

Pileup Mitigation with Machine Learning (PUMML)

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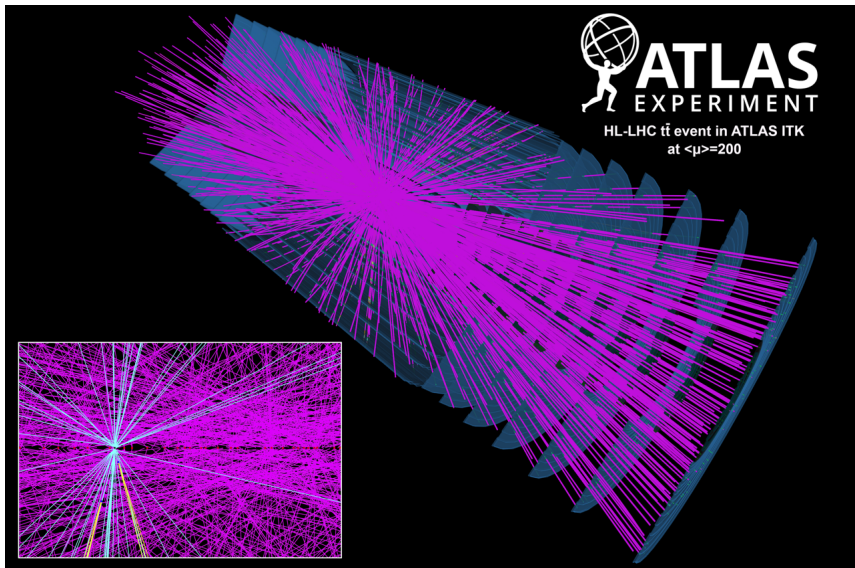
Work with Patrick T. Komiske, EMM, Benjamin P. Nachman, Matthew D. Schwartz

July 19, 2017

Overview

- Pileup
- Jet Images
- PUMML framework
- Performance

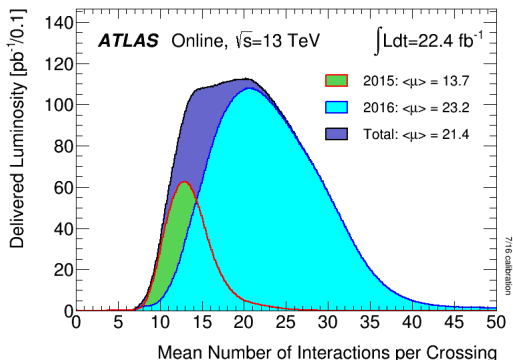
Pileup



Pileup

■ Pileup problem in context

- Presently: ~ 20 pileup vertices per bunch crossing
- Run 3: ~ 80 pileup vertices per bunch crossing
- HL-LHC: ~ 200 pileup vertices per bunch crossing



Mitigation Approaches

Pileup Per Particle Identification (PUPPI)

- Bertolini, Harris, Low, and Tran, [arXiv:1407.6013](#)
- Correct particle/calorimeter energies based on surrounding charged pileup distribution.

SoftKiller

- Cacciari, Salam, Soyez, [arXiv:1407.0408](#)
- Dynamically determined transverse momentum cut.

Jet Cleansing

- Krohn, Low, Schwartz, Wang, [arXiv:1309.4777](#)
- Rescaling subjet four-momenta using charged leading vertex/pileup information.

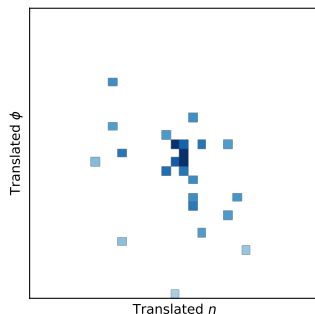
Used default parameters to give sense of performance.

Machine Learning?

- How to input the information?
 - The spirit is to organize all of our available local information.
 - Have information on whether charged particles are pileup or not.
 - Need low-level inputs.
- What sort of architecture?
 - Use tools from modern machine learning.
 - Don't necessarily have to go "deep"
- What sort of loss function?

