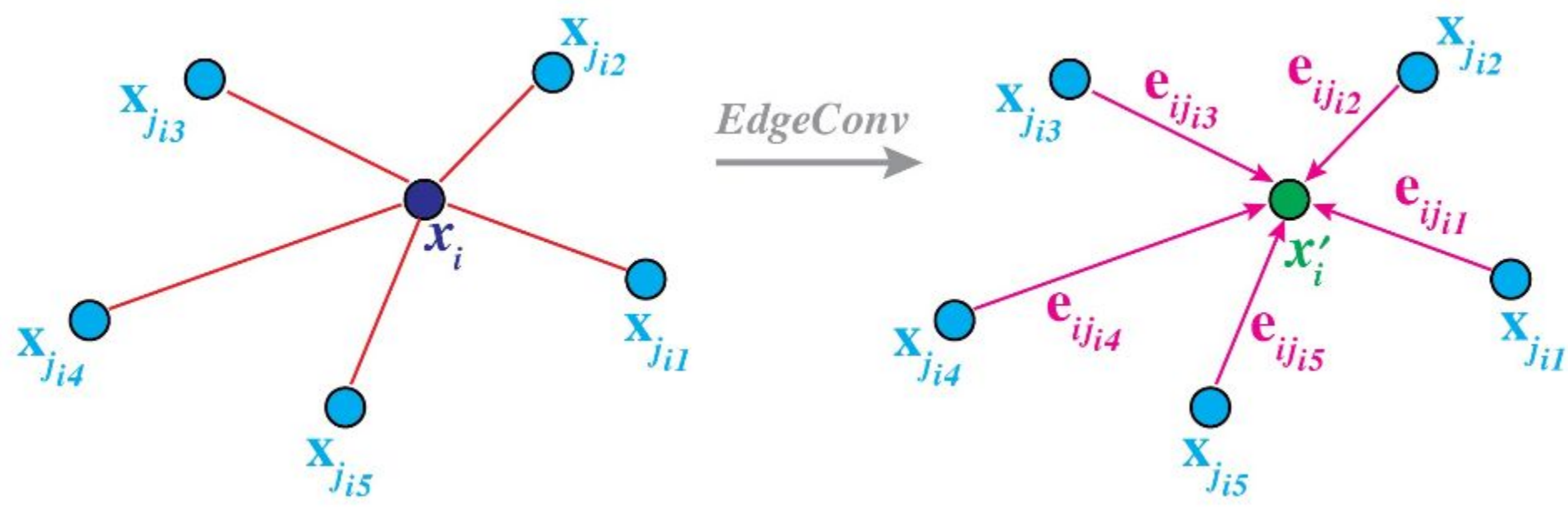


Introduction

In High energy physics, **graph-based implementations** have the advantage of treating the input data sets in the same way they are collected by **collider experiments**. We propose an **Attention Based Cloud neural Network** called **ABCNet**. To exemplify the flexibility of the implementation, two crucial problems in particle physics are investigated: **quark-gluon discrimination and pileup mitigation**.



