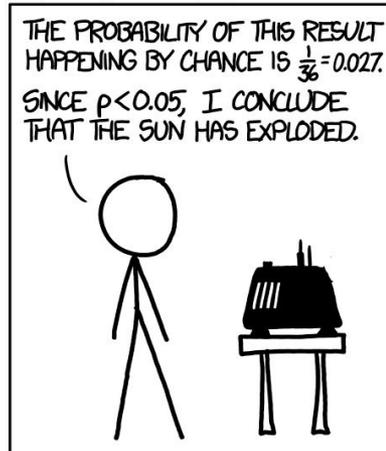


# Intermezzo

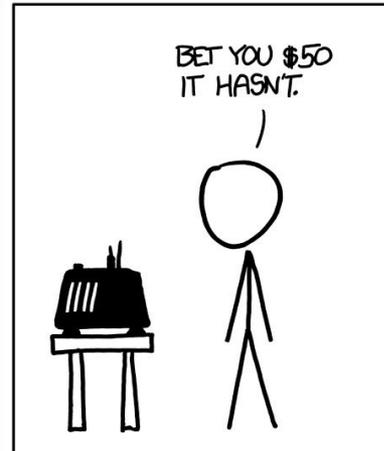
DID THE SUN JUST EXPLODE?  
(IT'S NIGHT, SO WE'RE NOT SURE.)



FREQUENTIST STATISTICIAN:

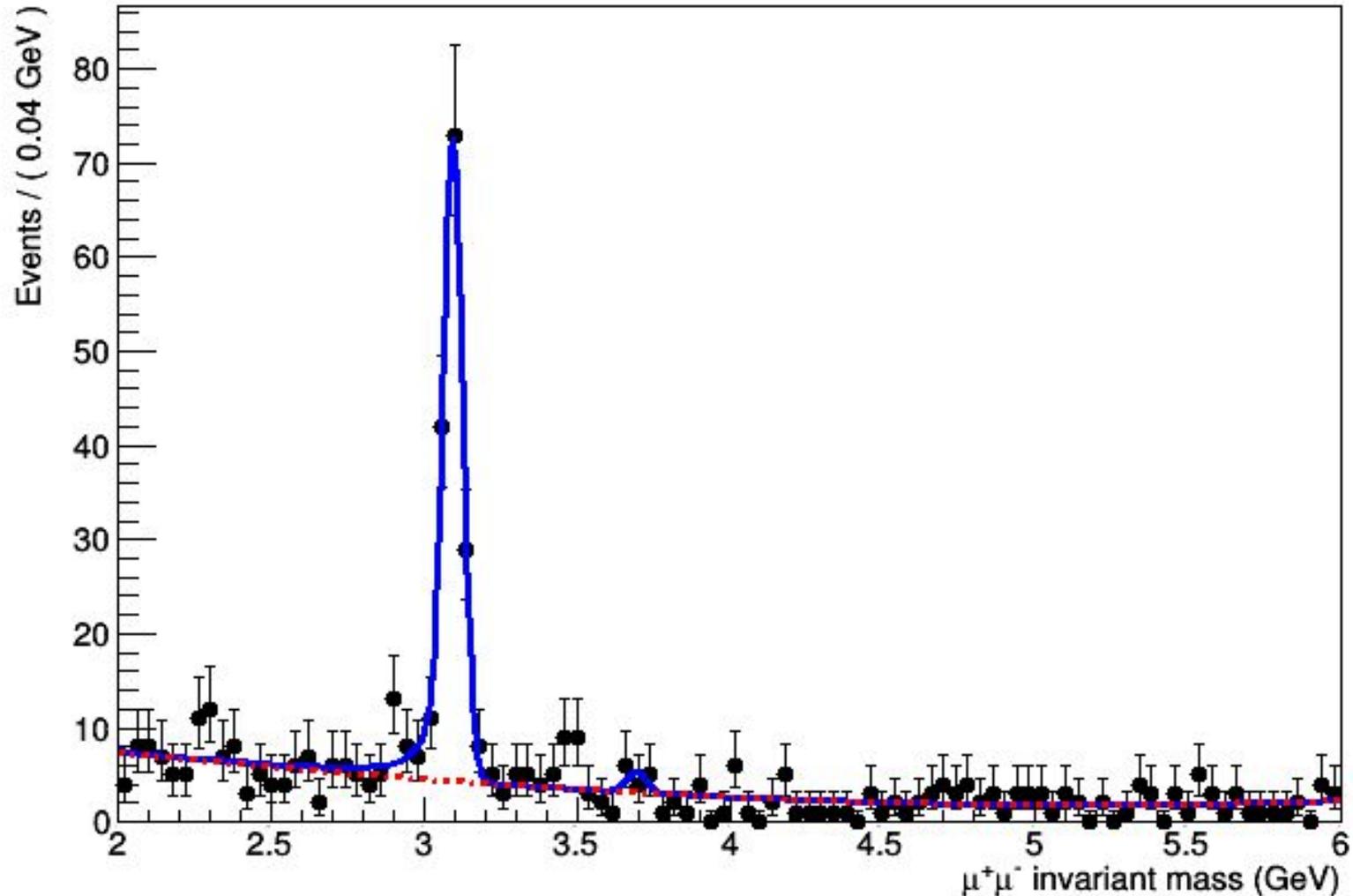


BAYESIAN STATISTICIAN:



# Result of exercise #0

A RooPlot of " $\mu^+\mu^-$  invariant mass"



# Complicating the problem

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Our current parametrization actually sensitive to

$$\sigma(pp \rightarrow \psi(2S) + X) \cdot BR(\psi(2S) \rightarrow \mu^+ \mu^-)$$

Additional exercise: modify  $N_{\psi(2S)}$  parametrization to actually measure the cross section!

