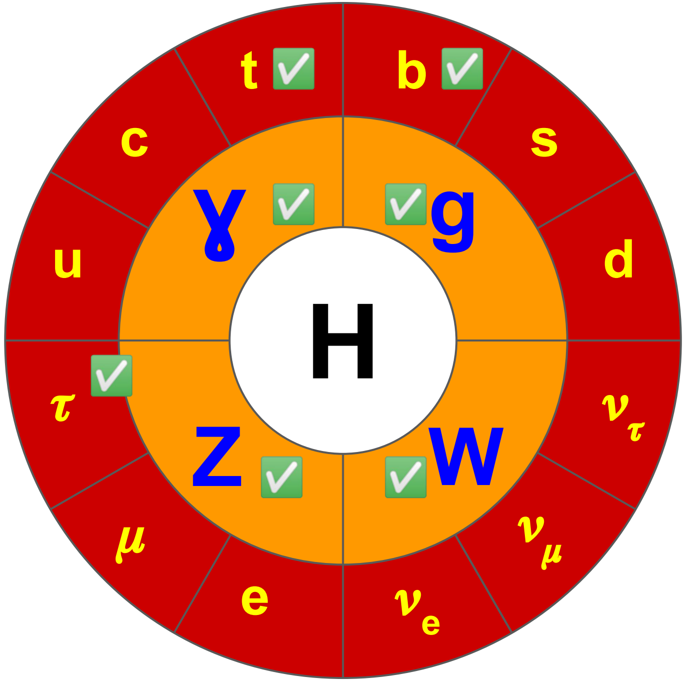
Measurements of Higgs bosons decaying into bb or cc pairs, and how to improve them with GNN-based flavour tagging techniques

Martino Tanasini, on behalf of the ATLAS Collaboration

Rencontres de Moriond EW 2023
Young Scientists Forum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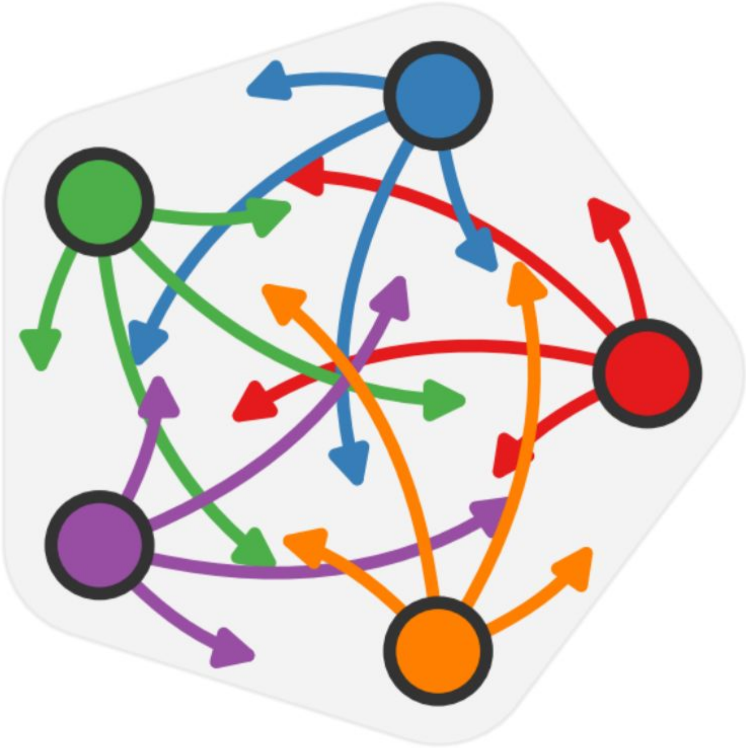
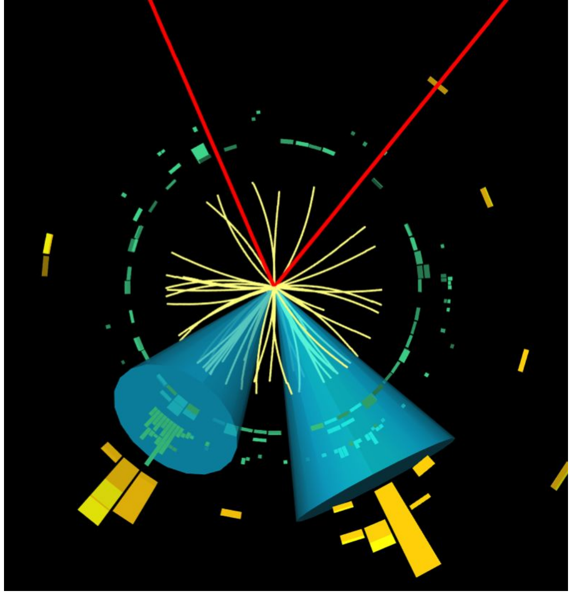


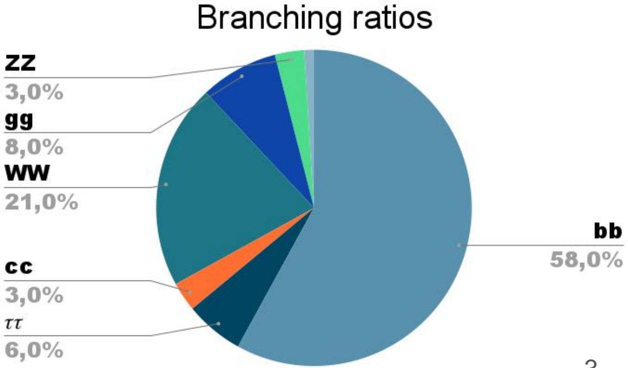
Search for VH(H→cc) decays

Motivation:
→ Higgs couplings to 3rd generation fermions (ttH, H→$\tau\tau$, H→bb) observed.
→ Probing couplings to lighter 2nd generation fermions could **open windows to new physics**.
→ H→cc: one of the **most common** yet unobserved decay modes.

Goal:
→ $\mu_{VH,Hcc}$ extracted with a fit on the invariant mass of the *c*-jet pair.

Focus of today:
→ **Deep learning based dedicated *c*-tagger** with 27% c-jet efficiency, 8.3% b-jet efficiency, and 1.7% light jet efficiency (on a ttbar sample).





