Jet physics at the EIC

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EIC User Group Meeting 2023, Warsaw

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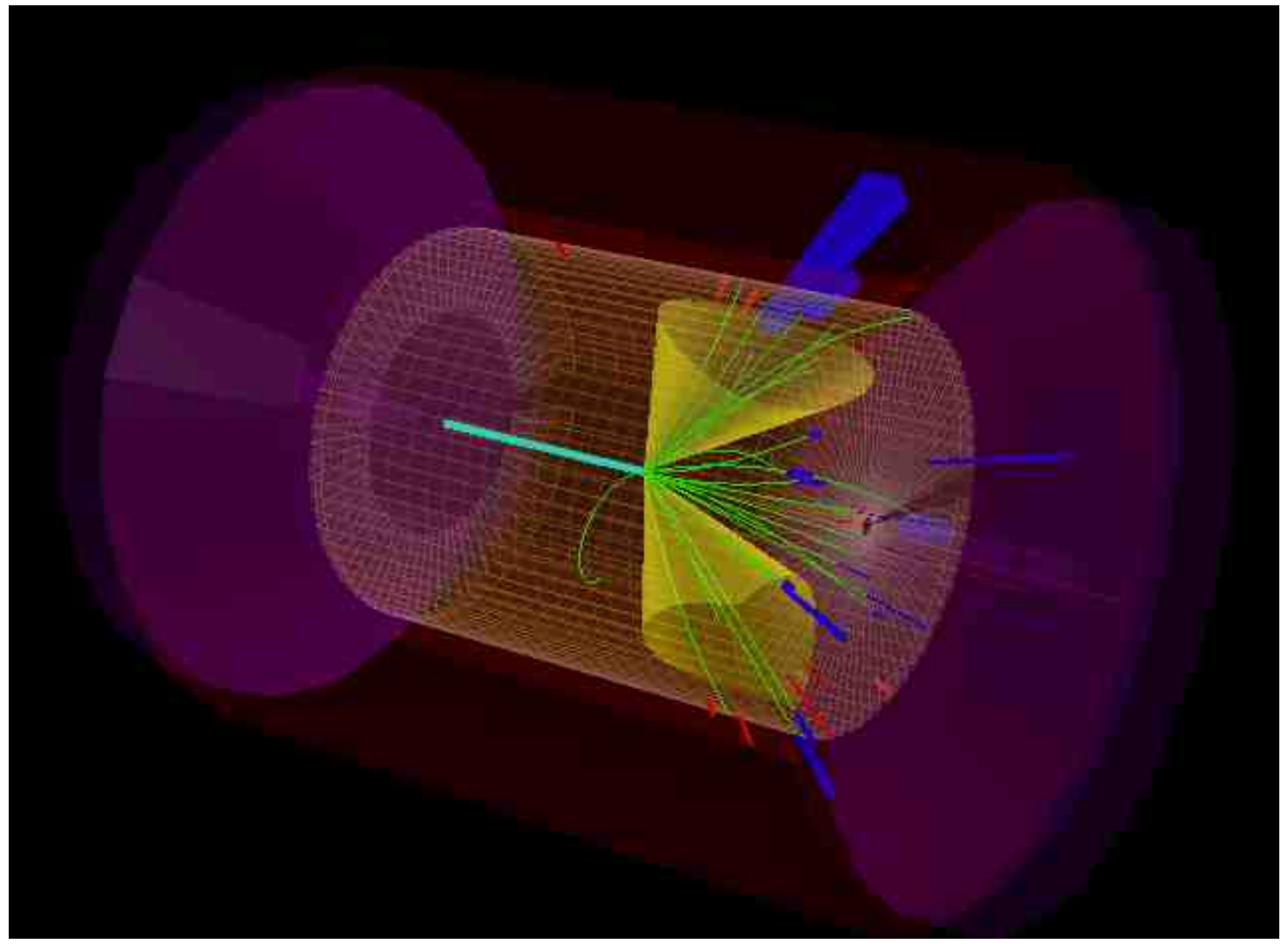
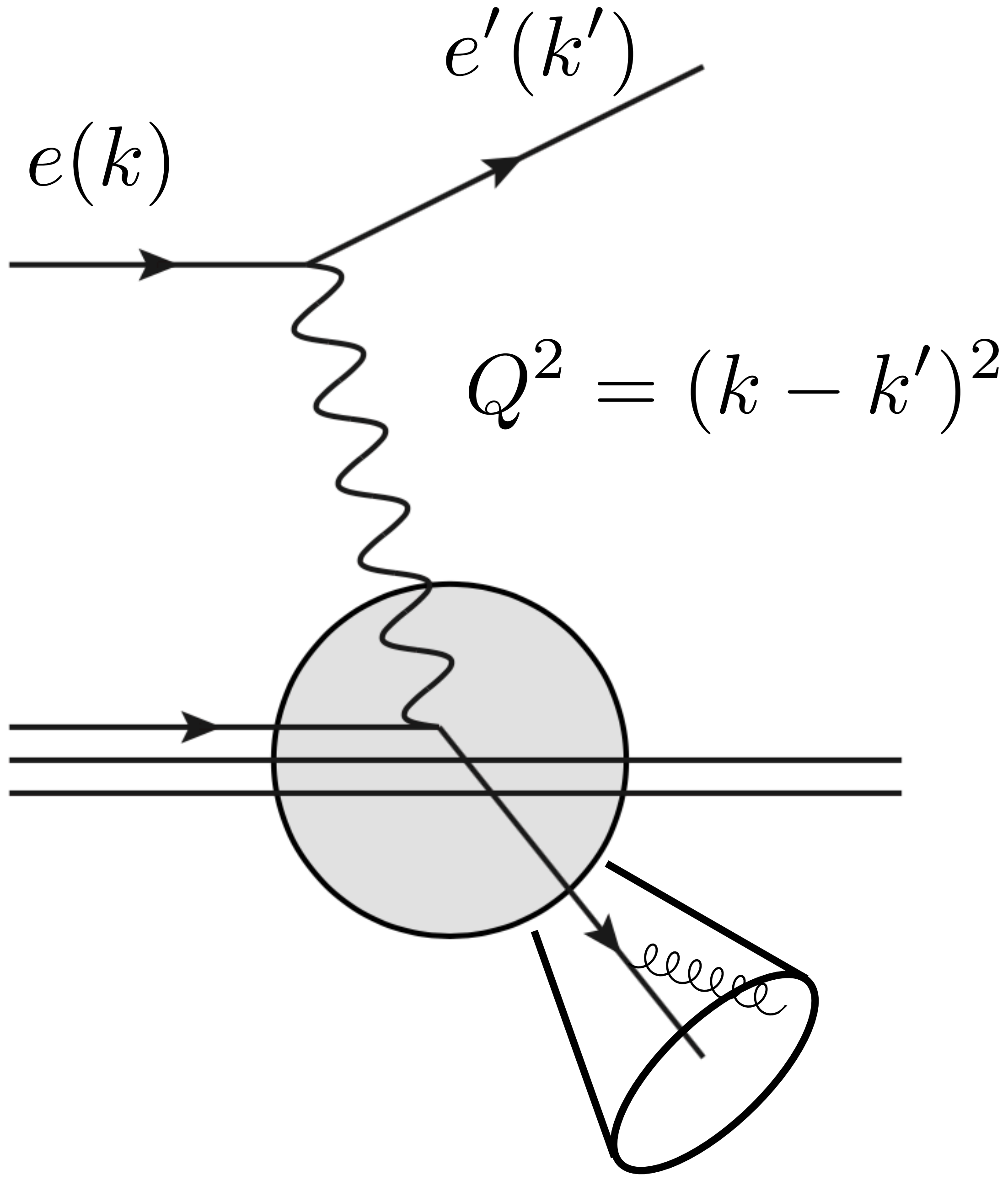
EIC jet physics

- Versatile jet reconstruction algorithms & frame dependence
- Rich jet substructure
- Clean EIC environment
- Relevant for e.g. TMDs, GPDs & hadronization

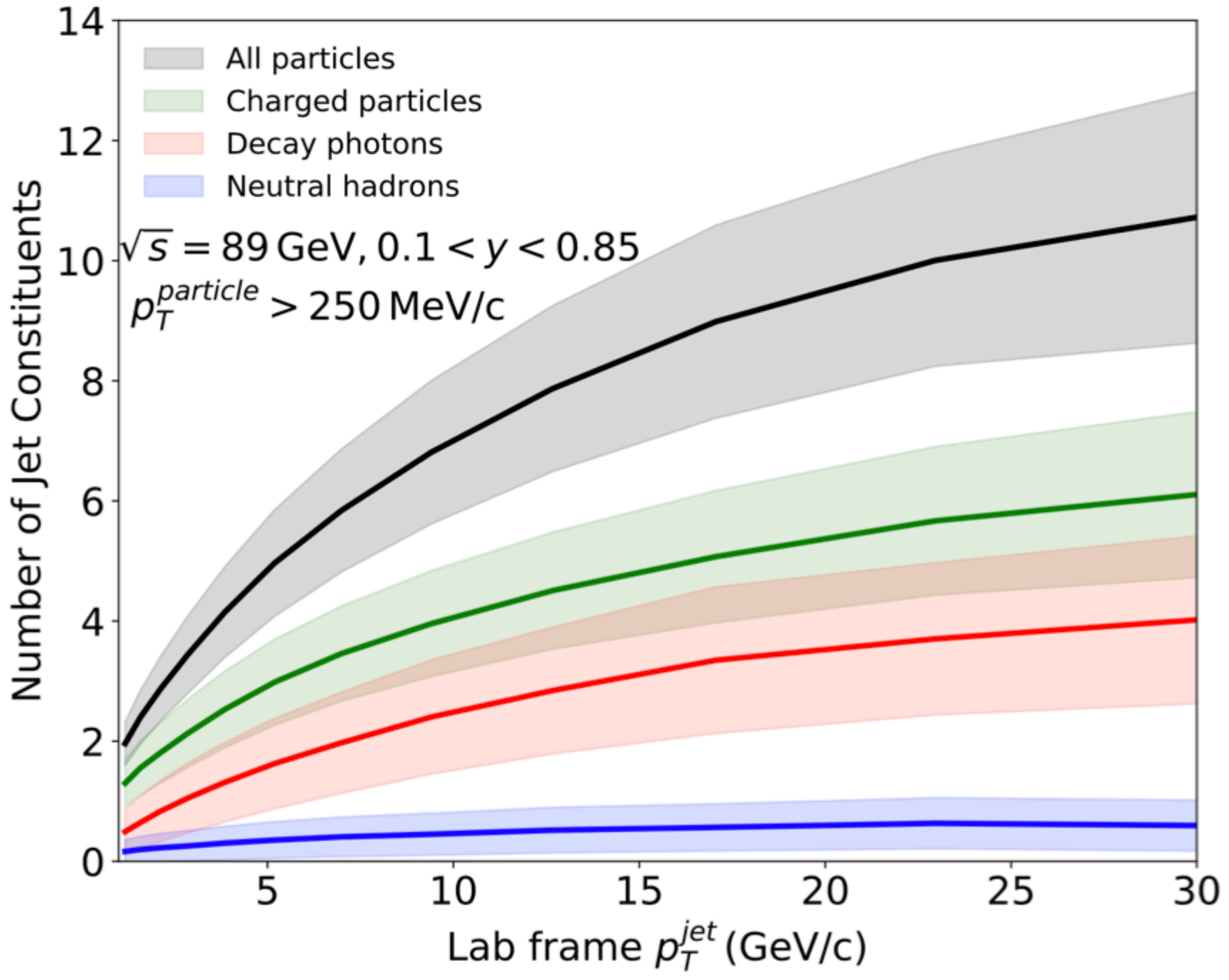


- New observables
- Information content (AI/ML)



