Jet Substructure Experiment Overview: New Ideas and Measurements

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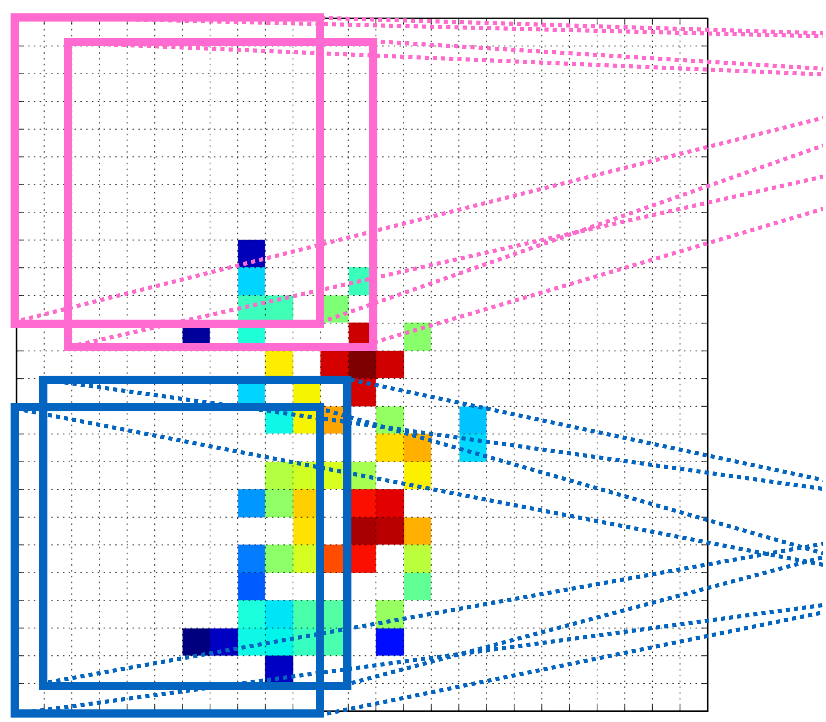

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Physics 290

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Disclaimer

This talk is not meant to be comprehensive. I will give a few examples and comments to spark discussion.

I will use representative examples, but will make no attempt at providing a balance across experiments from the LHC and beyond.

While I am a member of ATLAS (and H1), this talk is not on behalf of my collaborators.

Overview

What is jet substructure good for?

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A tool to tag Lorentz boosted,
hadronically decaying particles

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A probe of fundamental and emergent properties of the strong force

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Challenges: representation, calibration, decorrelation, …

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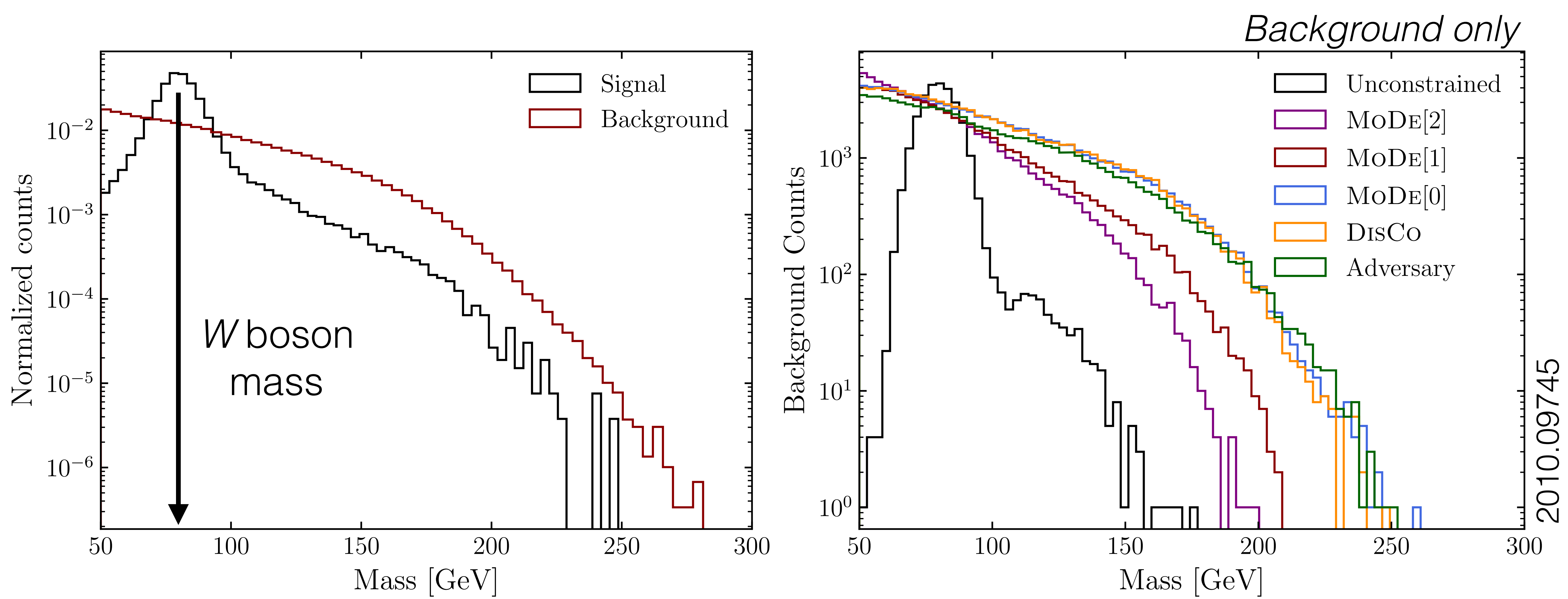

Challenges: representation, calibration, **decorrelation**, …

Overview

What is jet substructure good for?

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A probe of fundamental and emergent properties of the strong force

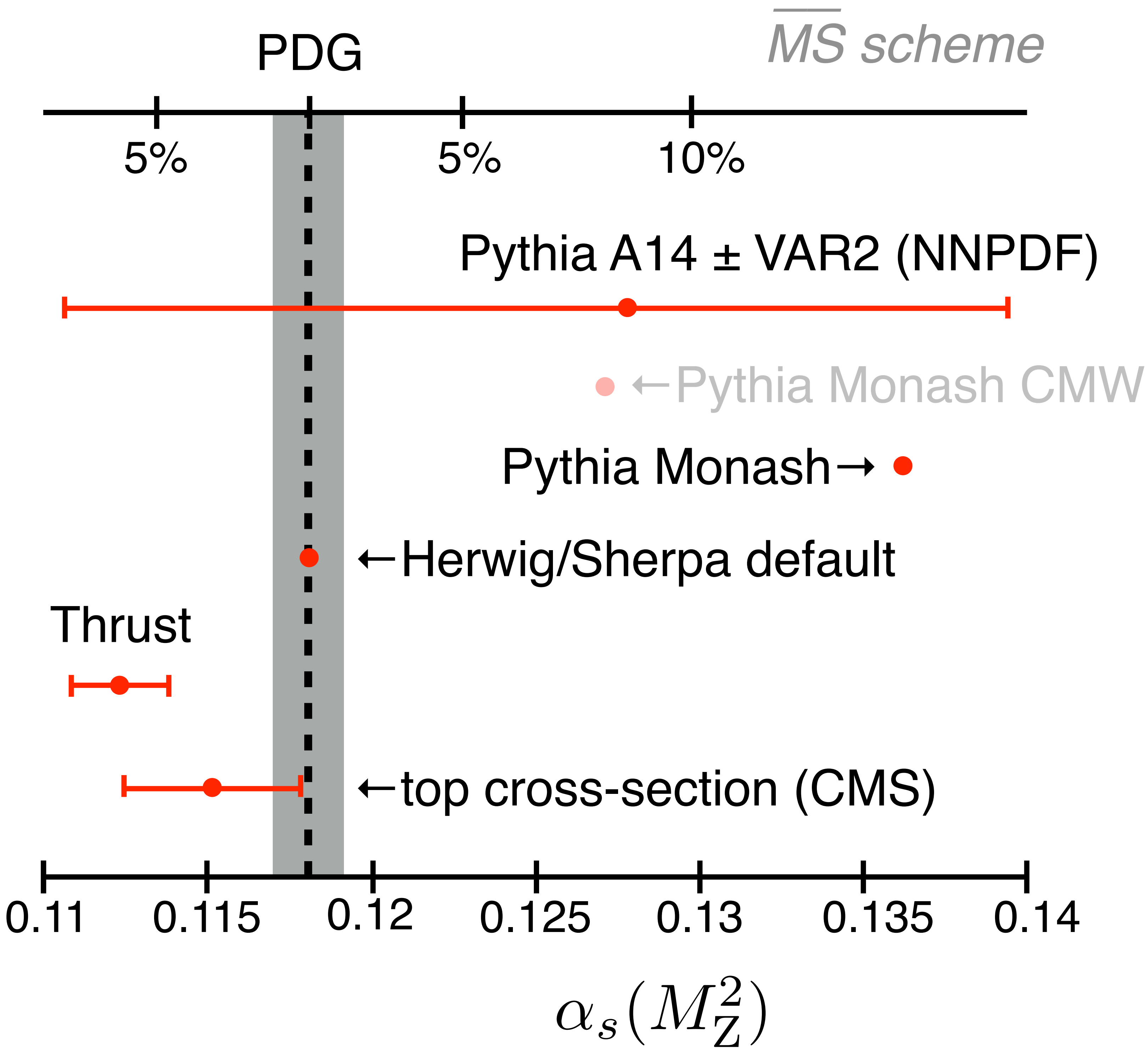
Overview

What is jet substructure good for?

1. *Fundamental parameters of the SM*
2. *BSM searches using small deviations from SM*
3. *Quantum properties of inherently exciting emergent pheno*
4. *Develop / tune Parton Shower Monte Carlo (to aid other searches / measurements)*

A probe of fundamental
and emergent properties of
the strong force

Strong Coupling from Jet Substructure



1803.07977

Why do we care about α_s from jets?

Resummation-senstiive obsrvable at LEP gives most precise collider measurement, but is ~3σ away from lattice.

See also: top quark mass

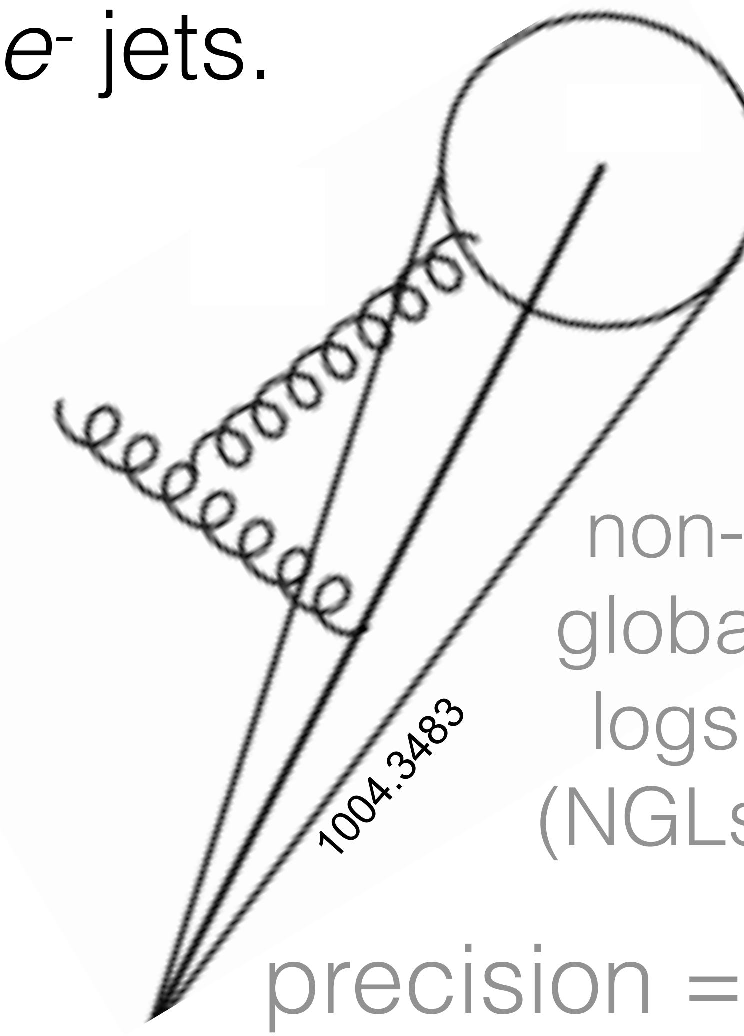
A. Larkoski, S. Marzani, G. Soyez, J. Thaler, JHEP 1405 (2014) 146

Precision jet substructure with grooming

Grooming makes *pp* jets “look like” e^+e^- jets.

Particular grooming algorithms (soft drop / modified mass drop) have desirable properties to make the above statement **quantitative**.

This makes observables on softdropped jets amenable to precision calculations for the ~**first time at a *pp* collider.**



non-global logs (NGLs)

precision = beyond LL (e.g. Pythia)

This is particularly important because JSS observables are dominated by **resummation** and **not fixed-order**!

The Soft Drop Procedure

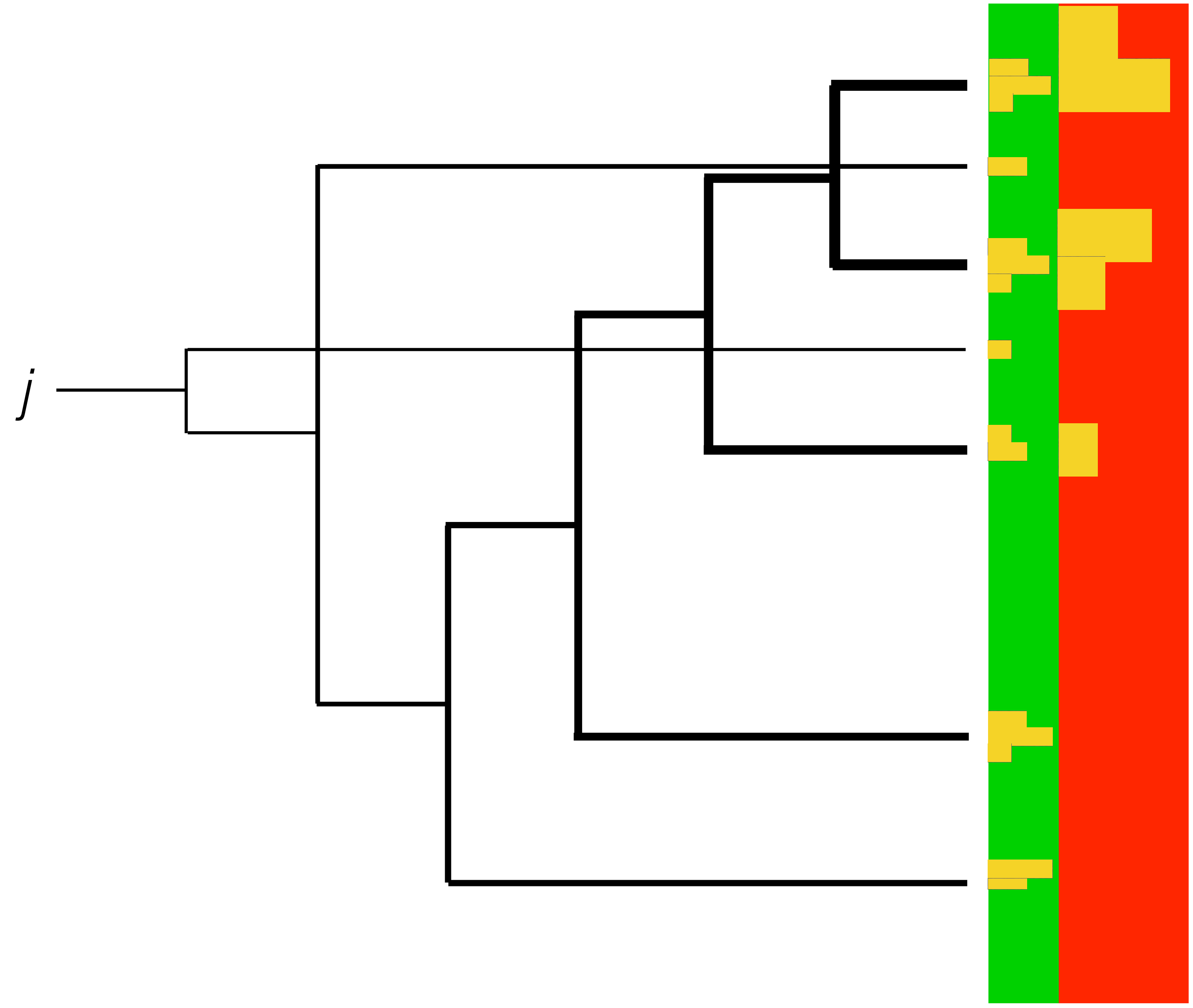
Take a jet clustered with e.g. anti-k_t

Re-cluster it with C/A

Traverse the clustering tree backwards

If a branch point satisfies the soft drop condition, stop.

Otherwise remove the softer branch and continue down the harder branch.



clusters hardest radiation first

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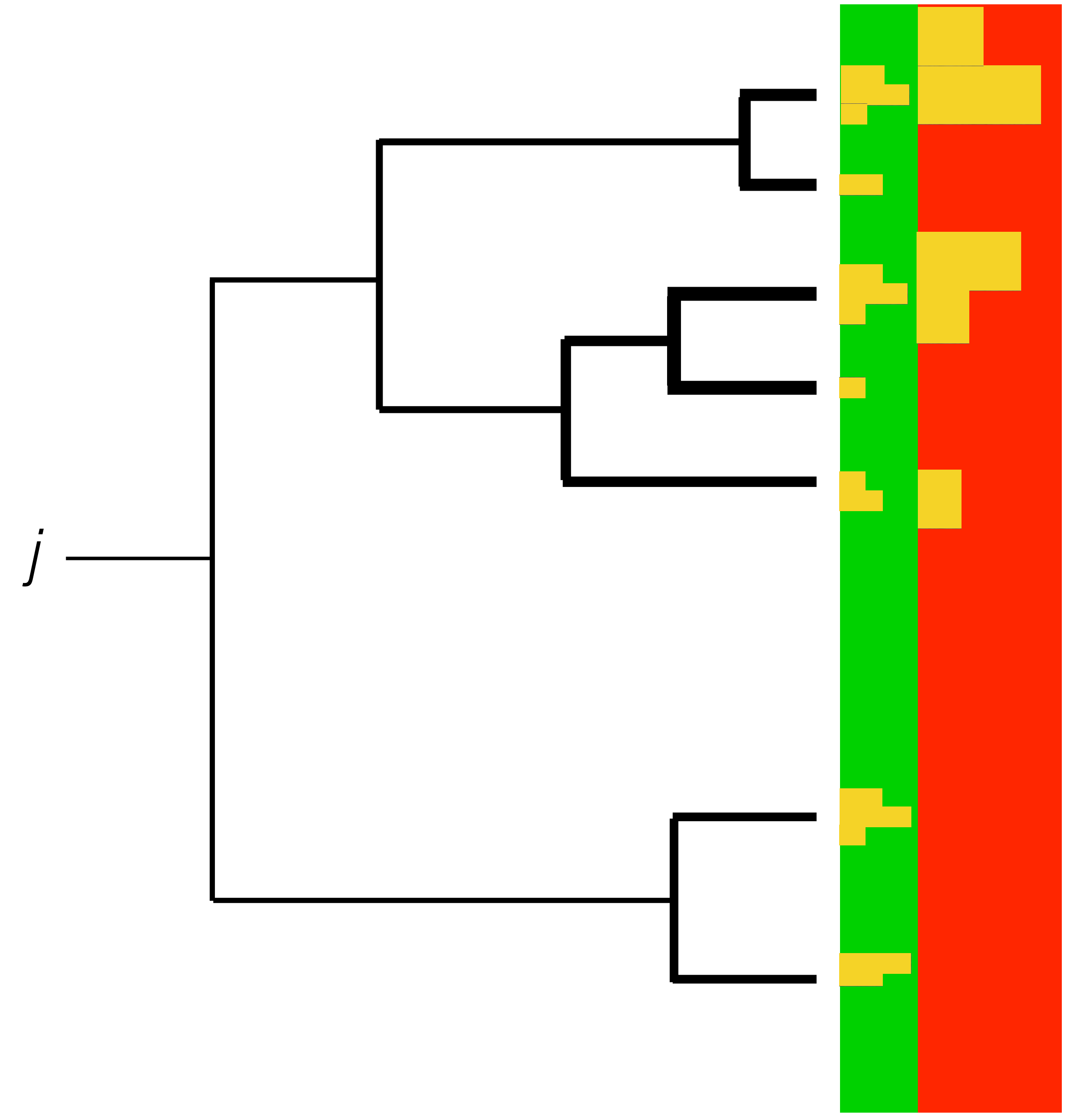

clusters closest radiation first

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Take a jet clustered with e.g. anti-k_t

↓

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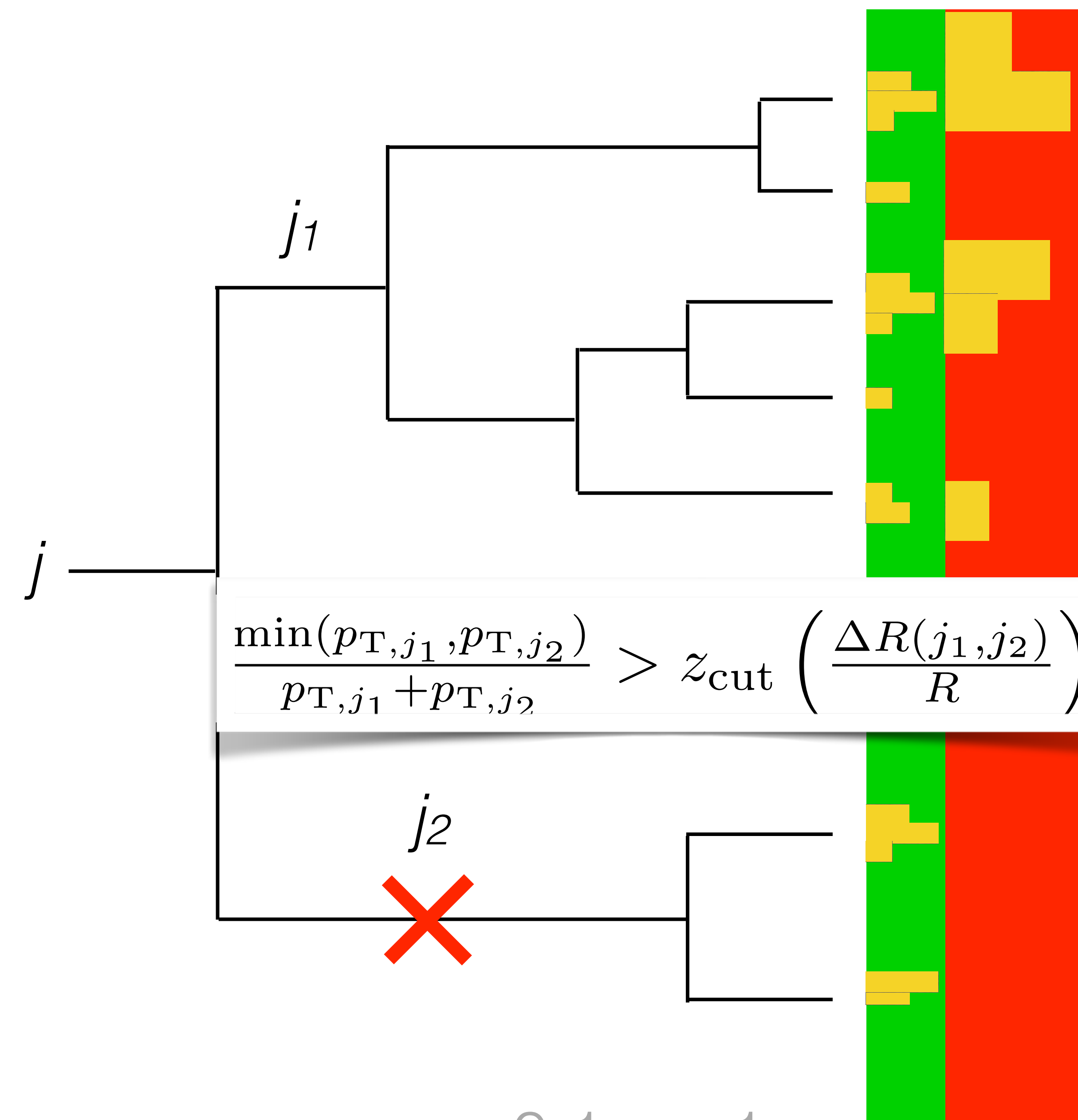

$$\frac{\min(p_{T,j_1}, p_{T,j_2})}{p_{T,j_1}+p_{T,j_2}} > z_{\mathrm{cut}} \left(\frac{\Delta R(j_1,j_2)}{R}\right)^{\beta}$$

$z_{cut} = 0.1 << 1$

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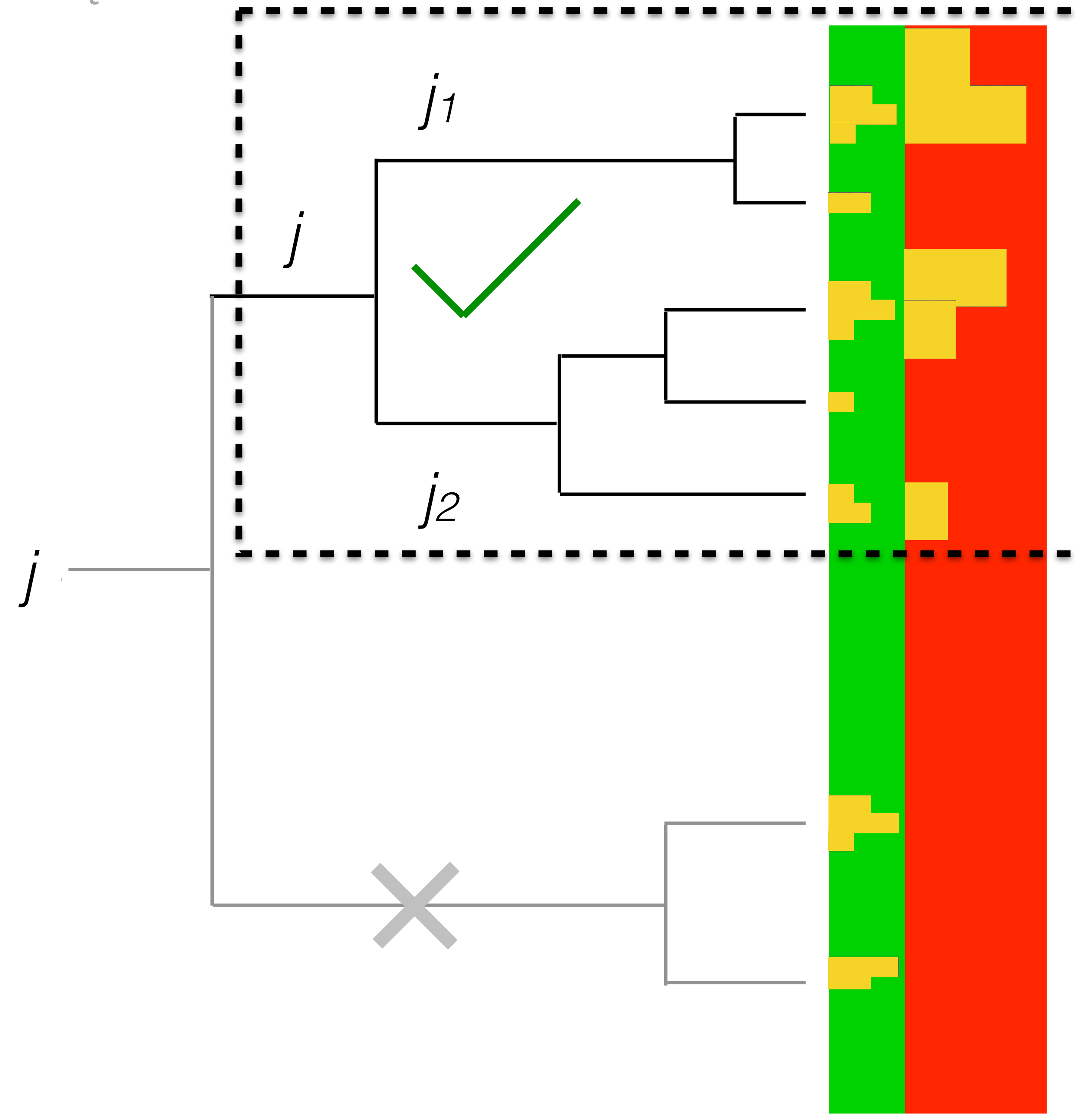
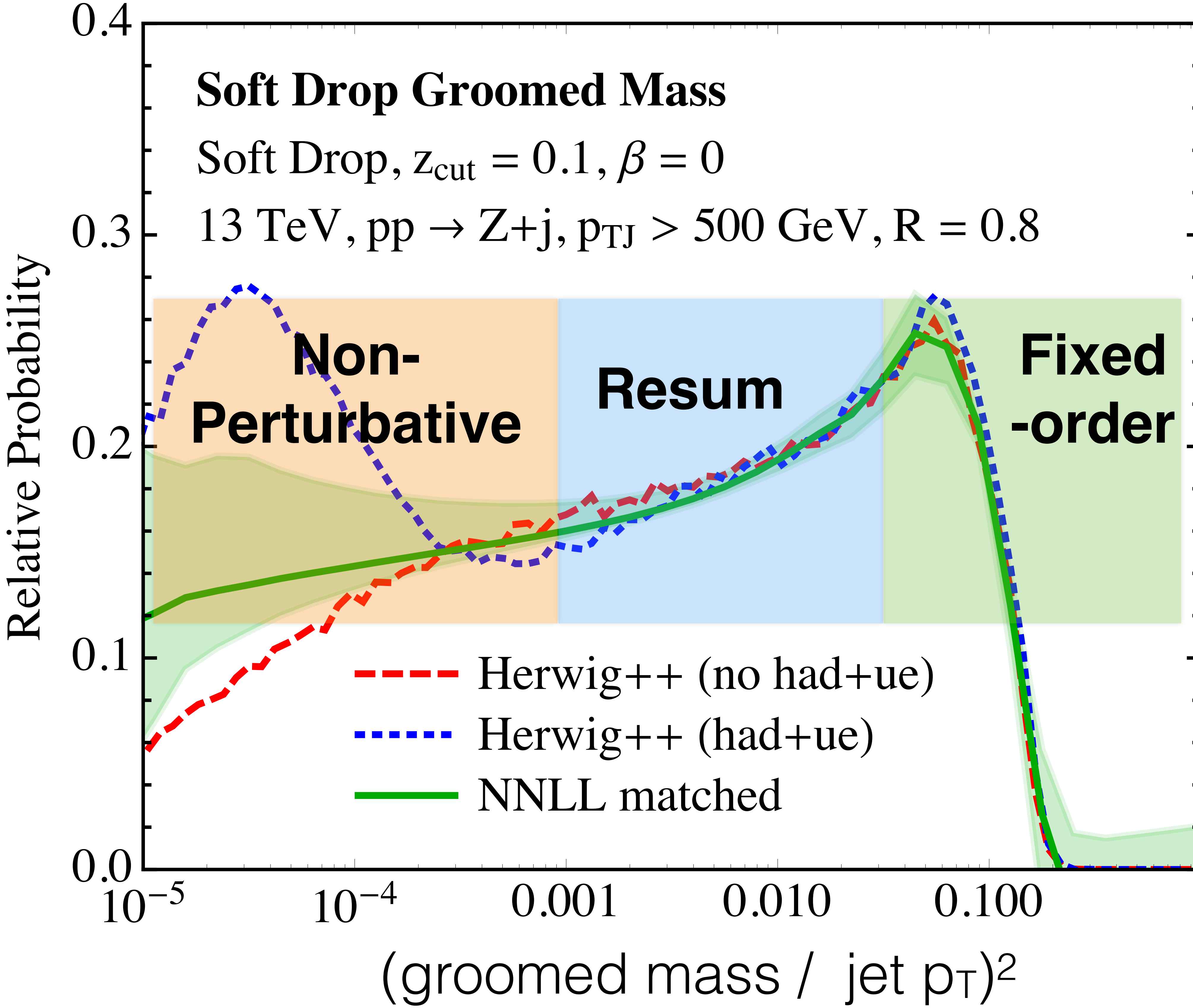


