Machine Learning Reconstruction of DIS Kinematics

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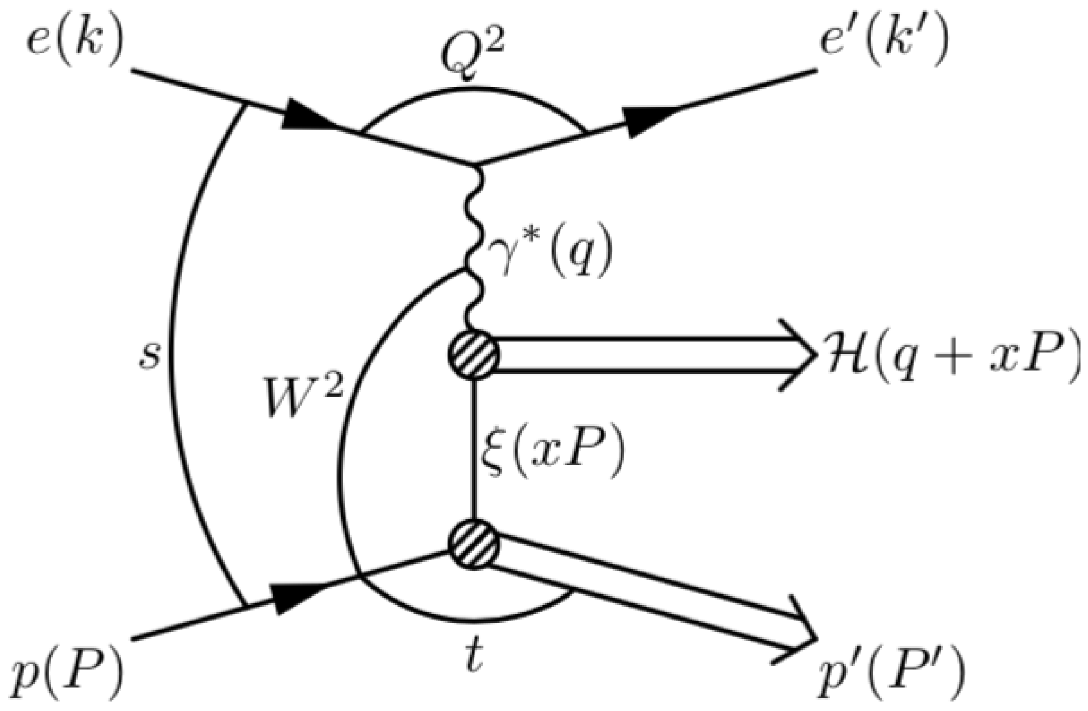
Inclusive Deep Inelastic Scattering



Inclusive DIS can be characterized by x (Bjorken scaling variable) and Q^2 (exchanged boson virtuality).

$$Q^2 = -q^2 = -(k - k')^2$$

$$x = \frac{Q^2}{2P \cdot q}$$

Reconstruction of DIS Kinematics

The kinematic variables x and Q^2 can be reconstructed using measurements from the scattered lepton (e') and hadronic final state ($\mathcal{H}$):

- energy ($E_{e'}$) and polar angle ($\theta_{e'}$) of the scattered lepton
- energy from the hadronic system in terms of:

$$\delta_{\mathcal{H}} = \sum_{i\in\mathcal{H}} E_i - P_{Z,i} \quad \text{and} \quad P_{T,\mathcal{H}} = \sqrt{\left(\sum_{i\in\mathcal{H}} P_{X,i}\right)^2 + \left(\sum_{i\in\mathcal{H}} P_{Y,i}\right)^2}$$

- Hadronic energy flow in terms of $\gamma_{\mathcal{H}}$, where

$$\cos\gamma_{\mathcal{H}} = \frac{P_{T,\mathcal{H}}^2 - \delta_{\mathcal{H}}^2}{P_{T,\mathcal{H}} + \delta_{\mathcal{H}}^2}$$

Motivation for a Machine Learning Reconstruction

The previously mentioned measurements overconstrain the reconstruction of DIS event kinematics.

Classical approaches at colliders (E.G., electron method, Jacques-Blondel method, double-angle method, …) reconstruct kinematics by a subset of these variables and have limitations.

