

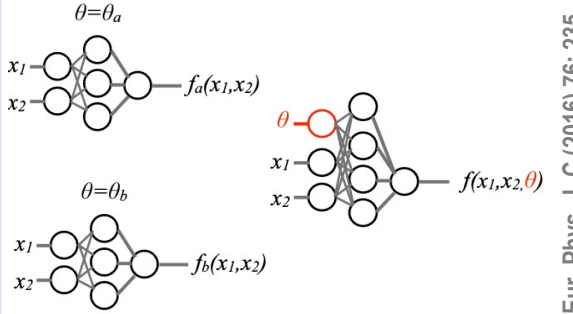
MACHINE LEARNING APPLICATIONS AT THE ATLAS EXPERIMENT

EUROPEAN AI FOR FUNDAMENTAL PHYSICS CONFERENCE

EuCAIFCon 2024, 30 April – 3 May 2024, Amsterdam, Netherlands

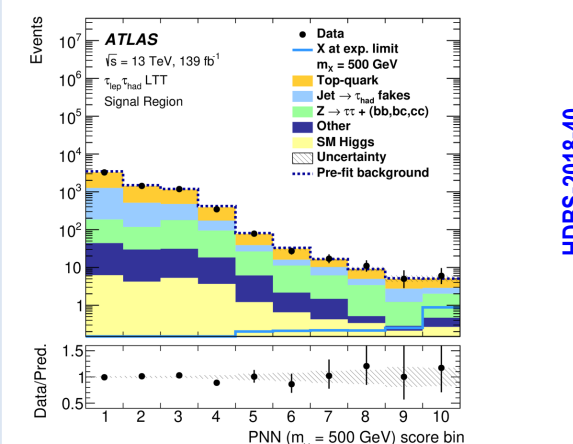
SUPERVISED, CLASSIFICATION S vs B

Parameterised DNN/BDT/GNN

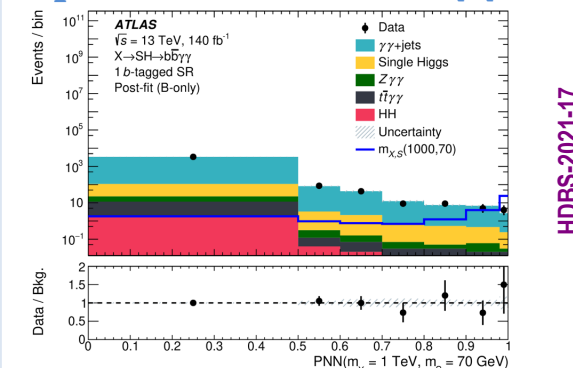


Increase training statistics by adding up multiple models, optimal for large range of parameters

1 par: $HH \rightarrow bb\tau\tau$



2 par: $X \rightarrow SH \rightarrow bb\gamma\gamma$



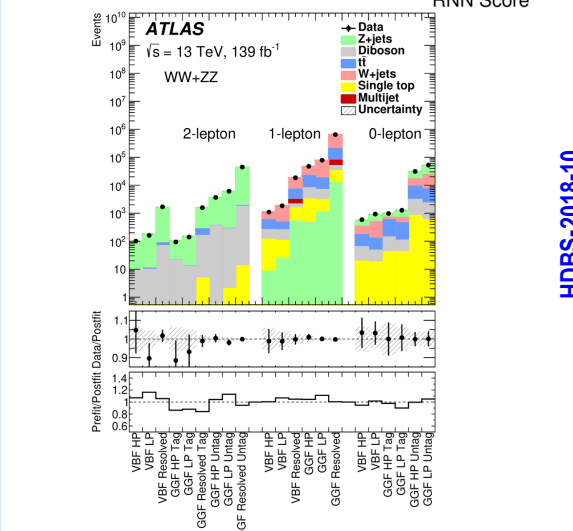
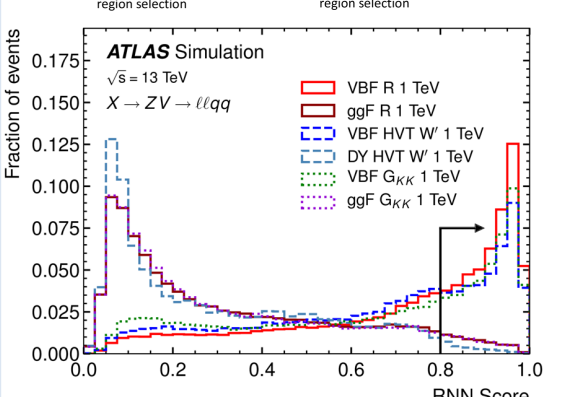
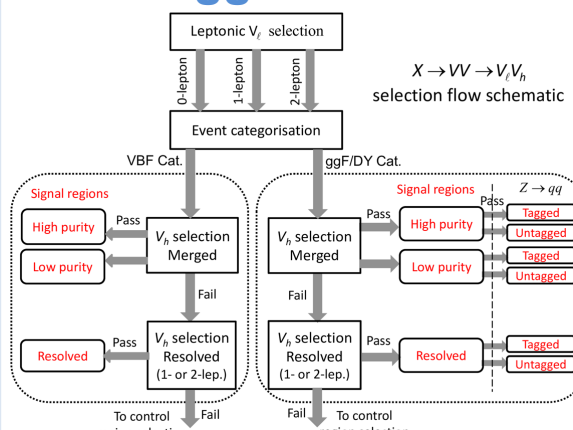
SUPERVISED, CLASSIFICATION S vs S

