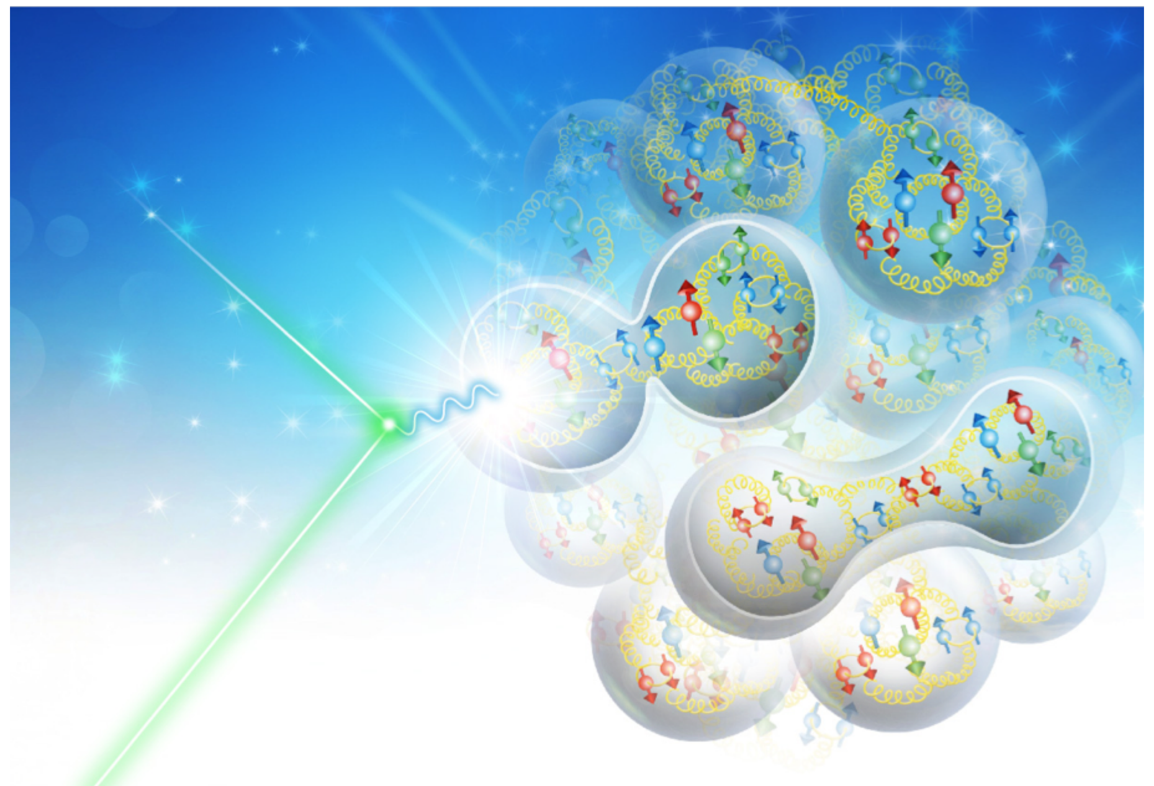
Jet physics in nuclear matter with machine learning

James Mulligan

UC Berkeley / LBNL

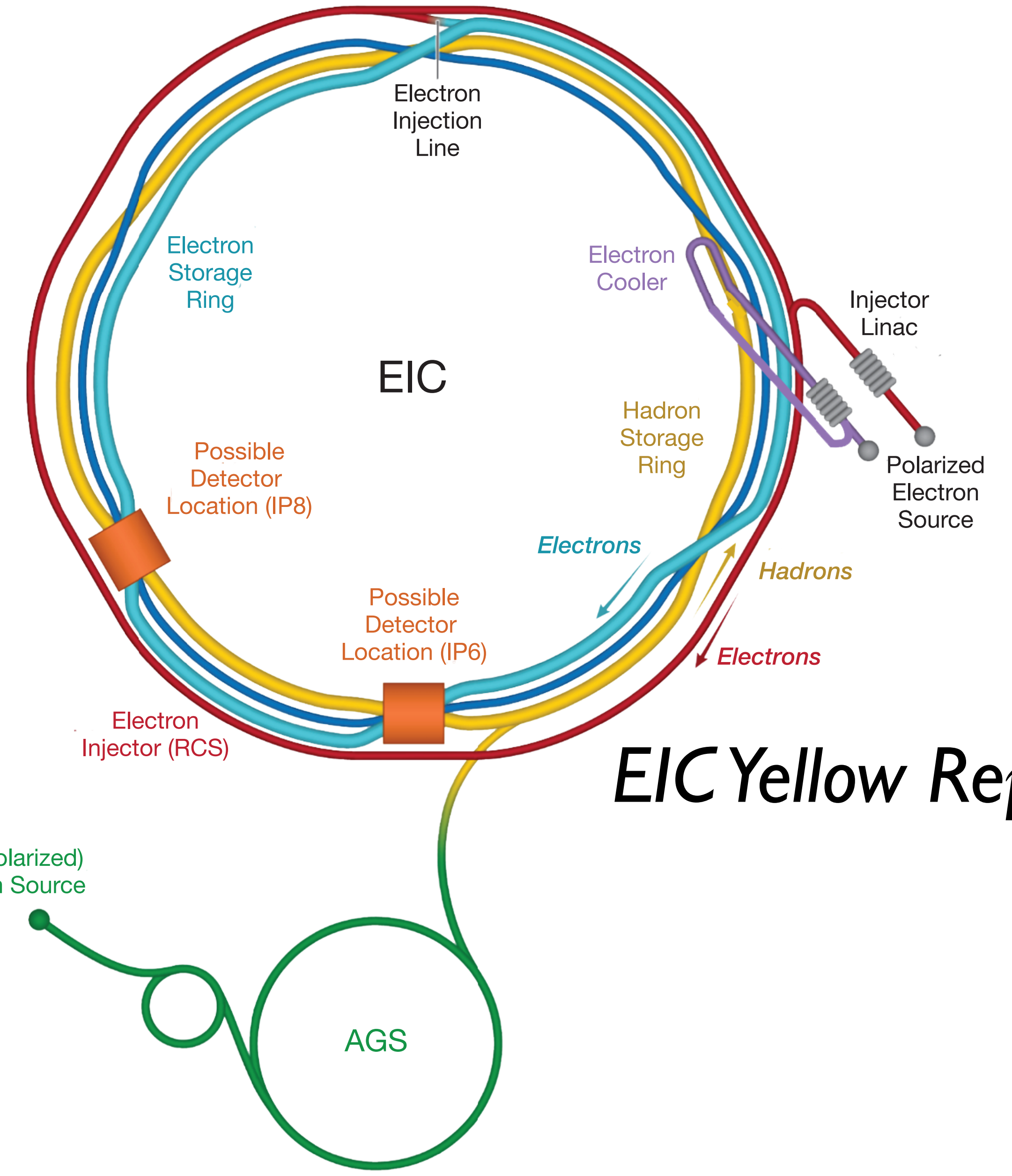


Berkeley
UNIVERSITY OF CALIFORNIA

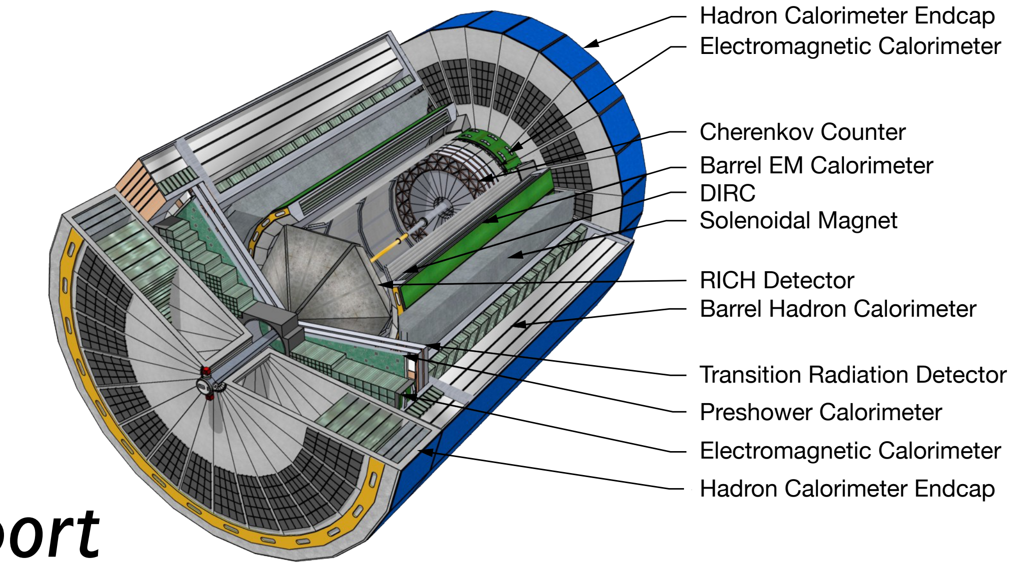
Workshop on Jets for 3D Imaging at the EIC
Stony Brook University
Sep 28, 2021

Where can ML play a role?

