## Recent developments in jet clustering algorithms

#### Gavin Salam work in progress with M. Cacciari

LPTHE, Universities of Paris VI and VII and CNRS

Università di Firenze 29 June 2006 Electrons & muons are fundamental, weakly coupled particles — it makes sense physically and experimentally to think of them as concrete objects.

Partons (quarks, gluons) are not so simple...



- Partons split into further partons
- Jets are a a way of thinking of the 'original parton'
- A 'jet' is a fundamentally ambiguous concept (e.g. requires a resolution)

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What is **needed** of a jet algorithm

- Must be infrared and collinear (IRC) safe
  - soft emissions shouldn't change jets collinear splitting shouldn't change jets
- Must be identical procedure at parton level, hadron-level So that theory calculations can be compared to experimental measurements

## What is *nice* for a jet algorithm

- Shouldn't be too sensitive to hadronisation, underlying event, pileup Because we can only barely model them
- Should be realistically applicable at detector level

Not too slow, not too complex to correct

Should behave 'sensibly'

e.g. don't want it to spuriously ignore large energy deposits

Mainstream jet-algorithms

Iterative cone algorithms (JetClu, ILCA/Midpoint, ...)

Searches for cones centred on regions of energy flow Dominant at hadron colliders

 Sequential recombination algorithms (k<sub>t</sub>, Cambridge/Aachen, Jade) Recombine closest pair of particles, next closest, etc.
 Dominant at e<sup>+</sup>e<sup>-</sup> and ep colliders

Other approaches

 'Optimal Jet Finder', Deterministic Annealing
 Fit jet axes (and #) so as to minimise a weight function [forms of 'k-means' clustering]

Jet energy flow project

As LHC startup approaches it's important for the choice of jet algorithm to be well-motivated.

## <u>This talk</u>

- Overview of iterative cone algorithms (& what's wrong with them)
- Clustering algorithms
  - How they work
  - ▶ Where they've been criticised (speed, underlying-event (UE) sensitivity)
  - How to solve the speed problem
  - Work in progress on understanding and reducing sensitivity to UE.

First 'cone algorithm' dates back to Sterman and Weinberg (1977) — the original infrared-safe cross section:

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

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

#### Where do you put the cones?

- Place a cone at some trial location
- Sum four-momenta of particles in cone find corresponding axis
- Use that axis as a new trial location, and *iterate*
- Stop when you reach a stable axis

### What are the initial trial locations?

'Seedless' — i.e. everywhere

But too slow on computer

Use locations with energy flow above some threshold as seeds lssue: is seed threshold = parton energy, hadron energy (collinear unsafe)? Or calorimeter tower energy (experiment and η-dependent)?

[or when you get bored]



[These and related figures adapted/copied from Markus Wobisch]

















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#### Jets can overlap



They are either *split* if the overlapping energy is

 $E_{
m overlap} < f_{
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m softer-jet}$ 

otherwise they are *merged*.

NB:  $f_{\rm overlap}$  is parameter of cone-algo

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Solution: add extra seeds at midpoints of all pairs, triplets, . . . of stable cones. Seymour '97 (?)



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Jet clustering (G. Salam, LPTHE) (p. 11) Cone algorithms

All of these considerations led recommendation of the *Improved Legacy Cone Algorithm* (ILCA), a.k.a. *Midpoint* algorithm. hep-ex/0005012

Quite complex and has several parameters:

$$\begin{array}{c} \text{cone radius } (R) \\ \text{seed threshold } (E_0) \\ f_{\text{overlap}} \end{array}$$

Only one of these is remotely physical: R.



 $2/3 \mbox{ of ILCA flowchart}$ 

## ILCA has "Dark Towers"



Considerable energy can be left out of jets  $\equiv$  **Dark Towers** 

S. Ellis, Huston & Tönnesmann '01

Search Cone

Dark towers are consequence of particles that are never in stable cones:



rapidity

Ellis, Huston and Tönnesmann suggest *iterating a smaller 'search-cone'* and then drawing final cone around it.

