Removing negative weights in Monte Carlo event samples

Andreas Maier

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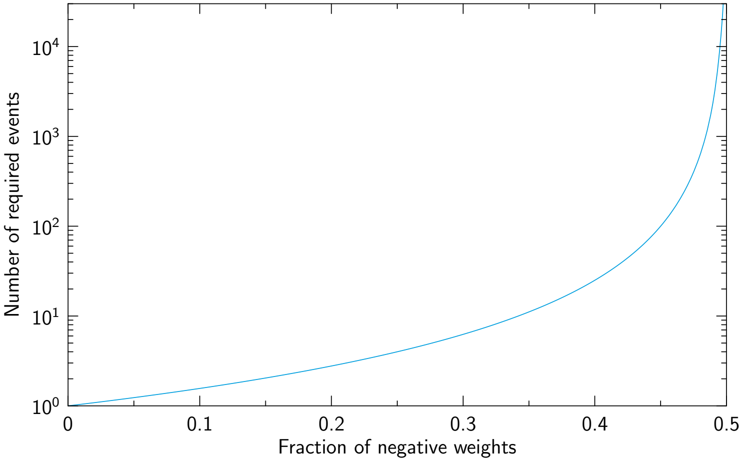
J. R. Andersen, A. Maier, D. Maître Eur.Phys.J.C 83 (2023) 9, 835
J. R. Andersen, A. Maier Eur.Phys.J.C 82 (2022) 5, 433
J. R. Andersen, C. Gütschow, A. Maier, S. Prestel Eur.Phys.J.C 80 (2020) 11, 1007
+ ongoing work with Ana Cueto, Stephen Jones

Why are negative event weights a problem?

Number of unweighted events to reach given accuracy:



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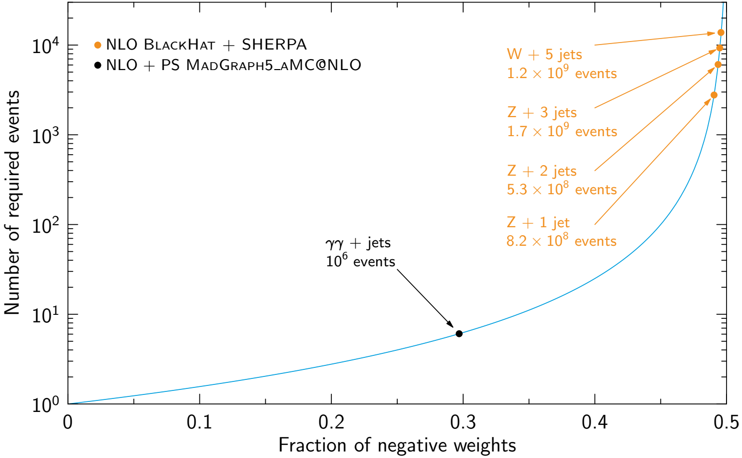
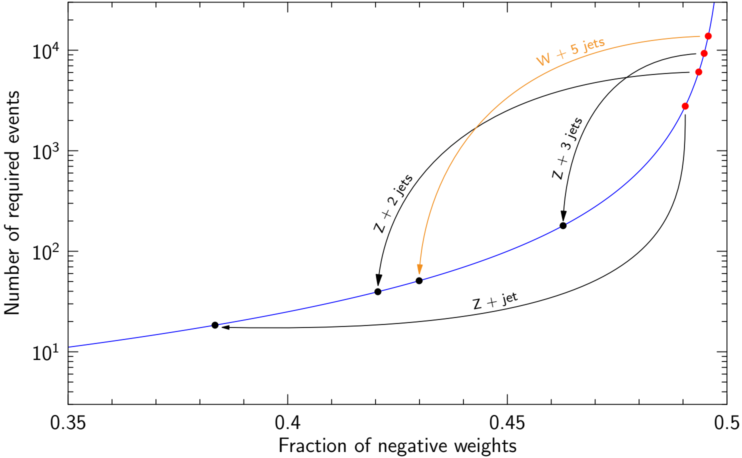