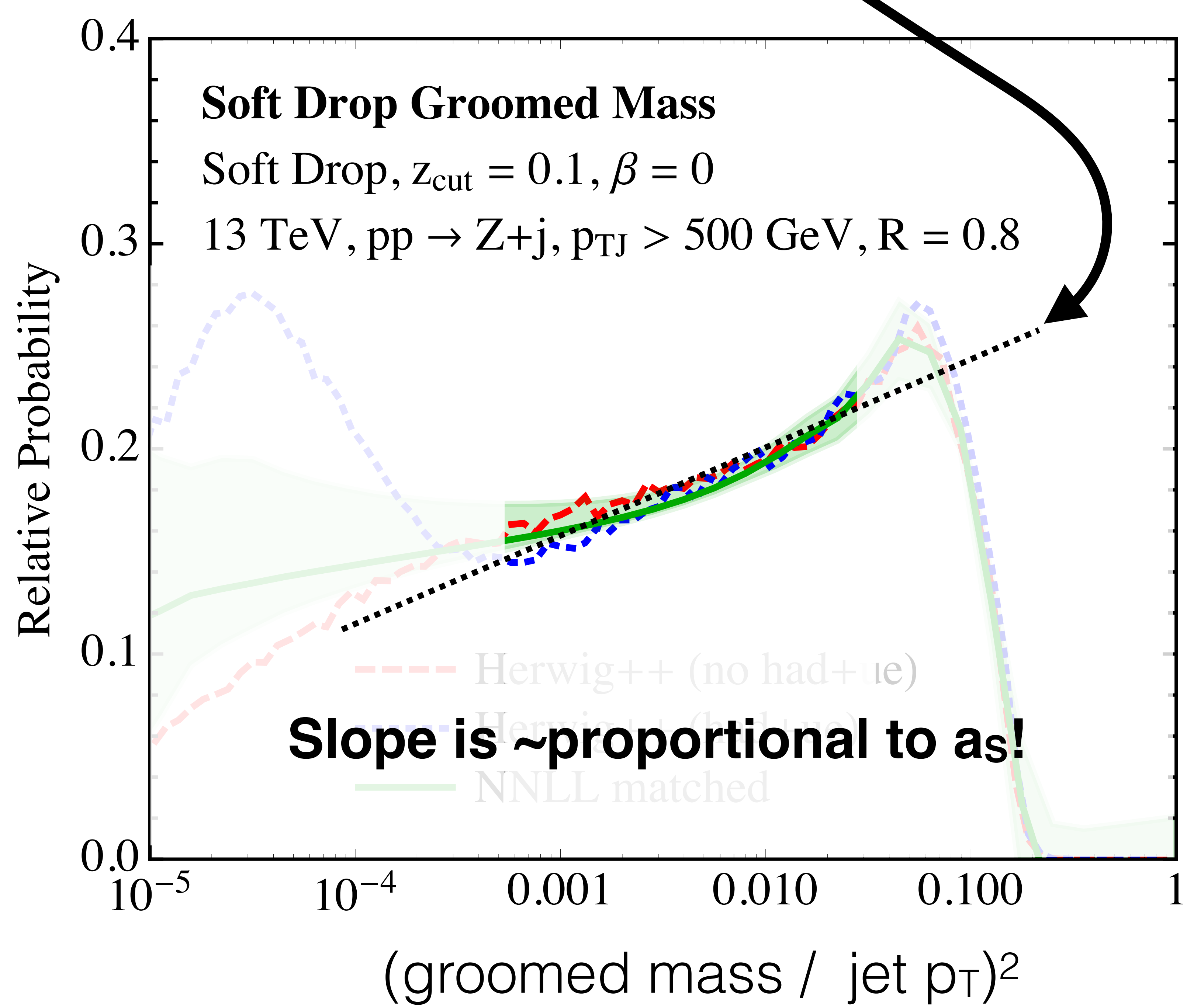
Groomed Jet Mass



C. Frye, A. Larkoski, M. Schwartz, K. Yan, JHEP 07 (2016) 064

Groomed Jet Mass for α_s

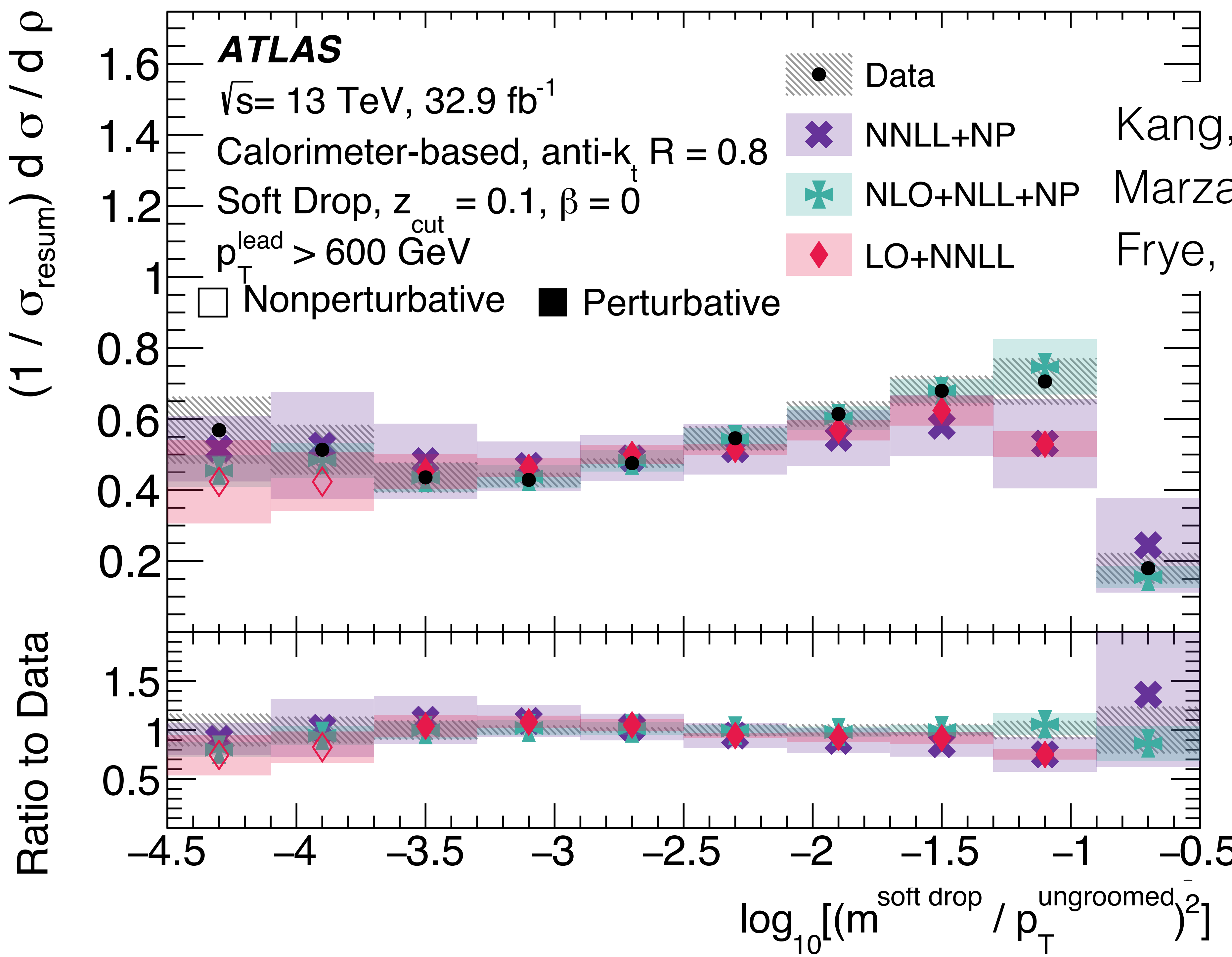
$$\frac{e_2^{(2)}}{\sigma}\frac{d\sigma}{de_2^{(2)}} \approx -\frac{\alpha_s C_i}{\pi}\left[\log(z_{\mathrm{cut}}) - B_i\right] \exp\left[\boxed{-\frac{\alpha_s C_i}{\pi}}\left[\log(z_{\mathrm{cut}}) - B_i\right]\log(e_2^{(2)})\right]$$



C. Frye, A. Larkoski, M. Schwartz, K. Yan, JHEP 07 (2016) 064

Experimental Status

PRD 101 (2020) 052007, PRL 121 (2018) 092001



Kang, Lee, Liu, Ringer

Marzani, Schunk, Soyez

Frye, Larkoski, Schwartz, Yan

The Path to α_s

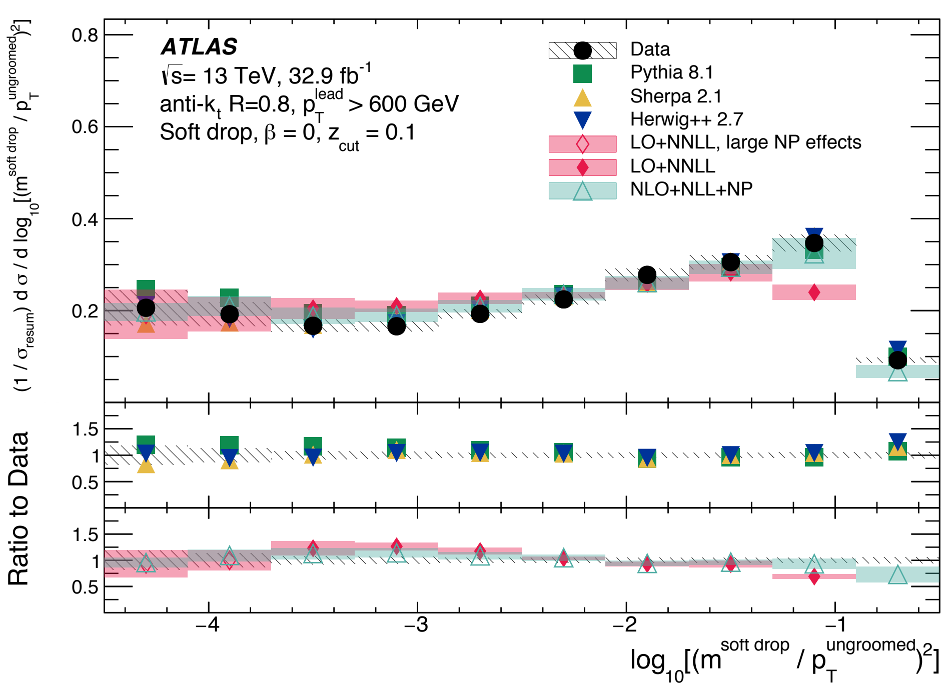
- Non-Perturbative control

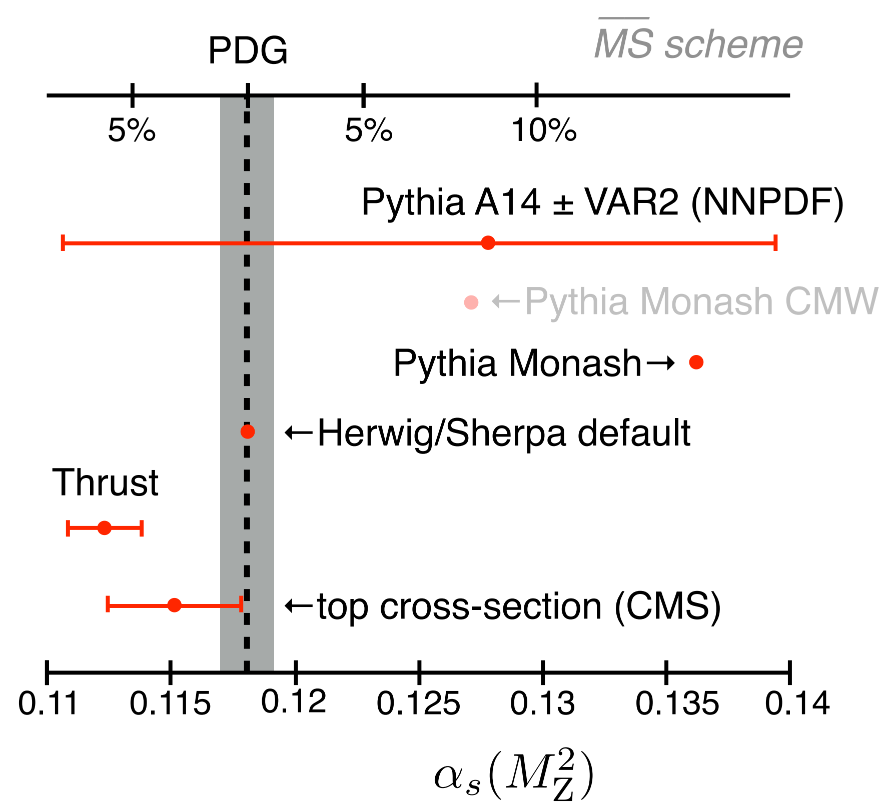
- Higher-order fixed-order (PDG requires NNLO)

- Sensitivity to q/g fractions

$$\frac{e_2^{(2)}}{\sigma}\frac{d\sigma}{de_2^{(2)}} = -\frac{\alpha_s C_i}{\pi}\left[\log(z_{\rm cut}) - B_i\right] \exp\left[-\frac{\alpha_s C_i}{\pi}\left[\log(z_{\rm cut}) - B_i\right]\log(e_2^{(2)})\right]$$

- Experimental precision



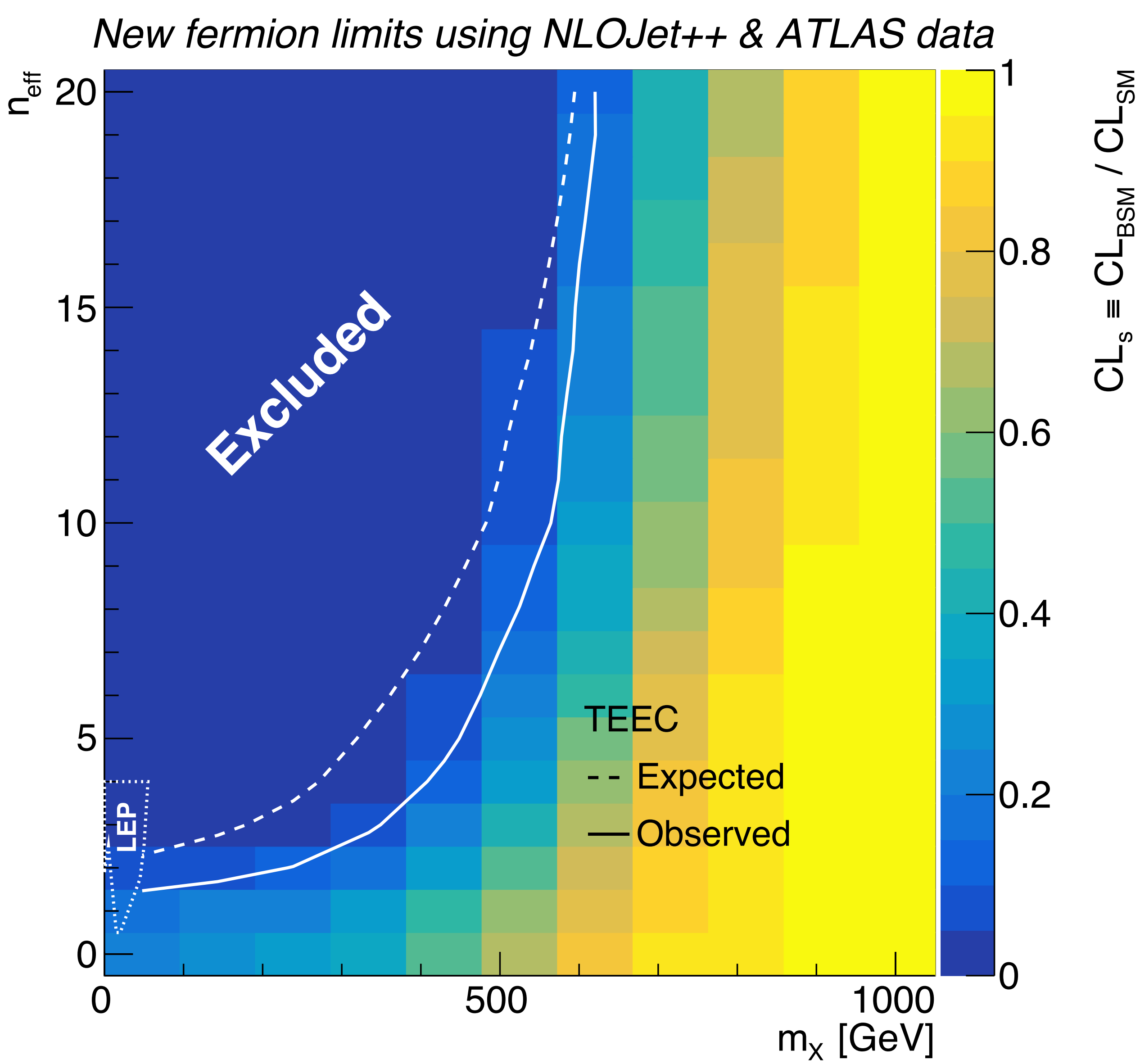


Beyond $\alpha_s(m_Z)$

Jet (substructure) allows us to probe QCD at many scales. The running of the strong coupling can be used as an indirect probe of BSM.

This approach complements direct searches, as this is agnostic about the decay properties of new particles.

(Intersting discussion: what is the scale probed by a particular observable? Seems not a trivial question)



J. Llorente and BPN, Nucl. Phys. B 936 (2018) 106

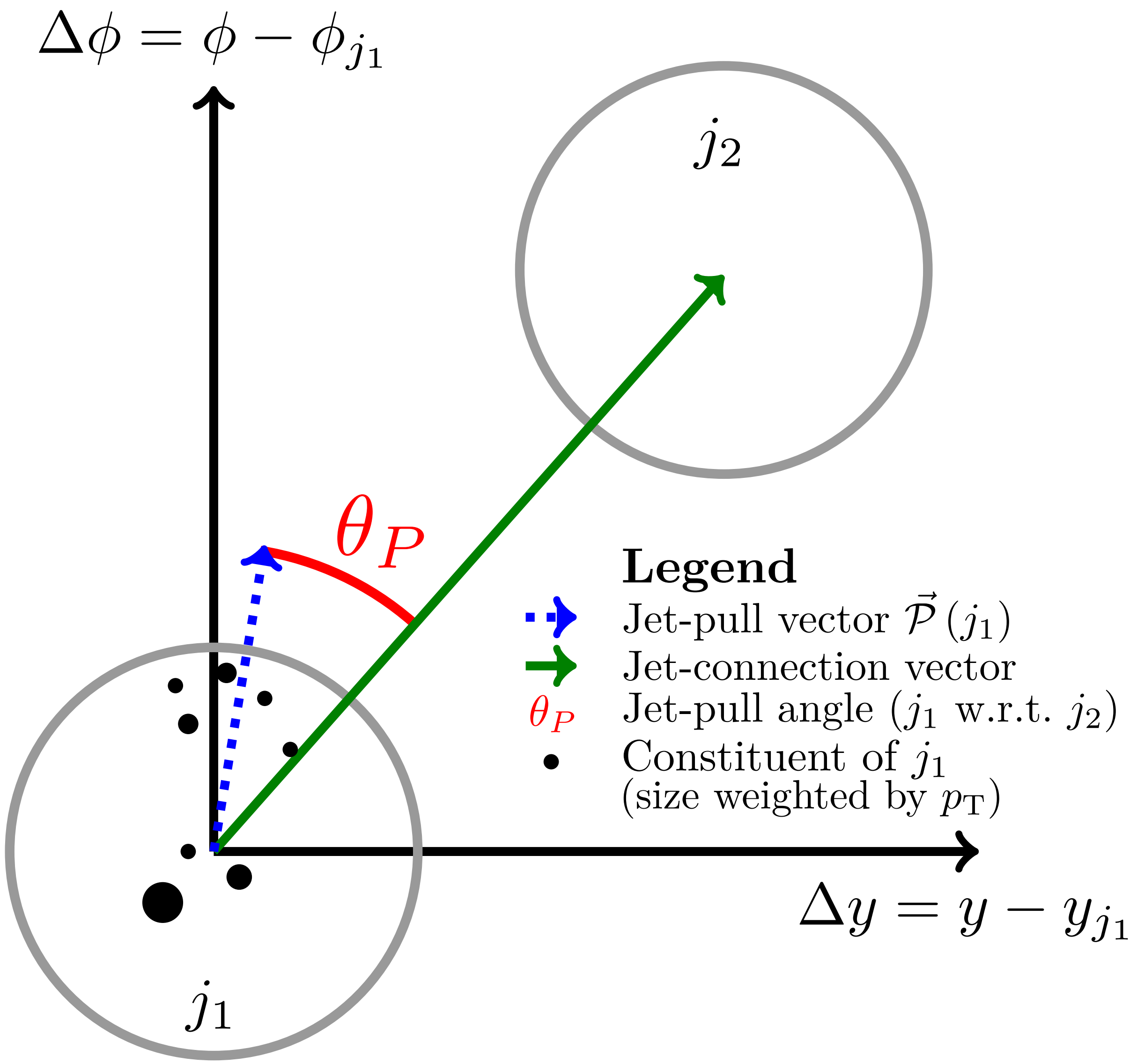
Jet Substructure and Emergent QCD

As in many other areas of physics, studying correlations gives us a handle on emergent properties of QCD

Correlations Part I: Jet Pull

As in many other areas of physics, studying correlations gives us a handle on emergent properties of QCD

Example 1: Jet pull



We can study QCD **entanglement** from correlations in the radiation patterns of pairs of jets.

An exciting laboratory for this work is boosted W bosons, a copious source of **singlet** → jets.

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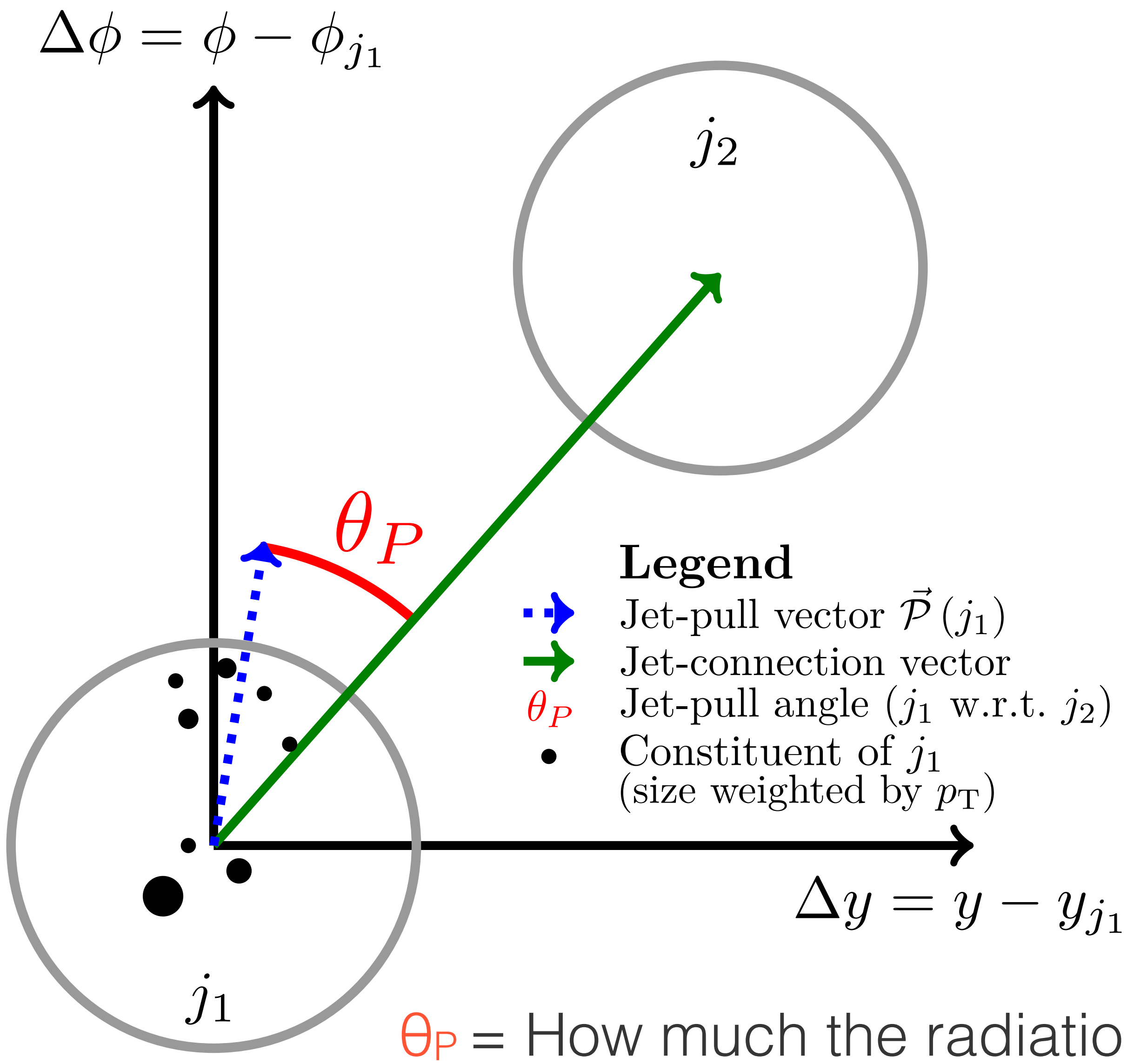
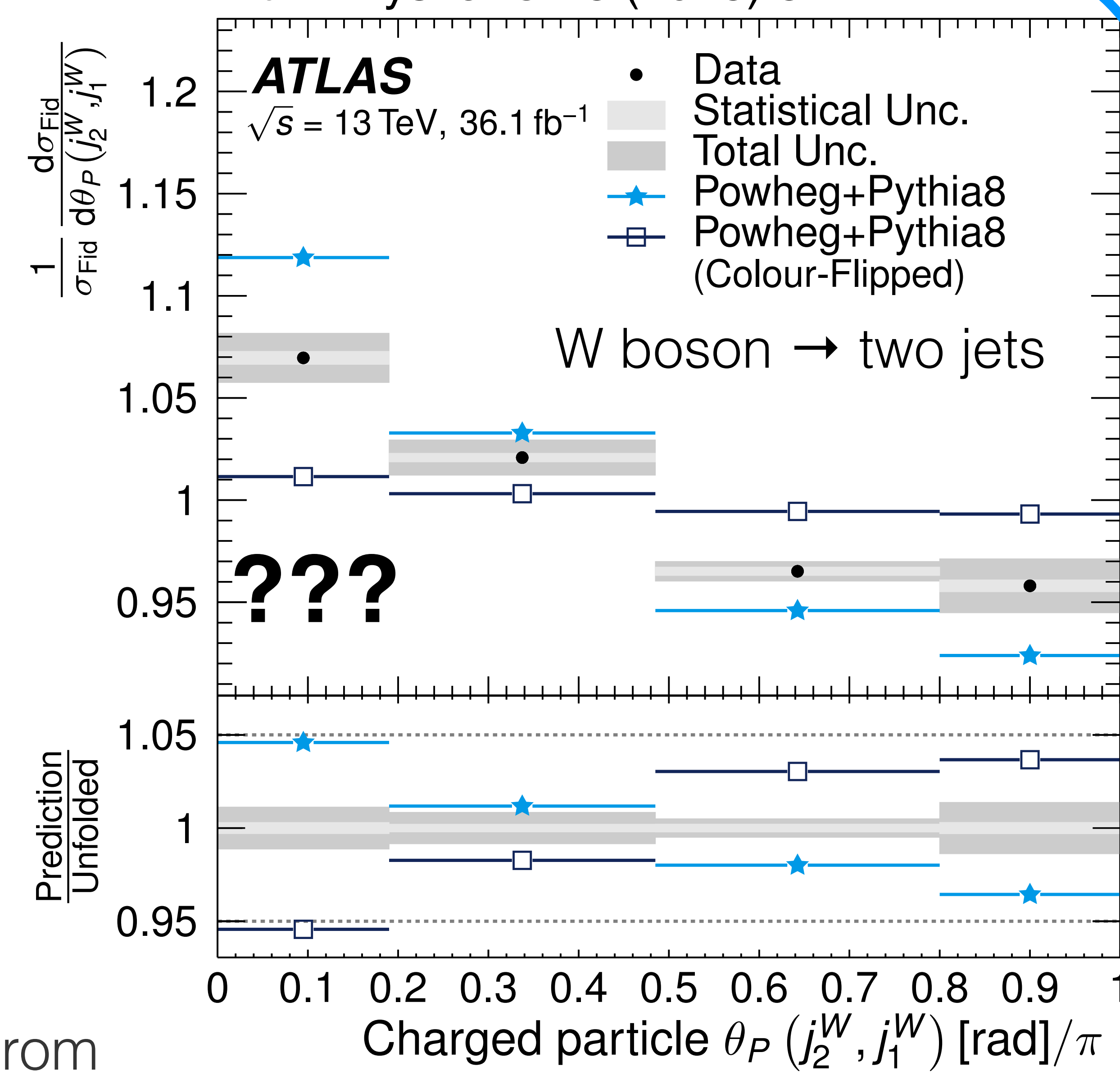


Eur. Phys. J. C 78 (2018) 847



θ_P = How much the radiation from one jet "leans" toward the other.

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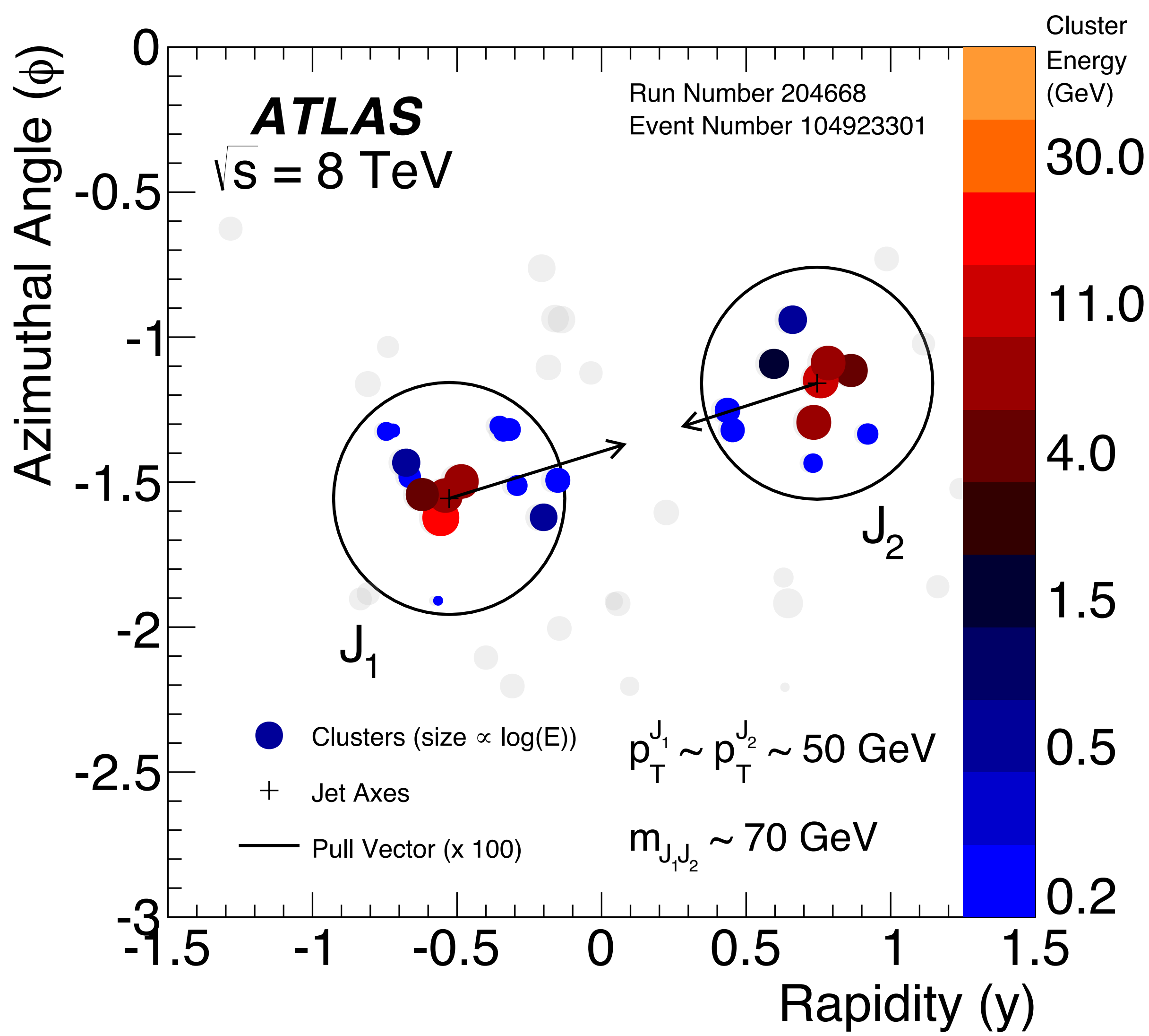

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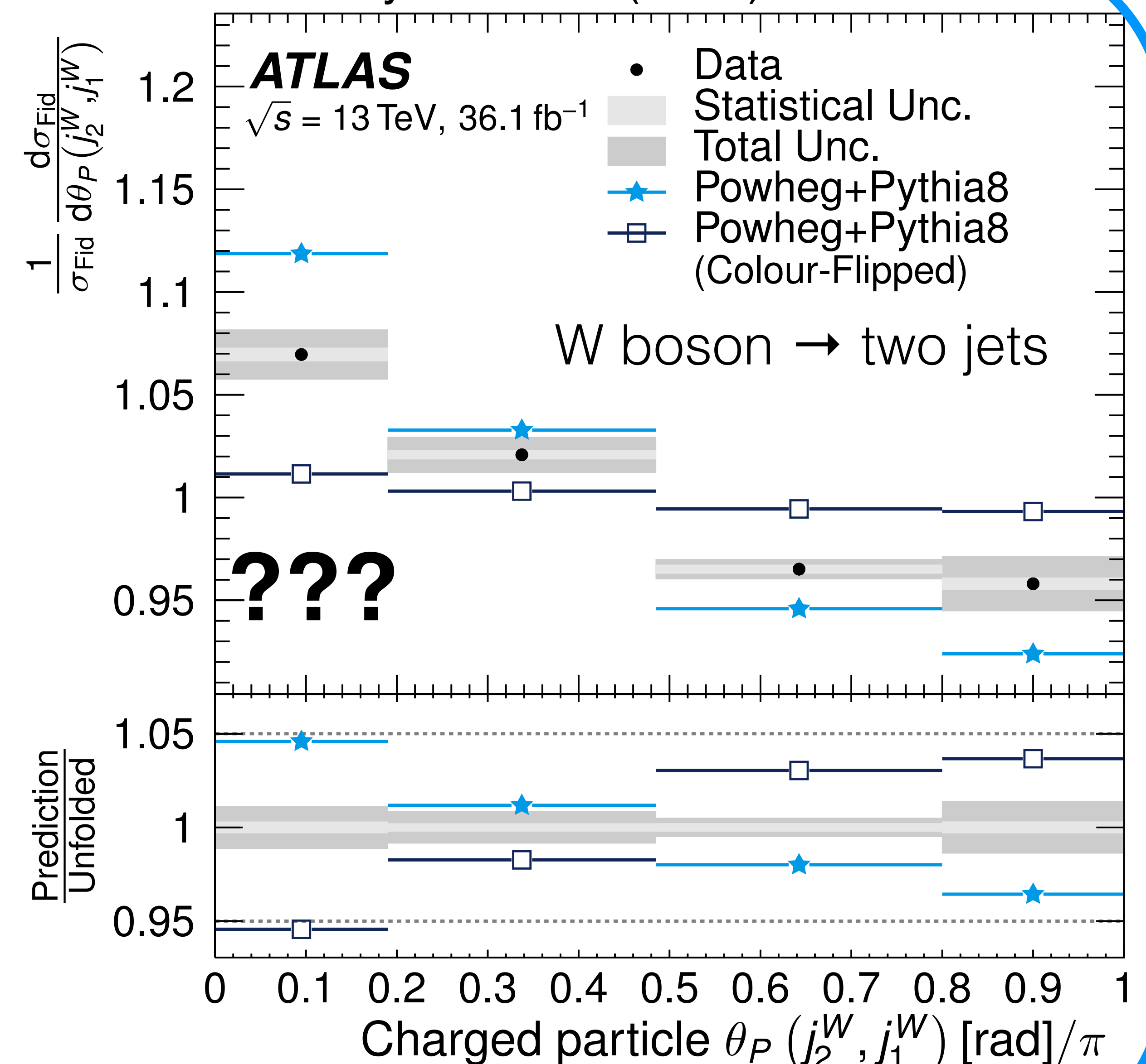

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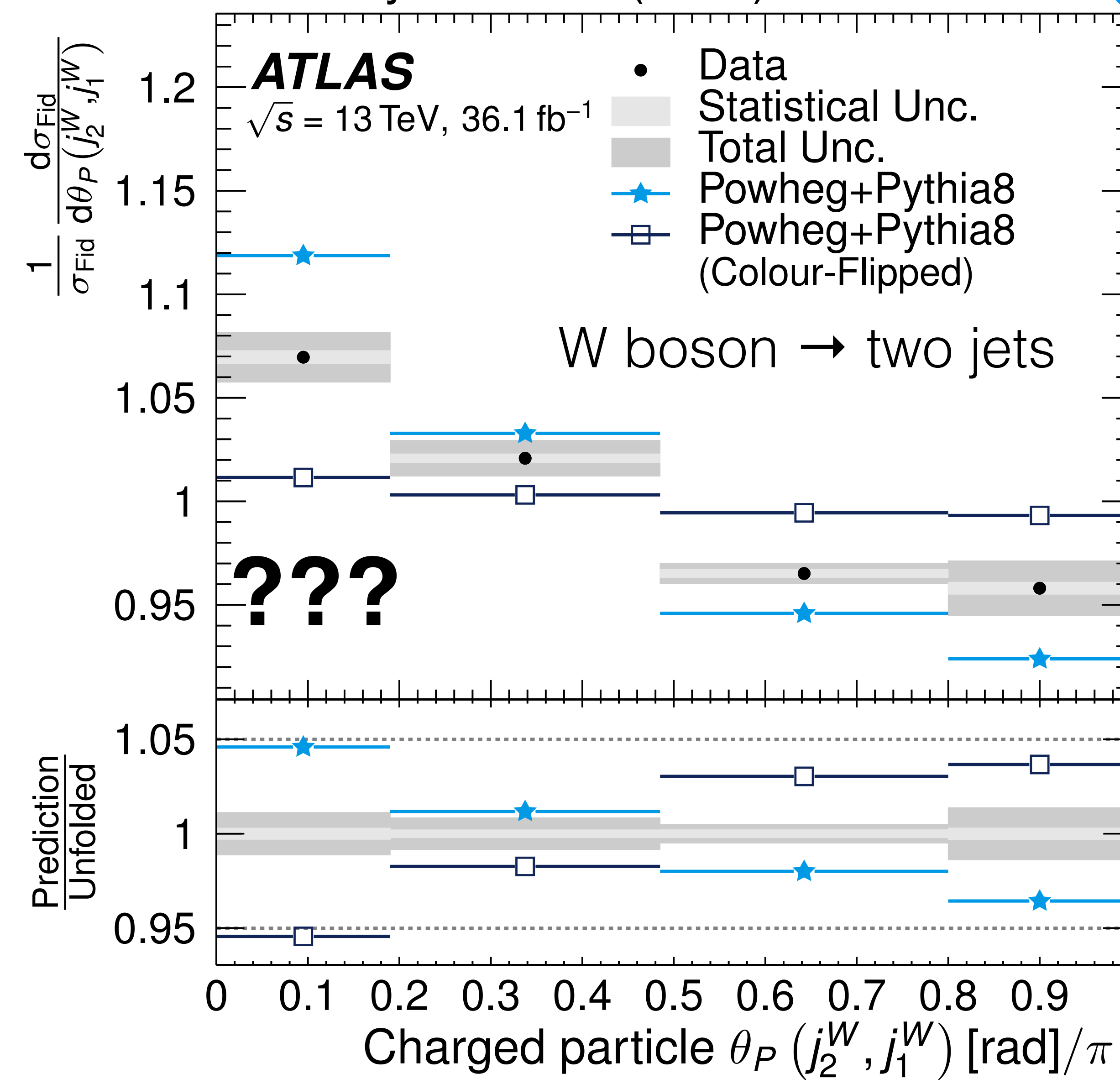
Example 1: Jet pull

Here is an observable where we can't distinguish between "entanglement" turned **"on"** and **"off"** !

