# The information content of jet quenching and machine learning assisted observable design

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in collaboration with
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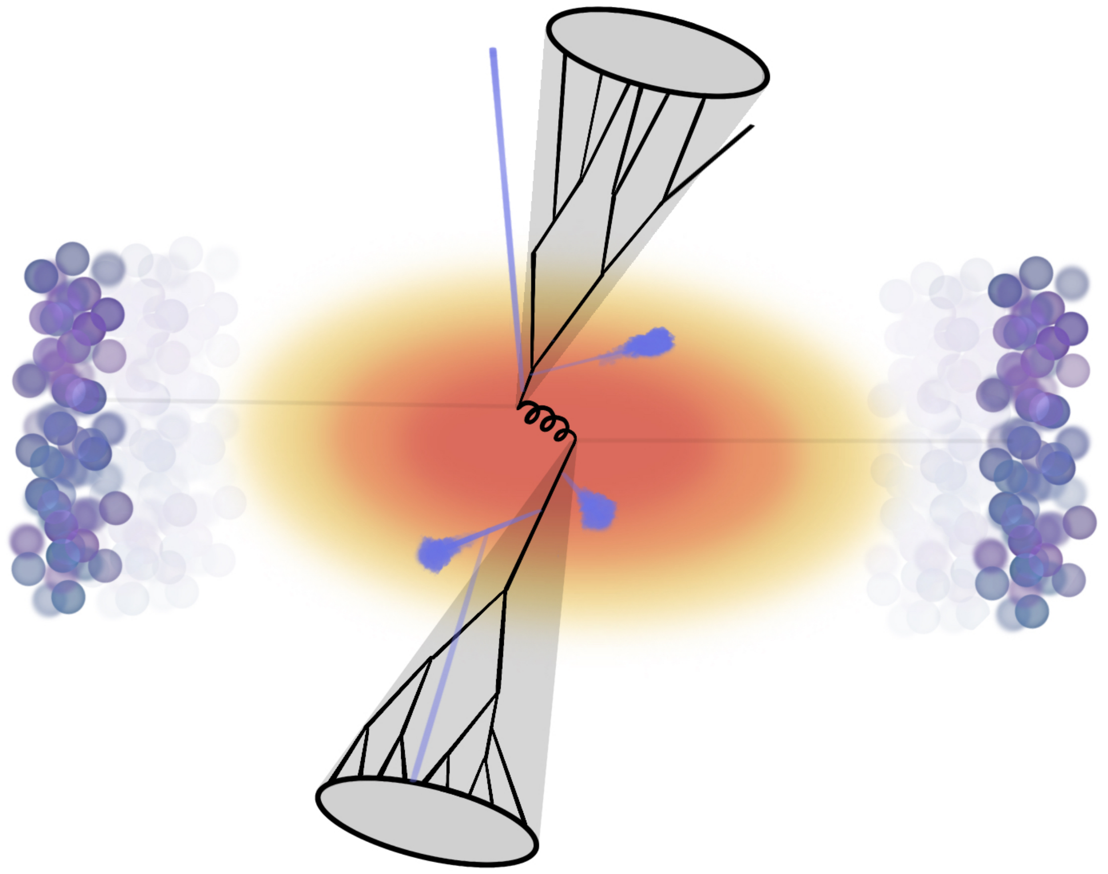

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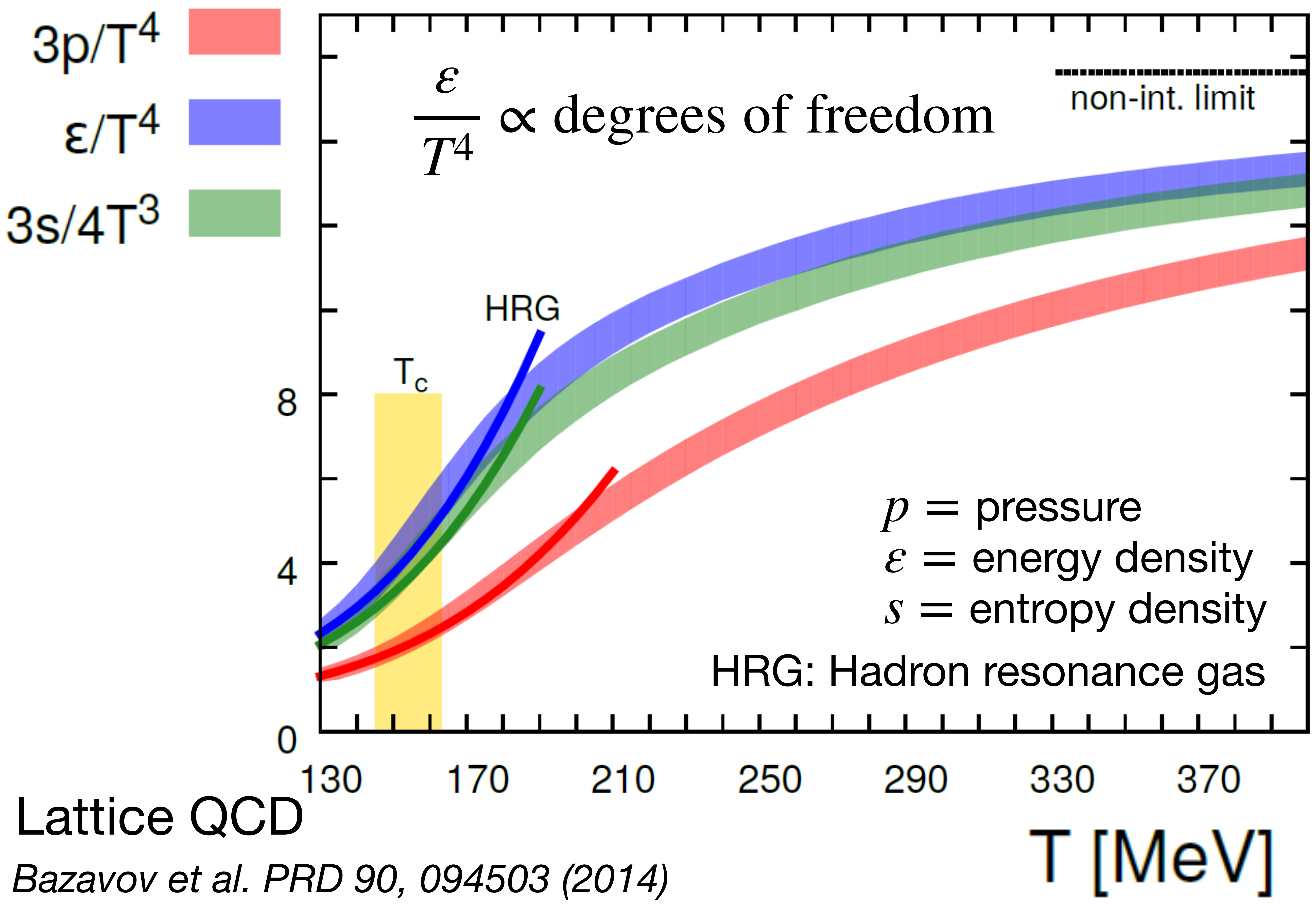
Berkeley
UNIVERSITY OF CALIFORNIA

# The quark-gluon plasma

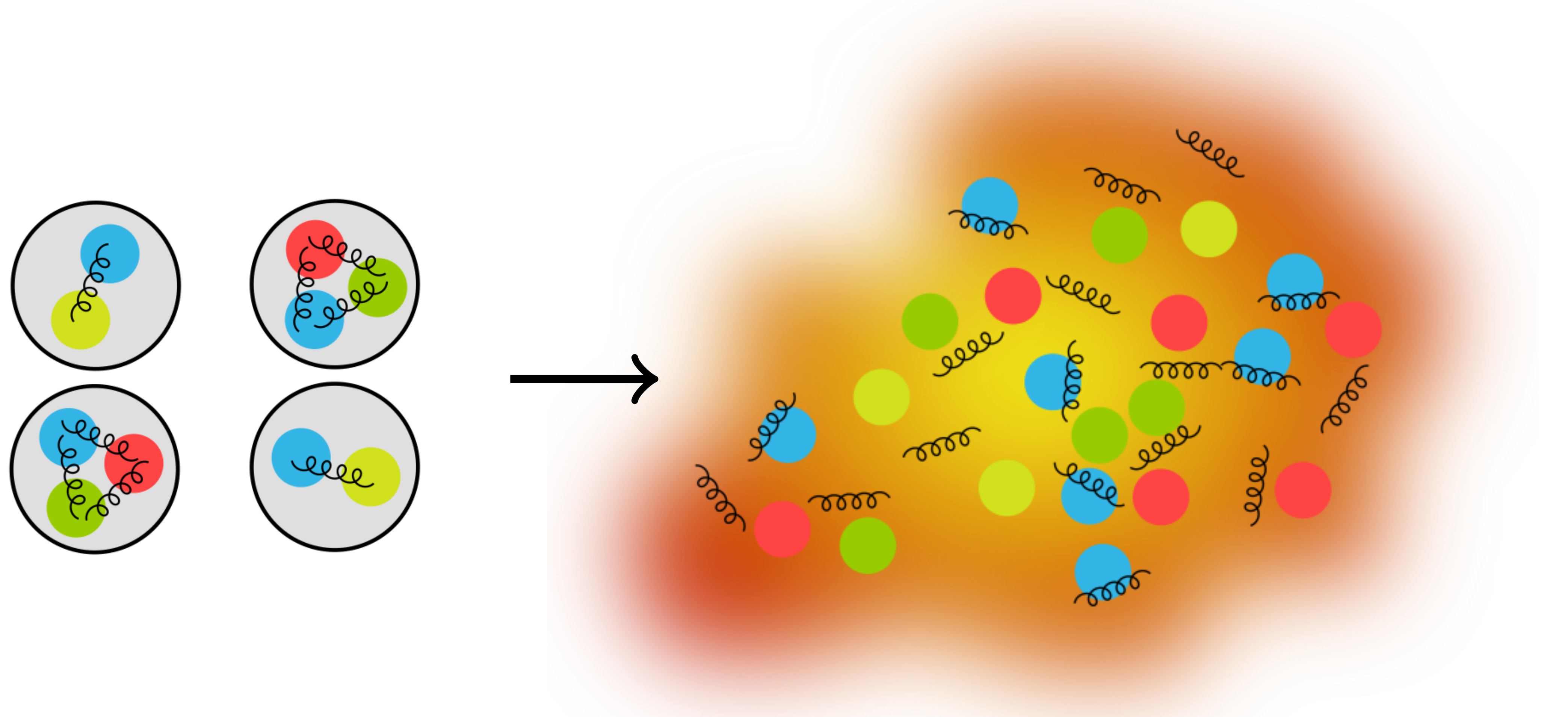
**If we heat nuclear matter to $T = \mathcal{O}(100\ \mathrm{MeV})$, thermodynamic quantities exhibit a rapid rise near a crossover temperature $T_c$**




Lattice QCD

*Bazavov et al. PRD 90, 094503 (2014)*

***Deconfinement of quarks and gluons***



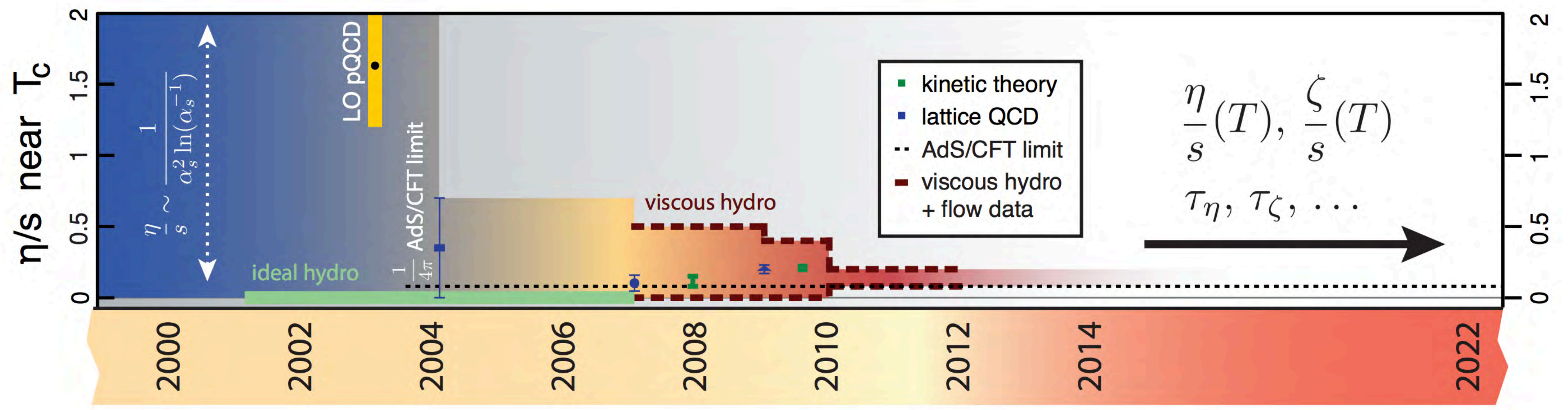
# The quark-gluon plasma

In the last two decades it has been established that hot QCD matter is:

- Deconfined
- Strongly-coupled

But much more to learn!

