

SIDIS kinematic reconstruction with ML

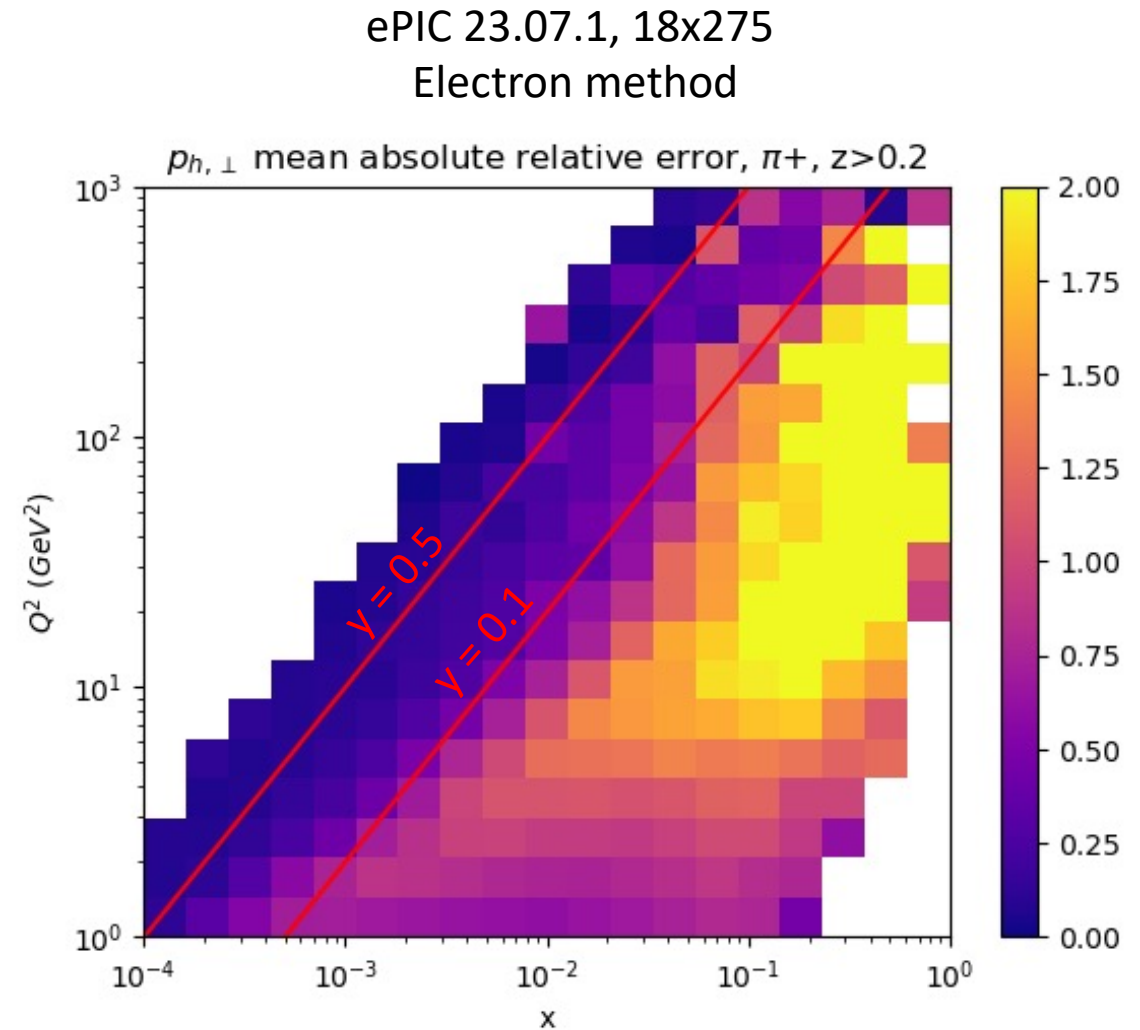
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SIDIS kinematic reconstruction at EIC/Introduction