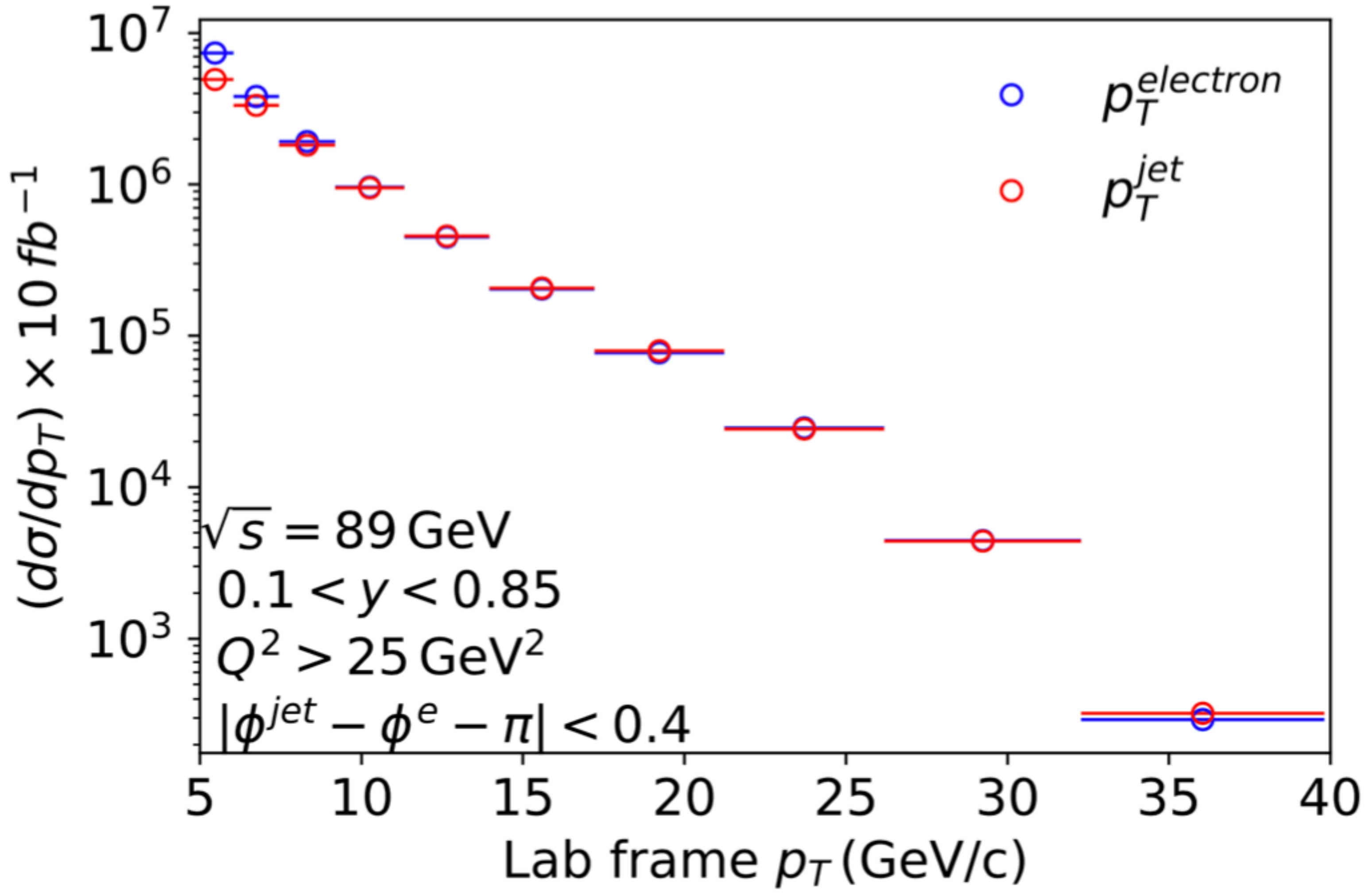
Nature of jets at the EIC

Particle #



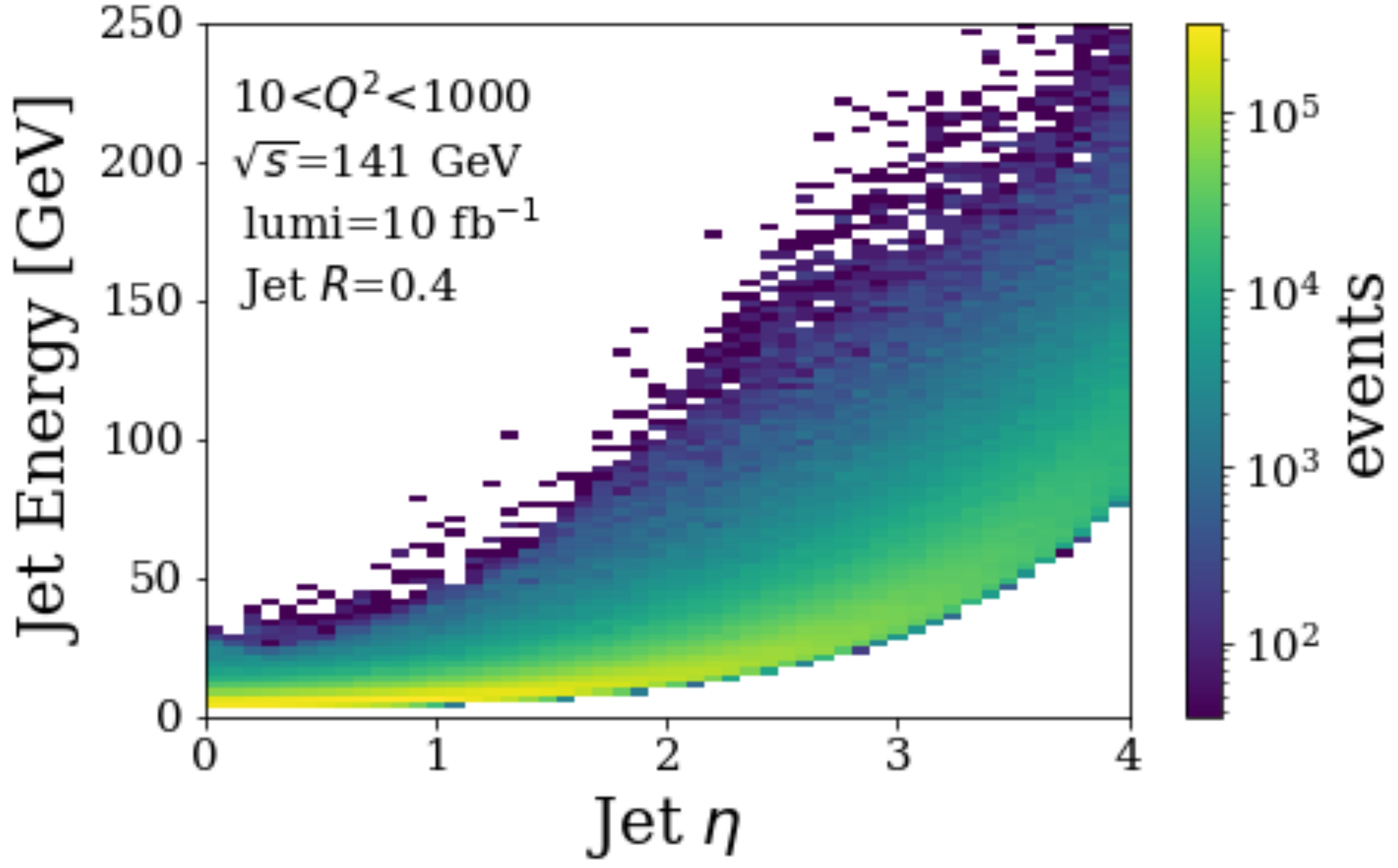
Arratia, Jacak, FR, Song `19

Transverse momentum



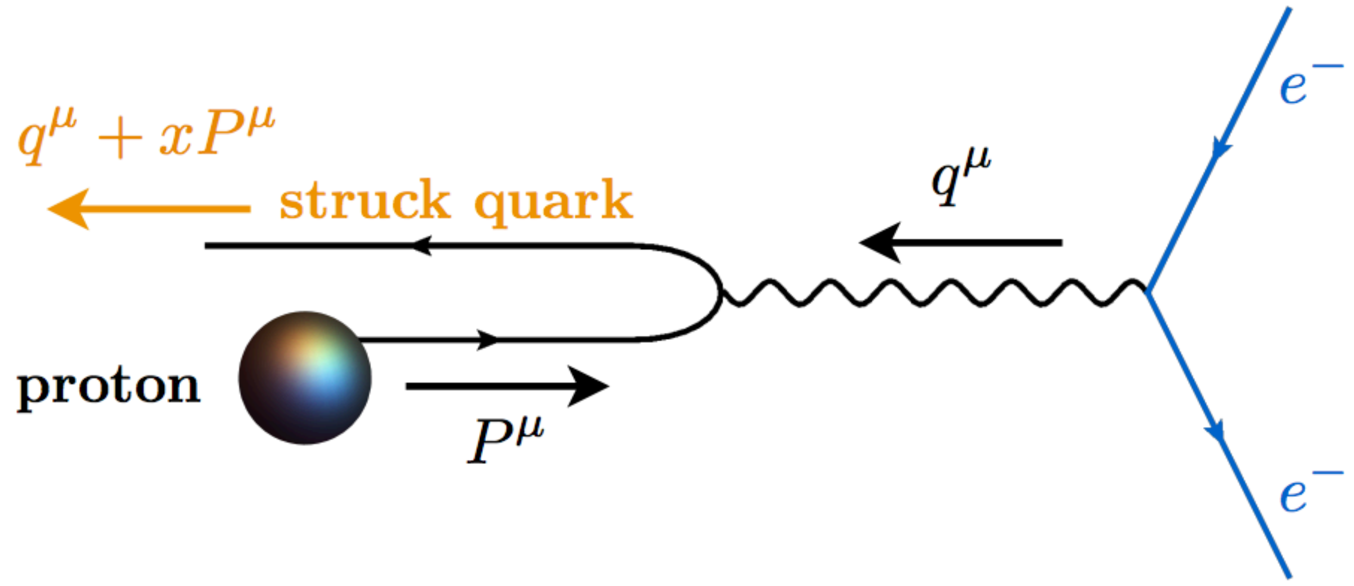
Jet energy

Arratia



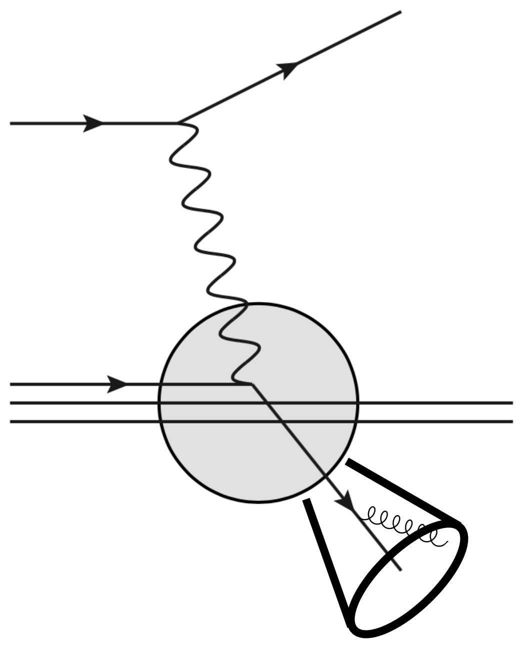
Hard scale p_T
and/or Q^2

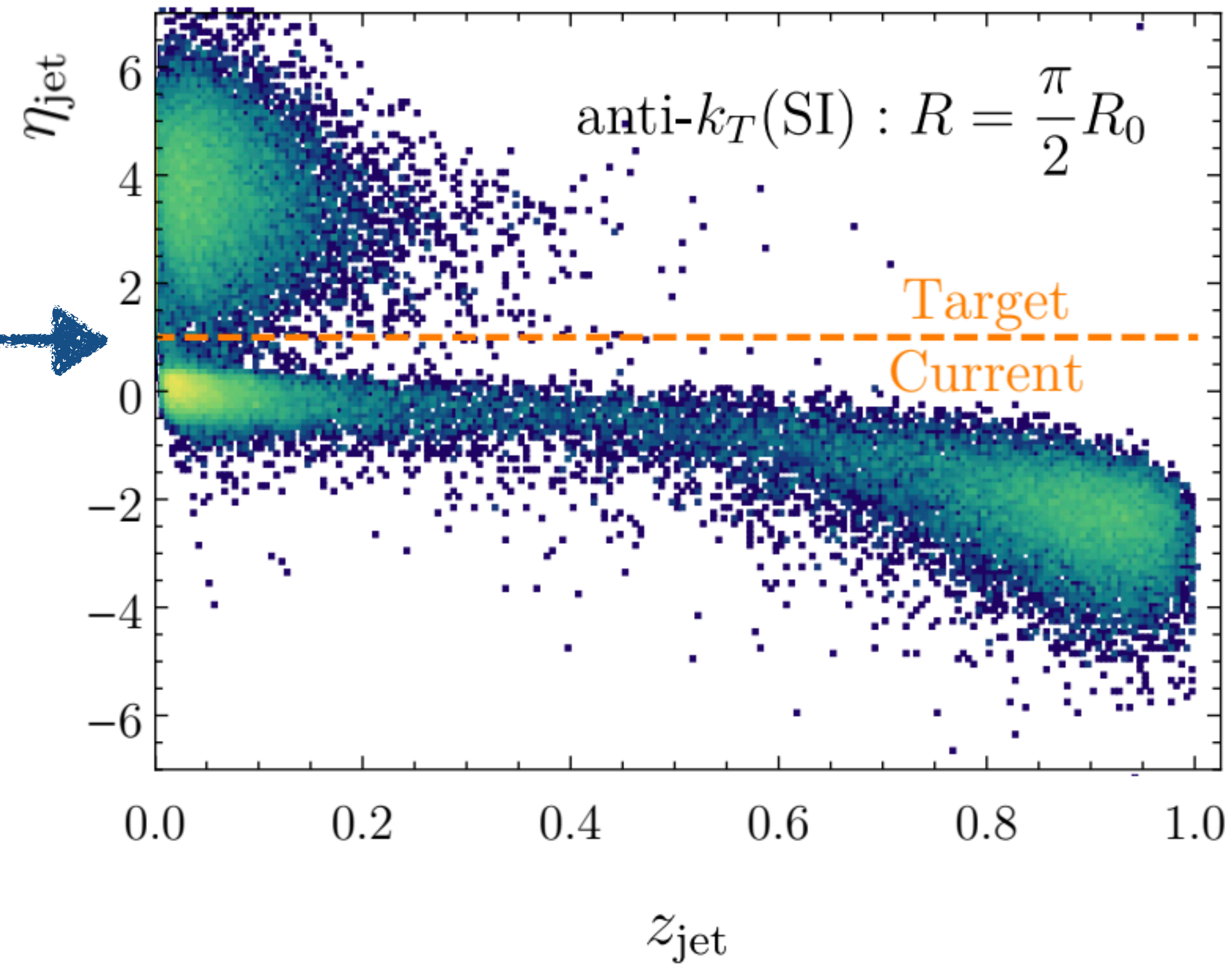
Jet algorithm design for the EIC

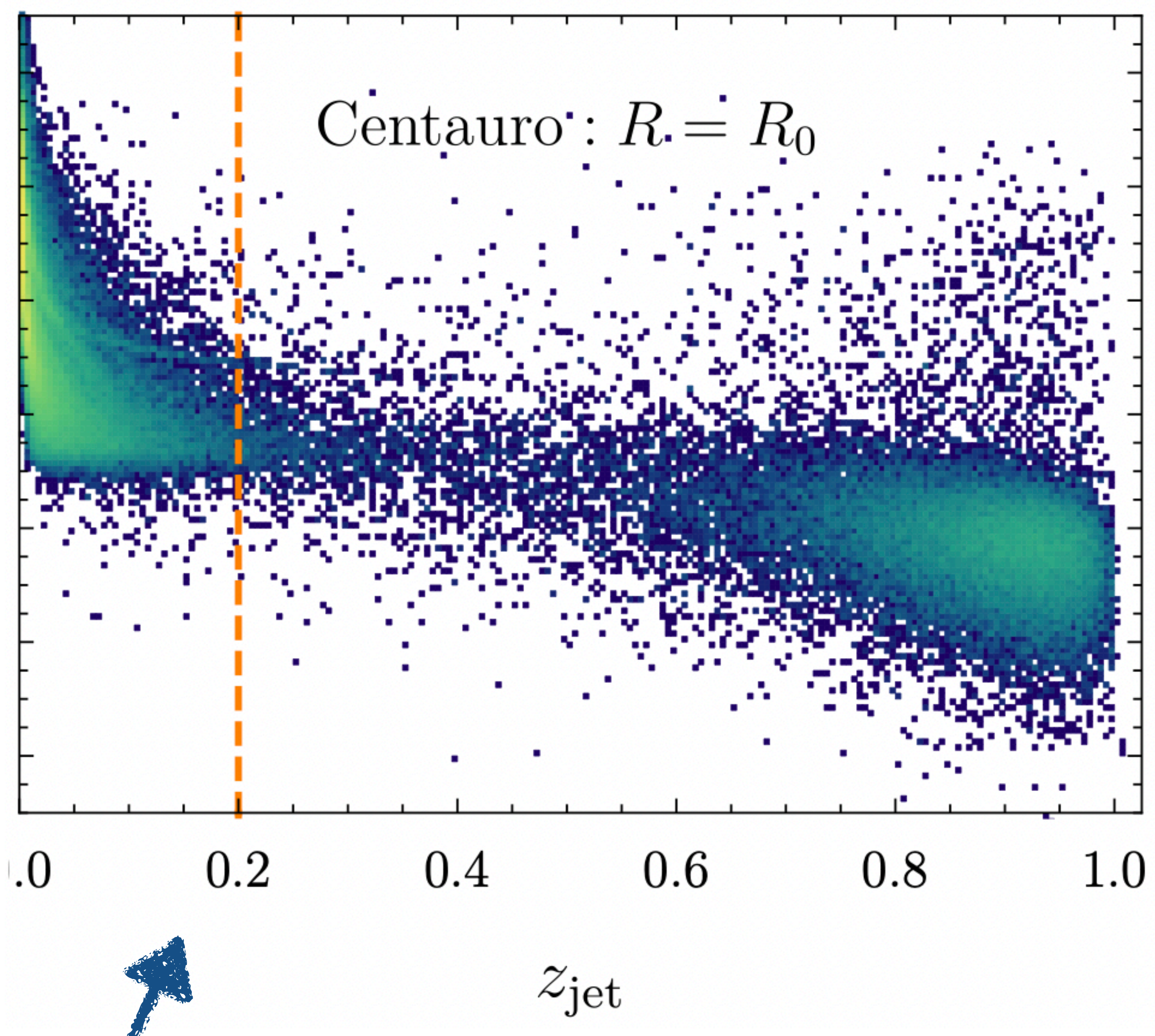


- Spherically invariant jets (E_i, θ_{ij}) in the Breit frame
