

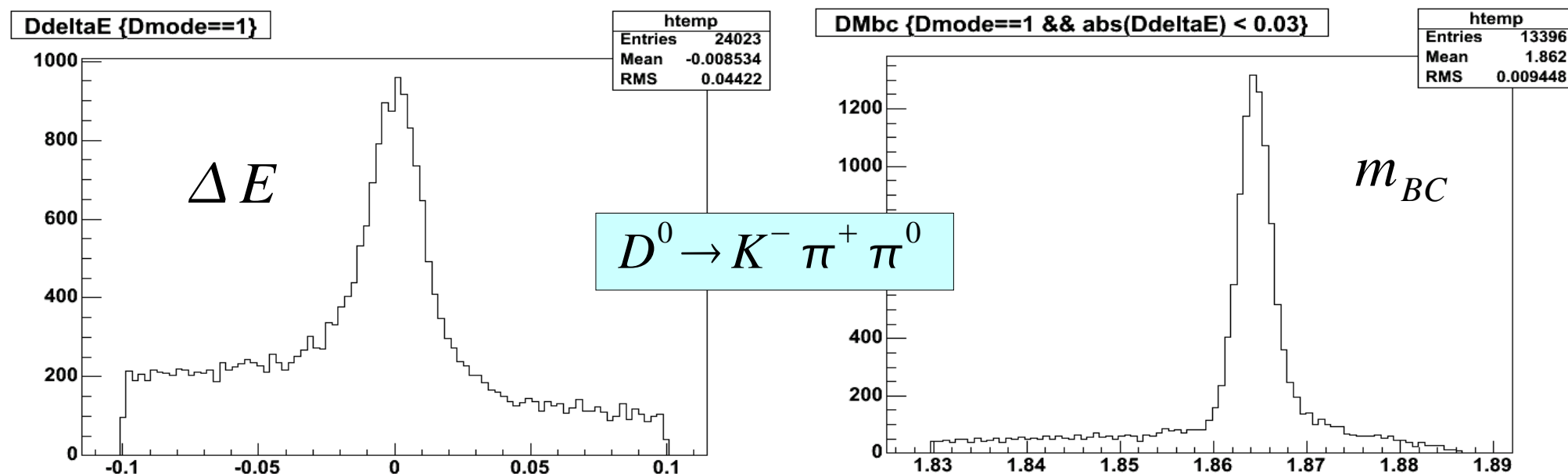
# Fitting with RooFit

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CLEO 101 Day 8  
June 16, 2006



# Why Do We Want to Fit?

- We can see from plots of  $\Delta E$  and  $m_{BC}$ , for example, that CLEO produces  $D^0$ 's, some of with decay to  $K^- \pi^+ \pi^0$ .
- But we also want to answer quantitative questions.
  - How many  $D^0$ 's were observed?
  - What is the width (“resolution”) of the  $\Delta E$  and  $m_{BC}$  peaks?



# Fitting Terminology

- Our experiment measures a number of “observables”  $x_i$  such as  $\Delta E$  and  $m_{BC}$ .
- We want to determine one or more “parameters”  $p_i$  from the data, such as the number of signal and background events, or the width of a peak.
- We describe the distribution of our observables by a “probability density function” (PDF) which is a function of both the observables and the parameters. We choose the PDF based on some guess about what function would match the data.

typically one observable in a fit (1-D fit)

  - The PDF is normalized over the observables:  $\int dx_1 \dots dx_n f(x_1 \dots x_n; p_1 \dots p_m) = 1$
  - $f(x, p) dx_1 \dots dx_n$  is the probability that for a given event, the observables will be in the range  $dx_1 \dots dx_n$ .
  - We vary the parameters to make the PDF match the actual distribution of the observables as well as possible. This is called “fitting.”

# Unbinned Maximum Likelihood Fits

- You're probably familiar with a least-squares fit:
  - Bin data into a histogram, minimize  $\chi^2 = \sum_i \frac{(y_i - y_{\text{expected}})^2}{\sigma_i^2}$
  - For a histogram,  $y_i = N_i$  and  $\sigma_i = \sqrt{N_i}$  (Poisson statistics in each bin)
- In RooFit, we'll use a fancier (and better) technique for fitting – an “unbinned maximum likelihood fit.”
  - Likelihood  $L(p_1, \dots, p_m) = \prod_{\text{events } i} f(x_{1,i}, \dots, x_{n,i}; p_1, \dots, p_m)$
  - Vary the parameters to maximize the likelihood. Equivalently, minimize 
$$-\log[L(p_1, \dots, p_m)] = - \sum_{\text{events } i} \log[f(x_{1,i}, \dots, x_{n,i}; p_1, \dots, p_m)]$$
  - A least-squares fit mimics a maximum-likelihood fit if the bins are narrow and all bins have many events.
  - A maximum-likelihood fit is better (especially for small datasets), but it takes longer.

