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 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

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: $HH \rightarrow bb \tau \tau$



$X \rightarrow ZV \rightarrow llqq$ VBF vs ggF/DY Leptonic V_ℓ selection $X \rightarrow VV \rightarrow V_{e}V_{b}$ selection flow schemation Event categorisation VBF Cat gnal regio High puri V_h selection V_h selectio Merged ... Merged Fail V_h selectio V_h selectio Resolved Resolved (1- or 2-lep. (1- or 2-lep.) To control Fail ____ To control ATLAS Simulation $\sqrt{s} = 13 \text{ TeV}$ VBF R 1 TeV ک 0.150 $X \rightarrow ZV \rightarrow \ell \ell q q$ ggF R 1 TeV لم 125 0.125 VBF HVT W' 1 TeV DY HVT W' 1 TeV VBF G_{KK} 1 TeV 0.100 ggF G_{KK} 1 TeV 0.075 0.050 0.025 0.000 0.2 0.4 0.6 0.8 1.0 **RNN Score** ATLAS Data Z+jets Dibos √s = 13 TeV, 139 fb WW+ZZ HDBS-2018-10 in the second second

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



Other features

- 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 $X \rightarrow j Y$, jet-Y resonance **Generic bump-hunt** for jet+Y resonance using anomaly score (j+j, j+b-jet, 2 b-jet, i+e, b-jet+e, j+ γ , j+ μ , b-jet+ μ , b-jet+ γ) ATLAS Ever 10¹ √s=13 TeV, 140 $W_{KK} \rightarrow W \phi (2 TeV)$ 10[°] Z' → E ℓ (2 TeV 10 SSM Z' / W' (2.2 TeV) Z' (DM) (2 TeV) EXOT-2022-07 10 10⁶ ---- 10 pb AR ---- 1 pb AR ----- 0.1 pb AR 10⁵ 10^{4} 103 log (Loss) $\rightarrow e^+e^-/\gamma\gamma$, clockwork **G*** **ATLAS** √s = 13 TeV, 13 Signature: periodic signal, wavelet of $m_{ee}, m_{\gamma\gamma}$ Clockwork k = 500 Ge Mr = 8000 Instead of bumphunt using XOT-2019-40 Continuous Wavelet CWT Transformation (CWT) B S+B Using CNN to 1. distinguish S+B from B Using auto encoder on data data to obtain model

BOOSTED W-BOSON TAGGING

ParT

PFN

q/g TAGGING

ATL-PHYS-PUB-2023-02

Lund Plane tagger

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



sit ---W jet QCD ATLAS Simulation Preliminary $\sqrt{s} = 13 \text{ TeV}, W \text{ tagging}$ anti- $k_r R$ =1.0 UFO Soft-Drop CS+SK jets p_T > 200 GeV, $|\eta| < 2.0$

H TAGGING $H \rightarrow bb$ tagger

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



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

agnostic p-values



FAST SIMULATION AtlFast3

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



FastCaloSim v2

 $(\Delta R_2, z_2)$

 $\ln(R/\Delta R)$

Uses longitudinal and lateral shower development parametrization with PCA

ATL-PHYS-PUB-2023-01

· Parametrised modelling using Geant4 single photon, electron and pion samples (energy and $|\eta|$ spaced bins)

0.8 0.9

- Separate parameterisation in longitudinal and lateral shower development
- Energy decorrelation in layers using PCA

- LundNet

- ParticleNe

EFN

0.3

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



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