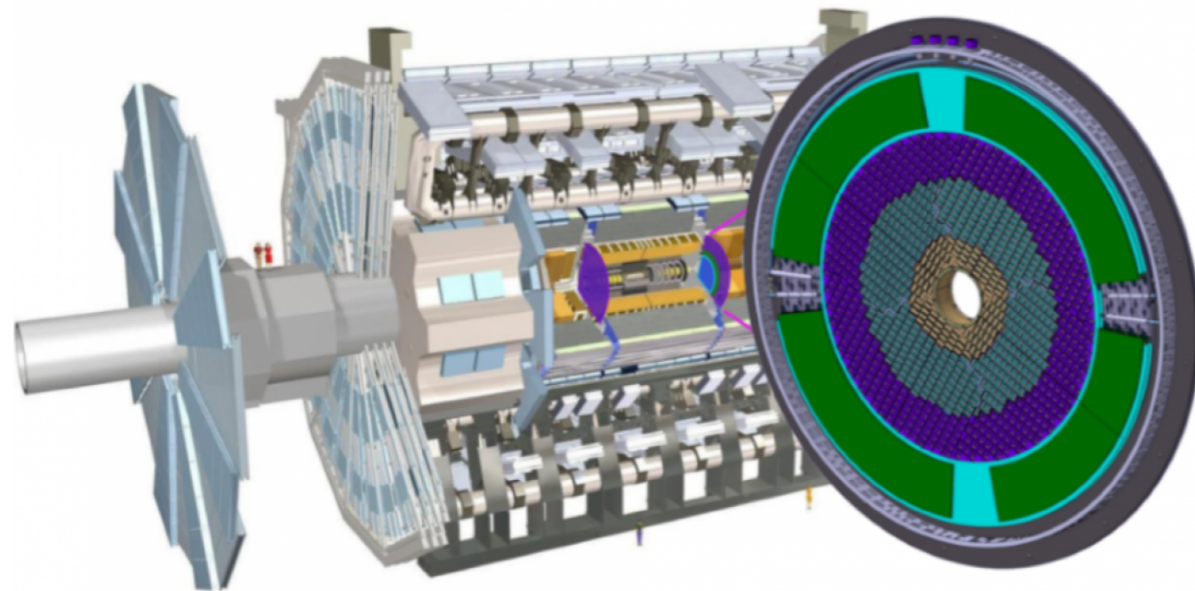
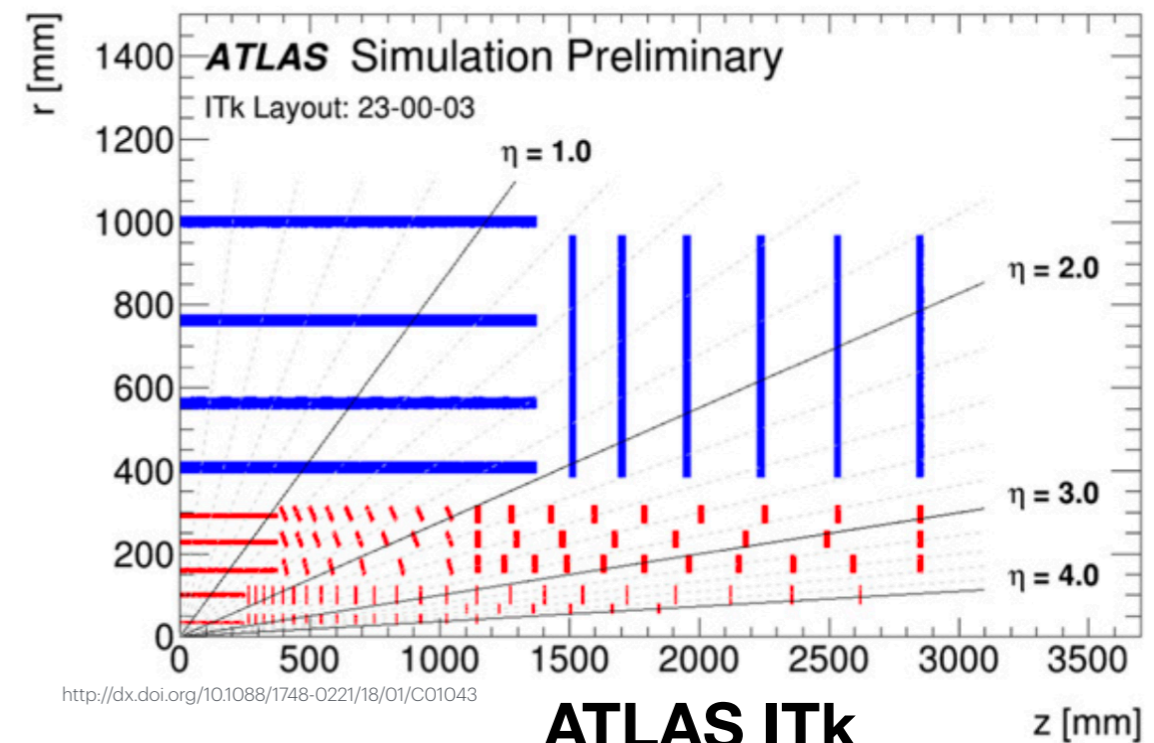


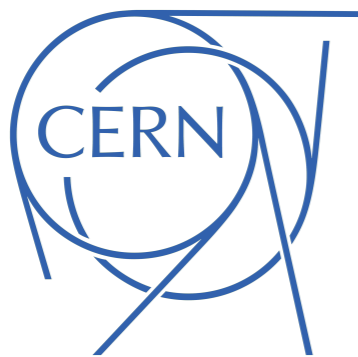
# Impact of 4D Tracking in Flavour Tagging Applications



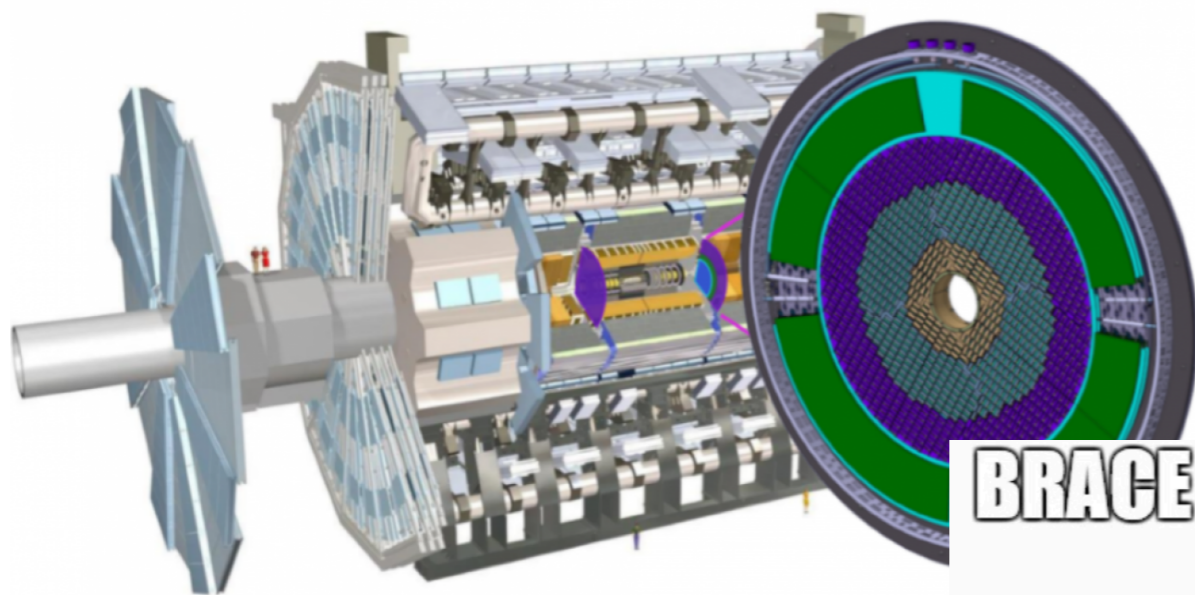
<https://ep-news.web.cern.ch/content/high-granularity-timing-detector-atlas-phase-ii-upgrade>