# What is RooFit?

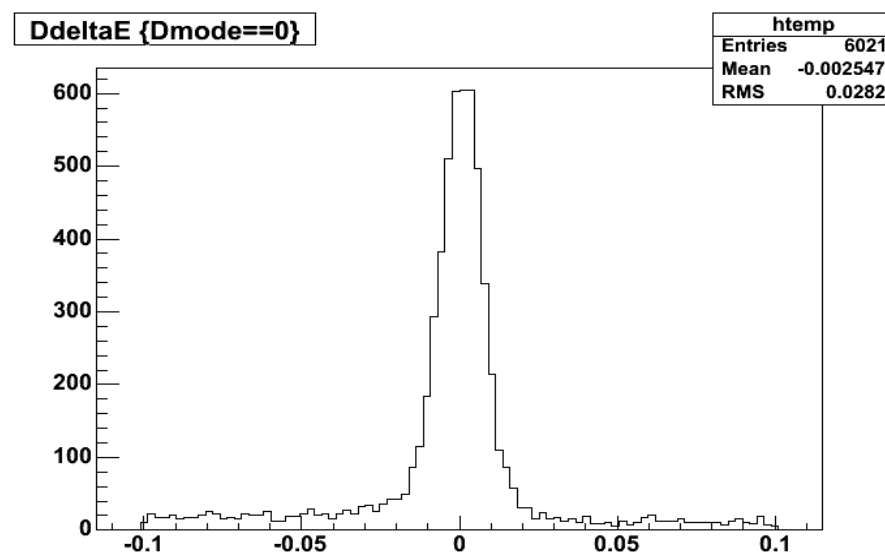
- ROOT is a collection of C++ classes.
  - ROOT can do fitting, but it isn't very convenient.
- RooFit provides more classes designed to make fitting easier.
  - We access RooFit through ROOT, and we can use any ROOT objects while using RooFit.
  - All RooFit class names begin with “Roo”.
  - RooFit handles many of the details for you, such as normalization.
- As of ROOT version 5, RooFit is included as part of ROOT. However, CLEO uses version 4, so we will have to load RooFit ourselves. (We will use version 1.92.)

# Steps to Do a Fit

- Load RooFit into ROOT.
- Load events into a `RooDataSet`.
- Make cuts.
- Define PDF(s).
- Do the fit.
- Make a plot.

# Ntuples Used in This Talk

- I'll be using ntuples created by RooFitExampleProc (available at [www.lepp.cornell.edu/~srs63/private/cleo101\\_2006\\_day08/src/RooFitExampleProc](http://www.lepp.cornell.edu/~srs63/private/cleo101_2006_day08/src/RooFitExampleProc))
  - This processor comes from `mkproc -dtag`, modified to create an ntuple with a few pieces of information for each DTag candidate.
- If you don't want to bother creating the ntuples yourself, you can get them at [www.lepp.cornell.edu/~srs63/private/cleo101\\_2006\\_day08/ntuple/](http://www.lepp.cornell.edu/~srs63/private/cleo101_2006_day08/ntuple/).
- In this talk, I'll show example code from fitting the  $\Delta E$  distribution with a linear background and a Gaussian signal peak.
- The code outputs info for DTags in the following decay modes:
  - 0  $D^0 \rightarrow K^- \pi^+$
  - 1  $D^0 \rightarrow K^- \pi^+ \pi^0$
  - 200  $D^+ \rightarrow K^- \pi^+ \pi^+$
  - 201  $D^+ \rightarrow K^- \pi^+ \pi^+ \pi^0$



# Loading RooFit Into ROOT

- Create a file called rootlogon.C in the directory from which you will run ROOT:

not necessary, and applies to ROOT generally

```
{  
gROOT->SetStyle("Plain"); // remove gray background from plots  
gSystem->Load("libMinuit.so") ;  
gSystem->Load("/path/to/this/file/libRooFitCore.so") ;  
gSystem->Load("/path/to/this/file/libRooFitModels.so") ;  
using namespace RooFit ;  
}
```

- In general, rootlogon.C is just a set of commands to be run every time ROOT starts.
- You can copy the file at [www.lepp.cornell.edu/~srs63/private/cleo101\\_2006\\_day08/fits/rootlogon.C](http://www.lepp.cornell.edu/~srs63/private/cleo101_2006_day08/fits/rootlogon.C)
- This file loads a copy of RooFit from  
/nfs/cor/user/srs63/RooFit/V01-09-02\_in\_20060224\_FULL\_2/  
This directory includes instructions on how to compile RooFit on you own, if you ever want to.
- You may get errors if you load RooFit in a different ROOT version.



# Getting a RooDataSet

- We need to create a RooDataSet object to hold the events we want to fit and plot.
- A RooDataSet can be created in two different ways – from a text file or from a ROOT tree. I'll cover the second way.

```
// Create variables to load from the ntuple.  
RooRealVar Dmode("Dmode", "decay mode of D candidate", -1, 1000);  
RooRealVar DdeltaE("DdeltaE", "delta E of D candidate", -0.1, 0.1, "GeV");  
RooArgSet ntupleVarSet(Dmode, DdeltaE);  
  
TFile* file1 = new TFile("data33.root");  
TTree* tree1 = file1->Get("RooFitExampleProc/nt1");  
RooDataSet dataSet("ntuple_of_D_candidates", "ntuple of D candidates", tree1,  
ntupleVarSet);  
  
TFile* file2 = new TFile("data31.root");  
TTree* tree2 = file2->Get("RooFitExampleProc/nt1");  
RooDataSet tempDataSet("temp", "temporary data set", tree2, ntupleVarSet);  
dataSet.append(tempDataSet);
```

name matches name in ROOT tree

only load events in this range

- See the file headers /GetRooDataSet.c on the Day 8 web page for a convenient function to create a RooDataSet from multiple files.
- Unfortunately, appending can be slow if the datasets are large.

# Making Cuts

- We can make cuts on our data:

```
TCut DmodeCut = "Dmode == 0"; // Only accept DTags in decay mode 0 (D0 -> K-pi+)
RooDataSet* ReducedDataSet = (RooDataSet*)dataSet.reduce(DmodeCut);
```

- In order to cut on a certain variable, it must be in the `RooDataSet`. That's why we loaded `Dmode` into the dataset, but not the other variables.

