EIC jet physics and machine learning

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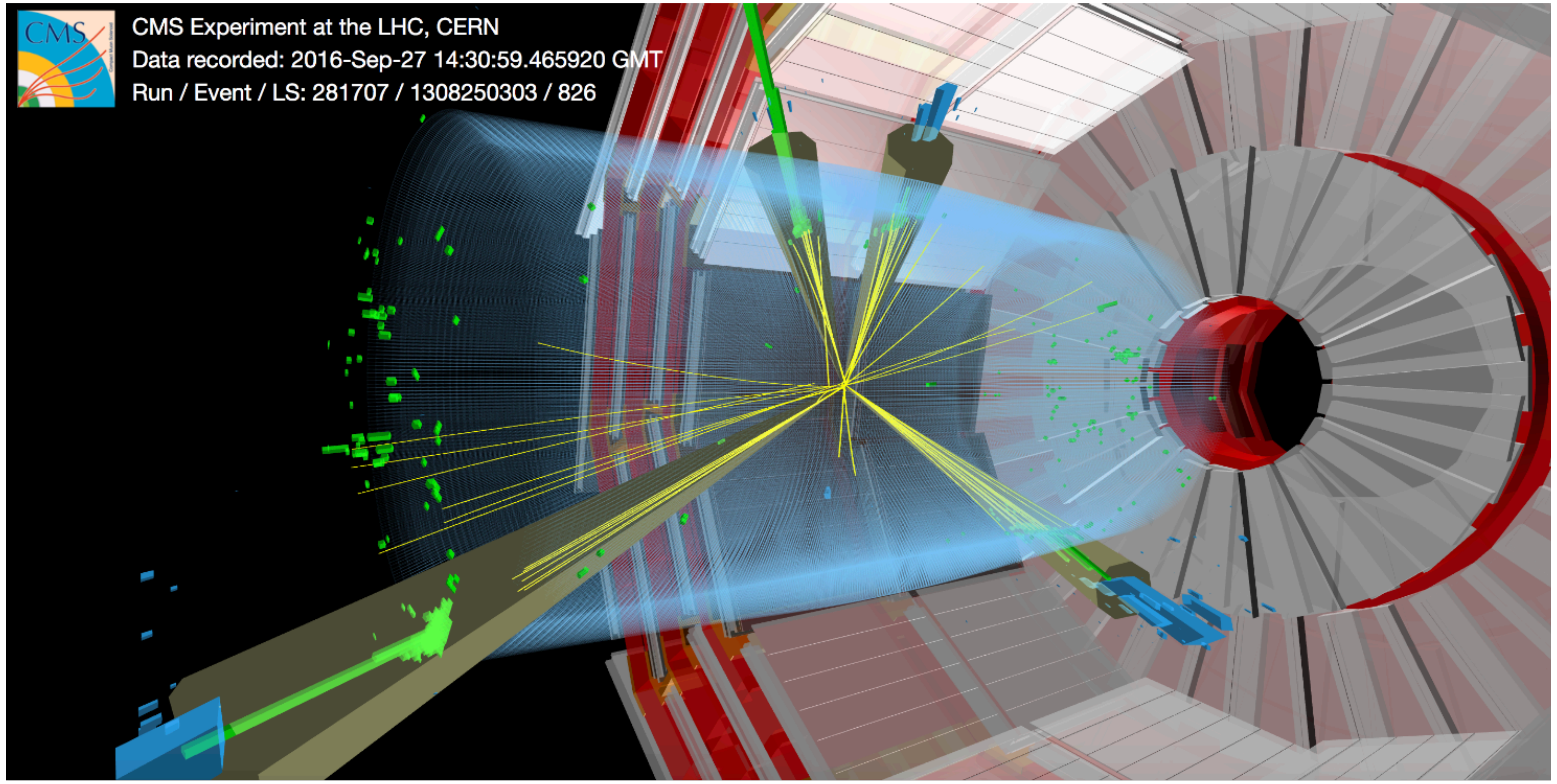
Probing Hadron Structure at the Electron-Ion Collider, ICTS, Bangalore

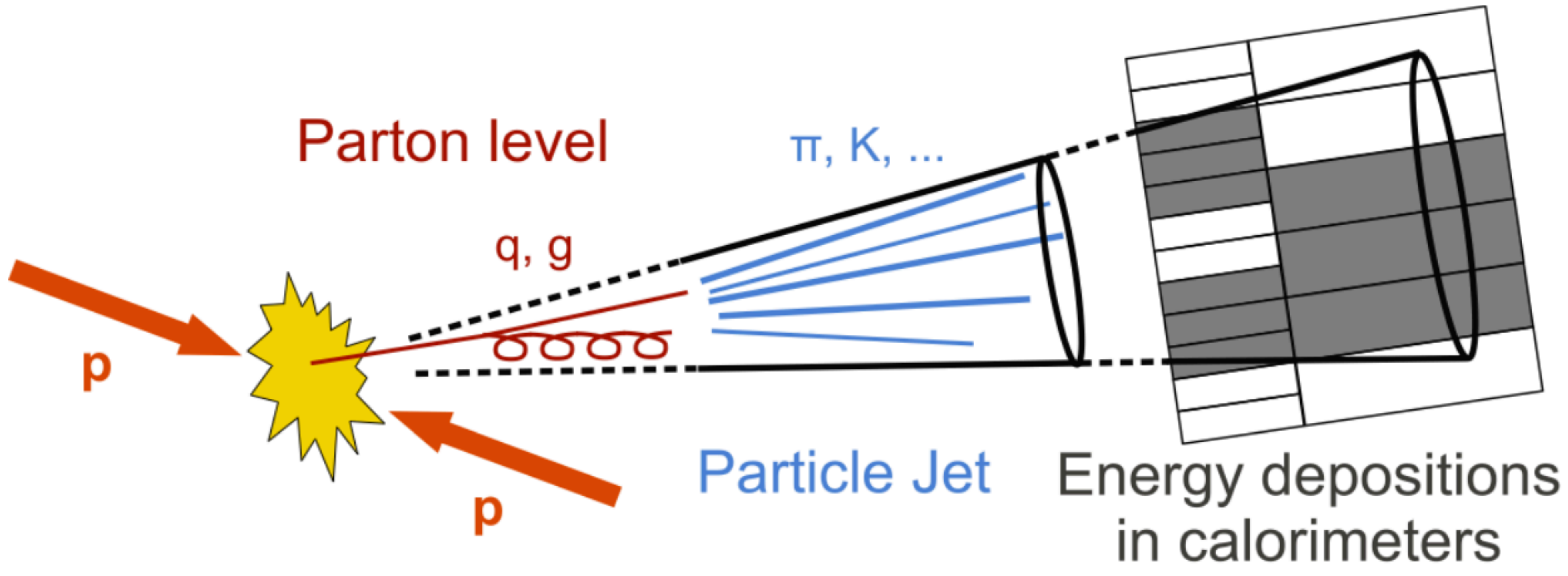
OLD DOMINION UNIVERSITY

Jefferson Lab

Jets at collider experiments

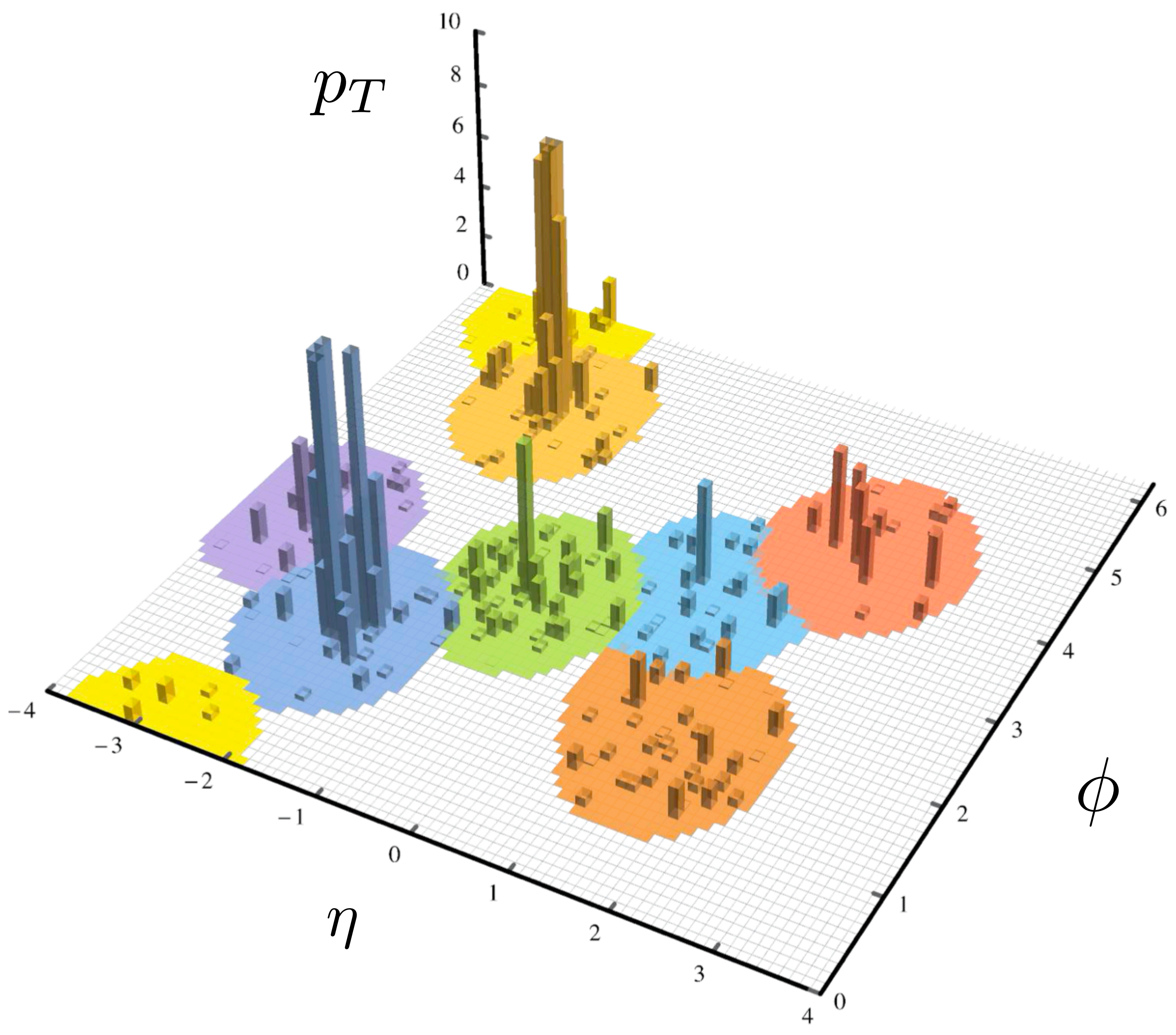
- Collimated sprays of particles
- Most direct access to high-energy quarks and gluons

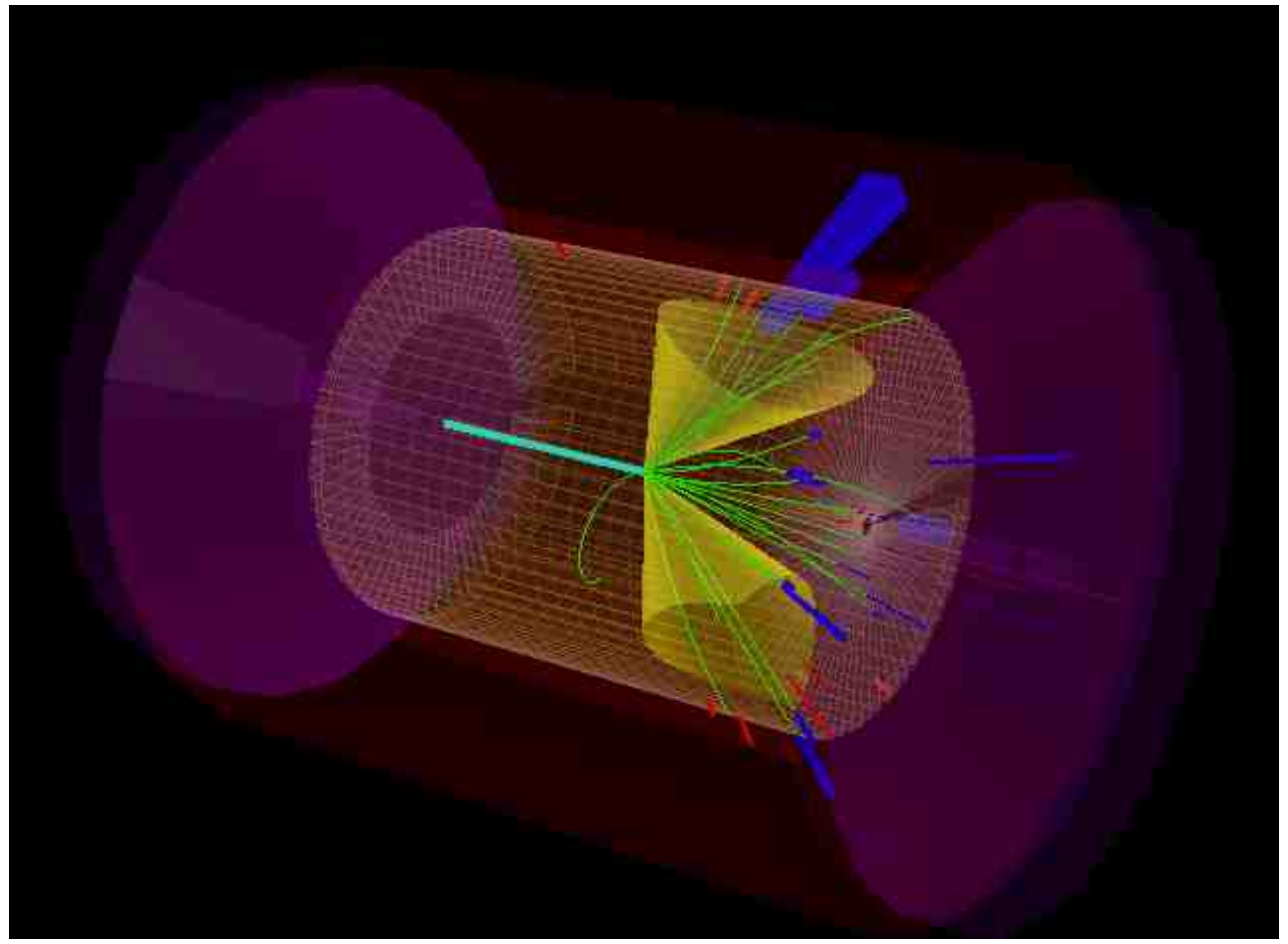




EIC jet physics

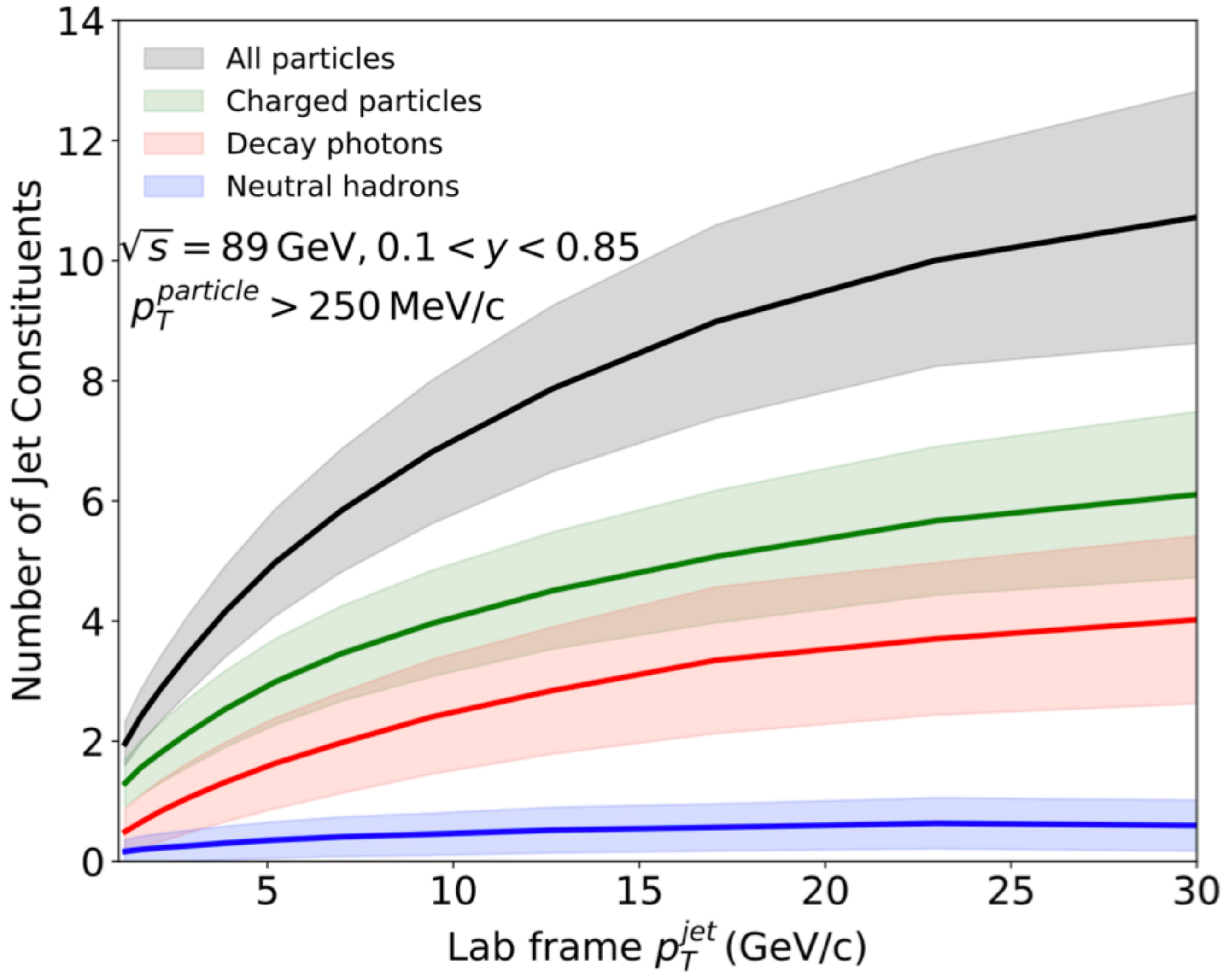
- Versatile jet reconstruction algorithms & frame dependence
- Clean EIC environment
- Jet substructure & correlations
- Relevant for e.g. TMDs, GPDs & hadronization



