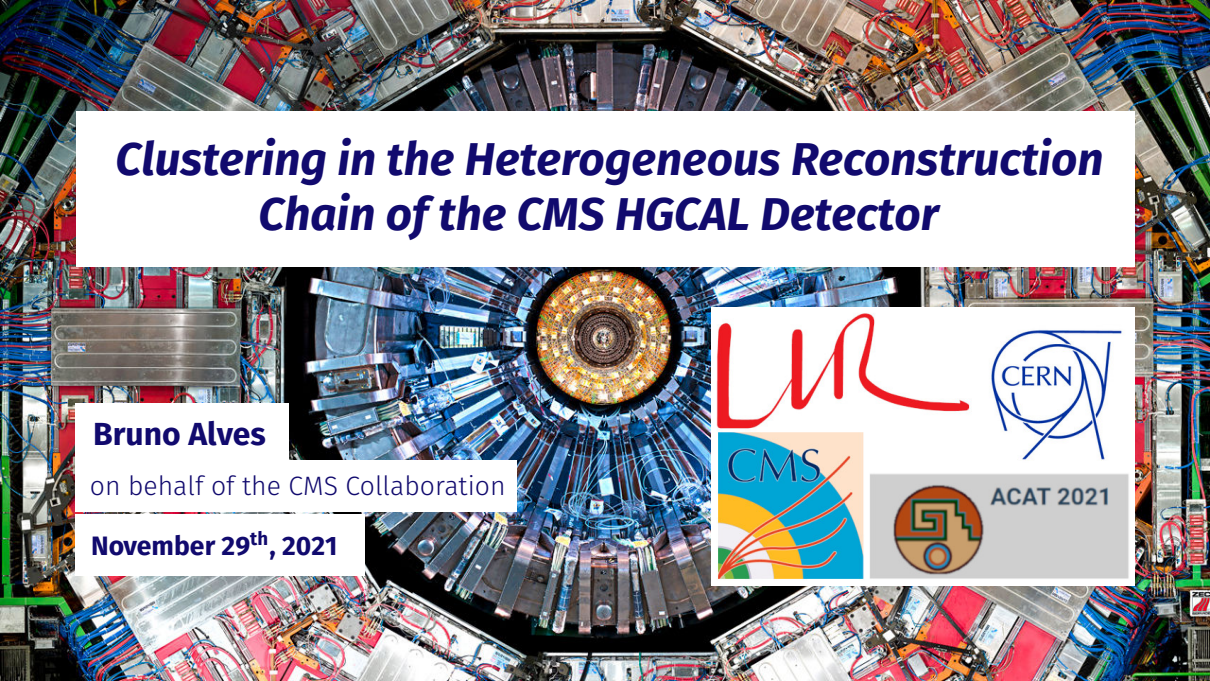
Clustering in the Heterogeneous Reconstruction Chain of the CMS HGCAL Detector



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on behalf of the CMS Collaboration

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Motivation

⇒ ***High Luminosity LHC*** (HL-LHC) will start its operation in 2028

- ***large pileup (PU)***: up to 200 collisions per bunch crossing
- ***high luminosities***: 5×10^{34} (7.5×10^{34}) $\mathrm{cm}^2\,\mathrm{s}^{-1}$ for 140 (200) PU in Run4 (Run5)

⇒ The biggest contributor to CPU usage is event reconstruction (∼5% by HGCAL)

⇒ ***GPU-based reconstruction***

- ***Flexibility*** to run on HPCs and upgraded WLCG sites
- Better computing and physics performance (new algorithms)
- Profit of potentially ***favourable GPU/CPU cost*** per unit capacity

⇒ ***Heterogeneous efforts in CMS***

- ***HGCAL***: this talk covers the clustering and geometry deployment steps
- In parallel: Pixel Tracks and Vertices, ECAL/HCAL
- Example for Run3: 30 % HLT reconstruction code will be offloaded to GPUs

