Quantum Computing for Track Reconstruction at LHCb

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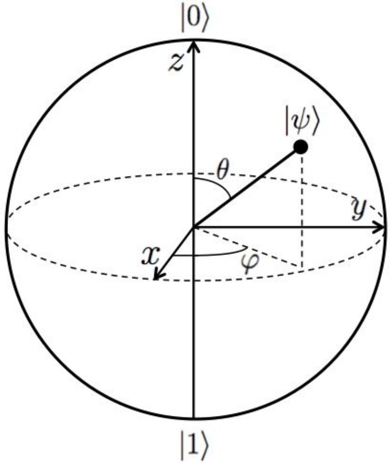
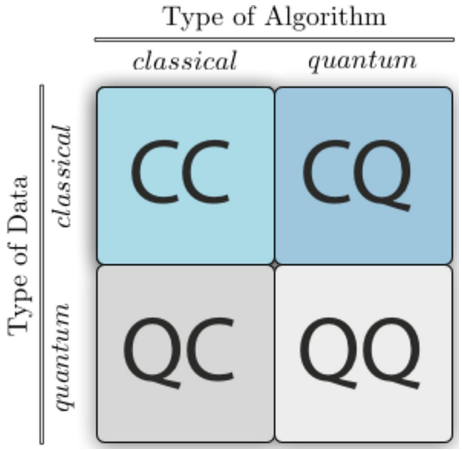
LHCb

What? Quantum Computing

- Instead of **bits** → qubits
- Quantum logic gates operate on these qubits



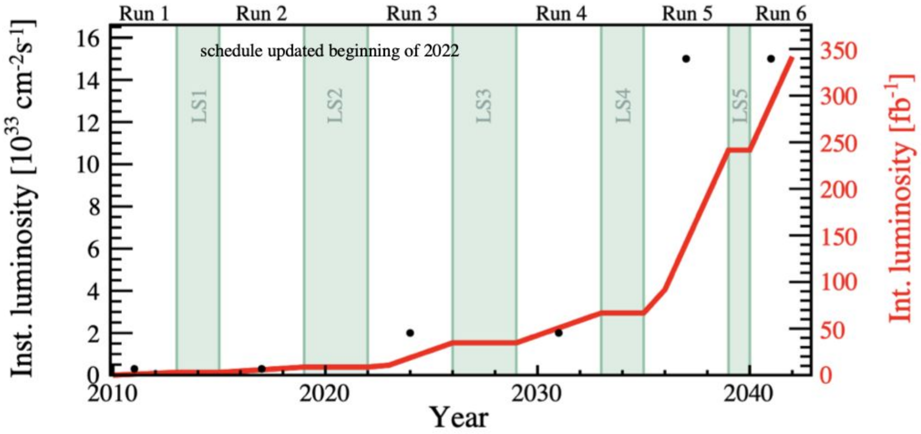
QC + Machine Learning = **Quantum Machine Learning**



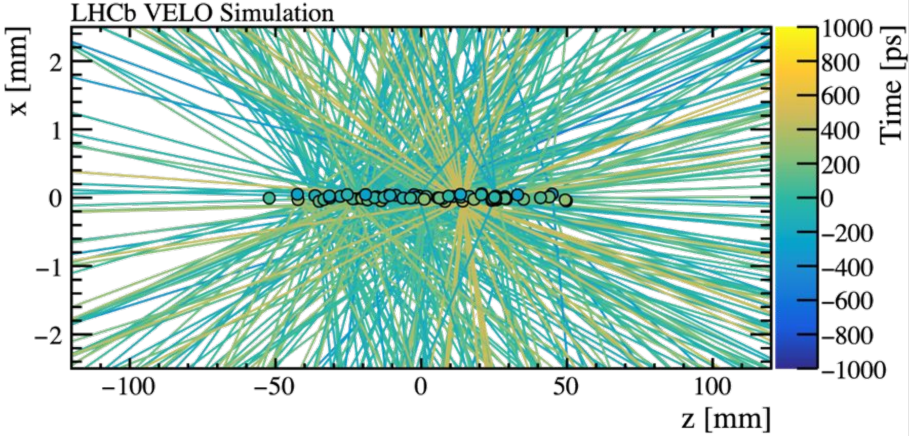
https://quantumalgorithmzoo.org/

Why QC?

- New algorithms and architectures needed to deal with the increased luminosity & limited bandwidth @ **HL-LHC**



[ECFA](#)



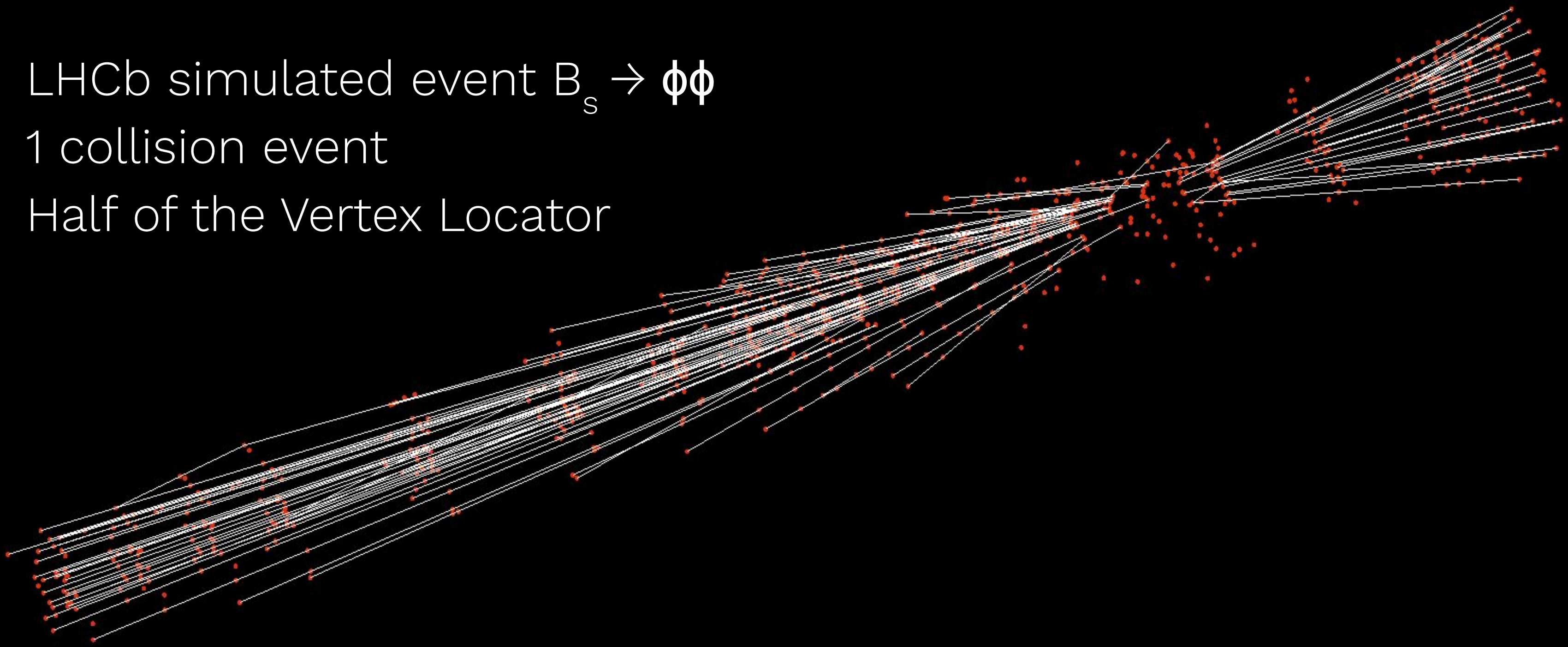
Courtesy of Robbert Geertsema

How?

LHCb simulated event $B_s \rightarrow \phi\phi$

1 collision event

Half of the Vertex Locator



Advances in developing deep neural networks for finding primary vertices in proton-proton collisions at the LHC

New approach based on Graph Neural Network

European AI for Fundamental Physics Conference
2024

S. Akar
University of Cincinnati

PV-finder motivations & context

- Over the next years, LHC detectors will face **significantly increased luminosities**
- One of the main challenges in this **high pile-up environment** will be the ability to perform **efficient vertexing**

- **The PV-finder project:**
  - train **DNN algorithms** to **find PVs** with **high efficiency** and **low false positives rates**
  - understand **how the results depend on underlying model architectures** and input features

- **PV-finder originally developed** targeting the **LHCb** geometry and conditions
  - Several studies and developments based on a Hybrid ***Fully connected*** **(FC)** + ***Convolutional Neural Networks*** **(CNN)** model over the past years: [CtD20 ; CHEP21 ; ACAT22 ; CHEP23; CERN IML24]
  - ***CNN**-based* approach recently adapted to the **ATLAS** experiment with extremely promising results [ATL-PHYS-PUB-2023-011]

PV-finder motivations

- Over the next years, the LHC detectors will face ***significantly increased luminosities***
- One of the main challenges in this ***high pile-up environment*** will be the ability to

Disclaimer

I will focus on *3 takeaway messages*, and will skip all details…
…for these see you tomorrow during the poster session!