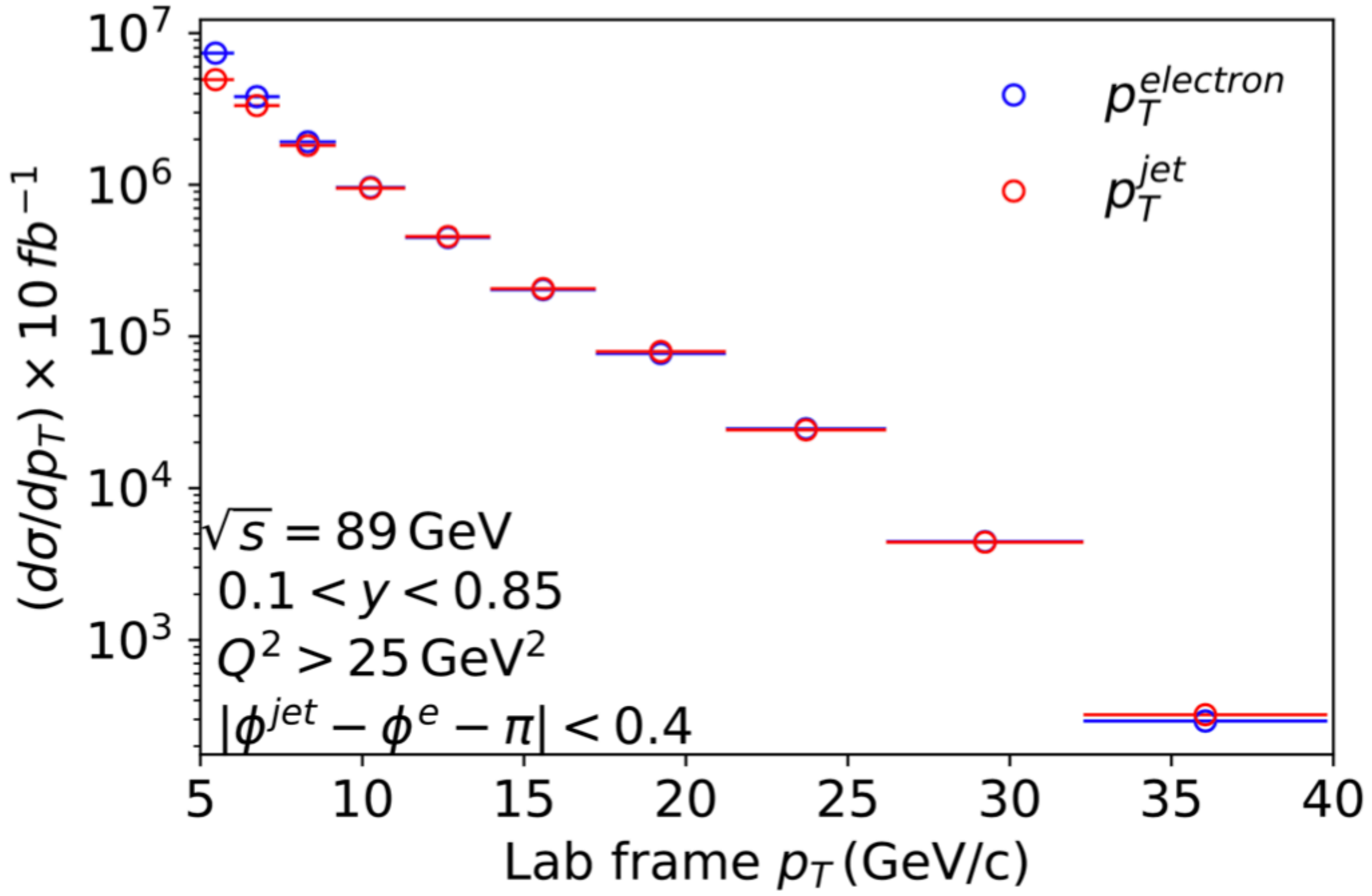


Nature of jets at the EIC

Particle #

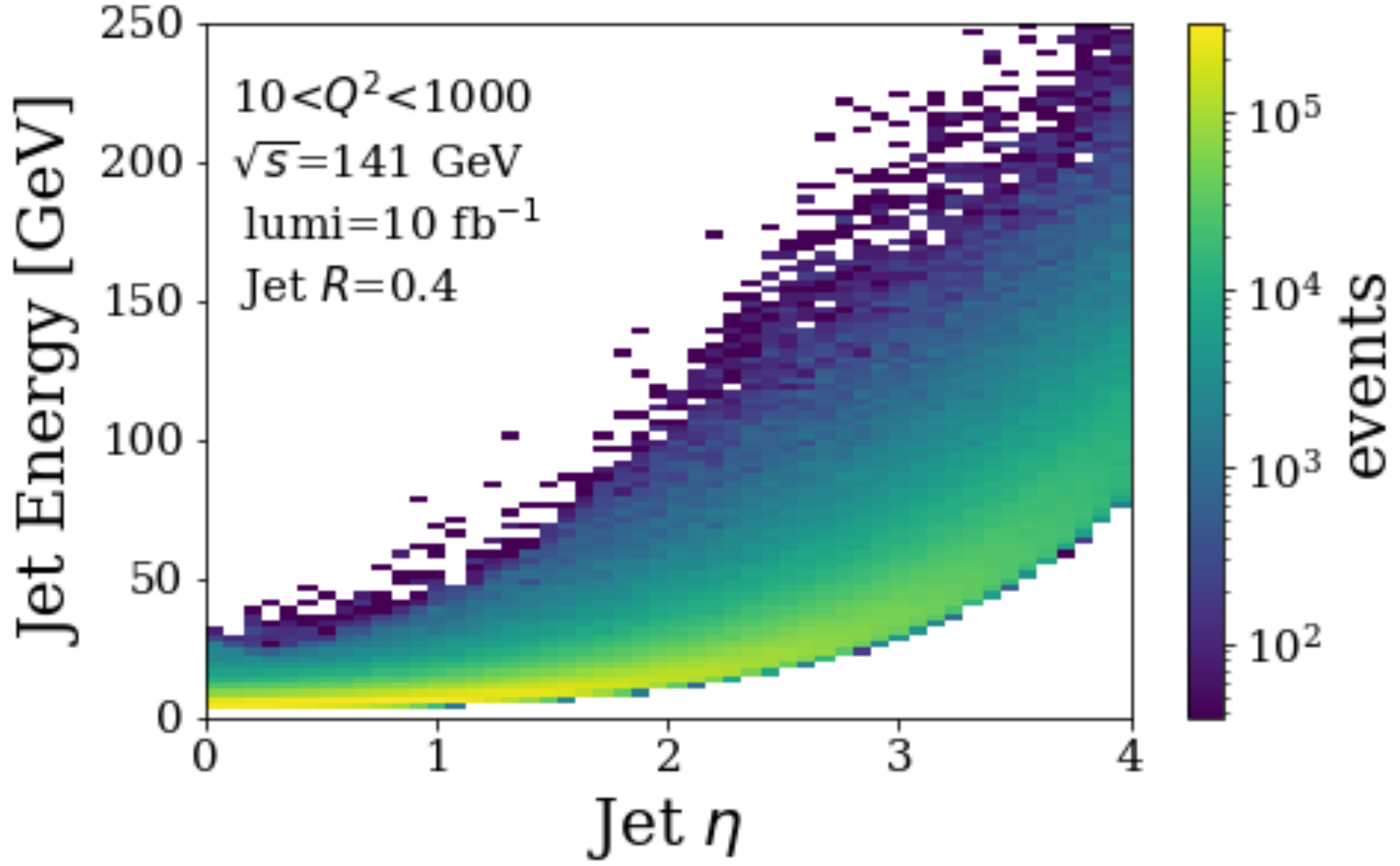


Transverse momentum



Jet energy

Arratia



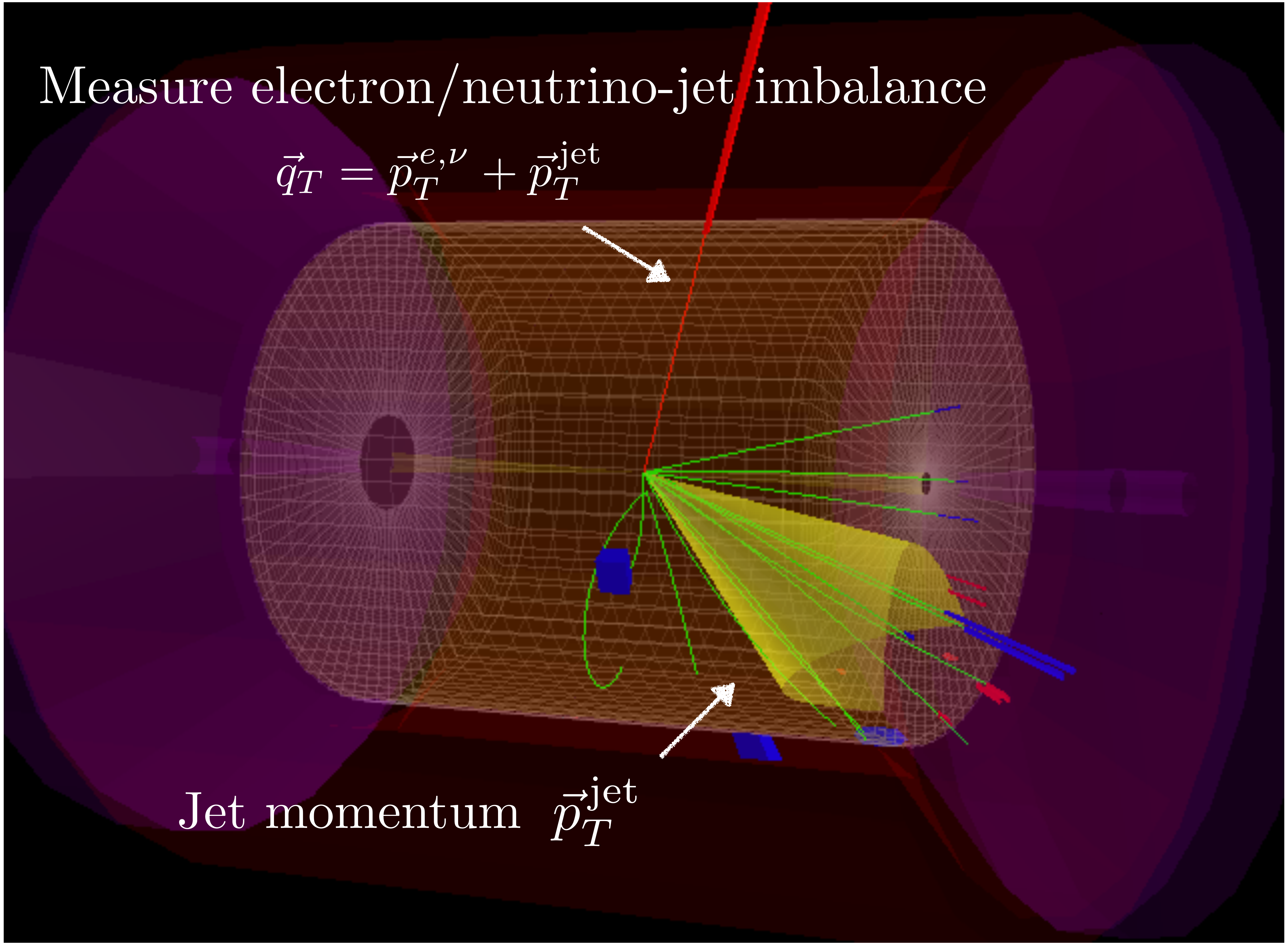
Hard scale p_T

and/or Q^2

Arratia, Jacak, FR, Song `19

see also Aschenauer et al.

Laboratory frame



Electron-jet correlations

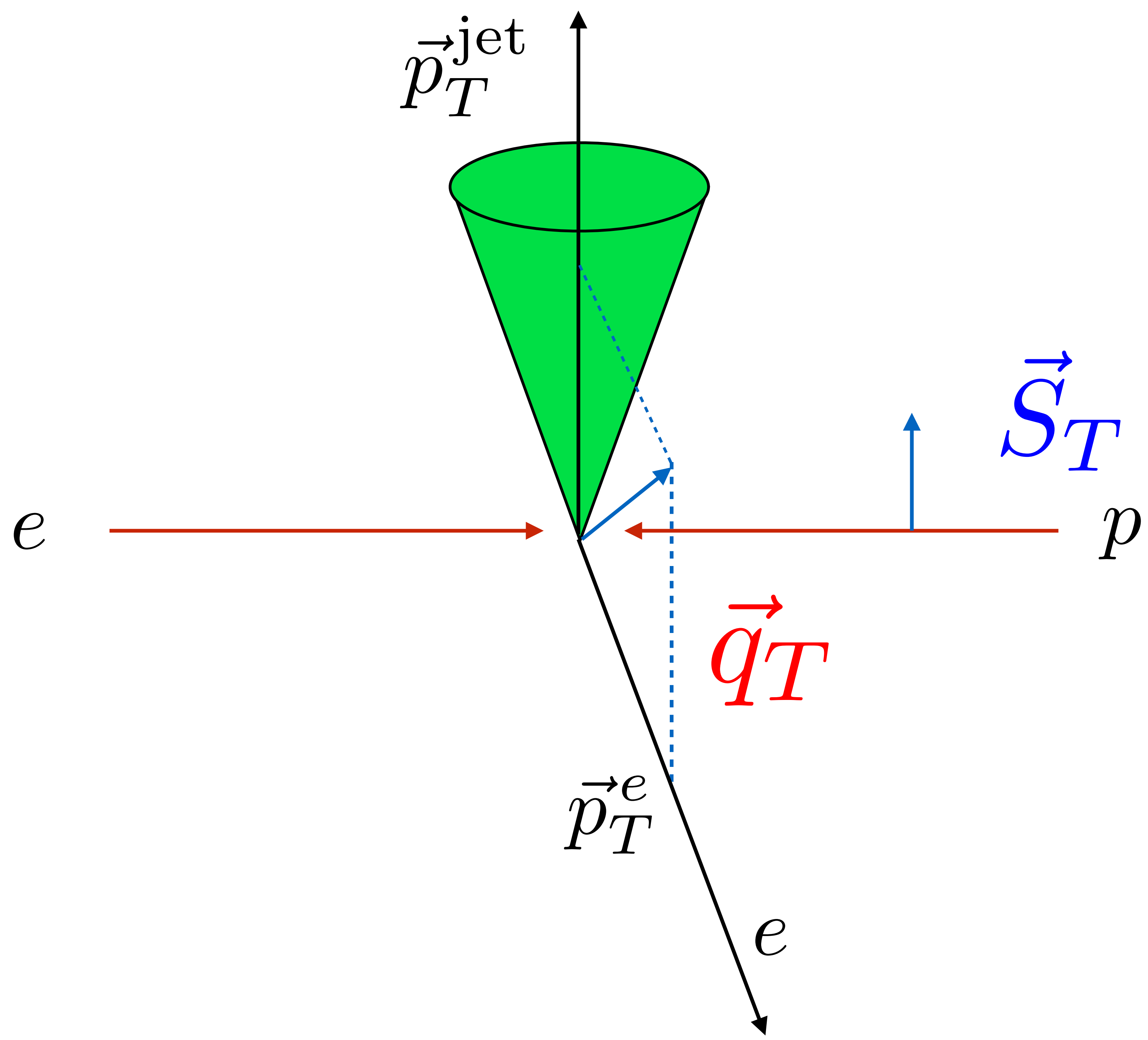
Liu, FR, Vogelsang, Yuan `18, `20

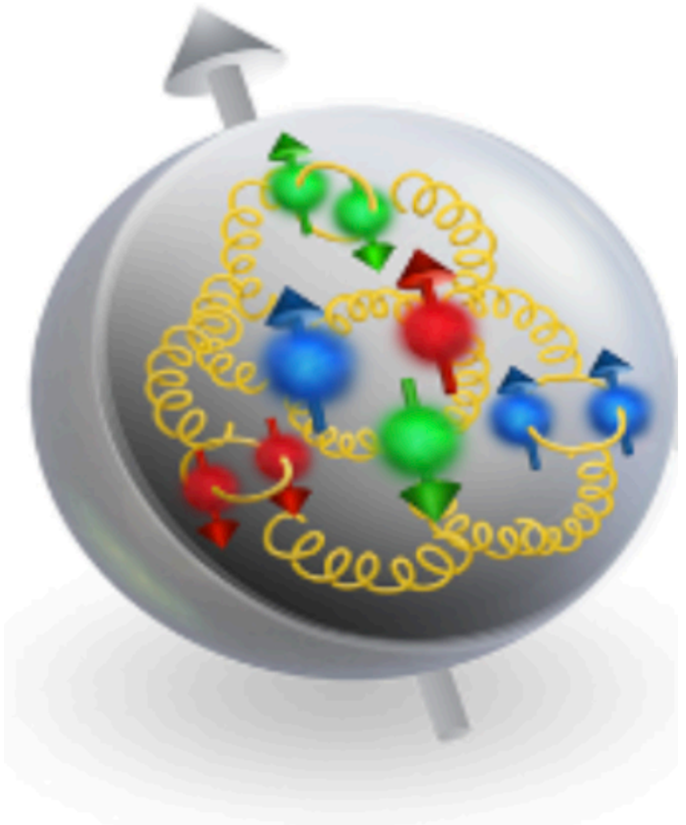
- Electron-jet imbalance at the EIC

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

- Sensitivity to TMD PDFs but no TMD FF
- 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

