Level up your performance calculation
of the fast shower simulation model

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CERN

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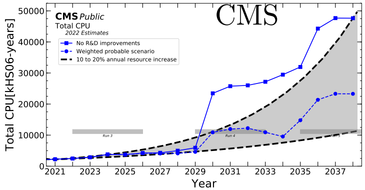
Why to use parameterisation / fast(er) simulation?

CERN-CMS-NOTE-2022-008

To speed-up simulation in order to generate more data within same CPU time:

- to fit within available computing resources;
- to provide sufficient amount of simulation data for comparison with the experimental data;



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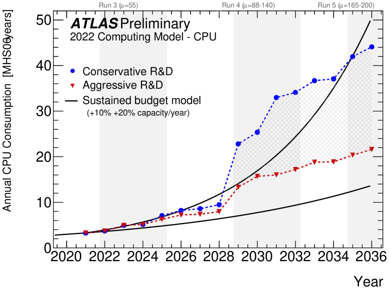
CERN-LHCC-2022-005



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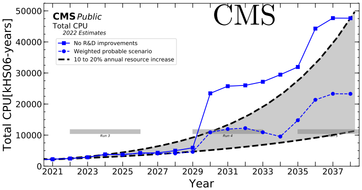

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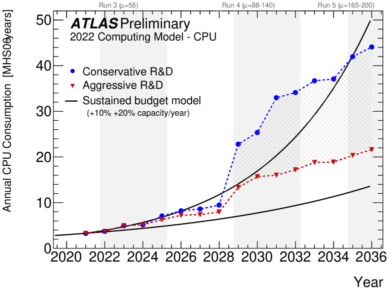

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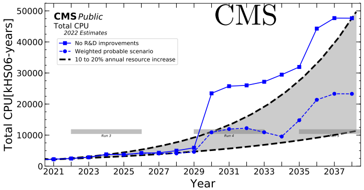
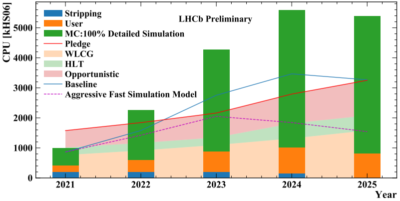
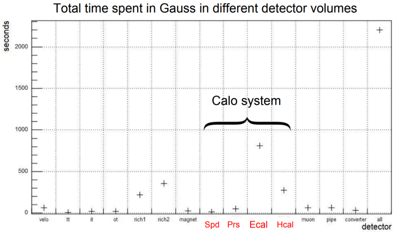


LHCb-FIGURE-2019-01



LHCb-TALK-2018-349



CPU time in calorimeter system: ~ 53%

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... in the meantime...

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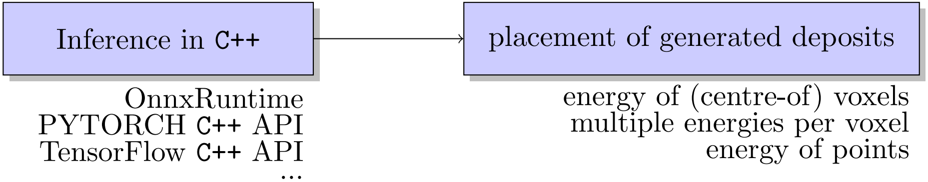

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Inference in `C++` → placement of generated deposits

OnnxRuntime
PYTORCH `C++` API
TensorFlow `C++` API
...

energy of (centre-of) voxels
multiple energies per voxel
energy of points

Memory-wise:

the larger the models
the larger the number of models ⇒ the larger memory usage
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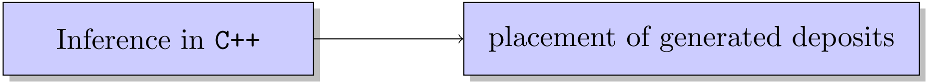

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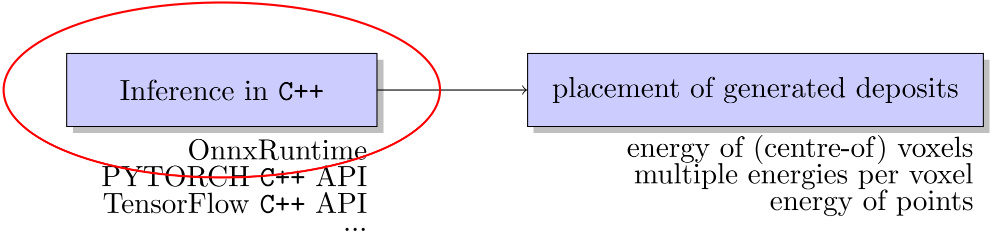