High-Granularity CALorimeter (HGCAL) @ CMS

Major CMS Phase2 upgrade: ***unprecedented spatial and timing resolution***

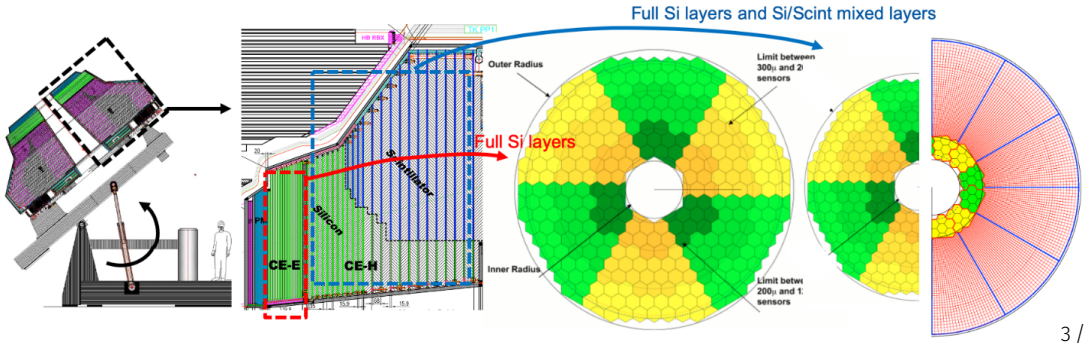
⇒ ***Silicon sensors*** (EM + HAD)

- 28 (EM) + 22 (HAD) layers, 640 m^2
- ∼30K wafers (∼6M channels)
- High and low density cells (LD/HD)

⇒ ***Plastic Scintillator + SiPM*** (HAD)

- 14 layers, 370 m^2
- ∼4K tiles (∼240K channels)

⇒ **Weight:** 200 t per endcap



CMSSW: General Concepts

⇒ HGCAL reconstruction chain is part of the ***CMS Software (CMSSW)***

⇒ A series of reconstruction steps (***modules***) make the chain. They:

- ***consume data collections*** from previous modules
- ***produce data collections*** for subsequent modules

⇒ CMSSW can handle ***multiple jobs and CPU threads***

⇒ It allows asynchronous and non-blocking offload to ***external accelerators***

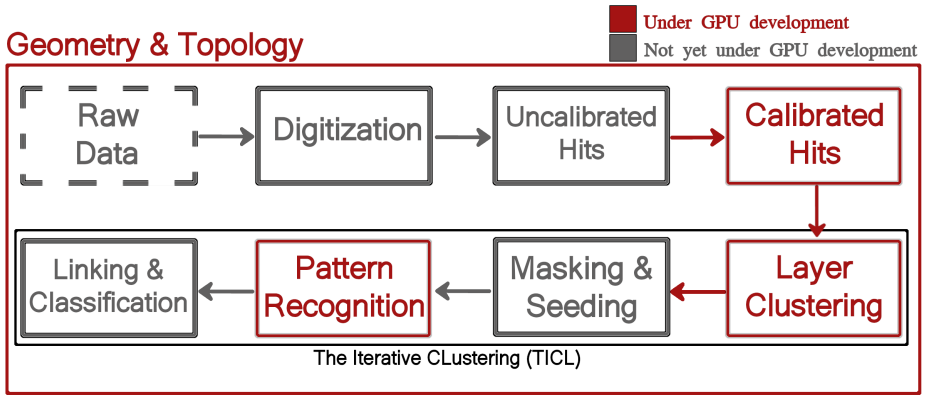
⇒ Modules may access ***conditions data***, i.e., data which are not directly linked to a particular physics event:

- Available instead per ***Interval of Validity***
- ***Detector geometry***: materials, detector element positions, ... (very complex for HGCAL: major contribution for Phase-2 simulation time)
- Other properties: alignment, calibration, ...

