



Introduction to ROOT: final part

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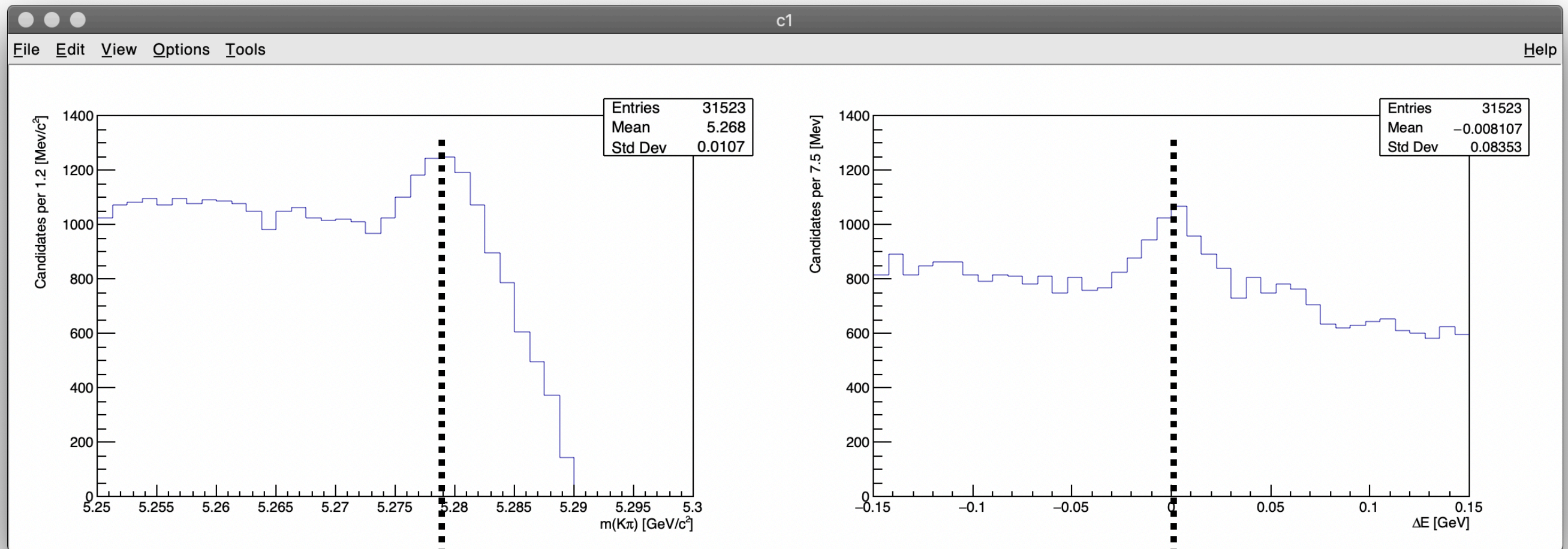
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Previous lesson

- Accessing the data from a `TTree` in a ROOT file
- Inspect the data looking at distributions, make a selection, in macros and live (also in 2 dimensions)
- Making a graph to display data pairs.
- Manipulating histograms (use of `Sum2w()`, and treatment of bin-content errors).

The peak

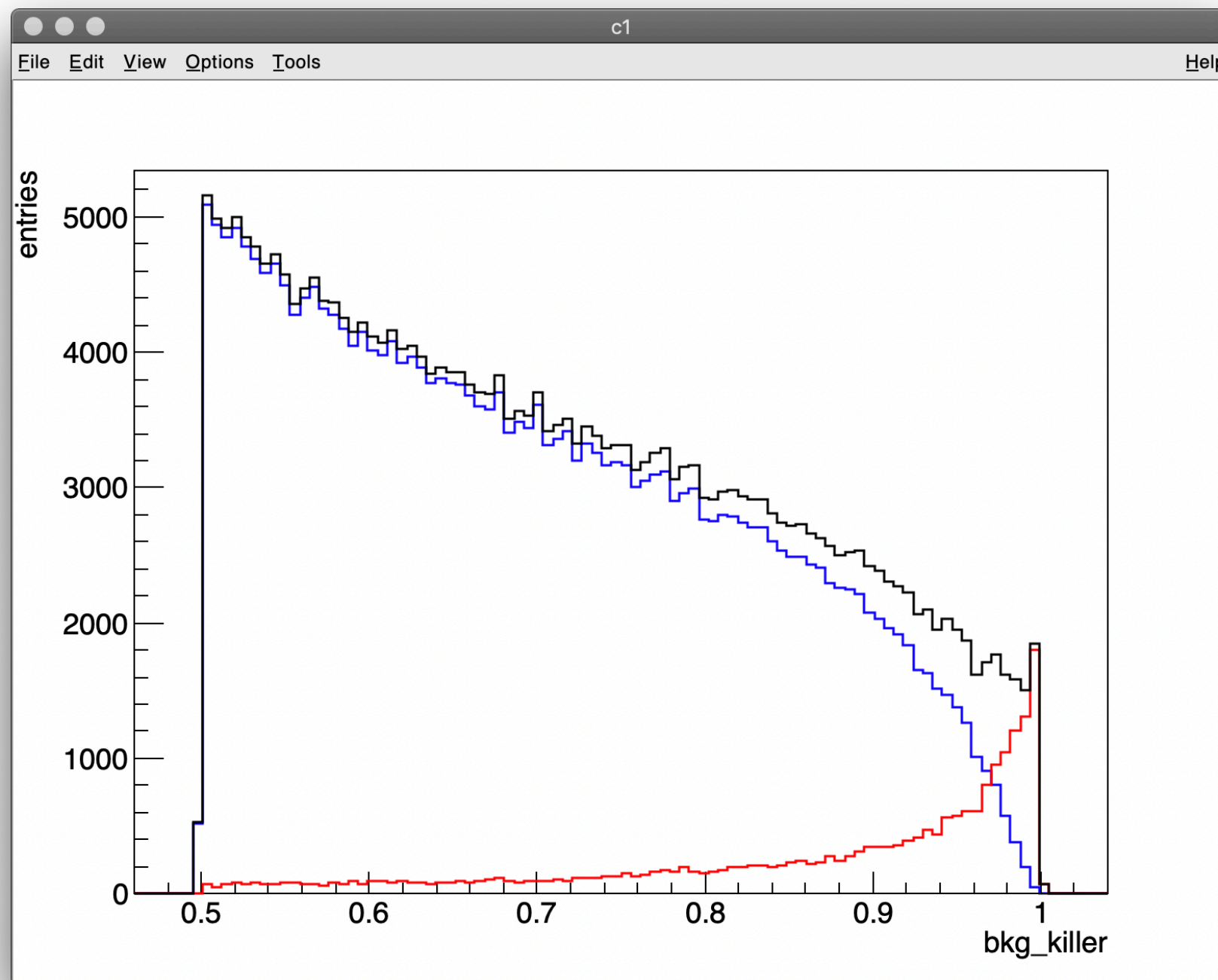


$m(B^0) \sim 5.280 \text{ GeV}/c^2$

Expect ~ 0 for a B^0

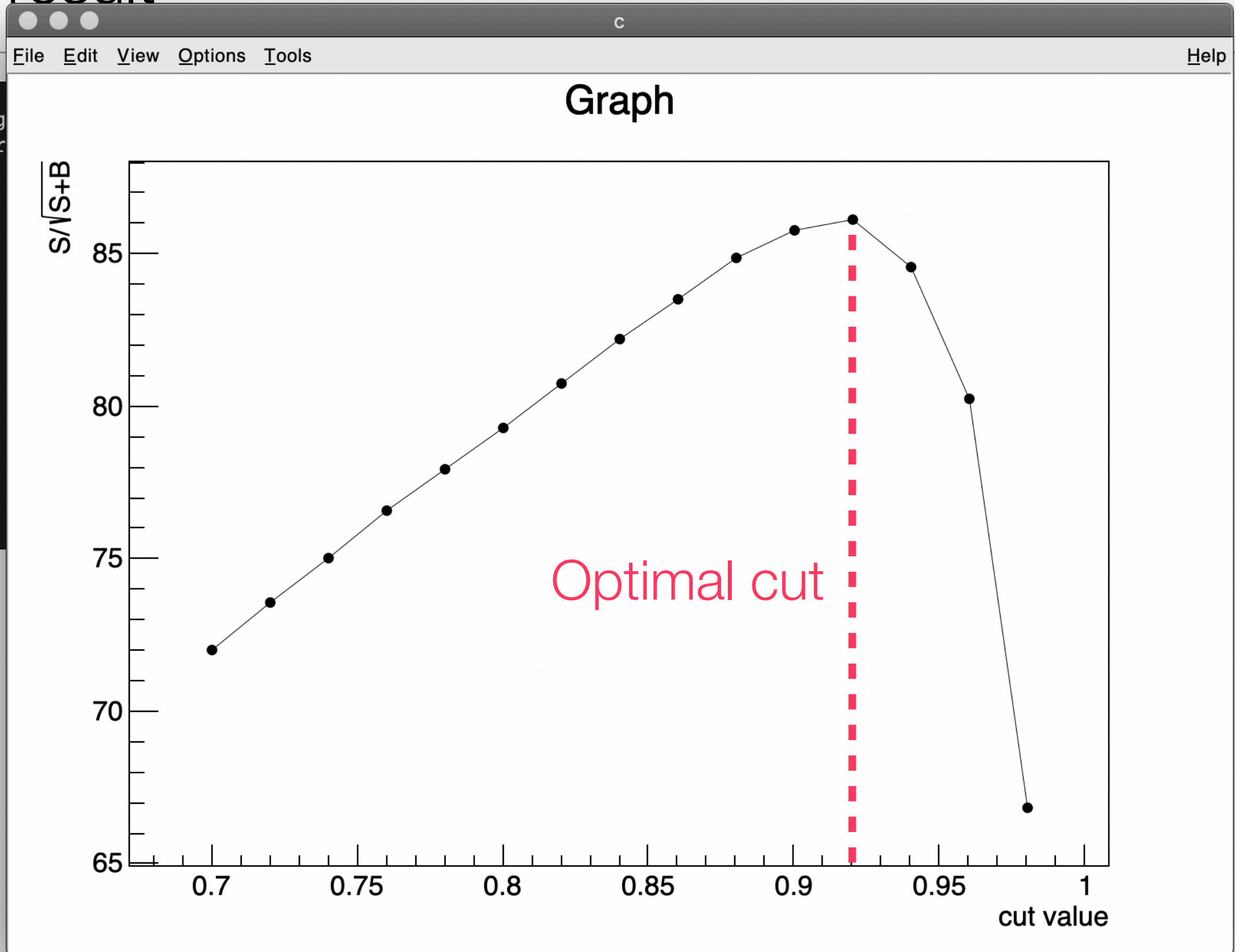
The background killer

- This is the output of the classifier in our **simulation**, separated for **signal**, **background**, and their sum.



