

# QCD and Jets at Colliders

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Lecture 1: QCD and perturbative calculations and tools  
**Lecture 2: Jet algorithms and substructure**

[Includes material from  
Gavin Salam and Grégory Soyez]

## ▶ Jet algorithms

- ▶ How are jets made

## ▶ Jet substructure

- ▶ What's inside them, and how to use it

# What is a jet?



No, not this....

A **jet** is something that happens  
in high energy events:  
**a collimated bunch of hadrons flying  
roughly in the same direction**

# Gluon 'discovery'

1979:

**Three-jet events** observed by TASSO, JADE, MARK J and PLUTO at PETRA in  $e^+e^-$  collisions at 27.4 GeV

**Interpretation:**  
large angle emission of a hard gluon

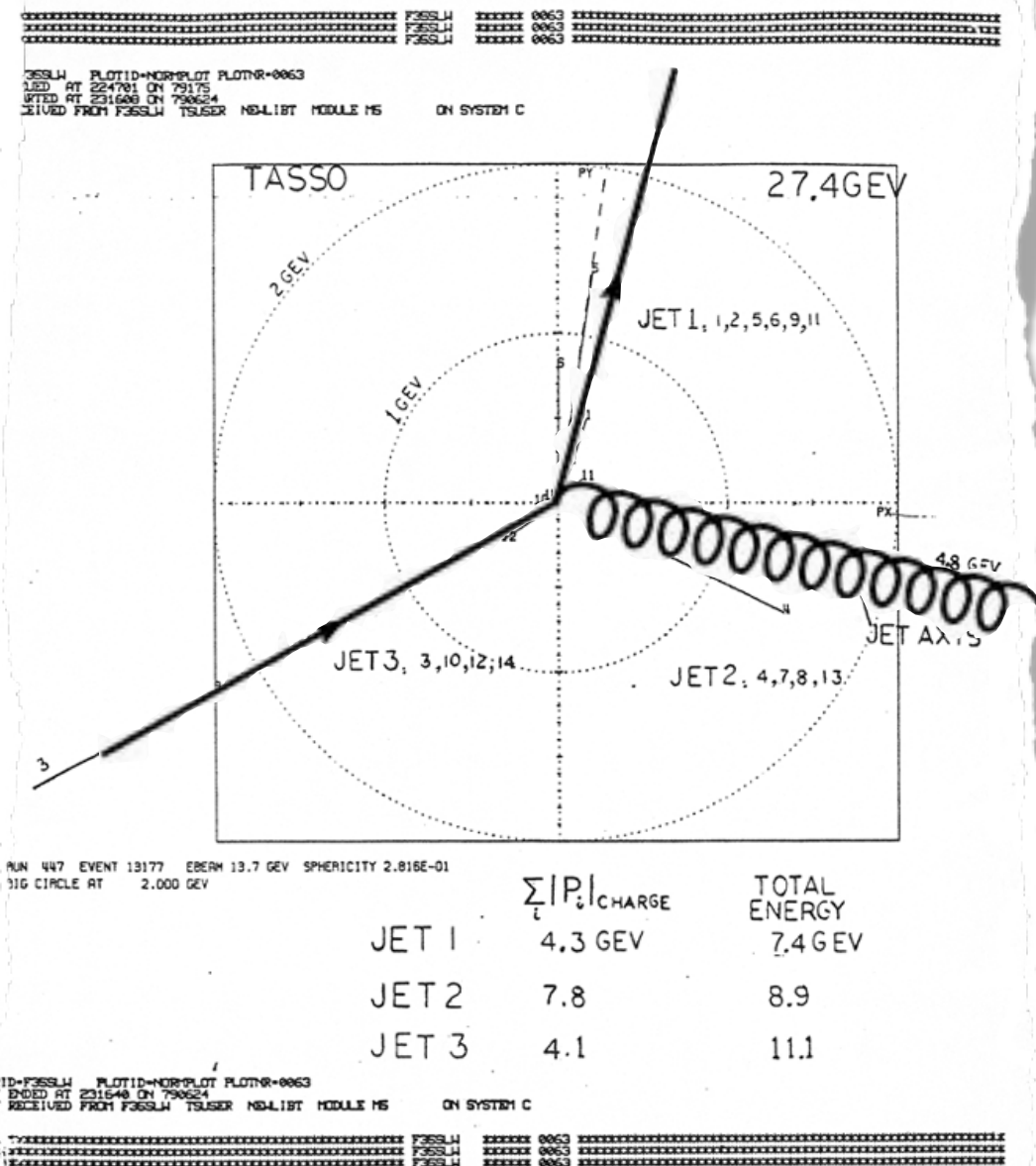


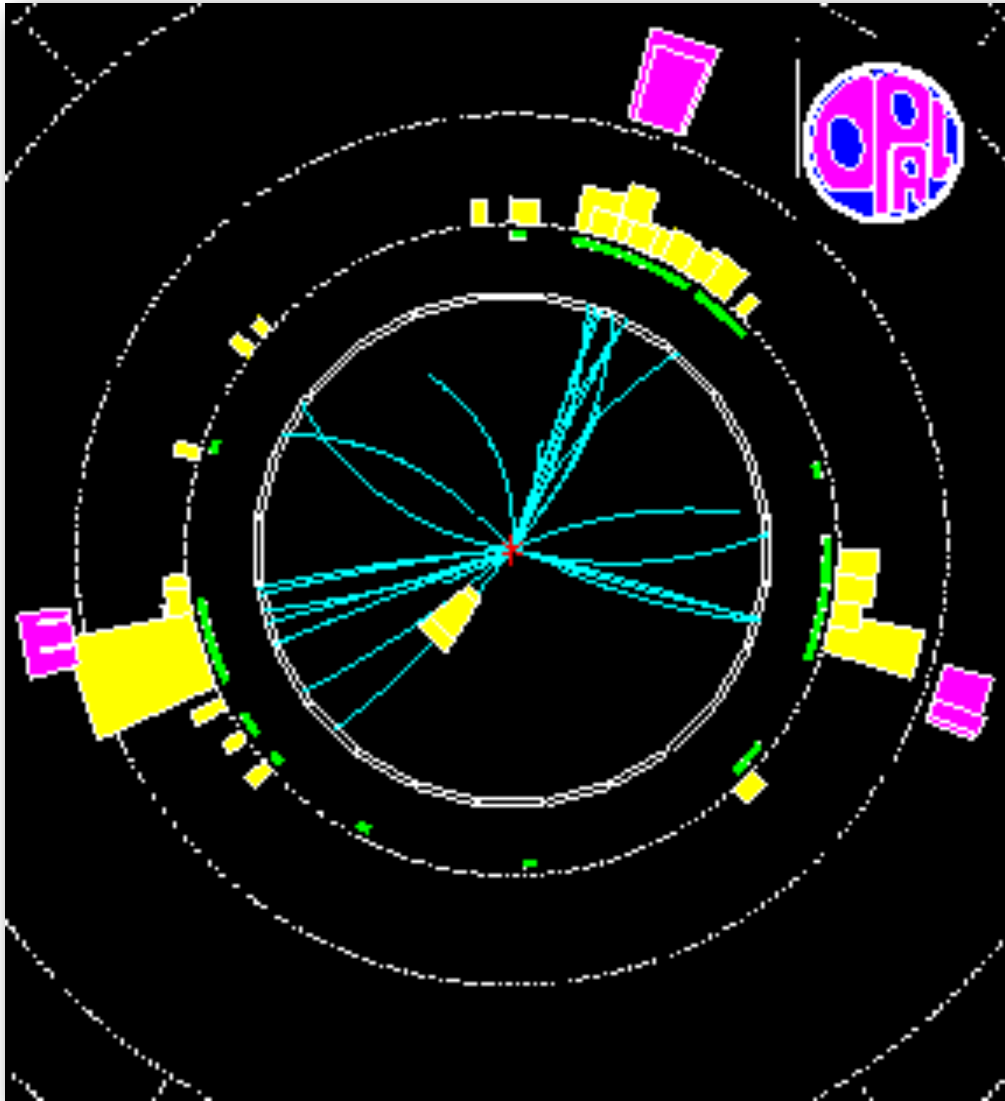
FIGURE 3

Jets viewed as a proxy to the initial partons

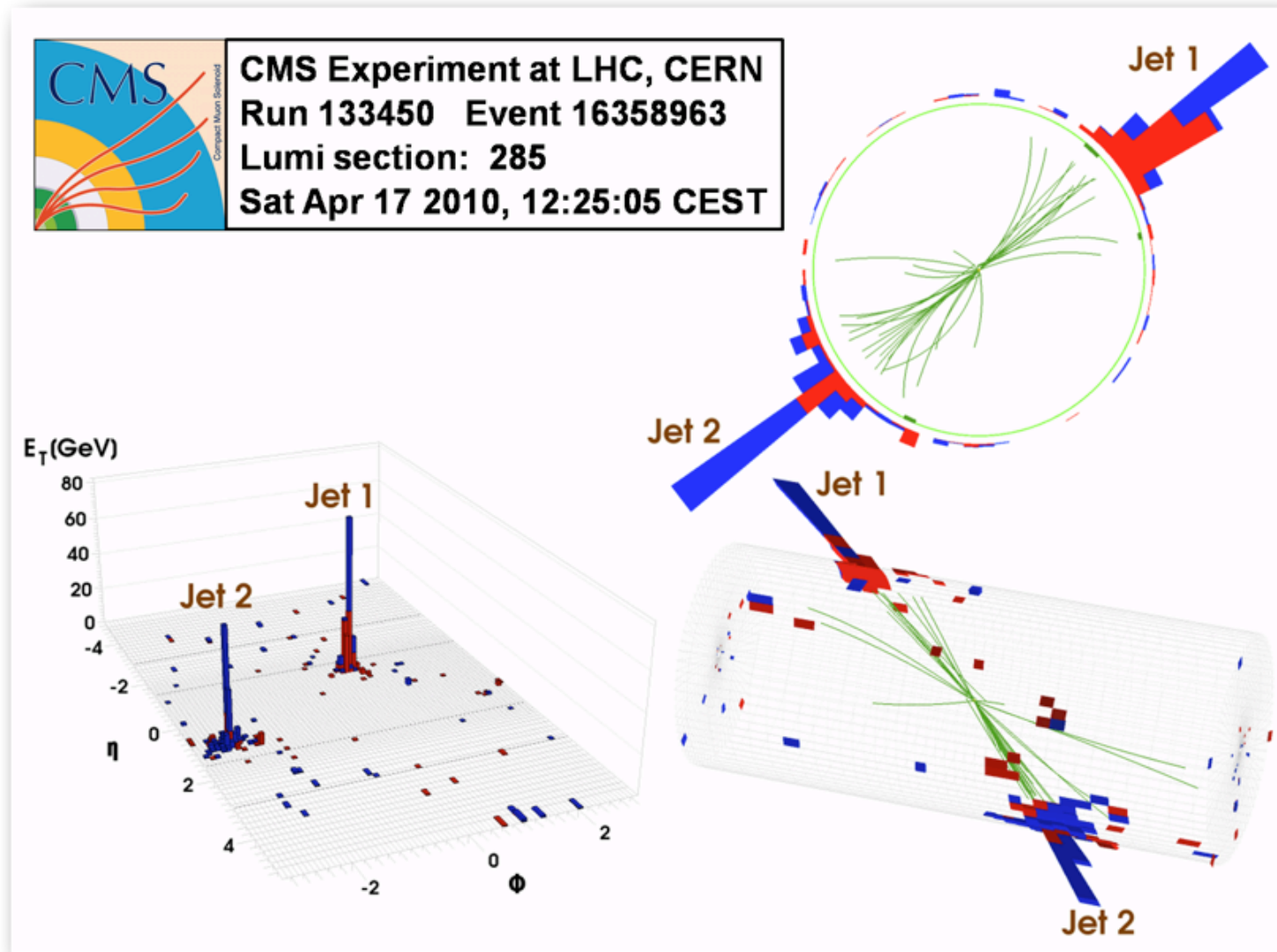
## From PETRA to LEP

We could eyeball the collimated bunches, but it becomes impractical with millions of events

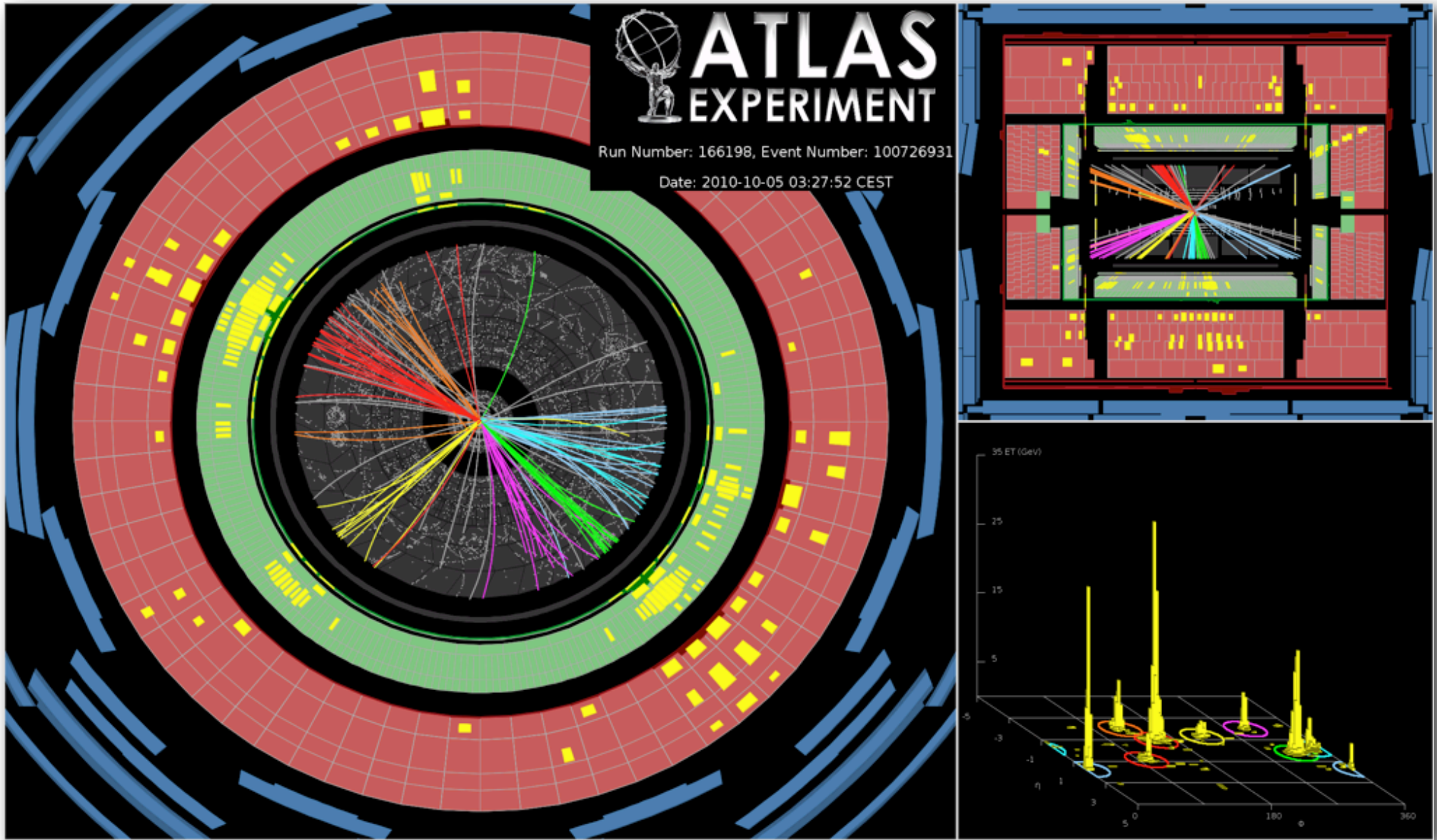
The classification of particles into jets is best done using a **clustering algorithm**



A few decades after PETRA and LEP, the event displays got prettier, but jets are still pretty much the same

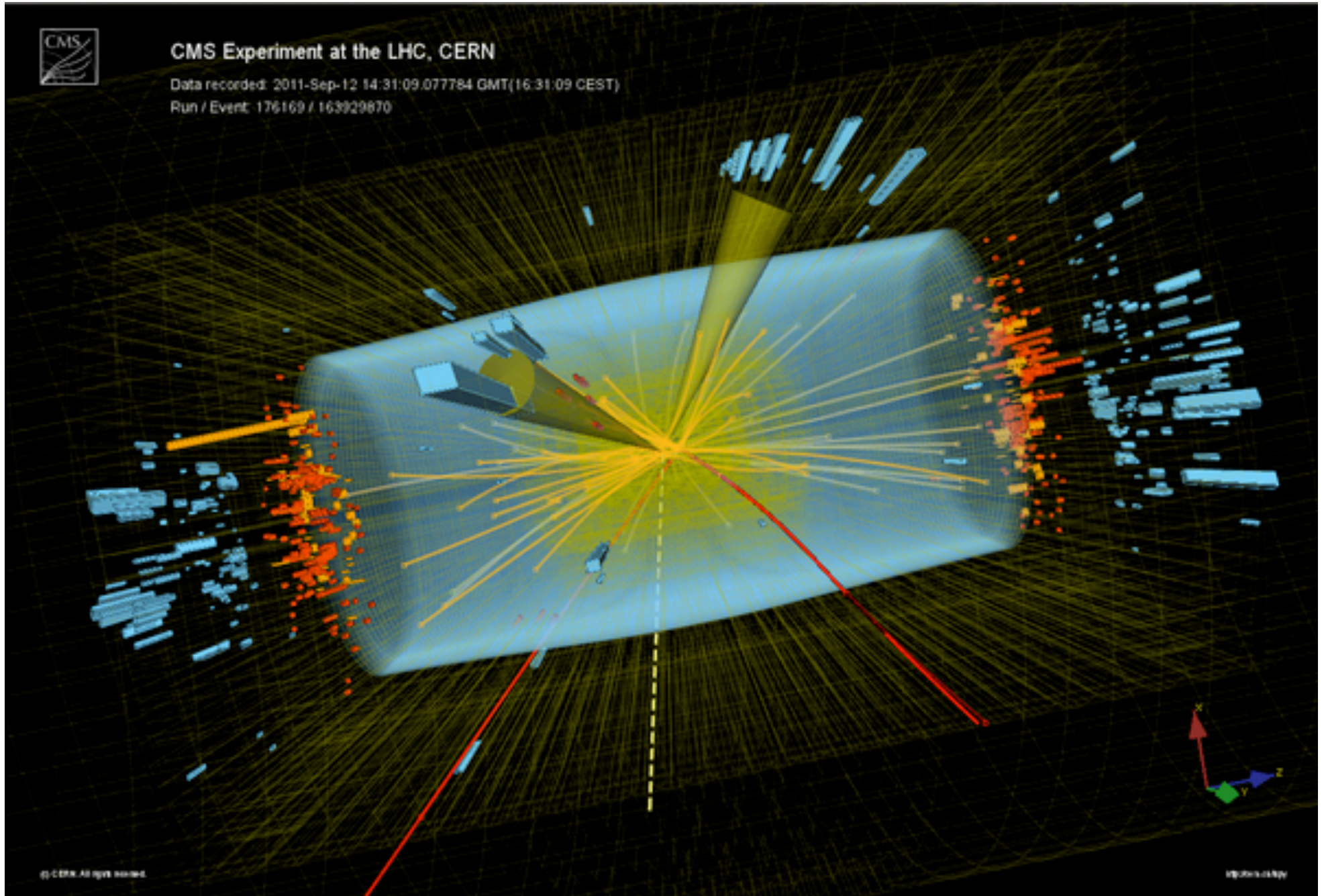


Dijet event from CMS



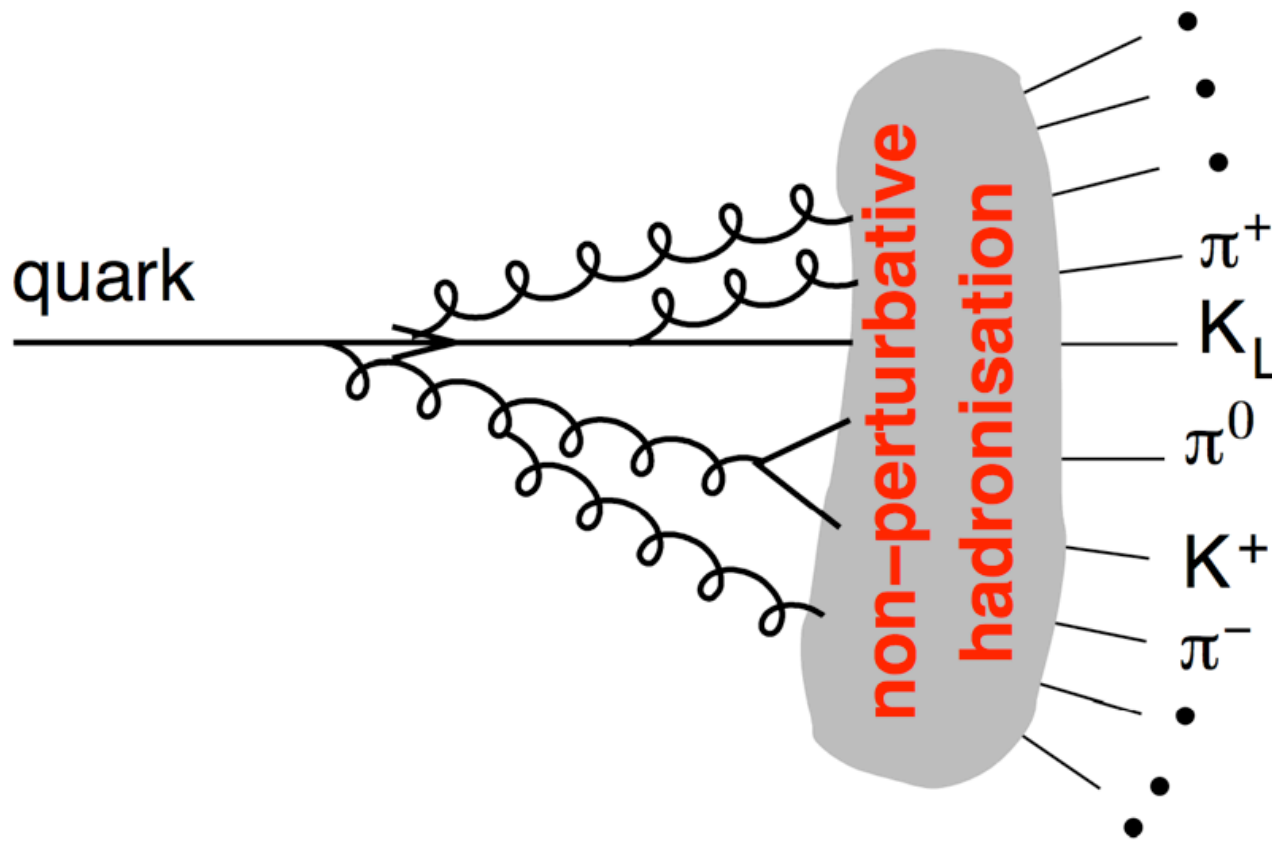
8(!) jets event from ATLAS

# Jets @ LHC





# Why do jets happen?



Gluon emission

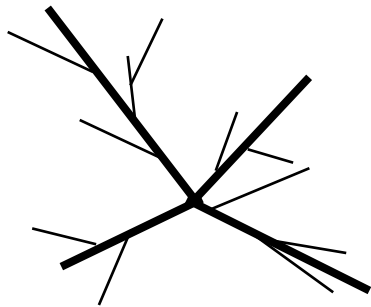
$$\int \alpha_s \frac{dE}{E} \frac{d\theta}{\theta} \gg 1$$

Non-perturbative physics

$$\alpha_s \sim 1$$

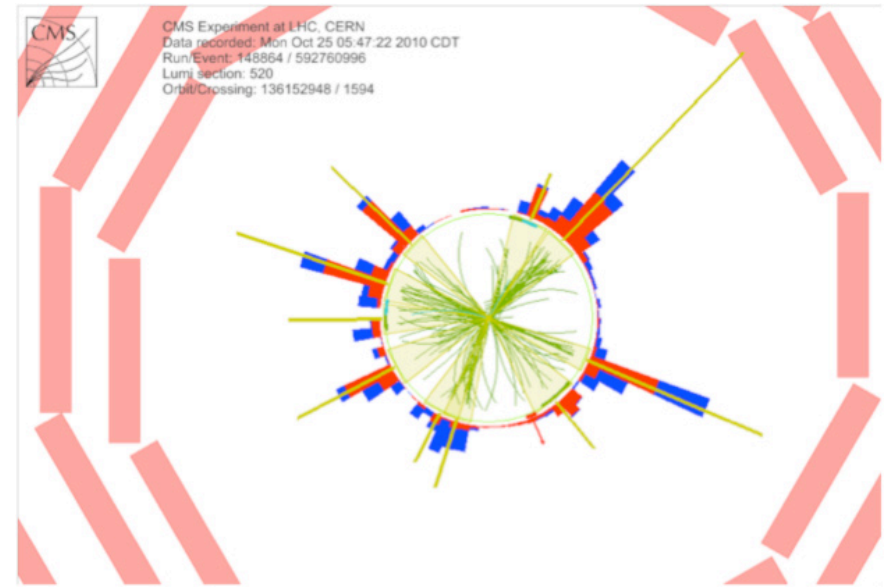
# Taming reality

Multileg + PS



QCD predictions

??

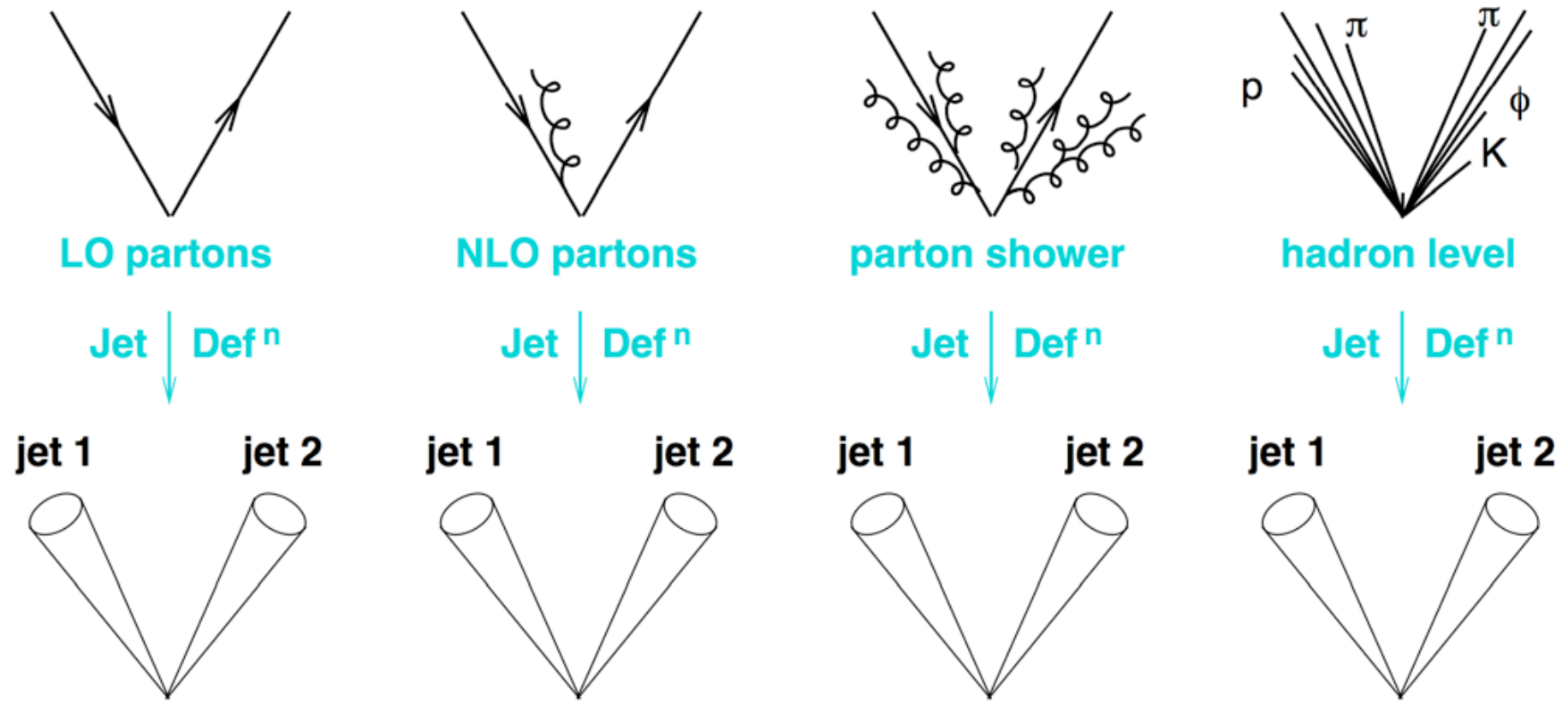


Real data

Jets

One purpose of a 'jet clustering' algorithm is to **reduce the complexity** of the final state, simplifying many hadrons to **simpler objects** that one can hope to **calculate**

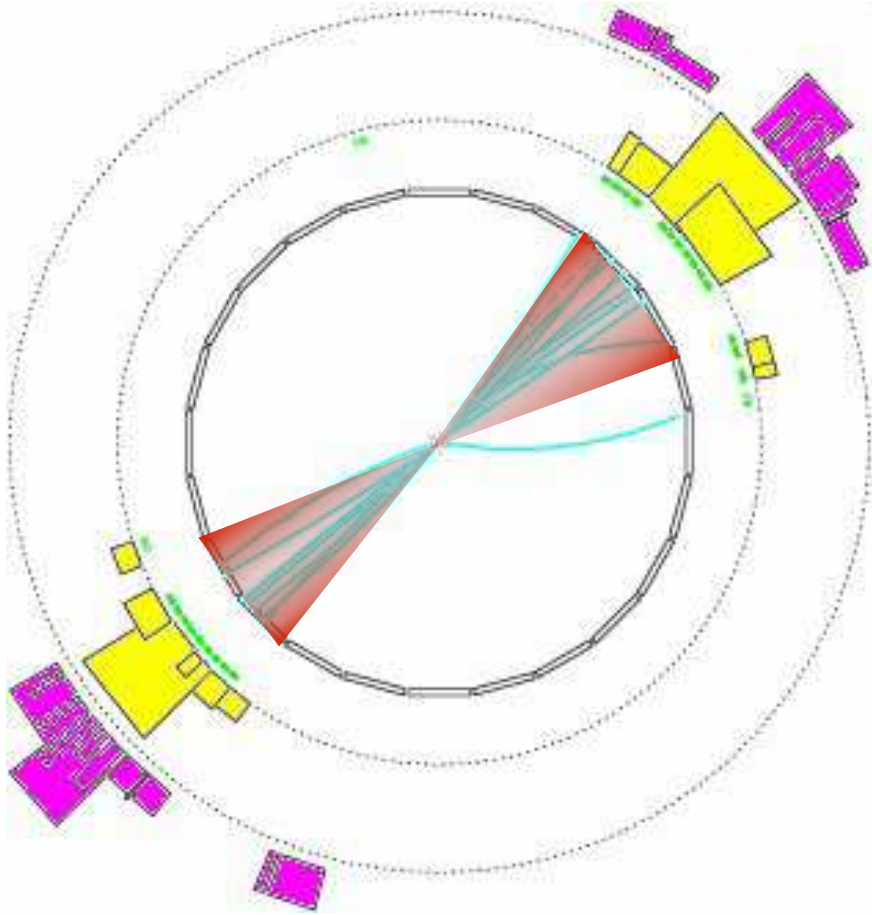
# Jet definitions as projections



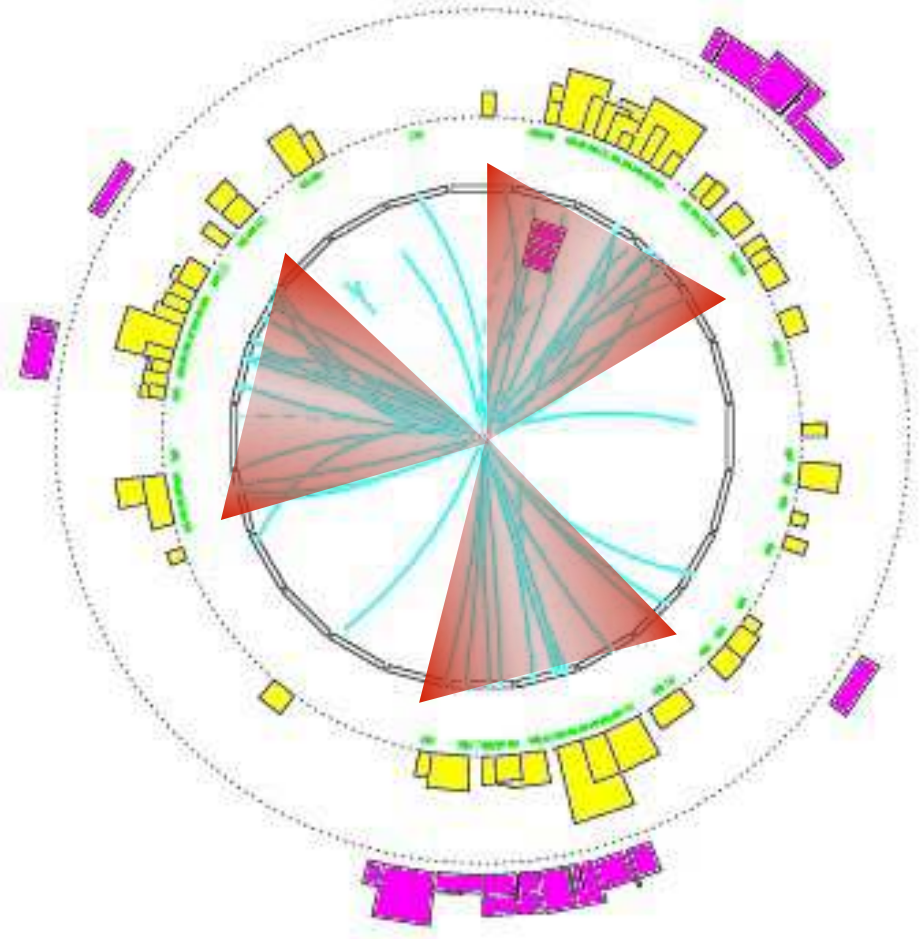
Projection to jets should be resilient to QCD effects

**NB: projections are NOT unique:  
a jet is NOT EQUIVALENT to a parton**

# Reconstructing jets is an ambiguous task

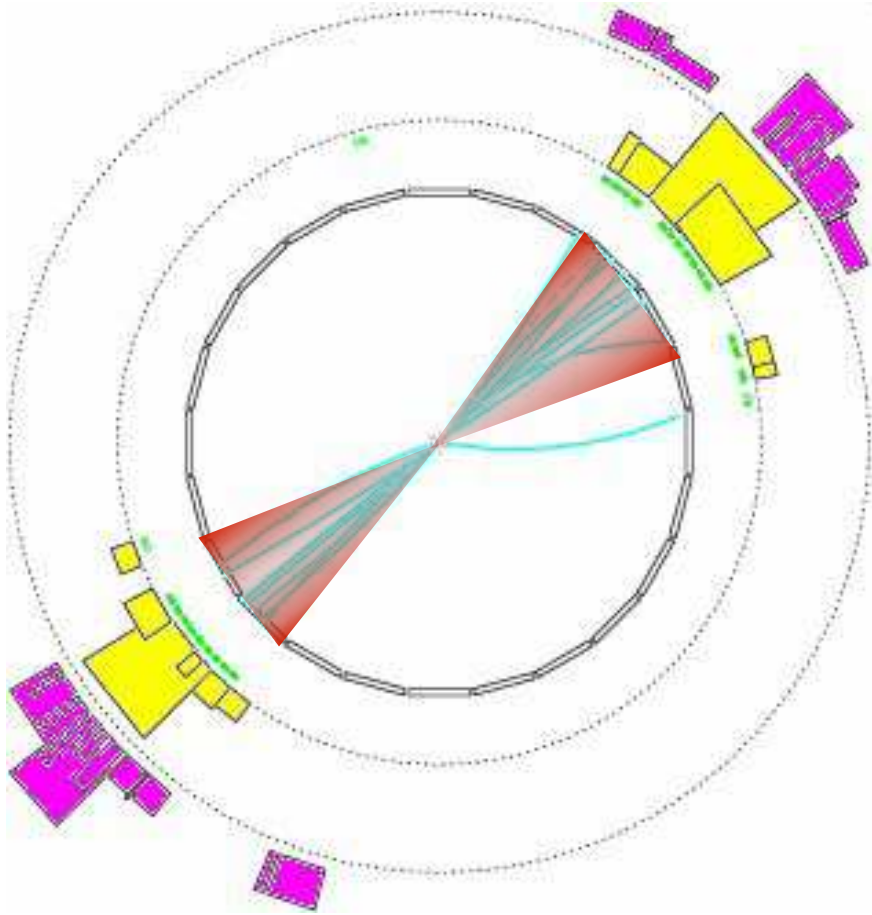


2 clear jets

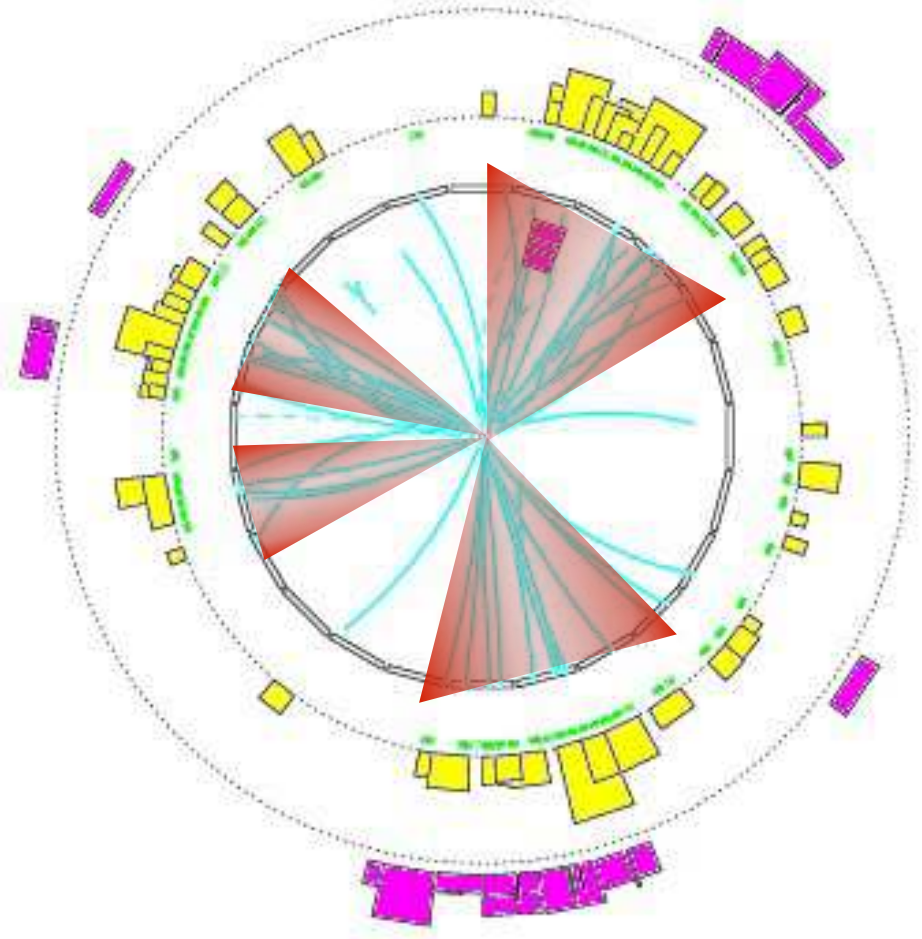


3 jets?

# Reconstructing jets is an ambiguous task



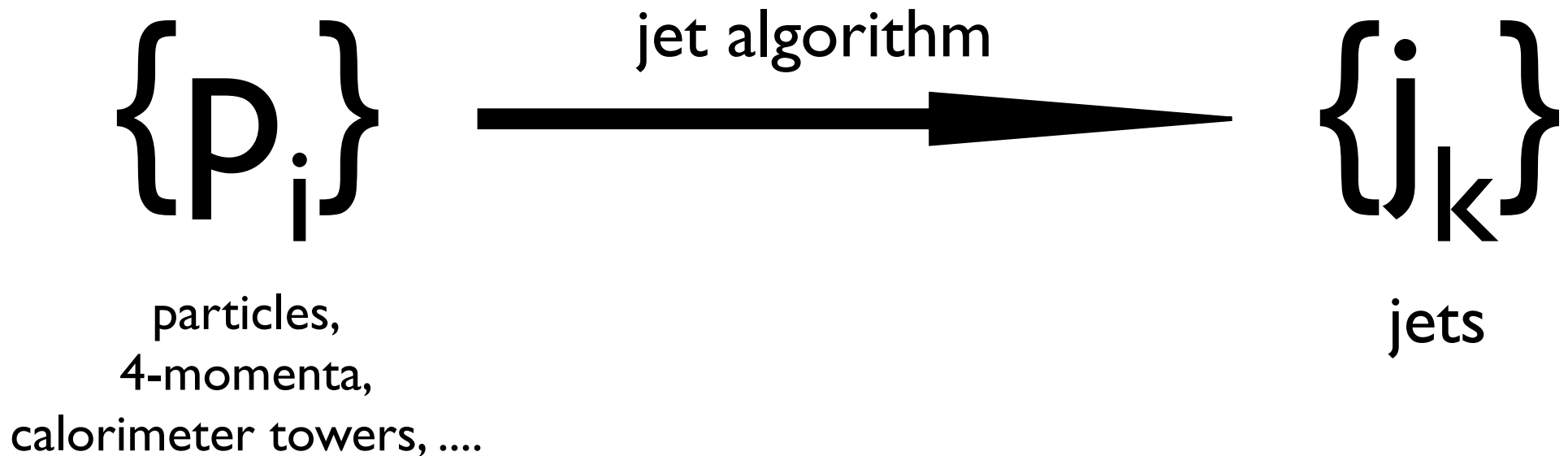
2 clear jets



3 jets?  
**or 4 jets?**

# Jet clustering algorithm

A **jet algorithm** maps the momenta of the final state particles into the momenta of a certain number of jets:



Most algorithms contain a resolution parameter, **R**, which controls the extension of the jet

*“Jet [definitions] are legal contracts between theorists and experimentalists”*  
-- MJ Tannenbaum

## Jets can serve **two** purposes

- ▶ They can be **observables**, that one can measure and calculate
- ▶ They can be **tools**, that one can employ to extract specific properties of the final state

Different clustering algorithms have different properties and characteristics that can make them more or less appropriate for each of these tasks

An observable is **infrared and collinear safe** if, in the limit of a **collinear splitting**, or the **emission of an infinitely soft** particle, the observable remains **unchanged**:

$$O(X; p_1, \dots, p_n, p_{n+1} \rightarrow 0) \rightarrow O(X; p_1, \dots, p_n)$$

$$O(X; p_1, \dots, p_n \parallel p_{n+1}) \rightarrow O(X; p_1, \dots, p_n + p_{n+1})$$

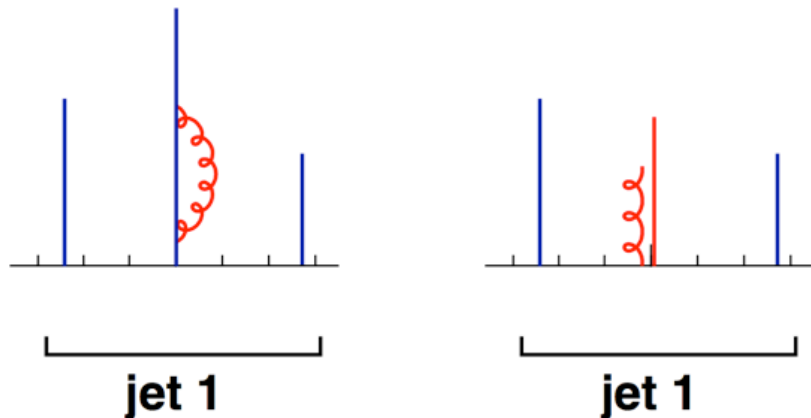
This property ensures cancellation of **real** and **virtual** divergences in higher order calculations

If we wish to be able to calculate a jet rate in perturbative QCD the jet algorithm that we use must be IRC safe:  
**soft emissions and collinear splittings must not change the hard jets**



# Reconstructing jets must respect rules

## Collinear Safe

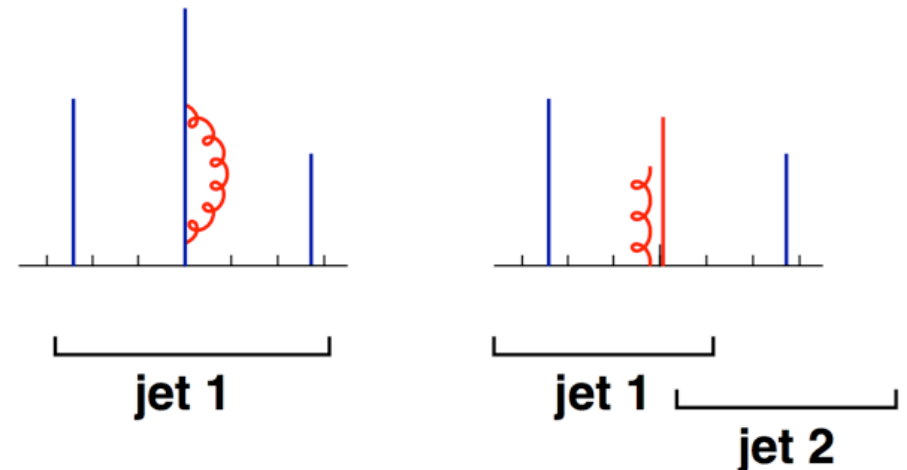


$$\alpha_S^n \times (-\infty)$$

$$\alpha_S^n \times (+\infty)$$

**Infinities cancel**

## Collinear Unsafe



$$\alpha_S^n \times (-\infty)$$

$$\alpha_S^n \times (+\infty)$$

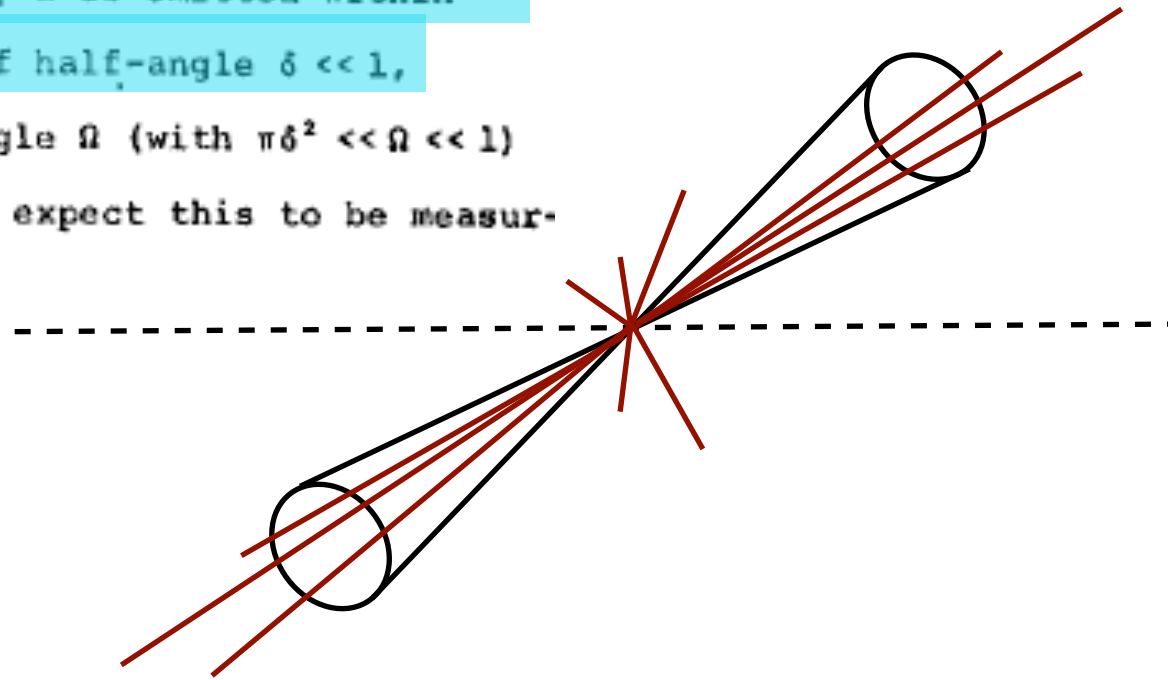
**Infinities do not cancel**

Perturbative calculations of jet observable will only be possible with collinear (and infrared) safe jet definitions

# Cone algorithms

The first rigorous definition of cone jets in QCD is due to Sterman and Weinberg  
Phys. Rev. Lett. **39**, 1436 (1977)

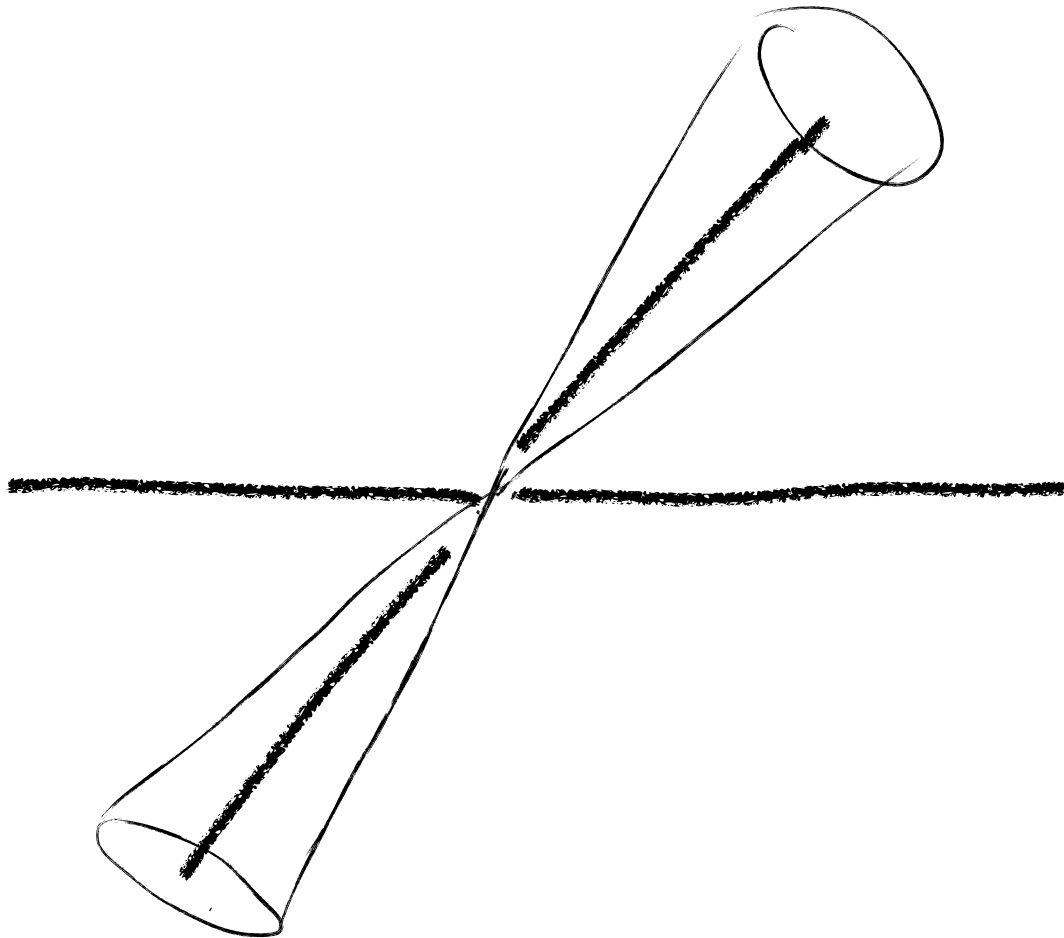
To study jets, we consider the partial cross section  
 $\sigma(E, \theta, \Omega, \epsilon, \delta)$  for  $e^+e^-$  hadron production events, in which all but a fraction  $\epsilon \ll 1$  of the total  $e^+e^-$  energy  $E$  is emitted within some pair of oppositely directed cones of half-angle  $\delta \ll 1$ , lying within two fixed cones of solid angle  $\Omega$  (with  $\pi\delta^2 \ll \Omega \ll 1$ ) at an angle  $\theta$  to the  $e^+e^-$  beam line. We expect this to be measur-



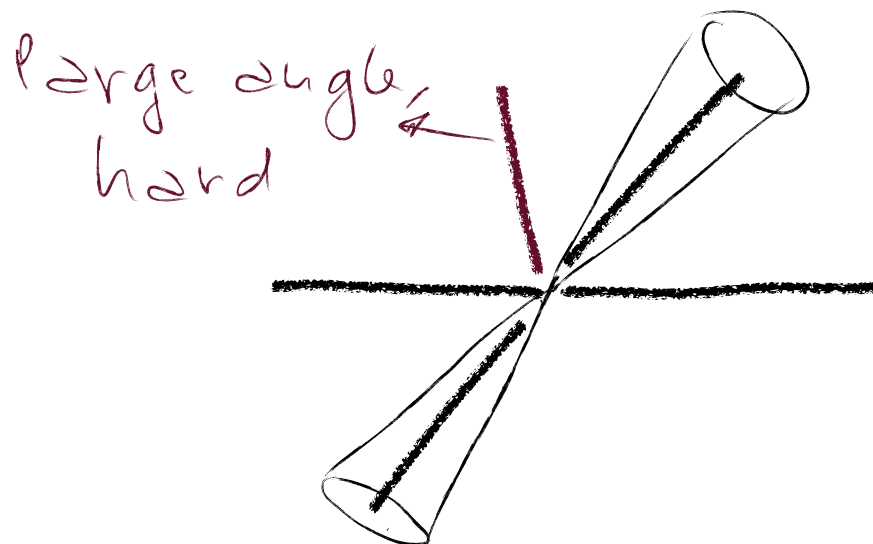
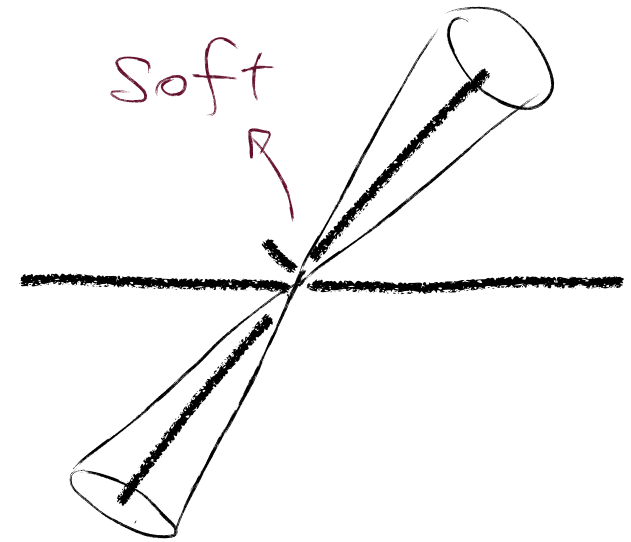
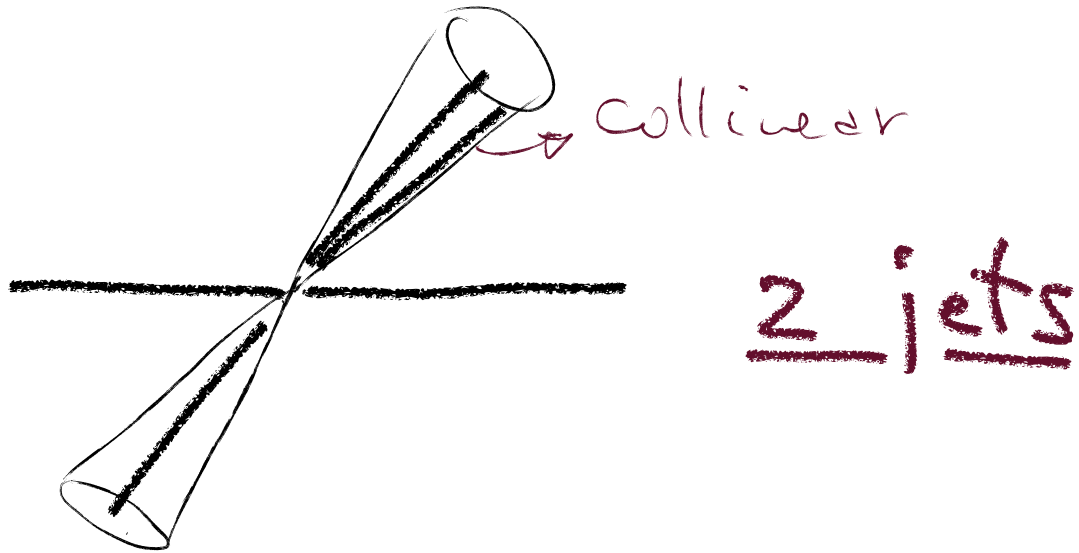
Two-jet rate:

$$\sigma(E, \theta, \Omega, \epsilon, \delta) = (d\sigma/d\Omega)_0 \Omega \left[ 1 - (g_E^2/3\pi^2) \left\{ 3\ln \delta + 4\ln \delta \ln 2\epsilon + \frac{\pi^3}{3} - \frac{5}{2} \right\} \right]$$

2 particles = 2 jets



3 particles  $\geq$  ?



