



Introduction to ROOT: final part

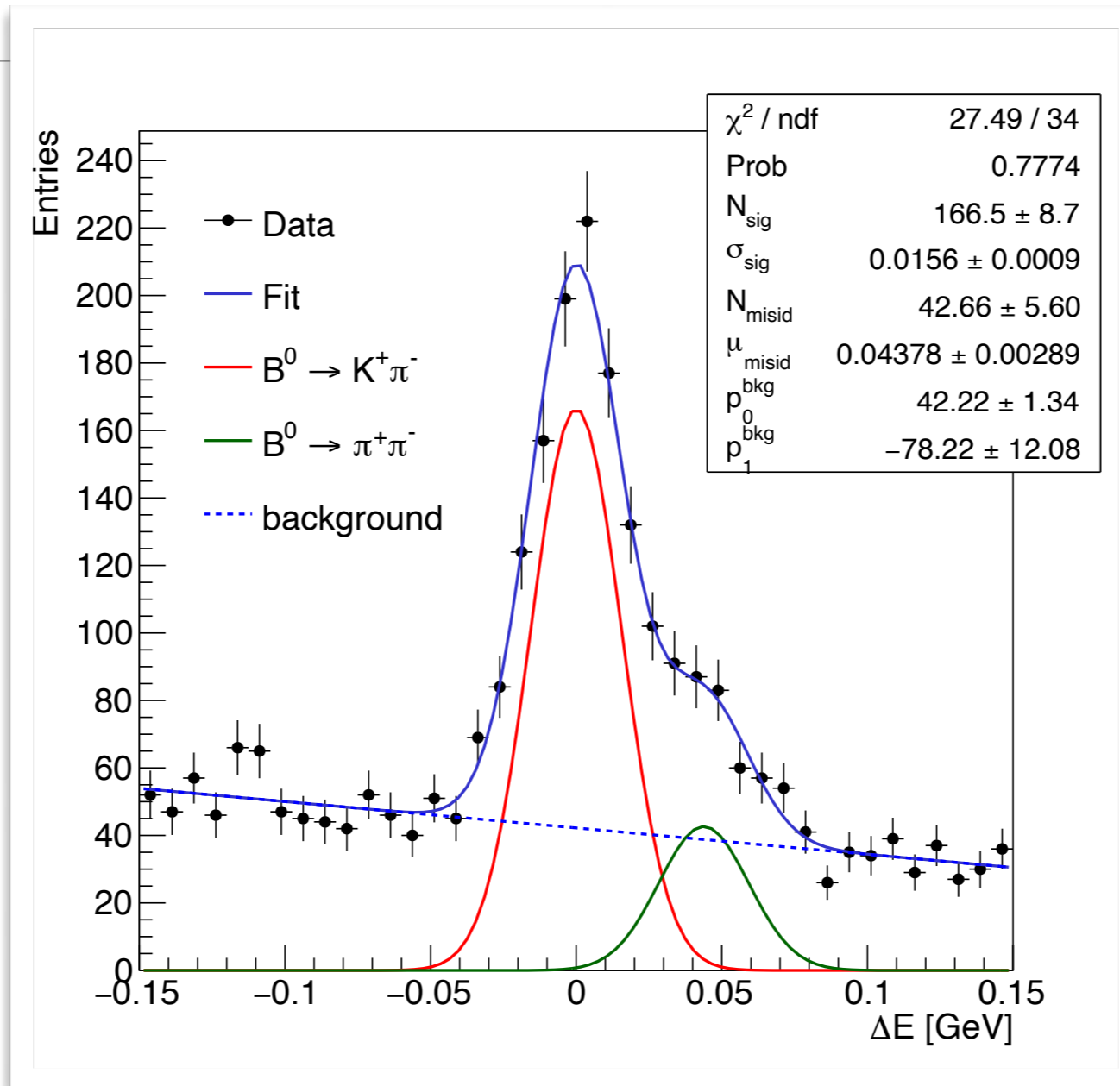
(for good!)

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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
```

The uncertainty is missing!

- We didn't compute the uncertainty on the signal yield yet!
- We used a gauss pdf for the signal, its integral (divided by the bin width w) gives the signal yield:

$$\text{pdf} = N e^{-\frac{(x - \mu)^2}{2\sigma^2}} \rightarrow S = N \sqrt{2\pi\sigma} / w$$

- To get the uncertainty on S , need to propagate the uncertainty from the fit on N and σ , considering their correlation.

Calculate S and its uncertainty

- Little addition in fitDeltaE.C

```
//option L = binned likelihood fit
//Use FitResultPtr to retrieve all information about the fit
//Need to add the option S
TFitResultPtr fit = h_data->Fit("pdf", "LRS");
//now we can get covariance matrix. We will store in a TMatrixDSym
TMatrixDSym cov = fit->GetCovarianceMatrix();
cov.Print();
```

- Now you have all information

```
cout << "=====" << endl;
cout << " Let's calculate the final result with its uncertainty " << endl;
//We can calculate the signal yield directly from the fit parameters
//of the signal pdf (gauss function)
double Nsig = fit->Parameter(0);
double sigma = fit->Parameter(2);
double S = Nsig*sqrt(2.*TMath::Pi())*sigma/binW;

// and propagate the uncertainty
double errS = S * sqrt(cov(0,0)/Nsig/Nsig + cov(2,2)/sigma/sigma + 2*cov(0,2)/Nsig/sigma);

printf("The measurement of the signal yield is %.0f +- %.0f \n", S, errS);
//for curiosity let's print the correlation between Nsig and sigma,
//is it negligible?
printf("Corr(Nsig,sigma) = %.3f \n\n",cov(0,2)/sqrt(cov(0,0)*cov(2,2)));
```

Calculate S and its uncertainty

```
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  
=====
```

Let's calculate the final result with its uncertainty
The measurement of the signal yield is 868 ± 47
Corr(Nsig, sigma) = -0.511

Exercise 1.

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`.

We will take `optimiseSelection.C` from the lesson and modify it.

Breaking down Exercise 1

```
1 #include "Riostream.h"
2 #include "TFile.h"
3 #include "TTree.h"
4 #include "TCanvas.h"
5 #include "TH1D.h"
6 #include "TGraph.h"
7
8 using namespace std;
9
10 void calculateEff(){
11
12     //define the number of cuts to probe,
13     //the range and the steps width
14     const int ncuts = 15;
15     double max_range = 1;
16     double min_range = 0.7;
17     double delta_cut = (max_range-min_range)/ncuts;
18
19     //define the graph of the efficiency,
20     //using TGraphErrors because I also want to
21     //show the error on the efficiency
22     TGraphErrors* g_eff = new TGraphErrors(ncuts);
23
24     //Open file and take the tree
25     TFile* file = TFile::Open("./simulation.root");
26     TTree* tree = (TTree*) file->Get("simTree");
```

TGraphErrors class

Breaking down Exercise 1

