Di-b-jet as a probe for new physics and phase-2 upgrade of the ATLAS pixel detector

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SYSU - PKU Collider Physics Forum For Young Scientists

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Motivation

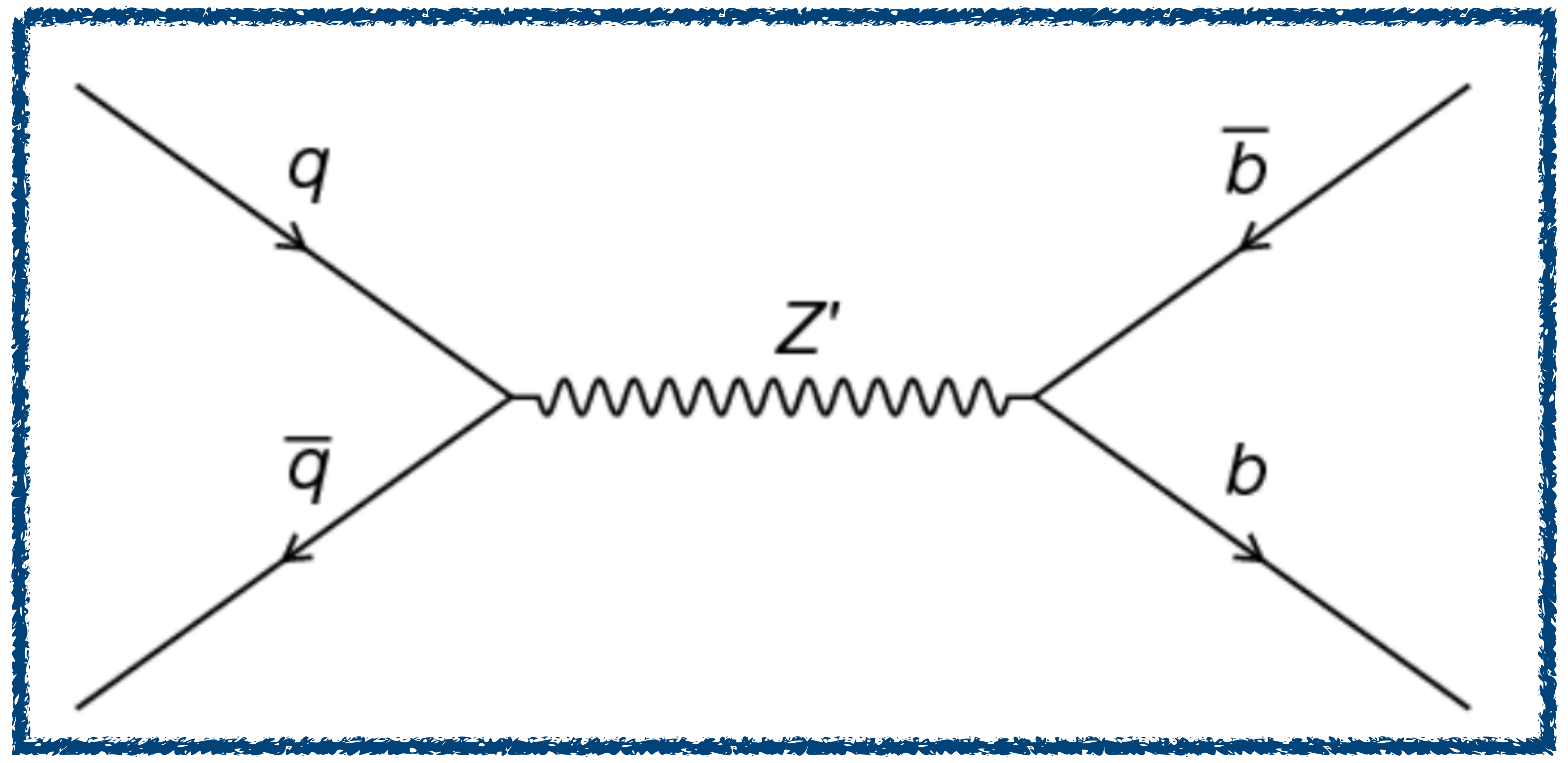
- The discovery of the Higgs boson is a great victory of the Standard Model (SM), however there are many questions remain unaddressed

- Many extensions to the SM have been proposed and a variety of searches targeting those models have been conducted. One of the most popular signatures at ATLAS: dijet final states
  - Created by quarks/gluons -> decay to quarks/gluons
  - Large statistics

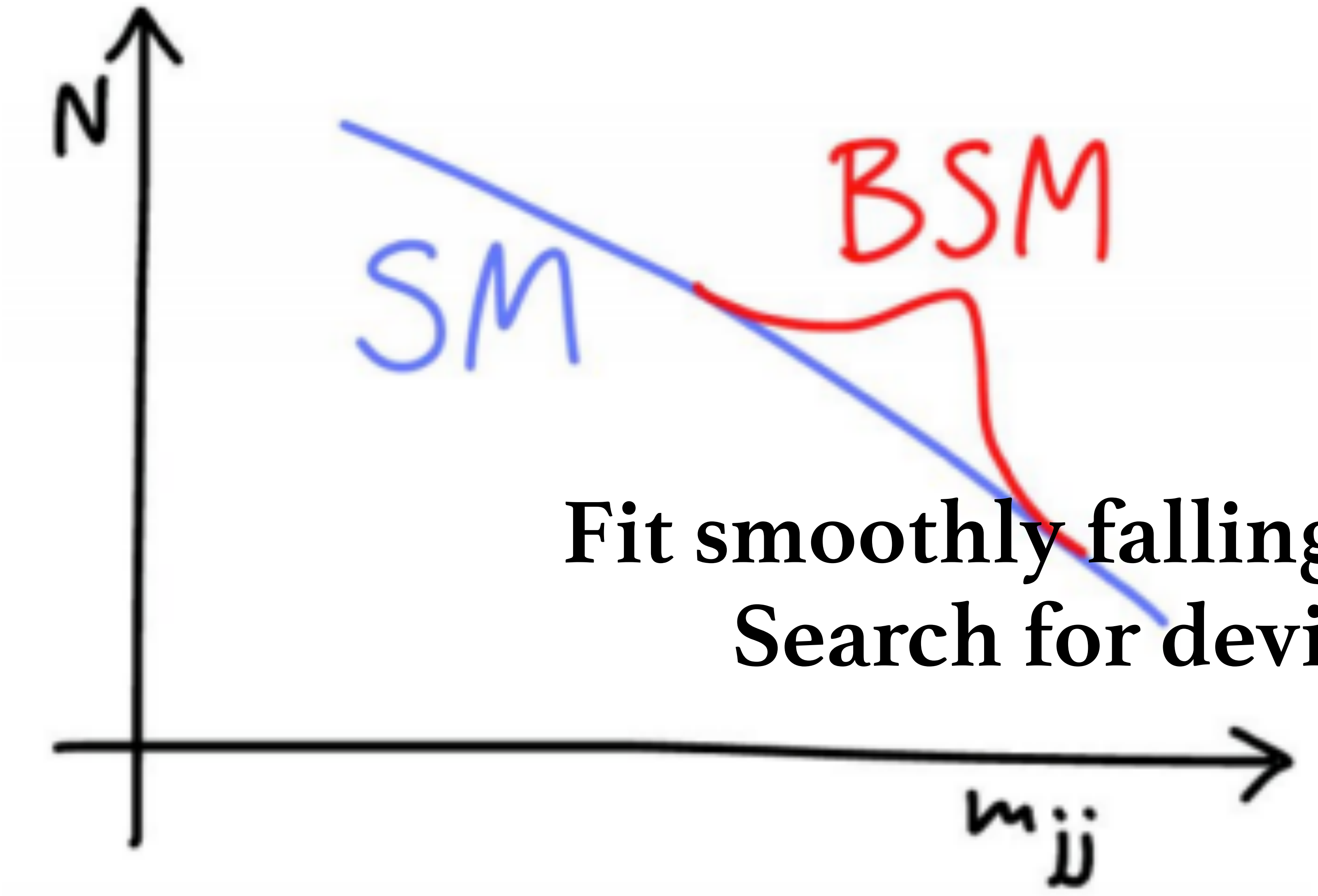
- For some beyond the SM models predict an enhanced coupling to the third-generation quarks
  - Sensitivity to such models can be dramatically improved by requiring the jets from the resonance decays to be tagged as originating from a b-quark

Di-b-jet Search

JHEP03(2020)145



Invariant mass distribution from
leading and sub-leading jets

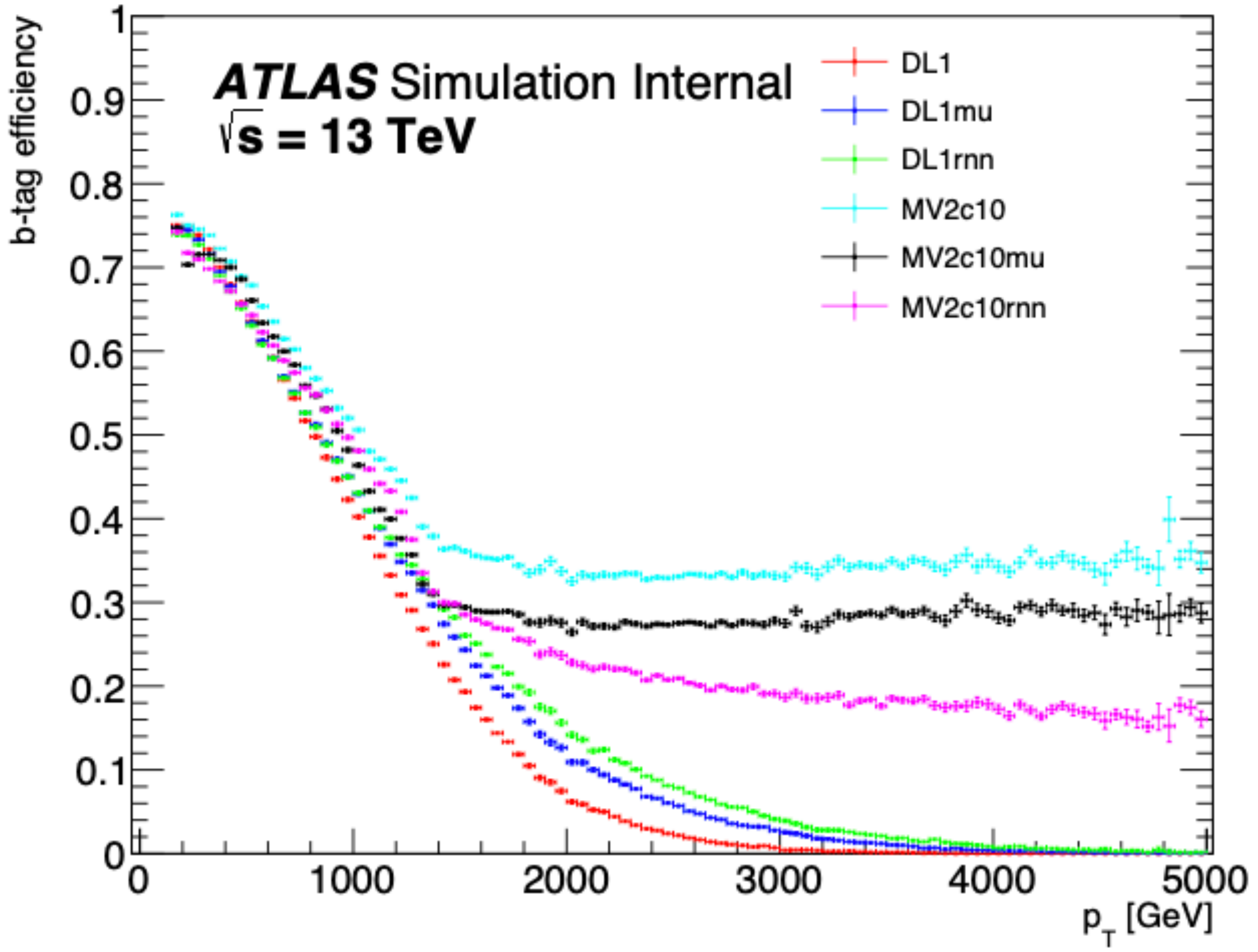


Fit smoothly falling SM background
Search for deviation from it

Limits setting on the BSM models if
no significant deviation found

Analysis Selection

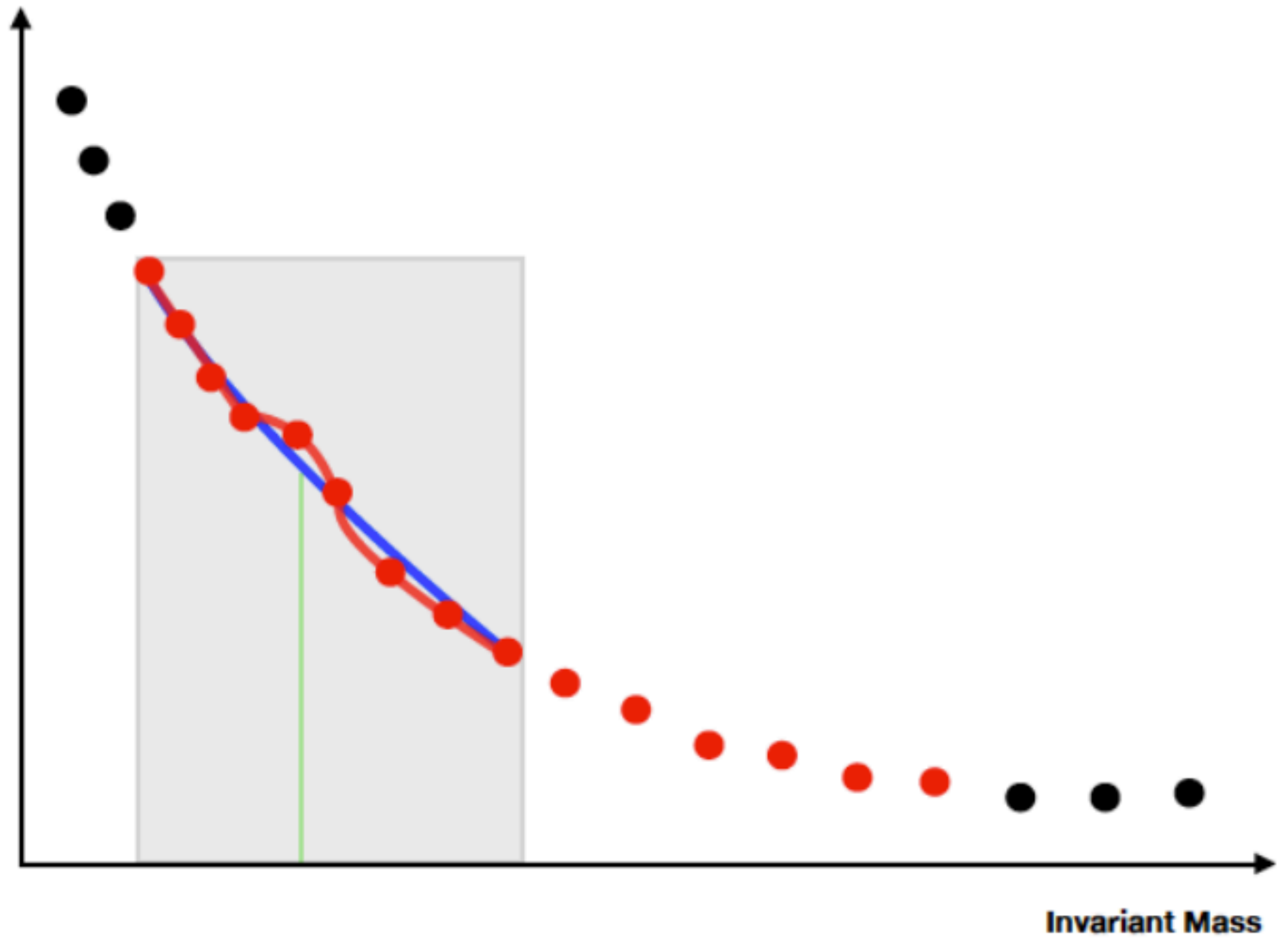
- Full Run-2 dataset collected by the ATLAS detector used
- Pre-selection
  - Single, small-radius jet trigger used: HLT-j420
  - To improve searching sensitivity:
    - Background: mainly 2-2 scattering in QCD; dominate in t-channel
    - Upper bound on jet rapidity difference placed: $|y^*| = \frac{1}{2}|y_1 - y_2|$
  - B-tagger: DL1r tagger at 77% selected
    - Smoothness of the invariant mass distribution
    - Sensitivity



