Flavor Tagging with Graph Neural Network with the ATLAS Detector

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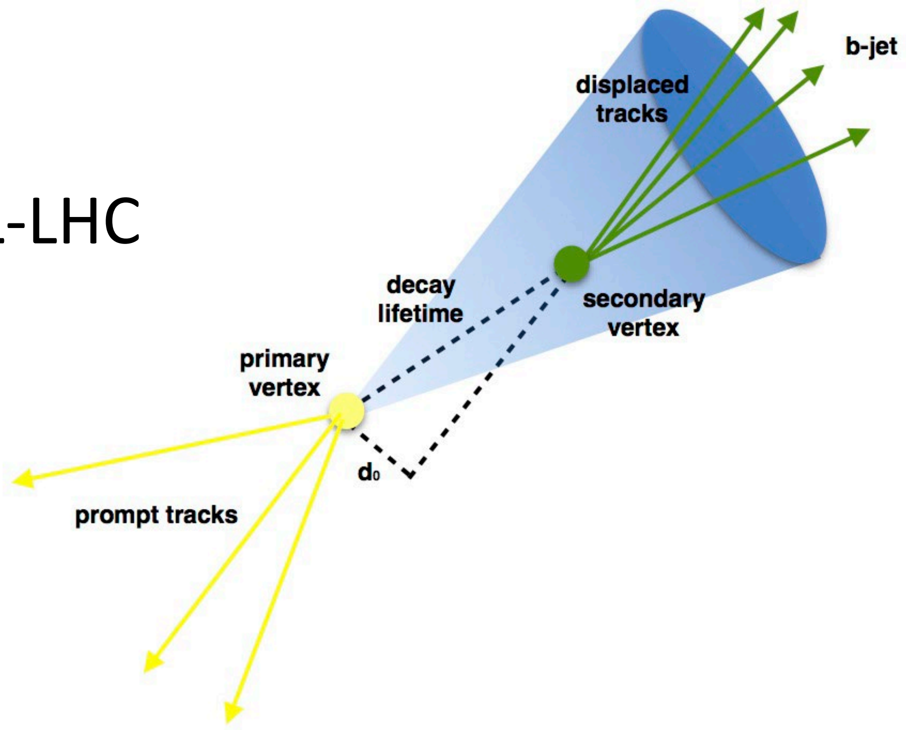
Outline

- Jet flavor tagging in ATLAS
- GNN tagging algorithm
  - description
  - performance
- Jet flavor tagging at the HL-LHC
- Conclusions