Jet Images

- Treat the detector as a camera and energy deposits as pixel intensities.
 - Cogan, Kagan, Strauss, Schwartzman. [arXiv:1407.5675](#)
- Make use of the extensively developed computer vision technology, such as convolutional neural nets.
 - de Oliveira, Kagan, Mackey, Nachman, Schwartzman. [arXiv:1511.05190](#)



An overview of recent machine learning applications with jet images.

■ Classification

- W vs QCD jets. (de Oliveira, Kagan, Mackey, Nachman, Schwartzman. [arXiv:1511.05190](#))
- Top vs QCD jets. (Kasieczka, Plehn, Russell, Schell. [arXiv:1701.08784](#))
- Quark vs Gluon jets. (Komiske, EMM, Schwartz. [arXiv:1612.01551](#))
- And more...

■ Generation

- Generative model. (de Oliveira, Paganini, Nachman. [arXiv:1701.05927](#))

■ Regression

- This work. For the first time!

Our Model

- Inputs: three-channel RGB “pileup image”
 - red = p_T of all neutral particles
 - green = p_T of charged PU particles
 - blue = p_T of charged LV particles
- Output: single-channel neutral image
 - output = p_T of neutral LV particles

Our Study

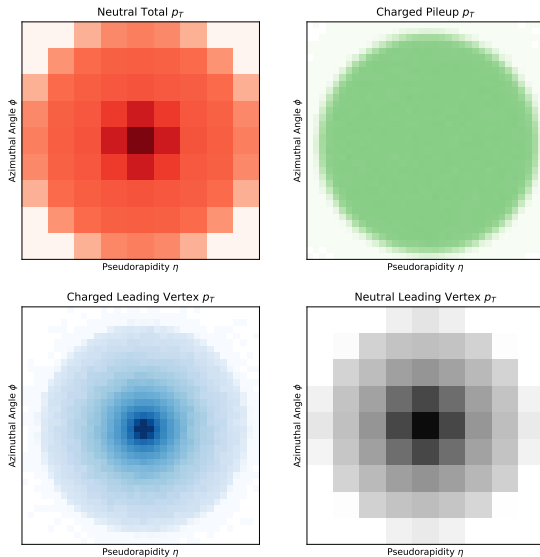
■ Process

- Leading vertex: 500GeV scalar to dijets with Pythia8
- $R = 0.4$ anti- k_T jets in $|\eta| < 2$ with $p_T > 100\text{GeV}$.
- Pileup: NPU=140 Poissonian of soft QCD events overlaid.

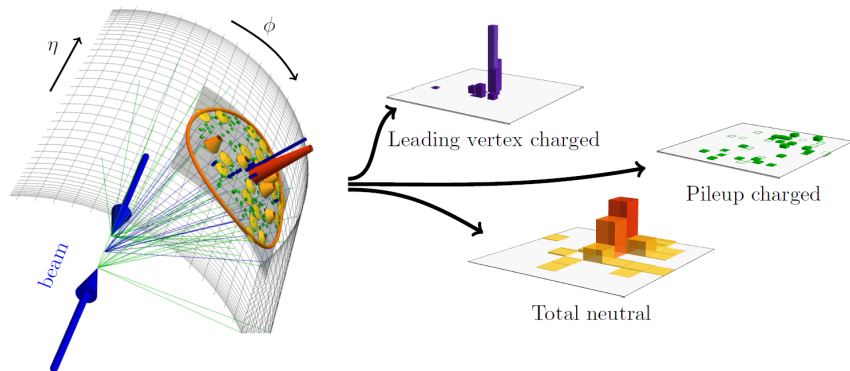
■ Image parameters:

- Charged jet image pixel resolution: $\Delta\eta \times \Delta\phi = 0.025 \times 0.025$
- Neutral jet image pixel resolution: $\Delta\eta \times \Delta\phi = 0.1 \times 0.1$
- Jet image size 0.9×0.9
- Leading vertex/pileup information for charged particles with $p_T > 500\text{MeV}$