3 jets

The Sterman-Weinberg definition is “inclusive enough”  
for IRC safety

Good for 2 jets and  $e^+e^-$  collisions

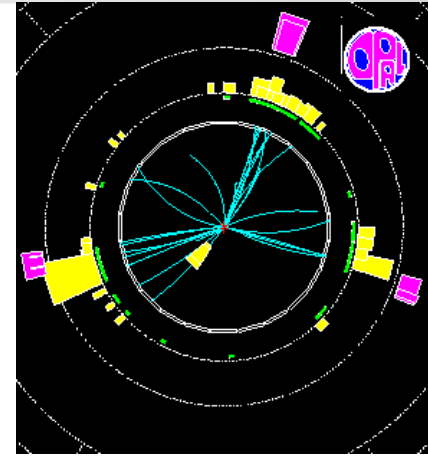
What happens in a more general case, where more than  
two jets are likely to exist?

**Where** do we place the cones? **How many?**

**Iterative** jet algorithms

# Two main approaches to jet clustering

1. Find regions where a lot of energy flows
2. Decide which particles are “close”, aggregate them



In HEP these are usually called **cone** and **sequential recombination** algorithms respectively

(in other fields they are often called partitional-type clustering and agglomerative hierarchical clustering)

# Two main classes of jet algorithms

## ▶ **Sequential recombination algorithms**

Bottom-up approach: combine particles starting from **closest ones**

**How?** Choose a **distance measure**, iterate recombination until few objects left, call them jets

Works because of mapping closeness  $\Leftrightarrow$  QCD divergence

Examples: Jade,  $k_t$ , Cambridge/Aachen, anti- $k_t$ , .....

Usually trivially made IRC safe, but their algorithmic complexity scales like  $N^3$

## ▶ **Cone algorithms**

Top-down approach: find coarse regions of energy flow.

**How?** Find **stable cones** (i.e. their axis coincides with sum of momenta of particles in it)

Works because QCD only modifies energy flow on small scales

Examples: JetClu, MidPoint, ATLAS cone, CMS cone, SISCone.....

Can be programmed to be fairly fast, at the price of being complex and IRC unsafe

# Recombination algorithms

- ▶ First introduced in  $e^+e^-$  collisions in the '80s
- ▶ Typically they work by calculating a **'distance'** between particles, and then recombine them pairwise according to a given order, until some condition is met (e.g. no particles are left, or the distance crosses a given threshold)

IRC safety can usually be seen to be trivially guaranteed



Distance:

$$y_{ij} = \frac{2E_i E_j (1 - \cos \theta_{ij})}{Q^2}$$

- ▶ Find the minimum  $y_{\min}$  of all  $y_{ij}$
- ▶ If  $y_{\min}$  is below some jet resolution threshold  $y_{\text{cut}}$ , recombine  $i$  and  $j$  into a single new particle ('pseudojet'), and repeat
- ▶ If no  $y_{\min} < y_{\text{cut}}$  are left, all remaining particles are jets

Problem of this particular algorithm:

two **soft** particles emitted at **large angle** get easily recombined into a single jet: counterintuitive and perturbatively troublesome

# $e^+e^- k_t$ (Durham) algorithm

[Catani, Dokshitzer, Olsson, Turnock, Webber '91]

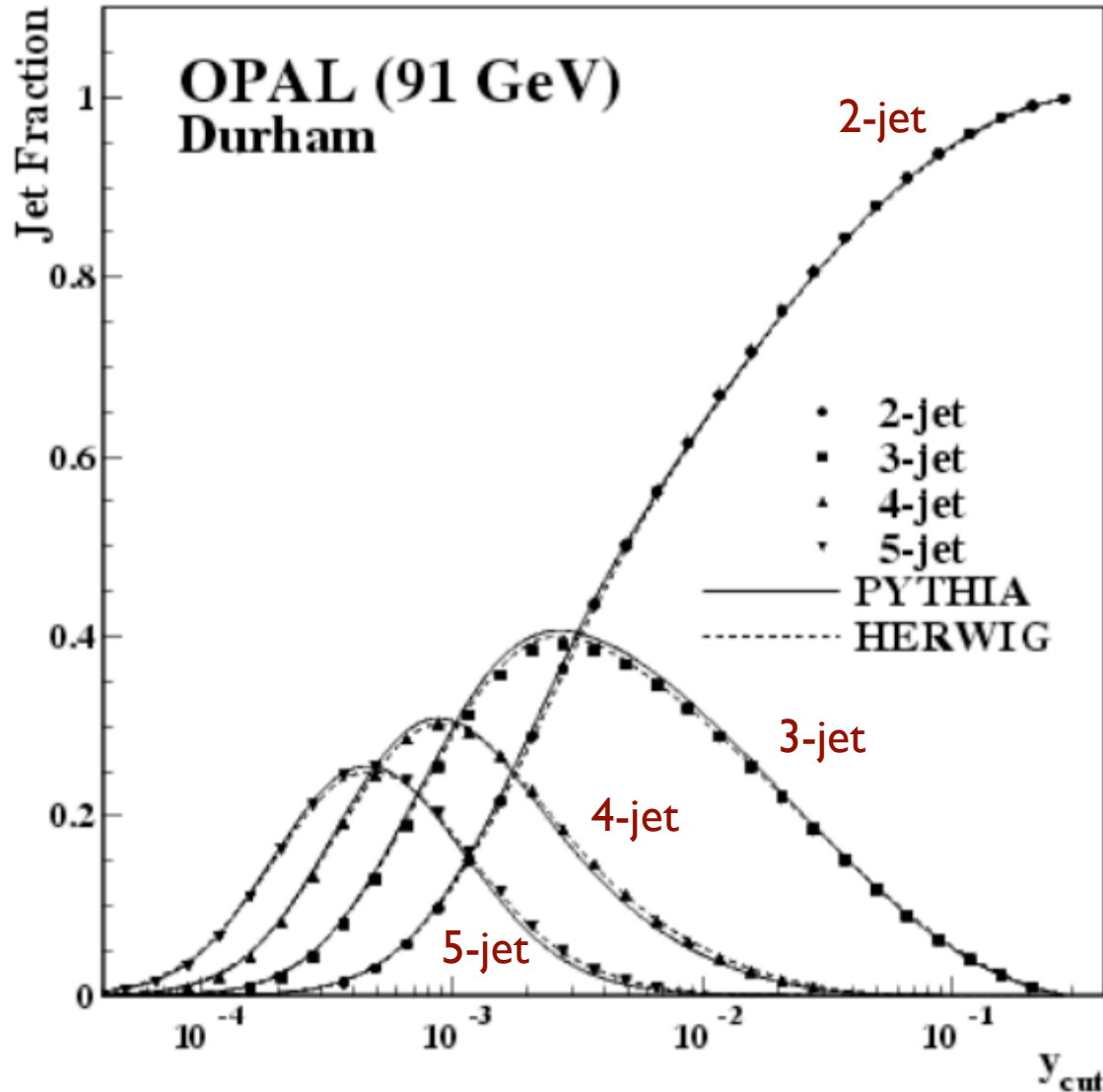
Distance:

$$y_{ij} = \frac{2 \min(E_i^2, E_j^2) (1 - \cos \theta_{ij})}{Q^2}$$

In the collinear limit, the numerator reduces to the **relative transverse momentum** (squared) of the two particles, hence the name of the algorithm

- ▶ Find the minimum  $y_{\min}$  of all  $y_{ij}$
- ▶ If  $y_{\min}$  is below some jet resolution threshold  $y_{\text{cut}}$ , recombine  $i$  and  $j$  into a single new particle ('pseudojet'), and repeat
- ▶ If no  $y_{\min} < y_{\text{cut}}$  are left, all remaining particles are jets

# $e^+e^-$ $k_t$ (Durham) algorithm in action



Characterise events  
in terms of number of jets  
(as a function of  $y_{cut}$ )

Resummed calculations for distributions of  $y_{cut}$  doable with the  $k_t$  algorithm

# $e^+e^- k_t$ (Durham) algorithm v. QCD

$k_t$  is a sequential recombination type algorithm

One key feature of the  $k_t$  algorithm is its relation to the structure of QCD divergences:

$$\frac{dP_{k \rightarrow ij}}{dE_i d\theta_{ij}} \sim \frac{\alpha_s}{\min(E_i, E_j)\theta_{ij}}$$

The  $y_{ij}$  distance is the inverse of the emission probability

- ▶ The  $k_t$  algorithm roughly inverts the QCD branching sequence (the pair which is recombined first is the one with the largest probability to have branched)
- ▶ The history of successive clusterings has **physical meaning**

# $k_t$ algorithm in hadron collisions

(Inclusive and longitudinally invariant version)

$$d_{ij} = \min(p_{ti}^2, p_{tj}^2) \frac{\Delta R_{ij}^2}{R^2} \quad d_{iB} = p_{ti}^2$$

- ▶ Calculate the distances between the particles:  $\mathbf{d}_{ij}$
- ▶ Calculate the beam distances:  $\mathbf{d}_{iB}$
- ▶ Combine particles with **smallest distance**  $d_{ij}$  or, if  $d_{iB}$  is smallest, call it a jet
- ▶ Find again smallest distance and repeat procedure until no particles are left (this stopping criterion leads to the *inclusive* version of the  $k_t$  algorithm)
- ▶ Only use jets with  $p_t > p_{t,\min}$

# The $k_t$ algorithm and its siblings

$$d_{ij} = \min(p_{ti}^{2p}, p_{tj}^{2p}) \frac{\Delta y^2 + \Delta \phi^2}{R^2} \quad d_{iB} = p_{ti}^{2p}$$

**p = 1**  $k_t$  algorithm

S. Catani, Y. Dokshitzer, M. Seymour and B. Webber, Nucl. Phys. B406 (1993) 187  
S.D. Ellis and D.E. Soper, Phys. Rev. D48 (1993) 3160

**p = 0** Cambridge/Aachen algorithm

Y. Dokshitzer, G. Leder, S. Moretti and B. Webber, JHEP 08 (1997) 001  
M. Wobisch and T. Wengler, hep-ph/9907280

**p = -1** **anti- $k_t$  algorithm**

MC, G. Salam and G. Soyez, arXiv:0802.1189

NB: in anti- $k_t$  pairs with a **hard** particle will cluster first: if no other hard particles are close by, the algorithm will give **perfect cones**

Quite ironically, a sequential recombination algorithm is the 'perfect' cone algorithm

# IRC safety of generalised- $k_t$ algorithms

$$d_{ij} = \min(p_{ti}^{2p}, p_{tj}^{2p}) \frac{\Delta y^2 + \Delta \phi^2}{R^2} \quad d_{iB} = p_{ti}^{2p}$$

## $p > 0$

New **soft** particle ( $p_t \rightarrow 0$ ) means that  $d \rightarrow 0 \Rightarrow$  clustered first, no effect on jets

New **collinear** particle ( $\Delta y^2 + \Delta \phi^2 \rightarrow 0$ ) means that  $d \rightarrow 0 \Rightarrow$  clustered first, no effect on jets

## $p = 0$

New **soft** particle ( $p_t \rightarrow 0$ ) can be new jet of zero momentum  $\Rightarrow$  no effect on hard jets

New **collinear** particle ( $\Delta y^2 + \Delta \phi^2 \rightarrow 0$ ) means that  $d \rightarrow 0 \Rightarrow$  clustered first, no effect on jets

## $p < 0$

New **soft** particle ( $p_t \rightarrow 0$ ) means  $d \rightarrow \infty \Rightarrow$  clustered last or new zero-jet, no effect on hard jets

New **collinear** particle ( $\Delta y^2 + \Delta \phi^2 \rightarrow 0$ ) means that  $d \rightarrow 0 \Rightarrow$  clustered first, no effect on jets

# IRC safe algorithms

$k_t$	<p>SR</p> $d_{ij} = \min(p_{ti}^2, p_{tj}^2) \Delta R_{ij}^2 / R^2$ <p>hierarchical in rel <math>p_t</math></p>	<p>Catani et al '91 Ellis, Soper '93</p>	$N \ln N$
Cambridge/ Aachen	<p>SR</p> $d_{ij} = \Delta R_{ij}^2 / R^2$ <p>hierarchical in angle</p>	<p>Dokshitzer et al '97 Wengler, Wobish '98</p>	$N \ln N$
anti- $k_t$	<p>SR</p> $d_{ij} = \min(p_{ti}^{-2}, p_{tj}^{-2}) \Delta R_{ij}^2 / R^2$ <p>gives perfectly conical hard jets</p>	<p>MC, Salam, Soyez '08 (Delsart, Loch)</p>	$N^{3/2}$
SISCone	<p>Seedless iterative cone with split-merge gives 'economical' jets</p>	<p>Salam, Soyez '07</p>	$N^2 \ln N$

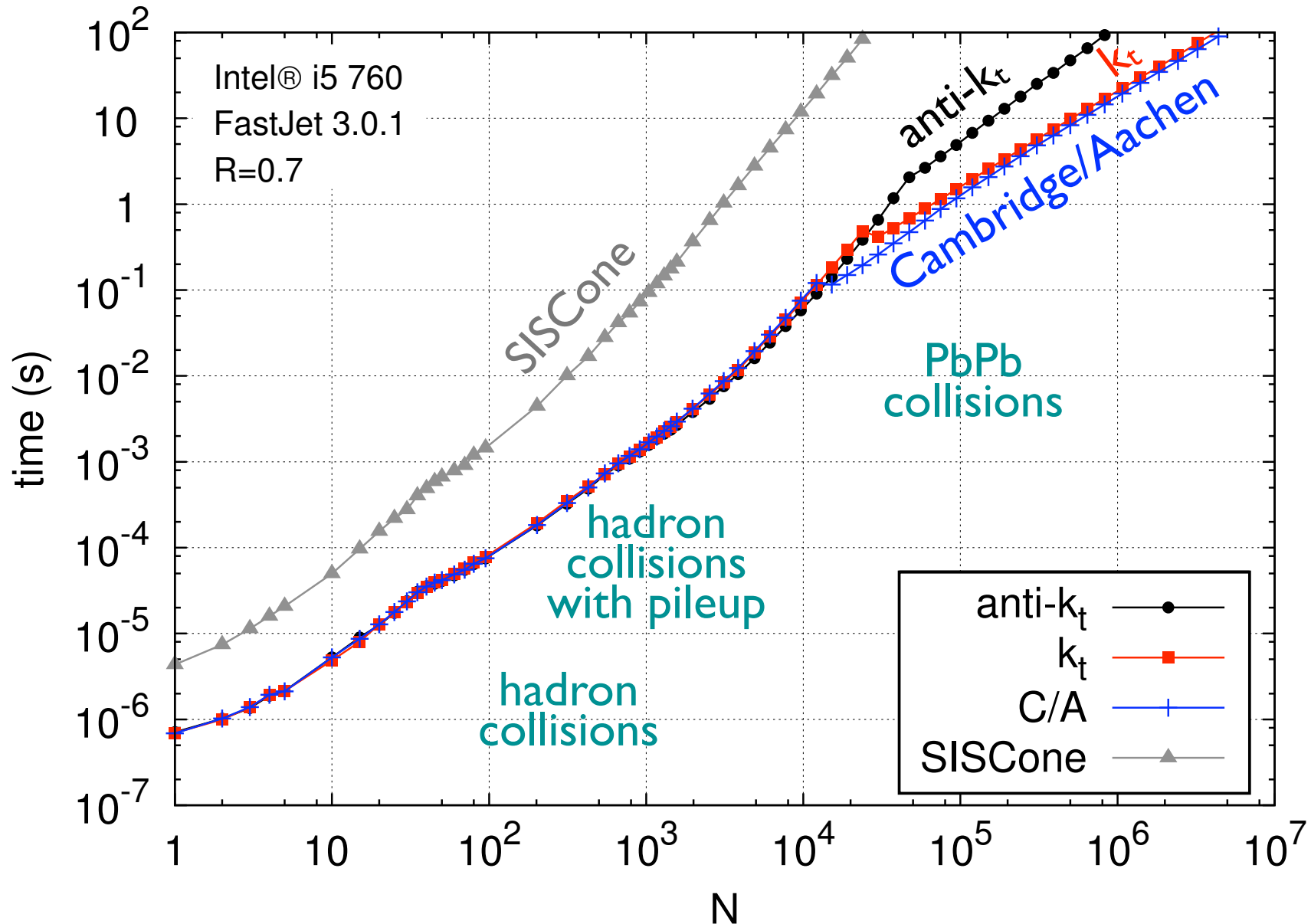
'second-generation' algorithms

All are available in FastJet, <http://fastjet.fr>

(As well as many IRC unsafe ones)



## Time needed to cluster an event with N particles

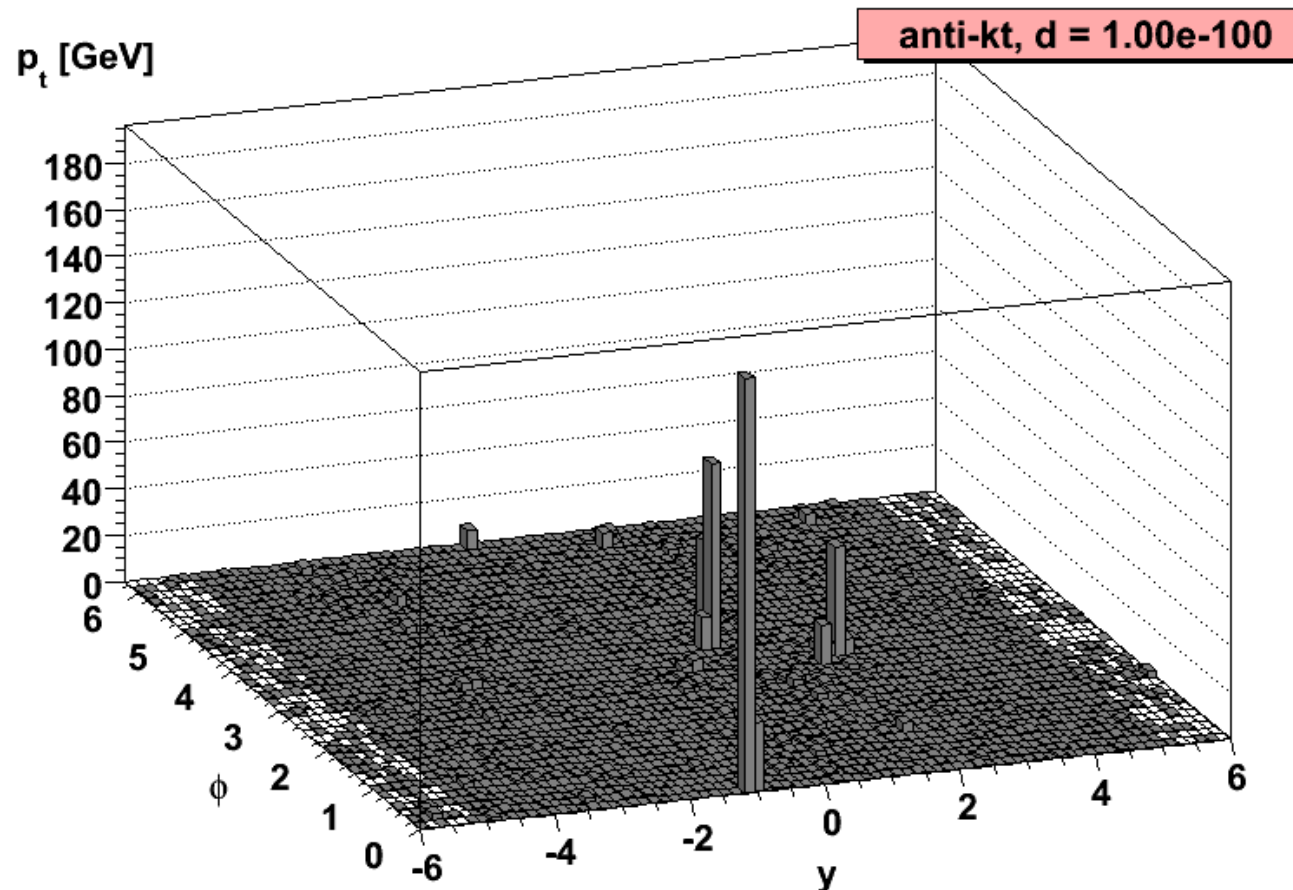


Clustering grows  
around hard cores

$$d_{ij} = \frac{1}{\max(p_{ti}^2, p_{tj}^2)} \frac{\Delta R_{ij}^2}{R^2}, \quad d_{iB} = \frac{1}{p_{ti}^2}$$

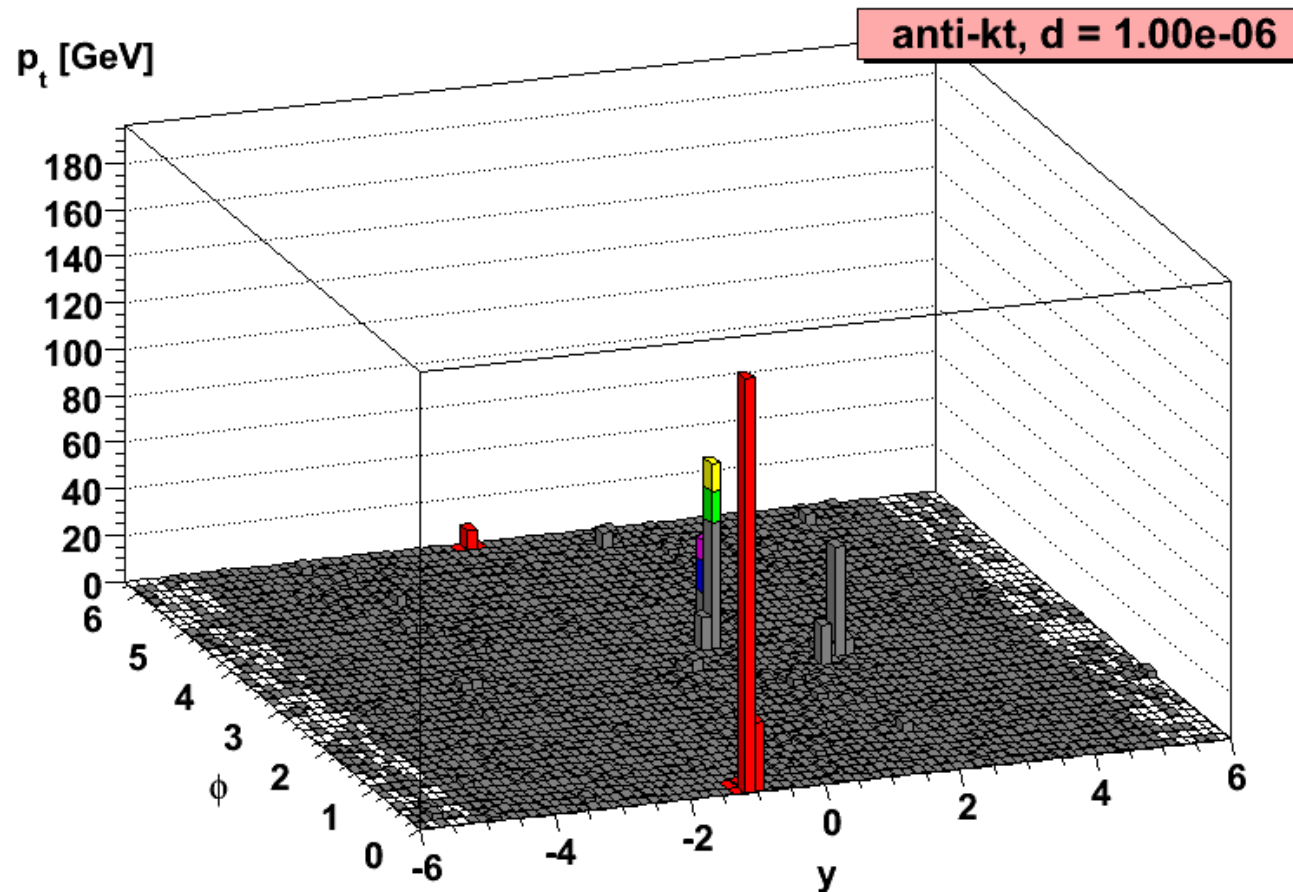
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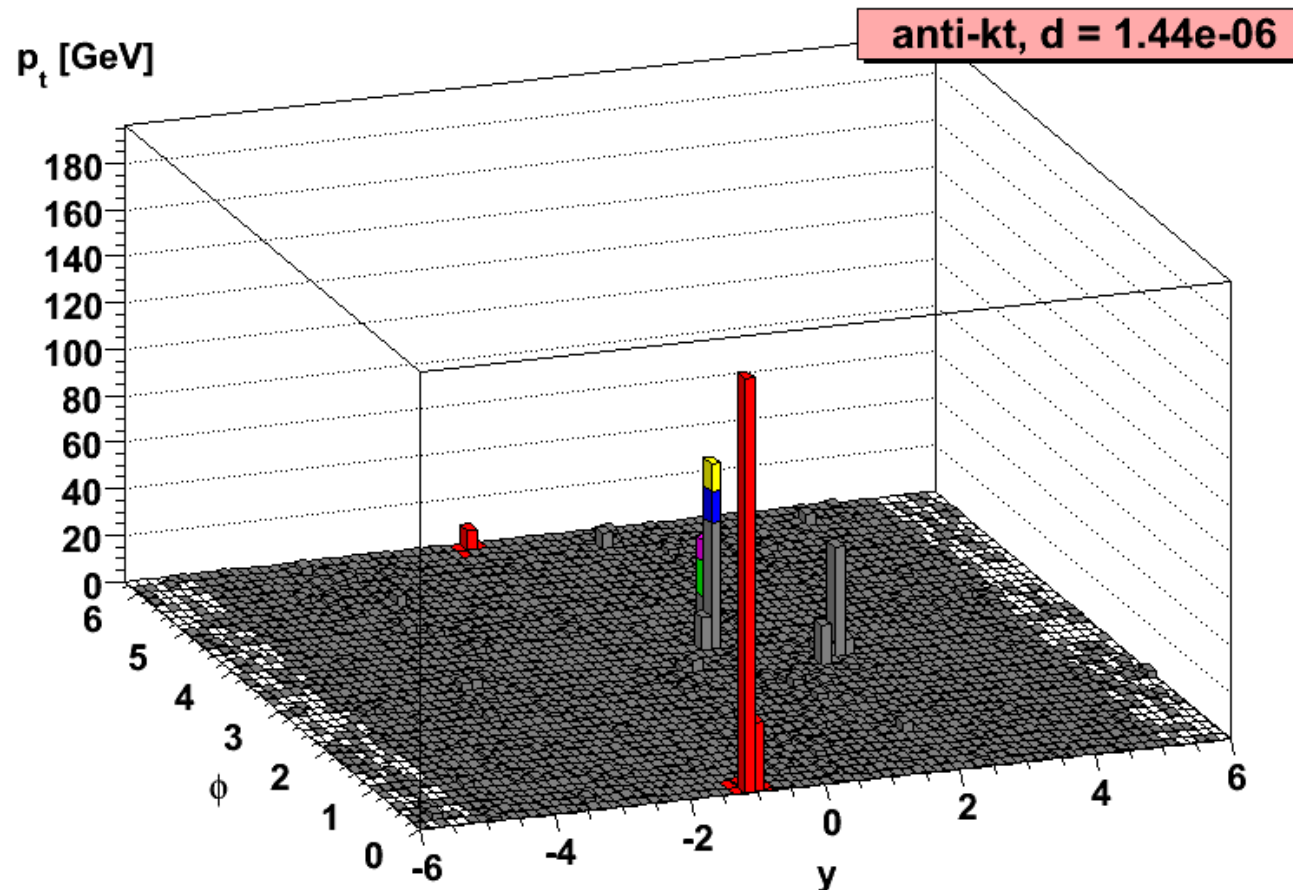
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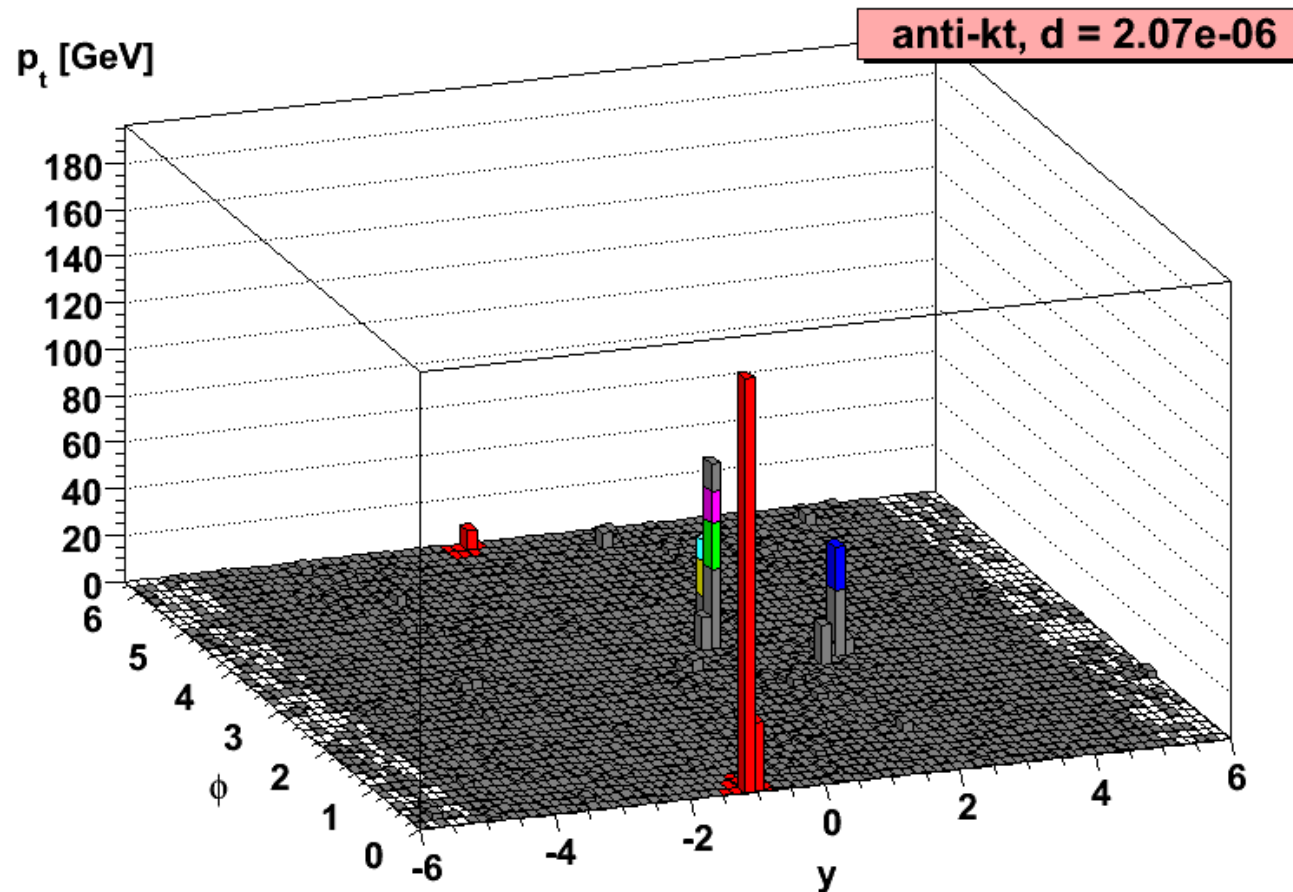
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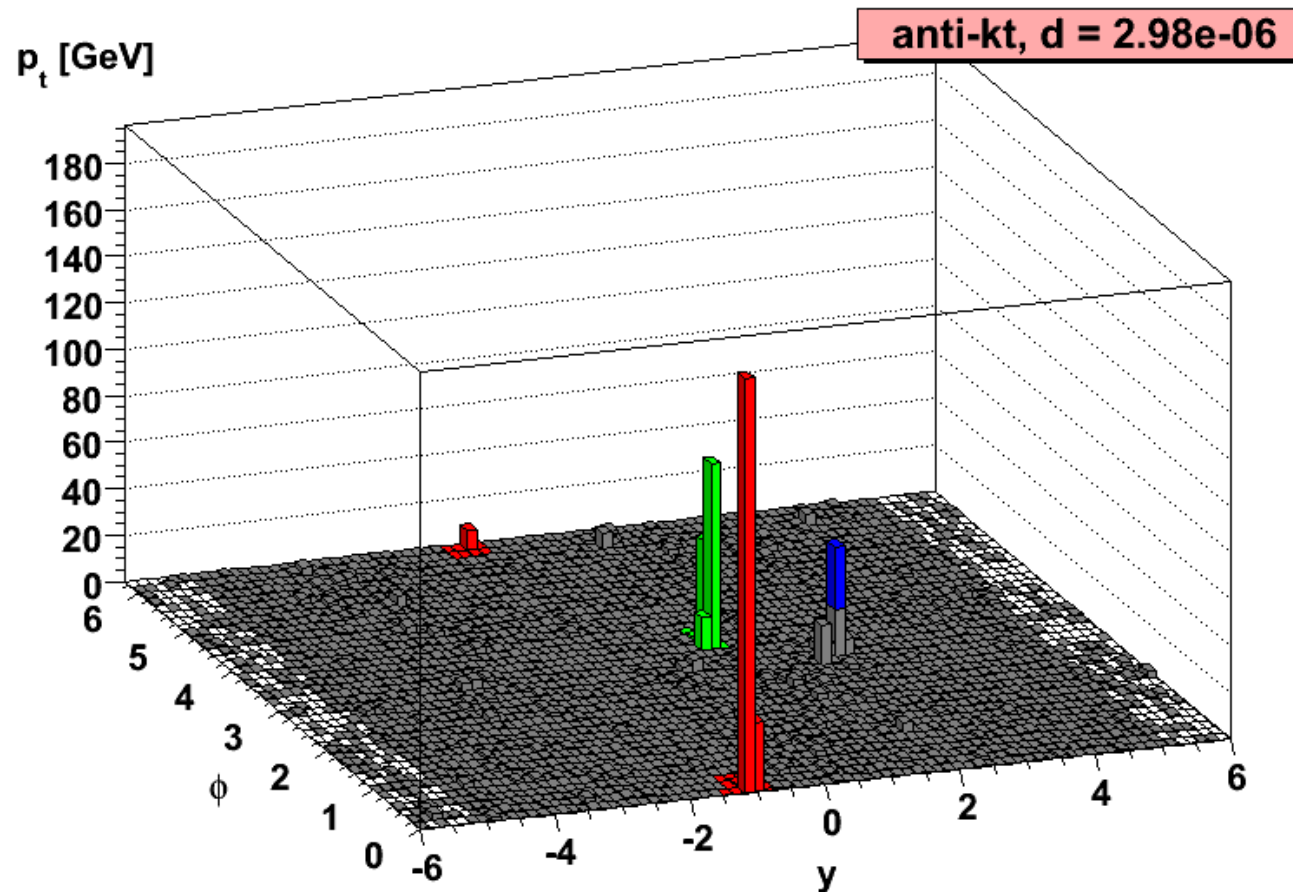
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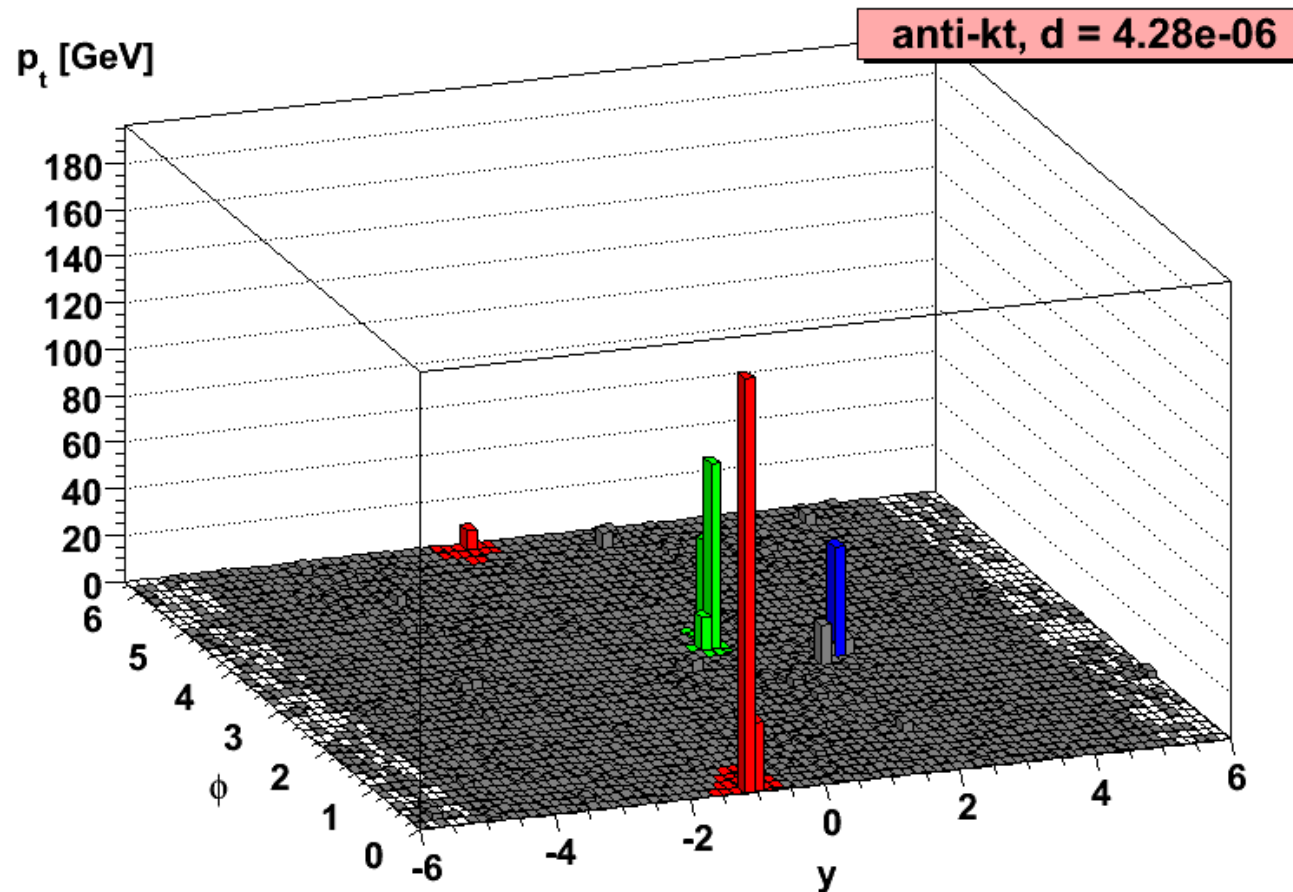
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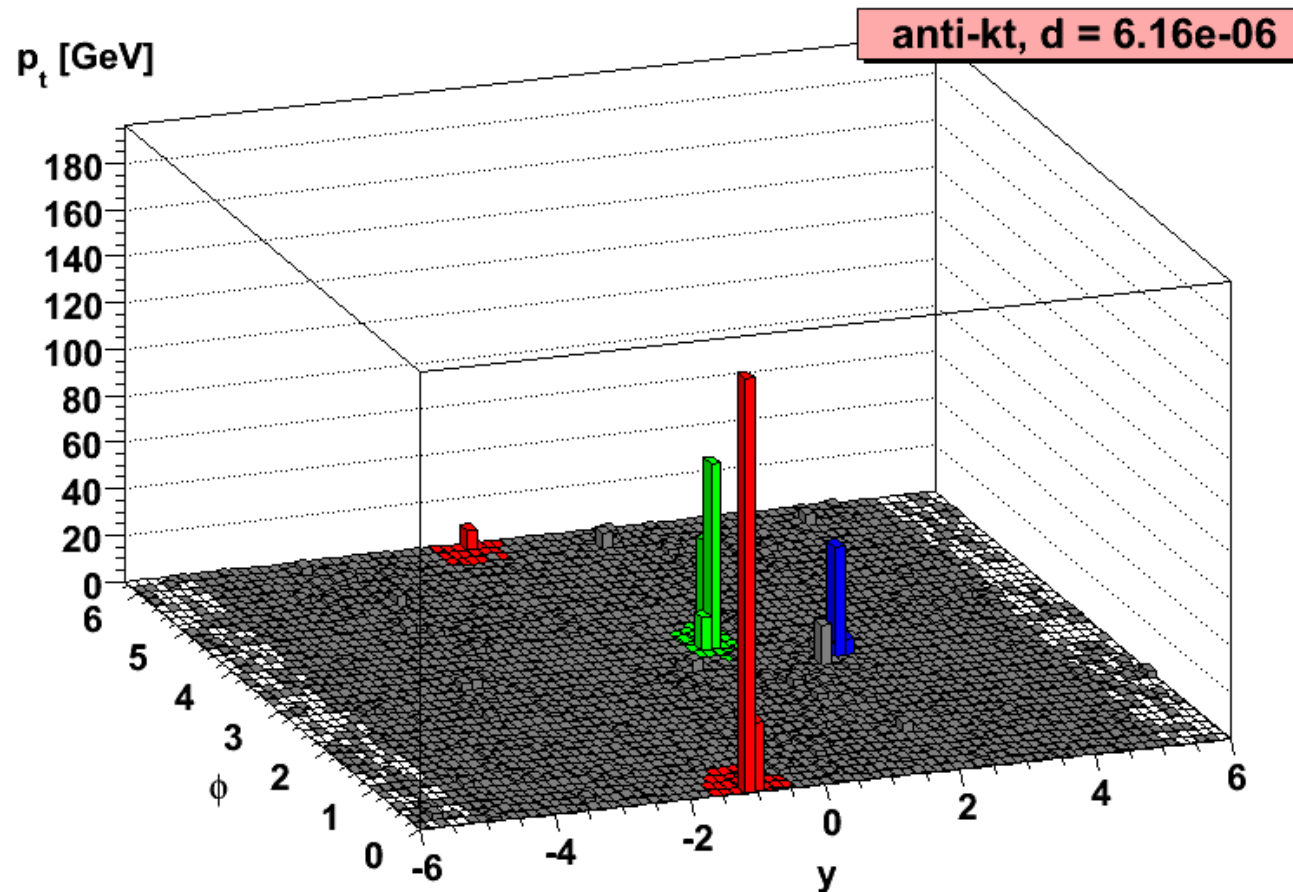
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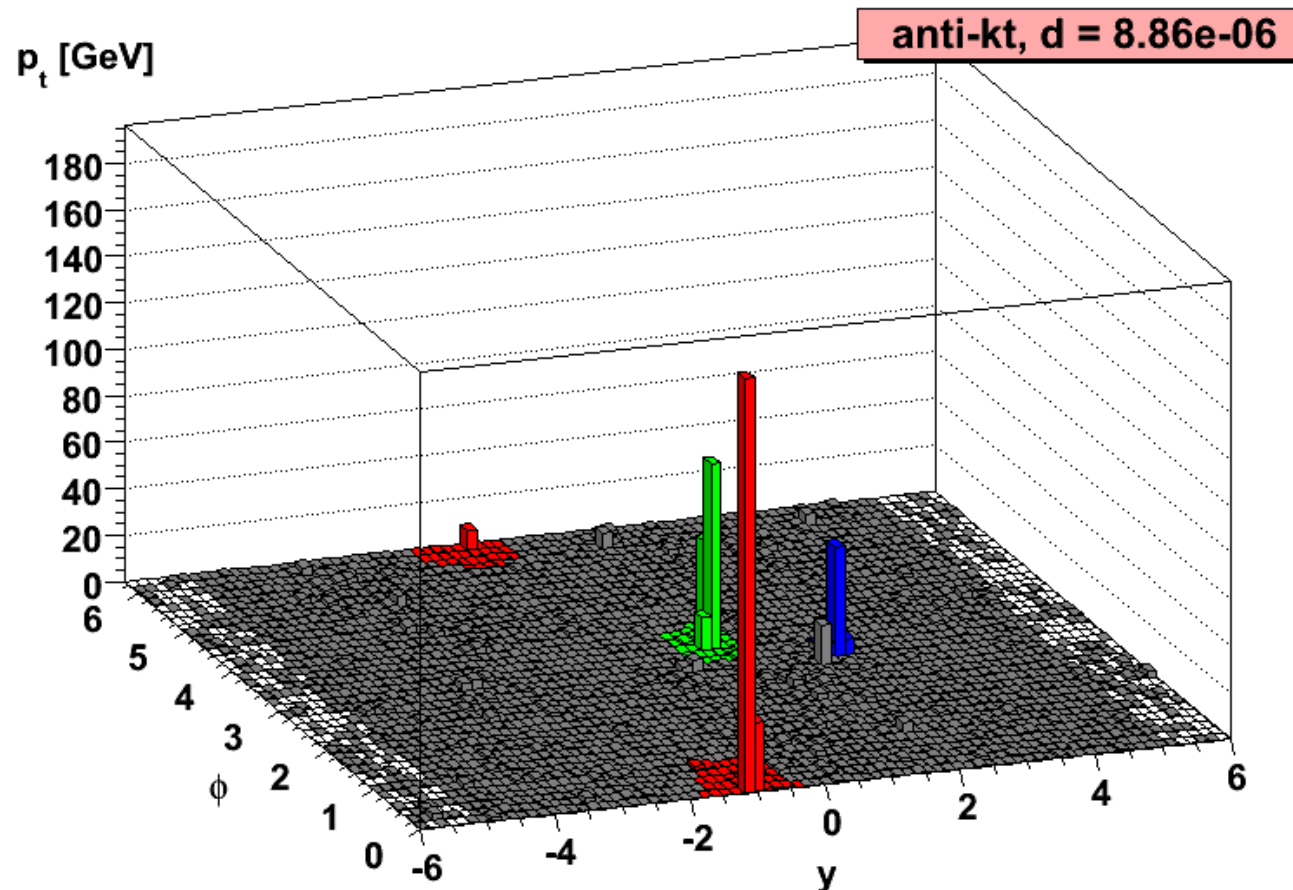
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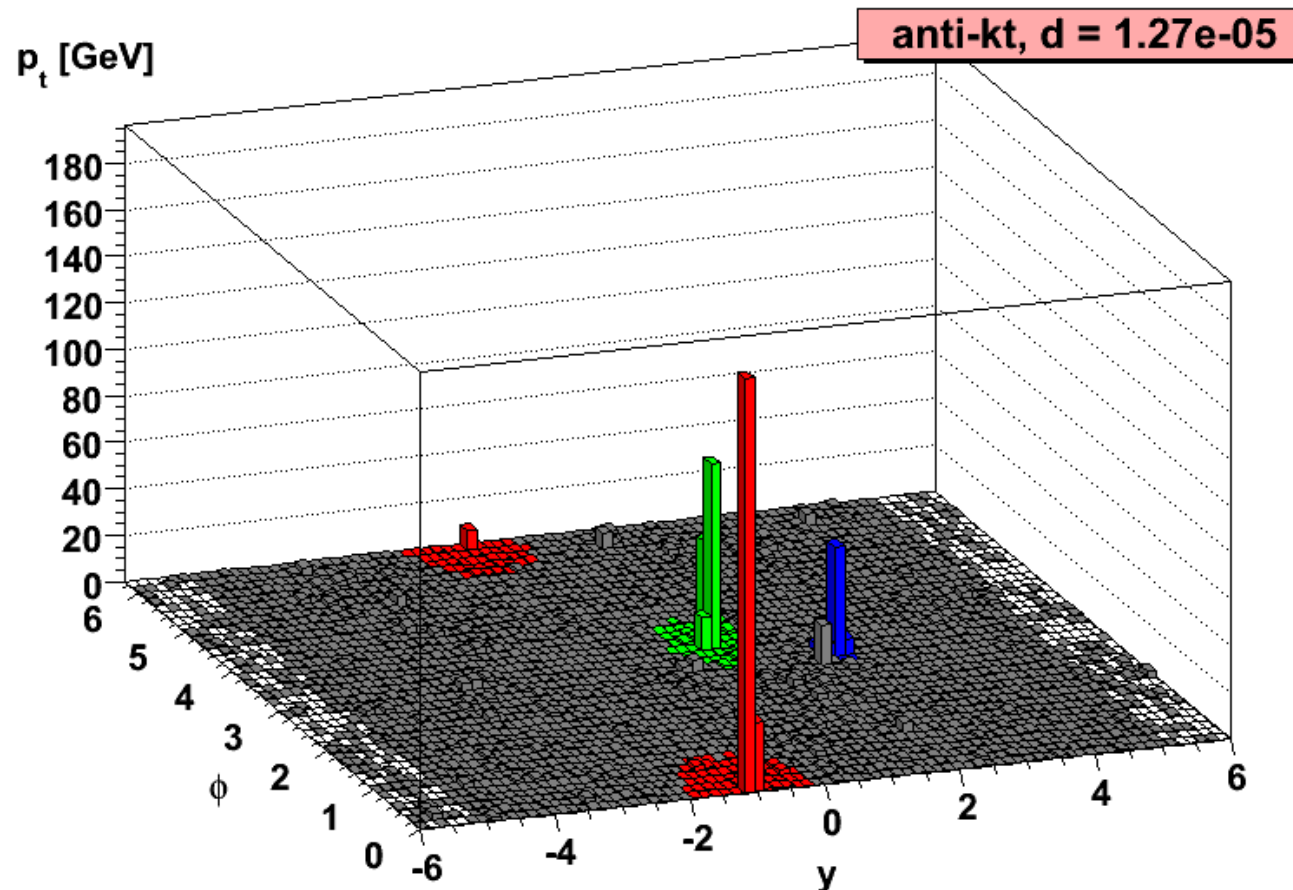
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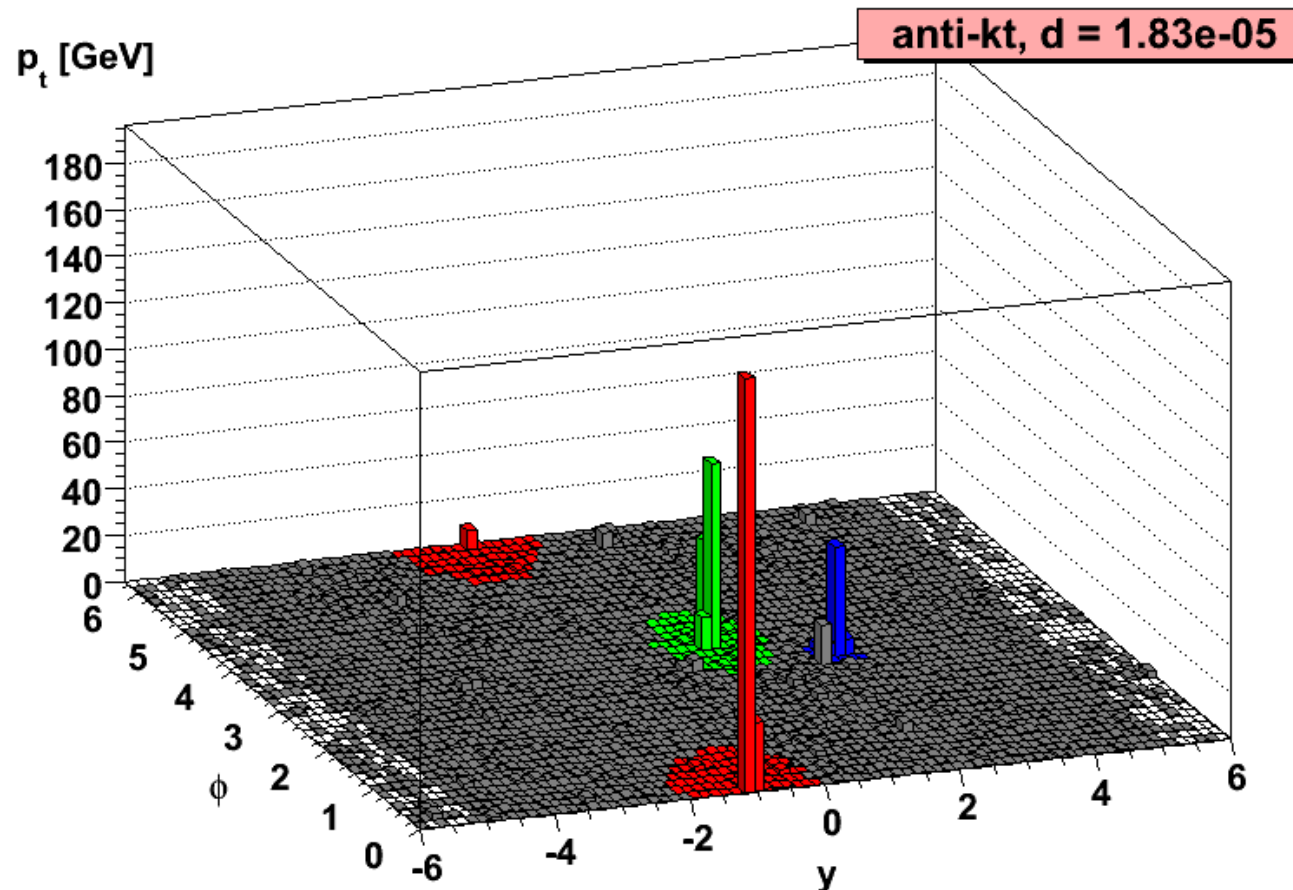
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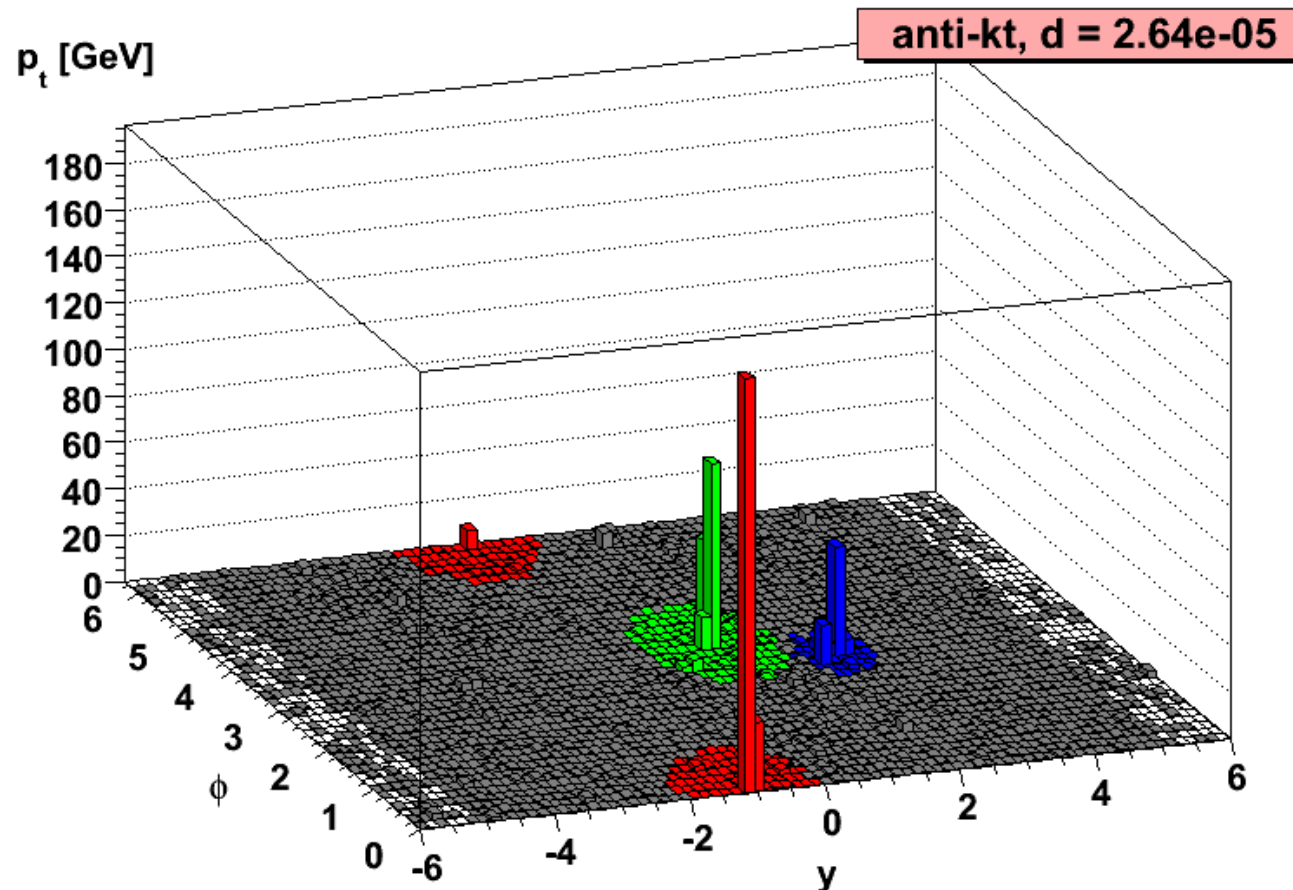
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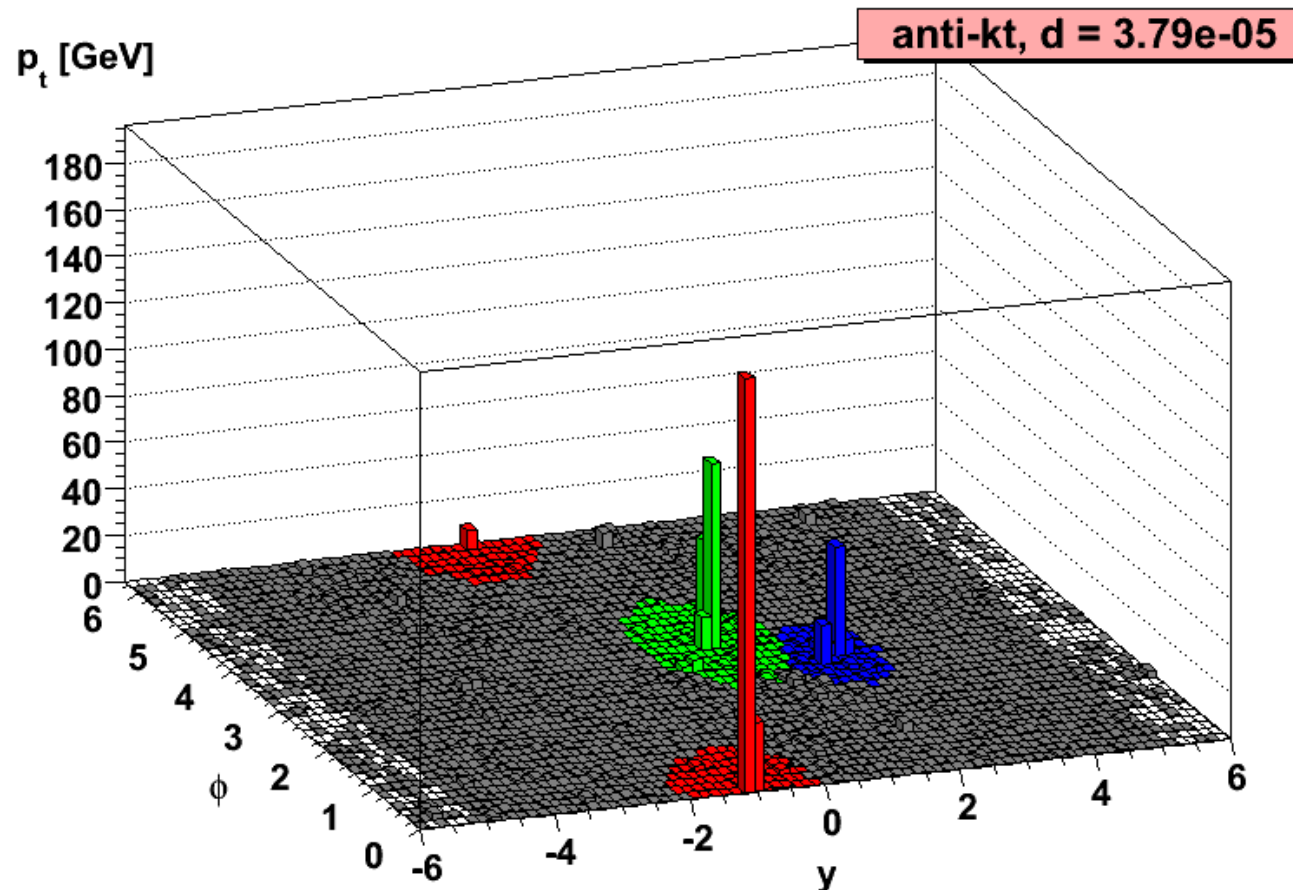
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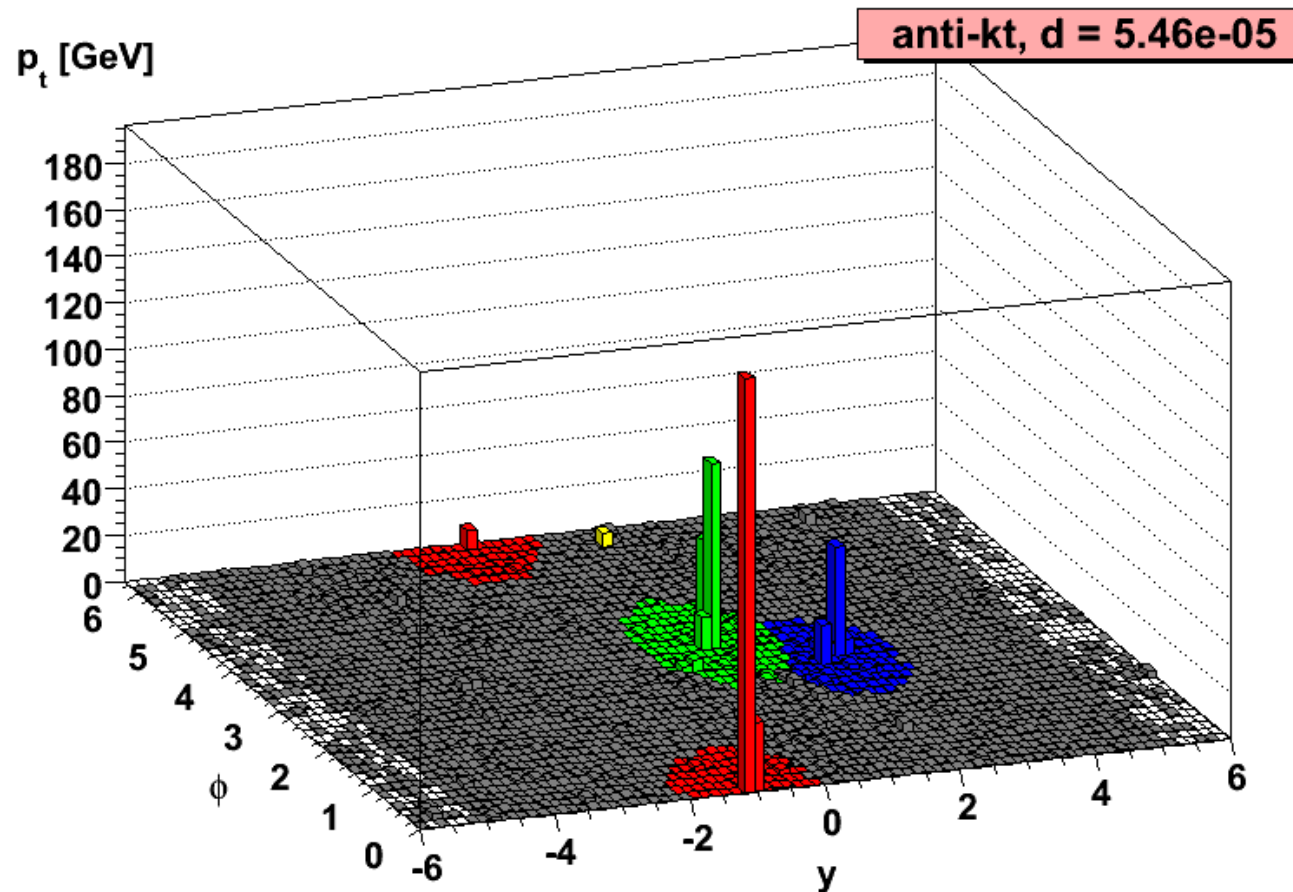
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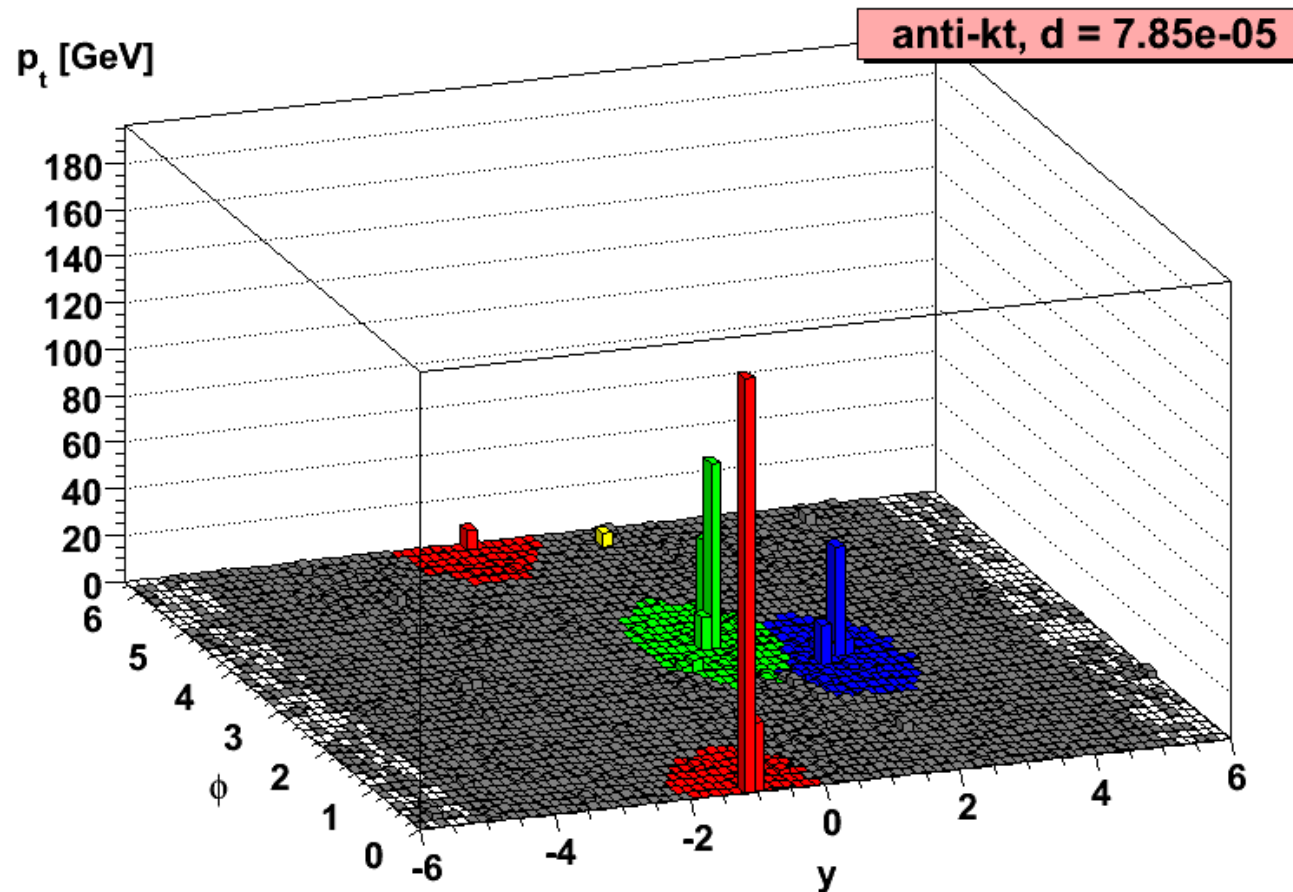
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around hard cores