10.1140/epjc/s10052-022-10588-3

Results

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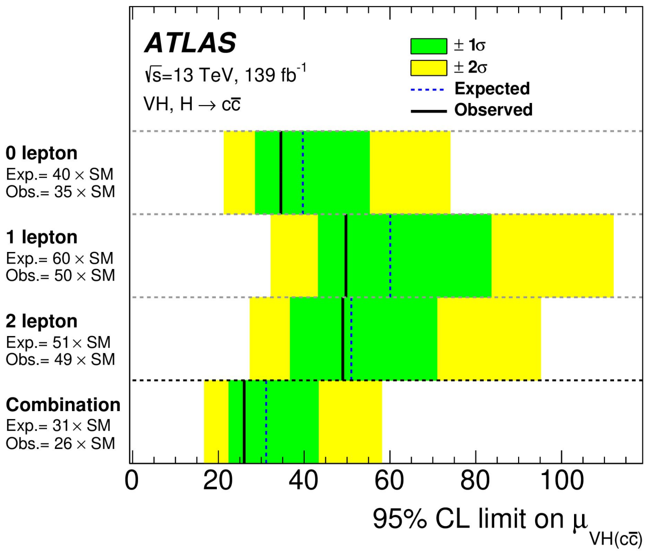
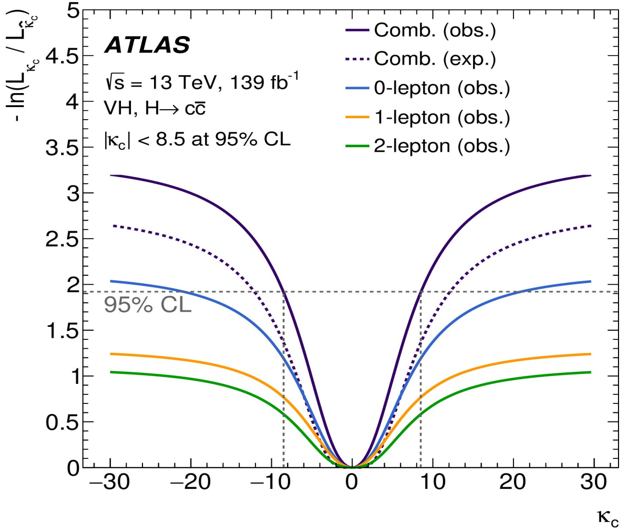
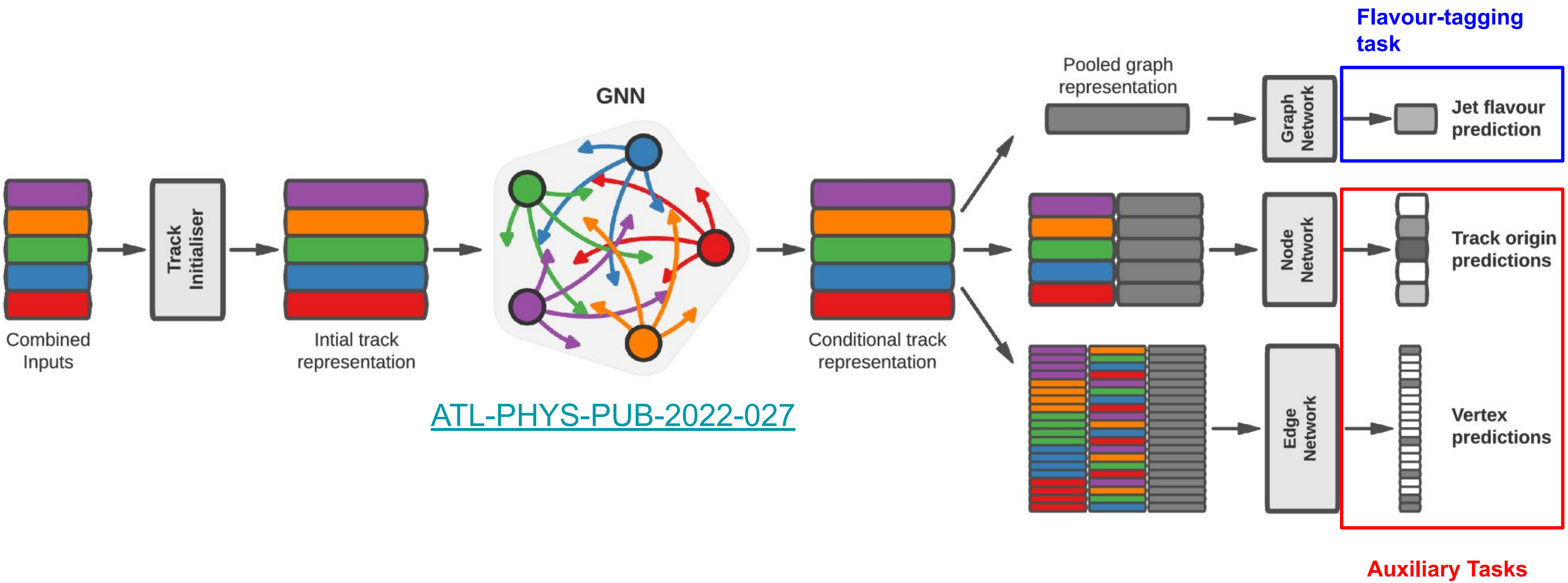




→ Upper limit is set on VH,H→cc process of **26 times the SM prediction**.
→ Results interpreted in the kappa framework constraining the coupling modifier **$|k_c|$<8.5 @ 95%CL** (fixing the other couplings to the SM prediction, assuming no BSM decay modes, considering modifications to decays only).

GN1: flavour-tagging with Graph Neural Networks



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→ **GN1:** state-of-the-art jet flavour-tagging algorithm in ATLAS.

→ Represents jets as **graphs of tracks of charged particles.**

GN1: Improved *c*-tagging performance

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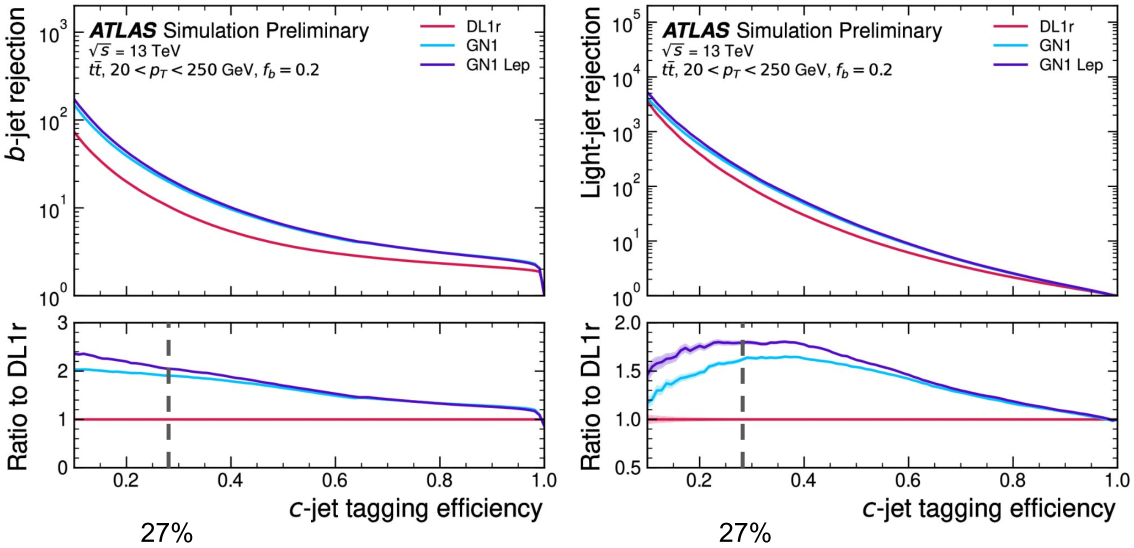


→ Factor ~2 improvement for b and light-flavour jet rejection @ a 27% c-jet tagging efficiency.
→ It will directly impact the sensitivity of the ATLAS experiment to the VH,H→cc process.

Boosted VH→bb

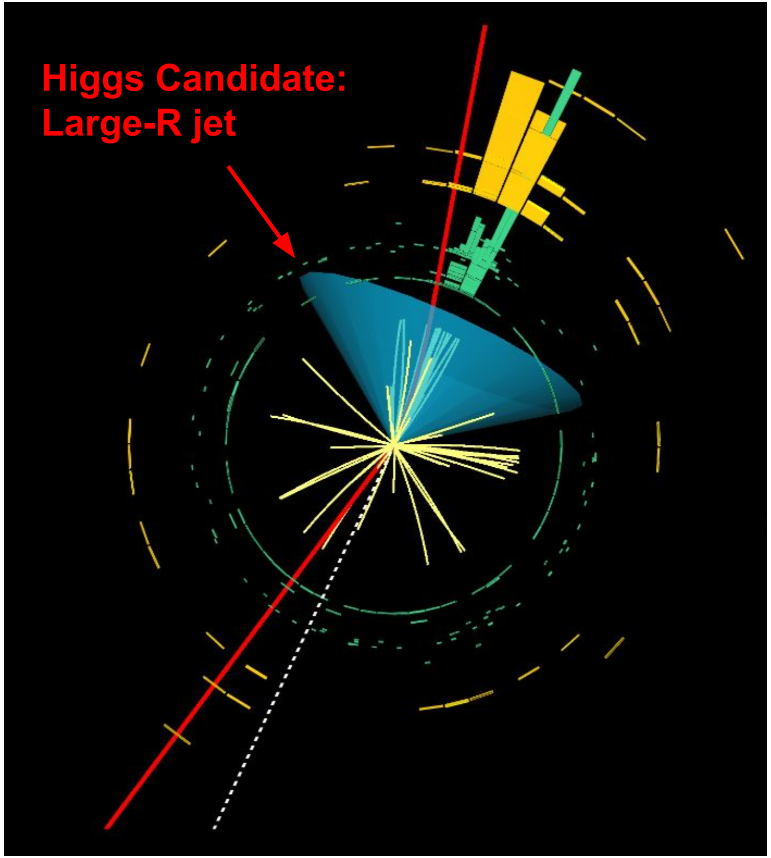
Motivation:

→ VH→bb process observed by ATLAS and CMS in 2018.

→ High-p_T Higgs boson production sensitive to BSM scaling with $\sim (\frac{p_T^H}{\Lambda})^2$

Goals:

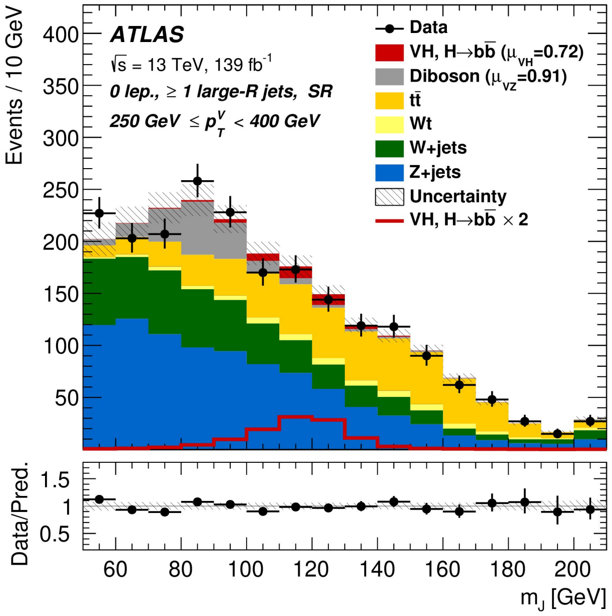
→ $\mu_{VH,Hbb}$ and cross section measurements in bins of p_T of the vector boson.