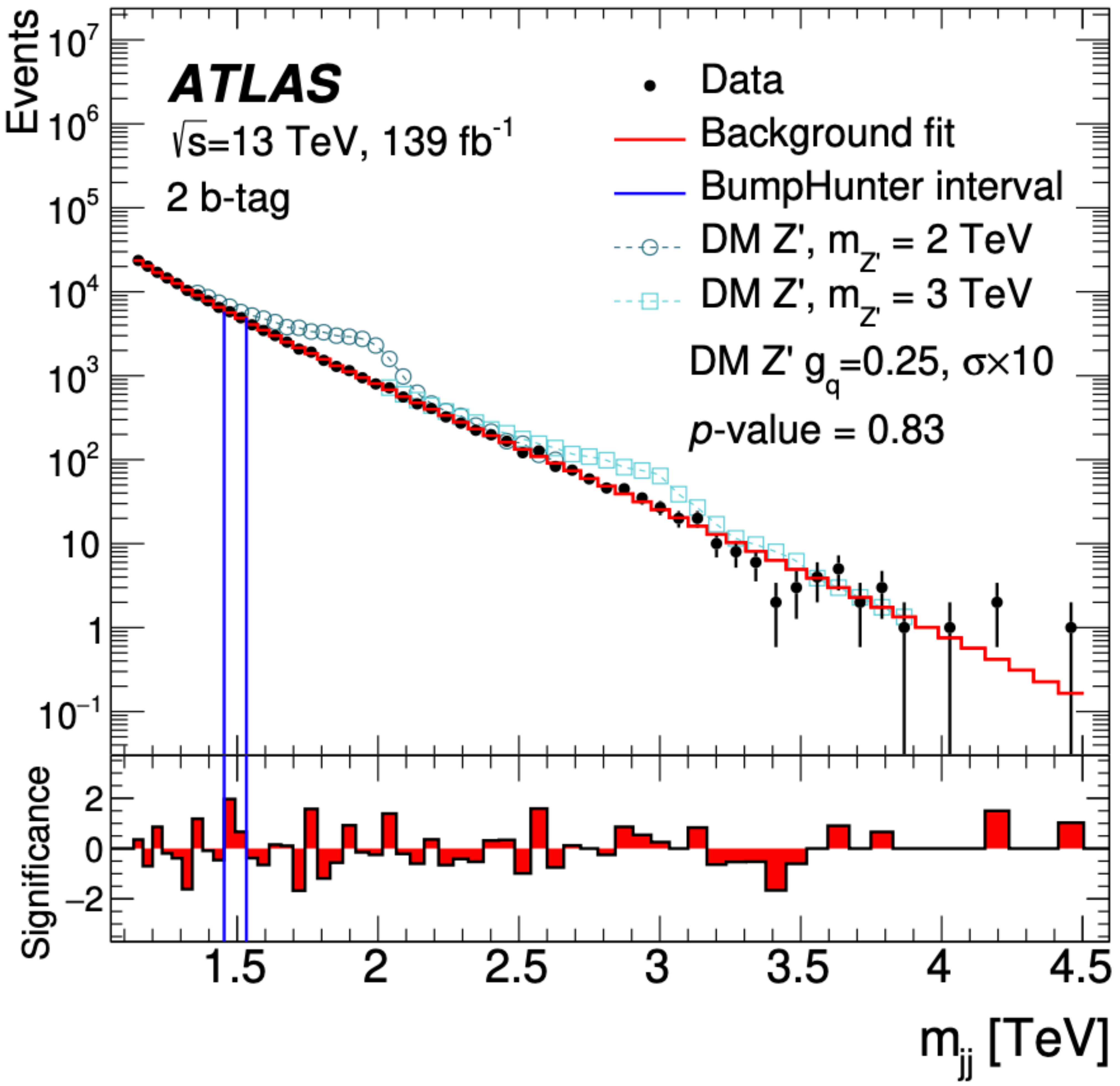
Search Result

- The SM background of the m_{jj} spectrum is determined by a functional fit to data:

  $f(x) = p_1(1-x)^{p_2}x^{p_3+p_4x}$, where $x = m_{jj}/\sqrt{s}$
- Sliding Window Fit (SWiFt) instead of global fit employ:
  - Sliding localized fit on smaller m_{jj} range
  - Background in each mass bin is predicted by fitting in a mass window around that bin

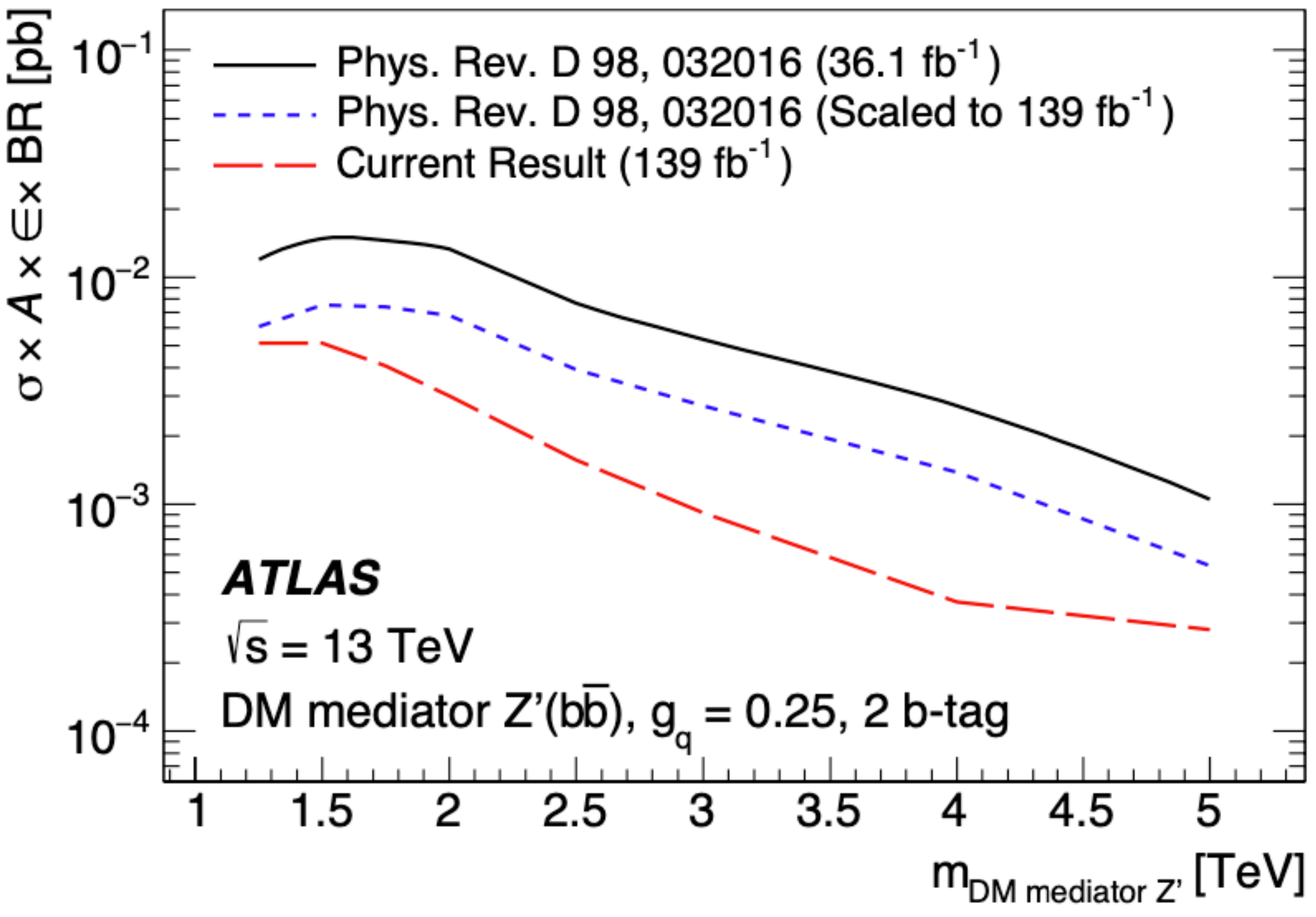


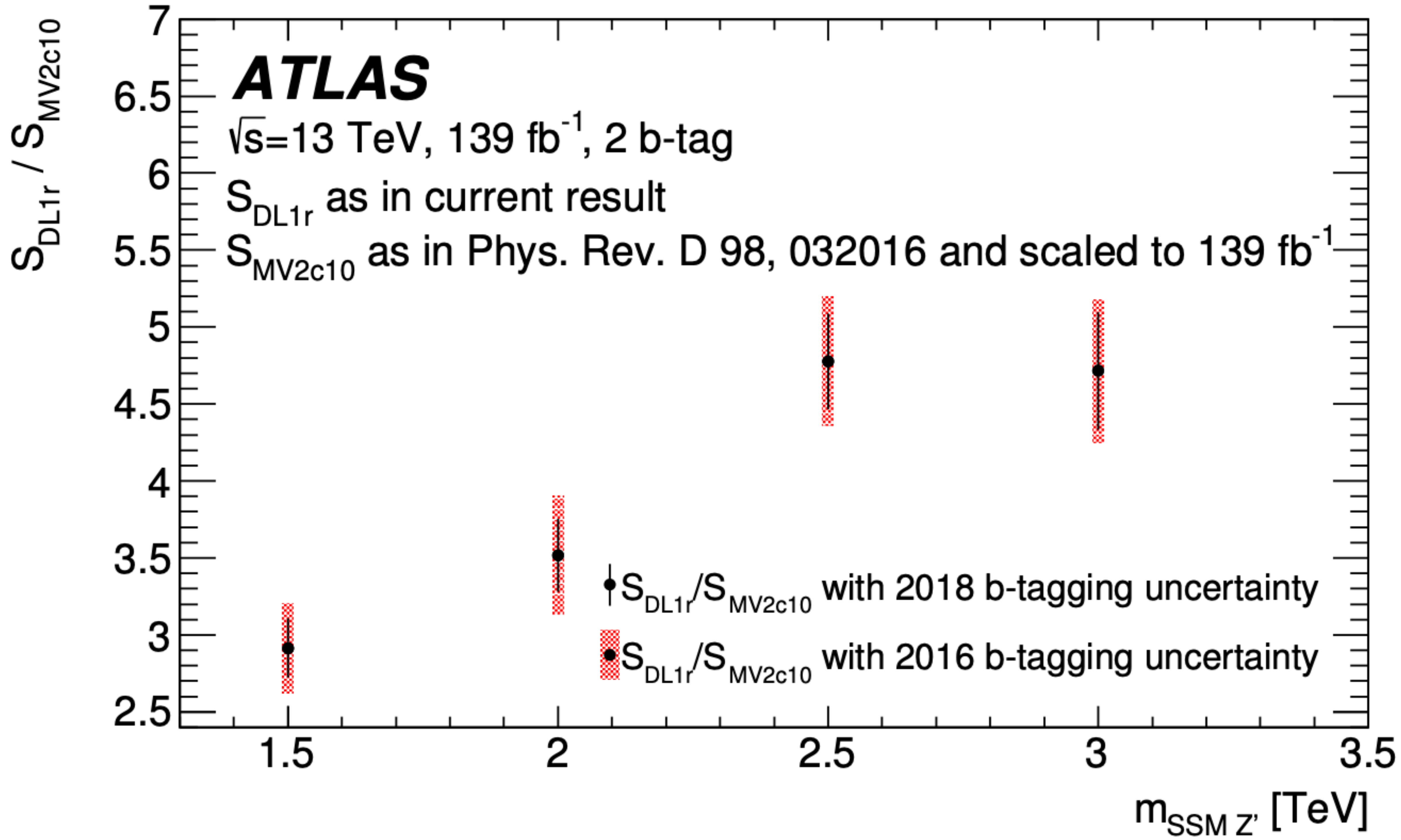
- No significant deviations observed.



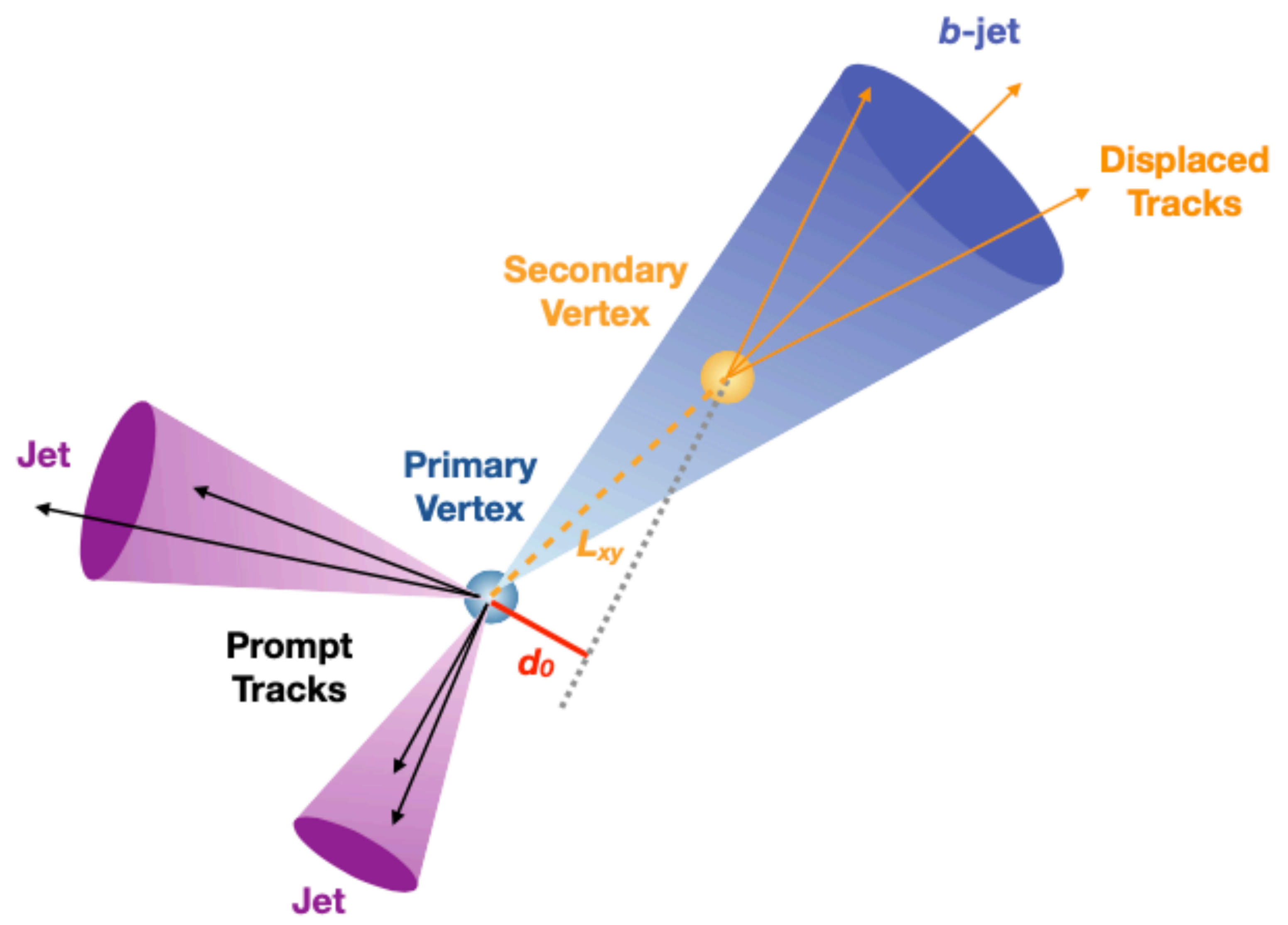
Limit & Improvement

- Stringent limit on models with heavy resonances in hadronic final states
- Comparing to previous di-b-jet analysis:
  - A factor within 1.2 and 3.5 improvement seen, maximum at 4 TeV
  - Benefits from substantial improvement in the b-jet tagging algorithm and associated systematic uncertainties





B-jet Identification … in ATLAS



B-tagging reply on B-hadron properties:

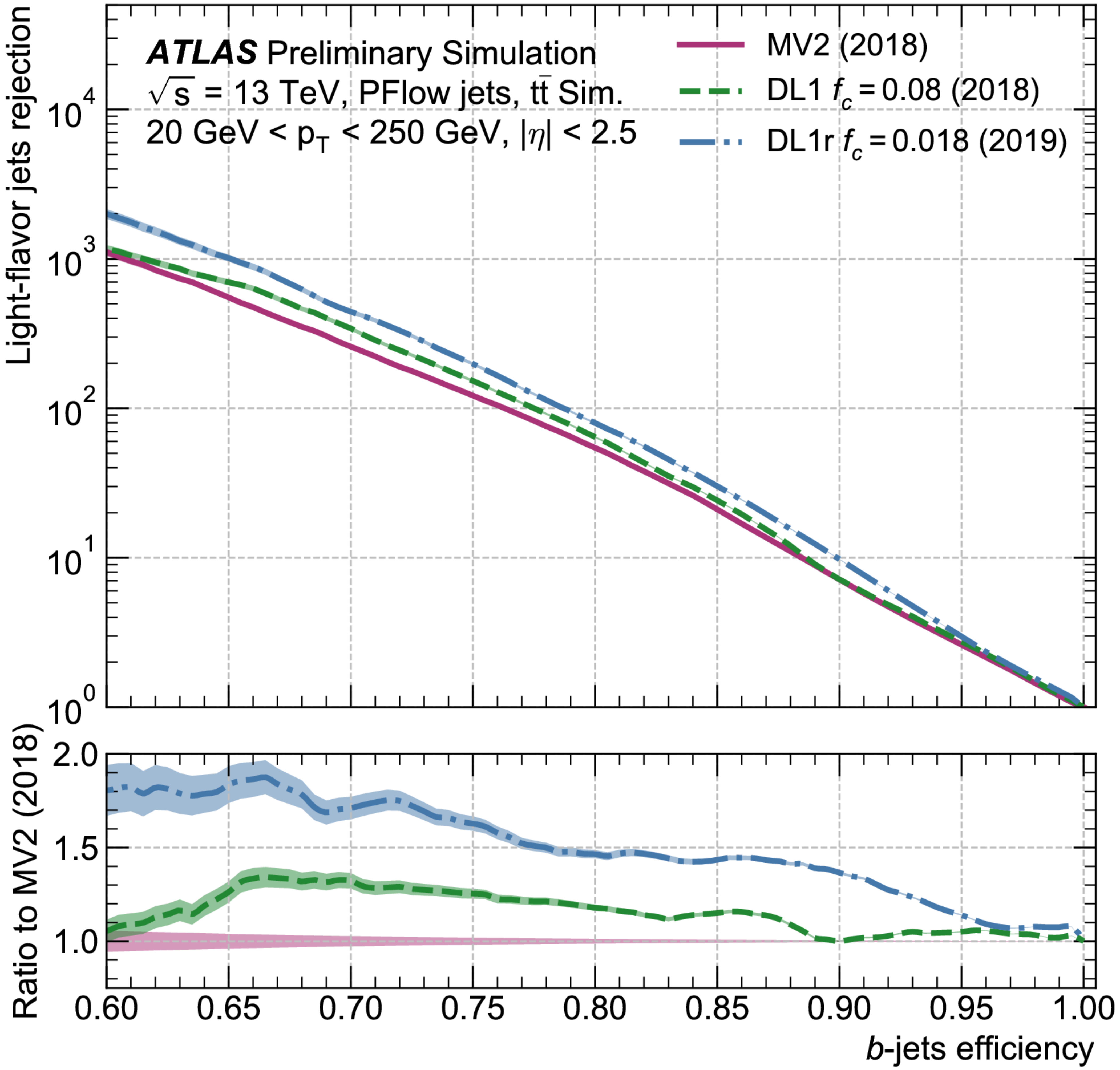
- **Relatively long lifetime**
  - Introduce a displaced vertex
- **Large mass**
  - Decay products tend to have higher transverse momentum
- **Semi-leptonic decay with a soft muon**
  - Have higher multiplicities

