Omega Cross-Section

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Starting Point

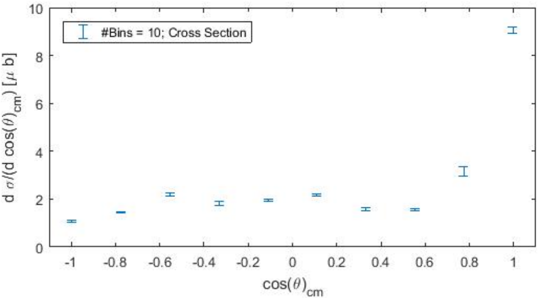


Figure 1: Olis Cross Section; Dip at about $\cos(\theta) = -0.3$

Increasing the Number of Bins

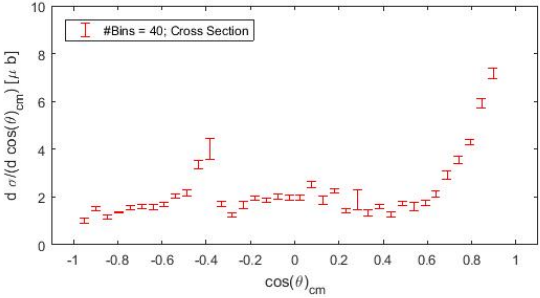


Figure 2: Increased number of bins to 40; now there is still a dip at $\cos(\theta) = -0.3$ but also a peak at $\cos(\theta) = -0.5$

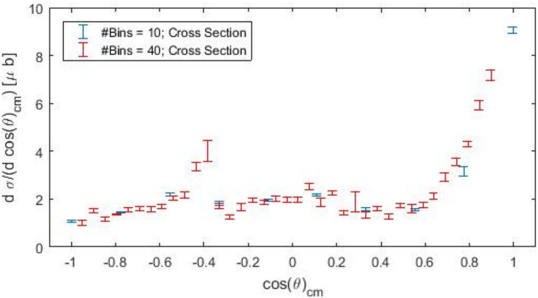
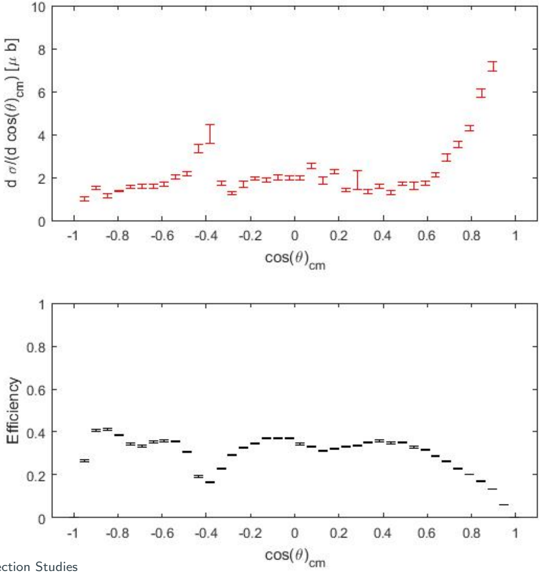


Figure 3: Both Cross Sections are shown.

Efficiency

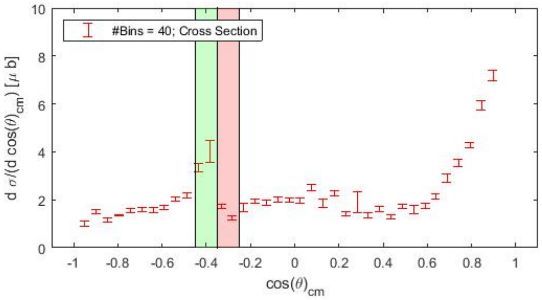


Taking a closer Look

$$\omega \to \gamma \; \underbrace{\pi^0}_{\hookrightarrow \gamma\gamma}$$

Closer look at:

- ω
- Bachelor Photon
- π^0
- $\gamma\gamma$
- Proton



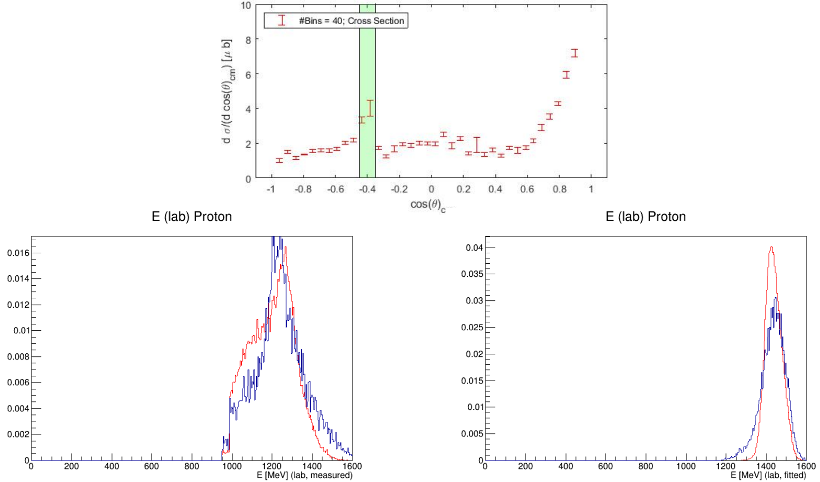


Figure 5: Energy of protons for $\cos(\theta\omega) = [-0.45, -0.35]$. Red are MC and blue are beamtime data. Left side is just measured, right side is after KFit.

θ of Proton for $\cos(\theta_\omega) = [-0.45, -0.35]$ (Peak)

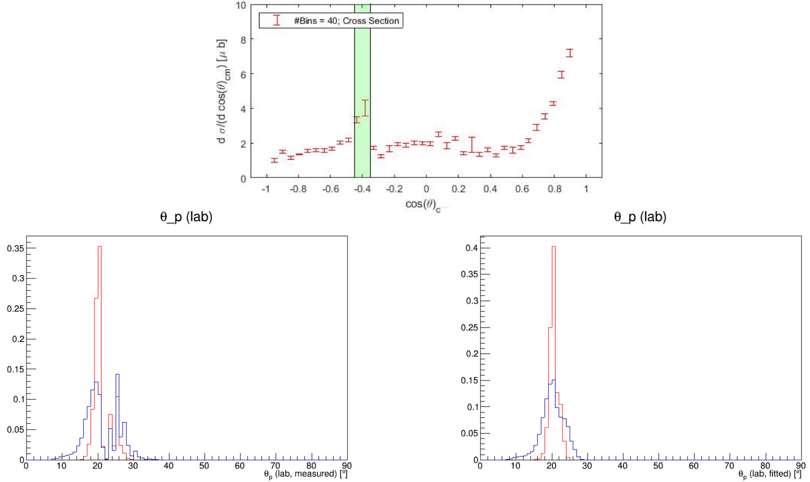


Figure 6: θ of protons for $\cos(\theta\omega) = [-0.45, -0.35]$. Red are MC and blue are beamtime data. Left side is just measured, right side is after KFit.

Energy of Protons for $\cos(\theta_\omega) = [-0.35, -0.25]$ (Dip)

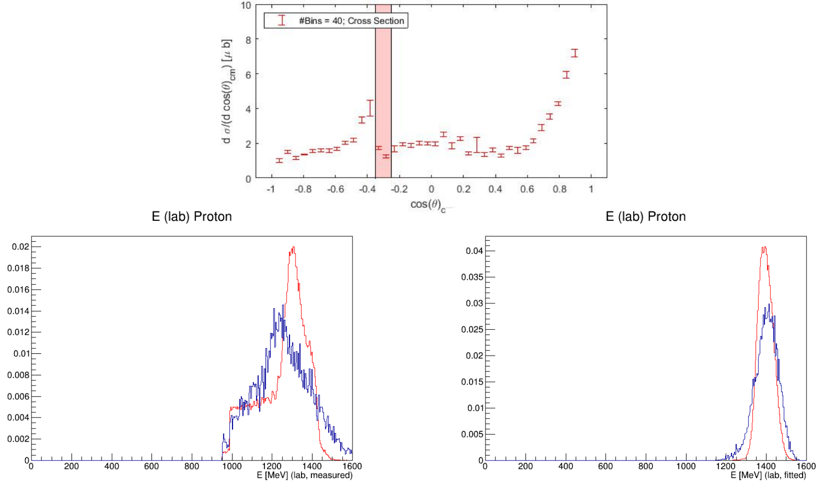


Figure 7: Energy of protons for $\cos(\theta\omega) = [-0.35, -0.25]$. Red are MC and blue are beamtime data. Left side is just measured, right side is after KFit.

