ATLAS EXPERIMENT

W UNIVERSITY of WASHINGTON

Challenges in HEP: Machine Learning

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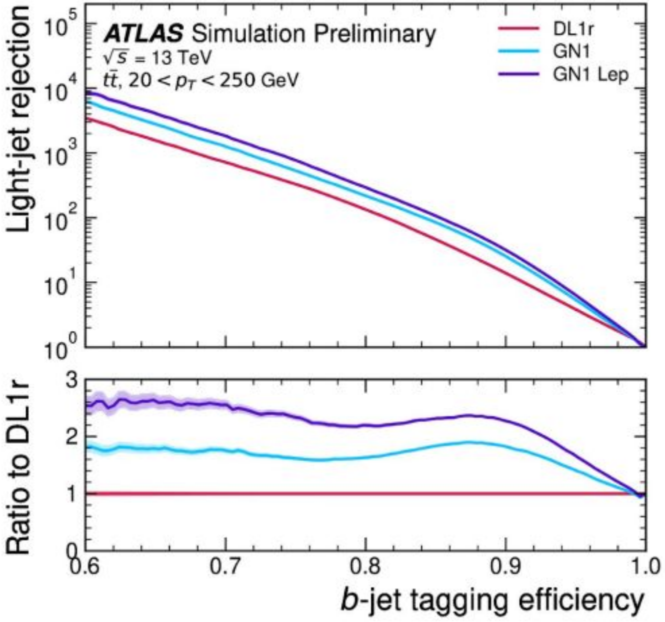
Machine Learning in HEP

- ML has been in HEP for ages: S-B separation and flavor tagging
- What's new:
  - Significant increase in compute power (GPUs) available for ML
  - Dramatic increase in ML architectures for different applications: transformers, large-language models (LLMs), graph neural networks (GNNs), convolutional neural networks (CNNs), etc
- ML advancements have already affected HEP, e.g., drastic improvement in flavor tagging (GN1).



MVAs used since Run 1 (MV1)

Machine Learning in HEP

- Increasing complexity, decreasing interpretability
- Compatibility with calibration techniques
  - Can you derive scale factors, systematics, etc?
- Systematics do not kill your gains
  - Study them early on!
  - Even a flat uncertainty can give you a rough idea
- ML enables portability (ability to run on different types of hardware, e.g., CPUs, GPUs, FPGAs)