$p_T, |\eta|$ | IPxD | SV1 | JetFitter | RNNIP | SMT

machine learning techniques → **Boosted Decision Tree** / **Deep Neural Network**

B-tagging Score

B-jet Identification … in ATLAS



Neural Network-based taggers outperform BDT-based tagger with increased statistics

- Tagger performance is better
- Less time consuming

DL1r outperform DL1 tagger

- Benefits from RNNIP: take correlations between tracks into account

New b-taggers for Run 3

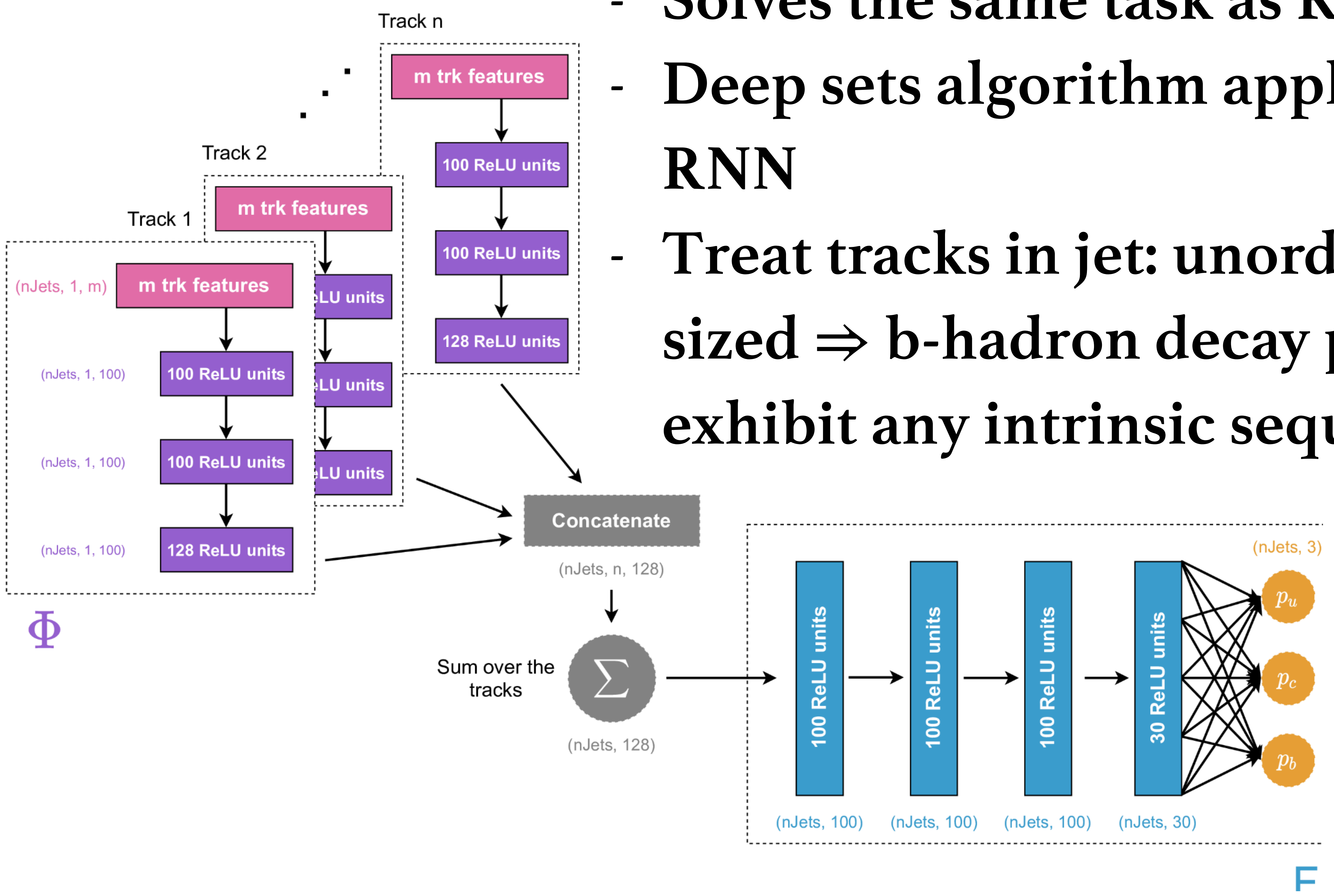
FTAG-2021-004
ATL-PHYS-PUB-2022-027

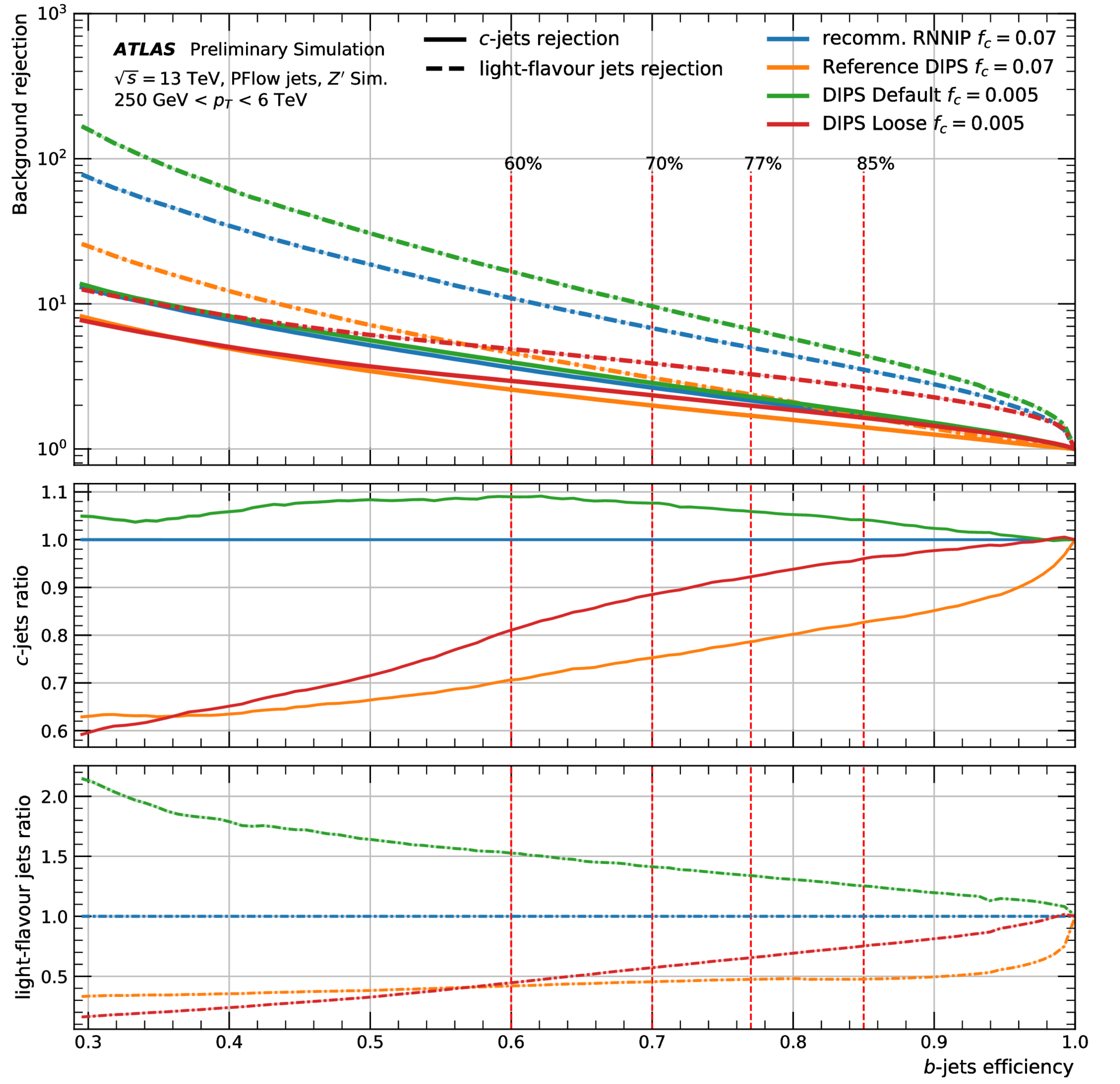
New b-taggers for Run 3 are being developed

- New machine learning techniques applied: deep sets, graph neural network
- Great improvements have been observed

DIPS:

- Solves the same task as RNNIP
- Deep sets algorithm applied instead of RNN
- Treat tracks in jet: unordered, variable-sized ⇒ b-hadron decay products do not exhibit any intrinsic sequential ordering





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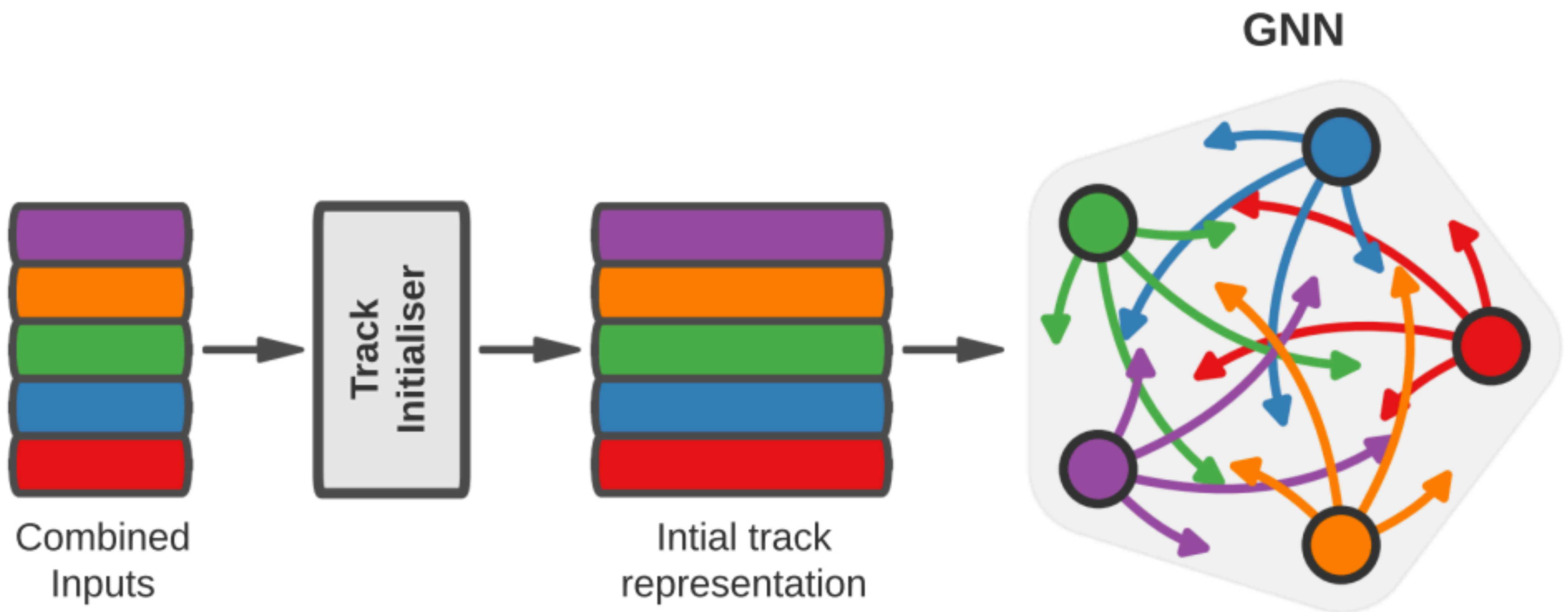
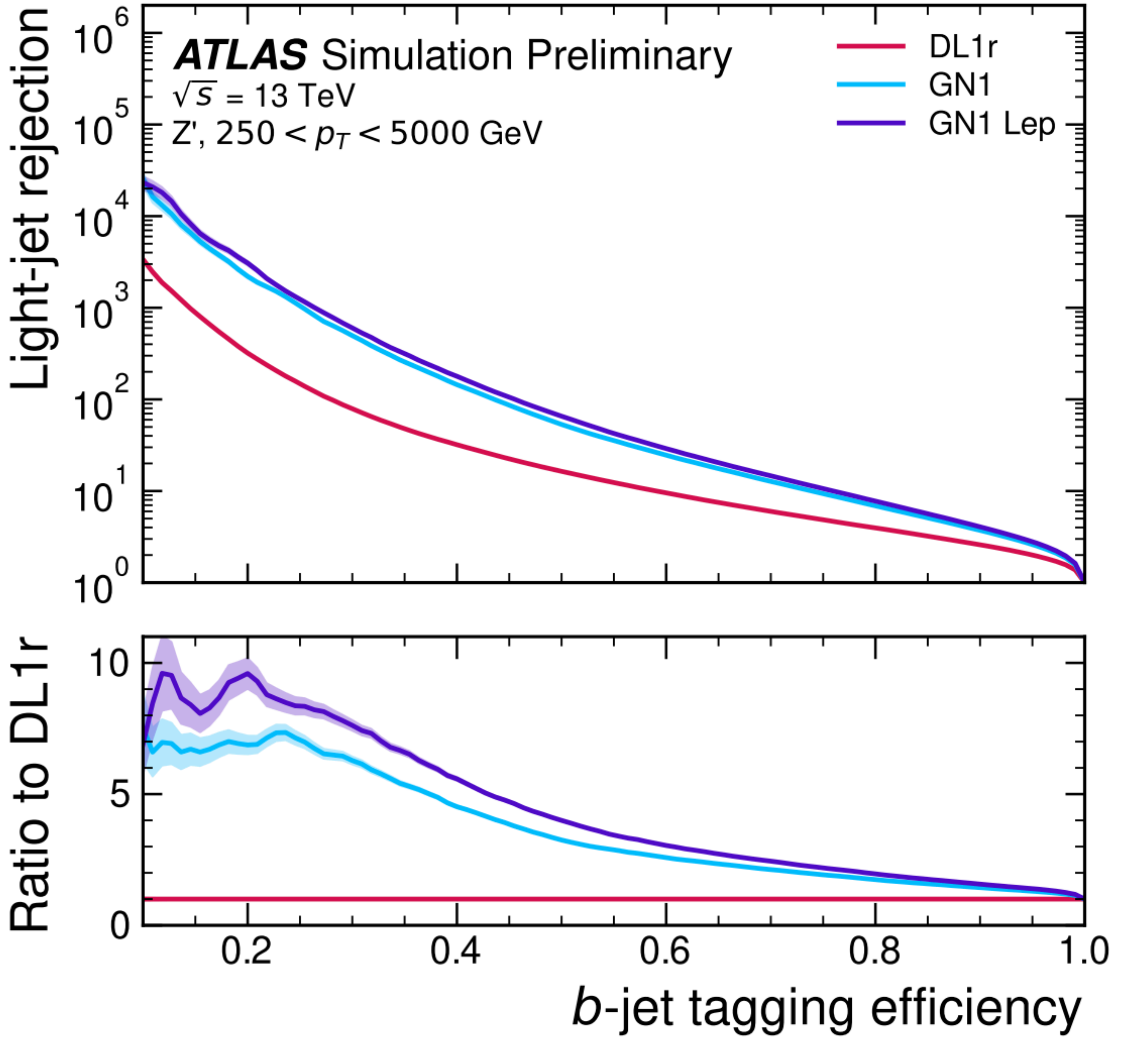
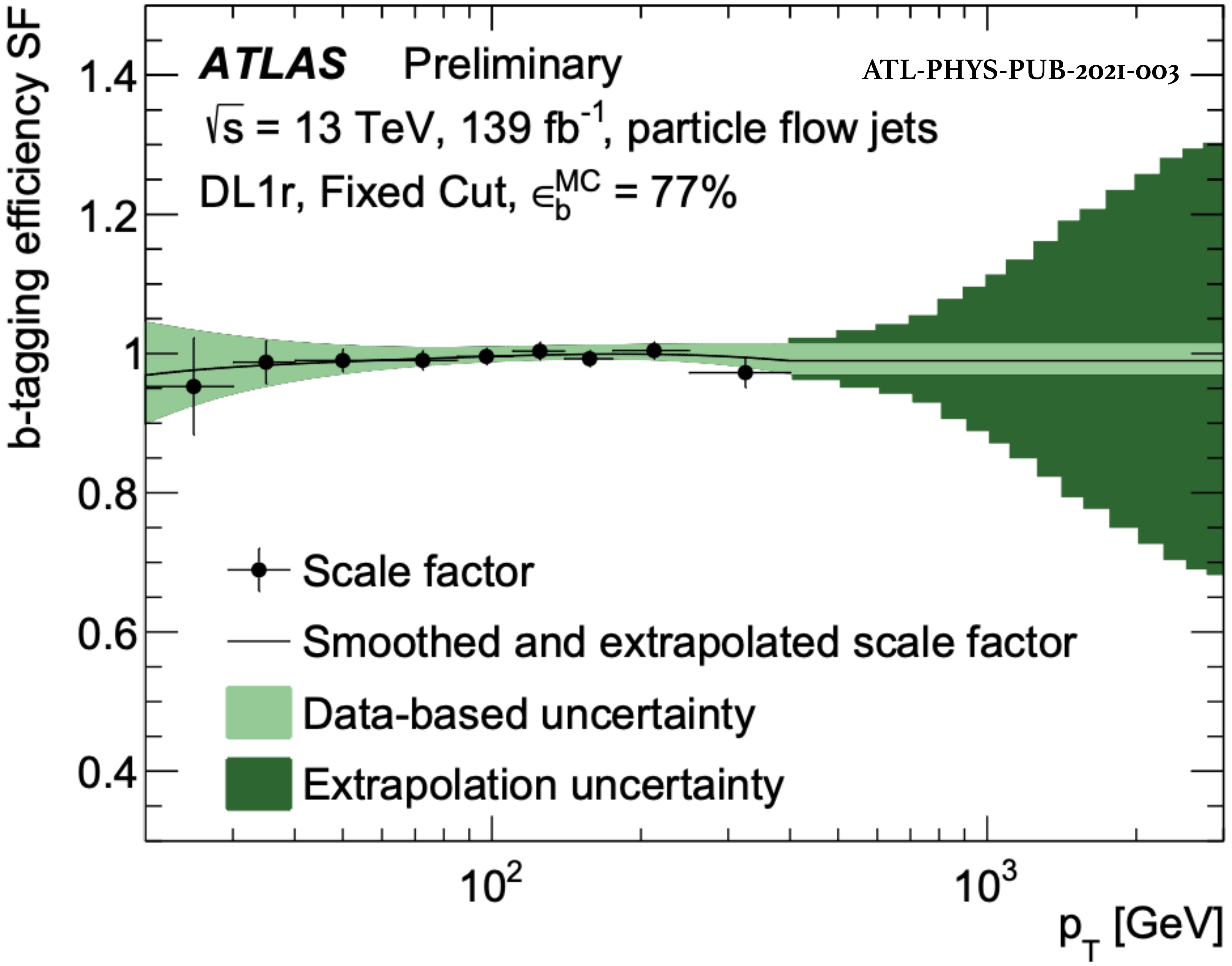