Assume  $BR(\psi(2S) \rightarrow \mu^+ \mu^-) \sim 8 \cdot 10^{-3}$

# Exercise #1: test fit with toy-MCs

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RooFit has tools to test robustness of model via toy-MC generation

Usually healthy to perform, especially on POI

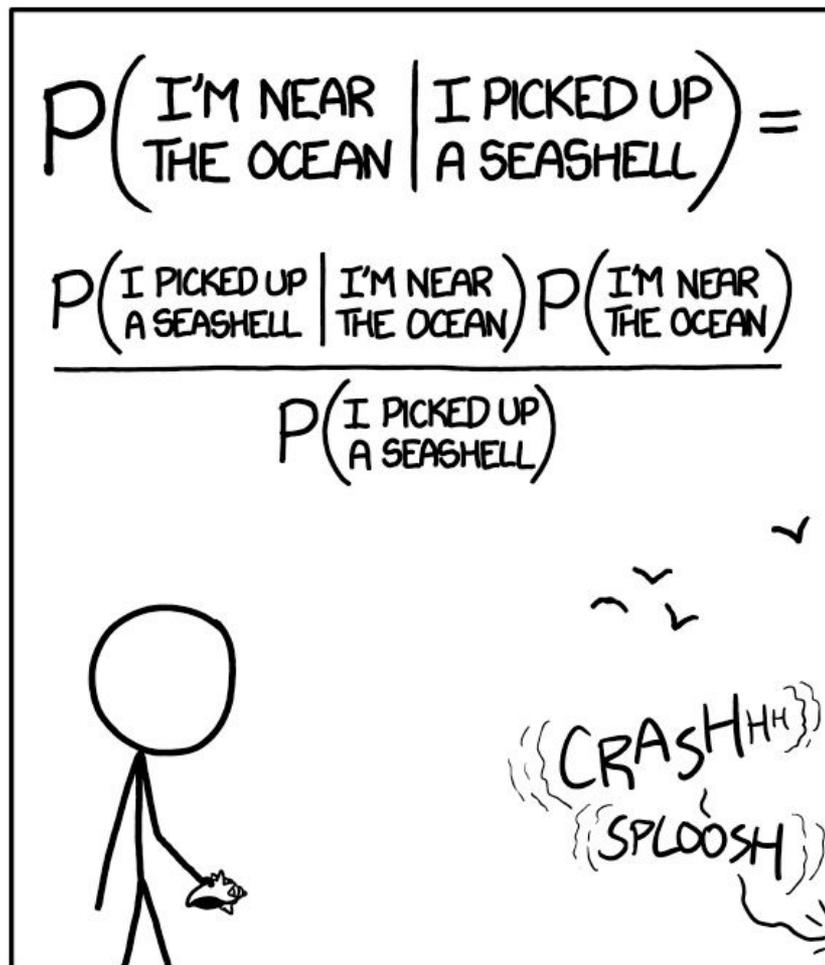
We do this in exercise 1

Approach:

- Use result of fit #0 as *true* model
- Generate 1k experiments, with same stats as CMS, using *true* model
  - Probably not enough, but time is limited
- Refit the 1k experiments with same model
- Compare with the *true* value of the parameters

RooFit can do this pretty easily

# Intermezzo



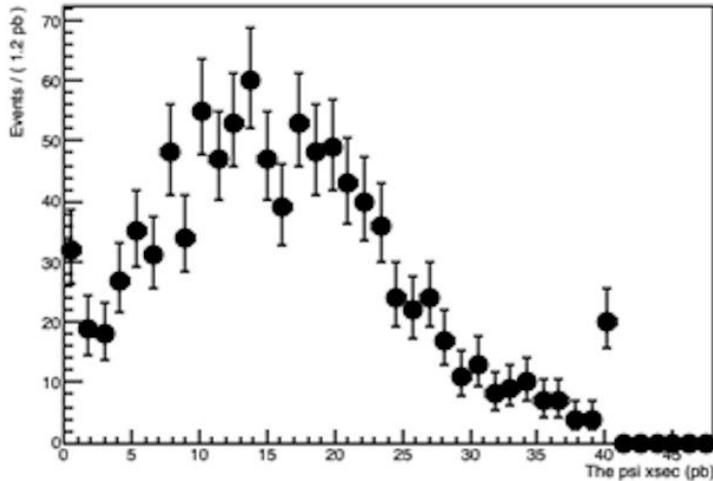
$$P\left(\begin{array}{l} \text{I'M NEAR} \\ \text{THE OCEAN} \end{array} \middle| \begin{array}{l} \text{I PICKED UP} \\ \text{A SEASHELL} \end{array}\right) =$$

$$\frac{P\left(\begin{array}{l} \text{I PICKED UP} \\ \text{A SEASHELL} \end{array} \middle| \begin{array}{l} \text{I'M NEAR} \\ \text{THE OCEAN} \end{array}\right) P\left(\begin{array}{l} \text{I'M NEAR} \\ \text{THE OCEAN} \end{array}\right)}{P\left(\begin{array}{l} \text{I PICKED UP} \\ \text{A SEASHELL} \end{array}\right)}$$