Low specific shear viscosity ($\eta/s$) → Strong coupling




*Burrows et al.*

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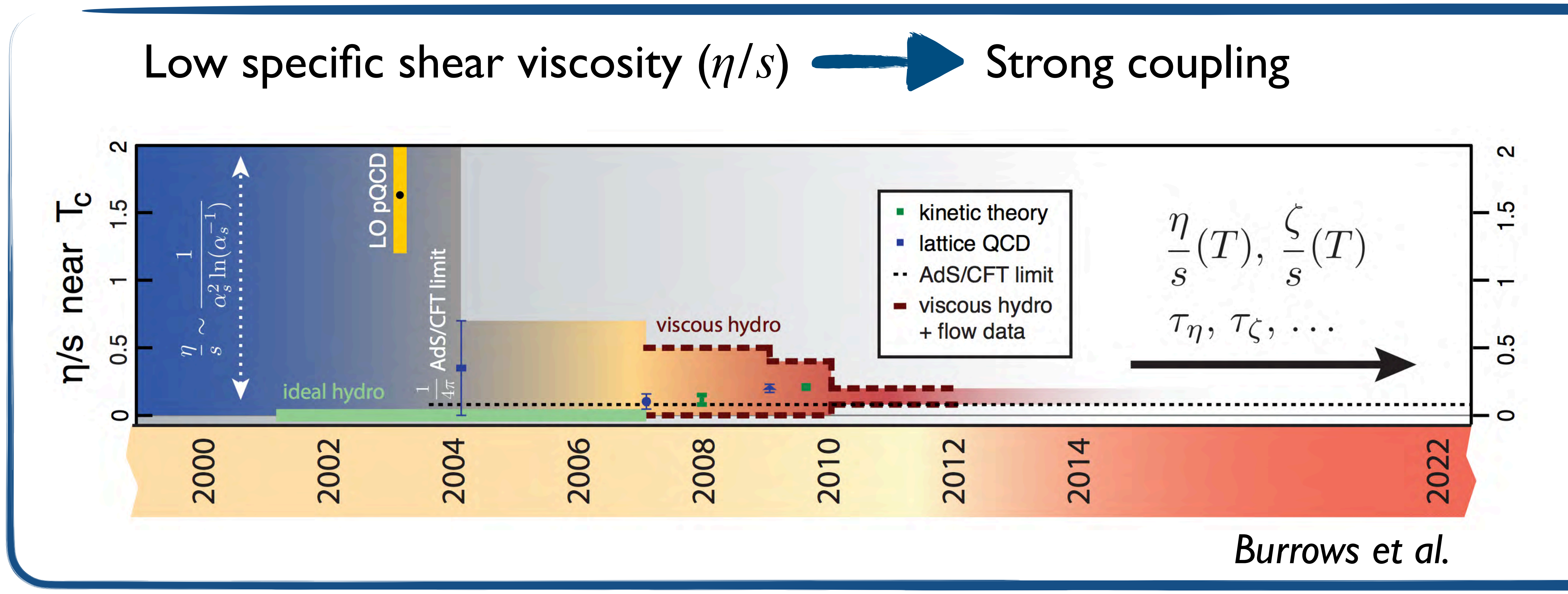



The quark-gluon plasma is a laboratory to study how complex properties emerge from the fundamental laws of quantum chromodynamics

*How does a strongly-coupled fluid arise from the Lagrangian of QCD?*

*What are the relevant degrees of freedom of the QGP as a function of resolution scale?*

*How does color confinement emerge?*

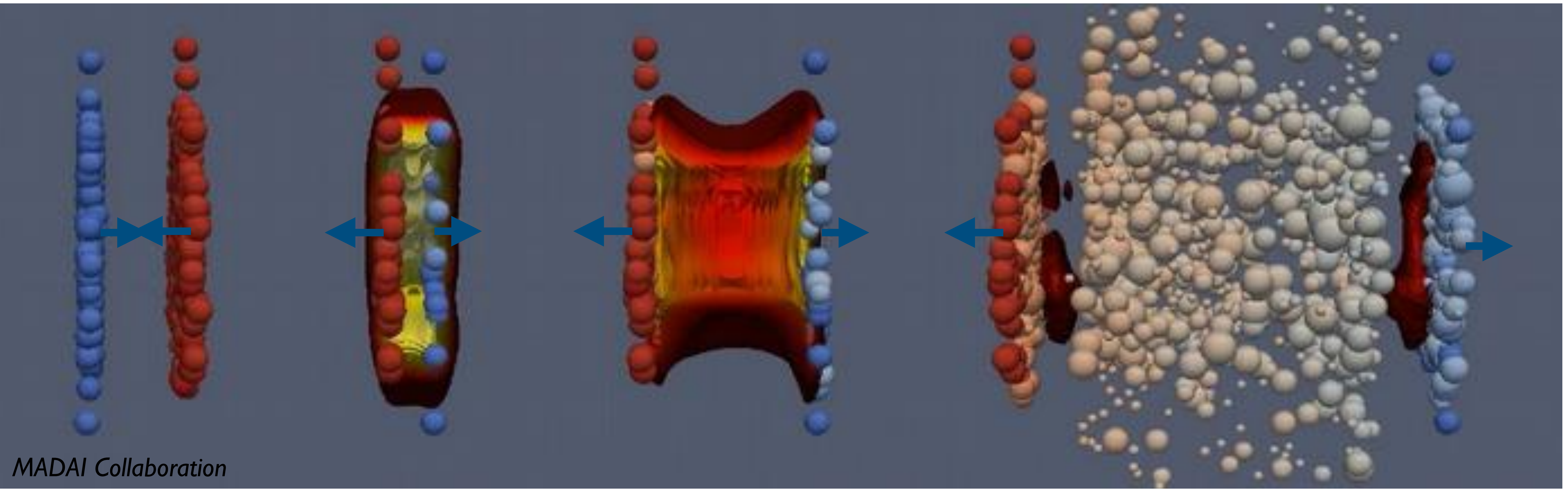
# Heavy-ion collisions


**We collide nuclei together at the**

*Large Hadron Collider (LHC)*

*Relativistic Heavy Ion Collider (RHIC)*

**to produce droplets of hot, dense quark-gluon plasma**

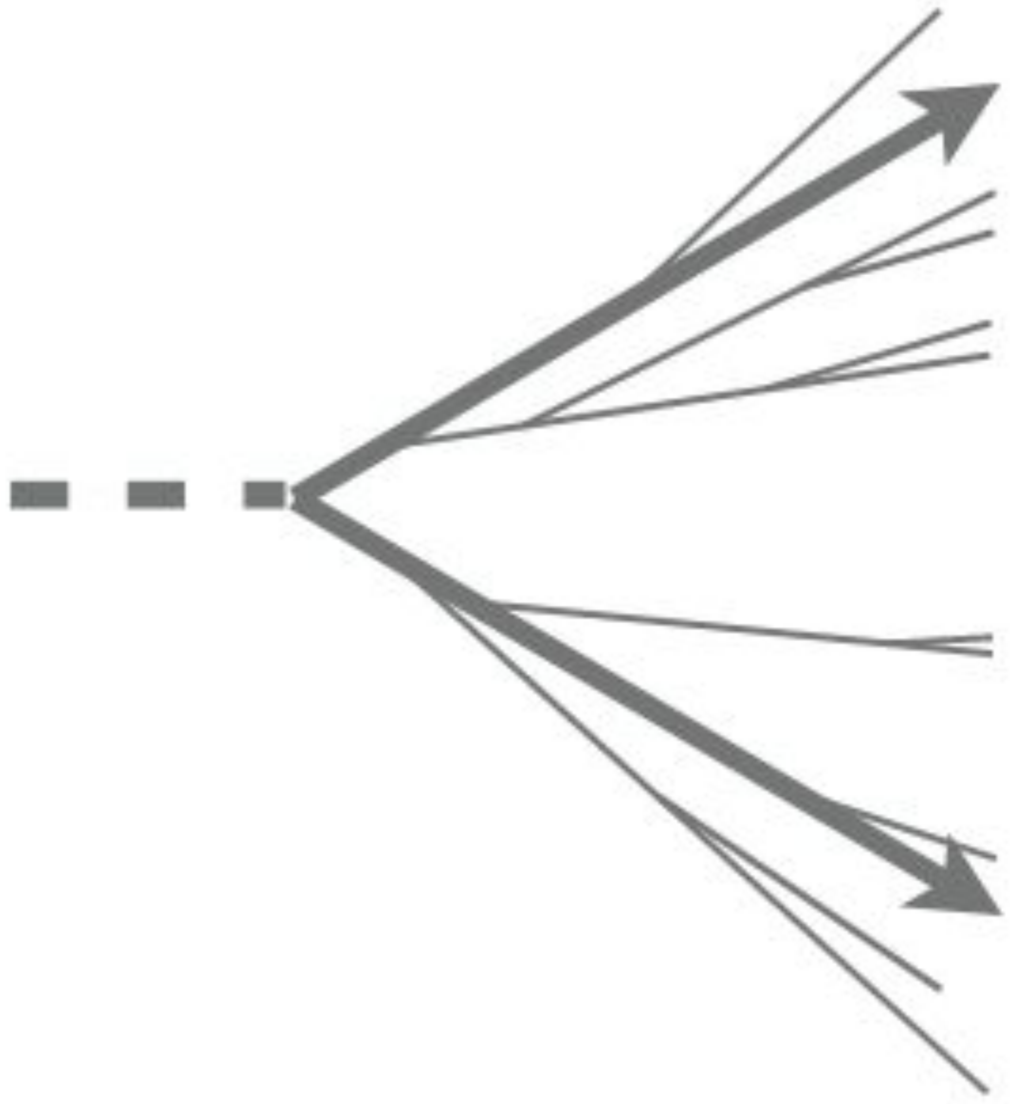



**Soft collisions transform kinetic energy of nuclei into region of large energy density**

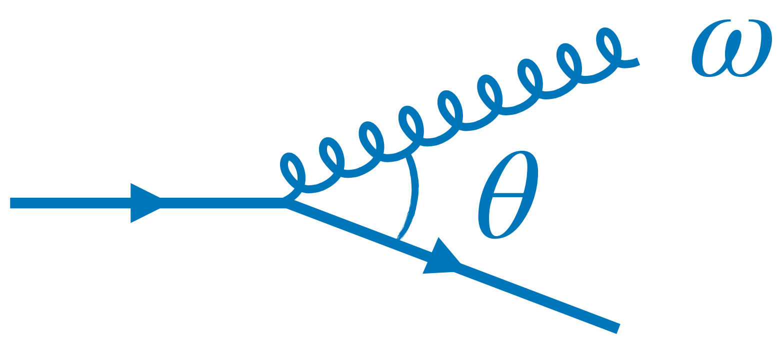
$T \approx 150\text{-}500$ MeV $\quad t \sim \mathcal{O}\left(10 \text{ fm}/c\right)$

