



Systematic Effects in Jet Tagging with the ATLAS Detector

ML4Jets

DESY, November 9th 2023

Kevin Greif, on behalf of the ATLAS collaboration

Jet Tagging in 2019...

[arxiv:1902.09914](https://arxiv.org/abs/1902.09914)

SciPost Physics

Submission

The Machine Learning Landscape of Top Taggers

G. Kasieczka (ed)¹, T. Plehn (ed)², A. Butter², K. Cranmer³, D. Debnath⁴, B. M. Dillon⁵,
M. Fairbairn⁶, D. A. Faroughy⁵, W. Fedorko⁷, C. Gay⁷, L. Gouskos⁸, J. F. Kamenik^{5,9},
P. T. Komiske¹⁰, S. Leiss¹, A. Lister⁷, S. Macaluso^{3,4}, E. M. Metodiev¹⁰, L. Moore¹¹,
B. Nachman,^{12,13} K. Nordström^{14,15}, J. Pearkes⁷, H. Qu⁸, Y. Rath¹⁶, M. Rieger¹⁶, D. Shih⁴,
J. M. Thompson², and S. Varma⁶

“Indeed, we will see that we can consider jet classification based on deep learning at the pure performance level an essentially solved problem.

For a systematic experimental application of these tools **our focus will be on a new set of questions related to training data, benchmarking, calibration, systematics, etc.”**

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This Talk!

“Indeed, we will see that we can consider jet classification based on deep learning at the pure performance level an essentially solved problem.*”

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...and Jet Tagging in 2023

[arxiv:2205.05550](https://arxiv.org/abs/2205.05550)

Search for Higgs boson decay to a charm quark-antiquark pair in proton-proton collisions at $\sqrt{s} = 13$ TeV

The CMS Colla

[arxiv:2204.12413](https://arxiv.org/abs/2204.12413)

Search for a massive scalar resonance decaying to a light scalar and a Higgs boson in the four b quarks final state with boosted

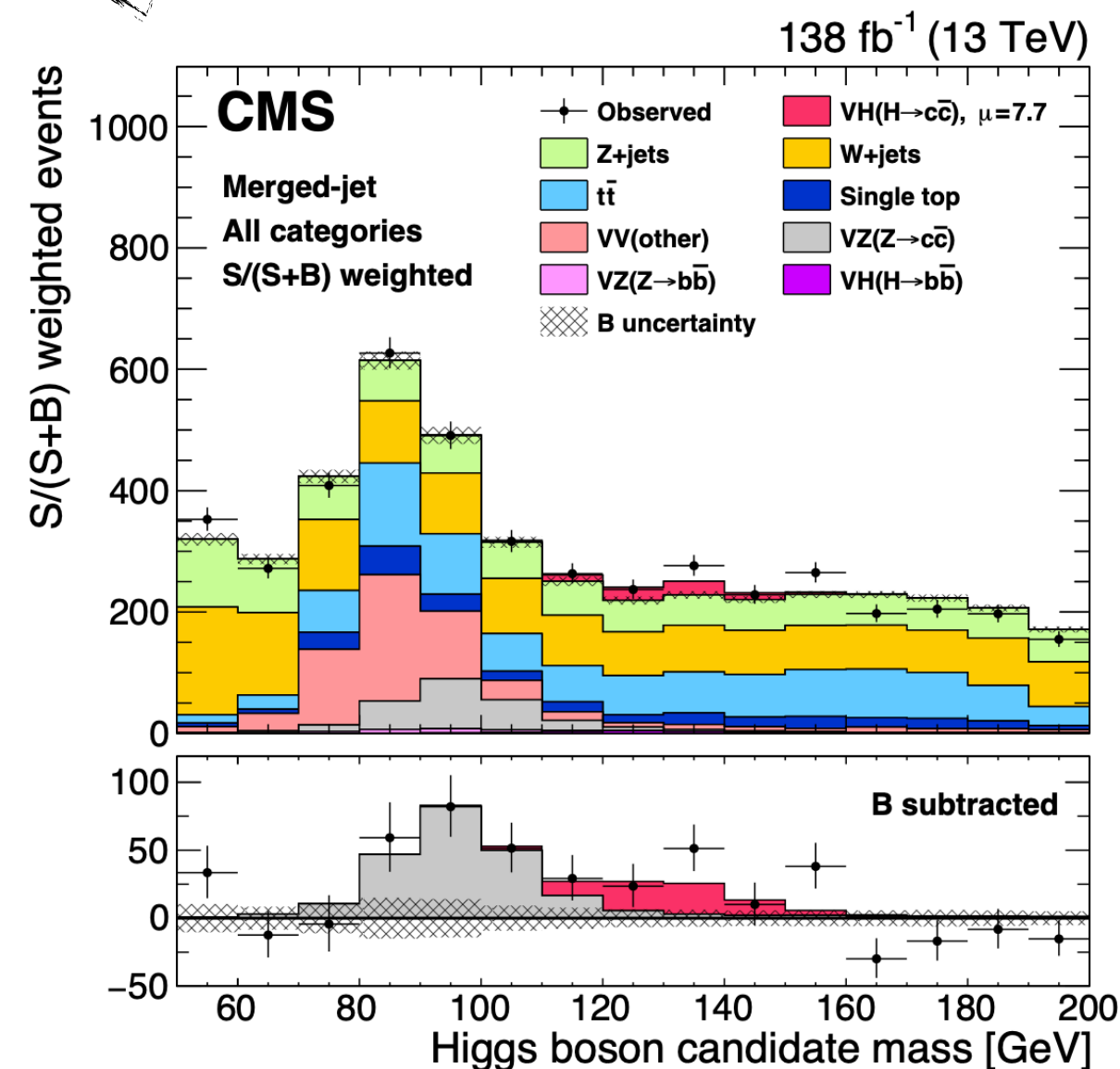
[arxiv:2205.02817](https://arxiv.org/abs/2205.02817)

The CMS Colla

Differential $t\bar{t}$ cross-section measurements using boosted top quarks in the all-hadronic final state with 139 fb^{-1} of ATLAS data

The ATLAS Collaboration

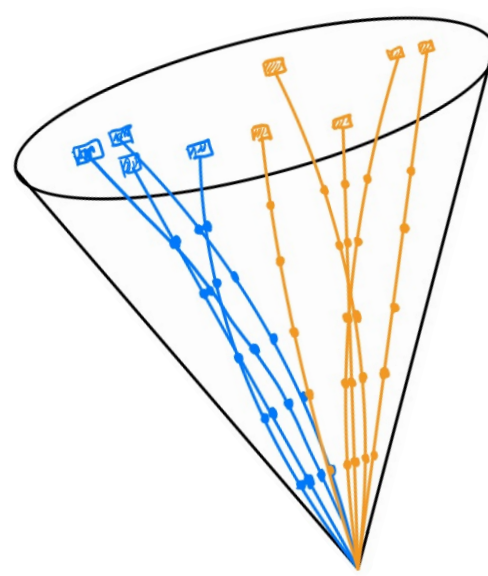
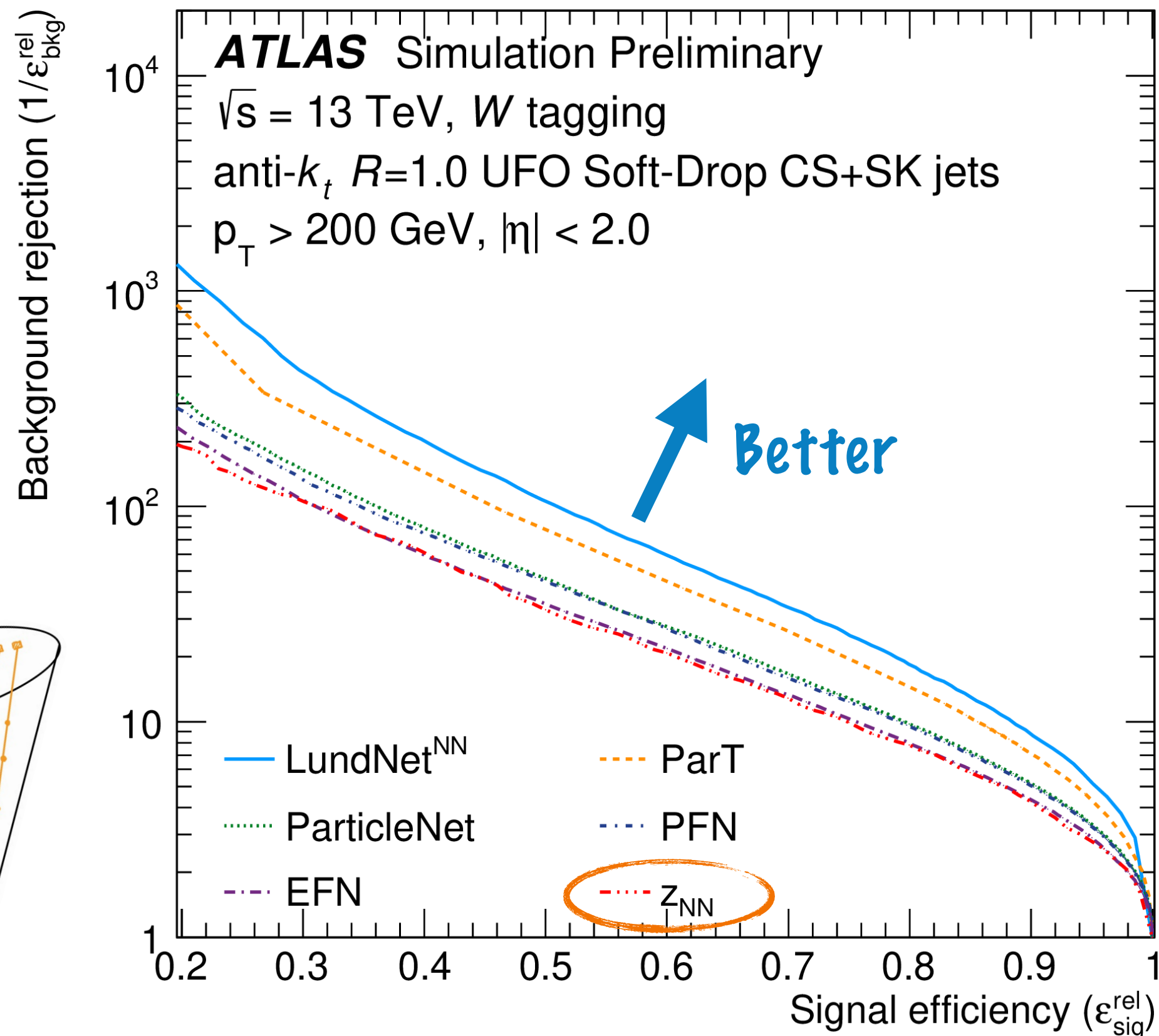
+ many others