Theory predictions are challenging, but in development

(see A. Larkoski, S. Marzani, C. Wu, PRD 99 (2019) 091502)

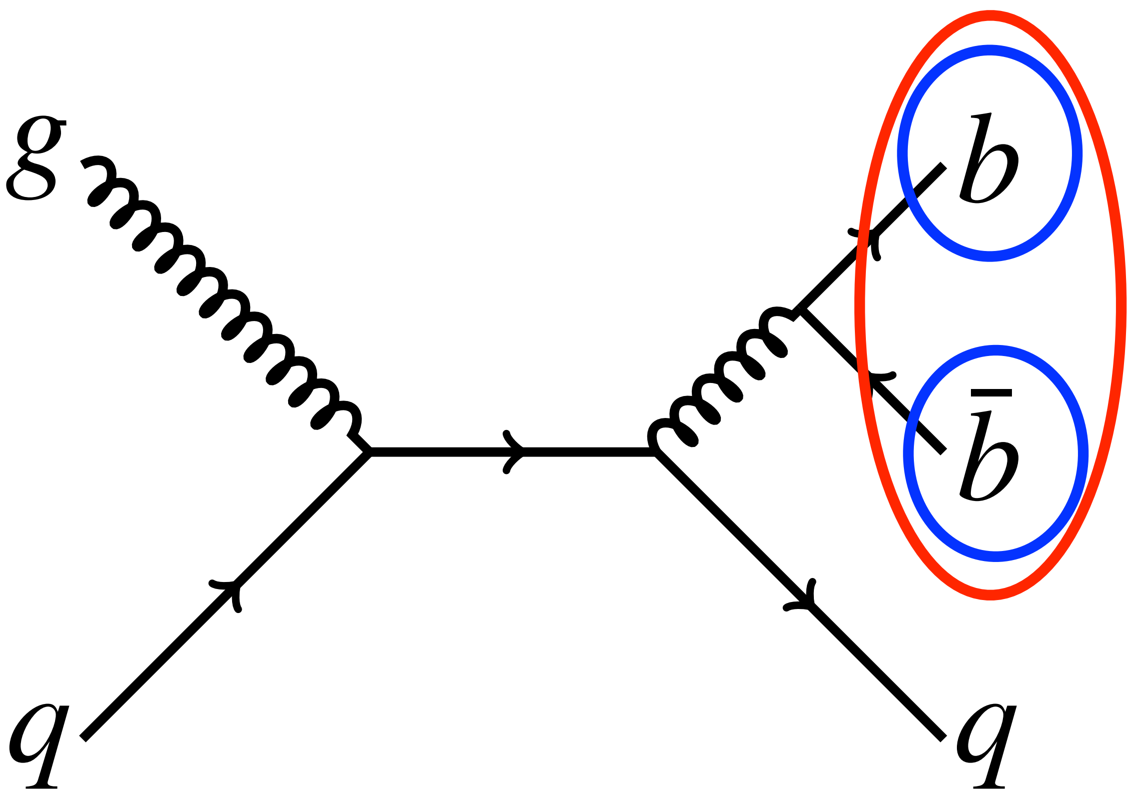
Eur. Phys. J. C 78 (2018) 847



Correlations Part II: $g \rightarrow b\bar{b}$

As in many other areas of physics, studying correlations gives us a handle on emergent properties of QCD

Example 2: $g \rightarrow bb$



Gluon splitting to bottom quarks gives us the only ~pure access to QCD splitting functions.

(and of course, this is a very important process for Higgs)

Correlations Part II: $g \to b\bar{b}$

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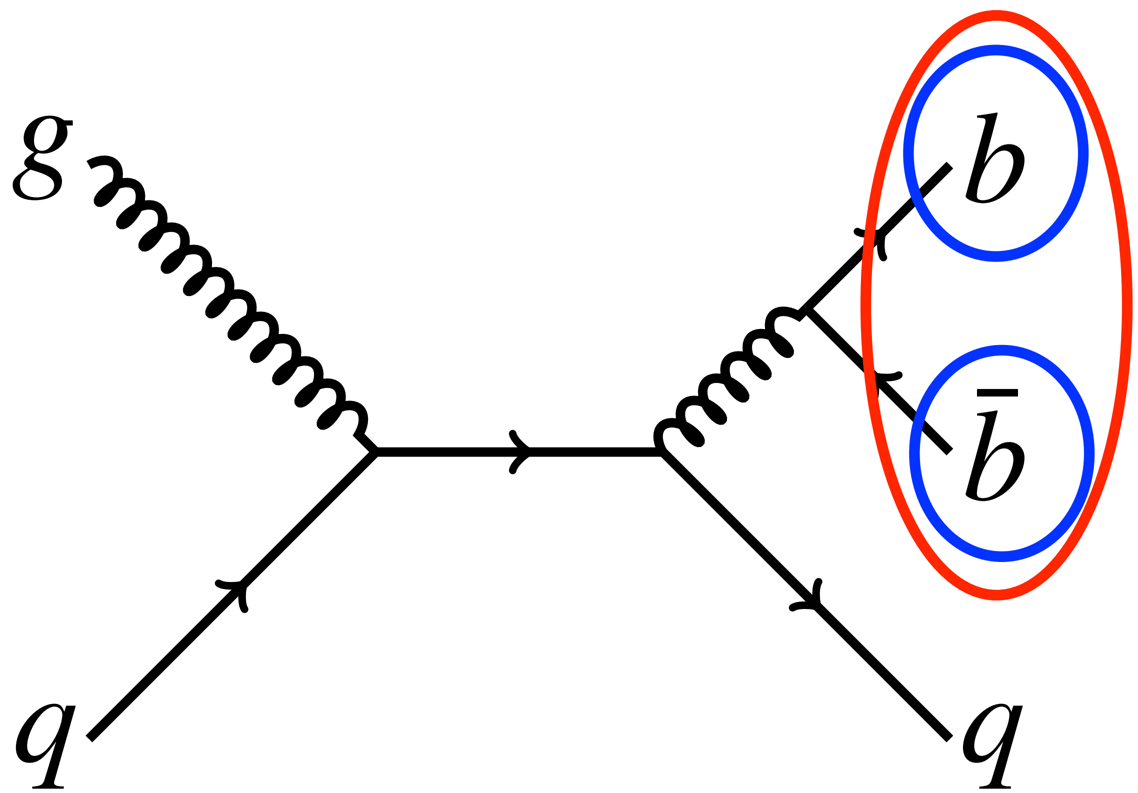
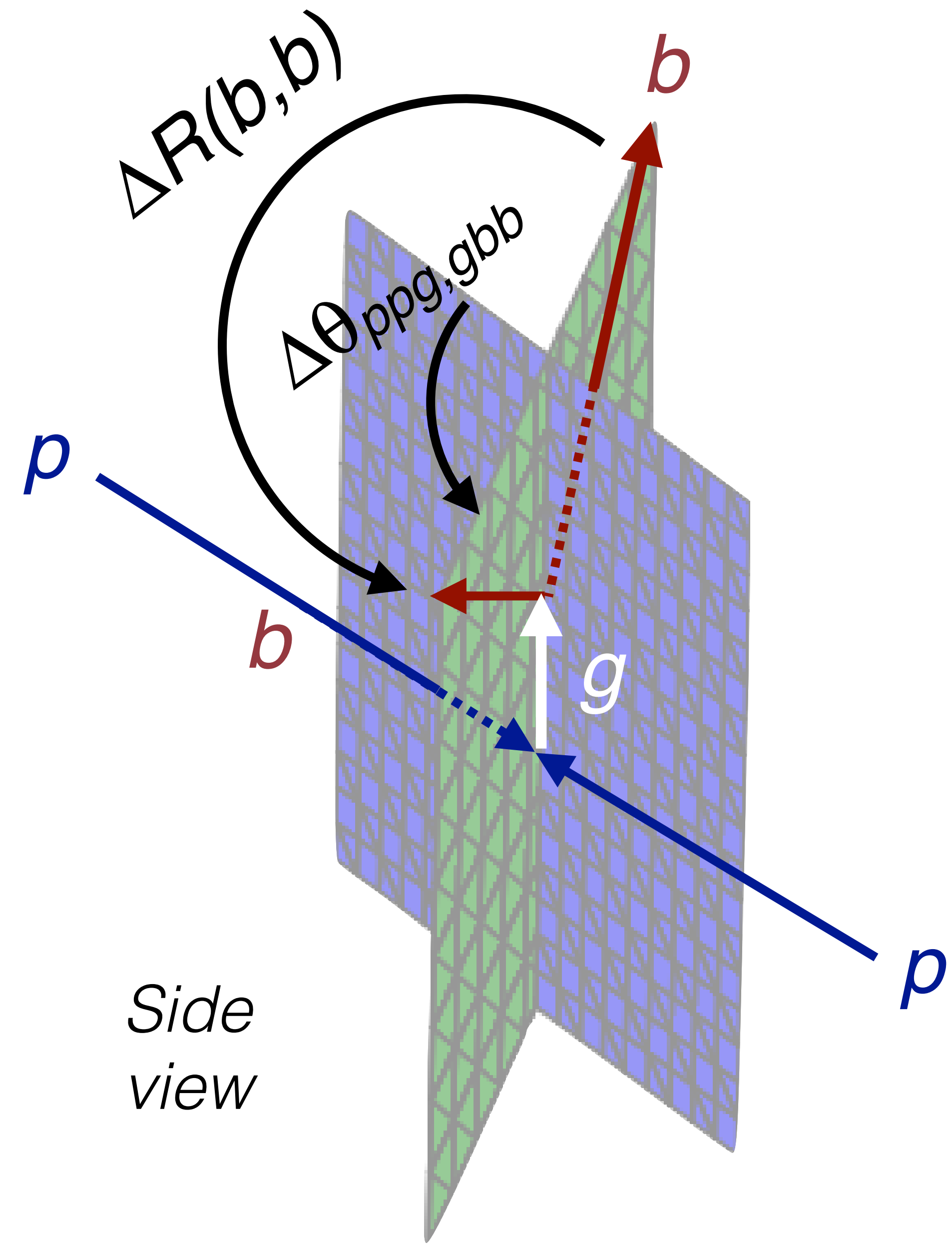


Relative angles to probe polarization



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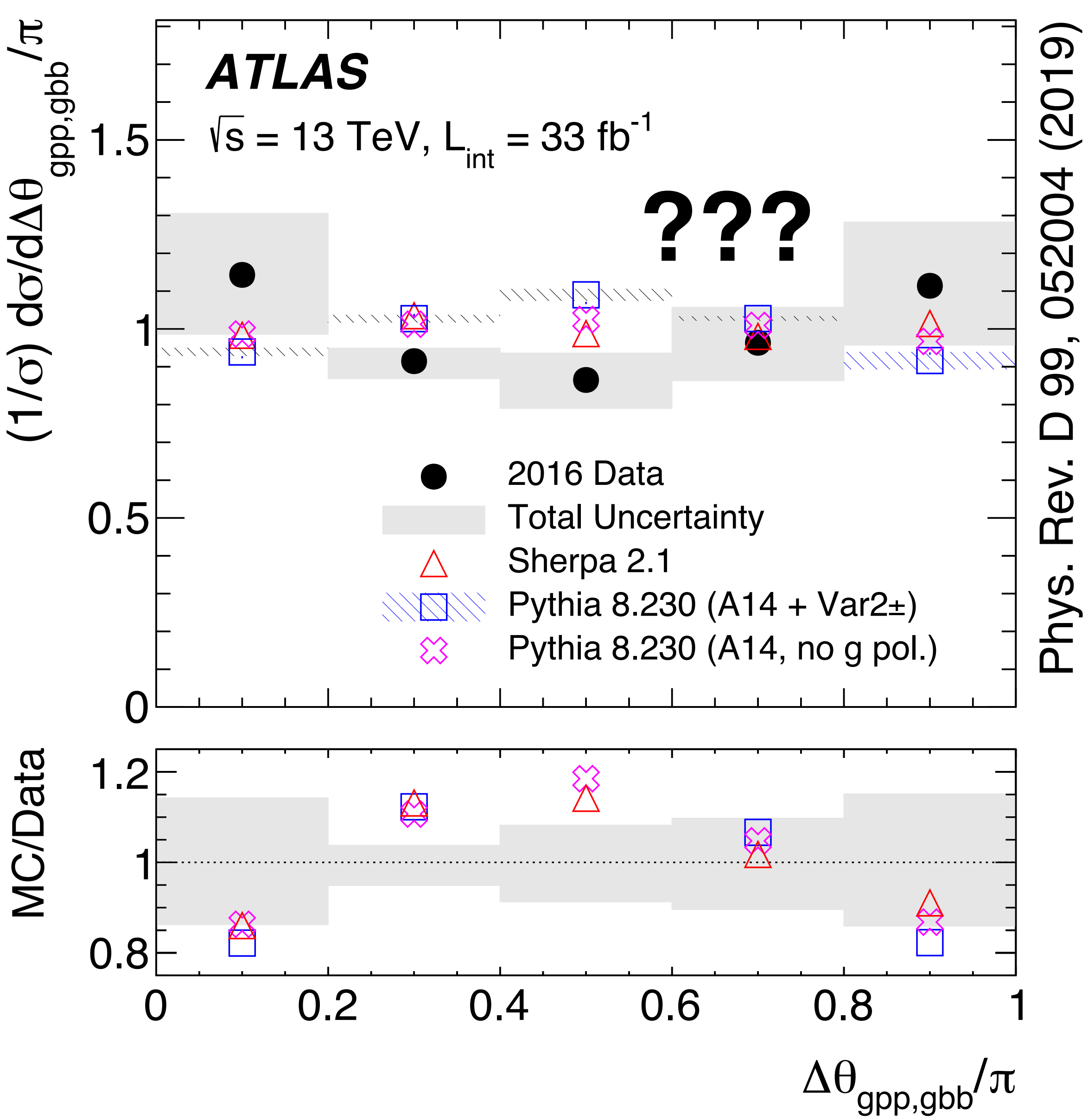

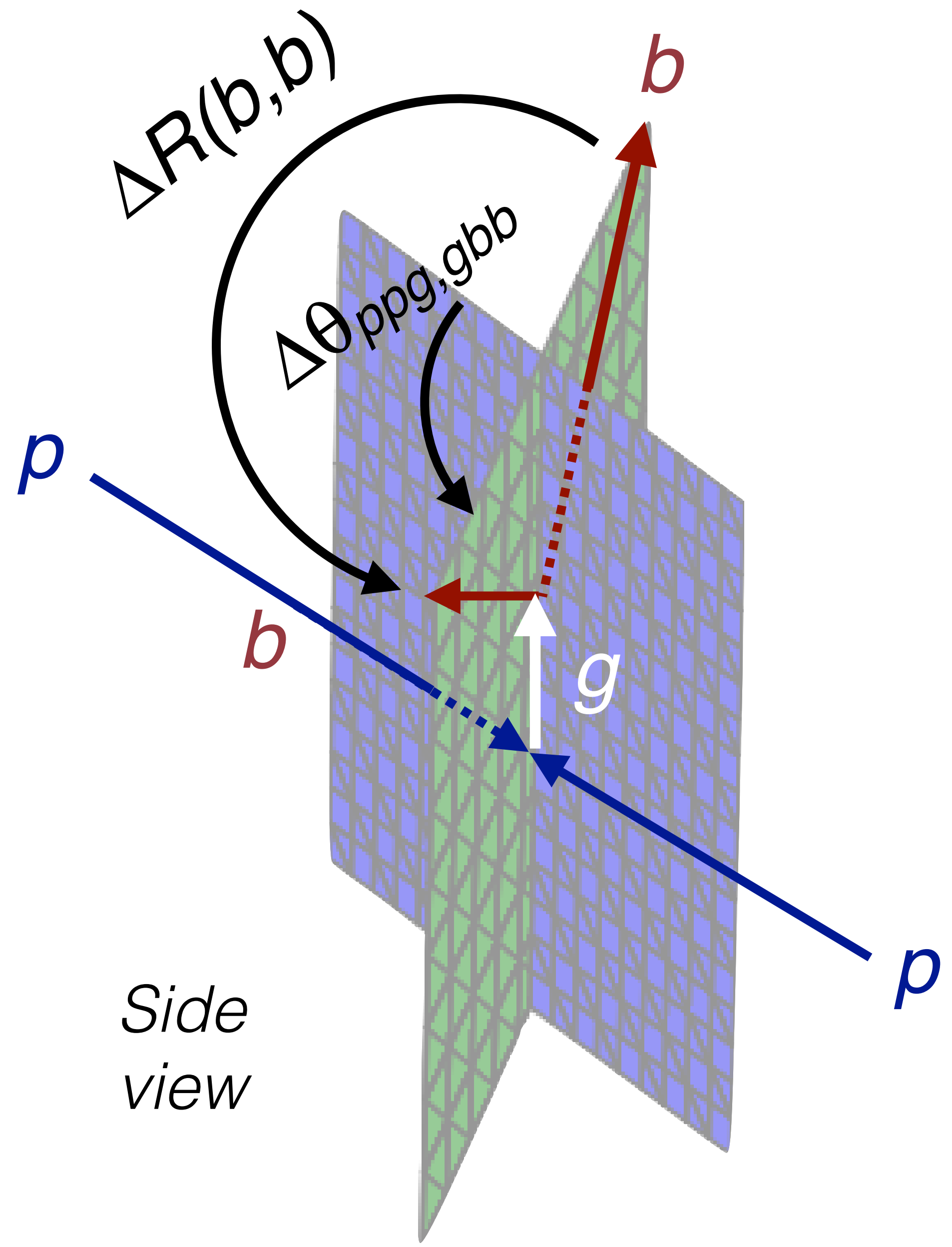

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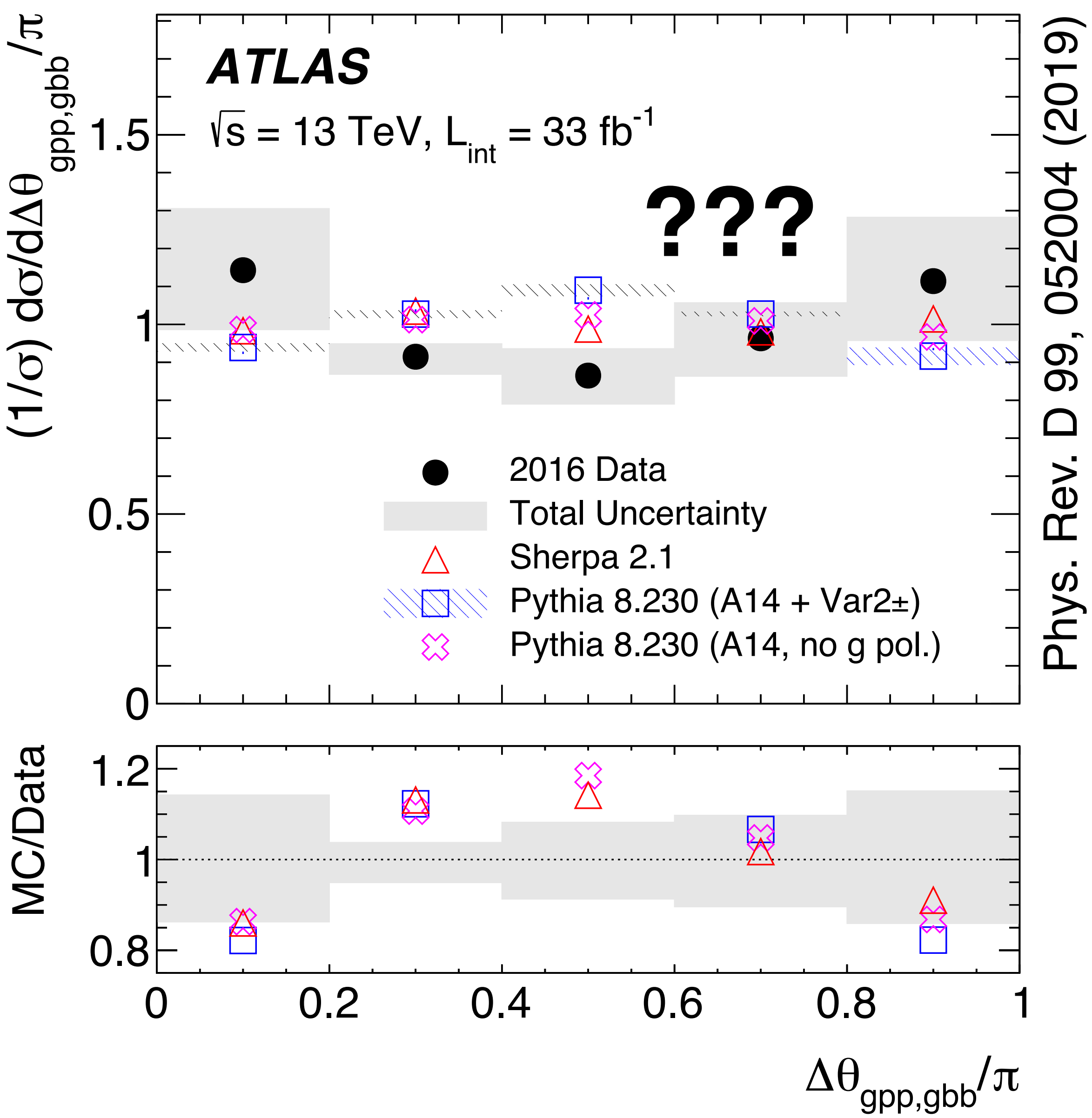


Gluons seems "more polarized" in data than in our predictions. Slight improvement from matrix element corrections (Sherpa 2 → 3).

See also Fischer, Lifson, Skands, EPJC 77 (2017) 719

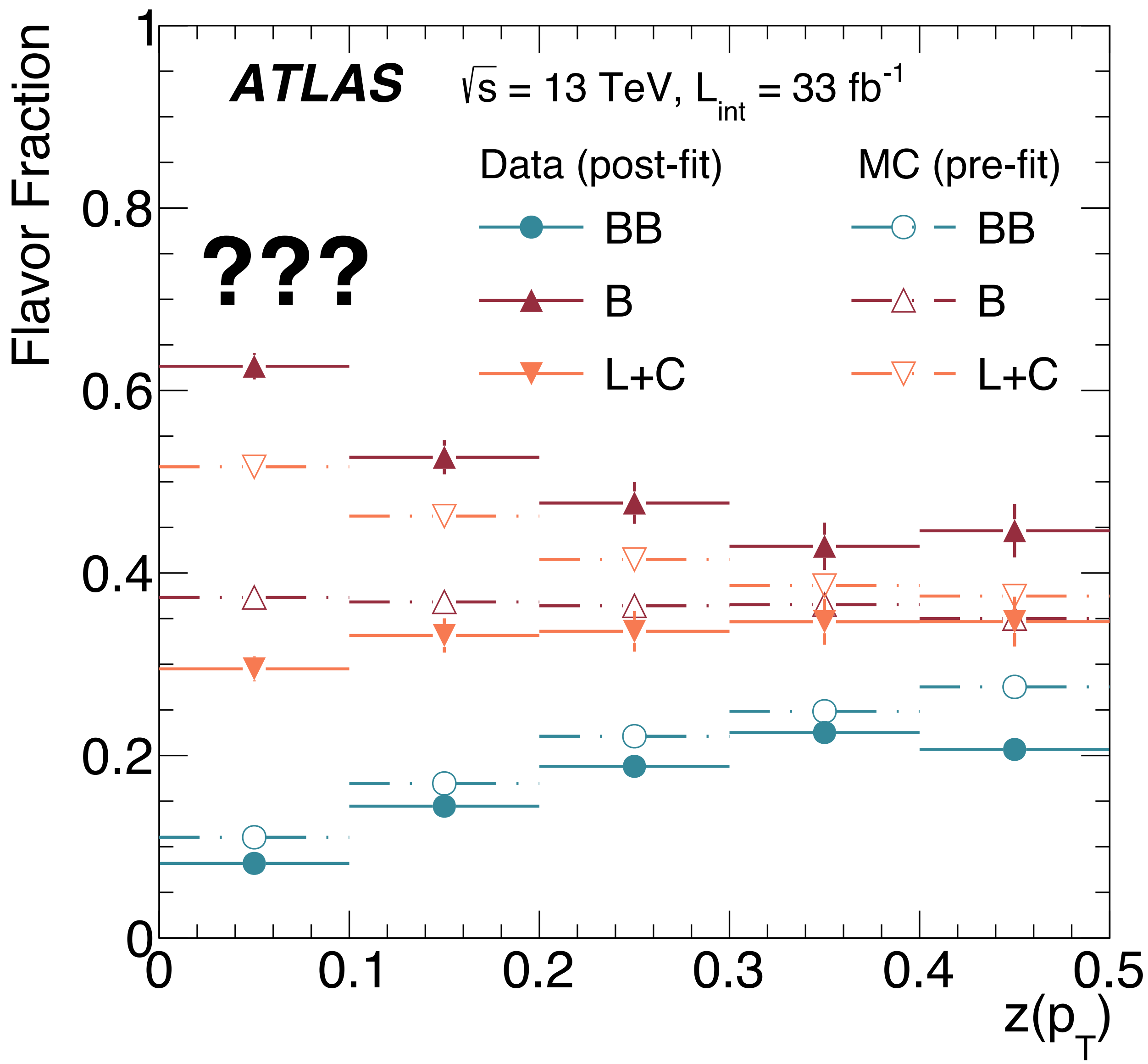
Correlations Part II: $g \to b\bar{b}$

As in many other areas of physics, studying correlations gives us a handle on emergent properties of QCD

Example 2: $g \to bb$

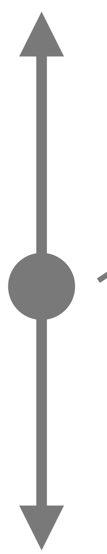
Also find that the flavor fractions are not quite correct?

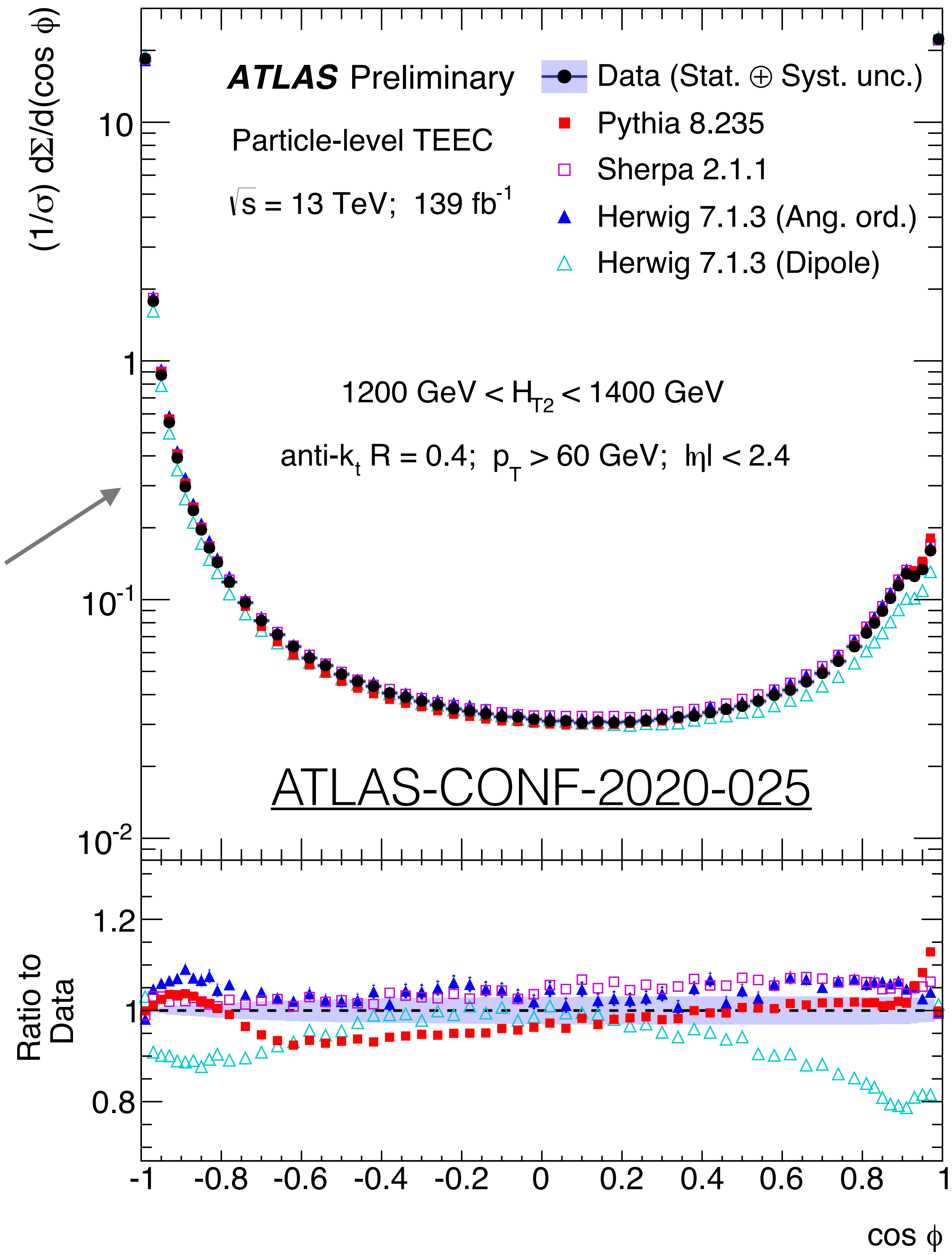
(determined from a fit to the displacement of tracks inside jets)

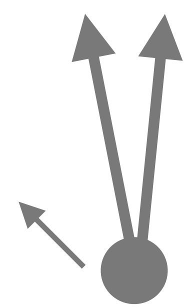


Phys. Rev. D 99, 052004 (2019)

Correlations Part III: TEECs







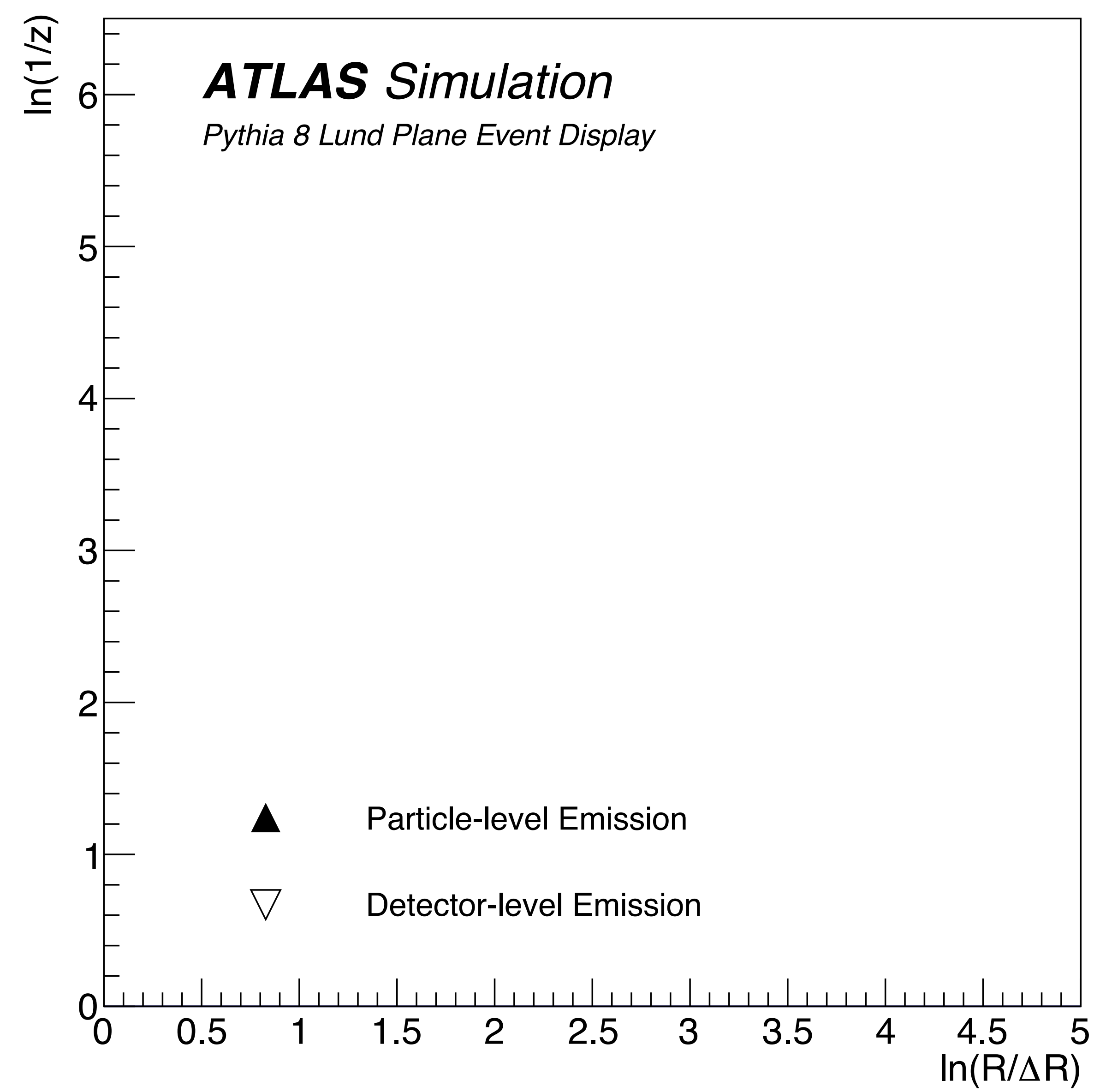
For probing angular scales larger than the jet radius, we can use jets to precisely probe event-level correlations

