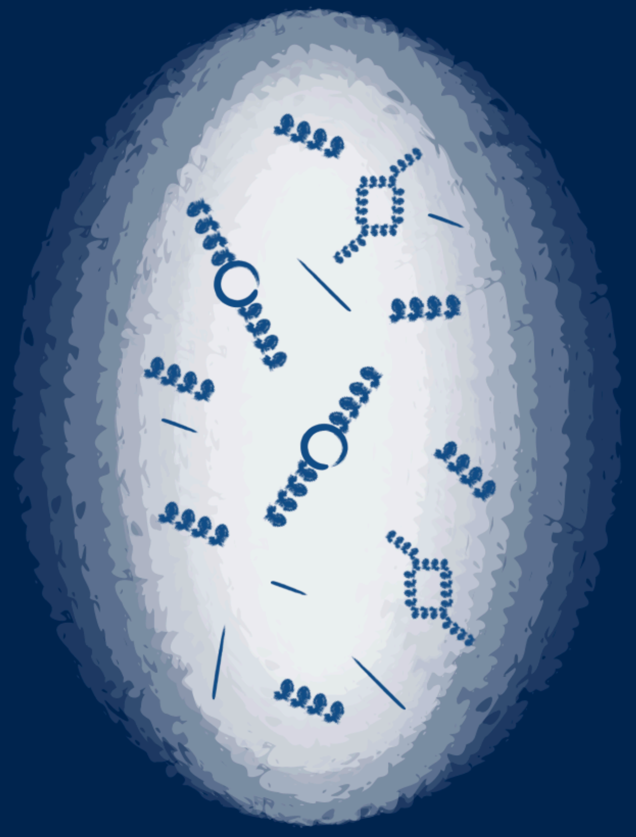
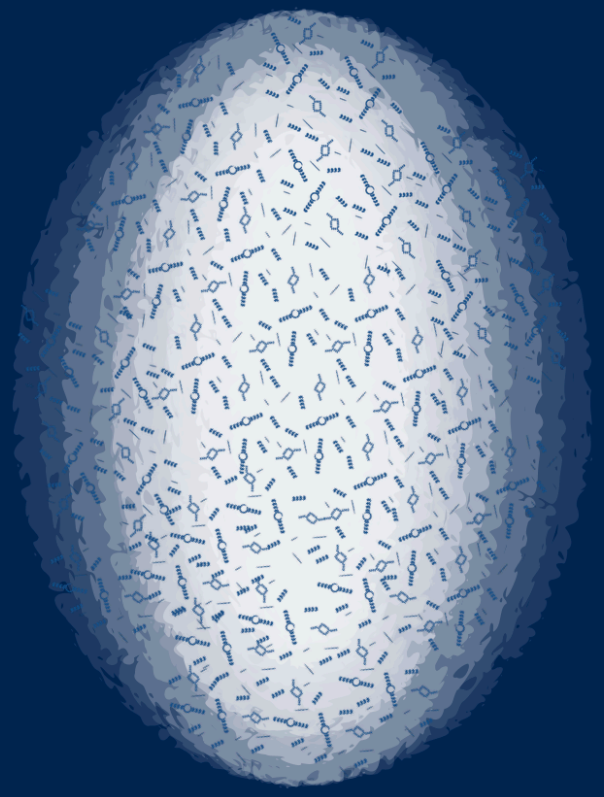
Using machine learning to interpret and guide jet quenching observables

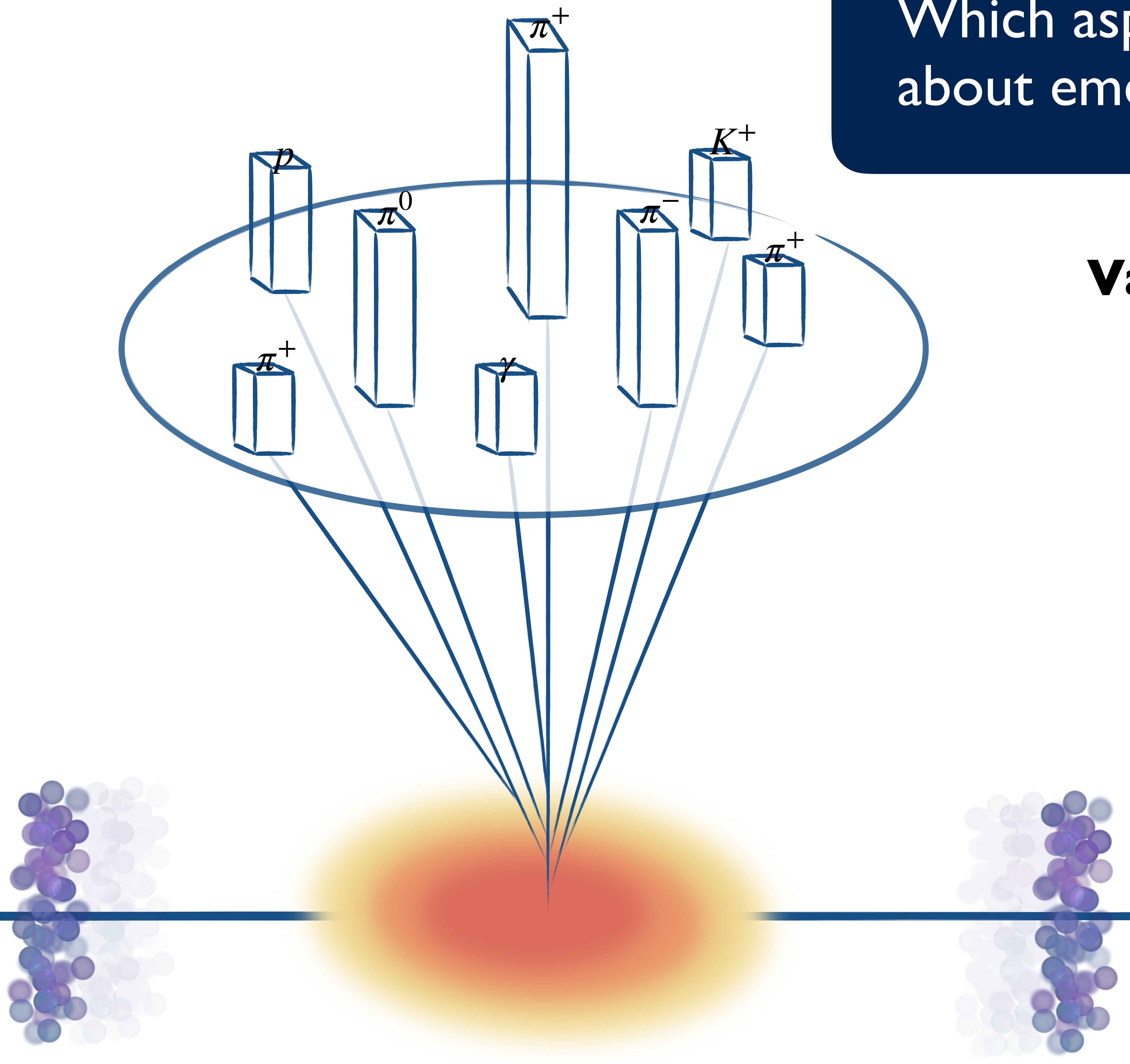


James Mulligan
UC Berkeley and LBNL



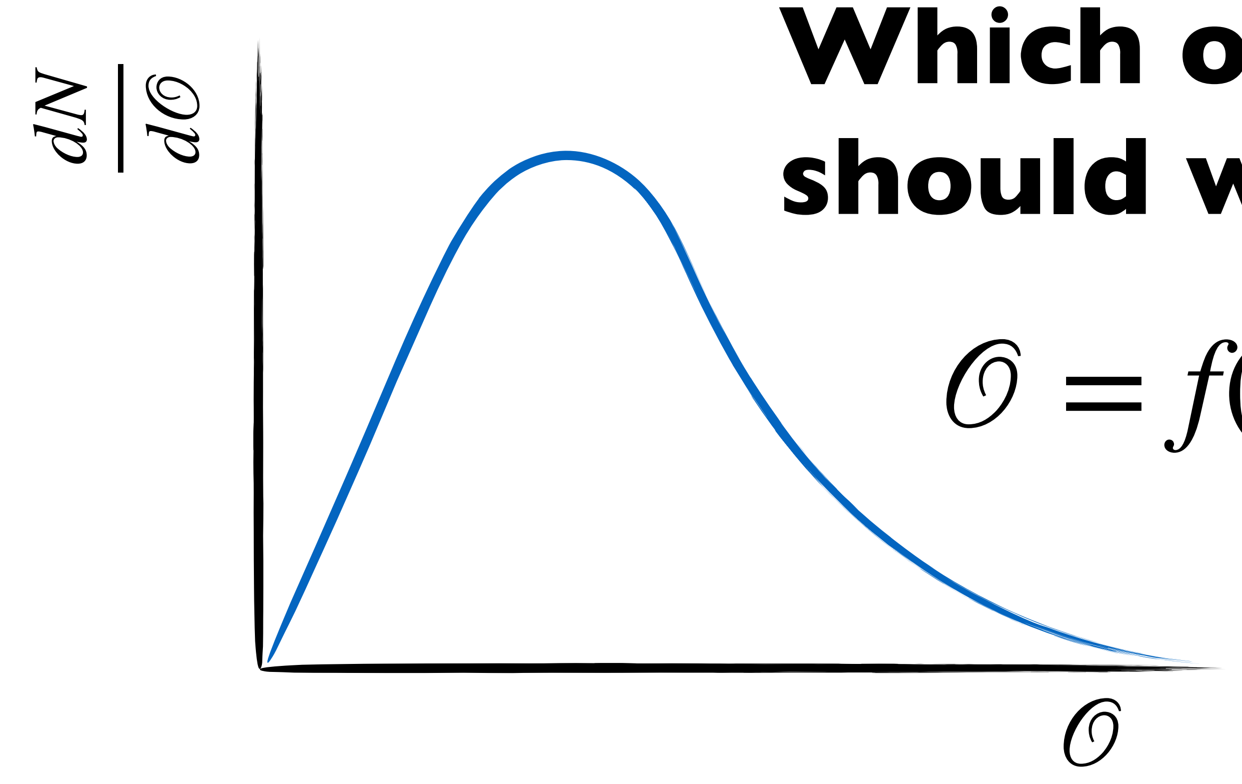
INT Jet Quenching Workshop
University of Washington
Oct 17, 2023

Which aspects of jets contain **useful information** about emergent properties of QCD?



Vast phase space

- $\mathcal{O}(10^2)$ correlated particles per jet
- Typically: 1D projection over ensemble

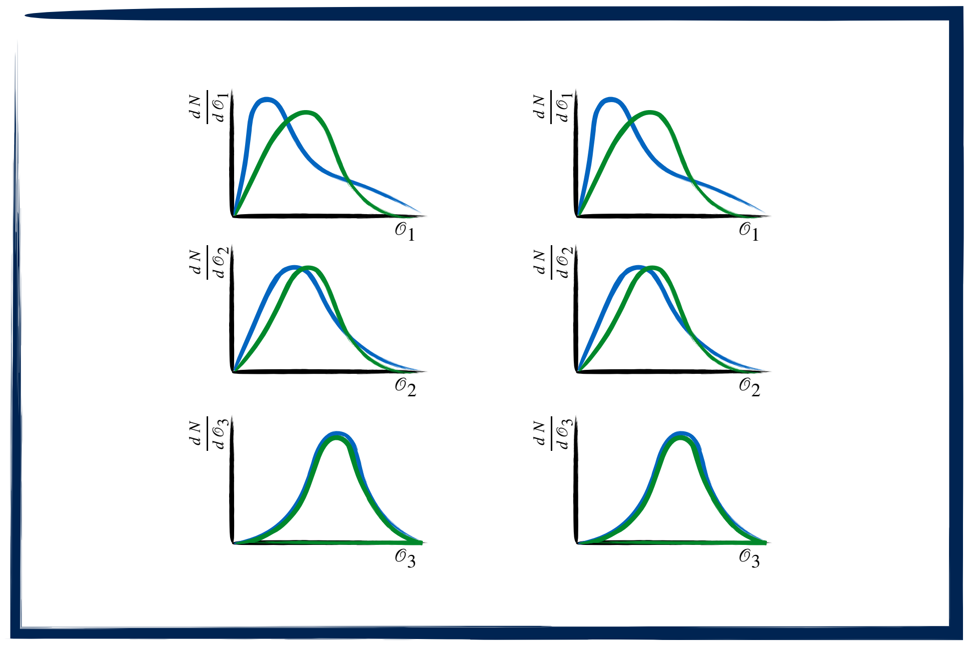


Which observables should we measure?

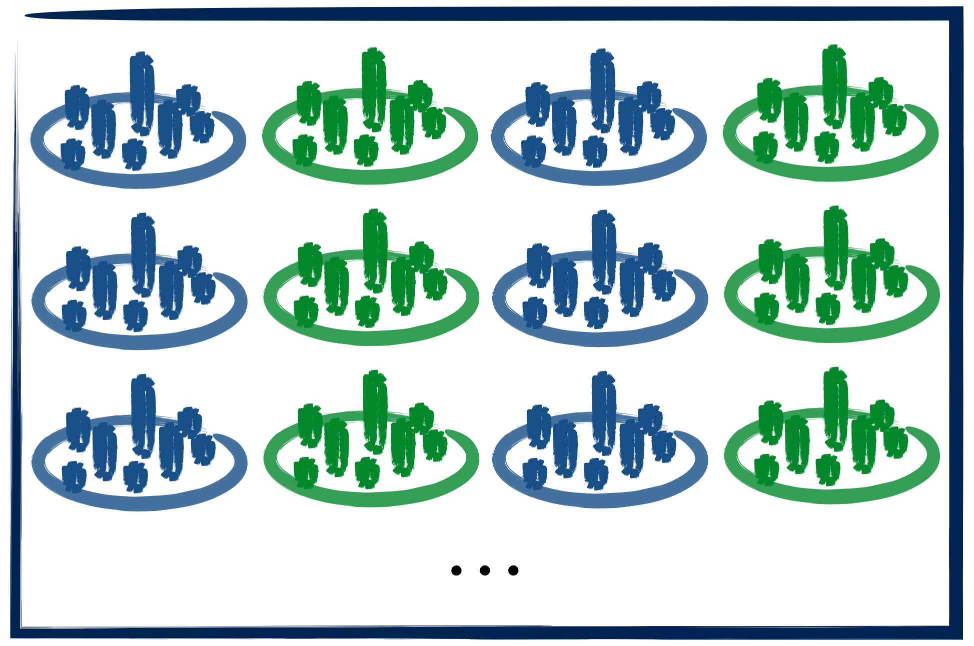
$$\mathcal{O} = f(\mathbf{p_0}, \ldots, \mathbf{p_n})$$