```
27
28  int tot_entries = tree->GetEntries("isBkg!=1");
29  cout << "Total signal entries in the tree: " << tot_entries << endl;
30
31  for(int icut=0; icut<ncuts; ++icut){
32
33      //define the cut value to probe
34      double cutval = min_range + icut*delta_cut;
35
36      //put the cut in a string
37      TString cutString = Form("bkg_killer > %.4f && isBkg!=1", cutval);
38
39      //and retrieve the entries, directly from the tree, passing the selection
40      double Nsig = tree->GetEntries(cutString);
41
42      //calculate the efficiency and the error
43      double eff = Nsig/tot_entries;
44      double err_eff =
45
46      //just a check
47      printf("cut value = %.3f, eff = %.4f +- %.4f \n",cutval, eff, err_eff);
48
49      //put the results in the graph
50      g_eff->SetPoint(icut,cutval,eff);
51      g_eff->SetPointError(icut,0,err_eff);
52
53 }
```

Signal only,
denominator of the efficiency

efficiency calculation

Set the point and the error in the graph

Breaking down Exercise 1

```
54
55     printf("\n The signal efficiency for bkg_killer>0.92 is %.3f \n",
56     g_eff->Eval(0.92));
57
58     //and draw the graph
59     TCanvas* c = new TCanvas("c","c",800,600);
60     g_eff->SetMarkerStyle(8);
61     g_eff->SetMarkerSize(0.2);
62     g_eff->GetXaxis()->SetTitle("cut value");
63     g_eff->GetYaxis()->SetTitle("signal efficiency");
64     g_eff->Draw("APL");
65
66     return;
67 }
68
```

Draw the result

Breaking down Exercise 1

The output

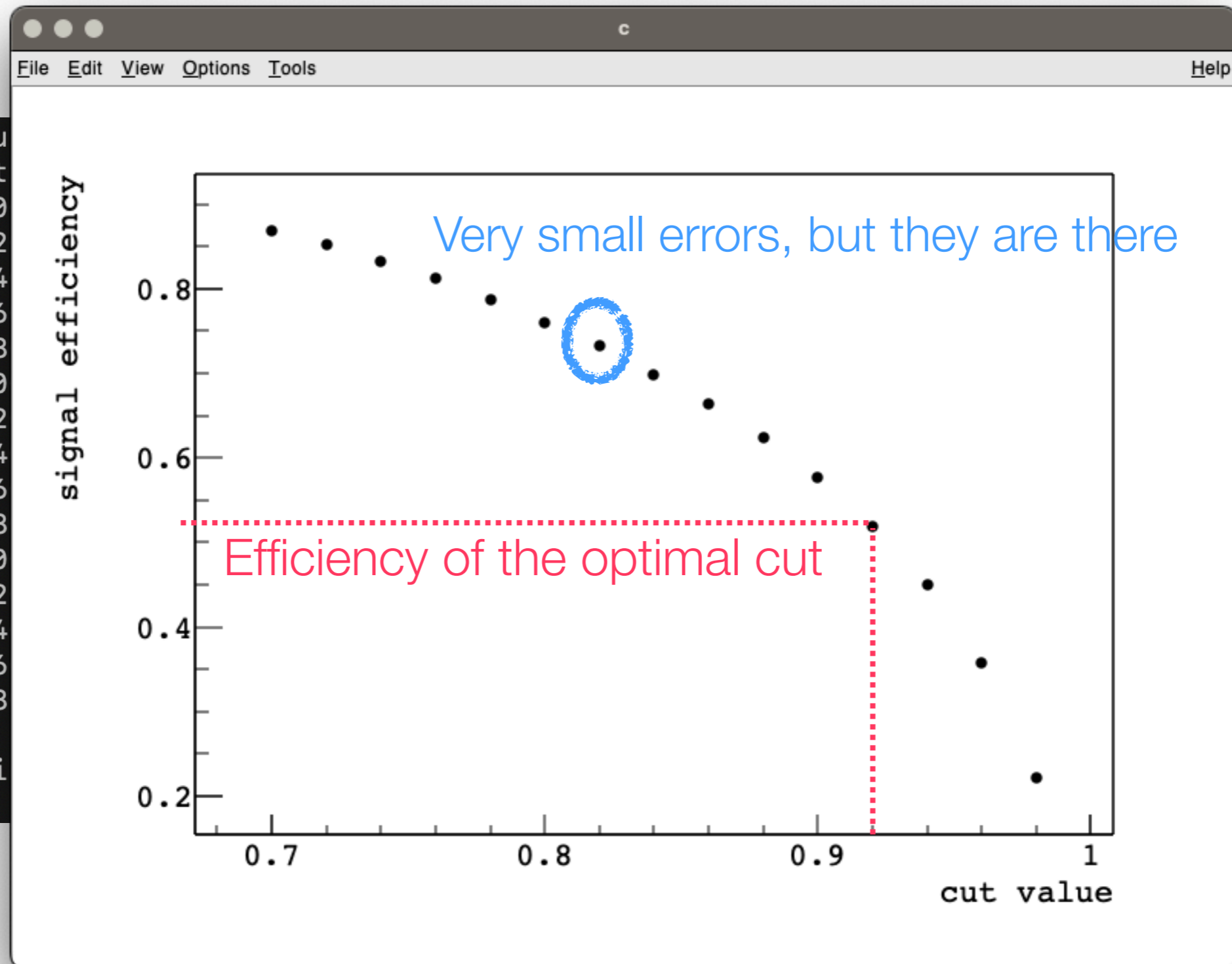
```
Processing calculateEff.C...
Total signal entries in the tree: 21456
cut value = 0.700, eff = 0.8680 +- 0.0023
cut value = 0.720, eff = 0.8524 +- 0.0024
cut value = 0.740, eff = 0.8330 +- 0.0025
cut value = 0.760, eff = 0.8120 +- 0.0027
cut value = 0.780, eff = 0.7871 +- 0.0028
cut value = 0.800, eff = 0.7598 +- 0.0029
cut value = 0.820, eff = 0.7318 +- 0.0030
cut value = 0.840, eff = 0.6988 +- 0.0031
cut value = 0.860, eff = 0.6628 +- 0.0032
cut value = 0.880, eff = 0.6246 +- 0.0033
cut value = 0.900, eff = 0.5761 +- 0.0034
cut value = 0.920, eff = 0.5197 +- 0.0034
cut value = 0.940, eff = 0.4504 +- 0.0034
cut value = 0.960, eff = 0.3578 +- 0.0033
cut value = 0.980, eff = 0.2223 +- 0.0028

