

The Lund jet plane: organising QCD radiation at colliders

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based on [arXiv:1807.04758](https://arxiv.org/abs/1807.04758) with
F. Dreyer, G. Soyez (with some of their slides)

** on leave from CERN and CNRS*



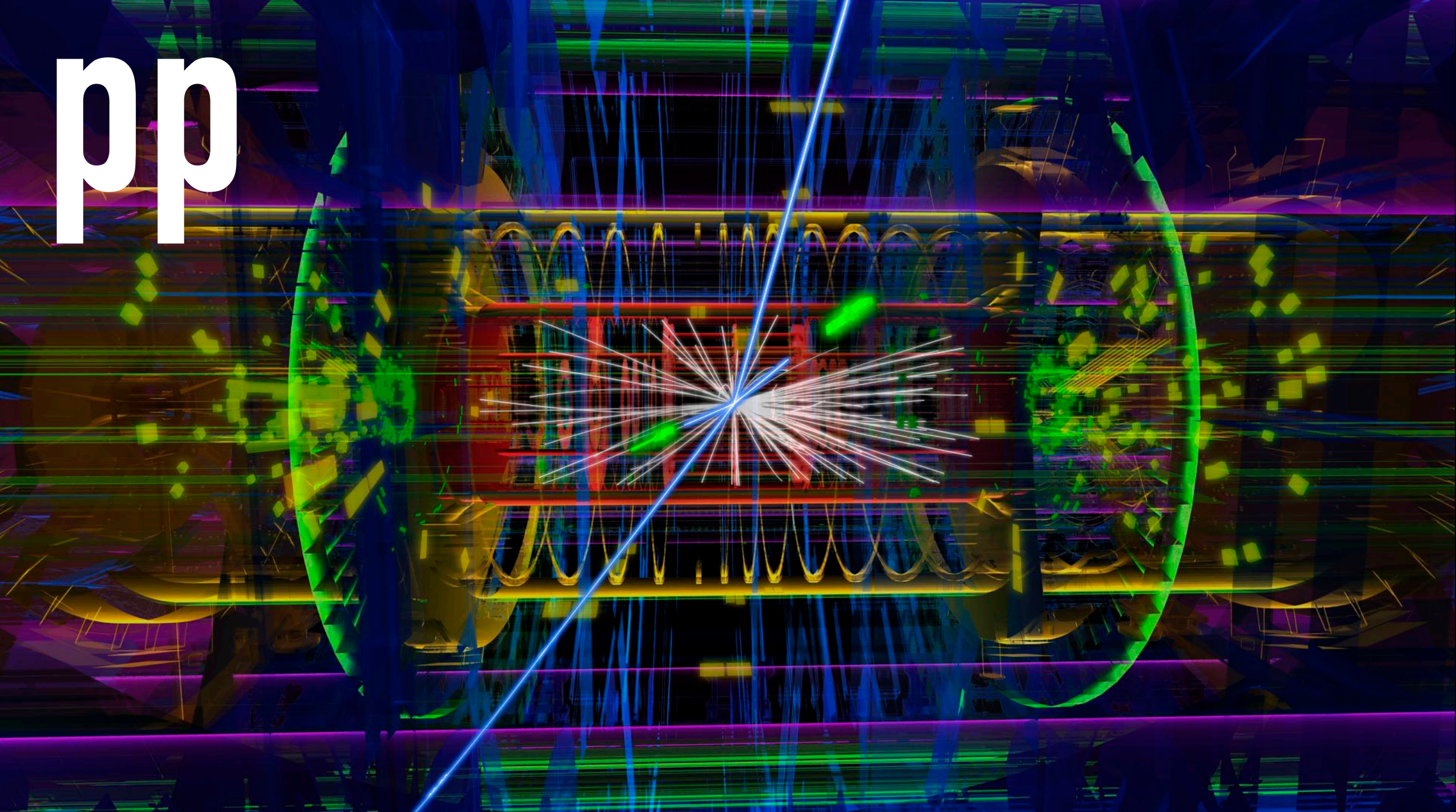
European Research Council
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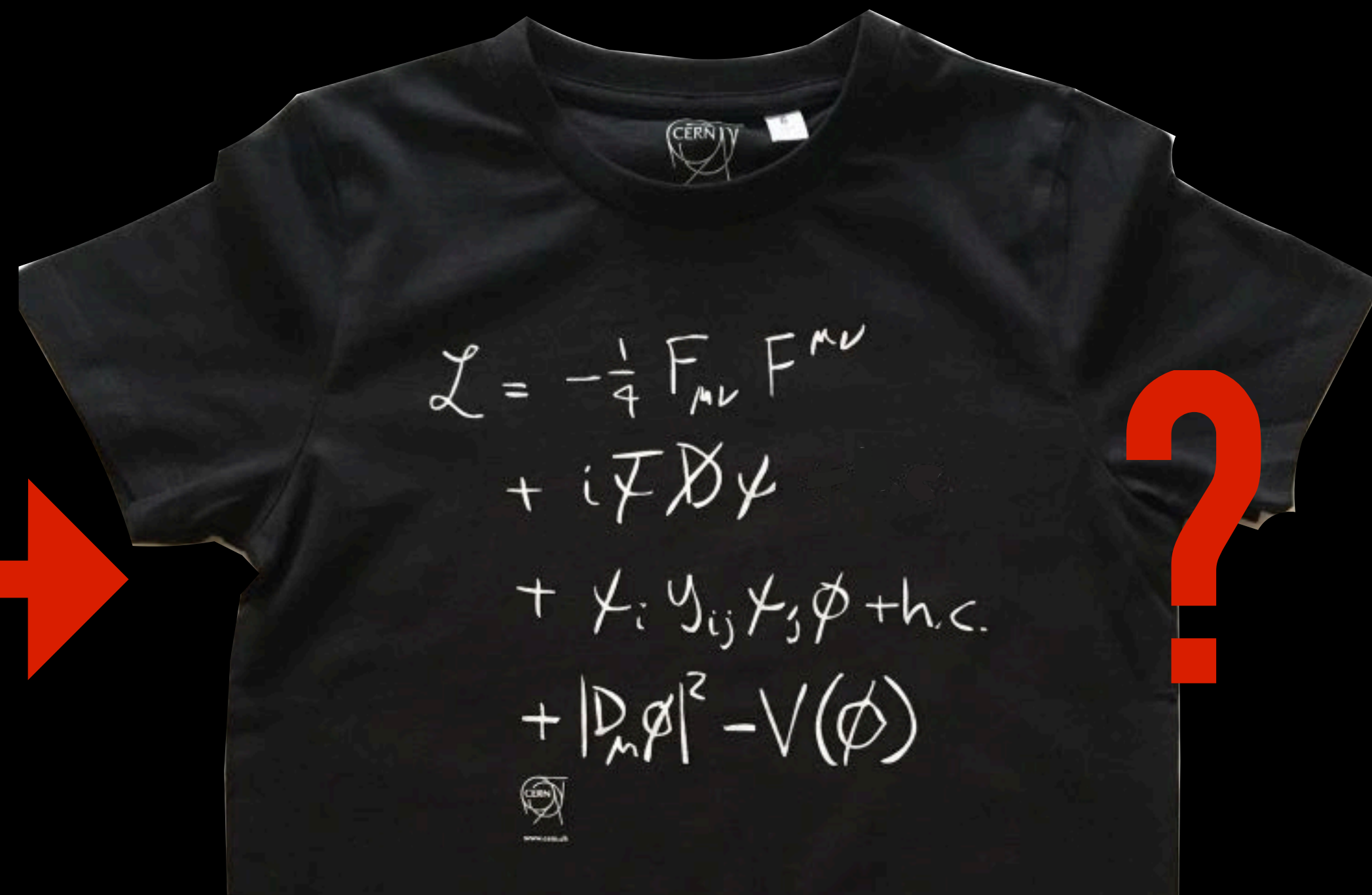
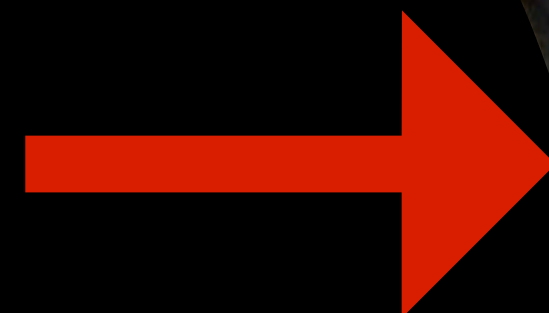
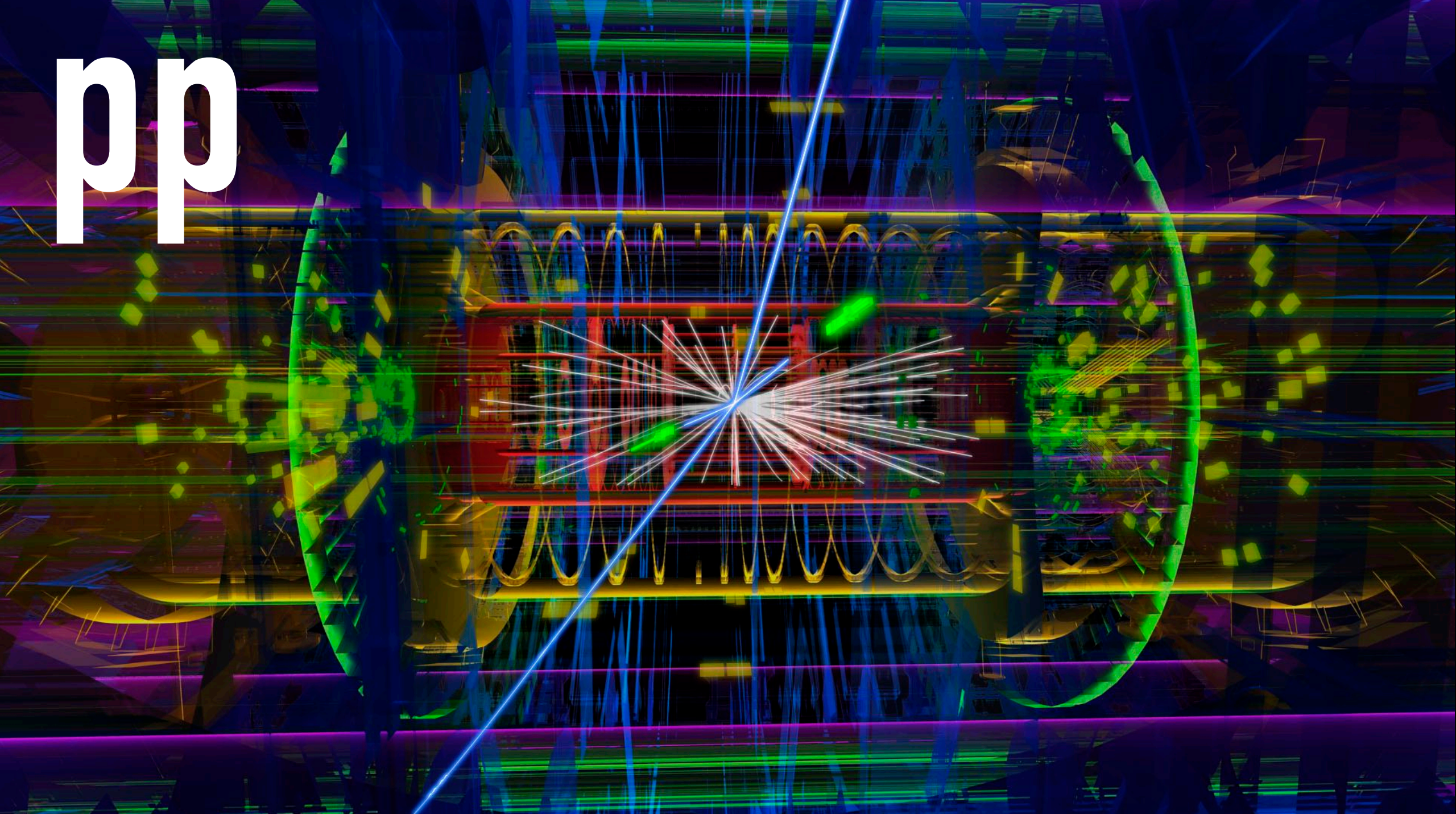
THE ROYAL SOCIETY

Birmingham
4/3/2019

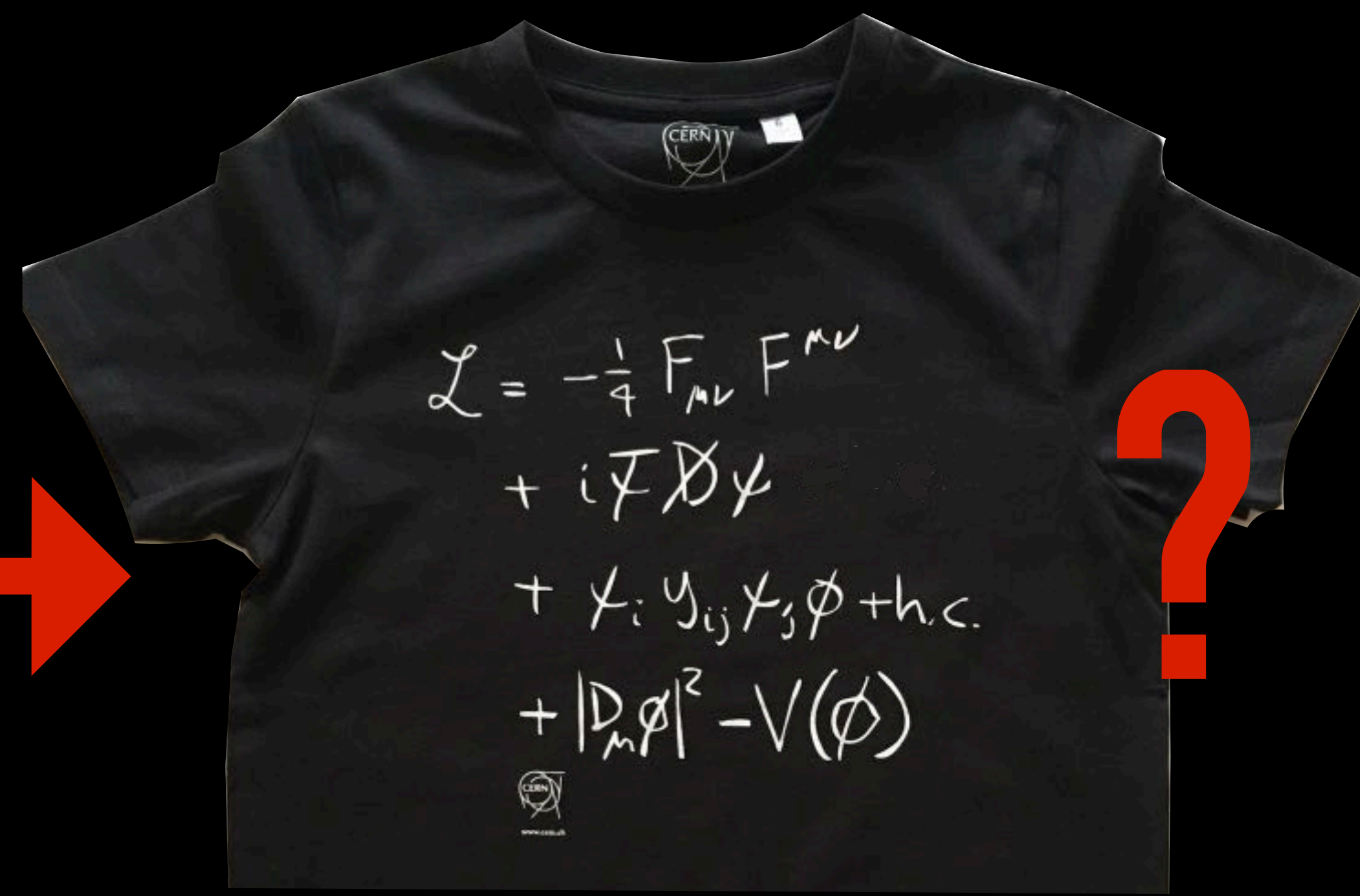
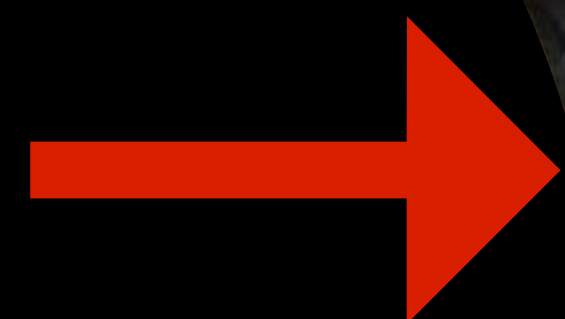
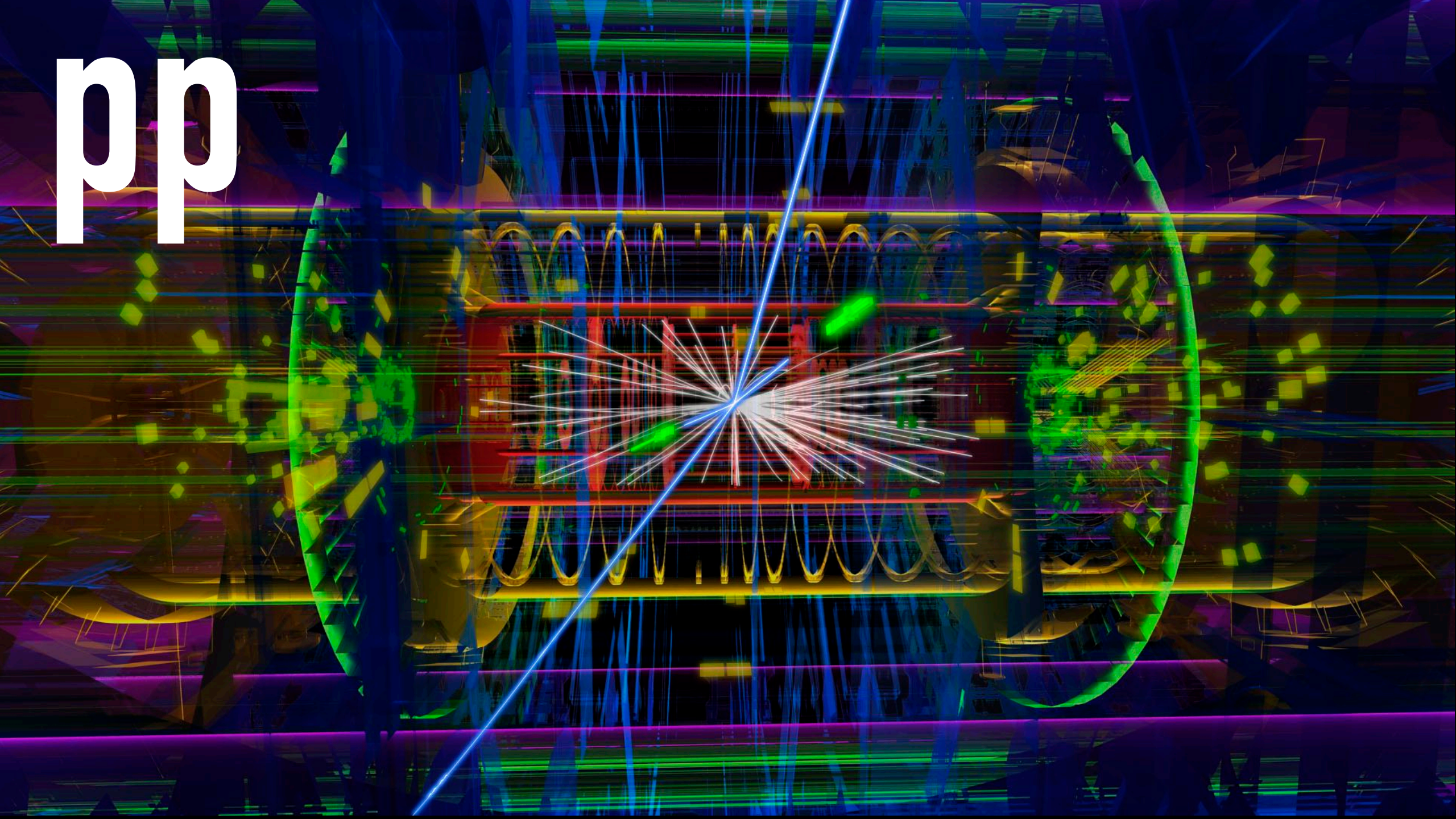
pp



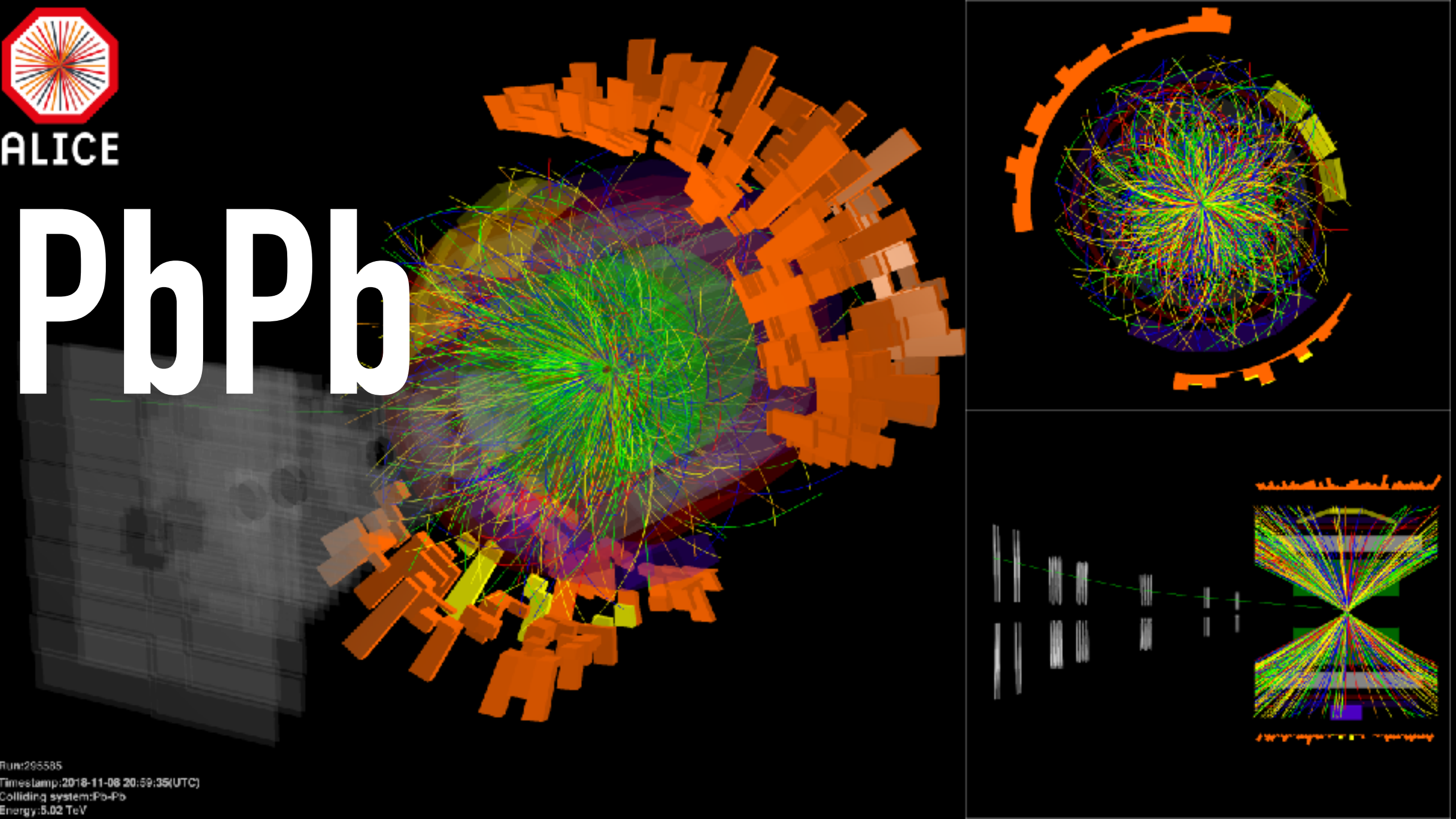
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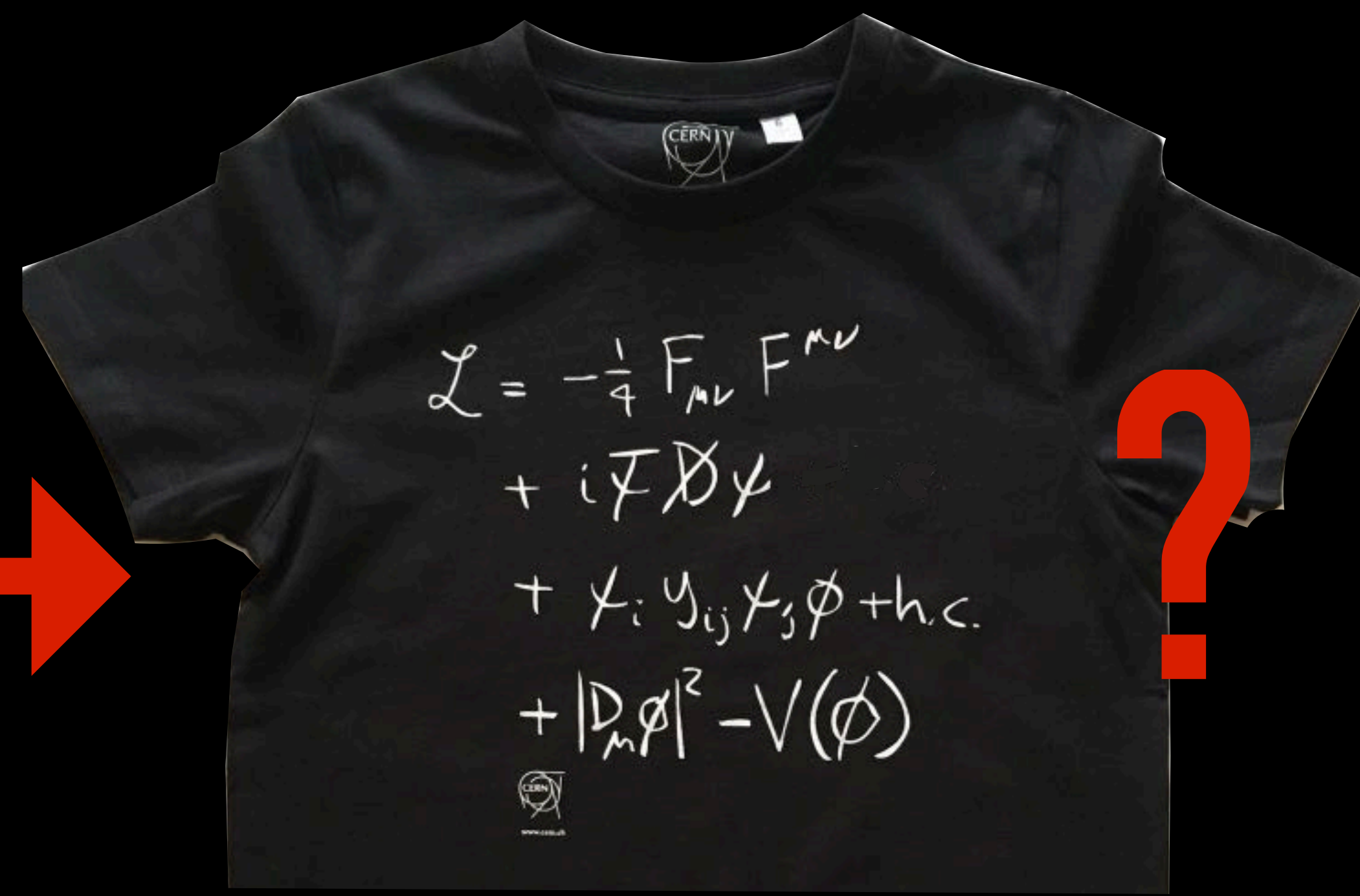
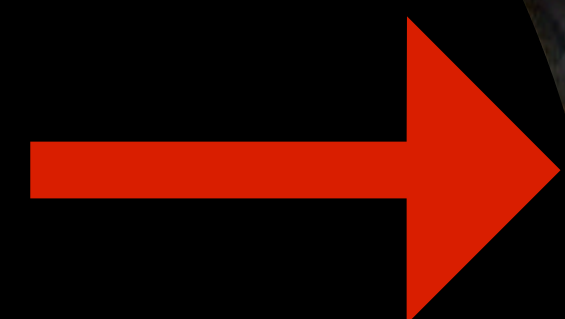
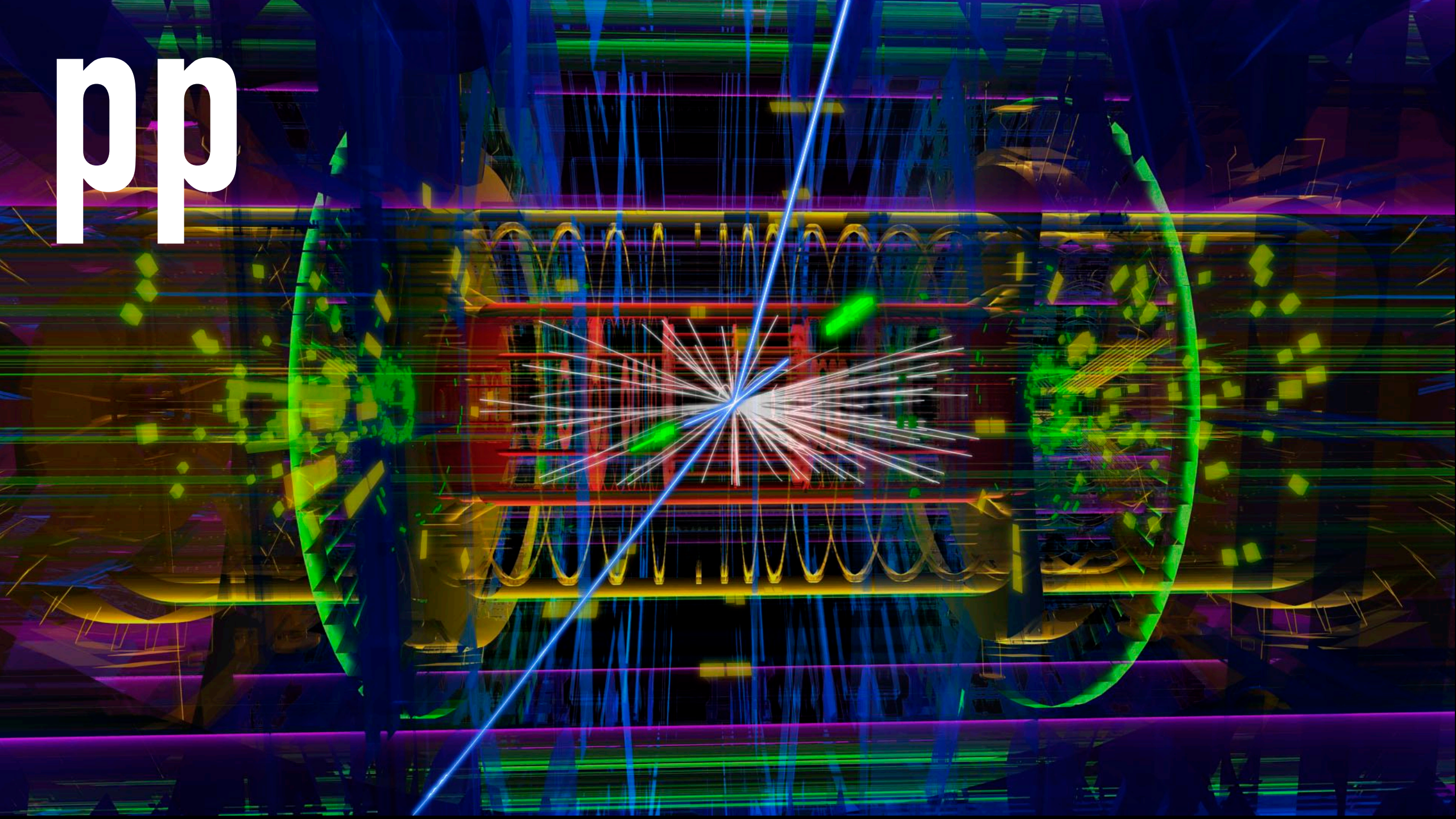
pp



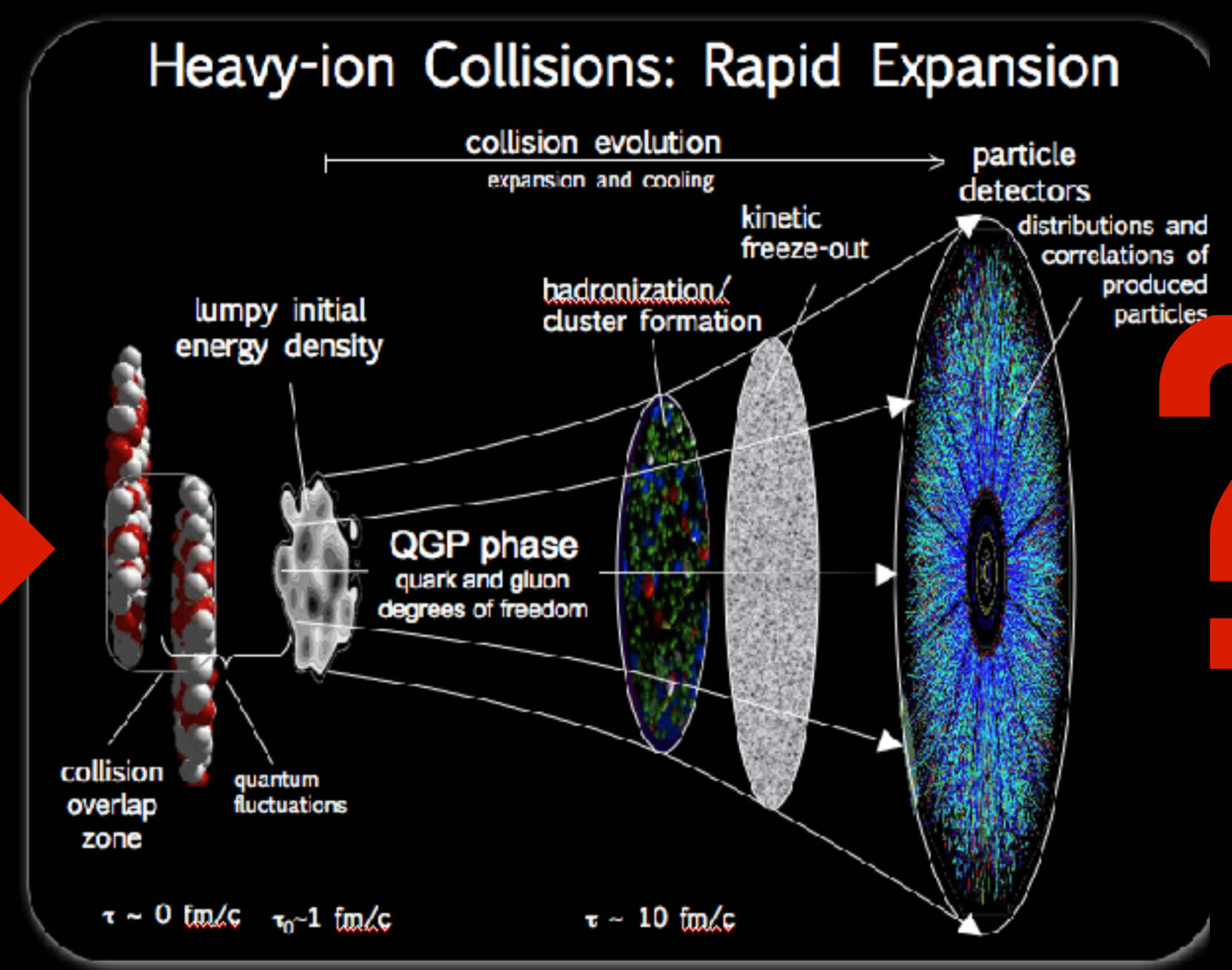
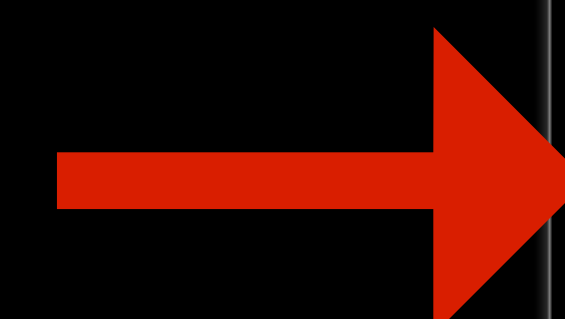
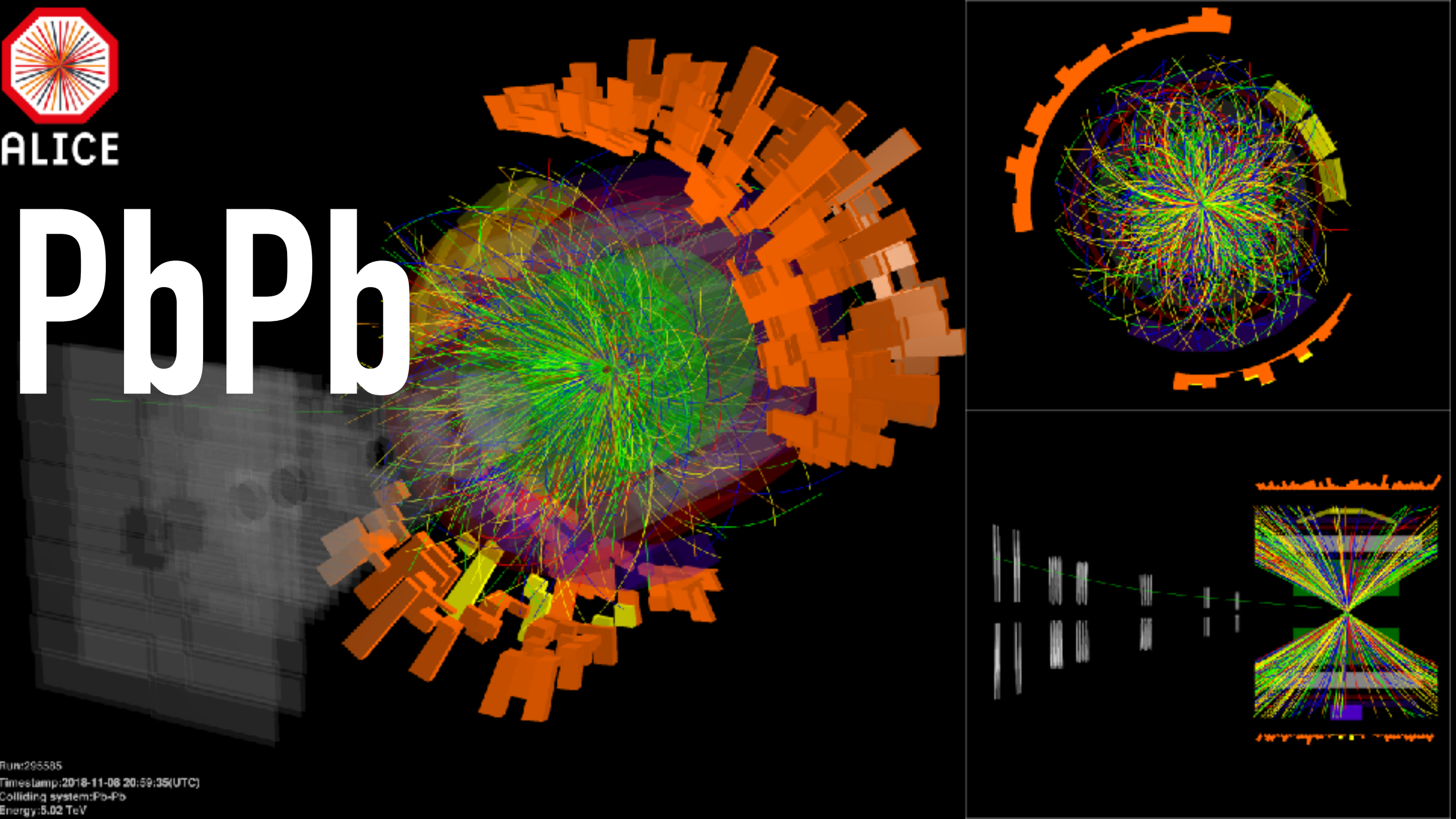
PbPb



pp



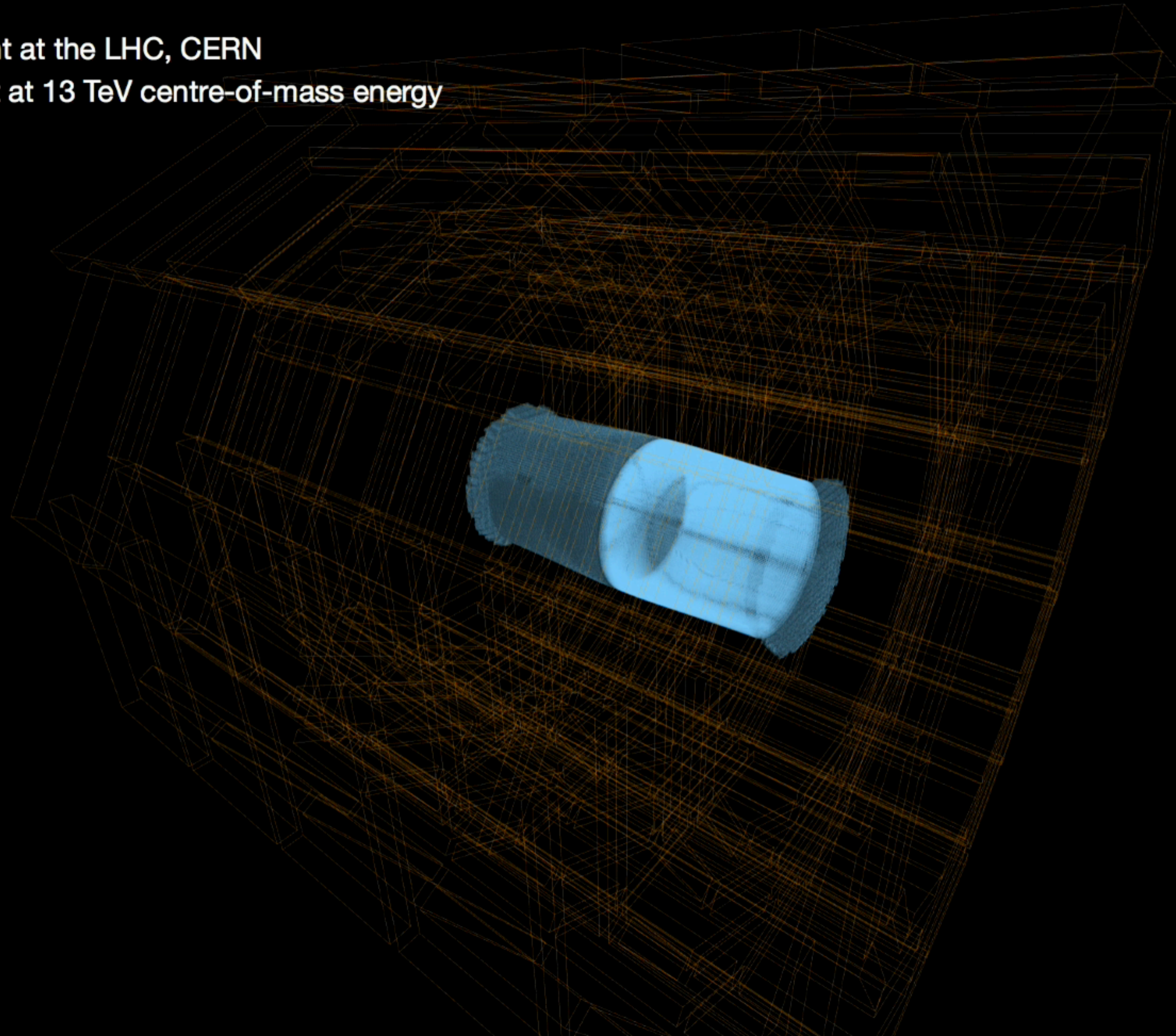
PbPb



jets

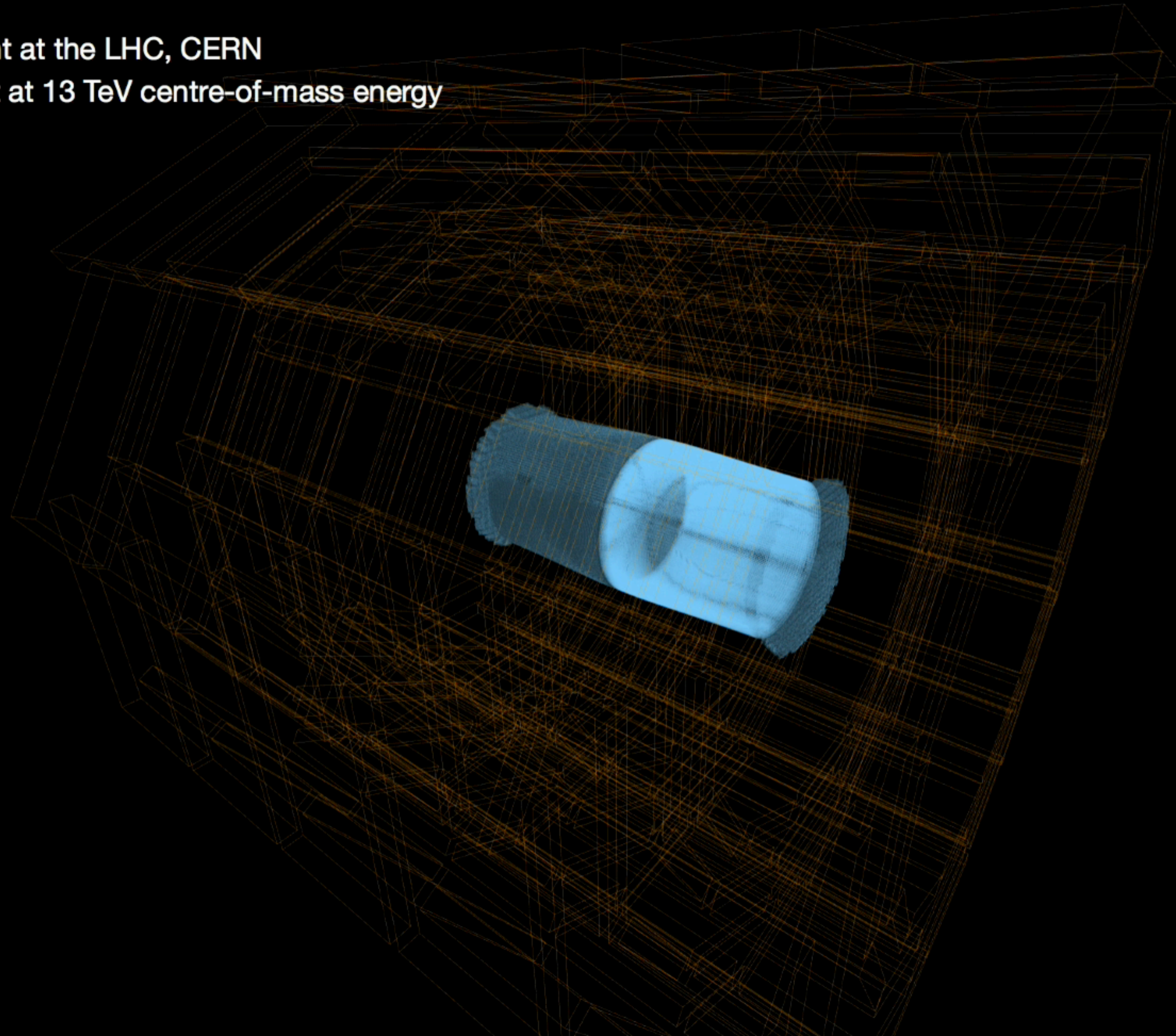


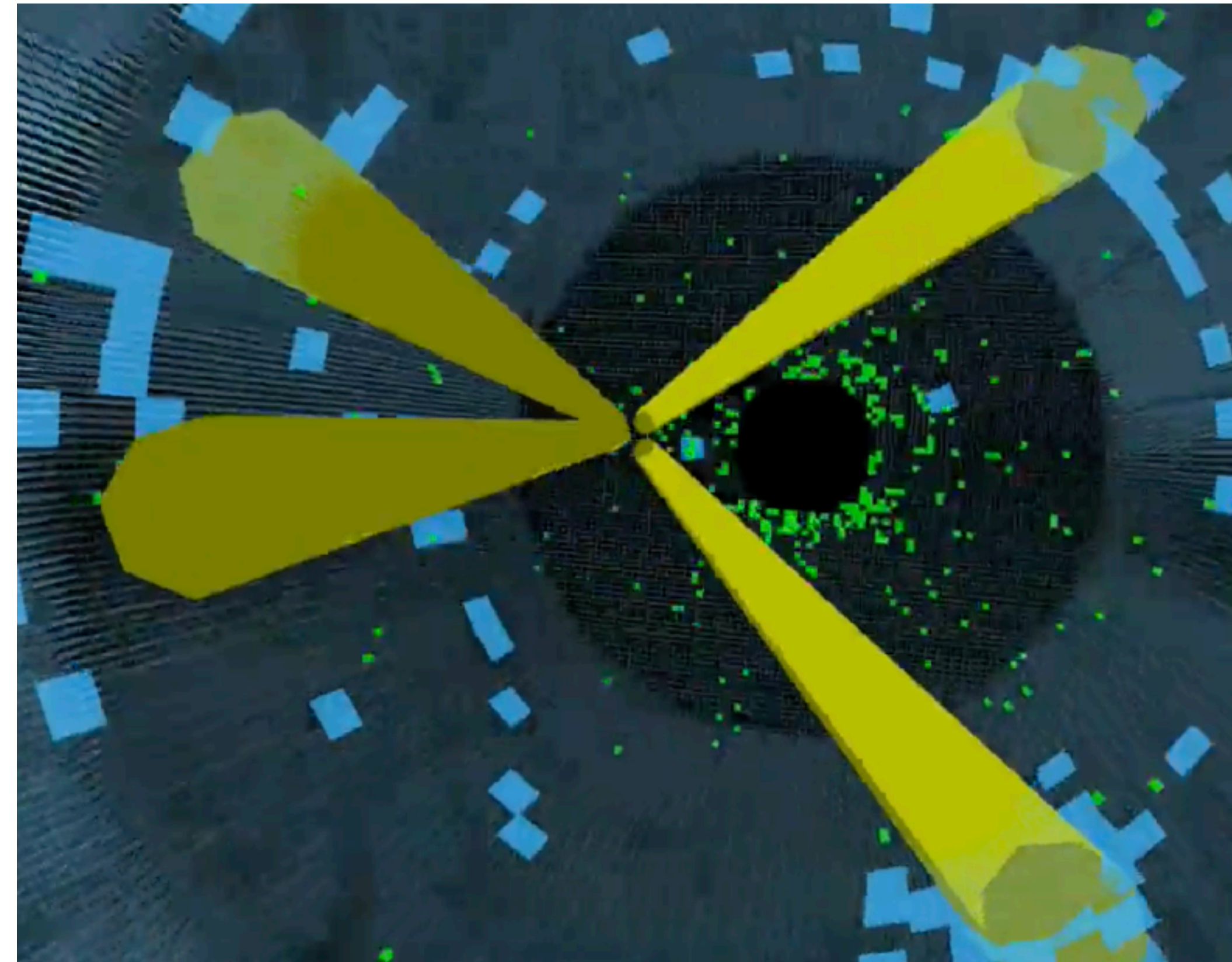
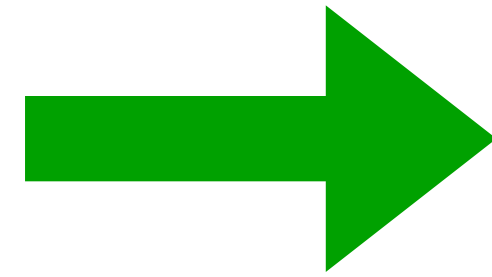
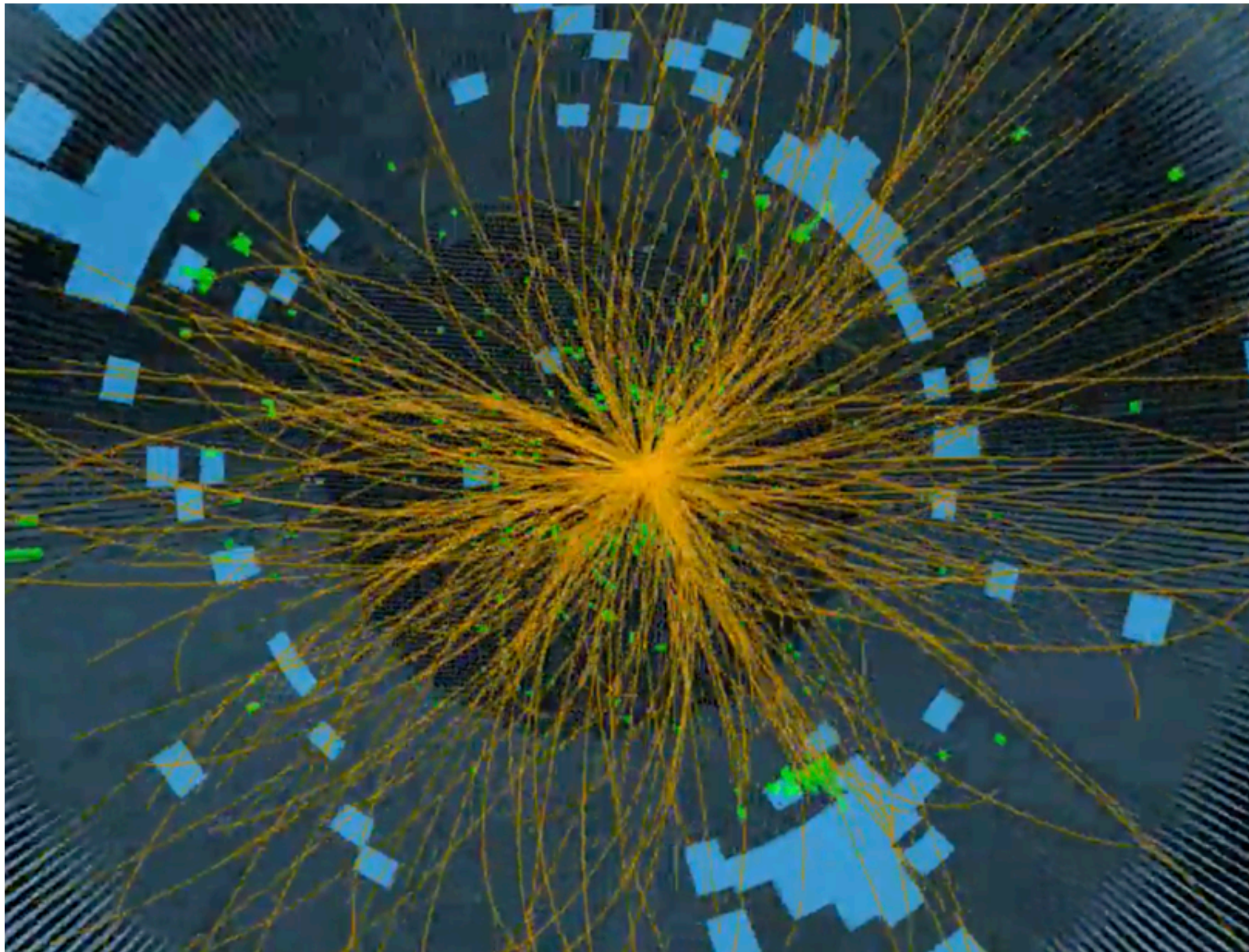
CMS Experiment at the LHC, CERN
Simulated event at 13 TeV centre-of-mass energy





