Nature of jets at the EIC

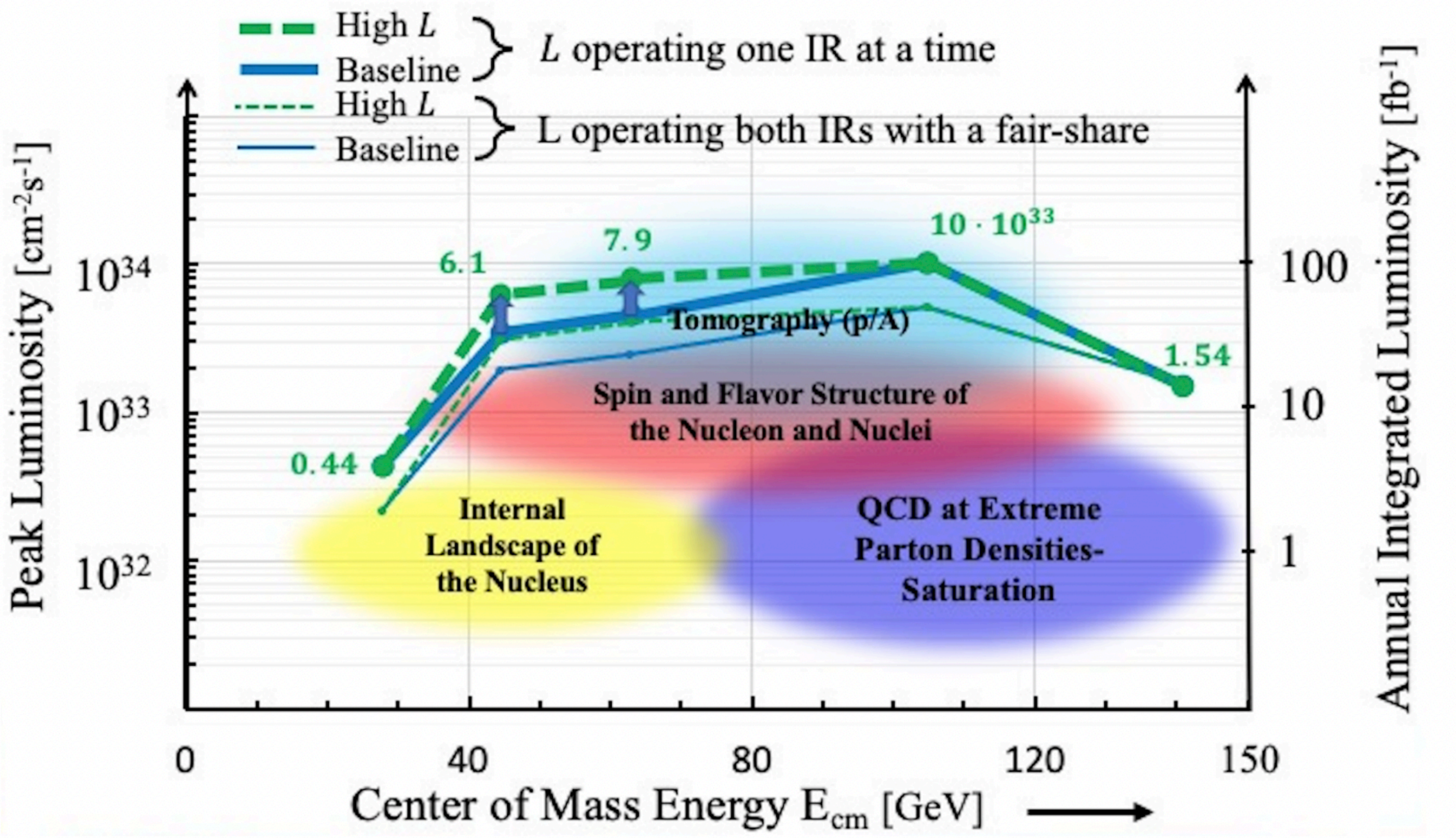
Felix Ringer

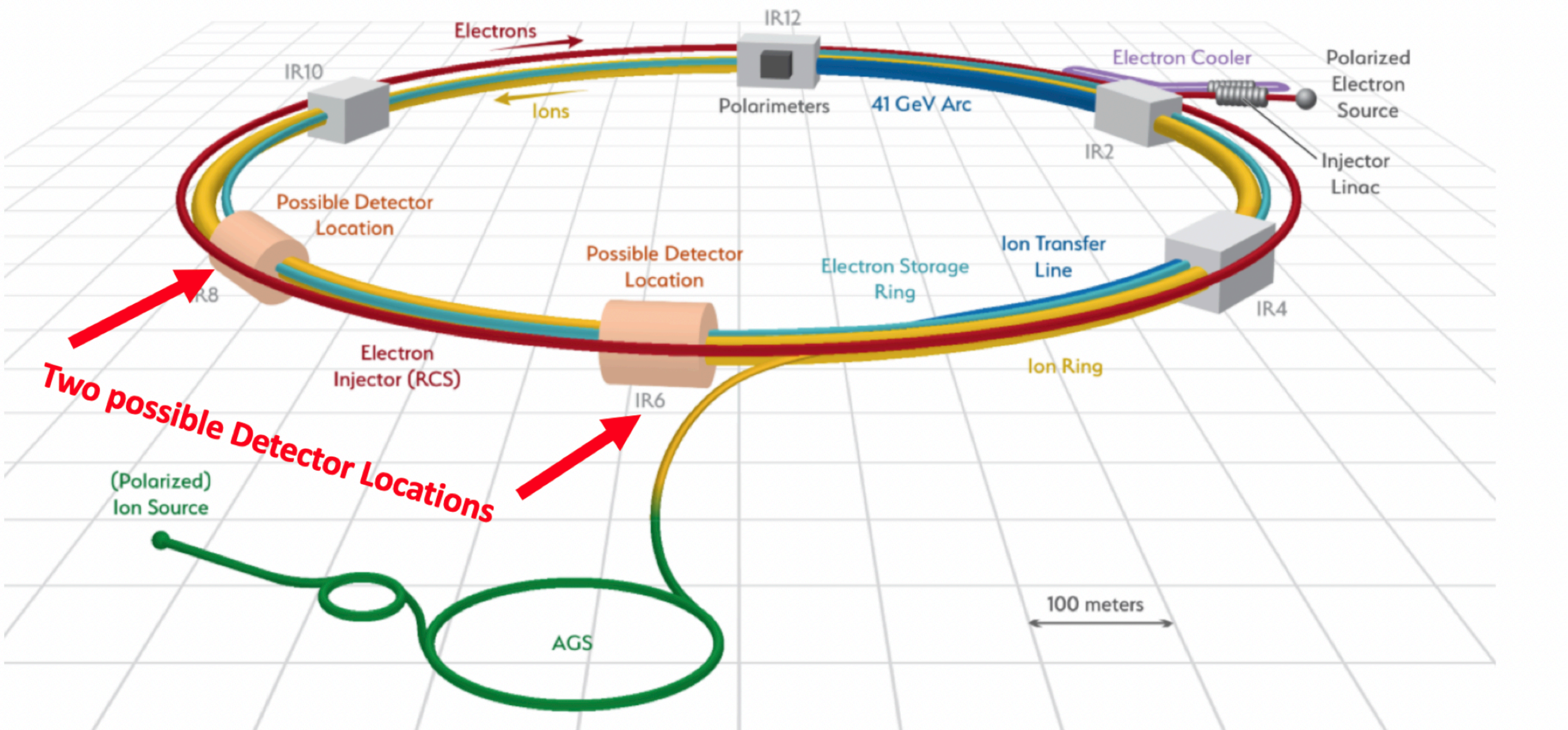
1st International Workshop on a 2nd
Detector for the EIC, Temple University

OLD DOMINION UNIVERSITY
Jefferson Lab

2nd detector for the EIC

- Reduced systematic uncertainties
- High luminosity, intermediate energies
- Far-forward detection capabilities

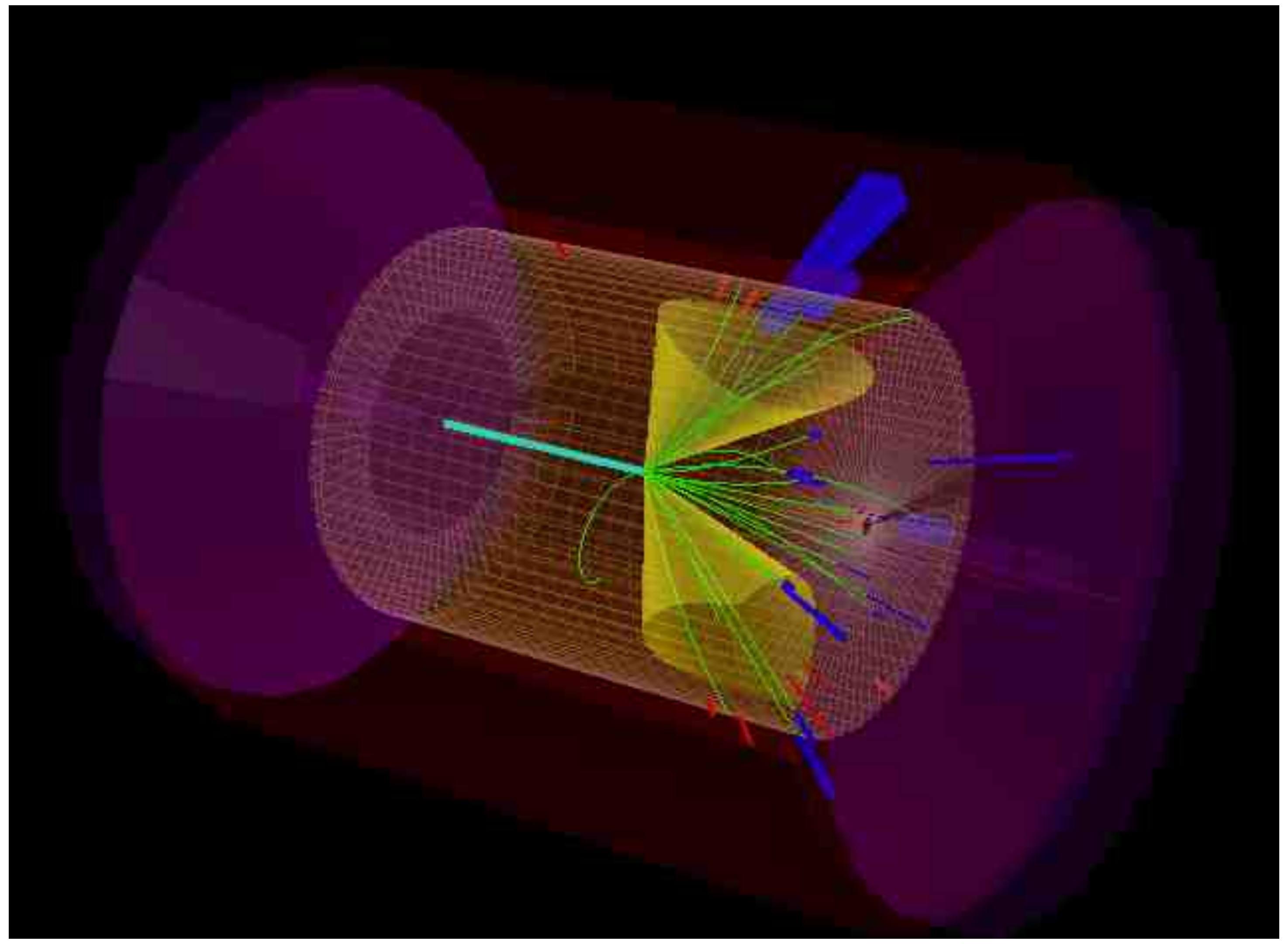




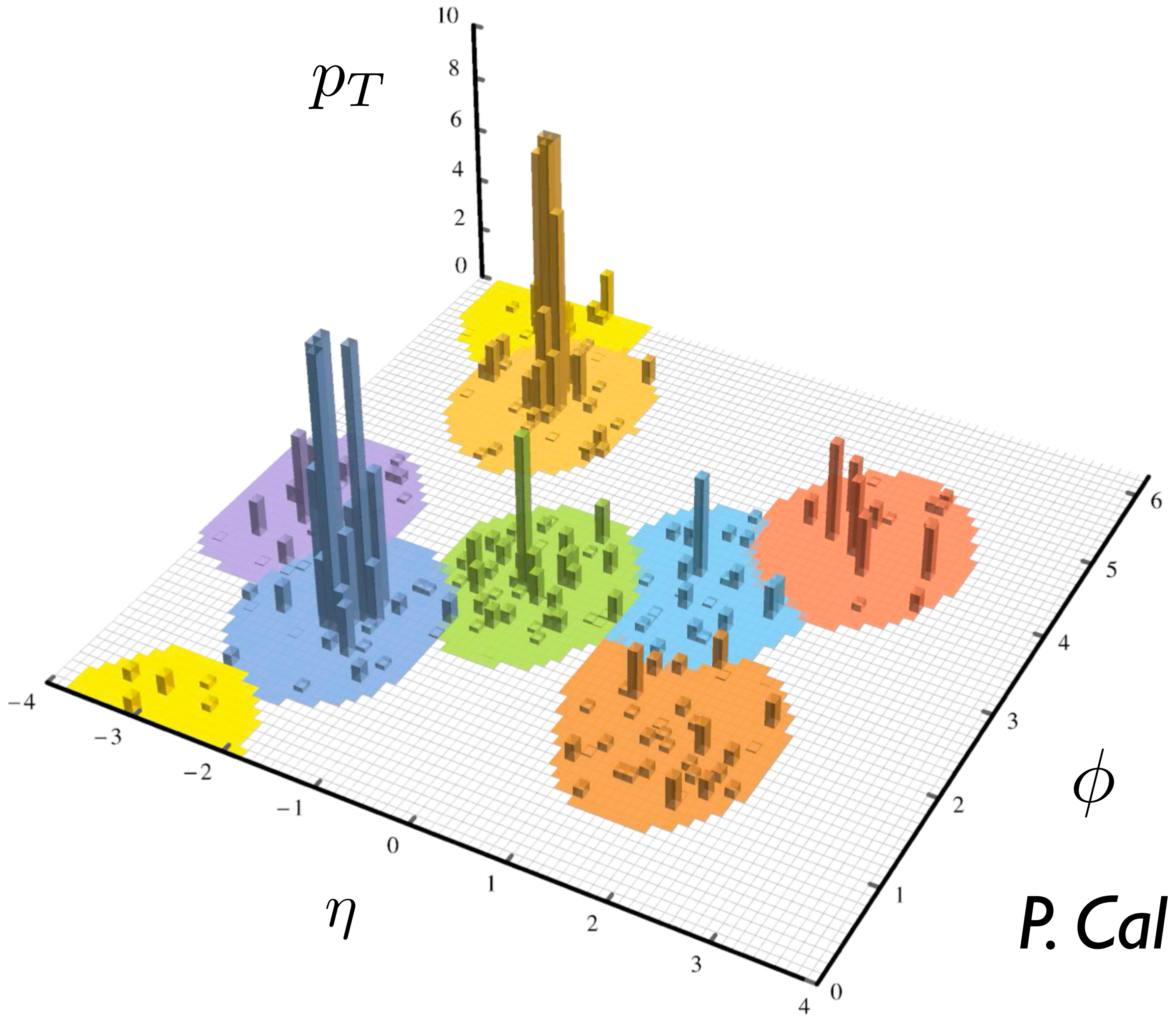
Source: Pre-Conceptional Design Report, 2019

