Global Fits to the 2016 Invariant Mass Distribution

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Office of Science

SLAC NATIONAL ACCELERATOR LABORATORY

Road Map

- Motivation
- Initial Studies
  - Invariant Mass Distribution Feature Comparison (all 2016 vs run 7800)
  - Even Ordered Polynomial Significance Comparison (bkg vs bkg+sig)
- Global Fitting Tool
  - creation and use
- Preliminary Results
  - chi2 probability as function of mass window minimum
- Next Steps

Motivation

In 2016, HPS claims A' resonance search sensitivity from 39 MeV - 179 MeV

- **May be able to increase reach** for some or all of this range if "wiggles" in background shape can be better understood and "frozen"
  - two current hypothesis: systematic triggering or systematic features in the background model

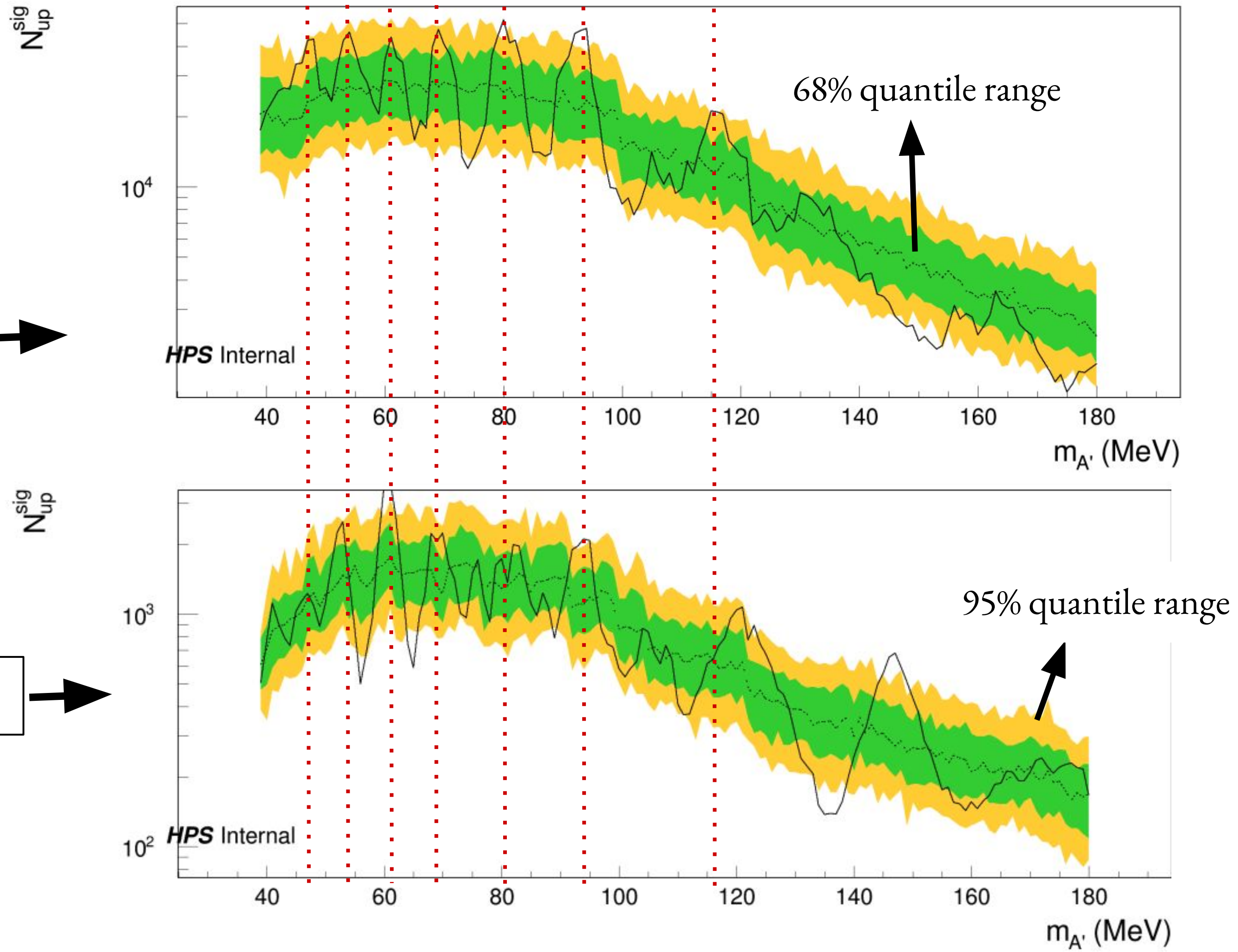
Initial Studies

- Feature Comparison
    - recreated 2016 upper limit plots using provided IMD
    - recreated similar plots for Run 7800 for feature comparison, was necessary to generate the IMD for run
- Polynomial Significance
    - compared *even ordered* polynomial coefficient significance between 2016 signal distribution to Signal+Background

signal yield upper limit including statistical and systematic effects plotted over limit bands