θ of Proton for cos(θ_ω) $= [-0.35, -0.25]$ (Dip)

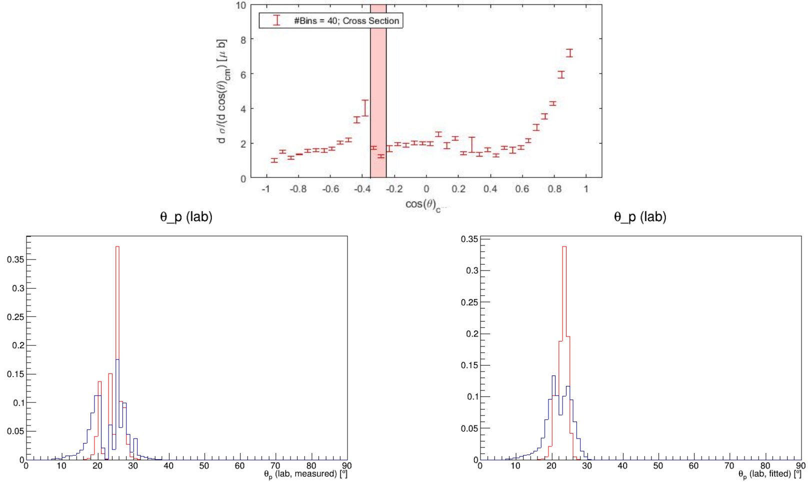


Figure 8: θ of protons for $\cos(\theta\omega) = [-0.35, -0.25]$. Red are MC and blue are beamtime data. Left side is just measured, right side is after KFit.

Proton: θ_{fit} vs. θ_{gen}

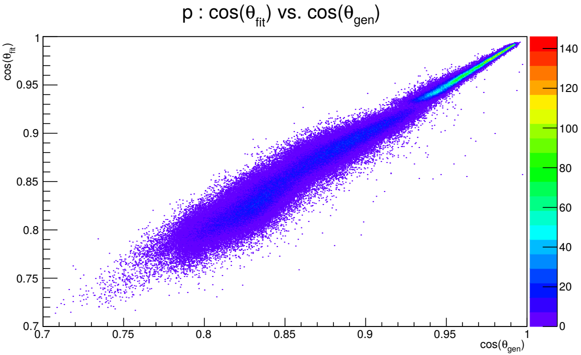


Figure 9: $\cos(\theta_{fit})$ vs. $\cos(\theta_{gen})$ for all protons.

ω: θ_{fit} vs. θ_{gen}

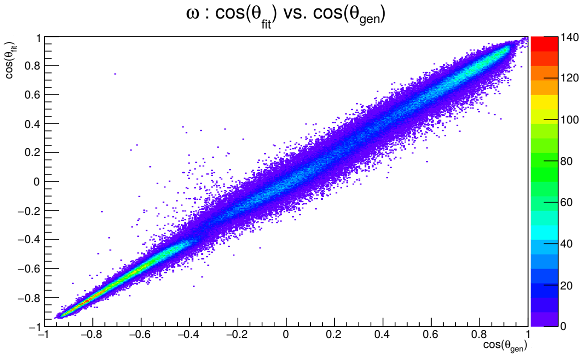


Figure 10: $\cos(\theta_{fit})$ vs. $\cos(\theta_{gen})$ for all ω.

Unfolding

Motivation

- μ is the *true* distribution given by nature
- detector effects are then described by the response function R. (inefficiencies, bias and smearing)
- This results in the distribution ν.

$$\nu_i = \sum_{j=1}^{M} R_{ij}\mu_j$$

- With infinite statistics, it would be possible to recover the original distribution by inverting the response matrix

$$\mu = R^{-1}\nu$$

What is Unfolding?