- Asymmetric jet algorithm

Clean separation of current & target region







Arratia, Makris, Neill, FR, Sato `18
see also recent work by Yang-Ting Chien et al.

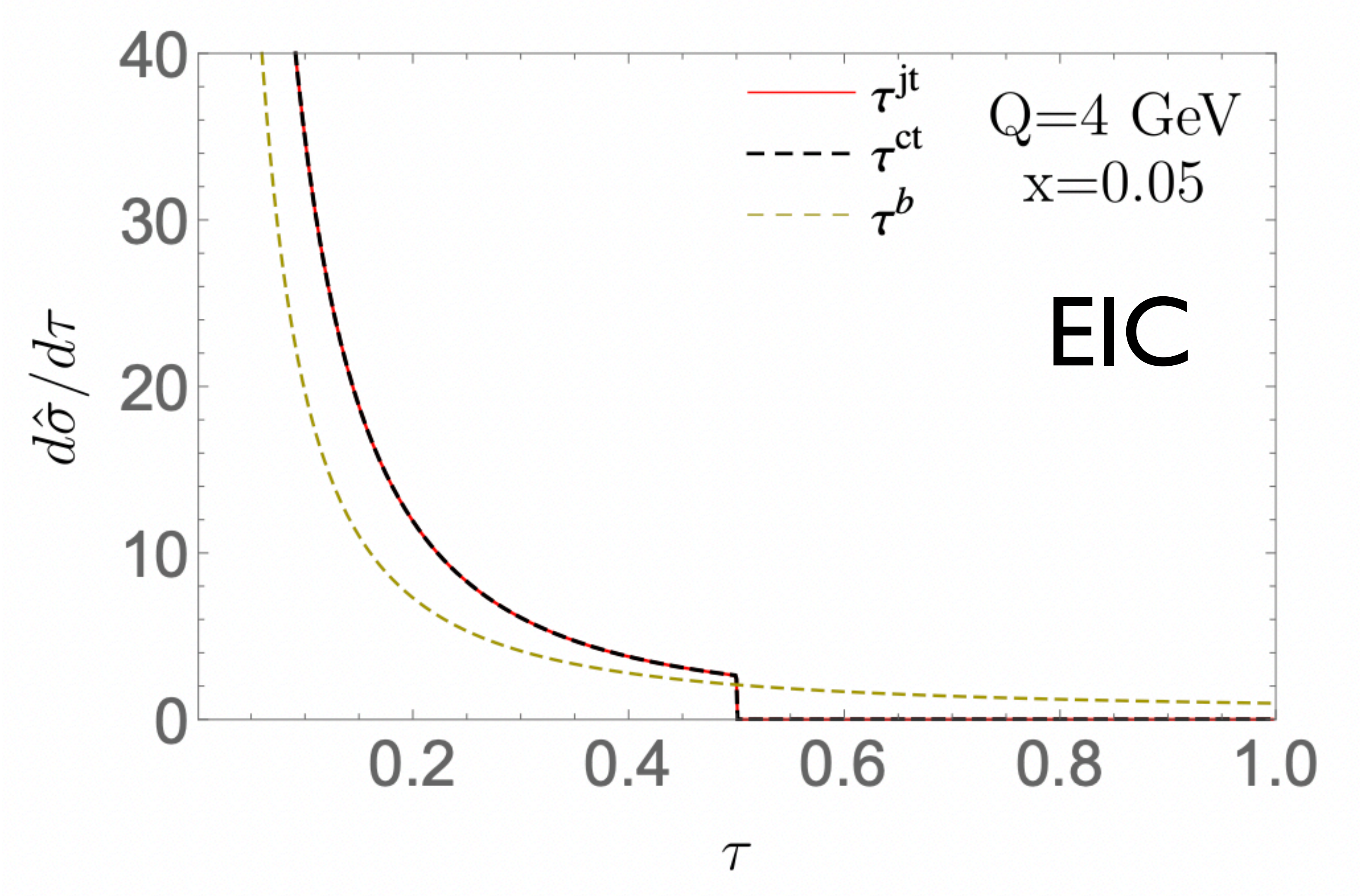
Useful for jet grooming

DIS event shapes

- 1-jettiness/thrust using 3 different axes τ^{kt} τ^{ct}

$$\tau^{\mathrm{jt}} = \frac{2}{Q^2}\sum_{i\in X}\min\{q_B\cdot p_i, q_J\cdot p_i\}$$

- Constrain α_s from DIS data $\frac{\mathrm{d}\sigma}{\mathrm{d}x\mathrm{d}Q^2\mathrm{d}\tau}$