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

- Sensitivity to TMD PDFs but no TMD FF

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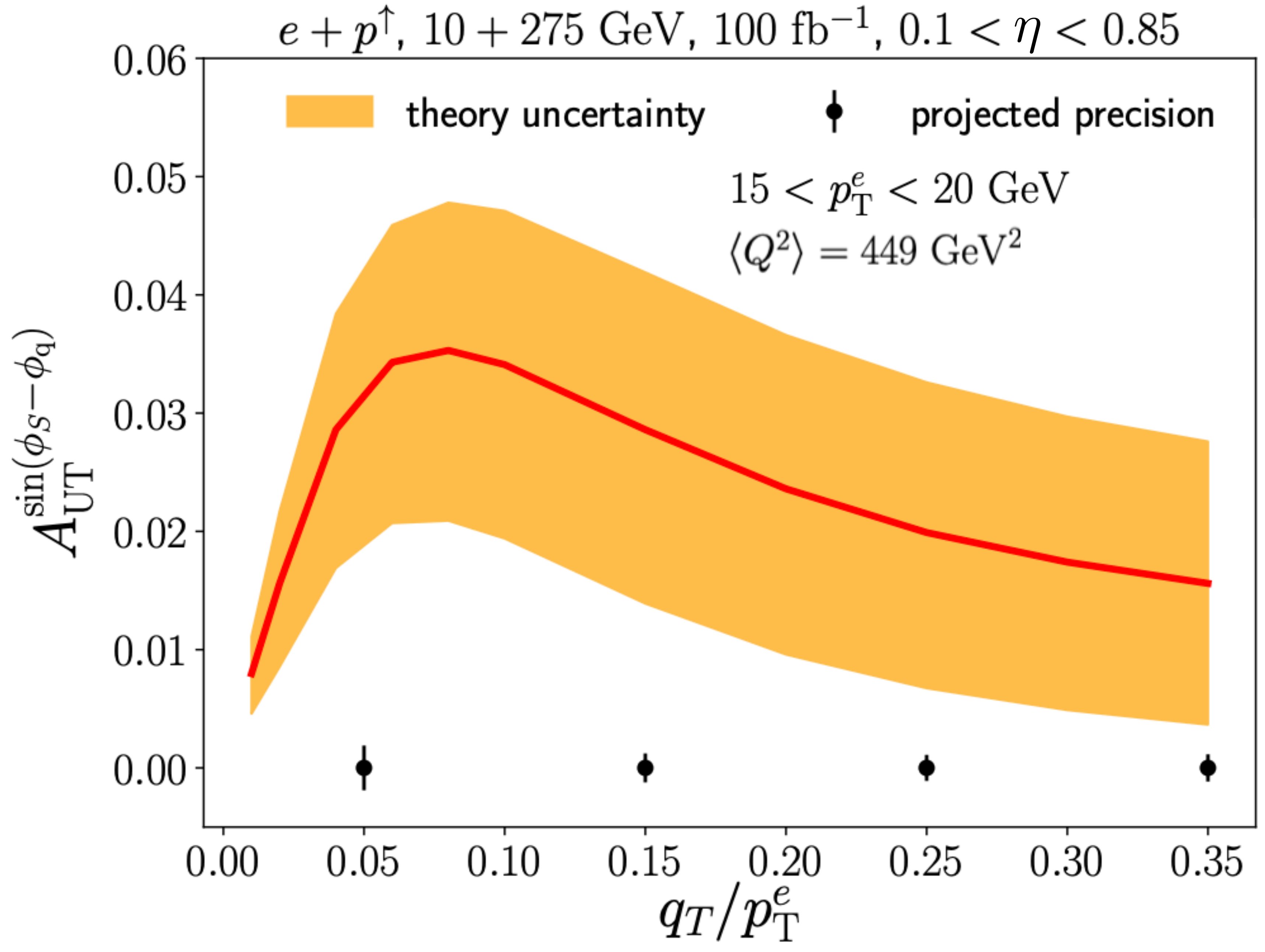


Liu, FR, Vogelsang, Yuan `18, `20
Arratia, Kang, Prokudin, FR`20
H1, PRL 128 (2022) 13, 132002

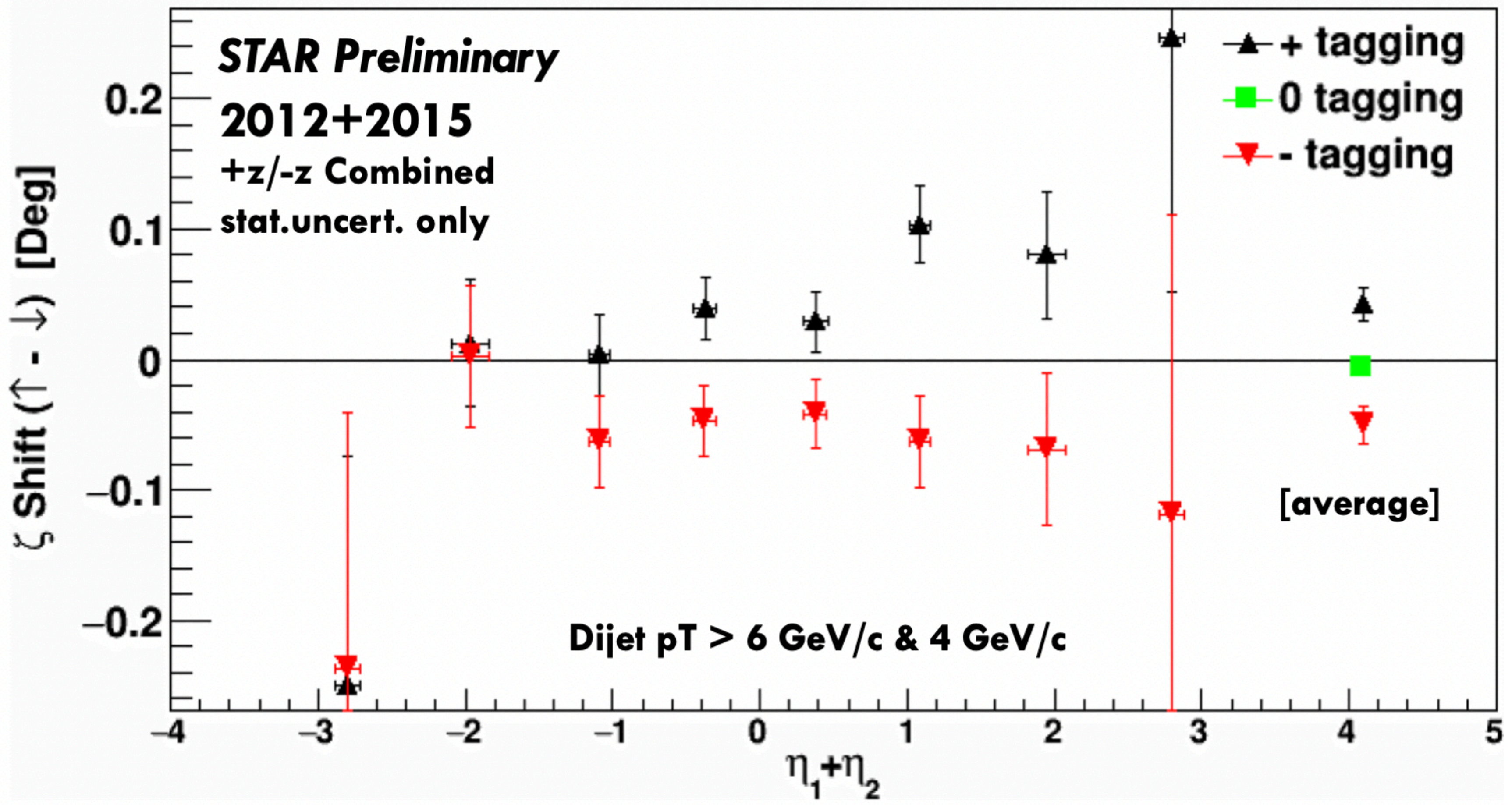
Jets & spin asymmetries

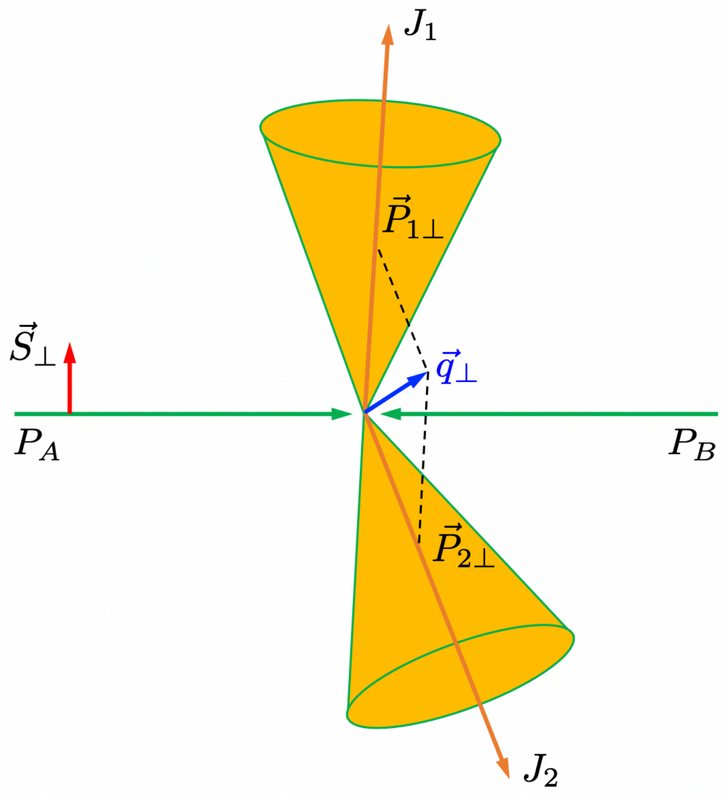
- E.g. Sivers asymmetries can be small due to large flavor cancellations

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

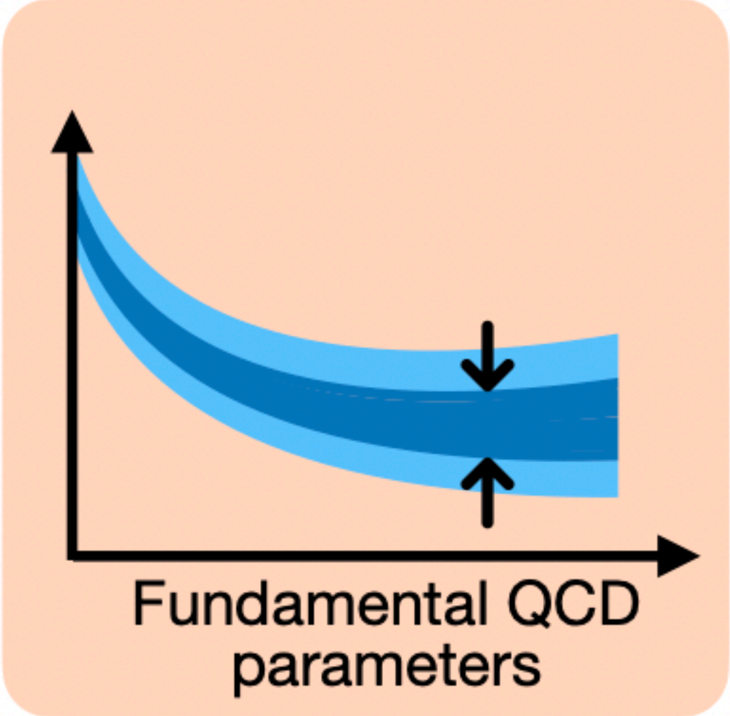
Burkardt sum rule *`04*

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



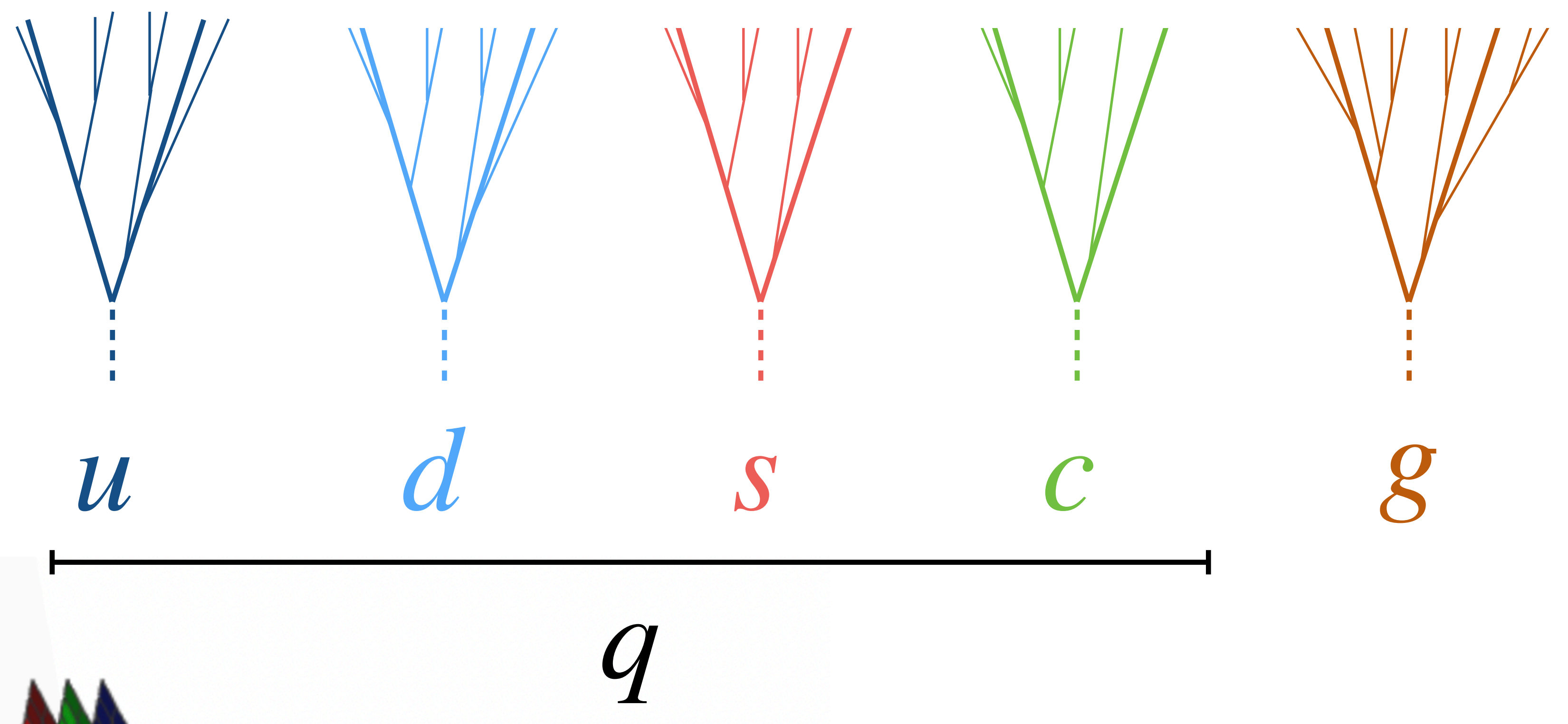


Can we obtain better constraints with ML-based jet classification?



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)



