Study on the performance of the ATLAS TopoCluster algorithm using GPGPU Acceleration

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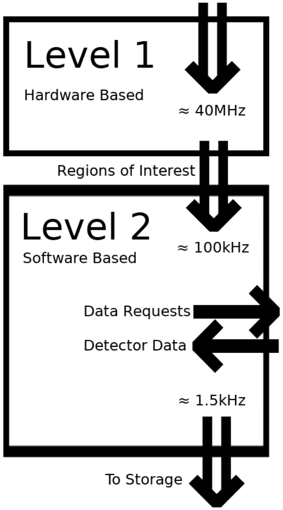
LIP · IST

05 Setember 2018

ATLAS Trigger and Data Acquisition System



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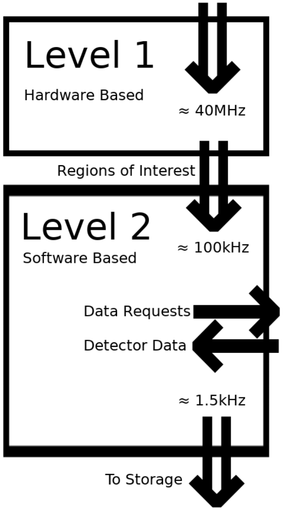

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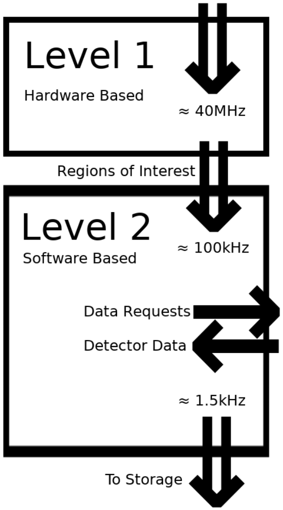

- The LHC @ CERN provides a bunch crossing rate of ≈ 40Mhz and 22 collisions per bunch crossing.

1. 1st Level - Hardware Based - Reduces the 40MHz event rate to ≈ 100kHz
2. 2nd Level - Software Based - Algorithms run on the previously selected events - Reduces to a rate of ≈ 1.5kHz to be stored for further processing

Motivation

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  1. 1st Phase (2019-20)
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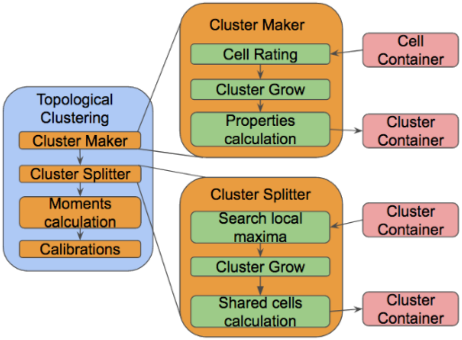
- Hi-Lumi LHC will further increase the amount of data collected per run.
- Computational power is constrained (by power, area, heat dissipation...) - Need to find new solutions to increase computational throughput.
- One particular alternative is being considered: Parallel processing using Nvidia GPGPU's using the Nvidia CUDA Techonology

Topological Clustering

- Our main focus: Accelerate the performance of the Topological Clustering Portion of the HLT
    - This handles the reconstruction of particle jets by grouping calorimeter cells into structures named Clusters



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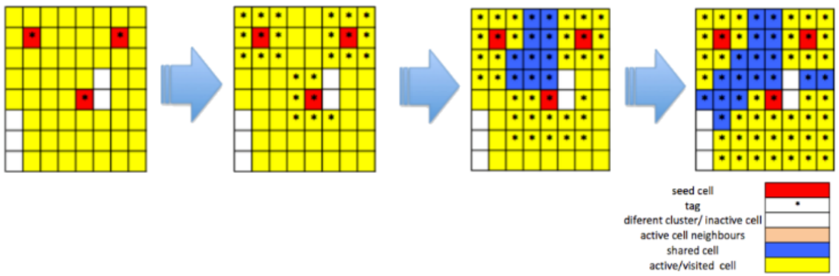
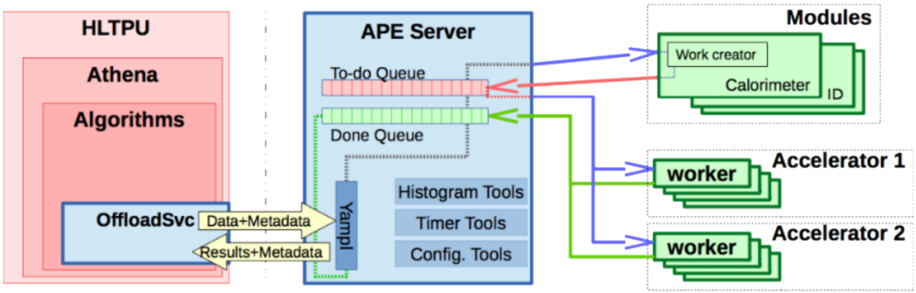
3. Assigns a thread to a pair of neighbour cells;
4. Each thread determines the pair's tag:
    - Higher Tags get propagated;
    - Cluster Growing stops when meets a cell with (S/N $\leq$ 1).