GN1: predict jet flavour without the need for intermediate low-level algorithms



Calibration

- For both BDT and NN-based taggers
  - Calibration obtained in the forms of data-to-simulation scale factors (SFs)
  - Uncertainties are added to the SFs
    - Data-based uncertainty at $p_T \leq 400$ GeV
    - Data-based + extrapolation uncertainty at $p_T > 400$ GeV



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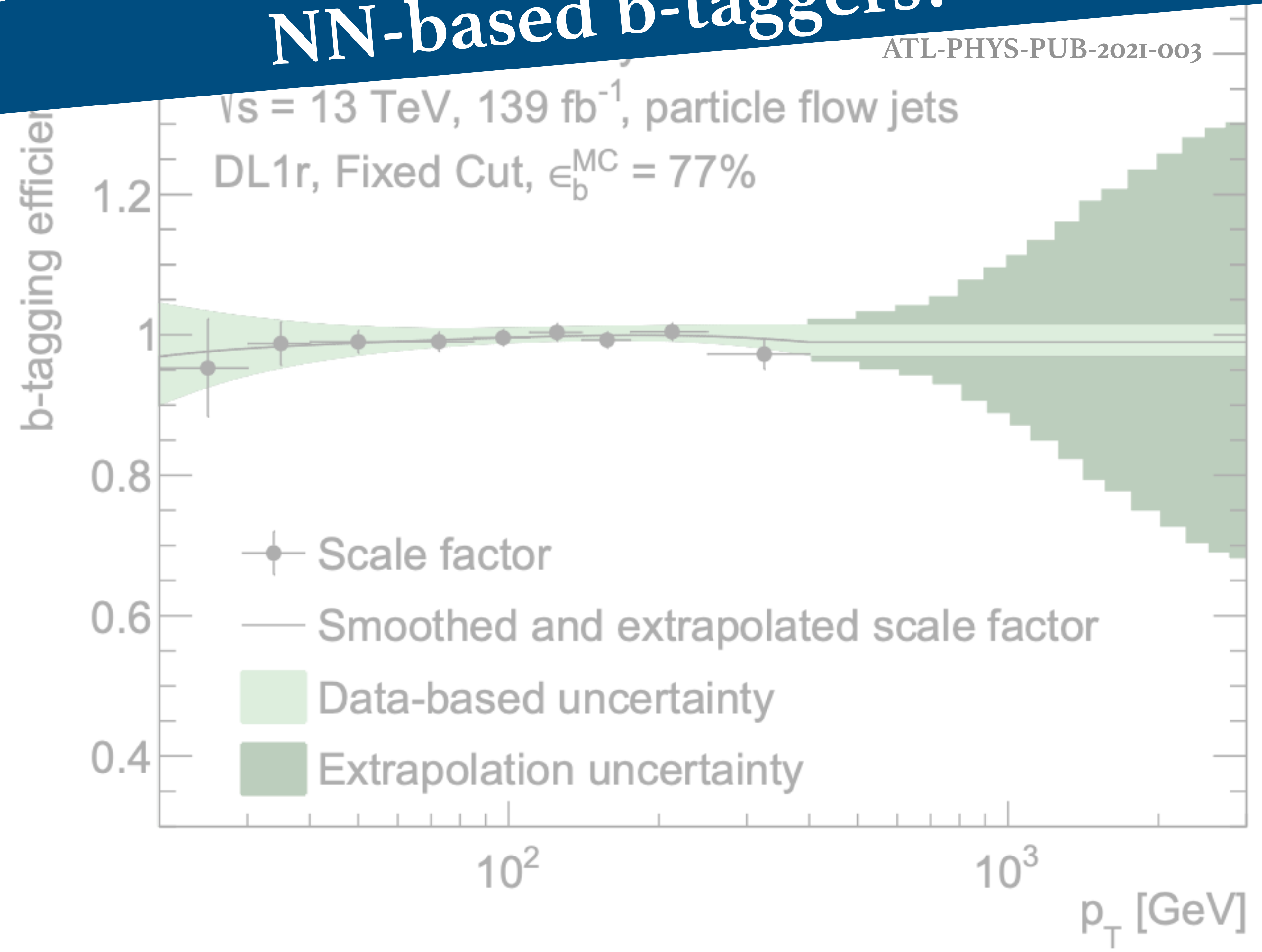
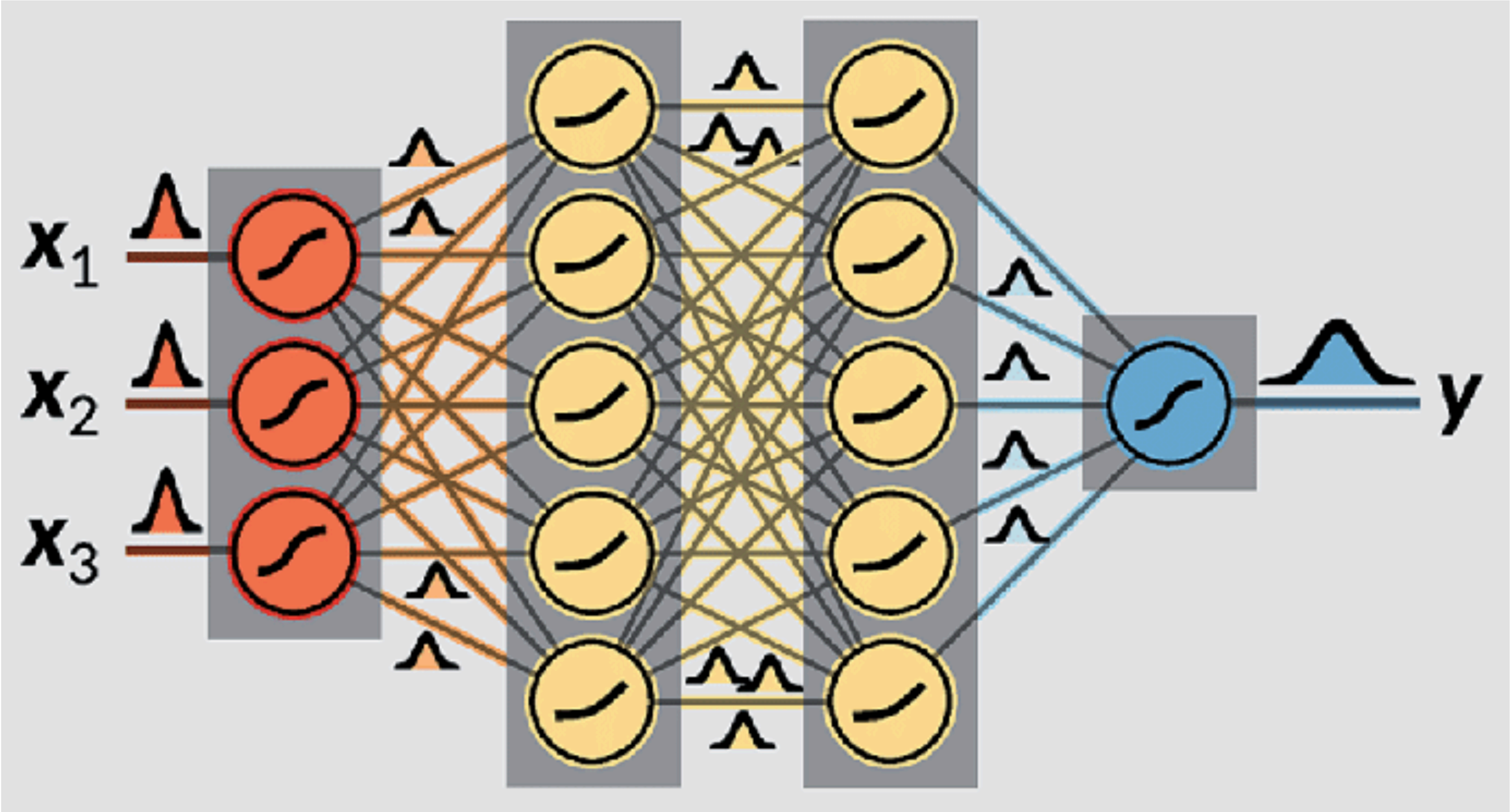
Are there other ways to handle the uncertainties of NN-based b-taggers?



NN Uncertainty Quantification

- **Deep neural network model:**
  - **What do the output "probabilities" tell us?**
  - **How to tell if the model is making sensible prediction or giving random answers?**
  - **Does the model know what it doesn't know?**

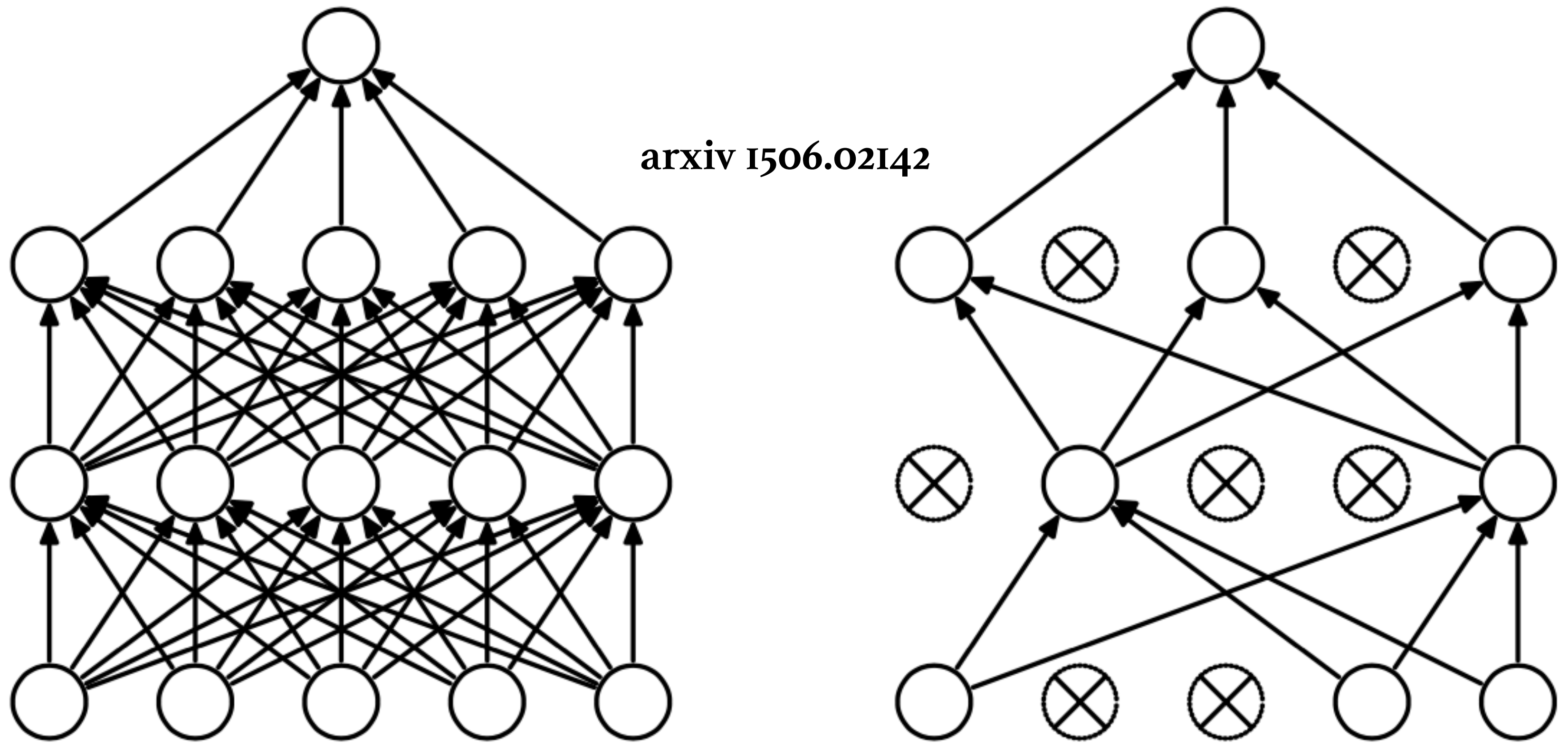
- **Uncertainty quantification (UQ) can help answer the questions:**
  - **Bayesian Neural Network (BNN): offers a mathematically grounded way, however**
    - Difficult to use
    - Hard to choose a good prior
    - Slow to train and computationally expensive
  - **Dropout Uncertainty Quantification (DUQ):**
    - Proposed by Y. Gal in 2016
    - Claims by enabling Dropout during evaluation provide an approximation of the network's posterior probability distribution



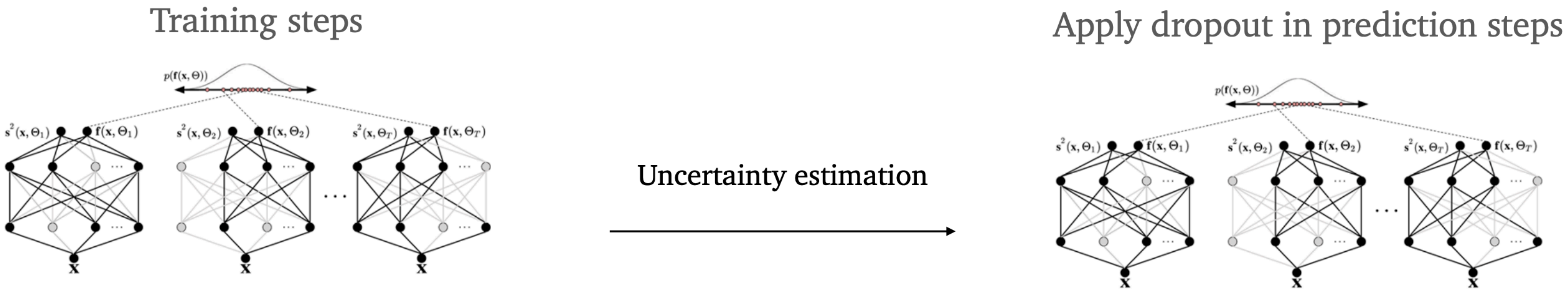
Monte - Carlo Dropout

- Dropout:
  - A standard technique for training neural networks
  - Avoids over-fitting by randomly deactivating connections between nodes of neural network during the training process

arxiv 1506.02142



(a) Standard Neural Net (b) After applying dropout.