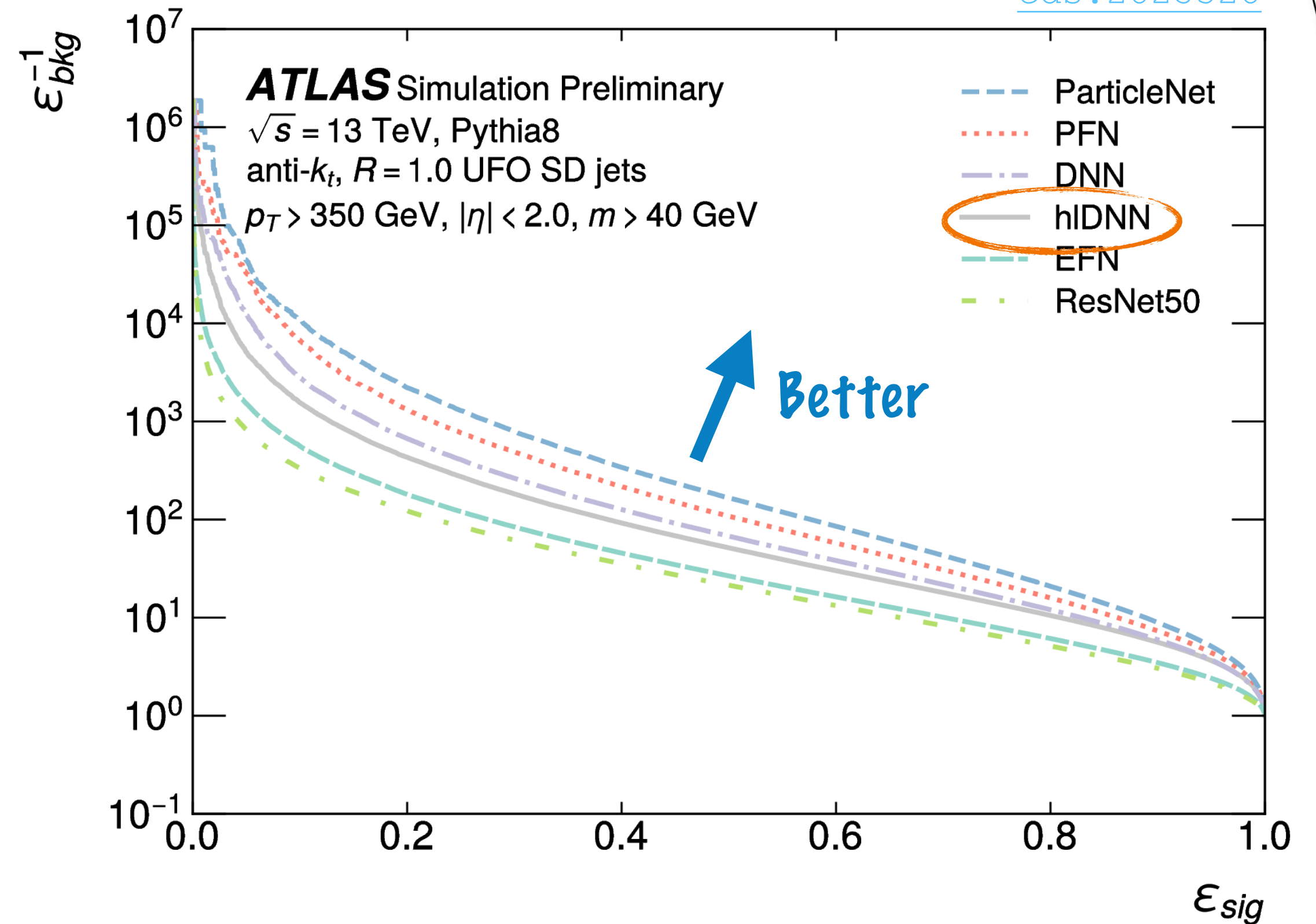
- Point cloud based jet tagging is enabling previously unimaginable measurements
- The networks are getting ever bigger and more powerful

Point Cloud Taggers in ATLAS

[cds:2864131](#) [cds:2866592](#)



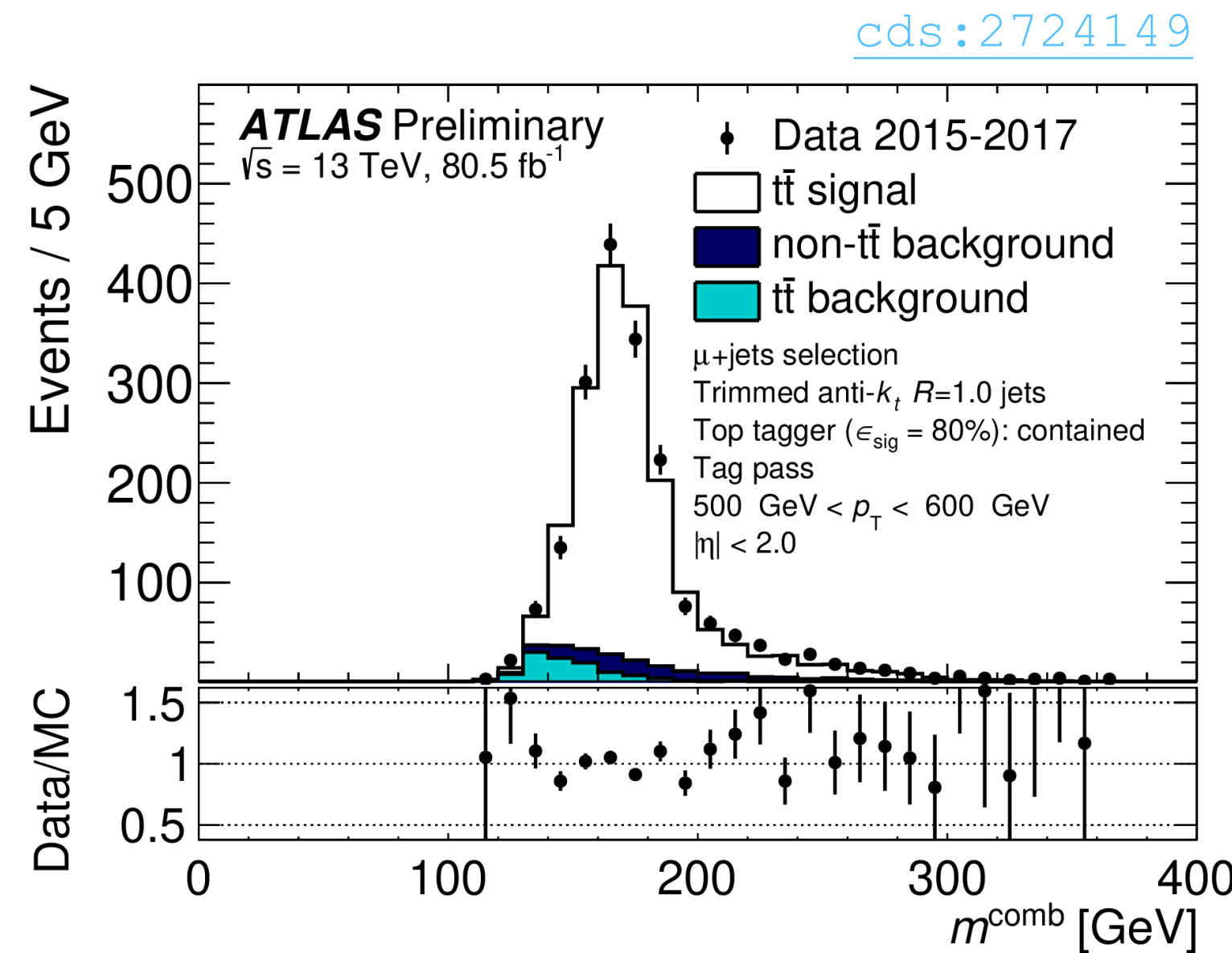
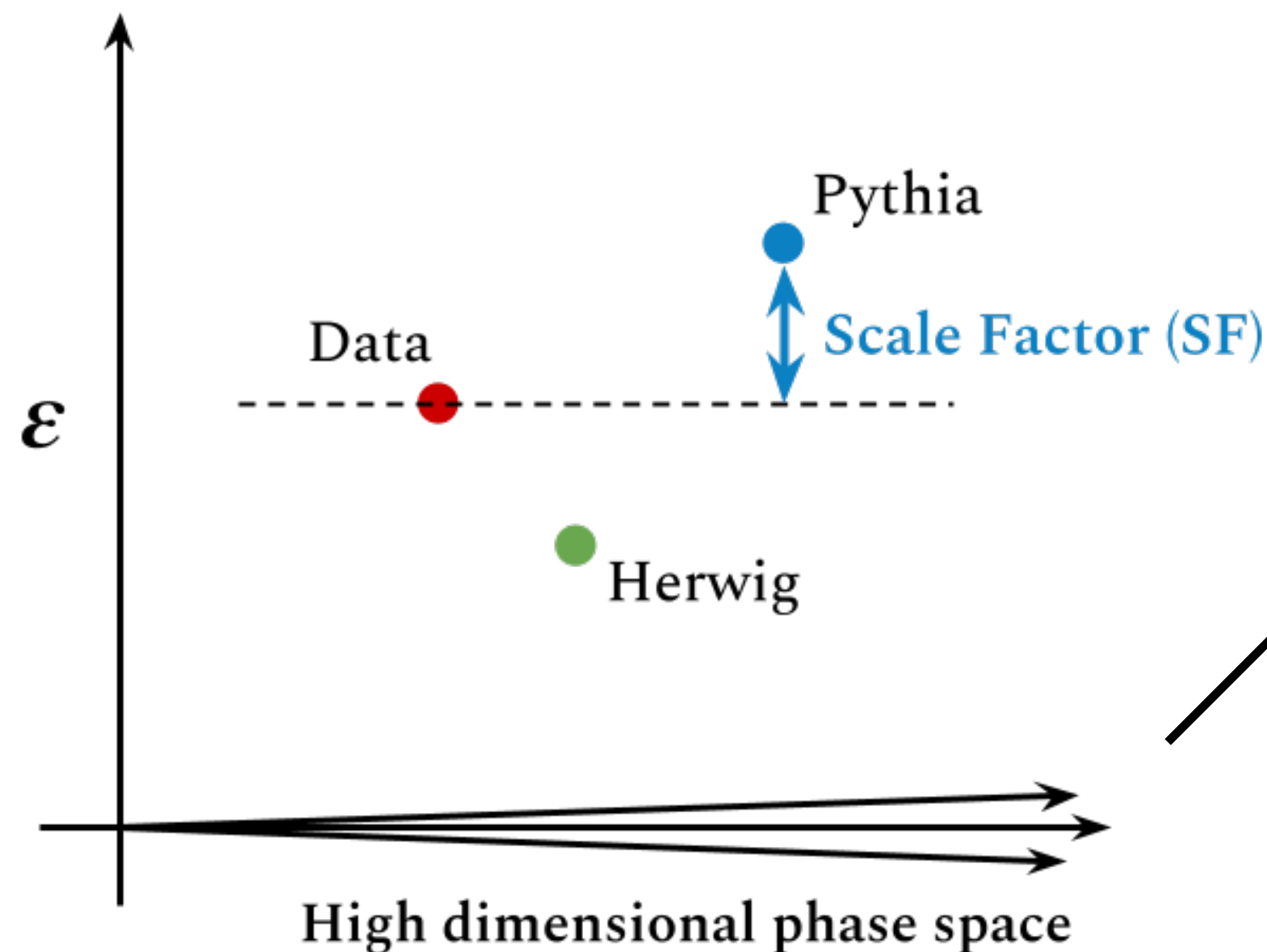
[cds:2825328](#)