Jet flavor tagging 101

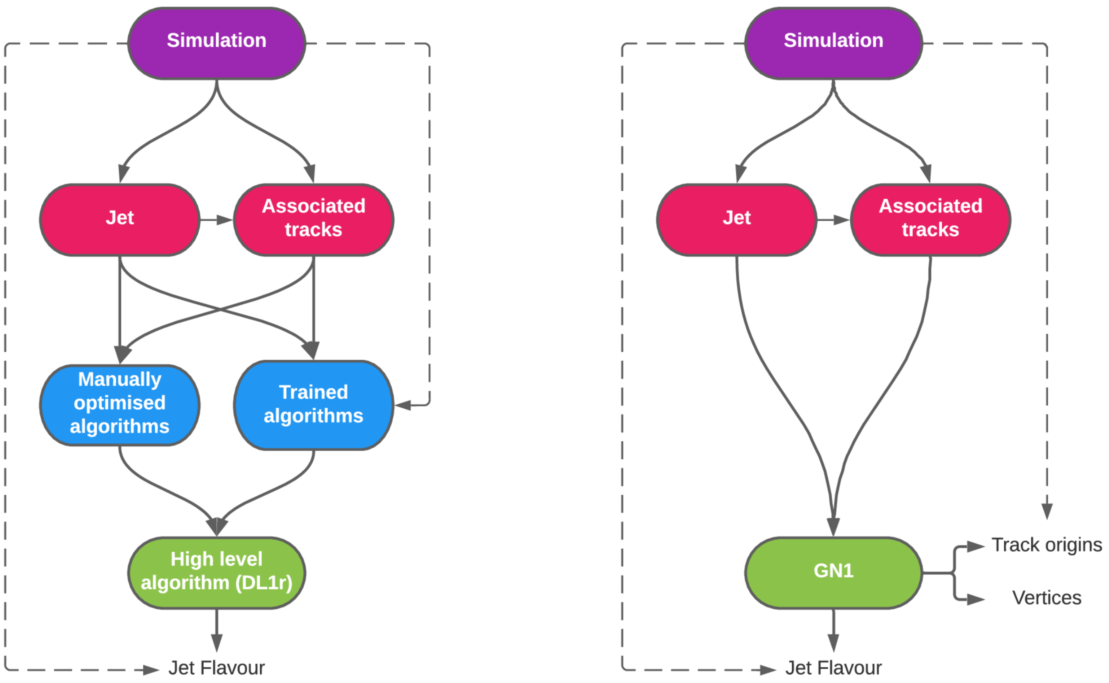
- Jet flavor tagging: identification of jets originating from b- and c-quarks
  - a b-jet is a jet that contains a B-hadron (decided by ghost association)
  - a c-jet is a jet that does not contain B-hadrons but contains a D-hadron
  - all other jets (except τ-jets) are called light
- Flavor tagging algorithm: a method to detect b- and c-jets
  - relies on significant lifetime of B/D hadrons
  - two main approaches based on either tracks with large impact parameter (IP) or explicit reconstruction of secondary vertices (SV)
- Performance of tagging algorithms is characterized by b-tagging efficiency ε_b (probability to correctly identify a b-jet) vs mistag rate ε_l (probability to misidentify a light jet as a b-jet)
  - ε_l as a function of ε_b is known as a ROC curve
  - similarly, the c-tagging performance is described by a ε_c vs ε_b ROC curve
- To be useful for physics analyses, the performance of the tagging algorithm needs to be calibrated against real data
  - since the calibration procedure is cumbersome, only a few points on the ROC curve (working points, WP) are used
  - physics analyses pick a WP that best suits their needs

Evolution of tagging algorithms in ATLAS

- Low level algorithms: IP3D, SV1, JetFitter
  - likelihood based algorithms looking at track IPs or SVs
  - limited consideration of track parameter correlations
- Combinations of low-level algorithms: IP3D+SV1
- Multivariate combination of low-level algorithms based on boosted decision trees: MV2
- Neural Network combination: DL1 and its flavors
  - DL1: original (IP3D+SV1+JetFitter)
  - DL1r: IP3D replaced with recurrent NN (RNNIP)
  - DL1d: RNNIP replaced with deep sets NN (DIPS)
- Graph Neural Network: GN1

GN1 overview

- GN1: graph NN with direct track input
- Why the new algorithm?
  - improved performance (of course)
  - flexibility: no need to re-optimize low-level taggers for a new task (Xbb, c-tagging,…)
  - better insight into tagging process (auxiliary vertex and track origin predictions)