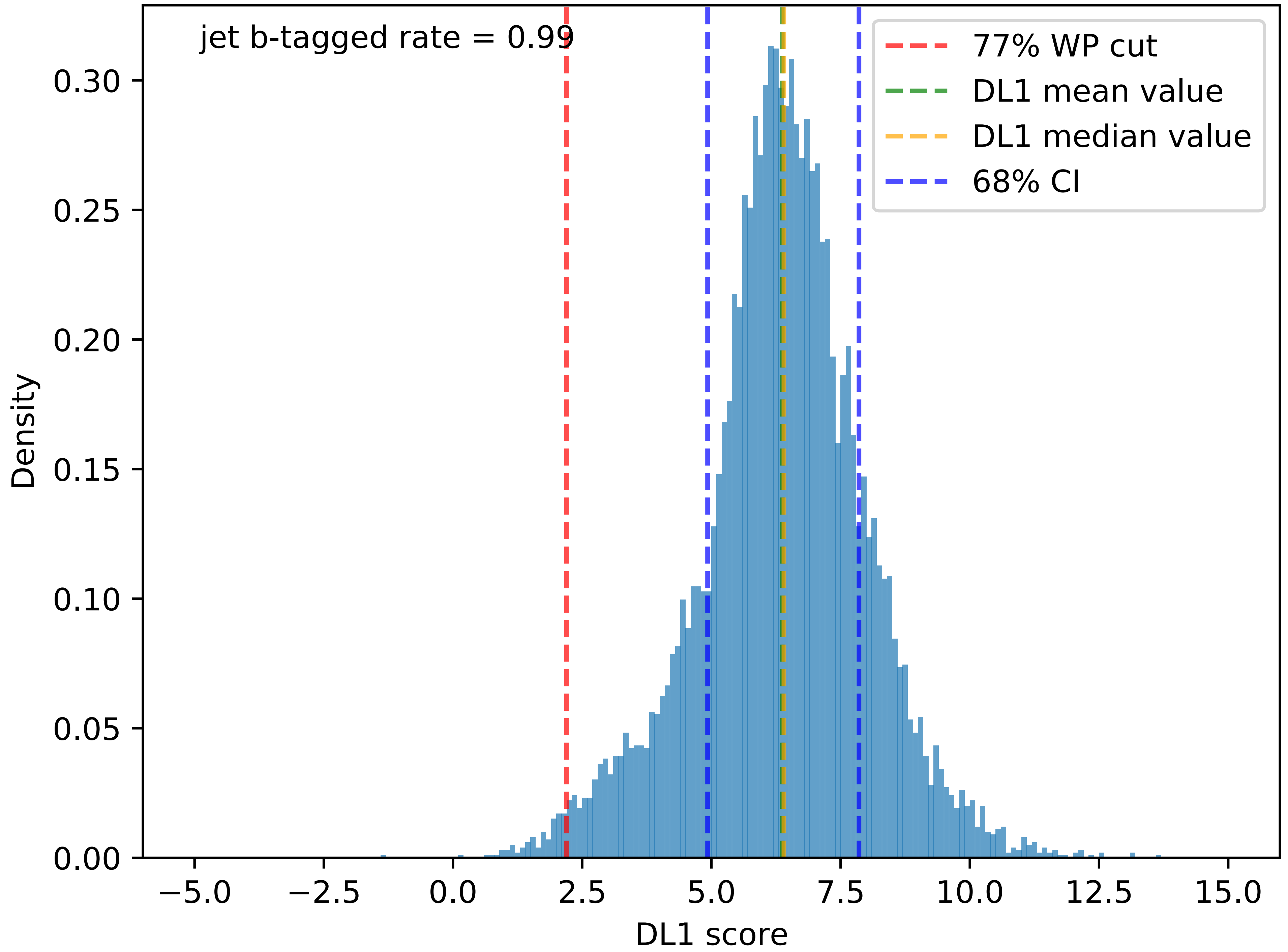


- As amazing as Y. Gal's claim sounds, it is not rigorously justified nor systematically evaluated
  - Proposed a method to fully validate the method
  - Novel application to b-tagging

DUQ Method Workflow

Evaluate multiple times with DL1r model with Dropout enabled

Jet → **DL1r Distribution for each jet** → **Validation**



- Calculate the significance for each jet

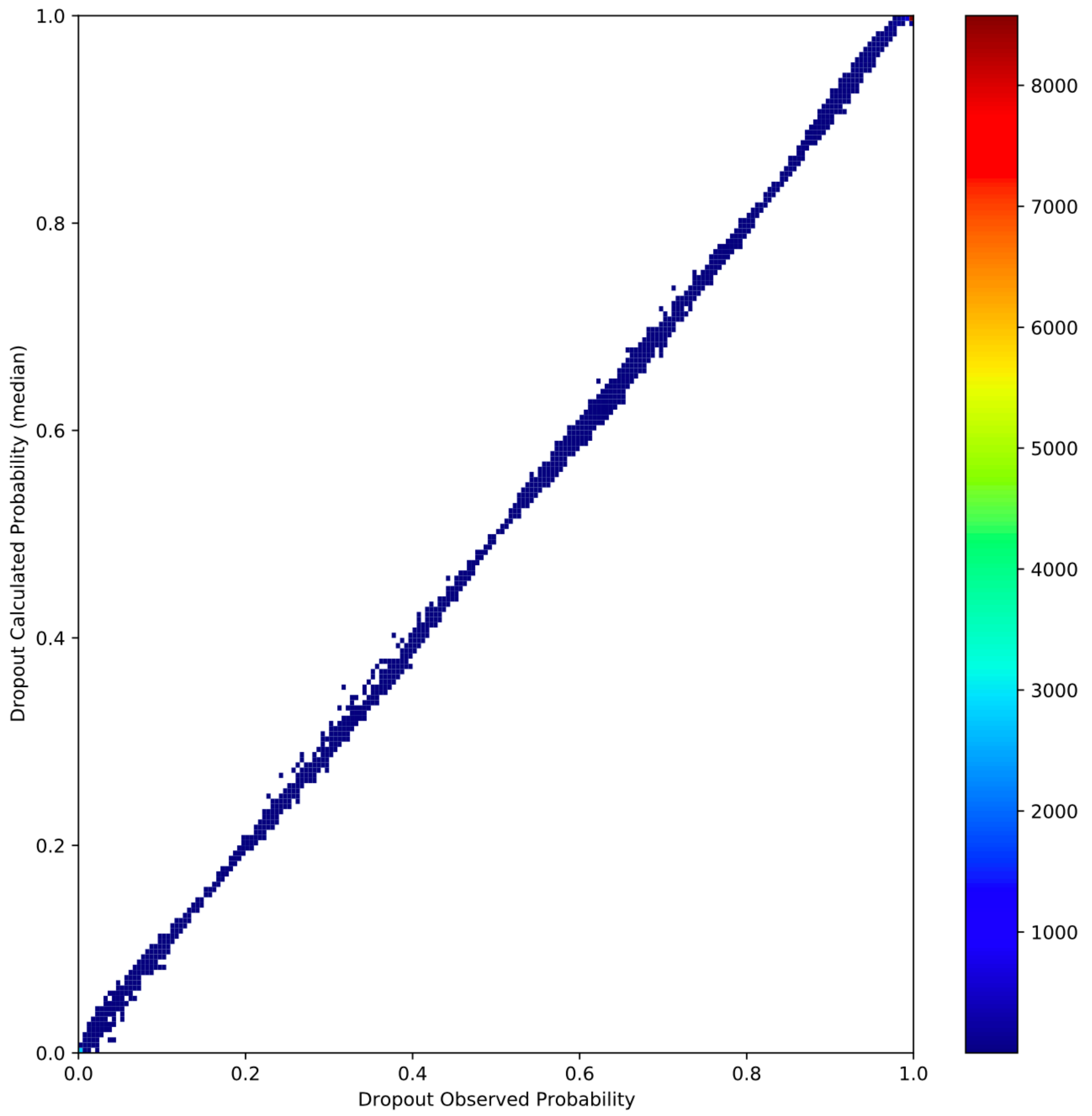
$$significance = \frac{DL1_{median} - cut}{\sqrt{(DL1_{median} - CI_j)^2}}$$

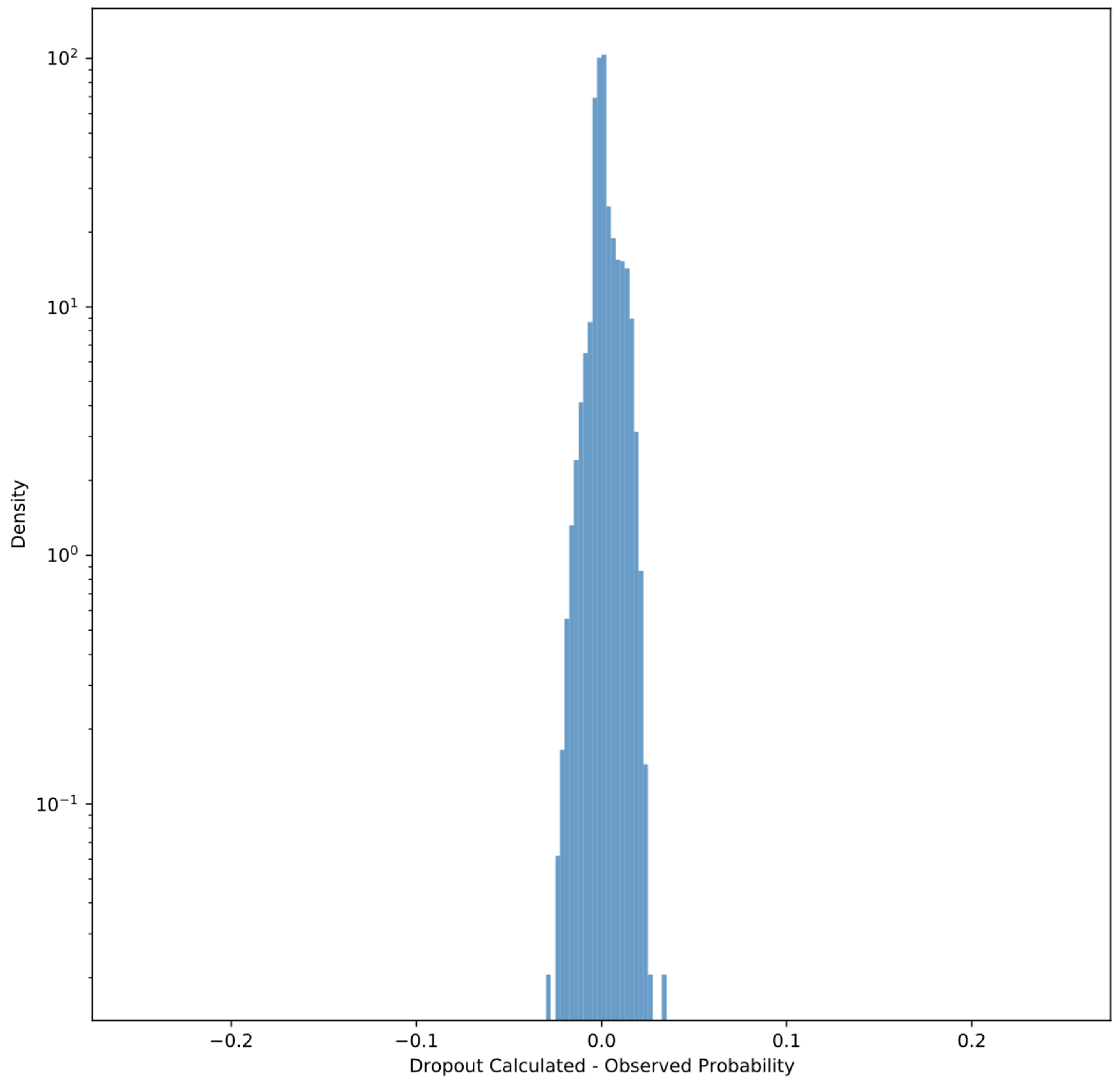
- The probability that a jet's significance will correspond to a correct categorization is calculated using a normal distribution's CDF

Validation

Jet-level closure test:

- Predicted probability vs jet accuracy
- The difference between each is mainly within 1%





	Accuracy* (w/o Dropout)	Accuracy (w Dropout)
	72.55	74.2
extended Z'	36.9	35.1

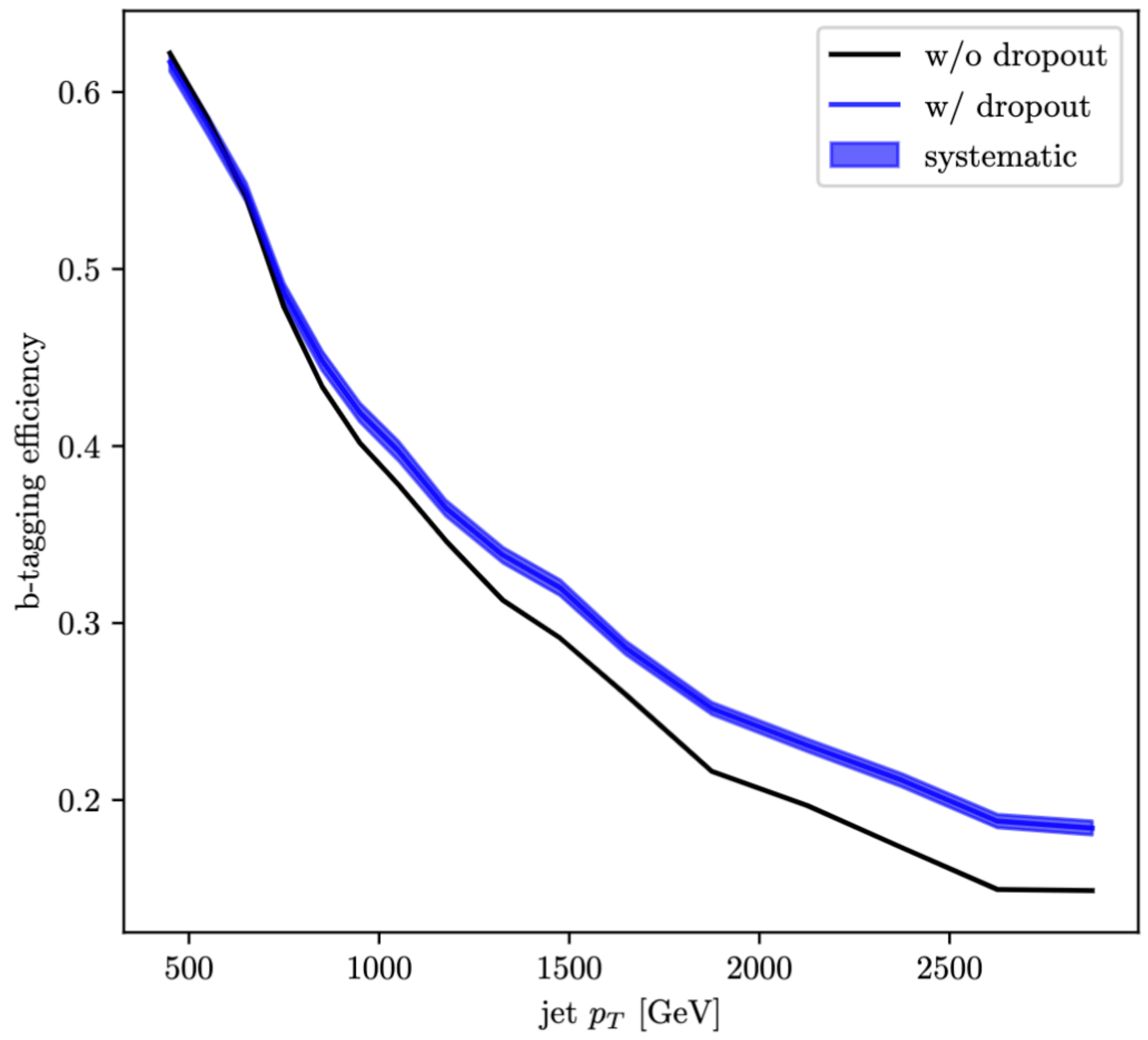
Sample-level closure test:

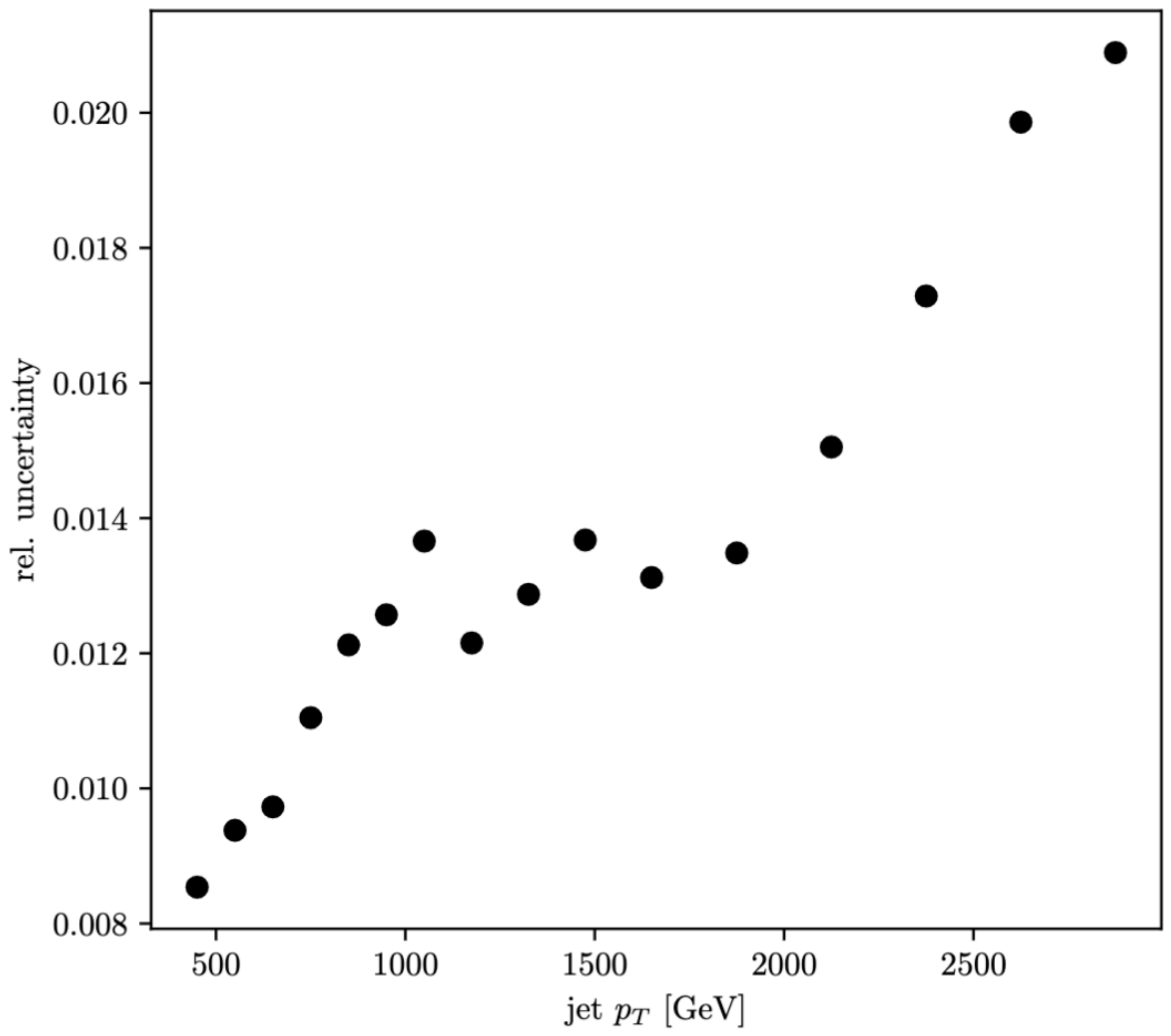
- Predicted probability vs sample accuracy
- Less than 2% difference noticed
  - Mainly covered by the statistical uncertainty

* ~100k jets used to perform sample closure test on both $t\bar{t}$ and Z' samples, statical uncertainty roughly ~1%