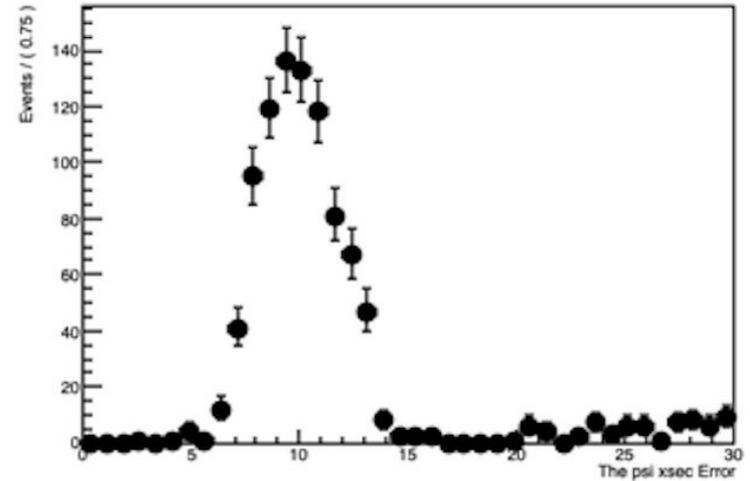
STATISTICALLY SPEAKING, IF YOU PICK UP A SEASHELL AND DON'T HOLD IT TO YOUR EAR, YOU CAN PROBABLY HEAR THE OCEAN.

# Results of exercise #1

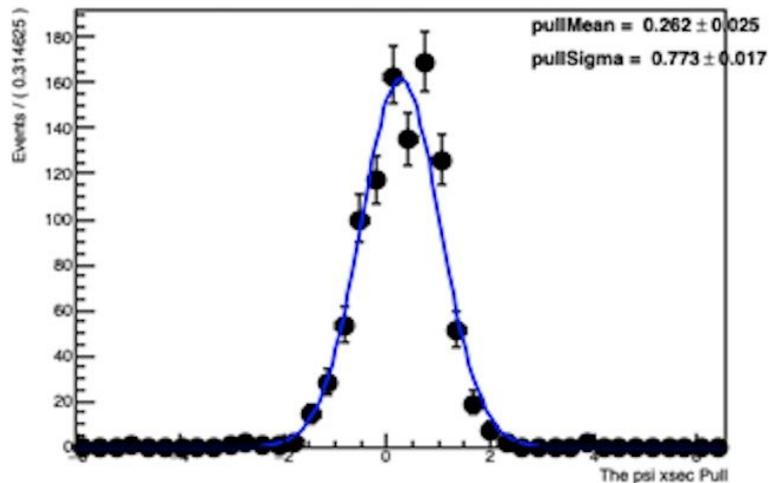
A RooPlot of "The psi xsec"



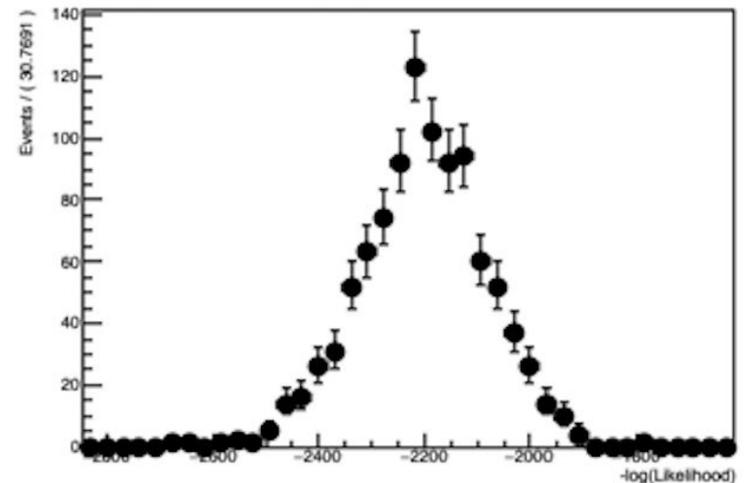
A RooPlot of "The psi xsec Error"



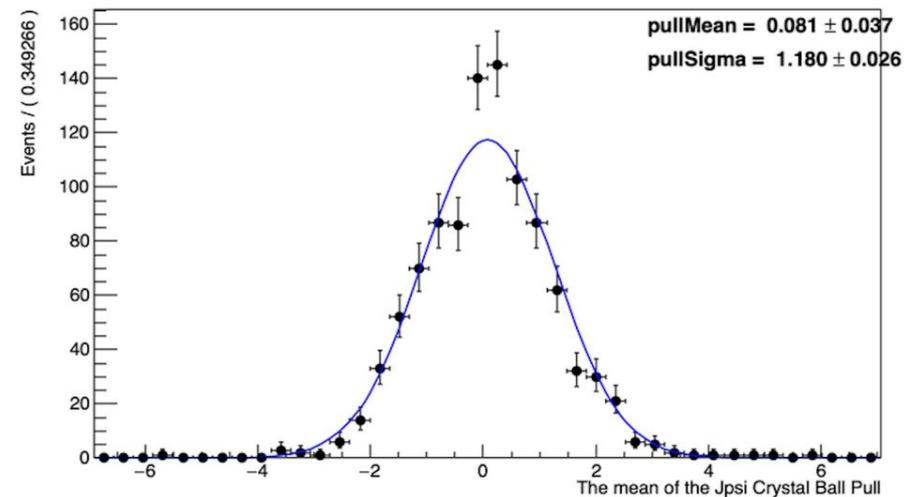
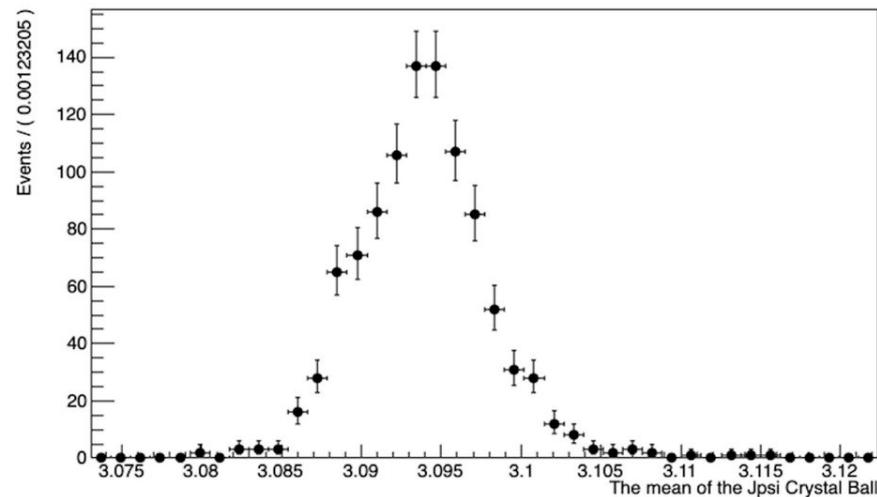
A RooPlot of "The psi xsec Pull"