The signal efficiency for bkg_killer>0.92 is 0.520
root [1]
```

Breaking down Exercise 1

The output

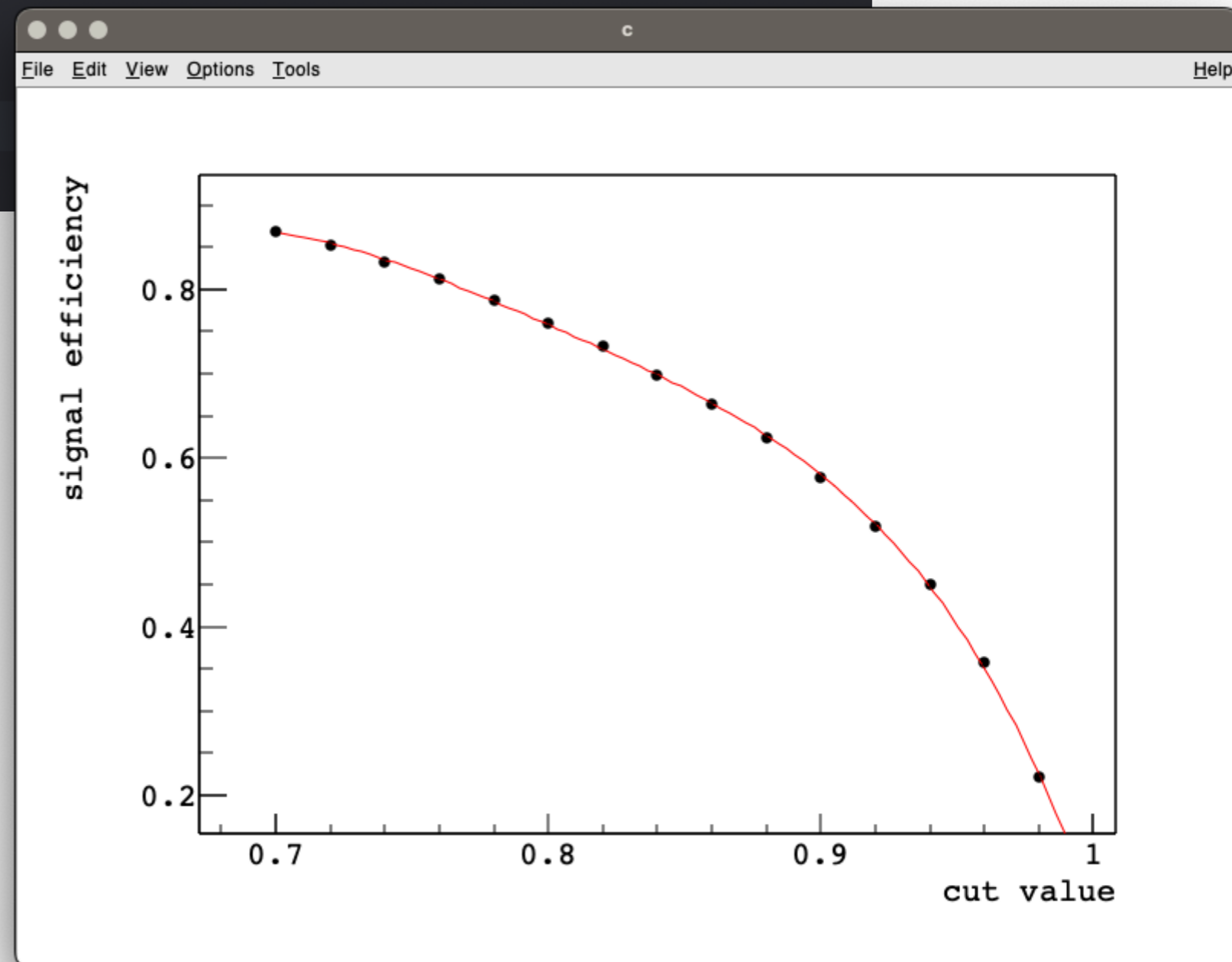
```
Processing calcula  
Total signal ent  
cut value = 0.70  
cut value = 0.72  
cut value = 0.74  
cut value = 0.76  
cut value = 0.78  
cut value = 0.80  
cut value = 0.82  
cut value = 0.84  
cut value = 0.86  
cut value = 0.88  
cut value = 0.90  
cut value = 0.92  
cut value = 0.94  
cut value = 0.96  
cut value = 0.98  
  
The signal effi  
root [1]
```



Breaking down Exercise 1 (with a little extra)

Let's add a fit to derive an efficiency function. We use a pol4.

```
TF1* efficiency = new TF1("efficiency", "pol4", min_range, max_range);  
efficiency->SetLineColor(kRed);  
efficiency->SetLineWidth(1);  
  
g_eff->Fit("efficiency", "R");  
g_eff->Draw("AP");
```



Fitting TGraphErrors with uncertainties on x

Does a (chi2) fit consider the uncertainties on x? How can it be?
Always have a look at the Reference Guide!

TGraphErrors fit:

In case of a **TGraphErrors** or **TGraphAsymmErrors** object, when x errors are present, the error along x, is projected along the y-direction by calculating the function at the points $x - ex_low$ and $x + ex_high$, where ex_low and ex_high are the corresponding lower and upper error in x. The chi-square is then computed as the sum of the quantity below at each data point:

$$\frac{(y - f(x))^2}{ey^2 + (\frac{1}{2}(exl + exh)f'(x))^2}$$

where x and y are the point coordinates, and $f'(x)$ is the derivative of the function $f(x)$.

In case of asymmetric errors, if the function lies below (above) the data point, ey is ey_low (ey_high).

The approach used to approximate the uncertainty in y because of the errors in x is to make it equal the error in x times the slope of the line. This approach is called "effective variance method" and the implementation is provided in the function `FitUtil::EvaluateChi2Effective`

Exercise 2

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.

We will take `inspectB.C` from the lesson and modify it.

We will take this occasion to revisit `Sumw2 ()`

Breaking down Exercise 2

```
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 compareM(){
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 mass, bkg_killer;
21     int bkg, sig;
22     tree->SetBranchAddresses("B_m",&mass);
23     tree->SetBranchAddresses("isBkg",&bkg);
24     tree->SetBranchAddresses("isSig",&sig);
25     tree->SetBranchAddresses("bkg_killer",&bkg_killer);
26
```

Breaking down Exercise 2

