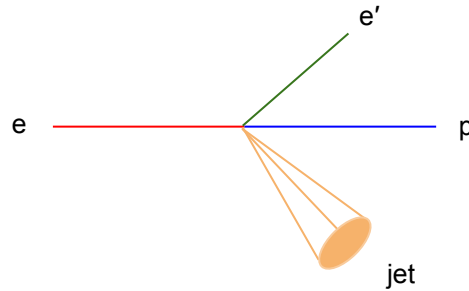


Jet Energy Reconstruction using Bayesian Deep Learning with UQ



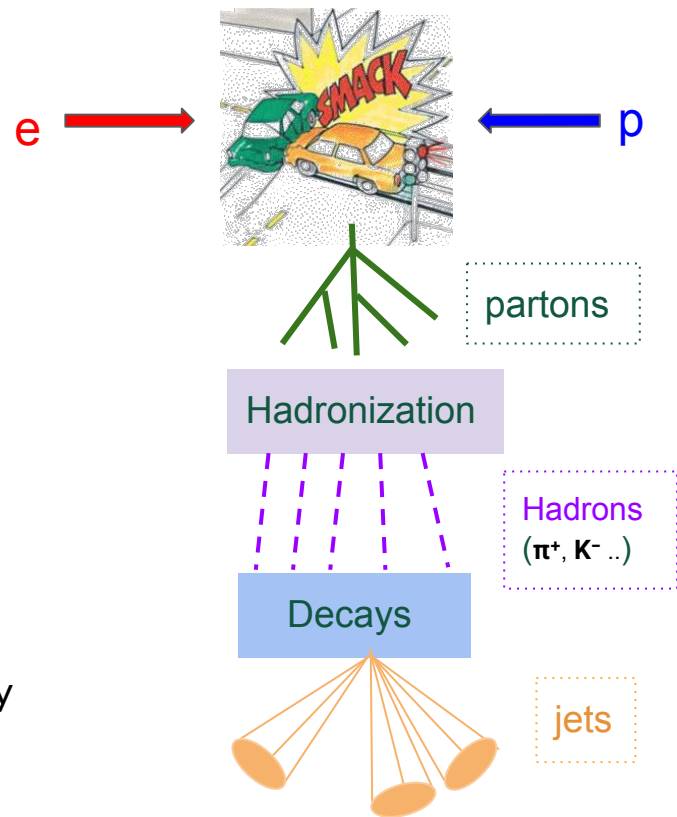
Hemalata Nayak (W&M)
July 2026 Joint ePIC/EICUG Meeting
7/16/2026

Jets at EIC

- Jets are collimated spray of outgoing particles resulted from Hadronization of Partons (i.e. fundamental particle like quarks and gluons).
- Due to color confinement, quarks and gluons are never found in isolation, they can be found only within Hadrons.

Multiple Physics Goals

- Excellent proxies for the underlying parton kinematics
- acts as a probe to QCD
- acts as a probe of the hot dense medium (QGP) created in heavy ion collision
- And more



[Source](#)

Motivation

Measured jet energy differs from theory due to :

- Energy loss in the detector material
- Non-linear response of the detector
- Pileup events - a situation where particle detector detect several events at the same time
- Missing neutrino energy

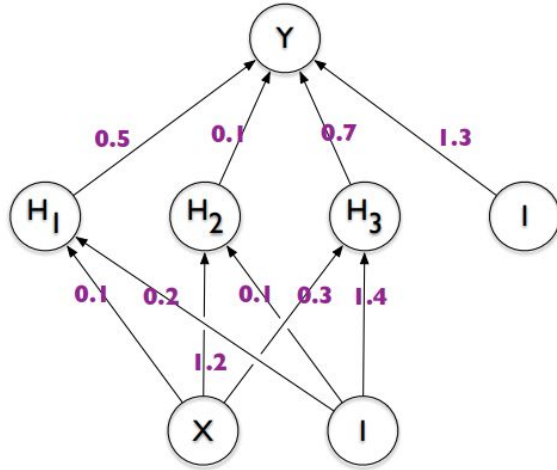
Primary Goal

Develop Bayesian Deep Learning Models that:

- Can overcome the jet energy loss.
- Surpass performance of classical estimates.
- Provide consistent performance with recent Deep Neural Networks.
- Provide robust estimates of **epistemic (model)** and **aleatoric (stochastic)** uncertainties to support high precision measurements.