Searchcone adopted by CDF (to confuse issue they call it 'midpoint'...). hep-ex/0505013, hep-ex/0512020

# Search Cone is IR unsafe



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- Cone algorithms are complicated beasts.
- So much so, it's often not clear *which* cone algorithm is being used!
- They often behave in unforeseen ways.
- Patching them makes them more complex and error-prone.

Didn't even mention the hacks people put into cone theory calculations to 'tune' them to hadron level: (cf.  $R_{sep}$ , which breaks the NLO jet X-section).

LHC experiments should be wary of cone algorithms

## Best known is kt algorithm:

1. Calculate (or update) distances between all particles *i* and *j*, and between *i* and beam:

$$d_{ij}=\min(k_{ti}^2,k_{tj}^2)rac{\Delta R_{ij}^2}{R^2}, \qquad d_{iB}=k_{ti}^2, \qquad \Delta R_{ij}^2=\Delta y_{ij}^2+\Delta \phi_{ij}^2$$

- 2. Find smallest of  $d_{ij}$  and  $d_{iB}$ 
  - If  $d_{ij}$  is smallest, recombine *i* and *j* (add result to particle list, remove *i*, *j*)
  - ▶ if *d<sub>iB</sub>* is smallest call *i* a jet (remove it from list of particles)
- 3. If any particles are left, repeat from step 1.

Catani, Dokshitzer, Olsson, Turnock, Seymour & Webber '91–93 S. Ellis & Soper, '93

One parameter: R (like cone radius), whose natural value is 1 Optional second parameter: stopping scale  $d_{cut}$  'exclusive'  $k_t$  algorithm

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Why  $k_t$ ?

 $k_t$  distance measures

$$d_{ij} = \min(k_{ti}^2, k_{tj}^2) \Delta R_{ij}^2, \qquad d_{iB} = k_{ti}^2$$

are closely related to structure of divergences for QCD emissions

$$[dk_j]|M^2_{g \to g_i g_j}(k_j)| \sim \frac{\alpha_{\sf s} C_A}{2\pi} \frac{dk_{tj}}{\min(k_{ti}, k_{tj})} \frac{d\Delta R_{ij}}{\Delta R_{ij}}, \qquad (k_{tj} \ll k_{ti}, \ \Delta R_{ij} \ll 1)$$

and

$$[dk_i]|M^2_{\text{Beam}\to\text{Beam}+g_i}(k_i)| \sim \frac{\alpha_{s}C_A}{\pi} \frac{dk_{ti}}{k_{ti}} d\eta_i , \qquad (k_{ti}^2 \ll \{\hat{s}, \hat{t}, \hat{u}\})$$

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*k*<sub>t</sub> algorithm attempts approximate inversion of branching process

 $k_t$  v. cone

### $k_t$ algorithm seems better than cone

- it's simpler, safer and better-defined
- exclusive variant is more flexible (allows cuts on momentum scales)
- less sensitive to hadronization
- In MC studies k<sub>t</sub> alg. is systematically as good as, or better than cone algorithms for typical reconstruction tasks
   Seymour '94

Butterworth, Cox & Forshaw '02

Benedetti et al (Les Houches) '06

But seldom used at Tevatron. Why?

- 1. Because it's slow?
- 2. Because it includes more underlying event?
- 3. Because it's harder to understand detector effects?

But all LEP and HERA experiments managed fine And as of '05, CDF too Jet clustering (G. Salam, LPTHE) (p. 20)  $L_{k_t}$  and Cam algorithms  $L_{Speed}$ 

### Time to cluster N particles



**Jet-clustering speed is an issue** for high-luminosity *pp* ( $\sim 10^8$  events) and Pb-Pb ( $\sim 10^7$  events) collisions at LHC.

NB: want to rerun jet-alg. with a range of parameter choices + want to run on multiple MC samples of similar size Jet clustering (G. Salam, LPTHE) (p. 20)  $L_{k_t}$  and Cam algorithms  $L_{Speed}$ 

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- 1. Given the initial set of particles, construct a table of all the  $d_{ij}$ ,  $d_{iB}$ .  $\left[\mathcal{O}\left(N^{2}\right) \text{ operations, done once}\right]$
- 2. Scan the table to find the minimal value  $d_{\min}$  of the  $d_{ij}$ ,  $d_{iB}$ . [ $\mathcal{O}$  (N<sup>2</sup>) operations, done N times]
- 3. Merge or remove the particles corresponding to  $d_{\min}$  as appropriate. [ $\mathcal{O}(1)$  operations, done N times]
- 4. Update the table of  $d_{ij}$ ,  $d_{iB}$  to take into account the merging or removal, and if any particles are left go to step 2.