CMS Experiment at the LHC, CERN
Simulated event at 13 TeV centre-of-mass energy

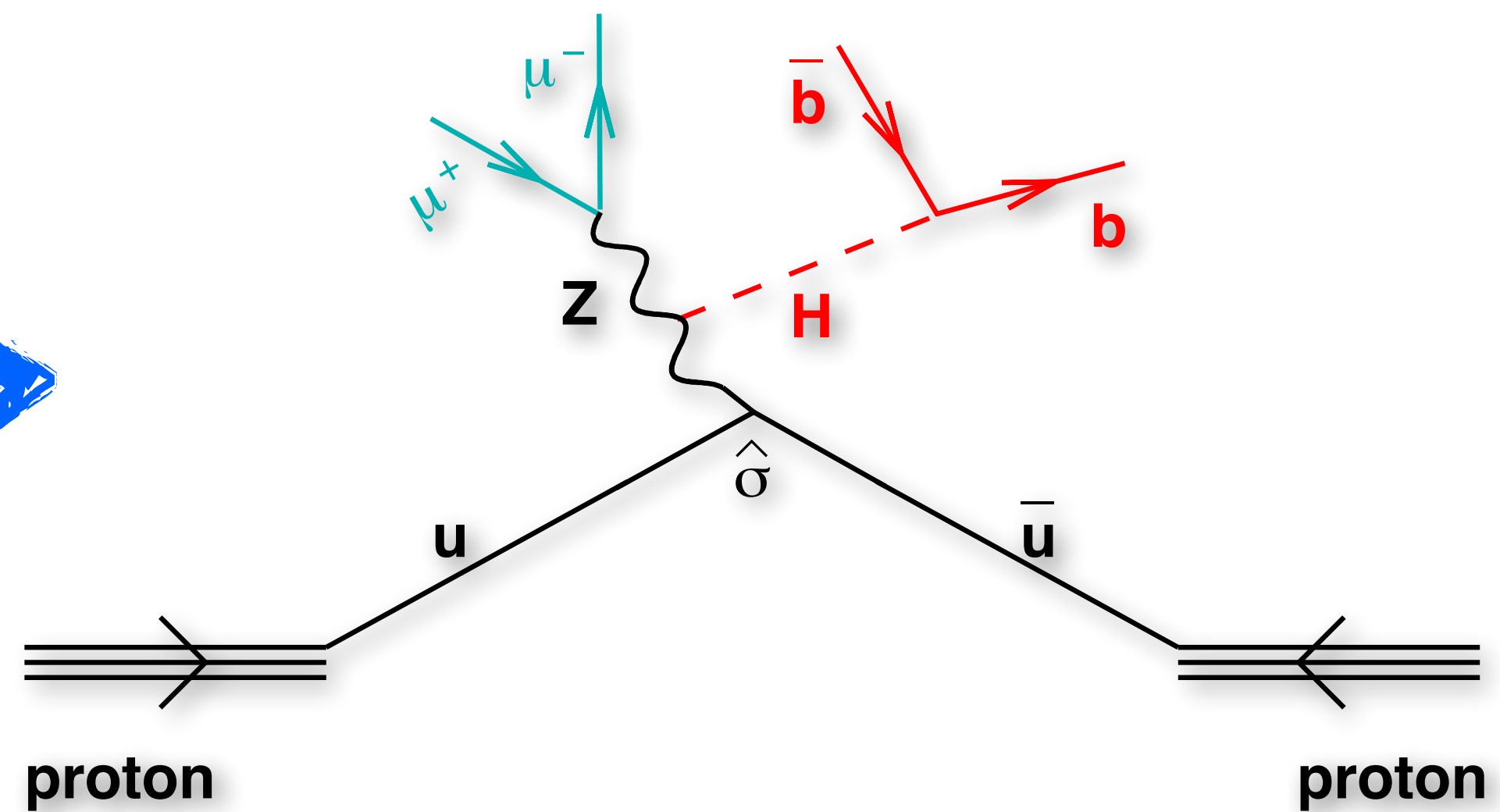
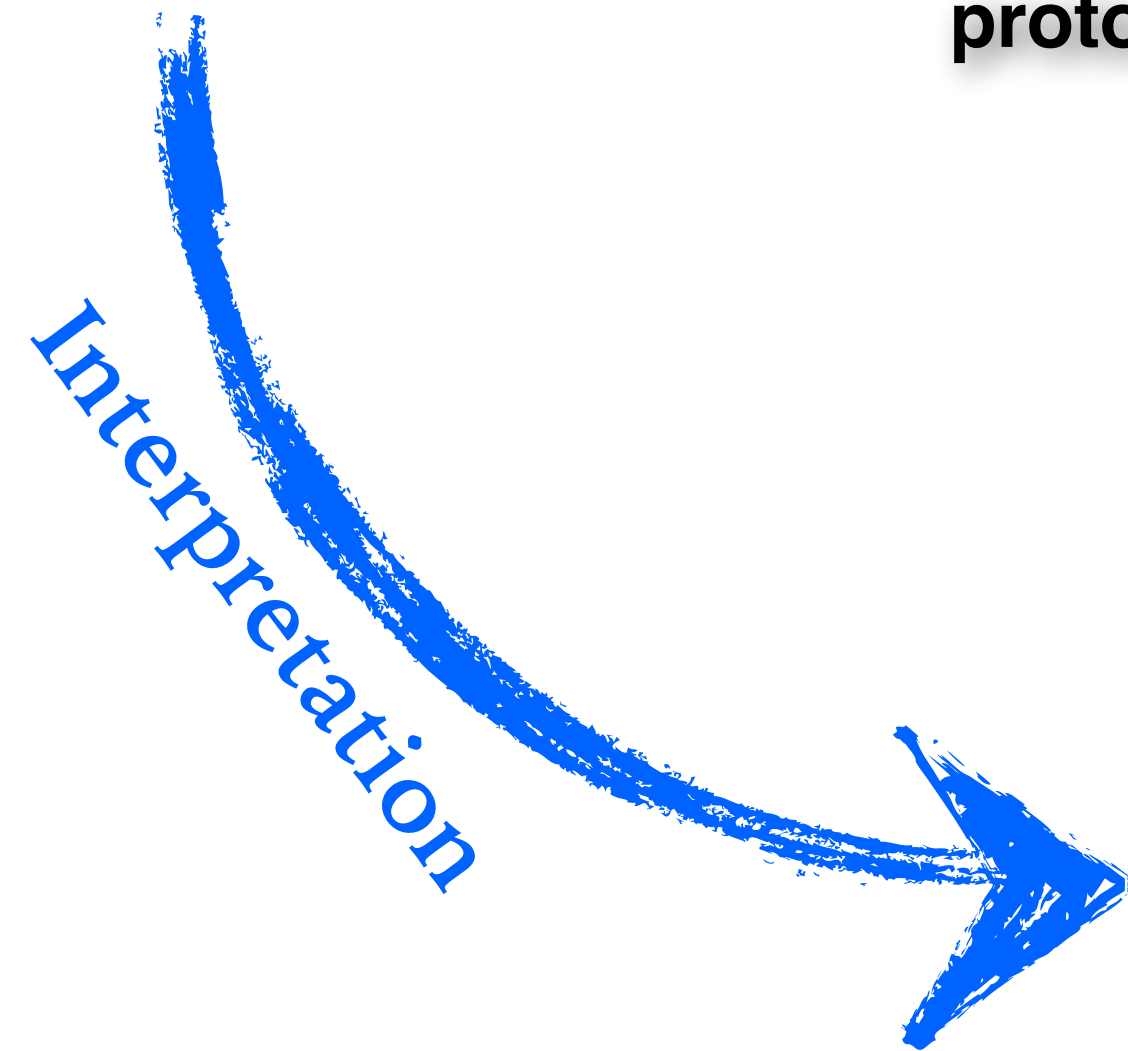
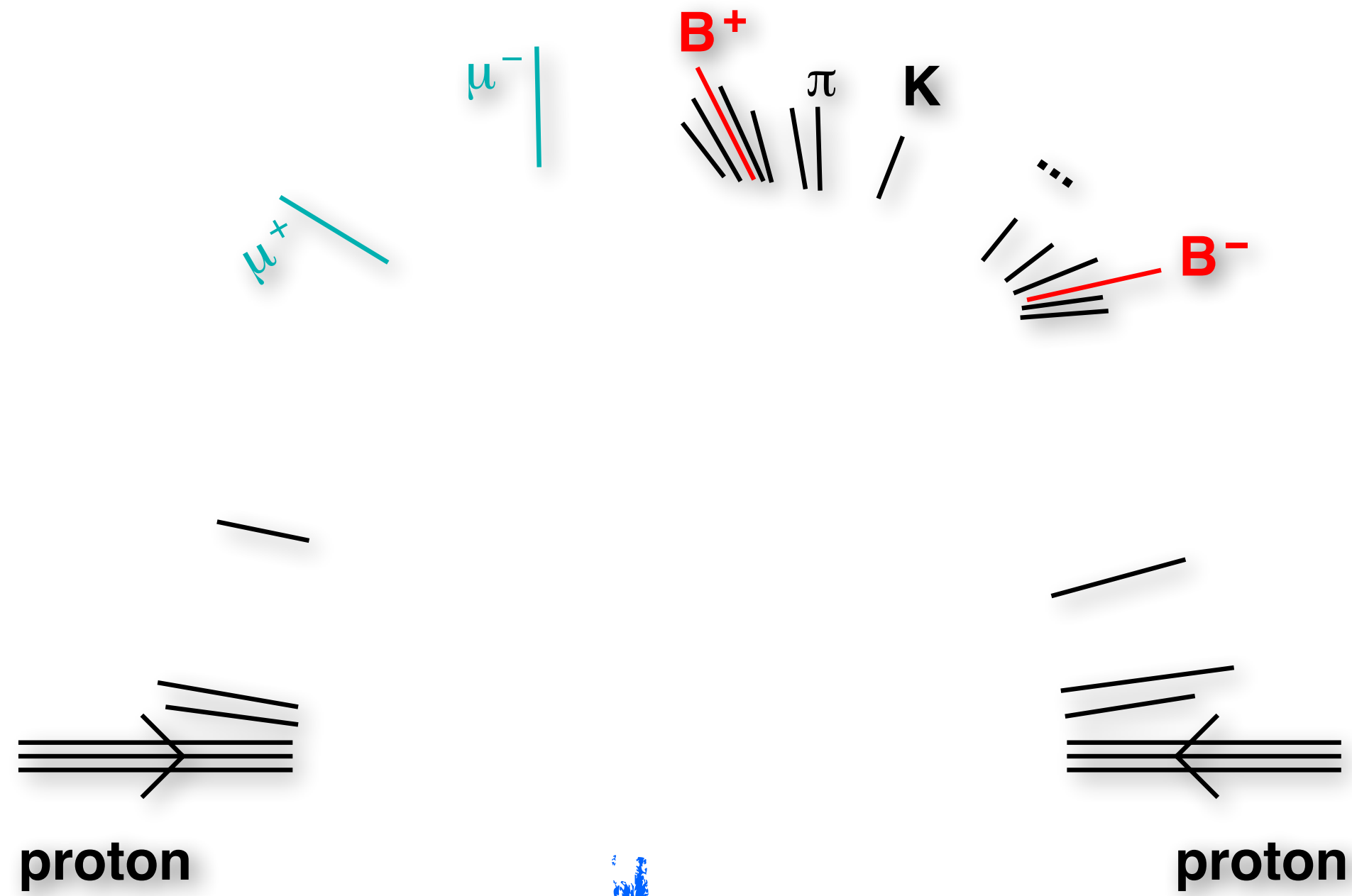




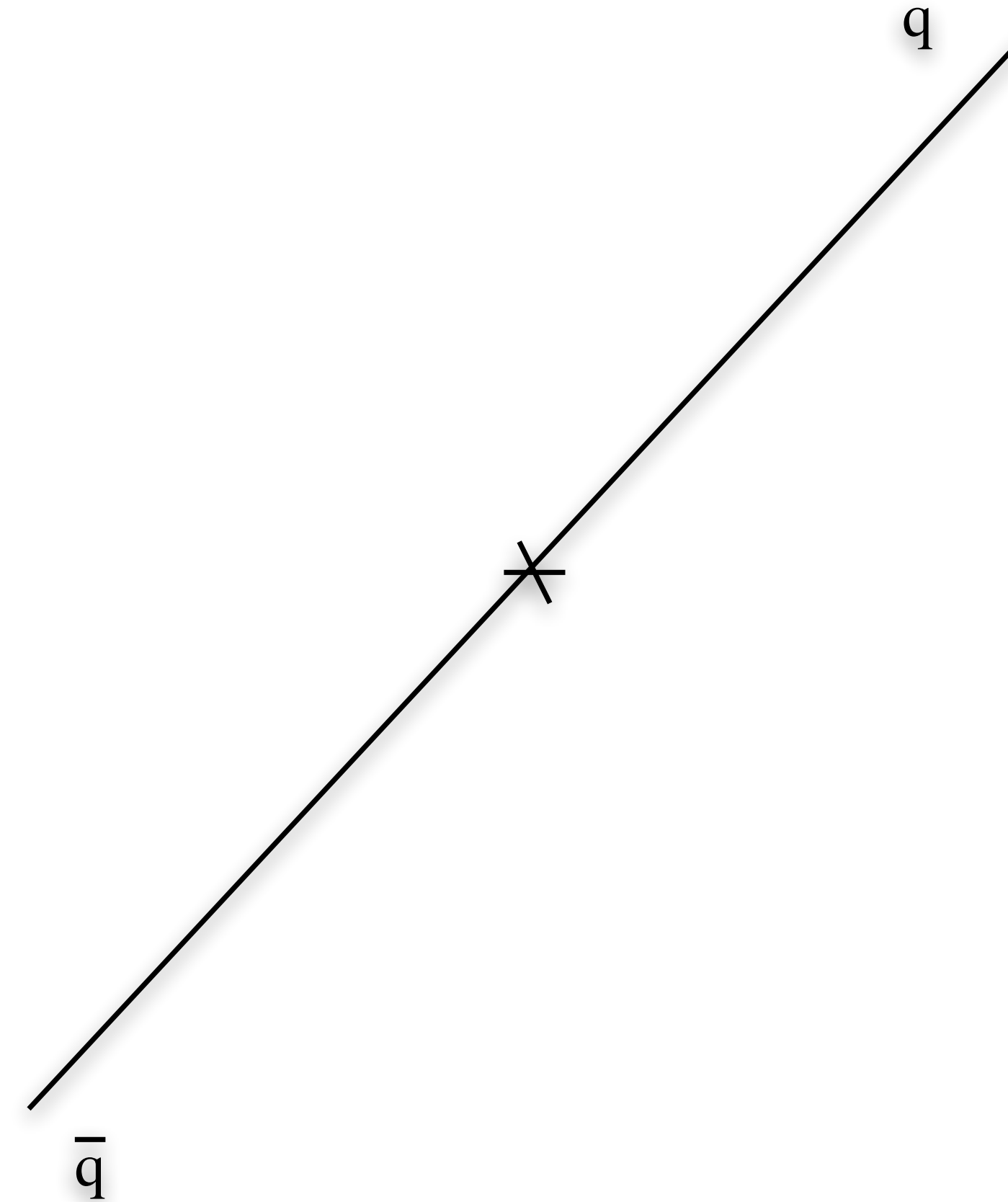
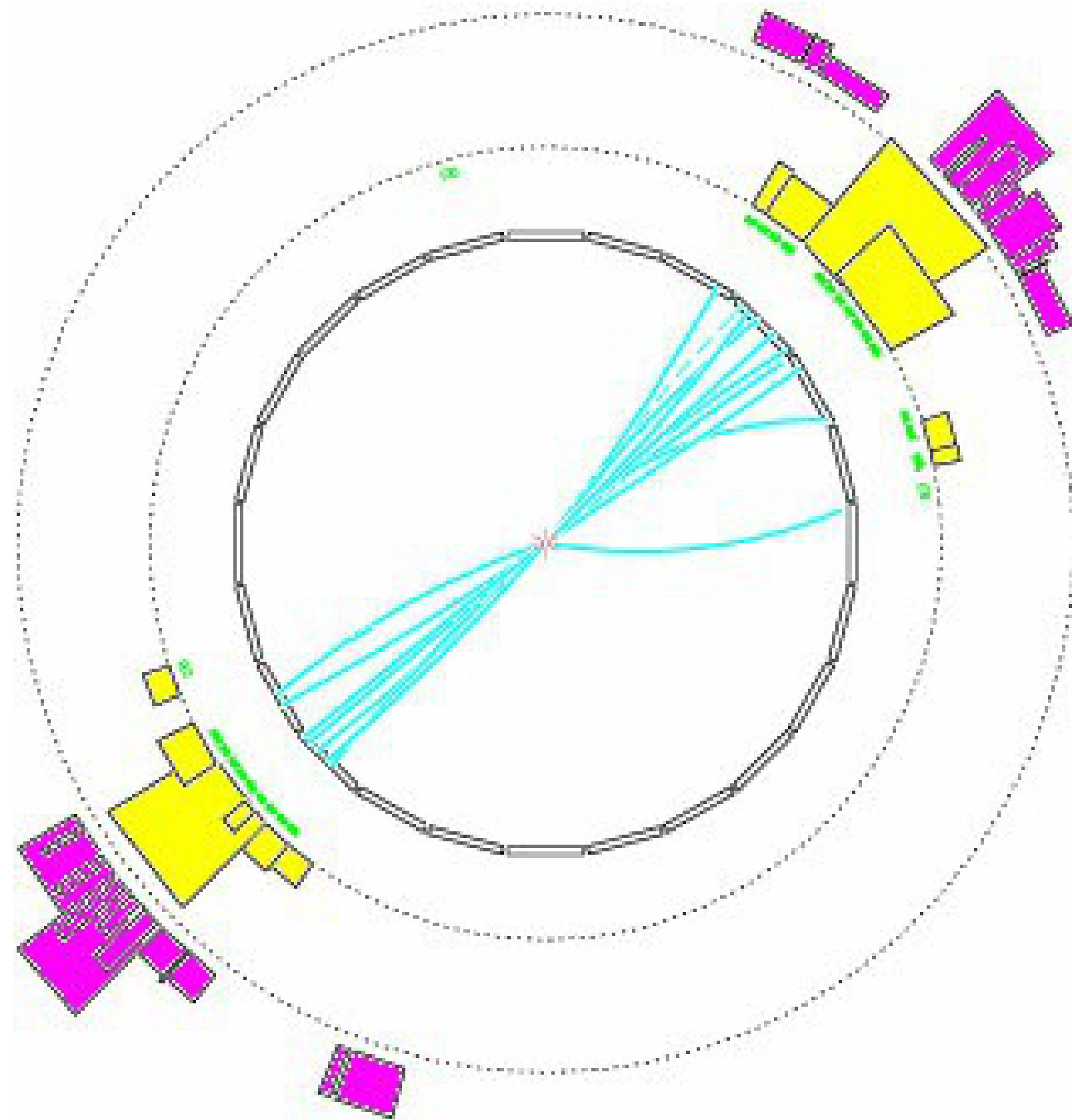
jets are about organizing the information from hundreds (or thousands) of particles into a form that we as humans can understand and process

jets

i.e. how we make sense of the hadronic part of events

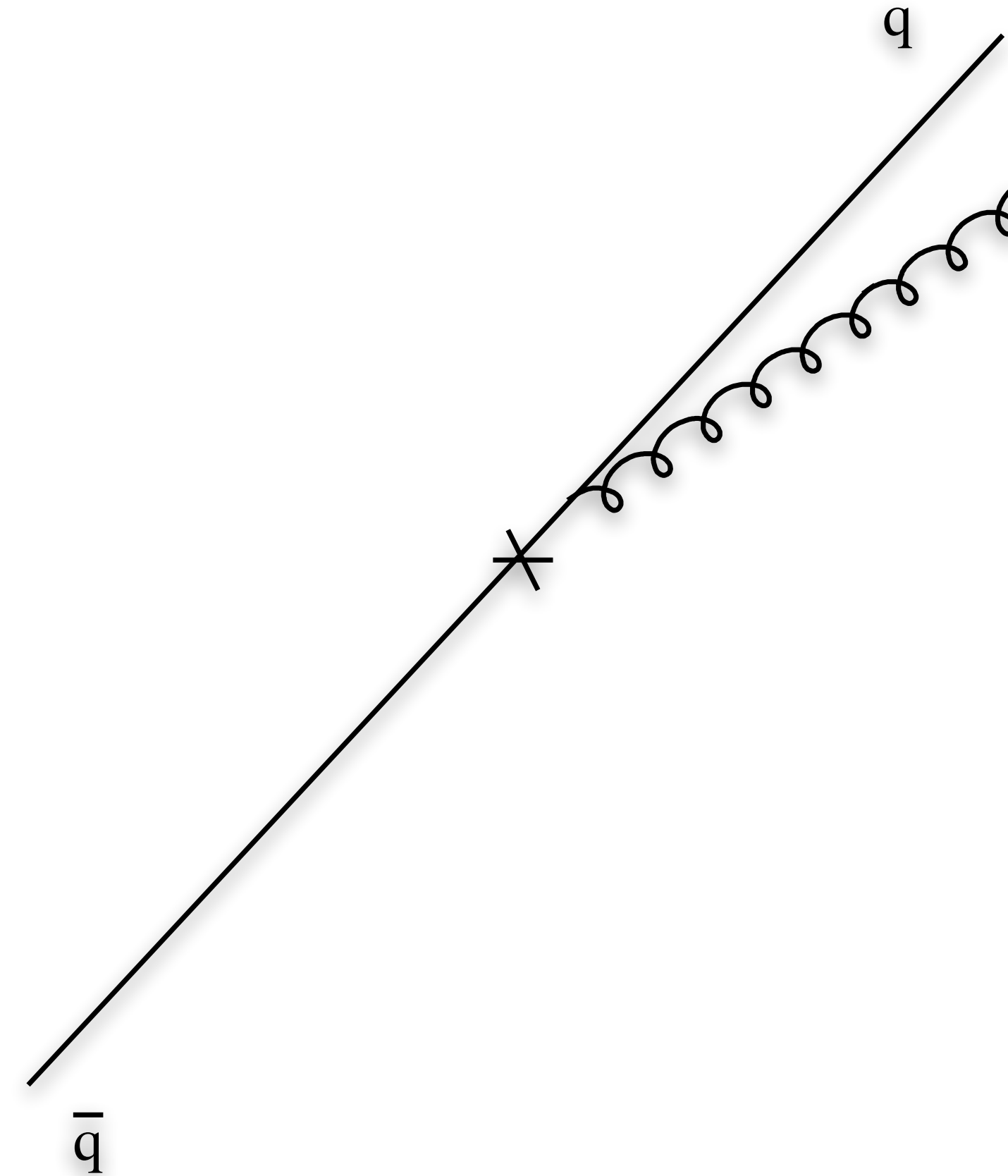
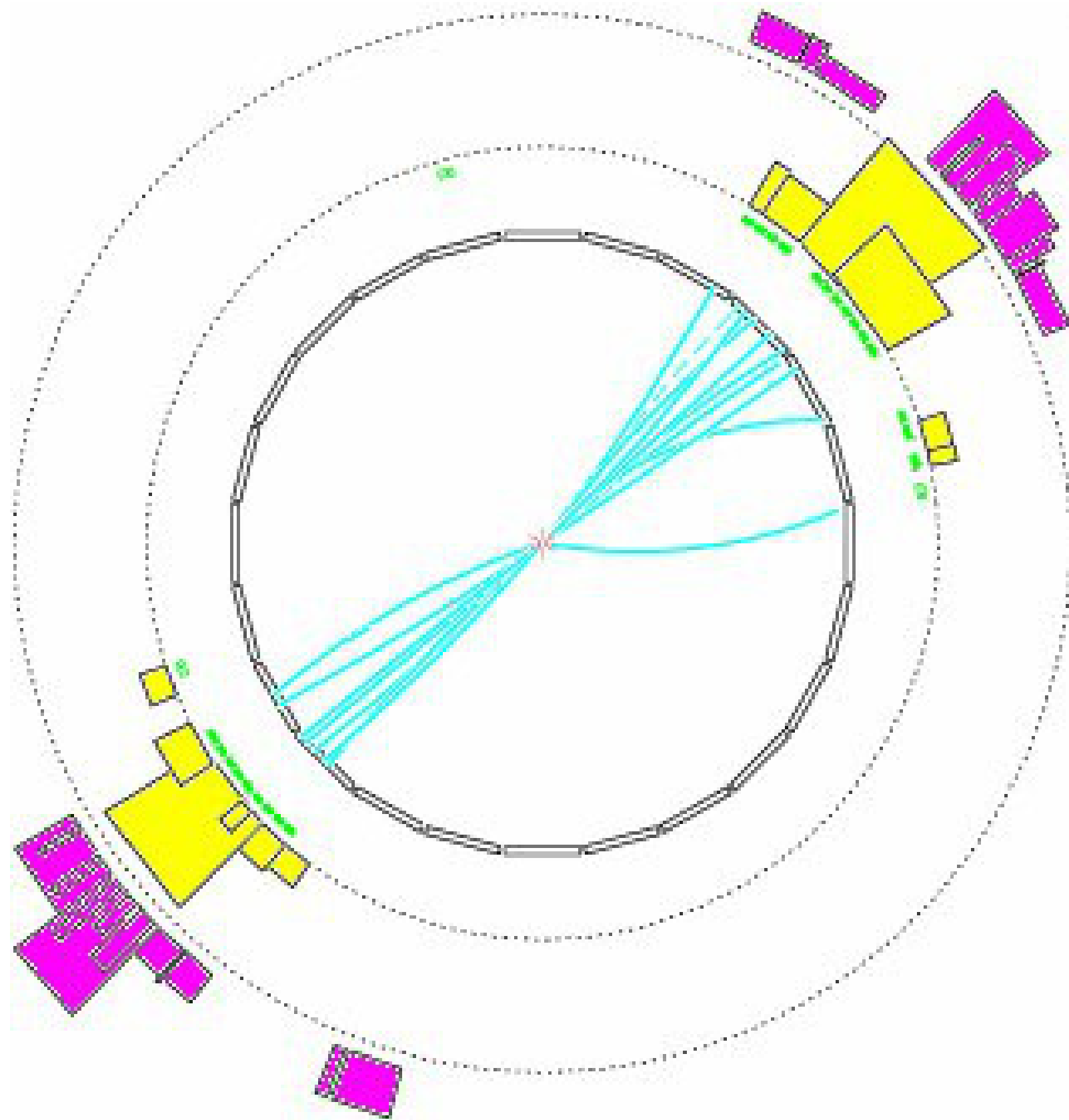


The Quantum-Chromodynamic (QCD) origin of jets



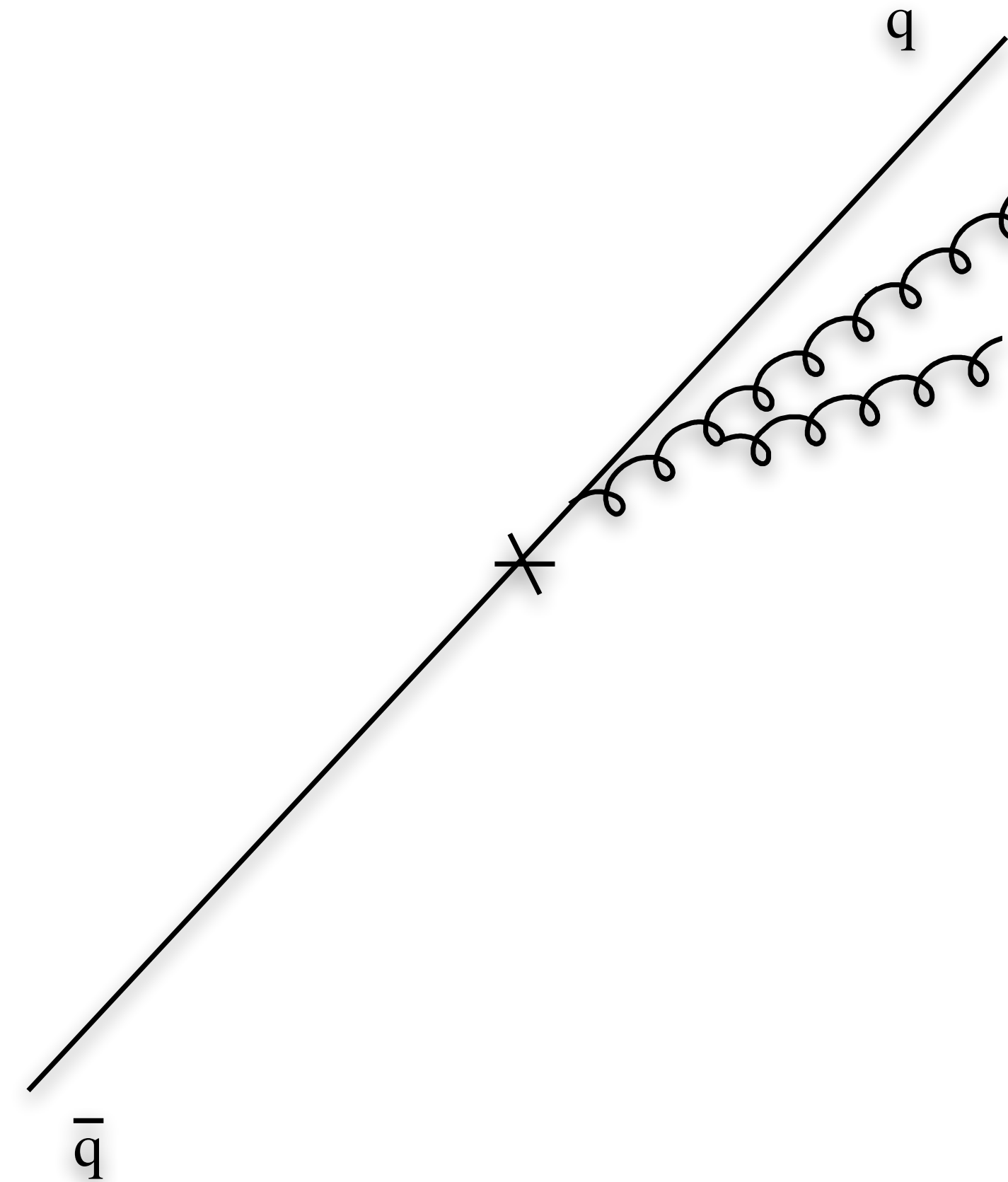
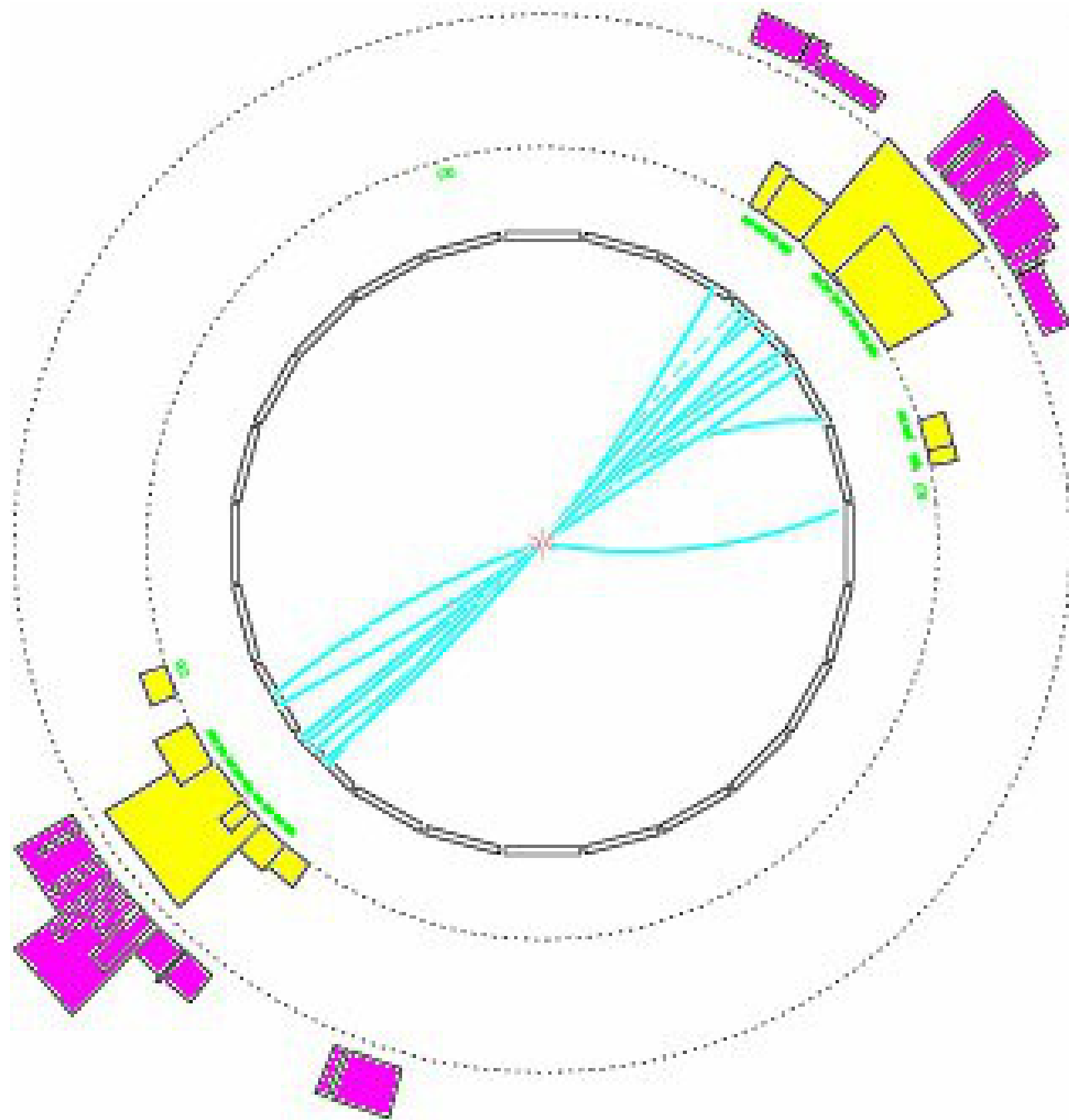
Start off with a $q\bar{q}$ system

A key QCD tool: jets



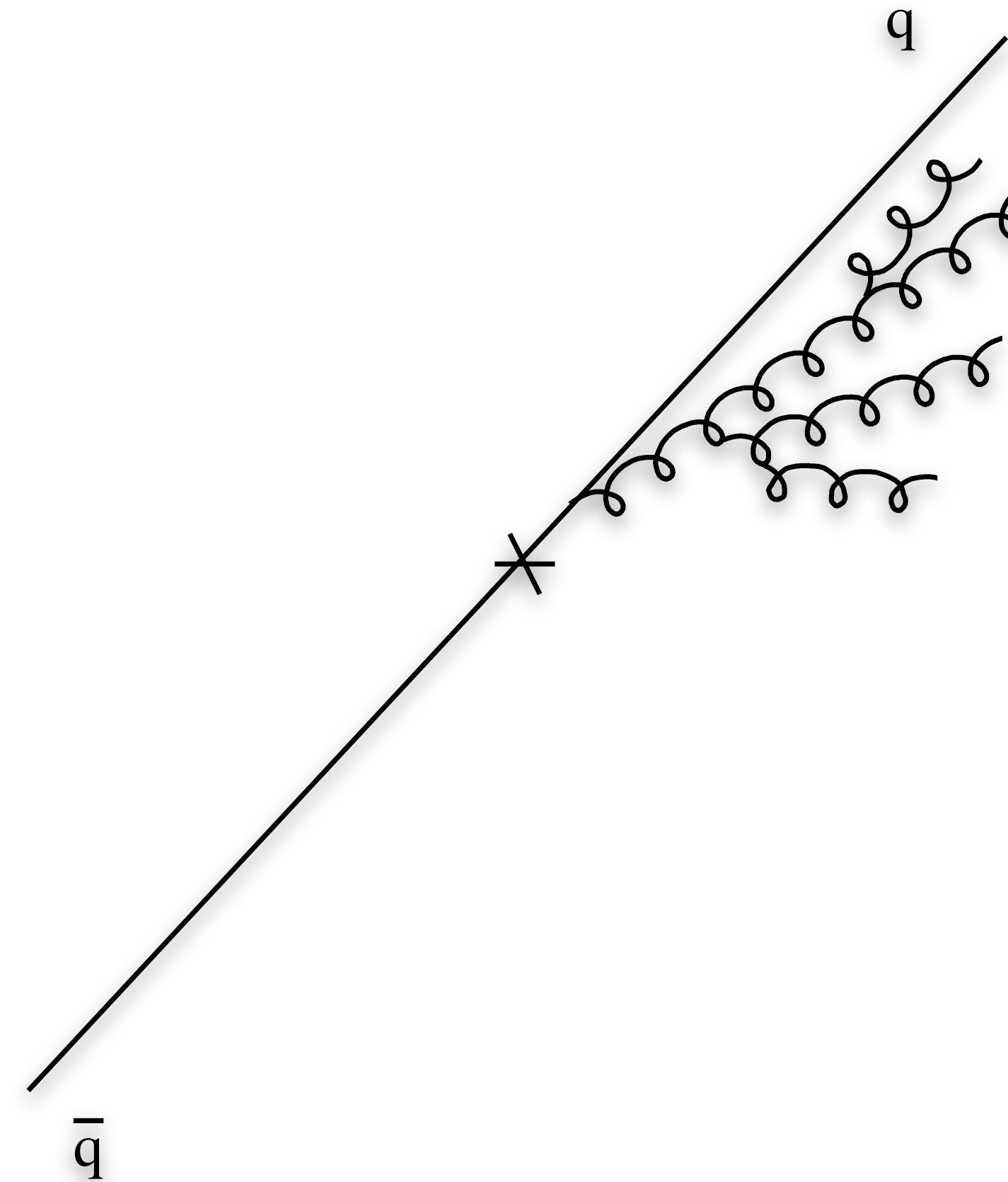
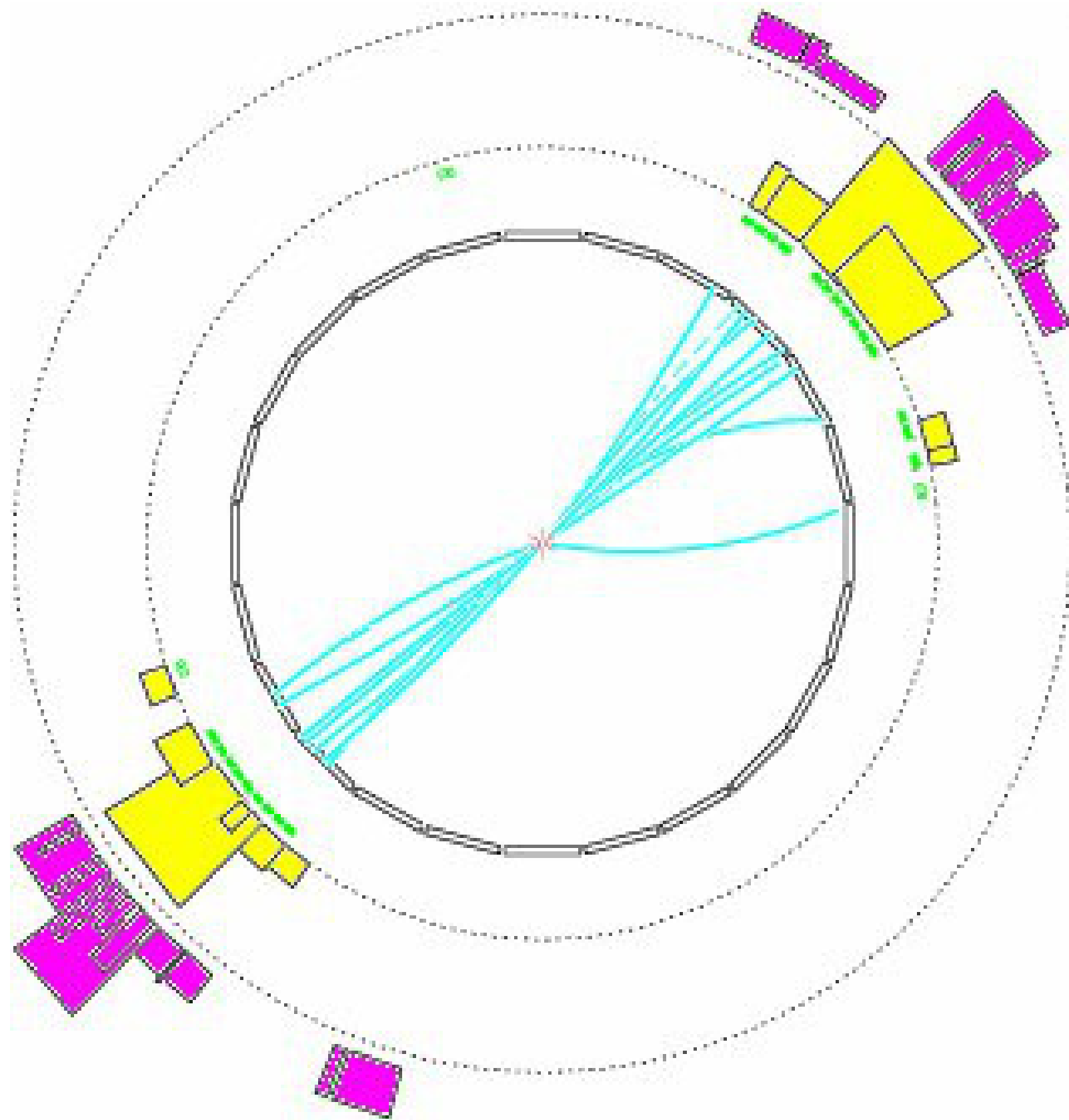
a gluon gets emitted at small angles

A key QCD tool: jets



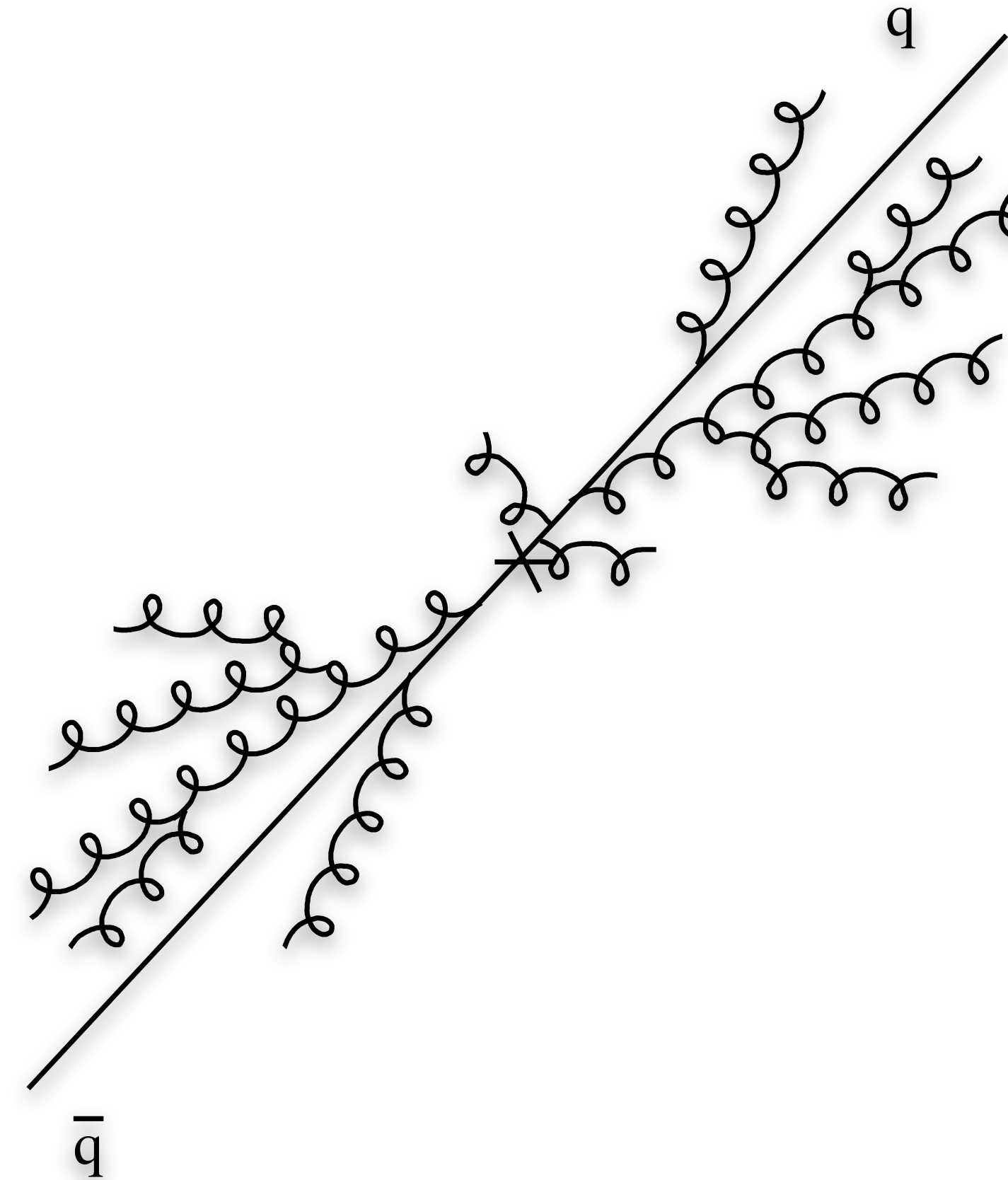
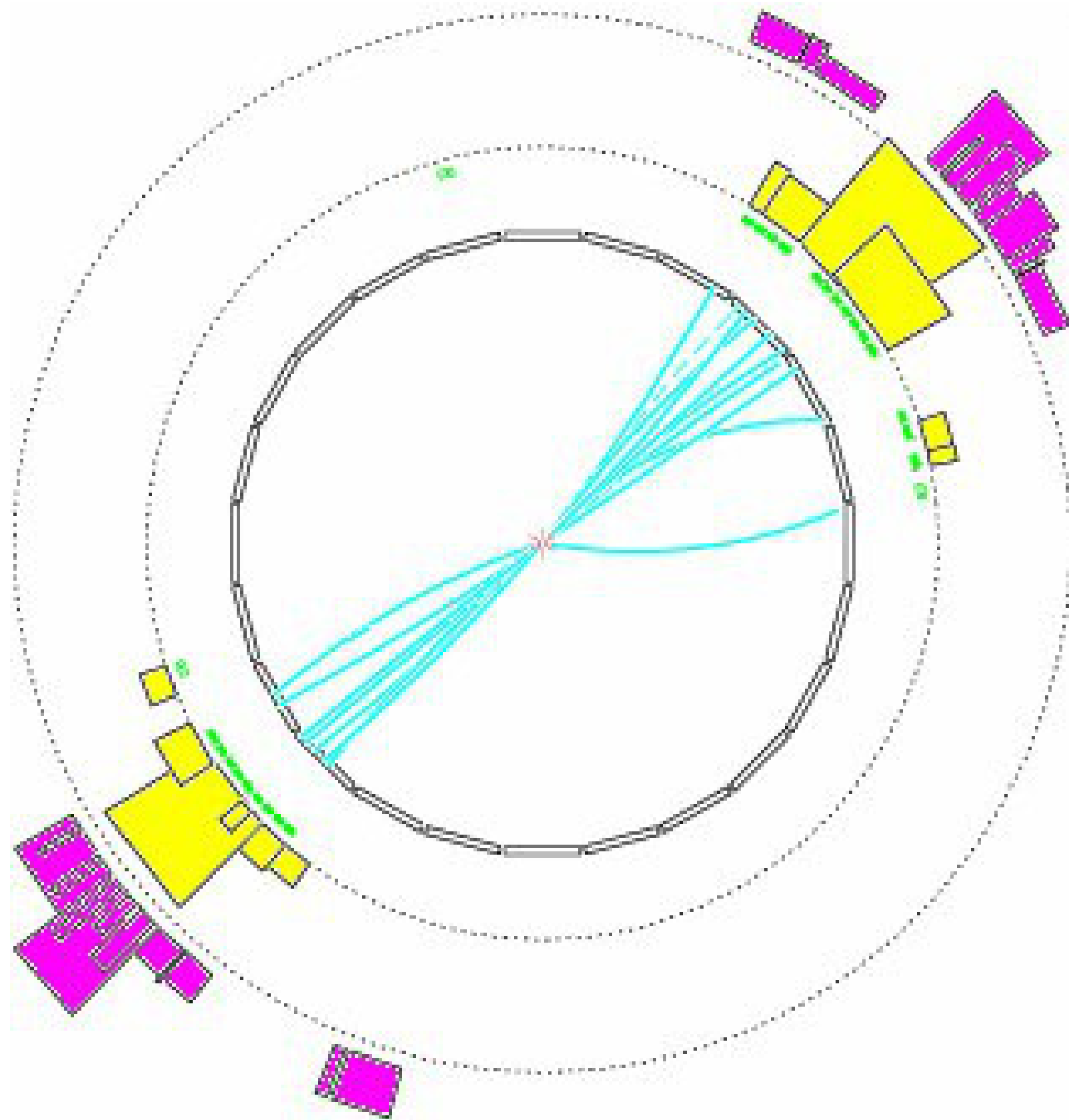
it radiates a further gluon

A key QCD tool: jets



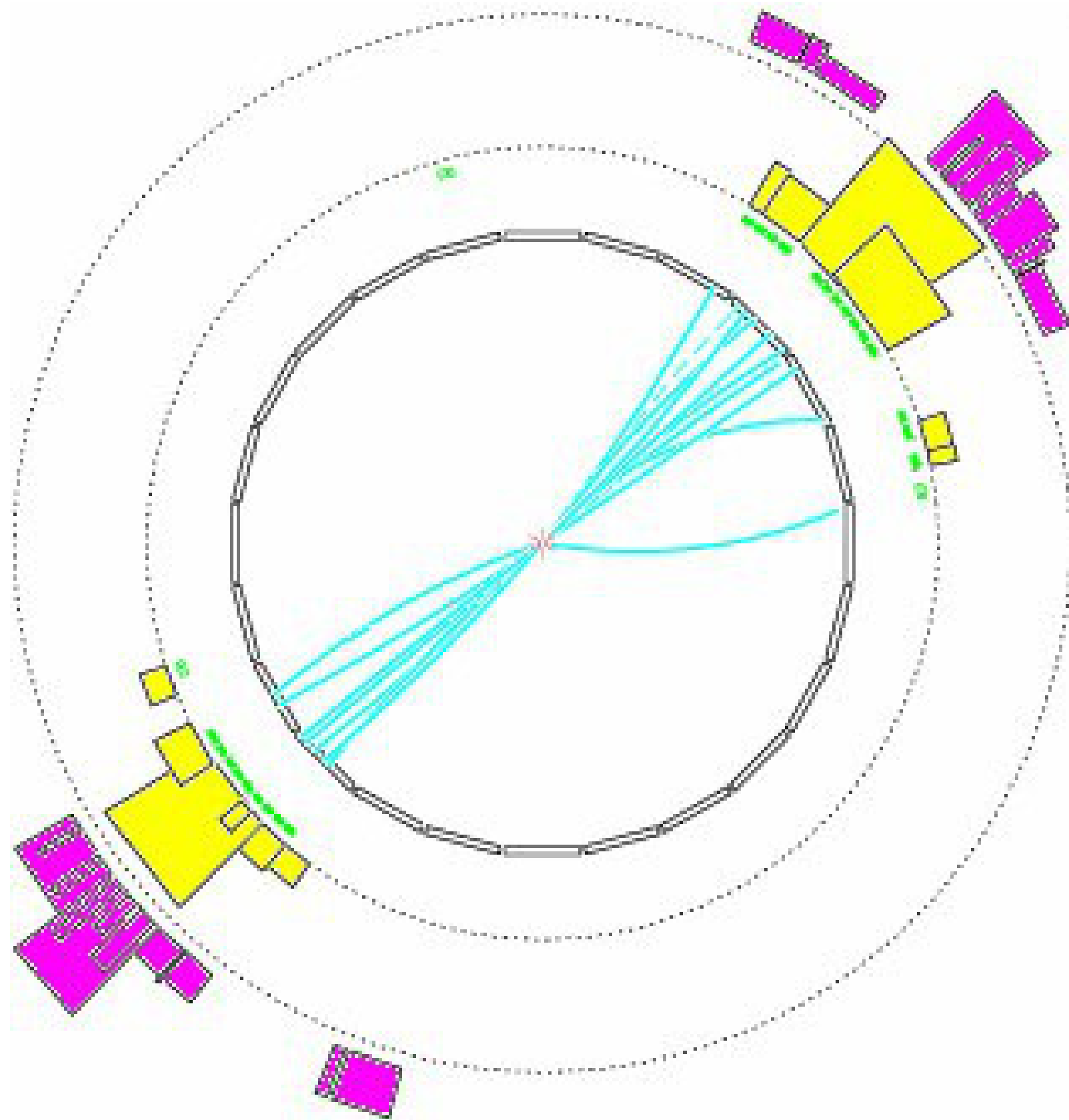
and so forth

A key QCD tool: jets



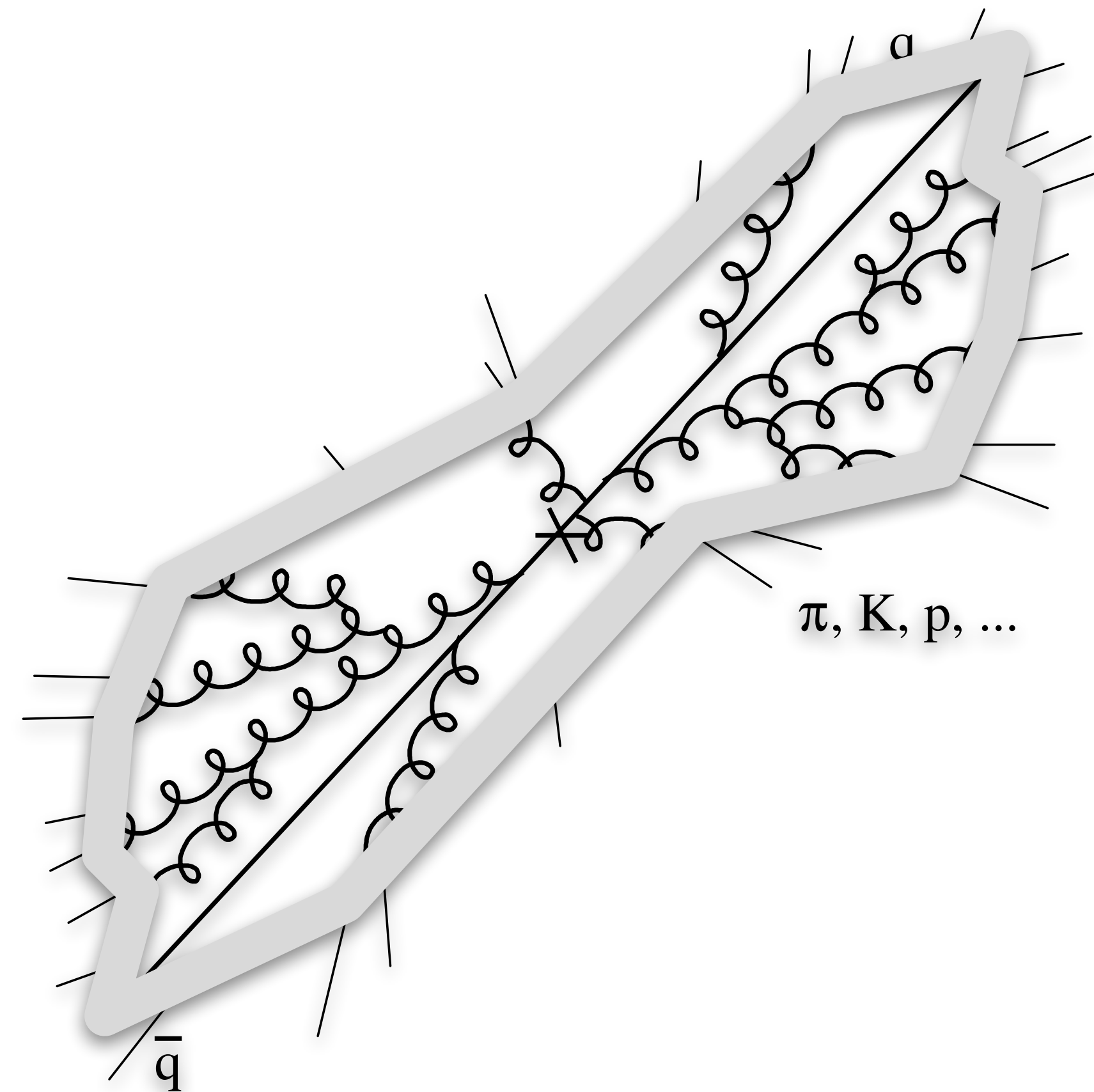
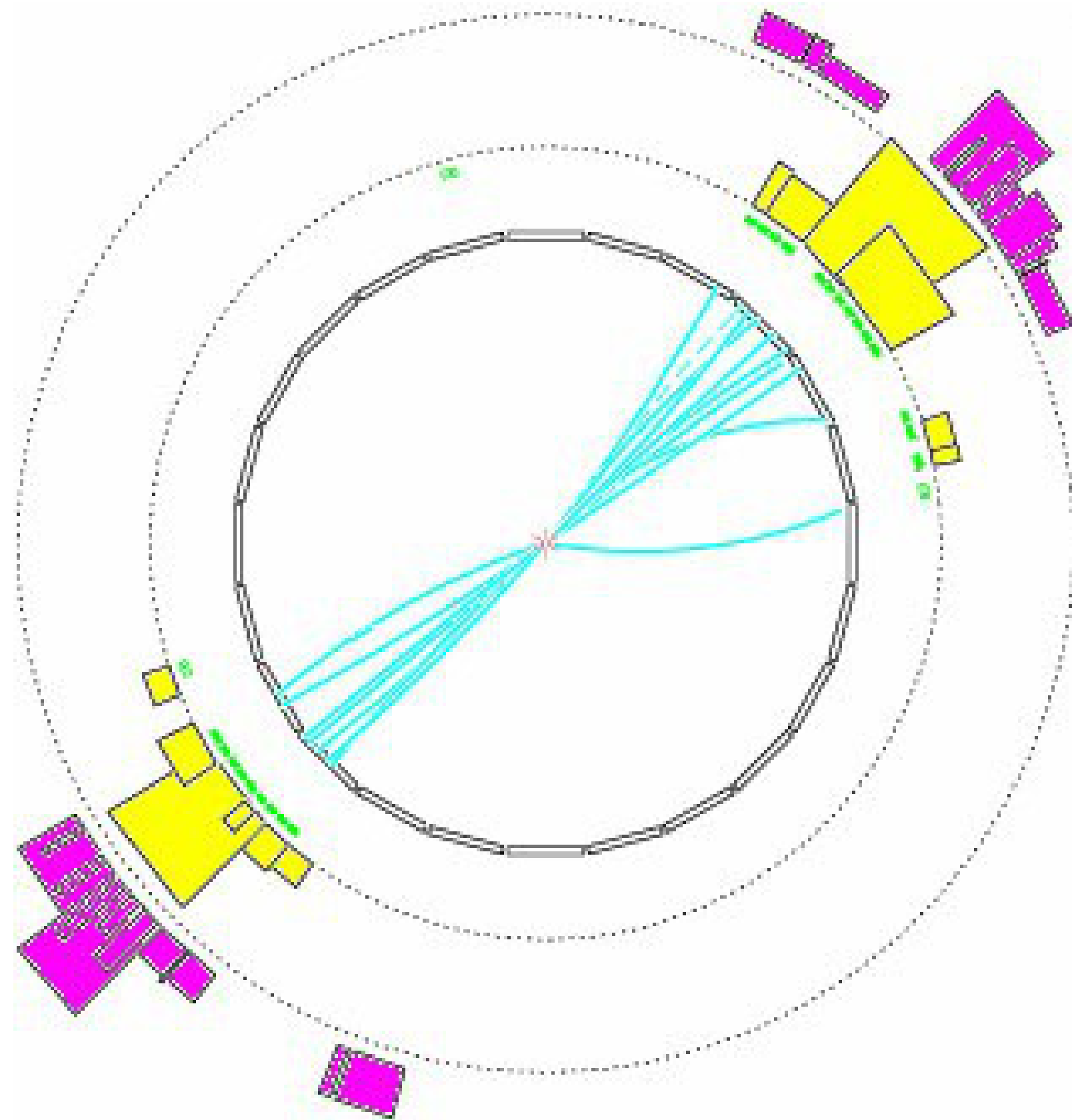
meanwhile the same happened on the other side