# Jets

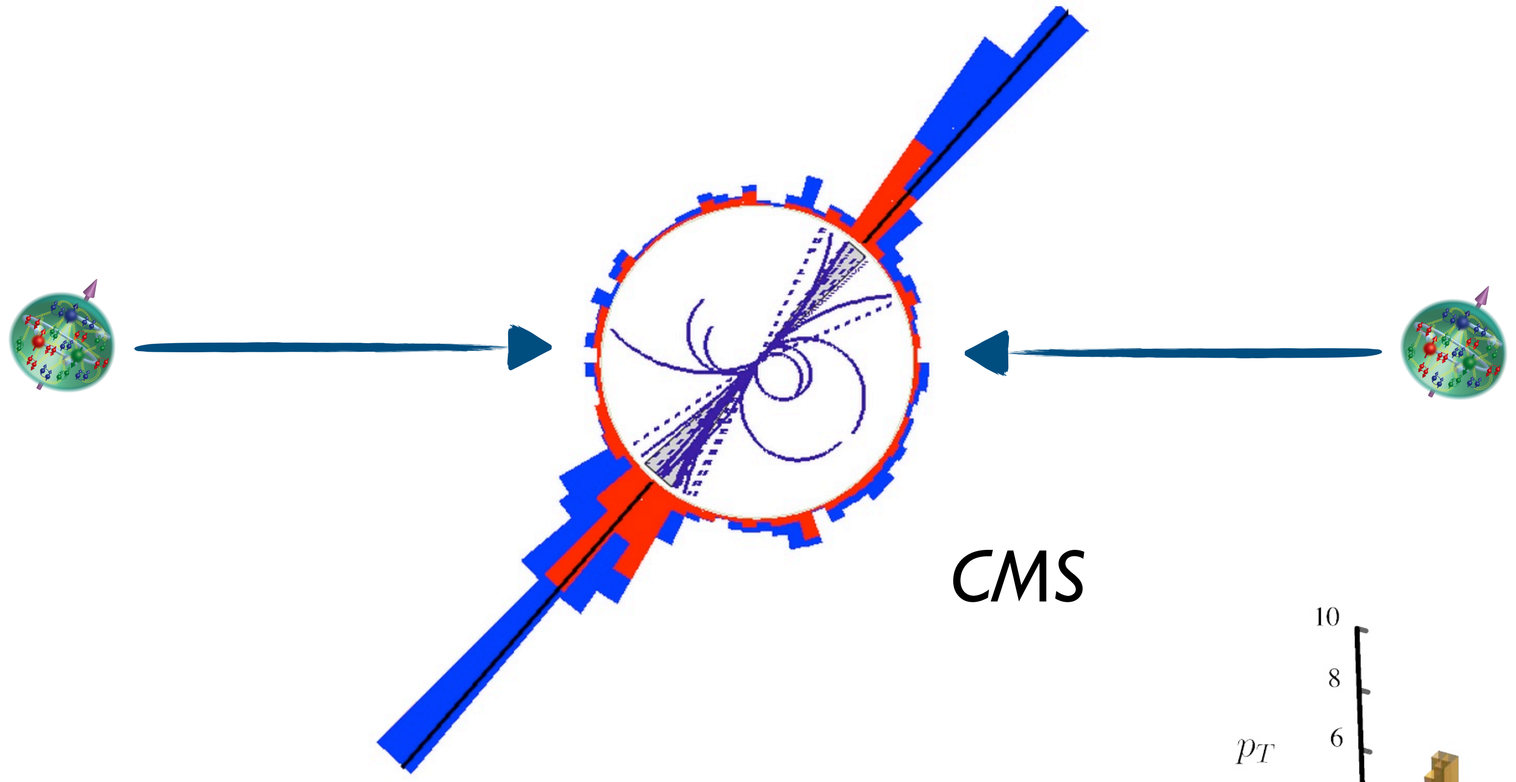
Collimated shower of particles arising from the iterative fragmentation of a **high energy quark or gluon**

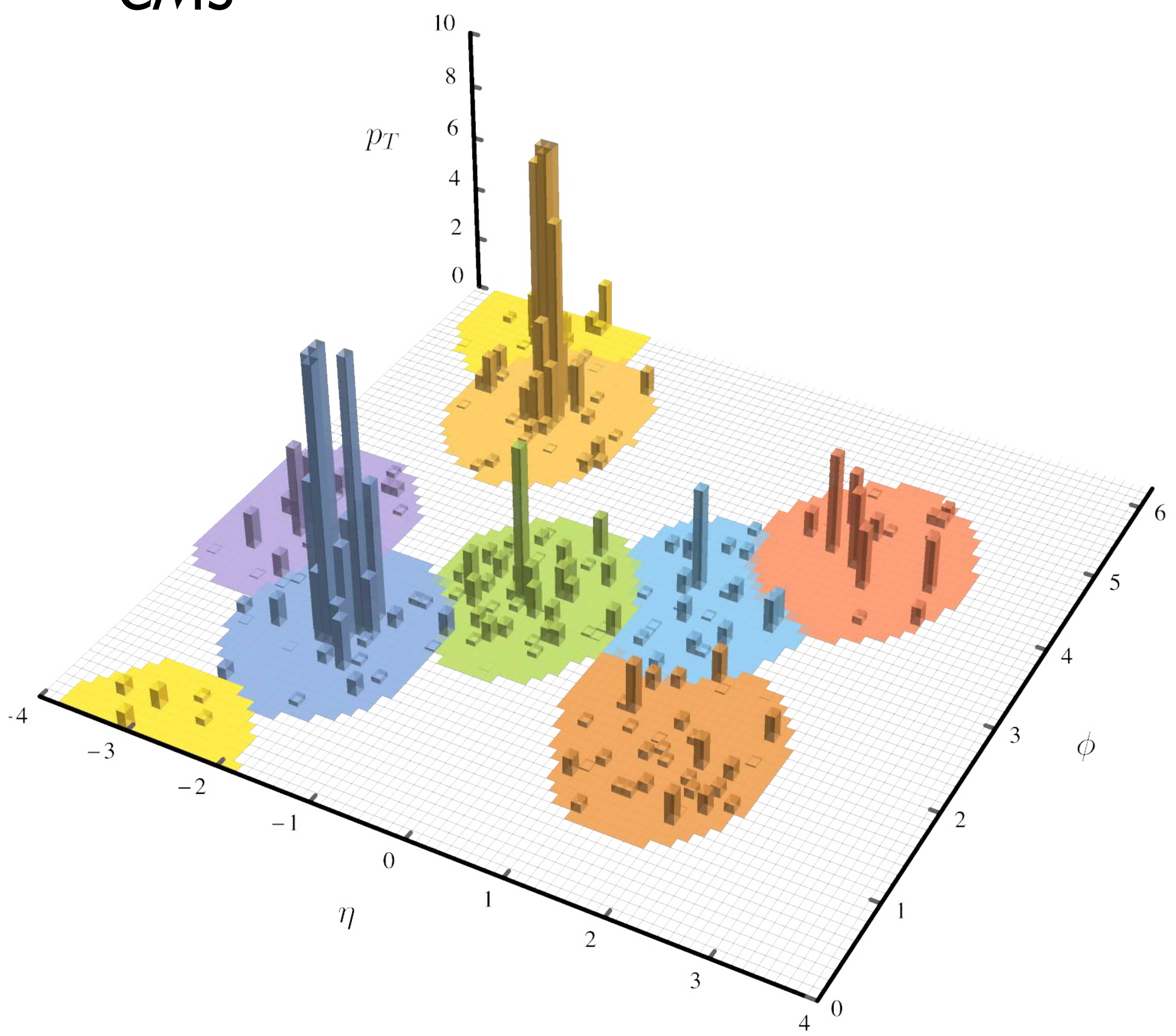


$$dP \sim \alpha_s C_R \frac{d\theta}{\theta}\frac{d\omega}{\omega}$$




Jets are produced abundantly in colliders

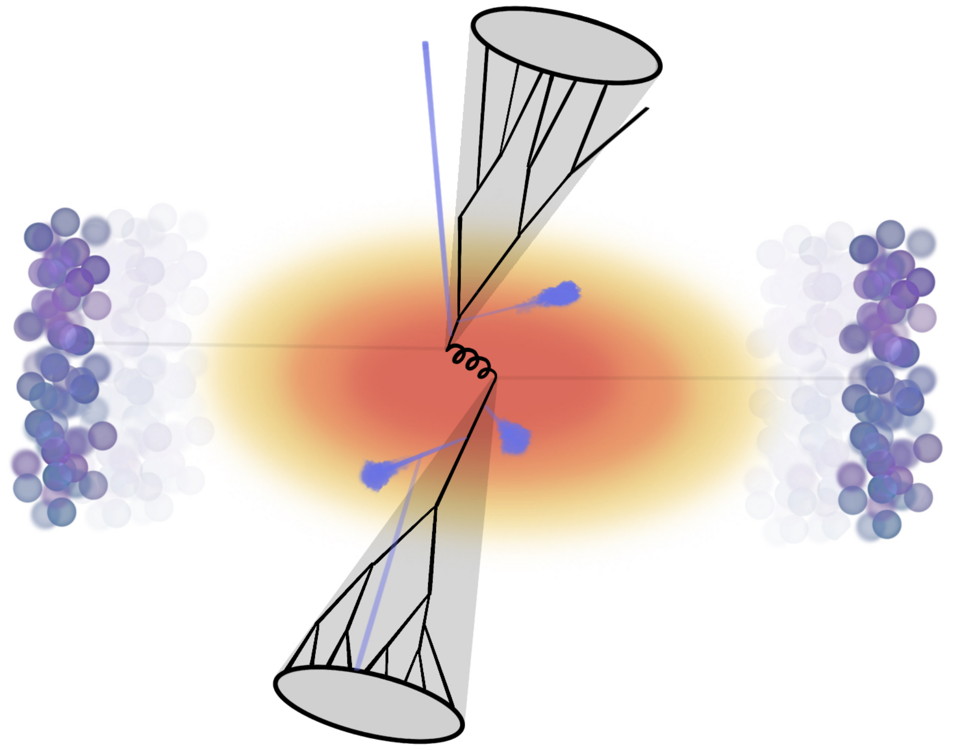


# Jet quenching in the quark-gluon plasma

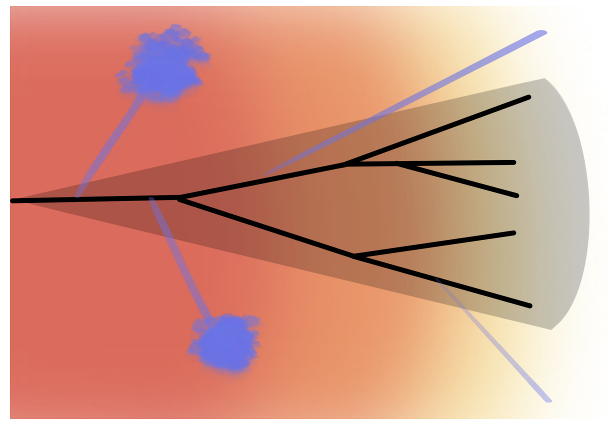
The QGP is too small and short-lived to be probed by traditional scattering beams

→ Use jets as probes

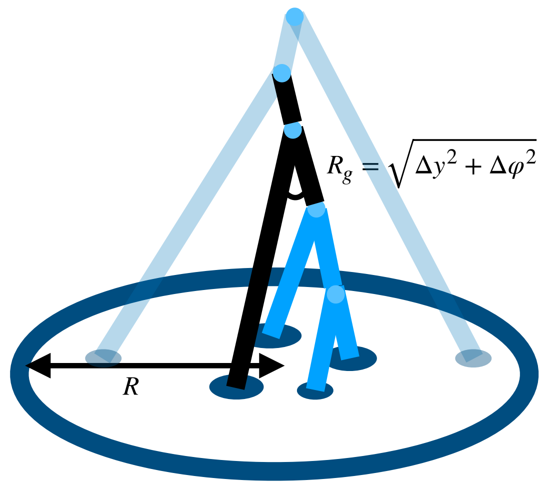


Jets interact with the quark-gluon plasma as they traverse it:

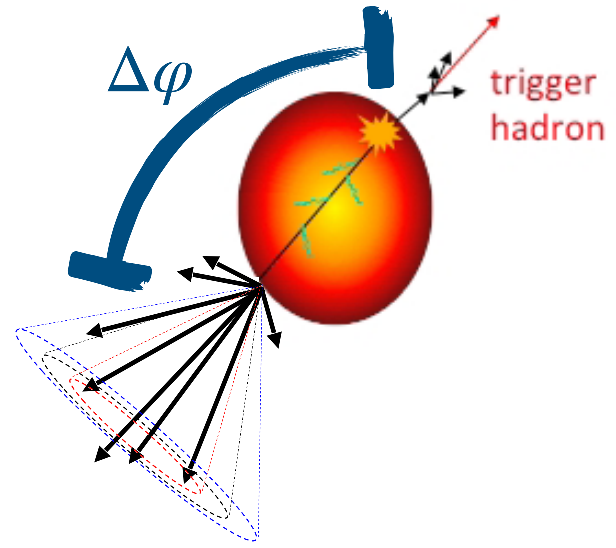
**"Energy loss"**



**Substructure modification**




**Deflection**

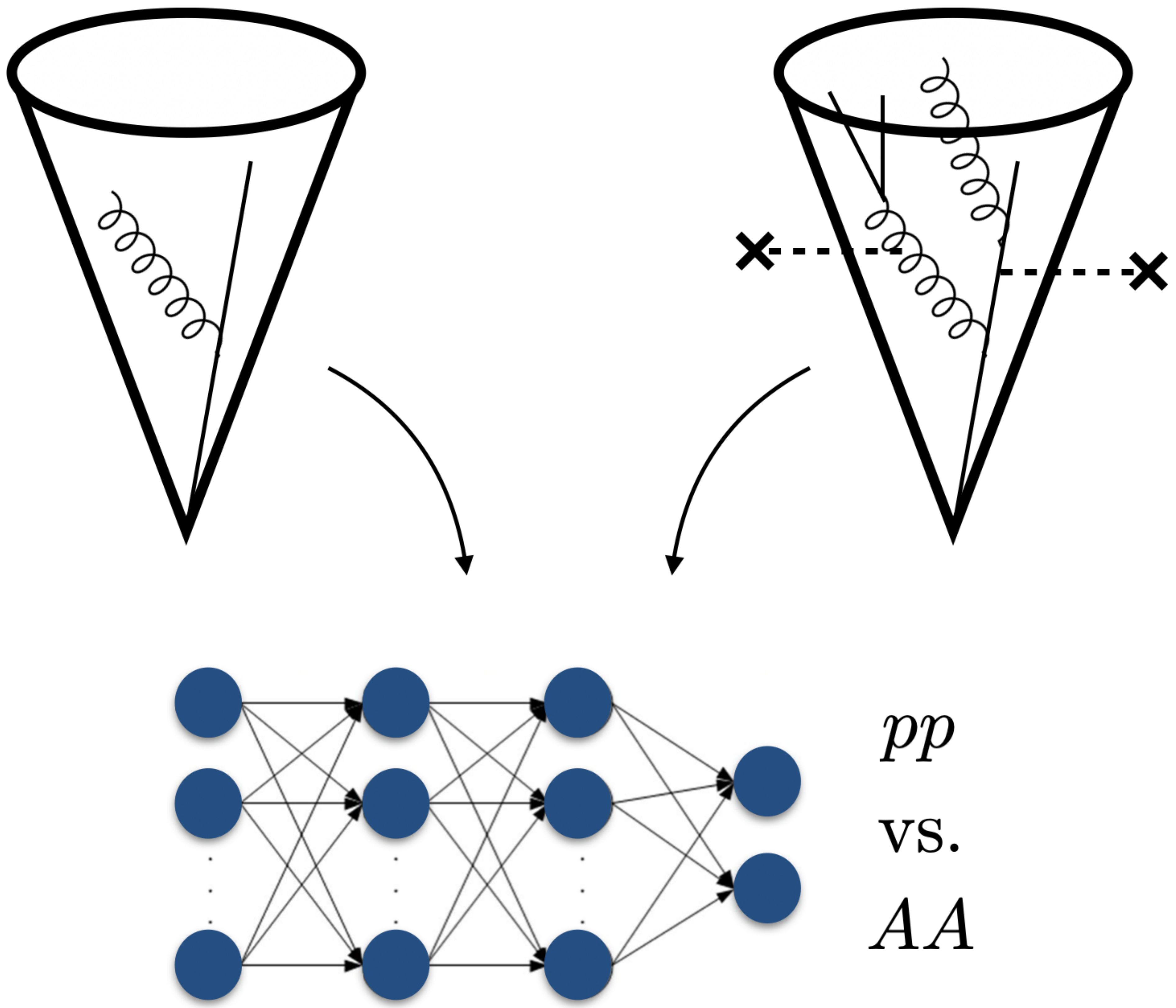



By modeling these interactions, we hope to determine the structure of the QGP

# Jet classification — pp vs. AA

We seek to understand how jets in heavy-ion collisions are different than jets in proton-proton collisions

→ Binary classification problem




**Goal:** Use ML to discriminate pp from AA jets in a way that is **theoretically interpretable**

# Outline

1. Identify the useful information content in the jet

2. Design optimal observables to maximize discrimination

3. Assess information loss due to backgrounds

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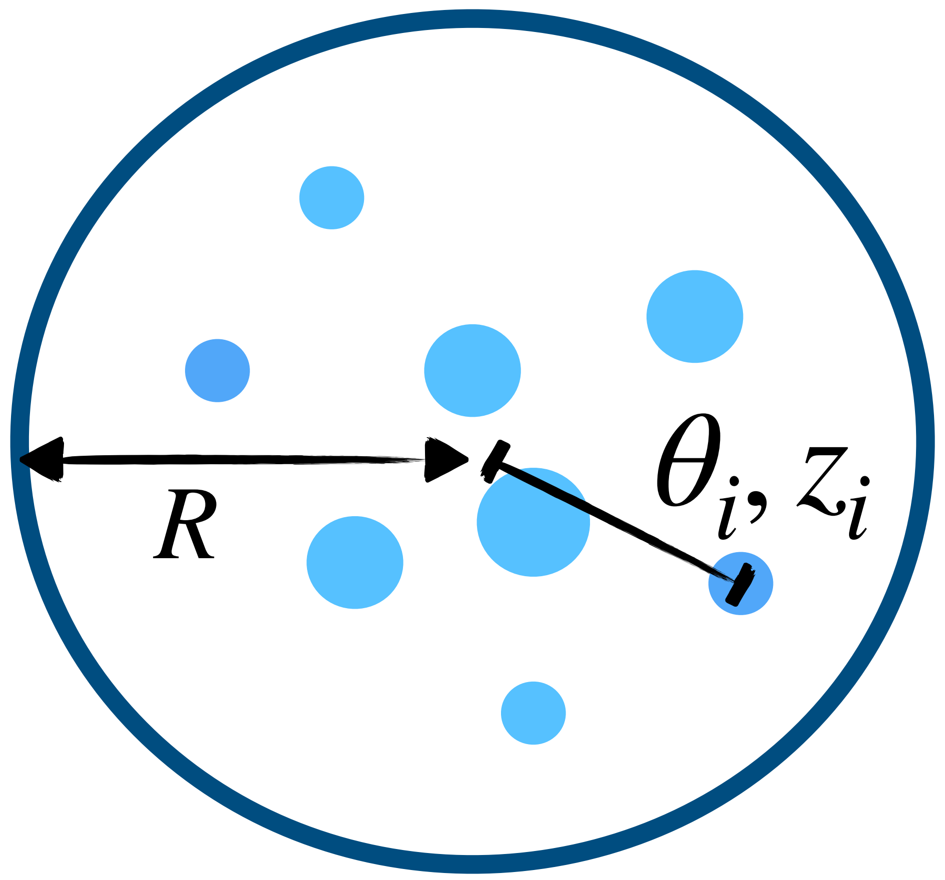
# Jet observables and IRC safety

We are free to construct any observable from the jet's constituents

e.g. $$\lambda_\alpha^\kappa = \sum_{i \in \text{jet}} z_i^\kappa \theta_i^\alpha$$

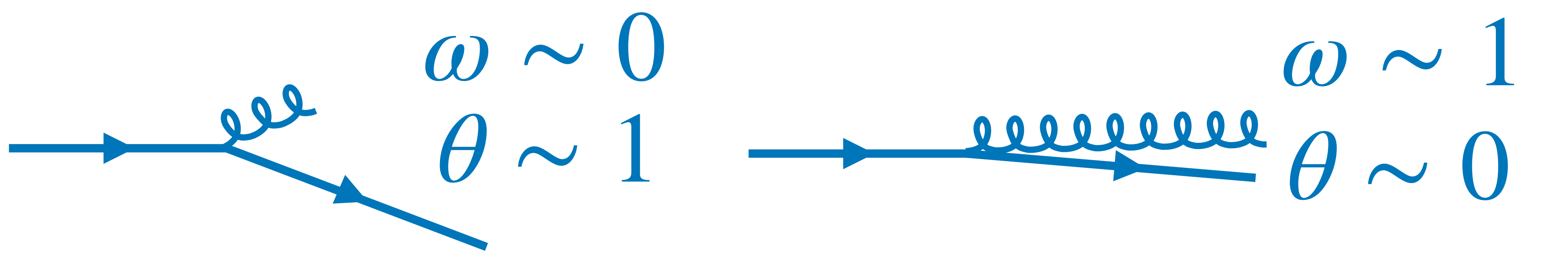



$$\theta_i = \frac{\sqrt{\Delta y^2 + \Delta \varphi^2}}{R}$$

$$z_i = \frac{p_{\mathrm{T},i}}{p_{\mathrm{T,jet}}}$$

However, usually only those combinations that obey **infrared-collinear (IRC) safety** are calculable in perturbative QCD

e.g. $$\lambda_{\alpha>0}^{\kappa=1} = \sum_{i \in \text{jet}} z_i \theta_i^\alpha$$




*Insensitive to soft/collinear emissions*

# IRC-safe vs. IRC-unsafe architectures

Permutation-invariant neural networks based on deep sets

Unordered, variable-length sets of particles as input

*Komiske, Metodiev, Thaler JHEP 01 (2019) 121*

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

**Particle Flow Network (PFN)**

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

Classifier

DNNs

latent space $d = 256$

Includes IRC-unsafe information

**Energy Flow Network (EFN)**

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

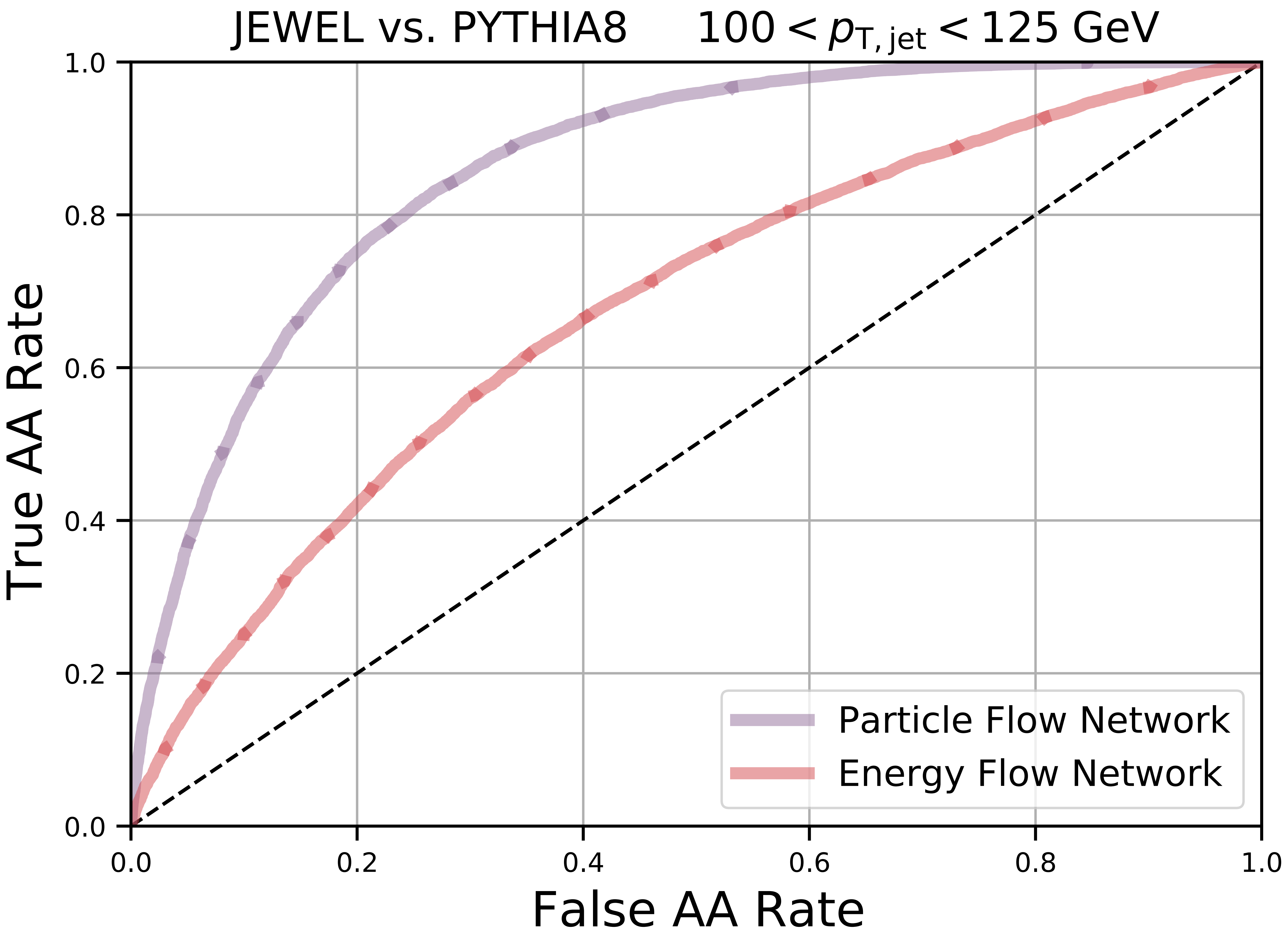
Classifier

DNNs

Includes only IRC-safe information

# IRC-safe vs. IRC-unsafe physics

*Lai, Mulligan, Płoskoń, Ringer arXiv 2111.14589*




We compare the IRC-unsafe network (PFN) to an IRC-safe network (EFN)

