Reconstructing DIS and SIDIS event properties with Machine Learning

2nd Workshop on Artificial Intelligence for the Electron Ion Collider

William & Mary, Oct. 11th, 2022

Connor Pecar, Duke University

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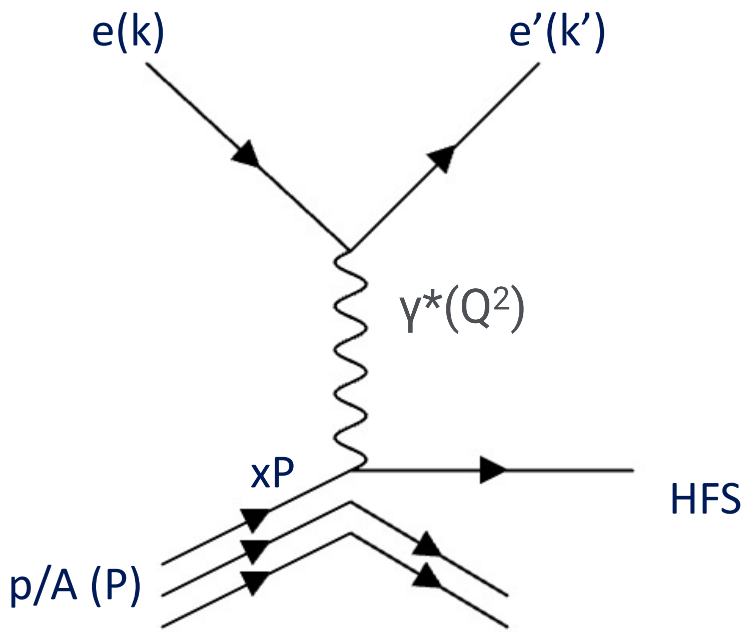
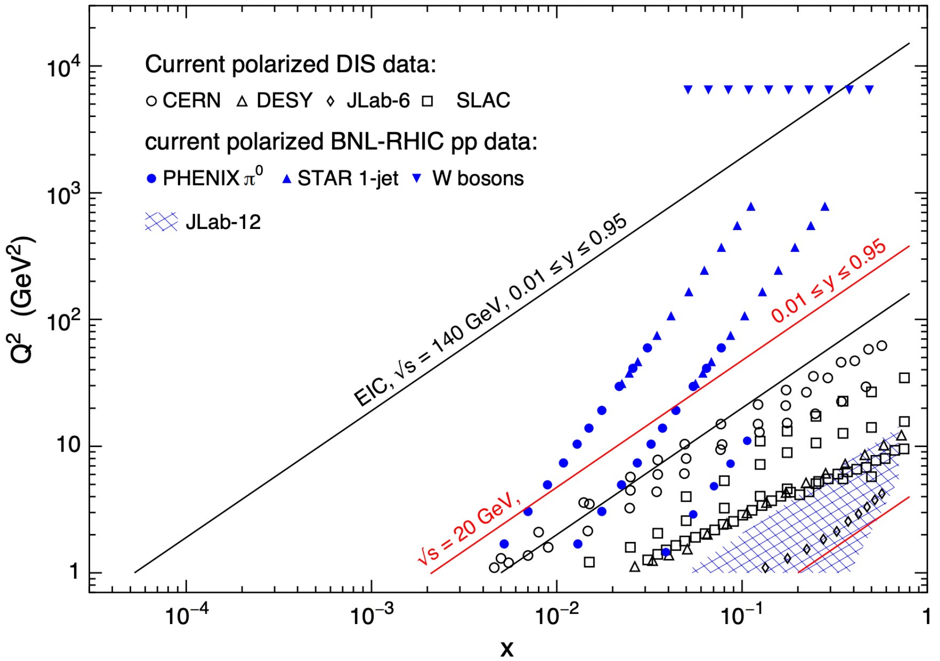
Deep-inelastic scattering (DIS)

- DIS: electroweak process between lepton and parton
  - Kinematics well-defined, but probe unknown
- Various final states to be studied with different requirements for kinematic reconstruction
  - Inclusive DIS (PDFs): measure only scattered lepton
  - Semi-inclusive DIS (SIDIS) (TMD-PDFs, FFs): measure scattered lepton/virtual photon and coincident hadron/dihadron, PID
  - DIS jets (TMD-PDFs, jet FFs): jet energy and transverse momentum resolution





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Classical DIS kinematic reconstruction

- Fixed target DIS/SIDIS: kinematics reconstructed from scattered lepton
  - At low-y ("inelasticity"), electron method fails severely
- Developments at HERA: hadronic final state (HFS) can also fully constrain DIS kinematics
- Inclusive DIS kinematics (x, Q^2, y) over-constrained by following set of experimentally measured variables:
  - Leptonic information: $E_{\ell'}$, $\theta_{\ell'}$
  - HFS information:

$$\Sigma = \sum_{i \in HFS} E_i - p_{z,i} \qquad p_{T,HFS} = \sqrt{(\sum p_{x,i})^2 + (\sum p_{y,i})^2}$$

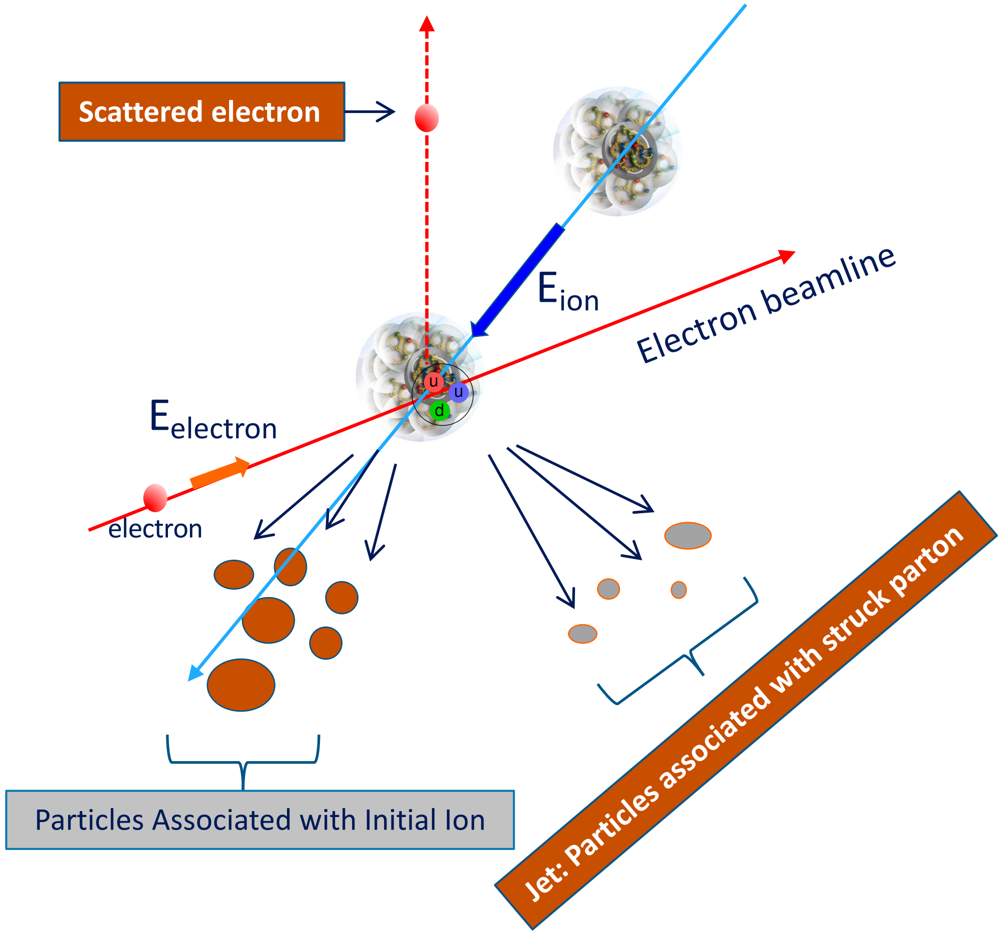

Figure from M. Diefenthaler

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HERA methods $\longrightarrow$ DL inclusive DIS variables

Method	Requires	Pro	Contra
Electron (EL)	$E_{l'}$, $\theta_{l'}$	precise	sensitive to QED radiation
Jacques-Blondel (JB)	$\delta_{\mathcal{H}}$, $P_{T,\mathcal{H}}$	resistant to QED radiation	needs precise jet energy measurements
Double Angle (DA)	$\theta_{l'}$, $\gamma_{\mathcal{H}}$	no need for precise jet energy measurements	poor resolution at low x and low Q^2