**ATLAS HGTD**

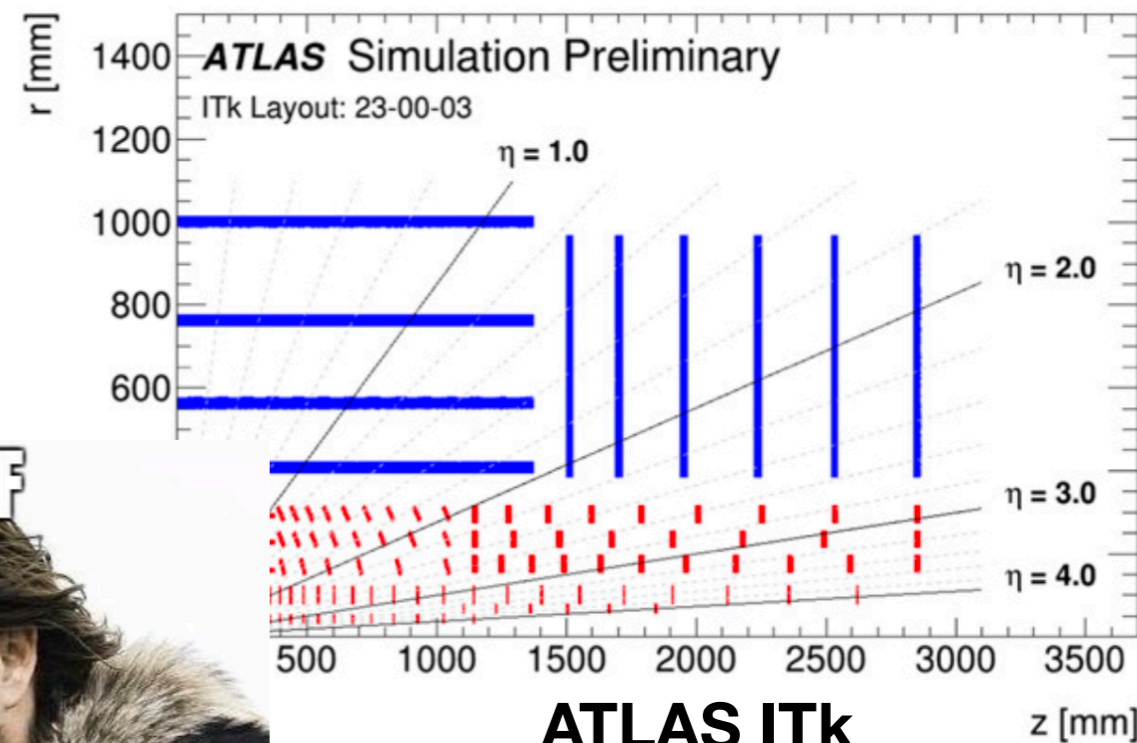




# Impact of 4D Tracking in Flavour Tagging Applications



ATLAS HGTD



ATLAS ITk

BRACE YOURSELF

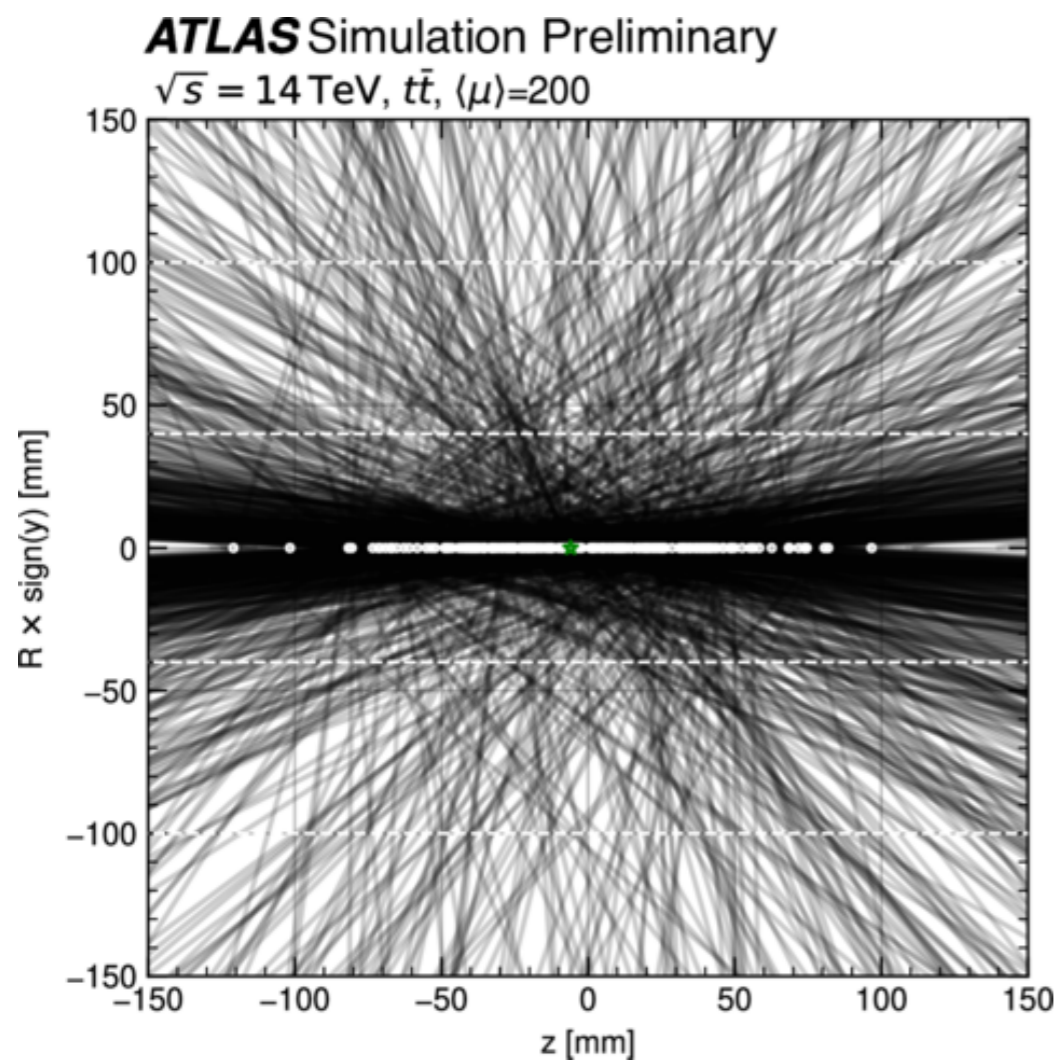
MERGE IS COMING



# Problem overview

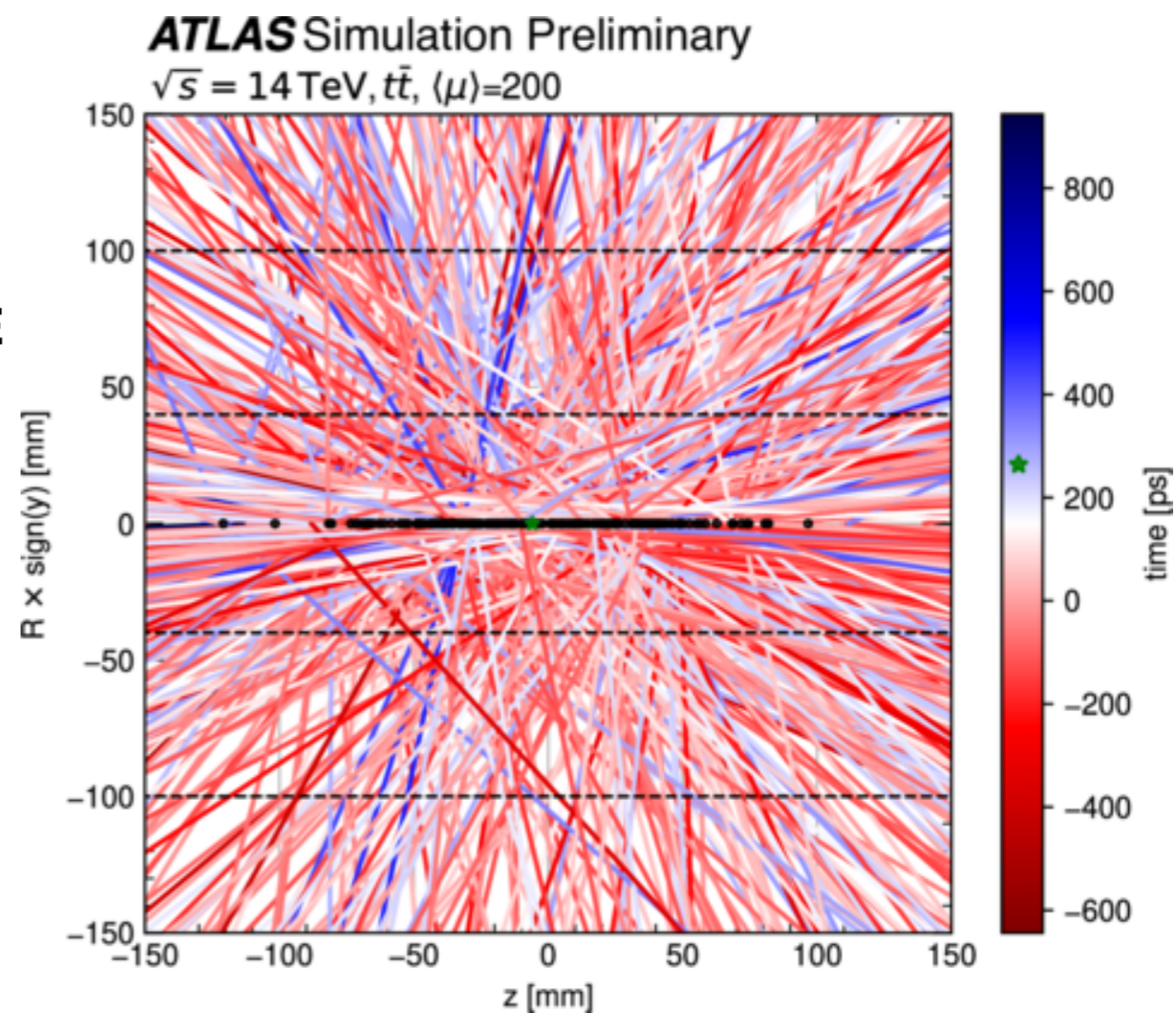
## Challenges:

- **HL-LHC:** more pp interactions per bunch crossing  $\rightarrow$  increased pile up (PU)
- Some PU tracks get falsely associated to a jet (noise)
- More noise decreases flavour tagging performance (ftag)



