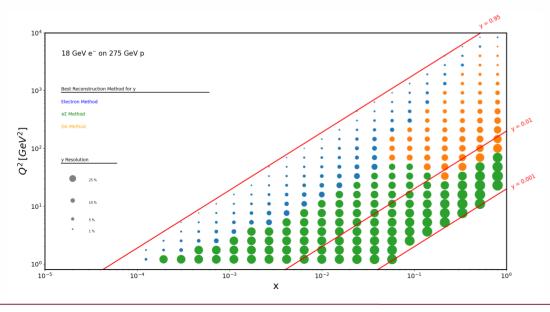


Reconstructing Inclusive variables in Radiative DIS

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Kinematic Reconstruction

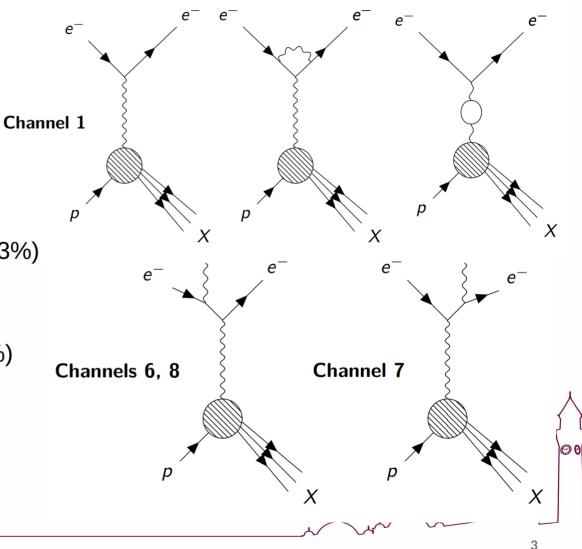
- The kinematics of DIS can be reconstructed from any <u>two of the measured</u> <u>quantities</u> $\vec{D} = \{E_e, \theta_e, \delta_h, p_{t,h}\}$
 - Where $\delta_h = \Sigma E_i(1 \cos(\theta_i))$. E_i and θ_i are the energies and angles of deposits in the calorimeters which are not assigned to the scattered electron.
 - P_{th} is the transverse momentum of the hadronic final state



- Electron and Double angle methods are best for much of the phase space for events without ISR
- Electron method deteriorates at low y and is sensitive to ISR
- DA method is sensitive to ISR
- → Other approaches possible that are less sensitive to ISR

Event generation

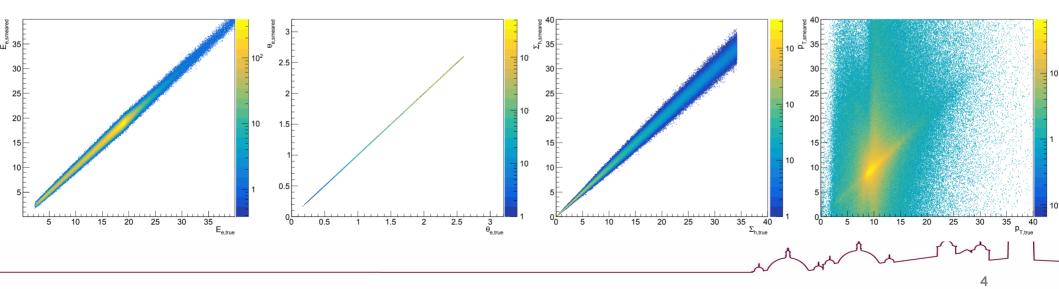
- Djangoh 4.6.10 used to generate 18x275 GeV² e-p events
 - ISR/FSR=ON
 - Q²>100GeV²
 - W>2GeV
- Channel 1: Non Radiative NC (~53%)
- Channel 6: ISR (~28%)
- Channel 7: FSR (~18%)
- Channel 8: "Compton event" (~1%)



Smearing

- "True" quantities smeared according to detector matrix:
- Use central/forward ECAL resolution (for Q²>100GeV² most electrons scattered into barrel)
- Angular resolution requirement not present in detector matrix \rightarrow 1mrad is conservative estimate