Two complementary approaches

1. Sets of observables



2. Particle-level information



Two complementary approaches

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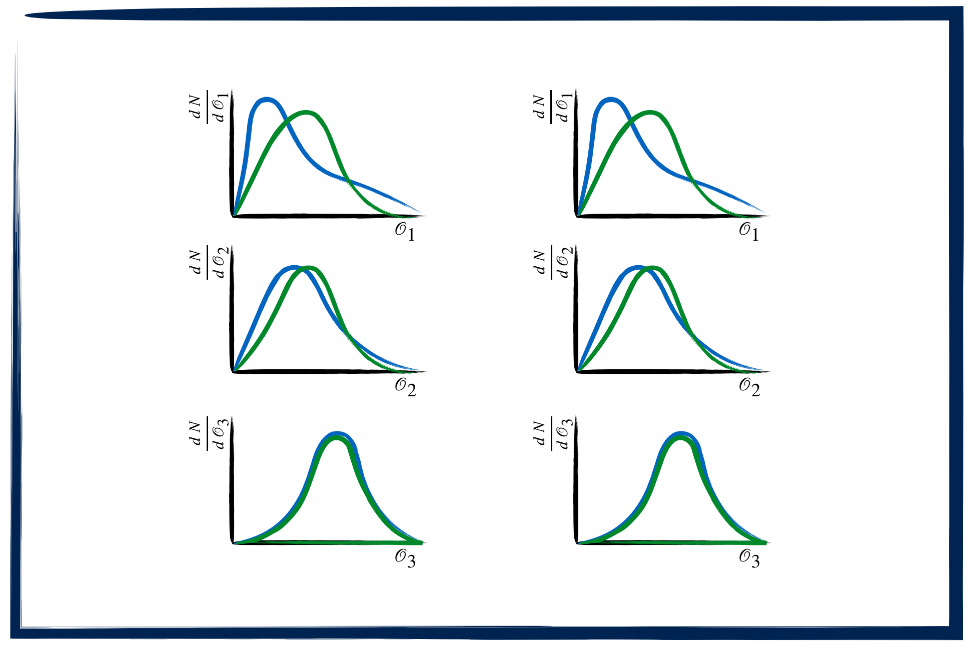
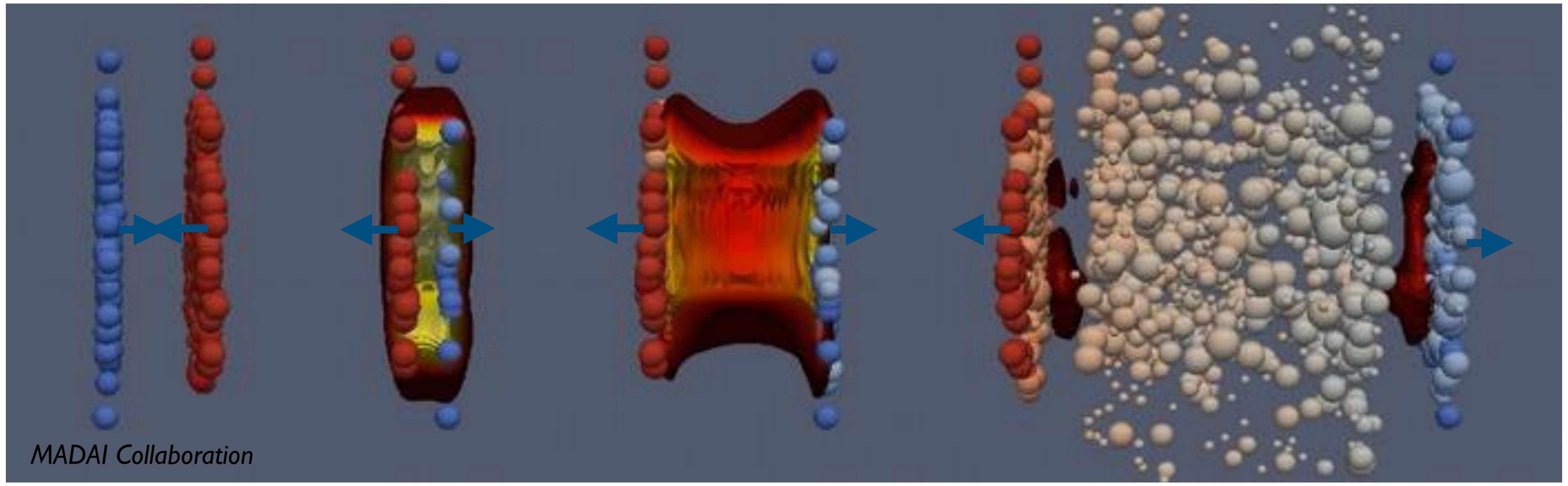


2. Particle-level information

There is no golden observable

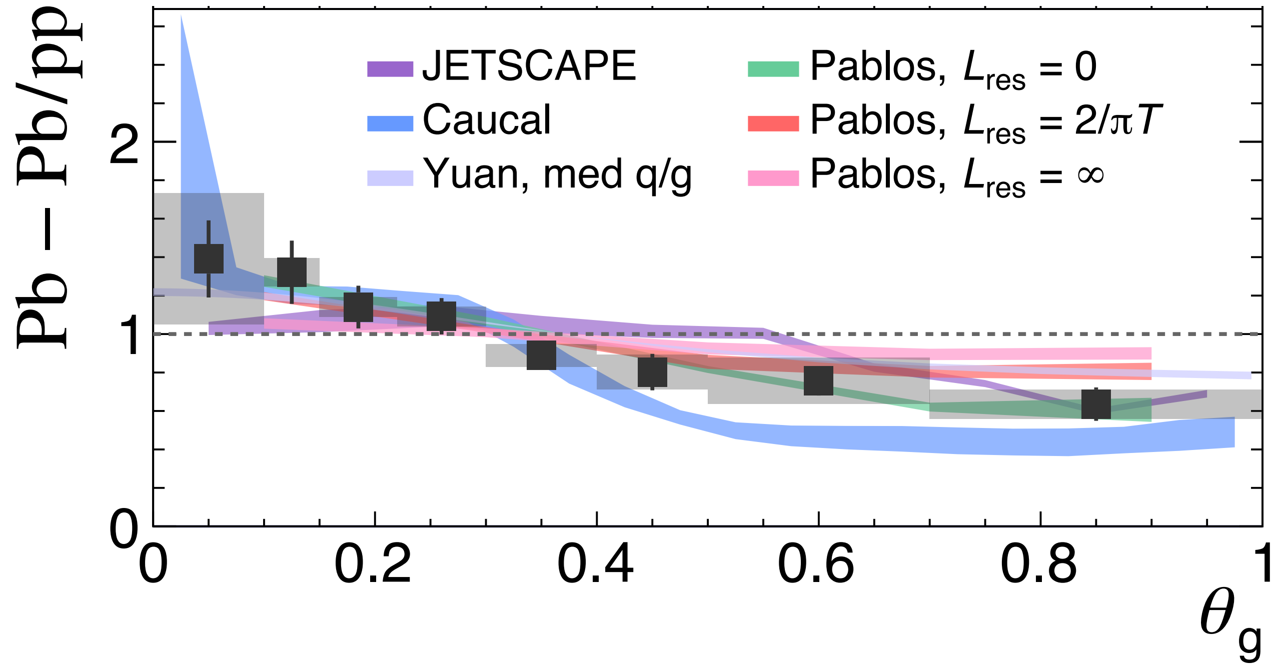
Multiple stages of heavy-ion collision — fit + predict

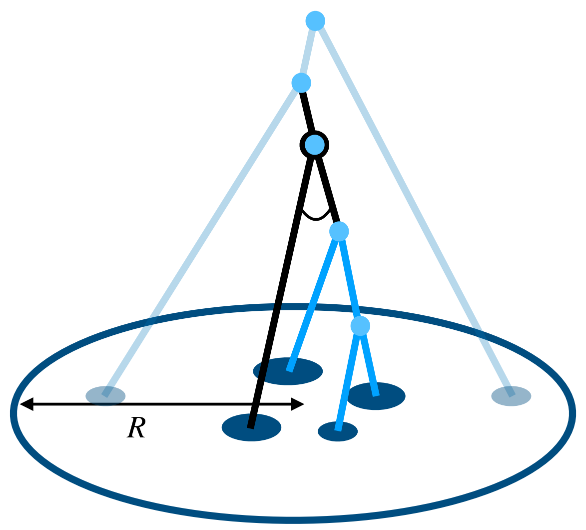


initial state | *hydrodynamic evolution medium response* | *hadronization hadronic rescattering*

Similar predictions for single observables

ALICE PRL 128 (10), 102001 (2022)





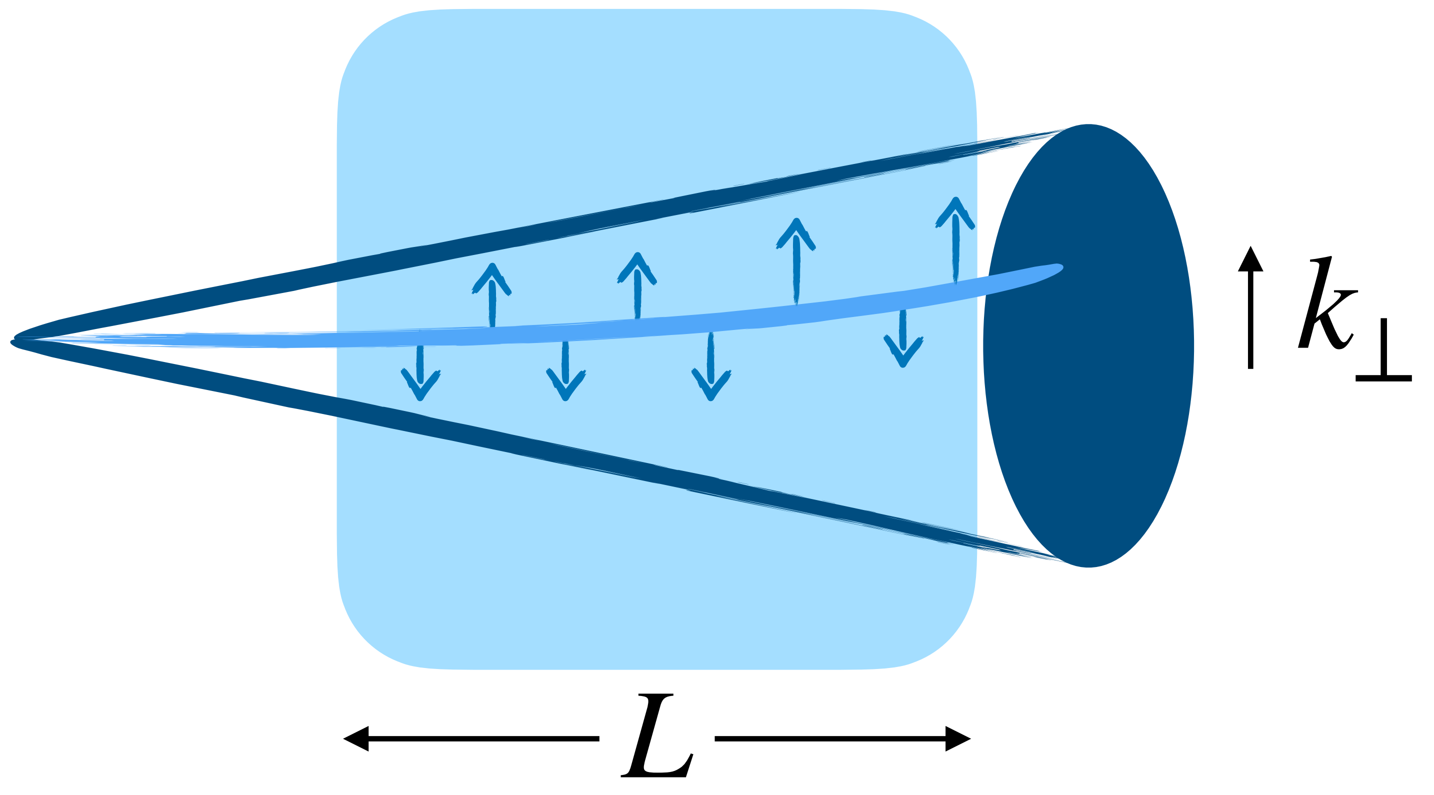
→ Need multiple observables to constrain medium properties

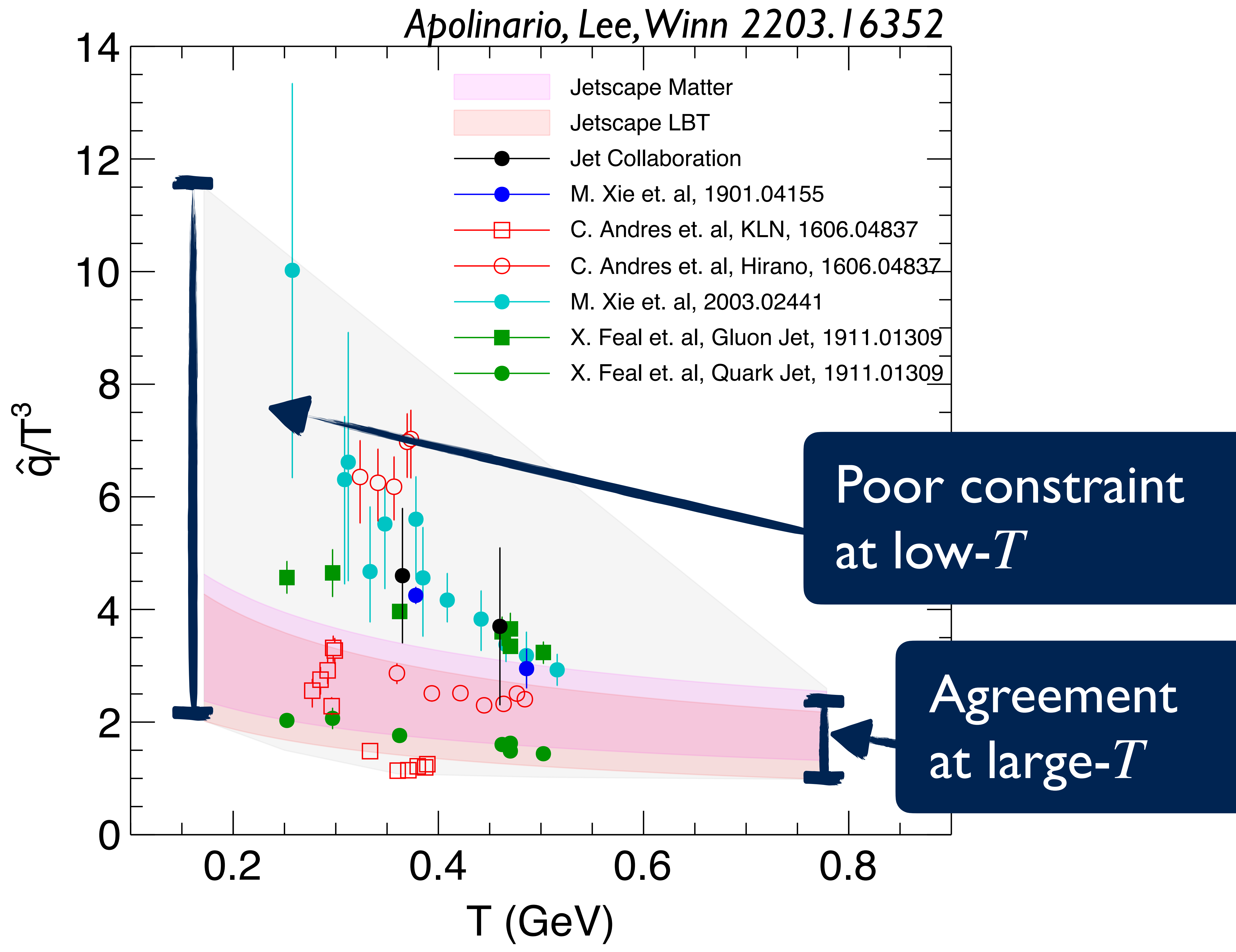
Bayesian estimation of $\hat{q}$

The jet transverse diffusion coefficient $\hat{q}$ encodes the microscopic structure of QGP partons