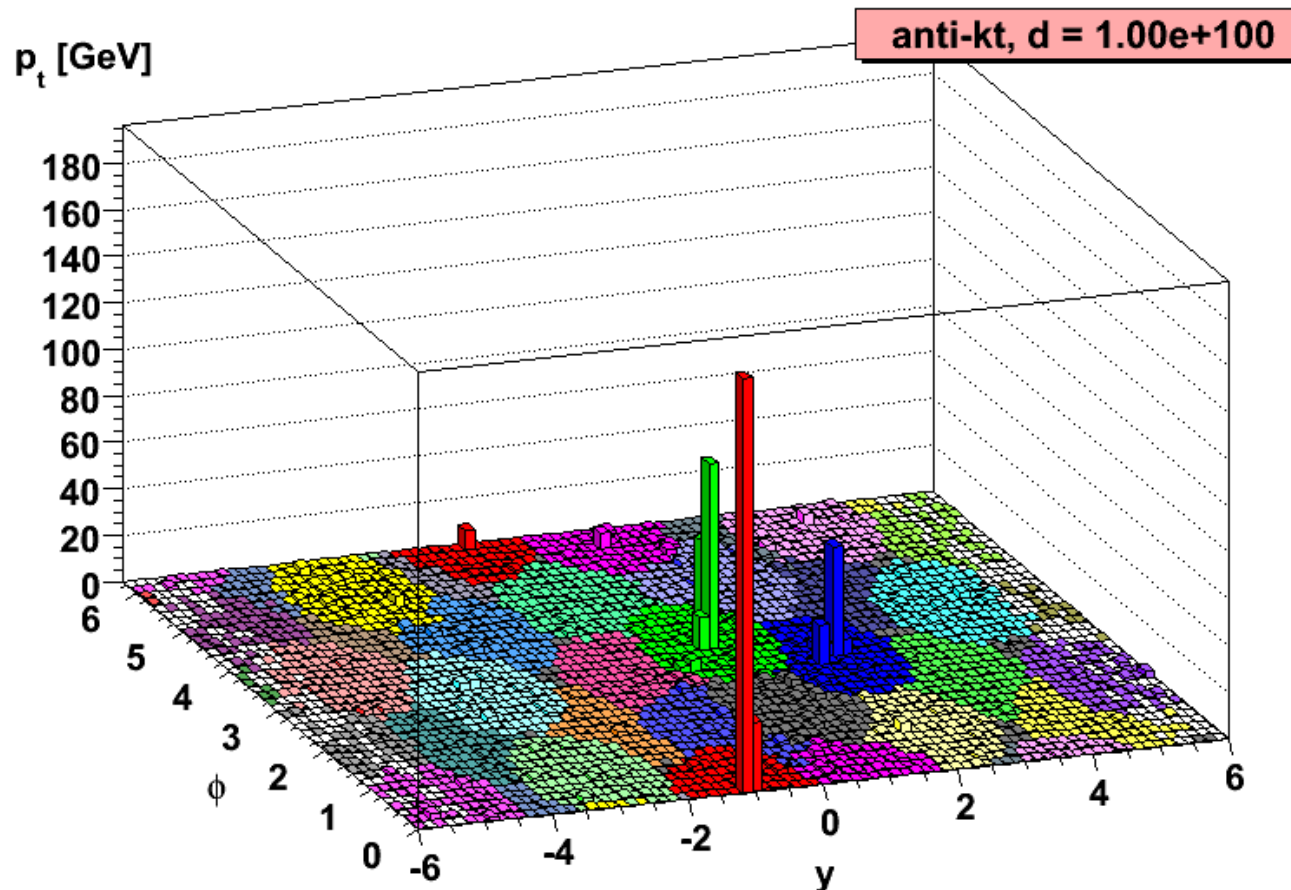
$$d_{ij} = \frac{1}{\max(p_{ti}^2, p_{tj}^2)} \frac{\Delta R_{ij}^2}{R^2}, \quad d_{iB} = \frac{1}{p_{ti}^2}$$



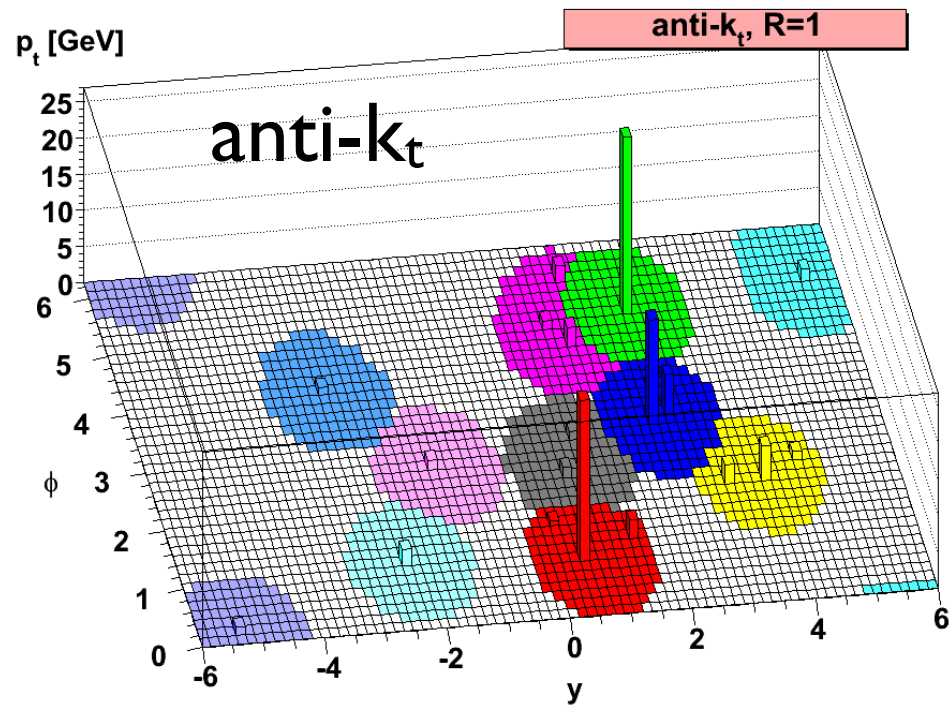
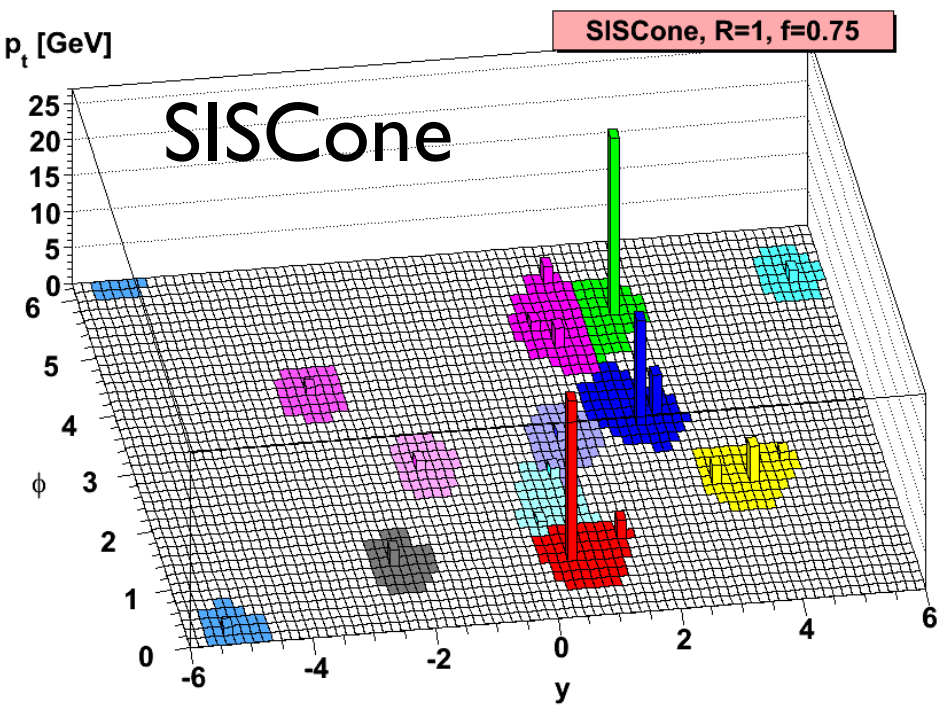
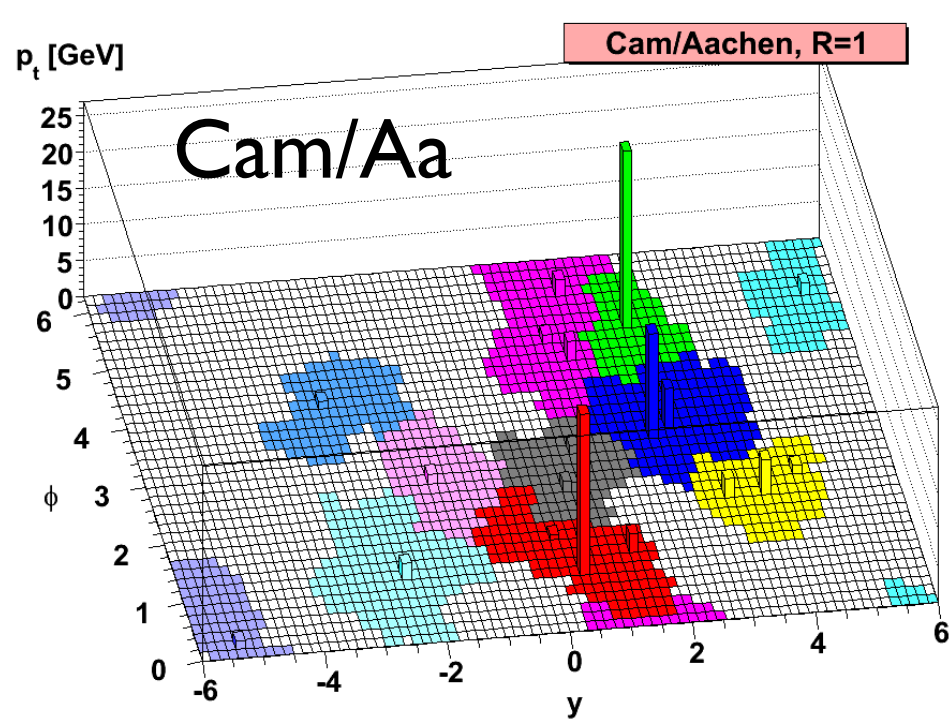
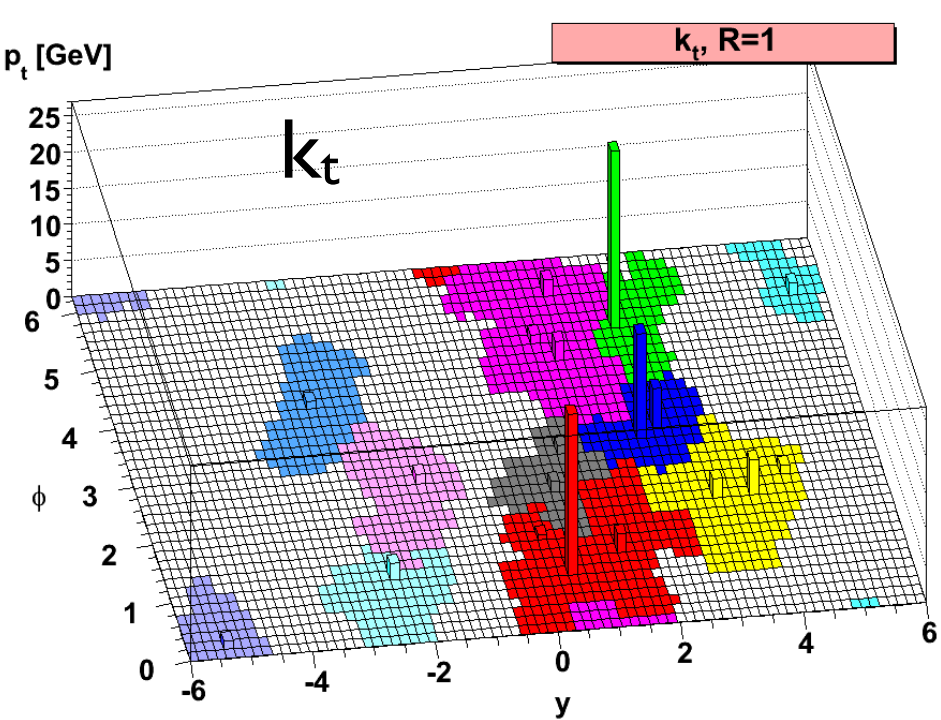


Clustering grows around hard cores

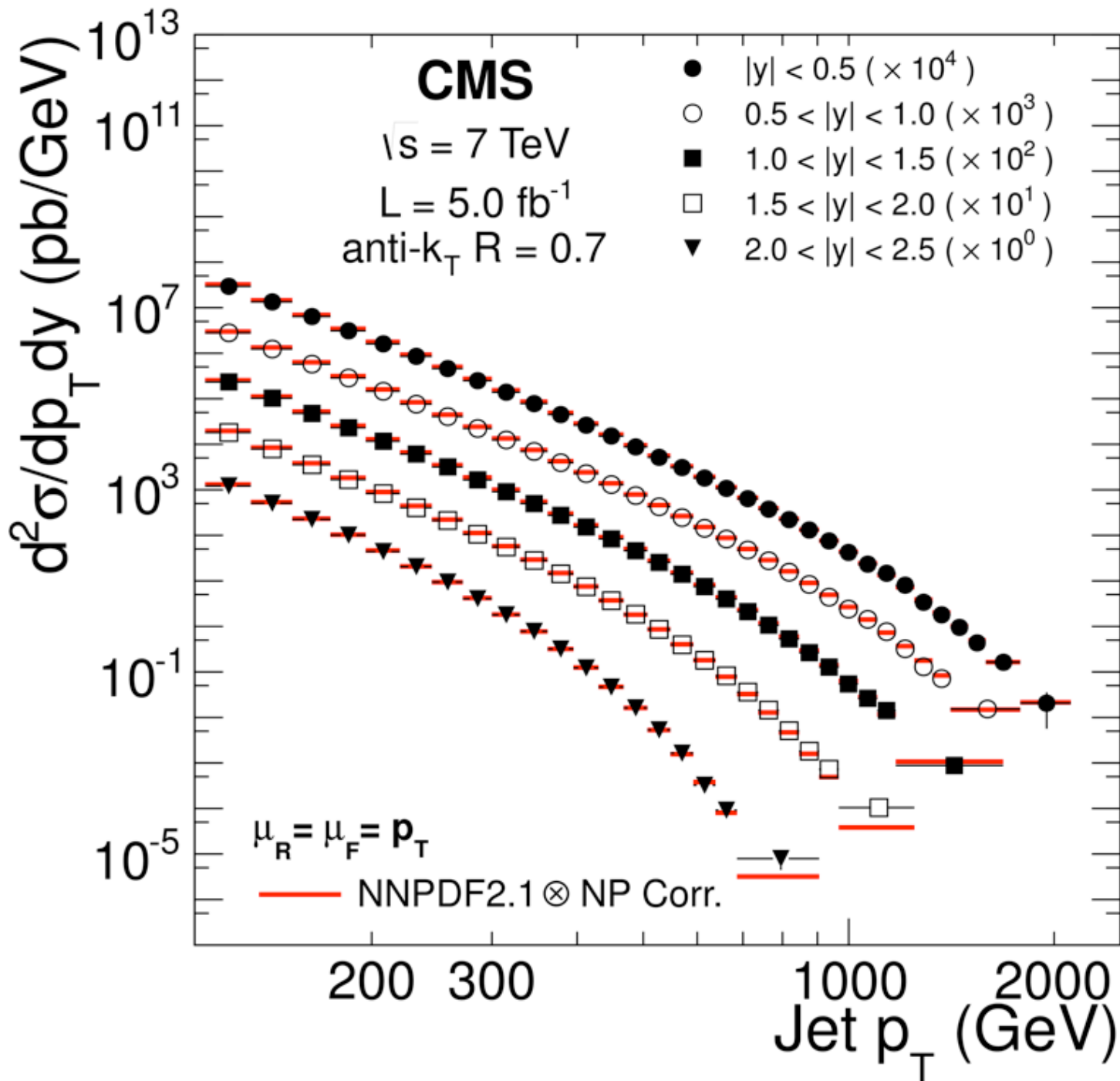
$$d_{ij} = \frac{1}{\max(p_{ti}^2, p_{tj}^2)} \frac{\Delta R_{ij}^2}{R^2}, \quad d_{iB} = \frac{1}{p_{ti}^2}$$



Anti- $k_t$  gives circular jets (“cone-like”) in a way that’s infrared safe



# Example of jet observable



Inclusive  
jet cross  
section

Excellent  
theory-data  
agreement over  
many orders of  
magnitude

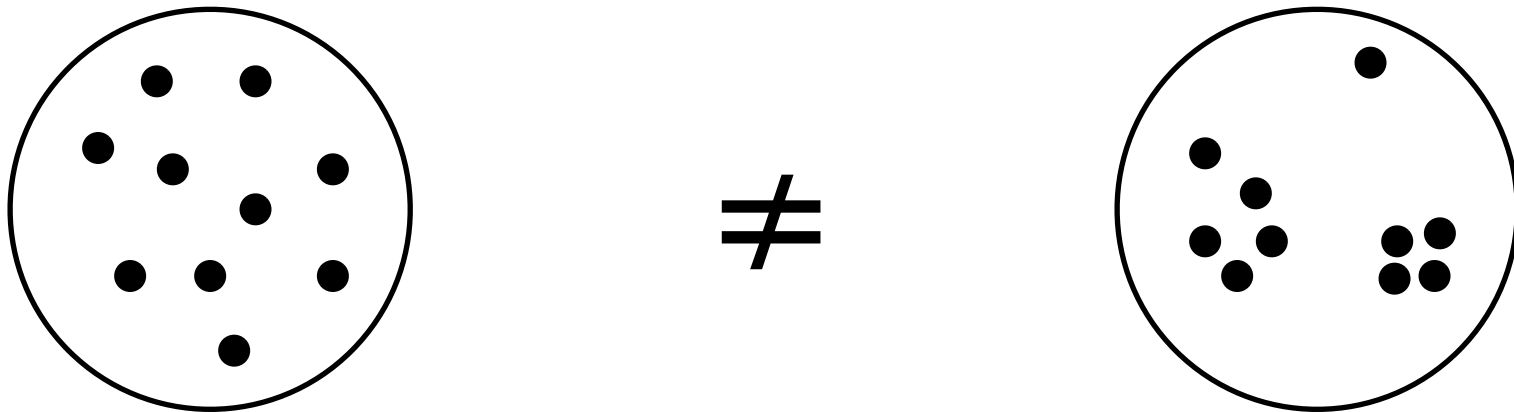
# Take home points

- ▶ A vast zoology of jet algorithms has been reduced in the past few years to **4 infrared and collinear safe algorithms**
  - ▶ All are implemented in an efficient and fast way
  - ▶ Of these, **anti- $k_t$**  is used by all the LHC collaborations as their main algorithm for “finding” jets and measuring inclusive cross sections
- ▶ The four algorithms have quite different characteristics, which makes them non easily swappable when specific properties are needed for specific tasks. On the other hand, chances are that one can chose the algorithm which is most appropriate for a specific job

# Jet substructure

At the end of a jet finding (i.e. clustering) procedure,  
a jet is a **collection of constituents** to which  
we assign a 4-momentum  
(related to the sum of the 4-momenta of the constituents)

What is the **arrangement** of the constituents  
inside the jet?

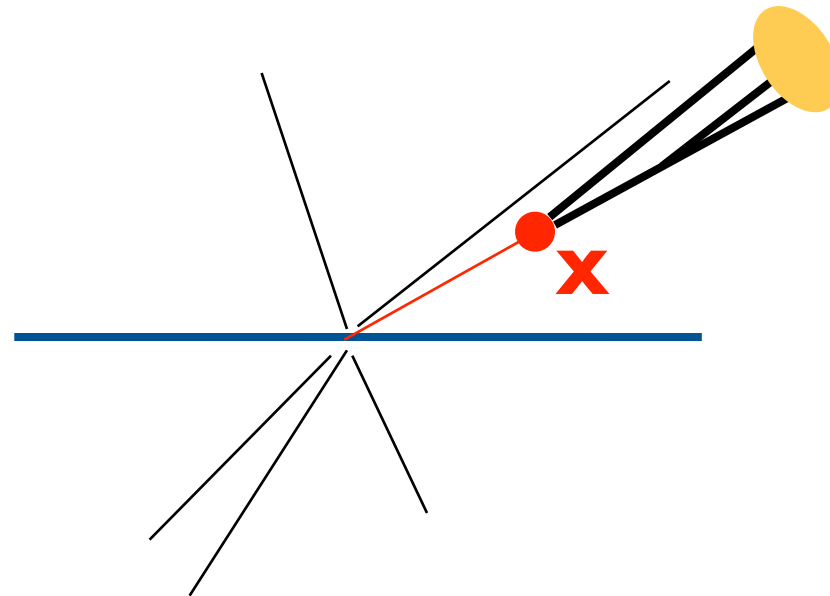


# Jet substructure

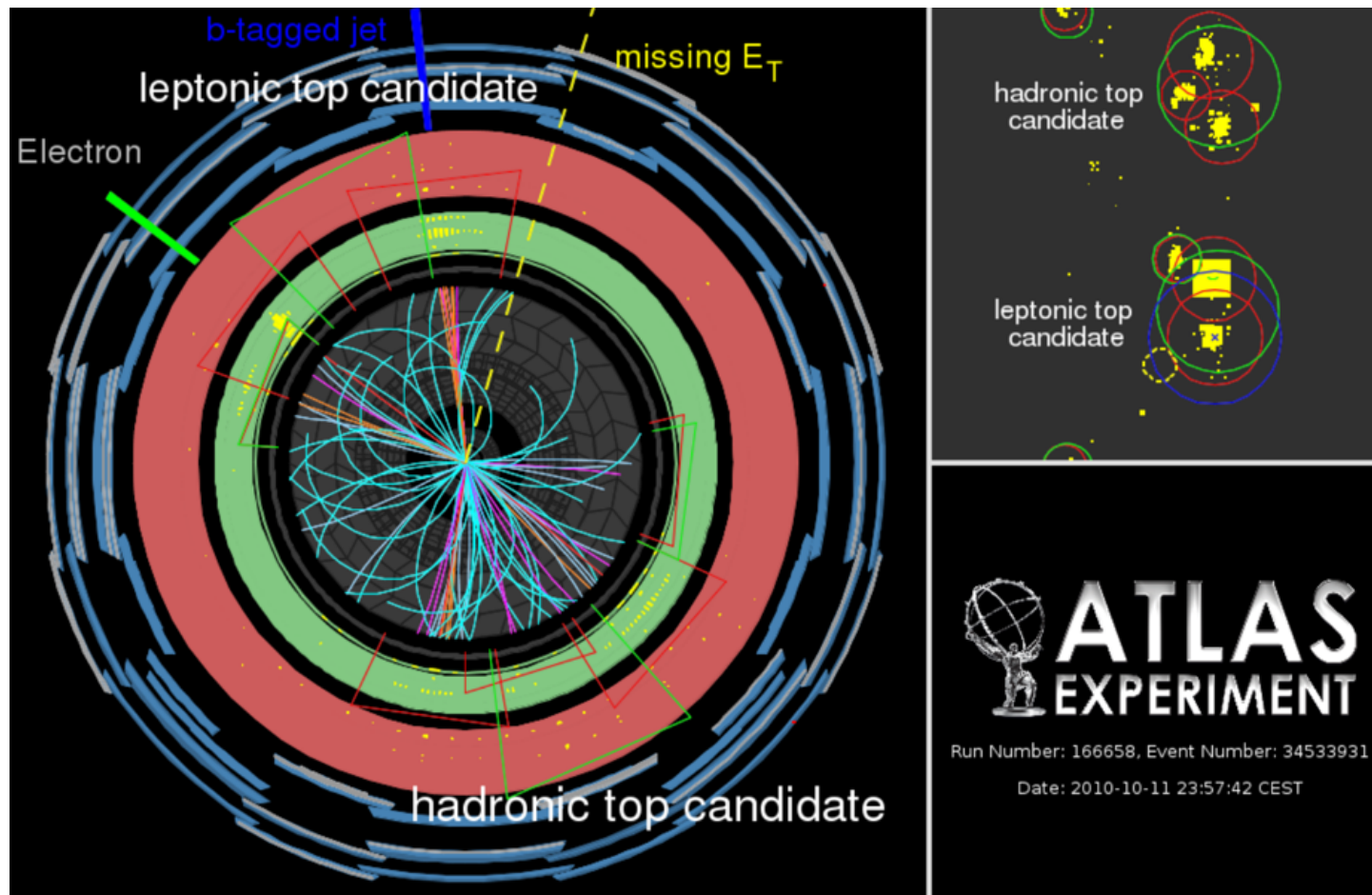
First studied by Mike Seymour in the early '90s  
to distinguish  $W$  jets from QCD jets

Topic revived about fifteen years  
ago in order to study boosted objects

[Butterworth, Davison, Rubin, Salam, 0802.2470]

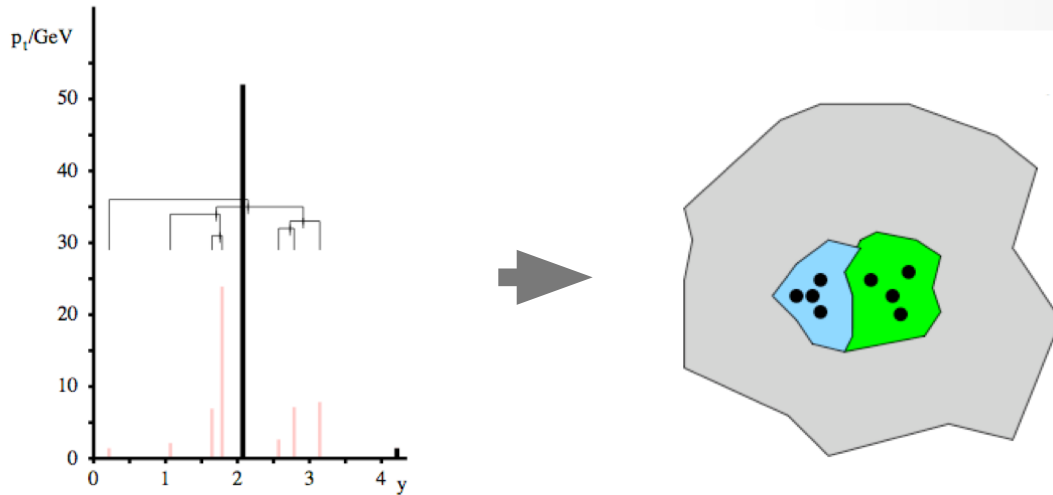


# Jet substructure



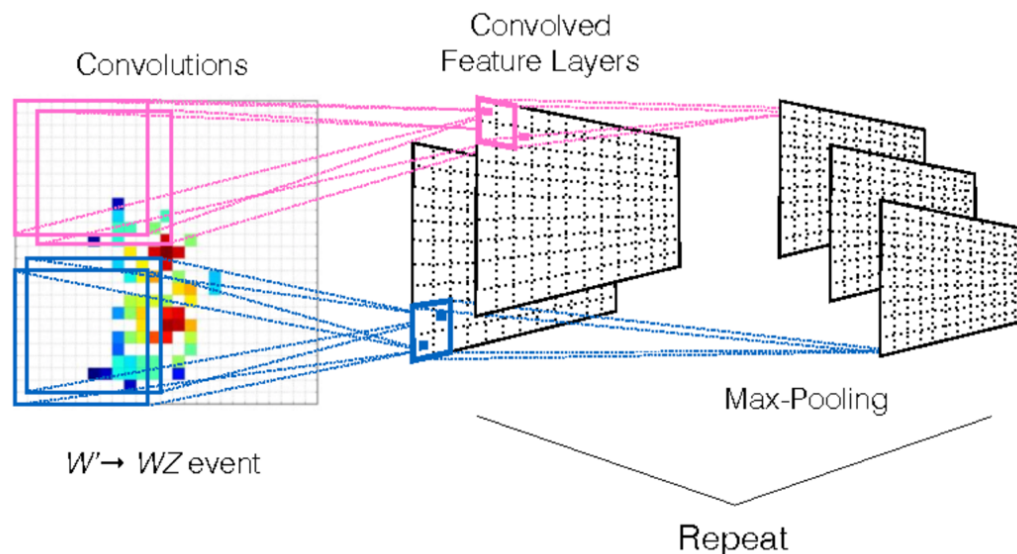
The past fifteen years have seen an explosion in jet substructure studies, i.e. **how radiation is arranged within jets**, and what it can tell us

# Jet substructure



Jet  
declustering

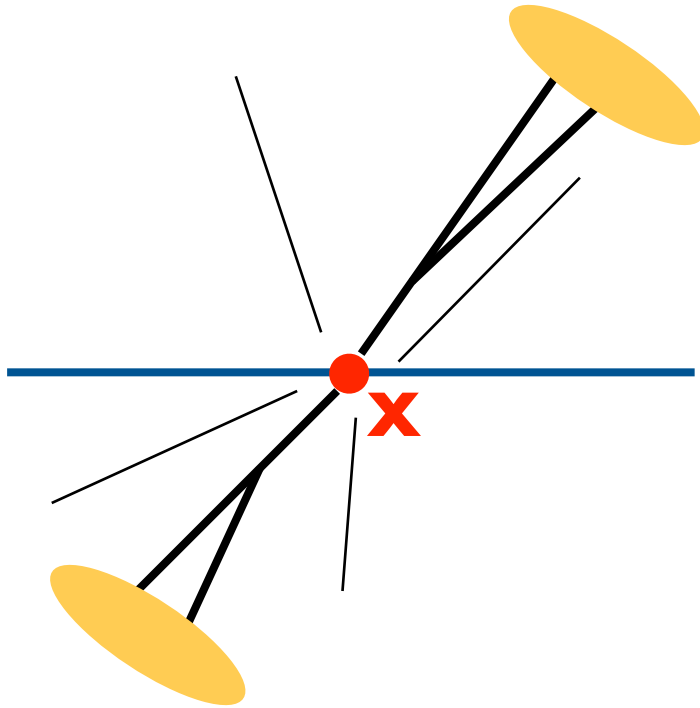
Jet shapes  
(calculate a function from  
radiation distribution)



Machine learning

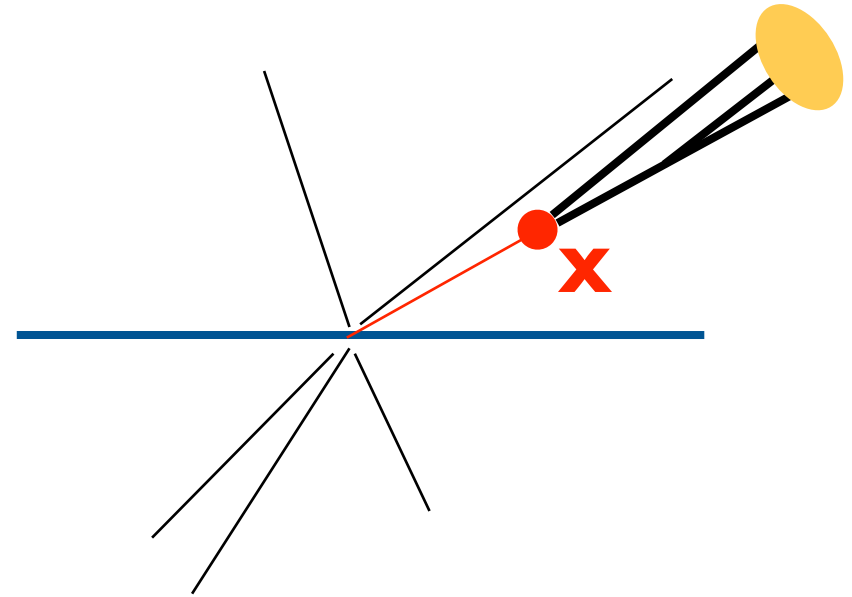


# Why boosted objects



Heavy particle X at **rest**

Easy to resolve jets and calculate invariant mass, but signal very likely swamped by background (eg  $H \rightarrow bb$  v.  $tt \rightarrow WbWb$ )

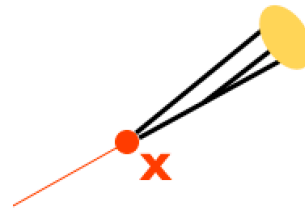
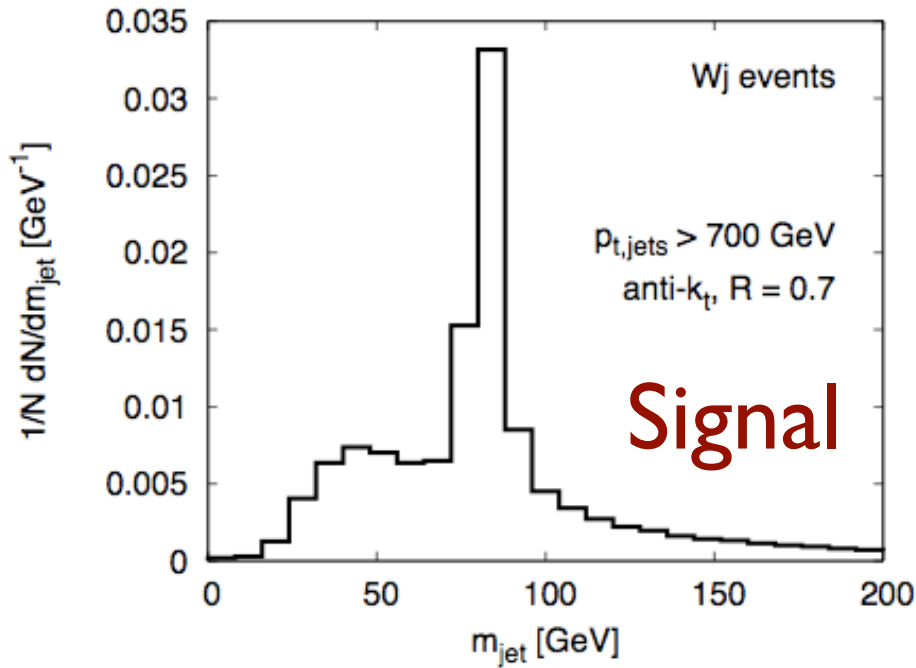


**Boosted** heavy particle X

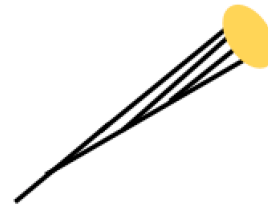
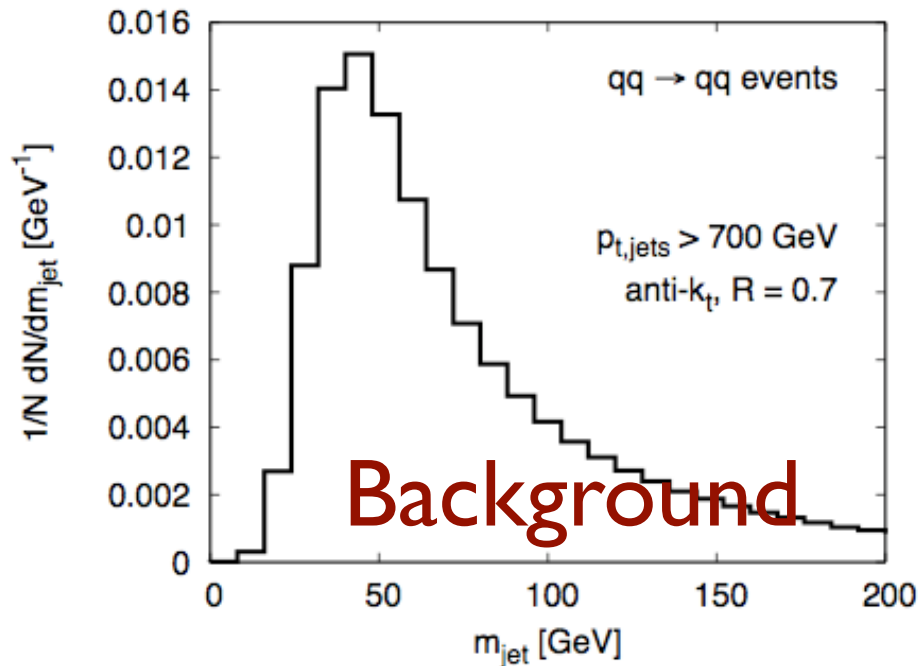
Cross section very much reduced, but acceptance better and some backgrounds smaller/reducible

# Mass of a single jet

G. Salam



A heavy object decaying into a single jet naturally gives it a mass...