A key QCD tool: jets



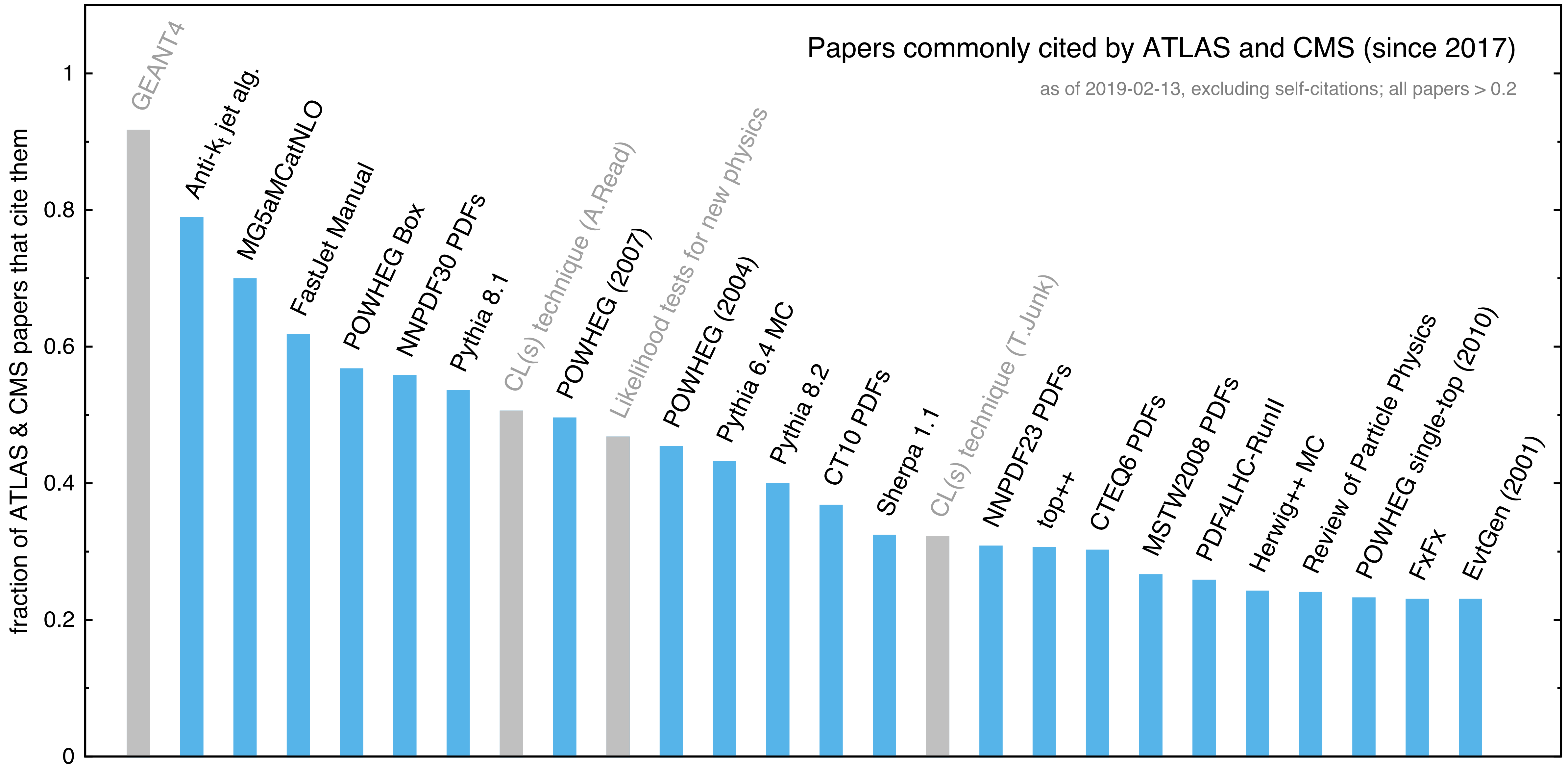
then a non-perturbative transition occurs

A key QCD tool: jets

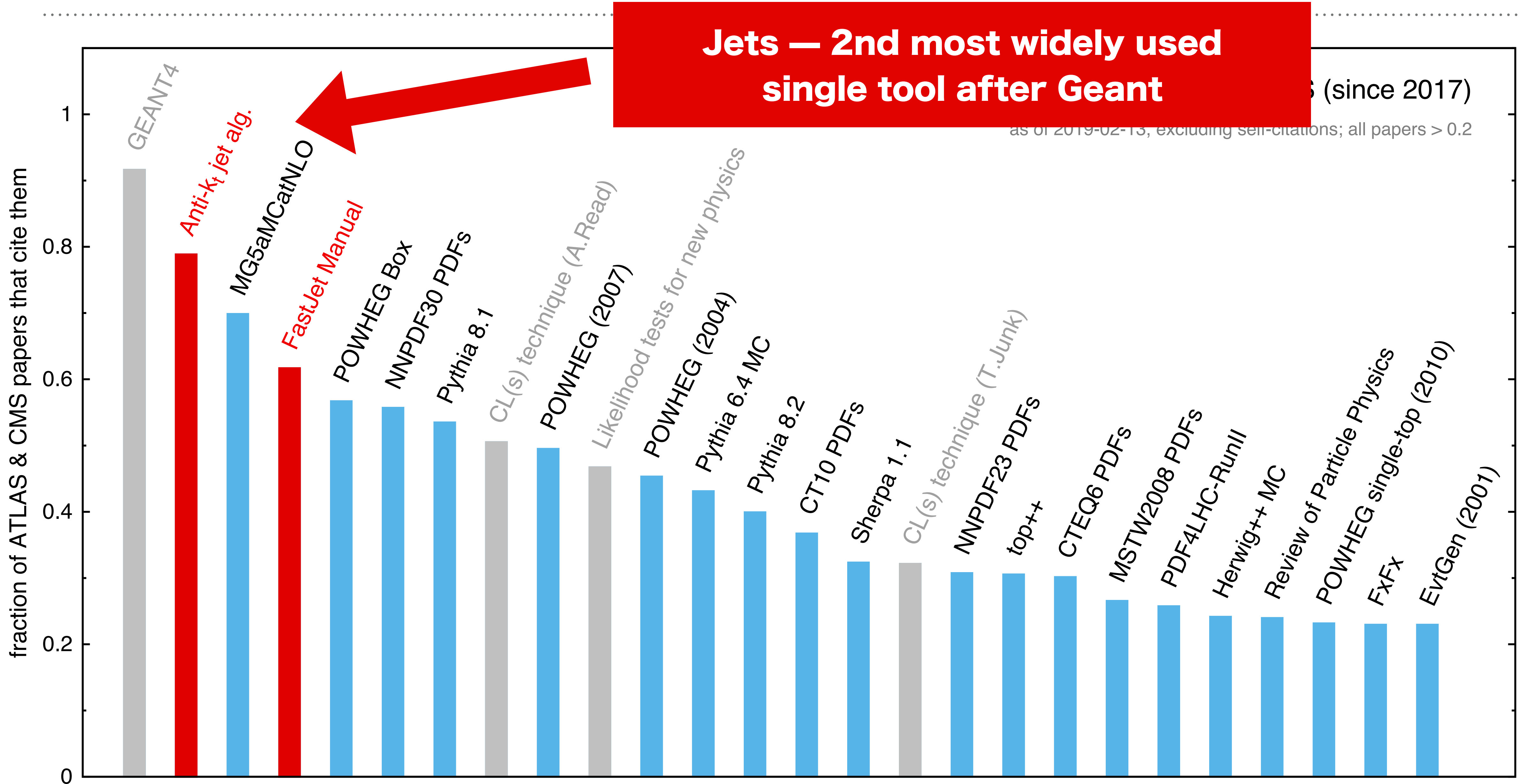


giving a pattern of hadrons that “remembers” the gluon branching
(hadrons mostly produced at small angles wrt $q\bar{q}$ directions — two “jets”)

The tools used by ATLAS & CMS



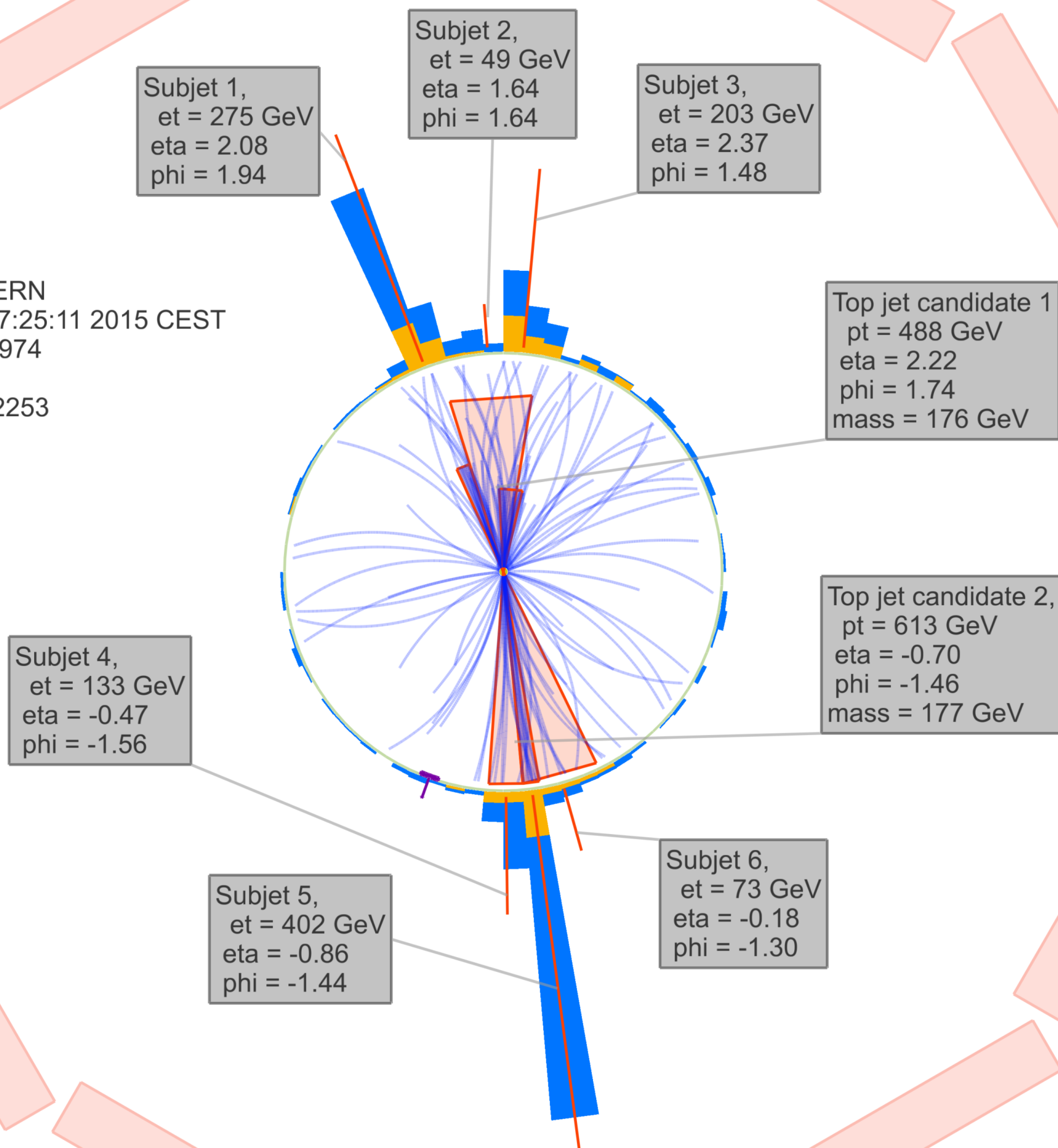
The tools used by ATLAS & CMS



Plot by GP Salam based on data from InspireHEP



CMS Experiment at LHC, CERN
Data recorded: Sun Jul 12 07:25:11 2015 CEST
Run/Event: 251562 / 111132974
Lumi section: 122
Orbit/Crossing: 31722792 / 2253

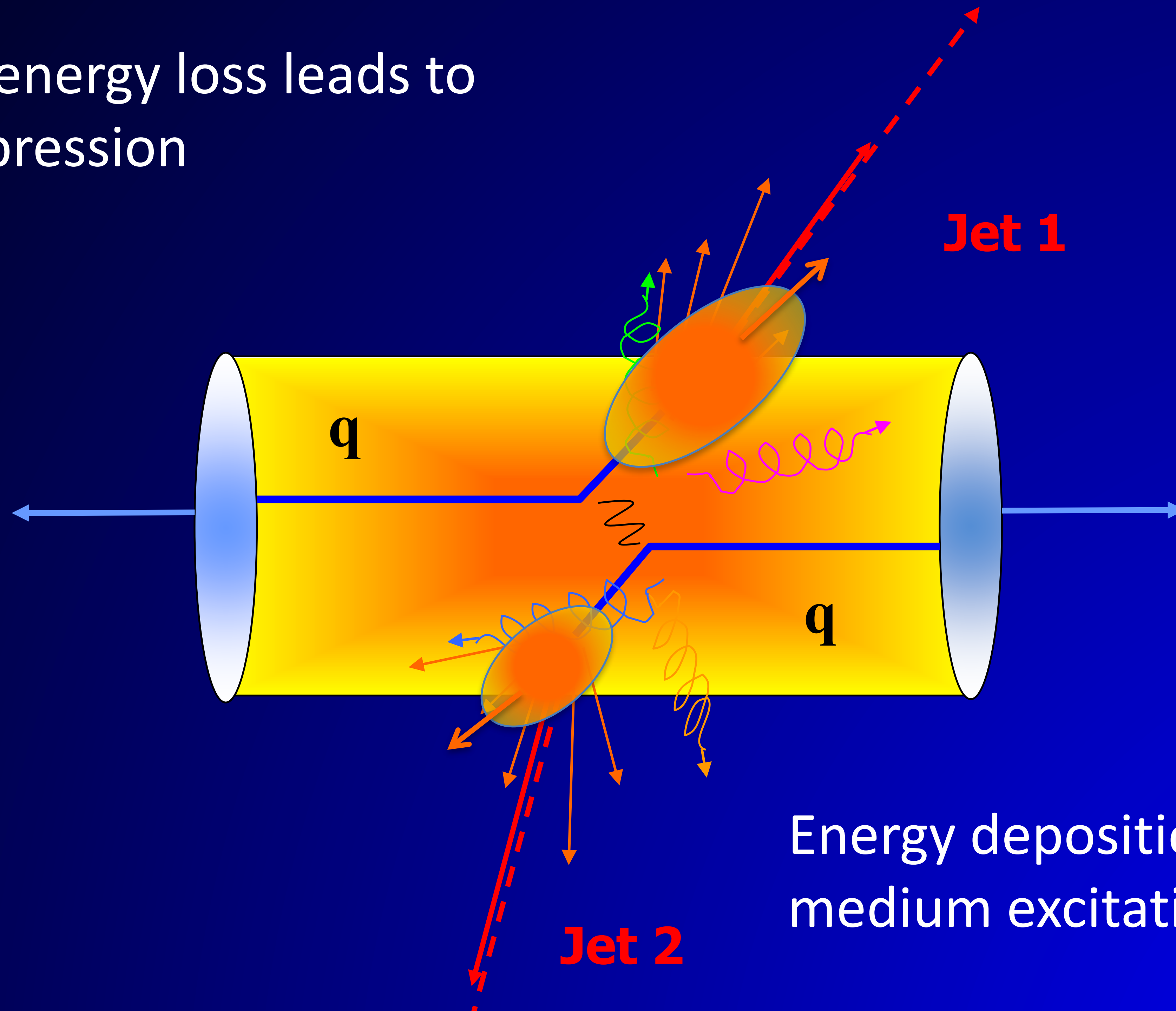


a pp collision that produces a high p_t top-antitop pair, resulting in two “top-jets”, each with subjets

Such events probe point-like nature of top quarks to TeV scale & allow you to search for new $t\bar{t}$ resonances

Parton energy loss leads to jet suppression

PbPb



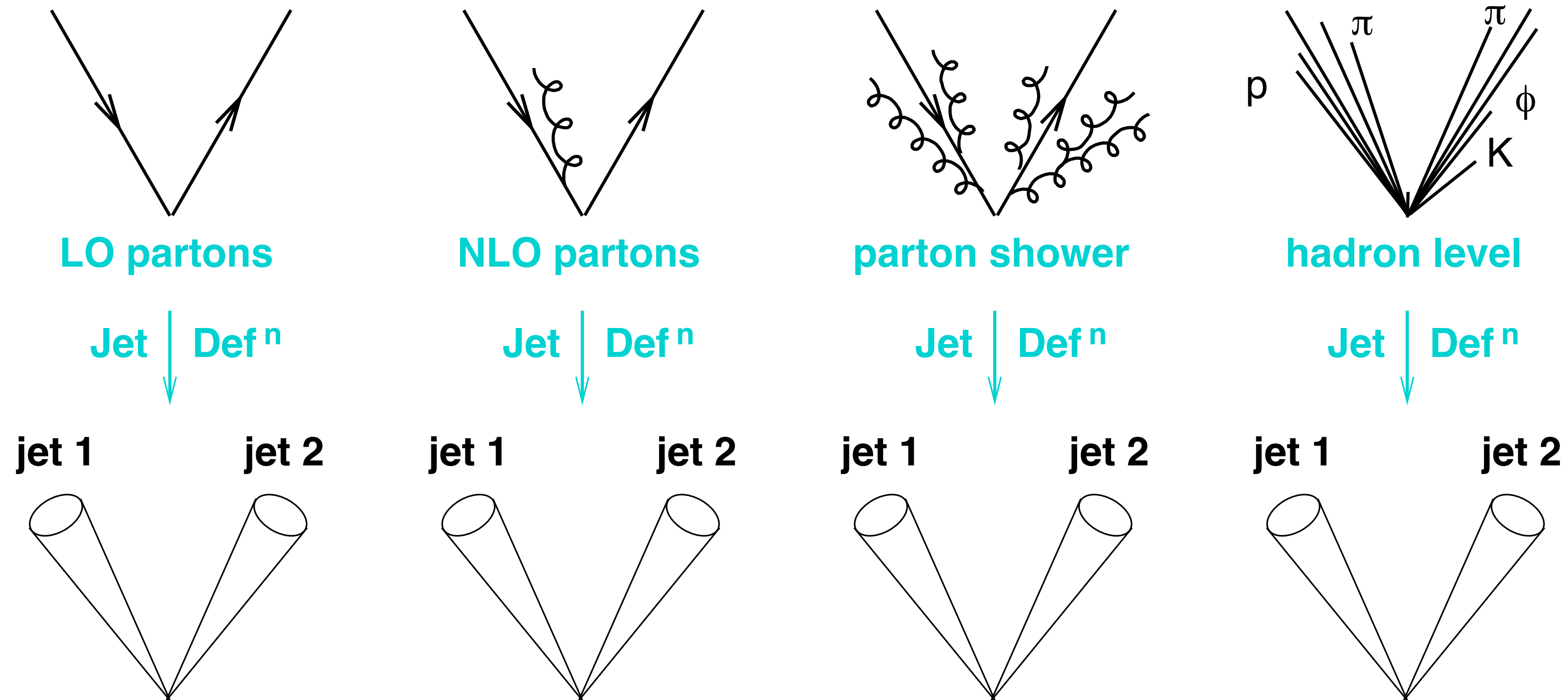
Jet 1

Jet 2

Energy deposition leads to medium excitation

jet substructure for pp

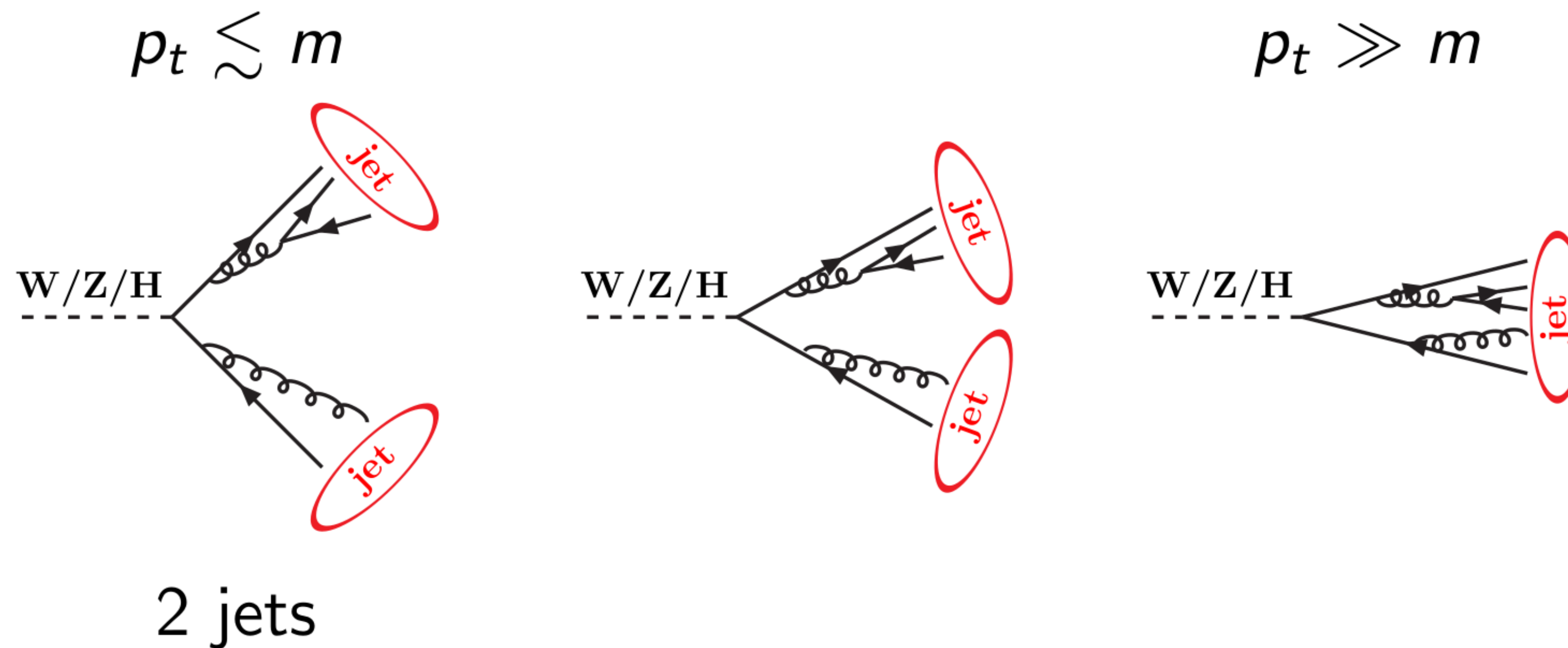
what should a jet definition achieve?



projection to jets should be resilient to QCD effects

Jet substructure for boosted hadronic W/Z/H/t etc. decays

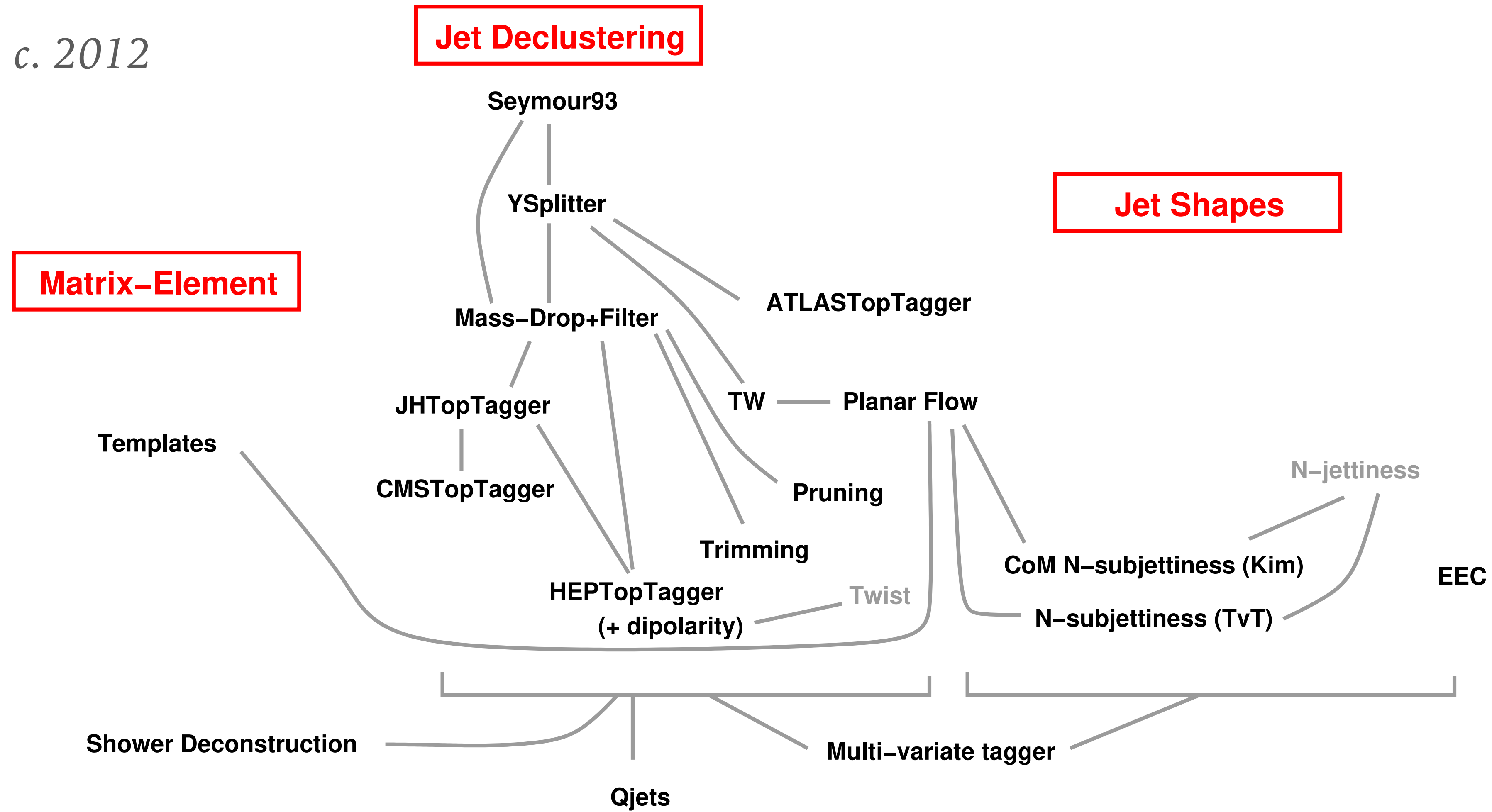
- ▶ At LHC energies, EW-scale particles (W/Z/t...) are often produced with $p_t \gg m$, leading to **collimated decays**.
- ▶ Hadronic decay products are thus often **reconstructed into single jets**.



[Figure by G. Soyez]

pp jet substructure field is full of activity

c. 2012



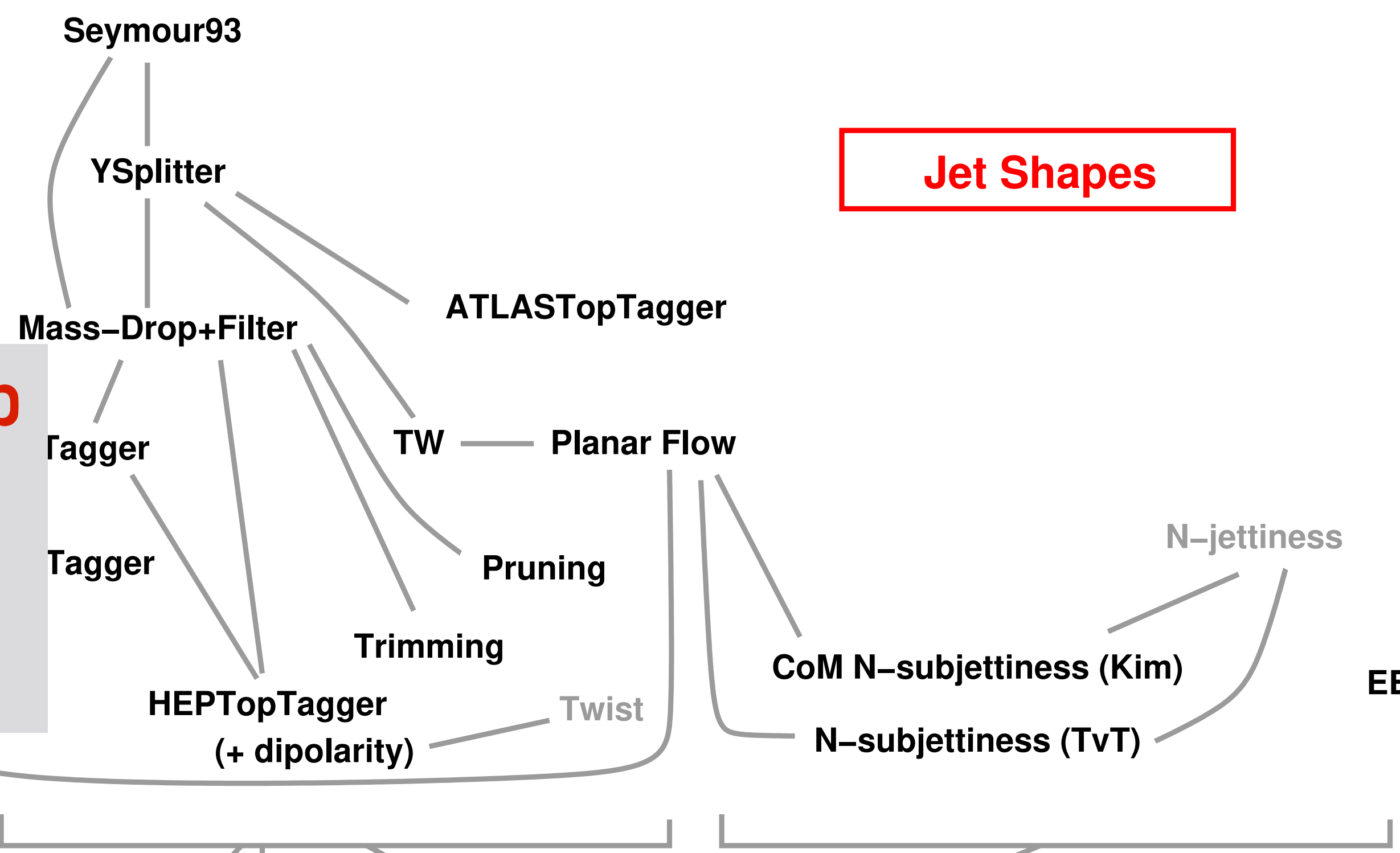
pp jet substructure field is full of activity

c. 2018

Jet Declustering

Matrix-Element

modified mass drop
soft drop
iterated soft drop
recursive soft drop



Jet Shapes

Degree	Connected Multigraphs
$d = 0$	
$d = 1$	
$d = 2$	
$d = 3$	
$d = 4$	
$d = 5$	

$C_n, D_n, v e_n^{(\beta)}, M_n, N_n, U_n, EFPs$

EEC

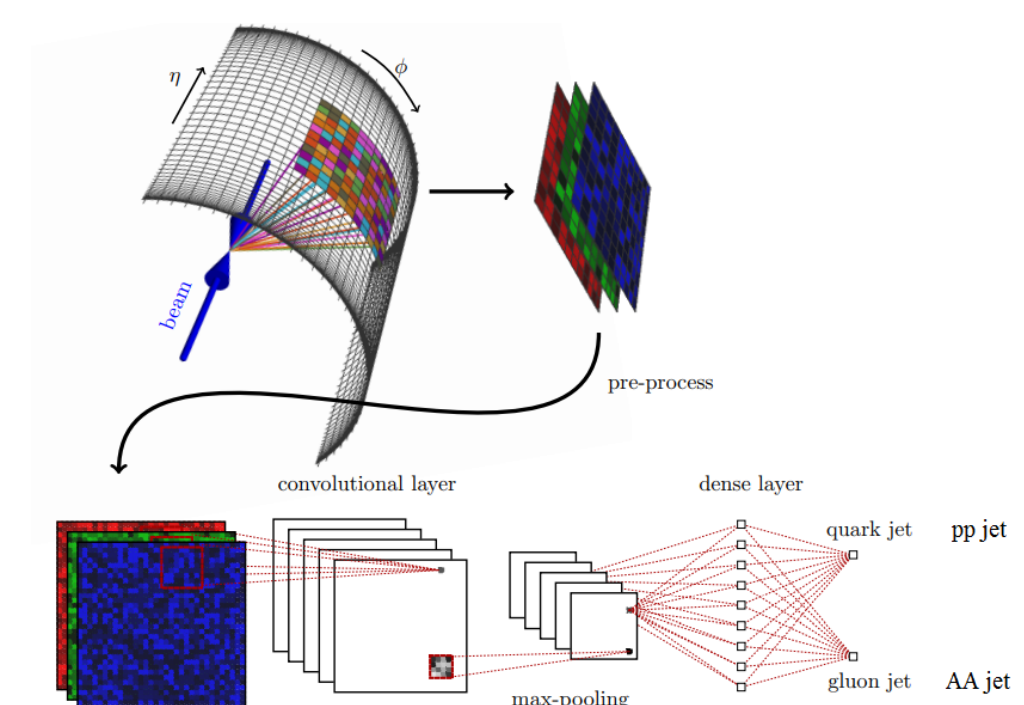
Shower Deconstruction

Qjets

Multi-variate tagger

classification without labels
weak supervision

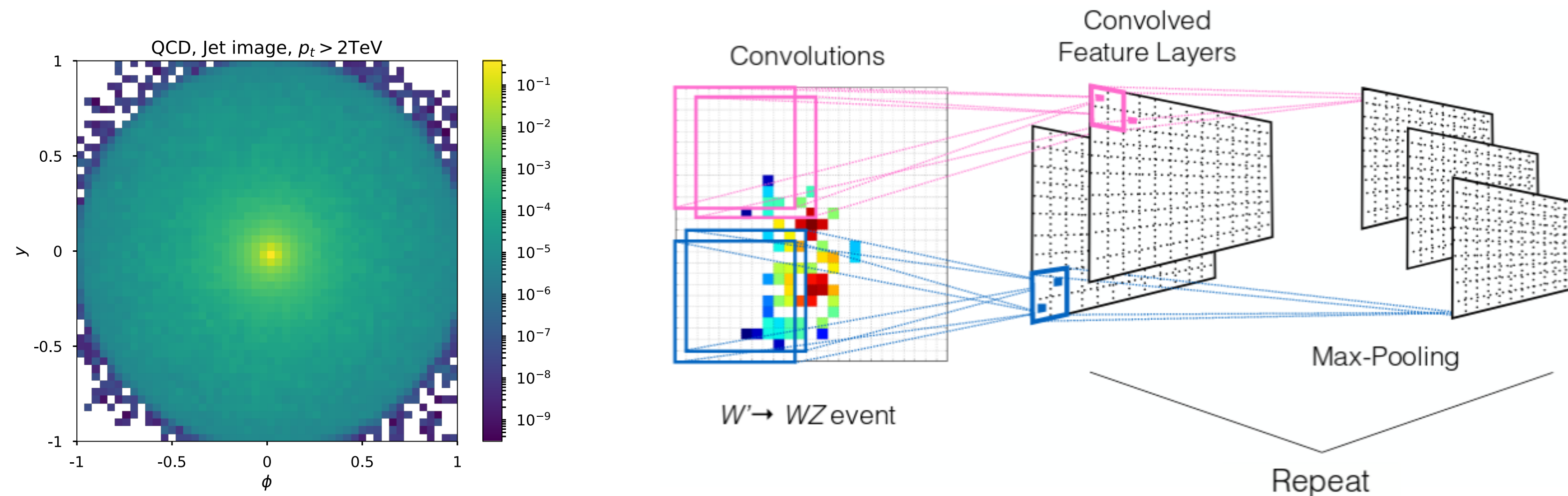
machine learning
DNN, CNN,
RNN, LSTM, etc



etc.

Convolutional neural networks and jet images

- ▶ Project a jet onto a fixed $n \times n$ pixel image in rapidity-azimuth, where each pixel intensity corresponds to the momentum of particles in that cell.
- ▶ Can be used as input for classification methods used in computer vision, such as deep convolutional neural networks.

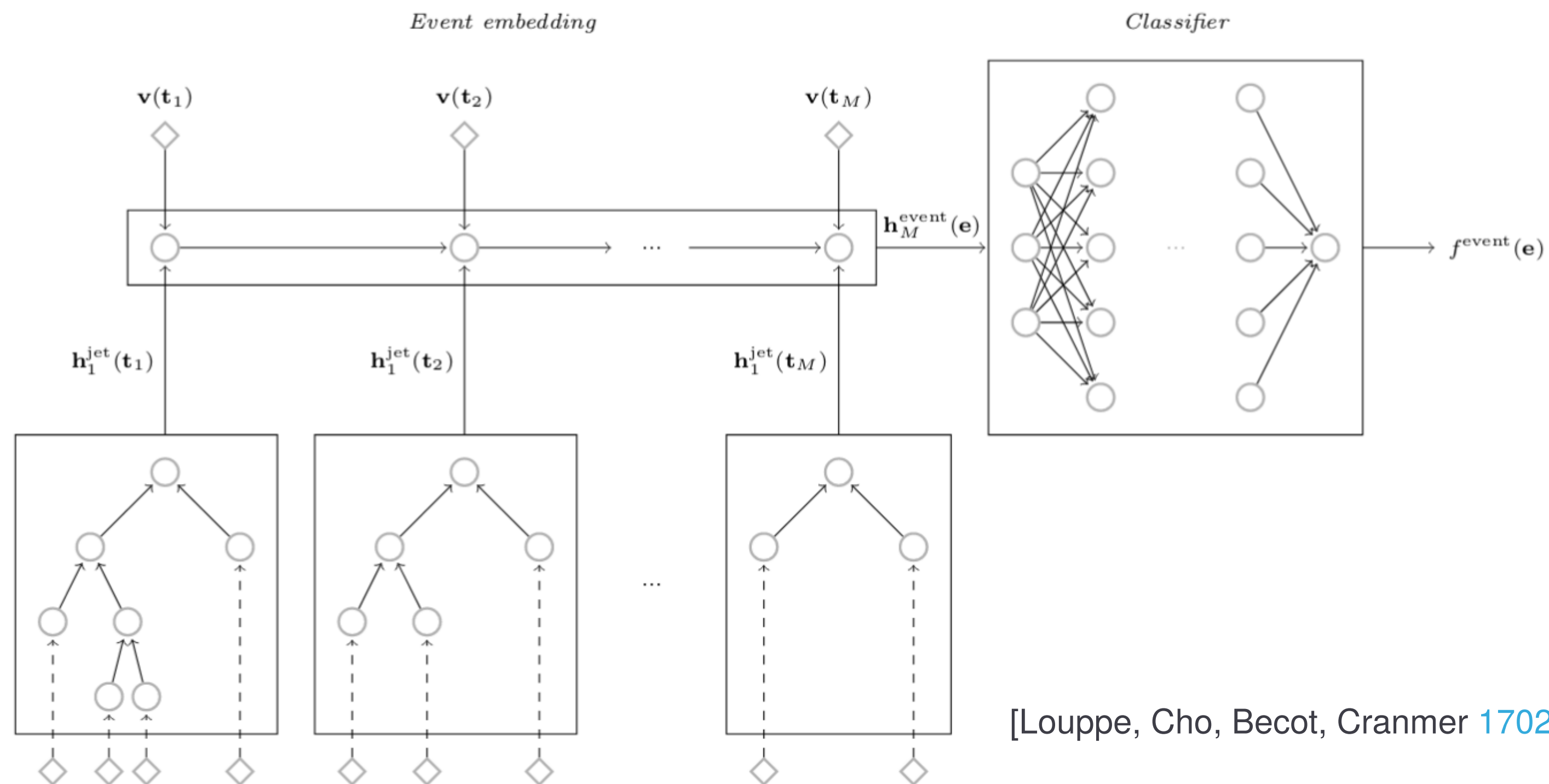


[Cogan, Kagan, Strauss, Schwartzman [JHEP 1502 \(2015\) 118](#)]

[de Oliveira, Kagan, Mackey, Nachman, Schwartzman [JHEP 1607 \(2016\) 069](#)]

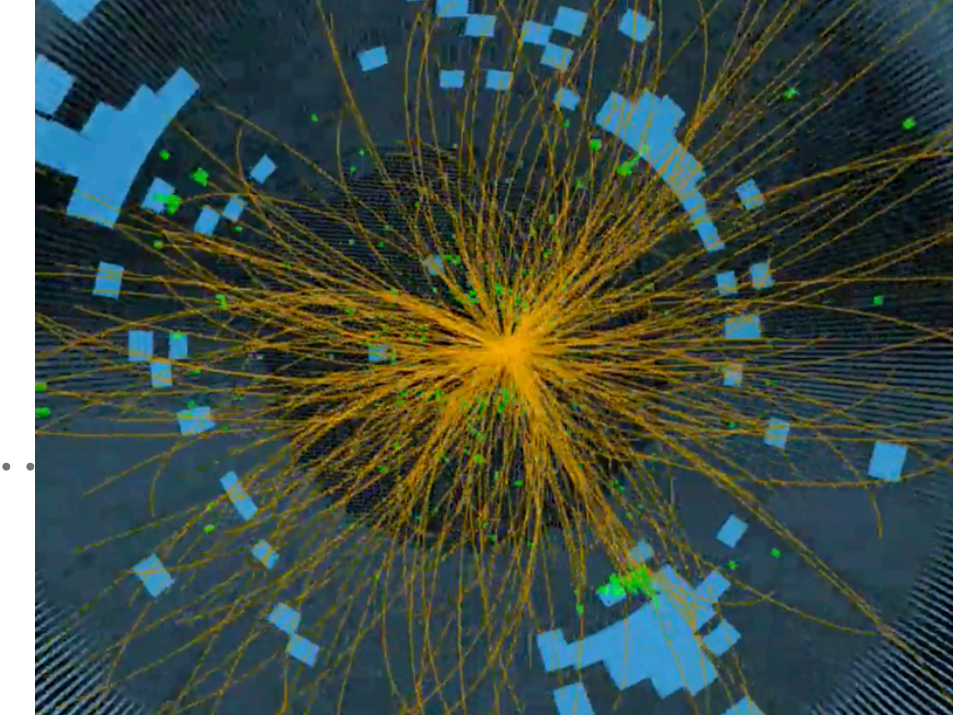
Recurrent neural network on clustering trees

- ▶ Train a recurrent neural network on successive declusterings of a jet.
- ▶ Techniques inspired from Natural Language Processing with powerful applications in handwriting and speech recognition.

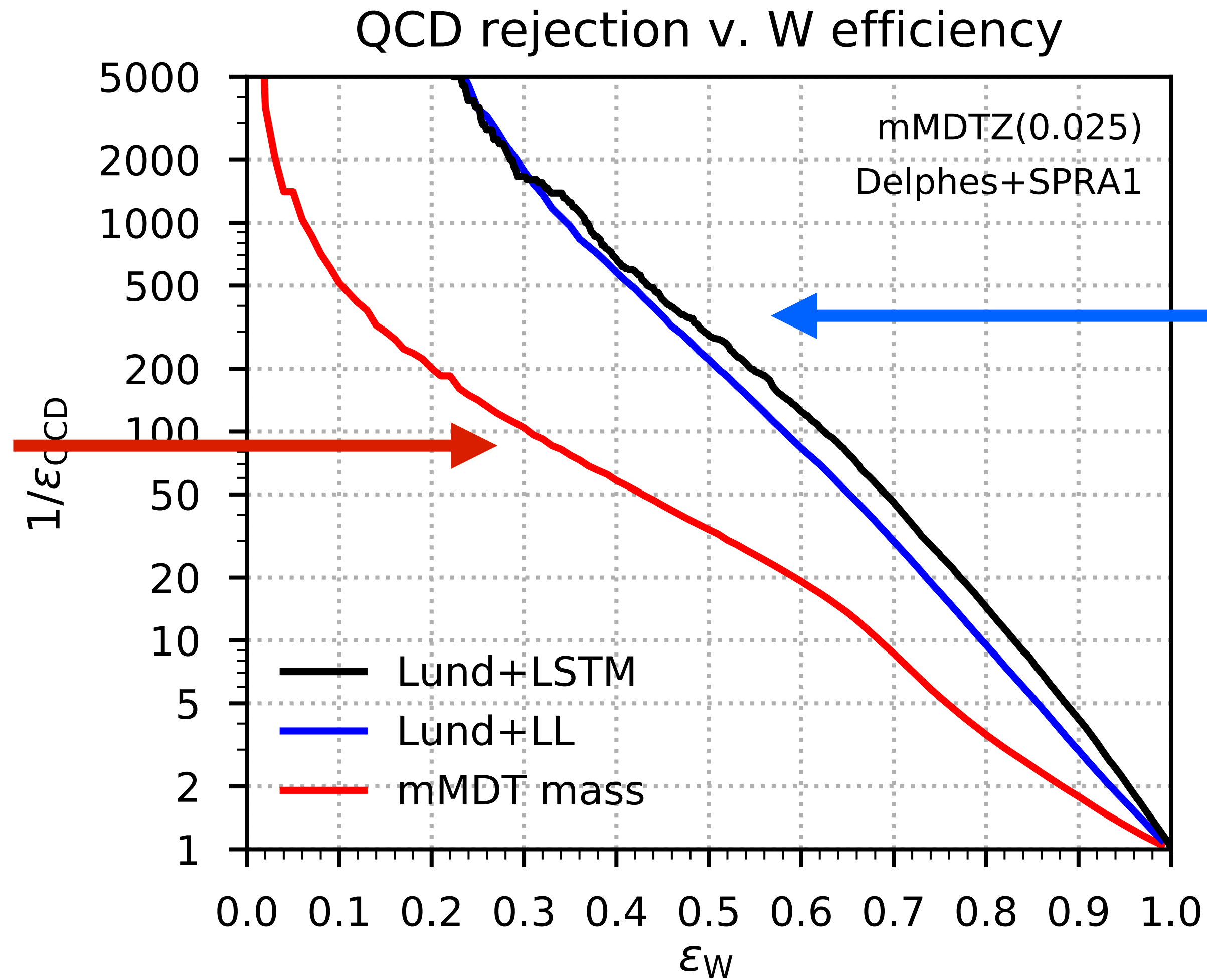


[Louppe, Cho, Becot, Cranmer [1702.00748](#)]

using full event information: jet substructure for W tagging



QCD rejection with
just jet mass
(SD/mMDT)



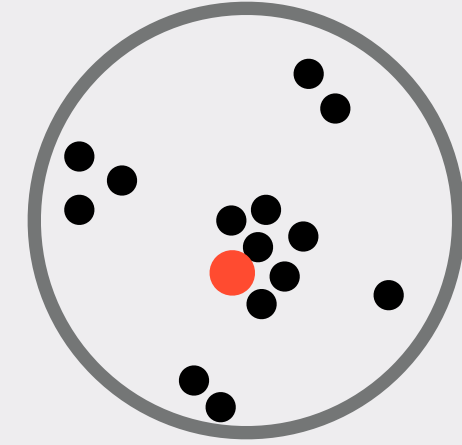
QCD rejection with use
of full jet
substructure
5–10x better

jet substructure for HI collisions

Jet structure observables

*fragmentation
function*

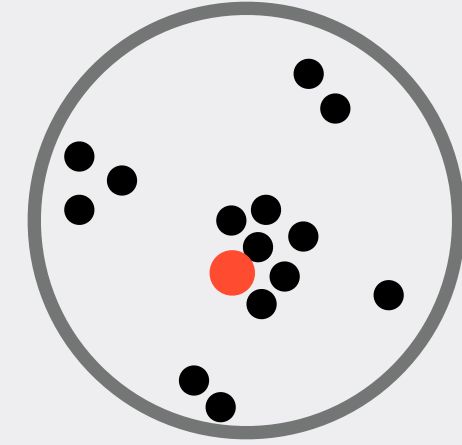
$$D(z) = \left\langle \sum_{i \in \text{jet}} \delta(z - p_{ti}/p_{t,\text{jet}}) \right\rangle_{\text{jets}}$$



Jet structure observables

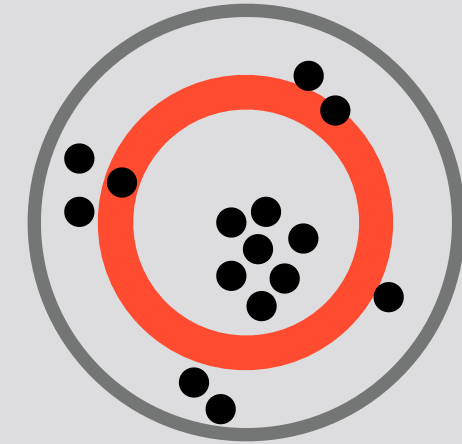
*fragmentation
function*

$$D(z) = \left\langle \sum_{i \in \text{jet}} \delta(z - p_{ti}/p_{t,\text{jet}}) \right\rangle_{\text{jets}}$$



*differential
jet shape*

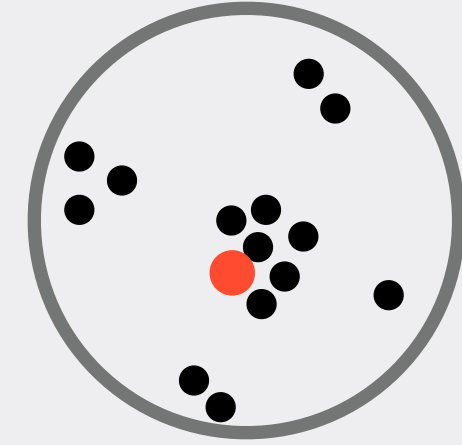
$$\rho(r) = \frac{1}{p_{\perp}^{\text{jet}}} \sum_{\substack{k \text{ with} \\ \Delta R_{kJ} \in [r, r + \delta r]}} p_{\perp}^{(k)},$$



Jet structure observables

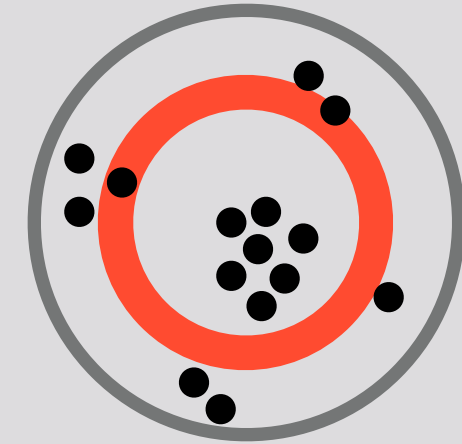
*fragmentation
function*

$$D(z) = \left\langle \sum_{i \in \text{jet}} \delta(z - p_{ti}/p_{t,\text{jet}}) \right\rangle_{\text{jets}}$$



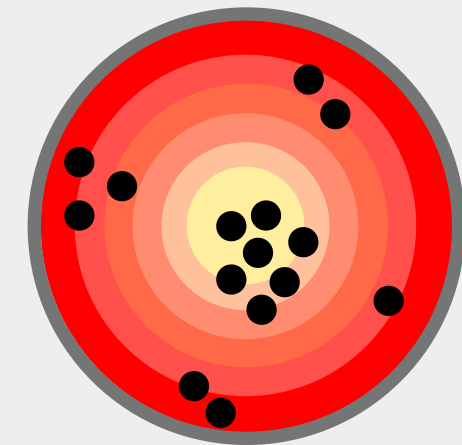
*differential
jet shape*

$$\rho(r) = \frac{1}{p_{\perp}^{\text{jet}}} \sum_{\substack{k \text{ with} \\ \Delta R_{kJ} \in [r, r + \delta r]}} p_{\perp}^{(k)},$$



girth \equiv broadening

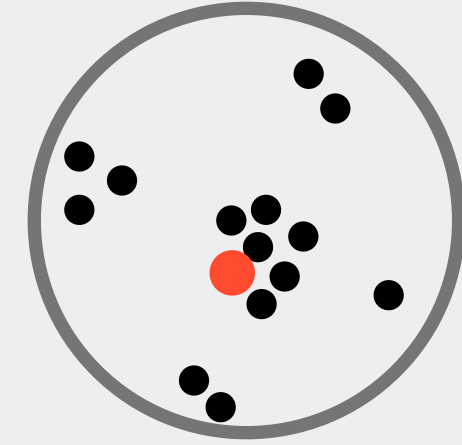
$$g = \frac{1}{p_{\perp}^{\text{jet}}} \sum_{k \in J} p_{\perp}^{(k)} \Delta R_{kJ},$$



Jet structure observables

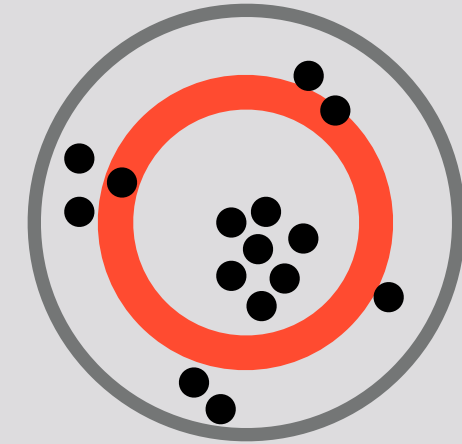
*fragmentation
function*

$$D(z) = \left\langle \sum_{i \in \text{jet}} \delta(z - p_{ti}/p_{t,\text{jet}}) \right\rangle_{\text{jets}}$$



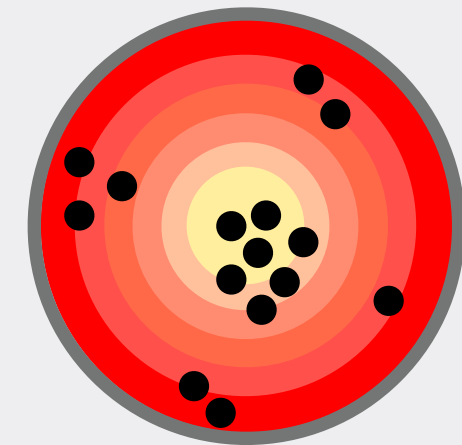
*differential
jet shape*

$$\rho(r) = \frac{1}{p_{\perp}^{\text{jet}}} \sum_{\substack{k \text{ with} \\ \Delta R_{kJ} \in [r, r + \delta r]}} p_{\perp}^{(k)},$$



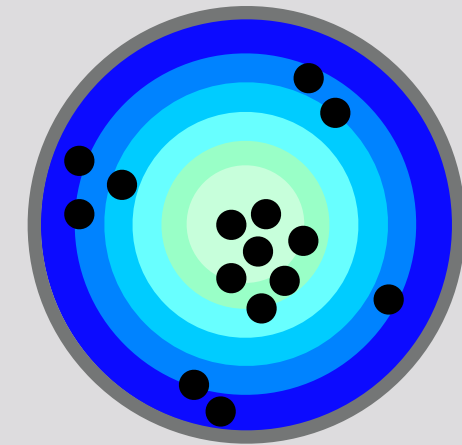
girth ≡ broadening

$$g = \frac{1}{p_{\perp}^{\text{jet}}} \sum_{k \in J} p_{\perp}^{(k)} \Delta R_{kJ},$$



*jet mass, groomed
& ungroomed*

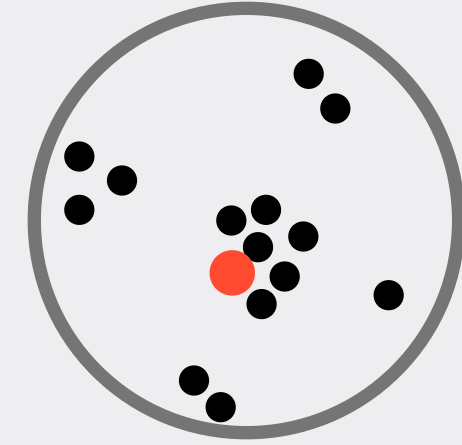
$$m^2 = \left(\sum_{i \in (\text{sub})\text{jet}} p_i^{\mu} \right)^2$$



Jet structure observables

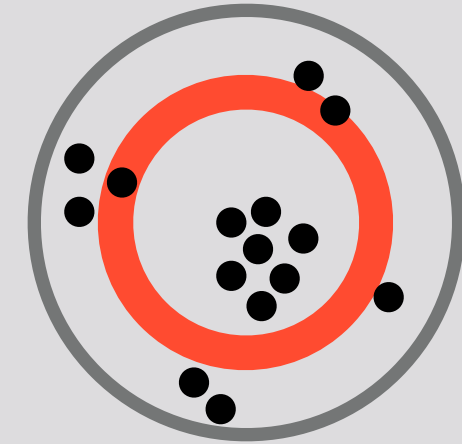
fragmentation
function

$$D(z) = \left\langle \sum_{i \in \text{jet}} \delta(z - p_{ti}/p_{t,\text{jet}}) \right\rangle_{\text{jets}}$$



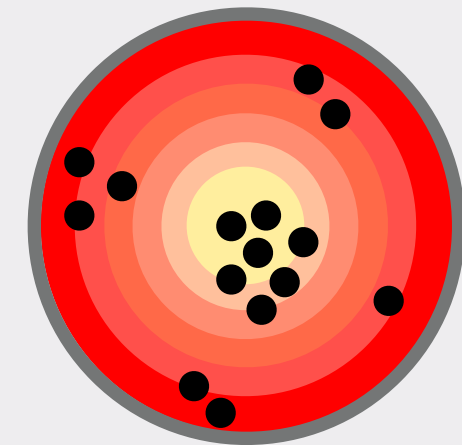
differential
jet shape

$$\rho(r) = \frac{1}{p_{\perp}^{\text{jet}}} \sum_{\substack{k \text{ with} \\ \Delta R_{kJ} \in [r, r+\delta r]} p_{\perp}^{(k)},$$