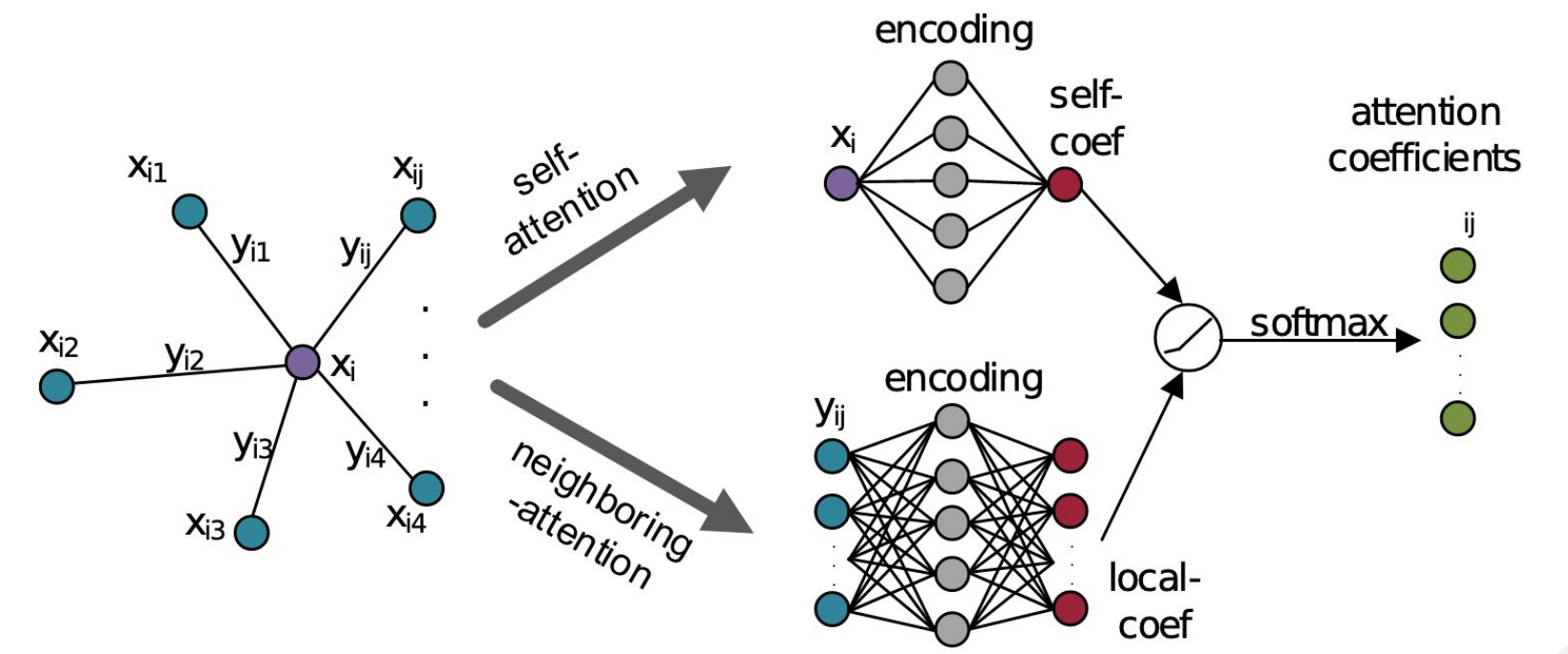
GAP layer

First, define a convolution-like operation invariant to permutations (**EdgeConv**) using **hadrons as vertices** [1].

A **Graph Attention based Point layer (GAP Layer)** [2] is created by connecting the **k-nearest** neighbors of a particle and adding:

- Self attention coefficients: Learn which particles are the most relevant.
- Neighboring attention coefficients: Learn which particles have important neighbors.

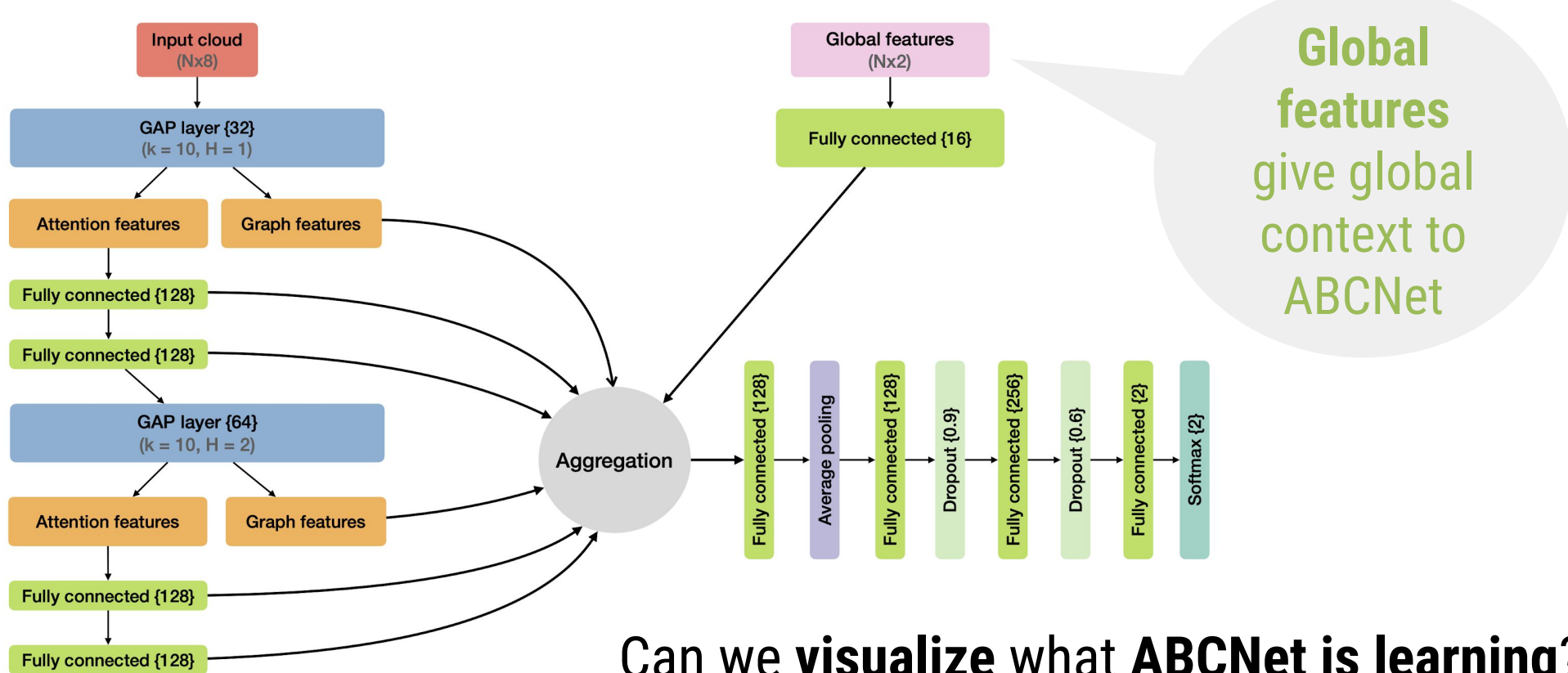
ABCNet stacks **GAP layers** with **fully connected nodes** to extract information!