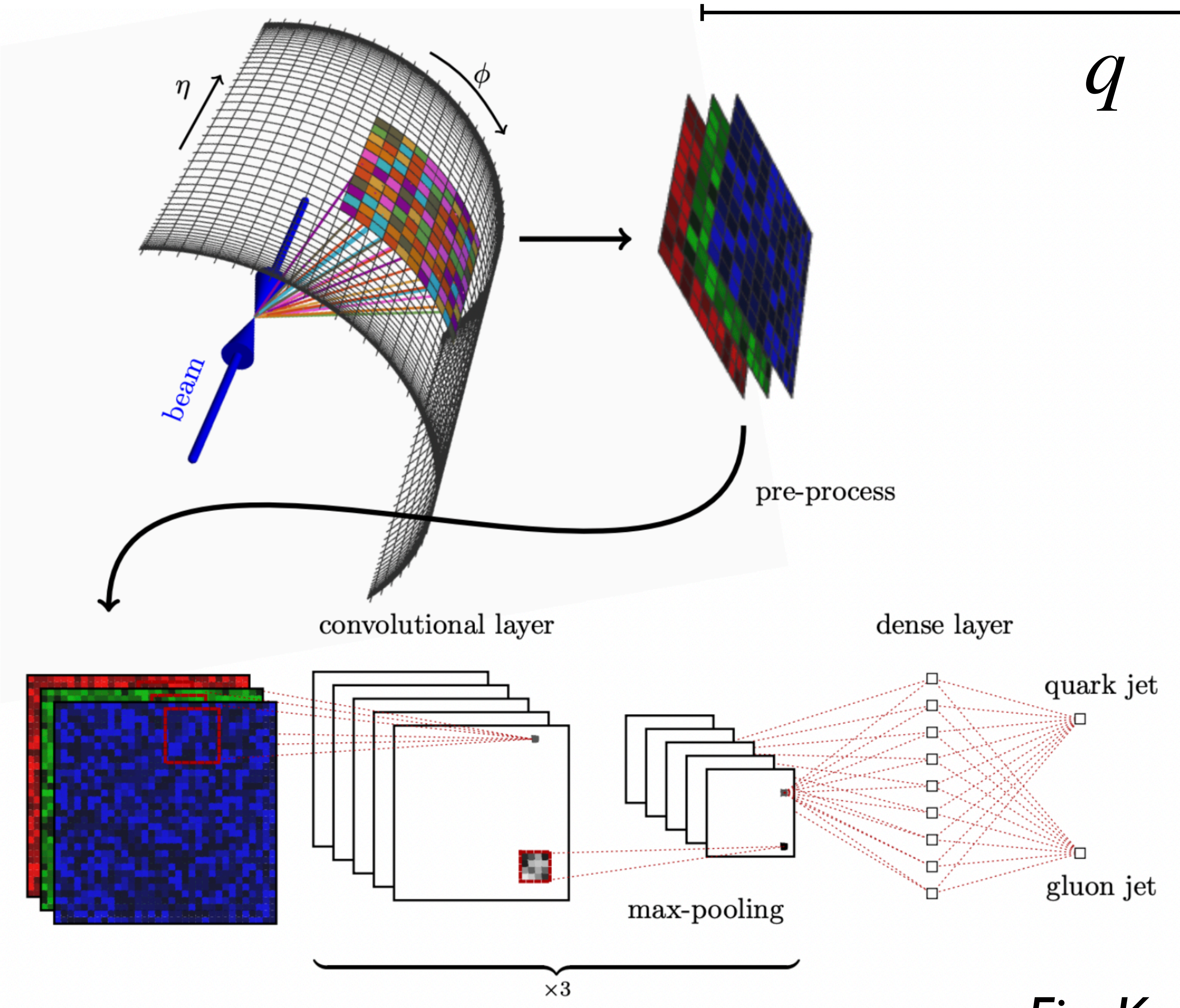
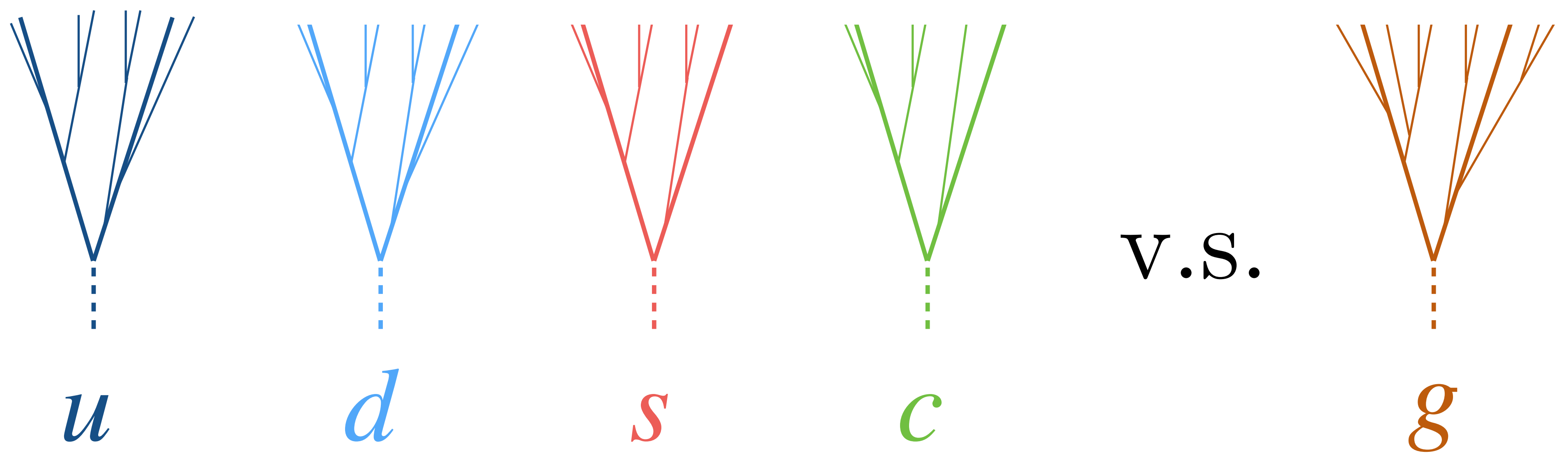
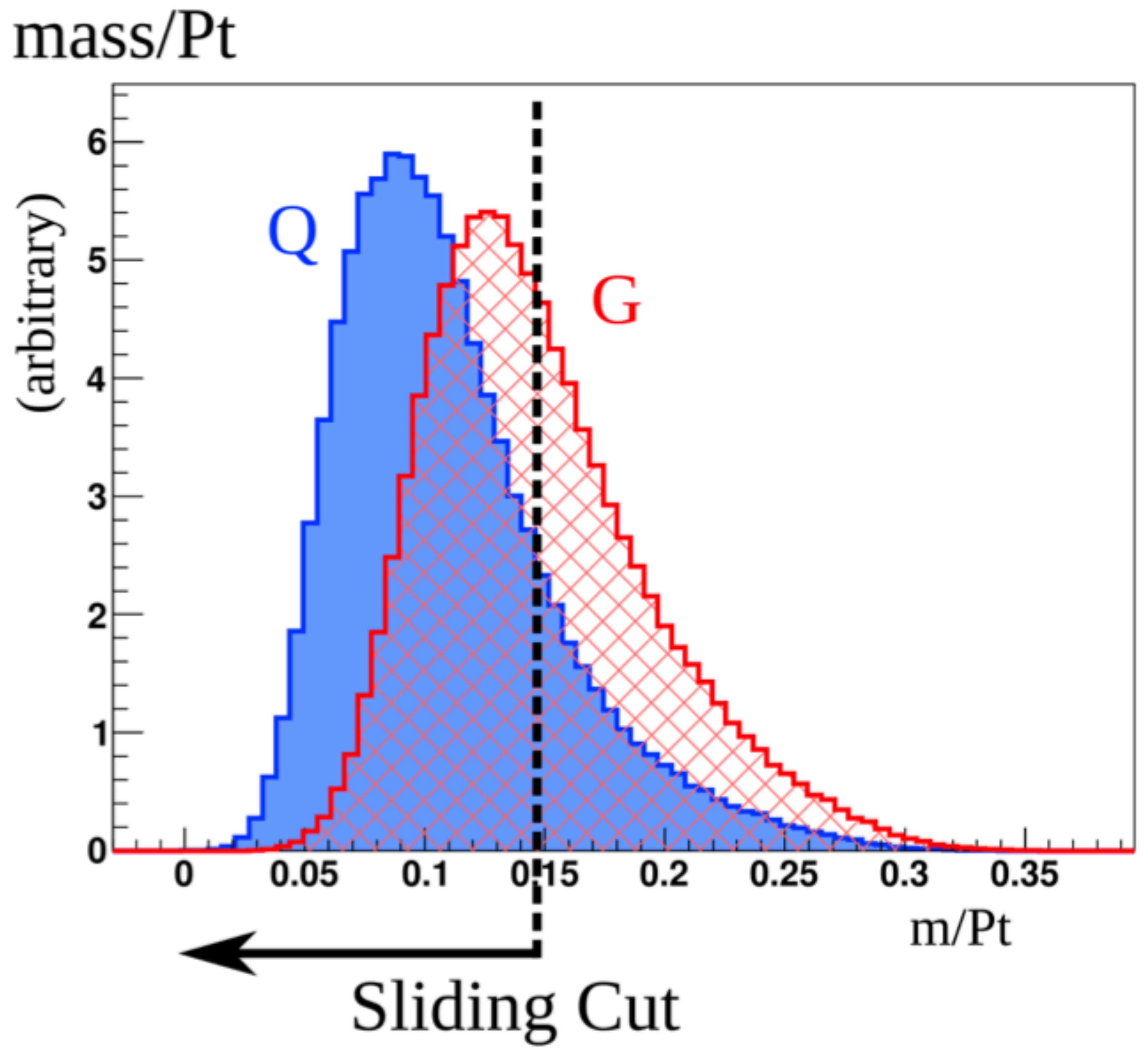


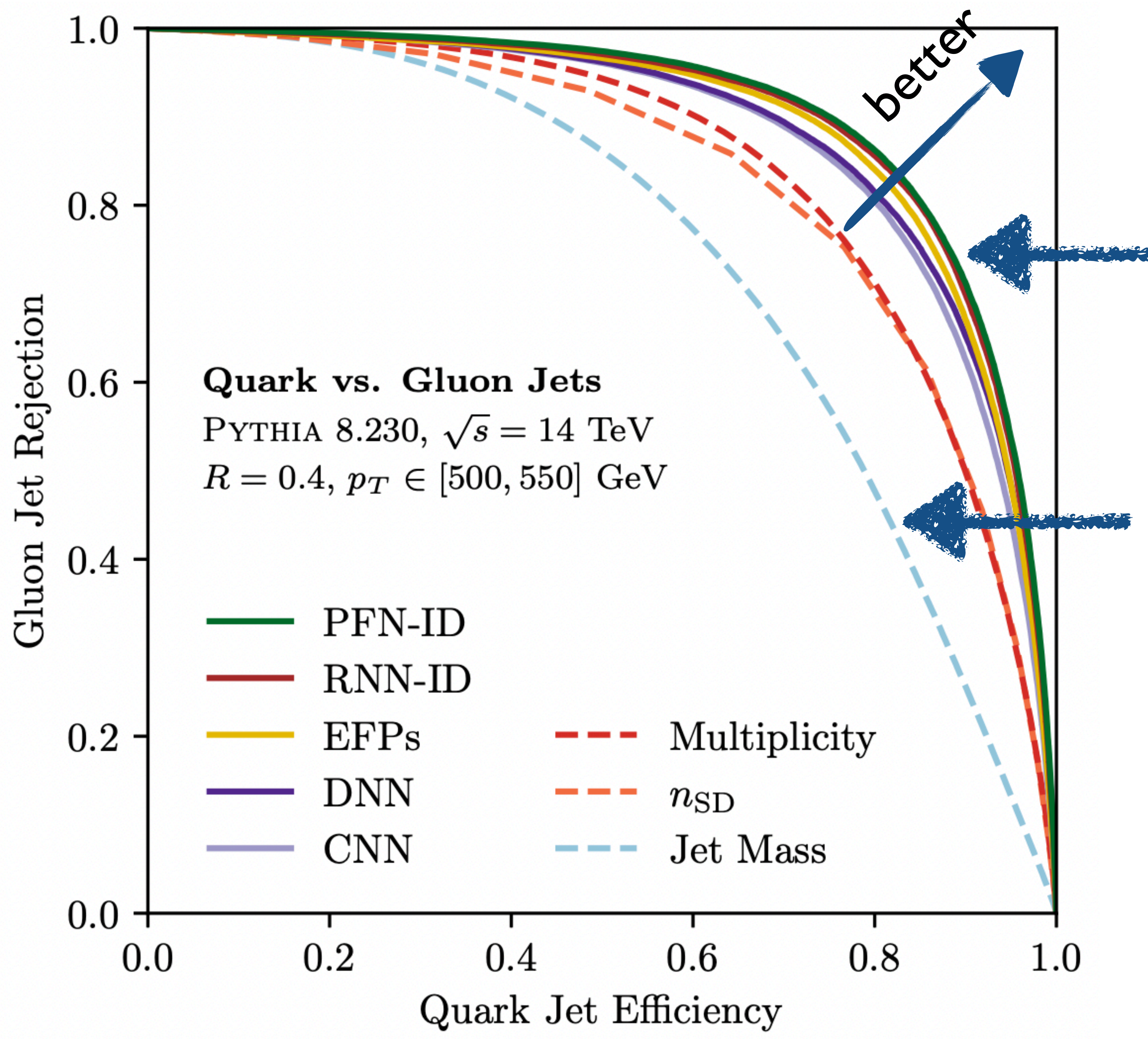
Fig. Komiske, Metodiev, Schwartz

Jet physics & Machine learning

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







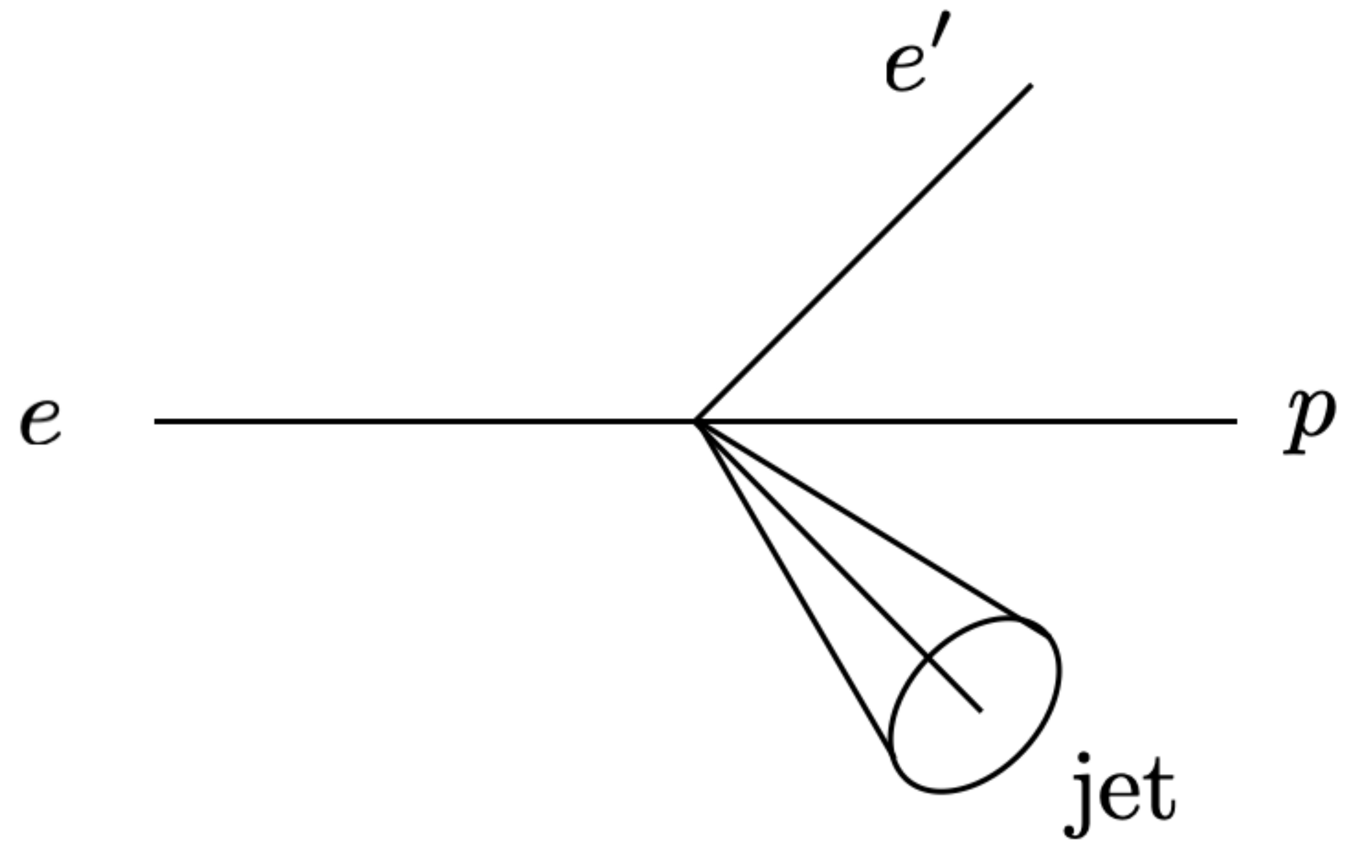
Gallicchio, Schwartz
Komiske, Metodiev, Thaler `19

Data sets using Pythia

Lee, Mulligan, Ploskon, FR, Yuan `22

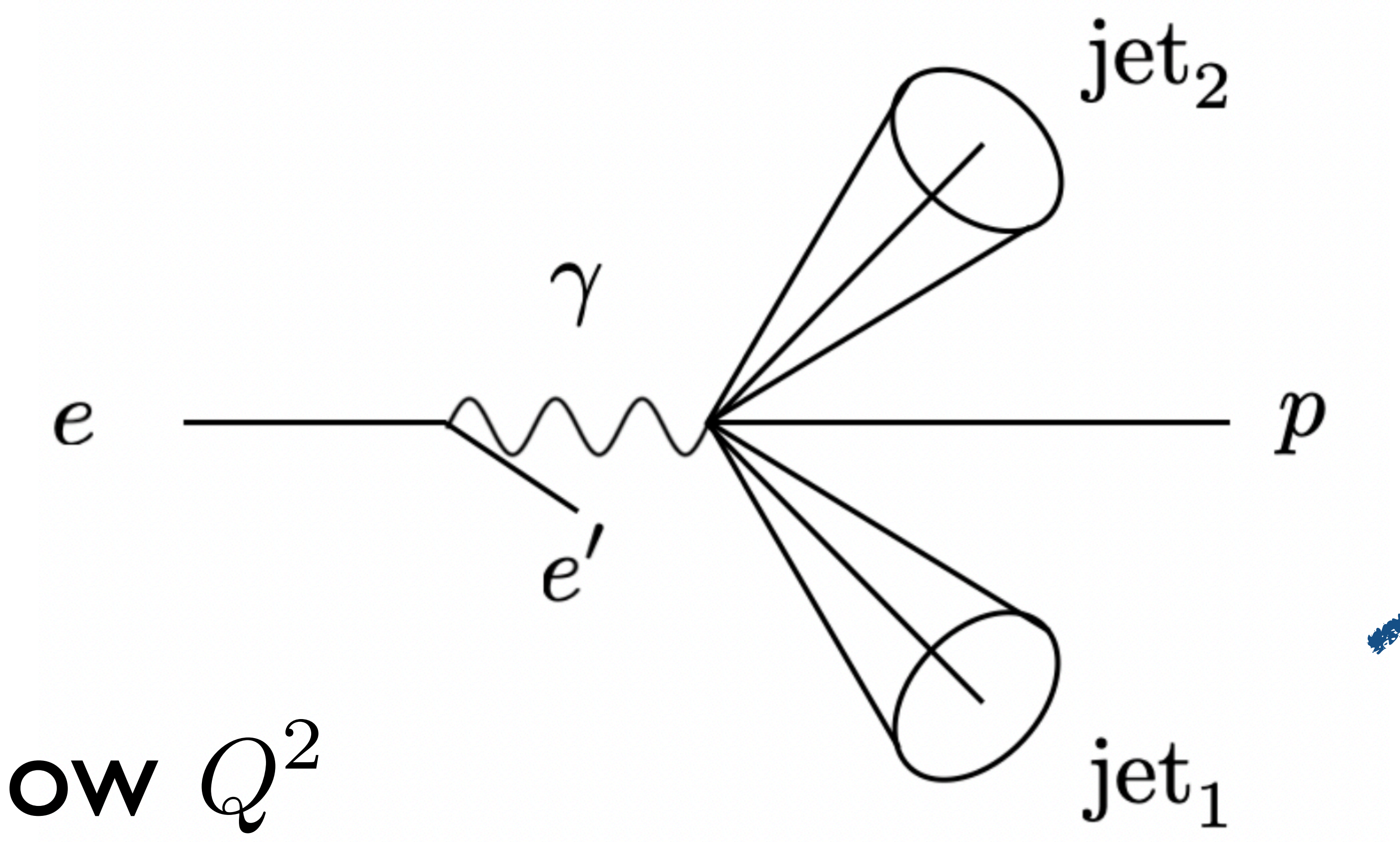
- Relatively low particle multiplicities at the EIC

- Pythia 6
  - No detector simulation
  - Laboratory frame jets
  - Particle $(p_{Ti}, \eta_i, \phi_i, \mathrm{PID}_i)$