**3D**

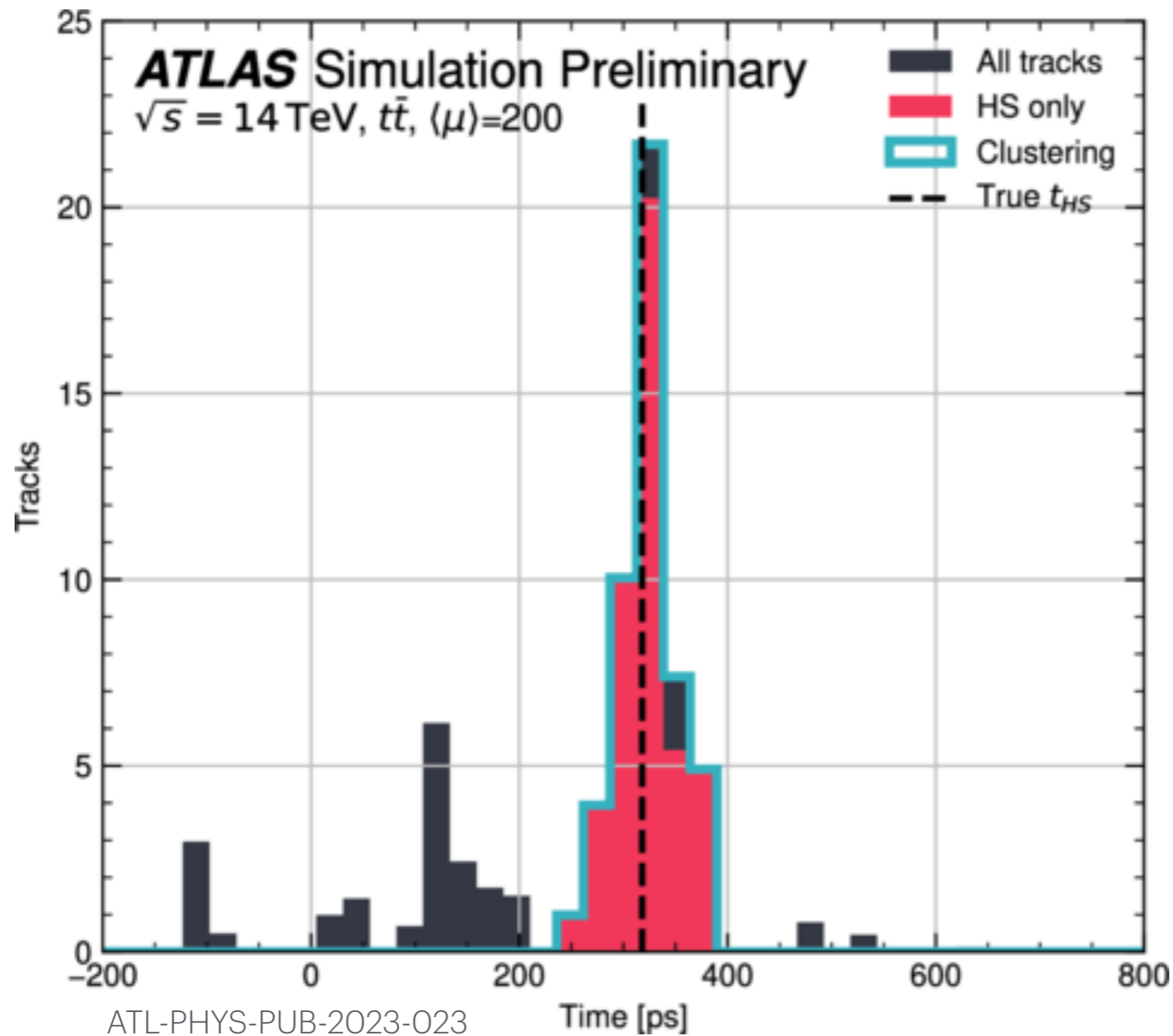
**TRACK TIME  
INFO**



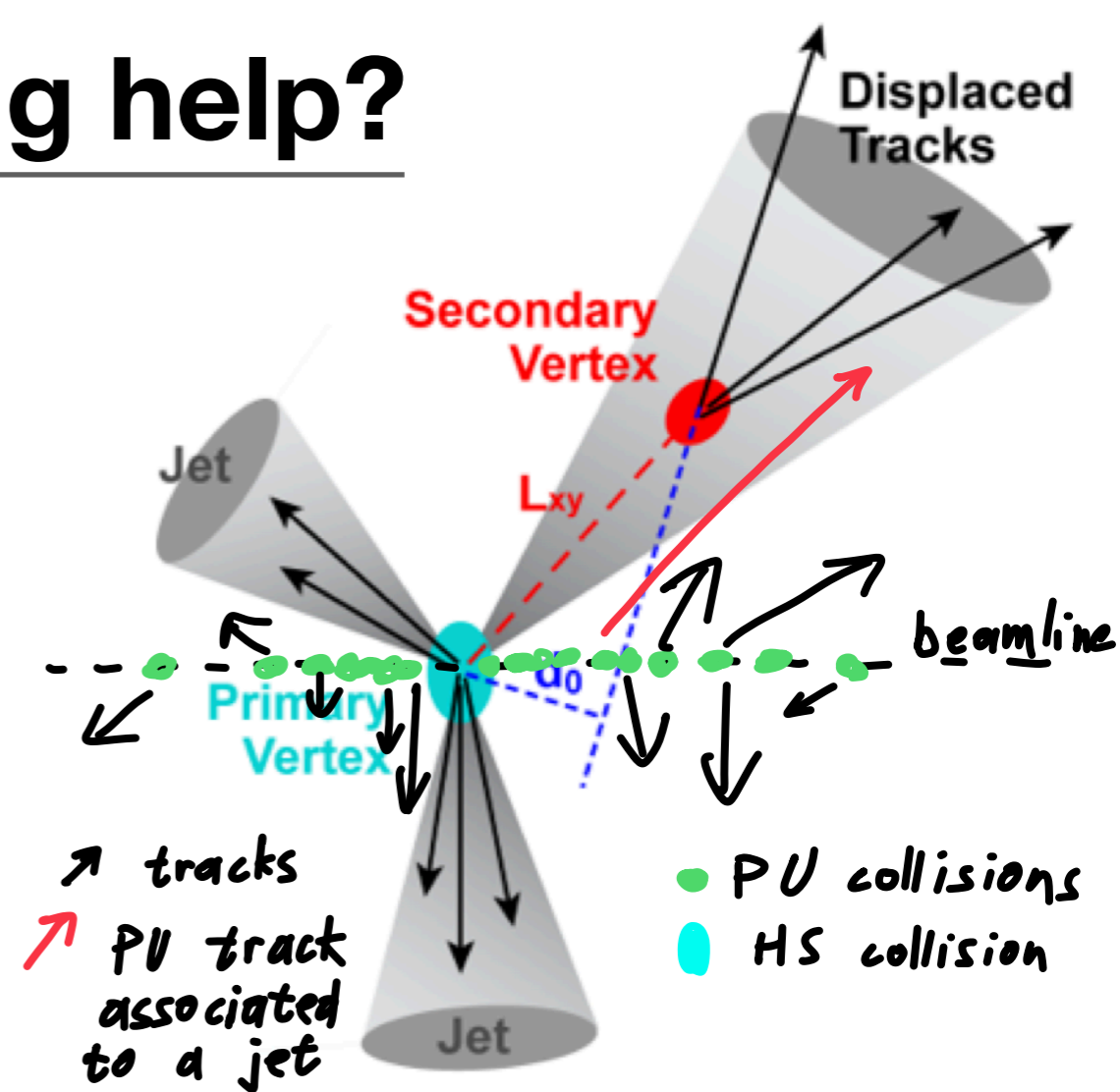
**4D**

ATL-PHYS-PUB-2023-023

# How does timing help?



**Timing helps distinguish between real HS and falsely associated PU tracks.**



## Track observables:

- **Impact parameters** such as  $d_0$  and  $L_{xy}$ 
  - help discriminate  $b$ -jets
- Functions of  $p_T$ , azimuthal angle, polar angle
- **Track time** relative to HS
- Many more...
- **Jet properties:** not used directly

# Methodology

## Task description:

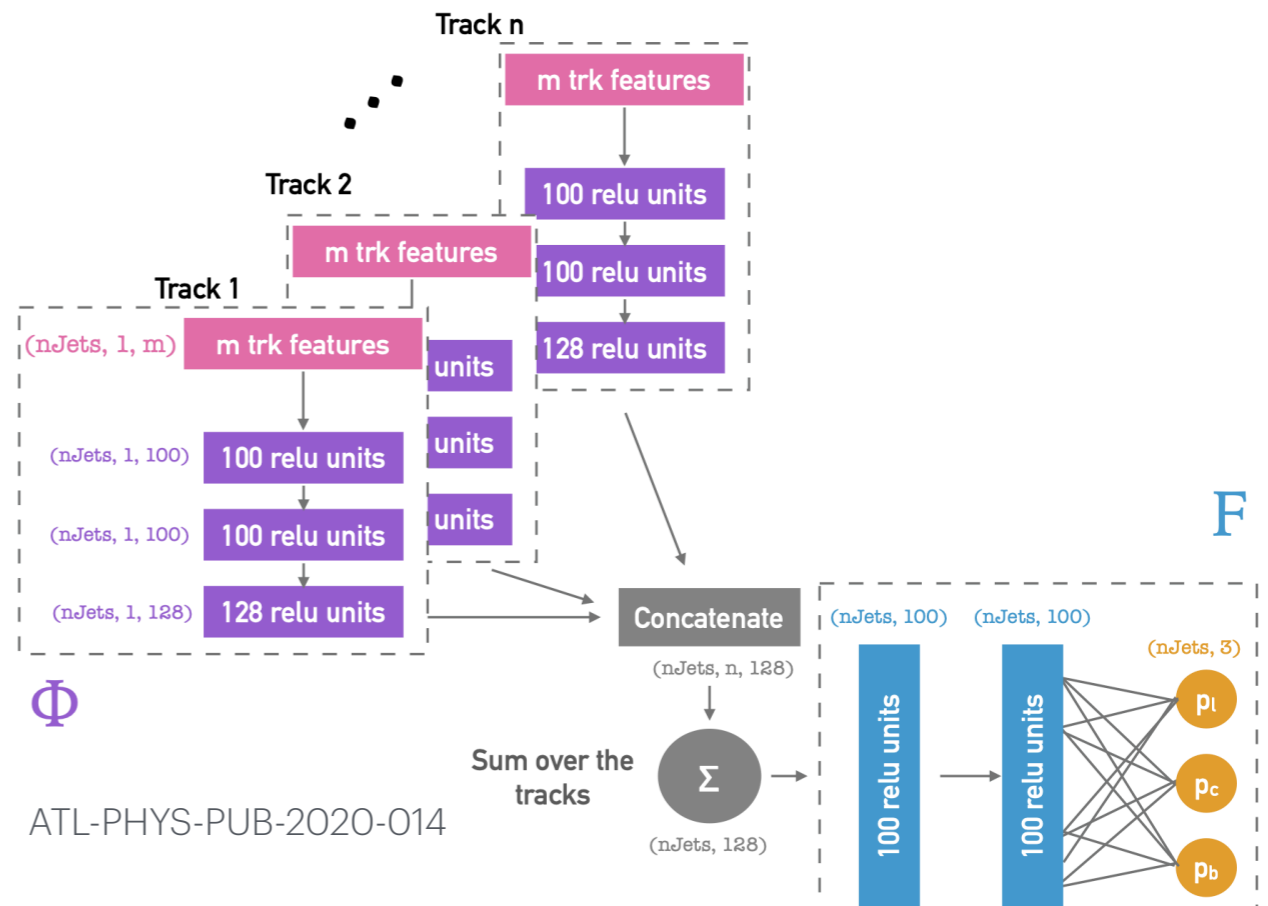
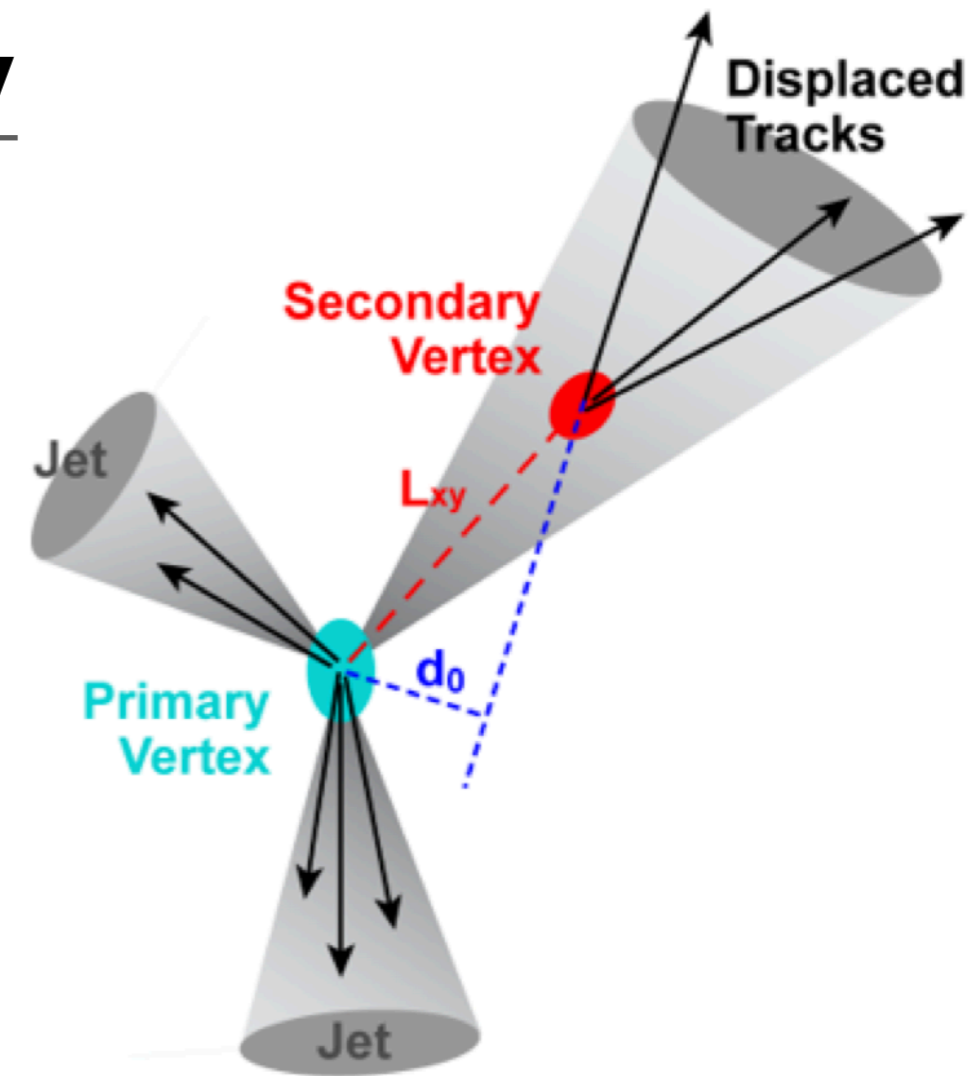
- ACTS for MC simulations of  $t\bar{t}b\bar{b}$  events
- Evaluate Neural Network (NN) ftag performance:
  - Train NN with and without timing