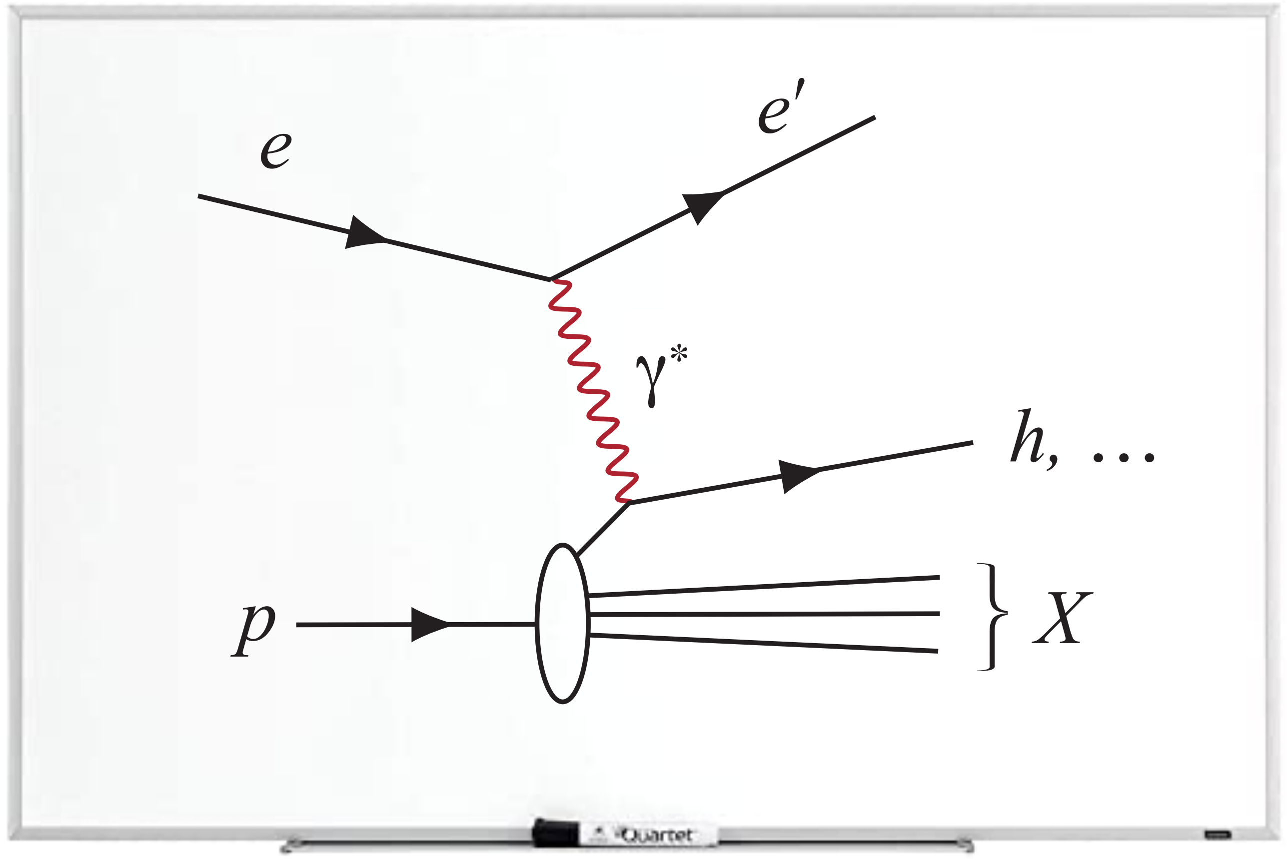
Experiment



EIC Yellow Report



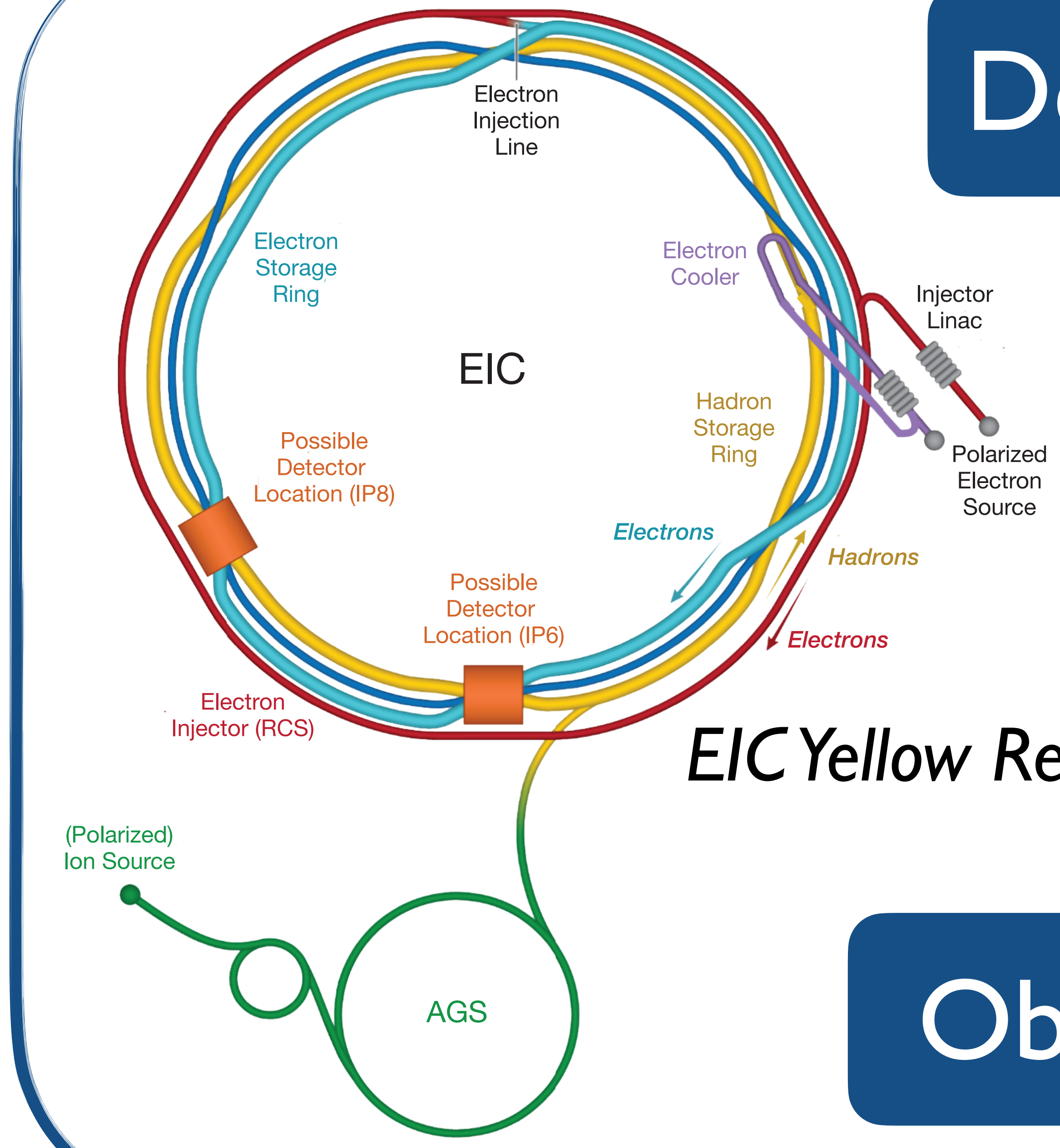
Theory



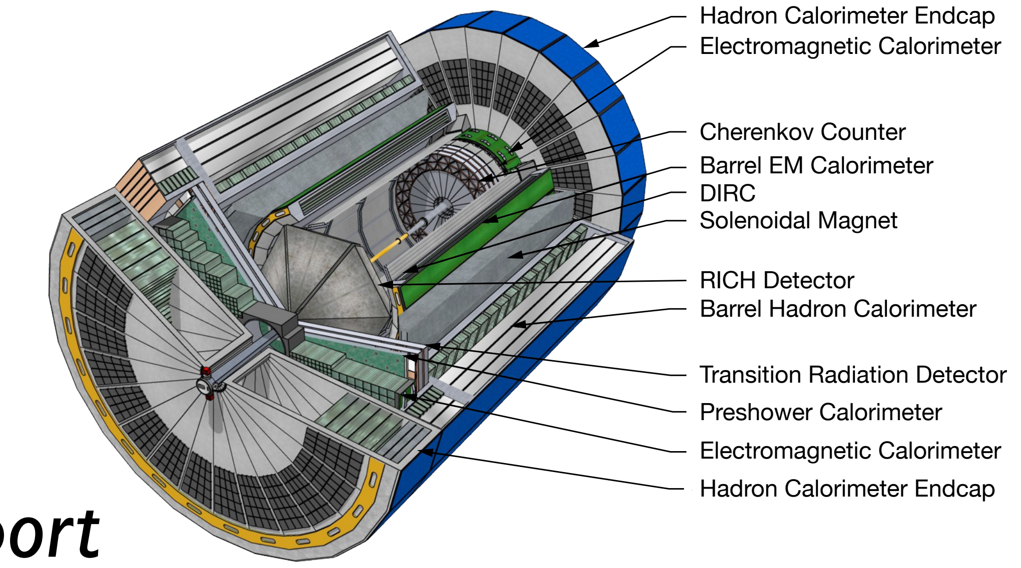
Data-Theory comparison

Understanding QCD

Where can ML play a role? (a few examples)

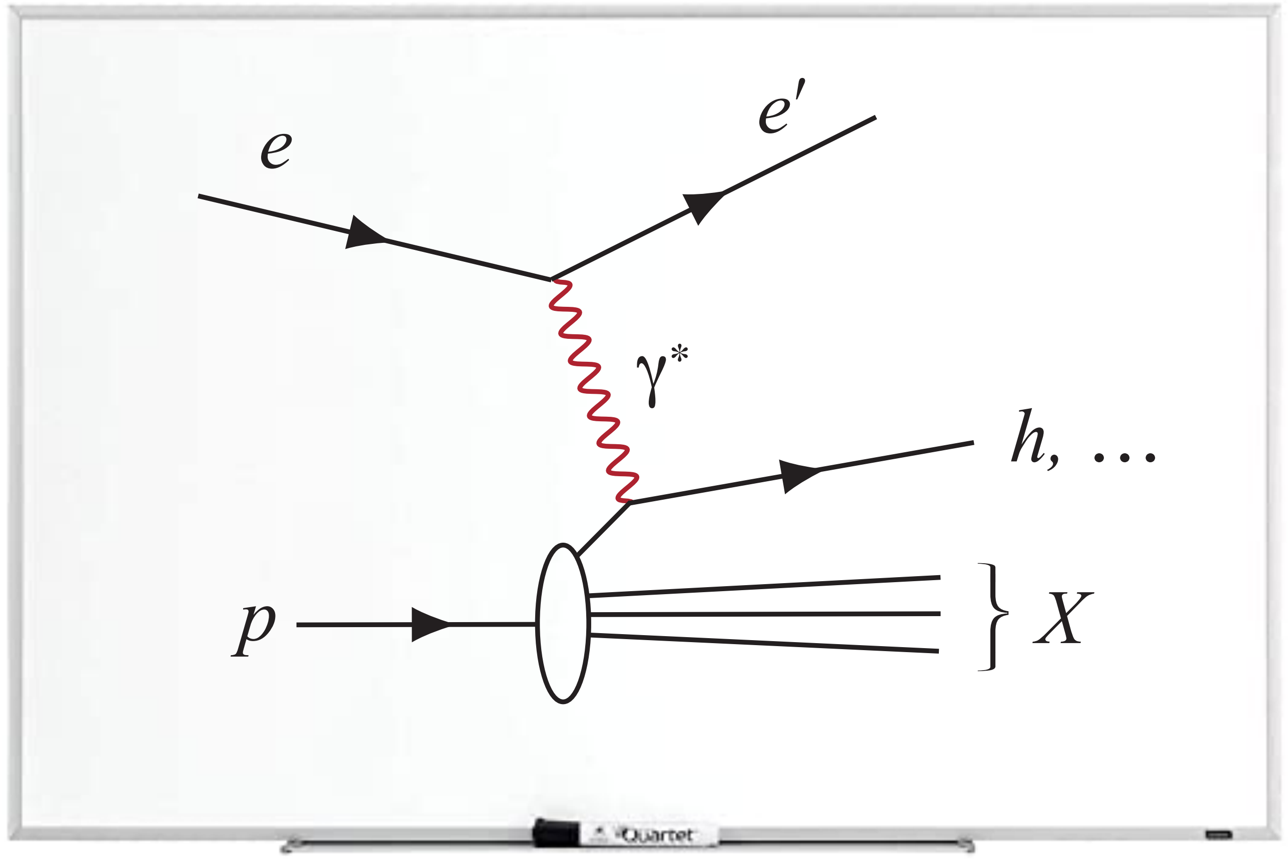


Detector optimization



EIC Yellow Report

Object reconstruction



Observable design

Data-Theory comparison

Unfolding

See B. Nachman talk

Model fitting / parameter estimation

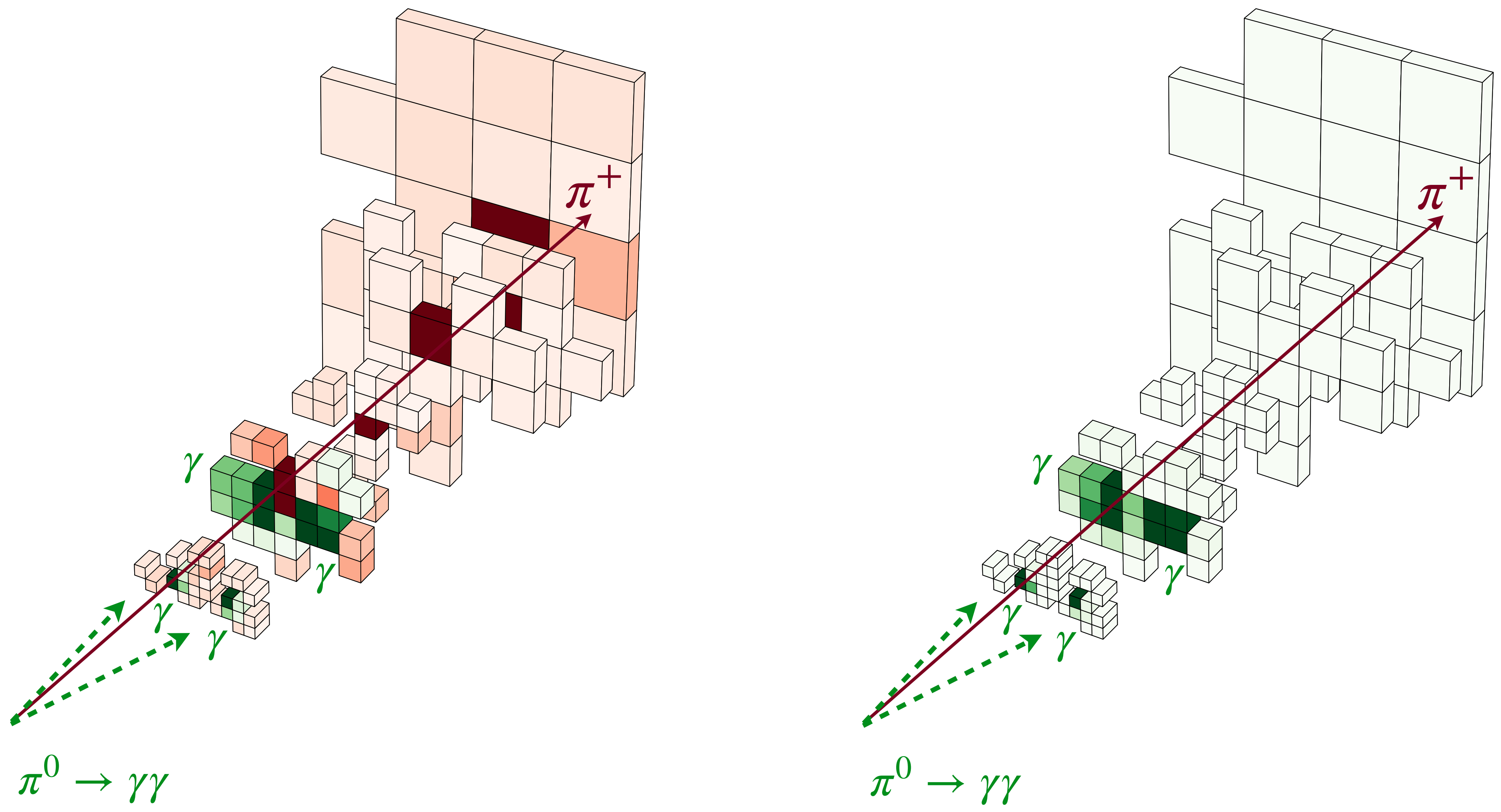
Understanding QCD

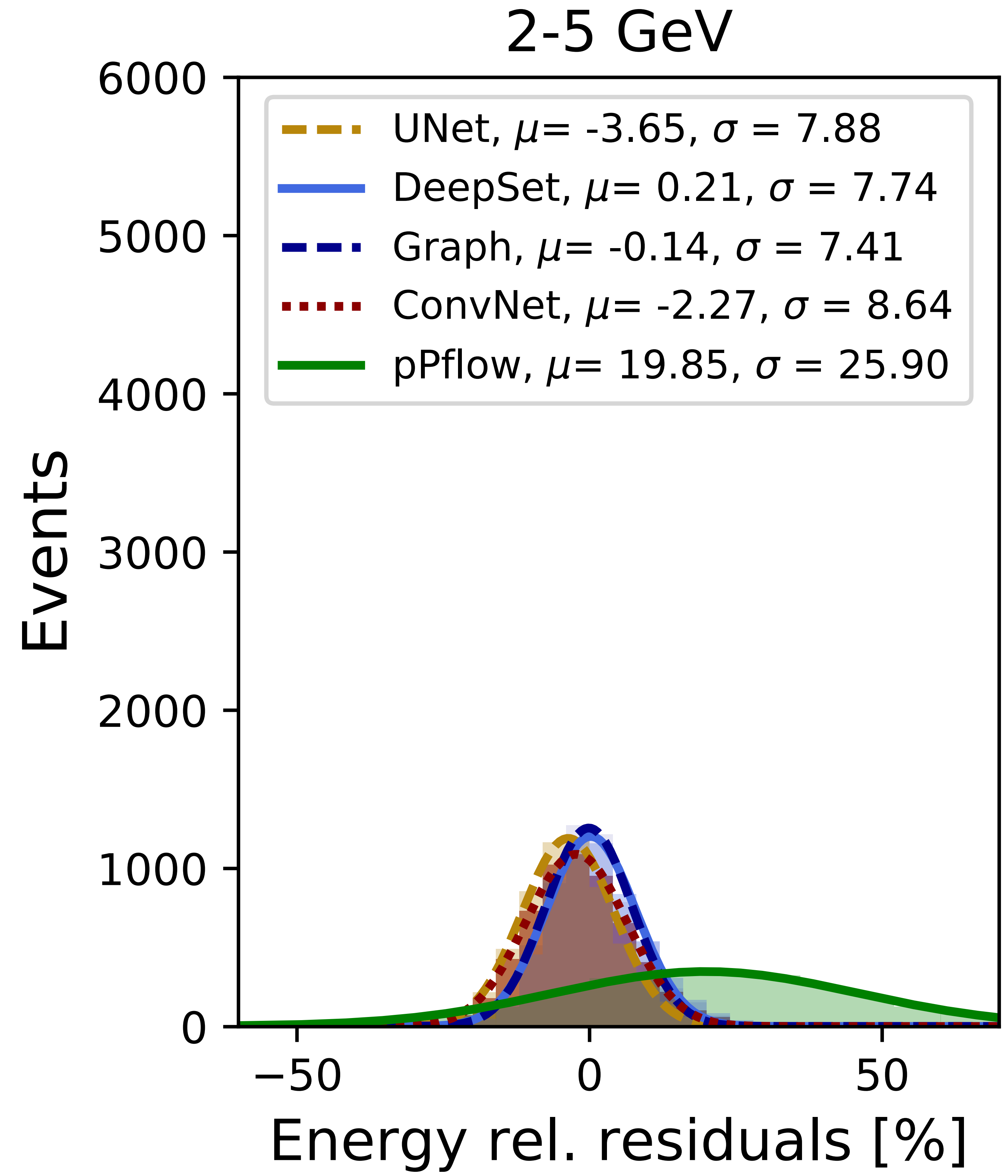
Particle flow

ML is promising to improve particle flow algorithms

- Identify/disentangle calorimeter showers

Di Bello et al. EPJC 81 107 (2021)