EIC jet physics

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

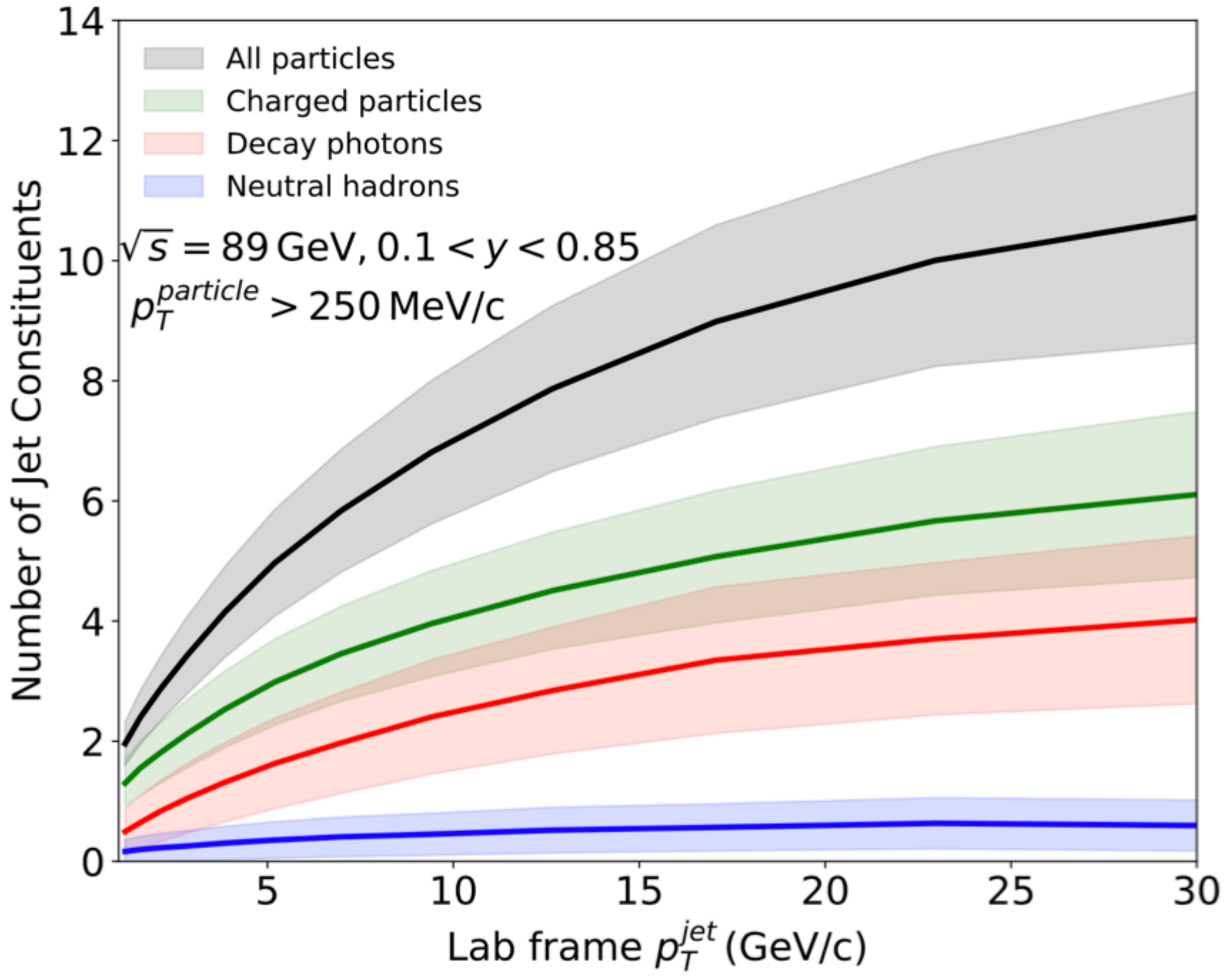


- Observables
- Information content (AI/ML)

