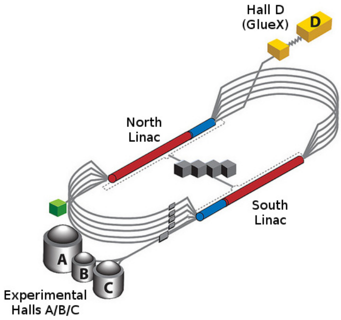
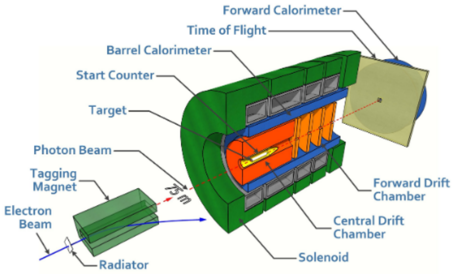
The GlueX Kinematic Fitter in $\sim$ 20 min

Daniel Lersch

May 23, 2022

The Gluonic Excitation Experiment - GlueX



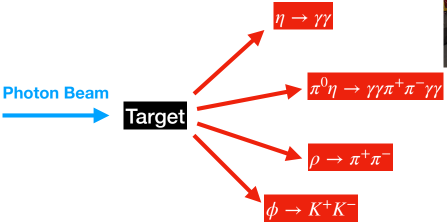


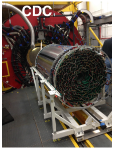
Experimental Hall D:

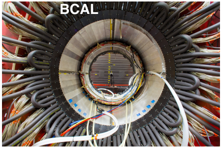
- Over 130 scientists from:
  - 30 Institutions
  - 10 Countries
- Experiments with polarized photon beam

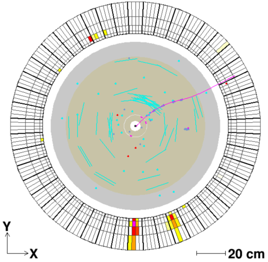
Phase	Run Period	Raw Data [PB]
GlueX-I	Spring 2017	0.9
	Spring 2018	1.9
	Fall 2018	1.1
GlueX-II	Spring 2020	2.8
	Summer 2020	1.7

Event Reconstruction









Charge q	Reconstructed via	Observables
>0, <0	FDC/CDC + mag. field	Momenta, track parameters, ddE/dx,...
0	BCAL/FCAL/CompCAL	Clusters, shower info, E,..

- **Goal:** Reconstruct entire reaction from final state particles
- Many final states particles
  - Overlapping topologies, combinatorics,... (See talk by Beni Zihlman)
  - Poorly reconstructed events
    $\to$ Need an efficient filter
- **Kinematic fit algorithm:** Information from detector + reaction hypothesis

Constrained Least Squares Fitting

- Backbone of kinematic fit algorithm

Constrained Least Squares Fitting

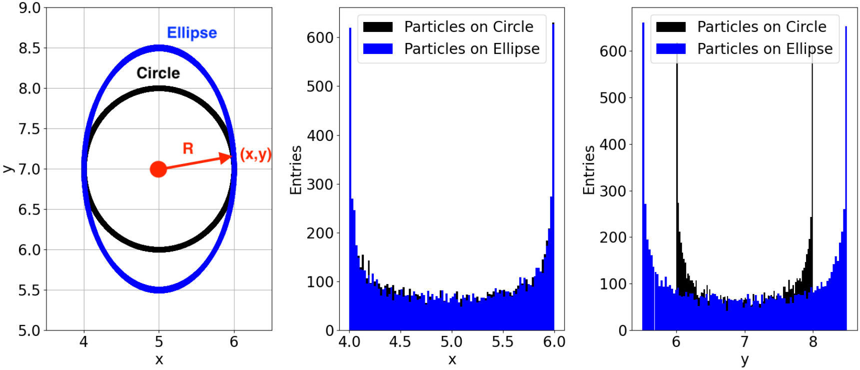
- Backbone of kinematic fit algorithm
- Requires knowledge about underlying data

Constrained Least Squares Fitting

- Backbone of kinematic fit algorithm
- Requires knowledge about underlying data
- Introduce method via a simple example: Particles in a 2D world...

  ...each particle is characterized by: $\vec{v} = \begin{pmatrix} x \\ y \end{pmatrix}$

  ...particles either live on a circle or on an ellipse

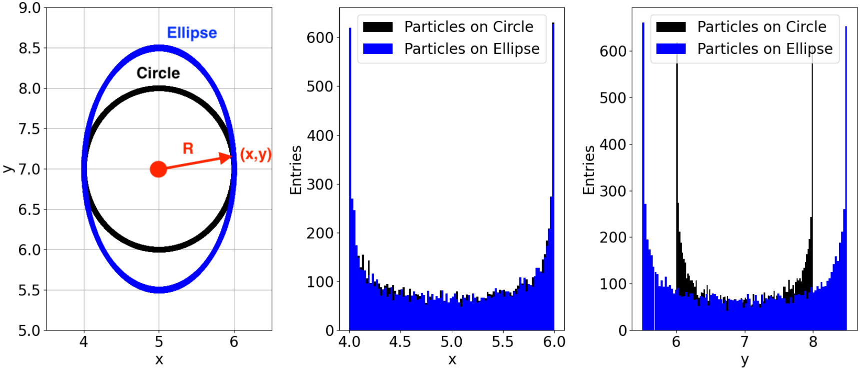


Constrained Least Squares Fitting

- Backbone of kinematic fit algorithm
- Requires knowledge about underlying data
- Introduce method via a simple example: Particles in a 2D world...