$Q^2 > 25\ \mathrm{GeV}^2,$
$p_T > 10\ \mathrm{GeV}$

ud, s jet classification



Photoproduction, low Q^2

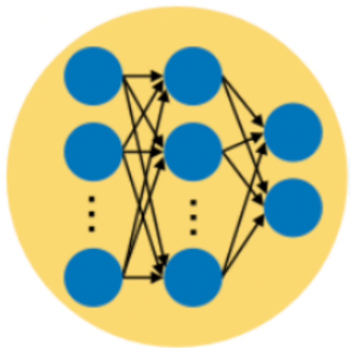
q, g jet classification

Machine learning architecture

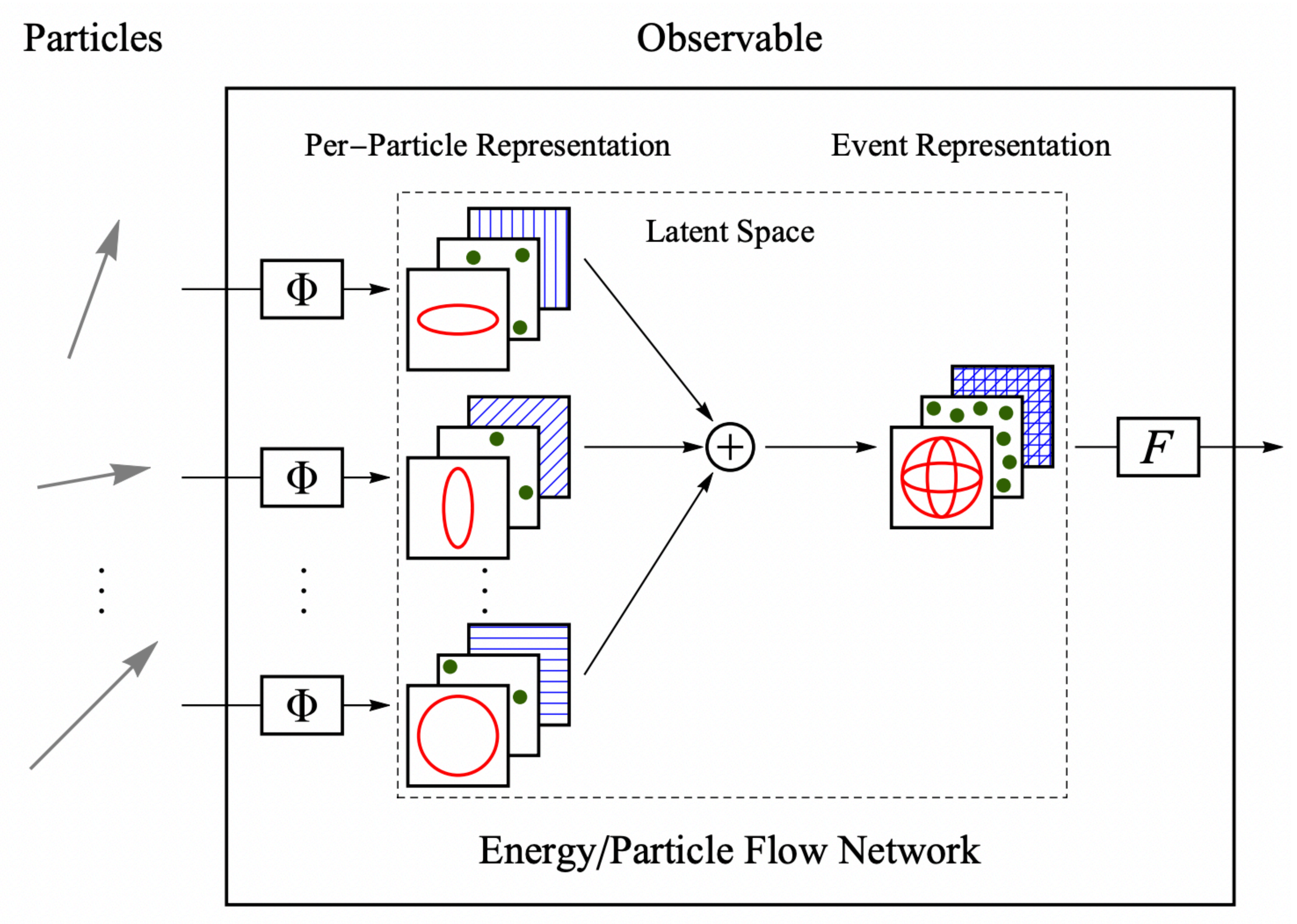
- Binary classification: u vs. d, ud vs. s, …
- Deep sets or Particle Flow Networks

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

Classifier



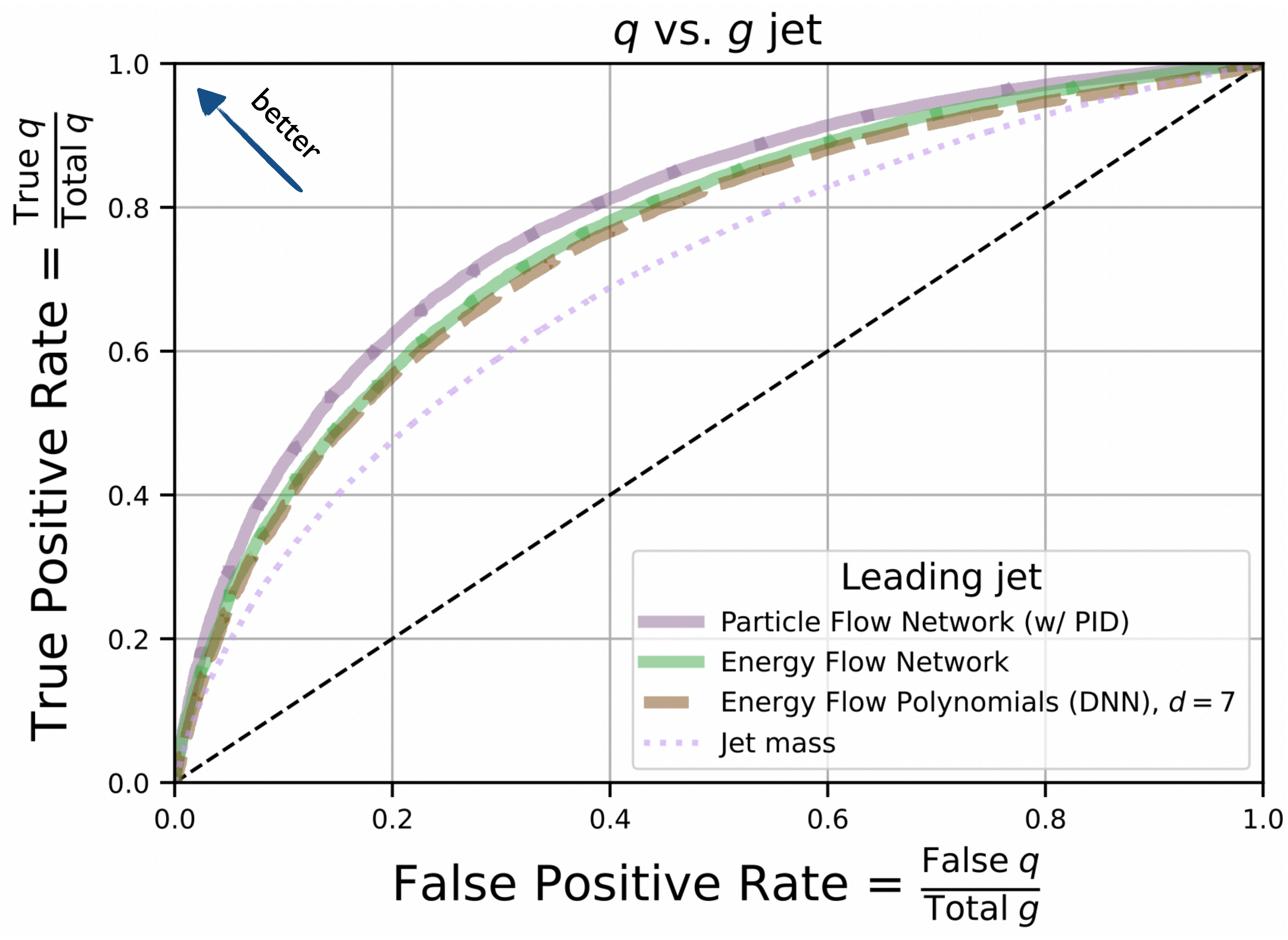
Neural networks



Komiske, Metodiev, Thaler JHEP 01 (2019) 121
Permutation invariant Deep Sets
See also GNNs, transformers

Quark vs. gluon jet tagging

Lee, Mulligan, Ploskon, FR, Yuan `22



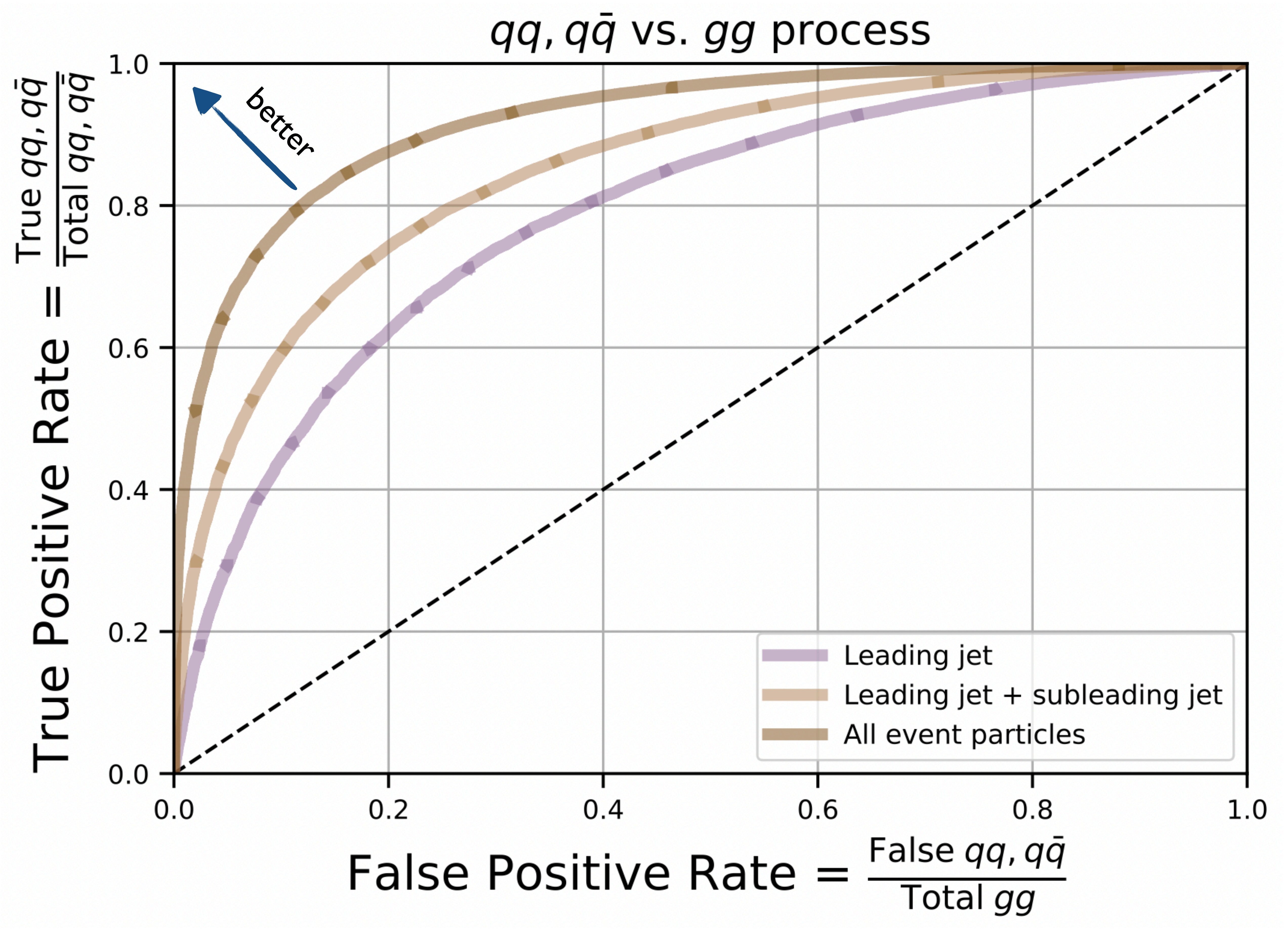
- Some improvement with ML
- Relatively few particles per jet, less information

Data & code available

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

Quark vs. gluon event tagging

Lee, Mulligan, Ploskon, FR, Yuan `22



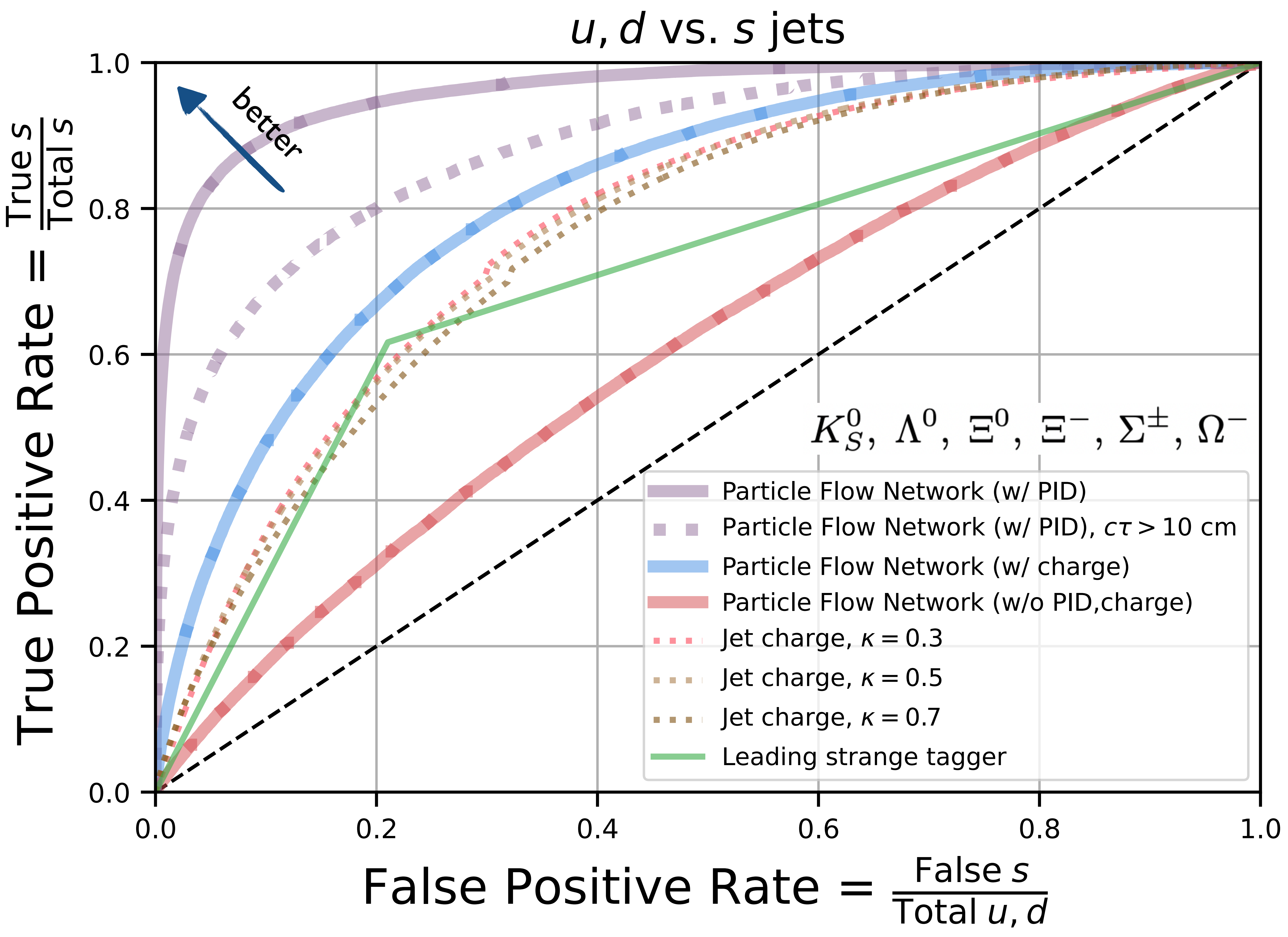
- ☐ Significant gain with ML!
- ☐ Use full event information
- ☐ Quantifies total information content
- ☐ Motivates further theory efforts

Data & code available

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

Strange jet tagging

Lee, Mulligan, Ploskon, FR, Yuan `22



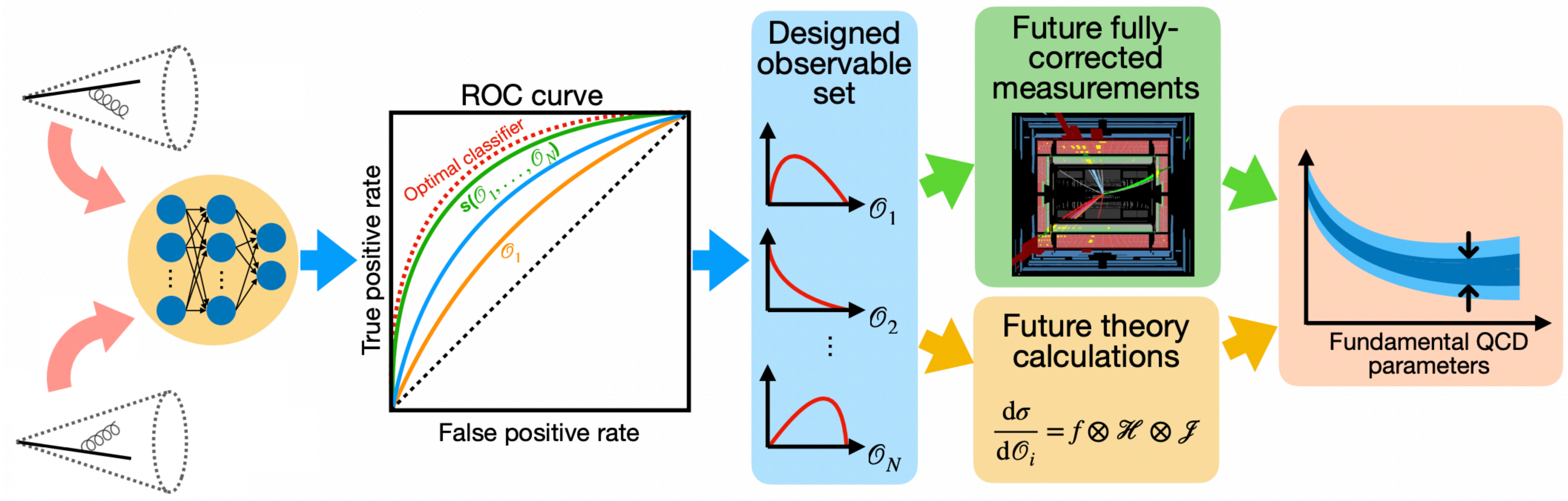
- Significant gain with ML!
- Soft particles, tracking & PID important
- Motivates further theory efforts
- Impact on EIC detector?