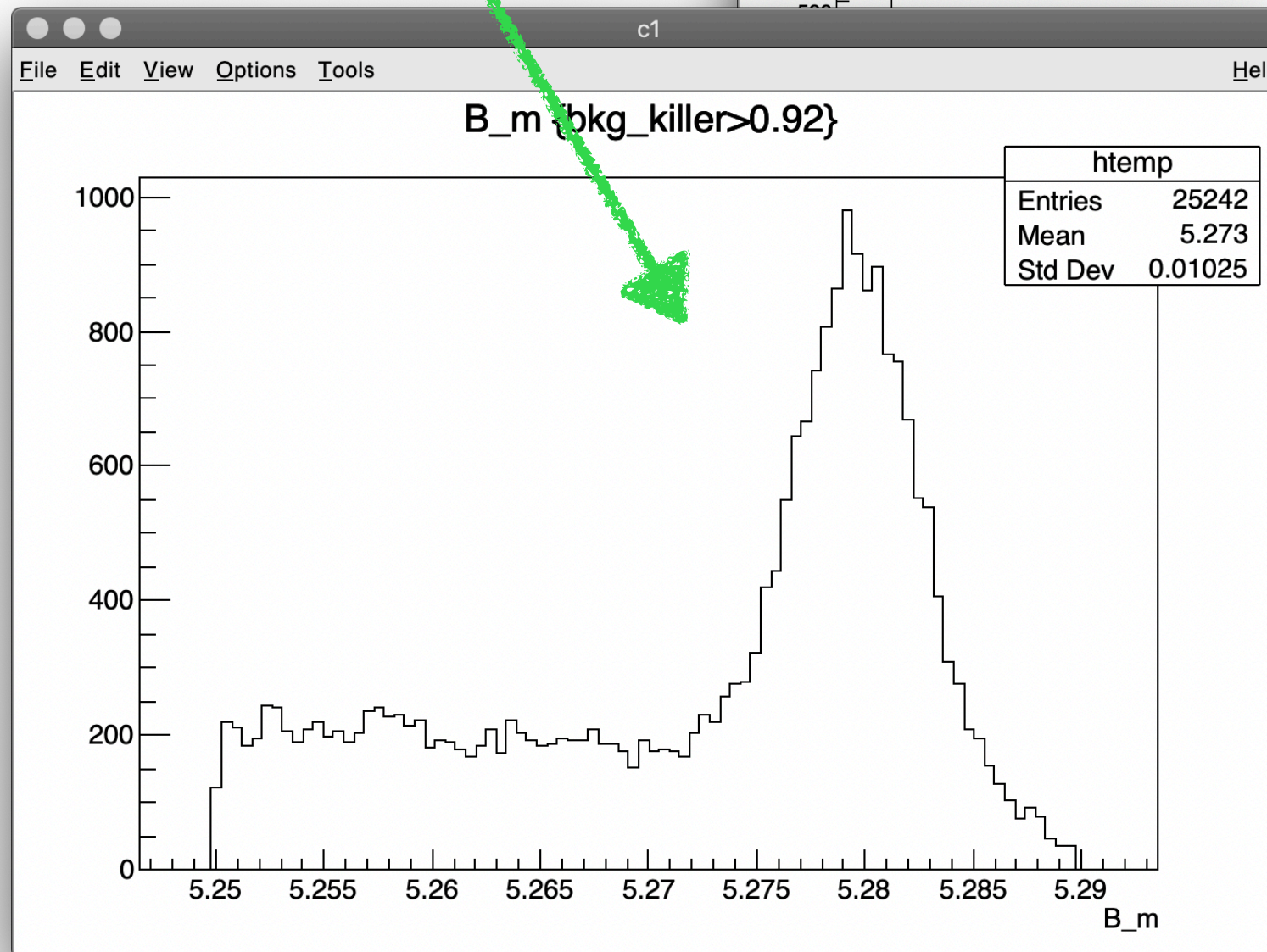
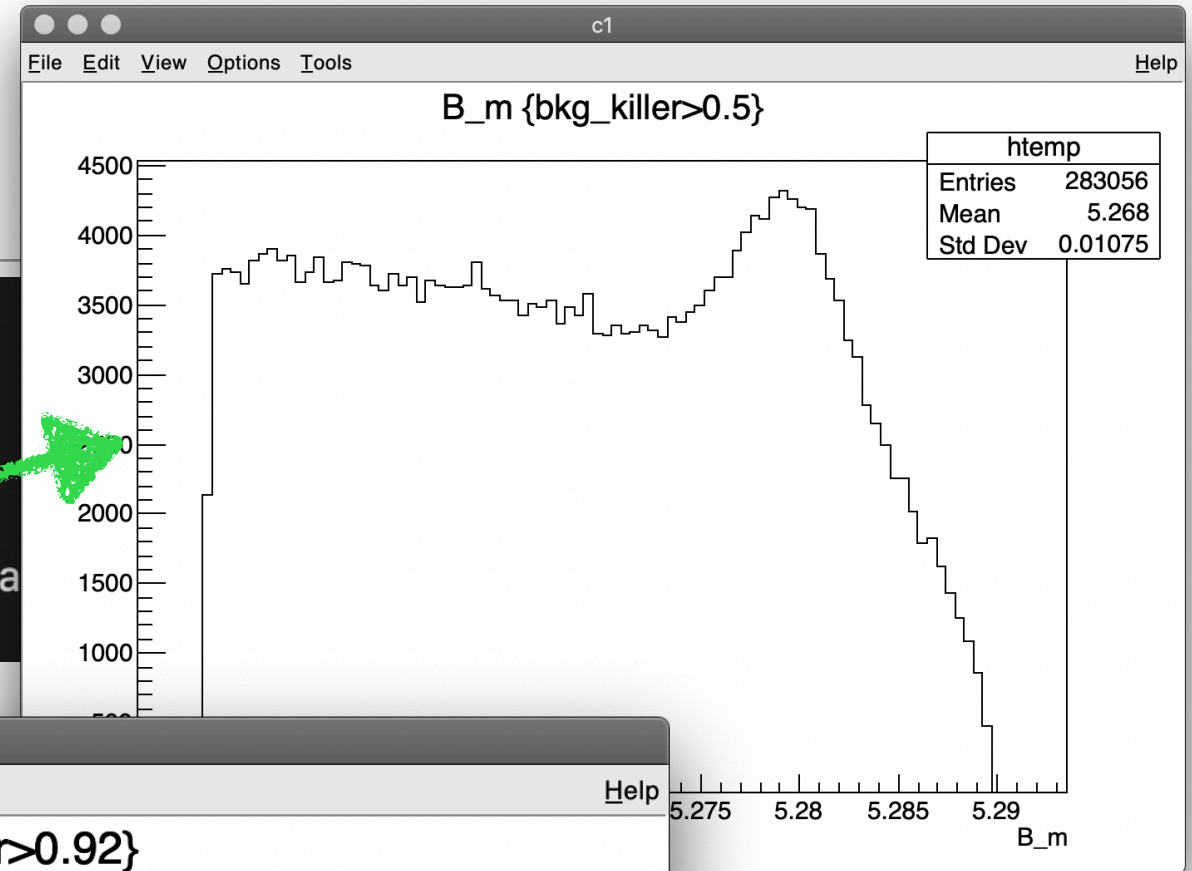
The result

```
root [0]  
Processing  
Total entr  
cut value  
cut value  
cut value  
cut value  
cut value  
cut value  
cut value  
cut value  
cut value  
cut value  
cut value  
cut value  
cut value  
cut value  
cut value  
cut value
```



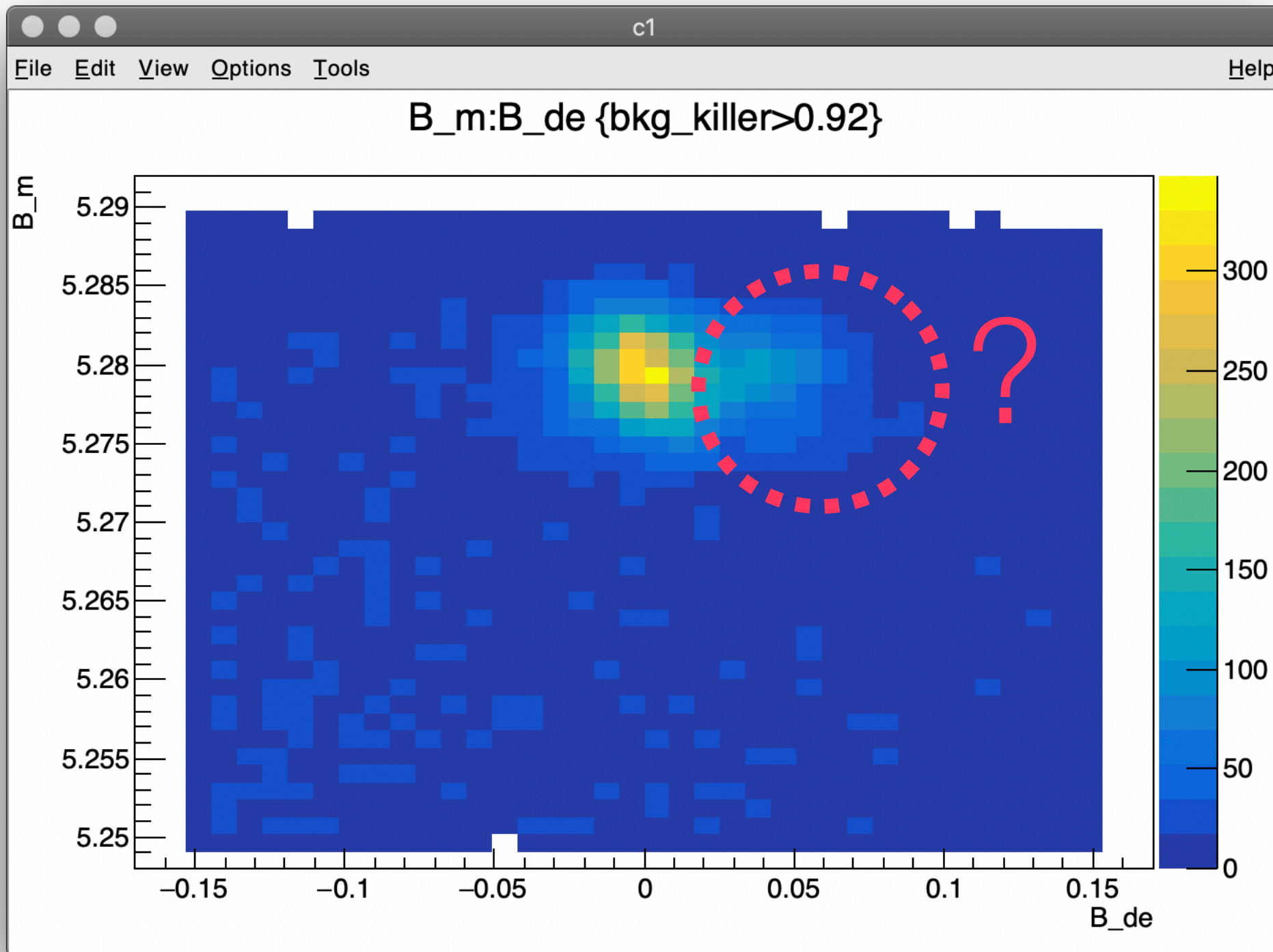
Let's see on simulated data

```
mb-md-01:thirdLesson dorigo$ root simulation.root
root [0]
Attaching file simulation.root as _file0...
(TFile *) 0x7f981b8de6f0
root [1] simTree->Draw("B_m","bkg_killer>0.5");
Info in <TCanvas::MakeDefCanvas>: created default TCa
root [2] simTree->Draw("B_m","bkg_killer>0.92");
```



