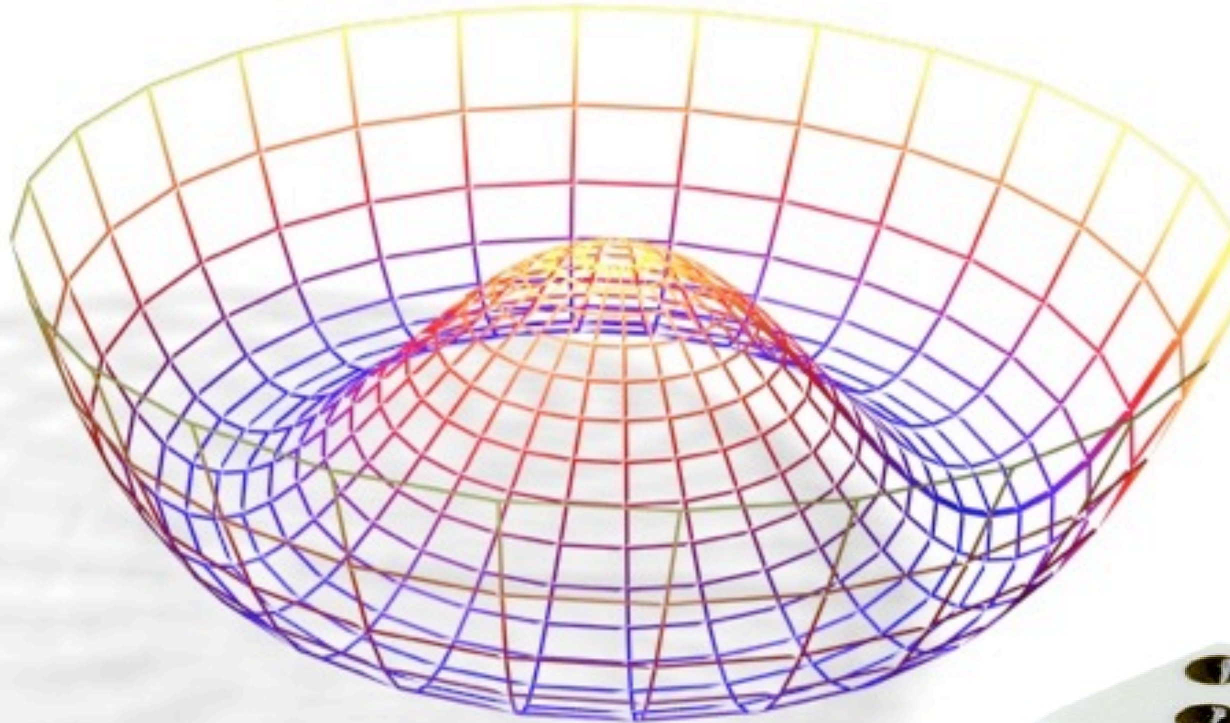
CENTER FOR
COSMOLOGY AND
PARTICLE PHYSICS

Statistics for the LHC: Quantifying our Scientific Narrative



Kyle Cranmer,
New York University

Introduction

Statistics plays a vital role in science, it is the way that we:

- quantify our knowledge and uncertainty
- communicate results of experiments

Big questions:

- make discoveries, test theories, measure or exclude parameters, etc.
- how do we get the most out of our data
- how do we incorporate uncertainties
- how do we make decisions

Statistics is a very big field, and it is not possible to cover everything in 4 hours. In these talks I will try to:

- **explain** some fundamental ideas & prove a few things
- **enrich** what you already know
- **expose** you to some new ideas

I will try to go slowly, because if you are not following the logic, then it is not very interesting.

- Please feel free to ask questions and interrupt at any time

Further Reading

By physicists, for physicists

G. Cowan, Statistical Data Analysis, Clarendon Press, Oxford, 1998.

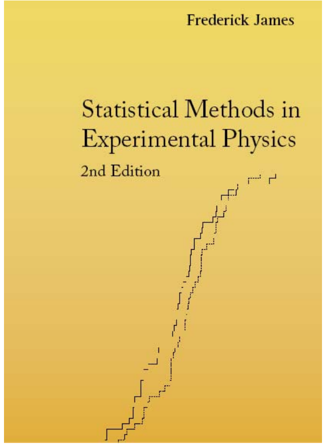
R.J.Barlow, A Guide to the Use of Statistical Methods in the Physical Sciences, John Wiley, 1989;

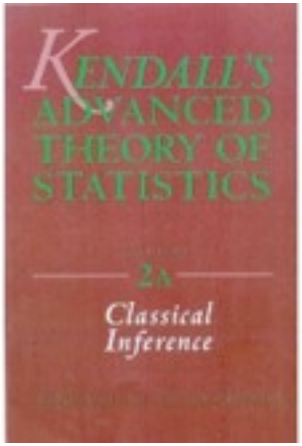
F. James, Statistical Methods in Experimental Physics, 2nd ed., World Scientific, 2006;

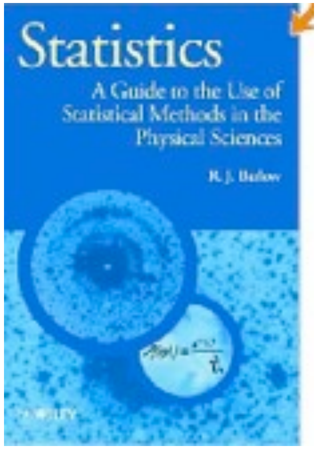
- W.T. Eadie et al., North-Holland, 1971 (1st ed., hard to find);

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

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







My favorite statistics book by a statistician:

Stuart, Ord, Arnold. "Kendall's Advanced Theory of Statistics" Vol. 2A *Classical Inference & the Linear Model.*

Other lectures

Fred James's lectures

http://preprints.cern.ch/cgi-bin/setlink?base=AT&categ=Academic_Training&id=AT00000799

http://www.desy.de/~acatrain/

Glen Cowan's lectures

http://www.pp.rhul.ac.uk/~cowan/stat_cern.html

Louis Lyons

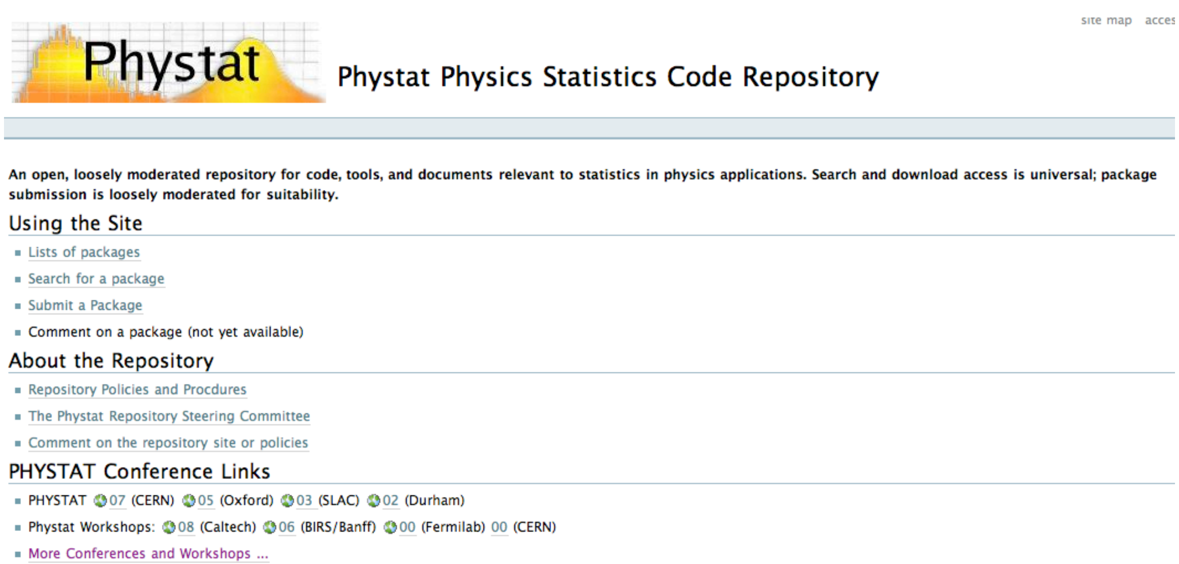
http://indico.cern.ch/conferenceDisplay.py?confId=a063350

Bob Cousins gave a CMS lecture, may give it more publicly

Gary Feldman "Journeys of an Accidental Statistician"

http://www.hepl.harvard.edu/~feldman/Journeys.pdf

The PhyStat conference series at PhyStat.org:



Comments on these lectures

I also gave “Statistics for LHC” academic training lectures in 2009

http://indico.cern.ch/conferenceDisplay.py?confId=48425

Now that we have data, I will put emphasis on realistic problems representative of current analyses

2009	2011
	Modeling & Scientific Narrative
Foundations of Probability	Hypothesis Tests
Hypothesis Tests	Confidence Intervals
Confidence Intervals	Bayesian Methods
Generalization for complex problems	Likelihood Methods

Lecture 1

Probability Density Functions

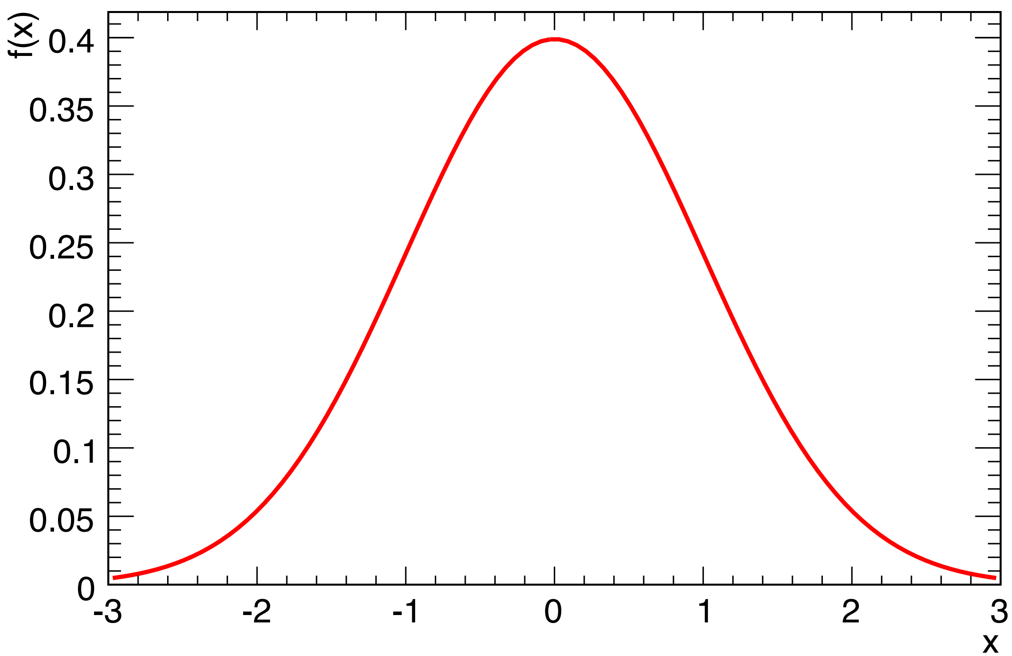
When dealing with continuous random variables, need to introduce the notion of a **Probability Density Function** (PDF... not parton distribution function)

$$P(x \in [x, x+dx]) = f(x)dx$$

Note, $f(x)$ is NOT a probability

PDFs are always normalized

$$\int_{-\infty}^{\infty} f(x)dx = 1$$



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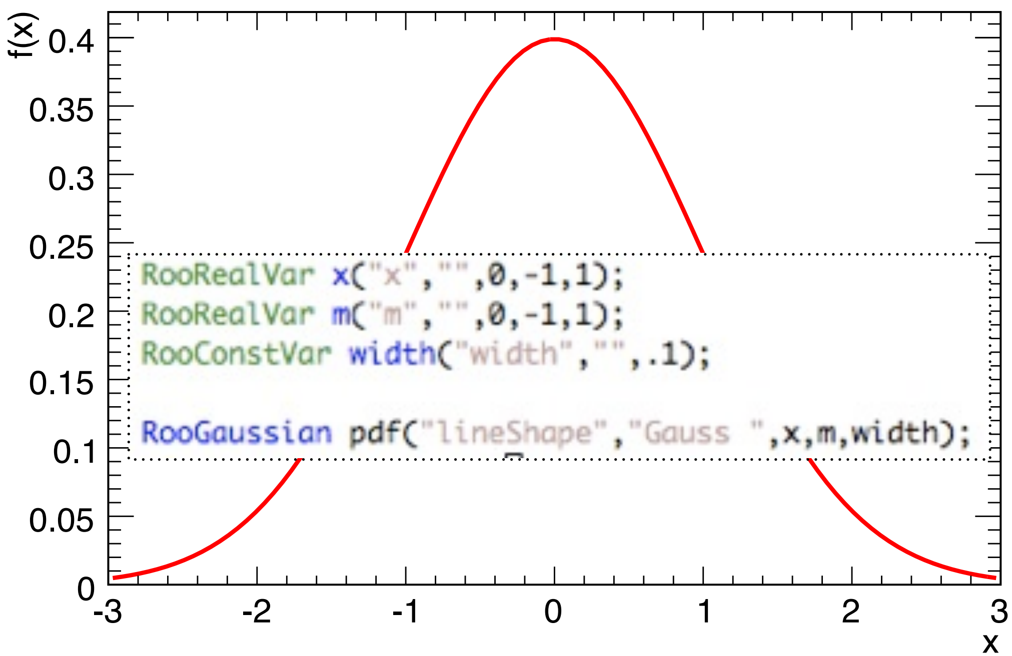

Parametric PDFs

Many familiar PDFs are considered **parametric**

- eg. a Gaussian $G(x|\mu,\sigma)$ is parametrized by (μ,σ)
- defines a family of distributions
- allows one to make inference about parameters

I will represent PDFs graphically as below (directed acyclic graph)

- every node is a real-valued function of the nodes below

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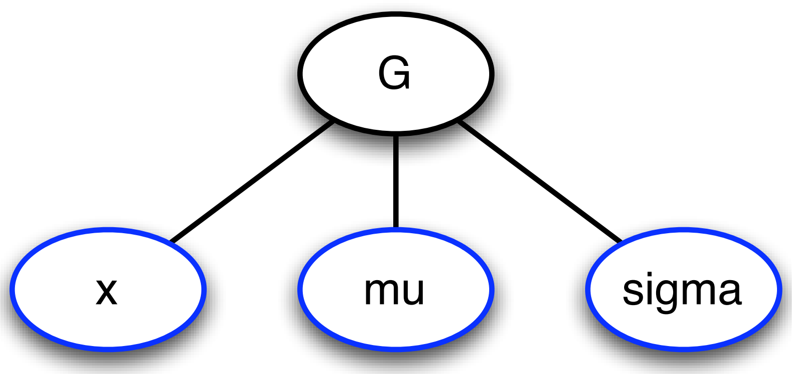

Parametric PDFs

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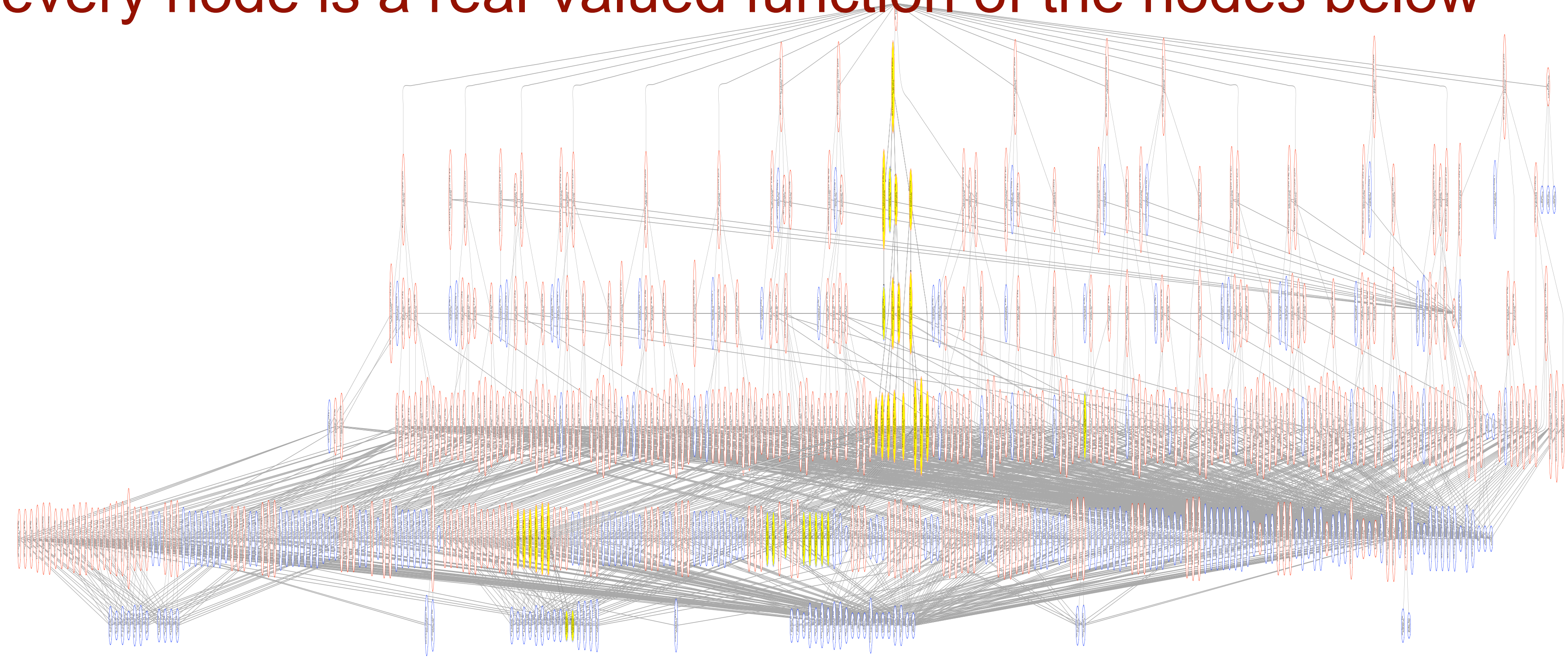


Modeling:
The Scientific Narrative

Building a model of the data

Before one can discuss statistical tests, one must have a "**model**" for the data.

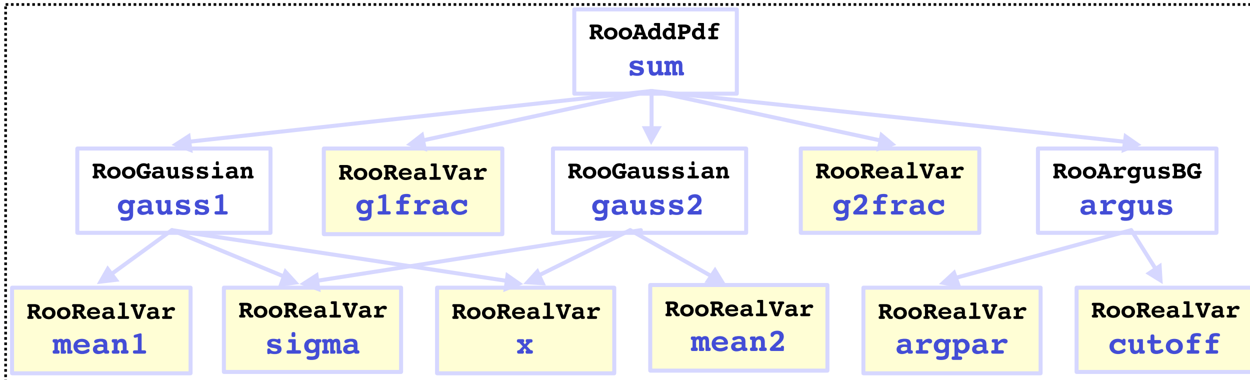
- by "model", I mean the full structure of P(data | parameters)
  - holding parameters fixed gives a PDF for data
  - ability to evaluate generate pseudo-data (Toy Monte Carlo)
  - holding data fixed gives a **likelihood function** for parameters
    - note, likelihood function is not as general as the full model because it doesn't allow you to generate pseudo-data

Both Bayesian and Frequentist methods start with the model

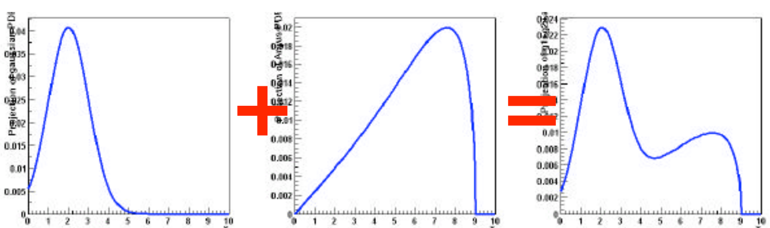
- it's the objective part that everyone can agree on
- it's the place where our physics knowledge, understanding, and intuiting comes in
- building a better model is the best way to improve your statistical procedure

RooFit: A data modeling toolkit

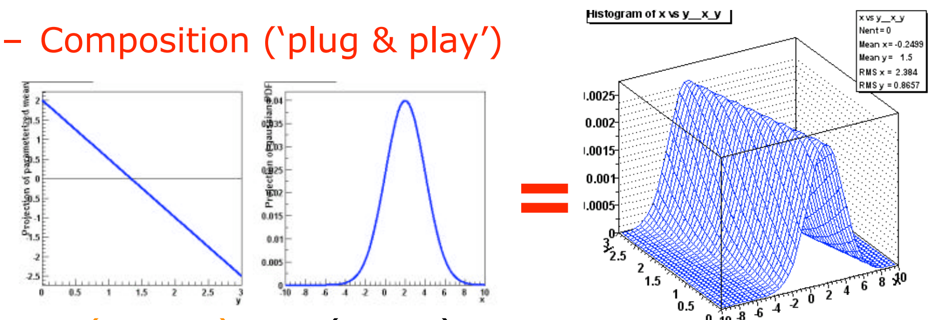
RooFit is a major tool developed at BaBar for data modeling. RooStats provides higher-level statistical tools based on these PDFs.



– Addition



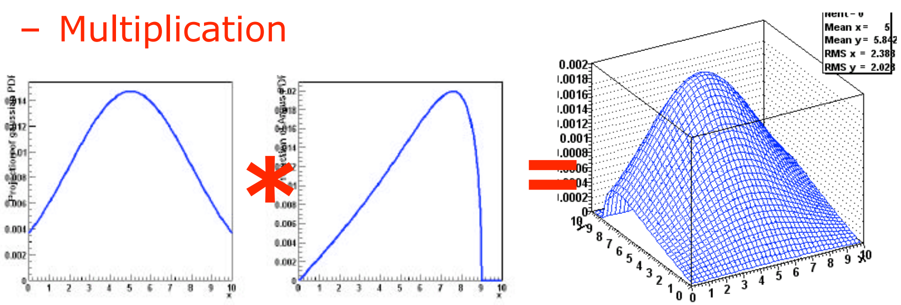
– Composition ('plug & play')



$m(y;a_0,a_1)$ $g(x;m,s)$ $g(x,y;a0,a1,s)$

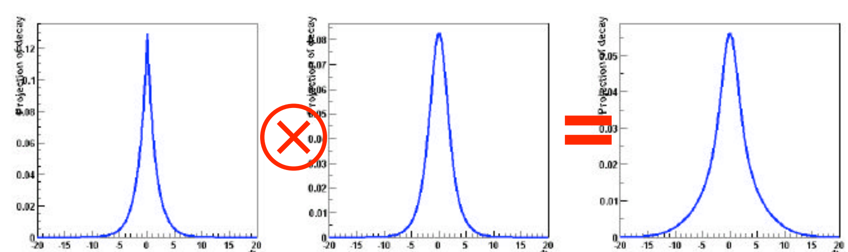
Possible in *any* PDF
No explicit support in PDF code needed

– Multiplication



Wouter Verkerke,

– Convolution



Wouter Verkerke, UCSB

The Scientific Narrative

The model can be seen as a quantitative summary of the analysis

- If you were asked to justify your modeling, you would tell a **story** about why you know what you know
  - based on previous results and studies performed along the way
- the quality of the result is largely tied to how convincing this story is and how tightly it is connected to model

I will describe a few “narrative styles”

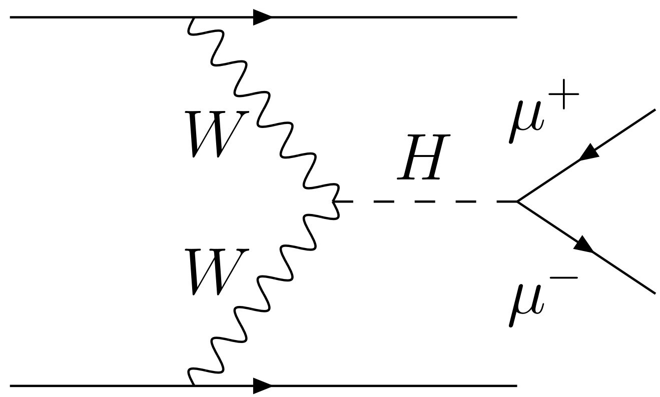
- The “Monte Carlo Simulation” narrative
- The “Data Driven” narrative
- The “Effective Modeling” narrative
- The “Parametrized Response” narrative

Real-life analyses often use a mixture of these

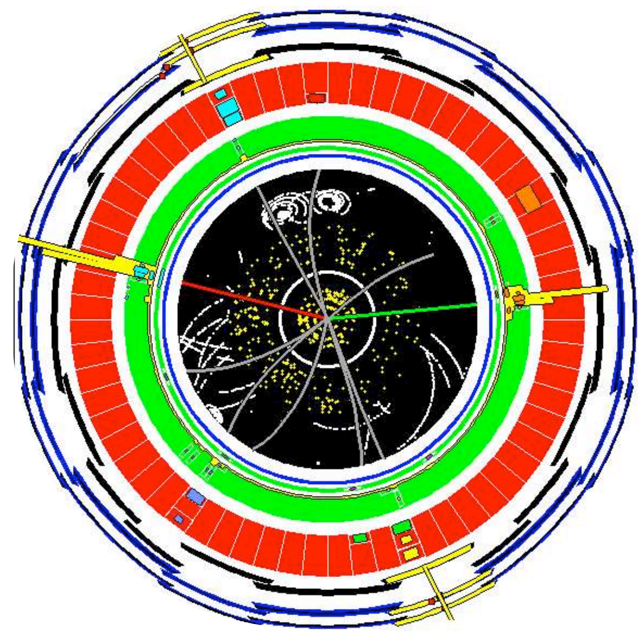
The Monte Carlo Simulation narrative

Let's start with "the Monte Carlo simulation narrative", which is probably the most familiar

$P =$



$\oplus$



Cross-sections and event rates

From the many, many collision events, we impose some criteria to select n candidate signal events. We hypothesize that it is composed of some number of signal and background events.

$$\mathrm{Pois}(n|s+b)$$

The number of events that we expect from a given interaction process is given as a product of

- L : a time-integrated luminosity (units 1/cm^2) that serves as a measure of the amount of data that we have collected or the number of trials we have had to produce signal events
- σ : "cross-section" (units cm^2) a quantity that can be calculated from theory
- ε : fraction of signal events selected by selection criteria

The simulation narrative

1) The language of the Standard Model is Quantum Field Theory
Phase space Ω defines initial measure, sampled via Monte Carlo

$$P = \frac{|\langle f|i\rangle|^2}{\langle f|f\rangle\langle i|i\rangle}$$

$$P \to L\sigma$$

$$d\sigma \to |\mathcal{M}|^2 d\Omega$$

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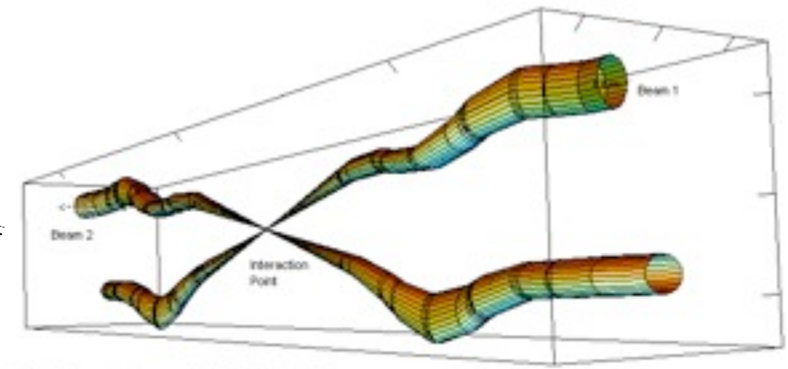

