Learning to Remove Pileup at the LHC with Jet Images

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arXiv:1707.08600

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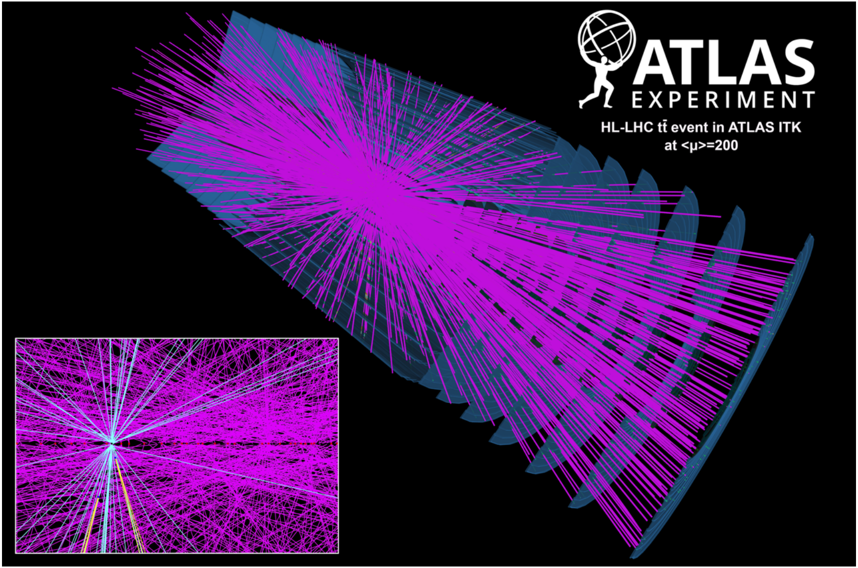
Overview

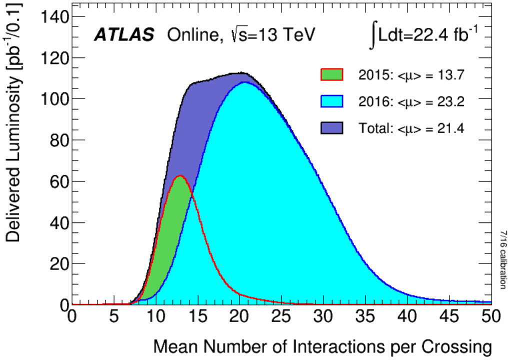
- Pileup
- Jet Images
- Pileup Mitigation with Machine Learning (PUMML)
- Performance and Robustness
- What is being learned?

Pileup



Pileup

- Pileup problem in context
  - Presently: $\sim$20 pileup vertices per bunch crossing
  - Run 3: $\sim$80 pileup vertices per bunch crossing
  - HL-LHC: $\sim$200 pileup vertices per bunch crossing



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?

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.

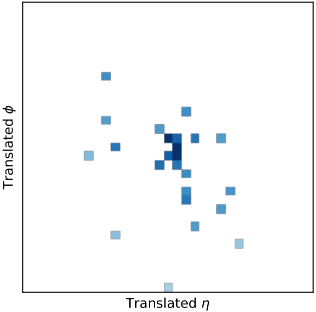
Jet Cleansing

- 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.

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 Oliviera, Kagan, Mackey, Nachman, Schwartzman. arXiv:1511.05190



Modern ML in HEP

An overview of recent machine learning applications with jet images.

- Classification
  - W vs QCD jets. (de Oliviera, 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.

Our Model

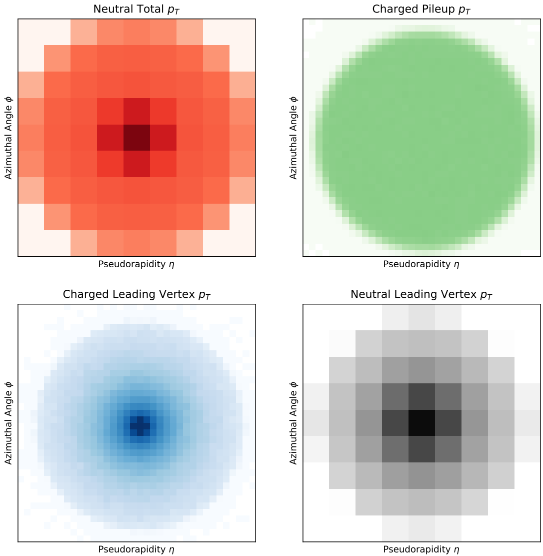
- Inputs: three-channel RGB "pileup image"
  - red $= p_T$ of all neutral particles
  - green $= p_T$ of charged PU particles
  - blue $= p_T$ of charged LV particles
- Output: single-channel neutral image
  - output $= p_T$ of neutral LV particles

Our Study

- Process
  - Leading vertex: 500GeV scalar to dijets with Pythia8
  - $R = 0.4$ anti-k_T jets in $|\eta| < 2$ with $p_T > 100$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 $p_T > 500$MeV