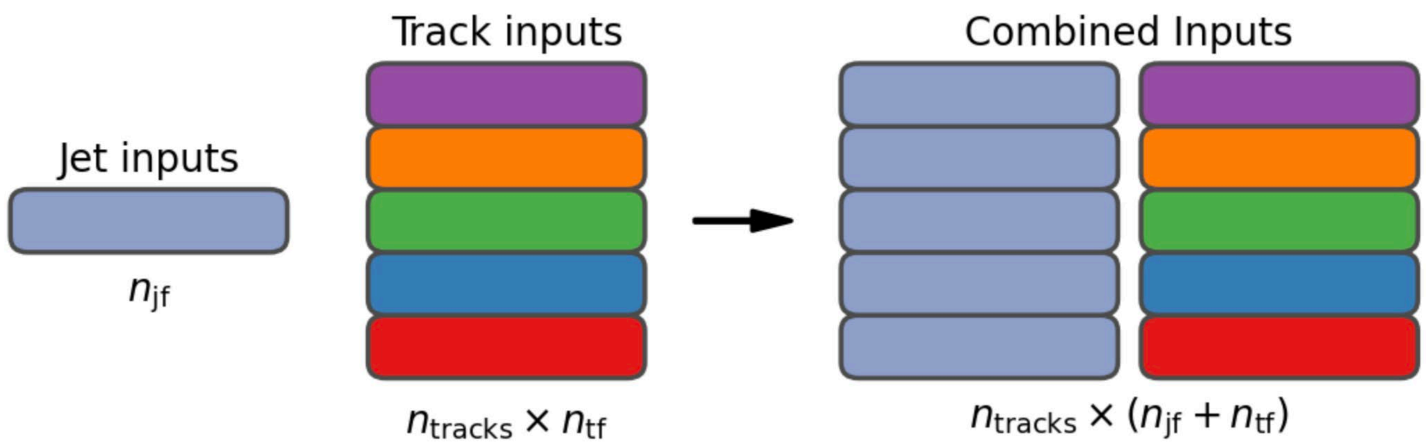


GN1 model

- Inputs: two jet variables (p_T, η) and n_{tracks}×21 tracking variables (n_{tracks}≤40)
  - five track parameters + their uncertainties (q/p, direction relative to the jet axis, track IP in transverse and longitudinal plane)
  - hit patterns
  - (optional) lepton track ID

rescaled to mean=1, var=1

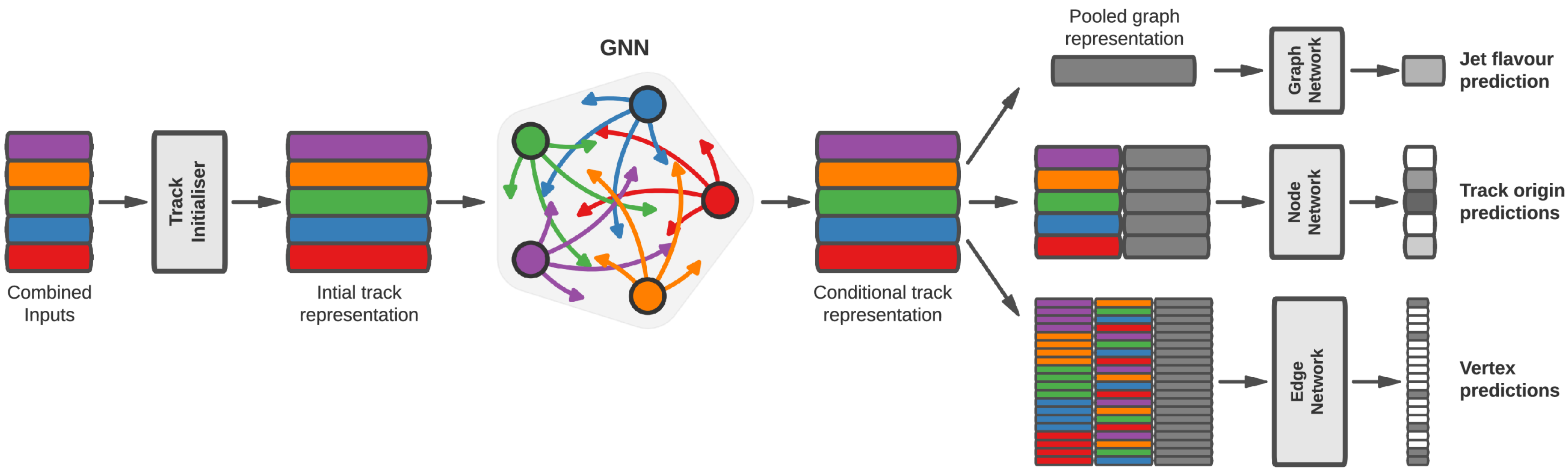
- Labels: jet flavor (b, c, light)
- Auxiliary training objectives
  - track origin (pileup, fake, primary, b, b→c, c, other secondary)
  - track-pair vertex compatibility (binary)