Data & code available

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

Information content of jets & events

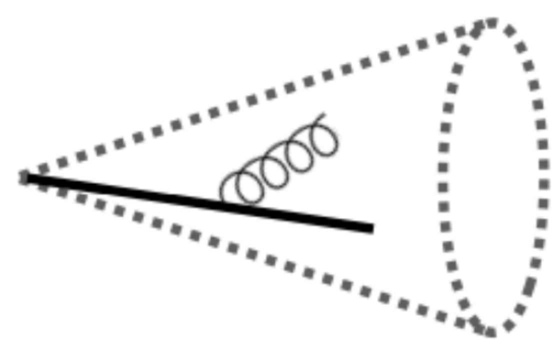
How can we make use of all this additional information?



Information content of jets & events

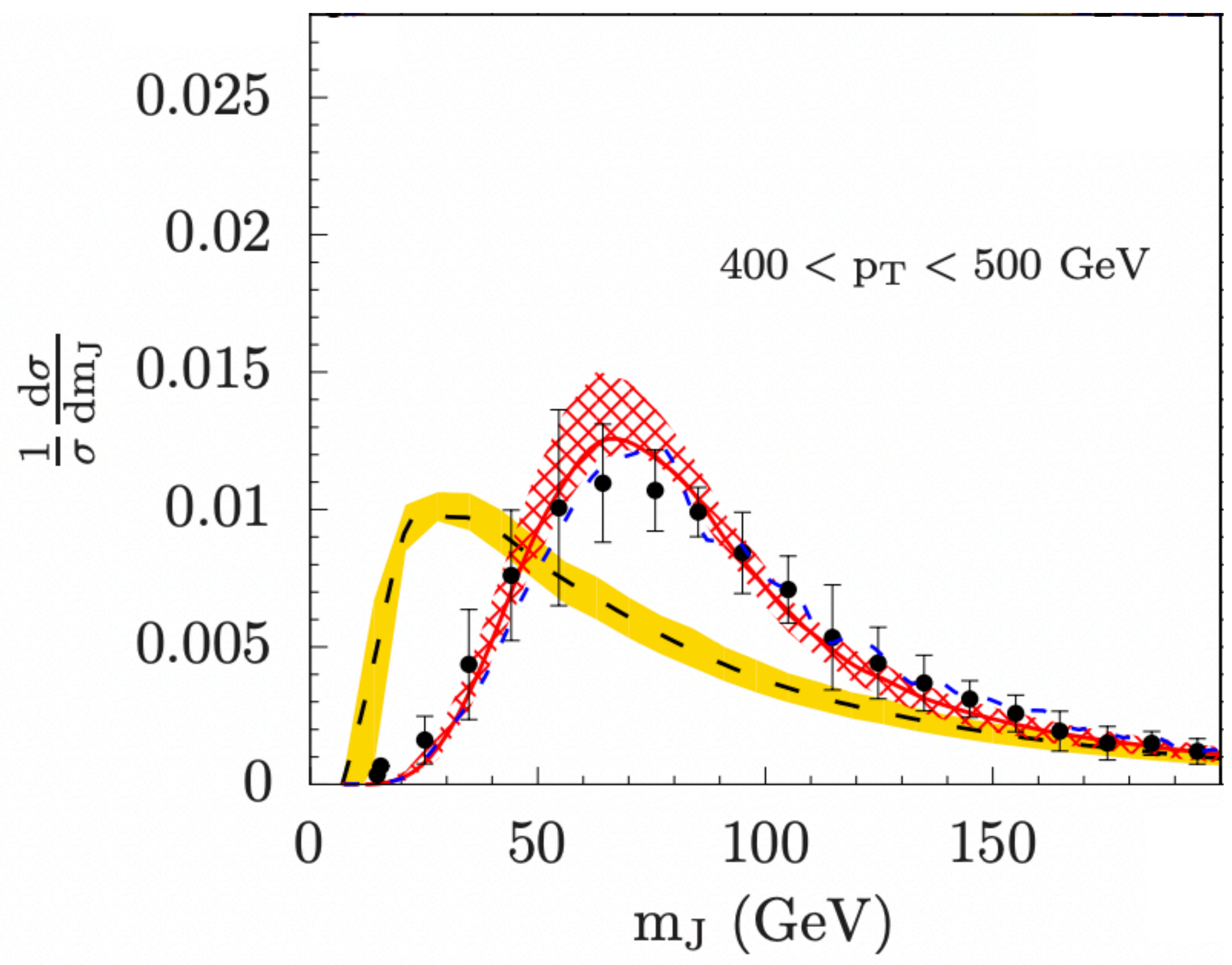
How can we make use of all this additional information?

- Need complete sets of observables
- Observables at the level of events vs. ensemble



Measure m_J per jet

Histogram event samples

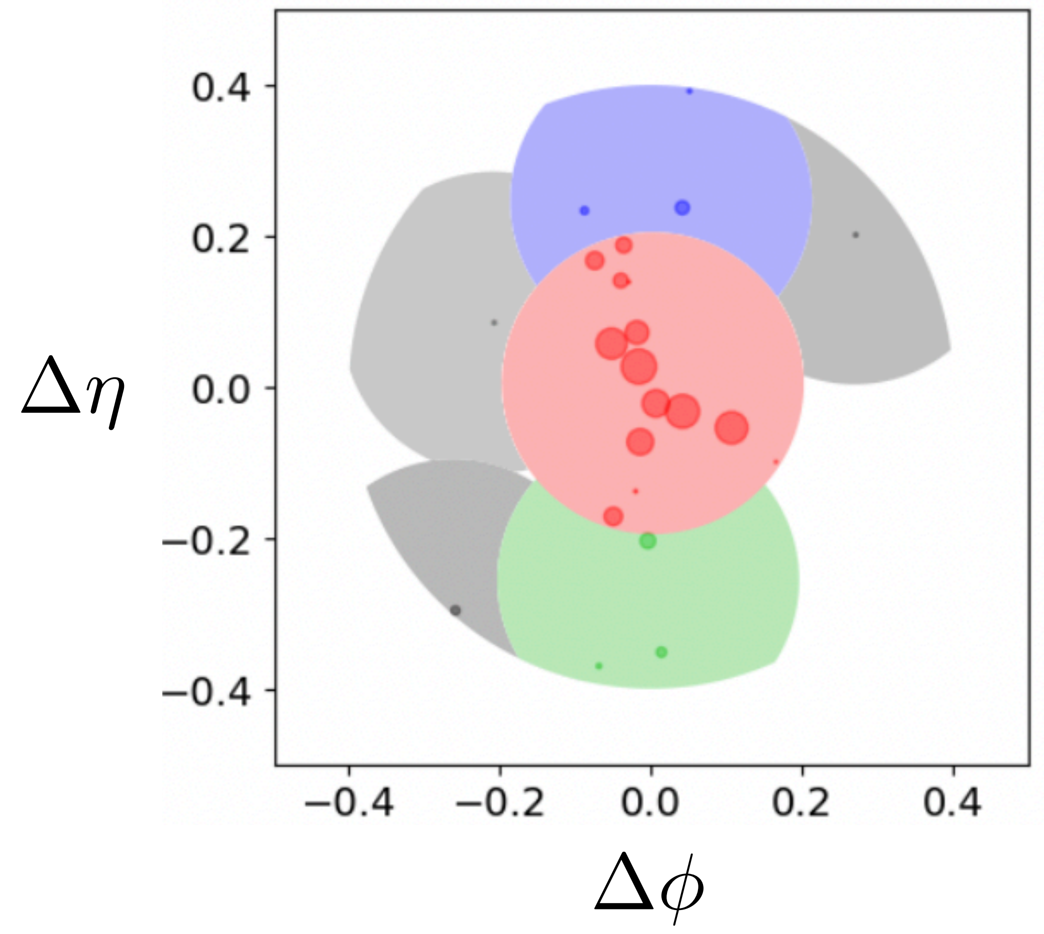


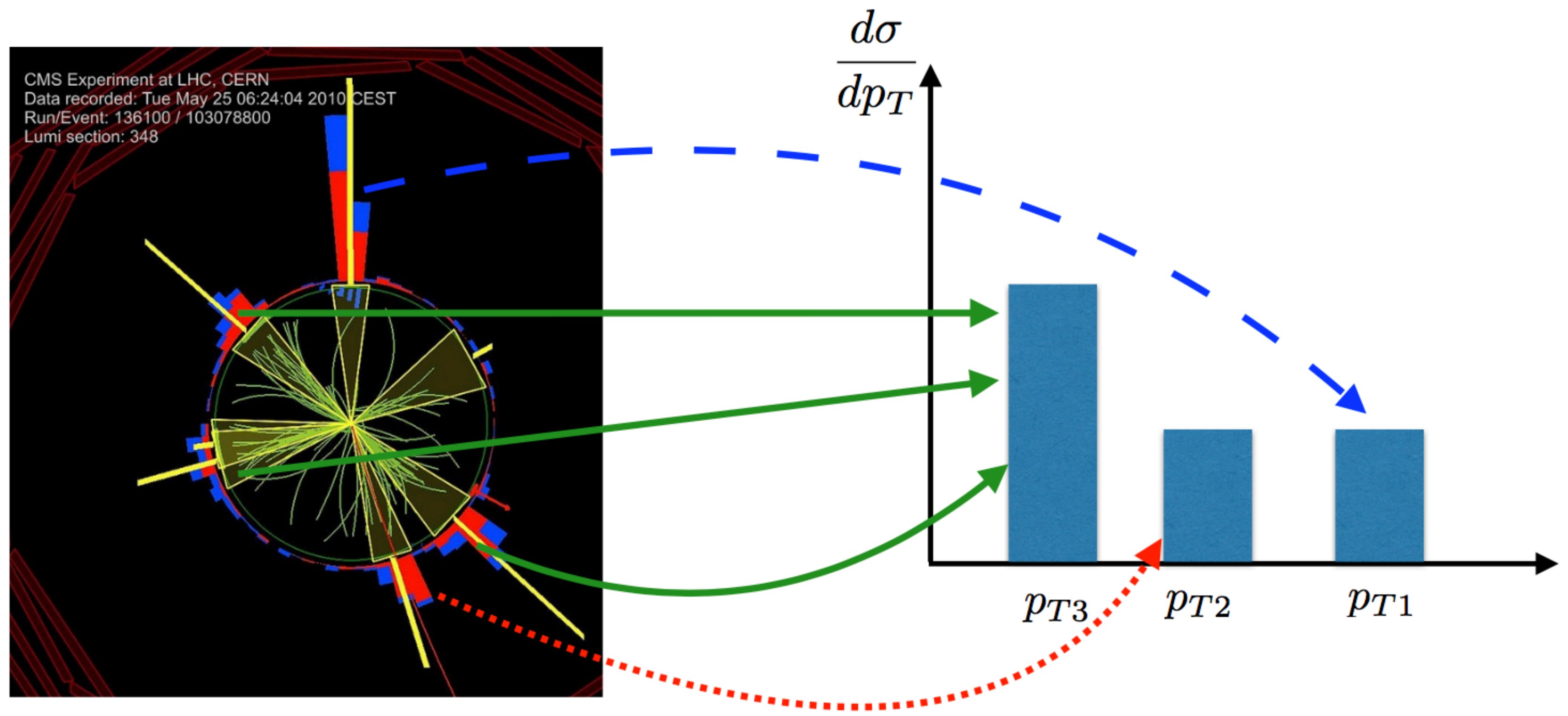
Compare to QCD calculation

Information content of jets & events

How can we make use of all this additional information?

- Need complete sets of observables
- Observables at the level of events vs. ensemble
  - <u>Event only</u>: Position information (η_i, ϕ_i)
  - <u>Ensemble only</u>: Inclusive jets and correlators





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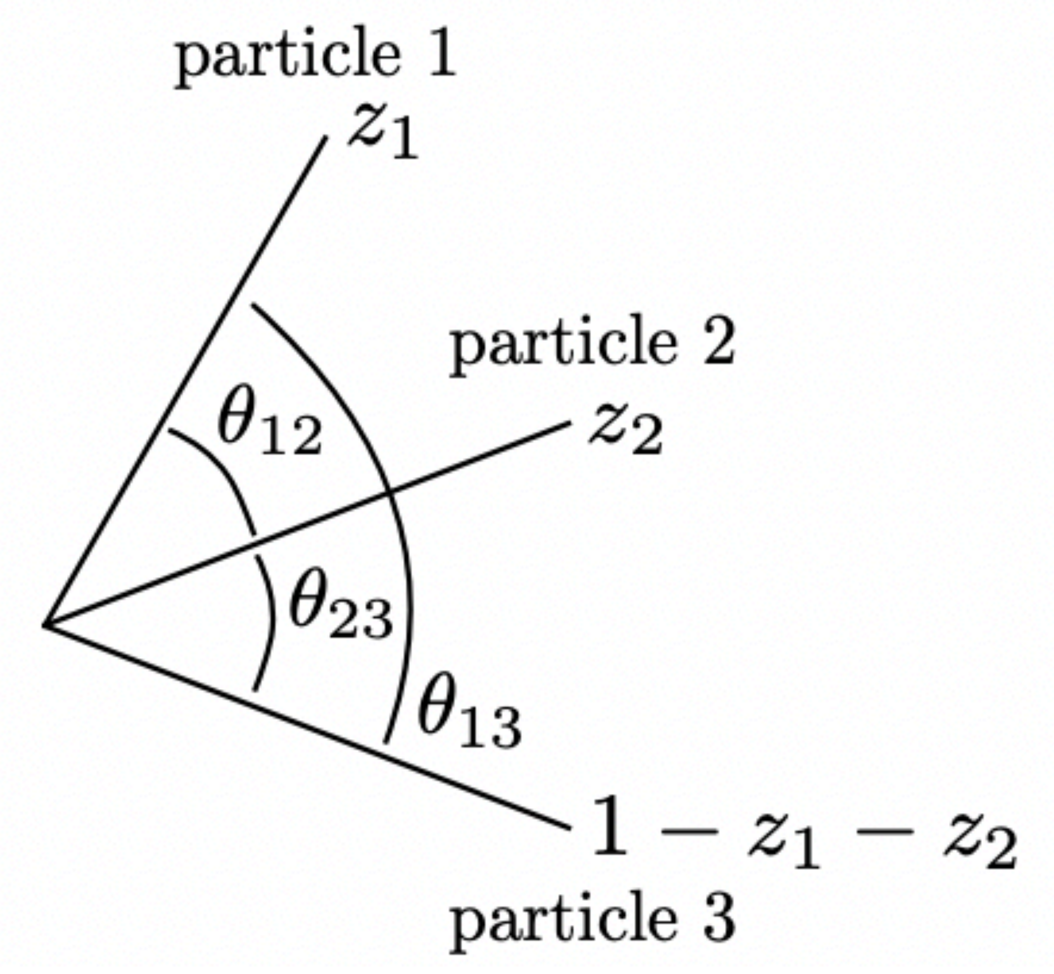


- Need complete set of observables
- N-jettiness basis & Energy Flow Polynomials

Datta, Larkoski `17* *Metodiev, Komiske, Thaler `18

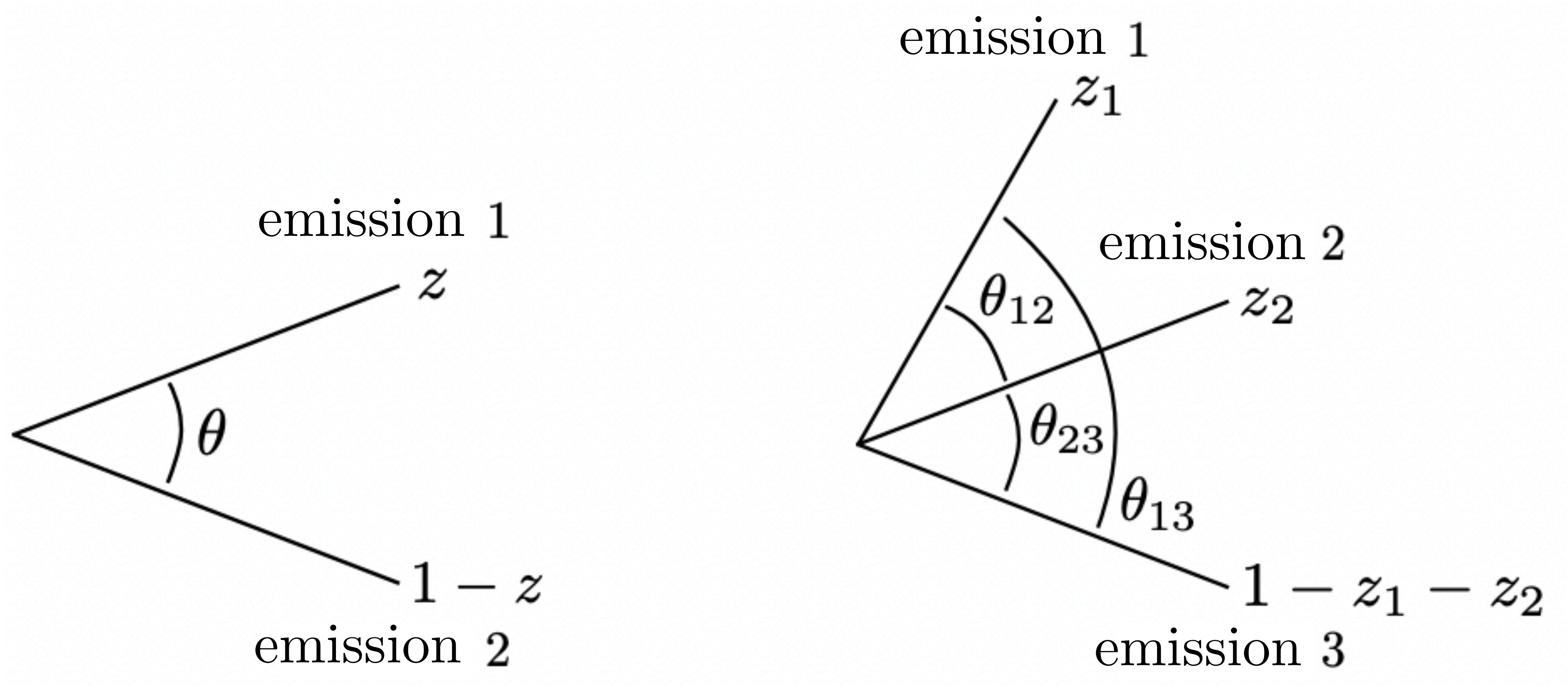
Both are IRC safe & defined at the event and ensemble level

→ Can use AI to identify the most useful observables!