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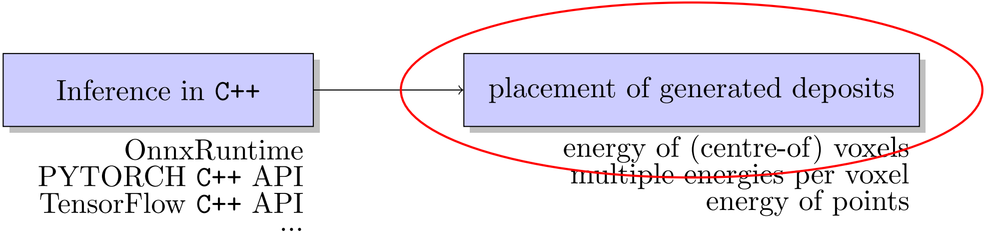

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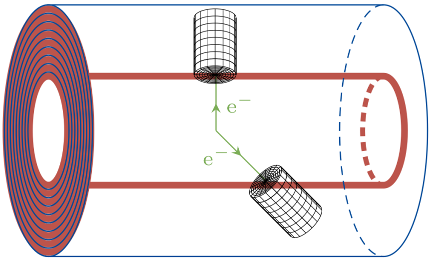
Detector setup

Presented data comes from the `Par04` example of Geant4.

Simple cylinders of active (Si) and passive (W) materials.



Detector setup

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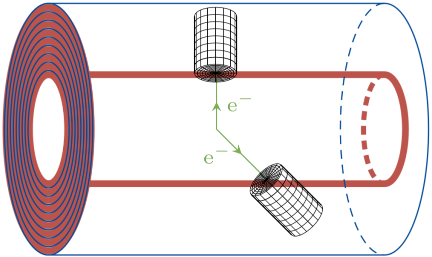
Simple cylinders of active (Si) and passive (W) materials.

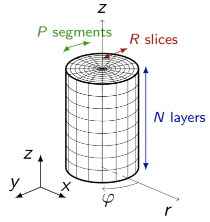
New: introduced (physical) cells, with the total number in the detector: either 300k or 3M.

The total voxelisation of showers is 6.5k (like CaloChallenge dataset2) or 40k (like dataset3) and created around the shower center.

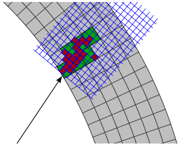
Voxelisation is used first to produce training data, and then generated showers at those (voxels') positions must be placed at/mapped to the cells.

$\longrightarrow$ No matter if voxels or point clouds are used: it's their number in generated shower that counts.





dataset2:
$R \times P \times N = 9 \times 16 \times 45$
dataset3:
$R \times P \times N = 18 \times 50 \times 45$



detector cells vs shower voxels

Disclaimer

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Par04 example of Geant4:

300k readout granularity: gitlab.cern.ch/fastsim/par04/-/tree/v11.1_lowgran
3M readout granularity: gitlab.cern.ch/fastsim/par04/-/tree/v11.1_highgran

CaloChallenge dataset 3 is the default, dataset 2 obtained by changing the input macro parameters.

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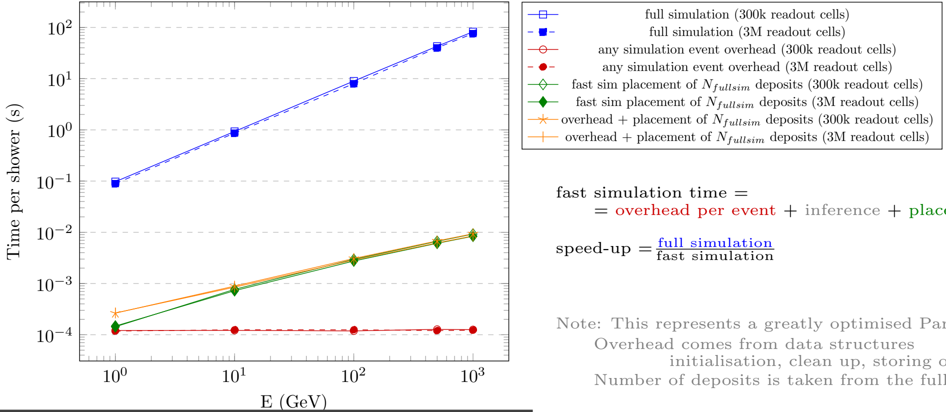
CaloChallenge dataset 3 is the default, dataset 2 obtained by changing the input macro parameters.