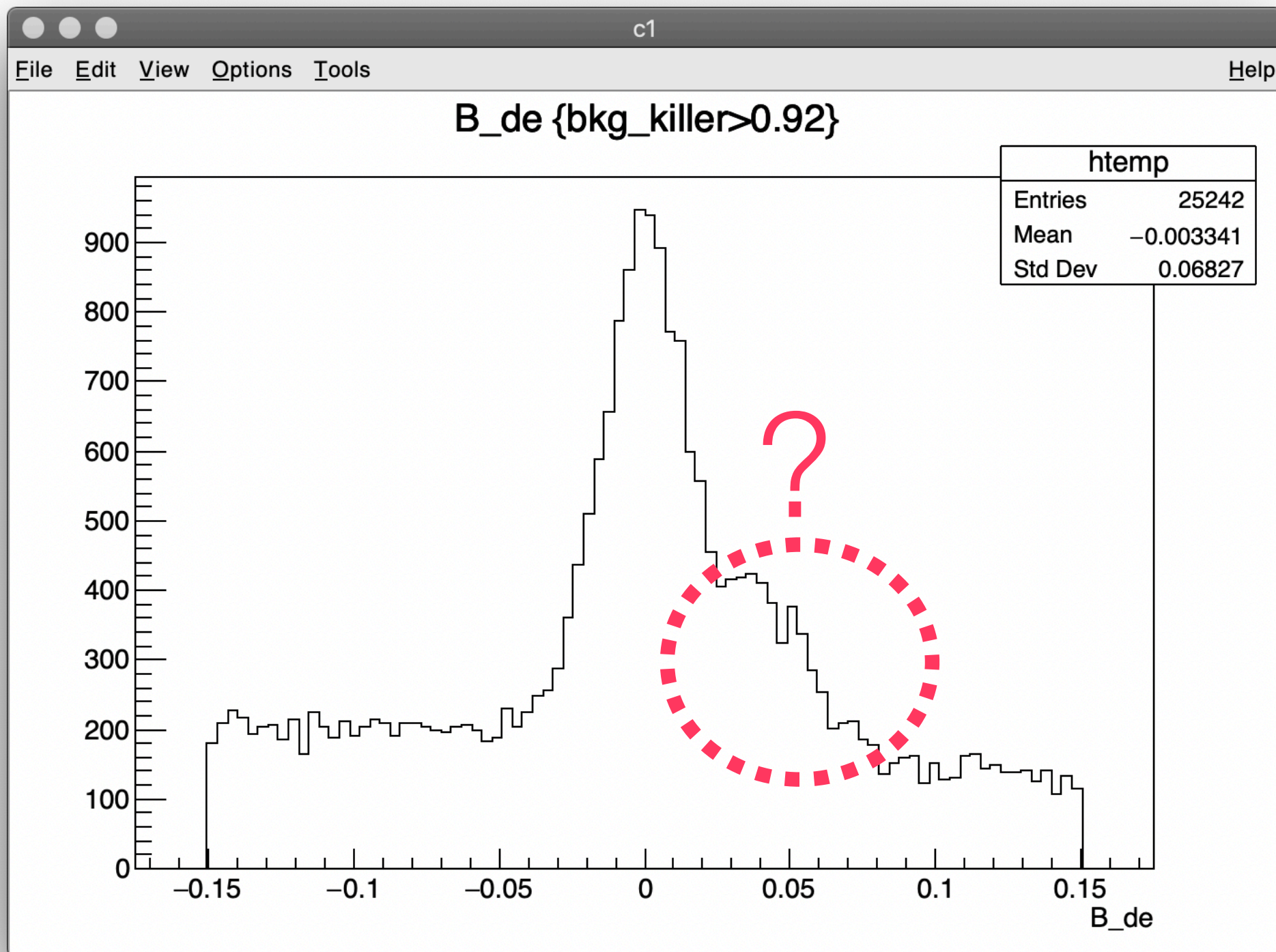
Let's see on simulated data

```
[root [3] simTree->Draw("B_m:B_de", "bkg_killer>0.92", "colz");
```



What's this shoulder?

```
root [7] simTree->Draw("B_de", "bkg_killer>0.92");
```



Background from other B decays

- `bkg_killer` is built to suppress events that are *not* $\Upsilon(4S) \rightarrow B\bar{B}$.
- Among $\Upsilon(4S) \rightarrow B\bar{B}$ events, there are B decays that are not signal, but that can be mis-reconstructed as our signal.
- For instance a pion in $B^0 \rightarrow \pi^+\pi^-$ decays can be mis-identified as kaon and be reconstructed as $B^0 \rightarrow K^+\pi^-$
- Let's check in simulation. We have a variable that flag real $B^0 \rightarrow K^+\pi^-$ signal candidates only.

Inspect B decays (inspectB.C)

```
1 #include "Riostream.h"
2 #include "TFile.h"
3 #include "TTree.h"
4 #include "TCanvas.h"
5 #include "TH1D.h"
6 #include "TLegend.h"
7
8 using namespace std;
9
10 void inspectB(){
11
12     //open file and take the tree
13     TFile* file = TFile::Open("simulation.root");
14     TTree* tree = (TTree*) file->Get("simTree");
15
16     int tot_entries = tree->GetEntries();
17     cout << "Total entries in the tree: " << tot_entries << endl;
18
19     //link the variables with tree banches
20     double B_de, bkg_killer;
21     int isBkg, isSig;
22     tree->SetBranchAddress("B_de",&B_de);
23     tree->SetBranchAddress("isBkg",&isBkg);
24     tree->SetBranchAddress("isSig",&isSig);
25     tree->SetBranchAddress("bkg_killer",&bkg_killer);
```

A class to add legends in plot
(search the reference class)

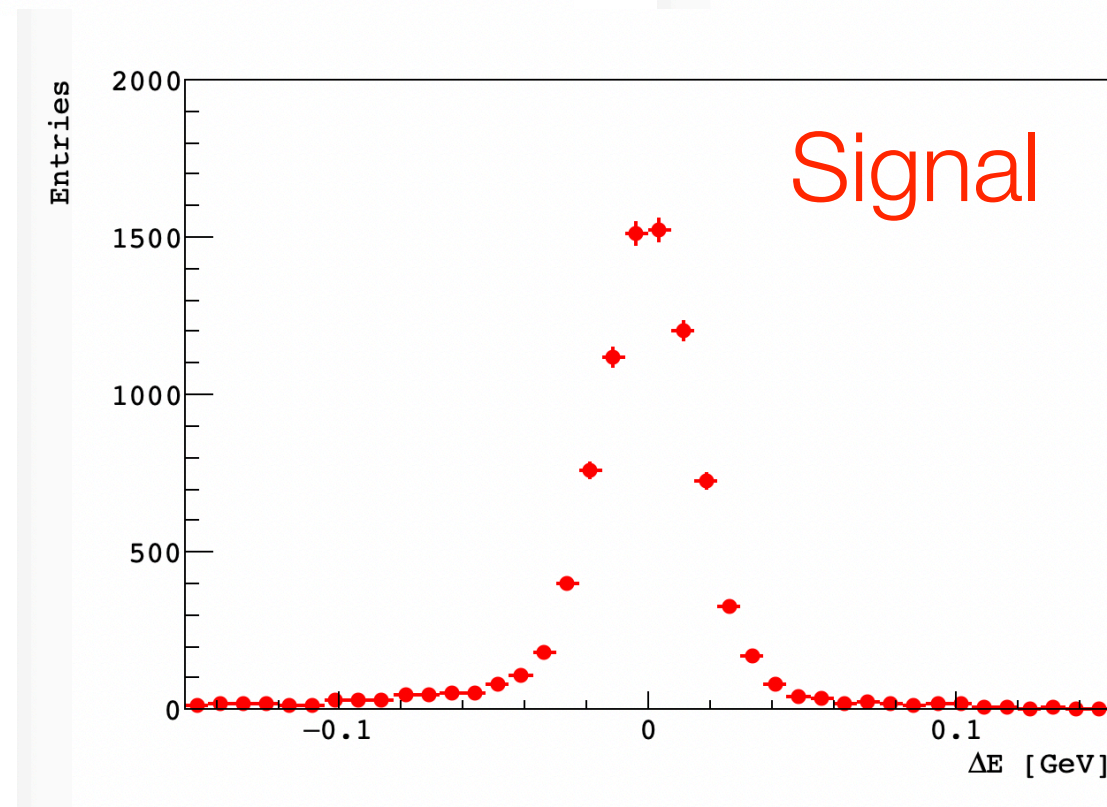
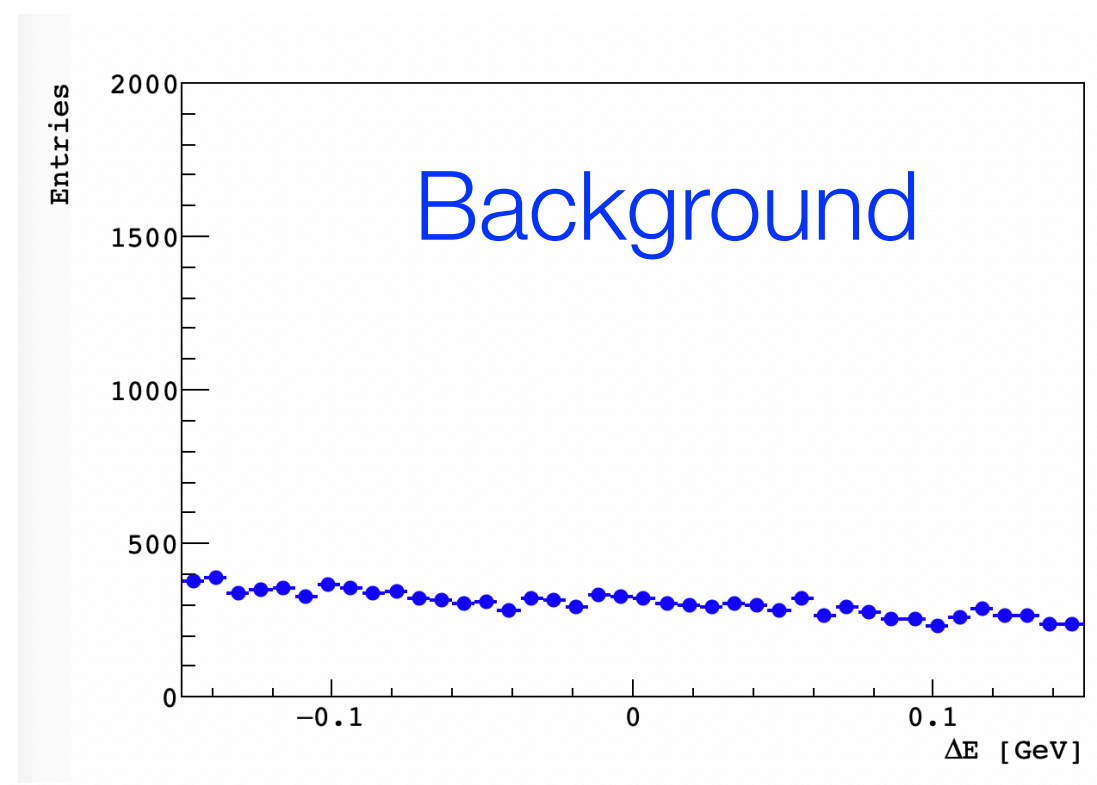
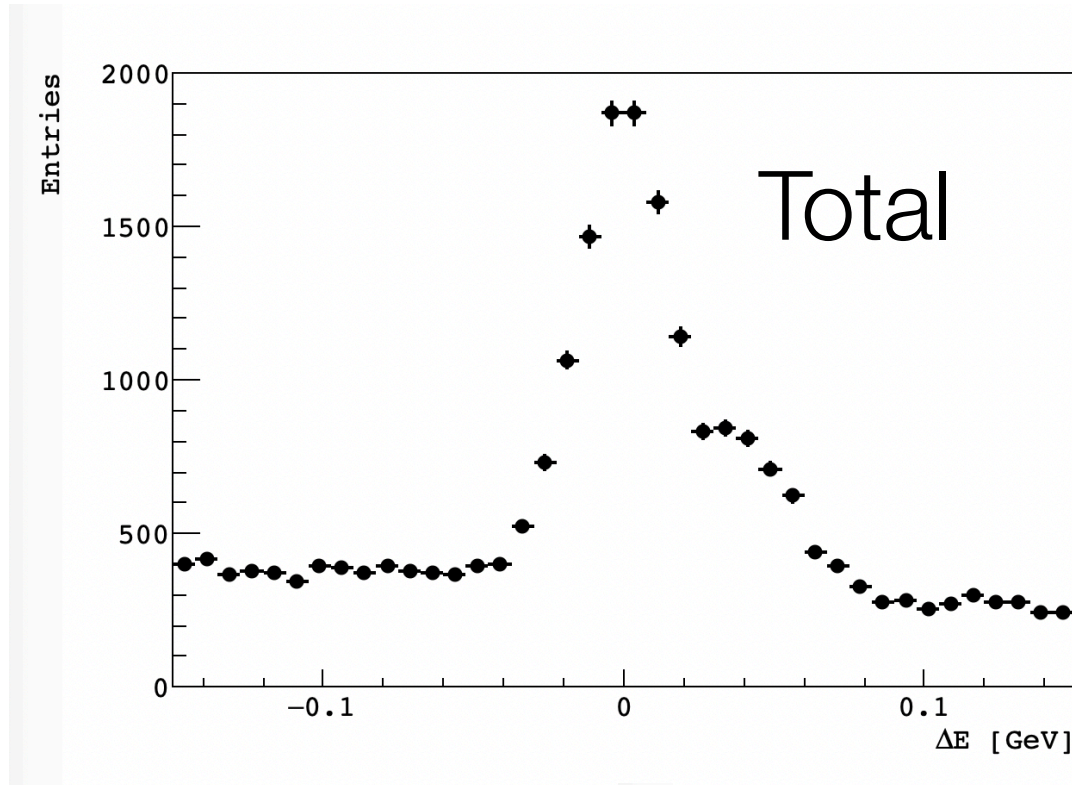
All quite standard now