- Diefenthaler, Farhat, Verbytskyi, Xu (2021, arXiv:2108.11638):
  - Physics-motivated NN architecture, deep learning using HERA inclusive DIS methods as input

$$Q^2_{NN} = A_{Q^2}\left(Q^2_{EL}, Q^2_{DA}, Q^2_{JB}\right) + L_{Q^2}\left(A_{Q^2}, E_{l'}, \theta_{l'}\right) + H_{Q^2}\left(A_{Q^2}, \delta_{\mathcal{H}}, P_{T,\mathcal{H}}\right)$$

$$x_{NN} = A_x\left(x_{EL}, x_{DA}, x_{JB}\right) + L_x\left(A_x, Q^2_{NN}, E_{l'}, \theta_{l'}\right) + H_x\left(A_x, Q^2_{NN}, \delta_{\mathcal{H}}, P_{T,\mathcal{H}}\right)$$

  - A, L, H -> fully connected linear neural networks
- Network structured as learned average of HERA methods + corrections terms from scattered electron, hadronic final state
- Method validated on ZEUS full simulation

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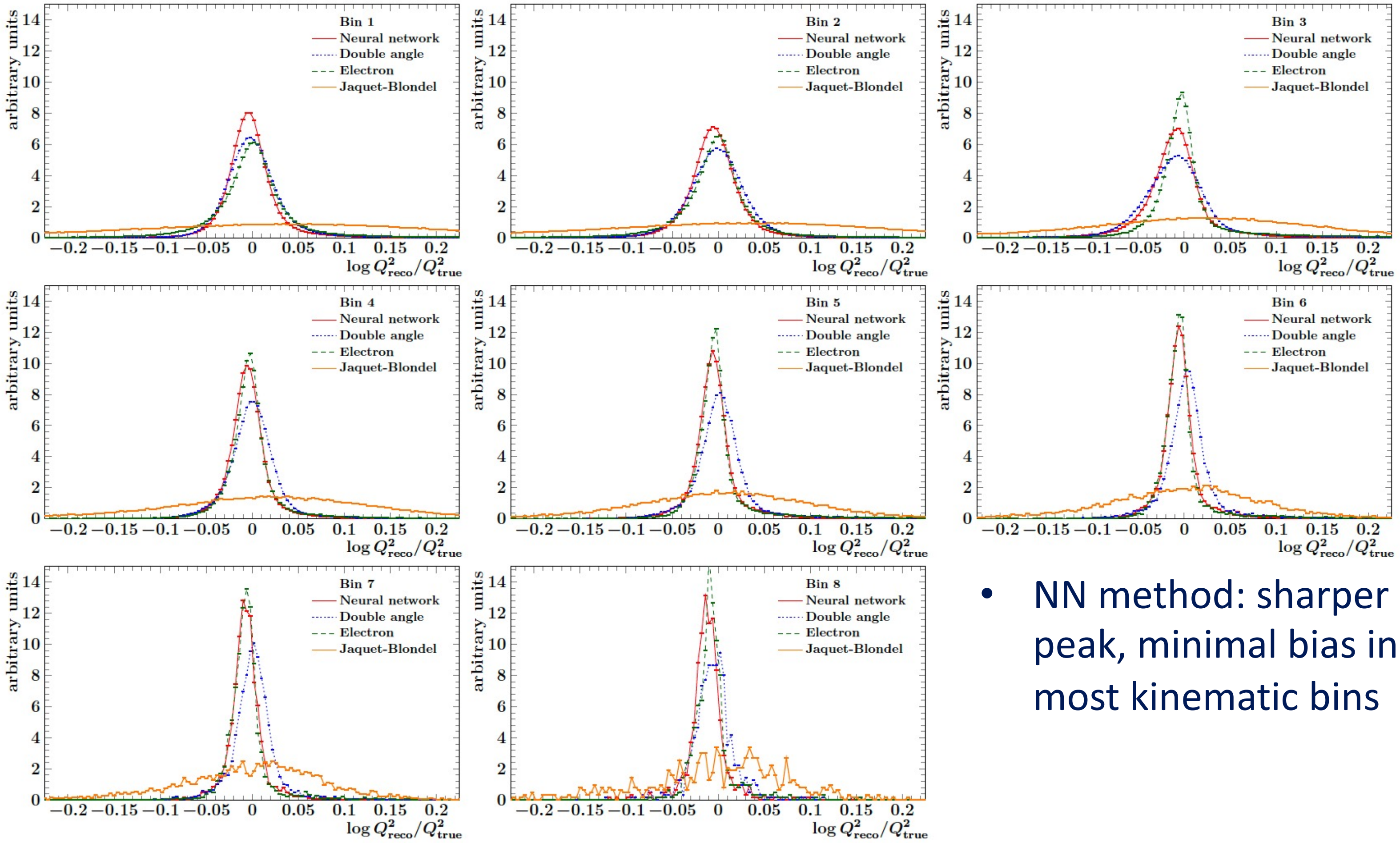
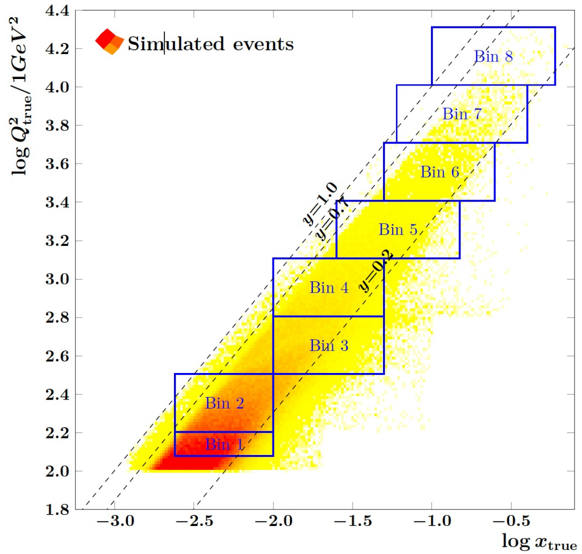
HERA methods ⟶ DL inclusive DIS variables

ZEUS full simulation results, $\log(Q^2/Q^2_{true})$:



- NN method: sharper peak, minimal bias in most kinematic bins



Diefenthaler et. al, arXiv:2108.11638,
And DIS2022 talk by A. Farhat

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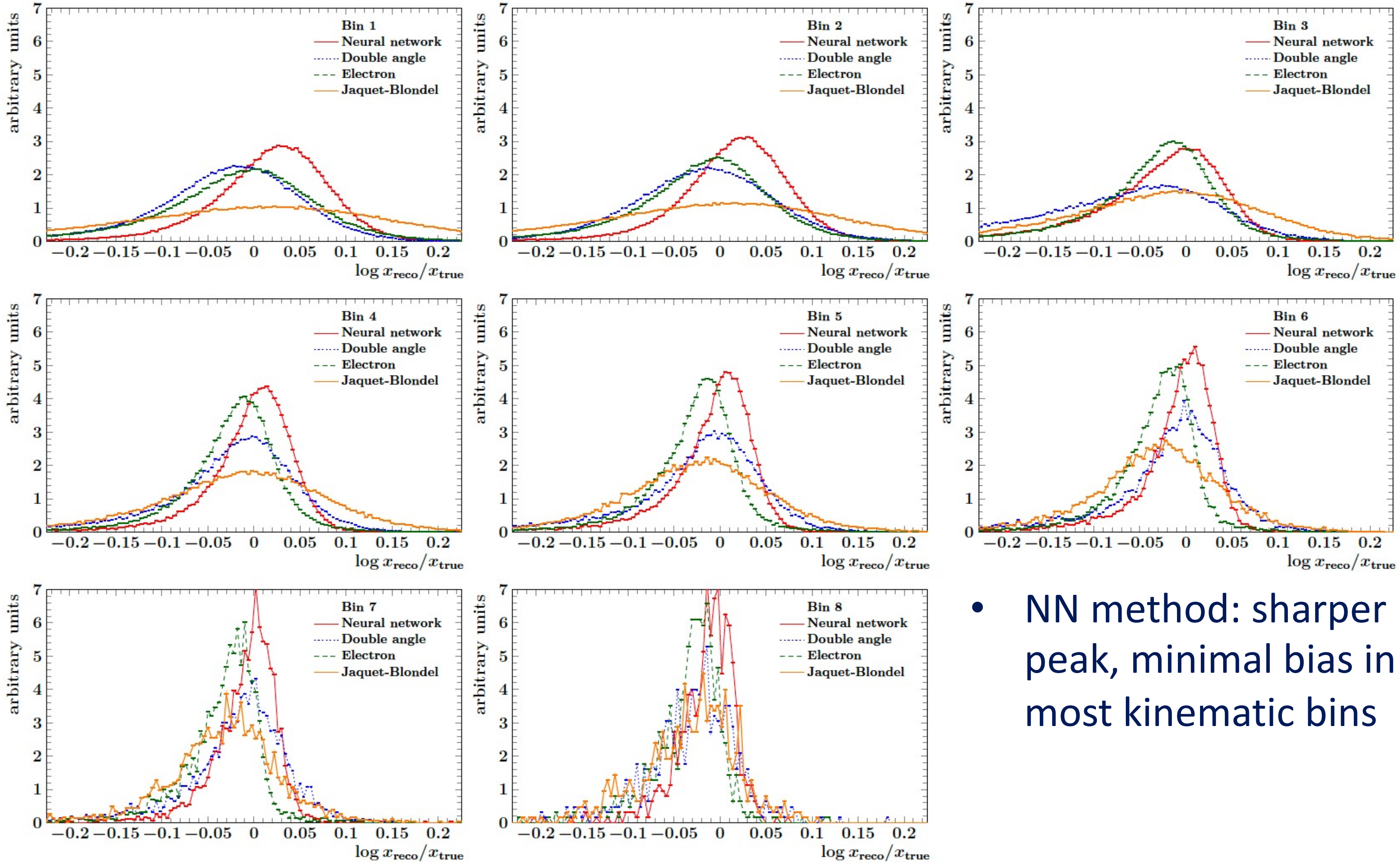
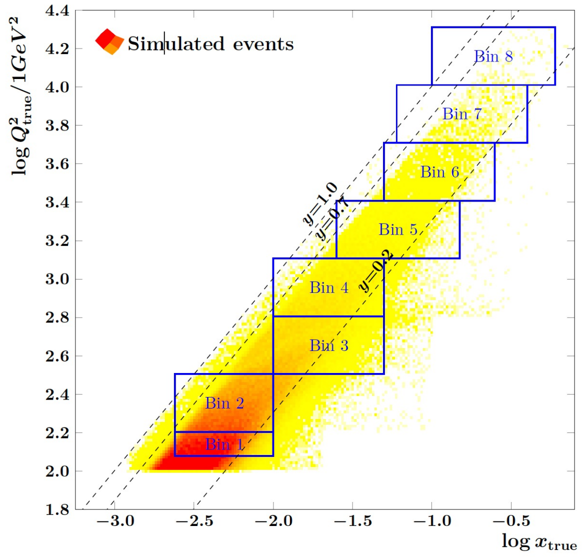
HERA methods ⟶ DL inclusive DIS variables

ZEUS full simulation results, $\log(x/x_{true})$:





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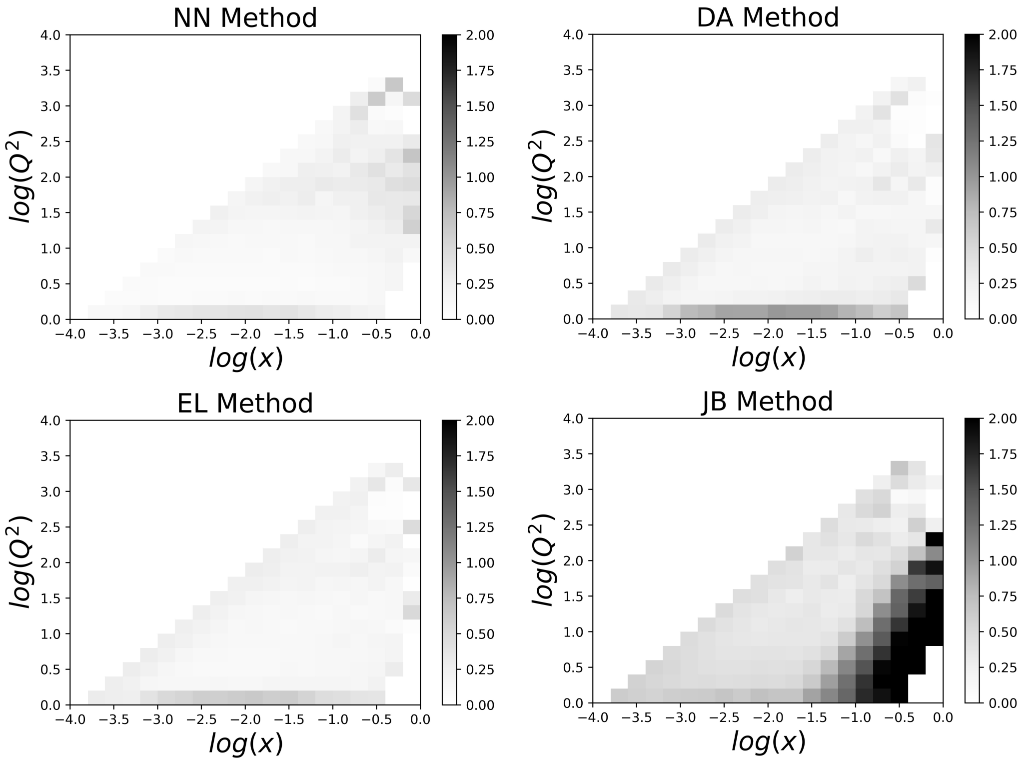
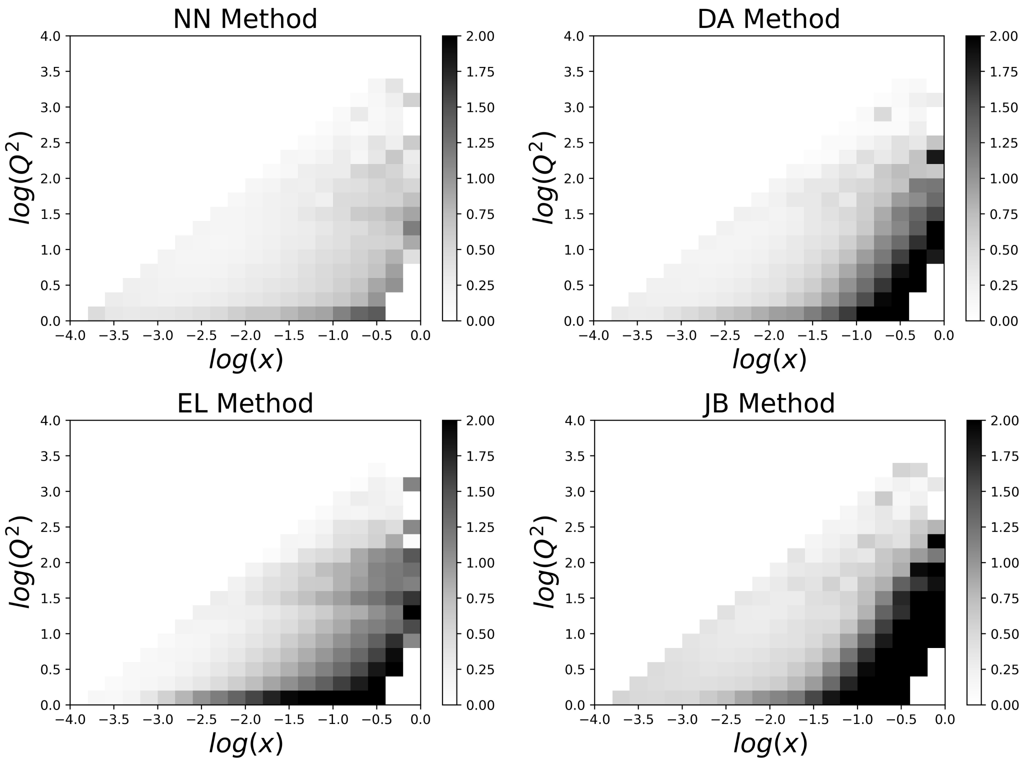
HERA methods → DL inclusive DIS variables

ECCE full simulation:

RMSE, Q^2



RMSE, x



- On ECCE full simulation: network does produce optimal combination of detector level reconstruction methods