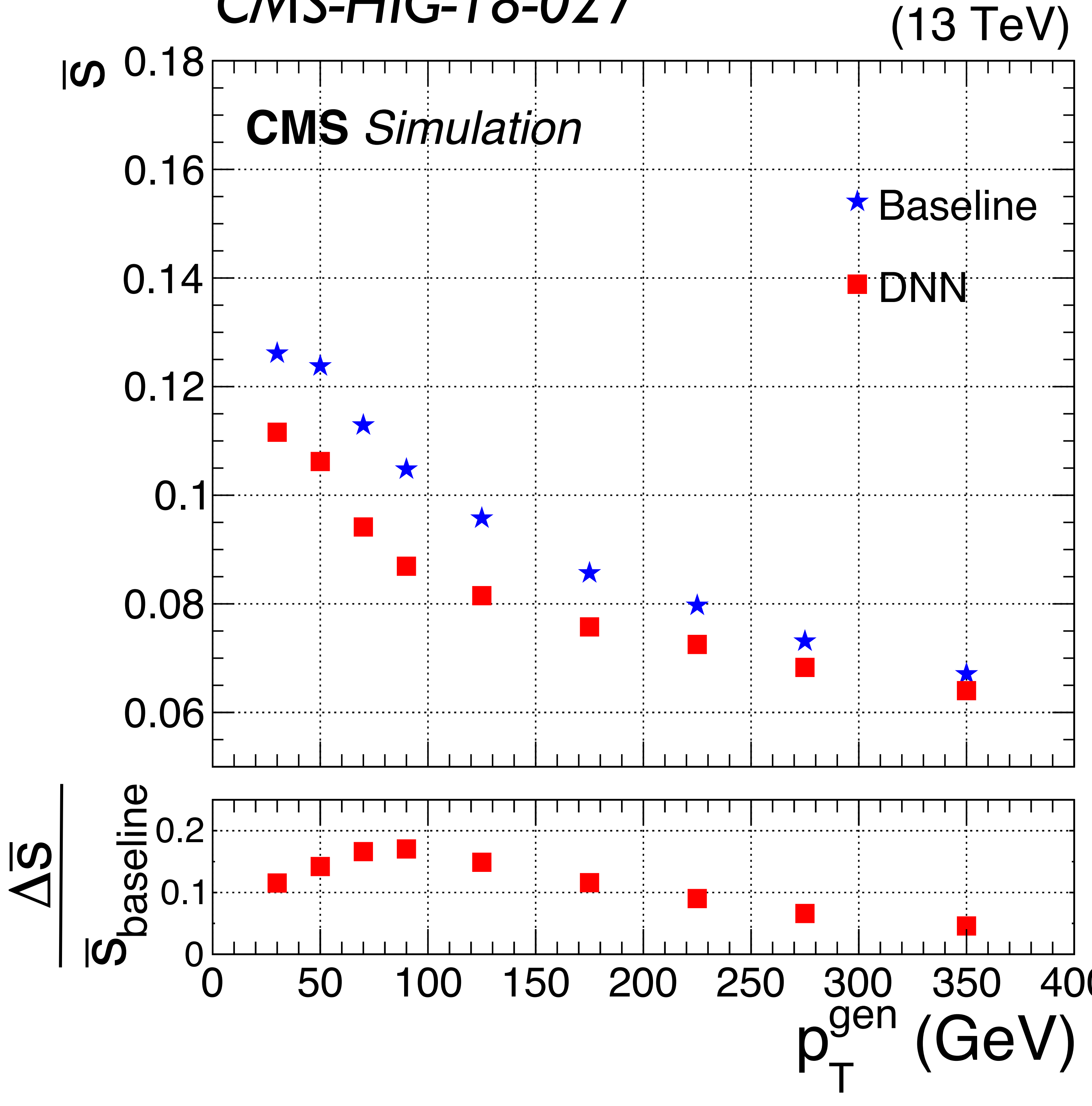
Relevant for EIC jets: neutral information at mid-rapidity, high granularity at forward rapidity

Jet calibration

Jet energy, mass resolution

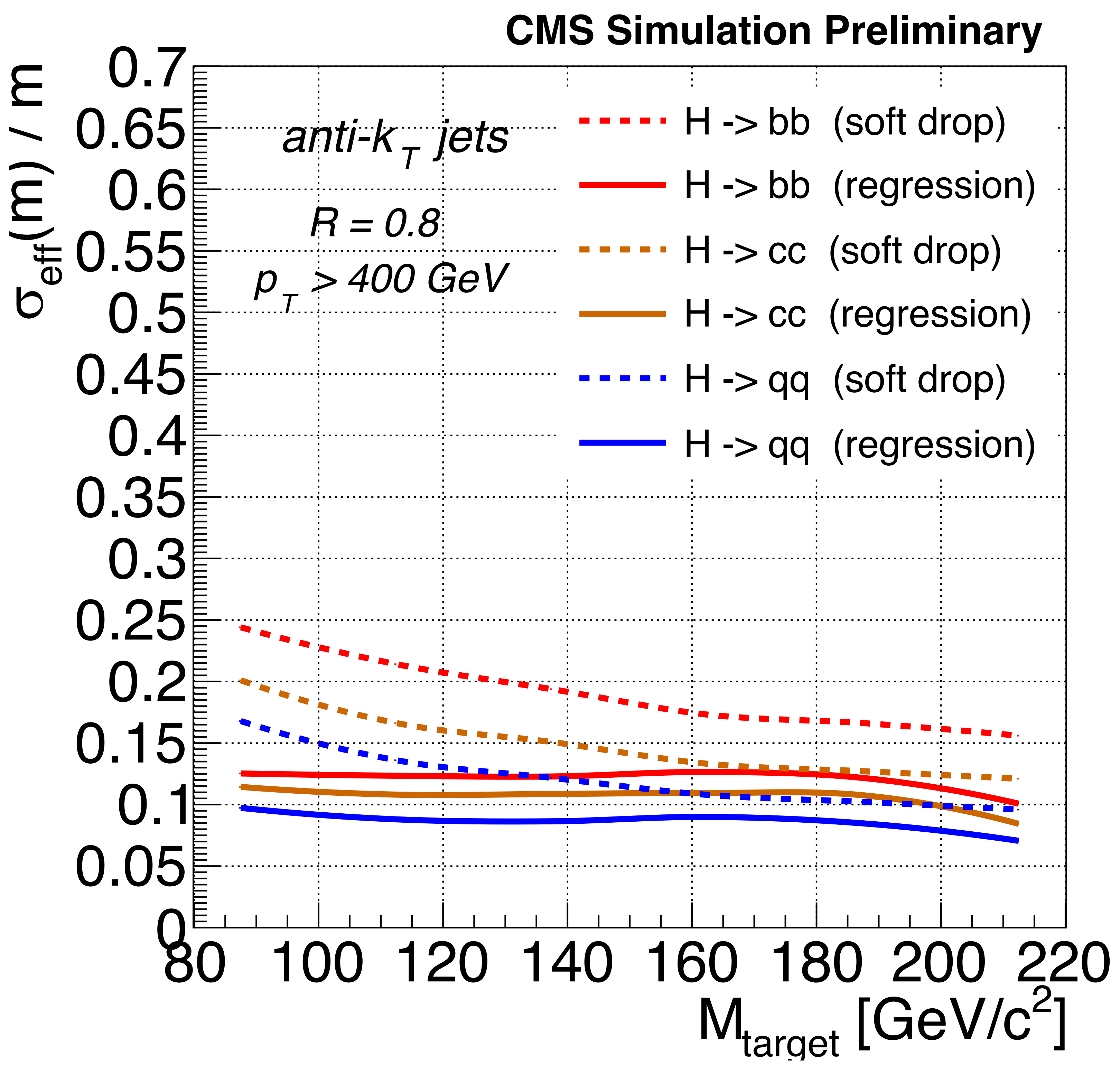
ML-based regression improves resolution

CMS-HIG-18-027



b-jet energy resolution

CMS-DP-2021/017



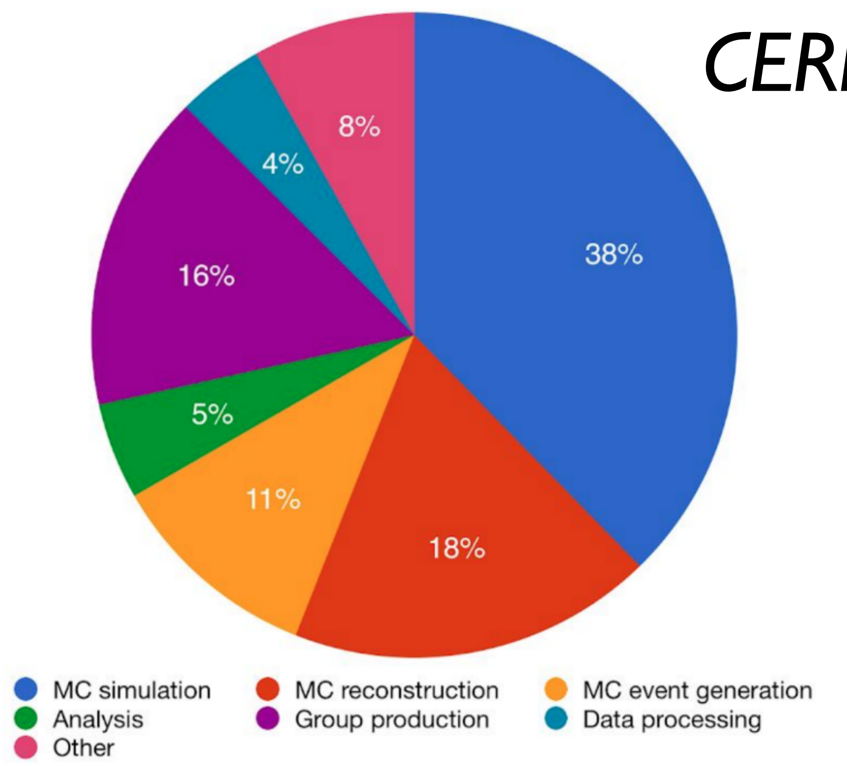
boosted jet mass resolution

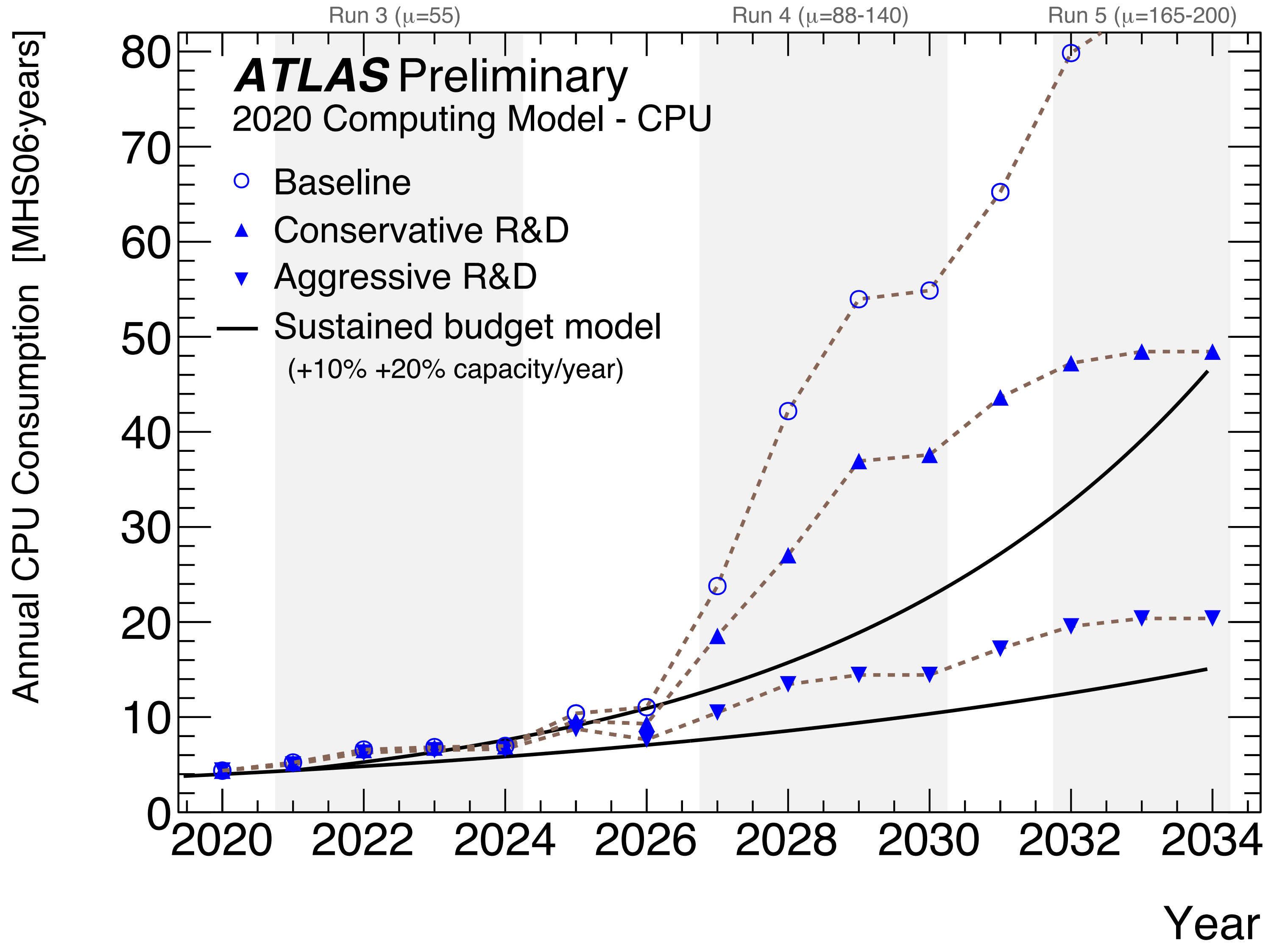
Fast Detector Simulation

High luminosity requires massive computation effort

- Detector simulation is largest component

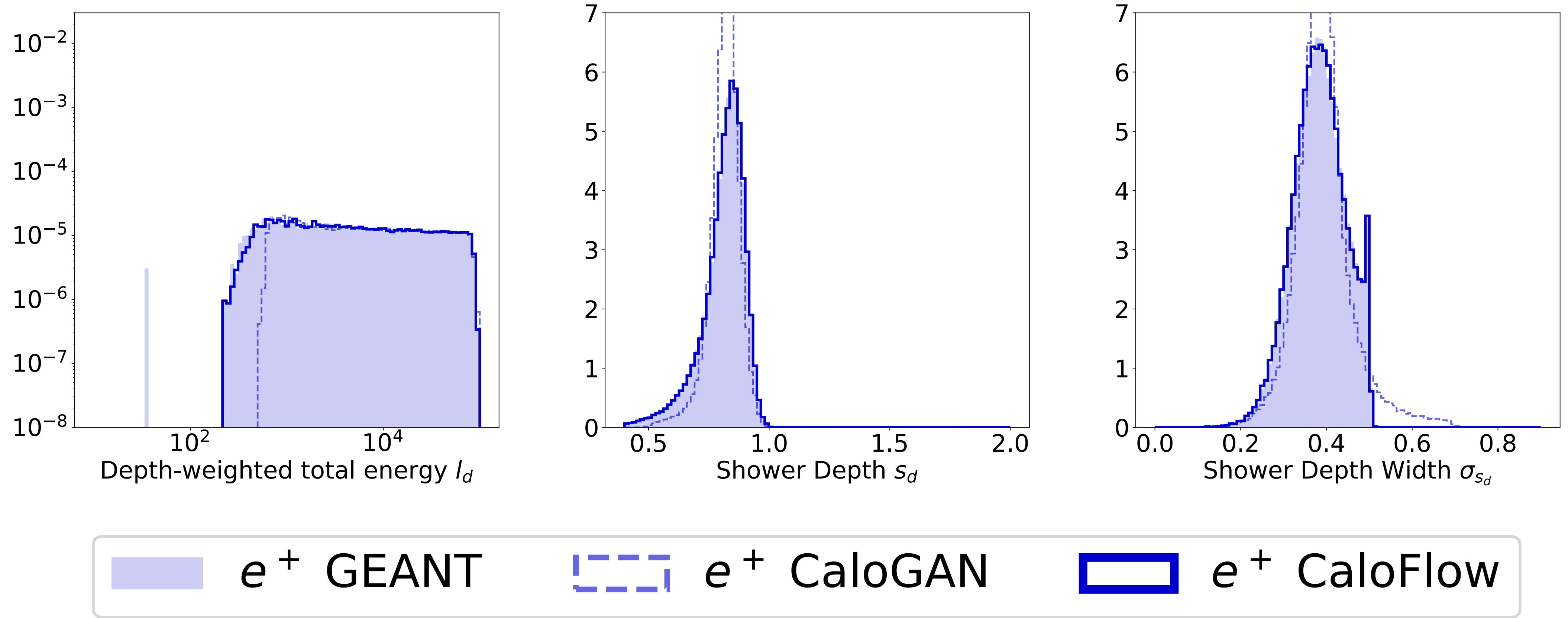
CERN-LHCC-2020-015





ML-assisted fast simulation: significant speedup

CaloFlow
Kraus, Shi 2106.05285
CaloGAN
Paganini, de Oliveira, Nachman
PRD 97 (2018) 1, 014021
AtlFast3
ATLAS 2109.02551
…