There is **no model**, no calculation (ML or parameterisation). Results represent the 'extra' cost of high granularity.

All data points are an average over 10 runs, from 1000 shower samples per particle energy.

Time performance

E (GeV)	1	10	100	500	1000
full sim (300k)	0.097	0.93	9.0	42.9	82.3
full sim (3M)	0.089	0.86	8.0	40.0	76.0
event overhead (300k)	0.00012	0.00012	0.00012	0.00013	0.00013
event overhead (3M)	0.00012	0.00012	0.00013	0.00012	0.00012
fast sim deposits placement (300k, dataset3)	0.00014	0.00077	0.00296	0.00666	0.00923
fast sim deposits placement (3M, dataset3)	0.00015	0.00073	0.00273	0.00609	0.00837
overhead + placement (300k)	0.00026	0.00089	0.00308	0.00679	0.00936
overhead + placement (3M)	0.00027	0.00085	0.00287	0.00621	0.00849



fast simulation time =
= overhead per event + inference + placement of N deposits

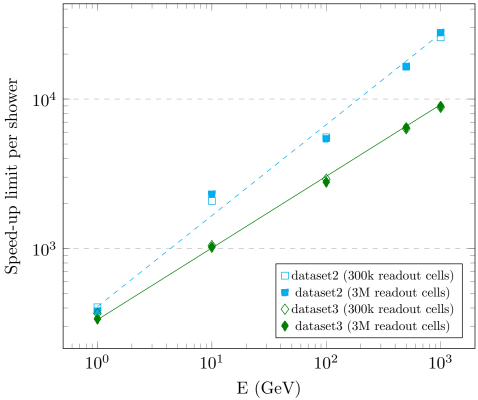
speed-up $= \frac{\text{full simulation}}{\text{fast simulation}}$

Note: This represents a greatly optimised Par04 simulation.
Overhead comes from data structures initialisation, clean up, storing output, ...
Number of deposits is taken from the full simulation.

Speed-up limit

E (GeV)	1	10	100	500	1000
speed-up limit for dataset 2 (fit)	358	2143	6061	17146	28108
speed-up limit for dataset 3 (fit)	321	1073	3029	6547	9274

$$\text{speed-up limit} = \frac{\text{full simulation}}{\text{overhead} + \text{placement}}$$



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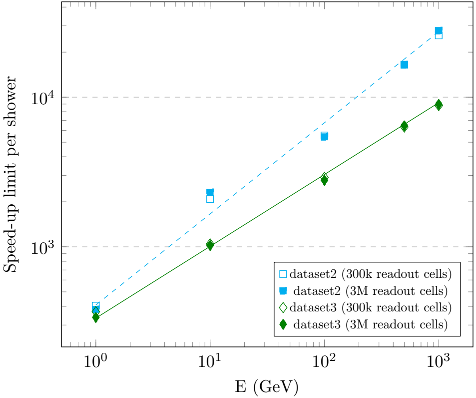
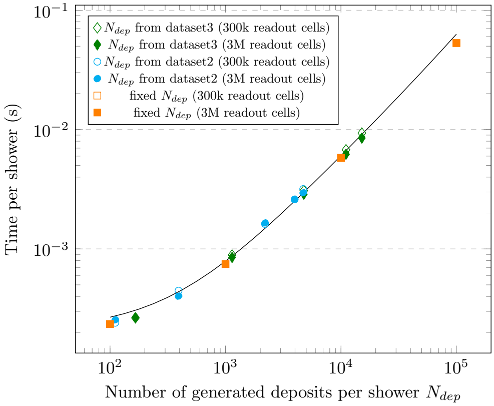


Low energy particles are most populous,
so likely the average speed-up per shower is no larger than $\mathcal{O}(1000)$.