GPU Cluster Splitter



- The splitter takes as input the previously produced cluster and outputs new smaller clusters.

Architecture



- The Trigger will now use an client-server architecture:
  - Athena (ATLAS Trigger Software), running in a CPU, will interface with another machine, APE.
  - APE will receive Athena's requests and execute them using the several accelerator resources available.
  - APE will then return the processed data back to Athena
- This allows Athena to be independent of the specific accelerator details.

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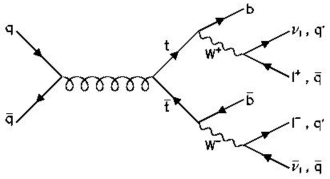
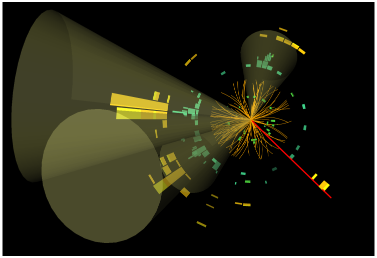
- Finally the two were combined.
- Input data was a collection of sample pre processed Athena jets and $t\bar{t}$ events.
- Test Bed:
  - CPU: AMD FX-8320 8-core @ 3.5GHz
  - GPU: Nvidia GeForce GTX 650 (2048MB of VRAM)
  - RAM: 8GB