HGCAL Reconstruction Chain in the CMS Software (CMSSW)

⇒ The chain below has many ***modules***: from ***Raw Data*** up to ***Physics Objects***

⇒ TICL is a modular framework which iteratively builds 3D clusters from 5D (x, y, z, t, E) calorimetric data and outputs particle properties and probabilities[1]

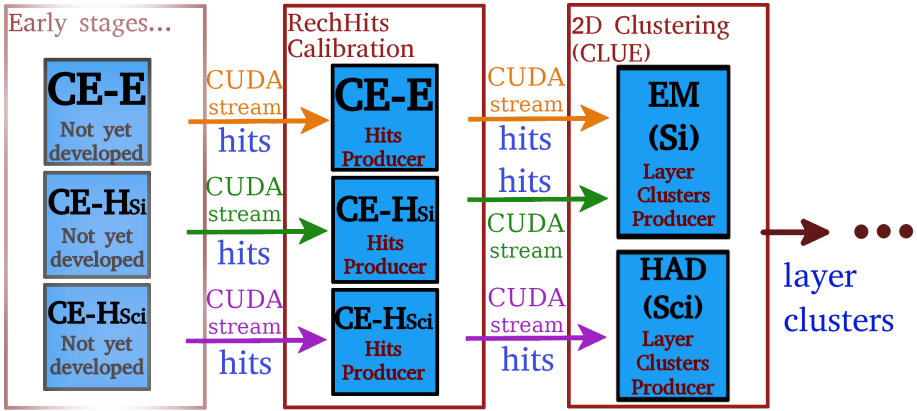


[1] see F. Pantaleo's plenary talk

Subdetectors in HGCAL's Chain

⇒ By splitting data from the same reconstruction step, modules can process it in parallel (and differently if need be):

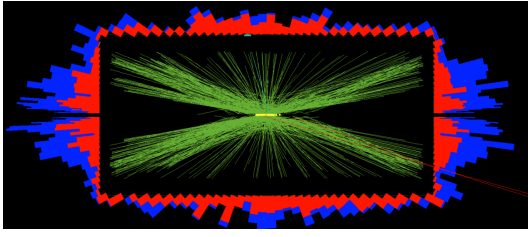
- ***Multiple subdetectors***: Silicon (***EM*≡*CE-E*+*CE-H$_{Si}$***) and Scintillator (***HAD*≡*CE-H$_{Sci}$***)
- Single ***CUDA stream*** per subdetector: ×***2 throughput*** for pixel reconstruction

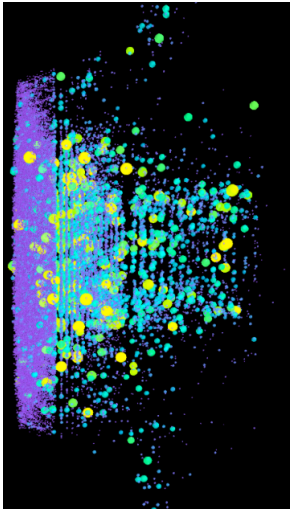


Clustering in HGCAL: High Multiplicity and Granularity Challenges

To give an idea: 78 PU in the tracker (below) / ***200 PU*** in HGCAL (right)

- ⇒ ***O(100K)*** hits per event
- ⇒ ***O(10K)*** 2D layer clusters
- ⇒ 2D clusters collections form 3D objects
- ⇒ Increased complexity: design fast and accurate algorithms, staying within the High Level Trigger PU200 time budget
  - Benefits from GPU Computing





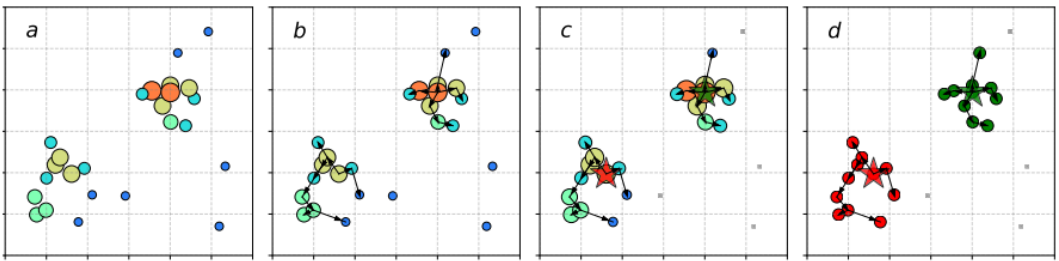
CLUstering by Energy (CLUE) in a Nutshell [1]–[3]

a), b) ***Fast and fully-parallelizable density-based clustering algorithm***: energy densities + separation distances are assigned to all hits;

c) Hits are classified as ***seeds***, ***followers*** or ***outliers*** based on a critical distances and densities (tunable parameters);

d) Clusters are built by ***traversing each seed followers' tree***, and assigning the same seed index to all its followers.