# Understanding RooRealVar

- All observables and parameters will be of type RooRealVar.
- Example: Variable constrained to be between -1 and 1:

```
RooRealVar myVar("myVar_name", "description of myVar", -1, 1, "units of myVar");
```

- “myVar\_name” is RooFit's internal identifier string for myVar.
  - The units argument is optional.
  - This form is typically used for RooRealVars that hold observables.
- Variable fixed to 0.5:

```
RooRealVar myFixedVar("myFixedVar_name", "description of myFixedVar", 0.5,  
                      "units of myVar");
```

- Variable floating between -1 and 1, with initial value 0.5:

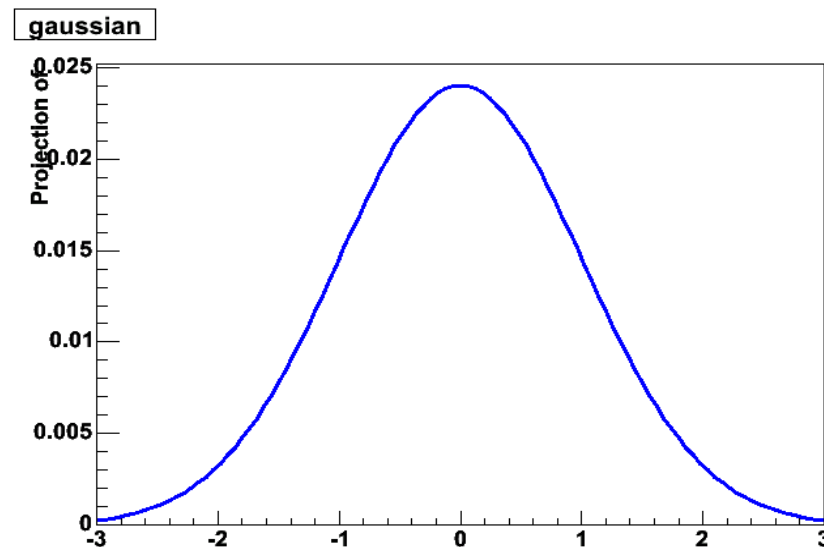
```
RooRealVar myFloatingVar("myFloatingVar_name", "description of myFloatingVar",  
                         0.5, -1, 1, "units of myVar");
```

- This form is typically used for fit parameters.

# Defining a PDF: RooGaussian

- We'll use a Gaussian for the signal peak:

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right\}$$



initial guess, lower bound, upper bound

```
// Define shape parameters
RooRealVar peak_gaussian_mean("peak_gaussian_mean", "mean of gaussian for signal
peak", 0, -0.1, 0.1, "GeV");
RooRealVar peak_gaussian_sigma("peak_gaussian_sigma", "width of gaussian for signal
peak", 0.01, 0.0, 0.05, "GeV");

// Define Gaussian PDF
RooGaussian peak_gaussian("peak_gaussian", "gaussian for signal peak", DdeltaE,
peak_gaussian_mean, peak_gaussian_sigma);

// Define yield parameter
RooRealVar peak_yield("peak_yield", "yield of signal peak", 1000, 0, 1000000);
```

# Defining a PDF: RooPolynomial

- We'll use a linear function for the background.
- To create a linear function, we use the more general PDF RooPolynomial. For instance, for a cubic polynomial:

```
// Define shape parameters
RooRealVar poly_c1("poly_c1", "coefficient of x^1 term", 0, -10, 10);
RooRealVar poly_c2("poly_c2", "coefficient of x^2 term", 0, -10, 10);
RooRealVar poly_c3("poly_c3", "coefficient of x^3 term", 0, -10, 10);

// Define cubic polynomial PDF
RooPolynomial poly("poly", "cubic polynomial", x, RooArgList(poly_c1, poly_c2,
poly_c3) );
```

$$f(x) = 1 + c_1 x + c_2 x^2 + c_3 x^3$$

- For fitting the background of  $\Delta E$ , a linear function:

```
// Define shape parameter
RooRealVar bkgd_poly_c1("bkgd_poly_c1", "slope of background", 0, -10, 10, "GeV^-1");

// Define linear PDF
RooPolynomial bkgd_poly("bkgd_poly", "linear function for background", DdeltaE,
RooArgList(bkgd_poly_c1));
```

$$f(x) = 1 + c_1 x$$

- Incidentally, here's a constant (flat) function:

```
RooPolynomial constant("constant", "flat function", x, RooArgList());
```

(no shape parameters)

$$f(x) = 1$$

# Creating the Total PDF

- Now, we need to add together our signal and background PDFs to create the total PDF that we'll fit to the  $\Delta E$  distribution:

```
// Signal peak
RooRealVar peak_gaussian_mean("peak_gaussian_mean", "mean of gaussian for signal
peak", 0, -0.1, 0.1, "GeV");
RooRealVar peak_gaussian_sigma("peak_gaussian_sigma", "width of gaussian for signal
peak", 0.01, 0.0, 0.05, "GeV");
RooGaussian peak_gaussian("peak_gaussian", "gaussian for signal peak", DdeltaE,
peak_gaussian_mean, peak_gaussian_sigma);
RooRealVar peak_yield("peak_yield", "yield signal peak", 1000, 0, 1000000);

// Background
RooRealVar bkgd_poly_c1("bkgd_poly_c1", "slope of background", 0, -10, 10, "GeV^-
1");
RooPolynomial bkgd_poly("bkgd_poly", "linear function for background", DdeltaE,
RooArgList(bkgd_poly_c1));
RooRealVar bkgd_yield("bkgd_yield", "yield of background", 100, 0, 1000000);

// Total PDF
RooArgList shapes;
RooArgList yields;
shapes.add(bkgd_poly);      yields.add(bkgd_yield);
shapes.add(peak_gaussian);  yields.add(peak_yield);
RooAddPdf totalPdf("totalPdf", "sum of signal and background PDF's", shapes,
yields);
```

A RooArgList is an ordered list of RooFit objects.