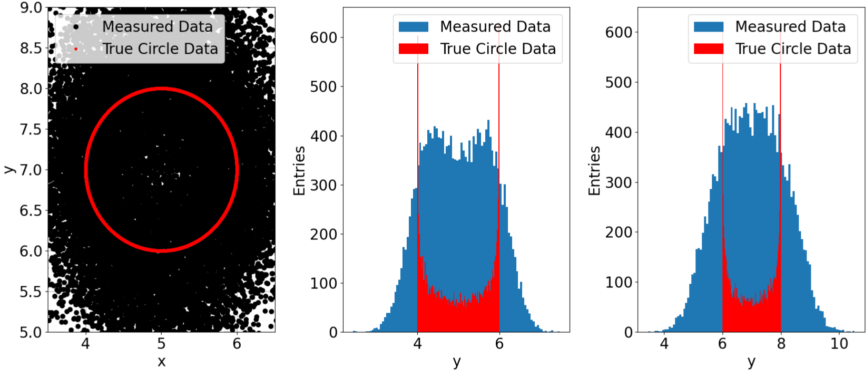
  ...each particle is characterized by: $\vec{v} = \begin{pmatrix} x \\ y \end{pmatrix}$

  ...particles either live on a circle or on an ellipse



- Measure particles with imperfect apparatus
  $\rightarrow$ finite precision: $\sigma_x \approx 0.4$ and $\sigma \approx 0.6$

Measuring 2D Particles



- Measurement not very precise
  - Altered particle distributions
  - Can not distinguish between circular and elliptic particles
- **Approach(es):**
  1. Update / buy new apparatus → Requires money and time
  2. Recover true particle information via Least Squares Fit → Requires knowledge about experiment
- Your budget got cut → Go for option 2

Least Squares Fit

- Knowing the uncertainties on x an y, one may formulate:

$$\chi^2 = \left(\frac{x - x_{fit}}{\sigma_x}\right)^2 + \left(\frac{y - y_{fit}}{\sigma_y}\right)^2 \qquad (1)$$

Least Squares Fit

- Knowing the uncertainties on x an y, one may formulate:

$$\chi^2 = \left(\frac{x - x_{fit}}{\sigma_x}\right)^2 + \left(\frac{y - y_{fit}}{\sigma_y}\right)^2 \tag{1}$$

- Just find new coordinates $\vec{v}_{fit} = (x_{fit}, y_{fit})$ which minimize Eq. 1 within the given uncertainties

Least Squares Fit

- Knowing the uncertainties on x an y, one may formulate:

$$\chi^2 = \left(\frac{x - x_{fit}}{\sigma_x}\right)^2 + \left(\frac{y - y_{fit}}{\sigma_y}\right)^2 \tag{1}$$

- Just find new coordinates $\vec{v}_{fit} = (x_{fit}, y_{fit})$ which minimize Eq. 1 within the given uncertainties
- This does not help much $\rightarrow$ Just set: $x = x_{fit}$ and $y = y_{fit}$ $\rightarrow$ No improvement

Least Squares Fit

- Knowing the uncertainties on x an y, one may formulate:

$$\chi^2 = \left(\frac{x - x_{fit}}{\sigma_x}\right)^2 + \left(\frac{y - y_{fit}}{\sigma_y}\right)^2 \tag{1}$$

- Just find new coordinates $\vec{v}_{fit} = (x_{fit}, y_{fit})$ which minimize Eq. 1 within the given uncertainties
- This does not help much $\rightarrow$ Just set: $x = x_{fit}$ and $y = y_{fit}$ $\rightarrow$ No improvement
- We need more information:
  - New coordinates need to reflect physics of the measured particles
  - Particles live on a circle: $(x_{fit} - x_c)^2 + (y_{fit} - y_c)^2 \stackrel{!}{=} R^2$

Least Squares Fit with Constraints

- Knowing the uncertainties on x an y AND the underlying physics, one may formulate:

$$\chi^2 = \left(\frac{x - x_{fit}}{\sigma_x}\right)^2 + \left(\frac{y - y_{fit}}{\sigma_y}\right)^2 + 2\lambda \cdot F(x_{fit}, y_{fit}) \tag{2}$$

Least Squares Fit with Constraints

- Knowing the uncertainties on x an y AND the underlying physics, one may formulate:

$$\chi^2 = \left(\frac{x - x_{fit}}{\sigma_x}\right)^2 + \left(\frac{y - y_{fit}}{\sigma_y}\right)^2 + 2\lambda \cdot F(x_{fit}, y_{fit}) \qquad (2)$$

with: $F(x_{fit}, y_{fit}) = (x_{fit} - x_c)^2 + (y_{fit} - y_c)^2 - R^2$

$F(x_{fit}, y_{fit}) = 0$, if new particle coordinates are on a circle

Least Squares Fit with Constraints

- Knowing the uncertainties on x an y AND the underlying physics, one may formulate:

$$\chi^2 = \left(\frac{x - x_{fit}}{\sigma_x}\right)^2 + \left(\frac{y - y_{fit}}{\sigma_y}\right)^2 + 2\lambda \cdot F(x_{fit}, y_{fit}) \tag{2}$$

  with: $F(x_{fit}, y_{fit}) = (x_{fit} - x_c)^2 + (y_{fit} - y_c)^2 - R^2$

  $F(x_{fit}, y_{fit}) = 0$, if new particle coordinates are on a circle

- λ is the *Lagrange-Multiplier* (and a free fit parameter)

Least Squares Fit with Constraints

- Knowing the uncertainties on x an y AND the underlying physics, one may formulate:

$$\chi^2 = \left(\frac{x - x_{fit}}{\sigma_x}\right)^2 + \left(\frac{y - y_{fit}}{\sigma_y}\right)^2 + 2\lambda \cdot F(x_{fit}, y_{fit}) \tag{2}$$

  with: $F(x_{fit}, y_{fit}) = (x_{fit} - x_c)^2 + (y_{fit} - y_c)^2 - R^2$

  $F(x_{fit}, y_{fit}) = 0$, if new particle coordinates are on a circle

- λ is the *Lagrange-Multiplier* (and a free fit parameter)
- Find new the new coordinates $\vec{v}_{fit} = (x_{fit}, y_{fit})$ by minimizing Eq. 2:

$$\frac{\partial\chi^2}{\partial\vec{v}_{fit}} = \left(\frac{\partial\chi^2}{\partial x_{fit}}, \frac{\partial\chi^2}{\partial y_{fit}}\right) = 0 \tag{3}$$

Least Squares Fit with Constraints

- Knowing the uncertainties on x an y AND the underlying physics, one may formulate:

$$\chi^2 = \left(\frac{x - x_{fit}}{\sigma_x}\right)^2 + \left(\frac{y - y_{fit}}{\sigma_y}\right)^2 + 2\lambda \cdot F(x_{fit}, y_{fit}) \quad (2)$$