- Several studies and developments based on a **hybrid** ***Fully connected*** **(FC)** + ***Convolutional Neural Networks*** **(CNN)** model over the past years allowing for continuous improvements [CtD20 ; CHEP21 ; ACAT22 ; CHEP23; CERN IML24]
- ***CNN****-based* approach recently adapted to the **ATLAS** experiment with extremely promising results [ATL-PHYS-PUB-2023-011]

GNN approach: motivation

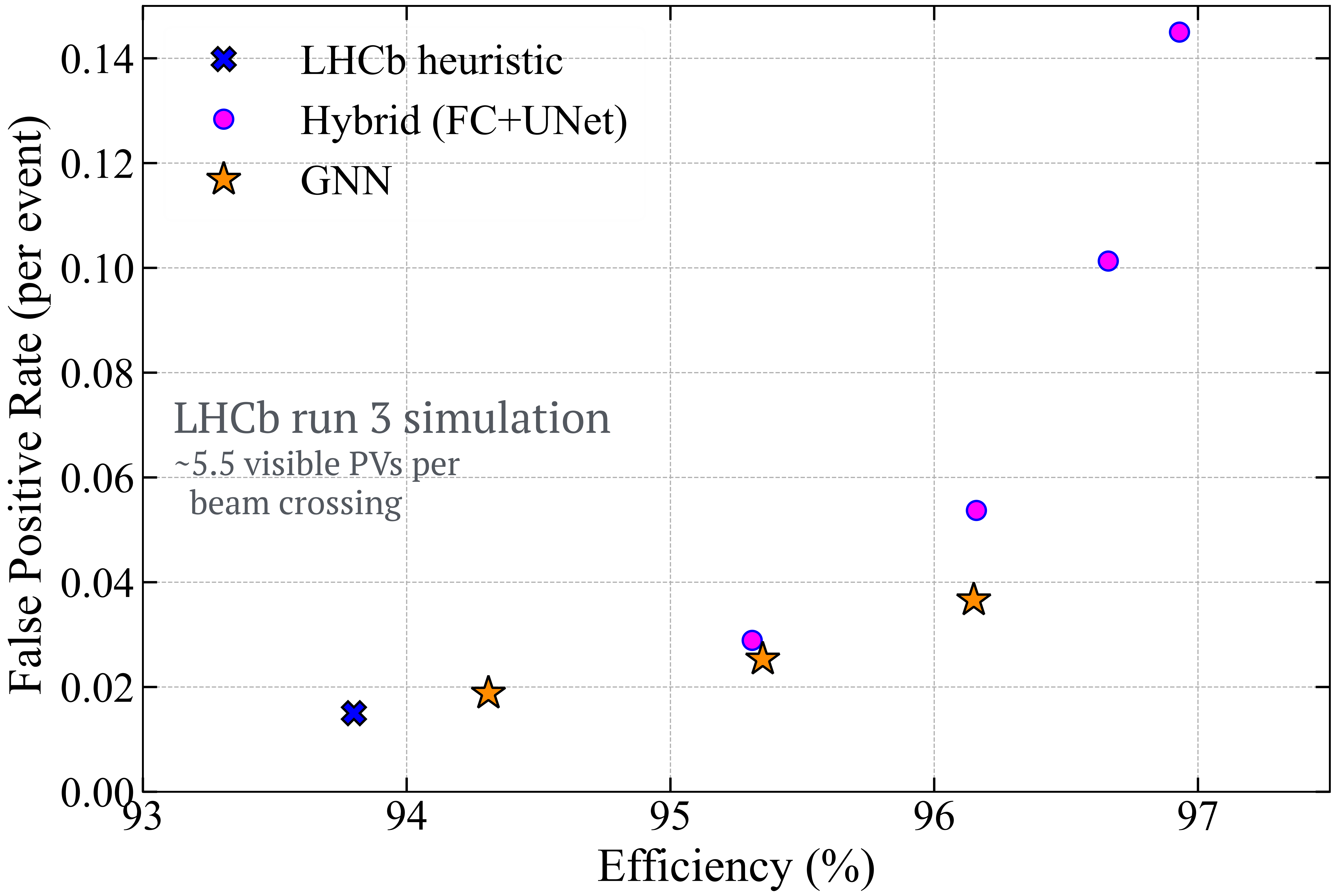
- **Graph Neural Network (GNN)** approach has been demonstrated to outperform heuristic algorithm in terms of physics performances:
  - GNN-based pipeline for track finding from hits in the Velo at LHCb [talk@CTD23]

- **GNN** models appear to be quite **versatile**:
  - With **minimal adaptation, similar models allow to perform very different tasks:**
    - edge classification for track reconstruction
    - node feature prediction for PV finding

Hybrid vs GNN: model performances

- **Hybrid best model results** from developments over the past years with refined models
- **GNN model achieve slightly better physics performance** than hybrid model

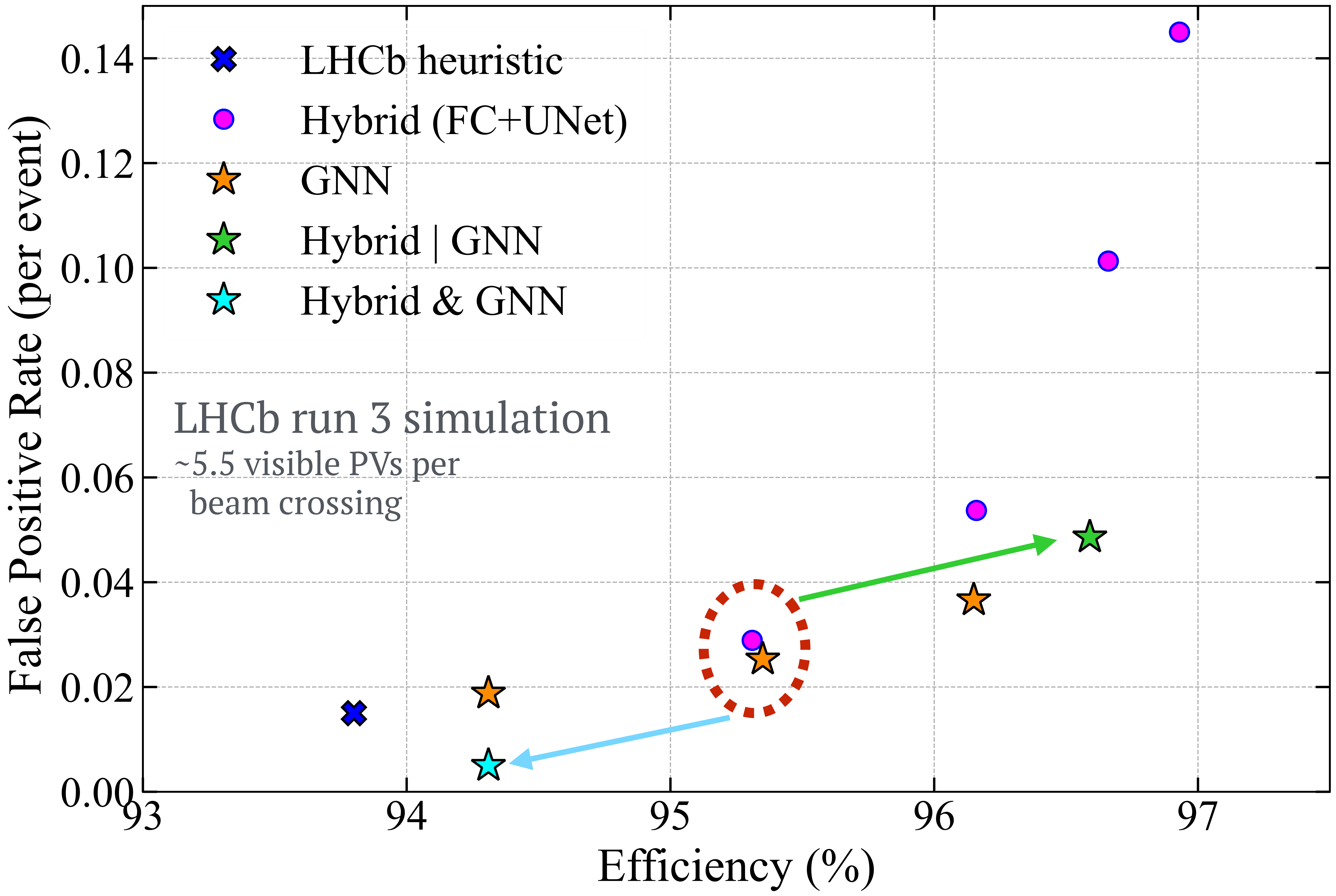
Conceptually different ML approach yields similar performances!



Hybrid vs GNN: model performances

- Compare GNN and hybrid models outputs with similar intrinsic performances

- Combination of output from models allows to either significantly increase efficiency or decrease false positive rate



PV-finder GNN approach: Summary

Takeaway messages:

1. **GNN** models appear quite **versatile**
   similar model achieve good performances for different tasks (tracking vs PV finding)

2. **GNN** and **Hybrid** **models** achieve **similar intrinsic physics performances…**

3. …but only partial overlap meaning **GNN** and **Hybrid** **models** did **not learn exactly the same relations from identical input data!**

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All of the machine learning training described here was done in PyTorch using nvidia GPUs

EUROPEAN AI FOR FUNDAMENTAL PHYSICS CONFERENCE EuCAIFCon 2024

MACHINE LEARNING APPLICATIONS AT THE ATLAS EXPERIMENT

Judita Mamužić on behalf of the ATLAS collaboration

EUROPEAN AI FOR FUNDAMENTAL PHYSICS CONFERENCE (EuCAIFCon 2024)