Architectures

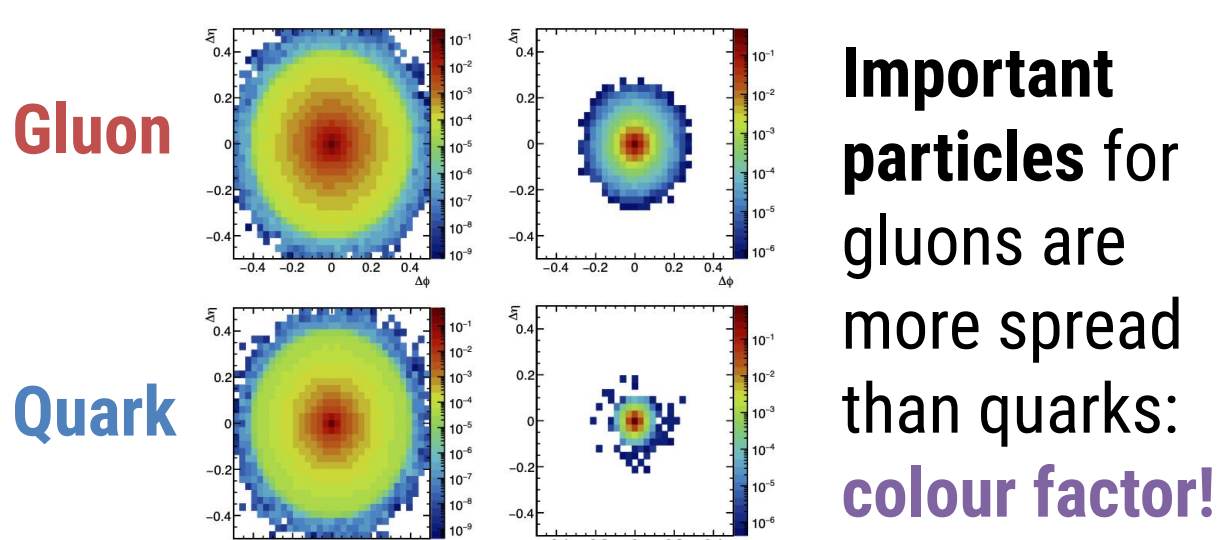
Quark-gluon tagging

Every hadron collision at the **LHC** produces many charged and neutral hadrons, that are clustered into objects called **jets**. **Quark-gluon tagging** refers to the task to identify the origin of a jet as **quark or gluon initiated**.