# Doing the Fit

- Now, to do the fit, we just use:

```
totalPdf.fitTo(*ReducedDataSet, Extended() );
```

- `Extended()` tells RooFit to do an “extended likelihood” fit.
  - Instead of fixing the normalization to the number of events in the histogram (which is the default), an extended likelihood fit includes the overall yield as a parameter.
  - We need this type of fit if we are fitting for the yields of every component.
  - The uncertainties in the yields reported by the fit will include the statistical ( $\sqrt{N}$ ) uncertainty.
  - If we weren't fitting for the yields, we wouldn't need this option.
- Other options are available to control and speed up the fit. They are listed in the RooFit user's guide on the RooFit web page, or at [http://sourceforge.net/project/shownotes.php?release\\_id=308954](http://sourceforge.net/project/shownotes.php?release_id=308954) (search for “fitTo”)

# More on Fitting

- RooFit uses MINUIT, a standard package, to do the fit.
- You will see MINUIT output on the screen. At the end, it should look like this:

```
FCN=-62473.3 FROM MINOS STATUS=SUCCESSFUL 301 CALLS 492 TOTAL
EDM=0.000104002 STRATEGY= 1 ERROR MATRIX ACCURATE
EXT PARAMETER PARABOLIC MINOS ERRORS
NO. NAME VALUE ERROR NEGATIVE POSITIVE
1 bkgd_poly_c1 -3.69964e+00 4.41224e-01 -4.37798e-01 4.44728e-01
2 bkgd_yield 1.51699e+03 4.46900e+01 -4.42032e+01 4.51886e+01
3 peak_gaussian_mean 4.38537e-04 1.15903e-04 -1.16119e-04 1.15696e-04
4 peak_gaussian_sigma 7.00617e-03 1.00148e-04 -1.00171e-04 1.00124e-04
5 peak_yield 4.50372e+03 7.05955e+01 -7.00657e+01 7.11417e+01
ERR DEF= 0.5
```

- If the fit is unsuccessful or if the error matrix is not accurate, you will have to tweak your fit functions and/or initial guesses for the parameters, and then redo the fit.
- If you include `Save( )` as an argument to `fitTo( )`, you will get a `RooFitResult` object containing more information, such as the covariance (aka error) matrix (which is sometimes very important!).



# Plotting the Result

- OK, we've done the fit, and now we're ready to look at the result!

```
// Create RooPlot object with DdeltaE on the axis.
RooPlot* DdeltaEFrame=DdeltaE.frame(Bins(50), Name("deltaE"), Title("delta E of D
candidates") );

// Plot histogram of DdeltaE.
ReducedDataSet->plotOn(DdeltaEFrame, MarkerSize(0.9) );

// Display fit parameters.
totalPdf.paramOn(DdeltaEFrame, Format("NELU", AutoPrecision(2)), Layout(0.1, 0.4,
0.9) );

// Plot just the background.
totalPdf.plotOn( DdeltaEFrame, Components(bkgd_poly) , LineColor(kGreen) );

// Plot total PDF.
totalPdf.plotOn(DdeltaEFrame,LineColor(kRed)); // plot fit pdf

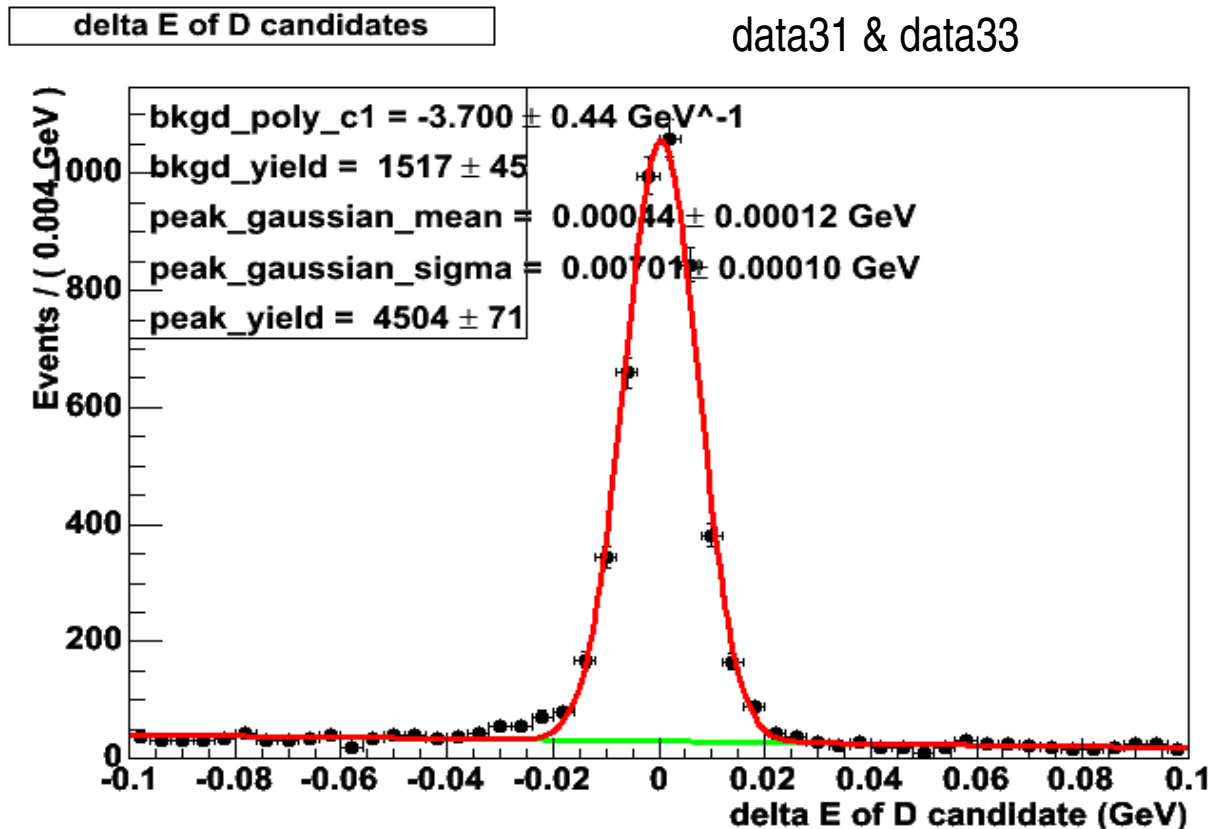
// The plot is not on the screen yet -- we have only created a RooPlot object.

// Put the plot on the screen.
TCanvas* DdeltaEcanvas = new TCanvas("DdeltaEcanvas", "Fit of delta E"); // make
new canvas
DdeltaEFrame->Draw(); // Put our plot on the canvas.
```