all 2016

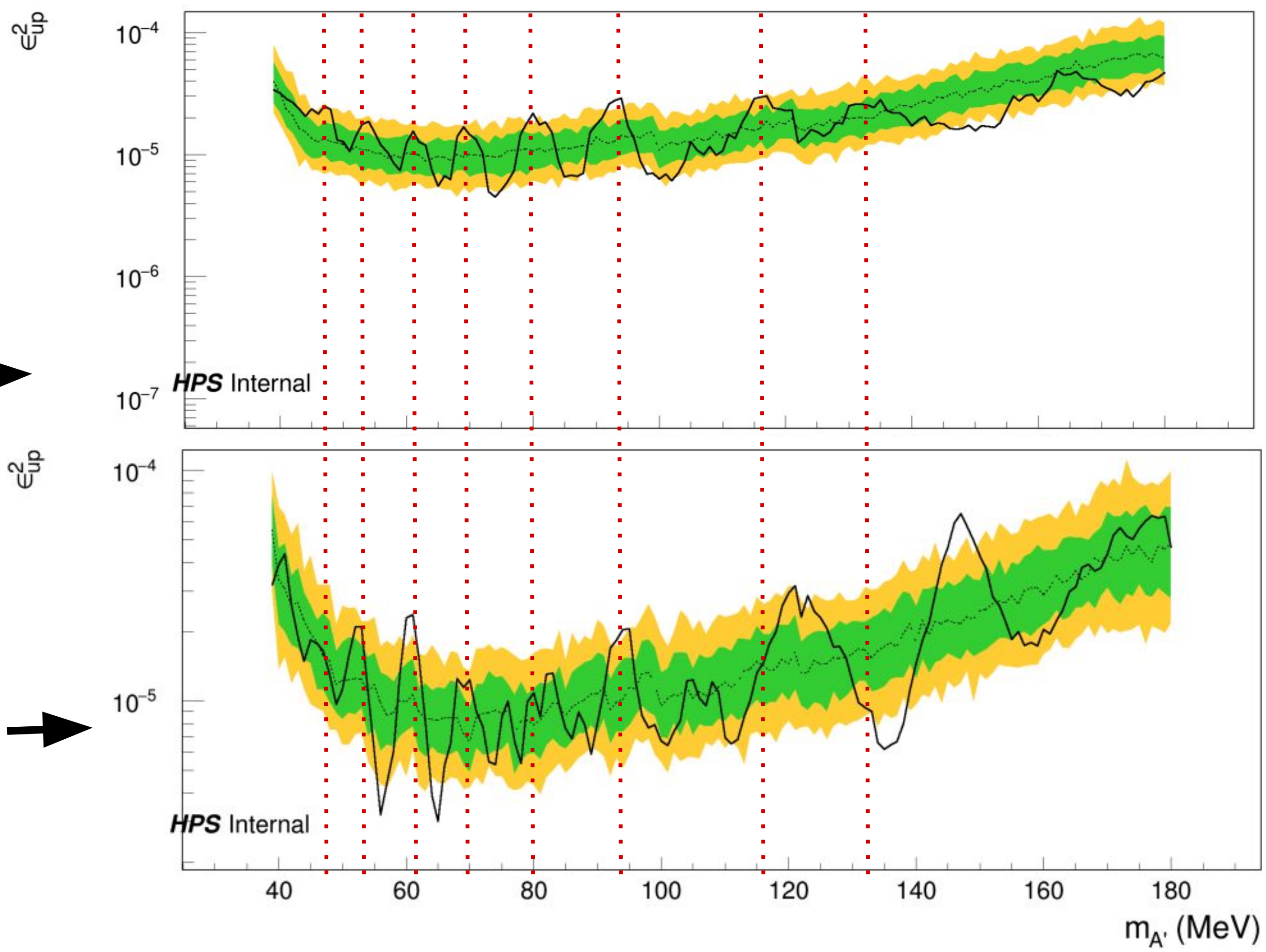
run 7800



ε2 upper limit including statistical and systematic effects plotted over limit bands

all 2016

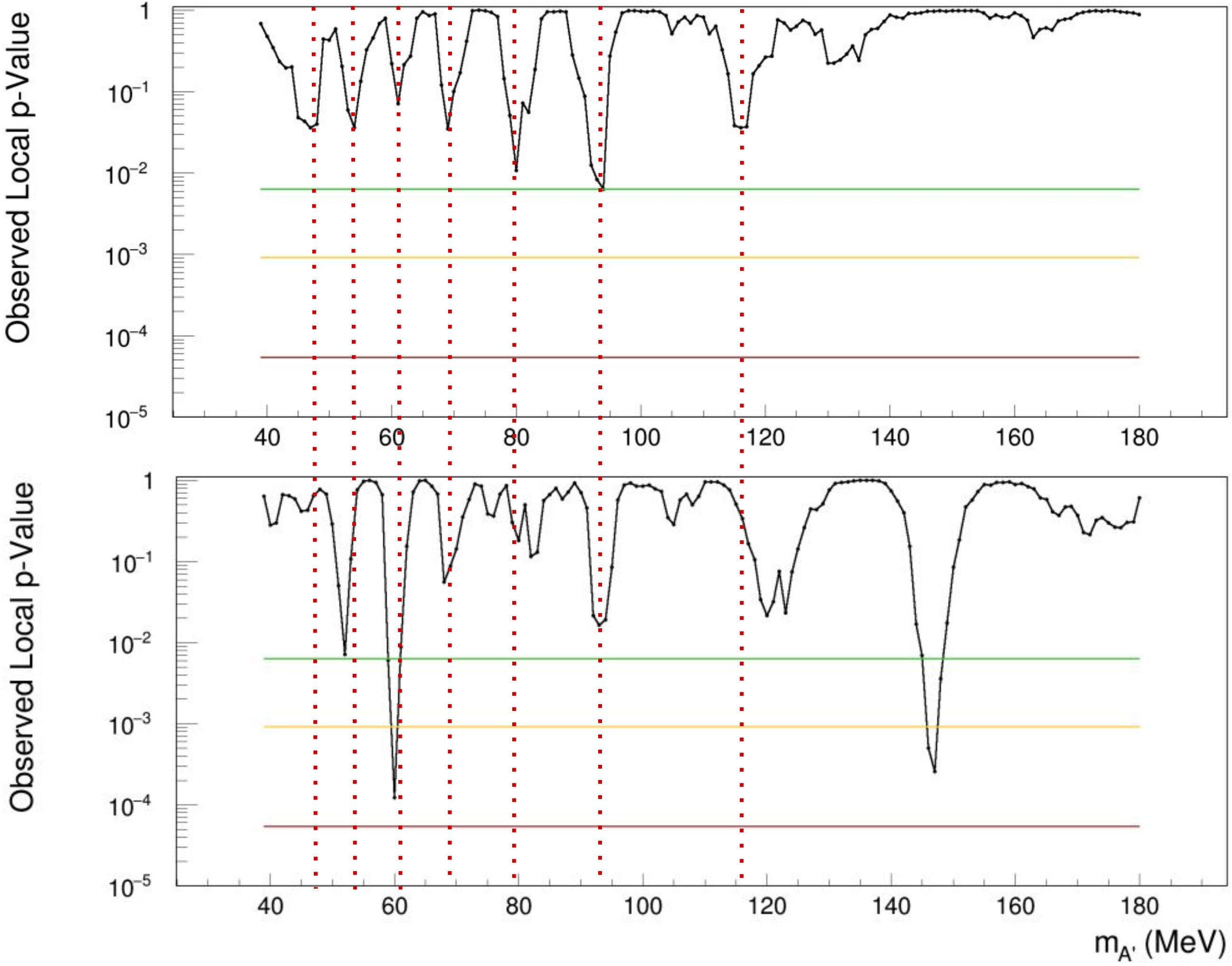
run 7800



mass resolution systematics included

all 2016

run 7800



Current Format of Polynomials Fit to Background

In 2016, 3rd and 5th order Legendre polynomials were fit to different portions of the background in a variety of ranges or windows.

Coefficients for the polynomials are stored as:

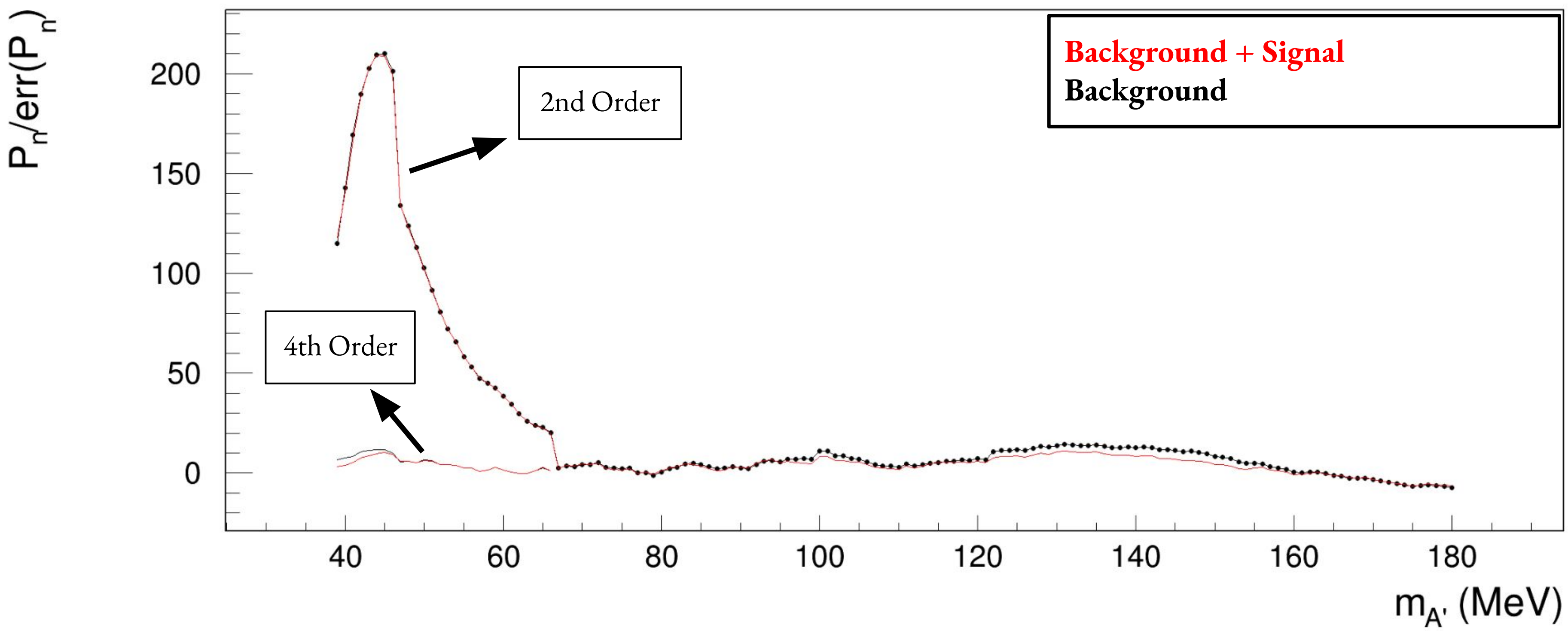
$$\mathcal{P}(3) = \{P_0, P_1, P_2, P_3\}$$
$$\mathcal{P}(5) = \{P_0, P_1, P_2, P_3, P_4, P_5\}$$