A RooPlot of "-log(Likelihood)"



# Comparing with higher stats



Additional exercise: what happens if

- you increase number of experiments?
- you increase statistics of each experiment?

→ different effect on what toy-MCs can tell you

# RooStats

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Set of libraries for statistical interpretation of your results  
→ communicates with RooFit via RooWorkspace

RooStats does essentially two things:



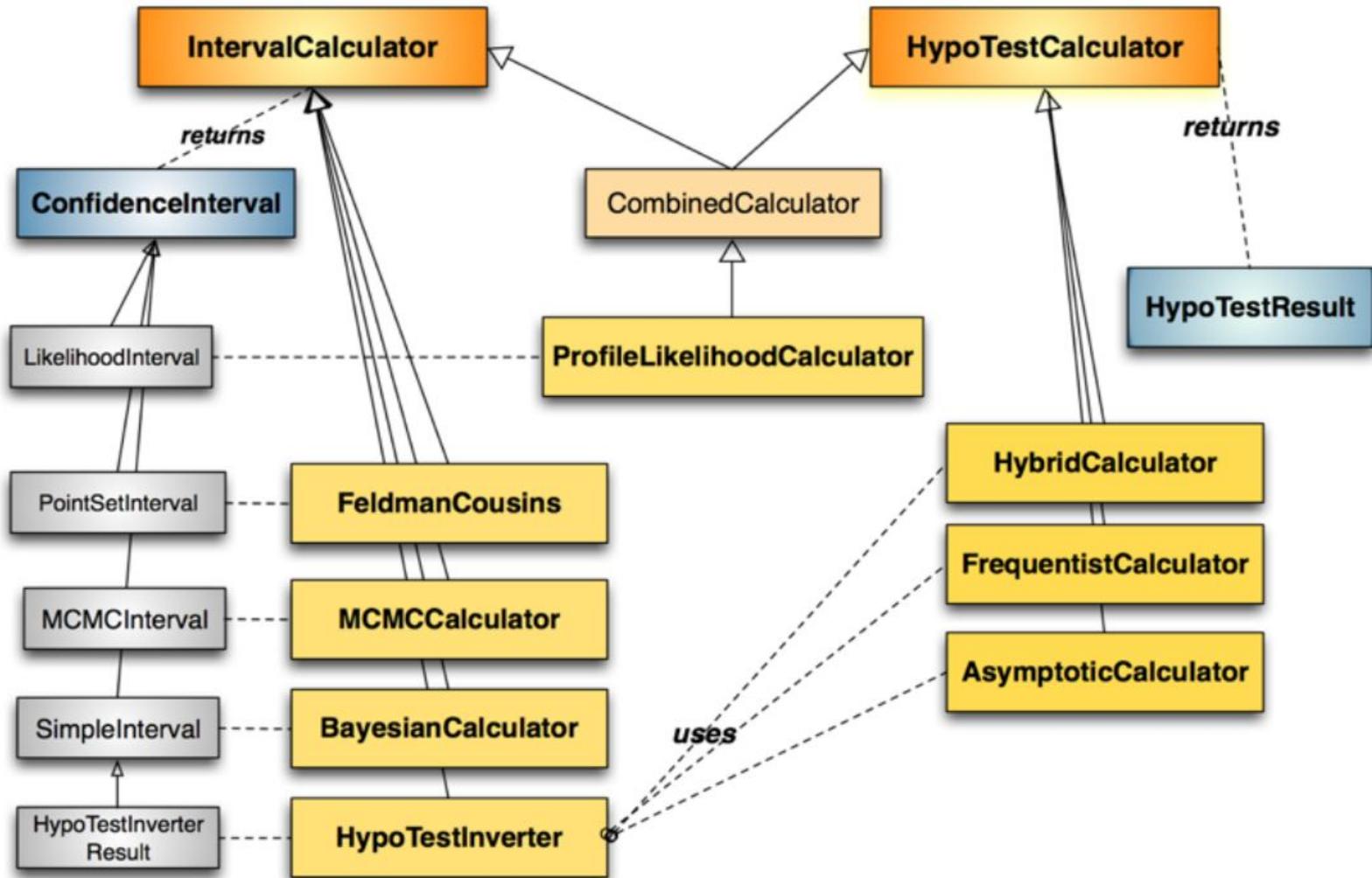
Interval calculation

Hypothesis testing

To do this, it uses “calculators”