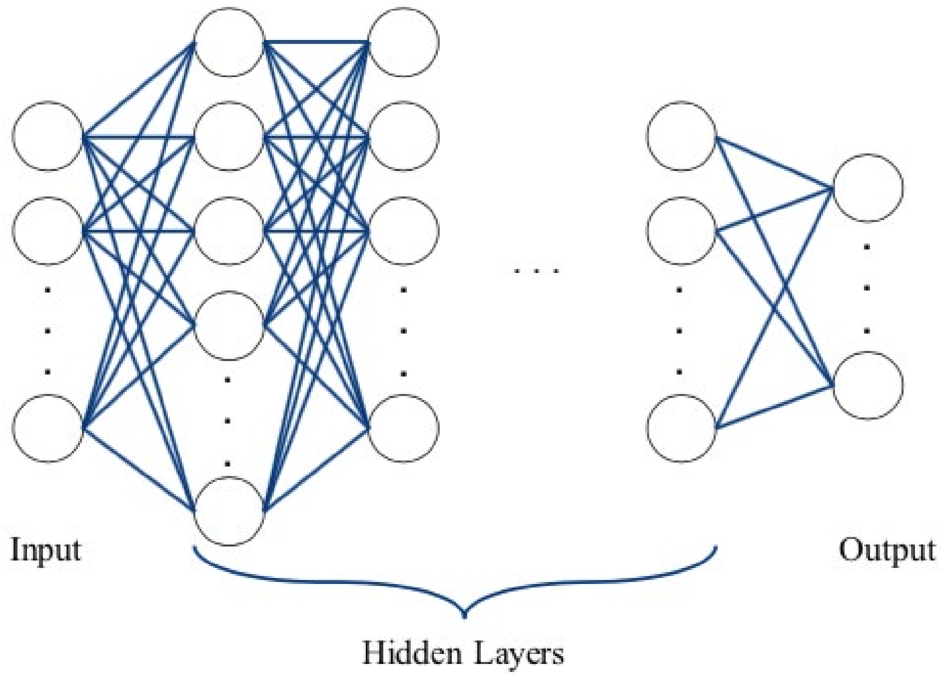
Motivation for a Machine Learning Reconstruction

Method	Required Measurements	Strengths	Limitations
Electron	$E_{e'}, \theta_{e'}$	Precise	Sensitive to QED radiation
Jacques-Blondel	$\delta_{\mathcal{H}}, P_{T,\mathcal{H}}$	Resistant to QED radiation	Needs precise energy measurements
Double-Angle	$\theta_{e'}, \gamma_{\mathcal{H}}$	Does not need precise energy measurements	Poor resolution at low x, low Q^2

The choice of reconstruction method determines the size of systematic uncertainties

Motivation for a Machine Learning Reconstruction

A deep neural network can be trained on a large sample of Monte Carlo events to reconstruct x and Q^2 based on all four available measurements.



Neural Network Reconstruction of DIS Kinematics

Monte Carlo events were generated in the context of $e^{\pm}p$ scattering at the ZEUS experiments at HERA.

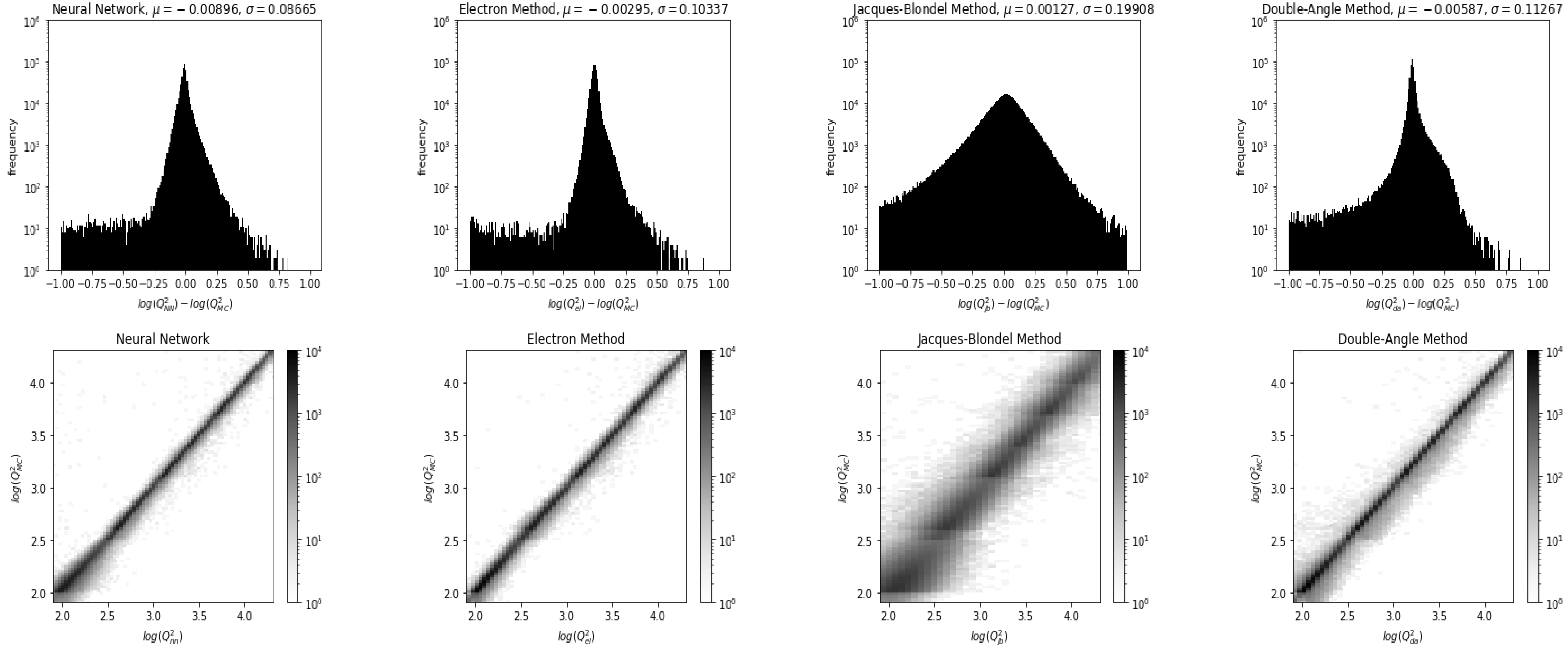
We focus on the kinematic region:

$$0.0024 < x < 0.6 \quad \text{and} \quad 80\ \mathrm{GeV}^2 < Q^2 < 20480\ \mathrm{GeV}^2$$

The selection of the training set coincides with the process of identifying the scattered lepton and selecting DIS events, in order to:

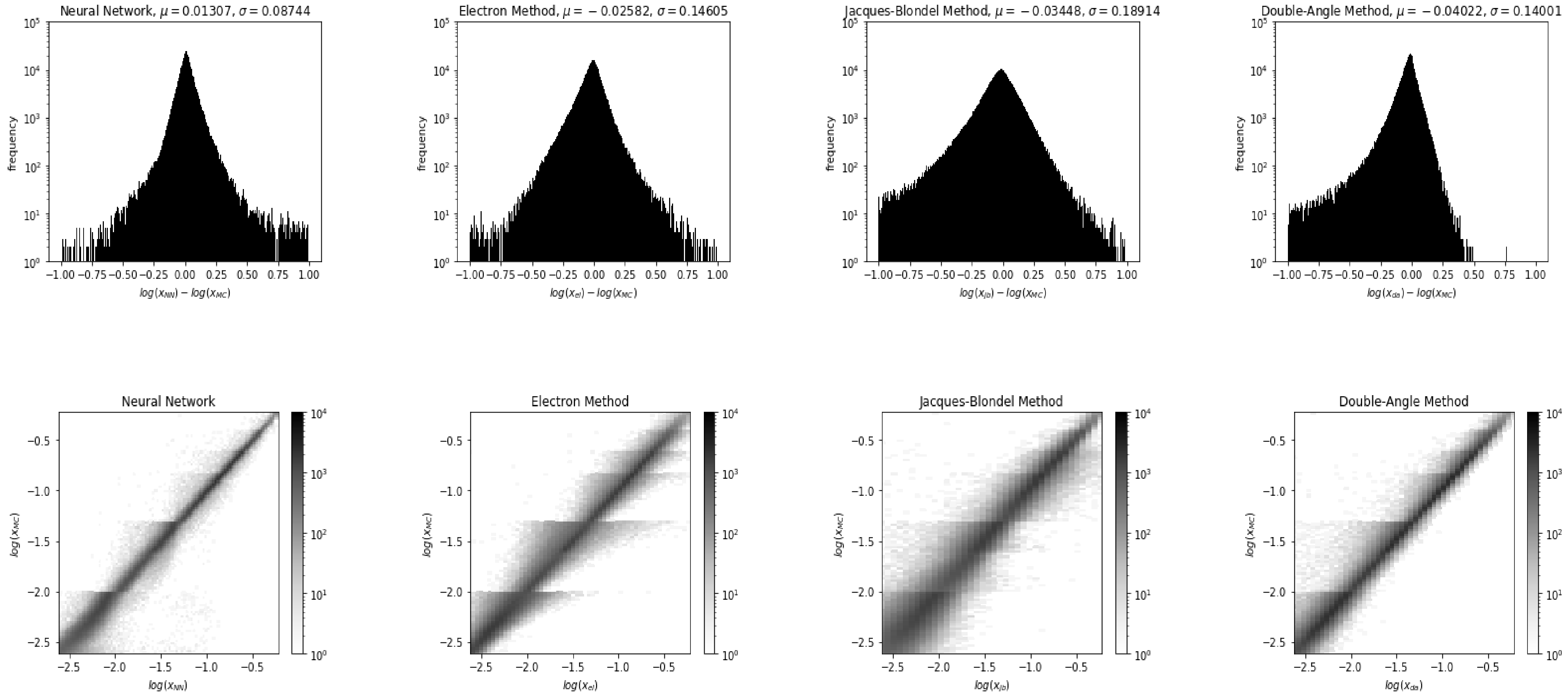
- Define the phase space of measurement
- Ensure a low fraction of background contamination (e.g. photoproduction, beam-gas interactions, cosmic muons, beam-halo muons, QED Compton scattering, etc.)
- Provide a reasonable description of detector acceptance by Monte Carlo simulations