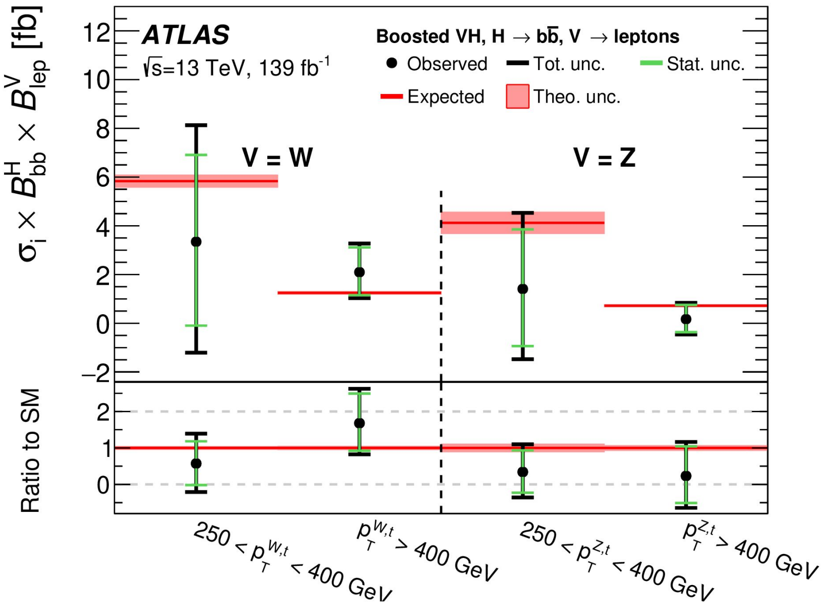


https://doi.org/10.1016/j.physletb.2021.136204

Results

https://doi.org/10.1016/j.physletb.2021.136204





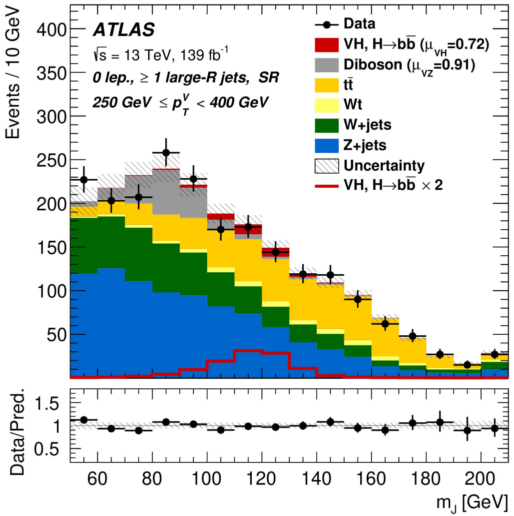
→ Fit of the invariant mass m_J of the Large-R jet:

- $\mu_{VHbb} = 0.72\ ^{+0.39}_{-0.36} = 0.72^{+0.29}_{-0.28}$ (stat.) $^{+0.26}_{-0.22}$(syst).
- Cross section measurements in bins of $p_T^{W,Z}$ compatible with the SM (interpreted in an Effective Field Theory to constrain new-physics effects).

Truth-Tagging Technique

→ Main backgrounds simulated with MC generators.
→ **Truth-Tagging:** weighting events with their *probability* of passing the flavour-tagging cuts, instead of applying the cuts themselves.
→ Important for light-jets (cuts discard most of simulated events).

The Truth-tagging technique strongly relies on the knowledge of the tagging efficiency ϵ for each jet.



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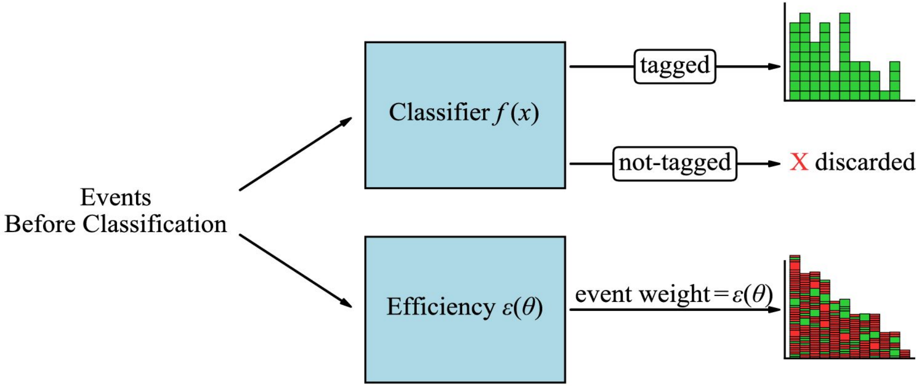

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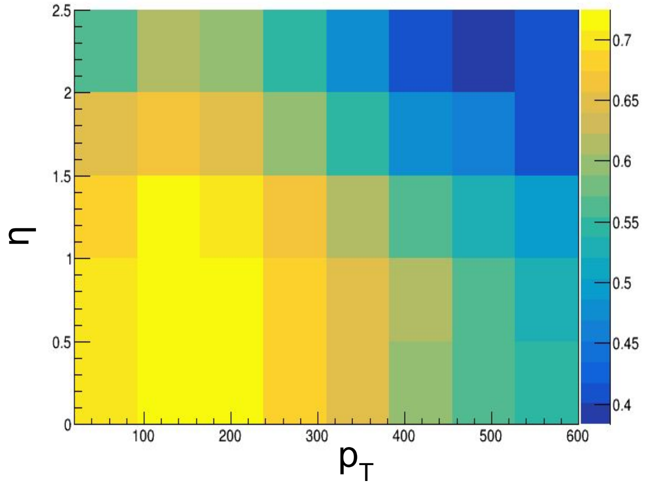
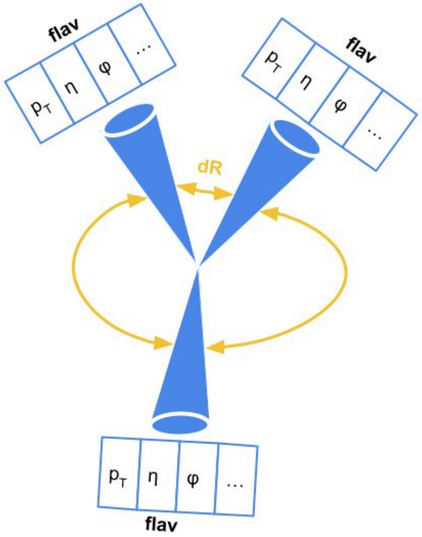
Truth-Tagging with GNNs

$\epsilon_{jet}=\epsilon_{jet}(\vartheta)$, with ϑ set of parameters (e.g. p_T and η) of each jet/event.



VS



Flavour-tagging Efficiency Maps:

→ Simple jet by jet approach.

→ Limited in number of parameters.

GNNs:

→ Events as graphs of fully-connected jets.
→ Allow to scale the problem to higher dimensionalities.
→ Can take into account dependence on event-level variables.

Performance

Good parametrization of ϵ_{jet} → Good closure on cut-based **Direct Tagging,** and less **statistical uncertainty.**

→ **GNN** better than **Maps** at low dR.

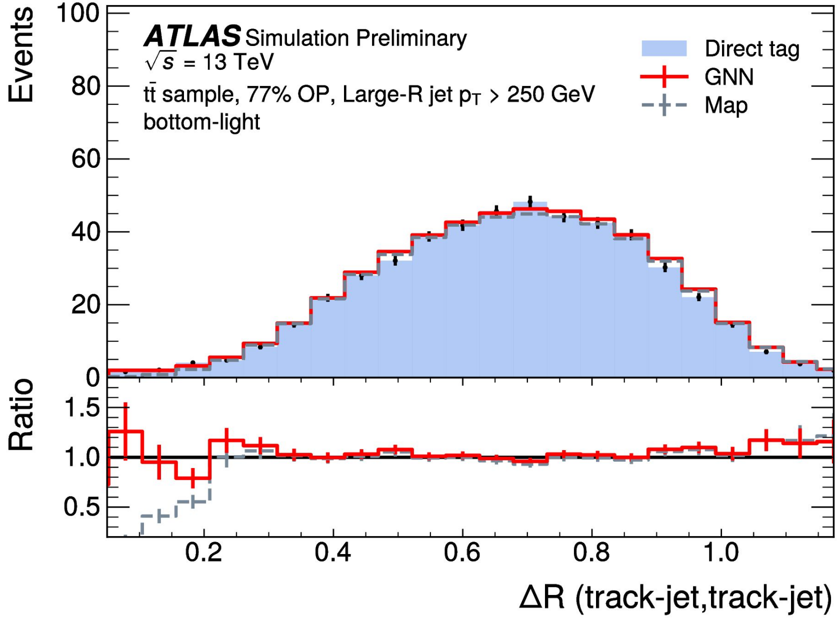
VH, H→cc: impact of uncertainties

Source of uncertainty		$\mu_{VH(c\bar{c})}$	$\mu_{VW(cq)}$	$\mu_{VZ(c\bar{c})}$
Total		15.3	0.24	0.48
Statistical		10.0	0.11	0.32
Systematic		11.5	0.21	0.36
...				
Flavour tagging	c-jets	1.6	0.05	0.16
	b-jets	1.1	0.01	0.03
	light-jets	0.4	0.01	0.06
	τ-jets	0.3	0.01	0.04
Truth-flavour tagging	ΔR correction	3.3	0.03	0.10
	Residual non-closure	1.7	0.03	0.10