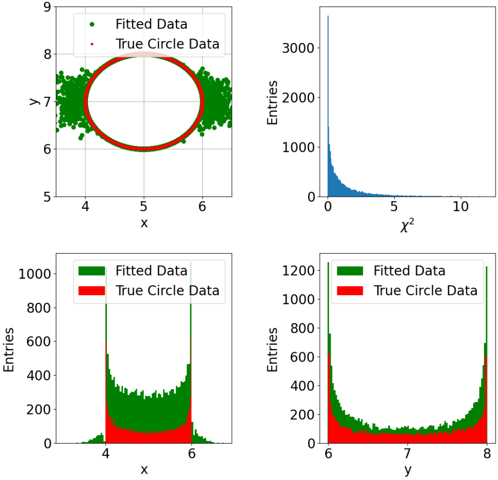
  with: $F(x_{fit}, y_{fit}) = (x_{fit} - x_c)^2 + (y_{fit} - y_c)^2 - R^2$

  $F(x_{fit}, y_{fit}) = 0$, if new particle coordinates are on a circle
- λ is the *Lagrange-Multiplier* (and a free fit parameter)
- Find new the new coordinates $\vec{v}_{fit} = (x_{fit}, y_{fit})$ by minimizing Eq. 2:

$$\frac{\partial \chi^2}{\partial \vec{v}_{fit}} = \left(\frac{\partial \chi^2}{\partial x_{fit}}, \frac{\partial \chi^2}{\partial y_{fit}}\right) = 0 \quad (3)$$

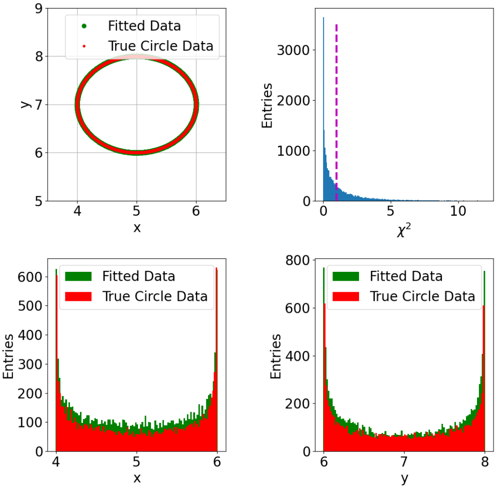
- The details of the (iterative) minimization routine can be found in the backup slides of this talk

Results from Least Squares Fit



- Fitted particle coordinates resemble a circle
- Recovered true information via constrained least squares fit

Results from Least Squares Fit



- Fitted particle coordinates resemble a circle
- Recovered true information via constrained least squares fit
- Further background removal via: $\chi^2 \leq 1.0$

From Circles to entire Physics Reactions

- Constrained least squares fitting is very successful, just needed:
  1. Uncertainties related to measurements
  2. Constraints, i.e. physics
- Use this technique to find particle coordinates for an entire physics reaction!

Particles	Coordinates	Uncertainties	Constraints
on a circle	(x, y)	σ_x,σ_y	$(x_{fit} - x_c)^2 + (y_{fit} - y_c)^2 - R^2 = 0$
from a reaction	(p, θ, ϕ, m)	$\sigma(p)$, $\sigma(\theta)$, $\sigma(\phi)$	Energy and momentum conservation
	(X, Y, Z)	$\sigma(X)$, $\sigma(Y)$, $\sigma(Y)$	Production vertex
	M	Γ	Mass of decaying particle

Kinematic Fitting at GlueX

- Master equation

$$\chi^2 = \boldsymbol{\epsilon}^T \hat{V}^{-1} \boldsymbol{\epsilon} + 2\boldsymbol{\lambda}^T \boldsymbol{F} \tag{4}$$

Kinematic Fitting at GlueX

- Master equation

$$\chi^2 = \boldsymbol{\epsilon}^T \hat{V}^{-1} \boldsymbol{\epsilon} + 2\boldsymbol{\lambda}^T \boldsymbol{F} \tag{4}$$

- Residuals: $\boldsymbol{\epsilon} \equiv \begin{pmatrix} p_{fit,1} - p_{meas,1} \\ \theta_{fit,1} - \theta_{meas,1} \\ \vdots \\ \phi_{fit,N} - \phi_{meas,N} \end{pmatrix} \in \mathbb{R}^{3N}$

Kinematic Fitting at GlueX

- Master equation

$$\chi^2 = \boldsymbol{\epsilon}^T \hat{V}^{-1} \boldsymbol{\epsilon} + 2\boldsymbol{\lambda}^T \boldsymbol{F} \tag{4}$$

- Residuals: $\boldsymbol{\epsilon} \equiv \begin{pmatrix} p_{fit,1} - p_{meas,1} \\ \theta_{fit,1} - \theta_{meas,1} \\ \vdots \\ \phi_{fit,N} - \phi_{meas,N} \end{pmatrix} \in \mathbb{R}^{3N}$

- Uncertainties from experiment:

$$\hat{V} = \begin{pmatrix} \sigma^2(p_1) & \rho_{p_1,\theta_1}\sigma(p_1)\sigma(\theta_1) & \cdots & \rho_{p_1,\phi_{3N}}\sigma(p_1)\sigma(\phi_{3N}) \\ \rho_{p_1,\theta_1}\sigma(p_1)\sigma(\theta_1) & \sigma^2(\theta_1) & \cdots & \rho_{\theta_2,\phi_{3N}}\sigma(\theta_1)\sigma(\phi_{3N}) \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{p_1,\phi_{3N}}\sigma(p_1)\sigma(\phi_{3N}) & \rho_{\theta_2,\phi_{3N}}\sigma(\theta_1)\sigma(\phi_{3N}) & \cdots & \sigma^2(\phi_{3N}) \end{pmatrix}$$

Kinematic Fitting at GlueX

- Master equation

$$\chi^2 = \boldsymbol{\epsilon}^T \hat{V}^{-1} \boldsymbol{\epsilon} + 2\boldsymbol{\lambda}^T \boldsymbol{F} \tag{4}$$

- Residuals: $\boldsymbol{\epsilon} \equiv \begin{pmatrix} p_{fit,1} - p_{meas,1} \\ \theta_{fit,1} - \theta_{meas,1} \\ \vdots \\ \phi_{fit,N} - \phi_{meas,N} \end{pmatrix} \in \mathbb{R}^{3N}$