To select only signal

Inspect B decays (inspectB.C)

```
27 //define an histogram to look at deltaE distribution
28 TH1D* h_de_tot = new TH1D("h_de_tot", ";m(B) [GeV]; Entries", 40, -0.15, 0.15);
29
30 //very very important to rember when manipulating histograms!!! IMPORTANT!!!
31 h_de_tot->Sumw2();
32
33 //clone the same histogram structure for signal, bkg, and unknown bkg
34 TH1D* h_de_sig = (TH1D*) h_de_tot->Clone("h_de_sig");
35 TH1D* h_de_bkg = (TH1D*) h_de_tot->Clone("h_de_bkg");
36 TH1D* h_de_unknown = (TH1D*) h_de_tot->Clone("h_de_unknown");
37
38 //loop over the entries
39 for(int iEntry; iEntry<tot_entries; ++iEntry){
40
41     tree->GetEntry(iEntry);
42
43     //skip all candidates below the optimal cut point
44     if(bkg_killer<0.92) continue;
45
46     //fill the histograms
47     h_de_tot->Fill(B_de);
48     if(isBkg) h_de_bkg->Fill(B_de);
49     else if(isSig) h_de_sig->Fill(B_de);
50
51 }
```

Inspect B decays (`inspectB.C`)



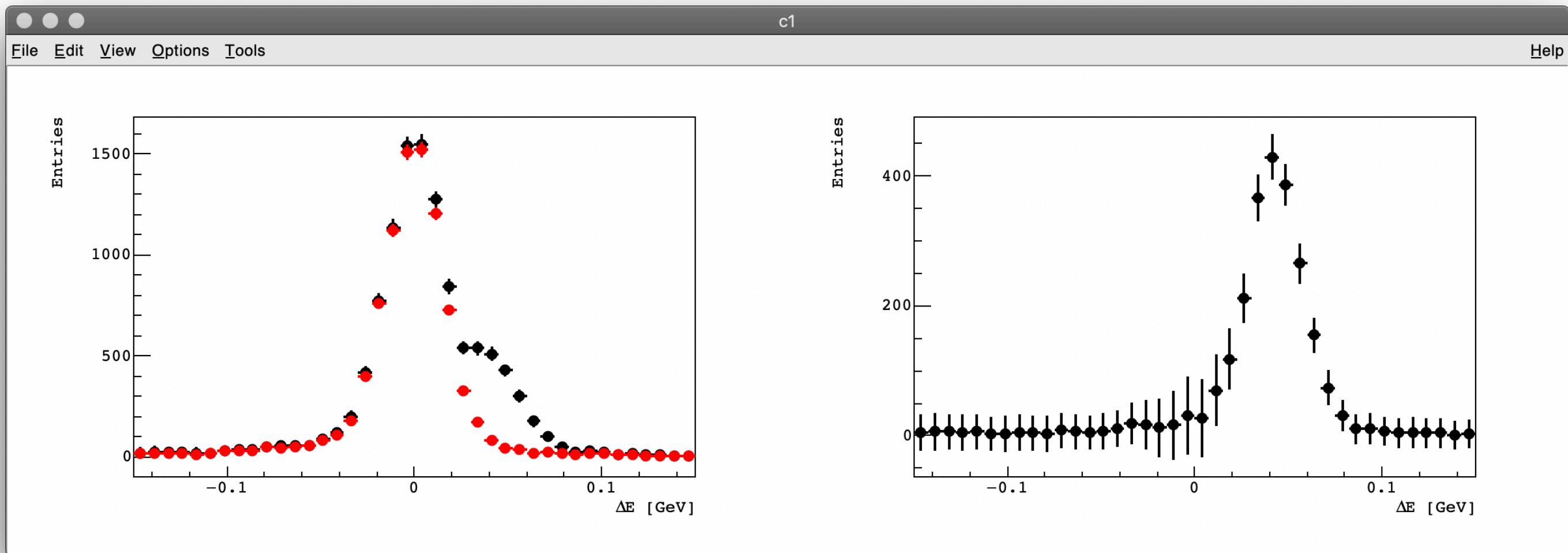
Inspect B decays (inspectB.C)

```
53 //subtract the background from the total
54 h_de_tot->Add(h_de_bkg,-1);
55
56 //subtract the signal
57 h_de_unknown->Add(h_de_tot, h_de_sig, 1, -1);
58
59
60 //draw the histograms
61 TCanvas* c1 = new TCanvas("c1","c1",1200,400);
62 c1->Divide(2,1);
63 c1->cd(1);
64 h_de_tot->Draw();
65 h_de_sig->SetLineColor(kRed);
66 h_de_sig->SetMarkerColor(kRed);
67 h_de_sig->Draw("same");
68 c1->cd(2);
69 h_de_unknown->Draw();
70
71 //compare signal and unknwn background shapes
72 TCanvas* c2 = new TCanvas("c2","c2",600,400);
73 h_de_unknown->DrawNormalized("histo");
74 h_de_sig->DrawNormalized("histo same");
75
76 //put a legend
77 TLegend* leg = new TLegend(0.2,0.65,0.5,0.8);
78 leg->AddEntry(h_de_sig,"Signal","L");
79 leg->AddEntry(h_de_unknown,"Unknown backgr.,""L");
80 leg->Draw();
81
82 cout << "Integral from signal: " << h_de_sig->Integral() << endl;
83 cout << "Integral from unkn. back.: " << h_de_unknown->Integral() << endl;
```

We are manipulating the bin contents of the histograms here.

Only with `Sumw2()` the uncertainty on the bin content is properly calculated

The output

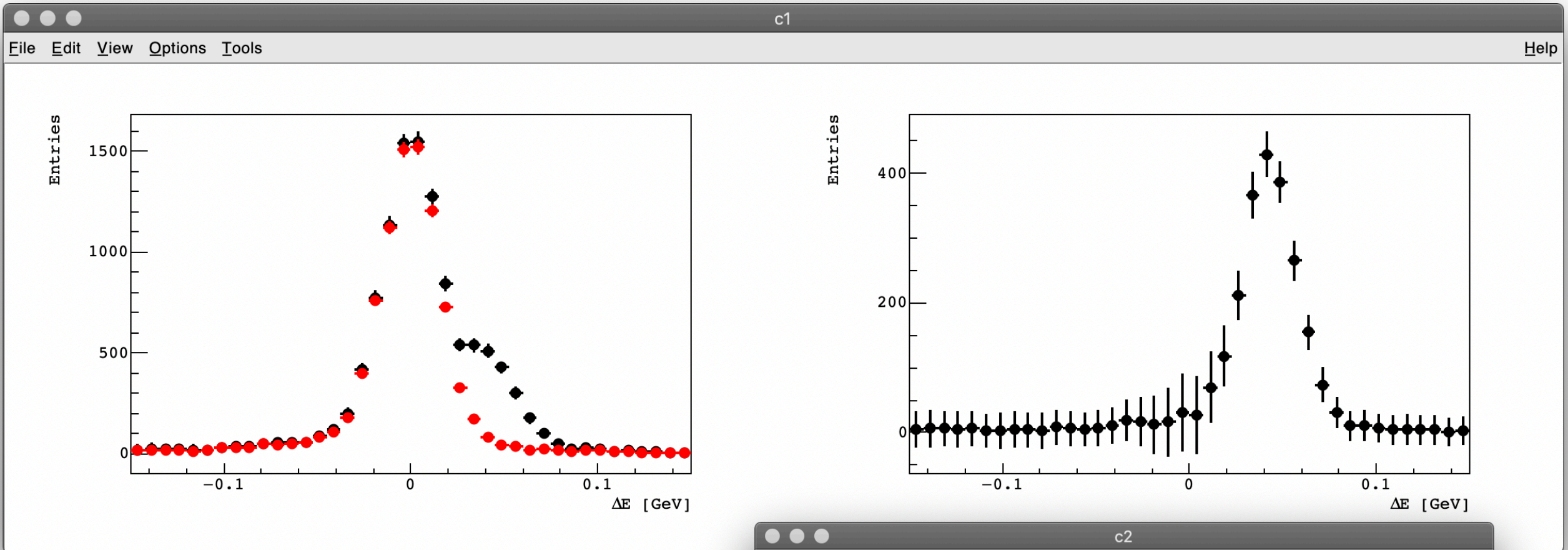


Inspect B decays (inspectB.C)