30 April – 3 May 2024, Amsterdam, Netherlands

IFAE Institut de Física d'Altes Energies

EXCELENCIA SEVERO OCHOA

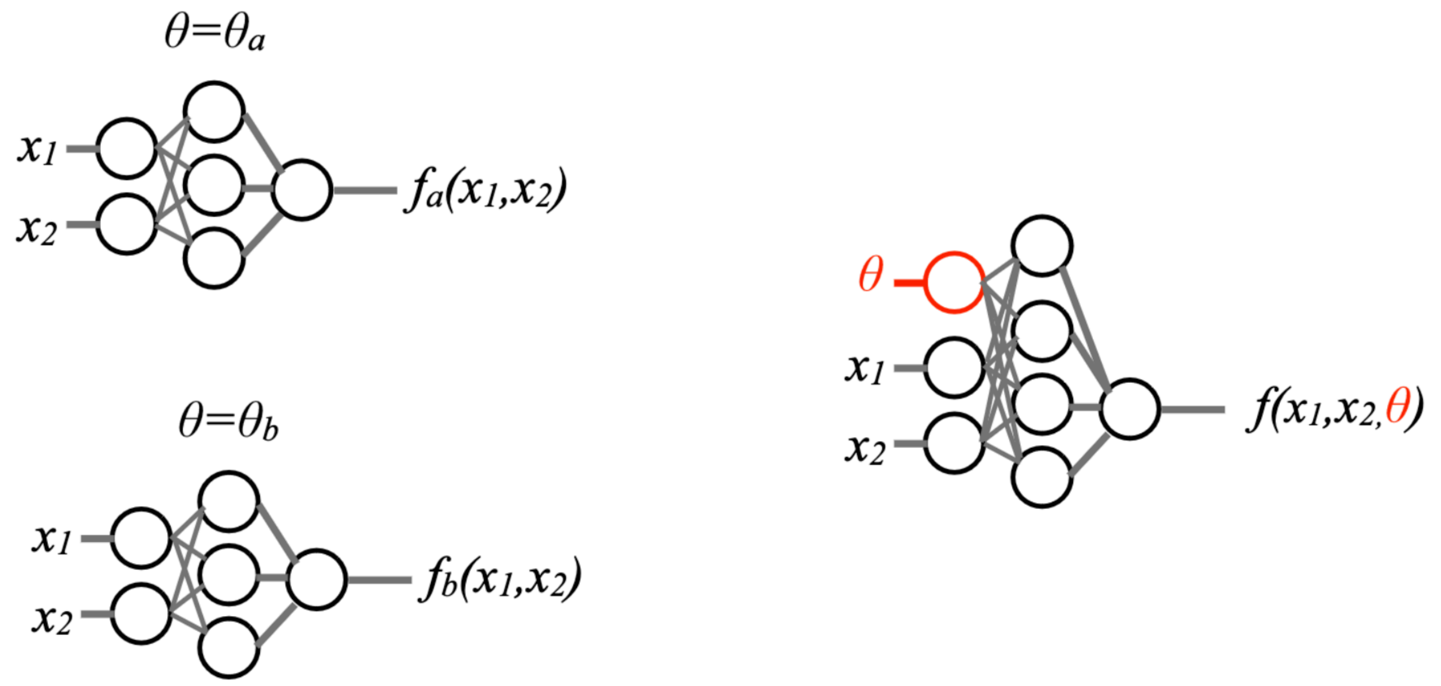
ATLAS EXPERIMENT

SEARCHES - 1

SUPERVISED, CLASSIFICATION S vs B

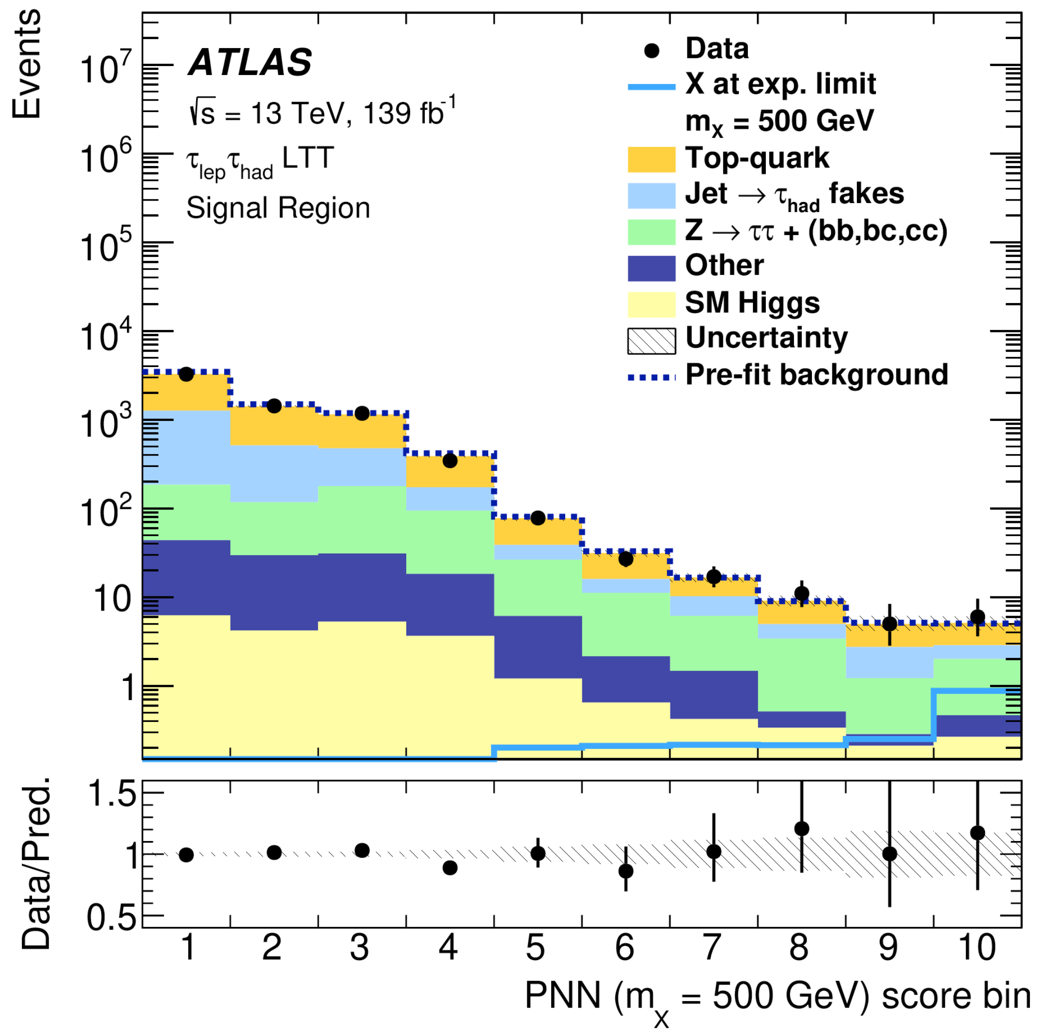
Parameterized DNN/BDT/GNN

Eur. Phys. J. C (2016) 76: 235



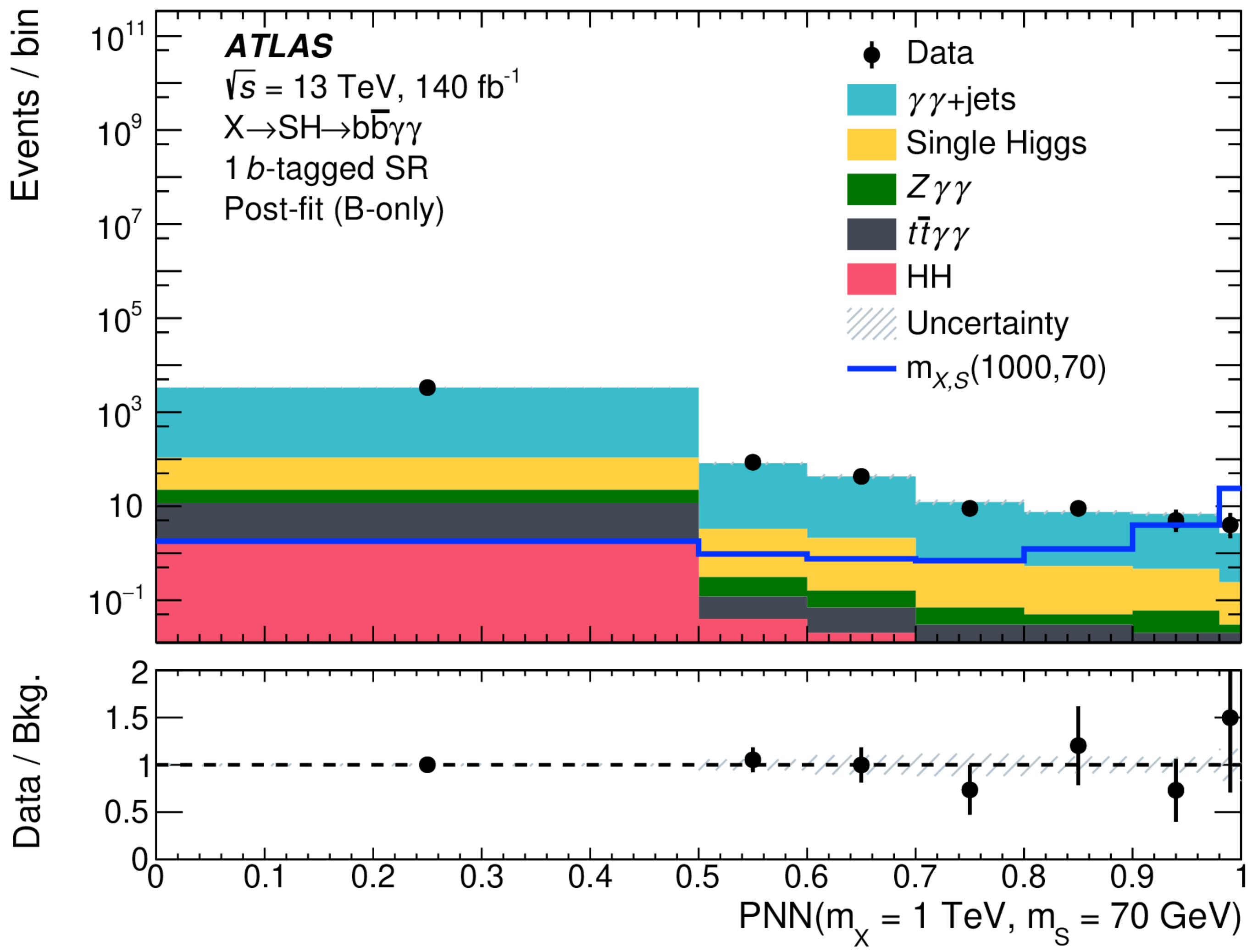
Increase training statistics by adding up multiple models, optimal for large range of parameters