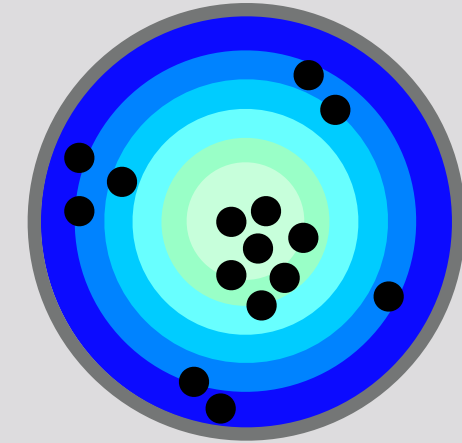
girth \equiv broadening

$$g = \frac{1}{p_{\perp}^{\text{jet}}} \sum_{k \in J} p_{\perp}^{(k)} \Delta R_{kJ},$$



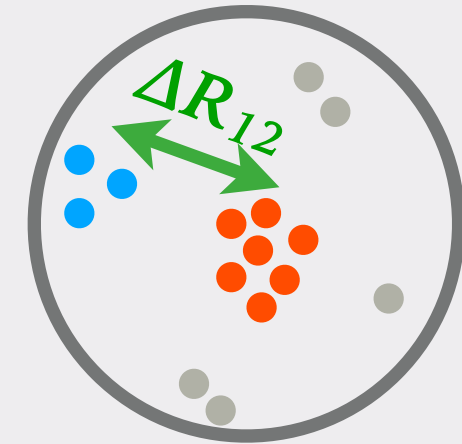
jet mass, groomed
& ungroomed

$$m^2 = \left(\sum_{i \in (\text{sub})\text{jet}} p_i^{\mu} \right)^2$$

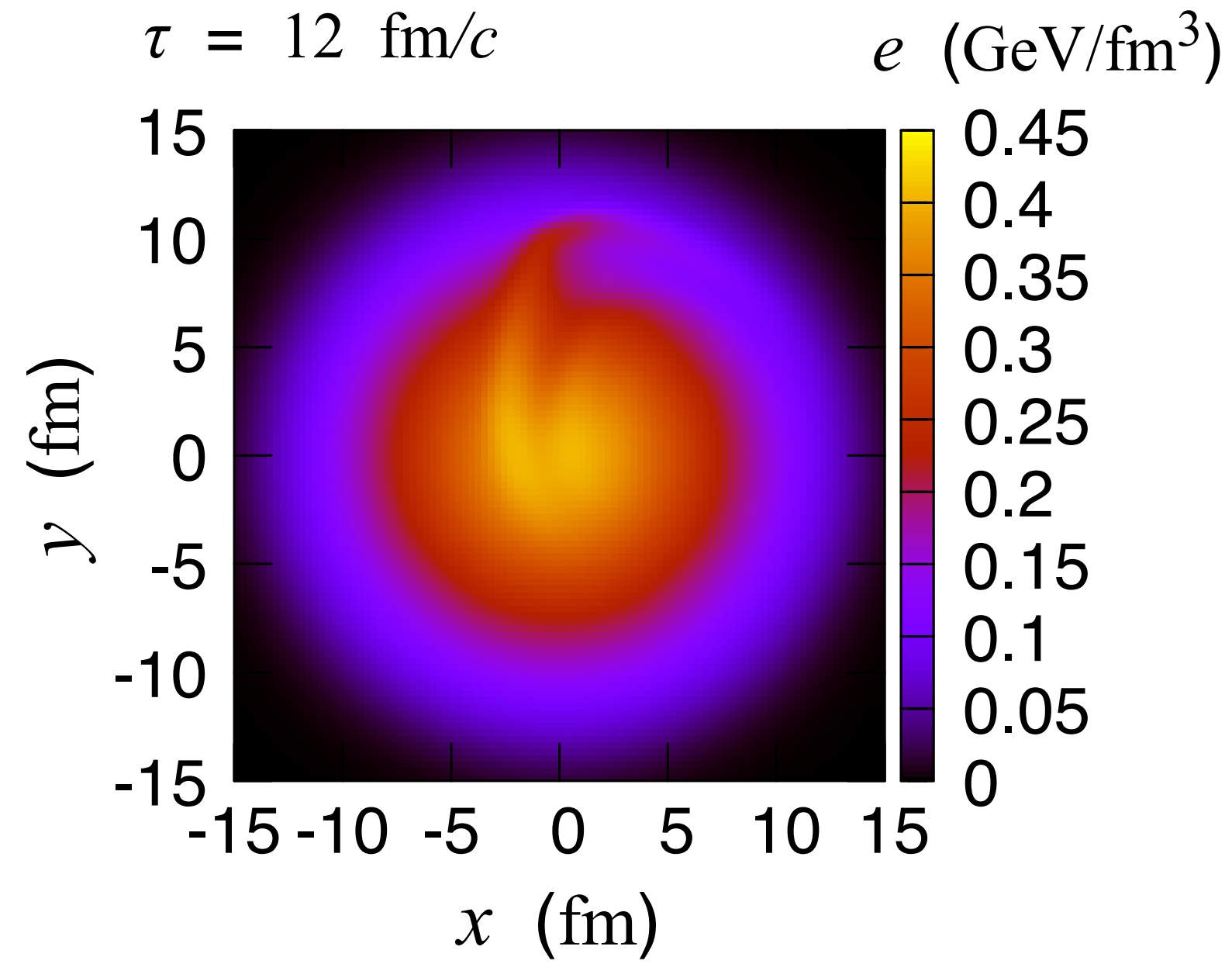


$z_g, \Delta R_{12}$

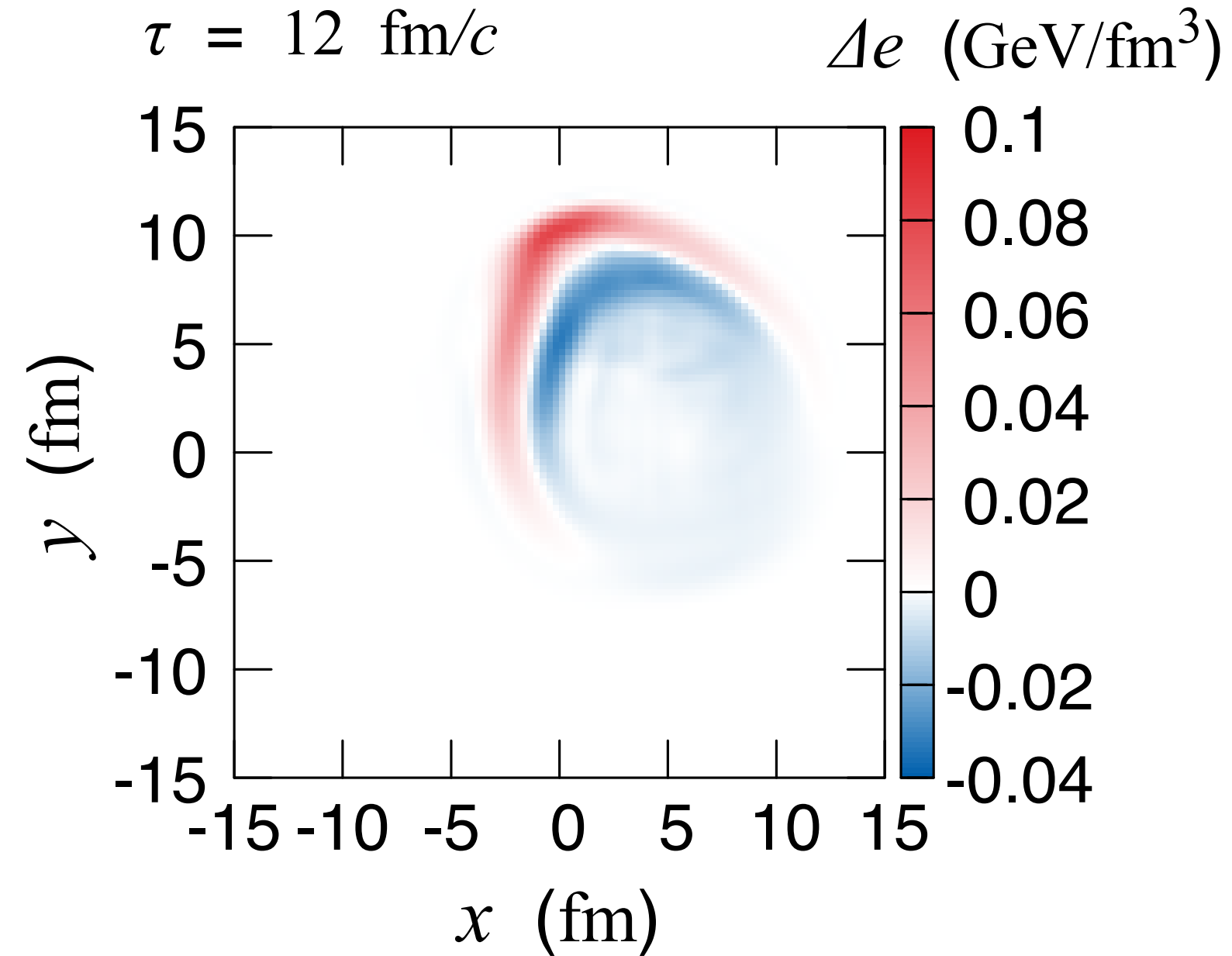
$$z_g = \frac{\min(p_{\perp,1}, p_{\perp,2})}{p_{\perp,1} + p_{\perp,2}} > z_{\text{cut}} \left(\frac{\Delta R_{1,2}}{R_J} \right)^{\beta}$$



(a-3)

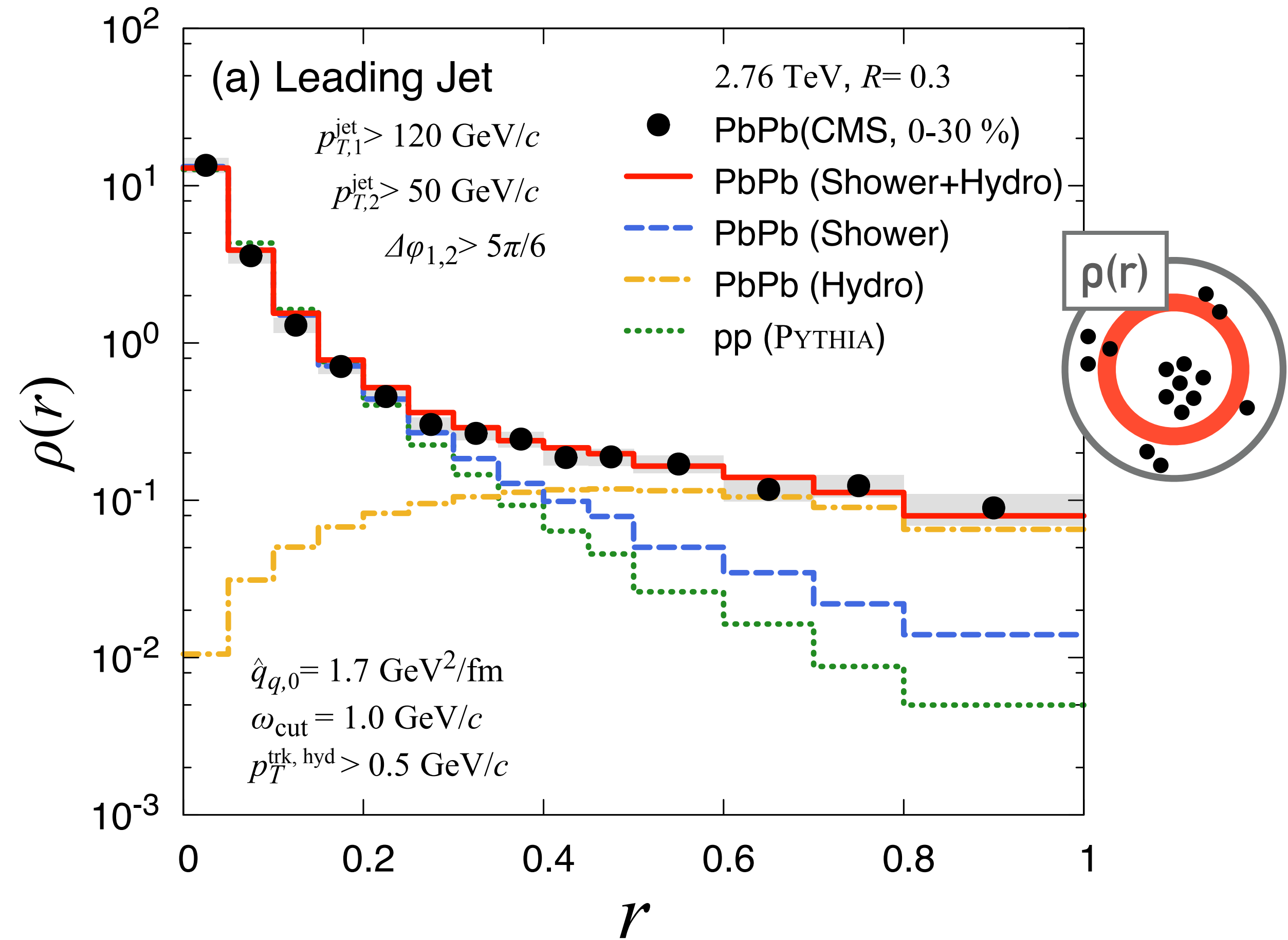


(b-3)



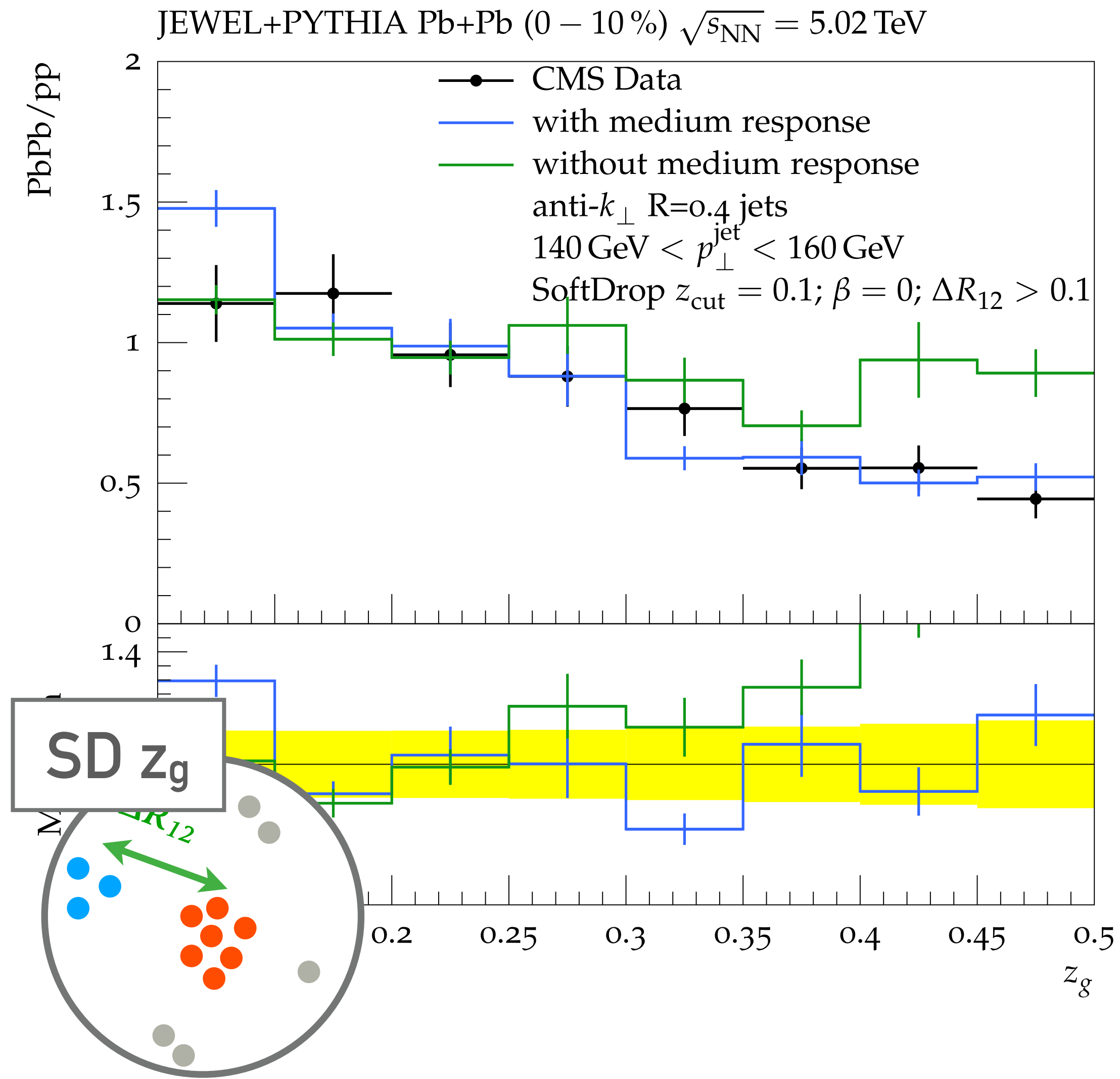
medium mach-cones

► Tachibana, Chang & Qin,
1701.07951, 12fm/c

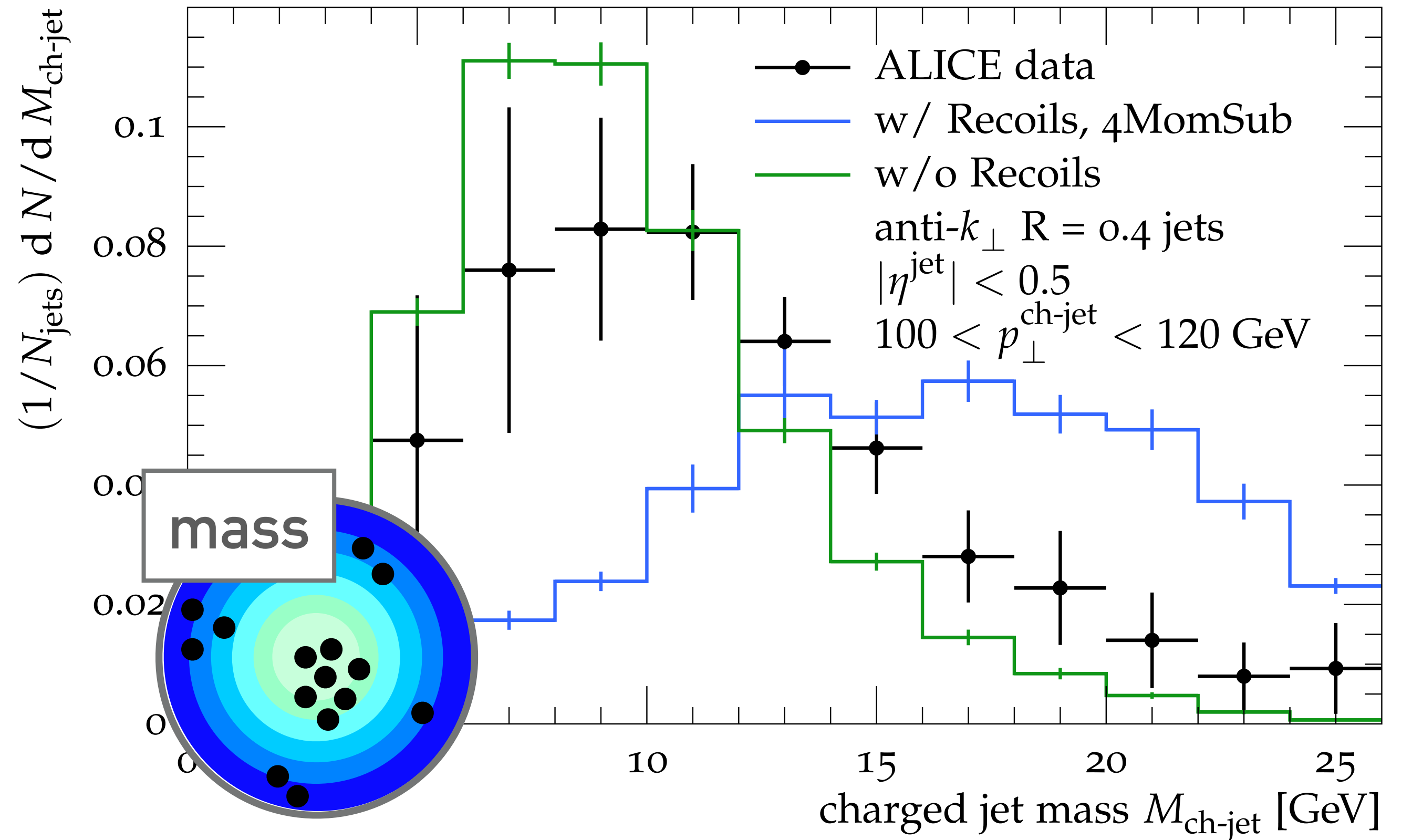


JEWEL v. data

► [arXiv:1707.01539](https://arxiv.org/abs/1707.01539), by Milhano, Wiedemann and Zapp with medium response



JEWEL+PYTHIA Pb+Pb (0 – 10%) (2.76 TeV)



recurrent theme in heavy-ion calculations: 2d phasespace plots

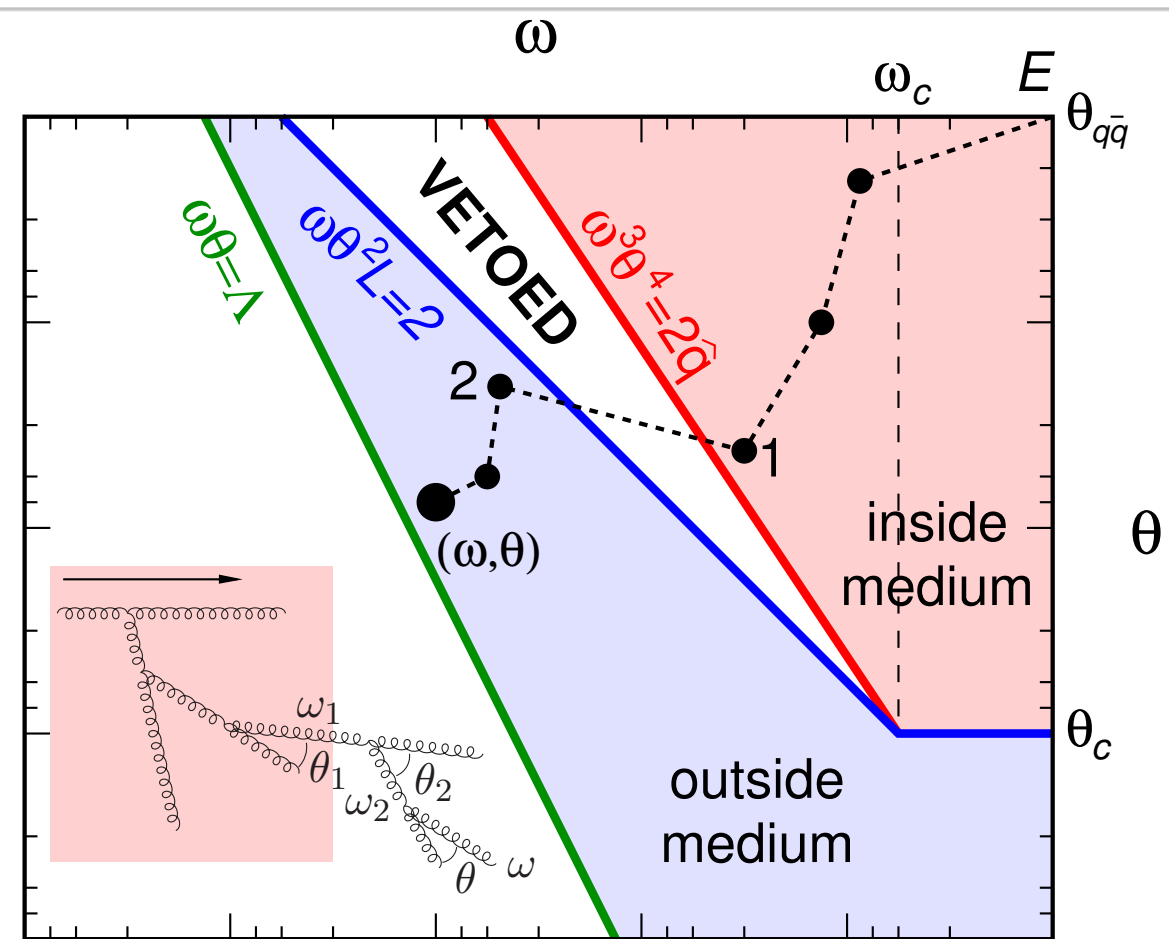
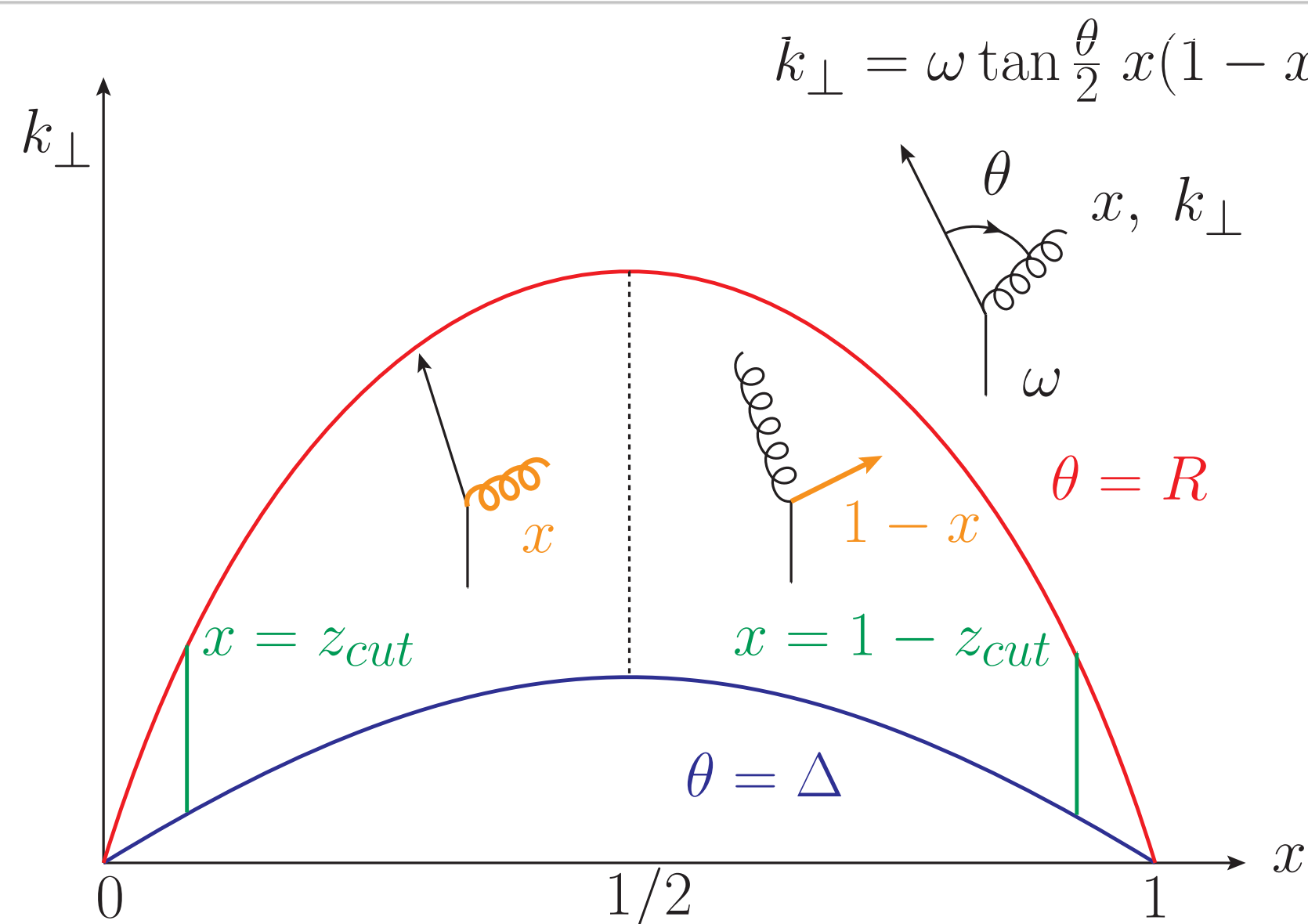
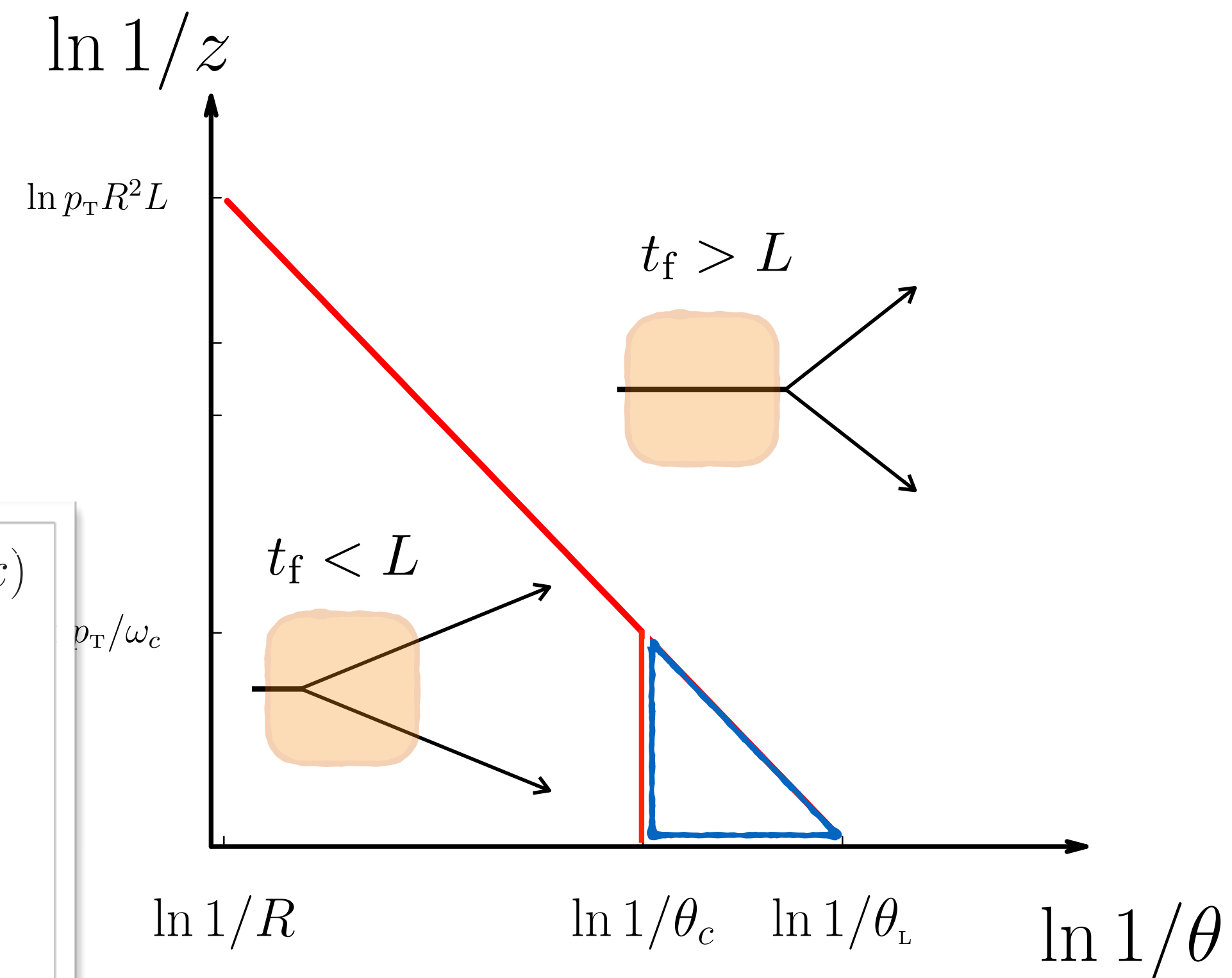


FIG. 1. Schematic representation of the phase-space available for VLEs, including an example of a cascade with “1” the last emission inside the medium and “2” the first emission outside

*P. Caucal, E. Iancu,
A.H. Mueller, G. Soyez*



Yang-Ting Chien^{a,b} and Ivan Vitev^a



Mehtar-Tani & Tywoniuk@QM18

recurrent theme in heavy-ion calculations: 2d phasespace plots

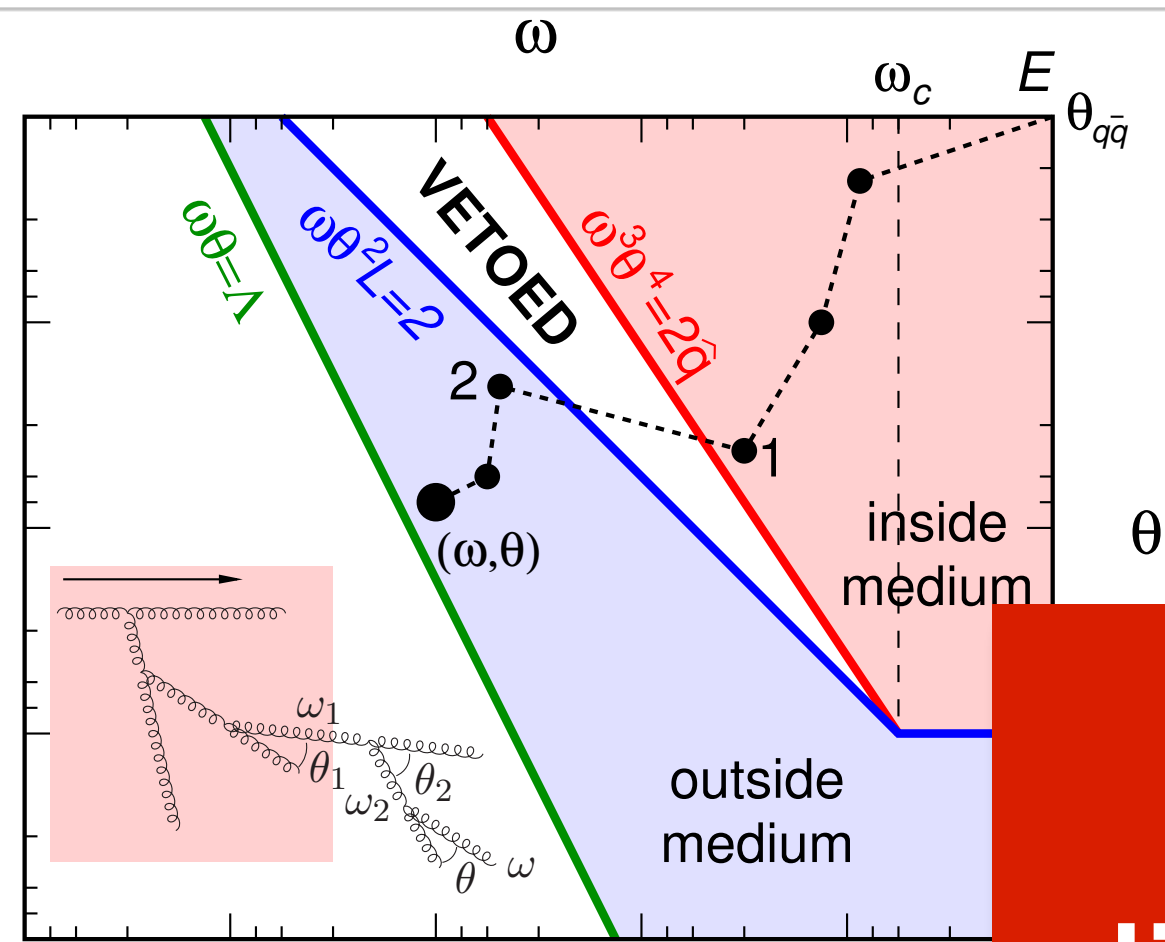
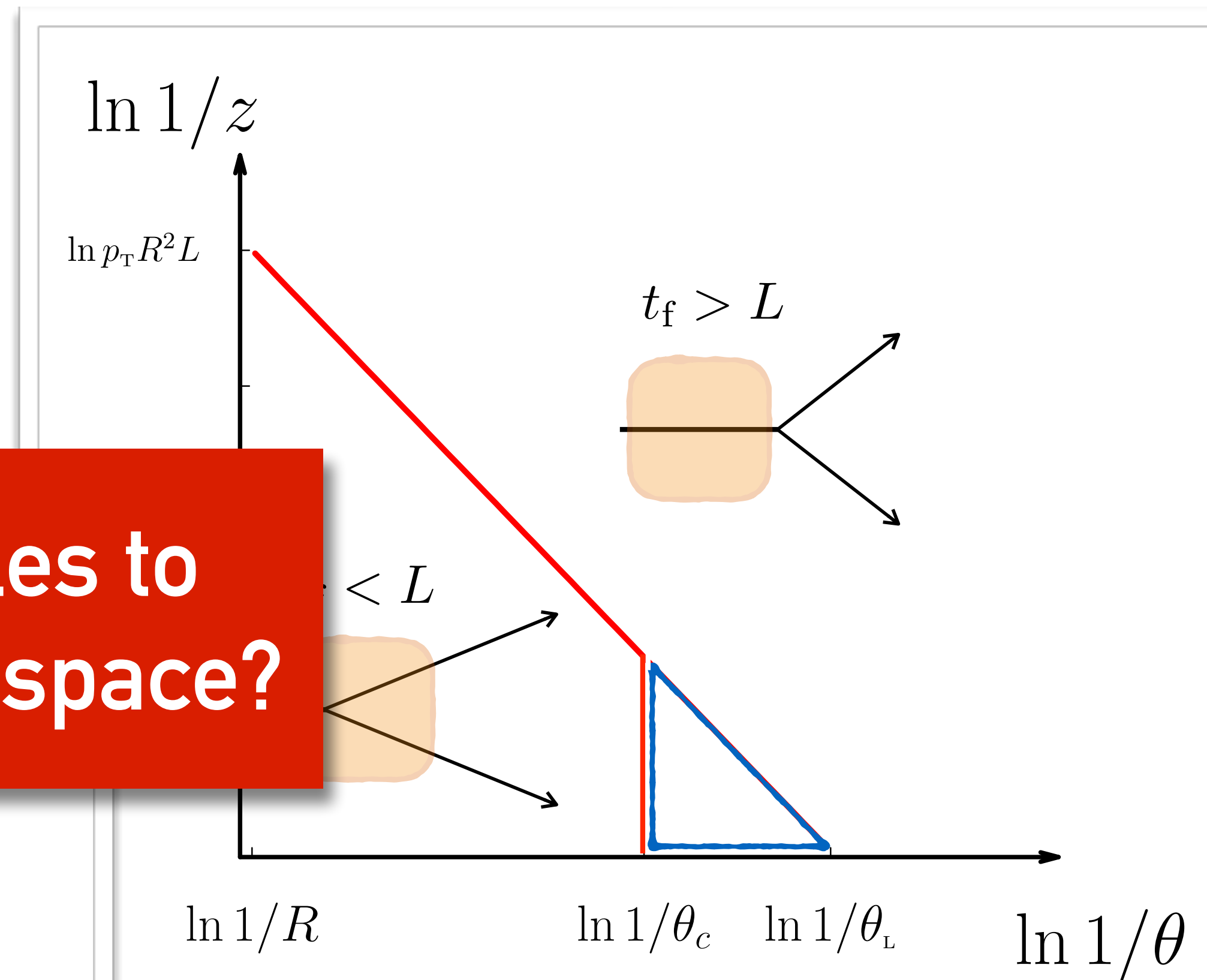


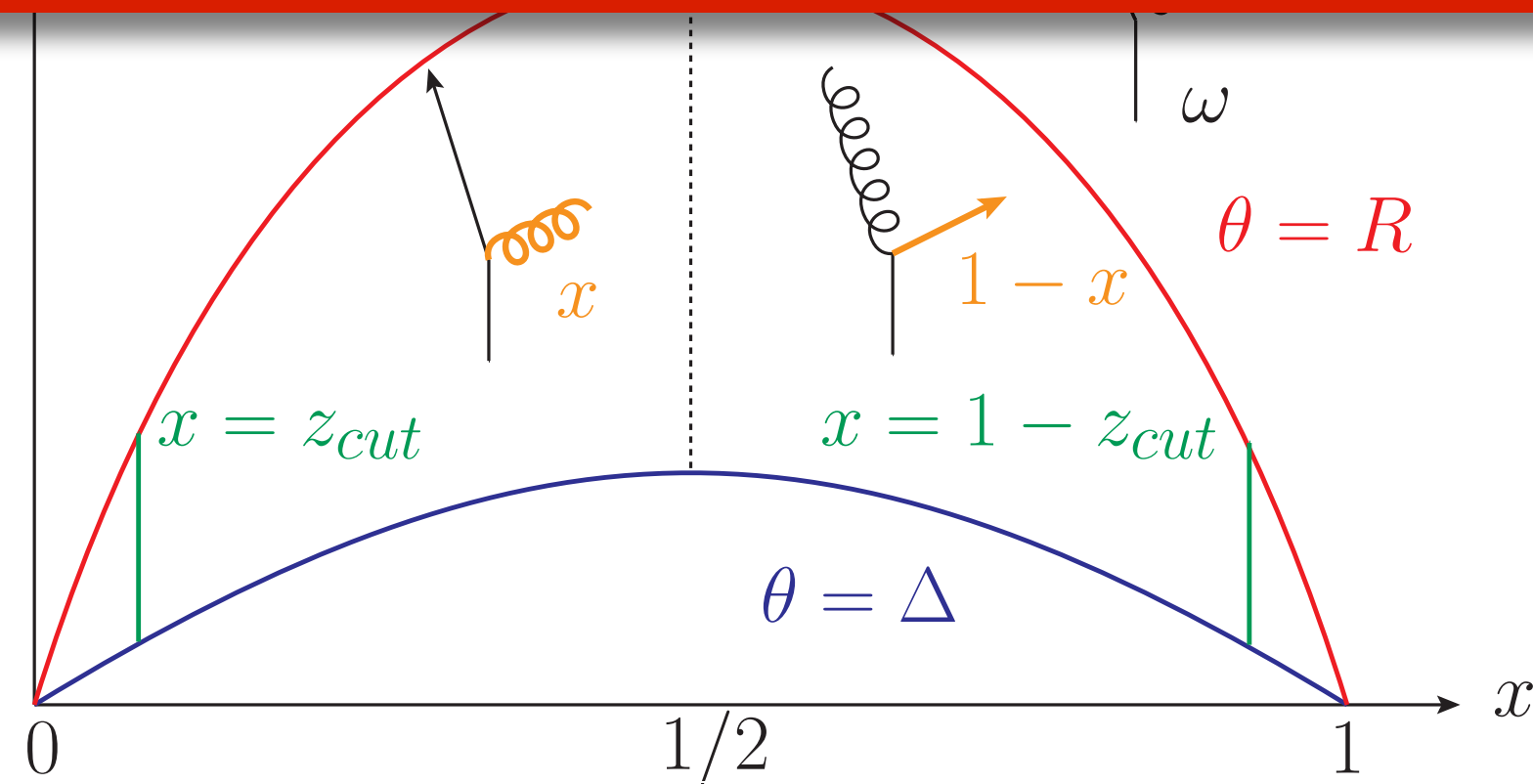
FIG. 1. Schematic representation of the phase-sp for VLEs, including an example of a cascade with emission inside the medium and “2” the first emis

*P. Caucal, E. Iancu,
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Can we design observables to directly probe the 2d phasespace?



Mehtar-Tani & Tywoniuk@QM18



Yang-Ting Chien^{a,b} and Ivan Vitev^a

the “Lund plane”

can we construct observables that are

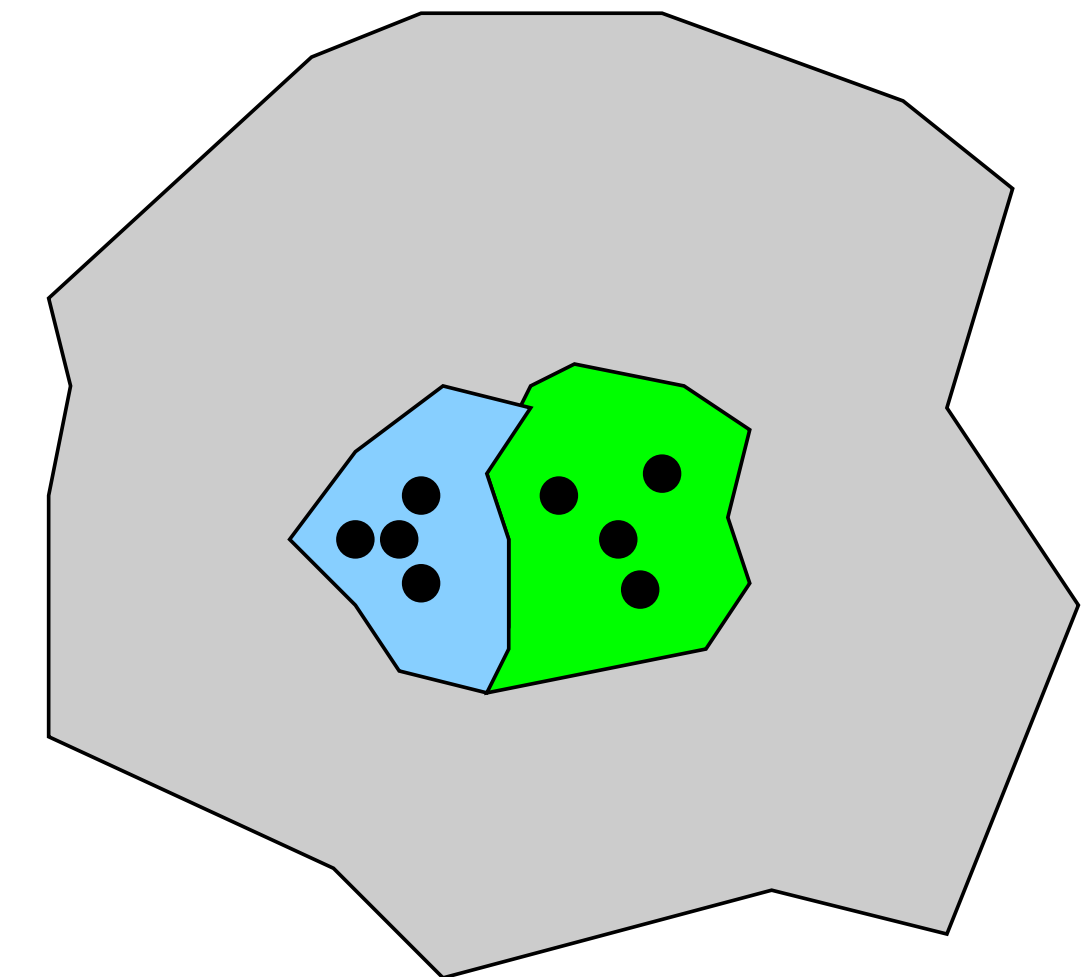
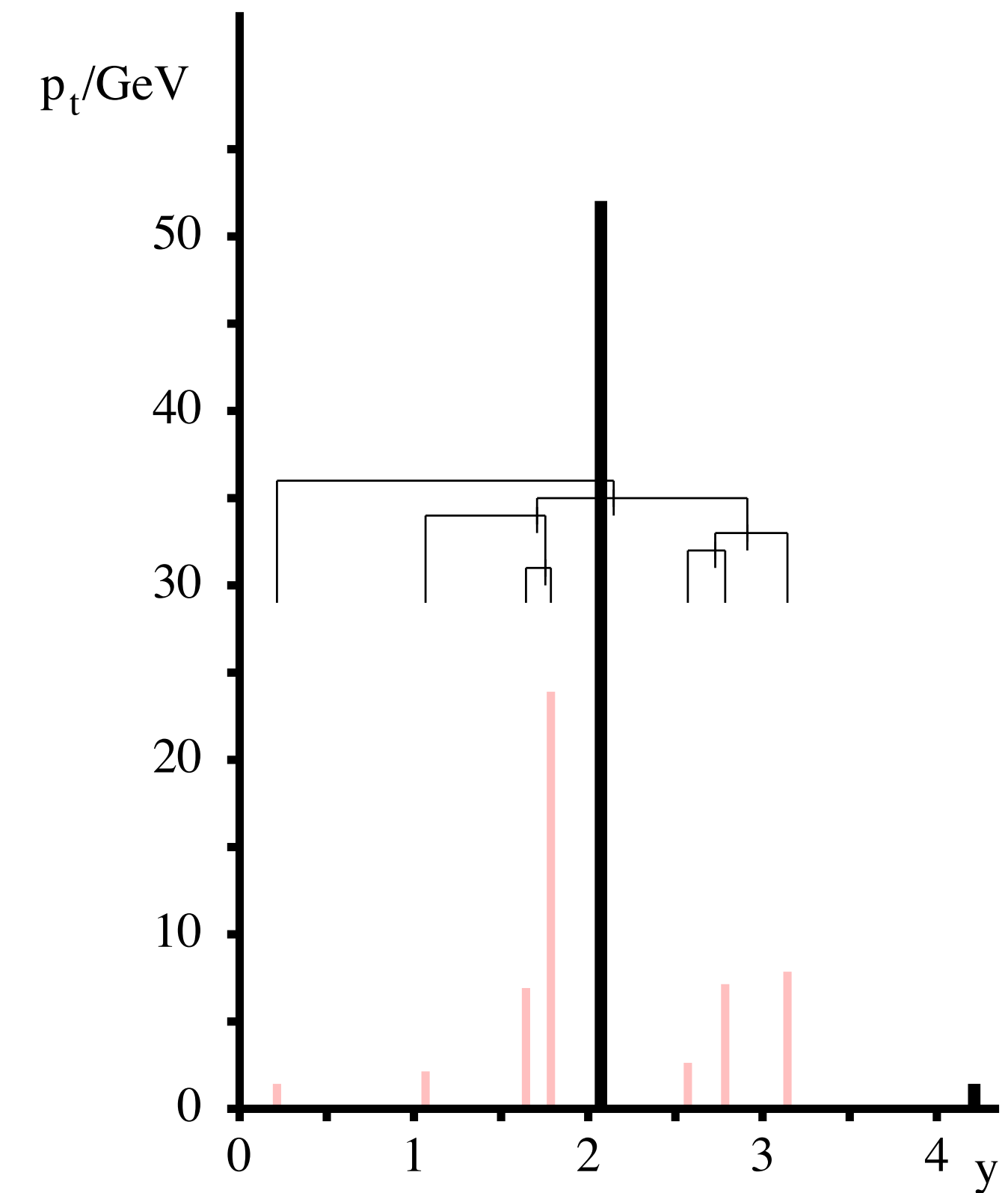
- (a) **more transparent** in terms of the physical info they extract?*
- (b) close to **optimal** for multivariate techniques & machine-learning?*

A sequence of jet substructure tools taggers

- 1993: k_t declustering for boosted W's: [Seymour]
- 2002: Y-Splitter (k_t declustering with a cut) [Butterworth, Cox, Forshaw]
- 2008: Mass-Drop Tagger (C/A declustering with a k_t/m cut) [Butterworth, Davison, Rubin, GPS]
- 2013: Soft Drop, $\beta=0$ [Dasgupta, Fregoso, Marzani, GPS]
- 2014: Soft Drop, $\beta \neq 0$ [Larkoski, Marzani, Soyez, Thaler]

1. Undo last clustering of C/A jet into subjects 1, 2
2. Stop if $z = \frac{\min(p_{t1}, p_{t2})}{p_{t1} + p_{t2}} \left(\frac{\Delta R_{12}}{R} \right)^\beta > z_{\text{cut}}$
3. Else discard softer branch, repeat step 1 with harder branch

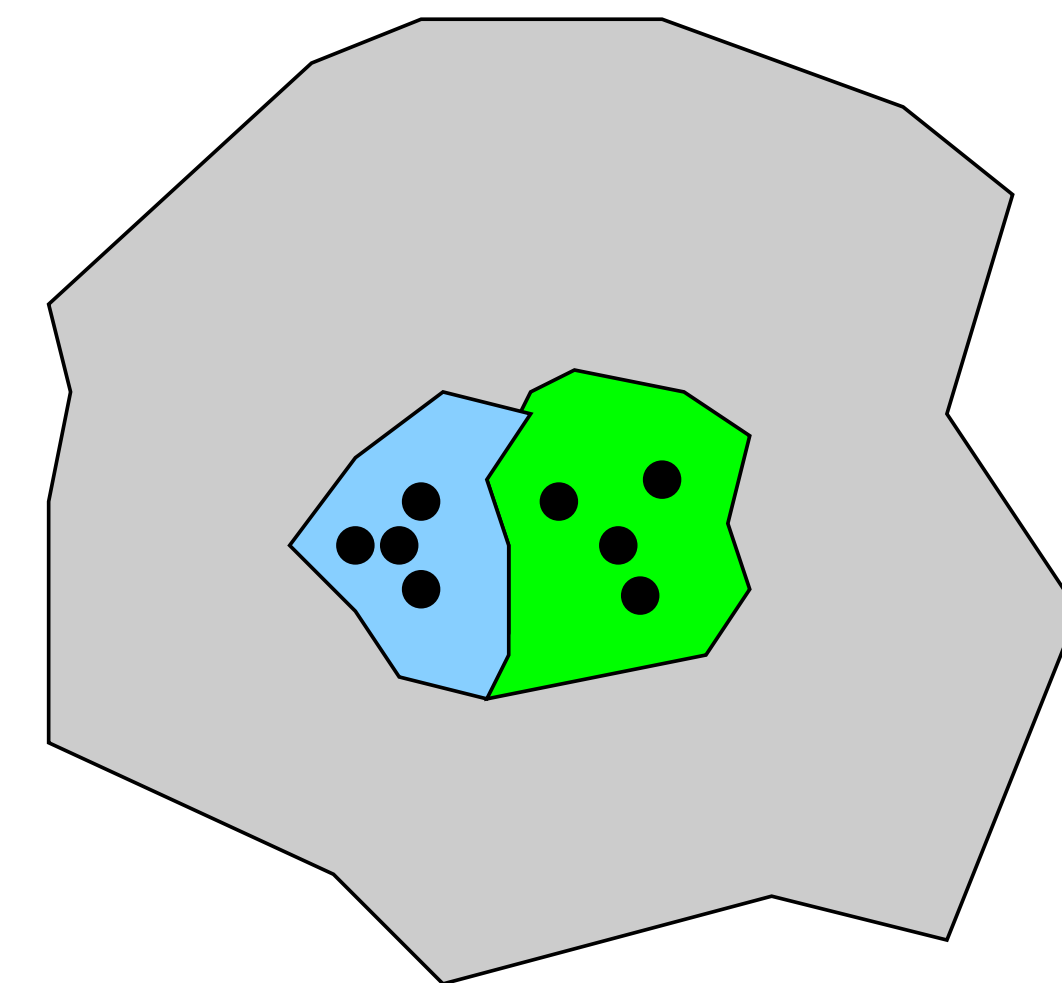
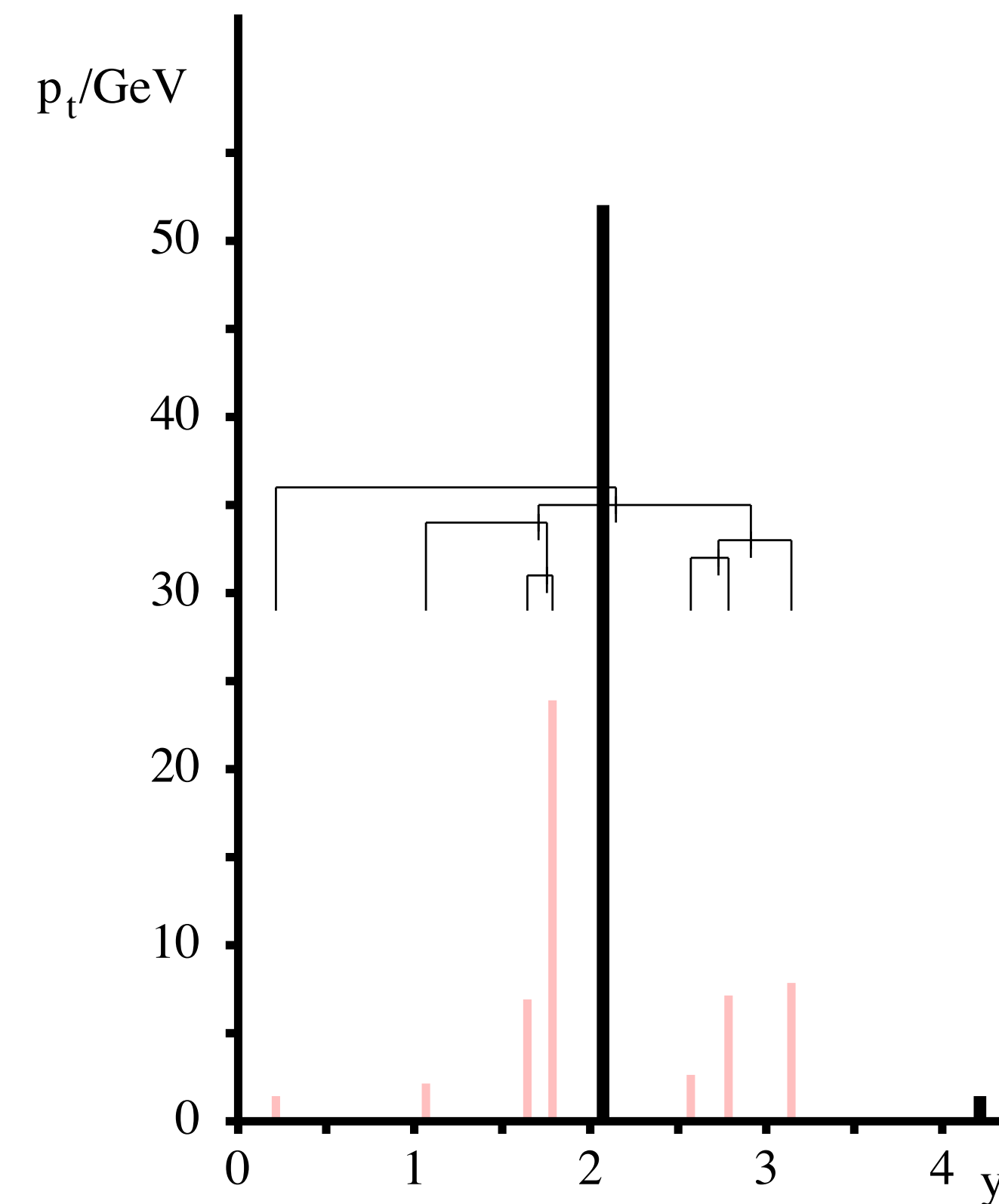
Cambridge/Aachen



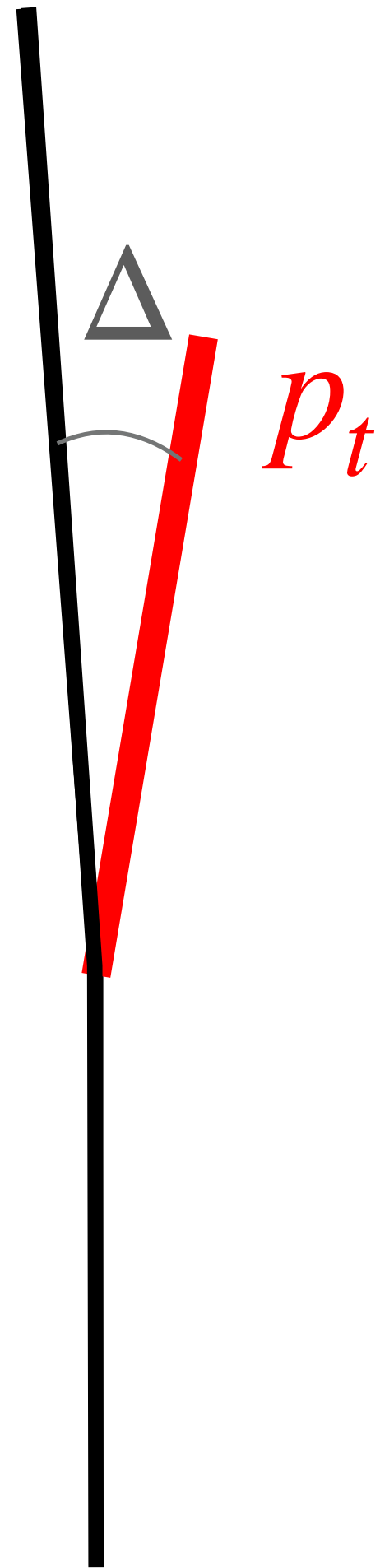
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- 2014: Soft Drop, $\beta\neq 0$ [Larkoski, Marzani, Soyez, Thaler]
- 2017: Iterated Soft Drop [Frye, Larkoski, Thaler, Zhou]
count number of iterations until you reach 1 particle
- 2018/19: ?