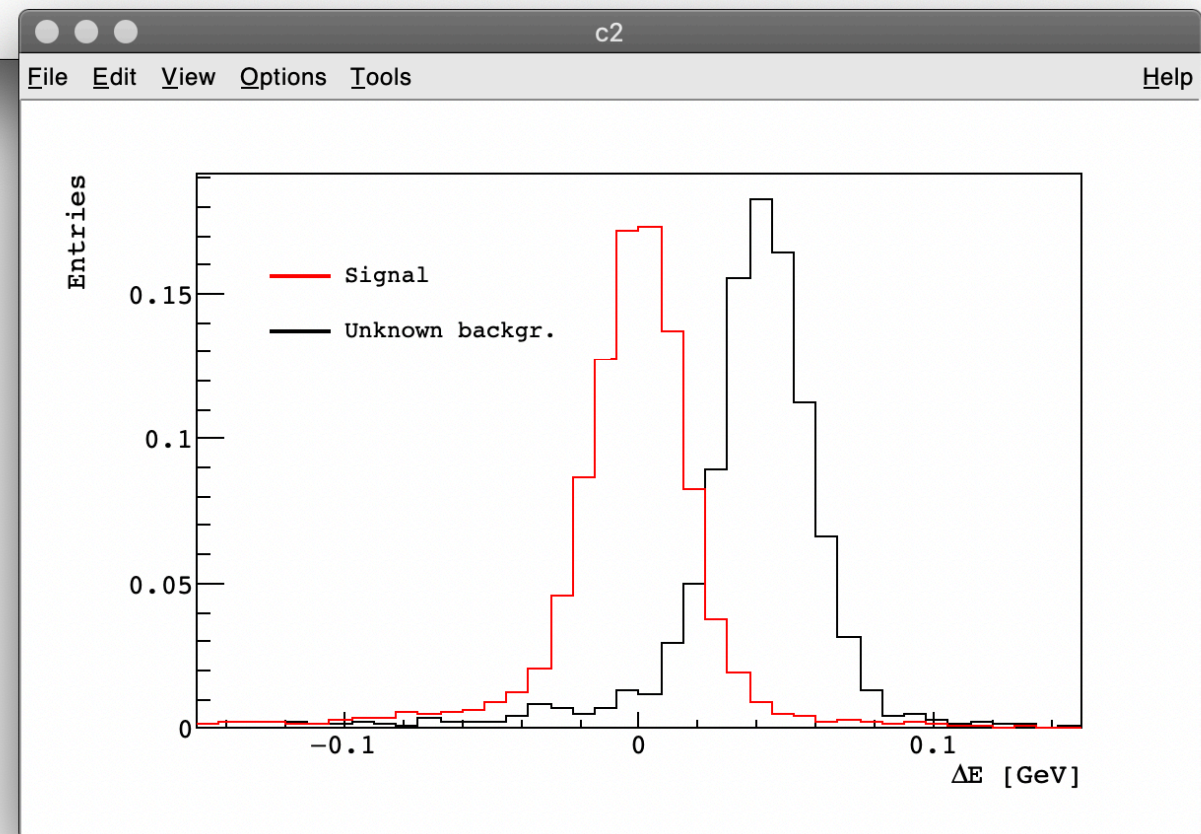
```
53 //subtract the background from the total
54 h_de_tot->Add(h_de_bkg,-1);
55
56 //subtract the signal
57 h_de_unknown->Add(h_de_tot, h_de_sig, 1, -1);
58
59
60 //draw the histograms
61 TCanvas* c1 = new TCanvas("c1","c1",1200,400);
62 c1->Divide(2,1);
63 c1->cd(1);
64 h_de_tot->Draw();
65 h_de_sig->SetLineColor(kRed);
66 h_de_sig->SetMarkerColor(kRed);
67 h_de_sig->Draw("same");
68 c1->cd(2);
69 h_de_unknown->Draw();
70
71 //compare signal and unknown background shapes
72 TCanvas* c2 = new TCanvas("c2","c2",600,400);
73 h_de_unknown->DrawNormalized("histo");
74 h_de_sig->DrawNormalized("histo same");
75
76 //put a legend
77 TLegend* leg = new TLegend(0.2,0.65,0.5,0.8);
78 leg->AddEntry(h_de_sig,"Signal","L");
79 leg->AddEntry(h_de_unknown,"Unknown backgr.,""L");
80 leg->Draw();
81
82 cout << "Integral from signal: " << h_de_sig->Integral() << endl;
83 cout << "Integral from unkn. back.: " << h_de_unknown->Integral() << endl;
```

To compare shape of distributions,
draw them normalised to the same
(unit) area in the same canvas
(for proper uncertainties
also this requires Sumw2())

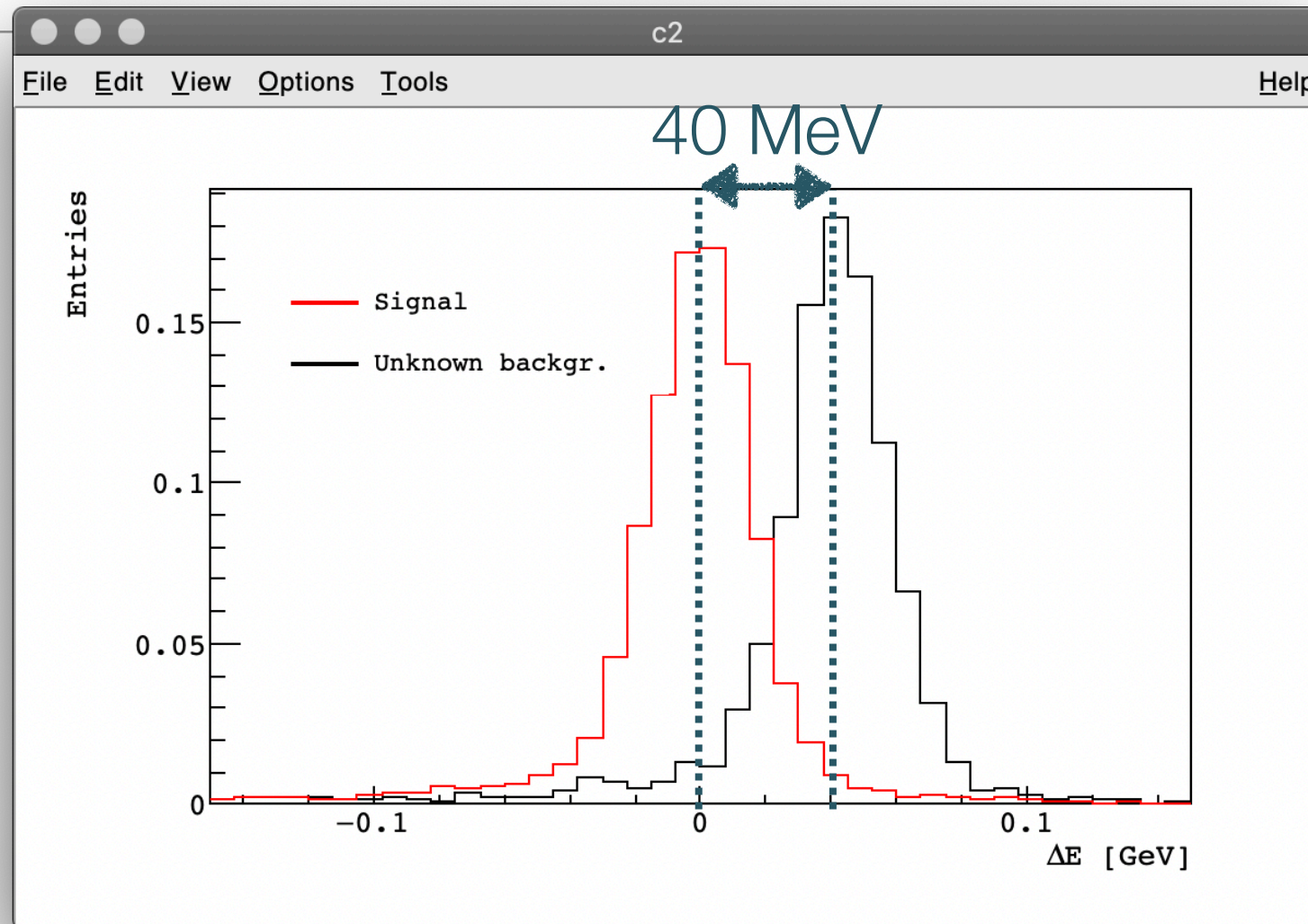
The output



```
root [0]
Processing inspectB.C...
Total entries in the tree: 283056
Integral from signal: 8798
Integral from unkn. back.: 2352
```



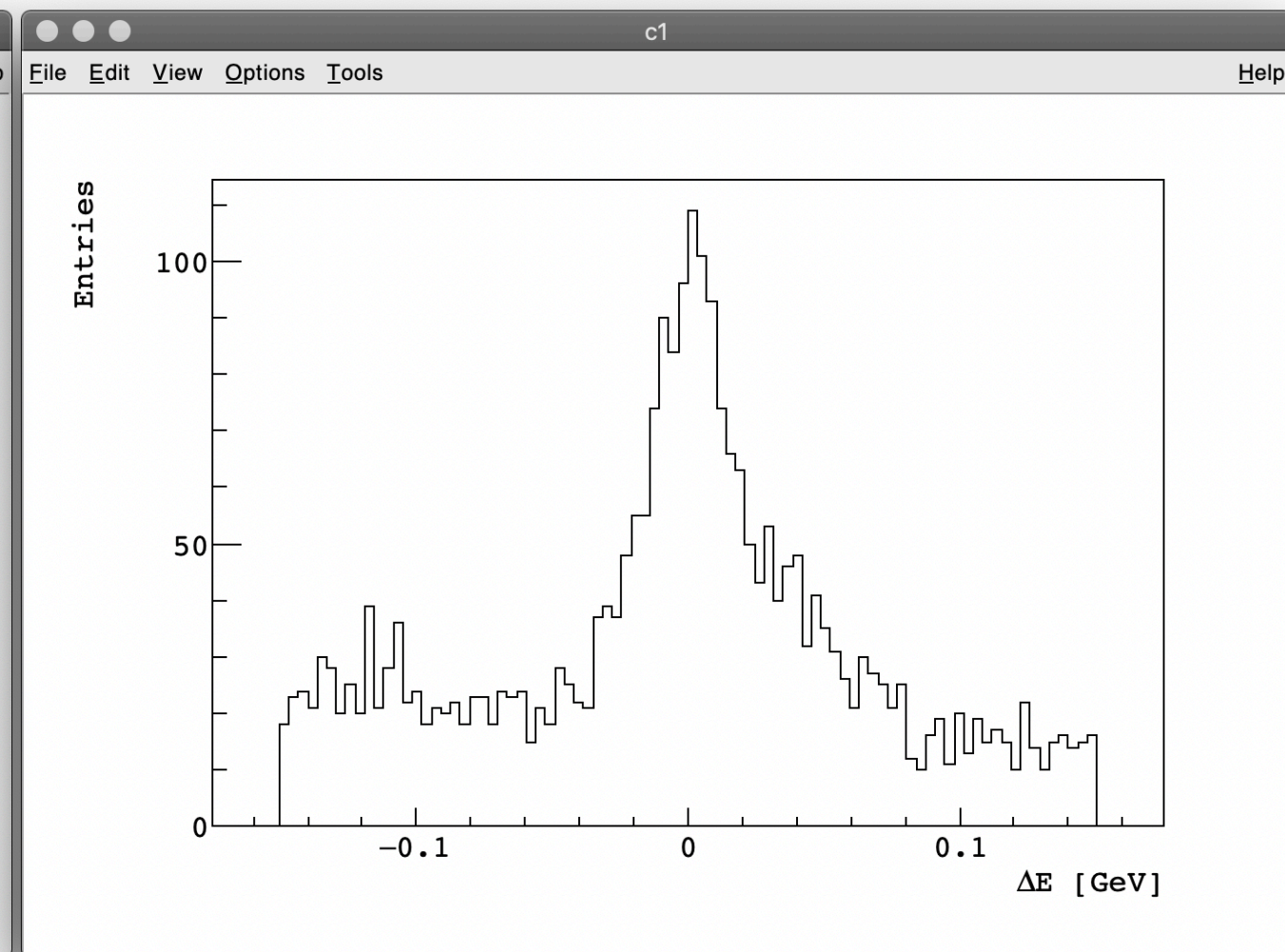
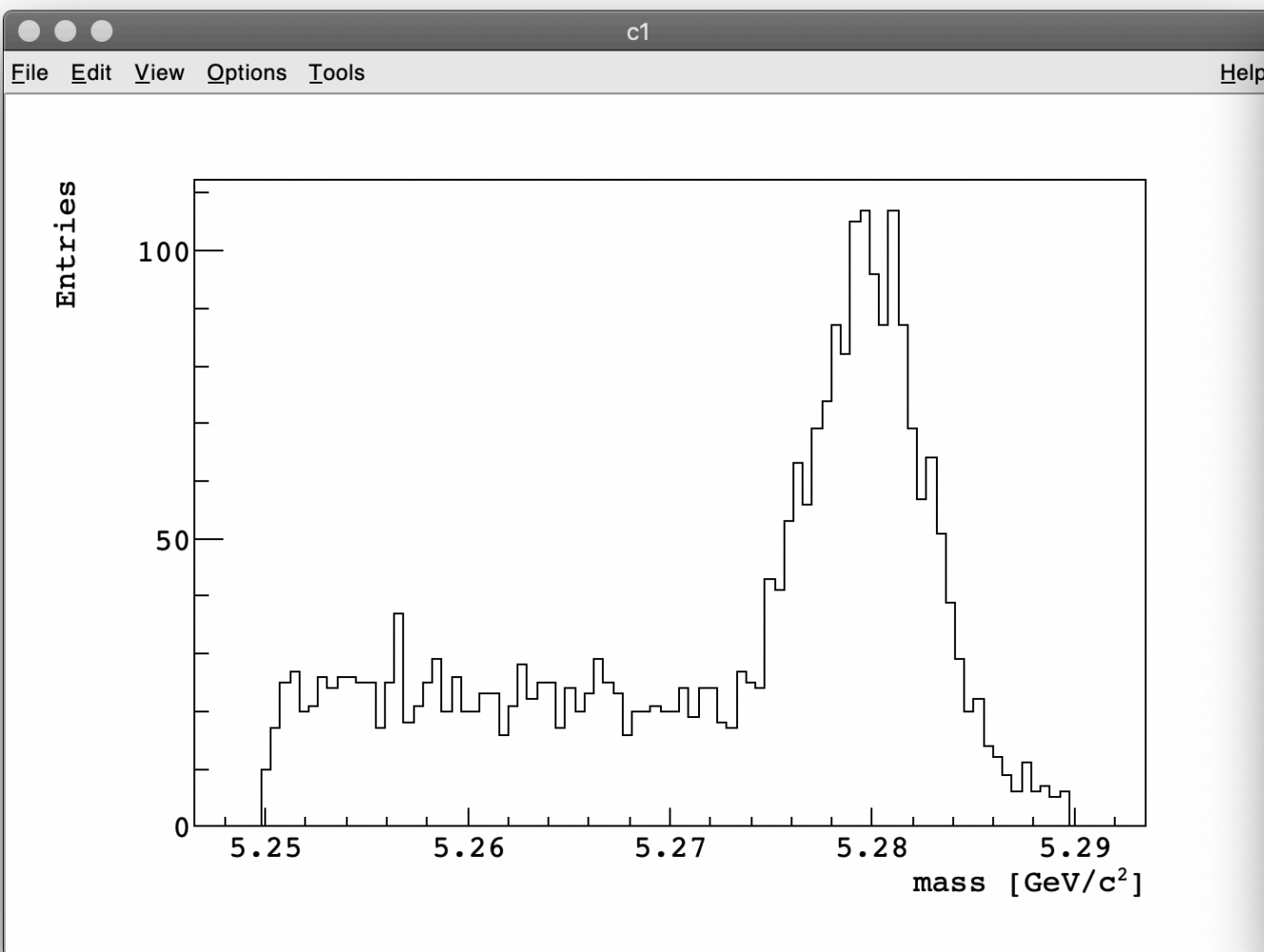
Misidentified background