ML4Pions

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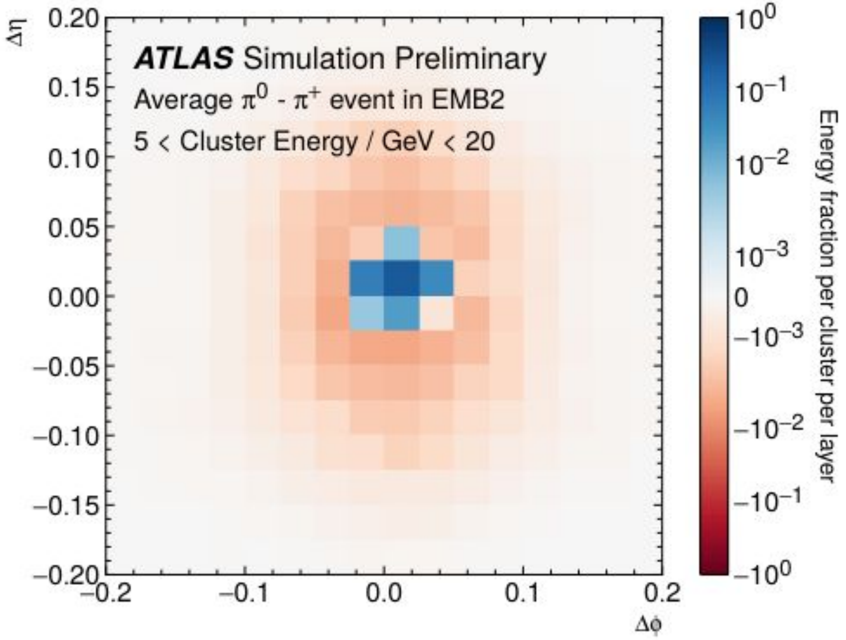
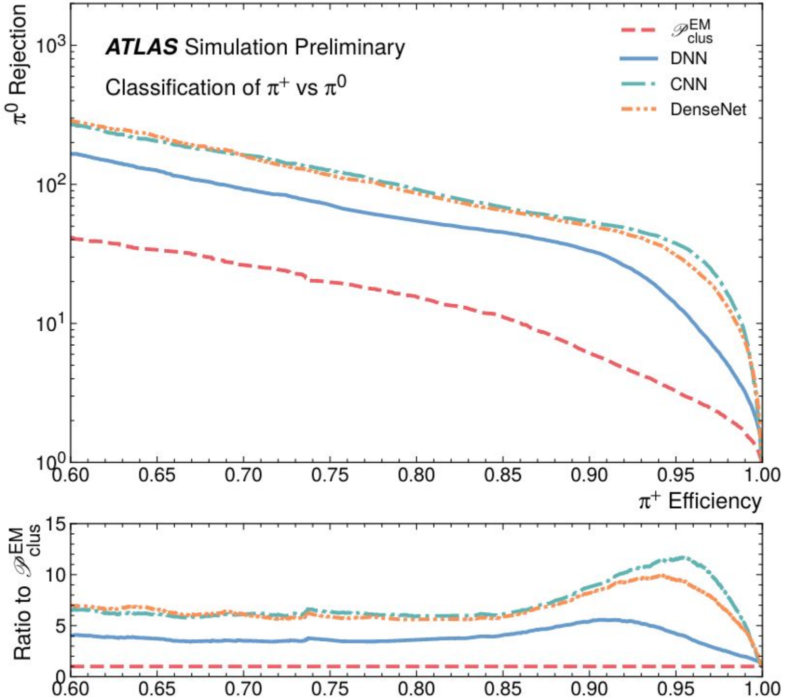
- Pixelated calorimeter images: Convolutional NN (CNN)
- The ML techniques all do an excellent job of distinguishing π^0 from $\pi^{\pm}$ showers





Why use Machine Learning?

- ML to exploit high-dimensional correlations
  - Our multidimensional distributions are rarely rectangular
  - Rectangular cuts won't maximize signal efficiency and background rejection
  - Maximizing our performance is essential in luminosity era

- ML as a surrogate model: fast and/or can run many types of hardware: e.g., ML-based track reconstruction, AtlFastSim3

- ML for non-standard data: data that is less confined than our physics objects (e.g., operational data), variable length input, etc