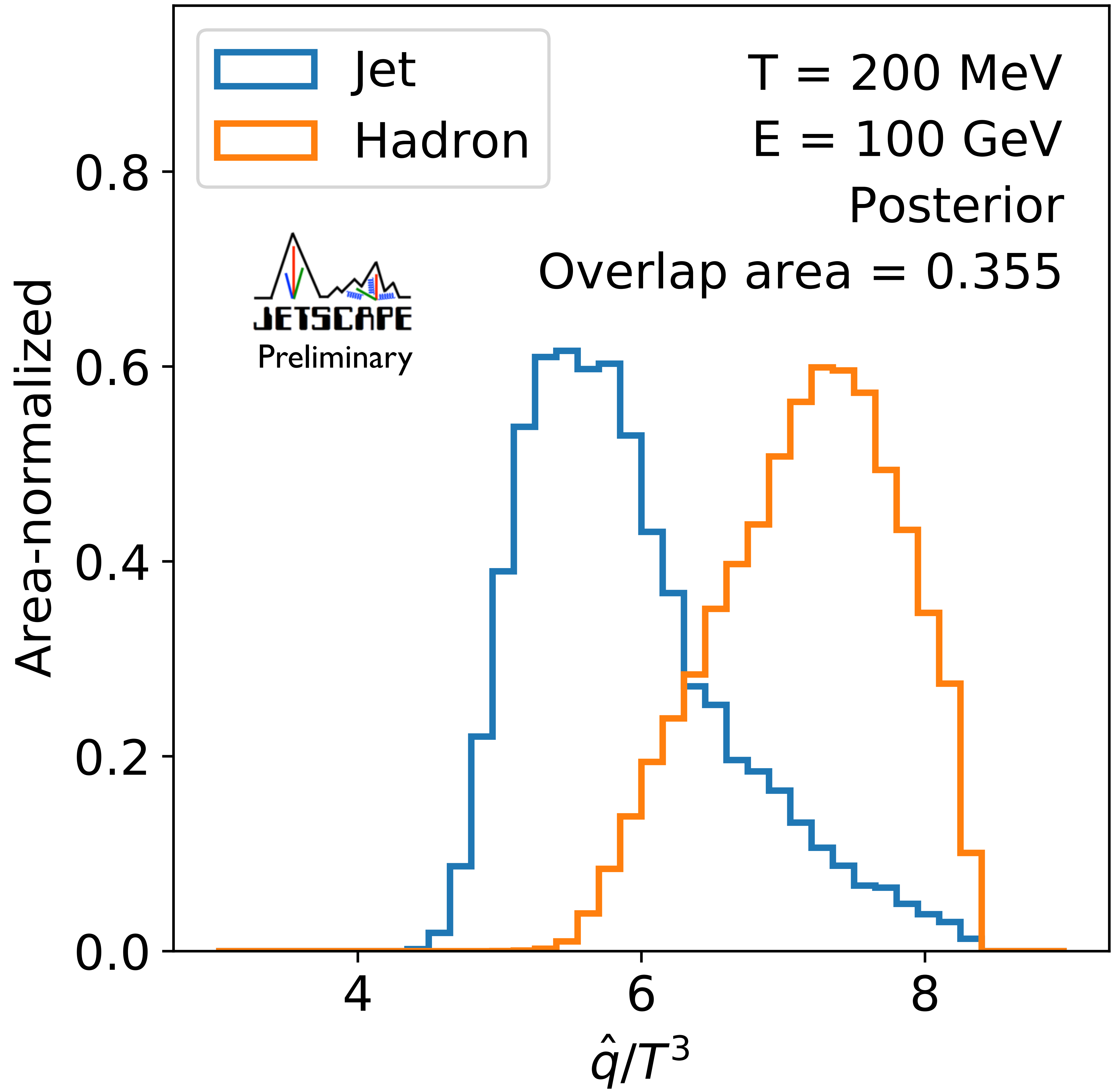
$$\hat{q} \equiv \frac{\langle k_\perp^2 \rangle}{L} = \frac{1}{L}\int dk_\perp^2 k_\perp^2 \frac{dP\left(k_\perp^2\right)}{dk_\perp^2}$$

where $P\left(k_\perp^2\right)$ is a scattering kernel.



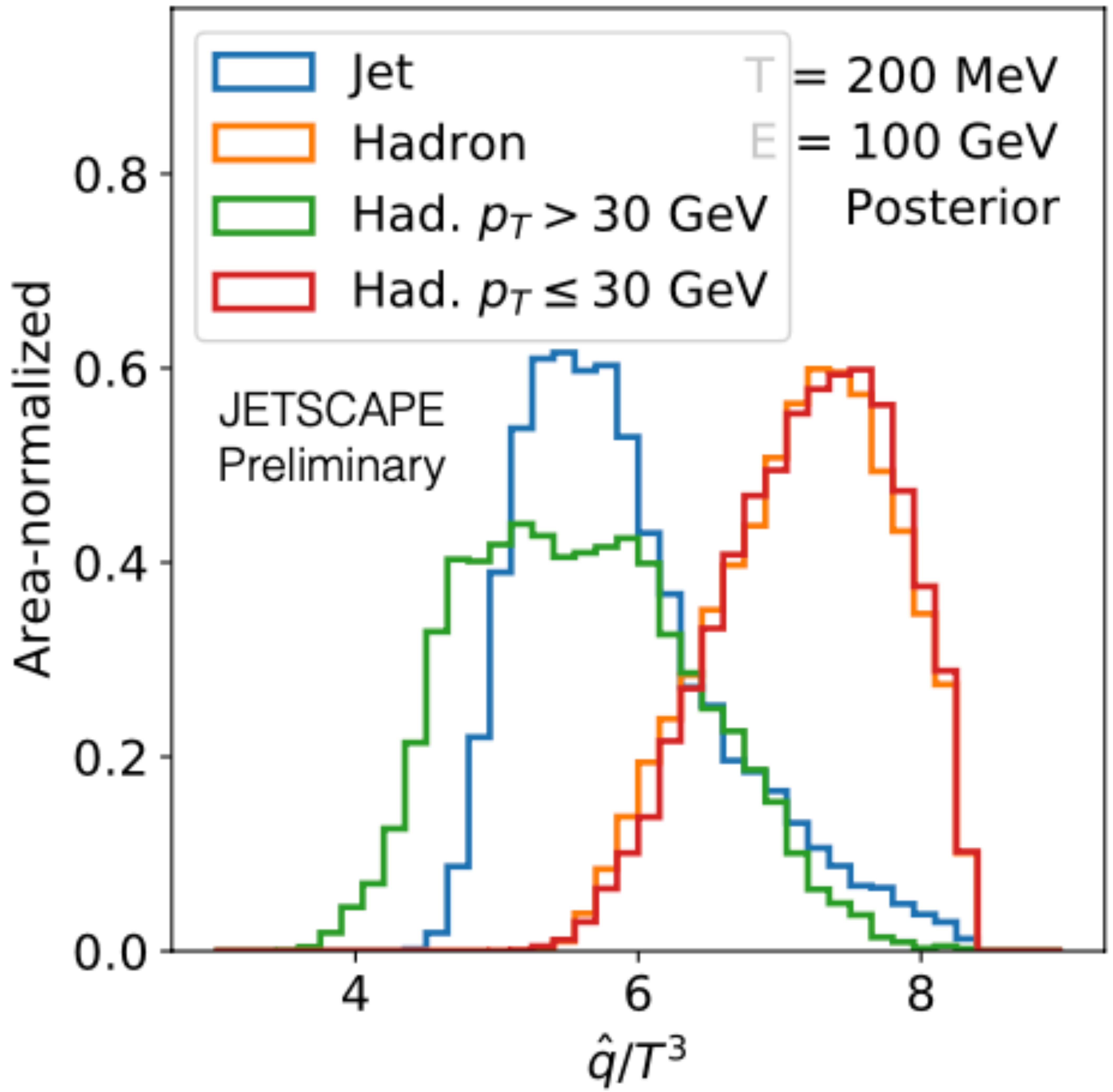


Which observables should be included?



Tension between $\hat{q}$ extracted with jet R_{AA} vs. hadron R_{AA}

Which observables should be included?



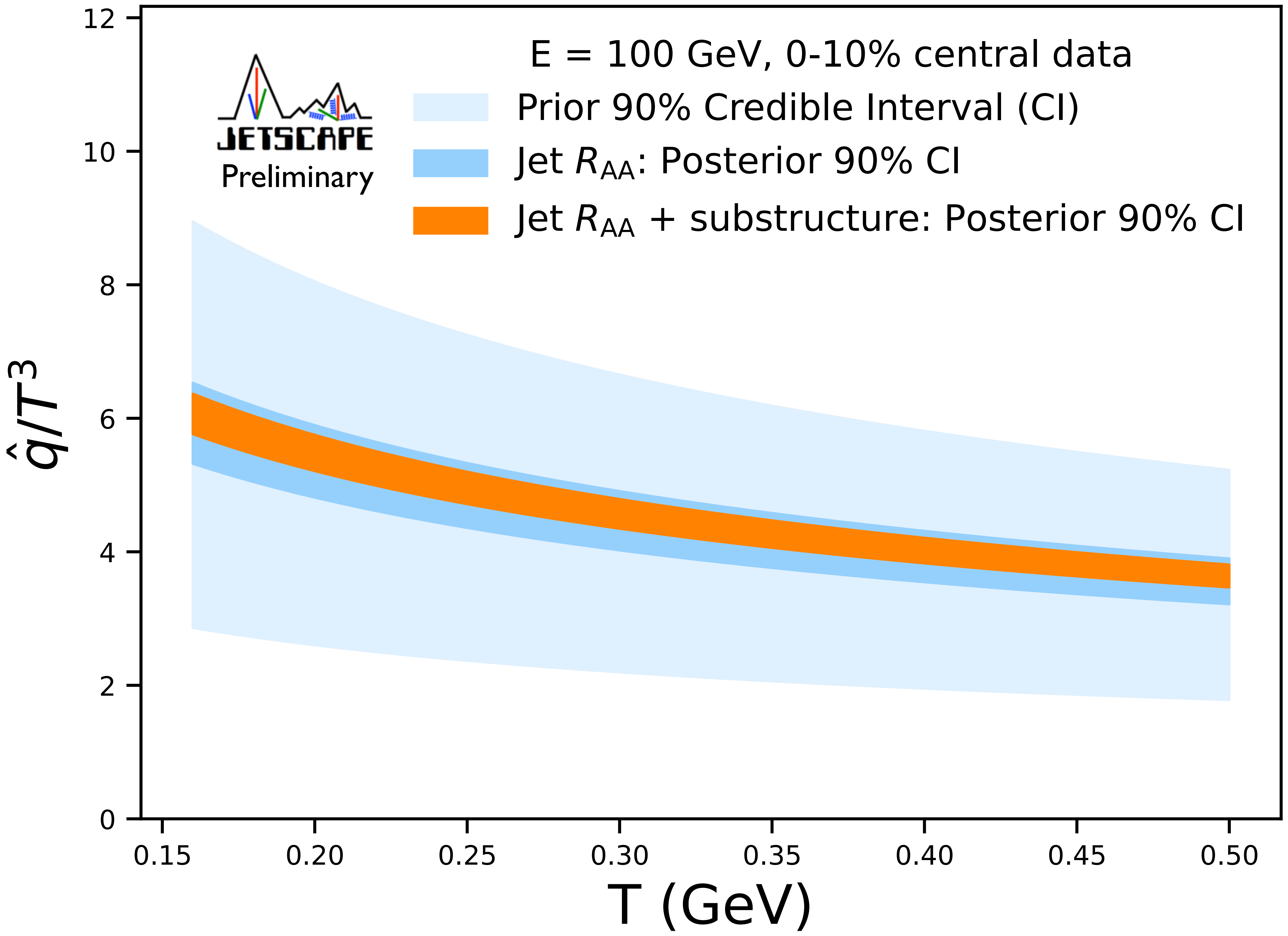
Tension between $\hat{q}$ extracted with jet R_{AA} vs. hadron R_{AA}

Source of tension: low-p_T hadron R_{AA} data

Highest-precision experimental data ⟷ Lowest-precision theoretical regime

Sensitivity of $\hat{q}$ to jet substructure

Jet substructure constrains $\hat{q}$



Starting point: **systematic, iterative selection of observables** to constrain QGP properties