# RooStats design

C++ classes that reproduce statistical concepts



# Main RooStats calculators

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## ProfileLikelihood calculator

- interval estimation using asymptotic properties of the likelihood function

## Bayesian calculators

- interval estimation using Bayes theorem

**BayesianCalculator** (analytical or adaptive numerical integration)

**MCMCCalculator** (Markov-Chain Monte Carlo)

## HybridCalculator, FrequentistCalculator

- frequentist hypothesis test calculators using toy data (difference in treatment of nuisance parameters)

## AsymptoticCalculator

- hypothesis tests using asymptotic properties of likelihood function

## HypoTestInverter

- invert hypothesis test results (from Asymptotic, Hybrid or FrequentistCalculator) to estimate an interval
- main tools used for limits at LHC (limits using CLs procedure)

## NeymanConstruction and FeldmanCousins

- frequentist interval calculators

# Exercise #2

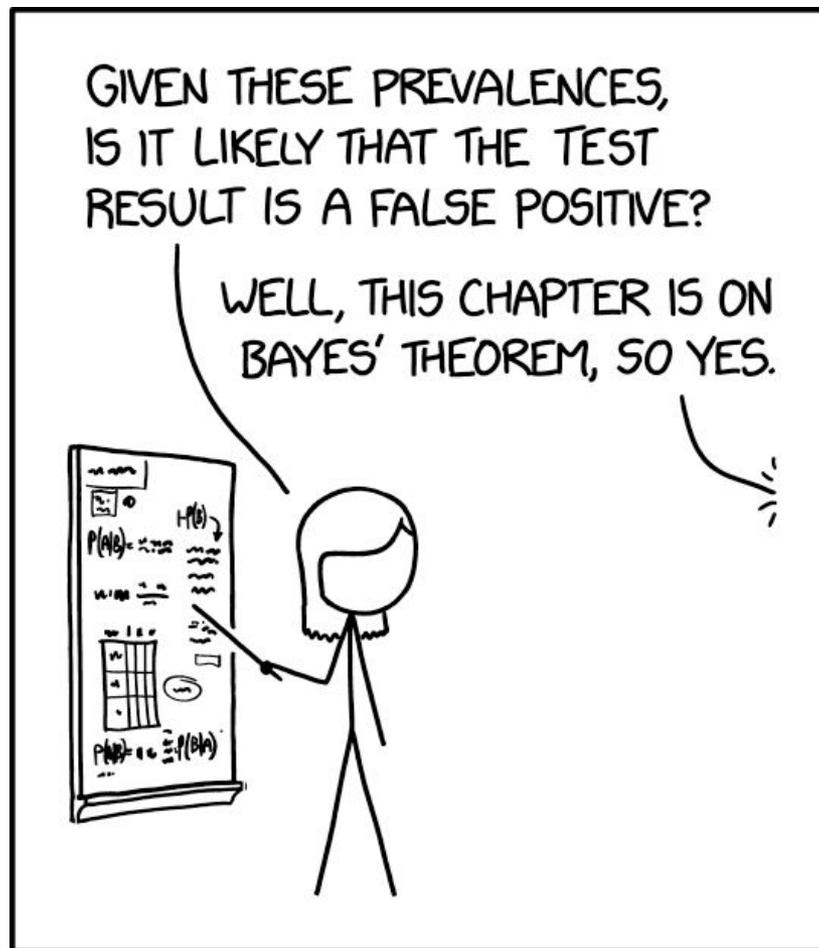
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Exercise #0 told us that there's clearly no significant peak in the distribution

Is this actually clear? How do we quantify?

Let's use the likelihood ratio!

# Intermezzo



SOMETIMES, IF YOU UNDERSTAND  
BAYES' THEOREM WELL ENOUGH,  
YOU DON'T NEED IT.

# Exercise #3

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From exercise #2 we know that our excess is “not significant”.

The normal procedure here is to evaluate an upper limit on our parameter of interest.

For the frequentist method, we will use  $CL_s$ ...

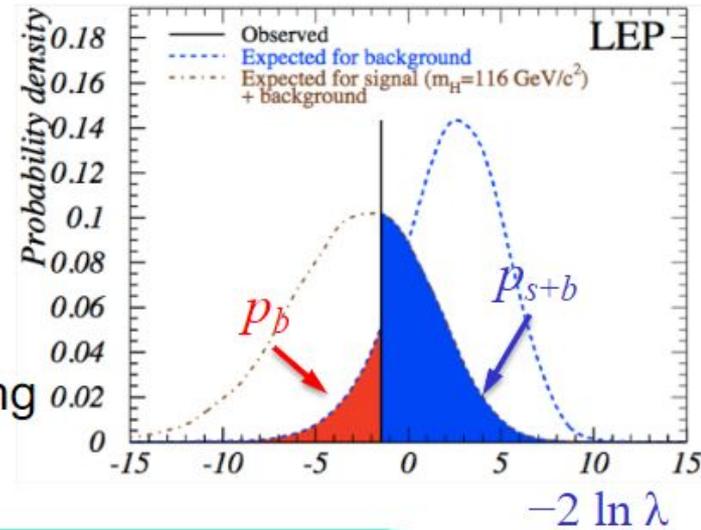
# Understanding $CL_s$

- A **modified approach** was proposed for the first time when combining the limits on the Higgs boson search from the four LEP experiments, ALEPH, DELPHI, L3 and OPAL
- Given a test statistic  $\lambda(x)$ , determine its distribution for the two hypotheses  $H_1(s + b)$  and  $H_0(b)$ , and compute:

$$\left\{ \begin{array}{l} p_{s+b} = P(\lambda(x|H_1) \leq \lambda^{\text{obs}}) \\ p_b = P(\lambda(x|H_0) \geq \lambda^{\text{obs}}) \end{array} \right.$$