10.1140/epjc/s10052-022-10588-3

Non-closure of map-based truth-tagging

Boosted VH,H→bb: Closure



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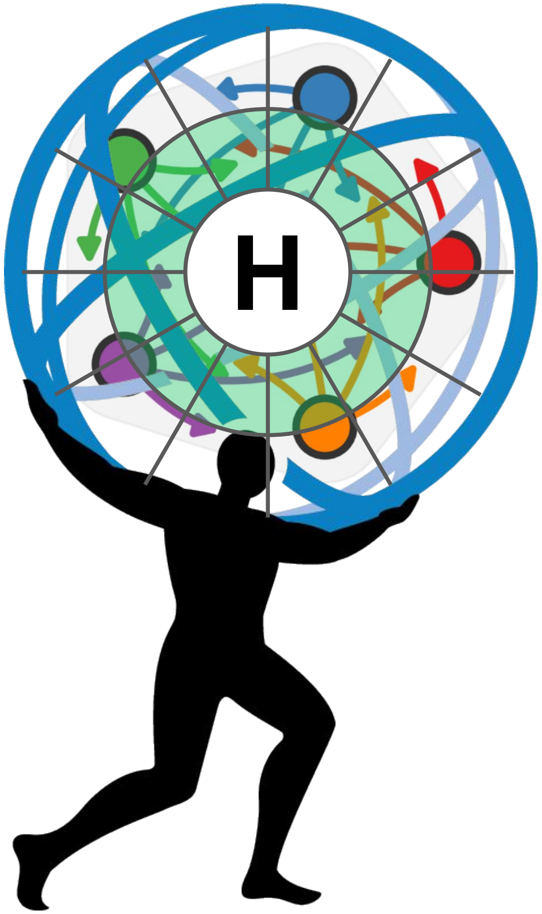
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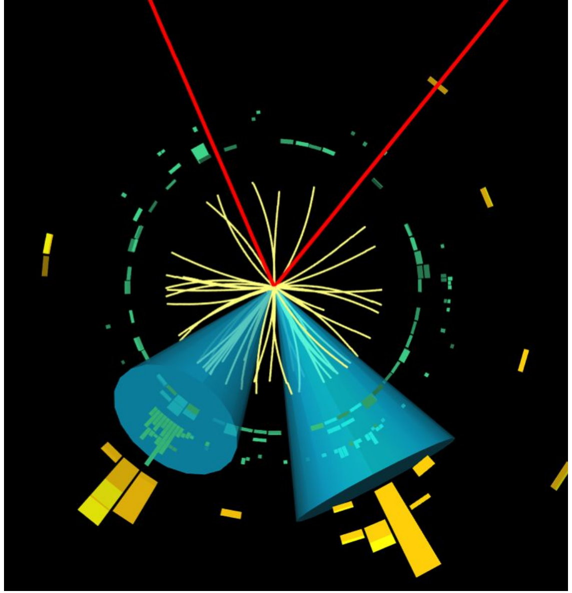
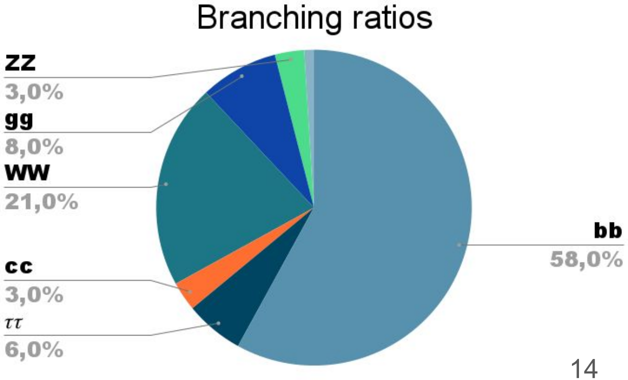
Backup

Search for VH(H→cc) decays

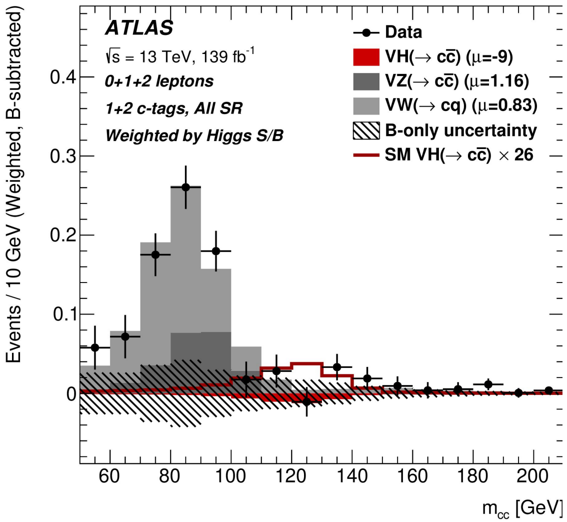


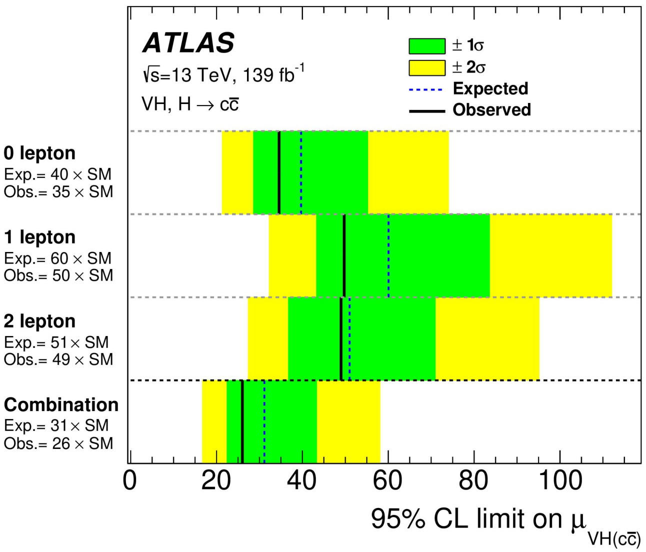
Motivation:
→ So far, we observed directly only Higgs couplings to 3rd generation fermions (ttH, H→$\tau\tau$, H→bb).
→ Probing couplings to lighter 2nd generation fermions could **open windows on new physics**.
→ H→cc is one of the **most common** unobserved decay modes of the Higgs boson.

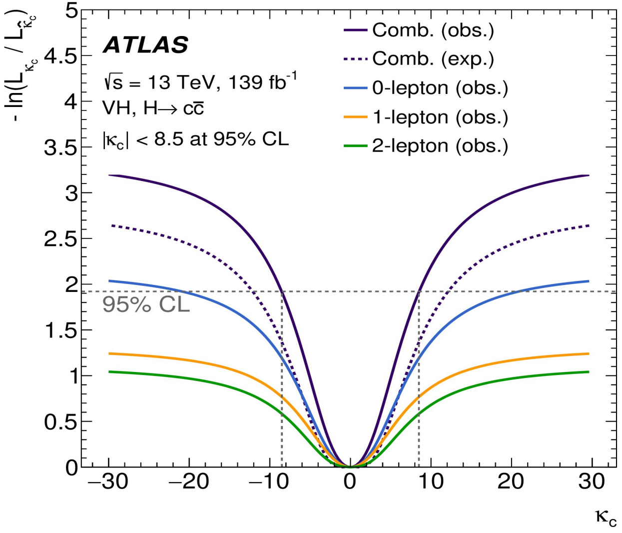
Strategy:
→ Overwhelming QCD background suppressed using leptonic decays of W and Z bosons.
→ **Deep learning based dedicated *c*-tagger** with 27% c-jet efficiency, 8.3% b-jet efficiency, and 1.7% light jet efficiency.
→ Dedicated control regions to constrain main backgrounds (ttbar and V+jets).
→ Profile likelihood fit on the invariant mass of the *c*-jet pair to extract the three parameters of interest μ_{VHcc} , μ_{VWcc} and μ_{VZcc}. The VZ/VW → cc signal strengths are extracted to validate the strategy.