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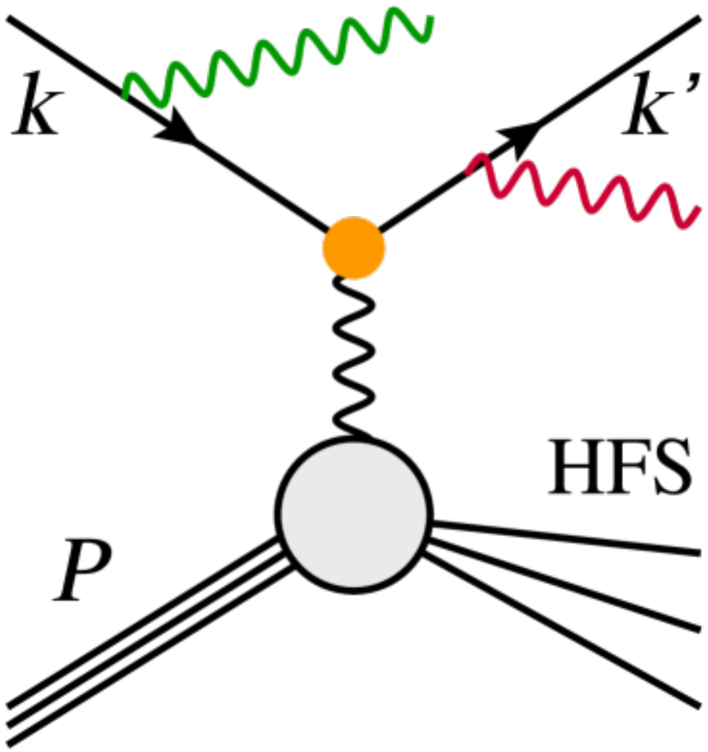
Diefenthaler et. al, arXiv:2108.11638,
And DIS2022 talk by A. Farhat

ML inclusive DIS and identifying QED ISR/FSR

- Arratia, Britzger, Long, Nachman (2021, 10.1016/j.nima.2021.166164):
  - Directly addressing QED radiative impact on inclusive DIS kinematics at the EIC
    - Classify events as ISR, FSR, or no QED radiation
  - Momentum imbalance variables defined to quantify QED radiation:

$$p_T^{bal} = 1 - \frac{p_{T,e}}{p_{T,HFS}} \qquad p_z^{bal} = 1 - \frac{\Sigma_e + \Sigma}{2E_0}$$

    - Both zero if no ISR or FSR, correspond to magnitude of radiation



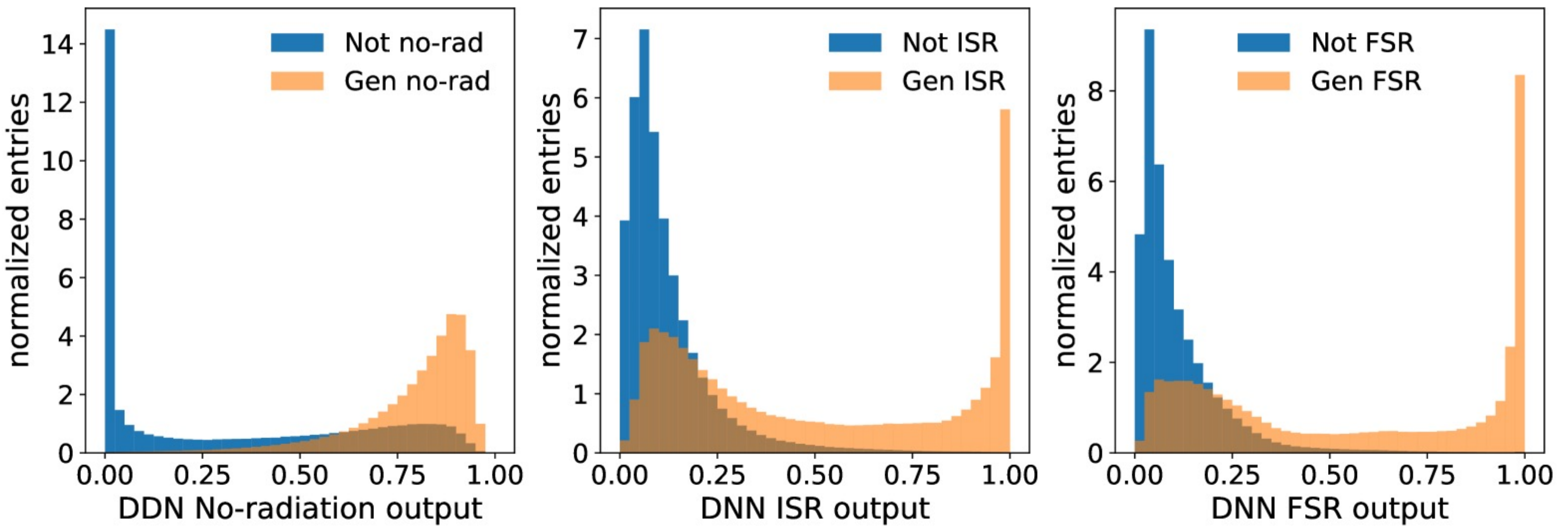
(From Arratia et. al)

ML for identifying QED ISR/FSR

Arratia et. al, arXiv:2110.05505

- Identification of ISR/FSR events achieved using deep learning
  - Also prove capability to regress momentum balance terms previously defined
- Input variables motivated by event shape effects of QED radiation:
  - QED radiation impact variables defined on previous slide
  - ECAL energy and cluster information around scattered electron
  - Photon nearest to electron
  - Total HFS and scattered electron energy, longitudinal and transverse momenta
  - Angle between HFS and scattered electron

ATHENA fast simulation (Rapgap+Delphes)



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ML inclusive DIS and identifying QED ISR/FSR

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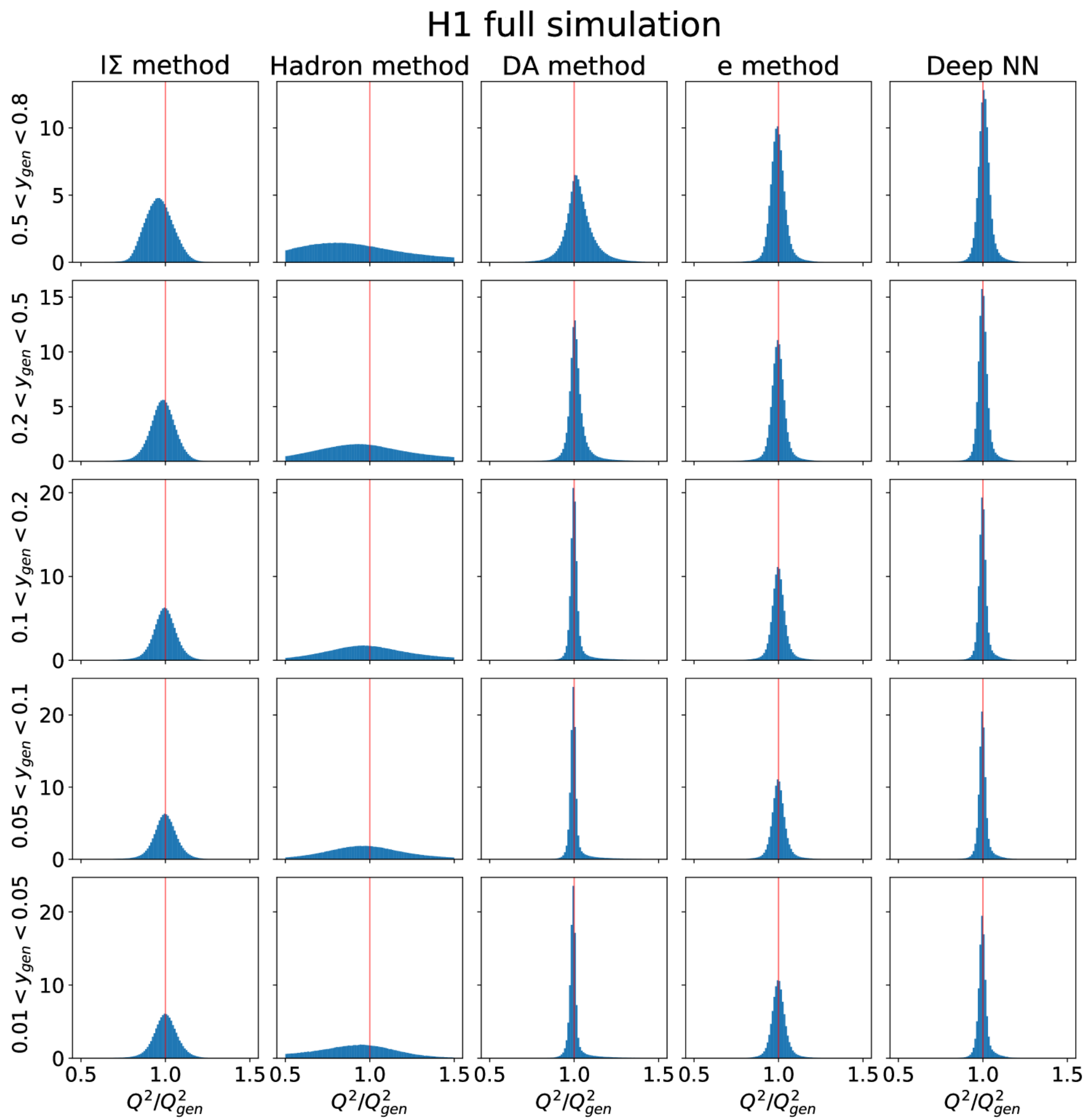

y_{gen}

- Same input variables used to train NN to simultaneously reconstruct inclusive DIS kinematics Q^2, x, y
  - Method validated using H1 full simulations, ATHENA fast simulations