⇒A ***standalone version*** (no CMSSW) is available for testing and optimizations



Intermezzo: Structure of Arrays (SoAs) as Data Format

⇒ SoAs improve access to global memory and exploit CPU vectorization

⇒ Device data uses the SoA format

- takes advantage of ***memory coalescing*** and ***warp alignment***

⇒ CMS is currently investigating novel CPU SoA-like formats (eg. AoSoA):

- decrease/eliminate the time for SoA ↔ Legacy conversions (next slide)
- potentially ***accelerate CPU code***

```
//Structure of Arrays
struct pointlist3D {
  float x[N];
  float y[N];
  float z[N];
};
struct pointlist3D points;
float get_point_x(int i) {
    return points.x[i]; }
```

```
//Array of Structures
struct point3D {
  float x;
  float y;
  float z;
};
struct point3D points[N];
float get_point_x(int i) {
    return points[i].x; }
```

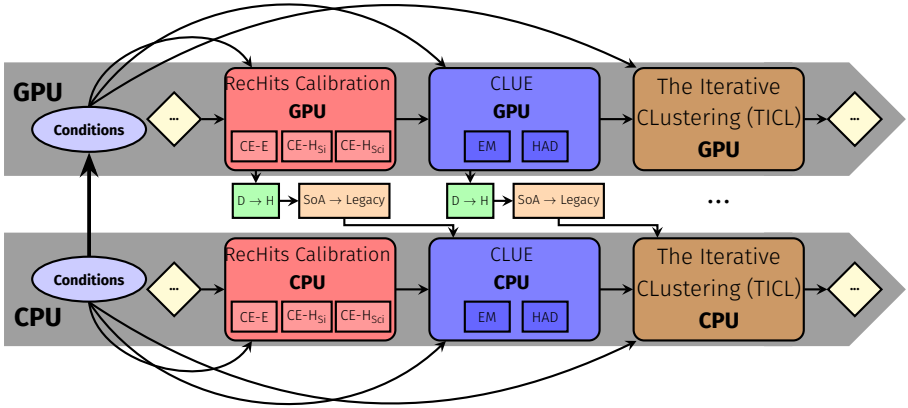
Heterogeneous HGCAL Reconstruction Flowchart

⇒ Different modules run on CPUs and GPUs, where conditions are deployed

⇒ ***GPU → CPU data conversion modules*** bring flexibility and ease validation:

- Modules for data conversions: Device-Host (D→H) and SoA to CPU Legacy

⇒ The diagram is simplified: jobs and CPU threads increase complexity



Benefits Accrued from Porting CLUE to CMSSW

⇒ ***General:***
- ✓ Integration with other reconstruction steps
- ✓ Custom caching allocator
- ✓ Use the full HGCAL geometry
- ✓ Linking modules in the GPU
- ✓ Bonus #1: Cluster energy and position calculation in the device
- ✓ Bonus #2: Conditions data deployment to the GPU

⇒ ***Data Format:*** Single SoA memory block
- ✓ Increased spatial locality
- ✓ Smaller allocation and initialization time
- ✓ Warp data alignment

⇒ ***Dynamic memory allocations:***
- ✓ Allocate depending on event size (further optimizations are being explored)

⇒ ***Subdetectors*** (Silicon vs Scintillator changes the algorithm):
- ✓ Exploit subdetectors parallelism

Bonus #1: Clusters Energy and Position Calculation

⇒ A ***reduced cluster SoA is introduced*** to forward the information to TICL:

- *hit-level* → *cluster-level*
- Its defining quantities are ***energies*** and ***positions***

⇒ Calculations in the GPU are parallelized at cluster-level:

- ***Energy:*** sum the energy of all hits in a cluster
- ***X and Y positions*** ($Z \in \{x, y\}$, E_i is the energy of hit i, and W_0 is a tunable parameter)***:***

$$Z = \frac{\sum Z_i W_i}{\sum W_i}, \quad W_i = W_0 + \log\left(\frac{E_i}{\sum E_i}\right)$$

⇒ Both imply ***traversing trees*** (or chains) ***of followers***

- The CPU version instead flattens the tree before the calculation

Bonus #1: Local Stack & Loop or Function Recursion?

