Machine learning based jet & event classification with applications to hadron structure & spin physics

Felix Ringer

In collaboration with K. Lee, J. Mulligan, M. Ploskon, F. Yuan, arXiv:2210.06450 (JHEP)

Deep-Inelastic Scattering 2023, Michigan State University

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Jefferson Lab

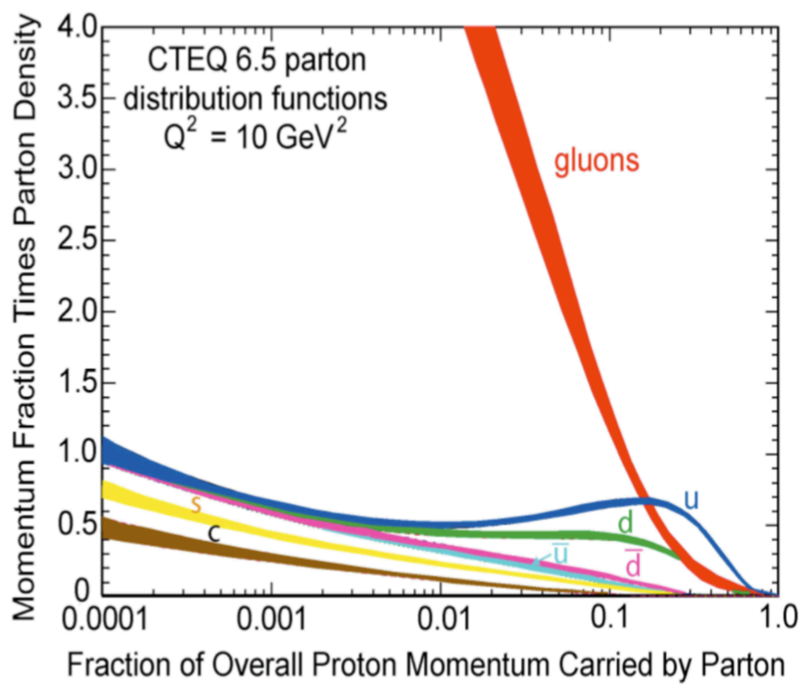
Hadron structure & spin physics

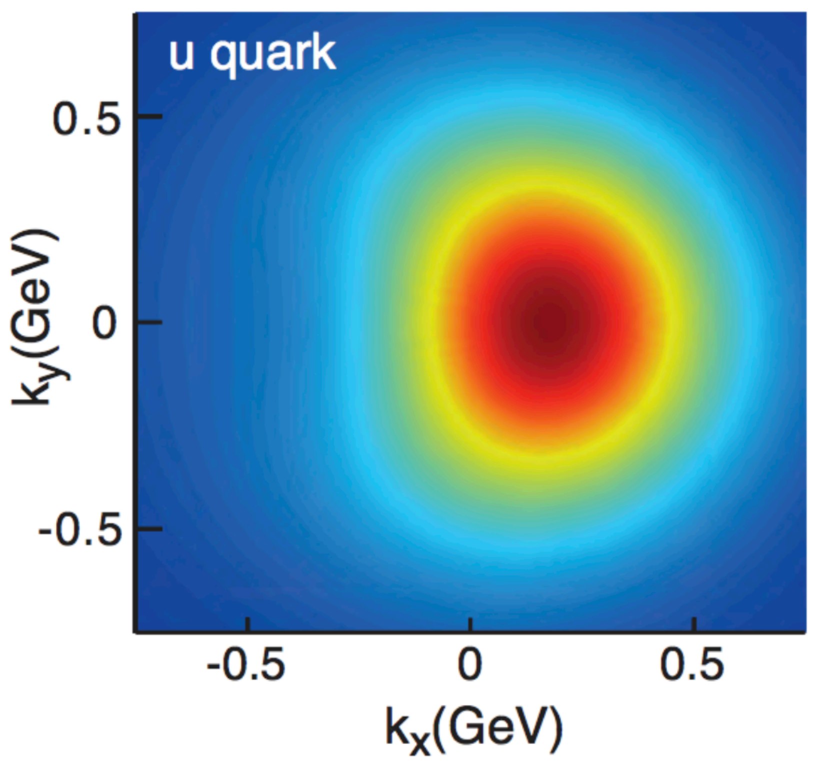
Fatemi EINN `19, Liu DNP `19
see also Kang et al., Yuan et al.

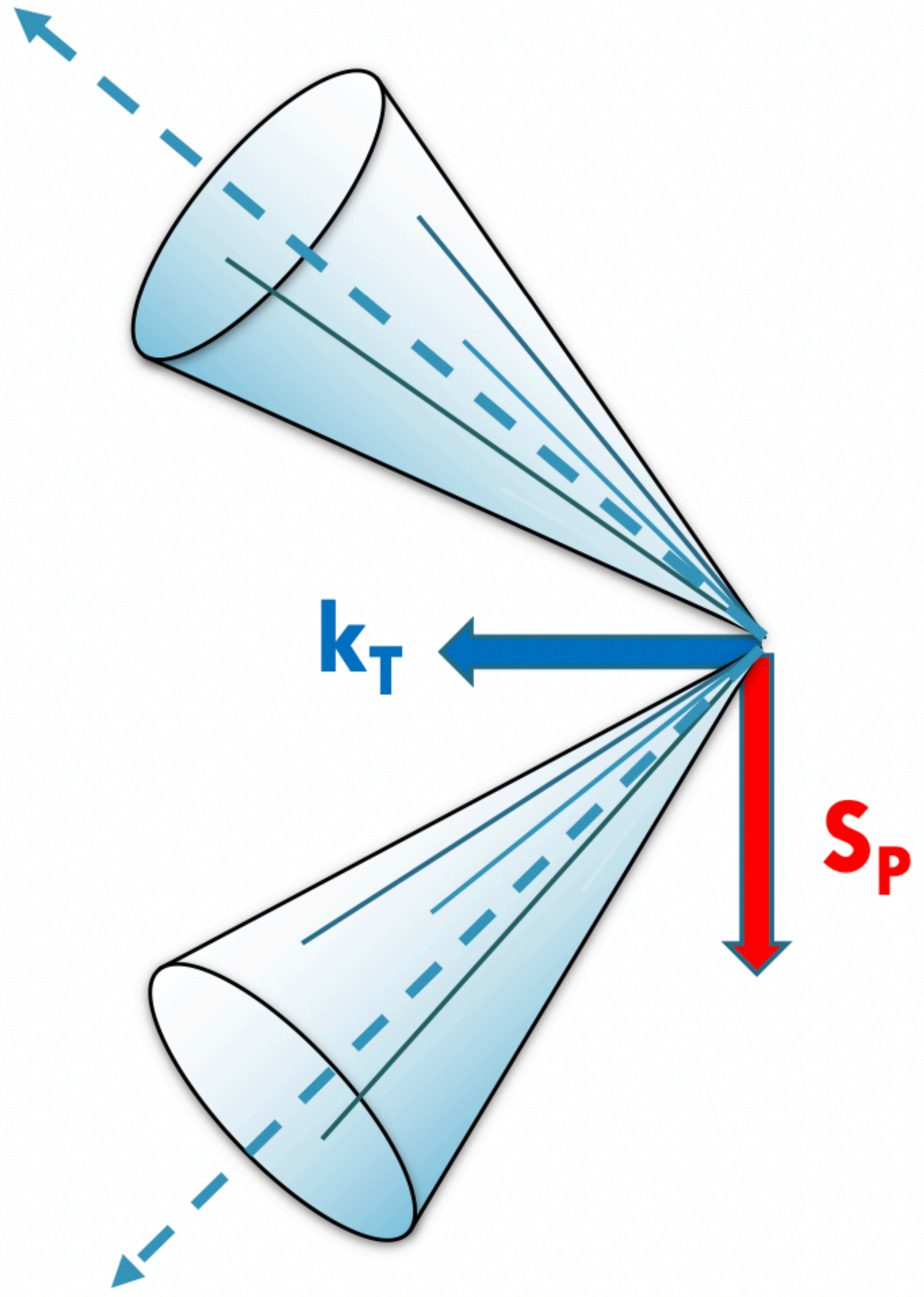
- Transverse single spin asymmetries

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

- E.g. back-to-back di-jets at RHIC
- Similar measurements at the EIC







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- Transverse single spin asymmetries

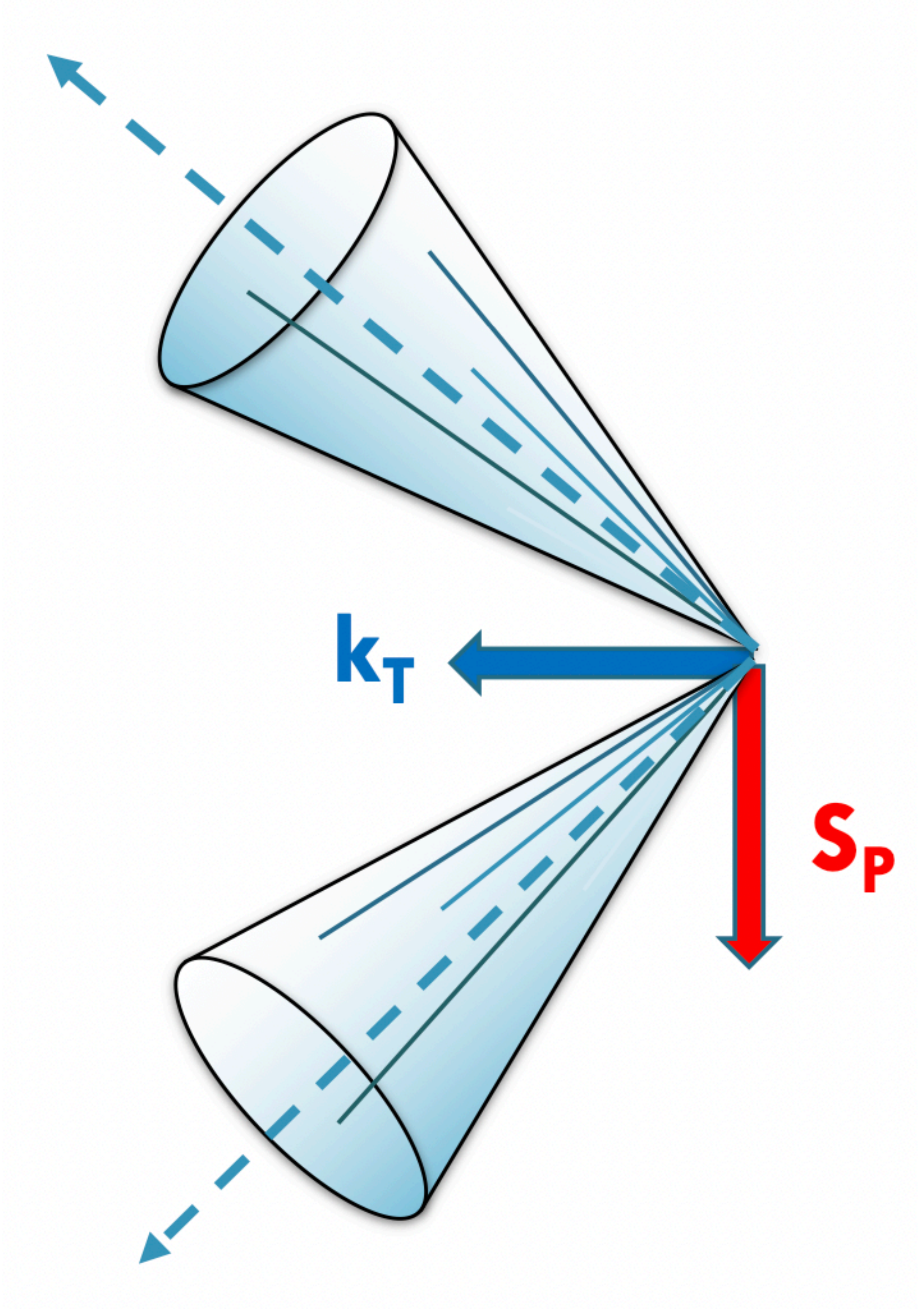
$$A_{UT} = \frac{d\sigma^{\uparrow} - d\sigma^{\downarrow}}{d\sigma^{\uparrow} + d\sigma^{\downarrow}}$$

- Size of the Sivers asymmetries can be small due to flavor cancellations

Burkardt sum rule *`04*

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

- Expect u and d-quark Sivers to have opposite sign and similar magnitude (confirmed by fits)



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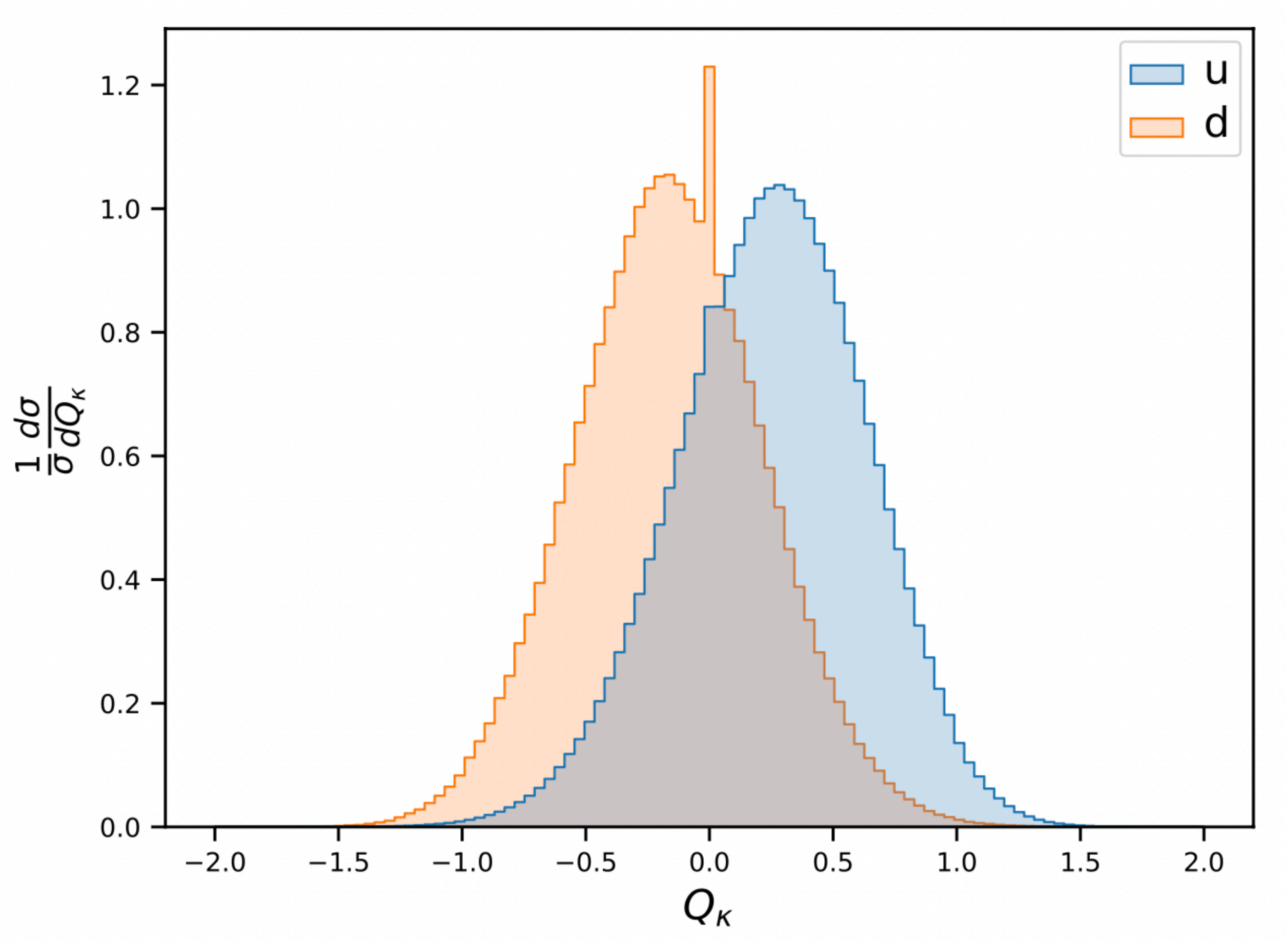
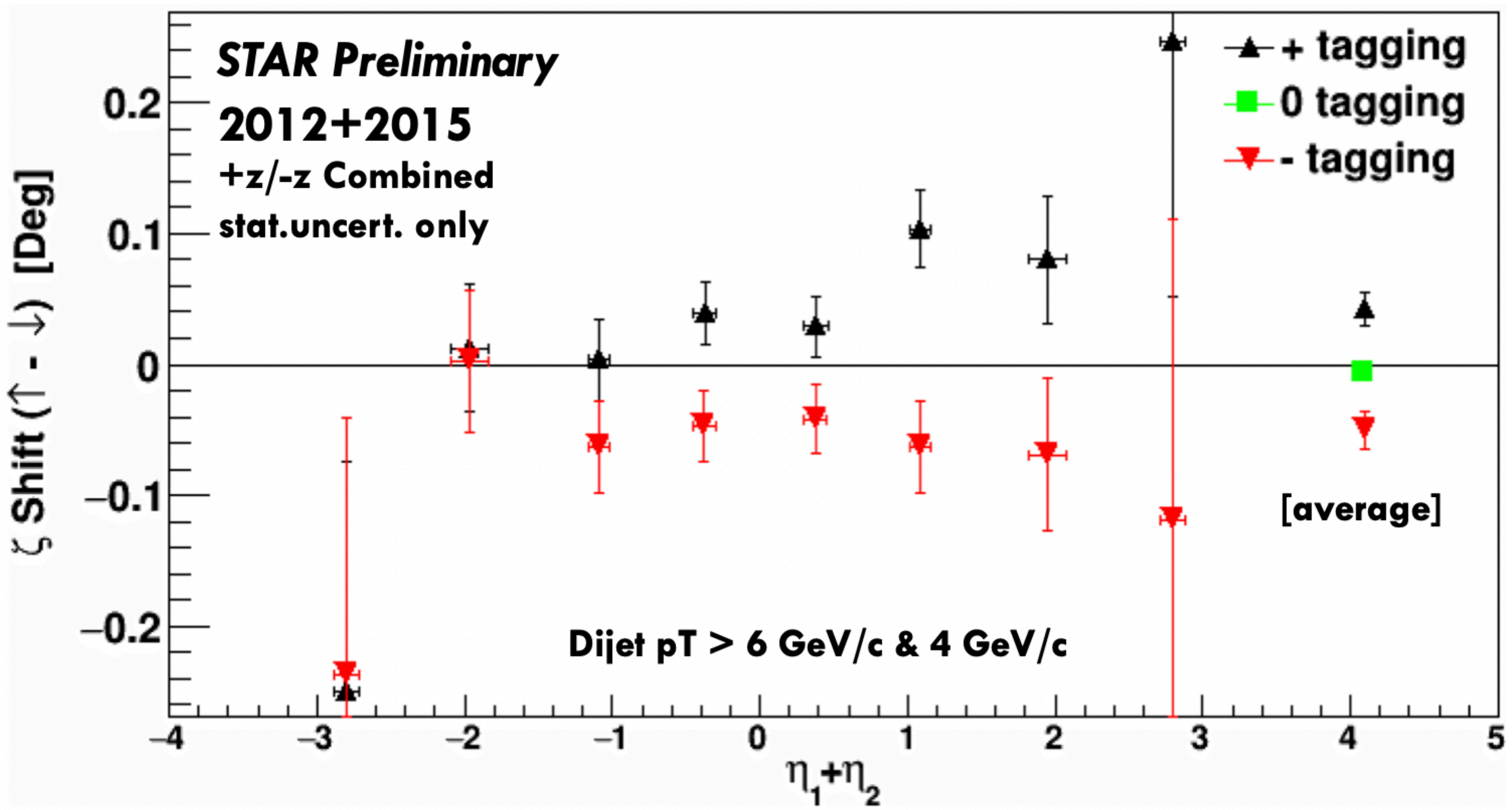
$$A_{UT} = \frac{d\sigma^{\uparrow} - d\sigma^{\downarrow}}{d\sigma^{\uparrow} + d\sigma^{\downarrow}}$$