V + jets: Phys. Rev. D 88 (2013) 014025, Phys. Rev. D 97 (2018) 096010

$\gamma\gamma$ + jets: parameters from background modelling for ATLAS $H \to \gamma\gamma$ measurement arXiv:2306.11379

Cell resampling for V + jets at NLO

Negative weights

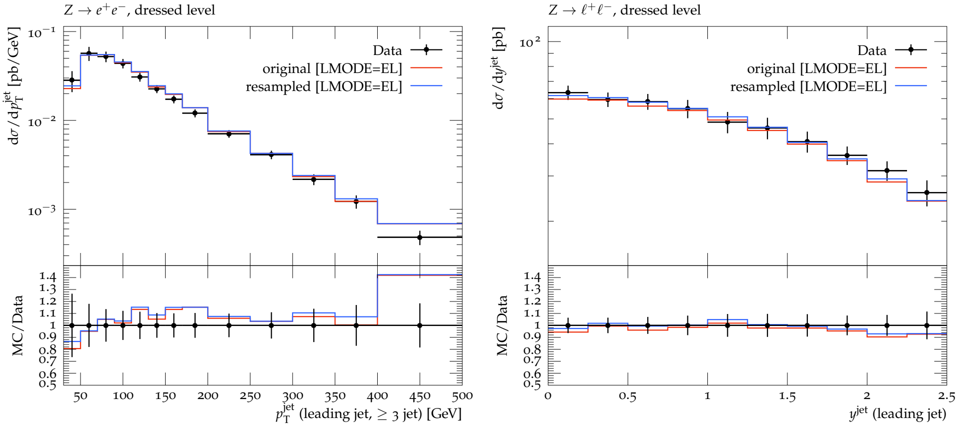


Cell resampling drastically reduces the number of required events

Cell resampling for V + jets at NLO

Predictions

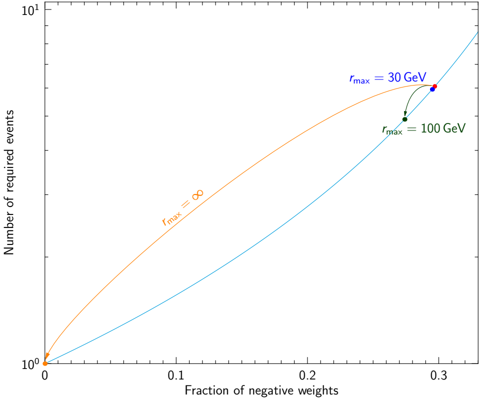
Analysis from ATLAS, Eur. Phys. J. C77 (2017) 361:

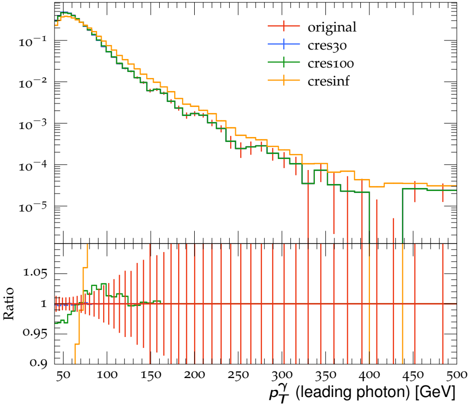


Cell resampling preserves predictions within a few per cent

Work in progress: showered samples

$pp \to \gamma\gamma +$ jets, 10^6 events:

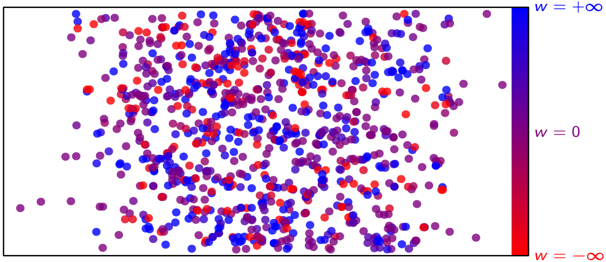




Expect more efficient negative-weight reduction for larger sample

Observables

Weighted events in 2D projection of phase space:



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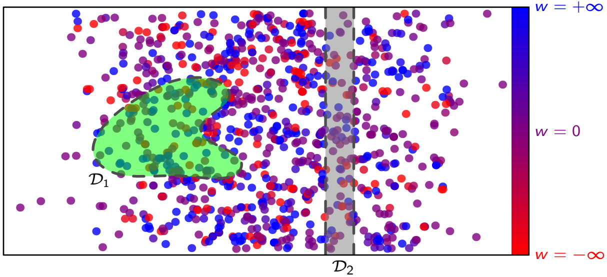


Observables $\mathcal{O}$:

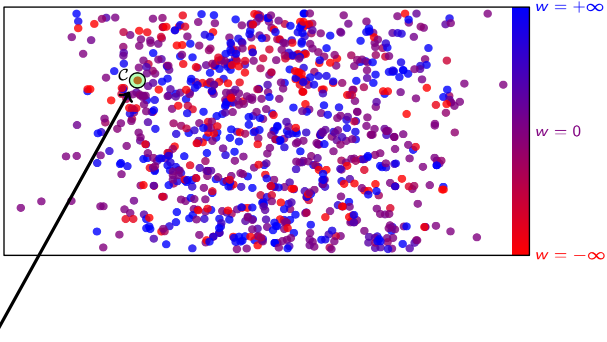
- Select region $\mathcal{D}$ in phase space $\geq$ experimental resolution
- $\mathcal{O} = \sum_{i \in \mathcal{D}} w_i \geq 0$ with sufficient statistics

e.g. histogram bins

Redistribute weights without affecting any observable

Cell resampling

[Andersen, Maier 2021]

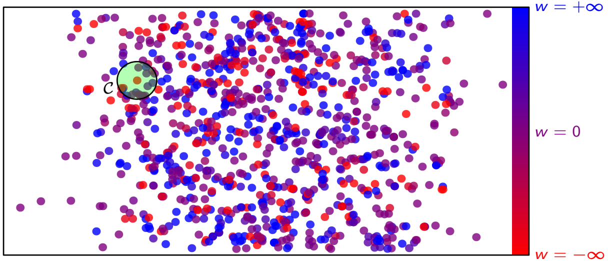


Cell resampling:

1. Choose seed event with negative weight for cell $\mathcal{C}$

Cell resampling

[Andersen, Maier 2021]



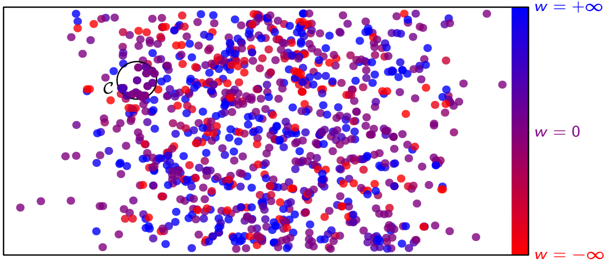
Cell resampling:

1. Choose seed event with negative weight for cell $\mathcal{C}$
2. Iteratively add nearest event to cell until $\sum_{i \in \mathcal{C}} w_i \geq 0$ or radius exceeds $r_{\max}$

Cells get systematically smaller with increasing statistics

Cell resampling

[Andersen, Maier 2021]



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3. Redistribute weights, e. g. average over cell: $w_i \to w = \frac{\sum_{j \in \mathcal{C}} w_j}{\text{\# events in } \mathcal{C}}$
4. Repeat

Cell resampling

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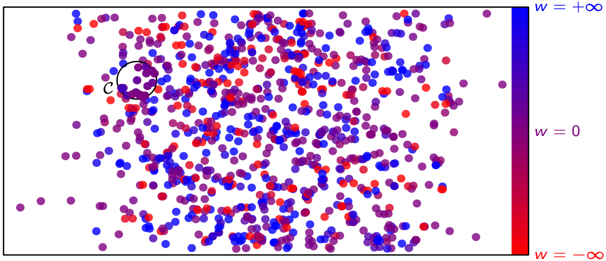