- Large performance gains for point-cloud taggers over **high-level quantity baselines**
- Also see [Samuel's talk](#) on q/g tagging from yesterday!

A Brief Aside on Scale Factors

- Both ATLAS and CMS train taggers on MC, but need to know efficiency in data
- Measure **scale factor** to correct MC efficiency to data efficiency



Fit normalizations (N) of MC distributions to data

$$\epsilon_{\text{data}}(p_T) = \frac{N_{\text{fitted signal}}^{\text{tagged}}(p_T)}{N_{\text{fitted signal}}^{\text{tagged}}(p_T) + N_{\text{fitted signal}}^{\text{not tagged}}(p_T)}$$

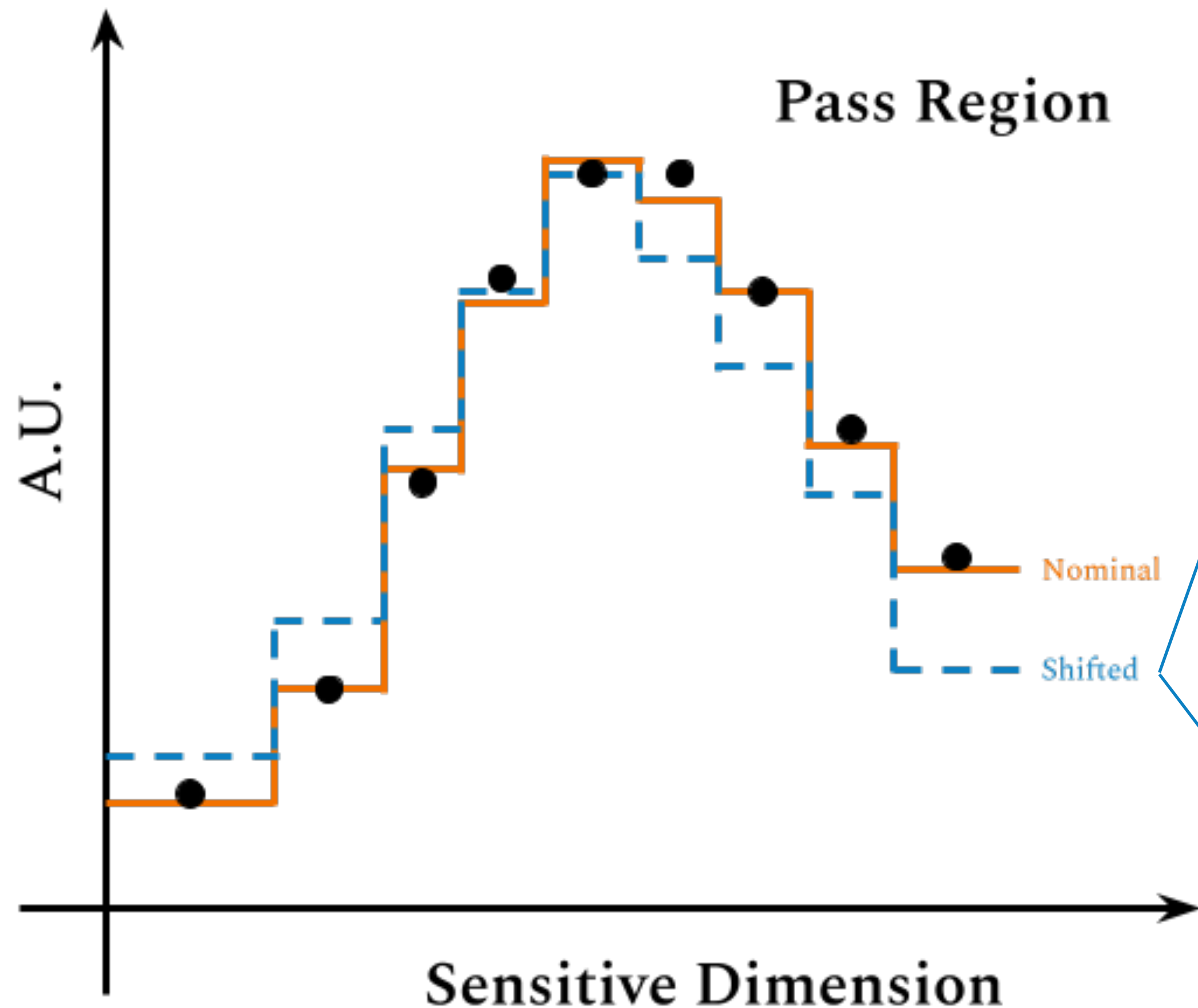
$$\text{SF}(p_T) = \frac{\epsilon_{\text{data}}(p_T)}{\epsilon_{\text{MC}}(p_T)}$$

Project to one dimension sensitive to efficiency

Scale Factor Uncertainties

$$SF(p_T) = \frac{\epsilon_{\text{data}}(p_T)}{\epsilon_{\text{MC}}(p_T)}$$

Like any measurement SFs have **uncertainties**:



Theoretical

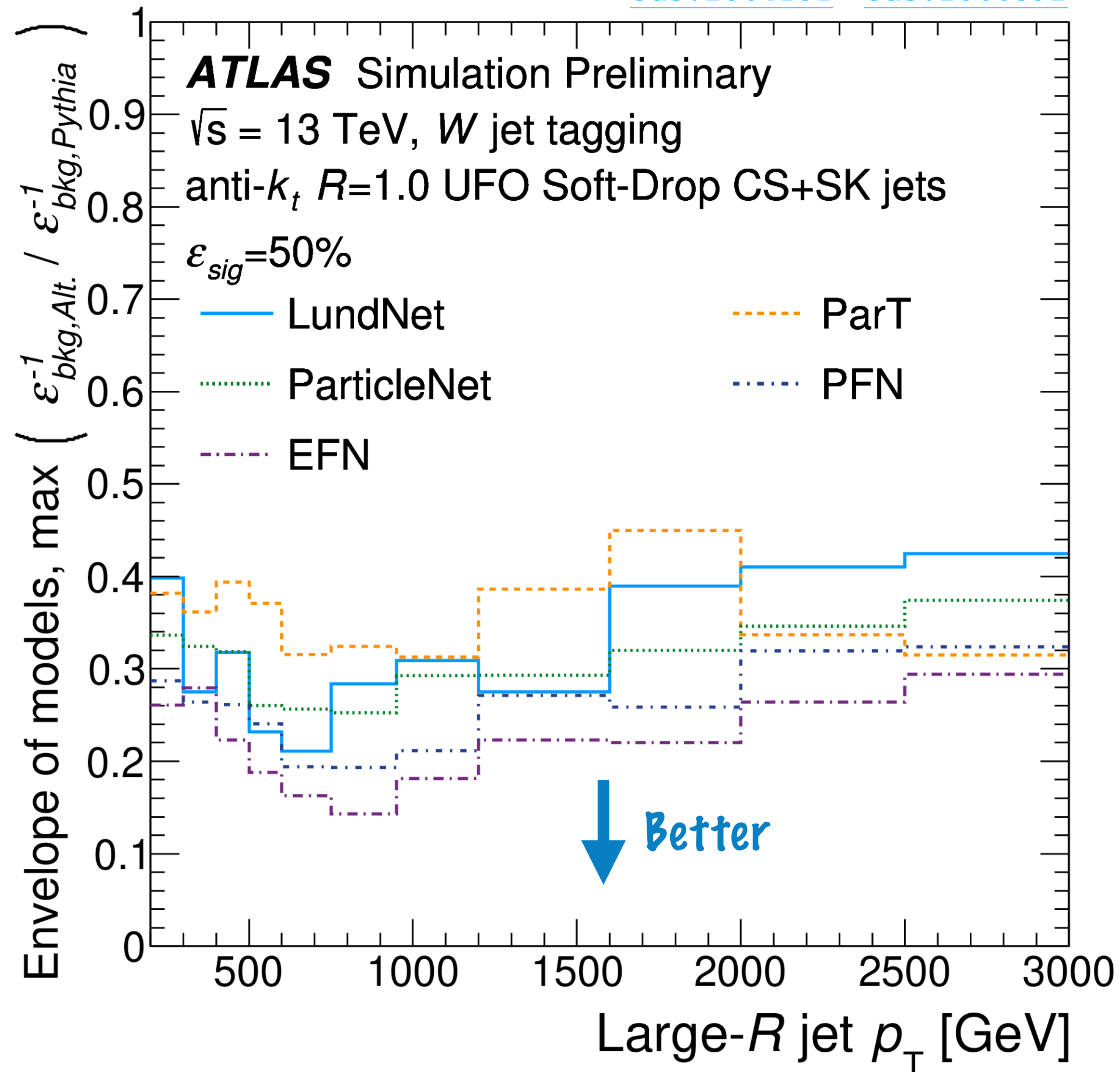
- Parton shower + hadronization modeling
- Renormalization scale
- Cross sections
- PDFs

Experimental

- Jet mass scale / resolution or similar
- Statistical
- Other SFs (e.g. b-tagging)
- Luminosity

W Tagger Modeling Dependence

[cds:2864131](#) [cds:2866592](#)



- The most powerful taggers (LundNet, ParT) show variations in performance of up to 40%
- Likely to produce larger SF uncertainties

Beyond Modeling Dependence

[cds:2724149](#)

Modeling uncertainties were dominant for simple high-level quantity based taggers.