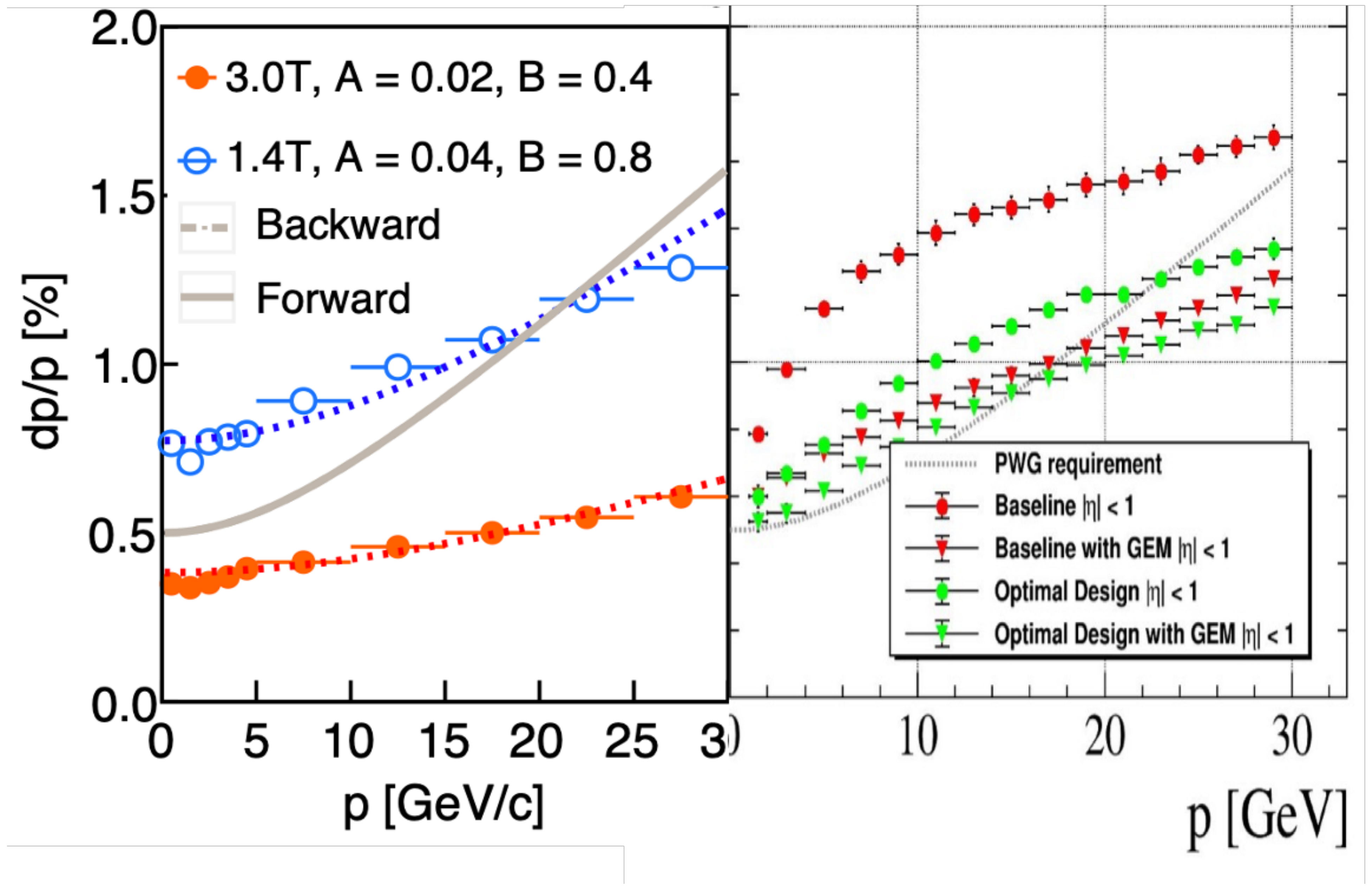


Detector design

ML-assisted detector design to improve reconstruction performance

ECCE optimization of tracking system

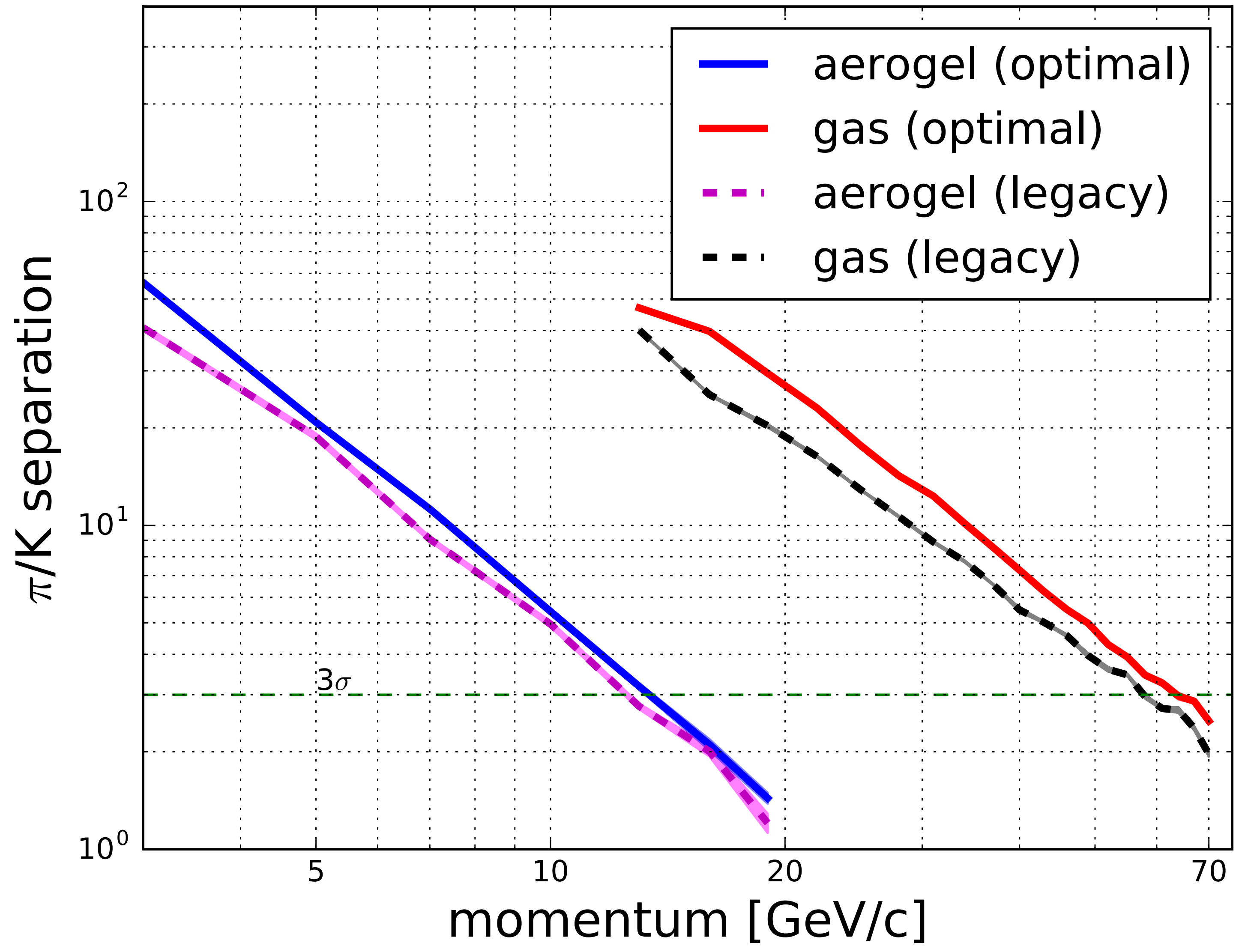
See J. Lajoie talk



Bayesian optimization of dRICH

Cisbani et al. *JINST* 15 (2020) 05, P05009

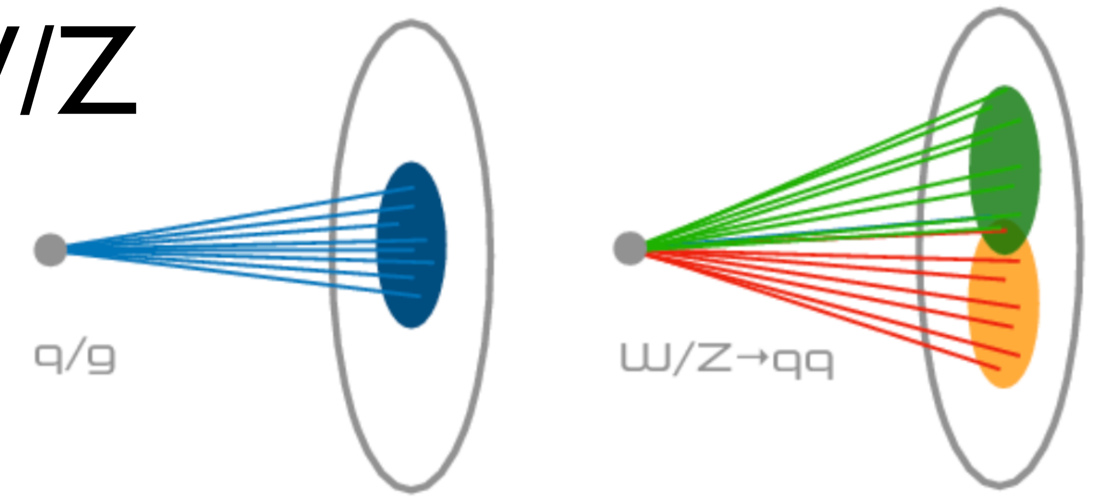
parameter	description
R	mirror radius
pos r	radial position of mirror center
pos l	longitudinal position of mirror center
tiles x	shift along x of tiles center
tiles y	shift along y of tiles center
tiles z	shift along z of tiles center
$n_{aerogel}$	aerogel refractive index
$t_{aerogel}$	aerogel thickness



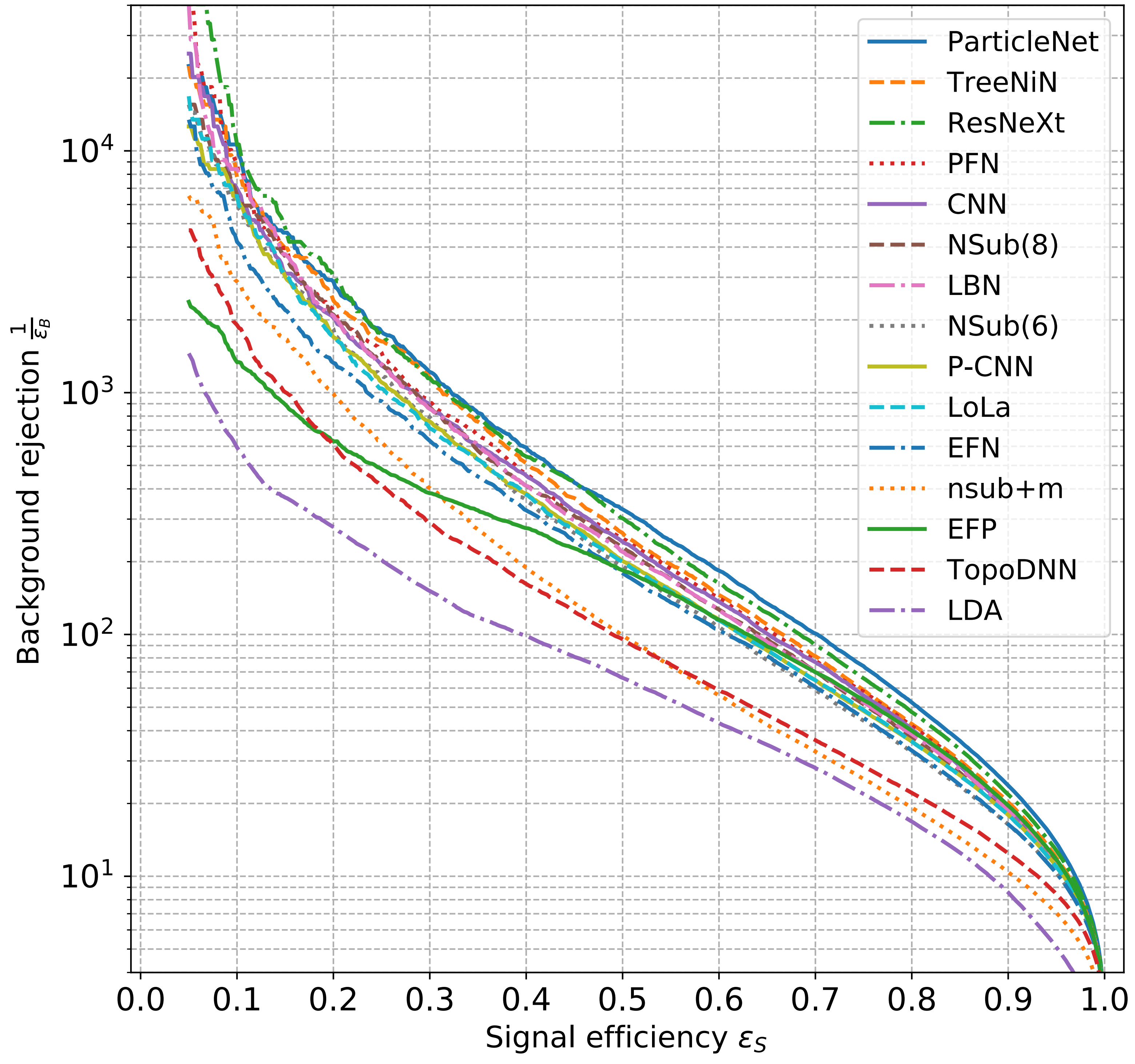
First major detectors with opportunity to take advantage of ML at design stage

Jet tagging

At LHC: quark/gluon, boosted top/h/W/Z



Kasieczka et al., SciPost Phys. 7 (2019) 014

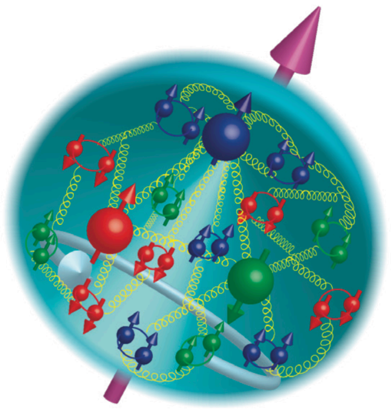


ML models outperform physics observables

- Point clouds w/NNs
  - ParticleNet *Qu, Gouskos PRD 101 (2020) 5, 056019*
  - ABCNet Mikuni, Canelli *EPJP* 135 (2020) 6, 463
  - PFNs, EFNs *Komiske, Metodiev, Thaler JHEP 01 (2019) 121*
- Lund image w/GNN: LundNet *Dreyer, Qu JHEP 52 (2021)*

Jet tagging at EIC

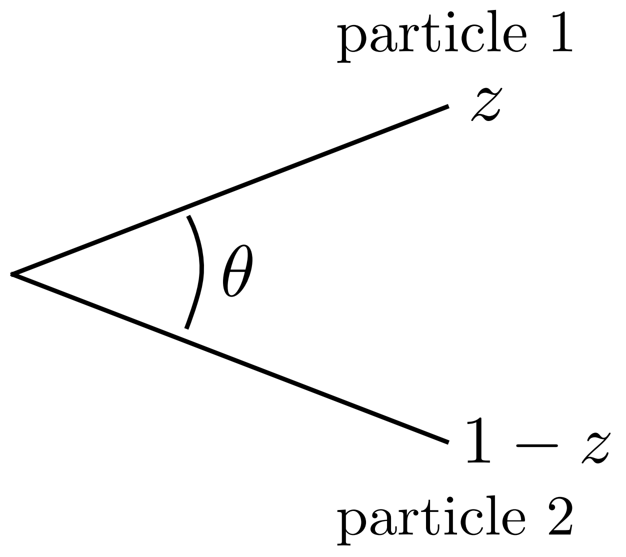
- Charm-jet tagging *Arratia, Furletova, Hobbs, Olness, Sekula 2006.12520*
- Tagged jet populations to be used for 3D structure?