Relative beam sizes around IP1 (Atlas) in collision

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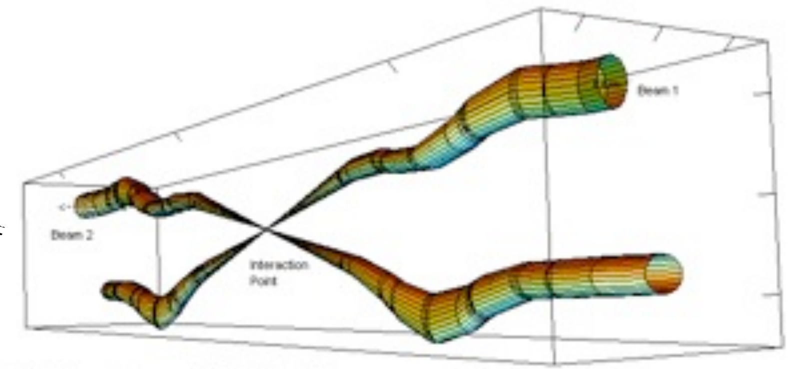


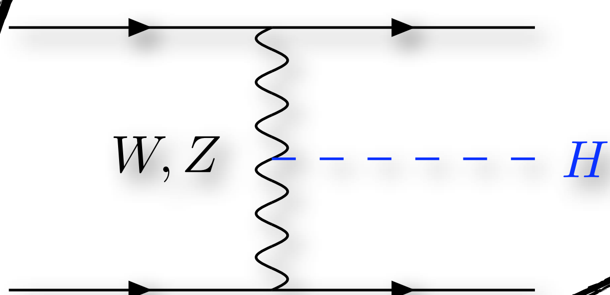
Relative beam sizes around IP1 (Atlas) in collision

$$\mathcal{L}_{SM} = \underbrace{\frac{1}{4}\mathbf{W}_{\mu\nu}\cdot\mathbf{W}^{\mu\nu} - \frac{1}{4}B_{\mu\nu}B^{\mu\nu} - \frac{1}{4}G^a_{\mu\nu}G^{\mu\nu}_a}_{\text{kinetic energies and self-interactions of the gauge bosons}}$$

$$+ \underbrace{\bar{L}\gamma^\mu(i\partial_\mu - \frac{1}{2}g\tau\cdot\mathbf{W}_\mu - \frac{1}{2}g'YB_\mu)L + \bar{R}\gamma^\mu(i\partial_\mu - \frac{1}{2}g'YB_\mu)R}_{\text{kinetic energies and electroweak interactions of fermions}}$$

$$+ \underbrace{\frac{1}{2}\left|(i\partial_\mu - \frac{1}{2}g\tau\cdot\mathbf{W}_\mu - \frac{1}{2}g'YB_\mu)\,\phi\right|^2 - V(\phi)}_{W^\pm, Z, \gamma, \text{and Higgs masses and couplings}}$$

$$+ \underbrace{g''(\bar{q}\gamma^\mu T_a q)\,G^a_\mu}_{\text{interactions between quarks and gluons}} + \underbrace{(G_1\bar{L}\phi R + G_2\bar{R}\phi_c L + h.c.)}_{\text{fermion masses and couplings to Higgs}}$$

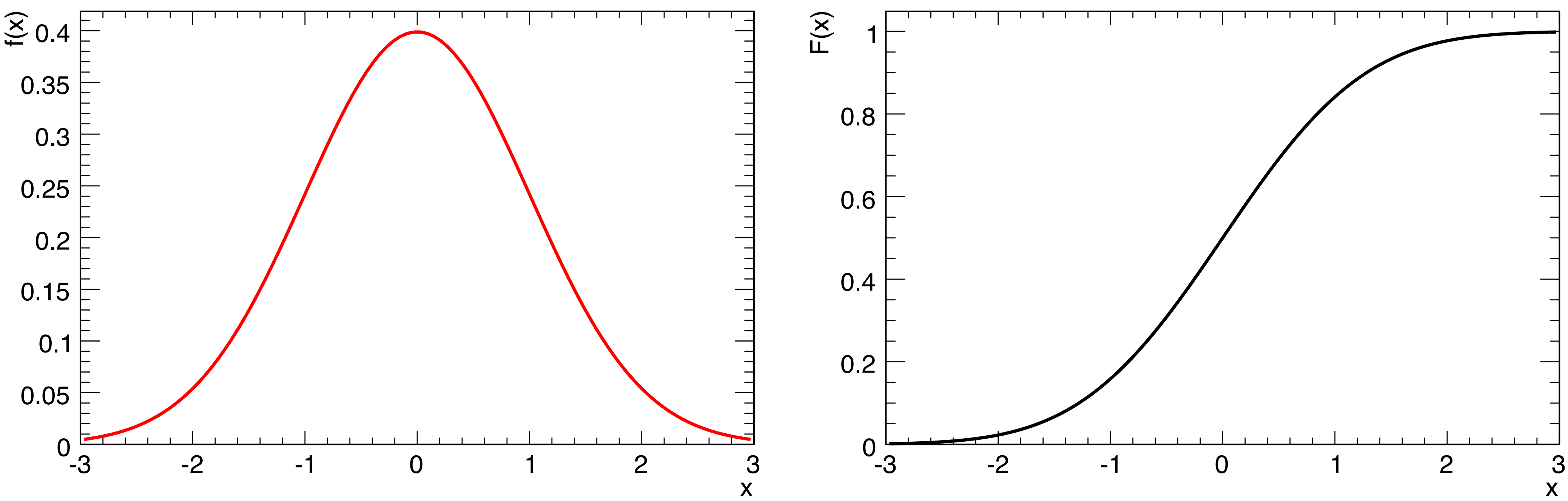


Cumulative Density Functions

Often useful to use a cumulative distribution:

- in 1-dimension:

$$\int_{-\infty}^{x} f(x')dx' = F(x)$$



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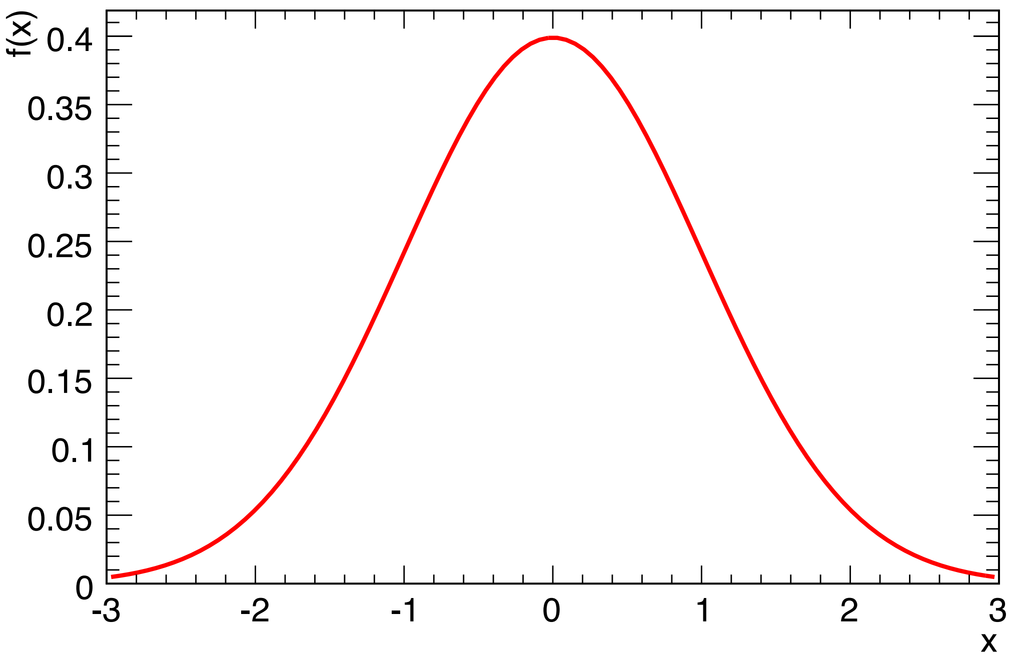

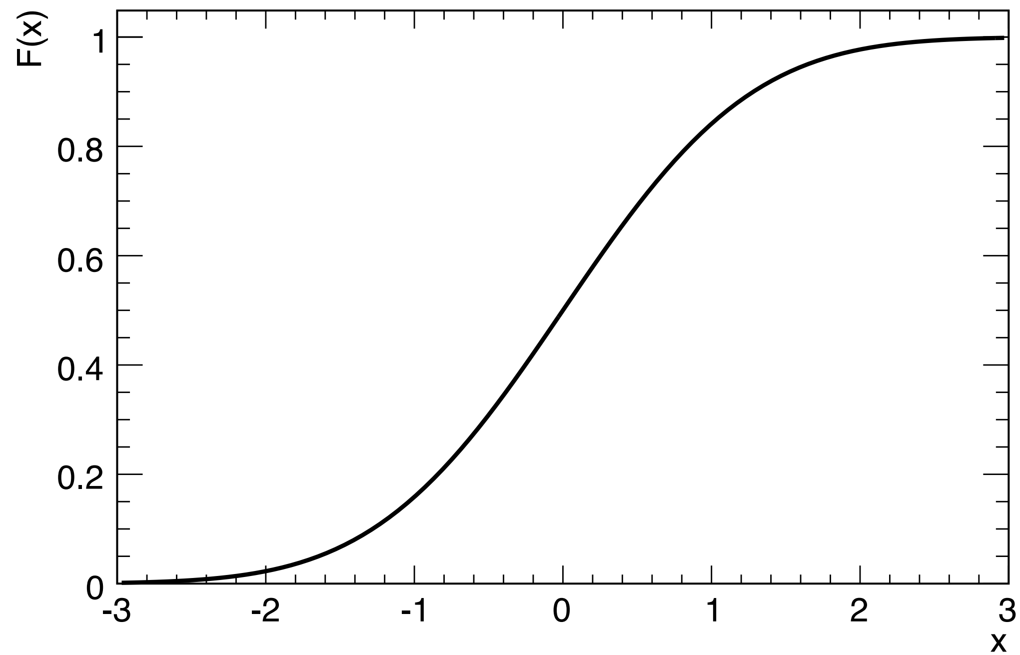

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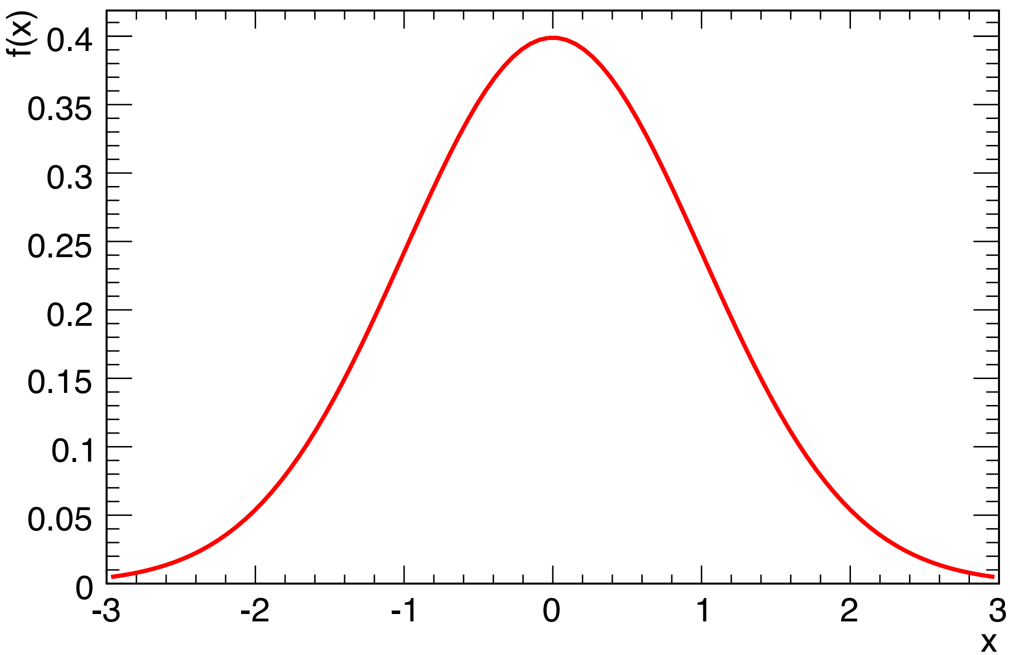

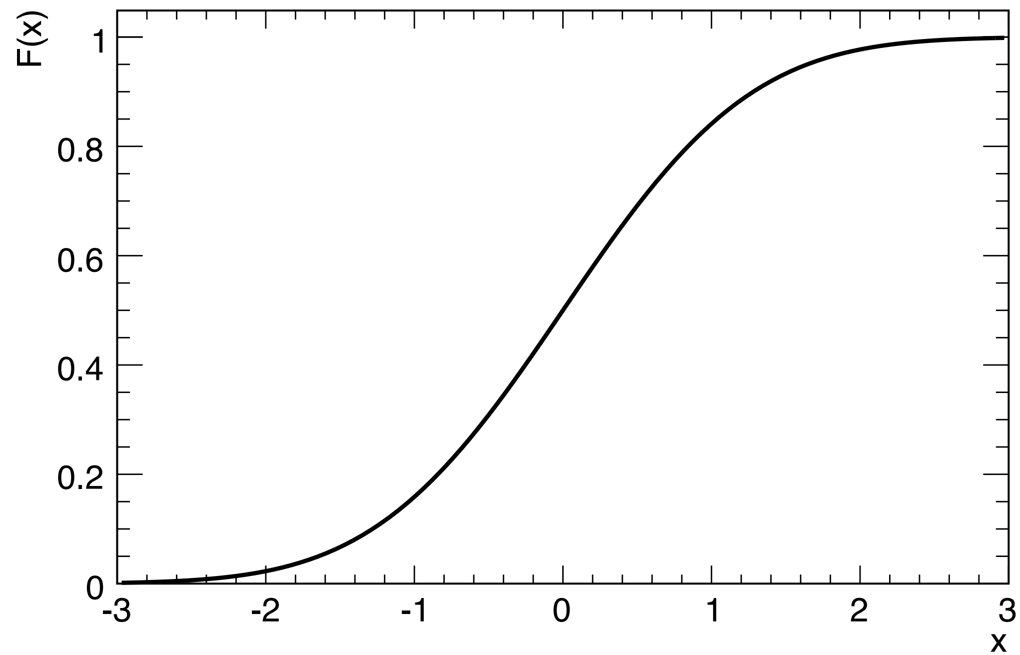

- alternatively, define density as partial of cumulative:

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- same relationship as total and differential cross section:

$$f(E) = \frac{1}{\sigma}\frac{\partial \sigma}{\partial E}$$

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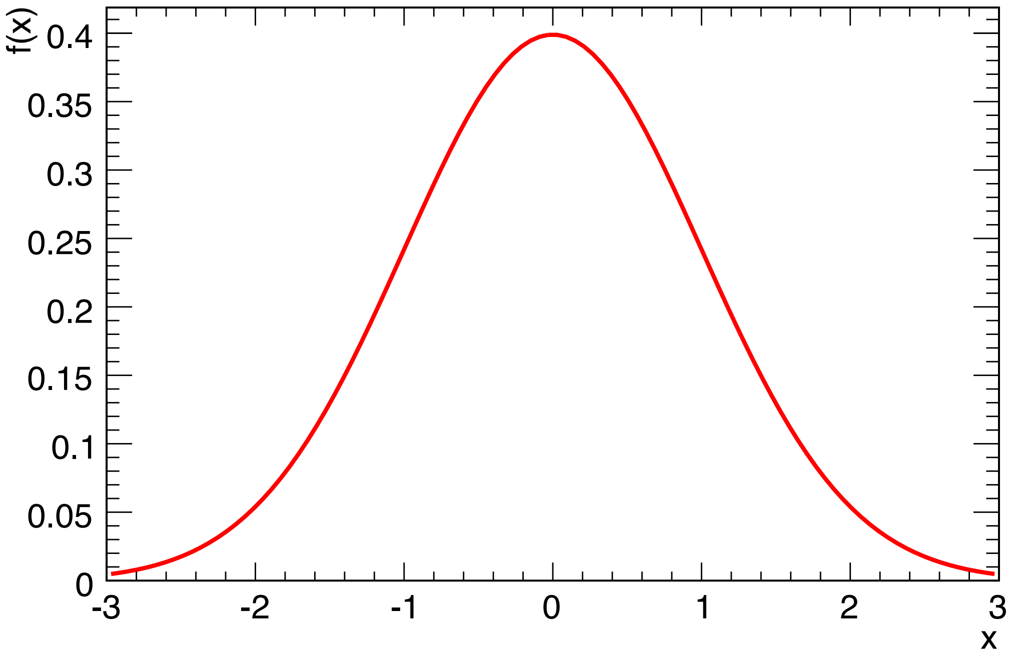

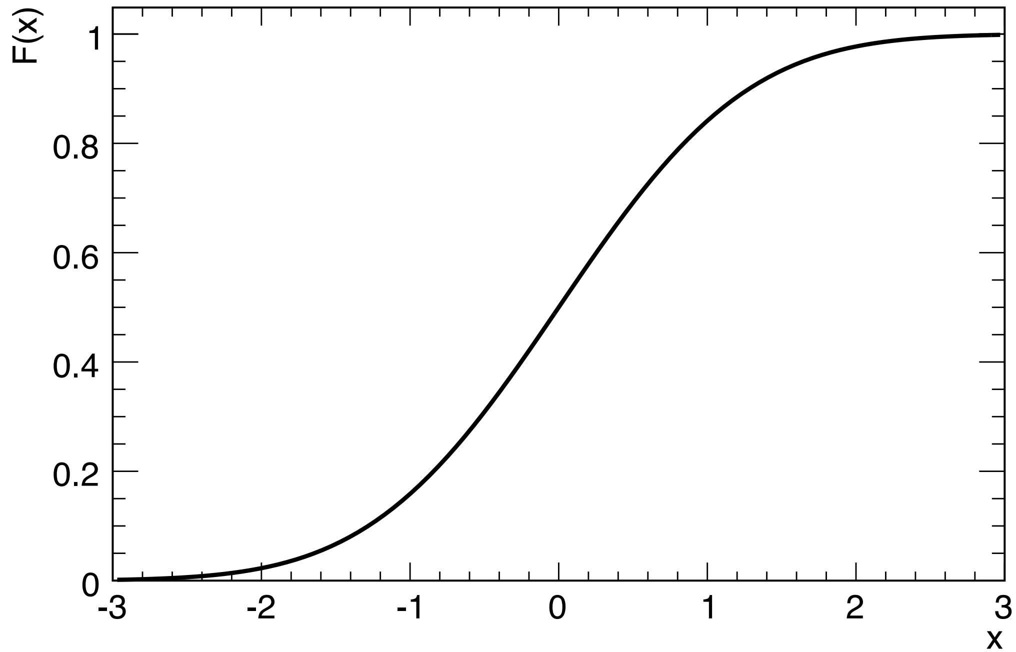

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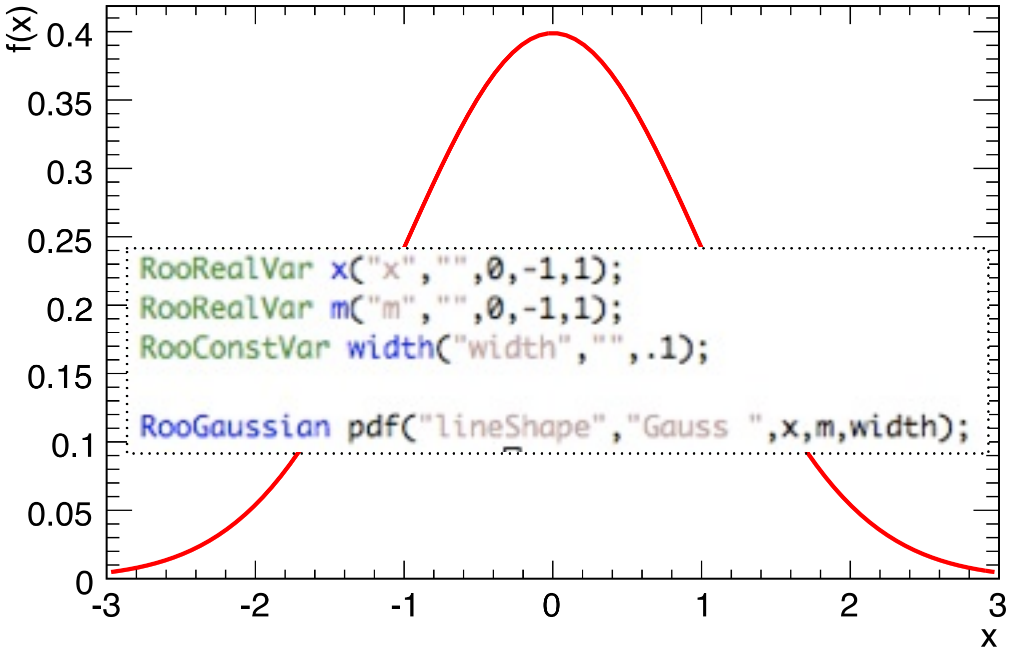

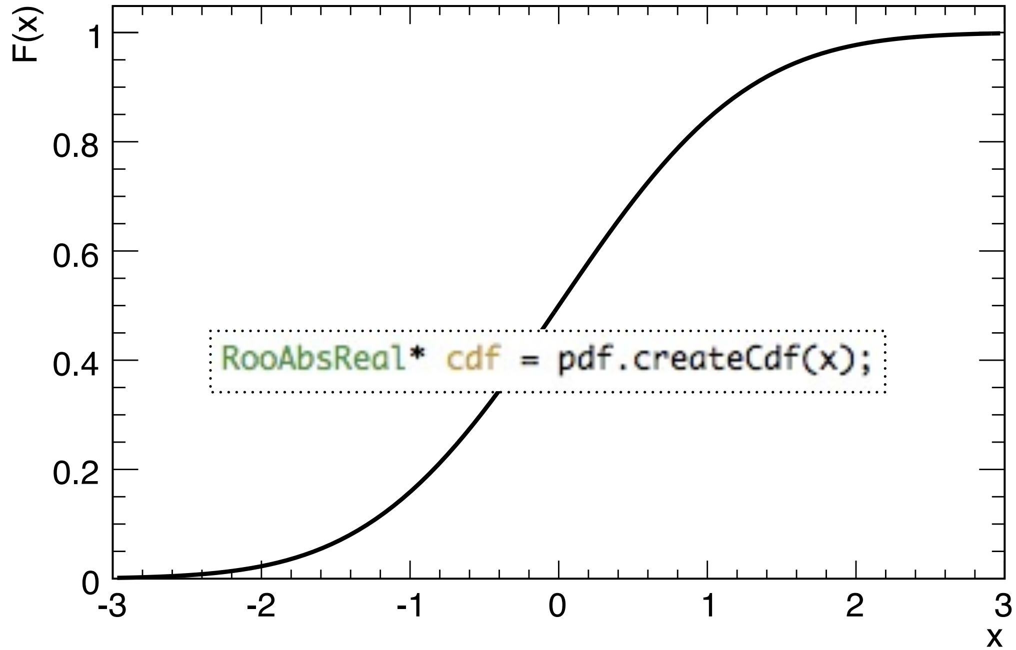

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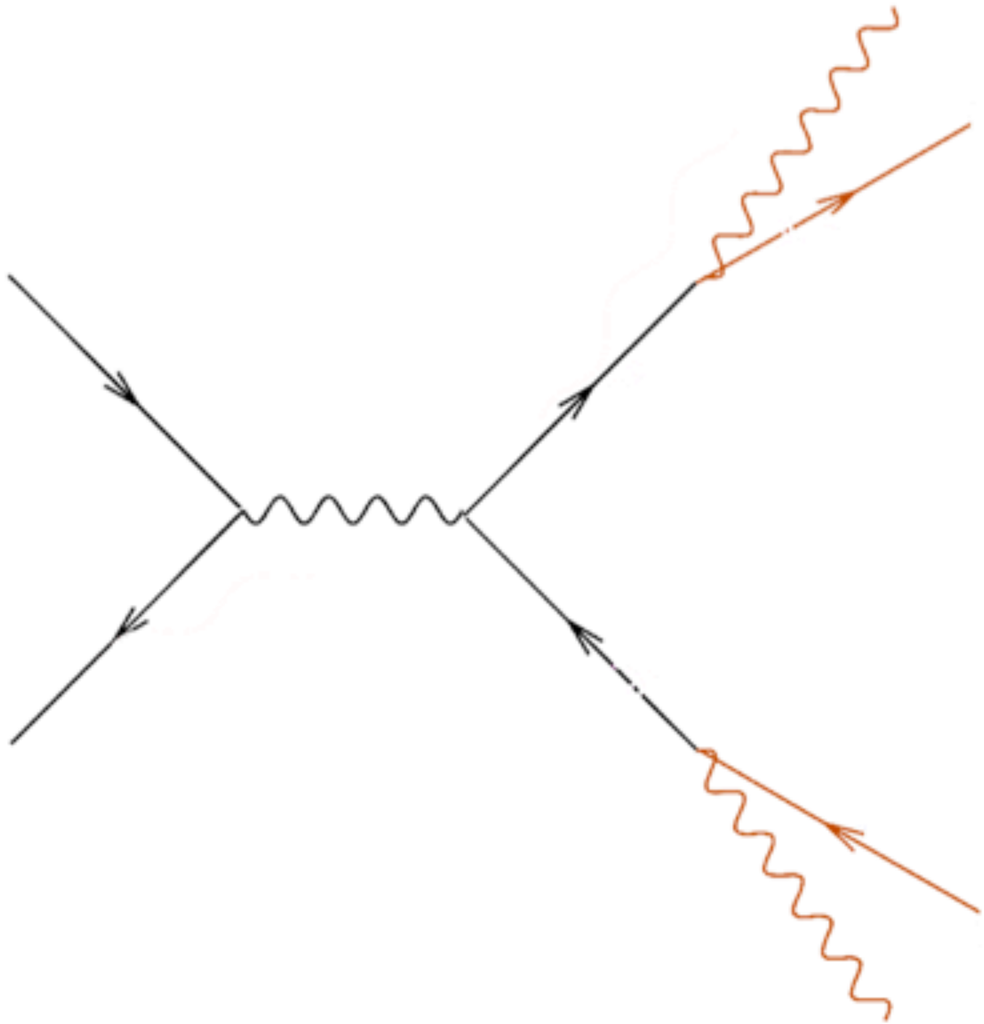
The simulation narrative

2) a) Perturbation theory used to systematically approximate the theory.
b) splitting functions, Sudokov form factors, and hadronization models
c) all sampled via accept/reject Monte Carlo **P(particles | partons)**



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- partonic decays, e.g. $t \to bW$