- Uncertainties from experiment:

$$\hat{V} = \begin{pmatrix} \sigma^2(p_1) & \rho_{p_1,\theta_1}\sigma(p_1)\sigma(\theta_1) & \cdots & \rho_{p_1,\phi_{3N}}\sigma(p_1)\sigma(\phi_{3N}) \\ \rho_{p_1,\theta_1}\sigma(p_1)\sigma(\theta_1) & \sigma^2(\theta_1) & \cdots & \rho_{\theta_2,\phi_{3N}}\sigma(\theta_1)\sigma(\phi_{3N}) \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{p_1,\phi_{3N}}\sigma(p_1)\sigma(\phi_{3N}) & \rho_{\theta_2,\phi_{3N}}\sigma(\theta_1)\sigma(\phi_{3N}) & \cdots & \sigma^2(\phi_{3N}) \end{pmatrix}$$

- Reaction specific constraints: $\boldsymbol{F}$

Kinematic Fitting at GlueX

- Master equation

$$\chi^2 = \boldsymbol{\epsilon}^T \hat{V}^{-1} \boldsymbol{\epsilon} + 2\boldsymbol{\lambda}^T \boldsymbol{F} \quad (4)$$

- Residuals: $\boldsymbol{\epsilon} \equiv \begin{pmatrix} p_{fit,1} - p_{meas,1} \\ \theta_{fit,1} - \theta_{meas,1} \\ \vdots \\ \phi_{fit,N} - \phi_{meas,N} \end{pmatrix} \in \mathbb{R}^{3N}$

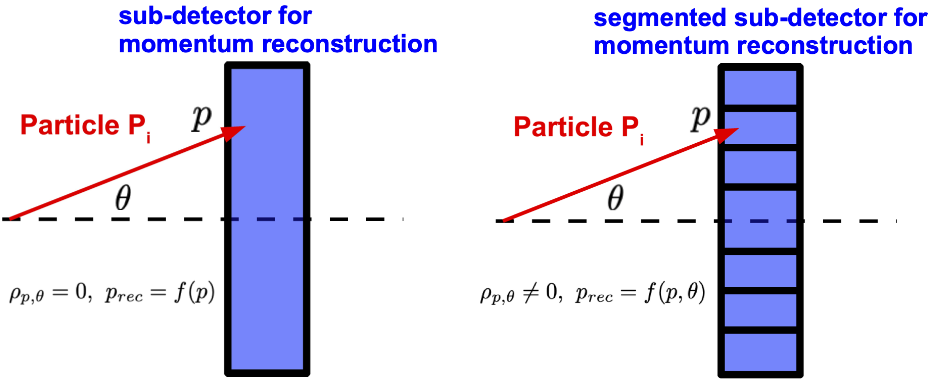
- Uncertainties from experiment:

$$\hat{V} = \begin{pmatrix} \sigma^2(p_1) & \rho_{p_1,\theta_1}\sigma(p_1)\sigma(\theta_1) & \cdots & \rho_{p_1,\phi_{3N}}\sigma(p_1)\sigma(\phi_{3N}) \\ \rho_{p_1,\theta_1}\sigma(p_1)\sigma(\theta_1) & \sigma^2(\theta_1) & \cdots & \rho_{\theta_2,\phi_{3N}}\sigma(\theta_1)\sigma(\phi_{3N}) \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{p_1,\phi_{3N}}\sigma(p_1)\sigma(\phi_{3N}) & \rho_{\theta_2,\phi_{3N}}\sigma(\theta_1)\sigma(\phi_{3N}) & \cdots & \sigma^2(\phi_{3N}) \end{pmatrix}$$

- Reaction specific constraints: $\boldsymbol{F}$
- Find $\boldsymbol{\epsilon}$ by solving:

$$\frac{d\chi^2}{d\boldsymbol{\epsilon}} = 0 \quad (5)$$

Know your Detector - Know your Covariance Matrix $\hat{V}$



- **Left:** Detector response is uniform with respect to $\theta \rightarrow$ Reconstructed momentum p_{rec} does not depend on
- **Right:** Detector response is not uniform with respect to $\theta \rightarrow$ Reconstructed momentum p_{rec} depends on θ

Covariance Matrix, Constraints and NDF

- Covariance matrix $\hat{V}$ is determined for every event and every particle

Particle Charge	Track Info	Dimension of $\hat{V}$
$q \neq 0$	P_x, P_y, P_z, X_x, X_y, X_z, t	7×7
$q = 0$	X_x, X_y, X_z, E, t	5×5

Covariance Matrix, Constraints and NDF

- Covariance matrix $\hat{V}$ is determined for every event and every particle

Particle Charge	Track Info	Dimension of $\hat{V}$
$q \neq 0$	$P_x,\ P_y,\ P_z,\ X_x,\ X_y,\ X_z,\ t$	7×7
$q = 0$	$X_x,\ X_y,\ X_z,\ E,\ t$	5×5

- Basic constraints:

Fit Type	Constraint	Observable used
P4-Fit	$\sum_{i=1}^{N} P_{i,\mu} = 0,\ \mu = x, y, z, E$	$P_\mu,\ \mu = x, y, z,\ m$
P4-Vertex-Fit	$\sum_{i=1}^{N} P_{i,\mu} = 0,\ \sum_{i=1}^{N} X_{i,\mu} = 0\ ,\ \mu = x, y, z, (E)$	$P_\mu,\ X_\mu\ ,\mu = x, y, z,\ m$
Vertex-Fit	$\sum_{i=1}^{N} X_{i,\mu} = 0$	$X_\mu\ ,\mu = x, y, z$

Covariance Matrix, Constraints and NDF

- Covariance matrix $\hat{V}$ is determined for every event and every particle

Particle Charge	Track Info	Dimension of $\hat{V}$
$q \neq 0$	$P_x,\ P_y,\ P_z,\ X_x,\ X_y,\ X_z,\ t$	7×7
$q = 0$	$X_x,\ X_y,\ X_z,\ E,\ t$	5×5

- Basic constraints:

Fit Type	Constraint	Observable used
P4-Fit	$\sum_{i=1}^{N} P_{i,\mu} = 0,\ \mu = x, y, z, E$	$P_\mu,\ \mu = x, y, z,\ m$
P4-Vertex-Fit	$\sum_{i=1}^{N} P_{i,\mu} = 0,\ \sum_{i=1}^{N} X_{i,\mu} = 0\ ,\ \mu = x, y, z, (E)$	$P_\mu,\ X_\mu\ , \mu = x, y, z,\ m$
Vertex-Fit	$\sum_{i=1}^{N} X_{i,\mu} = 0$	$X_\mu\ , \mu = x, y, z$

- Number of degrees of freedom: NDF$= N_m - 3N + N_c$

  N: Number of all particles in the reaction
  N_m: Number of measured observables
  N_c: Number of constraints

Covariance Matrix, Constraints and NDF

- Covariance matrix $\hat{V}$ is determined for every event and every particle

Particle Charge	Track Info	Dimension of $\hat{V}$
$q \neq 0$	$P_x,\ P_y,\ P_z,\ X_x,\ X_y,\ X_z,\ t$	7×7
$q = 0$	$X_x,\ X_y,\ X_z,\ E,\ t$	5×5

- Basic constraints:

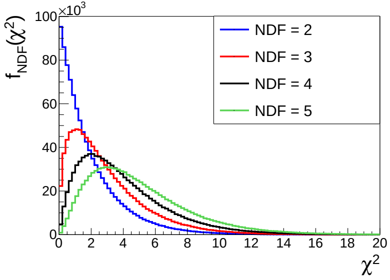
Fit Type	Constraint	Observable used
P4-Fit	$\sum_{i=1}^{N} P_{i,\mu} = 0,\ \mu = x, y, z, E$	$P_\mu,\ \mu = x, y, z,\ m$
P4-Vertex-Fit	$\sum_{i=1}^{N} P_{i,\mu} = 0,\ \sum_{i=1}^{N} X_{i,\mu} = 0\ ,\ \mu = x, y, z, (E)$	$P_\mu,\ X_\mu\ , \mu = x, y, z,\ m$
Vertex-Fit	$\sum_{i=1}^{N} X_{i,\mu} = 0$	$X_\mu\ , \mu = x, y, z$

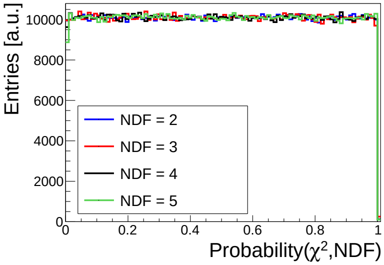
- Number of degrees of freedom: NDF$= N_m - 3N + N_c$

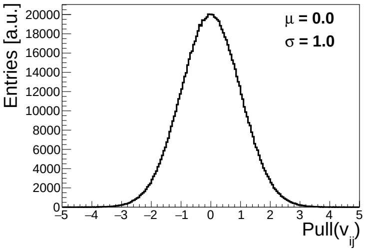
  N: Number of all particles in the reaction
  N_m: Number of measured observables
  N_c: Number of constraints

- **Example:** All particles measured + P4-Fit
  $\Rightarrow$ NDF $= N_m - 3N + N_c = 3N - 3N + 4 = 4$

Performance Monitoring Tools

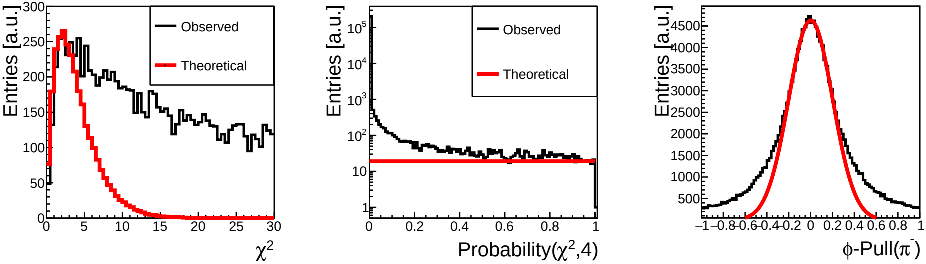






- Expected distributions for gaussian errors and independent measurements
- $f_{NDF}(x) = \frac{x^{(NDF/2-1)}}{2^{(NDF/2)}\Gamma(NDF/2)} \cdot e^{-x/2}$
- $\text{Probability}(\chi^2, NDF) = \frac{\int_{\chi^2}^{\infty} t^{NDF/2-1} e^{-t/2} dt}{\sqrt{2^{NDF}\Gamma(NDF/2)}}$
- $\text{Pull}(v_{ij}) = \frac{v_{meas,ij} - v_{fit,ij}}{\sqrt{|\sigma^2_{meas,ij} - \sigma^2_{fit,ij}|}}$

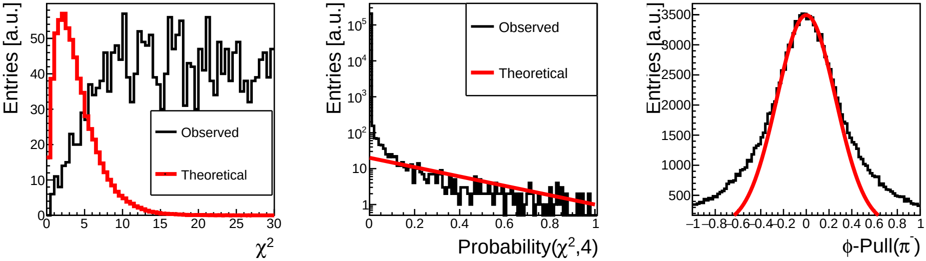
Impact of Error Estimation in $\hat{V}$



mean[ϕ-Pull(π^-)]	≈ 0
σ[ϕ-Pull(π^-)]	0.201

- Look at toy data set: $pp \to pp\eta[\eta \to \pi^+\pi^-\pi^0[\pi^0 \to \gamma\gamma]]$
- Measured particle observables are correlated
- Realistic error estimation for $\hat{V}$

