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Determination of Diffractive PDFs from HERA Data using Neural Networks and Fracture Functions

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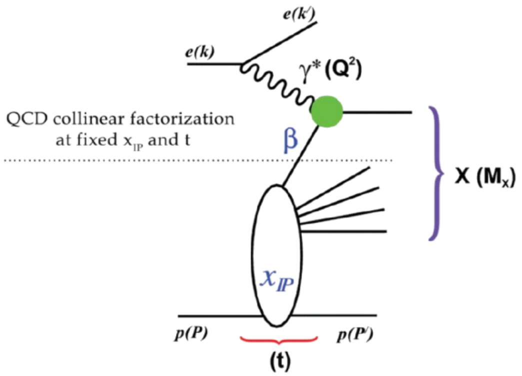
Introduction

- **DPDFs** are important in understanding **diffractive processes** in Deep Inelastic Scattering (DIS).
- Traditional methods involve analytical approaches; introduce the idea of using a **neural network** as a modern, flexible alternative.

$$Q^2 = -q^2 = (k - k'), \quad y = \frac{P.q}{P.k}, \quad x = \frac{-q^2}{2P.q}, \beta = \frac{Q^2}{2(P - P') \cdot q} = \frac{Q^2}{M_X^2 + Q^2 - t}.$$

$$x_{\mathbb{P}} = \frac{q.(P - P')}{P.q}$$



Introduction

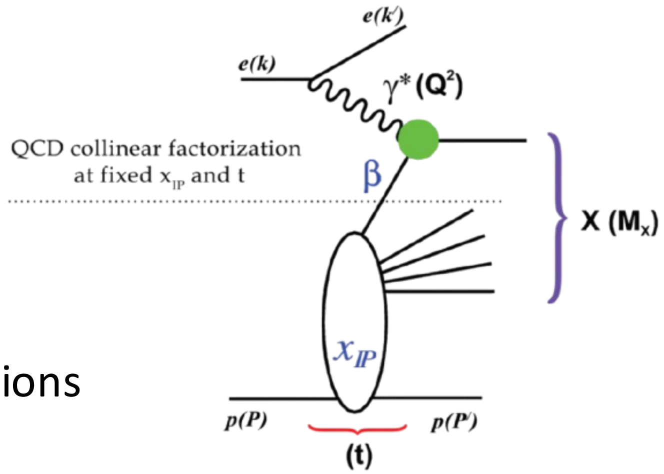
Triple differential Cross section

$$\frac{d\sigma^{ep\to epX}}{d\beta dQ^2 dx_{I\!P}} = \frac{2\pi\alpha^2}{\beta Q^4}\left[1+(1-y)^2\right]\sigma_r^{D3}(\beta, Q^2; x_{I\!P}).$$

$$\sigma_r^{D(3)}(\beta, Q^2; x_{I\!P}) = F_2^{D(3)}(\beta, Q^2; x_{I\!P}) - \frac{y^2}{1+(1-y)^2}F_L^{D(3)}(\beta, Q^2; x_{I\!P}).$$

Using the factorization theorem on Fracture functions

$$F_k^D(\beta, Q^2; x_{I\!P}) = \sum_i \mathcal{F}_i^D(\beta; x_{I\!P}, Q^2) \otimes C_{ki}(\beta, Q^2, \alpha_s)$$

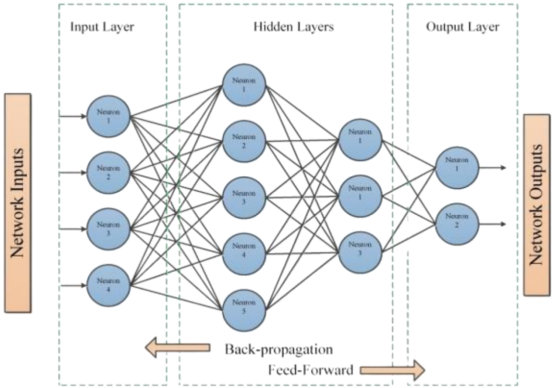


Fracture functions: An Improved description of inclusive hard processes in QCD
Phys. Lett. B 323, 201 (1994)