# A Look at the Result

- Here's what we see on the screen. The green line is the background, and the red line is the sum of the background and signal PDF's.
- Notice the peak and signal yields. The uncertainties are larger than  $\sqrt{N}$ .
- The fit looks good, except around -0.02. This excess is due to initial state radiation (when the initial state radiates a photon before forming  $c\bar{c}$  ).

$$D^0 \rightarrow K^- \pi^+ \text{ (mode 0)}$$

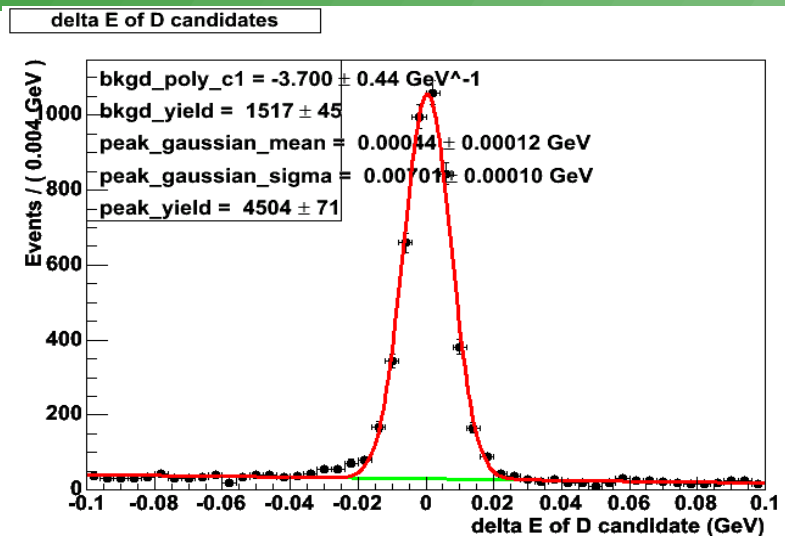


# Additional Topics

- OK, now we've seen the basics of how to do a fit with RooFit.
- Let's look at a few more things that will be useful:
  - More fitting functions
    - RooCBShape
    - RooArgusBG
    - RooGenericPdf
    - RooAddPdf (another form)
  - RooFormulaVar
  - Doing integrals