- Using MC we can train the unfolding algorithm
- Create a 2D-Hist with $\cos(\theta_\omega)$ of all generated and all reconstructed ω (ω which are generated but not reconstructed are label *miss*)
- Then we can solve for μ iteratively

Example with Gaussian

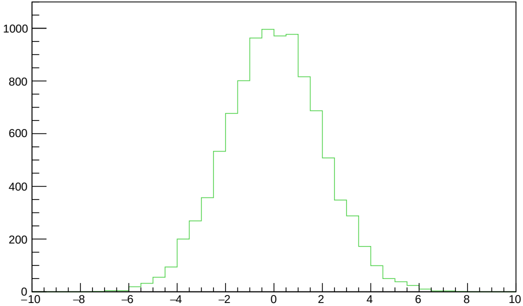


Figure 11: Example for a working Unfolding Algorithm

Example with Gaussian

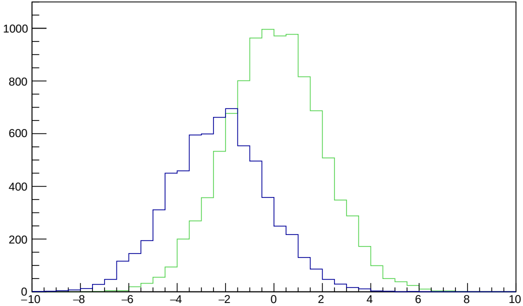


Figure 11: Example for a working Unfolding Algorithm

Example with Gaussian

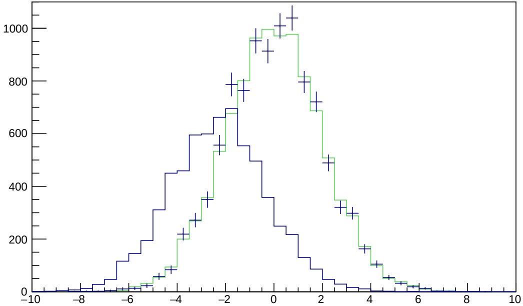


Figure 11: Example for a working Unfolding Algorithm

Folded

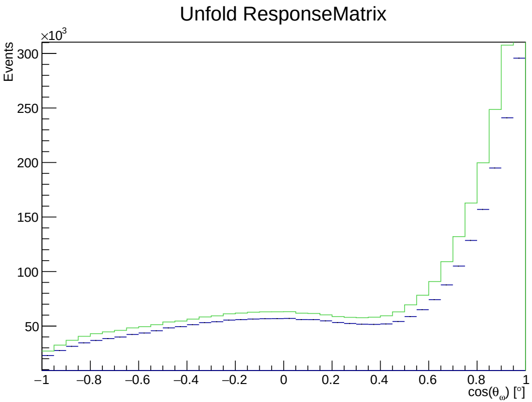


Figure 12: Folded; same cuts

Flat ω

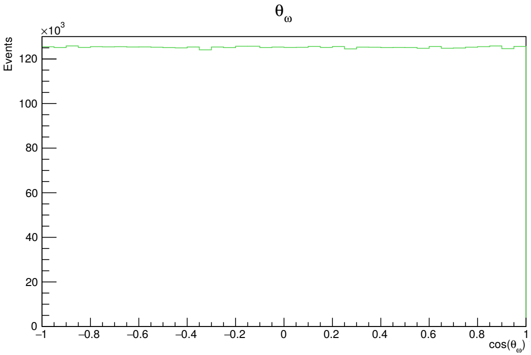


Figure 13: Distribution of the ω in center of mass frame

Flat ω; Folded MC Data

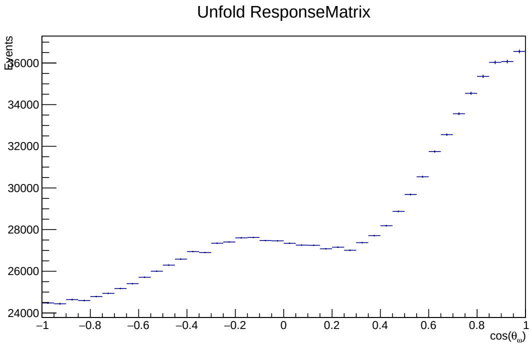


Figure 14: Flat ω was used. MC fitted data were folded.