Architecture

- Inputs are fed into a per-track initialization network (3 hidden + 1 output layer ×64 neurons)
- Outputs (latent track representations) are used to populate a fully connected GNN (a node = a track)
- Resulting node representations are fed to classification networks

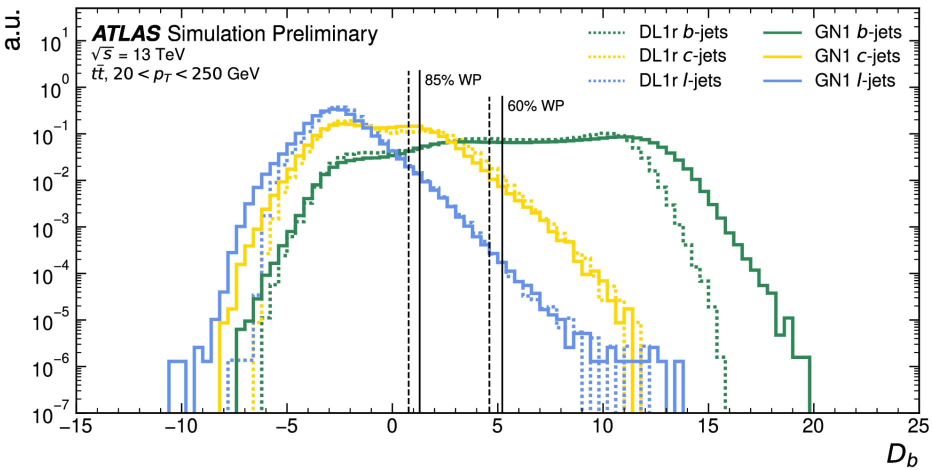
Network	Hidden layers	Output
Node	128,64,32	7
Edge	128,64,32	1
Graph	128,64,32,16	3



Training

- MC samples: $t\bar{t} \rightarrow l$+jet/dileptons, $Z' \rightarrow q\bar{q}$ (flat jet p_T up to 5 TeV, equal $b\bar{b}$/$c\bar{c}$/light)
  - 30M jets (60% $t\bar{t}$ + 40% Z')
- Goal: minimize total loss $L_{total}=L_{jet}+\alpha L_{vertex}+\beta L_{track}$
  - L_{jet}: categorical cross entropy loss over jet flavors
  - L_{vertex}: binary cross entropy loss averaged over track pairs
  - L_{track}: categorical cross entropy loss over track origins
- Optimal choice: α=1.5, β=0.5
  - verified that the algorithm works with L_{jet} minimization alone

Performance



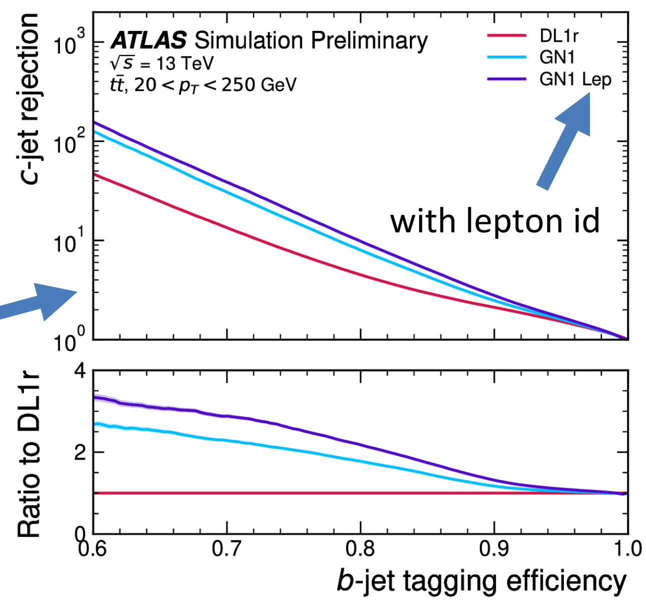
b-tag score: $D_b = \log \frac{p_b}{(1-f_c)p_l + f_c p_c}$

fraction of c-jets (0.05)