- Jet charge tagging can lead to a flavor separation and a non-zero asymmetry

$$Q_\kappa = \sum_{i\in \text{jet}} z_i^\kappa Q_i$$





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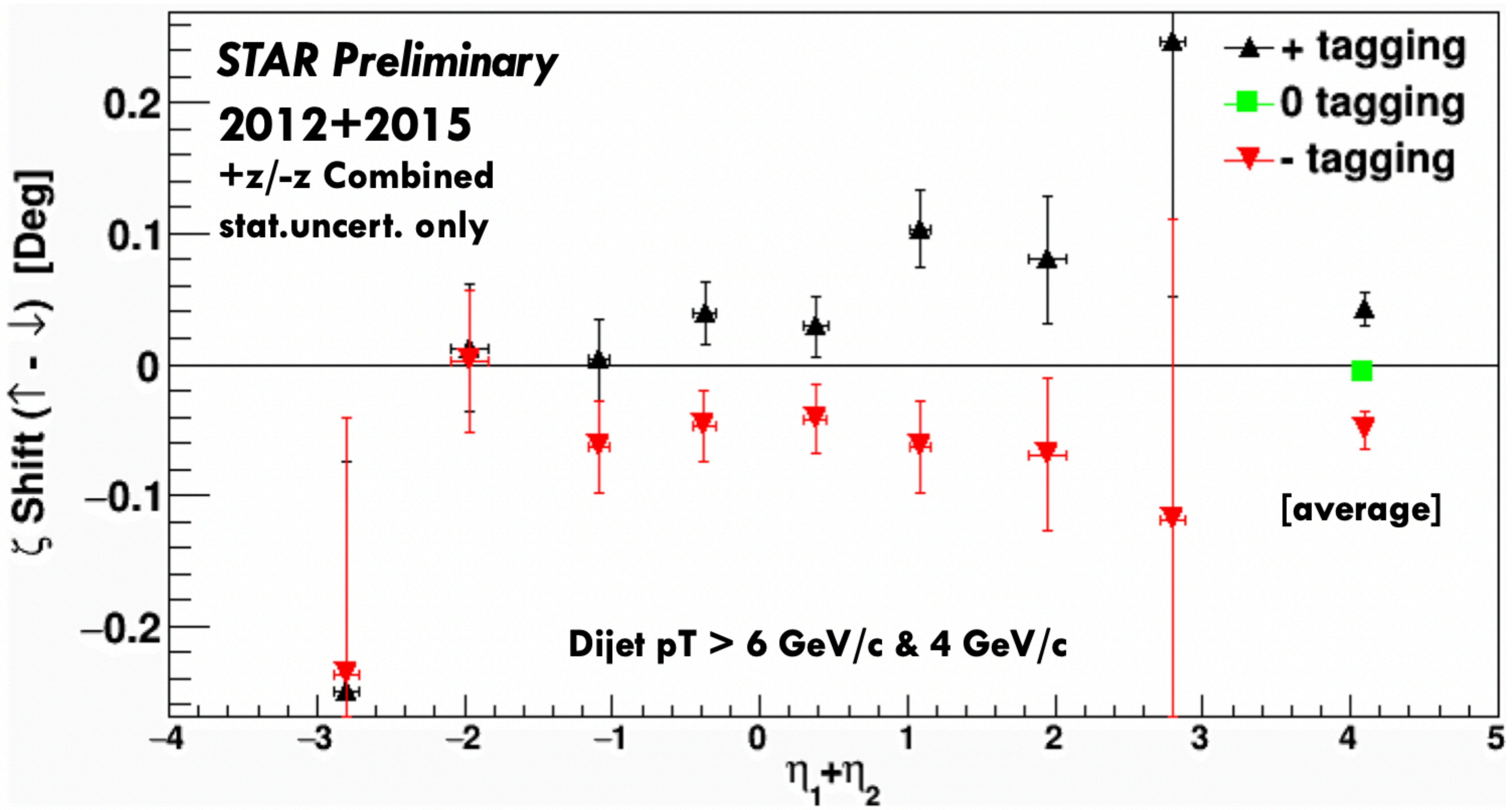
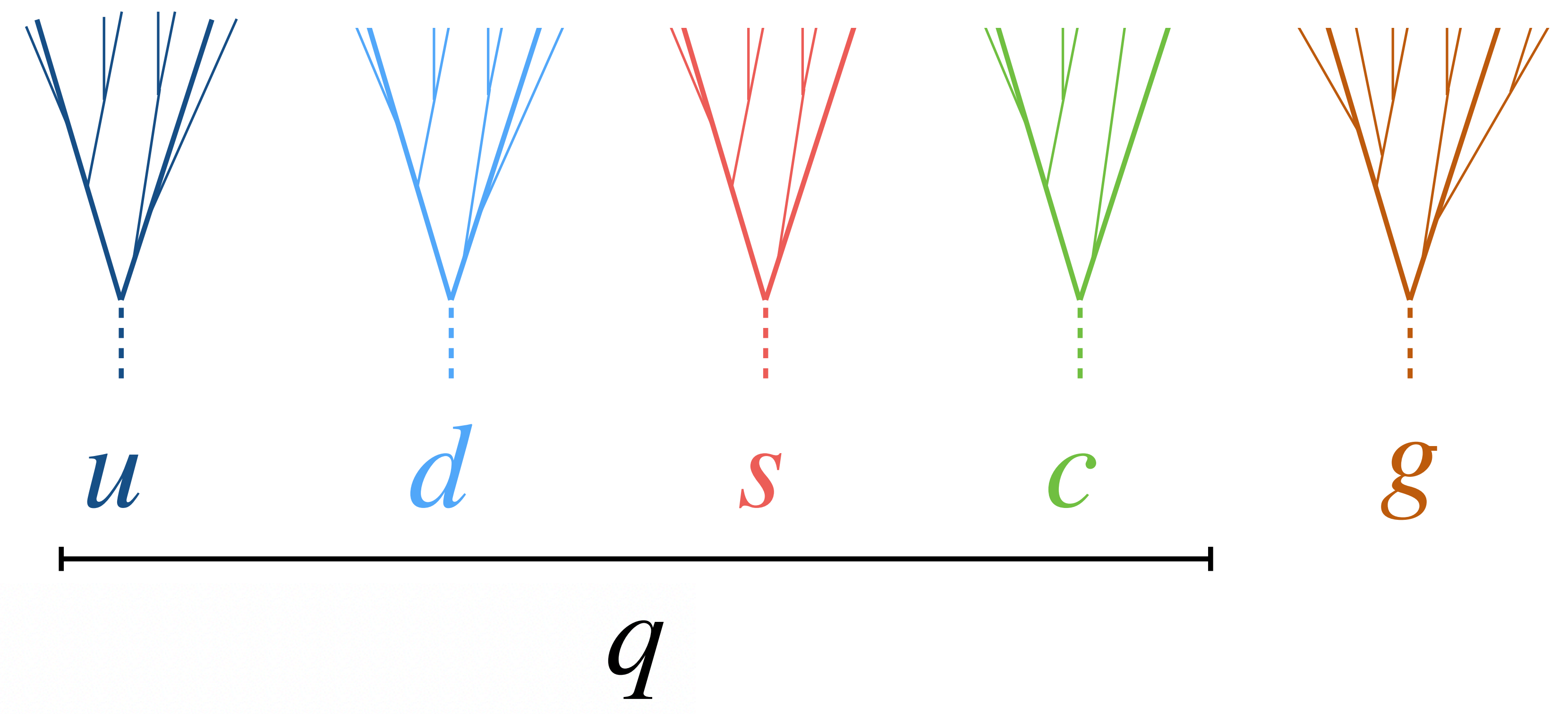


→ Can we potentially do even better?

Machine learning at the LHC

- Various jet taggers have been developed
  - Higgs, Z/W, quarks, gluon, BSM etc.
  - ML significantly outperformed traditional observables
  - ML can use the full event-by-event information
  - Interpretability



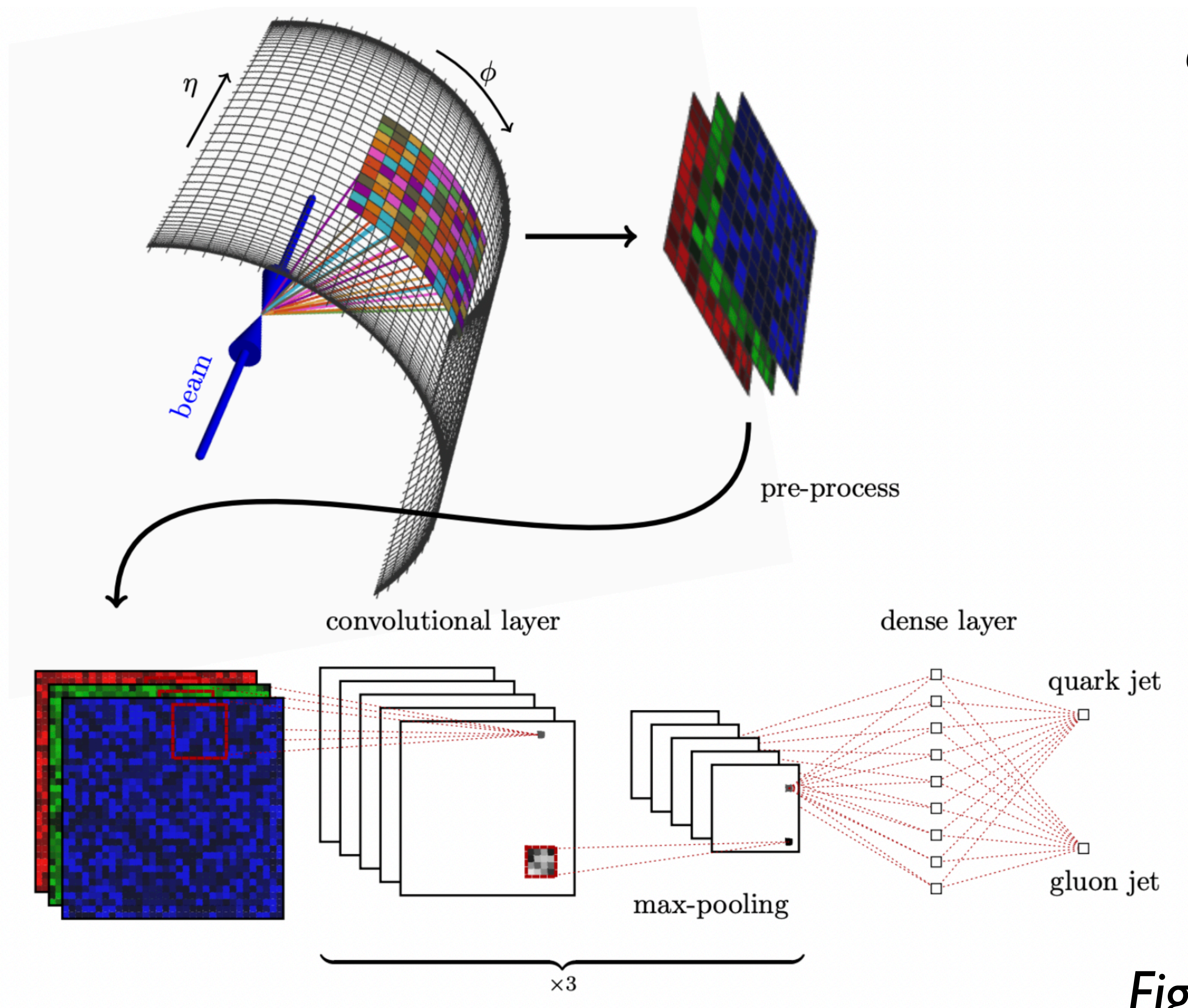
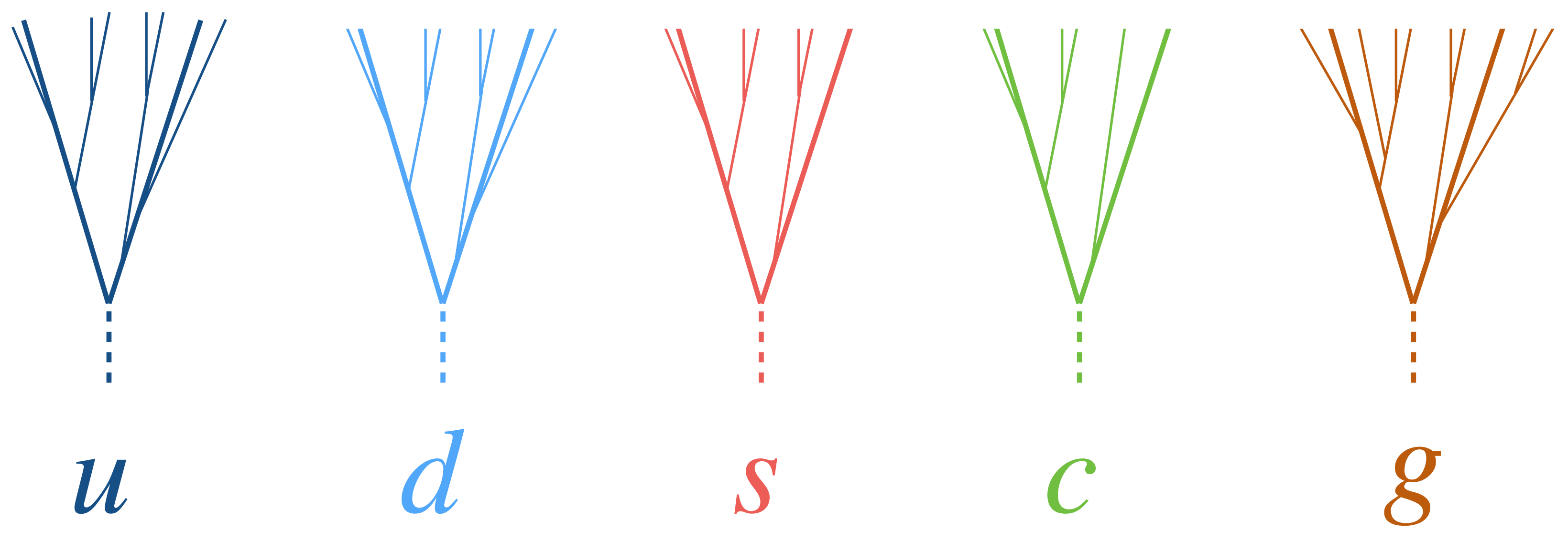
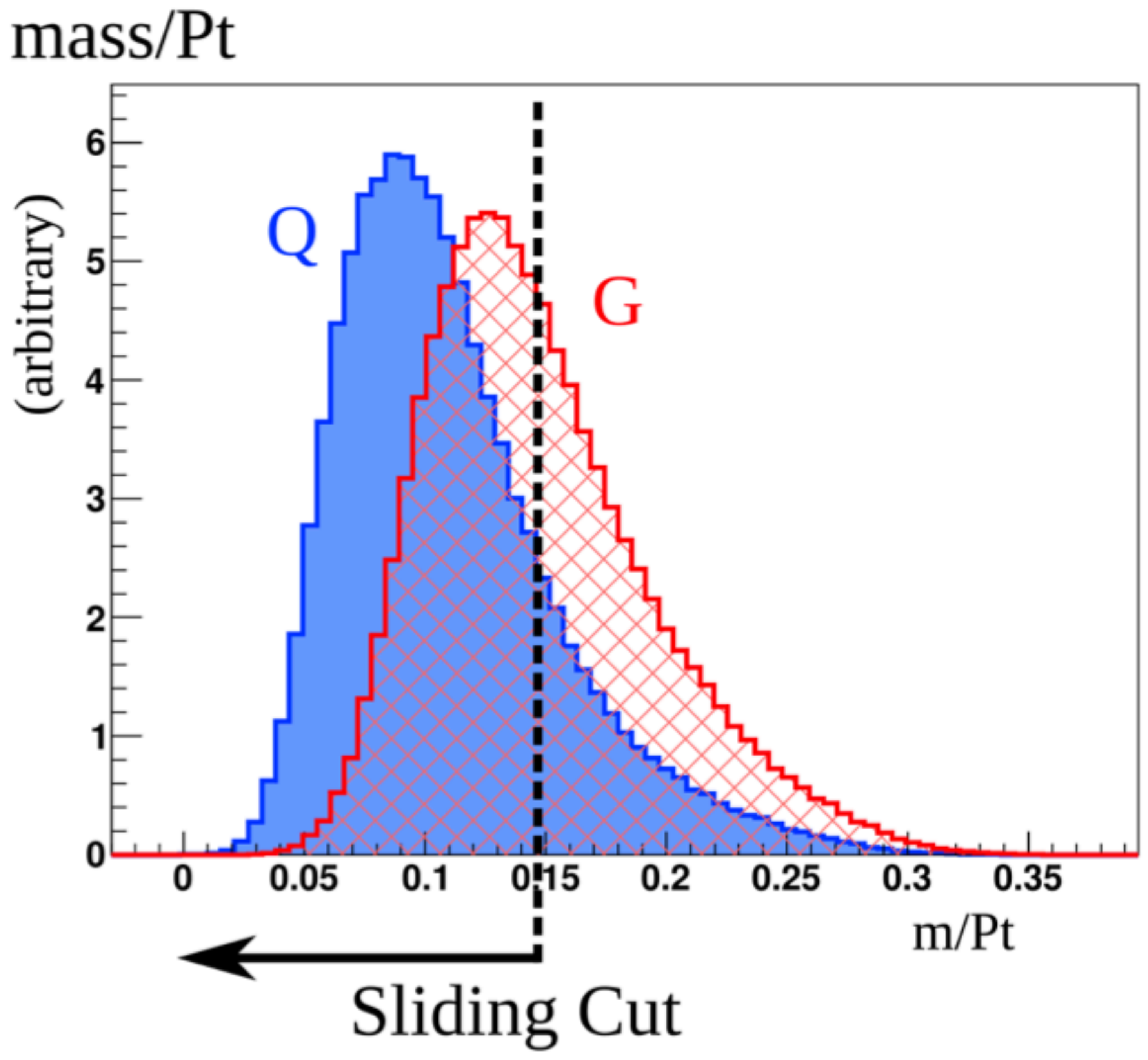