Results







→ The Diboson cross check measurement is in agreement with the SM.

→ Upper limit is set on VH→cc process of **26 times the SM prediction**.

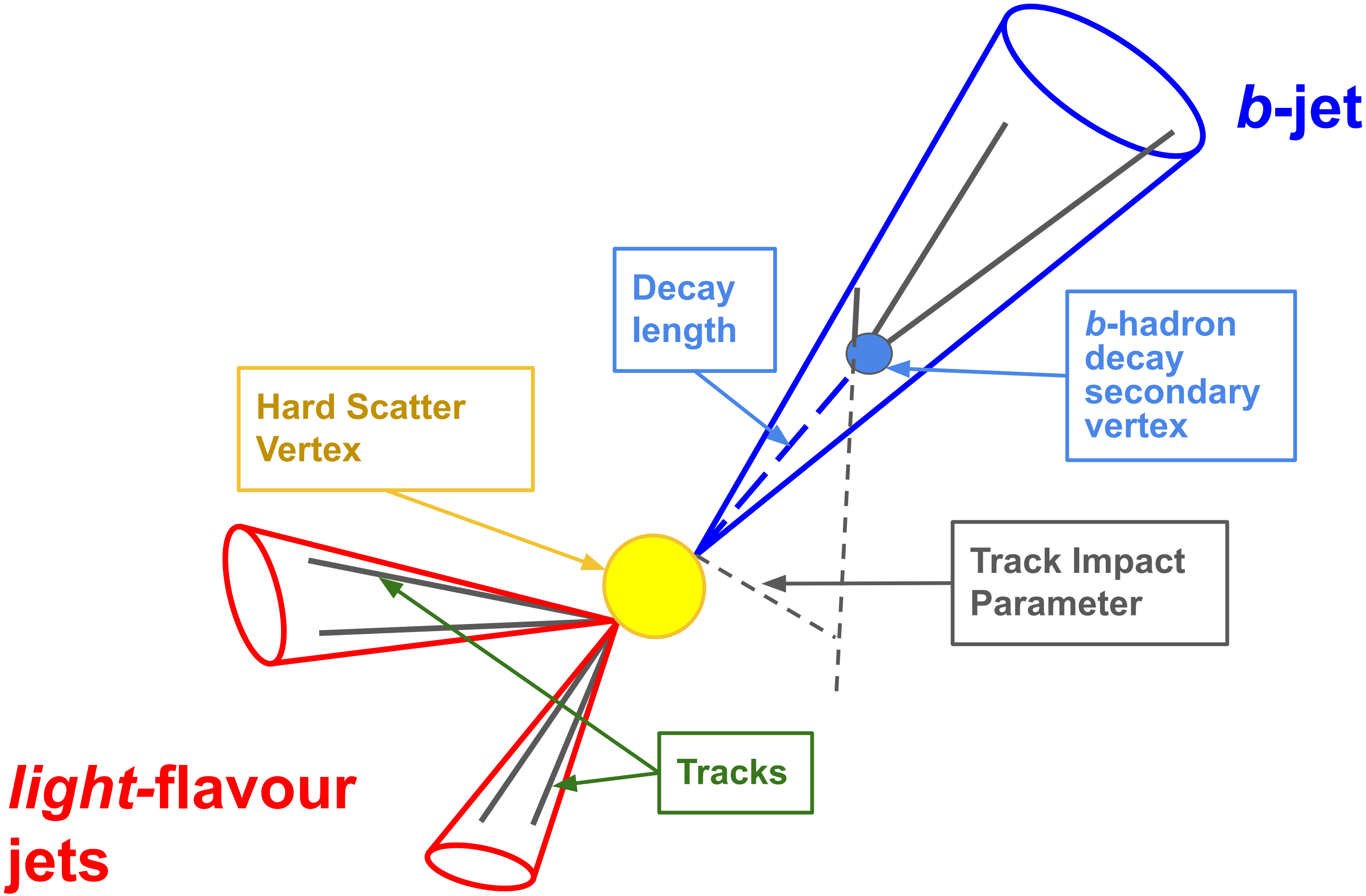
→ Results interpreted in the kappa framework as constraining the coupling modifier **$|k_c|$<8.5 @ 95%CL.**

Kc - definition and caveats from 10.1140/epjc/s10052-022-10588-3

The best-fit value of the $VH(\to c\bar{c})$ signal strength is interpreted within the kappa framework [37, 38], by reparameterising $\mu_{VH(c\bar{c})}$ in the likelihood function in terms of the Higgs–charm coupling modifier, κ_c, assuming that the coupling modifier only affects the Higgs boson decays. Including effects in both the partial and full width, considering only SM decays and setting all other couplings to their SM predictions, $\mu_{VH(c\bar{c})}$ is parameterised as a function of κ_c

$$\mu_{VH(c\bar{c})}(\kappa_c) = \frac{\kappa_c^2}{1 + B^{\mathrm{SM}}_{H\to c\bar{c}}(\kappa_c^2 - 1)},$$

where $B^{\mathrm{SM}}_{H\to c\bar{c}}$ is the $H \to c\bar{c}$ branching fraction predicted in the SM.

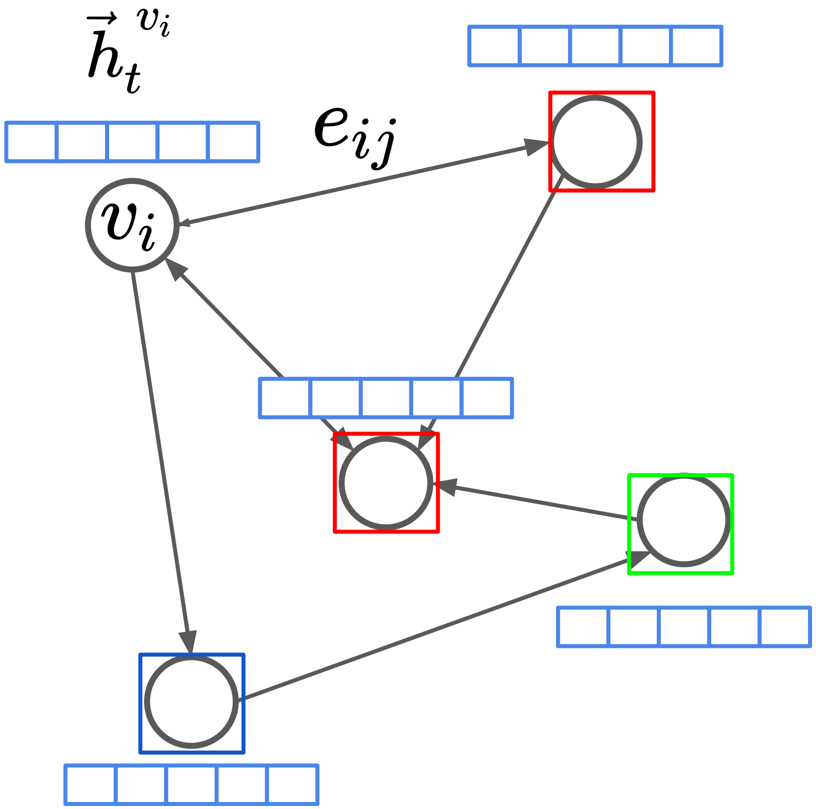

b-jet
Decay length
b-hadron decay secondary vertex
Hard Scatter Vertex
Track Impact Parameter
Tracks
light-flavour jets

Graph Neural Network

A graph G(V,E): a set of vertices (V) and edges (E) with their vector representations

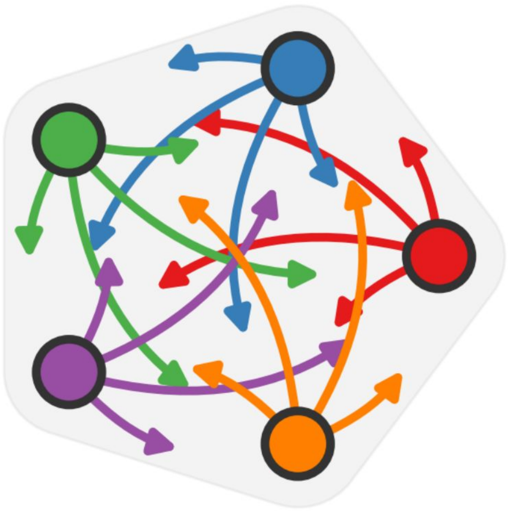
Graph -> Graph

Builds distributed vector representations of the entities (vertices) based on a loss minimization problem. After various updates, each vertex carries information about the overall structure.



$$\vec{h}_t^{v_i} = q(\vec{h}_{t-1}^{v_i}, \boxed{\sum_{j;\forall j: v_j \rightarrow v_i}} f_t(\vec{h}_{t-1}^{v_i}, e_{ij}, \vec{h}_{t-1}^{v_j}))$$

Inside the GN1 black-box



→ Initial node representation h_i.