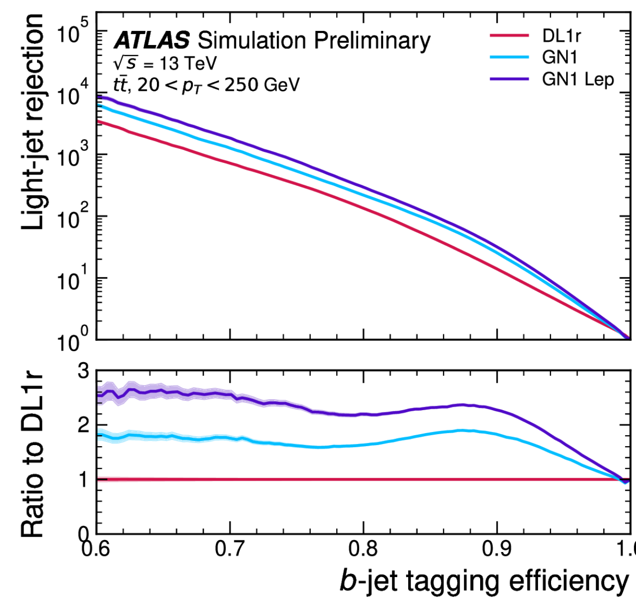
60% WP

70% WP

85% WP



with lepton id



significant improvement in both light and c-jet rejection (×~2 at 70% WP)