## Objectives:

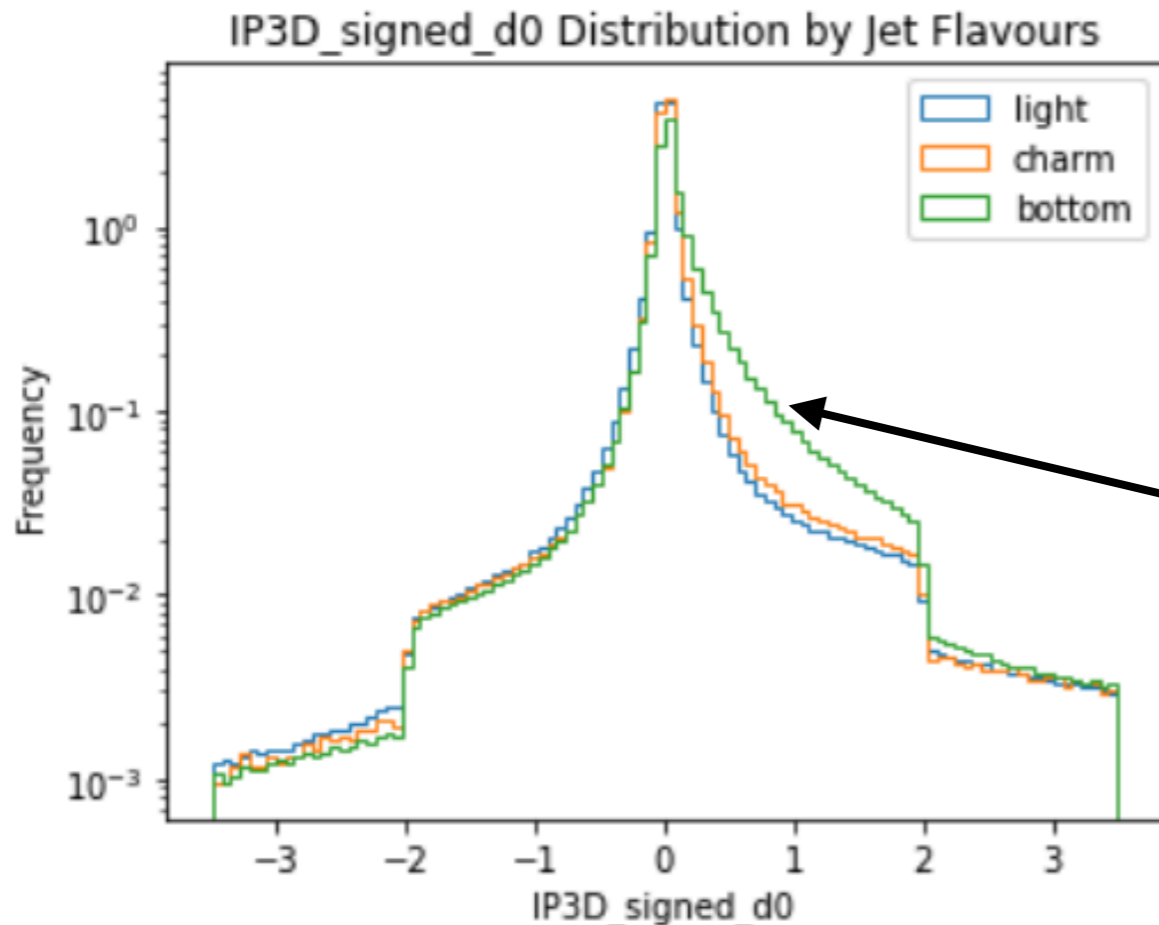
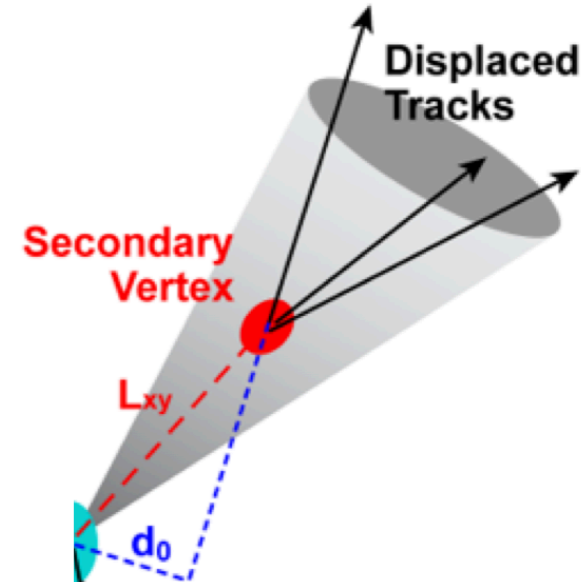
- Multi class classification Targets: l-jet, c-jet, b-jet
- Goal: Try improving accuracy, efficiency for b-jet reconstruction with inclusion of timing

## DIPS (Deep Sets):

- Simplified Graph NN (GNN)
- Use **observables of tracks** associated to a jet
- **GNN idea:** Use a small NN to extract info from each track and later combine this information into a single vector (sum or mean)

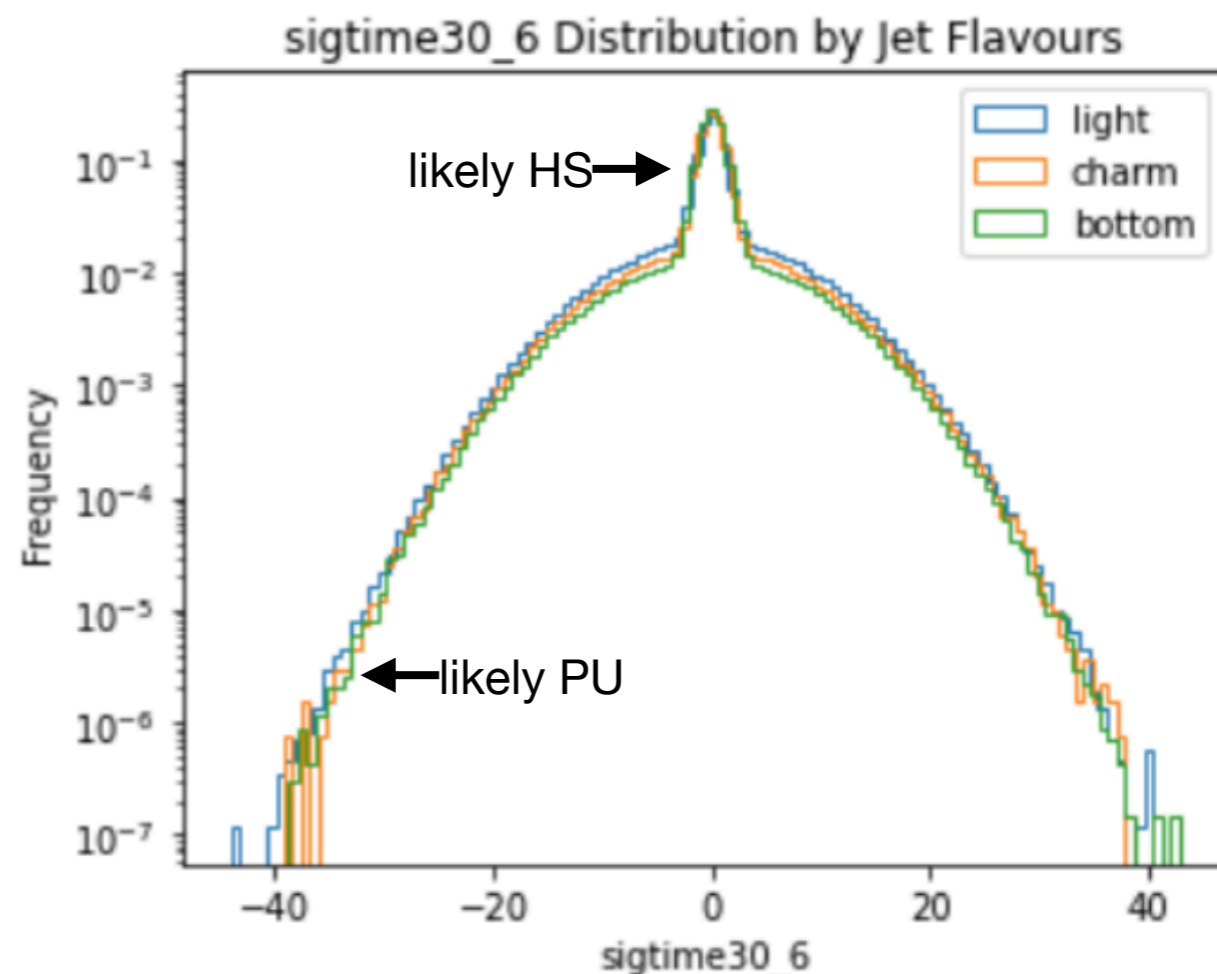


# Observables Analysis



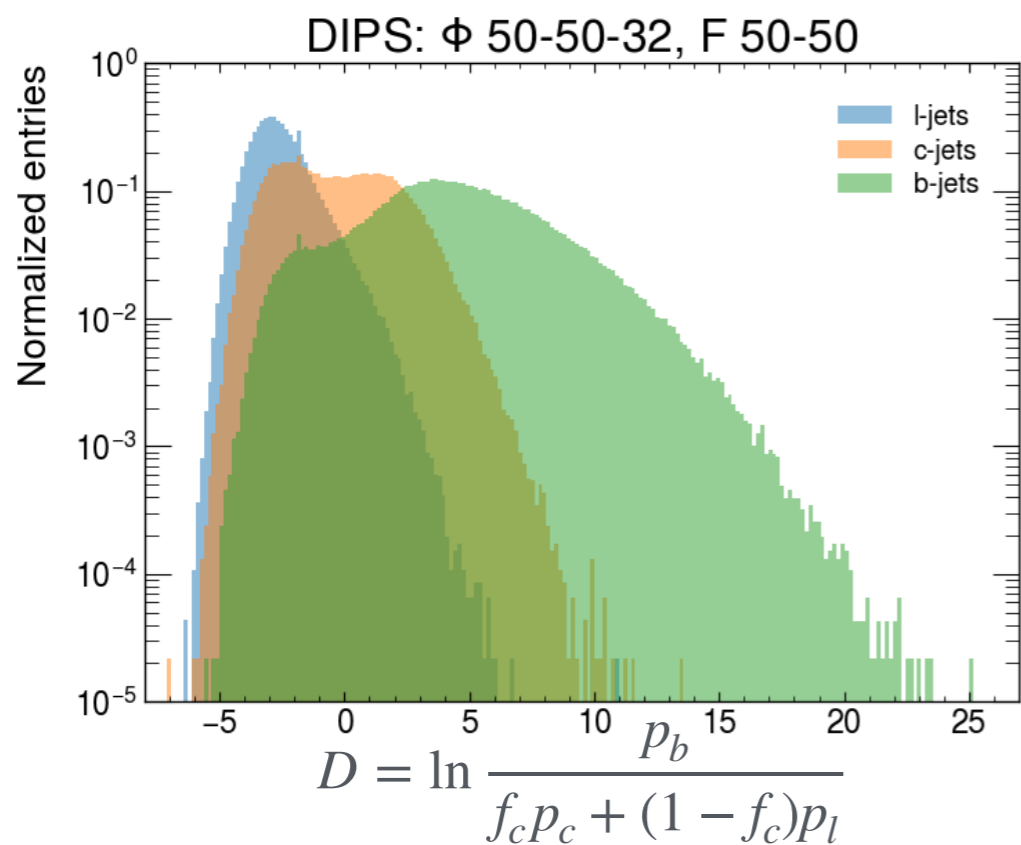
- **Impact parameters** such as  $d_0$  and  $z_0$ :
  - $b$ -hadrons have longer decay time → bigger impact parameters on average

- **Track time (relative to HS):**
  - Tracks with large times are likely to originate from PU.
  - Tracks close to 0 (limited by resolution) likely originate from HS.