Note: Very few published jet observables can be directly compared to theory

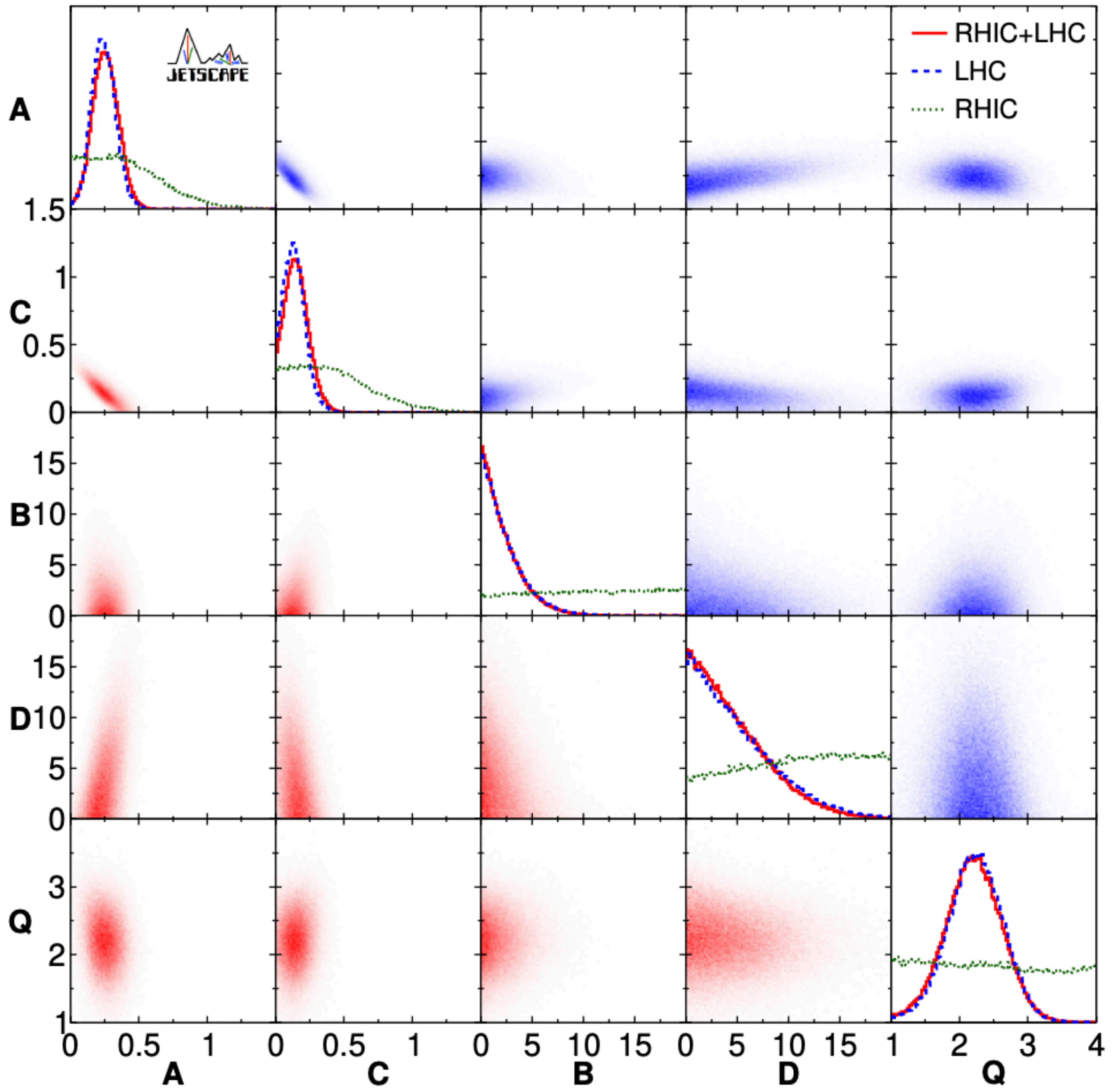
- This analysis: $D(z), z_g, \theta_g$

Experimental guidance from Bayesian inference

Long-term planning

Example:
Restrict to either RHIC or LHC data

JETSCAPE *PRC 104, 024905 (2021)*

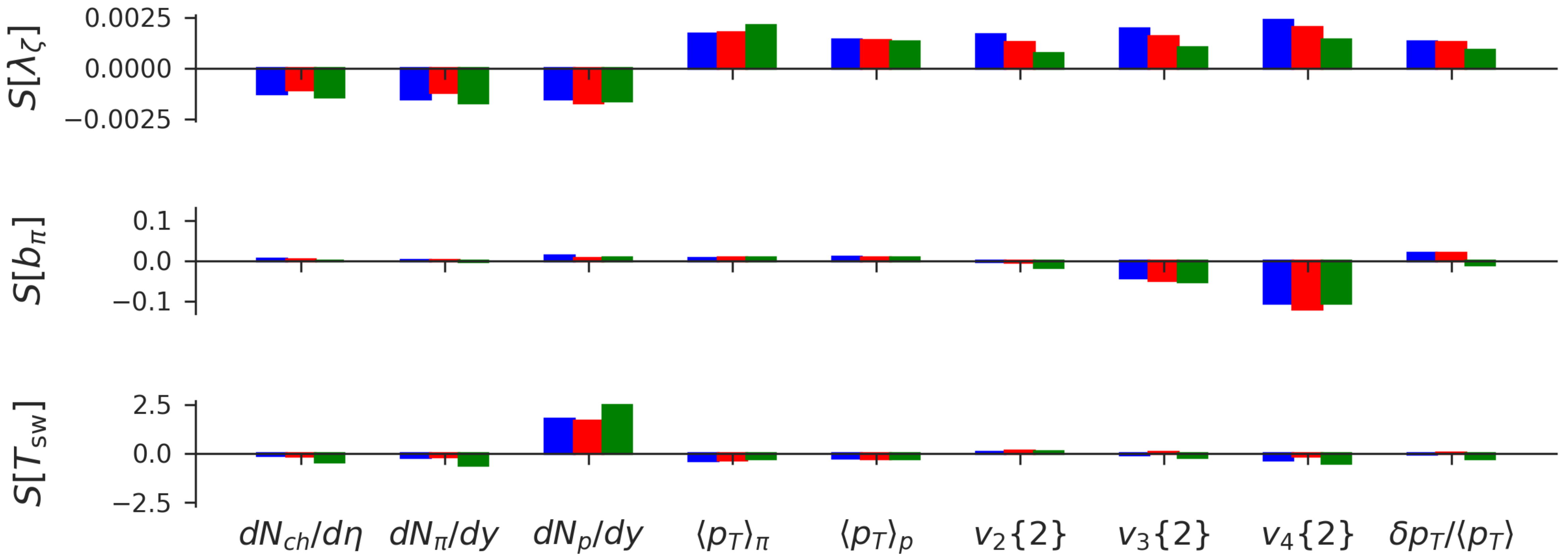


Fit dominated by LHC data

Parameter sensitivity

Quantify impact of a model parameter on measured observables

JETSCAPE *PRC 103, 054904 (2021)*



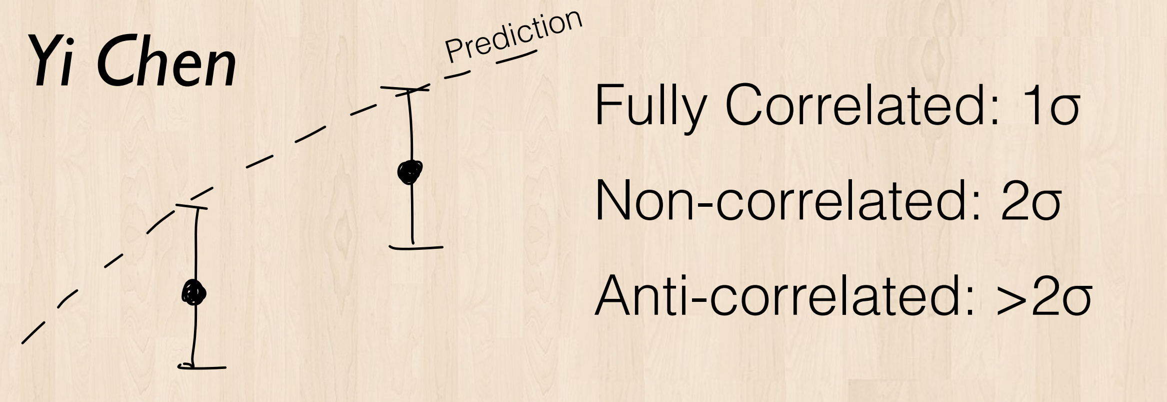
See also:
Lai arXiv 1810.00835
Sangaline, Pratt PRC 93, 024908 (2016)

Model-dependent guidance on where to focus experimental effort

Current bottlenecks in Bayesian inference

Experiment

Report uncertainty correlations



Report **signed** unc. breakdowns in HEPData (or cov. matrix) Example

Easy but crucial — experiments should require this

Theory

Current bottlenecks in Bayesian inference

Experiment

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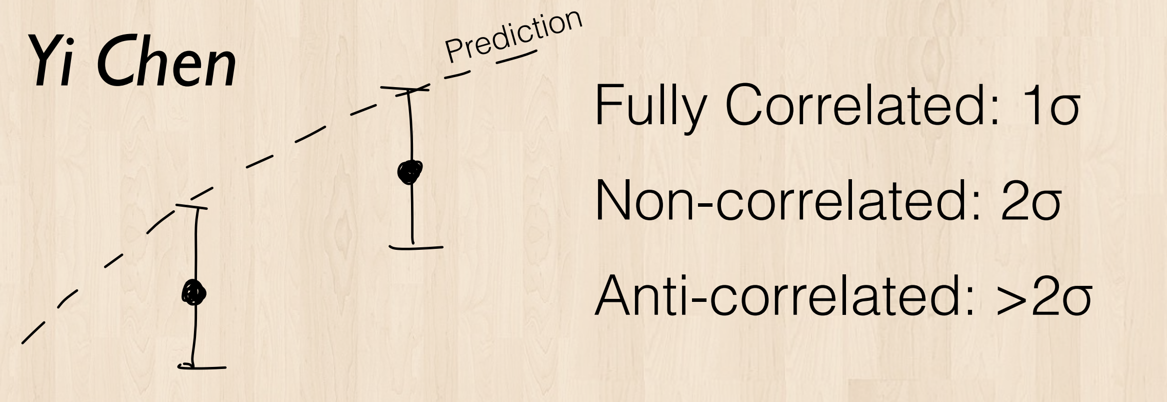
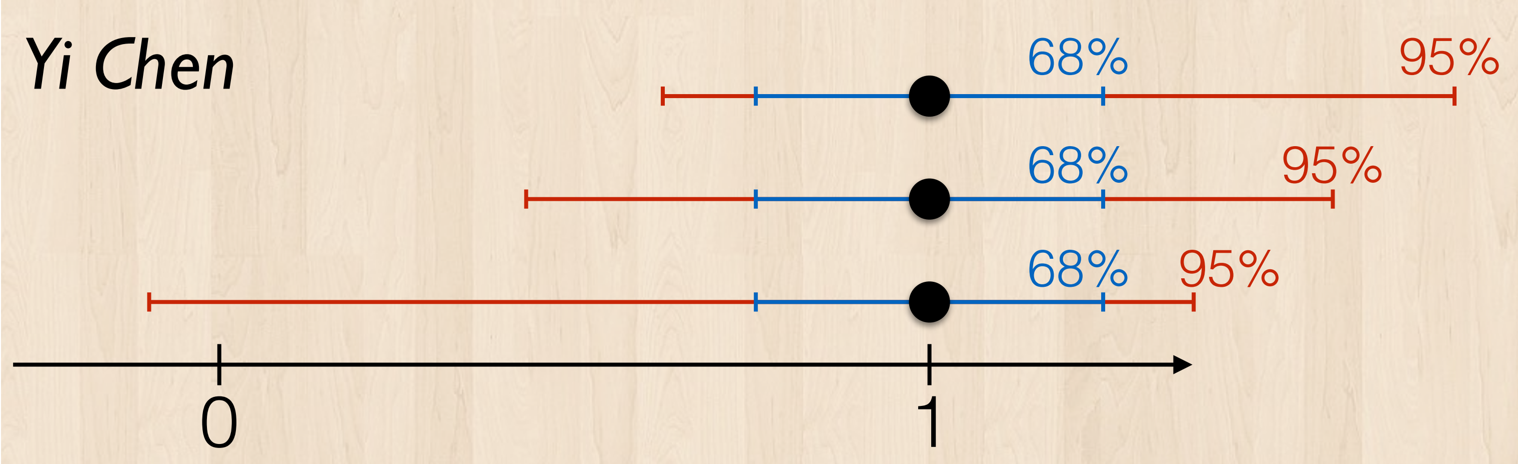


Report **signed** unc. breakdowns in HEPData (or cov. matrix) [Example]

Easy but crucial — experiments should require this

Characterize shape of likelihood



Ideally: report more than 1σ interval

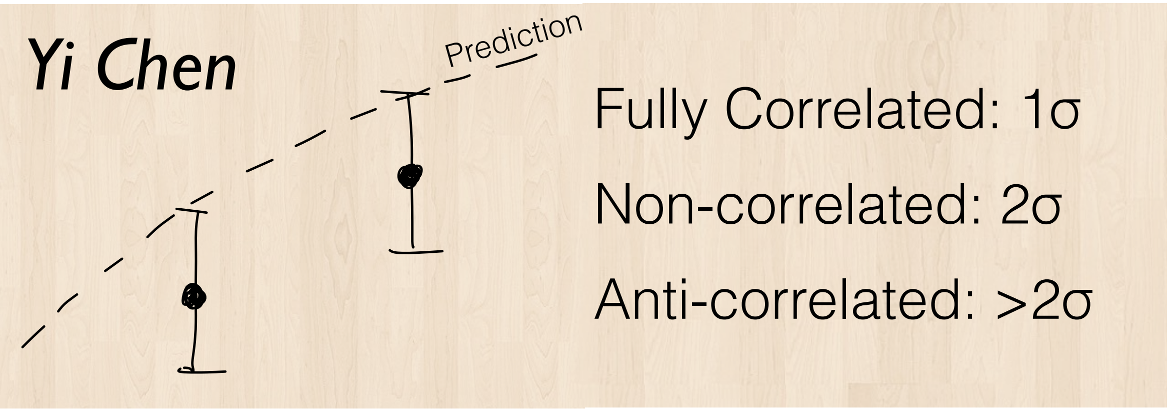
Should explore this for key observables

Theory

Current bottlenecks in Bayesian inference

Experiment

Report uncertainty correlations



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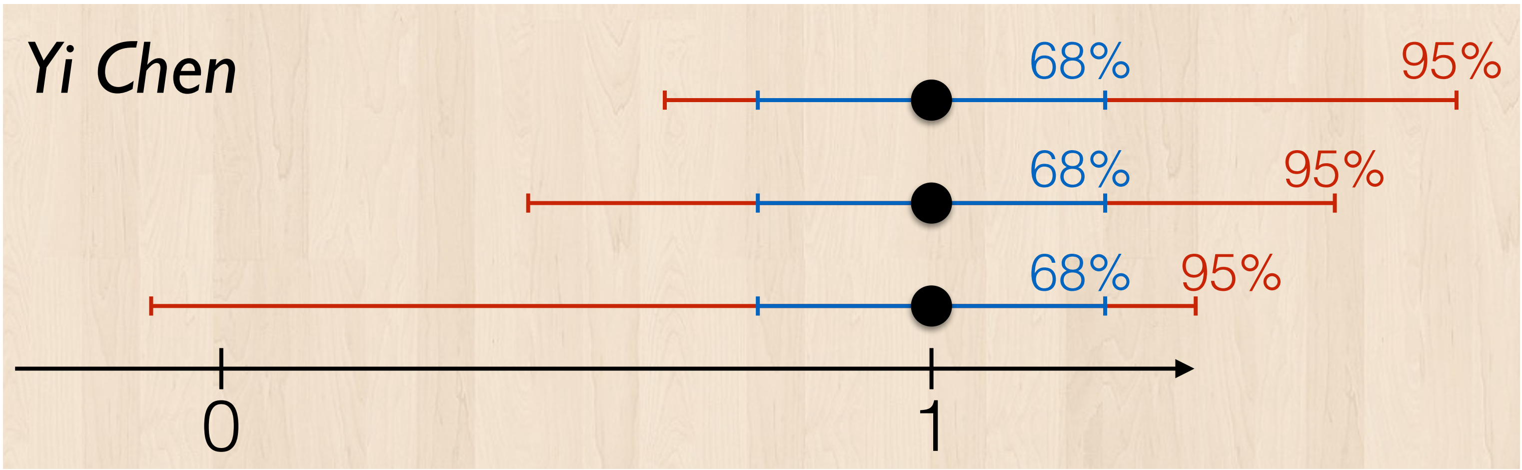

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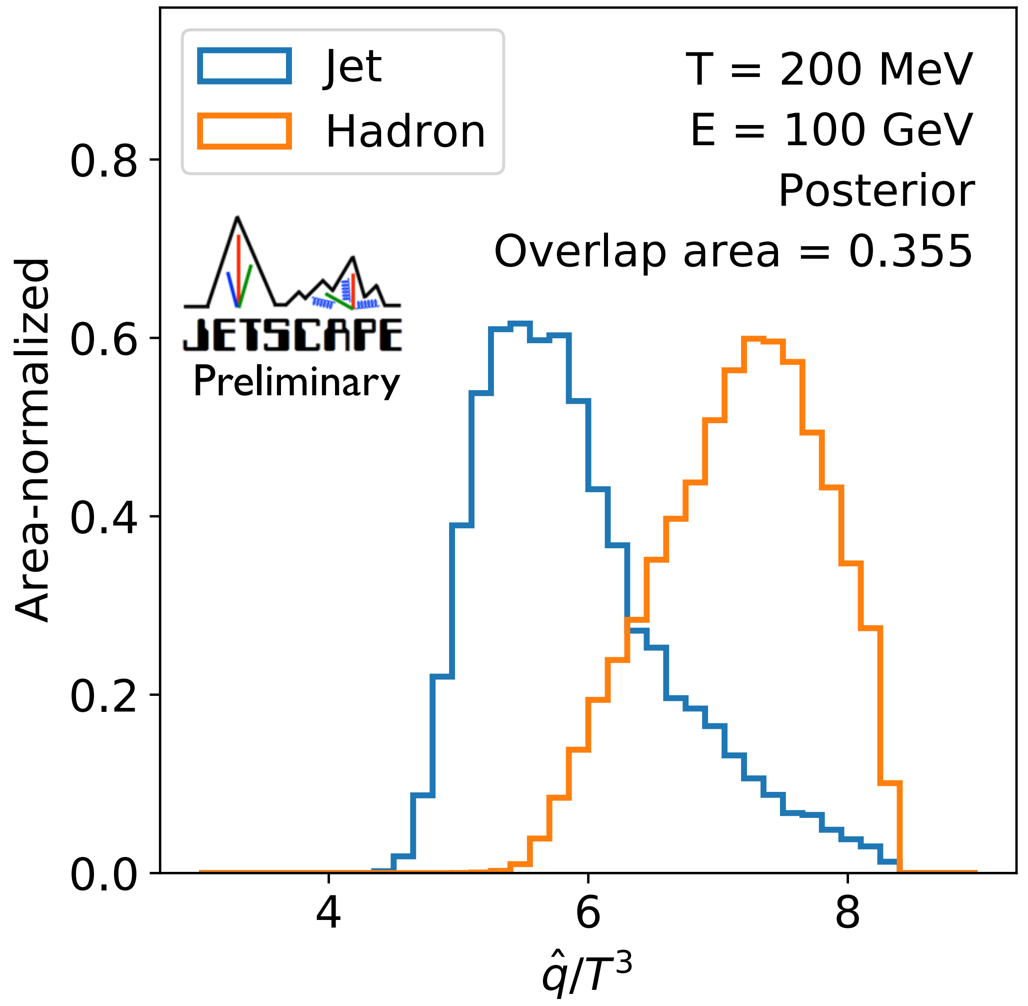
Theory