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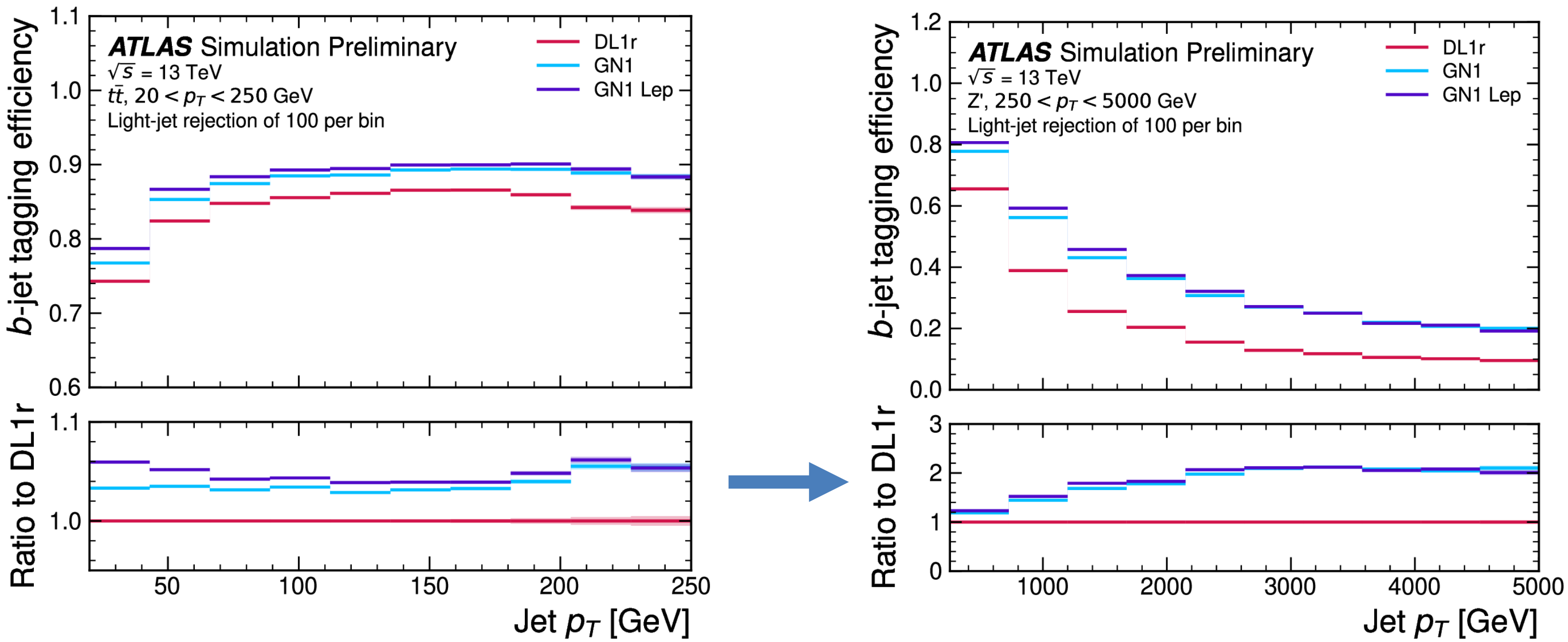
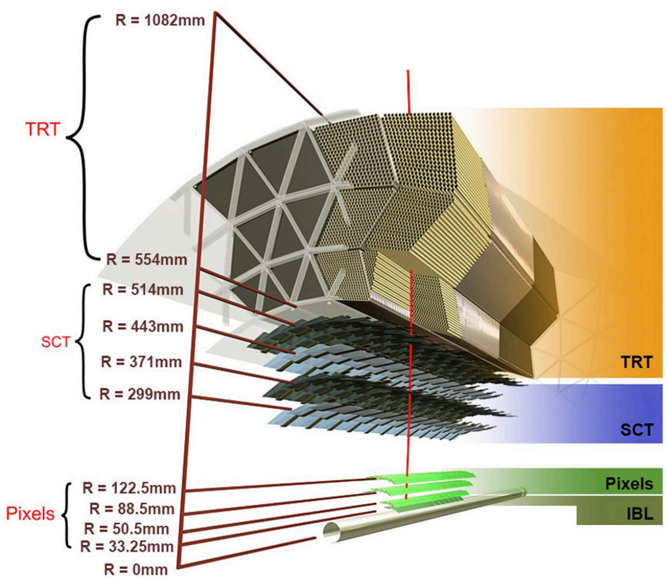
Performance (2)

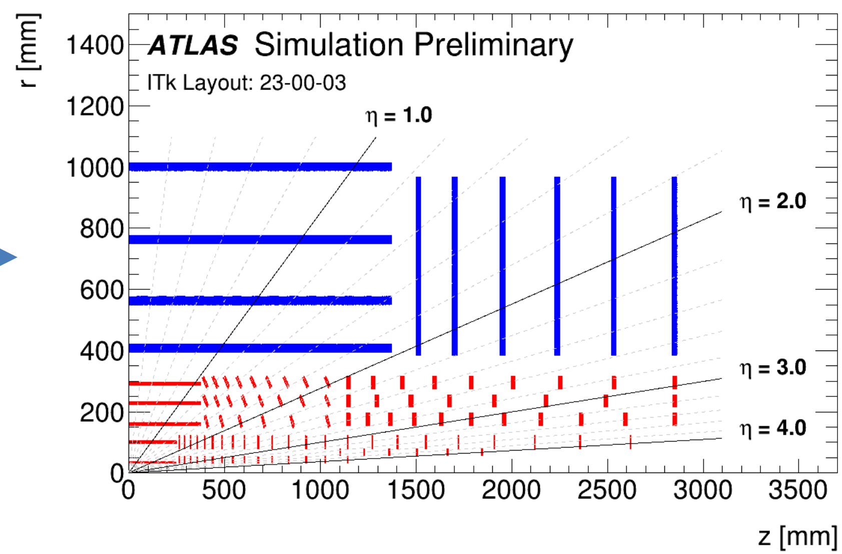
- Improvement in b-tagging efficiency at fixed mistag rate (0.01) is particularly significant at large jet p_T
- Vertexing performance: inclusive b-vertex reco efficiency ~80%
- Track classification performance: weighted AUC ~0.95