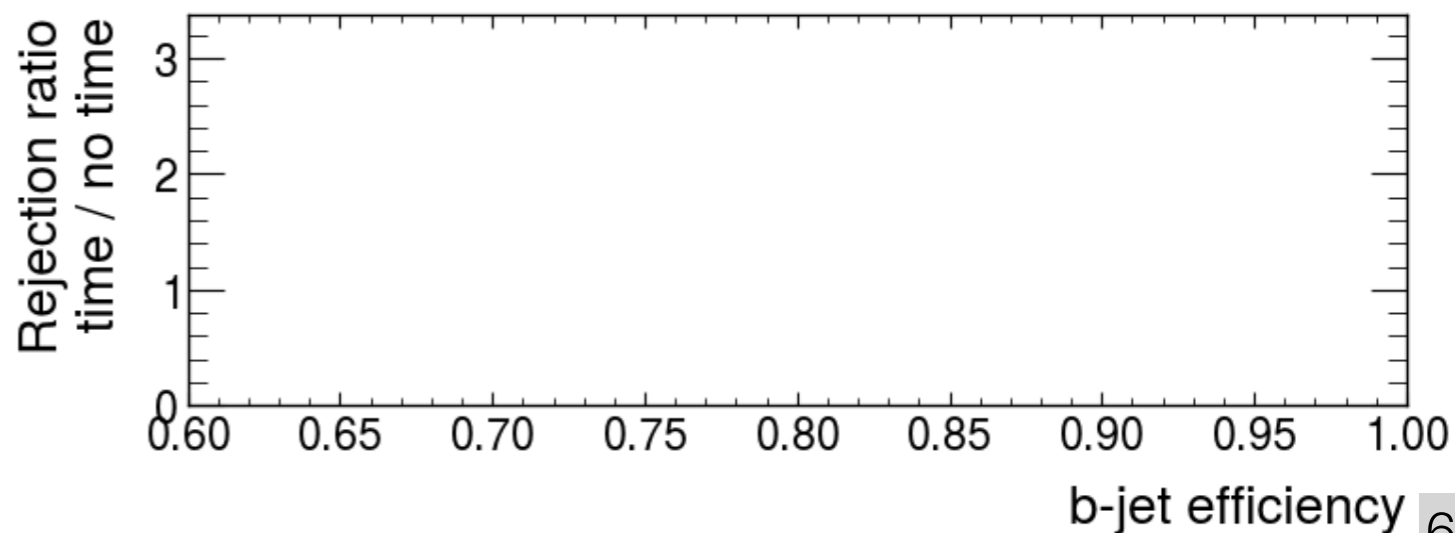
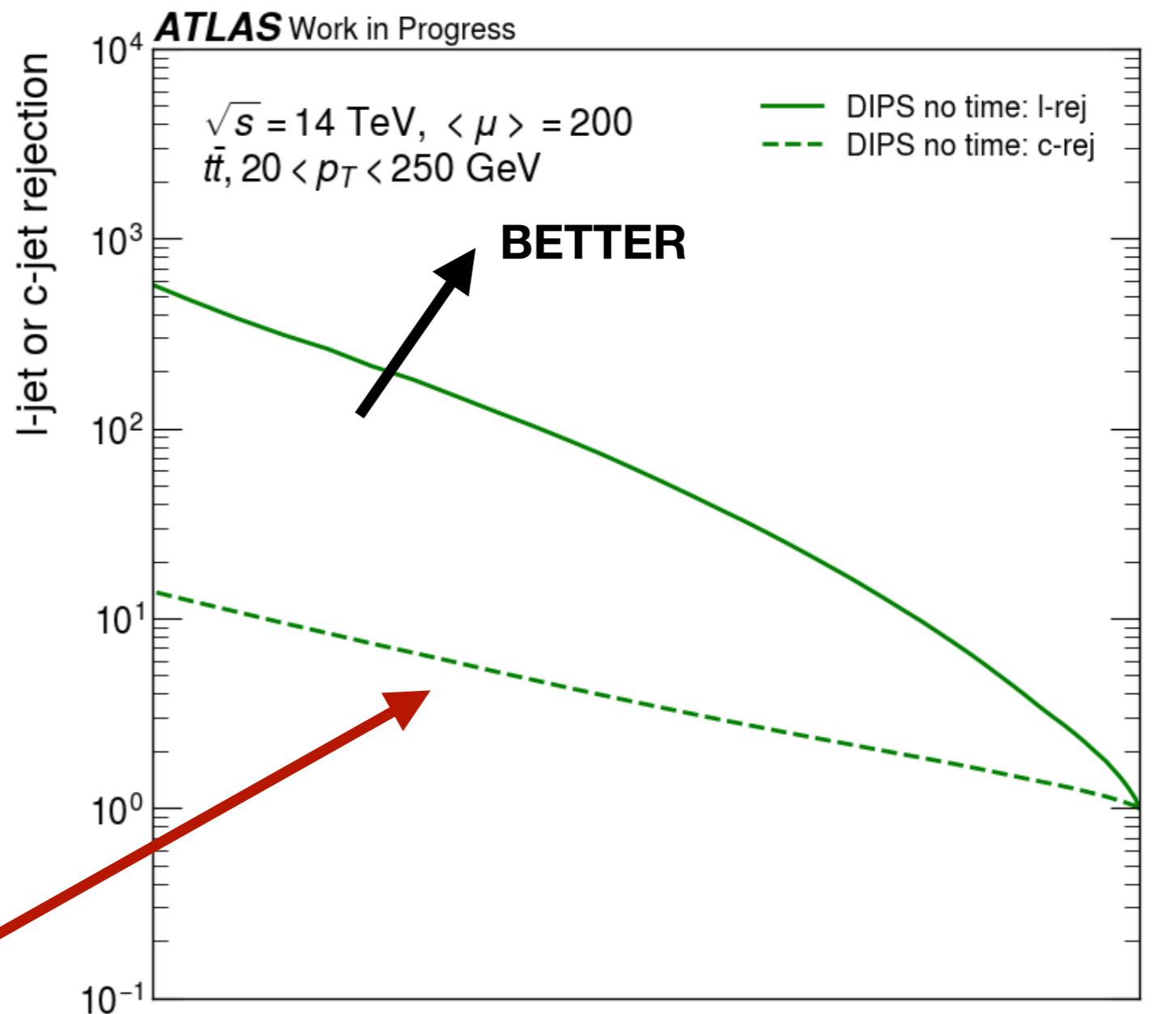
Many more features are used for NN.

# DIPS flavour tagging results

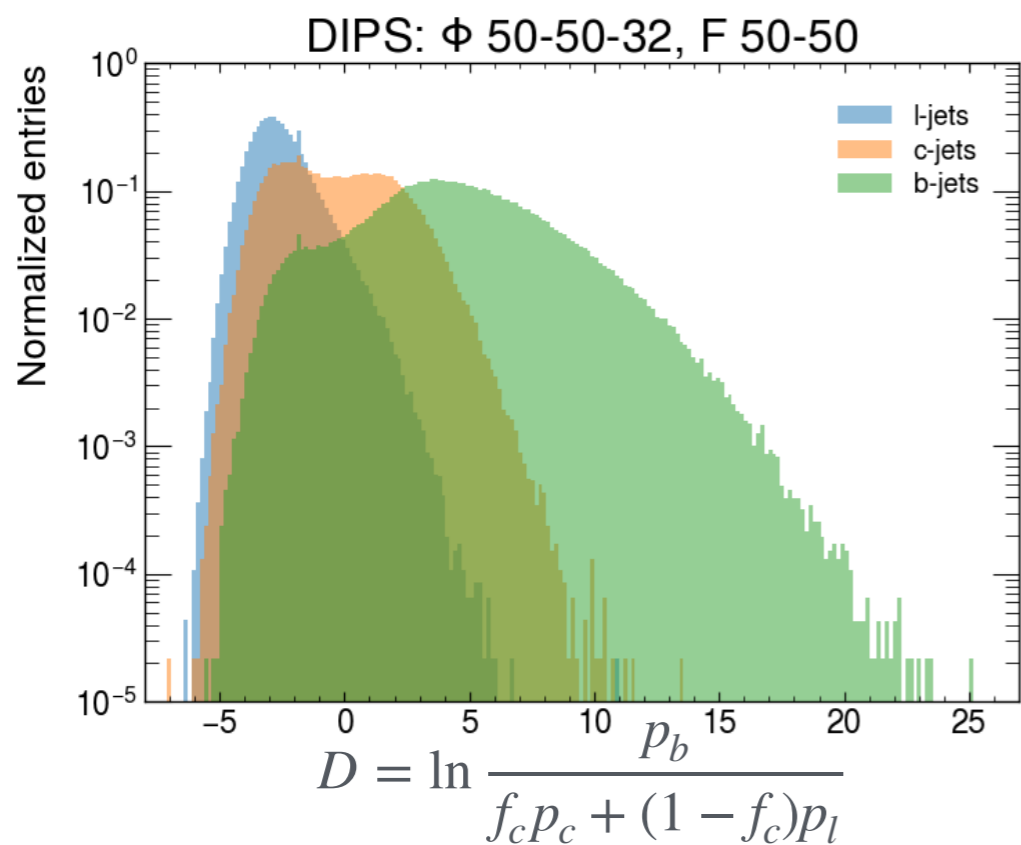


Typical distribution over NN score for flavour tagging.

Different simulated time resolutions of the detector are compared.