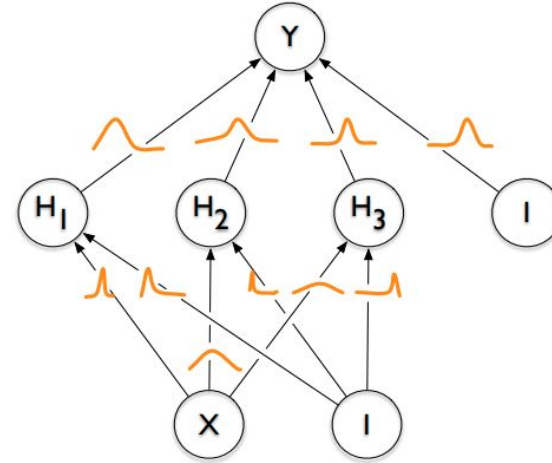
Why bayesian?

Standard Neural Net



- Weights represented by **single, fixed values (point estimates)**

Bayesian Neural Net



- Weights represented by **distributions**
- Introduce a **prior distribution** on the weights $P(w)$ and obtain the **posterior** $P(w|D)$ through **Bayesian learning**
- Uncertainty Quantification (Epistemic Uncertainty, Aleatoric Uncertainty)

Simulation Sample

1. Type of Simulation Sample:

- D^0 samples:
- e+P: 5*41
- Campaign: 25.12.0
- epic_craterlake/SIDIS/D0_ABCONV/HFsim-PYTHIA/pythia8.306-1.2/ep/5x41/q2_1to10000/hiDiv/

2. Selection cuts:

- Jet doesn't have electron
- No duplicate tracks
- genJet E > 5 GeV
- recoJetE > 0 GeV
- $|\eta| \leq 2.5$
- Track $p_T > 0.2 \text{ GeV}/c$

3. For this study we are using charged particle jet

Features

1. Input features:
 - a. Jet Mass (m)
 - b. Jet Eta (η)
 - c. Jet Phi (Φ)
 - d. Jet Multiplicity
 - e. Jet Girth
2. Target: jet pT

Preliminary results

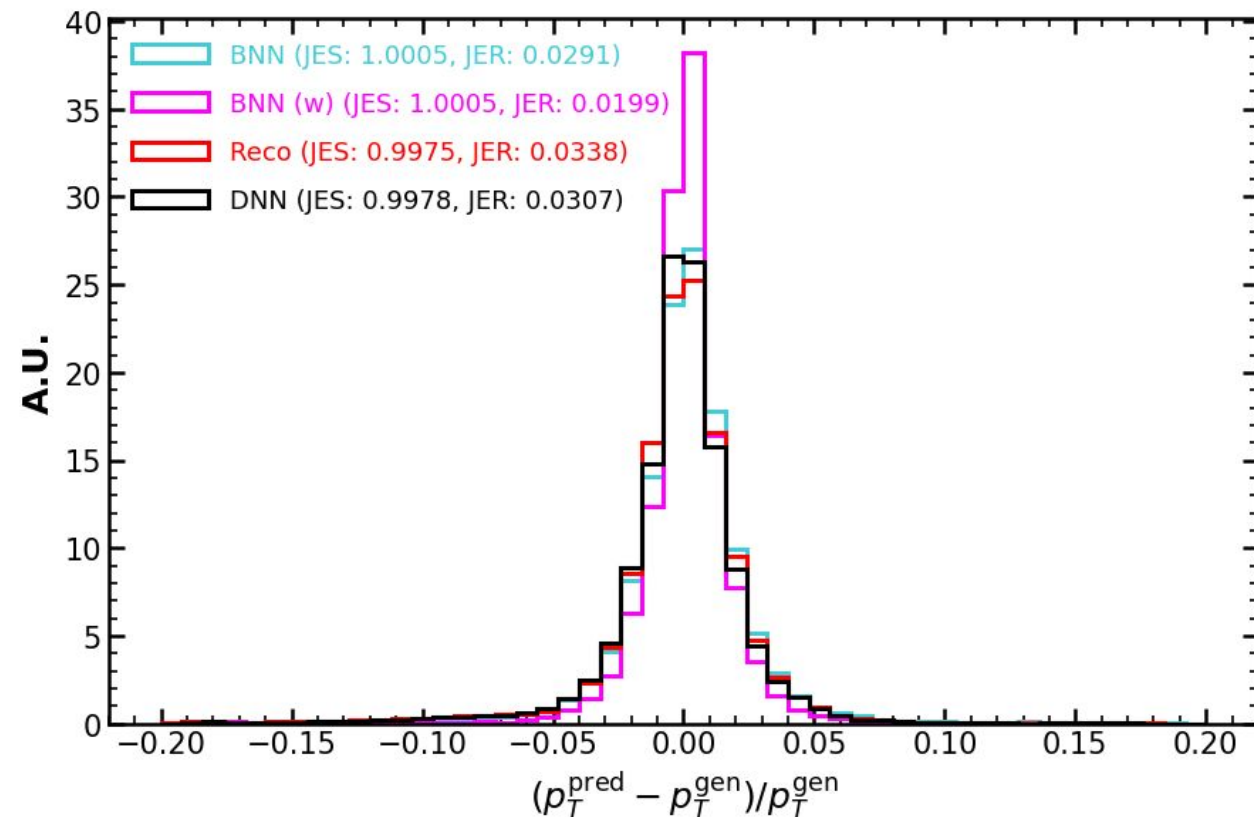
$$r = \frac{p_{T,i}^{\text{pred}} - p_{T,i}^{\text{gen}}}{p_{T,i}^{\text{gen}}}$$