Multi-class classification

Use ML to optimise purities of signal classes, then optimise background rejection
Pro: exploit different signal topologies in a single search, better signal class purity

$X \rightarrow ZV \rightarrow llqq$

VBF vs ggF/DY

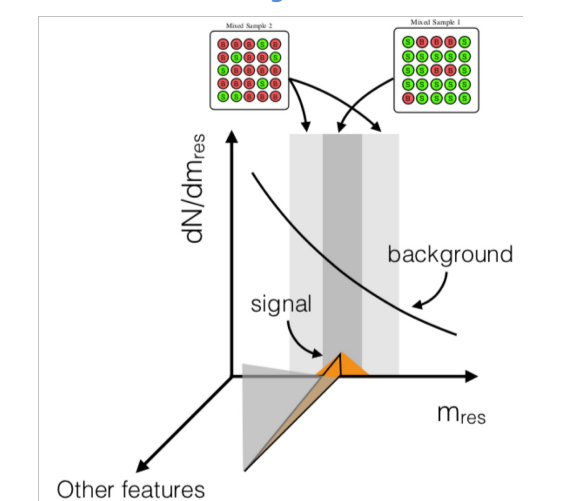


WEAKLY-SUPERVISED, CLASSIFICATION S vs B

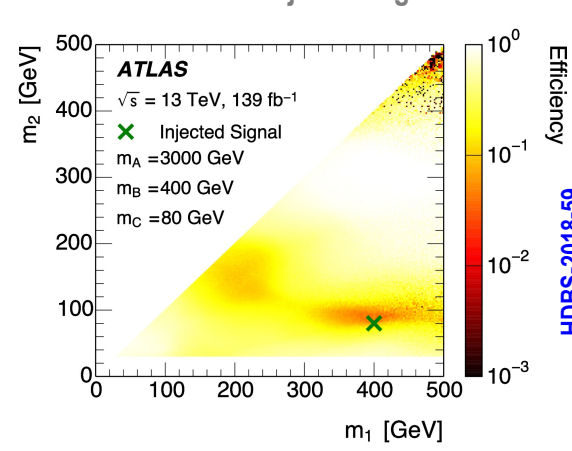
Classification without labels (CWoLA)