Global features give global context to ABCNet

Can we **visualize** what **ABCNet** is learning? Plot the **5%** hadrons with the highest **self-attention coefficient** per jet



Important particles for gluons are more spread than quarks: **colour factor!**

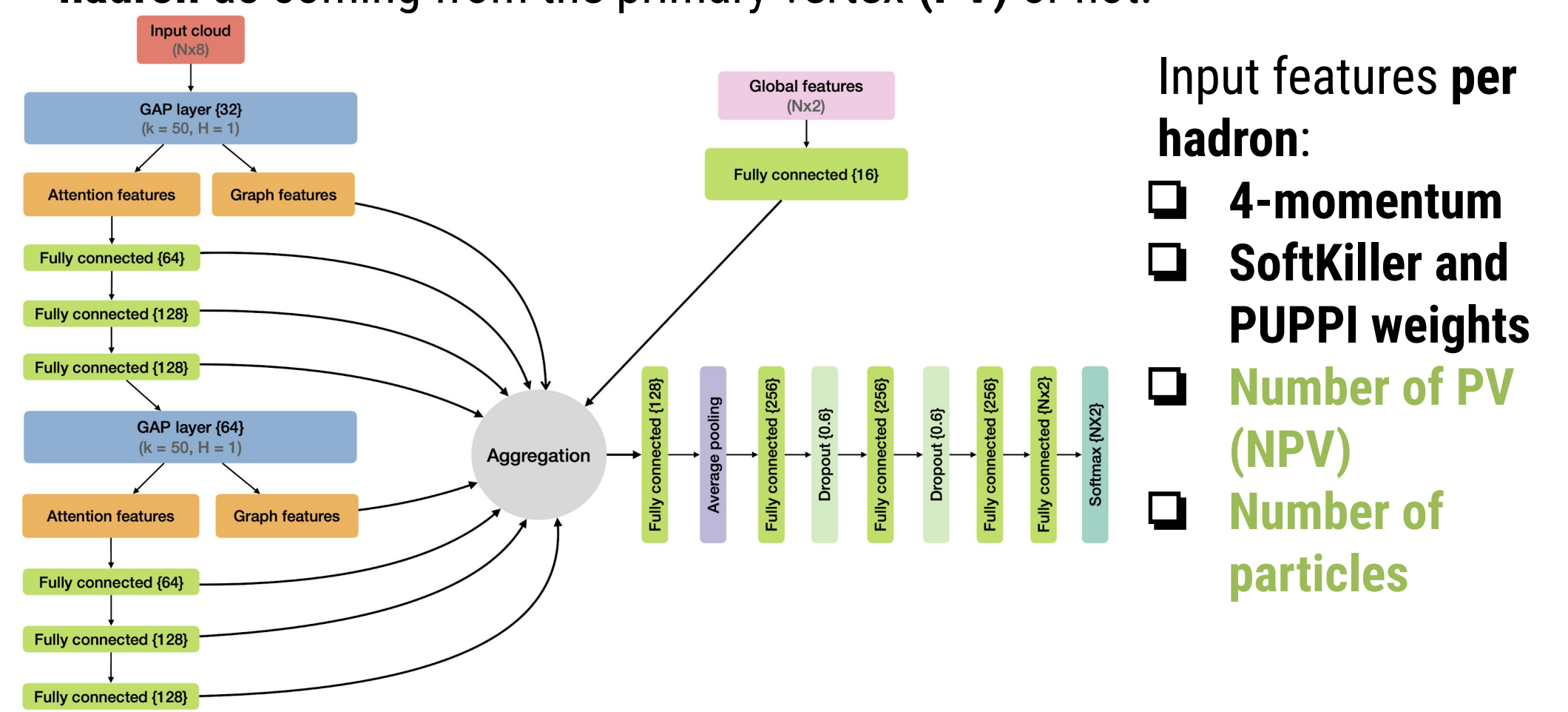
Input features per hadron:

- PID
- 4-momentum
- Distance from jet axis
- Jet mass
- Jet transverse momentum

	Acc	AUC	$1/\epsilon_B$ ($\epsilon_S = 0.5$)	$1/\epsilon_B$ ($\epsilon_S = 0.3$)	Parameters
ResNeXt-50	0.821	0.960	30.9	80.8	1.46M
P-CNN	0.827	0.9002	34.7	91.0	348k
PFN	-	0.9005	34.7±0.4	-	82k
ParticleNet-Lite	0.835	0.9079	37.1	94.5	26k
ParticleNet v2	0.840	0.9116	39.8±0.2	98.6±1.3	366k
ABCNet	0.840	0.9126	42.6±0.4	118.4±1.5	230k