1 par: HH→bb ττ



HDBS-2018-40

2 par: X→SH→bbγγ



HDBS-2021-17

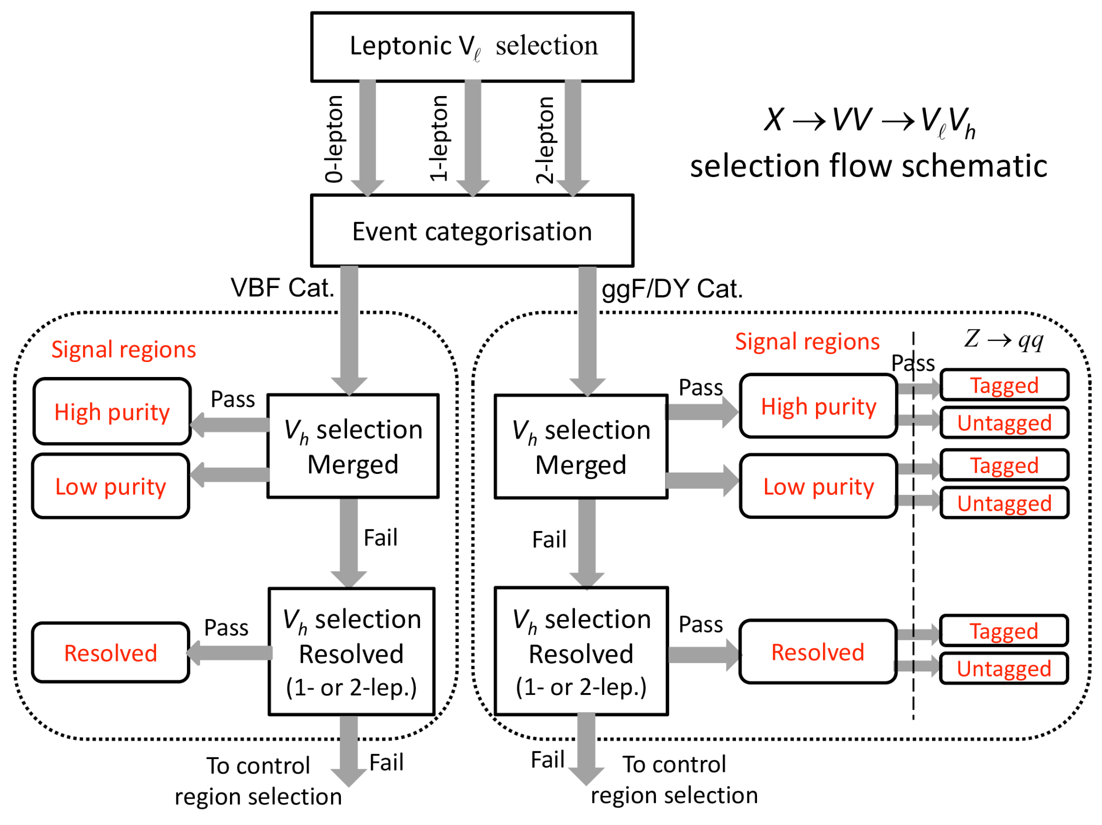
SUPERVISED, CLASSIFICATION S vs S

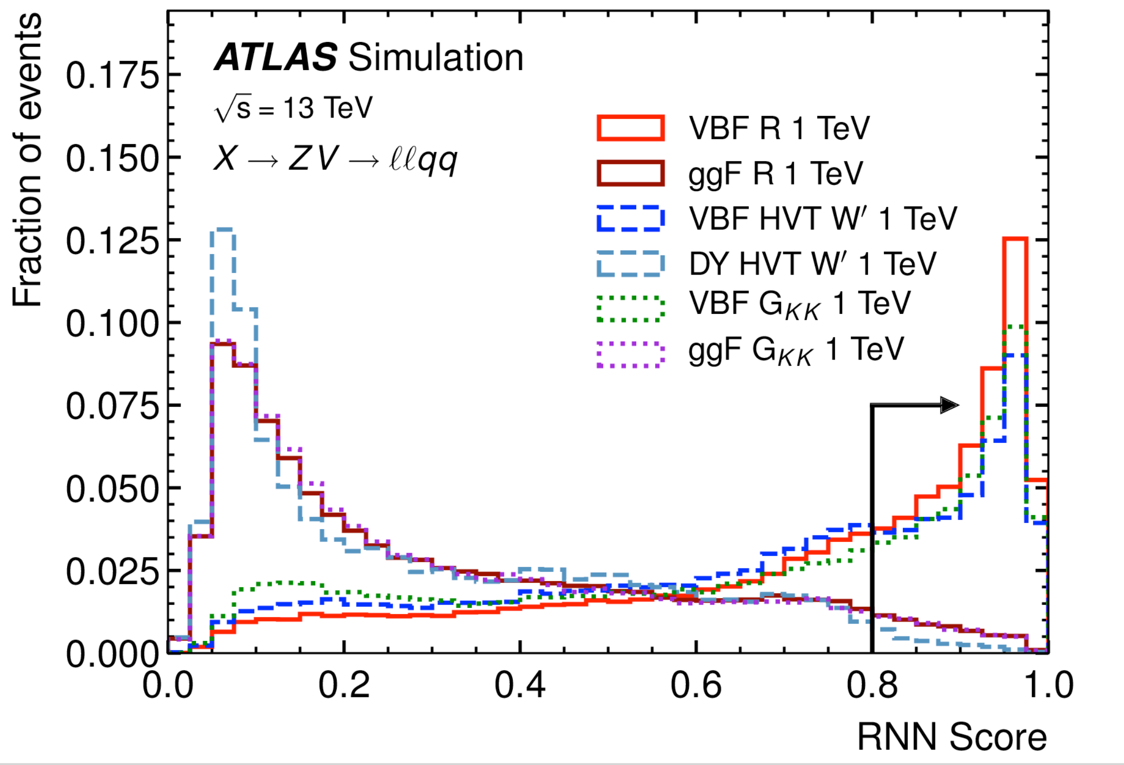
Multi-class classification

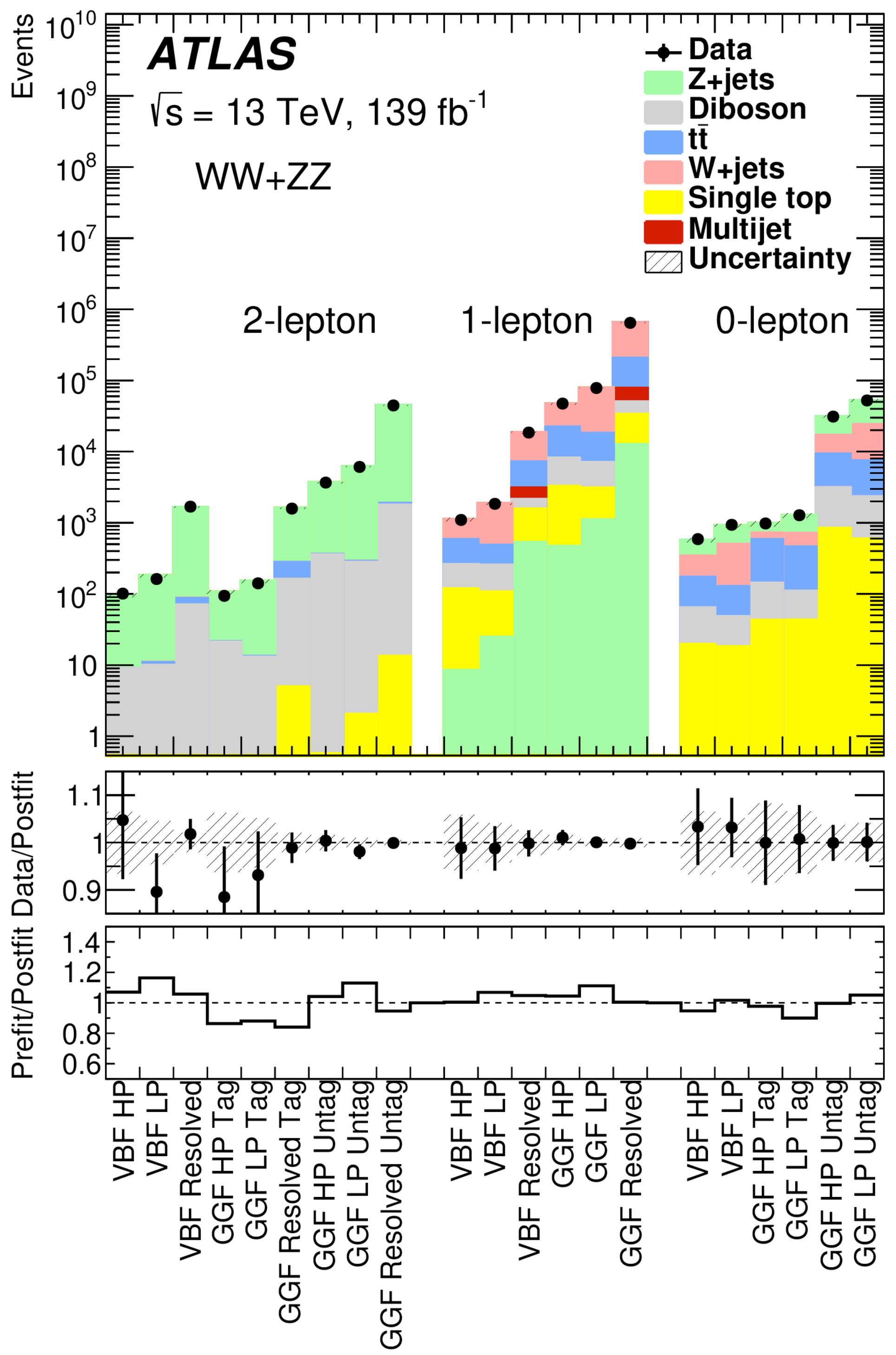
Use ML to optimize purities of signal classes, then optimize background rejection

Exploit different signal topologies in a single search, better signal class purity

X→ZV→llqq, VBF vs ggF/DY







HDBS-2018-10

SEARCHES - 2

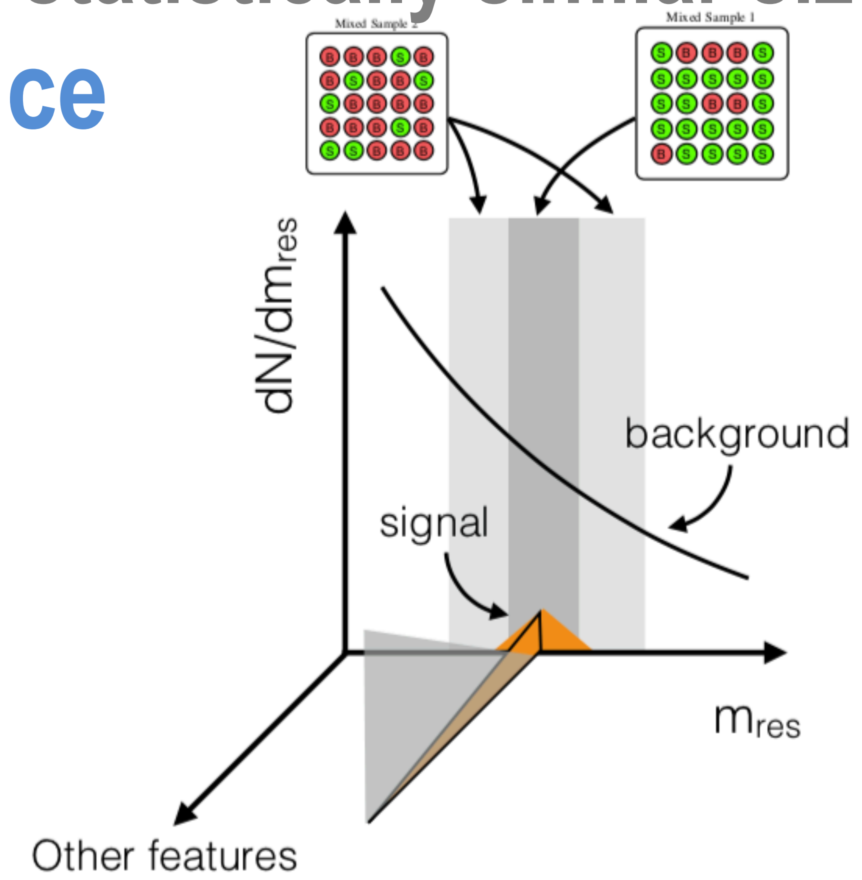
WEAKLY-SUPERVISED, CLASSIFICATION S vs B