What about constituent based taggers?

Systematic Group	W tagger p_T bins [GeV]			
	[200,250]	[250,300]	[300,350]	[350,600]
Statistical	0.01	0.02	0.03	0.04
Theory	< 0.01	< 0.01	< 0.01	< 0.01
$t\bar{t}$ modeling	0.21	0.20	0.15	0.12
Large- R jet	0.01	0.01	< 0.01	< 0.01
Other experimental	< 0.01	< 0.01	< 0.01	< 0.01
b -tagging	< 0.01	< 0.01	< 0.01	< 0.01
Total Uncertainty	0.21	0.20	0.15	0.12

Available on the CERN CDS information server CMS PAS BTV-22-001

CMS Physics Analysis Summary

Contact: cms-pog-conveners-btag@cern.ch 2023/07/29

Performance of heavy-flavour jet identification in boosted topologies in proton-proton collisions at $\sqrt{s} = 13$ TeV

The CMS Collaboration

Abstract

Physics measurements in the highly Lorentz-boosted regime, including the search for the Higgs boson or beyond standard model particles, are a critical part of the LHC physics program. In the CMS Collaboration, various boosted-jet tagging algorithms, designed to identify hadronic jets originating from a massive particle decaying to $b\bar{b}$ or $c\bar{c}$, have been developed and deployed in a variety of analyses. This note highlights their performance on simulated events, and summarises the novel calibration methods of these algorithms with 2016-2018 data collected in proton-proton collisions at $\sqrt{s} = 13$ TeV. Three distinct control regions are studied, selected via machine learning techniques or the presence of reconstructed muons from $g \rightarrow b\bar{b}$ ($c\bar{c}$) decays, as well as regions selected from Z boson decays. The calibration results, derived through a combination of measurements in these three regions, are presented.

[cds:2866276](#)

st-fit histograms in the sBBDT method for passing (left) and failing (right) the derivation of the scale factor of the ParticleNet-MD X -> cC discriminator working point. This example is based on data and simulated events in the jet p_T range of (450, 500) GeV.

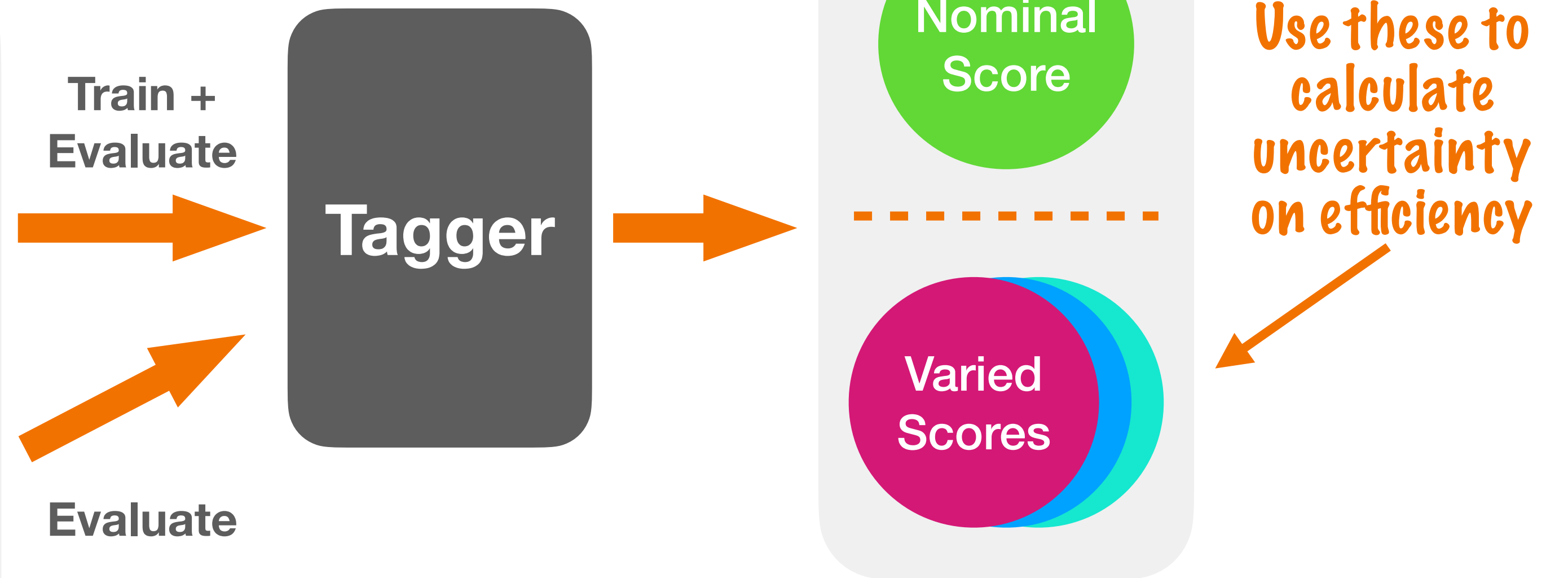
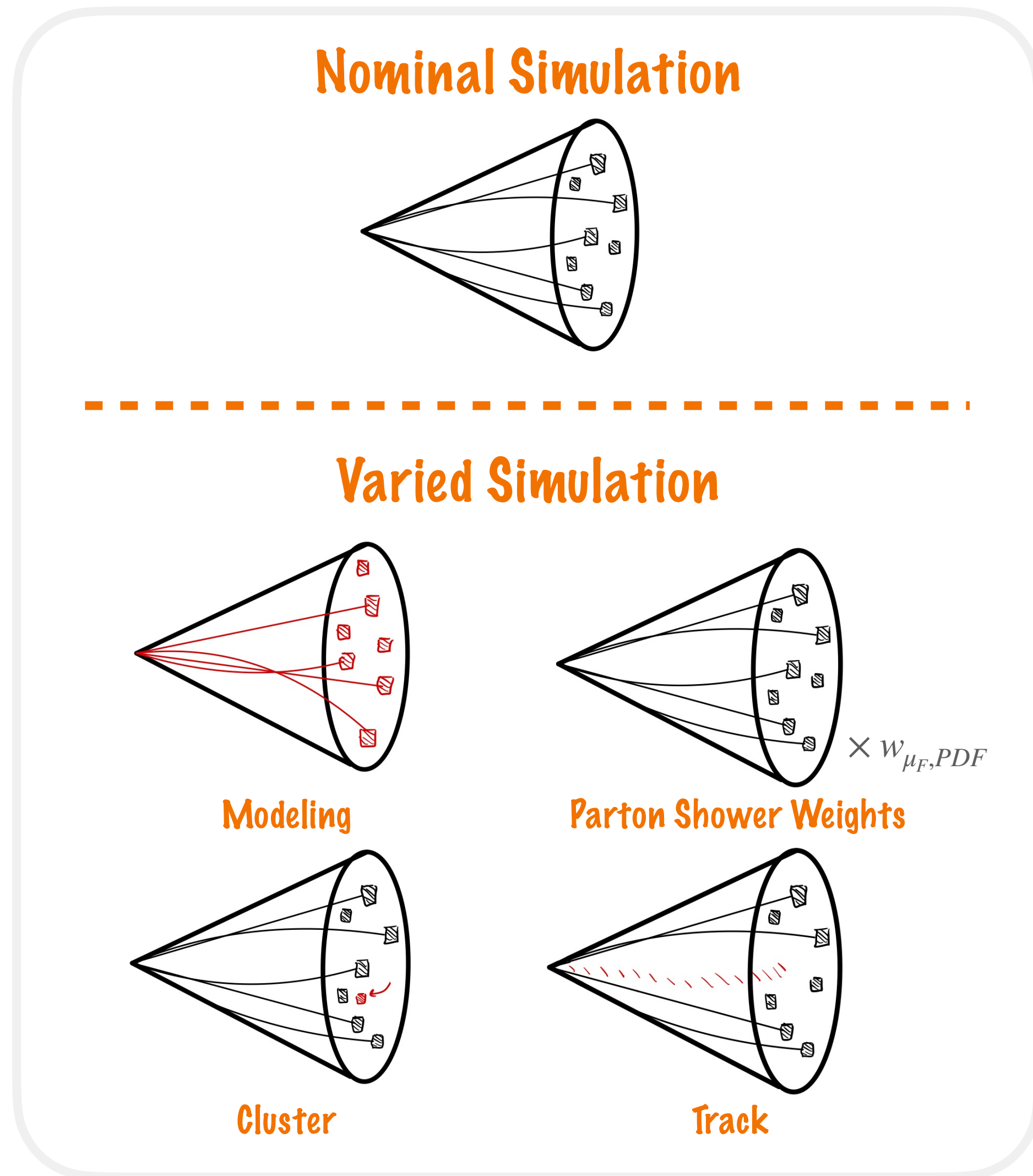
st-fit histograms in the sBBDT method for passing (left) and failing (right) the derivation of the scale factor of the ParticleNet-MD X -> cC discriminator working point. This example is based on data and simulated events in the conditions, in the jet p_T range of (450, 500) GeV.