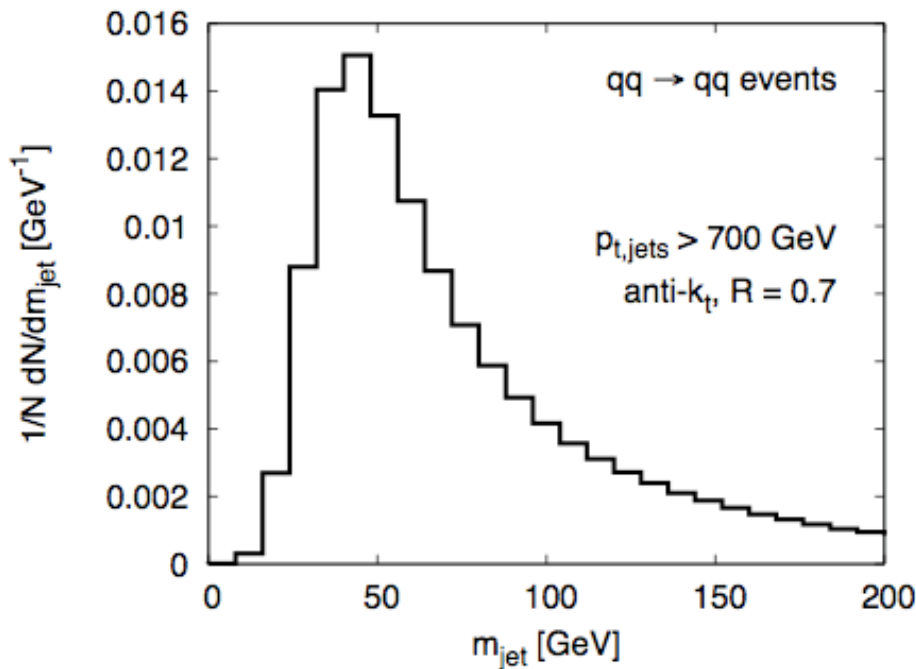


... but pure QCD jets can be massive too:

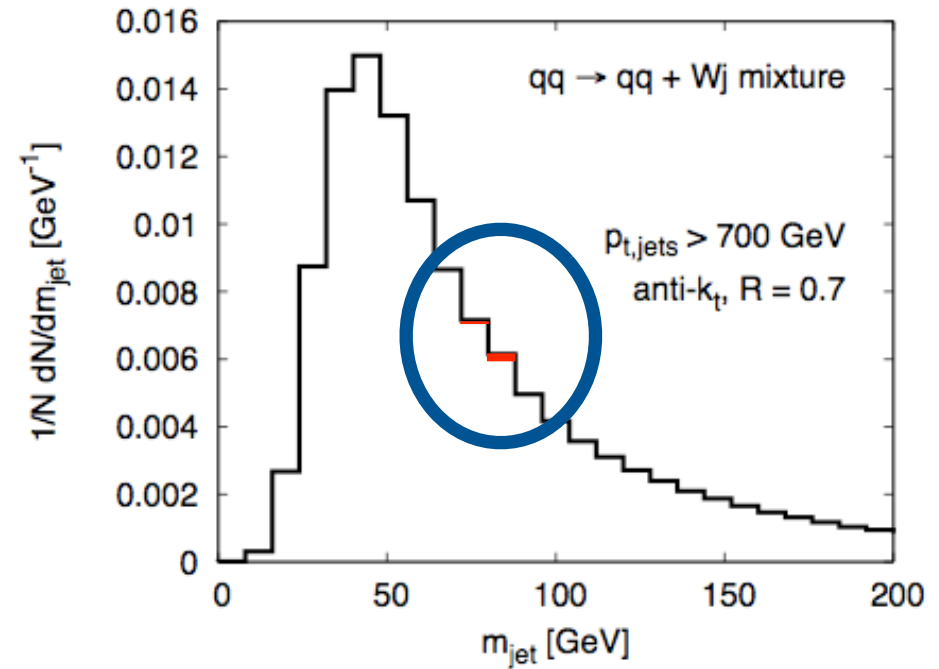
$$\frac{dN}{d \ln m} \sim \alpha_s \ln \frac{p_t R}{m} \times \text{Sudakov}$$

# Mass of a single jet

Summing 'signal' and 'background' (with appropriate cross sections) shows how much the background dominates



**Background only**

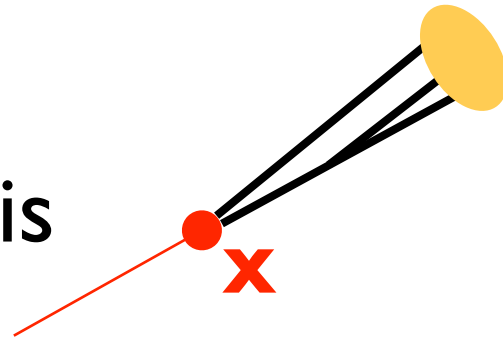


**Signal + background**

**Practically identical**

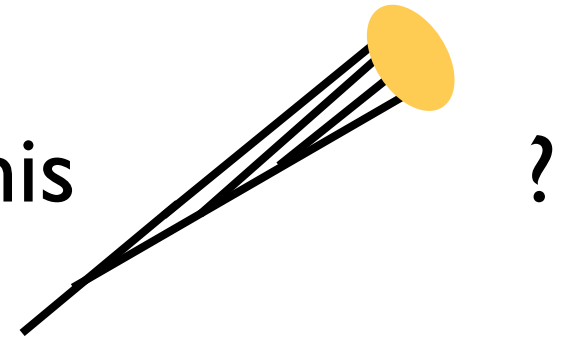
This means that one can't rely on the invariant mass only.  
An appropriate strategy must be found to reduce the background and enhance the signal

How to tell this



Decay of a heavy  
(boosted) object

from this



Light parton  
fragmentation

# Tagging and Grooming

- ▶ The substructure of a jet can be exploited to
  - ▶ **tag** a particular structure inside the jet, i.e. a massive particle
    - ▶ First examples: Higgs (2-prong decay), top (3-prong decay)
  - ▶ remove background contamination from the jet or its components, while keeping the bulk of the perturbative radiation (often generically denoted as **grooming**)
    - ▶ First examples: filtering, trimming, pruning

## ▶ Groomer

- ▶ procedure that always returns an output jet (i.e. it only subtracts uncorrelated ‘UE/pileup’ radiation from it. This is used to “clean” the jets from radiation largely unrelated to the fragmentation of the particle of interest)

## ▶ Tagger

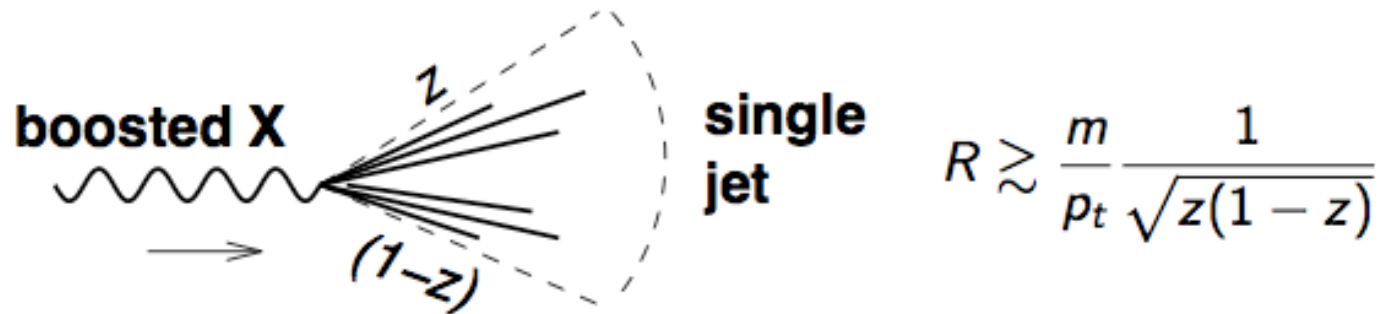
- ▶ procedure that might not return an output jet (i.e. it either tags a heavy particle originating the jet or returns zero. This is used to identify a specific particle originating the jet.)

In practice, this classification is not always followed. In some cases it also denoted a ‘tagger’ a procedure that rejects background jets more often than signal jets

# Why substructure

Scales:  $m \sim 100 \text{ GeV}$ ,  $p_t \sim 500 \text{ GeV}$

(e.g. electroweak particle from decay of  $\sim 1 \text{ TeV}$  BSM particle)



- ▶ need **small R** ( $< 2m/p_t \sim 0.4$ ) to resolve **two** prongs
- ▶ need **large R** ( $> \sim 3m/p_t \sim 0.6$ ) to cluster into a **single** jet

## Possible strategies

- ▶ Use large R, get a single jet : **background large**
- ▶ Use small R, resolve the jets : **what is the right scale?**
  - ▶ Also: small jets lead to huge combinatorial issues

**Let an algorithm find the 'right' substructure**

# What jets to use for substructure?

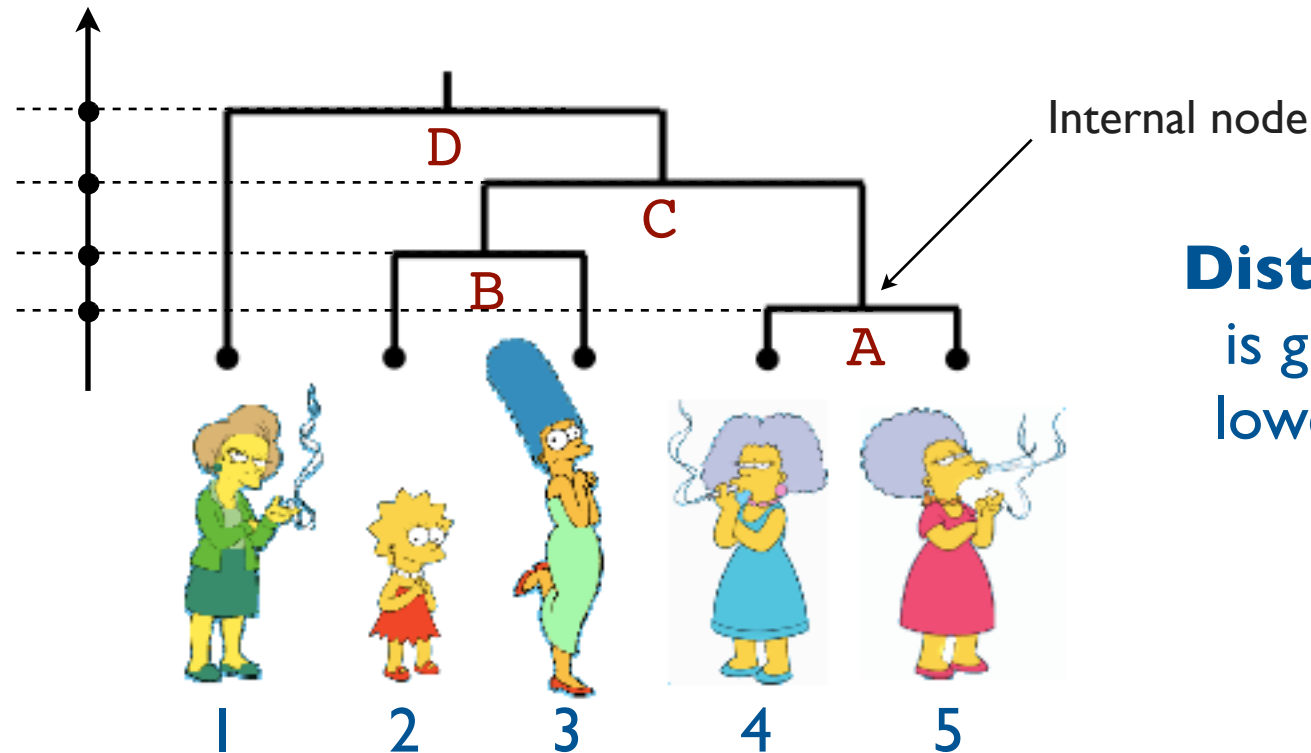
Different jet algorithms will give different ‘pictures’  
of what’s inside a jet



# Dendrogram

Used to represent graphically the sequence of clustering steps in a sequential recombination algorithm

Distance



**Distance** between two objects is given by the **height** of the lowest internal node that they share.

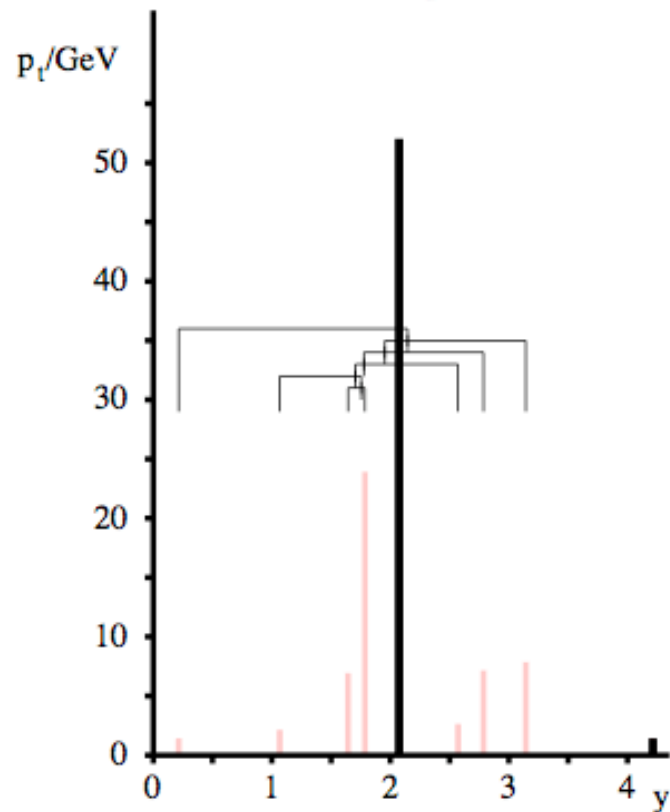
Order of clustering here is A, B, C, D

The **clustering sequence** is 4-5 (A), 2-3 (B), 23-45 (C), 1-2345 (D)

anti-kt

# Hierarchical substructure

## anti- $k_t$ algorithm



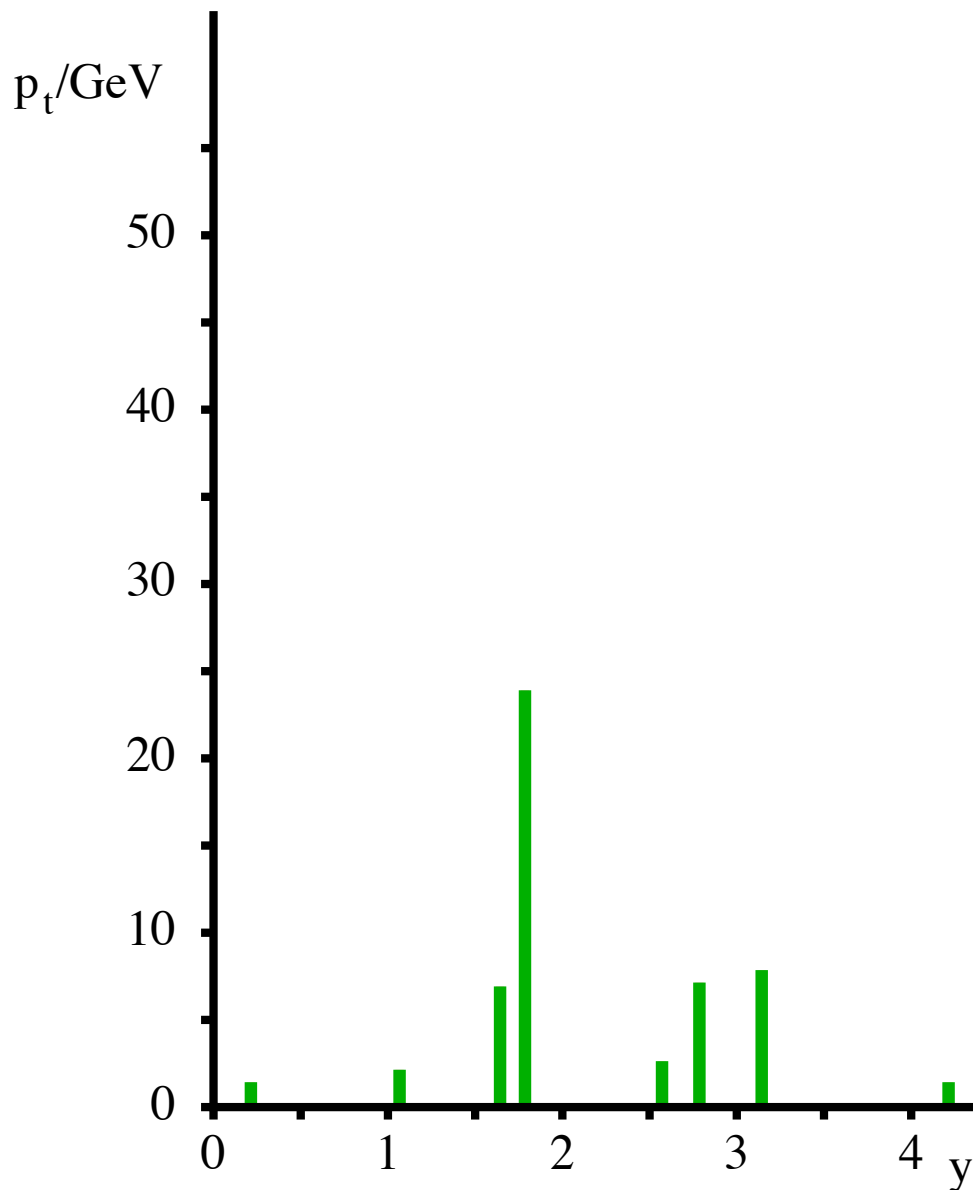
## Anti- $k_t$ distance measure

$$d_{ij} = \min \left( \frac{1}{p_{ti}^2}, \frac{1}{p_{tj}^2} \right) \frac{\Delta y^2 + \Delta \phi^2}{R^2}$$

Cluster by merging  
to the **hardest/closest** particle

# Identifying jet substructure: try out anti- $k_t$

## anti- $k_t$ algorithm



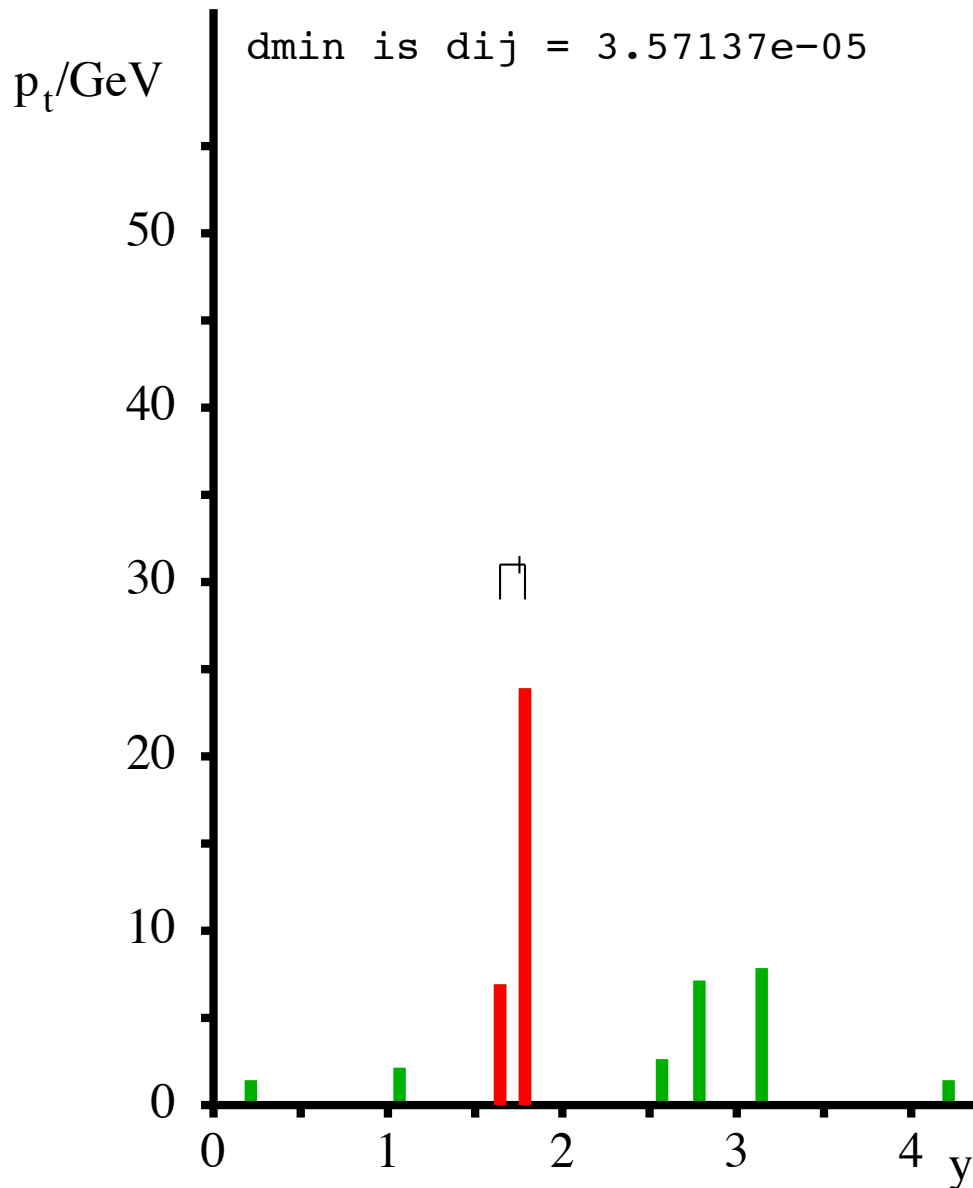
How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

This is crucial for identifying the kinematic variables of the partons in the jet (e.g.  $z$ ).

# Identifying jet substructure: try out anti- $k_t$

## anti- $k_t$ algorithm

$d_{\min}$  is  $d_{ij} = 3.57137e-05$

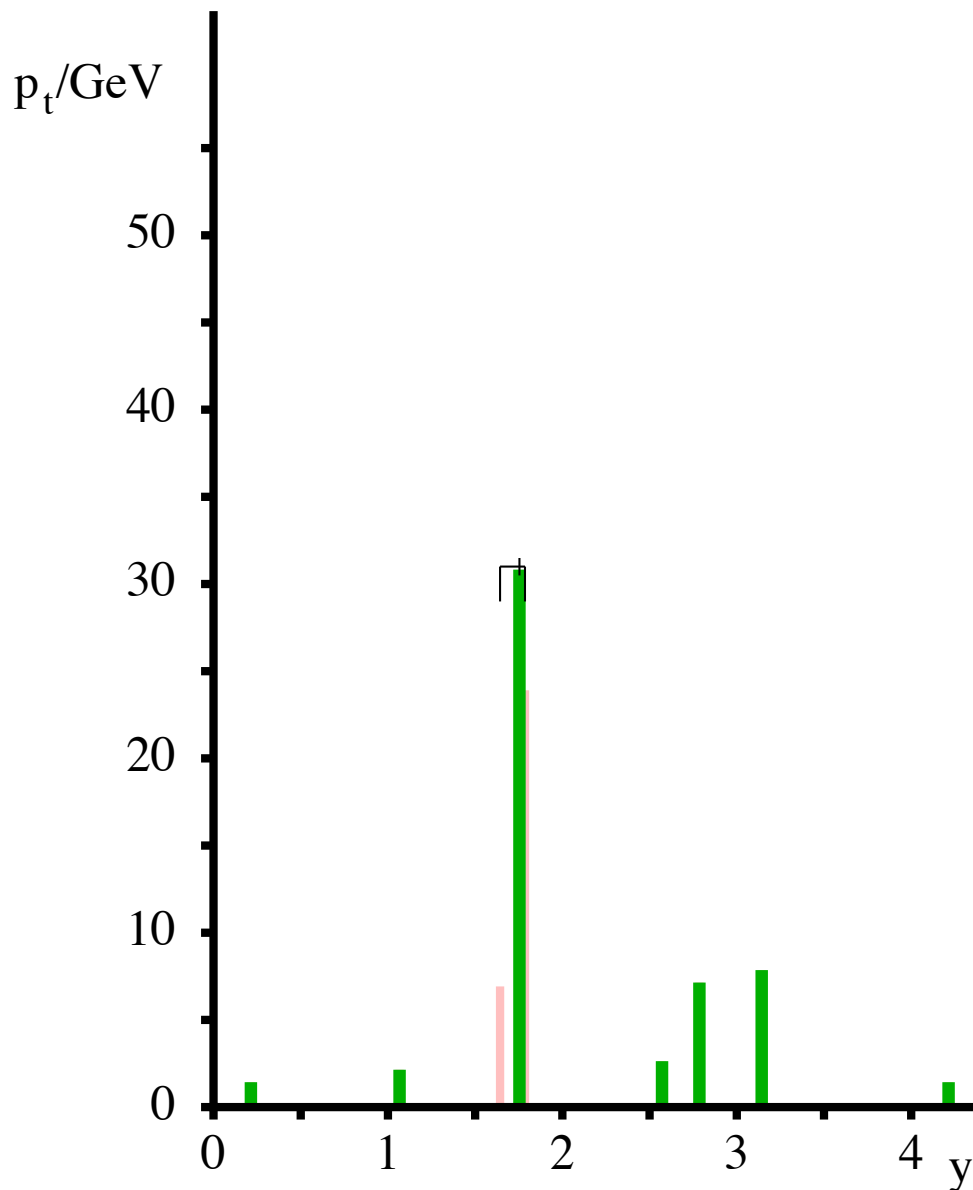


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## anti- $k_t$ algorithm



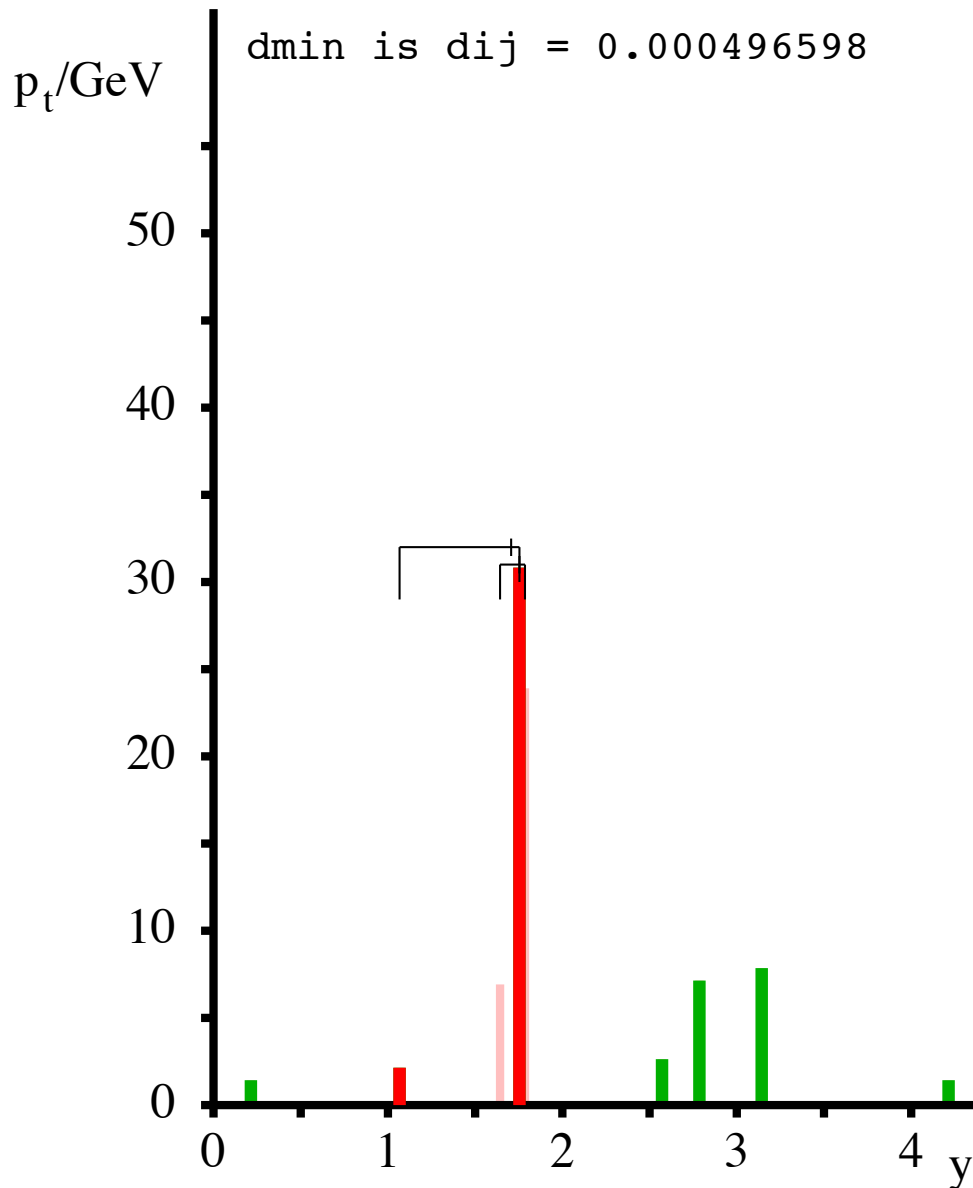
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# Identifying jet substructure: try out anti- $k_t$

## anti- $k_t$ algorithm

$d_{\min}$  is  $d_{ij} = 0.000496598$

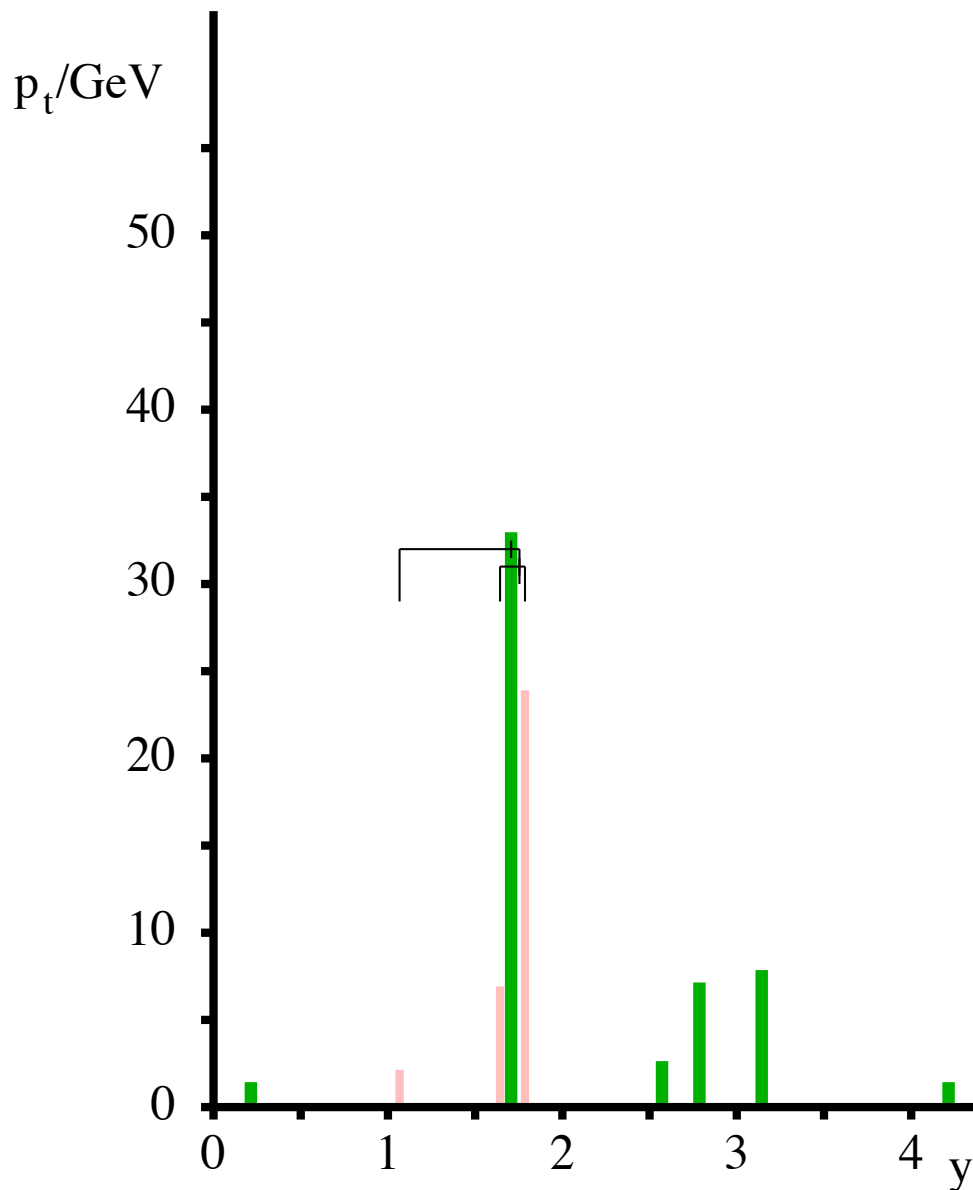


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## anti- $k_t$ algorithm



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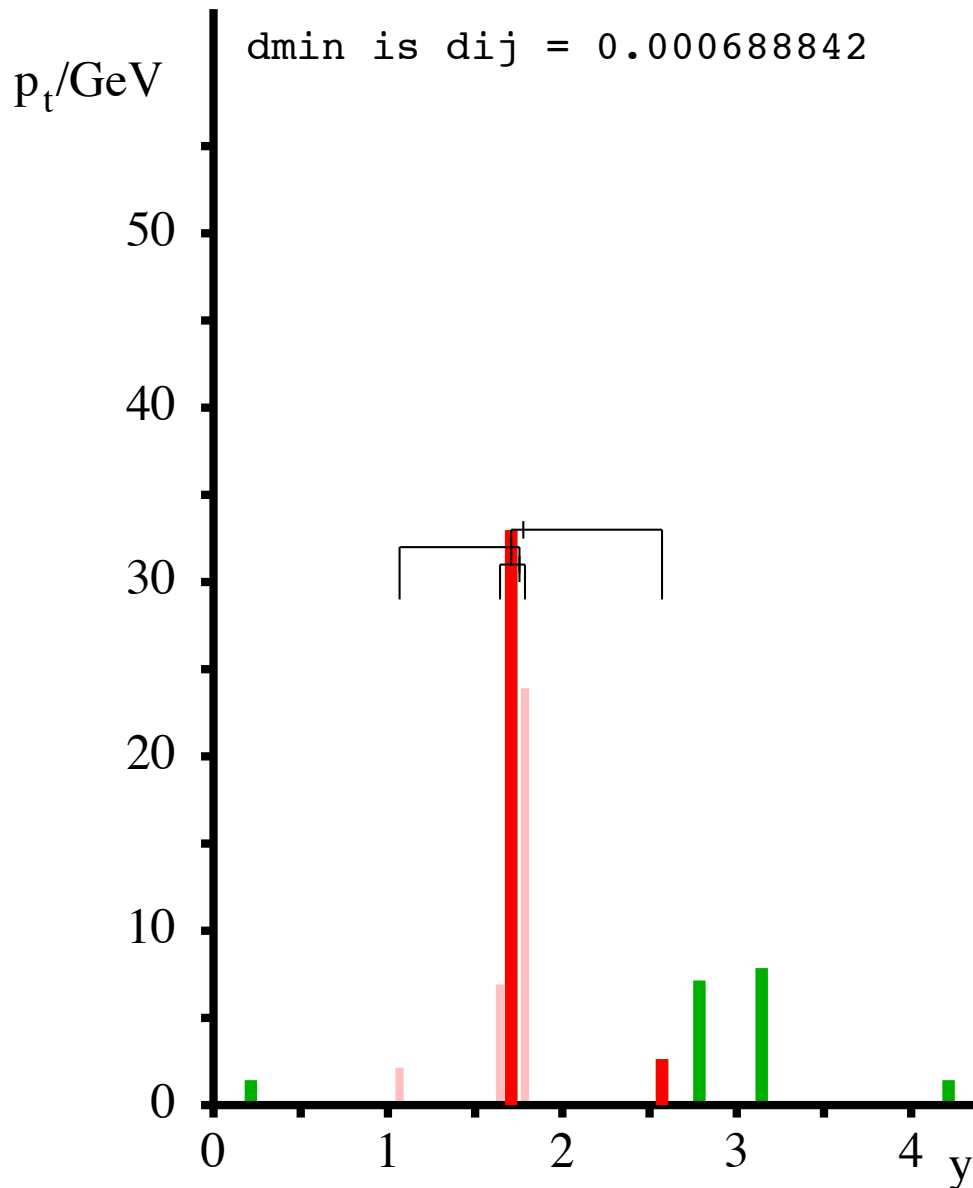
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# Identifying jet substructure: try out anti- $k_t$

## anti- $k_t$ algorithm

$d_{\min}$  is  $d_{ij} = 0.000688842$

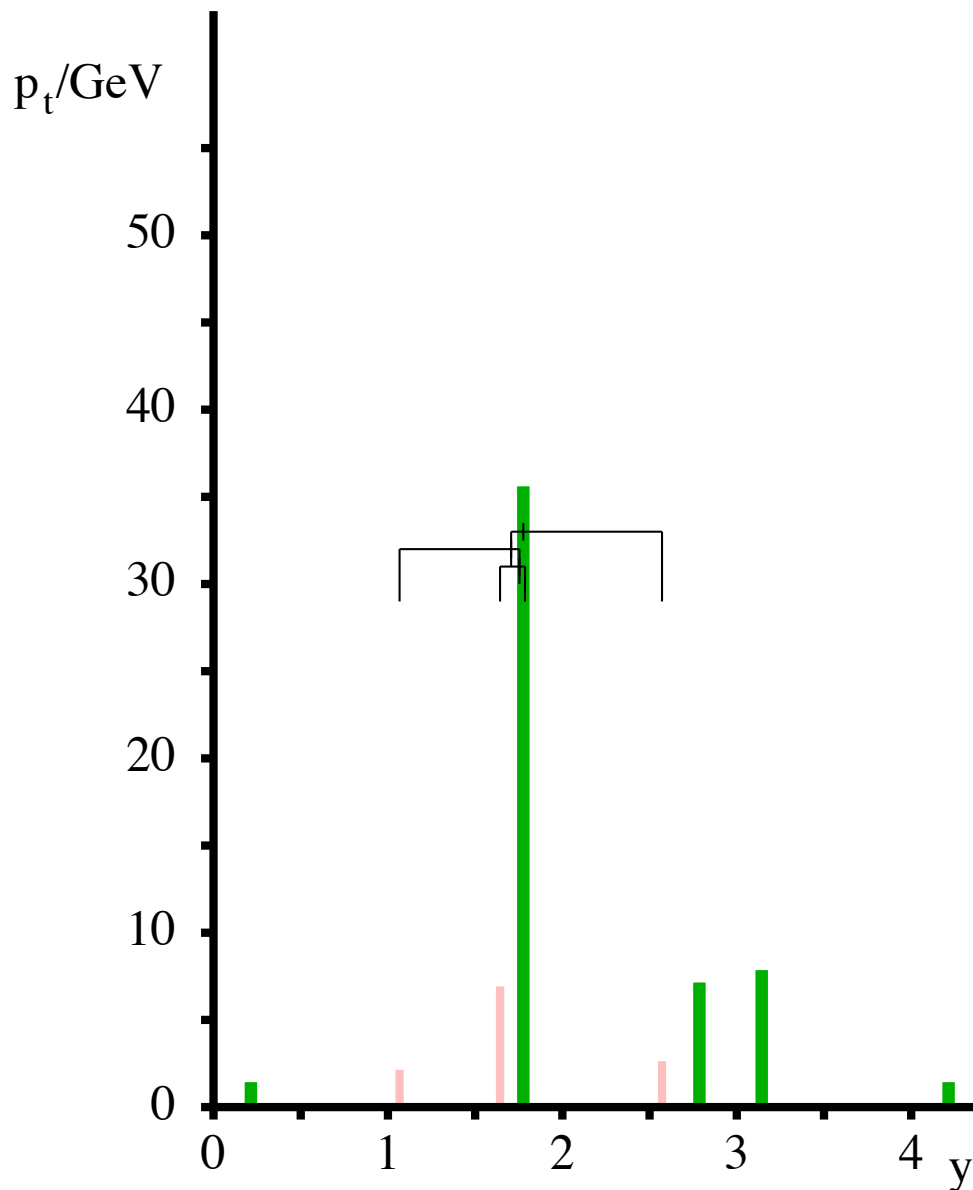


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# Identifying jet substructure: try out anti- $k_t$

## anti- $k_t$ algorithm



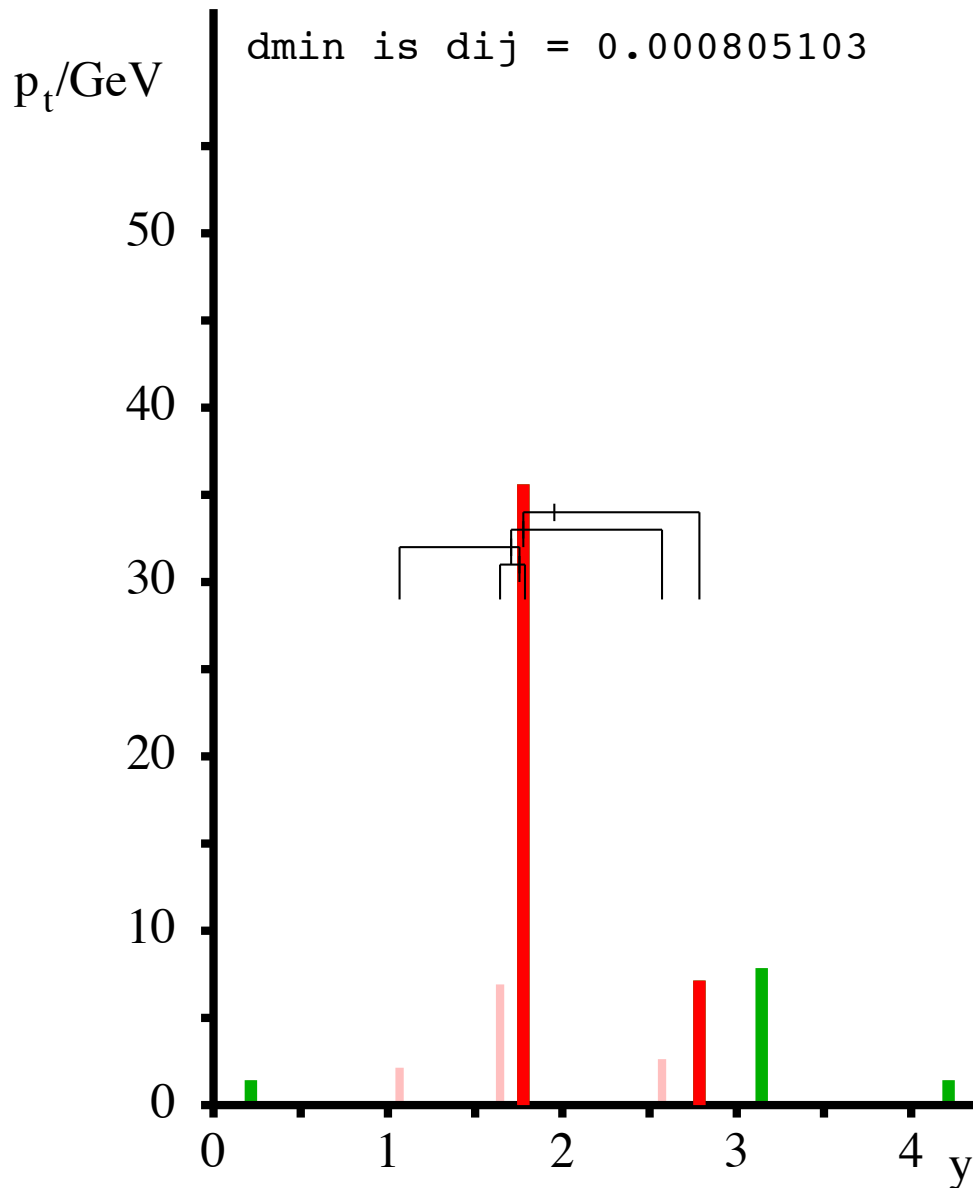
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# Identifying jet substructure: try out anti- $k_t$

## anti- $k_t$ algorithm

$d_{\min}$  is  $d_{ij} = 0.000805103$



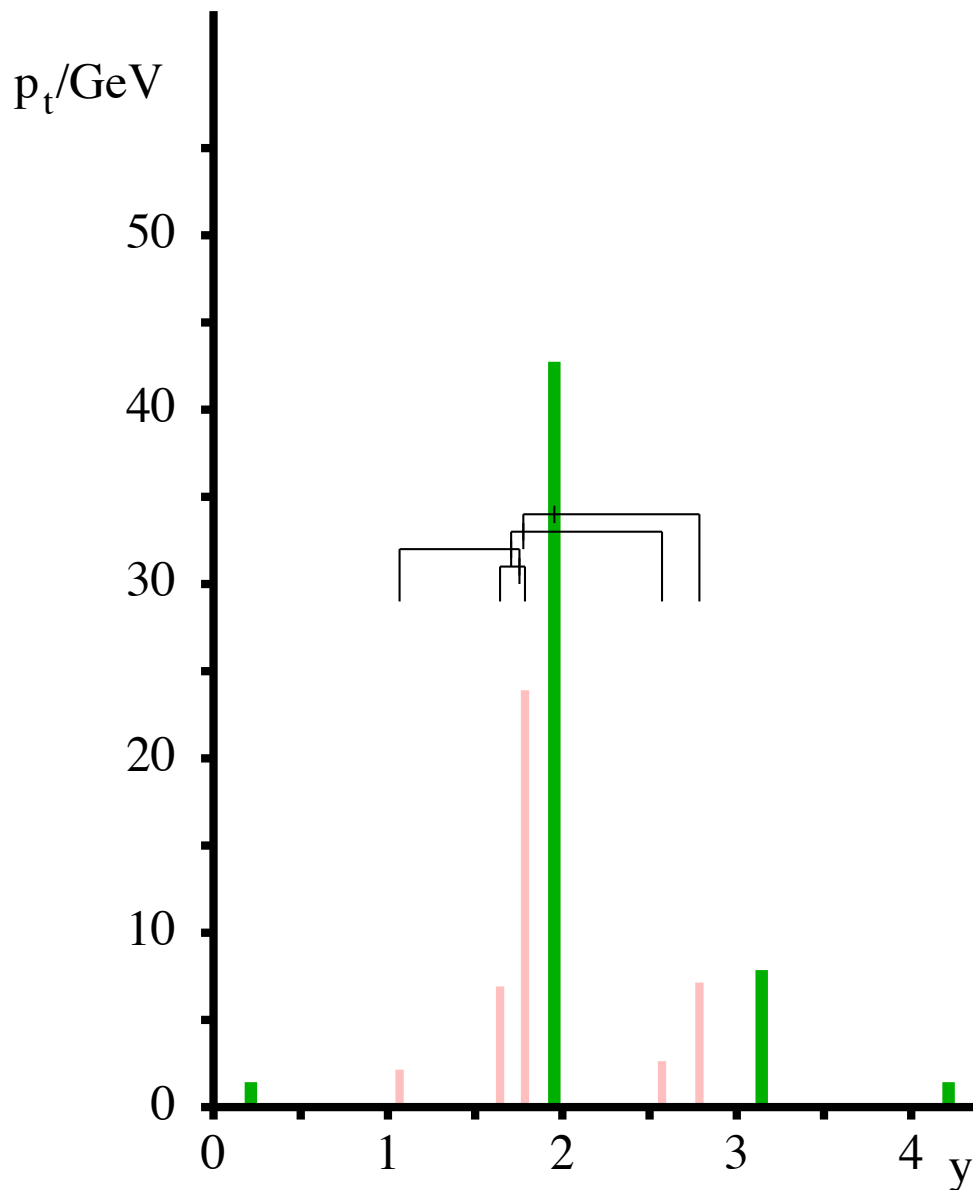
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This is crucial for identifying the kinematic variables of the partons in the jet (e.g.  $z$ ).