 δ E/E = 11%/√(E) ⊕ 2% δθ = 1mrad



Kinematic Fitting in BAT (Bayesian Analysis Toolkit)

- Reconstruction is overconstrained: only need 2 quantities to obtain x, y, Q²
- From the measured quantities $\vec{D} = \{E_e, \theta_e, \delta_h, p_{t,h}\}$ we can use a kinematic fit to reconstruct an additional piece of information: $\vec{\lambda} = \{x, y, E_v\}$
- All we need is a prior and a likelihood function:

$$P_o(\vec{\lambda}) = \frac{1 + (1 - y)^2}{x^3 y^2} \frac{[1 + (1 - E_{\gamma}/A)^2]}{E_{\gamma}/A}$$

Prior

Likelihood*

$$P(\overrightarrow{D}|\overrightarrow{\lambda}) \propto \frac{1}{\sqrt{2\pi\sigma_E}} e^{-\frac{(E_e - E_e^{\lambda})^2}{2\sigma_E^2}} \frac{1}{\sqrt{2\pi\sigma_\theta}} e^{-\frac{(\theta_e - \theta_e^{\lambda})^2}{2\sigma_\theta^2}} \frac{1}{\sqrt{2\pi\sigma_{\delta_h}}} e^{-\frac{(\delta_h - \delta_h^{\lambda})^2}{2\sigma_{\delta_h}^2}} \frac{1}{\sqrt{2\pi\sigma_{P_{T,h}}}} e^{-\frac{(P_{T,h} - P_{T,h}^{\lambda})^2}{2\sigma_{P_{T,h}}^2}}$$

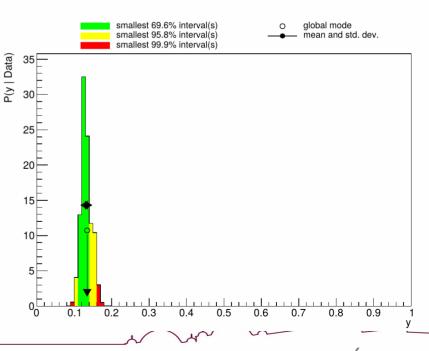
* Likelihood comes from parametrisation of resolution of measured values in \vec{D} according to detector resolution \rightarrow Required as input for model

Reconstruction with Kinematic Fit

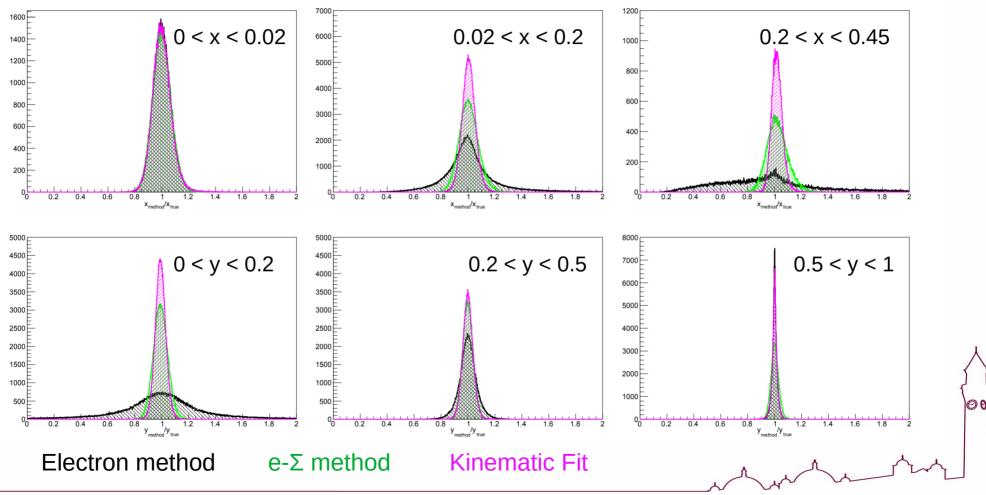
- Input smeared (or reconstructed) variables $\vec{D} = \{E_e, \theta_e, \delta_h, p_{t,h}\}$
- Define prior distribution and likelihood