$m_{A'}$	$\mathcal{O}(N)$	n_σ	$m_{A'}$	$\mathcal{O}(N)$	n_σ	$m_{A'}$	$\mathcal{O}(N)$	n_σ	$m_{A'}$	$\mathcal{O}(N)$	n_σ	$m_{A'}$	$\mathcal{O}(N)$	n_σ
39	5	10	68	3	6	97	3	6	126	3	8	155	3	8
40	5	10	69	3	6	98	3	6	127	3	8	156	3	8
41	5	10	70	3	6	99	3	6	128	3	8	157	3	8
42	5	10	71	3	6	100	3	7	129	3	8	158	3	8
43	5	10	72	3	6	101	3	7	130	3	8	159	3	8
44	5	10	73	3	6	102	3	7	131	3	8	160	3	8
45	5	10	74	3	6	103	3	7	132	3	8	161	3	8
46	5	10	75	3	6	104	3	7	133	3	8	162	3	8
47	5	9	76	3	6	105	3	7	134	3	8	163	3	8
48	5	9	77	3	6	106	3	7	135	3	8	164	3	8
49	5	9	78	3	6	107	3	7	136	3	8	165	3	8
50	5	9	79	3	6	108	3	7	137	3	8	166	3	8
51	5	9	80	3	6	109	3	7	138	3	8	167	3	8
52	5	9	81	3	6	110	3	7	139	3	8	168	3	8
53	5	9	82	3	6	111	3	7	140	3	8	169	3	8
54	5	9	83	3	6	112	3	7	141	3	8	170	3	8
55	5	9	84	3	6	113	3	7	142	3	8	171	3	8
56	5	9	85	3	6	114	3	7	143	3	8	172	3	8
57	5	9	86	3	6	115	3	7	144	3	8	173	3	8
58	5	9	87	3	6	116	3	7	145	3	8	174	3	8
59	5	9	88	3	6	117	3	7	146	3	8	175	3	8
60	5	9	89	3	6	118	3	7	147	3	8	176	3	8
61	5	9	90	3	6	119	3	7	148	3	8	177	3	8
62	5	9	91	3	6	120	3	7	149	3	8	178	3	8
63	5	9	92	3	6	121	3	7	150	3	8	179	3	8
64	5	9	93	3	6	122	3	8	151	3	8	180	3	8
65	5	9	94	3	6	123	3	8	152	3	8			
66	5	9	95	3	6	124	3	8	153	3	8			
67	3	6	96	3	6	125	3	8	154	3	8			

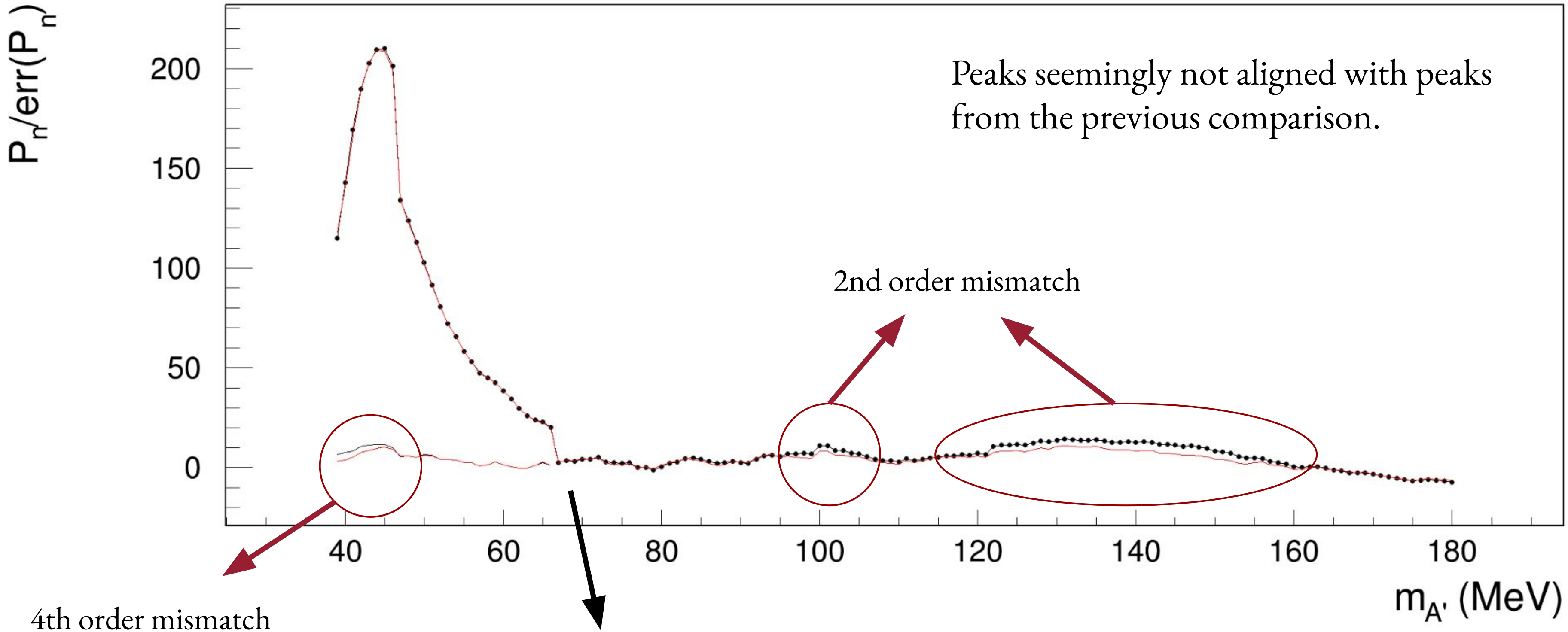
Table 15: The models for each $m_{A'}$ used in the unblinded resonance search. All masses $m_{A'}$ are in units of MeV.

From 2016 note: **insert link**

Even Ordered Polynomial Coefficient Significance Comparison



Notable Features



4th order mismatch

switching from 5th order to 3rd order polys

Global Fit to the Invariant Mass Distribution

May be able to take into account systematic features present in background shape.