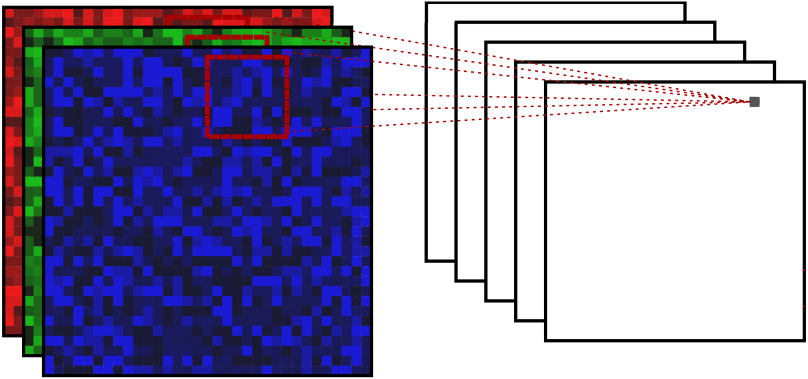
Pileup Images



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

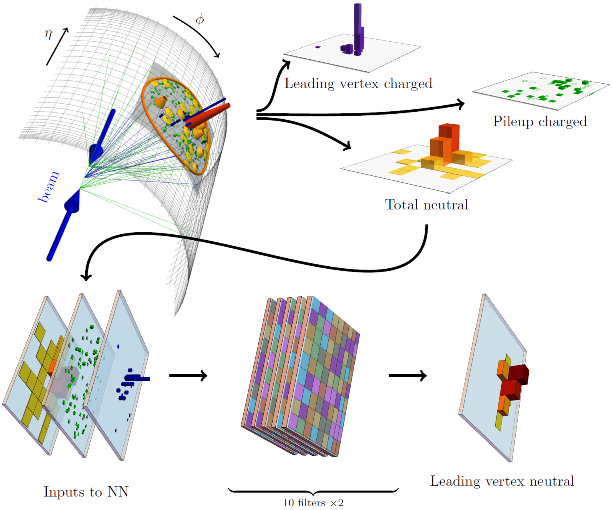


Architecture

- Architecture: Two convolutional layers
  - 6×6 filter sizes
  - 10 filters per layer
  - Only 4711 parameters

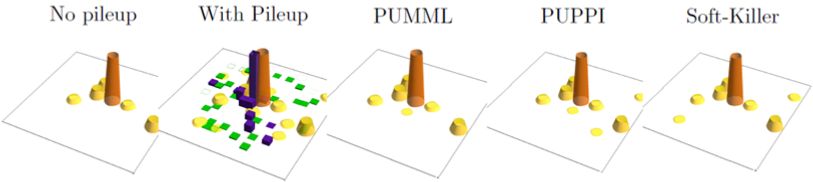
- Architecture is *local*:
  - Pileup removal of a pixel depends only on the information in a window around it
  - Can apply the trained model at the event-level, jet level, or on any specified region

PUMML Framework



Subtracted Jets

An example event with pileup and subtracted with each method.



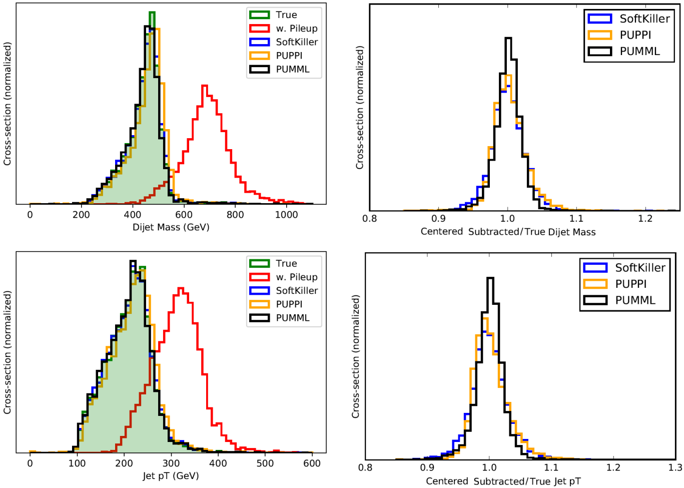
Loss function: Should we treat all p_T errors equally or penalize hard/soft errors more?

$$\ell = \left\langle \log\left(\frac{p_T^{\text{(pred)}} + \bar{p}}{p_T^{\text{(true)}} + \bar{p}}\right)^2 \right\rangle,$$

with $\bar{p} \to 0$ favoring soft pixels and $\bar{p} \to \infty$ favors all p_T equally.

