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Advanced Machine Learning at the Service of Identifying Boosted Higgs bosons with ATLAS

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INTRODUCTION

Since its discovery, Higgs boson properties measured with precision

- Studying heavy-flavour decays remains central
- Observation of decay into b-quark pairs provided direct evidence of Yukawa coupling
- Challenging channel $H \rightarrow c \bar{c}$ still to be observed



THE HIGH-ENERGY REGIME

- Expected sensitivity to New Physics
- Helping to probe rare processes
- Highly boosted decay products become collimated, requiring dedicated tagging techniques





FLAVOUR-TAGGING A KEY INGREDIENT

- Identifying heavy-flavour jets in inclusive approach
 - Discriminating b, c and light-flavour jets
- A key ingredient to a majority of physics analyses
 - From precision measurements to direct searches
 - To increase signal efficiency and background rejection
- Exploit specific topology of heavy flavour-jets
 - Lifetime, high-mass & decay multiplicity of B/D-hadrons
 - Using several complementary algorithms (c.f. backup)

Anatomy of a b-jet



HISTORICAL ATLAS TAGGING STRATEGIES



Worked fine, but somehow blind to the entire picture of the jet activity





Worked fine, but somehow blind to the entire picture of the jet activity



THE TRANSFORMER EXPLOSION

Towards a 3rd Generation of Tagging Algorithm

7



- Recent progress in Machine Learning expanded realm of possibilities
 - Considering new generation of tagging algorithms
 - Learning from low-level information, avoiding intermediate reconstruction algorithms
 - ATLAS Combined performance groups at the forefront of adopting such technologies (e.g. flavour-tagging, tracking, etc.)
- Transformer introduced by a team at Google Brain in 2017 [link]
 - Emerged as a dominant paradigm in Machine Learning across various applications
 - Ability to model complex relationships and deliver outstanding performance



Understanding Transformer with a Social Network Analogy

Axiom

People with similar characteristics or interests tend to interact and influence each other more ...



... one can imagine individuals Paying attention to others based on their similarities

 \rightarrow Attention mechanism

... individual have multiple perspectives or sources of influence

 \rightarrow Multi-head attention concept

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Now, let's map the analogy to large-Rjets

Imagine each track as an individual in an "large-Rjet" network

2

Their kinematics represent their unique characteristics or attributes



Tracks similarities measured using dot-products, indicating feature alignment or correlation

 \rightarrow Attention mechanism

4

Runs parallel attention operations, attending to input parts differently → Multi-head attention concept



GN2X ARCHITECTURE





10

FOCUS ON JET CLASSIFICATION

- Multi-class classification trained on 62 million jets
 - Generate probability scores for identifying $H \rightarrow b\overline{b}, H \rightarrow c\overline{c}$, Top and Multi-jet (QCD)
- When assessing tagging efficiencies, probability score combined into discriminant

$$D_{\text{Hbb}}^{\text{GN2X}} = \ln \left(\underbrace{p_{\text{Hcc}}}_{f_{\text{Hcc}}} \cdot p_{\text{Hcc}} + f_{\text{top}} \cdot p_{\text{top}} + (1 - f_{\text{Hcc}} - f_{\text{top}}) \cdot p_{\text{QCD}} \right)$$

Free parameters to control trade-off
among background rejections
(e.g. $f_{\text{Hcc}} = 0.02$, $f_{\text{top}} = 0.25$)

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TAGGING PERFORMANCE

- Significantly outperformed previous models
 - 1.6x and 2.5x increase in top and multi-jet rejections respectively at 50% $H \rightarrow b\bar{b}$ efficiency

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TAGGING PERFORMANCE

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• Remarkable stable efficiency as a function of jet p_T



