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AI Acceleration of HEP Collider Simulation

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Motivation

- Detector simulation is a critical part of High Energy Physics (HEP), but is computationally expensive
- Generative Neural Networks (GANs) have been explored as a machine learning solution (Ref. [1])
  - GANs can generate new simulated events from a large database of existing events, but could have mathematical and practical concerns
- We use of a Convolutional Neural Network (CNN) as a solution
  - This CNN takes in quickly generated low-quality events and enhances them to a more useful resolution (See Fig. 1)

Introduction

- A CNN is an artificial intelligence architecture used to classify images (ex. Search engines)
- Inspired by Ref. [2] (See Fig. 2) we:
  - Feed the CNN a low-quality image
  - Train it to predict the true energy for each pixel
  - Have the CNN to return a higher quality image (regression, rather than classification)
- We train out CNN so we can simulate high quality data quickly by generating low quality events and enhancing them using the trained network

Model and Training

- Our CNN has 9 convolutional layers and 3x3 kernels with N=100 features
- A simplified approach has worked in the past, where a CNN was used to remove noise artificially added to high quality simulated events
  - This approach was successful Ref. [3]
- In this project, we build out that framework to enhance actual low-quality events with simplifications
  - We use single photon events generated at 850 MeV

Figure 1: A visualization of our overall process for accelerating collider simulation.

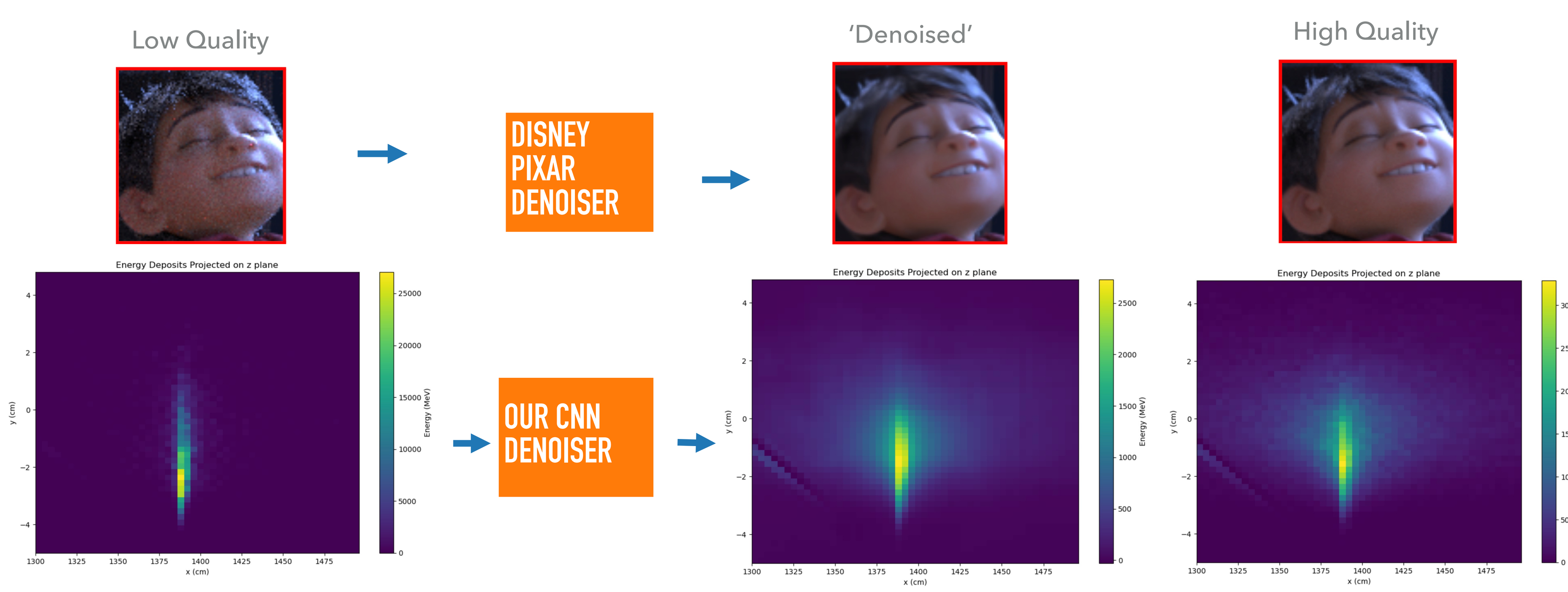

Figure 2: This use of a CNN was inspired by a similar regression algorithm used by Disney Pixar to speed up the production of their computer-simulated films, where instead of enhancing images for films, we enhance photon simulation data