$$\text{JES} = 1 + \frac{1}{N} \sum_{i=1}^N r$$

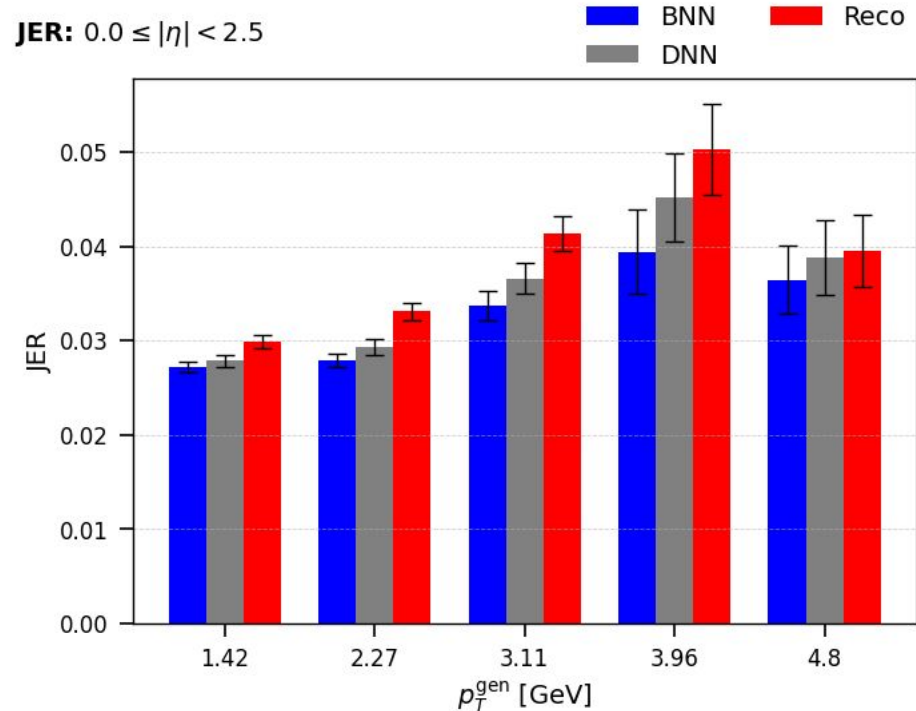
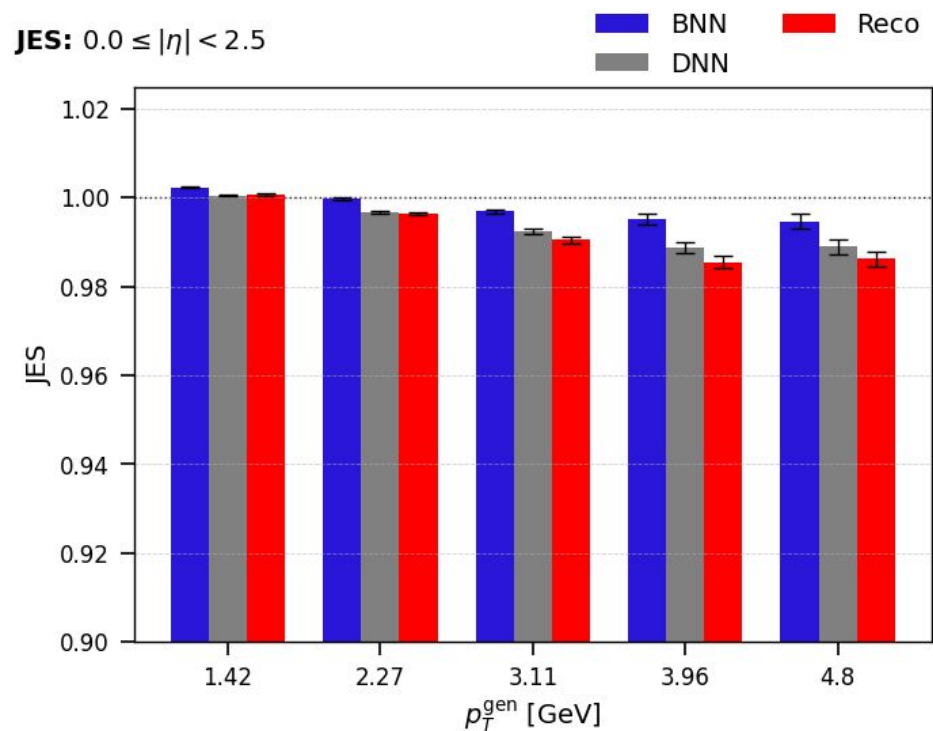
$$\text{JER} = \sqrt{\langle r^2 \rangle}$$