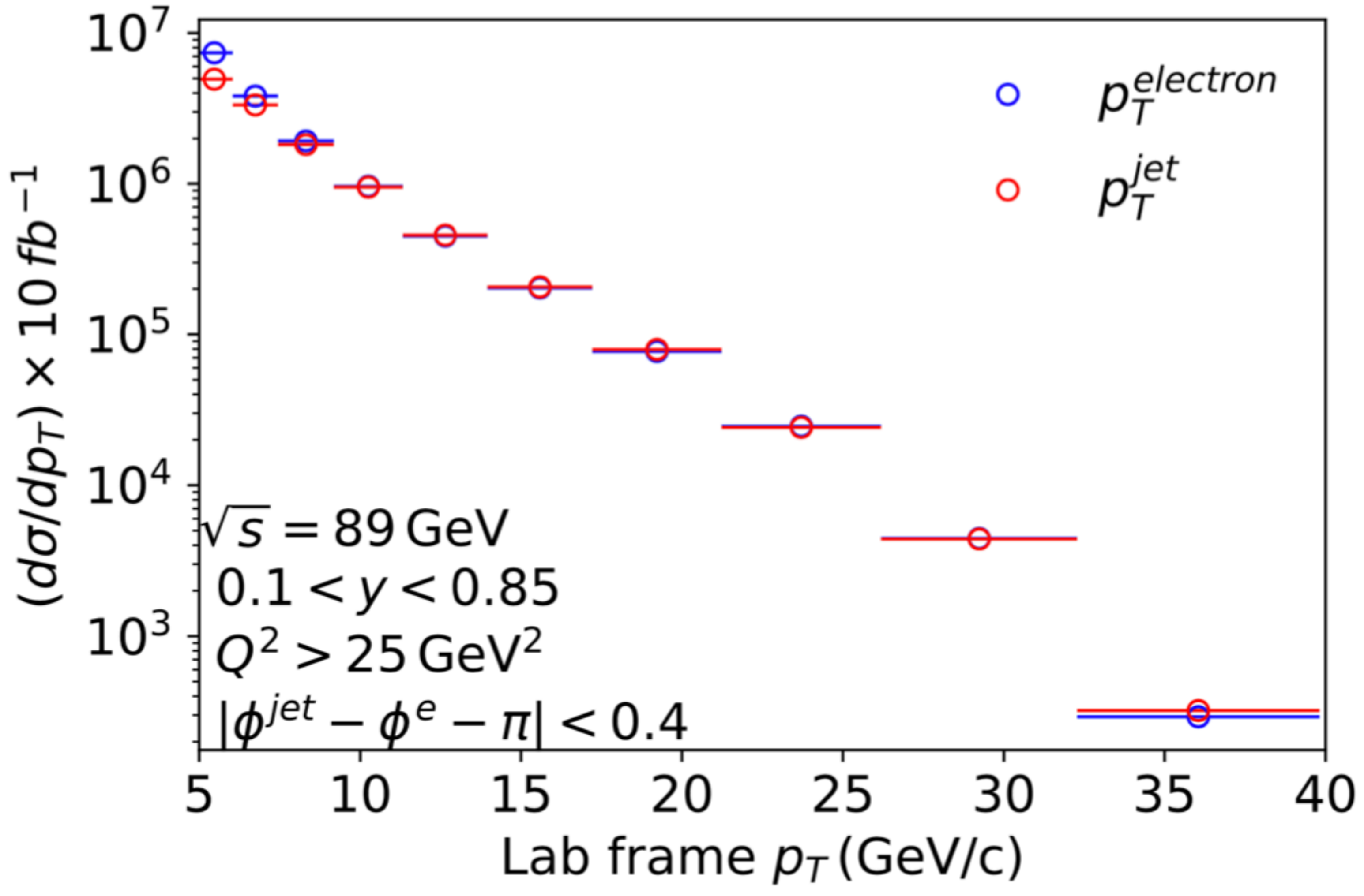


Nature of jets at the EIC

Particle #

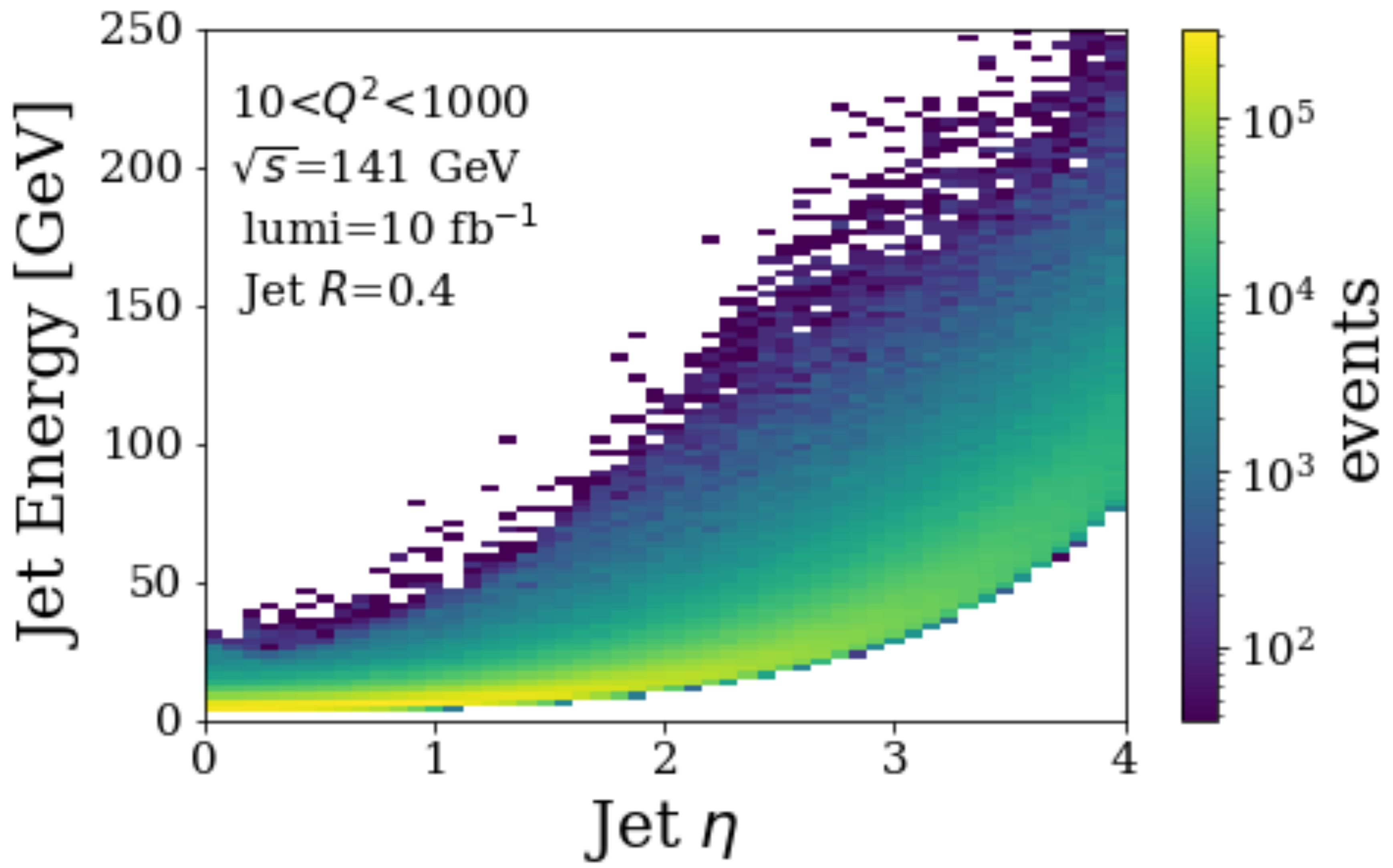


Transverse momentum



Arratia, Jacak, FR, Song `19

Jet energy



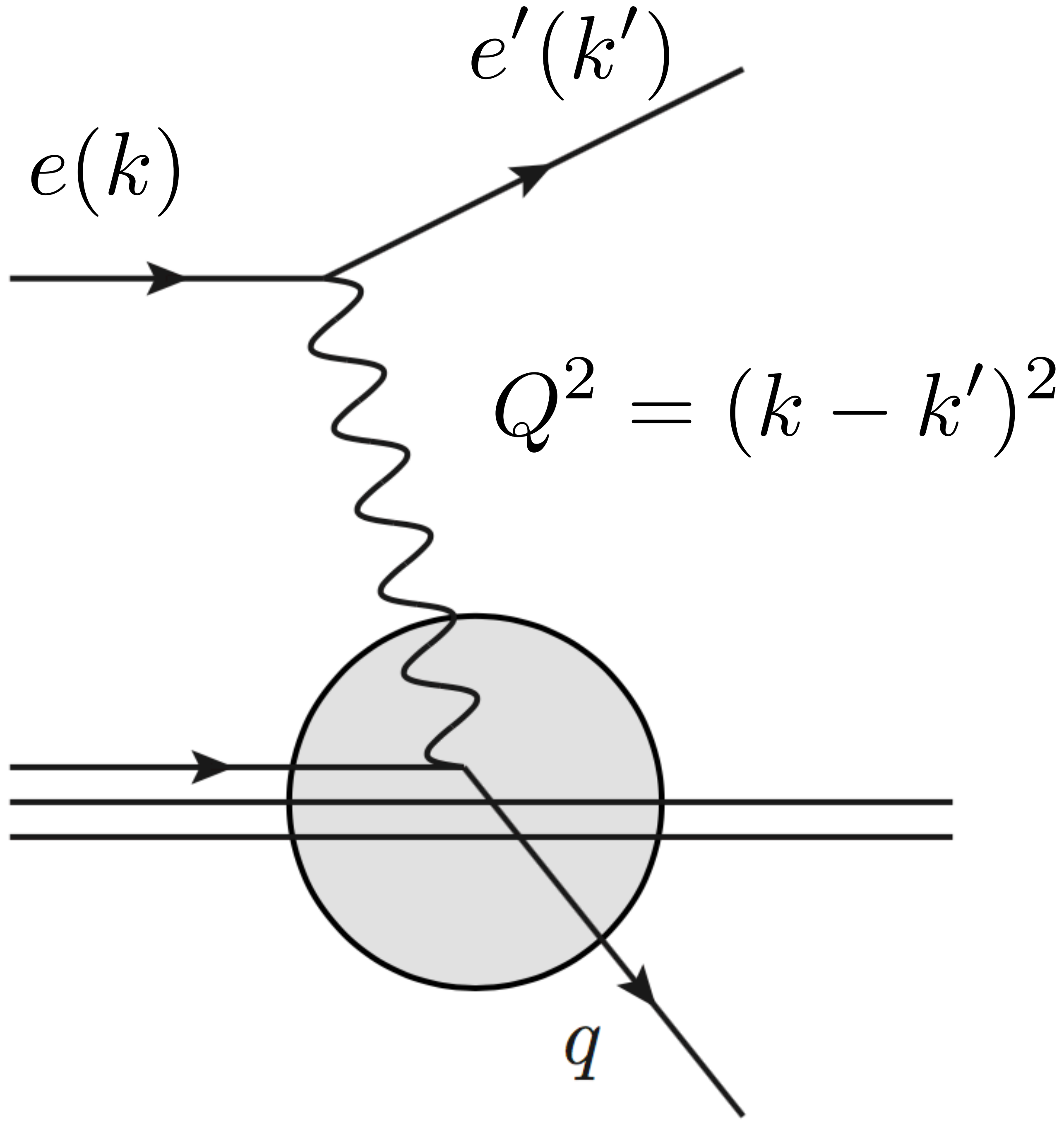
Arratia

Hard scale p_T

and/or Q^2

EIC jet physics

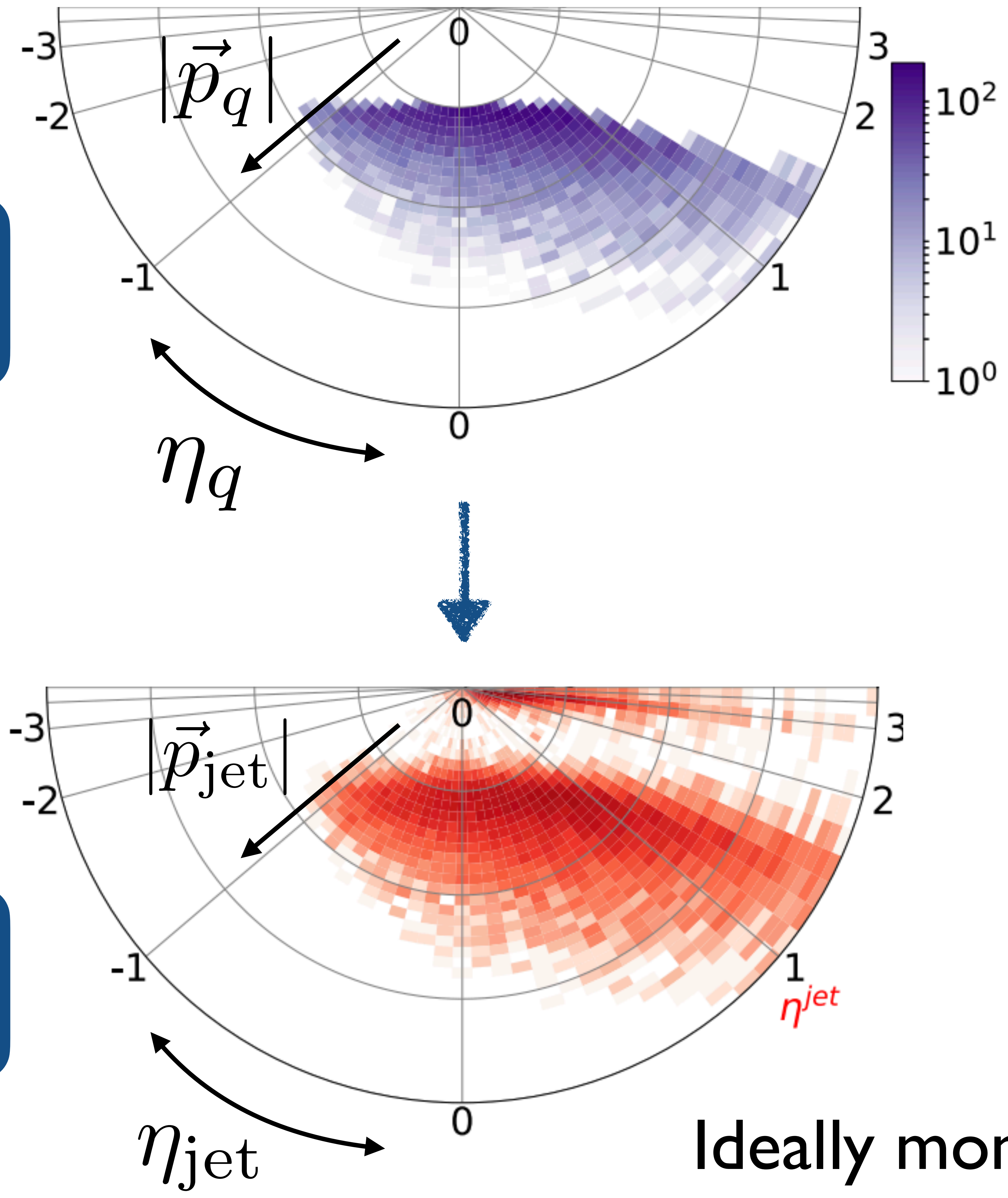
EIC kinematics



Arratia, Jacak, FR, Song `19

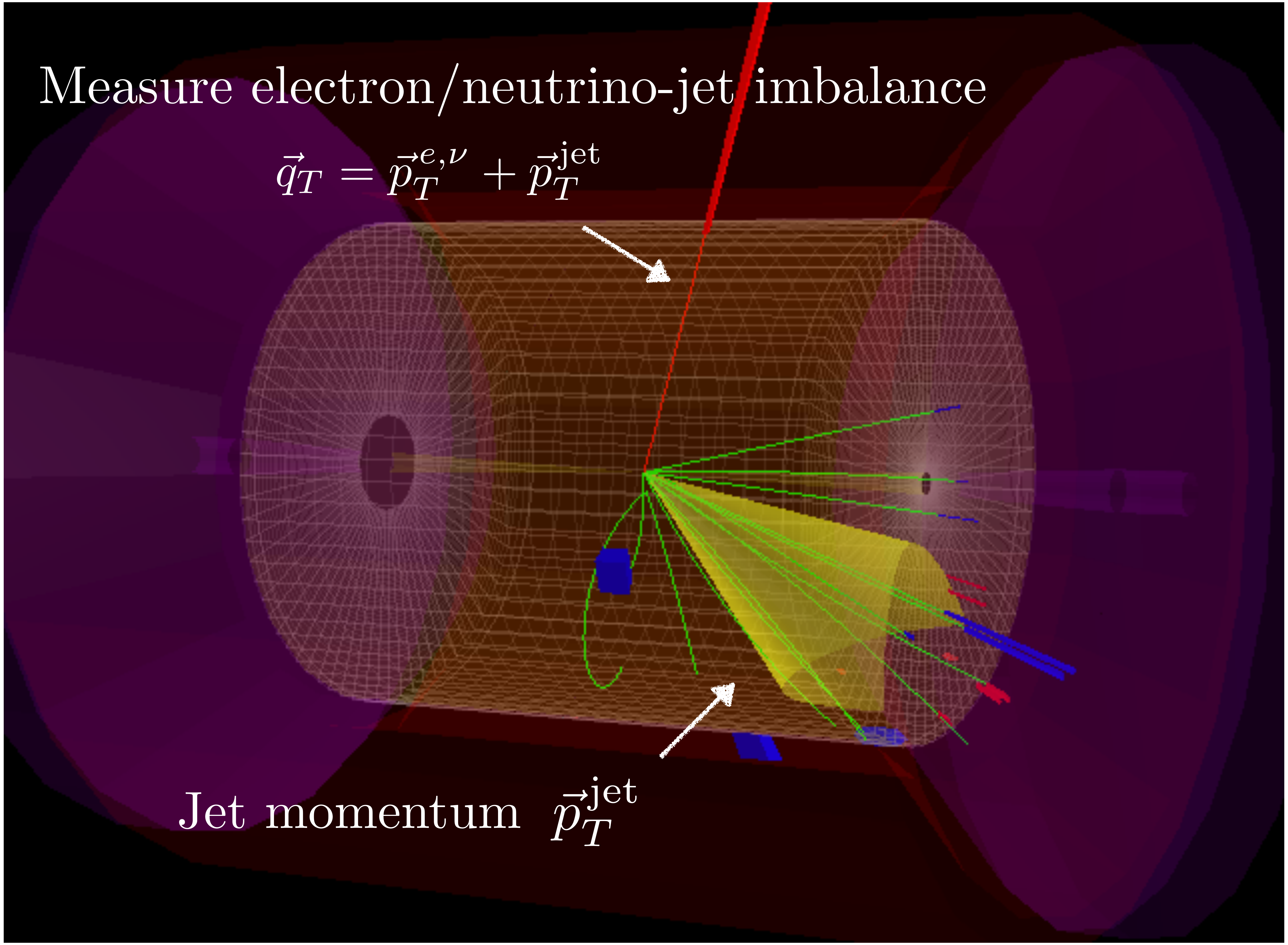
Struck quark

Jets



Ideally momentum, charge, flavor, spin

Laboratory frame



Electron-jet correlations

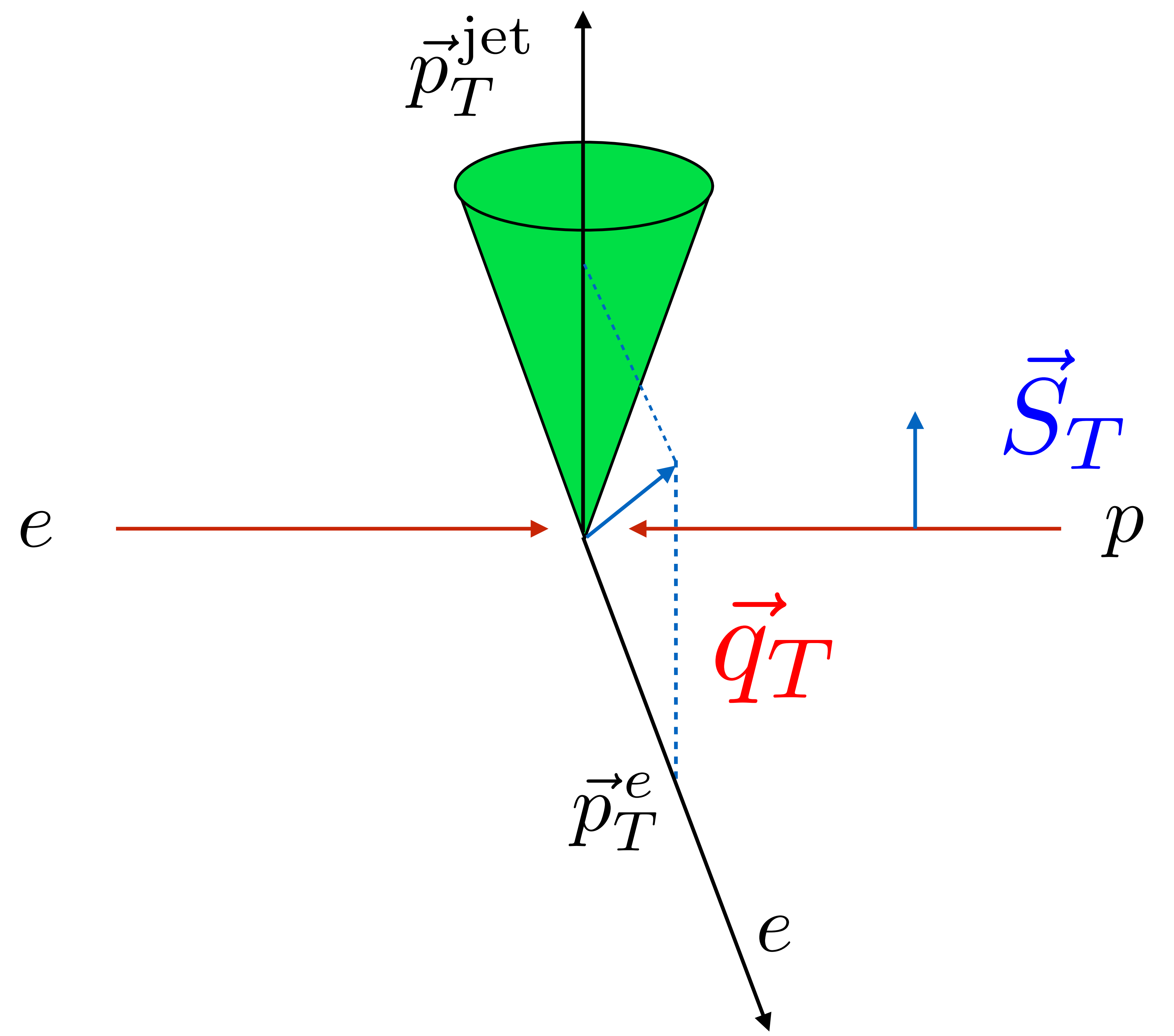
Liu, FR, Vogelsang, Yuan `18, `20

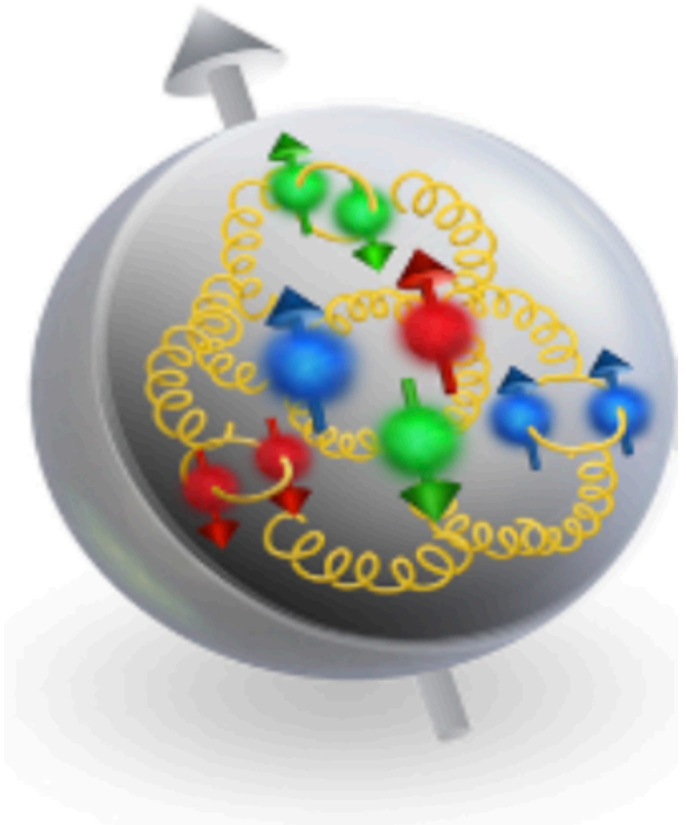
- Electron-jet imbalance at the EIC

$$\color{red}{\vec{q}_T} = \vec{p}_T^{\,e} + \vec{p}_T^{\,\mathrm{jet}}$$

- Sensitivity to TMD PDFs but no TMD FF
- Different energy ranges need to be explored
- TMD factorization

$$F_{UU} = \sigma_0\, H_q(Q,\mu) \sum_q e_q^2\, J_q(p_T^{\mathrm{jet}} R,\mu)$$
$$\times \int \frac{\mathrm{d}^2\vec{b}_T}{(2\pi)^2}\, e^{i\vec{q}_T\cdot\vec{b}_T}\, f_q^{\mathrm{TMD}}(x,\vec{b}_T,\mu)\, S_q(\vec{b}_T, y_{\mathrm{jet}}, R,\mu)$$





see also Boer, Vogelsang `05
Gutierrez-Reyes, Scimemi, Waalewijn, Zoppi `18, `19

Electron-jet correlations

- Electron-jet imbalance at the EIC

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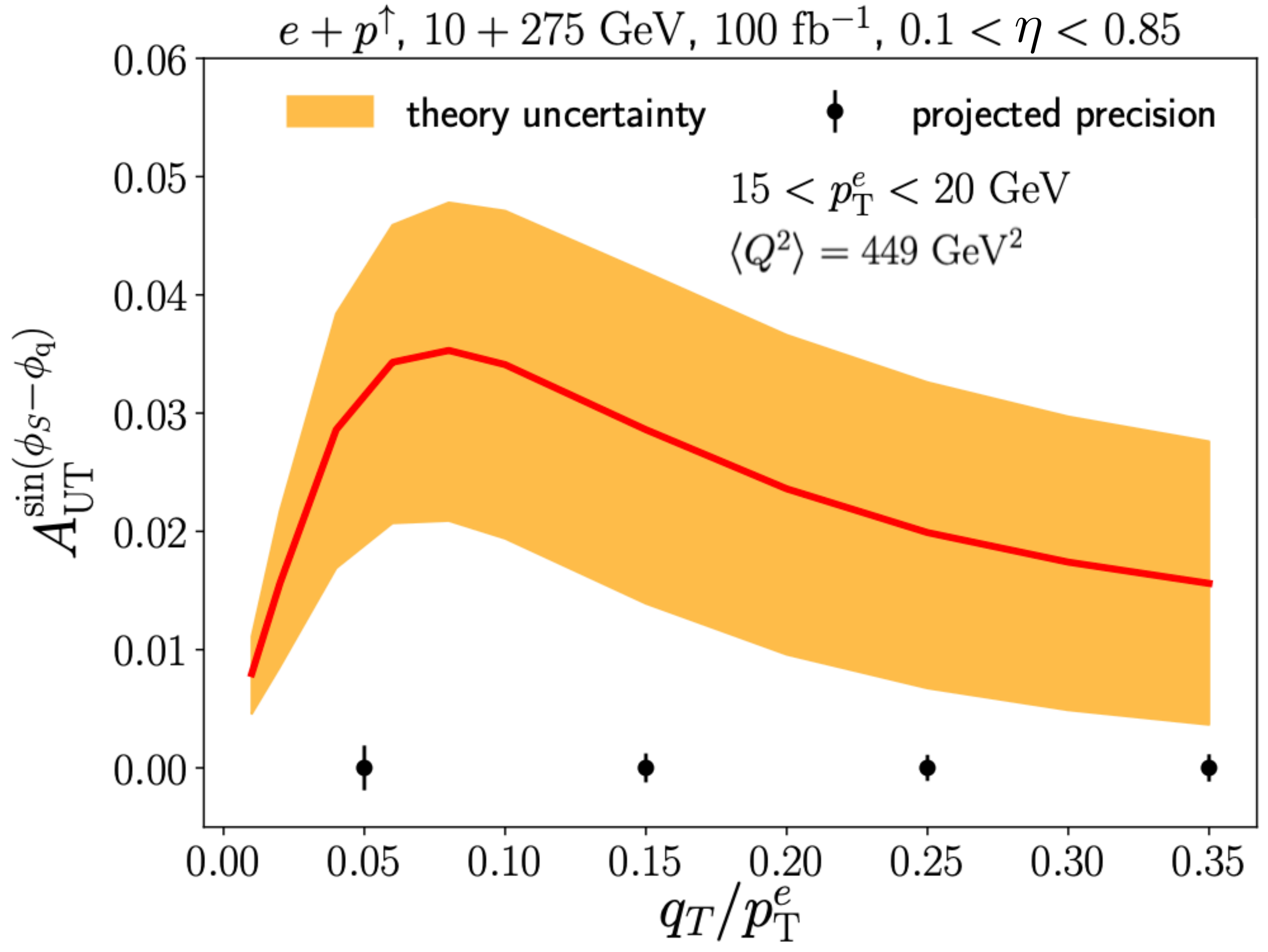


