

# An alternative PID and channel identification for **KaonLT** analysis

Ioana & Gabriel Niculescu,  
James Madison University

# Introduction



## As advertised in previous updates...

- in the larger context of analyzing the 10.6 GeV **KaonLT** data & extracting  $\Sigma^0/\Lambda$  ratios (possibly excited states too!)...
- (for awhile now) the JMU group worked on improving the hyperon identification (PID & channel identification)
- we are happy(-ish) to report that the latter work is done (10.6 GeV only)
- furthermore, in the process, we developed (we adapted/improved, not **invent!**) a new PID approach, which can be used in other Hall C (and A) experiments.
- ...and this is what I would like to talk about today.

## But why?

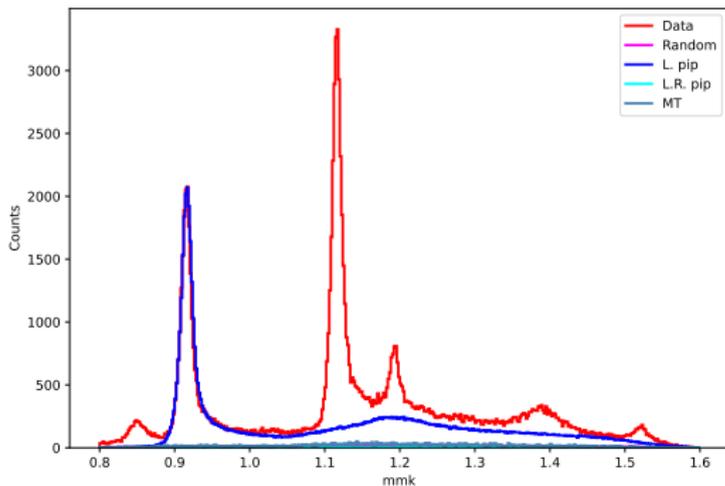
- std. ID procedure breaks down in statistically-limited bins
- can lead to biases, syst. errors unaccounted for
- so we sought a different/better/more consistent approach.

# Motivation



## “Standard” MM fit approach

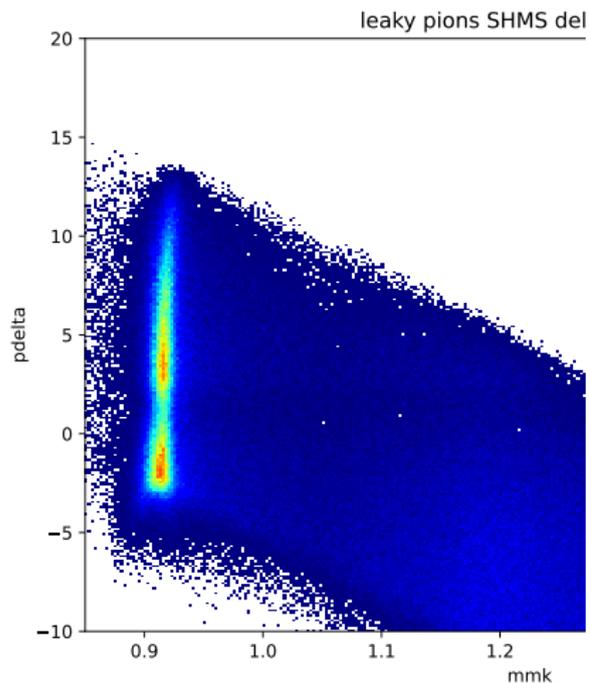
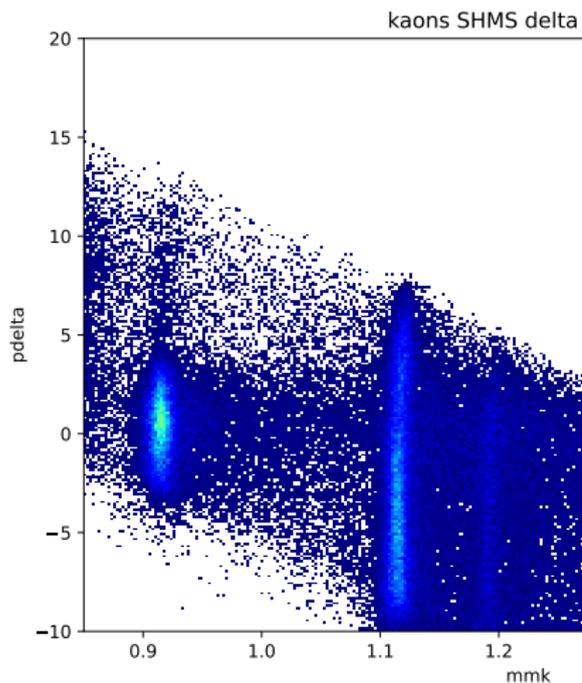
- The typical Hall C experiment (usually) involves a **2 into 3** reaction
- With only two particles detected in the final state, the third particle is **identified** using  $E$  and  $\vec{p}$  conservation constraints (i.e. missing mass plot)
- After applying cuts, this might look like this:



## then...

- subtract or not **leaky**  $\pi^+$
- also randoms, MT, etc.
- still **irreducible** bkg.
- fit peaks+bkg.
- ...for **EACH** physics bin!

(as a side note...)



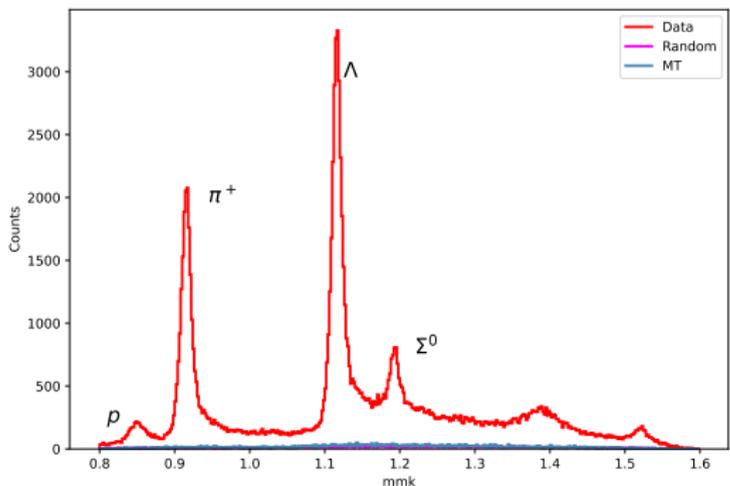
# What if we make, 12 bin in $\phi$ (for example)?

# Closely & Critically examining these slides...

## There a few undeniable (if uncomfortable) truths:

- leaky  $\pi^+$ s have completely diff. distribution, so subtracting might not be ideal
- even if subtracting..., there is still background under the peaks (**irreducible!**)
- background itself has a shape right under the peaks
- background size & shape differs from bin to bin, as do peaks!  
(physics a/o detector peculiarities...)
- inferring bkg. **things** for the whole **mm** does not help for individual bins!
- the peaks+bkg. fit need to be carried out for each bin
- ...and dwindling statistics do not help.
- Leaving aside the latter problem, let's take a look at some fits.

# Two peaks and a background...



## We shall:

- pick peak shape
- pick bkg. form
- set limits for the parameters of the above
- **adhere** to the choices!!!
- do a **mm** fit for the whole setting (no bins) (in the  $\Lambda$  &  $\Sigma^0$  region)
- ...repeatedly

# Two peaks and a background (II)

## Model selection

- there are many diff. choices for both **peak** and **background** shapes
- all of them come w/ **+**-es and **-**-es...
- which do not go away only because we happen to like a particular choice!
- on the next couple of pages...
- we list our choice & possible alternatives
- *Cave cadas!*: (choices that seem linear but aren't!)

# Peak



## Peak model:

- skewed Voigt profile - the convolution between a Cauchy–Lorentz distribution and a (skewed) Gaussian. Centered **vp**, peaking at zero:

$$V(x; \sigma, \gamma) = \int_{-\infty}^{\infty} G(x'; \sigma) L(x - x'; \gamma) dx'$$

$$G(x; \sigma) = \frac{e^{-\frac{x^2}{2\sigma^2}}}{\sqrt{2\pi}\sigma} \quad L(x; \gamma) = \frac{\gamma}{\pi(\gamma^2 + x^2)} \text{ see Wikipedia for extra details}$$

- ours uses a **skewed Gaussian** so:

$$f(x; A, \mu, \sigma, \gamma, skew) = V(x; A, \mu, \sigma, \gamma) \left( 1 + erf\left(\frac{skew(x - \mu)}{\sqrt{2}\sigma}\right) \right)$$

- NOTE:** we keep  $\gamma = \sigma$  (default option)

# Peak (II)

## Alternative peak choices:

- *Vanilla Gaussian* - only the tip of the distribution
- **Lorentzian** - might be too narrow (not account for resolution effects)
- **skewed** versions of the above (better but w/ same reservations)
- simc-based **template** fit. tempting, but beware of the *ouroboros*!