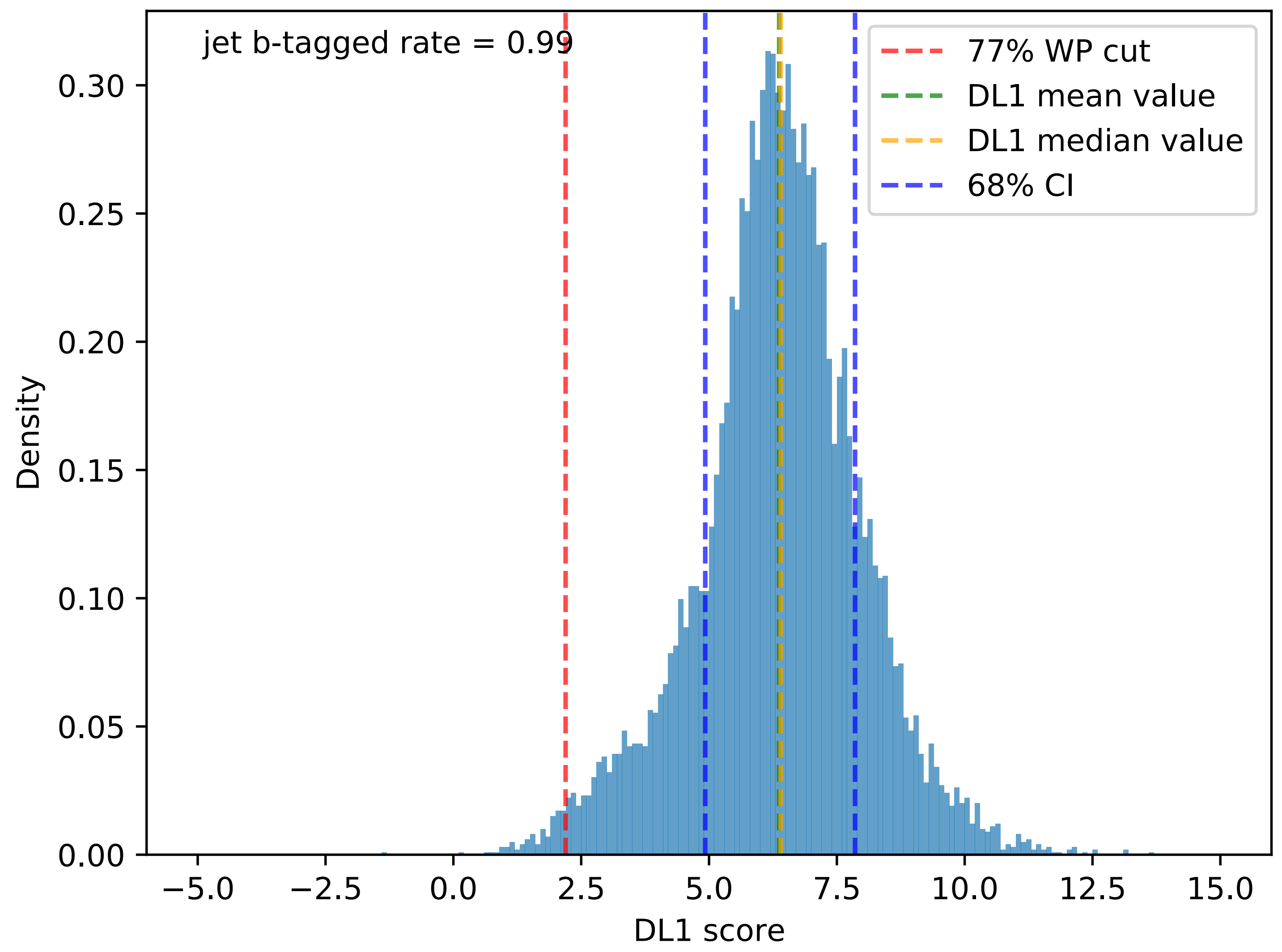
Uncertainty vs. pT

- Apply DUQ method on nominal samples, captures the NN uncertainty
  - Small uncertainty noticed as expected



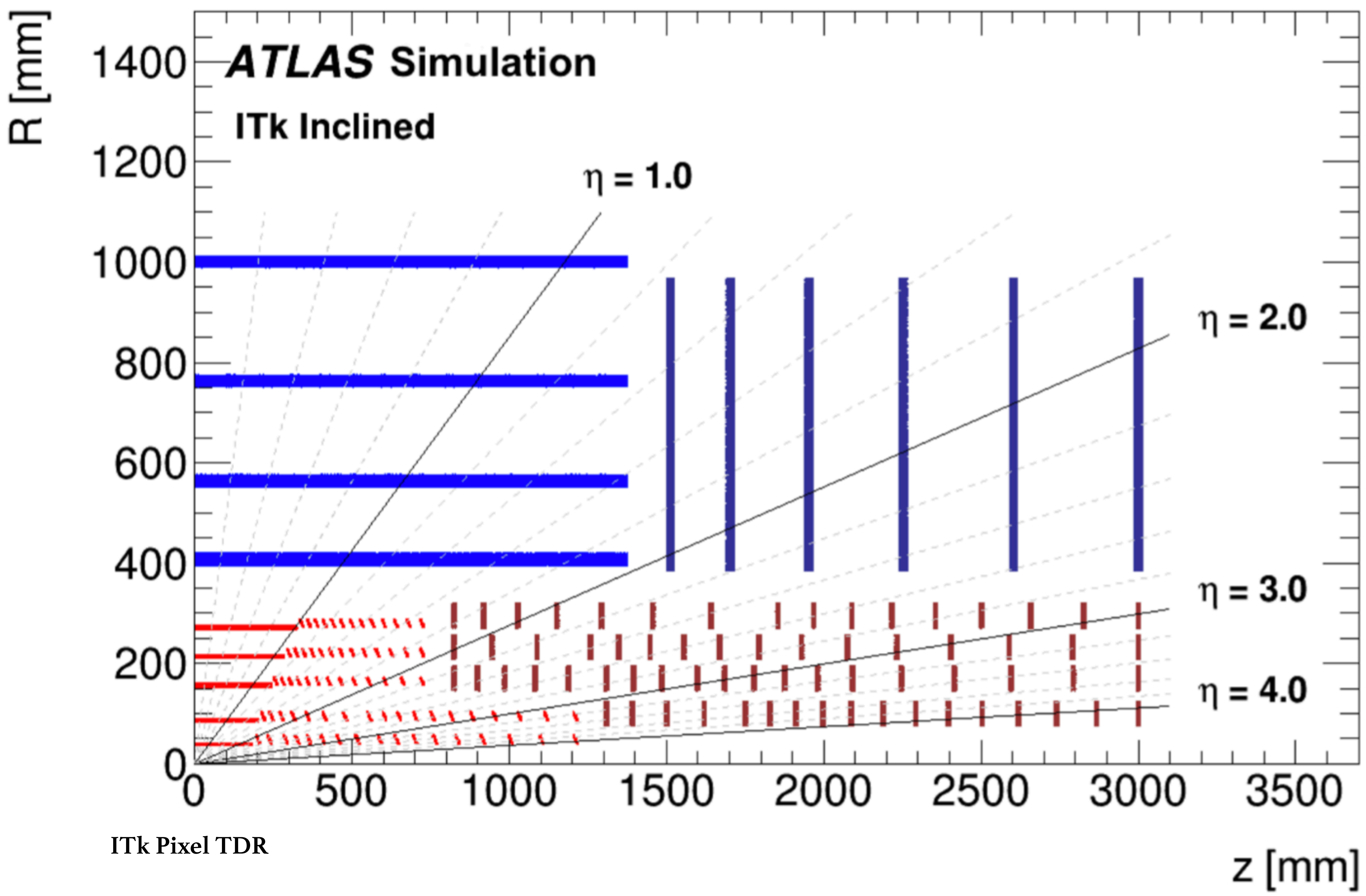


- Would without binning be an option?



Entering into HL-LHC

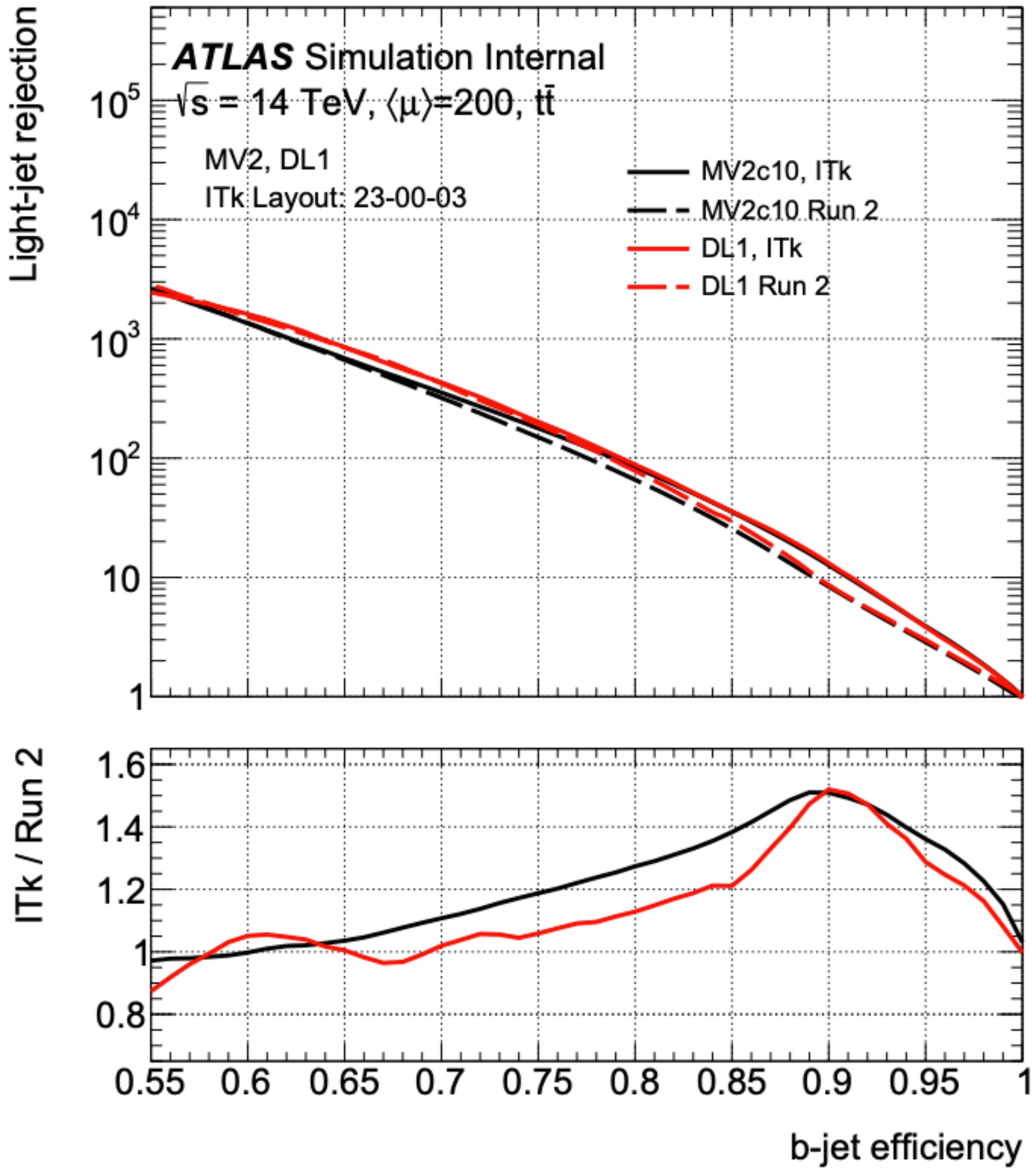
- LHC will enter high-luminosity phase in 2025
  - An integrated luminosity of 3000 fb^{-1} will be expected
- To cope with the harsh radiation environment, detector occupancy and bandwidth saturation, ATLAS Inner Detector will be replaced by an all-silicon detector, Inner Tracker (ITk)



ITk Pixel TDR

Entering into HL-LHC

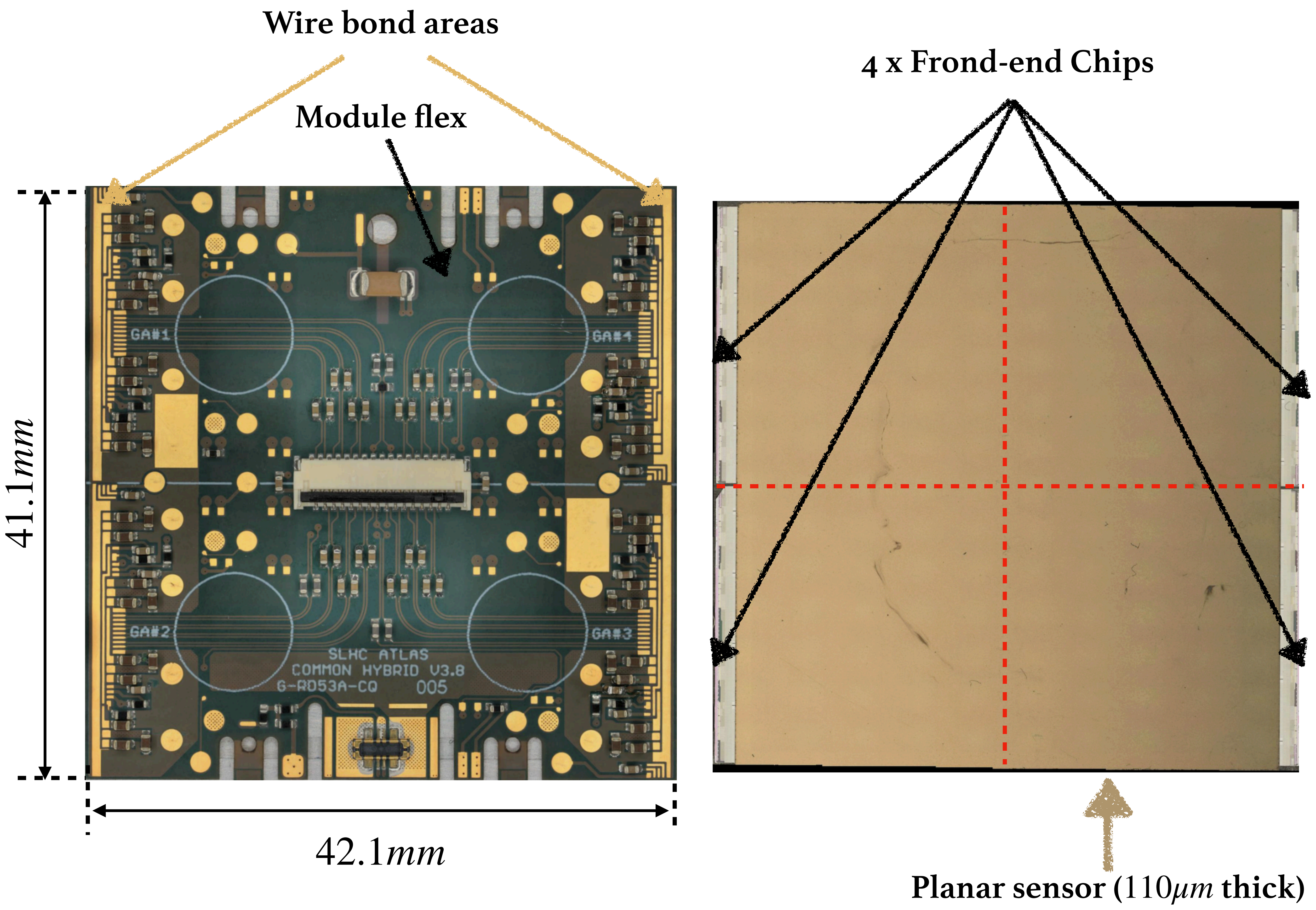
- **Design goal: ITk should have the same or better performance as the current detector but in the harsher environment of the HL-LHC**



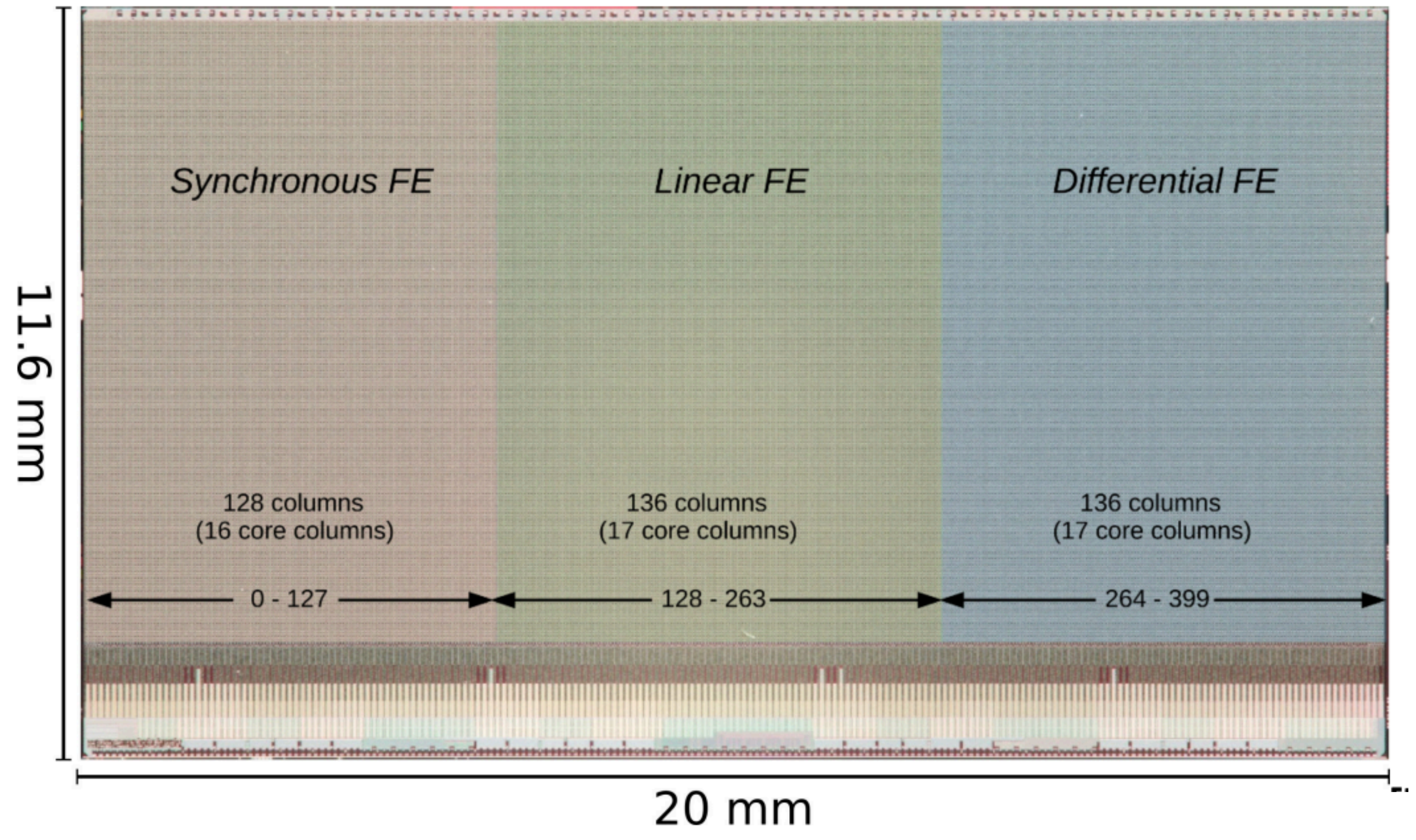
Module

Module, as the basic unit of pixel detector, needs to be tested.