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1. Choose seed event with negative weight for cell $\mathcal{C}$
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   What does "nearest" mean?
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Distances in phase space

Criteria for distance function:

- Small distance between events that look similar in detector or differ only in properties the event generator can't predict
- Large distance between events that look different in detector

Define distance in terms of infrared & collinear safe objects, e.g. jets

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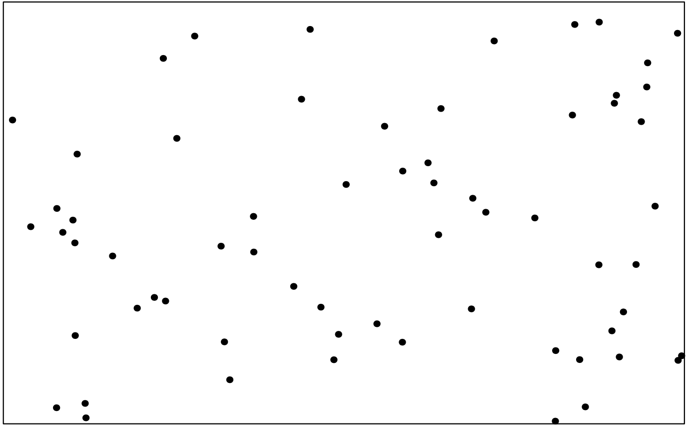
Current choice:

1. Find optimal pairing between observable objects in both events
2. Sum up spatial momentum differences

Nearest-neighbour search



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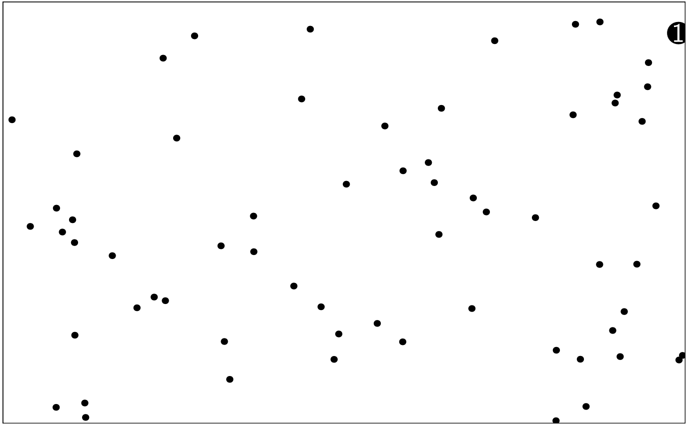
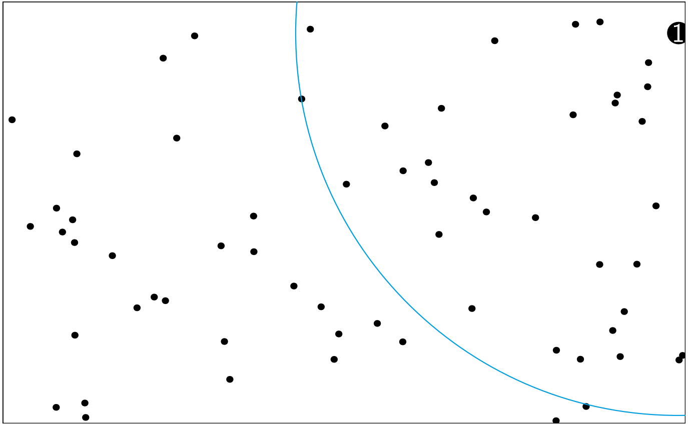


Vantage-point tree:

➊

Nearest-neighbour search



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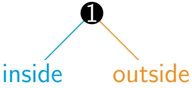