# Background

## Background model. Huge array of choices:

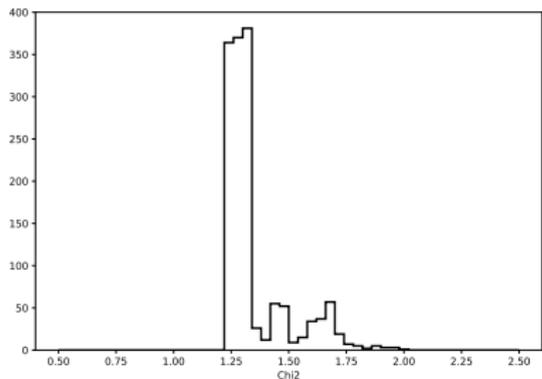
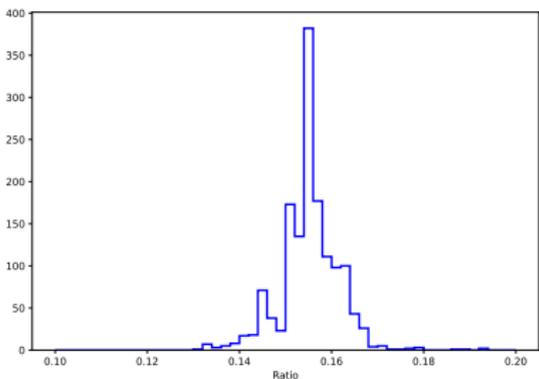
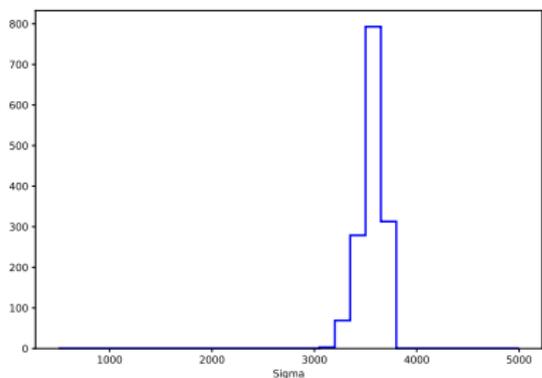
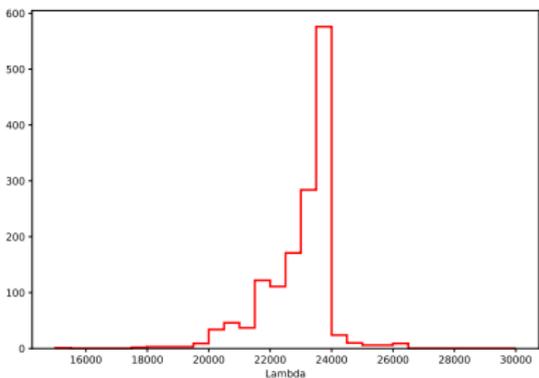
- polynomial (degree? **+**-ity constraint?)
- **Chebyshev** polynomial. better. truncated where?
- **cubic splines**. # of nodes? location??
- **template** - based on a better/more complete **simc** for bkg. proc. errors?
- **Gaussian** representation. i.e. sum of Gaussians. (how many?)
- **skewed Gaussian sum**. Our choice.

**NOTE 1:** Regardless of peak & background choice, the fit is **NOT** linear!  
Therefore the outcome will depend on the initial *ansatz* for the parameters.

**NOTE 2:** Look for yield variation within a given choice.

# w/ our choices: 10,000 fits!

# 10k 2p+bkg. Summary plots



# Therefore...

## With given choice of peak and background:

- one gets a 10–15% variation in the yield
- ...at full statistics (could get worse for smaller bins!!!)
- this is a systematic, point-to-point effect

## But wait...

- Inspired by these...

[2] M. Williams, M. Bellis, and C. A. Meyer, "Multivariate side-band subtraction using probabilistic event weights", JINST 4, P10003, 2009. (see also arXiv:0809.2548v3 [nucl-ex])

[3] P. Roy *et al* CLAS collaboration, "Measurement of single- and double- polarization observables in the photoproduction of  $\pi^+\pi^-$  meson pair off the proton using CLAS at Jefferson Laboratory", arXiv:2504.21119v1, April 2025.