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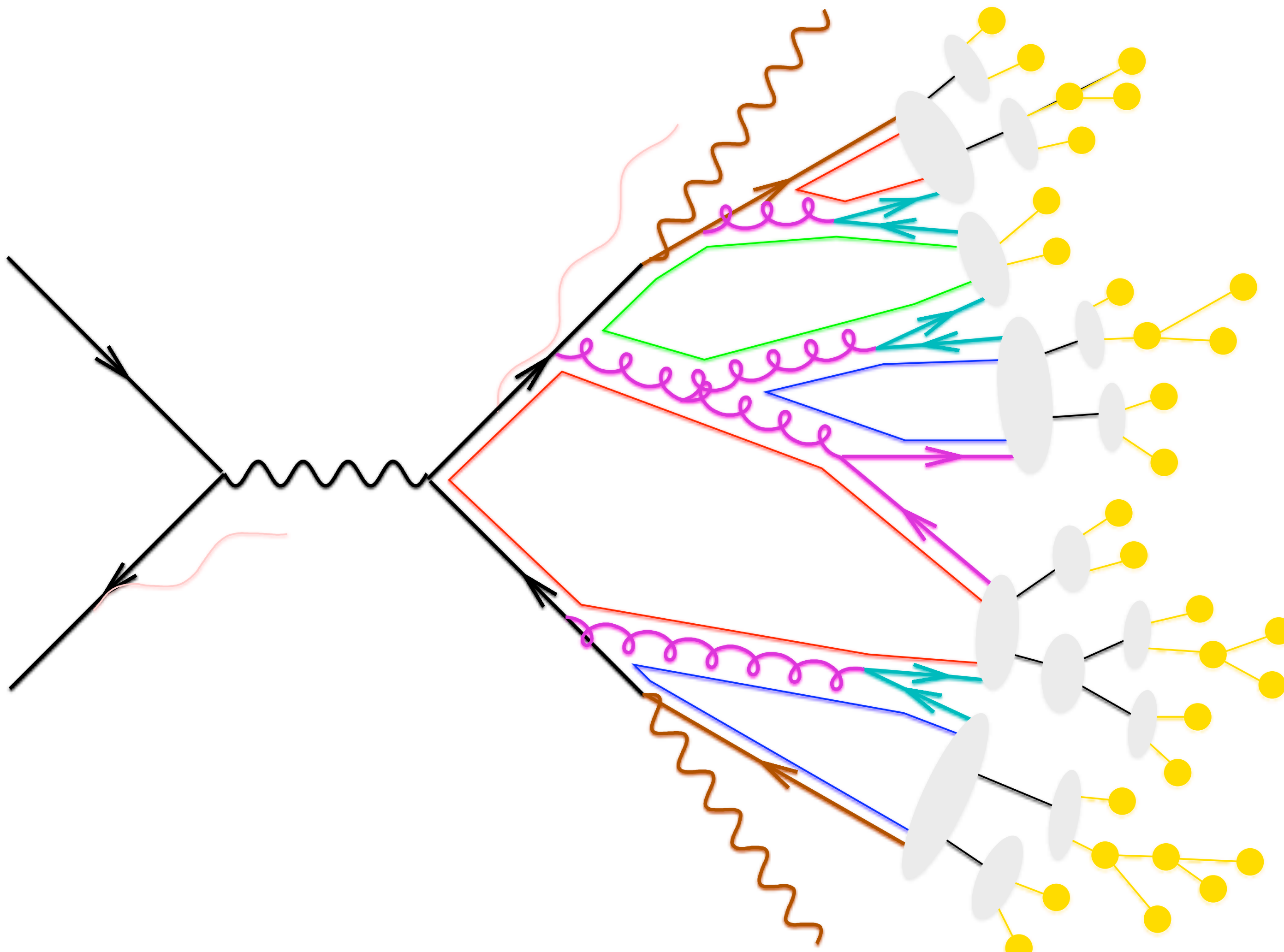

- hard scattering
- (QED) initial/final state radiation
- partonic decays, e.g. $t \to bW$
- parton shower evolution
- nonperturbative gluon splitting
- colour singlets
- colourless clusters
- cluster fission
- cluster $\to$ hadrons
- hadronic decays

The simulation narrative

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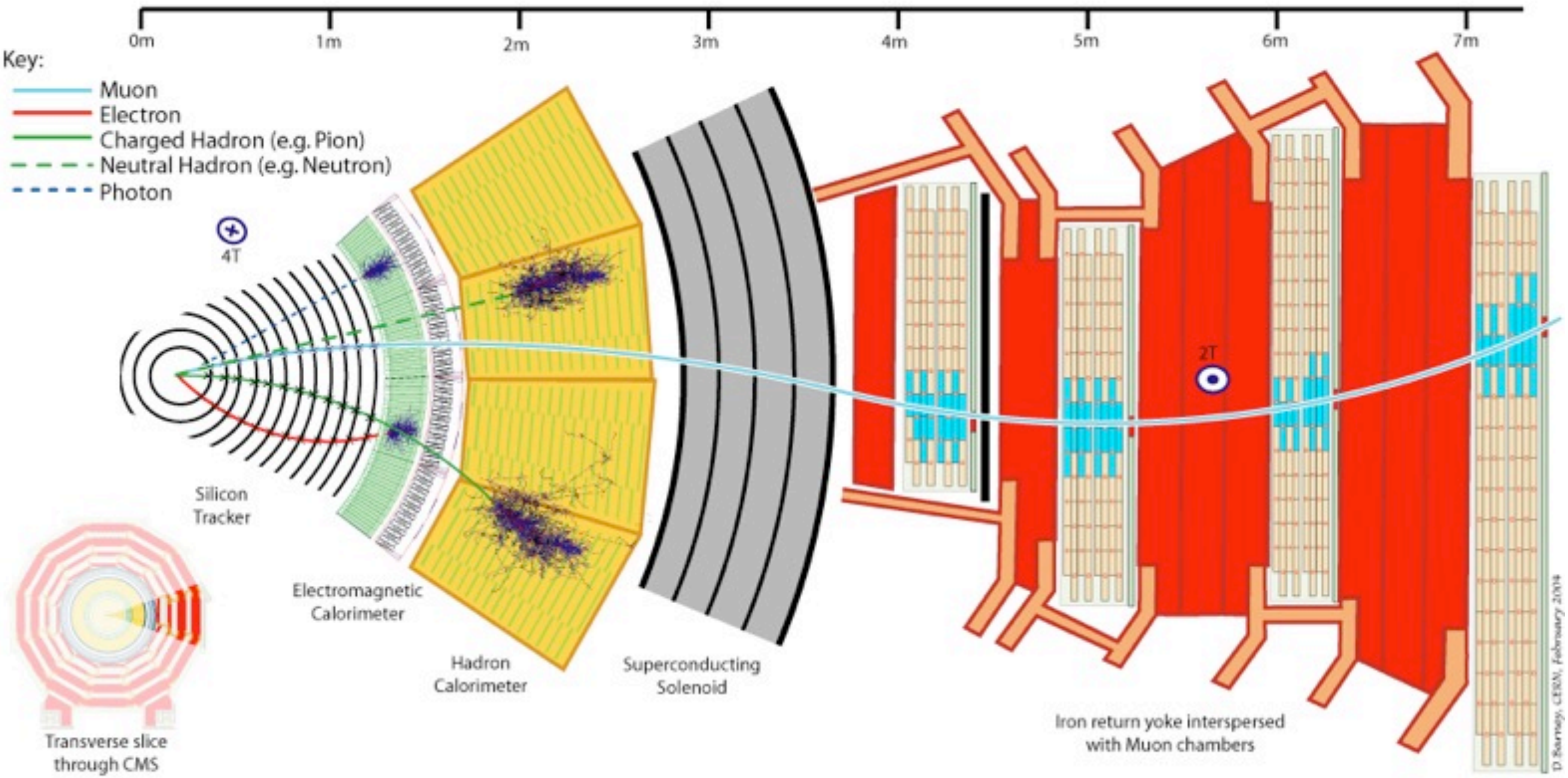
3) Next, the interaction of outgoing particles with the detector is simulated.
Detailed simulations of particle interactions with matter.
Accept/reject style Monte Carlo integration of very complicated function
P(detector readout | initial particles)



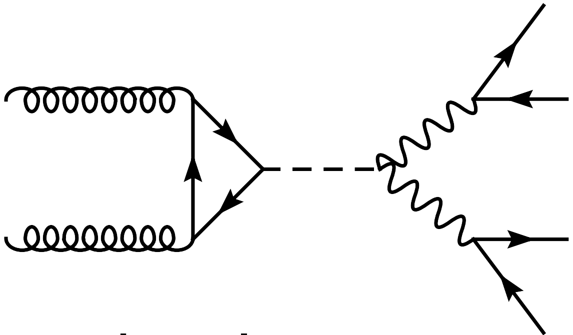
Theoretical Predictions

In addition to the rate of interactions, our theories predict the distributions of angles, energies, masses, etc. of particles produced

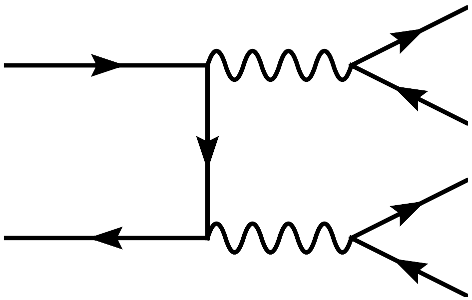
- we form functions of these called **discriminating variables** *m*,
- and use Monte Carlo techniques to estimate *f(m)*

In addition to the hypothesized signal process, there are known background processes.

- thus, the distribution of *f(m)* is a **mixture model**
- the full model is a **marked Poisson process**



signal process



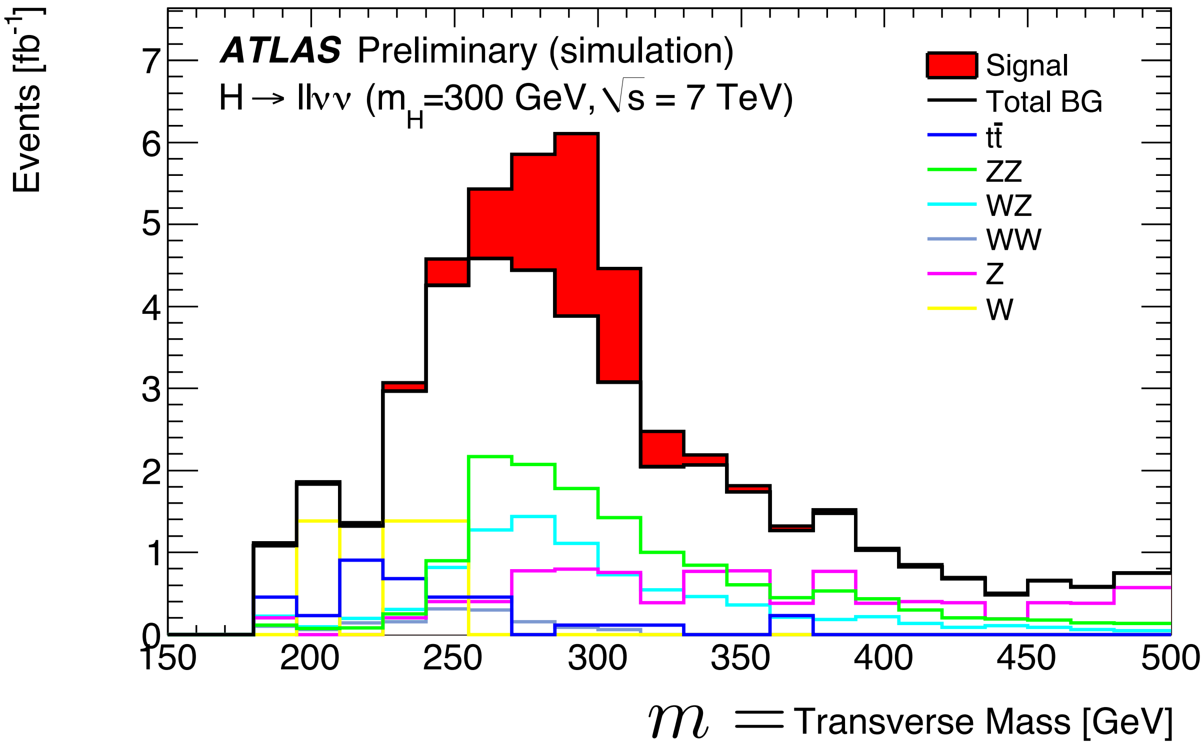
background process

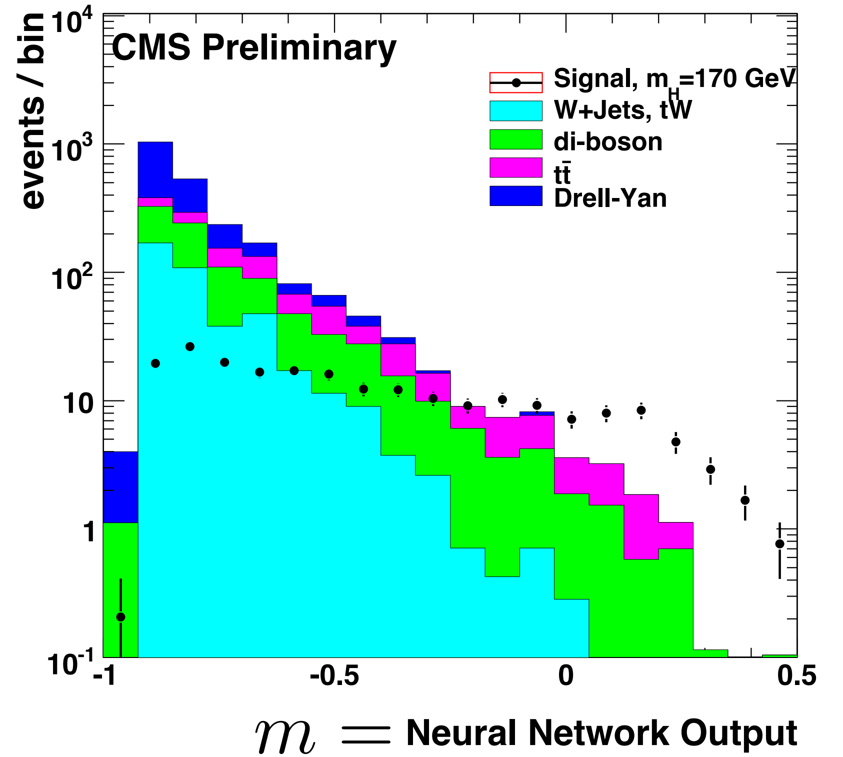
$$P(\mathbf{m}|s) = \mathrm{Pois}(n|s+b) \prod_{j}^{n} \frac{s f_s(m_j) + b f_b(m_j)}{s+b}$$

Example model

Here is an example prediction from search for H→ZZ and H→WW

- sometimes multivariate techniques are used





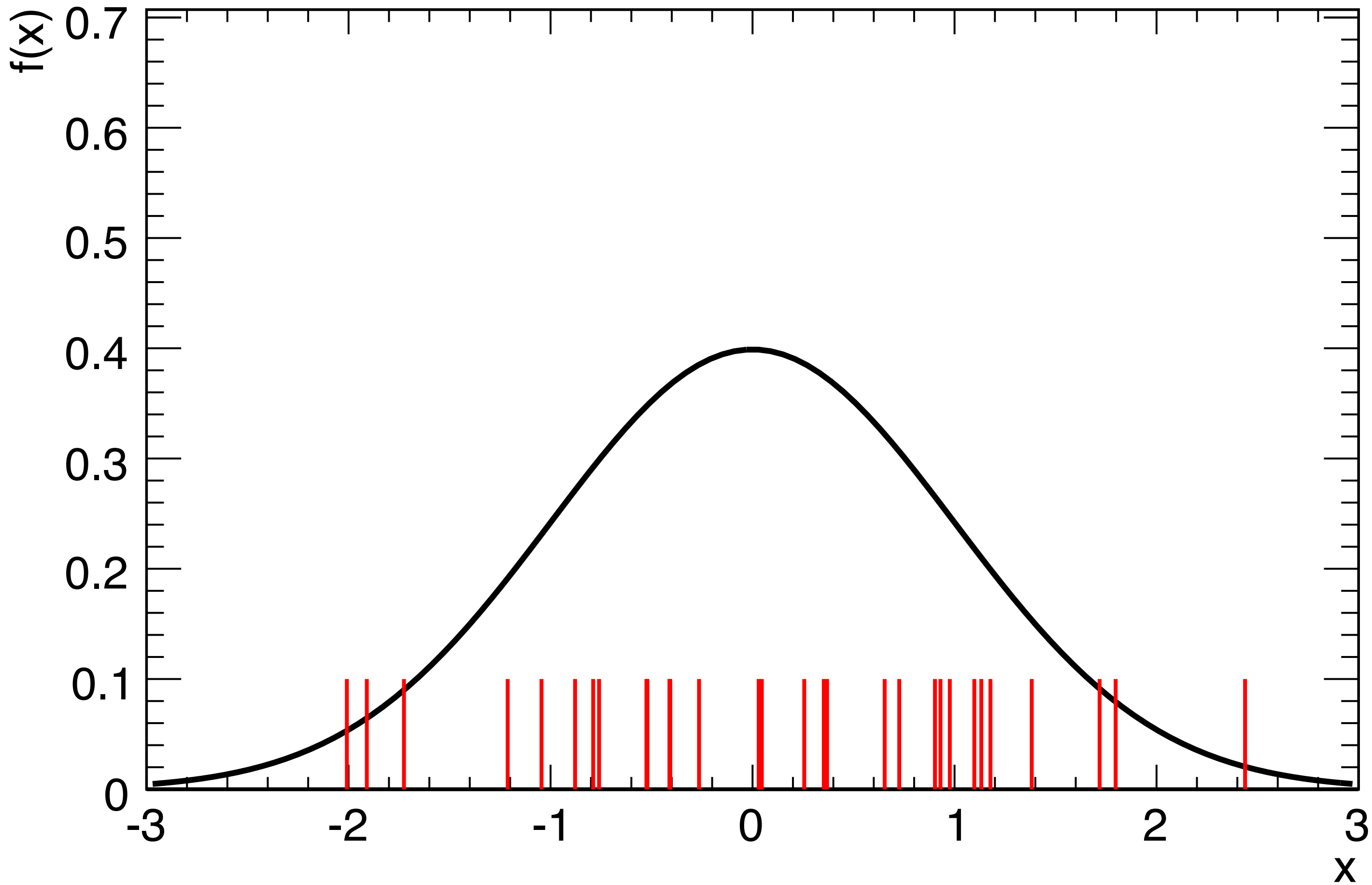
$$P(\mathbf{m}|s) = \text{Pois}(n|s+b) \prod_j^n \frac{s f_s(m_j) + b f_b(m_j)}{s+b}$$

Parametric vs. Non-Parametric PDFs

No parametric form, need to construct **non-parametric** PDFs

From Monte Carlo samples, one has empirical PDF

$$f_{emp} = \frac{1}{N}\sum_{i}^{N}\delta(x - x_i)$$



Parametric vs. Non-Parametric PDFs

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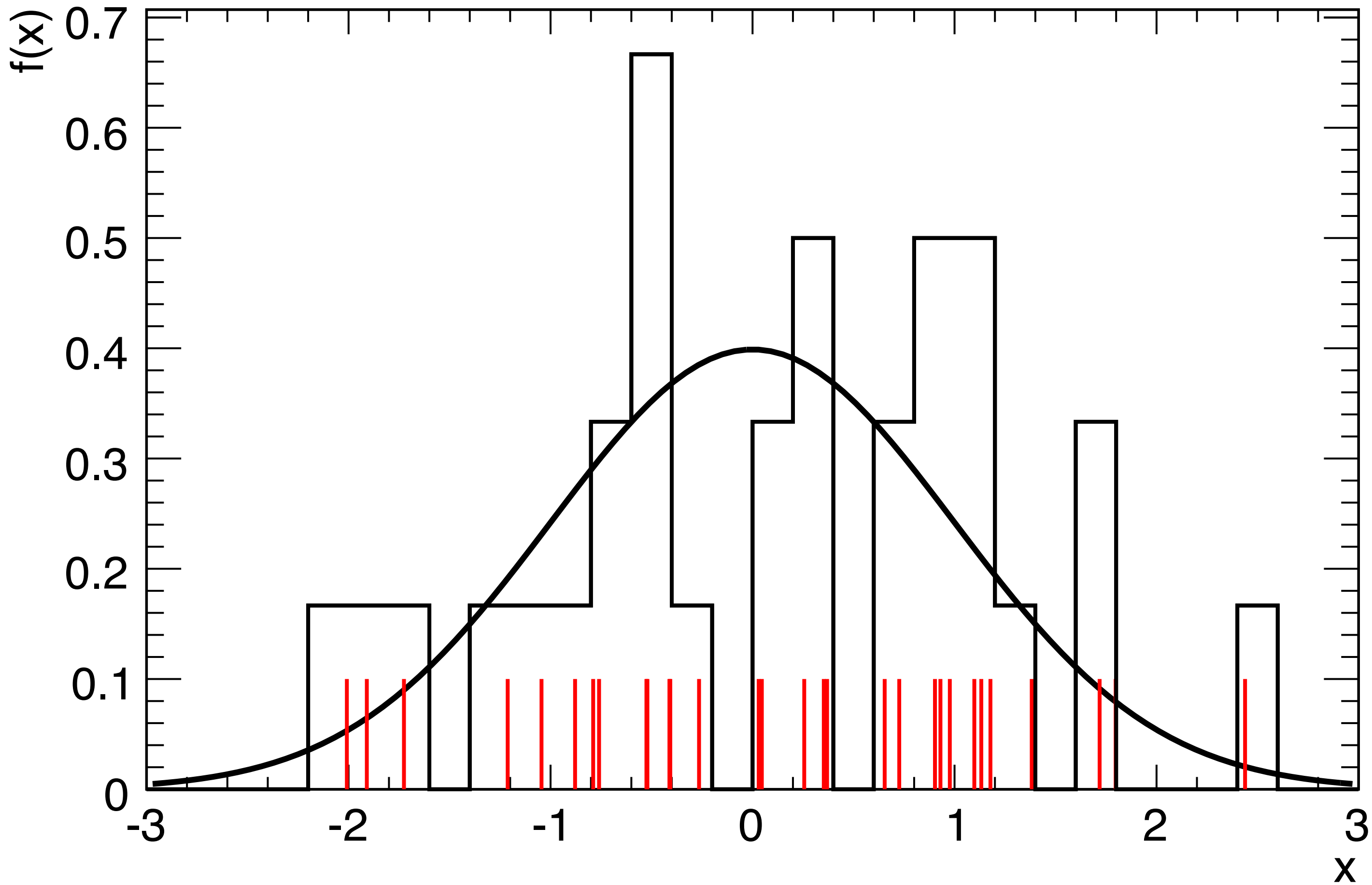
Classic example of a **non-parametric** PDF is the histogram

$$f^{w,s}_{hist}(x) = \frac{1}{N}\sum_i h_i^{w,s}$$

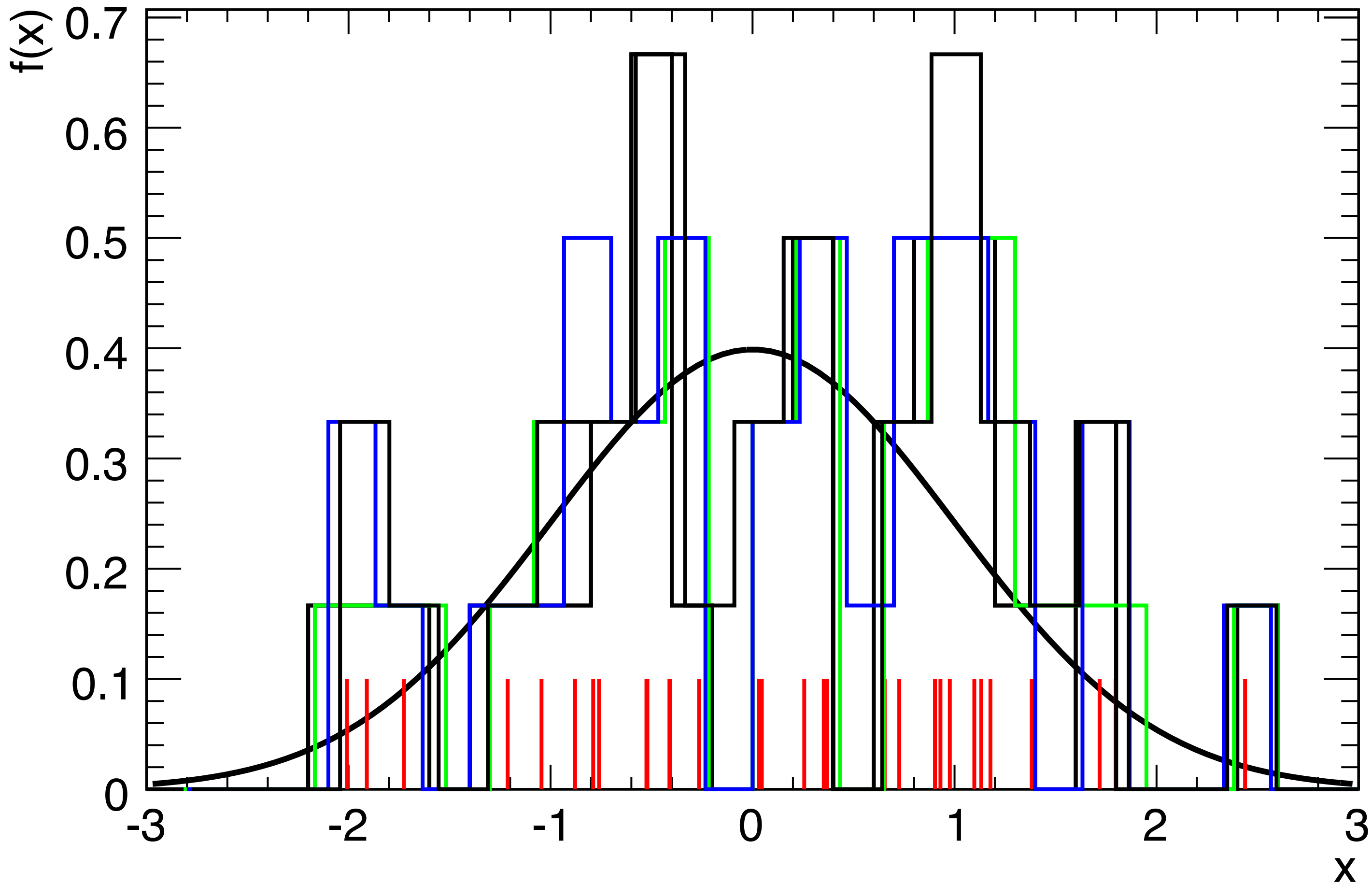


Parametric vs. Non-Parametric PDFs

Classic example of a **non-parametric** PDF is the histogram

but they depend on bin width and starting position

$$f^{w,s}_{hist}(x) = \frac{1}{N}\sum_i h_i^{w,s}$$

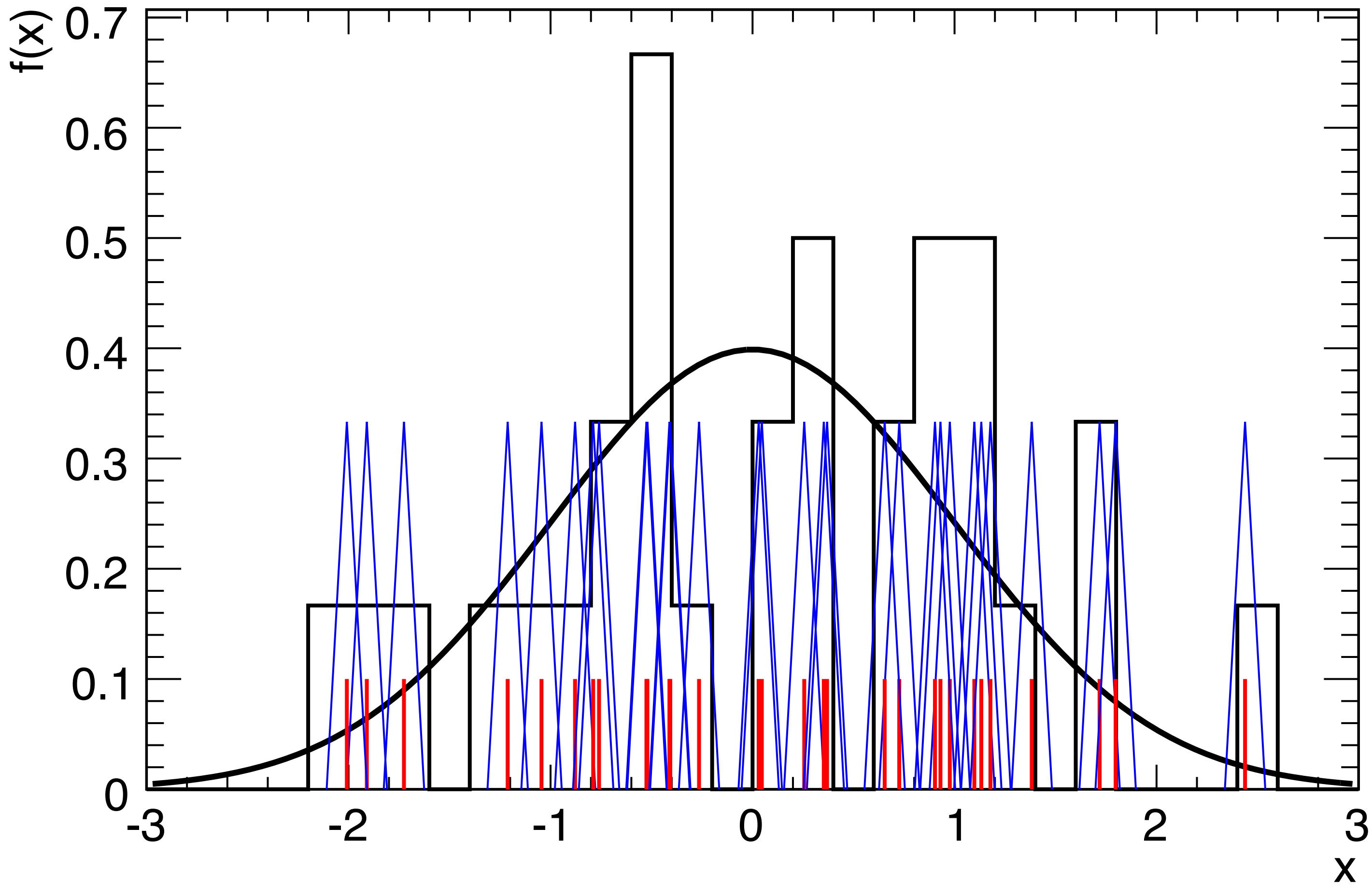


Parametric vs. Non-Parametric PDFs

Classic example of a **non-parametric** PDF is the histogram

"Average Shifted Histogram" minimizes effect of binning

$$f^w_{ASH}(x) = \frac{1}{N}\sum_i^N K^w(x - x_i)$$

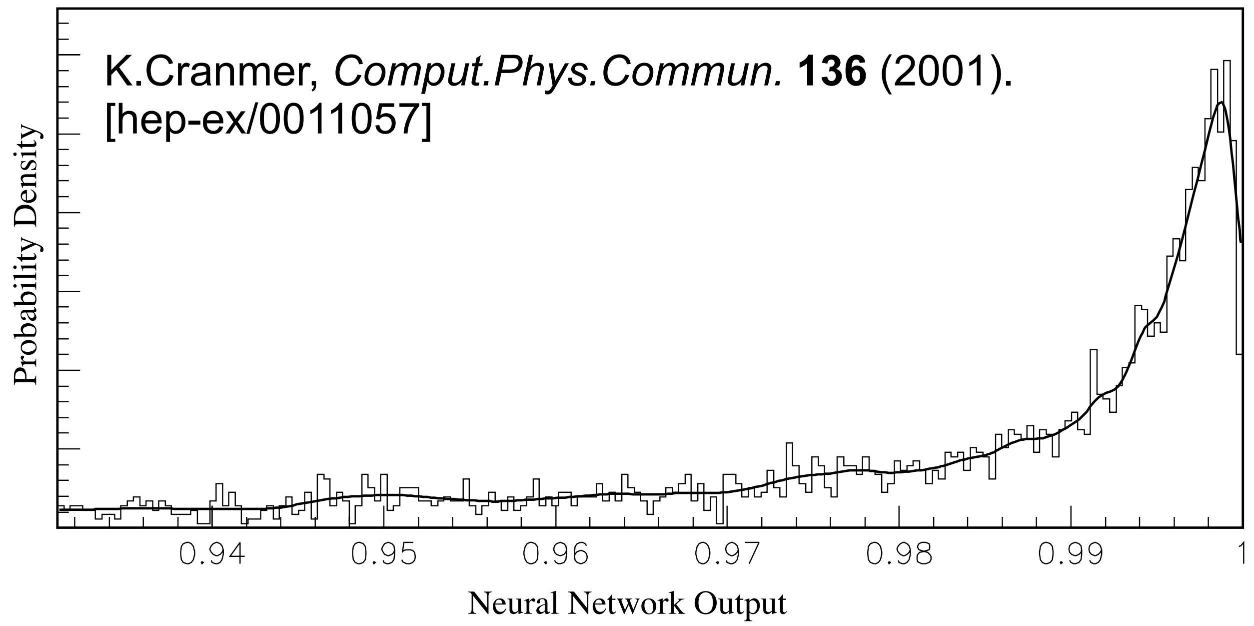


Kernel Estimation

Kernel estimation is the generalization of Average Shifted Histograms

$$\hat{f}_1(x) = \sum_i^n \frac{1}{nh(x_i)} K\left(\frac{x - x_i}{h(x_i)}\right)$$

$$h(x_i) = \left(\frac{4}{3}\right)^{1/5} \sqrt{\frac{\sigma}{\hat{f}_0(x_i)}}\, n^{-1/5}$$