⇒ Different approach: ***device function recursion*** instead of CLUE stack + loop

- ✓ adds clarity, reduces algorithm allocated memory
- ⊗ potential function stack frame growth

⇒ Profiling required!

```
void func() {
    buffer[stackSize] = allocate();
    while(!buffer.empty()) {
        i = buffer.back();
        buffer.pop_back();

        for(auto fl : i.followers()) {
            fl.clusterID = i.clusterID;
            buffer.push_back(fl);
        }
    }
}
func();
```

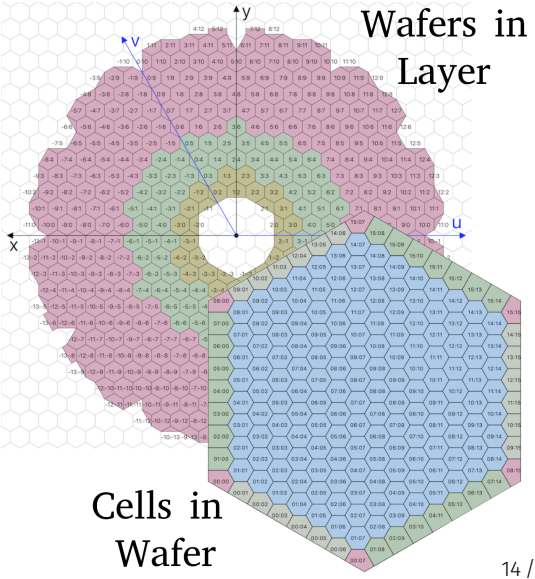
Cluster ID assignment with stack + loop

```
void func(&vars, &followers) {

    for(auto fl : followers()) {

        //energy and positions
        some_calculation(vars);

        func(vars, fl.followers());
    }
}

vars = set_variables();
func(vars, followers);
```

Calculations with function recursion

Second Intermezzo: Detector IDs

- ⇒ CMS ***detector elements*** are encoded in 32 bit ***IDs***, part of which reserved to HGCAL (layers, wafers, cells, ...)
- ⇒ An ***ID*** gives access to all geometry-related information for a detector element
  - *x* and *y* positions required by CLUE!
- ⇒ The ***ID*** class is ported to the GPU
  - Device kernels are now able to access its information



Bonus #2: Geometry Deployment to the GPU

- ⇒ ***Remove host-device transfers*** of conditions data between modules
- ⇒ Data available to all reco chain via a ***single transfer per Interval of Validity***
- ✓ Avoids slow and recurrent CPU → GPU data transfers
- ✓ Reduced memory consumption of modules (including CLUE) by avoiding directly storing conditions data
- ✓ Makes data transfers faster, since they are ***now done in parallel***:
  - Only the IDs of detector elements are transferred serially
  - From the GPU-converted ID all geometry information can be retrieved
  - The (x, y) positions GPU filling is embarassingly parallel

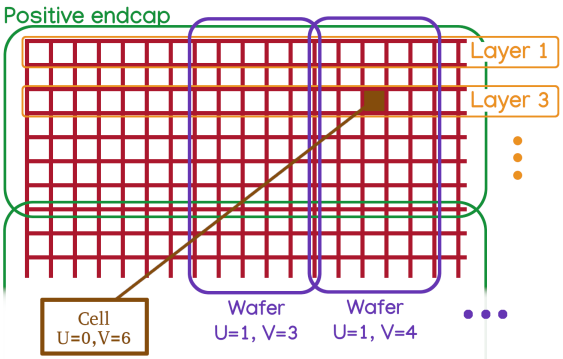
Bonus #2: Geometry Deployment and Access from the GPU

⇒ A ***fast***, ***user-friendly*** and ***generalizable*** mechanism to deploy conditions

