

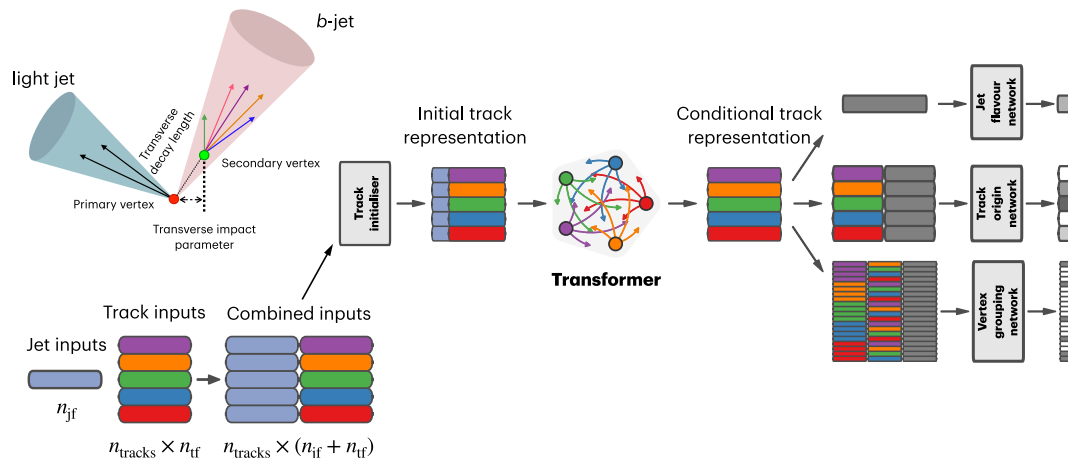
Analysis methods: overview

Higgs Hunting 2026 - 16/09/2026

Nicolas Chanon - IP2i Lyon, CNRS/IN2P3 (France)

CMS: “All analyses show improvements exceeding luminosity gain”

ATLAS: “Improvements in sensitivity no longer come only from larger datasets”

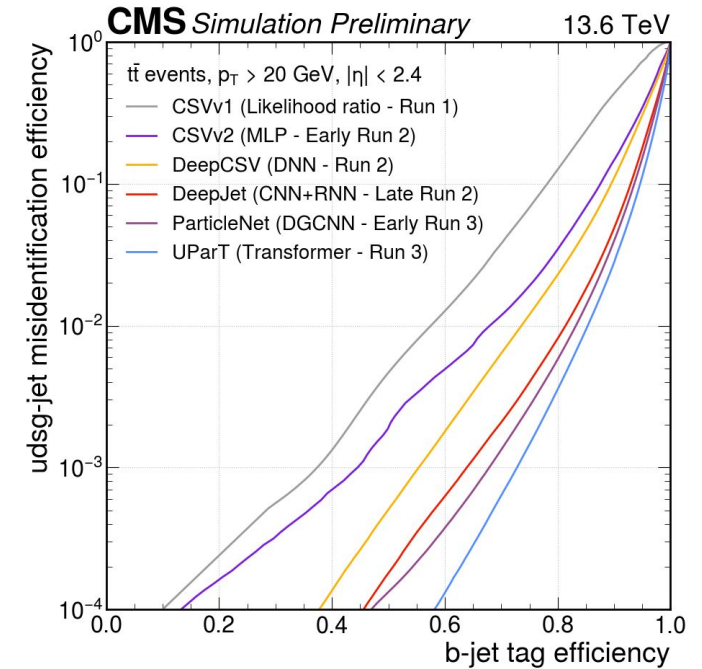


ATLAS Collaboration,
“Transforming jet flavour tagging
at ATLAS,”
Nature Commun. 17 (2026) no.1,
541

Object reconstruction and identification

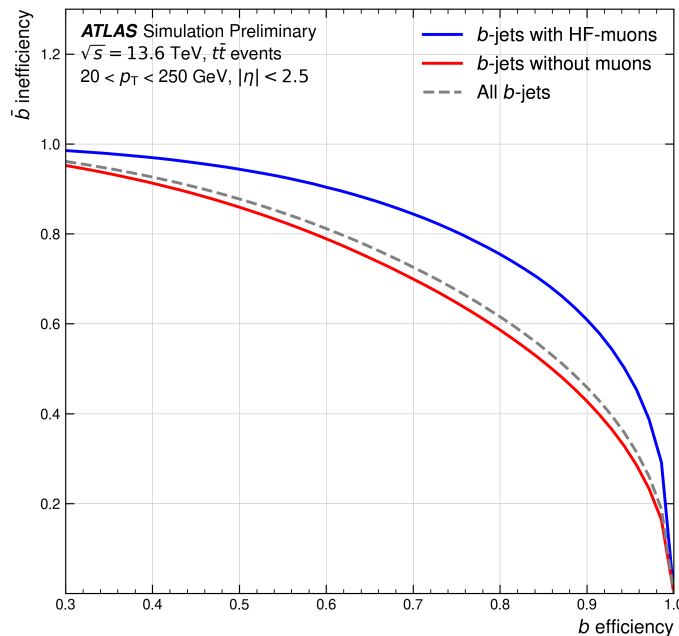
From Run 1 to Run 3, continuous progress in Machine Learning algorithms for object reconstruction, identification, and more:

- **Impressive progress in reconstruction/identification:** Jet flavour tagging, tau reconstruction, identification of jets in boosted topologies
- Technology ported at **trigger level** and bringing large improvements
- By now we use **global classifiers, targeting several tasks** in addition: jet charge identification, energy or mass regression, etc.
- Work appearing on the particle-flow, clustering, etc.



- **1 to 2 orders of magnitude in background rejection at fixed b-jet efficiency, from Run 1 to Run 3**

“A unified approach for jet tagging in Run 3 at $\sqrt{s}=13.6$ TeV in CMS,” CMS DP-2024/066



- **Charge of jets can be identified even without leptons**

“Identification of the charge of heavy-flavour jets using transformers with the ATLAS experiment,” ATL-PHYS-PUB-2026-005

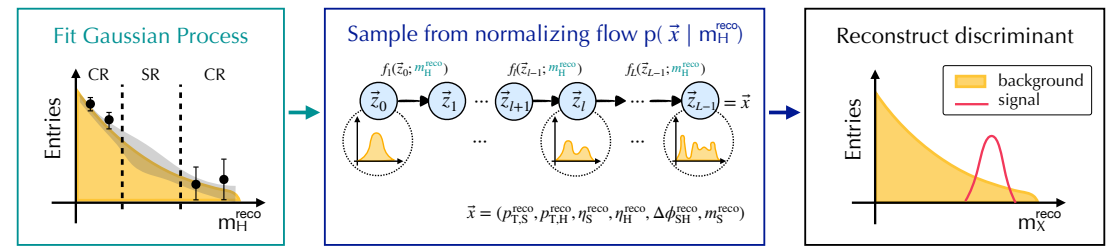
Improving background modeling and signal extraction

Improvement in physics analysis techniques

- Adversarial training, normalising flows, multi-variable reweighing for data-driven **background modelling**
- **Event classification for signal extraction**: multi-class classifiers neural networks: from DNN to GNNs, and by now transformers

“Search for new scalars via $X \rightarrow SH \rightarrow bbbb$ in proton-proton collisions at $\sqrt{s}=13$ TeV with the ATLAS detector,” arXiv:2607.18484

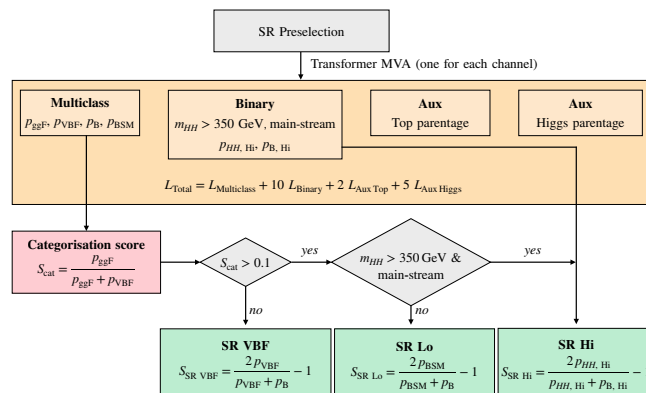
- **Non-closure uncertainty reduced by x2 wrt previous techniques**



The signal extraction is performed using two DNNs [61–64] discriminants trained separately to identify the qqHH and ggHH production modes. The DNN targeting the qqHH production mode is used in the VBF category, while the one targeting the ggHH production mode is used in all other categories. Both classifiers consist of three networks: a feature engineering Lorentz Boost Network [65], a $\tau\tau$ mass regression network [66] and finally a classifying DenseNet [67].

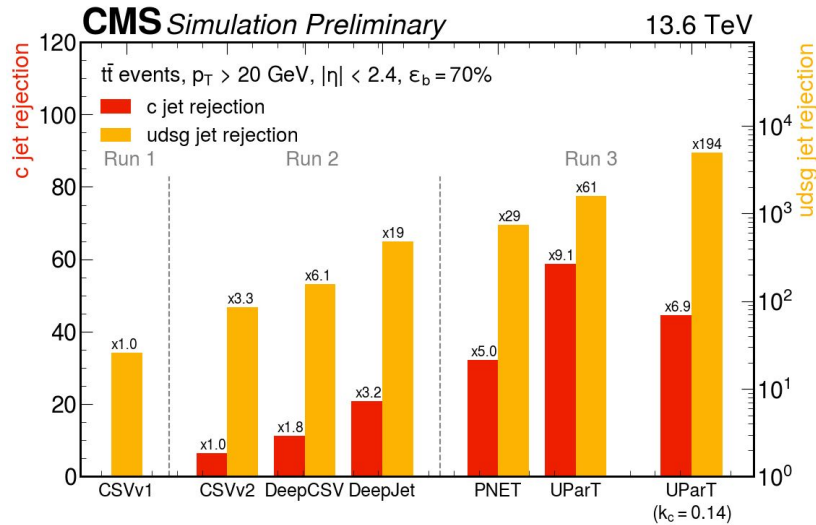
- **Multiple NN architecture + other improvements: 20% improvement when scaled to Run2 luminosity**