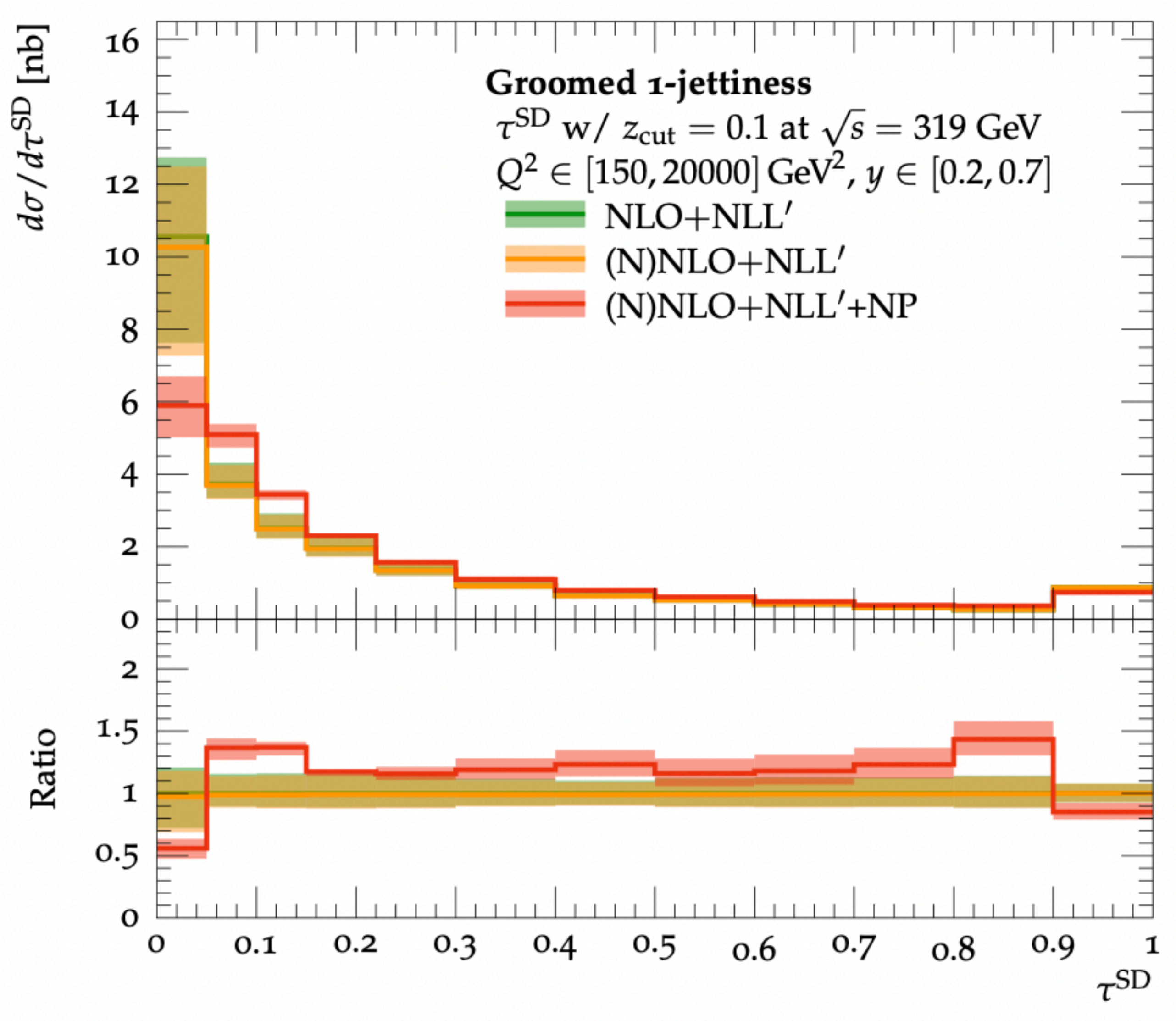
Chu, Wang, Ee, Chen, Kang `22

- With soft drop grooming

Makris `21

HERA

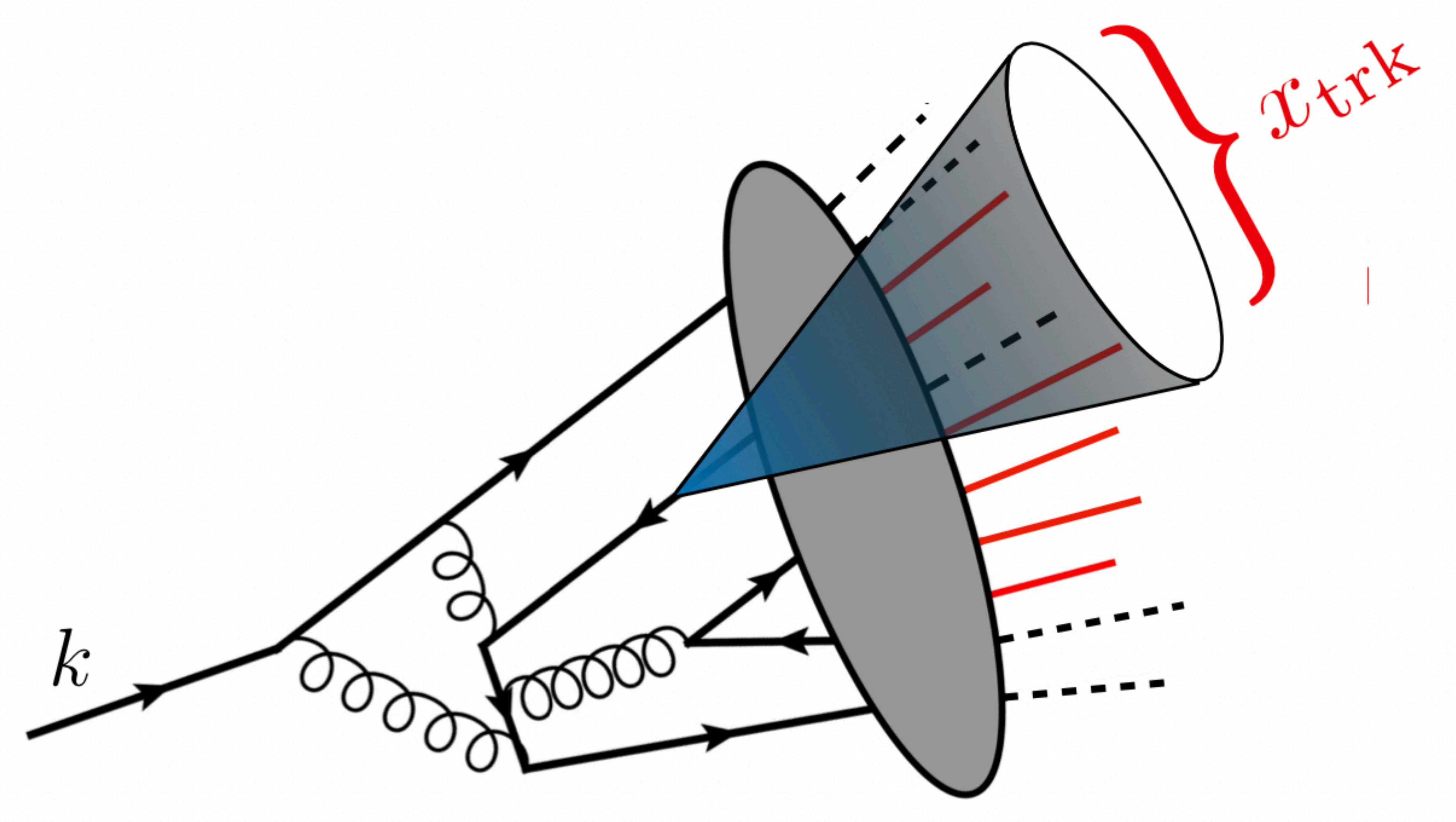
Knobbe, Reichelt, Schumann `23



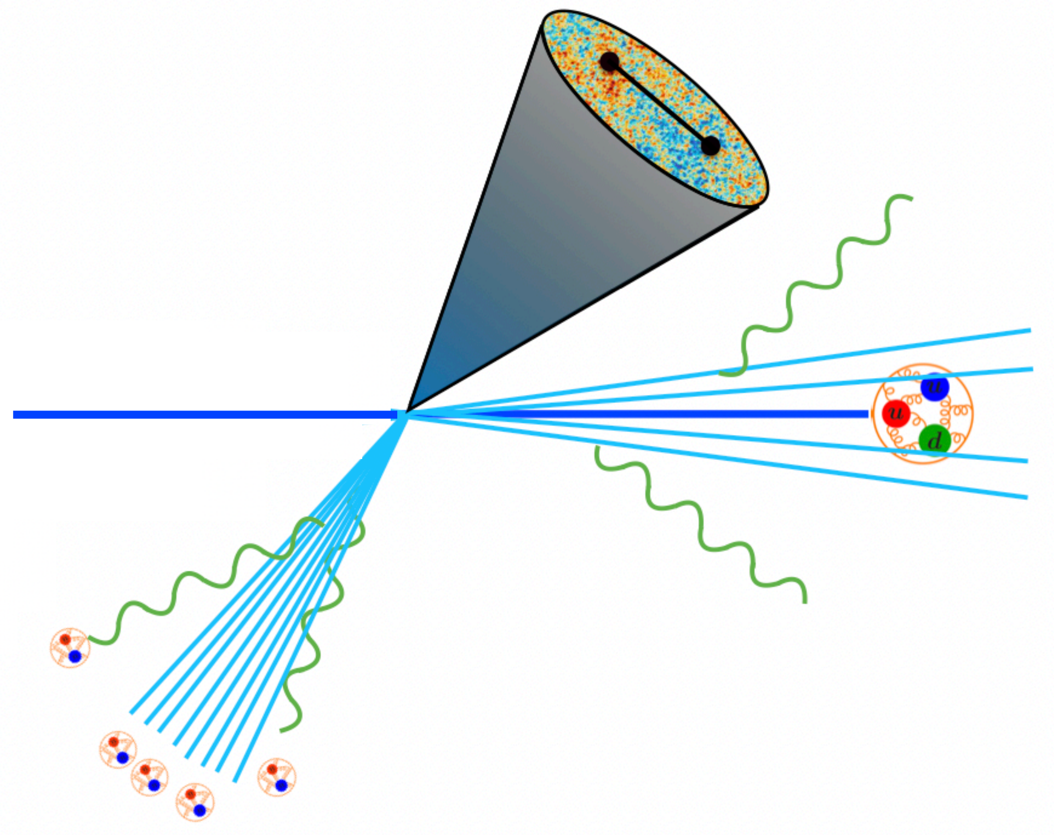
Charged particle vs. full jets

Chang, Procura, Thaler, Waalewijn `13

- Measure all or only a subset of particles in the jet
- Requires nonperturbative track function $T_{q,g}(x)$
- Momentum fraction carried by charged particles x_{trk}
- Especially suitable for use in energy-energy correlators

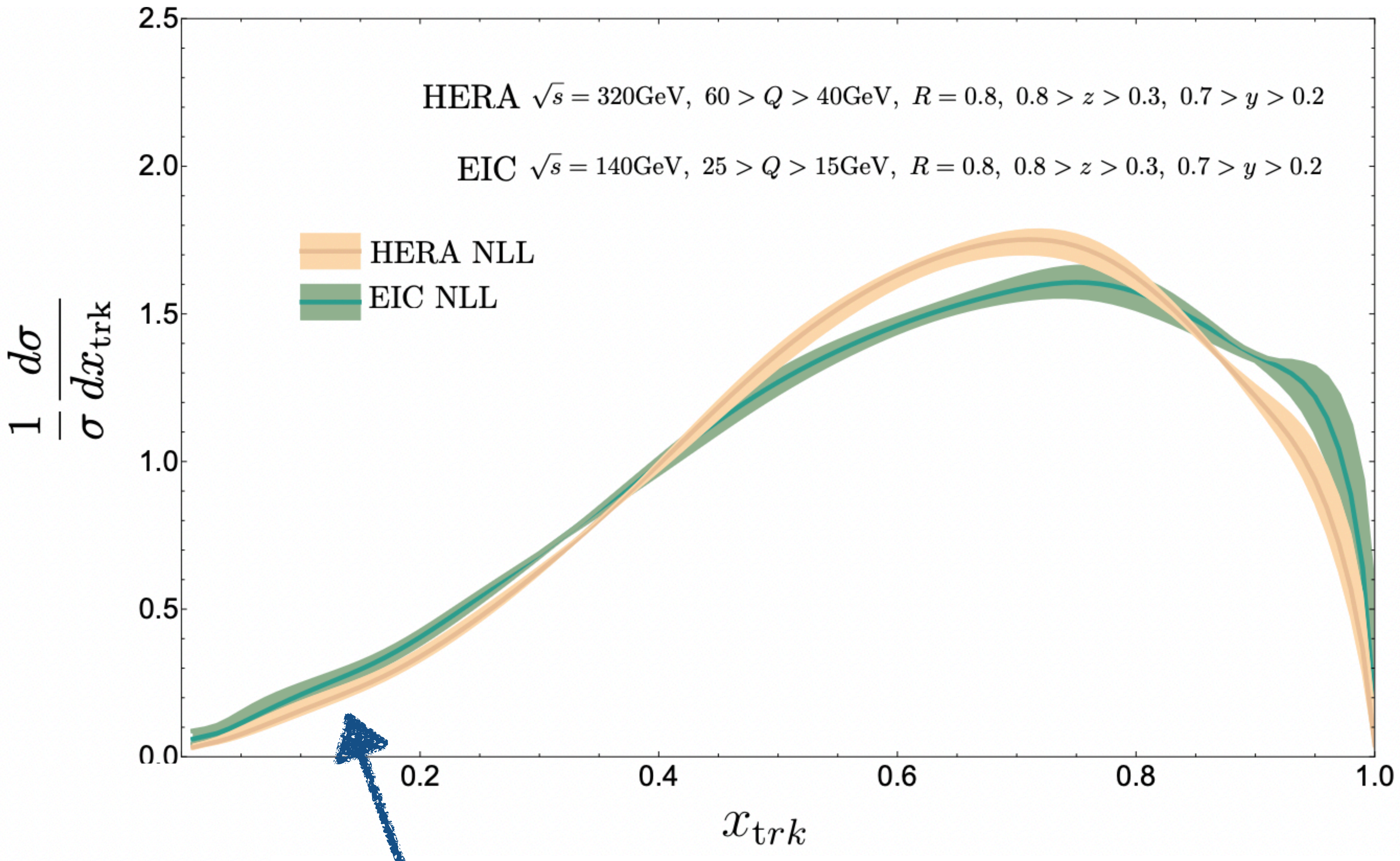


Dixon, Lee, Mecaj, Moult, Zhu et al.