Cambridge/Aachen



Phase space: two key variables (+ azimuth)



ΔR (or just Δ)

opening angle of a splitting

$$k_t = p_t \Delta$$

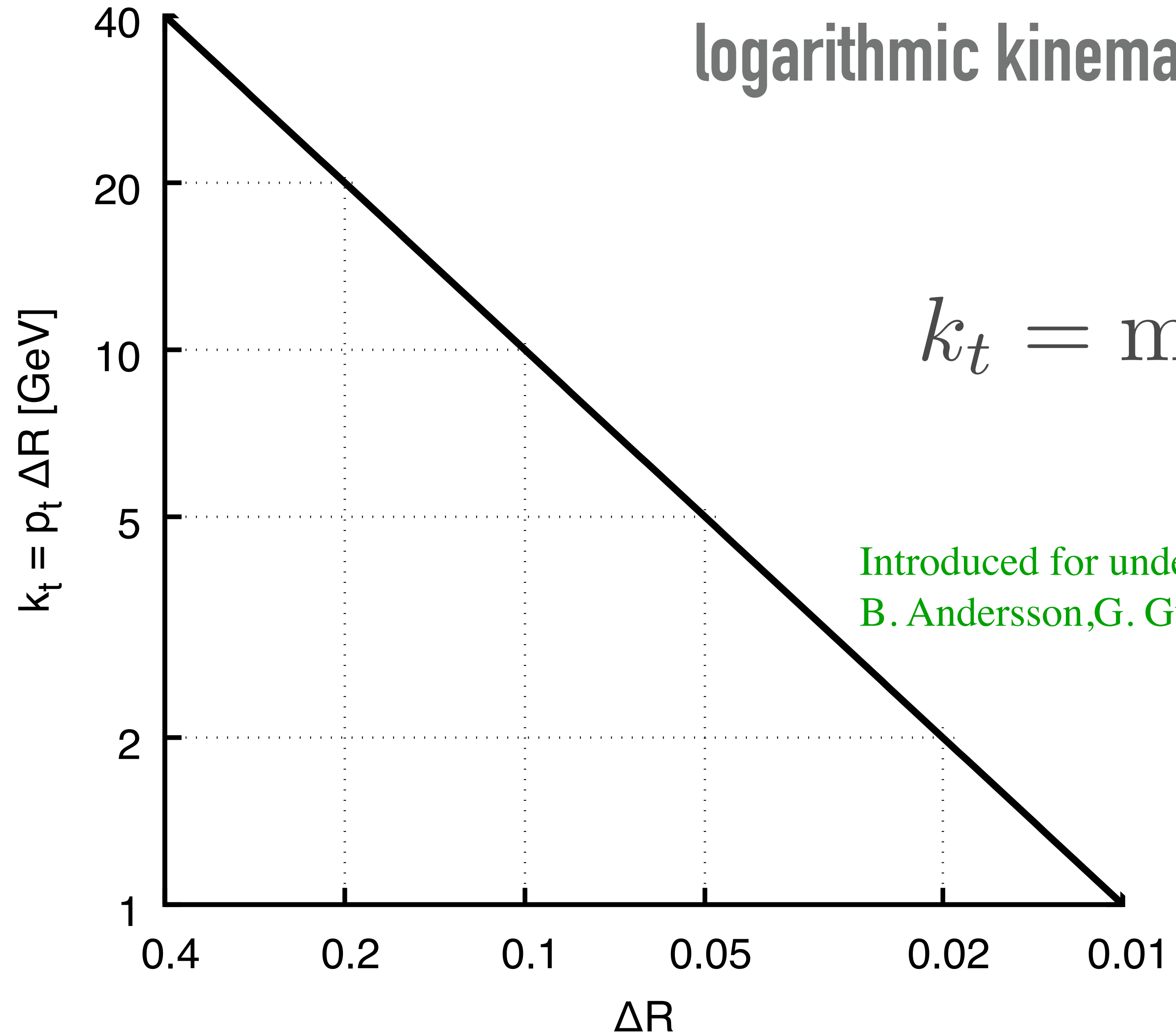
p_t (or p_\perp) is transverse momentum wrt beam

k_t is \sim transverse momentum wrt jet axis

logarithmic kinematic plane whose two variables are

$$\Delta R_{ij}$$

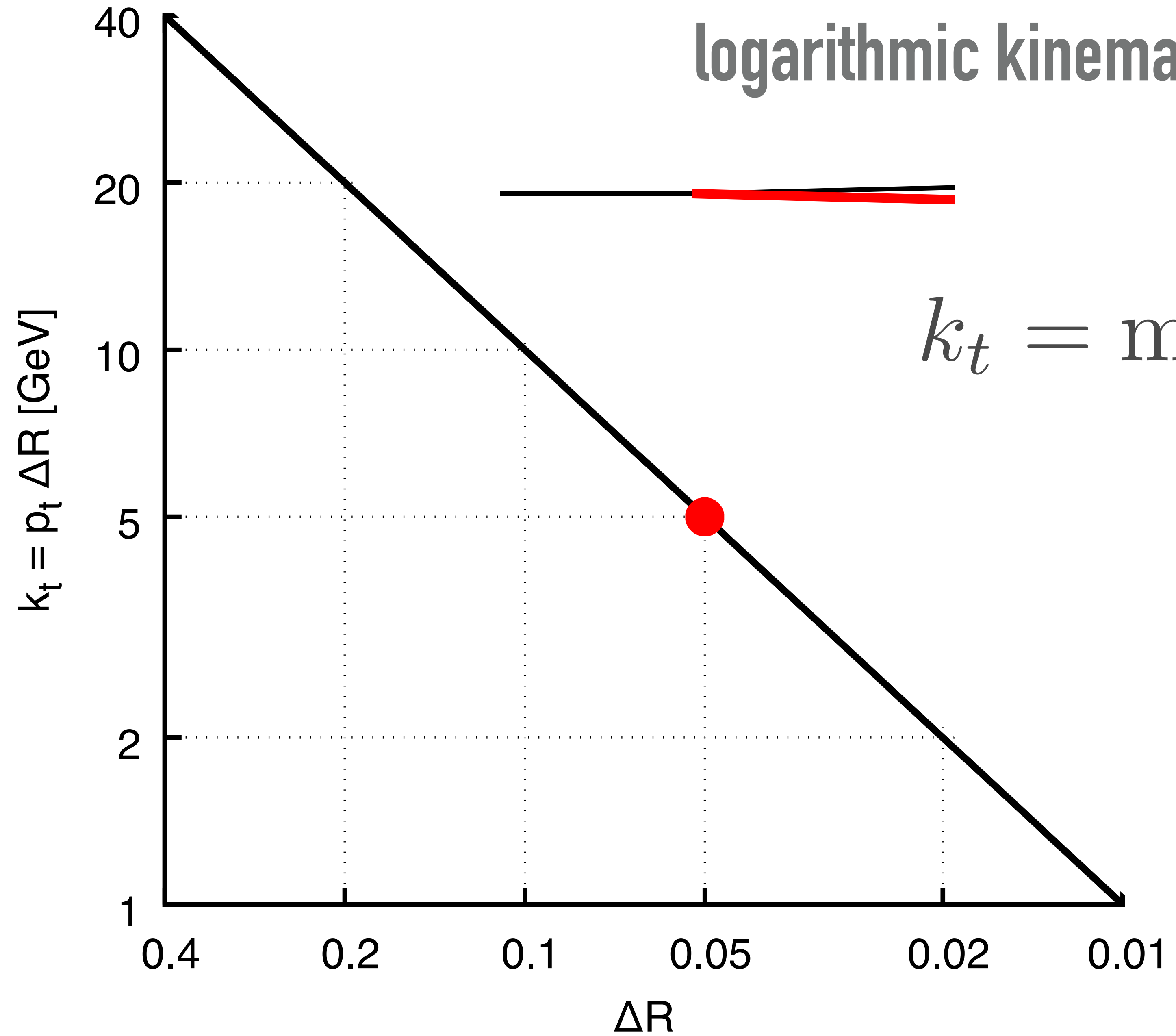
$$k_t = \min(p_{ti}, p_{tj}) \Delta R_{ij}$$



Introduced for understanding Parton Shower Monte Carlos by
B. Andersson, G. Gustafson L. Lonnblad and Pettersson 1989

The Lund Plane

jet with $R = 0.4$, $p_t = 200$ GeV



logarithmic kinematic plane whose two variables are

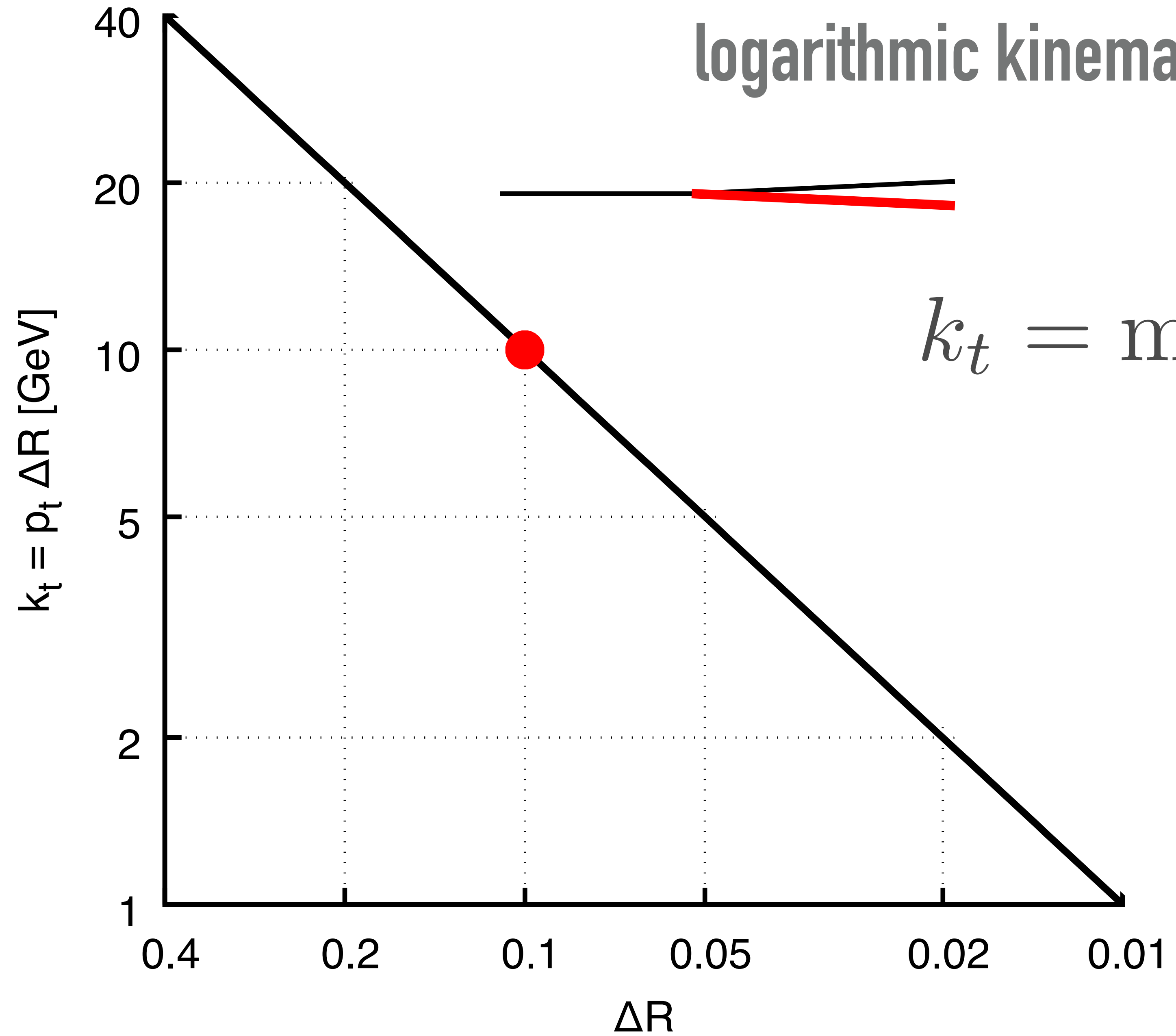
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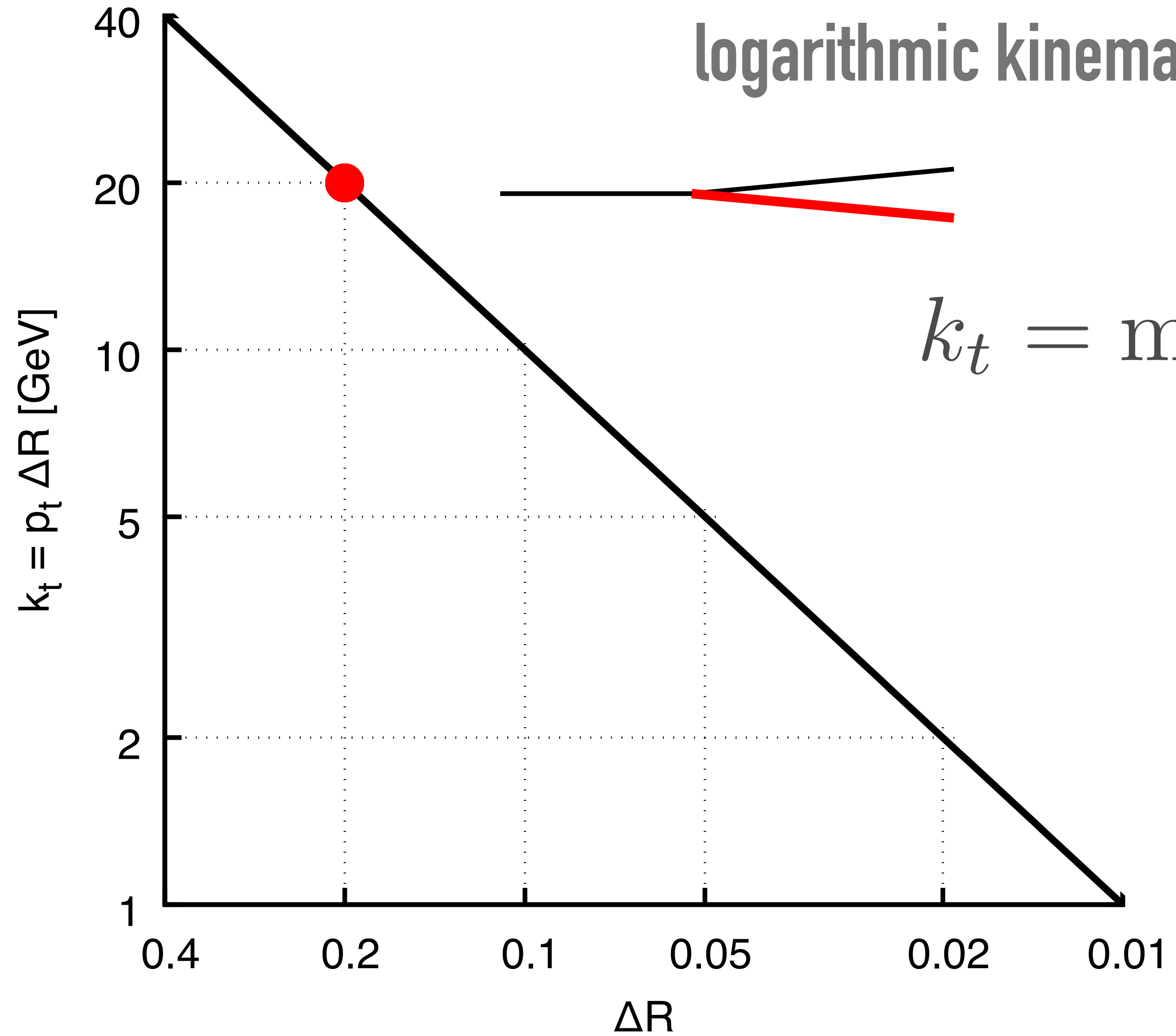
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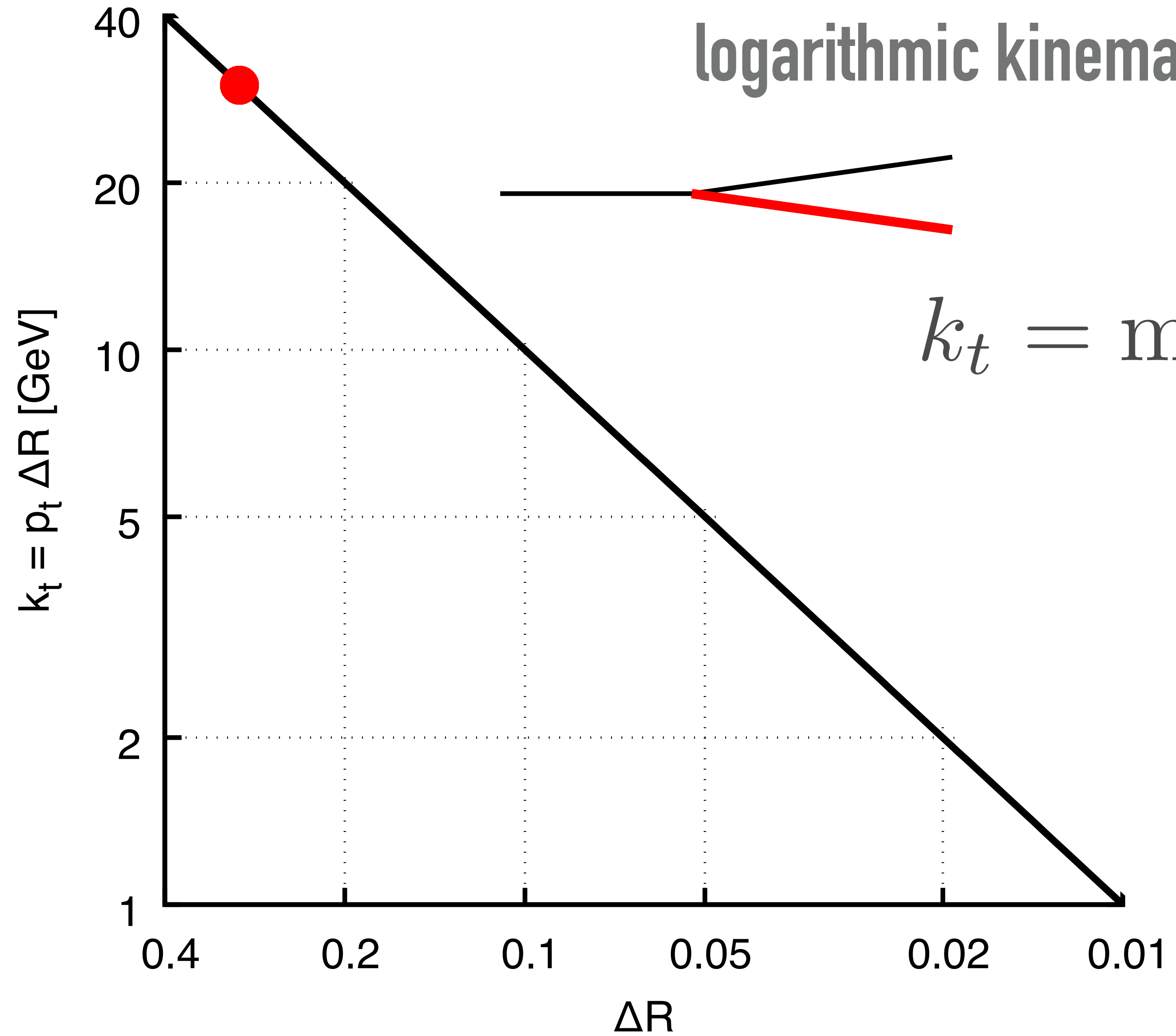
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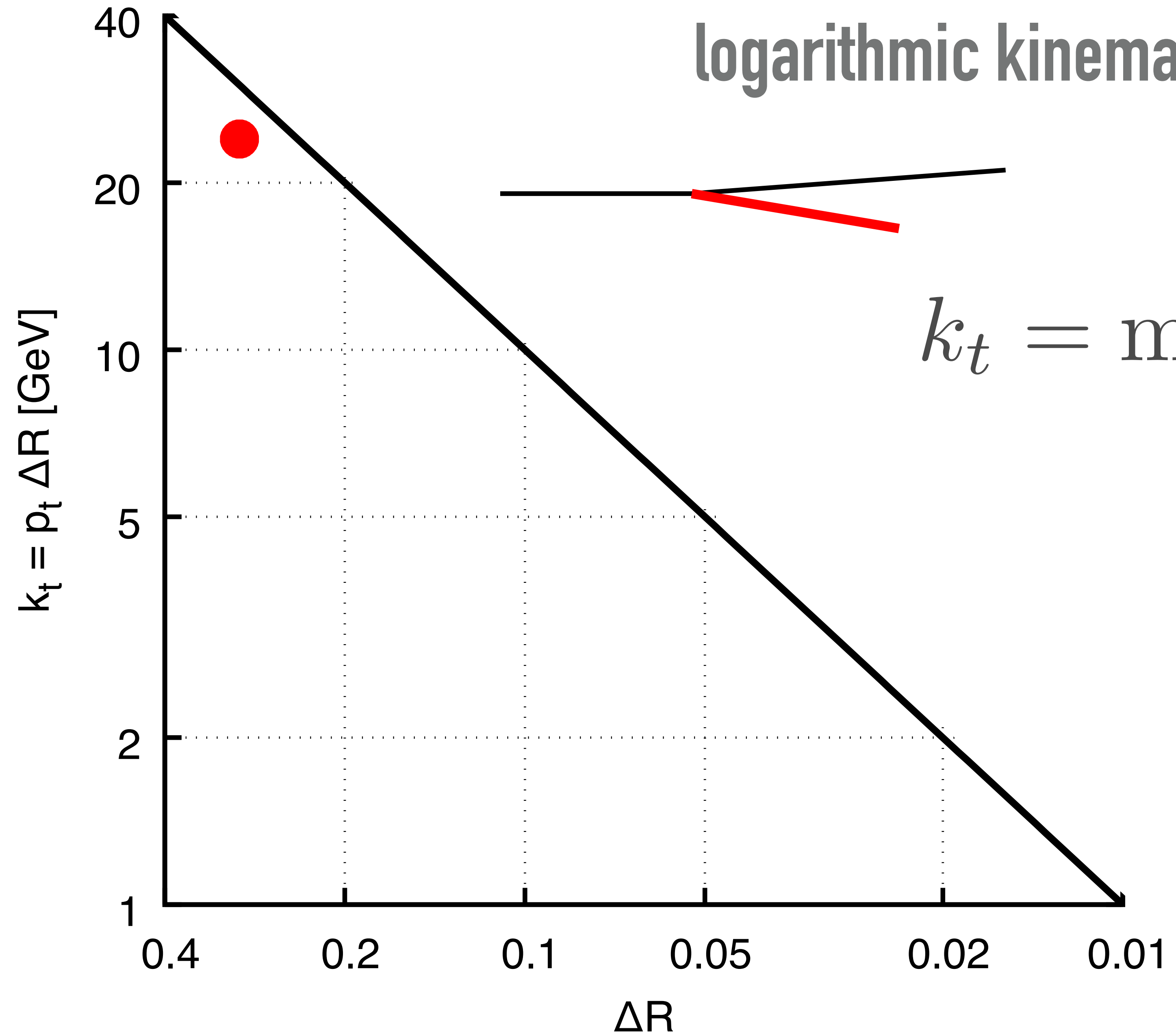
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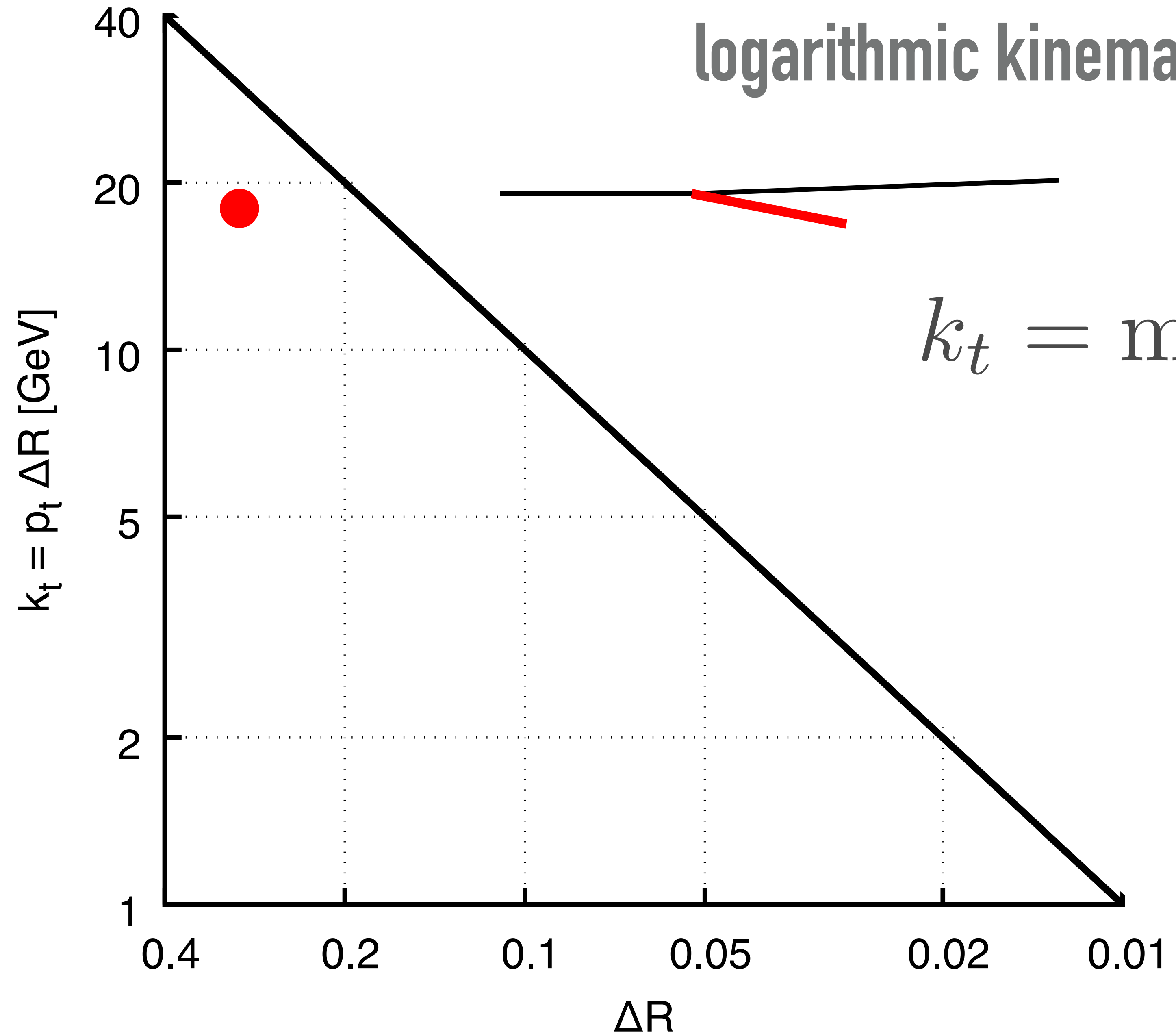
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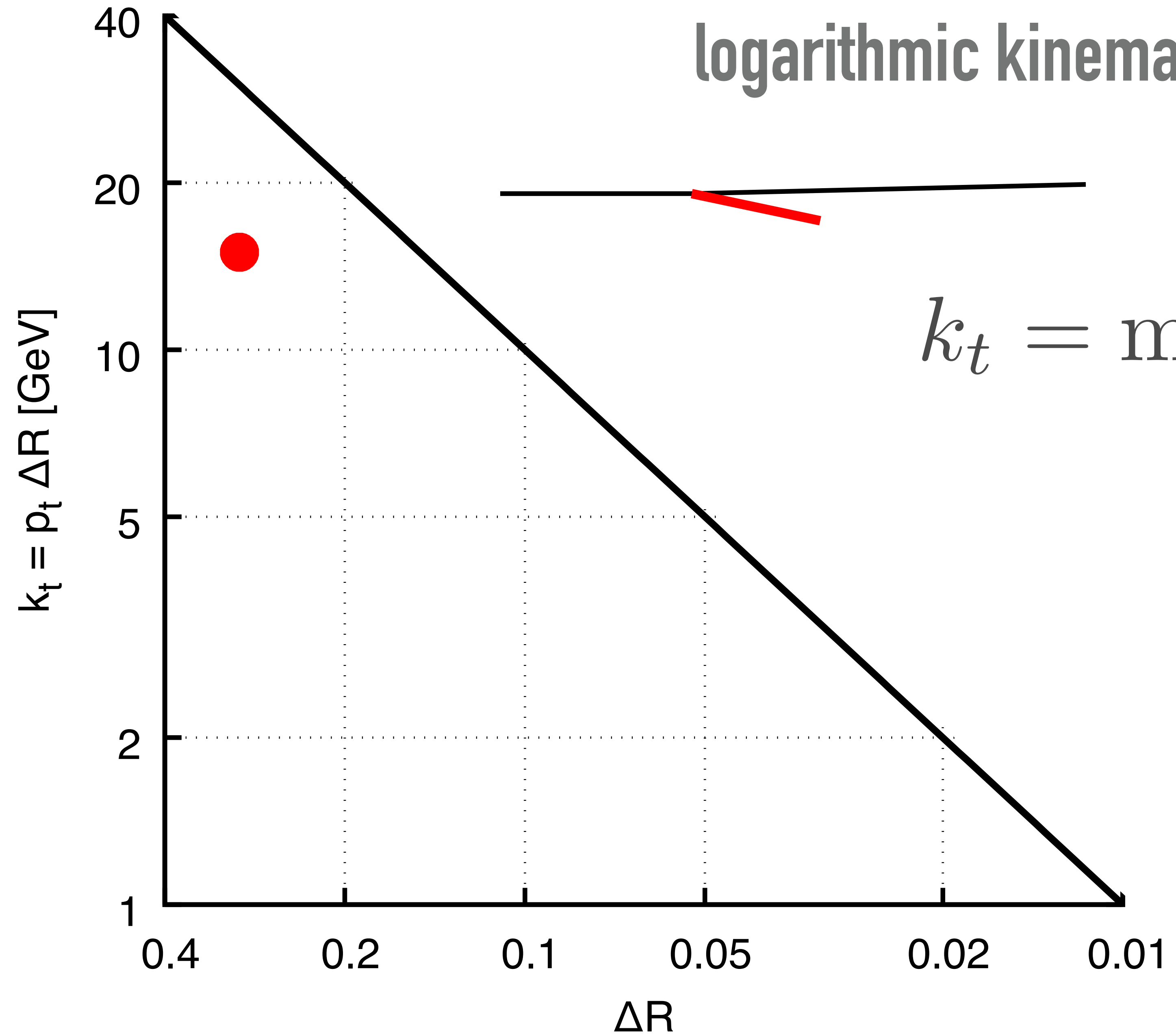
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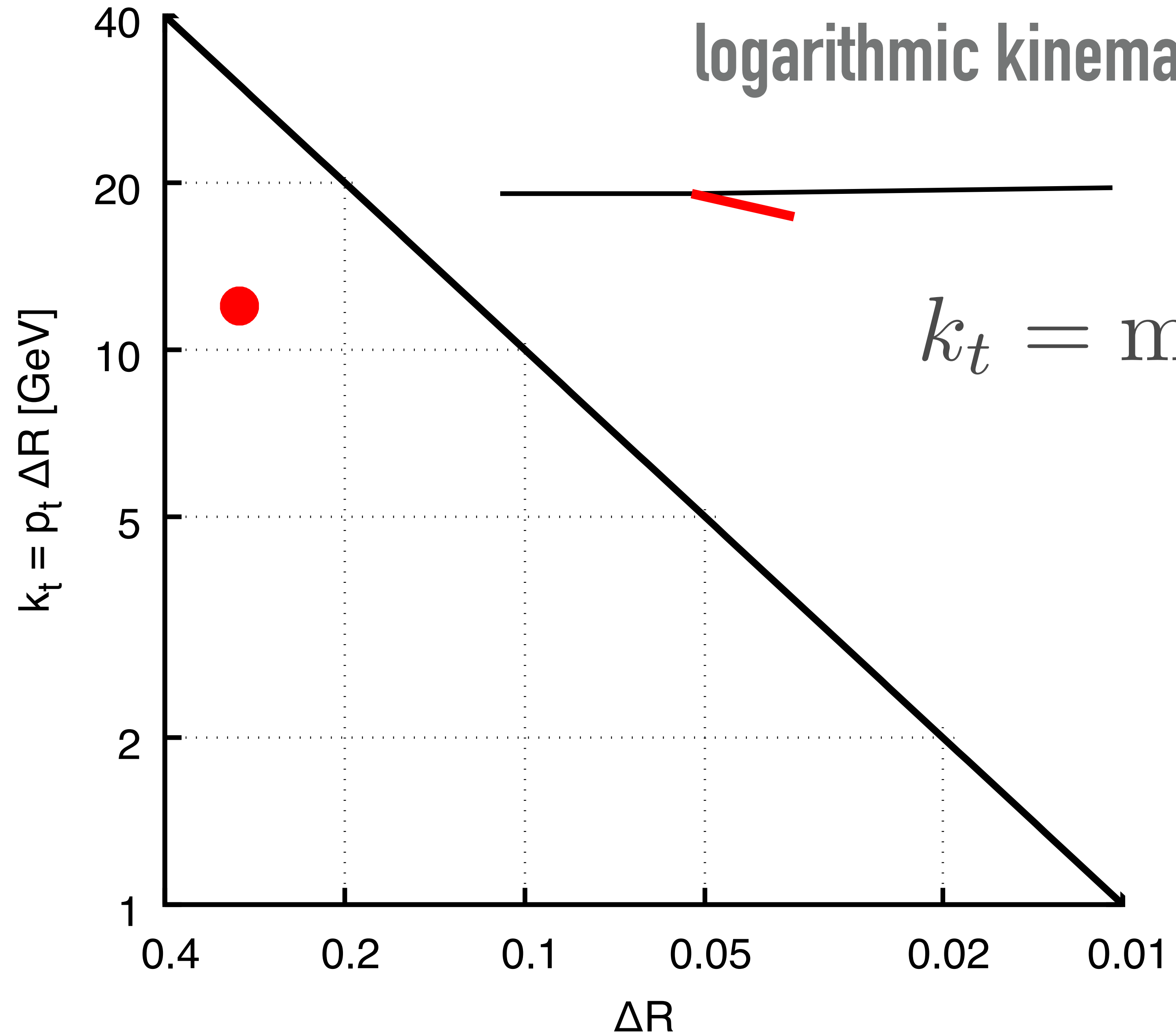
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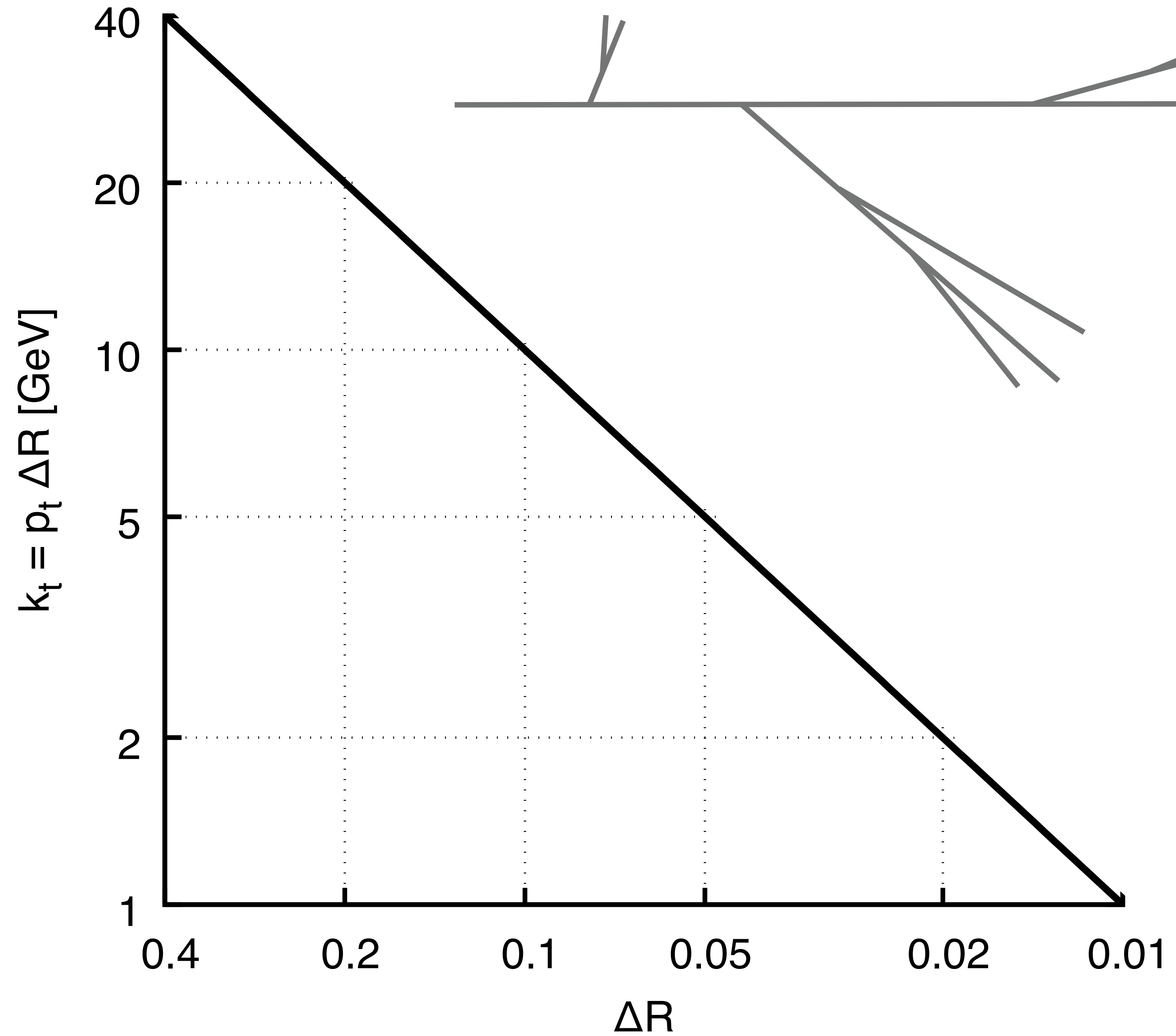
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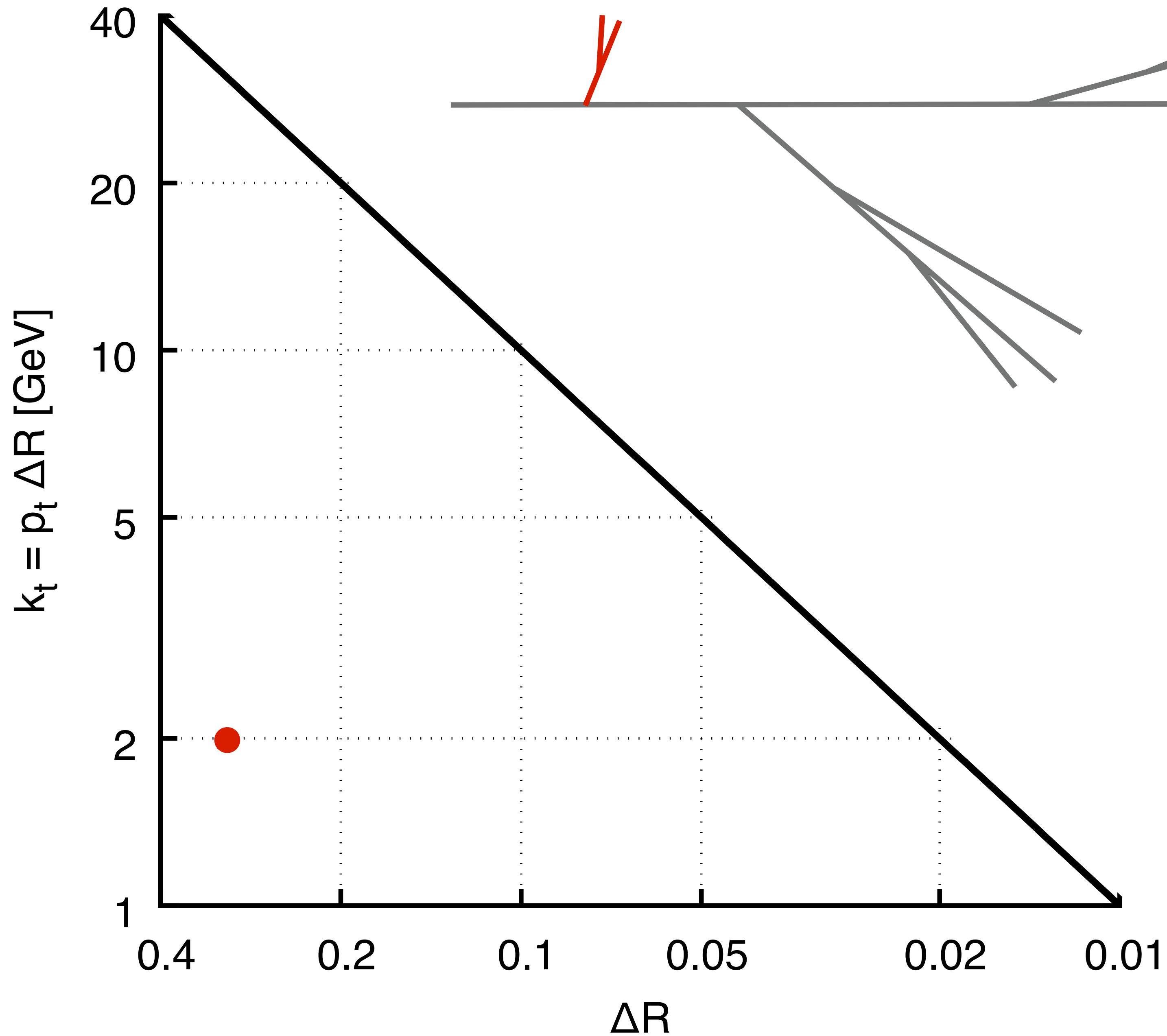
jet with $R = 0.4$, $p_t = 200 \text{ GeV}$



**decluster a C/A jet:
at each step record $\Delta R, k_t$
as a point in the Lund plane
repeatedly follow harder branch**

5th heavy-ion workshop @ CERN, [1808.03689](#)
Dreyer, Soyez & GPS, [1807.04758](#) (for pp applications)