Information content of jets & events

- N-jettiness basis *Datta, Larkoski `17*

Systematically map 3M-4 phase space variables to a set of observables e.g.



$$z(1-z) = \frac{\left(\tau_1^{(1)}\right)^2}{4\tau_1^{(2)}}, \qquad \theta = \frac{2\tau_1^{(2)}}{\tau_1^{(1)}}$$

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

$$\left\{\tau_1^{(0.5)}, \tau_1^{(1)}, \tau_1^{(2)}, \tau_2^{(0.5)}, \tau_2^{(1)}, \tau_2^{(2)}, \dots\right\} \longrightarrow$$

Use as input to a neural network for classification and feature selection

see e.g. *Lai, Mulligan, Ploskon, FR `21*

Information content of jets & events

- N-jettiness basis *Datta, Larkoski `17*

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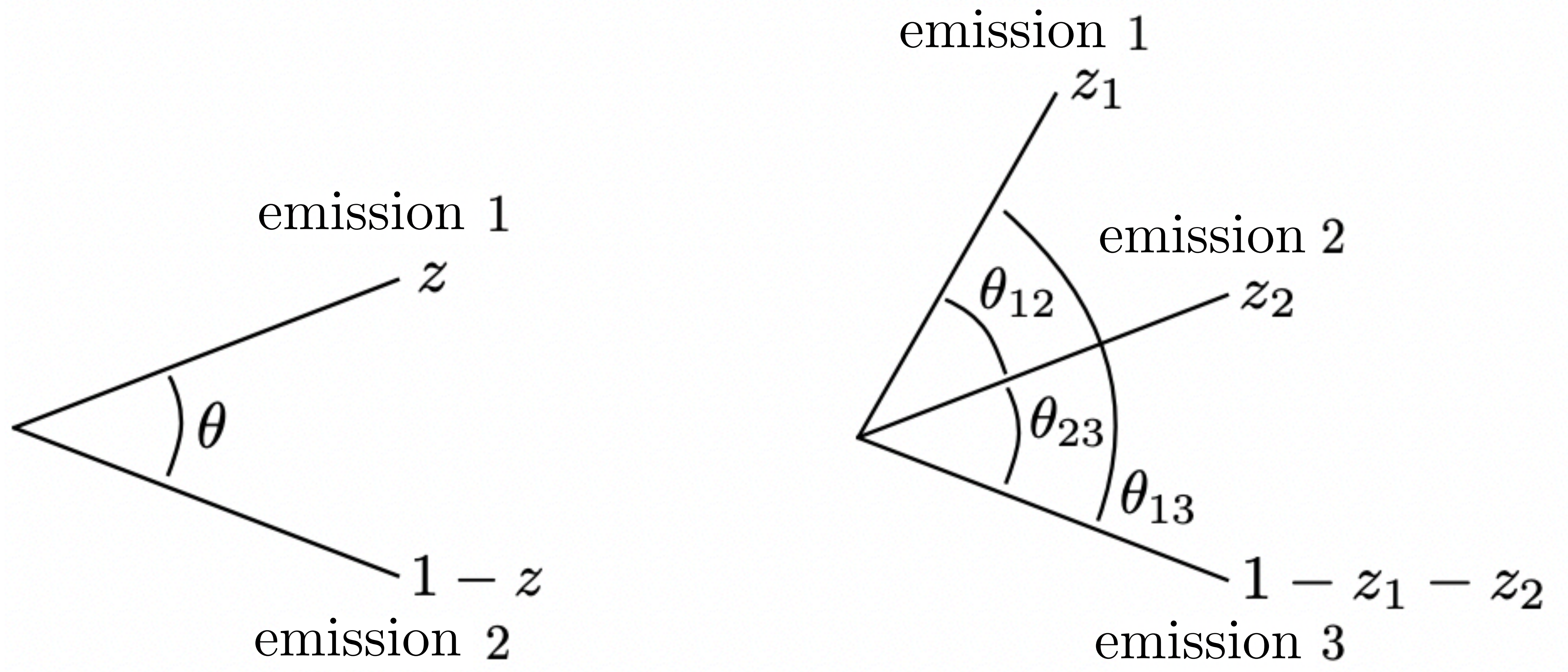

$$z(1-z) = \frac{\left(\tau_1^{(1)}\right)^2}{4\tau_1^{(2)}}\,, \qquad \theta = \frac{2\tau_1^{(2)}}{\tau_1^{(1)}}$$

Sudakov safe

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

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IRC safe

Use as input to a neural network for classification and feature selection

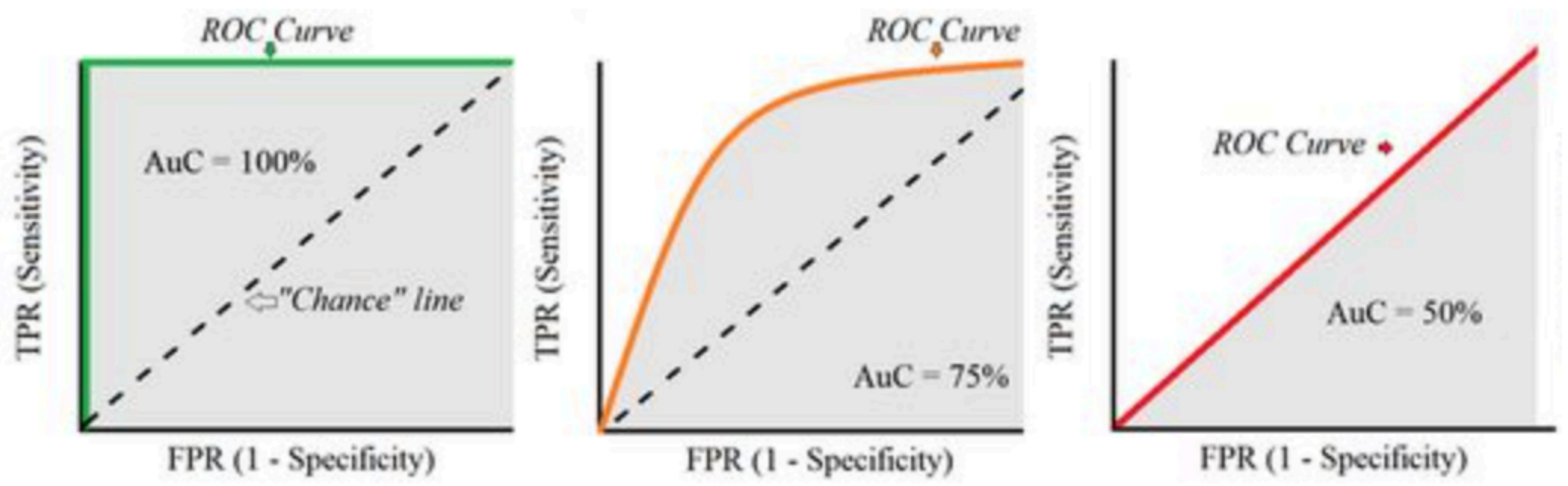
see e.g. *Lai, Mulligan, Ploskon, FR `21*

Information content of jets & events

- N-jettiness basis *Datta, Larkoski `17*

  … but there appears to be a performance gap *e.g. Metodiev, Komiske, Thaler `18*

  Quantify using the area under the ROC curve



Model	AUC
PFN-ID	**0.9052** $\pm$ 0.0007
PFN-Ex	0.9005 $\pm$ 0.0003
PFN-Ch	0.8924 $\pm$ 0.0001
PFN	0.8911 $\pm$ 0.0008
EFN	0.8824 $\pm$ 0.0005
RNN-ID	0.9010
RNN	0.8899
EFP	0.8919
DNN	0.8849
CNN	0.8781
M	0.8401
n_{SD}	0.8297
m	0.7401

IRC unsafe classifier

⋮

N-jettiness observables

Information content of jets & events

- N-jettiness basis *Datta, Larkoski `17*

… but there appears to be a performance gap *e.g. Metodiev, Komiske, Thaler `18*

The gap could be due to…

- IRC safety?
- the type of input?
- the network architecture?

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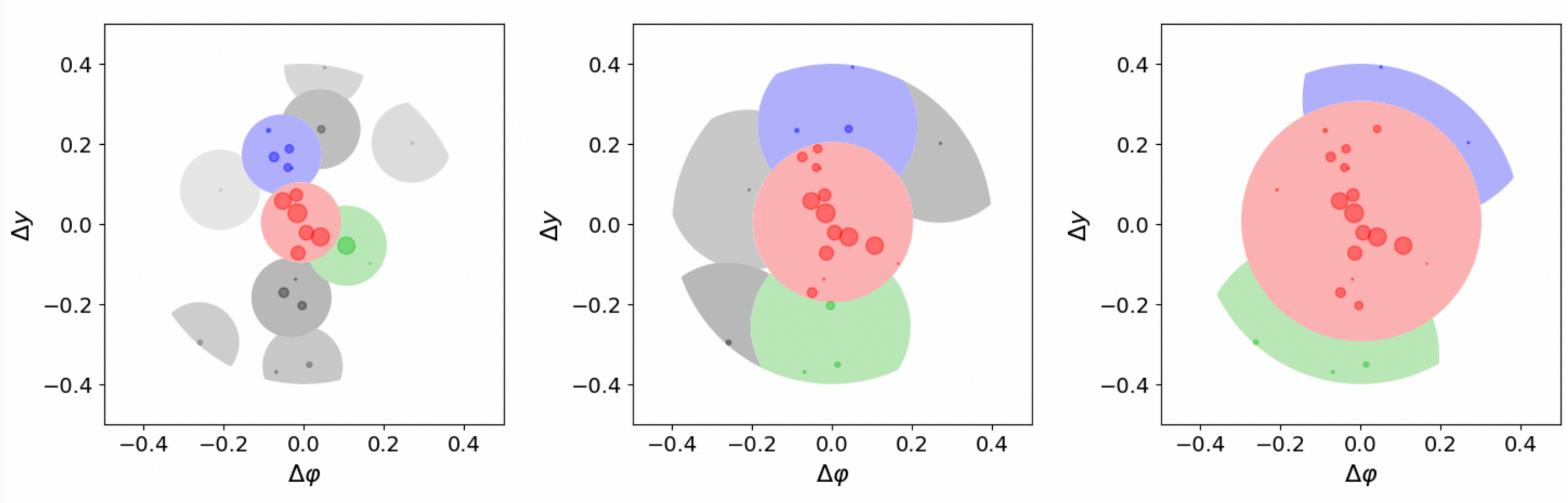
⋮

N-jettiness observables

Is IRC-safe information all you need for jet classification?

Athanasakos, Larkoski, Mulligan, Ploskon, FR `23

- Use the same ML algorithm as the best classifier
- … but cluster jet constituents into subjets first

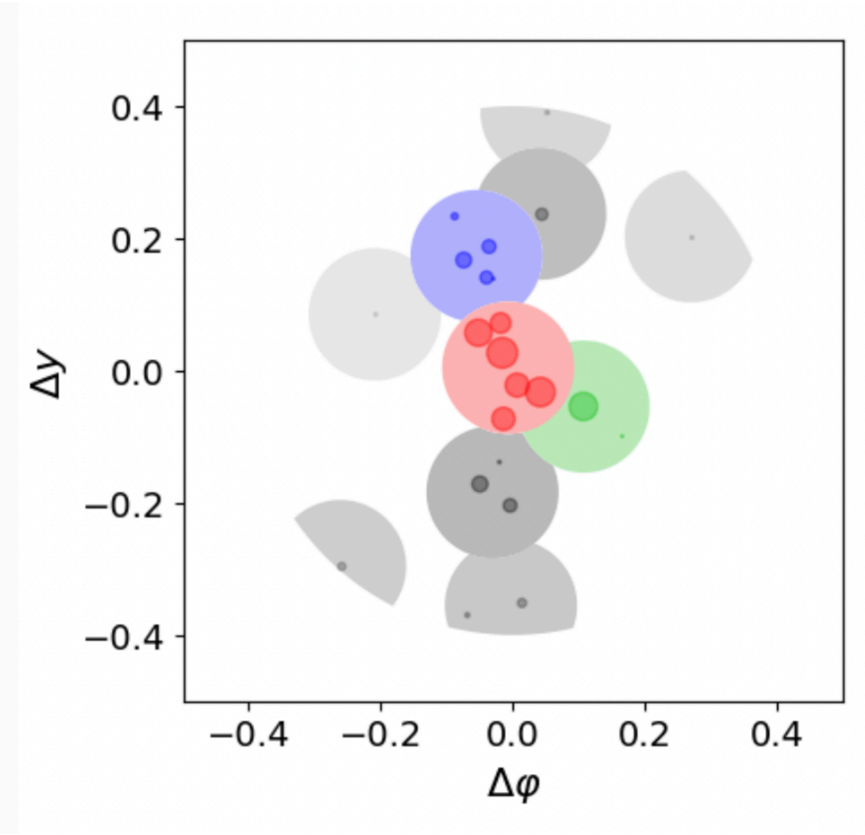


Decrease subjet radius r

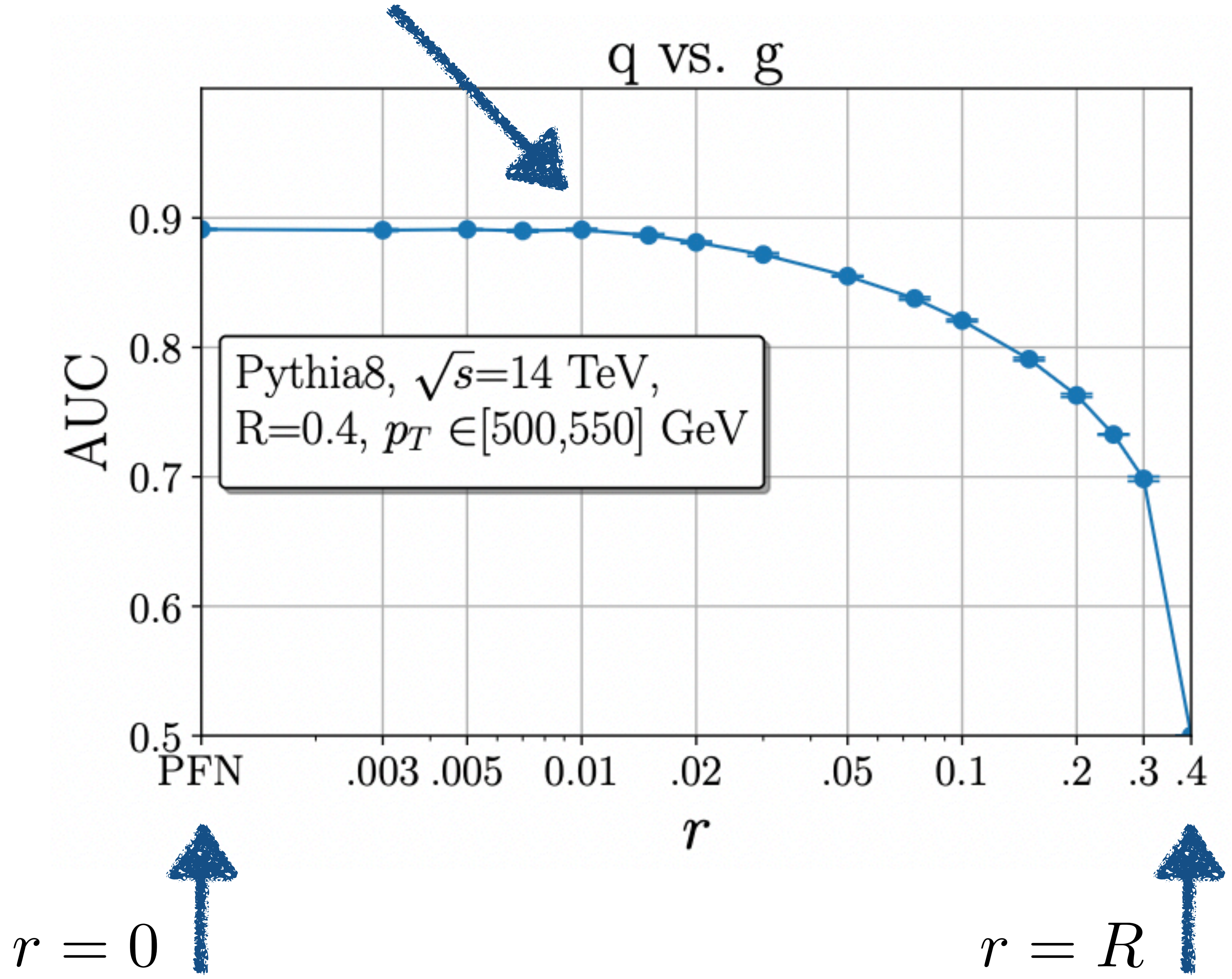
Is IRC-safe information all you need for jet classification?

Athanasakos, Larkoski, Mulligan, Ploskon, FR `23

- Cluster jet constituents into subjets
- Train deep sets on (η_i, ϕ_i) of subjets with different radii
- Max performance, IRC-unsafe limit obtained for $r \to 0$



Performance plateaus for a finite subjet radius!