Results



Neural Network, $\mu = -0.00896$, $\sigma = 0.08665$
Electron Method, $\mu = -0.00295$, $\sigma = 0.10337$
Jacques-Blondel Method, $\mu = 0.00127$, $\sigma = 0.19908$
Double-Angle Method, $\mu = -0.00587$, $\sigma = 0.11267$
frequency
$log(Q^2_{NN}) - log(Q^2_{MC})$
$log(Q^2_{el}) - log(Q^2_{MC})$
$log(Q^2_{jb}) - log(Q^2_{MC})$
$log(Q^2_{da}) - log(Q^2_{MC})$
Neural Network
Electron Method
Jacques-Blondel Method
Double-Angle Method
$log(Q^2_{MC})$
$log(Q^2_{nn})$
$log(Q^2_{el})$
$log(Q^2_{jb})$
$log(Q^2_{da})$

Results


Neural Network, $\mu = 0.01307$, $\sigma = 0.08744$
Electron Method, $\mu = -0.02582$, $\sigma = 0.14605$
Jacques-Blondel Method, $\mu = -0.03448$, $\sigma = 0.18914$
Double-Angle Method, $\mu = -0.04022$, $\sigma = 0.14001$
frequency
$log(x_{NN}) - log(x_{MC})$
$log(x_{el}) - log(x_{MC})$
$log(x_{jb}) - log(x_{MC})$
$log(x_{da}) - log(x_{MC})$
Neural Network
Electron Method
Jacques-Blondel Method
Double-Angle Method
$log(x_{MC})$
$log(x_{NN})$
$log(x_{el})$
$log(x_{jb})$
$log(x_{da})$

Bin	Events	$Q^2\ (GeV^2)$	x	x RMSE		Q^2 RMSE	
1	114606	80 – 160	0.0024 – 0.010	NN: 0.0040 JB: 0.0042	EL: 0.0029 **DA: 0.0012**	NN: 22.705 JB: 204.39	**EL: 14.810** DA: 20.753
2	65501	160 – 320	0.0024 – 0.010	NN: 0.0049 JB: 0.0053	EL: 0.0014 **DA: 0.0013**	NN: 35.068 JB: 405.88	**EL: 29.609** DA: 36.397
3	74382	320 – 640	0.01 – 0.05	**NN: 0.0053** JB: 0.0086	EL: 0.0226 DA: 0.0063	**NN: 60.198** JB: 311.52	EL: 64.426 DA: 82.069
4	47055	640 – 1280	0.01 – 0.05	**NN: 0.0046** JB: 0.0103	EL: 0.0061 DA: 0.0047	**NN: 96.406** JB: 792.58	EL: 105.55 DA: 151.91
5	60684	1280 – 2560	0.025 – 0.150	**NN: 0.0102** JB: 0.0194	EL: 0.0262 DA: 0.0154	**NN: 195.70** JB: 1012.1	EL: 216.84 DA: 283.20
6	46242	2560 – 5120	0.05 – 0.25	**NN: 0.0154** JB: 0.0303	EL: 0.0333 DA: 0.0249	**NN: 410.11** JB: 1694.9	EL: 435.00 DA: 509.29
7	47380	5120 – 10240	0.06 – 0.40	**NN: 0.0197** JB: 0.0452	EL: 0.0358 DA: 0.0327	**NN: 712.45** JB: 3368.6	EL: 745.37 DA: 831.62
8	28507	10240 – 20480	0.10 – 0.6	**NN: 0.0288** JB: 0.0791	EL: 0.0454 DA: 0.0433	**NN: 1553.4** JB: 7096.9	EL: 1660.8 DA: 1796.4

Results

Relative Resolution Values (in percent)								
Region	x_{nn}	x_{el}	x_{jb}	x_{da}	Q^2_{nn}	Q^2_{el}	Q^2_{jb}	Q^2_{da}
$Q^2 < 200$	20	18	32	**16**	11	**6**	40	8
$Q^2 > 200$	**10**	15	20	11	**5**	6	26	7

Initial Conclusions & Challenges

With the appropriate selection of a training set, Monte Carlo data can enhance neural networks sufficiently to outperform classical reconstruction methods on most of the kinematic range considered.

Main Challenge = The scale of the variables

- x and Q^2 have different scales
- The values of each range between 5 orders of magnitude

QUESTIONS?