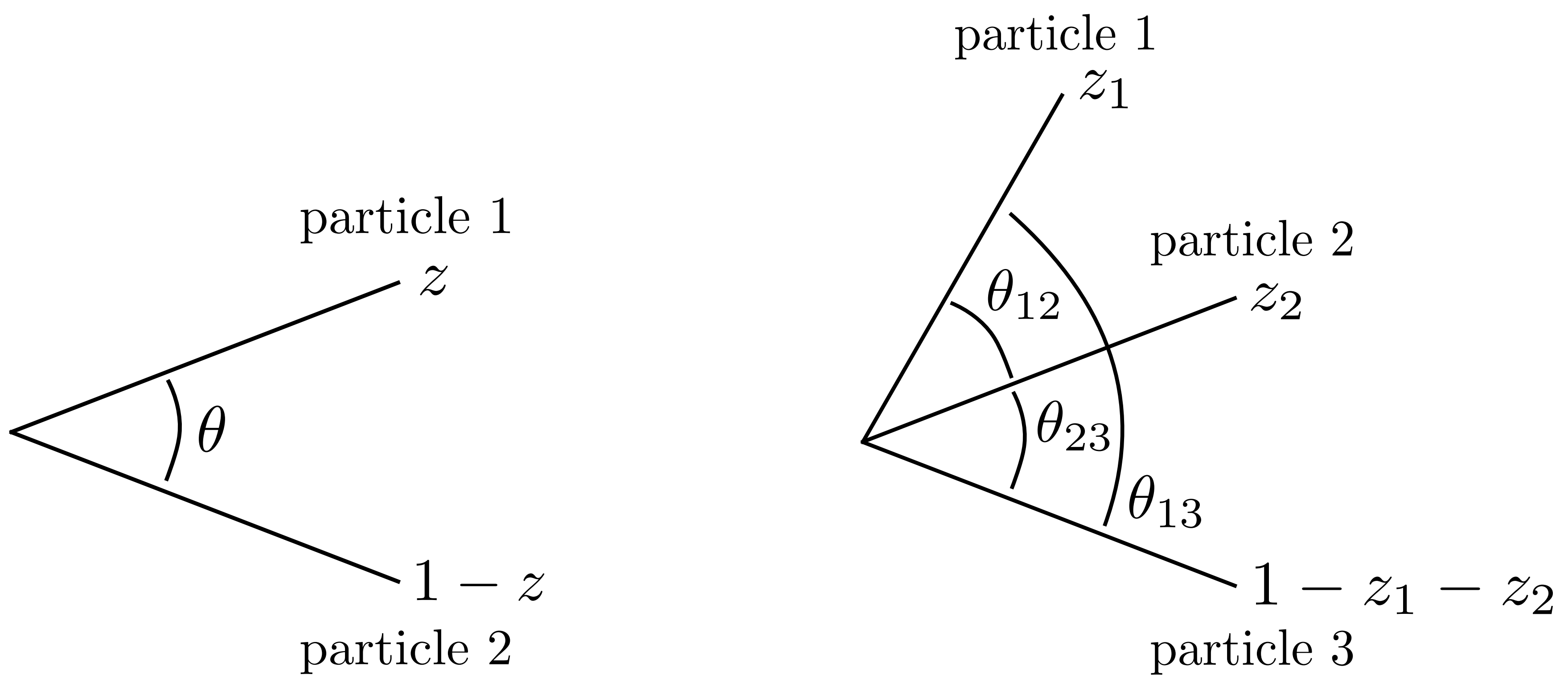
The PFN performs significantly better than the EFN

IRC-unsafe information contains significant discriminating power

# Jet classification in vacuum: Information content

*Datta, Larkoski JHEP 06 (2017) 073*

The substructure of a jet with $M$ final-state partons can be specified by $3M-4$ observables



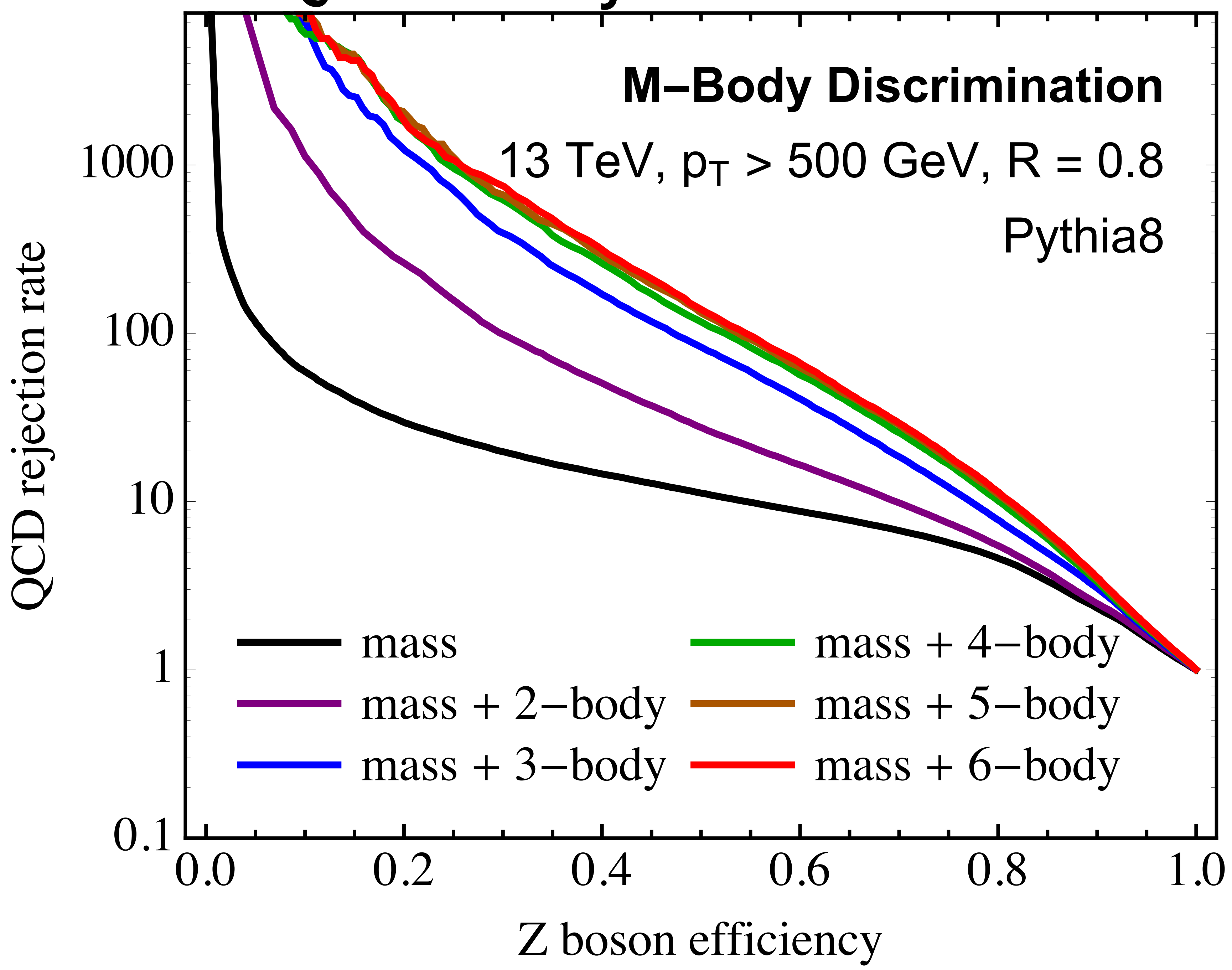

e.g. *N*-subjettiness basis:

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

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

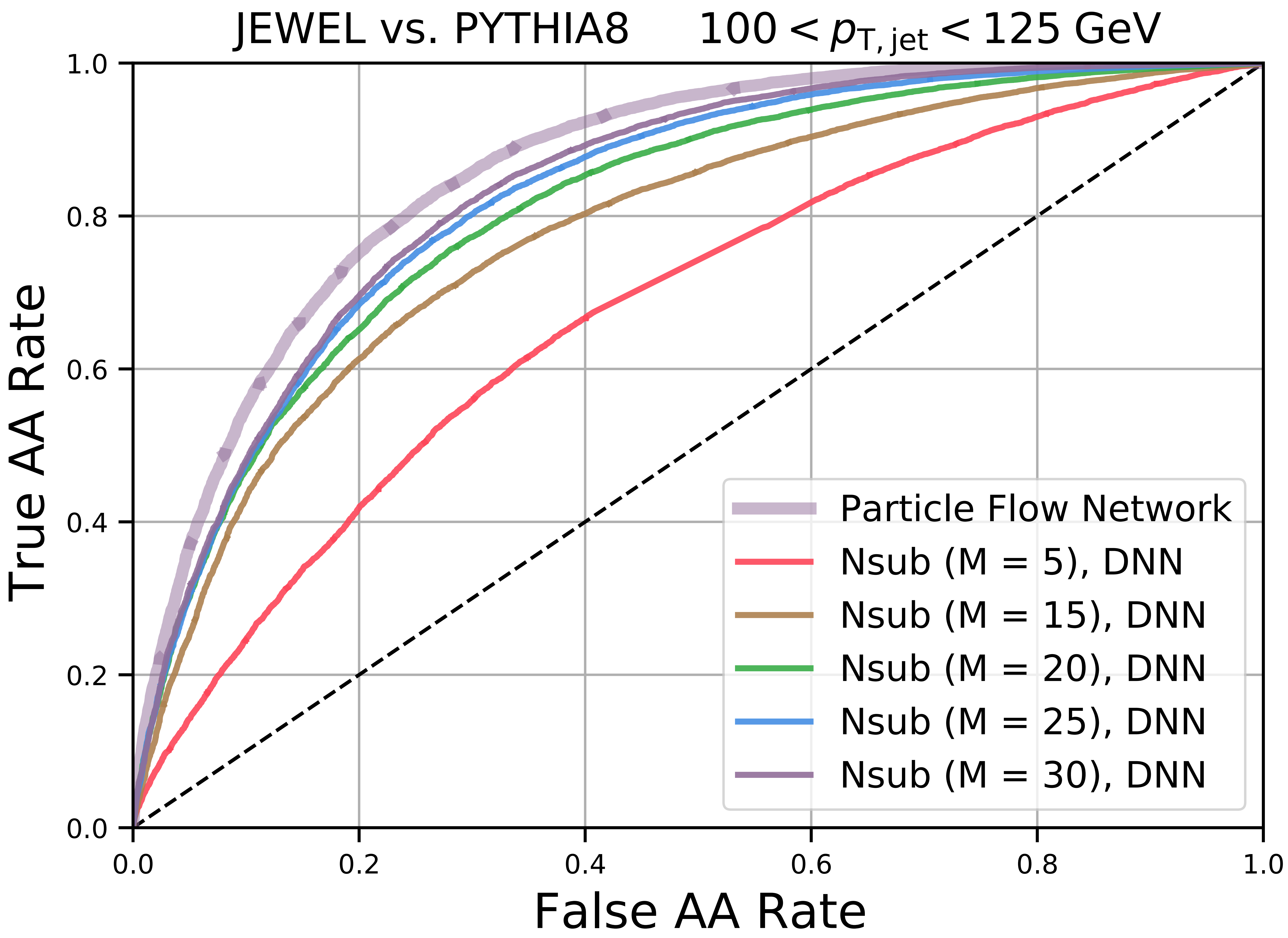
By constructing a complete set of observables encoding the jet's internal structure, can study at what point the information content saturates