- SIDIS reconstruction centered around reconstruction of virtual photon four-momentum, q
 - Past fixed target/HERA analyses: from scattered lepton, $q = l - l'$
- Studies for YR, ATHENA/ECCE, etc. show electron performs very poorly at low- y
- Anselm introduced method reconstructing q using hadronic final state (HFS) in the YR
- I previously presented results of ML SIDIS kinematic reconstruction on ATHENA full sim. (DIS proceedings, <https://inspirehep.net/literature/2158328>)
- We are now hoping to publish these two methods demonstrated on the ePIC full simulation

SIDIS kinematics at ePIC

- Known problem since yellow report studies: electron method performance drops off significantly at low- y
 - Low- y : small electron energy loss
- Tail of very poorly reconstructed events cut off here (require absolute error of $p_T < 1000\%$)

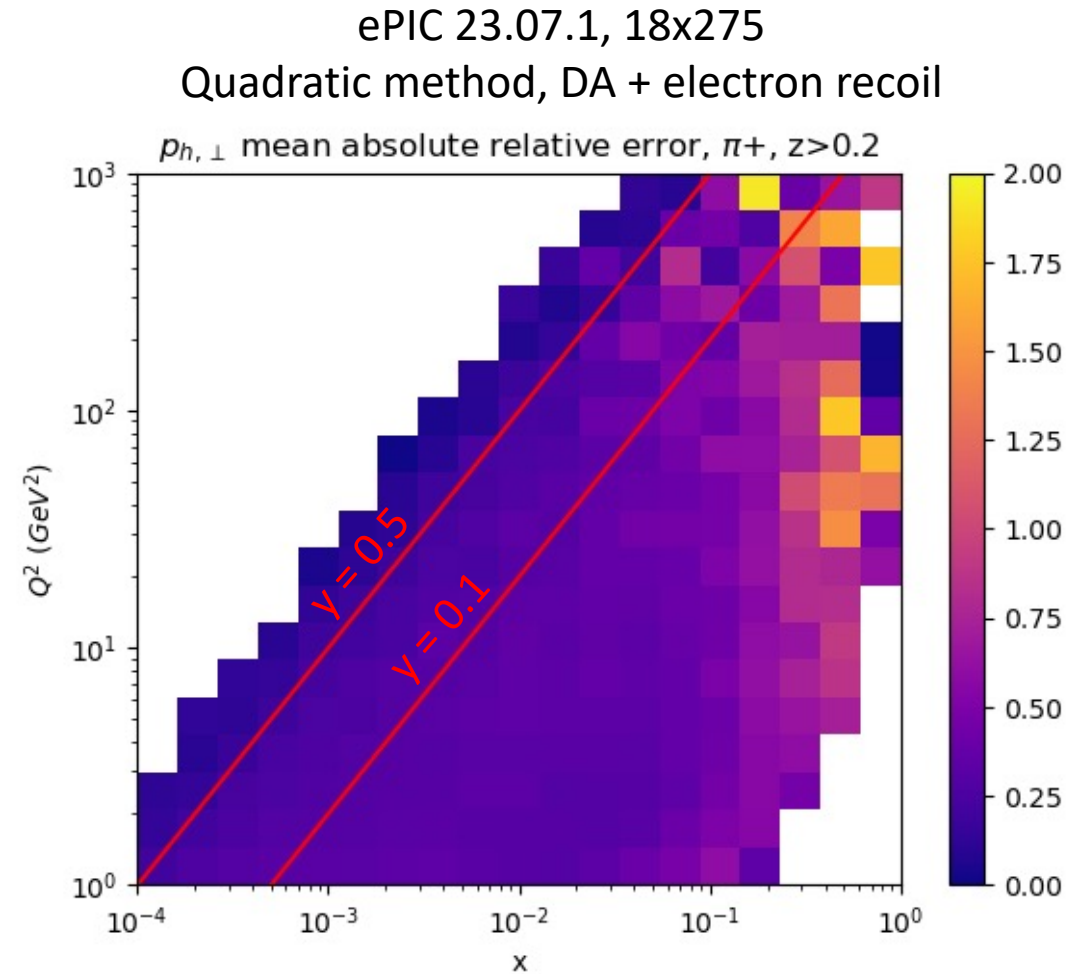


First hadronic final state method

- Introduced in YR by Anselm: extending HERA kinematic reconstruction methods for (x, Q^2, y) to constraining q

$$\left. \begin{aligned} (q_x, q_y) &= \text{HFS } \vec{p}_T \parallel \text{electron } \vec{p}_T, \\ Q^2 &= -q^2, \\ y &= \frac{P \cdot q}{P \cdot k} \end{aligned} \right\} (q_x, q_y, q_z, q_t)$$