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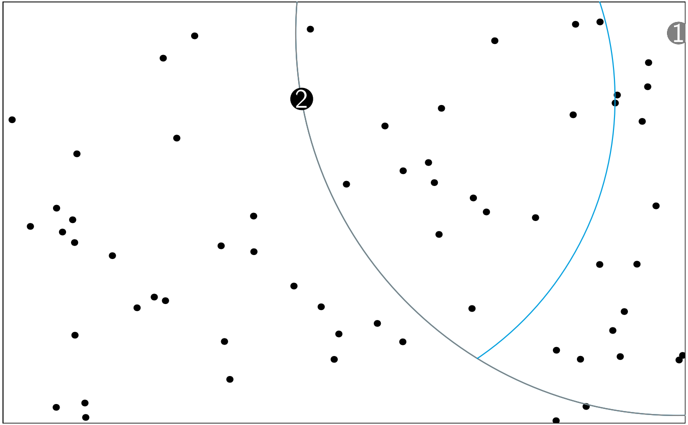

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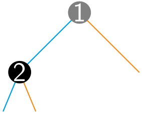

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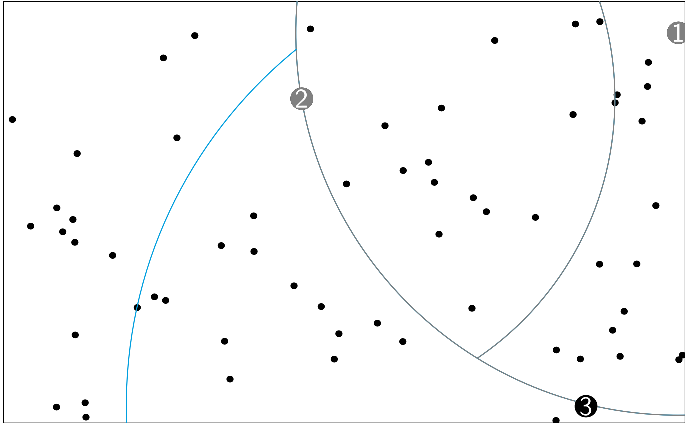

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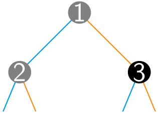

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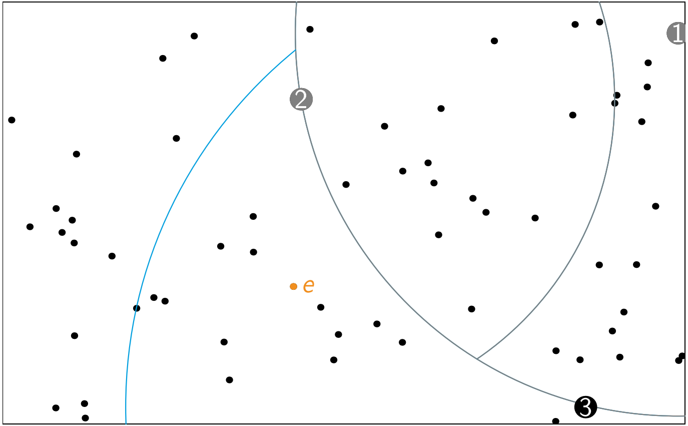

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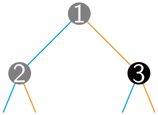

Search nearest neighbour for *e*:

- Find candidate in region containing *e*
- Search neighbouring regions only if better candidate may be found

Computing requirements

Memory

Fast + exact nearest-neighbour search: keep all events in memory

Need $\sim$ (byte size of event) GB for $\sim 10^9$ events

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Read + convert events → Cell resampling → Read + write events

Current requirements:

- Persistent event samples with reasonably fast sequential access
- 300 GB to 400 GB of memory per 10^9 events,
  no huge increase from showering expected