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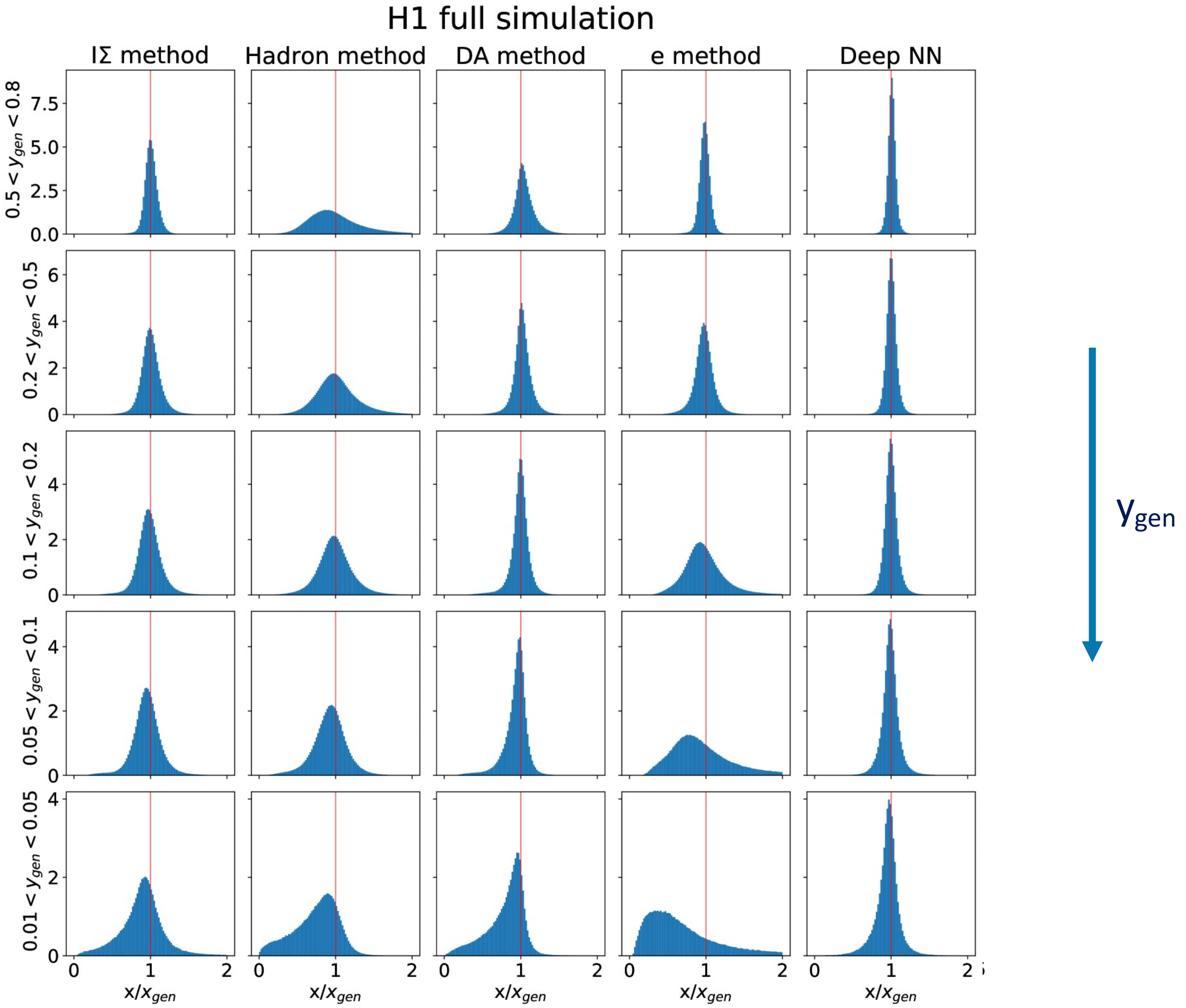

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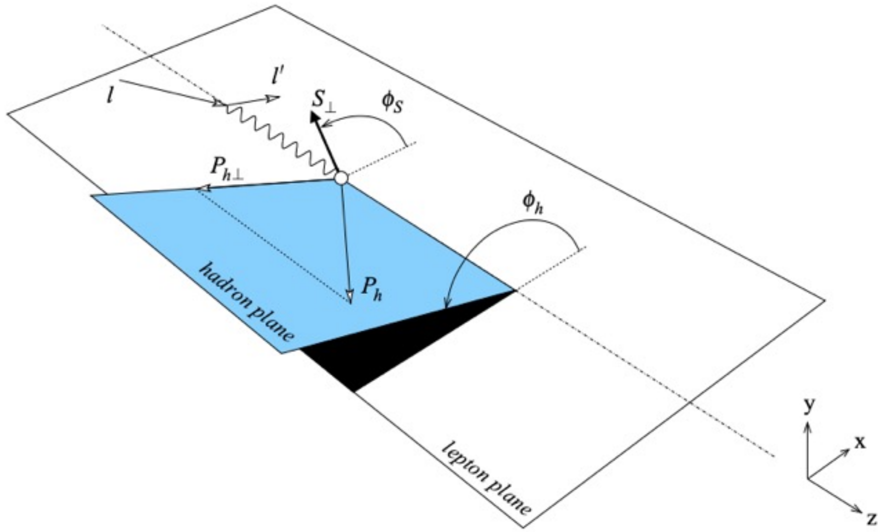
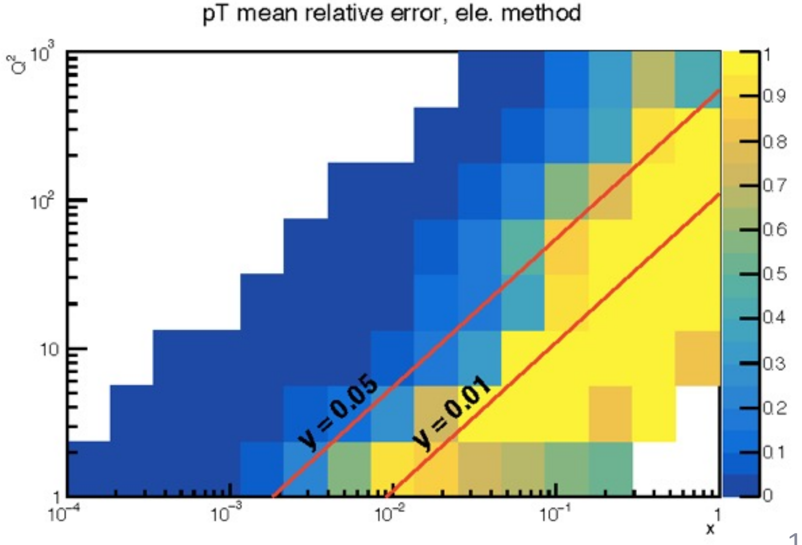
Semi-inclusive DIS reconstruction at the EIC

Pecar, Vossen: arXiv:2209.14489



- SIDIS only previously studied in fixed-target experiments
  - Electron reconstruction of virtual photon four-momentum (q) largely reliable in fixed target
- Significant uncertainty anticipated for SIDIS kinematics at low-y at EIC
  - Similar severity to inclusive DIS reconstruction, but without any methods previously developed specifically for low-y
- Reconstructing q with HFS and scattered electron first explored in EIC YR and detector proposals

ATHENA full simulation:



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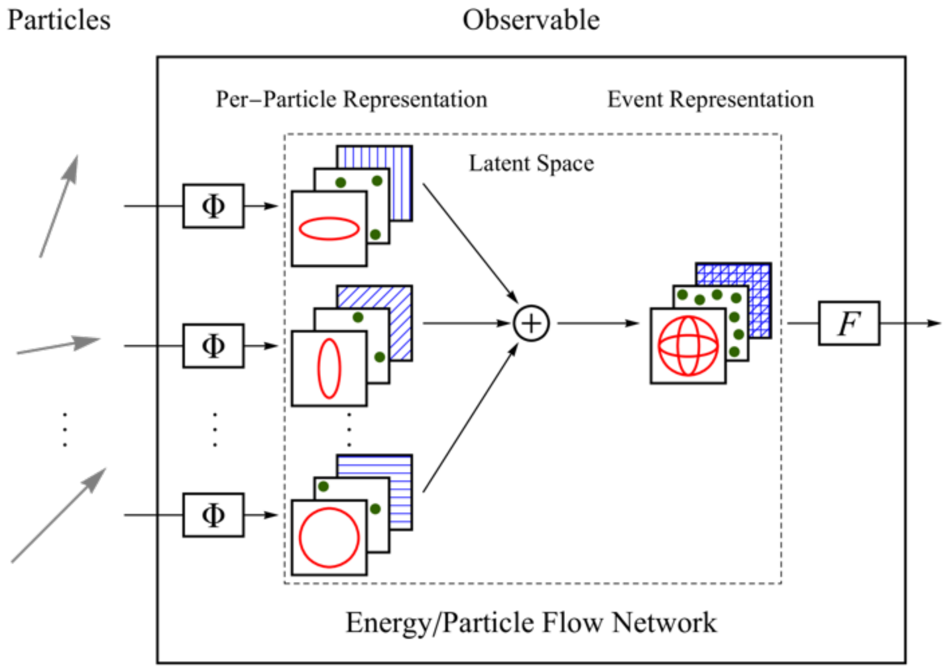
Semi-inclusive DIS reconstruction with ML

- Our approach: utilizing full information from both scattered electron and HFS
- Rather than directly regressing SIDIS kinematics per hadron, regressing virtual photon four-momentum by event

- Particle Flow Network utilized (arXiv:1810.05165, https://energyflow.network/)
    - Learns function of features of unordered set of particles to compute observable
    - Like graph neural network, but with no connections between particles prior to summation
    - Successful in tasks like jet classification at LHC



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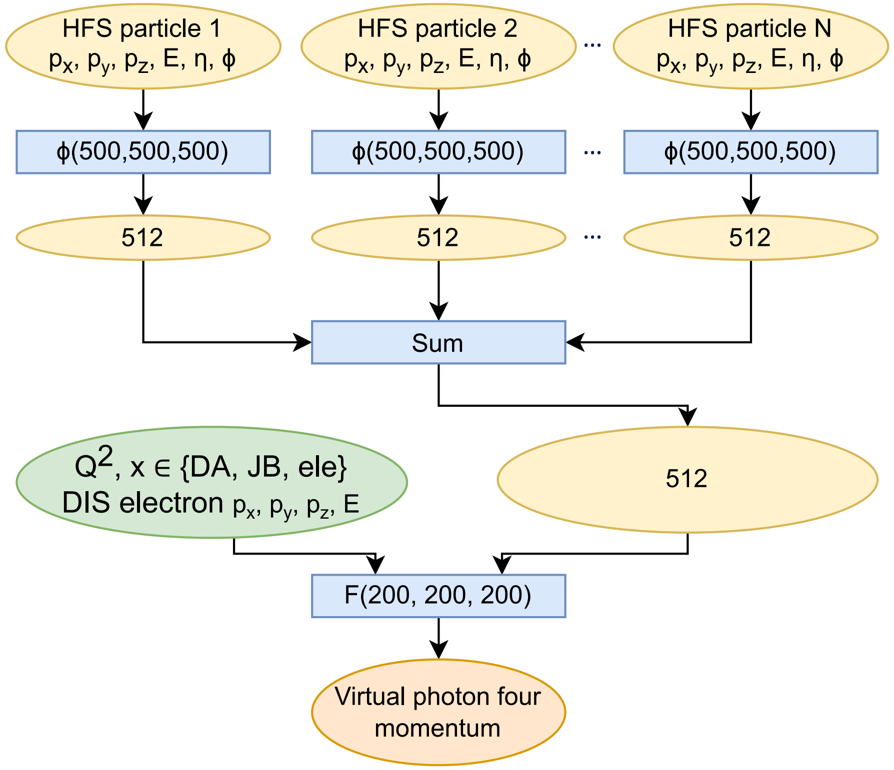
Semi-inclusive DIS reconstruction with ML

Pecar, Vossen

- HFS particle features supplied:
  - Momenta, energy, angular information
- Scattered electron input to network at latent space level
  - DIS electron unique among final state particles, so in a fixed place in network
- Inclusive DIS variables from DA, JB, electron methods also input at latent space level
- Trained on low Q^2 ATHENA full simulation sample



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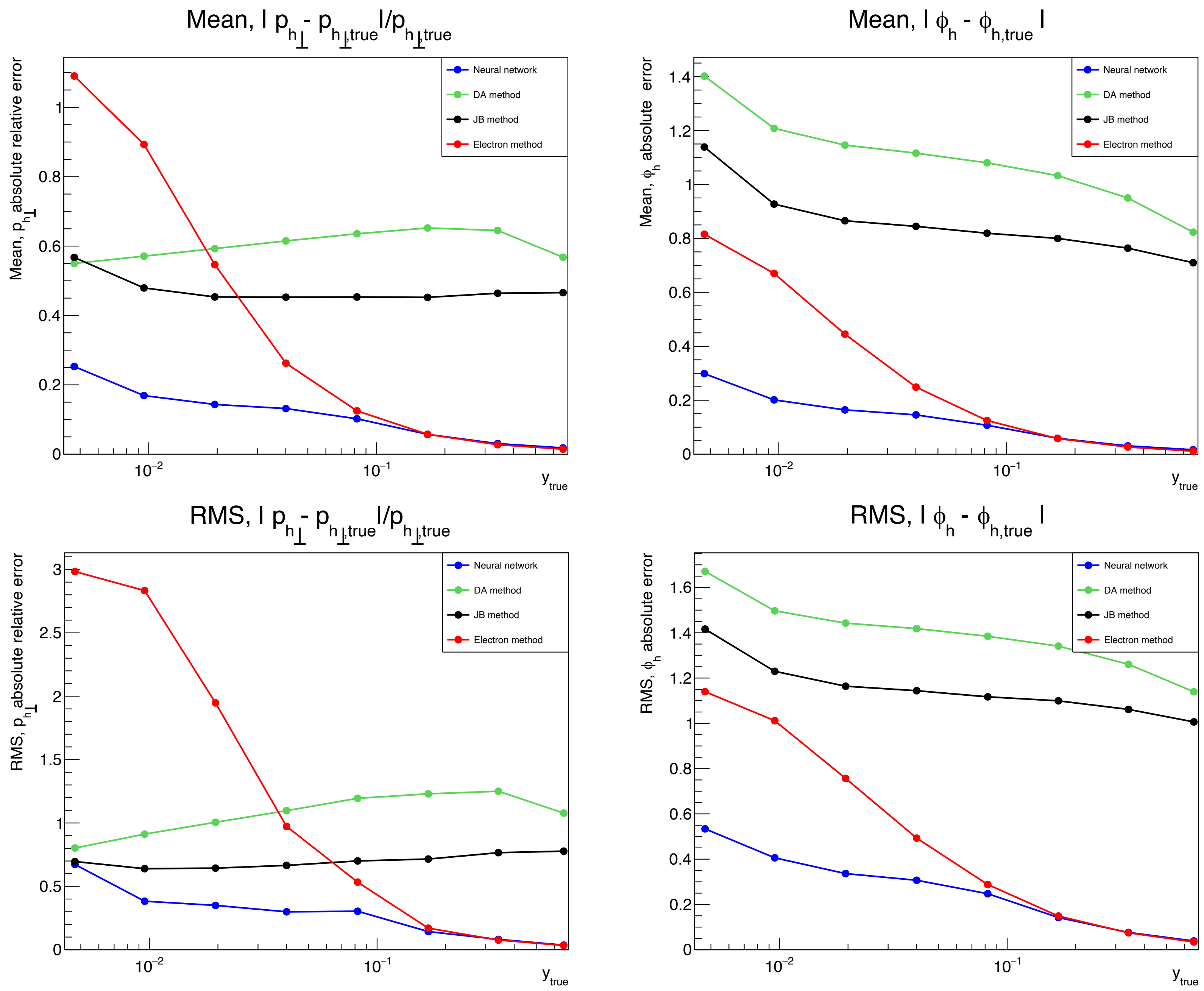
Resolutions as a function of y:

ATHENA full simulation, 10x275, pi+, z > 0.2

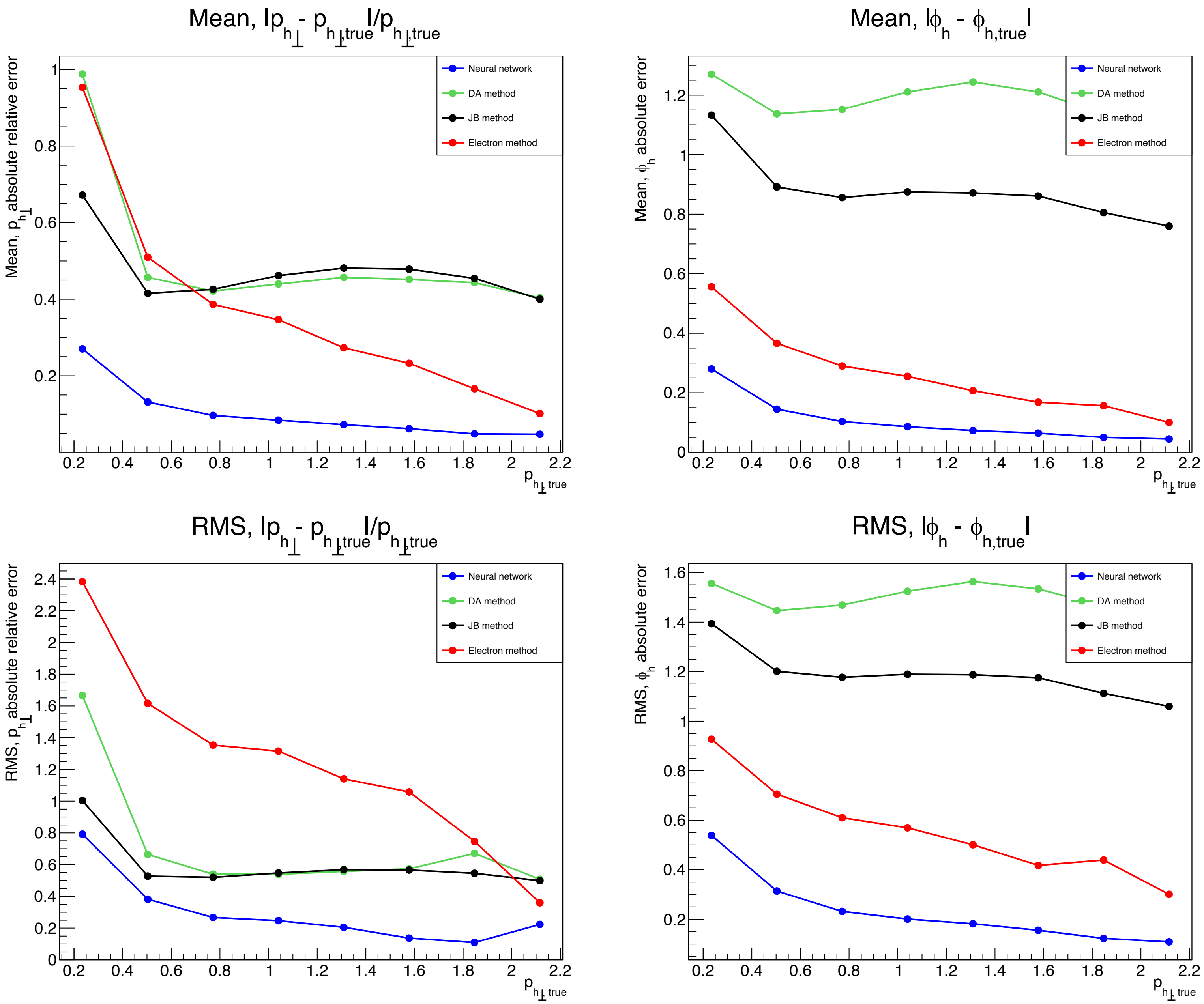
- Resolution very significantly improved over electron method
    - Equal to electron at large-y as expected
    - Remains stable at low-y when electron method fails



Pecar, Vossen

Resolutions as a function of $p_{h,\perp}$:

ATHENA full simulation,
10x275, pi+, z > 0.2



- Similar behavior observed as a function of SIDIS transverse momentum
  - q with PFN provides significant improvement in resolution at low $p_{h,\perp}$

Pecar, Vossen

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Next steps in SIDIS reconstruction

- Currently working on testing similar implementation with different architectures like GNNs
- Plan to continue benchmarking performance as project detector simulations developed
- Need further testing of impact of QED radiation
  - Options like including momentum balance terms (Arratia et. al), other QED impact-proportional variables within network

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ML for heavy ion partonic kinematics (arXiv:2112.05043)

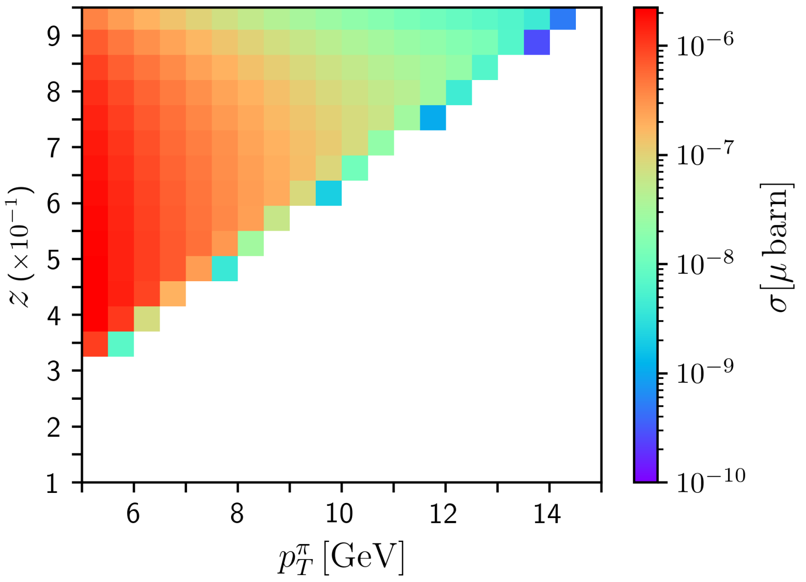
- Rentería-Estrada, Hernández-Pinto, Sborlini, & Zurita (2021): ML approaches to heavy ion collision kinematics
  - Partonic kinematics not well-defined at higher orders
- Ion-collision process:

$$H_1(P_1) + H_2(P_2) \to h(P^h) + \gamma(P^\gamma)$$

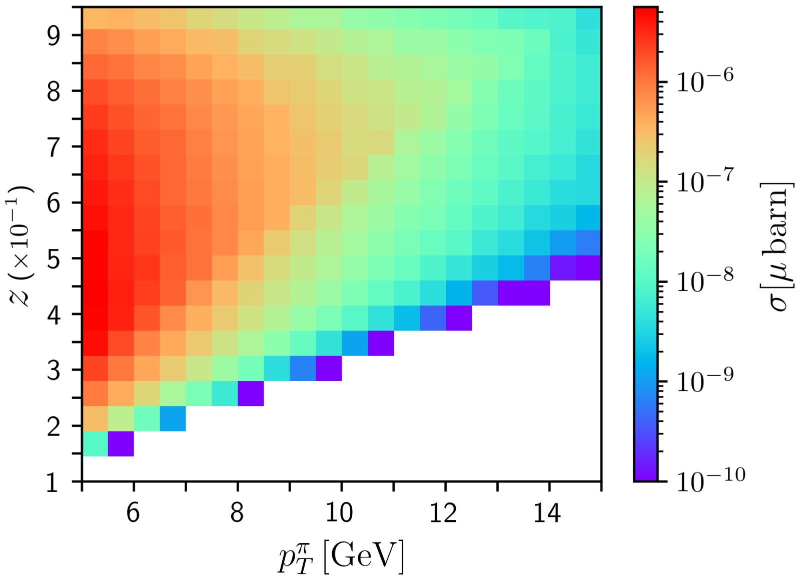
  - Want to connect to partonic variables x_1, x_2, z
  - Complex dependence on final state information at NLO QCD + LO QED

$$p_j = \{\bar{p}_T^\gamma, \bar{p}_T^\pi, \bar{\eta}^\gamma, \bar{\eta}^\pi, \overline{\cos}(\phi^\pi - \phi^\gamma)\} \in \bar{\mathcal{V}}_{\text{Exp}}$$

LO QCD:



NLO QCD + LO QED:



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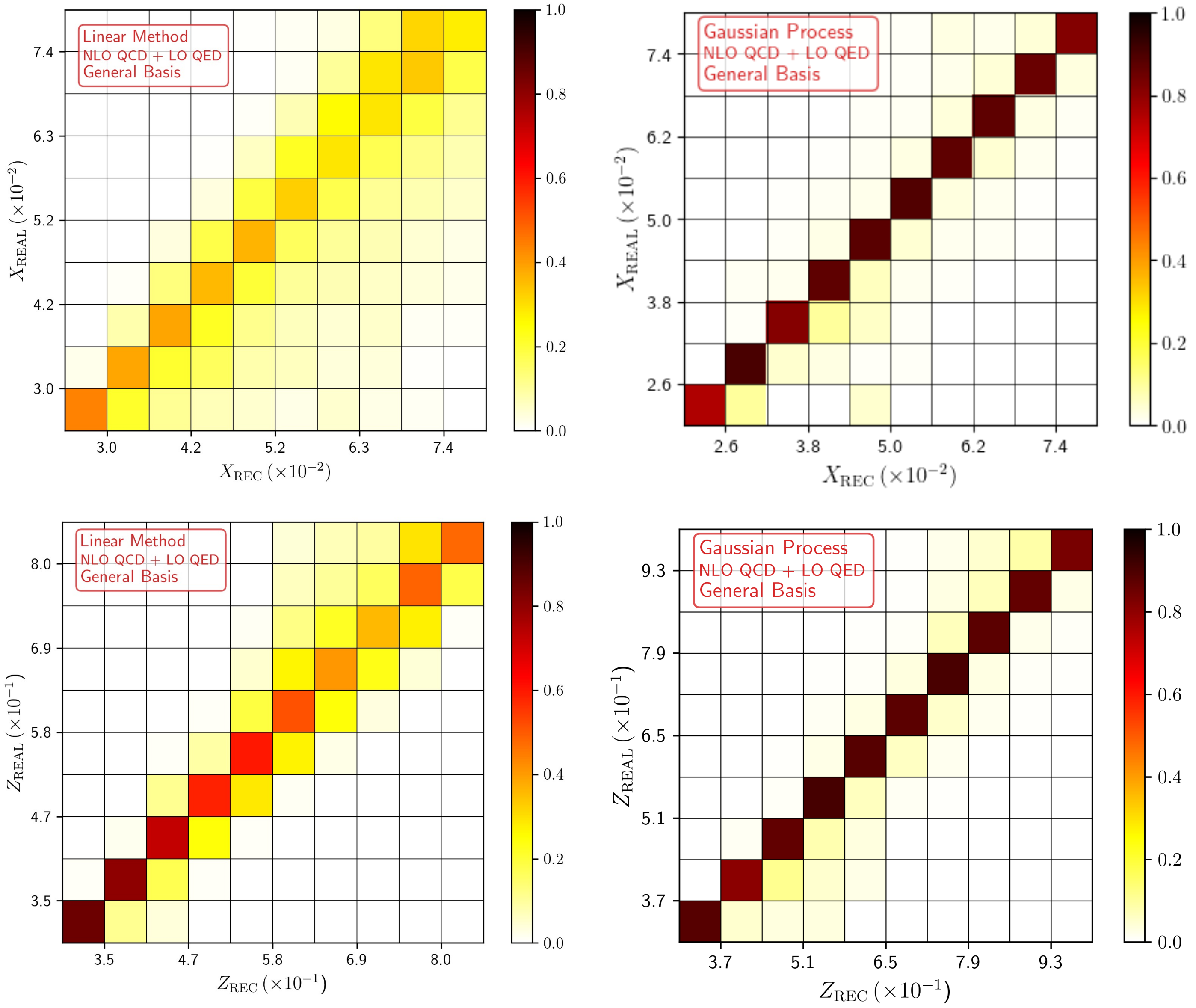


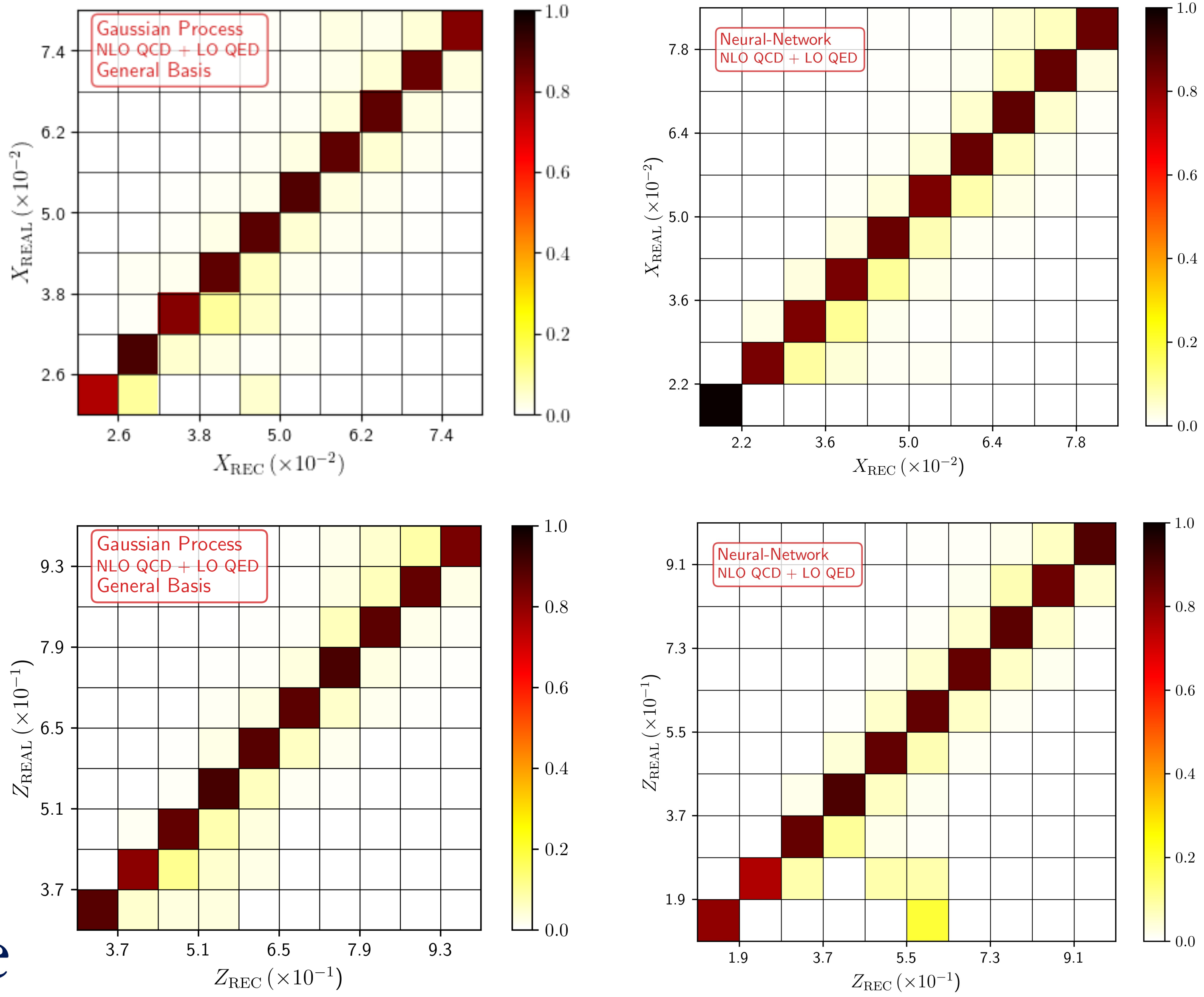
$$(x_{1,2})_j = \sum_i (x_{1,2})_i \frac{d\sigma_j}{dx_{1,2}}(p_j; (x_{1,2})_i), \quad (z)_j = \sum_i z_i \frac{d\sigma_j}{dz}(p_j; z_i)$$

$$p_j = \{\bar{p}_T^\gamma, \bar{p}_T^\pi, \bar{\eta}^\gamma, \bar{\eta}^\pi, \overline{\cos}(\phi^\pi - \phi^\gamma)\} \in \bar{\mathcal{V}}_{\mathrm{Exp}}$$

- Basis for regression constructed from products of up to three kinematic variables
- Gaussian process found to better account for higher order QCD + QED effects
  - Without needing to construct basis of higher order terms
- Both methods strongly dependent on choosing a proper basis

Rentería-Estrada et. al

ML for heavy ion kinematics (arXiv:2112.05043)



- Neural network: not dependent on basis with well-chosen network structure, non-linear activation

Rentería-Estrada et. al

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Conclusions

- Machine learning applicable to many aspects of DIS kinematic reconstruction
  - Improved precision in regressing well-defined kinematics
  - Identification of QED-radiation in initial or final state
  - Better determination of virtual photon axis (SIDIS)
- Different approaches to regression of DIS kinematics already shown to be effective on first EIC detector simulations, HERA simulations
- Machine learning shown to be effective in studies of regression of partonic kinematics in ion collisions