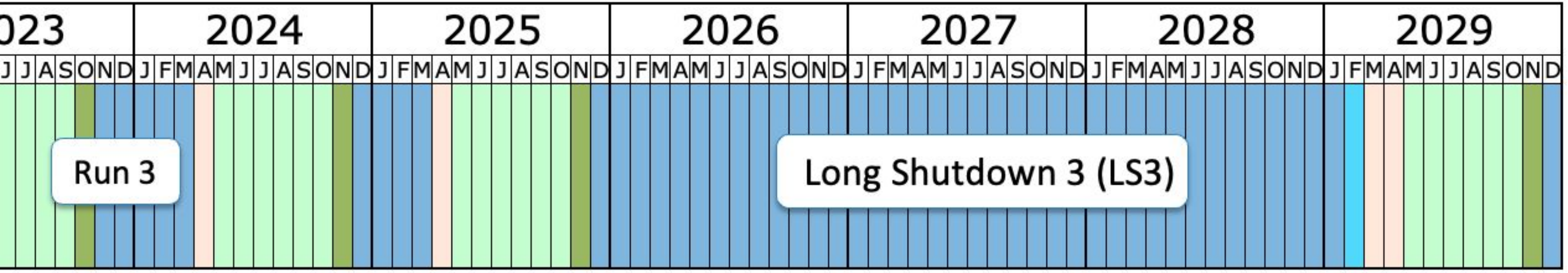
High Luminosity - LHC

Trigger & data acquisition challenge

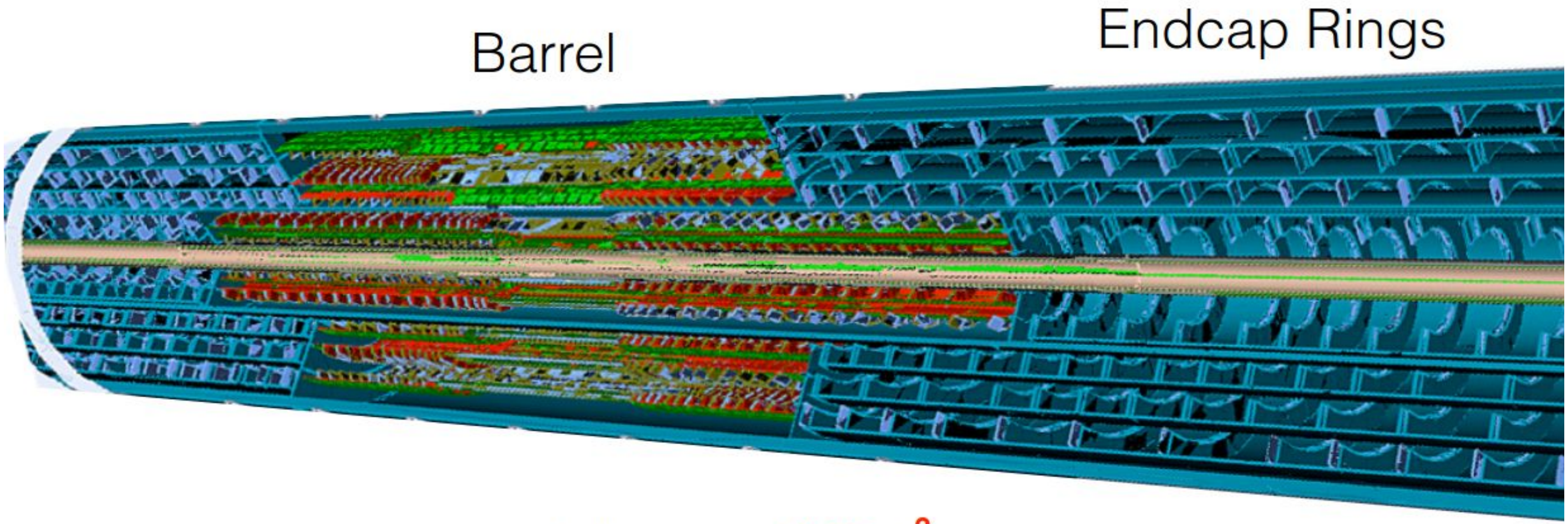
- Luminosity: $2 \mapsto 7.5 \cdot 10^{34}\ \mathrm{cm}^{-2}\ \mathrm{s}^{-1}$
- Pileup: $60 \mapsto 200$
  - more time consuming
  -

ATLAS detector upgrade

- New Tracker, new Timing Detector, additional muon chambers, new Tile electronics, ...



Why use Machine Learning?