$$P_o(\overrightarrow{\lambda}) = \frac{1 + (1 - y)^2}{x^3 y^2} \frac{\left[1 + (1 - E_{\gamma}/A)^2\right]}{E_{\gamma}/A} P(\overrightarrow{D}|\overrightarrow{\lambda}) \propto \frac{1}{\sqrt{2\pi}\sigma_E} e^{-\frac{(E_e - E_e^{\lambda})^2}{2\sigma_E^2}} \frac{1}{\sqrt{2\pi}\sigma_\theta} e^{-\frac{(\theta_e - \theta_e^{\lambda})^2}{2\sigma_\theta^2}} \frac{1}{\sqrt{2\pi}\sigma_{\delta_h}} e^{-\frac{(\delta_h - \delta_h^{\lambda})^2}{2\sigma_{\delta_h}^2}} \frac{1}{\sqrt{2\pi}\sigma_{P_{T,h}}} e^{-\frac{(P_{T,h} - P_{T,h})^2}{2\sigma_{P_{T,h}}^2}} e^{-\frac{(\Phi_e - \Phi_e^{\lambda})^2}{2\sigma_{\delta_h}^2}} \frac{1}{\sqrt{2\pi}\sigma_{\delta_h}} e^{-\frac{(\Phi_e - \Phi_e^{\lambda})^2}{2\sigma_{\delta_h}^2}}} \frac{1}{\sqrt{2\pi}\sigma_{\delta_h}} e^{-\frac{(\Phi_e - \Phi_e^{\lambda})^2}{2\sigma_{\delta_h}^2}}} e^{-\frac{(\Phi_e - \Phi_e^{\lambda})^2}{2\sigma_{\delta_h}^2}} \frac{1}{\sqrt{2\pi}\sigma_{\delta_h}} e^{-\frac{(\Phi_e - \Phi_e^{\lambda})^2}{2\sigma_{\delta_h}^2}}} e^{-\frac{(\Phi_e - \Phi_e^{\lambda})^2}{2\sigma_{\delta_h}^2}} \frac{1}{\sqrt{2\pi}\sigma_{\delta_h}} e^{-\frac{(\Phi_e - \Phi_e^{\lambda})^2}{2\sigma_{\delta_h}^2}}} e^{-\frac{(\Phi_e - \Phi_e^{\lambda})^2}{2\sigma_{\delta_h}^2}} \frac{1}{\sqrt{2\pi}\sigma_{\delta_h}} e^{-\frac{(\Phi_e - \Phi_e^{\lambda})^2}{2\sigma_{\delta_h}^2}}} \frac{1}{\sqrt{2\pi}\sigma_{\delta_h}} e^{-\frac{(\Phi_e - \Phi_e^{\lambda})^2}{2\sigma_{\delta_h}^2}}} e^{-\frac{(\Phi_e - \Phi_e^{\lambda})^2}{2\sigma_{\delta_h}^2}} e^{-\frac{(\Phi_e - \Phi_e^{\lambda})^2}{2\sigma_{\delta_h}^2}}} e^{-\frac{(\Phi_e - \Phi_e^{\lambda})^2}{2\sigma_{\delta_h}^2}}} e^{-\frac{(\Phi_e - \Phi_e^{\lambda})^2}{2\sigma_{\delta_h}^2}}} e^{-\frac{(\Phi_e - \Phi_e^{\lambda})^2}{2\sigma_{\delta_h}^2}} e^{-\frac{(\Phi_e - \Phi_e^{\lambda})^2}{2\sigma_{\delta_h}^2}} e^{-\frac{(\Phi_e - \Phi_e^{\lambda})^2}{2\sigma_{\delta_h}^2}} e^{-\frac{(\Phi_e - \Phi_e^{\lambda})^2}{2\sigma_{\delta_h}^2}}} e^{-\frac{(\Phi_e - \Phi_e^{\lambda})^2}{2\sigma_{\delta_h$$