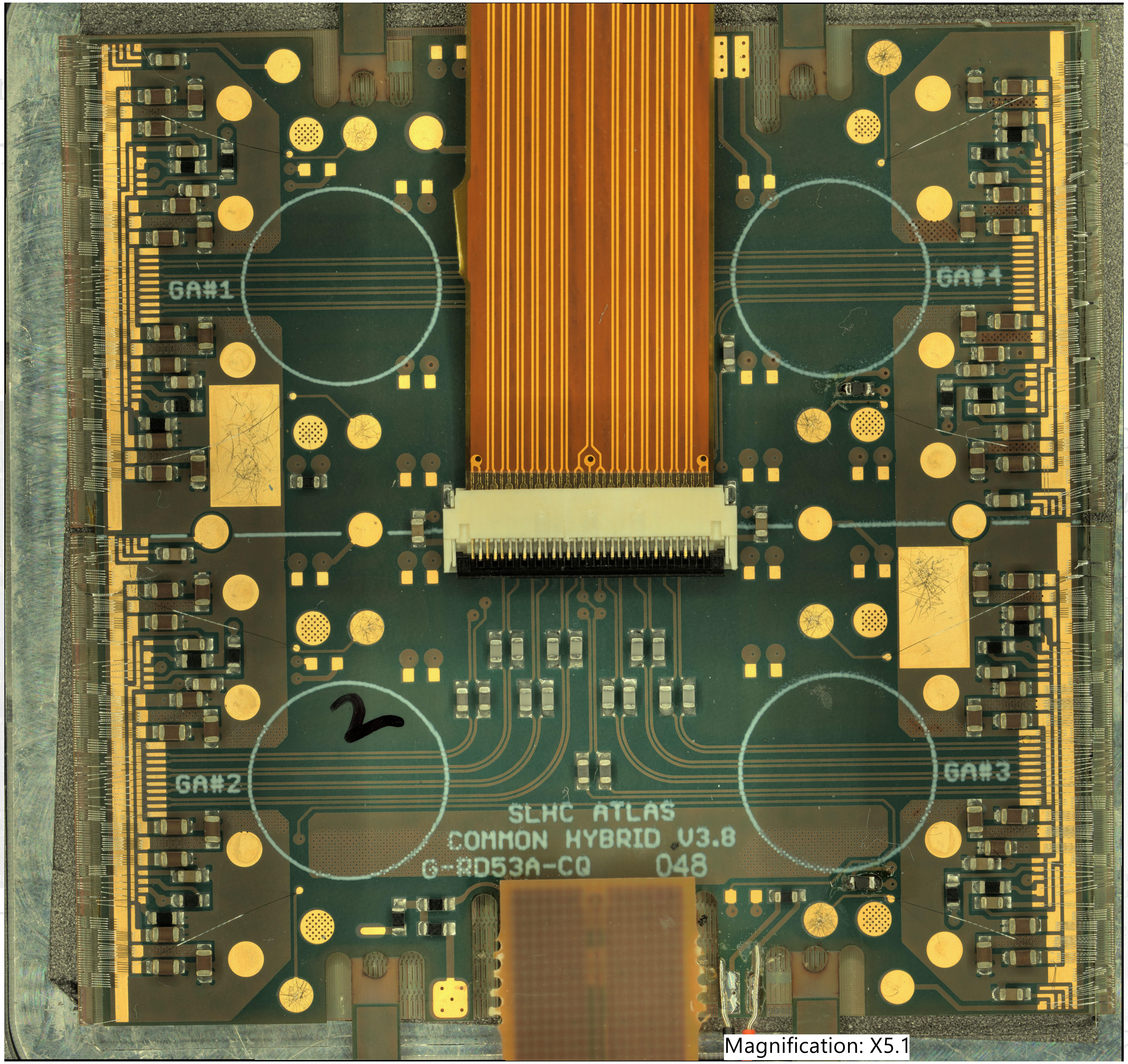
- Consists of a silicon sensor bump-bonded to a front-end (FE) chip glued to a flexible PCB



- **RD53A chip:**
  - **Size:** 400pixels by 192 pixels
    - **Pixel size:** 50μm by 50μm
  - 3 FEs under evaluations



Module

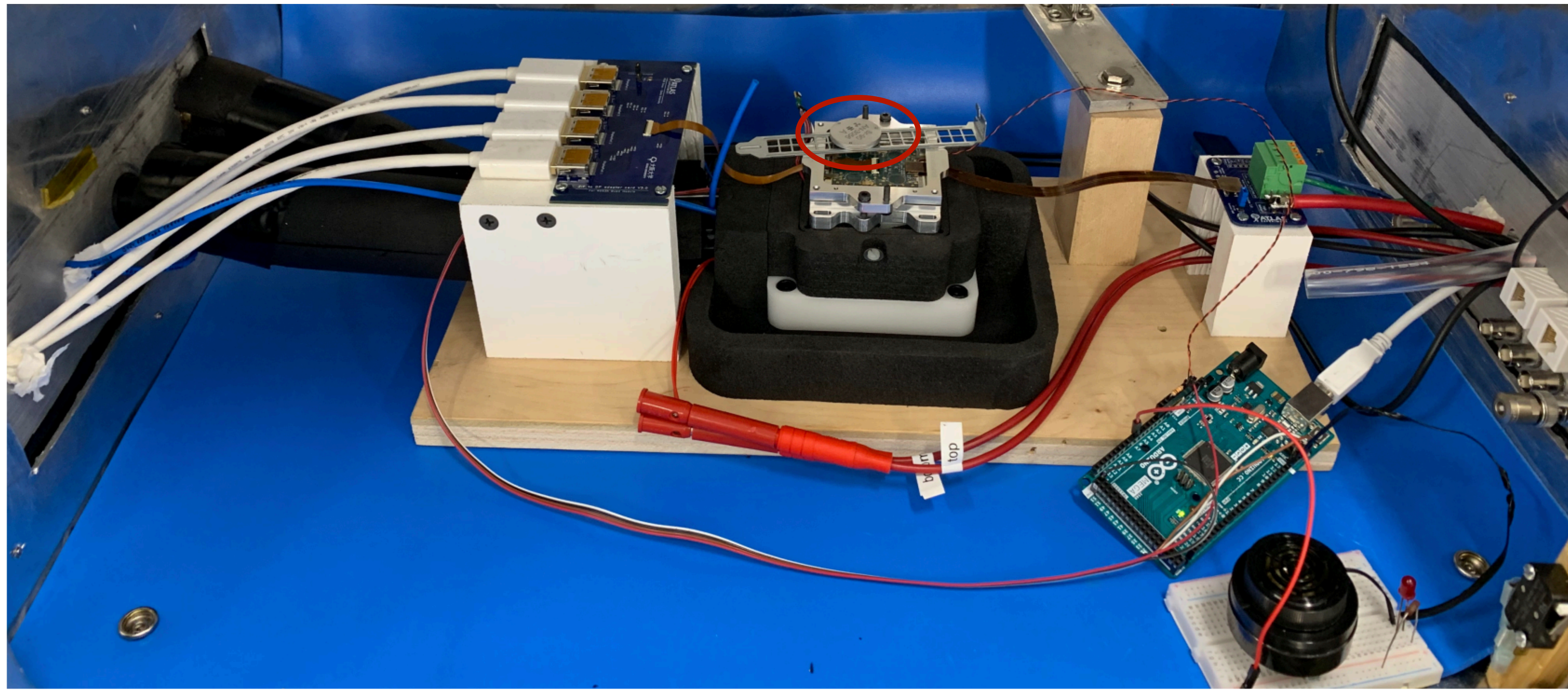

GA#1
GA#4
2
GA#2
GA#3
SLHC ATLAS
COMMON HYBRID V3.8
G-RD53A-CQ 048
Magnification: X5.1

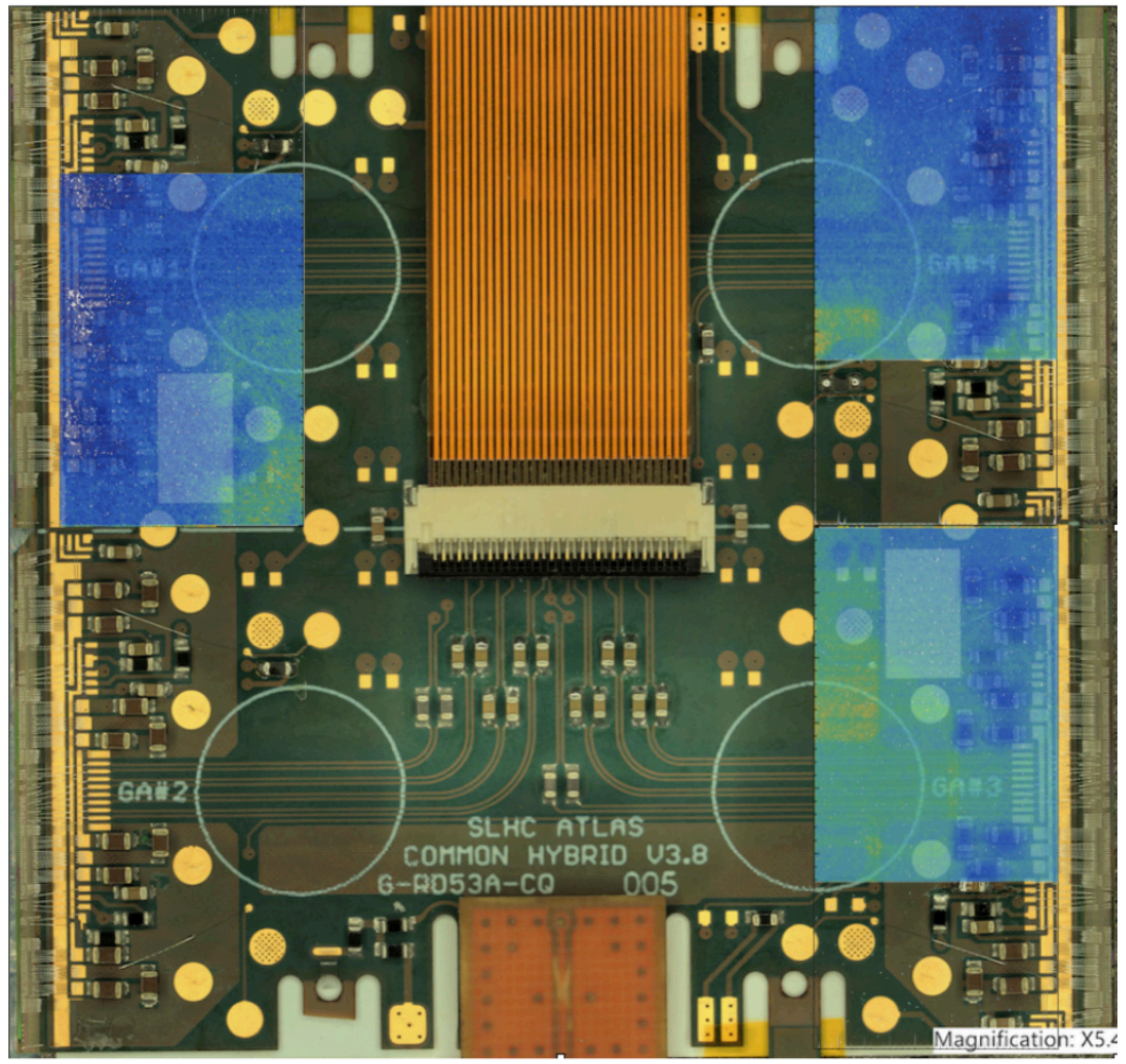
Module Testing

- To develop the necessary testing infrastructure for the electrical qualification of each assembled module, a phased approach has been adopted across the collaboration to achieve these different testing capabilities:

  - Basic electrical tests
    - Turn on module at 20°C
    - Module tuning
  - Full QC test
    - Thermal cycling
      - 1 extreme cycle from -55°C to 60°C
      - 10 cycles from - 45°C to 45°C
    - Source scan at 20°C (around 10 hours)
    - Burn-in test at -15°C for at least 8 hours