Model uncertainty

Goal: Model-independent QGP properties

Requires: quantifiable model uncertainties

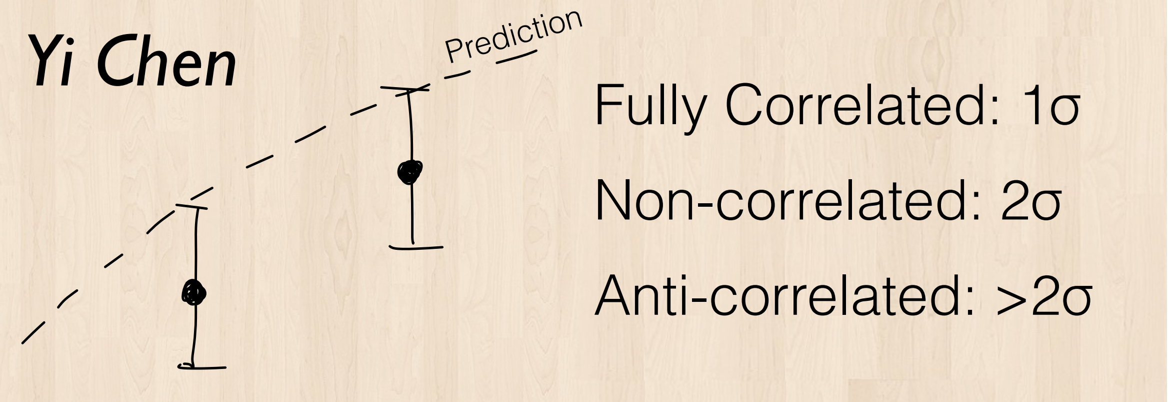
Difficult — but necessary



Current bottlenecks in Bayesian inference

Experiment

Report uncertainty correlations



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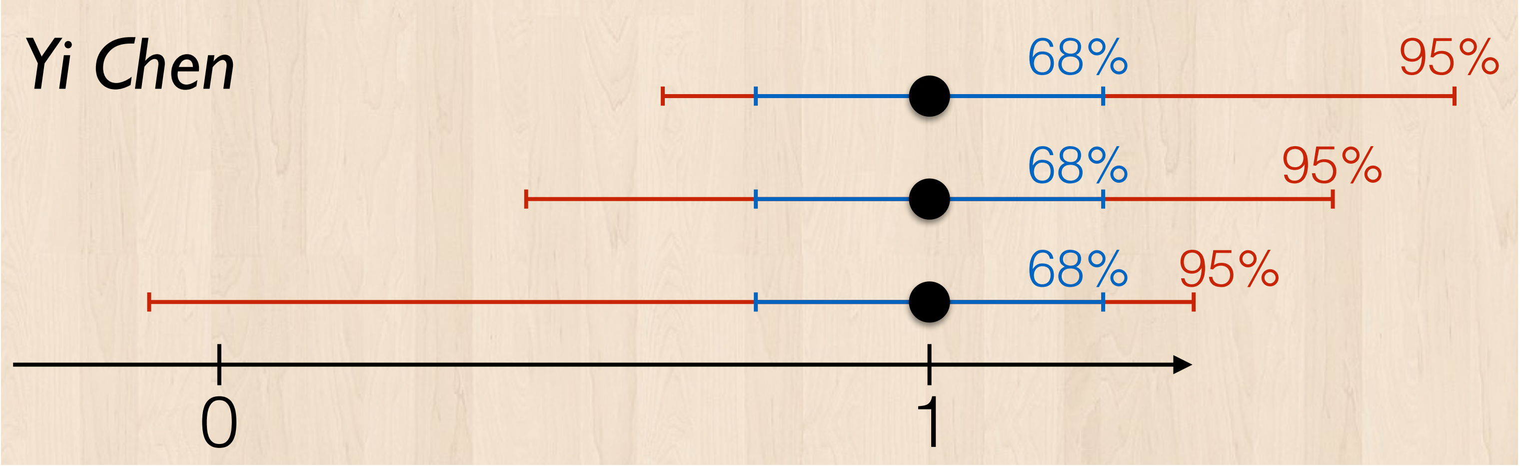
Easy but crucial — experiments should require this

Characterize shape of likelihood



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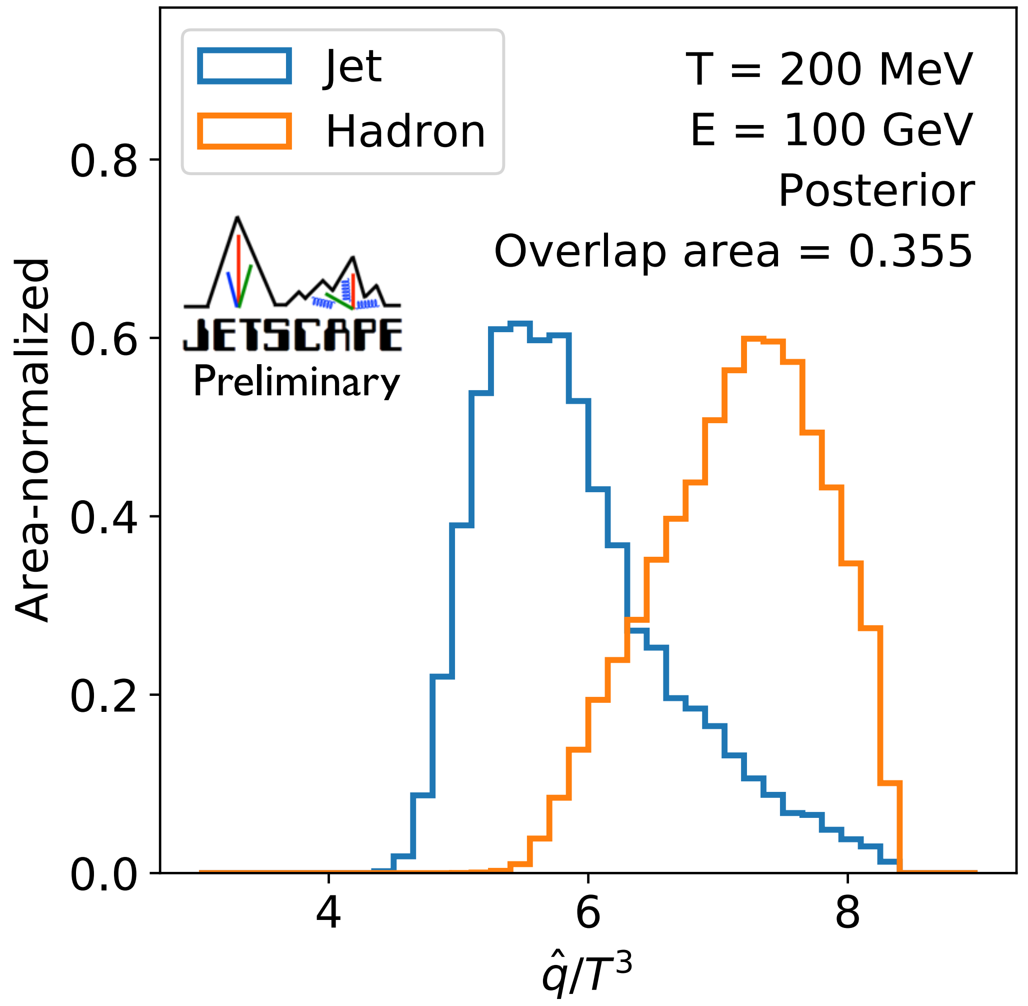
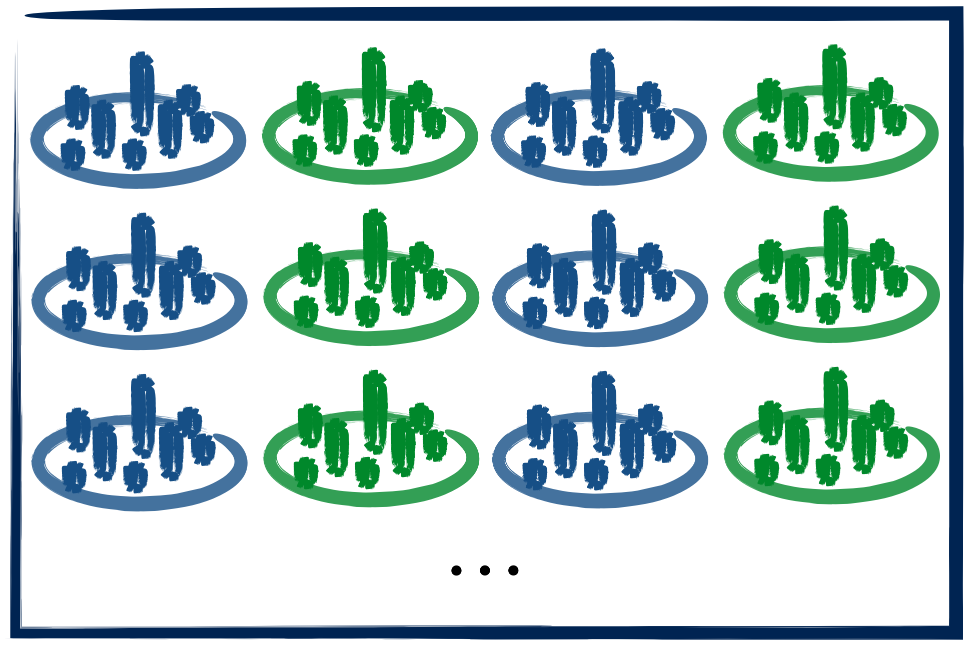


Long-term: compare extracted quantity to calculated quantity e.g. lattice

Two complementary approaches

1. Sets of observables

2. Particle-level information



Learning from data

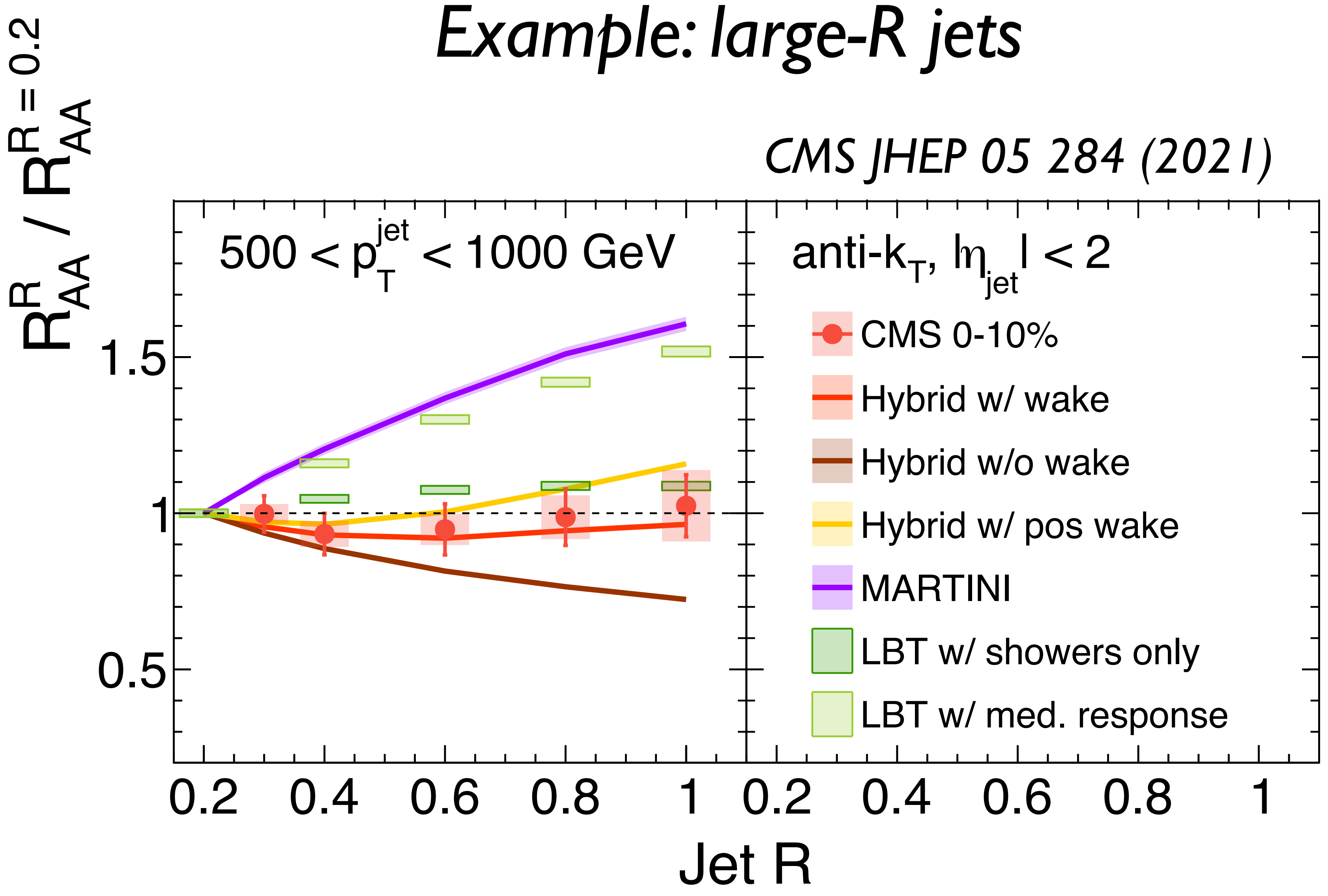
Can we guide the experimental program in a *model-independent* way?

Models are imperfect

- Non-perturbative processes
- Parton shower approximations
- Real-time quantum dynamics
- …

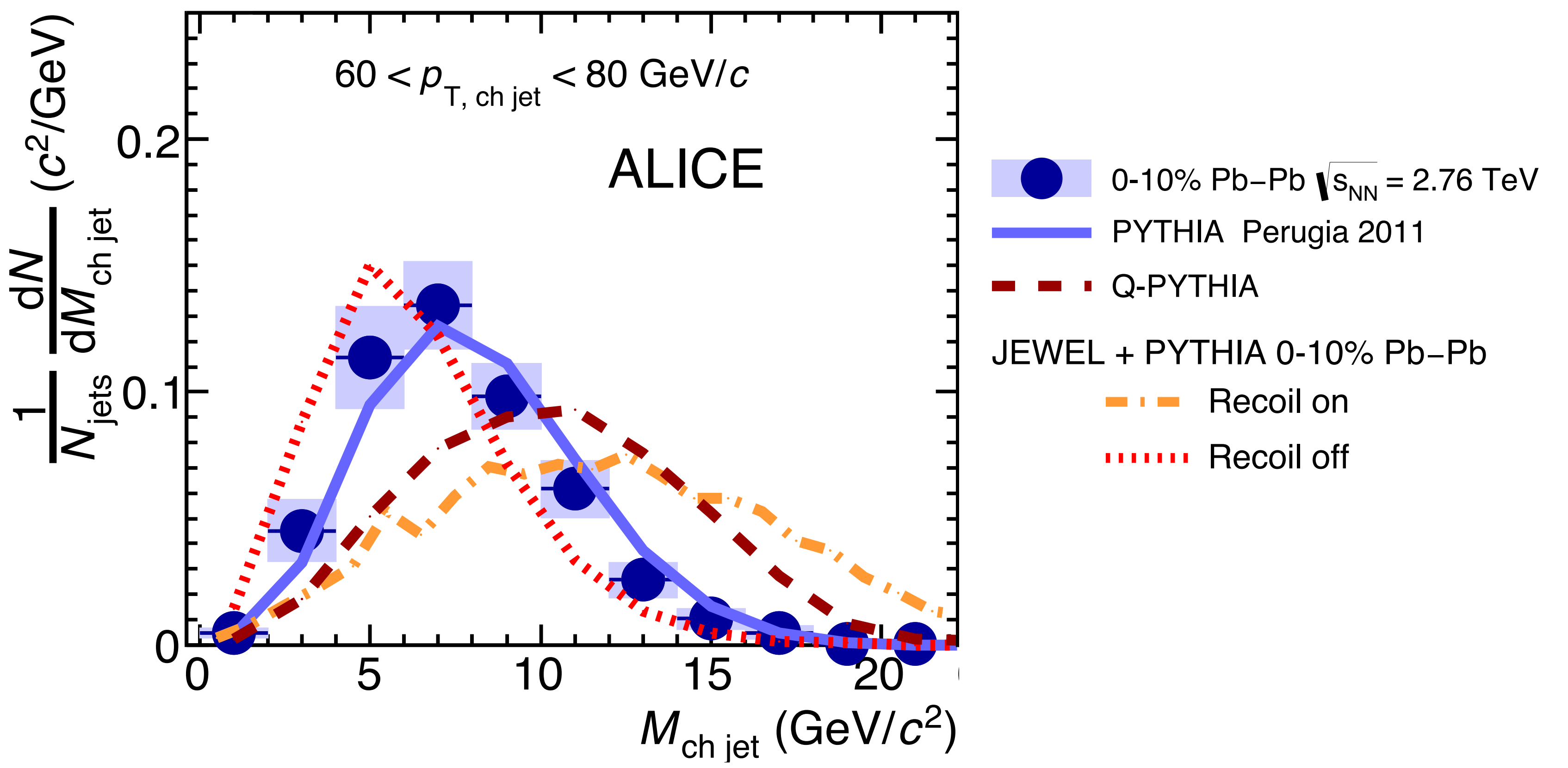
Example: large-R jets

CMS JHEP 05 284 (2021)