- Indeed, this is given by pion-to-kaon misidentification. If you calculate the shift in ΔE due to the different pion-kaon mass, you will find about $+40 \text{ MeV}$.
- We can use a variable, built from PID detectors, to suppress this background.

Look at data

- Our original goal was to measure the signal yield in data.
- Let's take a look at data: check out M and ΔE distributions in `data.root`, after the cut `bkg_killer>0.92`.
- Put them in a ROOT file.



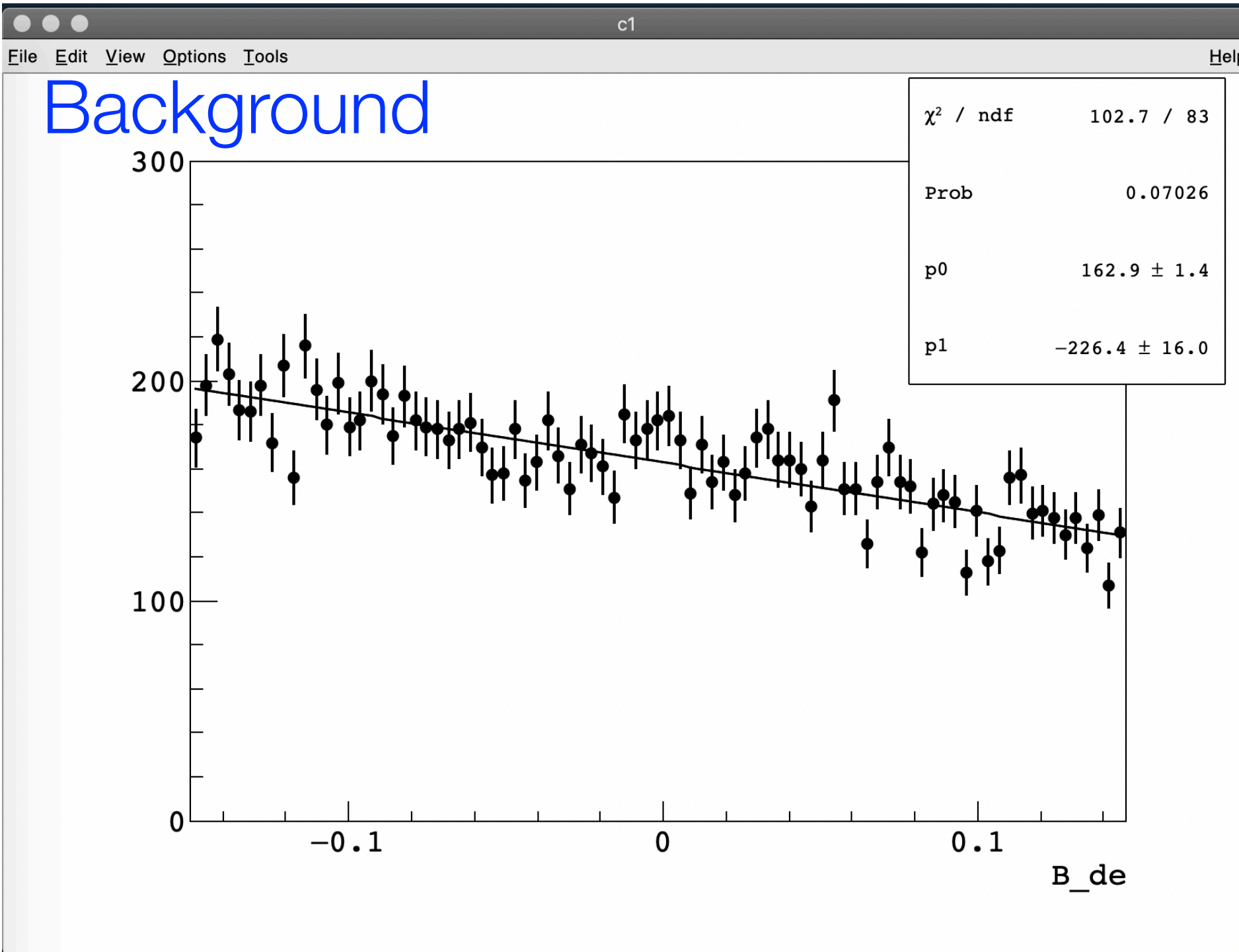
Let's make a fit of our data sample

- We will fit the ΔE distribution (why?).
- Of course, we cannot just select only signal as in simulation. We can “statistically disentangle” the components that make up the observed distribution. We will do a fit to get the sample composition.
- We can model the fit function (probability density function, pdf) from simulation, studying each component.
- Then we will apply our model to fit the data.

A note

- Fitting is a very large topic that would require several lessons.
- I'm sure you have some background: that you have seen already topics like parameter estimation, χ^2 , likelihood, pdf, and so on...
- Here we will see very simple fits to histograms (i.e. binned data) that enables us to achieve already some good results.
- Bear in mind that's not the full story at all!

Model the components using the FitPanel



Fit Panel

Data Set: TH1F::htemp

Fit Function

Type: Predef-1D pol1

Operation

Nop Add NormAdd Conv

pol1

Selected:

pol1

Set Parameters...

General Minimization

Fit Settings

Method

Chi-square User-Defined...

Linear fit Robust: 0.95

Fit Options

Integral Use range

Best errors Improve fit results

All weights = 1 Add to list

Empty bins, weights=1 Use Gradient

Draw Options

SAME

No drawing

Do not store/draw

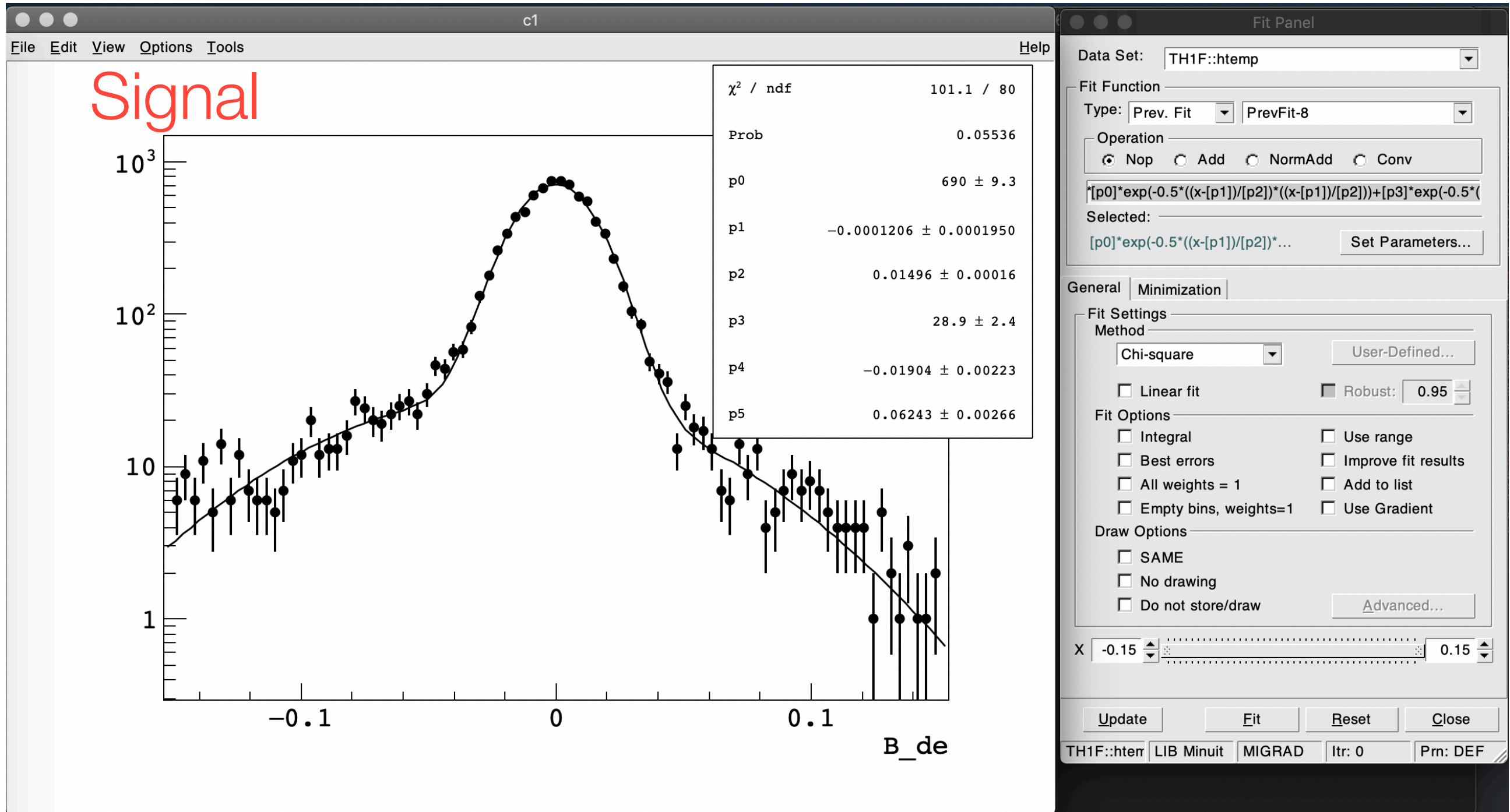
Advanced...