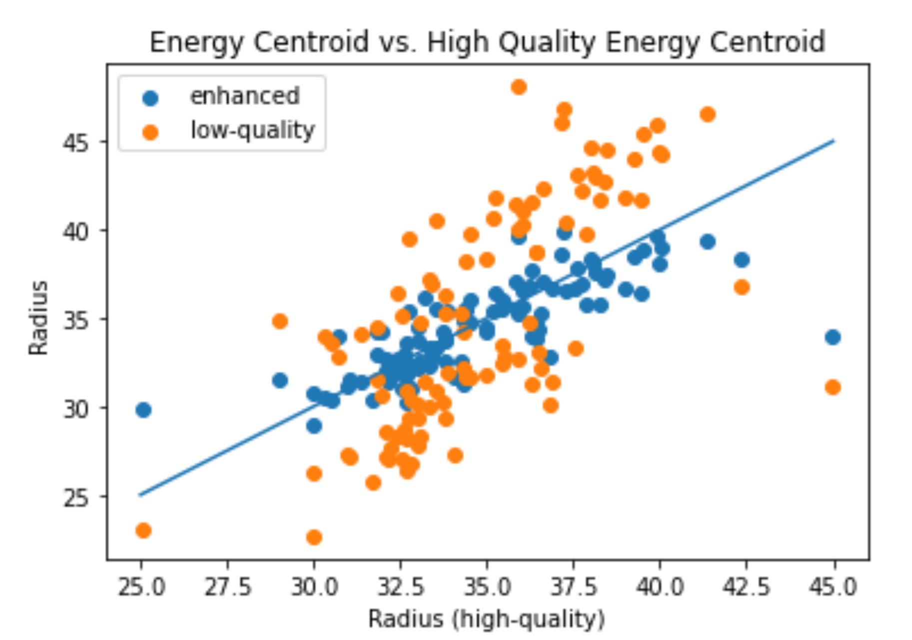

Figure 3: Compares the energy centroid of both the enhanced and low-quality data against the high-quality data. The line, y=x, represents perfect correspondence

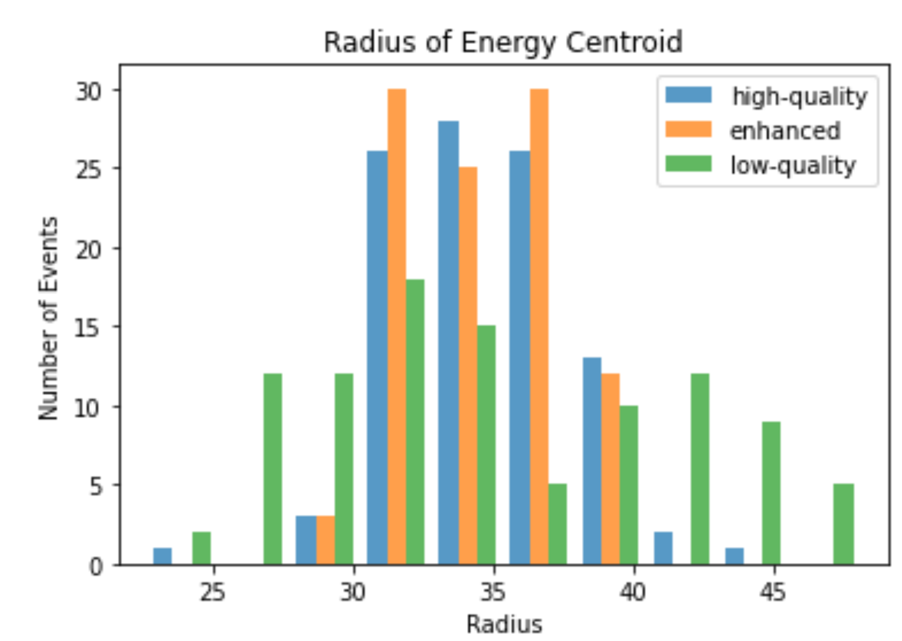

Figure 4: Energy centroid for high-quality, low-quality, and CNN enhanced event. Enhanced data matches the high-quality much better than the low-quality

