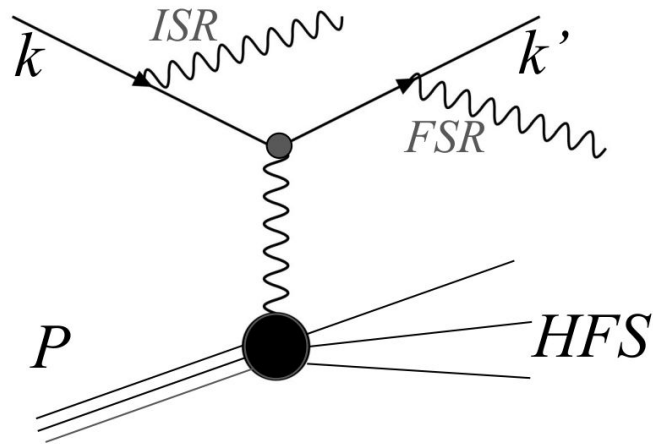


ELUQuant: Event Level Uncertainty Quantification - A DIS Study



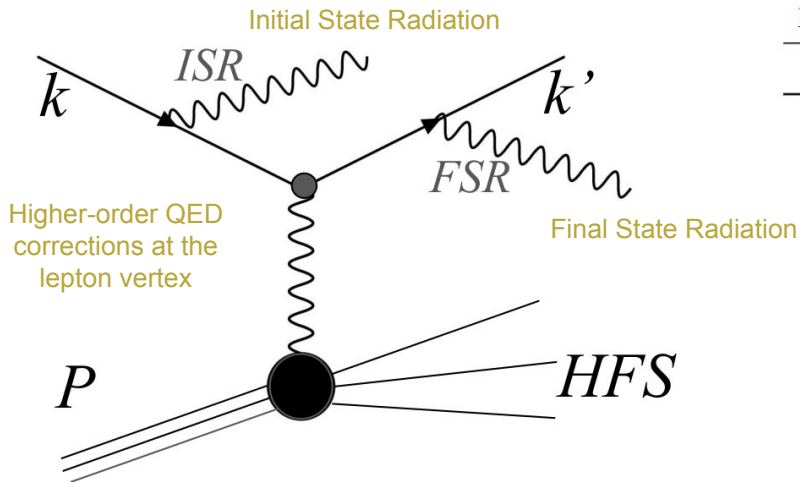
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[1] C. Fanelli and J. Giroux, "ELUQuant: Event-Level Uncertainty
Quantification in Deep Inelastic Scattering," [arXiv:2310.02913](https://arxiv.org/abs/2310.02913)

Deep Inelastic Scattering

DIS is governed by the four-momentum transfer squared of the exchanged boson Q^2 , the inelasticity y , and the Bjorken scaling variable x .



Dataset	Training Events	Validation Events	Testing Events	Size on Disk
H1	8.7×10^6	1.9×10^6	1.9×10^6	8 GB

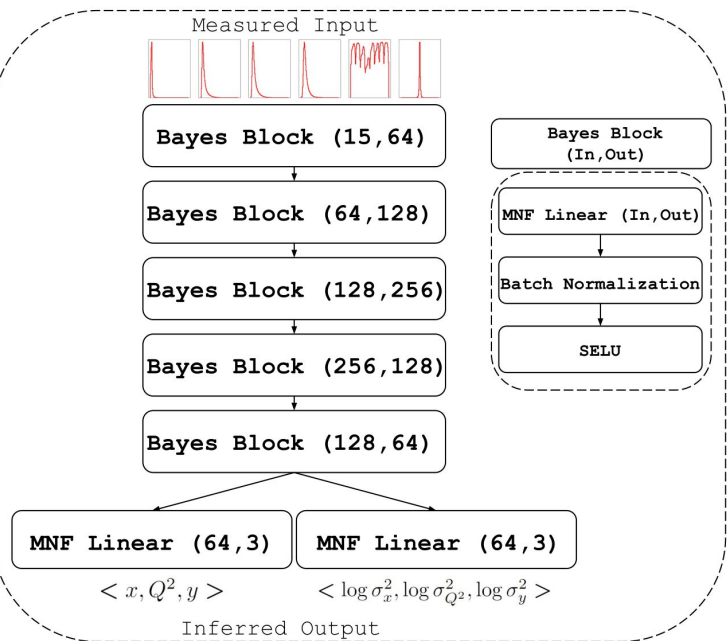
- Dataset designed in [2]
- Monte Carlo from HERA
- Full QED radiation and Lund hadronization simulation
- Features Sensitive to QED Radiation

These kinematic variables are related via the relation $Q^2 = sxy$, where s is the square of the center-of-mass energy.

$$Q^2 = -q^2 = (k - k')^2, \quad y = \frac{q \cdot P}{k \cdot P}, \quad x = \frac{Q^2}{sy}$$

ELUQuant

Lightweight



Learn the Posterior over the weights

$$\mathcal{L}_{MNF} = \mathbb{E}_{q(\mathbf{W}, \mathbf{z}_T)} [-KL(q(\mathbf{W} | \mathbf{z}_{T_f}) || p(\mathbf{W})) + \log r(\mathbf{z}_{T_f} | \mathbf{W}) - \log q(\mathbf{z}_{T_f})]$$