JER Improvement
(relative to Reco)

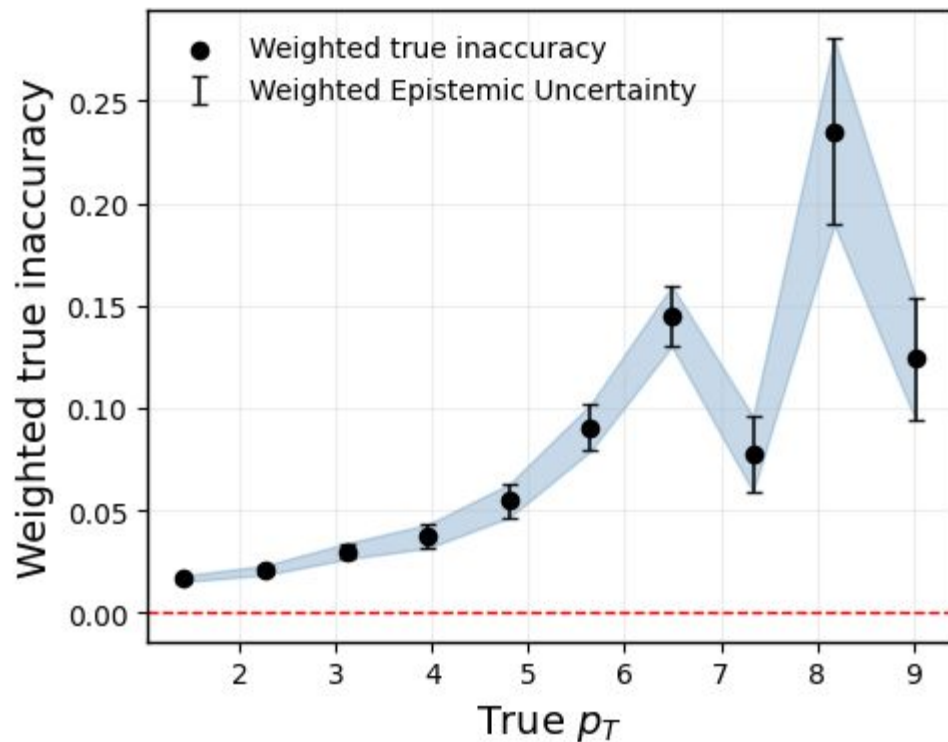
- DNN : 9.2%
- BNN : 14.2%
- BNN (weighted): 41.3%