Active area: **12.7 m^2**

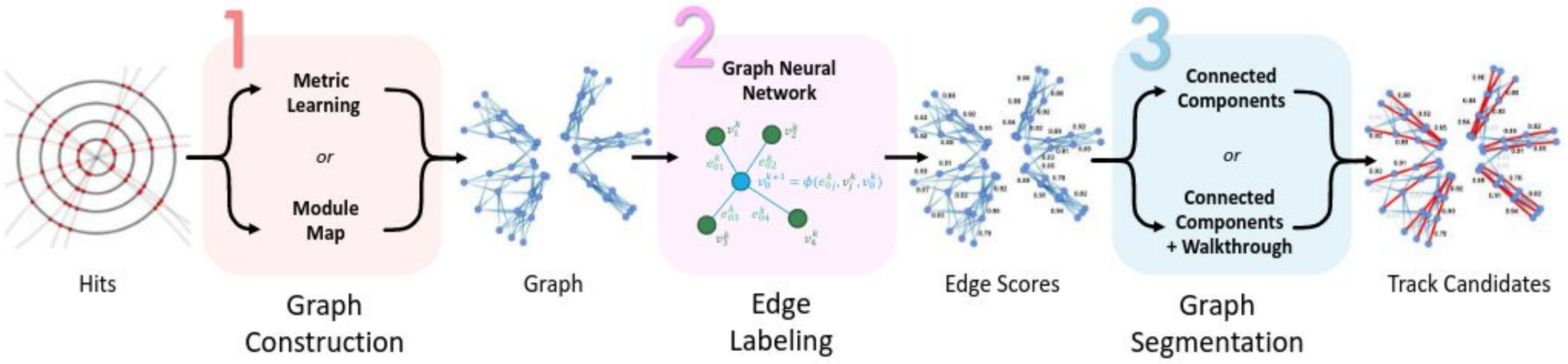
Pixel size: 50x50 (or 25x100) μm^2

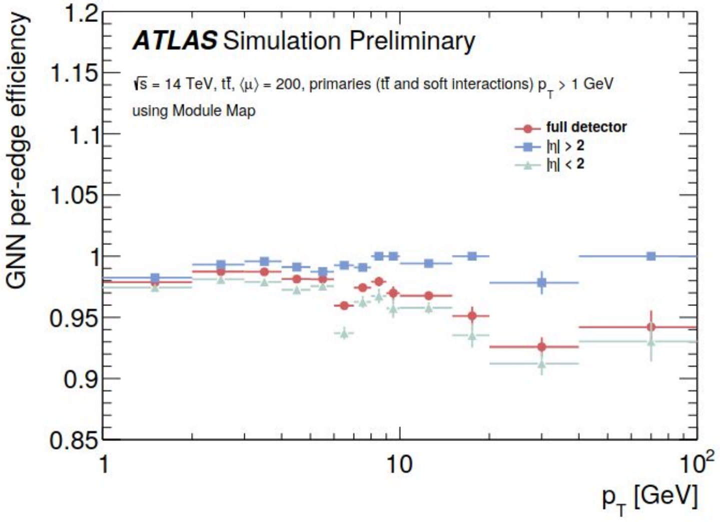
# of modules: 10276

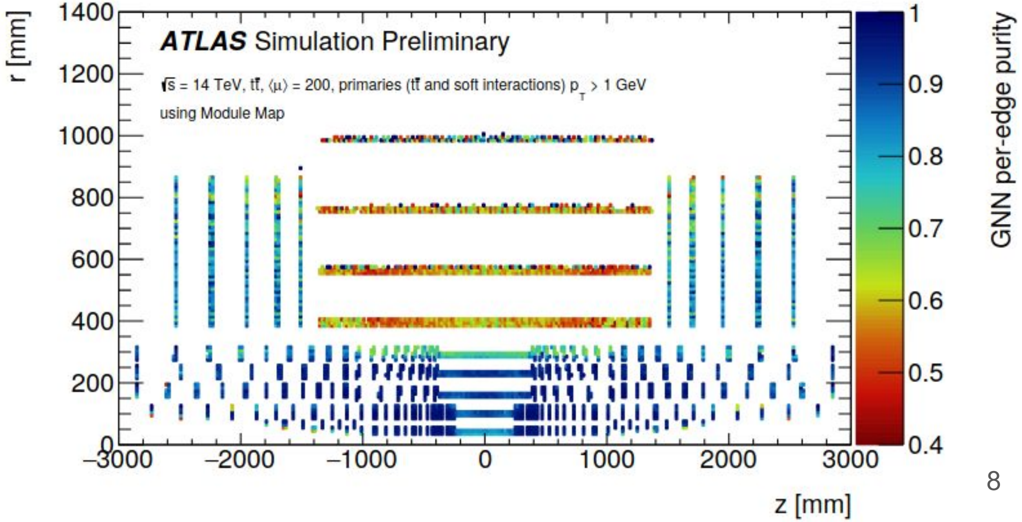
# of FE chips: 33184

# of channels: **$\sim 