"the data is the model"

Adaptive Kernel estimation puts wider kernels in regions of low probability

Used at LEP for describing pdfs from Monte Carlo (KEYS)

Multivariate, non-parametric PDFs

Kernel Estimation has a nice generalizations to higher dimensions

- practical limit is about 5-d due to curse of dimensionality

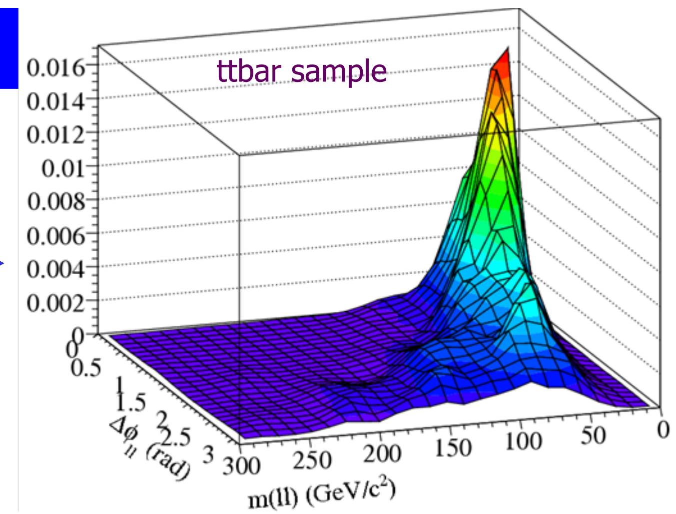
Max Baak has coded N-dim KEYS pdf described in Comput.Phys.Commun. **136** (2001) in RooFit.

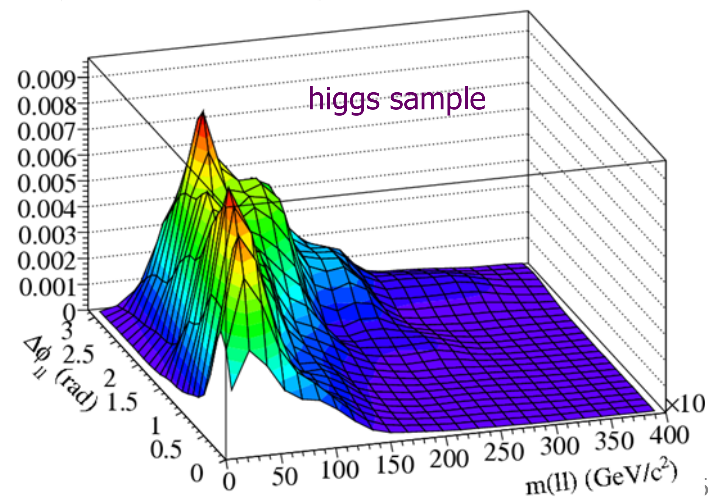
These pdfs have been used as the basis for a multivariate discrimination technique called "PDE"

$$D(\vec{x}) = \frac{f_s(\vec{x})}{f_s(\vec{x}) + f_b(\vec{x})}$$

Correlations

- 2-d projection of pdf from previous slide.
- RooNDKeys pdf automatically models (fine) correlations between observables ...



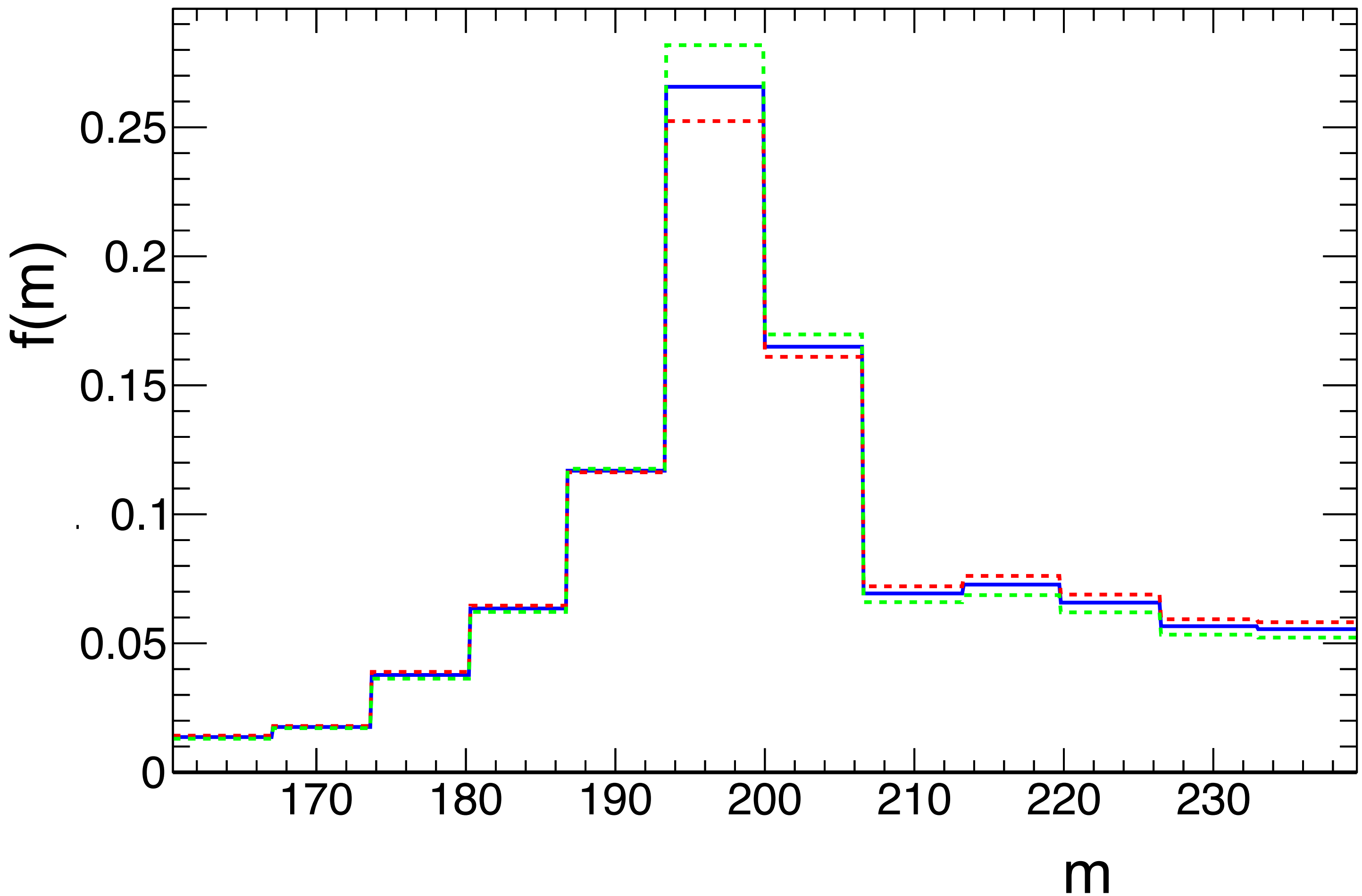


Max Baak

Incorporating Systematic Effects

Of course, the simulation has many adjustable parameters and imperfections that lead to systematic uncertainties.

- one can re-run simulation with different settings and produce **variational histograms** about the **nominal prediction**



Explicit parametrization

Important to distinguish between the **source** of the systematic uncertainty (eg. jet energy scale) and its **effect.**

- The same 5% jet energy scale uncertainty will have different effect on different signal and background processes
  - not necessarily with any obvious functional form
- Usually possible to decompose to independent “uncorrelated” sources

Imagine a table that **explicitly quantifies** the effect of each source of systematic.

- Entries are either normalization factors or variational histograms

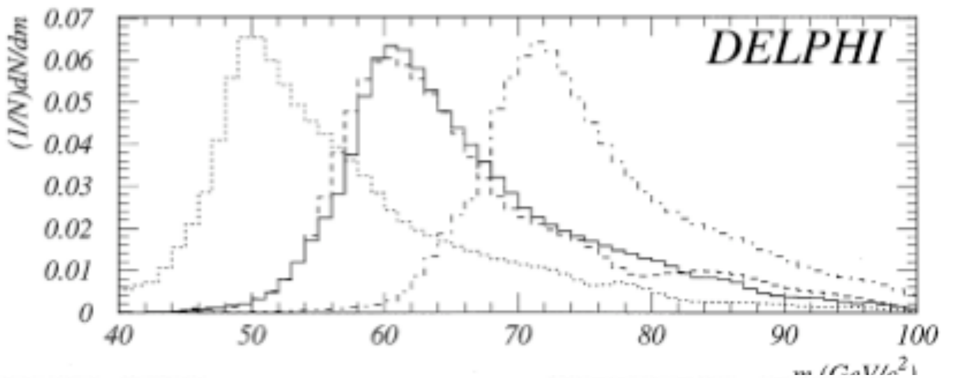
	sig	bkg 1	bkg 2	...
syst 1				
syst 2				
...				

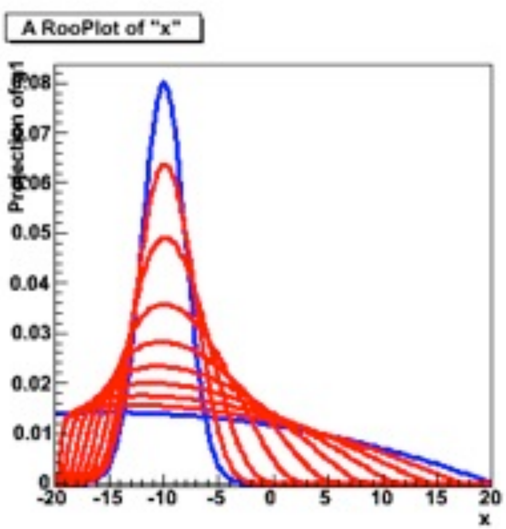
Histogram Interpolation

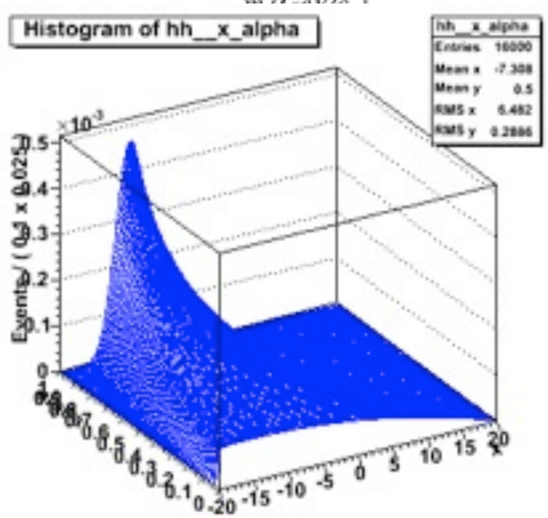
Several interpolation algorithms exist: eg. Alex Read's "horizontal" histogram interpolation algorithm (RooIntegralMorph in RooFit)

- take several PDFs, construct interpolated PDF with additional **nuisance parameter** α

A.L. Read / Nuclear Instruments and Methods in Physics Research A 425 (1999) 357–360







Simple "vertical" interpolation bin-by-bin.

Alternative "horizontal" interpolation algorithm by Max Baak called "RooMomentMorph" in RooFit (faster and numerically more stable)

Incorporating systematics

Center for Cosmology and Particle Physics

Let's consider a simplified problem that has been studied quite a bit to gain some insight into our more realistic and difficult problems

- number counting with background uncertainty
  - in our main measurement we observe n_{on} with $s+b$ expected

$$\mathrm{Pois}(n_{\mathrm{on}}|s+b)$$

- and the background has some uncertainty
  - but what is "background uncertainty"? Where did it come from?
  - maybe we would say background is known to 10% or that it has some pdf $\pi(b)$
    - then we often do a smearing of the background:

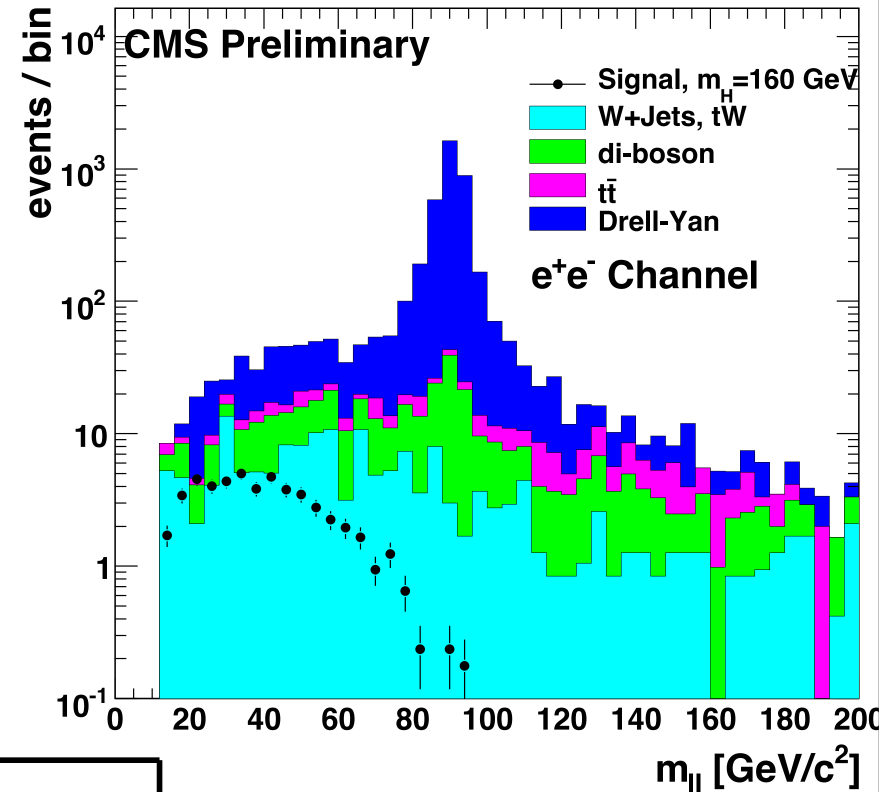
$$P(n_{\mathrm{on}}|s) = \int db\, \mathrm{Pois}(n_{\mathrm{on}}|s+b)\, \pi(b),$$

  - Where does $\pi(b)$ come from?
    - did you realize that this is a Bayesian procedure that depends on some prior assumption about what b is?

The Data-driven narrative

Regions in the data with negligible signal expected are used as control samples

- simulated events are used to estimate extrapolation coefficients
- extrapolation coefficients may have theoretical and experimental uncertainties



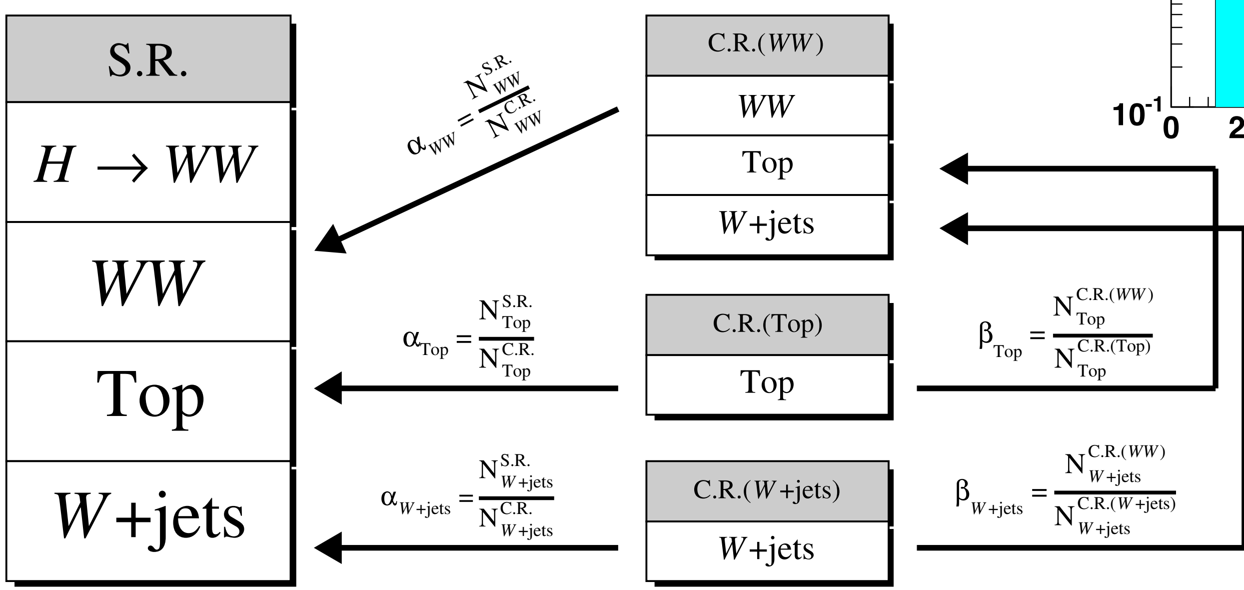


Figure 10: Flow chart describing the four data samples used in the $H \to WW^{(*)} \to \ell\nu\ell\nu$ analysis. S.R and C.R. stand for signal and control regions, respectively.

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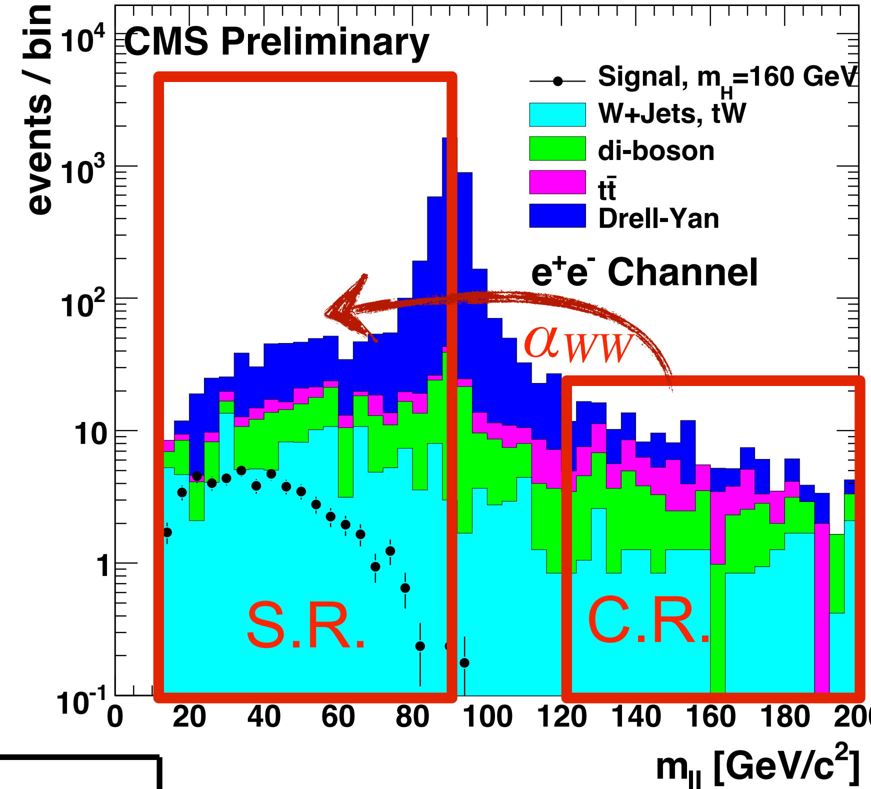


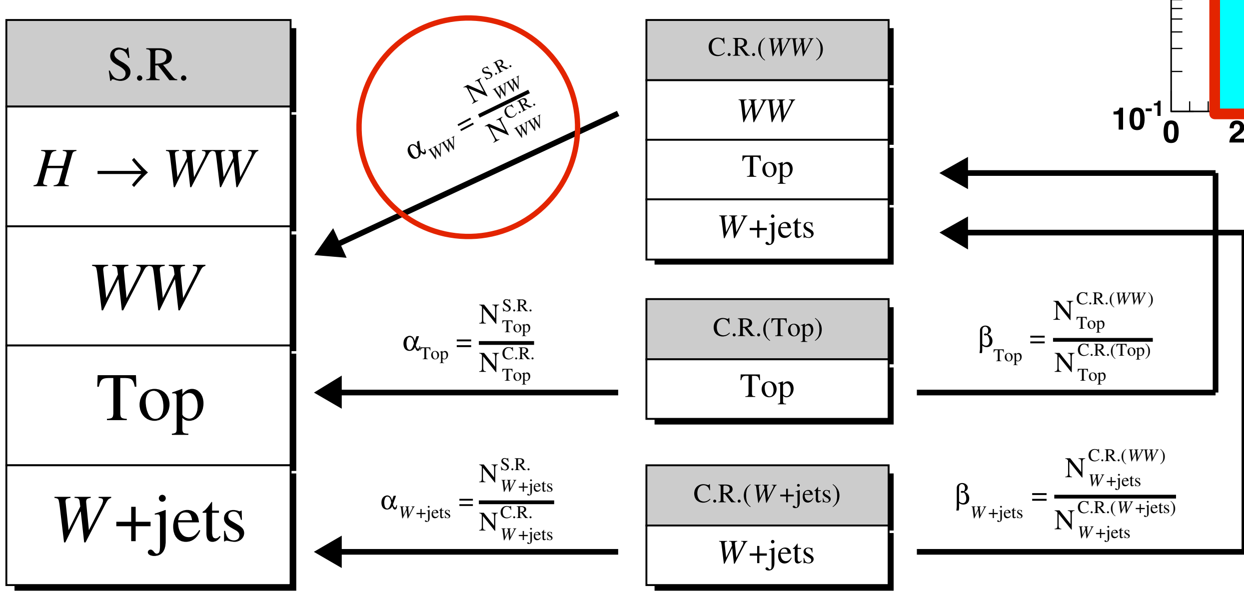


Figure 10: Flow chart describing the four data samples used in the $H \to WW^{(*)} \to \ell\nu\ell\nu$ analysis. S.R and C.R. stand for signal and control regions, respectively.

The "on/off" problem

Now let's say that the background was estimated from some control region or sideband measurement.

- We can treat these two measurements simultaneously:
  - main measurement: observe n_{on} with $s+b$ expected
  - sideband measurement: observe n_{off} with τb expected

$$\underbrace{P(n_{\rm on}, n_{\rm off}|s,b)}_{\text{joint model}} = \underbrace{\mathrm{Pois}(n_{\rm on}|s+b)}_{\text{main measurement}}\ \underbrace{\mathrm{Pois}(n_{\rm off}|\tau b)}_{\text{sideband}}$$

  - In this approach "background uncertainty" is a statistical error
  - justification and accounting of background uncertainty is much more clear

How does this relate to the smearing approach?

$$P(n_{\rm on}|s) = \int db\, \mathrm{Pois}(n_{\rm on}|s+b)\, \pi(b),$$

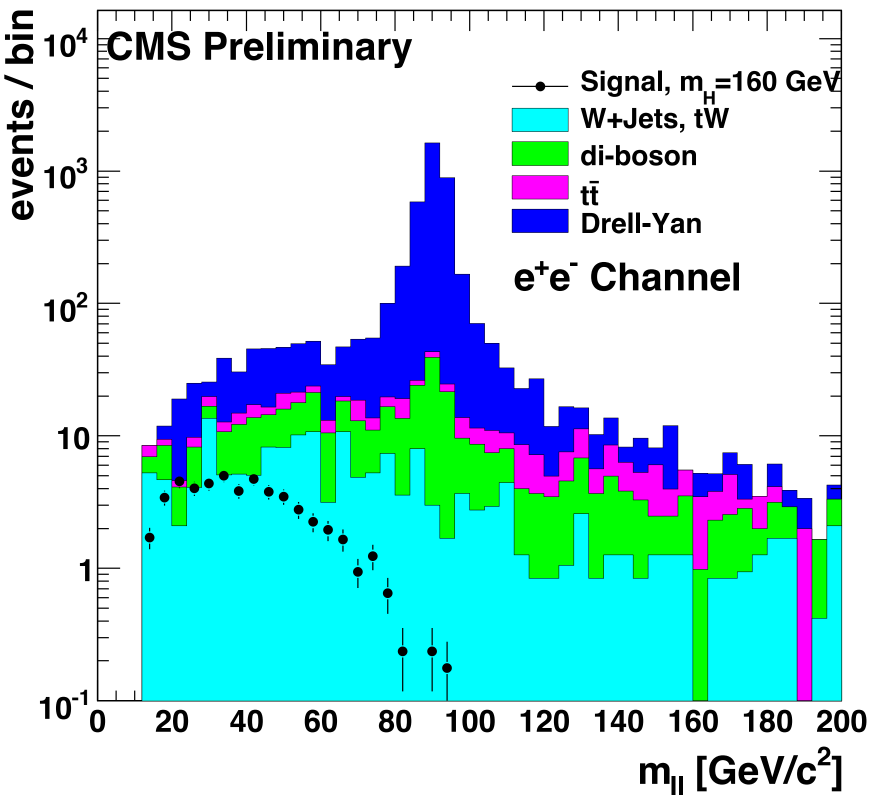
- while $\pi(b)$ is based on data, it still depends on a prior $\eta(b)$

$$\pi(b) = P(b|n_{\rm off}) = \frac{P(n_{\rm off}|b)\eta(b)}{\int db P(n_{\rm off}|b)\eta(b)}.$$

Going beyond on/off

Often the extrapolation parameter has uncertainty

- introduce a new measurement to constrain it as in the ABCD method
- what if..., what if ..., what if..., what if ..., what if..., what if ...