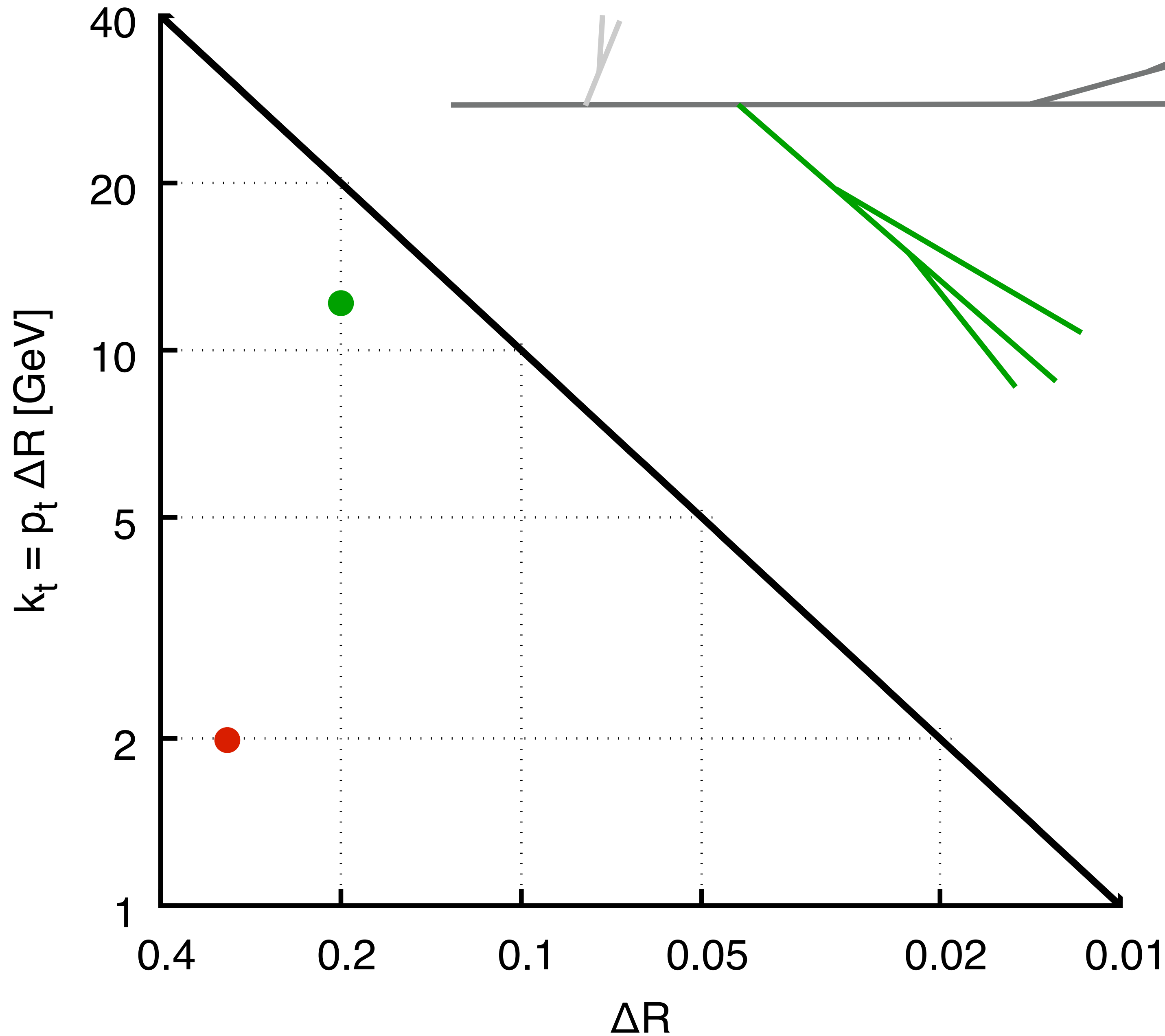
constructing the Lund plane



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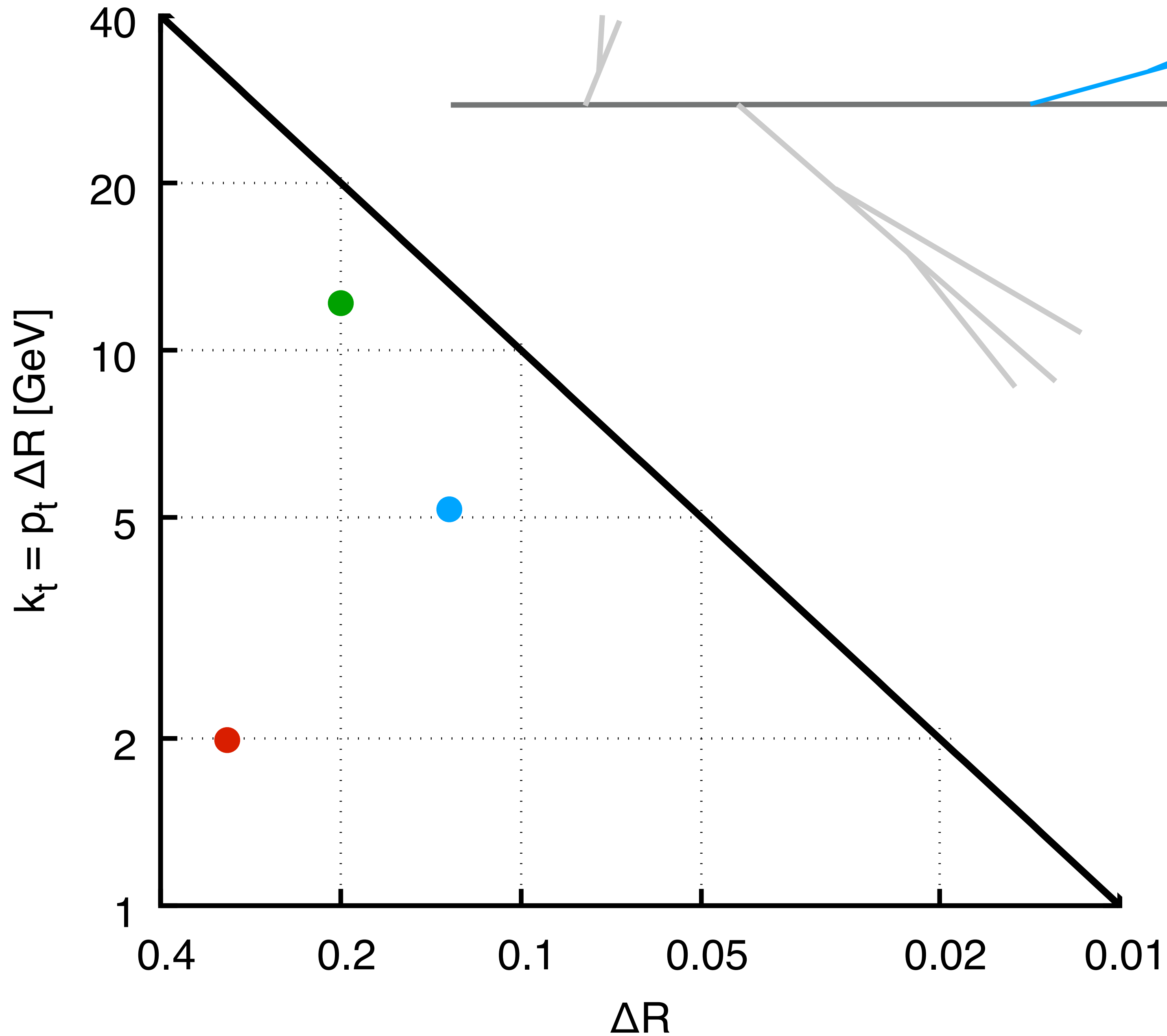
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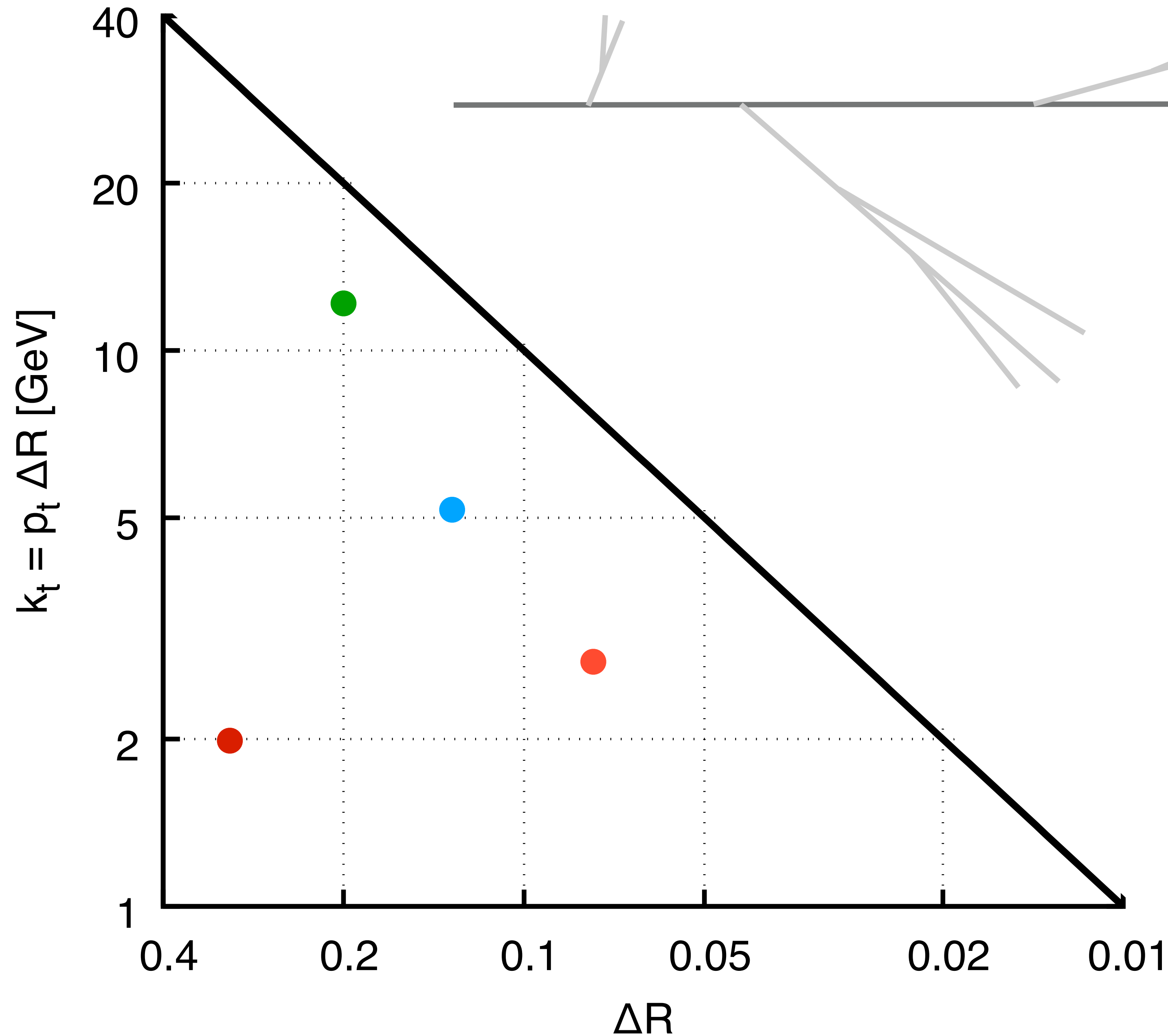
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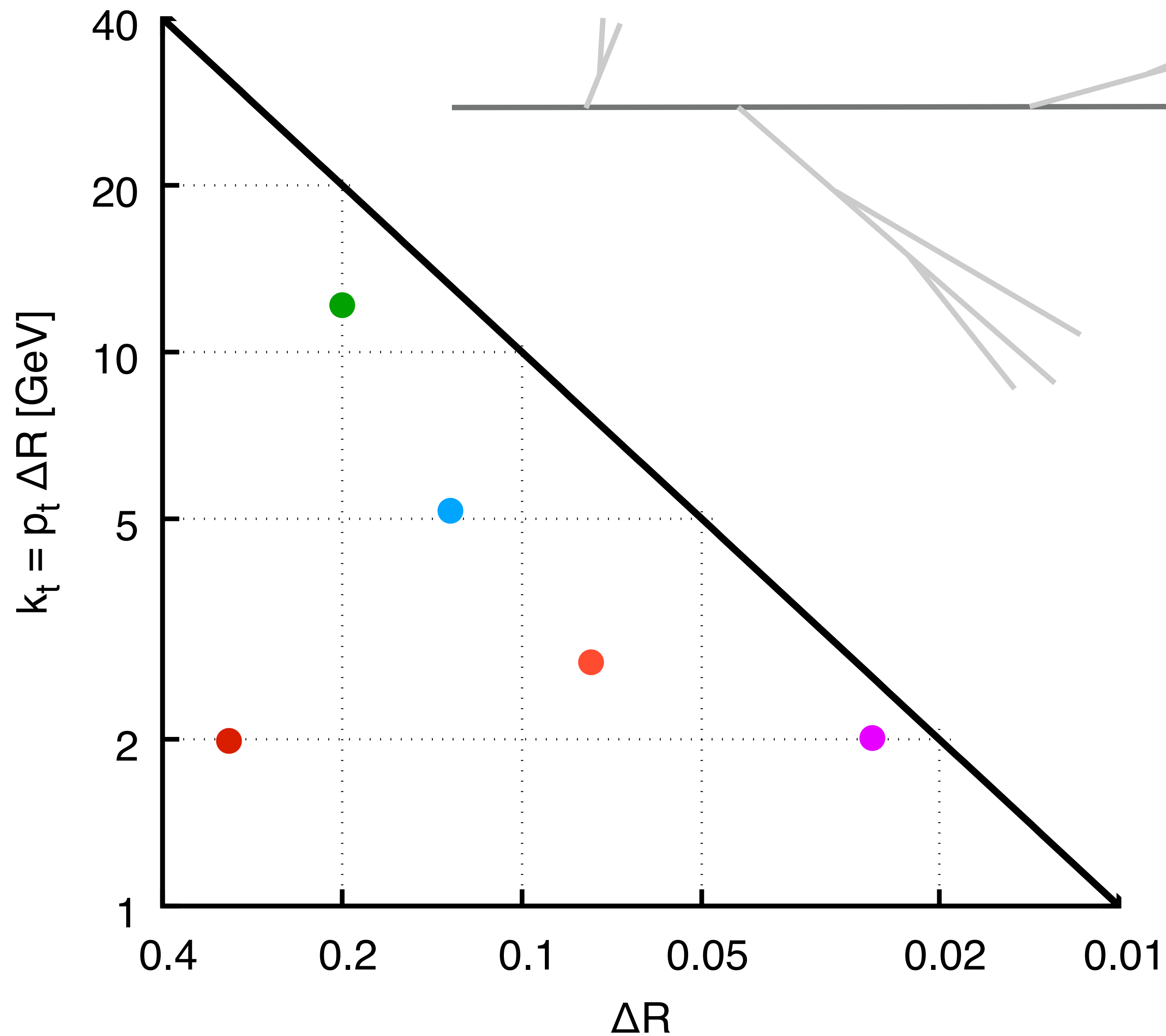
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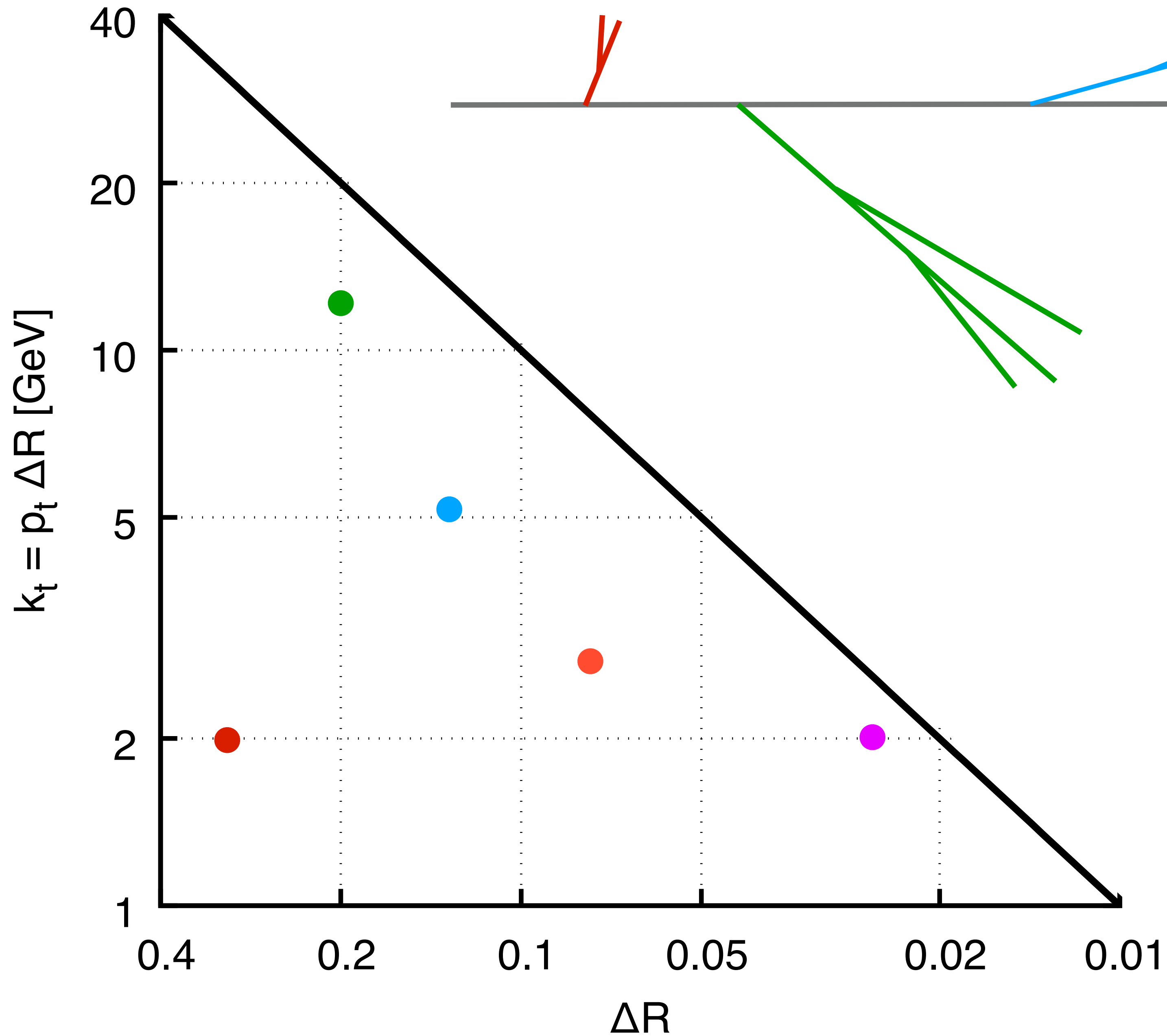
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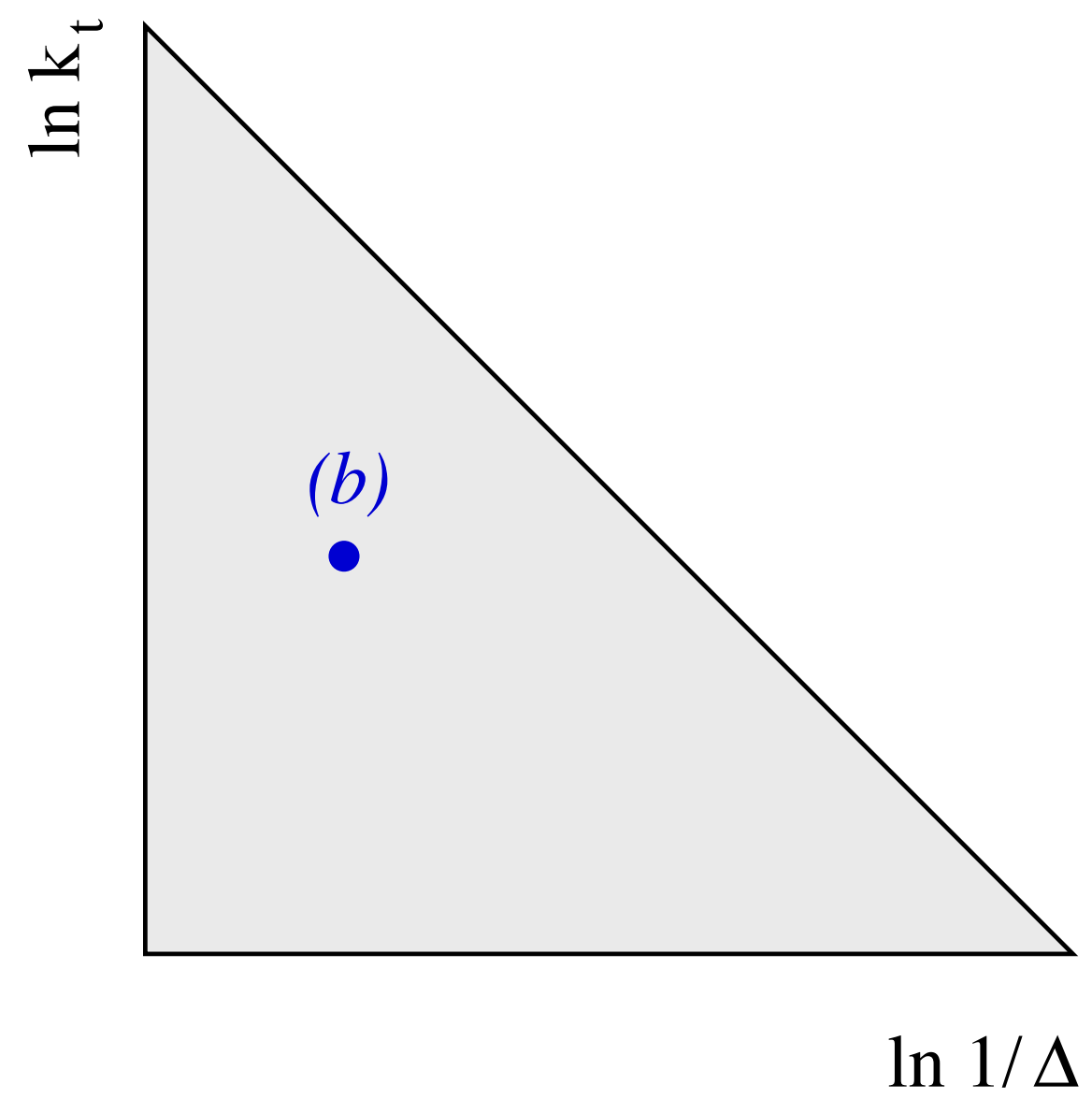
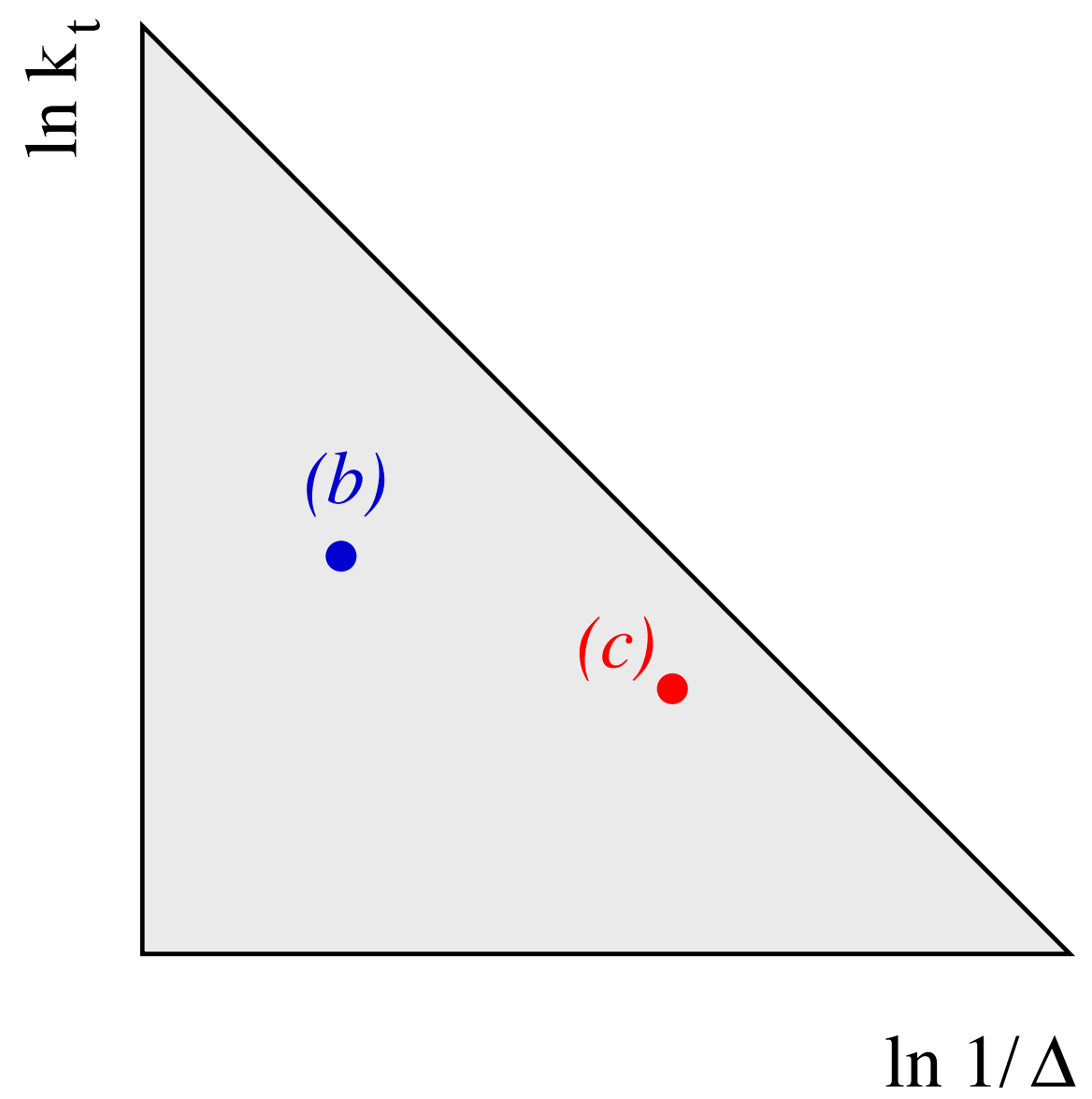
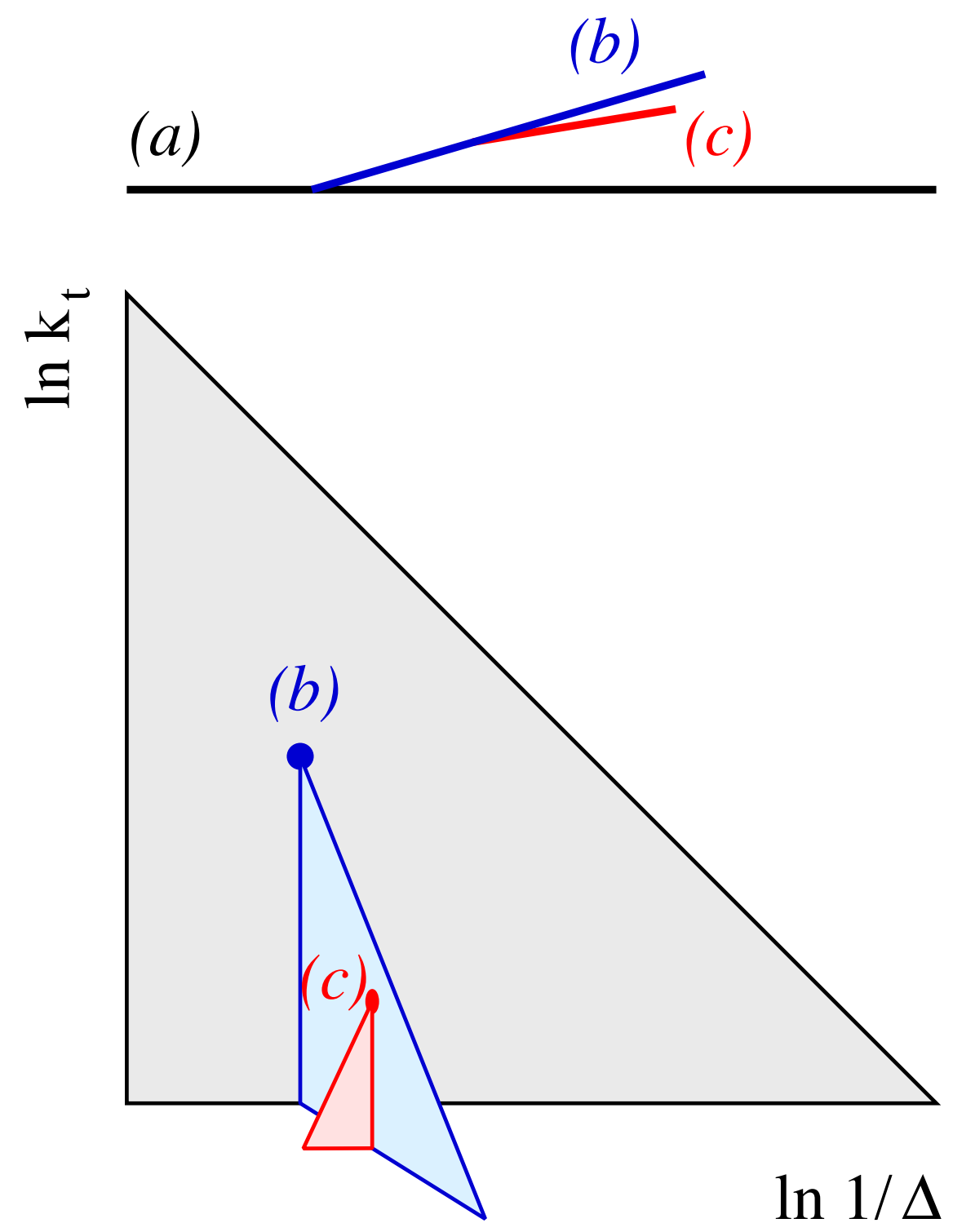
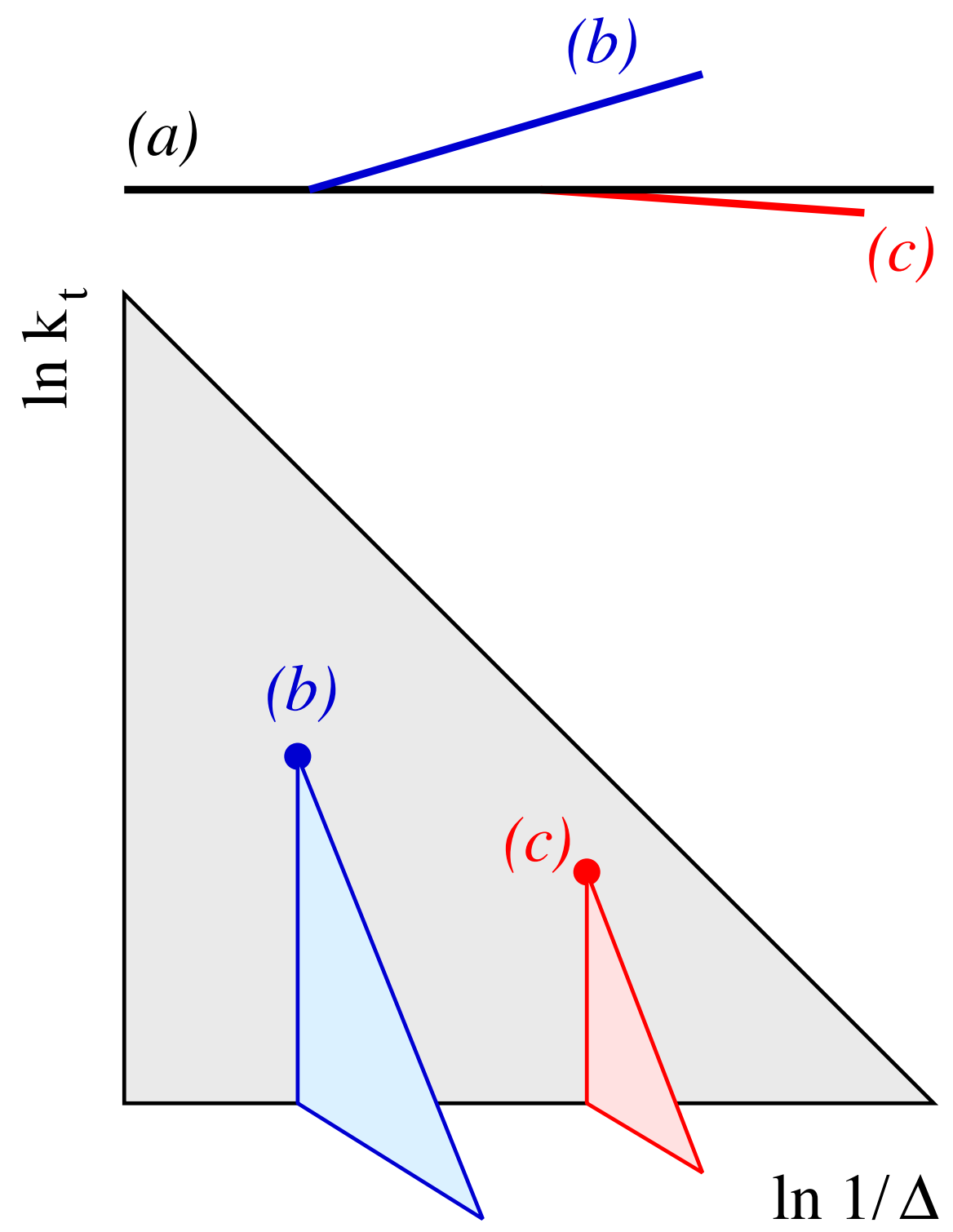
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constructing the Lund plane

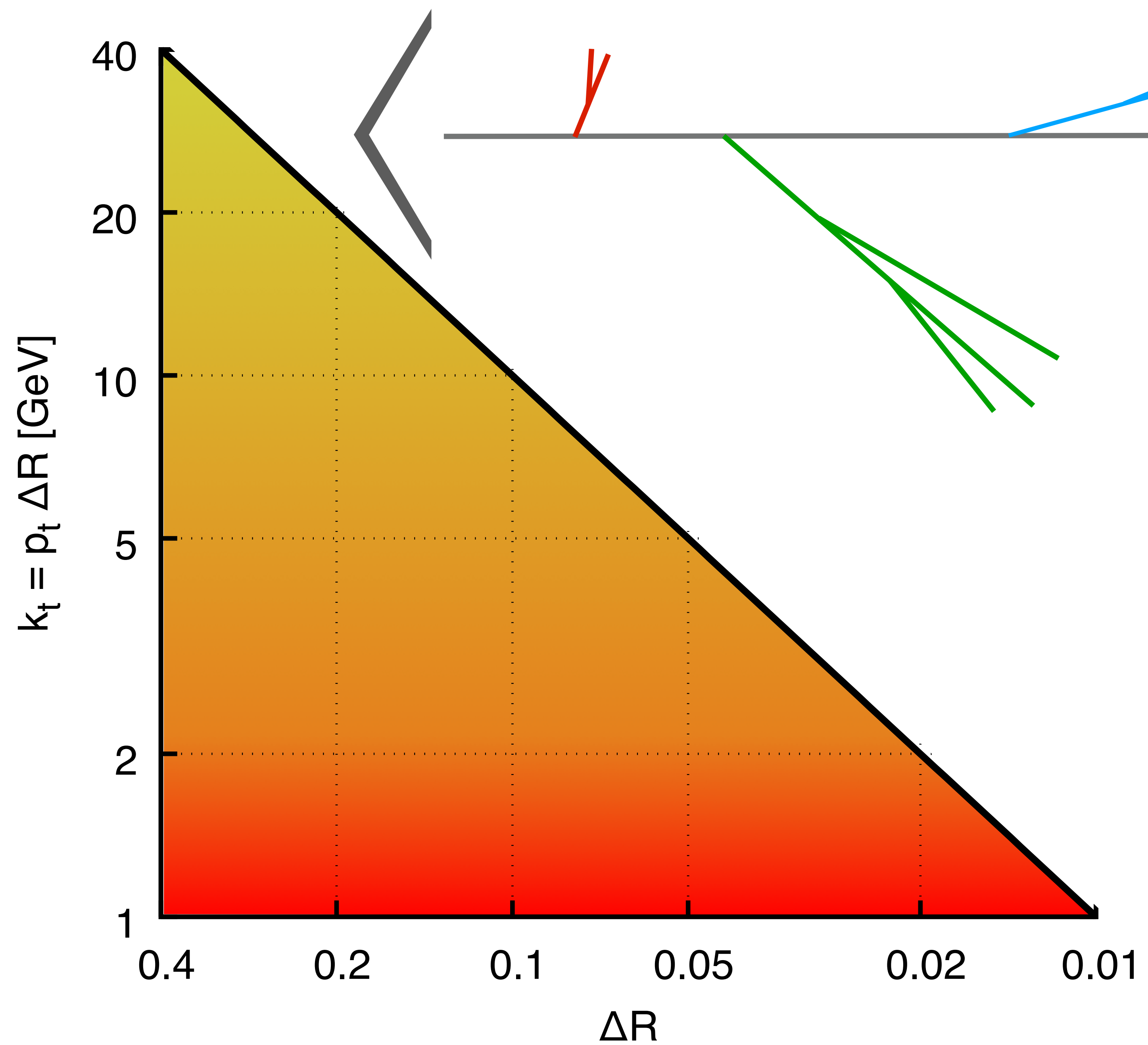
JET

LUND DIAGRAM

PRIMARY LUND PLANE



jet with $R = 0.4$, $p_t = 200 \text{ GeV}$

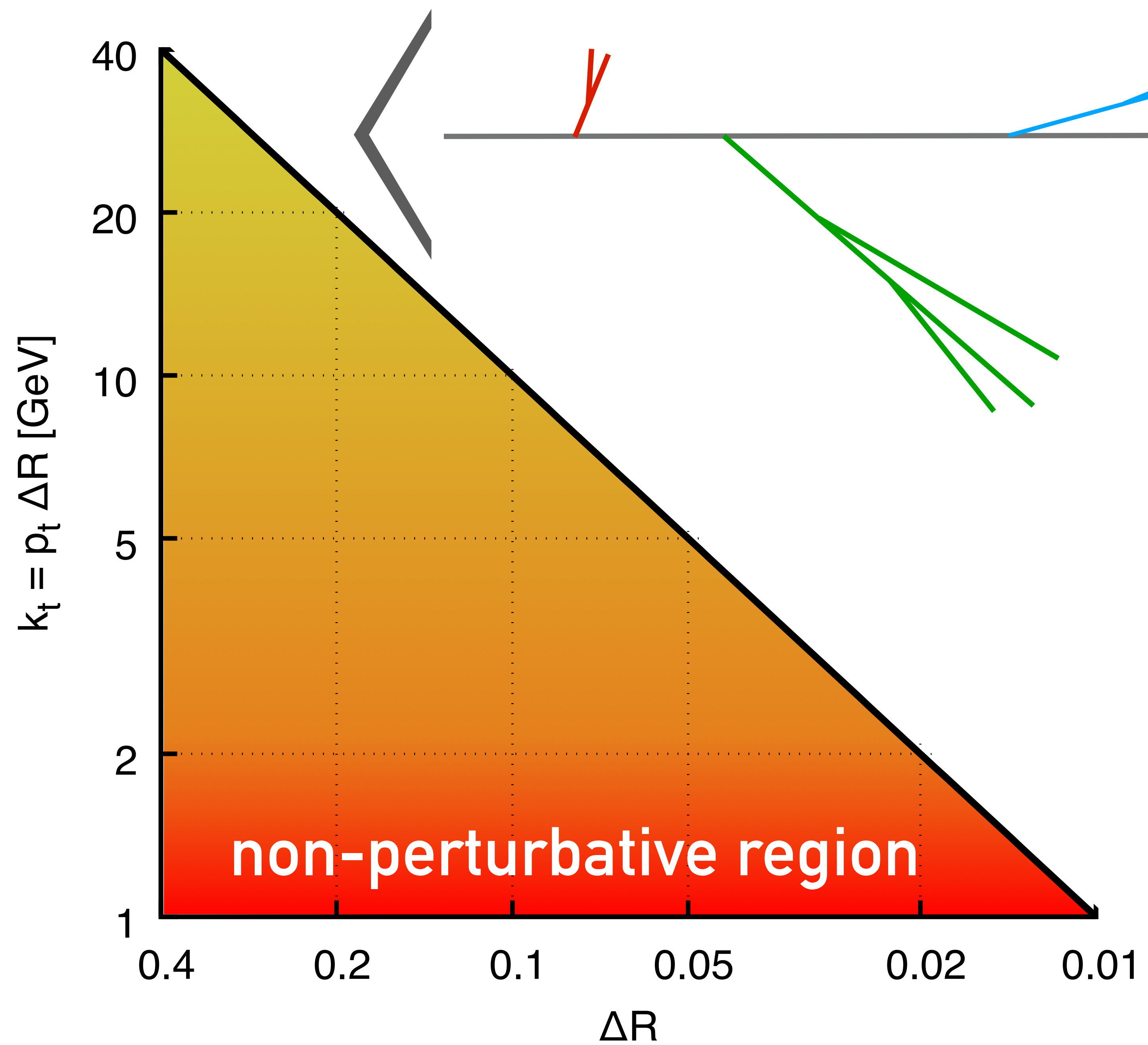


average over many jets:
Lund plane density

5th heavy-ion workshop @ CERN, [1808.03689](#)
Dreyer, Soyez & GPS, [1807.04758](#) (for pp applications)

constructing the Lund plane

jet with $R = 0.4$, $p_t = 200$ GeV

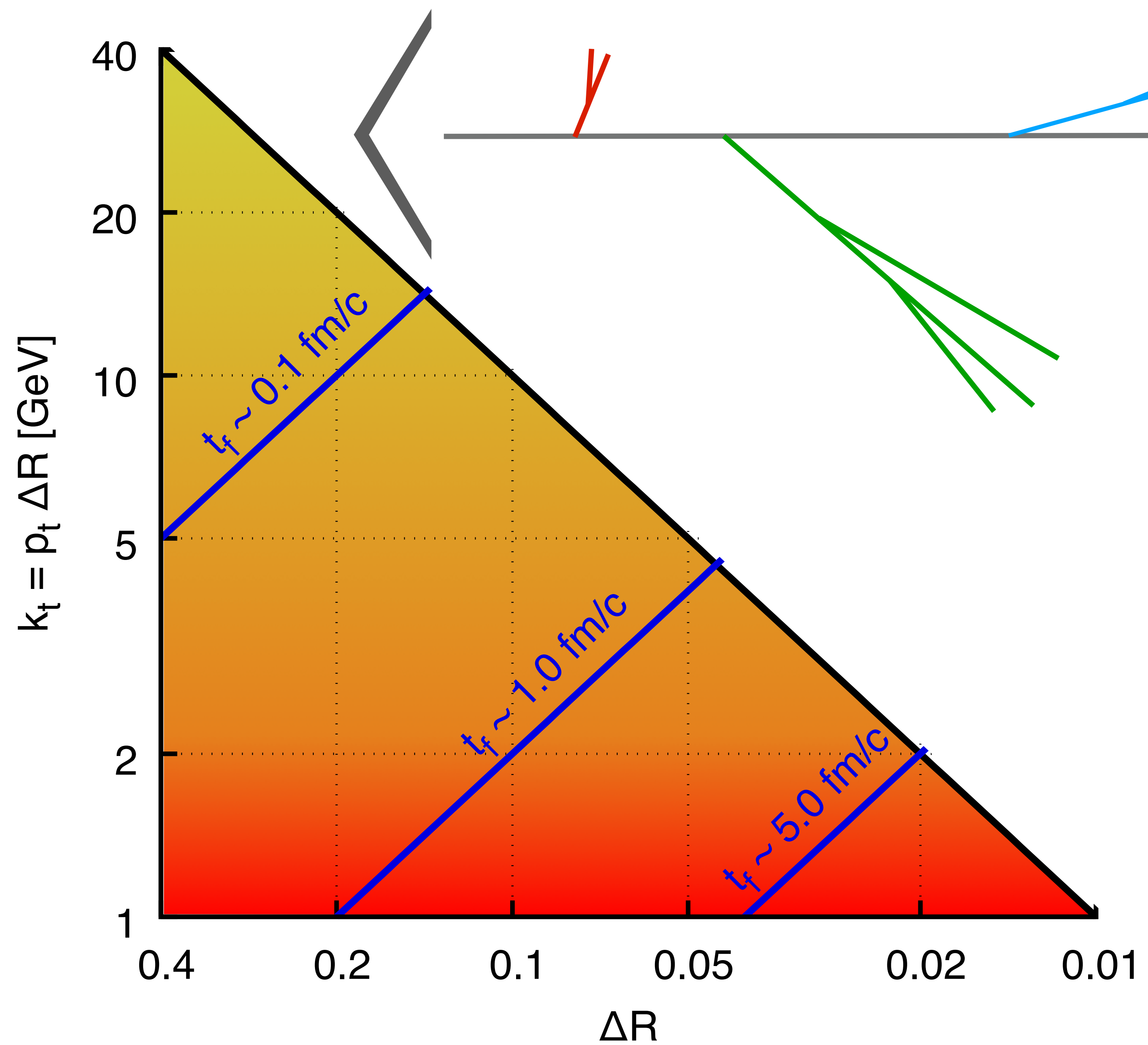


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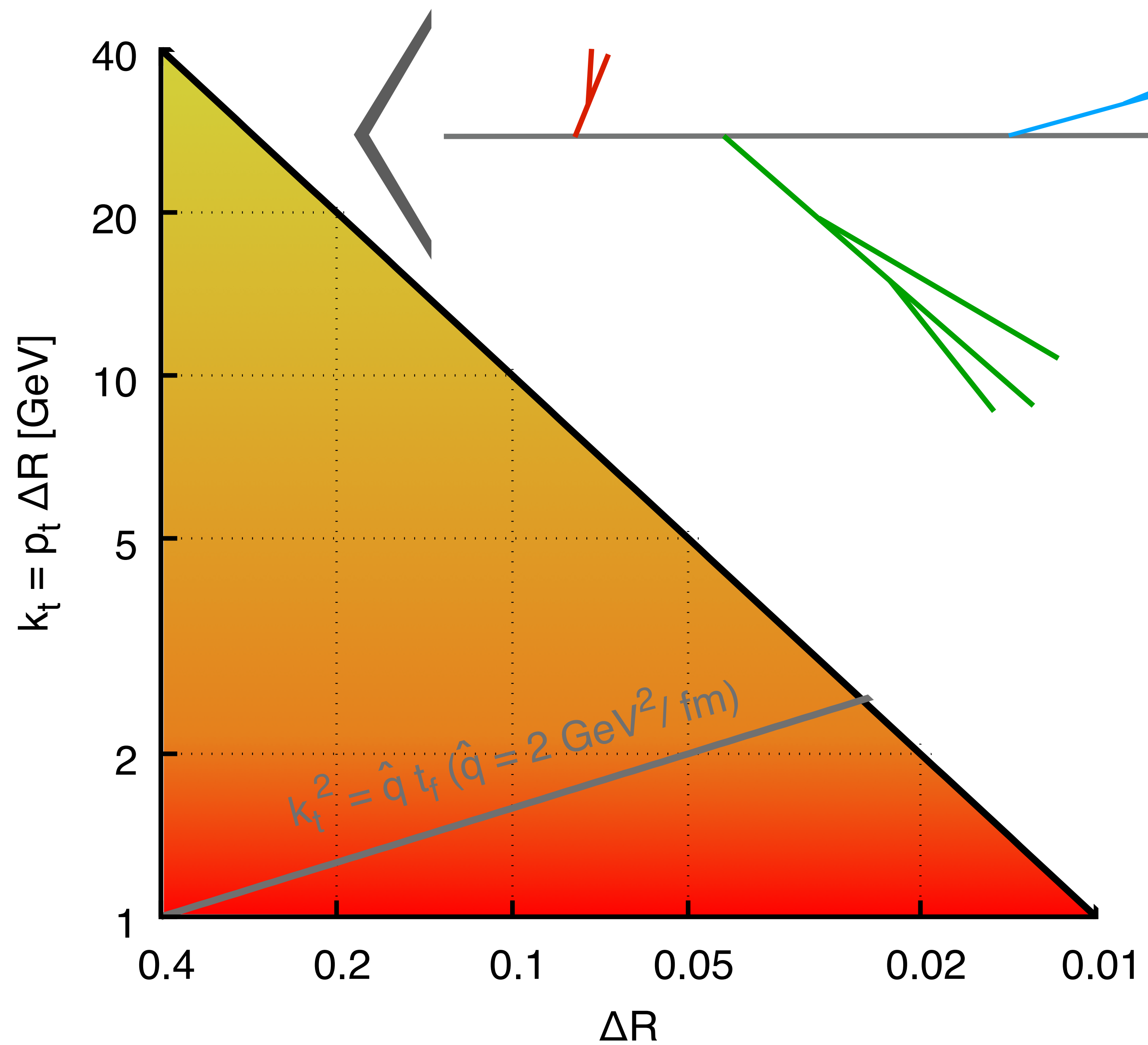


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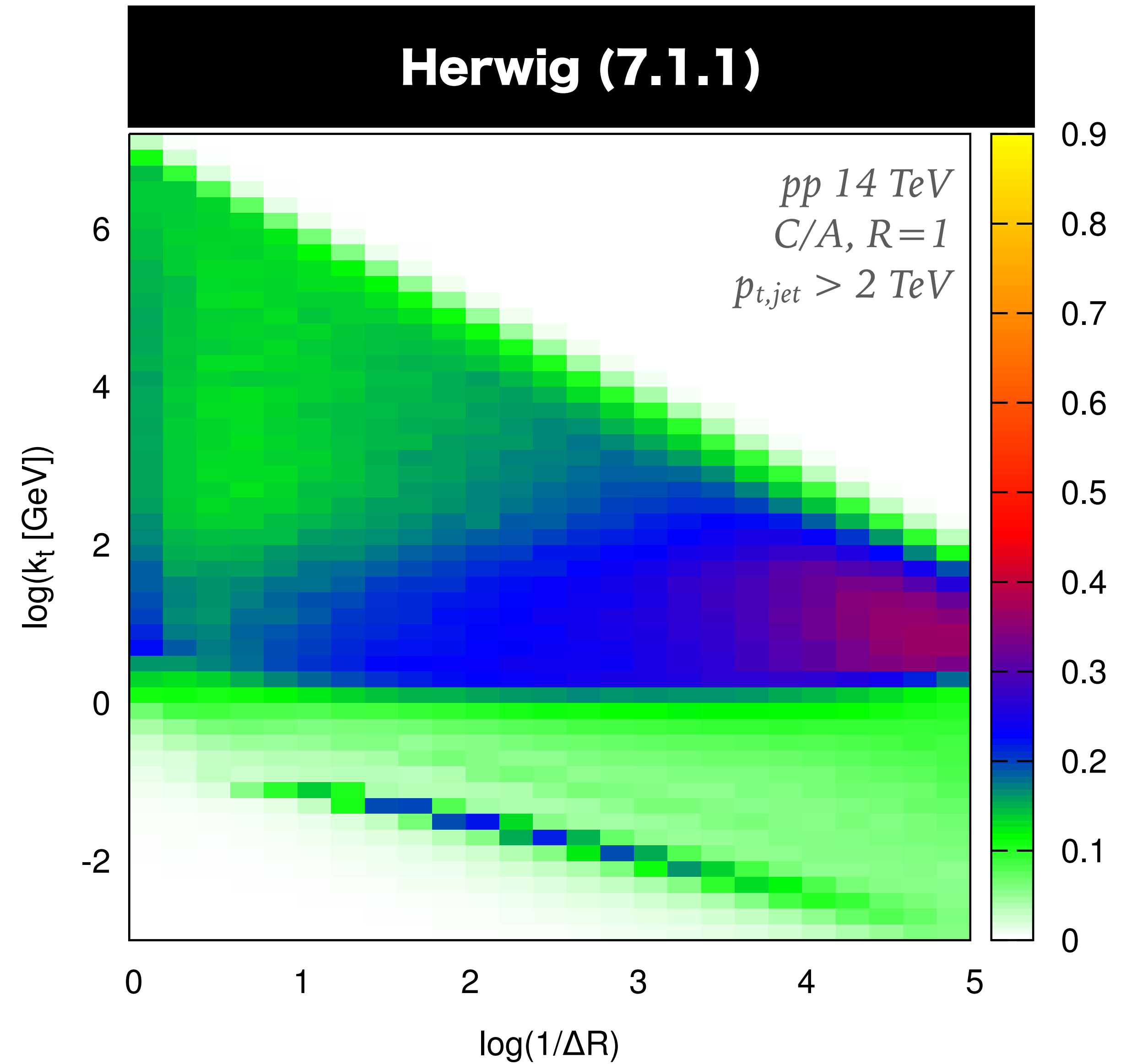
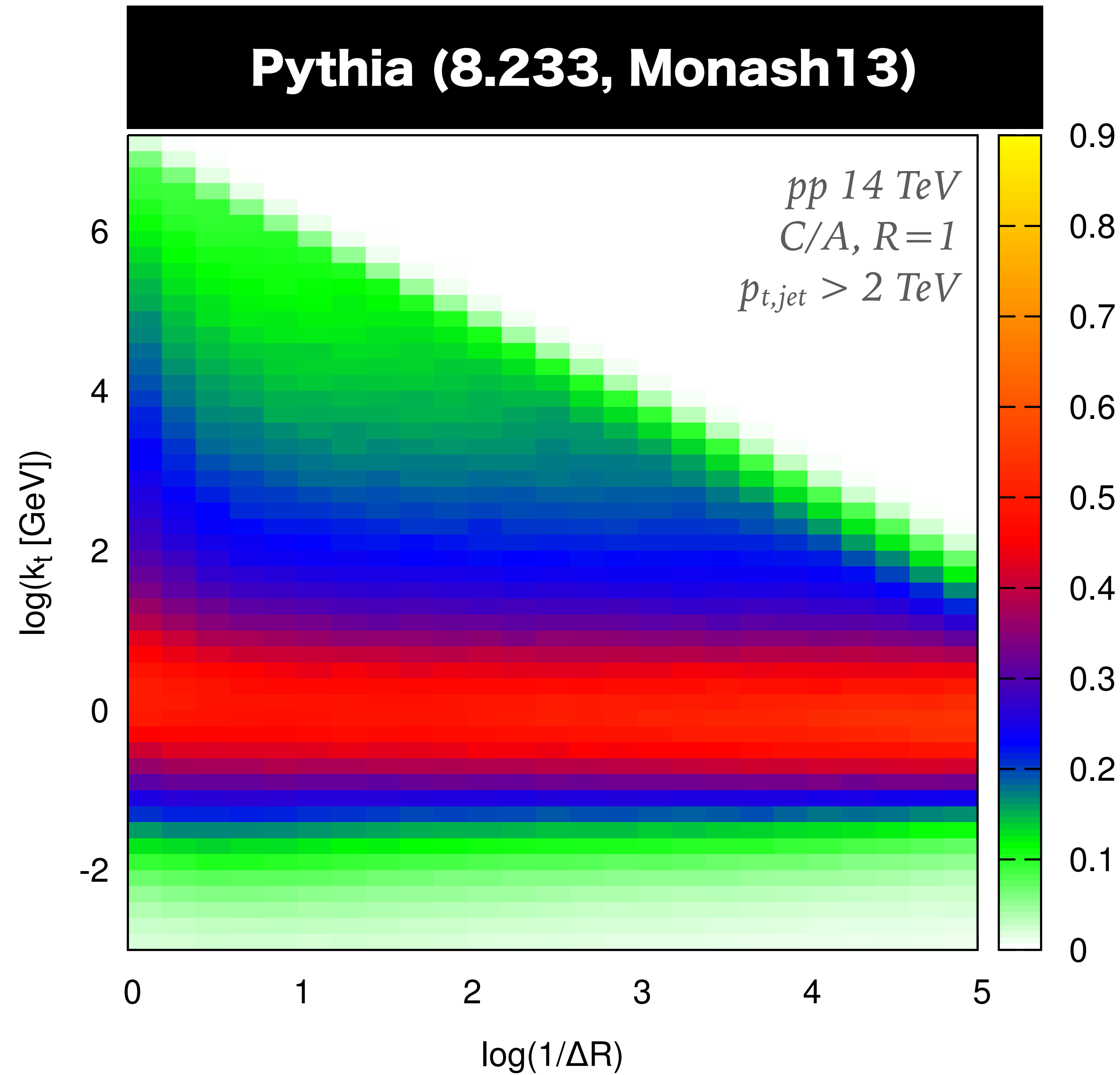
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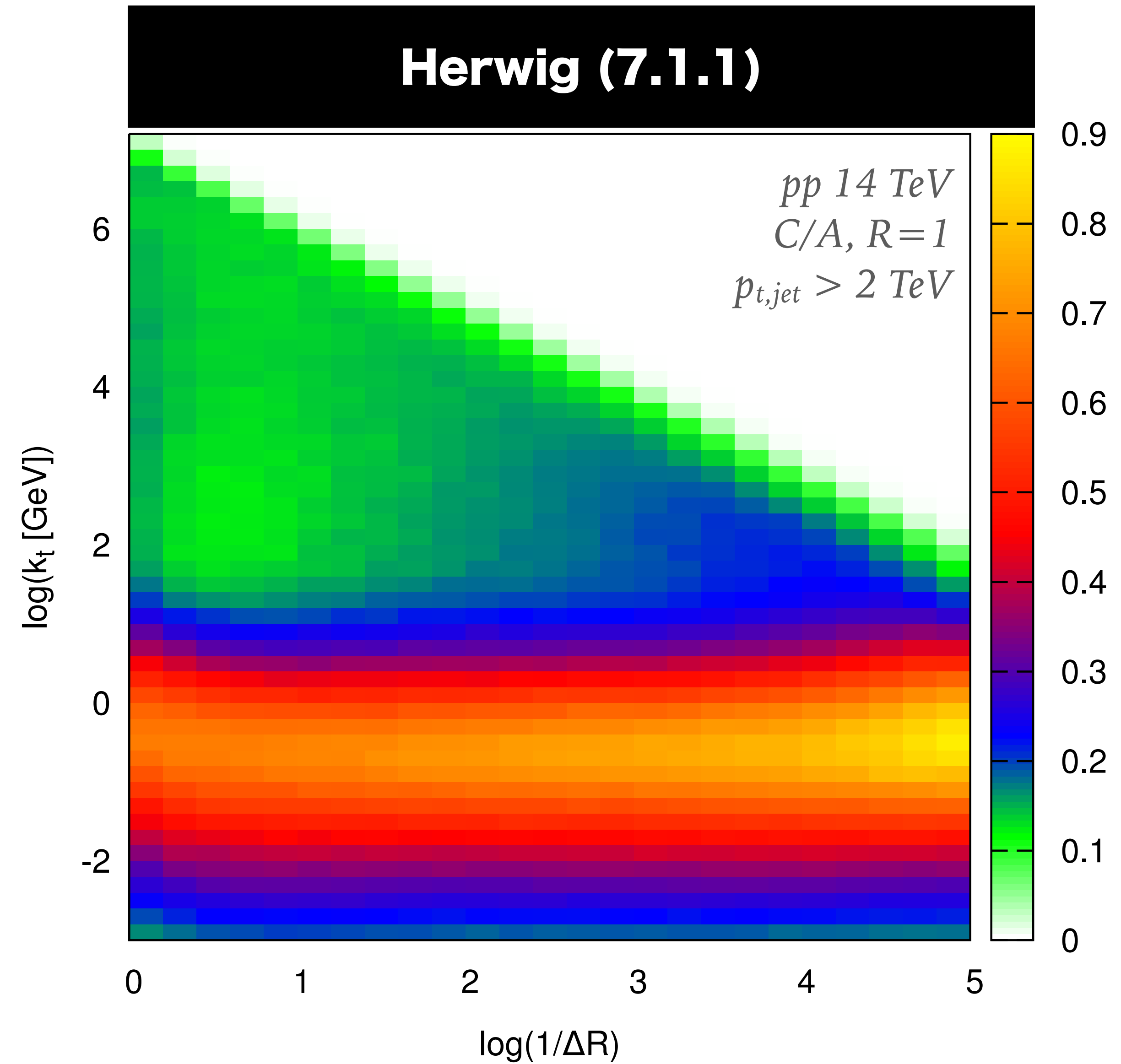
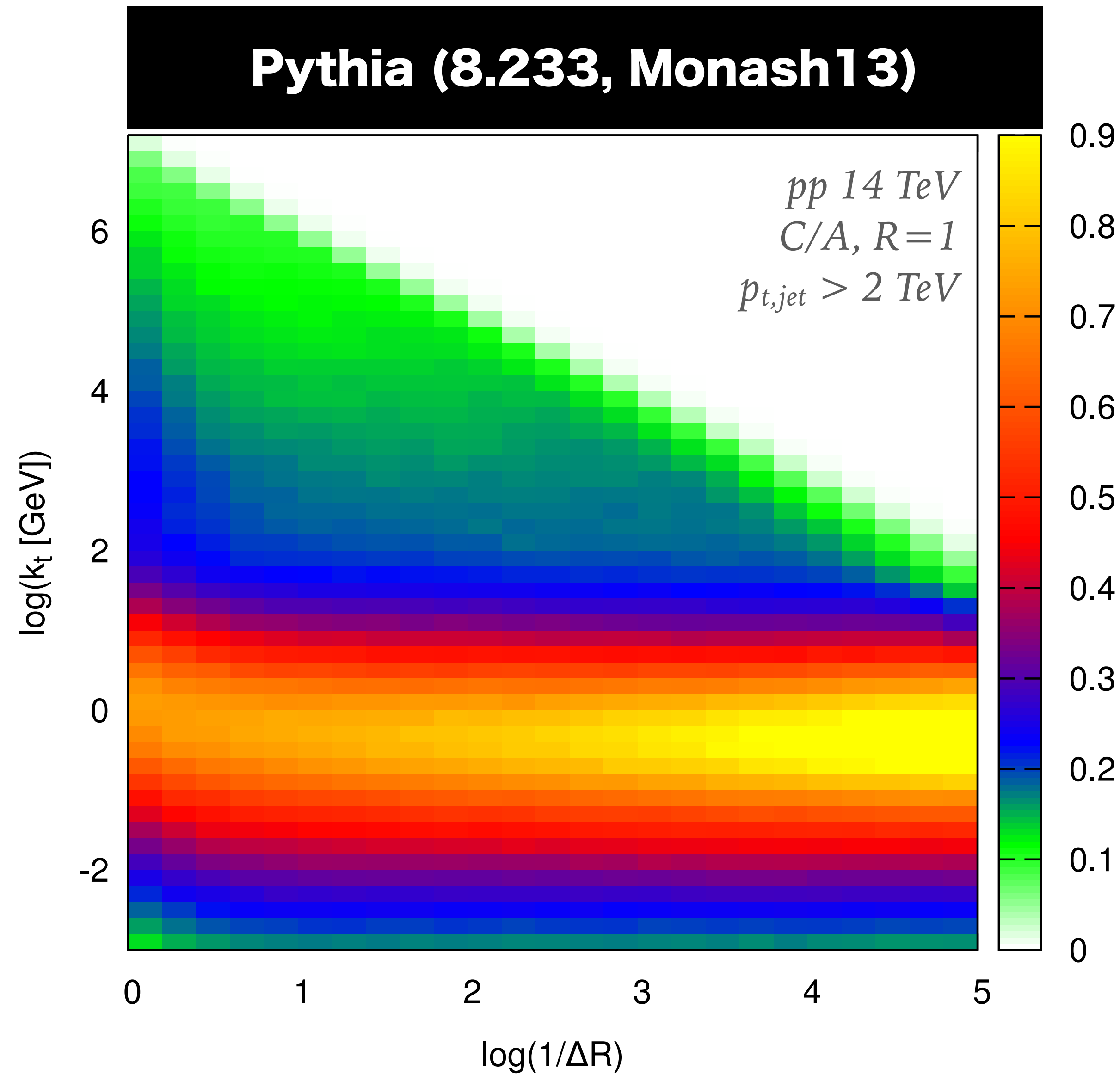
constructing the Lund plane

application to pp QCD studies

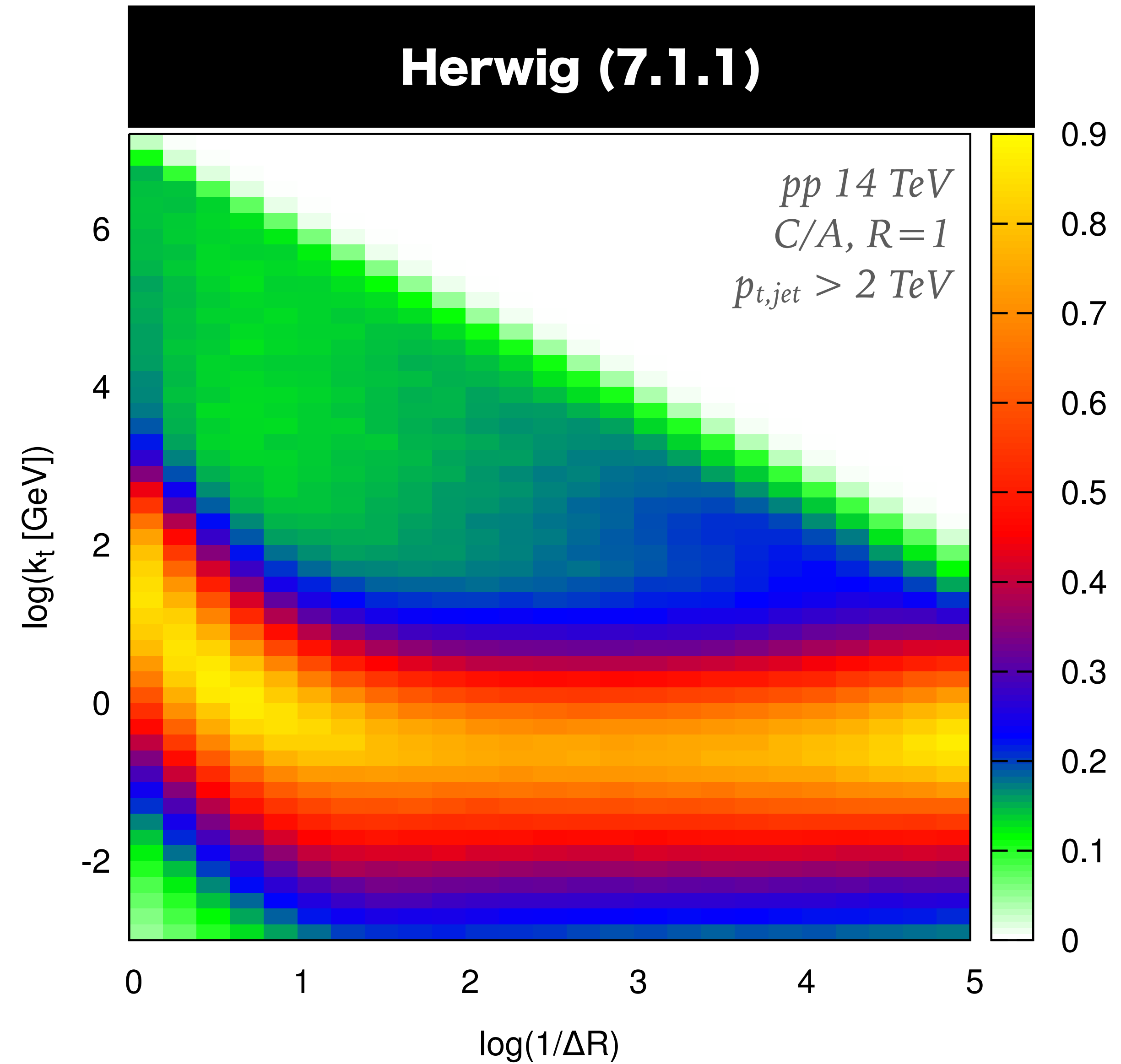
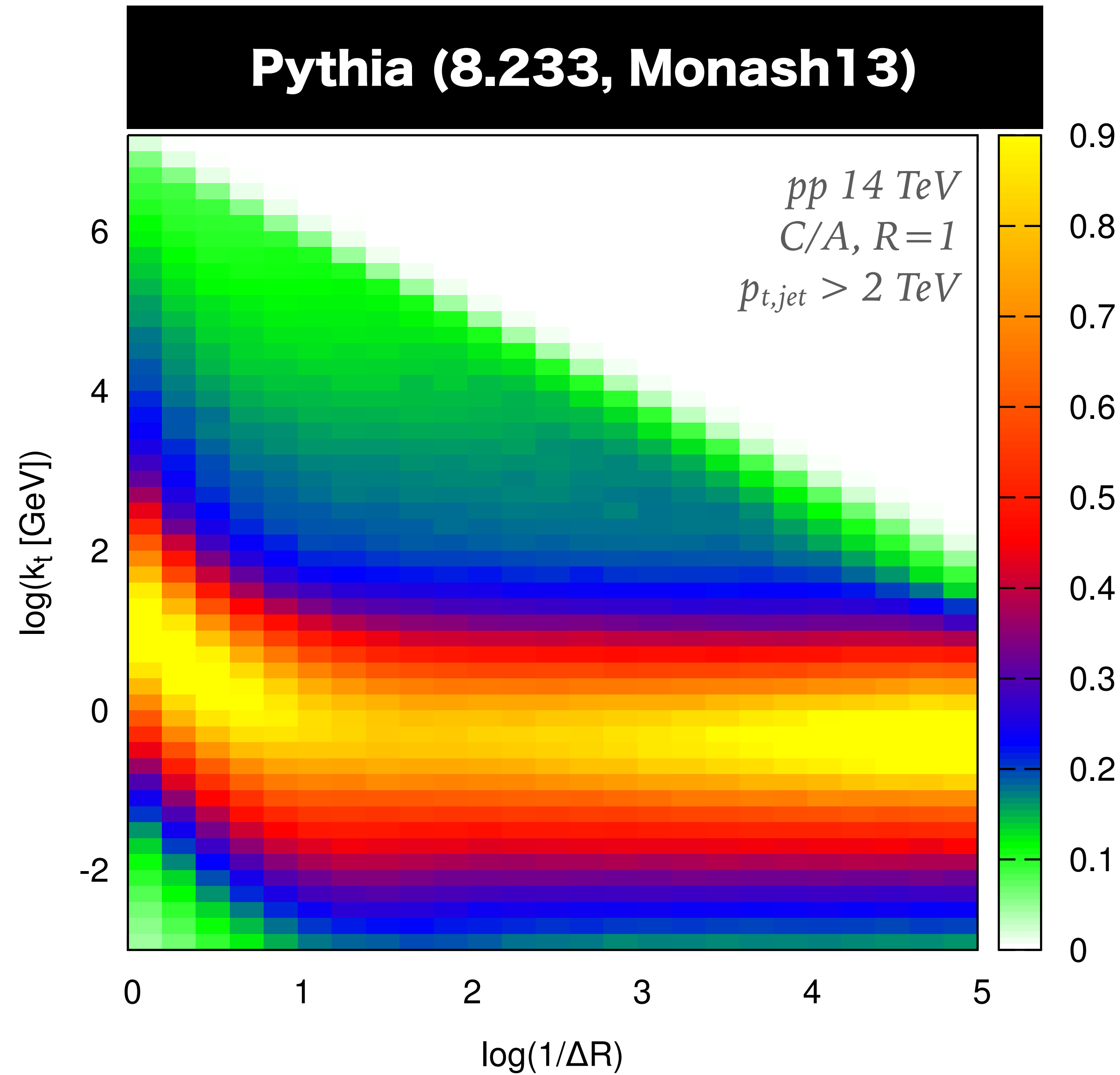
average pp Lund density: **parton level**