HL-LHC upgrade

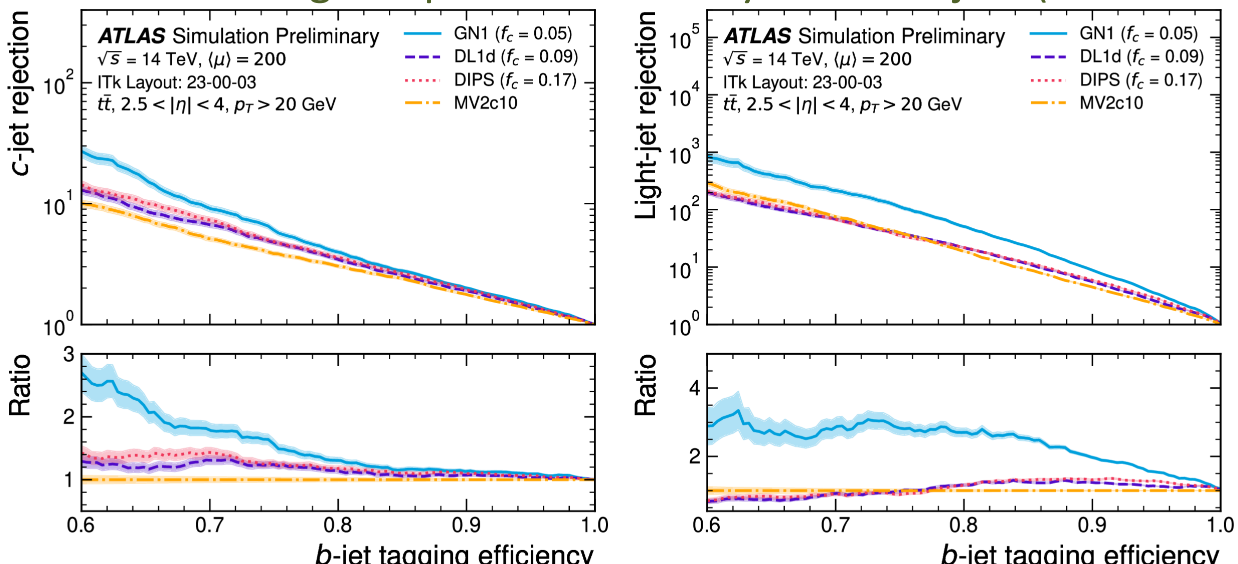
- High-Luminosity LHC is expected to operate from 2029
  - instantaneous luminosity $2\times10^{34} \rightarrow 7.5\times10^{34}/cm^2s$
  - average number of interactions per bunch crossing 55→200
- ATLAS inner tracker will be replaced with all-silicon ITk
  - jet flavor taggers are going to work under tough pileup conditions, especially given extended pseudorapidity range (|η|<2.5 -> |η|<4.0)





GN1 performance with HL-LHC

- Presenting here very recent (three months old) first results on the GN1 jet tagger performance with HL-LHC
  - so far, all published physics projections of ATLAS physics reach at the HL-LHC have been done with MV2
- Don't take them as the ultimate flavor tagging performance, but rather as a demonstration of the flexibility of the new GN1 tagger, and its adaption to HL-LHC
  - note that training samples for GN1 only have 4M jets (after downsampling)