Pileup Images



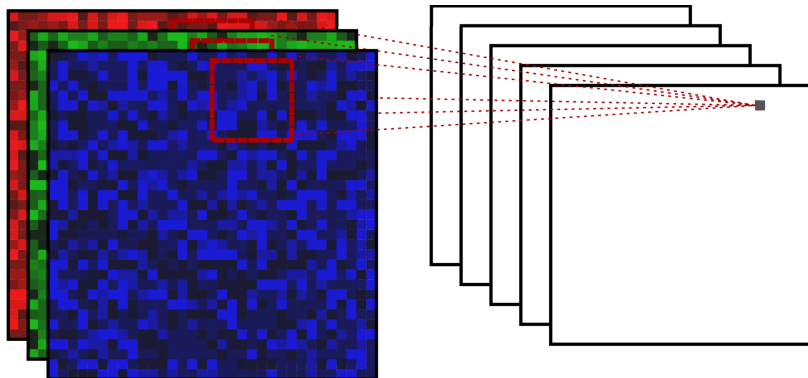
Pileup Images



Architecture

What sort of neural network layers should we use?

- Dense: Units connected to every input pixel with different weights
- Locally connected: Units connected to local input patches with different weights
- Convolutional: Units connected to local input patches with weight sharing



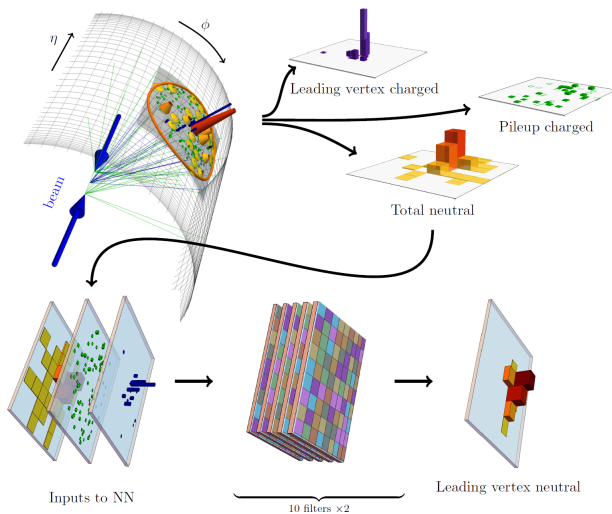
- Architecture: Two convolutional layers

- 6×6 filter sizes
- 10 filters per layer
- Only 4711 parameters

- Architecture is *local*:

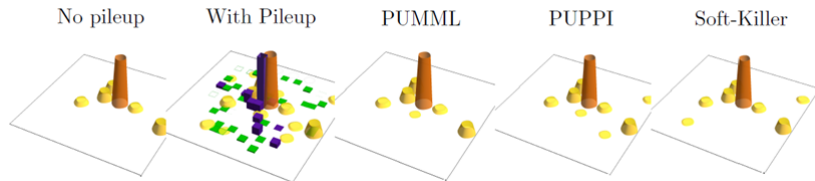
- Pileup removal of a pixel depends only on the information in a window around it
- Can apply the trained model at the event-level, jet level, or on any specified region

PUMML Framework



Subtracted Jets

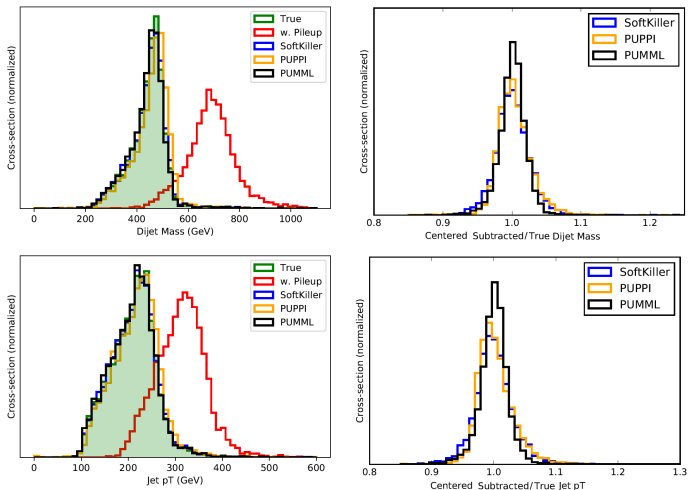
An example event with pileup and subtracted with each method.



Loss function: Should we treat all p_T errors equally or penalize hard/soft errors more?

