

Jets, UE and early LHC data

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LHC@BNL

Joint Theory/Experiment Workshop on Early Physics at the LHC

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Brookhaven National Laboratory, Upton, USA

Based on work with

Jon Butterworth, Andrea Banfi, Matteo Cacciari, John Ellis,
Are Raklev, Sebastian Sapeta, Gregory Soyez, Giulia Zanderighi

LHC is a parton collider

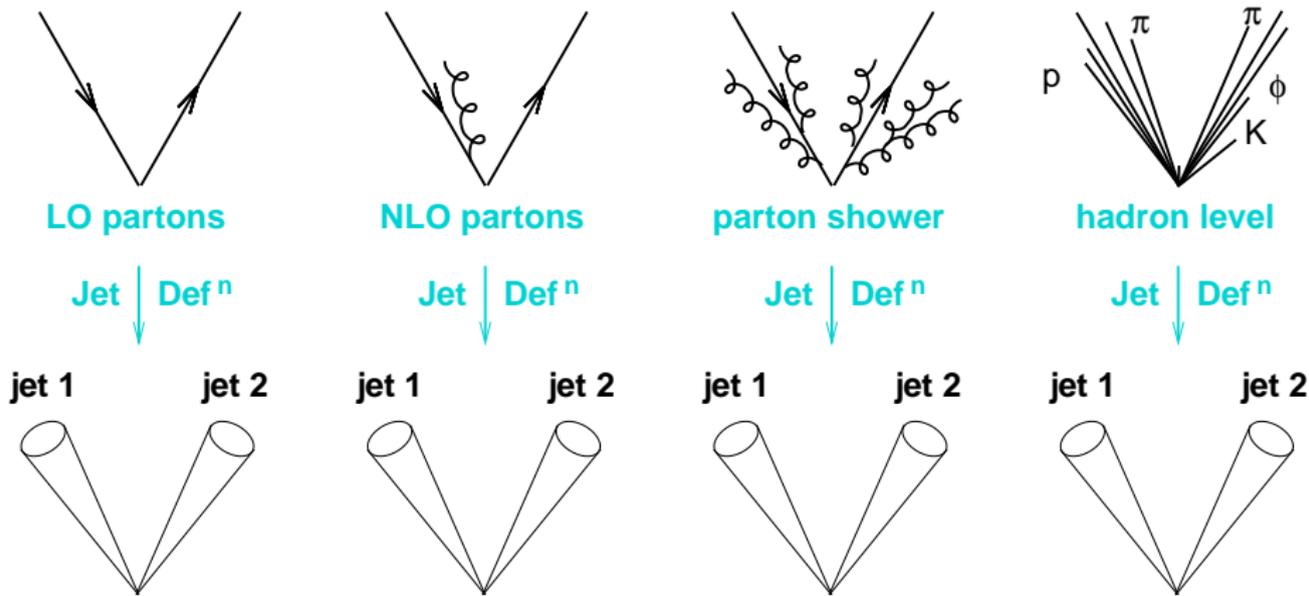
- ▶ Quarks and gluons are inevitable in initial state
- ▶ and ubiquitous in the final state

Partons — quarks and gluons — are key concepts of QCD.

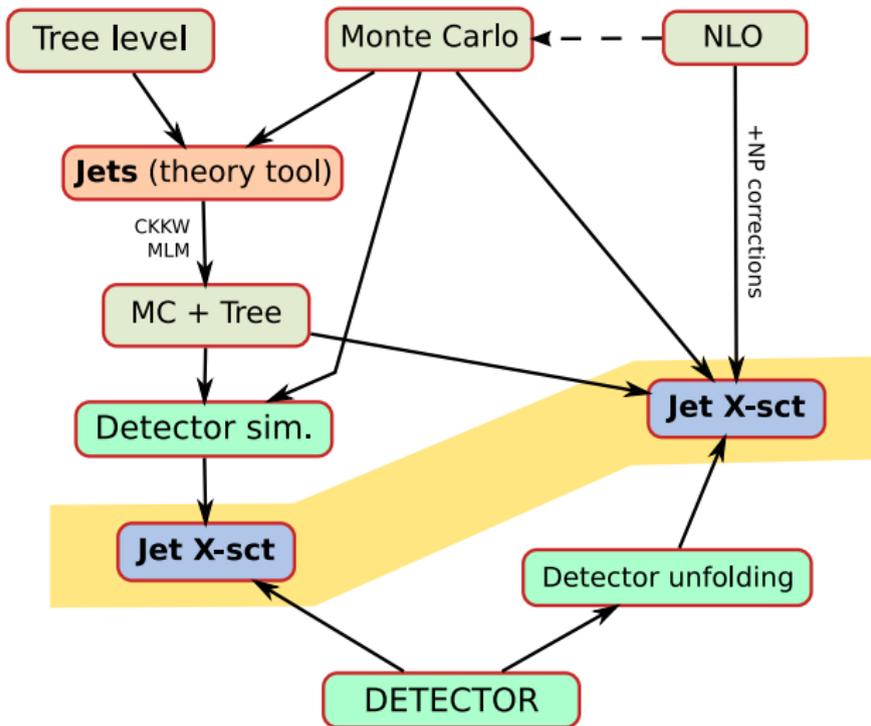
- ▶ Lagrangian is in terms of quark and gluon fields
- ▶ Perturbative QCD *only* deals with partons

Though we often talk of quarks and gluons, we never see them

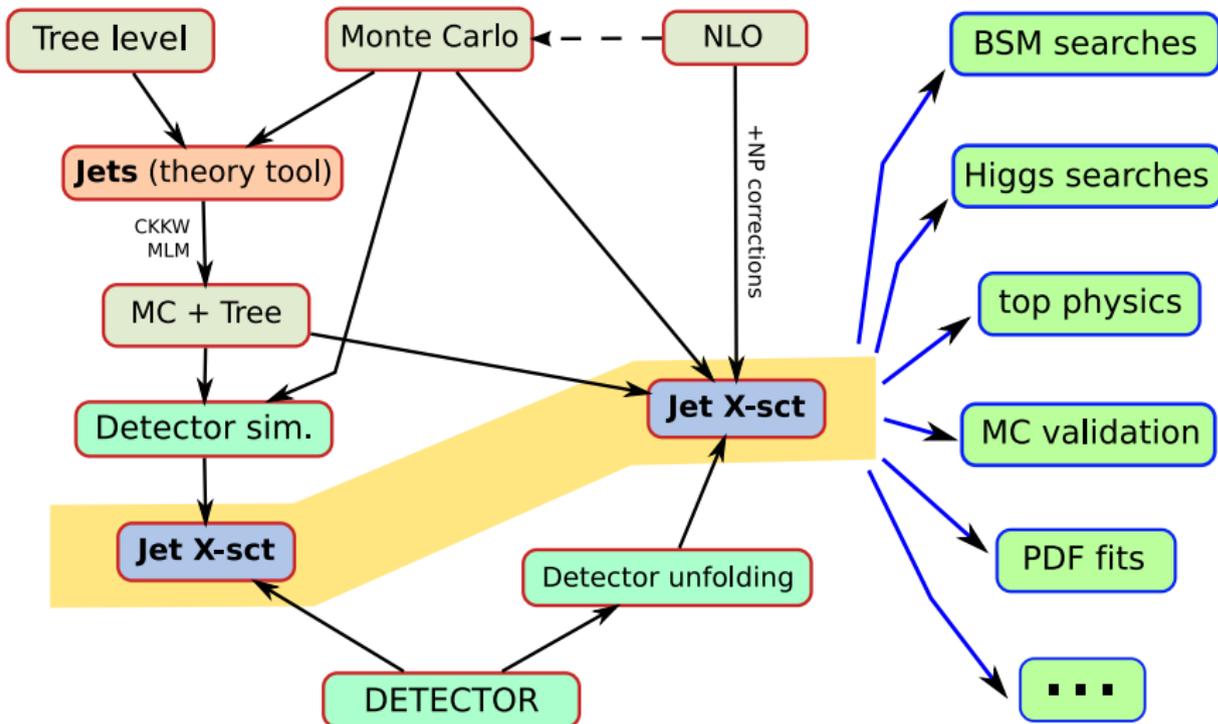
- ▶ Not an asymptotic state of the theory — because of confinement
- ▶ But also even in perturbation theory
 - because of collinear divergences (in massless approx.)
- ▶ The closest we can get to handling final-state partons is **jets**



Projection to jets provides "universal" view of event



Jet (definitions) provide central link between expt., "theory" and theory
And jets are an input to almost all analyses



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k_t algorithm

Catani, Dokshitzer, Olsson, Seymour, Turnock, Webber '91-'93
Ellis, Soper '93

- ▶ Find smallest of all $d_{ij} = \min(k_{ti}^2, k_{tj}^2) \Delta R_{ij}^2 / R^2$ and $d_{iB} = k_i^2$
- ▶ Recombine
- ▶ Repeat

**Bottom-up jets:
Sequential recombination
(attempt to invert QCD branching)**

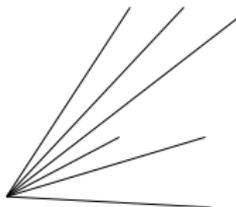


- variables
- ▶ $\Delta R_{ij} = (\phi_i - \phi_j)^2 + (y_i - y_j)^2$
 - ▶ rapidity $y_i = \frac{1}{2} \ln \frac{E_i + p_{zi}}{E_i - p_{zi}}$
 - ▶ ΔR_{ij} is boost invariant angle

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NB: hadron collider variables

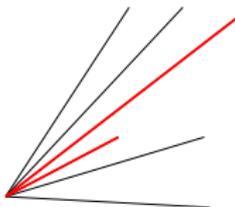
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R sets minimal interjet angle