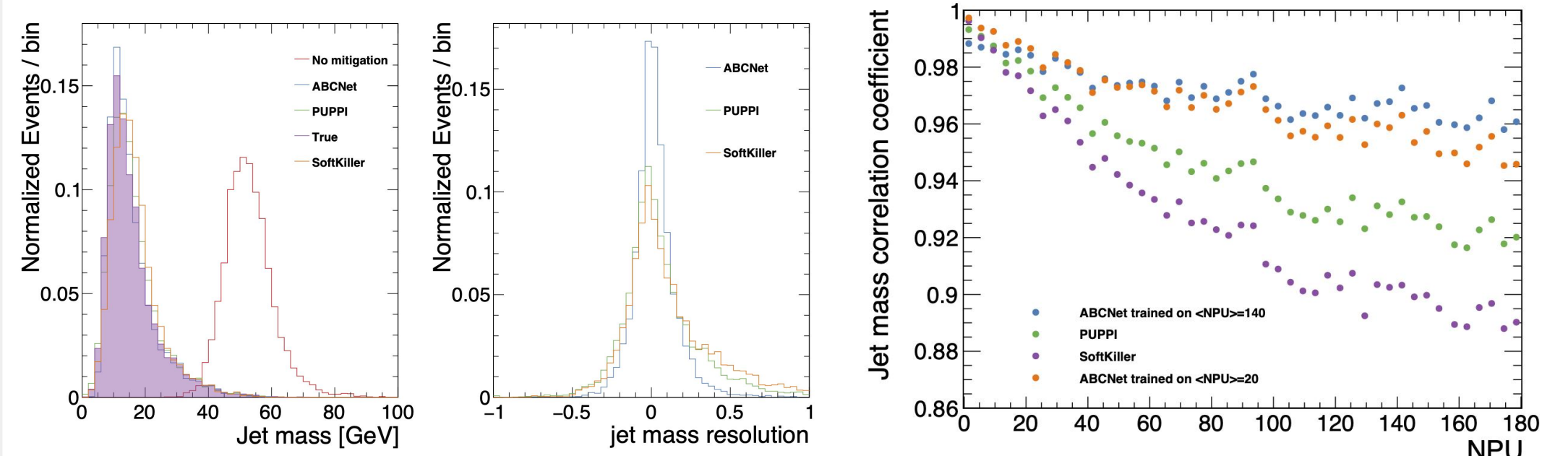
Pileup mitigation

For every **bunch crossing** at the **LHC**, more than one proton-proton collision can take place. Those additional **soft collisions** are difficult to **separate** from the **events of interest**. Use **ABCNet** to **classify each hadron** as coming from the **primary vertex (PV)** or not.



Input features per hadron:

- 4-momentum
- SoftKiller and PUPPI weights
- Number of PV (NPV)
- Number of particles



Reweight each particle's **4-momentum** by the **ABCNet probability** output. **Better jet mass resolution** than common methods

Generalization: Train on events with **<NPU> = 20 or 140**. Test the performance on **different NPU**. **Better performance everywhere!**

Conclusions and prospects

Graph implementations have the advantage of using particle collisions in the same fashion as they are detected. With the **high luminosity LHC**, each collision will produce **~O(1000) particles**. Using **attention mechanisms**, we can **filter the relevant particles** for each classification problem, while providing a simple way to **visualize the learning process**. In both problems presented, ABCNet excels other available implementations.

What could be used for: Searches for heavy resonances, flavour tagging, particle track reconstruction, ECAL shower reconstruction, unsupervised searches, and more!

Bibliography

- [1] Y. Wang, Y. Sun, Z. Liu, S. E. Sarma, M. M. Bronstein and J. M. Solomon, *Dynamic graph CNN for learning on point clouds*, CoRR [abs/1801.07829](https://arxiv.org/abs/1801.07829) (2018)
 [2] C. Chen, L. Z. Fragonara, and A. Tsourdos, *GAPNet: Graph Attention based Point Neural Network for Exploiting Local Feature of Point Cloud*.