Project Proposal: Differentiable Modeling of Systematic Uncertainties in ATLAS Object Corrections

Applicant: Cody Tanner
Mentor: Gordon Watts
Duration: July–September 2025 (≈ 3 months)

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1. Motivation & Objectives

Modern ATLAS correction procedures rely on histogram lookups and conditional logic, which are computationally intensive and non-differentiable. This limits their integration into end-to-end, gradient-based analysis pipelines.

Primary Goal: Build a neural network model that replicates the full ATLAS object corrections and systematic errors. The network will be both **differentiable** and **computationally fast**, enabling seamless inclusion of correction steps directly within higher-level analyses.

Secondary Objectives:

1. Provide a proof-of-concept on small-R jets using the JZ2 dataset.
2. Compare model performance against official corrections, targeting sub-percent residuals.

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2. Methodology & Timeline

1. **Existing Baseline (Week 0)**
    - I already have a fully connected 4-layer, 128-neuron per layer network (ReLU activations, normalized inputs $\{p_T, \ln p_T, \eta, \phi, N_{jets}\}$), trained for 20 epochs on 155 k small-R jets.
    - Baseline performance:
        - $\sigma(\Delta p_T/p_T) \approx 10.18\%$
        - $\sigma(\Delta\eta) \approx 0.1$
        - $\sigma(\Delta\phi) \approx 0.1$
    - **Target:** reduce p_T residuals to ~1% and similarly improve angular resolutions.
2. **Literature Review & Input Design (Weeks 1–2)**
    - Survey model correction methods (e.g., Neos, arXiv:2311.08885) achieving sub-percent residuals for large-R jets.

- Refine network **inputs** (initial five features are provisional; may add per-object uncertainties, shower-shape variables, or pileup metrics) and **loss functions** (e.g., weighted MSE, heteroscedastic losses).

3. **Enhanced model Training (Weeks 3–6)**
   - **Data preparation:** Normalization of all inputs, look into centering of η and ϕ.
   - **Architecture exploration:** Test deeper or residual-connected networks, alternative architectures, batch-norm/dropout, and uncertainty-conditioned inputs.
   - **Training regimen:** extend epochs beyond 20, employ learning-rate schedules, early stopping, and hyperparameter scans to drive residuals toward 1%.
4. **Validation & Error Characterization (Weeks 7–8)**
   - Generate new percent-error and absolute error histograms; compute updated $\sigma(\Delta\, p_T / p_T)$, $\sigma(\Delta\, \eta)$, $\sigma(\Delta\phi)$.
   - Benchmark against both the baseline model and official ATLAS corrections on an independent test set.
5. **Uncertainty-Aware Prototype (Weeks 9–10)**
   - Design schema for per-object uncertainty inputs ($\sigma(p_T)$, $\sigma(\eta)$, etc.).
   - If real uncertainties are unavailable initially, simulate toy distributions to demonstrate network gains in high-uncertainty regions.
6. **Physics Case Study:** $Z \rightarrow jet\, jet$ **Peak (Weeks 11–12)**
   - Use the model to reconstruct the dijet mass peak; optimize selection cuts to minimize peak width.
   - Quantify improvements over baseline and illustrate the impact of uncertainty inputs.
7. **Reporting & Next-Phase Outline (Week 13)**
   - Summarize performance gains, residual distributions, and challenges.
   - Propose extension to electron/photon corrections and integration into full analysis frameworks.

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3. References

1. **The ATLAS Collaboration.** “Simultaneous Energy and Mass Calibration of Large-Radius Jets with the ATLAS Detector Using a Deep Neural Network.” *Machine Learning: Science and Technology*, vol. 5, no. 3, 1 Sept. 2024, article 035051, doi:10.1088/2632-2153/ad611e.
2. **ATLAS Collaboration.** “Jet Energy Scale Measurements and Their Systematic Uncertainties in Proton-Proton Collisions at √s = 13 TeV with the ATLAS Detector.” *arXiv*, 4 Aug. 2017, arXiv:1703.09665 [hep-ex].
3. **ATLAS Collaboration.** “New Techniques for Jet Calibration with the ATLAS Detector.” *arXiv*, 13 Sept. 2023, arXiv:2303.17312 [hep-ex].