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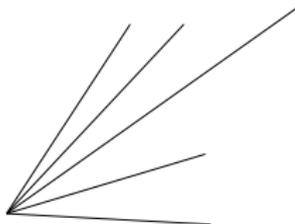
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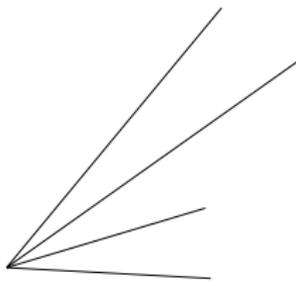
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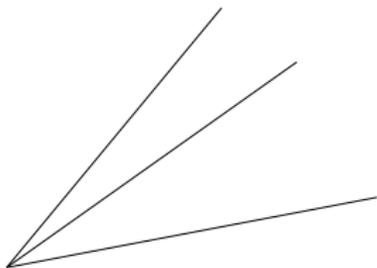
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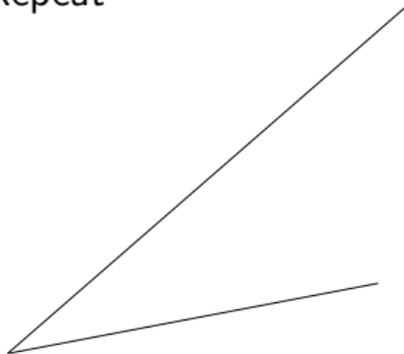
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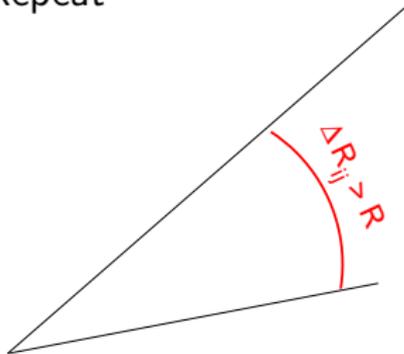
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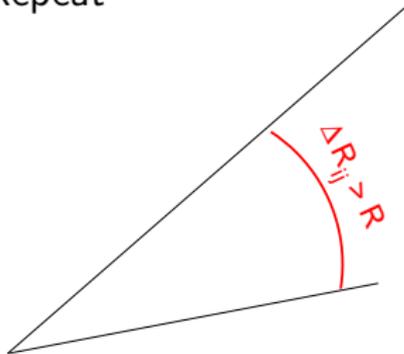
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NB: d_{ij} distance \leftrightarrow QCD branching probability $\sim \alpha_s \frac{dk_{tj}^2 dR_{ij}^2}{d_{ij}}$

Soft stuff clusters with nearest neighbour

$$k_t: d_{ij} = \min(k_{ti}^2, k_{tj}^2) \Delta R_{ij}^2 \longrightarrow \text{anti-}k_t: d_{ij} = \frac{\Delta R_{ij}^2}{\max(k_{ti}^2, k_{tj}^2)}$$

Hard stuff clusters with nearest neighbour
Privilege collinear divergence over soft divergence
Cacciari, GPS & Soyez '08

