Capstone Project

Team : Voyagers

Yurui Mu
Sudhir Nallam
Xiaoyu Wang
Wenqing Zhu

Advisor: Prof. Kyle Cranmer

Question/Goal

QCD-Aware Recursive Neural Networks for Jet Physics[1] uses techniques of NLP to represent the jet substructure as a ‘jet embedding’, which maps a set of 4-momenta(vector representing the particle) into R^q. Unfortunately, there is a large background from jets produced by more mundane QCD processes, which interferes the process of source determination. In our project we propose a few techniques to make the model proposed in [1] more robust to systematic uncertainties.

[1] G. Louppe, K. Cho, C. Becot, and K. Cranmer, QCD-Aware Recursive Neural Networks for Jet Physics, arXiv:1702.00748

Dataset

Jets are collimated sprays of energetic hadrons produced by collisions at the Large Hadron Collider (LHC). These jets are produced from the fragmentation and hadronization of quarks and gluons as described by quantum chromodynamics (QCD). Our data was collected from signals and background jets with full-event records from [2]'s PYTHIA benchmark samples, including both the particle-level data and the towers from the DELPHES detector simulation. Jets are represented as 4-momentum vector.

The training data was collected by sampling from the original data a total of 100,000 signal and background jets with equal prior. The testing data was assembled similarly by sampling 100,000 signal and background jets, without overlap with training data.

[2]James Barnard, Edmund Noel Dawe, Matthew J. Dolan, and Nina Rajcic. Parton Shower Uncertainties in Jet Substructure Analyses with Deep Neural Networks. 2016, 1609.00607.

Methodology

We want to approach this problem in several different ways:

1)1 x 1 convolution - Use multiple convolutions to represent non-linearity in the model.

2)GRU - Use Gated Recurrent Unit to represent the jet substructure

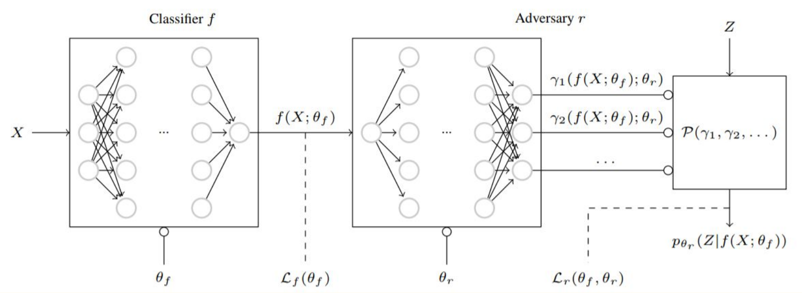
3) Pivot function:

$$E(\theta_f, \theta_r) = \mathcal{L}_f(\theta_f) - \mathcal{L}_r(\theta_f, \theta_r)$$

Adversarial for f(X)

$$\hat{\theta}_f, \hat{\theta}_r = \arg \min_{\theta_f} \max_{\theta_r} E(\theta_f, \theta_r).$$

Adversarial pivot for uncertain noise



Rubric

Results are reported in terms of the area under the ROC curve (ROC AUC) and of background rejection (i.e., 1/FPR) at 50% signal efficiency (R_ε=50%).

With uncertainty in the dataset, we will confirm that our result is stable by comparing with the case without noise.

(Model show little dependency on the nuisance factors)

Average scores reported include uncertainty estimates that come from training 30 models with distinct initial random seeds.