Example: jet mass

ALICE PLB 776 249 (2018)



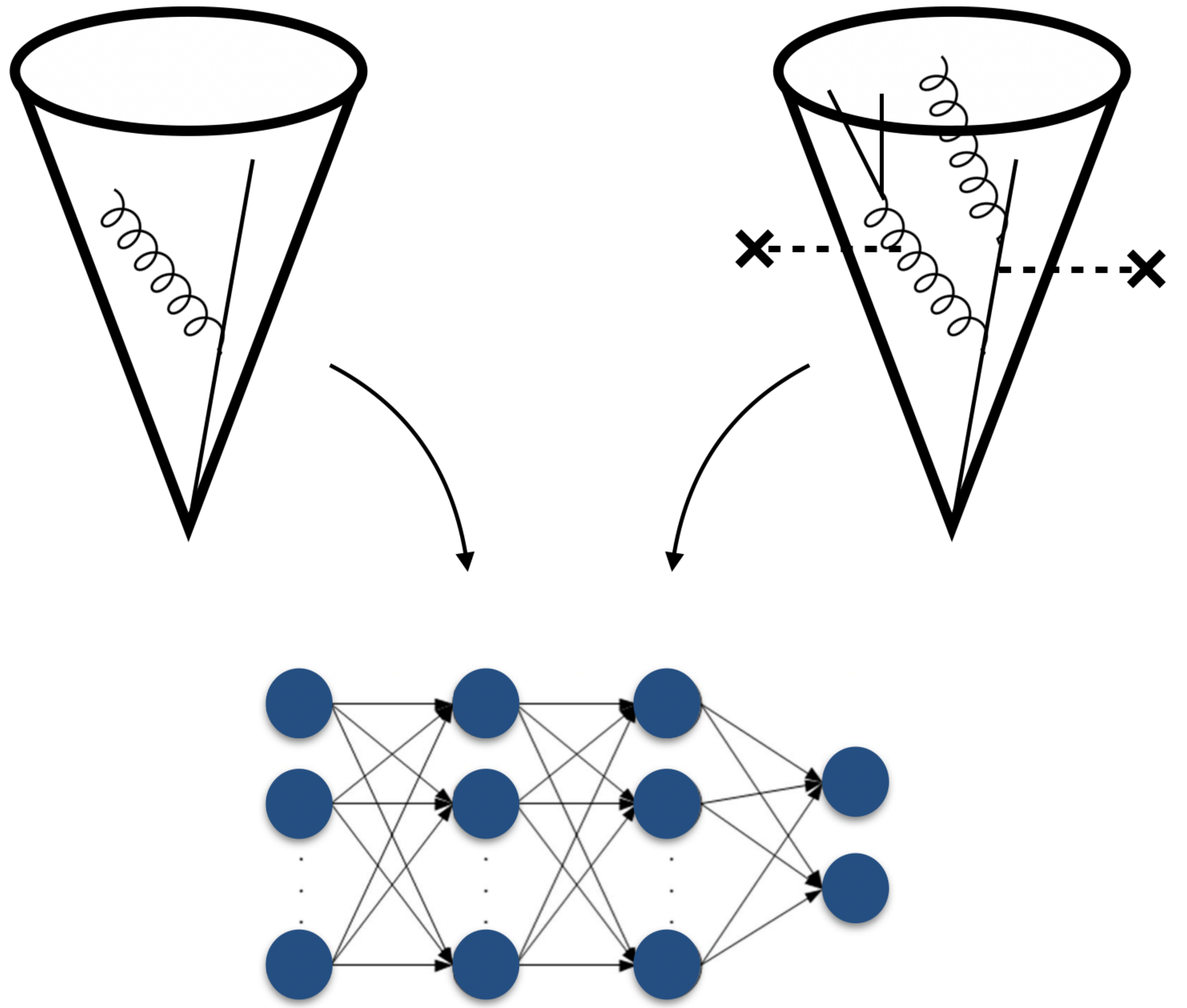
Learning from data

Chien, Elayavalli 1803.03589
Du, Pablos, Tywoniuk JHEP 03 206 (2021)
Apolinário et al. JHEP 11 219 (2021)
Lai et al. JHEP 10, 011 (2022)
Liu et al. JHEP 04 (2023) 140

The physics of jet quenching is encoded in the difference between ensembles of proton-proton and heavy-ion jets

Learn a function that encodes the differences between proton-proton and heavy-ion jets

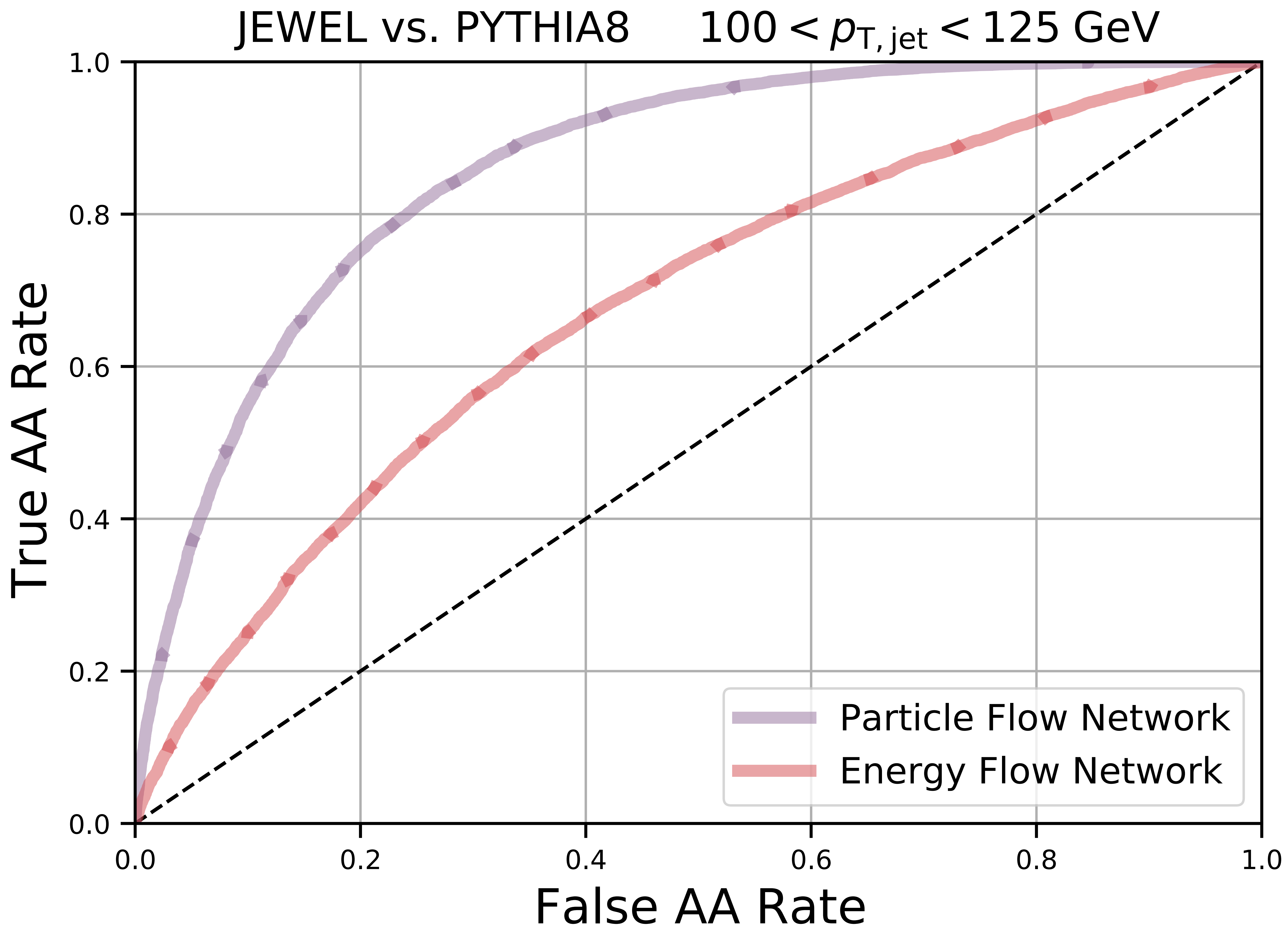
→ ML classifier trained **directly on experimental data**



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

IRC-safe vs. IRC-unsafe physics

Lai, Mulligan, Płoskoń, Ringer JHEP 10 (2022) 011



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

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

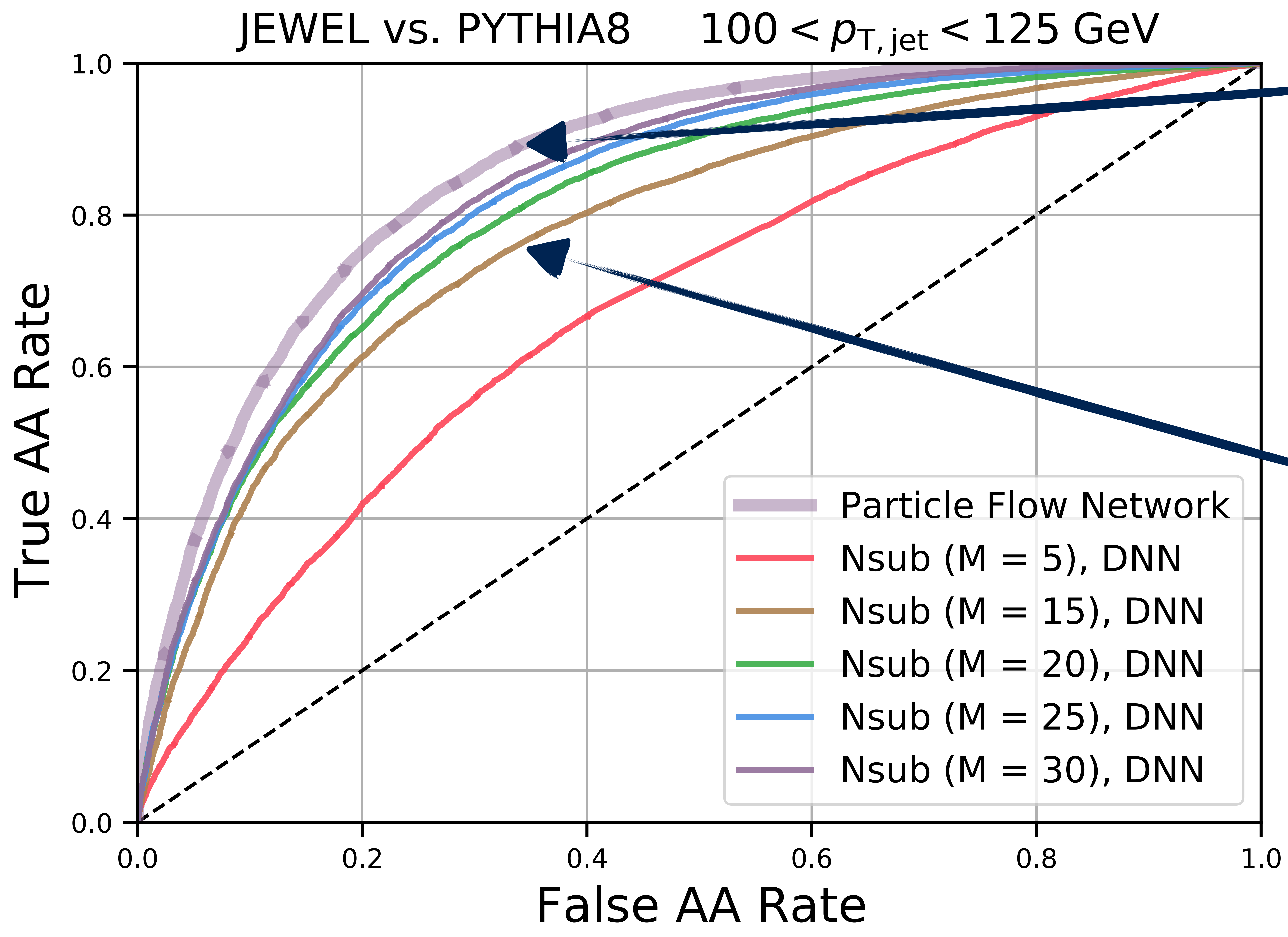
Classifier

DNNs

IRC-unsafe information contains significant discriminating power

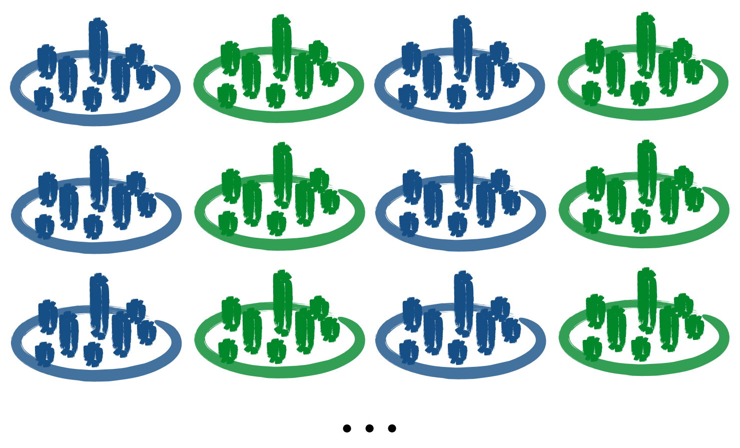
The information content of jet quenching

Lai, Mulligan, Płoskoń, Ringer JHEP 10, 011 (2022)



"Optimal" classifier

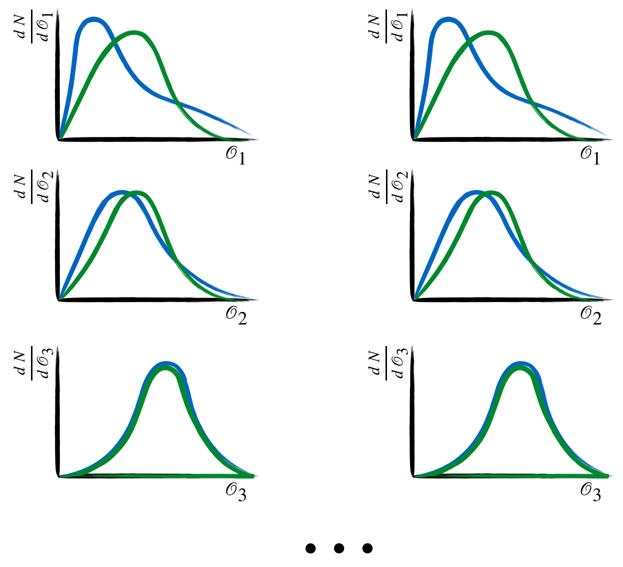
- Input: four-vectors of all jet particles



pp
AA

DNN with $3M - 4$ *N*-subjettiness basis observables as input:

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



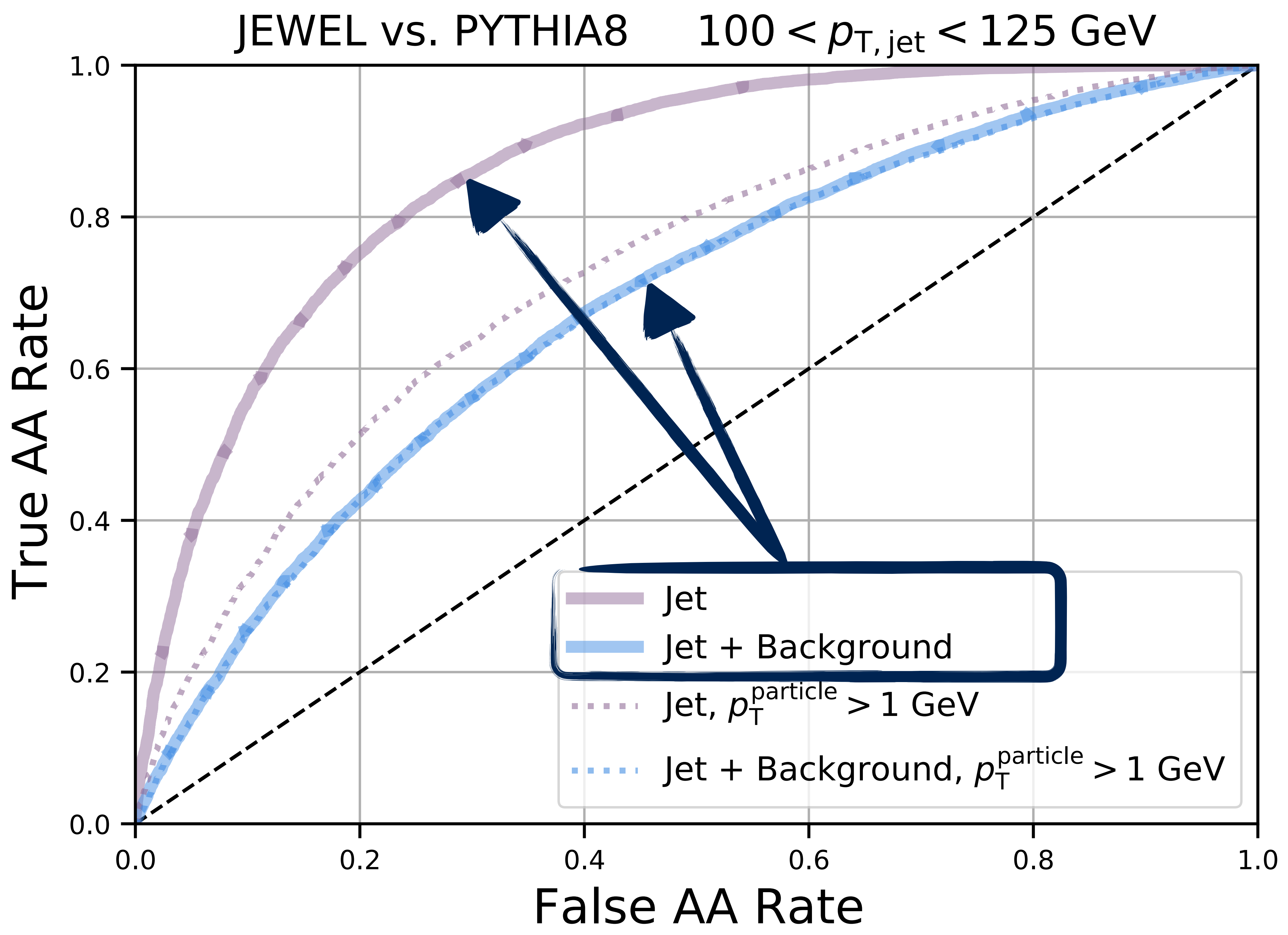
See also:
Lu et al., *JHEP* 08 046 (2022)
Romão et al. 2304.07196

Significant information in soft physics of quenched jets – systematic quantification

Information loss due to background

Lai, Mulligan, Płoskoń, Ringer JHEP 10 (2022) 011

Discriminating power is highly reduced by the fluctuating underlying event



Delicate challenge: soft information crucial, yet background prevents from being accessed

Information loss due to background

Lai, Mulligan, Płoskoń, Ringer JHEP 10 (2022) 011

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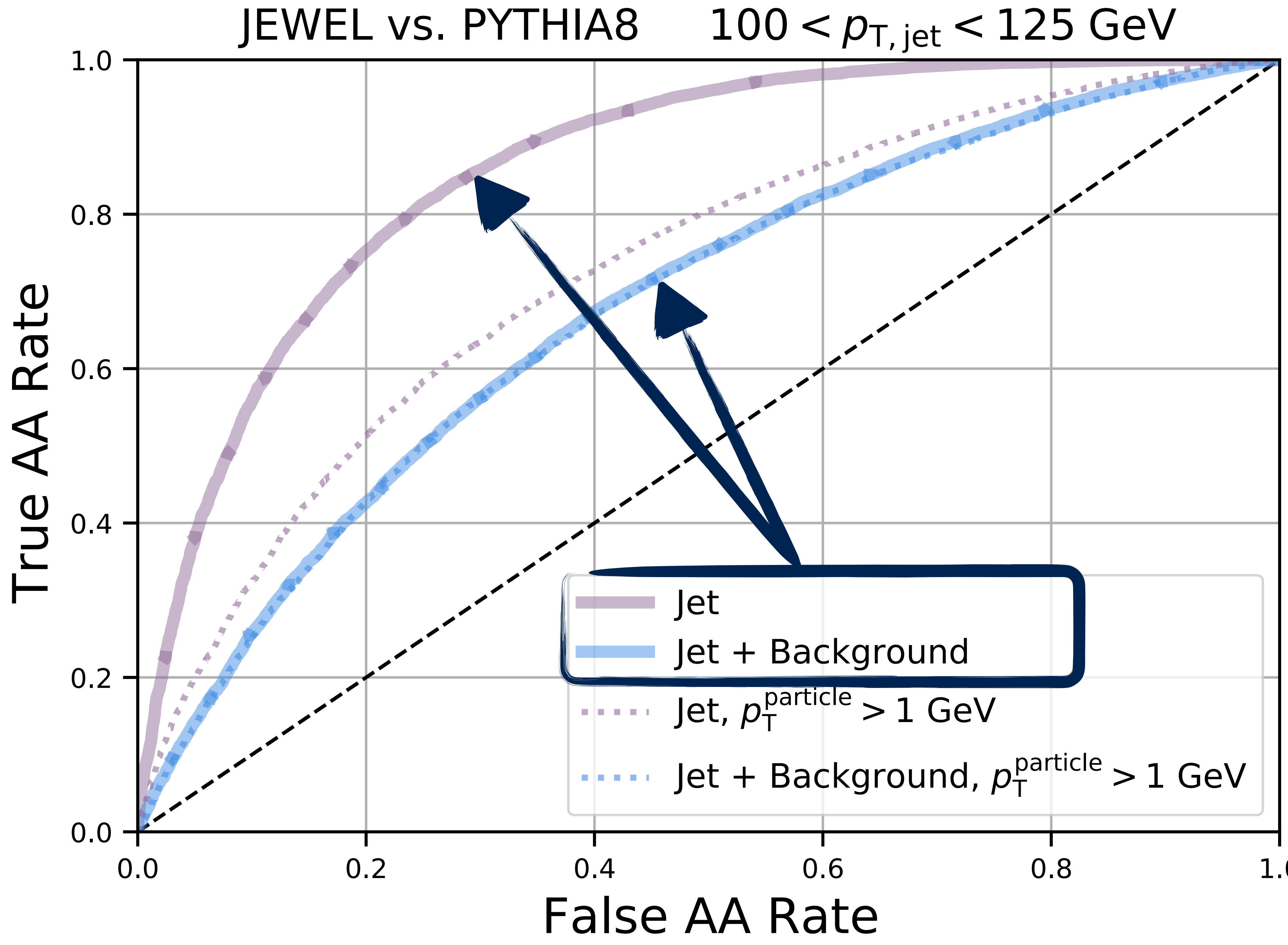
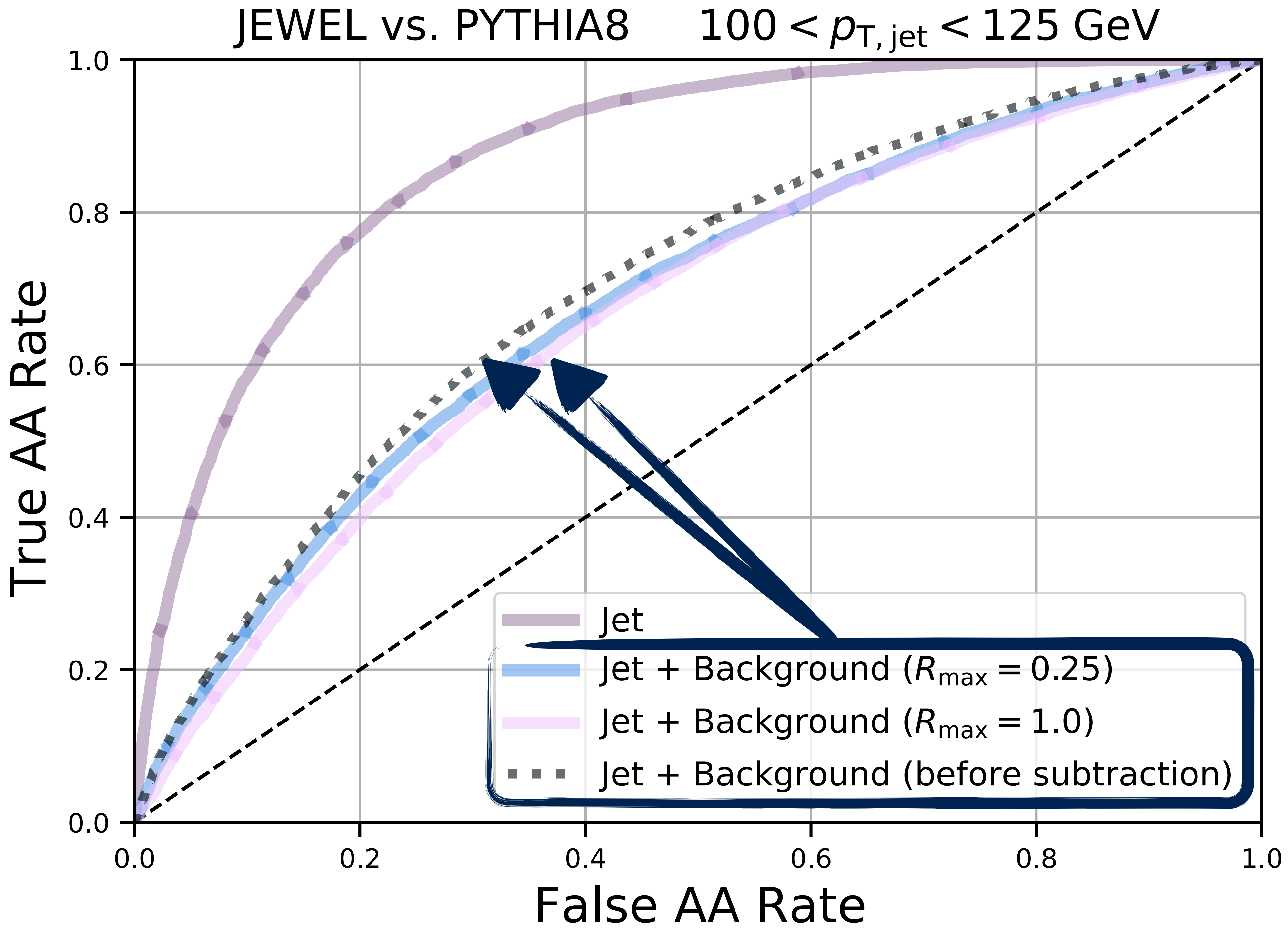


Delicate challenge: soft information crucial, yet background prevents from being accessed