1. Each h_i through a **W** MPL layer, becomes $\mathbf{W}h_i$.
2. Edge scores between node: $e(h_i,h_j)=\mathbf{a}\cdot\Theta(\mathbf{W}h_i \oplus \mathbf{W}h_j)$; where **a** MLP layer, Θ non-linear activation function, ⊕ is concatenation.
3. Attention weights a_{ij}=softmax[$e(h_i,h_j)$].

→ Updated representation $h'_i = \sigma[\sum a_{ij}\mathbf{W}h_j]$.

GN1(Lep): input variables

Jet Input	Description
p_{T}	Jet transverse momentum
η	Signed jet pseudorapidity

Track Input	Description
q/p	Track charge divided by momentum (measure of curvature)
$\mathrm{d}\eta$	Pseudorapidity of the track, relative to the jet η
$\mathrm{d}\phi$	Azimuthal angle of the track, relative to the jet ϕ
d_0	Closest distance from the track to the PV in the longitudinal plane
$z_0 \sin\theta$	Closest distance from the track to the PV in the transverse plane
$\sigma(q/p)$	Uncertainty on q/p
$\sigma(\theta)$	Uncertainty on track polar angle θ
$\sigma(\phi)$	Uncertainty on track azimuthal angle ϕ
$s(d_0)$	Lifetime signed transverse IP significance
$s(z_0)$	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
nPixHoles	Number of pixel holes
nSCTHoles	Number of SCT holes
leptonID	Indicates if track was used in the reconstruction of an electron or muon (only for GN1 Lep)

GN1: track classes

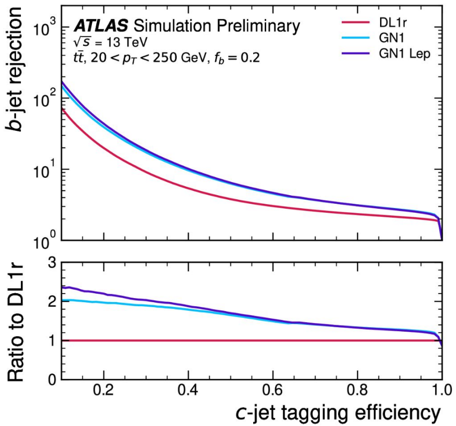
Truth Origin	**Description**
Pileup	From a *pp* collision other than the primary interaction
Fake	Created from the hits of multiple particles
Primary	Does not originate from any secondary decay
fromB	From the decay of a *b*-hadron
fromBC	From a *c*-hadron decay, which itself is from the decay of a *b*-hadron
fromC	From the decay of a *c*-hadron
OtherSecondary	From other secondary interactions and decays

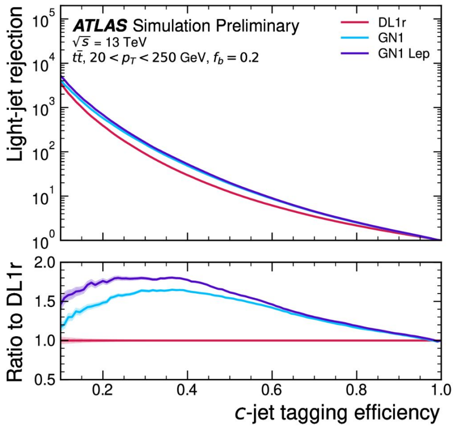
Improved *c*-tagging towards HL-LHC

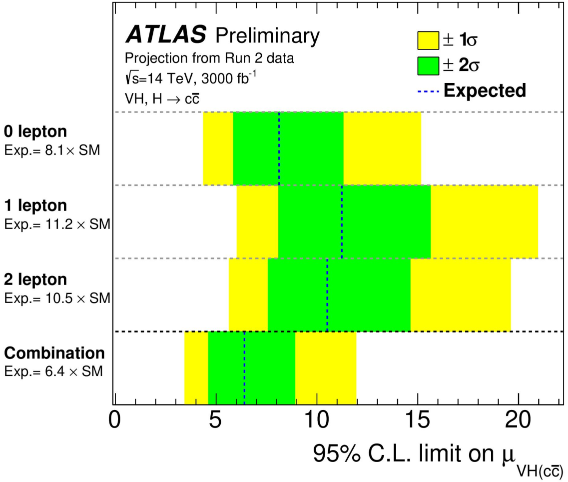
→ GN1 outperforms its predecessors of factors up to 100% (80%) for b (light) flavour jet rejection @ a 27% c-jet tagging efficiency.

→ The impressive improvement will directly impact the sensitivity of the ATLAS experiment to the VH→cc process.

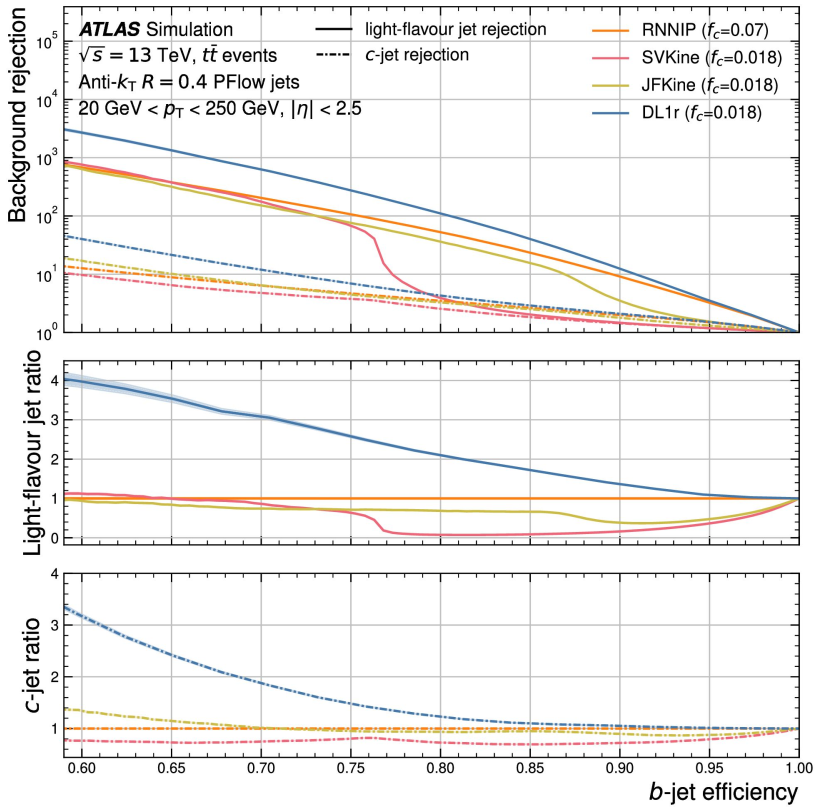
→ Extrapolations of the expected sensitivities of the ATLAS detector to the VH→cc process at the HL-LHC, assuming a dataset of 3000 fb^{-1} of *pp* collisions, the presence of ITk **and a *b* (light) flavour jet rejections improved of a factor of 1.5 (3)**, predict an upper limit on μ_{VHcc} of 6.4 x SM, corresponding to $|k_c|$<8.5 @ 95%CL.