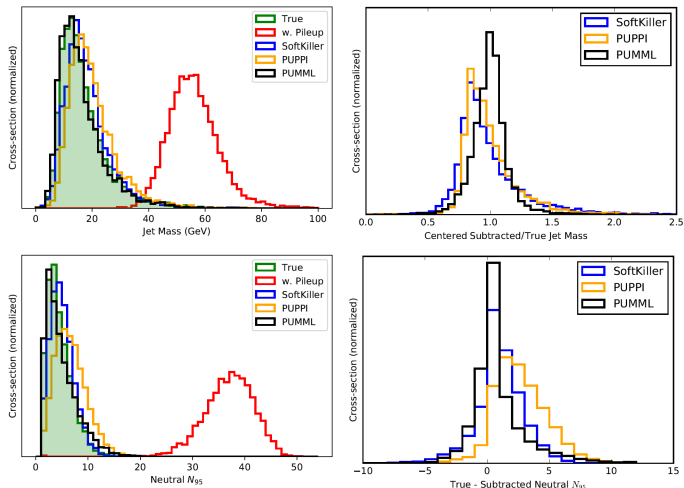
Subtracted Observables

Distributions before and after subtraction of jet p_T and dijet mass



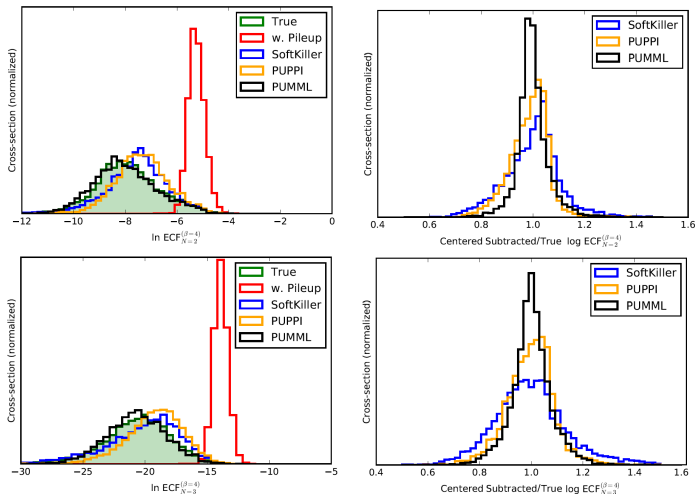
Subtracted Observables

Distributions before and after subtraction of jet mass and N_{95} .

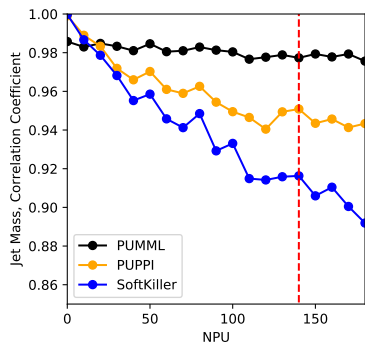


Subtracted Observables

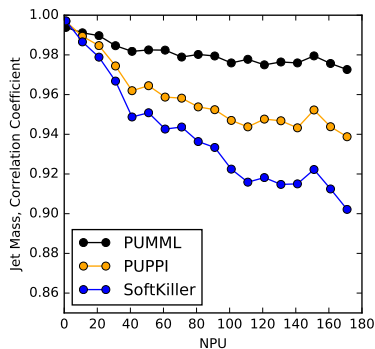
Distributions before and after subtraction of two energy correlation functions.



Model Robustness



- Train on NPU=140 Poissonian and test on different fixed-NPU samples.



- Train on wide range of NPUs uniformly in 180 and test on different fixed-NPU samples.

Learning from Data

- Training from simulation risks mis-modelling issues
- Prefer to train on data rather than simulation
 - Data overlay approach using minimum bias and zero-bias events already used by experimental groups in other contexts.
 - Promising for training PUMML directly with data for the relevant application.

Concluding Remarks

- We have developed an ML framework that successfully organizes all of the available local information to directly learn to mitigate pileup.
- Can use tools from modern machine learning without going “deep”.
- Pileup mitigation can be a good proving ground for modern machine learning techniques in high energy physics.

Thank You!