Preliminary results

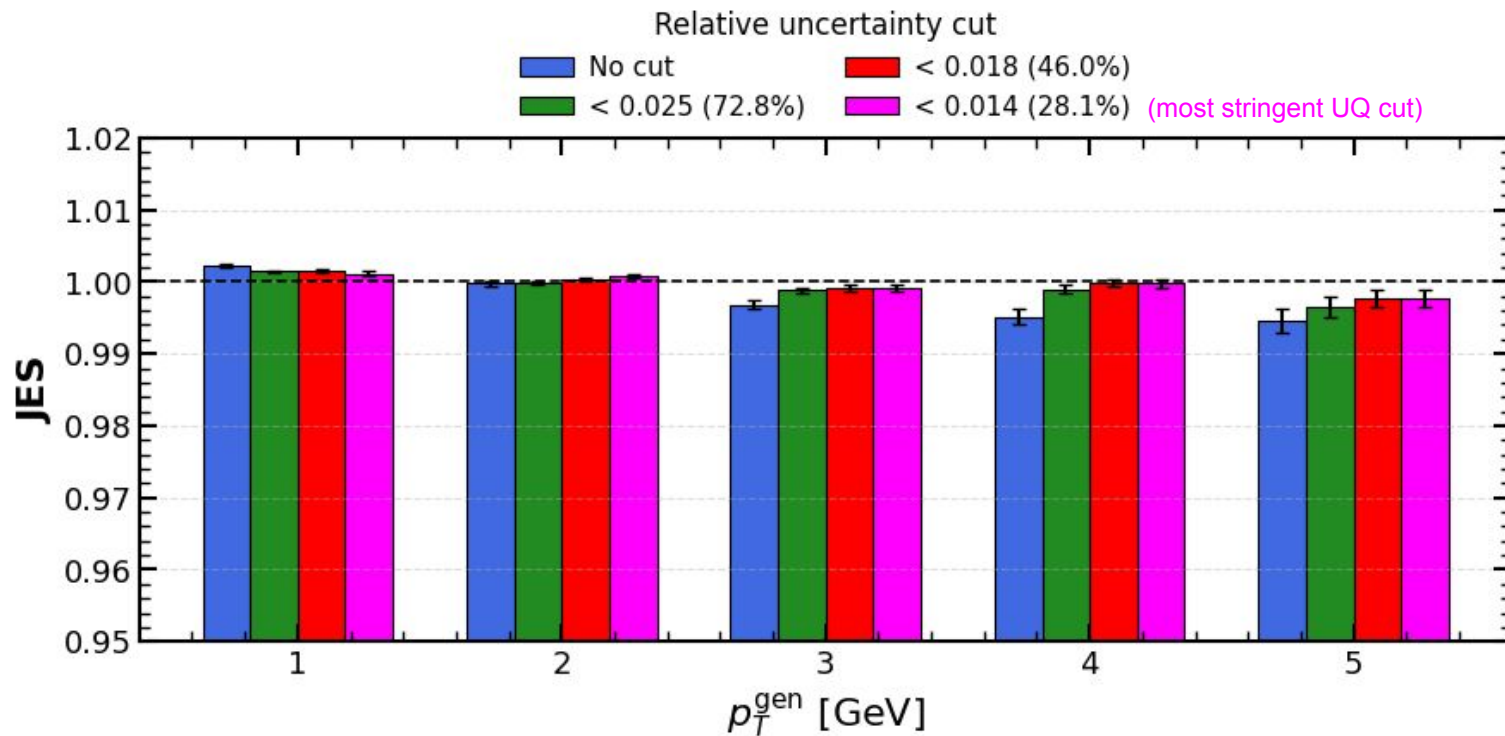


Preliminary results

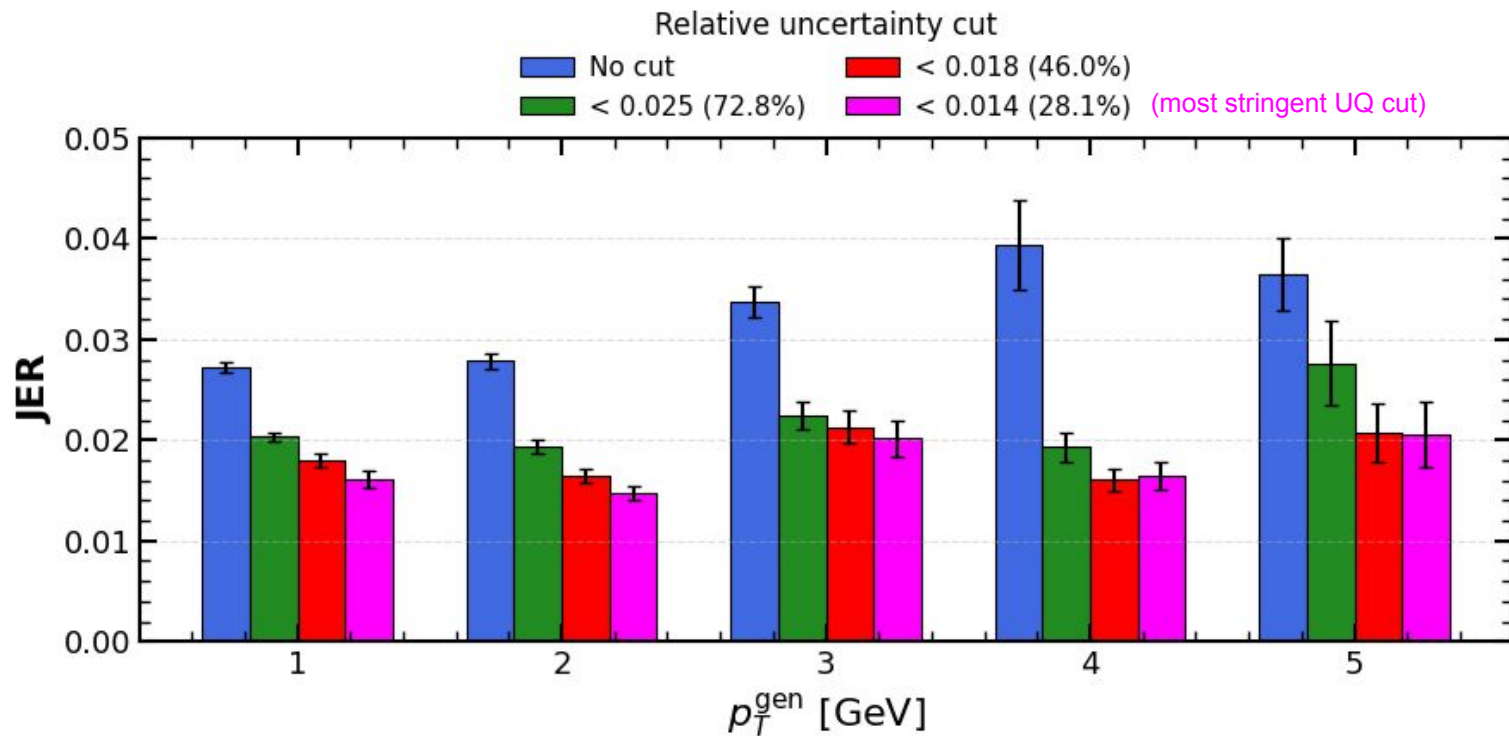


Epistemic uncertainty increases with the inaccuracy, as expected

Uncertainty-based Cuts: Preliminary results



Uncertainty-based Cuts: Preliminary results



Summary

To summarize,

- Bayesian deep learning improves jet energy reconstruction over both reconstructed jets and conventional neural networks.
- It provides calibrated uncertainty estimates.
- Those uncertainties can be used to select high-quality events, leading to further improvements in jet energy resolution.