“Search for nonresonant HH production in the $bb\tau\tau$ final state in proton-proton collisions at $\sqrt{s} = 13.6$ TeV” CMS HIG-25-008



Classification with a **multi-target transformer** in ATLAS Run2 + early Run 3 $HH \rightarrow bb\tau\tau$, arXiv:2607.26879

Transformers and scaling laws

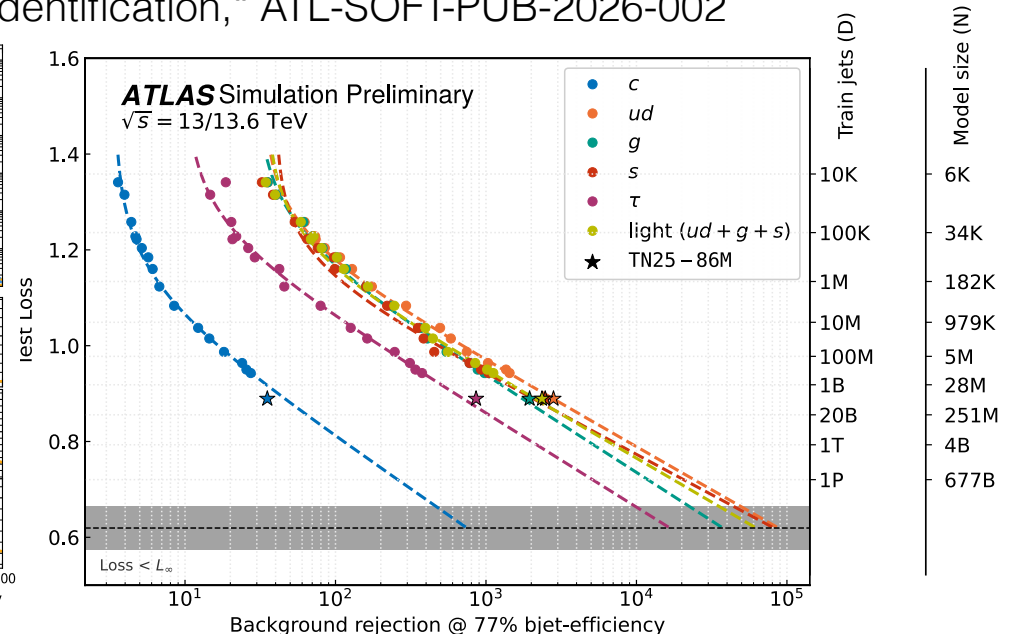
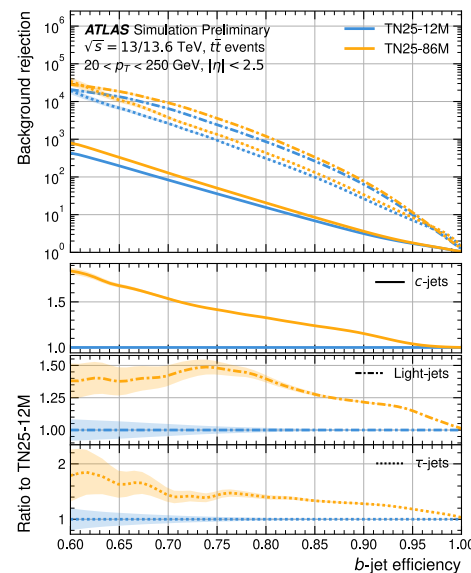


- Progresses arising from the NN **architecture** (GNN, Transformers), choice of inputs, but not only
- **Transformers** are becoming ubiquitous: excellent performance, relatively easy to train, scalable
- Employing lower level **inputs** is a key (from identification to low-level reconstruction?)
- **Scalability**: In order to get the best of the selected architecture, large datasets and number of parameters are needed

“A unified approach for jet tagging in Run 3 at $\sqrt{s}=13.6$ TeV in CMS,” CMS DP-2024/066

“Carpe Datum: Scaling behavior of transformers for heavy hadron flavor identification,” ATL-SOFT-PUB-2026-002

- This example shows the improvement obtained by a x20 larger dataset and a transformer with 7x more parameters



Discussion