- Q^2, y taken from HFS or hybrid reconstruction method (double-angle, Jacquet-Blondel, etc.)
- Transverse recoil from electron or HFS
- Quadratic formula to solve for remaining two components of q



Machine learning approach

- Utilizing Particle Flow Networks (PFN, arXiv:1810.05165)
 - Deep sets architecture: operate on unordered, permutation invariant set
 - First demonstrated on jet tagging tasks at LHC
- Training PFN to directly reconstruct q
 - Unordered set: All HFS particles
 - Also utilize electron information
 - First shown on ATHENA full simulation (DIS 2022: <https://inspirehep.net/literature/2158328>, and AI4EIC 2022)

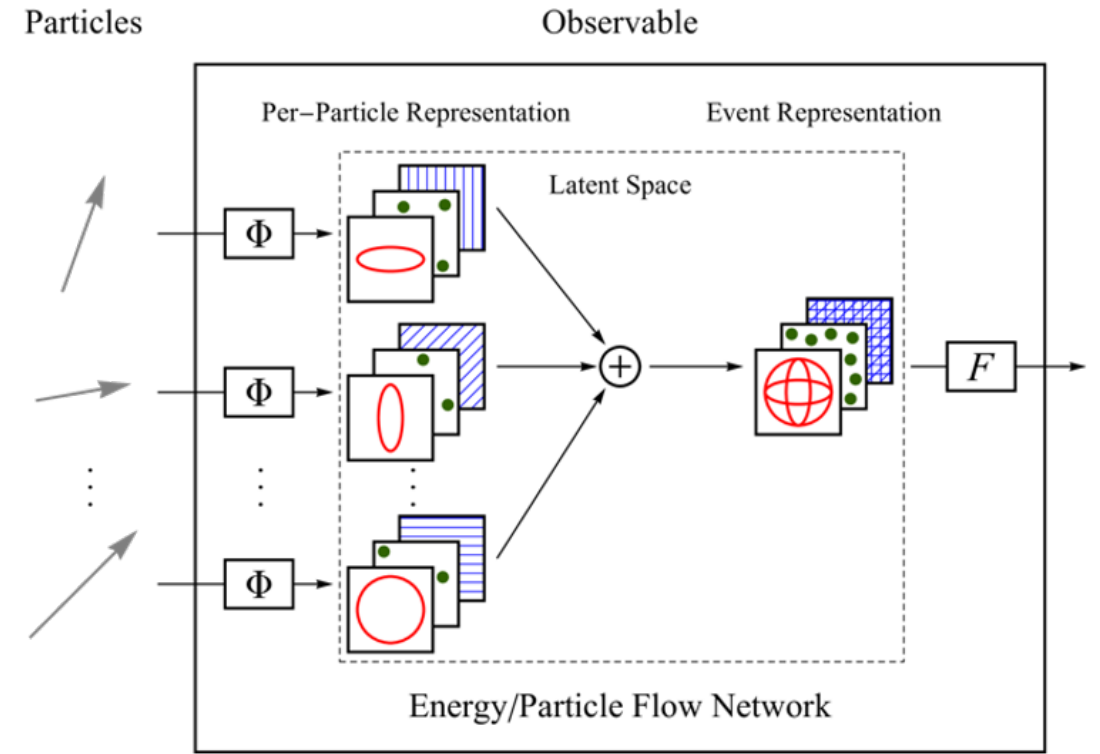


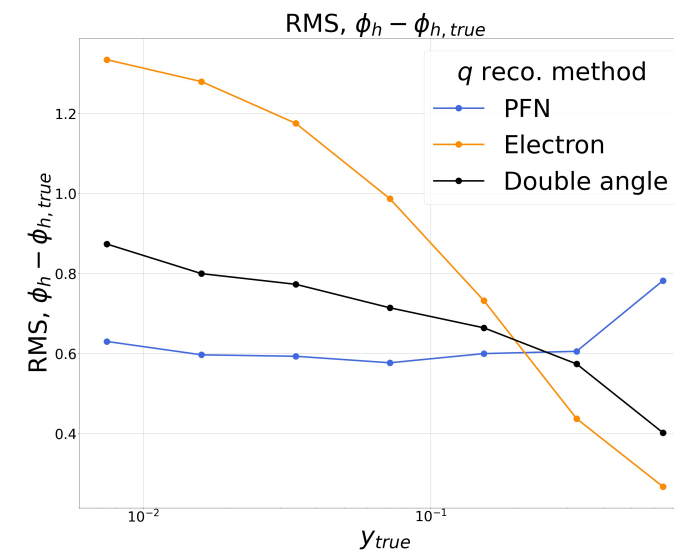
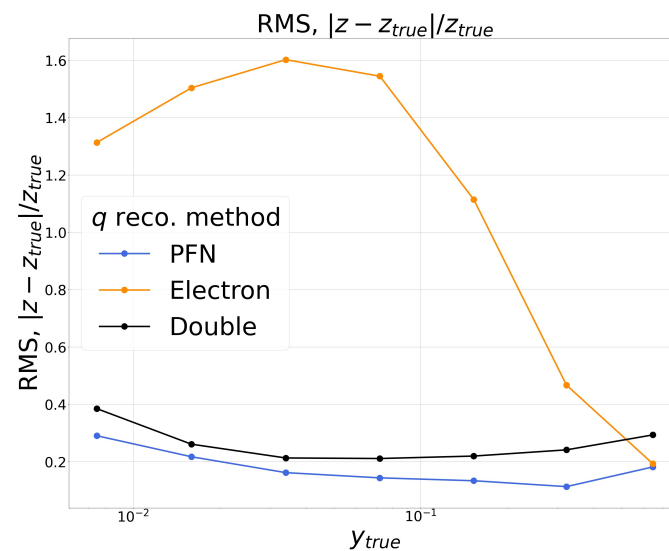
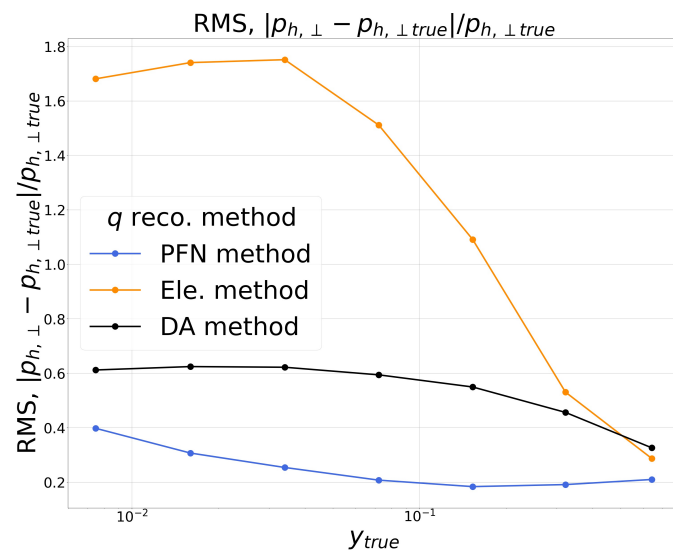
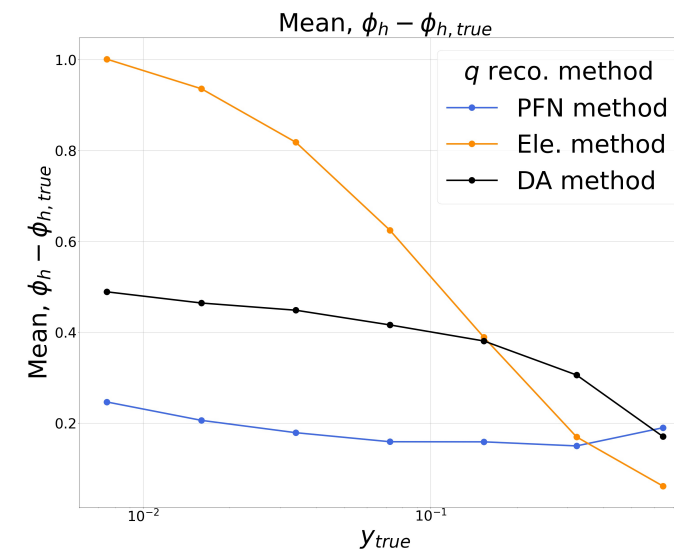
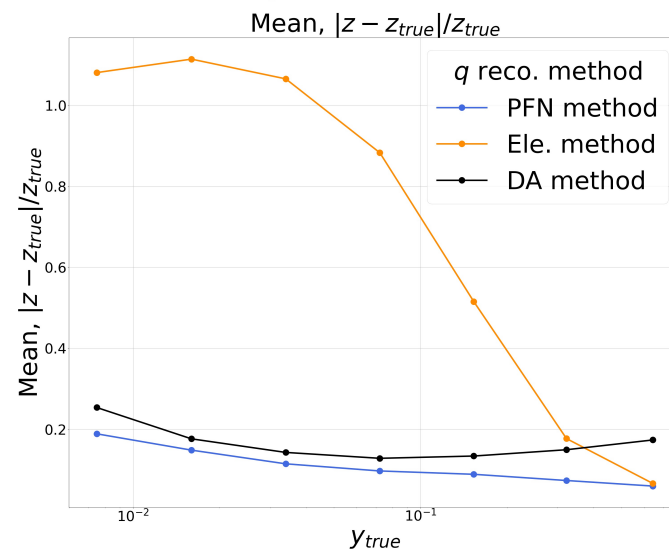
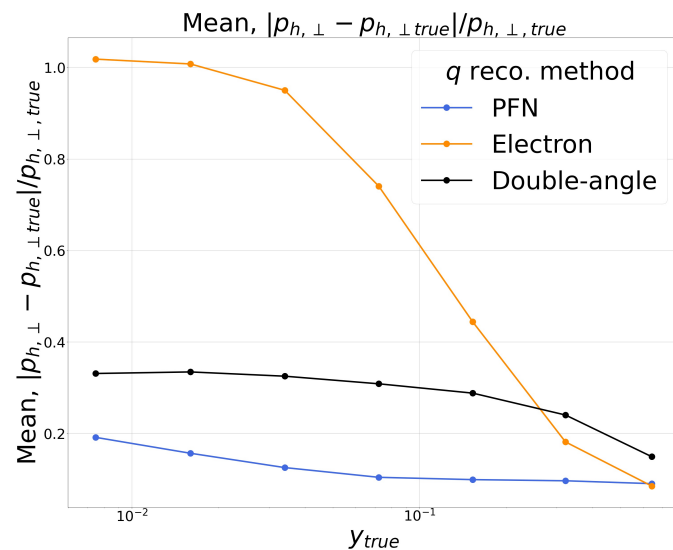
Diagram of Particle Flow Network, from arXiv:1810.05165