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TAGGING PERFORMANCE

- $H \rightarrow c\bar{c}$ tagging by redefining discriminant $D_{\text{Hcc}}^{\text{GN2X}} = \ln\left(\frac{p_{\text{Hcc}}}{f_{Hbb} \cdot p_{\text{Hbb}} + f_{\text{top}} \cdot p_{\text{top}} + (1 - f_{\text{Hbb}} - f_{\text{top}}) \cdot p_{\text{QCD}}}\right)$ e.g. with $f_{Hbb} = 0.3$, $f_{top} = 0.25$
- Significantly outperformed previous models
 - 3x, 5x, 6x increase in top, multi-jet and $H \rightarrow b\overline{b}$ rejections respectively at 50% $H \rightarrow c\overline{c}$ efficiency

PRESERVING LARGE-R JET MASS

- Key variable to discriminate signal & background
 - Shapes should remain distinct after applying $H \rightarrow b\bar{b}/c\bar{c}$ tagging in analysis
- Tagging perf. to be decorrelated from jet kinematics
 - Training on "flat-mass" Higgs-boson samples
 - Resampling in p_T , η and mass
- Mass sculpting kept under control
 - Residual dependences under investigations

ATL-PHYS-PUB-2023-021 Vormalised number of large-R jets ATLAS Simulation Preliminary \sqrt{s} = 13 TeV, Anti k, R=1.0 UFO jets ----- H(bb) D^{GAPX} (70% WP) $p_1 > 250 \text{ GeV}, 50 < m_1 < 200 \text{ GeV}, |n| < 2$ Multi et pre-tag ---- Multijet DGN2X (70% WP) 1//// stat. uncertain.y At 70% $H \rightarrow b\bar{b}$ efficiency 0.001 Ratio 100 120 140 180 200 80 160 M_I [GeV]



CONCLUSIONS

- Studying boosted Higgs-boson decays to heavy-flavours constitutes important aspect of ATLAS physics programme
- High-performance algorithm for tagging such Higgs-boson decays can play a crucial role in
 - Improving sensitivity of searches for New Physics
 - Precise measurements of the Higgs boson properties.
- ATLAS recently harnessed new cutting-edge tagging algorithm based on Transformer
 - Demonstrating remarkable performance improvements <u>ATL-PHYS-PUB-2023-021</u>
- Algorithm being deployed in Physics analyses
 - Precise calibration now subject to all attention
 - New exciting results are yet to come, stay tuned





Thank you for your "Attention"



Back up

OVERLAP BETWEEN RESOLVED & BOOSTED TOPOLOGIES



ATLAS-CONF-2021-051



CHANGE OF FLAVOUR-TAGGING PARADIGM



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THE SELF-ATTENTION MECHANISM



NB: Self attention can be seen as an example of message passing on a fully connected graph



GN2X INPUT KINTEMATICS

Jet Input	Description
p_{T}	Large- <i>R</i> jet transverse momentum
η	Signed large-R jet pseudorapidity
mass	Large-R jet mass
Track Input	Description
q/p	Track charge divided by momentum (measure of curvature)
$\mathrm{d}\eta$	Pseudorapidity of track relative to the large-R jet η
$\mathrm{d}\phi$	Azimuthal angle of the track, relative to the large-R jet ϕ
d_0	Closest distance from track to primary vertex (PV) in the transverse plane
$z_0 \sin \theta$	Closest distance from track to PV in the longitudinal plane
$\sigma(q/p)$	Uncertainty on q/p
$\sigma(heta)$	Uncertainty on track polar angle θ
$\sigma(\phi)$	Uncertainty on track azimuthal angle ϕ
$s(d_0)$	Lifetime signed transverse IP significance
$s(z_0\sin\theta)$	Lifetime signed longitudinal IP significance
nPixHits	Number of pixel hits
nSCTHits	Number of SCT hits
nIBLHits	Number of IBL hits
nBLHits	Number of B-layer hits
nIBLShared	Number of shared IBL hits
nIBLSplit	Number of split IBL hits
nPixShared	Number of shared pixel hits
nPixSplit	Number of split pixel hits
nSCTShared	Number of shared SCT hits



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