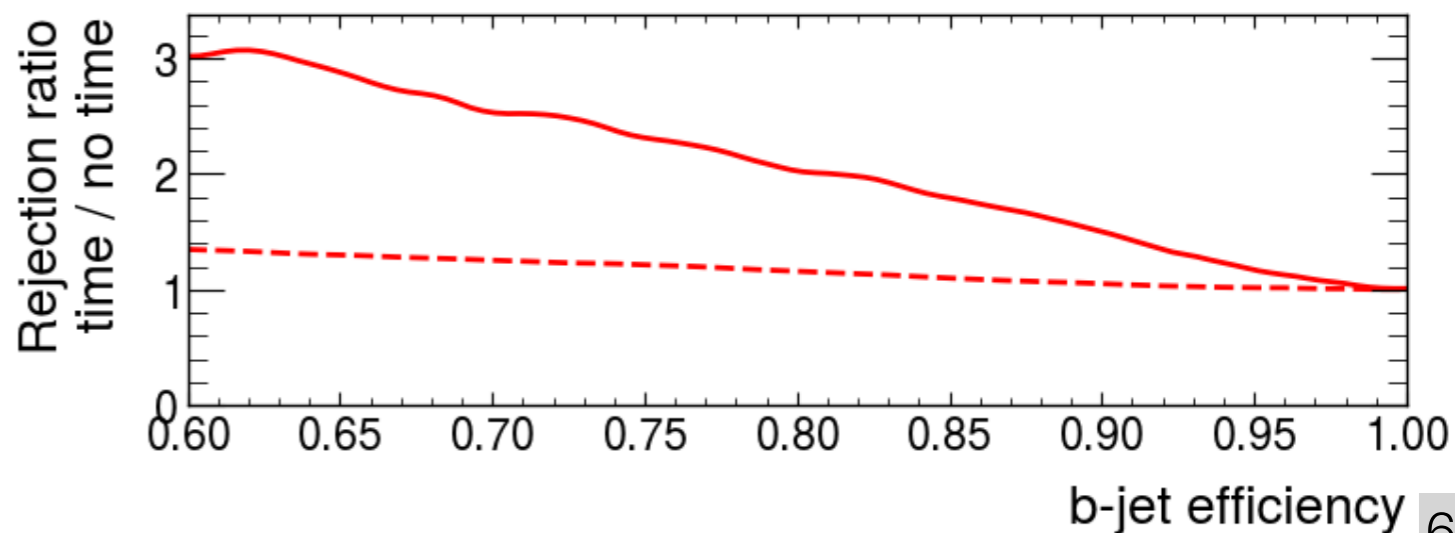
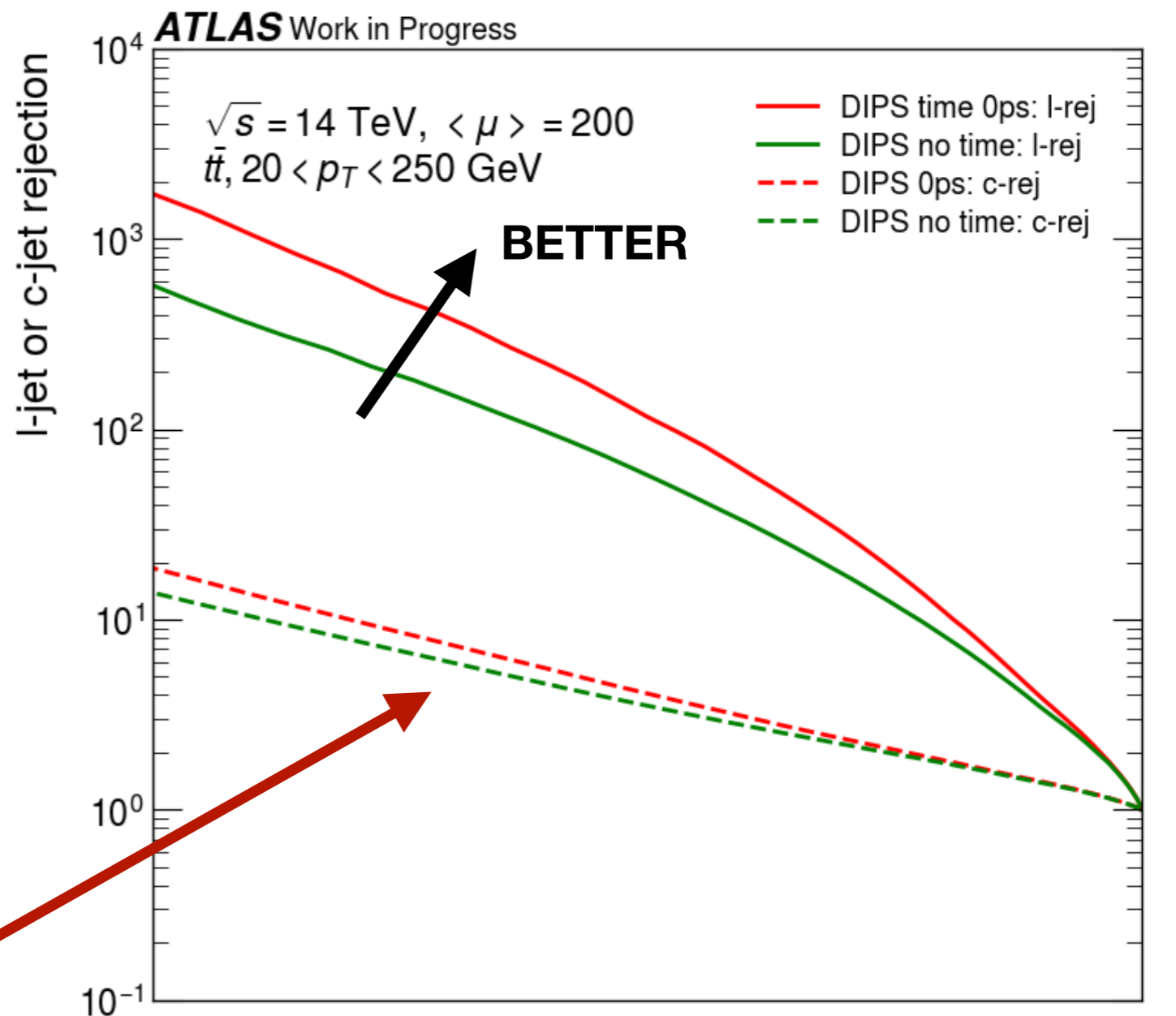
# DIPS flavour tagging results



Typical distribution over NN score for flavour tagging.

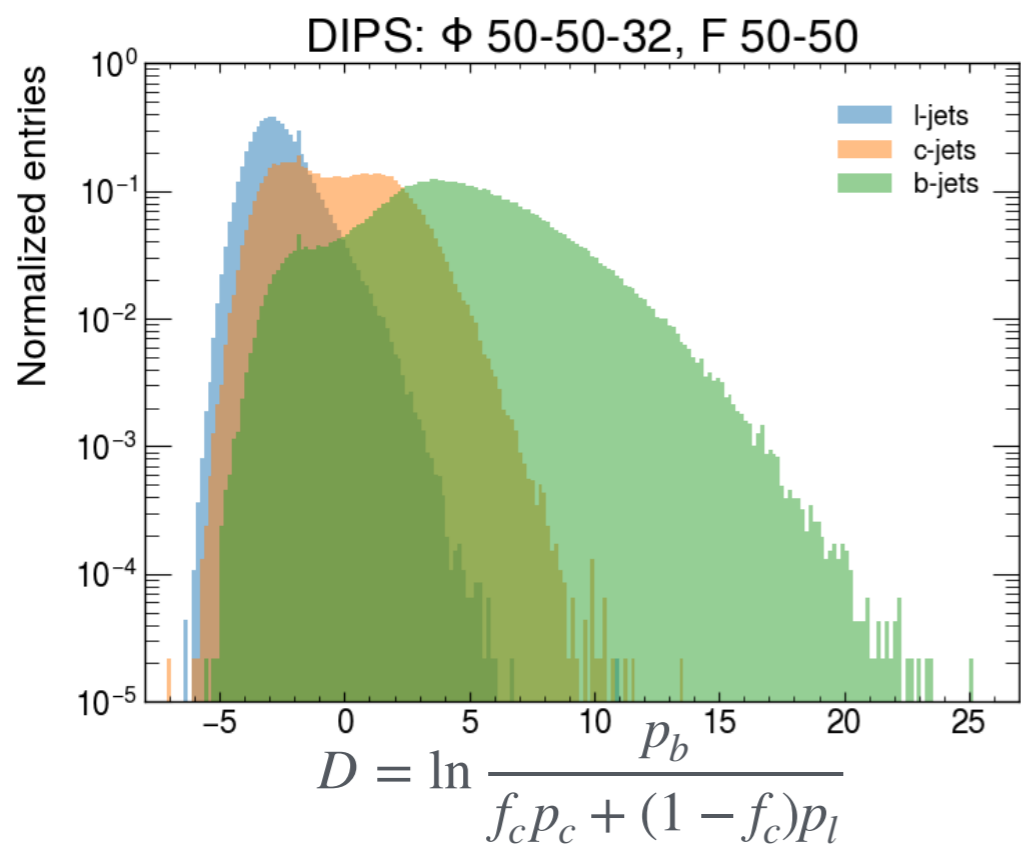
Different simulated time resolutions of the detector are compared.

**TIMING IMPROVES BACKGROUND REJECTION UP TO 3 TIMES FOR PERFECT RESOLUTION.**





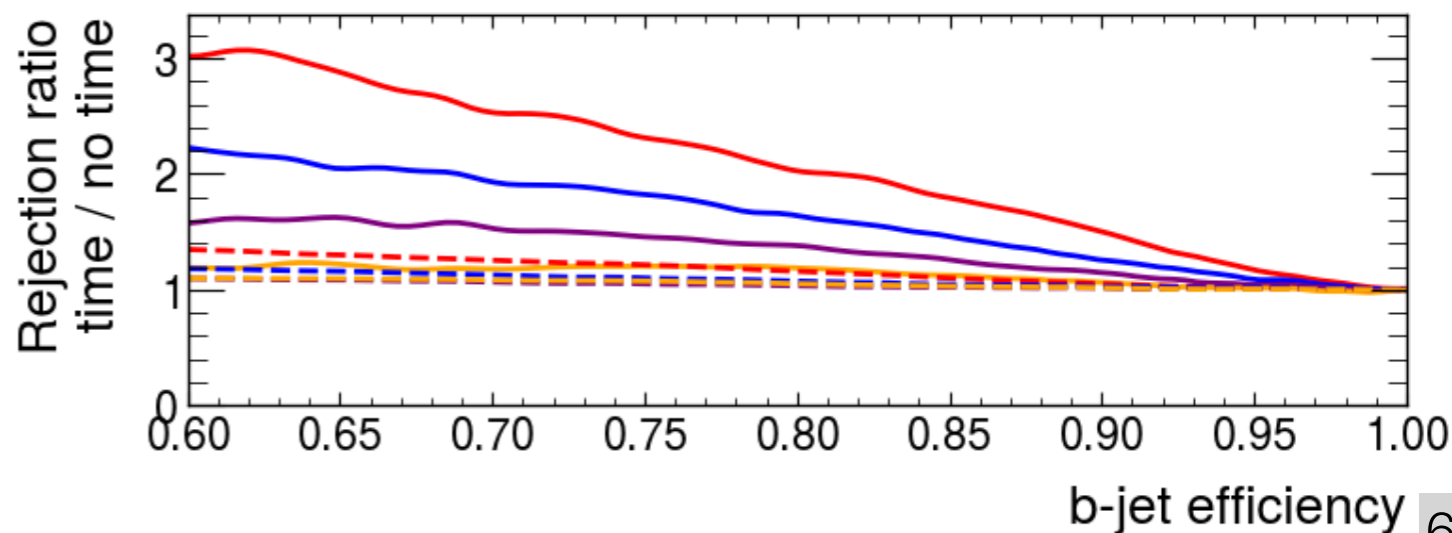
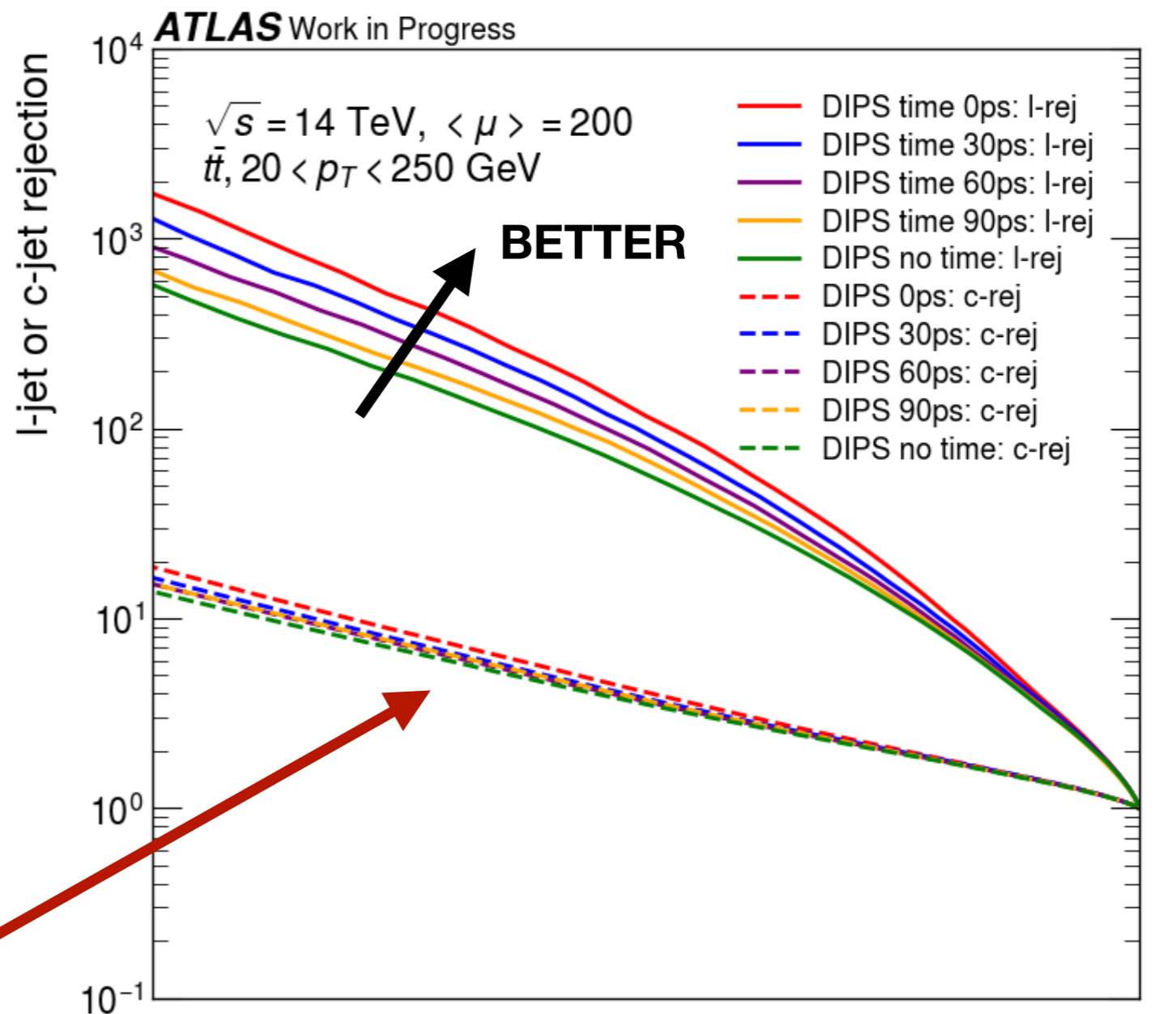
# DIPS flavour tagging results