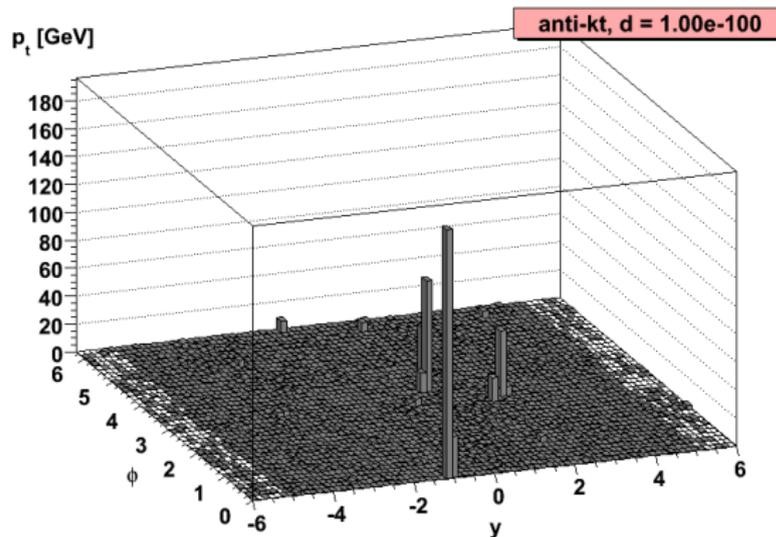
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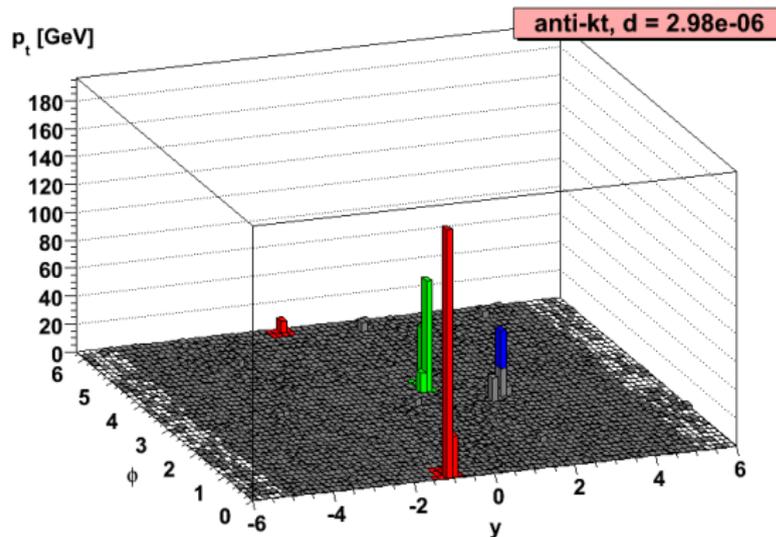
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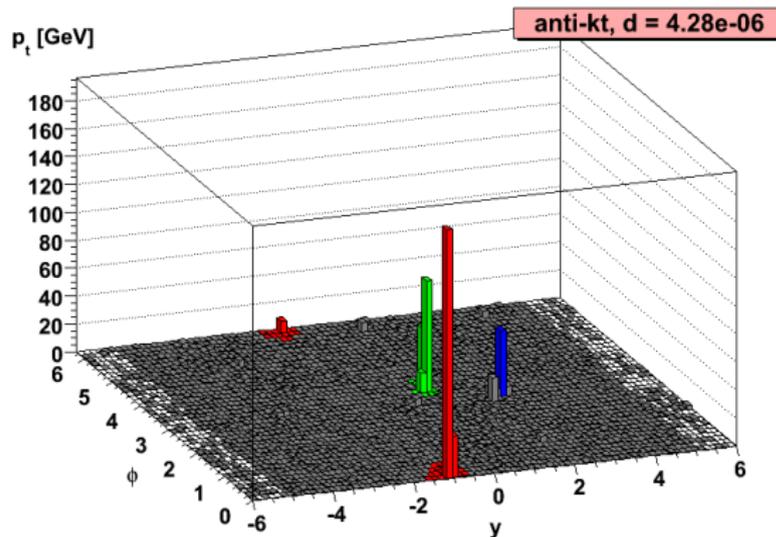
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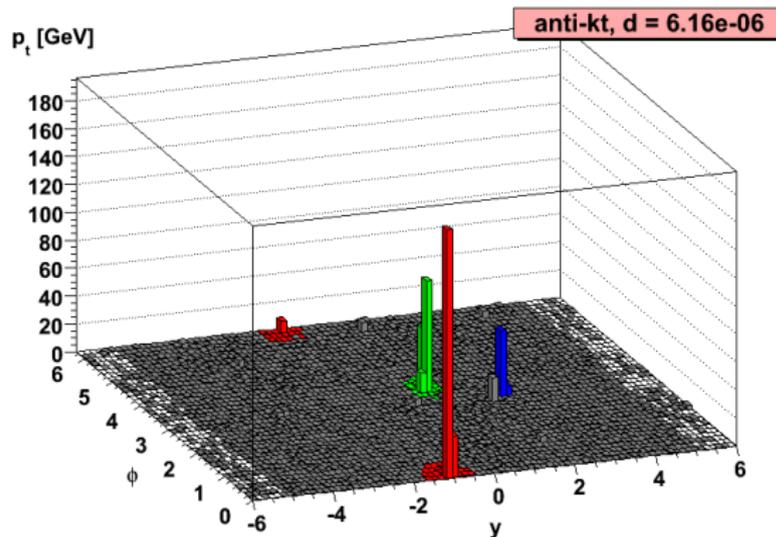
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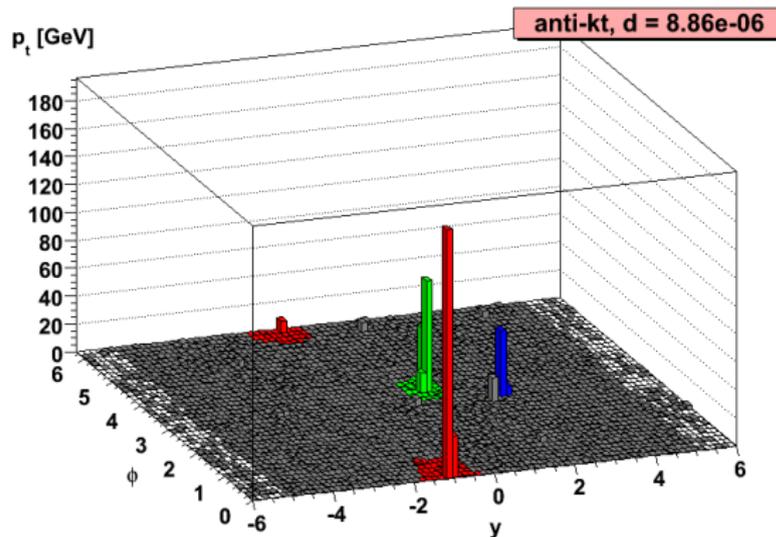
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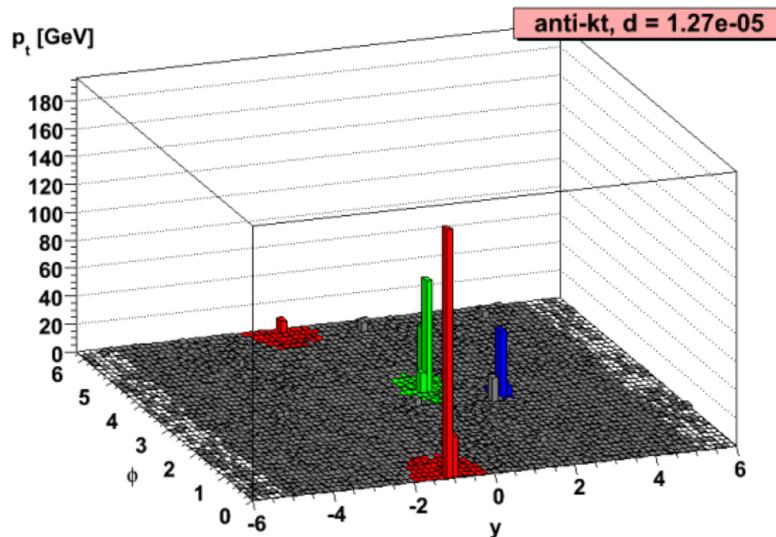
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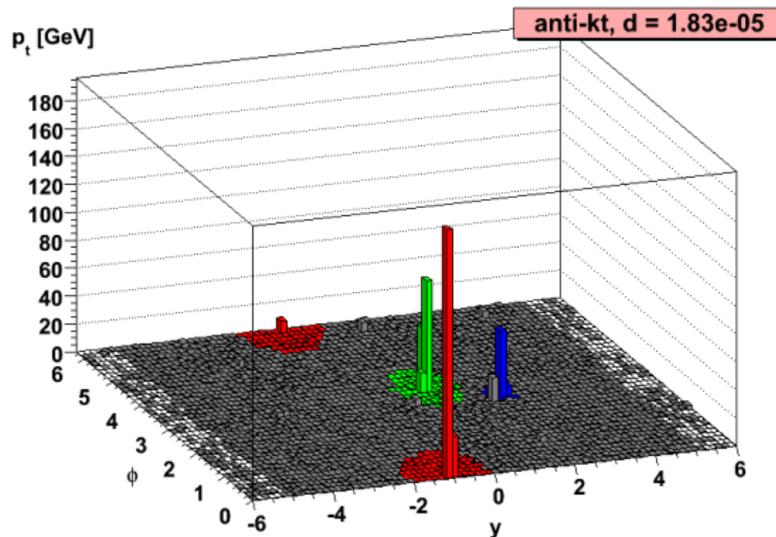
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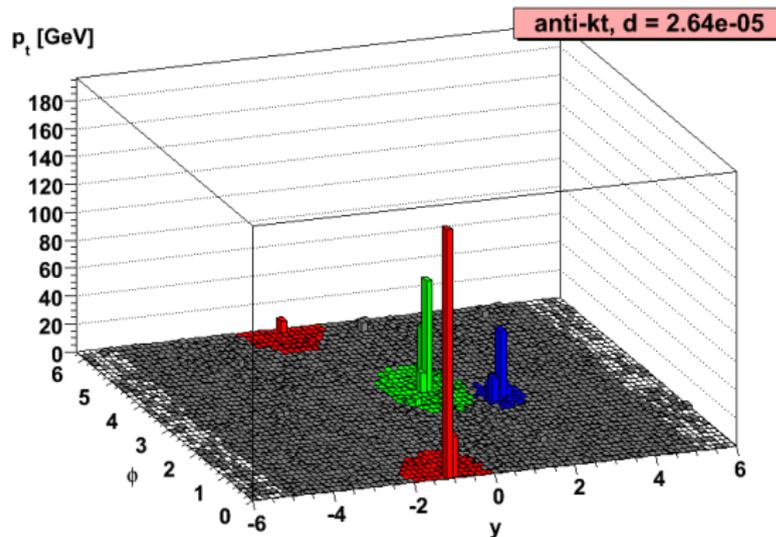
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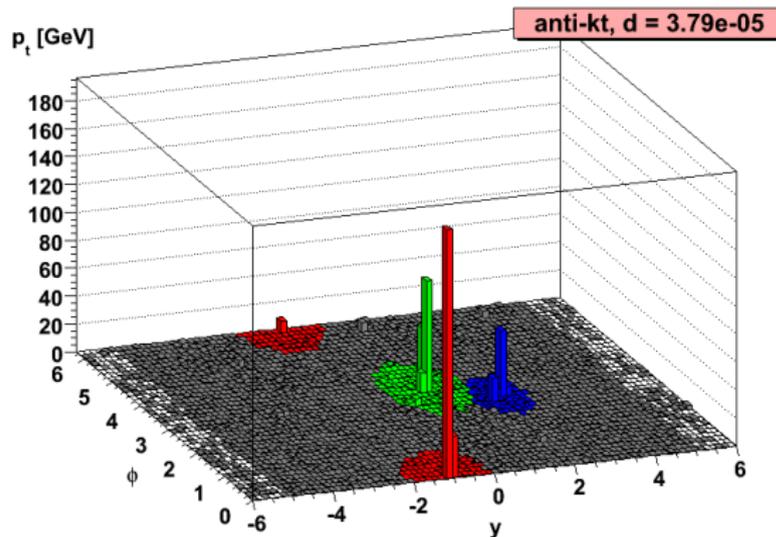
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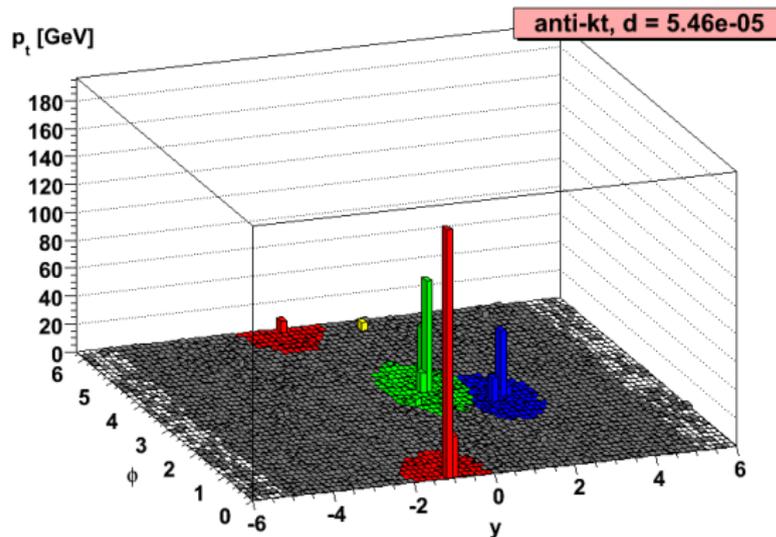
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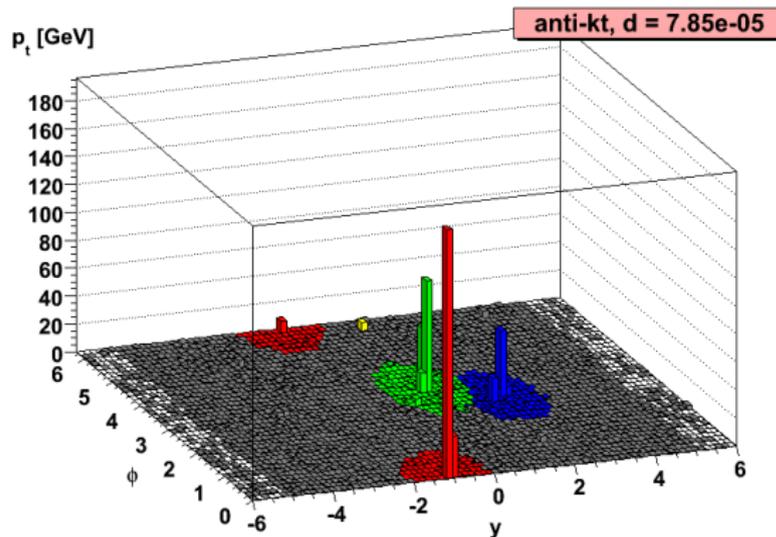
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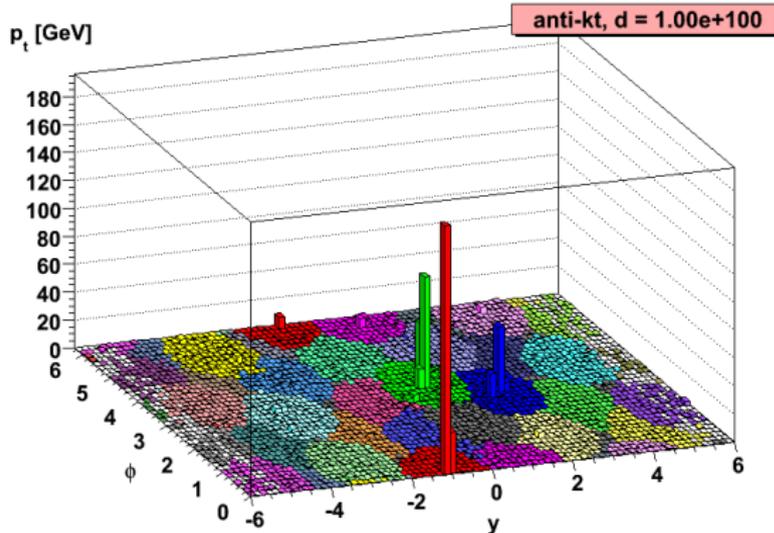
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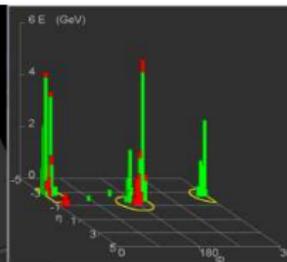
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anti- k_t gives
 cone-like jets
 without using stable
 cones