Liu, FR, Vogelsang, Yuan `18, `20
Arratia, Kang, Prokudin, FR`20
H1, PRL 128 (2022) 13, 132002

Neutrino-jet correlations

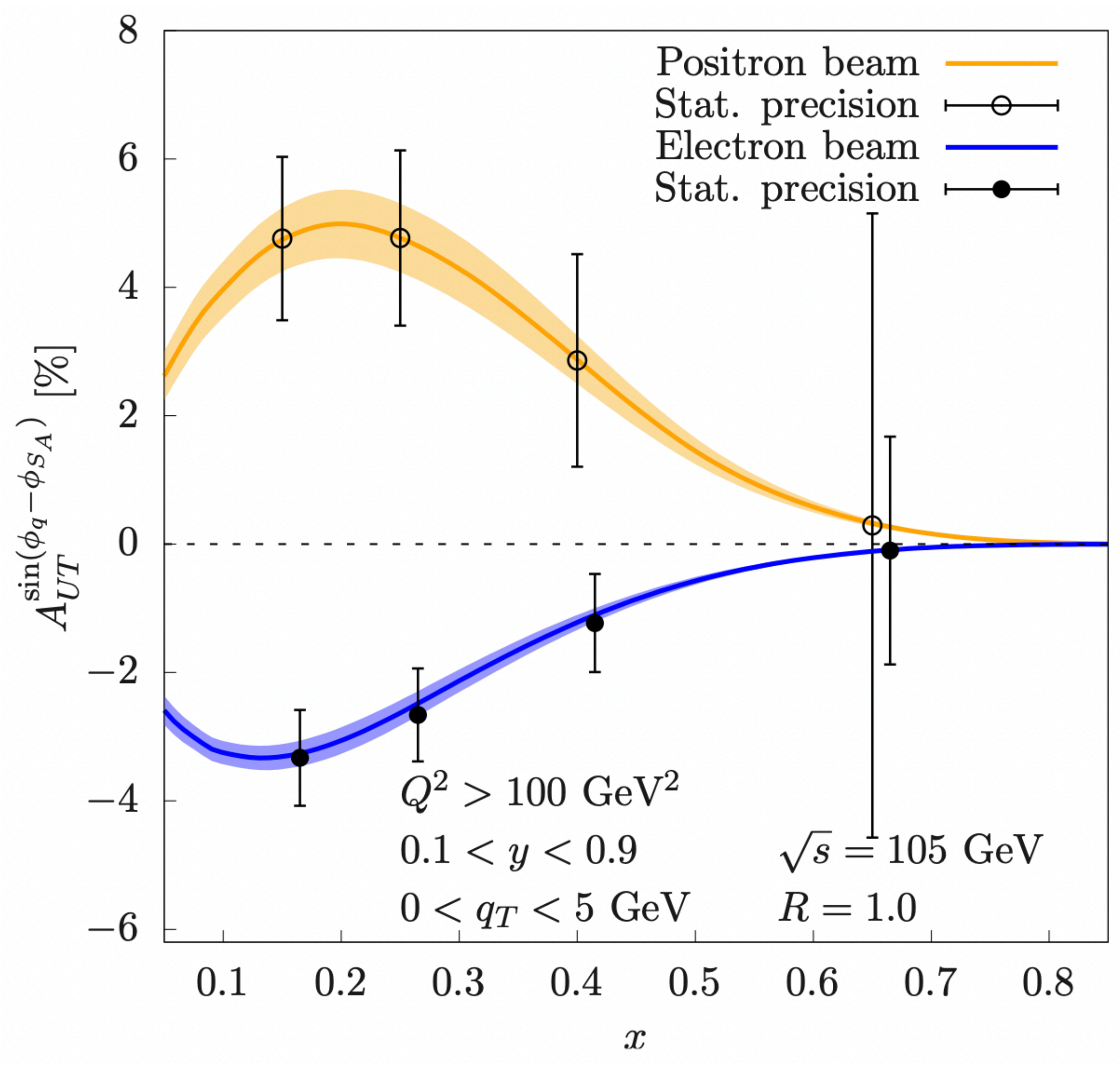
- Neutrino-jet imbalance at the EIC

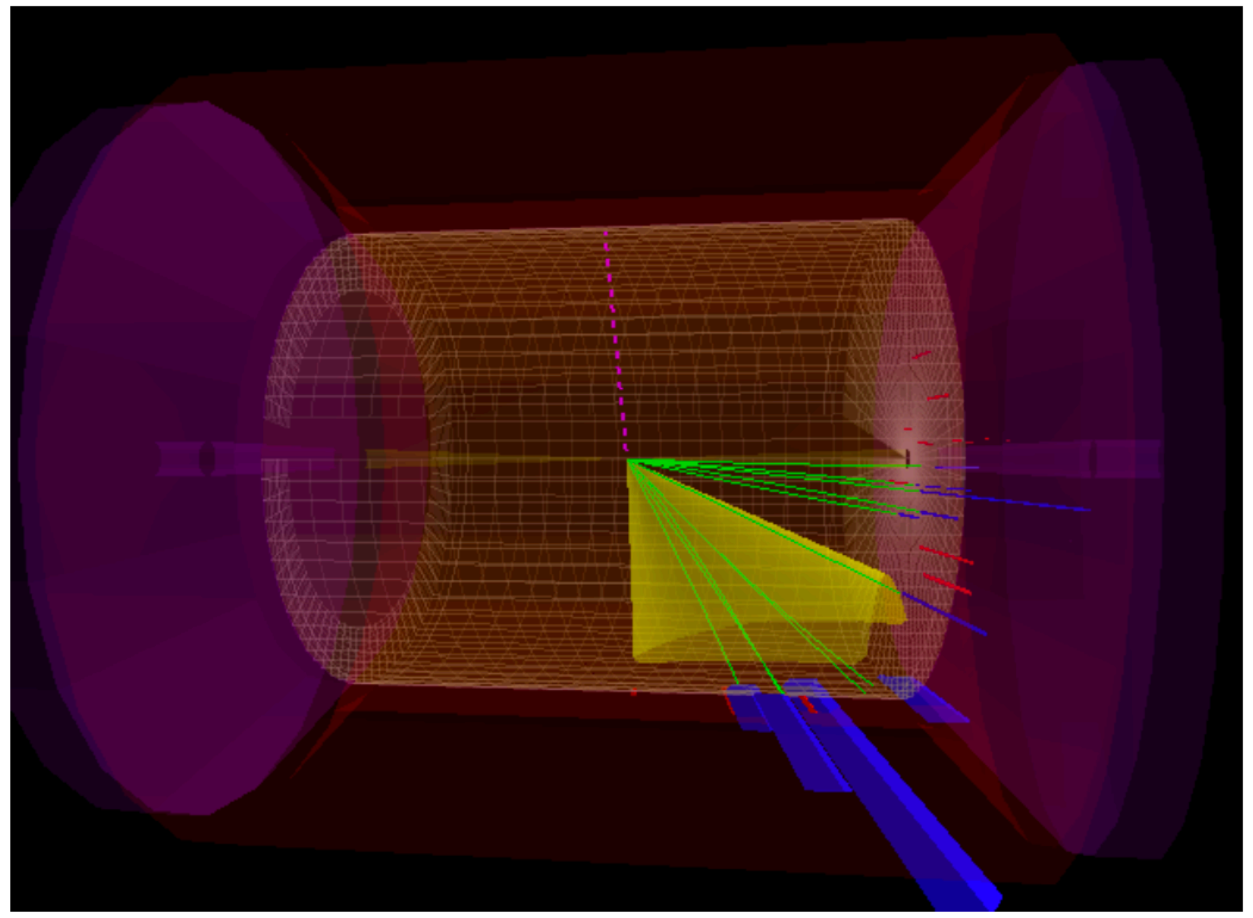
$$\color{red}{\vec{q}_T} = \vec{p}_T^{\,\nu} + \vec{p}_T^{\,\rm jet}$$

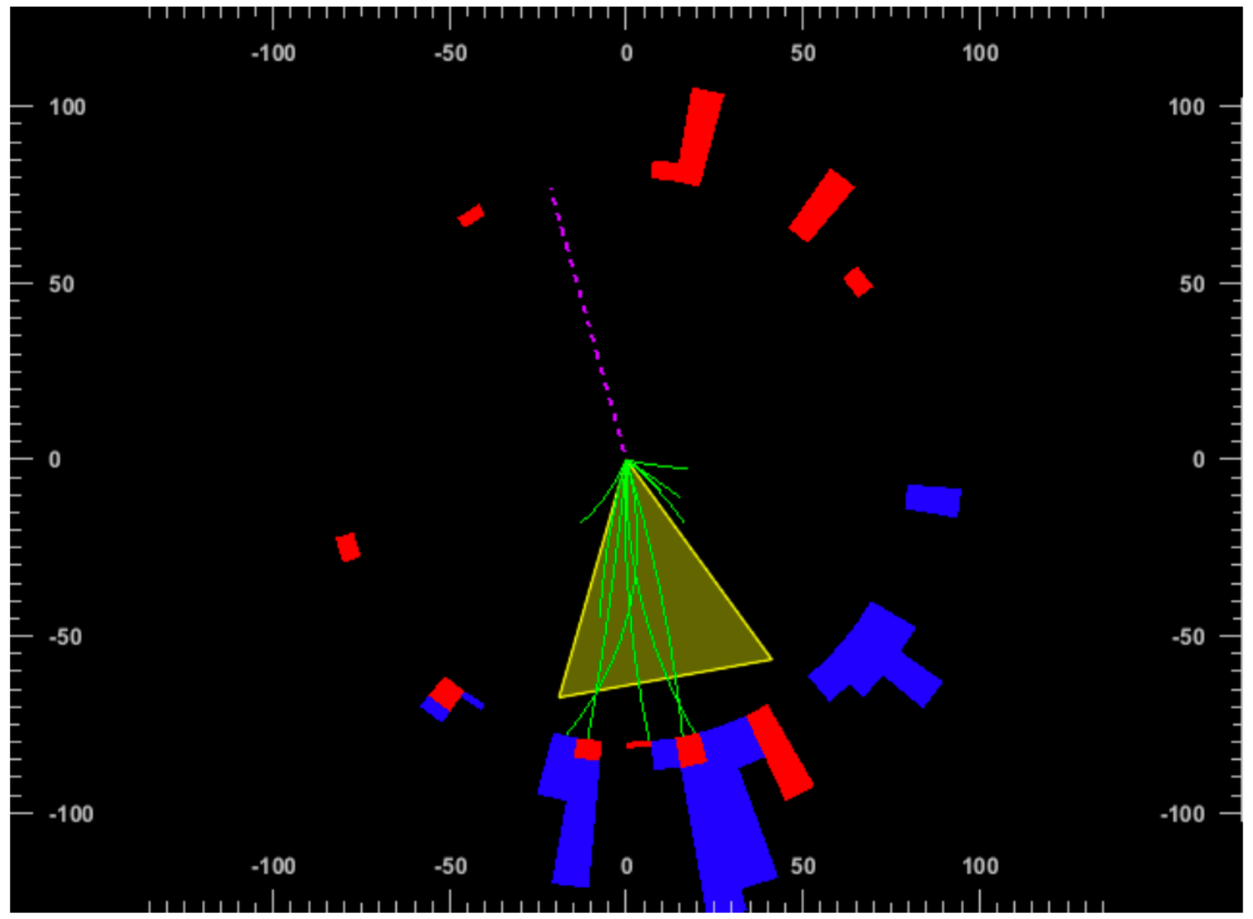
- Requires a sufficiently hermetic detector, here full azimuthal coverage and $|\eta| < 4$ and high luminosity