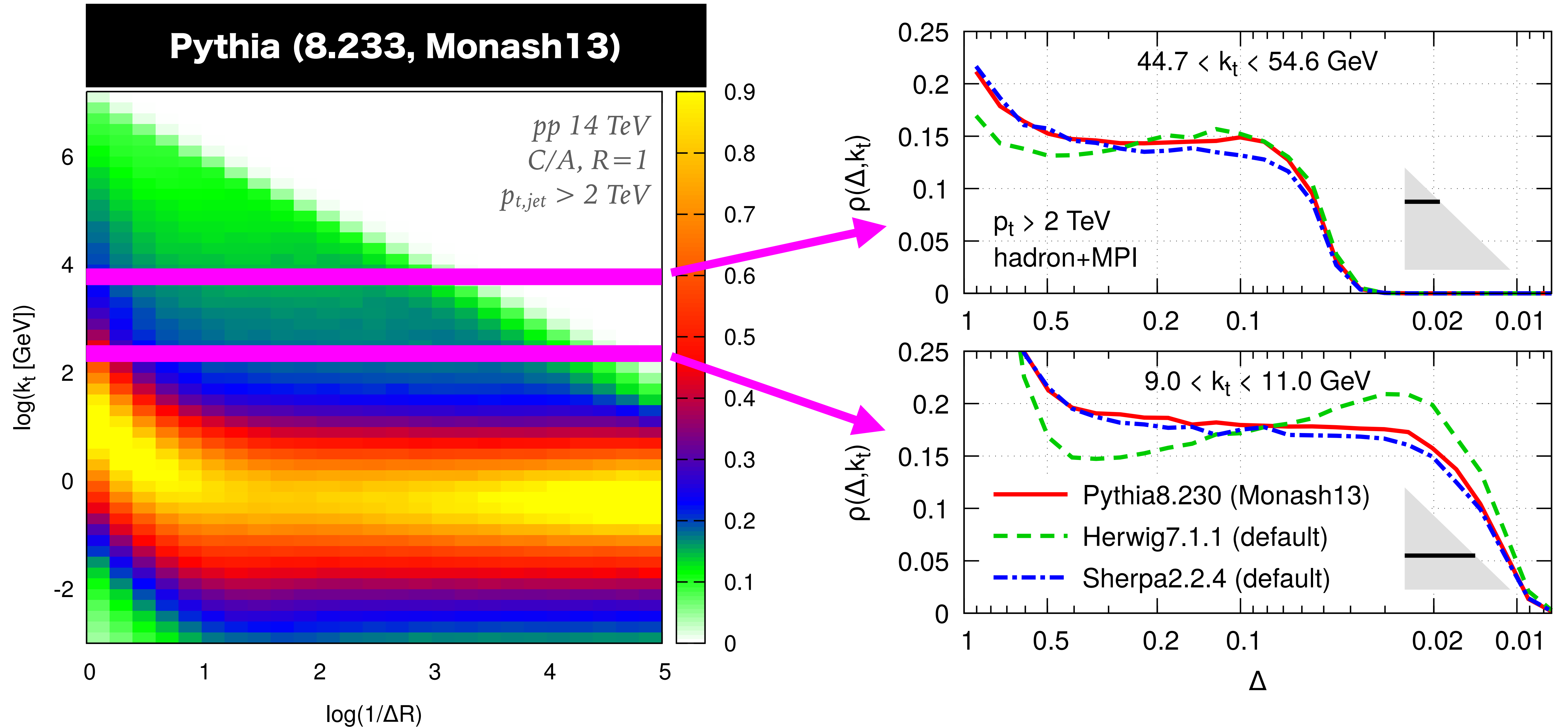
average pp Lund density: **hadron level (no underlying event / MPI)**



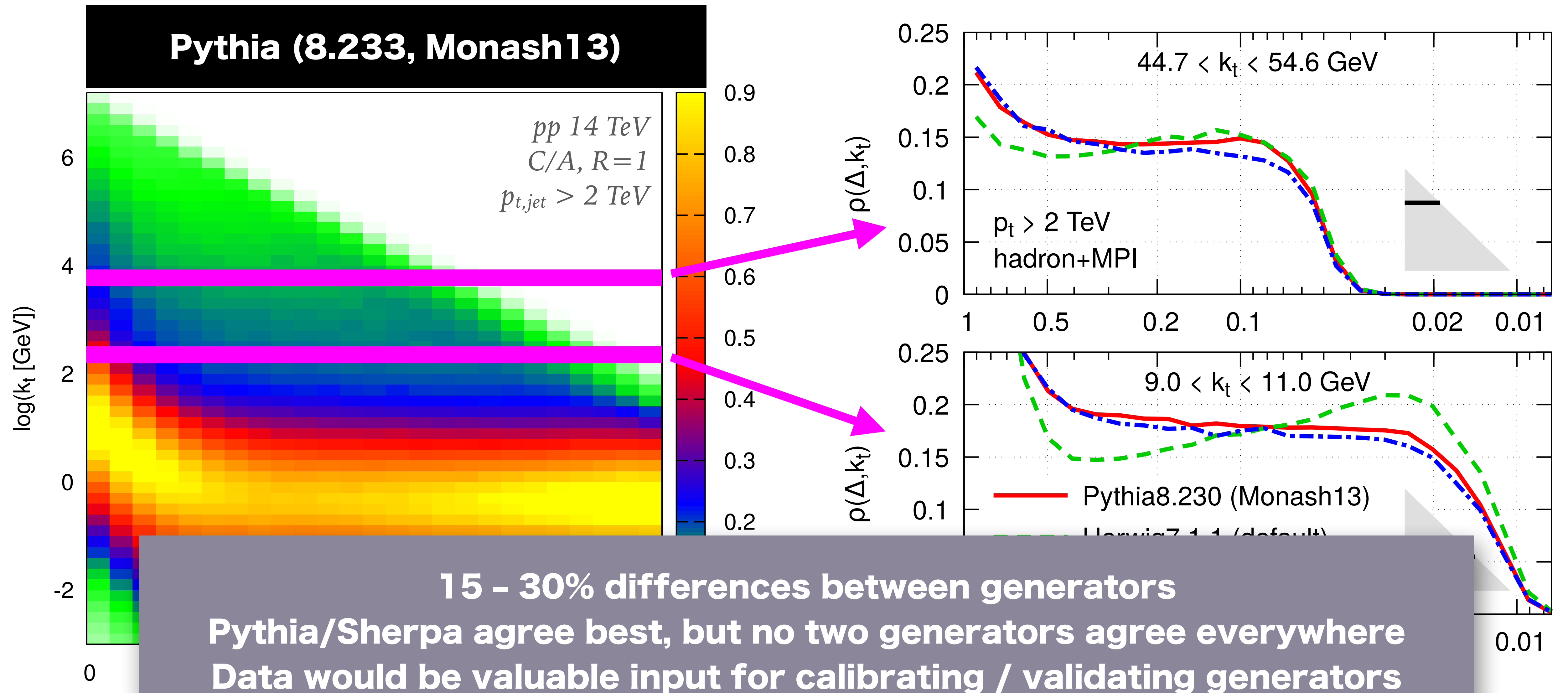
average pp Lund density: hadron level (with underlying event / MPI)



average pp Lund density: cross sections



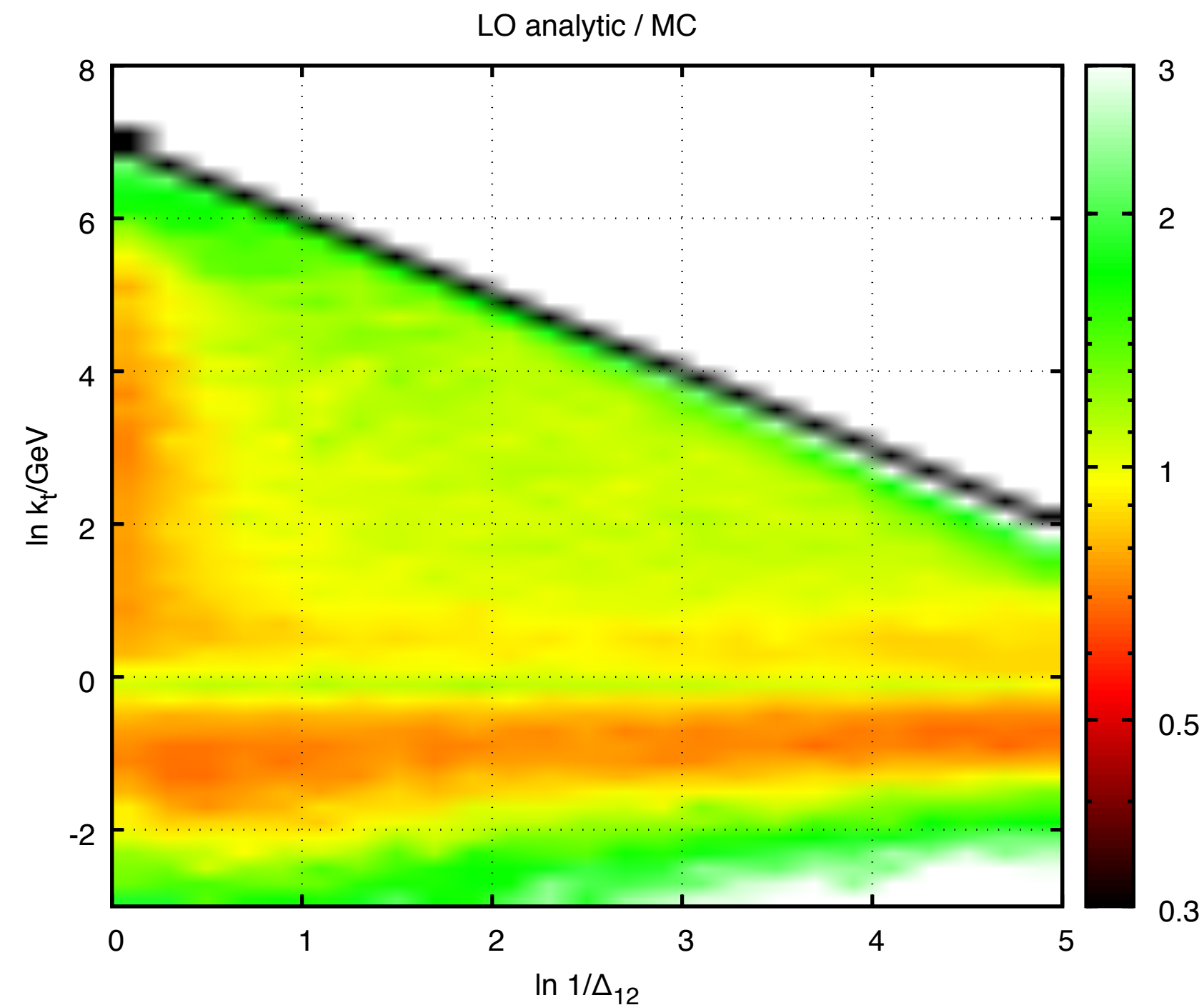
average pp Lund density: **cross sections**



analytic perturbative QCD control

To leading order in perturbative QCD and for $\Delta \ll 1$, one expects for a quark initiated jet

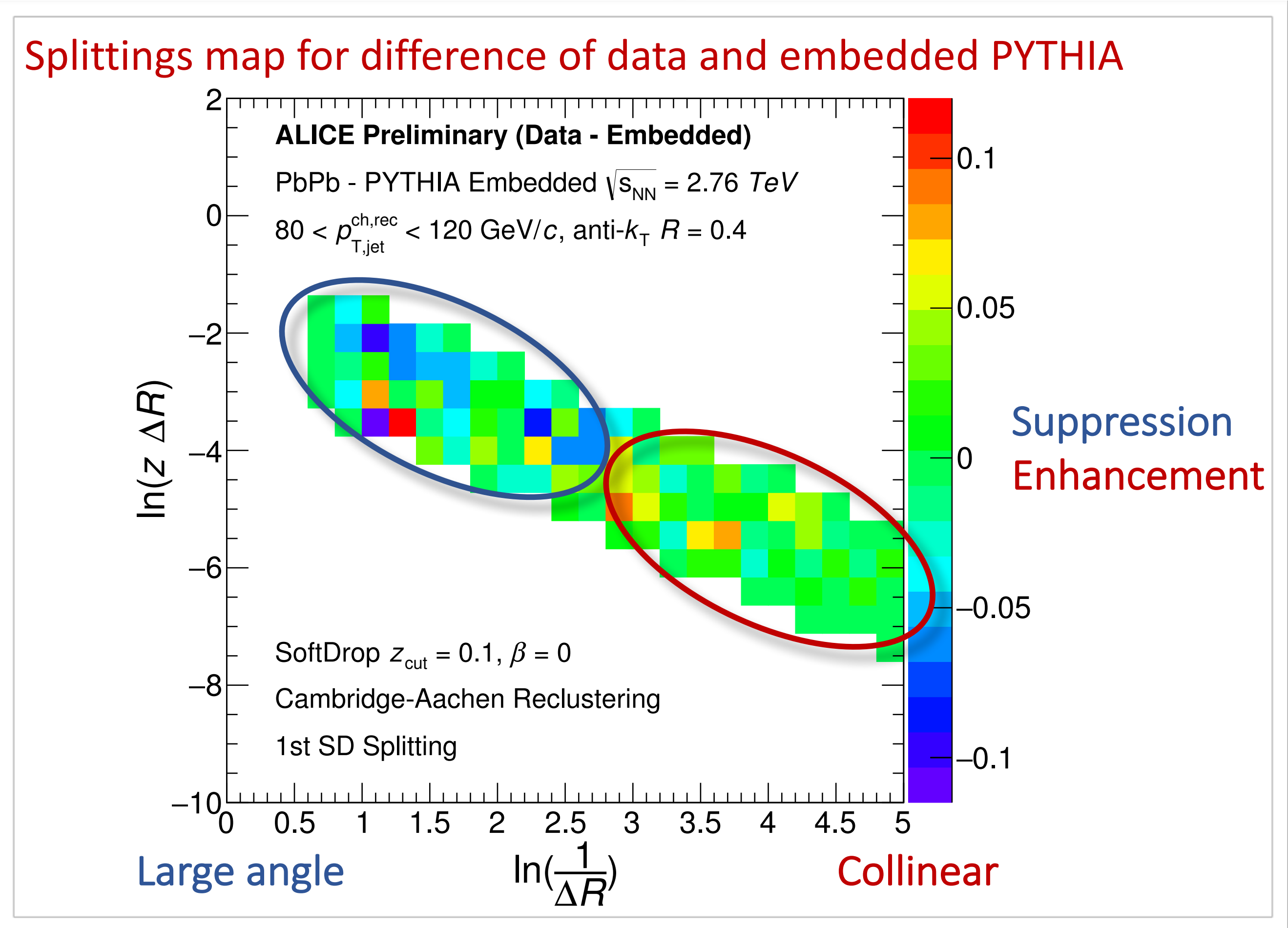
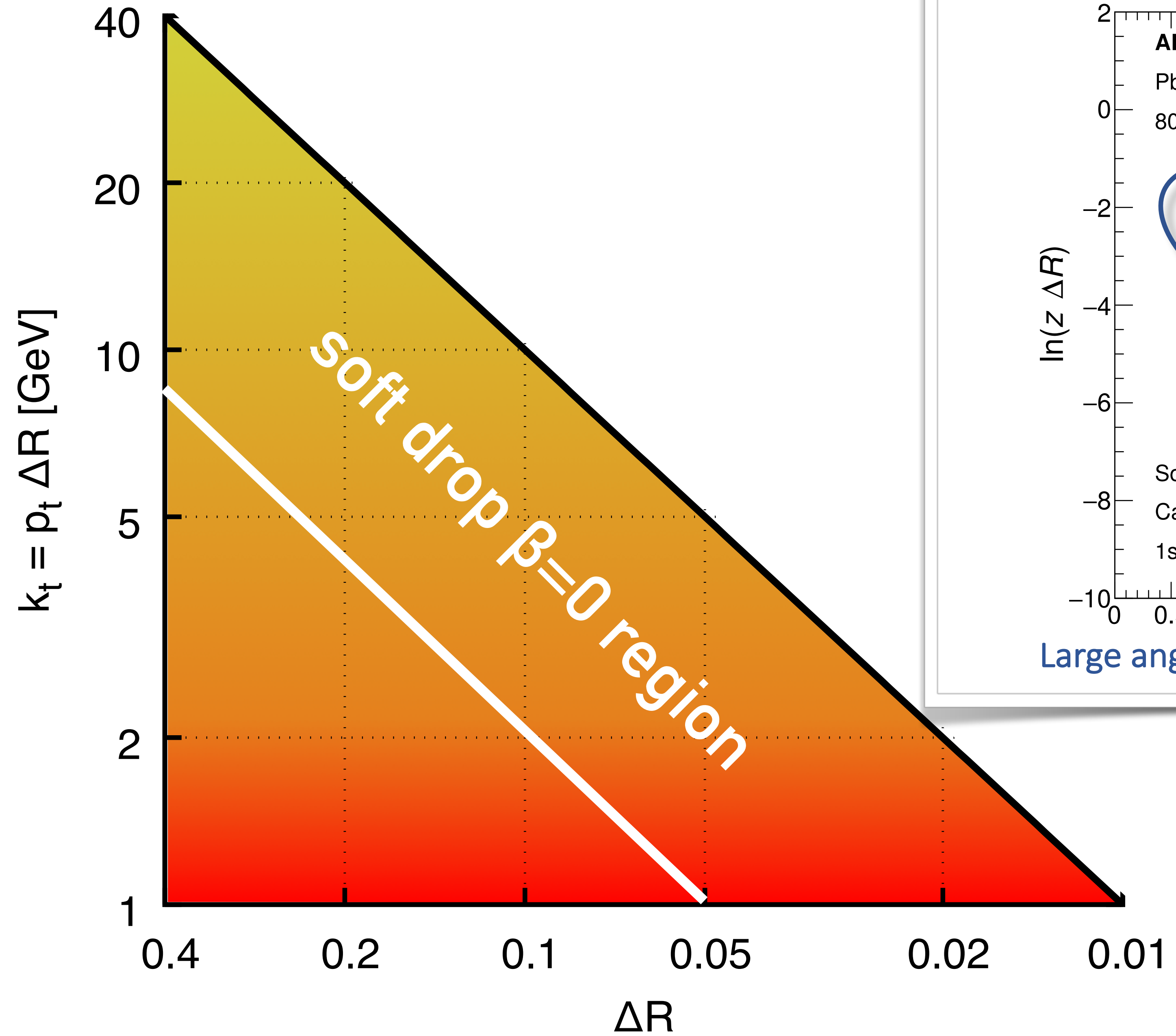
$$\rho \simeq \frac{\alpha_s(k_t)C_F}{\pi} \bar{z} (p_{gq}(\bar{z}) + p_{gq}(1 - \bar{z})) , \quad \bar{z} = \frac{k_t}{p_{t,\text{jet}}\Delta}$$



- ▶ Lund plane can be calculated analytically.
- ▶ Calculation is systematically improvable.

application to HI collisions

jet with $R = 0.4$, $p_t = 200$ GeV



This is not the average density, but the density of the 1st soft-drop splitting

HI MC studies

Andrews et al, [1808.03689](#)

- clear potential for distinguishing between models, with clear physical picture of where the differences arise

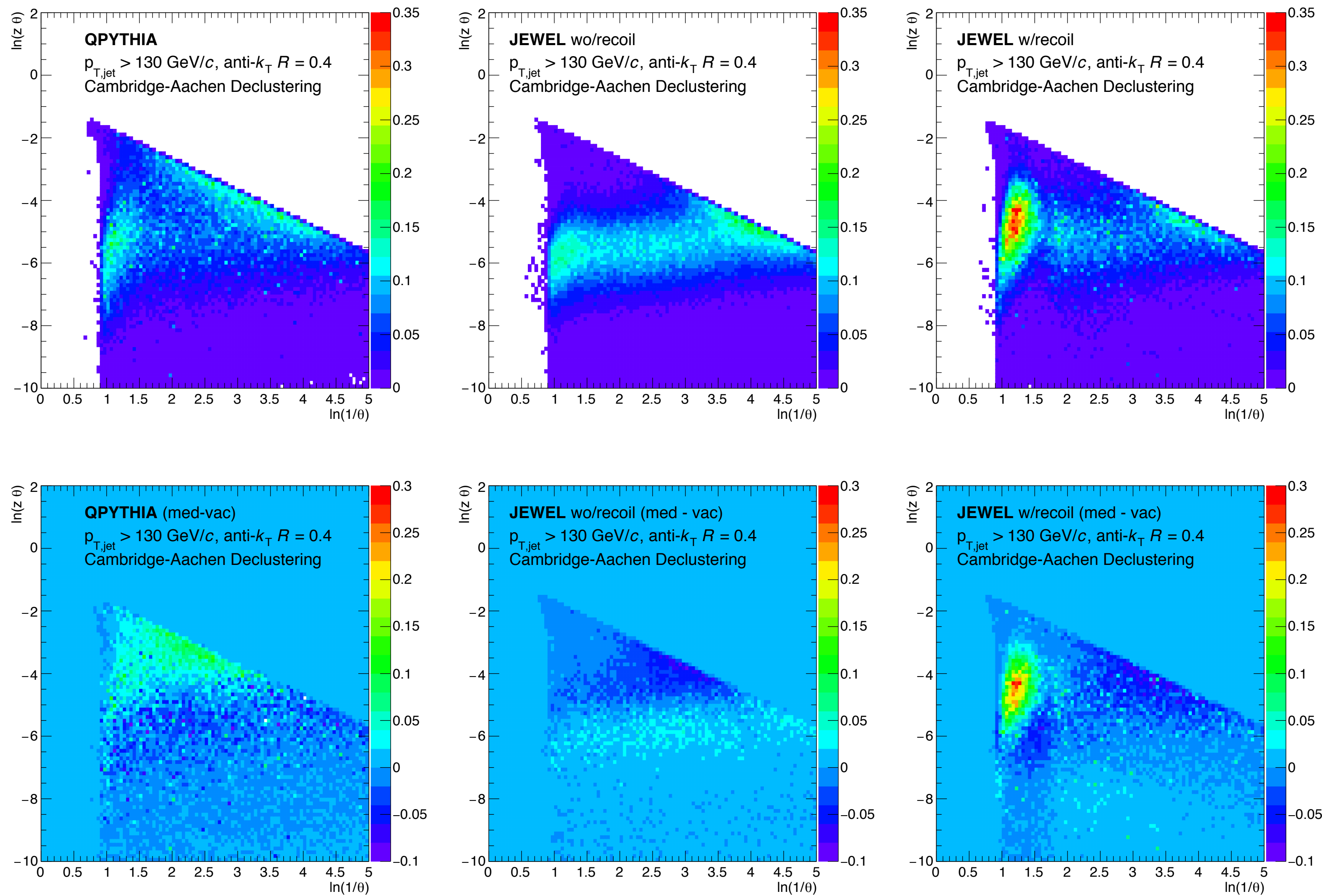
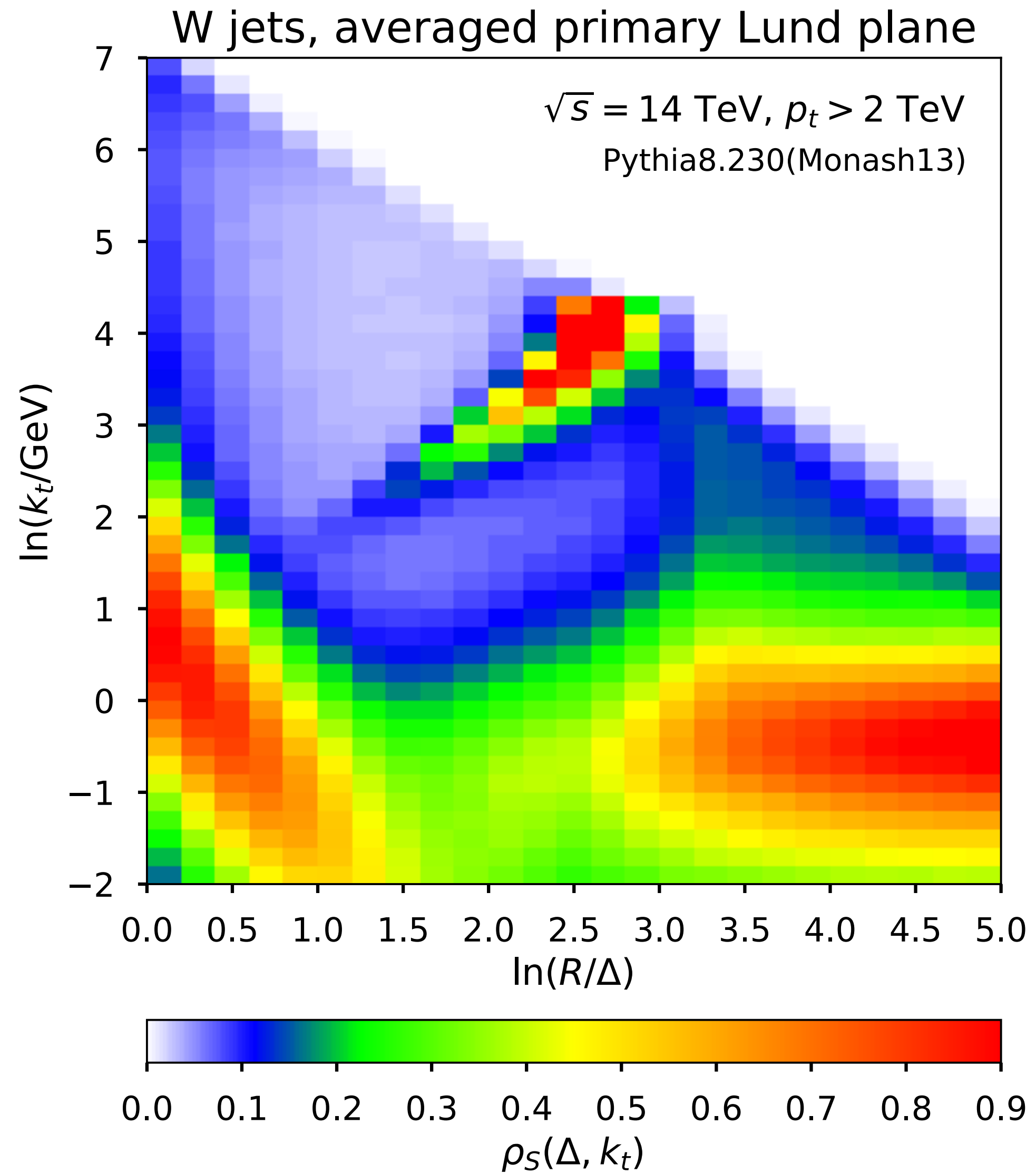
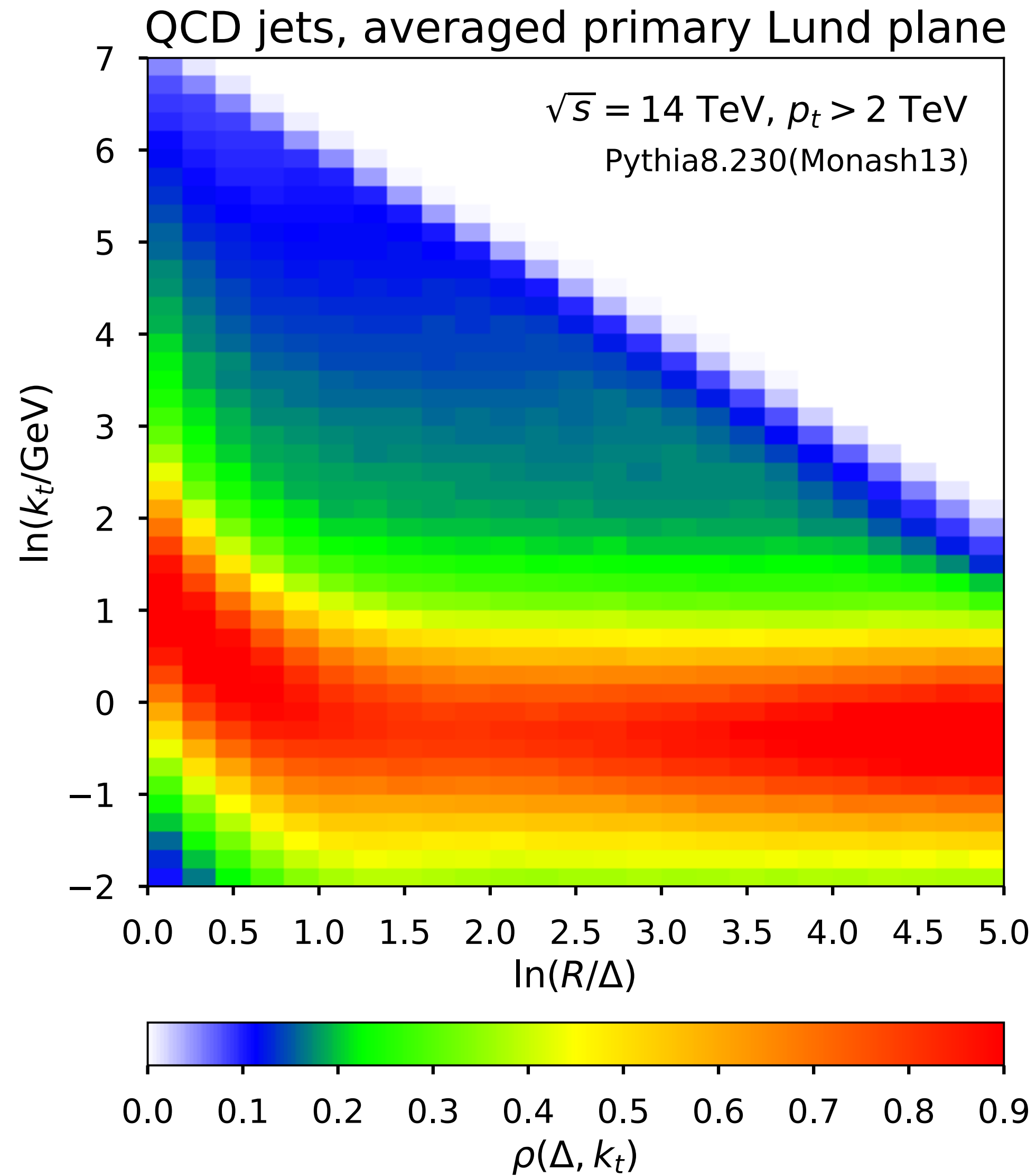


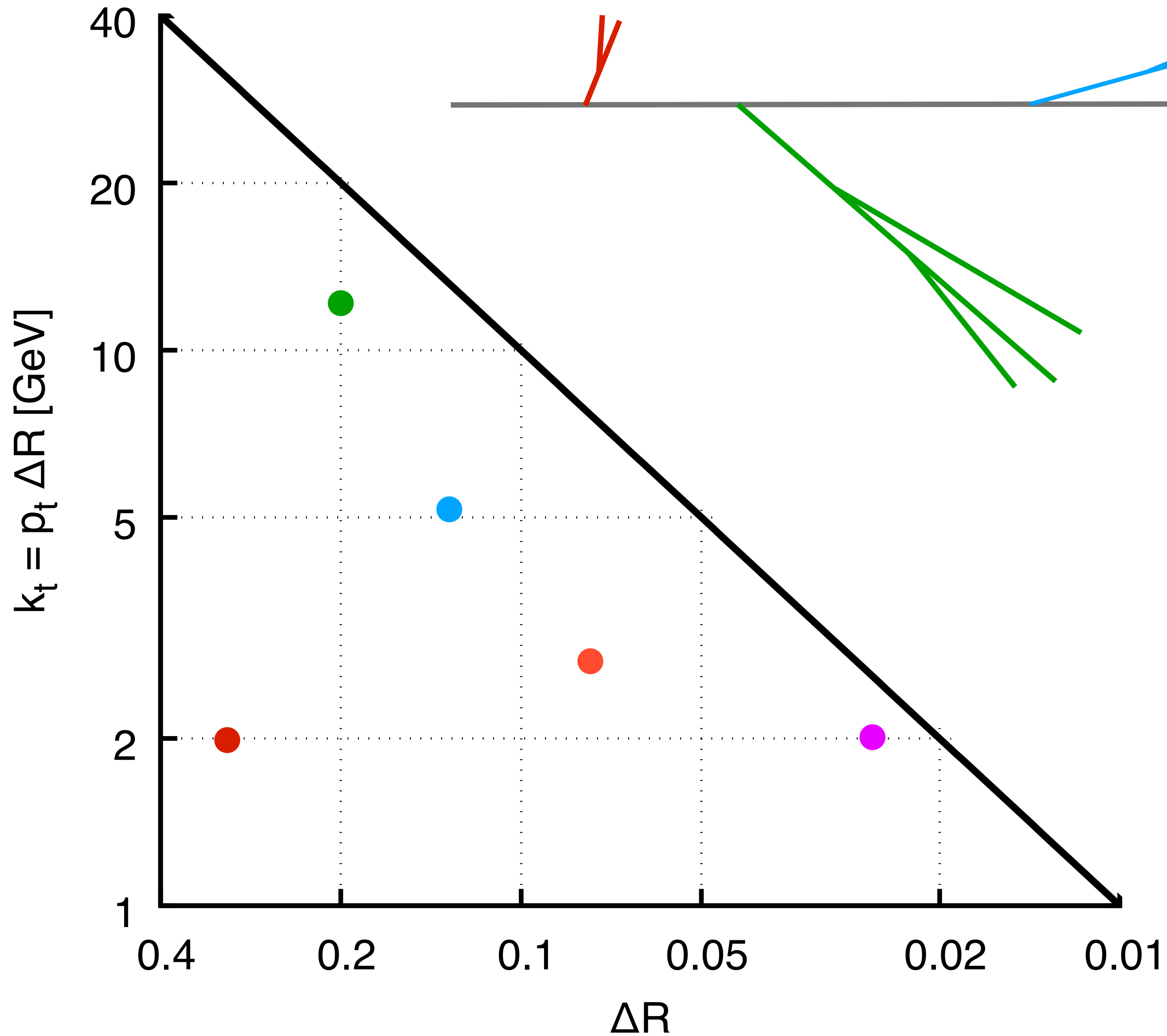
Figure 4: Lund diagram reconstructed from jets generated by QPYTHIA (left column), JEWEL without recoils (middle column) and JEWEL with recoils (right column). The lower panels correspond to the difference of the radiation pattern with and without jet quenching effects. Note that the scale of the z -axes varies between the panels.

application to high- p_t physics

e.g. new-physics searches and Higgs studies

Comparing quark/gluon v. W-induced jets



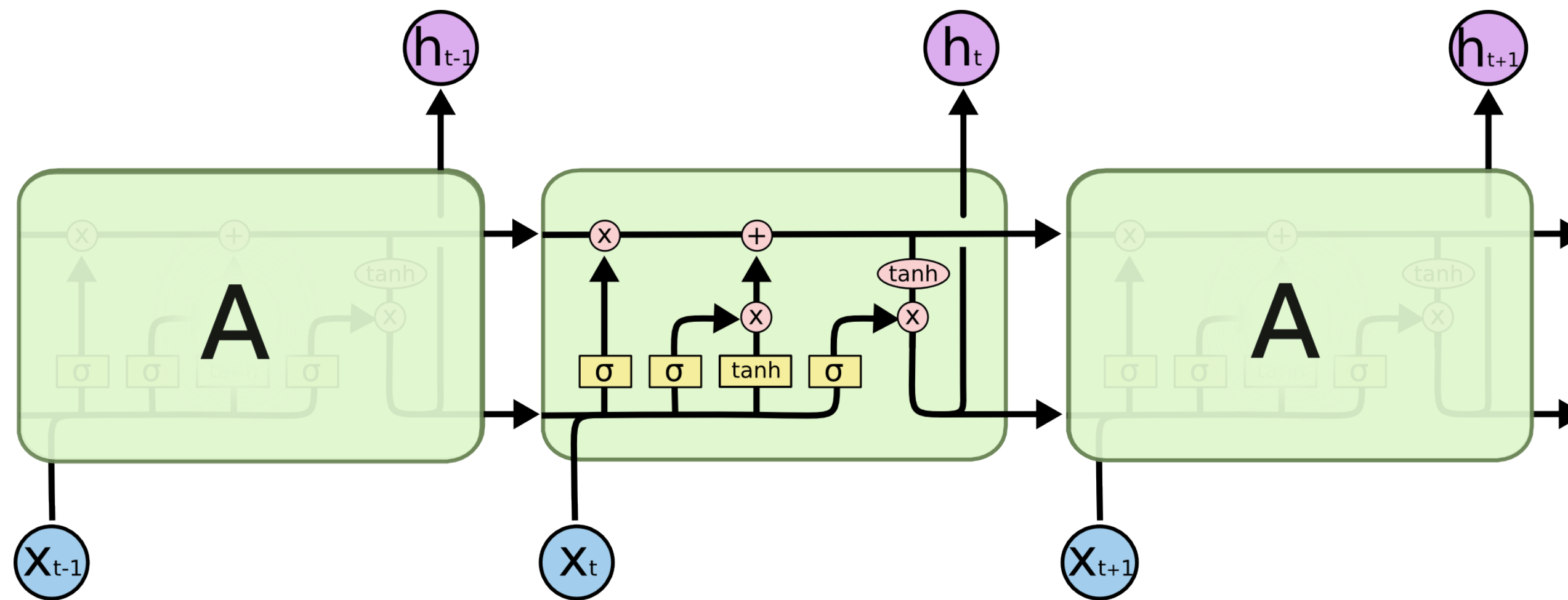


**Beyond average density:
any jet is a collection of points
in the (primary) Lund plane**

Lund declustering points as inputs to machine-learning

- ▶ Simple recurrent networks unable to handle dependencies that are widely separated in the data.
- ▶ **LSTM networks** designed to have memory over longer periods, by adding four layers for each module and including a no-activation function.

[Hochreiter, Schmidhuber (1997)]



Figures from

<http://colah.github.io/posts/2015-08-Understanding-LSTMs/>

**long-short-term
memory networks
(LSTMs)
gave us the best
performance**

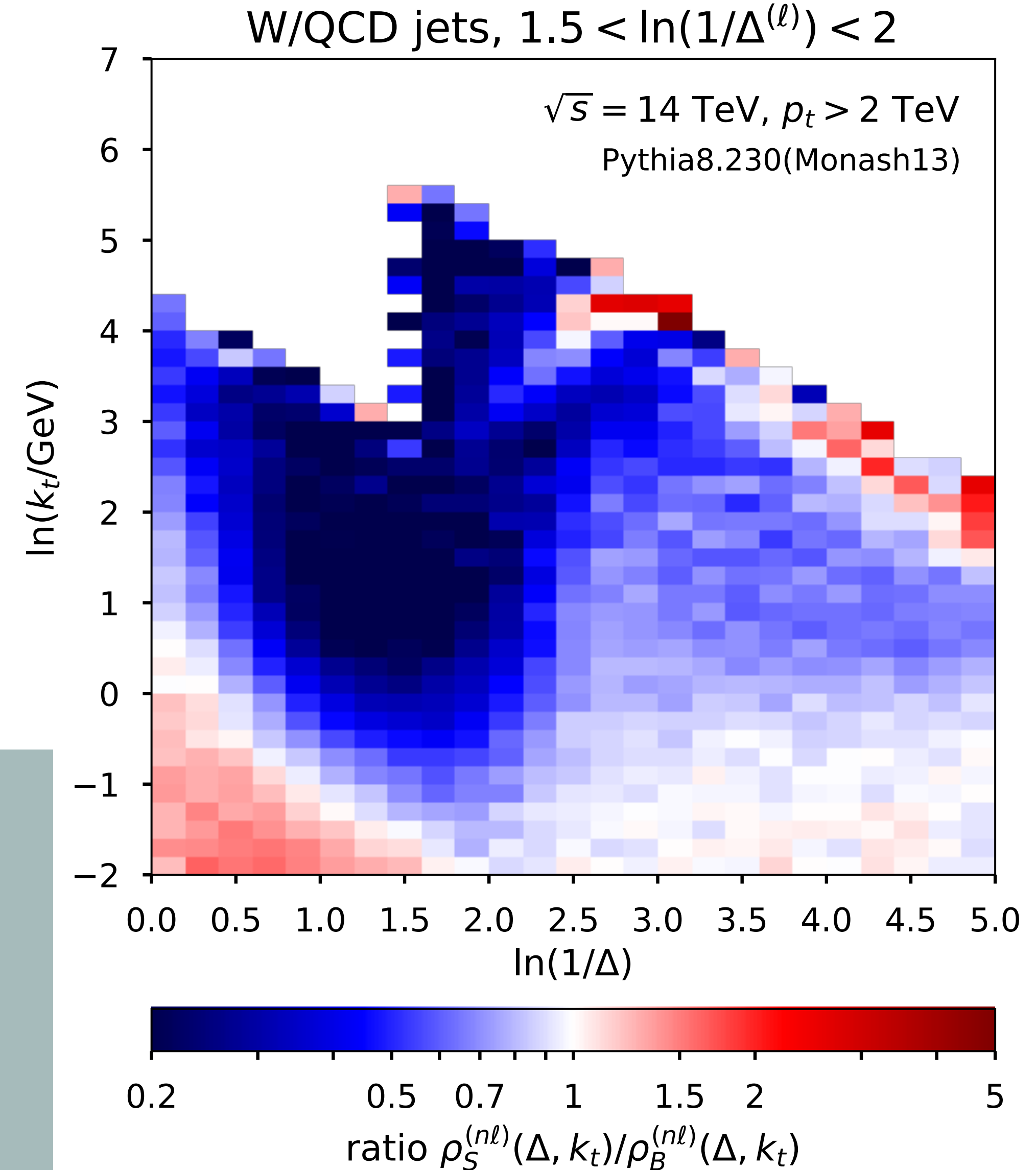
Lund declustering points as inputs to hand-crafted likelihood calculation

- Identify emission that generates the jet mass (with Soft-Drop)
- Assume all other emissions are independent of each other, i.e. random distribution just set by average density
- Get MC ratio of average densities for W (Signal=S) v. QCD (background = B) jets
- Build likelihood discriminator

$$\mathcal{L}_{\text{tot}} = \mathcal{L}_\ell(m^{(\ell)}, z^{(\ell)}) + \sum_{i \neq \ell} \mathcal{L}_{nl}(\Delta^{(i)}, k_t^{(i)}; \Delta^{(\ell)}) + \mathcal{N}(\Delta^{(\ell)})$$

$$\mathcal{L}_{nl}(\Delta, k_t; \Delta^{(\ell)}) = \ln \left(\rho_S^{(nl)} / \rho_B^{(nl)} \right)$$

$$\rho_X^{(nl)}(\Delta, k_t; \Delta^{(\ell)}) = \frac{dn_{\text{emission}, X}^{(nl)}}{d \ln k_t d \ln 1/\Delta d \ln \Delta^{(\ell)}} \bigg/ \frac{dN_X}{d \ln \Delta^{(\ell)}}$$

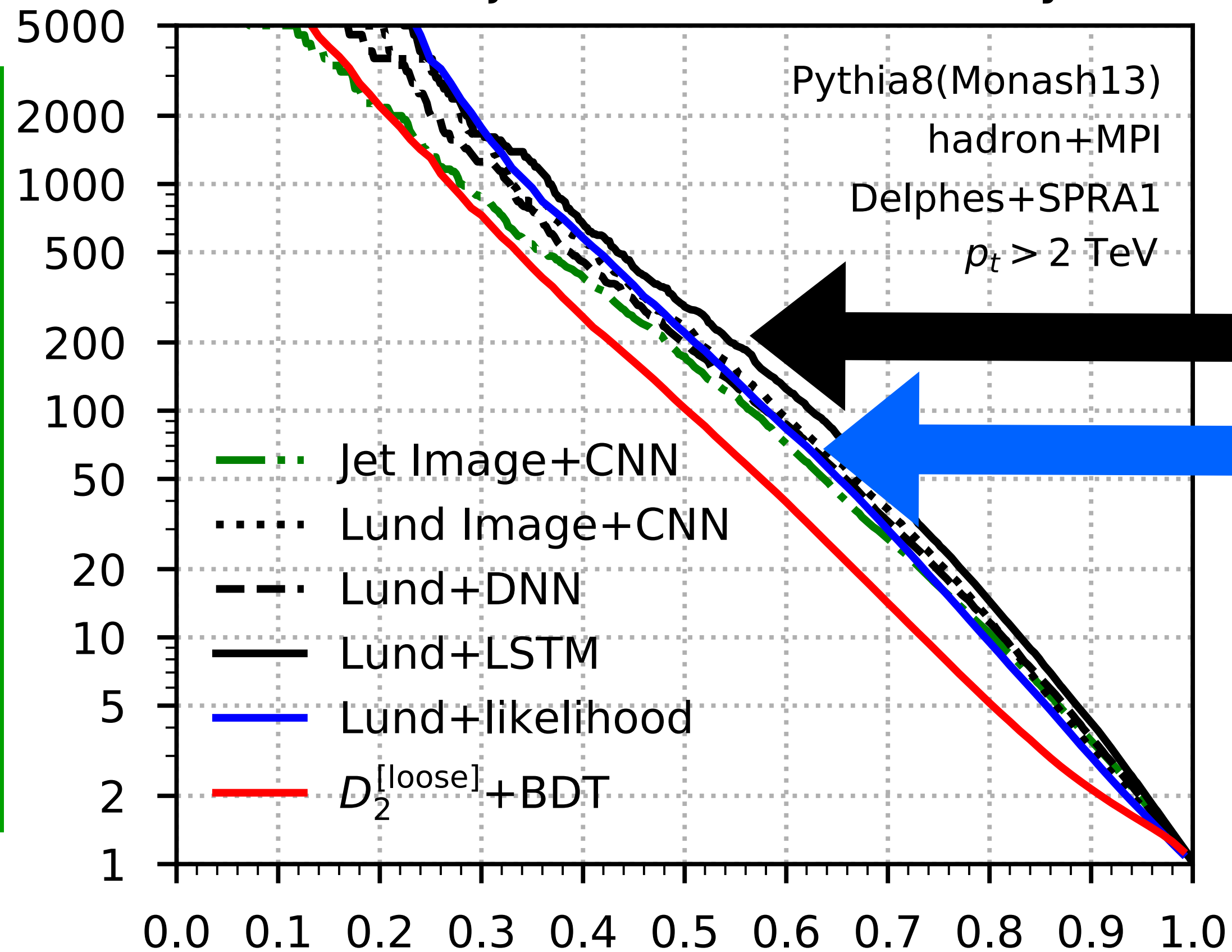


QCD rejection v. W efficiency

Performance:

background rejection v. signal efficiency

background rejection

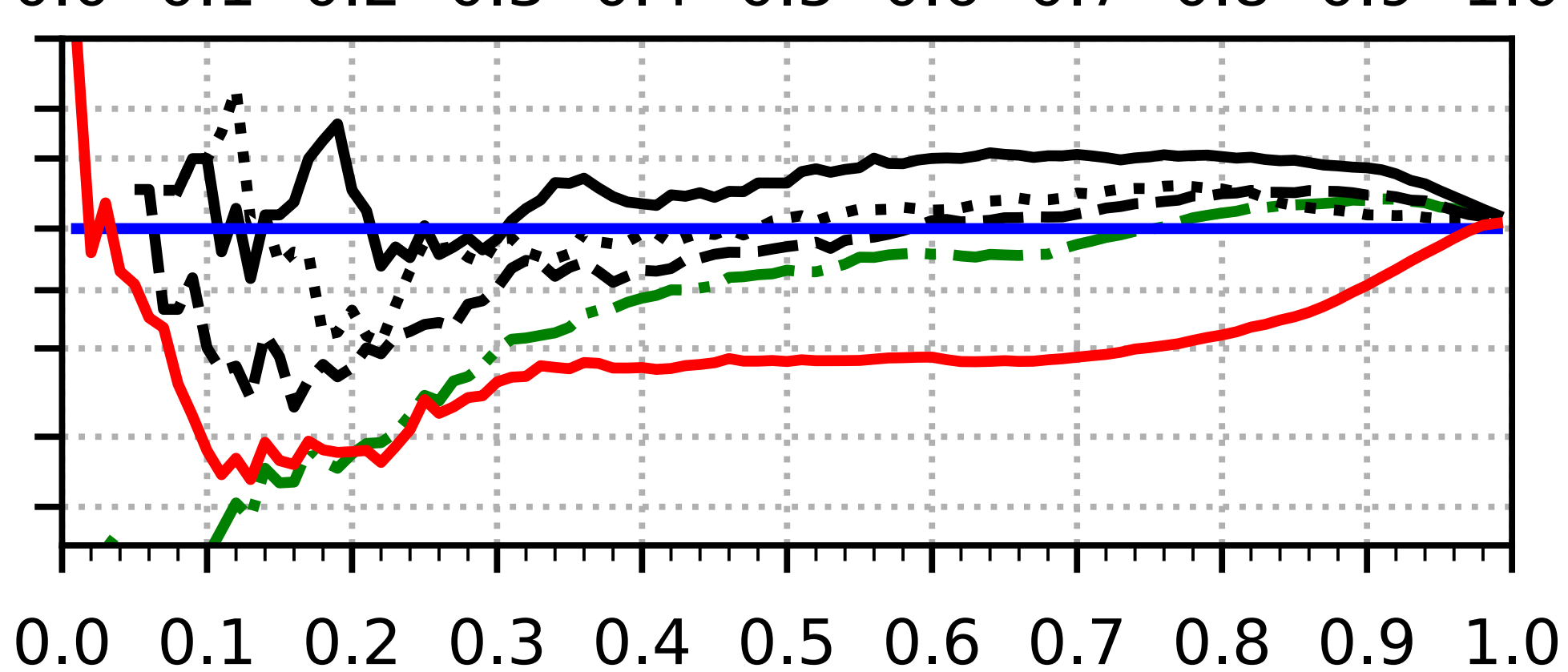


Lund + machine-learning (LSTM)

Lund + likelihood

(gets to within 70-80% of performance of best machine learning)

ratio to Lund+log.lik.

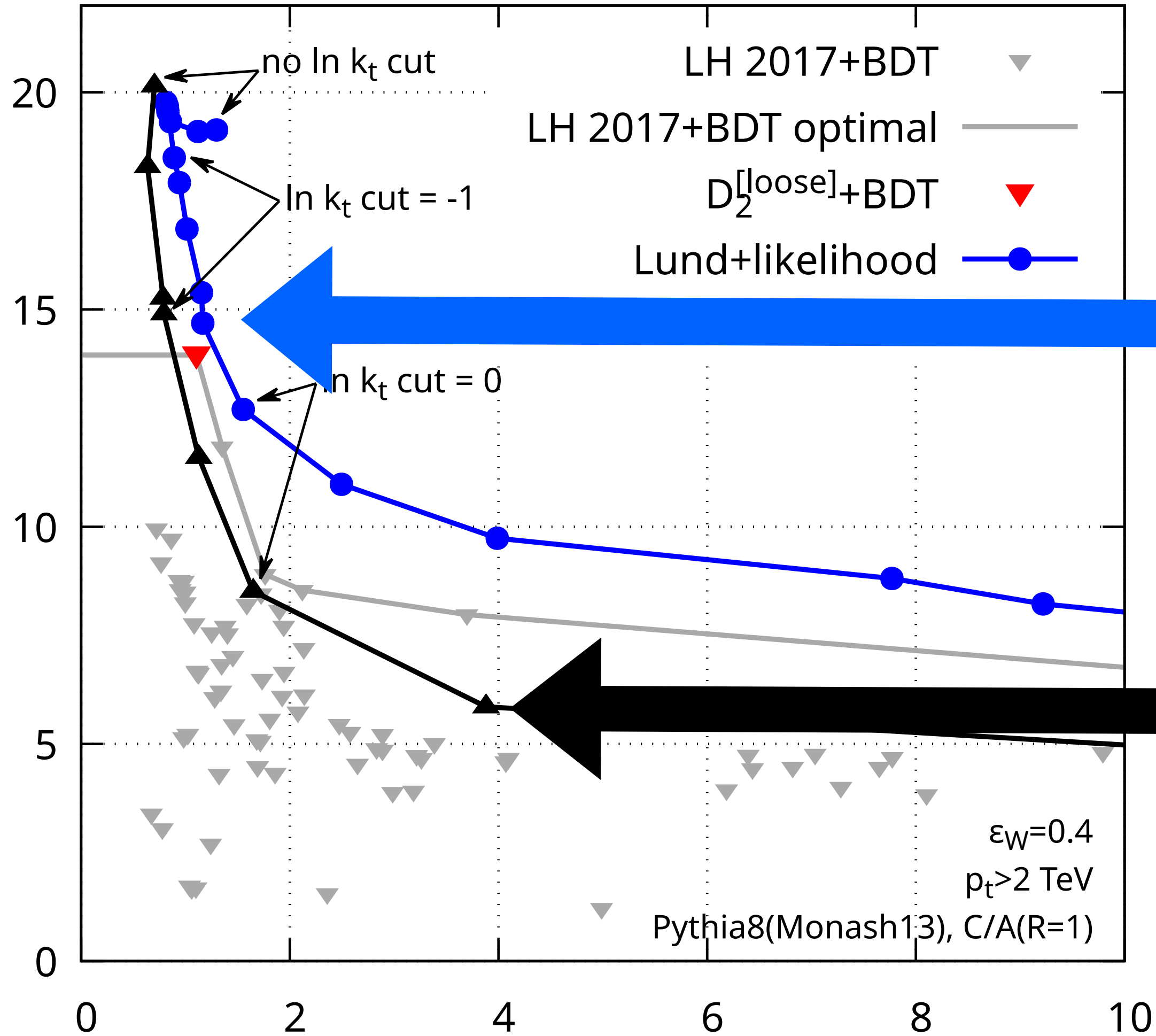


signal efficiency

Performance:

S/\sqrt{B} v. resilience to non-perturbative QCD

performance v. resilience [full mass information]



S/\sqrt{B}

Lund + likelihood performs better than machine learning when you exclude non-perturbative region ($k_t < 1$ GeV)

Lund + machine-learning (LSTM)

resilience to non-perturbative effects

$$\zeta = \left(\frac{\Delta\epsilon_W^2}{\langle\epsilon\rangle_W^2} + \frac{\Delta\epsilon_{QCD}^2}{\langle\epsilon\rangle_{QCD}^2} \right)^{-\frac{1}{2}}$$

closing

Conclusions

The QCD radiation in collider events (pp & HI) is a rich source of information, which we're only just starting to tap into.

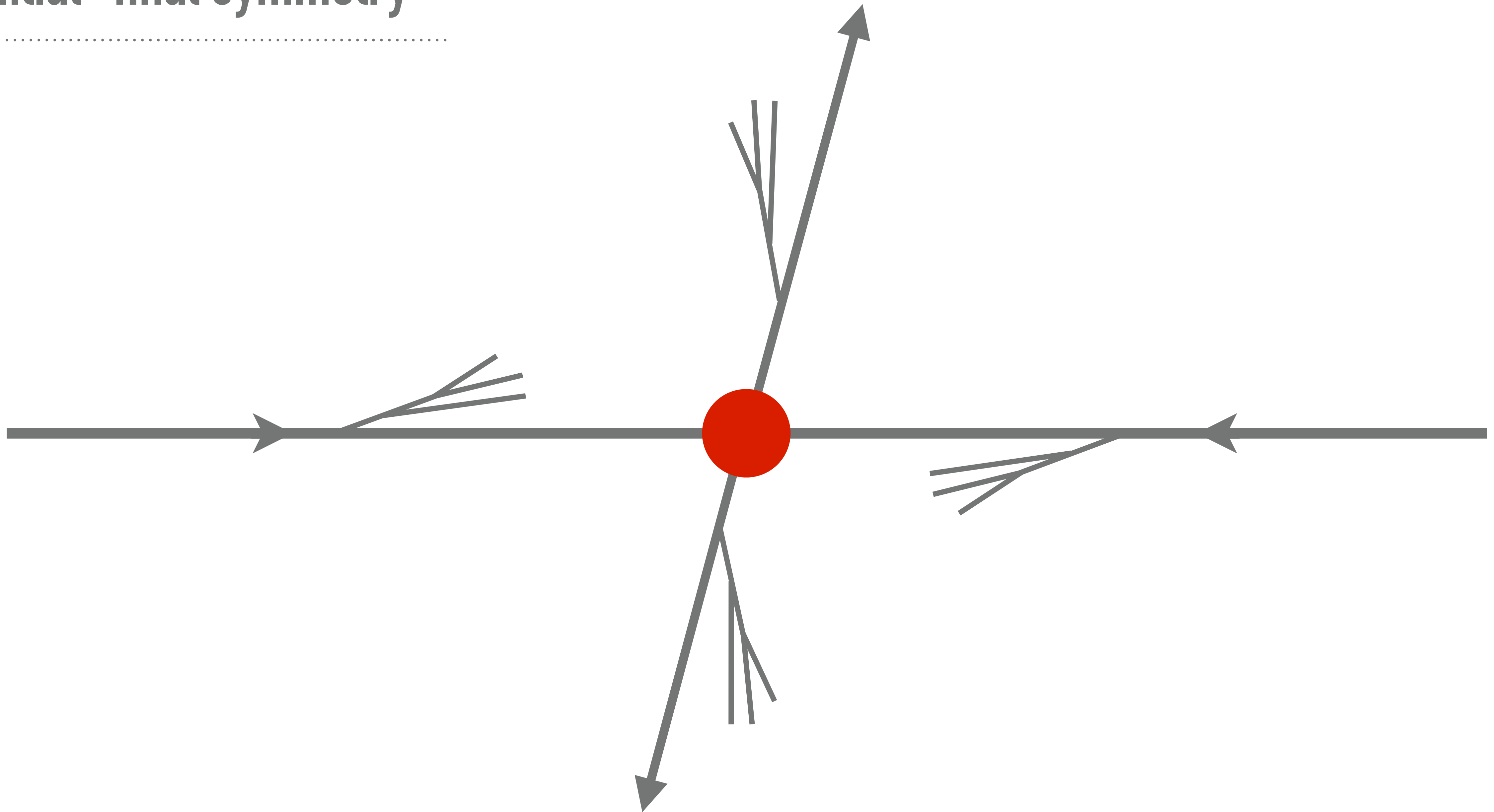
The difficulty is that there's a lot of it: how do we condense it down to something we can understand, measure & exploit quantitatively?