*QCD vs. Z jet discrimination*



# Hard vs. soft physics

*Lai, Mulligan, Płoskoń, Ringer arXiv 2111.14589*



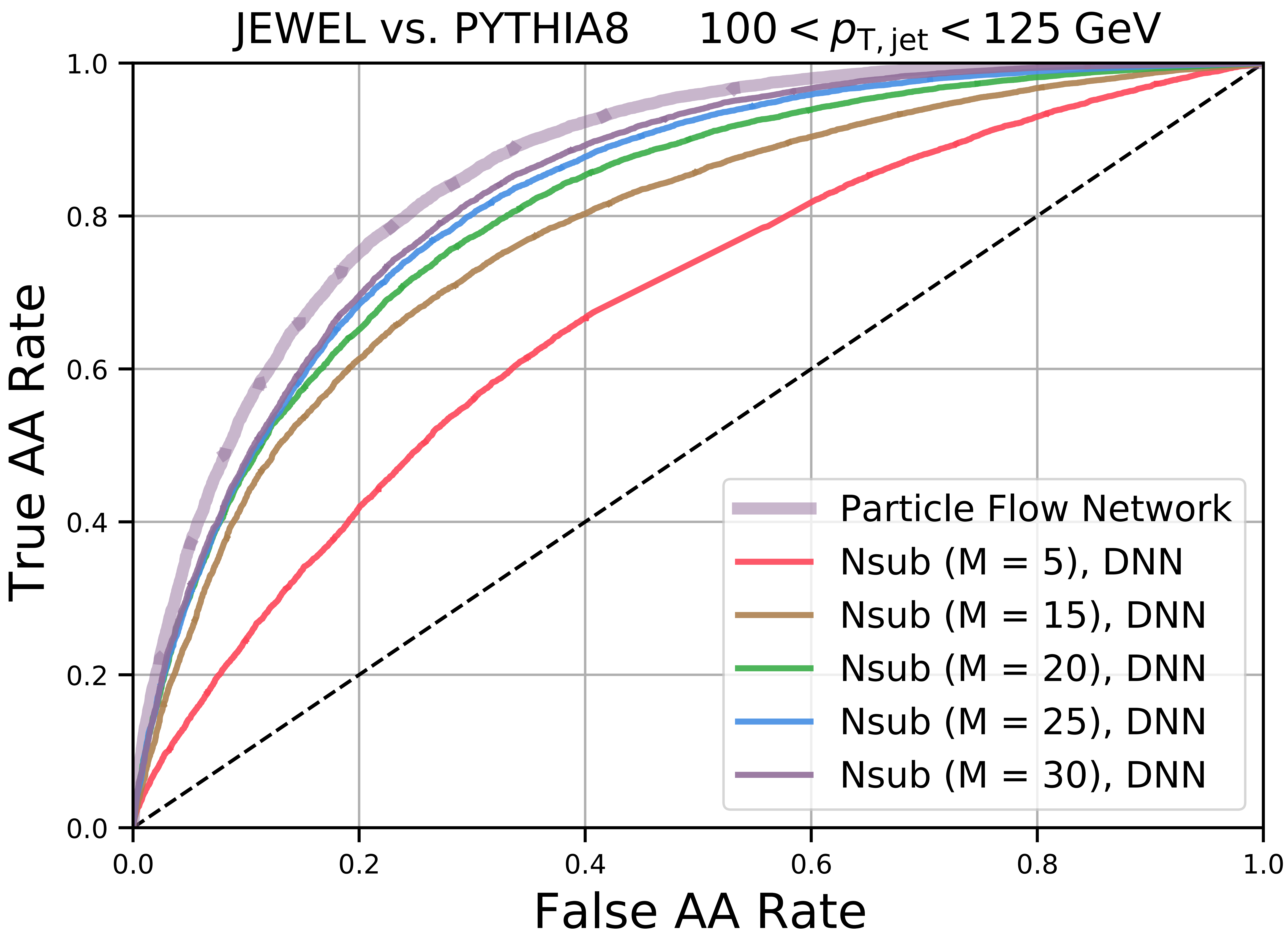

DNN with complete set of jet substructure observables as input

*N*-subjettiness basis:

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

Significant information in quenched jets up to $M \approx 25$

# Hard vs. soft physics

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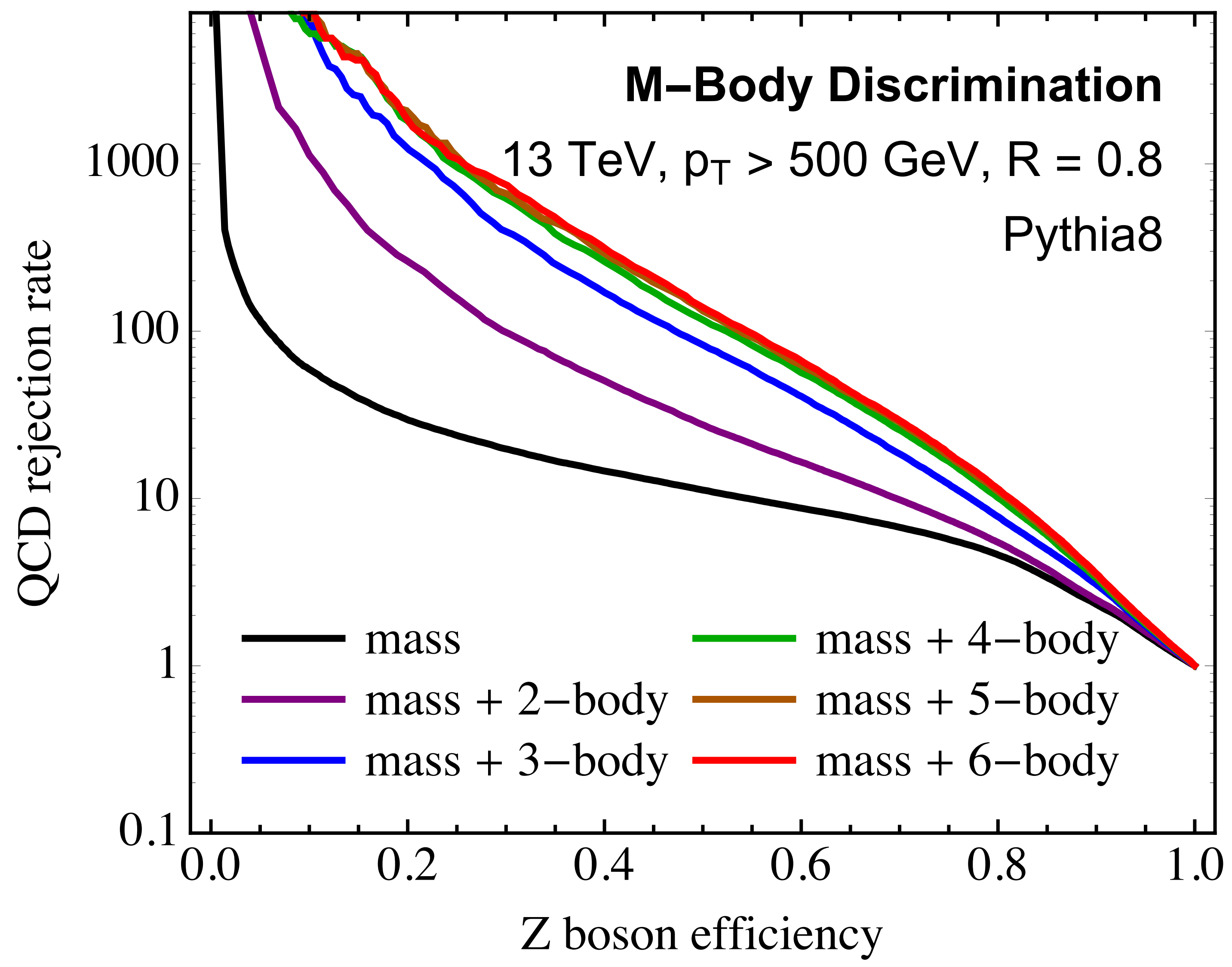
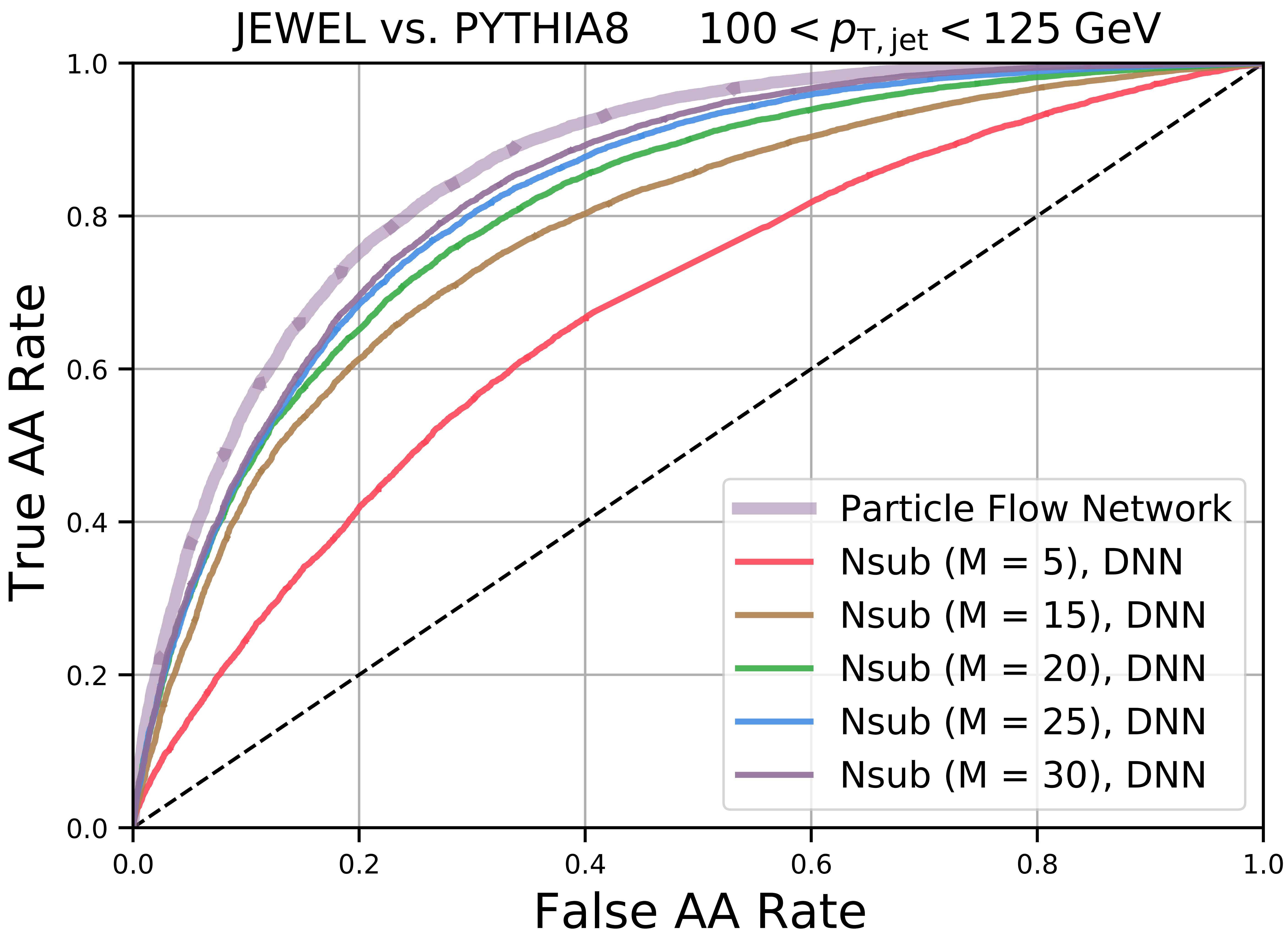



→ Unlike QCD vs. Z jets (which saturate at $M = 4$), vacuum vs. quenched jets contain discriminating power in soft physics (high $M$-body phase space)