- Flavor separation

Arratia, Kang, Paul, Prokudin, FR, Zhao `22



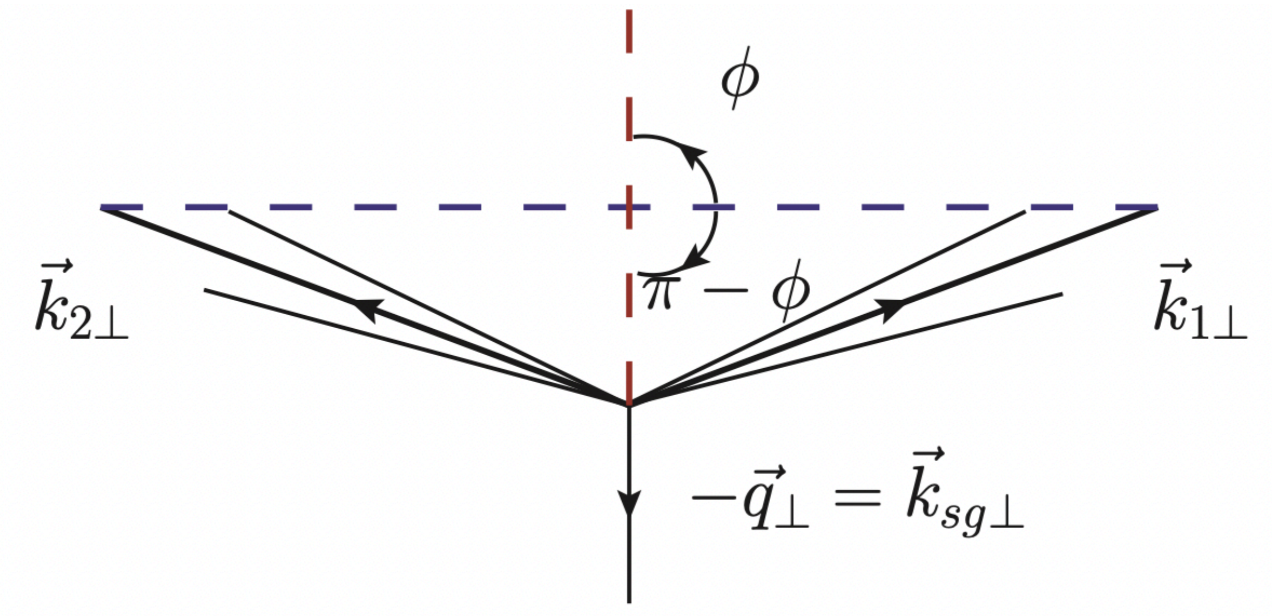




Delphes

Diffractive dijets

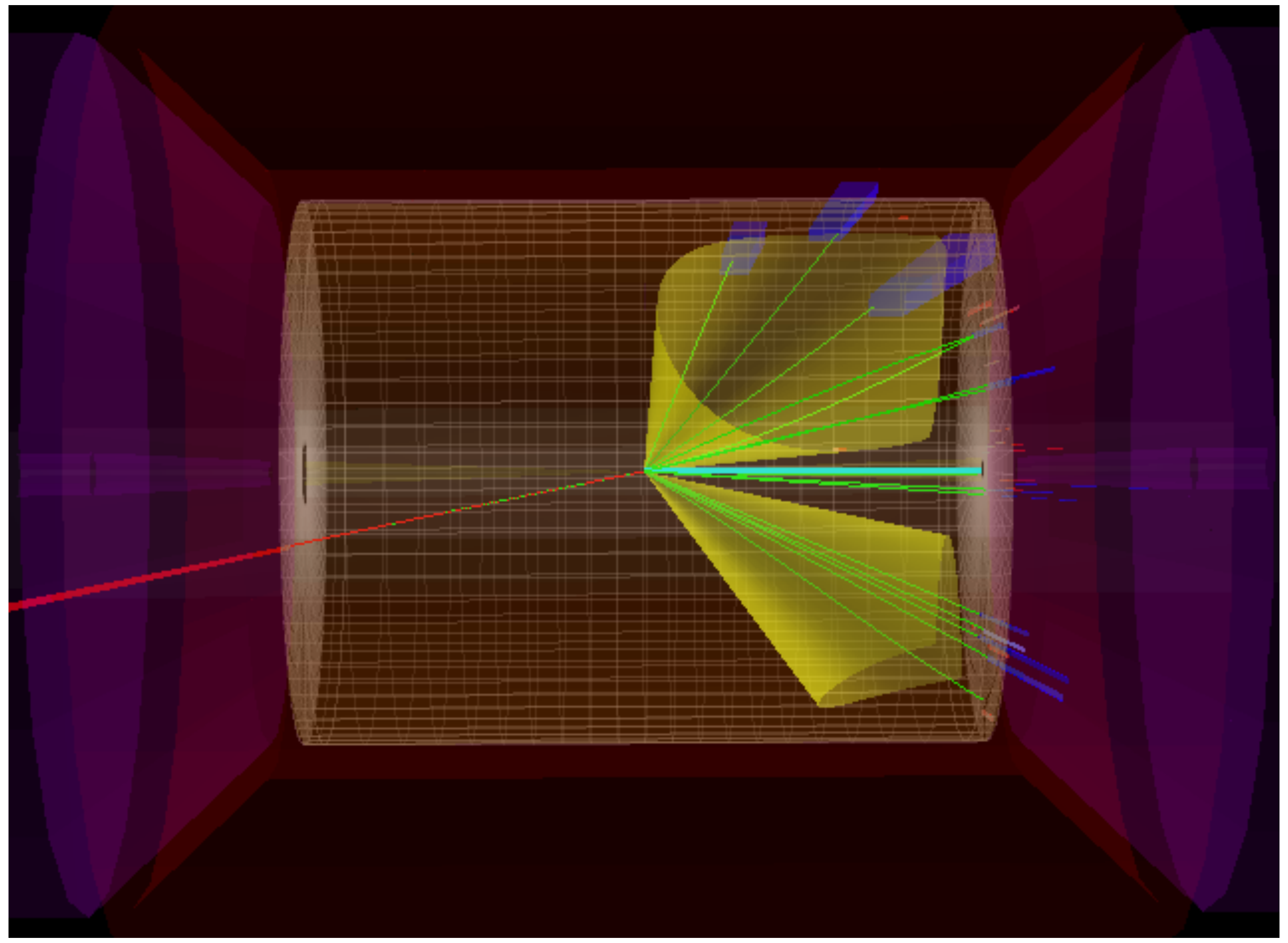
- GTMDs & Wigner functions



$$\frac{d\sigma}{dP_\perp dq_\perp d\phi} = \sigma_0 + \cos(\phi)\sigma_1 + \cos(2\phi)\sigma_2 + \cdots$$

$$\vec{q}_\perp = (\vec{k}_{1\perp} + \vec{k}_{2\perp}) \qquad \vec{P}_\perp = (\vec{k}_{1\perp} - \vec{k}_{2\perp})/2$$

$$\phi = \sphericalangle(\vec{q}_\perp, \vec{P}_\perp)$$



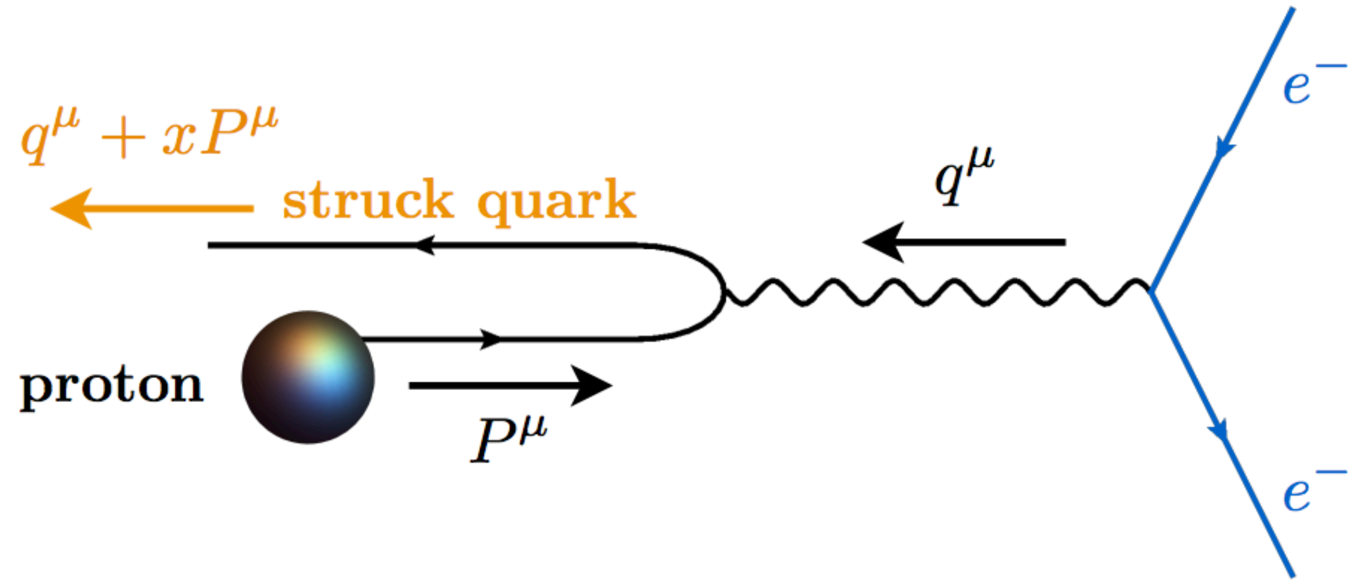
- Requires high luminosity & measurement of the scattered proton

Hatta, Mueller, Ueda, Yuan `19
Hatta, Xiao, Yuan `21

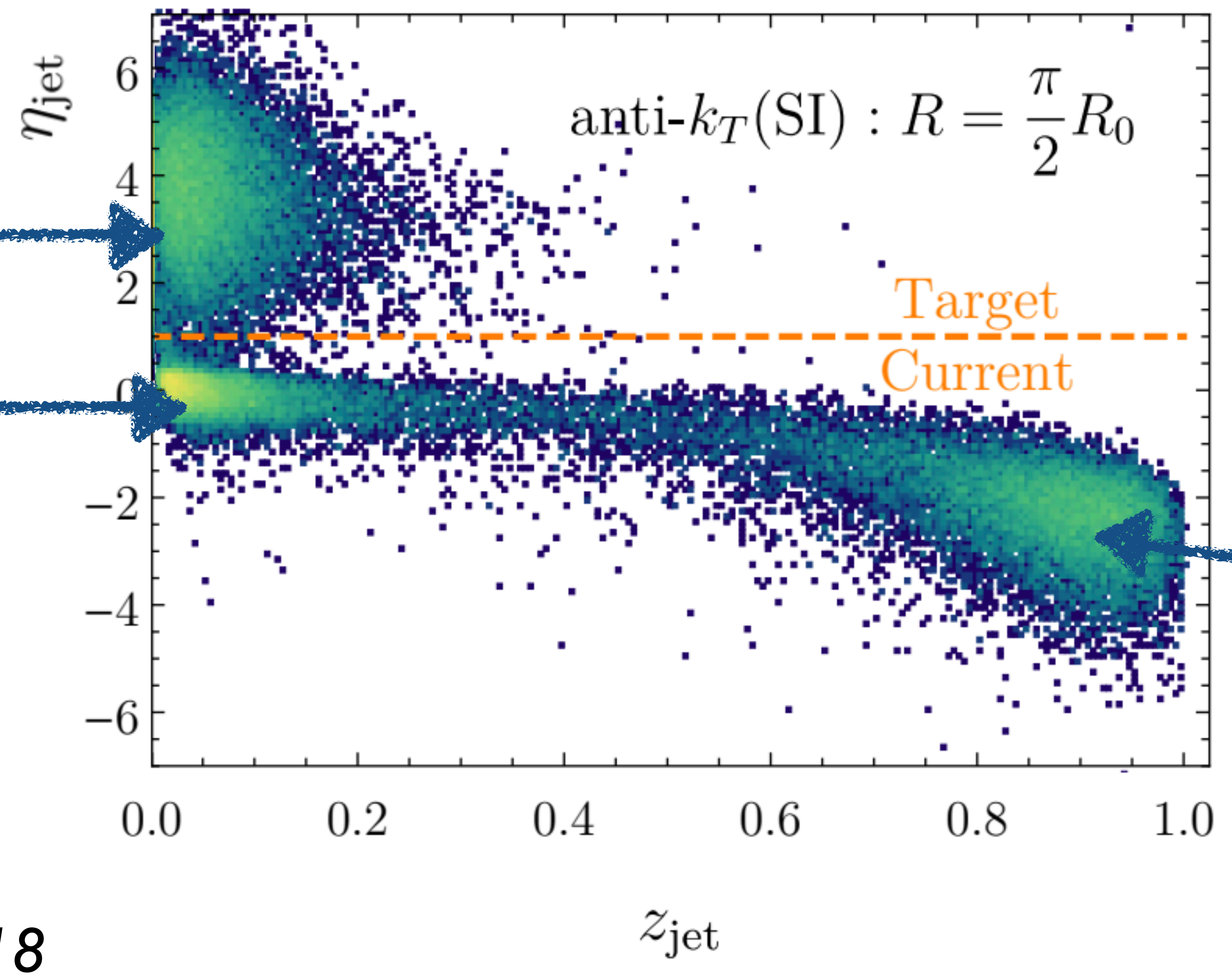
- See also jets in photoproduction events *Aschenauer, Lee, Page, FR `19*

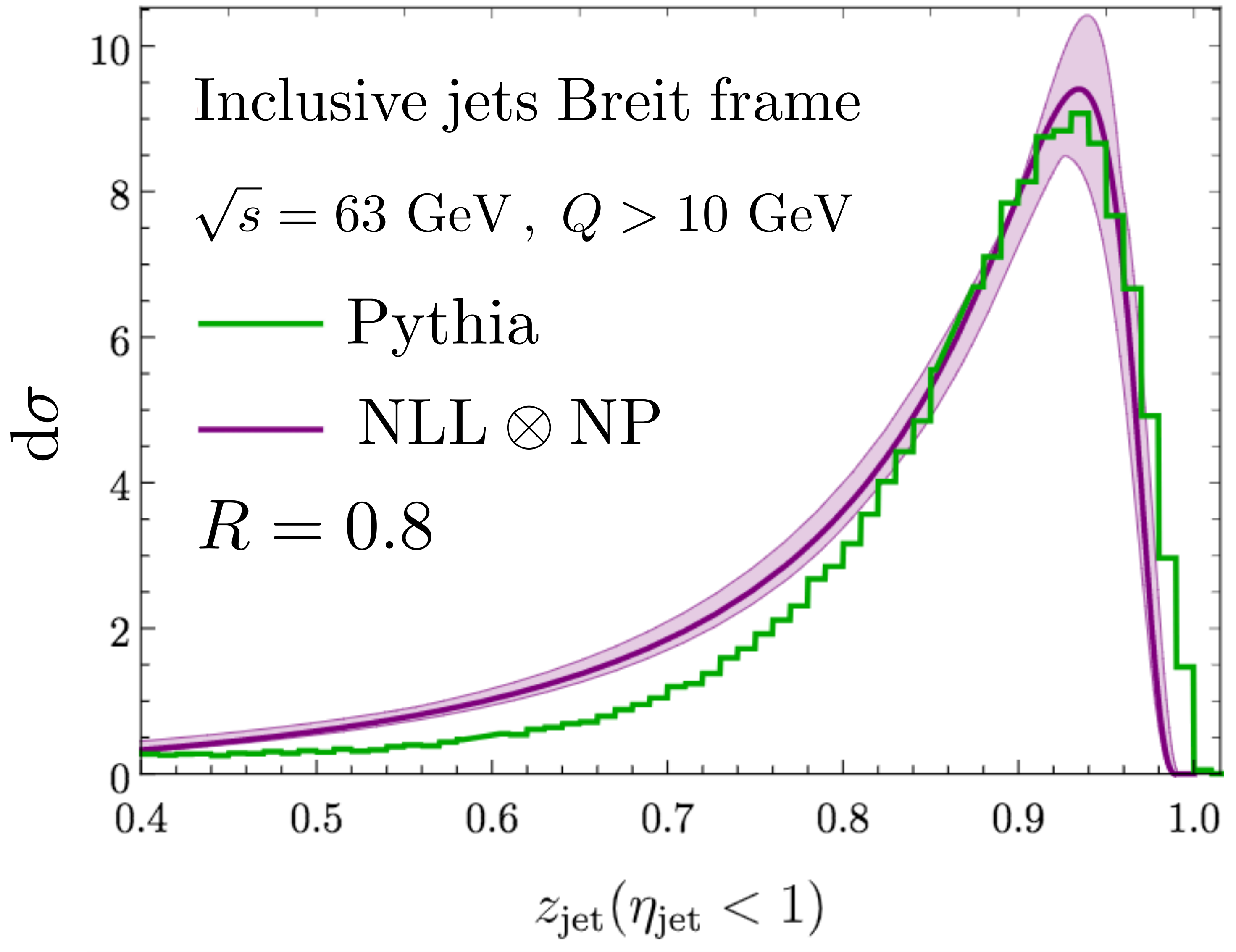
Current & target jets in the Breit frame

- Spherically invariant jets (E_i, θ_{ij}) in the Breit frame
- Seemingly clean separation of current & target region