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Measuring scale factors is difficult, and only possible within collaborations.

Can we find something approximate everyone can use?

Bottom-up Uncertainties

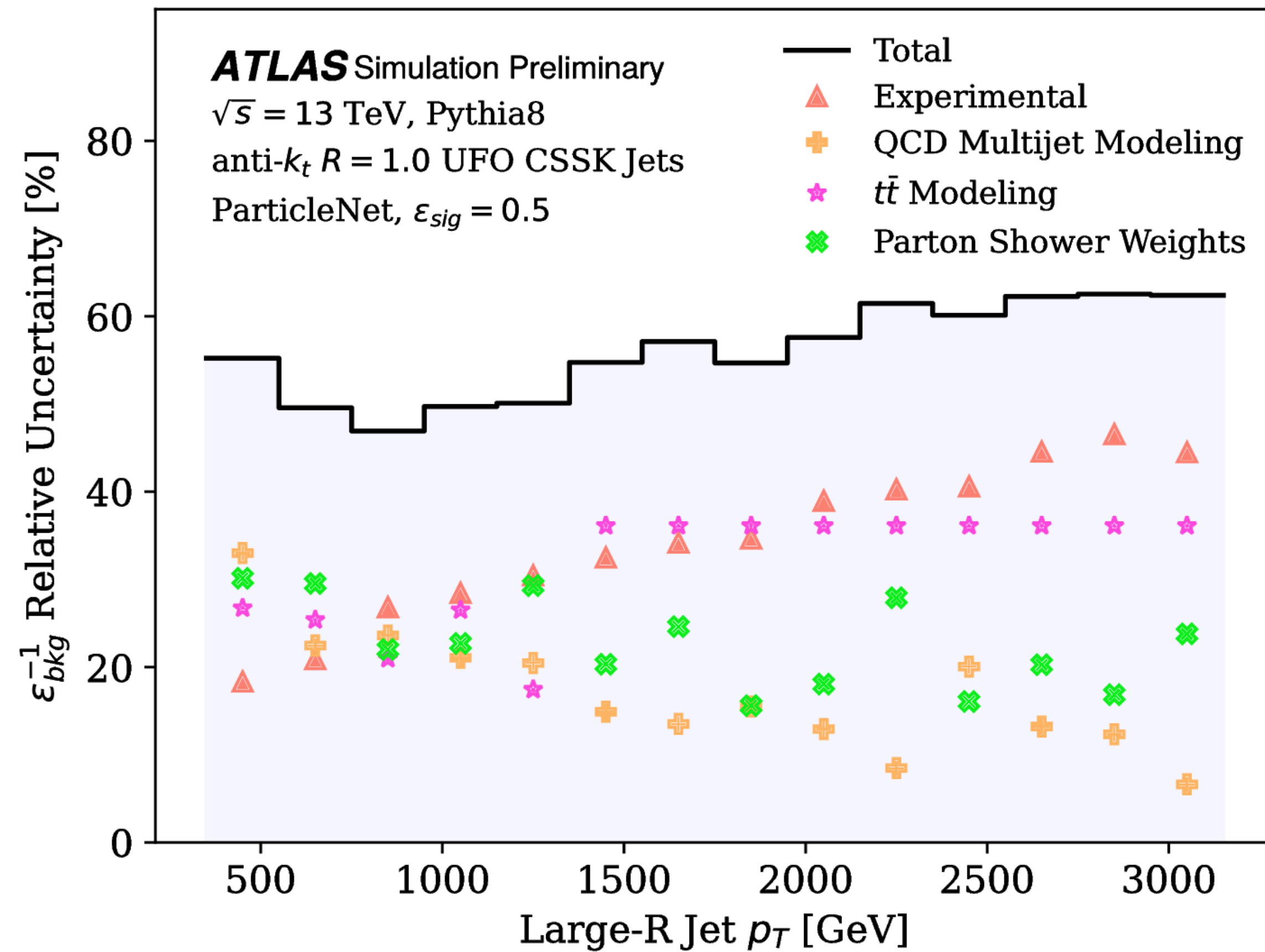


Benefits

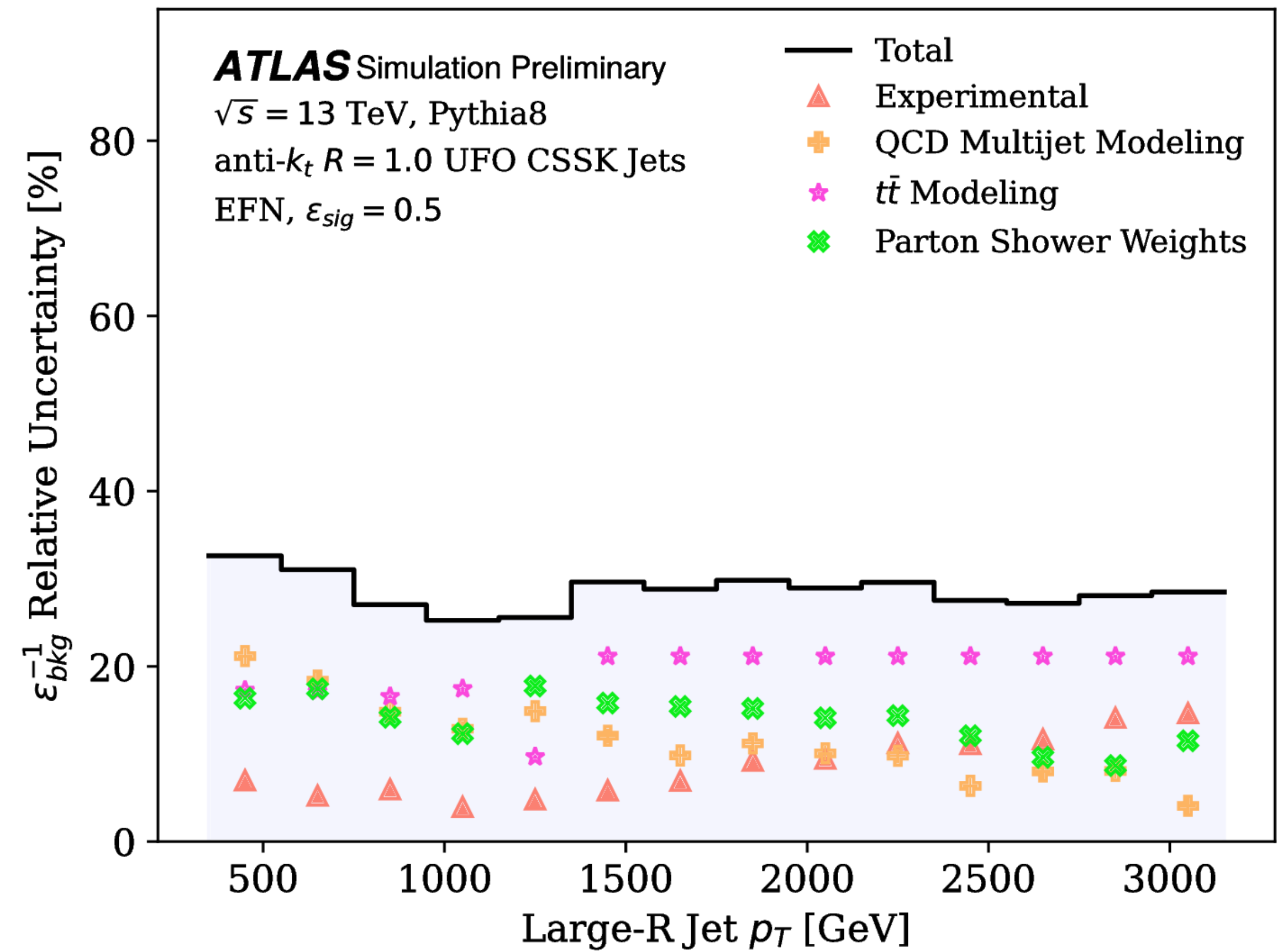
- No data required
- Once varied simulation is generated, can be used for arbitrary tagger
- Can define uncertainties on tagger efficiency with no signal enriched region in data

Top Tagger Uncertainties

Note these **are not** scale factor uncertainties. Expected to be conservative, but relative sensitivity of taggers is important.