Significant recent interest in EECs inside jets also

Correlations Part IV: Isolate the Physics

Important: isolate effects with different physical origin

Tool: Lund plane to categorize all hard splittings at once



[Dreyer, Salam, Soyez, JHEP 12 (2018) 064]

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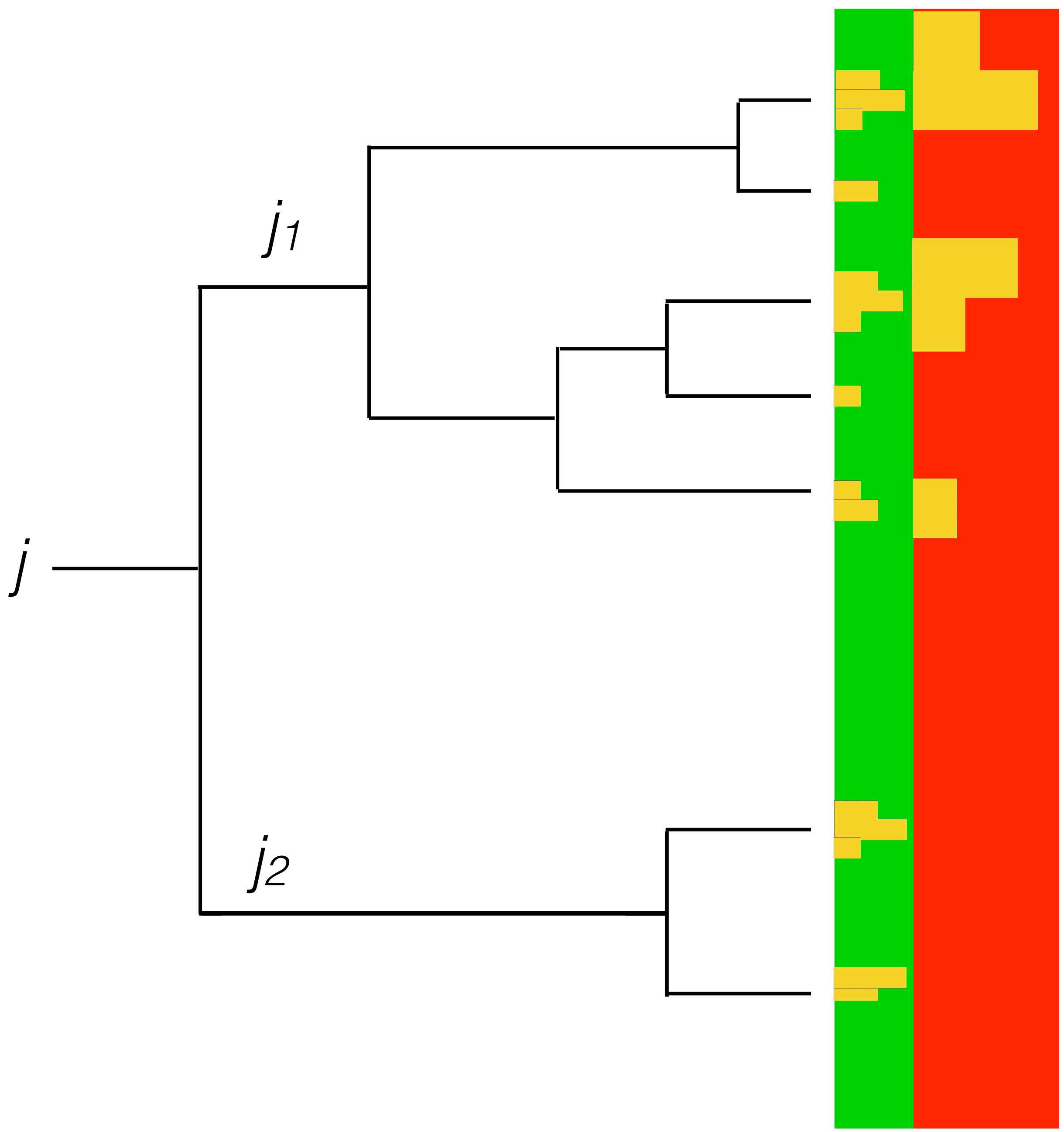
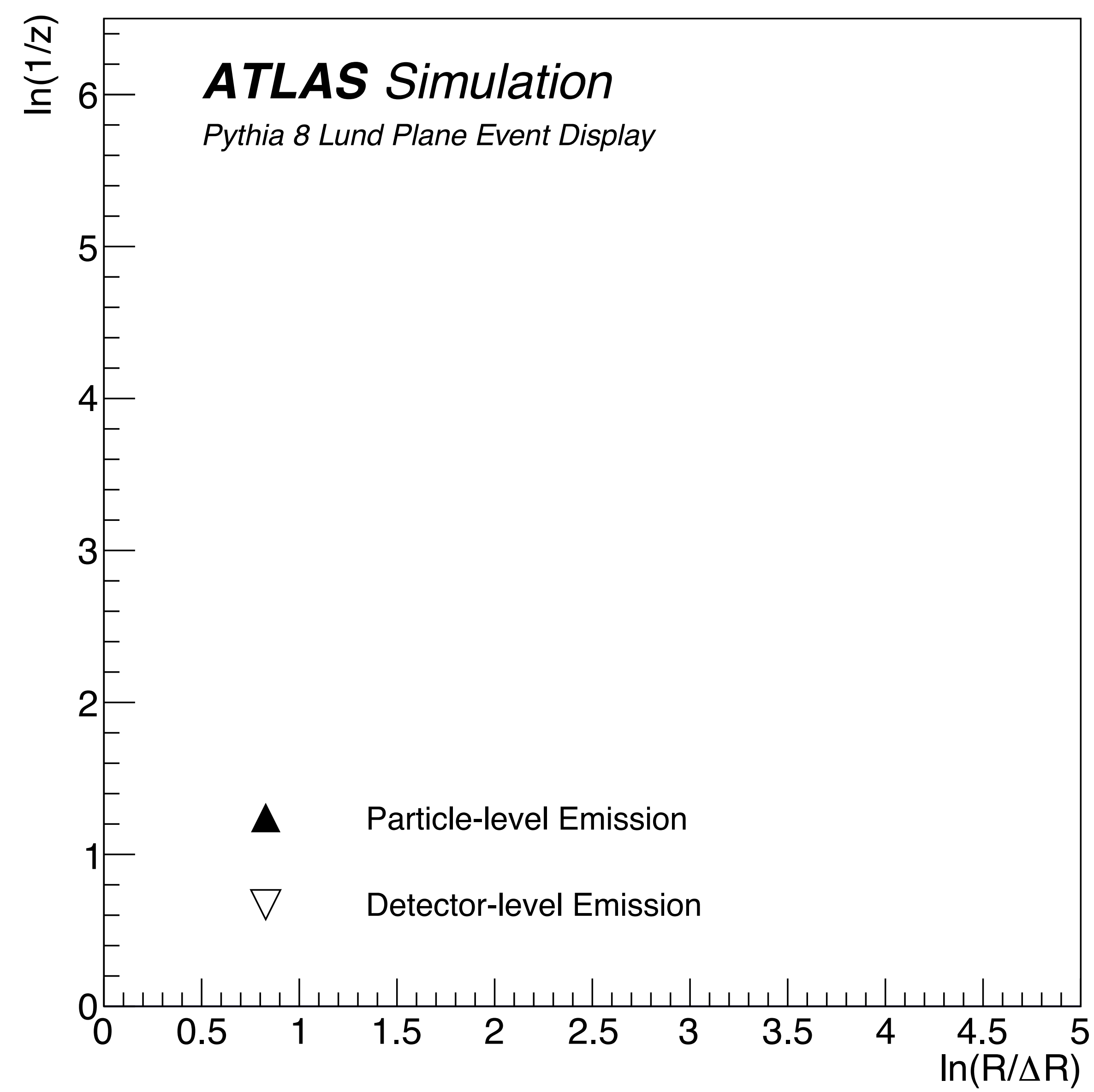


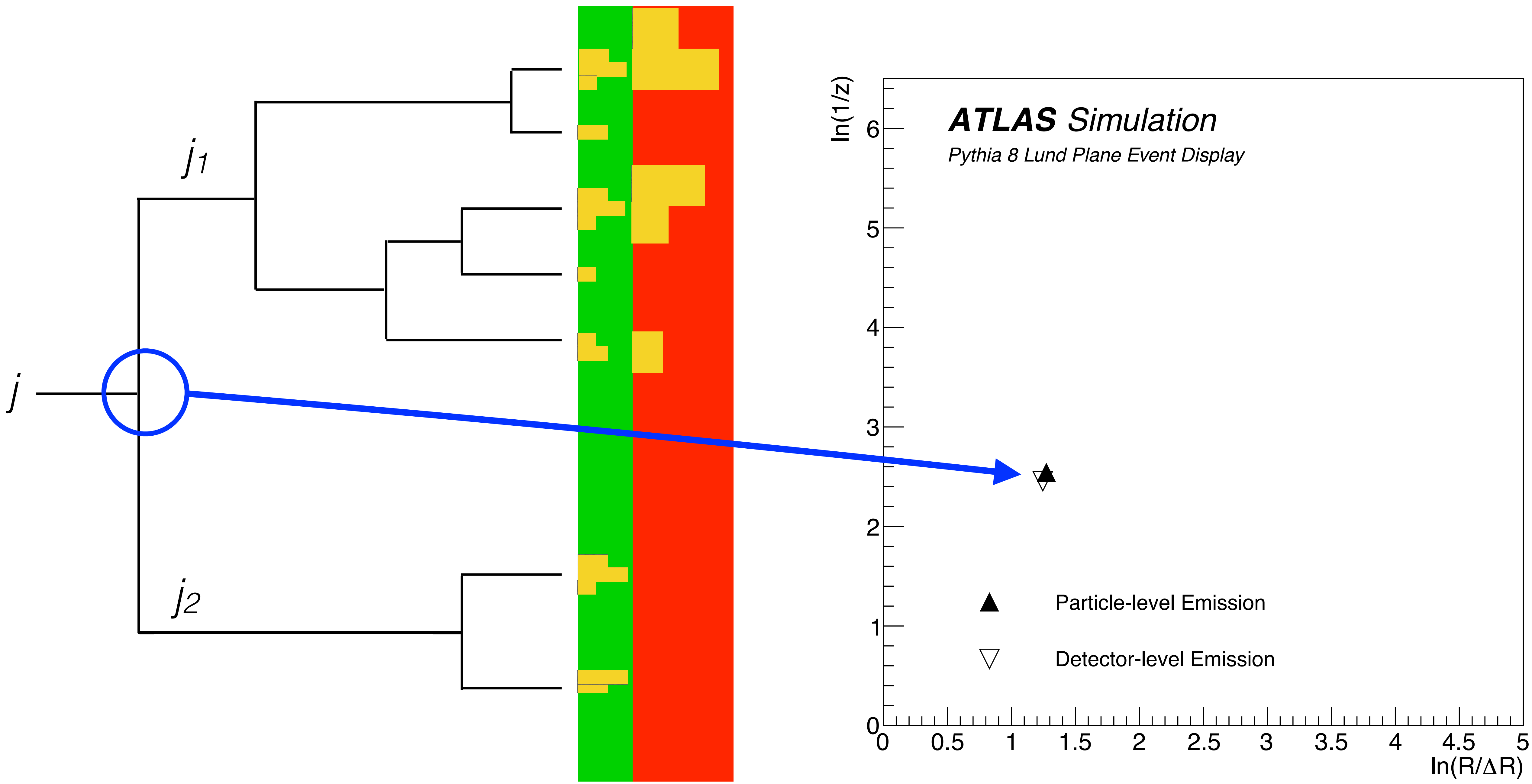


z = j_1 momentum fraction of j

ΔR = angle between j_1 and j_2

Phys. Rev. Lett. 124, 222002 (2020)

Correlations Part IV: Isolate the Physics



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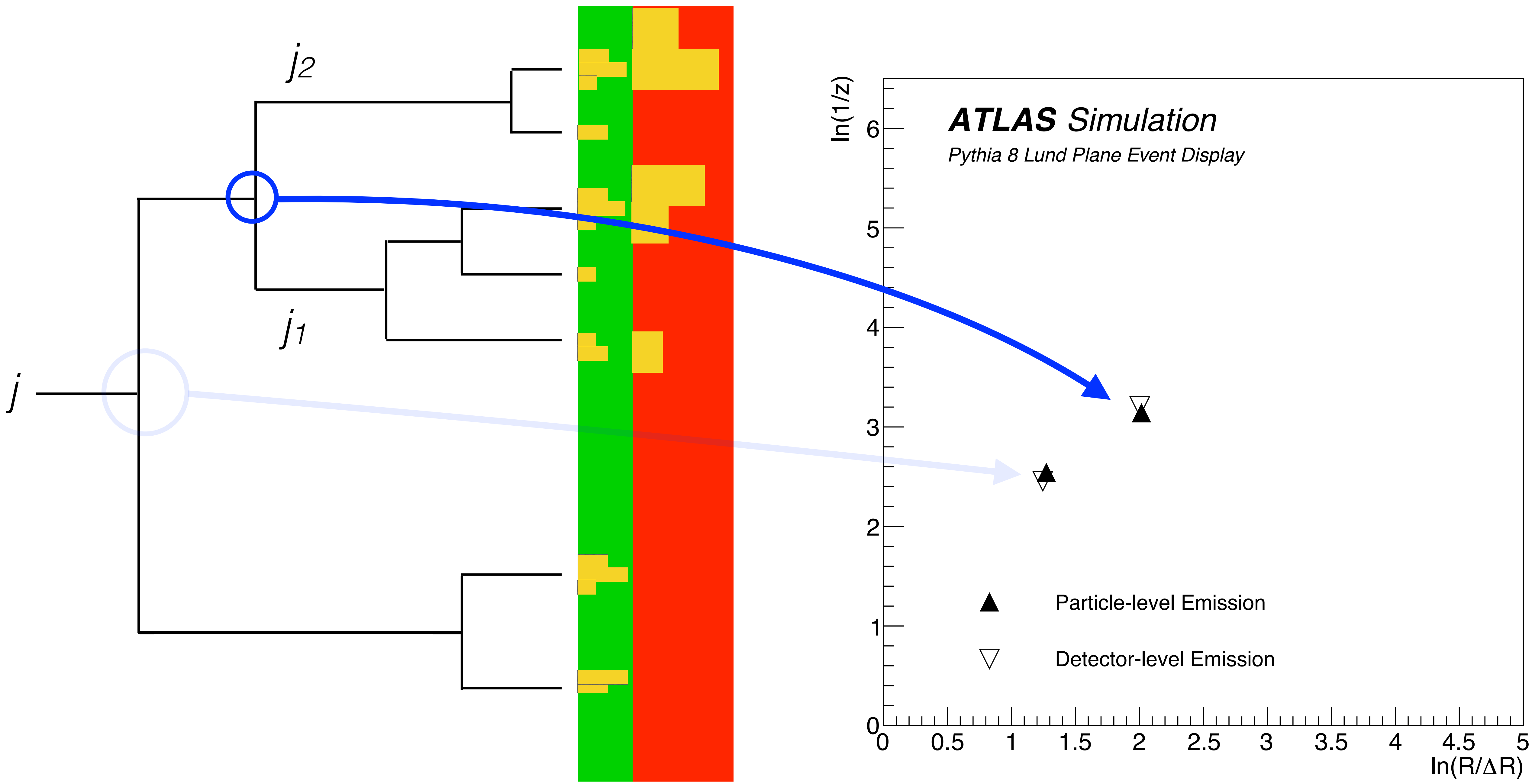

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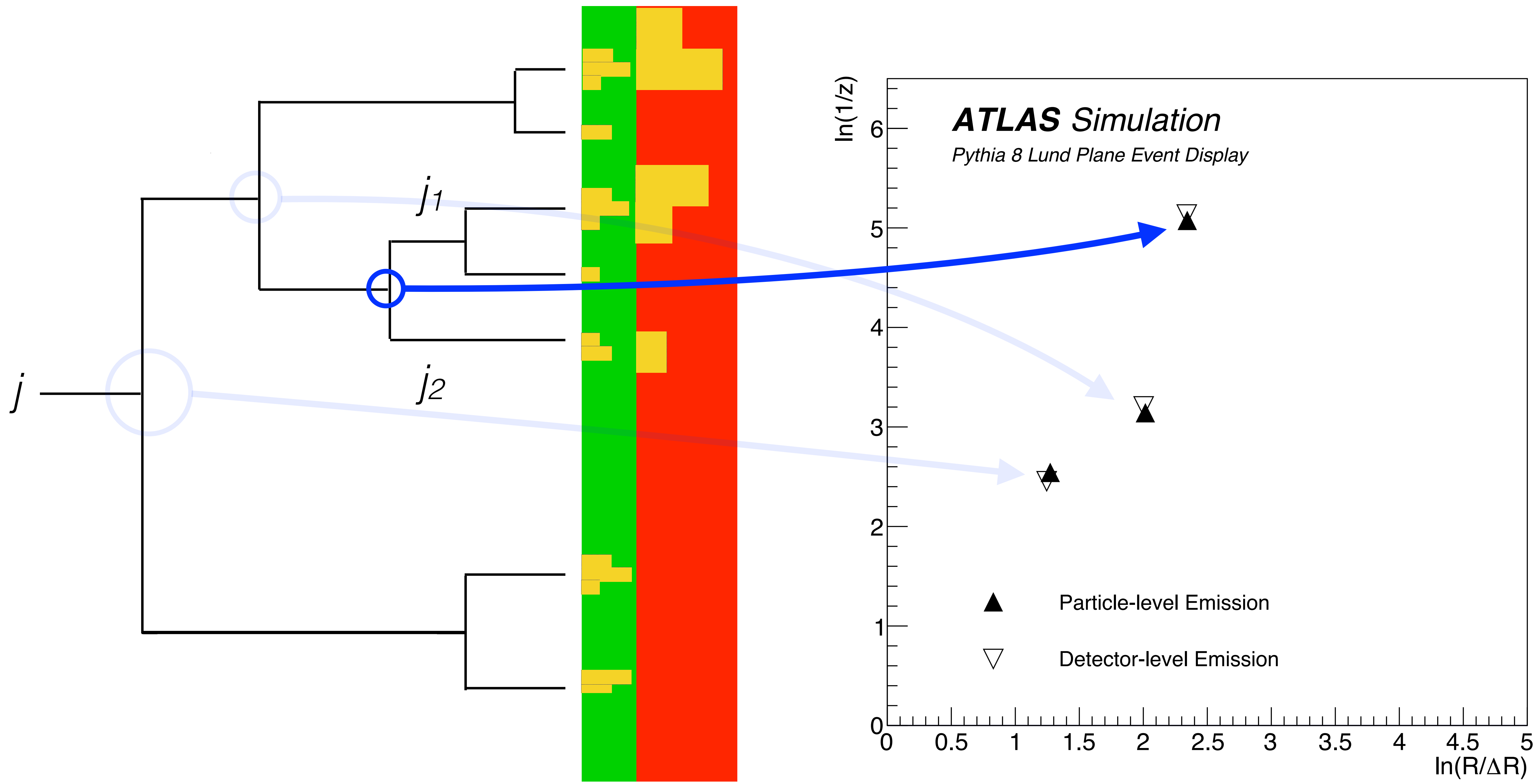

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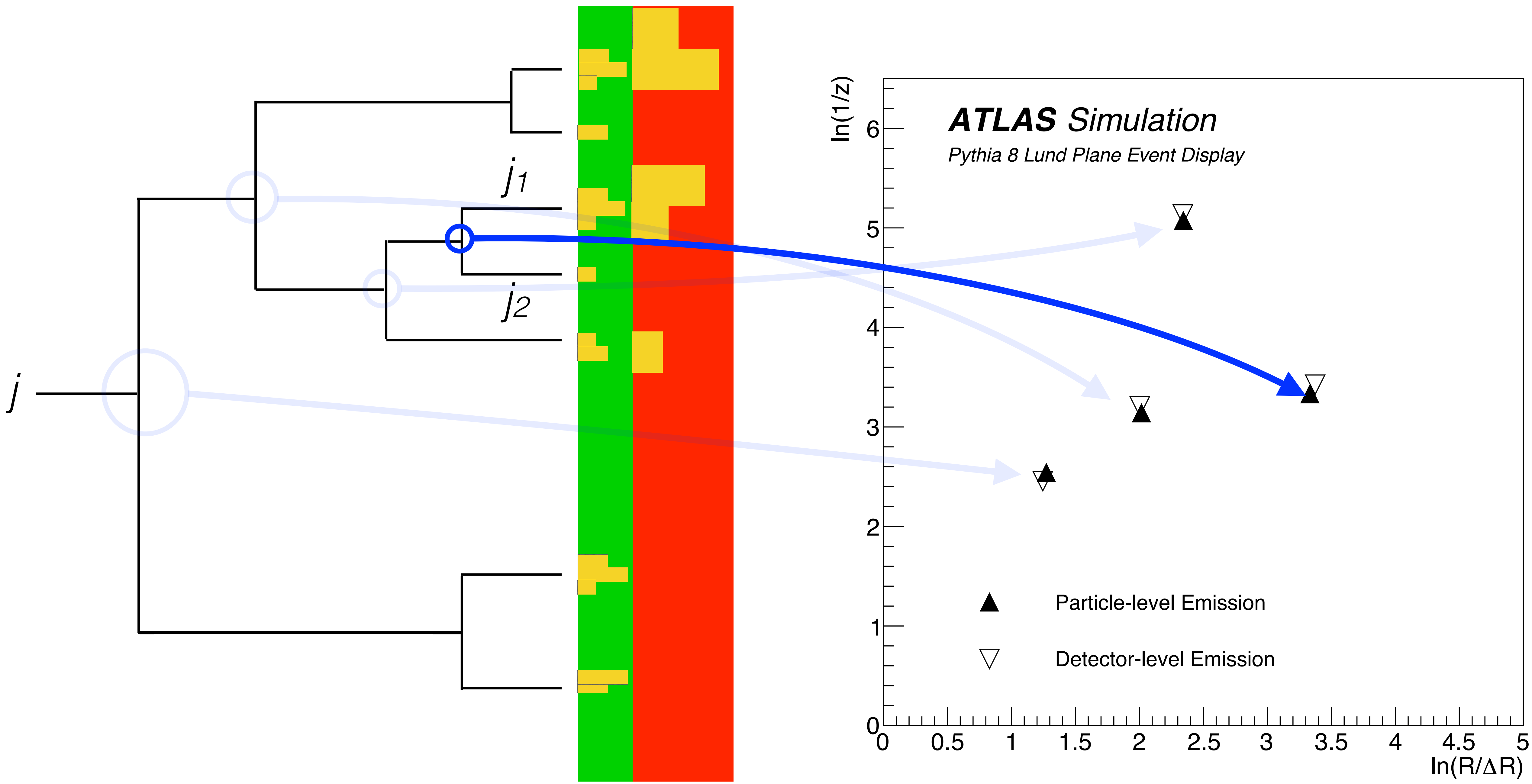

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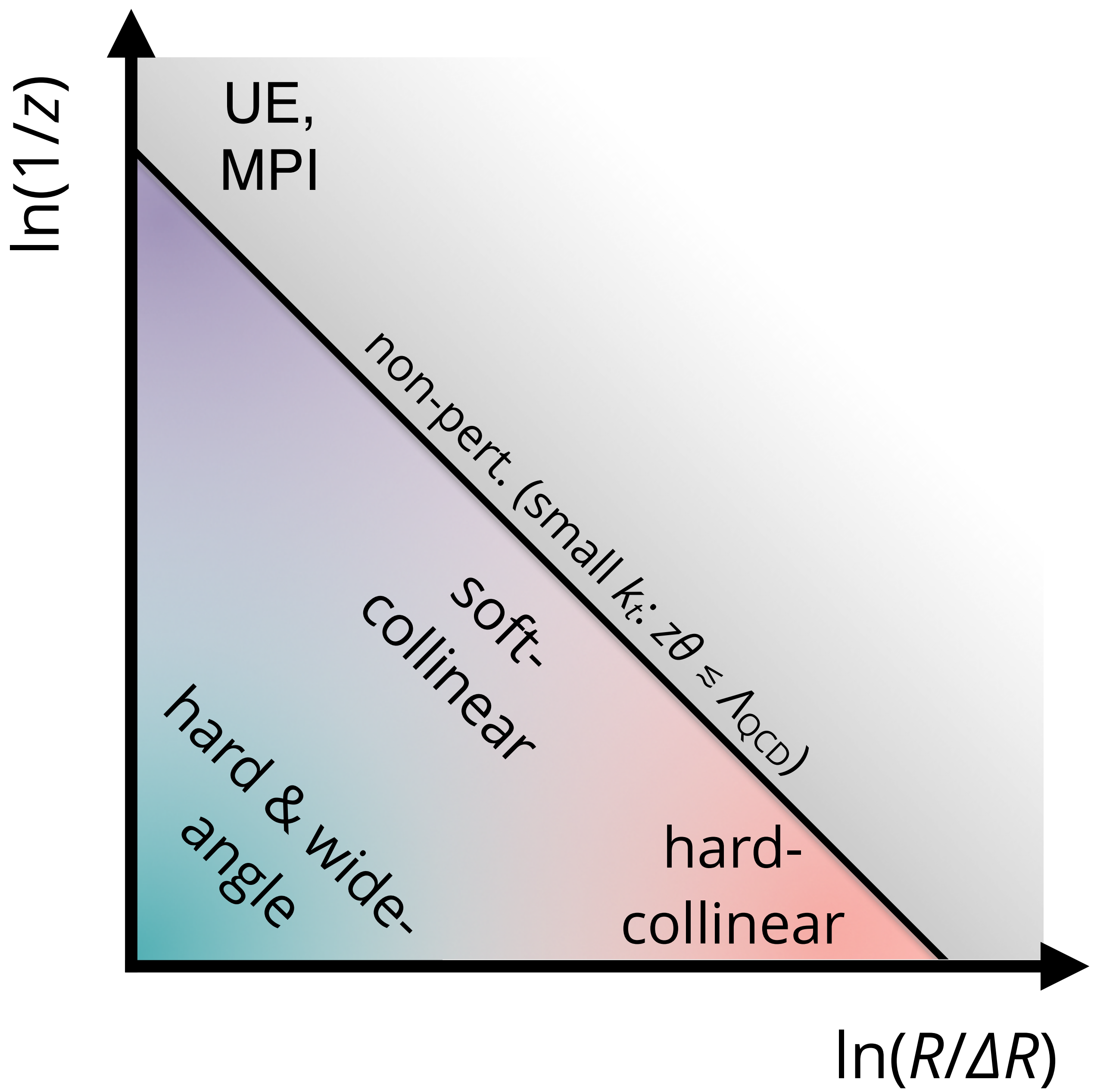
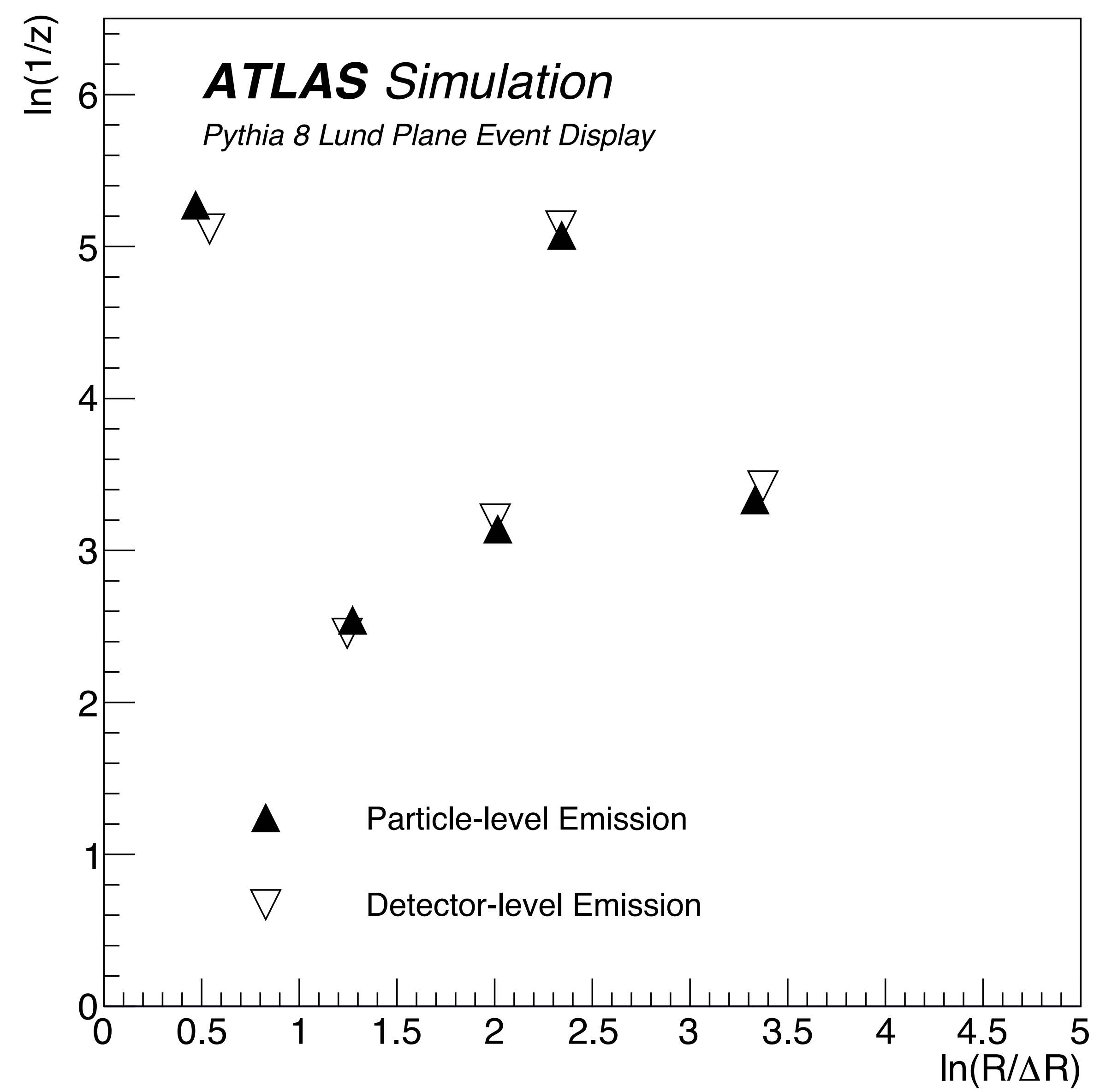
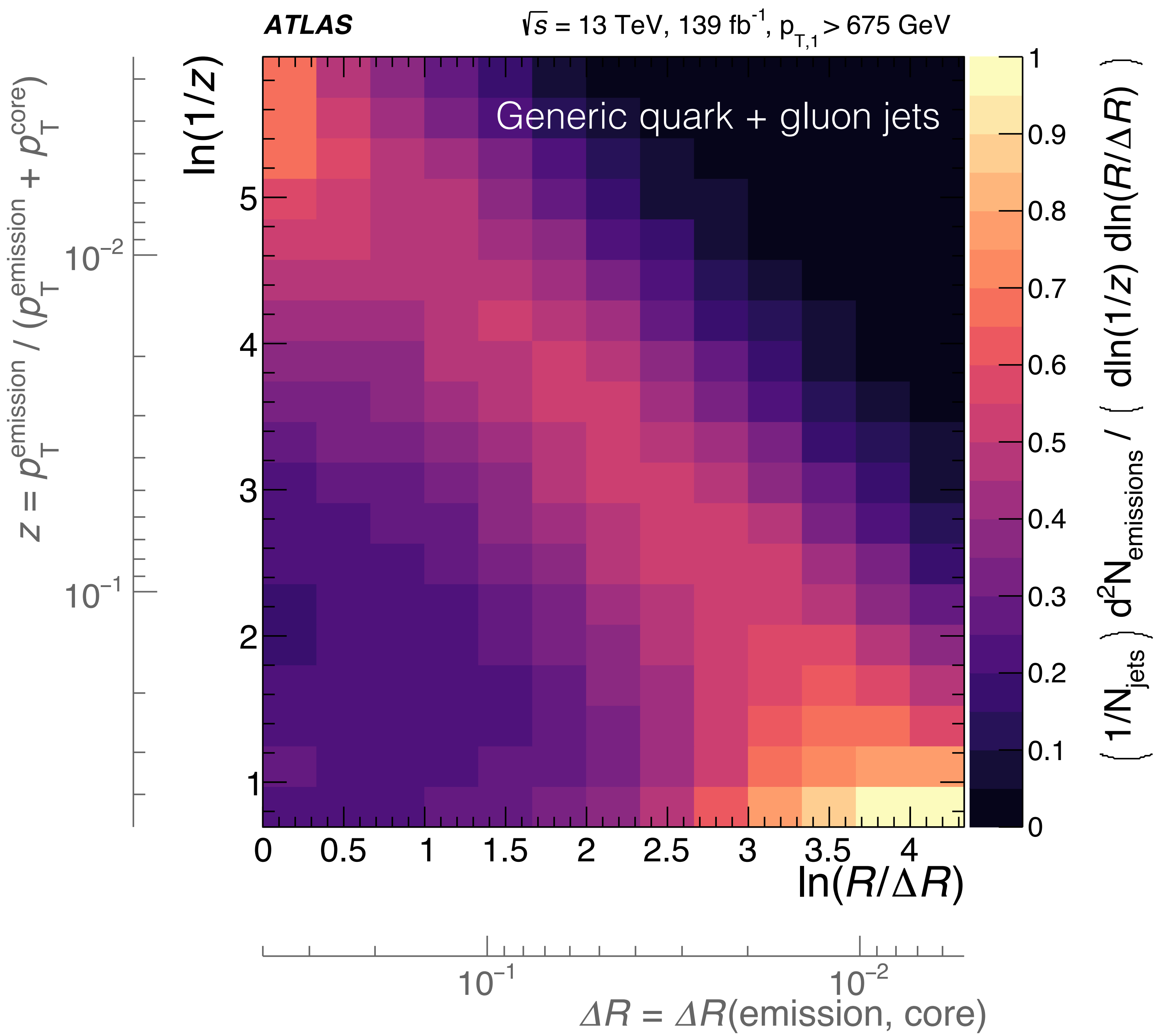




Factorize physical processes!