Requires large rapidity range

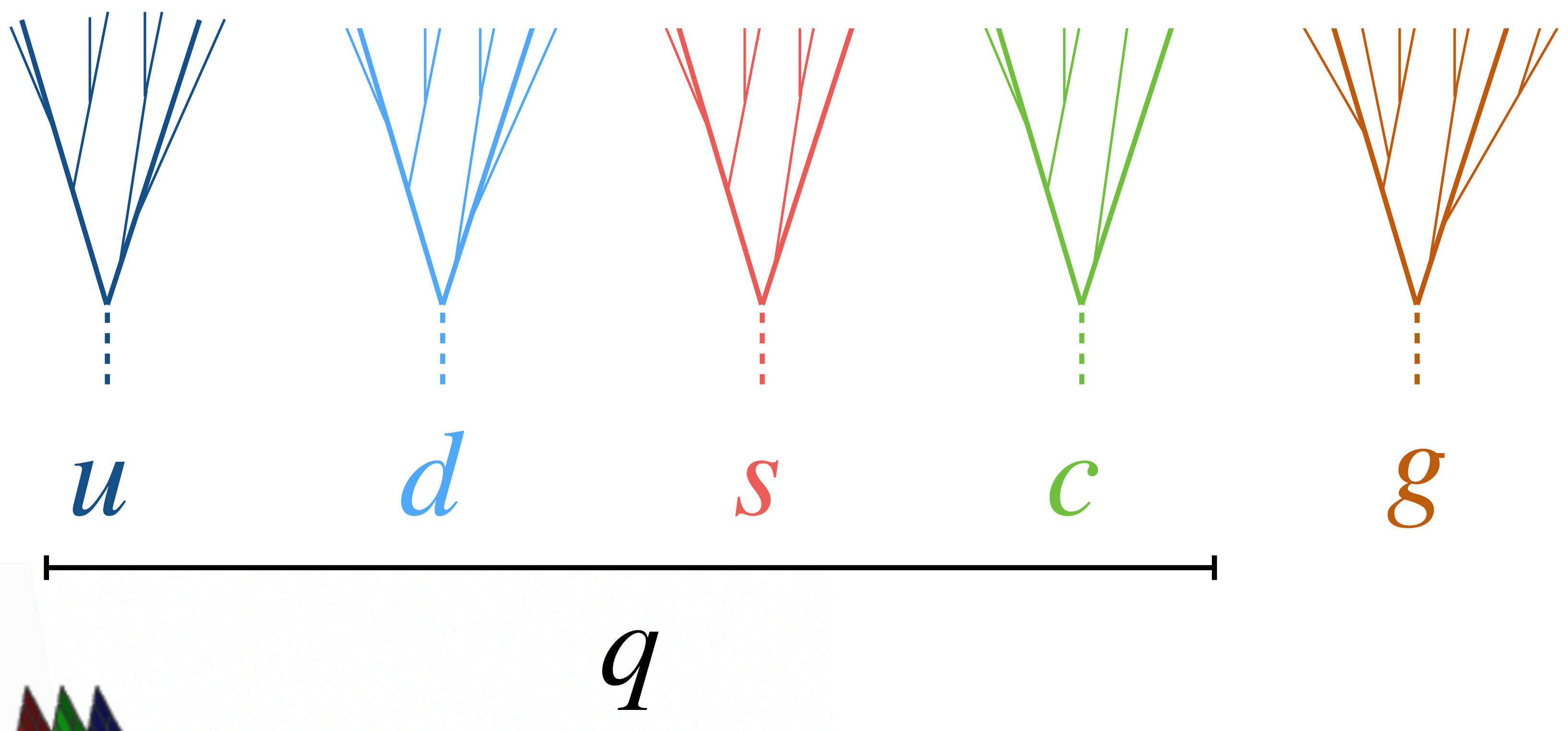




Arratia, Makris, Neill, FR, Sato `18
see also Yang-Ting's talk

Jet physics & Machine learning

- Various jet classifiers have been developed
  - Typically ML significantly outperformed traditional observables
  - Use full event-by-event information instead of low-dimensional projections (observables)



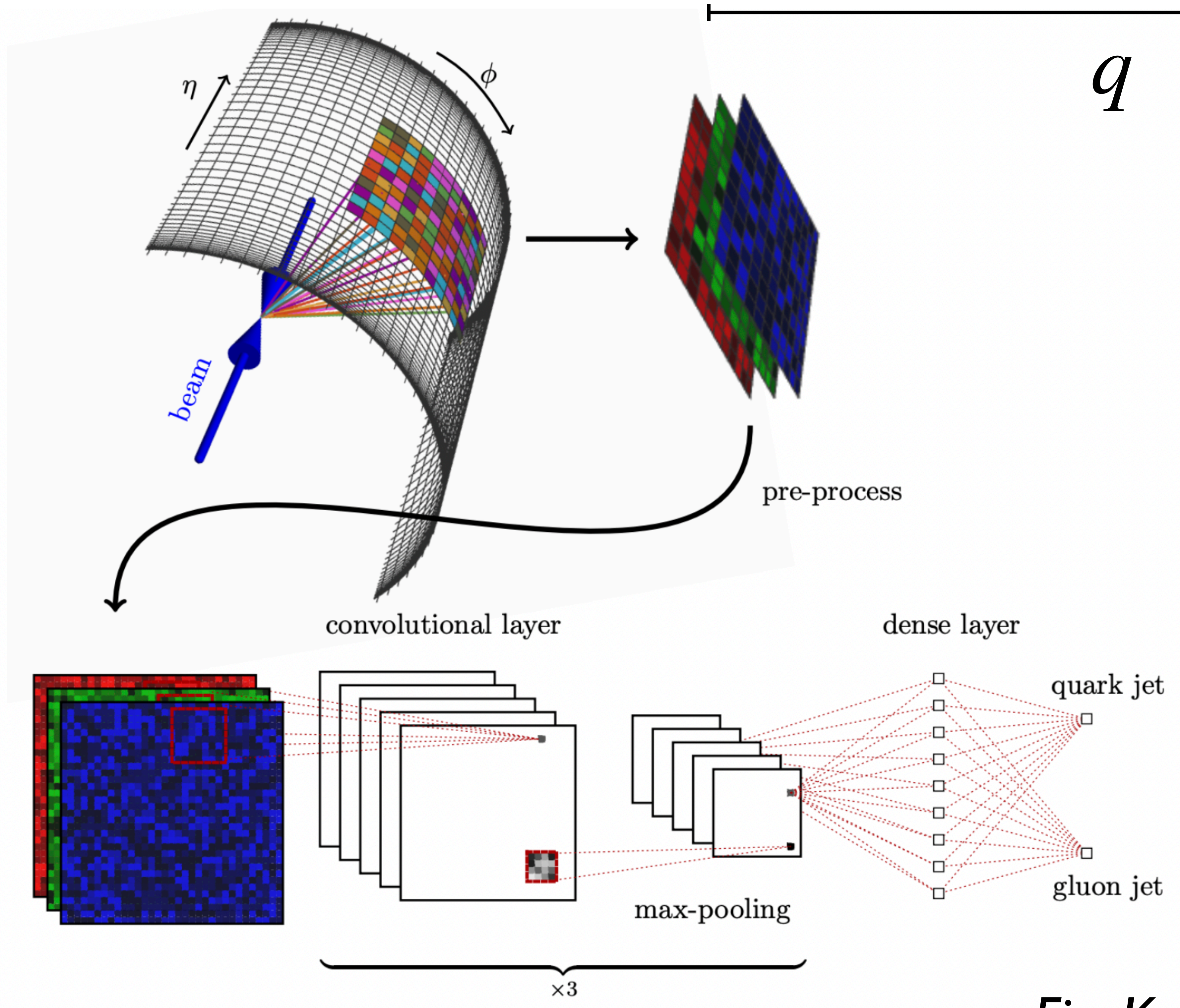
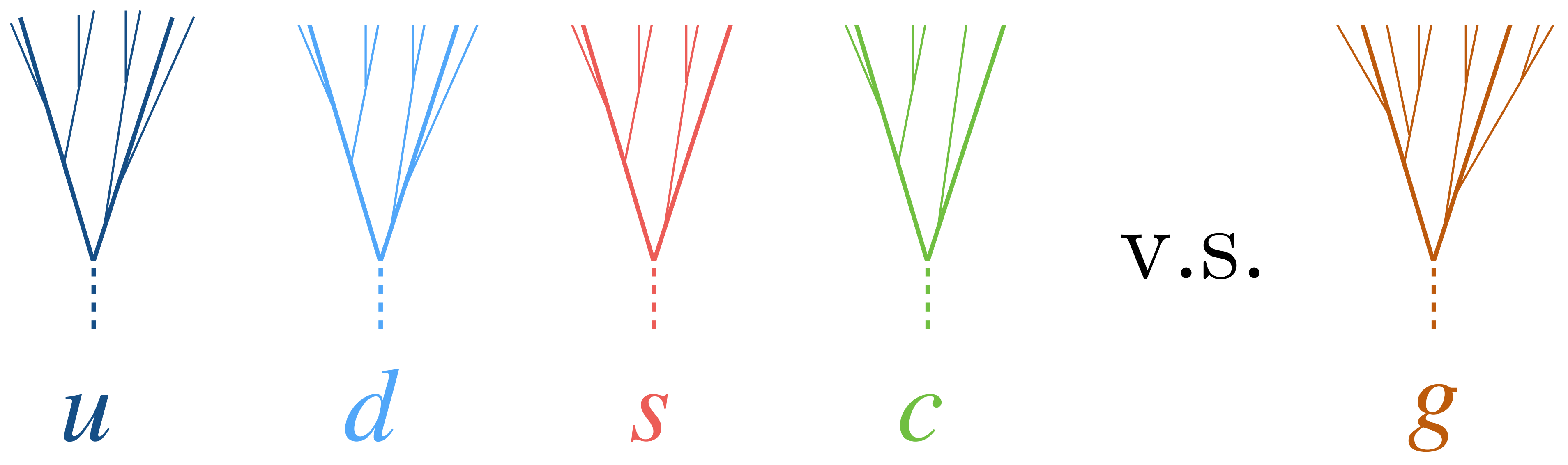
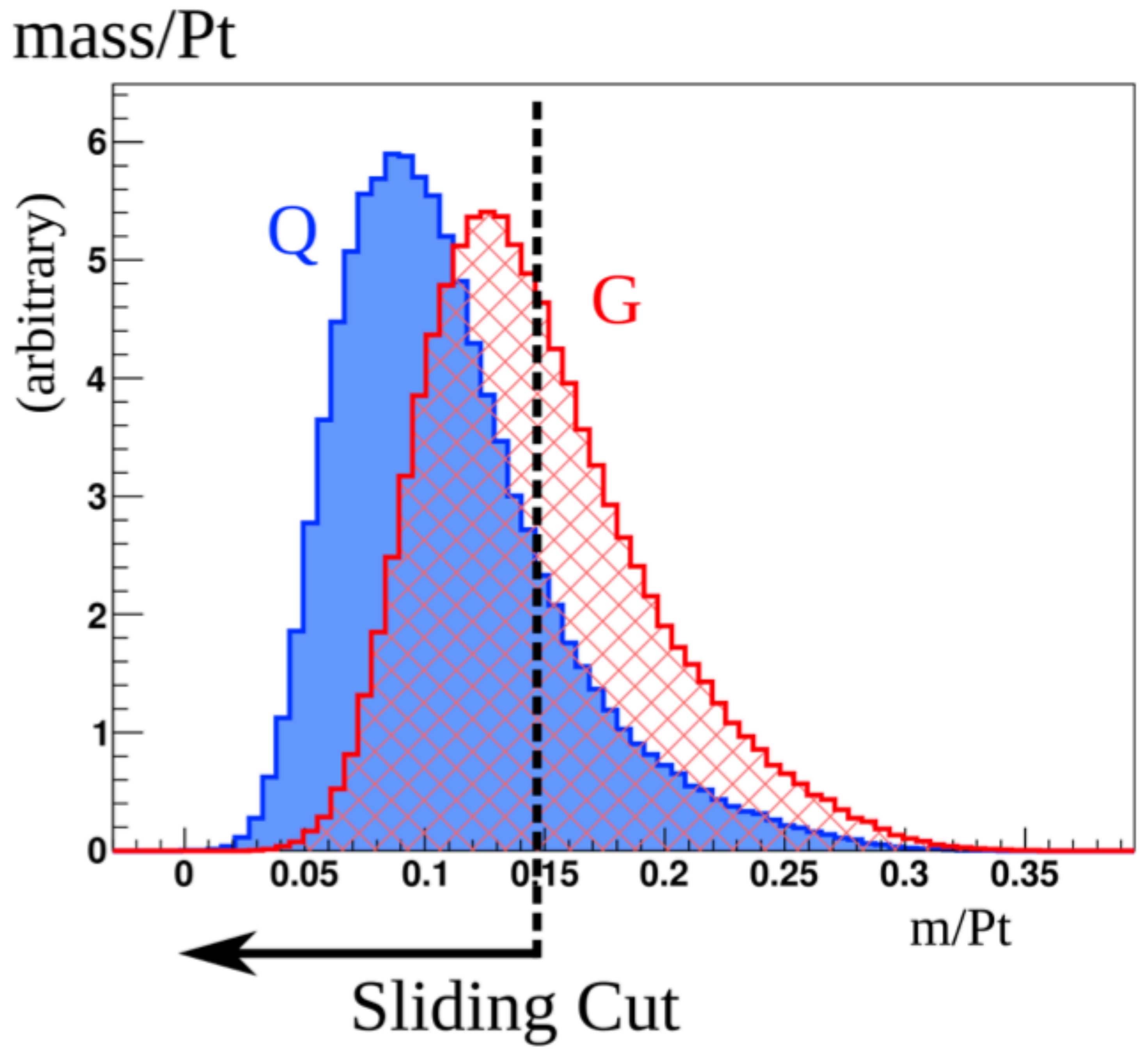