```
27 //define an histogram to look at mass distribution
28 TH1D* h_m_tot = new TH1D("h_m_tot", ";mass [GeV/c^{2}]; Entries", 40, 5.25, 5.30);
29
30 //very very important to rember when manipulating histograms!!!
31 h_m_tot->Sumw2();
32
33 //clone the same histogram structure for signal, bkg, and unknown bkg
34 TH1D* h_m_sig = (TH1D*) h_m_tot->Clone("h_m_sig");
35
36 h_m_sig->Sumw2();//with Clone() we have already set it
37 //from the original TH1D, it will issue a "Warning"
38
39 TH1D* h_m_bkg = (TH1D*) h_m_tot->Clone("h_m_bkg");
40 TH1D* h_m_unknown = (TH1D*) h_m_tot->Clone("h_m_unknown");
41
```

IMPORTANT!!!

Not an issue...

Warning in <TH1D::Sumw2>: Sum of squares of weights structure already created

Breaking down Exercise 2

```
41
42 //loop over the entries
43 for(int iEntry; iEntry<tot_entries; ++iEntry){
44
45     tree->GetEntry(iEntry);
46
47     //skip all candidates below the optimal cut point
48     if(bkg_killer<0.92) continue;
49
50     //fill the histograms
51     h_m_tot->Fill(mass);
52     if(bkg) h_m_bkg->Fill(mass);
53     else if(sig) h_m_sig->Fill(mass);
54
55 }
```

Fill the histograms,
just for the events
that pass the cut

Breaking down Exercise 2

- Let's inspect just a bin (here 24): print out its content error for all histograms.
- Make then the operations to obtain the mass histogram for mis-id backgrd.

```
56 int abin = 24;
57 cout << "\n From original histograms: " << endl;
58 printf("Total histo, bin %i content: %.1f +- %.1f \n", abin, h_m_tot->GetBinContent(abin), h_m_tot->GetBinError(abin) );
59 printf("Signal histo, bin %i content: %.1f +- %.1f \n", abin, h_m_sig->GetBinContent(abin), h_m_sig->GetBinError(abin) );
60 printf("Backgr histo, bin %i content: %.1f +- %.1f \n", abin, h_m_bkg->GetBinContent(abin), h_m_bkg->GetBinError(abin) );
61
62
63 // Subtract the signal
64 h_m_unknown->Add(h_m_tot, h_m_bkg, 1, -1);
65 h_m_unknown->Add(h_m_sig, -1);
66
67 cout << "\n The derived histogram: " << endl;
68 printf("B->pipi histo, bin %i content: %.1f +- %.1f \n", abin, h_m_unknown->GetBinContent(abin), h_m_unknown->GetBinError(abin) );
69 printf("B->pipi histo, sqrt(bin %i content): %.1f \n", abin, sqrt(h_m_unknown->GetBinContent(abin)) );
70
71 double error_prop = sqrt(h_m_tot->GetBinError(abin)*h_m_tot->GetBinError(abin) +
72                          h_m_sig->GetBinError(abin)*h_m_sig->GetBinError(abin) +
73                          h_m_bkg->GetBinError(abin)*h_m_bkg->GetBinError(abin) );
74 printf("B->pipi histo, from error propagation: %.1f \n\n", error_prop );
75
```

- Check the result. We expect:

$$N_{\text{unkn.}} = N_{\text{tot}} - N_{\text{bkg}} - N_{\text{sig}}$$
$$\sigma_{\text{unkn.}} = \sqrt{\sigma_{\text{tot}}^2 + \sigma_{\text{bkg}}^2 + \sigma_{\text{sig}}^2} = \sqrt{N_{\text{tot}} + N_{\text{bkg}} + N_{\text{sig}}}$$

Breaking down Exercise 2

- Check the result. We expect:

$$N_{\text{unkn.}} = N_{\text{tot}} - N_{\text{bkg}} - N_{\text{sig}}$$
$$\sigma_{\text{unkn.}} = \sqrt{\sigma_{\text{tot}}^2 + \sigma_{\text{bkg}}^2 + \sigma_{\text{sig}}^2} = \sqrt{N_{\text{tot}} + N_{\text{bkg}} + N_{\text{sig}}}$$

```
From original histograms:  
Total histo, bin 24 content: 2432.0 +- 49.3  
Signal histo, bin 24 content: 1667.0 +- 40.8  
Backgr histo, bin 24 content: 326.0 +- 18.1  
  
The derived histogram:  
B->pipi histo, bin 24 content: 439.0 +- 66.5  
B->pipi histo, sqrt(bin 24 content): 21.0  
B->pipi histo, from error propagation: 66.5
```

Breaking down Exercise 2

- Let's take out the command `Sumw2 ()`

$$N_{\text{unkn.}} = N_{\text{tot}} - N_{\text{bkg}} - N_{\text{sig}}$$
$$\sigma_{\text{unkn.}} = \sqrt{\sigma_{\text{tot}}^2 + \sigma_{\text{bkg}}^2 + \sigma_{\text{sig}}^2} = \sqrt{N_{\text{tot}} + N_{\text{bkg}} + N_{\text{sig}}}$$