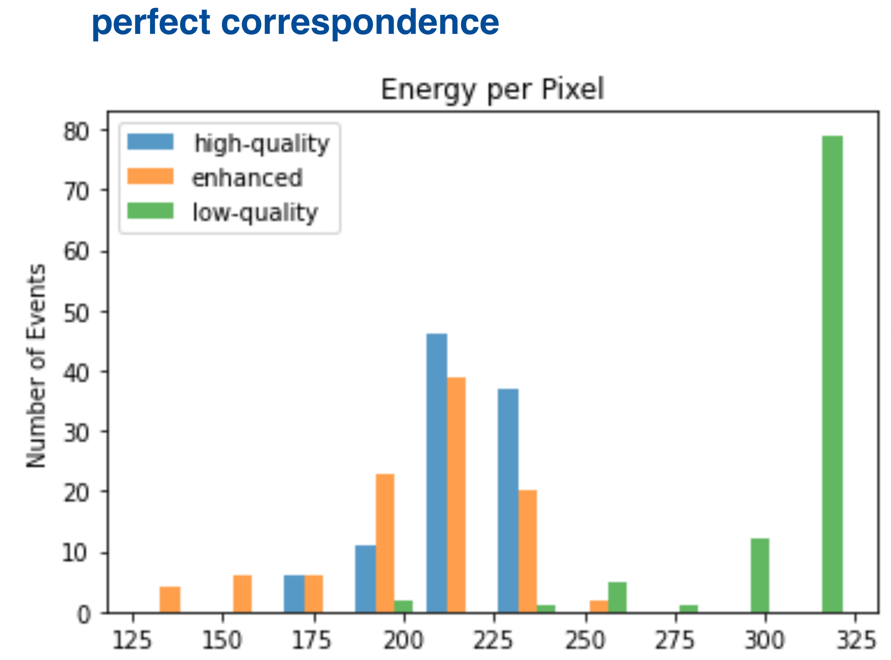

Figure 5: Average energy in an event. Again, enhanced and high-quality match much more closely than with low-quality.

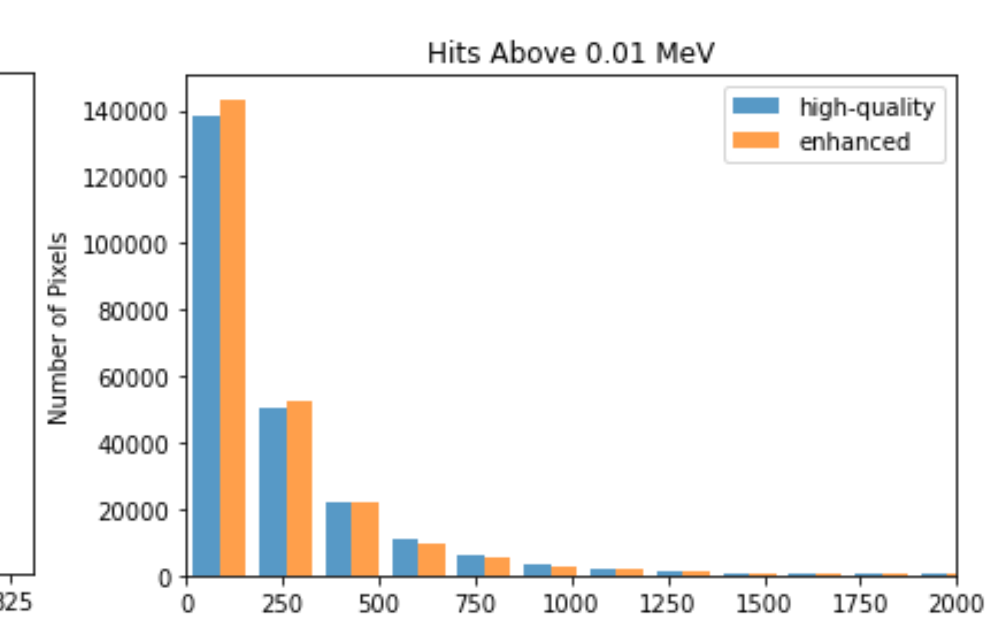

Figure 6: Distribution of energies of individual pixels, given energies are above 0.01 MeV. High-quality and enhanced match closely.

Analysis

- We want to generate a reasonable physical prediction, not predict a particular image, so pixel-by-pixel comparison may not be the only useful metric
- Previous metrics for AI simulation Ref. [1]
  - centroid of the energy data
  - number of bins above a given energy threshold
- We use these same metrics, but as we use a CNN and not a GAN, we can compare high quality, low quality, and CNN-enhanced events metrics against each other
- Enhanced images more closely match energy centroid data (see Fig. 3 & 4) than low-quality input data
- Also match aggregate energy data well (Fig. 5 & 6)

Future Work

- In the future, working with more types of desired simulated events (as opposed to just single-photon) would make this approach more usable
- The structure of the approach could be modified to incorporate an image classifier which would sort between real high quality simulated events, and low-quality events enhanced by our CNN
  - Satisfying this image classifier would mean we had been successful in training our CNN
- We plan to add more input features (in addition to energy) work with 3D data
- Examine different neural network architectures

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