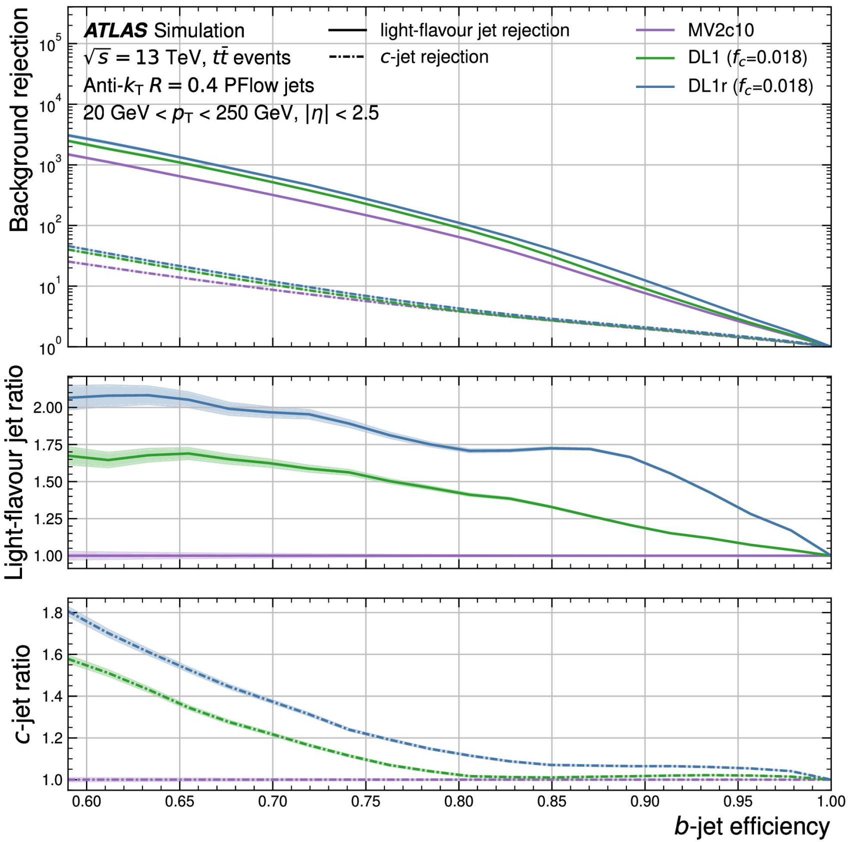




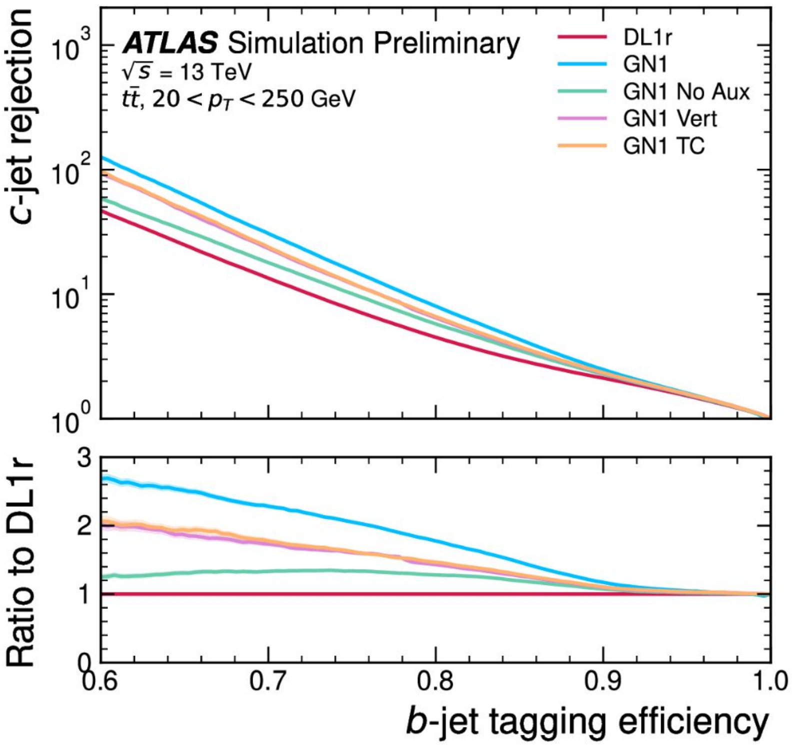


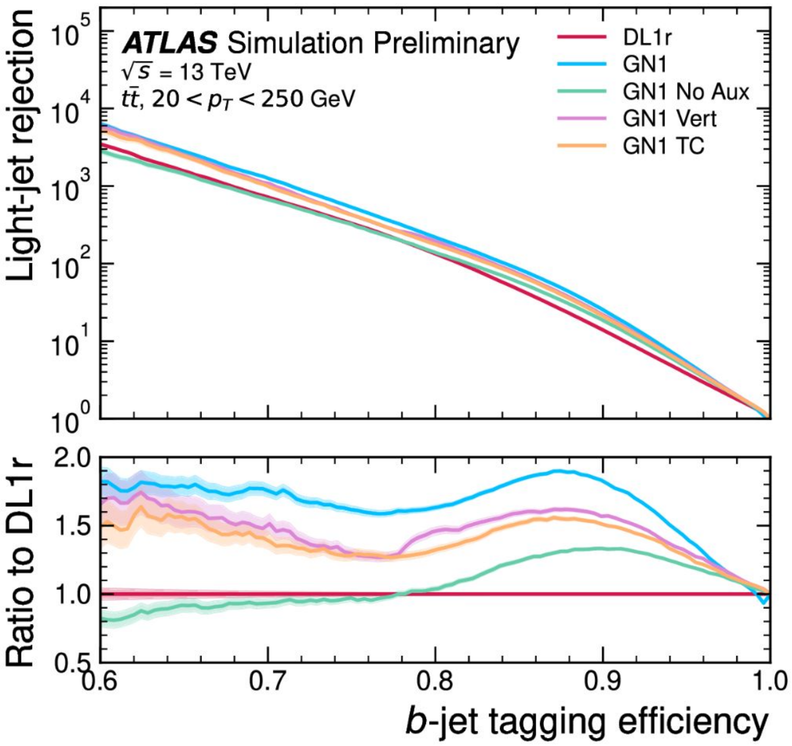
Low-Level Taggers, DL1, DL1r





GN1: Impact of Auxiliary Tasks





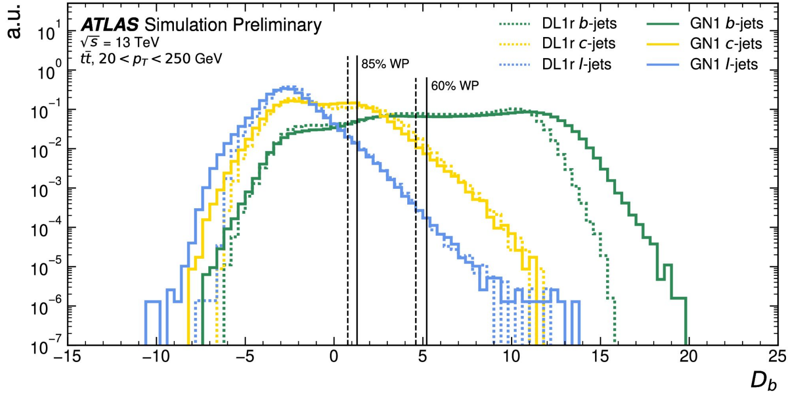
Truth-Tagging Technique

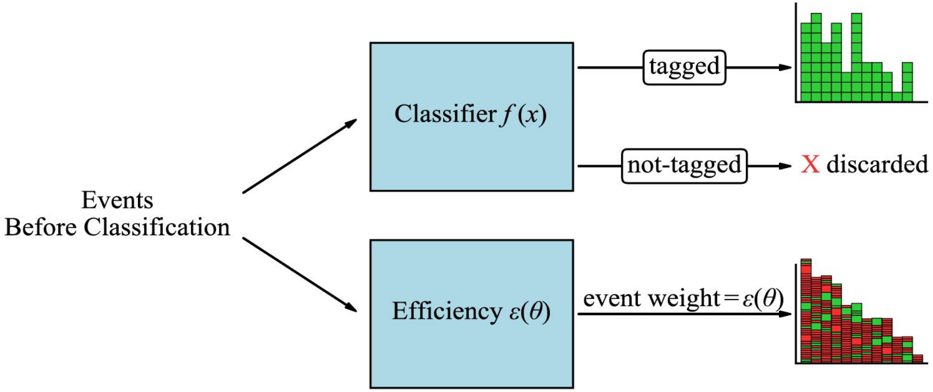
Direct Tagging (Pass or Fail): Define as "tagged" only jets passing a given cut on the flavour-tagging discriminant variable. Jets that don't pass the cut are discarded.

Truth Tagging: Weight jets with their *probability* of passing the cut and thus being tagged. No jet is discarded: **the statistical power of the simulated background samples is optimally exploited.**

The event weighting technique strongly relies on the *a priori* knowledge of the tagging efficiency ϵ for each jet.

ϵ is a function of a set of parameters (e.g. the phase space coordinates) ϑ of each jet: $\epsilon_{jet}=\epsilon_{jet}(\vartheta)$.





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Event Weighting for Truth Tagging

An alternative approach is to weight the events according to their probabilities of having n b-jets:

$$\boxed{P_{n_b}} = \sum_{(k_1,\ldots,k_{N_{jet}})\in M} \left(\prod_{i=1}^{N_{jet}} \left(\cancelto{0}{1 - k_i} + \cancelto{1}{(-1)^{1+k_i}} \boxed{\epsilon_i}\right)\right)$$

$$\boxed{M} = \left\{(k_1,\ldots,k_{N_{jet}}) \middle| k_i \in \{0,1\}, \sum_{i=1}^{N_{jet}} k_i = n_b\right\}$$

Tagging efficiency of each jet

Set that samples all the possible permutations of jets in the event with the constraint that n_b and only n_b are b-tagged (for the sake of simplicity)

Sum over all permutations of n_b b-tags, distributed over N_{jets}

If jet *i* is tagged (k_i=1), the tagging efficiency ϵ_i enters the added product

Otherwise if k_i=0, the mistagging efficiency 1-ϵ_i enters the added product

Sampling the permutation

Once the most probable n_b is computed, one of the possible permutation must be chosen. It can be done by tower sampling the cumulative probability of the permutations.