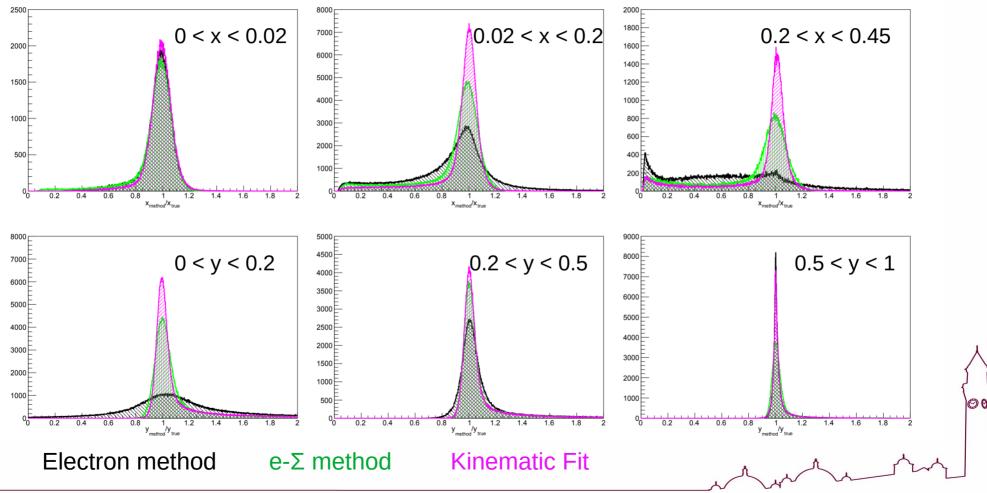
- Uniformly distribute parameters x, y, E_y until initial parameters with valid probability are found
- Run Metropolis algorithm (MCMC):
 - Propose new values of parameters and use likelihood and prior information to decide whether to accept the change
 - Update posterior distribution and repeat for new values
- Output values of x, y, E_v at mode of posterior



Comparison to to conventional methods – Channel 1 only

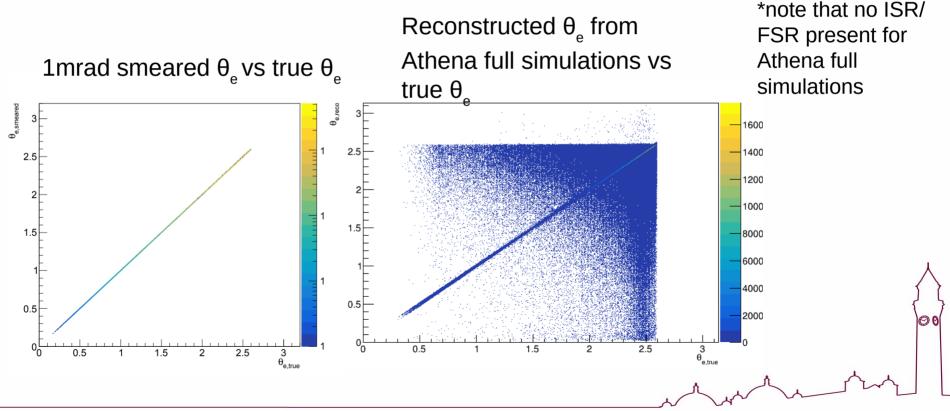


Comparison to to conventional methods – All Channels



Reconstructing a realistic detector output with kinematic fit

 The output of a "real" detector is not nearly as clean as gaussian smeared truth information



Reconstructing a realistic detector output with kinematic fit

- For kinematic fit, just need a prior and a means of calculating the likelihood
 - One way to calculate the likelihood is to continue with the approximation that the reconstructed variables $\vec{D} = \{E_e, \theta_e, \delta_h, p_{t,h}\}$ are uncorrelated, and gaussian distributed according to a known width:

$$P(\overrightarrow{D}|\overrightarrow{\lambda}) \propto \frac{1}{\sqrt{2\pi}\sigma_E} e^{-\frac{(E_e - E_e^{\lambda})^2}{2\sigma_E^2}} \frac{1}{\sqrt{2\pi}\sigma_\theta} e^{-\frac{(\theta_e - \theta_e^{\lambda})^2}{2\sigma_\theta^2}} \frac{1}{\sqrt{2\pi}\sigma_{\delta_h}} e^{-\frac{(\delta_h - \delta_h^{\lambda})^2}{2\sigma_{\delta_h}^2}} \frac{1}{\sqrt{2\pi}\sigma_{P_{T,h}}} e^{-\frac{(P_{T,h} - P_{T,h}^{\lambda})^2}{2\sigma_{P_{T,h}}^2}}$$