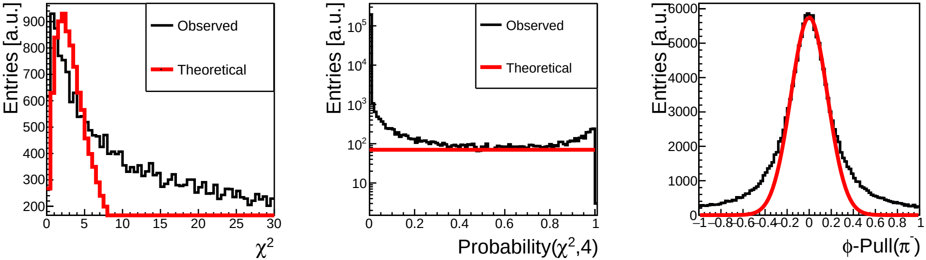
Impact of Error Estimation in $\hat{V}$



mean[ϕ-Pull(π^-)]	≈ 0
σ[ϕ-Pull(π^-)]	0.257

- Look at toy data set:
  $pp \rightarrow pp\eta[\eta \rightarrow \pi^+\pi^-\pi^0[\pi^0 \rightarrow \gamma\gamma]]$
- Measured particle observables are correlated
- Underestimated errors by $\sim 25\%$

Impact of Error Estimation in $\hat{V}$



mean[ϕ-Pull(π^-)]	≈ 0
σ[ϕ-Pull(π^-)]	0.165

- Look at toy data set: $pp \rightarrow pp\eta[\eta \rightarrow \pi^+\pi^-\pi^0[\pi^0 \rightarrow \gamma\gamma]]$
- Measured particle observables are correlated
- Overestimated errors by $\sim 25\%$

In a Nutshell

$$\chi^2 = \underbrace{\boxed{\epsilon^T \hat{V}^{-1} \epsilon}}_{\text{Inputs from experiment}} + \underbrace{\boxed{2\lambda^T \boldsymbol{F}}}_{\text{Inputs from physics}} \stackrel{!}{=} 0$$

Kinematic Fit provides:

1. Fitted particle 4-momenta

2. Possibility to reject events which do not match the reaction hypothesis

In a Nutshell

$$\chi^2 = \underbrace{\boxed{\epsilon^T \hat{V}^{-1} \epsilon}}_{\text{Inputs from experiment}} + \underbrace{\boxed{2\lambda^T \boldsymbol{F}}}_{\text{Inputs from physics}} \stackrel{!}{=} 0$$

Kinematic Fit provides:

1. Fitted particle 4-momenta

2. Possibility to reject events which do not match the reaction hypothesis

- Kinematic fitter is a least squares fit with constraints

In a Nutshell

$$\chi^2 = \underbrace{\boxed{\epsilon^T \hat{V}^{-1} \epsilon}}_{\text{Inputs from experiment}} + \underbrace{\boxed{2\lambda^T F}}_{\text{Inputs from physics}} \stackrel{!}{=} 0$$

Kinematic Fit provides:

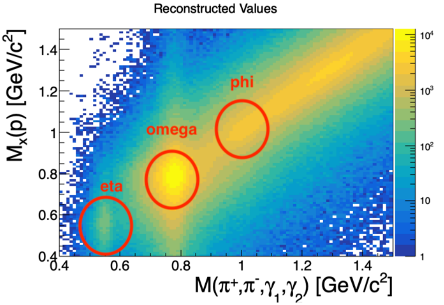
1. Fitted particle 4-momenta

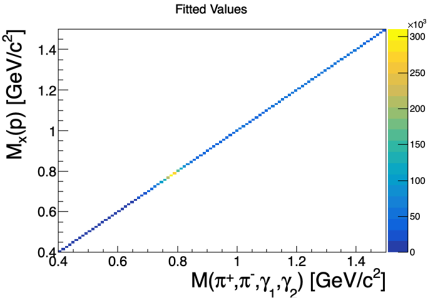
2. Possibility to reject events which do not match the reaction hypothesis

- Kinematic fitter is a least squares fit with constraints
- Use probability / χ^2 and pull-distributions to monitor and diagnose algorithm

mean[Pull(v_{ij})]	σ[Pull(v_{ij})]	Scenario
0	1.0	everything is fine
0	< 1.0	$\sigma_{meas,ij}$ is overestimated
0	> 1.0	$\sigma_{meas,ij}$ is underestimated
$\neq 0$	$\in [0, 1]$	introduced bias
n.a.	n.a.	non-gaussian pulls $\rightarrow$ you are in trouble

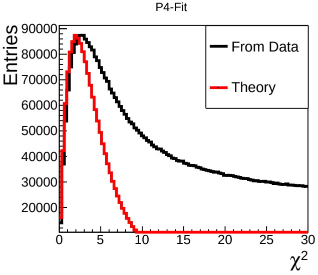
Analysis of $\gamma p \to \pi^+\pi^-\pi^0[\pi^0 \to \gamma\gamma]$ with the GlueX Kinematic Fit - Mass Spectra

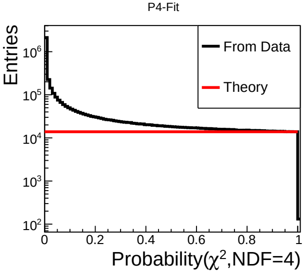




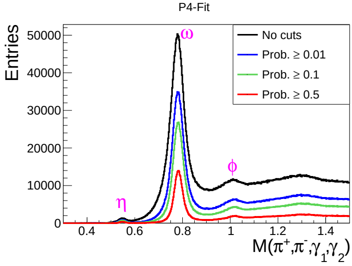
- Analyzed sub-sample of 2017 data
- Used a P4-Fit with no additional constraints
- **Missing Mass:** $M_x(p) \equiv \|P_{beam} + P_{target} - P_p\|$
- **Invariant Mass:** $M(\pi^+, \pi^-, \gamma_1, \gamma_2) \equiv \|P_{\pi^+} + P_{\pi^-} + P_{\gamma_1} + P_{\gamma_2}\|$
- **Ideally:** $M_x(p) = M(\pi^+, \pi^-, \gamma_1, \gamma_2)$ ($\rightarrow$ Fulfilled via kinematic fit)

Analysis of $\gamma p \to \pi^+\pi^-\pi^0[\pi^0 \to \gamma\gamma]$ with the GlueX Kinematic Fit - Performance Plots