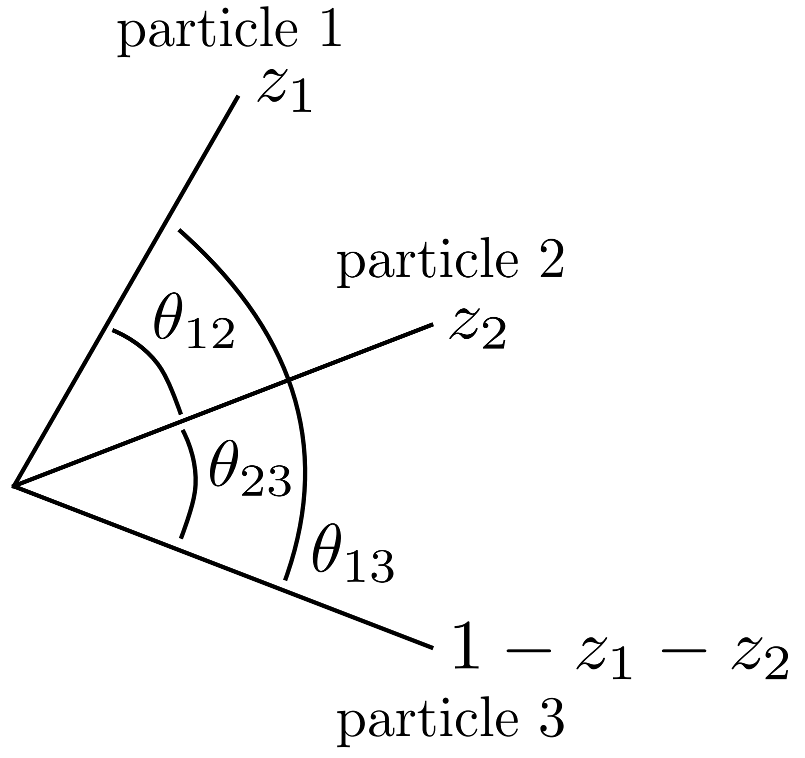


Jet classification: Information content

Datta, Larkoski JHEP 06 (2017) 073

A jet with K particles can be fully specified by $3K - 4$ observables



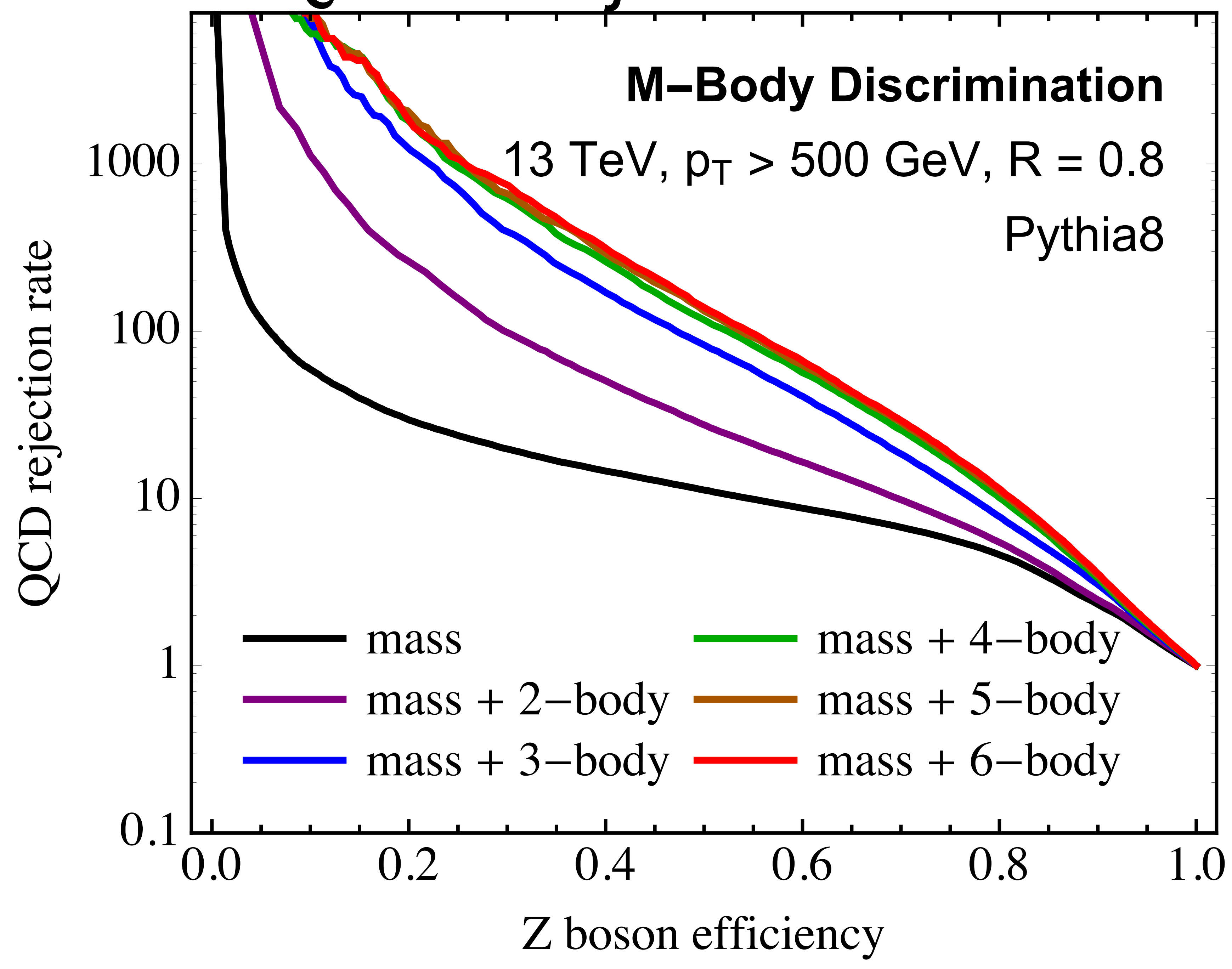


e.g. *N*-subjettiness basis:

$$\left\{\tau_1^{(0.5)}, \tau_1^{(1)}, \tau_1^{(2)}, \tau_2^{(0.5)}, \tau_2^{(1)}, \tau_2^{(2)}, \ldots, \tau_{M-2}^{(0.5)}, \tau_{M-2}^{(1)}, \tau_{M-2}^{(2)}, \tau_{M-1}^{(1)}, \tau_{M-1}^{(2)}\right\}$$

By constructing a complete set of IRC-safe observables, one can study at what point the information content saturates

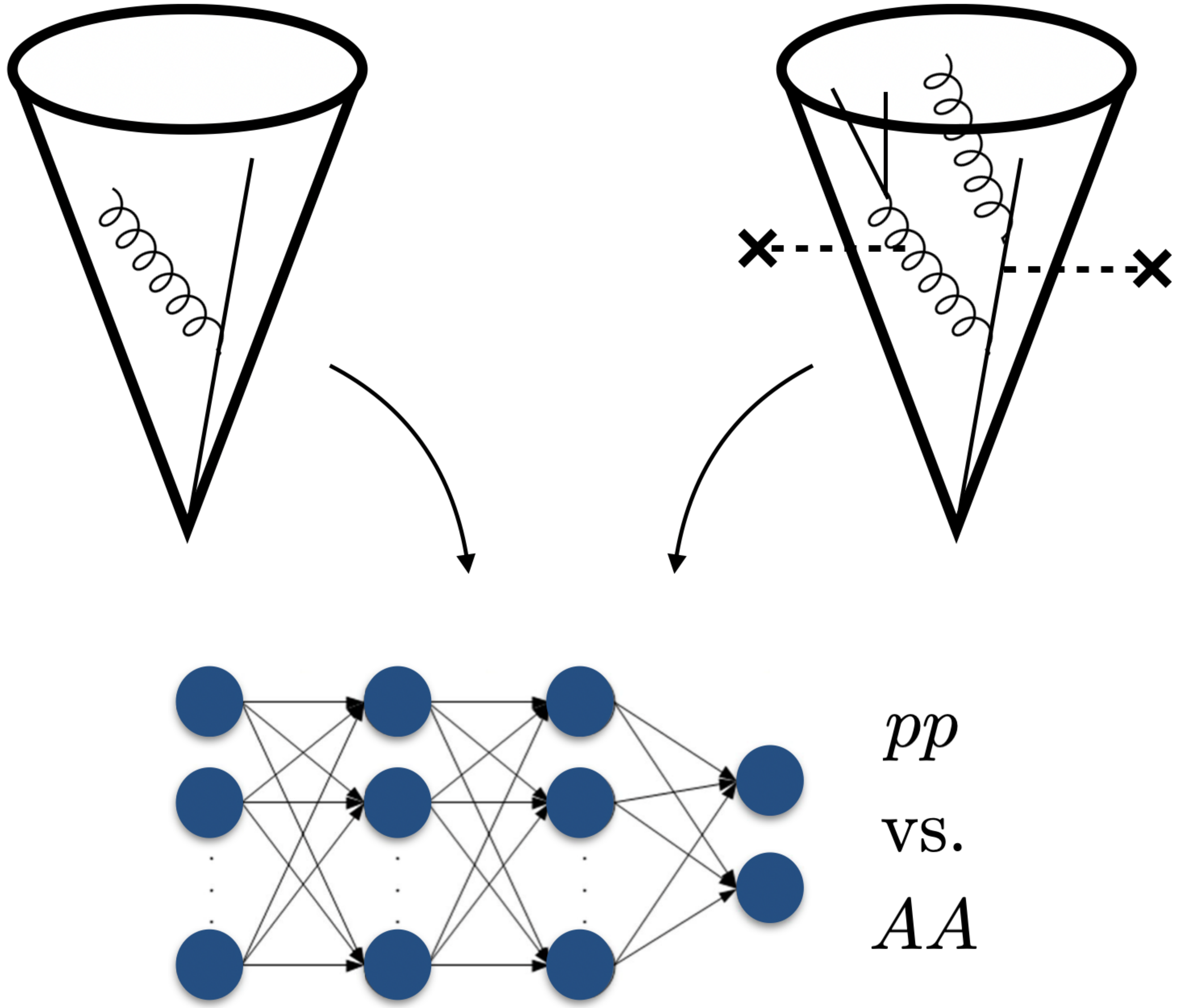
QCD vs. Z jet discrimination



Jet classification: quenched jets

This concept can be extended to medium modification of jets

→ Binary classification problem



Determine the minimal set of observables to optimally discriminate pp vs. AA jets

- Quantify *K*-body discriminating power
- Find observables that capture the most discriminating aspects of jet modification

See also:
Chien, Elayavalli 1803.03589
Lai 1810.00835
Du, Pablos, Tywoniuk JHEP 03 (2021) 206
Apolinário et al. 2106.08869

Two data representations

N-subjettiness basis with Dense Neural Network (DNN)

Input layer: Complete set of jet substructure observables

N-subjettiness: *Thaler, Tilburg JHEP 03 (2011) 015*

$$\tau_N^{(\beta)} = \frac{1}{p_T} \sum_{i \in \mathrm{Jet}} p_{Ti} \min\left\{R_{1i}^{\beta}, R_{2i}^{\beta}, \ldots, R_{Ni}^{\beta}\right\}$$

K-body phase space: *Datta, Larkoski JHEP 06 (2017) 073*

$$\left\{\tau_1^{(0.5)}, \tau_1^{(1)}, \tau_1^{(2)}, \tau_2^{(0.5)}, \tau_2^{(1)}, \tau_2^{(2)}, \ldots, \tau_{M-2}^{(0.5)}, \tau_{M-2}^{(1)}, \tau_{M-2}^{(2)}, \tau_{M-1}^{(1)}, \tau_{M-1}^{(2)}\right\}$$

DNN: $3K - 4$ inputs, 3 layers, tensorflow/keras

Note: Only includes IRC-safe information

Particle Flow Network (PFN)

Komiske, Metodiev, Thaler JHEP 01 (2019) 121

Deep sets *Zaheer et al. 1703.06114*
Wagstaff et al. 1901.09006
Bloem-Reddy, Teh JMLR 21 90 (2020)

Permutation-invariant neural network

$$f\left(p_1, \ldots, p_M\right) = F\left(\sum_{i=1}^{M} \Phi\left(p_i\right)\right)$$