Phys. Rev. Lett. 124, 222002 (2020)

Correlations Part IV: Isolate the Physics

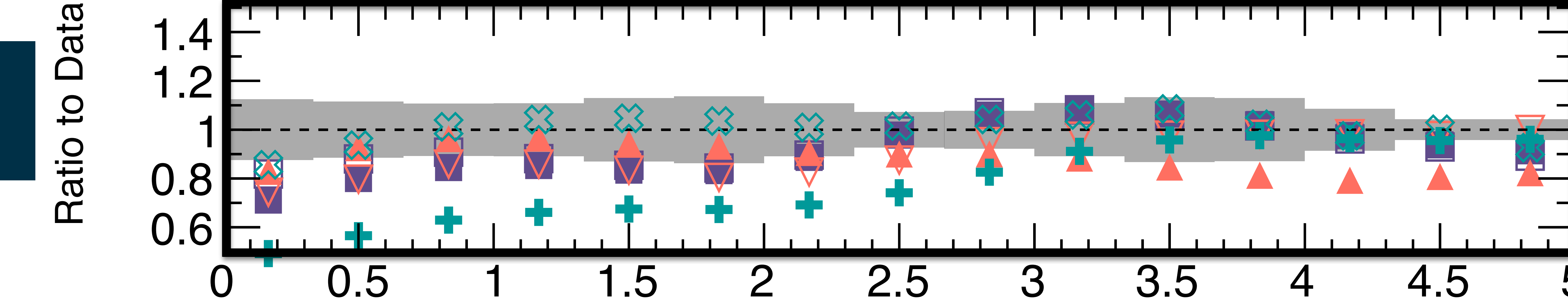


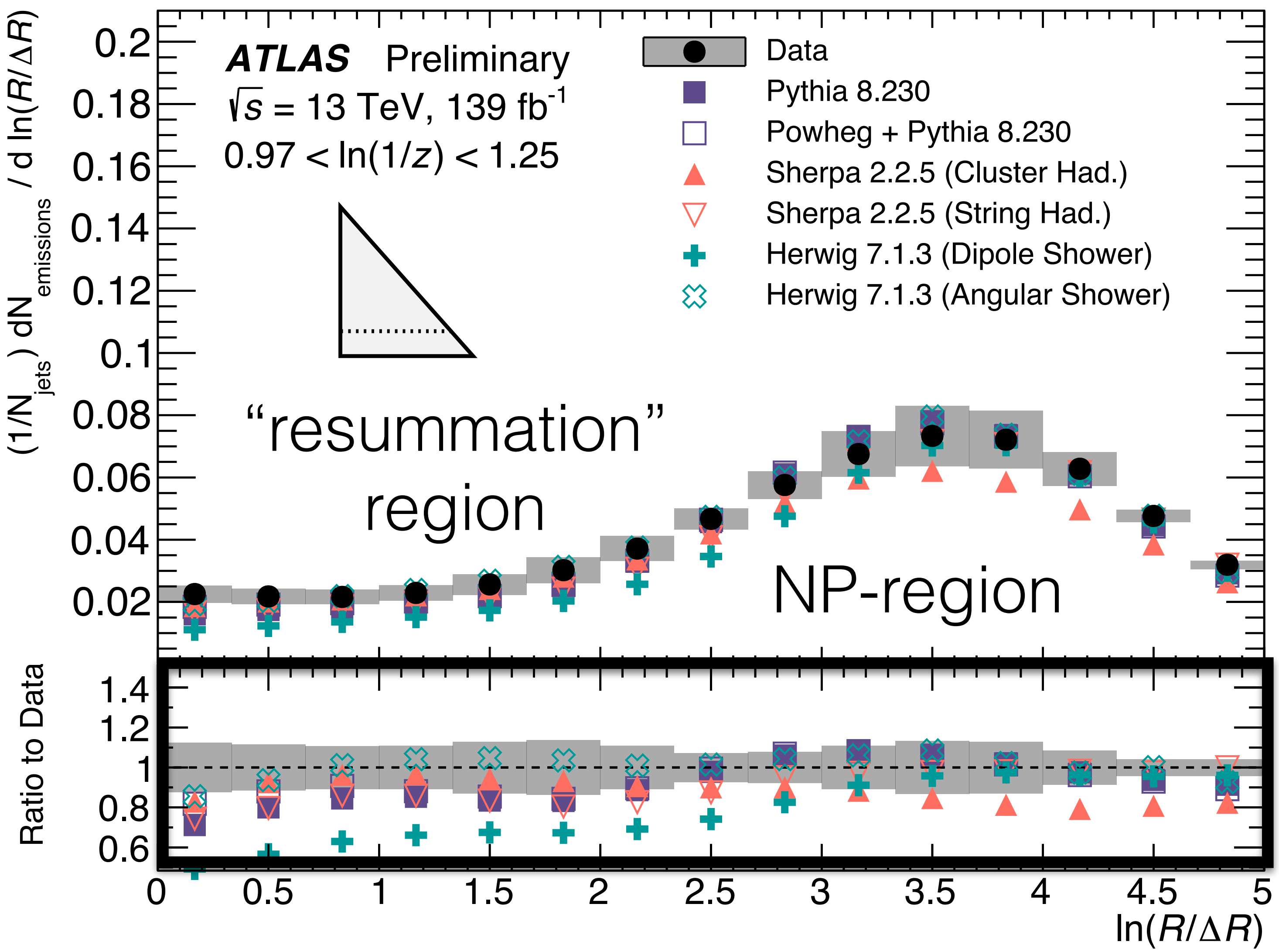
First measurement of the Lund jet plane!

…powerful tool for isolating hadronization, parton shower effects, and fixed-order effects

Key experimental challenge:
tracking inside dense environments

(now also measurements from other experiments)





First measurement of the Lund jet plane!

…powerful tool for isolating ***hadronization****,* ***parton shower effects****, and fixed-order effects*

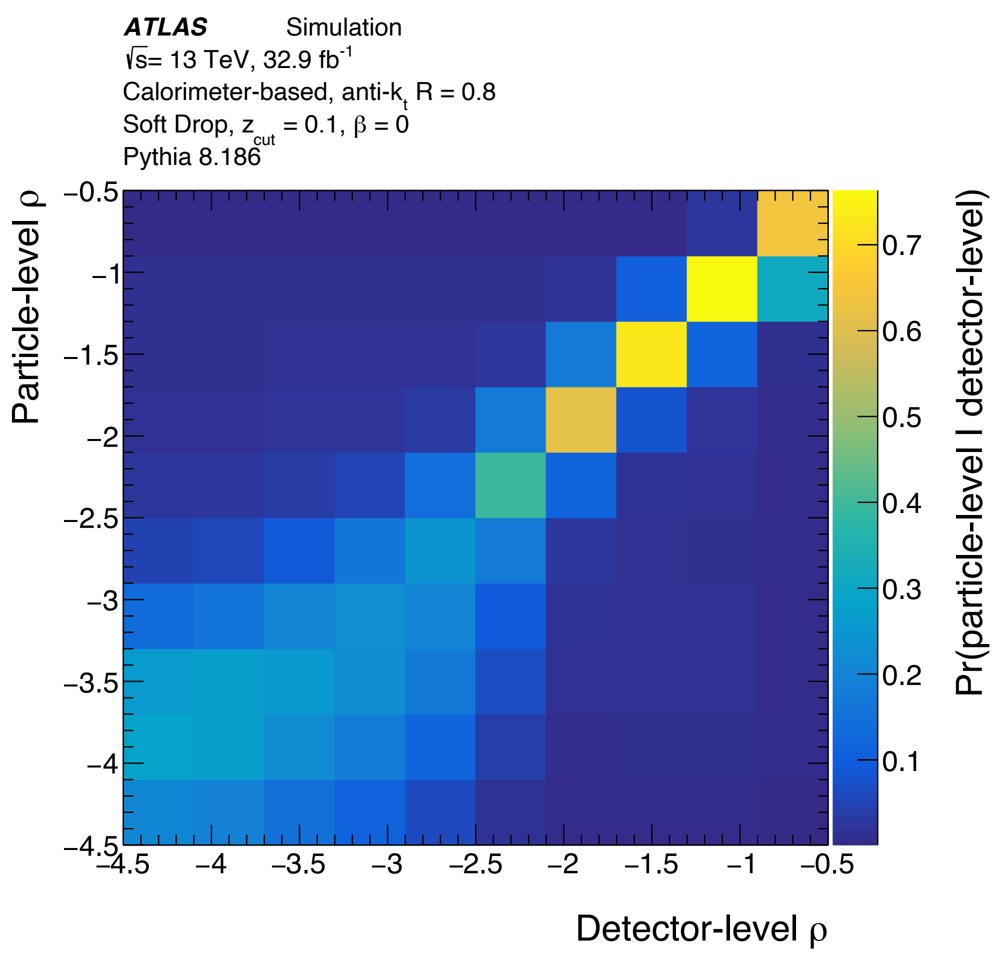
▲ vs. ▽ hadronization

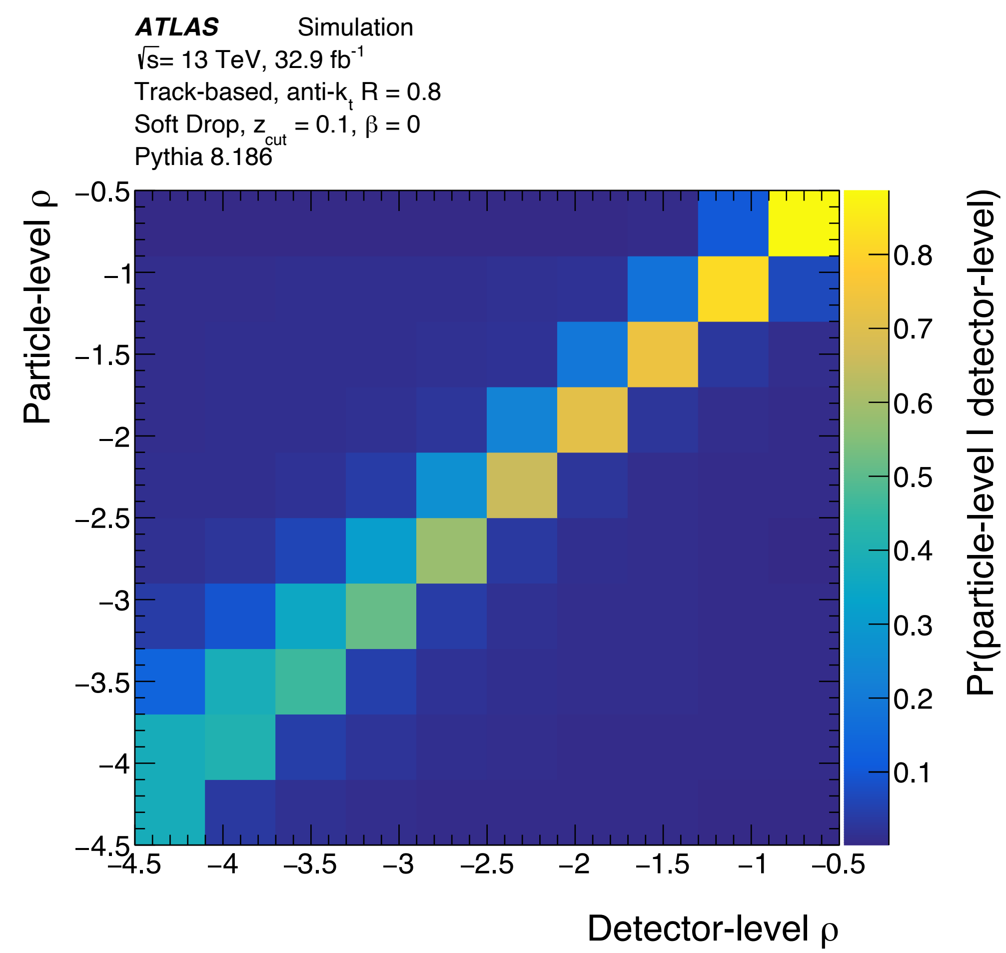
✚ vs. ✕ parton shower

Key experimental challenge:

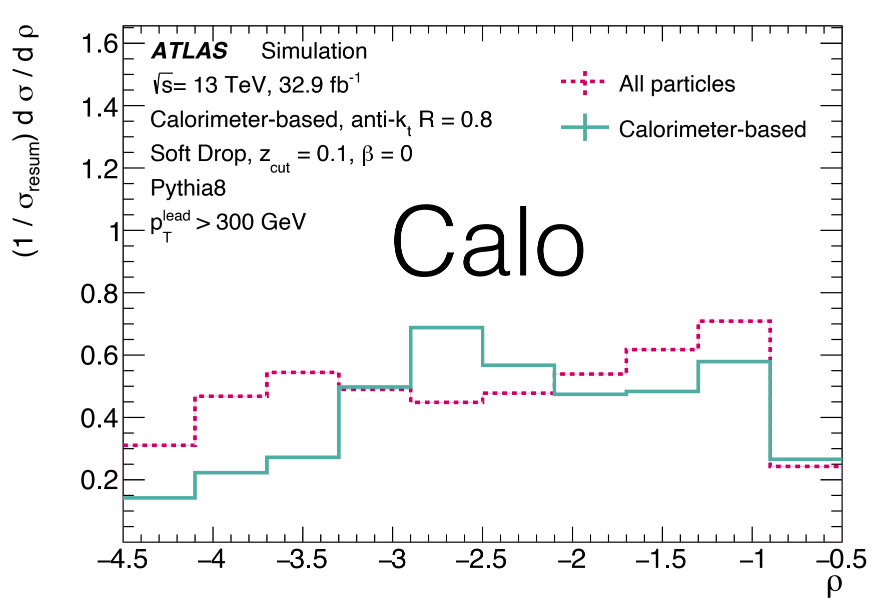
tracking inside dense environments

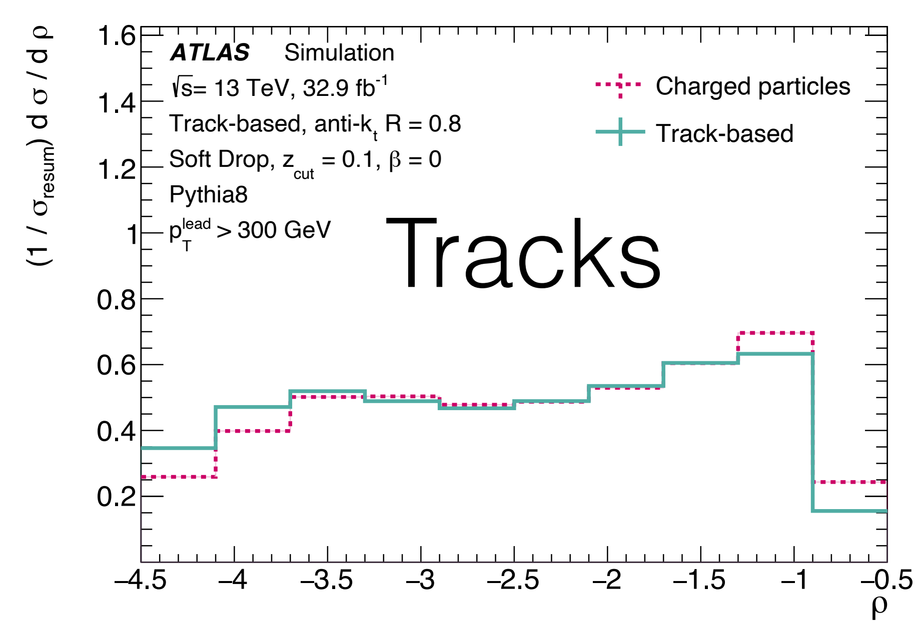
Correlations Part V: Tracks





PRD 101 (2020) 052007





ρ is (log) jet mass normalized by p_T

Correlations Part V: Tracks

ATLAS Simulation
$\sqrt{s}$= 13 TeV, 32.9 fb^{-1}
Calorimeter-based, anti-k_t R = 0.8
Soft Drop, z_{cut} = 0.1, β = 0

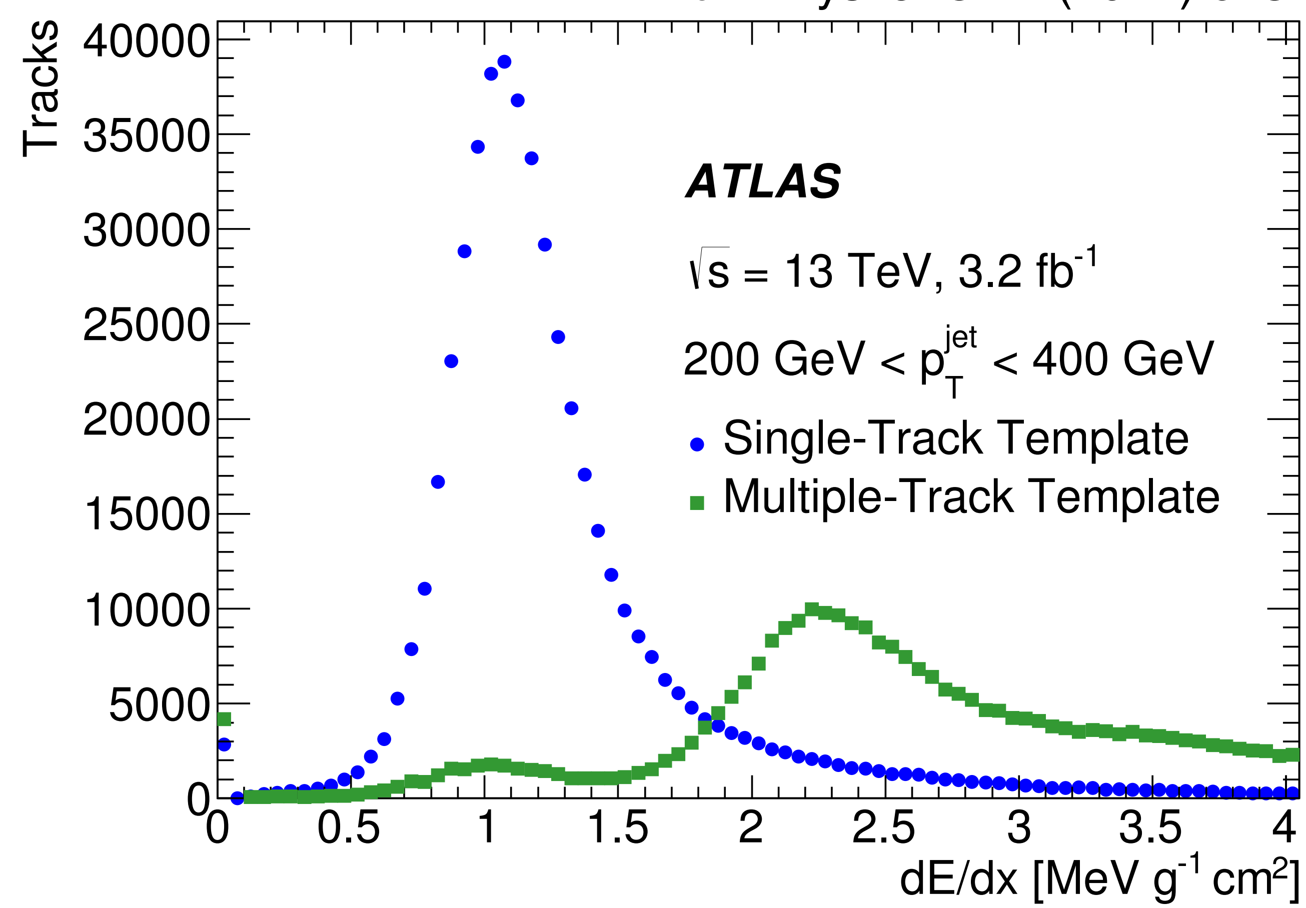
ATLAS Simulation
$\sqrt{s}$= 13 TeV, 32.9 fb^{-1}
Track-based, anti-k_t R = 0.8
Soft Drop, z_{cut} = 0.1, β = 0

PRD 101 (2020) 052007

It is not just about resolution - we have rigorous per-track uncertainties, also taking into account density effects.

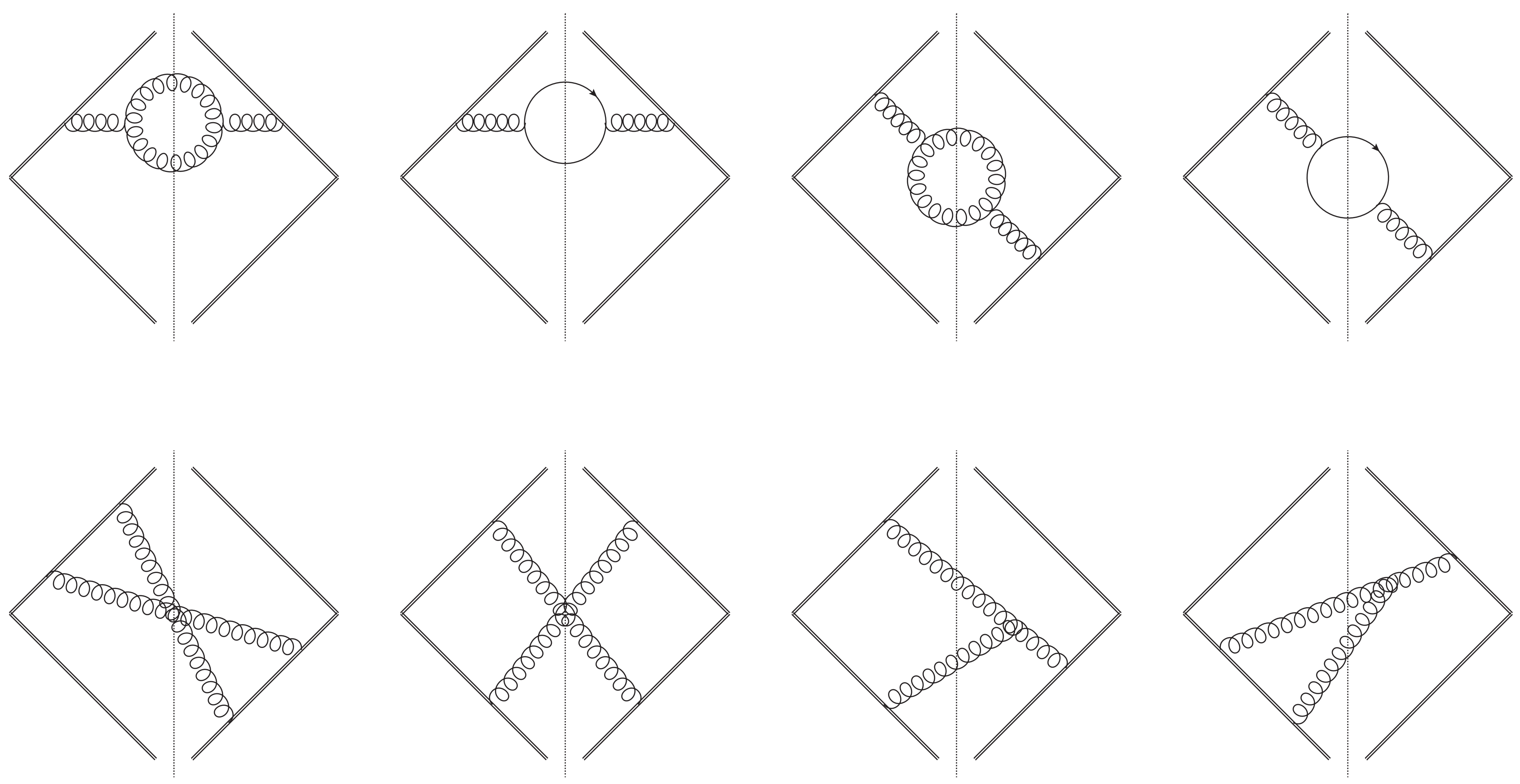
…what about on the theory side?

Eur. Phys. J. C 77 (2017) 673



Correlations Part VI: Machine Learning

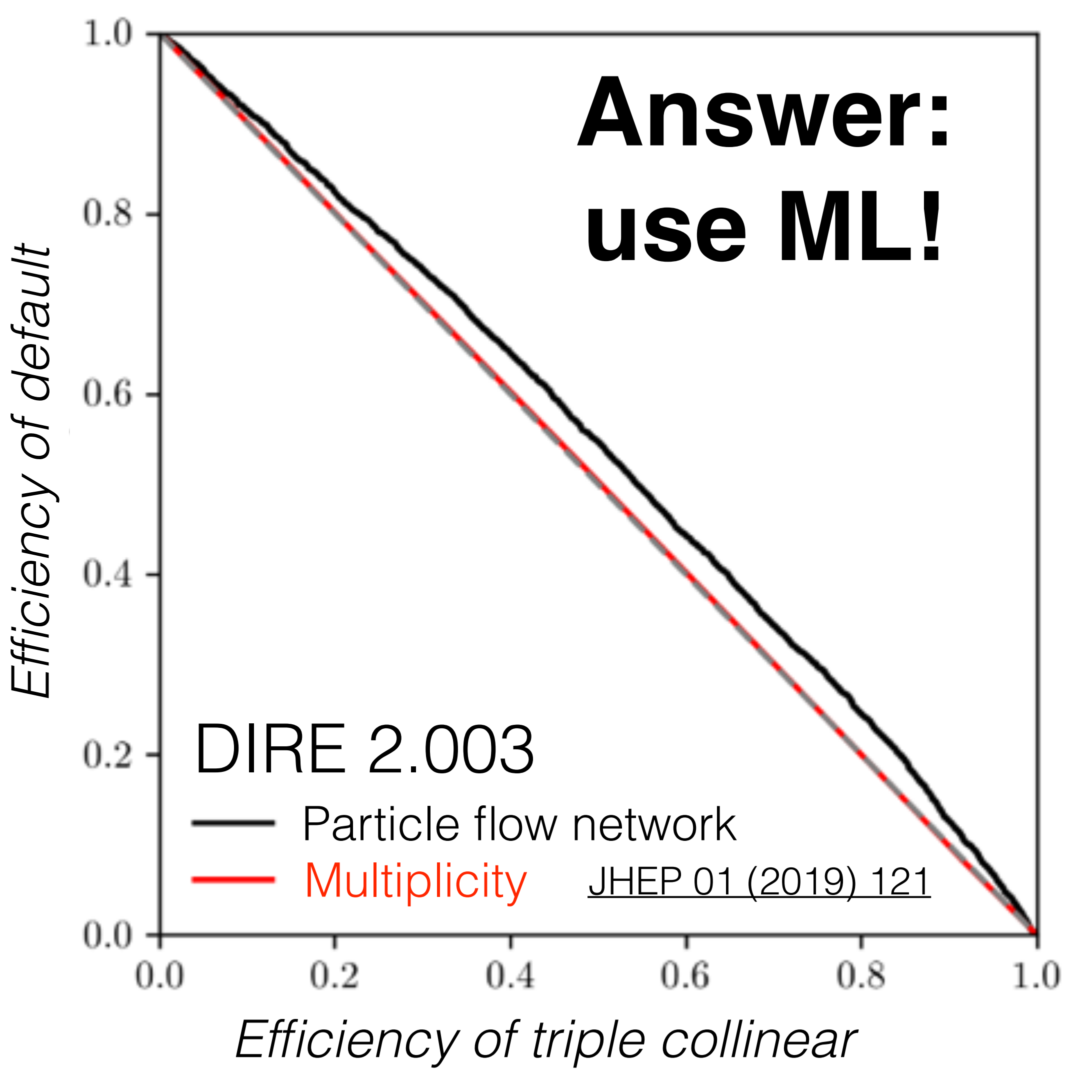
Impressive improvements in PSMC. How do we know the best observables to probe new effects?

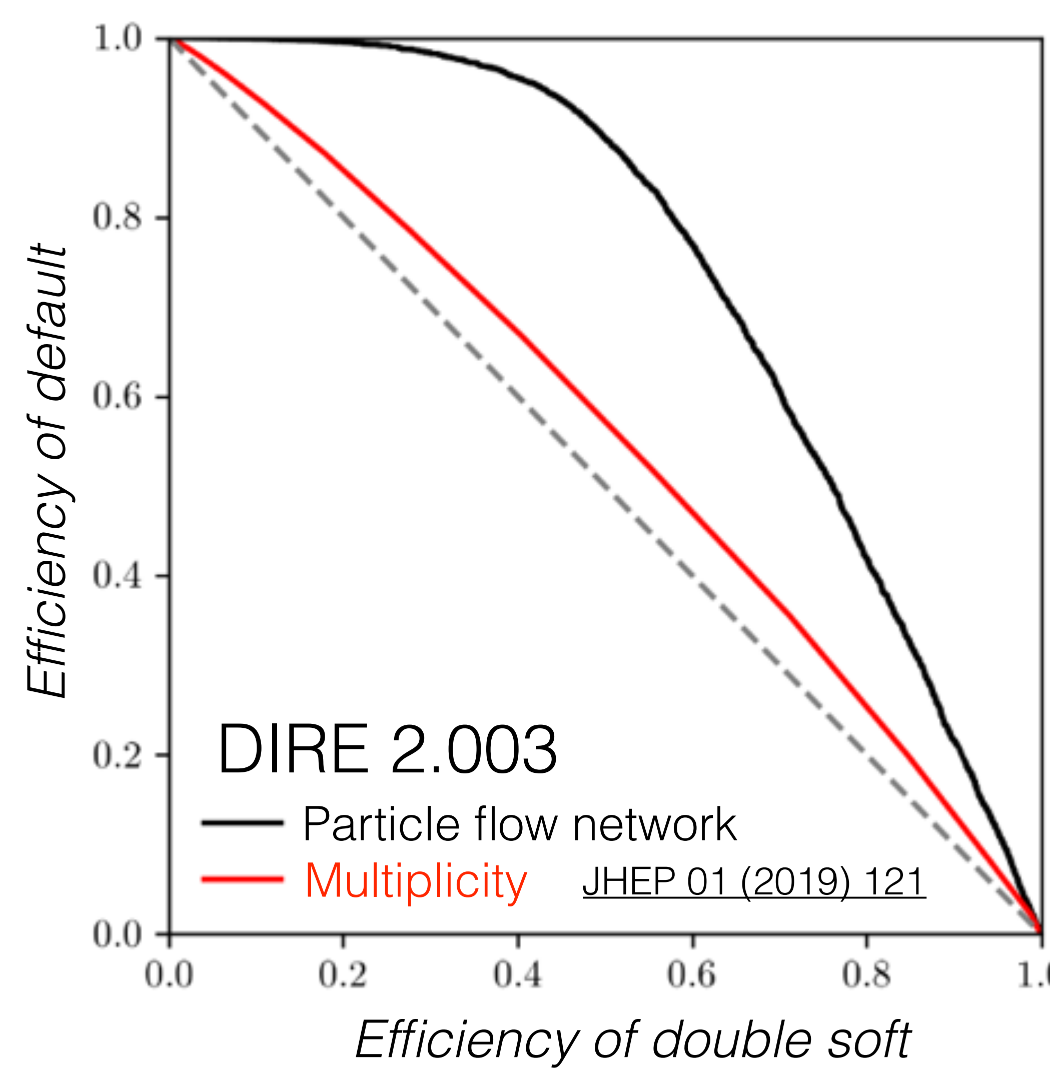


Les Houches, 2003.01700

Correlations Part VI: Machine Learning

Impressive improvements in PSMC. How do we know the best observables to probe new effects?





Les Houches, 2003.01700

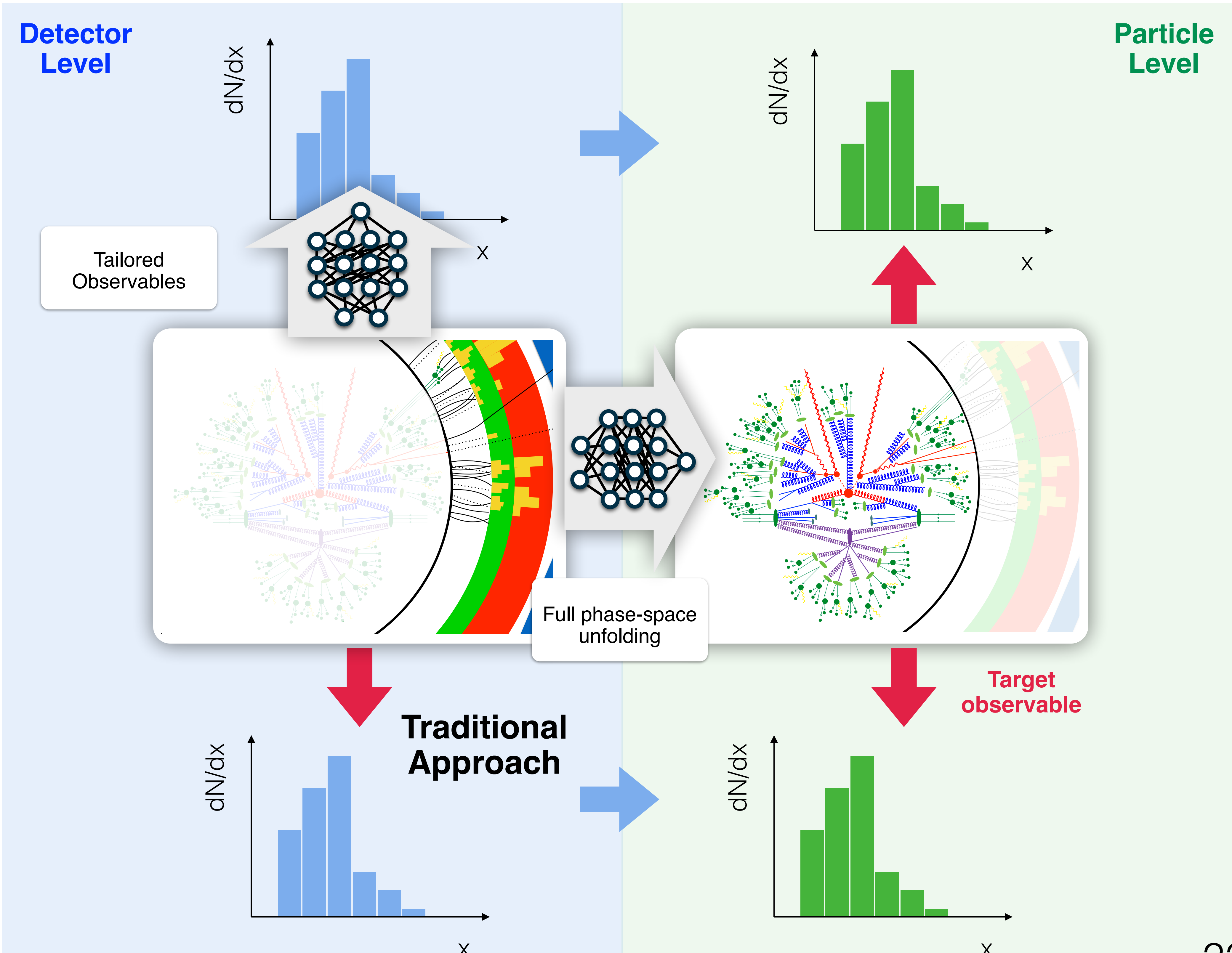
Maybe **not** observable? Should be observable?

Correlations Future

We are moving towards highly differential measurements (also powered by ML!) that will allow us to improve precision and probe QCD in new ways.

Key challenge: multi-dimensional unfolding!

Correlations Future



2203.16722

Correlations Future

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Key challenge: multi-dimensional unfolding!