5 \times 10^9$**

Why use Machine Learning?

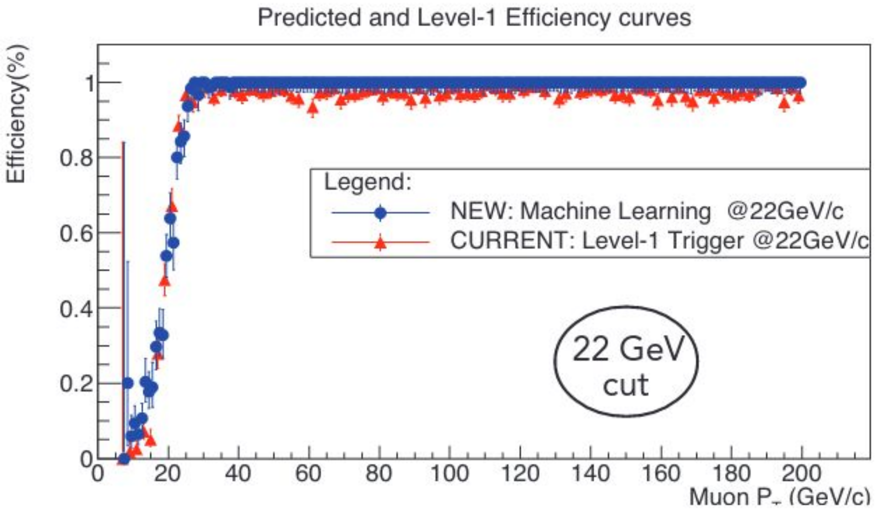


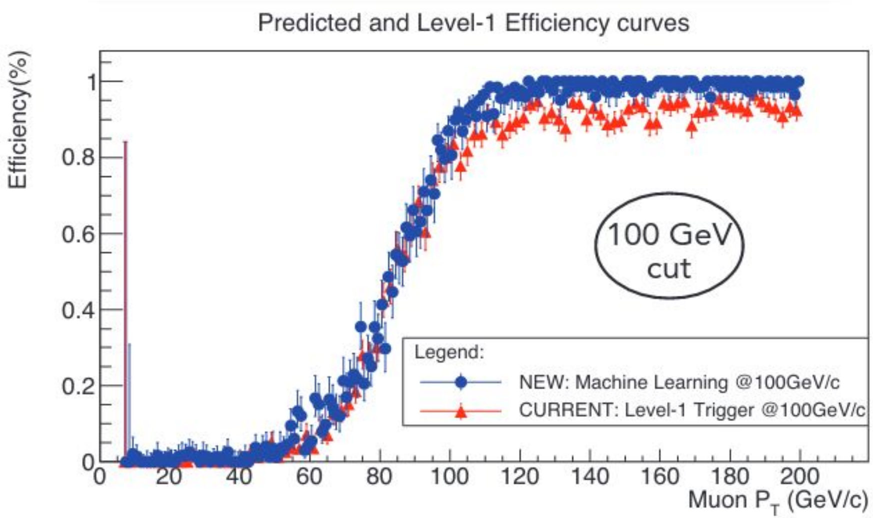




Real-time triggers

- Machine Learning based muon trigger algorithms for the Phase-2 upgrade of the CMS detector