[4] S. Adhikari *et al*, "Measurement of beam-recoil observables  $C_p$  and  $C_i$  for  $K^+\Lambda$  photoproduction", Phys.Rev.C, 2025

[5] Z. Baldwin, "A multidimensional, event-by-event, statistical weighting procedure for signal to background separation", EPJ web of conferences 295, 06002, 2024.

[6] M. Albrecht *et al*, "Coupled channel analysis of  $\bar{p}p \rightarrow \pi^0\pi^0\eta$ ,  $\pi^0\eta\eta$ , and  $K^+K^-\pi^0$  at 900 MeV/c and of  $\pi\pi$ -scattering data", arXiv:1909.07091v2 [hepex], 2020.

[7] Ablikim *et al*, "Evidence of doubly OZI-suppressed decay  $\eta_c \rightarrow \omega\phi$  in the radiative decay  $J/\Psi \rightarrow \gamma\eta_c$ ", arXiv:2504.01823v1, 2025.

- We think we found a better way!

# Introducing the Quality Factor Fitting (Q-fit)

## Projecting on the missing mass dimension...

- Loses all the additional information associated with the events
- The **mm** lumps together events from different portions of the acceptance
- also lumps together  $e^-K^+$  pairs w/ potentially diff.  $\vec{p}$
- which we know w/ good precision!
- Furthermore, **lumping** in 1D also exacerbates problems related to physics & detector-specific effects

# In contrast

## Q-fitting...

- Leverages the additional (high precision) information of the measurement
- It is **bin-less** (bin agnostic?)
- Provides a clear way of evaluation the uncertainties associated with the fit
- (and the systematic unc. is bin-independent!)
- Wide(-ish) spread usage in the field

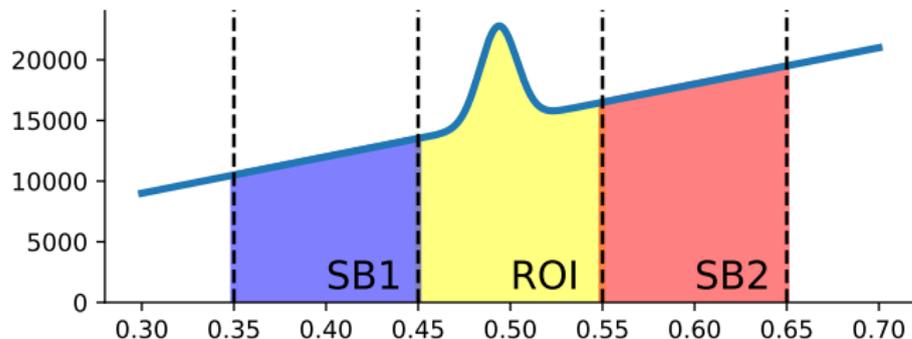
...

- Yes, it is CPU-intensive.
- But: “One cannot/doesn’t have to be stuck in the VAX/VMS era”! (IN)
- Especially given the issues of w/ the “standard” yield extraction procedure.
- **Hopefully you are interested/intrigued enough to find out more...**

# Enter the Q-fit

## Q-fit method

- aims to address the peak-over-background issue...
- by assigning a **quality factor** (Q-factor) for each event
- once found, the Q-factor can be used as a weight in further analysis
- it is (as it will become apparent later) a generalization of the **side-band** subtraction method (see below)



# Q-fit (IV)

## How does it work?

- After applying all cuts data contains **signal** and **irreducible** background
- Data is multidimensional:  $\xi_1, \xi_2, \dots, \xi_n$
- There is a dimension in which the **s** & **b** can more easily be distinguished: The reference variable,  $\xi_r$  (**mm**, **im**, **m**?). So:  $\xi_1, \xi_2, \dots, \xi_n = (\xi_r, \xi_{nr})$
- Assume\* that **s** & **b** can be parameterized, up to unknown constants, in  $\xi_r$
- No binning in  $\xi_{nr}$  is needed!
- Instead, and this is the **crux** of the method, the **N-nearest neighbors** (based on hyper-distances measured in the non-reference sub-space) of event  $i$  are used for the fit!!
- Provides statistical & systematic uncertainty associated with  $Q_i$ s