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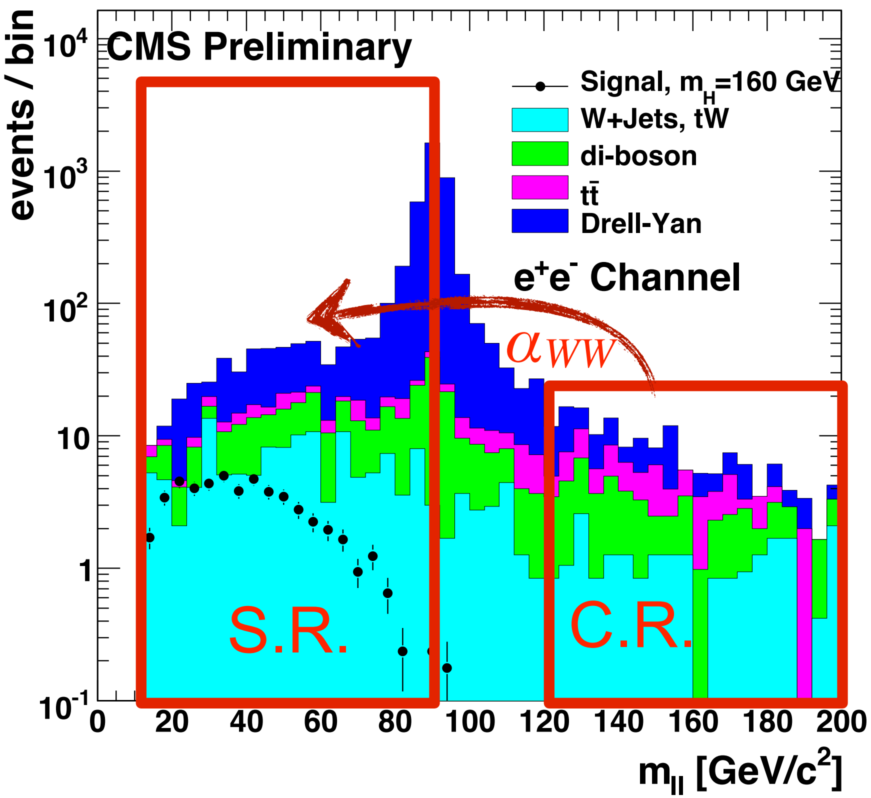

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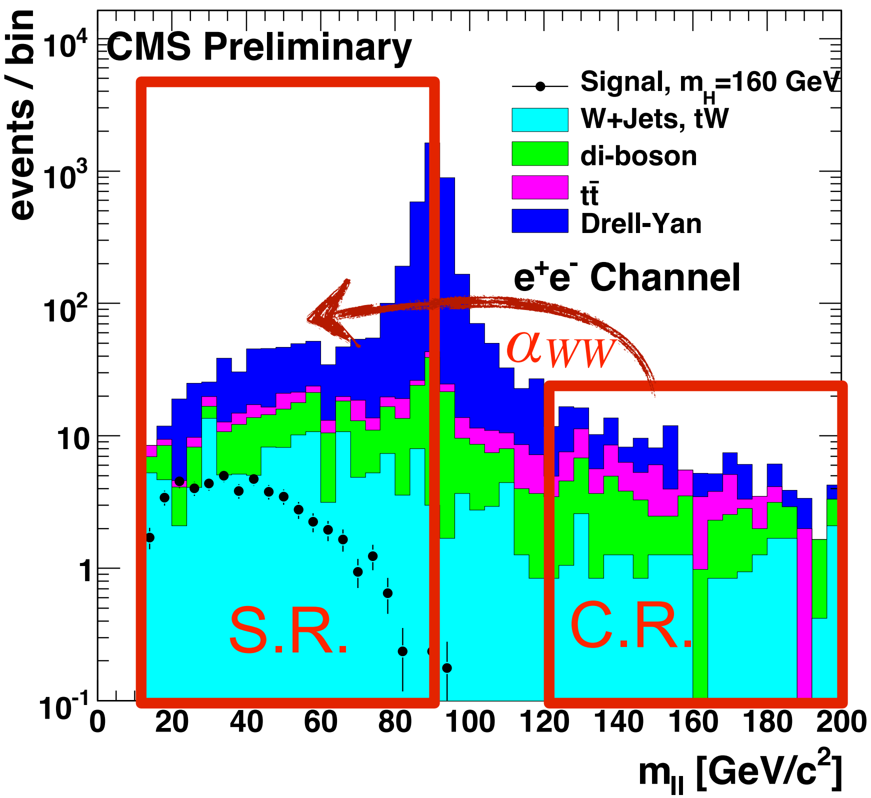

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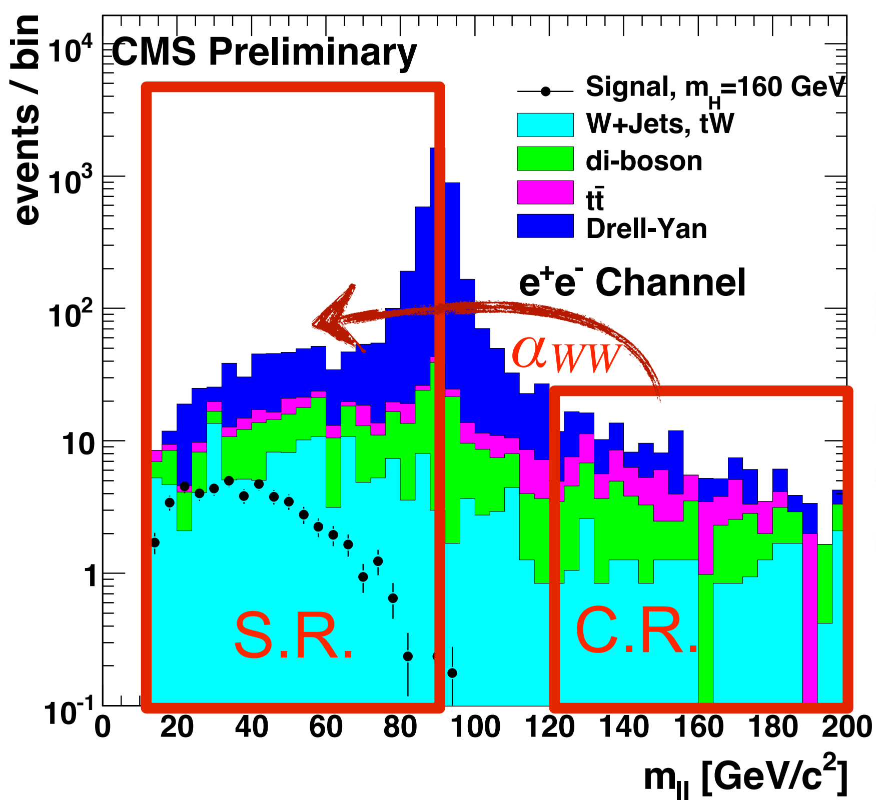

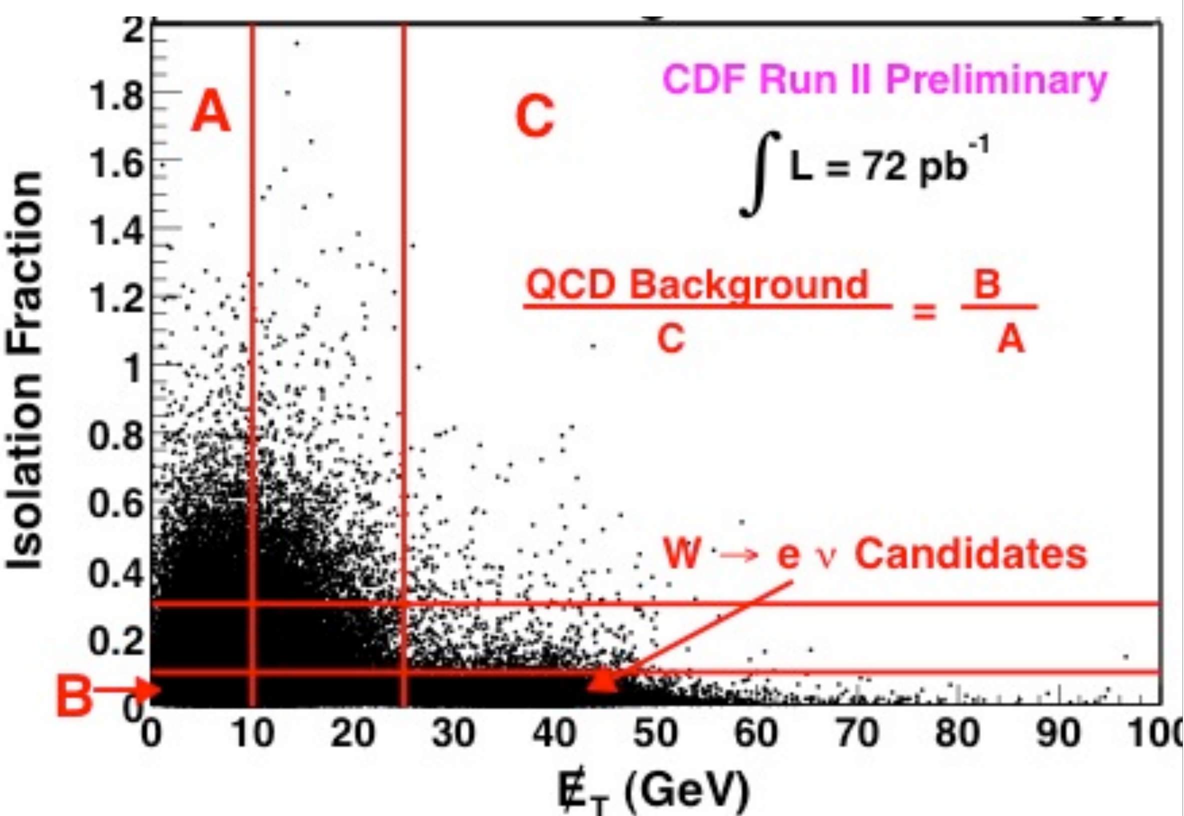

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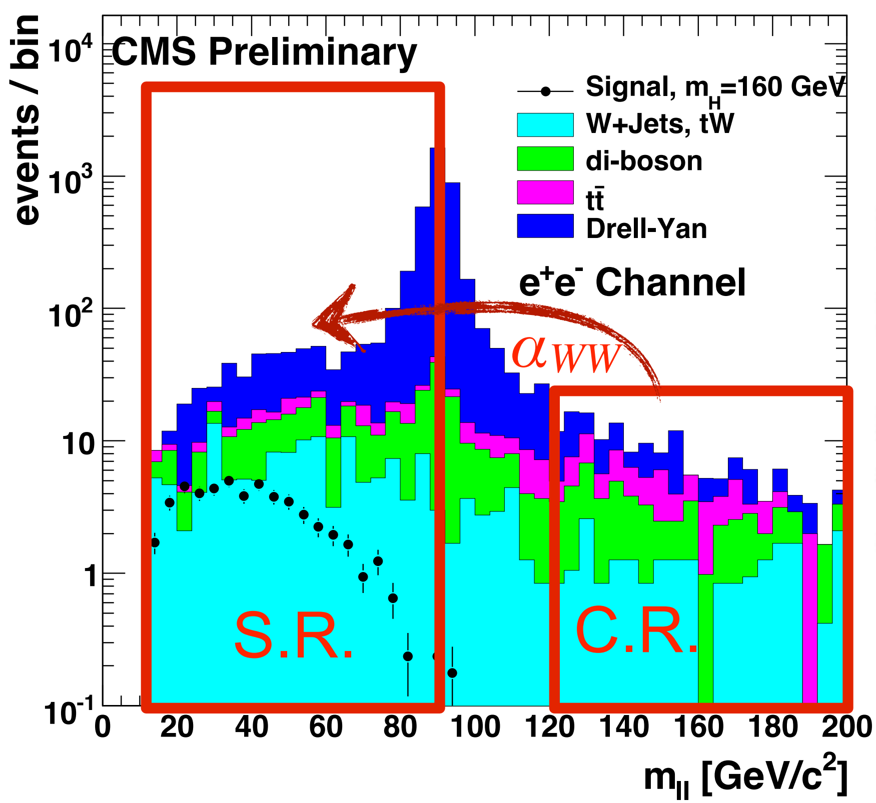

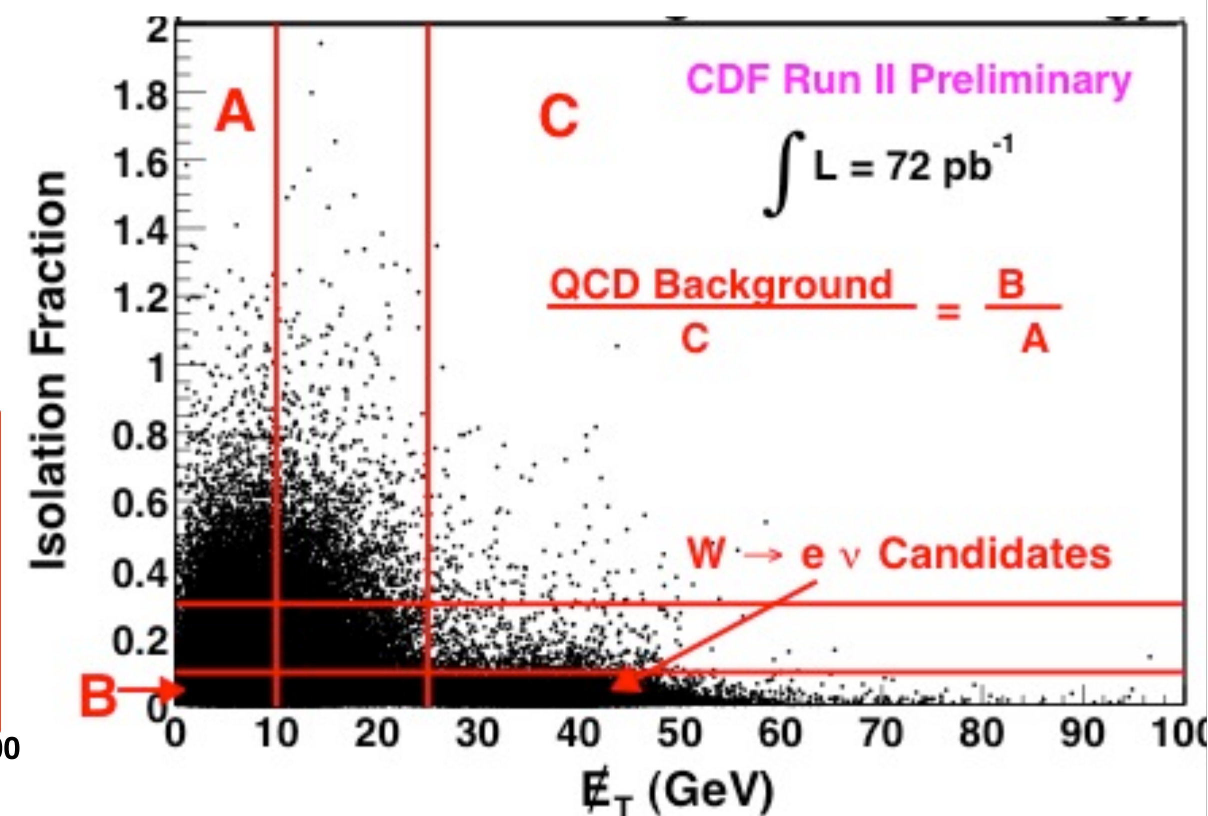

Going beyond on/off

Center for Cosmology and Particle Physics

Often the extrapolation parameter has uncertainty

- introduce a new measurement to constrain it as in the ABCD method
- what if..., what if ..., what if..., what if ..., what if..., what if ...

Classification of Systematic Uncertainties

Center for Cosmology and Particle Physics

Taken from Pekka Sinervo's PhyStat 2003 contribution

Type I - "The Good"

- can be constrained by other sideband/auxiliary/ ancillary measurements and can be treated as statistical uncertainties
  - scale with luminosity

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Type II - "The Bad"

- arise from model assumptions in the measurement or from poorly understood features in data or analysis technique
  - don't necessarily scale with luminosity
  - eg: "shape" systematics

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- arise from model assumptions in the measurement or from poorly understood features in data or analysis technique
  - don't necessarily scale with luminosity
  - eg: "shape" systematics

Type III - "The Ugly"

- arise from uncertainties in underlying theoretical paradigm used to make inference using the data
  - a somewhat philosophical issue

Separating the prior from the objective model

Recommendation: where possible, one should express uncertainty on a parameter as a statistical (random) process

- explicitly include terms that represent auxiliary measurements in the likelihood

Recommendation: when using a Bayesian technique, one should explicitly express and separate the prior from the objective part of the probability density function

Example:

- By writing $P(n_{\rm on}, n_{\rm off}|s,b) = {\rm Pois}(n_{\rm on}|s+b)\,{\rm Pois}(n_{\rm off}|\tau b).$
  - the objective statistical model is for the background uncertainty is clear
- One can then explicitly express a prior $\eta(b)$ and obtain:

$$\pi(b) = P(b|n_{\rm off}) = \frac{P(n_{\rm off}|b)\eta(b)}{\int db P(n_{\rm off}|b)\eta(b)}.$$

Constraints on Nuisance Parameters

Many uncertainties have no clear statistical description or it is impractical to provide

Traditionally, we use Gaussians, but for large uncertainties it is clearly a bad choice

- quickly falling tail, bad behavior near physical boundary, optimistic p-values, ...

For systematics constrained from control samples and dominated by statistical uncertainty, a Gamma distribution is a more natural choice [PDF is Poisson for the control sample]

- longer tail, good behavior near boundary, natural choice if auxiliary is based on counting

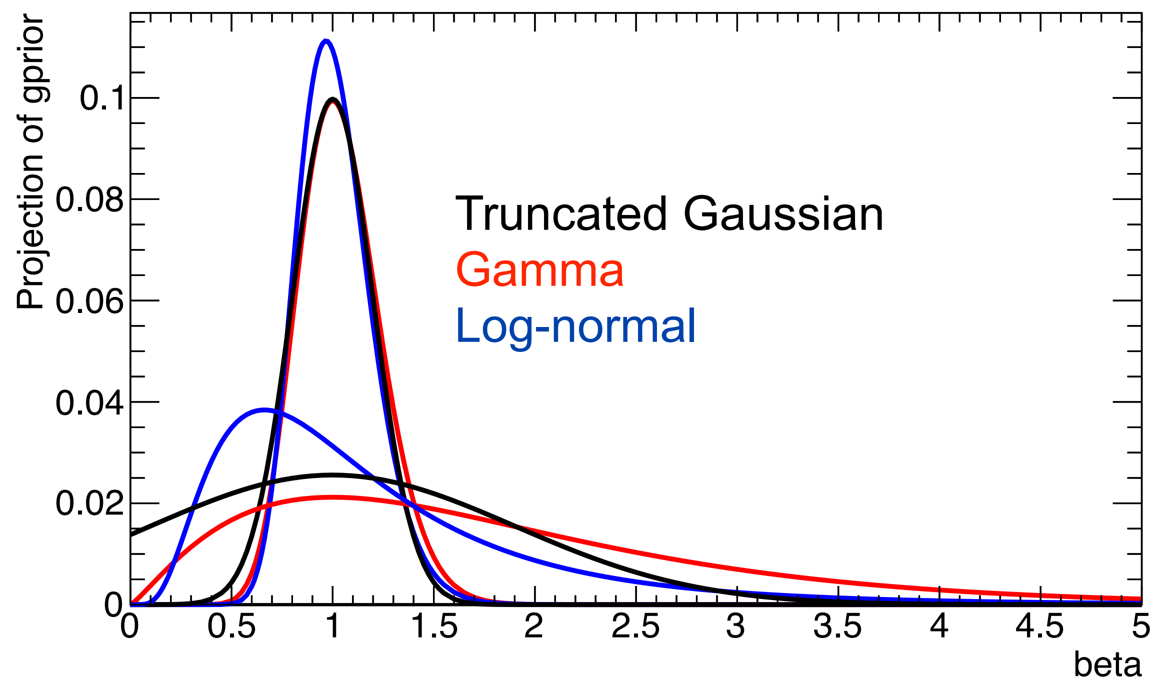
For “factor of 2” notions of uncertainty log-normal is a good choice

- can have a very long tail for large uncertainties

None of them are as good as an actual model for the auxiliary measurement, if available

To consistently switch between frequentist, Bayesian, and hybrid procedures, need to be clear about prior vs. likelihood function

PDF	Prior	Posterior
Gaussian	uniform	Gaussian
Poisson	uniform	Gamma
Log-normal	reference	Log-Normal



Building the model: `HistFactory (RooStats)`

Several analyses have used the tool called **`hist2workspace`** to build the model (PDF)

- command line: **`hist2workspace myAnalysis.xml`**
- construct likelihood function below via XML + histograms

$$\mathscr{L}(\mu, \alpha_i) = \prod_{m \in \text{bins}} \text{Pois}(n_m | \nu_m) \prod_{i = \in \text{Syst}} N(\alpha_i)$$

$$\nu_m = \mu L \eta_1(\alpha)\, \sigma_{1m}(\alpha) + \sum_{j \in \text{Bkg Samp}} L \eta_j(\alpha)\, \sigma_{jm}(\alpha),$$

interpolation convention

$$\eta_j(\alpha) = \prod_{i \in \text{Syst}} I(\alpha_i; \eta_{ij}^+, \eta_{ij}^-)$$

$$\sigma_{jm}(\alpha) = \sigma_{jm}^0 \prod_{i \in \text{Syst}} I(\alpha_i; \sigma_{ijm}^+/\sigma_{jm}^0, \sigma_{ijm}^-/\sigma_{jm}^0)$$

$$I(\alpha; I^+, I^-) = \begin{cases} 1 + \alpha(I^+ - 1) & \text{if } \alpha > 0 \\ 1 & \text{if } \alpha = 0 \\ 1 - \alpha(I^- - 1) & \text{if } \alpha < 0 \end{cases}$$

```xml
<!DOCTYPE Channel  SYSTEM 'Config.dtd'>

  <Channel Name="channel1" InputFile="./data/example.root" HistoName="" >
    <!--<Data Name="data" InputFile="" HistoPath="" HistoName=""/>-->
    <Sample Name="signal" HistoPath="" HistoName="signal">
      <OverallSys Name="syst1" High="1.05" Low="0.95"/>
      <NormFactor Name="SigXsecOverSM" Val="1" Low="0.5" High="1.8" Const="True" />
    </Sample>
    <Sample Name="background1" HistoPath="" NormalizeByTheory="True" HistoName="background1">
      <OverallSys Name="syst2" Low="0.95" High="1.05"/>
    </Sample>
    <Sample Name="background2" HistoPath="" NormalizeByTheory="True" HistoName="background2">
      <OverallSys Name="syst3" Low="0.95" High="1.05"/>
      <!-- <HistoSys Name="syst4" HistoPathHigh="" HistoPathLow="histForSyst4"/>-->
    </Sample>
  </Channel>
```

Constraint terms

For each systematic effect, we associated a nuisance parameter α

- for instance electron efficiency, JES, luminosity, etc.
- the background rates, signal acceptance, etc. are parametrized in terms of these nuisance parameters

These systematics are usually known (“constrained”) within ± 1σ.

- but here we must be careful about Bayesian vs. frequentist
- Why is it constrained? Usually b/c we have an **auxiliary measurement** *m* and a relationship like:

$$G(m|\alpha,\sigma)$$

- Saying that α has a Gaussian distribution is Bayesian.
  - has form “Probability of parameter”
- The frequentist way is to say that that *m* fluctuates about α

While *m* is a measured quantity (or “observable”), there is only one measurement of *m* per experiment. Call it a “**Global observable**”

An example ModelConfig from HistFactory

Center for Cosmology and Particle Physics

The RooStats tools, use the RooFit PDF interface, but the tools need some additional meta information. The **ModelConfig** class encapsulates this meta information

- The PDF itself, the observables, the "global observables", the parameter of interest, and the nuisance parameters. Also the prior for Bayesian methods.

root [7] modelConfig->Print()
=== Using the following for ModelConfig ===
Observables: RooArgSet:: = (obs_h2e2nu_200)

Parameters of Interest: RooArgSet:: = (SigXsecOverSM)

Nuisance Parameters: RooArgSet:: = (Lumi,alpha_SysBtagEff,alpha_SysElecScale,alpha_SysElecSmear,alpha_SysJetScale,alpha_SysJetSmear,alpha_SysMETHadScale,alpha_SysMETHadSmear,alpha_SysMuonScale,alpha_SysMuonSmear,alpha_dieleceff,alpha_mjet2enorm,alpha_signorm,alpha_topnorm,alpha_wnorm,alpha_wwnorm,alpha_wznorm,alpha_znorm,alpha_zznorm)

Global Observables: RooArgSet:: = (nominalLumi,nom_alpha_dieleceff,nom_alpha_signorm,nom_SysMuonScale,nom_SysMETHadSmear,nom_SysElecSmear,nom_SysMuonSmear,nom_SysJetSmear,nom_SysBtagEff,nom_SysJetScale,nom_SysMETHadScale,nom_SysElecScale,nom_alpha_topnorm,nom_alpha_wwnorm,nom_alpha_wznorm,nom_alpha_zznorm,nom_alpha_wnorm,nom_alpha_znorm,nom_alpha_mjet2enorm)

PDF: RooProdPdf::model_h2e2nu_200[lumiConstraint * alpha_dieleceffConstraint * alpha_signormConstraint * alpha_SysMuonScaleConstraint * alpha_SysMETHadSmearConstraint * alpha_SysElecSmearConstraint * alpha_SysMuonSmearConstraint * alpha_SysJetSmearConstraint * alpha_SysBtagEffConstraint * alpha_SysJetScaleConstraint * alpha_SysMETHadScaleConstraint * alpha_SysElecScaleConstraint * alpha_topnormConstraint * alpha_wwnormConstraint * alpha_wznormConstraint * alpha_zznormConstraint * alpha_wnormConstraint * alpha_znormConstraint * alpha_mjet2enormConstraint * h2e2nu_200_model] = 0

CMS Higgs example

CENTER FOR COSMOLOGY AND PARTICLE PHYSICS

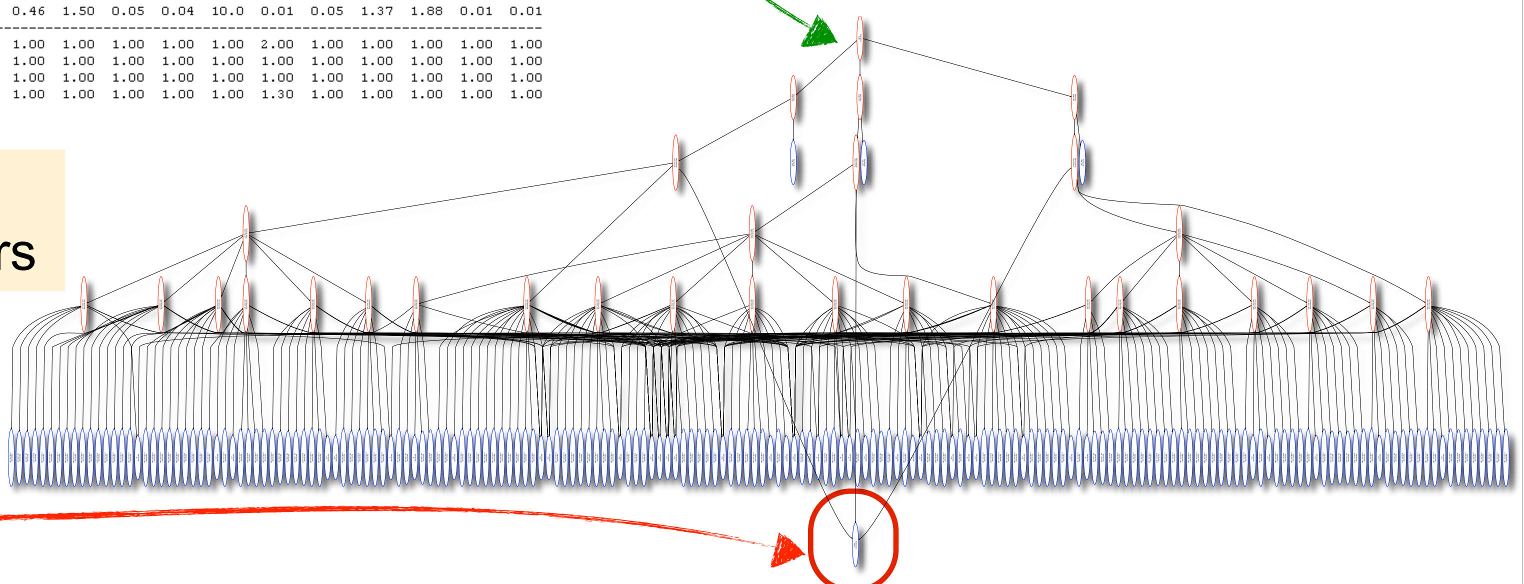
The CMS input:

- cleanly tabulated effect on each background due to each source of systematic
- systematics broken down into uncorrelated subsets
- used lognormal distributions for all systematics, Poissons for observations

Started with a txt input, defined a mathematical representation, and then prepared the RooStats workspace

```
Date: June 22, 2010
Description: HWW-->2l2v, 0jets, cut-and-count for 3 channels: mumu, ee, emu; made-up numbers for a ATLAS+CMS combination exercise
mH     160   Higgs mass hypothesis
comE   7.0    center of mass energy
lumi   1   luminosity in fb-1
----------------------------------------------------------------------------------------------------------------------------------------
imax    3   number of channels
jmax    6   number of backgrounds
kmax   37   number of nuisance parameters
----------------------------------------------------------------------------------------------------------------------------------------
Observation   15   7   13
----------------------------------------------------------------------------------------------------------------------------------------
bin          1     1     1     1     1     1     1     2     2     2     2     2     2     2     3     3     3     3     3     3     3
process      H    Wj    Zj    tX    WW    WZ    ZZ     H    Wj    Zj    tX    WW    WZ    ZZ     H    Wj    Zj    tX    WW    WZ    ZZ
process      0     1     2     3     4     5     6     0     1     2     3     4     5     6     0     1     2     3     4     5     6
----------------------------------------------------------------------------------------------------------------------------------------
rate      10.5  0.01  0.05  0.94  3.39  0.01  0.01  5.39  0.01  0.05  0.46  1.50  0.05  0.04  10.0  0.01  0.05  1.37  1.88  0.01  0.01
----------------------------------------------------------------------------------------------------------------------------------------
 1  lnN   1.00  2.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  2.00  1.00  1.00  1.00  1.00  1.00
 2  lnN   1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  2.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00
 3  lnN   1.00  1.30  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00
 4  lnN   1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.00  1.30  1.00  1.00  1.00  1.00  1.00  1.00  1.30  1.00  1.00  1.00  1.00  1.00
```

$$L_{b+rs} = \prod_i \left[\frac{\left(\sum_{j=0,1,..} \tilde{n}_{ij} \cdot \kappa_{ijk}^{\theta_k} \right)^{N_i}}{N_i!} \cdot \exp\left(- \sum_{j=0,1,..} \tilde{n}_{ij} \cdot \kappa_{ijk}^{\theta_k} \right) \right] \cdot \prod_k f(\theta_k)$$



3 observables and
37 nuisance parameters

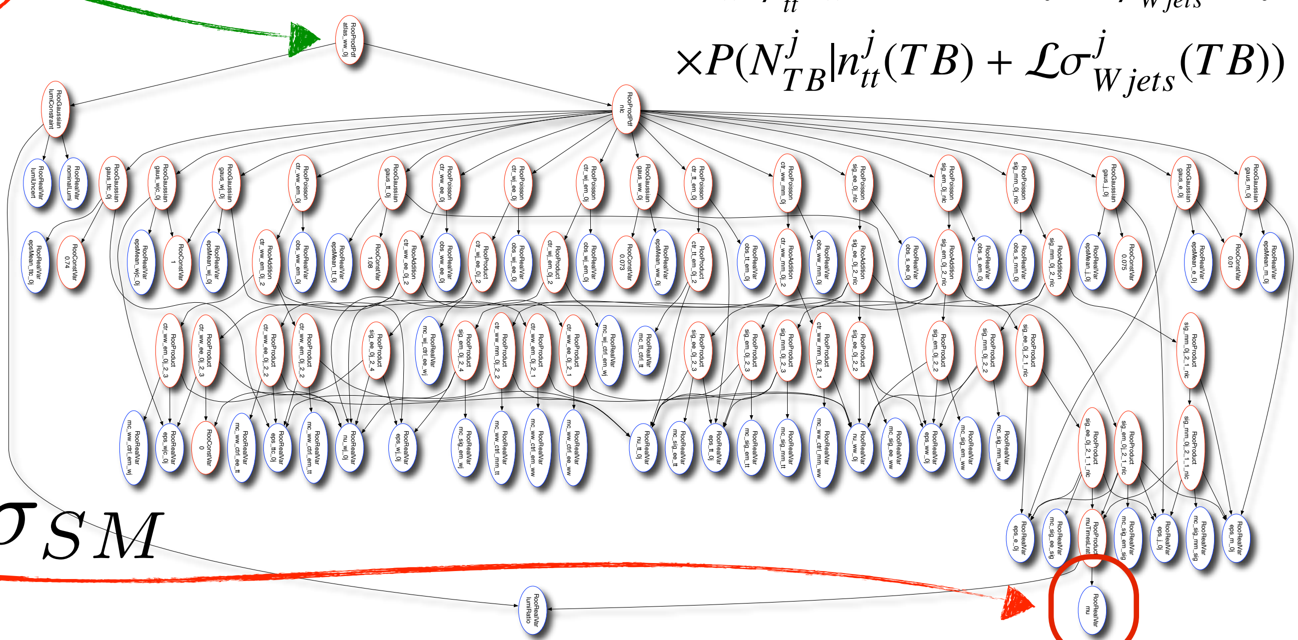
$$n = \mu L \epsilon \sigma_{SM}$$

ATLAS Higgs Example

The ATLAS input:

- Poisson terms 3 signal regions and 6 control regions
- Initially uncertainties in extrapolation coefficients treated with one Gaussians and it wasn't possible to identify individual systematics effects
    - thus, unable to identify any correlated systematic (eg. theory uncertainty)
- Now individual uncertainties are explicitly parameterized

$$
\begin{aligned}
L^{j,e\mu}_{Pois} = {} & P(N^j_{SR}|n^j_s(SR) + \alpha^j_{WW}\nu_{\alpha^j_{WW}} n^j_{WW}(CR) + \alpha^j_{t\bar{t}}\nu_{\alpha^j_{t\bar{t}}} n^j_{t\bar{t}}(TB) + \alpha^j_{Wjets}\nu_{\alpha^j_{Wjets}} n^j_{Wjets}(LL) + \mathcal{L}\sigma^j_{DY}(SR)) \\
& \times P(N^j_{CR}|n^j_s(CR) + n^j_{WW}(CR) + \beta^j_{t\bar{t}}\nu_{\beta^j_{t\bar{t}}} n^j_{t\bar{t}}(TB) + \beta^j_{Wjets}\nu_{\beta^j_{Wjets}} n^j_{Wjets}(LL) + \mathcal{L}\sigma^j_{DY}(CR)) \\
& \times P(N^j_{TB}|n^j_{tt}(TB) + \mathcal{L}\sigma^j_{Wjets}(TB)) \times P(N^j_{LL}|n^j_{Wjets}(LL))
\end{aligned}
$$



$$n = \mu L \epsilon \sigma_{SM}$$

Data driven estimates

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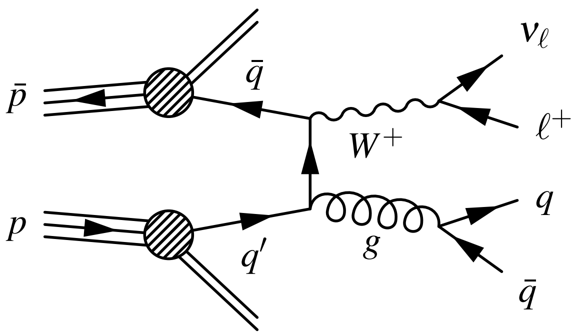
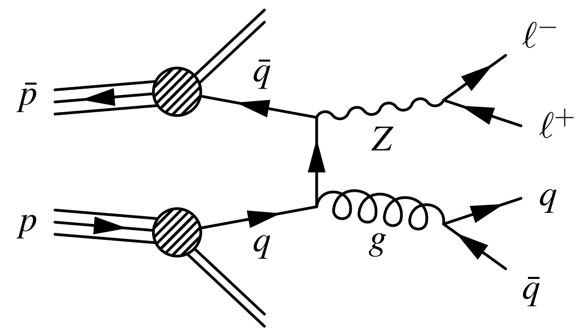
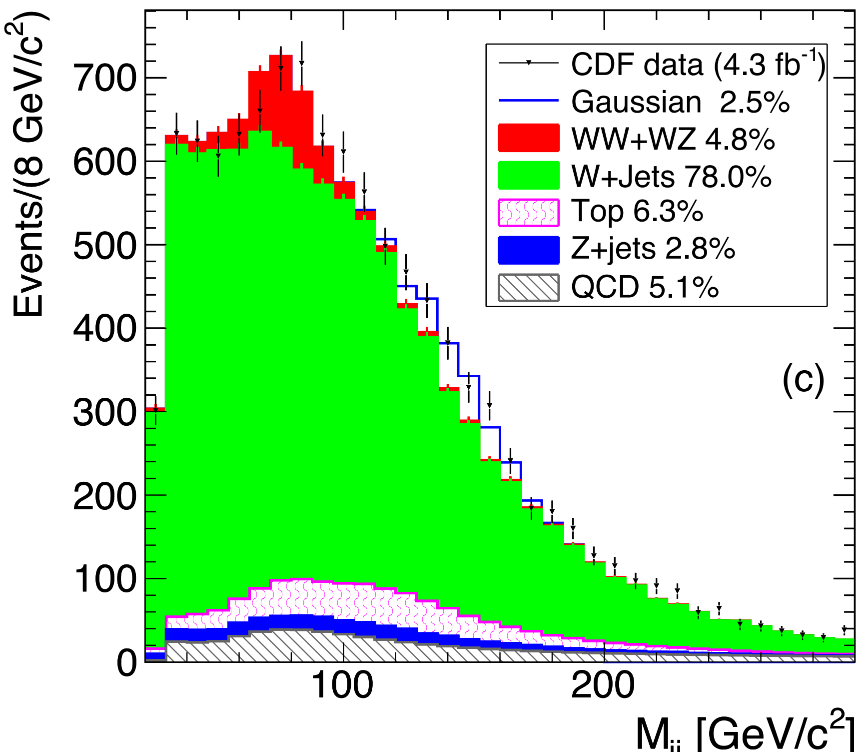
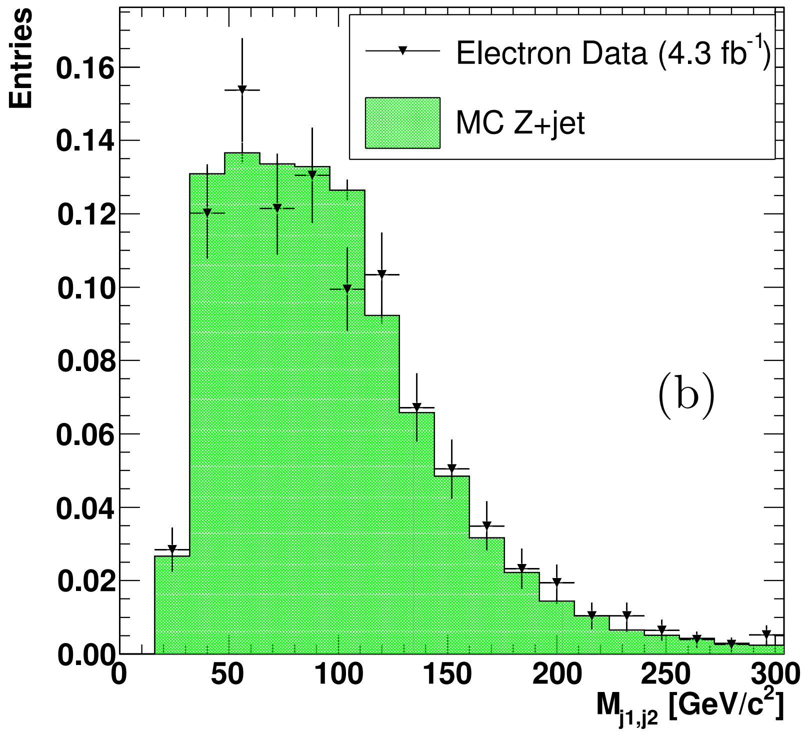
Cosmology and
Particle Physics

In the case of the CDF bump, the Z+jets control sample provides a data-driven estimate, but limited statistics. Using the simulation narrative over the data-driven is a **choice**. If you trust that narrative, it's a good choice.



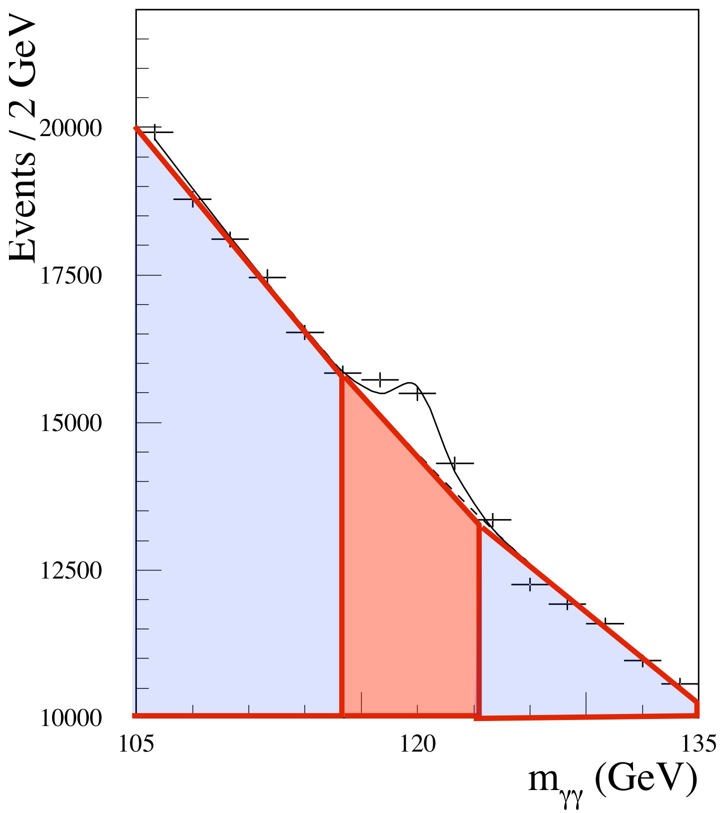






It is common to describe a distribution with some parametric function

- “fit background to a polynomial”, exponential, ...
- While this is convenient and the fit may be good, the narrative is weak



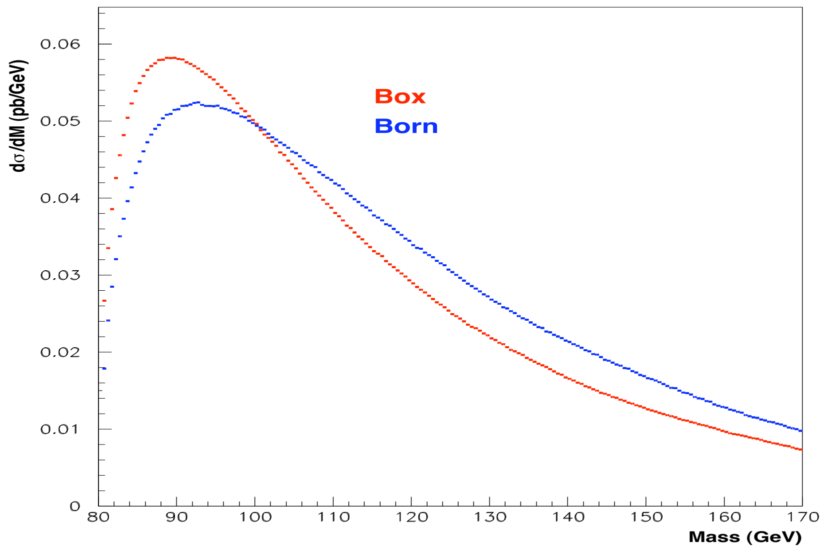
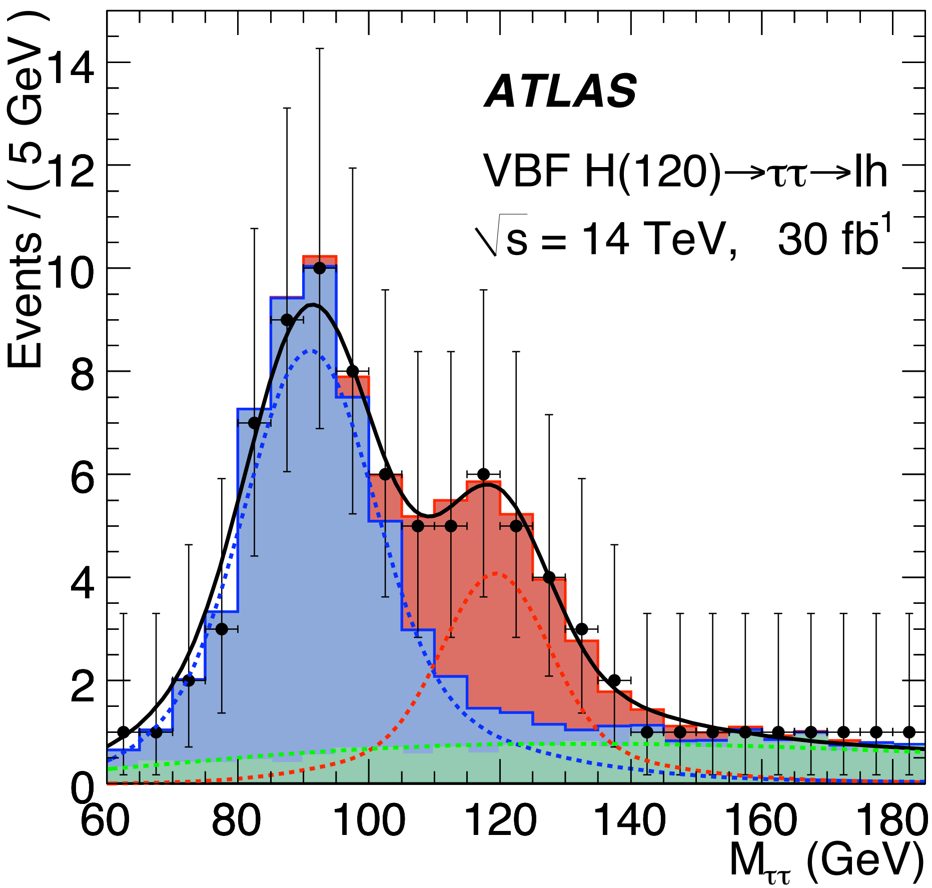


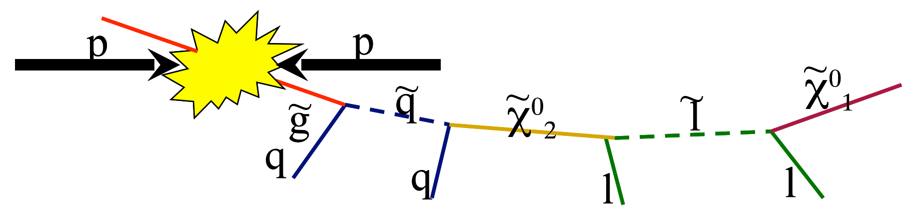
Figure 5. Two plausible shapes for the continuum $\gamma\gamma$ mass spectrum at the LHC.

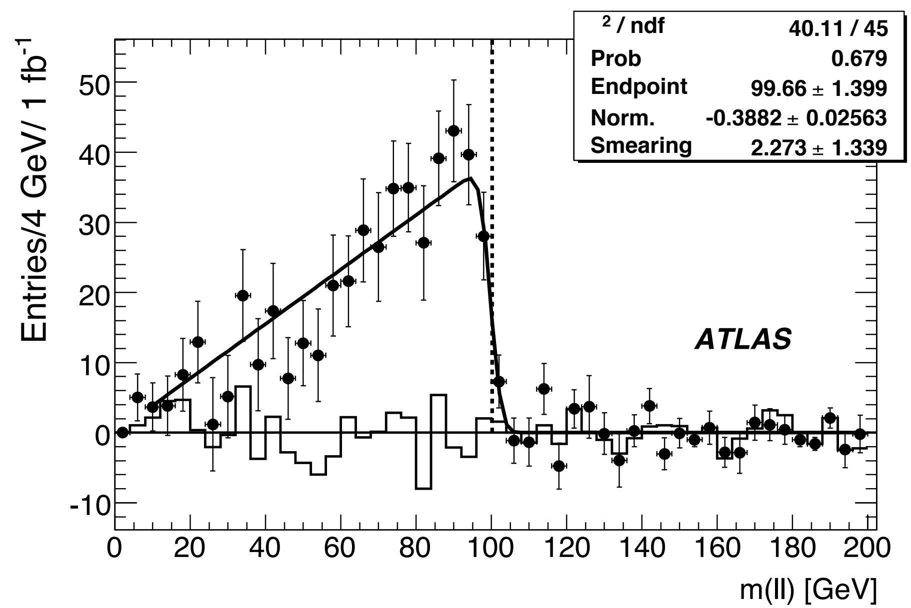
The Effective Model narrative

However, sometimes the effective model comes from a convincing narrative

- convolution of resolution with known distribution
- for example, the “invariant mass” of some final state particles





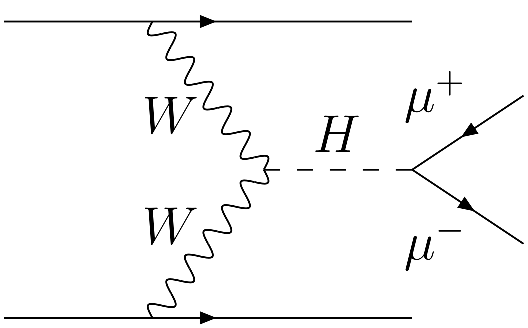


The parametrized response narrative

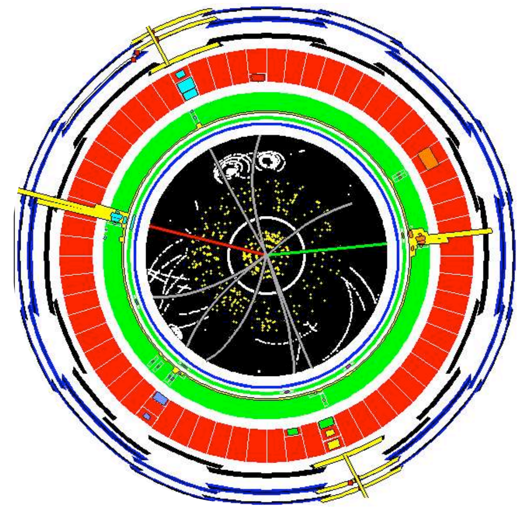
The Matrix-Element technique is conceptually similar to the simulation narrative, but the detector response is parametrized.

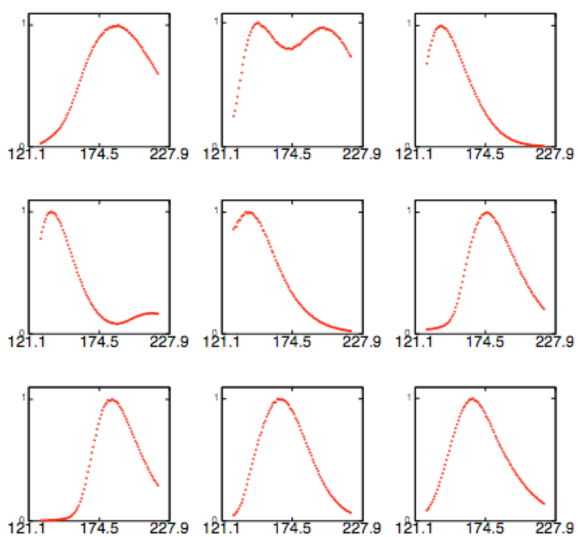
- Doesn't require building parametrized PDF by interpolating between non-parametric templates.

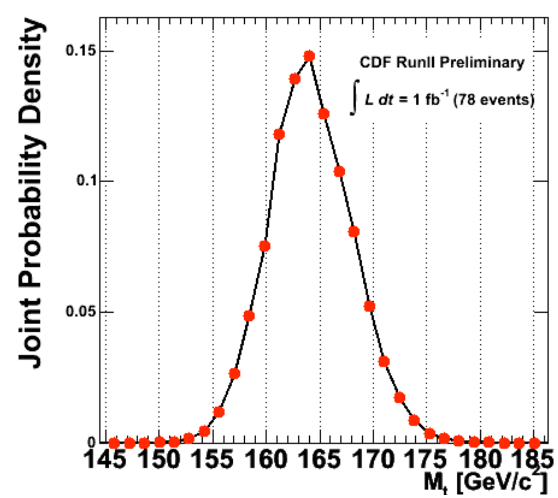
$$L(x|H_0) =$$



$$\oplus$$







The parametrized response narrative

The Matrix-Element technique is conceptually similar to the simulation narrative, but the detector response is parametrized.

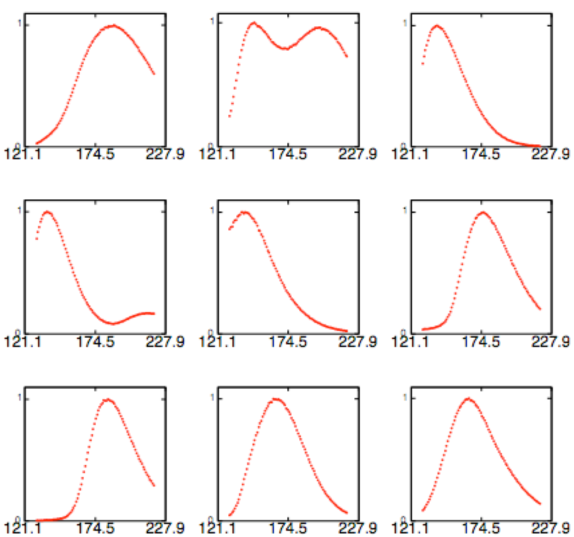
- Doesn't require building parametrized PDF by interpolating between non-parametric templates.