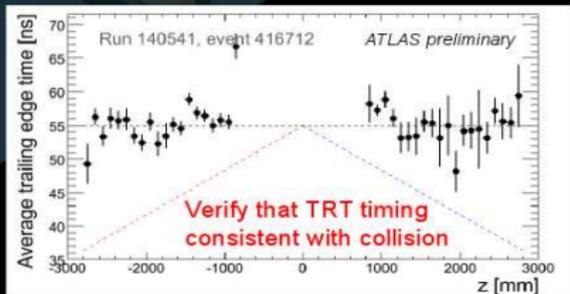
A di-jet candidate



Run 140541
Event 416712

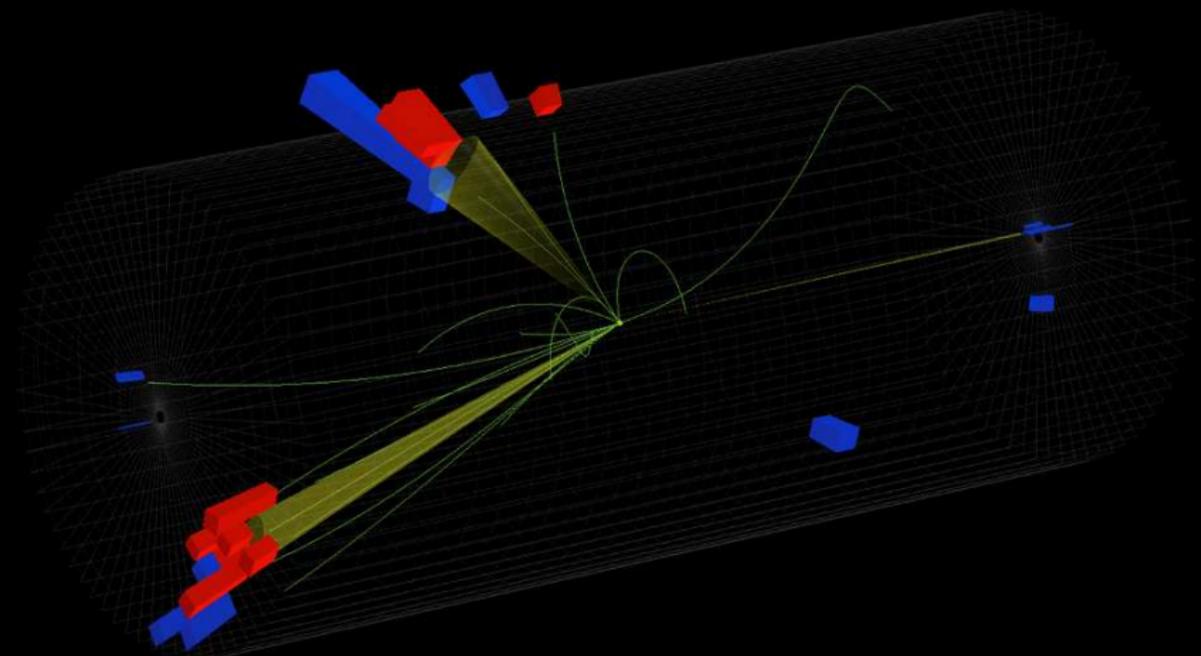
Two jets back-to-back in ϕ , both with (uncalibrated) $E_T \sim 10$ GeV, η of 1.3 and 2.5, \sim no missing E_T

Triggered by MBTS A/B in time, several hits
Also triggered by L1Calo EM3





CMS Experiment at the LHC, CERN
Date Recorded: 2009-12-06 07:18 GMT
Run/Event: 123596 / 6732761
Candidate Dijet Collision Event



With ATLAS and CMS having adopted anti- k_t as their default jet algorithm, LHC is the first hadron collider experiment to start running with a clear prospect for infrared and collinear jet-finding.

Crucial for future comparisons to QCD.

Limited luminosity

Jet energy scale poorly constrained ($\pm 10\%$?)

Steeply falling jet cross sections not well measured

Strategy?

Use purely hadronic events (large X-sct)

Measure ratios of jet p_t 's, ratios of cross sections

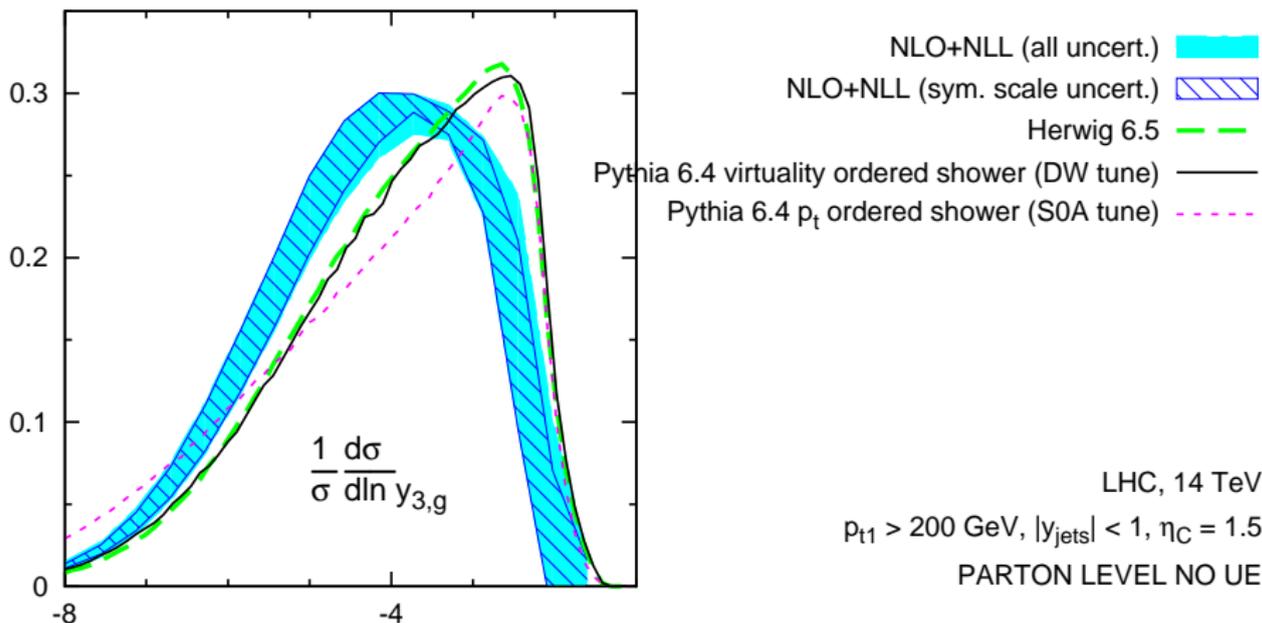
- 1) Select events with two central jets, hardest with $p_{t1} > 100$ GeV
 $\sigma = \mathcal{O}(100 \text{ nb}) @ 7 \text{ TeV}$
- 2) Define $d_{23} =$ maximum of
 - ▶ 3rd hardest jet, p_{t3}^2
 - ▶ k_t splitting scale of either of two central jets cf. substructure studies
- 3) Normalise to $Q^2 = (p_{t1} + p_{t2})^2$, $y_{23} = d_{23}/Q^2$
cancel (most of) Jet Energy Scale uncertainty
- 4) Plot differential distribution within selected events
uncertainty on selected X-section cancels

You can compare to Monte Carlo parton showers
Pythia, Herwig, Sherpa

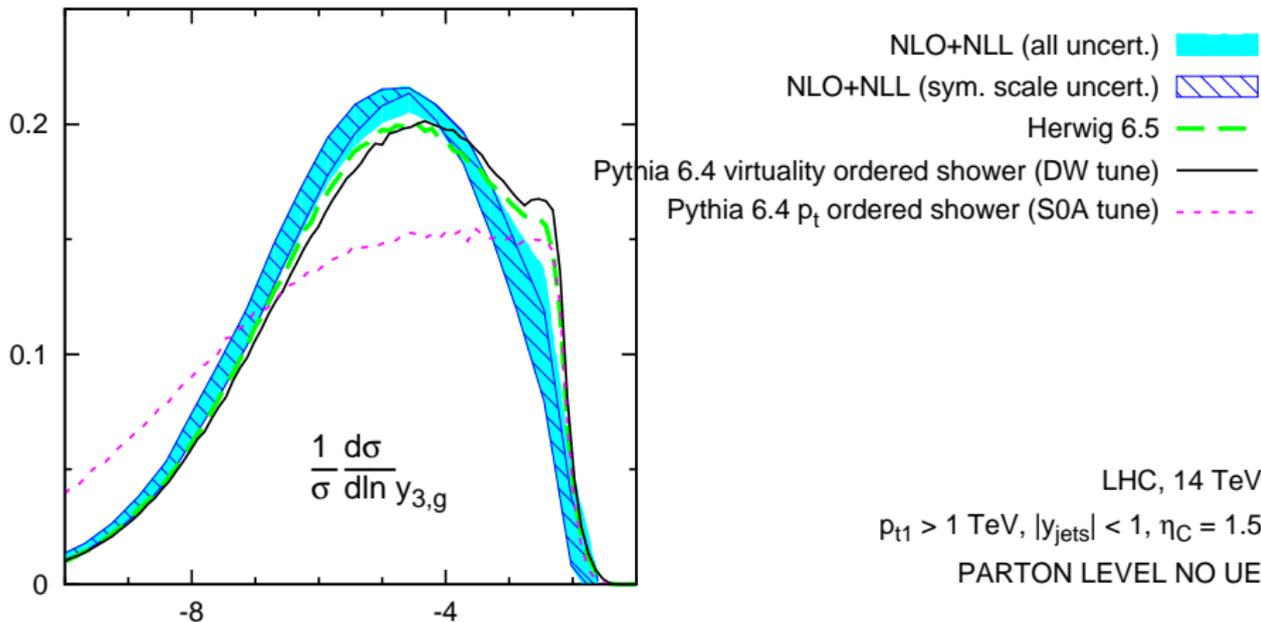
Parton showers matched to tree-level matrix elements
Alpgen (MLM), Madgraph (MLM), Sherpa (CKKW)

Non-MC predictions: NLL resummation + NLO
CAESAR + NLOJET: controlled approximations
Banfi, GPS & Zanderighi '10