# Q-fit (V)

## How does it work? (cont...)

- Manifestly unbinned, completely circumvents the low stat. bin issues
- ...assuming that a suitable number of neighbors ( $N_n$ ) can be found
- Data-centered, minimal assumptions on  $\mathbf{s}$  or  $\mathbf{b}$
- Generally selects a **tiny** portion of phase space (simpler background shape!)
- **GN's \$0.02:** “Each event is judged (in the  $\mathbf{s}$  or  $\mathbf{b}$  sense) by a jury of its peers!”
- So an event w/, say, the electron @  $\Delta = -5\%$  is compared w/ events whose electrons are also in the same range, not at  $\Delta = 5\%$ !!
- *ditto* for all other dimensions of  $\xi_{nr}$
- **Warning:** There is math on the next slide!

# Q-fit (VI). the math.

## Some notations. Some equations.

$$d^2 = \sum_{k=1}^n \left( \frac{\xi_k^i - \xi_k^j}{r_k} \right)^2 \quad (1)$$

- hyper-distance in the non-ref. subspace,  $r_k$  - **norm** for dimension  $k$

$$R_k^i = \frac{1}{N} \sqrt{\sum_{j=0}^N \left( \frac{\xi_k^i - \xi_k^j}{r_k} \right)^2} \quad (2)$$

- reduced hyper-sphere radius** in the  $k$  coordinate
- average  $R_k^i$  for all events in the sample to get:

$$R_k = \frac{1}{M} \sum_{i=0}^M R_k^i \quad (3)$$

- the average radius of the hyper-sphere in the  $k$  coord.

# more math.

## Defining $Q_i$

- With this notation, the data distribution in  $\xi_r$  becomes:

$$f(\xi_r) = f_s \cdot S(\xi_r) + (1 - f_s) \cdot B(\xi_r) \quad (4)$$

- $f_s$ : fitted signal fraction.  $S$ : **signal**,  $B$ : **background** (duh!)
- Fit eq. 4 to the sample of  $N_n$ , obtaining the parameters for  $S$  and  $B$  **for each event** in the ROI!
- Calculate the  $Q_i$  for the event as:

$$Q_i = \frac{f_s^i \cdot S(\xi_r^i)}{f(\xi_r^i)} \quad (5)$$

- N.B.:** Eq. 5 needs to be evaluated at the  $\xi_r$  of the current event  $i$ !!
- That is it!
- Q: Does it work? A: Thank you for the question! Let's take a look.**

# Q-fit implementation details

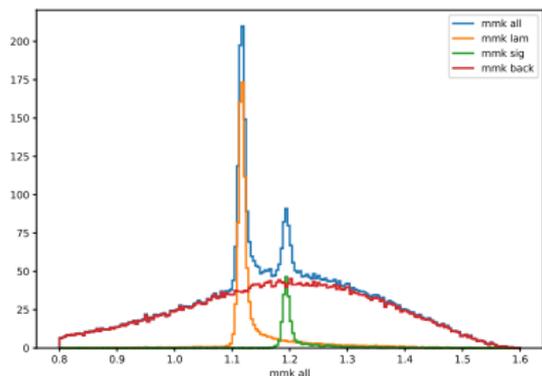
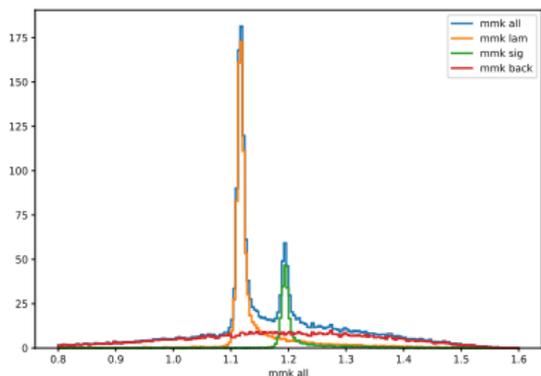
## ...in the JMU KaonLT software framework

- $\xi_r$ : **mmk**.  $\xi_{nr}$  choice: could have done  $Q^2$ ,  $W$ ,  $t$ ,  $\phi$ , etc...
- opted\* for 7D  $\xi_{nr}$ :  $E_z^{beam}$ ,  $2 \times (\Delta, x_{ptar}, y_{ptar})$  for HMS/SHMS
- tightly integrated w/ the framework  
(working on making the framework ready for release to the public!)
- most fit options controllable via config file (ROI lims,  $N_n$ , pdf output freq...)
- adds extra columns to the DST (Q#, R#e, Q#e, etc.)
- uses **lmfit** (which implements Voigt, skg, etc. already!)
- looking to add **iminuit2** option
- fairly fast (day-ish at most for the largest statistics settings)