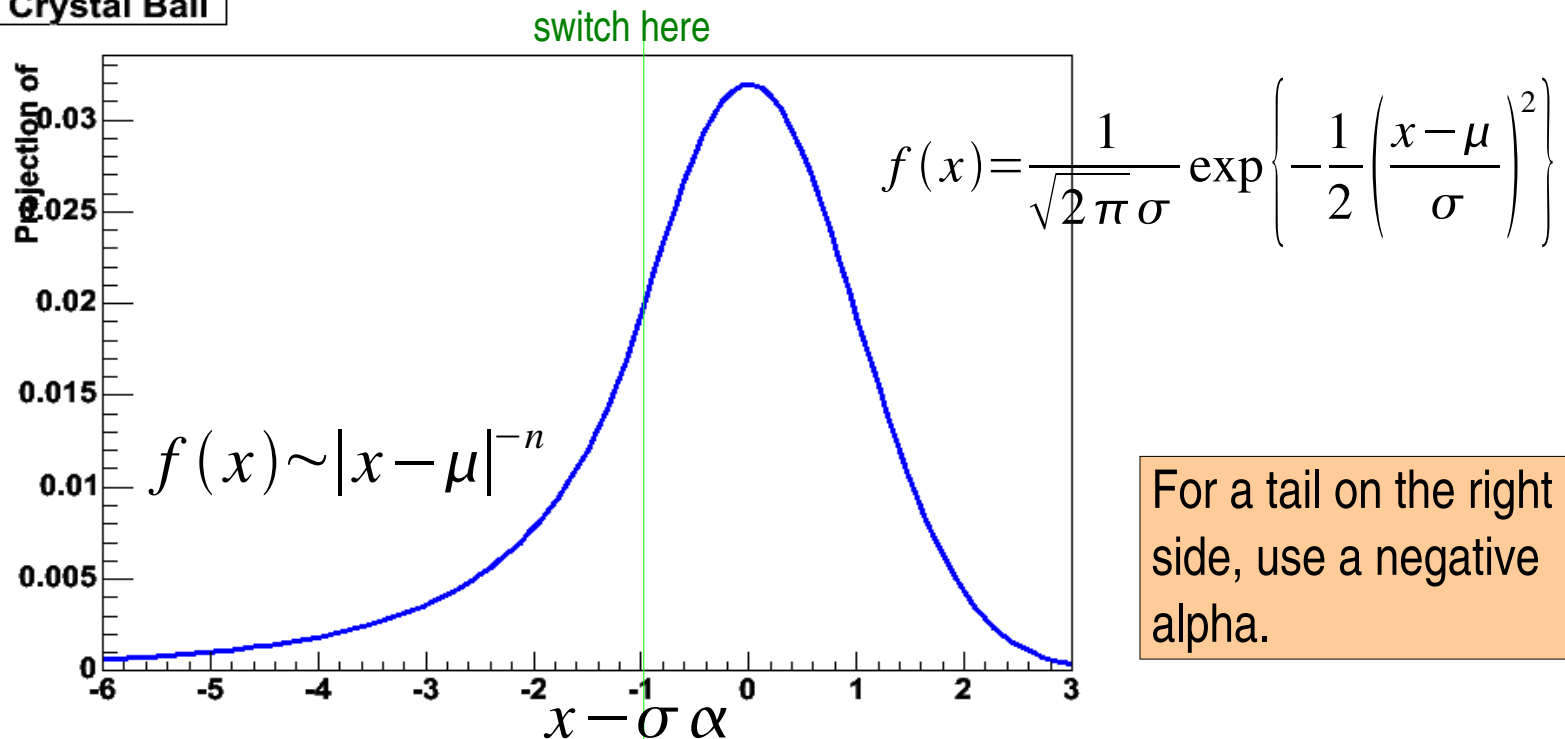
# Fitting Functions: RooCBShape

- What do we do when we have a peak that looks mostly like a Gaussian, but with a tail on one side?
- Use a “Crystal Ball” shape.
  - Gaussian with power-law tail.



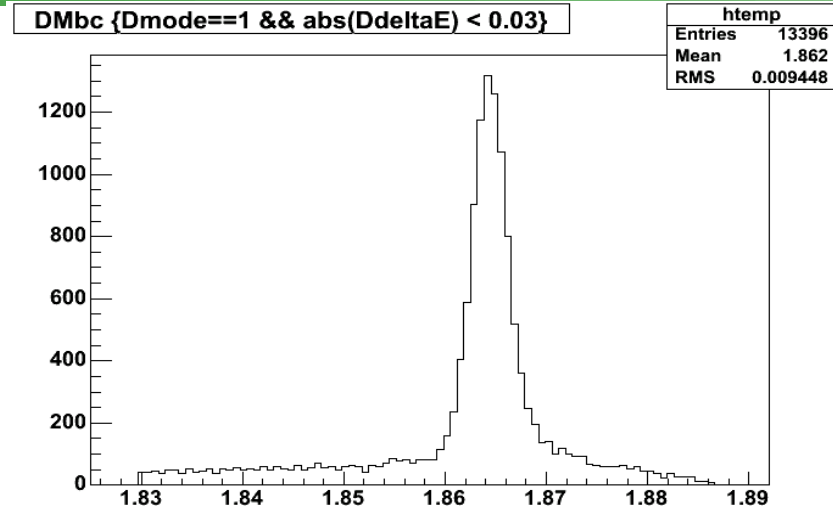
```
RooCBShape CBall("CBall", "Crystal Ball shape", x, mean, sigma, alpha, n);
```