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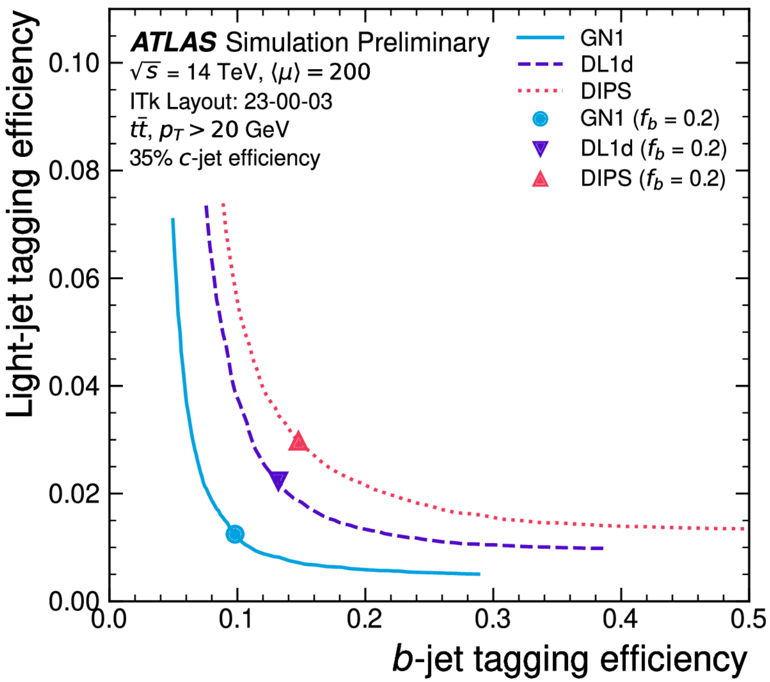
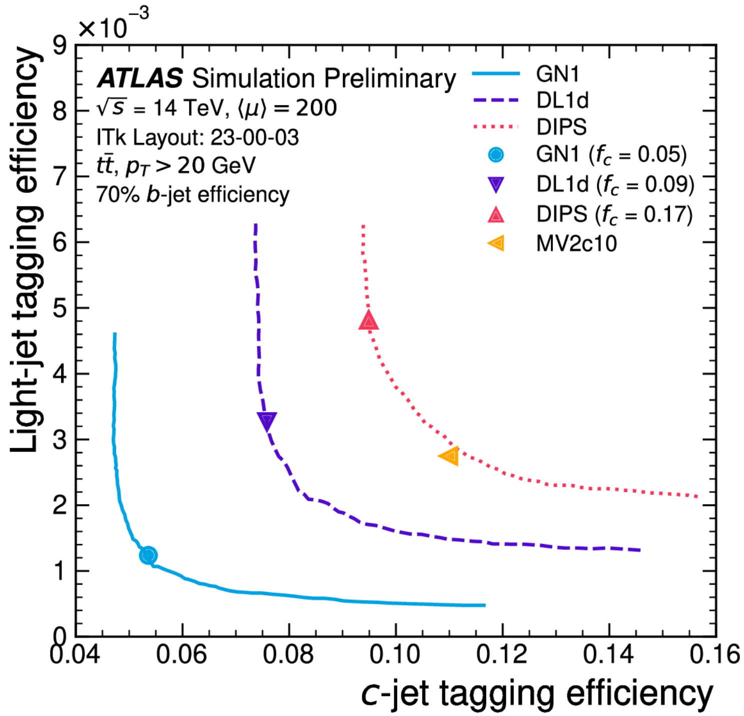
GN1 performance for HL-LHC (2)

- Iso-efficiency curves: a nice way to present tagger performance in terms of three efficiencies (b,c,light)
  - clear advantage of GN1 over other algorithms, especially for c-tagging





Summary

- GN1 is a novel jet tagger based on graph NN architecture and trained with auxiliary training targets
  - shown to significantly improve flavor tagging performance compared to the current ATLAS base line tagger (DL1r)
- Flexible, easier to optimize, simpler to maintain
- Demonstrates improved track classification performance and high b-tagging vertex finding efficiency
- The GN1 performance has been evaluated in the context of the HL-LHC environment
  - very promising performance can already be achieved
  - looking for further improvements due to in-depth tuning of NN configurations, better modeling (simulation of interaction of B/D hadrons), improved pileup jet rejection

Backup