Which is still a huge gain!

Time performance estimation (as a function on number of deposits)



green diamonds correspond to dataset 3,

cyan circles correspond to the dataset 2,

orange circles is an artificial placement of N_{dep}.

Fit to data:

$t(s) = 5.015e^{-13} N_{dep}^2 + 5.79e^{-7} N_{dep} + 0.00021$

↑ can be applied to any dataset 2 or 3 calculations on top of the inference time.

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- Possible batching within a single event can be larger for heavy events ($t\bar{t}$) and smaller for lighter ones (minimum bias).
- To remember: fast simulation may require more models (per particle, per detector region).
- This exercise give a rough estimate on calculated batch sizes. It is done using Pythia and looking at particles entering calorimeters.

Simplistic detector

Few layers of materials (average tracker budget) are placed in front of the calorimeter.

Particles are counted at the entrance to the calorimeters.

(mean and RMS given for minbias, Gaussian fit for $t\bar{t}$)

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		$\|\eta\| < 1.5$ E>100 MeV	E>1 GeV	E>10 GeV	$\|\eta\| < 3$ E>100 MeV	E>1 GeV	E>10 GeV
$t\bar{t}$ @ 14 TeV pp	e^+/e^-	58±22	**7.7** ± 6.0	0.6±0.9	311±184	**24.9**±10.7	1.2±1.5
	γ	107±40	**17.0** ± 8.9	1.2±1.6	536±432	**46.3**±16.8	2.2±2.2
	π^+/π^-	83±33	**29.6** ± 13.4	0.6±3.7	363±232	**104.7**±37.1	7.3±4.3
minimum bias @ 14 TeV	e^+/e^-	11.8±11.7	**0.3**±0.8	-	108±84	**2.7**±3.3	-
	γ	26.3±22.6	**1.2**±1.8	-	206±156	**7.8**±7.5	-
	π^+/π^-	24.5±20.9	**3.6**±4.5	-	160±118	**33.4**±27.5	0.3±0.6
$t\bar{t}$ @ 365 GeV ee	e^+/e^-	22.7±9.1	**4.0**±3.0	0.25±0.5	26.2±10.6	**4.5**±2.9	0.3±0.5
	γ	38.4±14.2	**8.8**±4.0	0.4±0.7	44.6±15.4	**9.7**±3.9	0.5±0.7
	π^+/π^-	29.9±11.4	**14.9**±6.0	0.4±1.4	32.4±12.1	**16.1**±6.1	0.5±1.5

See talk from yesteday for more details on ODD.
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		$\|\eta\| < 1.5$ *(barrel)*			$\|\eta\| < 3$ *(barrel + endcaps)*		
		$E > 100$ MeV	$E > 1$ GeV	$E > 10$ GeV	$E > 100$ MeV	$E > 1$ GeV	$E > 10$ GeV
$t\bar{t}$ **@ 14 TeV**	e^+/e^-	64.1±25.6	**9.1**±6.2	0.6±1.0	86.8±33.2	**15.5**±7.8	1.1±1.4
	γ	113.1±44	**19.3**±9.2	1.3±1.5	159±68	**35**±13.6	2.7±2.6
	π^+/π^-	83±31	**32.0**±13.0	1.6±3.5	119±45	**55.7**±20.4	4.4±5.9
minbias @ 14 TeV	e^+/e^-	12.0±11.6	**0.4**±0.8	**-**	19.7±18.4	**1.6**±2.2	-
	γ	24.3±21.8	**1.3**±2.0	-	41.2±35.0	**6.0**±6.4	-
	π^+/π^-	22.3±19.9	**4.0**±5.2	-	35.5±30.1	**11.8**±11.6	0.3±0.7

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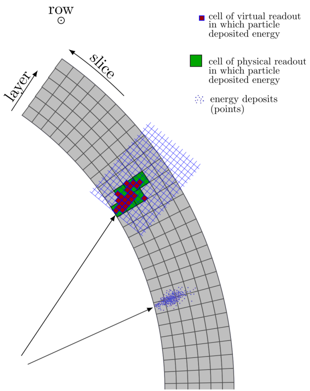
2. Any speed-up value, a comparison to GEANT4 simulation time **should** take into account a small event overhead + hit placement time (0.2–10 ms/shower)$\rightarrow$ otherwise only absolute measurements are fair.