Track functions at the EIC

- Probe of multi-parton and non-linear QCD dynamics
- Novel nonperturbative quantity related to multi-hadron fragmentation functions
- EIC can constrain flavor dependence



$$\frac{\mathrm{d}}{\mathrm{d}\ln\mu^2} T_i(x) = a_s \left[K^{(0)}_{i\to i} T_i + K^{(0)}_{i\to i_1 i_2} \otimes T_{i_1} T_{i_2} \right](x)$$
$$+ a_s^2 \left[K^{(1)}_{i\to i} T_i + K^{(1)}_{i\to i_1 i_2} \otimes T_{i_1} T_{i_2} + K^{(1)}_{i\to i_1 i_2 i_3} \otimes T_{i_1} T_{i_2} T_{i_3} \right](x)$$

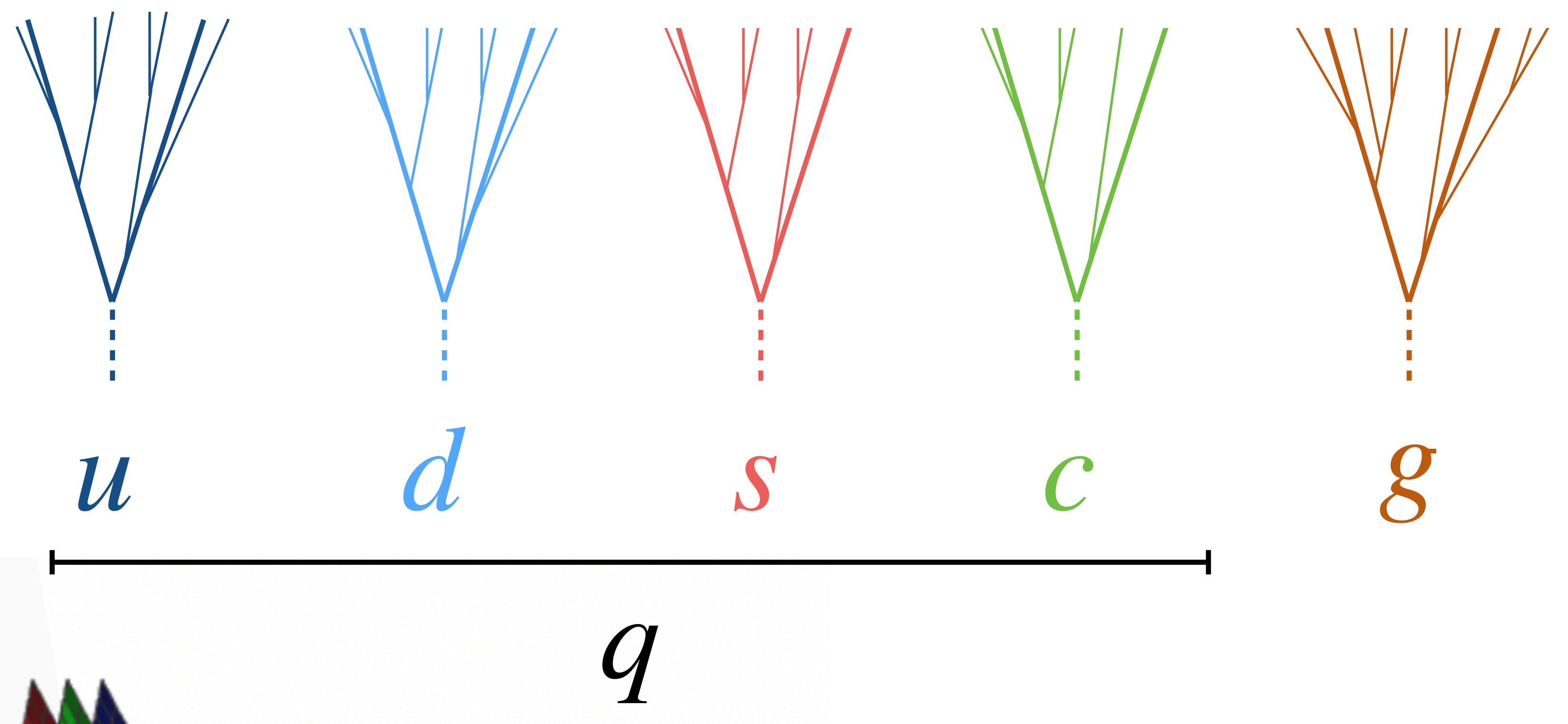
Small QCD scale uncertainty

Chen, Jaarsma, Li, Moult, Waalewijn, Zhu `22

Lee, Moult, FR, Waalewijn - in preparation

Jet physics & Machine learning

- Various jet classifiers have been developed
  - Typically ML significantly outperformed traditional observables
  - Full event-by-event information vs. low-dimensional observables



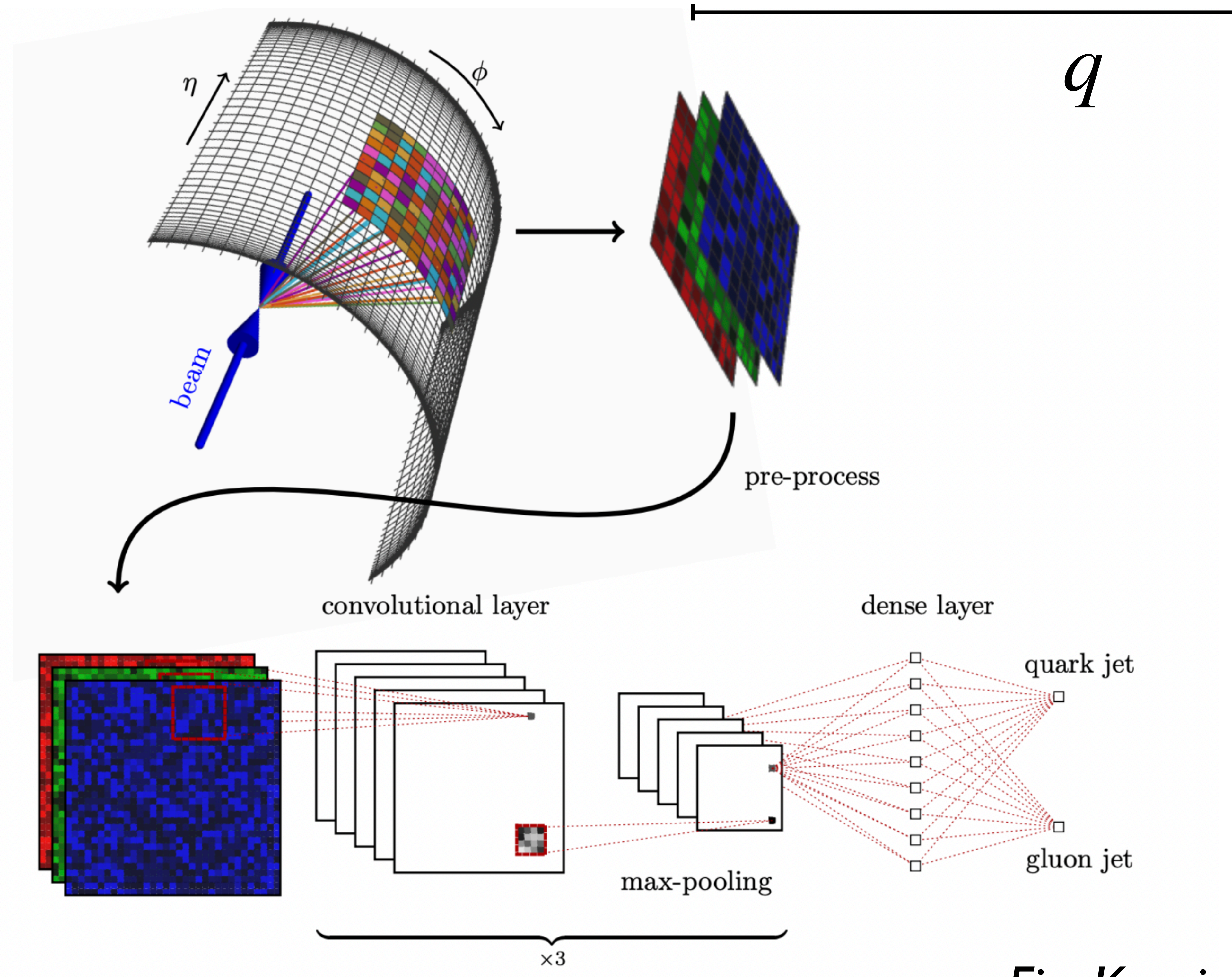
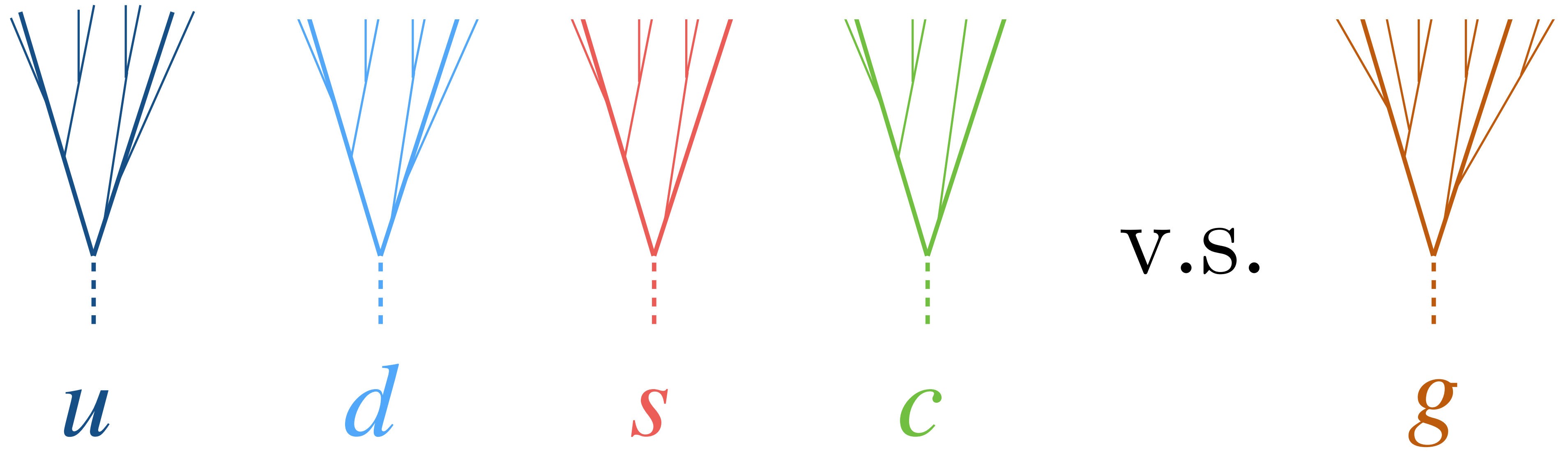
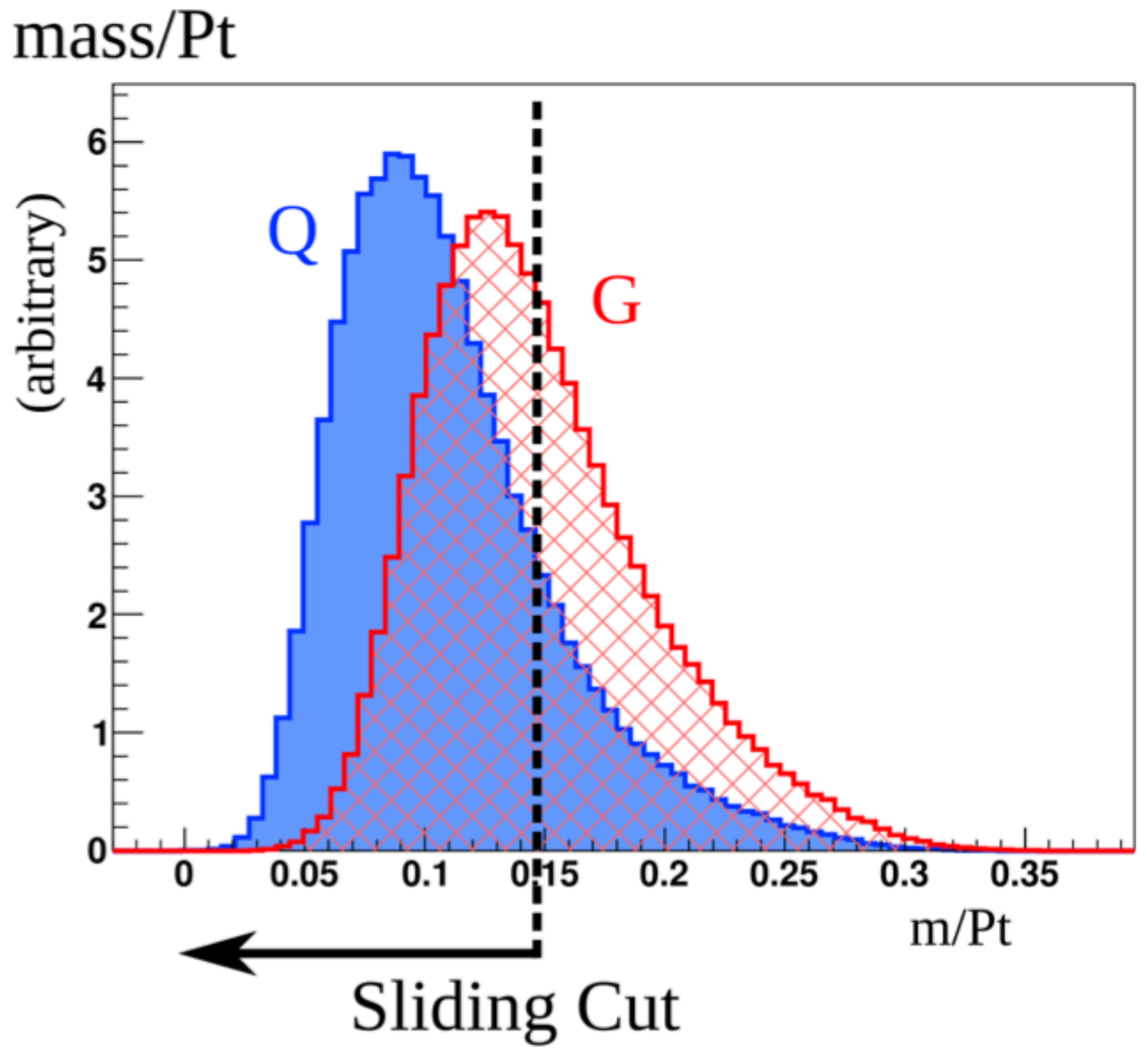