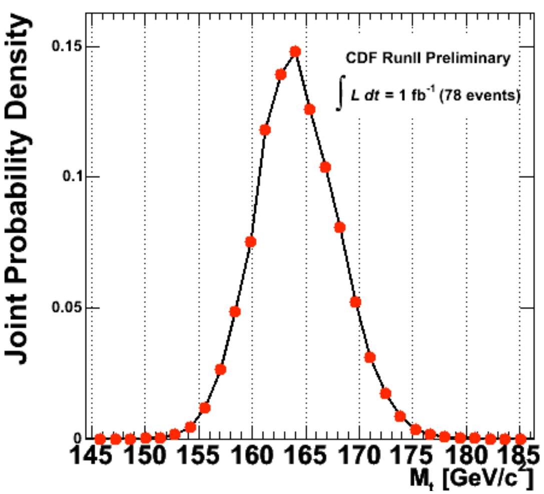
$$P(\mathbf{x}|M_t) = \frac{1}{N}\int d\Phi\ |\mathcal{M}_{t\bar{t}}(p;M_t)|^2 \prod_{jets} f(p_i,j_i) f_{PDF}(q_1) f_{PDF}(q_2)$$

Phase-space Integral

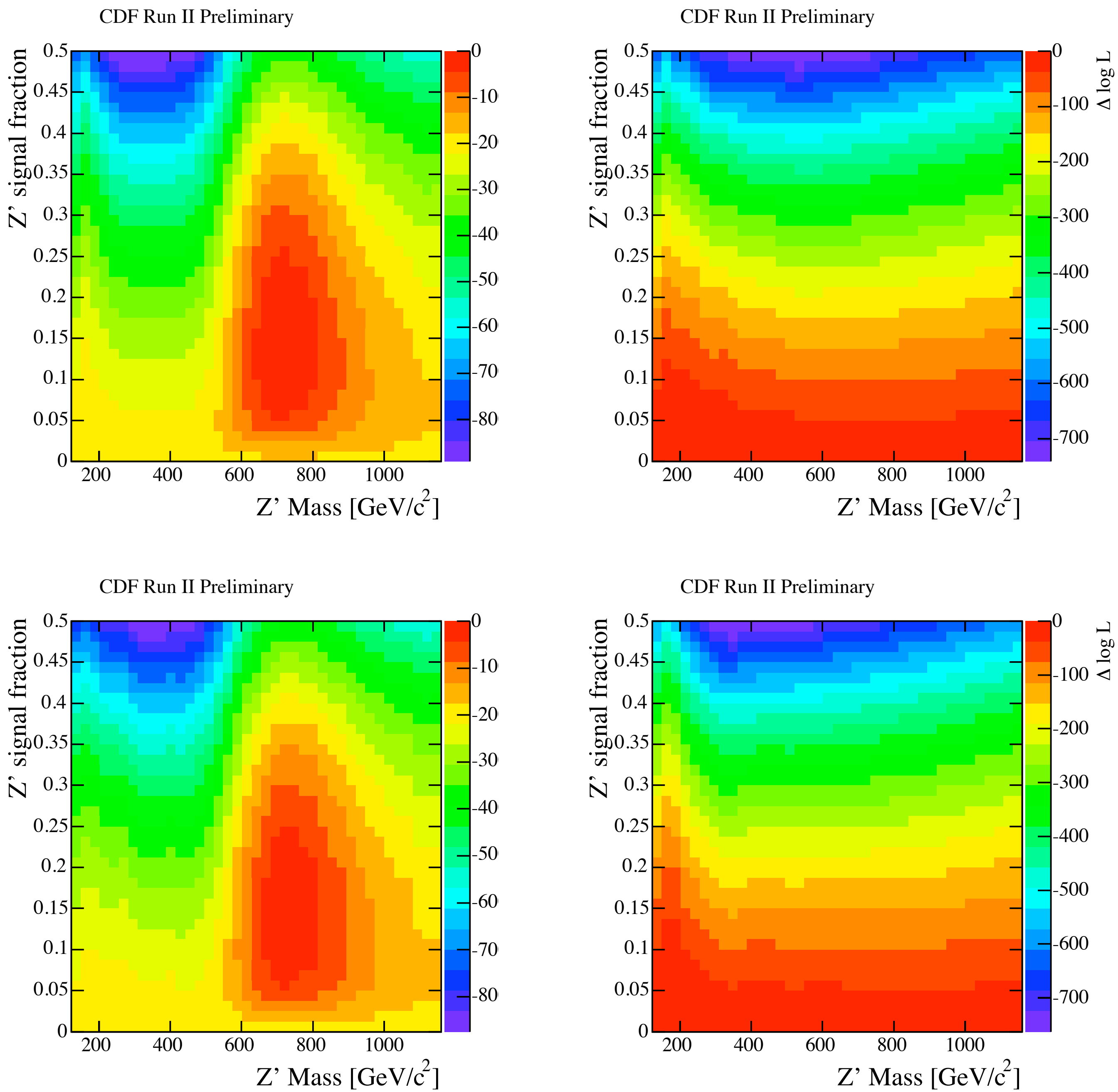
Matrix Element

Transfer Functions





Example likelihoods from CDF Z’



Fast Simulation

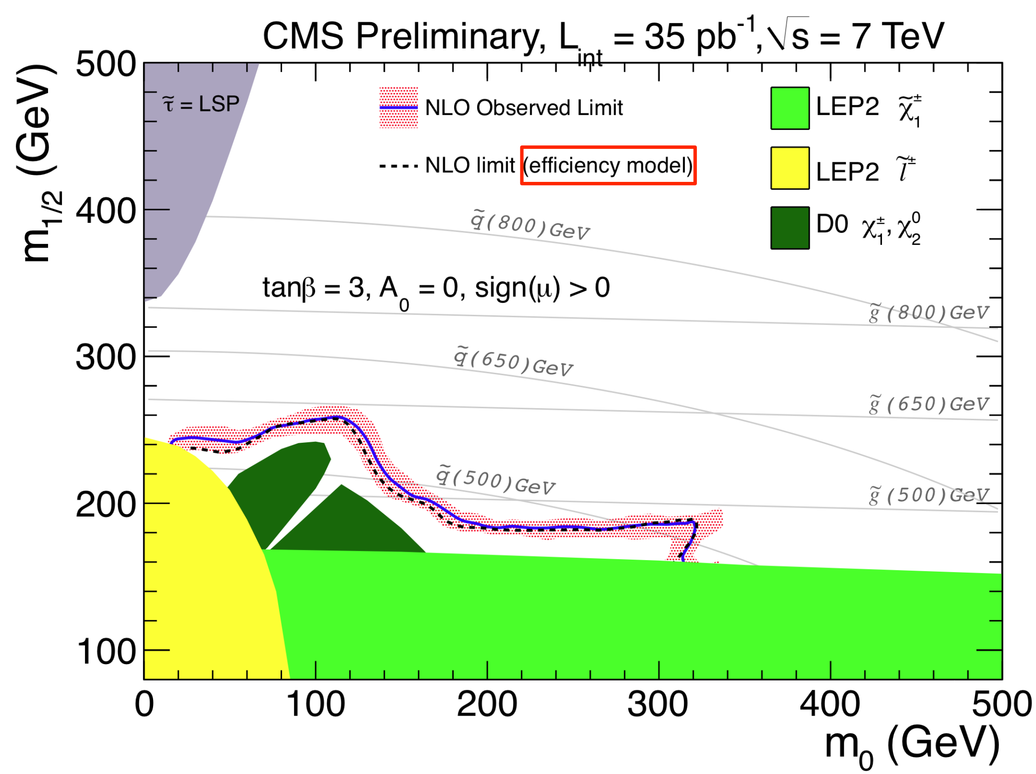
Fast simulations based on parametrized detector response are very useful and can often be tuned to perform quite well in a specific analysis context

- For example: tools like PGS, Delphis, ATLFAST, ...

But these tools still use accept/reject Monte Carlo.

- Would be much more useful if the parmaetrized detector response could be used as a transfer function in Matrix-Element approach

Same sign di-lepton + jets + MET search



Paper includes a simple efficiency model (i.e. for PGS calibrations) and compares full limit to limit with simple model.

CMS SUSY Results, D. Stuart, April 2011, SUSY Recast, UC Davis 36

Narrative styles

The Monte Carlo Simulation narrative (MC narrative)

- each stage is an accept/reject Monte Carlo based on P(out|in) of some microscopic process like parton shower, decay, scattering
- PDFs built from non-parametric estimator like histograms or kernel estimation
  - need to supplement with interpolation procedures to incorporate systematics
  - smearing approach fundamentally Bayesian
- **pros:** most detailed understanding of micro-physics
- **cons:** computationally demanding, loose analytic scaling properties, relies on accuracy of simulation
- **new ideas:** improved interpolation, Radford Neal's machine learning, "design of experiments"

The Data-driven narrative

- independent data sample that either acts as a proxy for some process or can be transformed to do so
- **pros**: nature includes "all orders", uses real detector
- **cons**: extrapolation from control region to signal region requires assumptions, introduces systematic effects. Appropriate transformation may depend on many variables, which becomes impractical

Narrative styles

Effective modeling narrative

- parametrized functional form: eg. Gaussian, falling exponential para polynomial fit to distribution, etc.
- **pros**: fast, has analytic scaling, parametric form may be well justified (eg. phase space, propagation of errors, convolution)
- **cons**: approximate, parametric form may be ad hoc (eg. polynomial from)
- new ideas: using non-parametric statistical methods

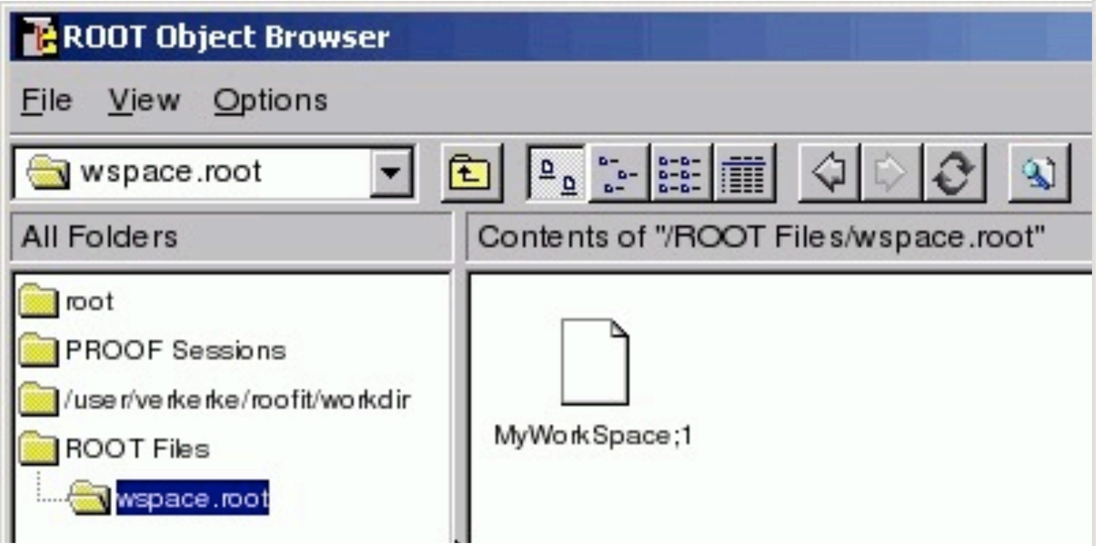
Parametrized detector response narrative (eg. kinematic fitting, Matrix-Element method, ~fast simulation)

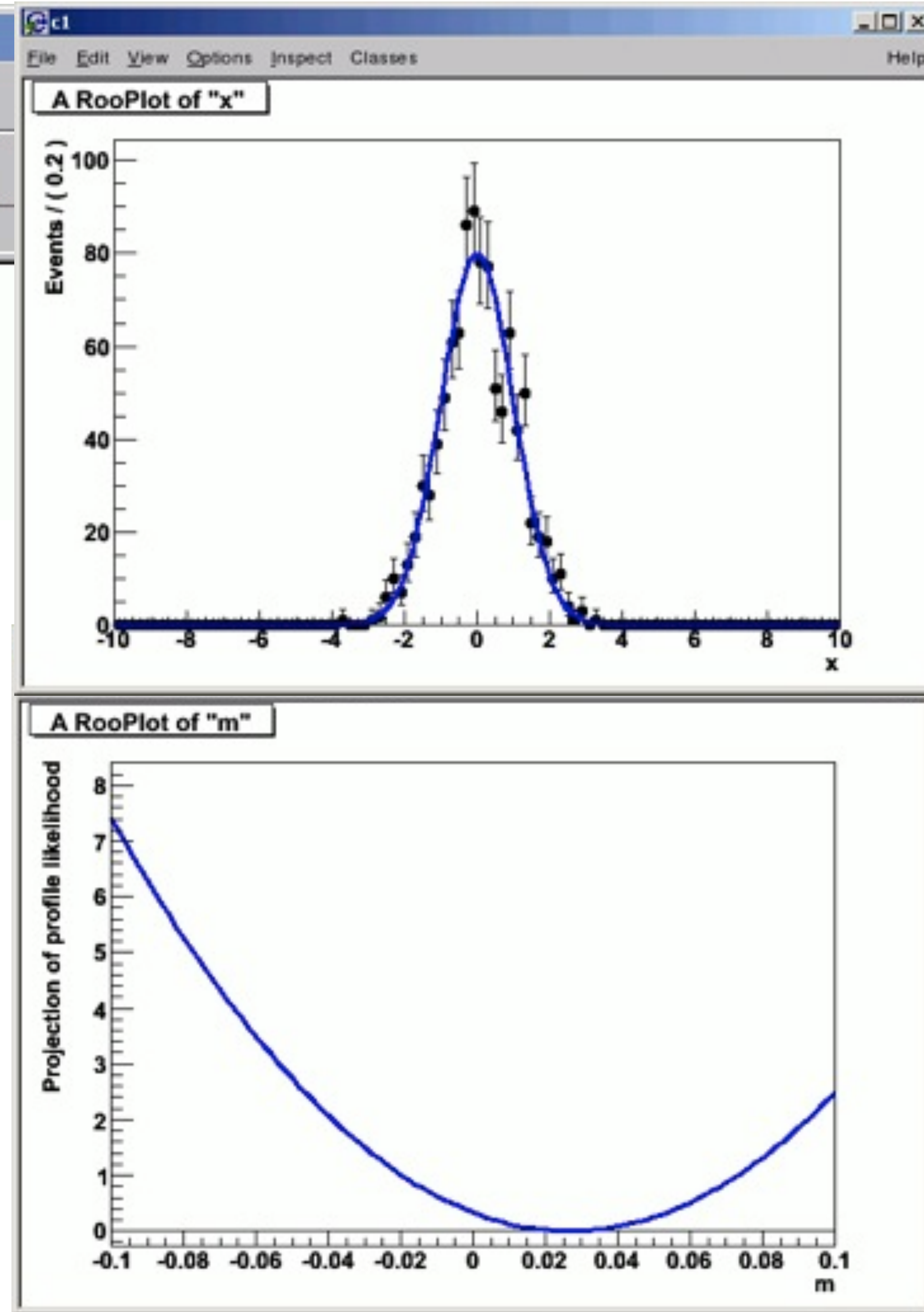
- **pros**: fast, maintains analytic scaling, response usually based on good understanding of the detector, possible to incorporate some types of uncertainty in the response analytically, can evaluate P(out|in) for arbitrary out,in.
- **cons**: approximate, best parametrized detector response is often not available in convenient form
- new ideas: fast simulation is typically parametrized, but we use it in an accept/ reject framework (see Geant5)

Combinations, Rich Modeling, and Publishing

Example of Digital Publishing

Center for
Cosmology and
Particle Physics





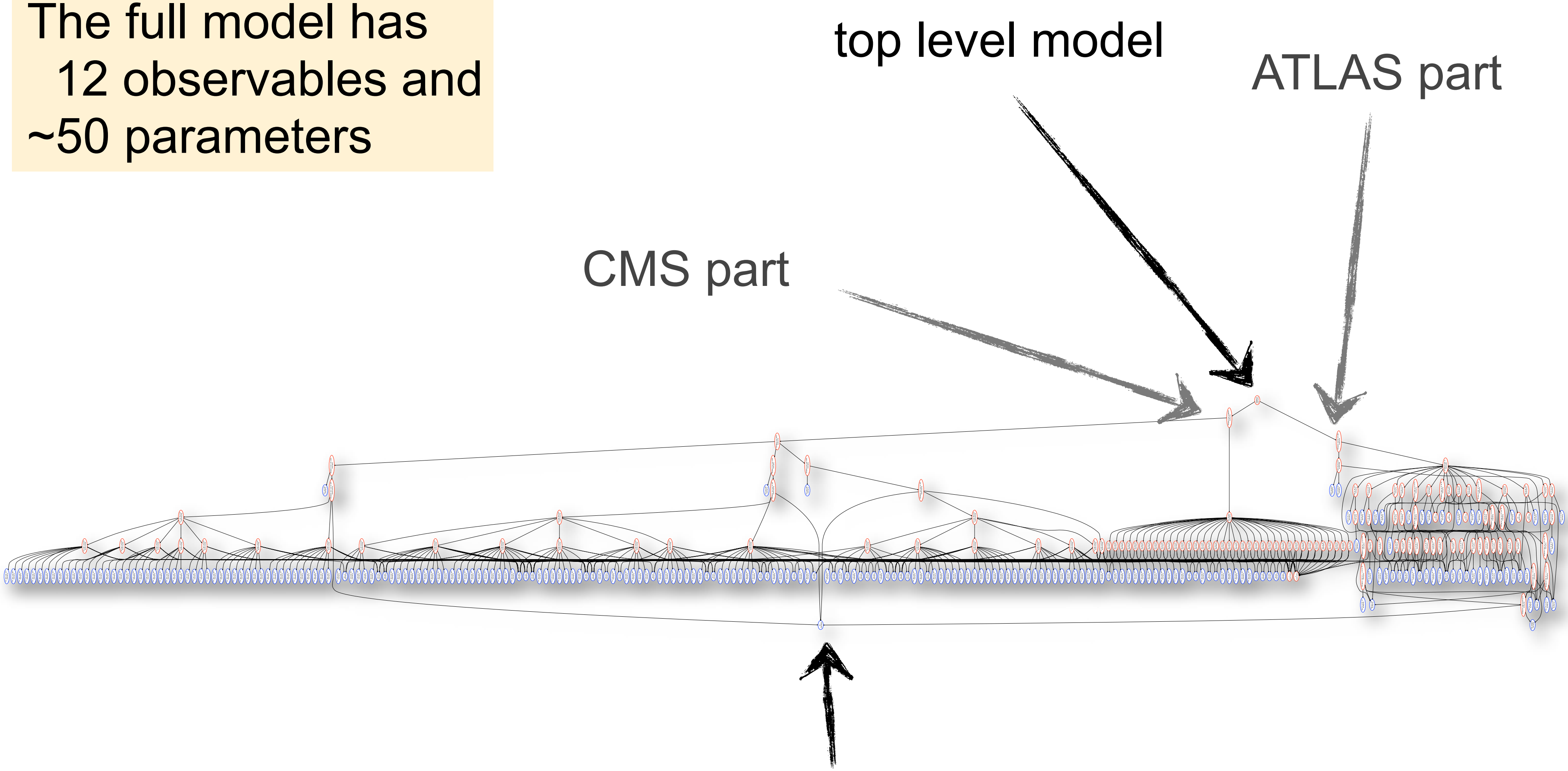
RooFit's Workspace now provides the ability to save in a ROOT file the full likelihood model, any priors you might want, and the minimal data necessary to reproduce likelihood function.

Need this for combinations, as p-value is not sufficient information for a proper combination.

Visualization of the ATLAS+CMS Workspace

Center for Cosmology and Particle Physics

The full model has 12 observables and ~50 parameters



$$\mu = \frac{\sigma BR}{\sigma_{SM} BR_{SM}}$$

Combinations & Rich Modeling

As we saw, constraint terms for nuisance parameters can often be related to auxiliary measurements

- we only considered very simple auxiliary measurements, like number of events in a sideband, but even in that case there are likely to be common systematics
- idea can be generalized to more sophisticated measurements
  - for example, γ-jet or Z-jet balance measurements to constrain the Jet Energy Scale uncertainty

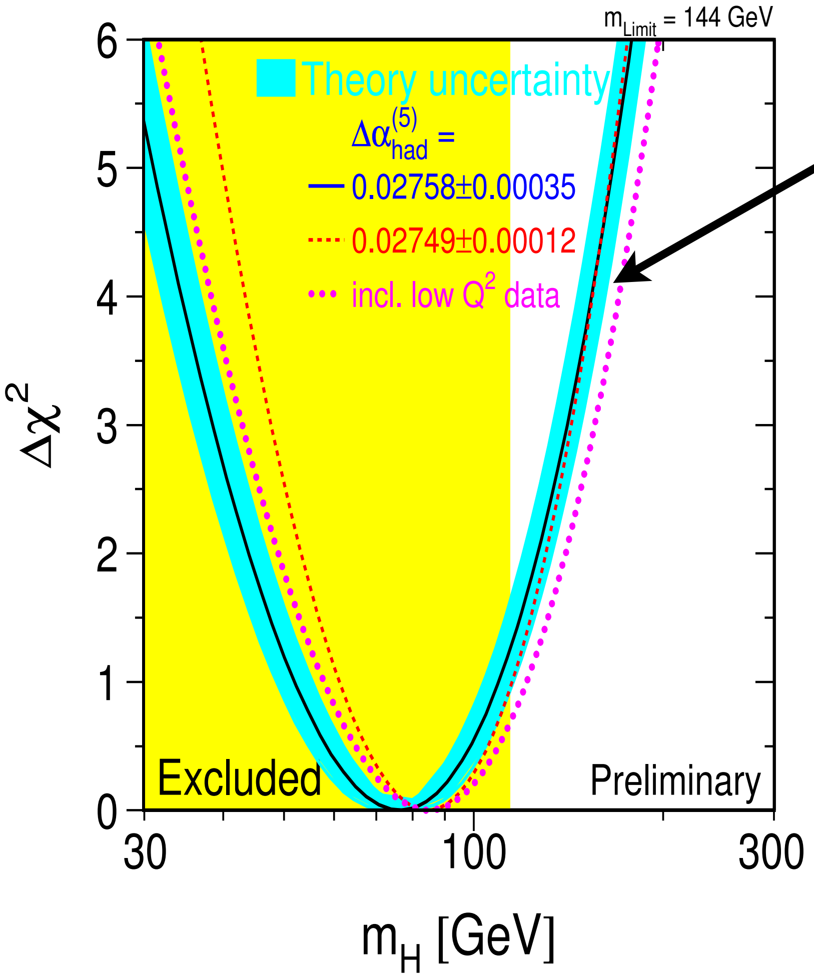
The point is that combining these models leads to a qualitiative change in how we represent what we know: **rich modeling**

Now the distinction has been blurred between a Higgs combination and a sophisticated modeling of systematics

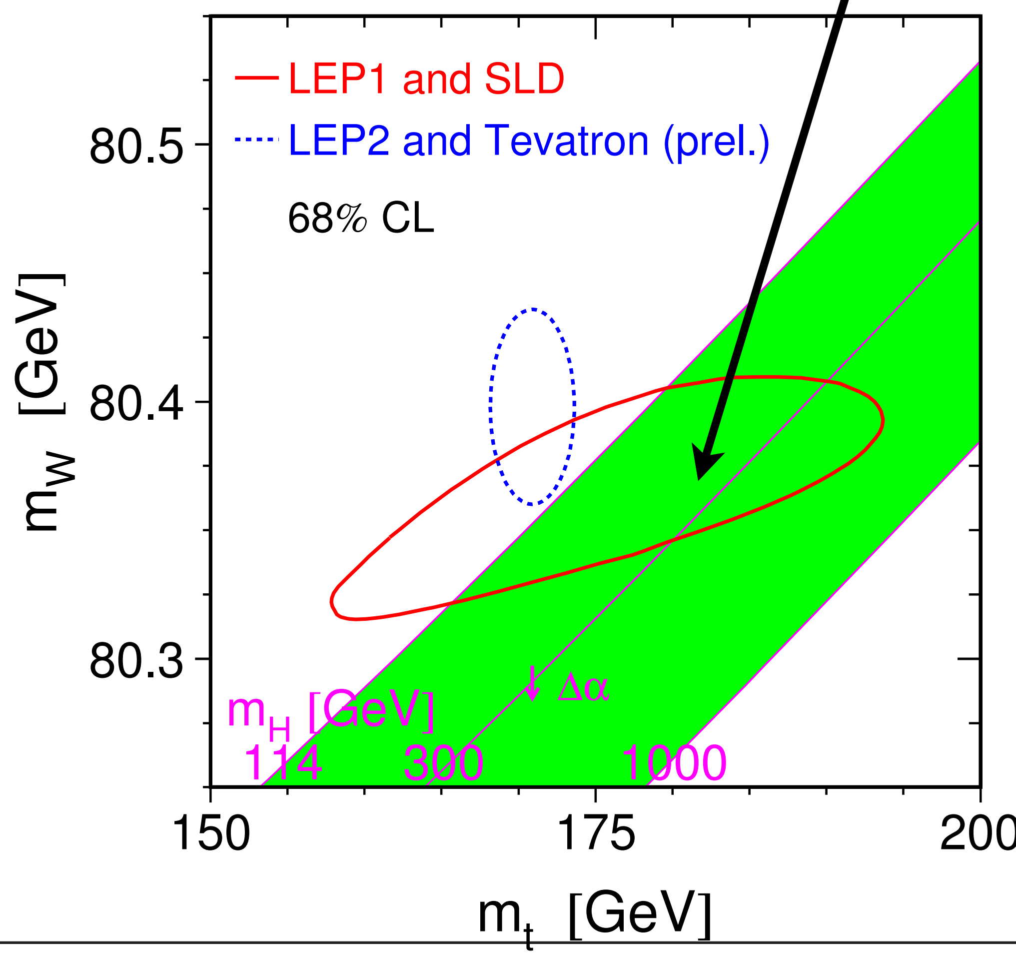
Examples of Published Likelihoods

At previous PhyStats, we agreed to publish likelihood functions

You can find examples of published likelihoods in 1D



In 2-D you just get the contours



Surely we can do better!

Origins I: The First "Statistics in HEP" conference

WORKSHOP ON CONFIDENCE LIMITS

CERN, Geneva, Switzerland
17–18 January 2000

CERN 2000–005

Massimo Corradi

Does everybody agree on this statement, to publish likelihoods?

Louis Lyons

Any disagreement ? Carried unanimously. That's actually quite an achievement for this Workshop.

...[Fred James wants to be able to calculate coverage, Don Groom wants to able to calculate goodness of fit]...

Cousins

I thought the point of unanimity was that publishing the likelihood function was a *necessary* condition, not a sufficient condition.

But a practical problem remained: *How* to communicate multi-D likelihood?

http://indico.cern.ch/conferenceDisplay.py?confId=100458

Current scenario

Taken from the GFitter paper

[23]This procedure only uses the M_H value under consideration, where Higgs-mass hypothesis and measurement are compared. It thus neglects that in the SM a given signal hypothesis entails background hypotheses for all M_H values other than the one considered. An analysis accounting for this should provide a statistical comparison of a given hypothesis with all available measurements. This however would require to know the correlations among all the measurement points (or better: the full experimental likelihood as a function of the Higgs-mass hypothesis), which are not provided by the experiments to date. The difference to the hypothesis-only test employed here is expected to be small at present, but may become important once an experimental Higgs signal appears, which however has insufficient significance yet

Combining Results: An Example

Center for
Cosmology and
Particle Physics

A combination example

- Combining 'ATLAS' and 'CMS' result from persisted workspaces

Read ATLAS workspace
```
TFile* f = new TFile("atlas.root") ;
RooWorkspace *atlas = f->Get("atlas") ;
```

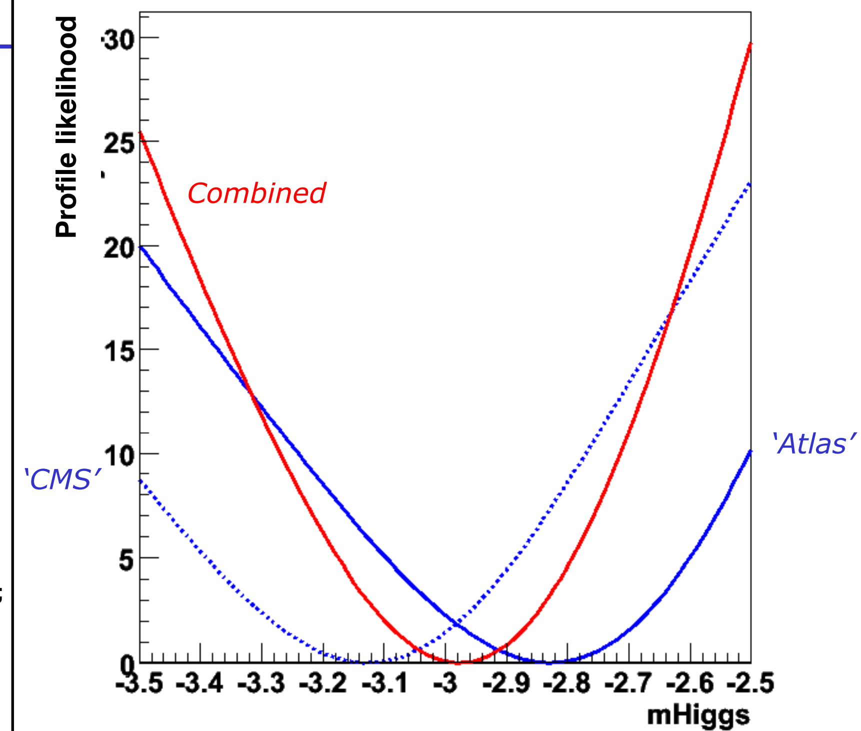
Read CMS workspace
```
TFile* f = new TFile("cms.root") ;
RooWorkspace *cms = f->Get("cms") ;
```

Construct combined LH
```
RooAddition nllCombi("nllCombi","nll CMS&ATLAS",
            RooArgSet(*cms->function("nll"),*atlas->function("nll"))) ;
```

Construct profile LH in mHiggs
```
RooProfileLL pllCombi("pllCombi","pll",nllCombi,*atlas->var("mHiggs")) ;
```

Plot Atlas,CMS, combined profile LH
```
RooPlot* mframe = atlas->var("mHiggs")->frame(-3.5,-2.5) ;
atlas->function("nll")->plotOn(mframe)) ;
cms->function("nll")->plotOn(mframe),LineStyle(kDashed)) ;
pllCombi.plotOn(mframe,LineColor(kRed)) ;
mframe->Draw() ; // result on next slide
```

Wouter Verkerke, NIKHEF



By using the workspace, it is easy to share results, ideal for combinations.