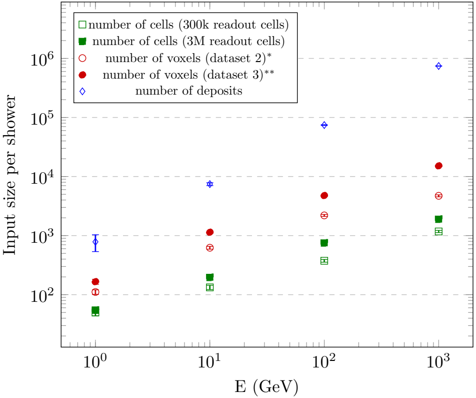
3. So far (per event) realistic batching is no larger than 20 – 40, depending if a single model can be used for barrel or barrel+endcap region (and it's for heavy events). Inference per batch=1 should probably always be measured (useful for lighter events).

BACKUP

Size of the input vs shower representation

E (GeV)	1	10	100	1000
N_{cells} (300k)	50±6	133±11	375±20	1175±51
N_{cells} (3M)	55±7	197±17	754±34	2796±55
N_{voxels} (dataset 2)	111 ±10	623 ± 34	2'198±84	4'712±186
N_{voxels} (dataset 3)	166 ± 16	1'140 ±53	4'769 ±162	15'164 ±470
$N_{deposits}$	785±249	7'444±423	74'318±1204	743'009±4267



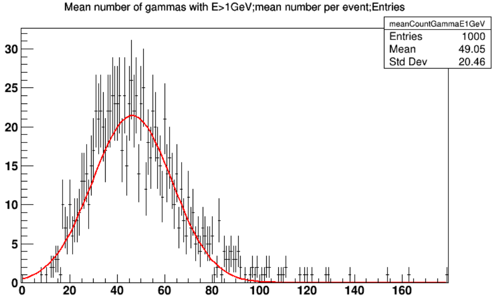


* voxelization with around 0.5 $X_0 \times 0.5\ R_M \times 0.4$ rad voxel size

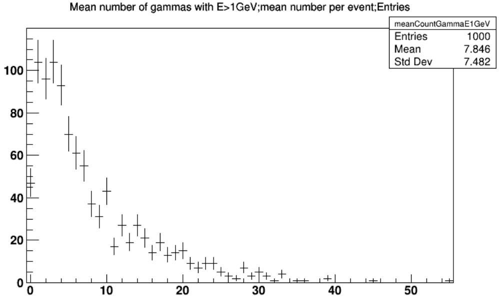
** voxelization with around 0.5 $X_0 \times 0.25\ R_M \times 0.125$ rad voxel size