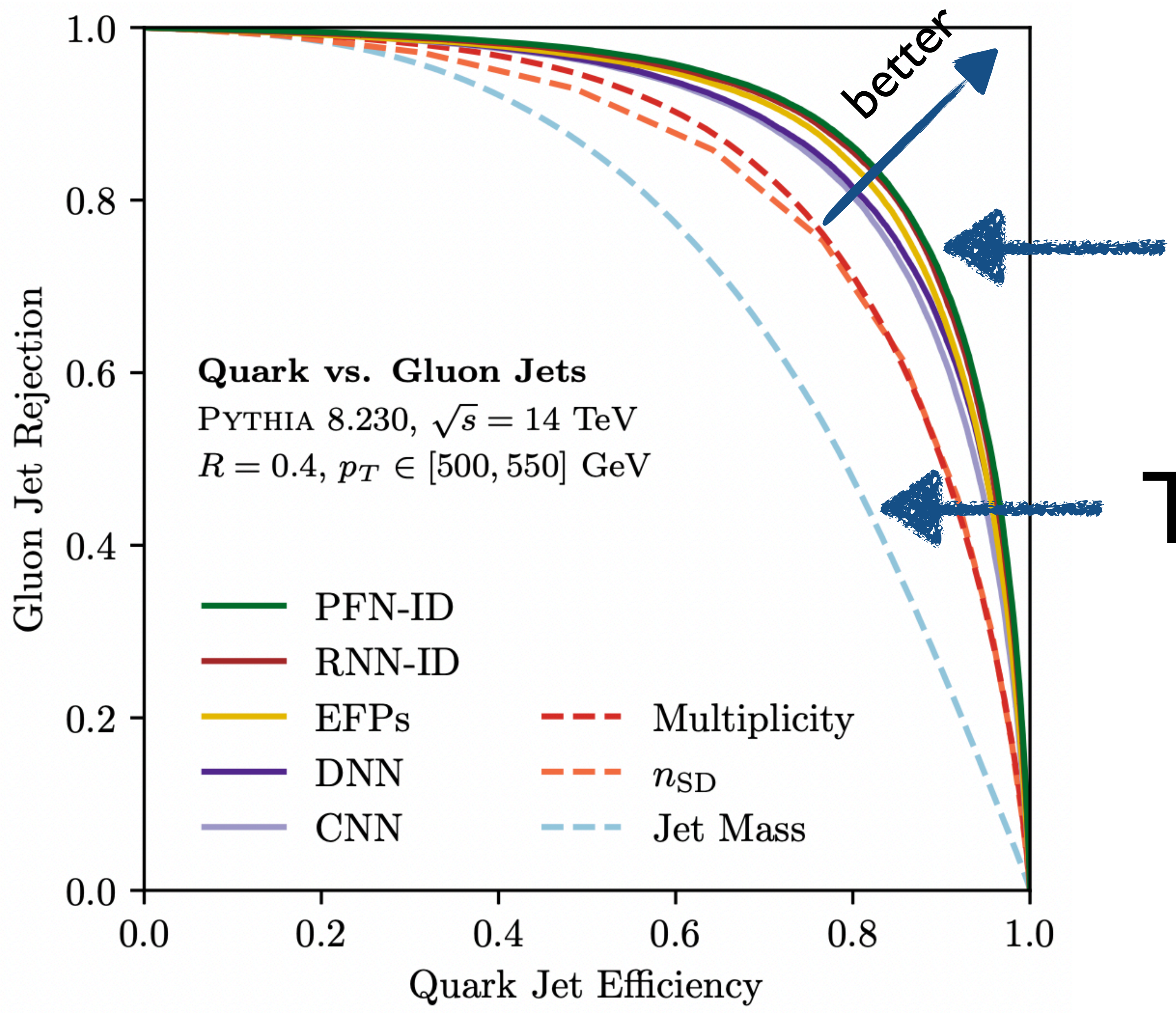
Fig. Komiske, Metodiev, Schwartz

Jet physics & Machine learning

- Various jet classifiers have been developed
  - Example: Quark vs. gluon jet classification
  - Quantify using a ROC curve







AI/ML

Traditional observable

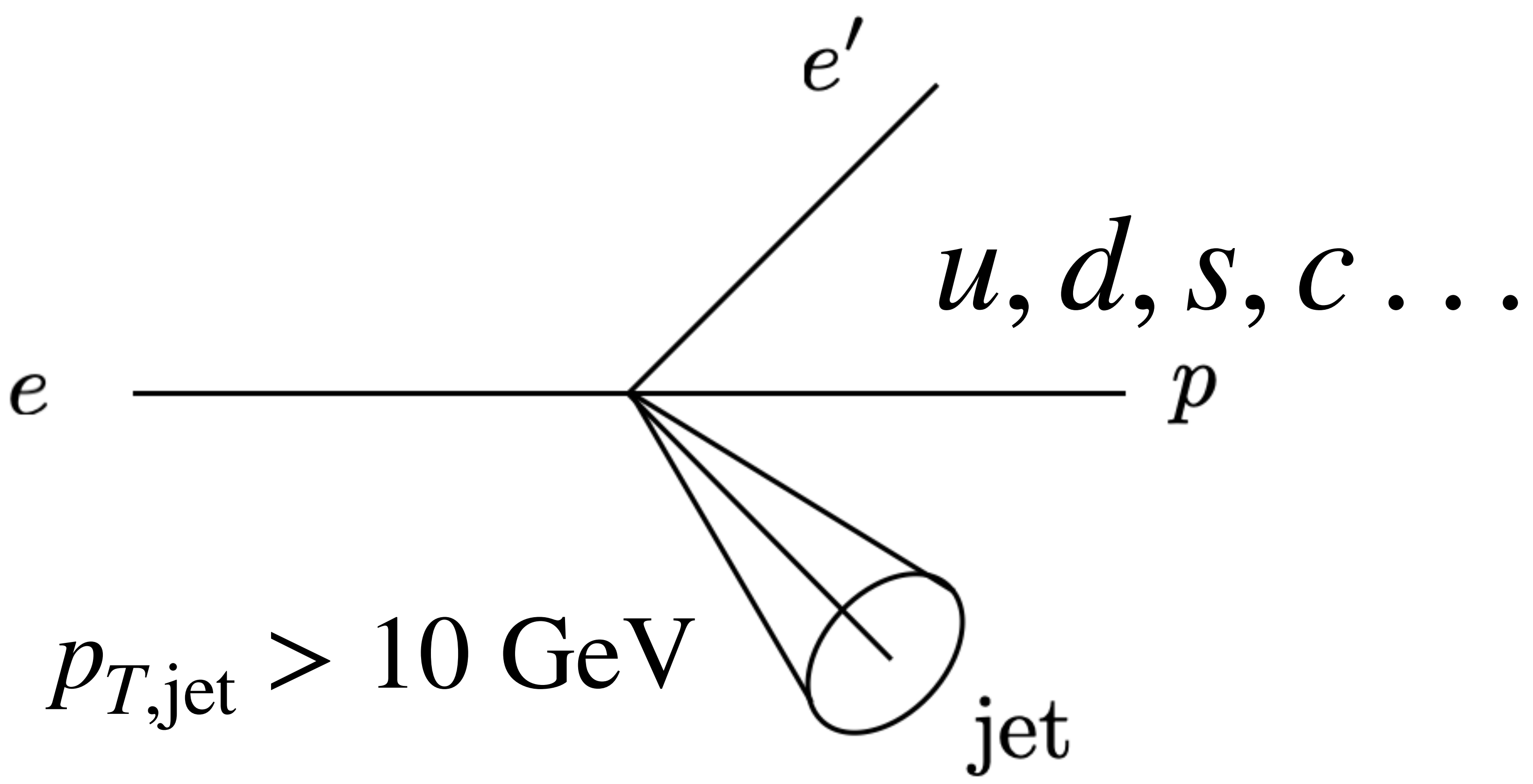
Gallicchio, Schwartz
Komiske, Metodiev, Thaler `19

Events & machine learning

Lee, Mulligan, Ploskon, FR, Yuan `22

- Relatively low particle multiplicities at the EIC

- PYTHIA6
  - No detector simulation
  - Partile $(p_{Ti}, \eta_i, \phi_i, \mathrm{PID}_i)$