Correlations Future

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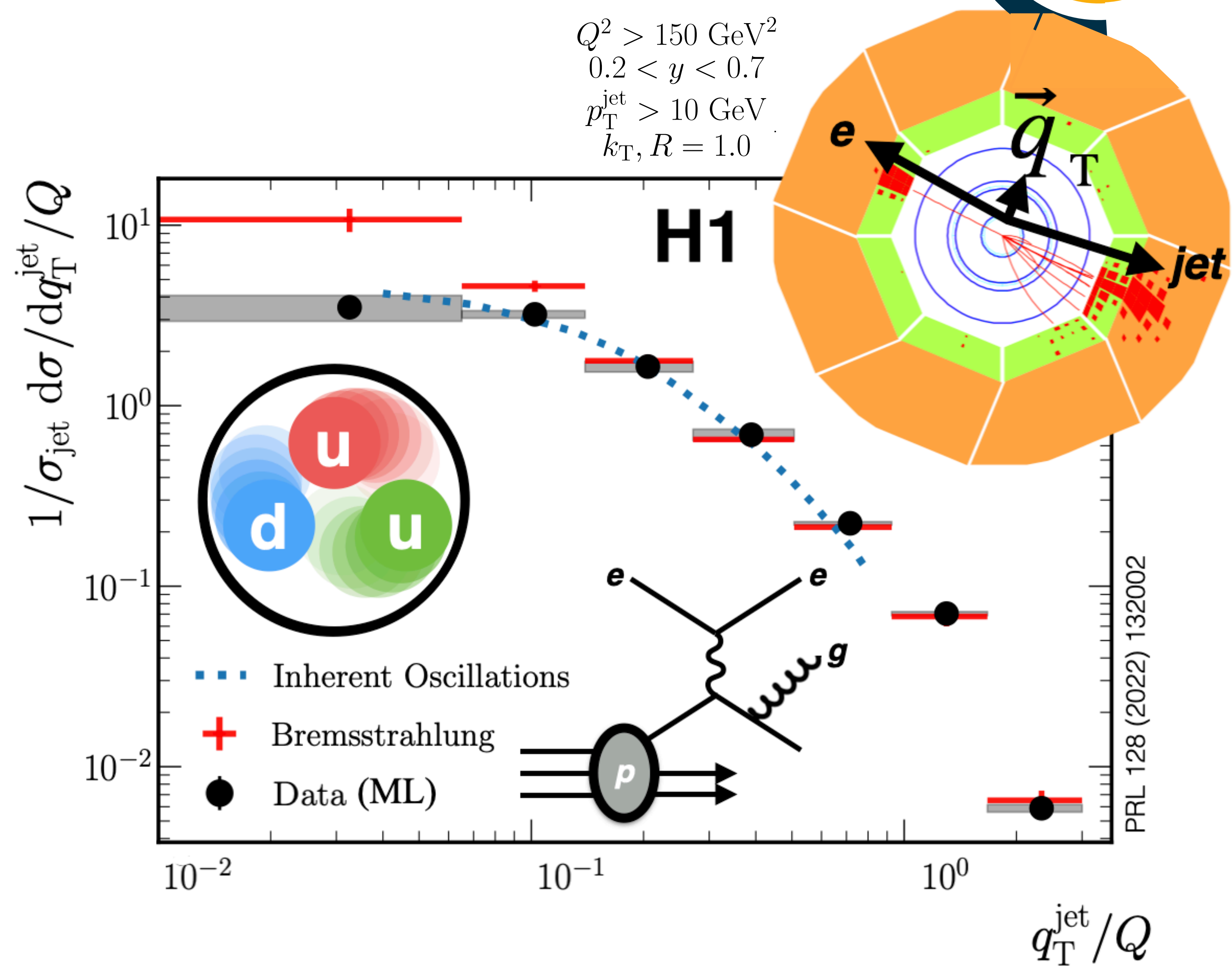
Stay tuned !



(8-dimensional measurement of lepton-jet correlations in *ep*)

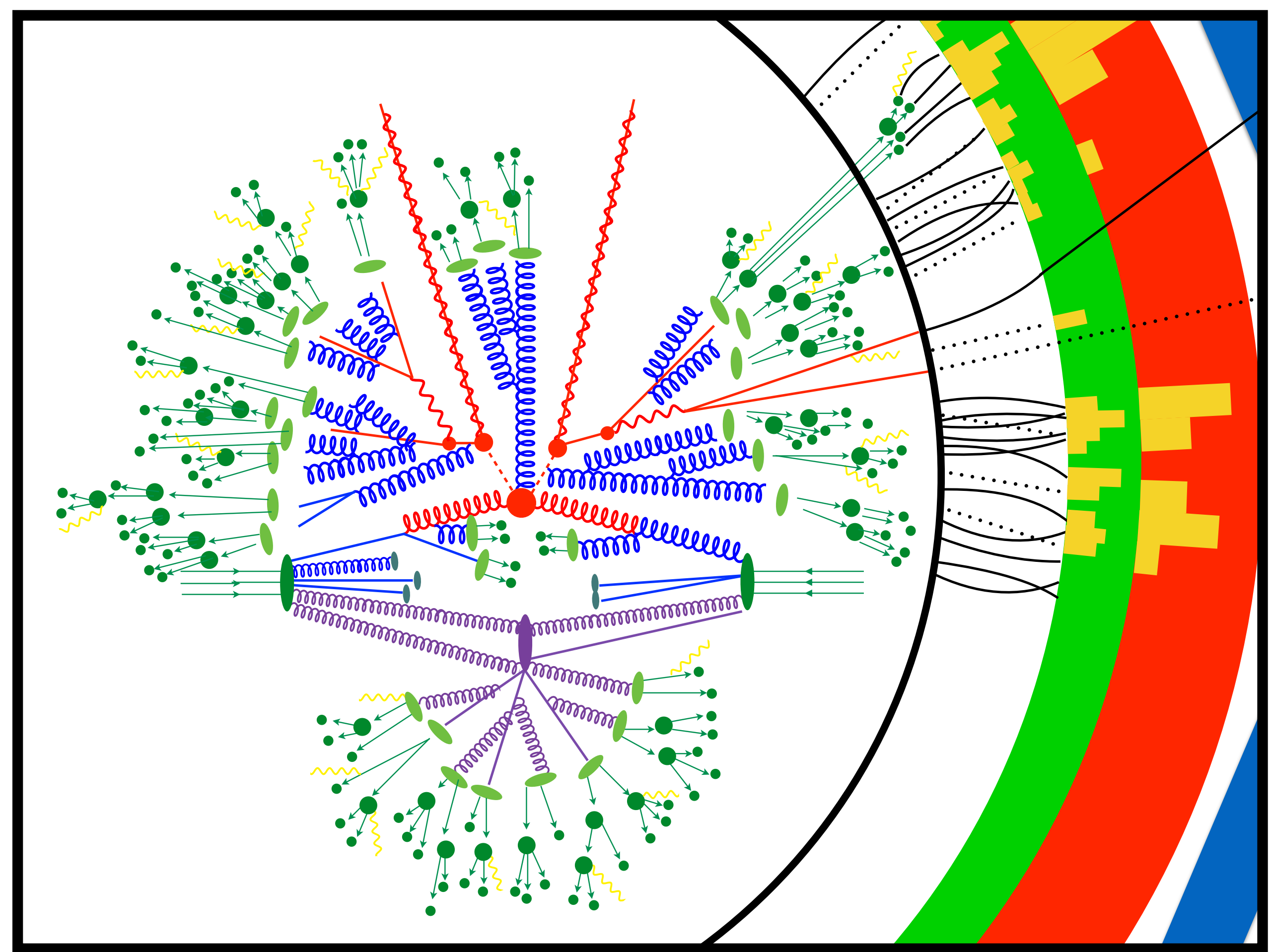
H1 Collaboration, PRL (2022), 2108.12376
A. Andreassen et al., PRL 124 (2020) 182001, 1911.09107

Overview

What is jet substructure good for?

1. *Fundamental parameters of the SM*
2. *BSM searches using small deviations from SM*
3. *Quantum properties of inherently exciting emergent pheno*
4. *Develop / tune Parton Shower Monte Carlo (to aid other searches / measurements)*

A probe of fundamental and emergent properties of the strong force



Overview

ABSTRACT: Even though jet substructure was not an original design consideration for the Large Hadron Collider (LHC) experiments, it has emerged as an essential tool for the current physics program. We examine the role of jet substructure on the motivation for and design of future energy frontier colliders. In particular, we discuss the need for a vibrant theory and experimental research and development program to extend jet substructure physics into the new regimes probed by future colliders. Jet substructure has organically evolved with a close connection between theorists and experimentalists and has catalyzed exciting innovations in both communities. We expect such developments will play an important role in the future energy frontier physics program.

- jet substructure Snowmass white paper (2203.07462)

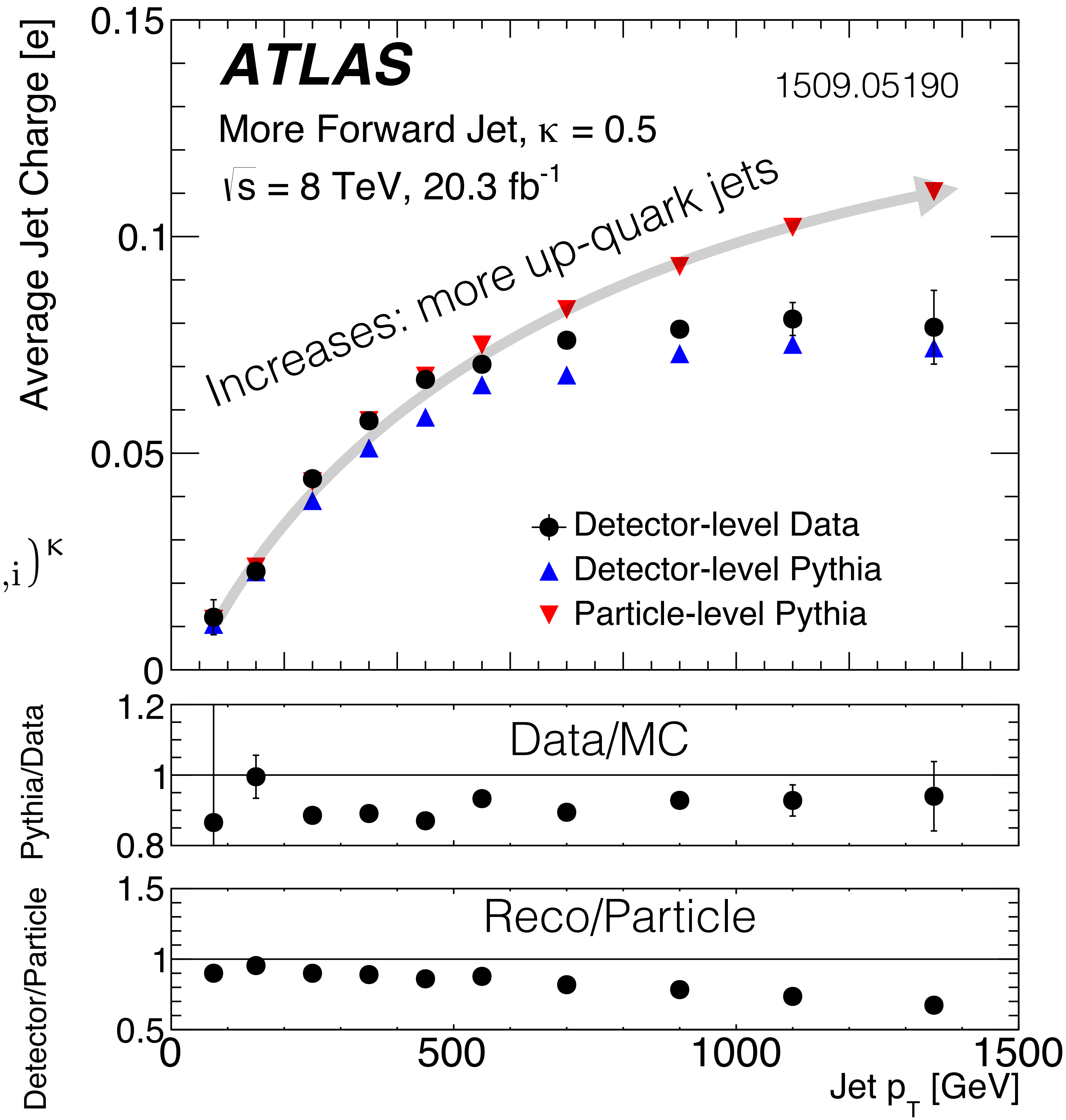
Backup

Extra nugget 1: Jet Charge

Weight the tracks with their charge!

$$Q_J = \frac{1}{(p_{TJ})^\kappa} \sum_{i \in \mathbf{Tracks}} q_i \times (p_{T,i})^\kappa$$

Allows us to look inside the proton "by eye" - more up quarks at high x!



Jet Charge Beyond PDFs

What happens when we 'remove' the PDF?
Does the jet charge for jets of a particular type depend on p_T?

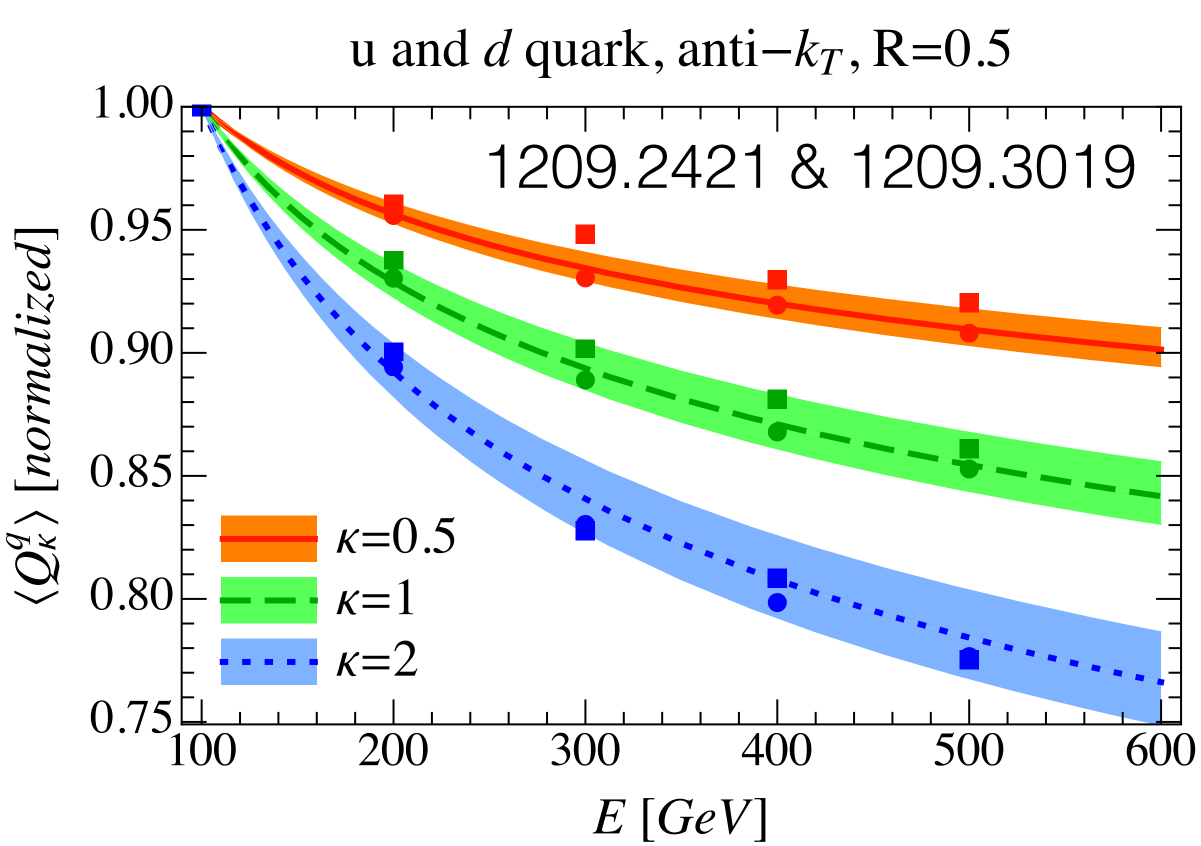
$$\langle Q_J \rangle = [1 + \mathcal{O}(\alpha_s)] \sum_h Q_h \widetilde{D}_q^h(\kappa, E \times R)$$

(scale violation)

h = hadron

Moment of a **fragmentation function**

Prediction:
$c < 0$ and $dc/dk < 0$



non-perturbative…but we know how it evolves with scale!

$$\frac{p_T}{\langle Q_\kappa \rangle} \frac{d}{dp_T} \langle Q_\kappa \rangle = \frac{\alpha_s}{\pi} \widetilde{P}_{qq}(\kappa) \equiv c(\kappa)$$

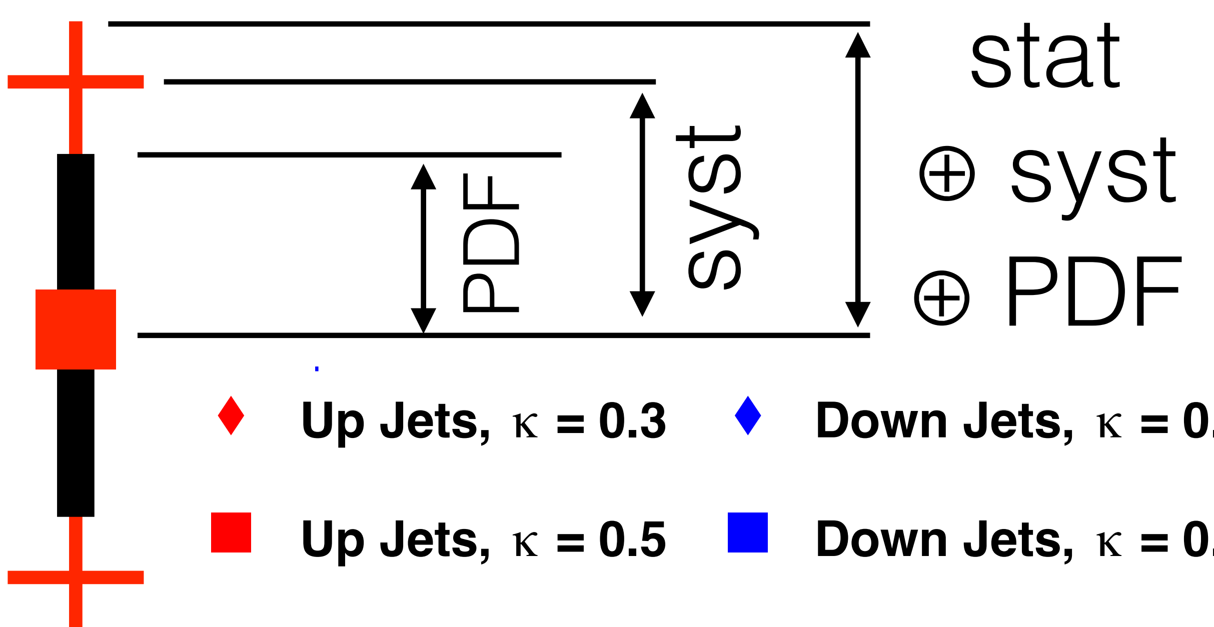
Moment of a **splitting function**

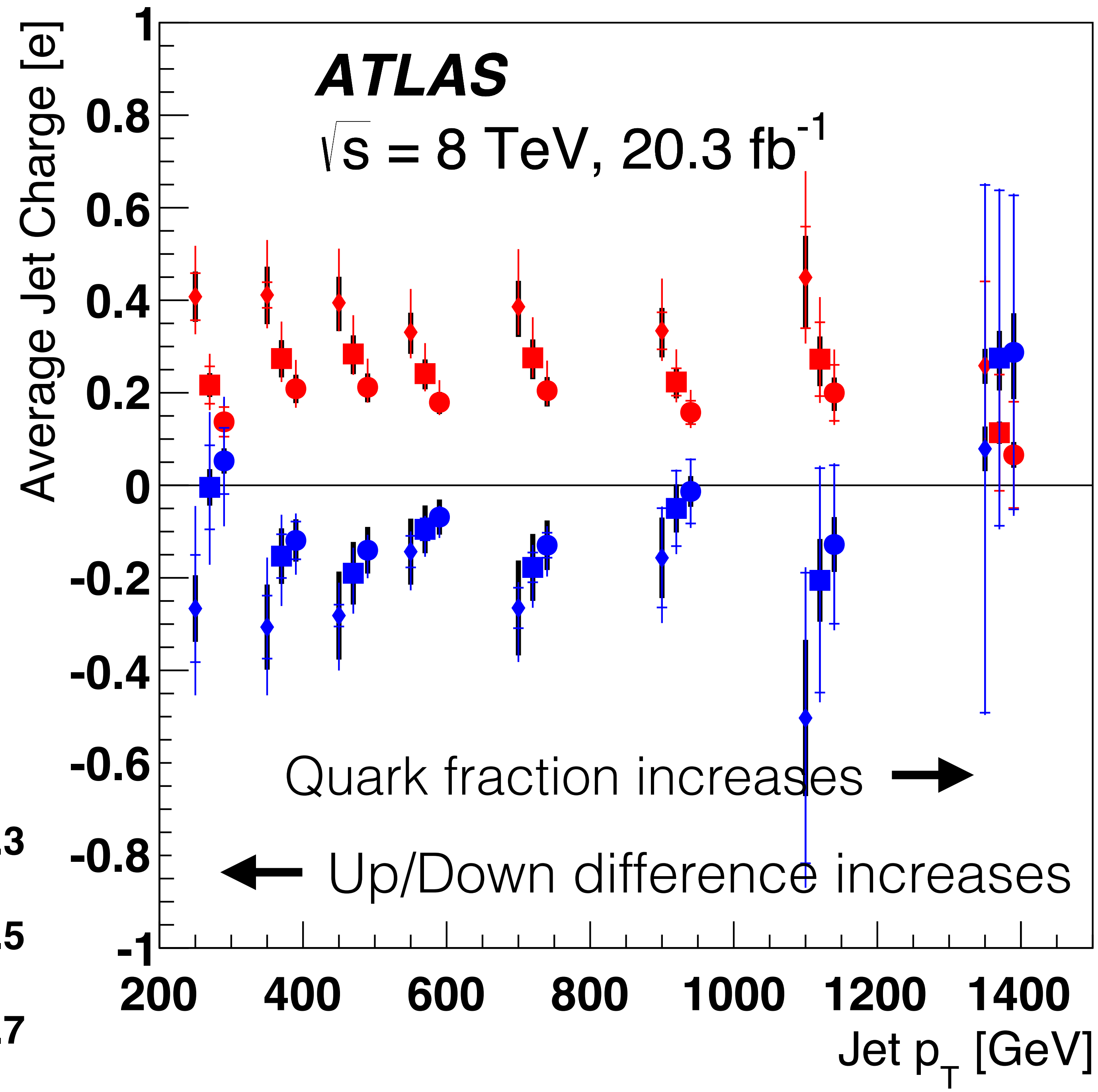
Jet charge per flavor: extraction

$$\langle Q_i^{\text{forward}} \rangle = \left(f_{\text{up,i}}^{\text{forward}} - f_{\text{anti-up,i}}^{\text{forward}} \right) Q_i^{\text{up}} + \left(f_{\text{down,i}}^{\text{forward}} - f_{\text{anti-down,i}}^{\text{forward}} \right) Q_i^{\text{down}}$$

$$\langle Q_i^{\text{central}} \rangle = \left(f_{\text{up,i}}^{\text{central}} - f_{\text{anti-up,i}}^{\text{central}} \right) Q_i^{\text{up}} + \left(f_{\text{down,i}}^{\text{central}} - f_{\text{anti-down,i}}^{\text{central}} \right) Q_i^{\text{down}}$$

Can exploit the **h**-dependence of the flavor fractions *f* to extract the **up**- and **down**-quark jet charge in each p_T bin.



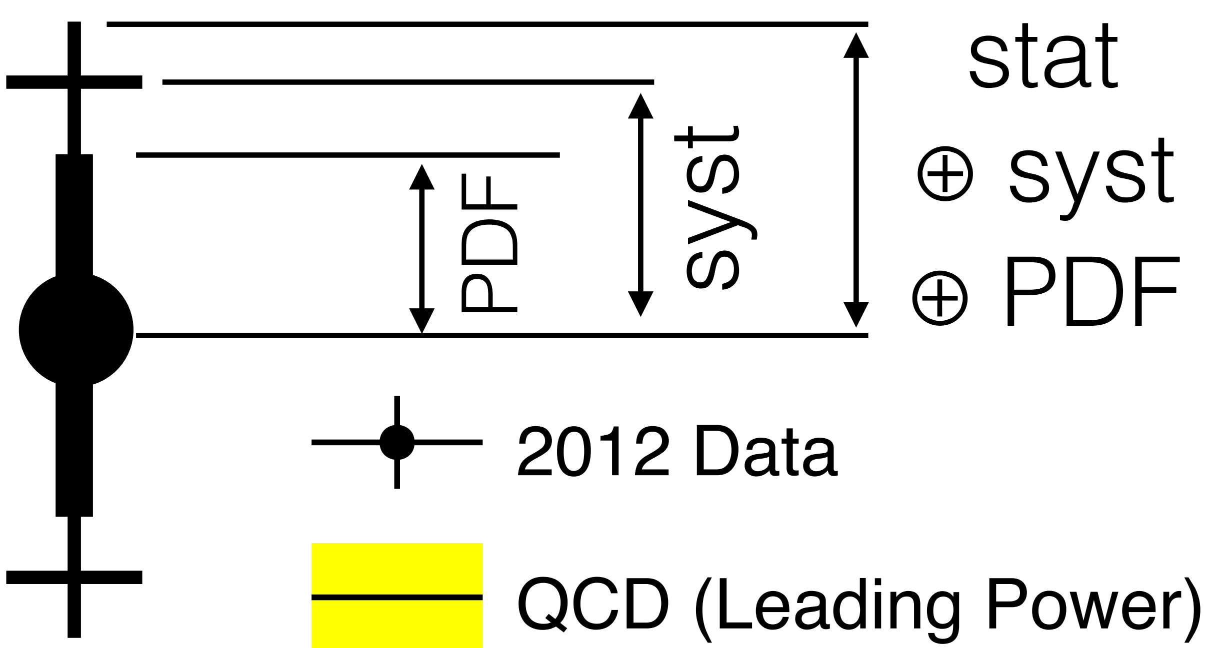


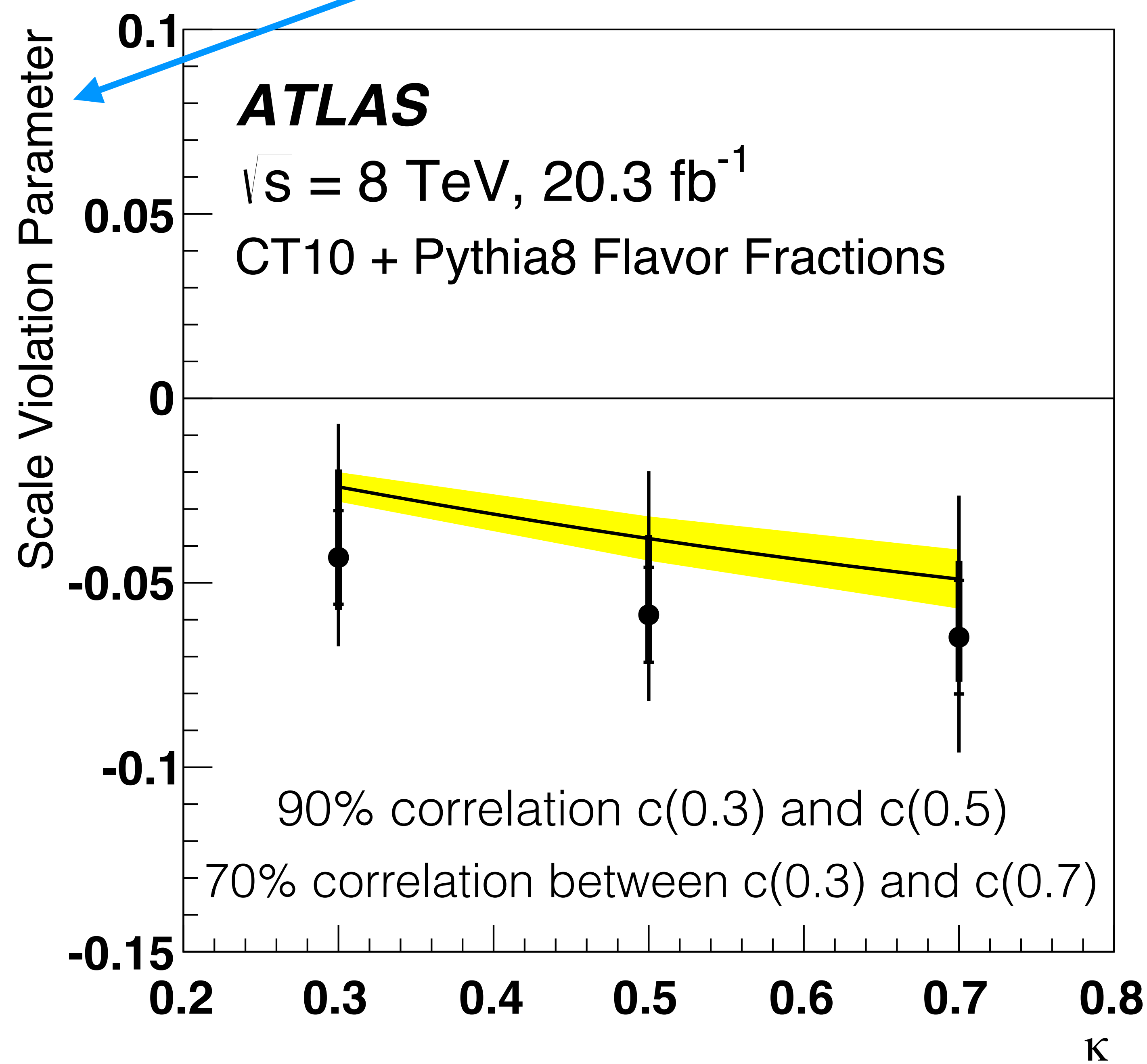
Jet charge per flavor: p_T dependence

$$\langle Q_i \rangle \approx \sum \alpha_{f,i} \bar{Q}_f (1 + c_f \log(p_{T,i}/\bar{p}_T))$$

Question: accounting for PDFs, does jet charge depend on p_T?

Data and theory agree: Yes!





[1209.2421 & 1209.3019]

Extra nugget 2: how to represent a jet?

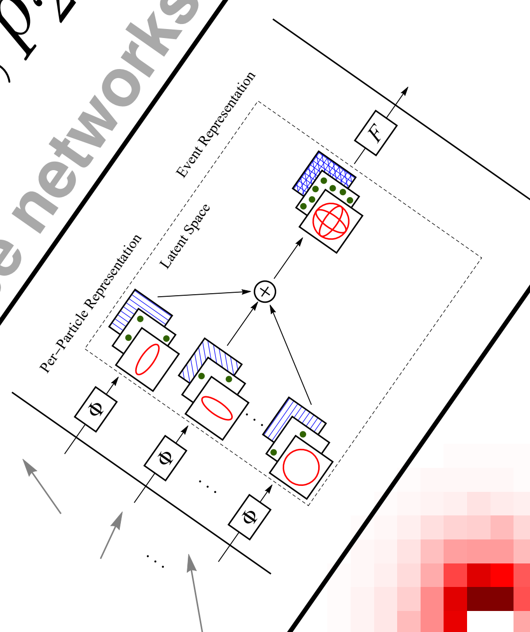
Fixed sets

$$J = \{p_1^\mu, p_2^\mu, \ldots, p_n^\mu\}$$

Dense networks

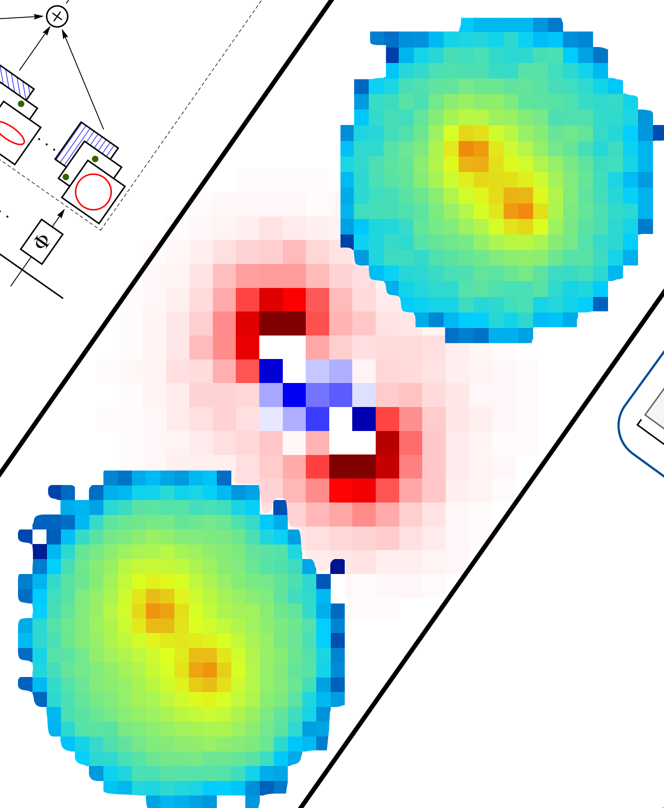
Variable sets

Deep sets



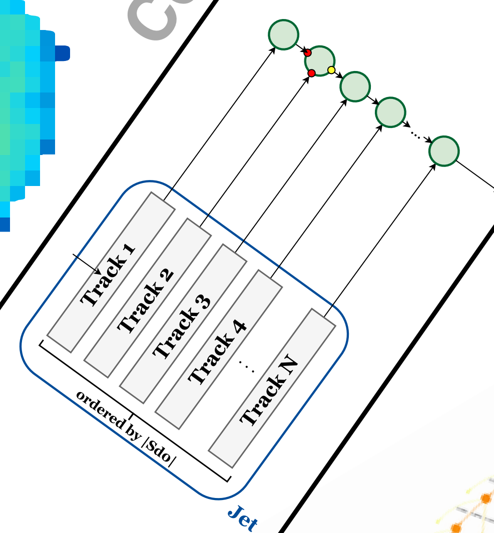
Images

Convolutional NNs (CNNs)



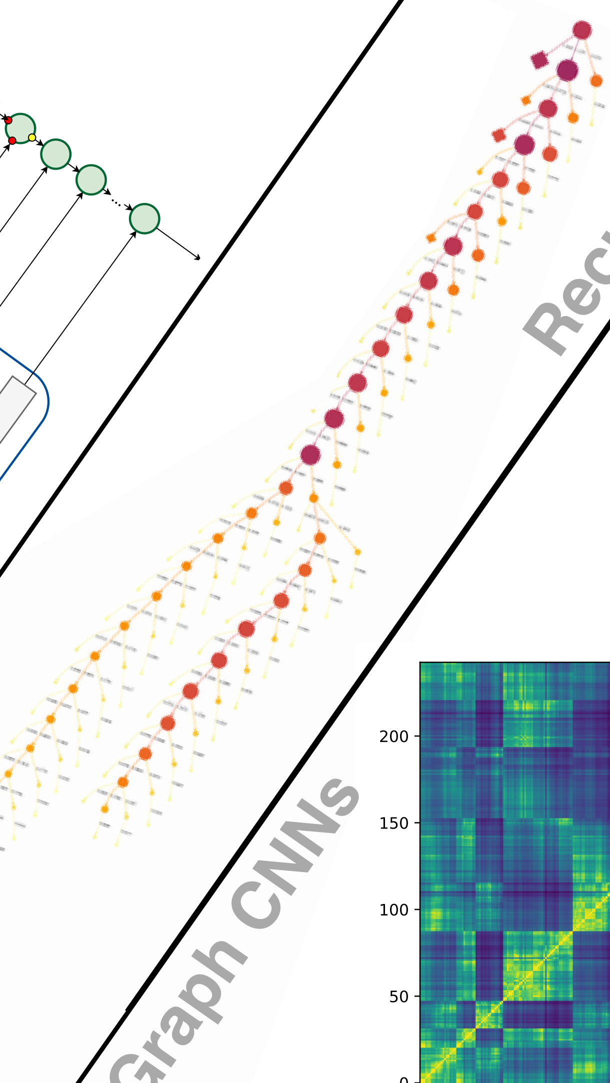
Sequences

Recurrent NNs



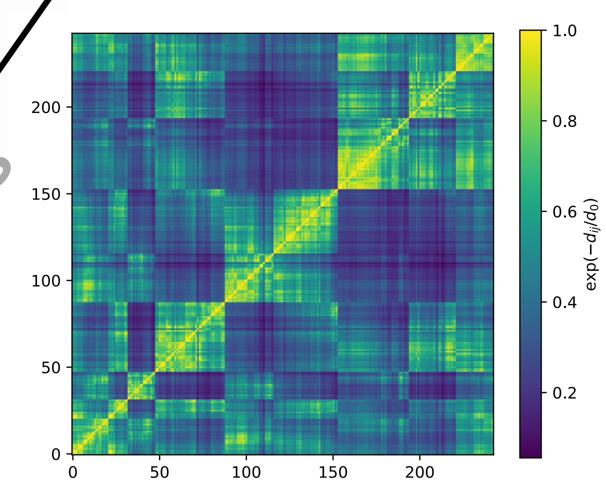
Trees

Recursive NNs



Graphs

Graph CNNs



How to represent our data?