Access epistemic (systematic) uncertainty through sampling MNF [3] layers

Learn the regression transformation

$$\mathcal{L}_{Reg.} = \frac{1}{N} \sum_i \sum_j \frac{1}{2} (e^{-s_j} \|\mathbf{v}_j - \hat{\mathbf{v}}_j\|^2 + s_j), \quad s_j = \log \sigma_j^2$$

Access aleatoric (statistical) as a function of regressed output [4]

Constrain the physics

$$\mathcal{L}_{Phys.} = \frac{1}{N} \sum_i \log \hat{Q}_i^2 - (\log s_i + \log \hat{x}_i + \log \hat{y}_i)$$

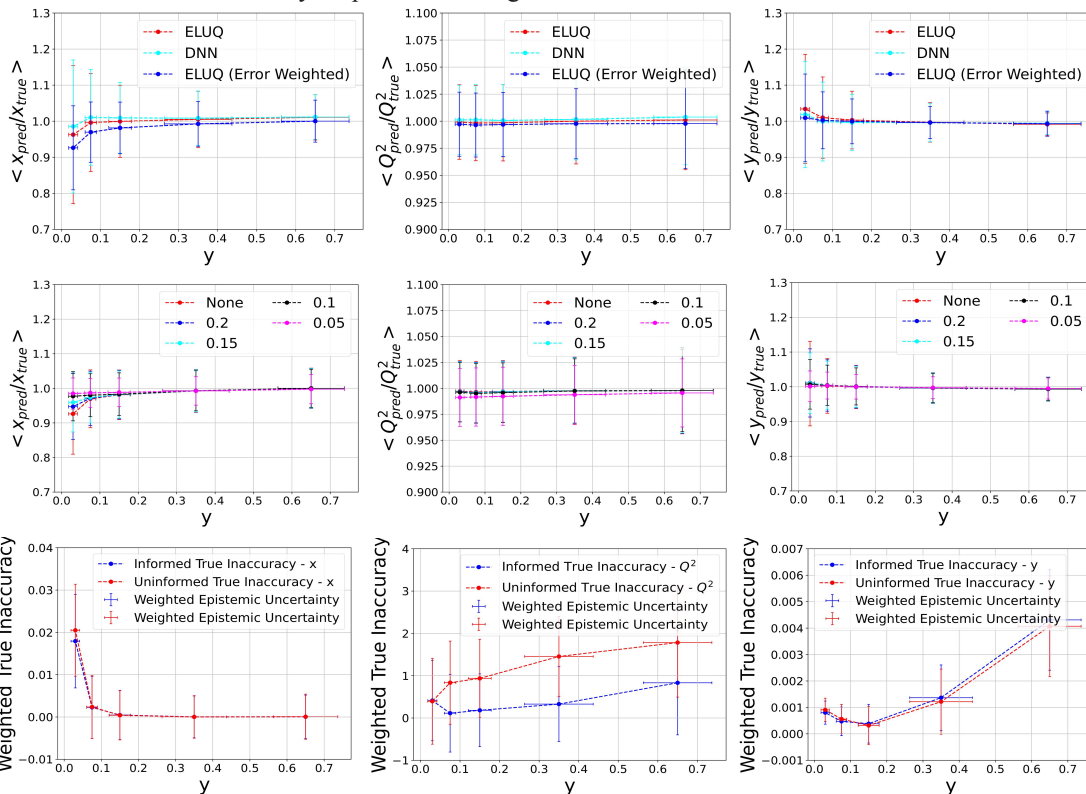
Event-Level Uncertainty Quantification

Weight Events with Uncertainty

$$\langle \hat{O} \rangle_w = \frac{\sum_{k=1}^N \frac{\hat{O}_k}{\sigma_k^2}}{\sum_{k=1}^N \frac{1}{\sigma_k^2}}, \quad \sigma_w(\langle \hat{O} \rangle_w) = \frac{1}{\sqrt{\sum_{k=1}^N \frac{1}{\sigma_k^2}}}$$

Uncertainty Based Selection

Uncertainty on plots are average uncertainties at the event-level



Conclusions

We thank the H1 Collaboration for allowing us to use the simulated MC event samples.

- Event-level uncertainty provides invaluable information at inference
- Physics informed networks improve regression quality
- Lightweight design provides fast inference with sampling $\sim 20\text{ms/event}$
- ELUQuant performs on par in large kinematics space with other regression methods
- ELUQuant additionally provides uncertainties on every event
- Epistemic increase with true inaccuracy

Potential applications at EIC in the future

References

- [1] C. Fanelli and J. Giroux, "ELUQuant: Event-Level Uncertainty Quantification in Deep Inelastic Scattering," [arXiv:2310.02913](https://arxiv.org/abs/2310.02913)
- [2] Arratia M, Britzger D, Long O and Nachman B Reconstructing the kinematics of deep inelastic scattering with deep learning 2022 Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment 1025 166164 ISSN 0168-9002
- [3] Louizos C and Welling M 2017 Multiplicative Normalizing Flows for Variational Bayesian Neural Networks Proceedings of the 34th International Conference on Machine Learning (Proceedings of Machine Learning Research vol 70) ed Precup D and Teh Y W (PMLR) pp 2218-2227
- [4] Kendall A and Gal Y 2017 What uncertainties do we need in bayesian deep learning for computer vision? Advances in Neural Information Processing Systems vol 30 (Curran Associates, Inc.)

For more detail see [1] and references therein...