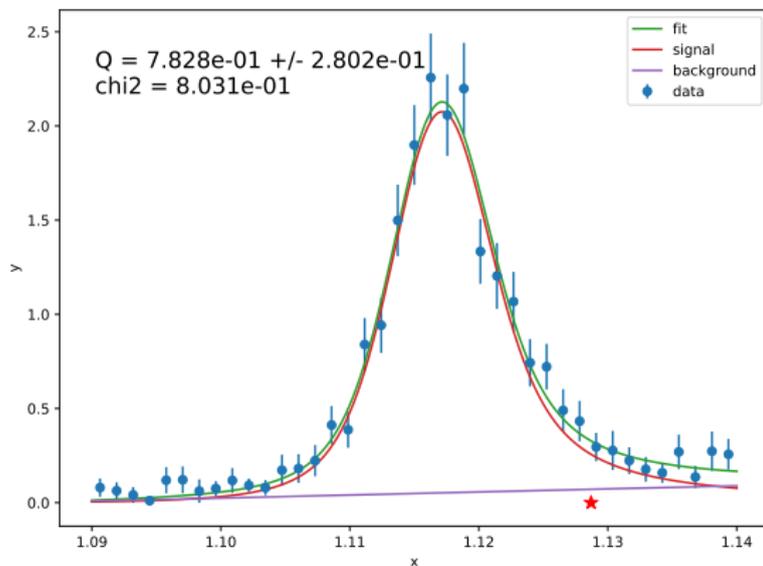
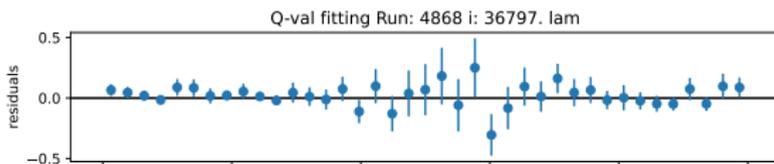
# MC validation

## To test the procedure:

- prepare a sample of  $\Lambda$ ,  $\Sigma^0$  and background **simc** events
- the latter obtained by scrambling  $e$  and  $K^+$  between events
- as we know the GT (ground truth) yield, we should be able to compare it w/ the eventual Q-fit yield.