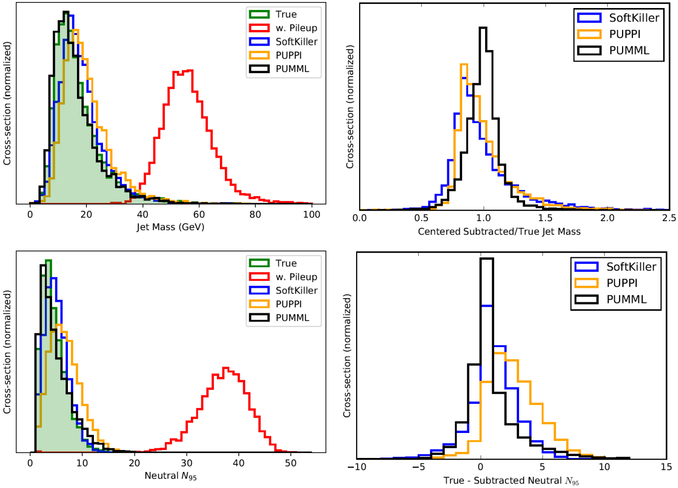
Subtracted Observables

Distributions before and after subtraction of jet p_T and dijet mass



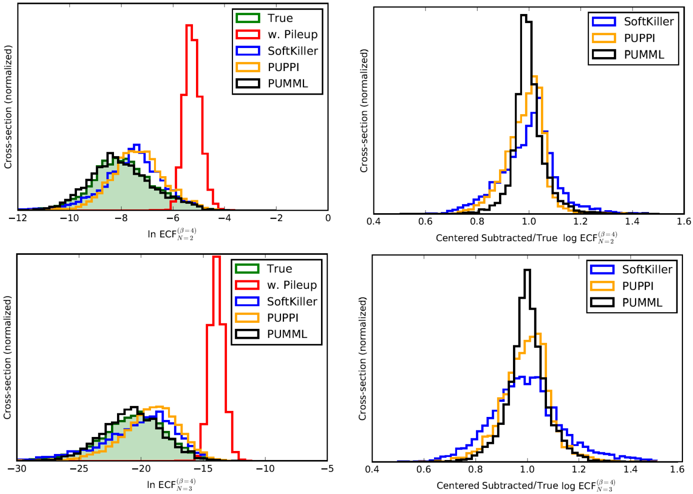
Subtracted Observables

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

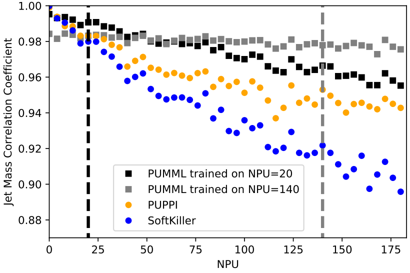


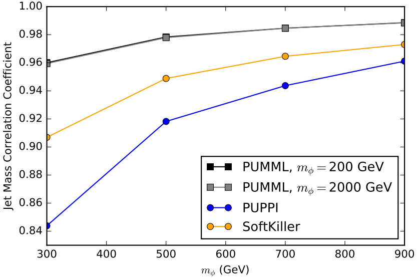
Subtracted Observables

Distributions before and after subtraction of two energy correlation functions.



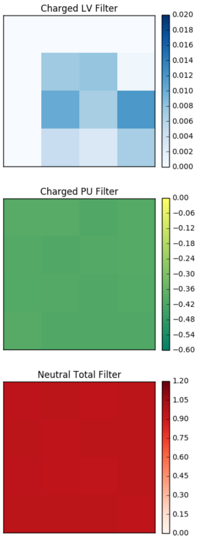
Model Robustness





- Study robustness to pileup by training and testing with different NPU.
- Study robustness to the process by training and testing with different m_ϕ.

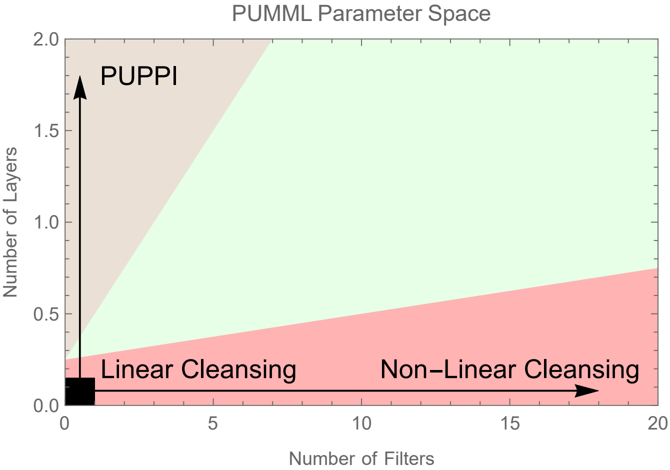
What is being learned?



- Train a single 4×4 filter and inspect it.
- Pixel-wise: $p_T^{N,LV} \approx p_T^{N,tot} - \frac{1}{2} p_T^{C,PU}$
- This is linear cleansing with $\bar{\gamma}_0 = 2/3$!

$$p_T^{N,LV} = p_T^{N,tot} + (1 - \frac{1}{\bar{\gamma}_0}) p_T^{C,PU}$$

What is being learned?



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 availabe 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.

The End

Thank You!