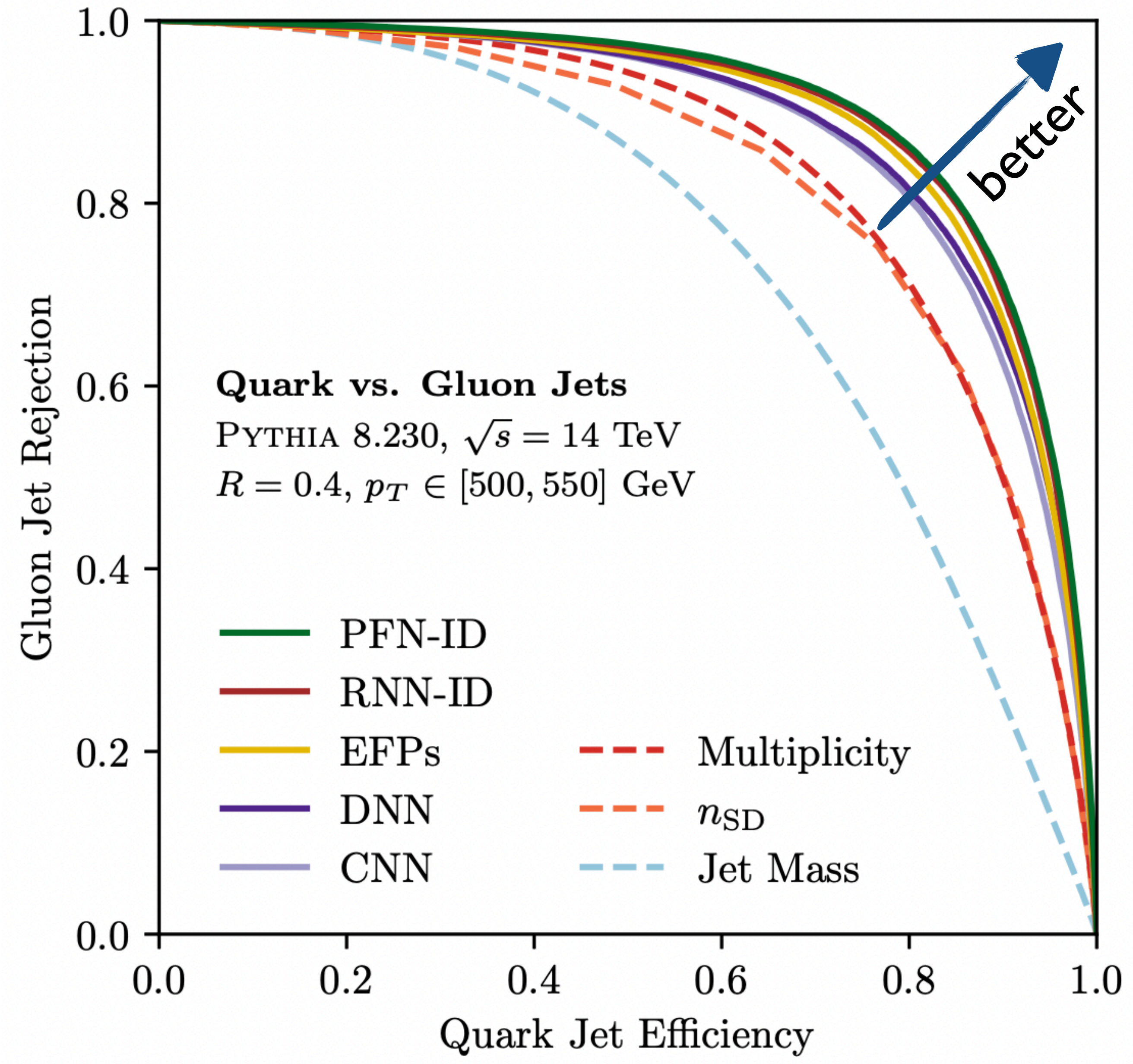
Fig. Komiske, Metodiev, Schwartz

Machine learning at the LHC

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







Gallicchio, Schwartz
Komiske, Metodiev, Thaler `19

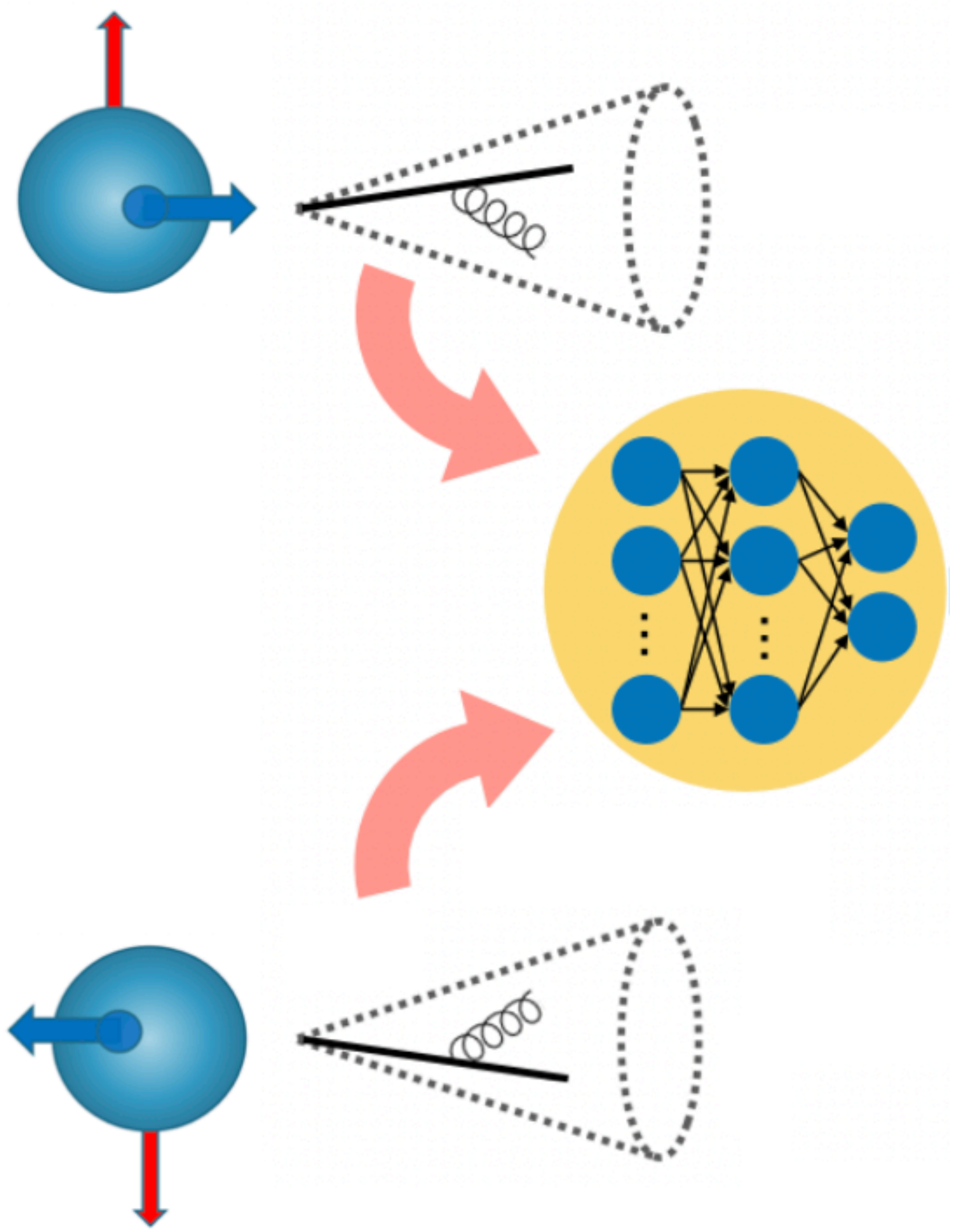
Hadron structure & spin physics

- How can we apply these techniques to spin physics?

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

- Regression problem $$\max_{\theta} |A_{UT}(\theta)|$$

Parameters of ML model



Hadron structure & spin physics

- How can we apply these techniques to spin physics?

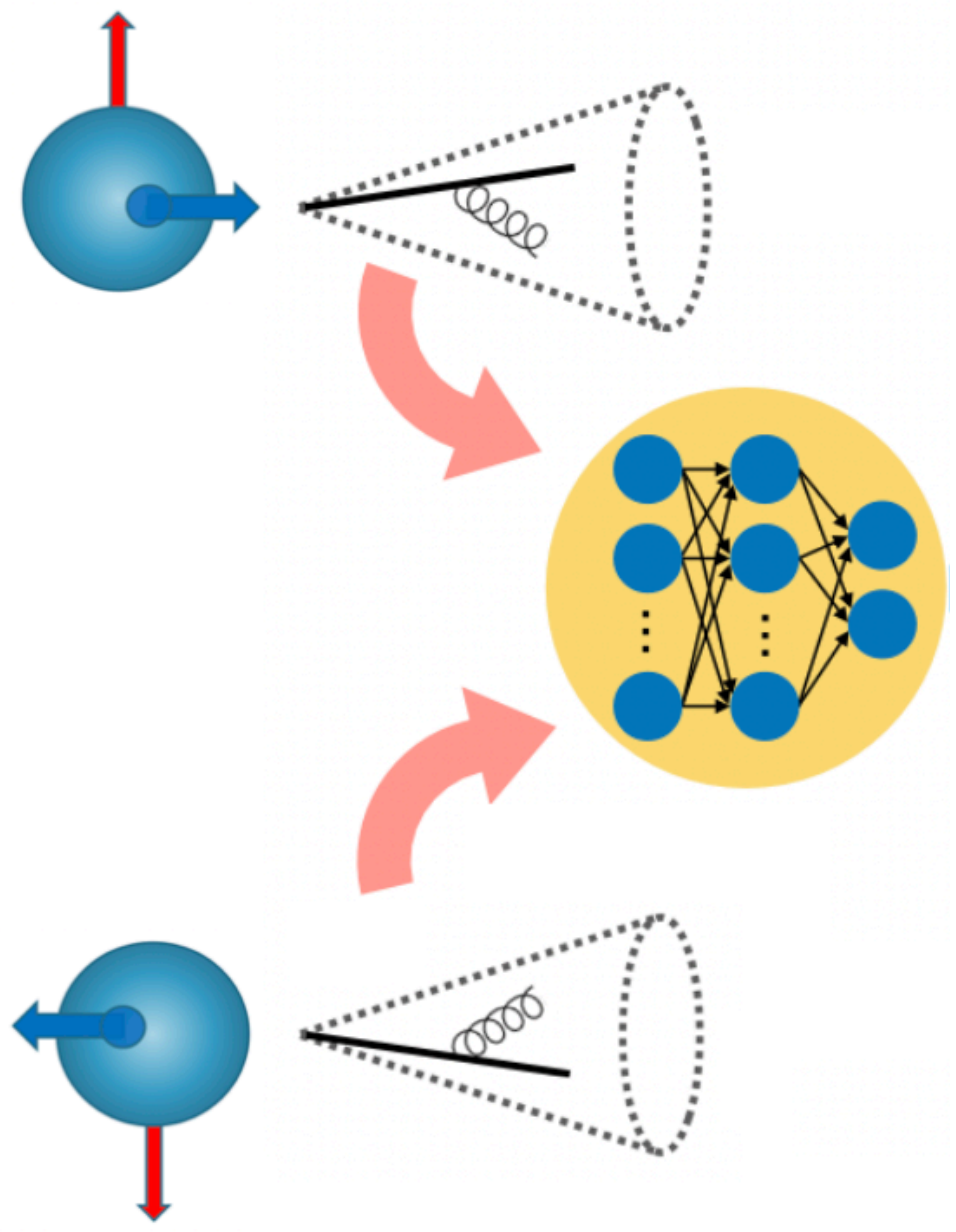
e.g. $A_{UT} = \dfrac{\mathrm{d}\sigma^{\uparrow} - \mathrm{d}\sigma^{\downarrow}}{\mathrm{d}\sigma^{\uparrow} + \mathrm{d}\sigma^{\downarrow}}$