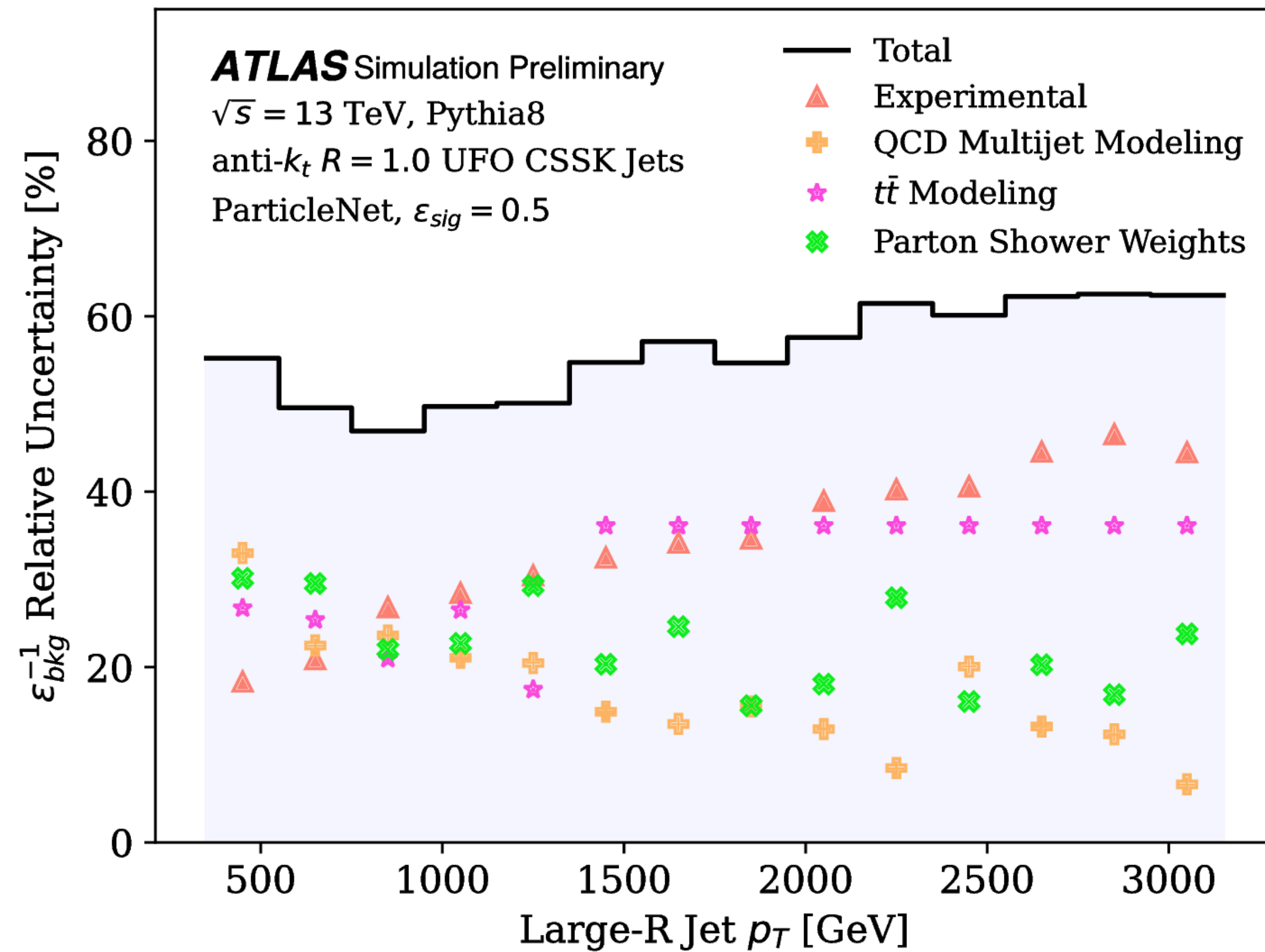
Large and Powerful GNN



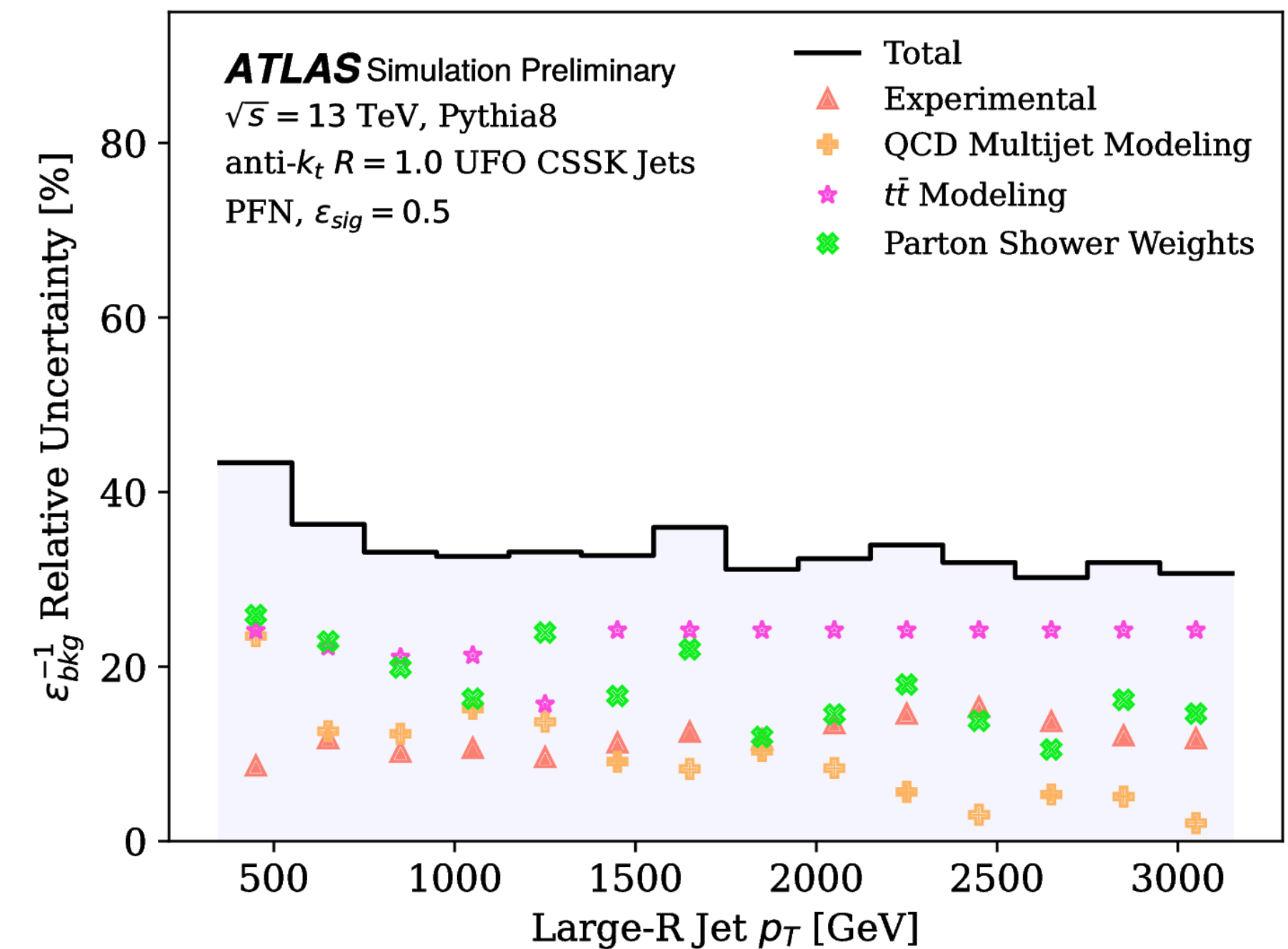
Theory Motivated IRC Safe Tagger

Top Tagger Uncertainties

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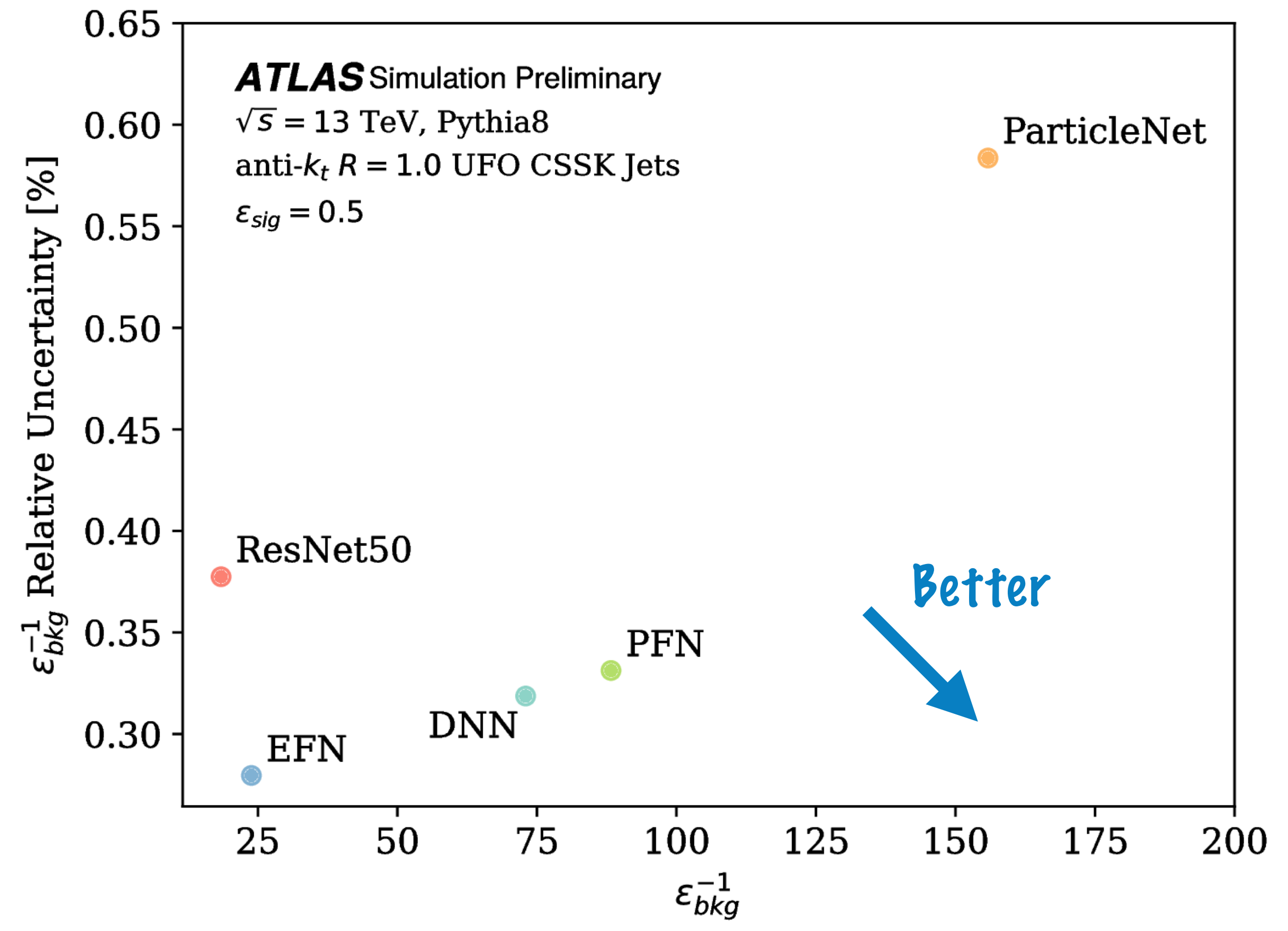
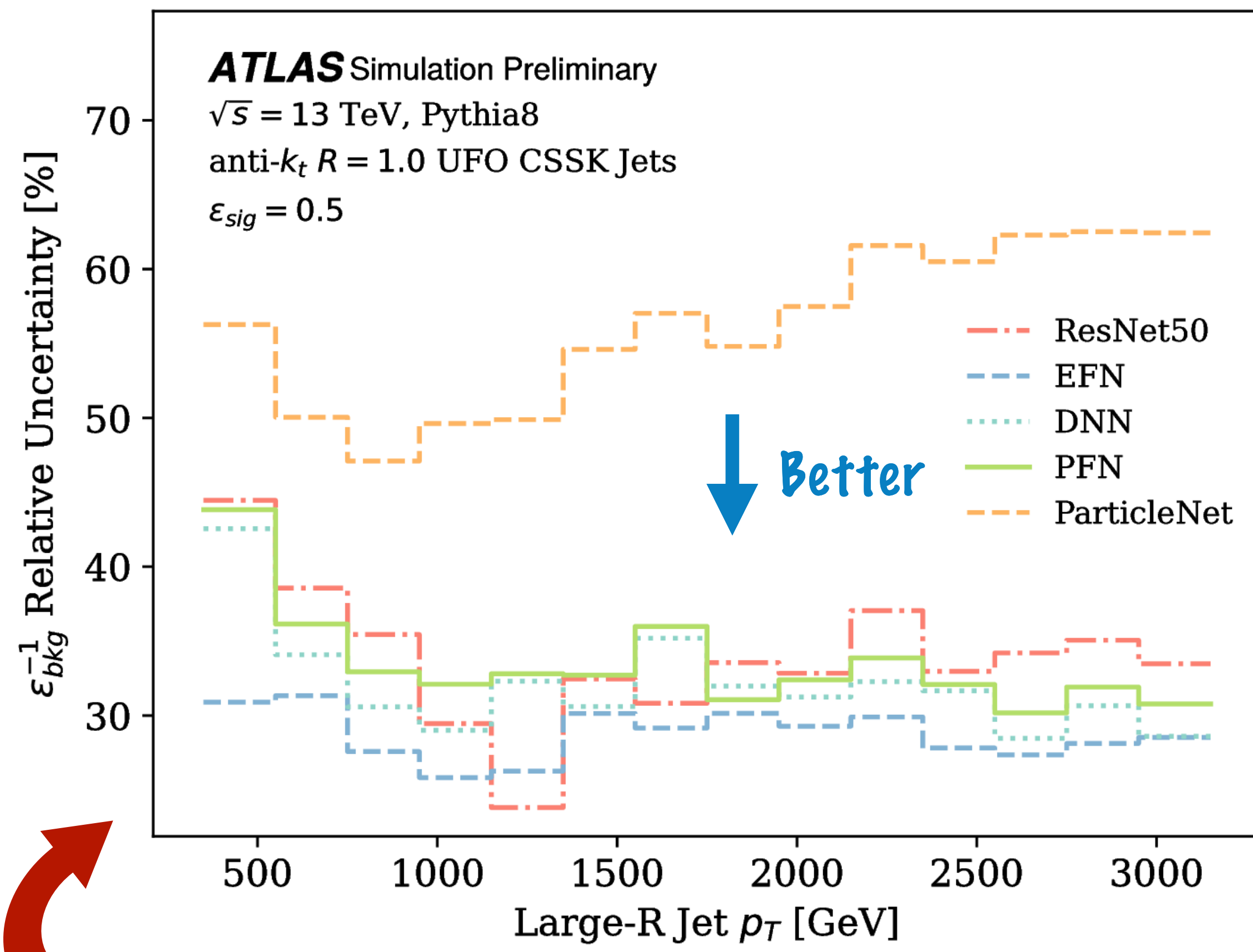
Large and Powerful GNN