⇒ Filling loop follows an intuitive ***geometrical order***

Loop over (Silicon example):

1. Two endcaps;
2. Three subdetectors;
3. Layers;
4. Square grid to cover all wafers;
5. Silicon cells (HD and LD).

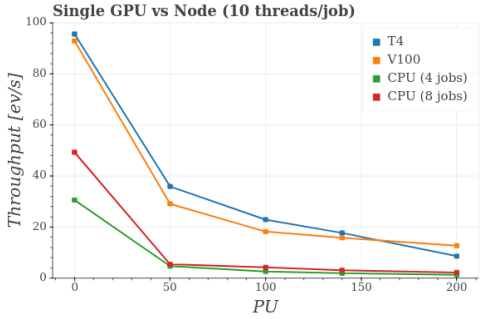


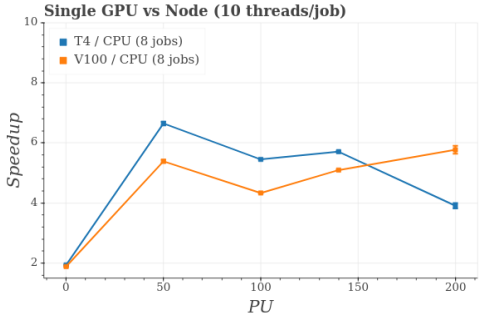
⇒ Given an ID, its memory location in the GPU is immediately found ($O(1)$).

⇒ A GPU user ***only needs to know the IDs*** of the elements it is interested in.

Performance of RecHit Calibration [4] + CLUE: Throughput and Speedup

⇒ ***Full*** Intel(R) Xeon(R) Silver 4114 with 40 logical cores vs. ***Single GPU*** (T4-16GB or V100-32GB), 10 CPU threads per job, 512 GPU threads per block





⇒ The speedup peaks between ***5*** and ***6*** for PU140 (Run4) and PU200 (Run5)

⇒ Additional measurements allows to conclude that ***data conversion modules and recursion functions do not affect the throughput***: CLUE is the bottleneck

Conclusions & Next Steps

- The ***CLUE standalone algorithm*** has been ***integrated in the CMS software***
- ***Conditions data have been deployed to the GPU*** with a new approach
- Performance measurements show ***speedup benefits***
- This work paves the way for future HGCAL accelerator developments:
  - ⇒ Facilitates the ***deployment of the clustering to multiple accelerators*** using abstraction libraries (*eg.* alpaka, see W. Redjeb's poster);
  - ⇒ Several optimizations are being studied: ***reducing memory footprint*** and ***decreasing the number and size of allocations***;
  - ⇒ Currently investigating ***novel SoA-like formats***
  - ⇒ Port the ***full HGCAL reconstruction*** into GPUs

Back-up

Acknowledgments

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- Fundação para a Ciência e Tecnologia (FCT): SFRH/BEST/150186/2019
- Organisation européenne pour la recherche nucléaire (CERN)

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[1] M. Rovere, Z. Chen, A. Di Pilato, F. Pantaleo, and C. Seez, "CLUE: A Fast Parallel Clustering Algorithm for High Granularity Calorimeters in High Energy Physics,", 2020. arXiv: *2001.09761*. [Online]. Available: *http://arxiv.org/abs/2001.09761*.

[2] Z. Chen, A. Di Pilato, F. Pantaleo, and M. Rovere, "GPU-based Clustering Algorithm for the CMS High Granularity Calorimeter," EPJ Web of Conferences, vol. 245, p. 05 005, 2020. DOI: *10.1051/epjconf/202024505005*.

[3] A. Rodriguez and A. Laio, "Clustering by fast search and find of density peaks," Science, vol. 344, no. 6191, pp. 1492–1496, 2014, ISSN: 10959203. DOI: *10.1126/science.1242072*.

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[4] B. Alves, A. Bocci, M. Kortelainen, F. Pantaleo, and M. Rovere, "Heterogeneous techniques for rescaling energy deposits in the CMS Phase-2 endcap calorimeter," EPJ Web of Conferences, vol. 251, p. 04 017, 2021. DOI: 10.1051/epjconf/202125104017.

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