- Classification of jets $\max\limits_{\theta} |A_{UT}(\theta)|$

- Reformulate as a classification problem of jets produced in collisions with different initial state polarization

- Can be trained on data

→ Upper limit on what can possibly be achieved



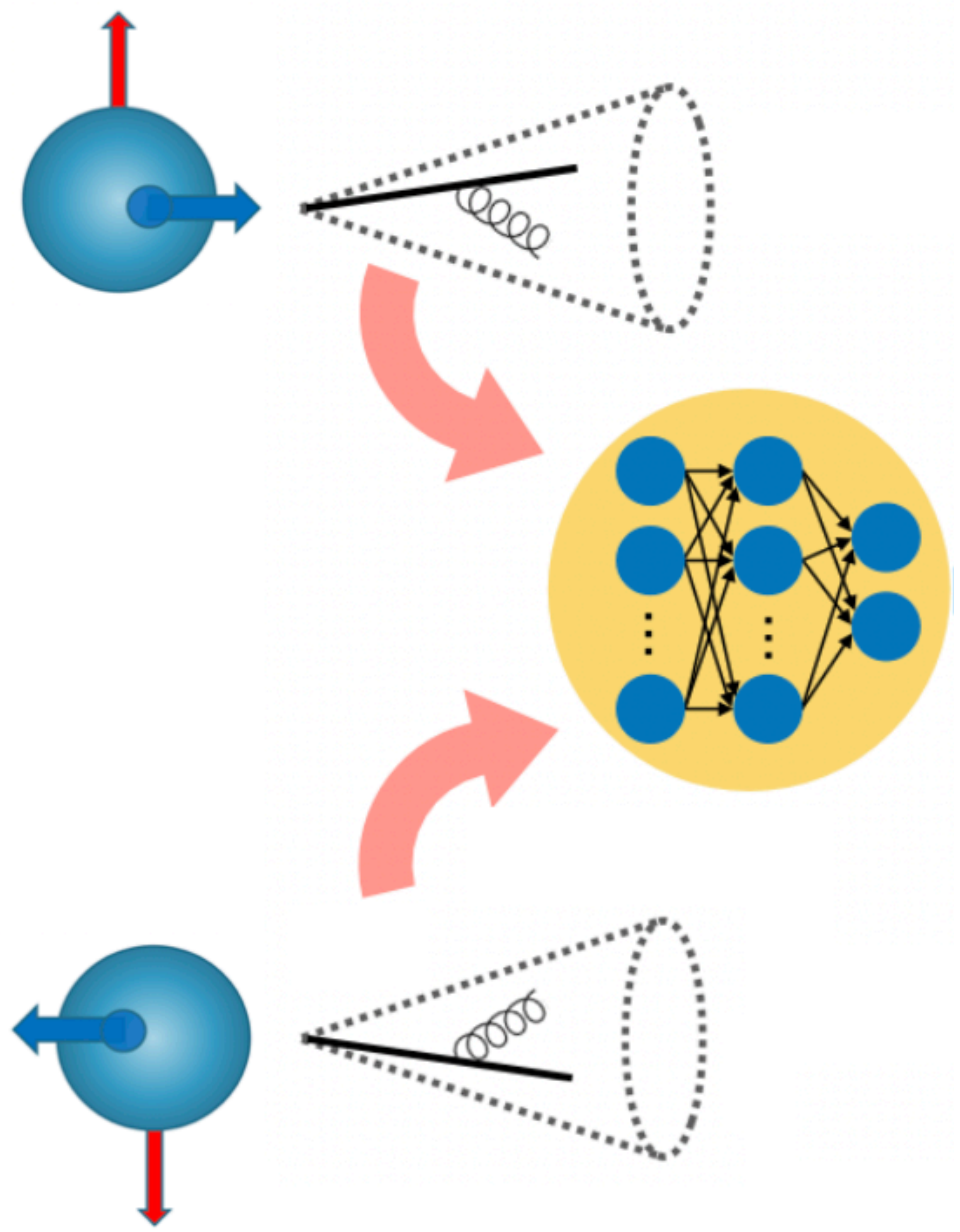
Hadron structure & spin physics

- How can we apply these techniques to spin physics?

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

- Classification of jets $\max_{\theta} |A_{UT}(\theta)|$
- Subsequently identify an ideal observable using e.g. a complete set of observables
- Ideally observable is tractable in pQCD & include in global fits

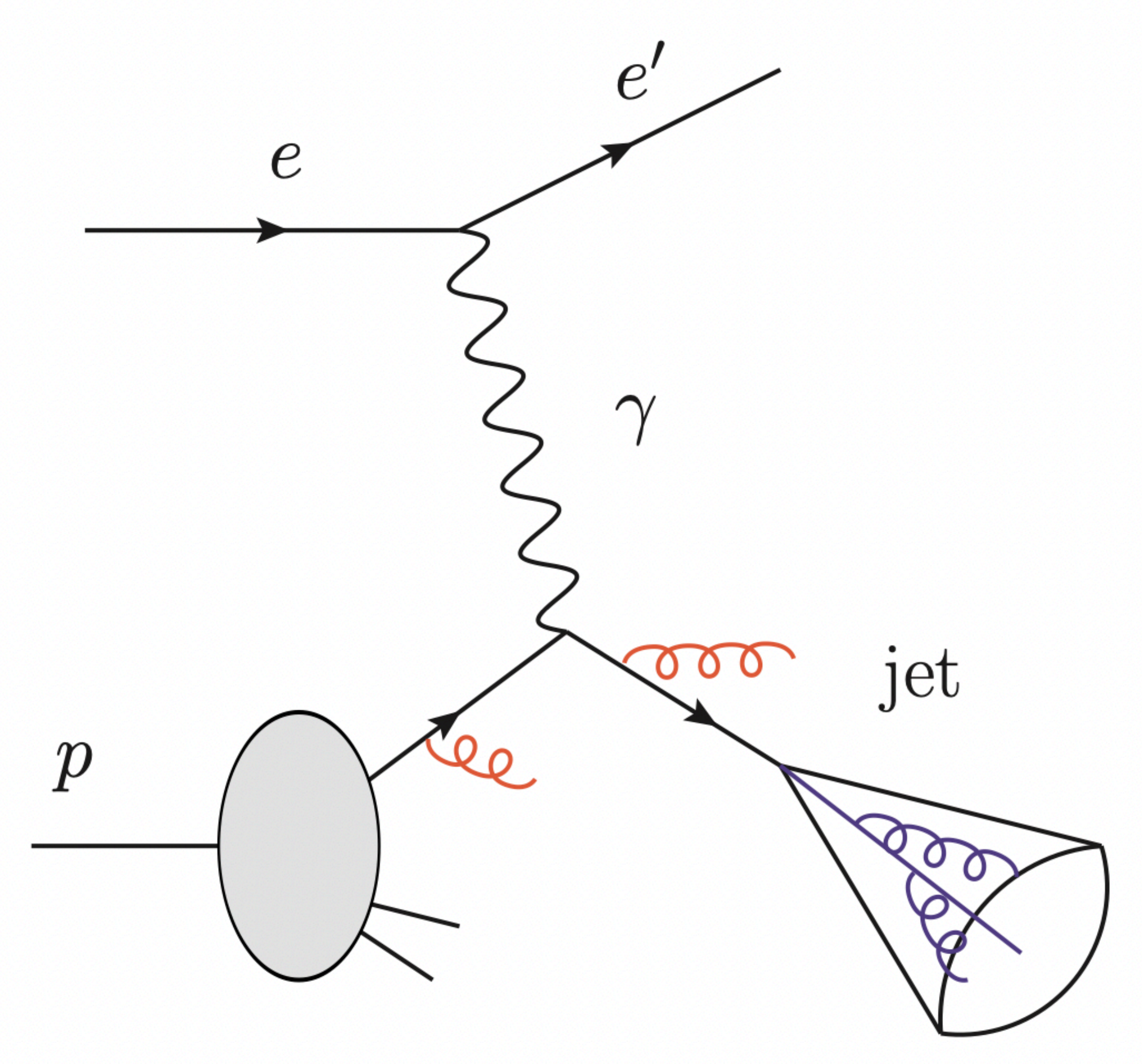
see e.g. Datta, Larkoski; Metodiev, Komiske, Thaler; Lai, Mulligan, Ploskon, FR

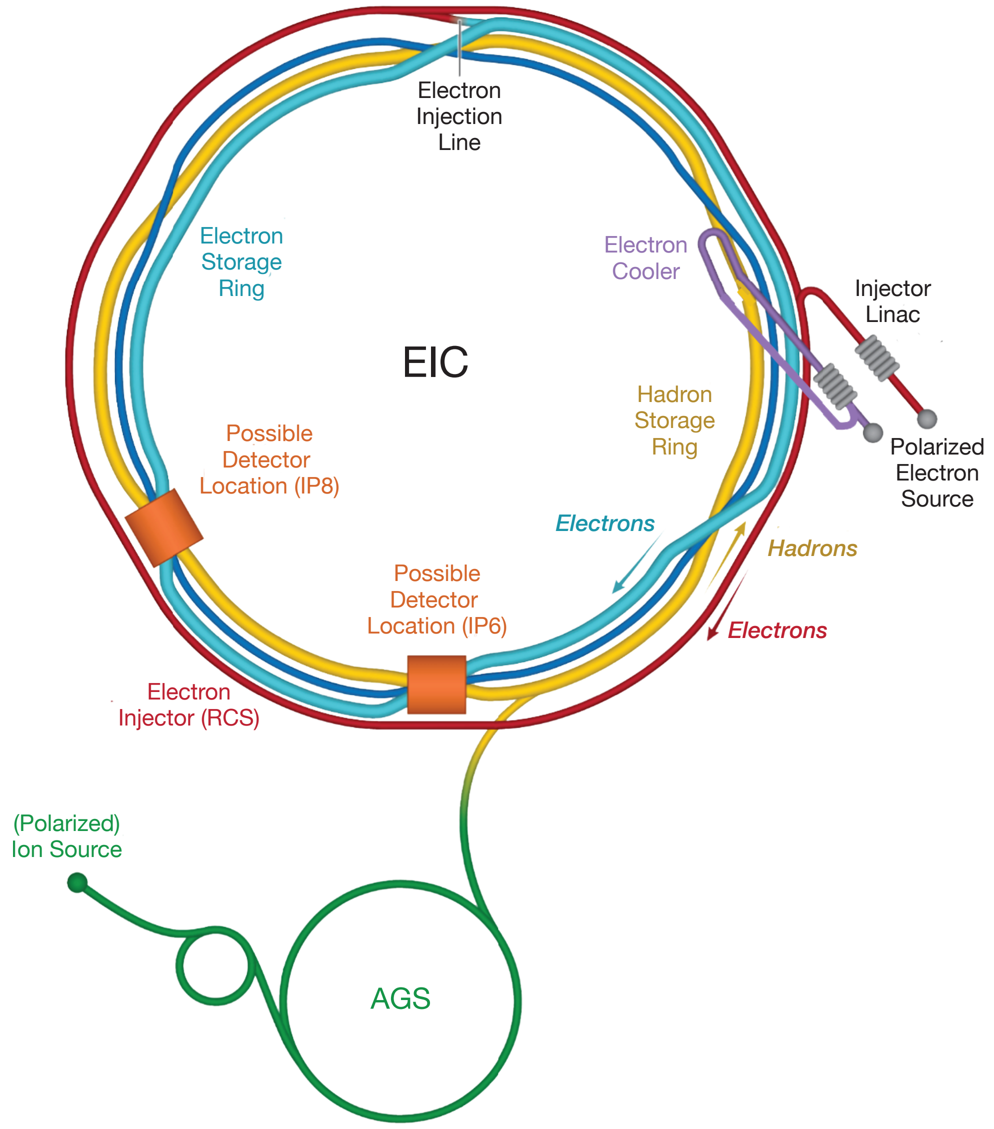


Other applications in hadron structure

- Identify strange jets, especially at the EIC

  Constrain strange PDFs





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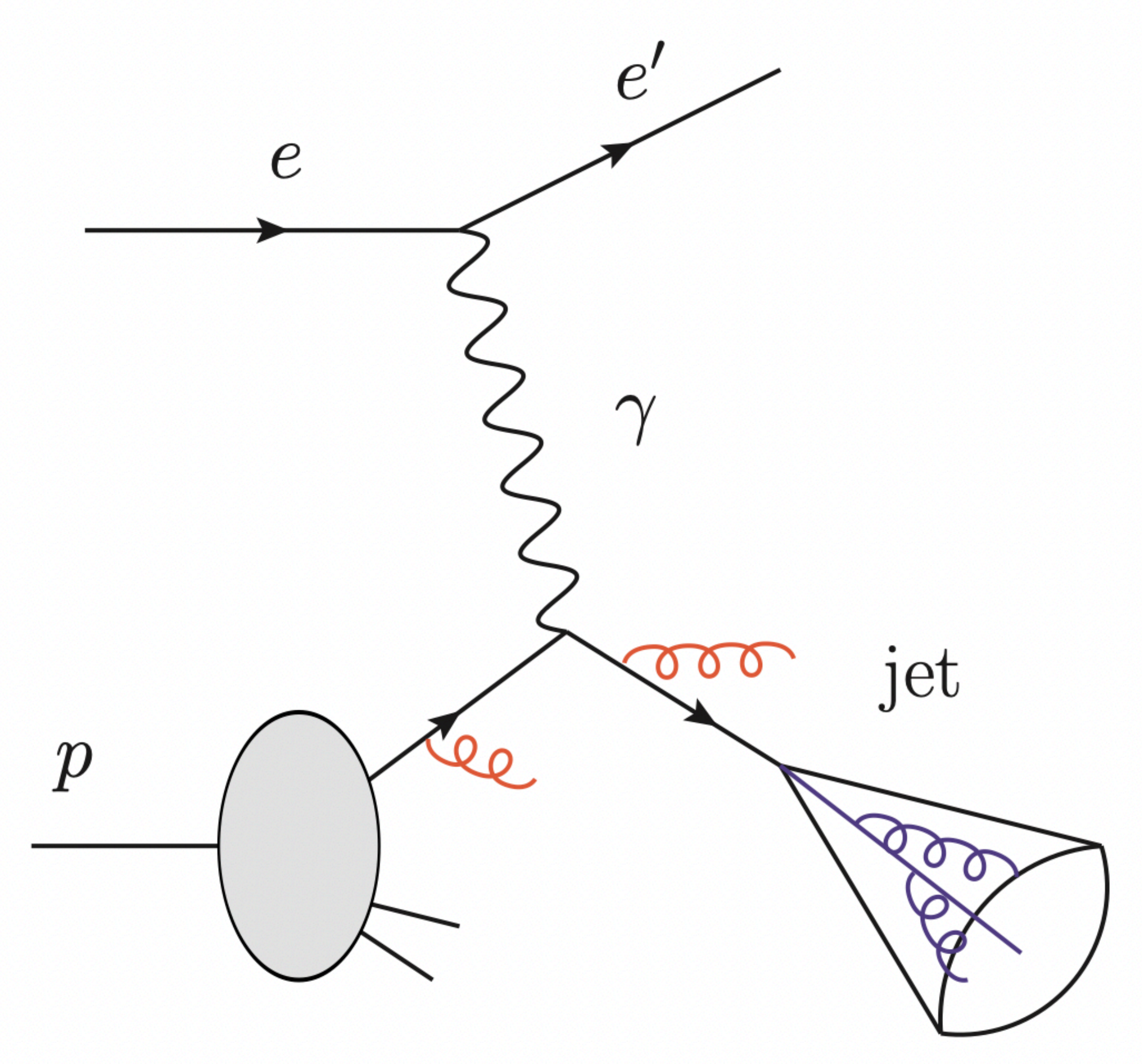
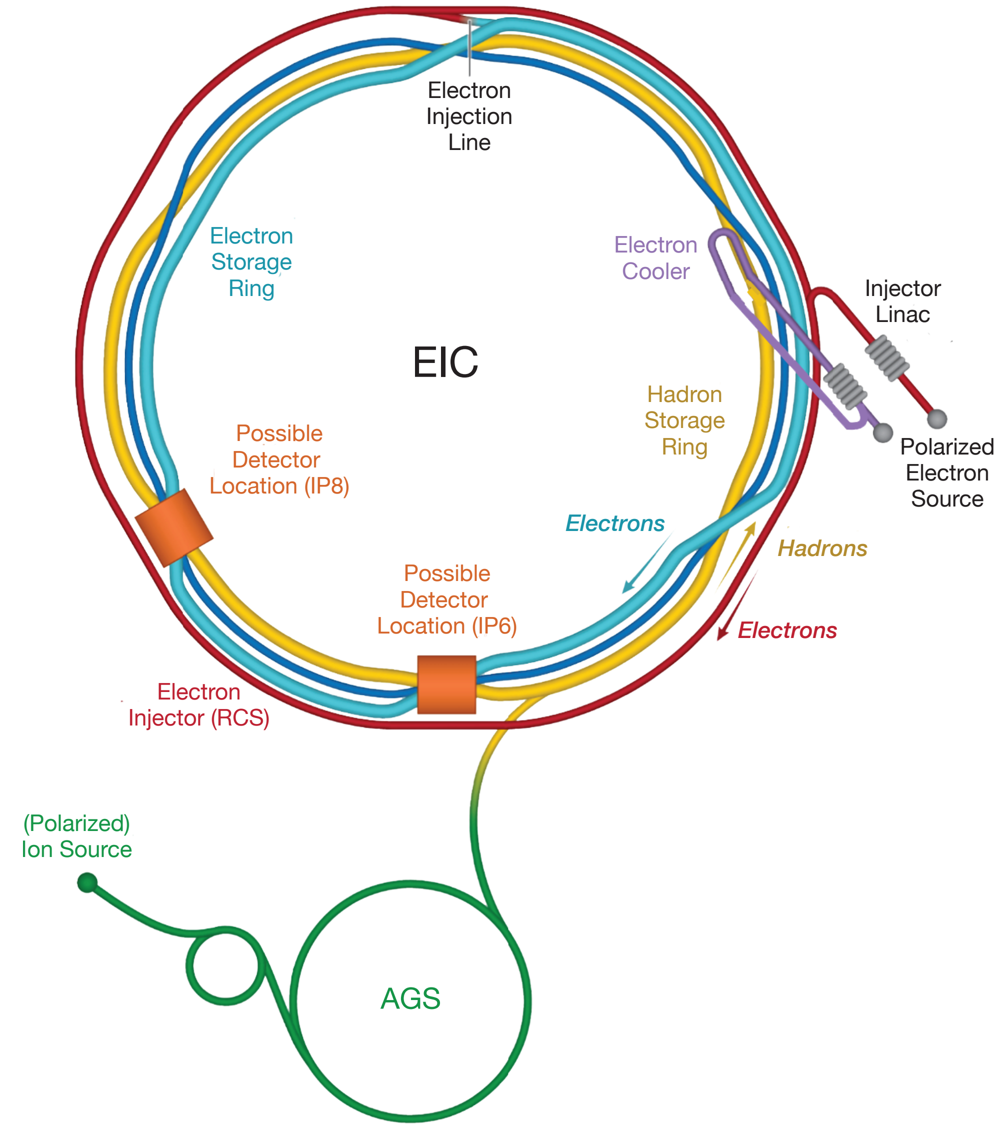
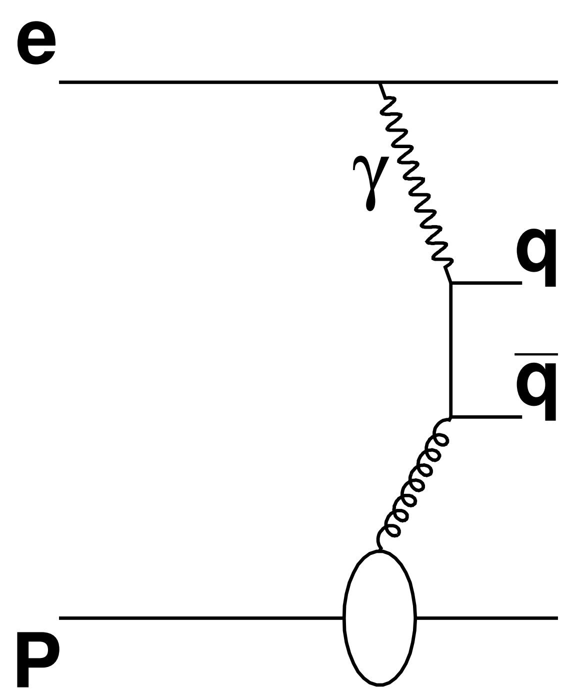