Fixed sets

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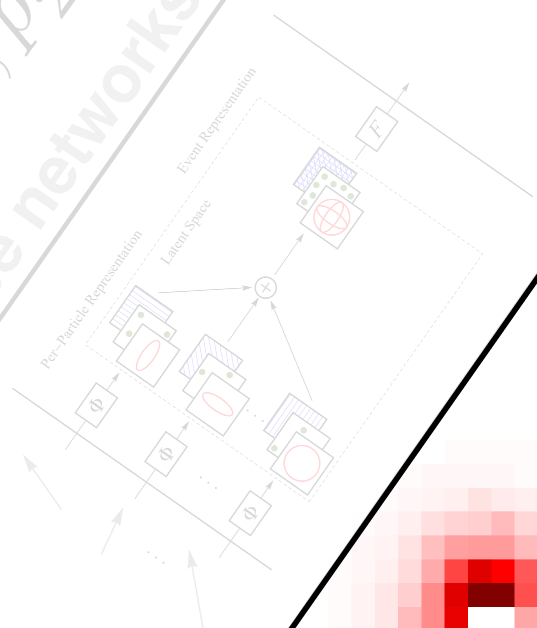
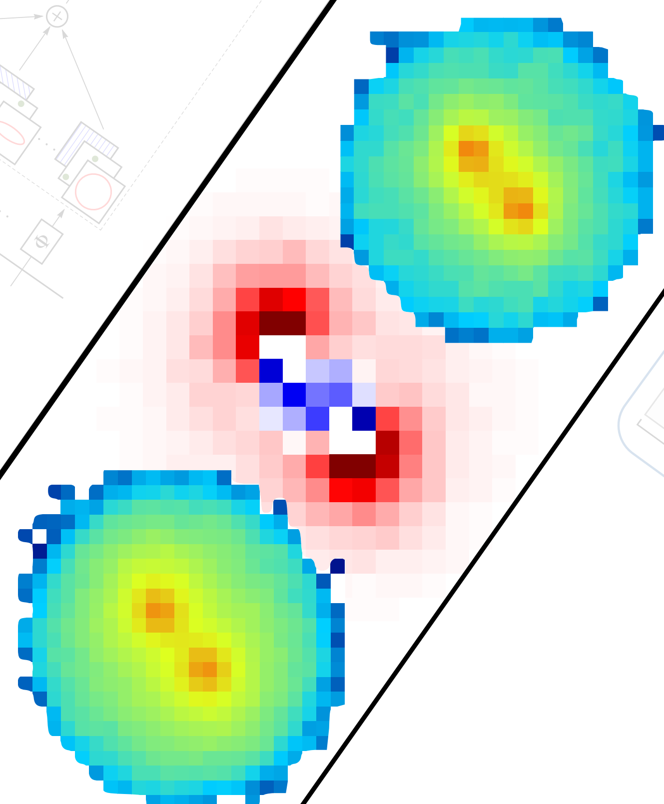
Dense networks



Variable sets

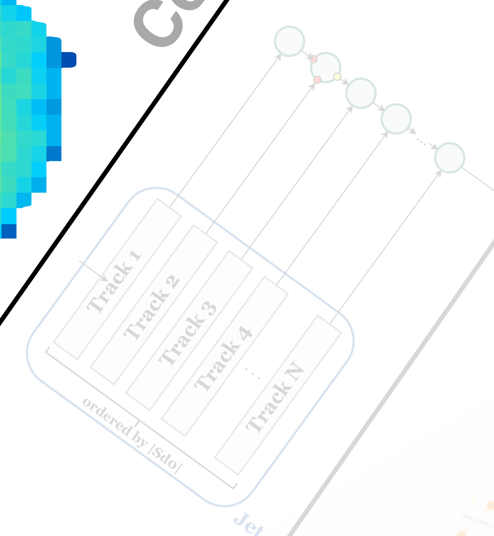
Deep sets

Images



Convolutional NNs (CNNs)

Sequences



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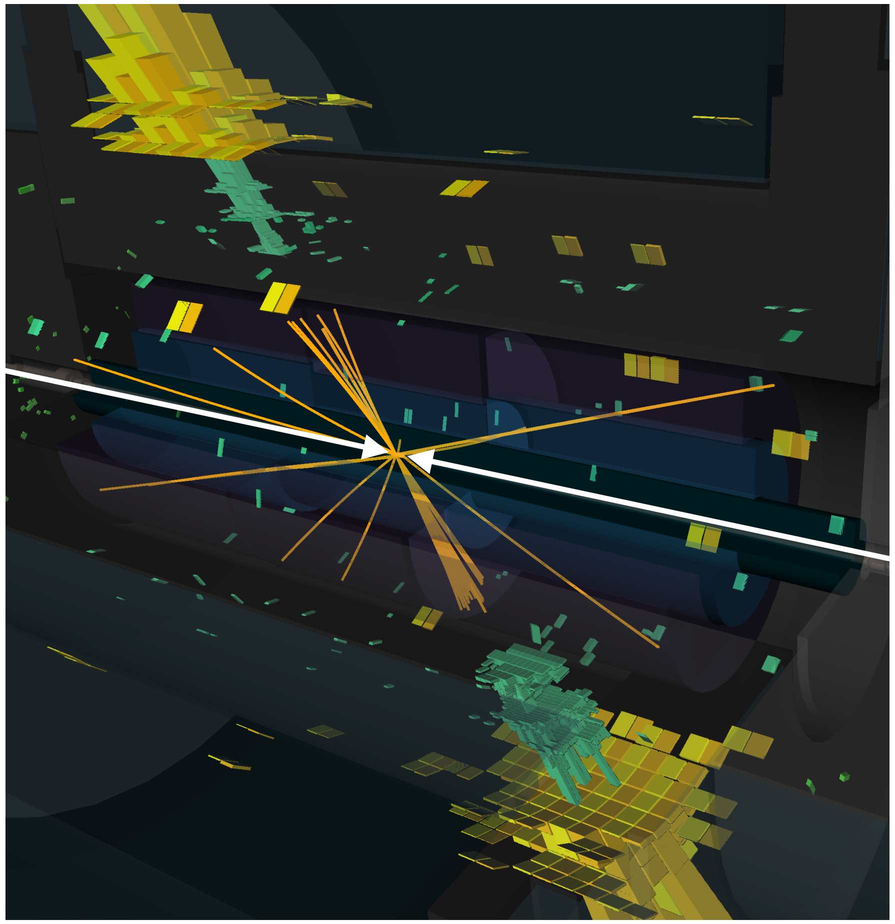
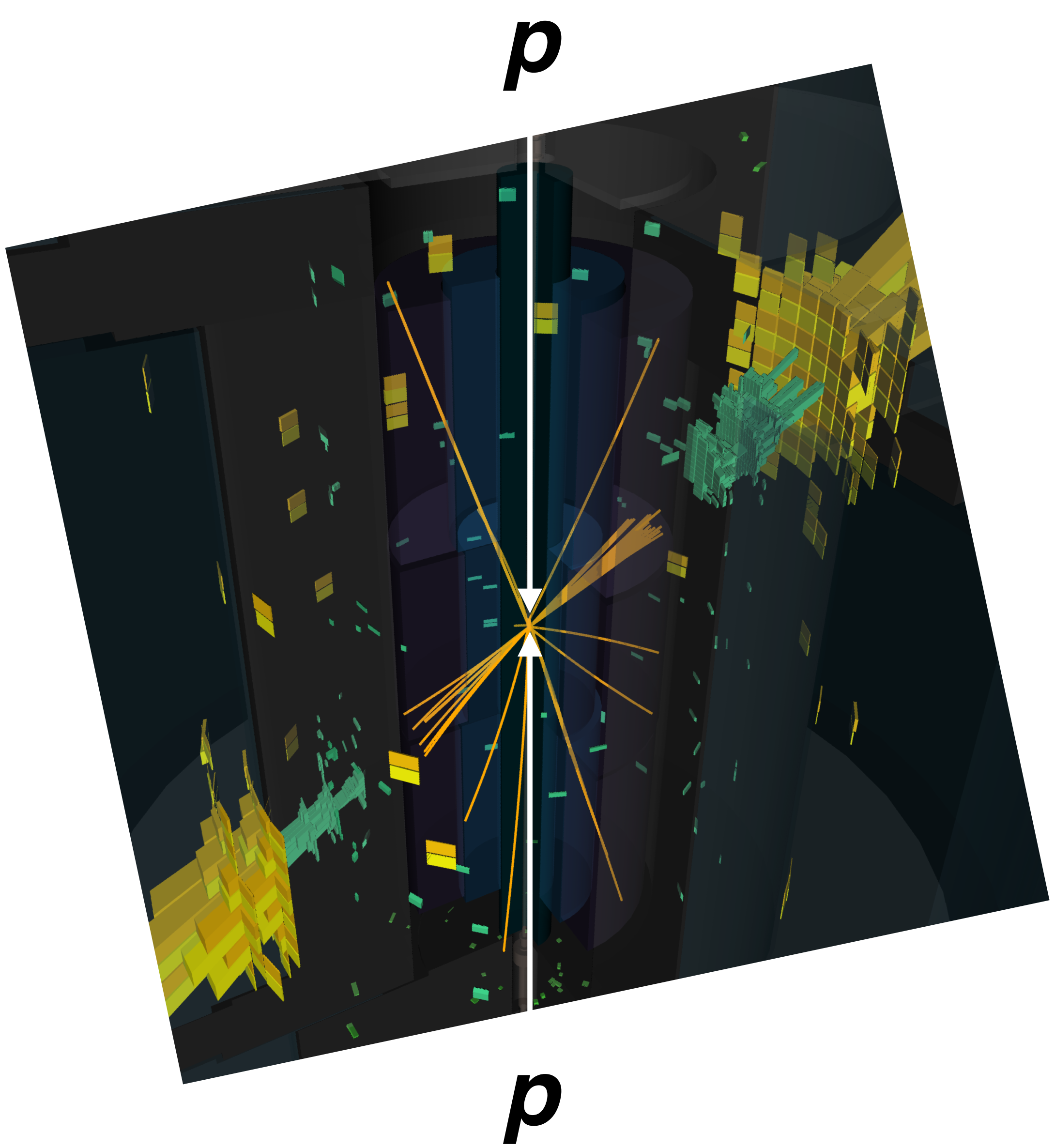
Collider data as an image

p



p

Collider data as an image



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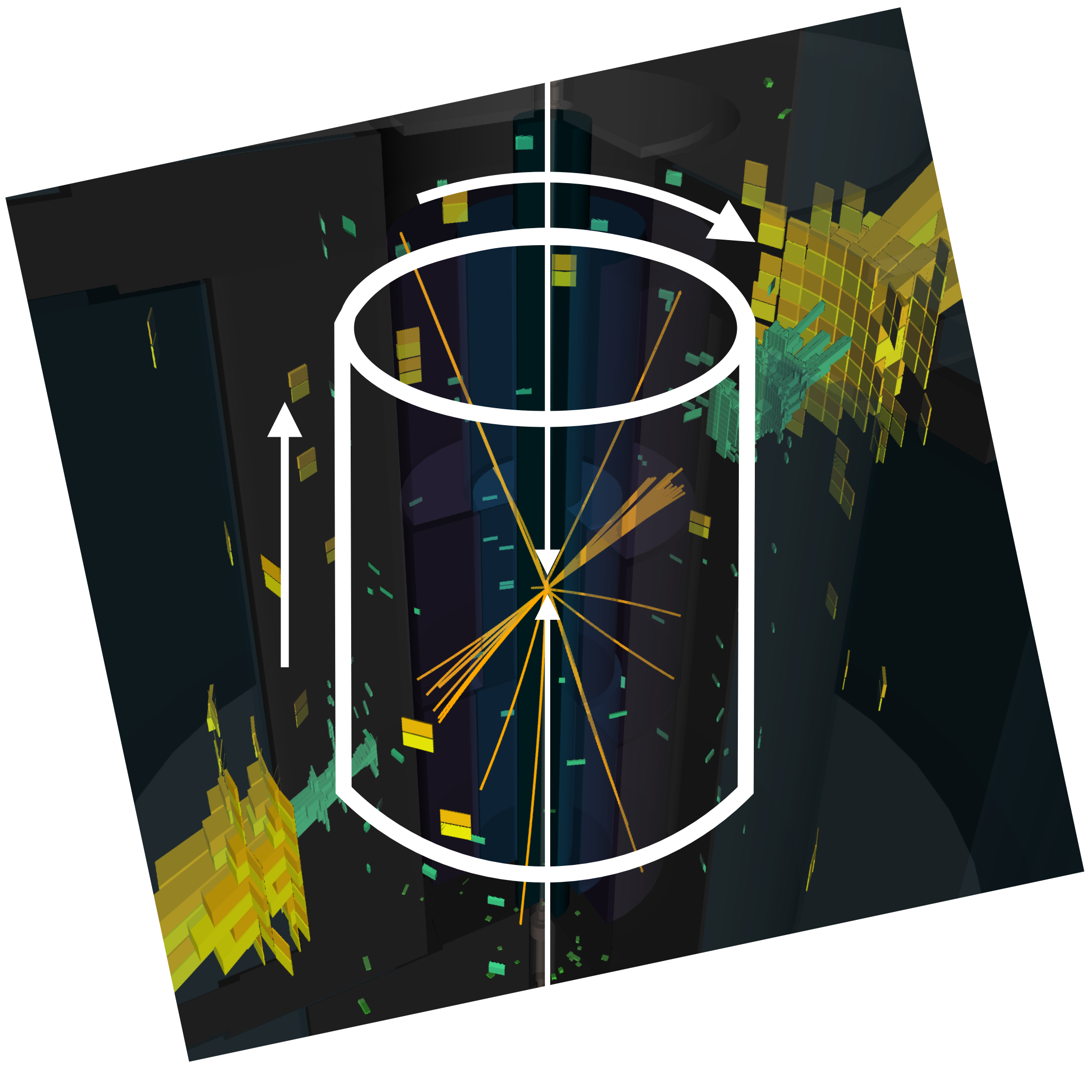

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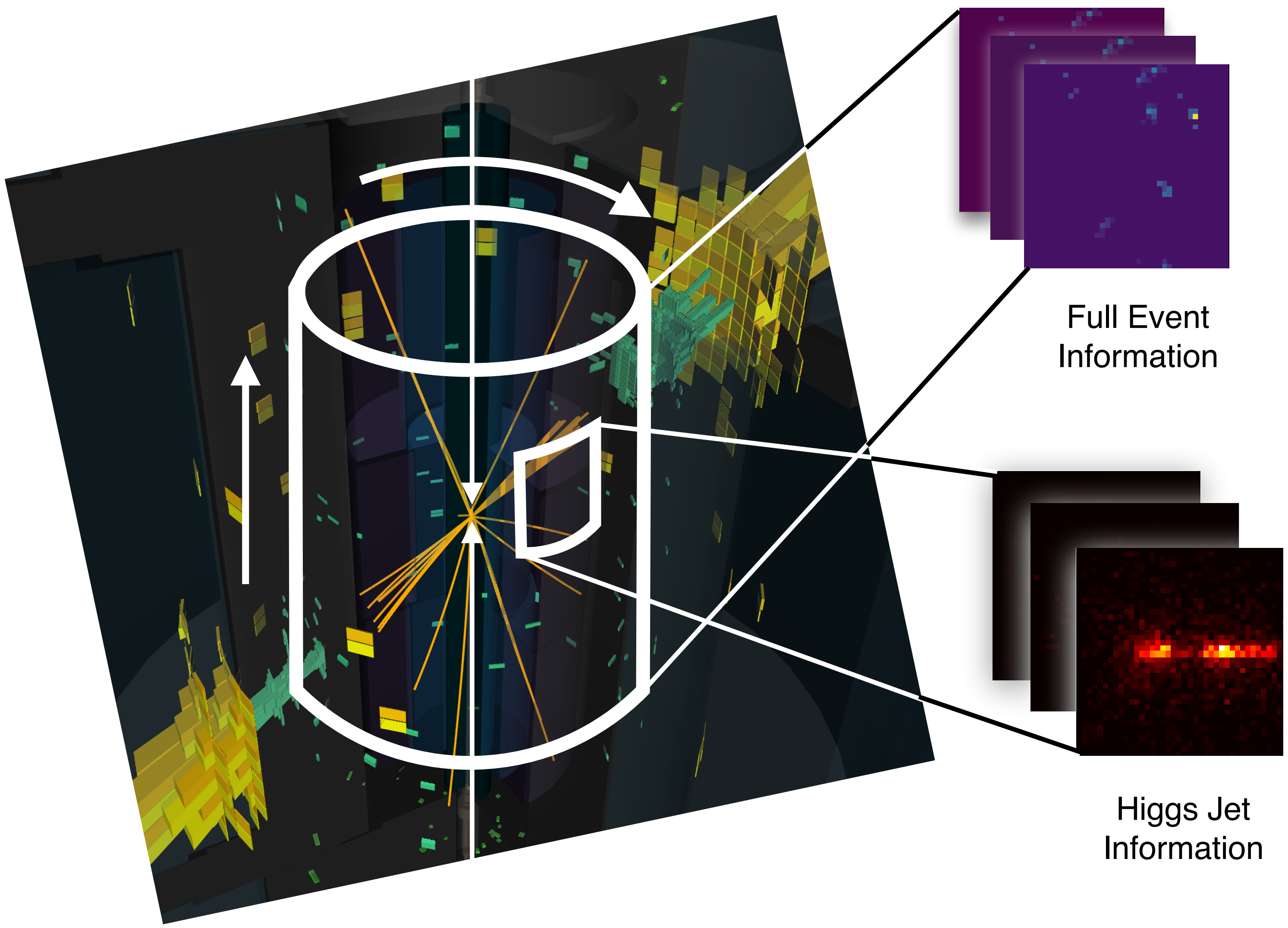

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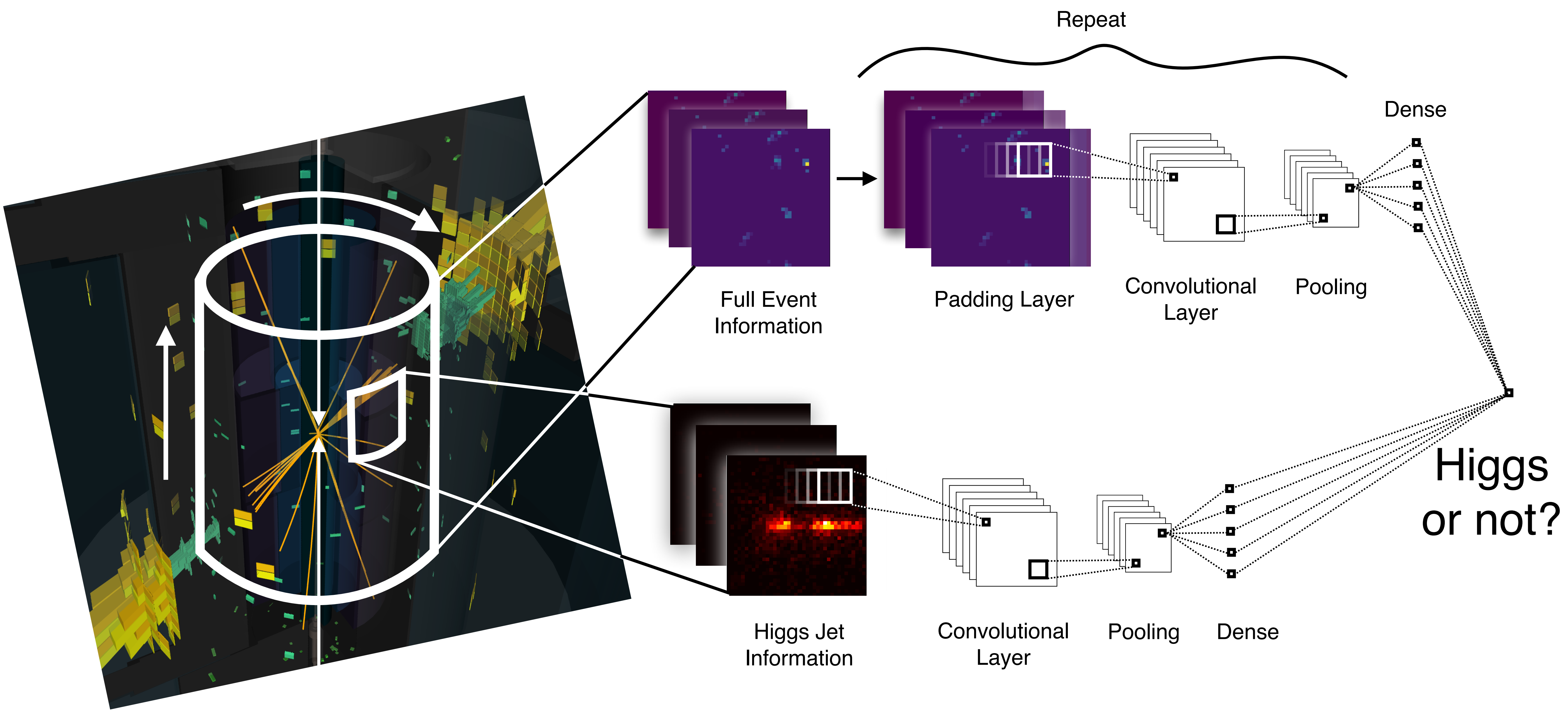
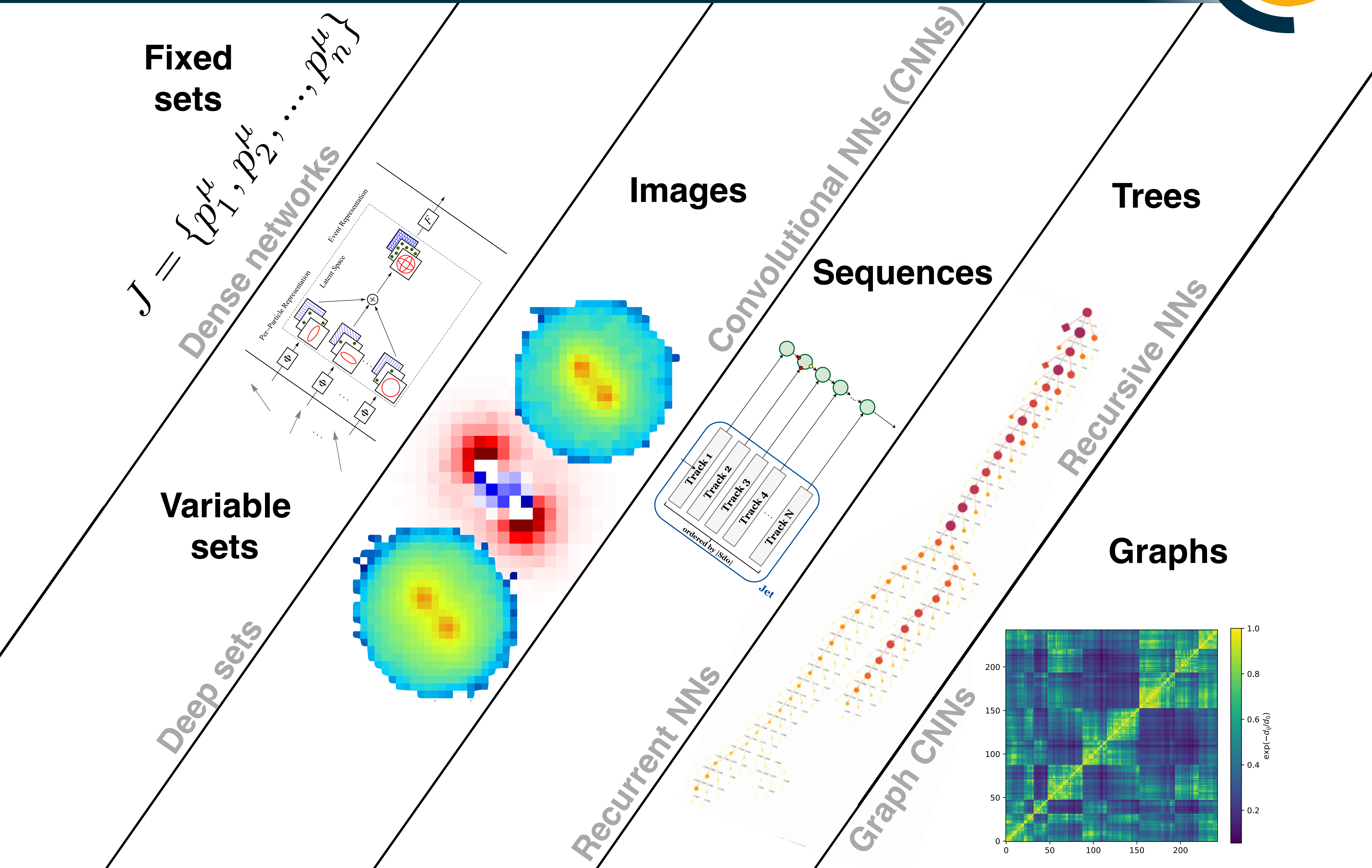


Can combine local and global information from jet images and “event” images.

1807.10768

See 1709.04464 for image refs.

How to represent our data?



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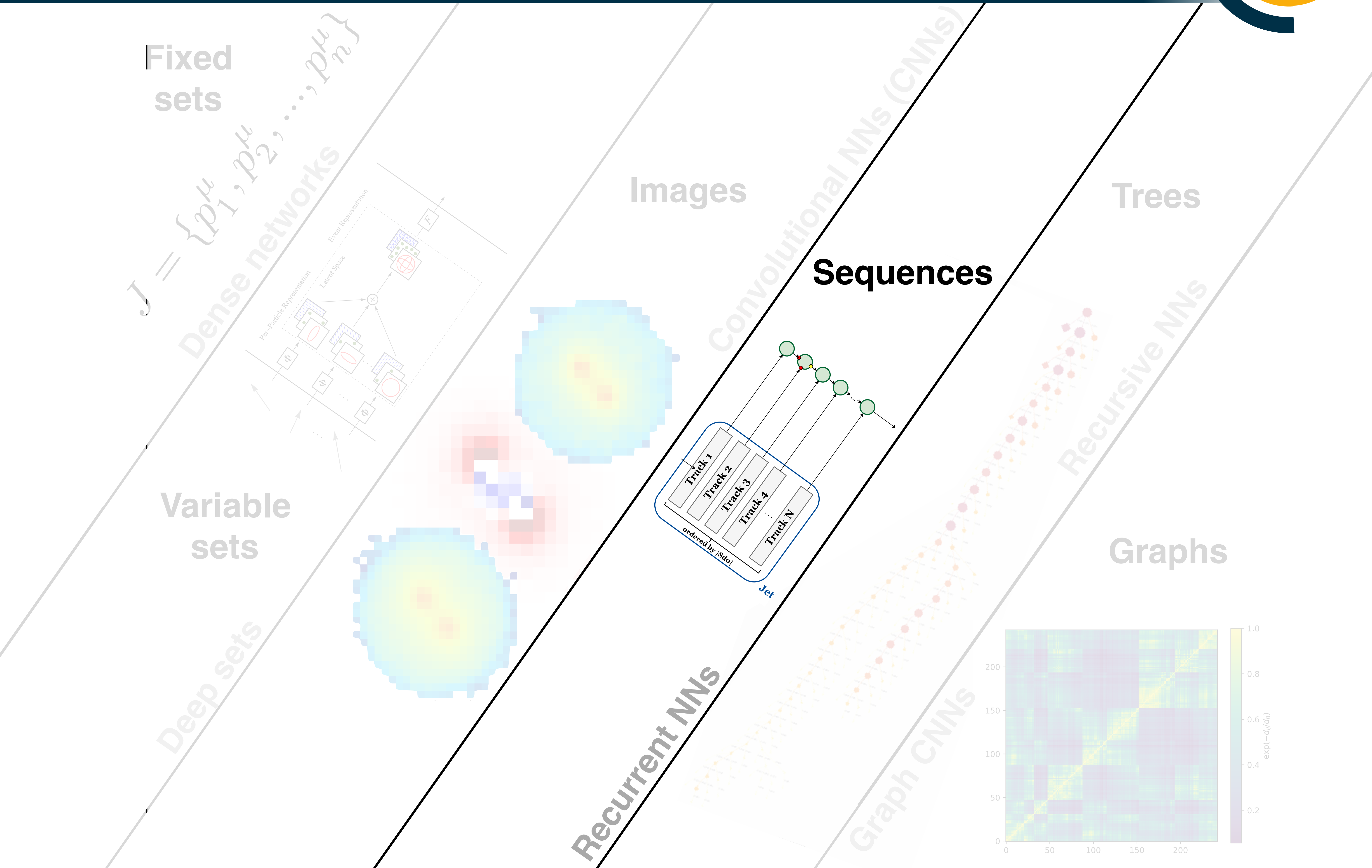

Sequence learning

One key challenge with images is that they have a fixed size.

In many contexts, this is ideal, because the data also have a fixed size. However, this is not always the case.

For example, events / jets have a variable number of particles.

One can represent these particles as a sequence in order to apply variable-length approaches that can access the full feature granularity.

Sequence learning with RNNs

Flavor tagging (classify jets from b-quark or not) has a long history of ML. Use features of the charged-particle tracks inside jets.

In the past, challenging to incorporate correlations between tracks.

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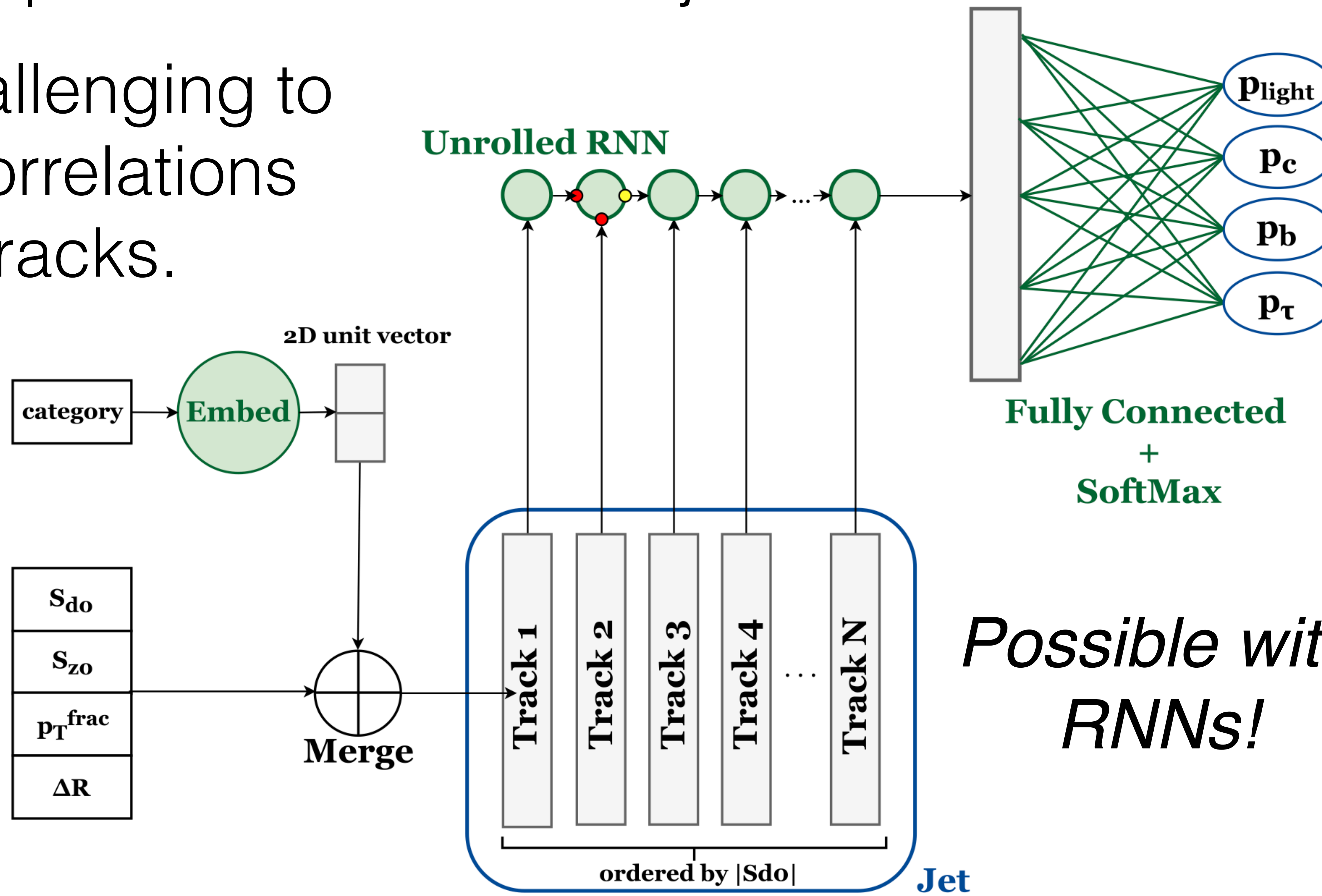

Possible with RNNs!