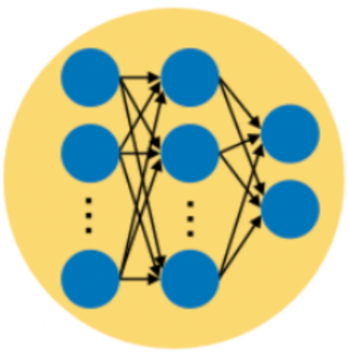


- Binary classification: u vs. d, ud vs. s, …

- ML architecture: Particle Flow Networks

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

Classifier

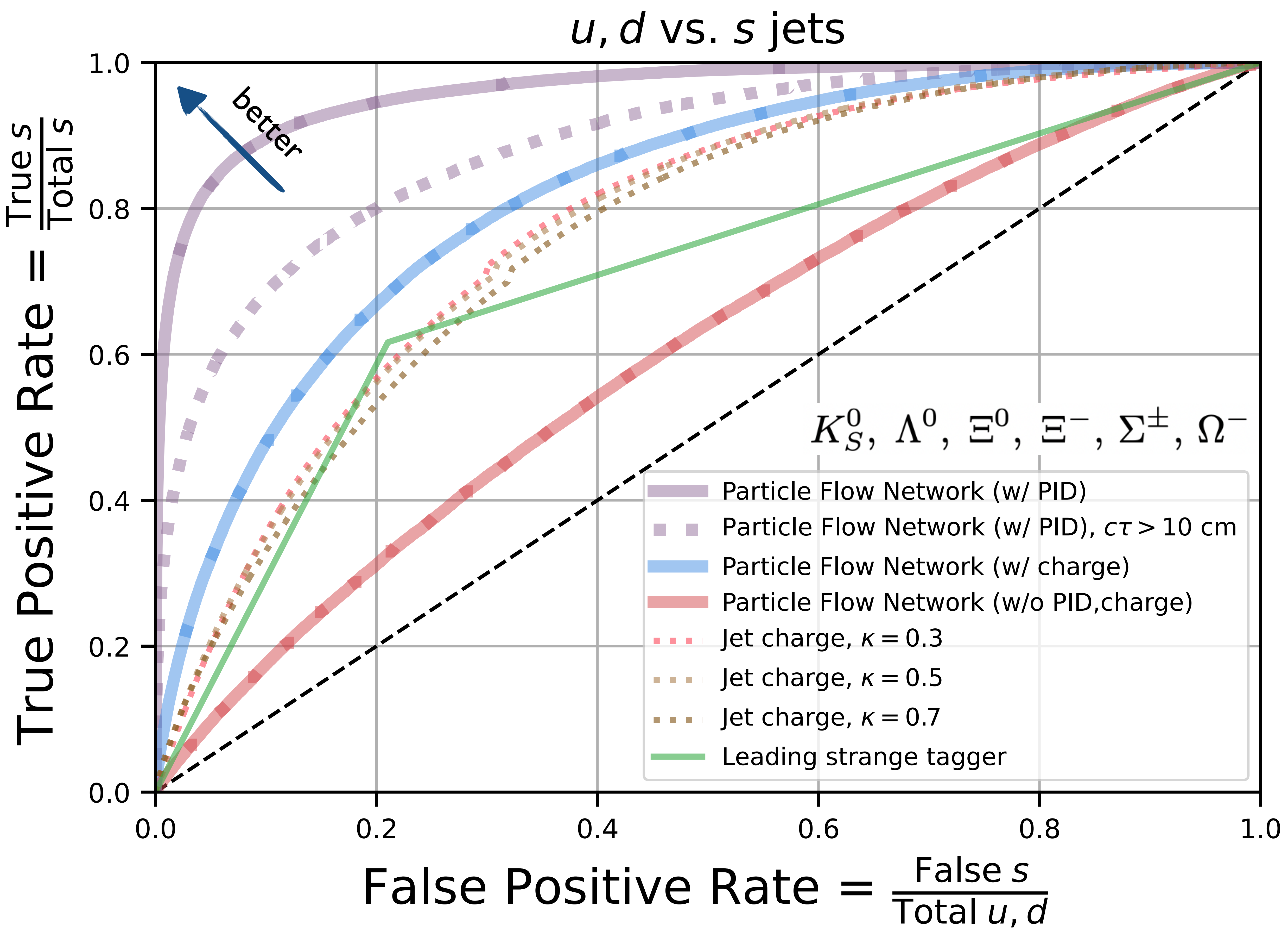


Neural networks

see Komiske, Metodiev, Thaler JHEP 01 (2019) 121
Permutation invariant Deep Sets

Example: strange jet identification

Lee, Mulligan, Ploskon, FR, Yuan `22



Significant gain with machine learning!

- Quantifies total information content
- Motivates further theory efforts
- Soft particles, tracking & PID important
- Can use event information, not limited to jet
- Impact on EIC detector?

Data & code available

https://zenodo.org/record/7538810#.Y8RcaS-B2gQ

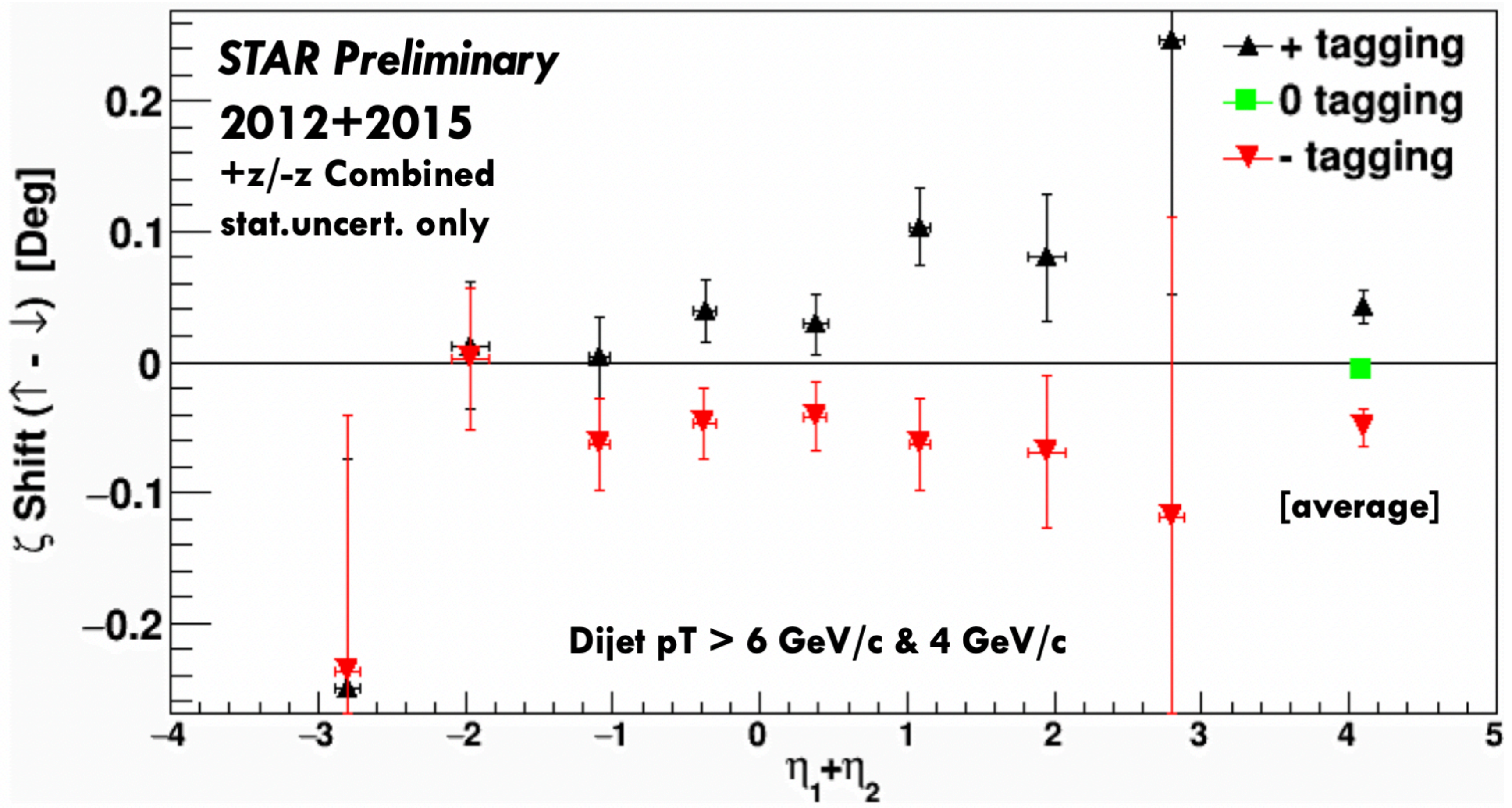
EIC jet physics with machine learning

Fatemi EINN `19, Liu DNP `19
see also Kang et al., Yuan et al.

- For example, the Sivers asymmetries can be small due to large flavor cancellations

Burkardt sum rule *`04*

$$\sum_{a=q,\bar{q},g} \int_0^1 \mathrm{d}x\, f_{1T}^{\perp(1)a}(x) = 0$$



Can we obtain better constraints with ML-based jet classification?

Hadron structure & spin physics

Lee, Mulligan, Ploskon, FR, Yuan `22

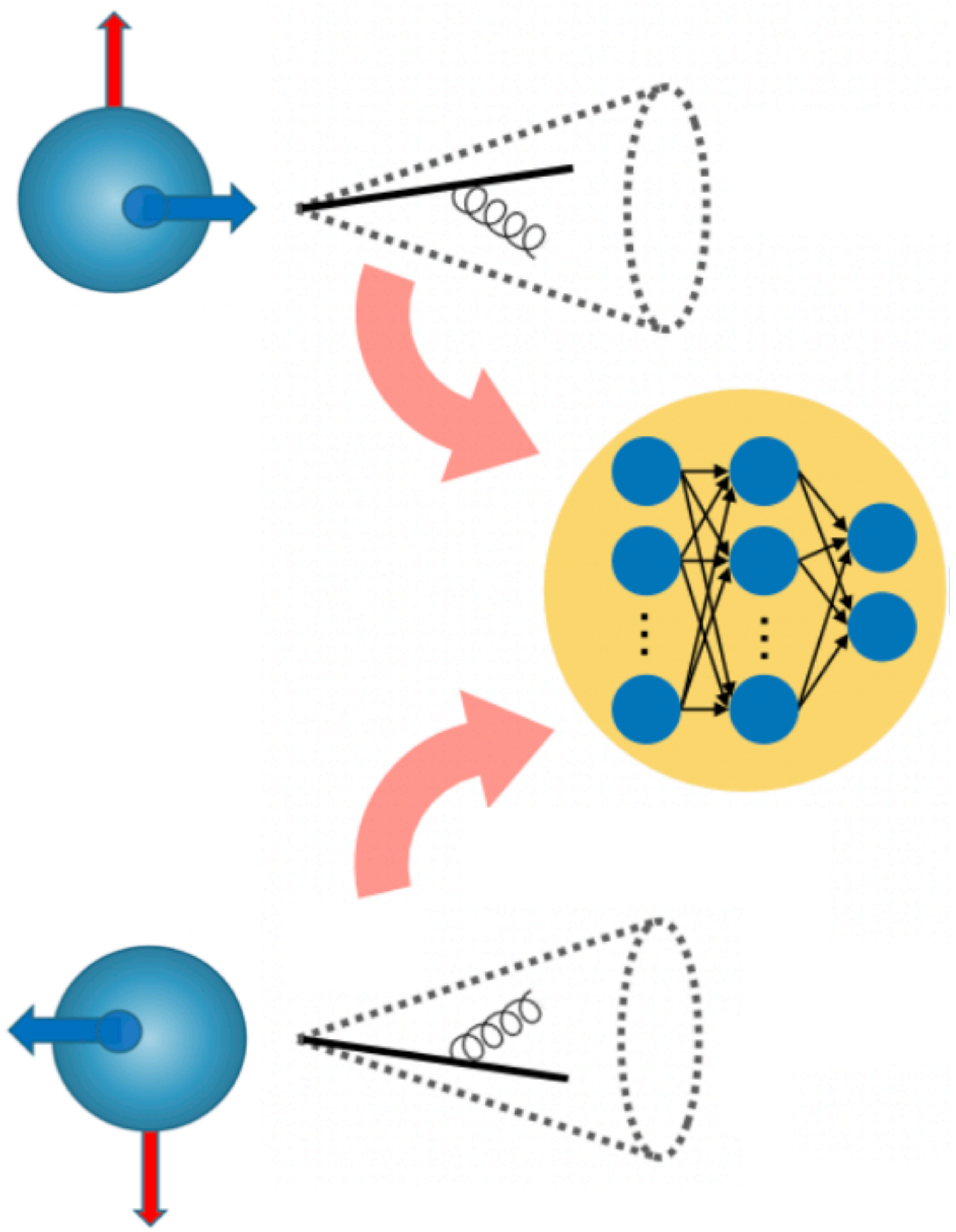
- How can we apply these techniques to hadron structure & spin physics?