- (ongoing) study a variety of functions to fit the distribution
  - will be useful then, to freeze these features as fittable features

$$f_{dijet1}(x) = \frac{p_0(1-x)^{p_1}}{x^{p_2}}$$

$$f_{dijet2}(x) = \frac{p_0(1-x)^{p_1}}{x^{p_2+p_3\log(x)}}$$

$$f_{dijet3}(x) = \frac{p_0(1-x)^{p_1}}{x^{p_2+p_3\log(x)+p_4\log^2(x)}}$$

$$f_{ATLAS1}(x) = \frac{p_0(1-x^{1/3})^{p_1}}{x^{p_2}}$$

$$f_{ATLAS2}(x) = \frac{p_0(1-x^{1/3})^{p_1}}{x^{p_2+p_3\log^2(x)}}$$

$$f_{UA2_1}(x) = p_0 x^{p_1} e^{p_2 x}$$

$$f_{UA2_2}(x) = p_0 x^{p_1} e^{p_2 x + p_3 x^2}$$

$$f_{UA2_3}(x) = p_0 x^{p_1} e^{p_2 x + p_3 x^2 + p_4 x^3}$$

$$f_{cmsBH1}(x) = \frac{p_0(1+x)^{p_1}}{x^{p_2\log x}}$$

$$f_{cmsBH2}(x) = \frac{p_0(1+x)^{p_1}}{x^{p_3+p_2\log x}}$$

$$f_{ATLASBH1}(x) = p_0(1-x)^{p_1} x^{p_2\log(x)}$$

$$f_{ATLASBH2}(x) = p_0(1-x)^{p_1}(1+x)^{p_2\log(x)}$$

$$f_{ATLASBH3}(x) = p_0(1-x)^{p_1} e^{p_2\log(x)}$$

$$f_{ATLASBH4}(x) = p_0(1-x^{1/3})^{p_1} x^{p_2\log(x)}$$

$$f_{ATLASBH5}(x) = p_0(1-x)^{p_1} x^{p_2 x)}$$

$$f_{ATLASBH6}(x) = p_0(1-x)^{p_1}(1+x)^{p_2 x}$$

C. Bravo. *Thesis link*

Global Fitting Tool

Plots Generated For Each Window

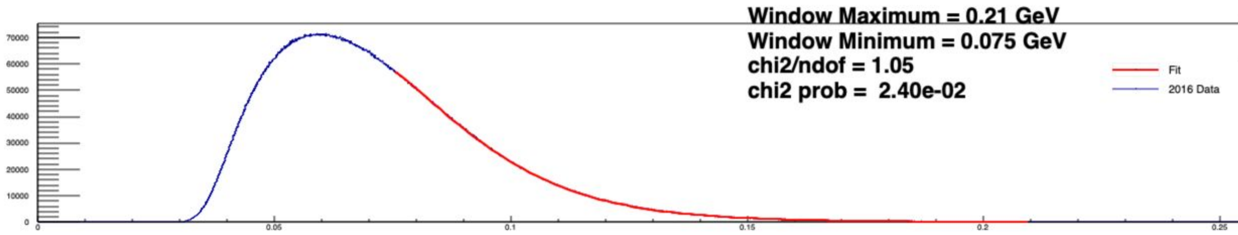
1. Best Fit of Specified Function on top of inv. mass dist.
2. Residual Plot of function and inv. mass dist.
3. Residual / sqrt(N(m)) ← N(m) = number of events at specified mass, m
4. Residual^2 / (N(m))
5. Pull Plot 1D Histogram

Plot(s) generated for each function

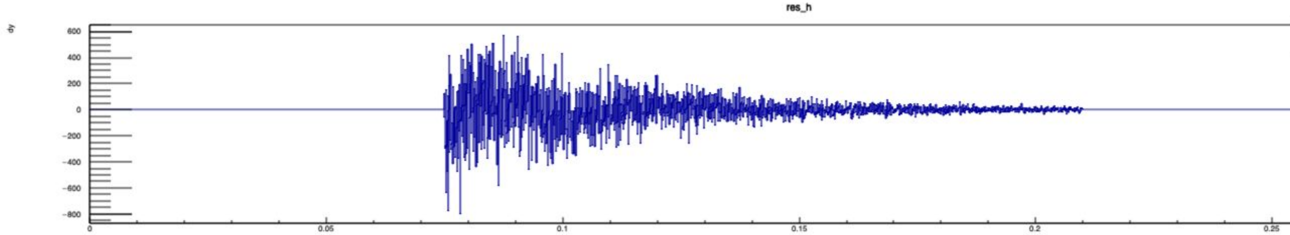
1. Chi2 Probability versus Minimum Window Used

EXAMPLE: fua23 fit (75-210 MeV)

Function on top of IMD

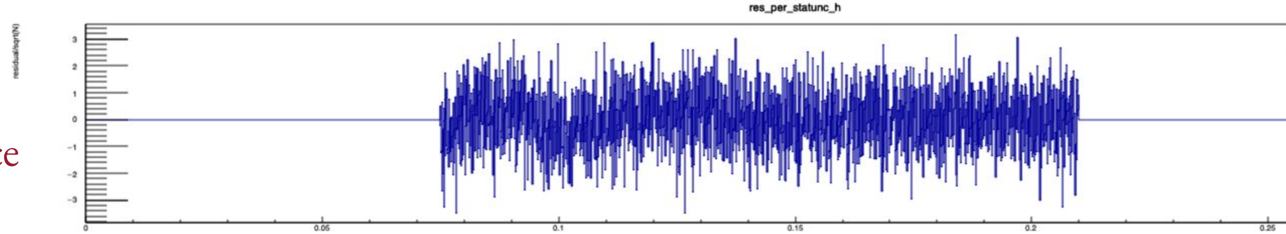


Residual Plot



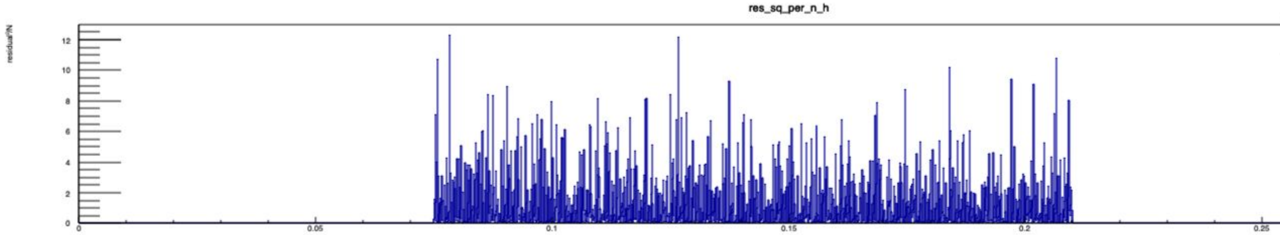
Residual / sqrt(N(m))