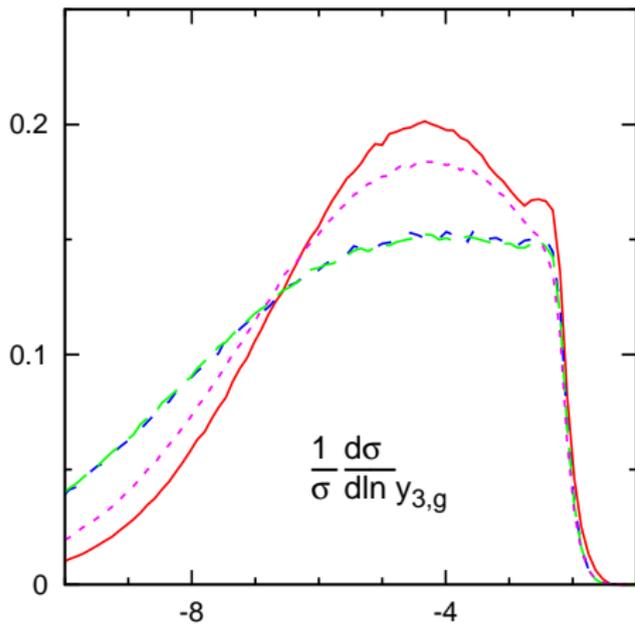
Low p_t , gluon dominated



High p_t , quark dominated



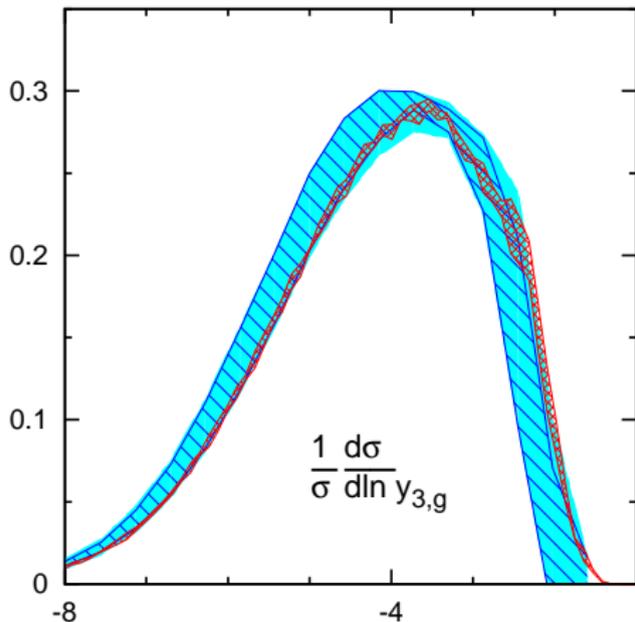
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DW ———
S0A - - -
Pto pT0 - - -
Perugia 0 - - -

LHC, 14 TeV
 $p_{t1} > 1 \text{ TeV}$, $|y_{\text{jets}}| < 1$, $\eta_C = 1.5$
PARTON LEVEL NO UE

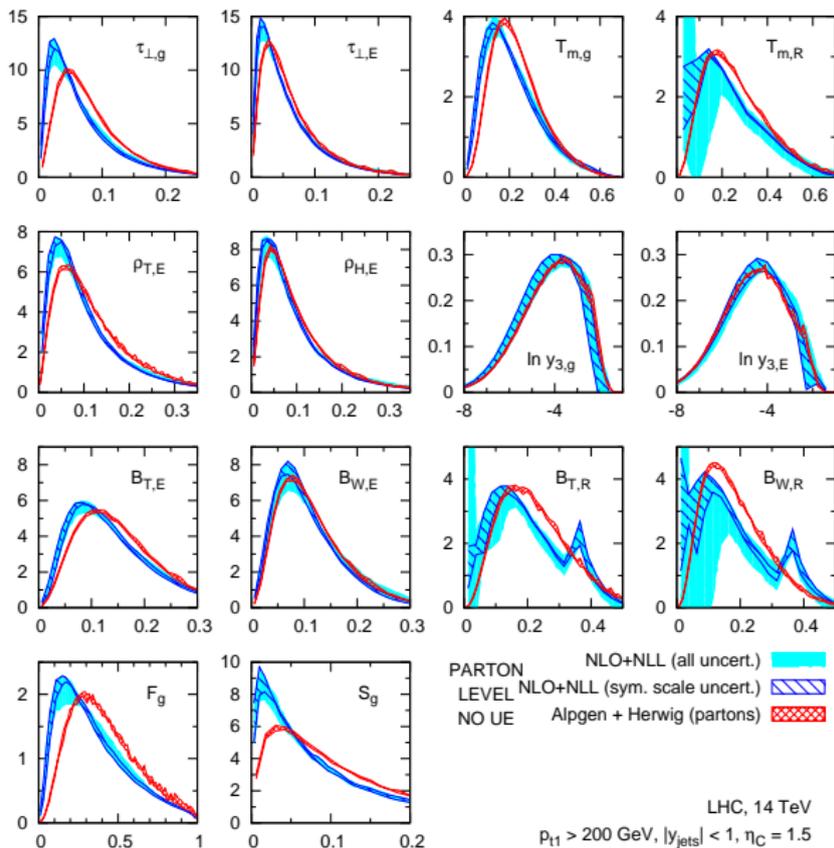
Low p_t , gluon dominated



- NLO+NLL (all uncert.)
- NLO+NLL (sym. scale uncert.)
- Alpgen + Herwig (partons)

LHC, 14 TeV
 $p_{t1} > 200$ GeV, $|y_{\text{jets}}| < 1$, $\eta_C = 1.5$
PARTON LEVEL NO UE

Other event shapes [http://tr.im/Nj9z]



There are many other ways of combining event particle momenta to get “event shapes”

e.g. transverse thrust

Each with different sensitivity to QCD branching.

Hadronic observables not just for constraining Monte Carlos

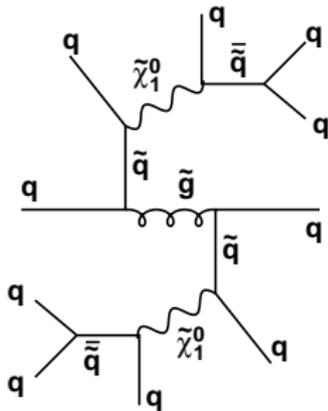
As an example, a search for neutralinos in R-parity violating supersymmetry.

Normal SPS1A type SUSY scenario, *except* that neutralino is not LSP, but instead decays, $\tilde{\chi}_1^0 \rightarrow qqq$.

Jet combinatorics makes this a tough channel for discovery

- ▶ Produce pairs of squarks, $m_{\tilde{q}} \sim 500$ GeV.
- ▶ Each squark decays to quark + neutralino, $m_{\tilde{\chi}_1^0} \sim 100$ GeV
- ▶ Neutralino is somewhat boosted \rightarrow jet with substructure

Butterworth, Ellis, Raklev & GPS '09



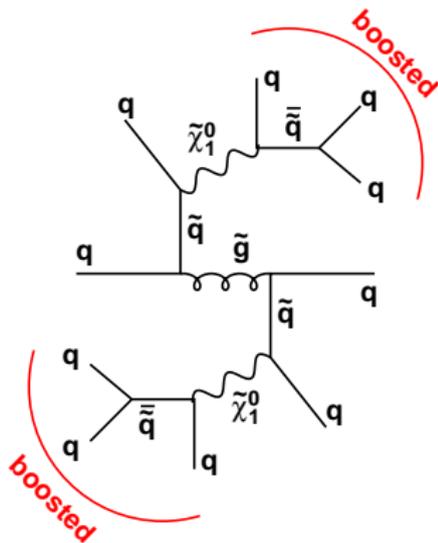
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Subject decomposition procedures are not *just* trial and error.

Mass distribution for undecomposed jet:

$$\frac{1}{N} \frac{dN}{dm} \sim \frac{2C\alpha_s \ln Rp_t/m}{m} e^{-C\alpha_s \ln^2 Rp_t/m + \dots}$$

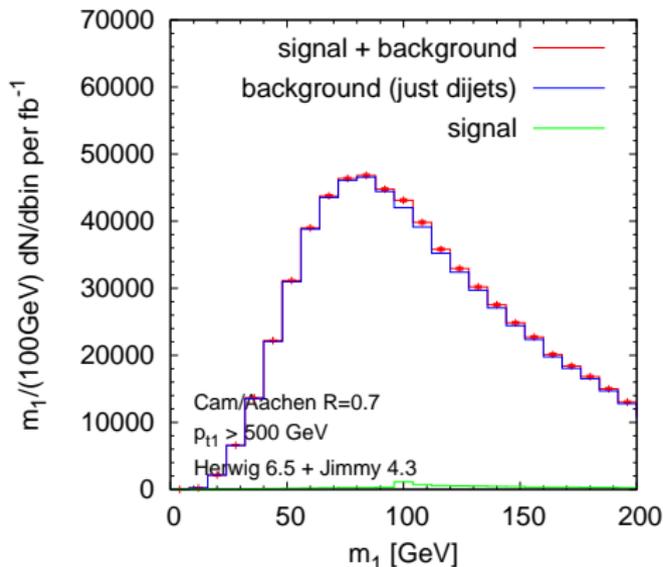
Strongly shaped, with Sudakov peak, etc.

Mass distribution for hardest (largest Jade distance) substructure within C/A jet that satisfies a symmetry cut ($z > z_{min}$):

$$\begin{aligned} \frac{1}{N} \frac{dN}{dm} &\sim \frac{C'\alpha_s(m)}{m} e^{-C'\alpha_s \ln Rp_t/m + \dots} \\ &\sim \frac{C'\alpha_s(Rp_t)}{m} \left[1 + \underbrace{(2b_0 - C')}_{\text{partial cancellation}} \alpha_s \ln Rp_t/m + \mathcal{O}(\alpha_s^2 \ln^2) \right] \end{aligned}$$

Procedure gives nearly flat distribution in mdN/dm

Neutralino procedure involves 2 hard substructures, but ideas are similar



Keep it simple:

Look at mass of leading jet

► Plot $\frac{m}{100 \text{ GeV}} \frac{dN}{dm}$ for hardest jet
 ($p_t > 500 \text{ GeV}$)

► Require 3-pronged substructure

► And third jet

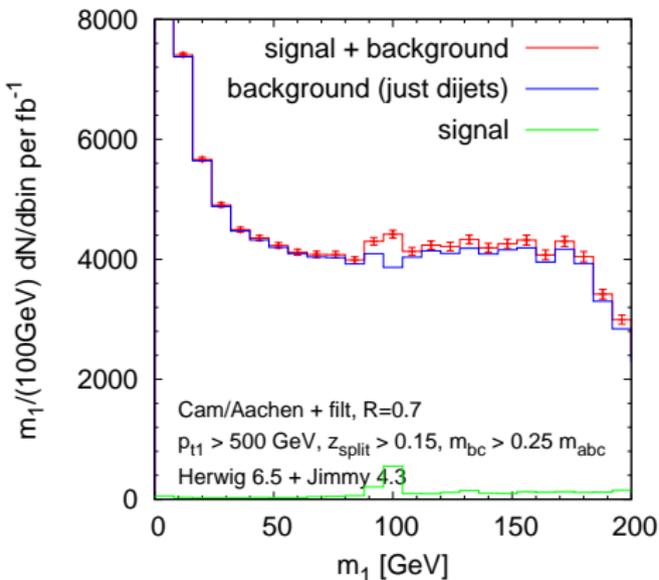
► And fourth central jet

99% background rejection
 scale-invariant procedure
 so remaining bkgd is flat

Once you've found neutralino:

► Look at m_{14} using events with
 m_1 in neutralino peak and in
 sidebands

Out comes the squark!