X -0.15 0.15

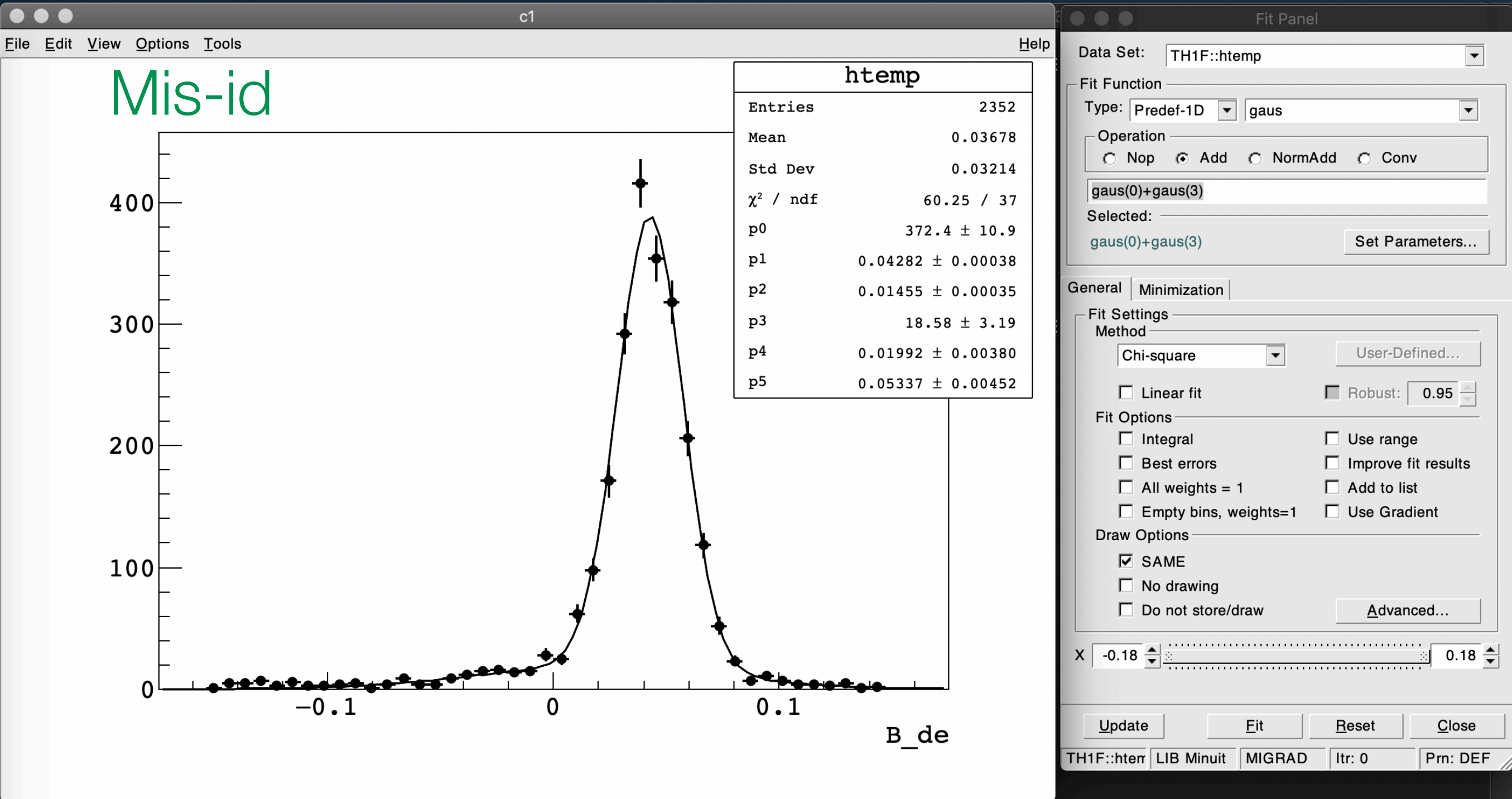
Update Fit Reset Close

TH1F::htemp LIB Minuit MIGRAD ltr: 0 Prn: DEF

Model the components using the FitPanel



Model the components using the FitPanel



Let's make the fit to data

- We have seen the possible function to fit each component
- In data, we have 10% of the statistic of the simulation:
we can afford also simpler model.
We will use just one Gaussian function to model the signal
and the mis-id component
- We will build a model that is the sum of the 3 components
- We will do it in a macro (although we could do it online too!)

Take fitDeltaE.C

```
7 #include "TLegend.h"
8 #include "TStyle.h"
9
10 using namespace std;
11
12 void fitDeltaE(){
13
14     const double min_de = -0.15;
15     const double max_de = 0.15;
16     //define an histogram to look at deltaE distribution
17     TH1D* h_data = new TH1D("h_data", "#DeltaE [GeV]; Entries", 40, min_de, max_de);
18
19     //open file and take the tree
20     TFile* file = TFile::Open("data.root");
21     TTree* tree = (TTree*) file->Get("treeData");
22
23     int tot_entries = tree->GetEntries();
24     cout << "Total entries in the tree: " << tot_entries << endl;
25
26     //link the variables with tree branches
27     double B_de;
28     double bkg_killer;
29     tree->SetBranchAddresses("B_de", &B_de);
30     tree->SetBranchAddresses("bkg_killer", &bkg_killer);
31
32     //loop over the entries
33     for(int iEntry; iEntry < tot_entries; ++iEntry){
34         == ==
35         tree->GetEntry(iEntry);
36
37         //skip all candidates below the optimal cut point
38         if(bkg_killer < 0.92) continue;
39
40         //fill the histograms
41         h_data->Fill(B_de);
42     }
```

First part pretty standard now...

Take fitDeltaE.C

```
45 //Let's define the PDF for the fit, using TF1
46 //https://root.cern.ch/doc/master/classTF1.html
47
48 //The total function that describes our observed distribution
49 TF1* pdf = new TF1("pdf", "gaus(0)+gaus(3)+pol1(6)", min_de, max_de);
50
51 //signal gauss, normalisation constant
52 pdf->SetParName (0, "N_{sig}");
53 pdf->SetParameter(0, 100);
54 //signal gauss, mean fixed
55 pdf->SetParName (1, "#mu_{sig}");
56 pdf->FixParameter(1, 0.);
57 //signal gauss, std dev fixed
58 pdf->SetParName (2, "#sigma_{sig}");
59 pdf->FixParameter(2, 0.015);
60 //mis-id gauss, normalisation constant
61 pdf->SetParName (3, "N_{misid}");
62 pdf->SetParameter(3, 10);
63 //mis-id gauss, mean fixed
64 pdf->SetParName (4, "#mu_{misid}");
65 pdf->FixParameter(4, 0.042);
66 //mis-id gauss, std dev fixed
67 pdf->SetParName (5, "#sigma_{misid}");
68 pdf->FixParameter(5, 0.015);
69 //background intercept and slope
70 pdf->SetParName (6, "p_{0}^{bkg}");
71 pdf->SetParName (7, "p_{1}^{bkg}");
```

[TF1 function](#)

All settings on parameters.
We fix parameters that we know already (from physics or simulation) to ease the work of the fit.
The simplest the model, the better.

Take `fitDeltaE.C`

- It's all happening here with a very simple line!

```
76 //and now fit, in the range defined by the histogram (option R)
77 //option N = not draw (otherwise it draws a canvas with a plot by default)
78 cout << "\n First fit, fixing all possible parameters: \n\n";
79 h_data->Fit("pdf", "RN");
```

- But plenty of options to do whatever we need...
- See the method `Fit()` in the reference guide.
- Note: `Fit()` works also for `TGraph (Errors)`.

Take fitDeltaE.C

Value of the fit function (χ^2 here)

Algorithm used to obtain the results

```
First fit, fixing all possible parameters: Important to check this!  
FCN=27.8948 FROM MIGRAD STATUS=CONVERGED 79 CALLS 80 TOTAL  
EDM=9.01287e-23 STRATEGY= 1 ERROR MATRIX ACCURATE  
EXT PARAMETER STEP FIRST  
NO. NAME VALUE ERROR SIZE DERIVATIVE  
1 N_{sig} 1.69595e+02 7.30230e+00 1.84336e-02 9.63651e-13  
2 #mu_{sig} 0.00000e+00 fixed  
3 #sigma_{sig} 1.50000e-02 fixed  
4 N_{misid} 4.55419e+01 5.18582e+00 1.26809e-02 -7.00404e-13  
5 #mu_{misid} 4.20000e-02 fixed  
6 #sigma_{misid} 1.50000e-02 fixed  
7 p_{0}^{bkg} 4.17642e+01 1.24868e+00 2.98156e-03 8.93671e-12  
8 p_{1}^{bkg} -7.71166e+01 1.19357e+01 3.07475e-02 -1.15545e-13
```

The fit results

Take fitDeltaE.C

Value of the fit function (χ^2 here)

Degrees of freedom (number of bins — parameters)

```
First fit, fixing all possible parameters:
*****
Minimizer is Minuit2 / Migrad
Chi2      =      27.8948
Ndf       =         36
Edm       =  3.46384e-23
NCalls    =         80
Norm_{sig} =      169.595 +/- 7.3023
#mu_{sig}  =         0      (fixed)
#sigma_{sig} =       0.015      (fixed)
Norm_{misid} =      45.5419 +/- 5.18582
#mu_{misid} =       0.042      (fixed)
#sigma_{misid} =       0.015      (fixed)
p_{0}^{bkg} =      41.7642 +/- 1.24868
p_{1}^{bkg} =     -77.1166 +/- 11.9357
```

The fit results

Take fitDeltaE.C

- Can play with parameters, to obtain more information from data

```
81     cout << "\n\n Let's try to release the signal std dev \n\n";
82     pdf->ReleaseParameter(2); //signal gauss, std dev fixed
83     h_data->Fit("pdf", "RN");
84
85     cout << "\n\n Update the mis-id std dev \n";
86     cout << " And release also the mis-id mean \n";
87     pdf->FixParameter(5, pdf->GetParameter(2)); //signal gauss, std dev fixed
88     pdf->ReleaseParameter(4);
89     //option L = binned likelihood fit
90     cout << " and do a binned-likelihood fit, instead of a chi2 \n\n";
91     h_data->Fit("pdf", "LR");
```

- Can try also different fit methods, so in the last iteration we ask to fit with a binned-likelihood function, instead of the default χ^2