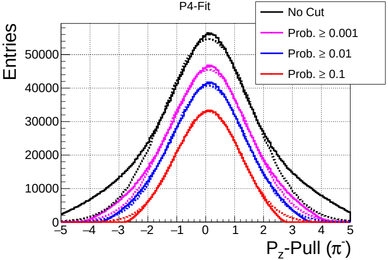




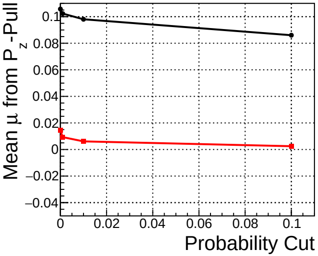
- Enhancement at small probabilities / large χ^2
  - Purely reconstructed events
  - Tracks with resolution outside of $\hat{V}$
  - Background reactions that do not match reaction hypothesis
- Check impact of different probability cuts

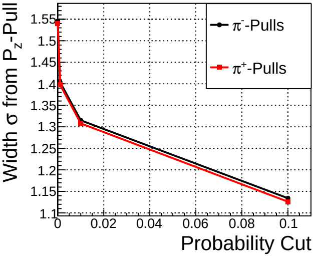


Analysis of $\gamma p \rightarrow \pi^+\pi^-\pi^0[\pi^0 \rightarrow \gamma\gamma]$ with the GlueX Kinematic Fit - Pull Distributions



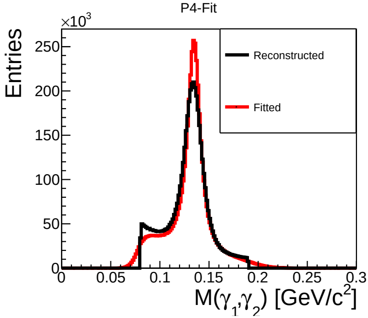
- Look at P_z-pulls for π^- and π^+
- Determine μ and σ for different probability cuts
- Fitter seems to "treat" oppositely charged pions differently
- Observe: $\lim_{\mathbf{prob}\rightarrow 1} \mu = 0$ and: $\lim_{\mathbf{prob}\rightarrow 1} \sigma = 1$ ($\rightarrow$ As it should)

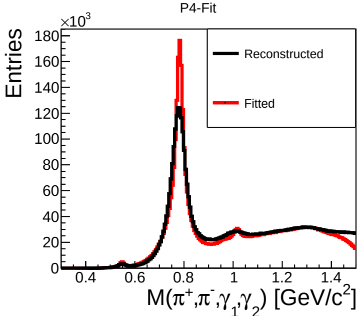




Analysis of $\gamma p \to \pi^+\pi^-\pi^0[\pi^0 \to \gamma\gamma]$ with the GlueX Kinematic Fit - Mass Constraints

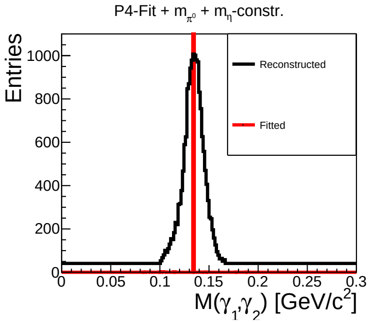
- Kinematic fit helps to improve the resolution
  ($\to$ Combine information from all sub-detectors)
- Wish to reconstruct: $\eta \to \pi^+\pi^-\pi^0$
- Why not using mass constraints ?
  $M(\gamma_1, \gamma_2) = m(\pi^0)$ and $M(\pi^+, \pi^-, \gamma_1, \gamma_2) = m(\eta)$

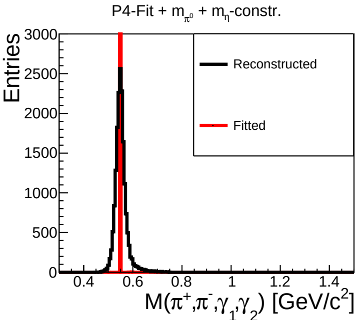




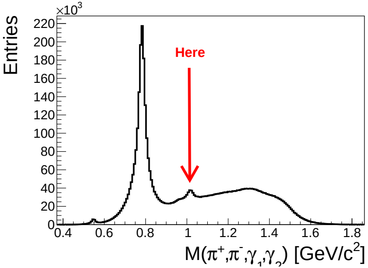
Analysis of $\gamma p \to \pi^+\pi^-\pi^0[\pi^0 \to \gamma\gamma]$ with the GlueX Kinematic Fit - Mass Constraints

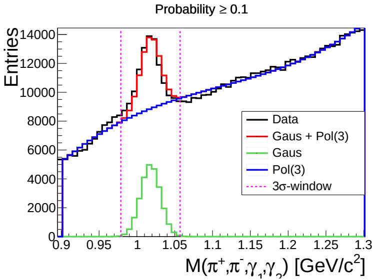
- Kinematic fit helps to improve the resolution
  ($\to$ Combine information from all sub-detectors)
- Wish to reconstruct: $\eta \to \pi^+\pi^-\pi^0$
- Why not using mass constraints ?
  $M(\gamma_1, \gamma_2) = m(\pi^0)$ and $M(\pi^+, \pi^-, \gamma_1, \gamma_2) = m(\eta)$
- Additional mass constraints are helpful, but make it impossible to judge the involved background

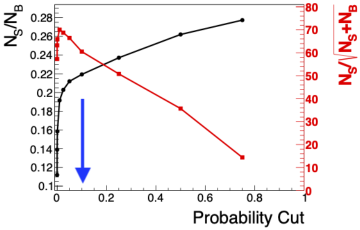




Analysis of $\gamma p \to \pi^+\pi^-\pi^0[\pi^0 \to \gamma\gamma]$ with the GlueX Kinematic Fit - Cut Optimization