 $[\mathcal{O}(N) \text{ operations, done } N \text{ times}]$ 

This is the "brute-force" or "naive" method



### $k_t$ is a form of Hierarchical Clustering

Fast Hierarchical Clustering and Other Applications of Dynamic Closest Pairs

David Eppstein UC Irvine

We develop data structures for dynamic closest pair problems with arbitrary distance functions, that do not necessarily come from any geometric structure on the objects. Based on a technique previously used by the author for Euclidean closest pairs, we show how to insert and delete objects from an n-object set, maintaining the closest pair, in  $O(n \log^2 n)$  time per update and O(n) space. With quadratic space, we can instead use a quadtree-like structure to achieve an optimal time bound, O(n) per update. We apply these data structures to hierarchical clustering, greedy matching, and TSP heuristics, and discuss other potential applications in machine learning. Gröbher bases, and local improvement algorithms for partition and placement problems. Experiments show our new methods to be faster in practice than previously used heuristics.

Categories and Subject Descriptors: F.2.2 [Analysis of Algorithms]: Nonnumeric Algorithms

General Terms: Closest Pair, Agglomerative Clustering

Additional Key Words and Phrases: TSP, matching, conga line data structure, quadtree, nearest neighbor heuristic

#### 1. INTRODUCTION

Hierarchical clustering has long been a mainstay of statistical analysis, and clustering based methods have attracted attention in other fields: computational biology (reconstruction of evolutionary trees; tree-based multiple sequence alignment), scientific simulation (n-body problems), theoretical computer science (network design and nearest neighbor searching) and of course the web (hierarchical indices such as Yahoo). Many clustering methods have been devised and used in these applications, but less effort has gone into algorithmic speedups of these methods.

In this paper we identify and demonstrate speedups for a key subroutine used in several clustering algorithms, that of maintaining closest pairs in a dynamic set of objects. We also describe several other applications or potential applications of the *k*<sub>t</sub> alg. is so good it's used throughout science!

NB HEP is not only field to use brute-force...

For general distance measures problem reduces to  $\sim N^2$  (factor  $\sim 20$  for N = 1000).

Eppstein '99 - Cardinal '03



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Of these naive methods, brute force recomputation may be most commonly used, due to its low space requirements and ease of implementation. Three hierarchical clustering codes we examined, Zupan's [Zupan 1982], CLUSTAL W [Thompson et al. 1994], and PHYLIP [Felsenstein 1995] use brute force. (Indeed, they do not even save space by doing so, since they all store the distance matrix.) Pazzani's learning code [Pazzani 1997] also uses brute force (M. Pazzani, personal communication), as does *Mathematica*'s Gröbner basis code (D. Lichtblau, personal communication). *k*<sub>t</sub> alg. is so good it's used throughout science!

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Eppstein '99 + Cardinal '03 There are N(N-1)/2 distances  $d_{ij}$  — surely we have to calculate them all in order to find smallest?

 $k_t$  distance measure is partly *geometrical*:

- Consider smallest  $d_{ij} = \min(k_{ti}^2, k_{tj}^2)R_{ij}^2$
- Suppose  $k_{ti} < k_{tj}$
- ▶ Then:  $R_{ij} \leq R_{i\ell}$  for any  $\ell \neq j$ . [If  $\exists \ \ell \ \text{s.t.} \ R_{i\ell} < R_{ij}$  then  $d_{i\ell} < d_{ij}$ ]

*In words:* if i, j form smallest  $d_{ij}$  then j is geometrical nearest neighbour (GNN) of i.

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Given a set of vertices on plane (1...10) a *Voronoi diagram* partitions plane into cells containing all points closest to each vertex Dirichlet '1850, Voronoi '1908

A vertex's nearest other vertex is always in an adjacent cell.