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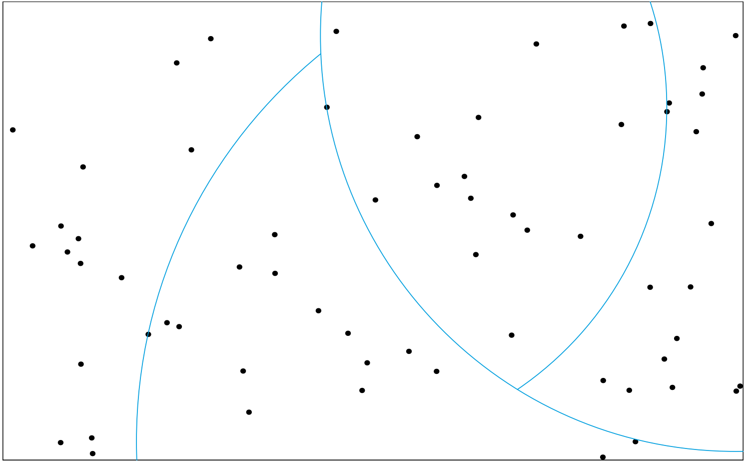
Can we go beyond $\sim 10^9$ events?

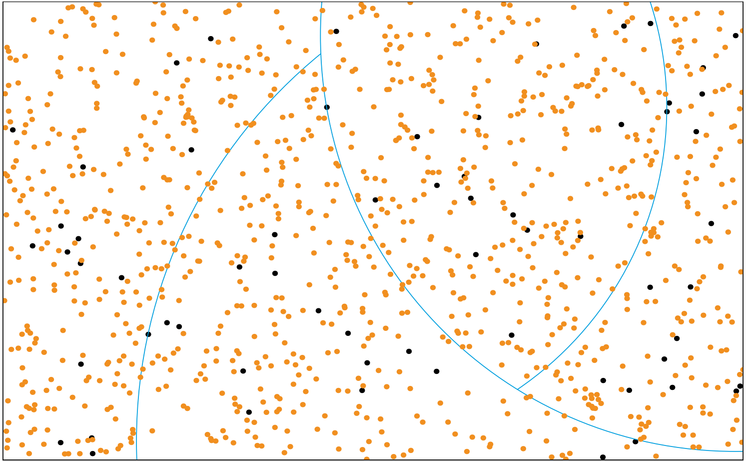
Work in progress: memory efficiency

1. Partition phase space using vantage-point tree from small event sample



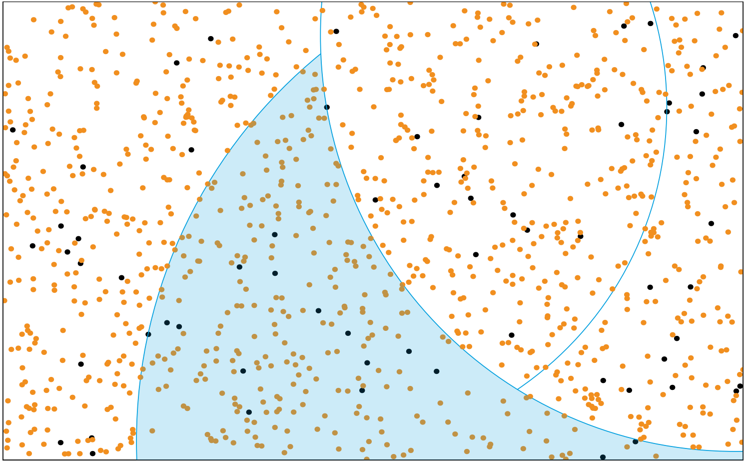
Work in progress: memory efficiency

2. Identify region for each event in large sample



Work in progress: memory efficiency

3. Independent cell resampling for each region



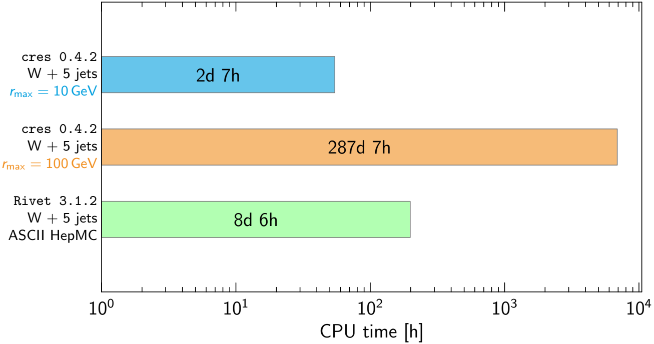
Computing requirements

CPU time

Benchmark machines:

# Cores	CPU model	Memory	Age
20	XEON E5-2640 @ 2.40GHz	400GB	$\sim$7 years
12	XEON E5-2643 @ 3.40GHz	800GB	$\sim$6 years

Local rotating disks, RAID 6



Computing requirements

Wall-clock time

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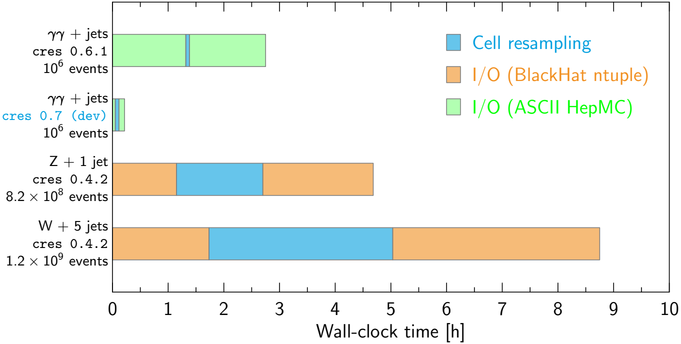

Summary

Current status:

- Remove event weights by smearing over small phase space regions
- Ready for large high-multiplicity samples
  - Computationally efficient: ~ 55 CPU hours for one billion events (W + 5 jets)
  - Significant memory requirements: 300 GB to 400 GB
  - Needs persistent event records
  - Work in progress: distribution over several nodes
- Proof of concept: showered samples

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Wishlist:

- Adoption & integration into existing workflows
  - Support more event file formats?
  - Definitions of observable objects: flavoured jets, isolated photons, . . .
  - Internal Monte Carlo optimisation $\hookrightarrow$ McMule
  - . . .
- Explore design space
  - Other distance measures, guided by detector sensitivities
  - Other prescriptions for redistributing weights
  - Further code optimisation?

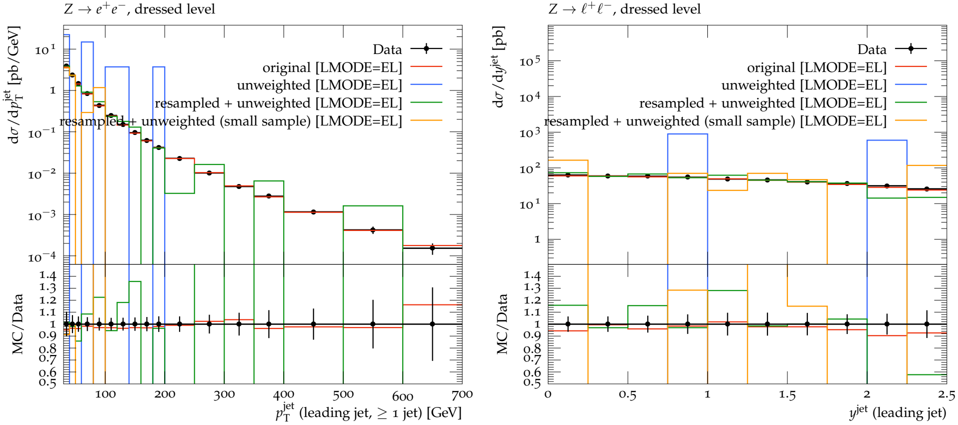
Backup

Event samples

[BlackHat + Sherpa 2013 + 2017]

Sample	Process	Centre-of-mass energy	# events
Z1	$pp \to (Z \to e^+e^-) + \text{jet}$	13 TeV	8.21×10^8
Z2	$pp \to (Z \to e^+e^-) + 2\ \text{jets}$	13 TeV	5.30×10^8
Z3	$pp \to (Z \to e^+e^-) + 3\ \text{jets}$	13 TeV	1.65×10^9
W5	$pp \to (W^- \to e^-\nu_e) + 5\ \text{jets}$	7 TeV	1.17×10^9