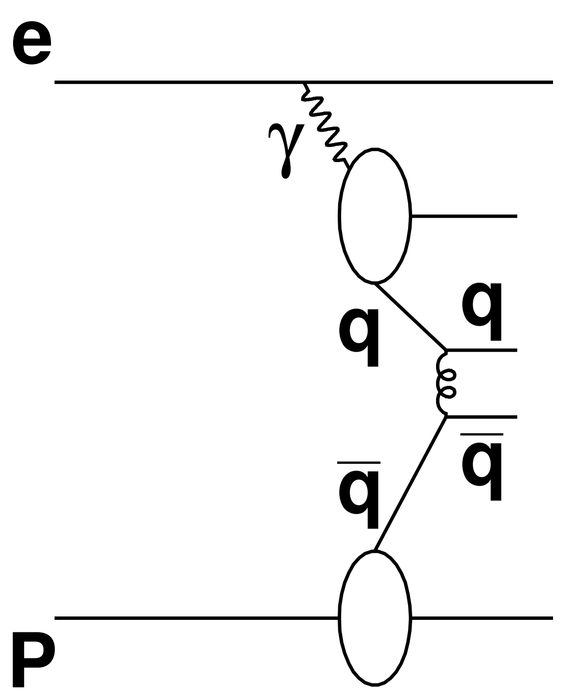


- Photon structure

  Direct vs. resolved

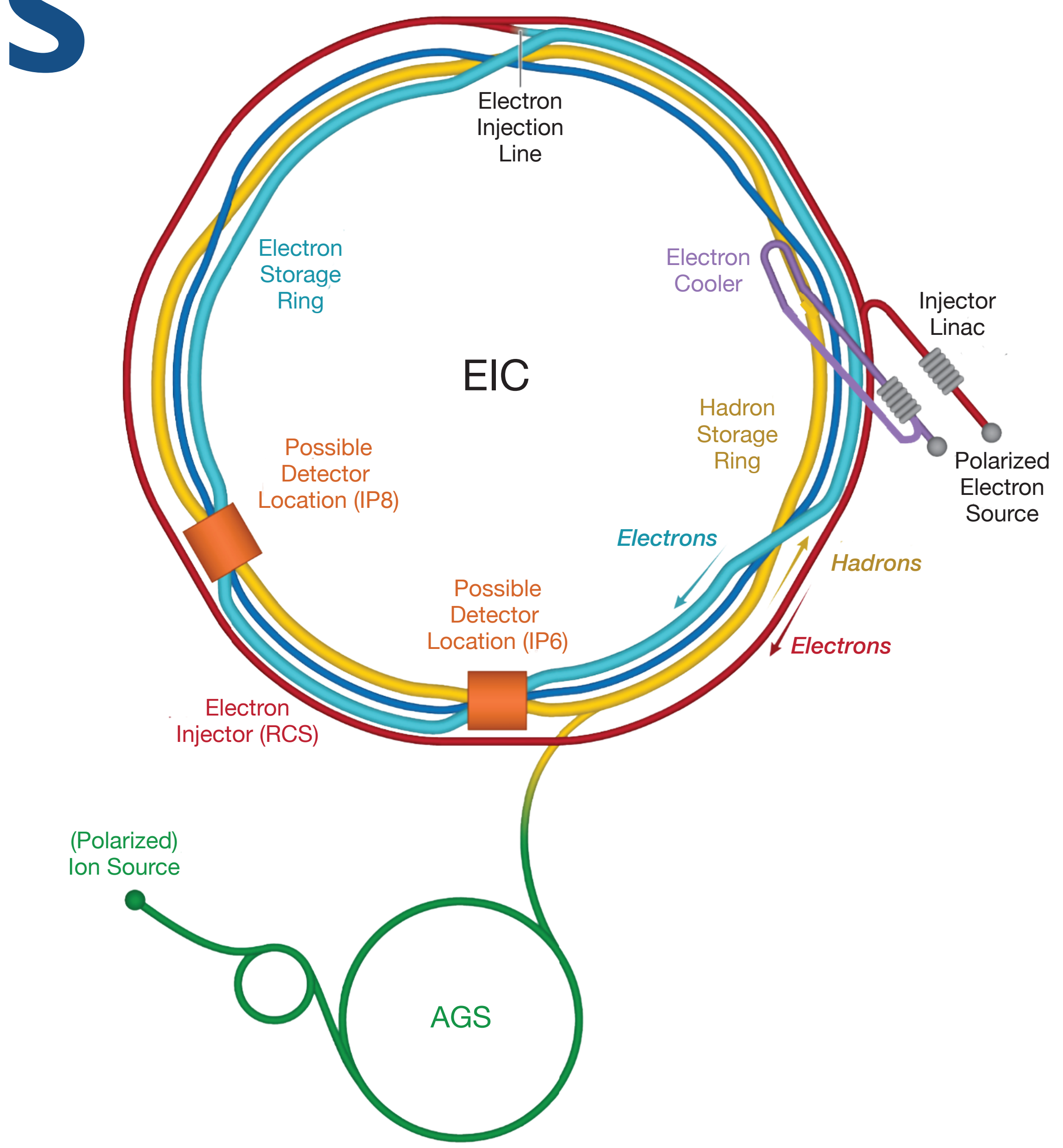
  Chu, Aschenauer, Lee, Zheng `17





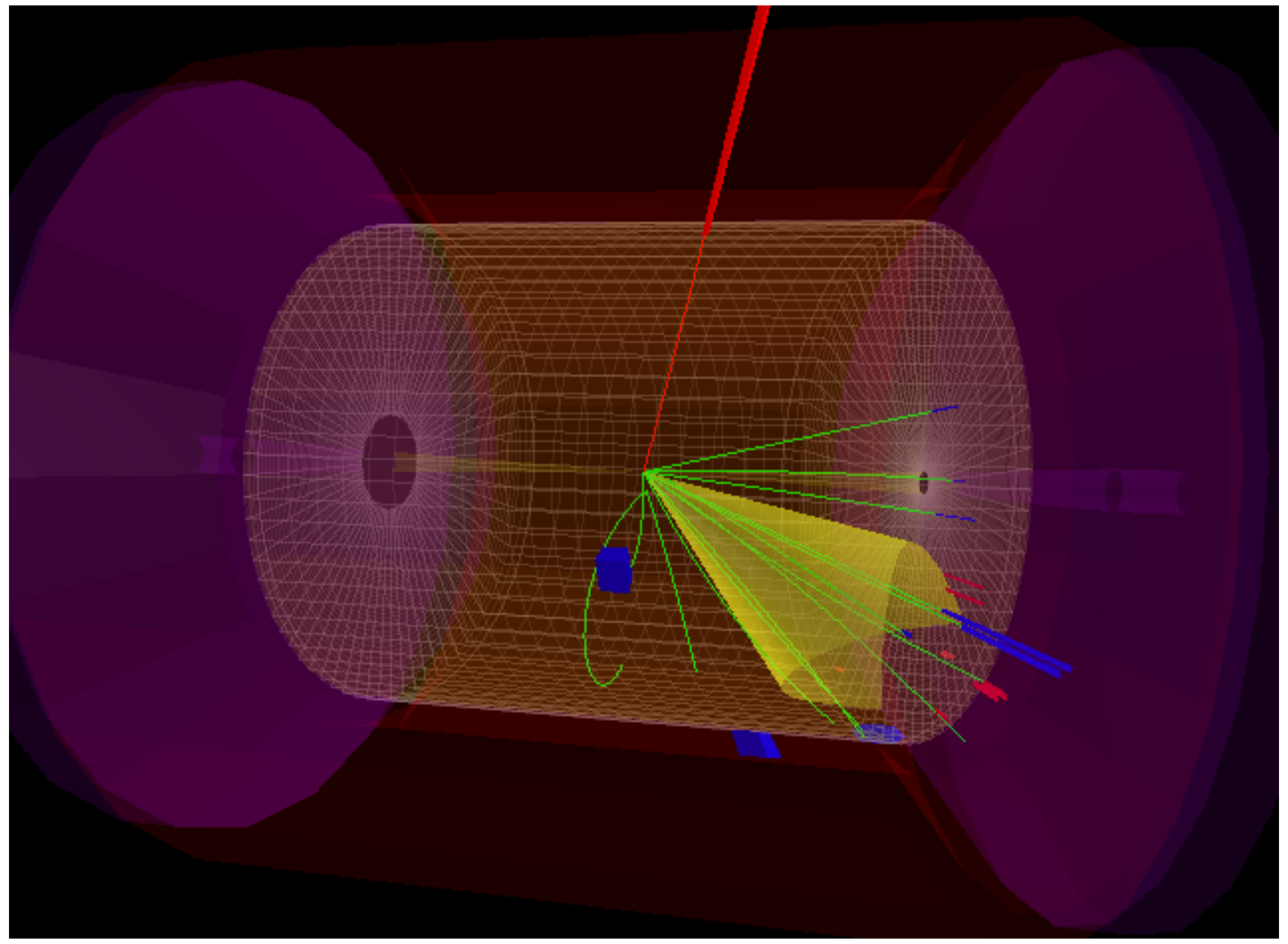
- Various related applications

First feasibility studies



- Are EIC/RHIC jets too low energy / few particles?

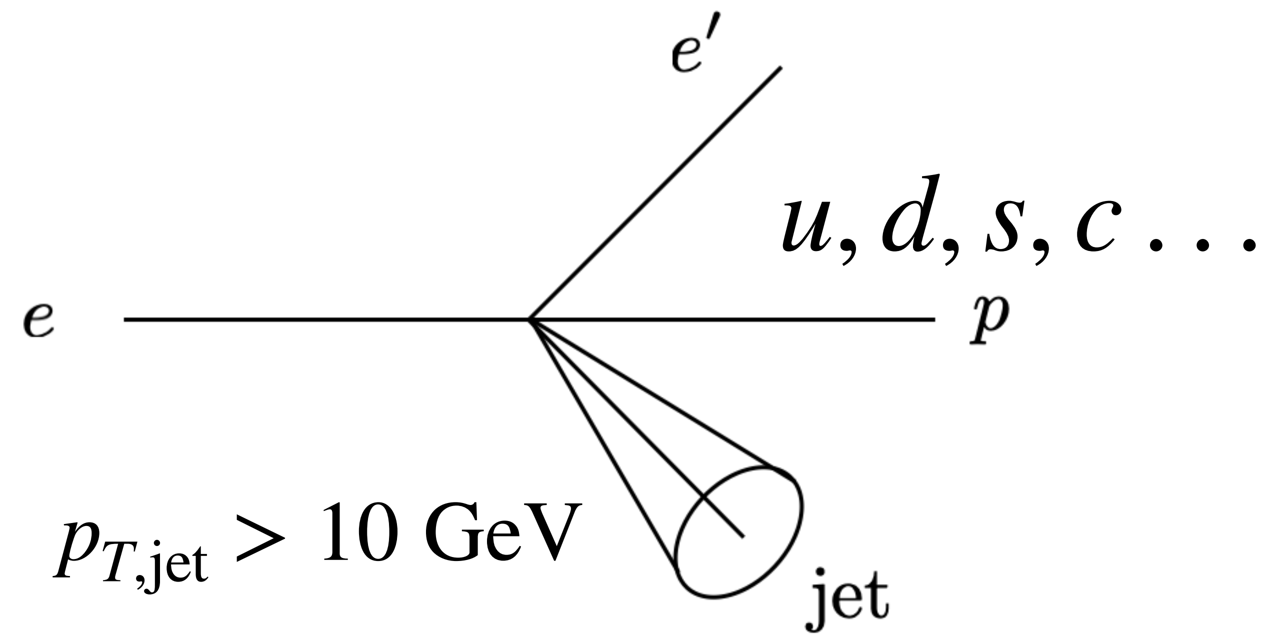
- Can we use the full event information?