#### E.g. GNN of point 7 will be found among 1,4,2,3 (it turns out to be 3)

Construction of Voronoi diagram for *N* points: *N* In *N* time Fortune '88 Update of 1 point in Voronoi diagram: In *N* time Devillers '99 [+ related work by other authors]

Convenient C++ package available: CGAL

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The FastJet algorithm:

Construct the Voronoi diagram of the N particles with CGAL  $O(N \ln N)$ 

Find the GNN of each of the N particles, calculate  $d_{ij}$  store result in a priority queue (C++ map)  $O(N \ln N)$ 

Repeat following steps N times:

- ▶ Find smallest *d<sub>ij</sub>*, merge/eliminate *i*, *j*
- Update Voronoi diagram and distance map

 $N \times O(1)$  $N \times O(\ln N)$ 

Overall an  $\mathcal{O}(N \ln N)$  algorithm

Cacciari & GPS, hep-ph/0512210 http://www.lpthe.jussieu.fr/~salam/fastjet/ Results identical to standard N<sup>3</sup> implementations The FastJet algorithm:

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#### Overall an $\mathcal{O}$ (N In N) algorithm

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### FastJet performance



NB: for  $N < 10^4$ , FastJet switches to a related geometrical  $N^2$  alg.





## What is speed good for?





Add dense coverage of infinitely soft *"ghosts"* See how many end up in jet to measure jet area

 $\sim$  10000 particles Clustering takes  $\sim$  20 minutes with old methods.

0.6s with FastJet.



Jet areas





Jet areas in  $k_t$  algorithm are quite varied Because  $k_t$ -alg adapts to the jet structure

► Contamination from min-bias ~ area

Complicates corrections: minbias subtraction is different for each jet.

> Cone supposedly simpler Area =  $\pi R^2$ ?

Try reconstructing  $M_Z$  from  $Z \rightarrow 2$  jets [Use inv. mass of two hardest jets]

On same events, compare uncorrected  $k_t$  v. ILCA (midpoint) cone



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Let clustering (G. Salam, LPTHE) (p. 31)  $L_{k_t \text{ and Cam algorithms}}$ Use jet areas to correct jet kinematics



NB: cone much harder to correct this way — too slow to add  $10^4$  ghosts

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Suppose incoming partons (colour charge  $C_i$ ) and outgoing jets (col. charge  $= C_o$ ) are not colour connected.

Mean outgoing jet area  $\langle A \rangle$  depends on jet  $P_t$  as follows:

$$\langle A \rangle = R^2 \left( \pi + (a_0 C_o + a_2 C_i R^2) \frac{\alpha_s}{\pi} \ln \frac{P_t^2}{Q_0^2} + \mathcal{O}\left(\alpha_s, \alpha_s^2 L^2\right) \right)$$
  
GPS & Cacciari, prelim.

	<i>a</i> 0	a <sub>2</sub>	comment	
k <sub>t</sub>	+1.771	+0.325	significant, positive	
ILCA (cone)	-0.200	-0.325	small, negative	
Cam / Aachen	+0.249	0	small, positive	
For $Q_0\sim 10$ GeV, $P_t\sim 100-1000$ GeV, $rac{lpha_{ m s}}{\pi}\ln P_t^2/Q_0^2\sim 0.2-0.4$				

Cambridge / Aachen algorithm? Like  $k_t$  with but  $d_{ij} = R_{ij}^2/R^2$  and $d_{iB} = 1.$ Dokshitzer, Leder, Moretti & Webber '97; Wobisch '00

# Reconstruct Z' mass [2 TeV]



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Corrected Cam (and *k*<sub>t</sub>) is best.

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Corrected Cam (and  $k_t$ ) is best.

- k<sub>t</sub> alg. is fast (faster than IR unsafe JetClu) key observation is geometrical reformulation
  Get code from http://www.lpthe.jussieu.fr/~salam/fastjet
- ► Jet areas (→ min. bias. contributions) do fluctuate Some aspects of areas amenable to analytical calculations
- But areas can (should) be measured and used for correction on jet-by-jet basis.
  Preliminary studies very promising
- k<sub>t</sub> is part of a class of algorithms other example deserving more attention is Cambridge/Aachen alg. It too can be made fast