- The upper limit is computed, instead of requiring  $p_{s+b} \leq \alpha$ , on the modified statistic  $CL_s \leq \alpha$ :

- Since  $1 - p_b \leq 1$ ,  $CL_s \geq p_{s+b}$ , hence upper limits computed with the  $CL_s$  method are always **conservative**



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

Note:  $\lambda \leq \lambda^{\text{obs}}$  implies  $-2\ln\lambda \geq \lambda^{\text{obs}}$

# Intermezzo

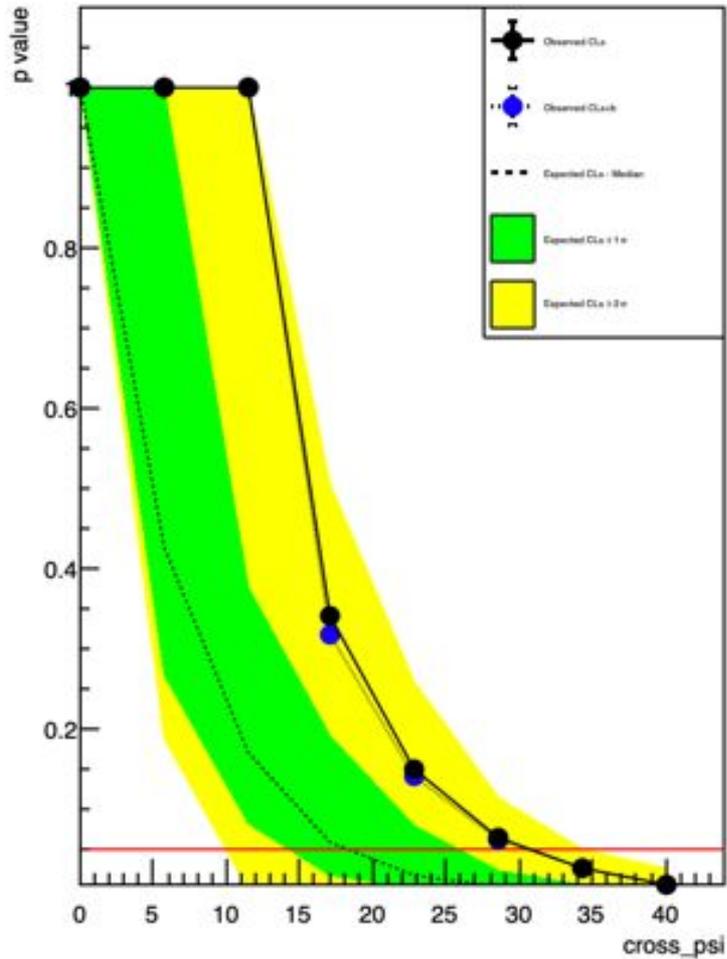
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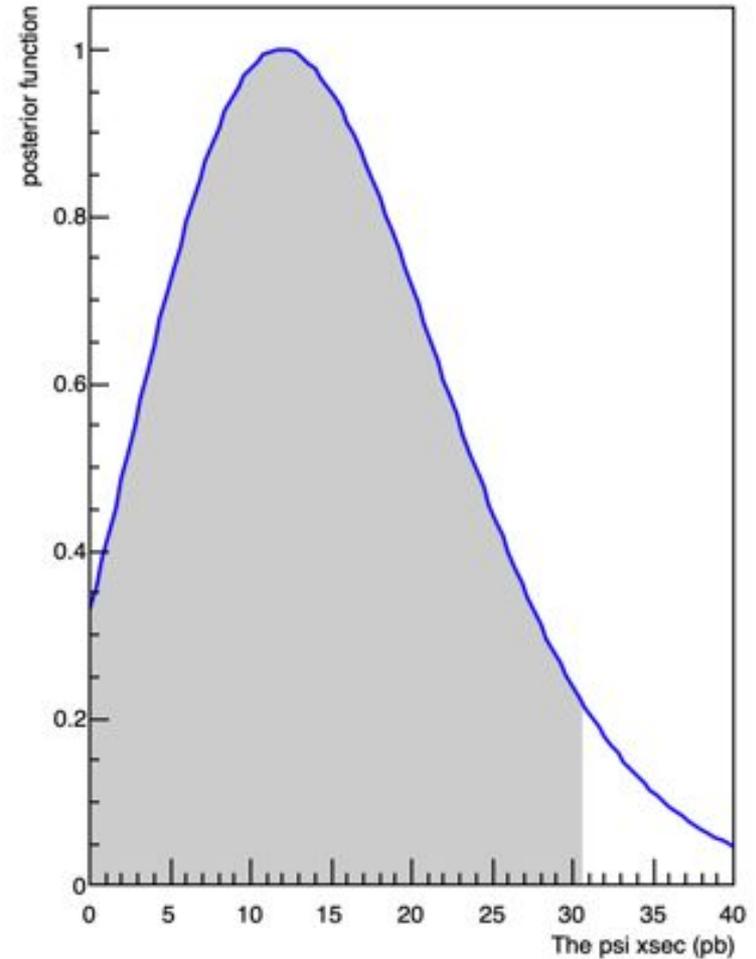
Statisticians have a different version of  
The Boy Who Cried Wolf.