```
From original histograms:  
Total histo, bin 24 content: 2432.0 +- 49.3  
Signal histo, bin 24 content: 1667.0 +- 40.8  
Backgr histo, bin 24 content: 326.0 +- 18.1
```

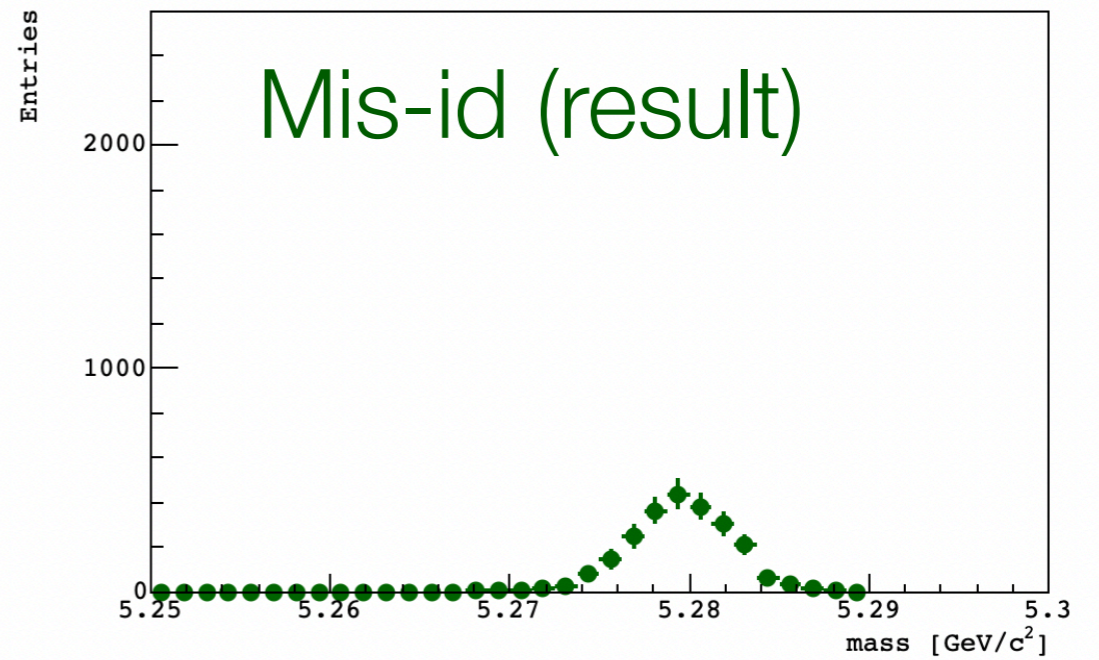
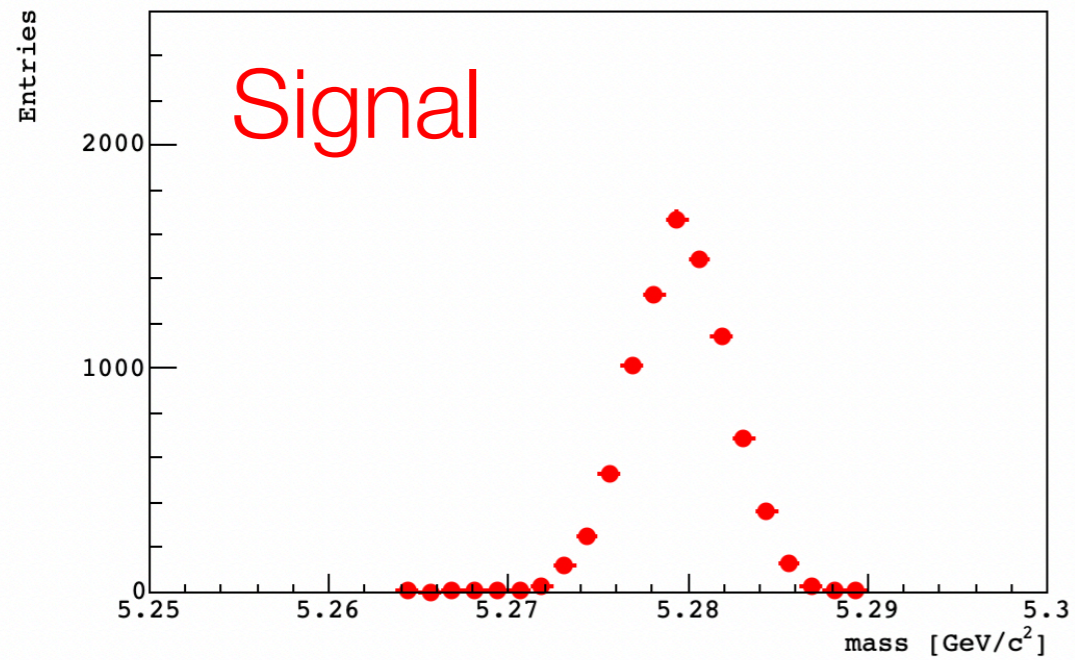
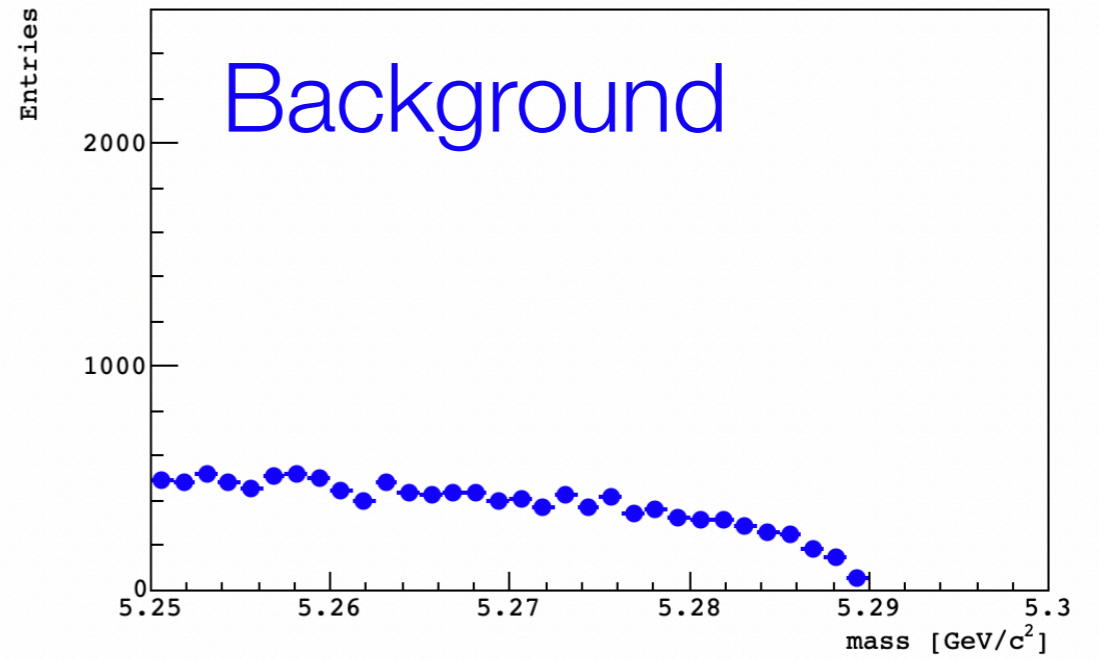
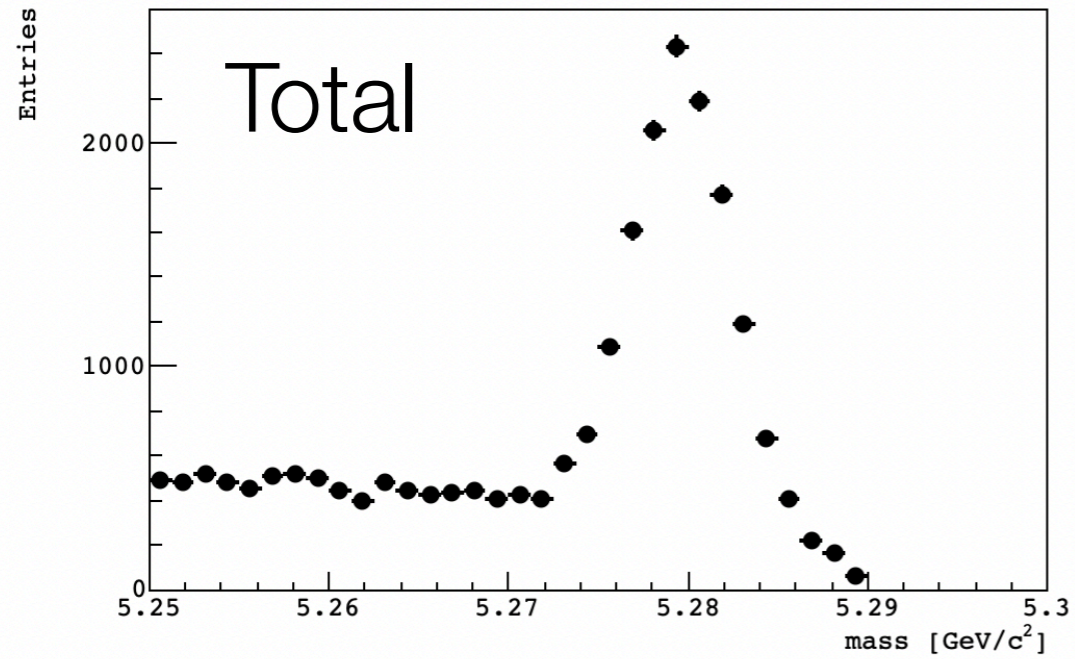
```
The derived histogram:  
B->pipi histo, bin 24 content: 439.0 +- 21.0  
B->pipi histo, sqrt(bin 24 content): 21.0  
B->pipi histo, from error propagation: 66.5
```

WRONG!!!

Breaking down Exercise 2

Just drawings...