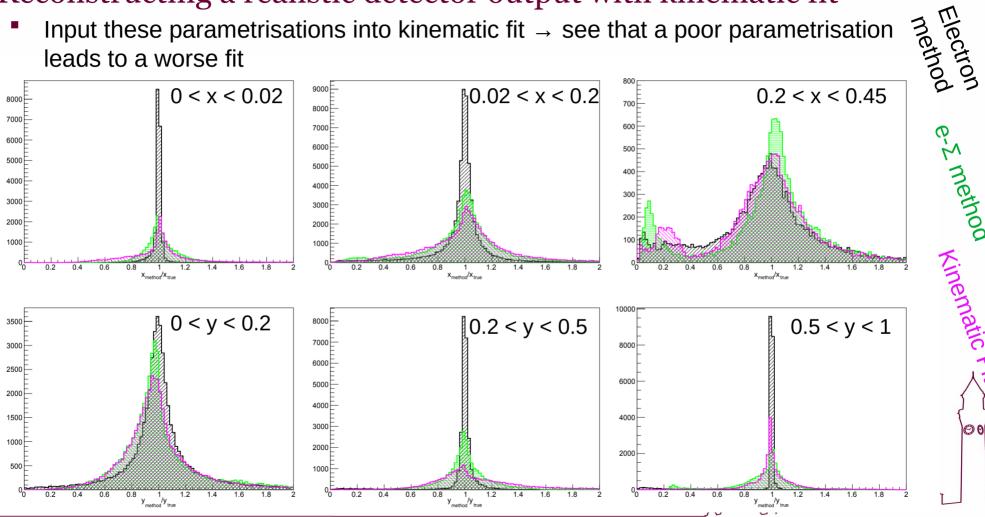
- Issues arise when attempting to obtain a resolution for this approximation:
 - Functional dependence of resolution on variables is not always obvious
 - Distribution of reconstructed variables w.r.t. true variables is often not Gaussian (for these reconstructed events)
 - → for these preliminary studies, where a gaussian fit is not possible the RMS value is used instead

Gaussian width vs Scattered Electron Energy RMS vs 0 plot χ^2 / ndf χ^2 / ndf 8.731/4 88.71/5 0.01103 ± 0.0001142 0.25 0.02 σ_E/GeV p0 p0 0.00948 ± 5.881e-05 0.018 See here a **very** basic p1 0.016 0.2 first effort at 0.014 parametrising the 0.15 0.012 0.01 Athena reconstructed 0.1 0.008 variables 0.006 0.05 0.004 0.002 16 18 1.6 2.4 2.6 1.2 1.4 22 Energy/GeV RMS vs p * Note that tracks are RMS vs \delta plot χ^2 / ndf χ² / ndf 583.8/4 6058/3 RMS P RMS 8_h used for electron 0.03336 ± 0.001402 p0 0.03834 ± 0.0005543 p0 0.1806 ± 0.001531 p1 0 ± 13.21 p1 energy calculation in Athena reconstruction 3.5 2.5 1.5 @0 0.5F 0.5 10 6 10 12 6 8 8 11

Reconstructing a realistic detector output with kinematic fit

Reconstructing a realistic detector output with kinematic fit

Input these parametrisations into kinematic fit \rightarrow see that a poor parametrisation leads to a worse fit



method

Kinematic

00

Summary

- Traditional reconstruction methods do not leverage all of the information available to us:
 - Using a kinematic fit can obtain a high quality reconstruction and the energy of a possible ISR photon

Next Steps

- Parametrising the quantities in D
 may not lead to the best possible reconstruction
 - → Produce likelihood distribution from MC information \rightarrow compare against results from parametrisation