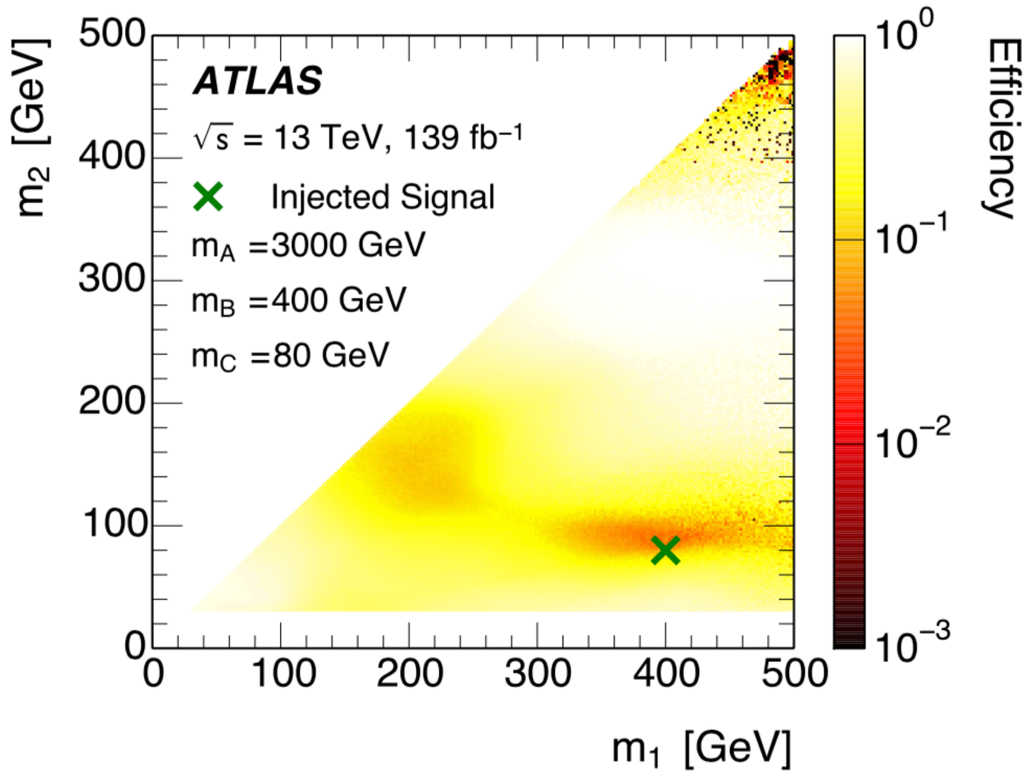
Classification without labels (CWoLA)

Instead of using signal and background, use mixed samples with different proportions of signal (S dominated vs B dominated). Relies on assumption that mixed samples are of statistically similar size

A →BC, di-jet resonance

- Features are masses of the first two jets (bump hunt)
- Generic search (small trial factor) for τ-leptons, b-quarks, t-quarks, W/Z/H bosons and asymmetric decays
- Signal regions and sidebands (background dominated), dedicated NN for each signal region
- NN able to detect injected signal





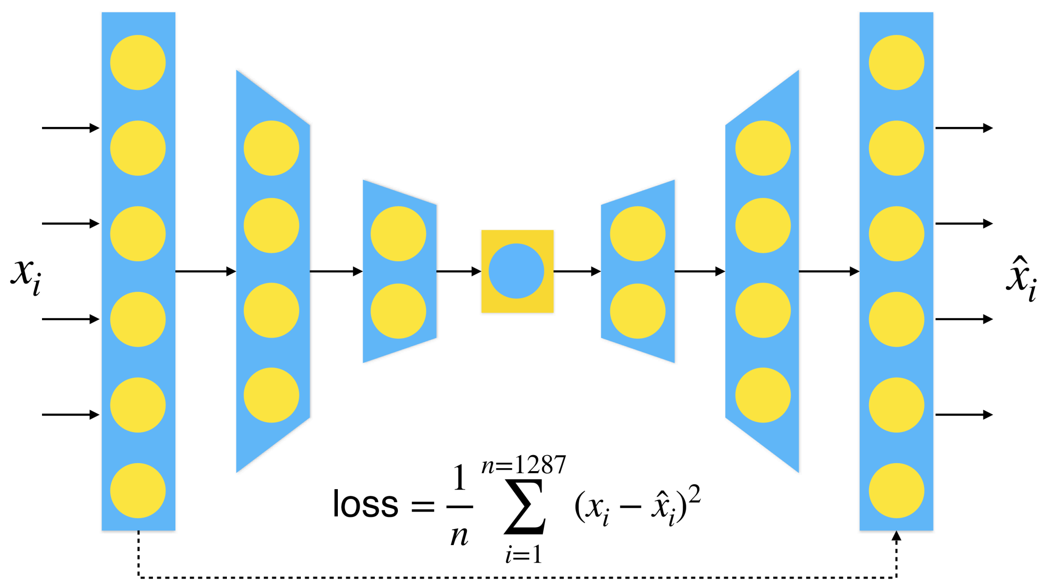
HDBS-2018-59

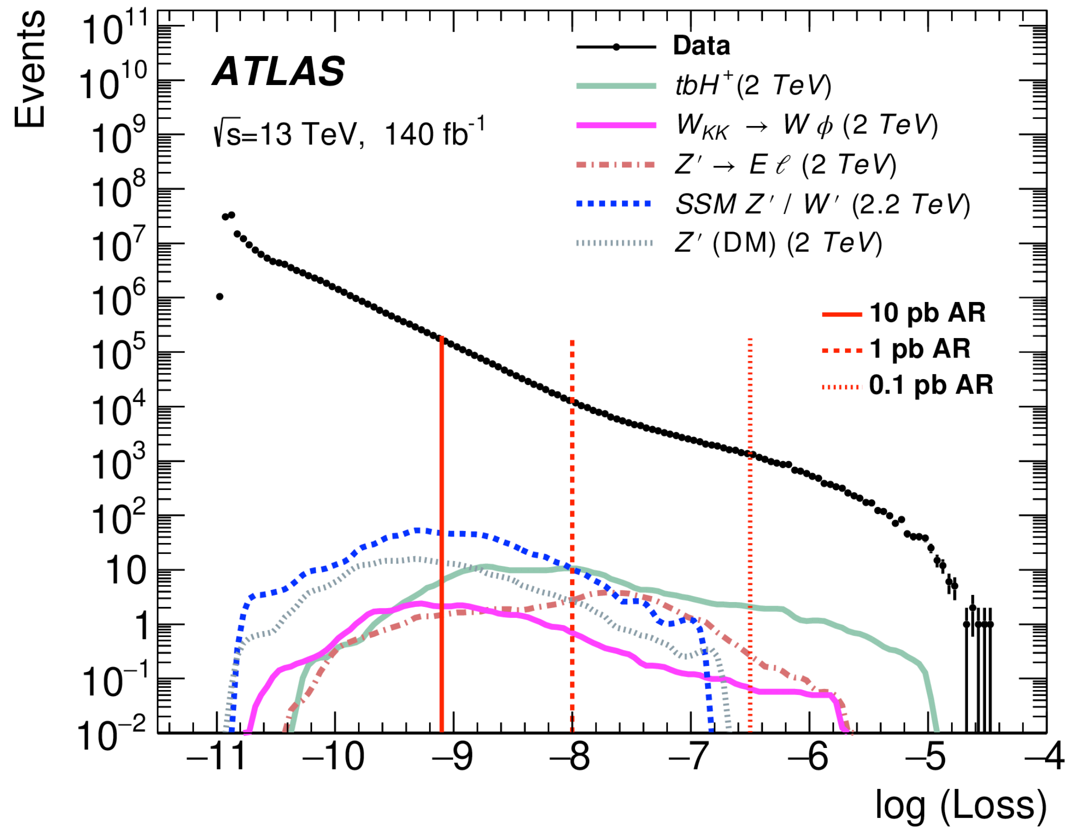
UNSUPERVISED, ANOMALY DETECTION

Model agnostic search

X →j Y, jet-Y resonance

Generic bump-hunt for jet+Y resonance using anomaly score (j+j, j+b-jet, 2 b-jet, j+e, b-jet+e, j+γ, j+μ, b-jet+μ , b-jet+ γ)