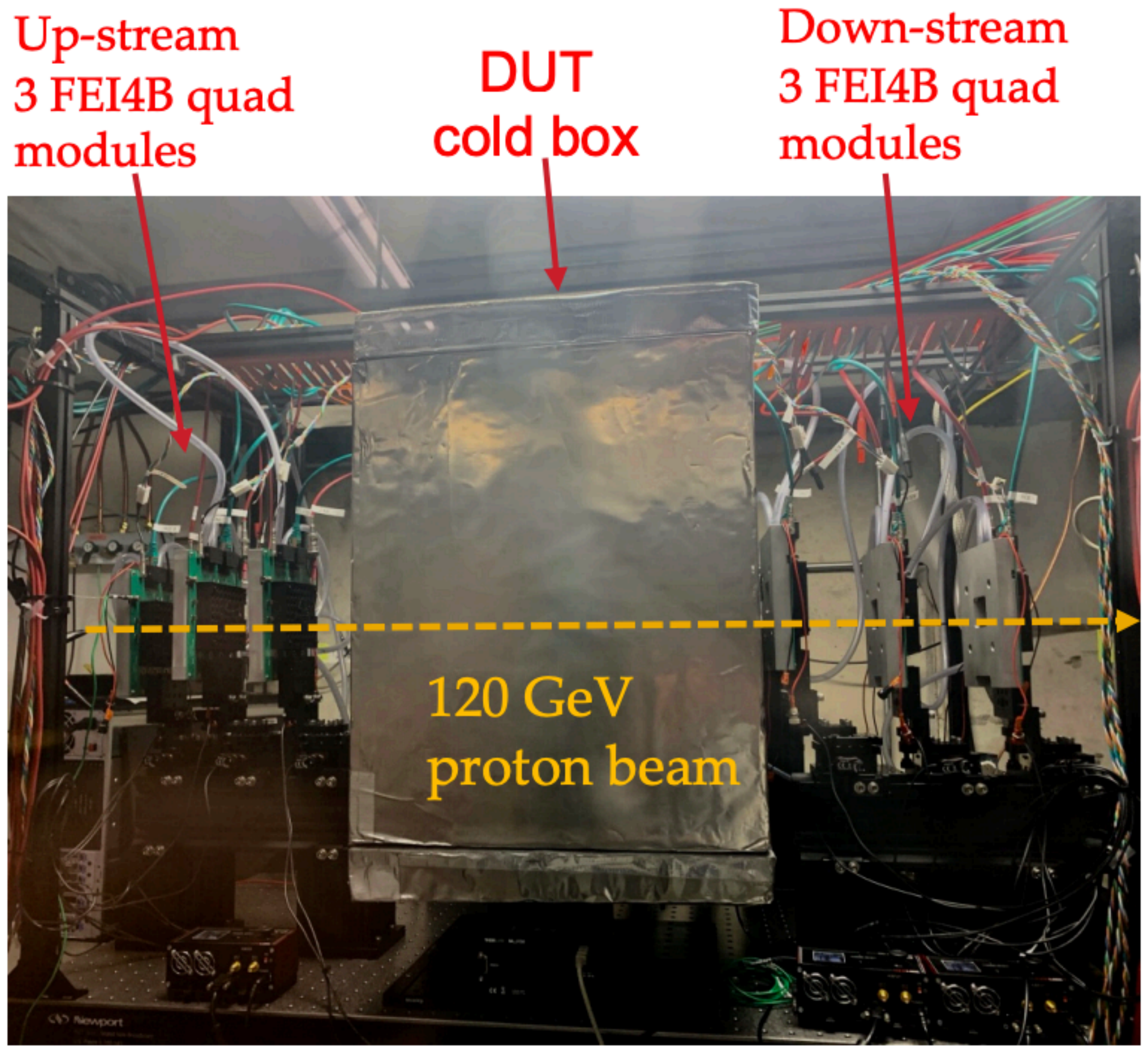
Module testing setup at Argonne

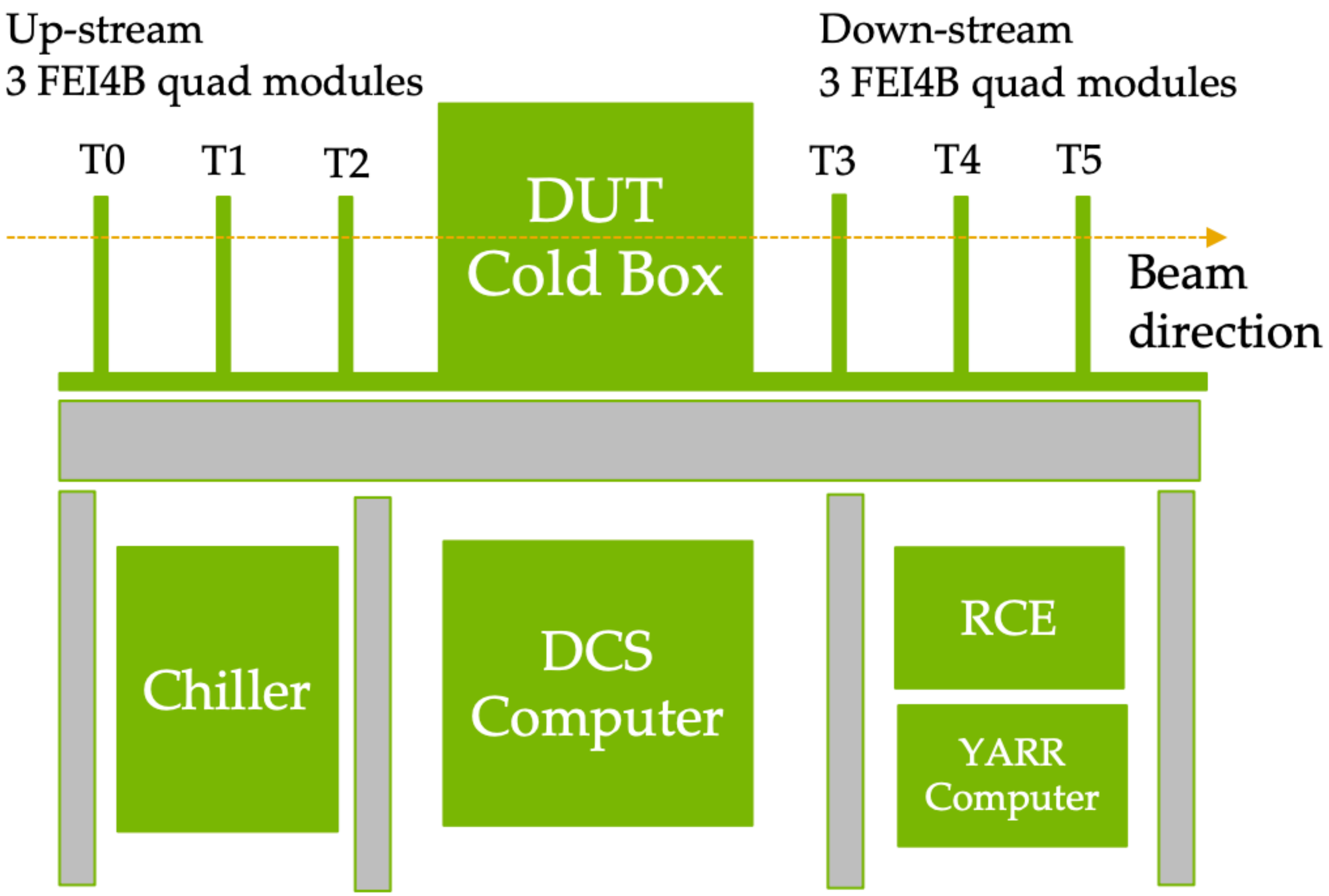




Argonne Pixel Telescope at Fermilab

- As part of the R&D programs towards the validation of a new detector technology, beam tests are required to evaluate the module designs
- An Argonne Pixel Telescope installed to perform such studies
  - 6 telescope planes installed with FEI4B quad modules
    - pixel size 50 x 250 µm2 and 200µm in thickness
  - YARR and FELIX setup as DAQ system





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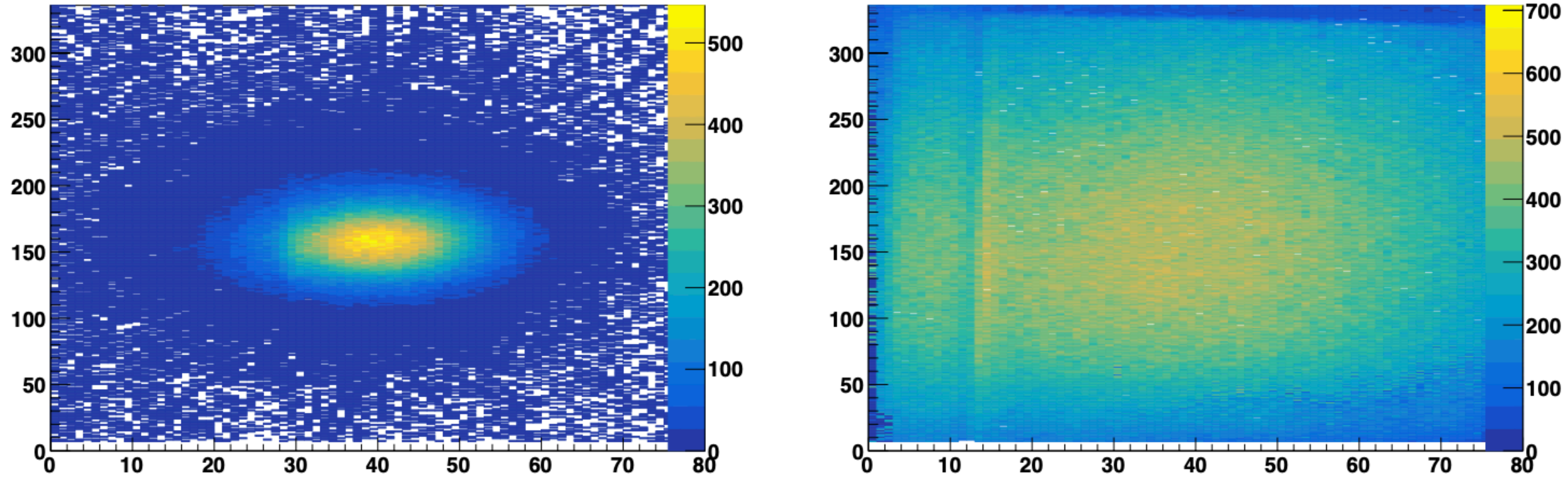
  - HitOR t
  - YARR a

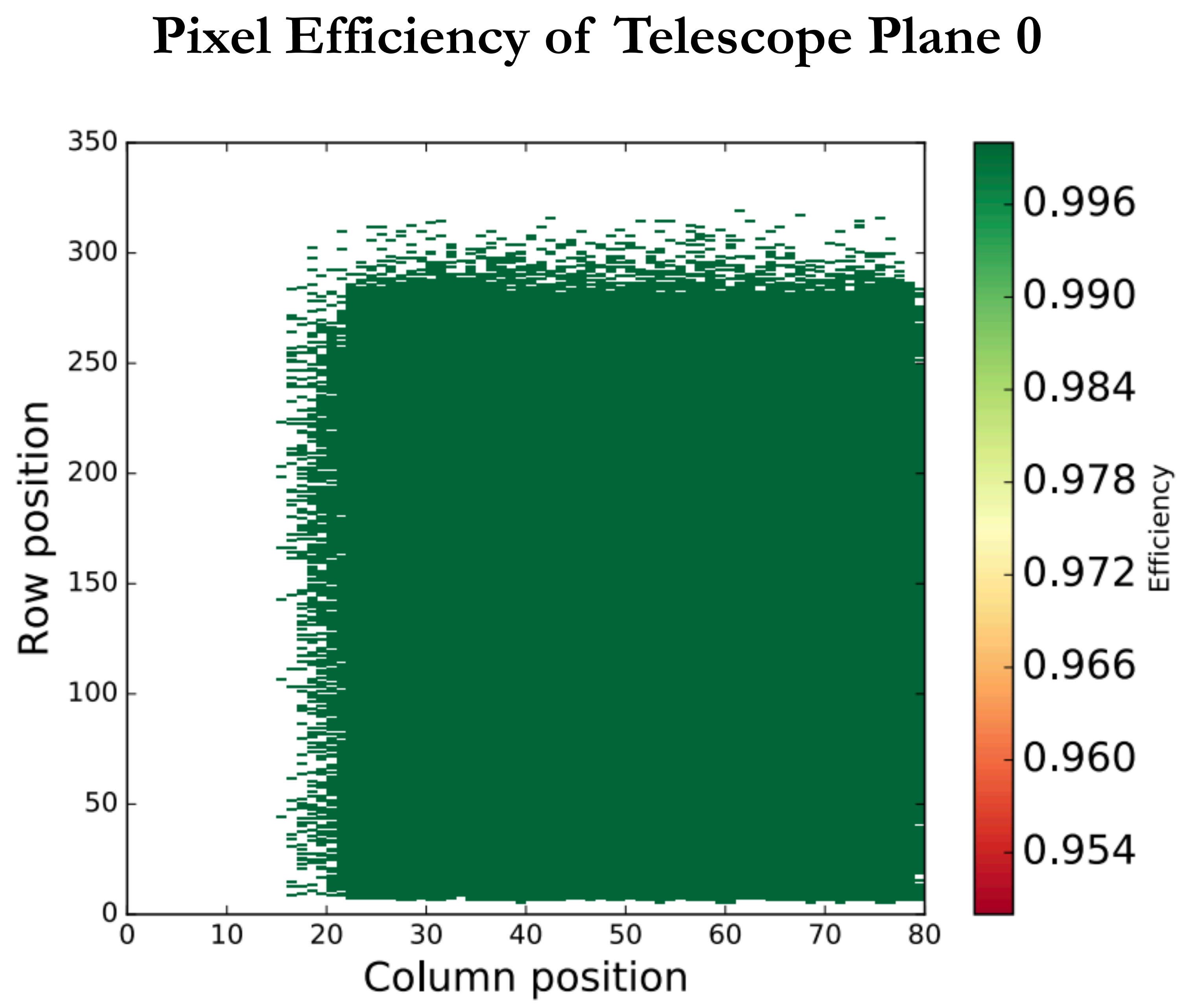
Hit occupancy with different beam profile

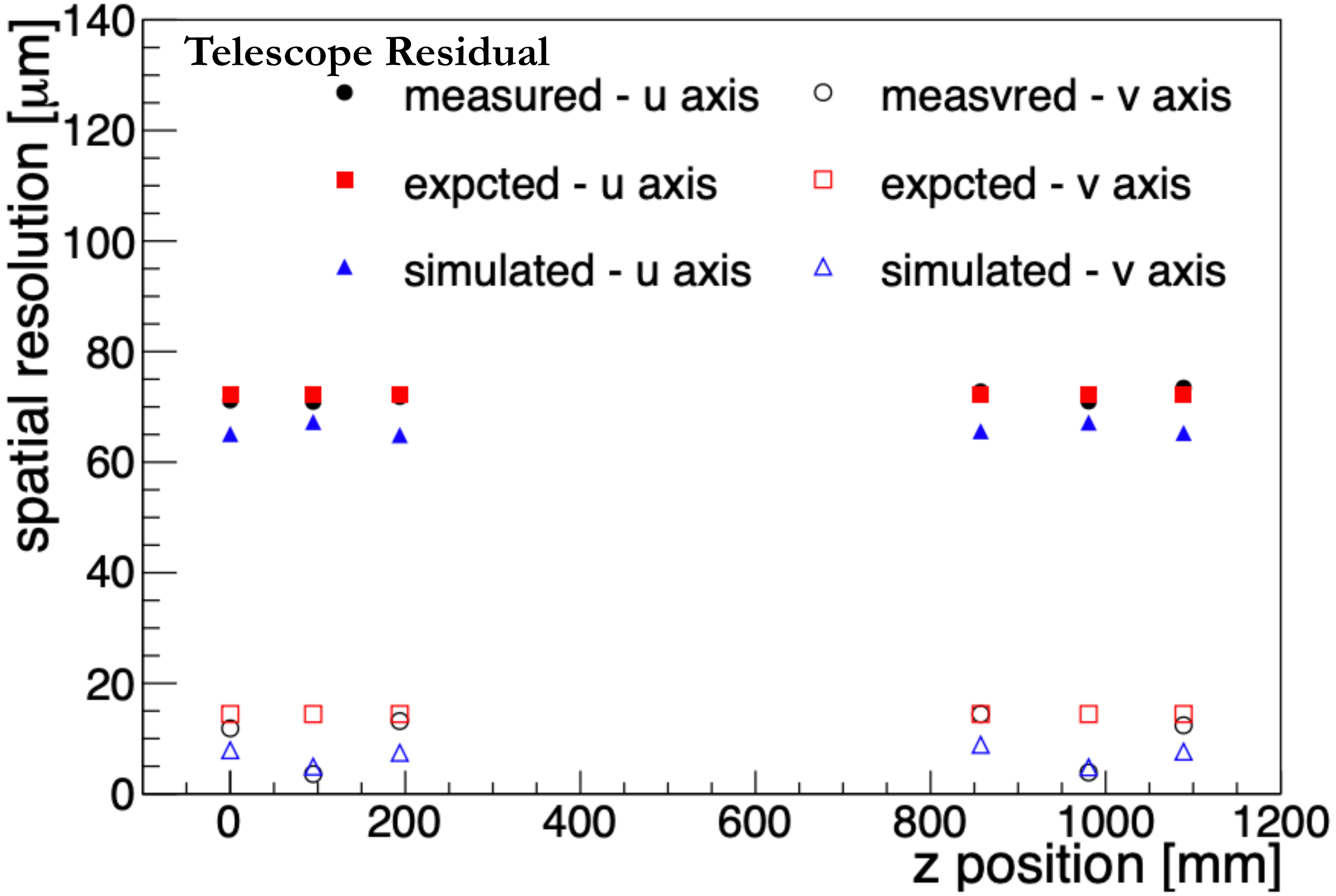


Telescope Performance

arxiv: 2202.05315

- Proteus software used to reconstruct the test beam data
  - Clustering
  - Alignment
  - Track reconstruction
- Test beam scenario simulated using AllPix² simulation software to validate the performance of the telescope



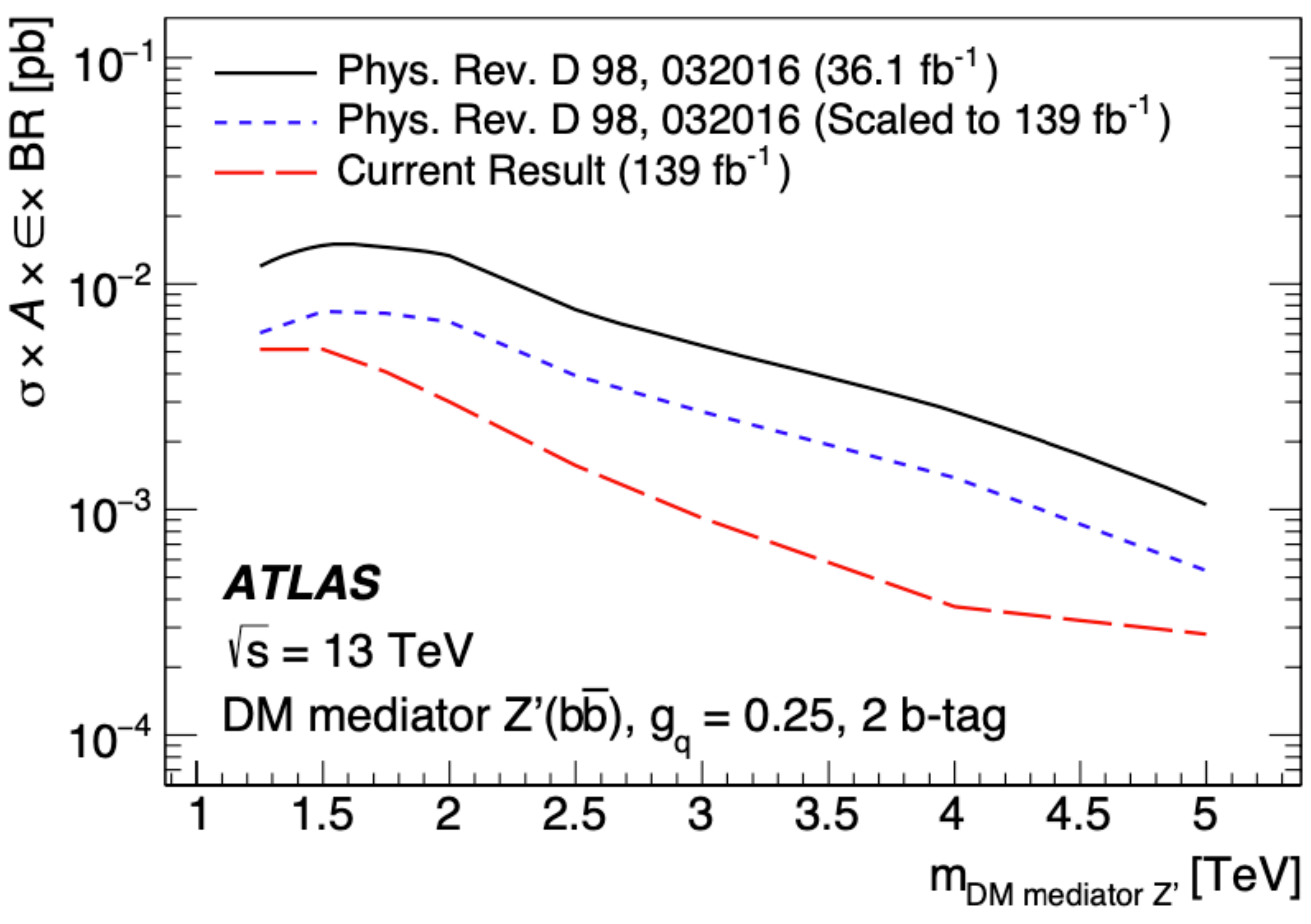


Summary

- Di-b-jet analysis performed to search for new heavy resonances
  - No significant deviations found from the SM background
  - Great improvement thanks to the amazing b-tagger

- New machine learning techniques are being applied to develop new, more powerful b-taggers

- For HL-LHC, ITk potentially helps to improve b-tagging performance
  - Test performed on basic detector unit
  - Fine tracking resolution from Argonne Pixel Telescope



Thank You!