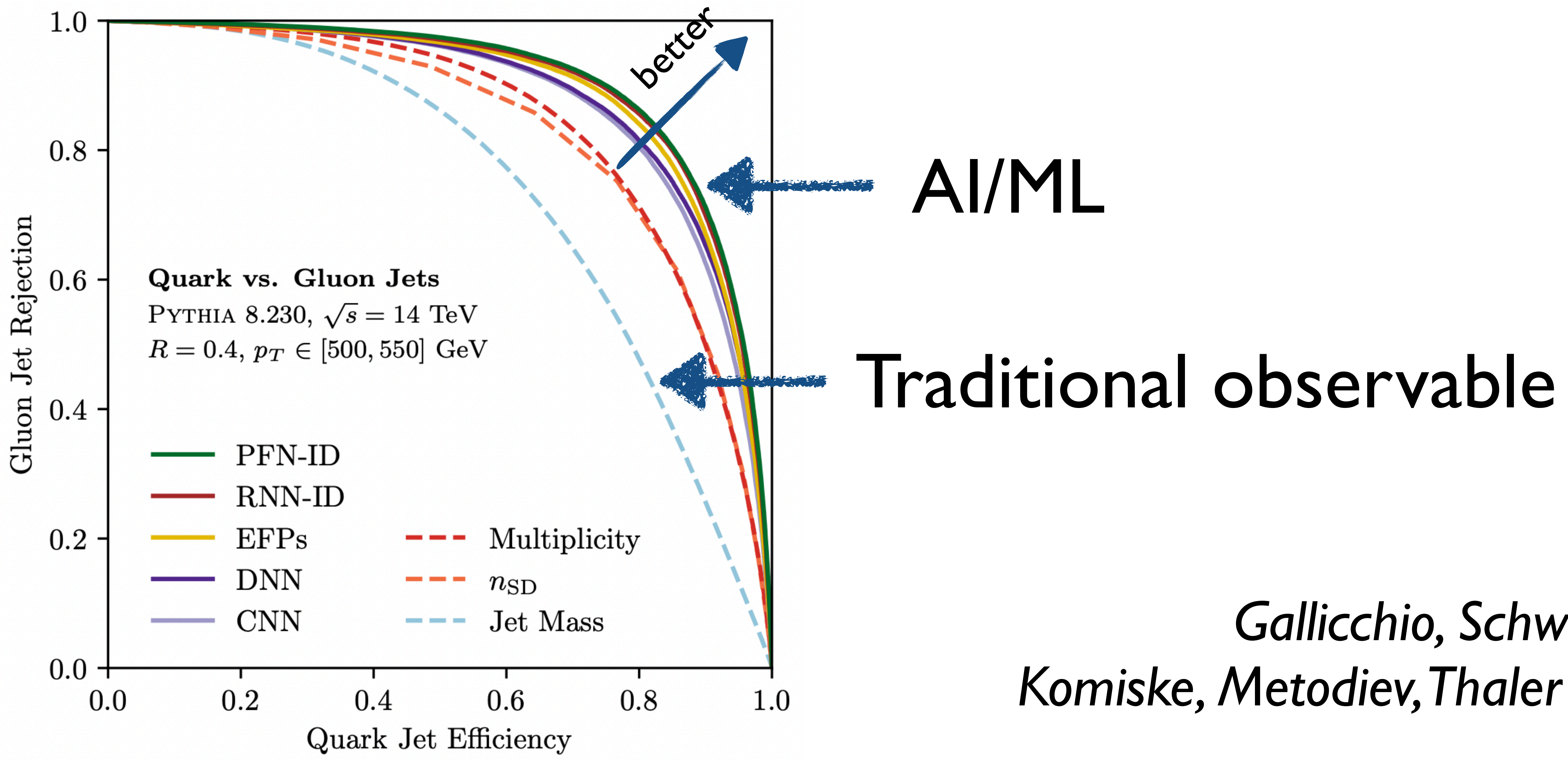
Fig. Komiske, Metodiev, Schwartz

Jet physics & Machine learning

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





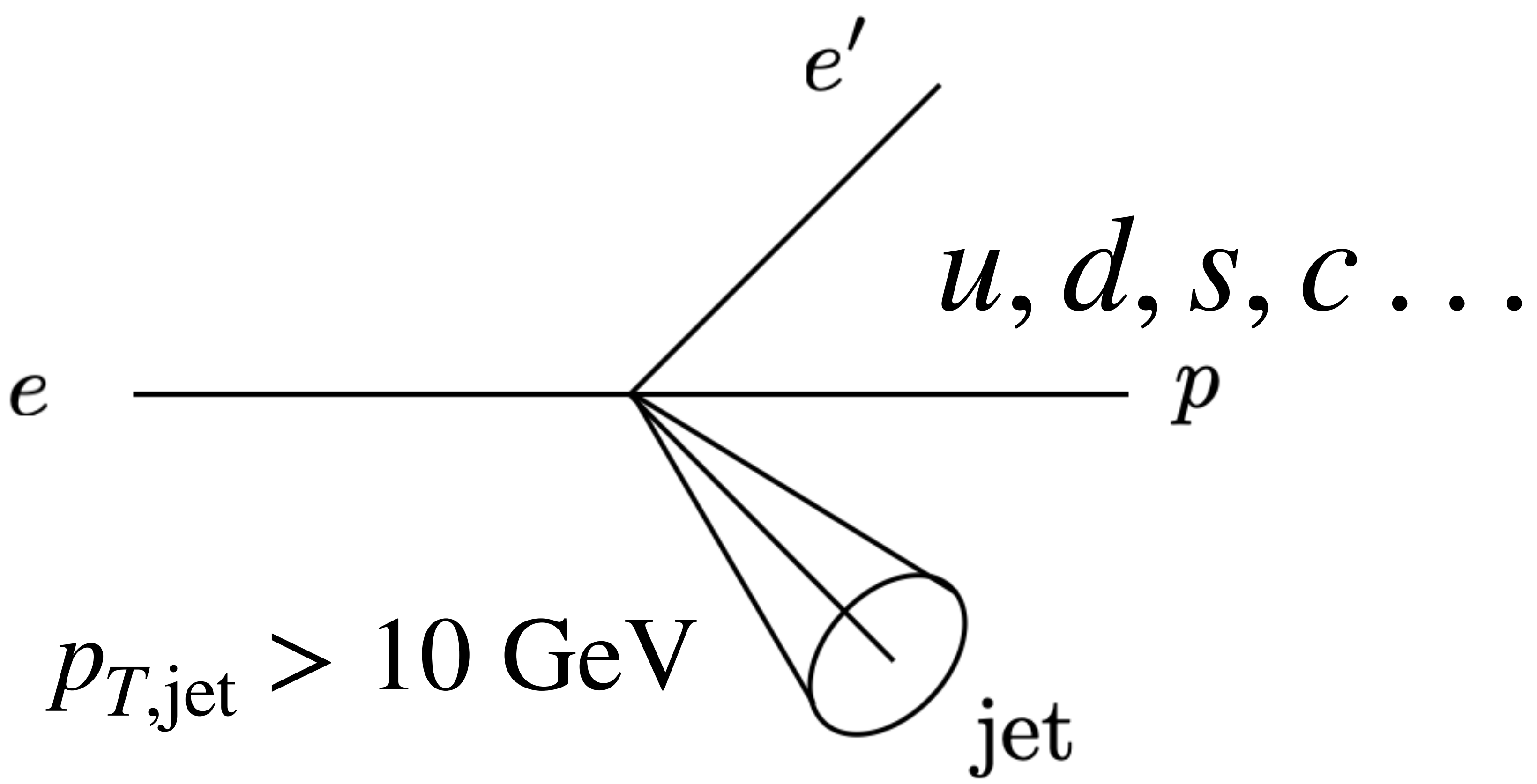


Gallicchio, Schwartz
Komiske, Metodiev, Thaler `19

Events & machine learning

- Relatively low particle multiplicities at the EIC

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



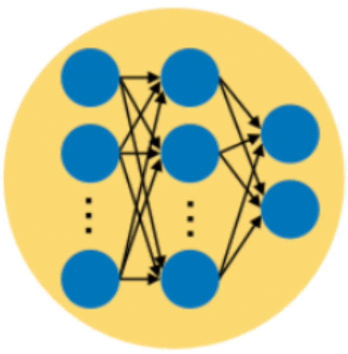
Lee, Mulligan, Ploskon, FR, Yuan `22

- 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

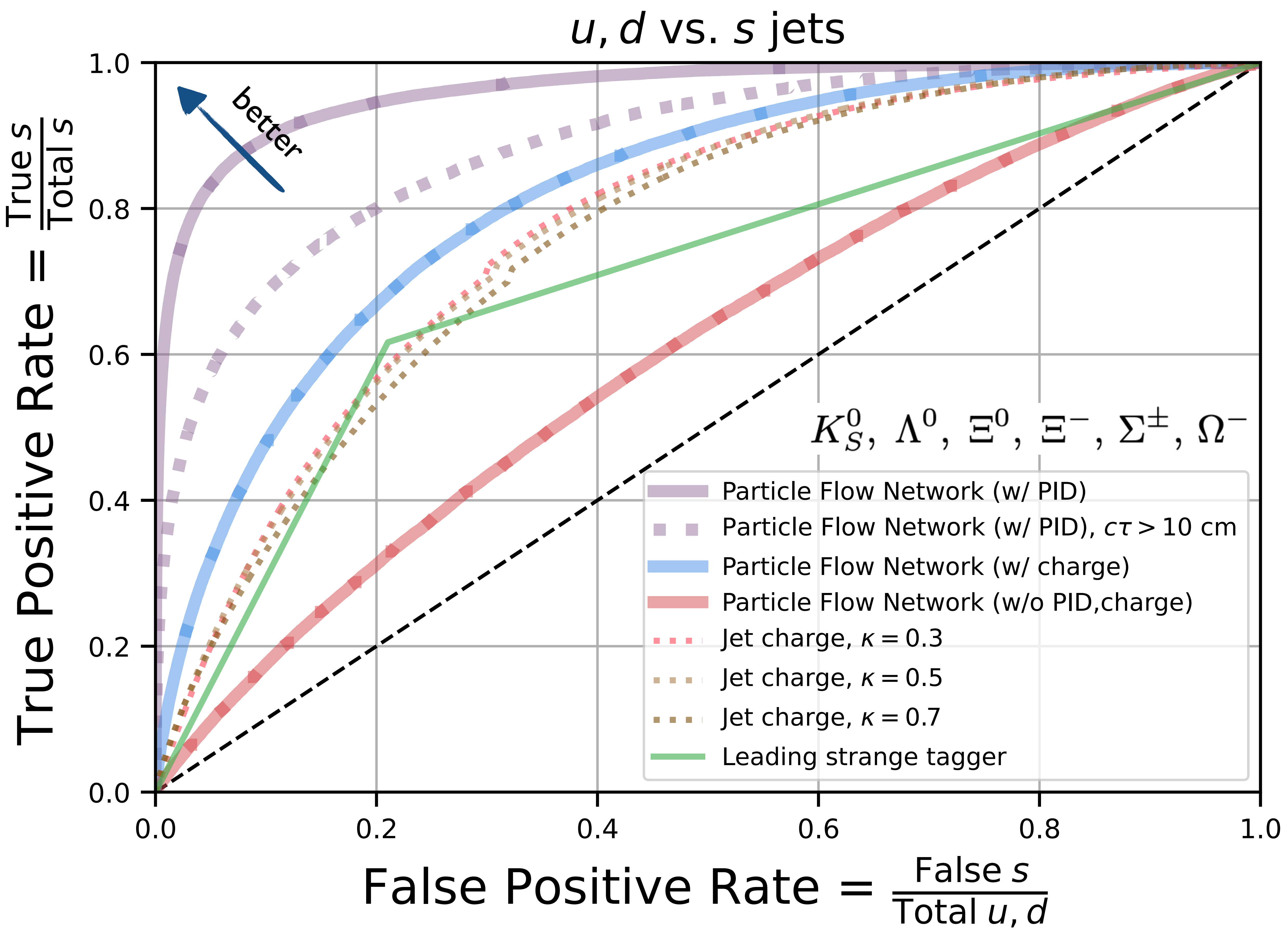


Neural networks

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

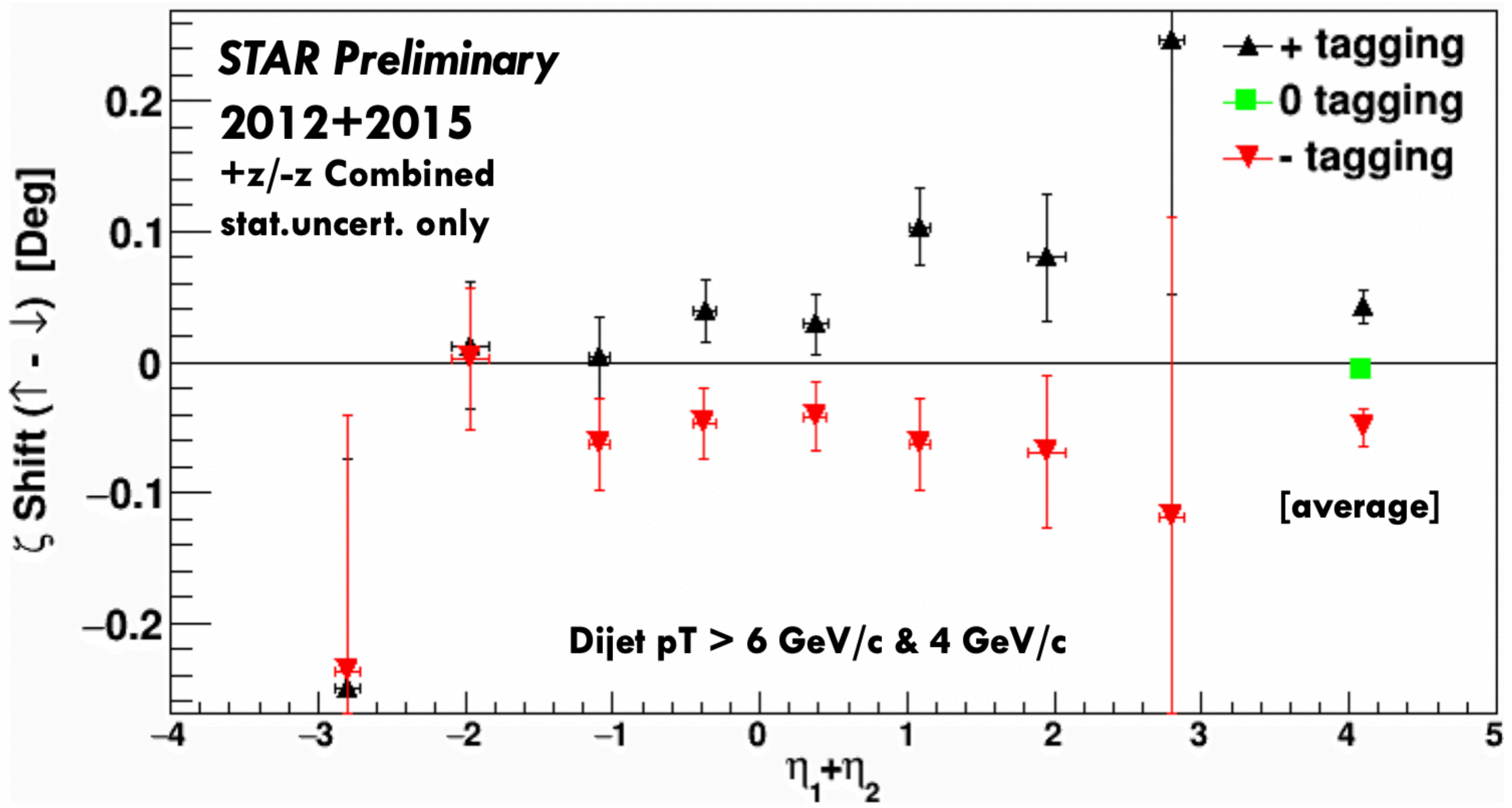
EIC jet physics with machine learning

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*

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



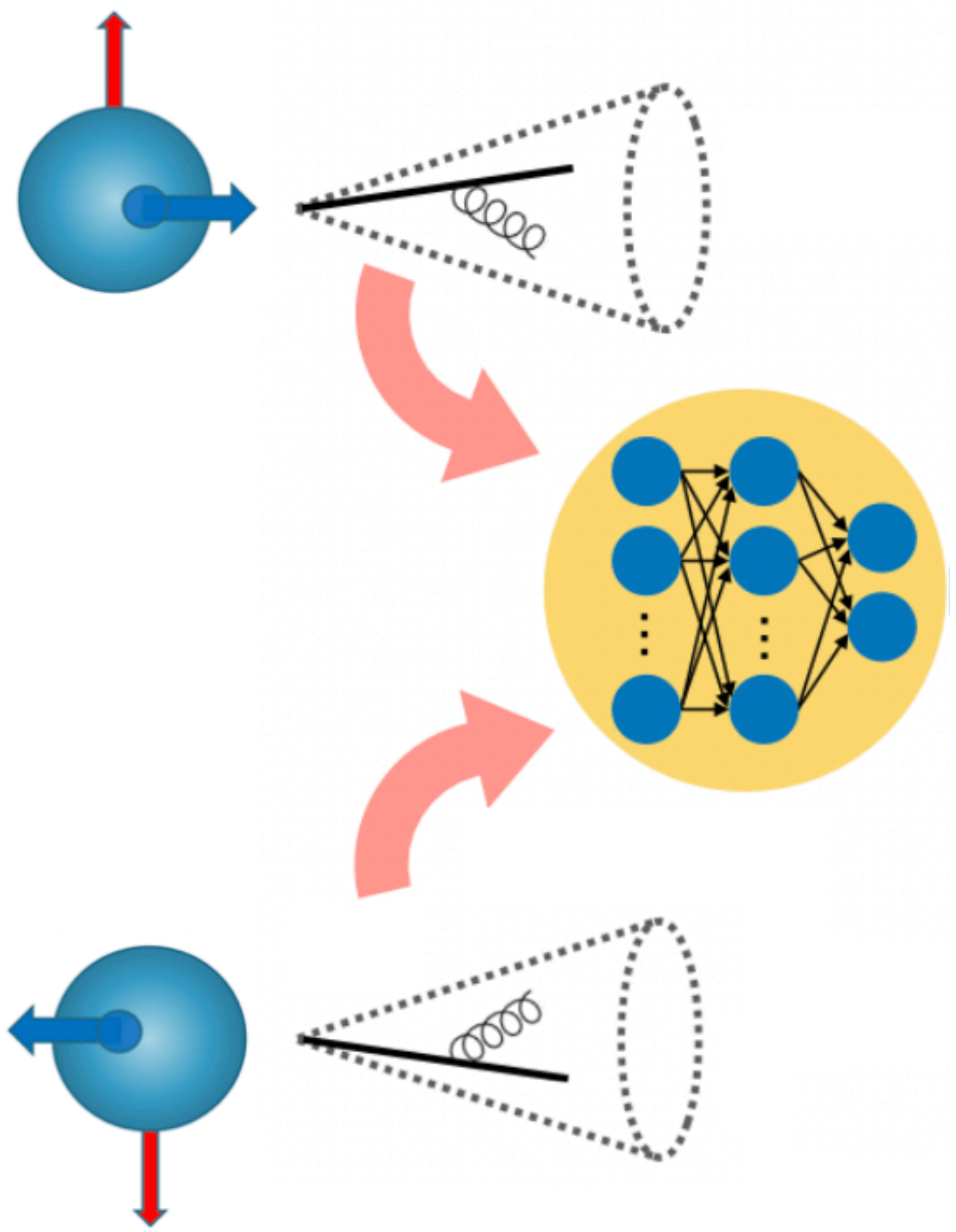
Can we obtain better constraints with ML-based jet classification?