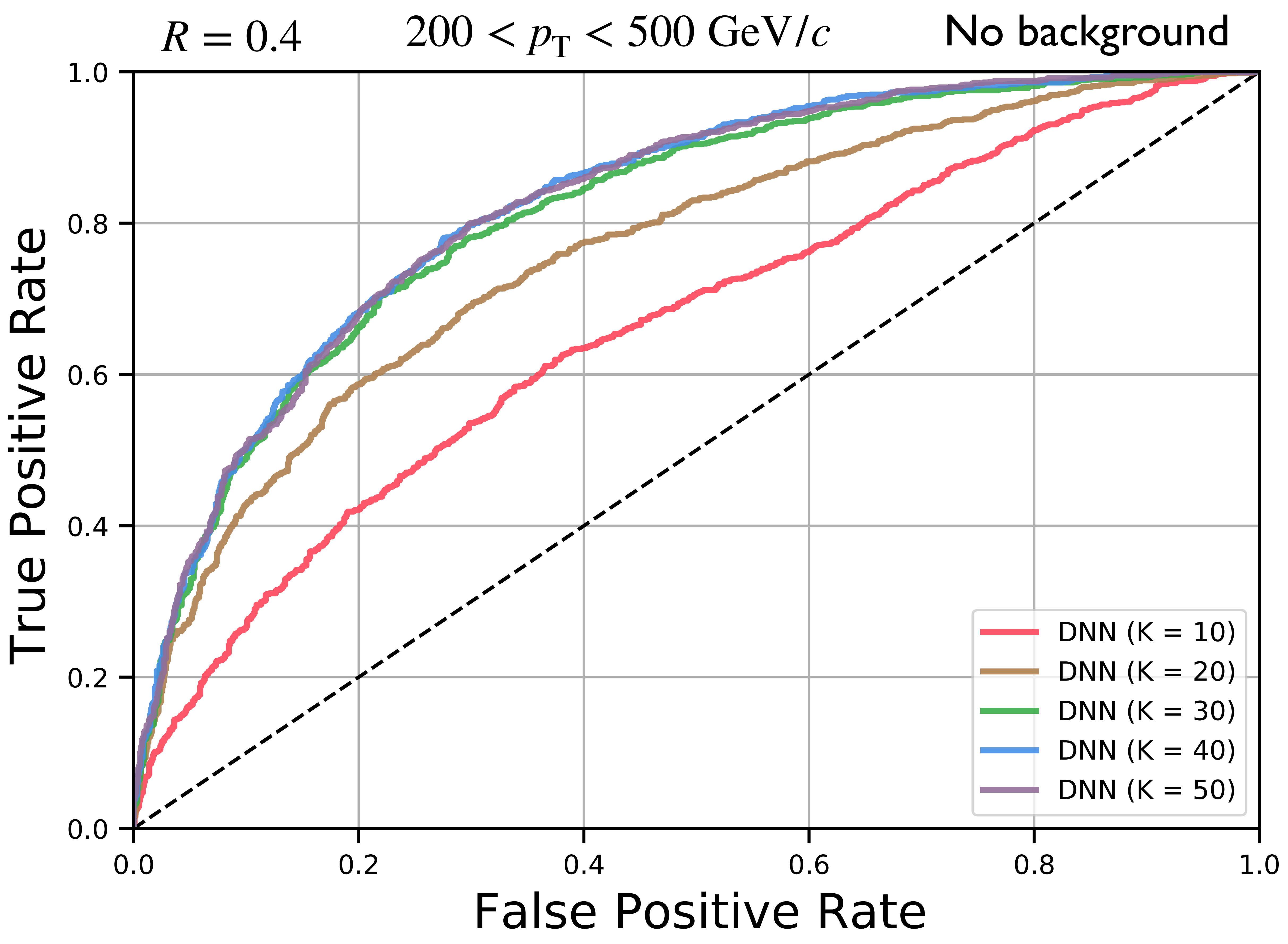
Classifier

DNNs

latent space $d = 256$

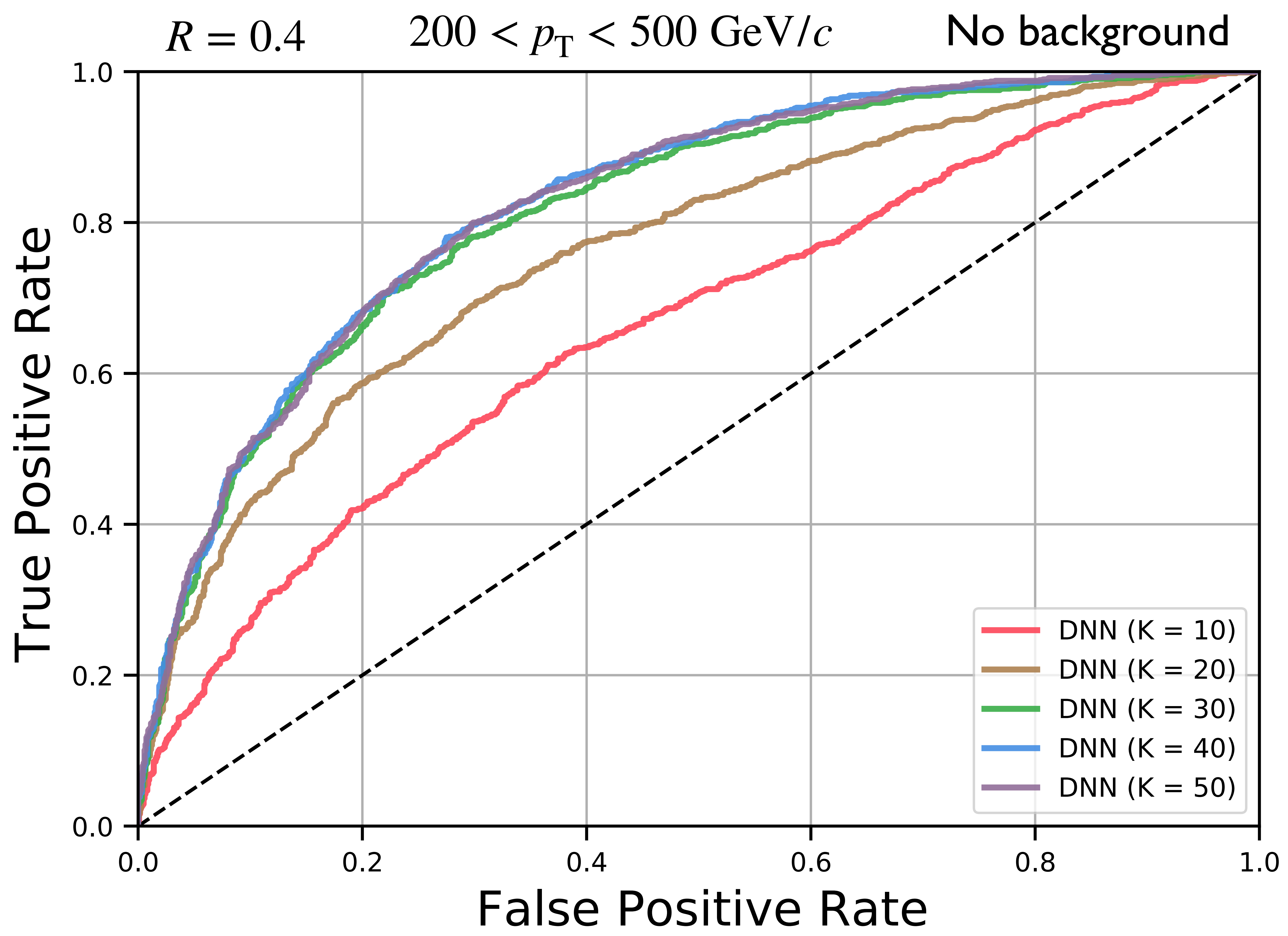
Note: Includes IRC-unsafe information

pp vs. AA

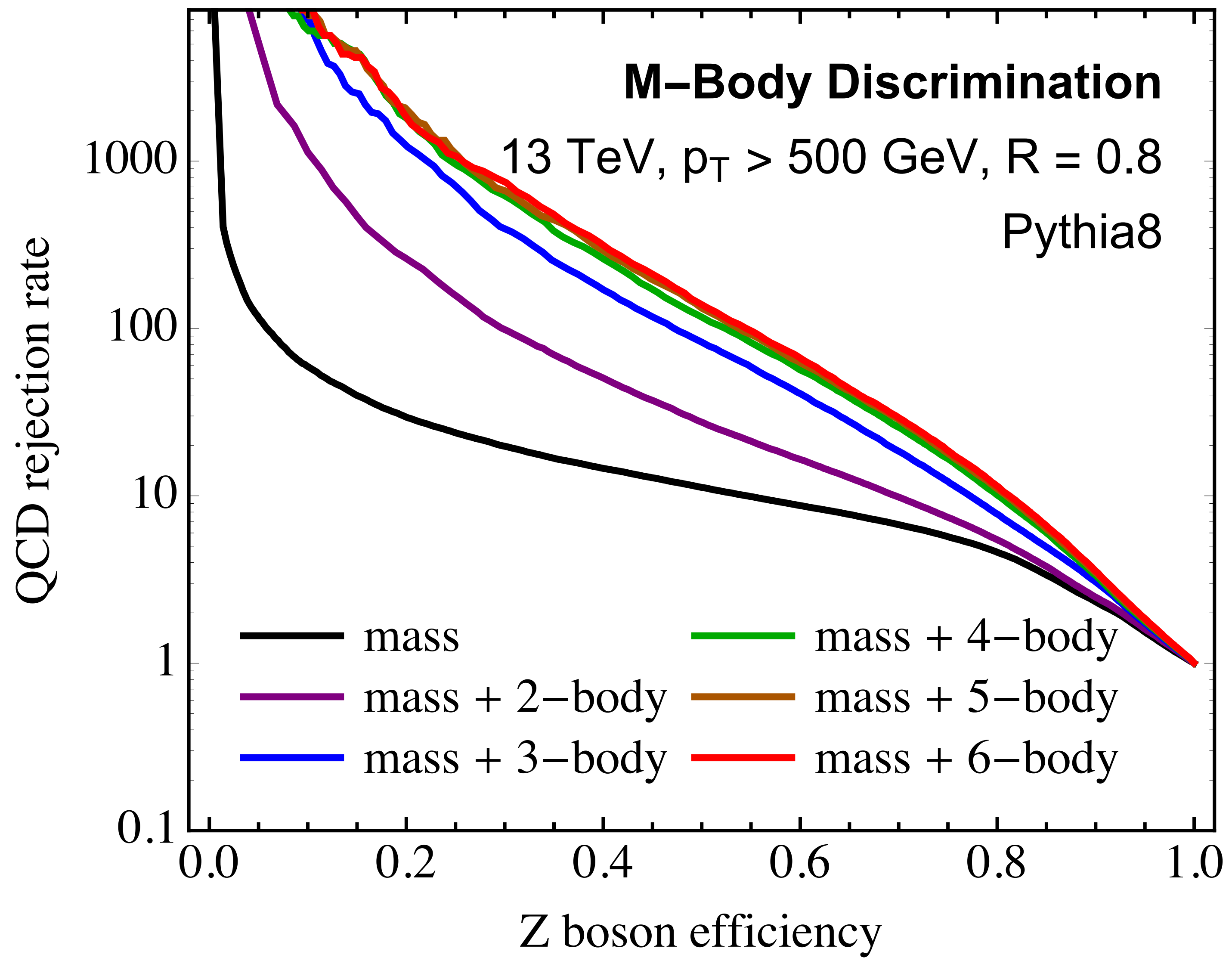


Significant information in quenched jets up to $K \approx 30$

pp vs. AA



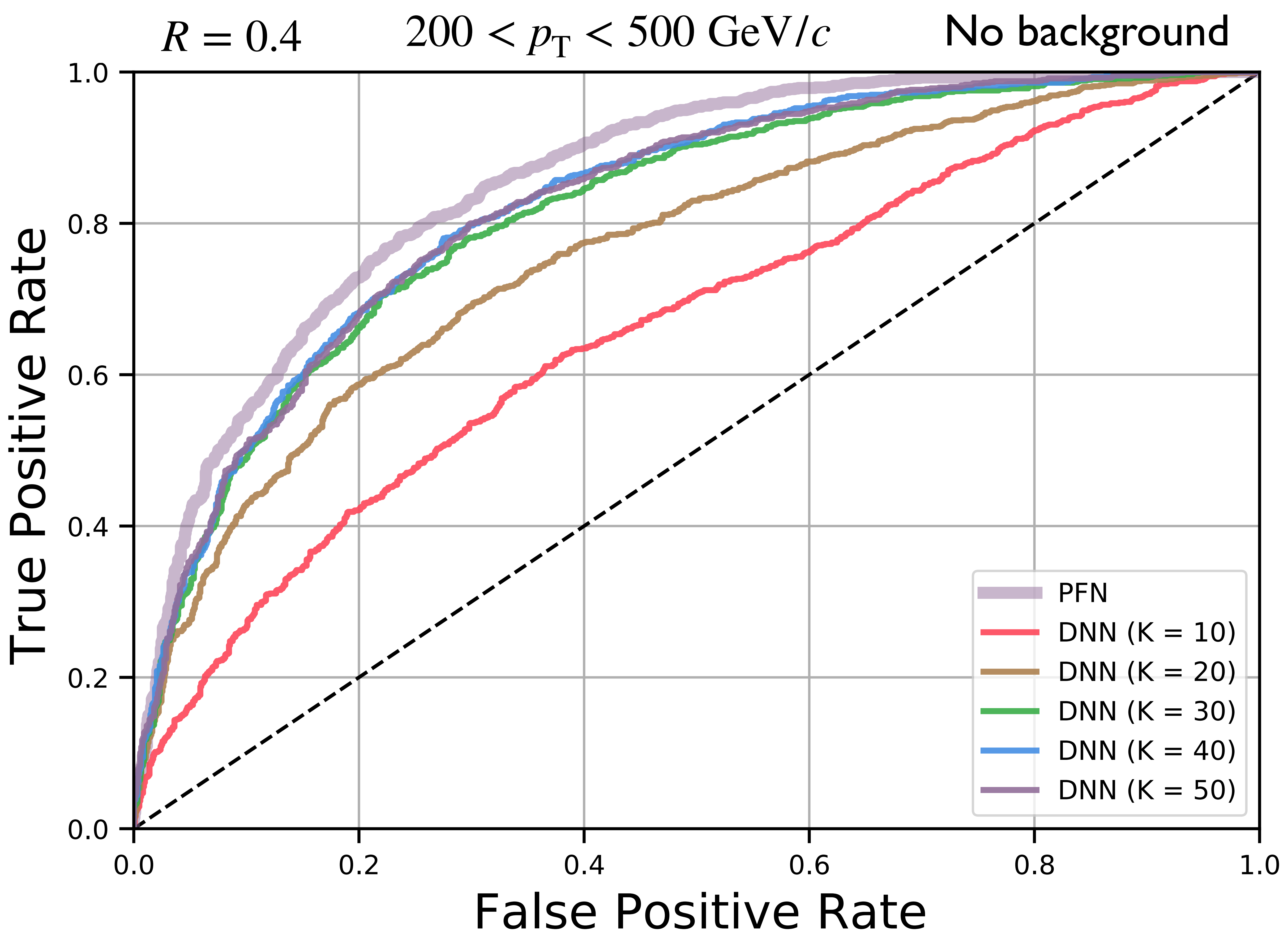
Datta, Larkoski JHEP 06 (2017) 073



→ Unlike QCD vs. Z jets (which saturate at $K = 4$), vacuum vs. quenched jets contain discriminating power in soft physics (high K-body phase space)

Significant information in quenched jets up to $K \approx 30$

pp vs. AA



Deep set data representation (PFN) performs slightly better than *N*-subjettiness basis (DNN)

The difference can be due to:

- IRC-unsafe information in PFN
- Different data representations / training / hyperparameter performance

Significant information in quenched jets up to $K \approx 30$

Automated design of observables

Lai 1810.00835
Datta, Larkoski JHEP 03 (2018) 086
Datta, Larkoski, Nachman PRD 100, 095016 (2019)

Now that we have demonstrated an ML classifier, we can find observable(s) that can approximate the classifier