Take fitDeltaE.C

Let's try to release the signal std dev

```
FCN=27.5849 FROM MIGRAD STATUS=CONVERGED 110 CALLS 111 TOTAL
EDM=4.36718e-08 STRATEGY= 1 ERROR MATRIX ACCURATE
EXT PARAMETER STEP FIRST
NO. NAME VALUE ERROR SIZE DERIVATIVE
1 N_{sig} 1.66753e+02 8.83060e+00 1.79772e-02 -3.65160e-05
2 #mu_{sig} 0.00000e+00 fixed
3 #sigma_{sig} 1.54440e-02 8.09241e-04 1.50628e-06 -3.72362e-01
4 N_{misid} 4.45076e+01 5.52977e+00 1.26128e-02 -3.30067e-06
5 #mu_{misid} 4.20000e-02 fixed
6 #sigma_{misid} 1.50000e-02 fixed
7 p_{0}^{bkg} 4.16391e+01 1.26990e+00 2.96553e-03 -8.98781e-05
8 p_{1}^{bkg} -7.64094e+01 1.20082e+01 3.05822e-02 -9.12170e-06
```

2nd fit results,
releasing the
sigma for
the signal

Update the mis-id std dev
And release also the mis-id mean
and do a binned-likelihood fit, instead of a chi2

Info in <TCanvas::MakeDefCanvas>: created default TCanvas with name c1

```
FCN=13.7672 FROM MIGRAD STATUS=CONVERGED 148 CALLS 149 TOTAL
EDM=5.36238e-08 STRATEGY= 1 ERROR MATRIX ACCURATE
EXT PARAMETER STEP FIRST
NO. NAME VALUE ERROR SIZE DERIVATIVE
1 N_{sig} 1.66476e+02 8.69389e+00 1.78671e-02 -3.46486e-06
2 #mu_{sig} 0.00000e+00 fixed
3 #sigma_{sig} 1.56044e-02 8.92083e-04 1.50313e-06 3.01092e-02
4 N_{misid} 4.26560e+01 5.59930e+00 1.22986e-02 1.88504e-05
5 #mu_{misid} 4.37828e-02 2.89346e-03 6.25797e-06 6.01764e-02
6 #sigma_{misid} 1.54440e-02 fixed
7 p_{0}^{bkg} 4.22155e+01 1.34014e+00 2.98857e-03 1.67546e-04
8 p_{1}^{bkg} -7.82222e+01 1.20763e+01 3.05956e-02 4.01627e-06
ERR DEF= 0.5
```

3rd fit results,
releasing also
mis-id mean.
Use the binned
likelihood here.

Take fitDeltaE.C

```
Let's try to release the signal std dev
*****
Minimizer is Minuit2 / Migrad
Chi2 = 27.5849
NDF = 35
Edm = 2.12854e-06
NCalls = 99
Norm_{sig} = 166.751 +/- 8.83072
#mu_{sig} = 0 (fixed)
#sigma_{sig} = 0.0154444 +/- 0.000809264
Norm_{misid} = 44.5125 +/- 5.5298
#mu_{misid} = 0.042 (fixed)
#sigma_{misid} = 0.015 (fixed)
p_{0}^{bkg} = 41.6391 +/- 1.2699
p_{1}^{bkg} = -76.4184 +/- 12.0082
*****
Minimizer is Minuit2 / Migrad
MinFCN = 13.7672
Chi2 = 27.5343
NDF = 34
Edm = 1.4323e-06
NCalls = 135
Norm_{sig} = 166.467 +/- 8.69358
#mu_{sig} = 0 (fixed)
#sigma_{sig} = 0.0156043 +/- 0.000892089
Norm_{misid} = 42.6549 +/- 5.5993
#mu_{misid} = 0.0437792 +/- 0.00289365
#sigma_{misid} = 0.0154444 (fixed)
p_{0}^{bkg} = 42.2166 +/- 1.34017
p_{1}^{bkg} = -78.2235 +/- 12.0766
```

2nd fit results,
releasing the
sigma for
the signal

3rd fit results,
releasing also
mis-id mean.
Use the binned
likelihood here.

Take fitDeltaE.C

```
93 //draw the result
94 gStyle->SetOptStat(0);
95 gStyle->SetOptFit(1111);
96 TCanvas* c1 = new TCanvas("c1", "c1", 600, 600);
97
98 h_data->SetMinimum(0);
99 h_data->SetMarkerColor(kBlack);
100 h_data->SetMarkerStyle(8);
101 h_data->SetMarkerSize(0.8);
102 h_data->SetLineColor(kBlack);
103
104 h_data->Draw("err");
105
106 //just to draw each component separately...
107 //the signal
108 TF1* pdf_sig = new TF1("pdf_sig", "gaus", min_de, max_de);
109 pdf_sig->SetParameters(pdf->GetParameter(0),
110                      pdf->GetParameter(1),
111                      pdf->GetParameter(2));
112 pdf_sig->SetLineColor(kRed);
113 pdf_sig->SetLineWidth(2);
114 pdf_sig->Draw("same");
115
116 //the mis-id B->pipi
117 TF1* pdf_misid = new TF1("pdf_misid", "gaus", min_de, max_de);
118 pdf_misid->SetParameters(pdf->GetParameter(3),
119                          pdf->GetParameter(4),
120                          pdf->GetParameter(5)).
```

Just nice drawing
of the results...

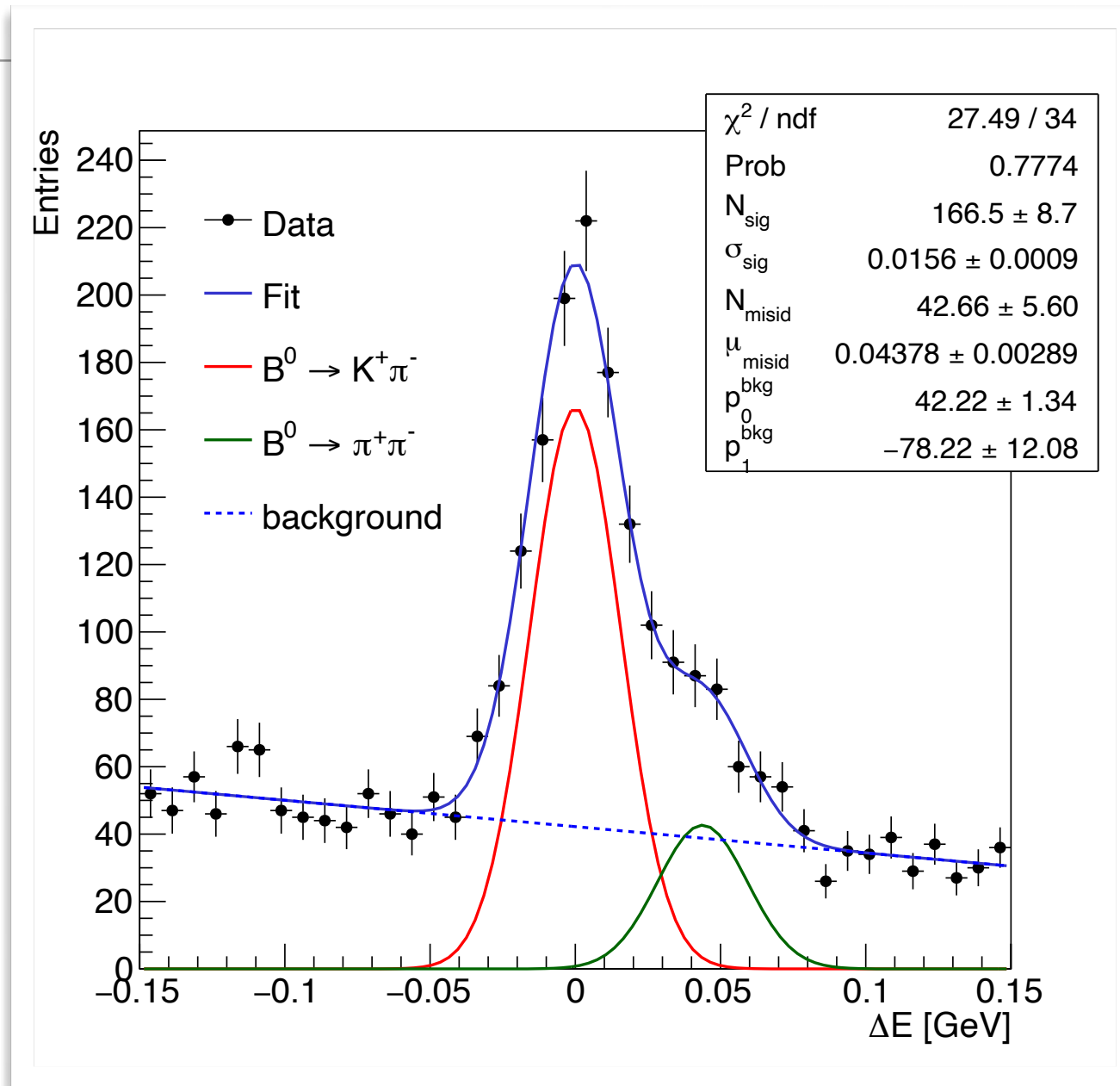
Take fitDeltaE.C

```
143 c1->SaveAs("myFit.pdf");  
144 c1->SaveAs("myFit.C");  
145  
146 //Get now what we wanted to know!  
147 double binW = h_data->GetXaxis()->GetBinWidth(1);  
148 cout << "\n\n From this fit model, \n";  
149 cout << "Candidate in data histogram: " << h_data->Integral() << endl;  
150 cout << "Total candidates from fit : " << pdf->Integral(min_de,max_de)/binW << endl;  
151 cout << "Signal B->Kpi candidates : " << pdf_sig->Integral(min_de,max_de)/binW << endl;  
152 cout << "Mis-id B->pipi candidates : " << pdf_misid->Integral(min_de,max_de)/binW << endl;  
153 cout << "Background candidates : " << pdf_bkg->Integral(min_de,max_de)/binW << endl;  
154  
155 return; Retrieve the information we want: the yield of the components  
156 }
```

Can also save the canvas to a pdf!

Retrieve the information we want: the yield of the components

We made it!



```
From this fit model,  
Candidate in data histogram: 2777  
Total candidates from fit : 2777.01  
Signal B→Kpi candidates : 868.211  
Mis-id B→pipi candidates : 220.176  
Background candidates : 1688.62
```

Exercises (3rd lesson)

1. Compute the signal efficiency, $\epsilon = S(\text{selected})/S(\text{total})$, for each cut `bkg_killer`. Draw a graph to show the efficiency as a function of the cut value, drawing also the error on the efficiency (that you need to calculate): use the class `TGraphErrors`.
2. What do you expect for the M distribution of the mis-id background? Draw it, by subtracting from the total distribution the signal and that of the non-B background (like we did for ΔE). Compare its distribution with that of the signal.
3. There is a variable `K_pid` in the tuples that gives the probability of a candidate kaon to be a real kaon. Draw its distribution: compare that of the signal (`isSig==1`) with that of the mis-id background (`isSig!=1 && isBkg!=1`).
4. Instead of using `DrawNormalized()`, scale to 1 the histogram integral using the `Scale()` method of `TH1` (check the integral value) and normal `Draw()` method.

Exercises (3rd lesson)

5. Find a cut value for K_{pid} , by maximising the $S/\sqrt{S+B}$, where S and B are the signal and mis-id background in the ΔE region $[-60,60]$ MeV.
6. Apply the full selection to the simulation and data samples (`data.root`), and draw the resulting distributions of M and ΔE .

NB: make sure all numbers and text in plots are well visible, by adjusting size of fonts, labels...

More exercises (4th lesson)

7. Make the likelihood scan for σ_{sig}
8. Check “a posteriori” that the cut $\text{bkg_killer} > 0.92$ is the optimal cut. What happens if you apply a tighter cut (> 0.98) or a looser cut (> 0.8)?
9. Couldn't we make the optimisation of the cut by fitting the data directly?