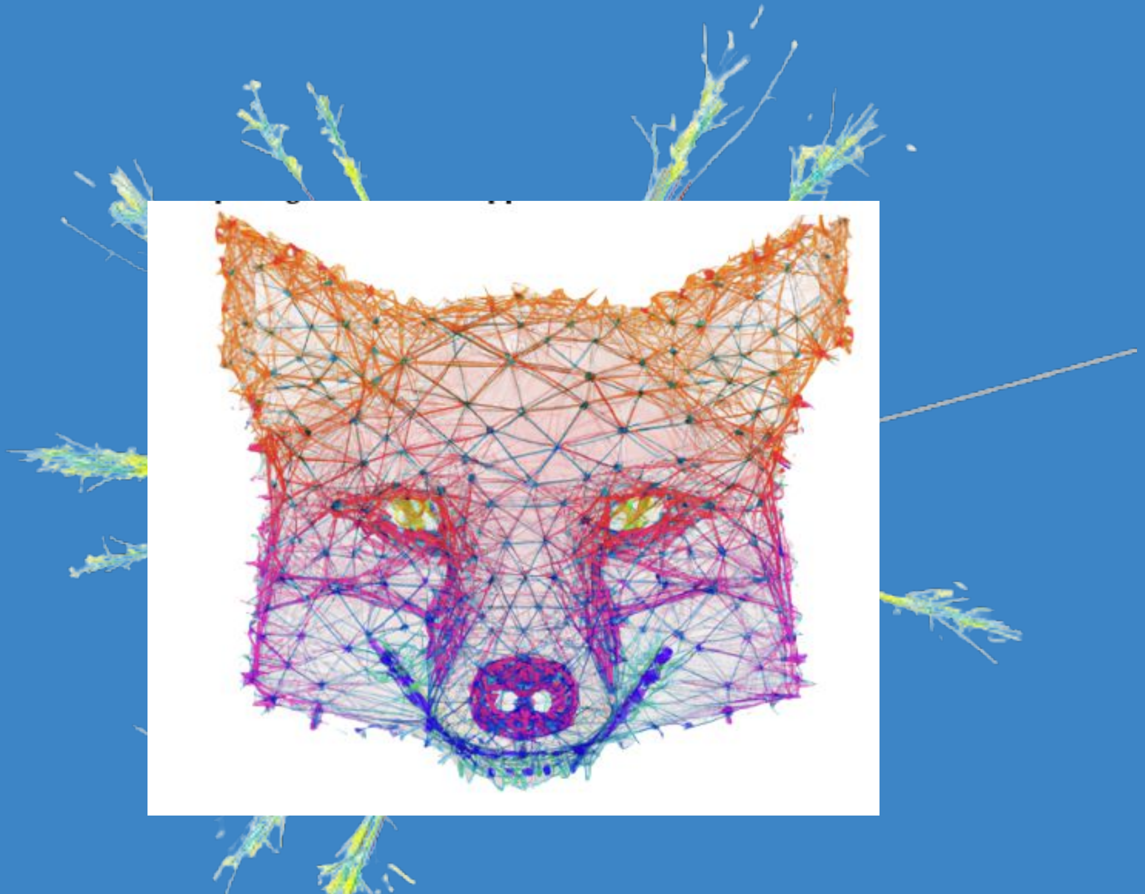




At high values of pT, the performances of the model predictions begin to decrease probably due to a low resolution for small bending muons.

Some ideas for the future

- Can we also improve our reconstruction for new sub-detectors as HGTD or New Small Wheel?
- Can we use reinforcement learning for automatic data quality monitoring in HEP experiments?
- Can we also have an electron/photon identification with a convolutional neural network similarly to the jets?
- Can we try to tag dark matter particles with ML? Or search for them?
- Can we study the systematic effects in Jet Tagging Performance?
- Can we use transformers for Particle Track Reconstruction and Hit Clustering?
- Can we improve the knowledge on heavy ions collisions by studying topological separation of dielectron signals?



Thanks for the attention!