1. Supervised machine learning
2. Train on data e.g. $A_{UT} = \dfrac{d\sigma^{\uparrow} - d\sigma^{\downarrow}}{d\sigma^{\uparrow} + d\sigma^{\downarrow}}$

- Reformulate regression task as classification problem $\max_{\theta} |A_{UT}(\theta)|$

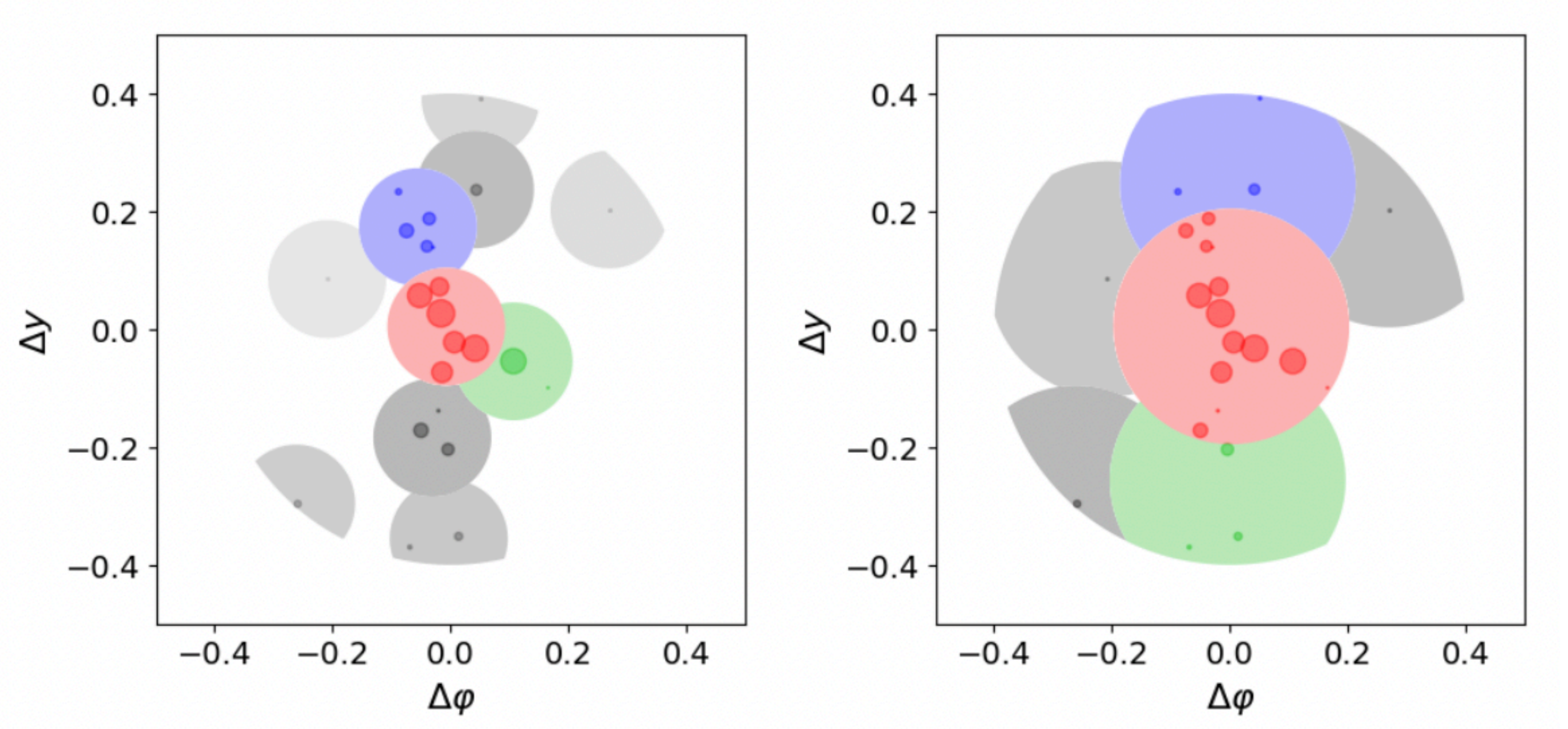
→ Upper limit on what can possibly be achieved

→ Identify new observables

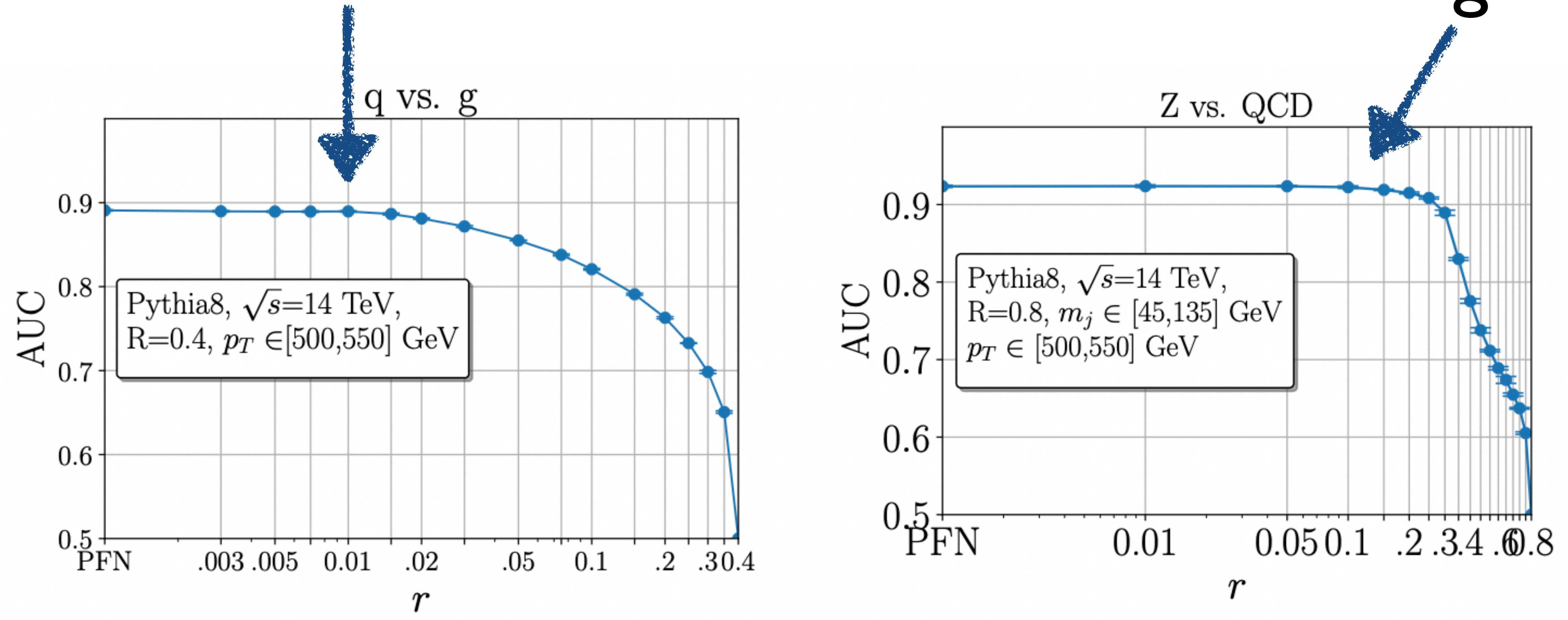


Jet classification & IRC safety

- Can we make use of all this additional information?
- Several jet classification tasks are IRC safe → we can find tractable observables in pQCD
- Recluster particles into IRC-safe subjets before training ML algorithms



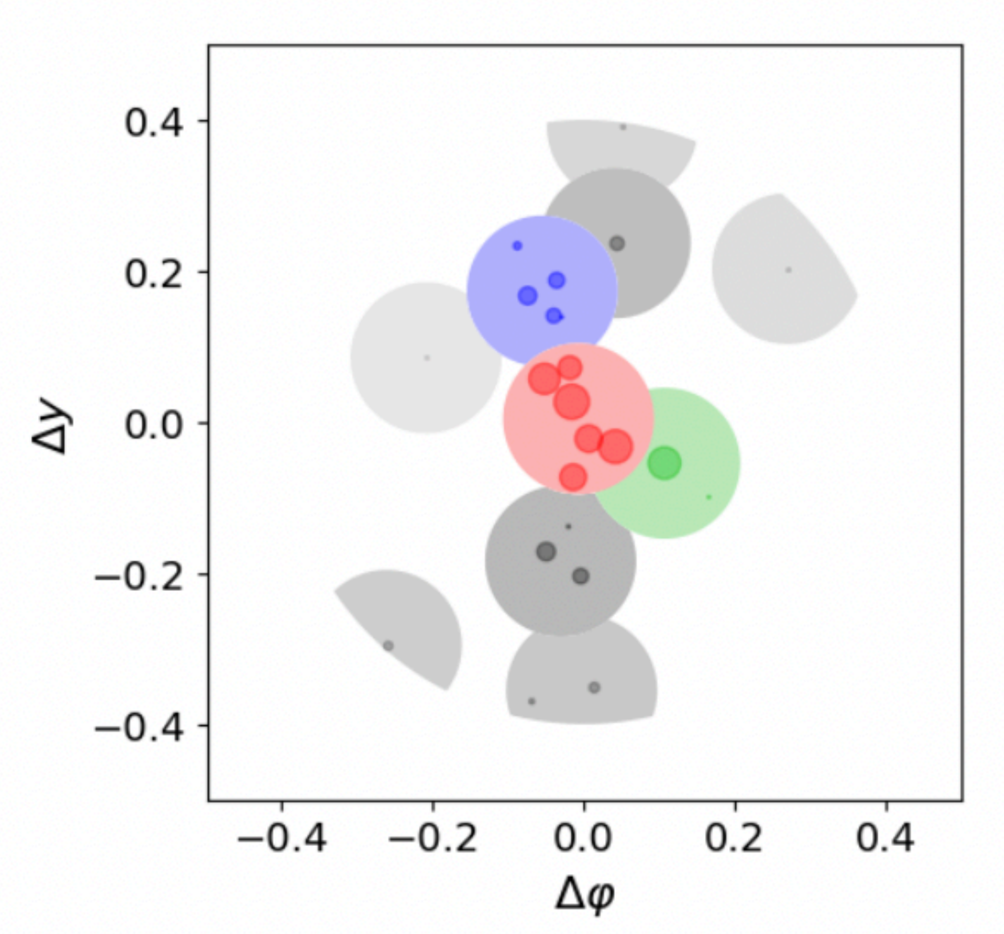
Matches IRC-unsafe ML algorithm

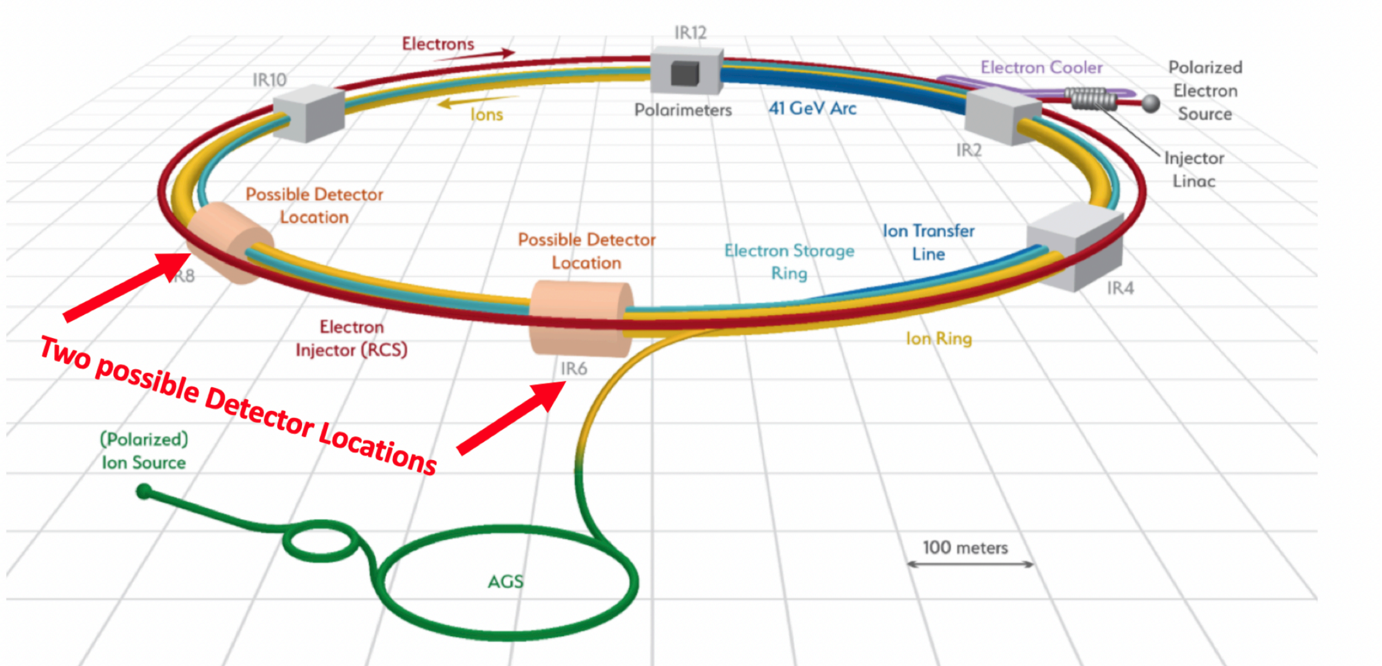


Athanasakos, Larkoski, Mulligan, Ploskon, FR `23
Metodiev, Larkoski `19

Summary

- Jets will be versatile tools at the EIC
- Take advantage of the EIC's clean environment
- New nonperturbative quantities like track functions
- AI/ML can complement hadron structure & spin physics program
- …and can further inform detector design?





Source: Pre-Conceptional Design Report, 2019