# Result of exercise #3

Frequentist scan result for psi xsec



Posterior probability of parameter "cross\_psi"



# Exercise #4

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Let's now go to a scenario where we have a significant excess

- Get the full 2010 statistics file
- Rerun exercise 0 and 2 to recreate the workspace and calculate the new significance

Now we can measure the properties of our discovery

# Intermezzo

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MODIFIED BAYES' THEOREM:

$$P(H|X) = P(H) \times \left( 1 + P(C) \times \left( \frac{P(x|H)}{P(x)} - 1 \right) \right)$$

H: HYPOTHESIS

X: OBSERVATION

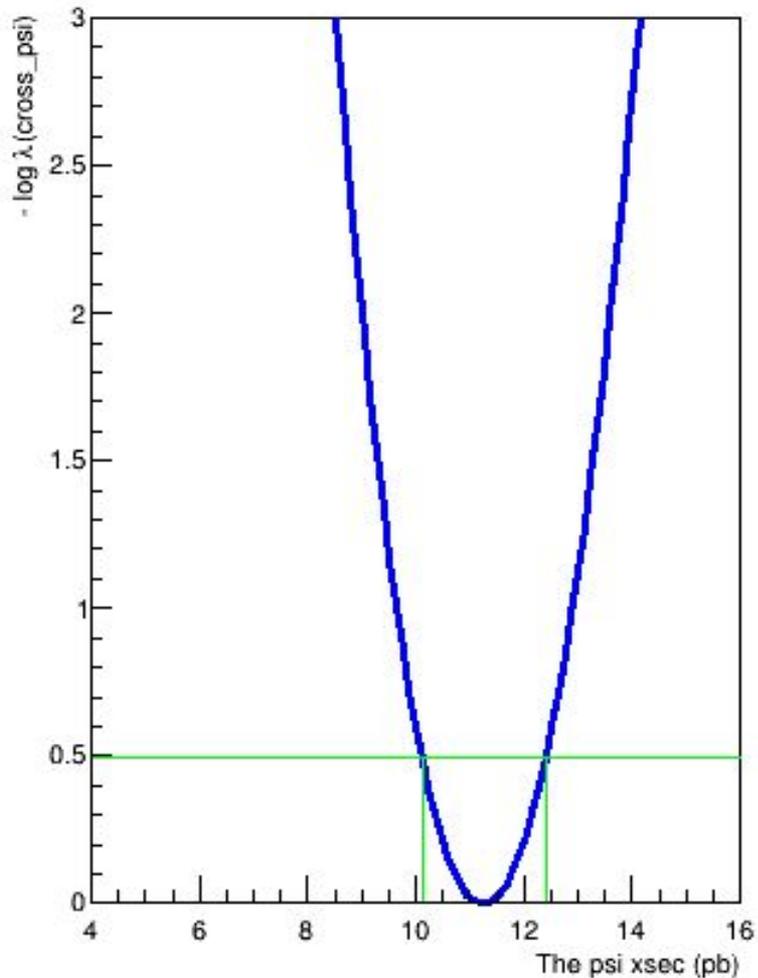
P(H): PRIOR PROBABILITY THAT H IS TRUE

P(x): PRIOR PROBABILITY OF OBSERVING X

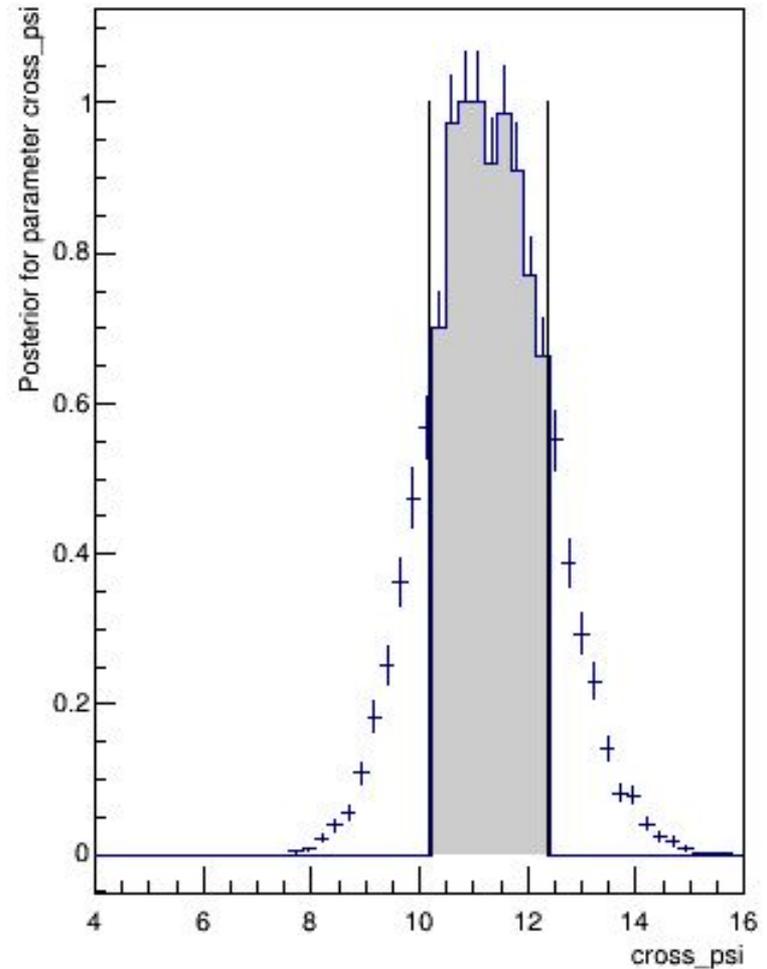
P(C): PROBABILITY THAT YOU'RE USING  
BAYESIAN STATISTICS CORRECTLY

# Result of exercise #4

Profile Likelihood Ratio



Bayesian probability interval (Markov Chain)



# Blinding

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In general, should not run interpretation on data before analysis strategy is decided

→ Check out the  $\sim 80$  GeV top quark “discovery” for a cautionary tale...