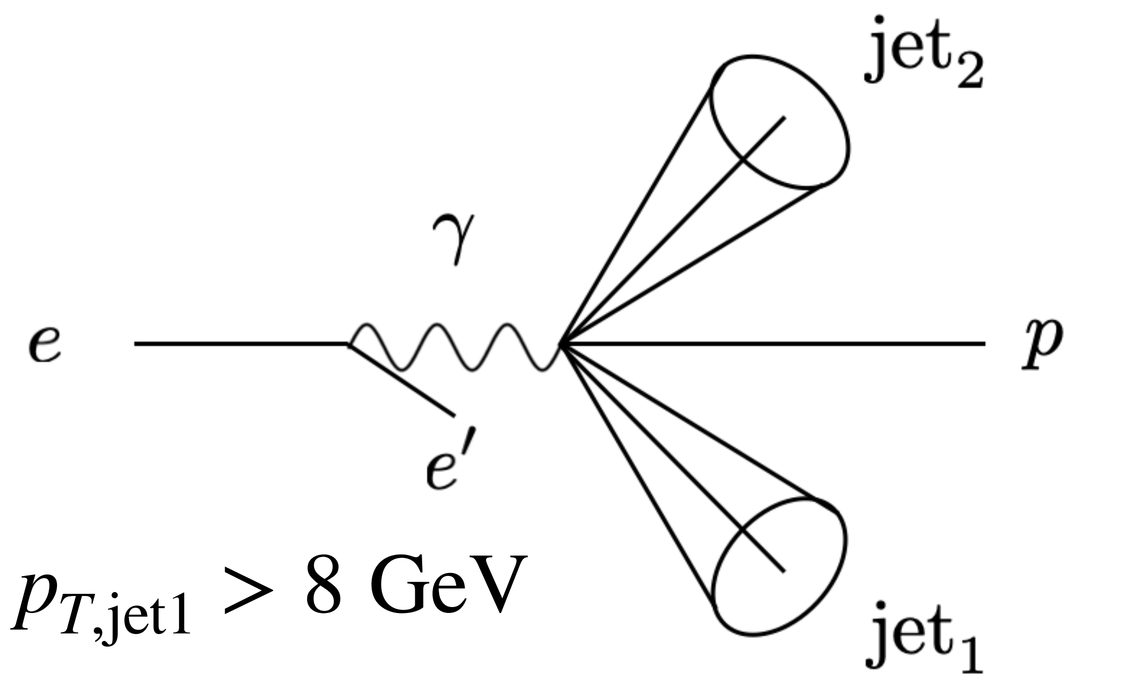
Events & machine learning

PYTHIA6

- No detector simulation
- Partile (p_T, η, ϕ, PID)



Photoproduction

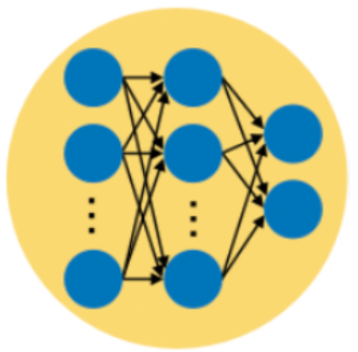


Binary classification: u vs. d, ud vs. s, …

ML architecture: Particle Flow Networks

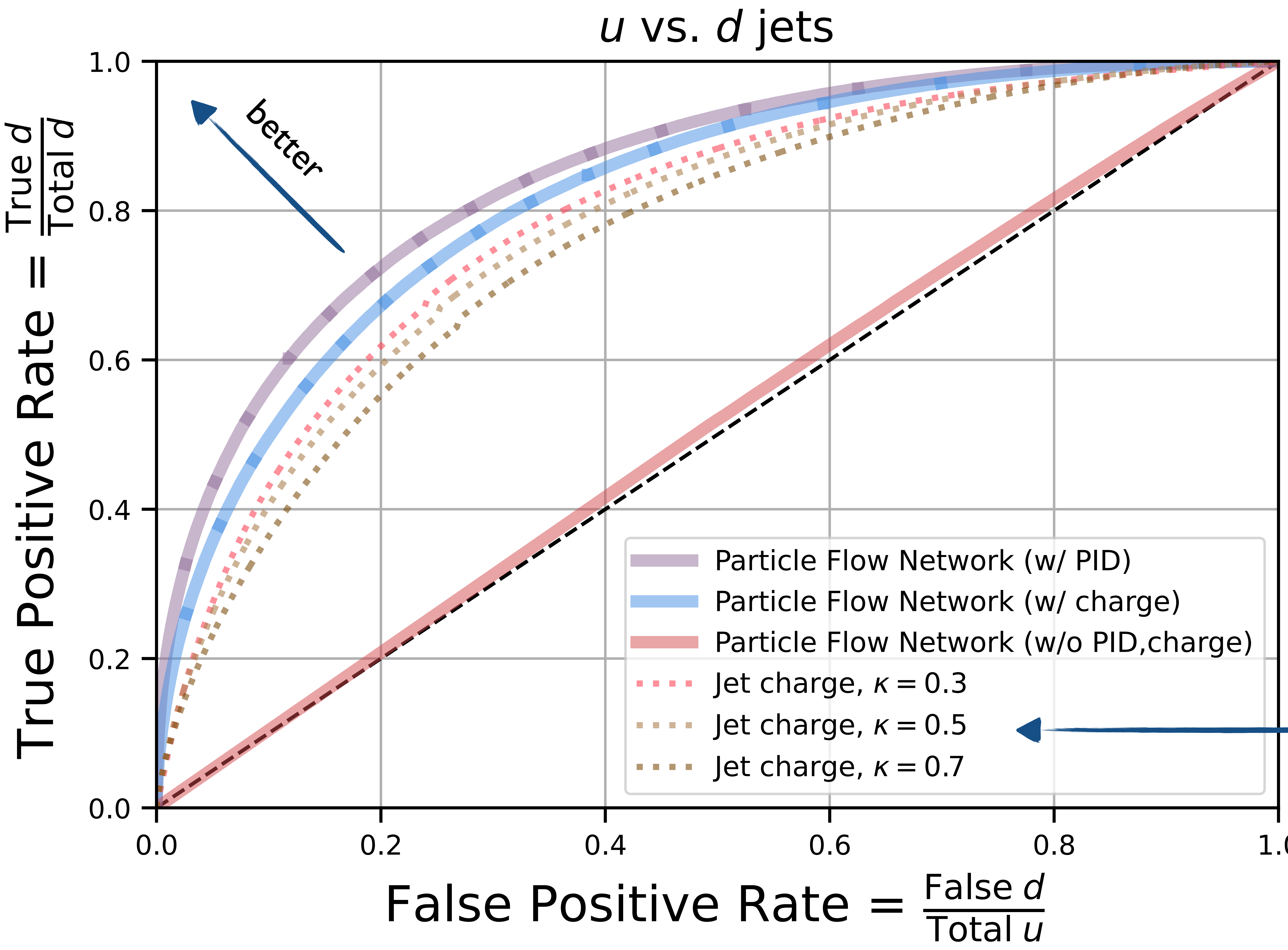
$$f(p_1, \ldots, p_M) = F\left(\sum_{i=1}^{M} \Phi\left(p_i\right)\right)$$

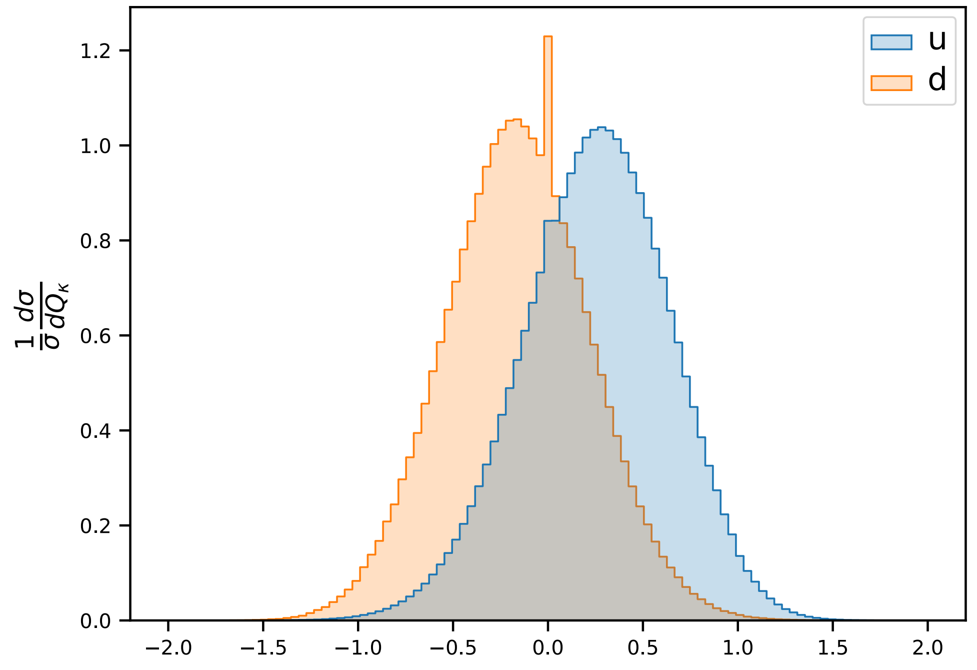
Classifier



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

Jet flavor tagging: u vs. d

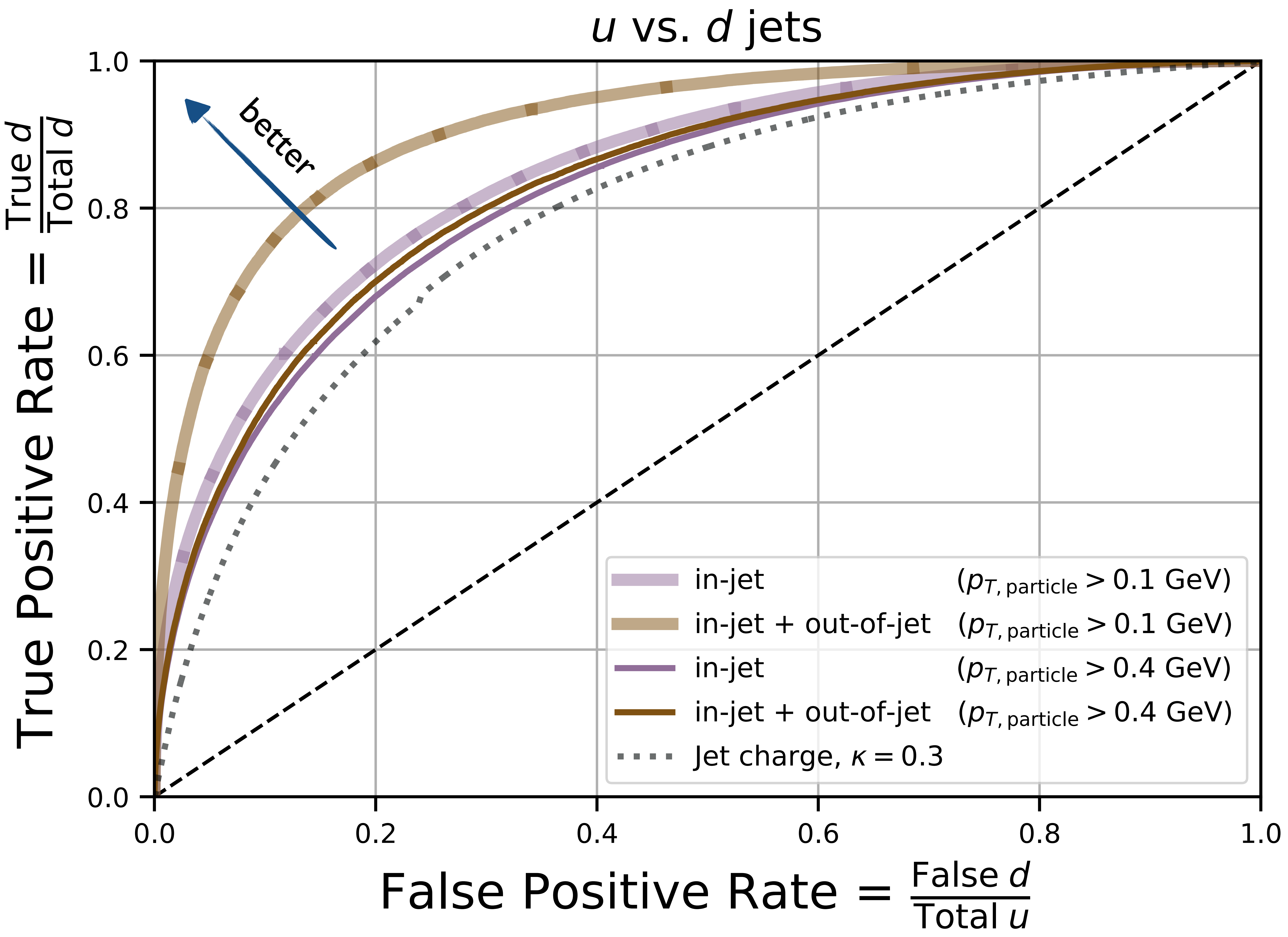




Jet charge, currently used

$$Q_\kappa = \sum_{i \in \text{jet}} z_i^\kappa Q_i$$

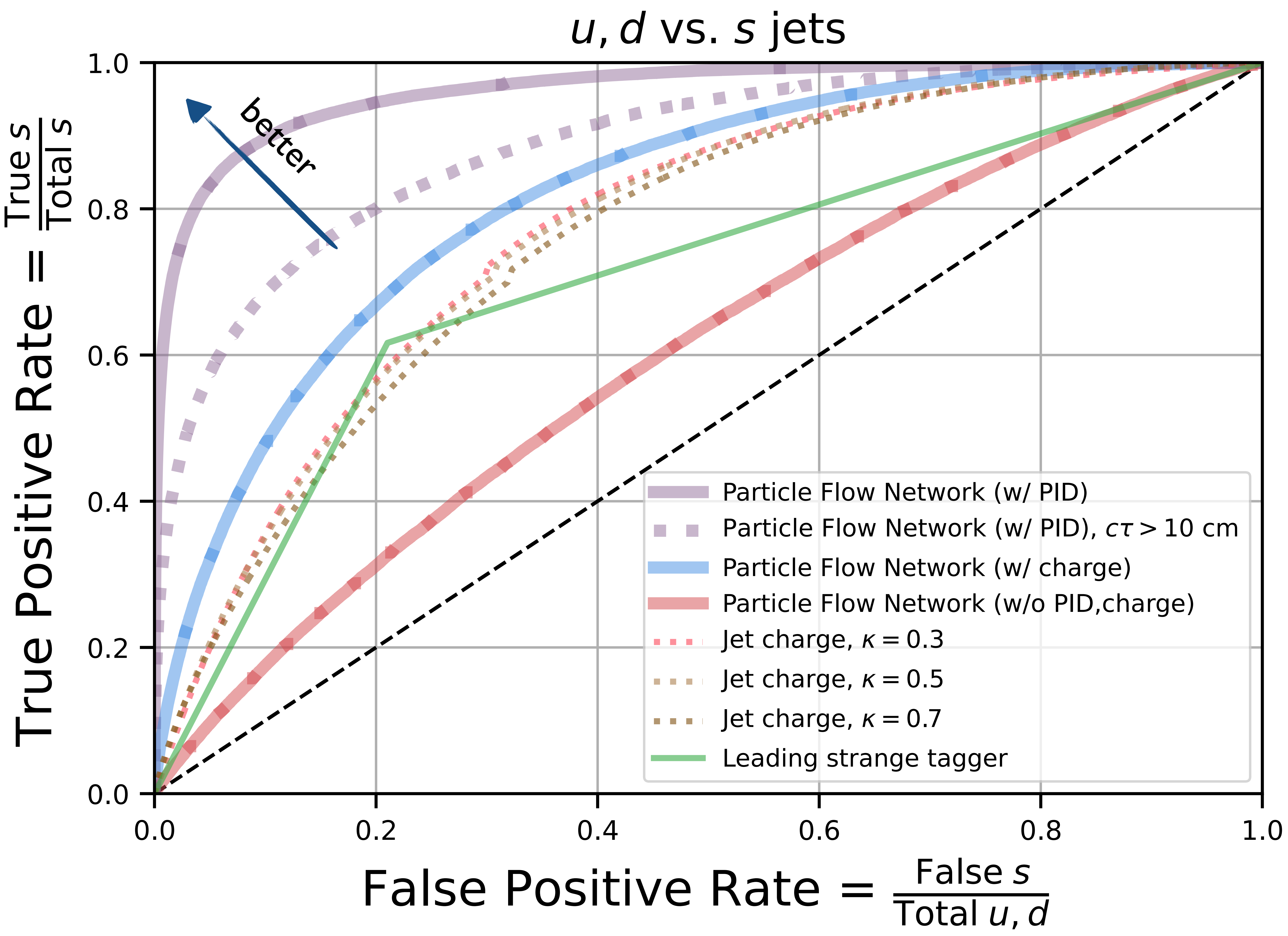
Jet flavor tagging: u vs. d



Significant gain from out-of-jet information!

- Motivates theory studies
- Impact on EIC detector?