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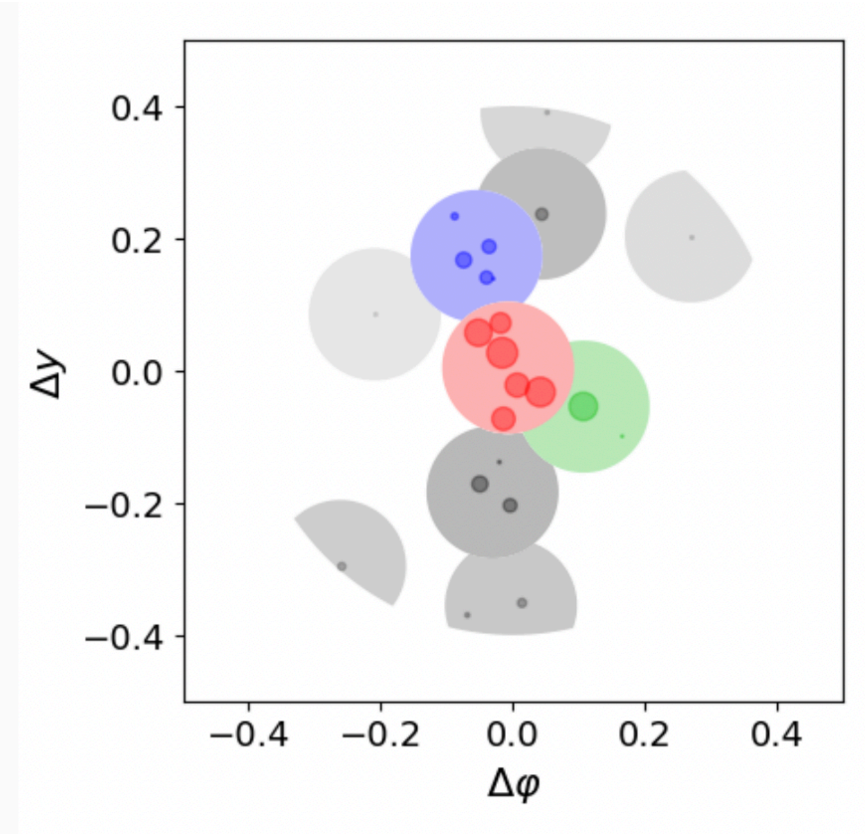
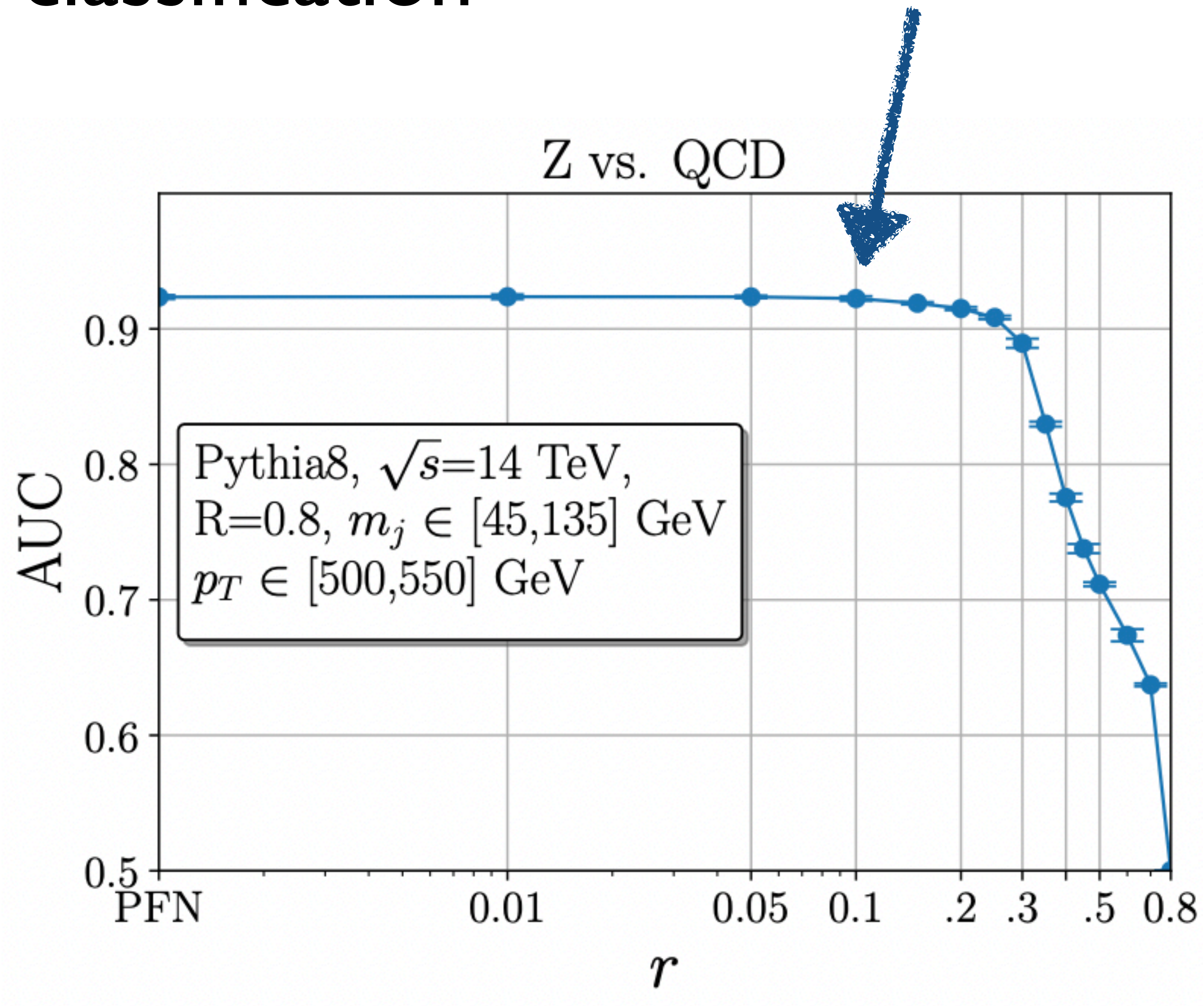


Similar for QCD vs. Z jet classification



Is IRC-safe information all you need for jet classification?

Athanasakos, Larkoski, Mulligan, Ploskon, FR `23

- Tentatively, the answer is - Yes!

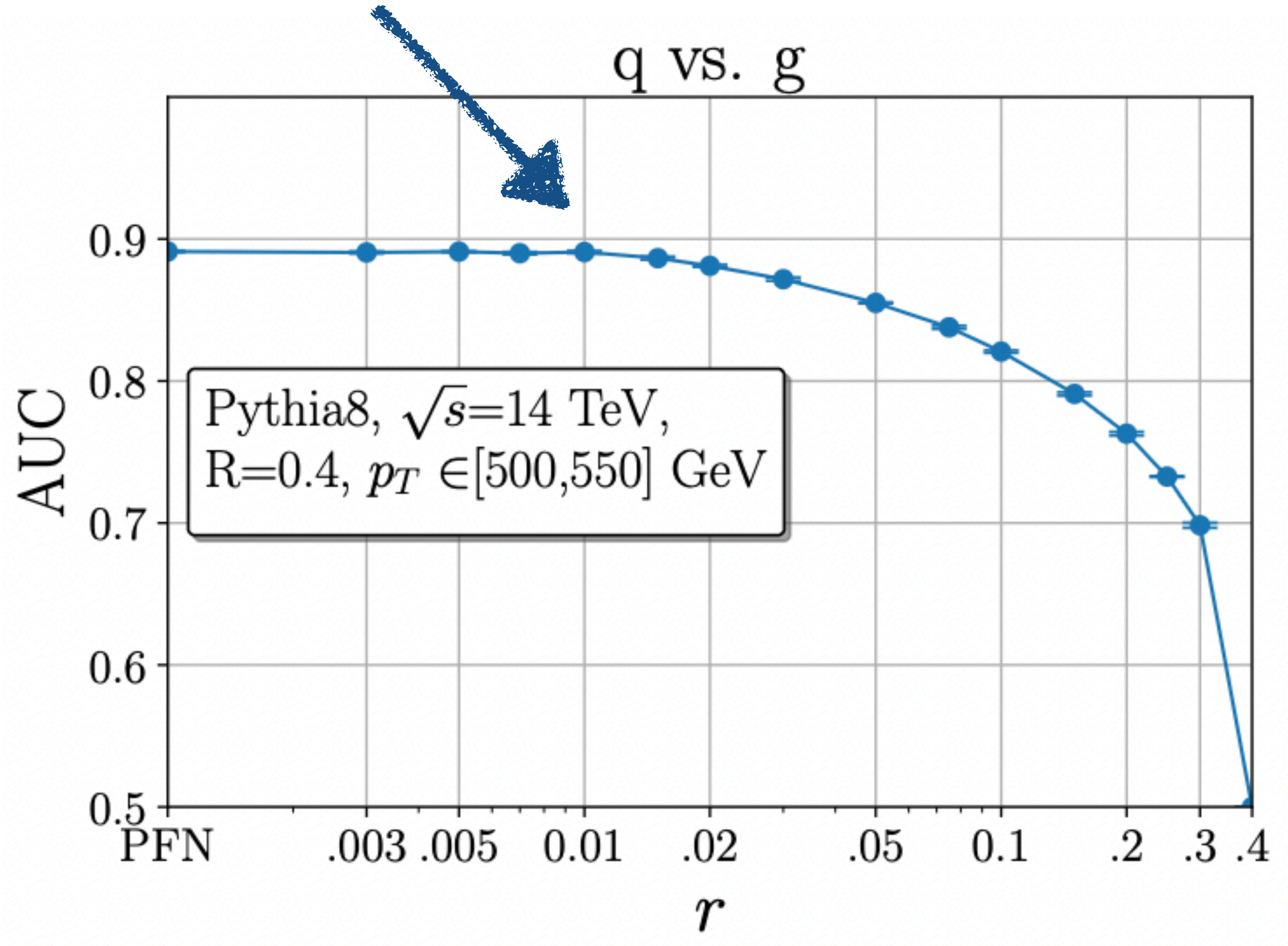
  Theoretical perspective, see Metodiev, Larkoski `19

- Emissions below some angular scale do not contain relevant information

- Jet Flow Networks are "gapless"

- Can identify the scale of the onset of the plateau

$$\boxed{p_T \cdot r \sim 5 \text{ GeV}}$$



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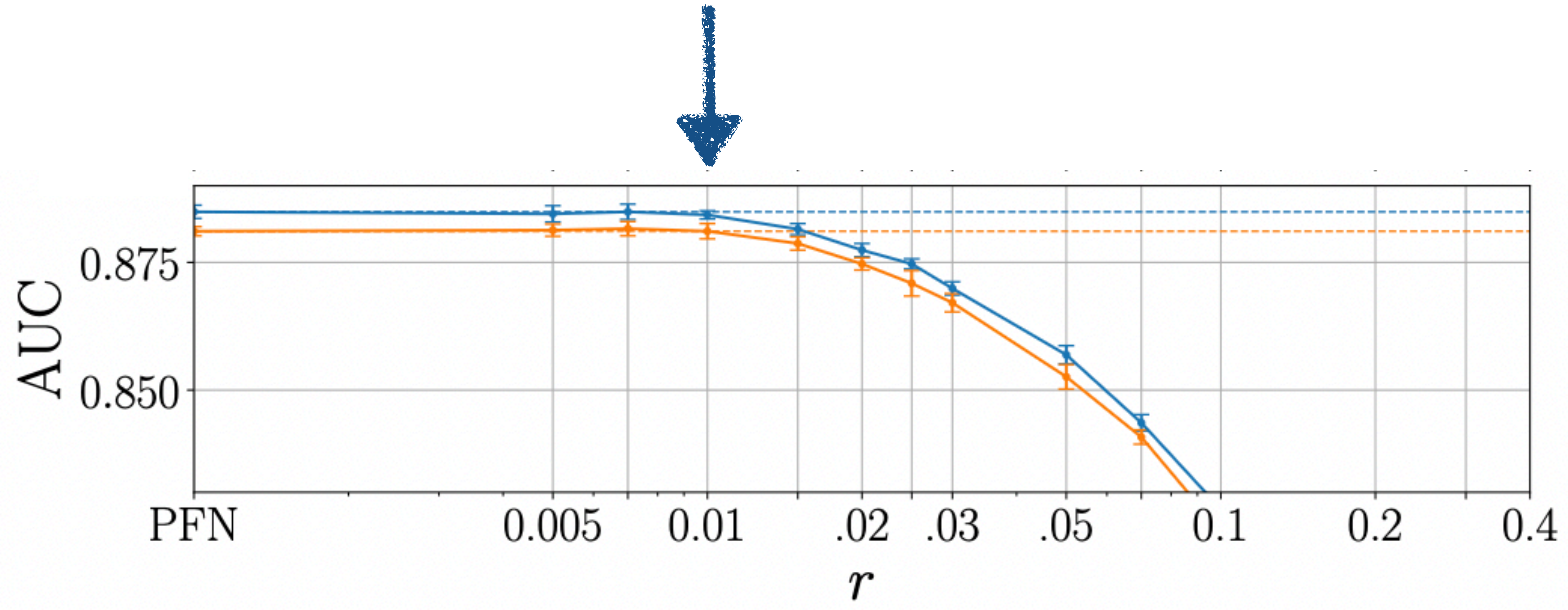

Scale is independent of the shower cutoff in Pythia p_T^{cut}

Information content of jets & events

- N-jettiness basis *Datta, Larkoski `17*
- The performance gap could be due to…
  - ~~IRC safety?~~ (✓)
  - the type of input? ?
  - the network architecture? ?

Answers will provide guidance for making use of the full information

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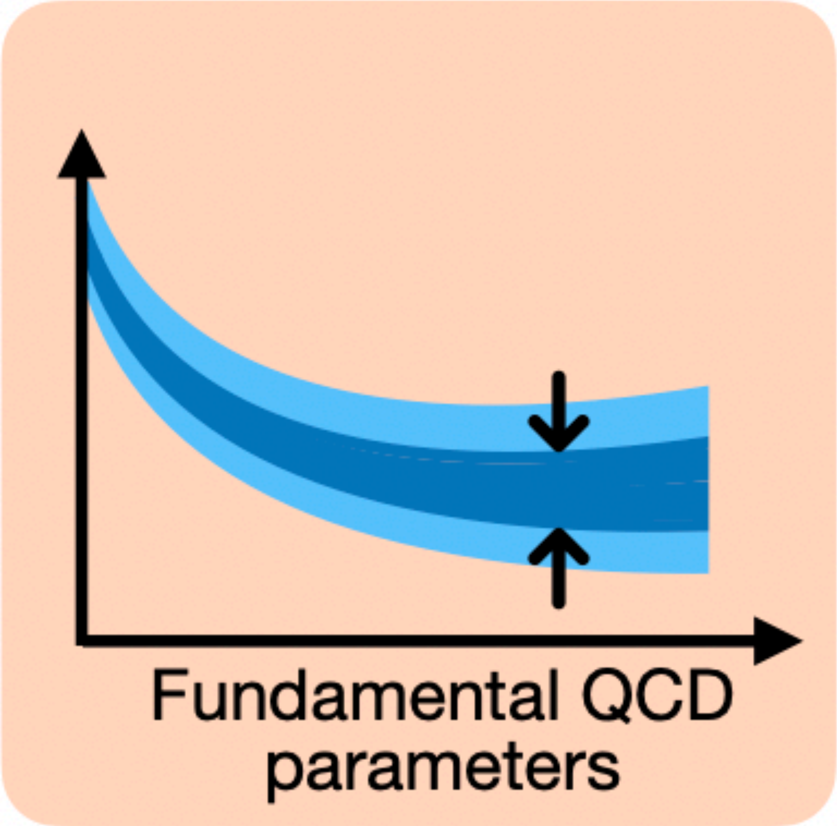
IRC unsafe classifier

⋮

N-jettiness observables

Metodiev, Komiske, Thaler `18

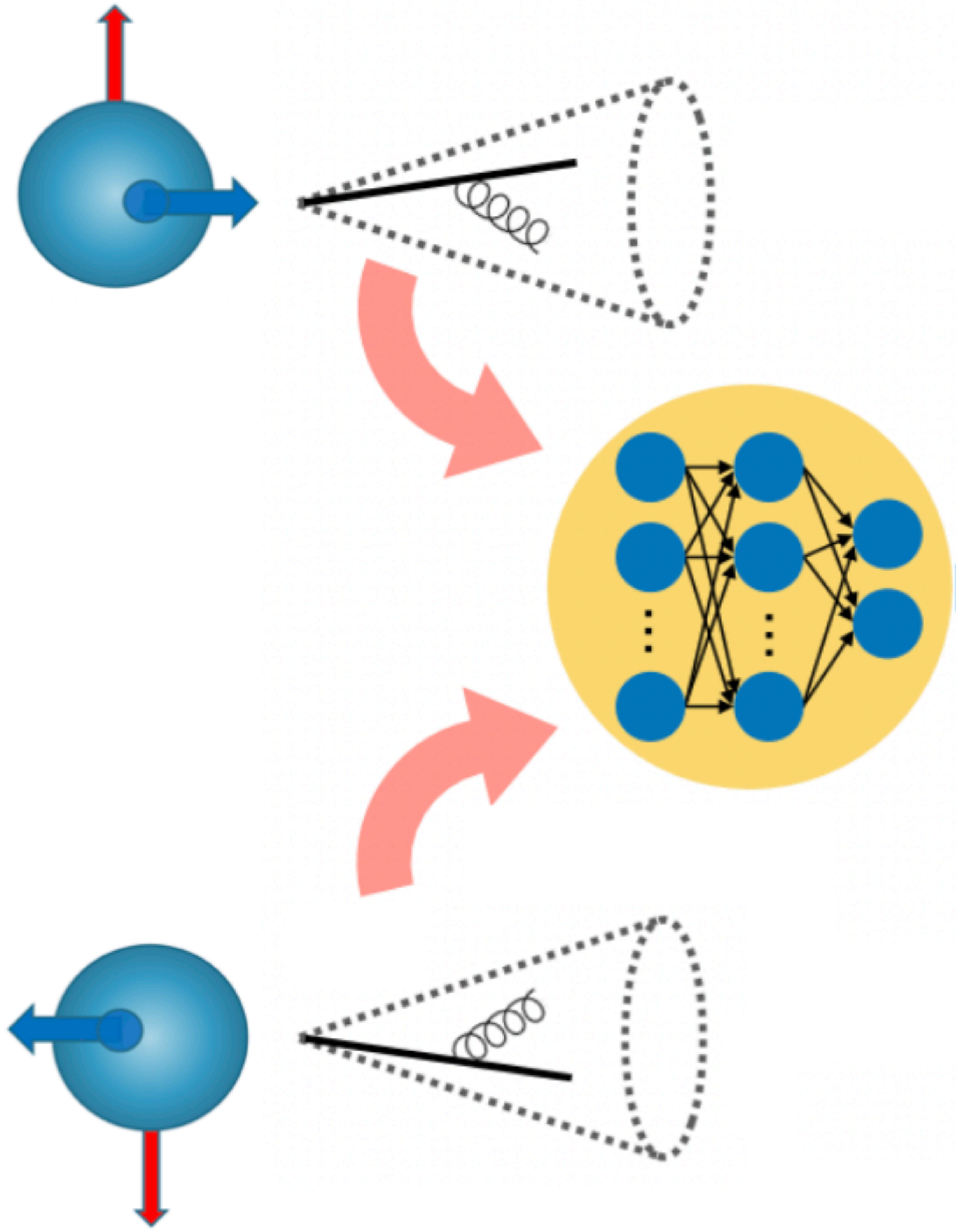


ML for spin spin physics

Lee, Mulligan, Ploskon, FR, Yuan `22

- How can we apply these techniques to spin-dependent observables?

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

Summary

- Jets will be versatile tools at the EIC
- Can take advantage of the EIC's clean environment, high luminosity etc.
- AI/ML can complement hadron structure & spin physics program
- Requires coordination with experiment
- …and can inform detector design?