Roofit has tools to ease blinding. For example

```
var1 = ROOT.RooUnblindOffset("var1","blinded var","Daredevil",1.0,my_poi)
```

my\_poi shifted by unknown quantity (seeded by “Daredevil” of same order)

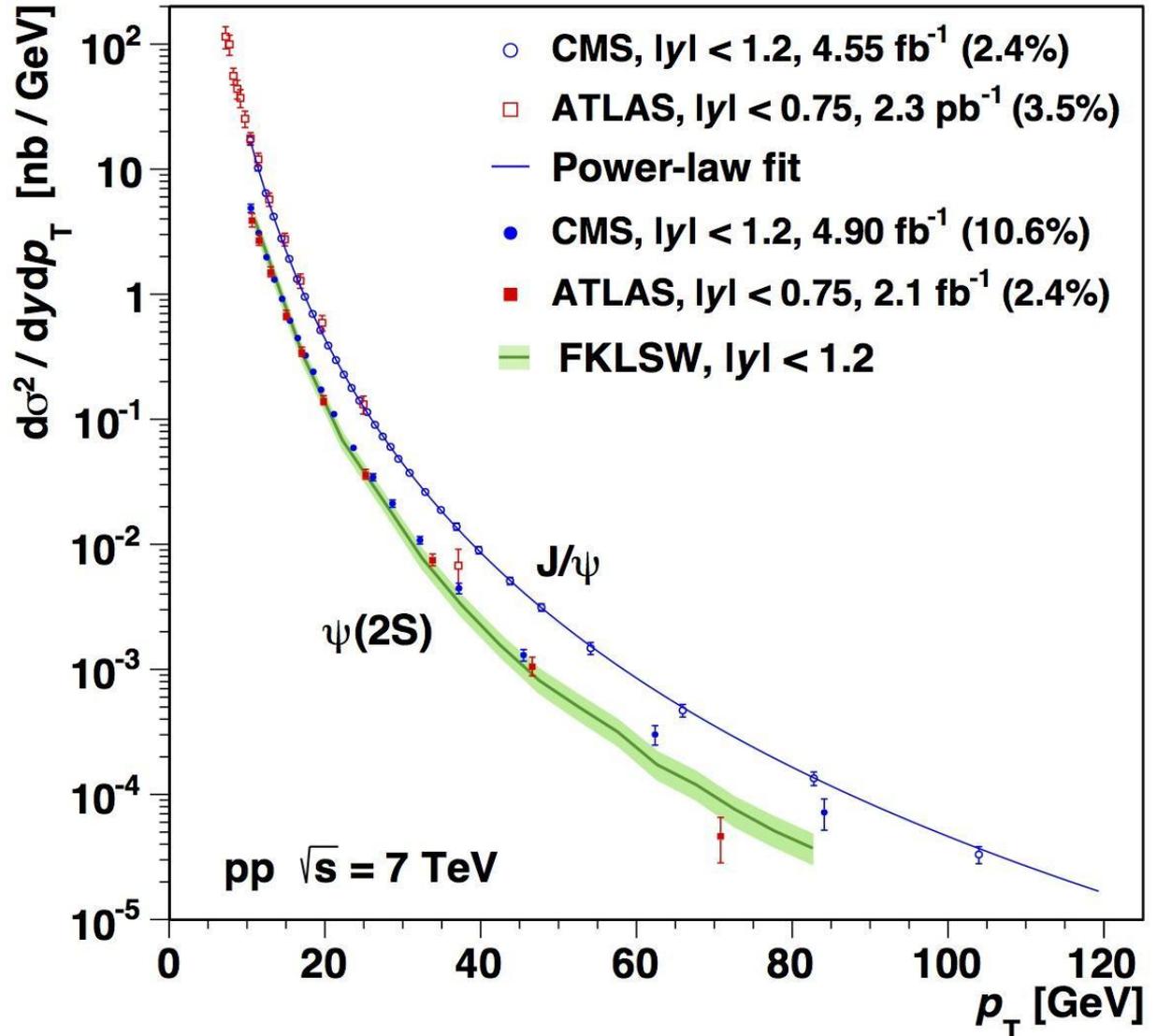
Can be used to study shifts (systematics!) directly on data while remaining blind

# $\psi(2S)$ cross section

From CMS-BPH-14-001

Remember that

$$\text{BR}(\psi(2S) \rightarrow \mu\mu) \sim 8 \cdot 10^{-3}$$



# Exercise #5

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Let's see how to incorporate systematic uncertainties in this workflow

Let's assume we have a 10% uncertainty on the efficiency

One possible way is to reparametrize the efficiency as

$$\sigma_{eff} = k * \sigma$$

Scale factor  $k=1$  for no uncertainty

Assuming a Gaussian behavior for this uncertainty, one can add this term to the total PDF

# Intermezzo

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```
int getRandomNumber()  
{  
    return 4; // chosen by fair dice roll.  
              // guaranteed to be random.  
}
```

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**That's all folks!**