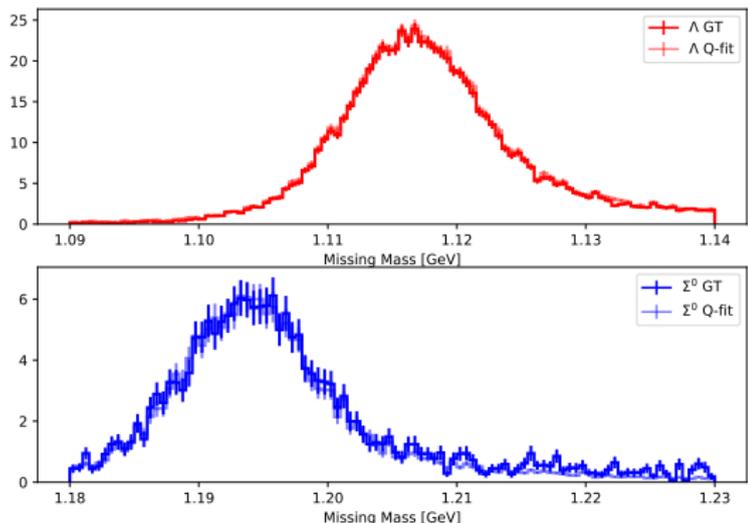


# Sample Q-fit



# $\Lambda$ and $\Sigma^0$ fits.

# simc Q-fit yields



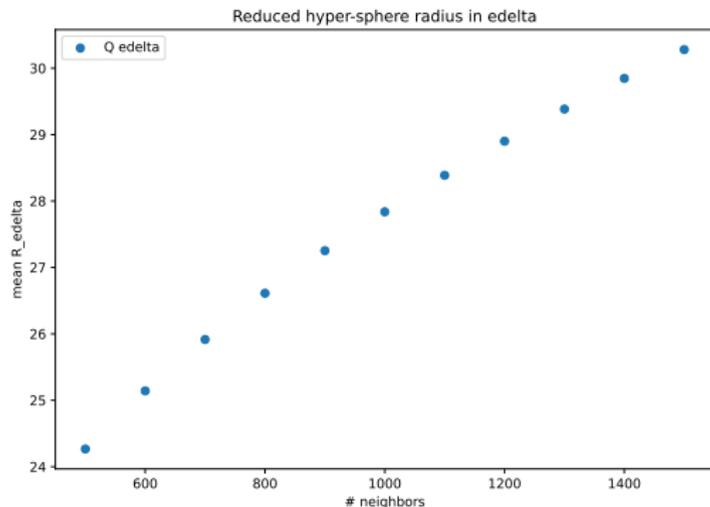
## GT & Q-fit overlay

- The Q-fitted distribution matches well the GT for both hyperons.
- Several kin. & bkg. levels: Q-fit matches GT w/ **3–5%** precision

# $N_n$ study

- redo Q-fit for several  $N_n$  choices
- examine the average hyper-sphere radius

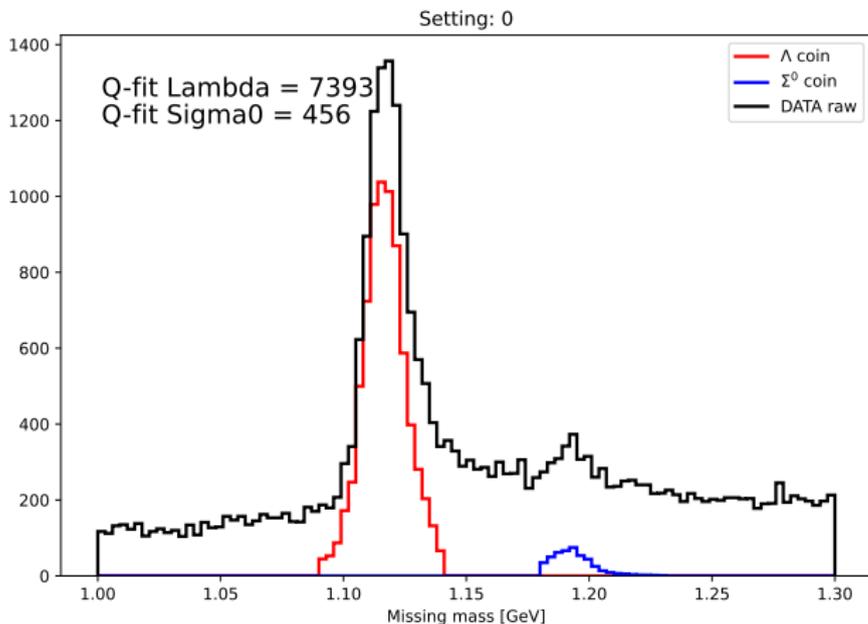
```
my_ref_var = mmk
my_var = edelta eph eth pdelta pph pth ebeamz
my_res = 5.e-2 2.e-4 2.e-4 5.e-2 2.e-4 2.e-4 5.e-5
```



So our choice of  $N_n$ , 1000, selects 1/5–1/10th of the range!

# DATA $\Lambda$ and $\Sigma^0$ fits

# Full setting signal-background separation *à la* Q-fit



- looks not too bad/plausible
- restricted to the respective ROIs (see discussion a few weeks back about data/simc tails...)

# Comparing 2-peak and Q-fit yields



Setting 0:

$$\Lambda = 7393.22$$

$$\Sigma^0 = 455.62$$

OK!

2 peak fit

$$\Lambda = 7320 \pm 399$$

$$\Sigma^0 = 449 \pm 46$$

## Translating in a more readable form...

- Setting 0:
- Q-fit yields:
- $\Lambda = 7383.22$
- $\Sigma^0 = 455.62$
- 2-peak fit:
- $\Lambda = 7329 \pm 399$
- $\Sigma^0 = 449 \pm 46$
- *q.e.d.!*





## Summary

### I hope I showed/convinced you that:

- an in-depth analysis of the “classic” yield extraction method
- reveals substantial & often neglected systematic unc.
- introduced an adapted form of the **Q-fit** method for Hall C work: unbinned, event-by-event, good syst. control
- validated **Q-fit** with **simc** events
- compares well w/ “classic” method on **KaonLT** data



### Quo Vadis?

- adapt method for excited hyperon identification
- explore **iminuit2** option
- paper (journal TBD) on the method

**THANK YOU!**