Permutation	j1	j2	j3	j4	Permutation probability	Rel. perm. probability	Cumulative rel. perm. prob
1	✓	✓			39%	83%	83%
2	✓		✓		4%	8%	91%
3	✓			✓	0.2%	0.4%	91.4%
4		✓	✓		4%	8%	99.4%
5		✓		✓	0.2%	0.4%	99.8%
6			✓	✓	0.01%	0.02%	99.82%

Event Weighting: Statistical Gain

Sample with N events:
→ Apply cuts which select N_p: relative stat uncertainty is sqrt(N_p)/N_p.
→ Weight events and include all: sqrt($\sum w_i^2$)/N.

So, statistical gain:

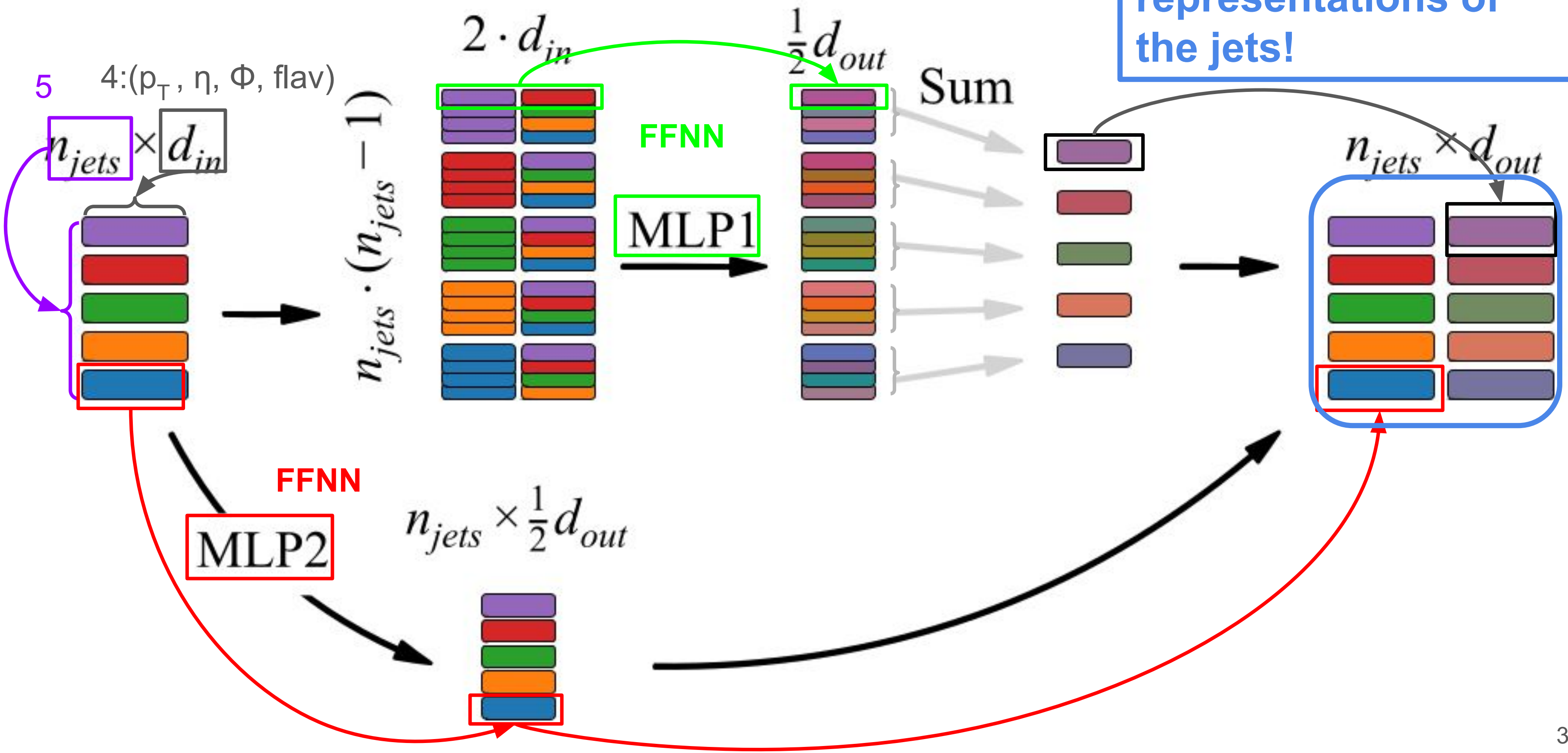
$$\frac{\sqrt{N_p}}{N_p} > \frac{\sqrt{N_p}}{N} > \frac{\sqrt{(\sum_{i\leq N} w_i^2)}}{N} \text{ if } \sqrt{N_p} > \sqrt{(\sum_{i\leq N} w_i^2)}.$$

GNN Truth-Tagging: Input Variables

Track-jet variables
Track-jet p_{T}
Track-jet η
Track-jet ϕ
Track-jet flavour label
Mass of the p_{T}-leading b- or c-hadron in the track-jet
p_{T} of the p_{T}-leading b- or c-hadron in the track-jet
η of the p_{T}-leading b- or c-hadron in the track-jet
ϕ of the p_{T}-leading b- or c-hadron in the track-jet
Event variables
Average number of interactions per event, $\langle\mu\rangle$
Jet-pair variables
Angular separation between two track-jets, ΔR

GNN truth-tagging GN block

Hidden representations of the jets!

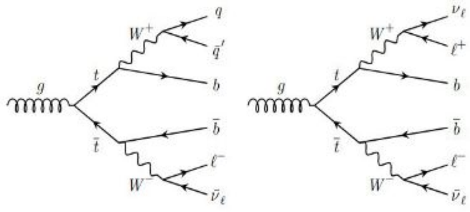


Full Systematics VH,H→cc

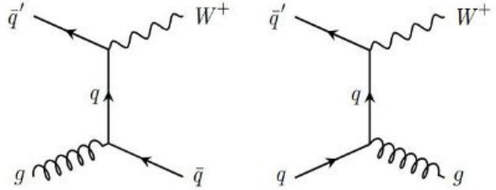
Source of uncertainty		$\mu_{VH(c\bar{c})}$	$\mu_{VW(cq)}$	$\mu_{VZ(c\bar{c})}$
Total		15.3	0.24	0.48
Statistical		10.0	0.11	0.32
Systematic		11.5	0.21	0.36
Statistical uncertainties				
Signal normalisation		7.8	0.05	0.23
Other normalisations		5.1	0.09	0.22
Theoretical and modelling uncertainties				
$VH(\rightarrow c\bar{c})$		2.1	< 0.01	0.01
$Z+$jets		7.0	0.05	0.17
Top quark		3.9	0.13	0.09
$W+$jets		3.0	0.05	0.11
Diboson		1.0	0.09	0.12
$VH(\rightarrow b\bar{b})$		0.8	< 0.01	0.01
Multi-jet		1.0	0.03	0.02
Simulation samples size		4.2	0.09	0.13
Experimental uncertainties				
Jets		2.8	0.06	0.13
Leptons		0.5	0.01	0.01
$E_{\mathrm{T}}^{\mathrm{miss}}$		0.2	0.01	0.01
Pile-up and luminosity		0.3	0.01	0.01
Flavour tagging	c-jets	1.6	0.05	0.16
	b-jets	1.1	0.01	0.03
	light-jets	0.4	0.01	0.06
	τ-jets	0.3	0.01	0.04
Truth-flavour tagging	ΔR correction	3.3	0.03	0.10
	Residual non-closure	1.7	0.03	0.10

Main Backgrounds for VH, Hbb/Hcc

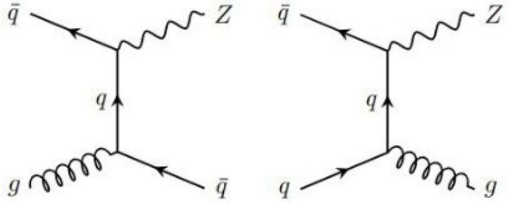
ttbar



W+jets



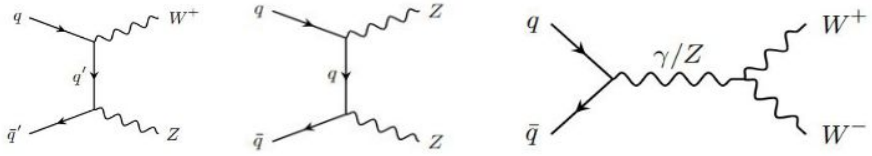
Z+jets



Dominant

Sub-dominant

Diboson



single top

s-channel

t-channel

Wt