→ statistical significance



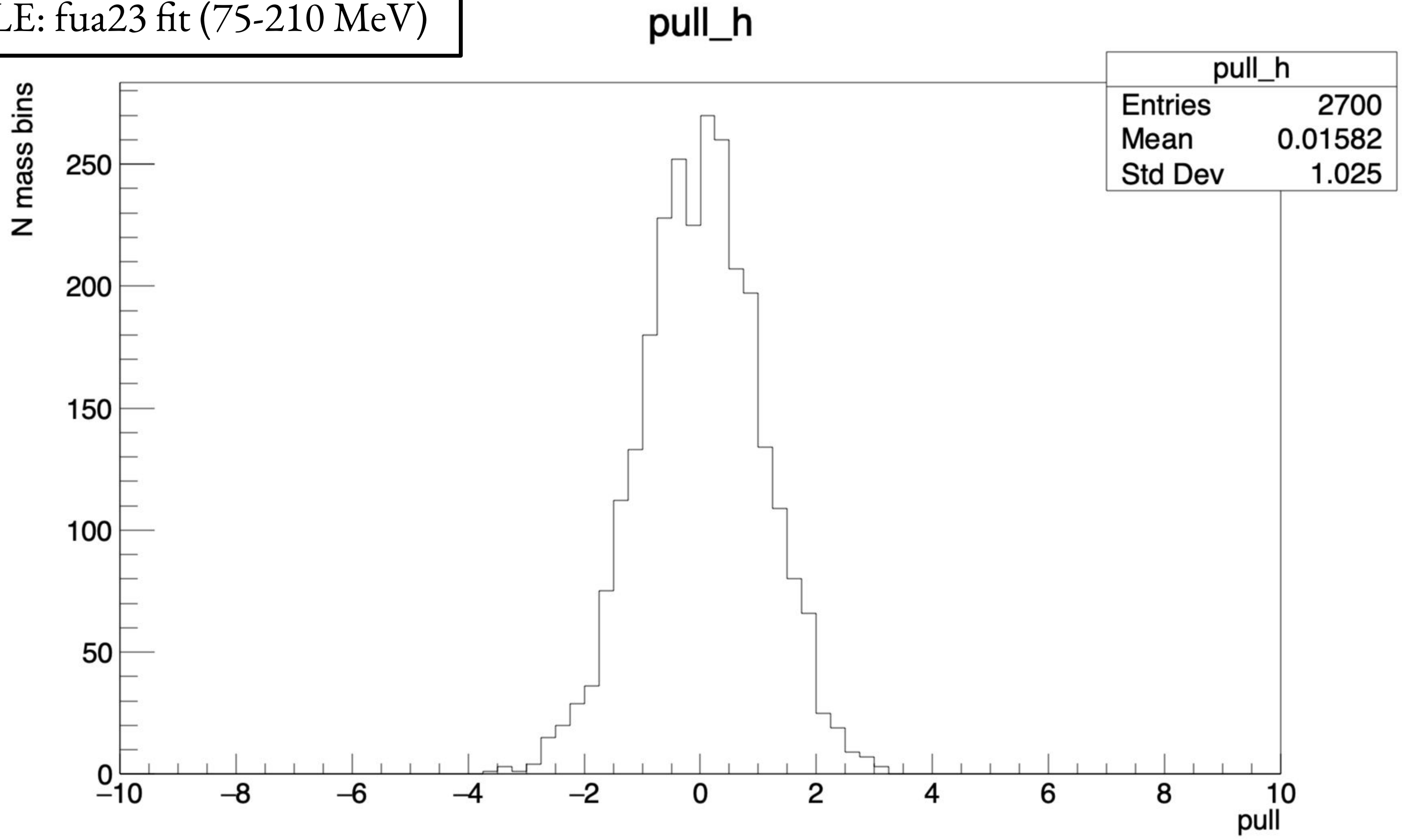
Residual^2 / (N(m))

→ sum = chi2



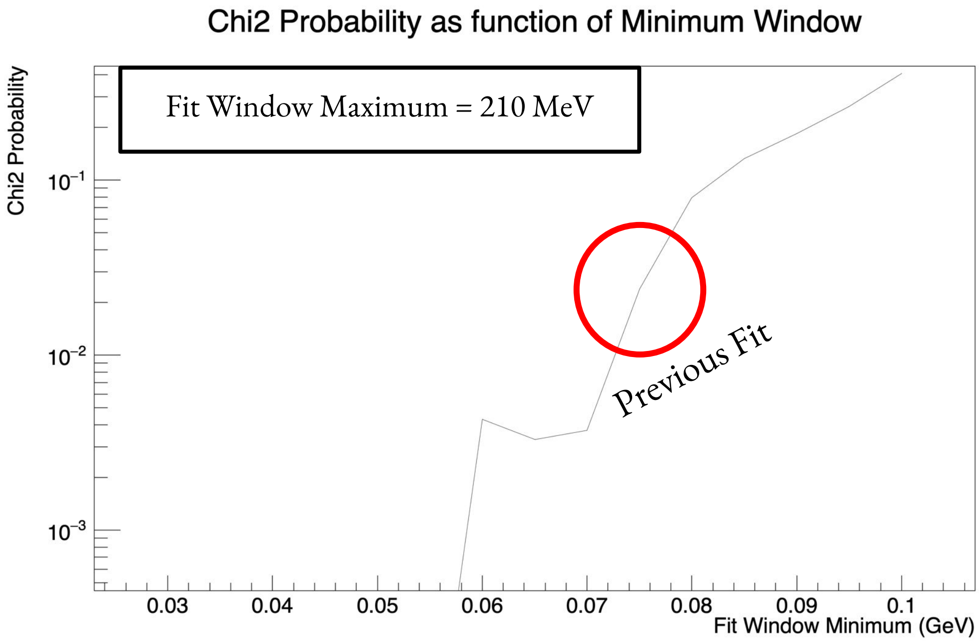
Example Continued

EXAMPLE: fua23 fit (75-210 MeV)



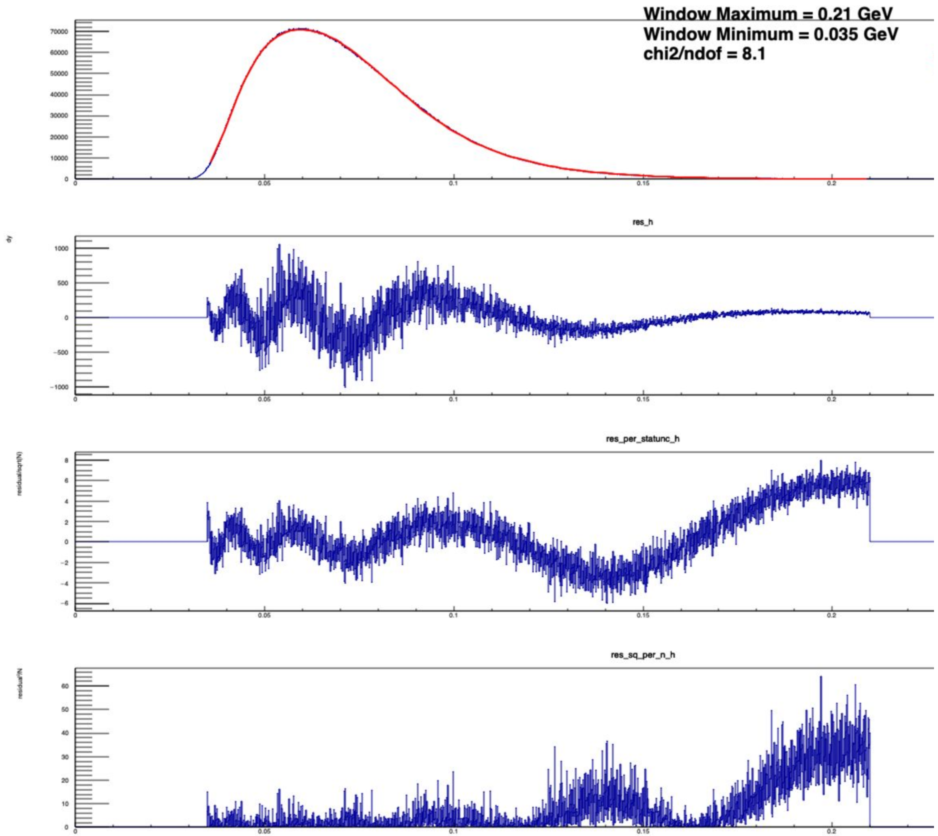
Example fua23 chi2 probability compilation