Background subtraction algorithms remove small but significant information

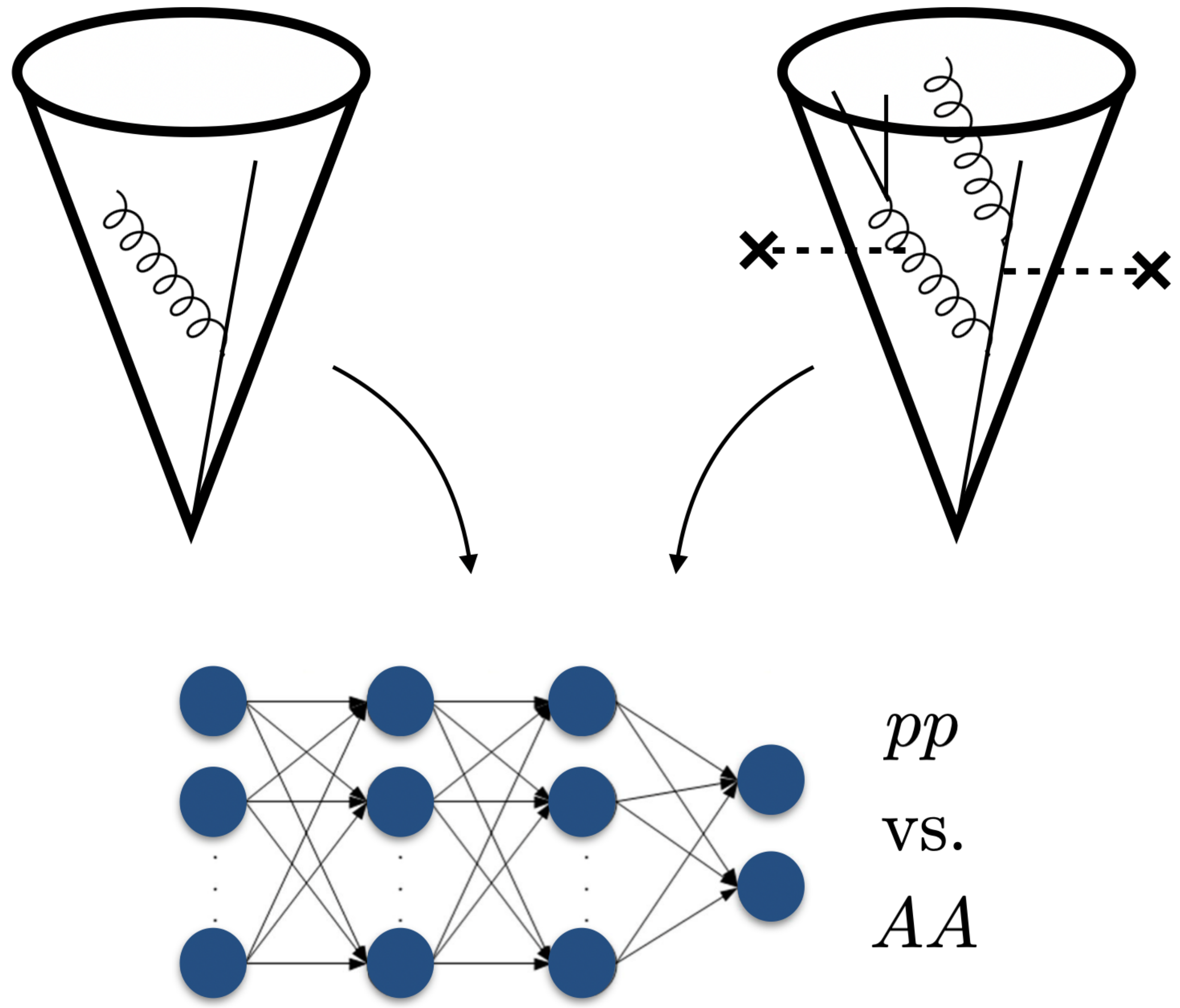


New metric to assess background subtraction algorithms

Observable design

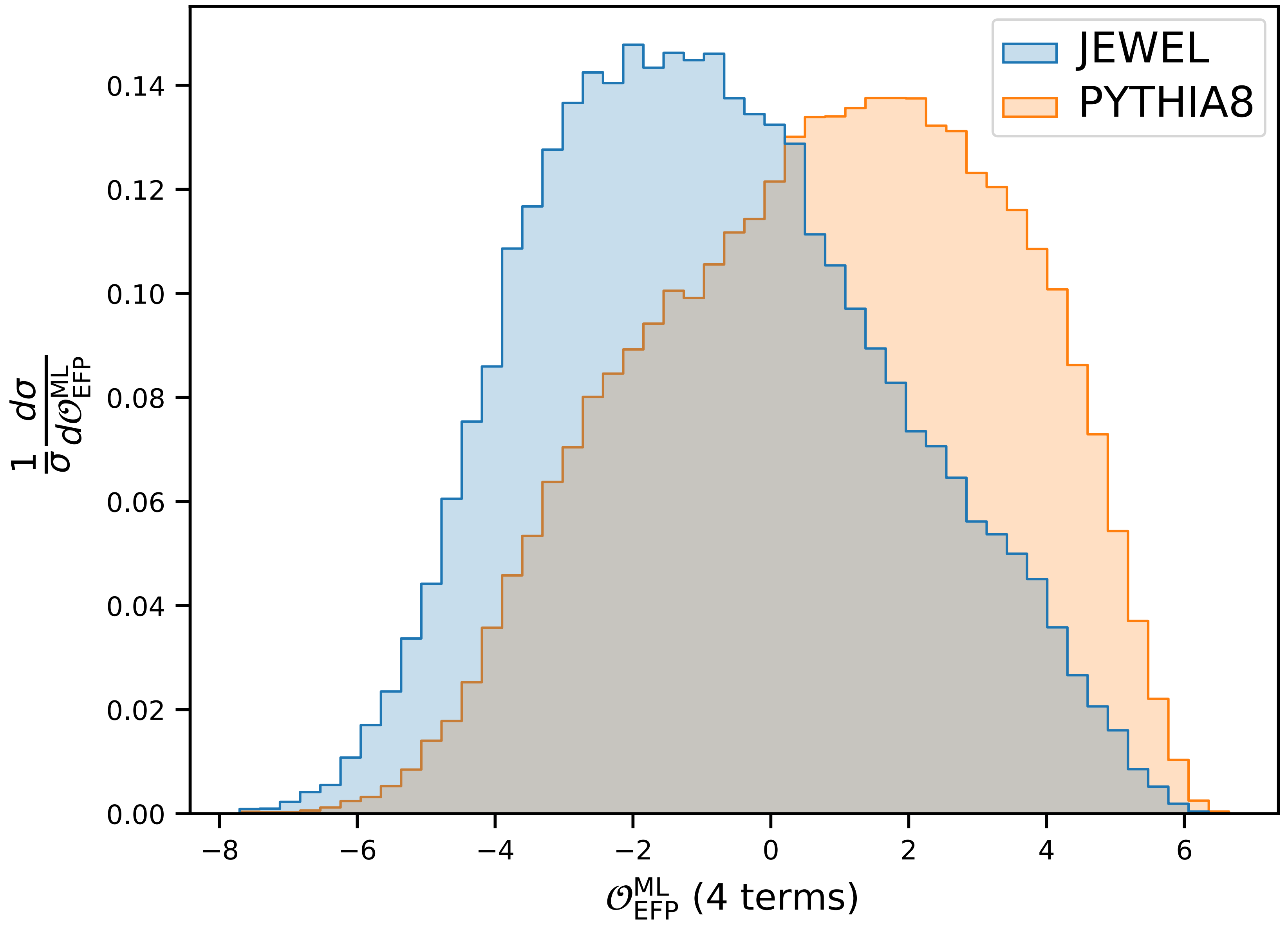
Lai, Mulligan, Płoskoń, Ringer JHEP 10, 011 (2022)

Design the **most strongly modified observable** that is **theoretically calculable**



$$\max_{\theta} \left| \frac{d\sigma_{AA}}{d\sigma_{pp}}(\theta) - 1 \right|$$

Symbolic regression

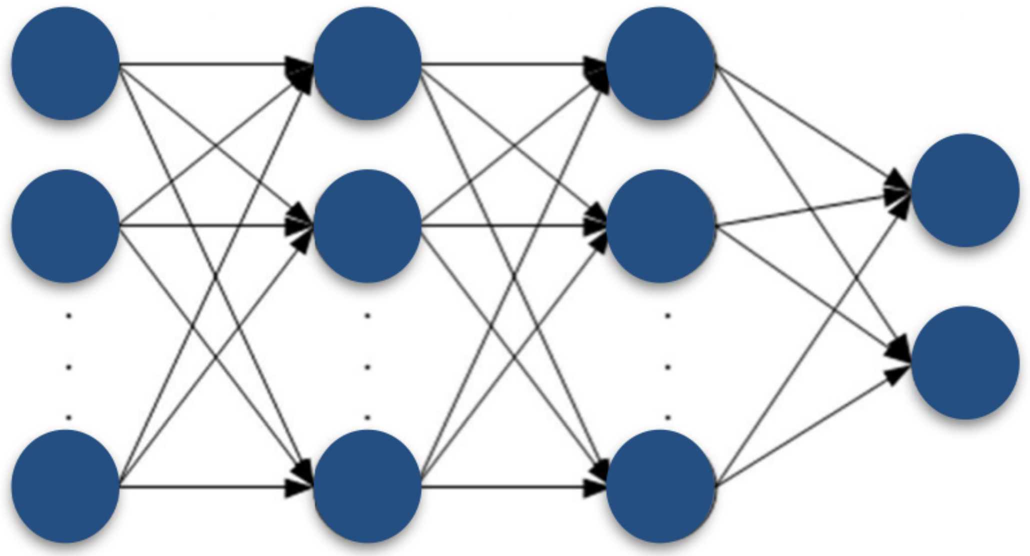


ML-assisted observable design provides guidance to experiments and theory — can then measure and calculate designed observables using traditional methods

Data-driven guidance across QCD systems

Lee, Mulligan, Płoskoń, Ringer, Yuan JHEP 03 (2023) 085

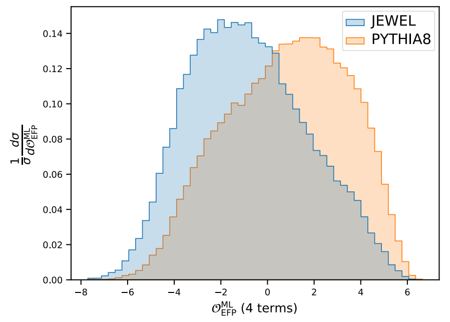
Cold nuclear matter



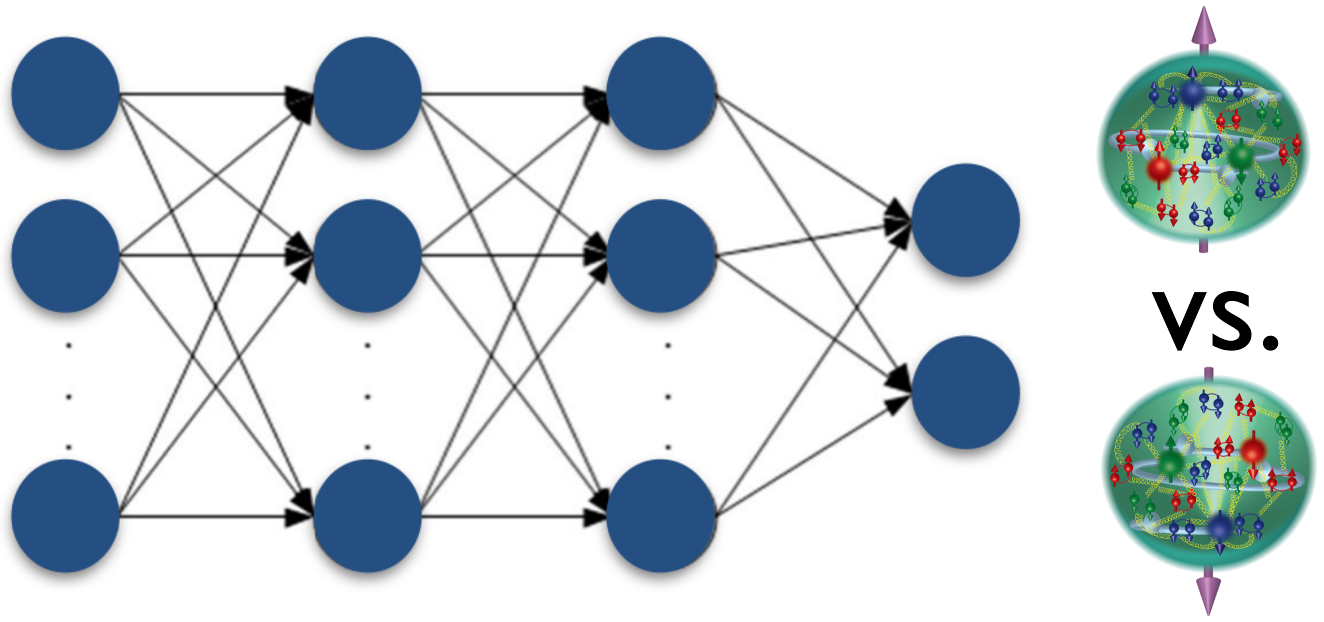
pA
vs.
pp

Data-driven bound on jet modification in small systems

$$\max_{\theta} \left| \frac{d\sigma_{pA}}{d\sigma_{pp}}(\theta) - 1 \right|$$



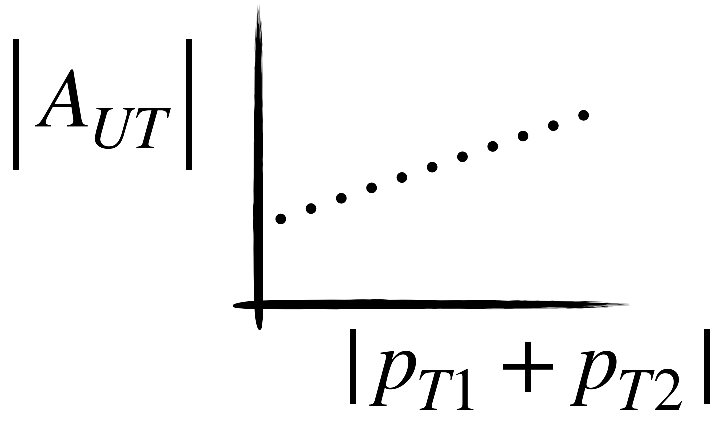
Spin physics



Data-driven observable design to maximize TSSAs — hadron structure

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

$$\max_{\theta} |A_{UT}(\theta)|$$



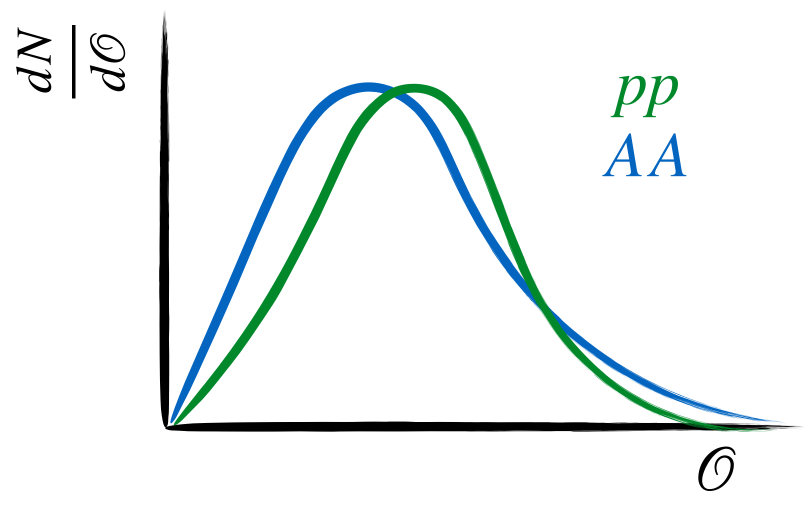
Can apply these directly on experimental data today at RHIC and LHC — and the future EIC

Summary

We have vast freedom in what we choose to measure at colliders in order to elucidate emergent behaviors of QCD — are we fully exploiting the data sets we have in hand?

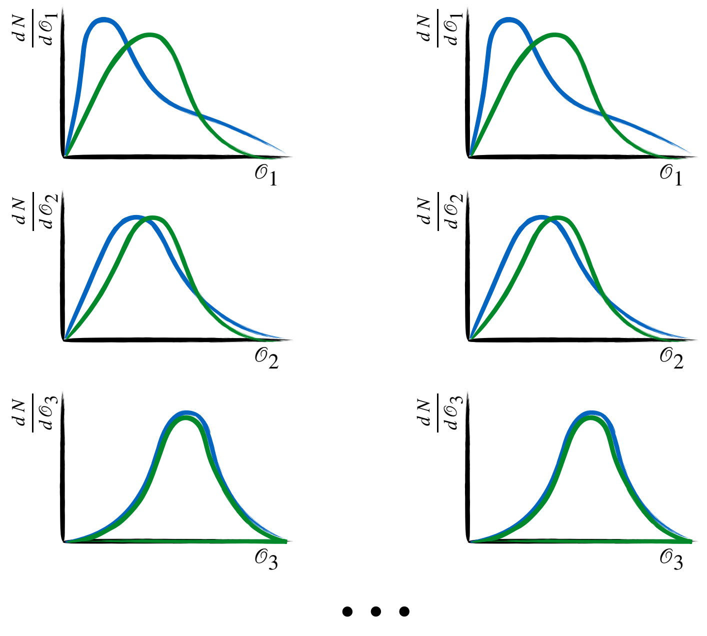
Single observables

Experimental and theoretical building blocks



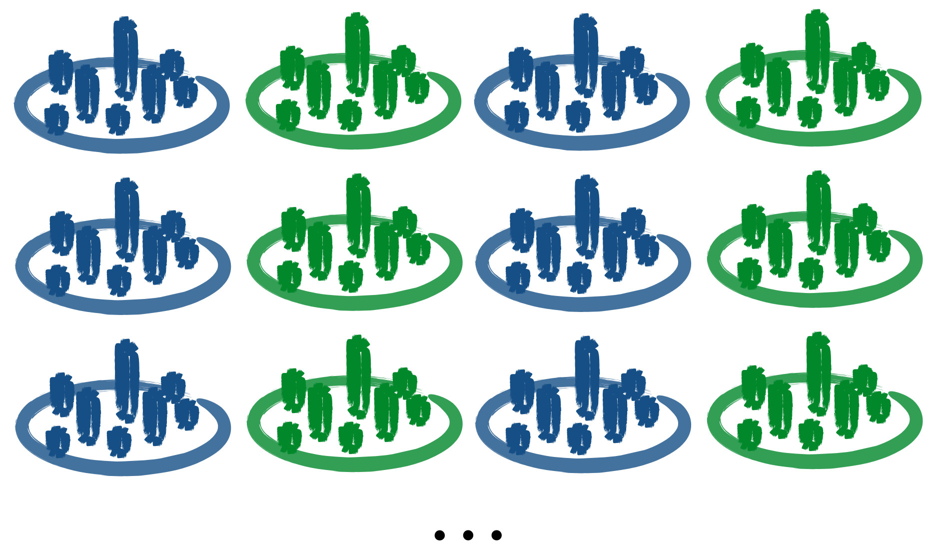
Sets of observables

Rigorous, model-dependent inference of QCD properties



Particle information

Model-independent learning directly from experimental data



A new opportunity: systematic, iterative design of sets of experimental analyses