The Lund plane “construction” offers an approach that

- maps transparently onto physically meaningful kinematic regions
- is amenable to calculations in QCD (work in progress)
- provides a powerful input to machine learning, but also can be used almost as effectively in simpler multivariate frameworks.

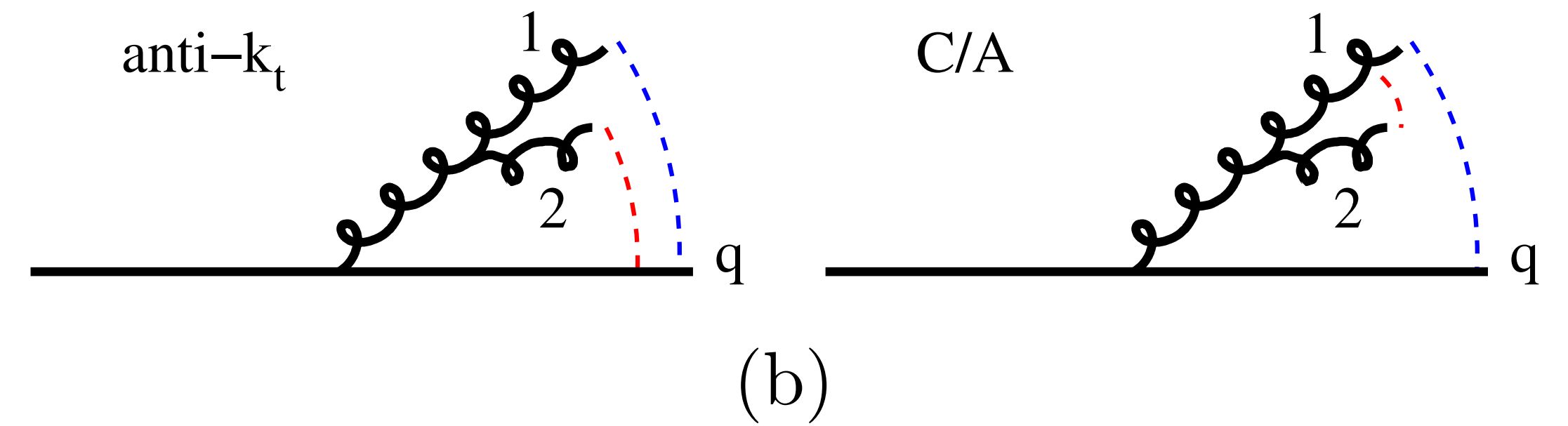
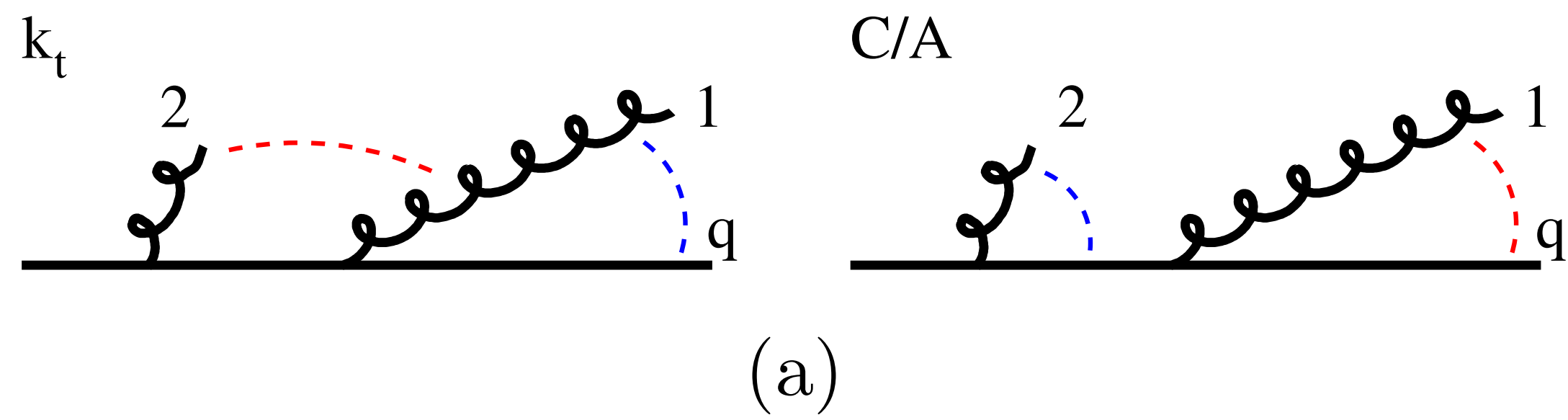
backup

Initial–final symmetry



choice of C/A for declustering

why the C/A algorithm?



why the C/A algorithm?

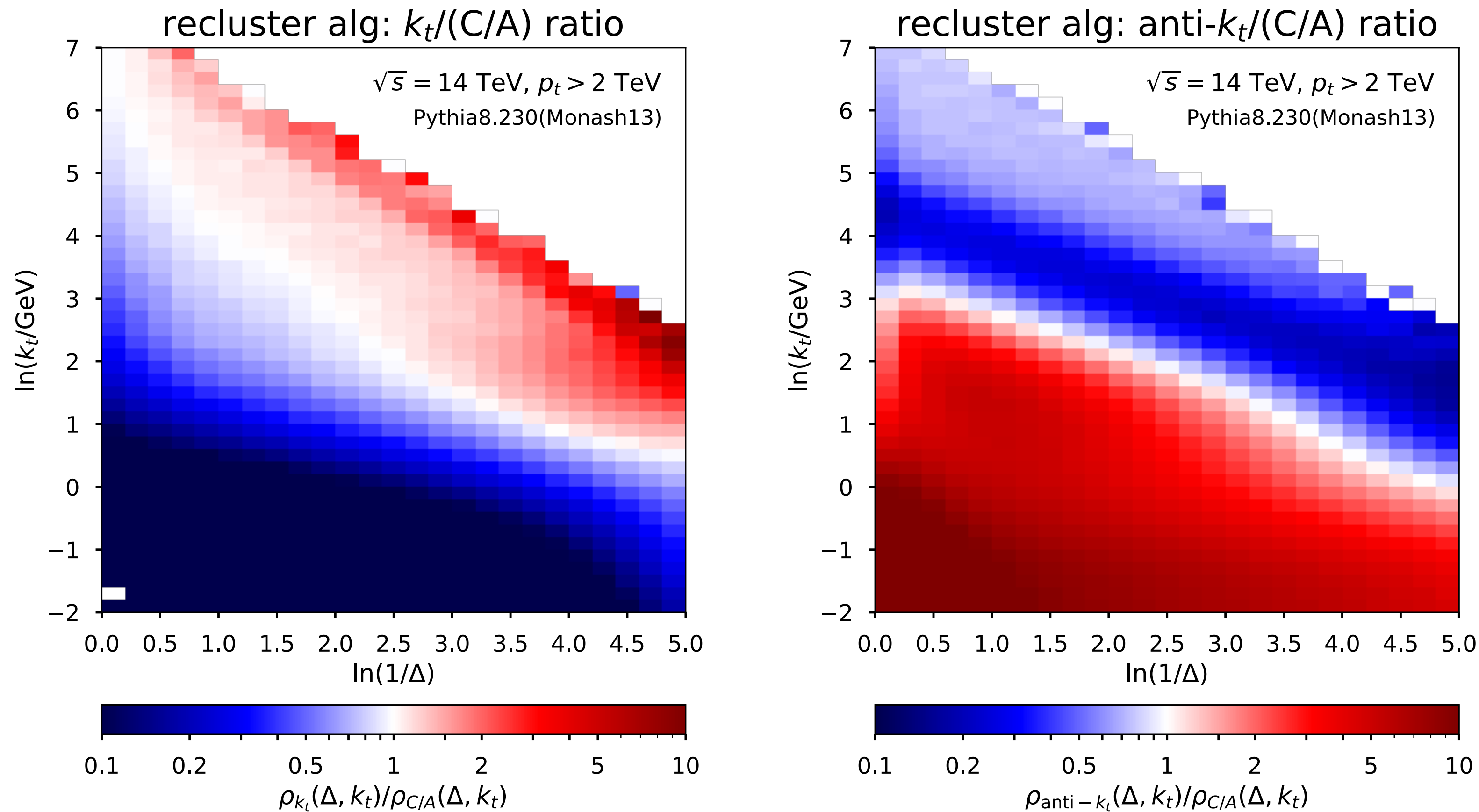


Figure 6: The $\rho(\Delta, k_t)$ results as obtained with k_t (left) and anti- k_t (right) declustering, normalised to the result for C/A declustering.

If you use jet algorithms other than C/A to provide the initial (de)clustering sequence, the jet algorithm itself introduces strong “unphysical” structure

why the C/A algorithm?

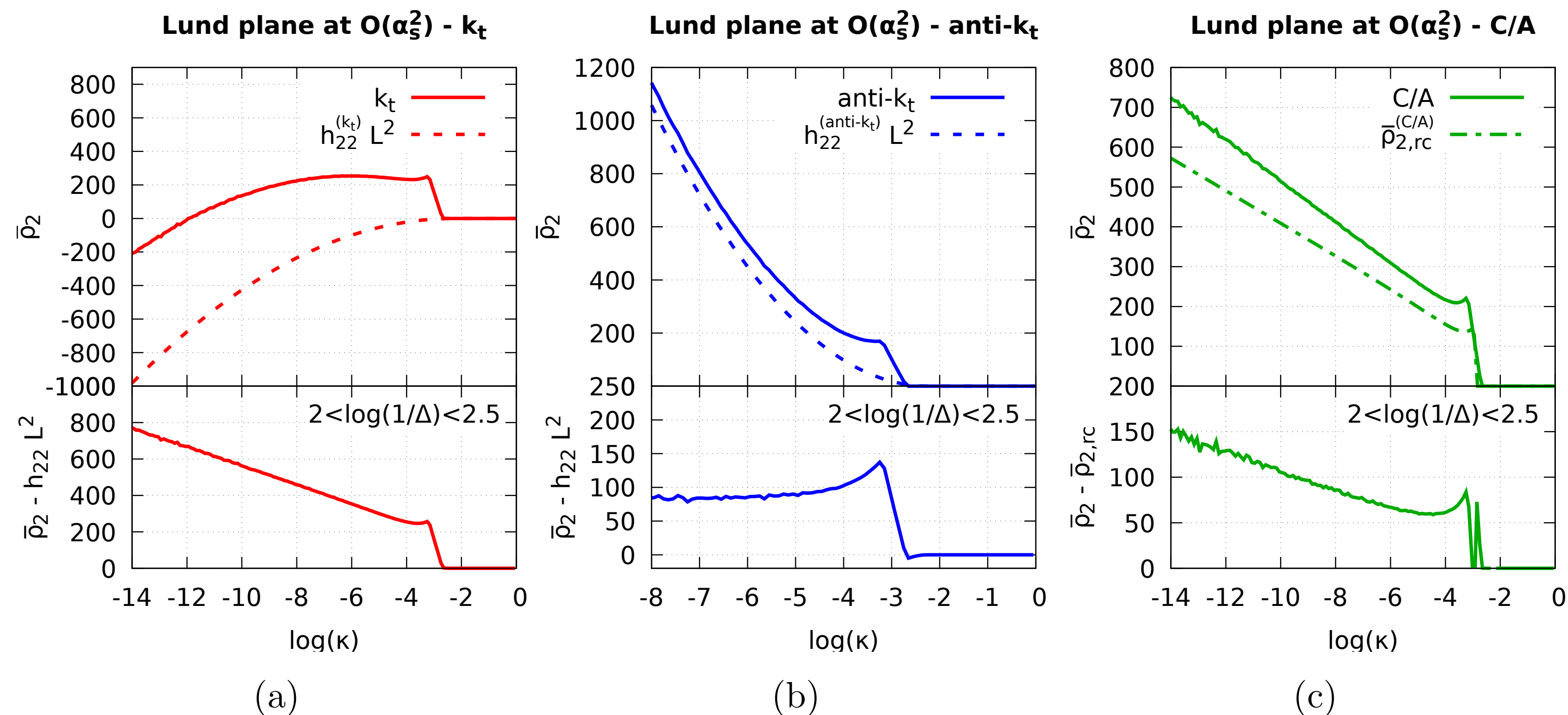


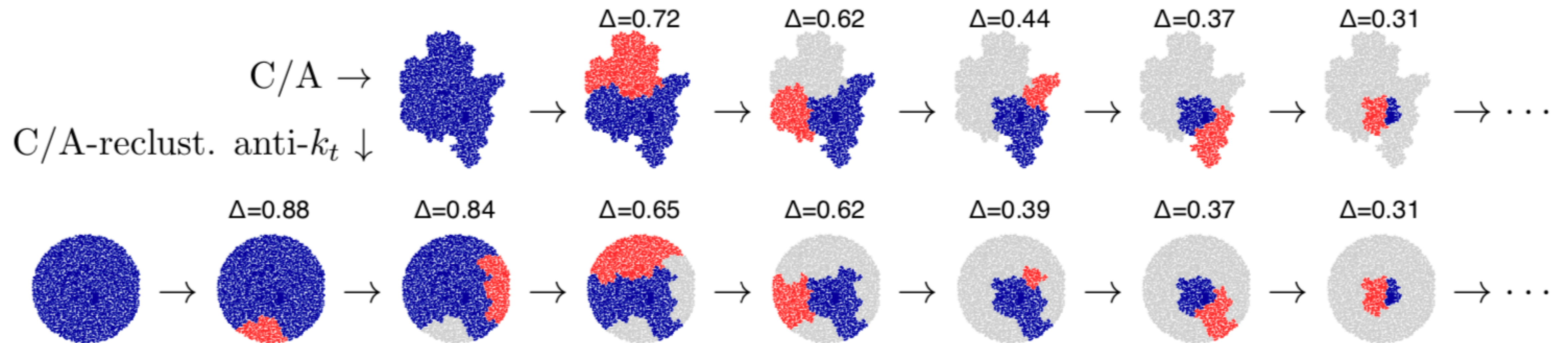
Figure 5: Evaluations with Event2 of the second-order contribution to the Lund plane, in a bin of $\ln 1/\Delta$, as a function of κ , for (de)clustering sequences obtained with the k_t , anti- k_t and C/A jet algorithms. In (a) and (b) the dashed line corresponds to the analytic expectations, Eqs. (2.9) and (2.10) for clustering-induced double-logarithms in the k_t and anti- k_t algorithms. In (c), for the C/A algorithm, which is seen here to be free of double logarithms, the dot-dashed line corresponds to the (single-logarithmic) running coupling correction, Eq. (2.11), illustrating that it dominates the second-order correction.

**mathematically,
the unphysical
structure is driven
by double
logarithms, $(\alpha L^2)^n$ in
the Lund-plane
density.**

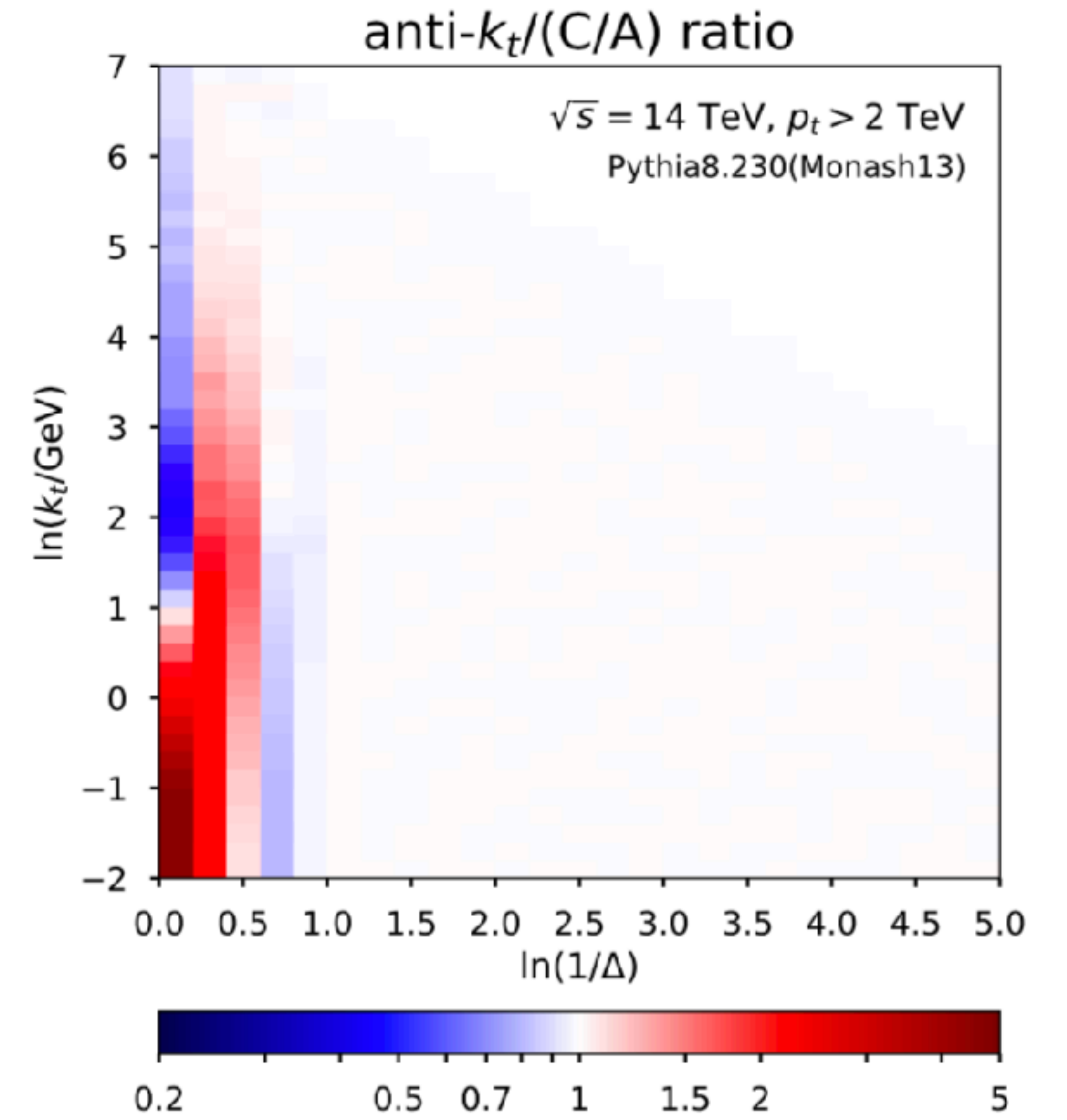
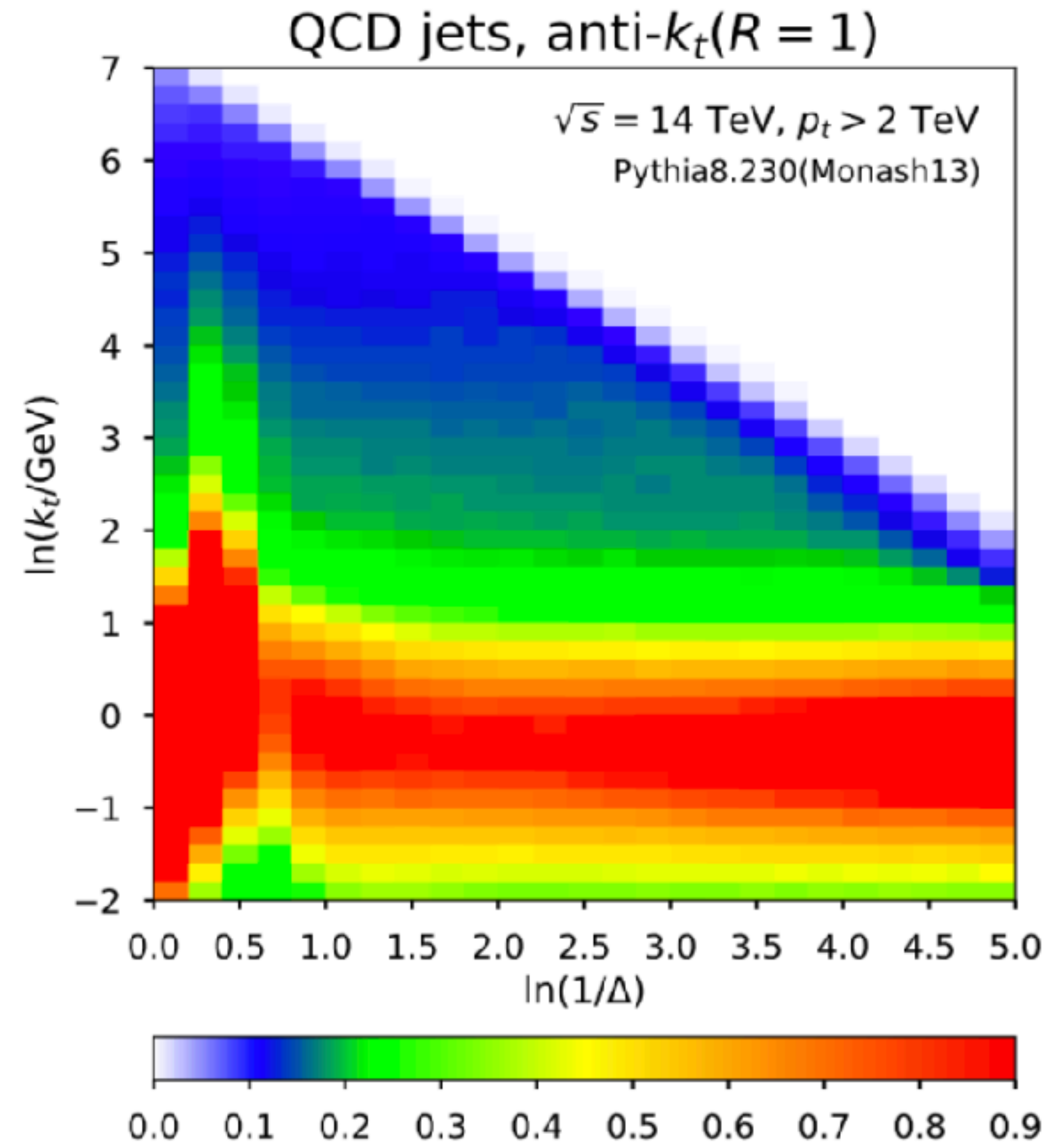
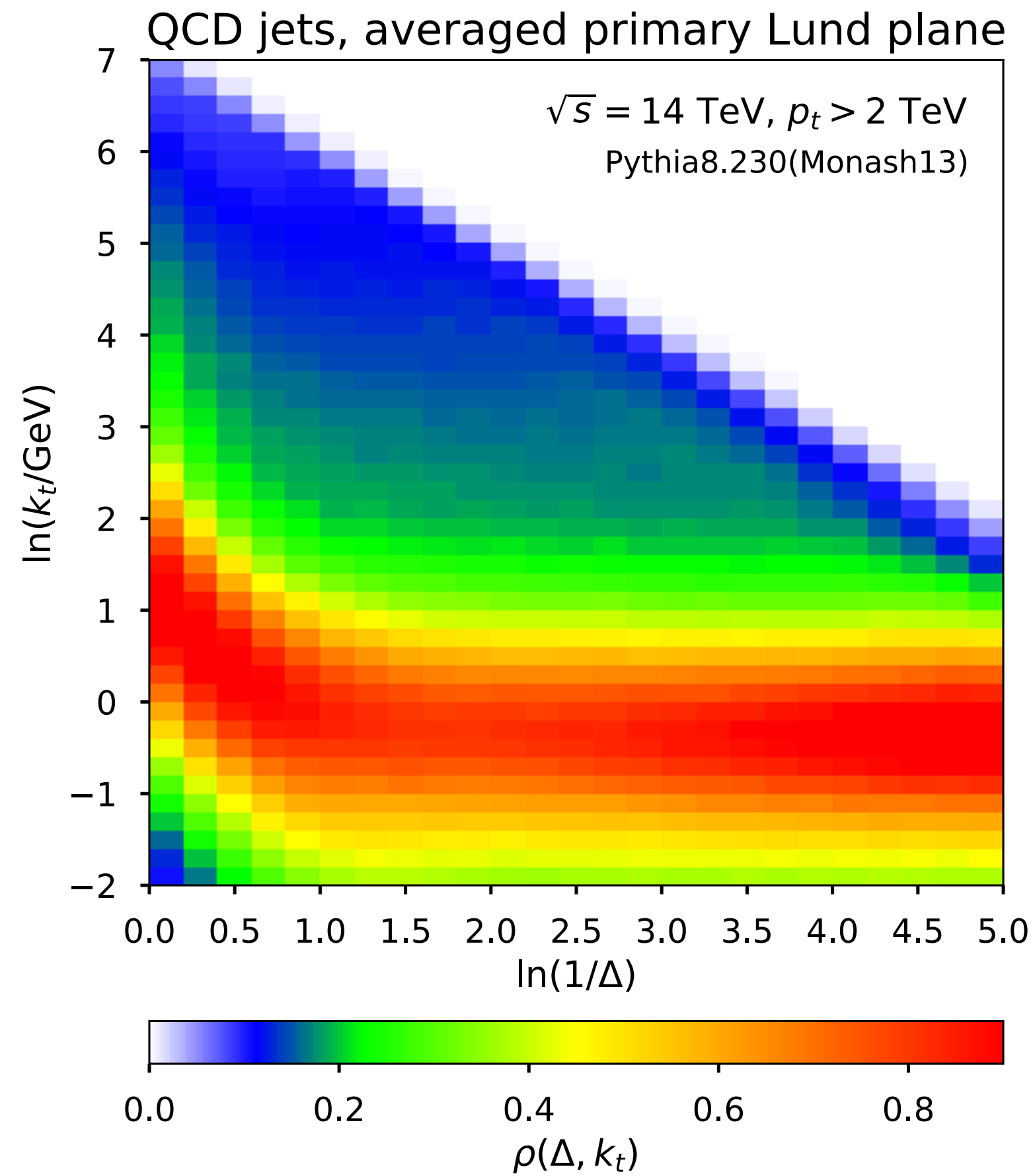
**C/A only produces
at most single
logarithms,
 $(\alpha L)^n$**

choice of original jet alg.

the declustering sequence from C/A v. anti- k_t starting points



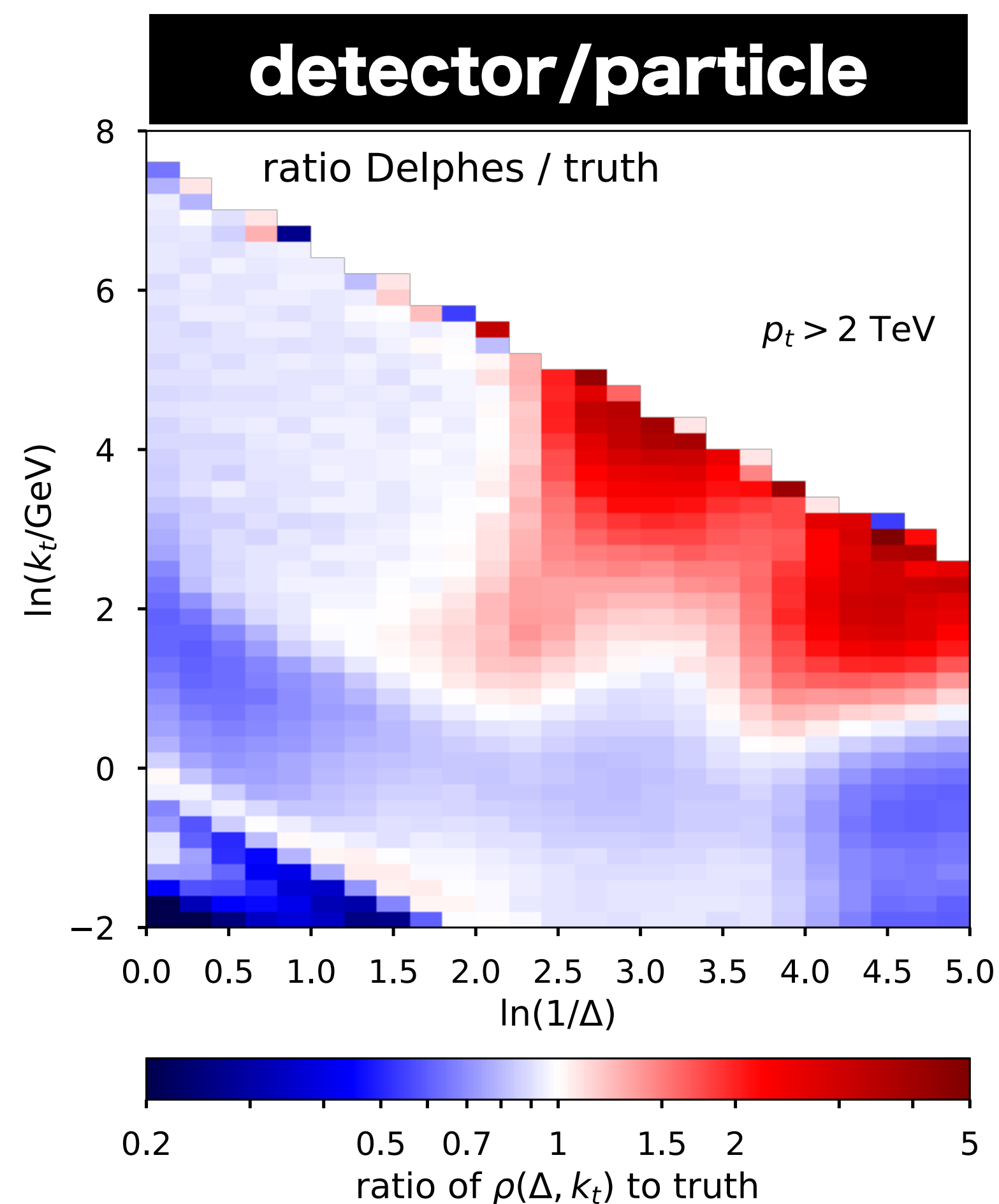
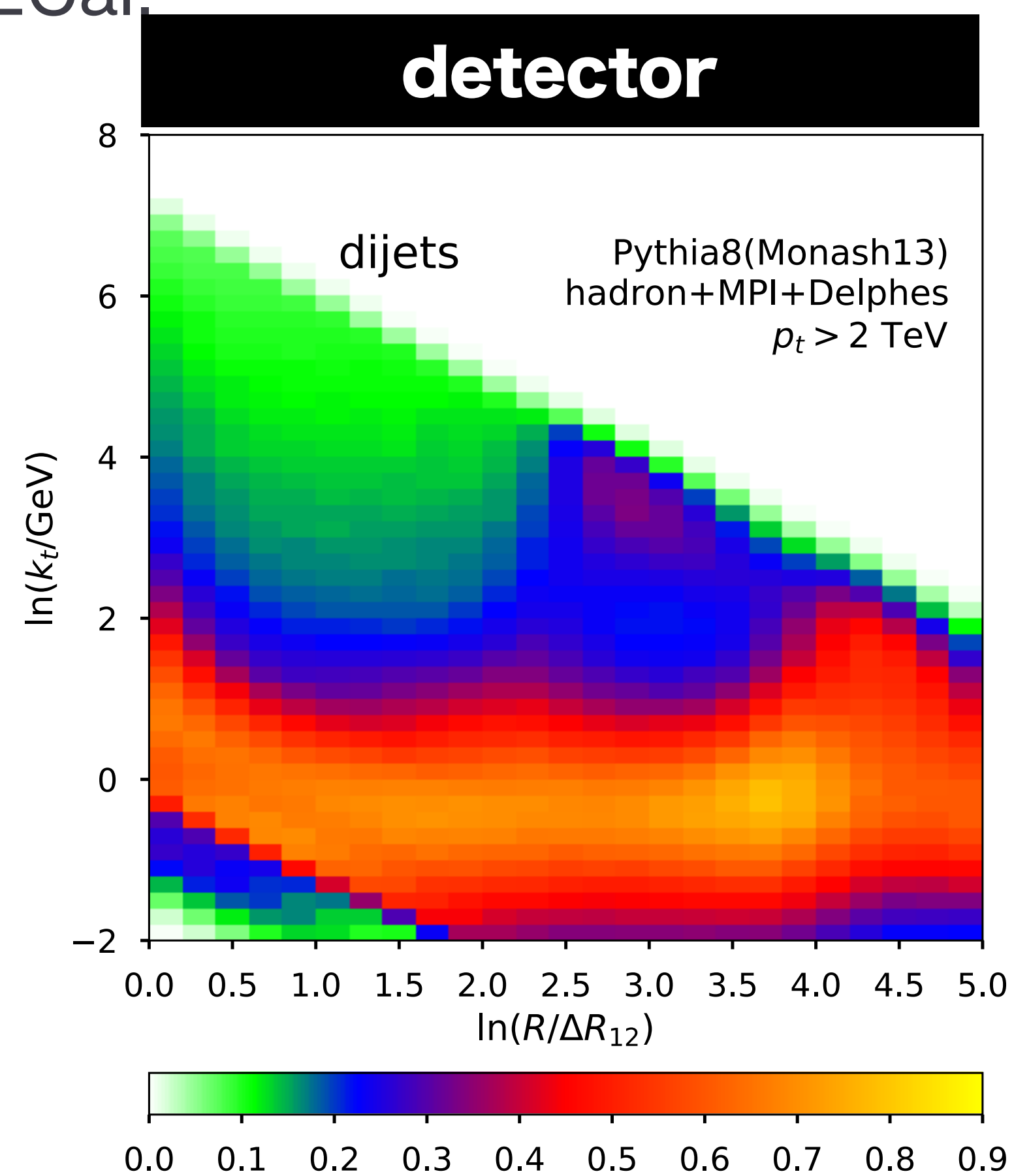
consequence for Lund plane density



detector effects

Detector effects: with Delphes simulation (+ particle flow)

- ▶ Detector effects have significant impact on the Lund plane at angular scales below the hadronic calorimeter spacing.
- ▶ Two enhanced regions corresponding to resolution scale of HCal and ECal



artefacts
induced
by ECal
& HCal
granularity

subjett-particle rescaling algorithm (SPRA)

Mitigate impact of detector granularity using a subjett particle rescaling algorithm:

- ▶ Recluster Delphes particle-flow objects into subjett using C/A with $R_h = 0.12$.
- ▶ Taking each subjett in turn, scale each PF charged-particle (h^\pm) and photon (γ) candidate that it contains by a factor f_1

$$f_1 = \frac{\sum_{i \in \text{subjett}} p_{t,i}}{\sum_{i \in \text{subjett}(h^\pm, \gamma)} p_{t,i}'}$$

and discard the other neutral hadron candidates.

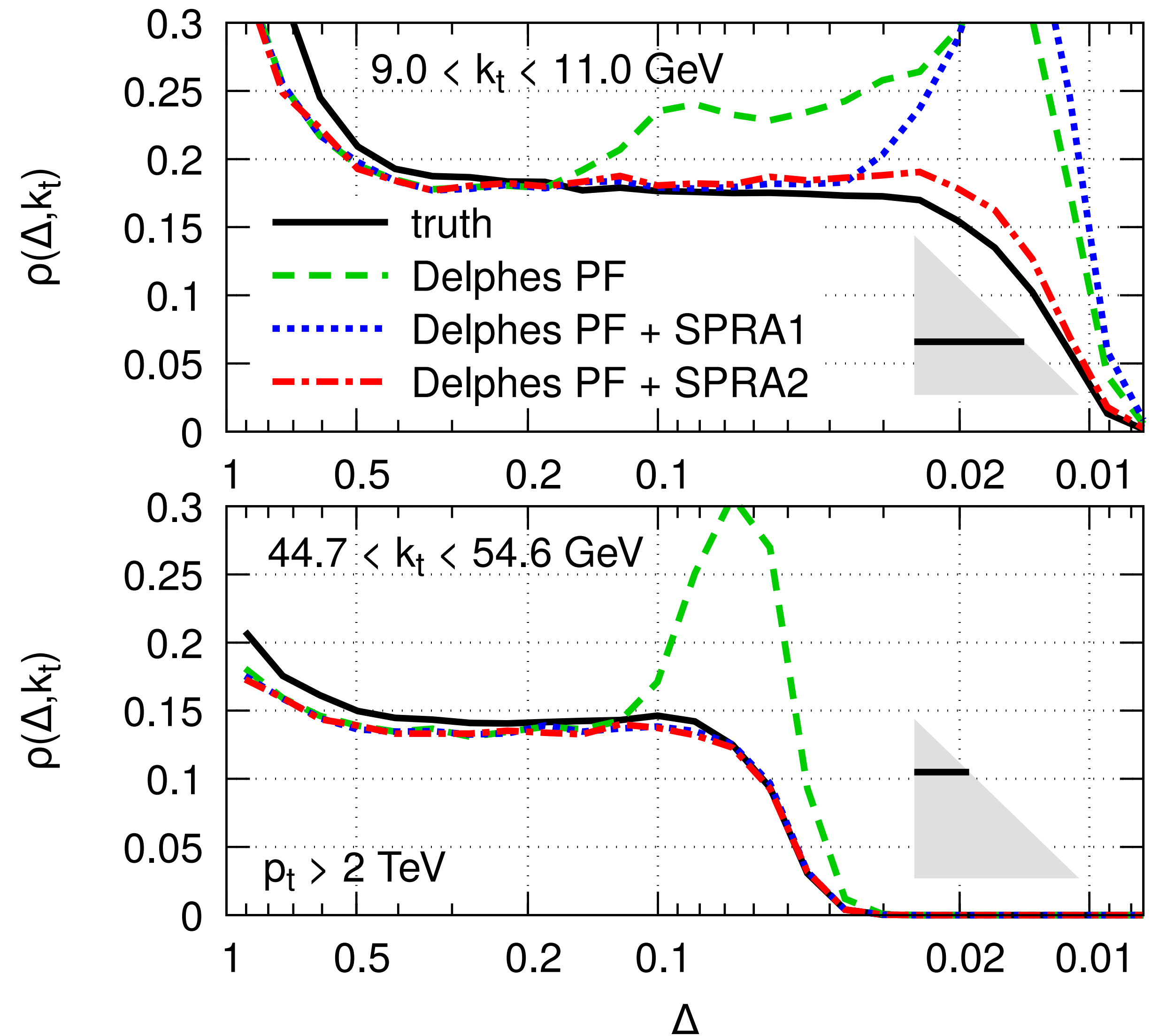
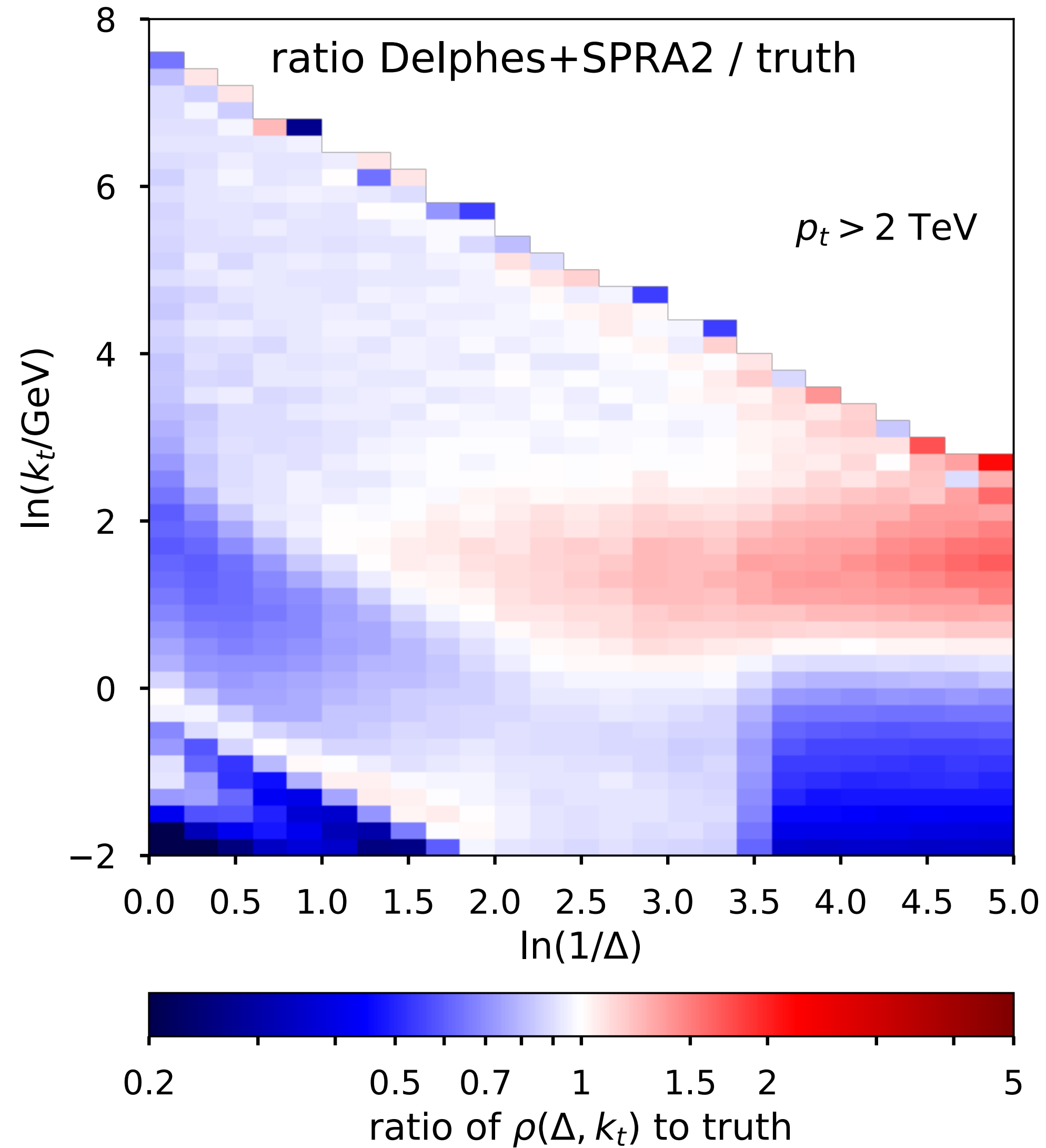
- ▶ If subjett doesn't contain photon or charged-particle candidates, retain all of the subjett's particles with their original momenta.

Recluster the full set of resulting particles (from all subjett) into a single large jet and use it to evaluate the mass and Lund plane.

not a new idea!

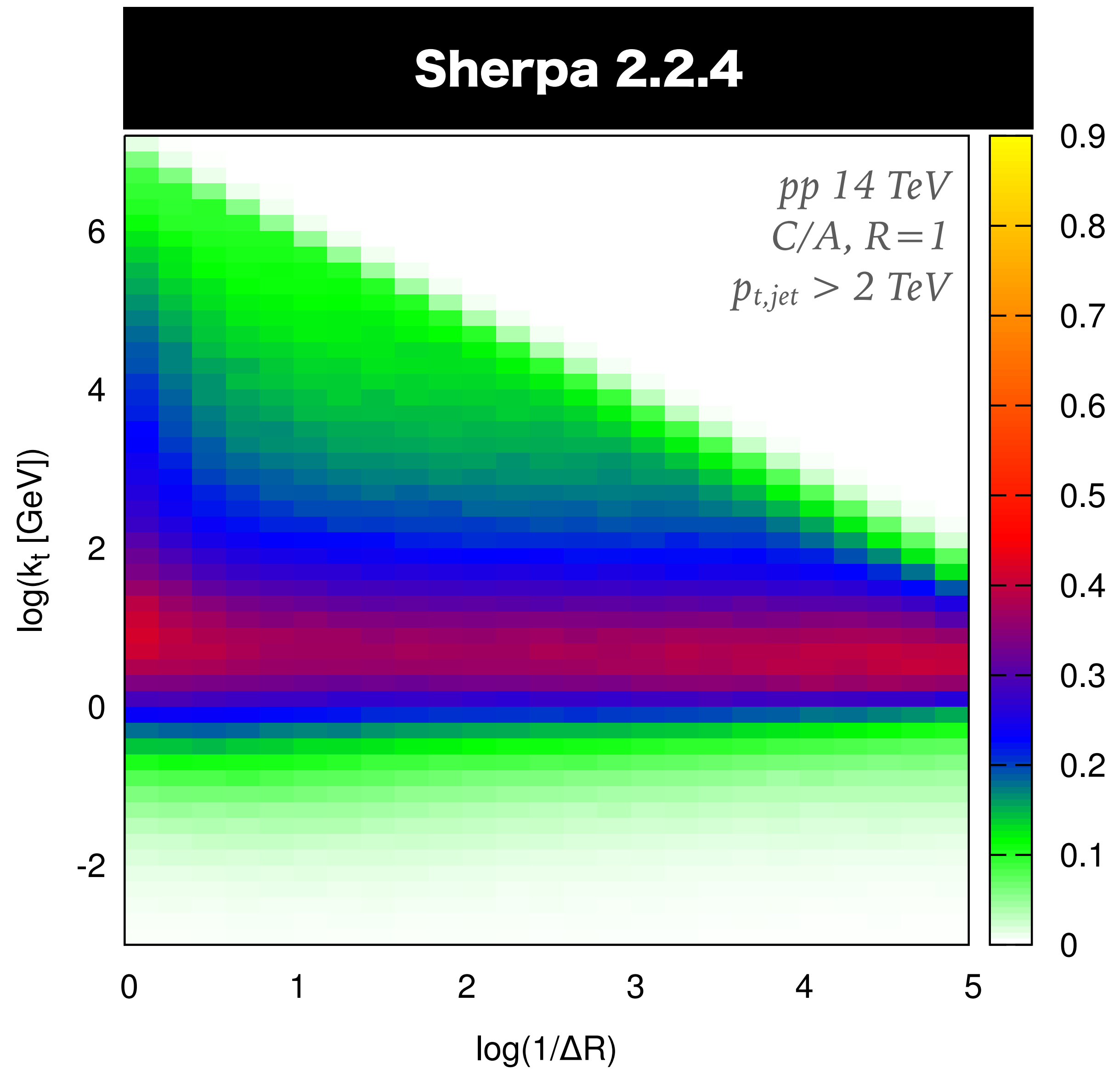
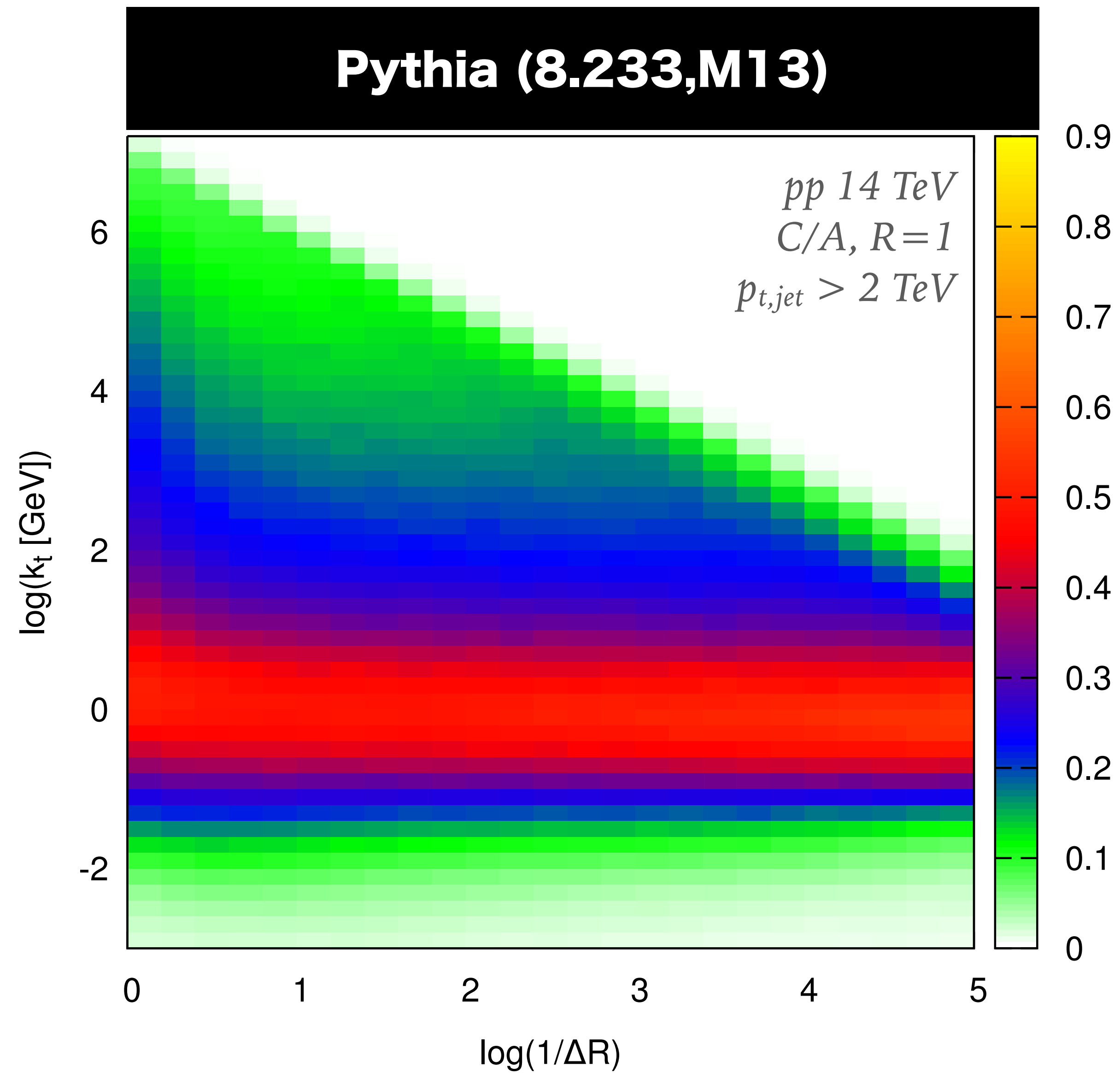
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subject-particle rescaling algorithm (SPRA)

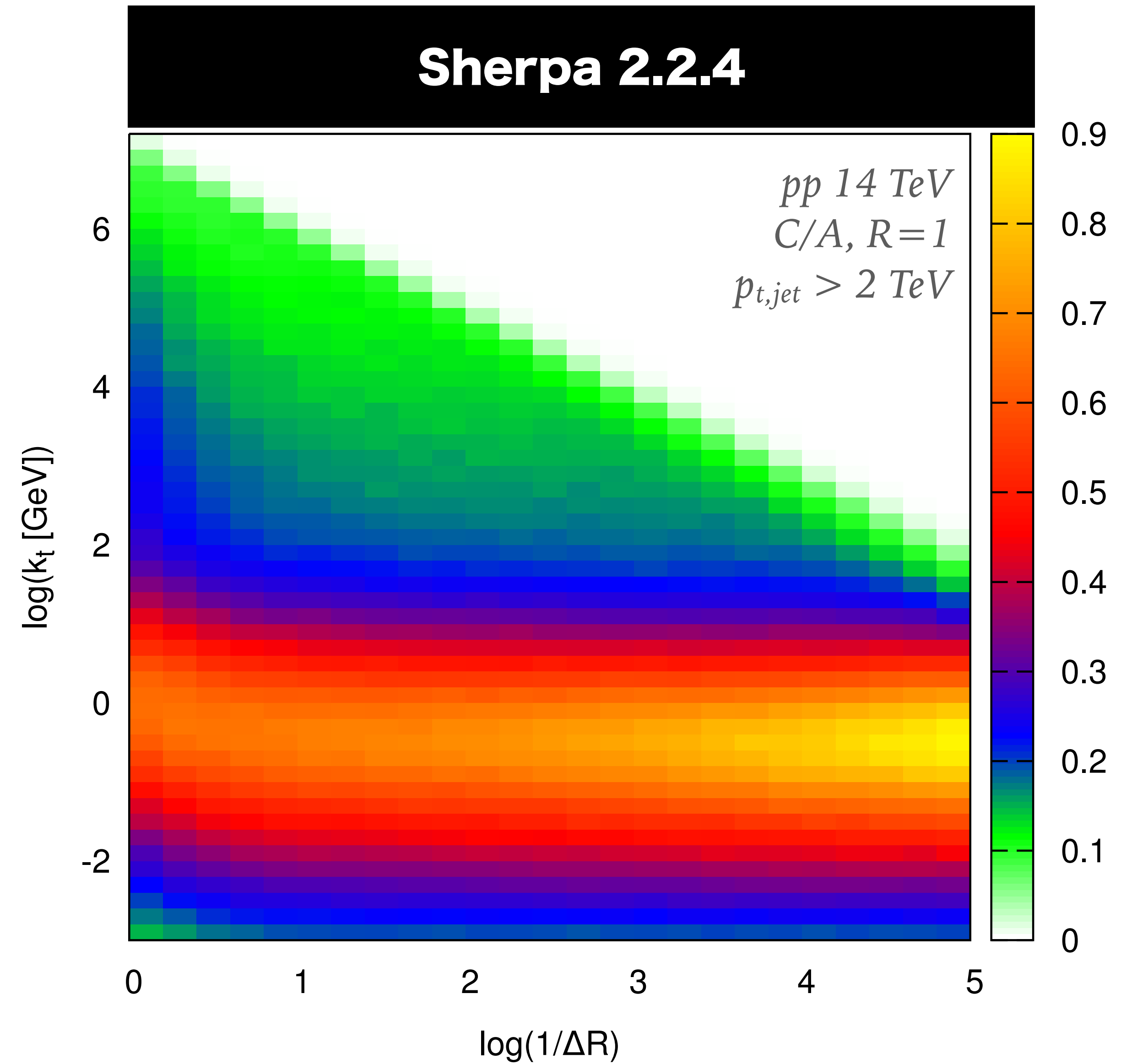
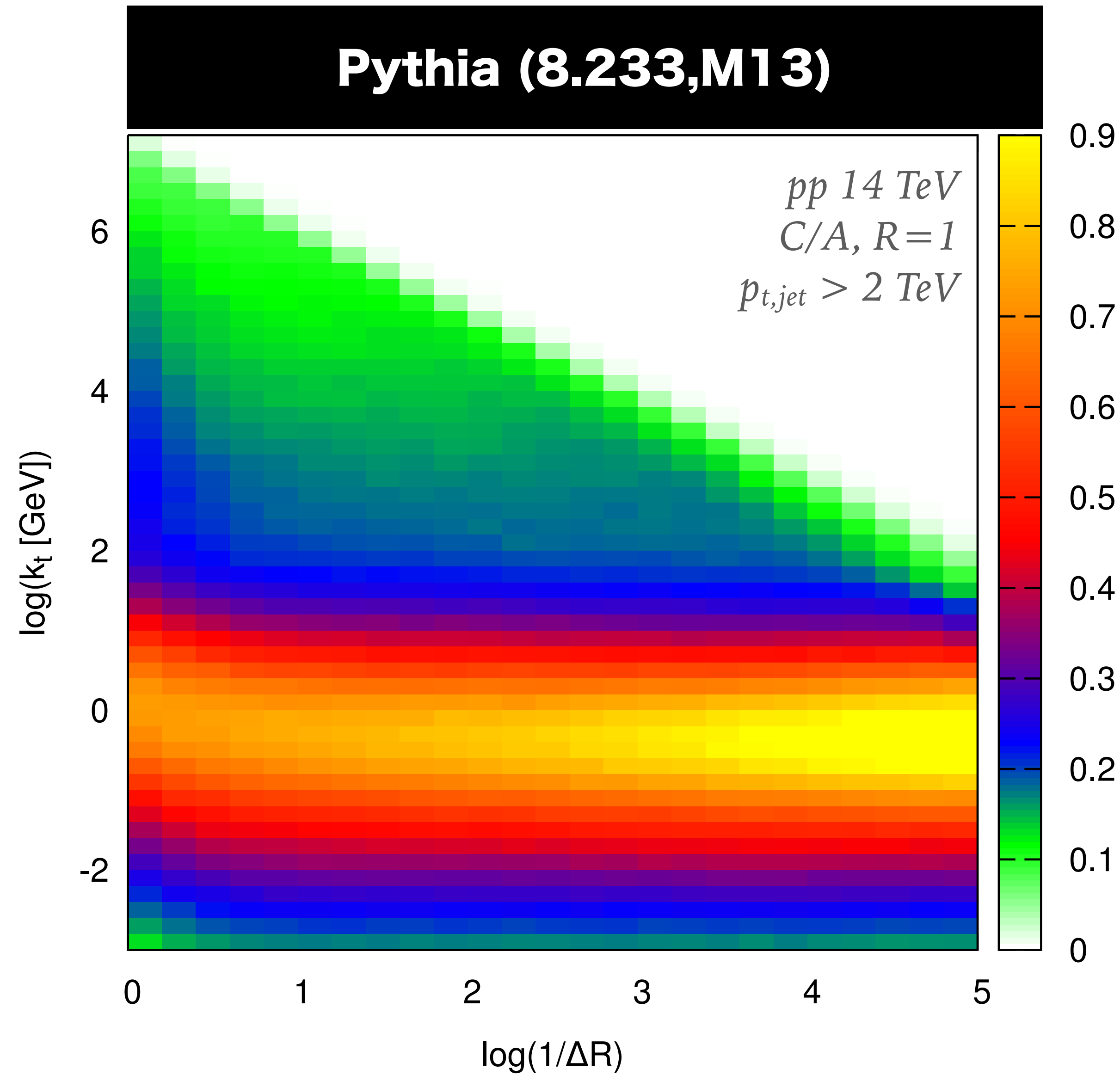


Pythia v. Sherpa

average pp Lund density: **parton level**



average pp Lund density: **hadron level (no underlying event / MPI)**



average pp Lund density: hadron level (with underlying event / MPI)