Particle multipliciies

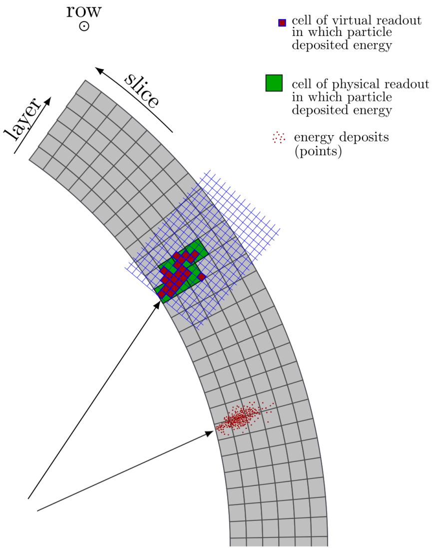
gg2ttbar @ 14 TeV



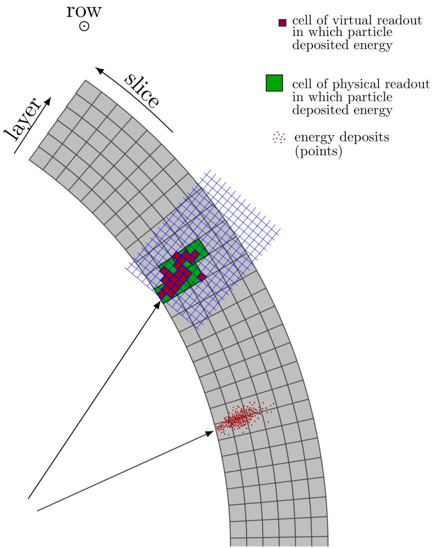
gg2minbias @ 14 TeV

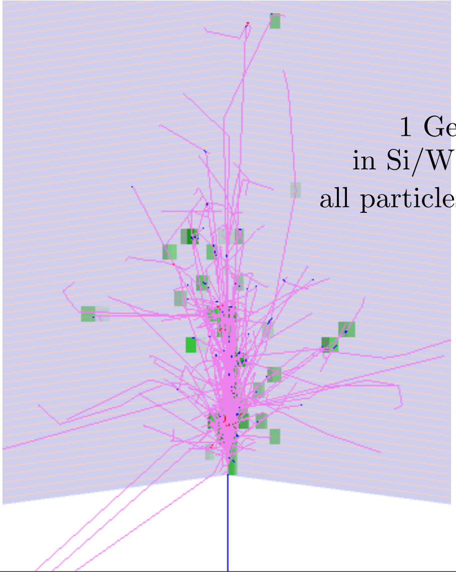


Shower data representation: cells, voxels, point clouds, ...



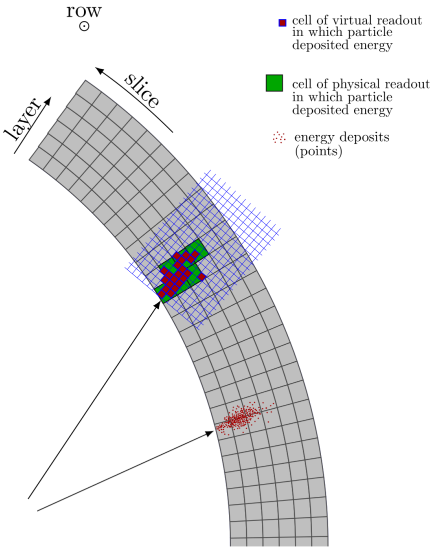
Shower data representation: cells, voxels, point clouds, ...

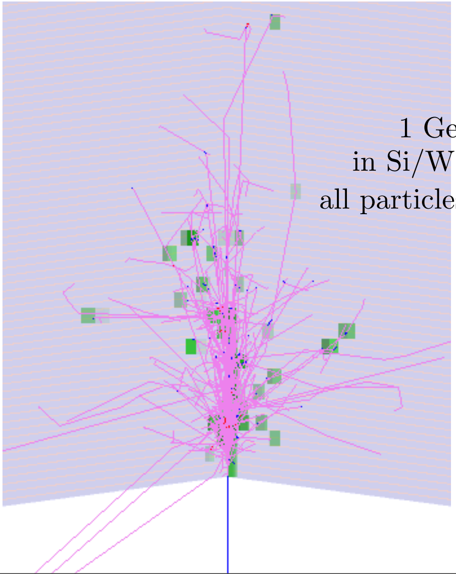




1 GeV e^-
in Si/W detector
all particles $> 1\,\mathrm{keV}$

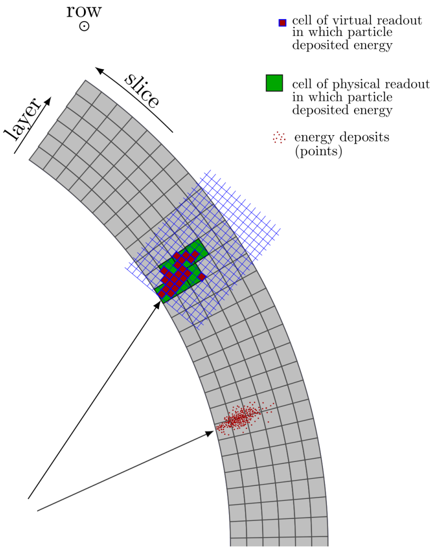
Shower data representation: cells, voxels, point clouds, ...