```
77 //draw the histograms
78 TCanvas* c1 = new TCanvas("c1", "c1", 1200, 800);
79 c1->Divide(2, 2);
80 c1->cd(1);
81 h_m_tot->GetYaxis()->SetRangeUser(0, 2600);
82 h_m_tot->Draw();
83 c1->cd(2);
84 h_m_bkg->GetYaxis()->SetRangeUser(0, 2600);
85 h_m_bkg->SetMarkerColor(kBlue);
86 h_m_bkg->SetLineColor(kBlue);
87 h_m_bkg->Draw();
88 c1->cd(3);
89 h_m_sig->GetYaxis()->SetRangeUser(0, 2600);
90 h_m_sig->SetMarkerColor(kRed);
91 h_m_sig->SetLineColor(kRed);
92 h_m_sig->Draw();
93 c1->cd(4);
94 h_m_unknown->GetYaxis()->SetRangeUser(0, 2600);
95 h_m_unknown->SetMarkerColor(kMagenta);
96 h_m_unknown->SetLineColor(kMagenta);
97 h_m_unknown->Draw();
```



Breaking down Exercise 2 and 4

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.

```
100 //compare signal and B->pipi shapes:
101
102 //first scale the histograms to the same unit area
103 cout << "Signal histo integral: " << h_m_sig->Integral() << endl;
104 cout << "B->pipi histo integral: " << h_m_unknown->Integral() << endl;
105
106 h_m_sig->Scale(1./h_m_sig->Integral());
107 h_m_unknown->Scale(1./h_m_unknown->Integral());
108
109 cout << "After normalisation to unit area: " << endl;
110 cout << "Signal histo integral: " << h_m_sig->Integral() << endl;
111 cout << "B->pipi histo integral: " << h_m_unknown->Integral() << endl;
112
113 //a useful way to spot differences in shape is making the ratio of the distributions
114 TH1D* h_ratio = (TH1D*) h_m_unknown->Clone("ratio");
115 h_ratio->Divide(h_m_sig);
116
```

Use of scale to normalise to unit area

Another common operation on histograms

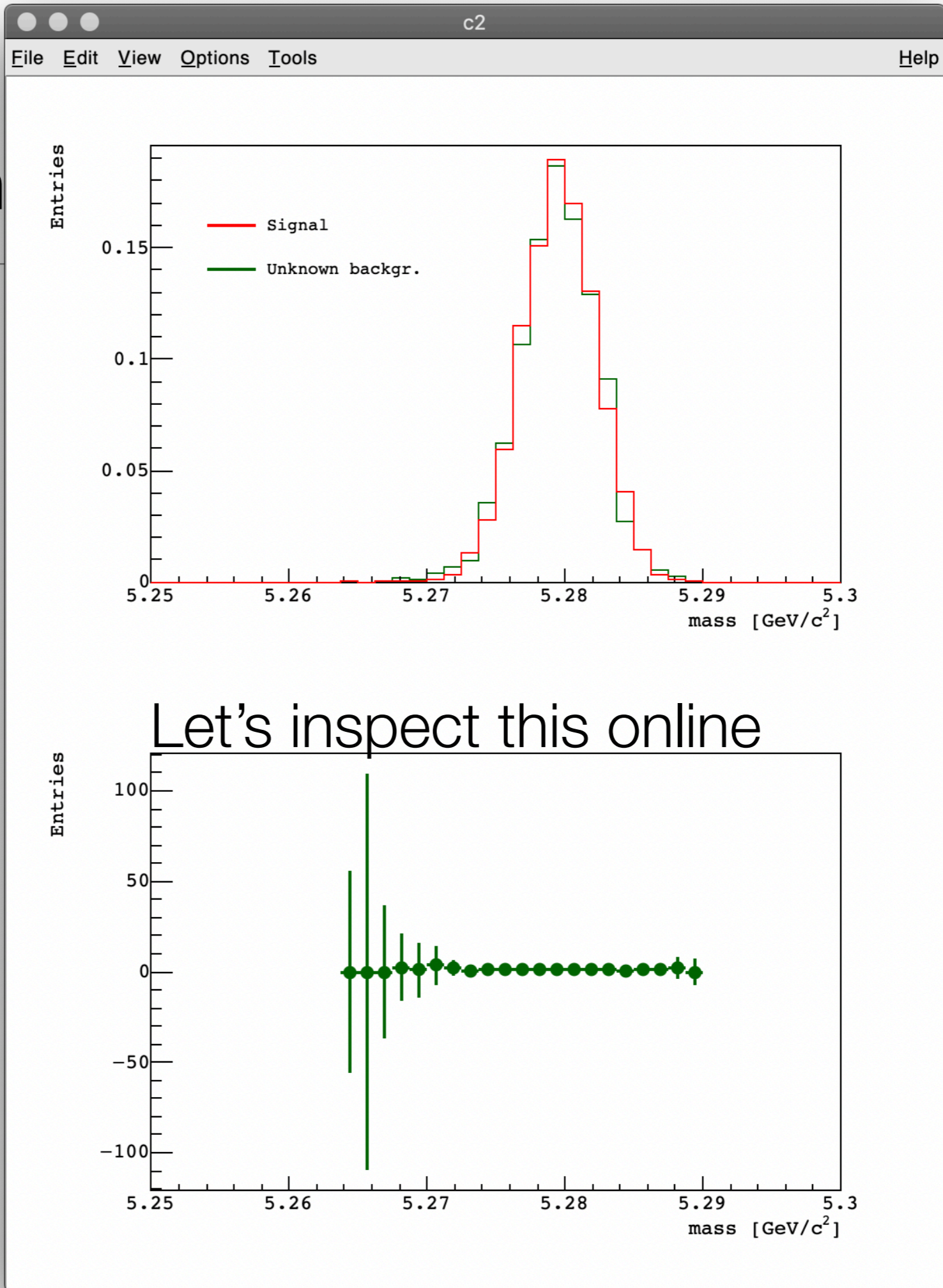
Breaking down Exercise 2 and 4

Draw the result