*Anti- $k_t$  gradually makes its way through the secondary blob  $\rightarrow$  no clear identification of substructure associated with 2nd parton.*

# Identifying jet substructure: try out anti- $k_t$

## anti- $k_t$ algorithm



How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

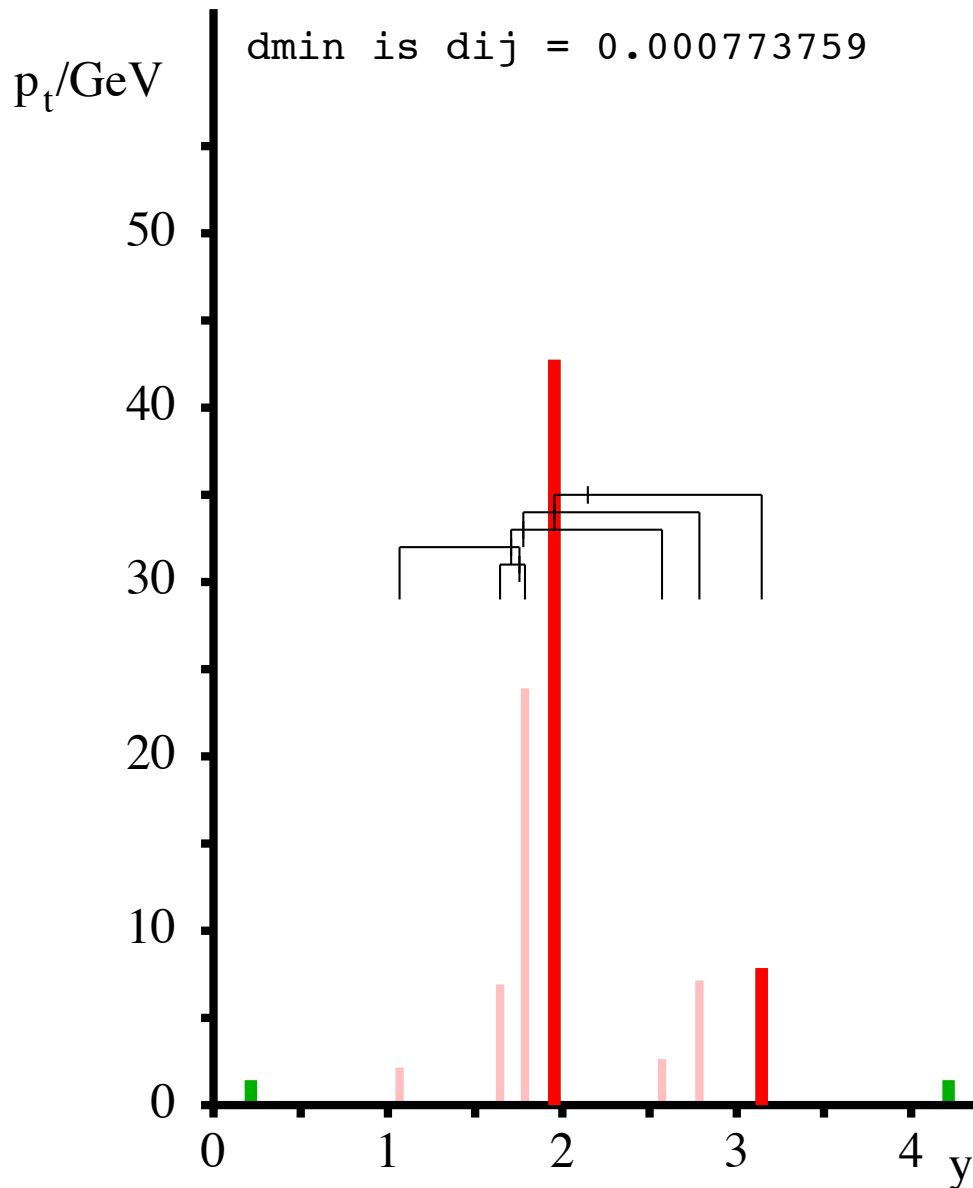
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# Identifying jet substructure: try out anti- $k_t$

## anti- $k_t$ algorithm

$d_{\min}$  is  $d_{ij} = 0.000773759$



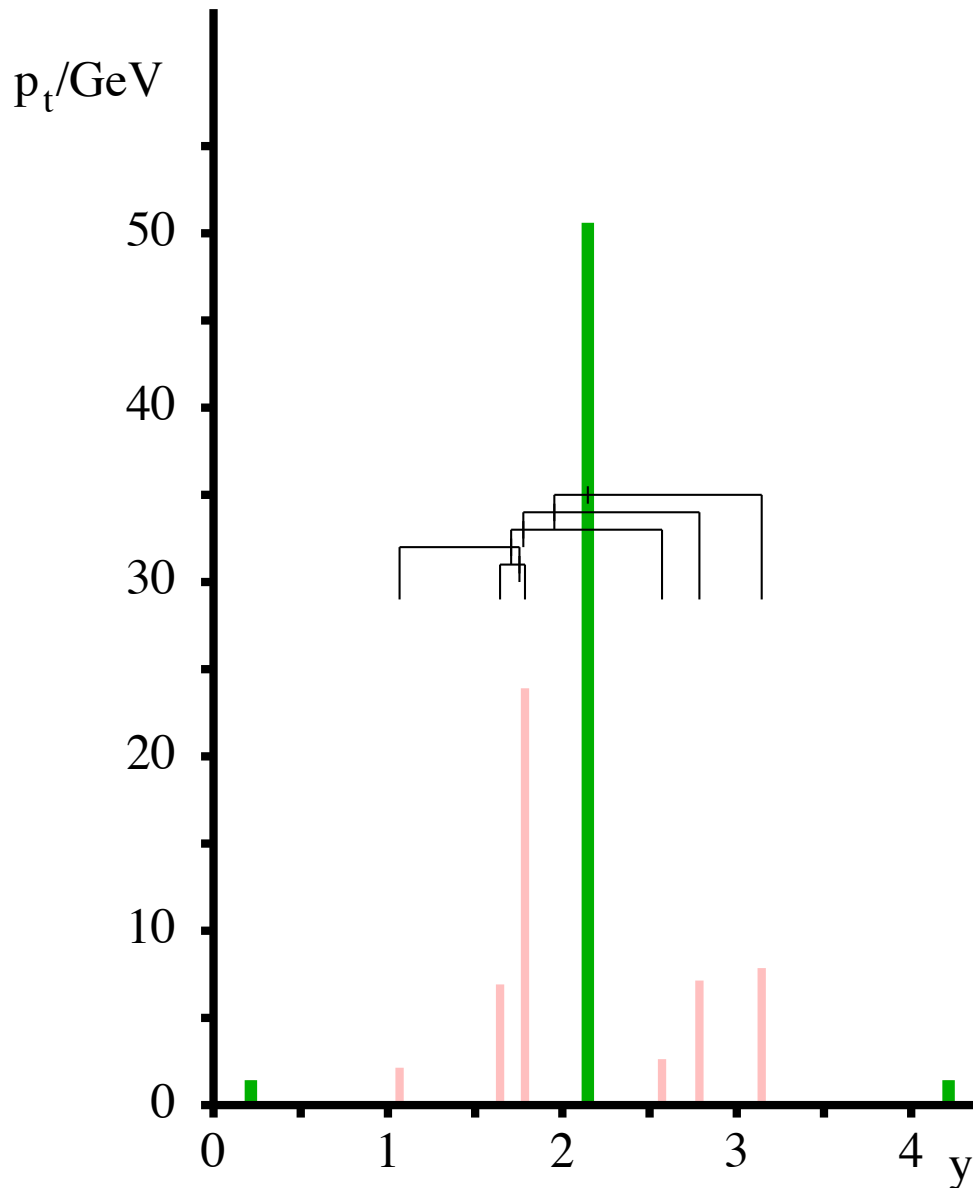
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## anti- $k_t$ algorithm



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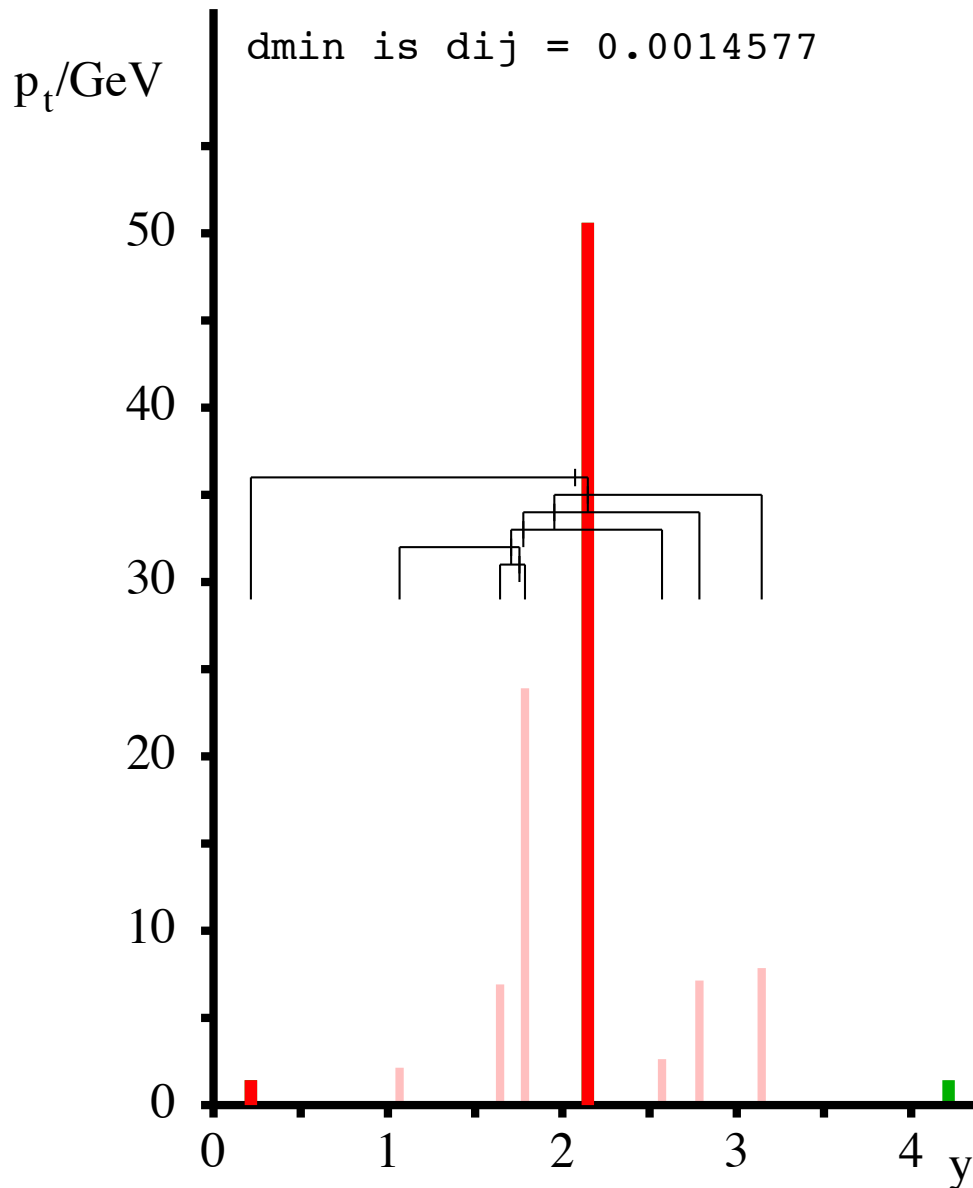
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# Identifying jet substructure: try out anti- $k_t$

## anti- $k_t$ algorithm

$d_{\min}$  is  $d_{ij} = 0.0014577$



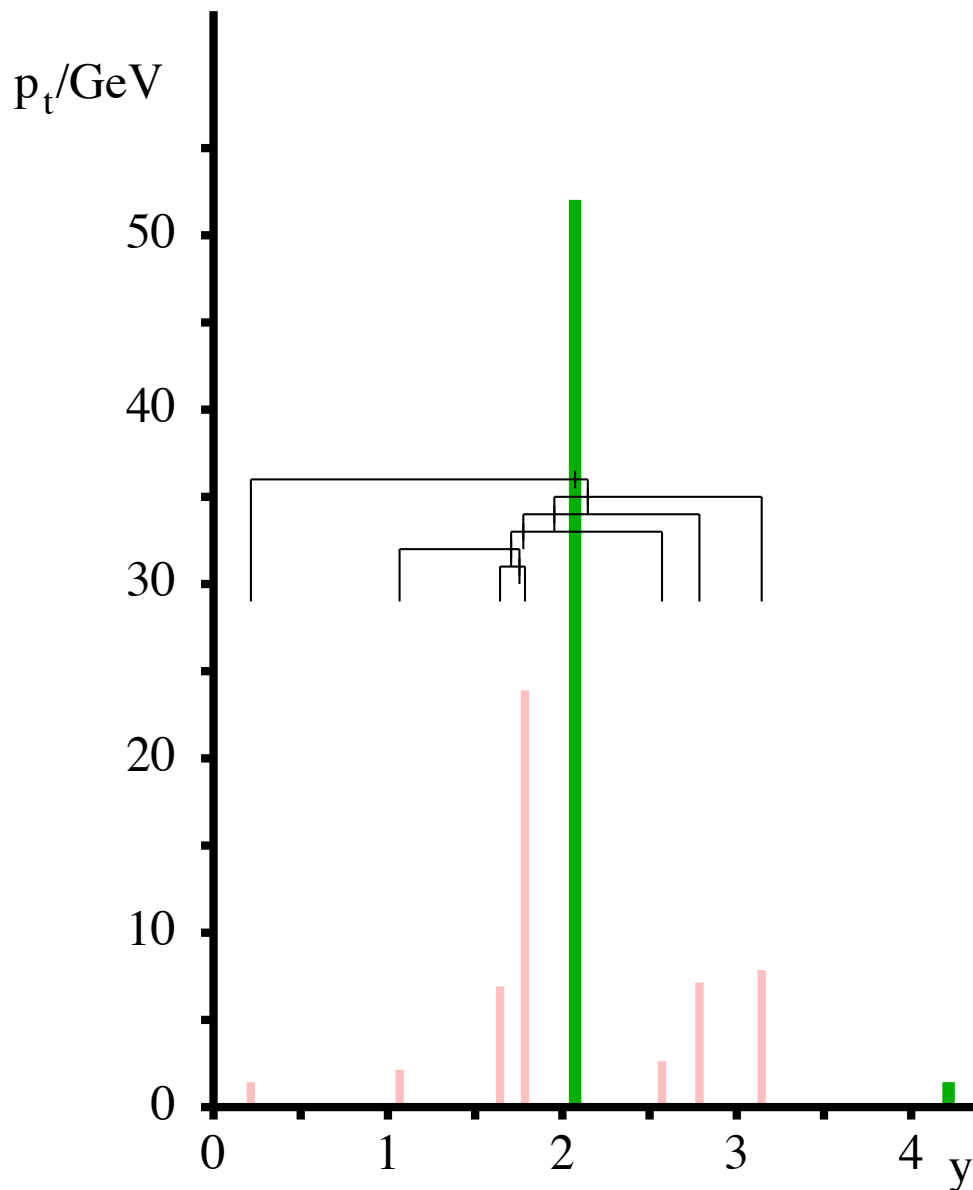
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# Identifying jet substructure: try out anti- $k_t$

## anti- $k_t$ algorithm



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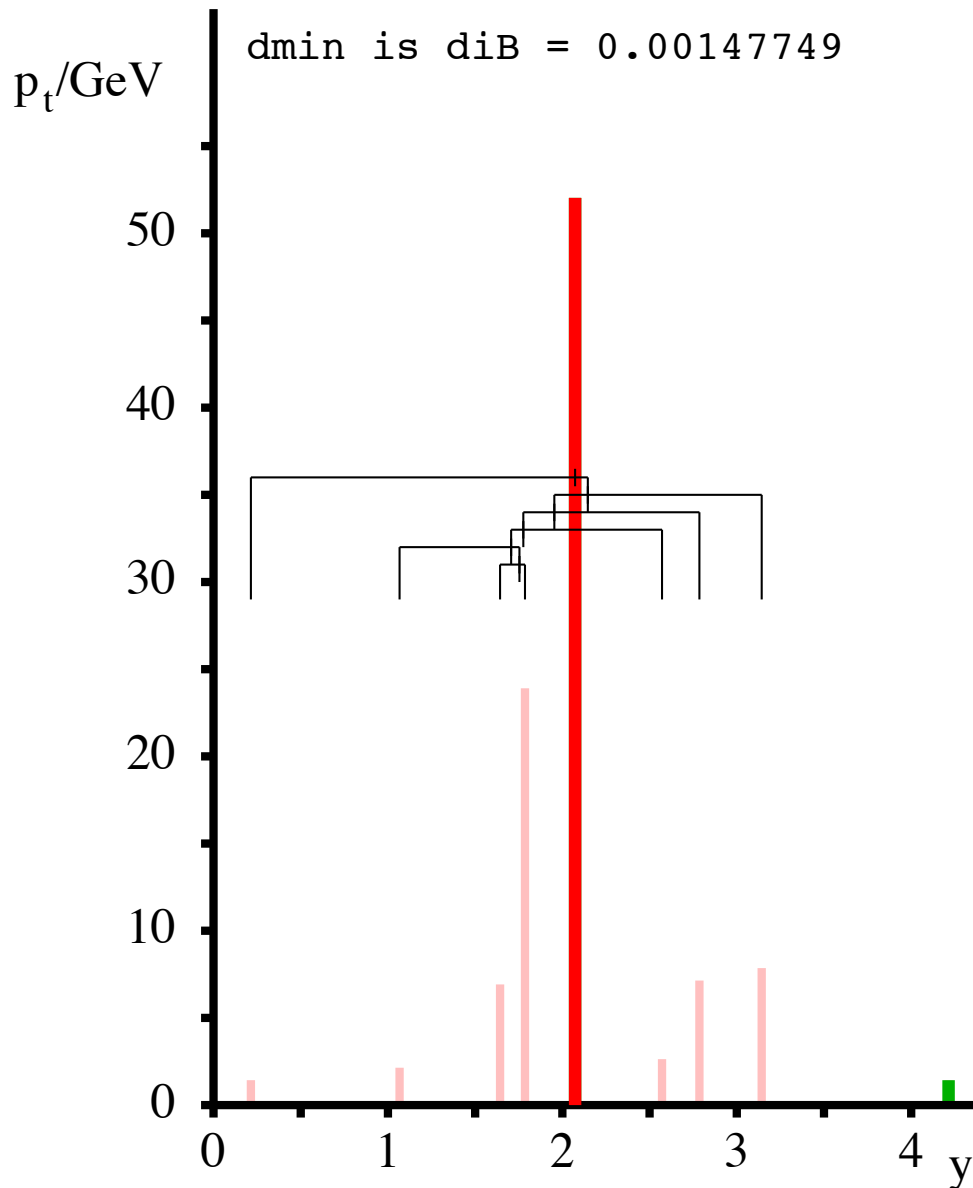
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# Identifying jet substructure: try out anti- $k_t$

## anti- $k_t$ algorithm

$d_{\min}$  is  $d_{iB} = 0.00147749$



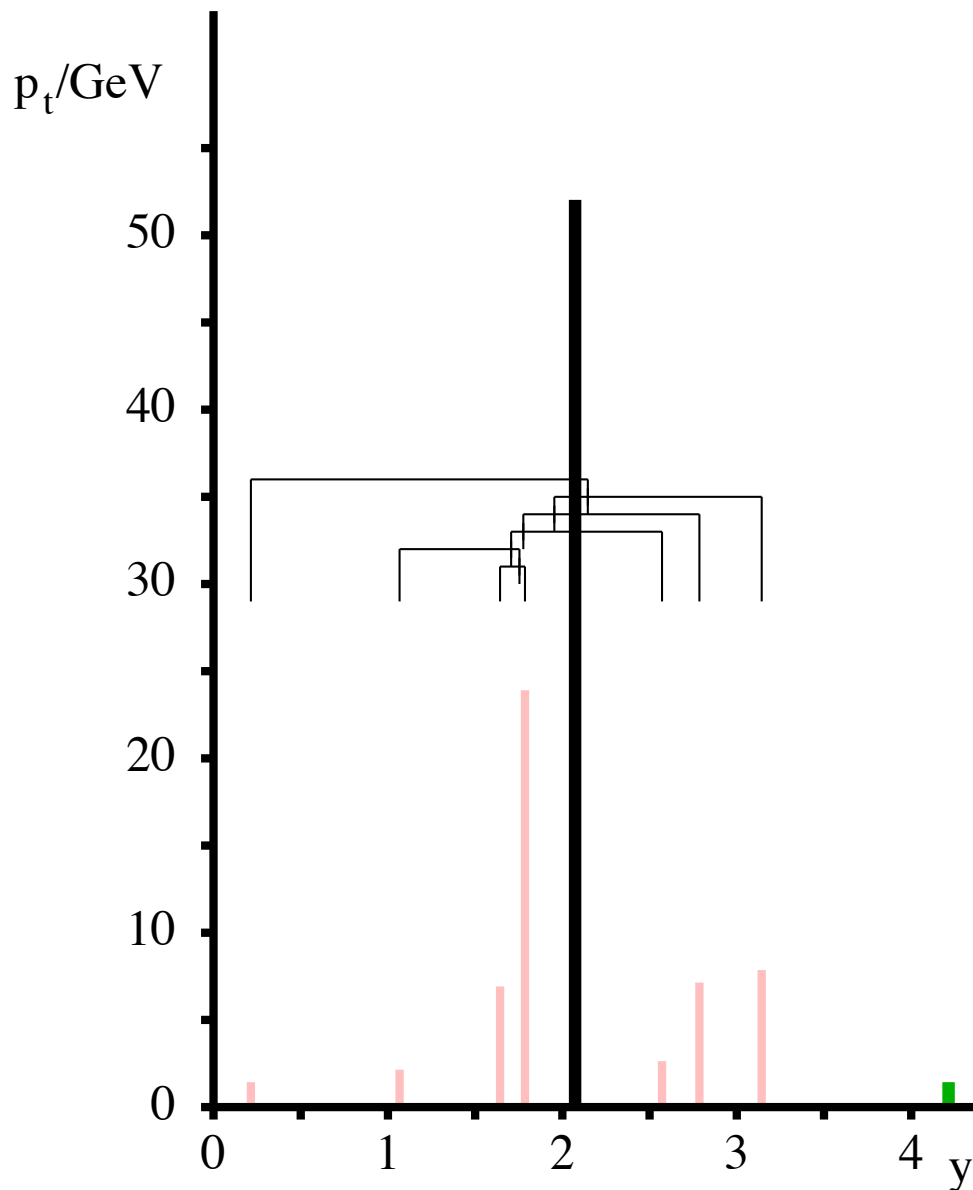
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# Identifying jet substructure: try out anti- $k_t$

## anti- $k_t$ algorithm



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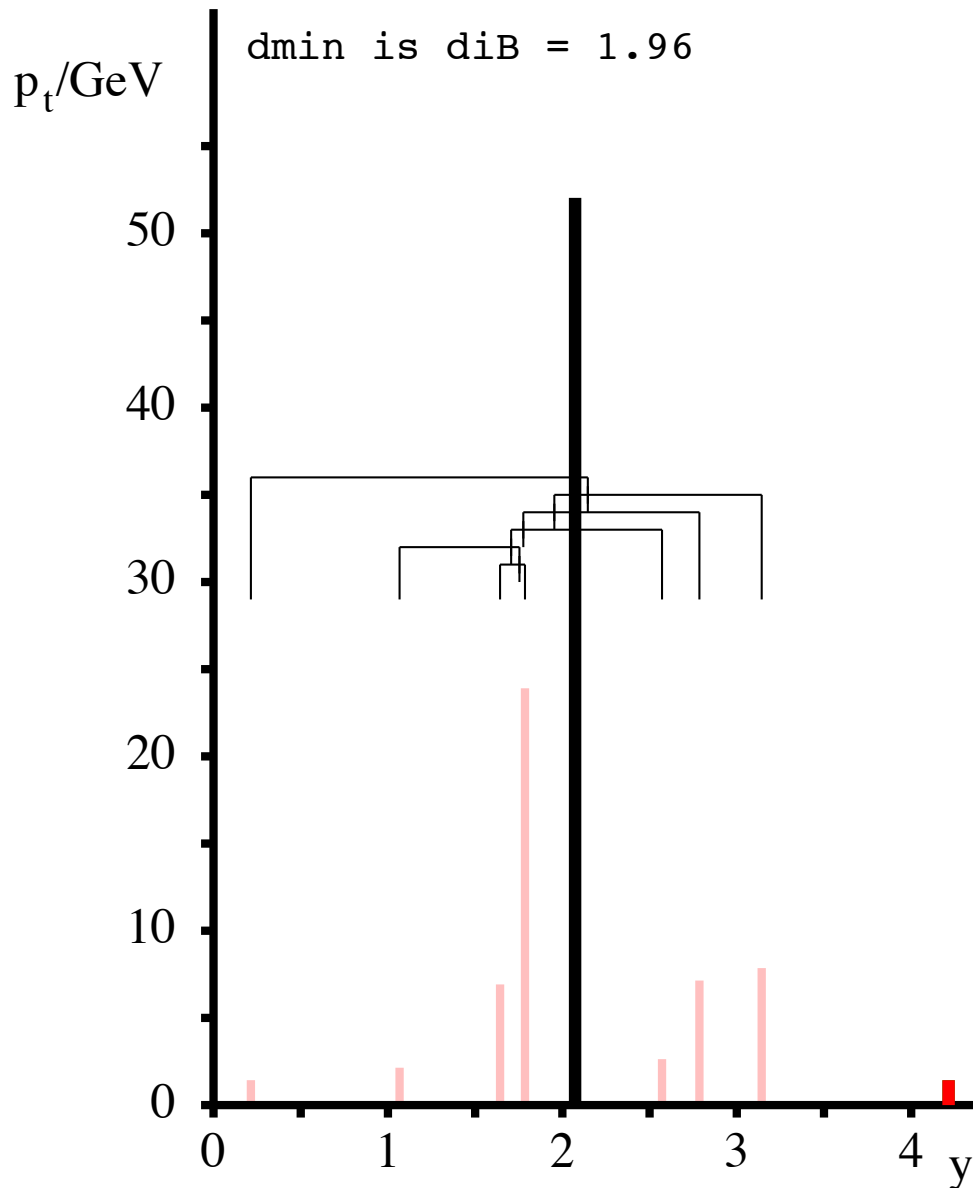
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# Identifying jet substructure: try out anti- $k_t$

## anti- $k_t$ algorithm

$d_{\min}$  is  $d_{iB} = 1.96$



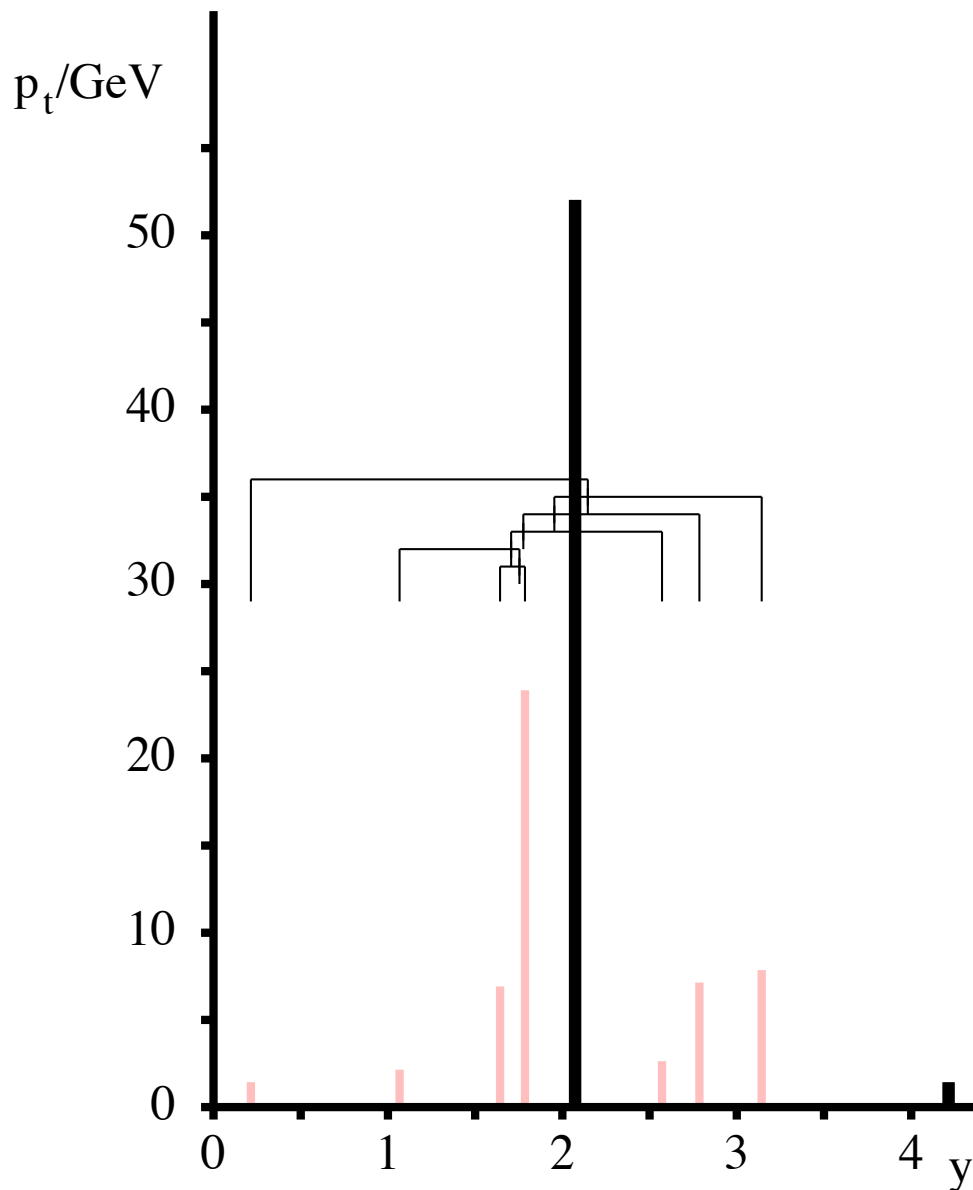
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# Identifying jet substructure: try out anti- $k_t$

## anti- $k_t$ algorithm



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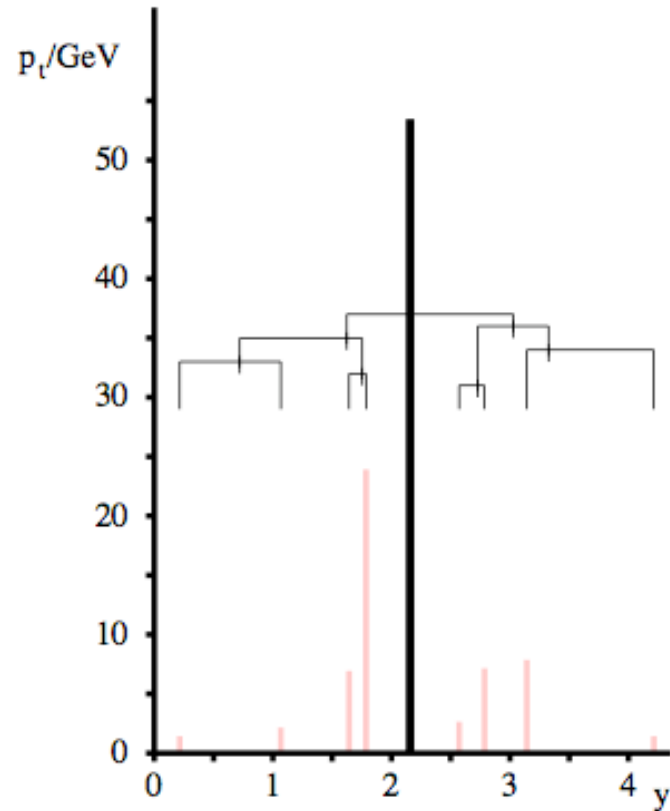
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kt

# Hierarchical substructure

## $k_t$ algorithm



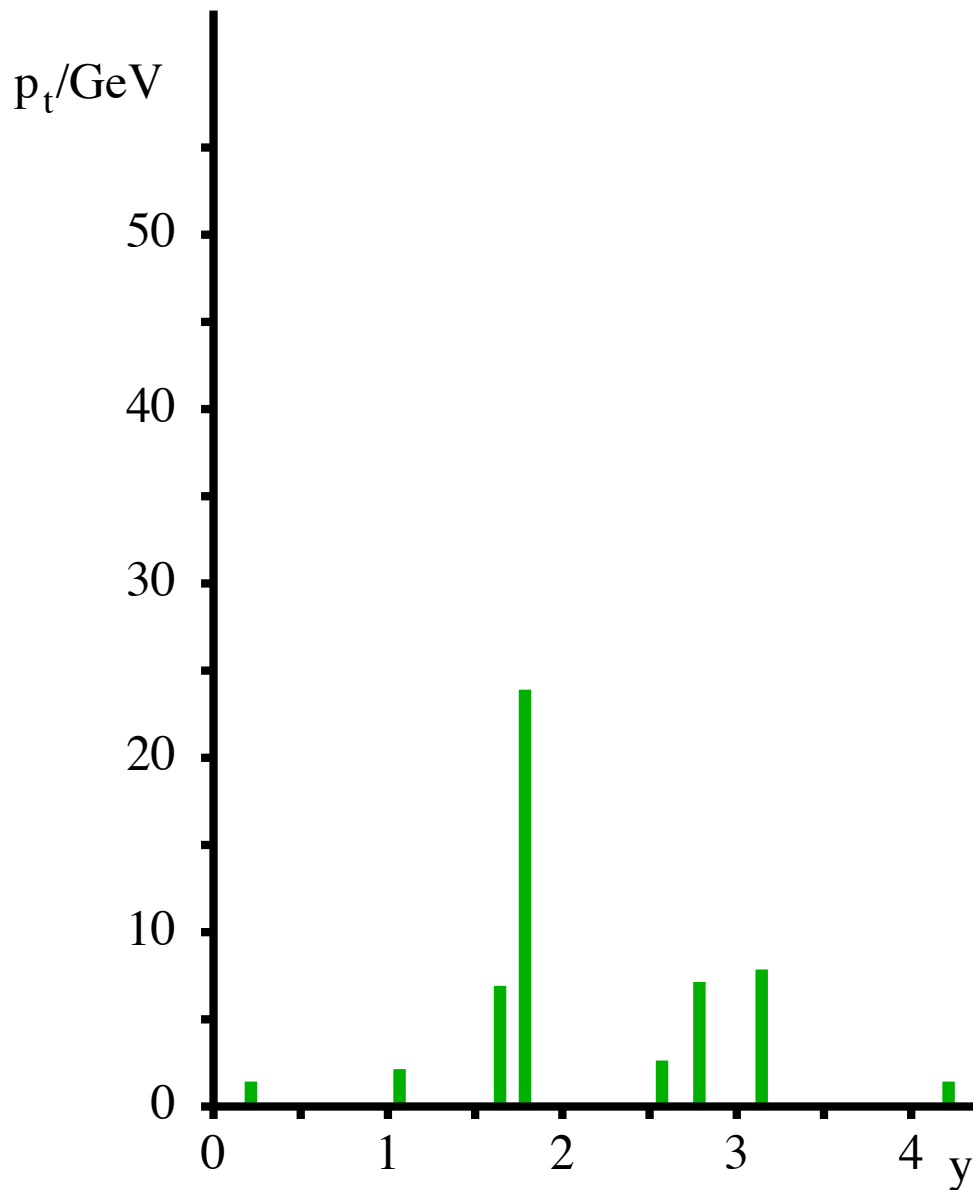
## $k_t$ distance measure

$$d_{ij} = \min(p_{ti}^2, p_{tj}^2) \frac{\Delta y^2 + \Delta \phi^2}{R^2}$$

Cluster by merging  
the **softest/closest** particles

# Identifying jet substructure: try out $k_t$

## $k_t$ algorithm



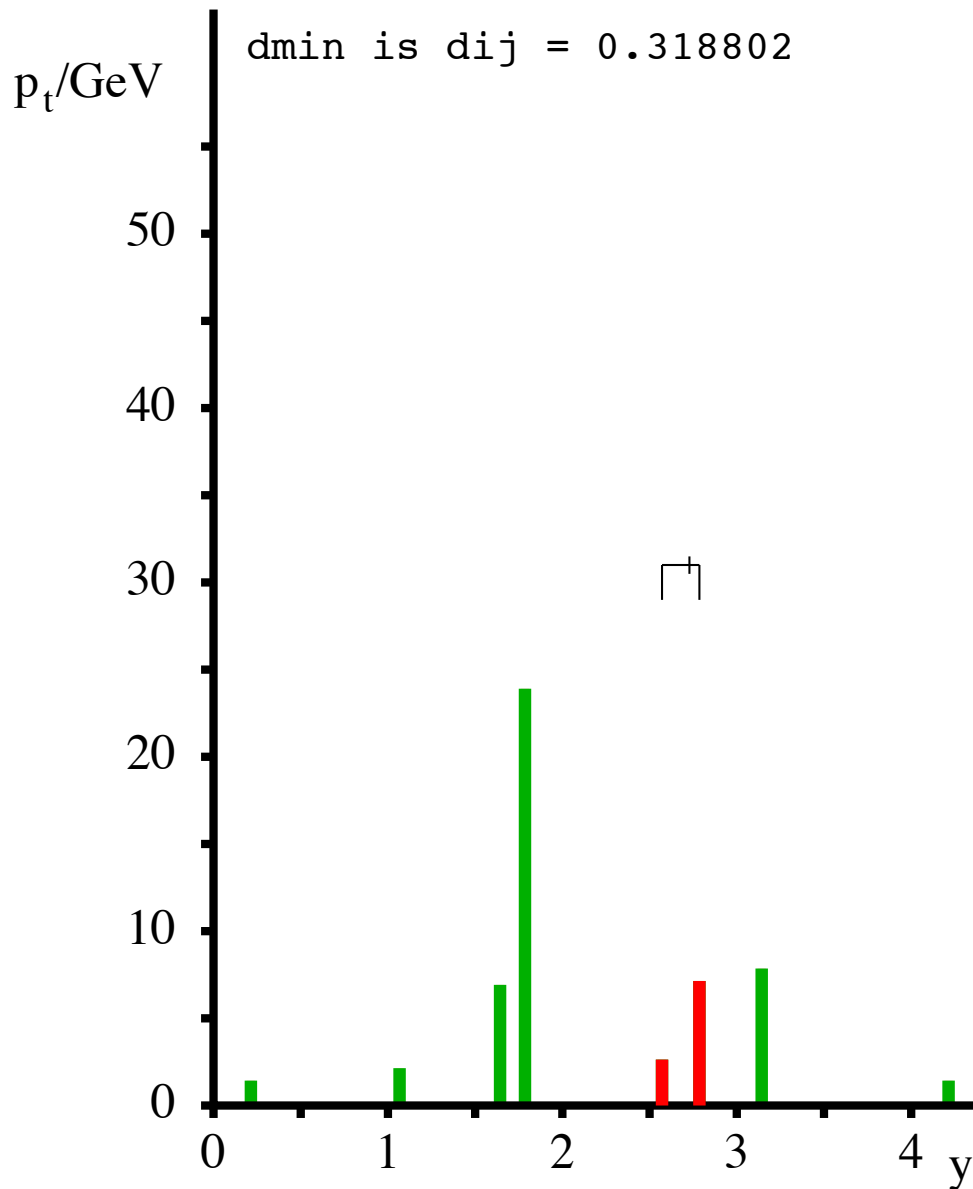
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# Identifying jet substructure: try out $k_t$

## $k_t$ algorithm

$d_{\min}$  is  $d_{ij} = 0.318802$



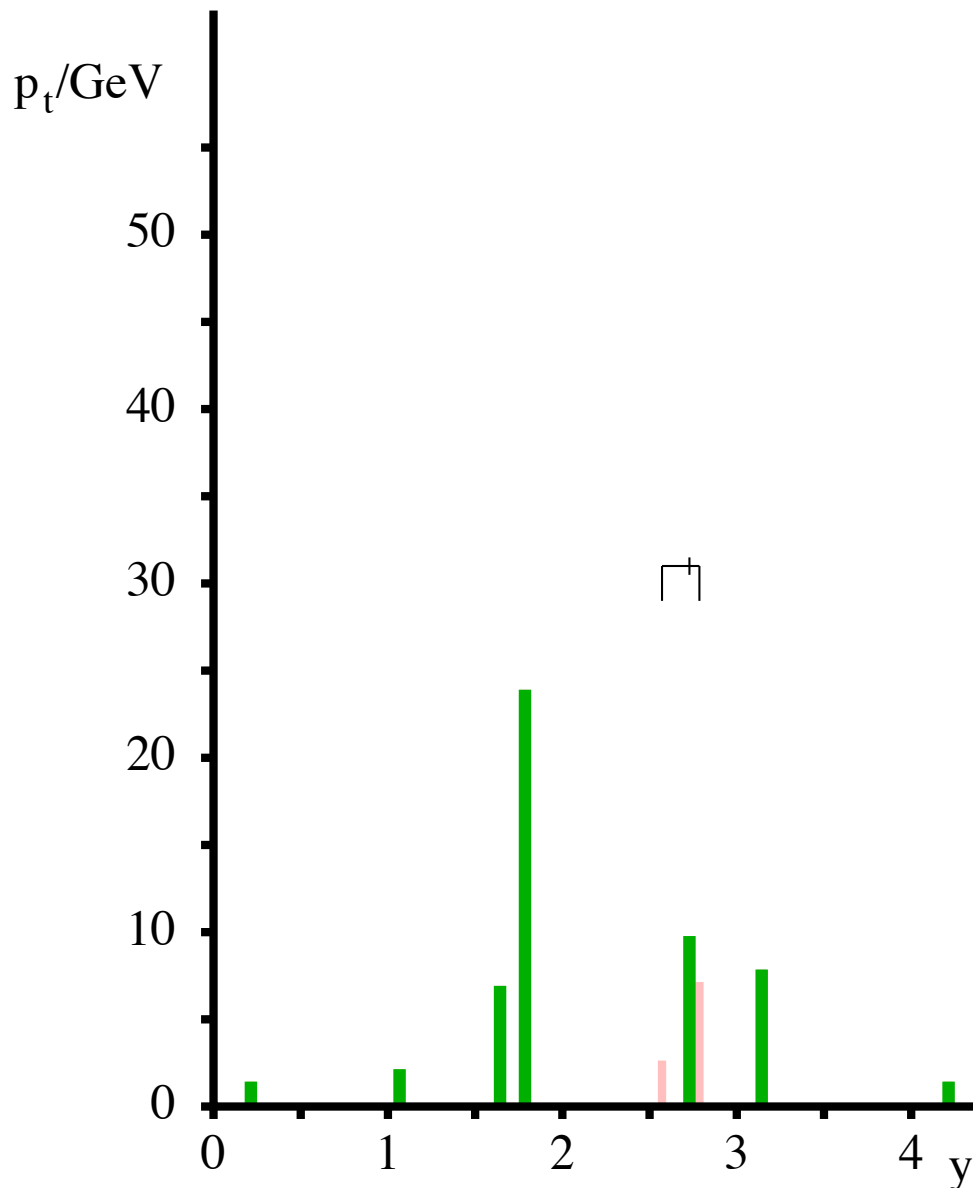
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# Identifying jet substructure: try out $k_t$

## $k_t$ algorithm



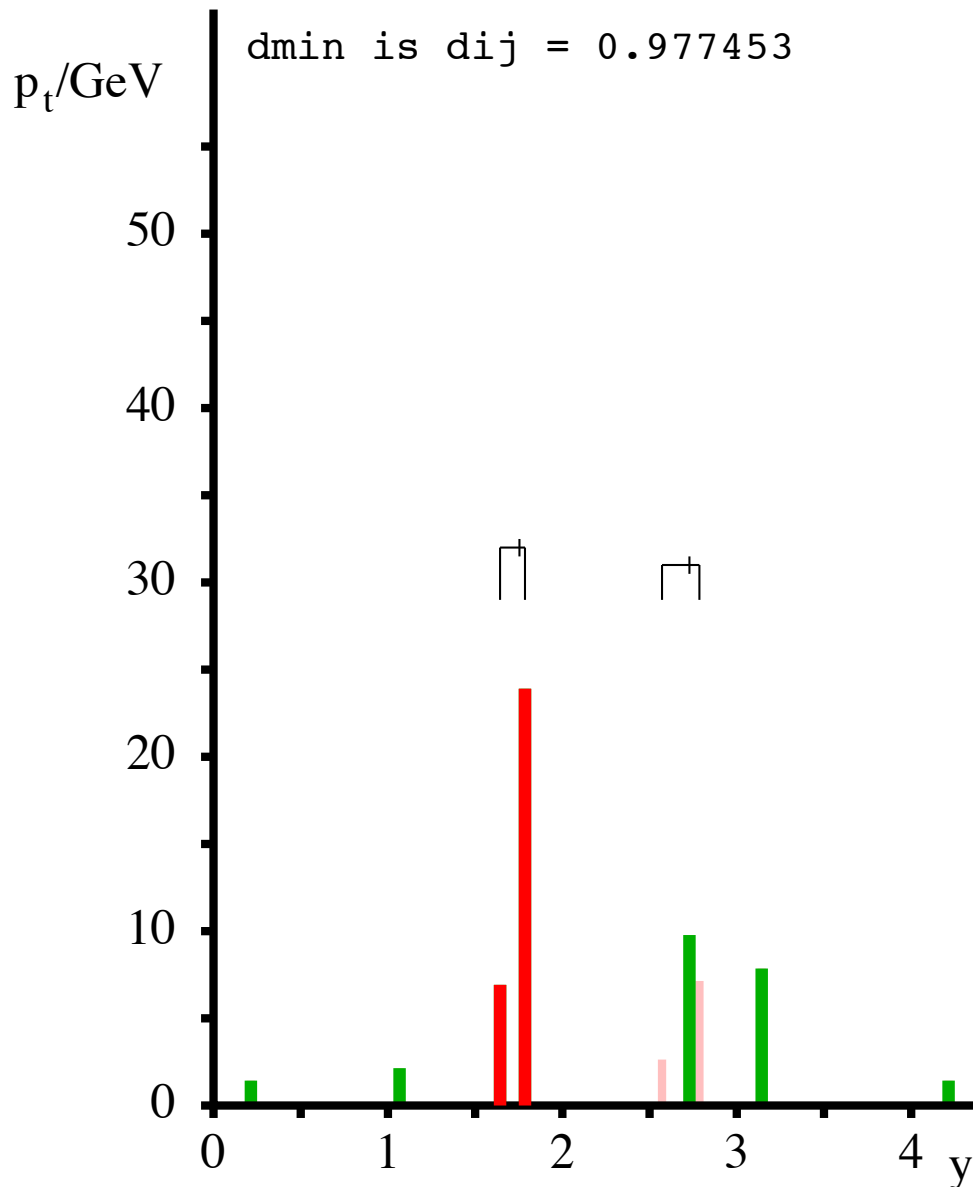
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# Identifying jet substructure: try out $k_t$

## $k_t$ algorithm

$d_{\min}$  is  $d_{ij} = 0.977453$

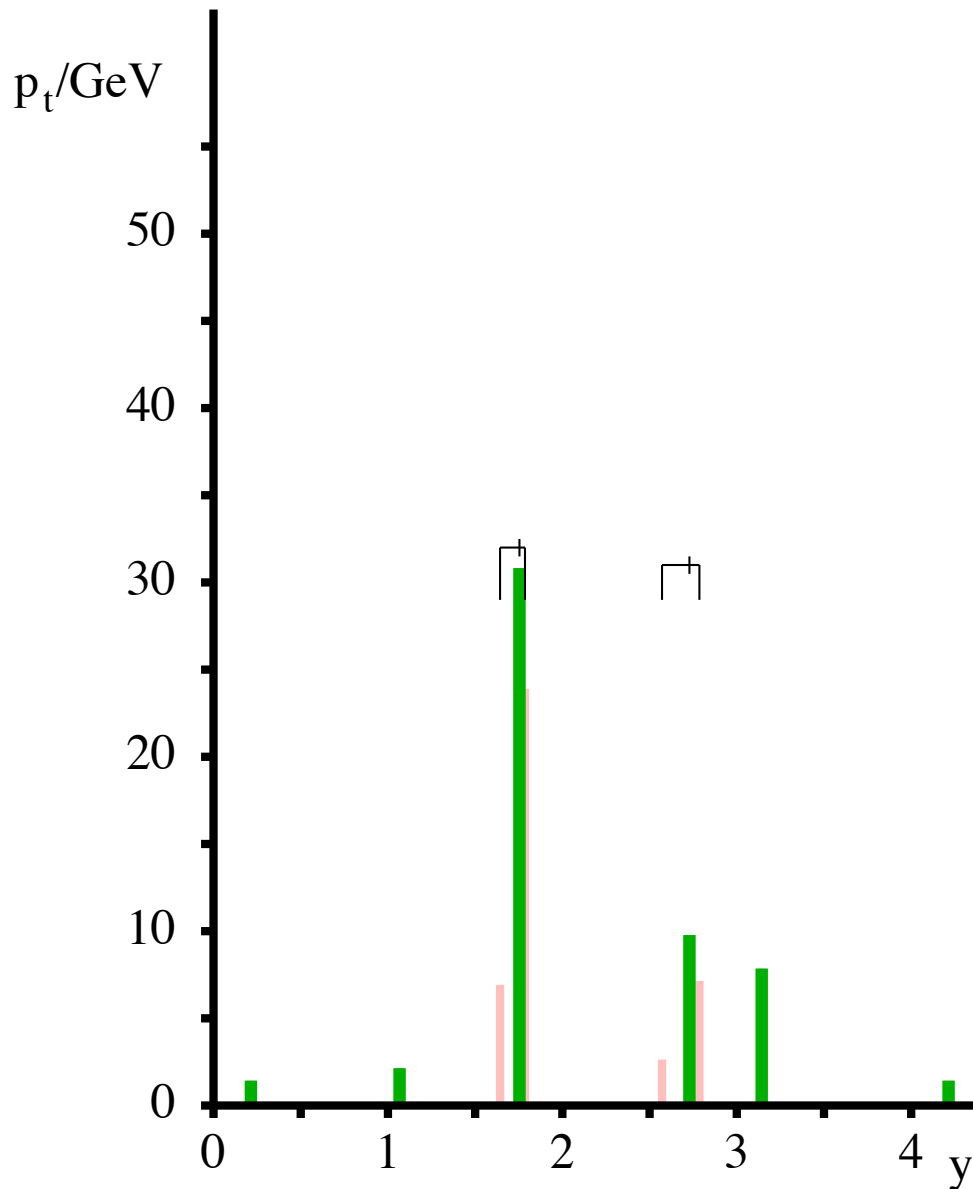


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# Identifying jet substructure: try out $k_t$

## $k_t$ algorithm



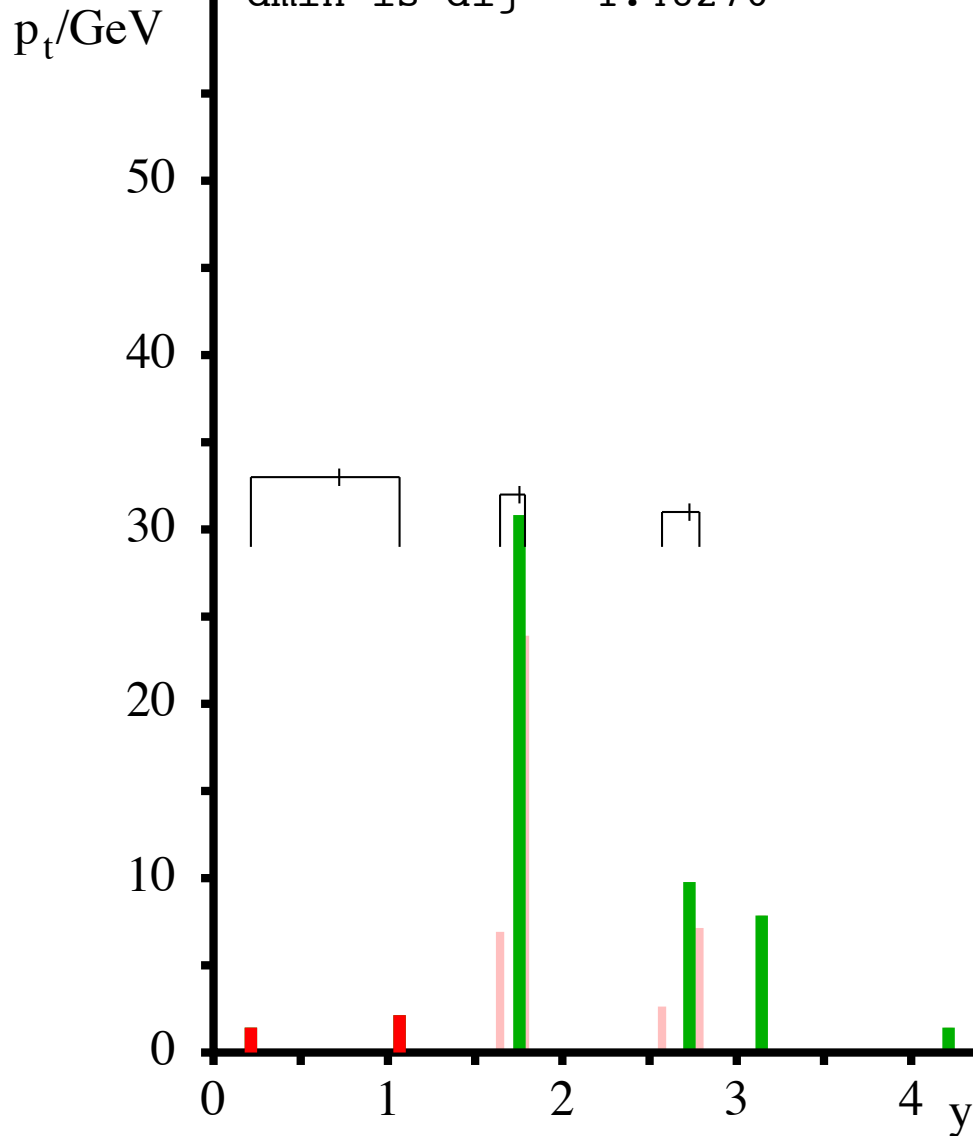
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# Identifying jet substructure: try out $k_t$

## $k_t$ algorithm

$d_{\min}$  is  $d_{ij} = 1.48276$



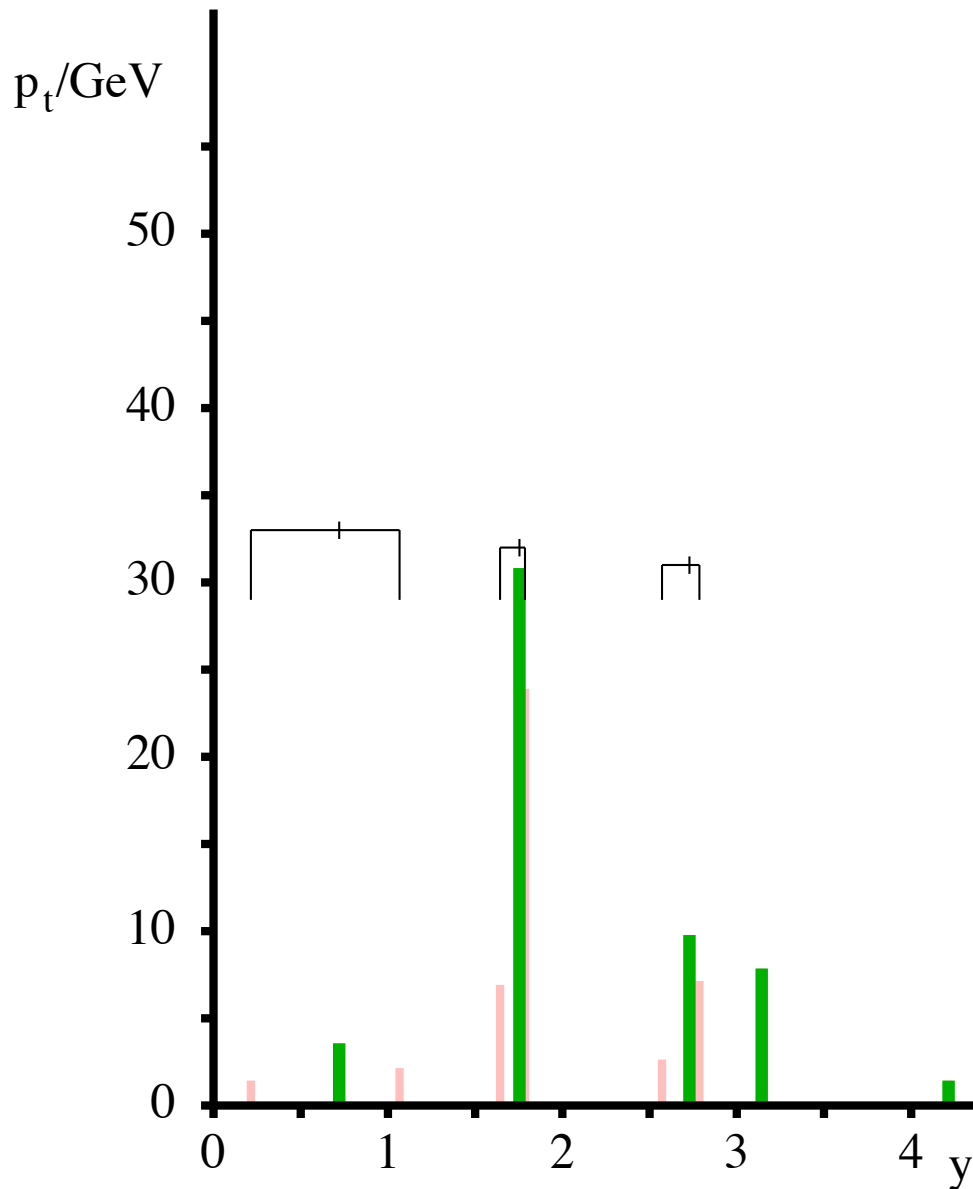
How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

This is crucial for identifying the kinematic variables of the partons in the jet (e.g.  $z$ ).