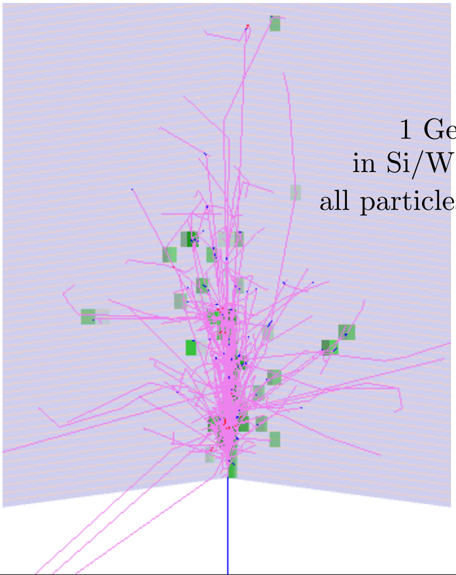




1 GeV e^-
in Si/W detector
all particles $> 10\,\mathrm{keV}$

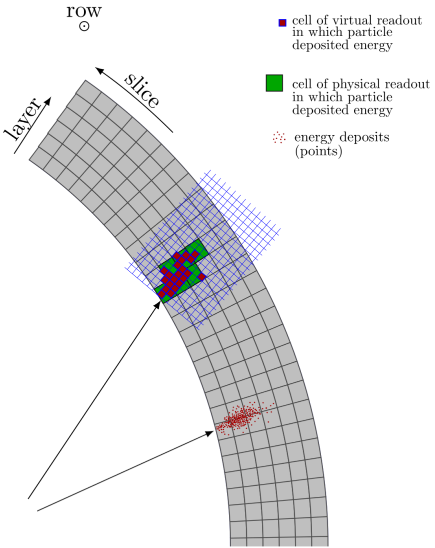
Shower data representation: cells, voxels, point clouds, ...

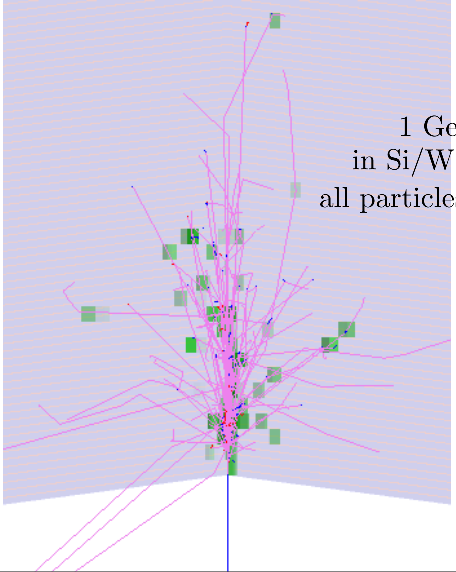




1 GeV e^-
in Si/W detector
all particles $> 100\,\mathrm{keV}$

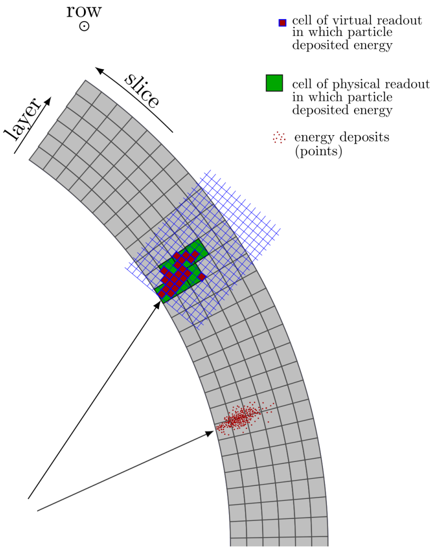
Shower data representation: cells, voxels, point clouds, ...