Example above shows opening an 'atlas' and 'cms' workspace, and performing a combined fit to a common parameter with profile likelihood.

Michelangelo's Likelihood Mandate (MLM):

A general assessment of the status and needs of the tools for setting limits on (or fitting) parameters of BSM models, using the multitude of data from searches at the LHC

Two related communities and ongoing discussions

- Characterization & Simplified Models
- Fitting Model Parameters

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Potential new tasks

- **Input for the Strategy Group**
  - LPCC and experiments required to produce combined assessment of the 2010-11(-12) findings in Higgs and BSM searches
  - TH community, and other expl communities (e.g. LinCol, SuperB, ...), will use this to assess the implications of LHC data for BSM and future exptl projects

➡ We need to prepare the framework/tools to enable:

  - combination of limits/evidence from ATLAS/CMS(/LHCb)
  - use of the results by the rest of the community (e.g. SUSY-models' fitters)

- This will require coordination with
  - ATLAS-CMS statistics forum
  - Fitters' groups
  - all LHC "search " efforts (Higgs, B decays, exotica of all sorts ....)
  - ...

Introduction

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  - ...

Goals for this meeting

- Review the progress made by the experiments
- Status report on the SLAC WG
- Collect further input from all fields (TH + exps)
- In the context of simplified models, start outlining the roadmap and the workflow to go from analysis, to publication, to combination of the results of different experiments, to conclude with the exploitation of the published results by a random theorist.

analysis

format of the published result

combination among experiments

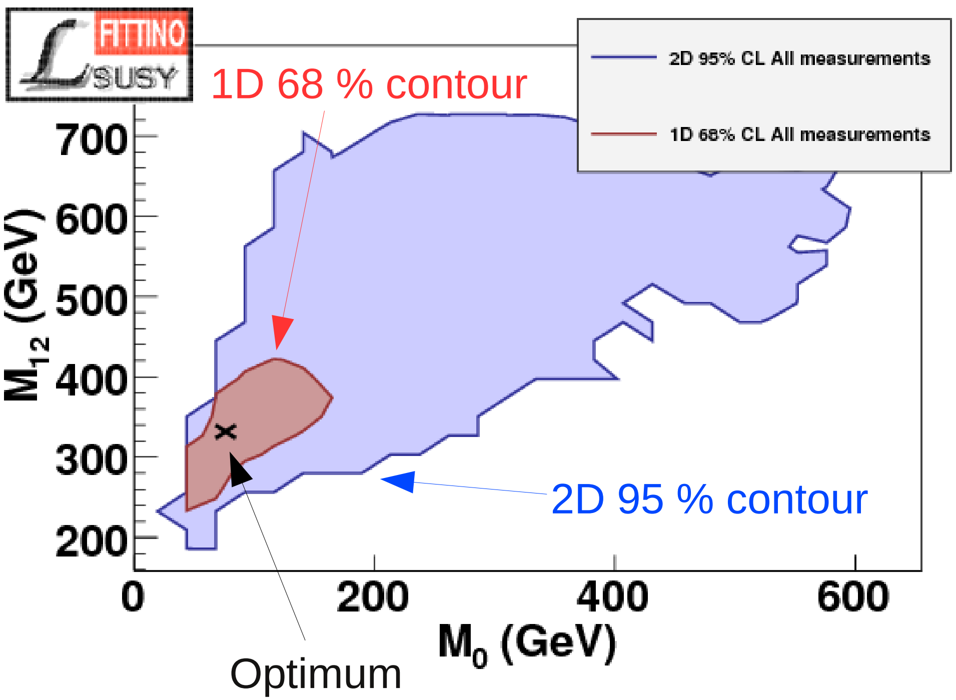
use of the results by a theorist, in the context of a new model

SUSY Fitting tools

Center for Cosmology and Particle Physics

Usually simplify input from experiments to be a single Gaussian

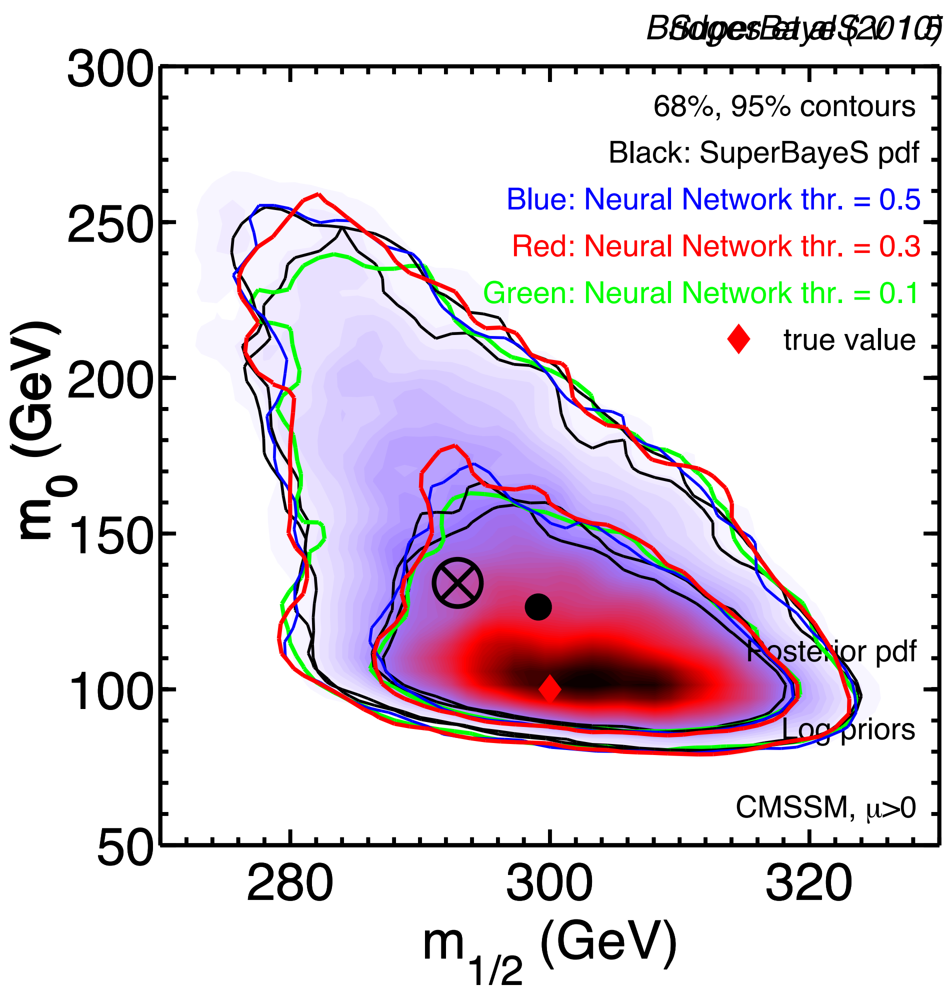
Observable	Experimental Value	Uncertainty stat	Uncertainty syst	Exp. Reference
$\mathcal{B}(B \to s\gamma)/\mathcal{B}(B \to s\gamma)_{\rm SM}$	1.117	0.076	0.096	[47]
$\mathcal{B}(B_s \to \mu\mu)$	$< 4.7\times10^{-8}$			[47]
$\mathcal{B}(B_d \to \ell\ell)$	$< 2.3\times10^{-8}$			[47]
$\mathcal{B}(B \to \tau\nu)/\mathcal{B}(B \to \tau\nu)_{\rm SM}$	1.15	0.40		[48]
$\mathcal{B}(B_s \to X_s\ell\ell)/\mathcal{B}(B_s \to X_s\ell\ell)_{\rm SM}$	0.99	0.32		[47]
$\Delta m_{B_s}/\Delta m_{B_s}^{\rm SM}$	1.11	0.01	0.32	[49]
$\frac{\Delta m_{B_s}/\Delta m_{B_s}^{\rm SM}}{\Delta m_{B_d}/\Delta m_{B_d}^{\rm SM}}$	1.09	0.01	0.16	[47,49]
$\Delta\epsilon_K/\Delta\epsilon_K^{\rm SM}$	0.92	0.14		[49]
$\mathcal{B}(K \to \mu\nu)/\mathcal{B}(K \to \mu\nu)_{\rm SM}$	1.008	0.014		[50]
$\mathcal{B}(K \to \pi\nu\bar{\nu})/\mathcal{B}(K \to \pi\nu\bar{\nu})_{\rm SM}$	< 4.5			[51]
$a_\mu^{\rm exp} - a_\mu^{\rm SM}$	30.2×10^{-10}	8.8×10^{-10}	2.0×10^{-10}	[52,53]
$\sin^2\theta_{\rm eff}$	0.2324	0.0012		[46]
Γ_Z	2.4952 GeV	0.0023 GeV	0.001 GeV	[46]
R_l	20.767	0.025		[46]
R_b	0.21629	0.00066		[46]
R_c	0.1721	0.003		[46]
$A_{\rm fb}(b)$	0.0992	0.0016		[46]
$A_{\rm fb}(c)$	0.0707	0.0035		[46]
A_b	0.923	0.020		[46]
A_c	0.670	0.027		[46]
A_l	0.1513	0.0021		[46]
A_τ	0.1465	0.0032		[46]
$A_{\rm fb}(l)$	0.01714	0.00095		[46]
$\sigma_{\rm had}$	41.540 nb	0.037 nb		[46]
m_h	> 114.4 GeV		3.0 GeV	[54,55,56]
$\Omega_{\rm CDM}h^2$	0.1099	0.0062	0.012	[57]
$1/\alpha_{em}$	127.925	0.016		[58]
G_F	$1.16637\times10^{-5}{\rm GeV}^{-2}$	$0.00001\times10^{-5}{\rm GeV}^{-2}$		[58]
α_s	0.1176	0.0020		[58]
m_Z	91.1875 GeV	0.0021 GeV		[46]
m_W	80.399 GeV	0.025 GeV	0.010 GeV	[58]
m_b	4.20 GeV	0.17 GeV		[58]
m_t	172.4 GeV	1.2 GeV		[59]
m_τ	1.77684 GeV	0.00017 GeV		[58]
m_c	1.27 GeV	0.11 GeV		[46]

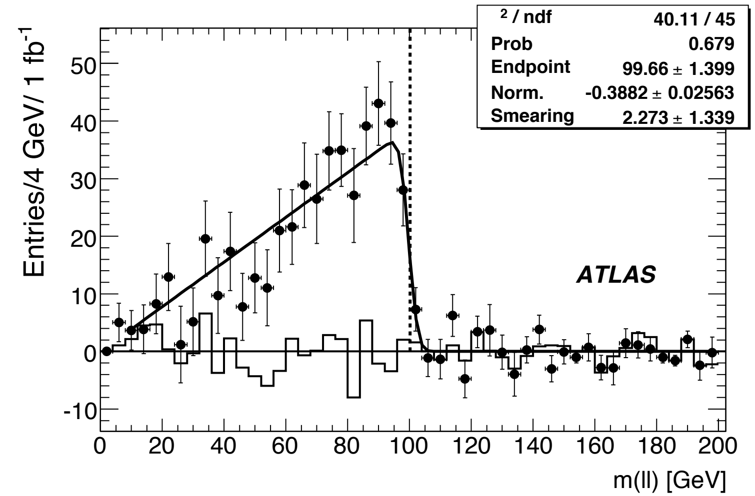


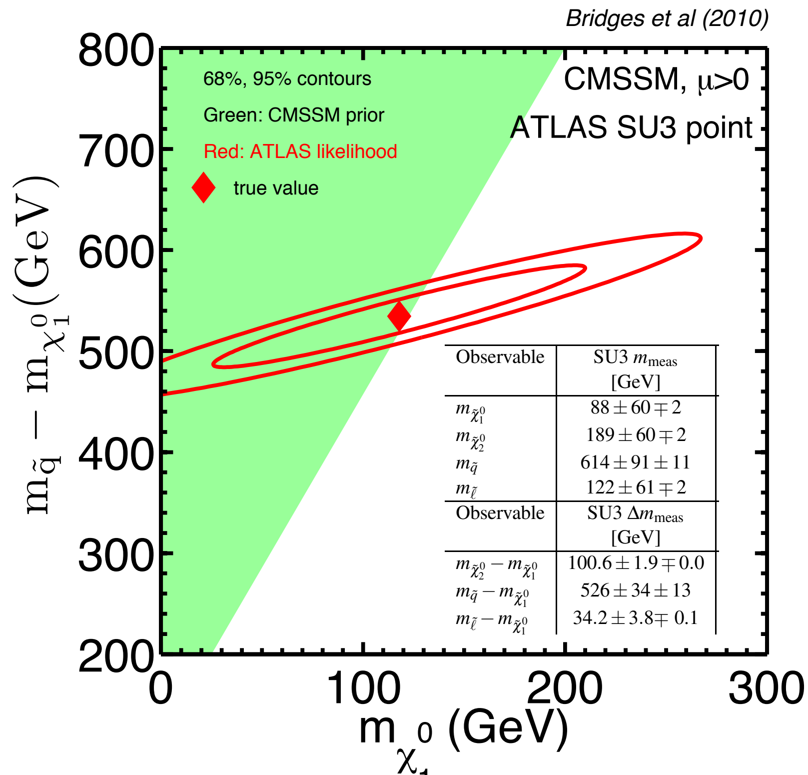
First interface with SuperBayes

Repeated same analysis as Bridges, KC, Trotta et al ([1011.4306](1011.4306)) with RooStats likelihood

- see consistent results!

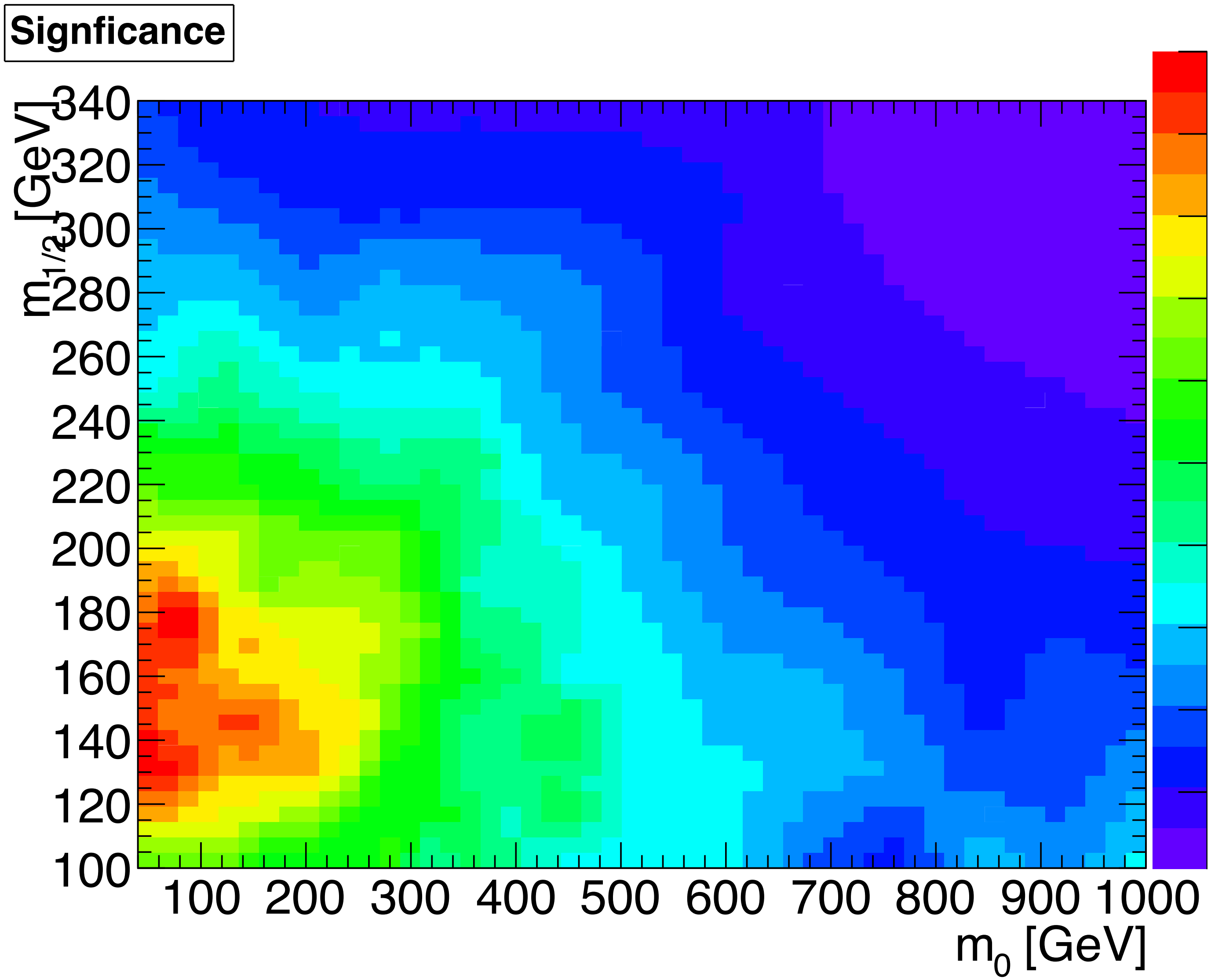






Benchmark based on counting

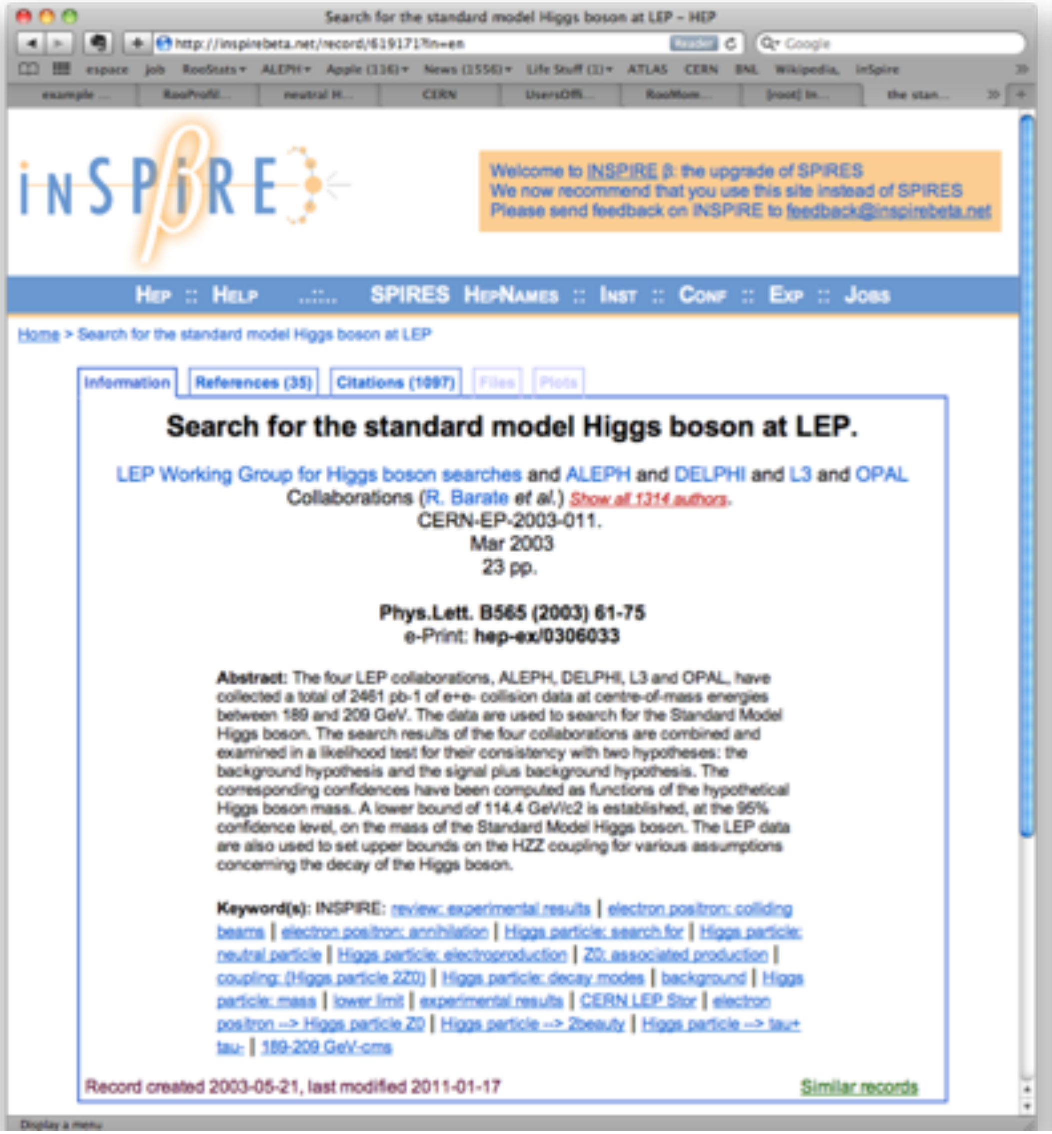
Max Baak's demonstrated interpolation of signal yield and uncertainties in a 3-d mSUGRA scan with a simple number counting analysis



Ultimate Goal

Publish likelihoods along with papers

- first goal, the LEP Higgs



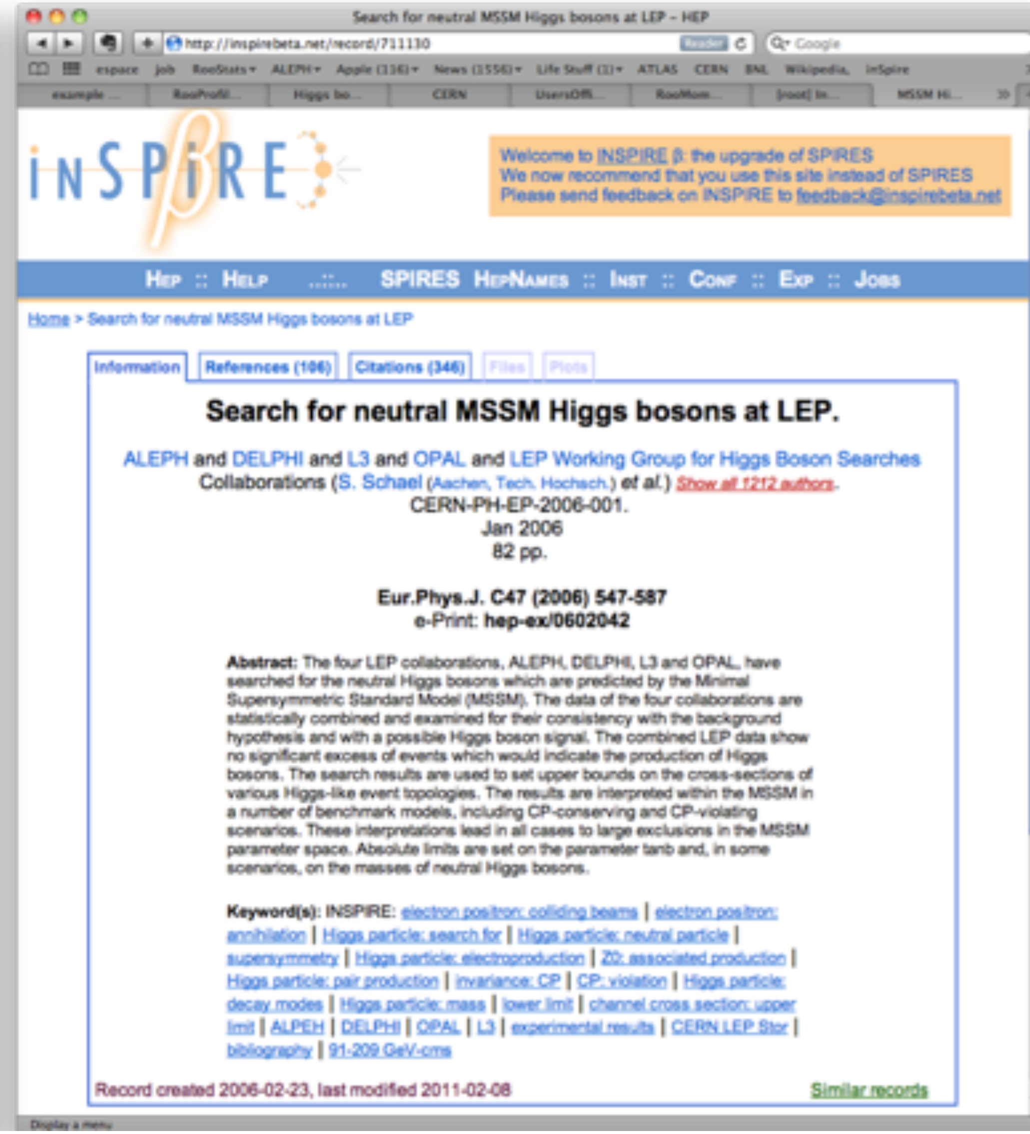
Search for the standard model Higgs boson at LEP.

LEP Working Group for Higgs boson searches and ALEPH and DELPHI and L3 and OPAL Collaborations (R. Barate *et al.*) Show all 1314 authors.
CERN-EP-2003-011.
Mar 2003
23 pp.

Phys.Lett. B565 (2003) 61-75
e-Print: **hep-ex/0306033**

Abstract: The four LEP collaborations, ALEPH, DELPHI, L3 and OPAL, have collected a total of 2461 pb-1 of e+e- collision data at centre-of-mass energies between 189 and 209 GeV. The data are used to search for the Standard Model Higgs boson. The search results of the four collaborations are combined and examined in a likelihood test for their consistency with two hypotheses: the background hypothesis and the signal plus background hypothesis. The corresponding confidences have been computed as functions of the hypothetical Higgs boson mass. A lower bound of 114.4 GeV/c2 is established, at the 95% confidence level, on the mass of the Standard Model Higgs boson. The LEP data are also used to set upper bounds on the HZZ coupling for various assumptions concerning the decay of the Higgs boson.

Record created 2003-05-21, last modified 2011-01-17



Search for neutral MSSM Higgs bosons at LEP.

ALEPH and DELPHI and L3 and OPAL and LEP Working Group for Higgs Boson Searches Collaborations (S. Schael (Aachen, Tech. Hochsch.) *et al.*) Show all 1212 authors.
CERN-PH-EP-2006-001.
Jan 2006
82 pp.

Eur.Phys.J. C47 (2006) 547-587
e-Print: **hep-ex/0602042**

Abstract: The four LEP collaborations, ALEPH, DELPHI, L3 and OPAL, have searched for the neutral Higgs bosons which are predicted by the Minimal Supersymmetric Standard Model (MSSM). The data of the four collaborations are statistically combined and examined for their consistency with the background hypothesis and with a possible Higgs boson signal. The combined LEP data show no significant excess of events which would indicate the production of Higgs bosons. The search results are used to set upper bounds on the cross-sections of various Higgs-like event topologies. The results are interpreted within the MSSM in a number of benchmark models, including CP-conserving and CP-violating scenarios. These interpretations lead in all cases to large exclusions in the MSSM parameter space. Absolute limits are set on the parameter tanb and, in some scenarios, on the masses of neutral Higgs bosons.

Record created 2006-02-23, last modified 2011-02-08

CERN Colloquium and Library Science Talk

SPEAKER: Lawrence Lessig (Edmond J. Safra Center for Ethics and Harvard Law School, Cambridge, MA, US)

TITLE: **"The architecture of access to scientific knowledge: just how badly we have messed this up"**

DATE: Mon 18/04/2011 16:30

PLACE: Council Chamber

ABSTRACT

In this talk, Professor Lessig will review the evolution of access to scientific scholarship, and evaluate the success of this system of access against a background norm of universal access. While copyright battles involving artists has gotten most of the public's attention, the real battle should be over access to knowledge, not culture. That battle we are losing.