```
116
117     TCanvas* c2 = new TCanvas("c2", "c2", 600, 800);
118     c2->Divide(1, 2);
119     c2->cd(1);
120     h_m_unknown->Draw("histo");
121     h_m_sig->Draw("histo same");
122
123     //put a legend
124     TLegend* leg = new TLegend(0.2, 0.65, 0.5, 0.8);
125     leg->AddEntry(h_m_sig, "Signal", "L");
126     leg->AddEntry(h_m_unknown, "Unknown backgr.", "L");
127     leg->Draw();
128
129     c2->cd(2);
130     h_ratio->Draw();
```


Breaking down

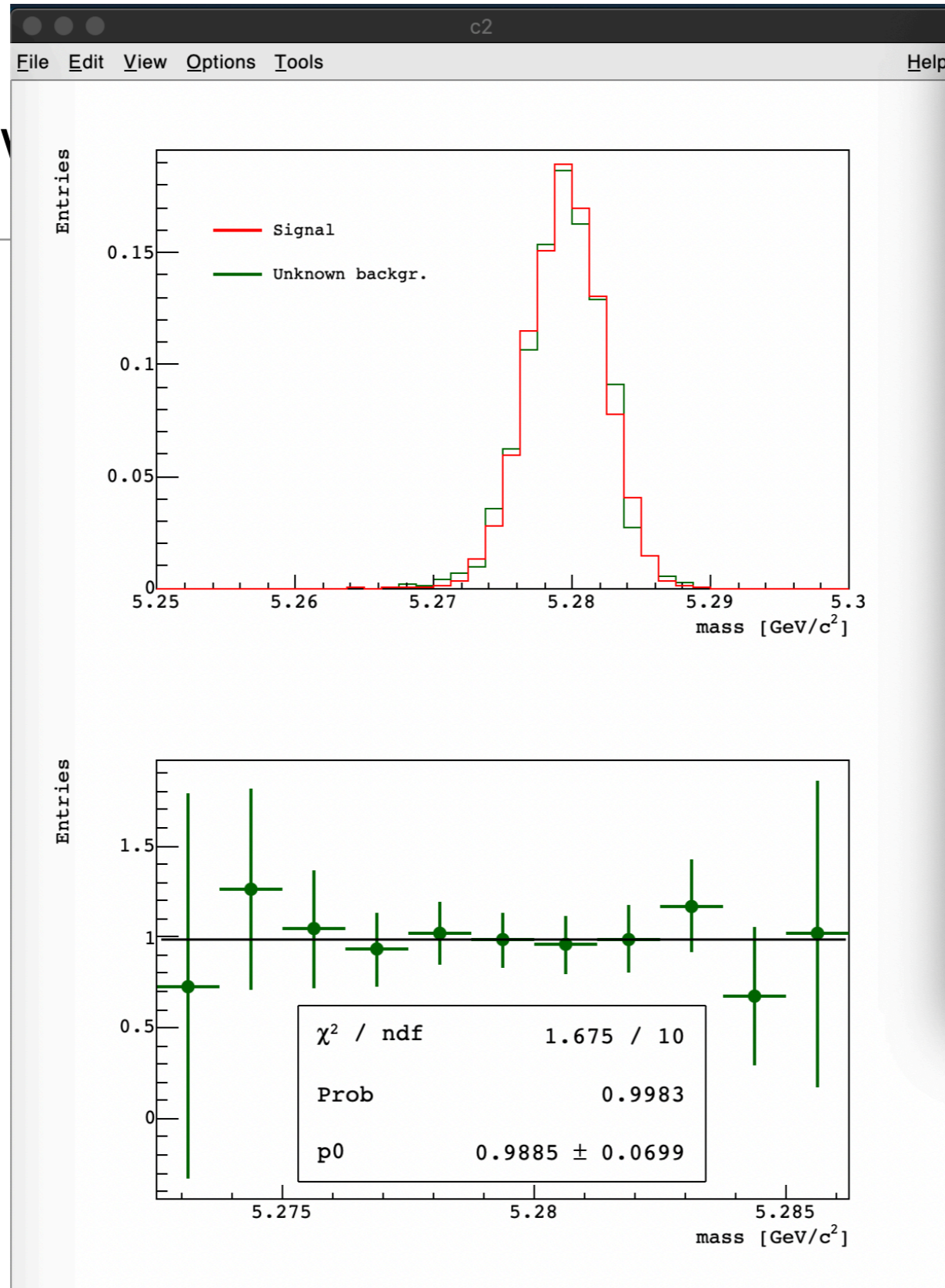
Draw the result



Breaking down

Zoom in the core of the distributions, to check the flatness of the ratio.

To quantify it, we can make a fit of the point with a constant and see the probability of the χ^2 . Here it is (ridiculously) high: this is because of the uncertainties of background distribution from the histograms' subtraction.



The 'Fit Panel' window shows the configuration for a fit. The 'Data Set' is 'TH1D::ratio'. The 'Fit Function' is 'Predef-1D' with 'pol0' selected. The 'Operation' is 'Nop'. The 'Fit Settings' are: Method: 'Chi-square', 'Linear fit' is checked, and 'Robust' is set to 0.95. The 'Fit Options' include: 'Integral', 'Best errors', 'All weights = 1', and 'Empty bins, weights=1'. The 'Draw Options' include: 'SAME', 'No drawing', and 'Do not store/draw'. The x-axis range is set from 5.27 to 5.29. Buttons for 'Update', 'Fit', 'Reset', and 'Close' are visible at the bottom.

We made it!

- Congratulations for completing your (1st?) analysis with ROOT
- Hope this tour with a real-life example was useful (and also more interesting than a standard tutorial).
- Take your time to revisit all material and try it yourself.
For questions, doubts, curiosity don't hesitate to contact me.
We can organise Q&A sessions.
- If you are into data analysis at a particle physics experiment,
come to talk about opportunities in Belle II.

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Extra

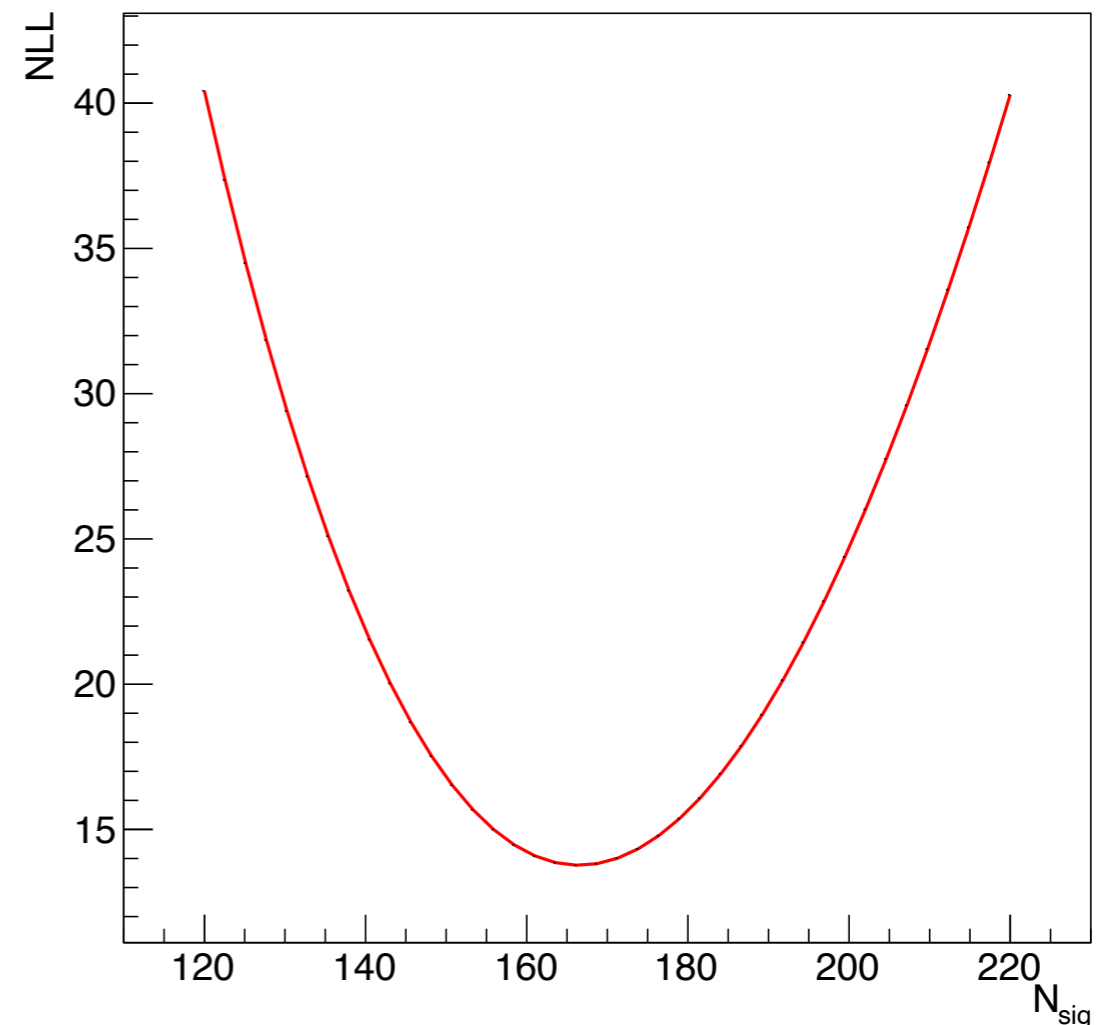
FCN (χ^2 or likelihood) scan