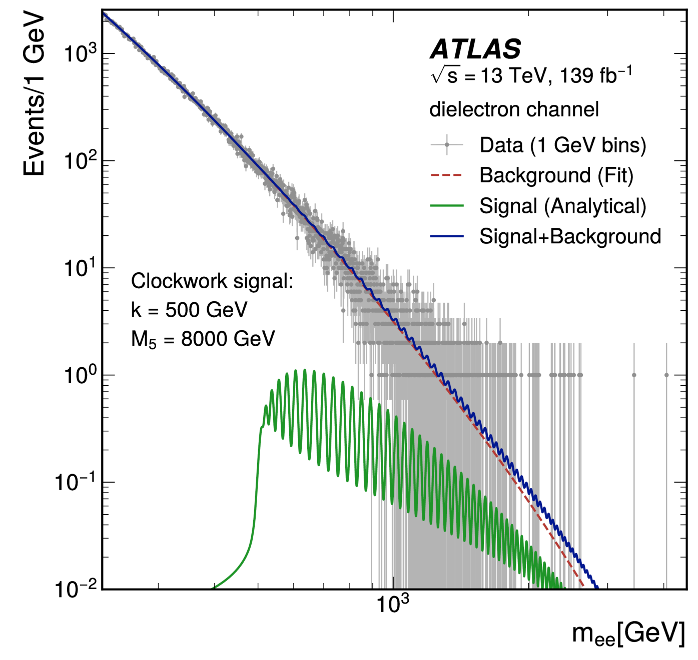


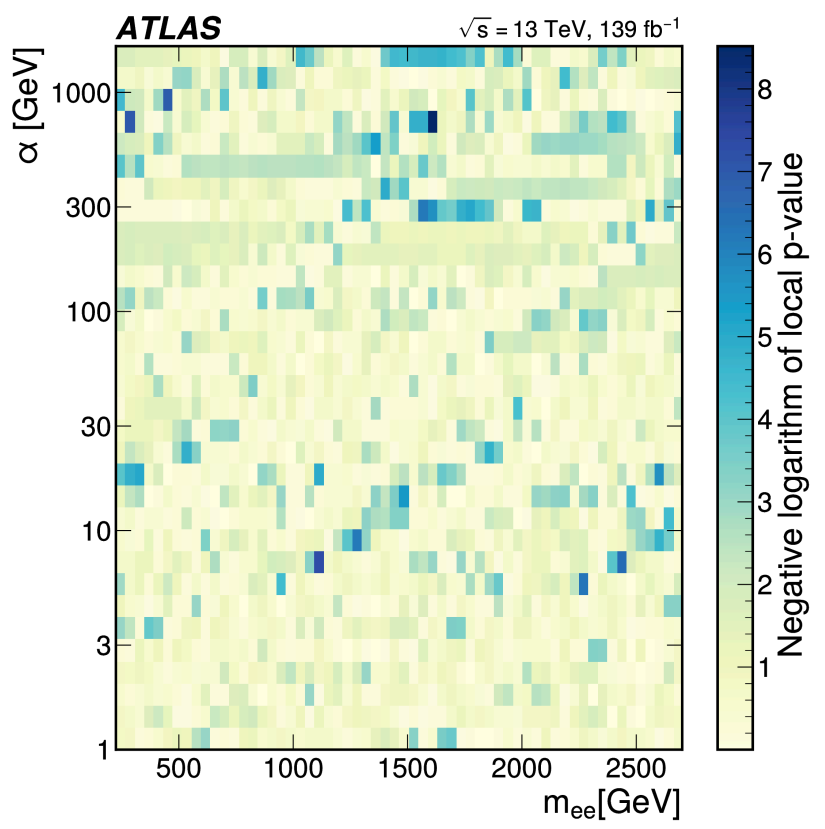


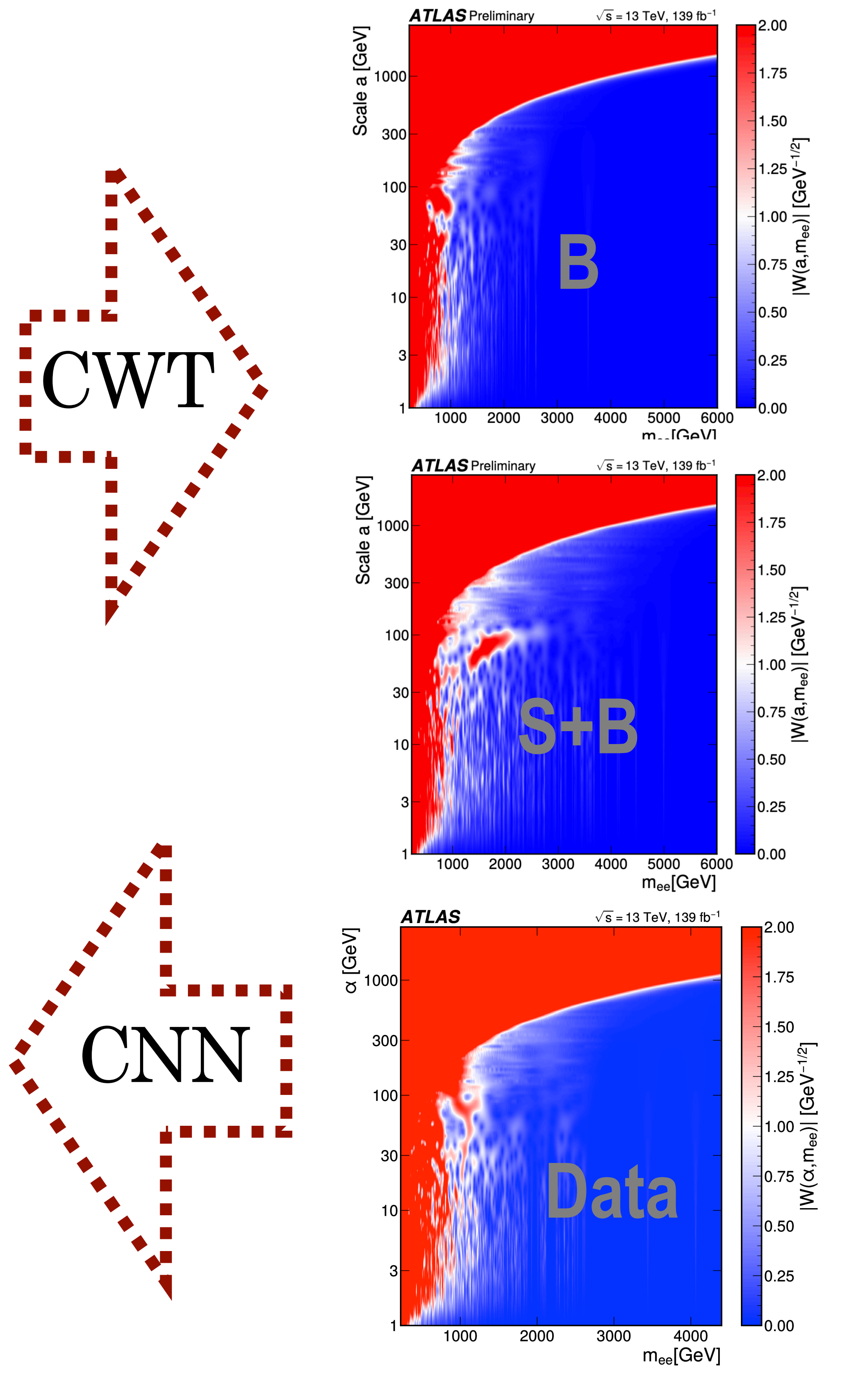
EXOT-2022-07

$G^* \to e^+e^-/\gamma\gamma$, clockwork

- Signature: periodic signal, wavelet of m_ee, m_γγ
- Instead of bump-hunt using Continuous Wavelet Transformation (CWT)