# Hard vs. soft physics




Deep set data representation (PFN) performs slightly better than substructure basis (DNN)

The difference can be due to:

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

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# ML-assisted observable design

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

→ Theoretical calculability

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

Product observable: Sudakov safe

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

N-subjettiness exponents become weights in linear regression

$$\ln O = \sum_{N<K,\ \beta\in\{0.5,1,2\}} c_{N\beta} \ln \tau_N^\beta$$

# ML-assisted observable design

*Lai, Mulligan, Płoskoń, Ringer arXiv 2111.14589*

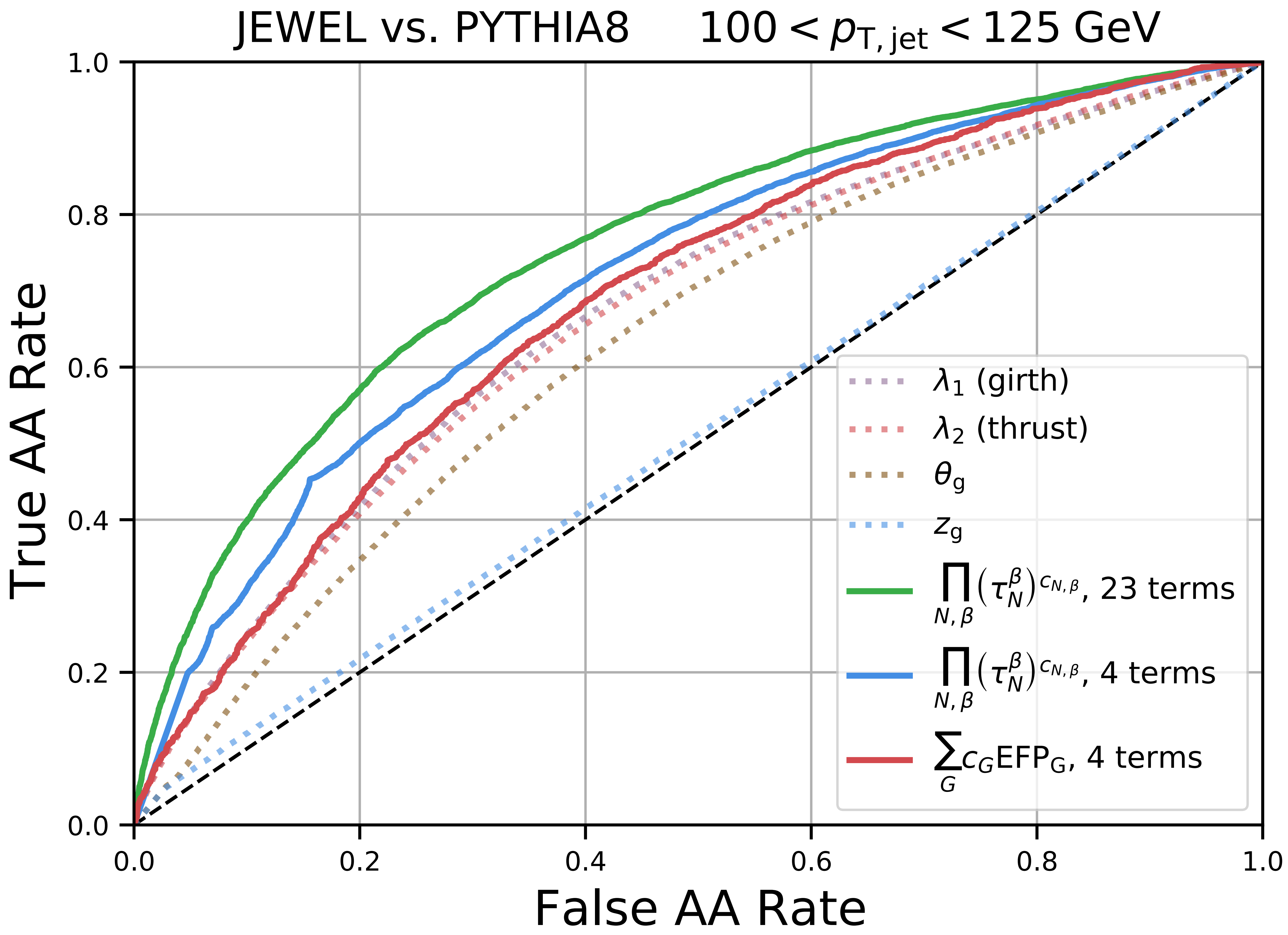
**Lasso regression**

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

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

$\alpha = 0.01$ → 24 terms
$\alpha = 0.1$ → 4 terms
$\alpha = 0.5$ → 1 term

e.g. $(\tau_1^2)^{1.437}(\tau_5^2)^{0.068}(\tau_6^2)^{1.712} \times \ldots$




By training ML classifier and balancing the tradeoff of discriminating power and complexity, we can design the *most strongly modified* calculable observable

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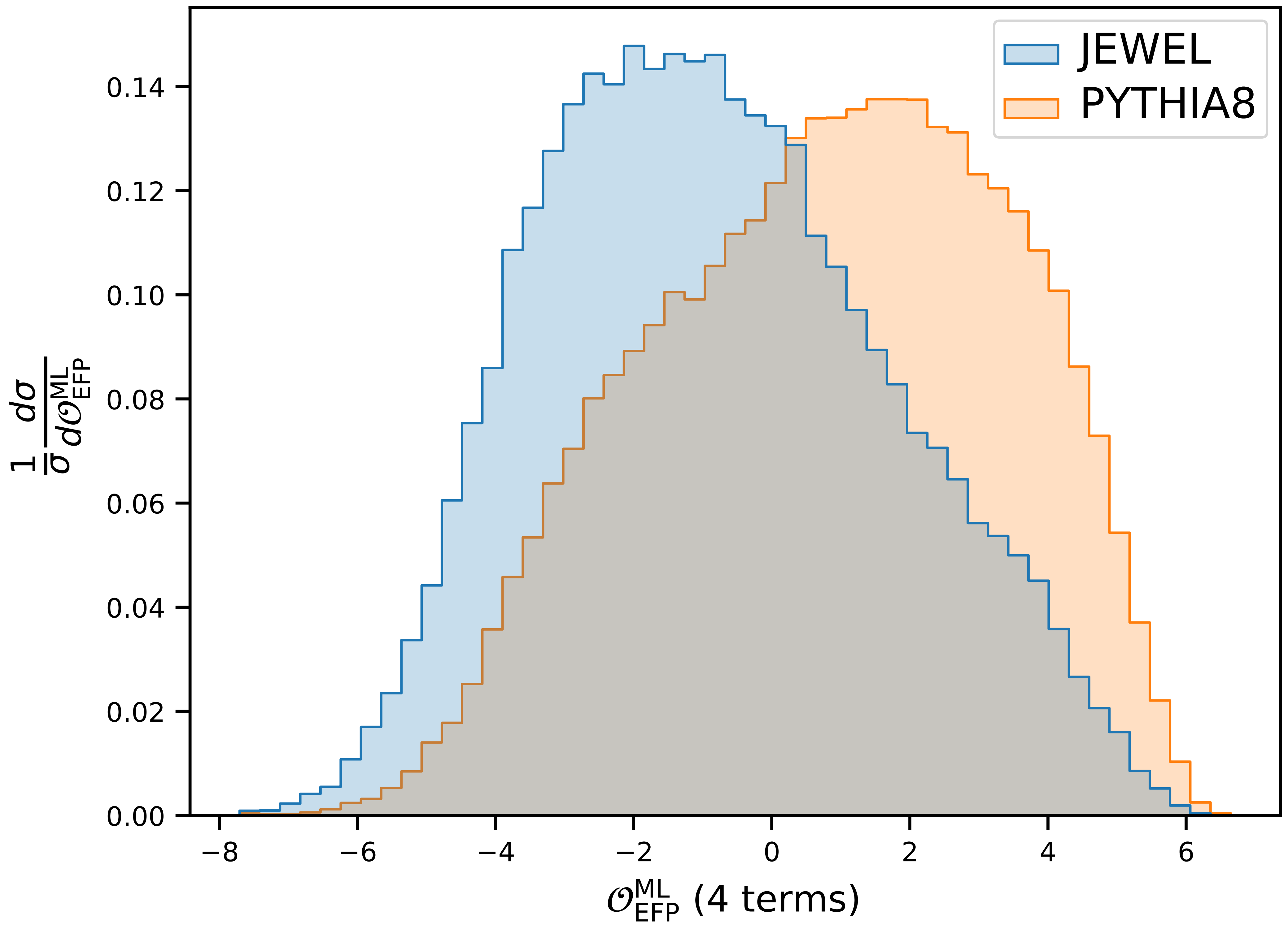


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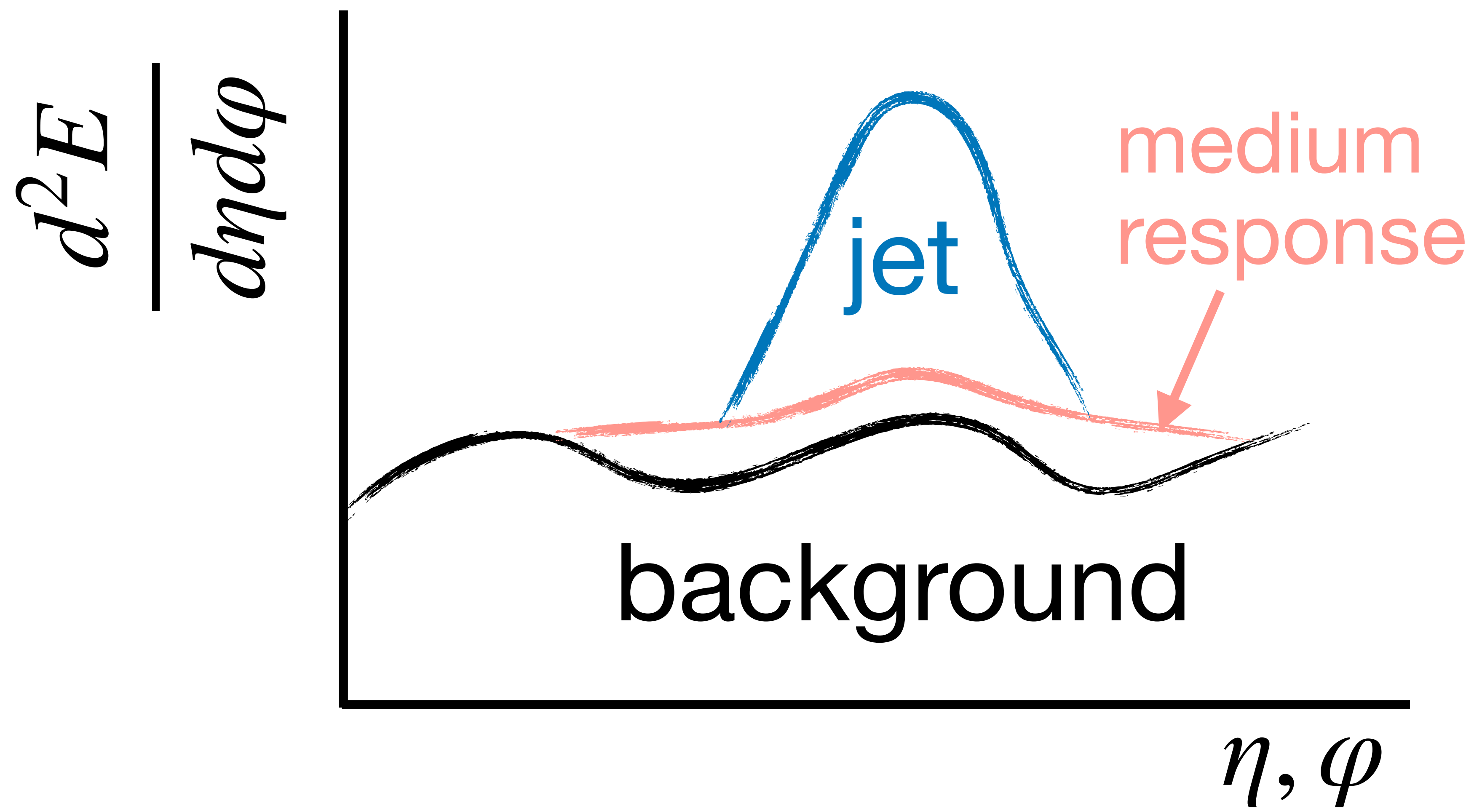
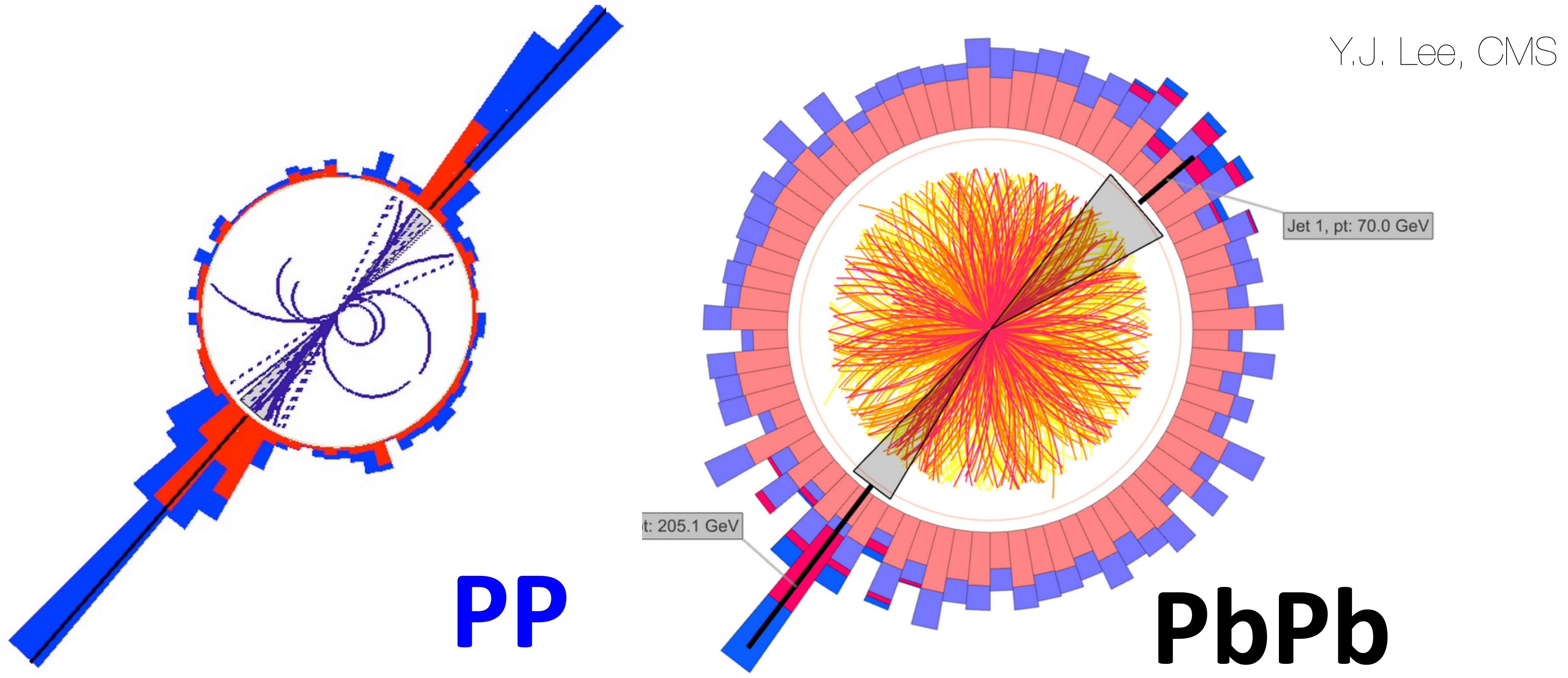
# Heavy-ion background