Unweighting for Z + jet



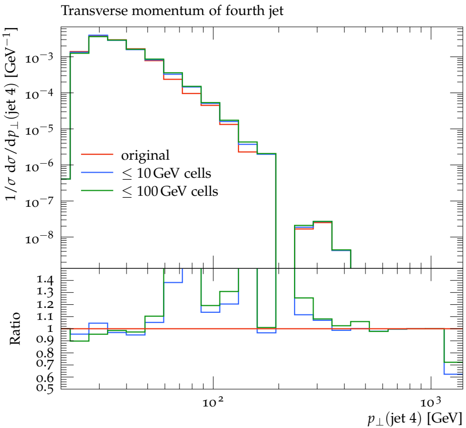
original: 8.21×10^8 events

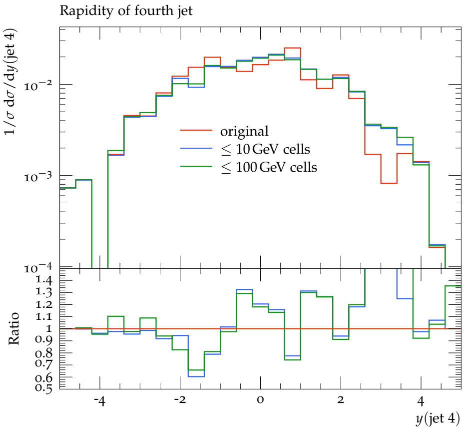
unweighted: 320 events

resampled + unweighted: 11574 events

resampled + unweighted (small sample): 320 events

Resampling for W + 5 jets





Distances in phase space

Need distance function $d(e, e')$ between events e, e'

- Essential: $d(e, e')$ small $\Rightarrow$ e, e' look similar in detector or differ only in properties the event generator can't predict
- Desirable: $d(e, e')$ large $\Rightarrow$ e, e' look different in detector

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Example: infrared safety

- $d(e, e')$ unaffected by collinear splittings with $\Theta \to 0$
- $d(e, e')$ unaffected by soft particles with $p \to 0$

$\Rightarrow$ define distance in terms of infrared-safe physics objects, e.g. jets

Here: Example for fixed-order (QCD) event generator

Distances in phase space

Concrete implementation

1. Collect all infrared-safe objects in event e into sets $\{\underbrace{s_1}_{\text{jets}}, \underbrace{s_2}_{\text{electrons}}, \ldots, s_T\}$

$$d(e, e') = \sum_{t=1}^{T} d(s_t, s'_t)$$

Distances in phase space

Concrete implementation

jets → s_1, electrons → s_2

1. Collect all infrared-safe objects in event e into sets $\{ s_1, s_2, \ldots, s_T \}$

$$d(e, e') = \sum_{t=1}^{T} d(s_t, s'_t)$$

2. Objects in s_t have four-momenta $(p_1, \ldots \ldots\ldots, p_P)$

   Objects in s'_t have four-momenta $(q_1, \ldots, q_Q, 0, \ldots, 0)$

$$d(s_t, s'_t) = \min_{\sigma \in S_P} \sum_{i=1}^{P} d_t(p_i, q_{\sigma(i)})$$

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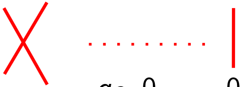

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Distances in phase space

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Efficient minimisation: Hungarian algorithm [Jacobi 1890]

Distances in phase space

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$$d(s_t, s'_t) = \min_{\sigma \in S_P} \sum_{i=1}^{P} d_t(p_i, q_{\sigma(i)})$$

3. Choose distance function between particle momenta
   Here: independent of particle type t, do not consider internal structure

$$d_t(p, q) = \sqrt{(\vec{p} - \vec{q})^2 + \tau^2 (p_\perp - q_\perp)^2} \qquad \tau\text{: tunable parameter}$$