Deep Set (PFN)

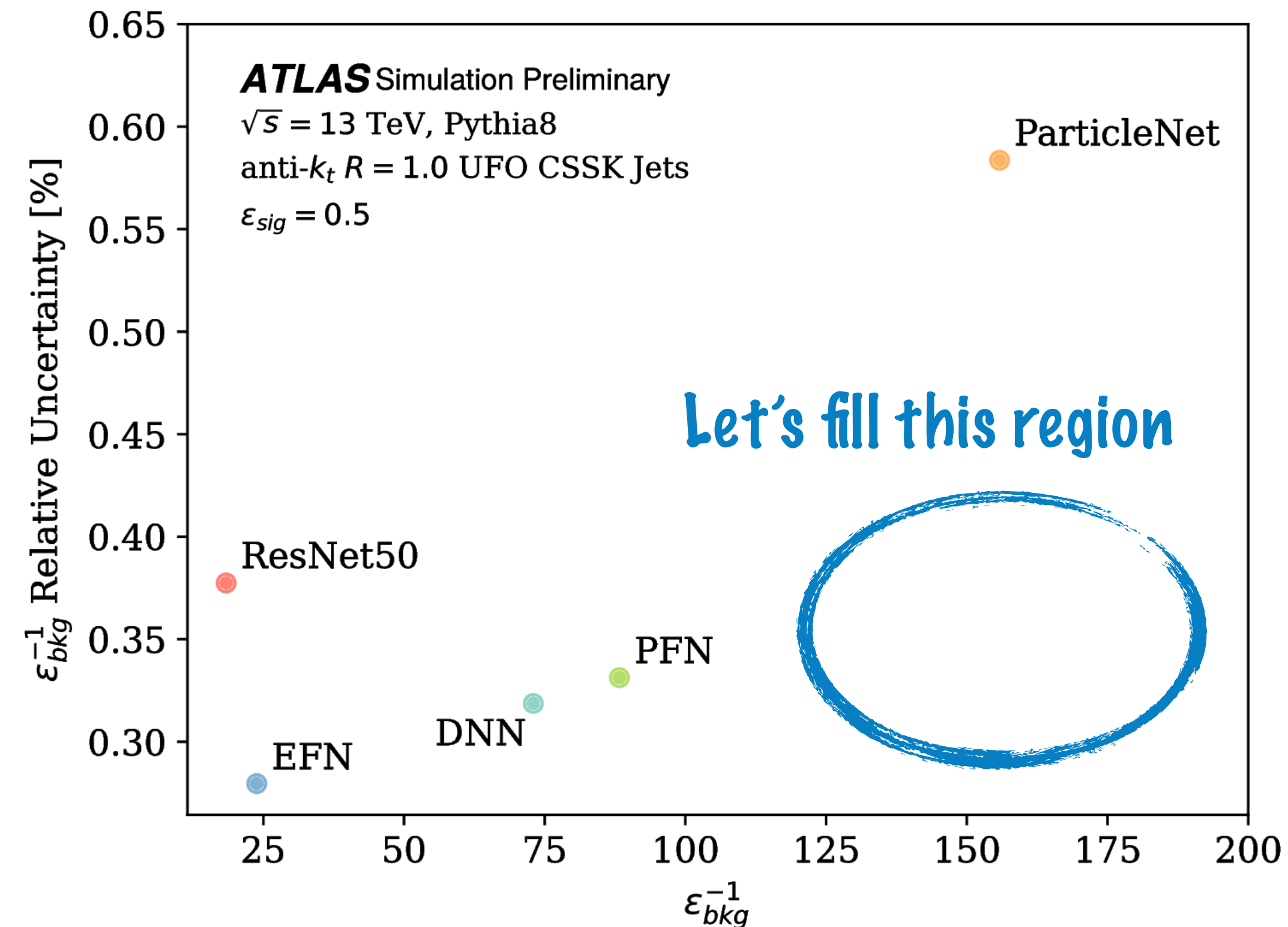
- ParticleNet more sensitive to modeling
- Dramatically more sensitive to experimental variations