1. Using CNN to distinguish S+B from B
2. Using auto encoder on data to obtain model agnostic p-values

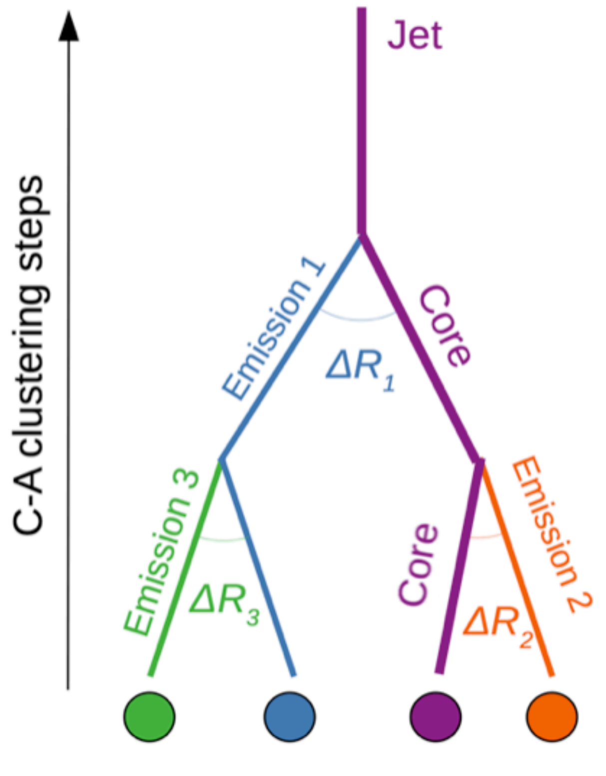
EXOT-2019-40

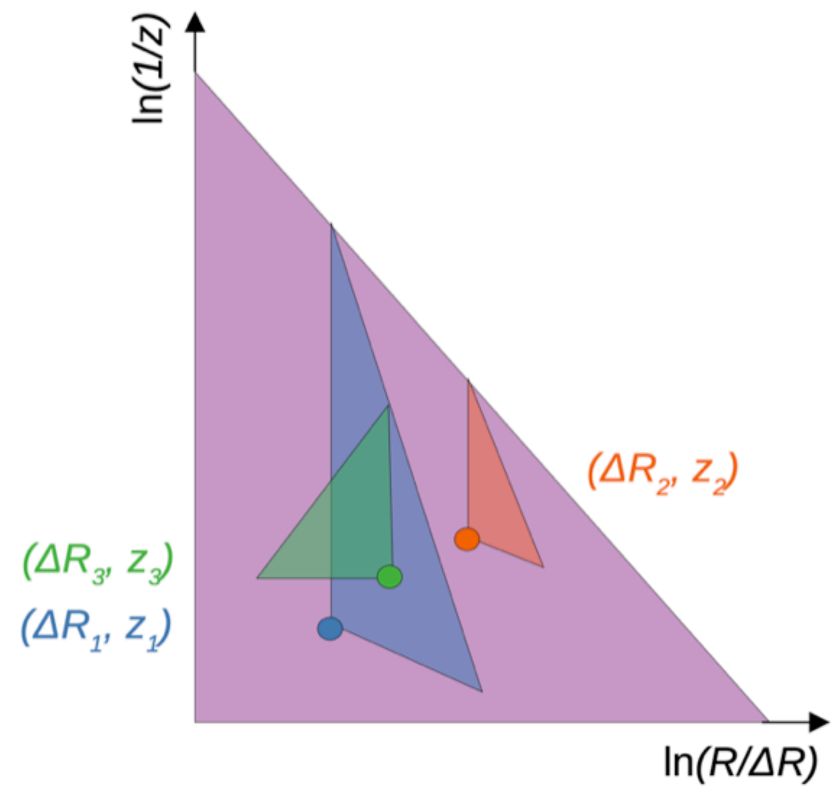
OBJECTS

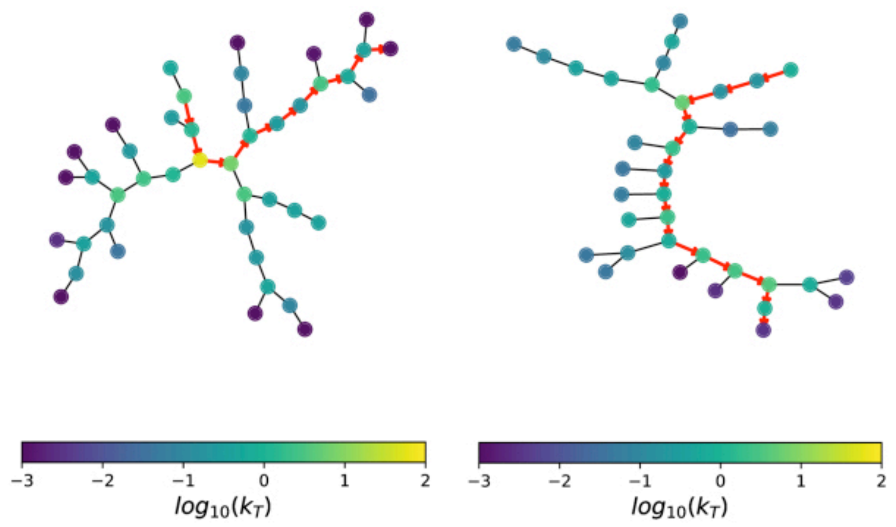
BOOSTED W-BOSON TAGGING

Lund Plane tagger

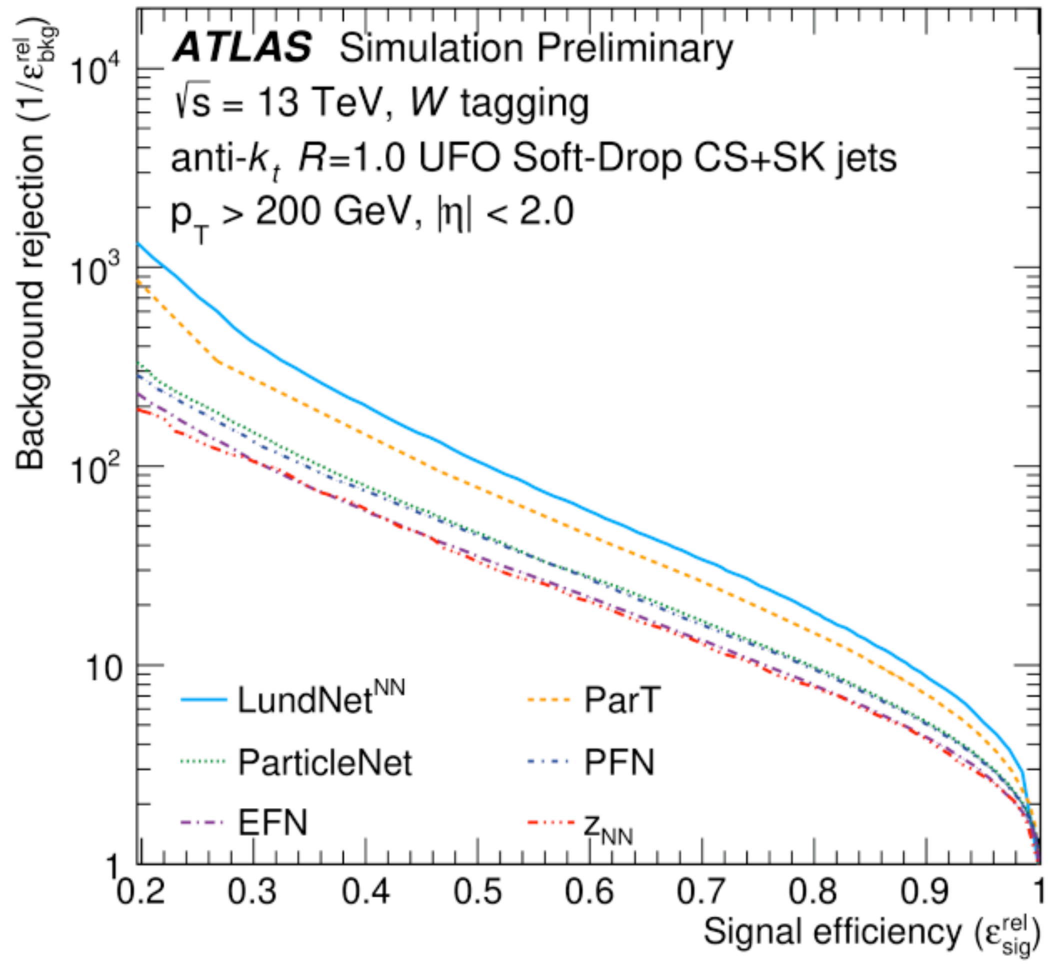
Identify jets originating from W bosons using the de-clustering information from successive splitting leading to its construction, and separate from QCD background







W jet QCD jet

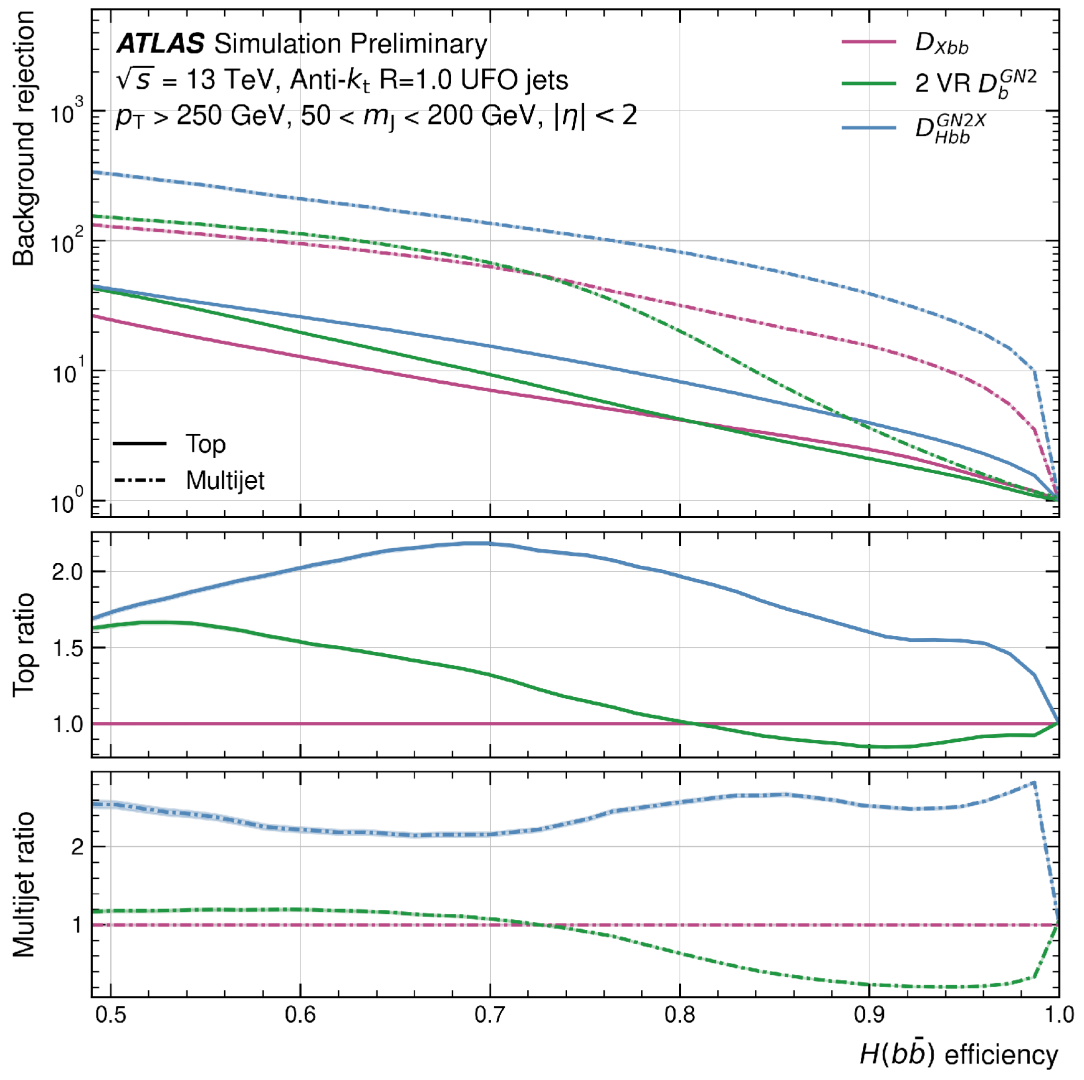


ATL-PHYS-PUB-2023-017

H TAGGING

H⟶bb tagger

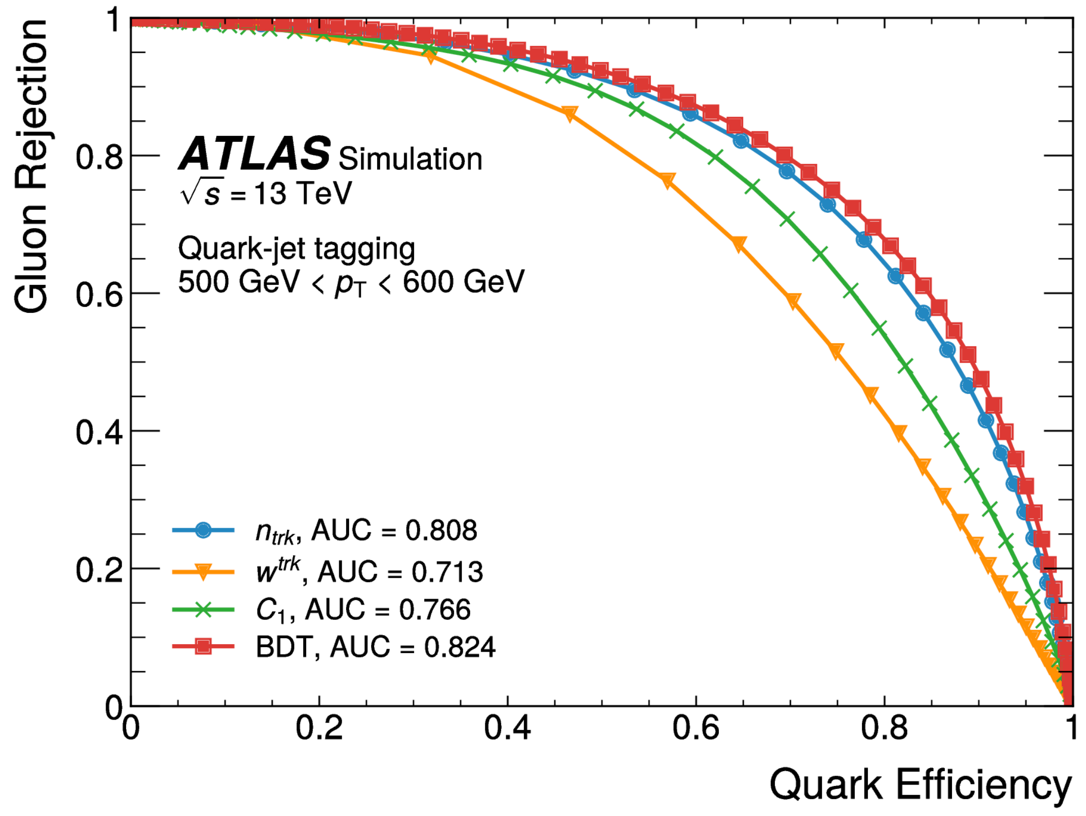
New boosted hadronically decaying Higgs tagger using low level information to identify two b/c-quarks outperforms previous high-level information taggers