Crystal Ball



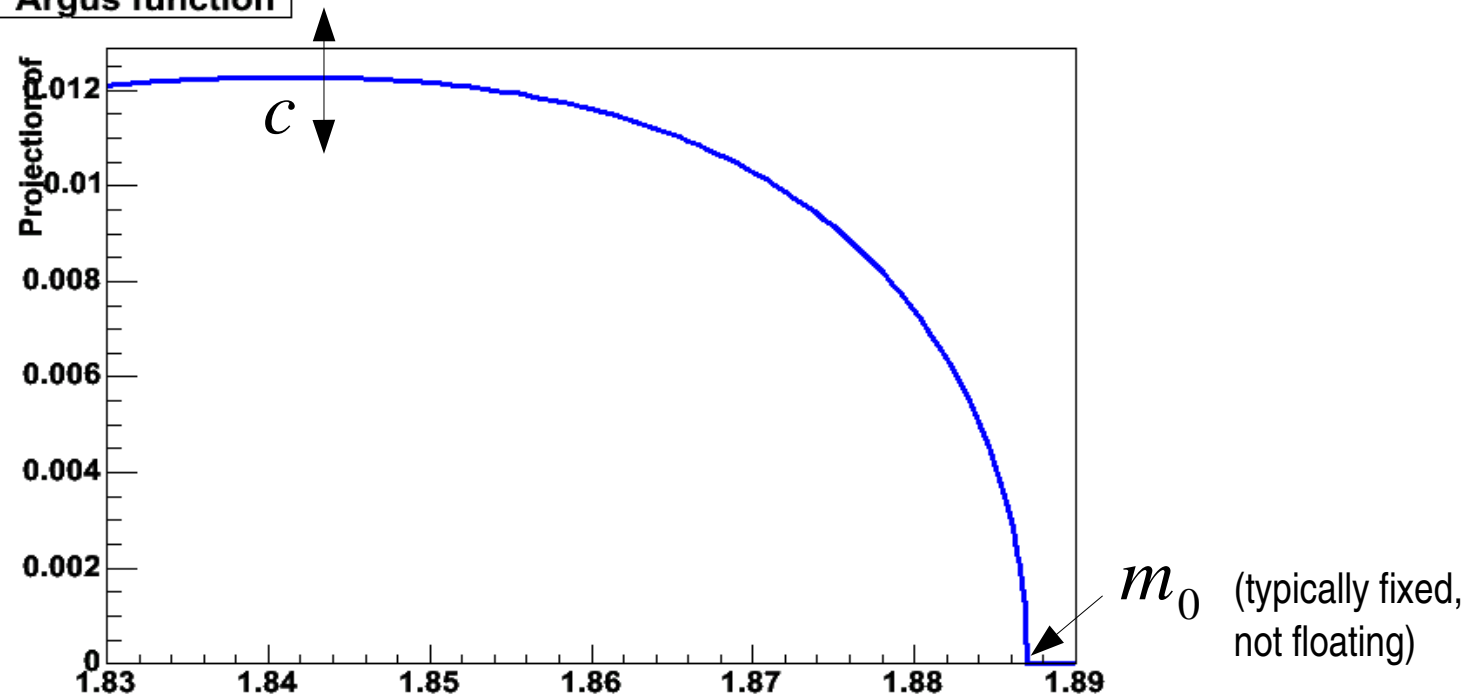
# Fitting Functions: RooArgusBG

- What function can we use for the combinatoric background in  $m_{BC}$ ?
- Use an “Argus” shape.
  - Cutoff ( $m_0$ ) at the beam energy.



```
RooArgusBG Argus("Argus", "Argus shape", x, m0, c);
```

Argus function



# Fitting Functions: RooGenericPdf

- If you want to use a function that RooFit doesn't provide, you can use a RooGenericPdf. For example:

```
RooRealVar cutOffVar("cutOff", "", 0.0182);  
RooGenericPdf nonNegLine("nonNegLine", "", "(xVar > cutOff)*(xVar - cutOff)",  
                          RooArgList(xVar, cutOffVar) );
```

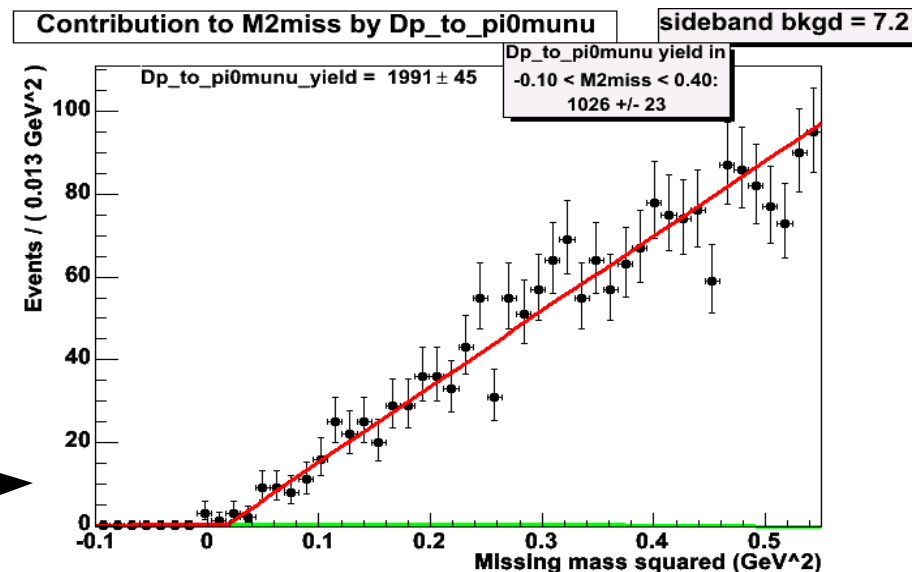
- Equivalently,

```
RooRealVar cutOffVar("cutOff", "", 0.0182);  
RooGenericPdf nonNegLine("nonNegLine", "", "(@0 > @1)*(@0 - @1)",  
                          RooArgList(xVar, cutOffVar) );
```

- @0 refers to the first element of the RooArgList, @1 refers to the second, @2 to the third, etc.

- Notice that RooFit handles the normalization.

- Here's what it looks like:



# RooAddPdf Explained More

- We already saw how to use `RooAddPdf` to get the sum of two PDF's. In fact, we can add any number of PDF's in this way:

```
RooAddPdf sumWithYields("sumWithYields", "", RooArgList(func1, func2, func3),  
                        RooArgList(yield1, yield2, yield3) );
```

- Here, `func[ 1-3 ]` are any three PDF's, and `yield[ 1-3 ]` are the number of events in each of them.
- Another way to use `RooAddPdf` is to specify a sum of  $n$  functions with  $n-1$  parameters for the fraction of the total found in each function:

```
RooAddPdf sumWithFrac("sumWithFrac", "", RooArgList(func1, func2, func3),  
                     RooArgList(frac1, frac2) );
```

- Here, `frac1` is the fraction of events in `sum2` that are found in `func1`, and `frac2` is the fraction in `func2`. There is no `frac3` since it's equal to  $1 - \text{frac1} - \text{frac2}$ .
- We can then specify a yield for `sumWithFrac`, just like any normal PDF.