Jet flavor tagging: *ud* vs. *s*



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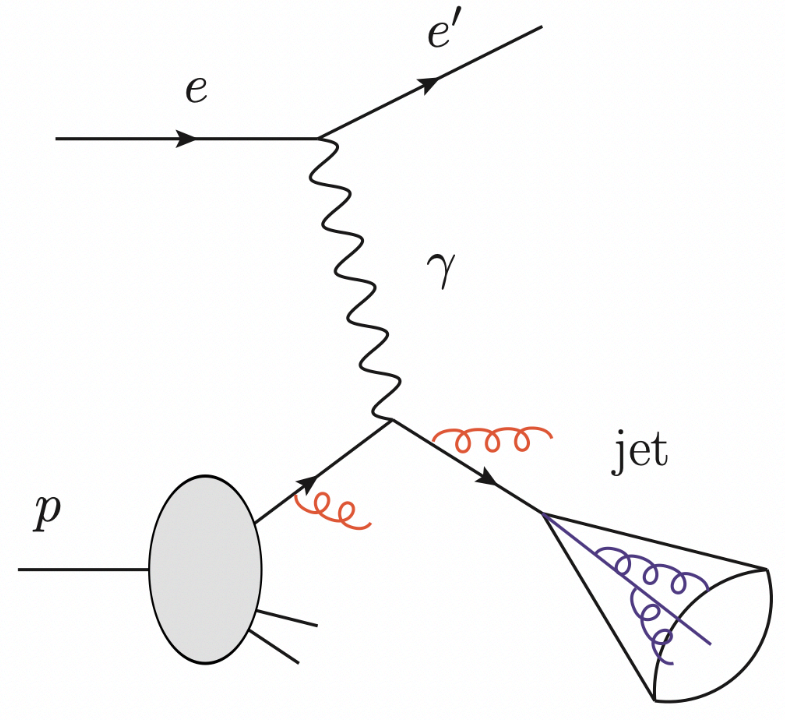
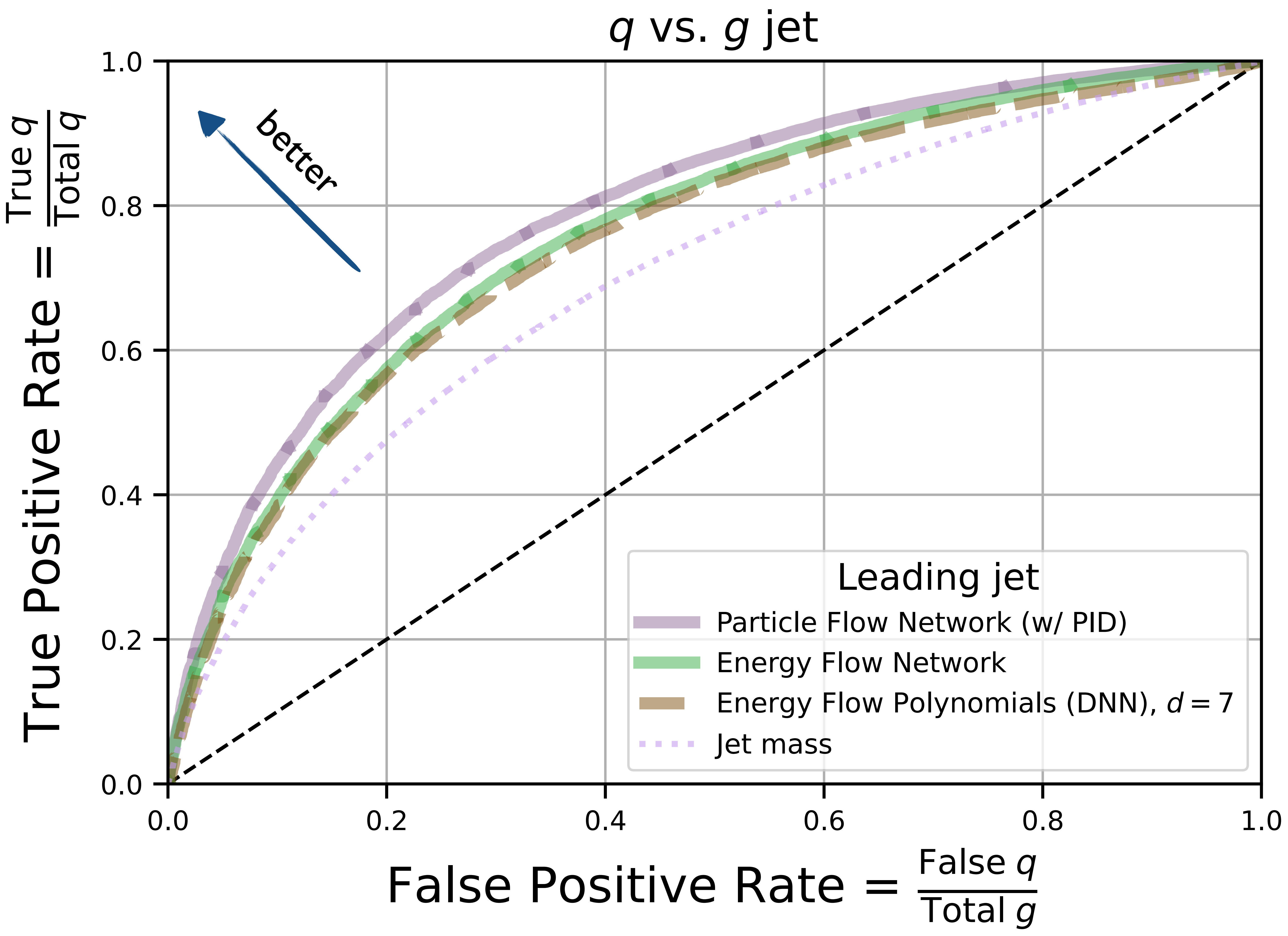


Quark vs. gluon jet tagging

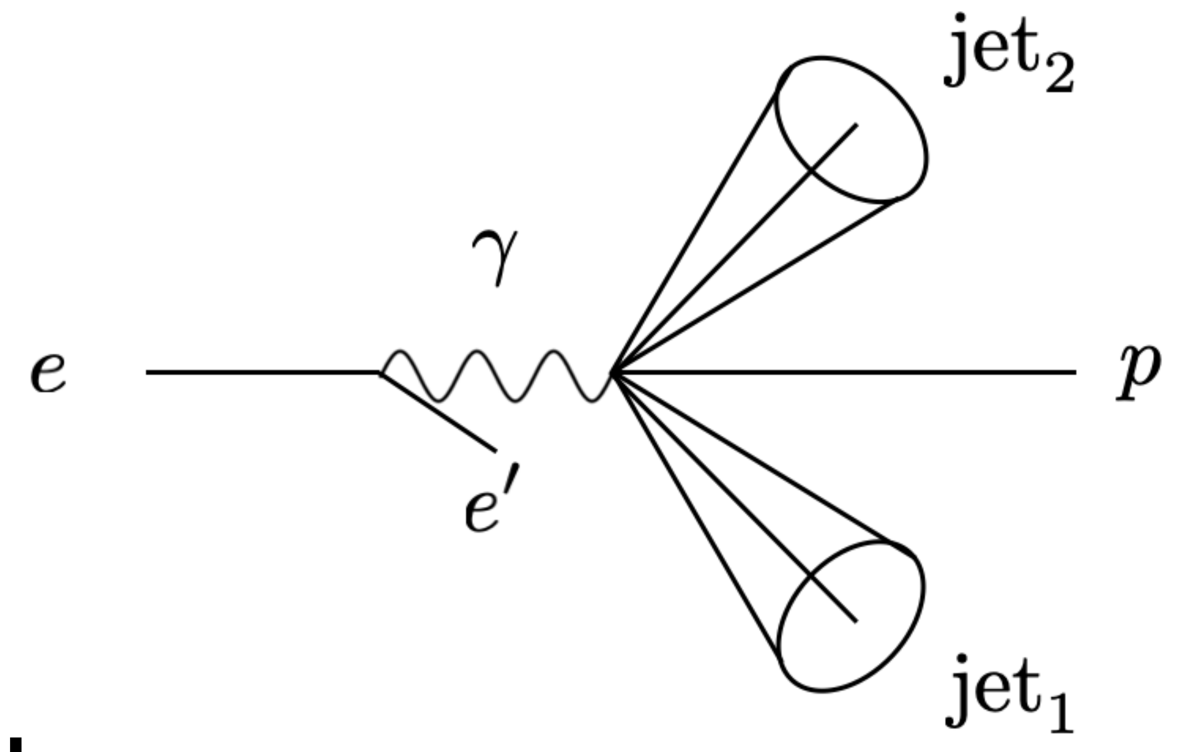


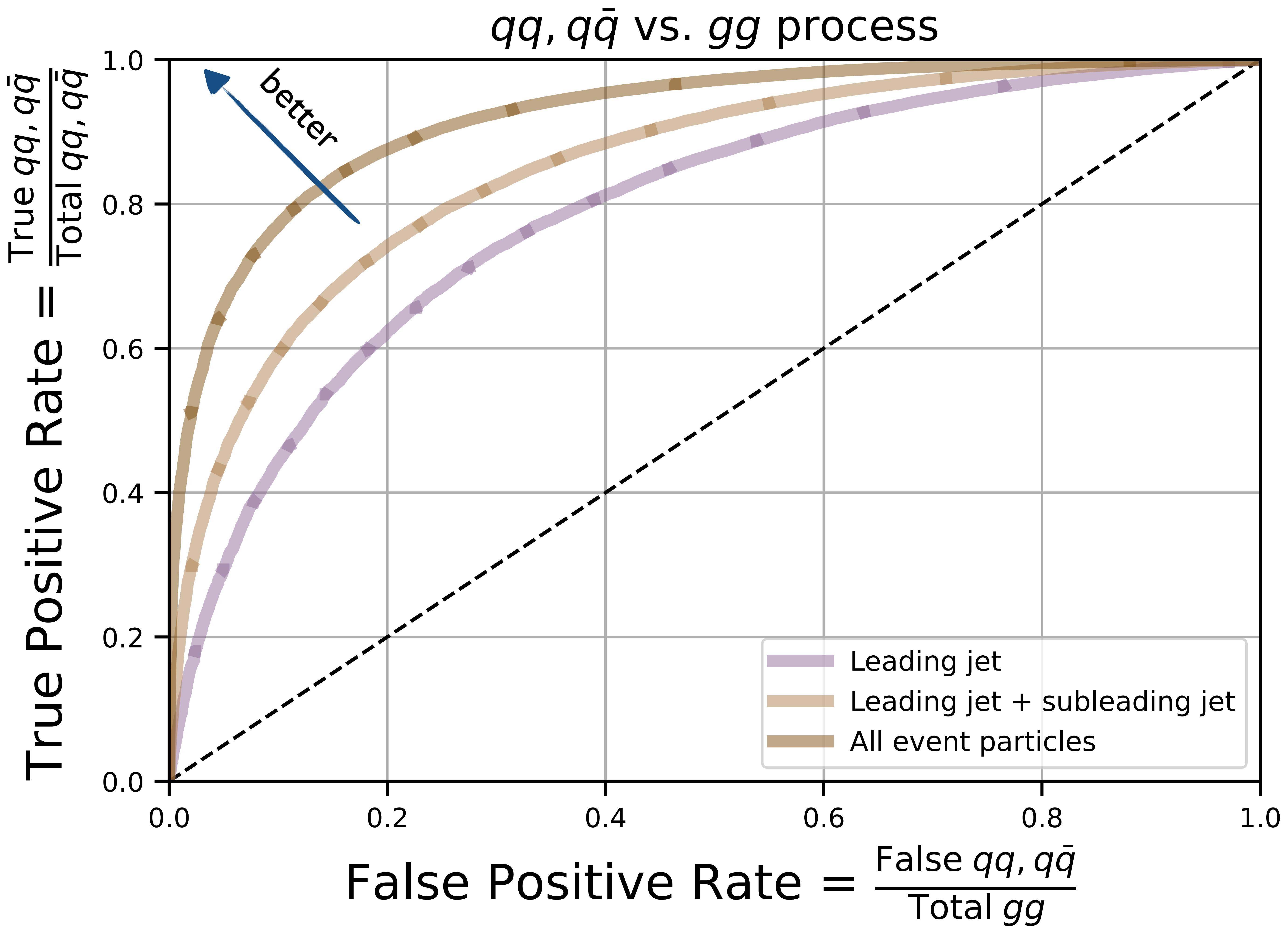
ML performance not as good as at LHC, but still reasonably good

AUC	EIC	LHC
Particle Flow Network	0.79	0.91
Energy Flow Network	0.76	0.88

Komiske, Metodiev, Thaler, `18, `19

Hard process tagging





We classify hard processes generating $qq/q\bar{q}$ vs. gg di-jets:

$$qq \to qq, q\bar{q} \to q\bar{q}, gg \to q\bar{q}, \gamma_T^* g \to q\bar{q}, \gamma_L^* g \to q\bar{q}$$

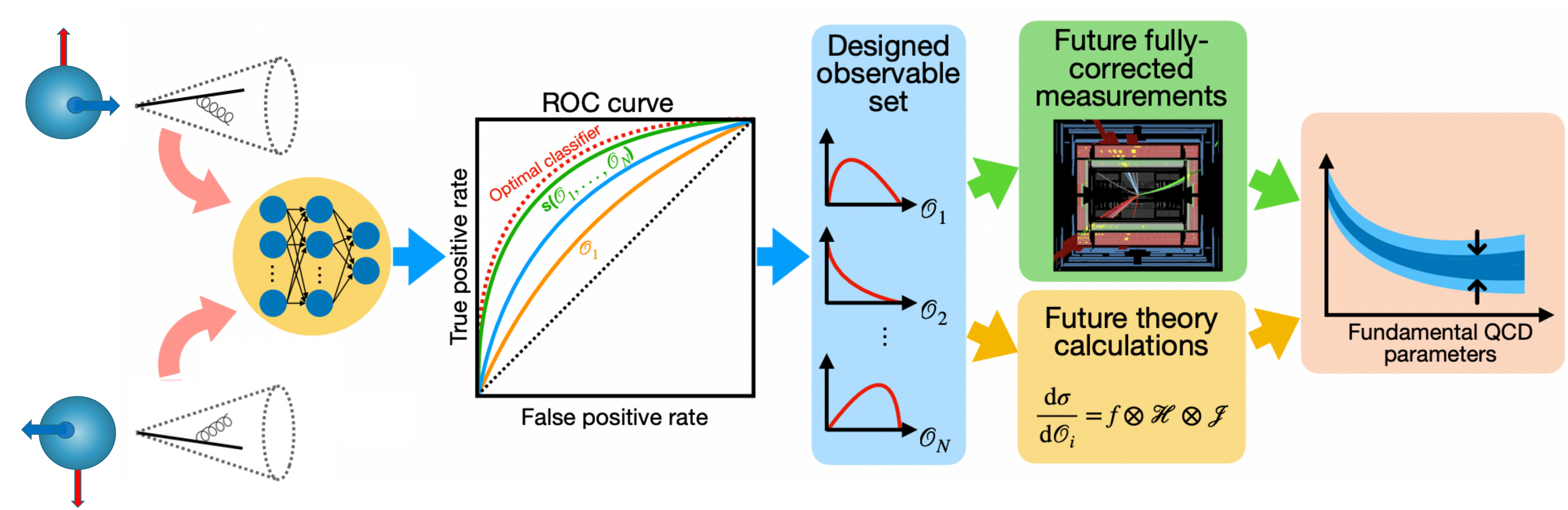
vs.

$$q\bar{q} \to gg, gg \to gg,$$

Significant improvement when adding subleading jet and out-of-jet particles

→ Can use this method to tag resolved photoproduction contributions

ML for hadron structure & spin physics



Summary

Improved access to hadron structure and spin physics at the EIC/RHIC

- Feasibility studies with potential impact on EIC design
- More quantitative work needed

PYTHIA6 indicates that ML tools are useful at EIC/RHIC

- Large performance boost for strange & charm
- Especially out-of-jet particles are relevant