→ Theoretical interpretability

Approximate the $3K-4$ N-subjettiness observables with e.g. product observables

Product observable: Sudakov safe

$$\mathcal{O} = \prod_{N<K,\ \beta\in\{0.5,1,2\}} \left(\tau_N^{\beta}\right)^{c_{N\beta}}$$

Automated design of observables

Lasso regression

$$O = \prod_{N<K,\ \beta\in\{0.5,1,2\}} \left(\tau_N^{\beta}\right)^{c_{N\beta}}$$

Stronger regularization drives $c_{N\beta}$ to zero

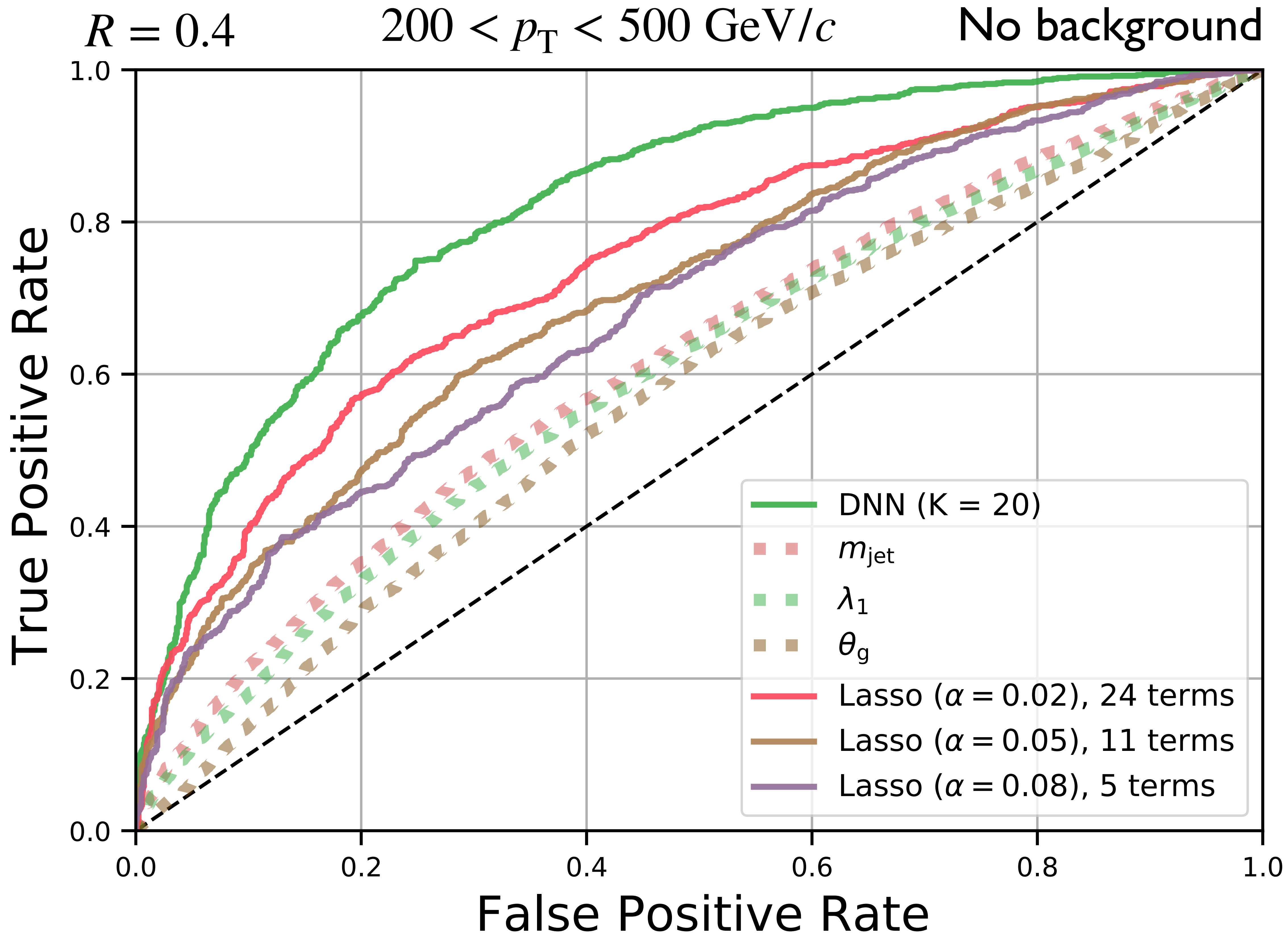
e.g. for $K = 15$:

$\alpha = 0.04 \rightarrow (\tau_1^2)^{-0.57}(\tau_6^2)^{-0.77}(\tau_7^2)^{-0.68}(\tau_{14}^{0.5})^{2.7}$

$\alpha = 0.15 \rightarrow \tau_{14}^1$

Suggests that large N is highly discriminating

Lai, JM, Płoskoń, Ringer — In Preparation

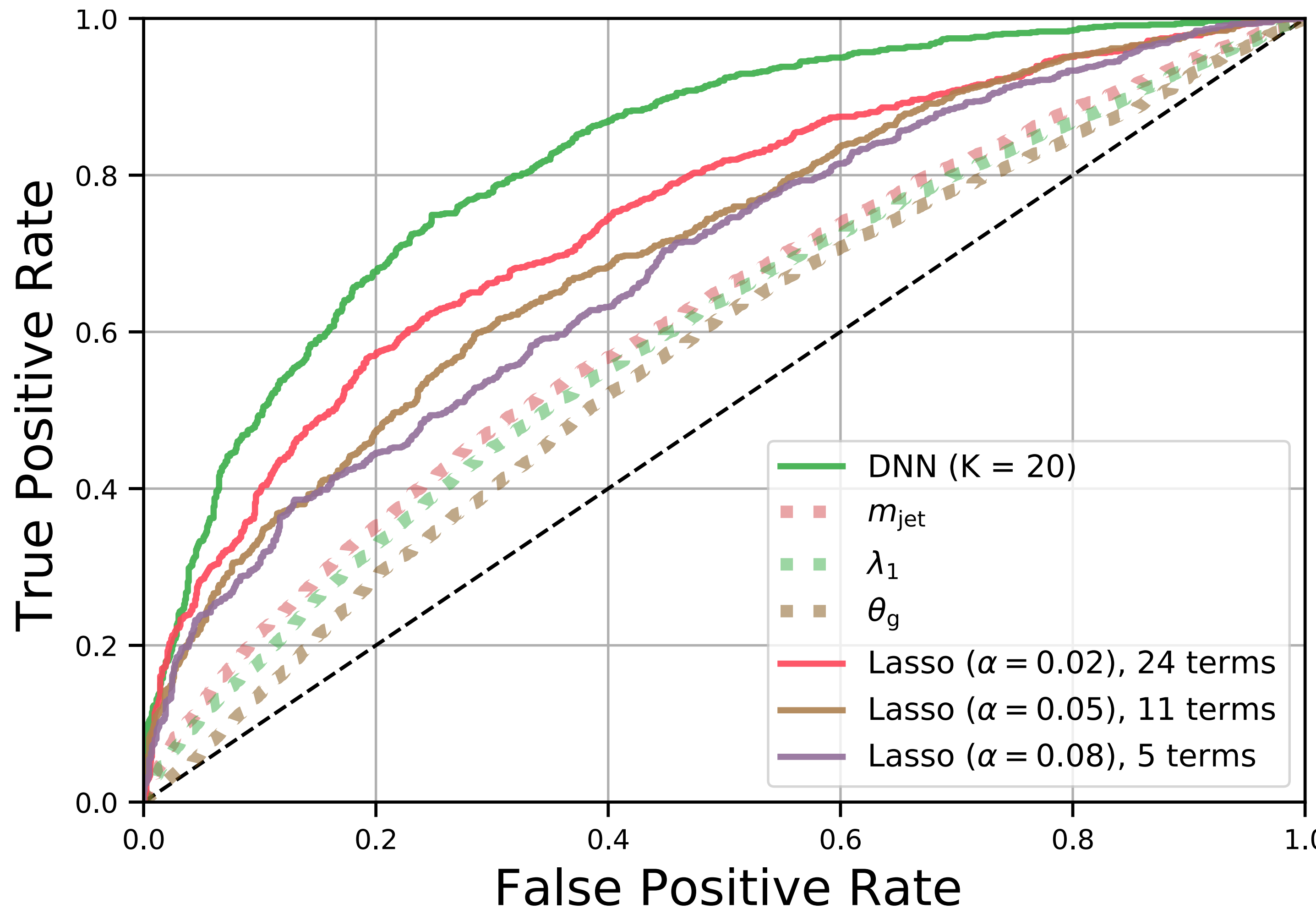


Balancing the tradeoff of discriminating power and complexity, we can design optimal observables for distinguishing pp and AA jets

Observable design at EIC

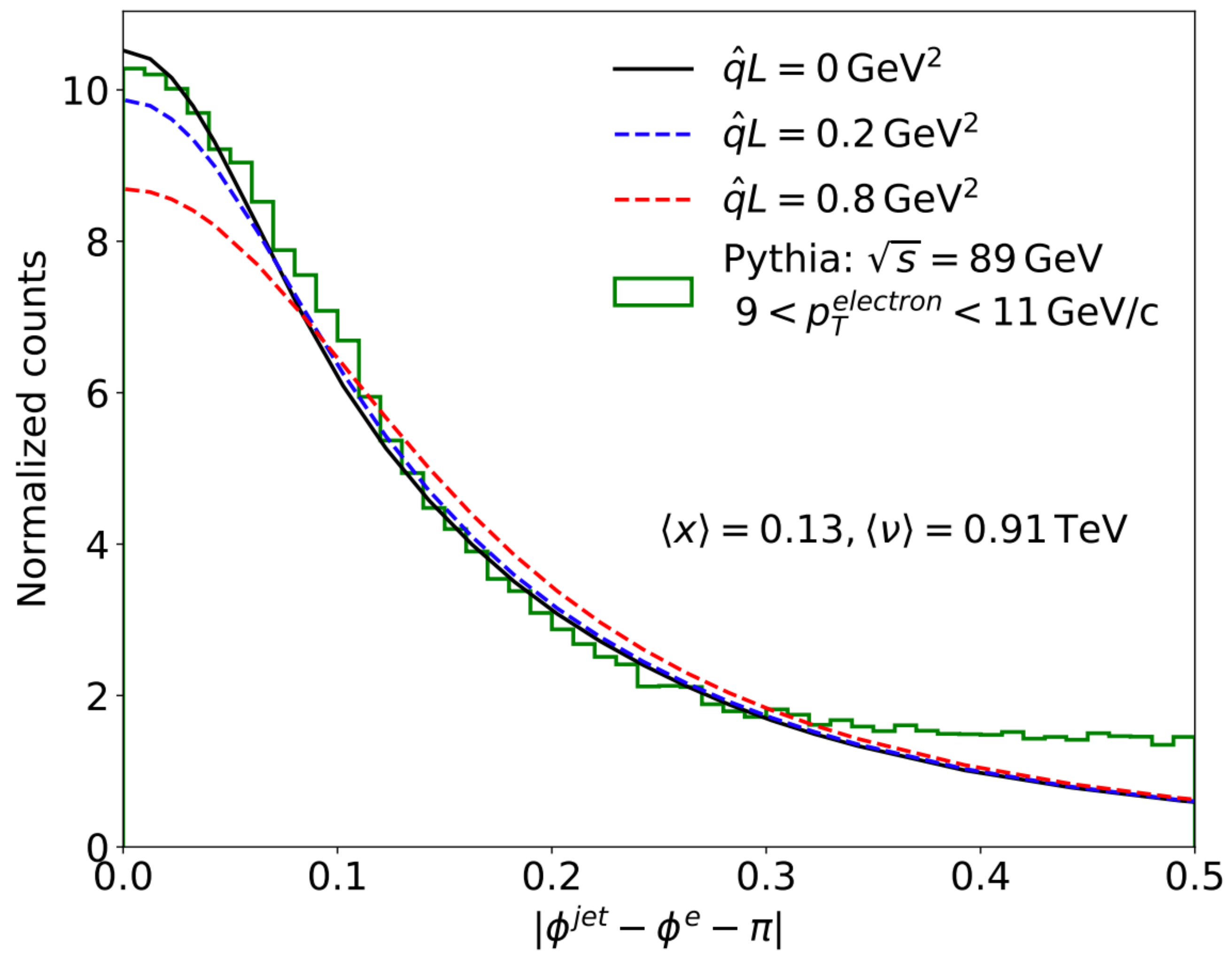
ML classifier + symbolic regression can be used at EIC
- Jet classification
- Event classification

Lai, JM, Płoskoń, Ringer — In Preparation



Theory+experiment guidance for medium modifications
- Cold nuclear matter effects
- Hadronization
- Explore sensitivity to gluon saturation

Liu, Ringer, Vogelsang, Yuan PRL 122 (2019), 192003



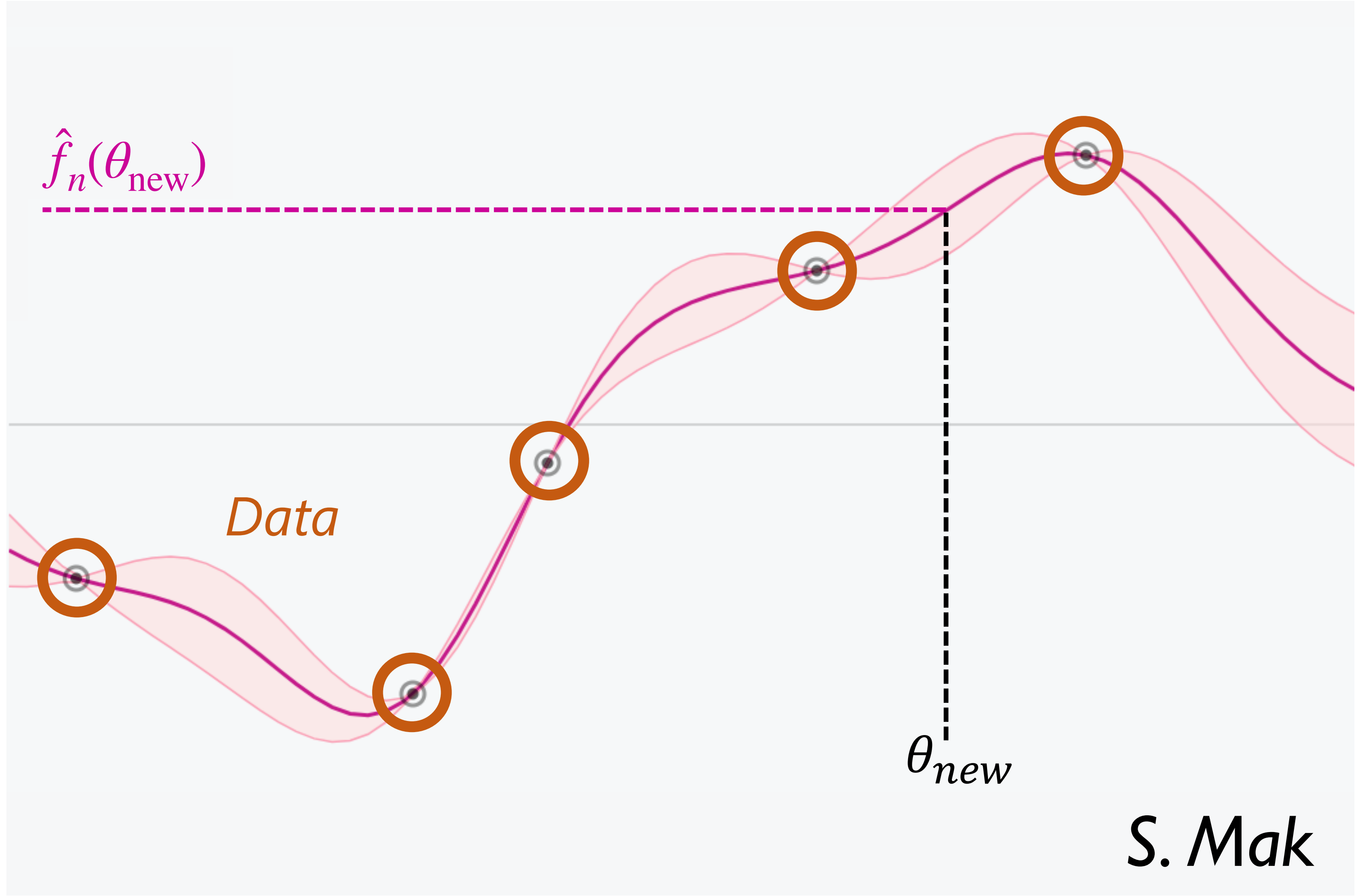
Can be applied directly on data! (labels are known)
- In the meantime: BeAGLE, eHIJING, JETSCAPE, …