Neural Network Approach to Parameterization

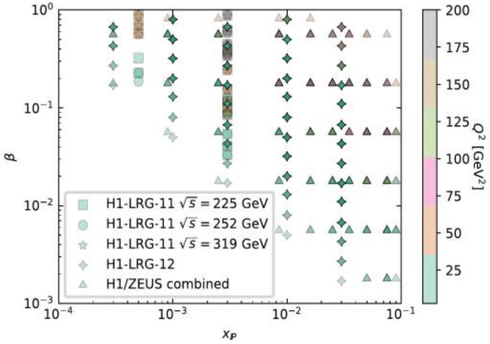
- **Feed-forward neural network** used to model the non-linear relationships in diffractive processes.
- Benefits of using NNs: **data-driven flexibility**, no need for strict theoretical assumptions.

$$\beta \mathcal{F}_q^D(\beta, Q_0^2; x_{I\!P}) = \mathcal{W}(x_{I\!P}) \left(NN1(\beta, Q_0^2) - NN1(1, Q_0^2) \right)^2$$
$$\beta \mathcal{F}_g^D(\beta, Q_0^2; x_{I\!P}) = \mathcal{W}(x_{I\!P}) \left(NN2(\beta, Q_0^2) - NN2(1, Q_0^2) \right)^2$$



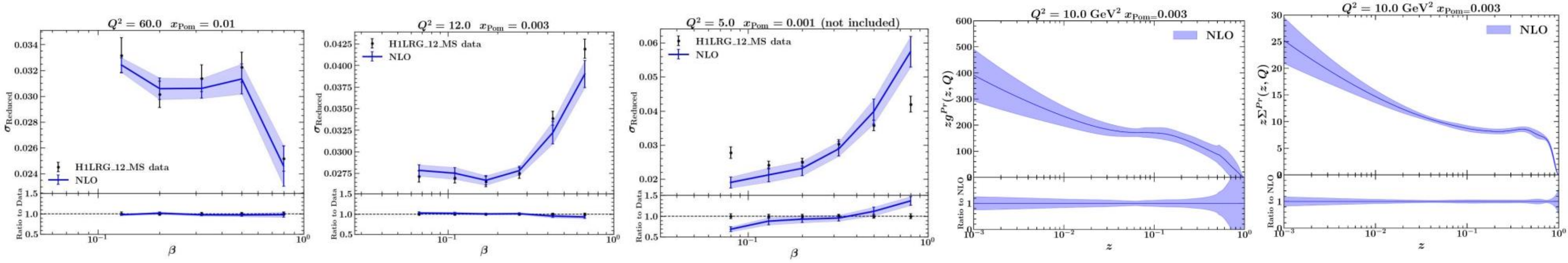
Training the Neural Network

- NN trained using **HERA reduced cross-section data**.NN adjusts weights iteratively, learning the correct mapping between input momentum fraction and DPDFs.
- **Optimization**: Chi-squared minimization between predicted and observed diffractive cross-sections.
- NN adjusts weights iteratively, learning the correct mapping between input momentum fraction and DPDFs.
- We use H1 Large rapidity gap data and H1/Zeus combined FPS data.
- Kinematical cuts:
  - $\beta \leq 0.80$
  - $Q^2 > 8.5$ GeV^2 for all the datasets
  - Study the sensitivity of chi-squared to variations in Q_{min} in future.



Results and Uncertainty Estimation

- NN results closely match previous DPDF determinations.
- **Monte Carlo method** applied for uncertainty estimation: generating pseudo-datasets (replicas) to calculate central values and uncertainties.
- Fair agreement between **data and NN predictions**.



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Conclusions and Future Directions

- NN approach offers a **robust and flexible parameterization** of DPDFs.
- Confirms reliability of existing models and opens new avenues for **future studies** at the **Electron-Ion Collider (EIC)**.
- NN-based parameterization is a powerful, **data-driven tool** for advancing diffractive scattering research.

Thank You!