ATL-PHYS-PUB-2017-003

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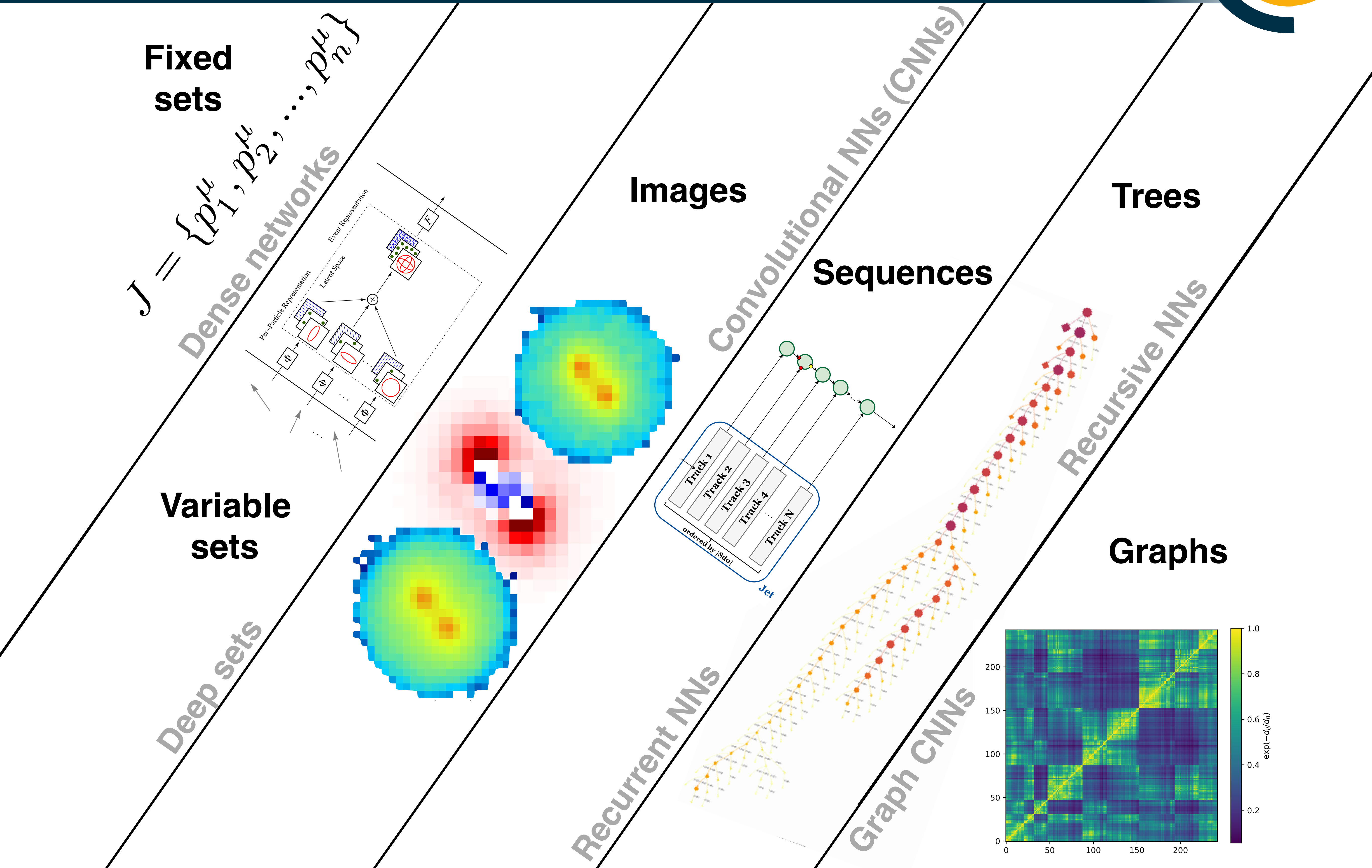

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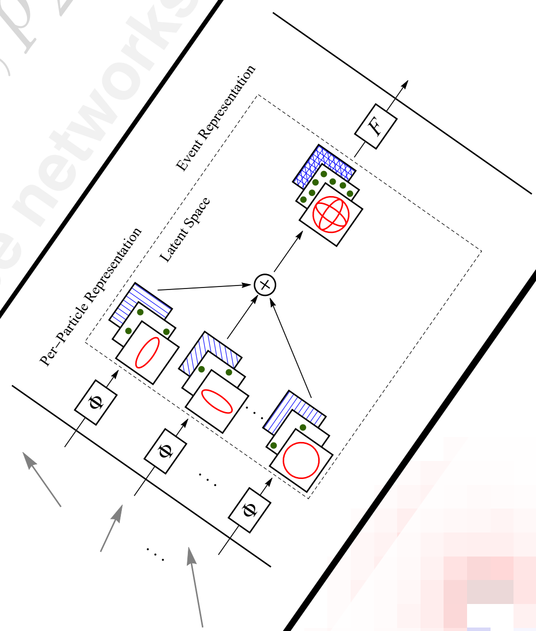
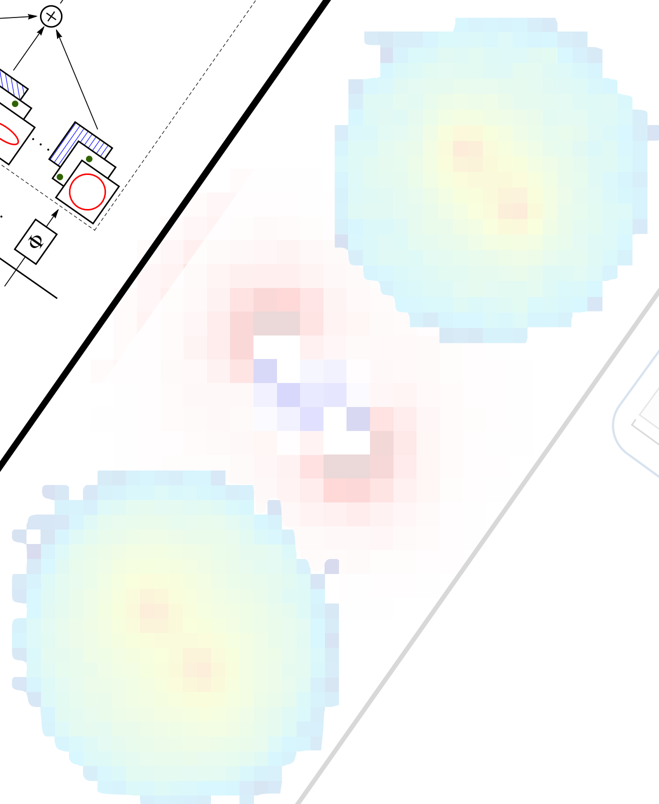


Deep sets

Images



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Learning with sets

A challenge with sequence learning is that thanks to quantum mechanics, there is often no unique order.

A common scenario is that we have a variable-length **SET** of particles and we would like to learn from them directly.

Solution: set learning / point cloud approaches

Solution 1: Deep sets / Particle flow Networks

Factorize the problem into two networks: one that embeds the set into a fixed-length latent space and one that acts on a permutation invariant operation on that latent space:

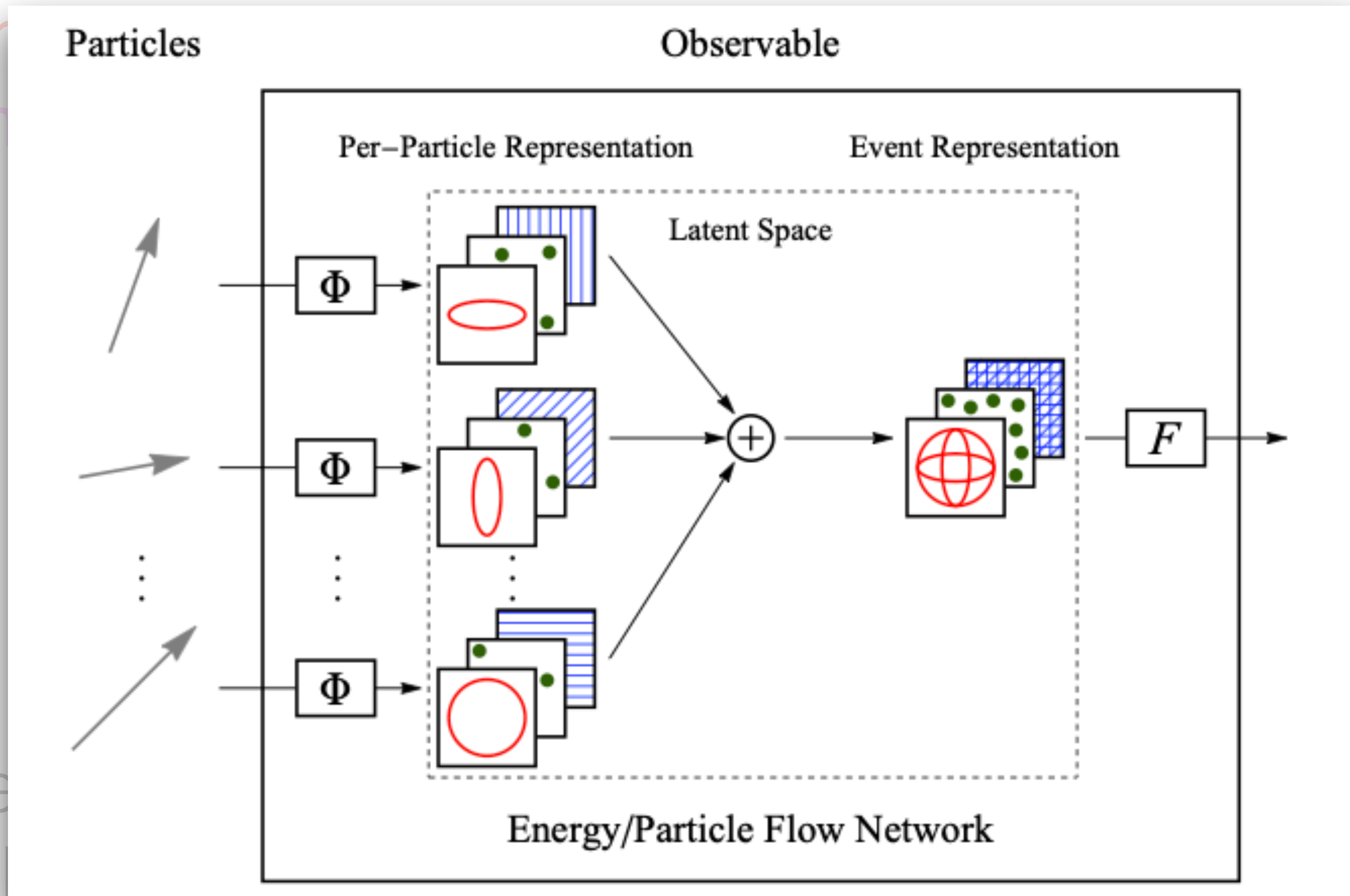
$$f(\{x_1, \ldots, x_M\}) = F\left(\sum_{i=1}^{M} \Phi(x_i)\right)$$

Due to the sum, this structure can operate on any length set and the order of the inputs doesn't matter.

1703.06114, 1810.05165

Solution 1: Deep sets / Particle flow Networks

Factorize the problem into two networks: one that embeds the set i… t acts on a perm… pace:



Due … any lengt… atter.

1703.06114, 1810.05165

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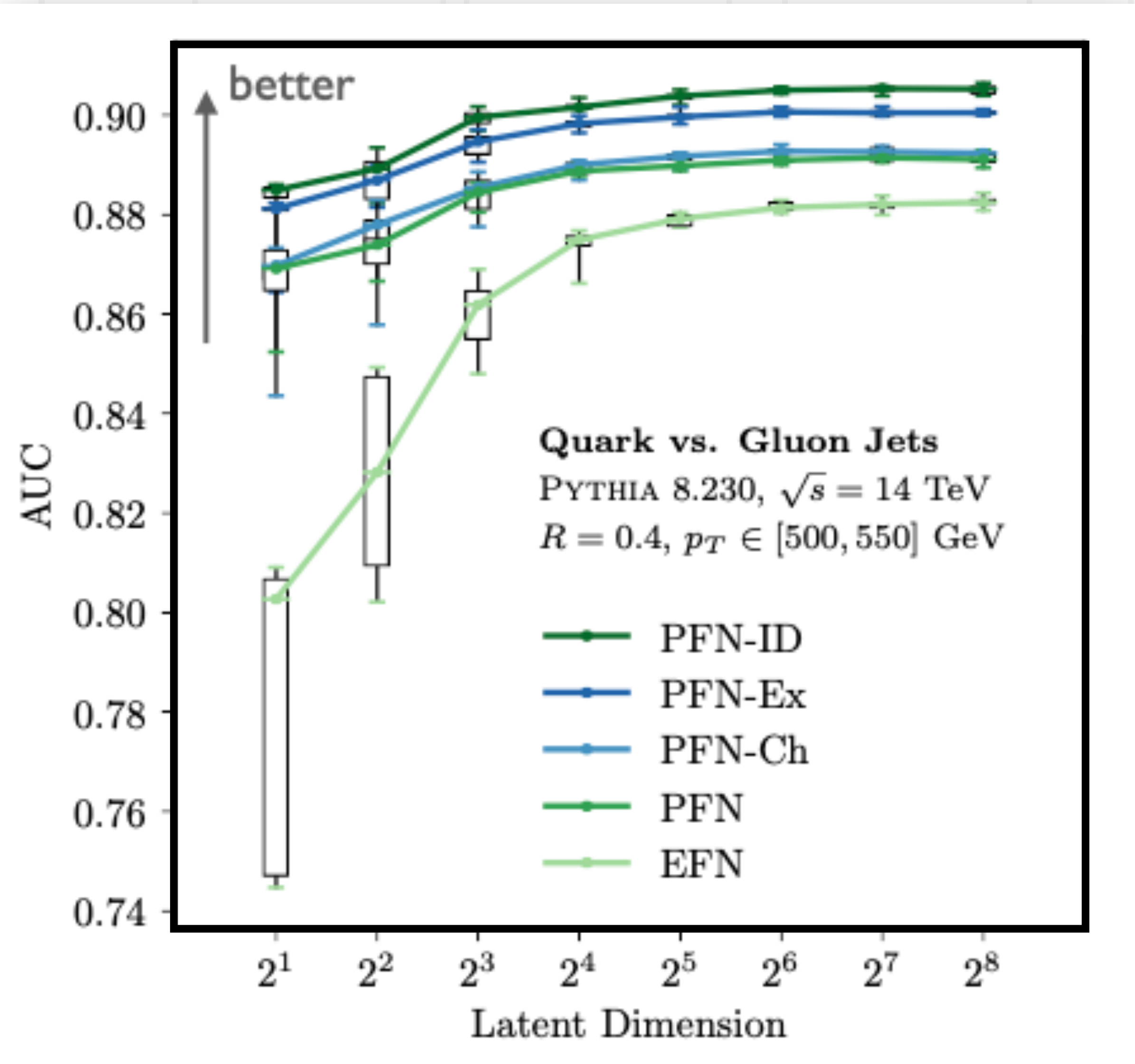
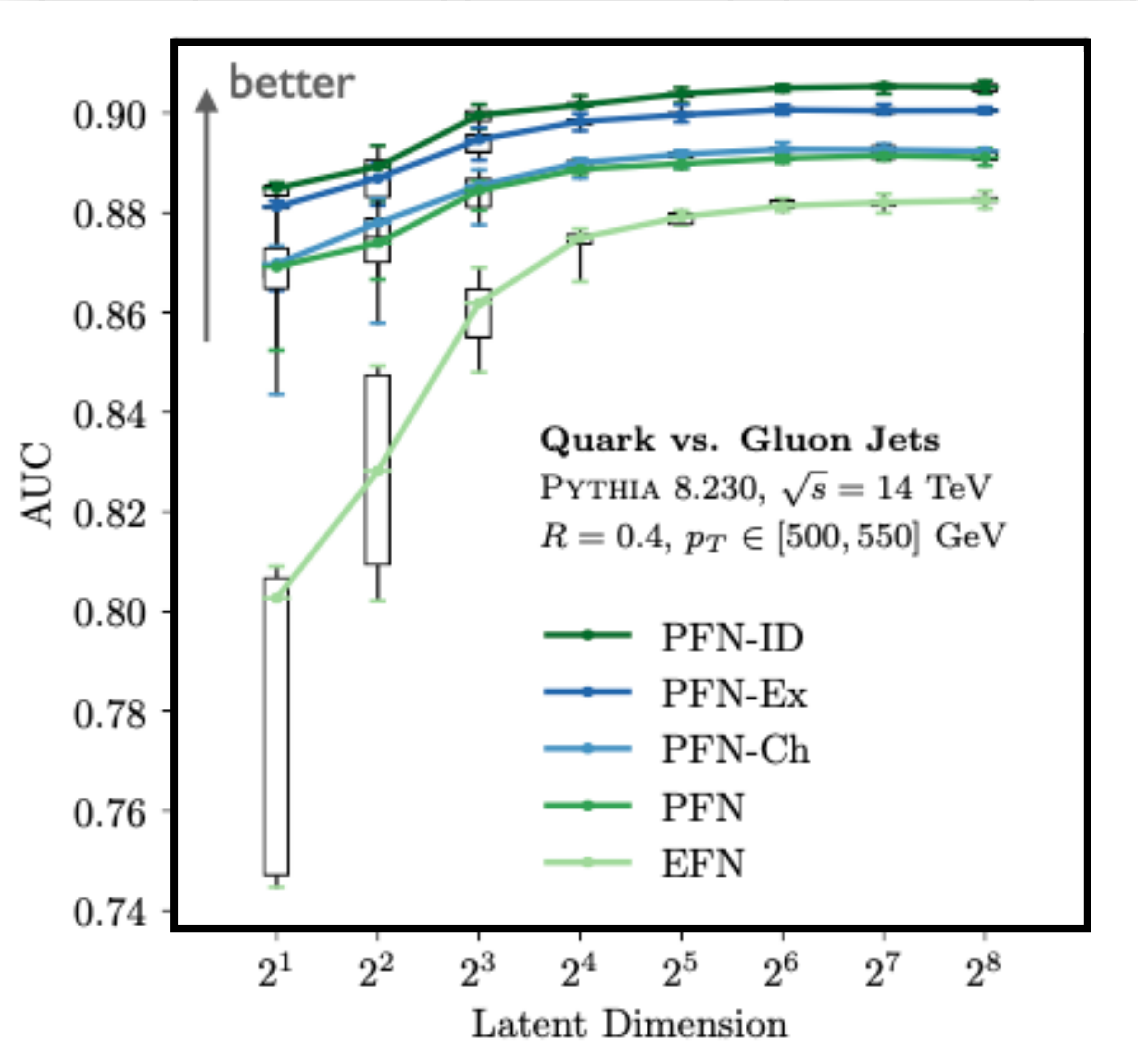
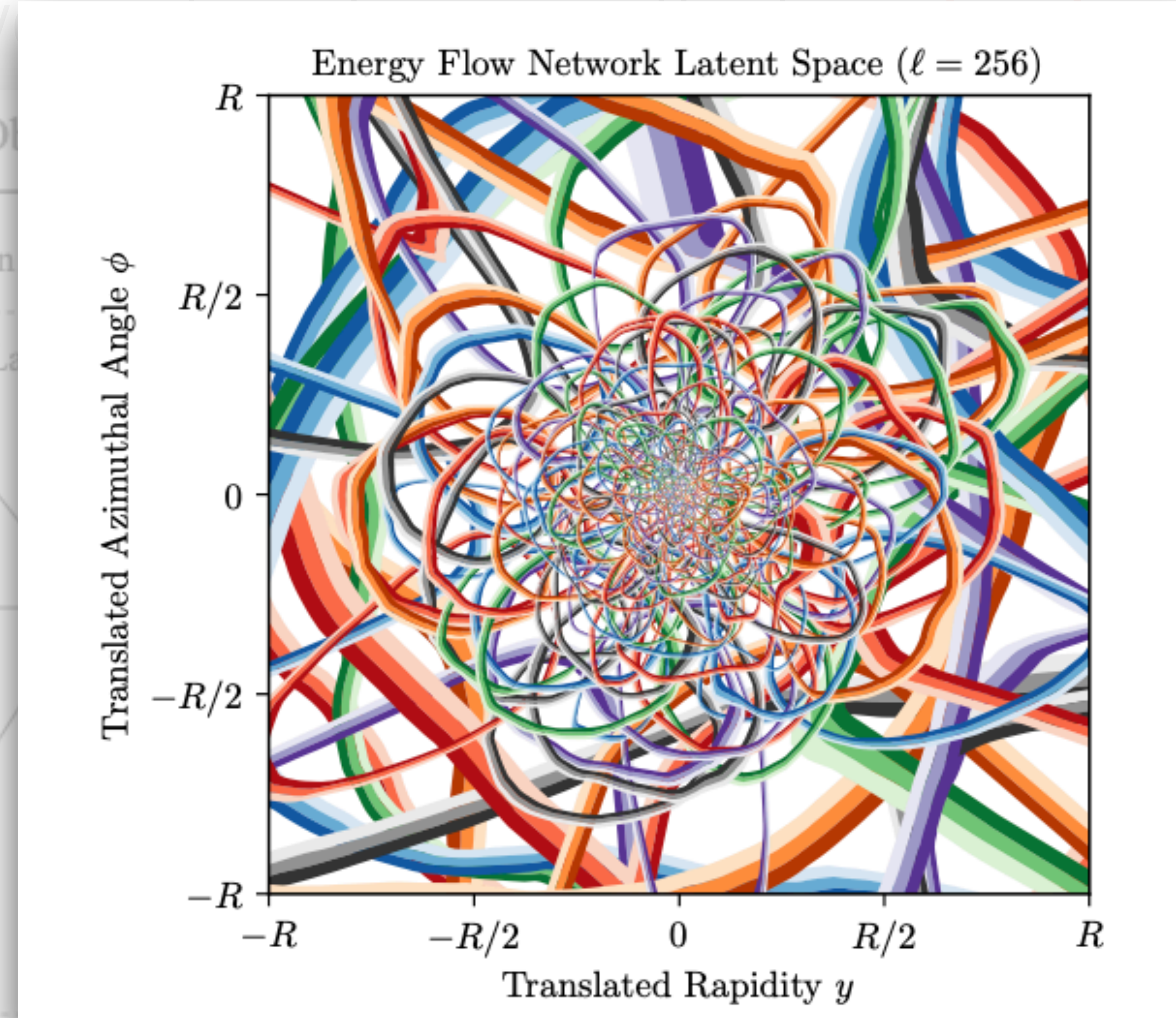


- Can readily incorporate per-particle features
- Can be made infrared and collinear safe (EFN) safe

1703.06114, 1810.05165

Solution 1: Deep sets / Particle flow Networks





Latent space in IRC safe case is interpretable (and predictable!)

1703.06114, 1810.05165

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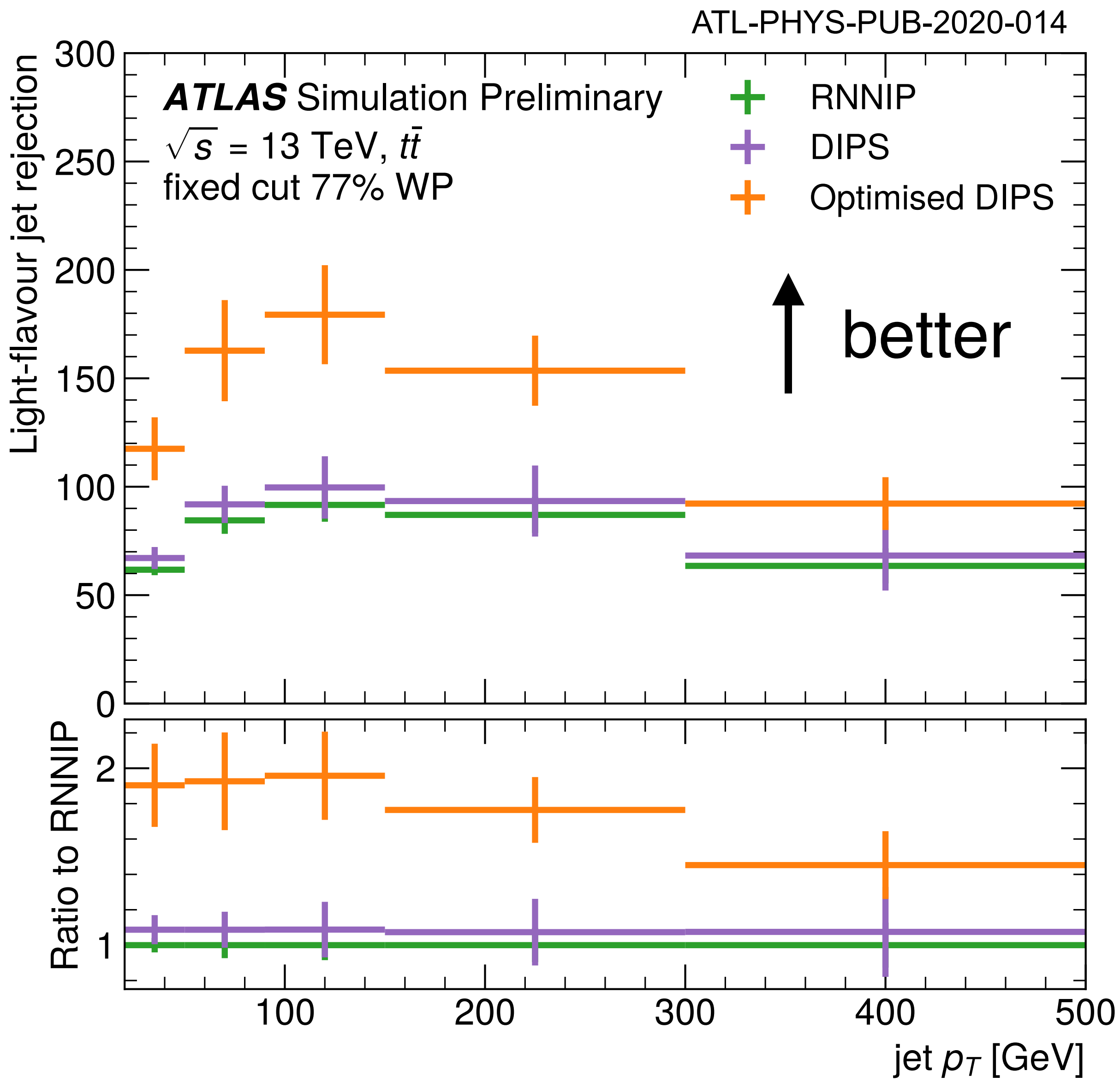


Faster to train than RNN so can do R&D on input features to improve overall performance.

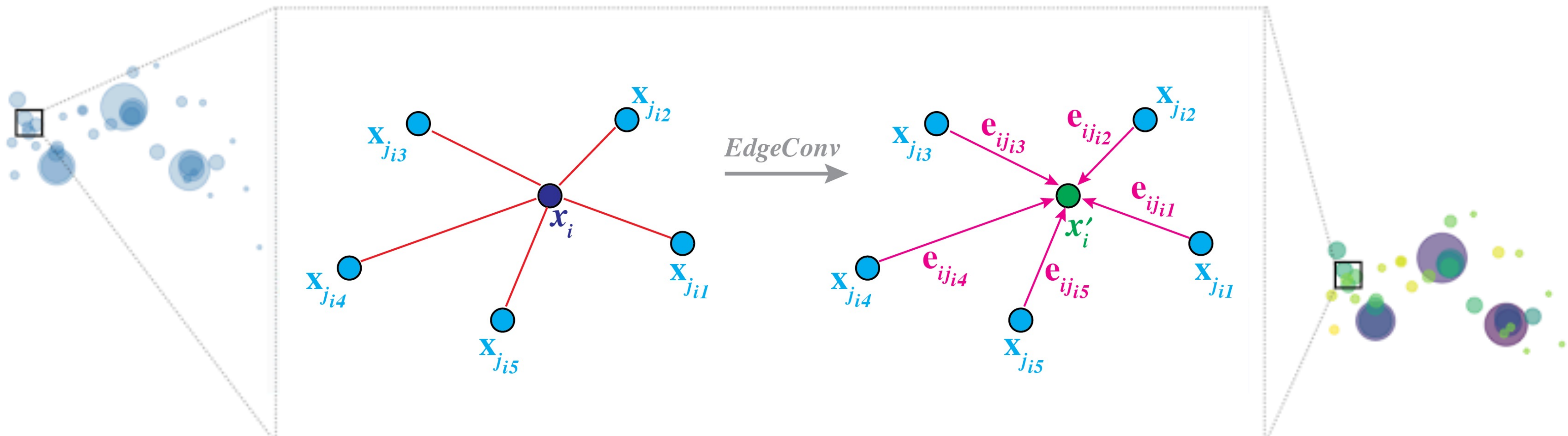
Latent space in IRC safe case is interpretable (and predictable!)

M. Zaheer et al. https://arxiv.org/abs/1703.06114; P. Komiske, E. Metodiev, & J. Thaler, JHEP 01 (2019) 121

Solution 2: Graph methods

Classic CNNs operate on a fixed grid and are not invariant under the permutation of points

Can generalize CNNs to act on graphs



Need to define distances using particle properties

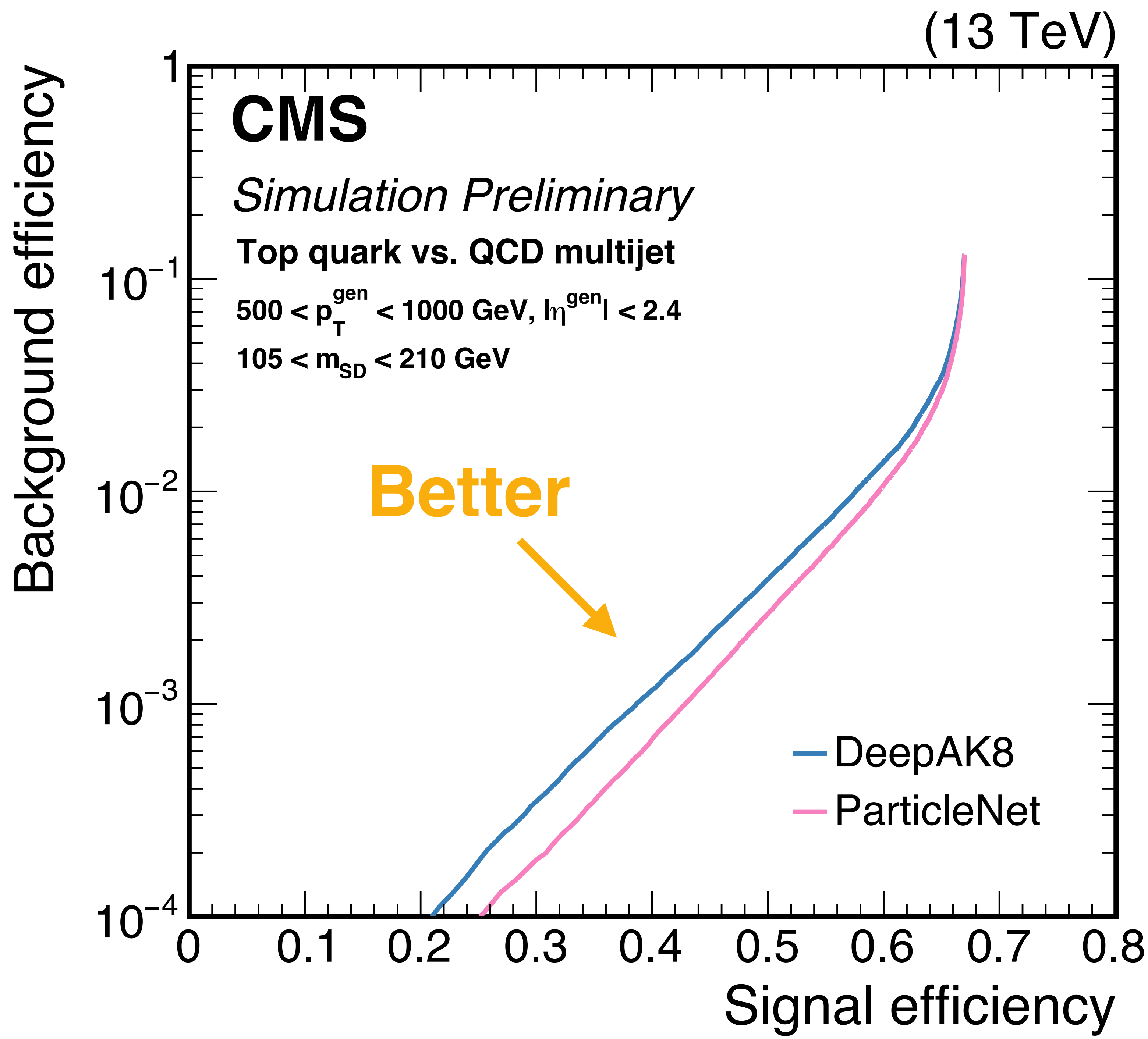
1801.07829 , 1902.08570

Solution 2: Graph methods

Classic CNNs (not invariant u

Can generali

Competitive performance to other state-of-the-art methods



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1801.07829 , 1902.08570

Bonus: equivariance (=covariance)

I've already mentioned permutation invariance as a symmetry that point cloud models respect.

What about other symmetries? What if we want the model to not be invariant but covariant?

e.g. 2203.06153

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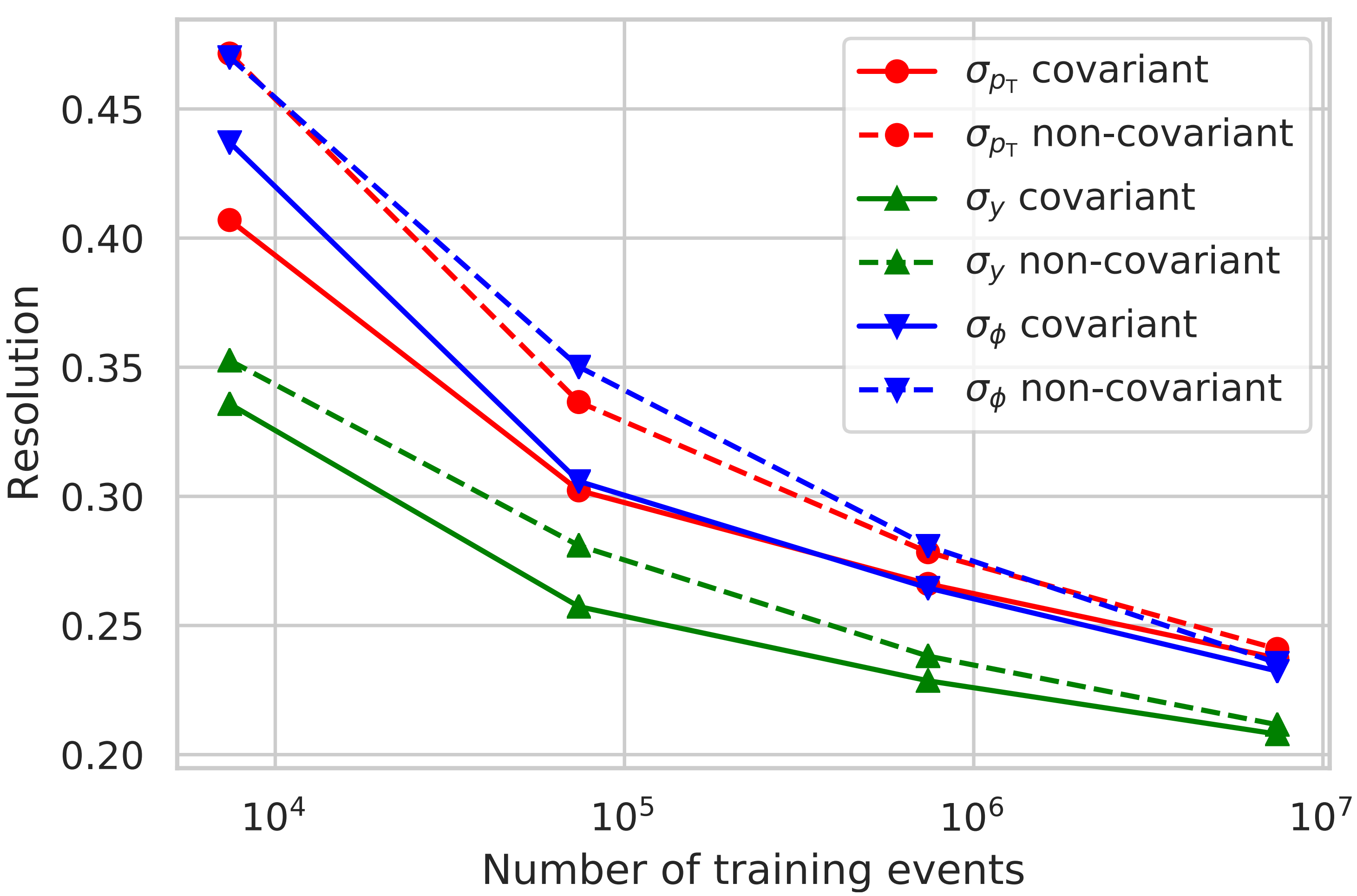
What about other symmetries? What if we want the model to not be invariant but covariant?

e.g. 2203.06153

2203.05687



Covariance architectures can reduce parameter count, improve robustness, enhance performance

[← this example is partial Lorentz covariance]