```
//Let's make a scan of the likelihood
//as a function of N_sig
TGraph* scan = new TGraph(40);
fit->Scan(0, scan, 120, 220);
TCanvas* c3 = new TCanvas("c3", "c3", 600, 600);
scan->SetTitle("NLL scan of N_{sig}; N_{sig}; NLL");
scan->SetLineColor(kRed);
scan->SetLineWidth(2);
scan->Draw("APL");
c3->SaveAs("myScan.pdf");
```

NB: this is not a likelihood profile

```
FCN=13.7672 FROM MIGRAD STATUS=CONVERGED 148 CA
EDM=5.36238e-08 STRATEGY= 1
EXT PARAMETER STEP
NO. NAME VALUE ERROR SIZE
1 N_{sig} 1.66476e+02 8.69389e+00 1.78671e
2 #mu_{sig} 0.00000e+00 fixed
3 #sigma_{sig} 1.56044e-02 8.92083e-04 1.5031
4 N_{misid} 4.26560e+01 5.59930e+00 1.22986e
5 #mu_{misid} 4.37828e-02 2.89346e-03 6.25797
6 #sigma_{misid} 1.54440e-02 fixed
7 p_{0}^{bkg} 4.22155e+01 1.34014e+00 2.98857
8 p_{1}^{bkg} -7.82222e+01 1.20763e+01 3.05956
ERR DEF= 0.5
```

NLL scan of N_{sig}



Confidence regions

```
//Let's have a look: make 2D confidence regions
//1sigma contour: region enclosing 68.3% probability
TGraph* cont1sigma = new TGraph(50);
fit->Contour(0,2,cont1sigma,0.683);
cont1sigma->SetLineWidth(2);
cont1sigma->SetLineColor(kBlue+4);

//2sigma contour: region enclosing 95.5% probability
TGraph* cont2sigma = new TGraph(50);
fit->Contour(0,2,cont2sigma,0.955);
cont2sigma->SetLineStyle(2);
cont2sigma->SetLineWidth(2);
cont2sigma->SetLineColor(kBlue+2);

//3sigma contour: region enclosing 99.7% probability
TGraph* cont3sigma = new TGraph(50);
fit->Contour(0,2,cont3sigma,0.997);
cont3sigma->SetLineStyle(3);
cont3sigma->SetLineWidth(2);
cont3sigma->SetLineColor(kBlue);

//Draw all together, need to use TMultiGraph
TCanvas* c2 = new TCanvas("c2","c2",600,600);
TMultiGraph *mg = new TMultiGraph();
mg->SetTitle("Confidence regions for #sigma_{sig} vs N_{sig}; N_{sig}; #sigma_{sig} [Gev/c^{2}]");
mg->Add(cont1sigma,"1");
mg->Add(cont2sigma,"1");
mg->Add(cont3sigma,"1");
mg->Draw("a");
```

Confidence regions

Confidence regions for σ_{sig} vs N_{sig}