Training details

- Utilized 2.6 million events from ePIC 23.07.1 campaign ($Q^2 > 1 \text{ GeV}^2$ sample)
 - 1.6 million used for training, remaining 1 million used for validation
 - Using MC truth matching to get scattered electron (what is currently done in epic-analysis)
 - Using tracks only for charged particles and calorimeter for neutrals
- HFS particle information input to first layers: p_x, p_y, p_z, E
- Electron information input in latent space: $q_{x,ele}, q_{y,ele}, q_{z,ele}, q_{E,ele}$
- Inclusive DIS information input to latent space: $-\log_{10}(x), \log_{10}(Q^2)$ from DA, Σ , electron methods
- Two networks trained: one reconstructing (q_x, q_y) , and one reconstructing (q_z, q_E)

Results, ePIC full simulation 23.07.1

SIDIS kinematic resolutions, $Q^2 > 1\text{GeV}^2$, π^+ , $z > 0.2$ ePIC 23.07.1



Conclusions

- Constraining (q_z, q_t) using (y, Q^2) from hybrid HFS-electron methods significantly improves reconstruction at low- y
- Training Particle Flow Networks to reconstruct virtual photon four momentum using scattered electron and all HFS particles outperforms other method across all y
- We would like to submit a write-up of these methods and results on ePIC 23.07.1 for publication (JINST or similar)