Keep it simple:

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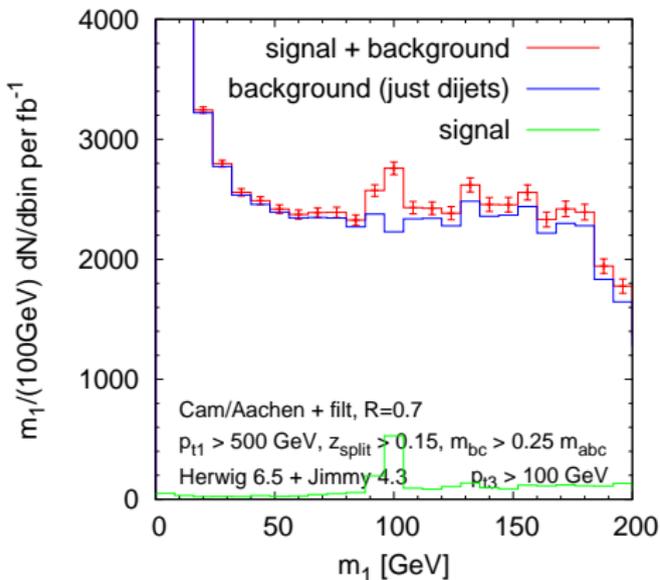
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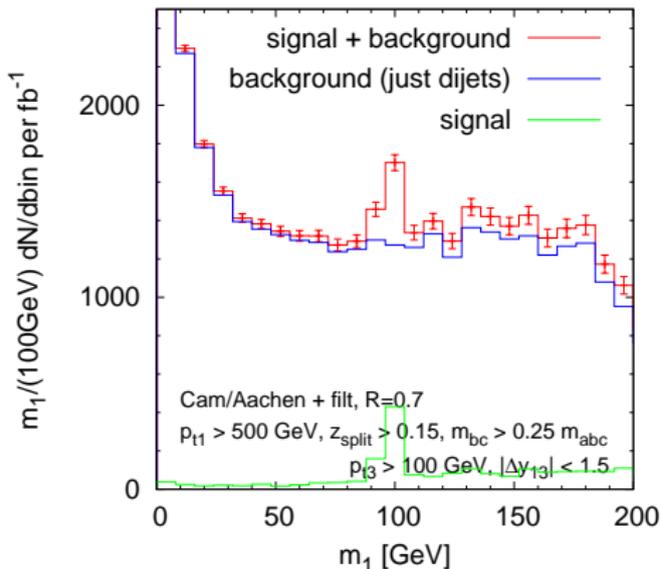
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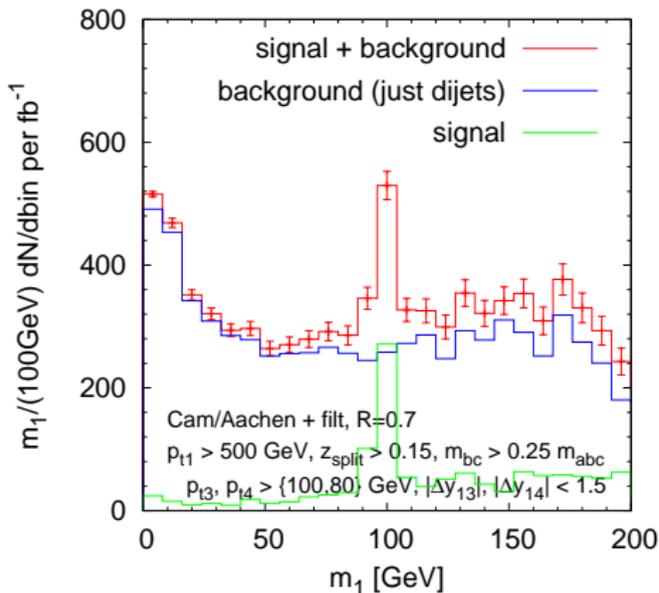
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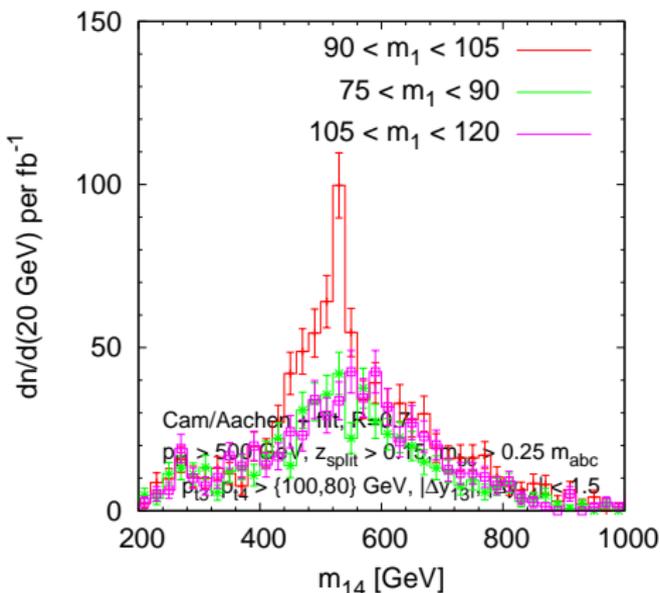
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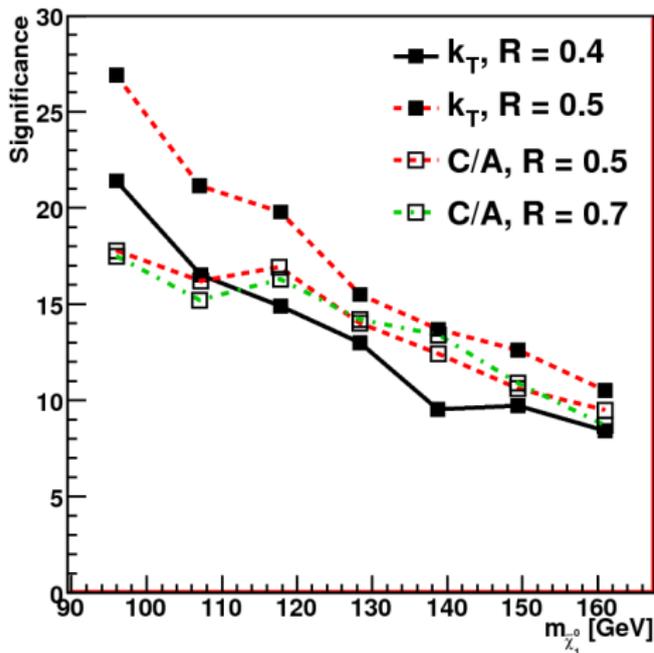
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RPV SUSY: significance v. mass scale



- ▶ All points use 1 fb^{-1} , 14 TeV
- ▶ Divide significance by ~ 3 for 7 TeV
- ▶ as $m_{\tilde{\chi}}$ increases, $m_{\tilde{q}}$ goes from 530 GeV to 815 GeV
- ▶ Same cuts as for main SPS1A analysis

no particular optimisation

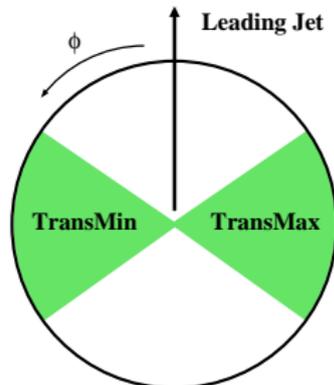
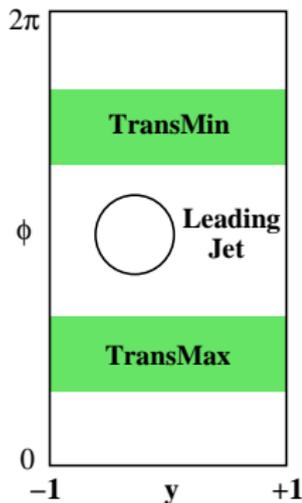
Constraining low- p_t part of Monte Carlos

Underlying Event

For each event

[Marchesini & Webber (1988), UA1 (1988), Field et al.]

1. take charged particles with $p_t > 0.5$ GeV and $|y| < 1$
2. cluster with cone jet algorithm with $R = 0.7$ to find the leading jet
3. define typical p_t of UE as $\langle p_t \rangle$ in TransMin, TransMax or TransAv regions



TransAv: $\mathcal{O}(\alpha_s)$

TransMax: $\mathcal{O}(\alpha_s)$

TransMin: $\mathcal{O}(\alpha_s^2)$

► **topological** separation: UE defined as particles entering certain region of (y, ϕ) space

For each event

[Cacciari, Salam, Soyez ('08), <http://fastjet.fr>]

1. cluster particles with an infrared safe jet finding algorithm (all particles are clustered so we have set of jets ranging from hard to soft) only k_t or C/A algs

2. from the list of all jets (no cuts required!) determine

$$\rho = \text{median} \left[\left\{ \frac{p_{t,j}}{A_j} \right\} \right]$$

and its uncertainty σ

- ▶ median gives a typical value of p_t/A for a given event
- ▶ using median is a way to **dynamically** separate hard and soft parts of the event

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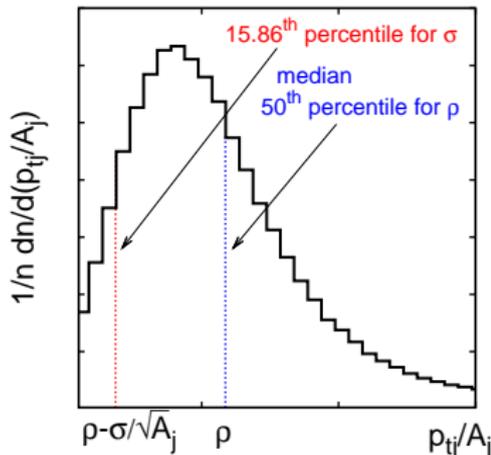
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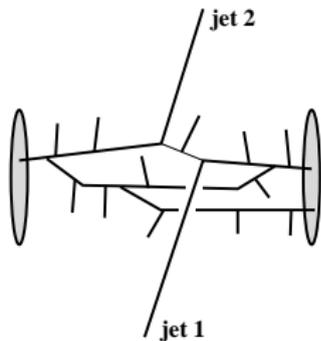
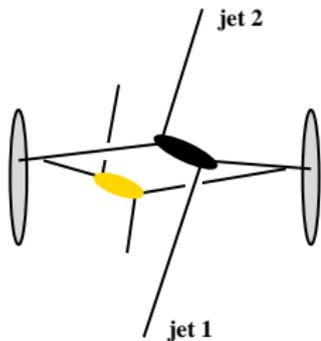
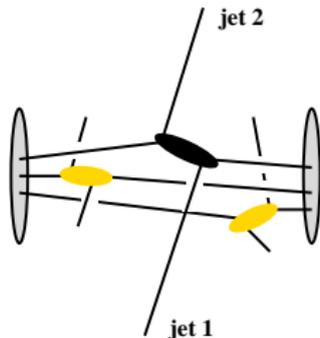


How do you decide when one method works better than another?