Bayesian parameter estimation

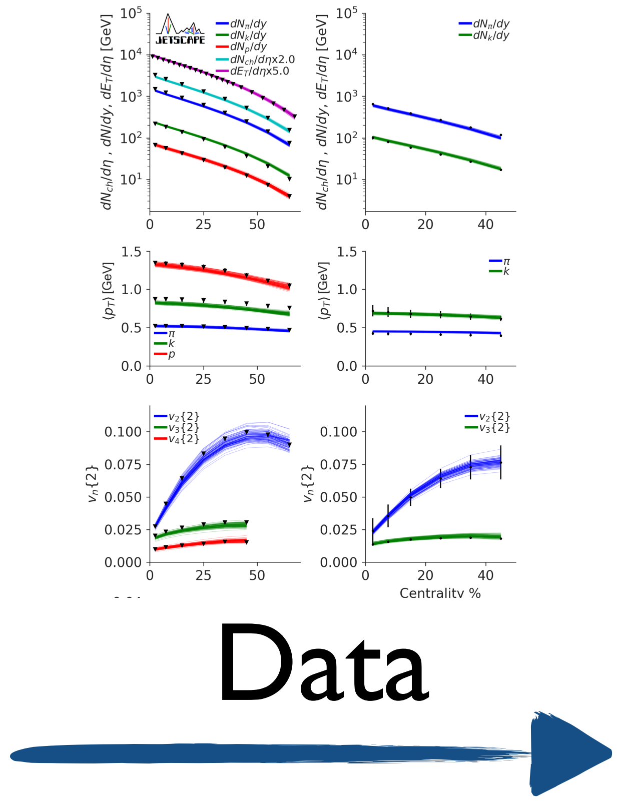
Studying cold nuclear matter effects at the EIC follows closely jet quenching in QGP

- Constraining model parameters requires collection of jet observables

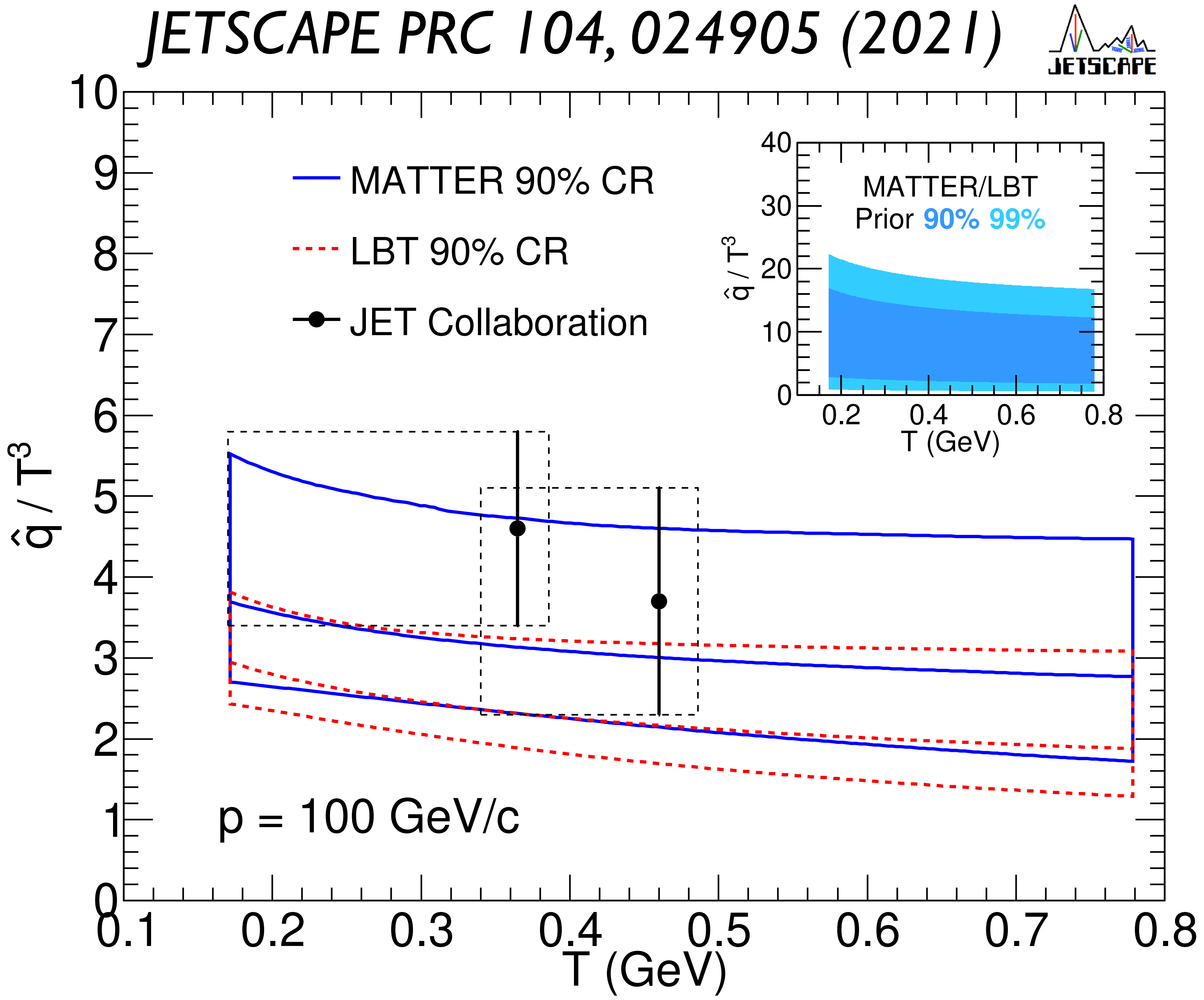
ML-assisted observable design can tell us what we should measure (and calculate) next in order to add new information to global fits



Gaussian Process Emulators: efficiently explore multi-dimensional model parameter space



JETSCAPE PRC 104, 024905 (2021)



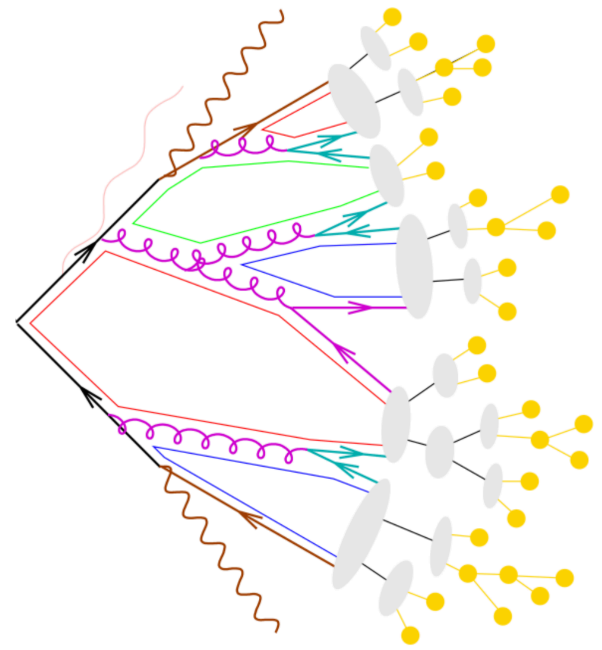
Explainable AI

A more ambitious goal:
Can we use ML to guide our physics understanding?

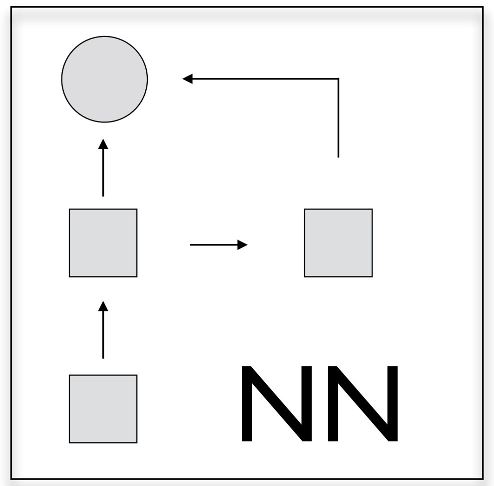
Train generative adversarial network (GAN) to learn physics of parton shower from final-state particles

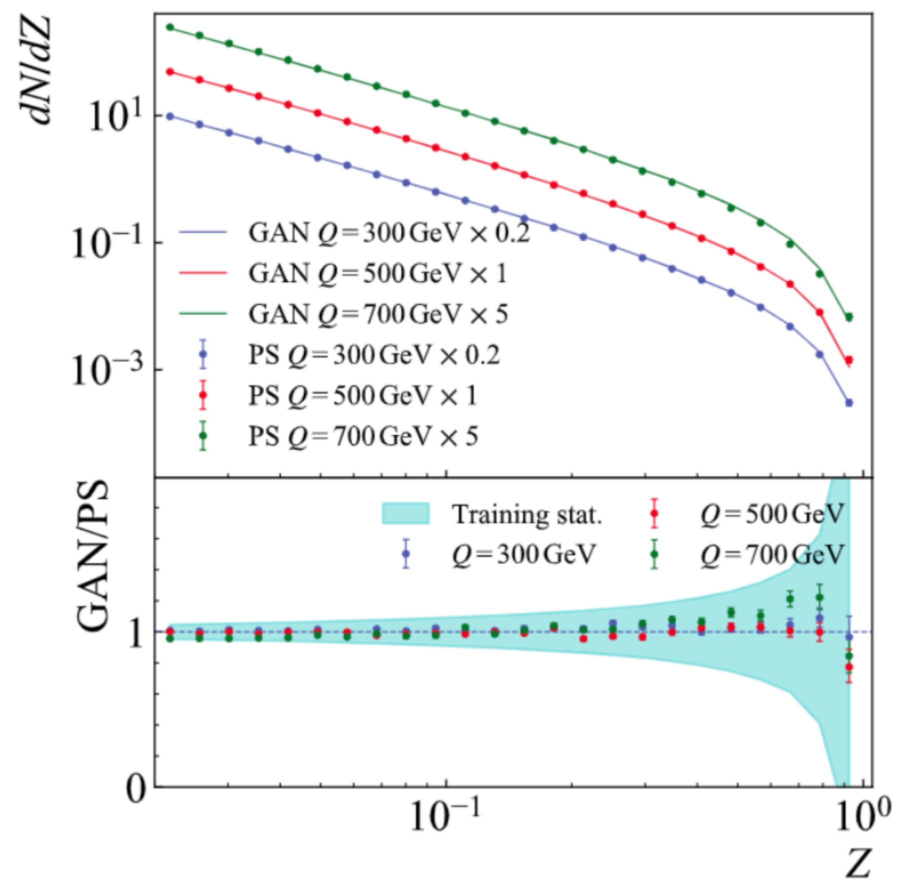
Fit nonperturbative physics at the EIC?

Lai, Neill, Ploskon, Ringer 2012.06582

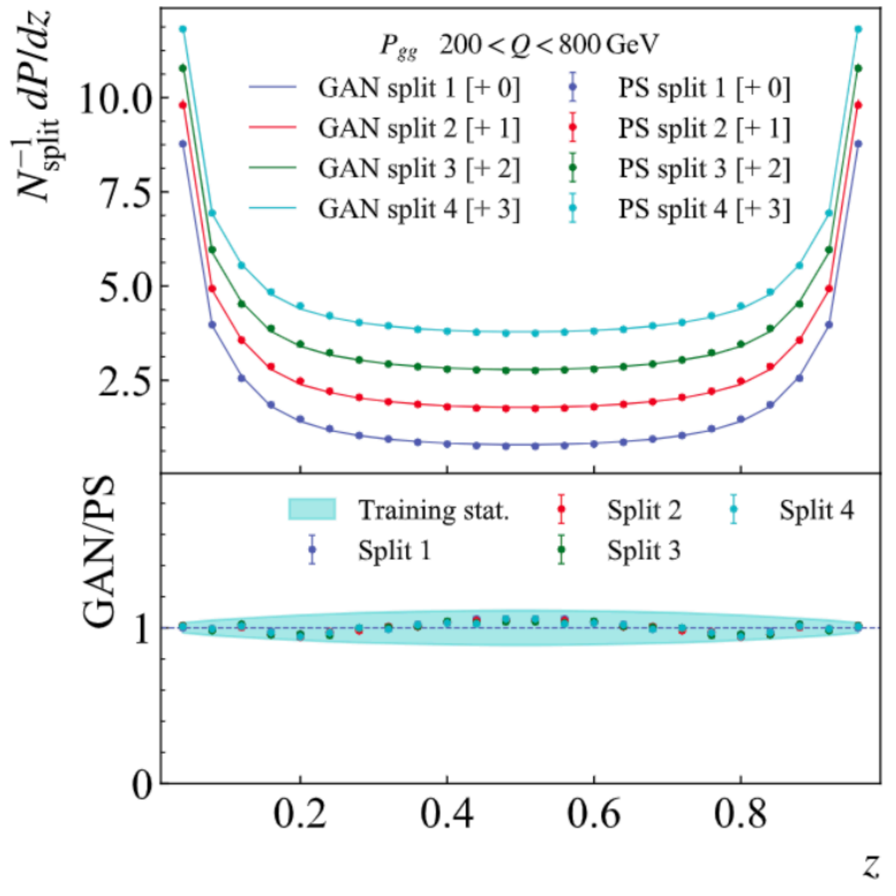


Train GAN on the final output of the shower





Final energy distribution



Intermediate splittings

Summary

ML is an important tool to improve precision and save computation in multiple aspects of the EIC physics program

- Detector design and jet reconstruction
- Jet tagging and classification
- ML-assisted observable design to guide global fits
- Explainable AI to guide underlying physics
- …and more

Methods are evolving rapidly — where will ML be in 10 years?

- It will remain a *tool* for our bread-and-butter experimental and theoretical techniques — but an increasingly valuable one