$k_t$  clusters soft “junk” early on in the clustering

# Identifying jet substructure: try out $k_t$

## $k_t$ algorithm



How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

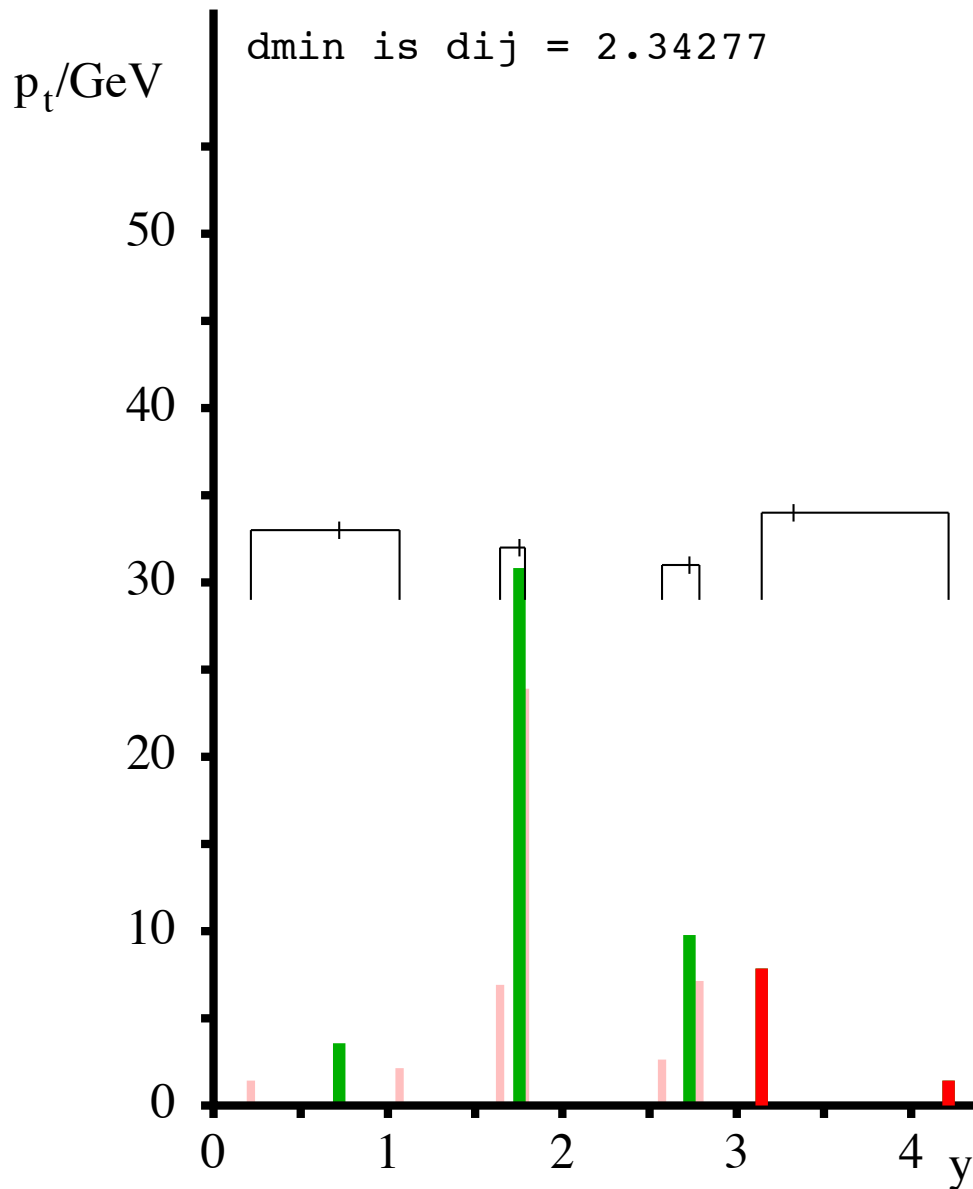
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# Identifying jet substructure: try out $k_t$

## $k_t$ algorithm

$d_{\min}$  is  $d_{ij} = 2.34277$



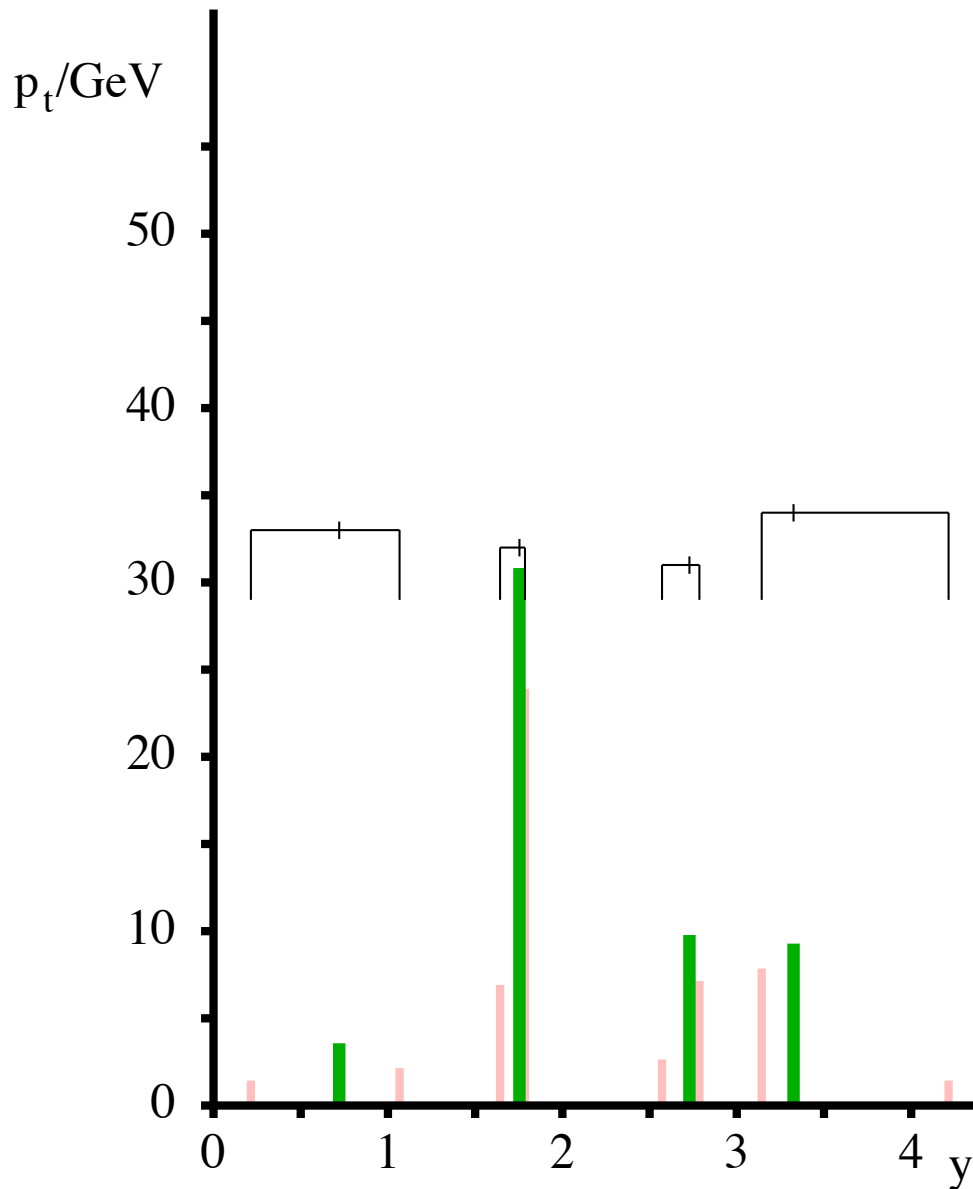
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# Identifying jet substructure: try out $k_t$

## $k_t$ algorithm



How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

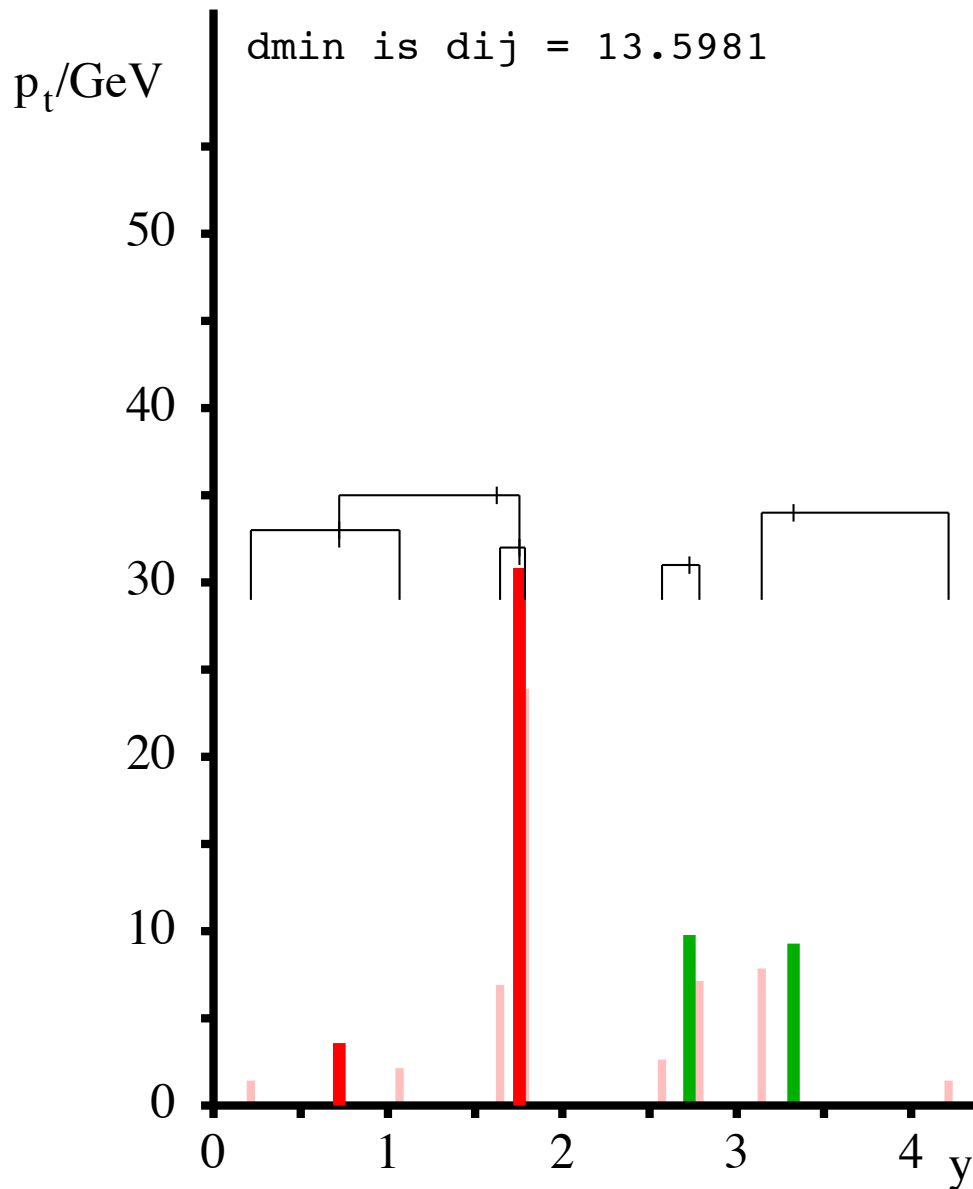
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$k_t$  clusters soft “junk” early on in the clustering

# Identifying jet substructure: try out $k_t$

## $k_t$ algorithm

$d_{\min}$  is  $d_{ij} = 13.5981$



How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

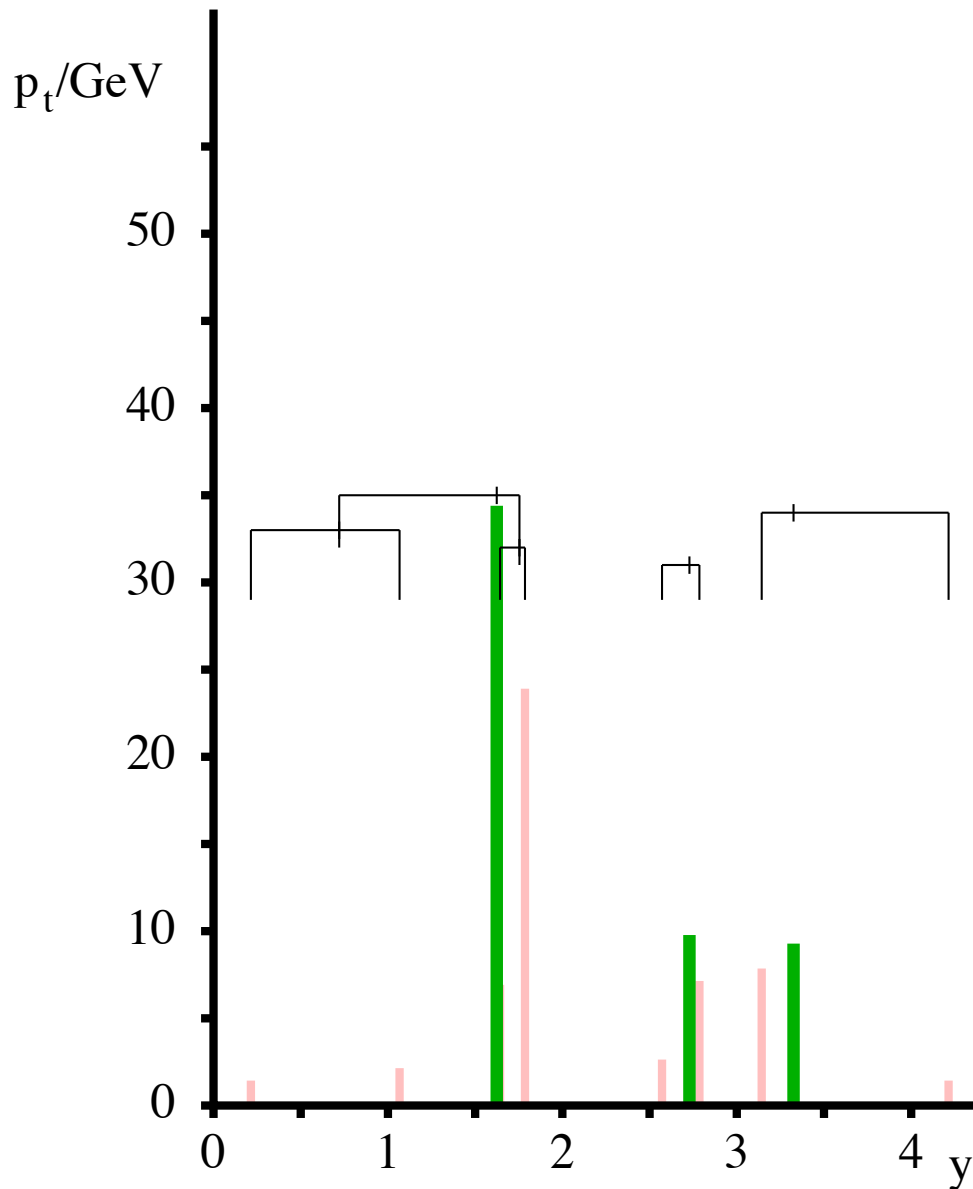
This is crucial for identifying the kinematic variables of the partons in the jet (e.g.  $z$ ).

$k_t$  clusters soft “junk” early on in the clustering



# Identifying jet substructure: try out $k_t$

## $k_t$ algorithm



How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

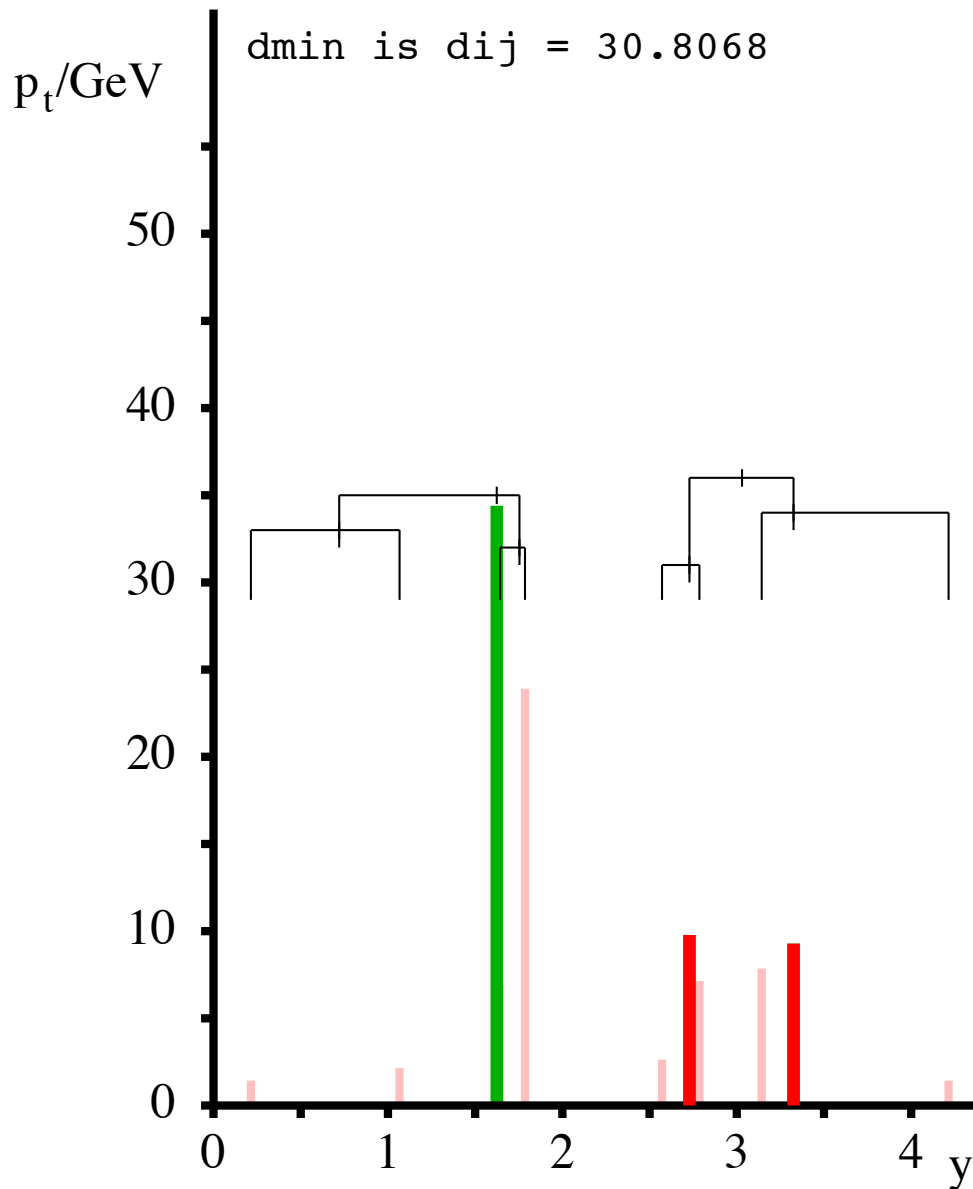
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$k_t$  clusters soft “junk” early on in the clustering

# Identifying jet substructure: try out $k_t$

## $k_t$ algorithm

$d_{\min}$  is  $d_{ij} = 30.8068$



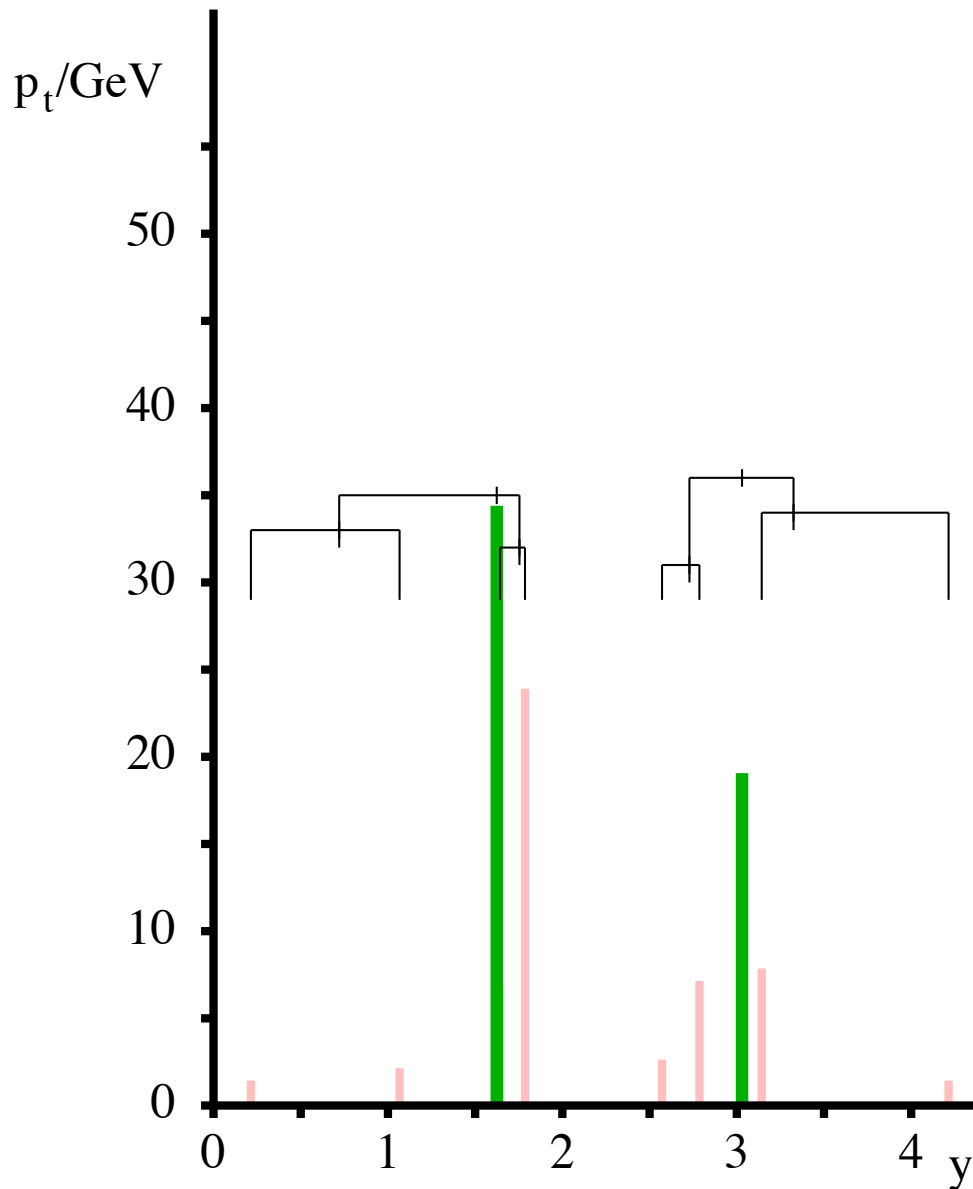
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This is crucial for identifying the kinematic variables of the partons in the jet (e.g.  $z$ ).

$k_t$  clusters soft “junk” early on in the clustering

# Identifying jet substructure: try out $k_t$

## $k_t$ algorithm



How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

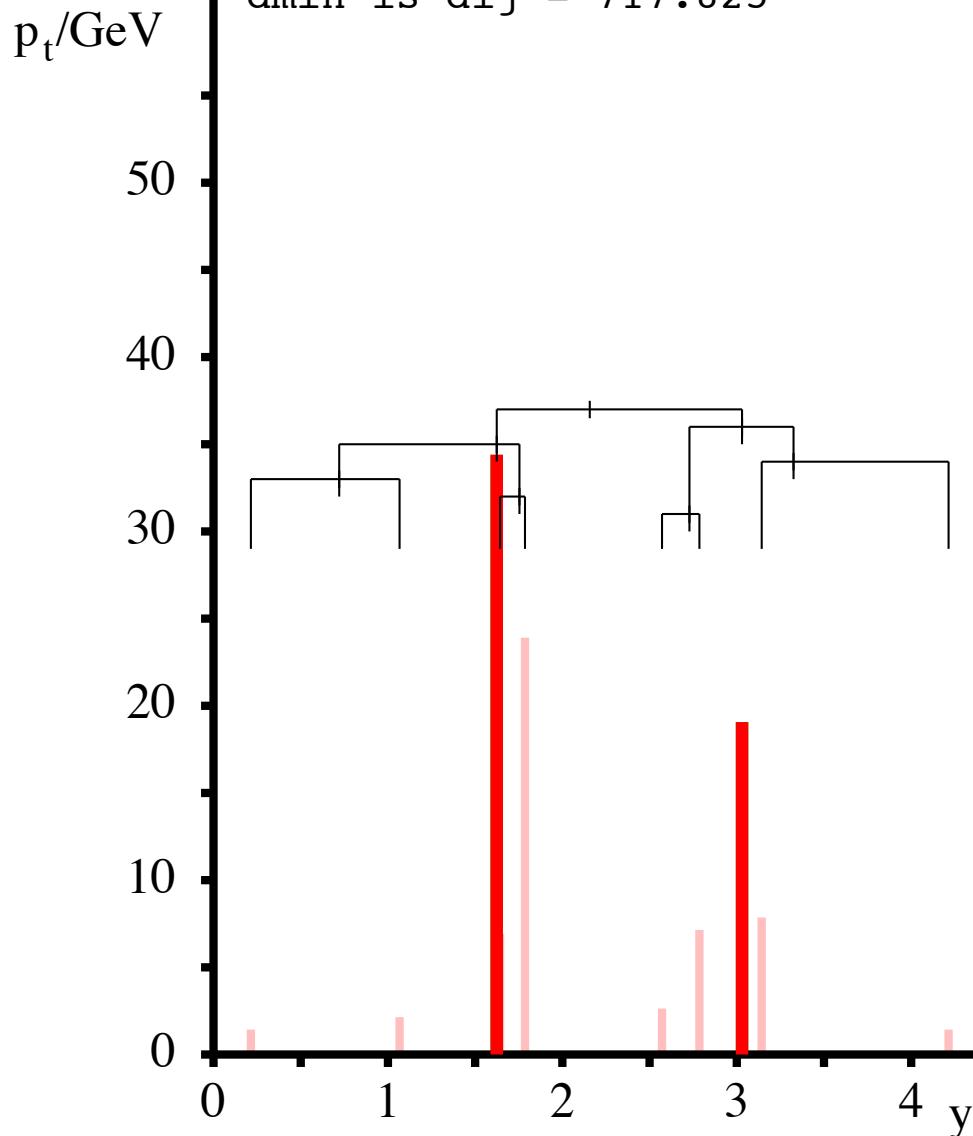
This is crucial for identifying the kinematic variables of the partons in the jet (e.g.  $z$ ).

$k_t$  clusters soft “junk” early on in the clustering

# Identifying jet substructure: try out $k_t$

## $k_t$ algorithm

$d_{\min}$  is  $d_{ij} = 717.825$



How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

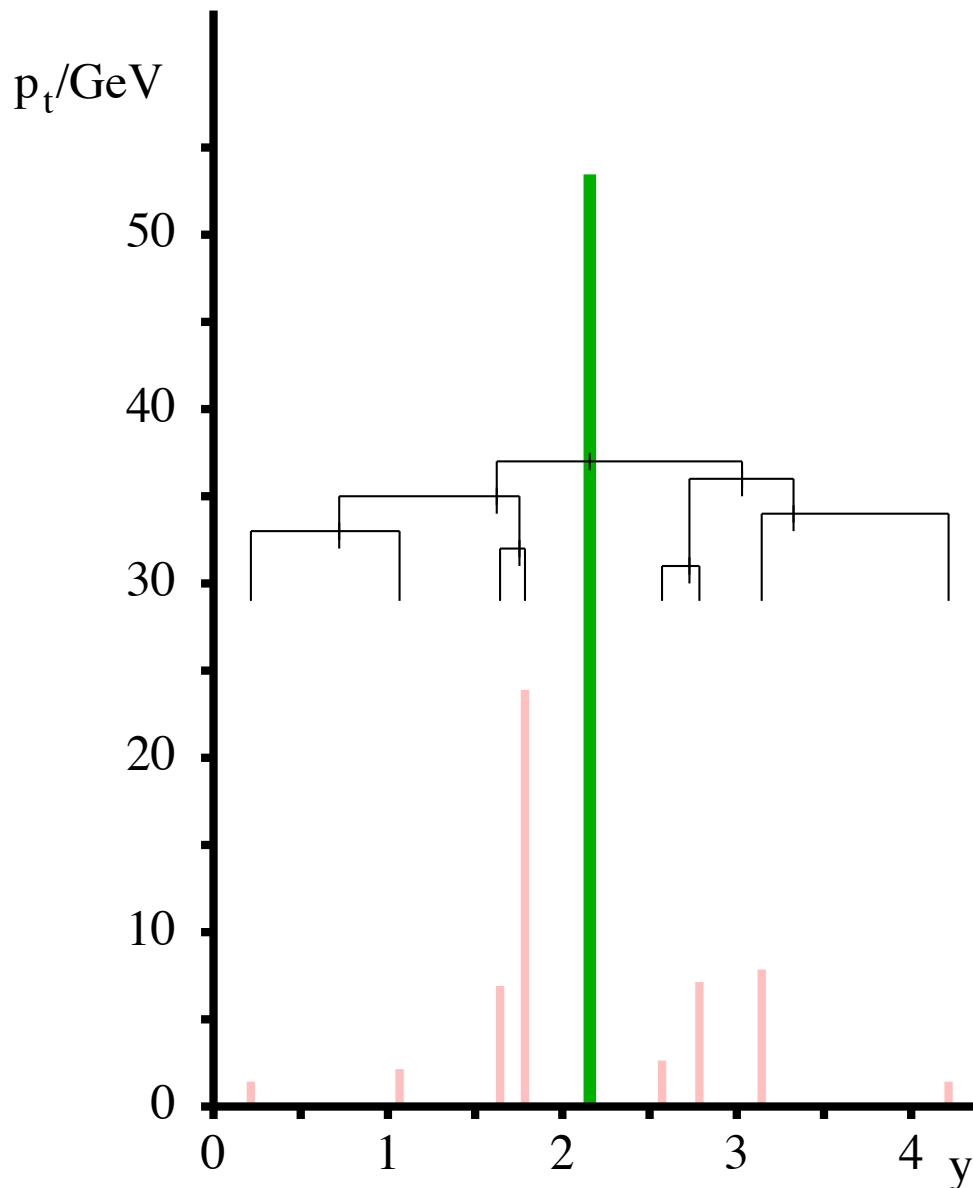
This is crucial for identifying the kinematic variables of the partons in the jet (e.g.  $z$ ).

$k_t$  clusters soft “junk” early on in the clustering

*Its last step is to merge two hard pieces. Easily undone to identify underlying kinematics*

# Identifying jet substructure: try out $k_t$

## $k_t$ algorithm



How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

This is crucial for identifying the kinematic variables of the partons in the jet (e.g.  $z$ ).

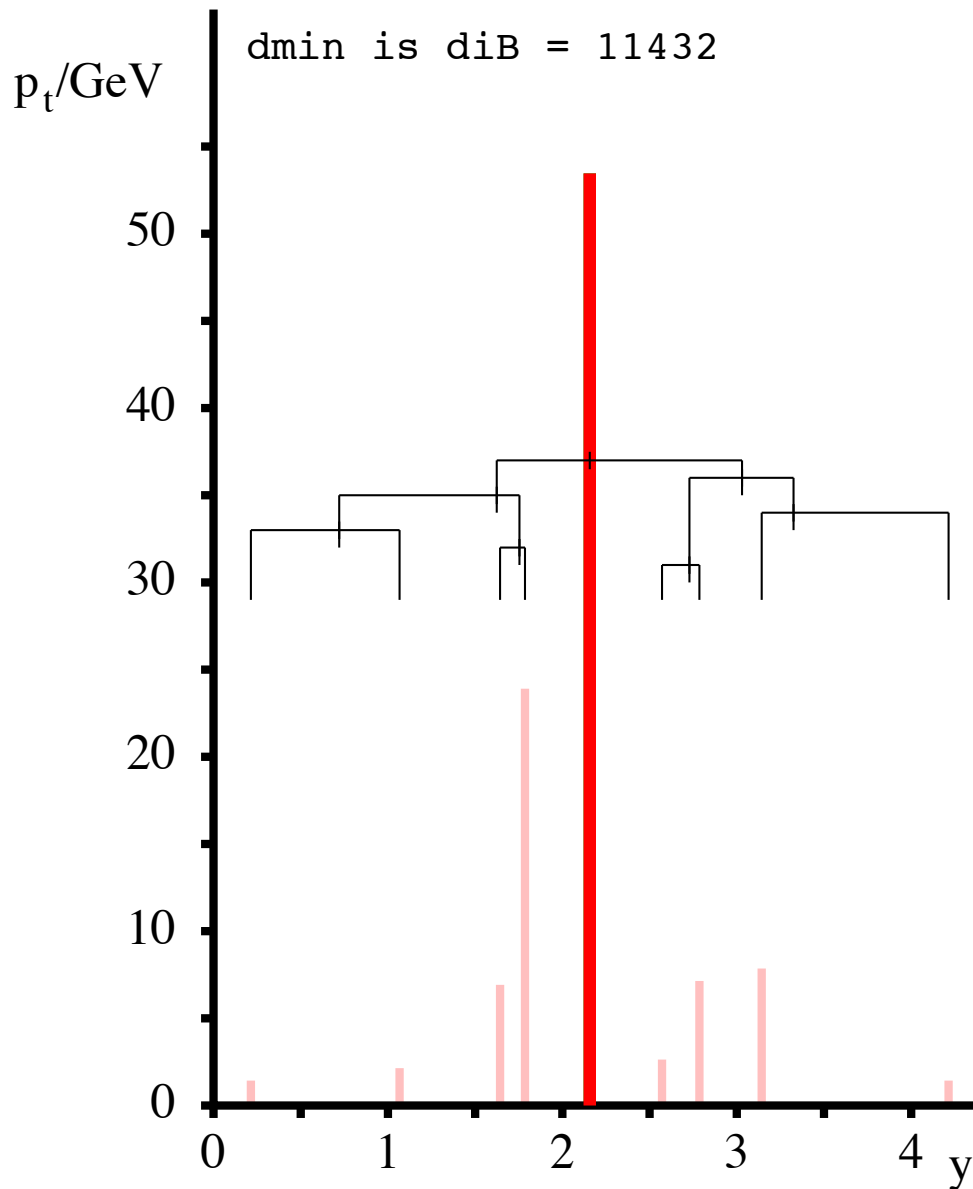
$k_t$  clusters soft “junk” early on in the clustering

*Its last step is to merge two hard pieces. Easily undone to identify underlying kinematics*

# Identifying jet substructure: try out $k_t$

## $k_t$ algorithm

$d_{\min}$  is  $d_{iB} = 11432$



How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

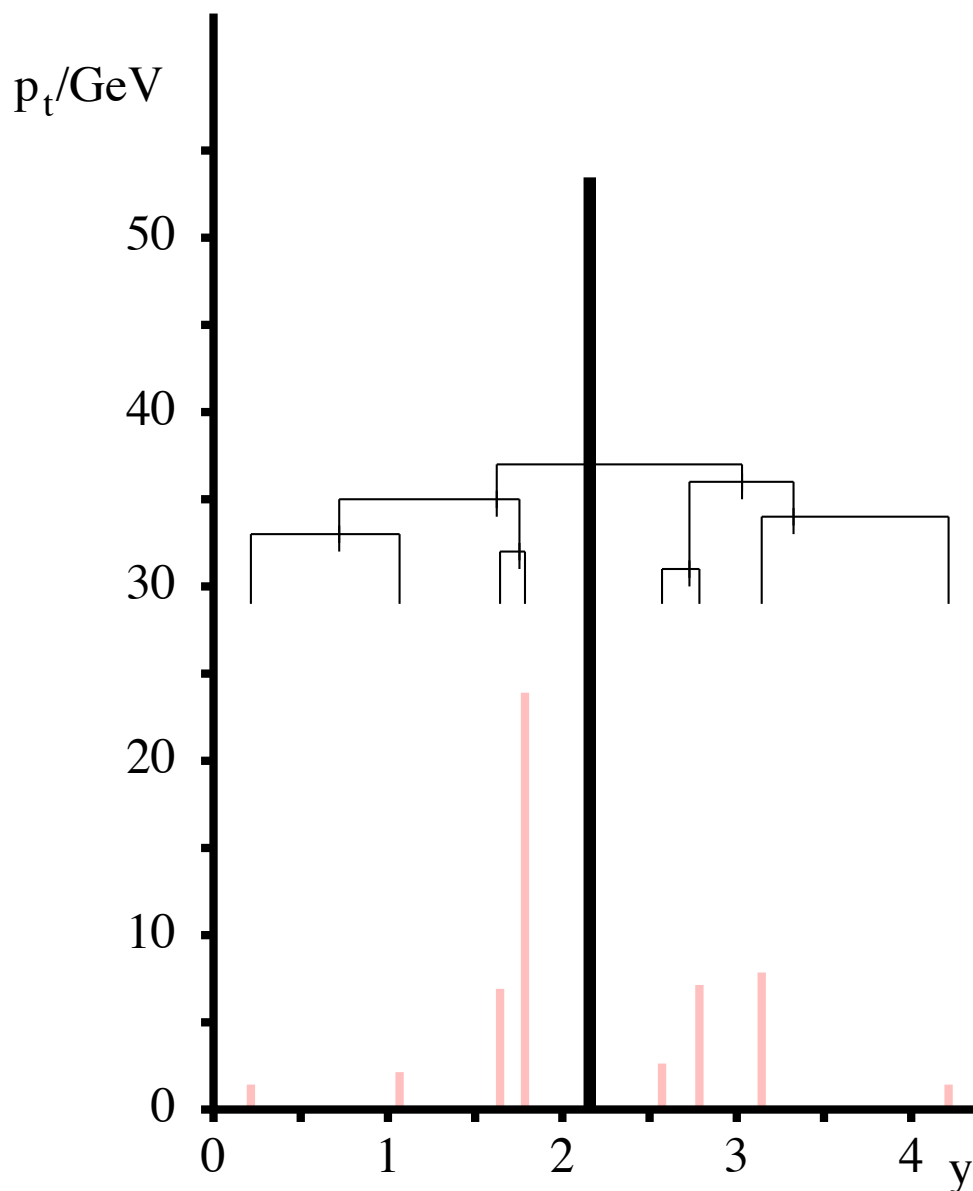
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# Identifying jet substructure: try out $k_t$

## $k_t$ algorithm



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This meant it was the first algorithm to be used for jet substructure.

Seymour '93

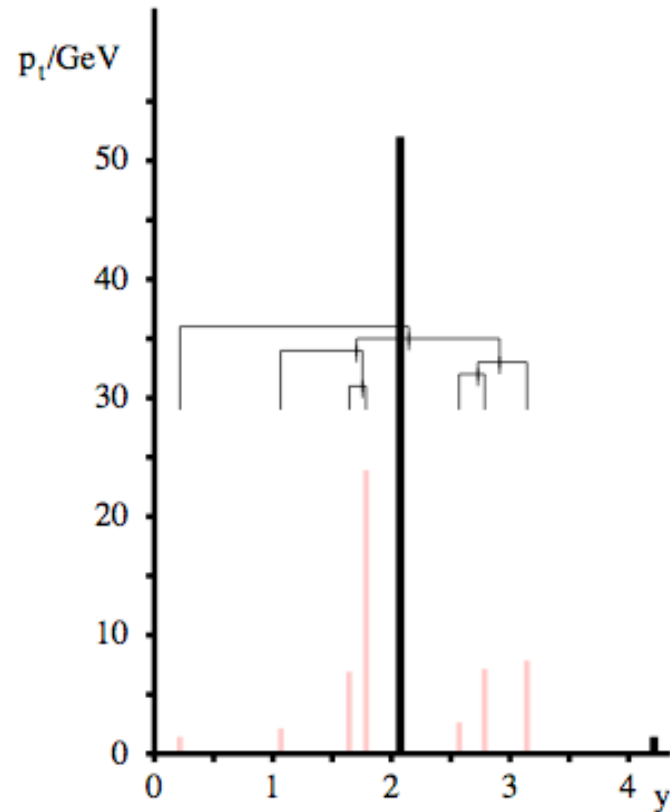
Butterworth, Cox & Forshaw '02

# Cambridge/Aachen



# Hierarchical substructure

## Cambridge/Aachen

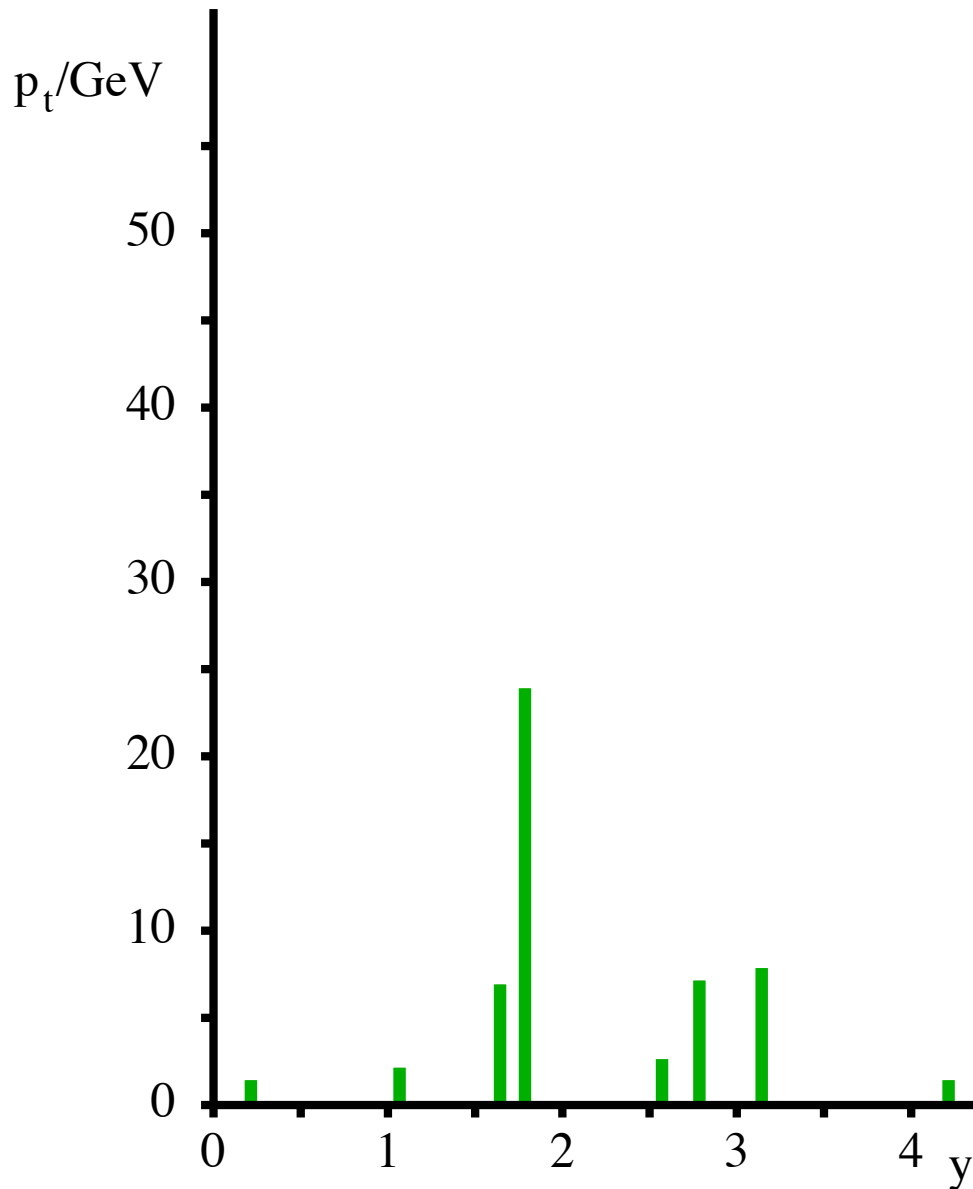


C/A distance measure

$$d_{ij} = \frac{\Delta y^2 + \Delta \phi^2}{R^2}$$

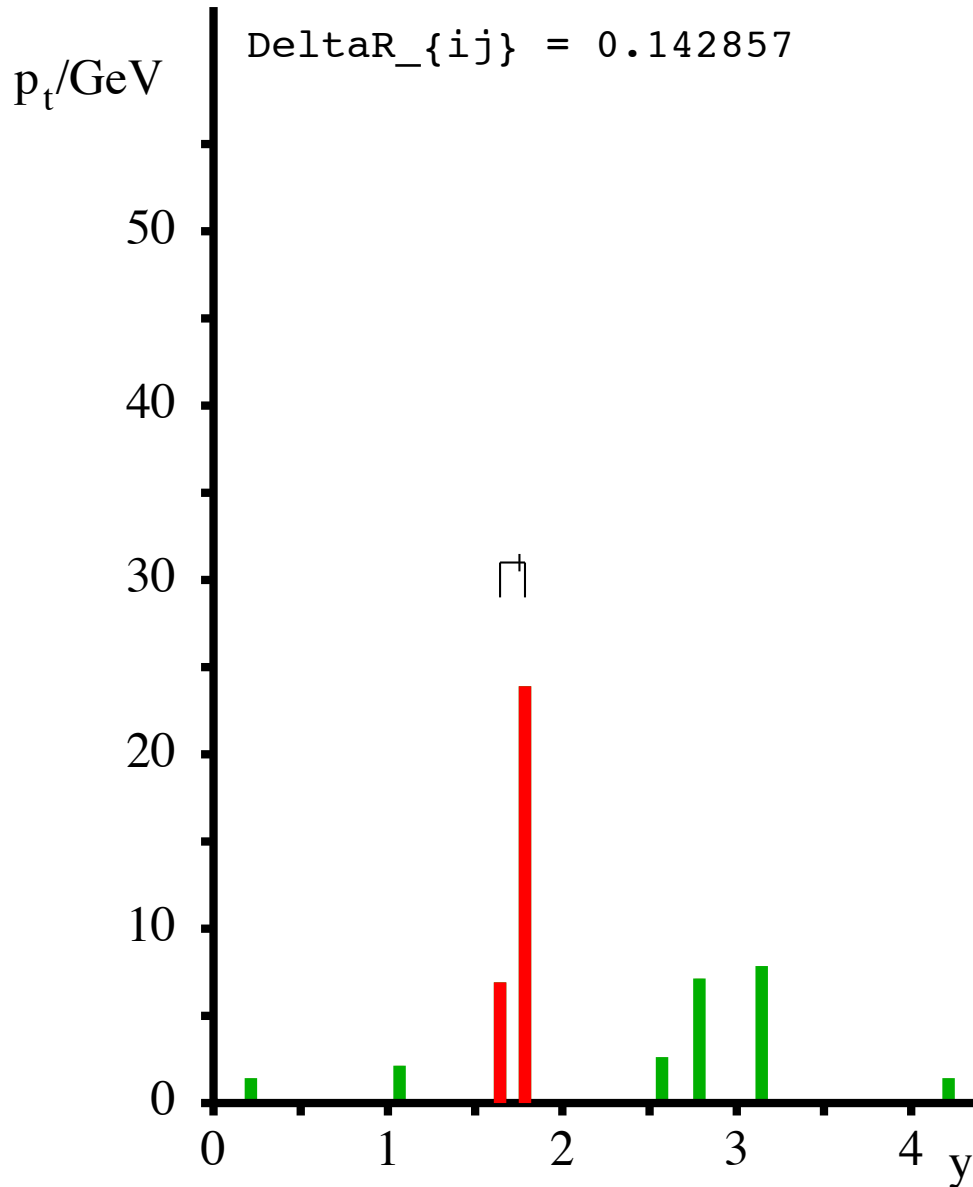
Cluster by merging  
the **closest** particles