Uncertainty Comparison



Larger uncertainties here are expected to produce larger SF uncertainties

Conclusions

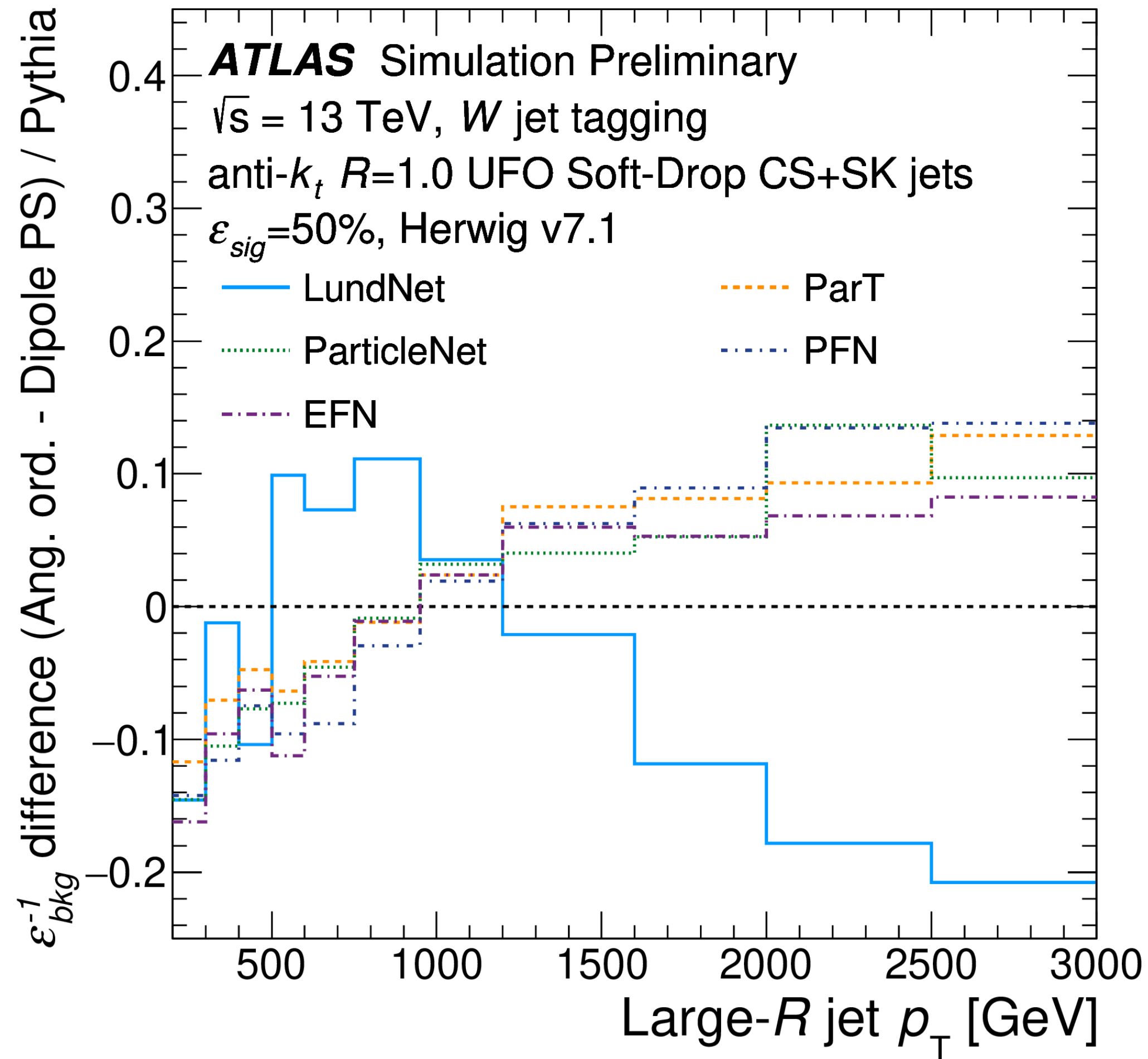


- Powerful ML based jet tagging is deployed and producing physics!
- However, the more powerful the tagger, the larger the uncertainties
 - Could be limiting for some analyses

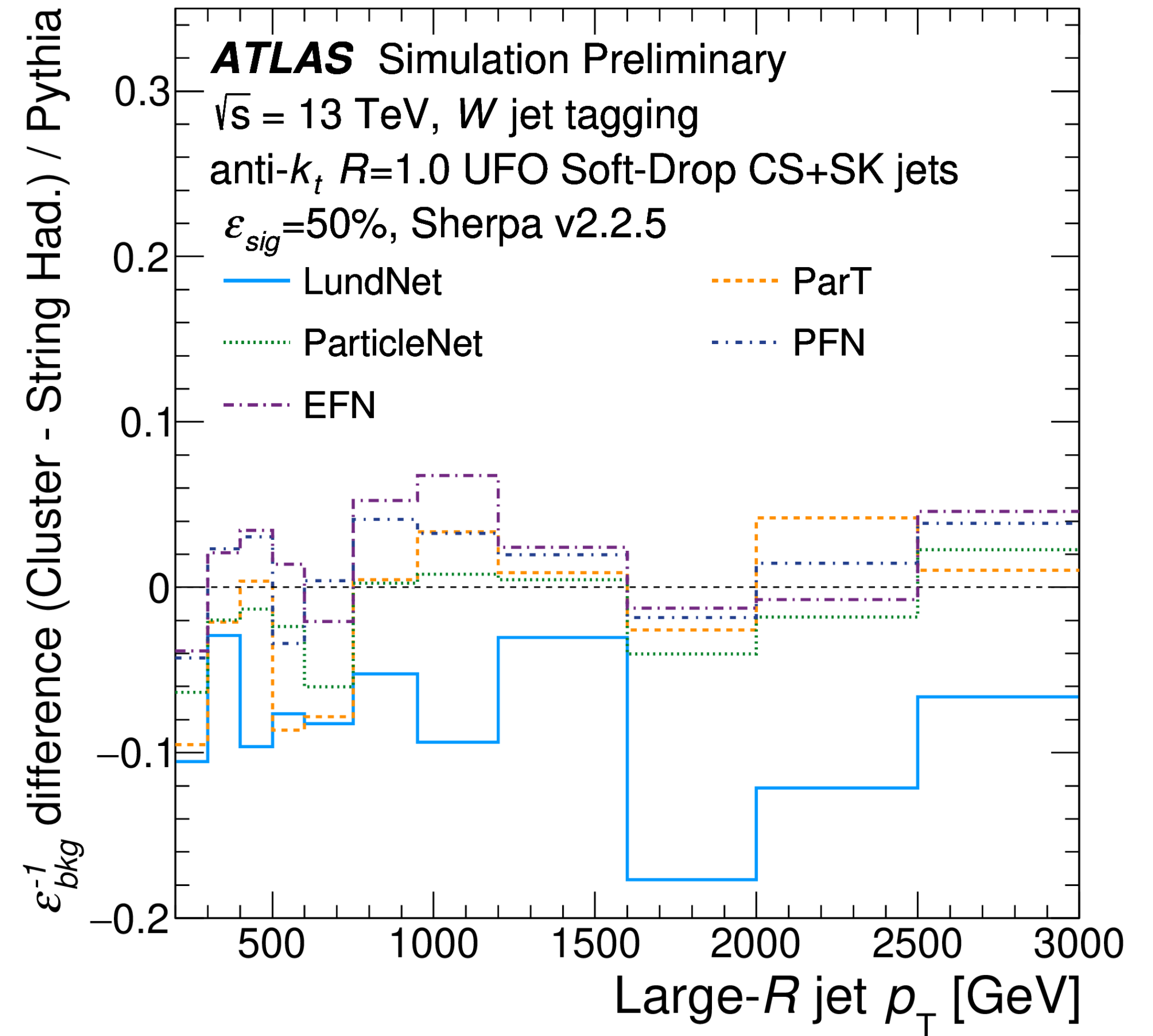
The new frontier is high performance and low uncertainties

Backup

W Tagger Modeling Dependence



Parton Shower



Hadronization

Top Tagging Systematic Variations

Modify nominal
Alternative samples
Pythia shower weights

Experimental

- Calorimeter Clusters¹
 - Energy Scale (Up / Down)
 - Energy Resolution
 - Position resolution
- Tracks
 - Fake rate
 - Efficiency
 - Sagitta bias

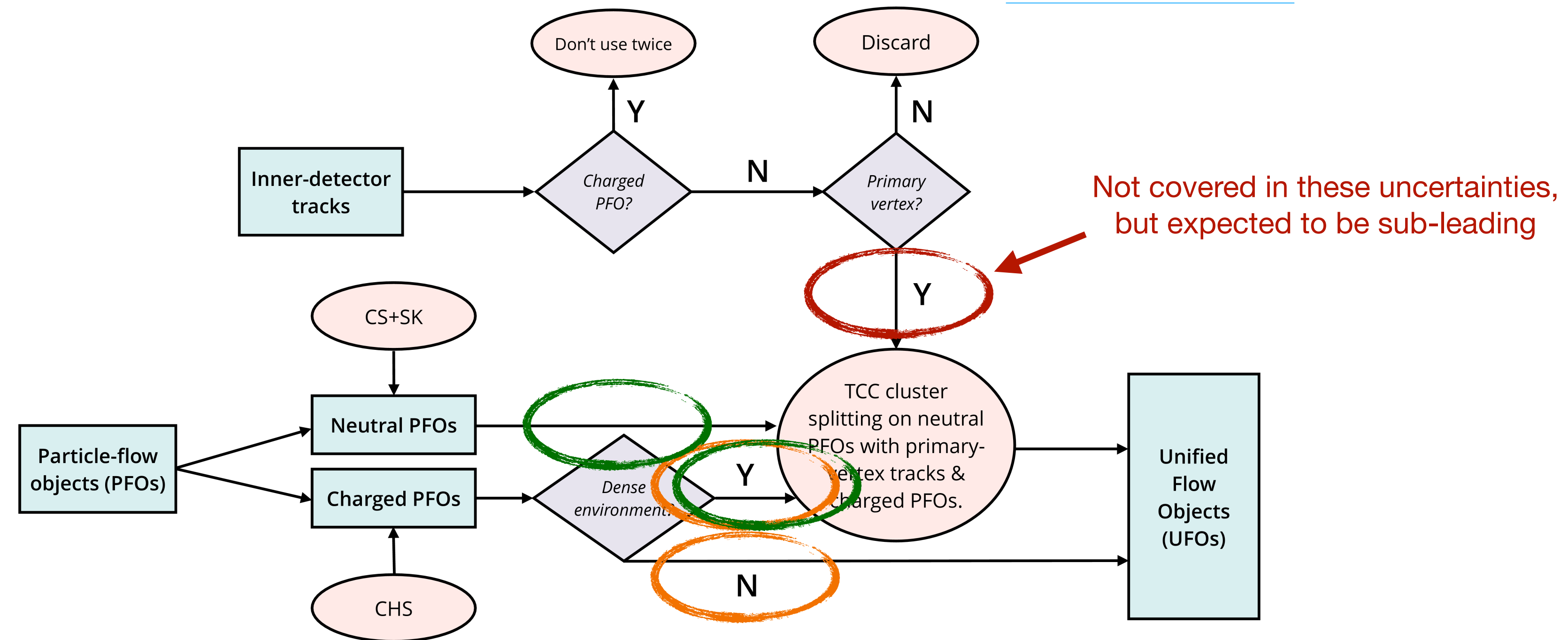
¹ - [arxiv: 1912.0983](https://arxiv.org/abs/1912.0983), [arxiv:1903.02942](https://arxiv.org/abs/1903.02942), [arxiv:2108.09043](https://arxiv.org/abs/2108.09043)

Theoretical

- $t\bar{t}$ modeling
 - Compare Pythia to Herwig in SM $t\bar{t}$ samples
- QCD multijet modeling
 - Compare Herwig angular ordered to dipole parton shower
 - Compare Sherpa cluster to string based hadronization model
- Renormalization scale
 - Vary scale up/down by factors of 2
- PDFs
 - Vary PDFs up/down

Experimental Uncertainties

[arxiv:2009.04986](https://arxiv.org/abs/2009.04986)



Tracks

- Apply to charged and “merged” UFOs
- Track fake rate and efficiency
- Track bias

Calorimeter Clusters

- Apply to neutral and “merged” UFOs
- Cluster energy scale and resolution
- Cluster position resolution

Top Tagger Uncertainties

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