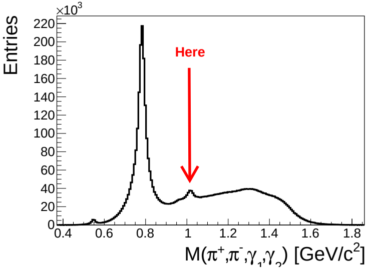


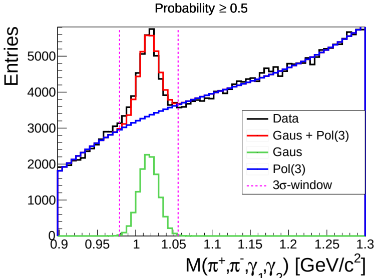


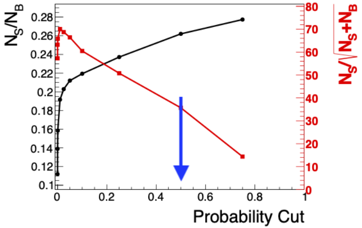


- **Goal:** Find optimum probability cut to select $\phi \to \pi^+\pi^-\pi^0$
- Vary probability cut and determine number of ϕ / background events

Analysis of $\gamma p \to \pi^+\pi^-\pi^0[\pi^0 \to \gamma\gamma]$ with the GlueX Kinematic Fit - Cut Optimization

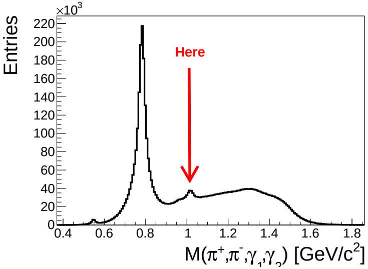


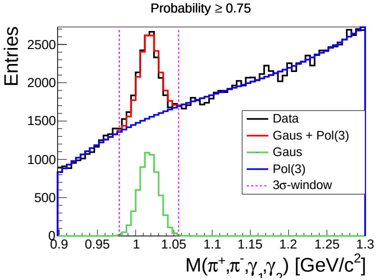


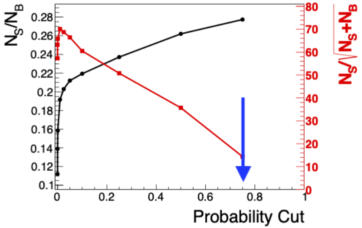


- **Goal:** Find optimum probability cut to select $\phi \to \pi^+\pi^-\pi^0$
- Vary probability cut and determine number of ϕ / background events

Analysis of $\gamma p \to \pi^+\pi^-\pi^0[\pi^0 \to \gamma\gamma]$ with the GlueX Kinematic Fit - Cut Optimization

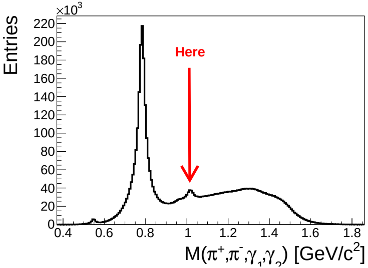


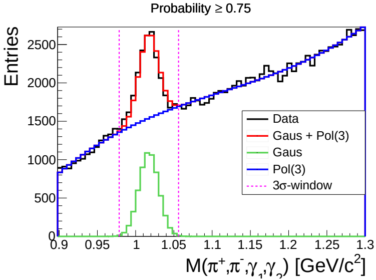


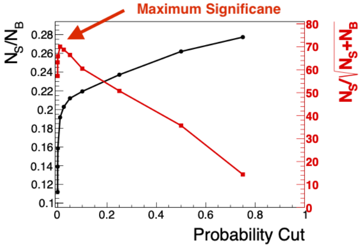


- **Goal:** Find optimum probability cut to select $\phi \to \pi^+\pi^-\pi^0$
- Vary probability cut and determine number of ϕ / background events

Analysis of $\gamma p \to \pi^+\pi^-\pi^0[\pi^0 \to \gamma\gamma]$ with the GlueX Kinematic Fit - Cut Optimization







- **Goal:** Find optimum probability cut to select $\phi \to \pi^+\pi^-\pi^0$
- Vary probability cut and determine number of ϕ / background events
- Significance at maximum for 0.01 $\Rightarrow$ Sweet spot between background rejection and signal loss

Summary and Outlook

- The kinematic fit is a very powerful tool $\Rightarrow$ But no silver bullet!
  - Filters data according to reaction hypothesis
  - Requires proper setting of $\hat{V}$ and constraints

Summary and Outlook

- The kinematic fit is a very powerful tool $\Rightarrow$ But no silver bullet!
  - Filters data according to reaction hypothesis
  - Requires proper setting of $\hat{V}$ and constraints
- Monitoring is key
  - Check probability / χ^2-distribution (low-level)
  - Check and compare pull distributions (mid-level)
  - Check impact of different χ^2 / probability cuts on your results (mid- to high-level)

Summary and Outlook

- The kinematic fit is a very powerful tool $\Rightarrow$ But no silver bullet!
  - Filters data according to reaction hypothesis
  - Requires proper setting of $\hat{V}$ and constraints
- Monitoring is key
  - Check probability / χ^2-distribution (low-level)
  - Check and compare pull distributions (mid-level)
  - Check impact of different χ^2 / probability cuts on your results (mid- to high-level)
- Be aware of pitfalls
  - A pull width < 1 is not the end of the world
    $\rightarrow$ Reality in many experiments
    $\rightarrow$ It is more important that pulls are similar in data and MC
  - The kinematic fit algorithm itself has no systematic error
    $\rightarrow$ Any observed cut dependency is most likely due to a mismatch in data / MC or a faulty reconstruction
  - Try not to solve everything with mass constraints

Summary and Outlook

- The kinematic fit is a very powerful tool $\Rightarrow$ But no silver bullet!
  - Filters data according to reaction hypothesis
  - Requires proper setting of $\hat{V}$ and constraints
- Monitoring is key
  - Check probability / χ^2-distribution (low-level)
  - Check and compare pull distributions (mid-level)
  - Check impact of different χ^2 / probability cuts on your results (mid- to high-level)
- Be aware of pitfalls
  - A pull width < 1 is not the end of the world
    $\rightarrow$ Reality in many experiments
    $\rightarrow$ It is more important that pulls are similar in data and MC
  - The kinematic fit algorithm itself has no systematic error
    $\rightarrow$ Any observed cut dependency is most likely due to a mismatch in data / MC or a faulty reconstruction
  - Try not to solve everything with mass constraints
- Use the kinematic fit in your own analysis (See following talk by Justin Stevens)
  - Define fitter settings in config file for reaction filter plugin
  - Use analysis-launch webpage