## Cambridge/Aachen algorithm



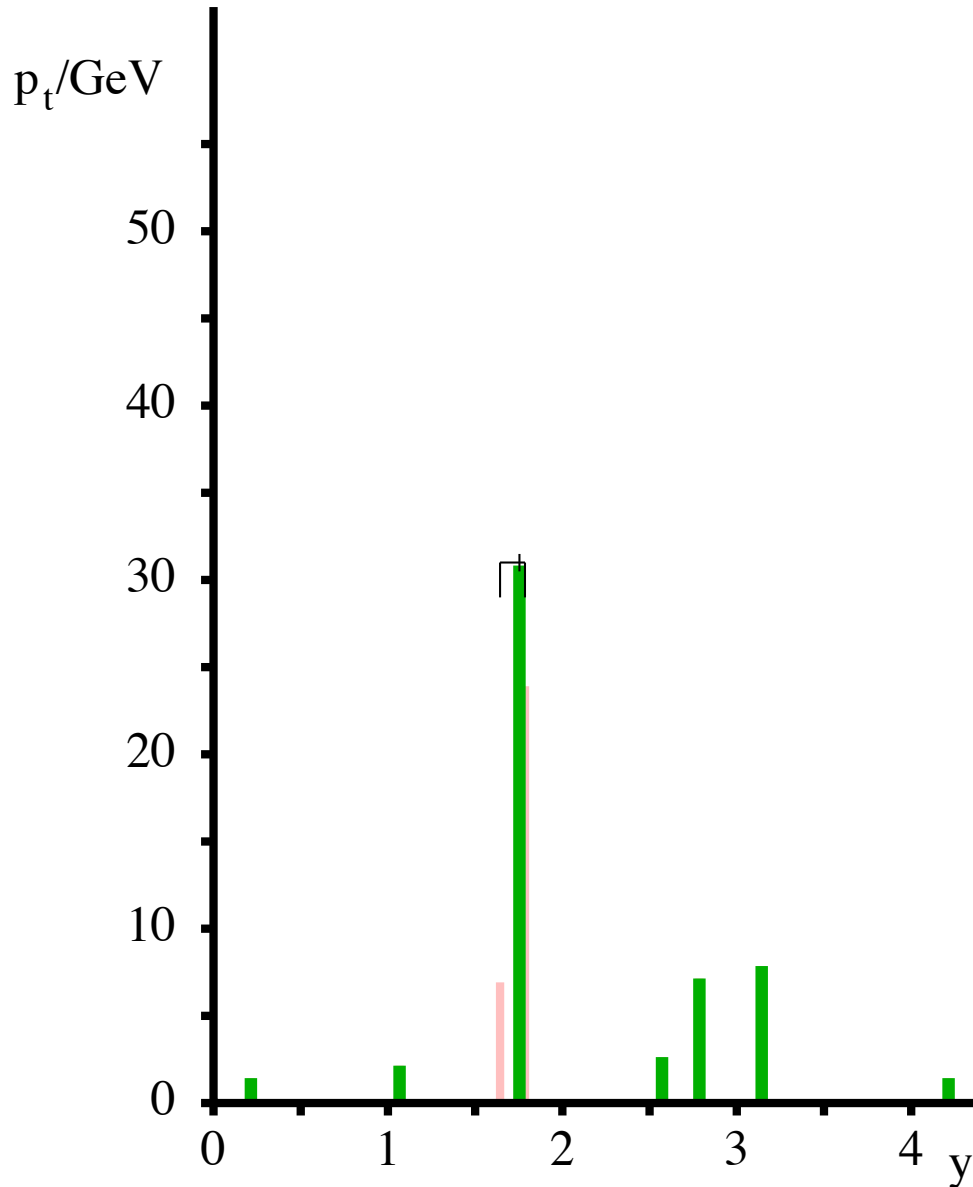
How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

## Cambridge/Aachen algorithm



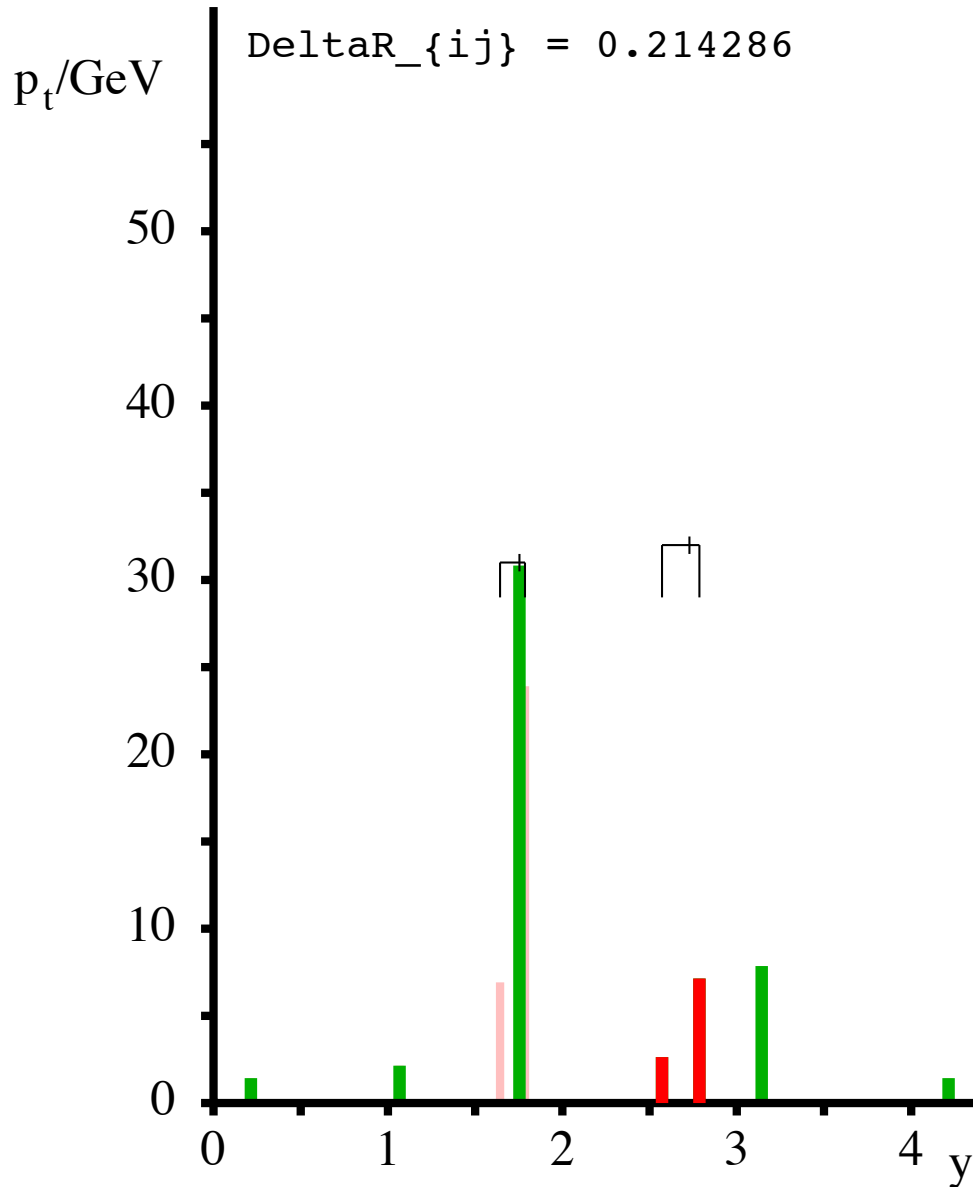
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## Cambridge/Aachen algorithm



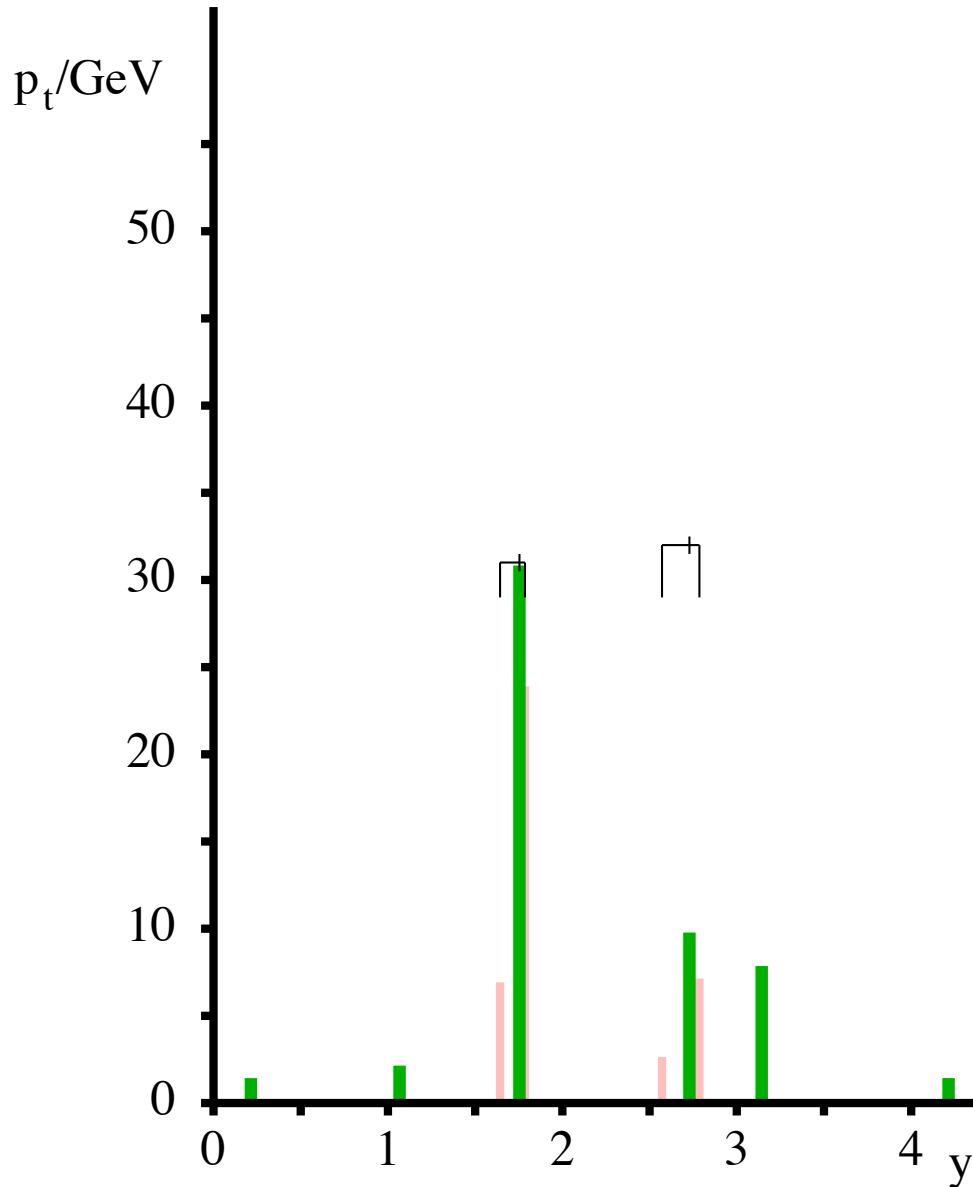
How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

## Cambridge/Aachen algorithm



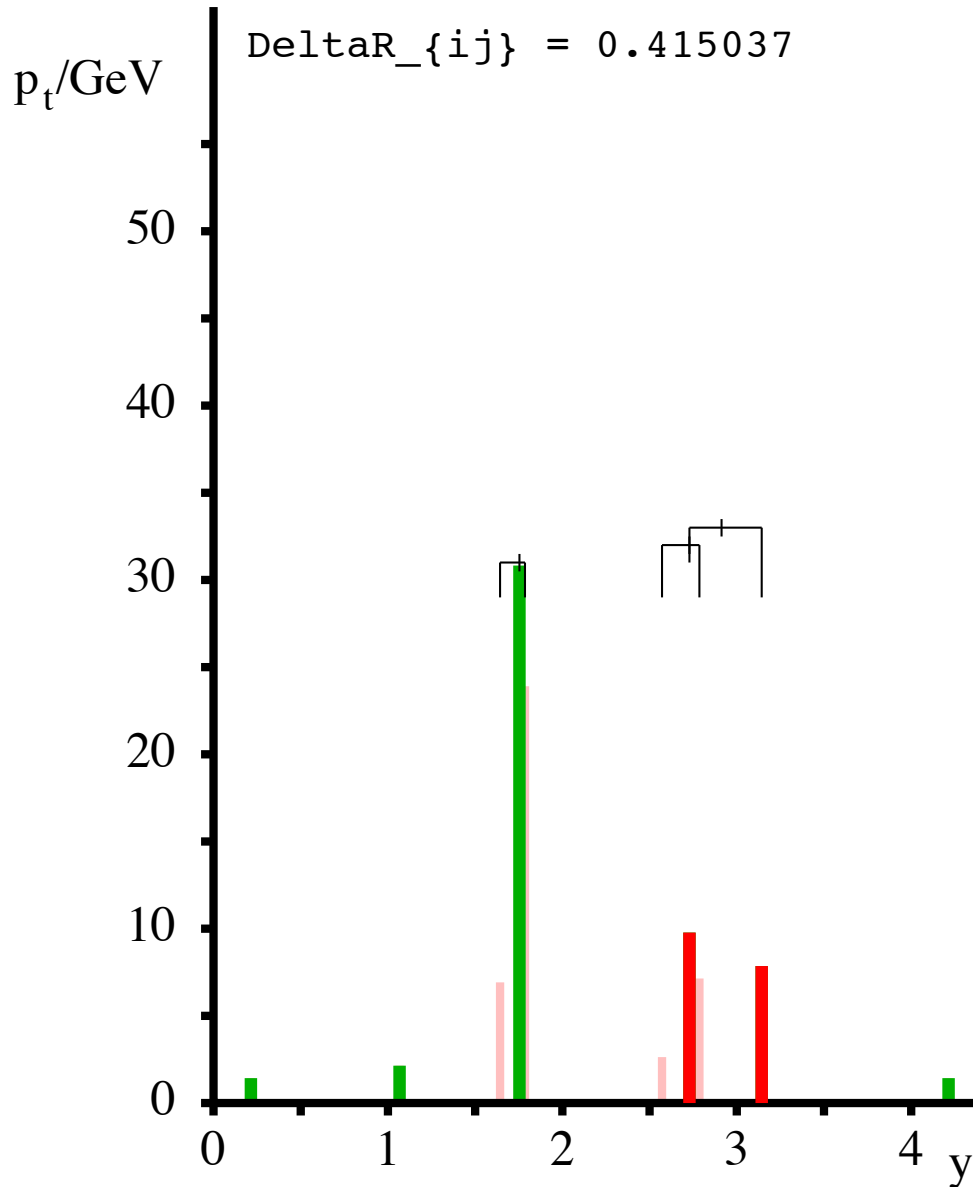
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## Cambridge/Aachen algorithm



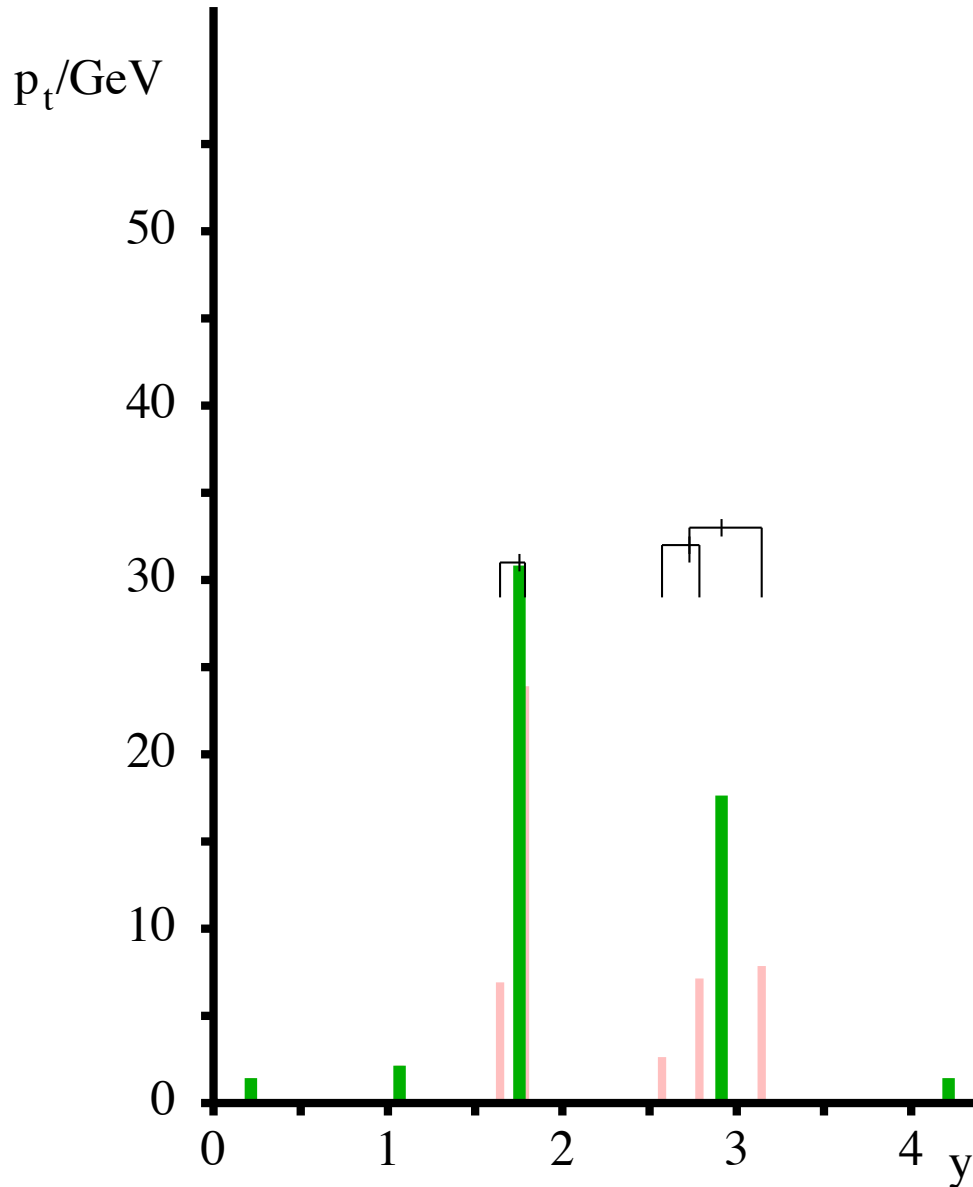
How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

## Cambridge/Aachen algorithm



How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

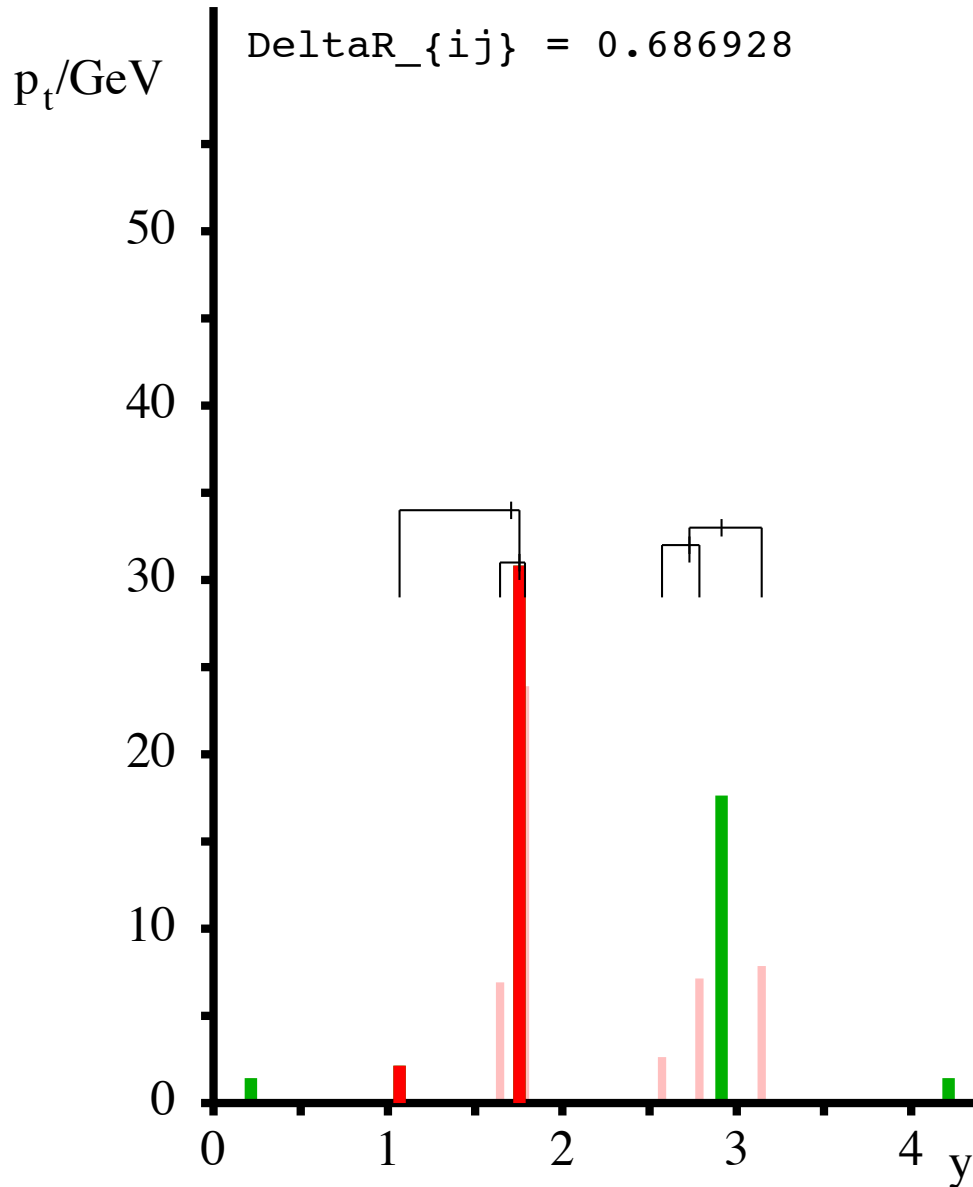
## Cambridge/Aachen algorithm



How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

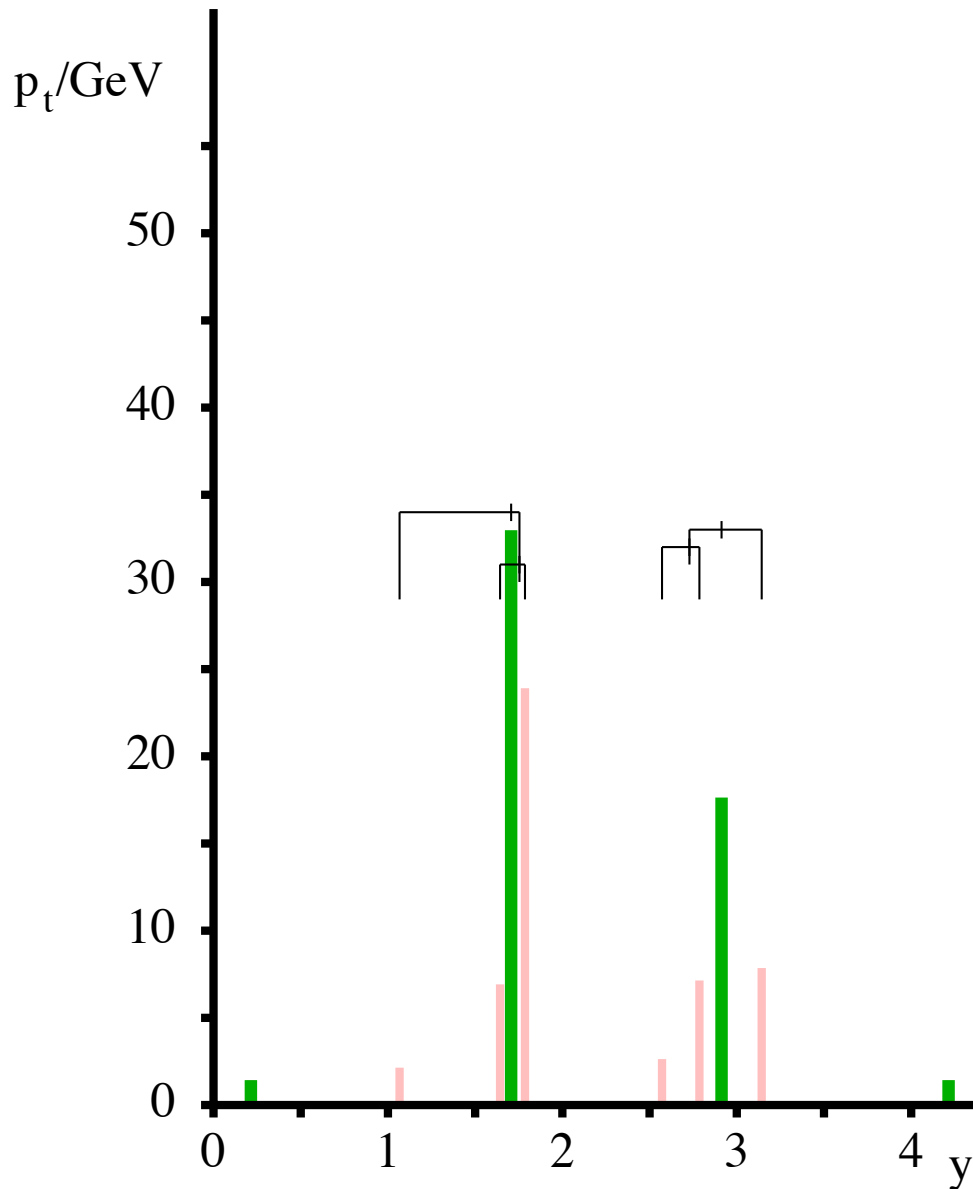


## Cambridge/Aachen algorithm



How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

## Cambridge/Aachen algorithm

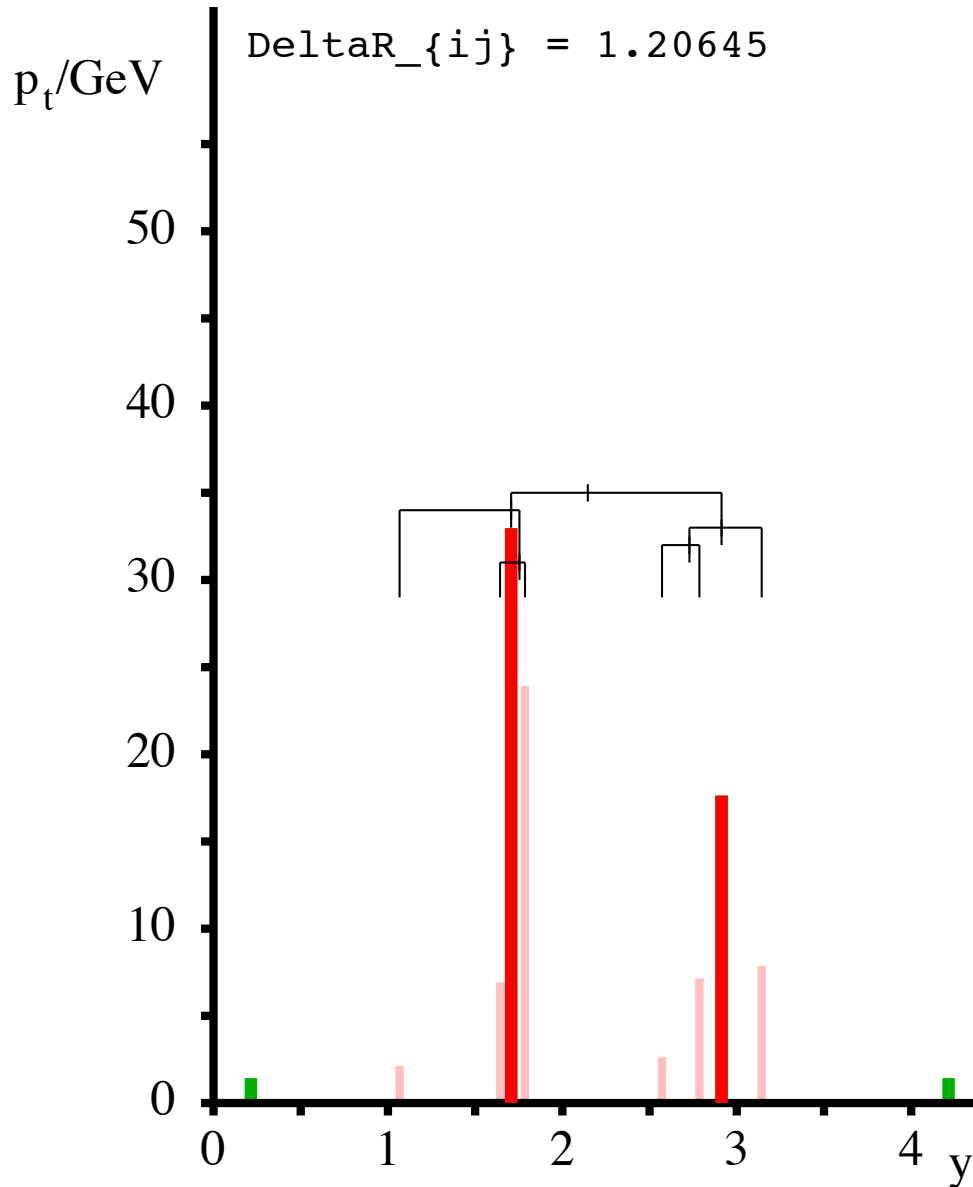


How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

**C/A identifies two hard blobs with limited soft contamination**

# Identifying jet substructure: Cam/Aachen

## Cambridge/Aachen algorithm

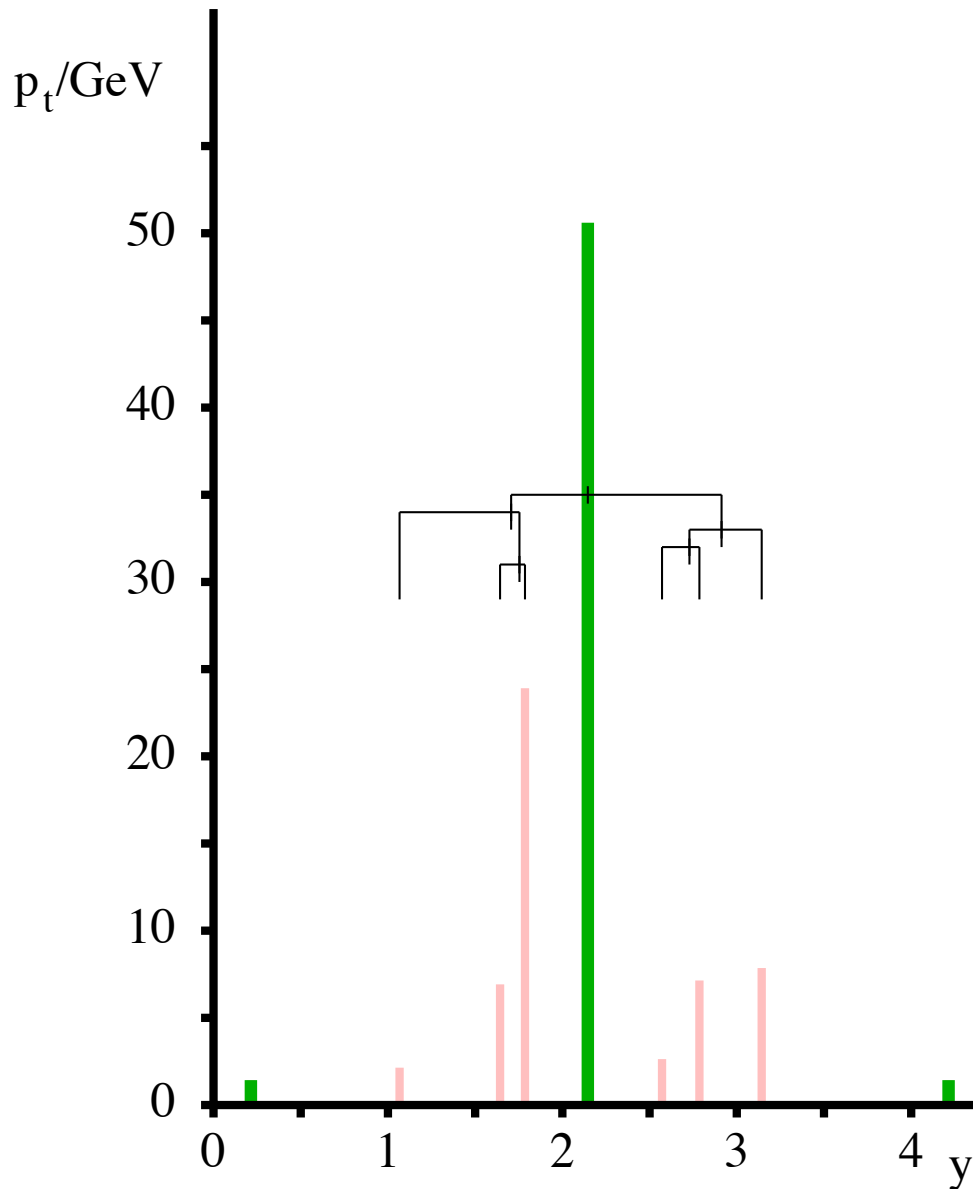


How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

C/A identifies two hard blobs with limited soft contamination, **joins them**

# Identifying jet substructure: Cam/Aachen

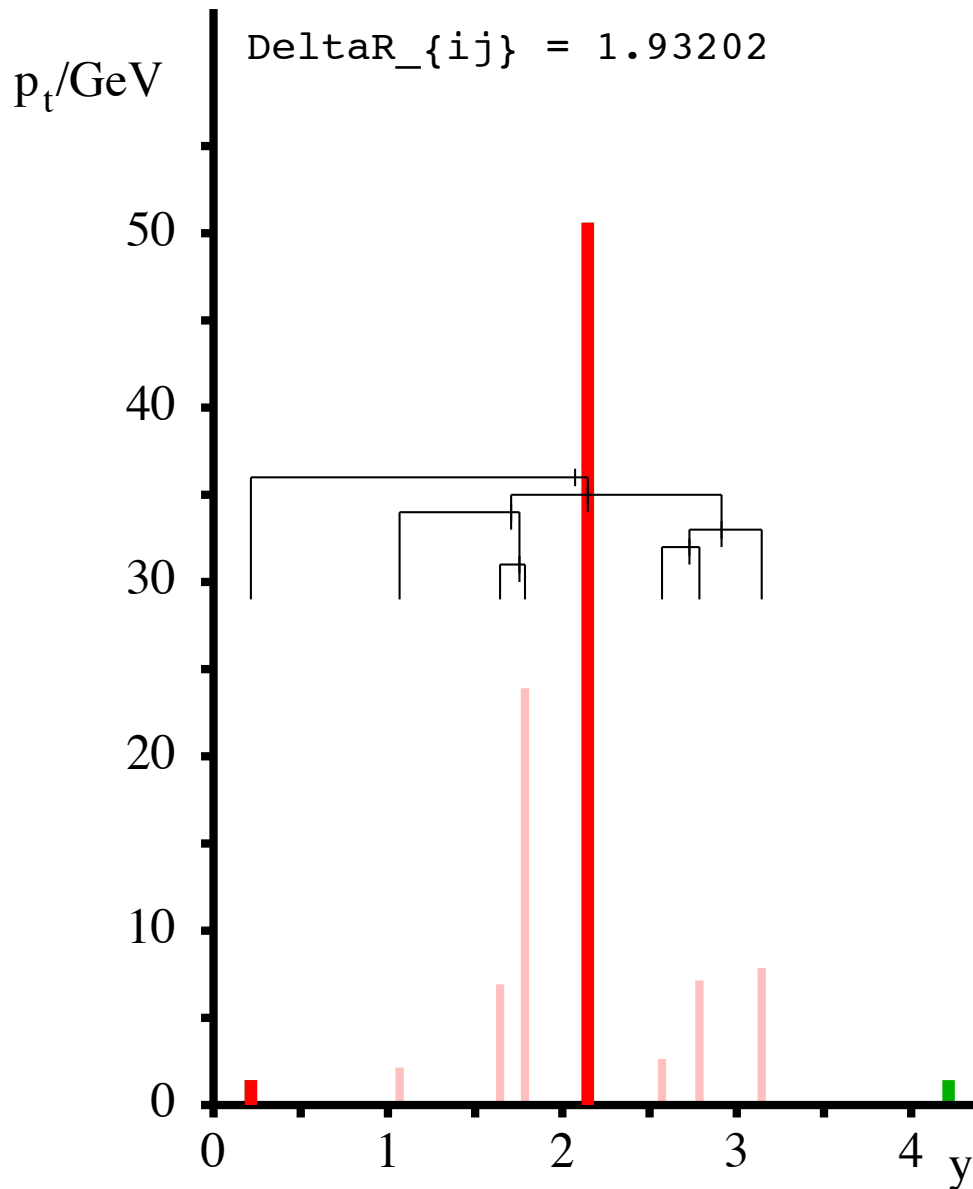
## Cambridge/Aachen algorithm



How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

C/A identifies two hard blobs with limited soft contamination, joins them

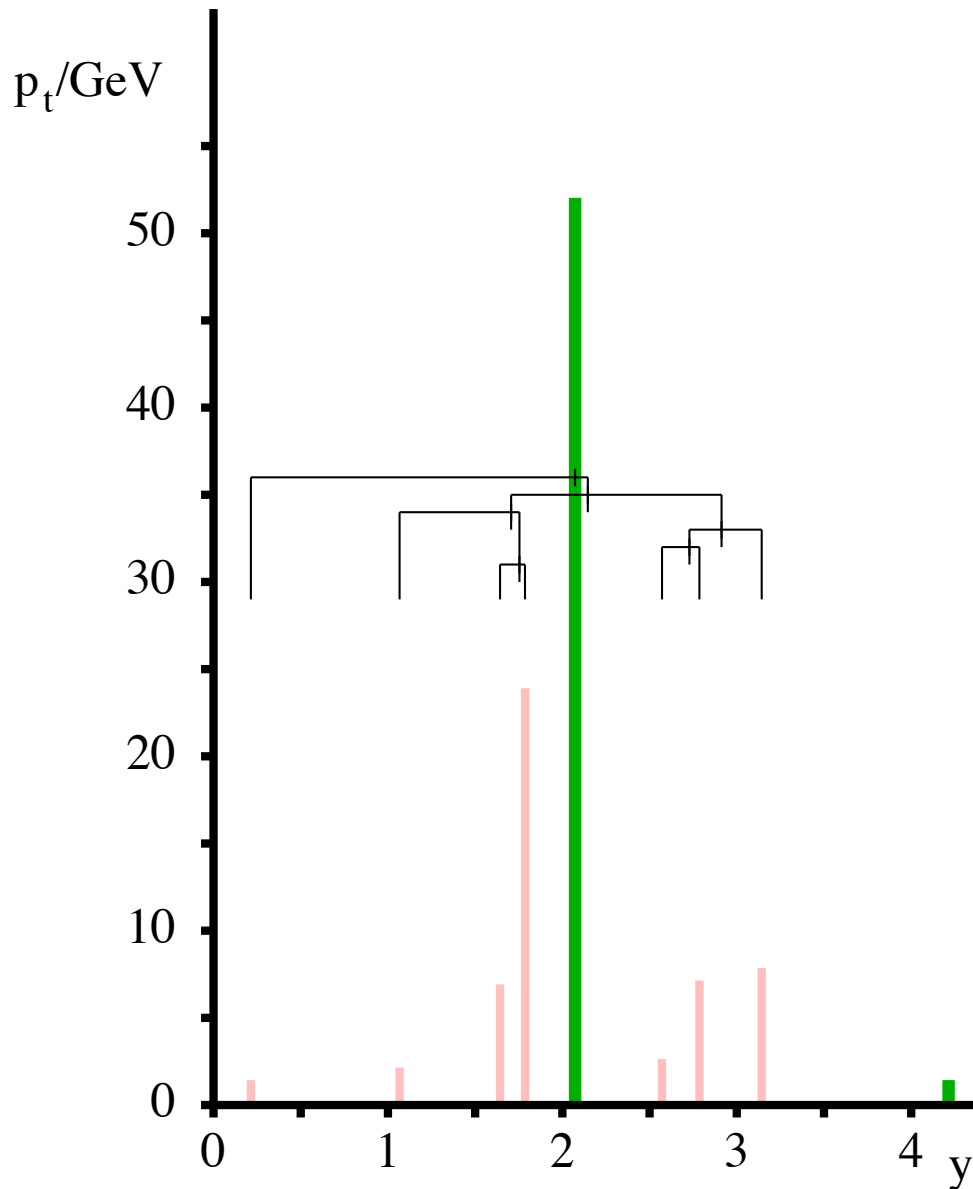
## Cambridge/Aachen algorithm



How well can an algorithm identify the “blobs” of energy inside a jet that come from different partons?

C/A identifies two hard blobs with limited soft contamination, joins them, and then adds in remaining soft junk

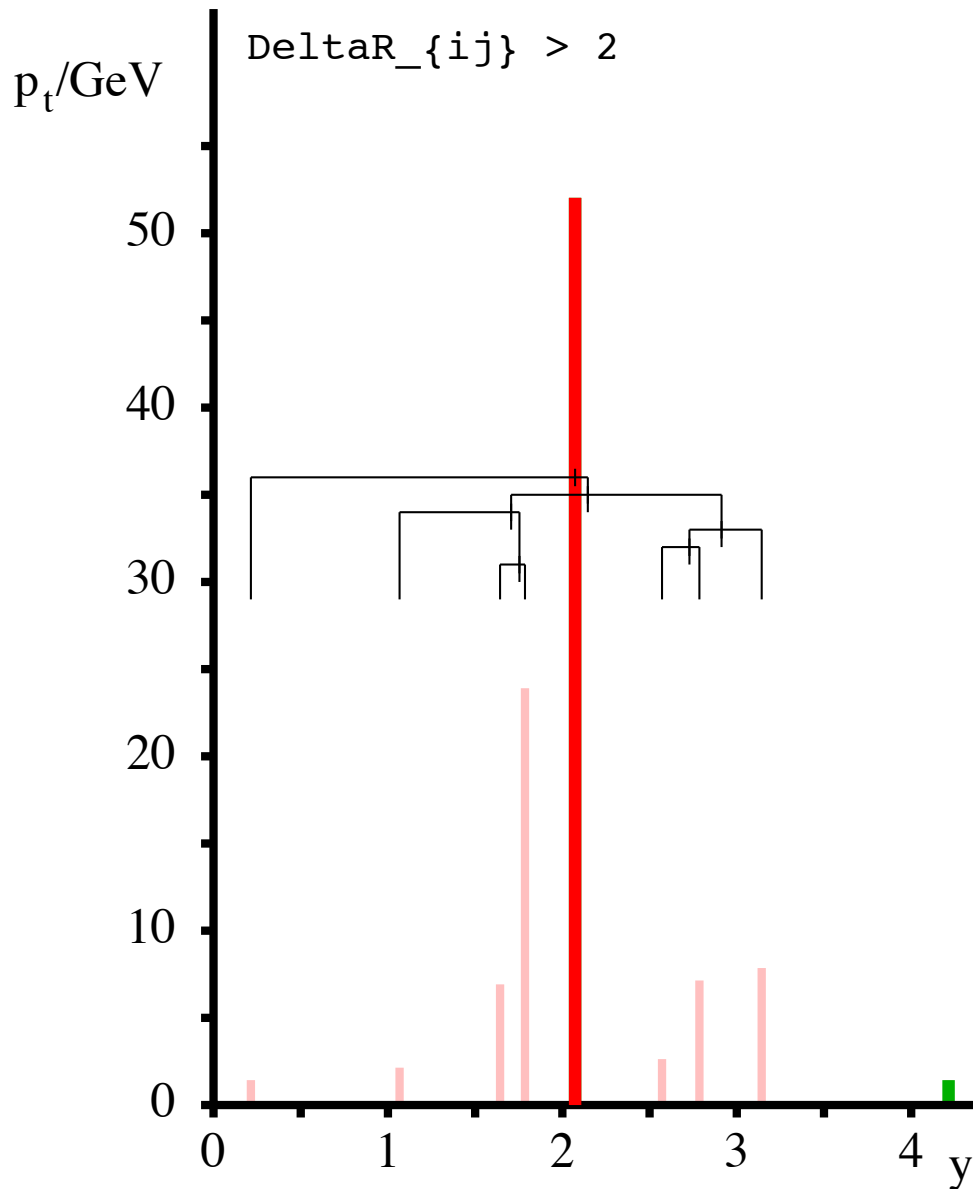
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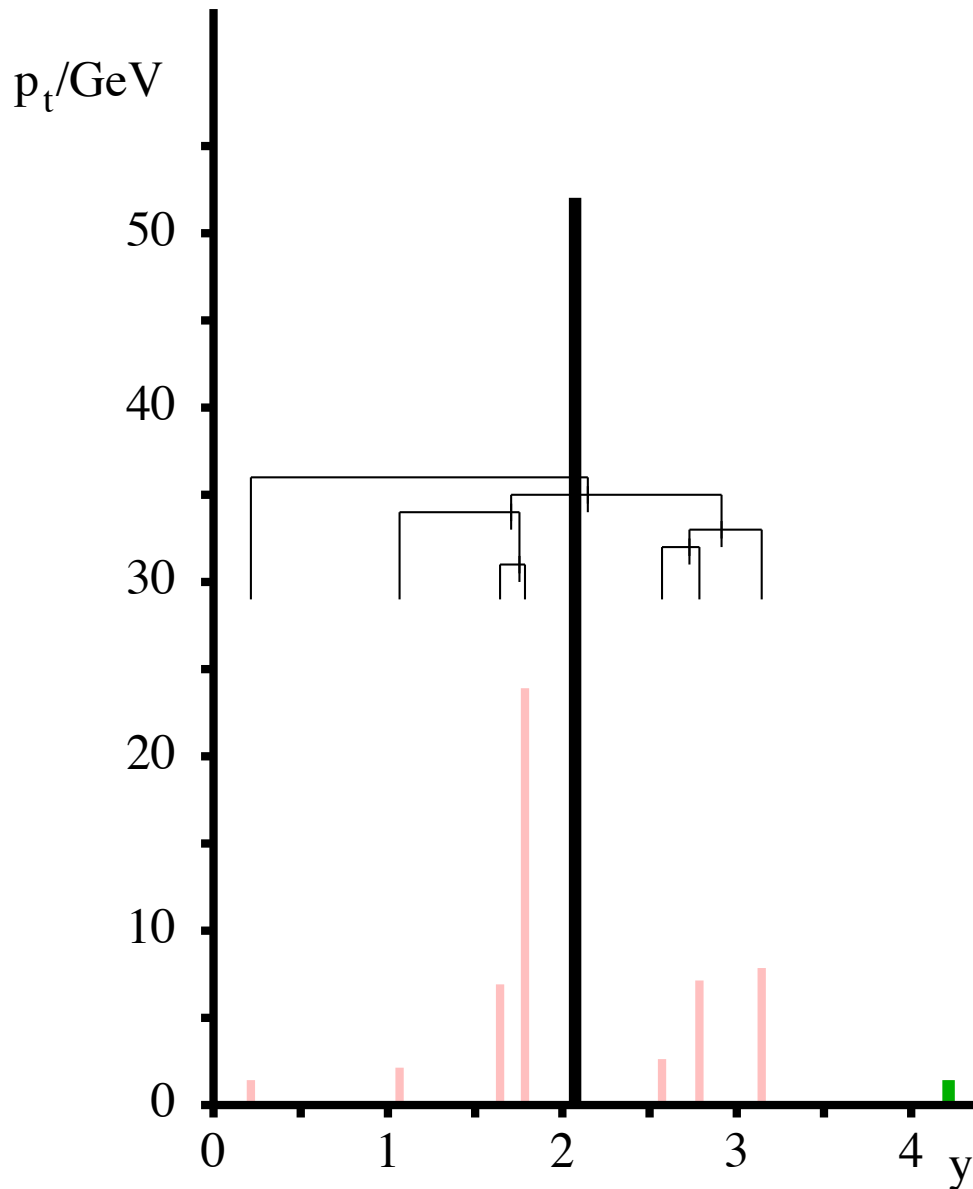
## Cambridge/Aachen algorithm



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## Cambridge/Aachen algorithm

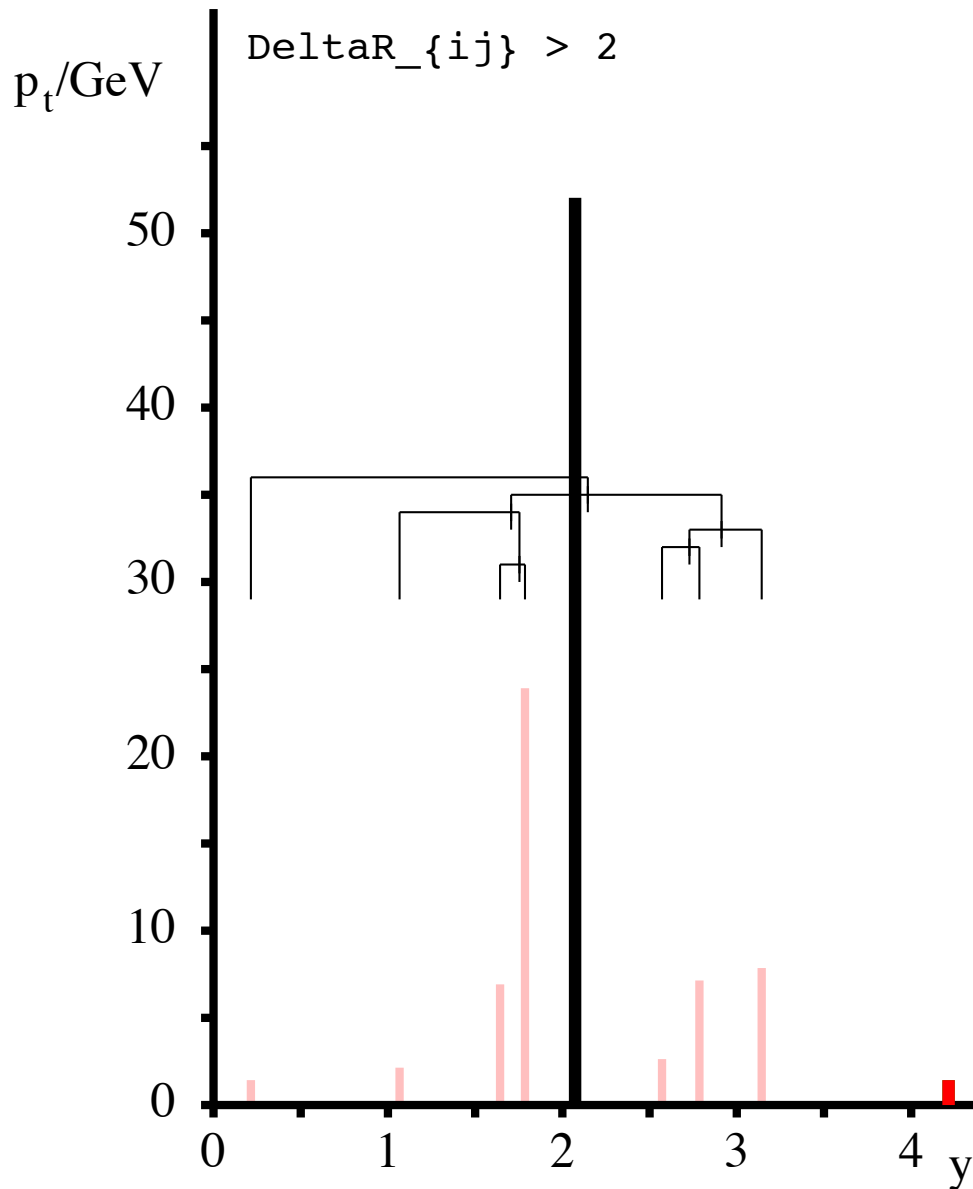


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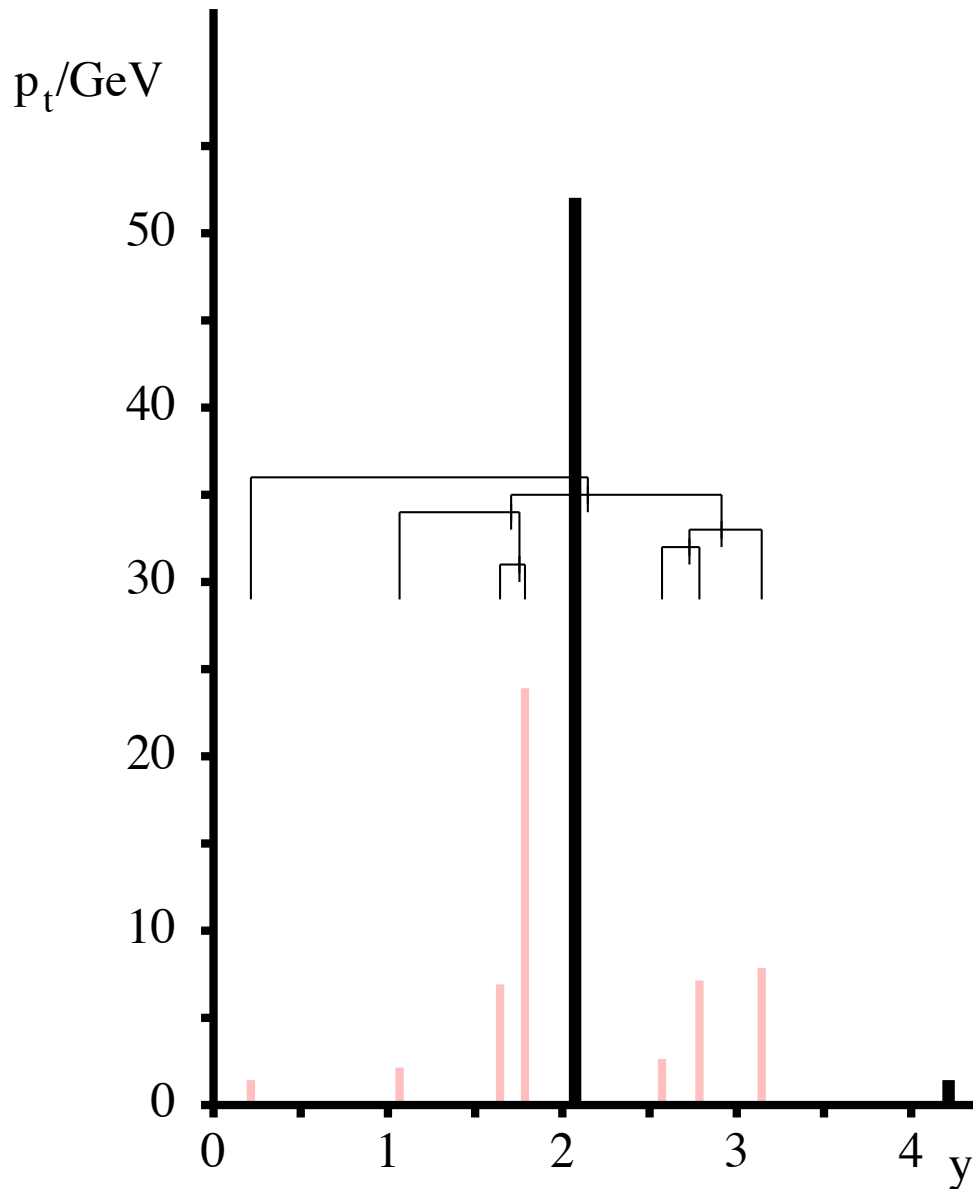
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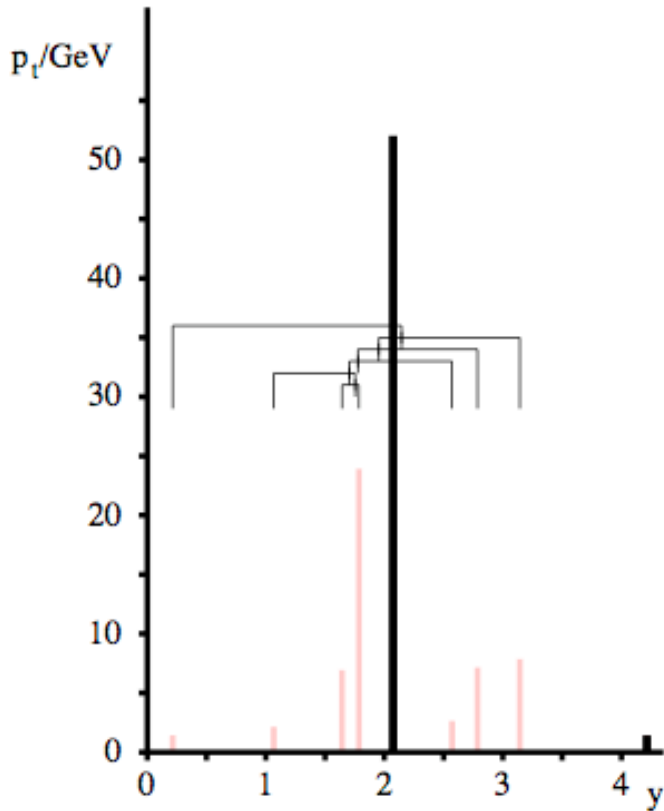
C/A identifies two hard blobs with limited soft contamination, joins them, and then adds in remaining soft junk