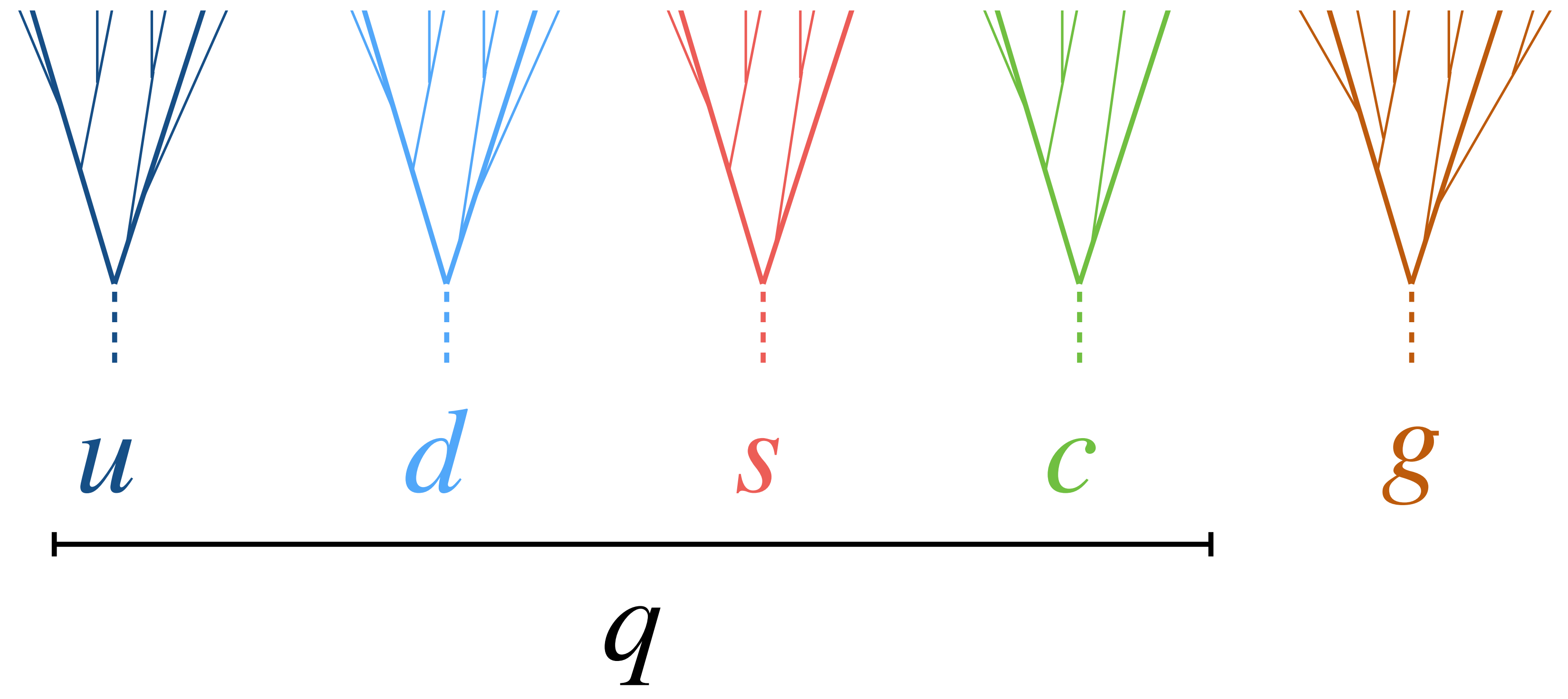
Data & code: *https://zenodo.org/record/7538810#.Y8RcaS-B2gQ*

- RHIC analysis could already be done now

backup

Constraining TMDs with jet flavor tagging

Determining the flavor of a jet allows stronger constraints on TMDs by avoiding spin asymmetry cancellations of different flavors



Example: Collins fragmentation function

Schäfer-Teryaev sum rule: $$\sum_h \int_0^1 \mathrm{d}z\, H_{1,h/q}^{\perp(3)}(z) = 0$$

One usually measures identified hadrons to avoid e.g. π^+ cancellation with π^-

However the fragmentation functions still contain large parton flavor cancellations:

$$\int_0^1 \mathrm{d}z \left(H_{1,\pi^+/u}^{\perp(3)}(z) + H_{1,\pi^+/d}^{\perp(3)}(z) \right) \approx 0$$

→ Tagging jet flavor will allow stronger constraints on Collins fragmentation function

e.g. *Arratia, Kang, Produkin, Ringer PRD 201 7, 074015 (2020)*

Additional applications of jet flavor tagging

- Longitudinally polarized gluon distribution Δg — quark flavor and quark vs. gluon

  Zhou, Sato, Melnitchouk (JAM), PRD 105, 074022 (2022)

- Gluon Sivers function — quark vs. gluon

  Zheng, Aschenauer, Lee, Xiao, Yin, PRD 98, 034011 (2018)
  Liu, Ringer, Vogelsang, Yuan, PRL122, 192003 (2019)

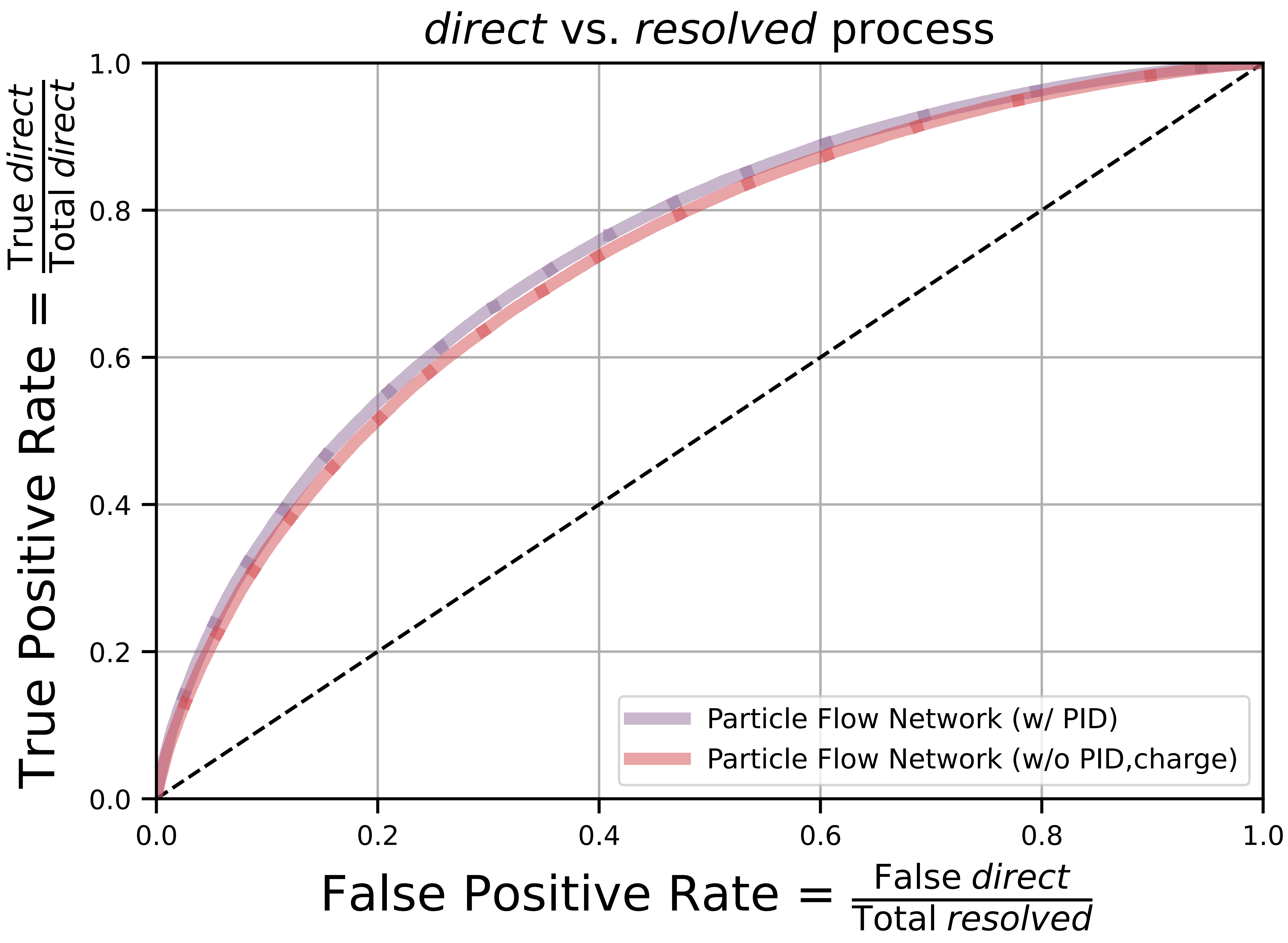
- Strange quark PDF — charm tagging

  Arratia, Furletova, Hobbs, Olness, Sekula, PRD 103, 074023 (2021)

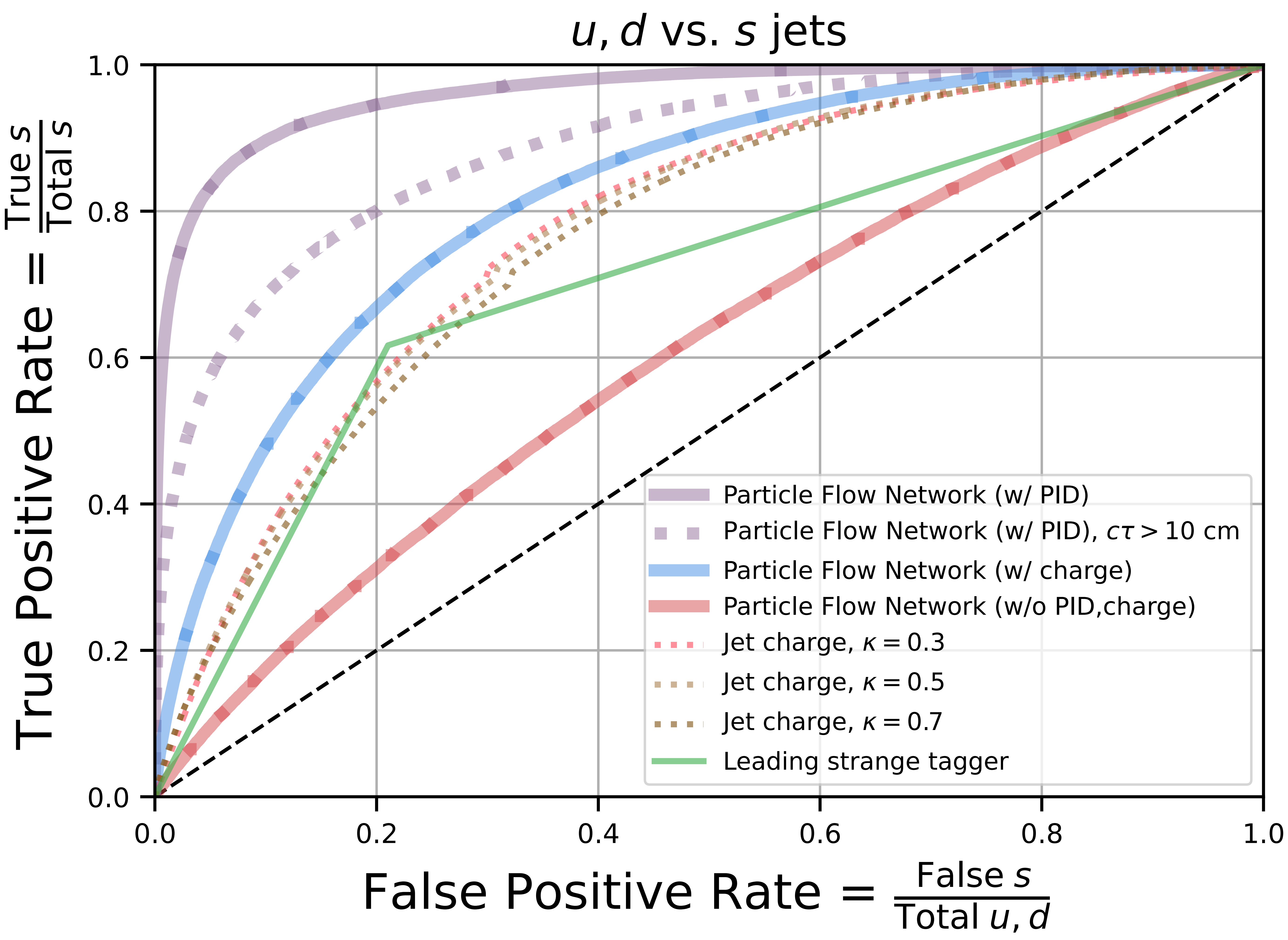
- BSM searches — quark flavor

  Li, Yan, Yuan, arXiv:2112.07747

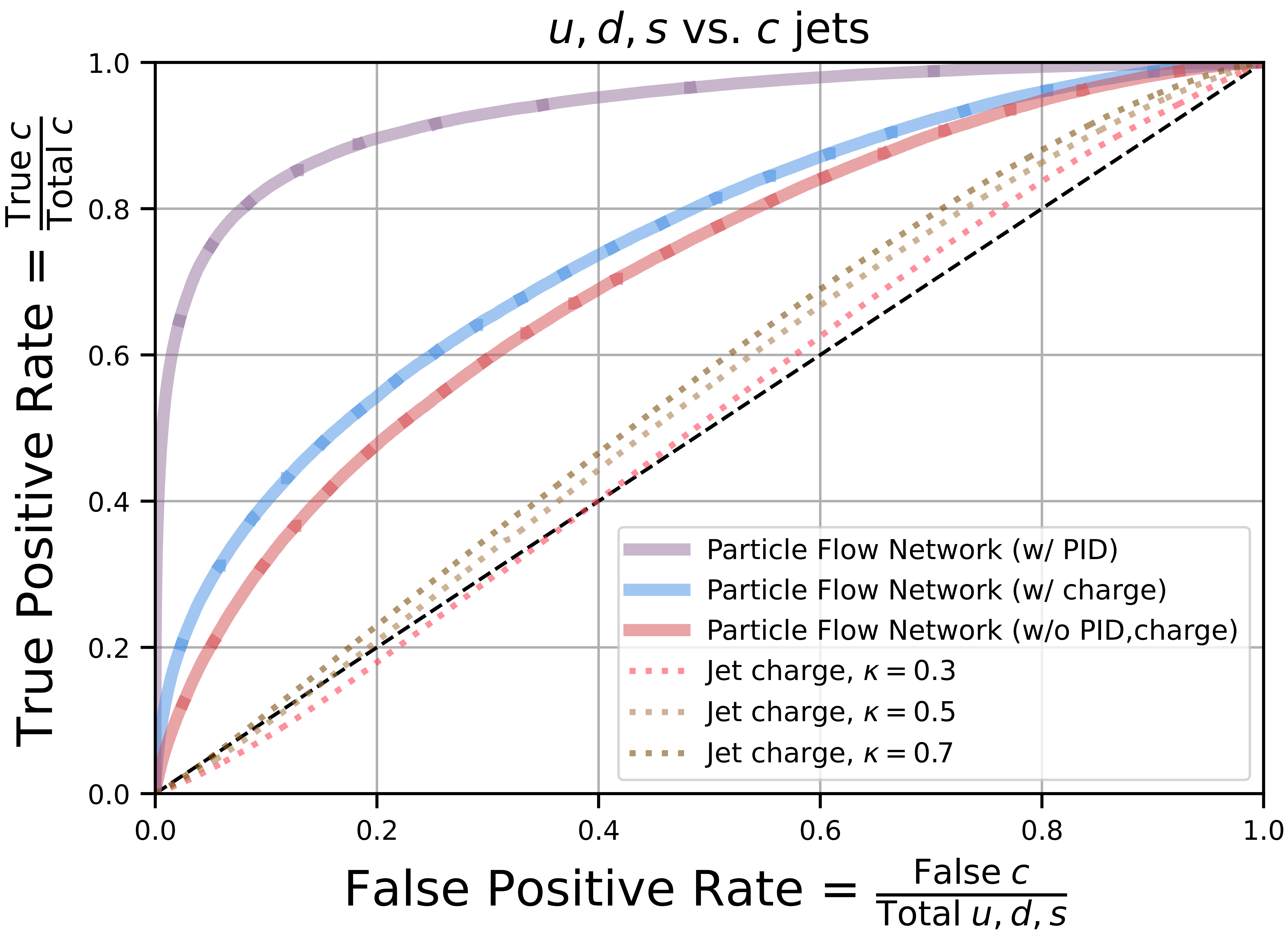
Direct vs. resolved photon tagging



ud vs. s


u, d vs. s jets
True Positive Rate = $\frac{\text{True } s}{\text{Total } s}$
False Positive Rate = $\frac{\text{False } s}{\text{Total } u, d}$
0.0
0.2
0.4
0.6
0.8
1.0
Particle Flow Network (w/ PID)
Particle Flow Network (w/ PID), $c\tau > 10$ cm
Particle Flow Network (w/ charge)
Particle Flow Network (w/o PID,charge)
Jet charge, $\kappa = 0.3$
Jet charge, $\kappa = 0.5$
Jet charge, $\kappa = 0.7$
Leading strange tagger

uds vs. c



u, d, s vs. c jets
True Positive Rate = $\frac{\text{True } c}{\text{Total } c}$
False Positive Rate = $\frac{\text{False } c}{\text{Total } u, d, s}$
1.0
0.8
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0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Particle Flow Network (w/ PID)
Particle Flow Network (w/ charge)
Particle Flow Network (w/o PID,charge)
Jet charge, $\kappa = 0.3$
Jet charge, $\kappa = 0.5$
Jet charge, $\kappa = 0.7$