# RooFormulaVar

- If you want to define one fit parameter in terms of other fit parameters, use a `RooFormulaVar`.
- For example,

```
RooRealVar var1("var1", "", 2, 1, 3);  
RooRealVar var2OverVar1("var2OverVar1", "", 2, 0, 999);  
RooFormulaVar var2("var2", "", "var2OverVar1*Var1", RooArgList(var2OverVar1, var1));
```

or "@0\*@1", like in `RooGenericPdf`

- `var2` can be used anywhere a `RooRealVar` can be used. But then the fit will use `var1` and `var2OverVar1` as the fit parameters.
- This can also be useful if you want to make two variables "float together." For instance, we could make `var2OverVar1` be constant.



# Two Gaussians Example

- For example, suppose we want to create a function which is the sum of two Gaussians with the same mean but different widths:

```
RooRealVar mean("mean", "", 0, -3, 3);
RooRealVar width1("width1", "", 2, 1, 3);
RooRealVar width2OverWidth1("width2OverWidth1", "", 2, 0, 999);
RooFormulaVar width2("width2", "", "@0*@1", RooArgList(width2OverWidth1, width1));
RooRealVar frac1("frac1", "fraction of events in gauss1", 0.5, 0, 1);

RooGaussian gauss1("gauss1", "first Gaussian", xVar, mean, width1);
RooGaussian gauss2("gauss2", "second Gaussian", xVar, mean, width2);
RooAddPdf twoGaussians("twoGaussians", "sum of two Gaussians",
                        RooArgList(gauss1, gauss2), RooArgList(frac1));
```

- If you wanted to, you could make the ratio of widths fixed by setting width2OverWidth1 to be constant instead of floating:

```
RooRealVar width2OverWidth1("width2OverWidth1", "", 2);
```

# Doing Integrals

- The fit gives us the yield of each component of the histogram, but what if we want to know the yield in a certain range of the histogram?
- We can find out the fraction of a PDF within a certain region with the following function, available at the Day 8 page at `headers/NormalizedIntegral.c`

```
double NormalizedIntegral(RooAbsPdf * function, RooRealVar& integrationVar,
                          double lowerLimit, double upperLimit)
{
    integrationVar.setRange("integralRange", lowerLimit, upperLimit) ;
    RooAbsReal* integral = (*function).createIntegral(integrationVar,
                                                       NormSet(integrationVar), Range("integralRange")) ;
    double normalizedIntegralValue = integral->getVal();

    printf("\nIntegrating %s from %f to %f\n", (*function).GetName(),
                                                lowerLimit, upperLimit);
    printf("Integral value: %f\n", normalizedIntegralValue);

    return normalizedIntegralValue;
}
```

# Advanced Topics

- Here are some advanced things you can do with RooFit that aren't covered in this talk:
  - Plot on a log scale. (See `fits/fitDeltaE.cc` on the Day 8 web page.)
  - Output `RooRealVars` to a text file, and load them from a text file.
  - Write your own fit function. (For instance, an error function – the integral of a Gaussian – called `RooErf`.)
  - Do two-dimensional fits.
  - Use “blind” parameters.
  - Load data from a text file. (In short, use `RooDataSet::read(fileName, variable)` where `fileName` is a file with one number per line, and `variable` is a `RooRealVar`.)

# Additional Resources

- RooFit web page
  - <http://roofit.sourceforge.net>
  - This page contains a user's manual and some (old) tutorial slides. Also, you can look up all the RooFit classes and functions.
- ROOT web page (since you're also using ROOT classes)
  - <http://root.cern.ch/>
- Some (maybe) useful utilities I've written in the headers area of the day 8 web page  
[www.lepp.cornell.edu/~srs63/private/cleo101\\_2006\\_day08/fits/headers/](http://www.lepp.cornell.edu/~srs63/private/cleo101_2006_day08/fits/headers/)
- Me, or other RooFit users

# Things to Try

- If you want to, run RooFitExampleProc over a dataset or two. It generates an ntuple with very basic information about DTags in 4 decay modes. If you prefer, you can use the ntuples on the day 8 web page (so you don't have to bother with processors or suesz at all!).
- Run the function in fitDeltaE.cc (available on the day 9 page). To run it:

```
.L fitDeltaE.cc  
fitDeltaE(0) // for D0->Kpi (1 for Kpipi0, 200 for D+ -> Kpipi, 201 for Kpipipi0)
```

- Examine the code in fitDeltaE.cc to see what it does. Uncomment some of the lines I've commented out, and observe the results.
- Modify fitDeltaE.cc to use a Crystal Ball instead of a Gaussian for the signal peak. (This will help with the tail on the left side of the peak.)
- Try to fit the Mbc distribution with an Argus background shape and a peak of some sort (Gaussian, Crystal Ball, Gaussian + Crystal Ball). Much of the code can be copied from fitDeltaE.cc – just switch deltaE to Mbc and change the fit functions. I've written a function in fitMbc.cc to do this, so look at that if you get stuck. However, you should try to write it yourself first. (You may want to look at a plot of Mbc first before you try to fit it.)

# Everything Begins with “Roo”!