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. $A_{UT} = \frac{\mathrm{d}\sigma^{\uparrow} - \mathrm{d}\sigma^{\downarrow}}{\mathrm{d}\sigma^{\uparrow} + \mathrm{d}\sigma^{\downarrow}}$



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

→ Upper limit on what can possibly be achieved

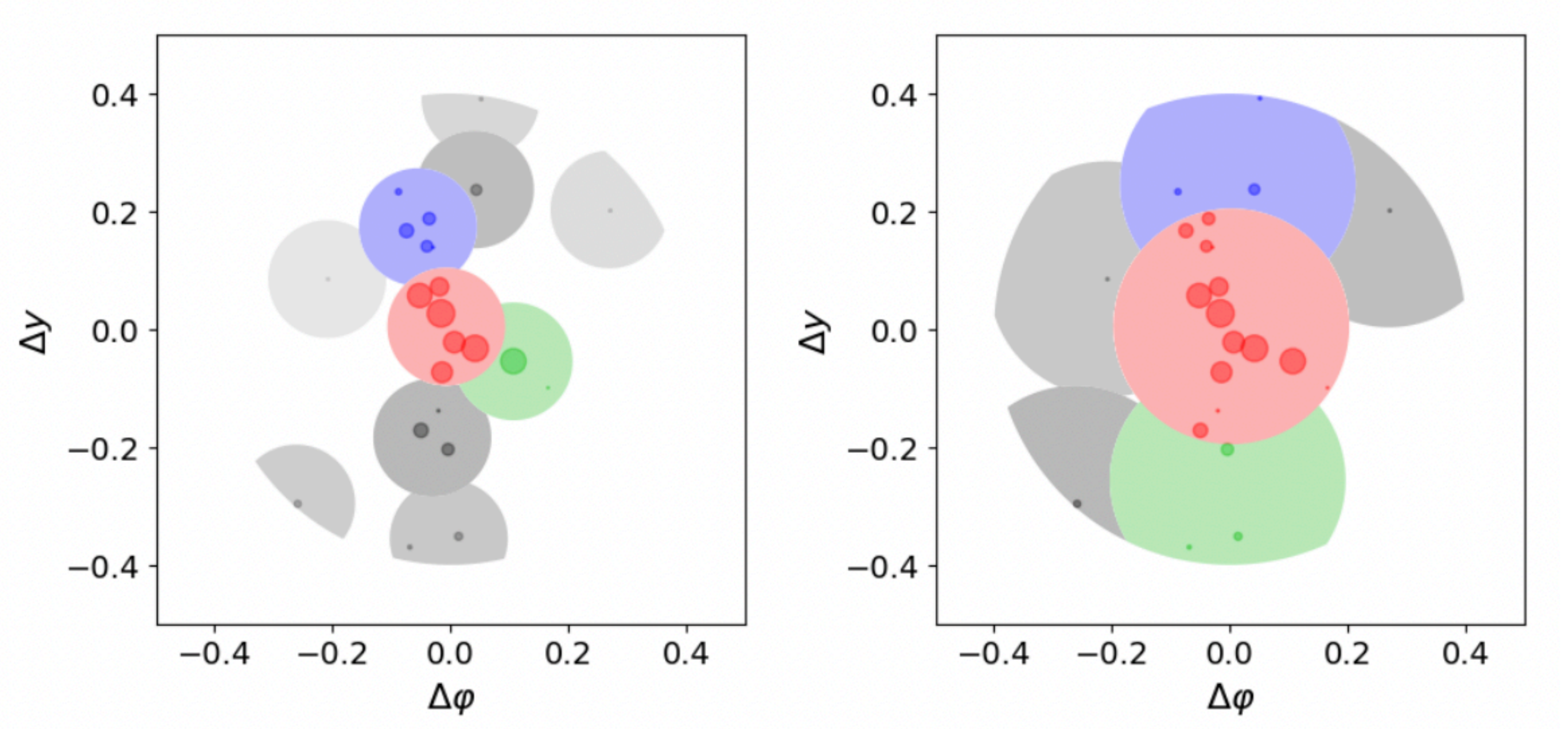
→ Identify new observables

Jet classification & IRC safety

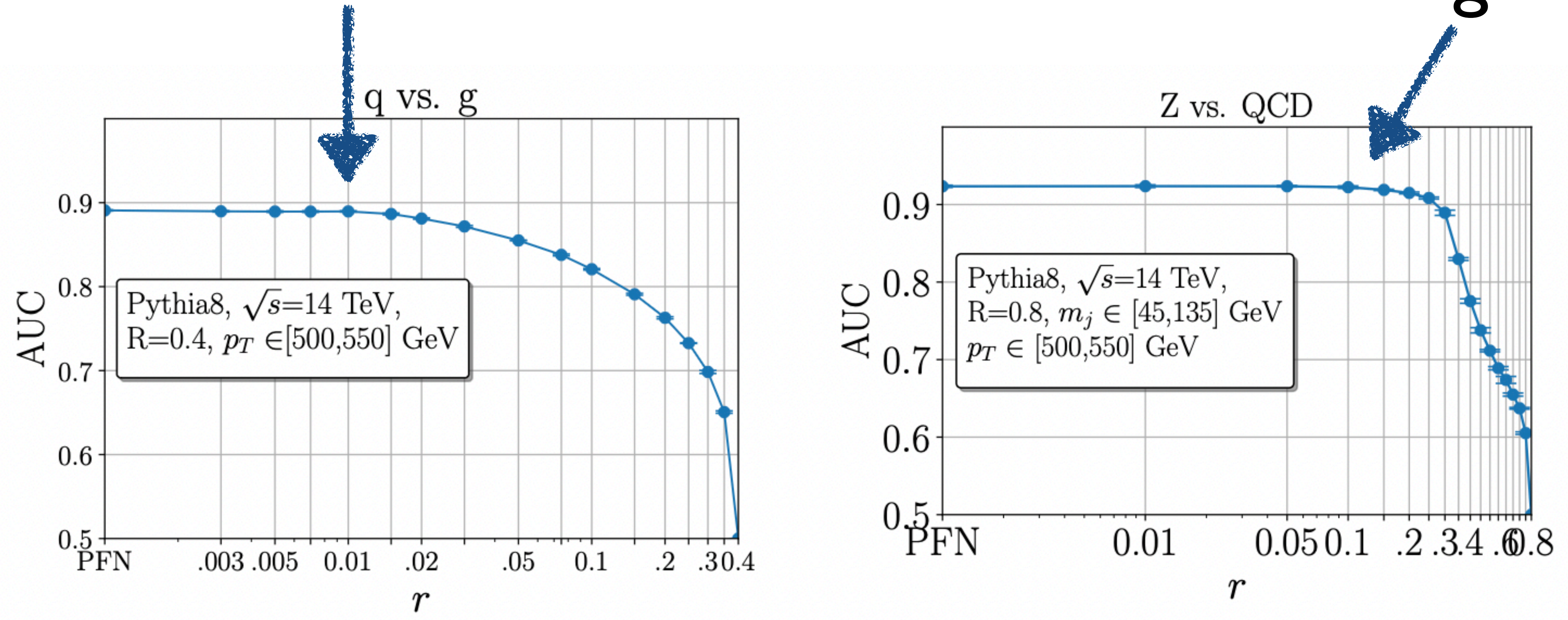
- Can we make use of all this additional information?

- Several jet classification tasks are IRC safe → we can find tractable observables in pQCD

- Recluster particles into IRC-safe subjets before training ML algorithms



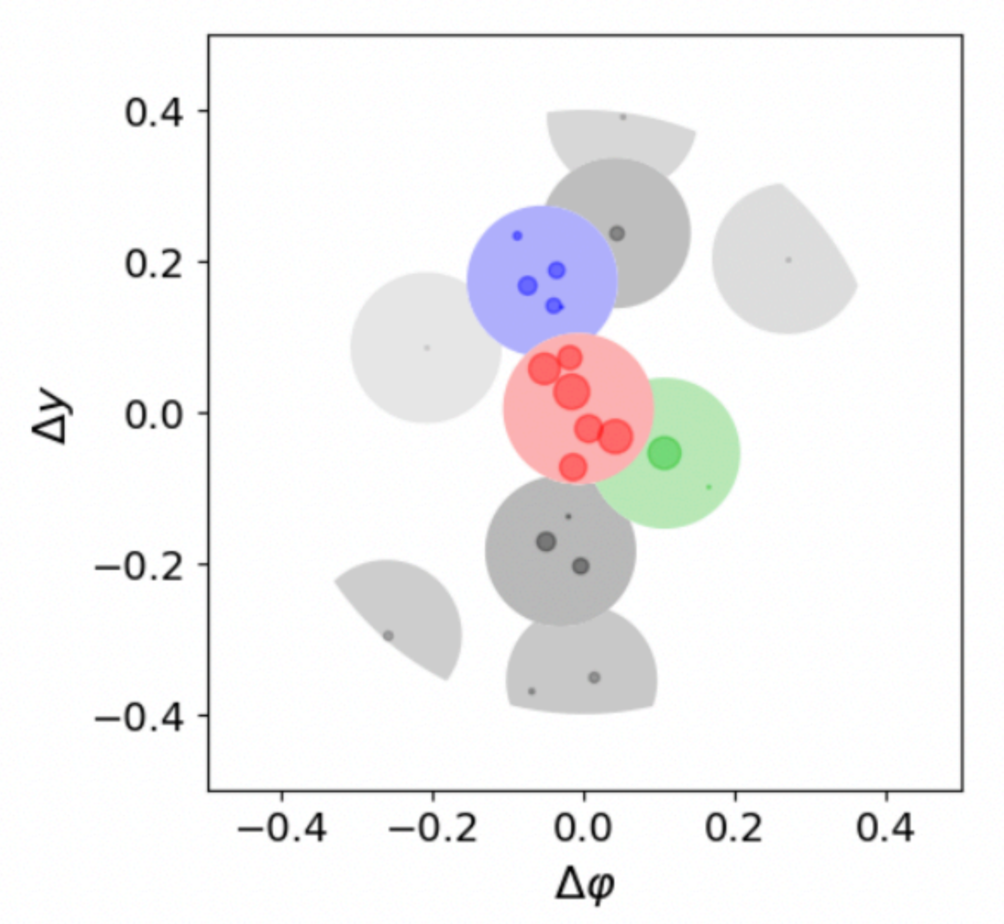
Matches IRC-unsafe ML algorithm

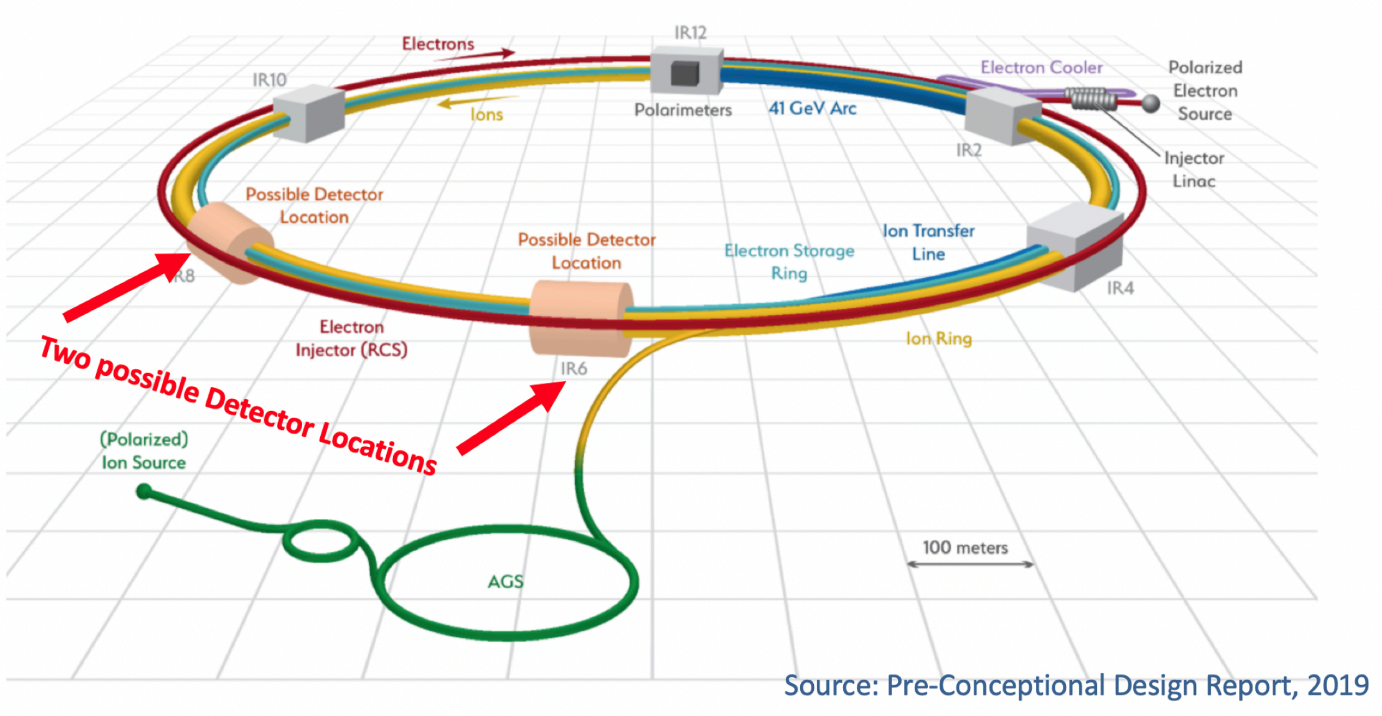


Athanasakos, Larkoski, Mulligan, Ploskon, FR `23
Metodiev, Larkoski `19

Summary

- Jets will be versatile tools at the EIC
- Can take advantage of the EIC's clean environment, high luminosity & forward PID capabilities
- TMD, GPDs, target fragmentation
- AI/ML can complement hadron structure & spin physics program
- …and can inform detector design?





Source: Pre-Conceptional Design Report, 2019