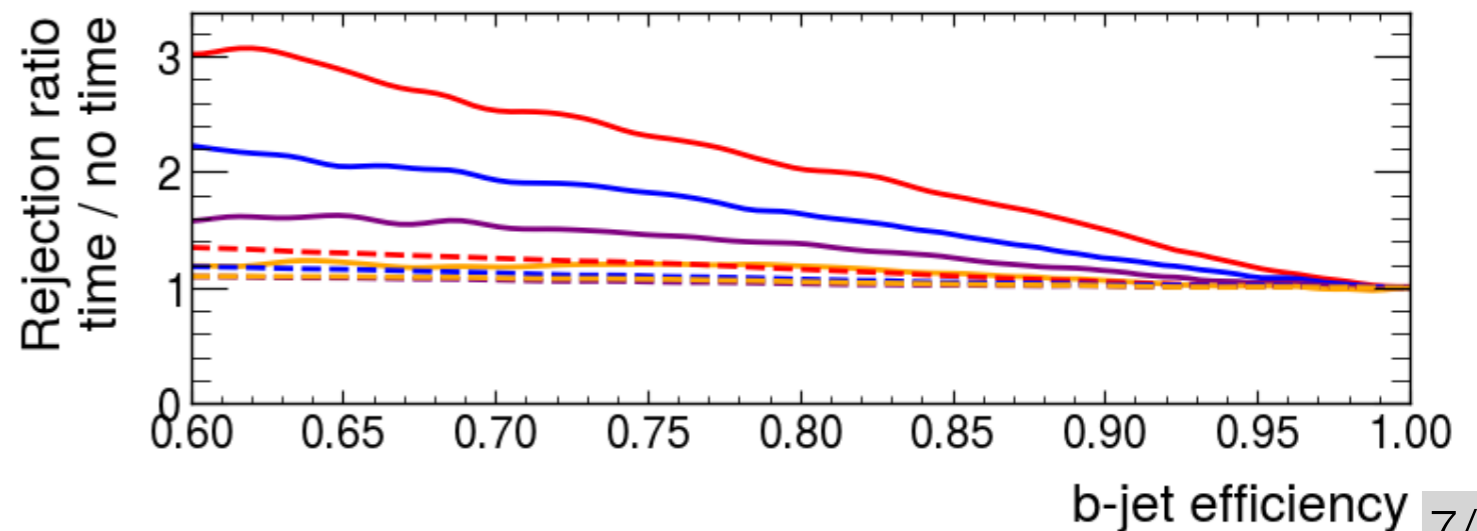
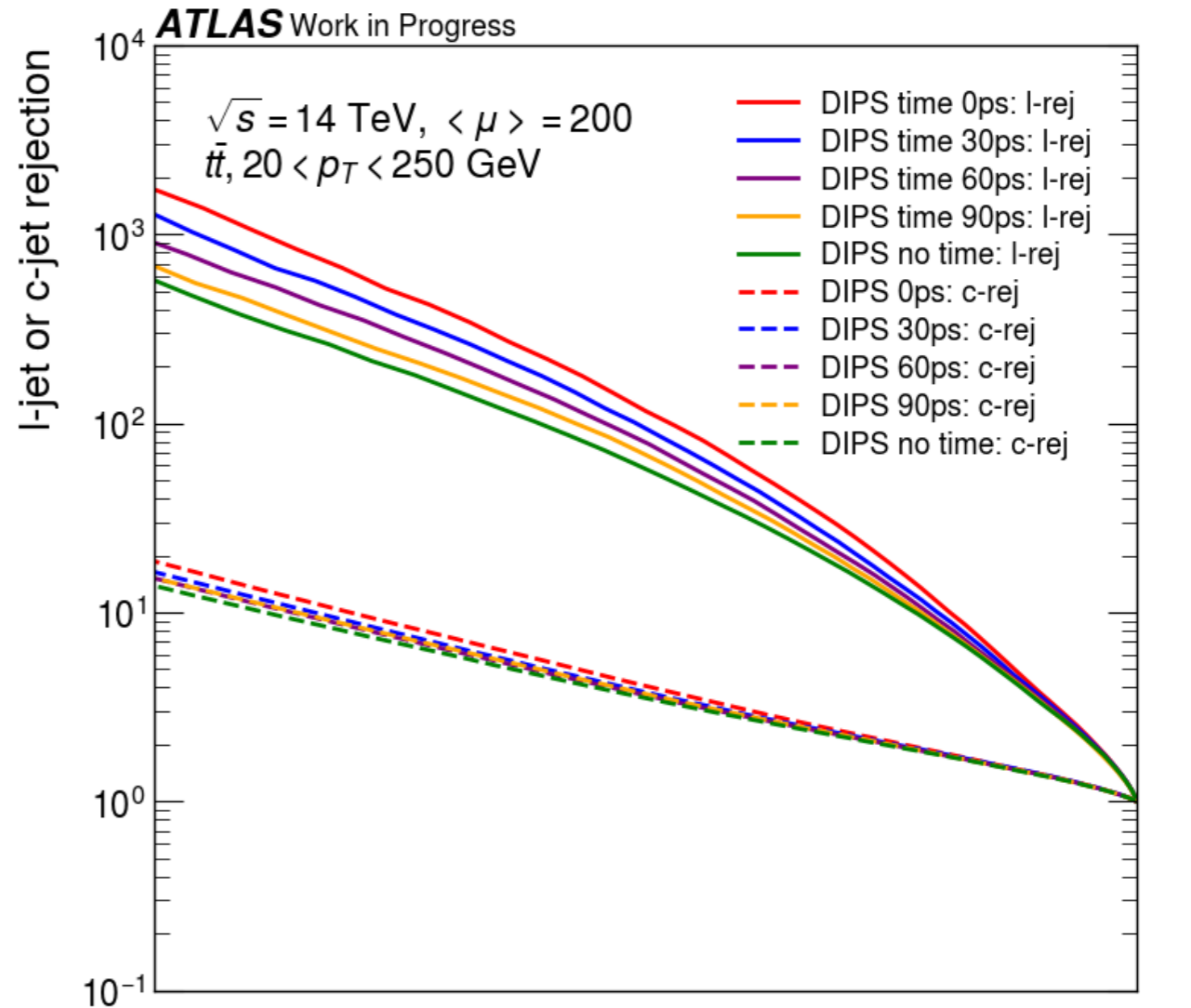
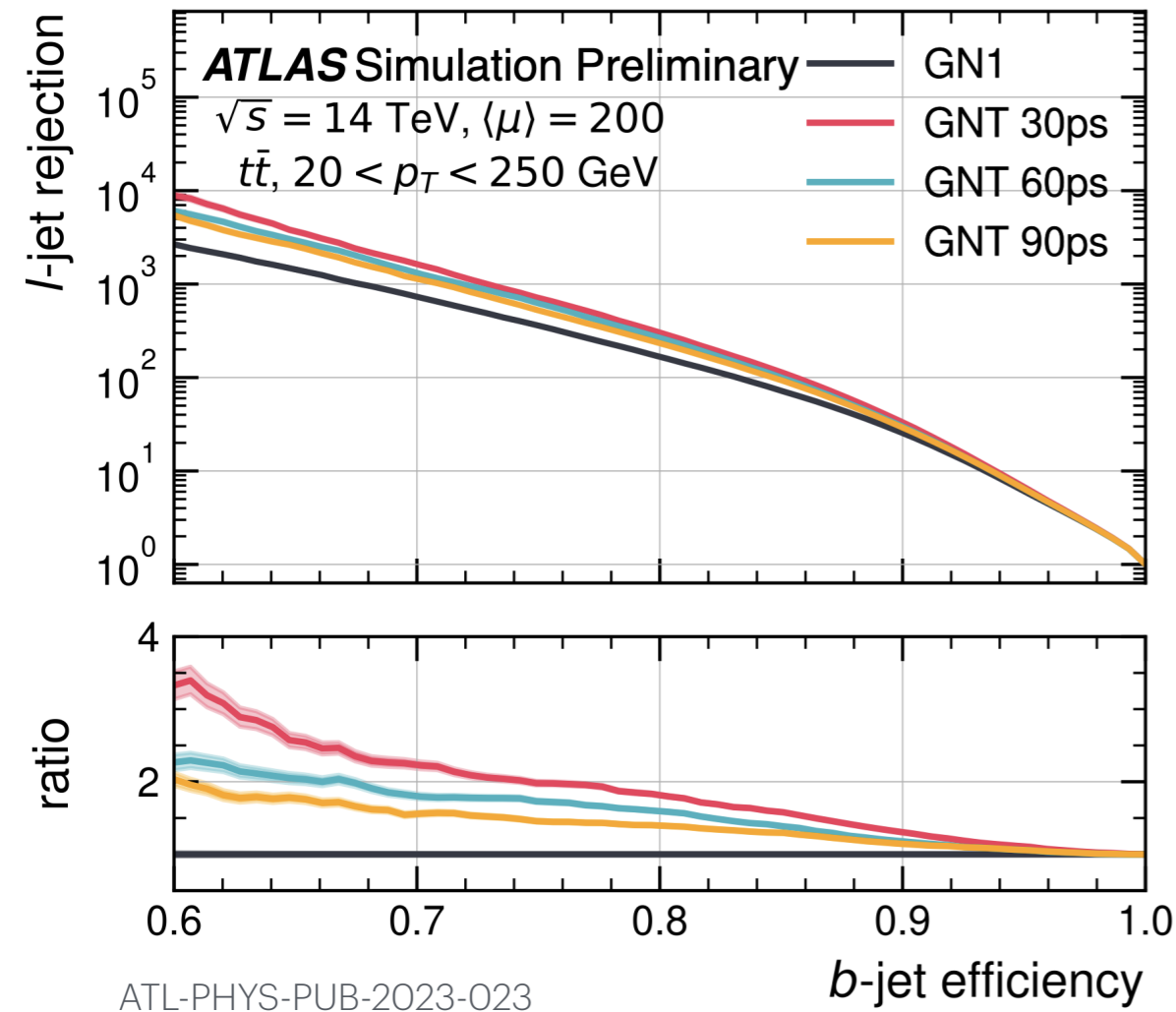
Typical distribution over NN score for flavour tagging.