Useful abstraction for determining range of good fits for each function

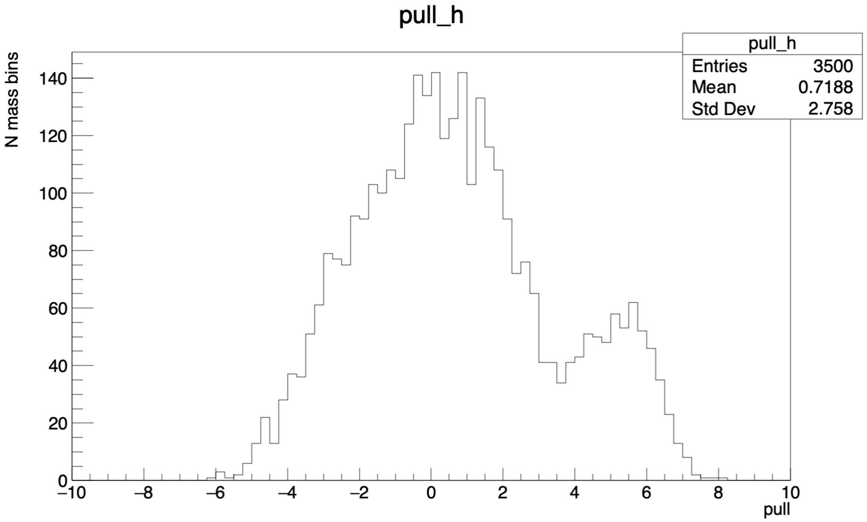


y-axis determines lower bound on the fit range, i.e. (window_minimum, window_maximum)

Poor Fit Example



Using dijet1



Preliminary Fitting Results

Error function used:

$$\mathrm{Er}(x) = \frac{1}{2}\left(\mathrm{Erf}\left(\frac{(x-[q_0])}{[q_1]}\right)+1\right)$$

Tested Functions

$$\mathrm{Er}(x)\cdot f_{\mathrm{dijet1}}(x) = \mathrm{Er}(x)\cdot \frac{p_0(1-x)^{p_1}}{x^{p_2}}$$

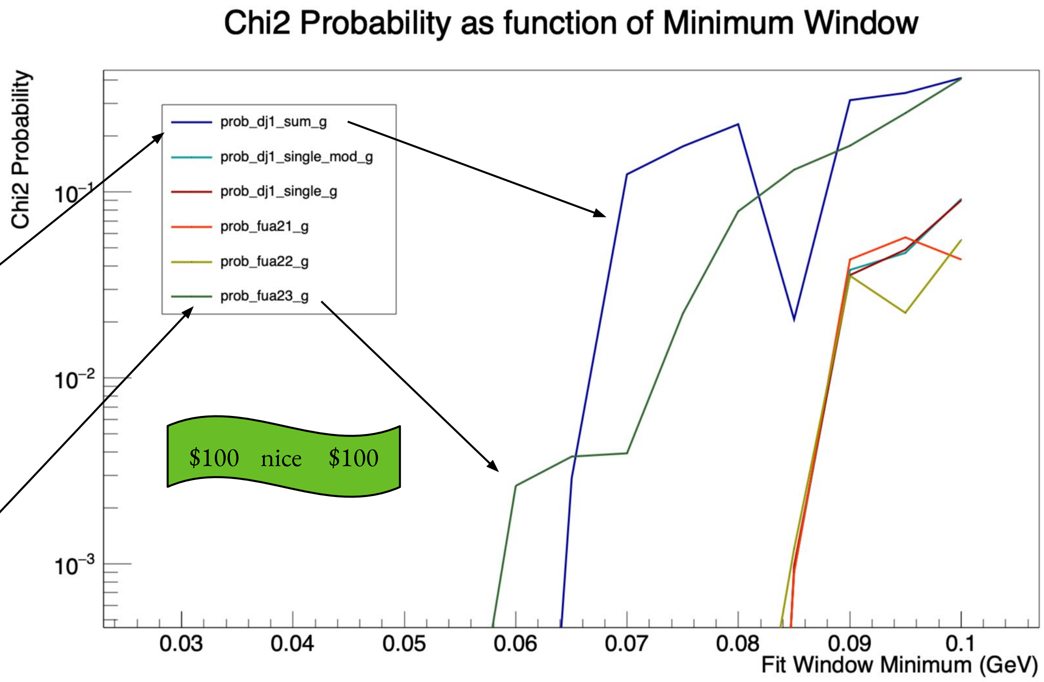
single mod ← $$\mathrm{Er}(x)\cdot \frac{p_0(p_3-x)^{p_1}}{x^{p_2}}$$

$$h(x) = \mathrm{Er}_1(x)\cdot f_{\mathrm{dijet1}}(x) + \mathrm{Er}_2(x)\cdot g_{\mathrm{dijet1}}(x)$$

$$\mathrm{Er}(x)\cdot f_{\mathrm{UA21}} = \mathrm{Er}(x)\cdot\left(p_0 x^{p_1} e^{p_2 x}\right)$$

$$\mathrm{Er}(x)\cdot f_{\mathrm{UA22}} = \mathrm{Er}(x)\cdot\left(p_0 x^{p_1} e^{p_2 x + p_3 x^2}\right)$$

$$\mathrm{Er}(x)\cdot f_{\mathrm{UA23}} = \mathrm{Er}(x)\cdot\left(p_0 x^{p_1} e^{p_2 x + p_3 x^2 + p_4 x^3}\right)$$



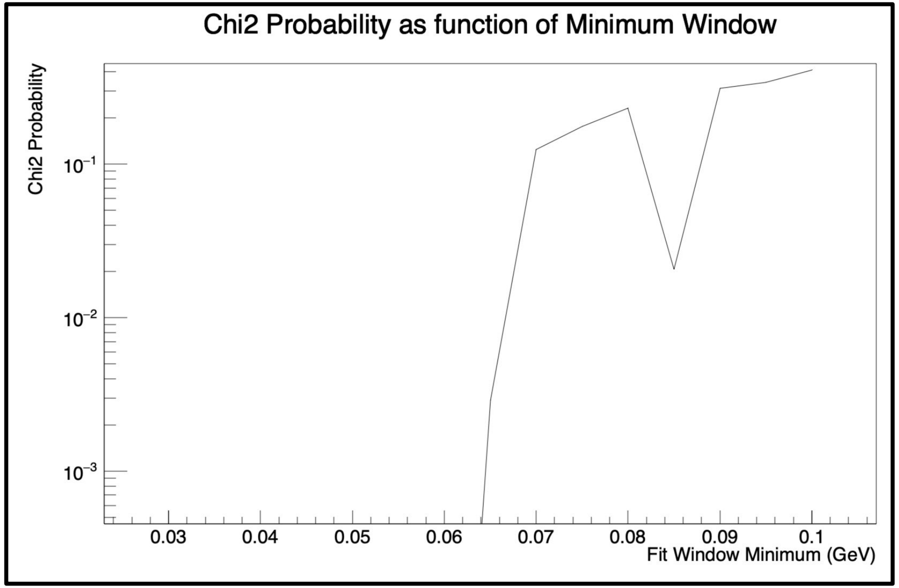
Next Steps

- determine if a function can fit the entire distribution and continue working through list
  - may find that a function works well with slightly limited range (cut out 5-10 MeV from rise and tail)
  - if this is true, how much are we willing to sacrifice for an improved fit??