The interesting substructure is buried inside the clustering sequence — **it's less contaminated by soft junk, but needs to be pulled out with special techniques**

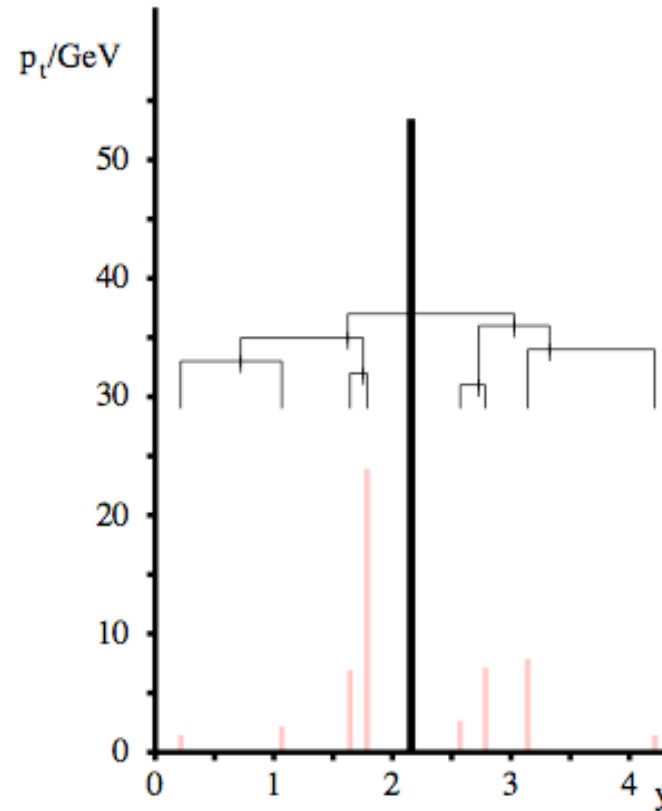
Butterworth, Davison, Rubin & GPS '08  
Kaplan, Schwartz, Reherman & Tweedie '08  
Butterworth, Ellis, Rubin & GPS '09  
Ellis, Vermilion & Walsh '09

# Hierarchical substructure

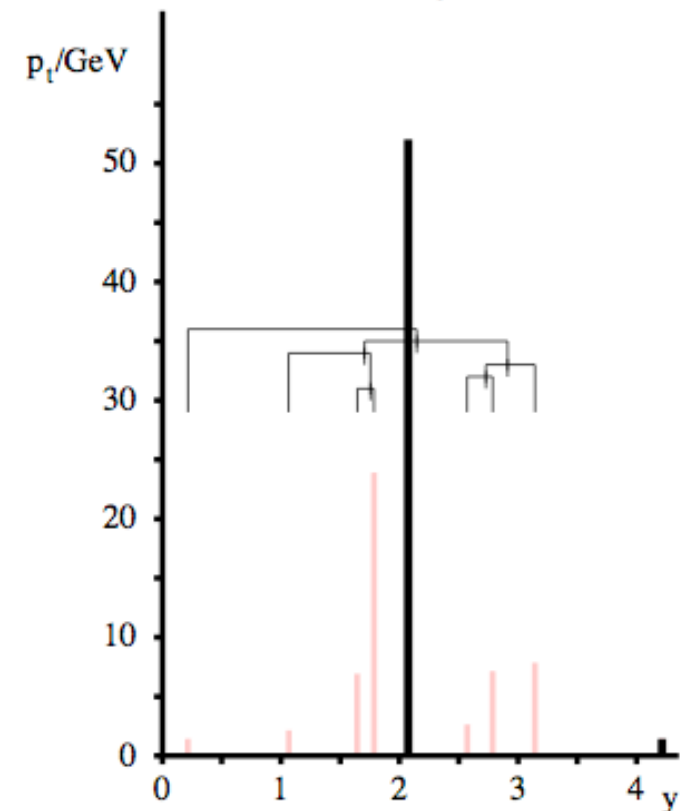
anti- $k_t$  algorithm



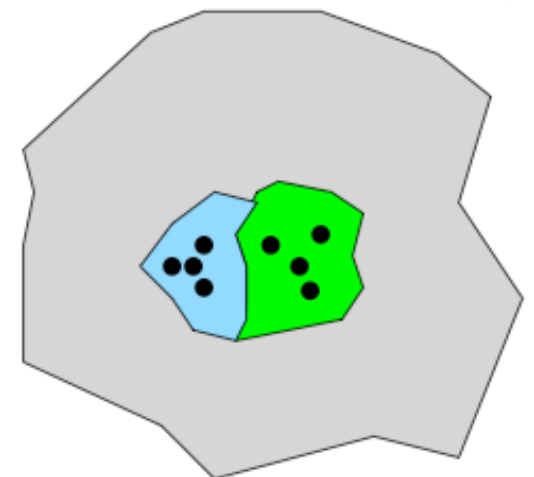
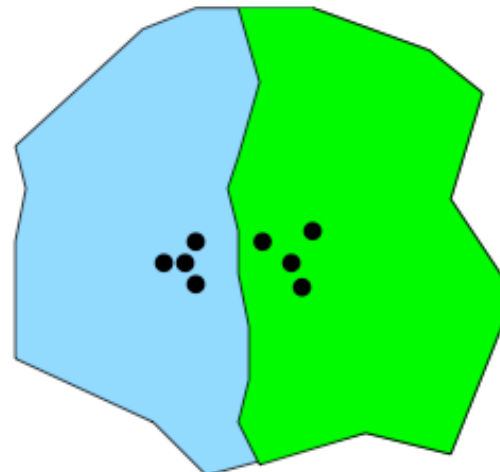
$k_t$  algorithm



Cambridge/Aachen



Undo the last  
clustering step(s)



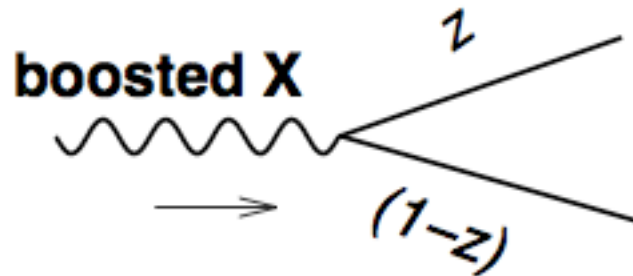
# The IRC safe algorithms

	Speed	Regularity	UE contamination	Backreaction	Hierarchical substructure
$k_t$	☺ ☺ ☺	☂	☂ ☂	☁ ☁	☺ ☺ ☺ ☺
Cambridge /Aachen	☺ ☺ ☺	☂	☂	☁ ☁	☺ ☺ ☺
anti- $k_t$	☺ ☺ ☺	☺ ☺ ☺ ☺	☁ / ☺	☺ ☺ ☺ ☺	✗
SISCone	☺ ☺	☁	☺ ☺ ☺ ☺	☁	✗

Array of tools with different characteristics.  
Pick the right one for the job

# QCD v. heavy decay

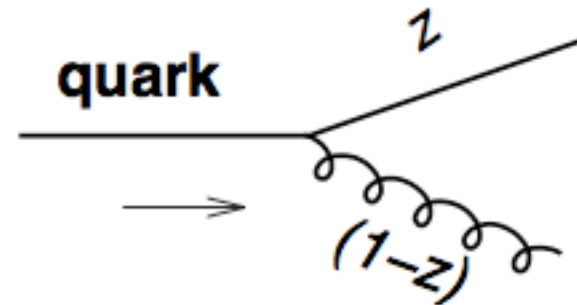
A possible approach for reducing the QCD background is to identify the two prongs of the heavy particle decay, and put a cut on their momentum fraction



**Signal:**

$$P(z) \sim 1$$

Will split mainly  
**symmetrically**



**Background:**

$$P(z) \sim \frac{1+z^2}{1-z} \qquad P(z) \sim \frac{1+(1-z)^2}{z}$$

Will split mainly  
**asymmetrically**

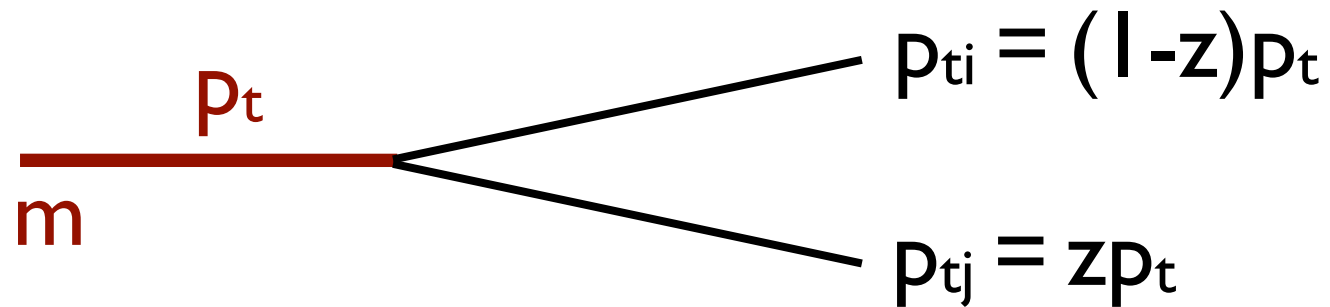
**Potential tagger: asymmetric splitting**

Possibly implemented via a cut on

$$y = \min(p_{ti}^2, p_{tj}^2) \frac{\Delta R_{ij}^2}{m^2} \simeq \frac{\min(p_{ti}, p_{tj})}{\max(p_{ti}, p_{tj})}$$

# Splittings and distances

Quasi-collinear  
splitting ( $p_{tj} < p_{ti}$ )



Invariant mass: 
$$m^2 \simeq p_{ti}p_{tj}\Delta R_{ij}^2 = (1-z)zp_t^2\Delta R_{ij}^2$$

$k_t$  distance: 
$$d_{ij}^{(p_{tj} < p_{ti})} \simeq z^2 p_t^2 \Delta R_{ij}^2 \simeq \frac{z}{1-z} m^2$$

For a given mass, the **background** will have **smaller distance**  $d_{ij}$  than the signal, i.e. it will tend to **cluster earlier** in the  $k_t$  algorithm

## Potential tagger: last clustering in $k_t$ algorithm

This is where the hierarchy of the  $k_t$  algorithm becomes relevant. QCD radiation is clustered first, and only at the end the symmetric, large-angle splittings due to decays are reclustered

# Alternative algorithms

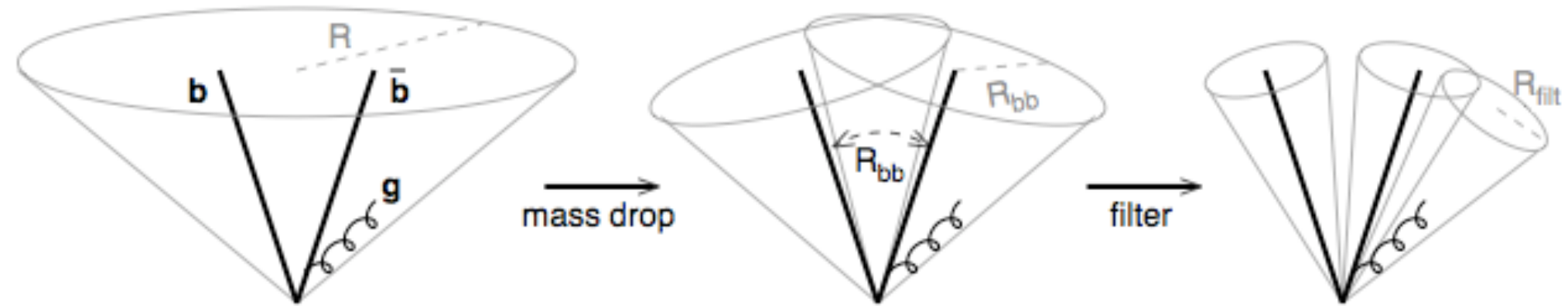
- ▶ Suppose that for some reasons (which will become clearer later) one does not wish to use the  $k_t$  algorithm
  - ▶ *One must then find a way to determine what the **relevant splitting** (i.e. the one due to the decay, not to QCD radiation) is.*

A possible approach is to use a **Mass-Drop** requirement: the clustering is **progressively undone**, and a splitting is **the relevant one** if **both subjects are much less massive than their combination**

$$pp \rightarrow ZH \rightarrow \nu\bar{\nu}b\bar{b}$$

# The BDRS tagger/groomer

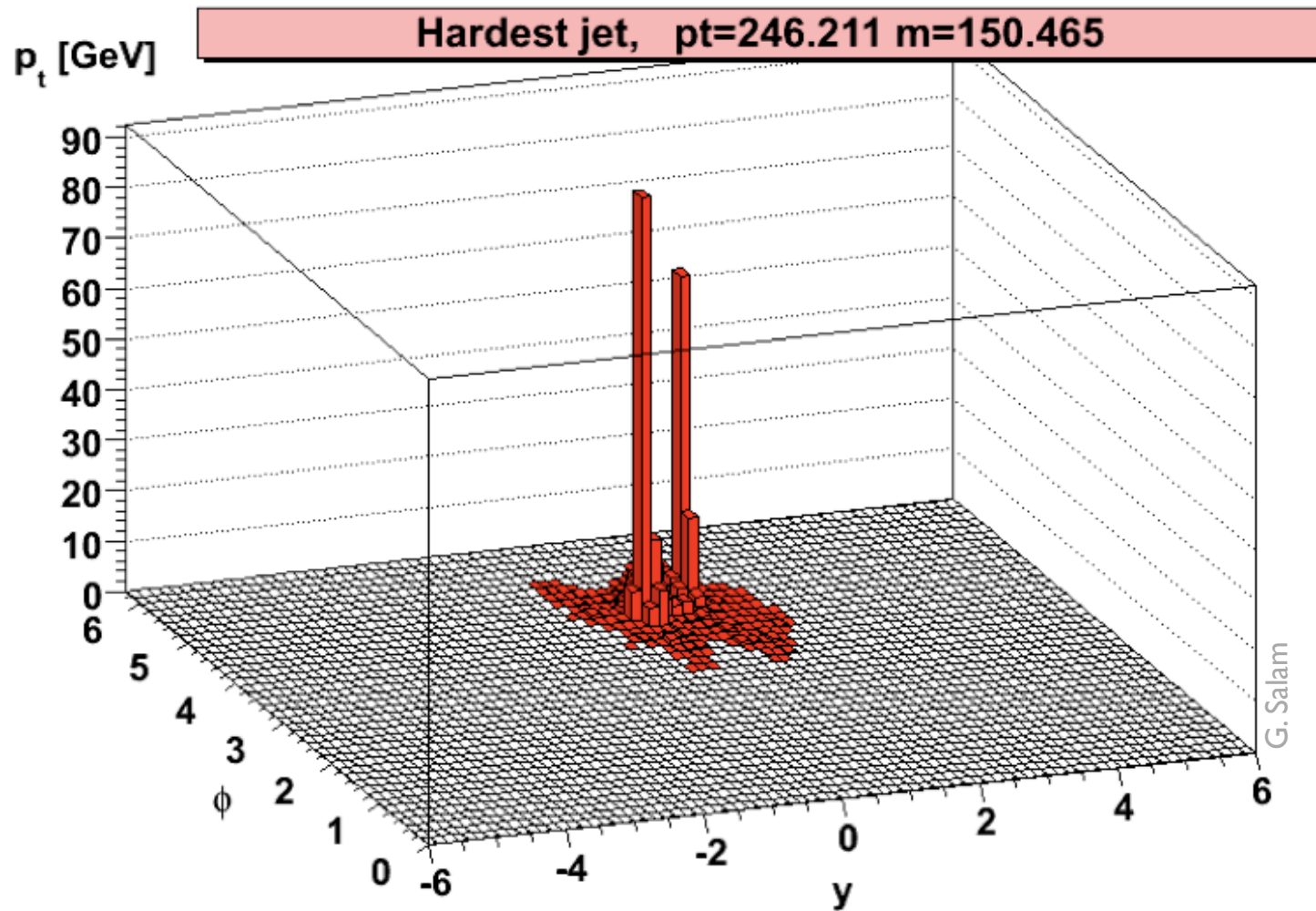
Butterworth, Davison, Rubin, Salam, 2008



- ▶ A two-prong tagger/groomer for boosted Higgs, which
  - ▶ Uses the **Cambridge/Aachen** algorithm (because it's 'physical')
  - ▶ Employs a **Mass-Drop** condition, as well as an **asymmetry cut** to find the **relevant splitting** (i.e. '**tag**' the heavy particle)
  - ▶ Includes a post-processing step, using '**filtering**' (introduced in the same paper) to clean as much as possible the resulting jets of UE contamination ('**grooming**')



$$pp \rightarrow ZH \rightarrow \nu\bar{\nu}b\bar{b}$$

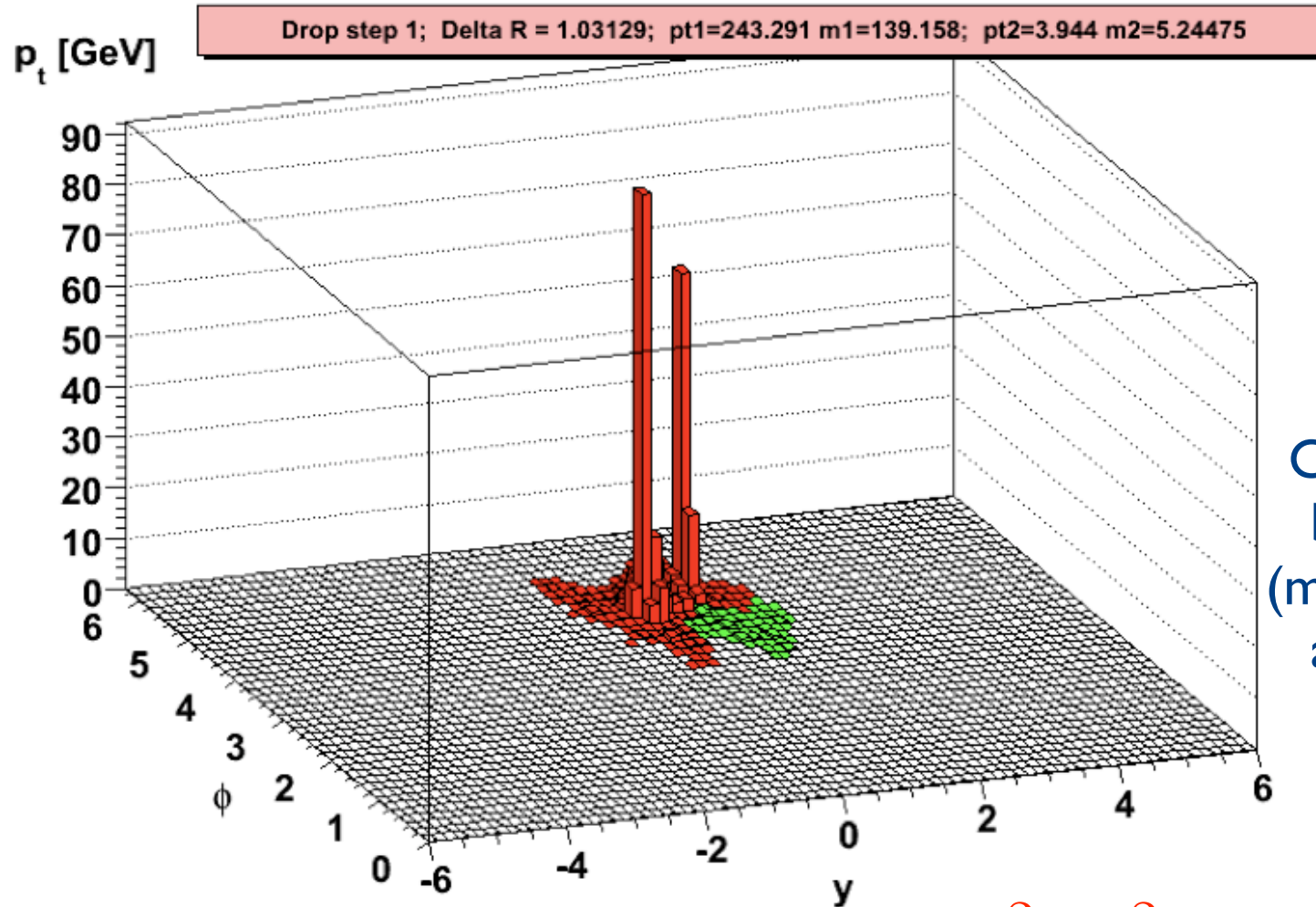


Start with the  
hardest jet

Use C/A with  
large  $R=1.2$

$m_j = 150$  GeV

$pp \rightarrow ZH \rightarrow \nu\nu b\bar{b}$

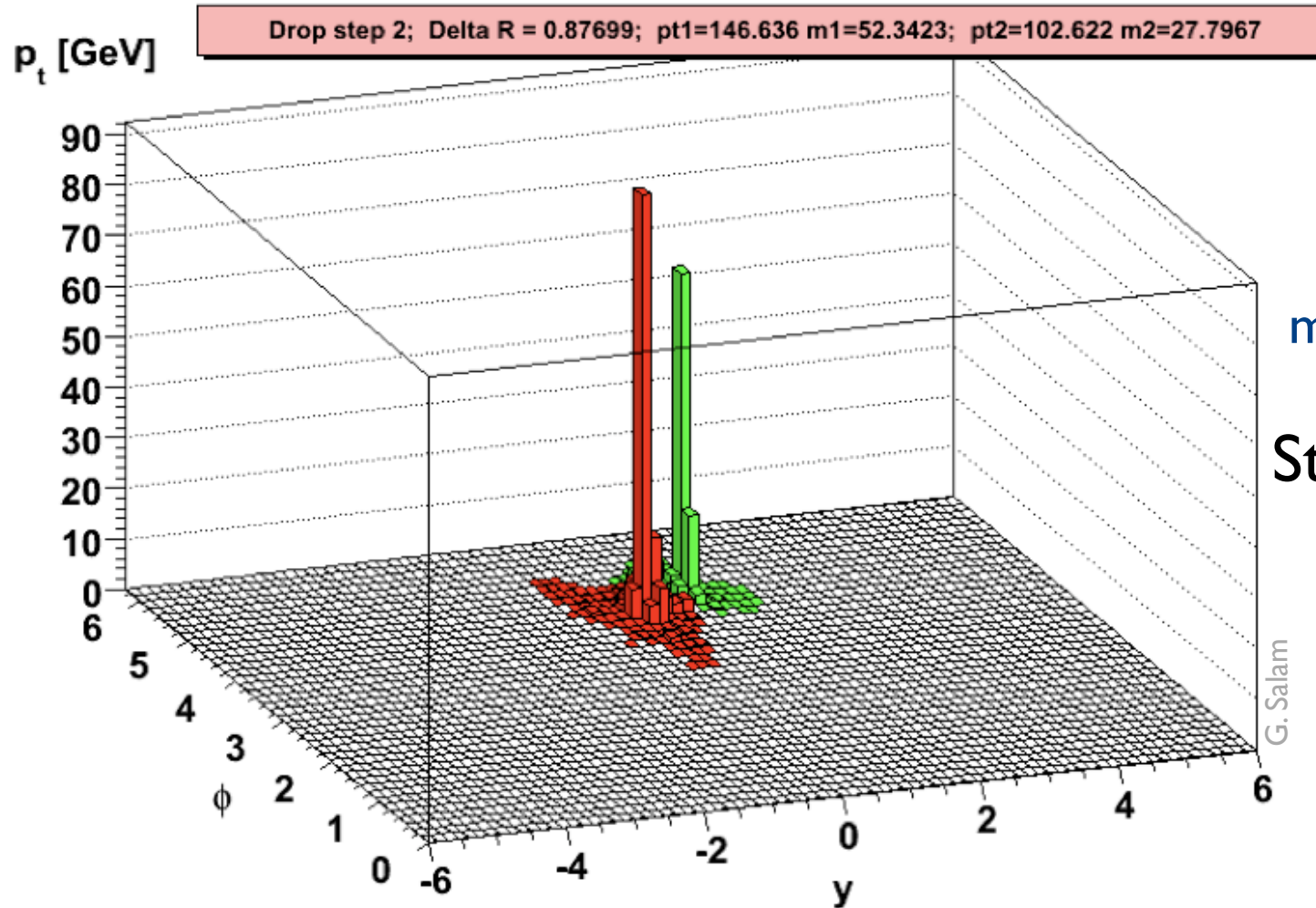


Undo last step of clustering

Check how the mass splits between the two subjects ( $m_1 = 139$  GeV,  $m_2 = 5$  GeV) and how asymmetric the splitting is

If  $\frac{\max(m_1, m_2)}{m_j} > \mu$  or  $\frac{\min(p_{t1}^2, p_{t2}^2)}{m_j^2} \Delta R_{12}^2 < y_{cut}$  repeat

$pp \rightarrow ZH \rightarrow \nu\nu b\bar{b}$

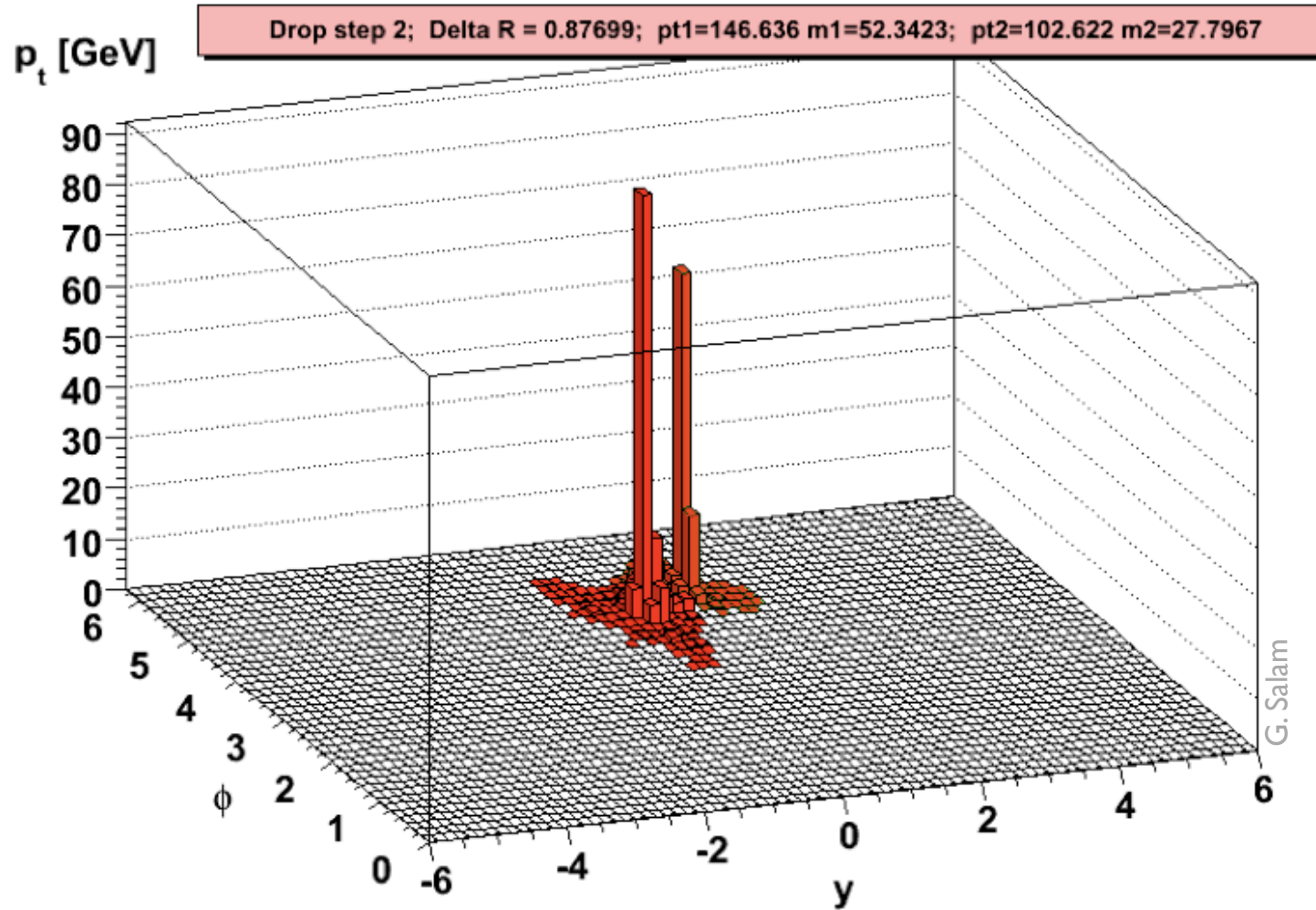


$m_1 = 52 \text{ GeV}, m_2 = 28 \text{ GeV}$

Stop when a **large mass drop** is observed  
(and **recombine** these two jets)

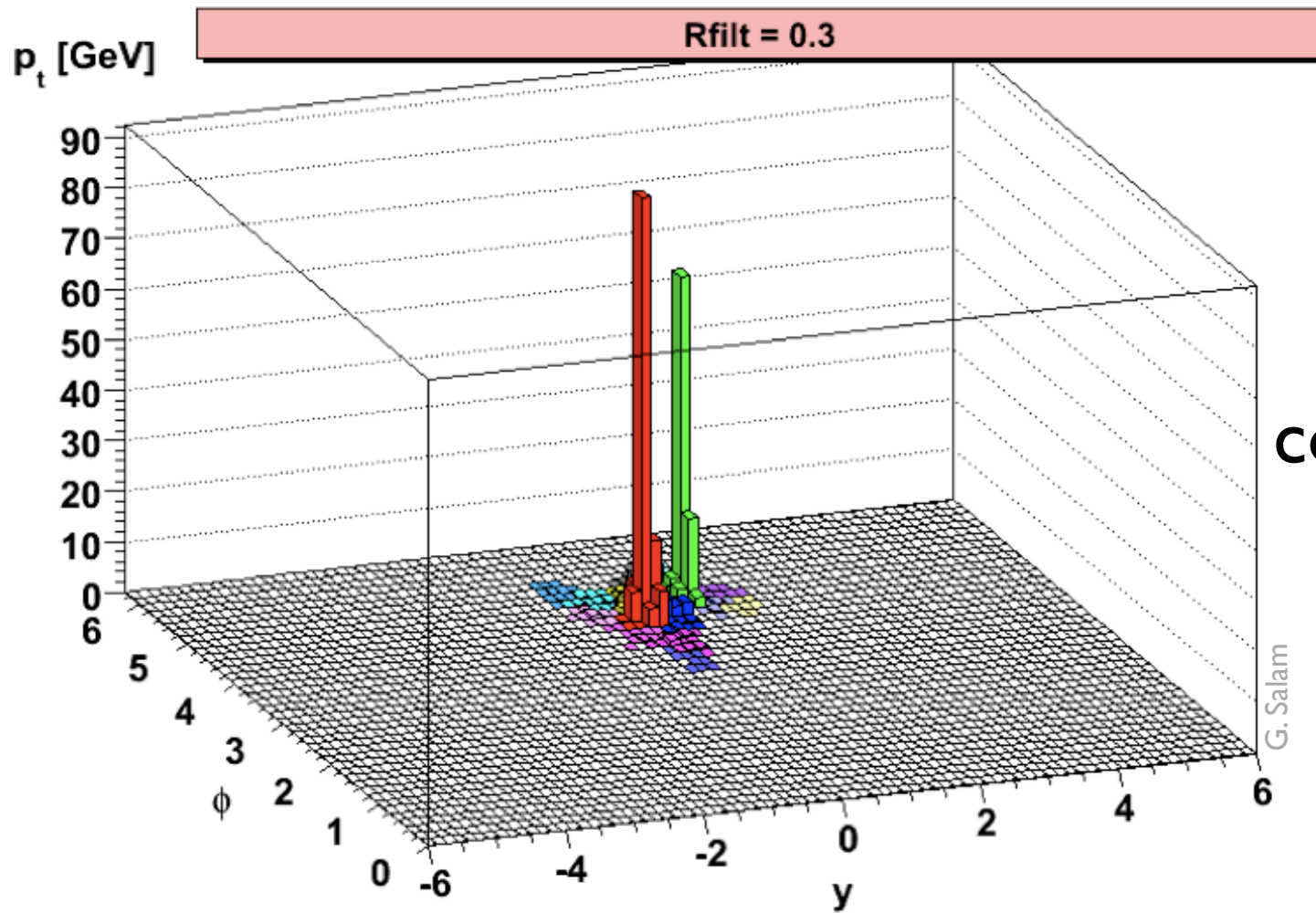
[NB. Parameters used  $\mu = 0.67$  and  $y_{\text{cut}} = 0.09$ ]

$pp \rightarrow ZH \rightarrow \nu\nu b\bar{b}$



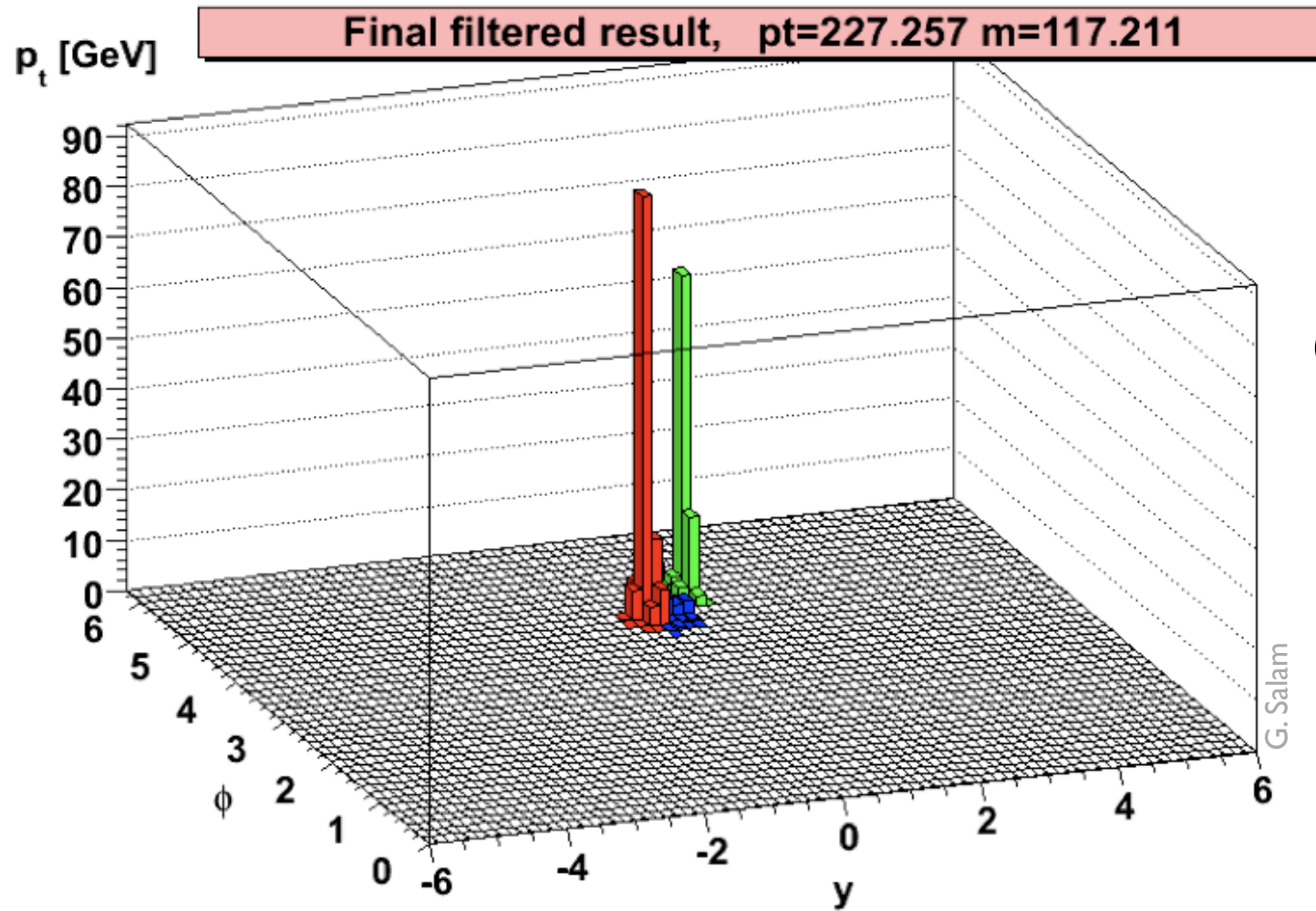
Start with the recombined jet

$pp \rightarrow ZH \rightarrow \nu\nu b\bar{b}$



Recluster the constituents with  $R_{\text{filt}}$

$pp \rightarrow ZH \rightarrow \nu\nu b\bar{b}$



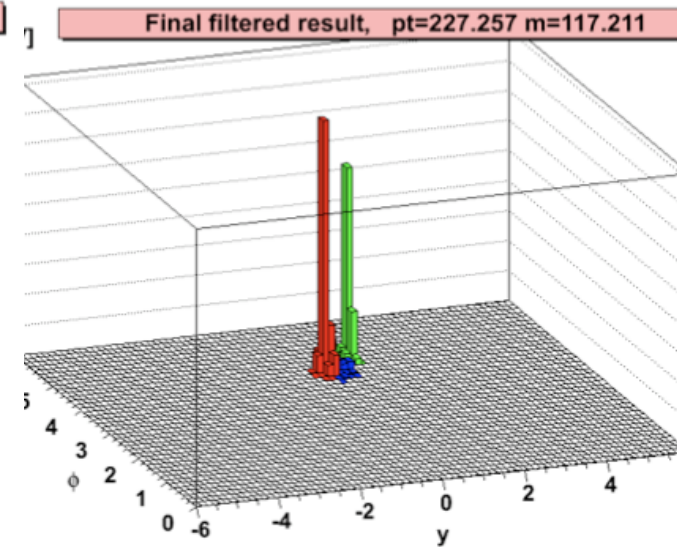
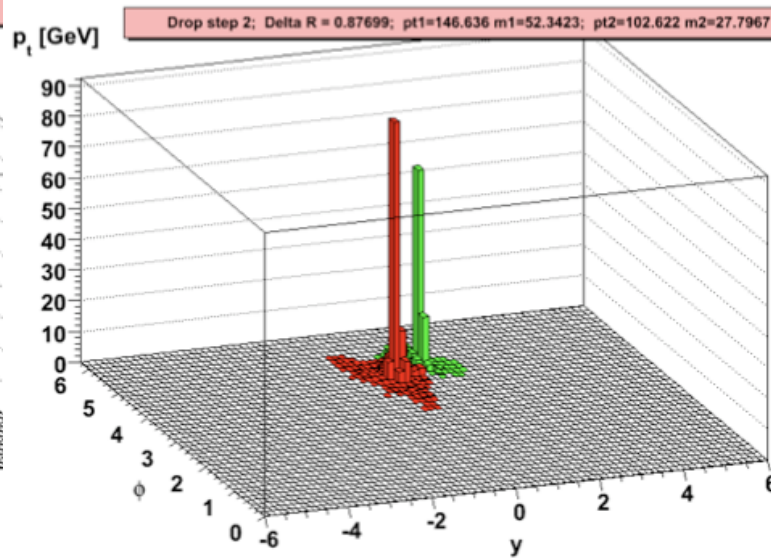
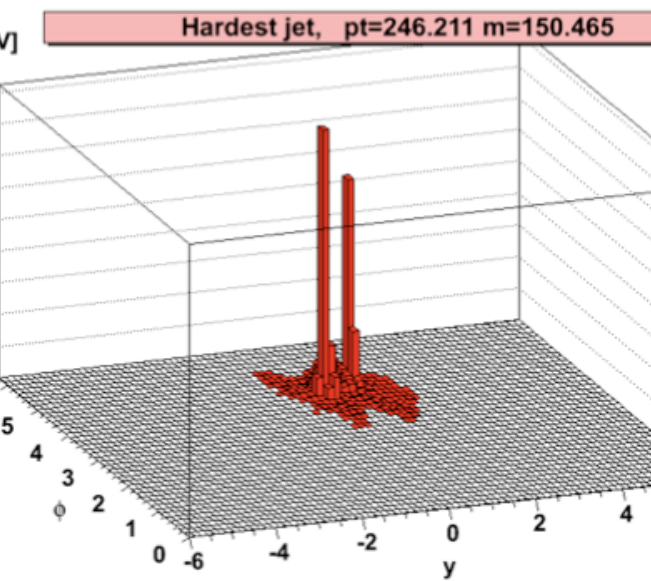
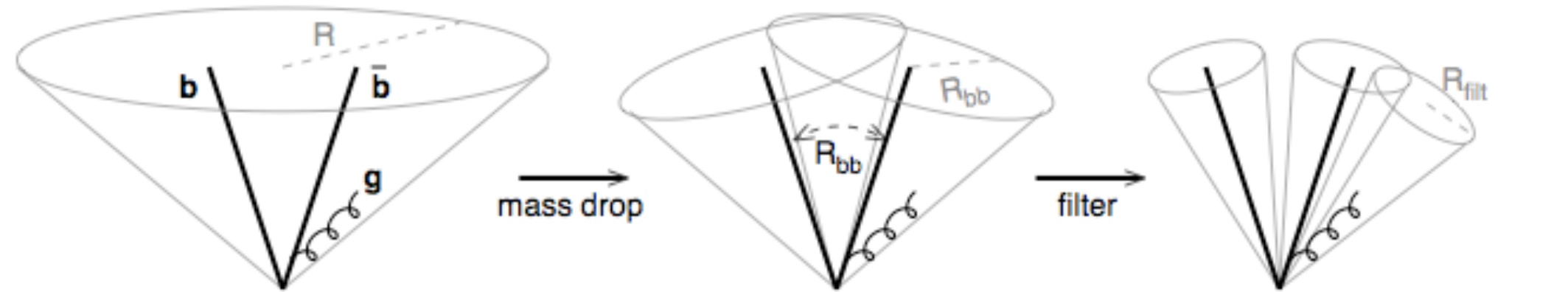
Only keep the  $n_{\text{filt}}$  hardest jets

The low-momentum stuff surrounding the hard particles has been removed

$$pp \rightarrow ZH \rightarrow \nu\bar{\nu}b\bar{b}$$

# Visualisation of BDRS

Butterworth, Davison, Rubin, Salam, 2008



Cluster with a large R

Undo the clustering into subjects, until a large asymmetry/mass drop is observed: tagging step

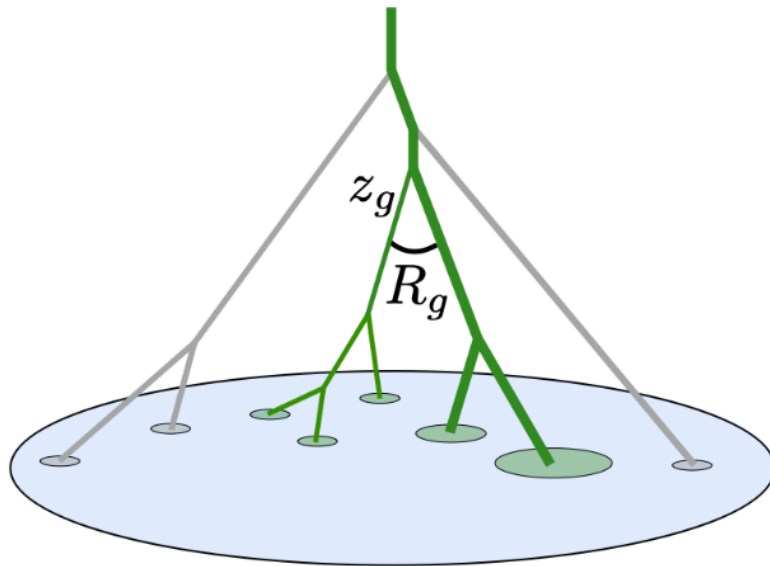
Re-cluster with smaller R, and keep only 3 hardest jets: grooming step

# Soft Drop declustering

Larkoski, Marzani, Soyez, Thaler, 2014

A generalisation of the (modified) Mass-Drop tagger.  
Progressively decluster and drop constituent unless

Soft Drop Condition: 
$$\frac{\min(p_{T1}, p_{T2})}{p_{T1} + p_{T2}} > z_{\text{cut}} \left( \frac{\Delta R_{12}}{R_0} \right)^\beta$$



[Drawing from  
2106.04589]

i.e. remove large-angle  
soft radiation from a jet

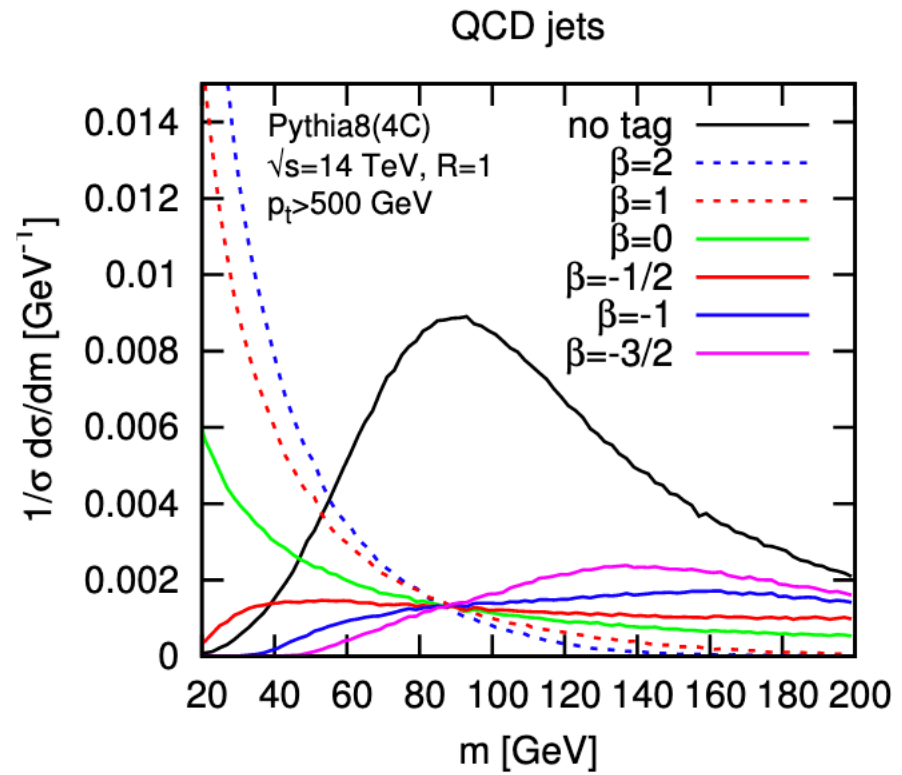
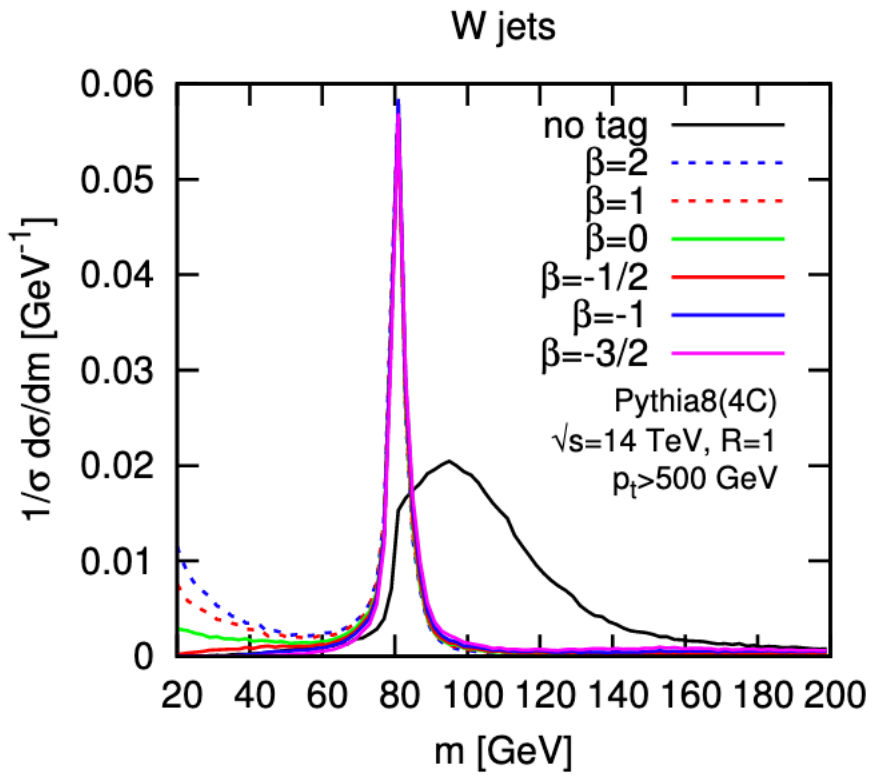


# Soft Drop declustering

Larkoski, Marzani, Soyez, Thaler, 2014

The paper contains

- ✓ analytical calculations and comparisons to Monte Carlos
- ✓ study of effect of non-perturbative corrections
- ✓ performance studies



Example of SoftDrop performance when used as a boosted W tagger

# Take home points

The big news of the past fifteen years has been the development of robust taggers and groomers using properties of jet substructure, through

- ▶ declustering
- ▶ jet shapes
- ▶ direct analysis of images (machine learning)

These techniques have been commissioned by experimental collaborations and have proven their worth in ‘Standard Model’ analyses. They are now being implemented in BSM searches