Cacciari, GPS & Sapeta '10

Questions

- ▶ should initial and final state radiation be called part of the underlying event?
- ▶ are multiple parton interactions responsible for most of the underlying activity?
- ▶ what about correlations? BFKL chains?



Do the methods measure “UE” or perturbative radiation?

If you can't define what UE is, you can't answer the question

So try a simplistic, but well-defined **toy model**

Soft component (UE)

Independent emission with spectrum

$$\frac{1}{n} \frac{dn}{dp_t} = \frac{1}{\mu} e^{-p_t/\mu}$$

$\langle \text{Number} \rangle$ of emissions and
 $\langle p_t \rangle = \mu$ set its characteristics

Hard component (PT)

Independent emission with spectrum

$$\frac{dn}{dp_t dy d\phi} = \frac{C_i \alpha_s(p_t)}{\pi^2 p_t}$$

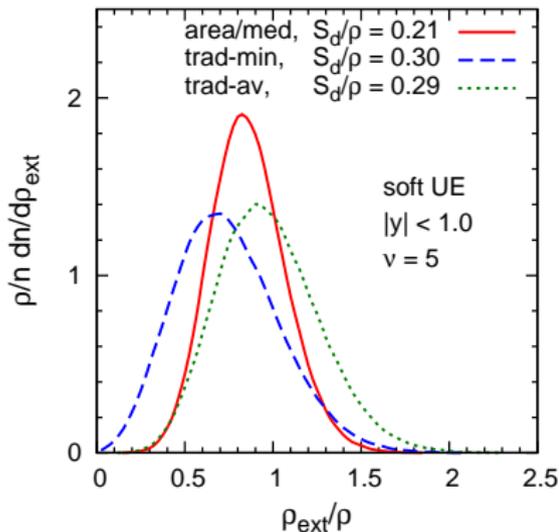
up to scale $Q \sim p_{t,hard}/2$
 (C_i is $C_A = 3$ or $C_F = \frac{4}{3}$)

In the toy model: the same ρ distribution used to generate all events

- ▶ nevertheless: event-to-event fluctuations of ρ due to restricted area
- ▶ this sets the lower limit for the uncertainty of ρ determination

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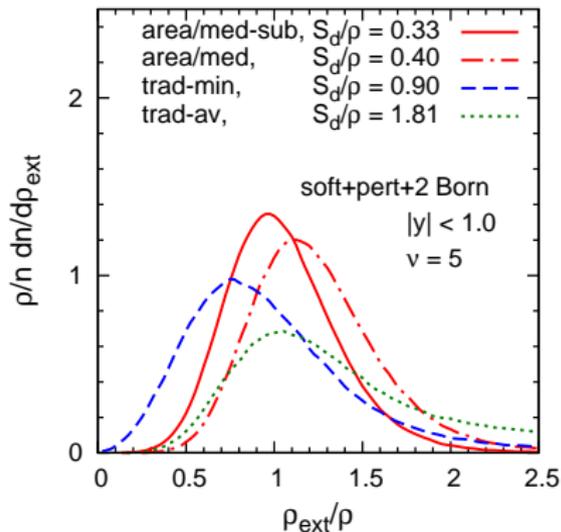
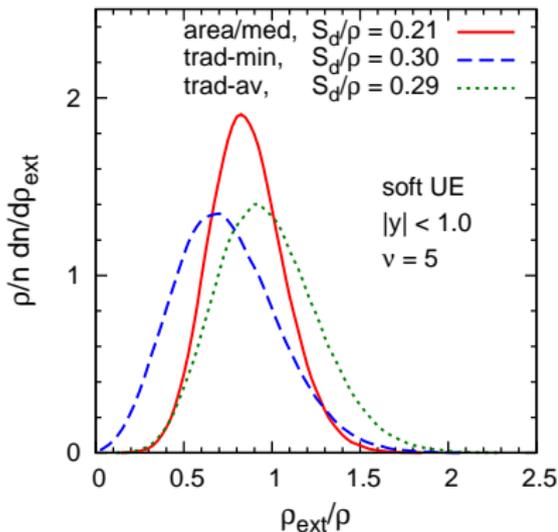
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- ▶ traditional approach suffers more from the hard contamination $S_d \sim Q$

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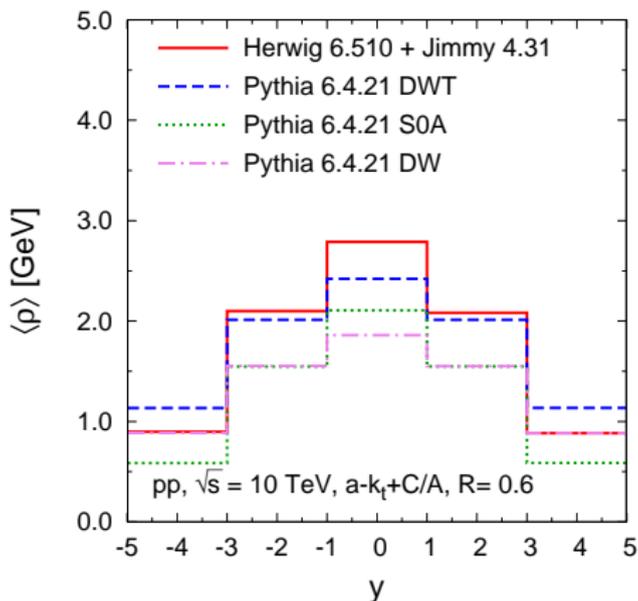
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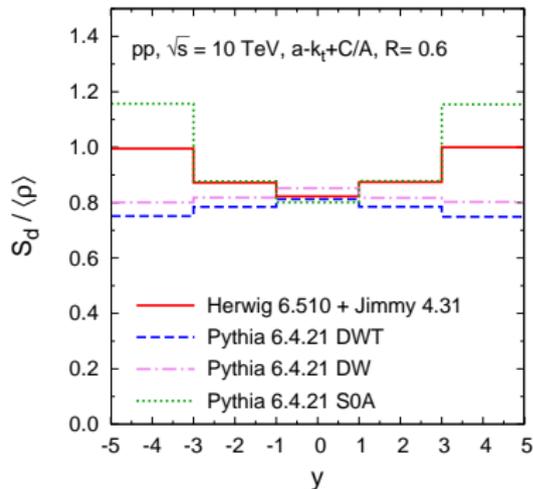
UE in Monte Carlo with median
method?

- ▶ dijets at the LHC, $\sqrt{s} = 10$ TeV, $p_t > 100$ GeV, $|y| < 4$

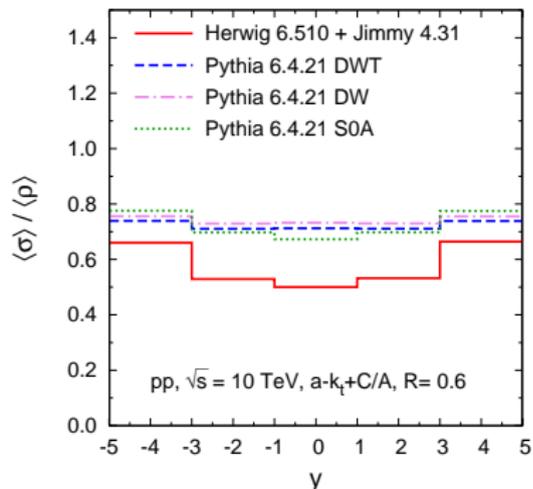


- ▶ significant y dependence
- ▶ strips of $\Delta y=2$ sufficient for robust ρ determination

▶ from event to event

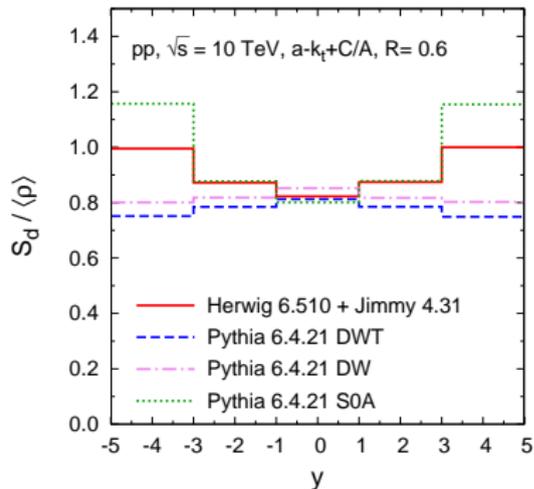


▶ within an event

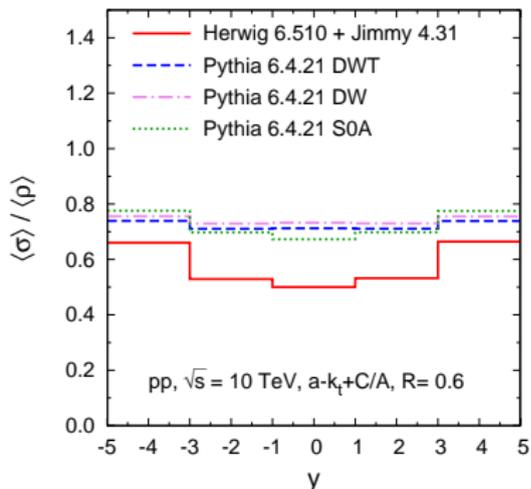


- ▶ large inter-event and intra-event
- ▶ two patterns of rapidity dependence
- ▶ sizable difference between Herwig+Jimmy and Pythia