ATL-PHYS-PUB-2023-021

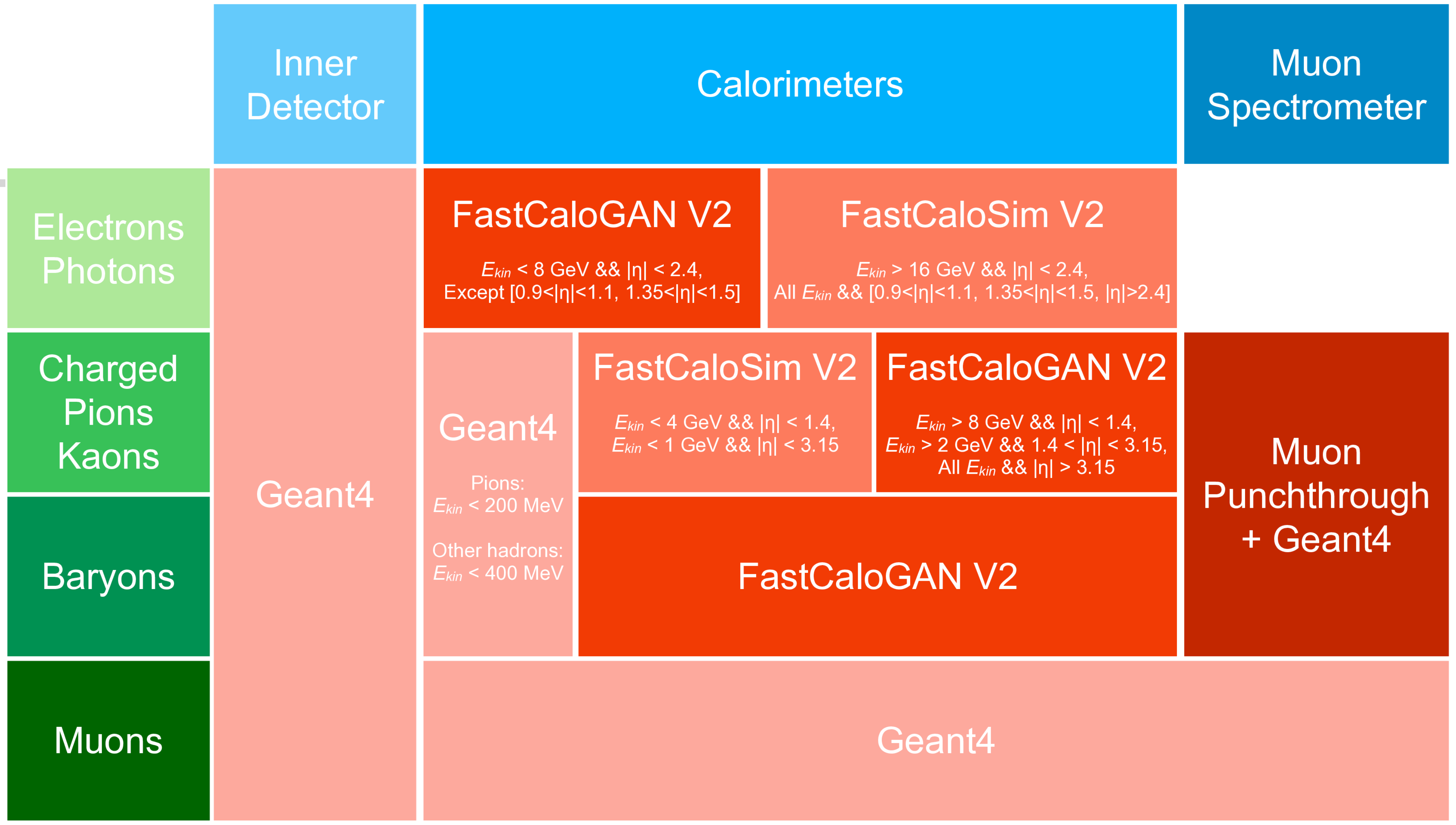
q/g TAGGING

Identification of jets coming from quarks or gluons shows better performance using more low-level information. Two new taggers: (1) charged-particle constituent multiplicity, (2) jet kinematic and substructure variables and BDT



JETM-2020-02

SIMULATION



FAST SIMULATION
AtlFast3

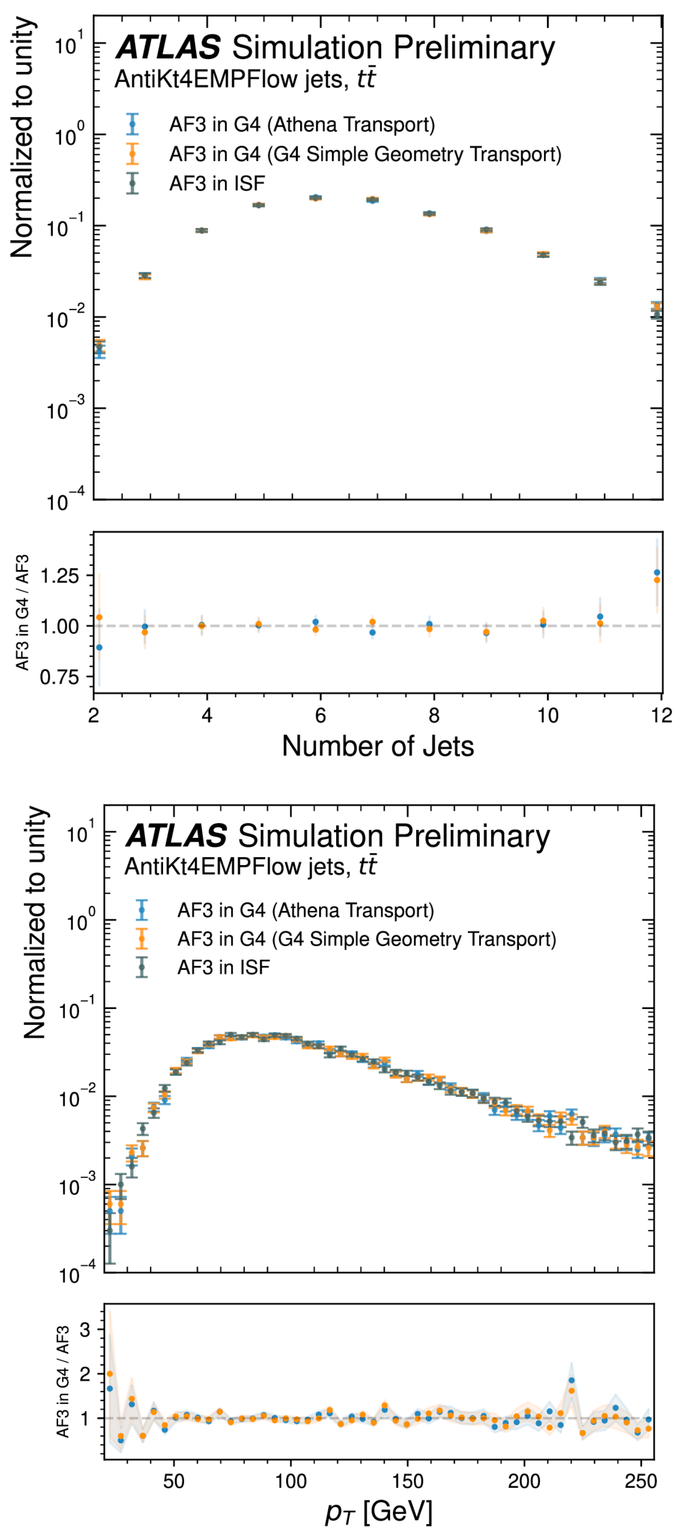
Fast simulation tool for Run3 that balances modeling performance and CPU requirements to address CPU needs in Run3 and beyond

FastCaloSim v2

- Uses longitudinal and lateral shower development parametrization with PCA
- Parametrised modelling using Geant4 single photon, electron and pion samples (energy and |η| spaced bins)
- Separate parameterisation in longitudinal and lateral shower development
- Energy decorrelation in layers using PCA
- Average lateral energy distribution parameterized as 2D probability functions

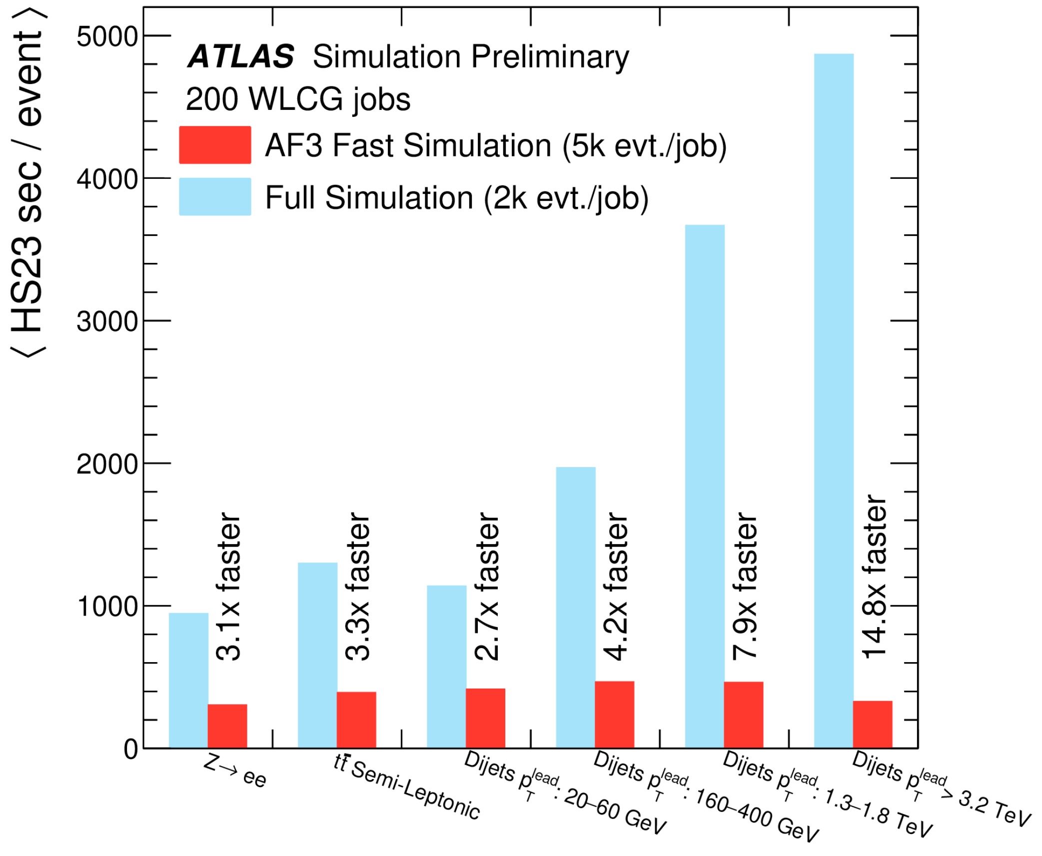
FastCaloGAN

- Parameterizes interactions of particles using 300 GAN, for each particle type and |η| slice, factorizes the shower parametrization into longitudinal and lateral energy distributions for different energy points with interpolation between them
- Using Wasserstein GANs trained on each of 100 bins in |η| and truth momentum condition
- Trained to reproduce energy in layers and total energy in a single step



SIM-2024-004

AF3 simulation 2-10 times faster than full simulation, greater improvement for samples with jets



SIM-2023-005