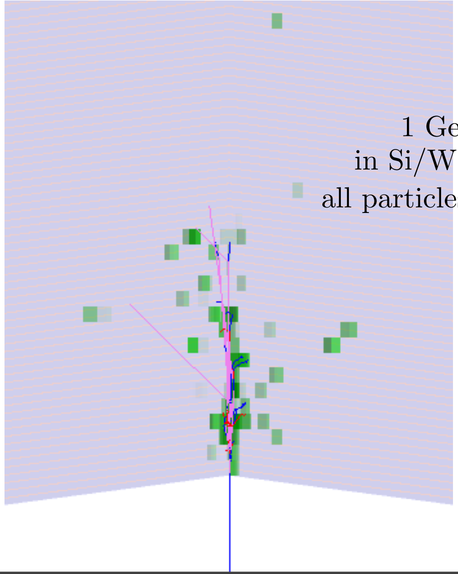




1 GeV e^-
in Si/W detector
all particles > 1 MeV

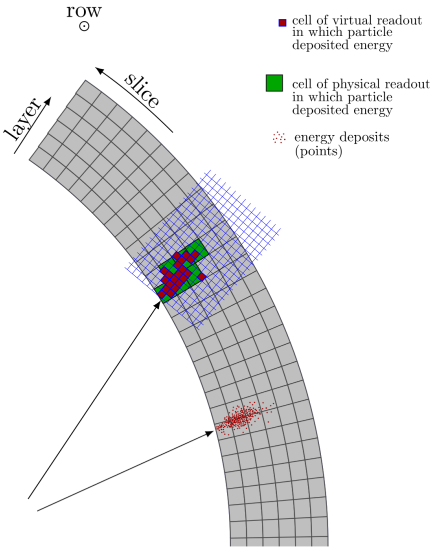
Shower data representation: cells, voxels, point clouds, ...

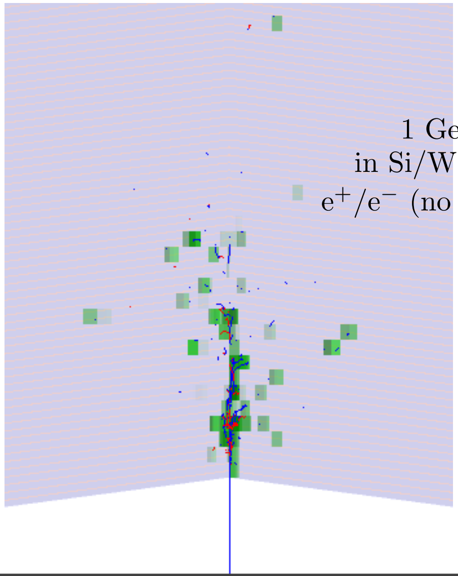




1 GeV e^-
in Si/W detector
all particles $> 10\,\text{MeV}$

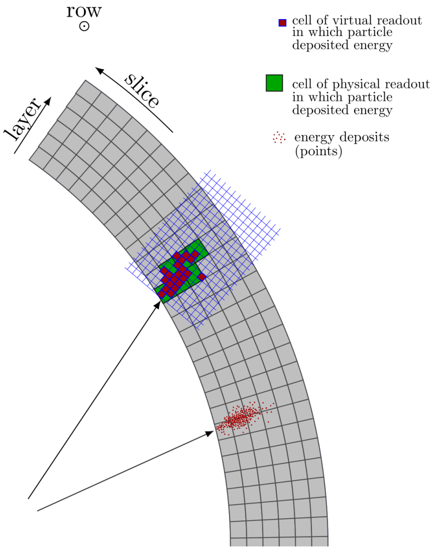
Shower data representation: cells, voxels, point clouds, ...

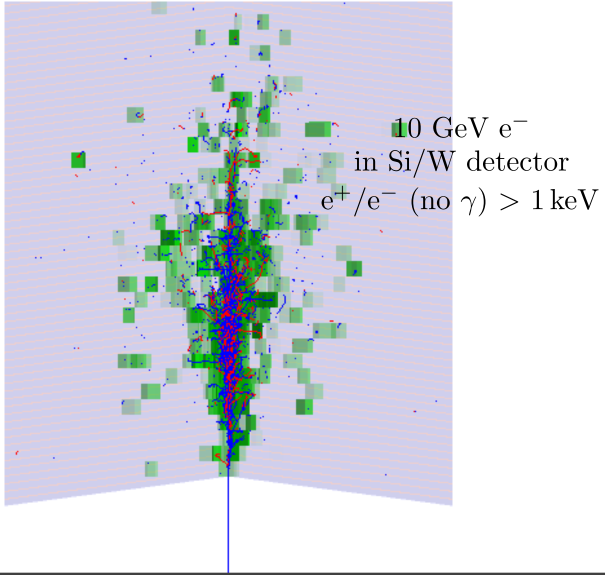




1 GeV e^-
in Si/W detector
e^+/e^- (no γ) $> 1\,\mathrm{keV}$

Shower data representation: cells, voxels, point clouds, ...





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unprocessed data that should have been added to the final page this extra page
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If you rerun the document (without altering it) this surplus page will go away,
because LaTeX now knows how many pages to expect for this document.