Different simulated time resolutions of the detector are compared.

**TIMING IMPROVES BACKGROUND REJECTION UP TO 3 TIMES FOR PERFECT RESOLUTION.**

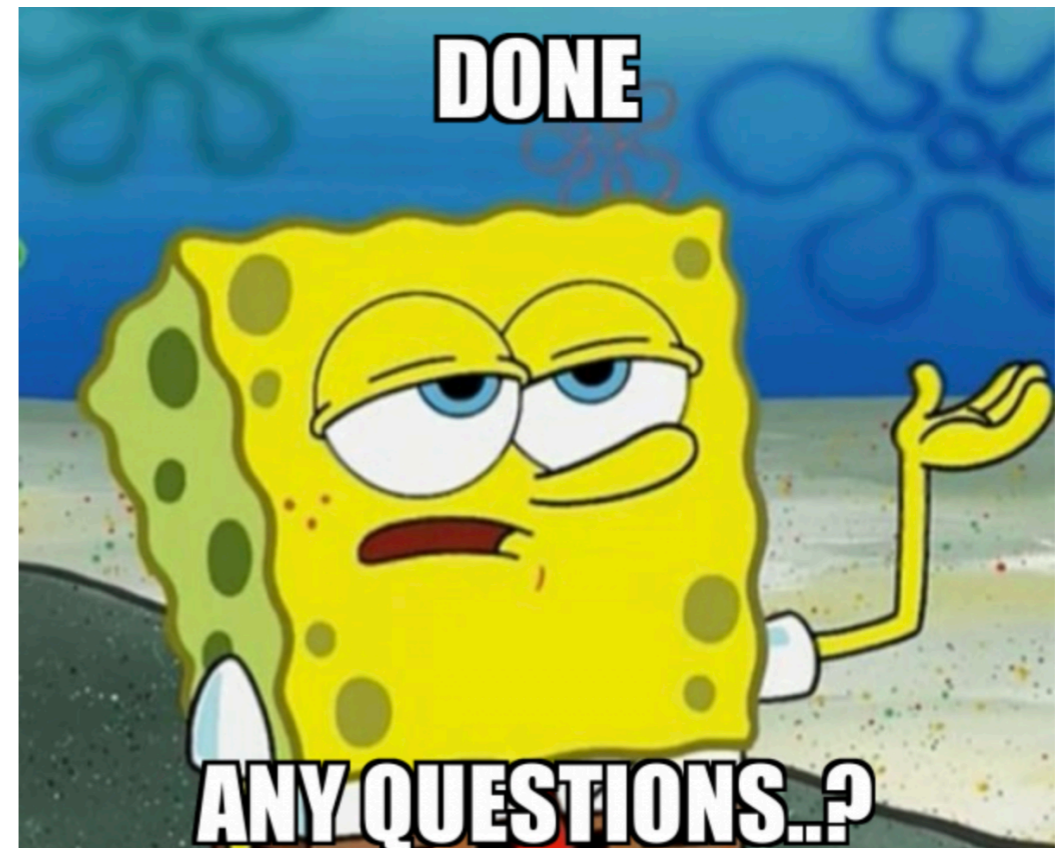


# DIPS vs State of the Art GNN



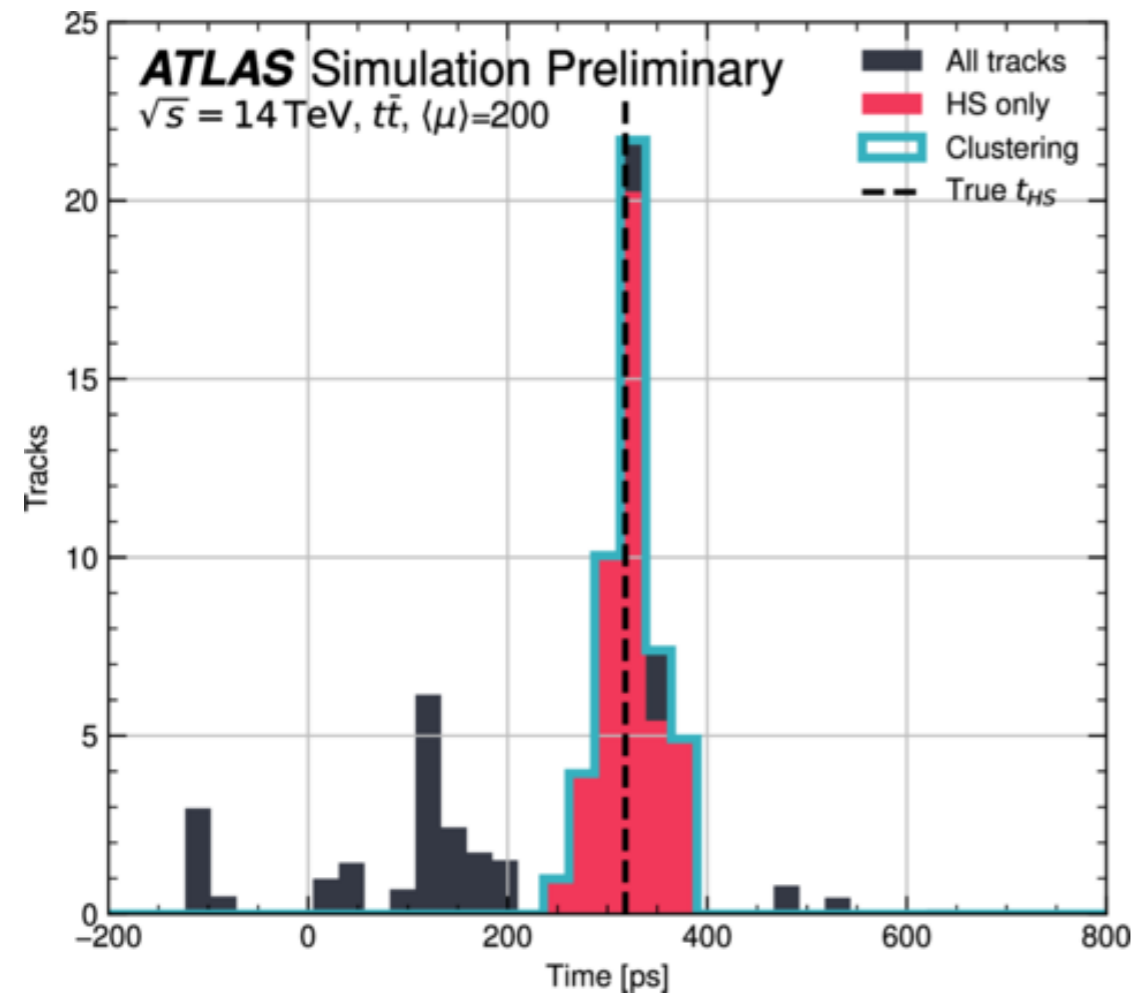
- ATLAS currently uses GN1 variation for ftag.
- GN1 shows even bigger improvement in (ratio of) background rejection with timing.
- Note: GNN was trained on approximately 50% more statistics than DIPS.

A big thanks to my supervisor, Valentina Cairo, and other members of the DIPactS team, including Lorenzo Santi, Pierfrancesco Butti, and Nicole Hartmann.

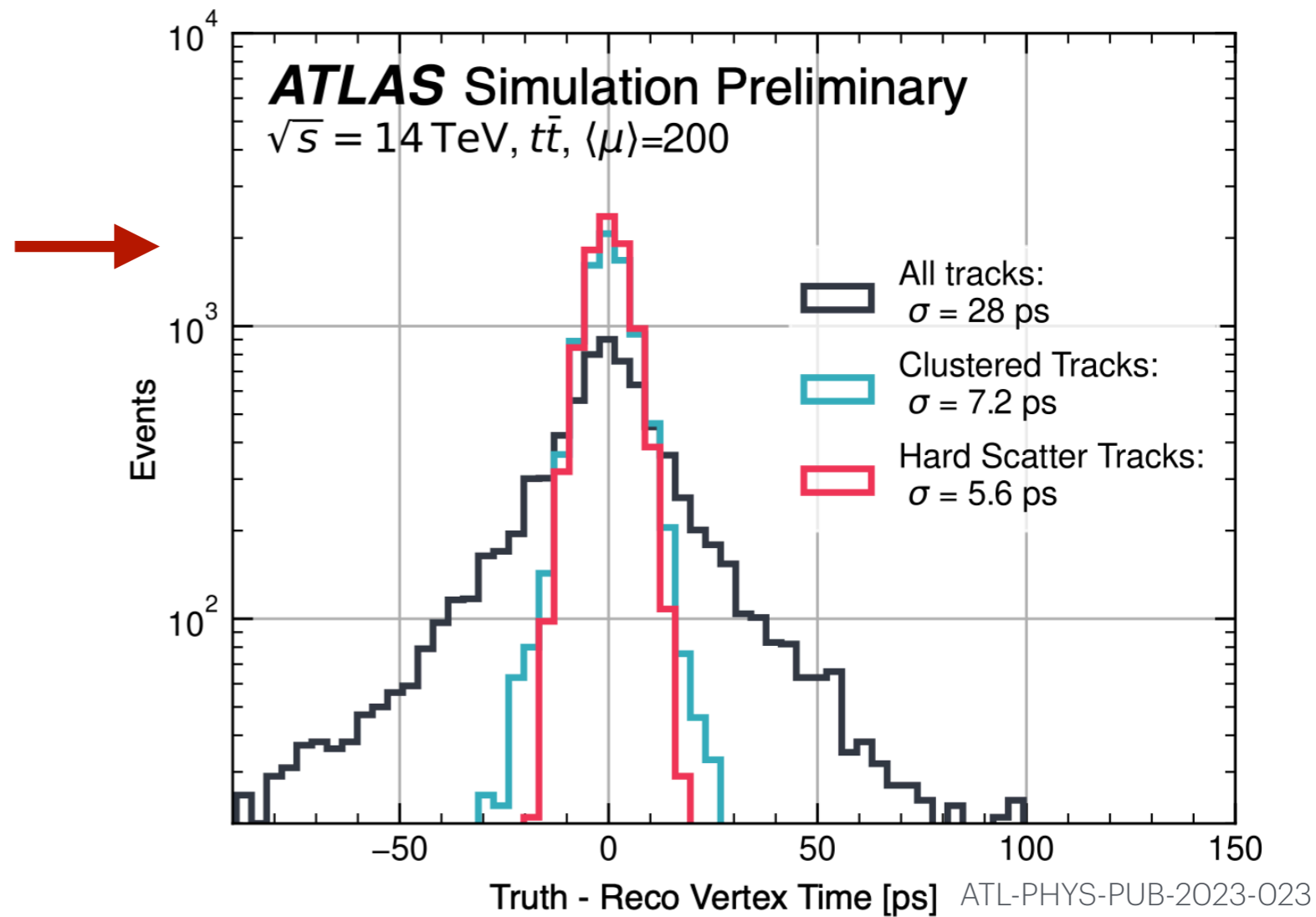


**BACKUP**

# How does timing help?



ATL-PHYS-PUB-2023-023



Timing helps NN reconstruct HS time more precisely.