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

$A \rightarrow BC$, 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

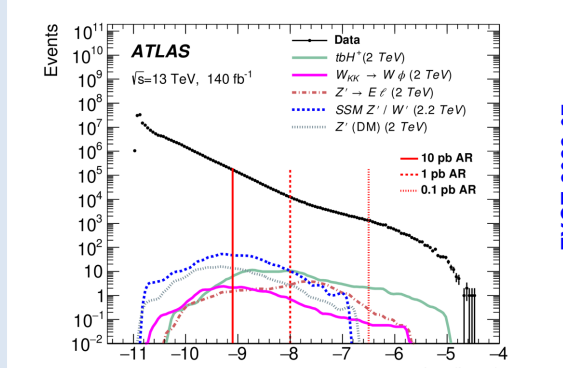


UNSUPERVISED, ANOMALY DETECTION

Model agnostic search

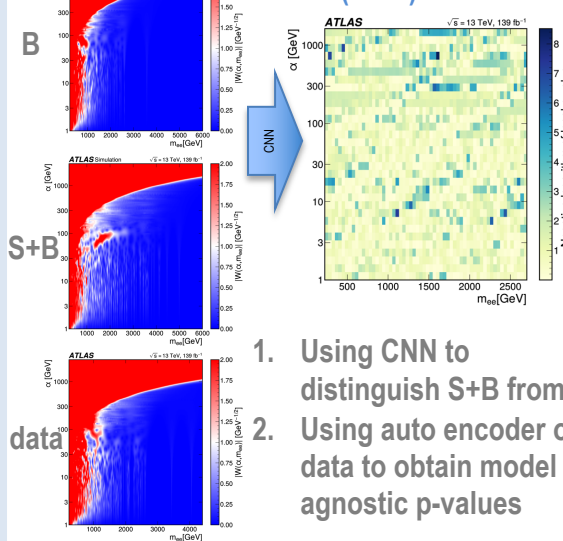
$X \rightarrow jY$, jet-Y resonance

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



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

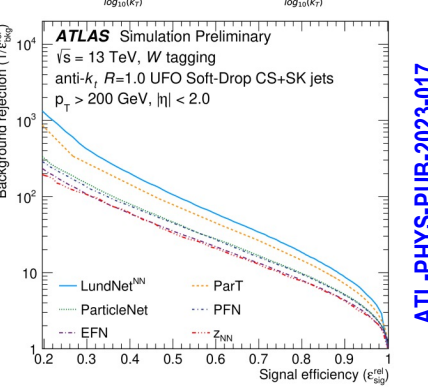
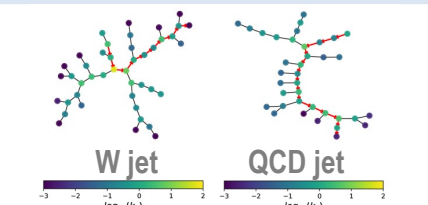
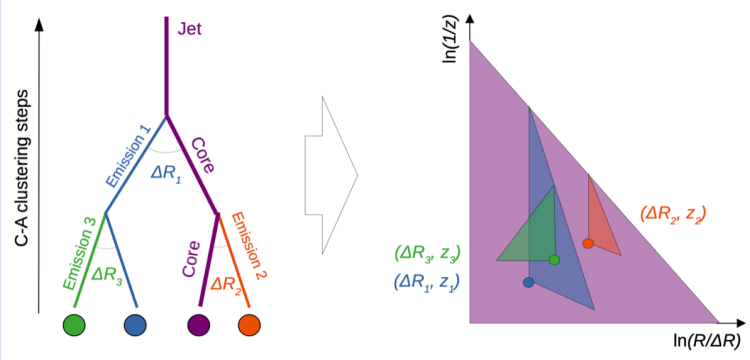
Signature: periodic signal, wavelet of $m_{ee}, m_{\gamma\gamma}$
Instead of bump-hunt using Continuous Wavelet Transformation (CWT)



BOOSTED W-BOSON TAGGING

Lund Plane tagger

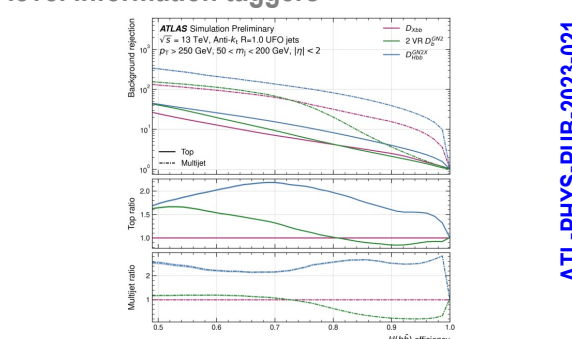
Identify jets originating from W bosons using the de-clustering information from successive splitting leading to its construction, and separate from QCD background



H TAGGING

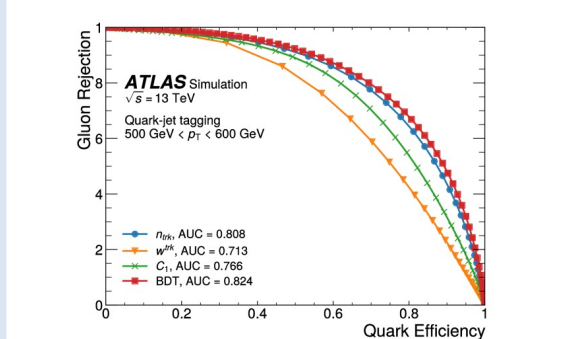
$H \rightarrow bb$ tagger

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



q/g TAGGING

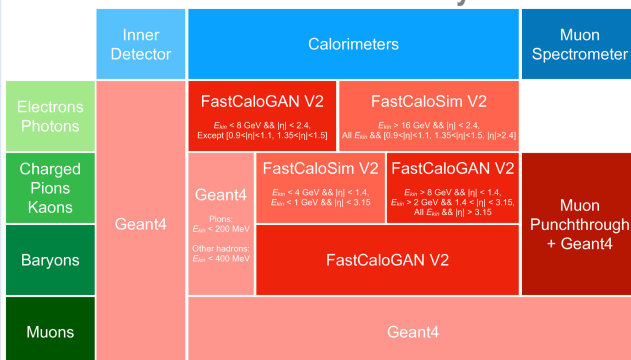
Identification of jets coming from quarks or gluons shows better performance using more low-level information. Two new taggers: (1) charged-particle constituent multiplicity, (2) jet kinematic and substructure variables and BDT



FAST SIMULATION

AtFast3

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

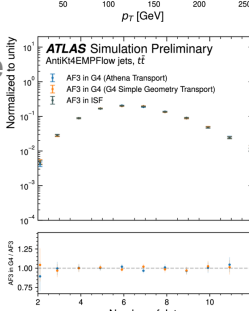
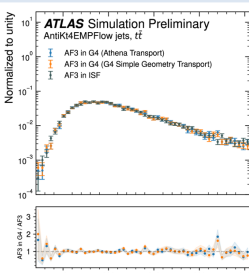


FastCaloSim v2

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

FastCaloGAN

- Parameterizes interactions of particles using 300 GAN, for each particle type and $|\eta|$ 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 $|\eta|$ and truth momentum condition
- Trained to reproduce energy in layers and total energy in a single step



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