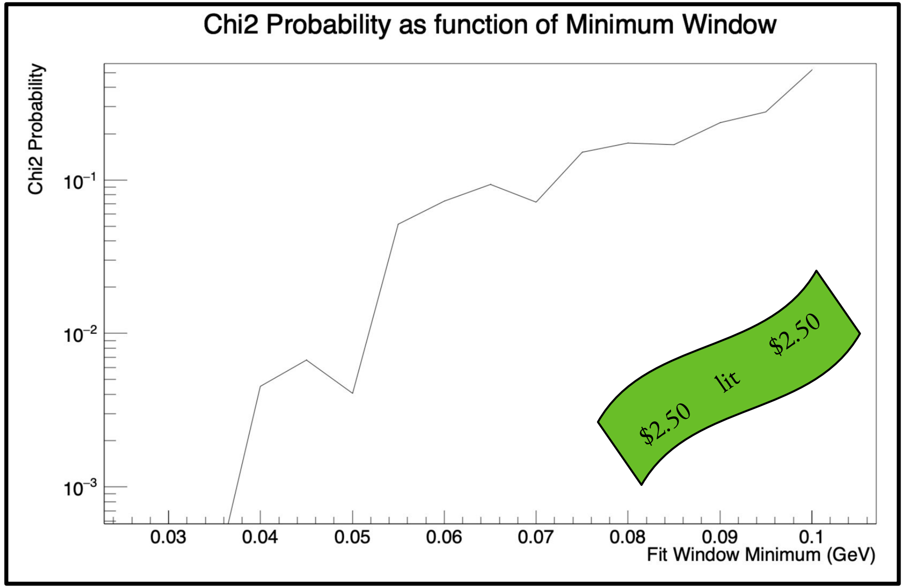
- if none of the functions seem to fit the distribution to everyone's satisfaction, may make sense to restrict the range and vary the window of the window maximum while fixing win_min
    - maybe make 2D tool to illustrate functions on optimal win_min and win_max