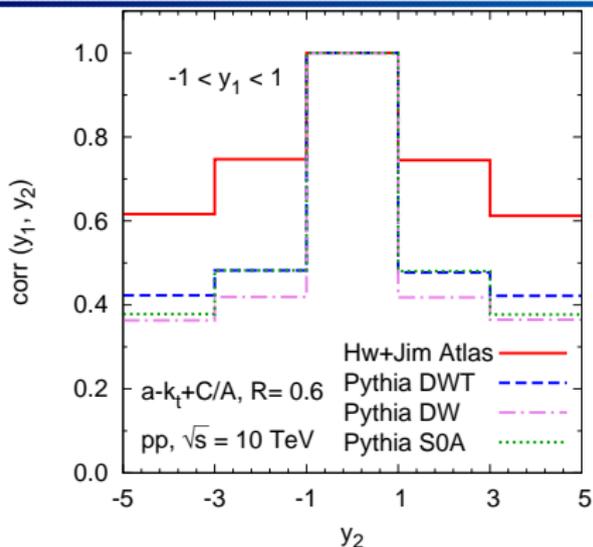
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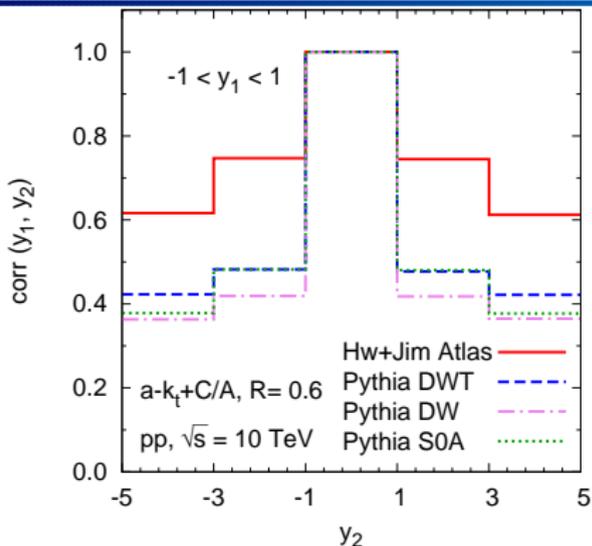
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- ▶ y_1, y_2 – rapidity bins of width $\Delta y = 2$
- ▶ $\langle \dots \rangle$ – average over many events

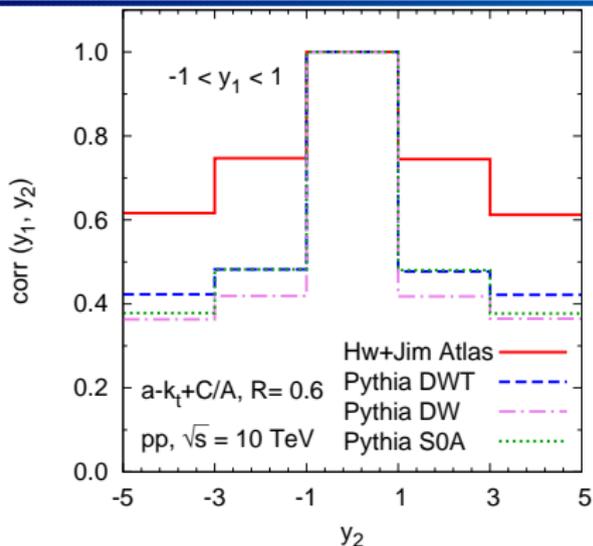
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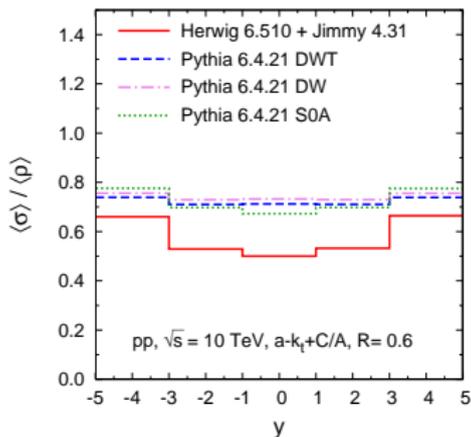
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- ▶ In early data, look at ratios of observables.
Much scope for constraining our QCD predictions
- ▶ There's more information in the Underlying Event than we're extracting currently
Jets offer a way of extracting it
- ▶ Searches, e.g. multi-jet + jet-substructure, have interesting potential in 2010-2011 data

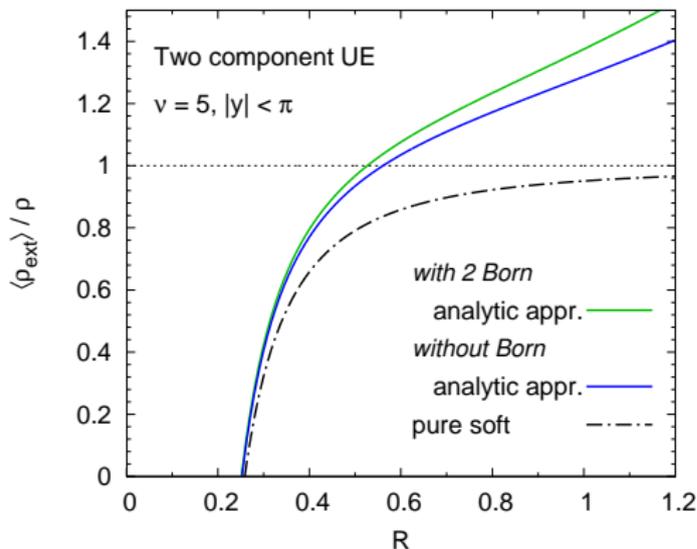
EXTRAS

7 TeV LHC (leading order, from Herwig 6.5):

dijets, $p_t > 100$ GeV	2.7×10^5 pb	65% glue
dijets, $p_t > 300$ GeV	1000 pb	
dijets, $p_t > 500$ GeV	53 pb	30% glue
$W \rightarrow e/\mu + \nu + j$, $p_{tW} > 50$ GeV	620 pb	
$W \rightarrow e/\mu + \nu + j$, $p_{tW} > 100$ GeV	90 pb	
$Z \rightarrow \mu^+ \mu^- / e^+ e^- + j$, $p_{tZ} > 50$ GeV	66 pb	
$t\bar{t}$	70 pb	
$t\bar{t}$, $p_{t,t} > 300$ GeV	1.5 pb	

Two component model: soft UE + hard PT

Area/median approach



$$\langle \rho_{\text{ext}} \rangle \simeq \langle \rho_{\text{ext}}^{(\text{soft})} \rangle + \sqrt{\frac{\pi c_J}{2}} \sigma R \frac{\langle n_h \rangle}{A_{\text{tot}}}$$

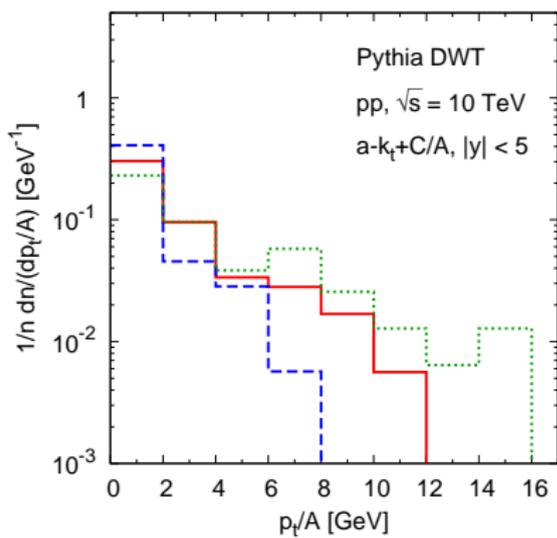
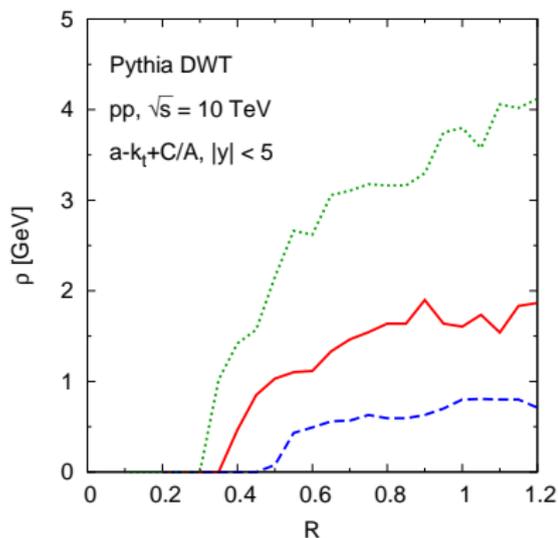
$\langle n_h \rangle$ – number of perturbative part.
 σ – measure of fluctuations
 ρ – true value of p_t/A

$$\langle \rho_{\text{ext}}^{(\text{soft})} \rangle \simeq \rho \frac{c_J R^{2\nu} - \ln 2}{c_J R^{2\nu} - \ln 2 + \frac{1}{2}} \Theta(R_{\text{cr}})$$

$$\frac{\langle n_h \rangle}{A_{\text{tot}}} \simeq \frac{n_b}{A_{\text{tot}}} + \frac{C_i}{\pi^2} \frac{1}{2b_0} \ln \frac{\alpha_s(Q_0)}{\alpha_s(Q)}$$

- ▶ the two terms bias $\langle \rho_{\text{ext}} \rangle$ in opposite directions
- ▶ for $R \simeq 0.5 - 0.6$ (used in most MC analysis of UE) the biases largely cancel
- ▶ similar picture and conclusions for σ

Comparison of characteristics: toy model vs MC



- ▶ the pattern for $\rho(R)$ from the toy model present in MC events:
 - turn-on at low R ,
 - linear growth at larger R
- ▶ variation in the curves indicative of the inter-event fluctuations
- ▶ growth of ρ with R produced by the tails of distributions of p_t/A