The soft collisions in a heavy-ion event produce a large, fluctuating underlying event



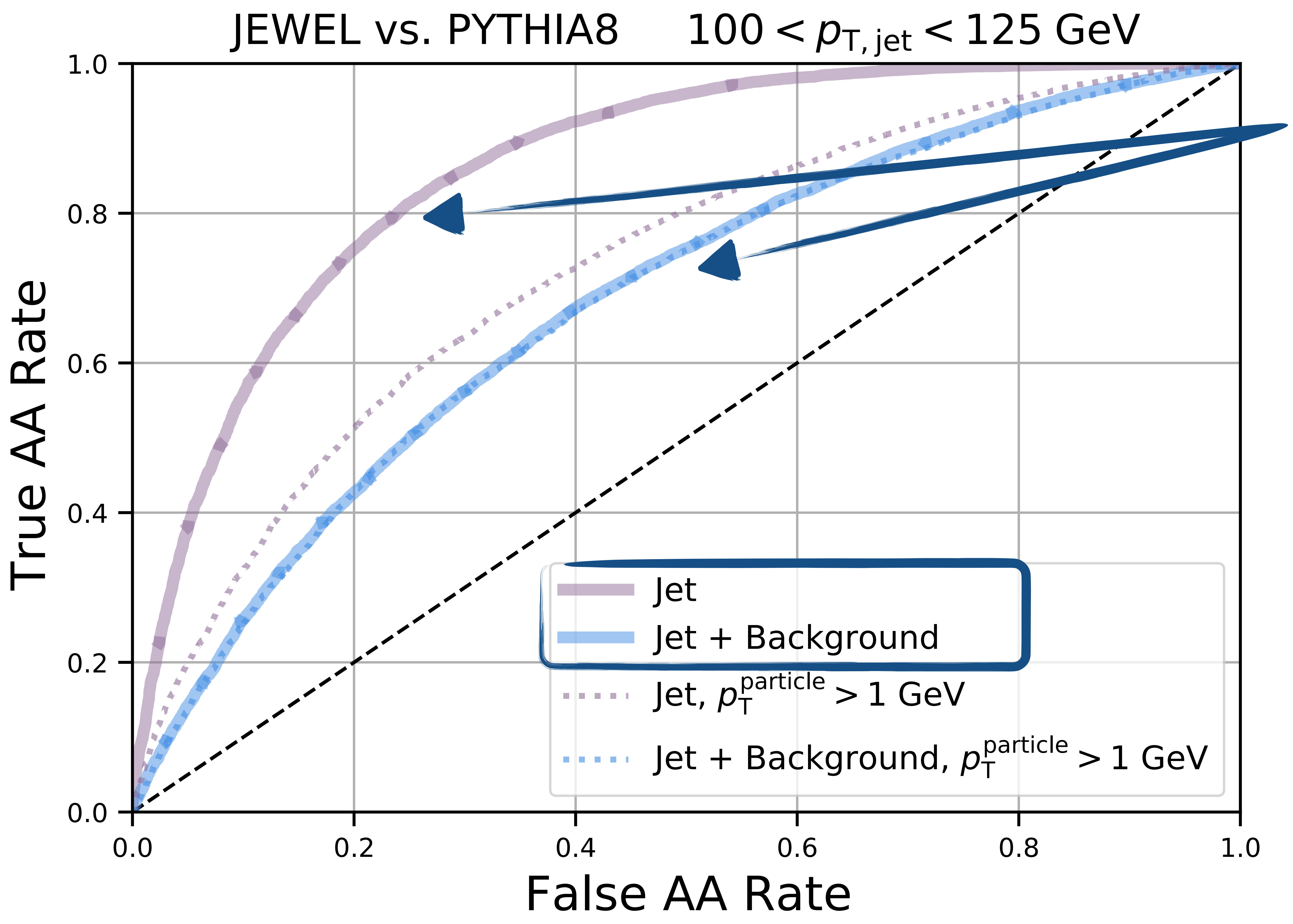




This is a major experimental and theoretical hurdle

**To what extent does the background destroy discriminating power?**

# Results — w/o vs. w/ background

*Lai, Mulligan, Płoskoń, Ringer arXiv 2111.14589*



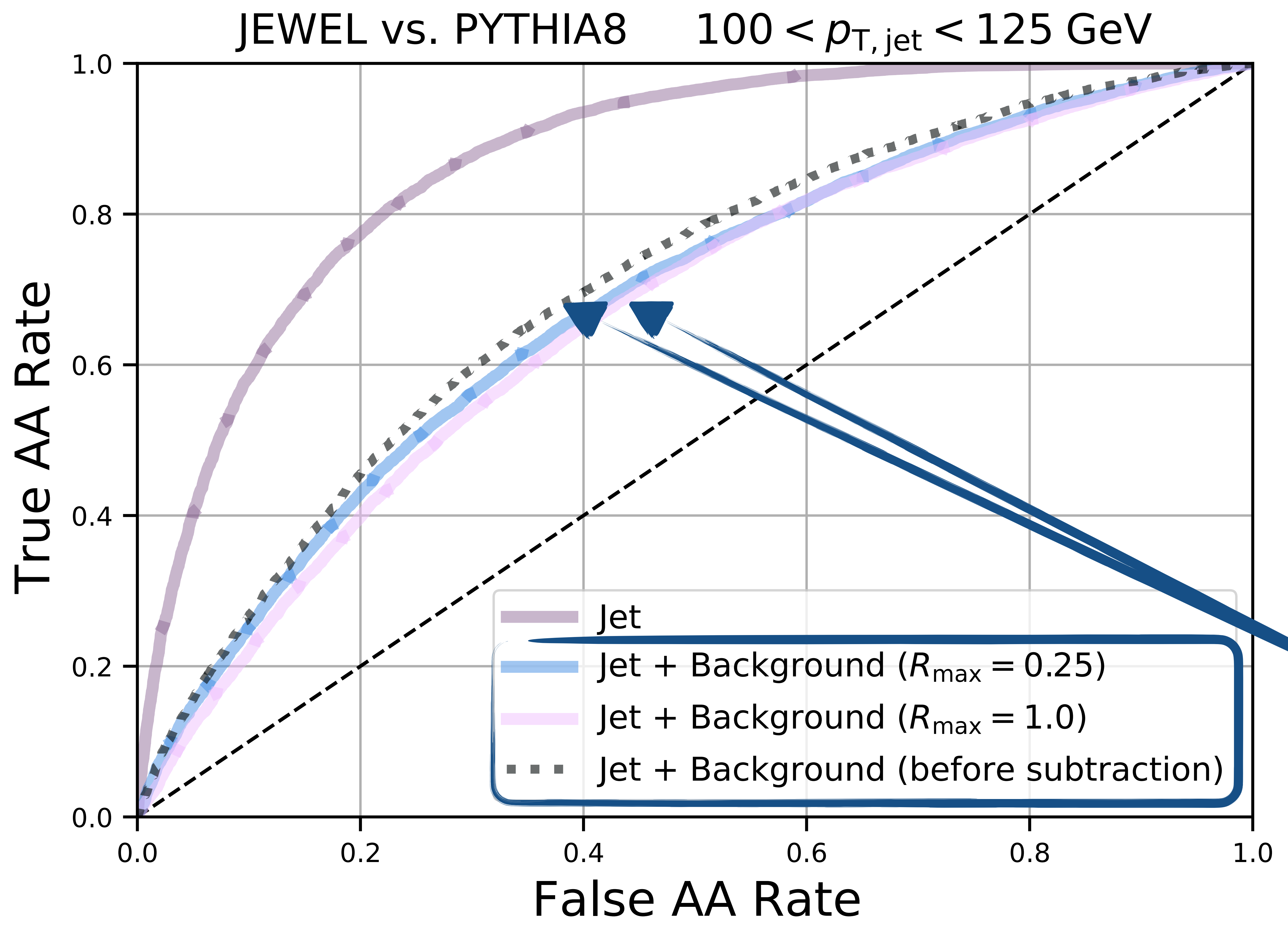

Discriminating power is highly reduced by the fluctuating underlying event

Large, irrecoverable information loss

Delicate challenge: soft information is crucial to discriminate, yet background fundamentally prevents much of this information from being accessed

# Assessing background subtraction algorithms

*Lai, Mulligan, Płoskoń, Ringer arXiv 2111.14589*




In practice, experiments must perform background subtraction procedures

This subtraction strictly removes information — use ML classifier performance as a metric to assess

Background subtraction does remove a small but significant amount of information

# Summary

## Theory-motivated binary classifiers to distinguish jets in heavy-ion collisions from those in proton-proton collisions

- New physics insights
  - Important information contained in soft emissions and IRC-unsafe physics
  - Large, irrecoverable information loss due to underlying event
- ML-assisted observable design of optimally discriminating (and calculable!) observables

## These methods can be applied directly to experimental data — labels are known

- Can also apply to full events: LHC, EIC