Preliminary Preliminary Study - Fitting the Rise

Range: **30 MeV - 210 MeV**



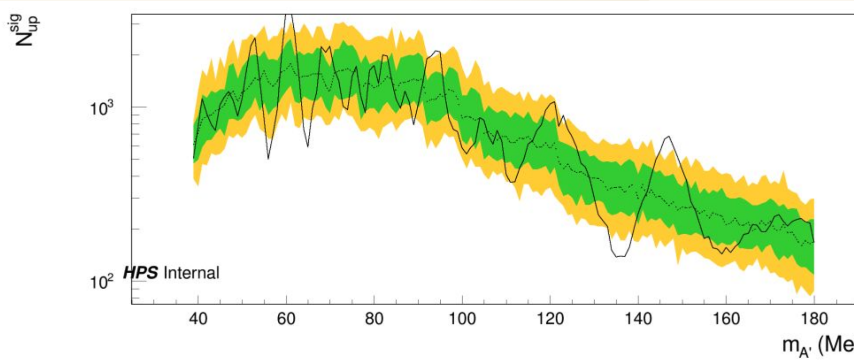
Range: **30 MeV - 110 MeV**

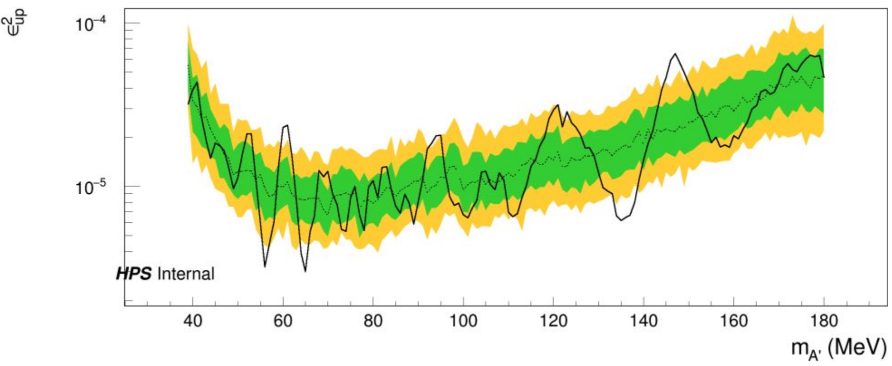


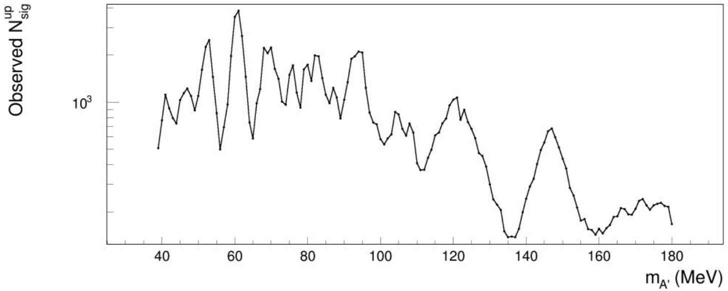
Using Dijet Sum Function

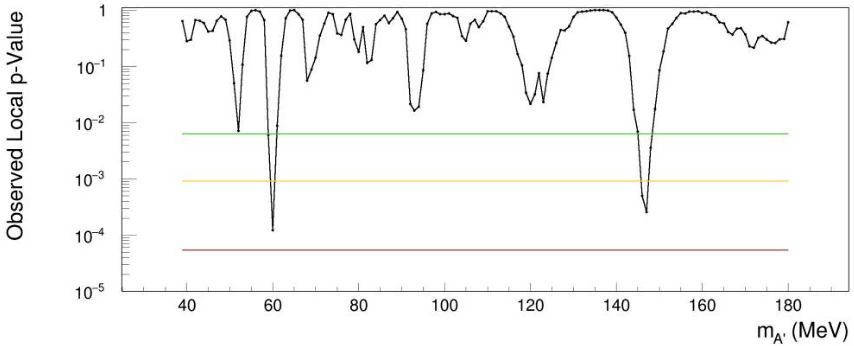
Additional Slides

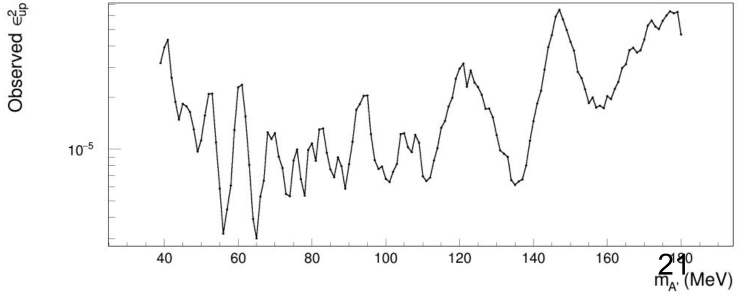
all run 7800 plots

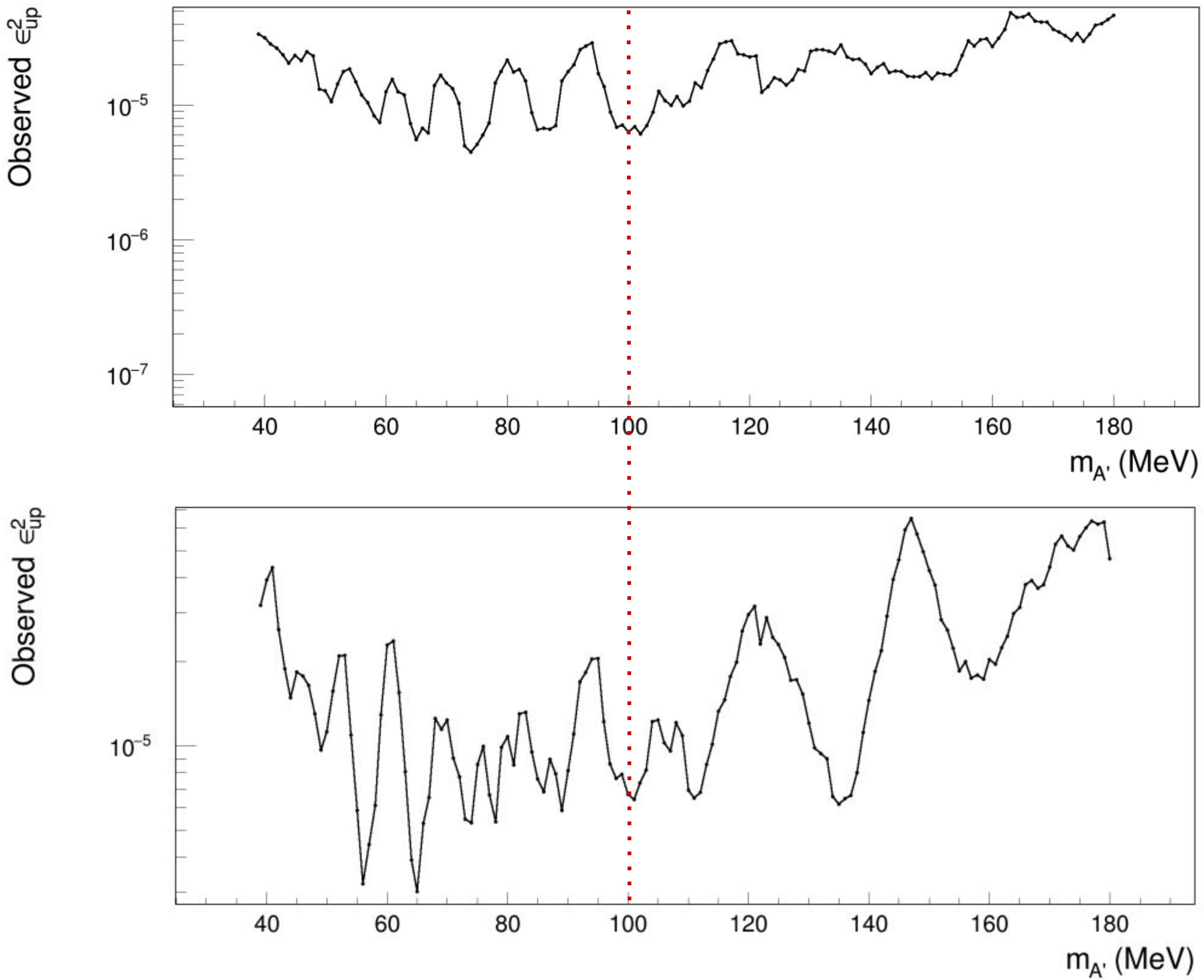




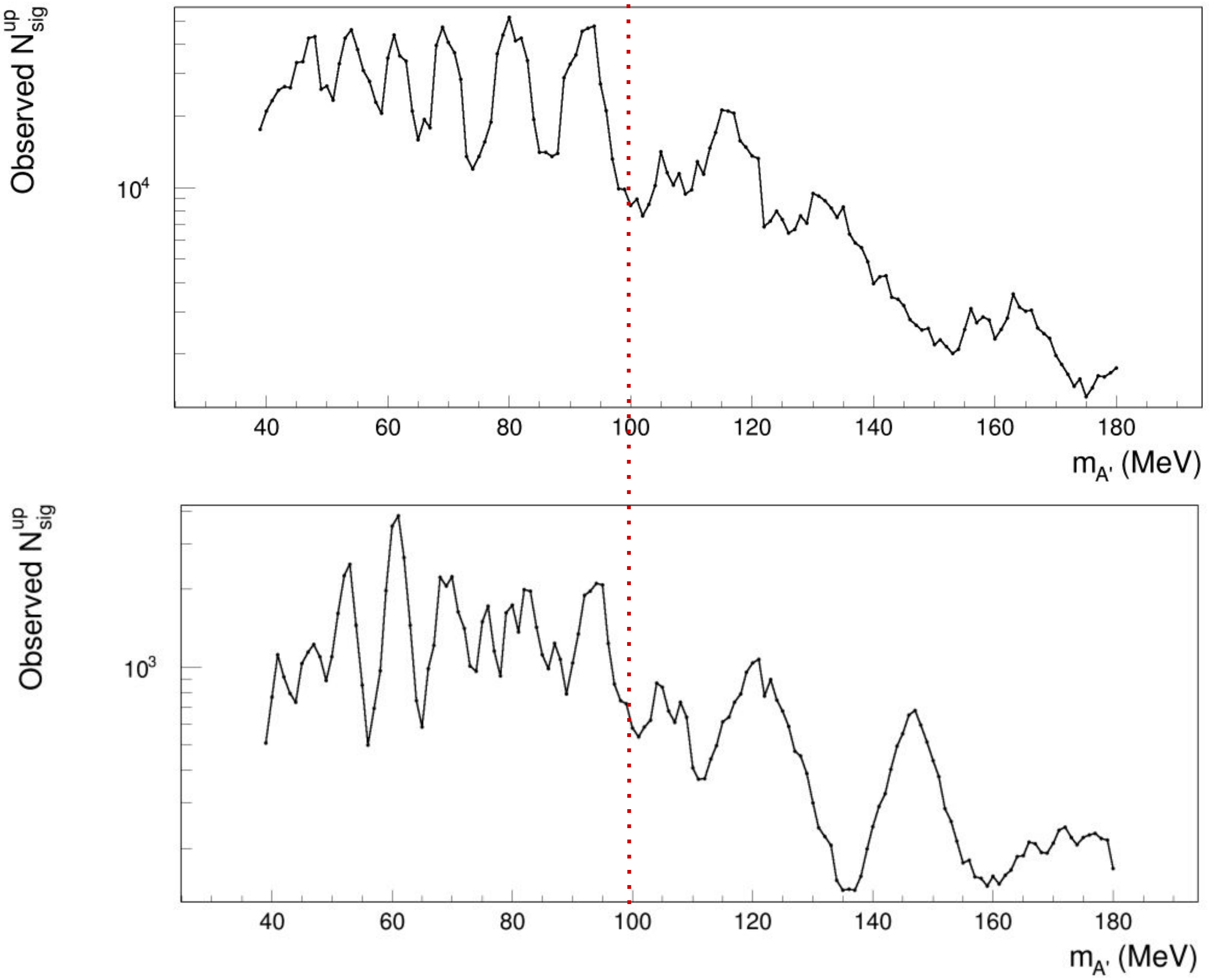








Observed ϵ^2_{up}
10^{-5}
10^{-6}
10^{-7}
40
60
80
100
120
140
160
180
$m_{A'}$ (MeV)
Observed ϵ^2_{up}
10^{-5}
40
60
80
100
120
140
160
180
$m_{A'}$ (MeV)


Observed N_{sig}^{up}
10^4
40
60
80
100
120
140
160
180
$m_{A'}$ (MeV)
Observed N_{sig}^{up}
10^3
40
60
80
100
120
140
160
180
$m_{A'}$ (MeV)

Run 7800 invariant mass distribution