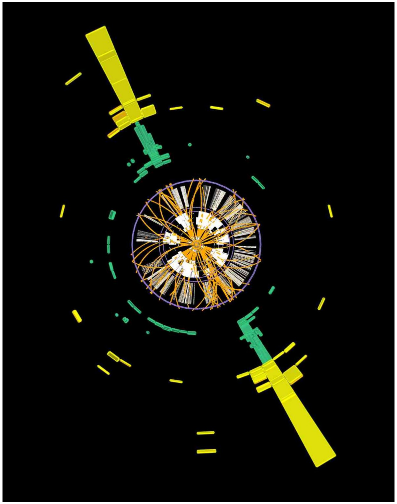
$t\bar{t}$ vs jets

$t\bar{t}$

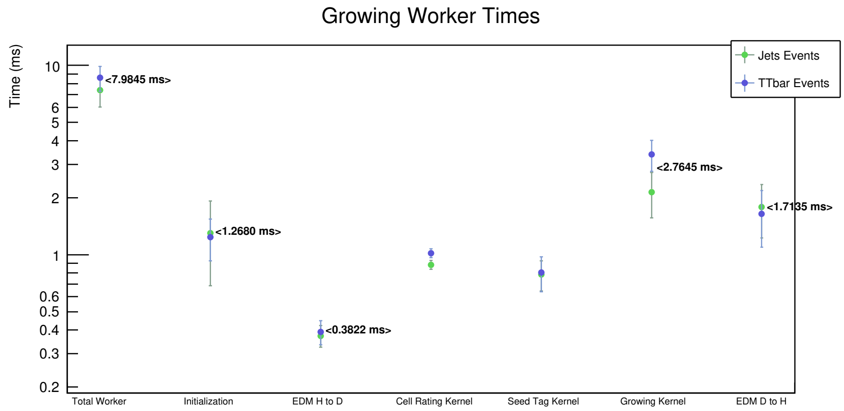




Jets

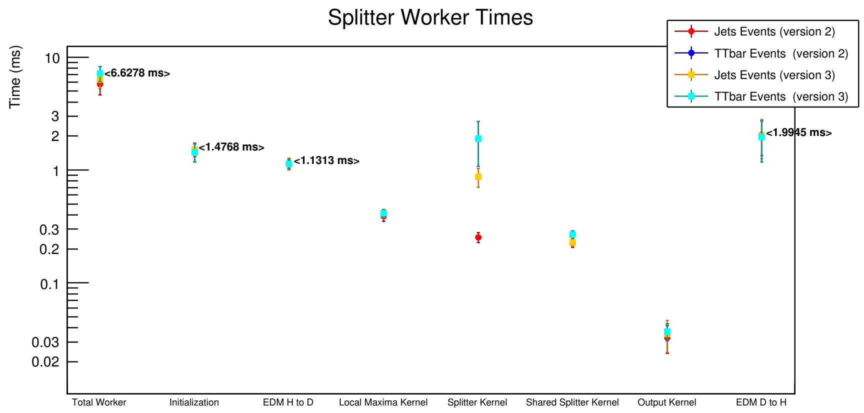


Growing Condensed Results



- Initialization and copying are significant
- Input: Cell Energy - Output: Clusters containing all cell information
- $t\bar{t}$ is more demanding than jets.

Splitter Condensed Results



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- Most kernels take less than 1ms.
- Two different versions

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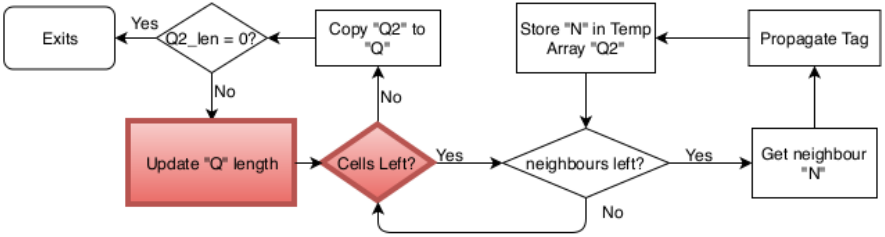
- This can create race conditions and synchronization problems.
- Global variables need special care: we must ensure writes and reads are in the order we desire.
- CUDA defines a special function to do this: `__syncthreads();`

Splitter Kernel Version 3 - Main Loop



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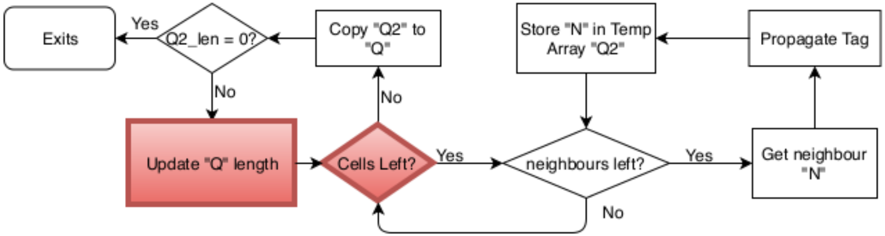

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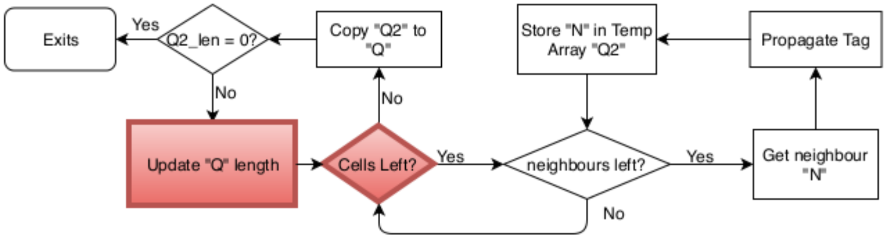

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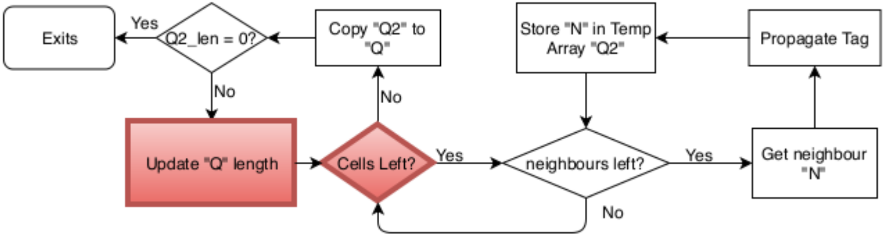

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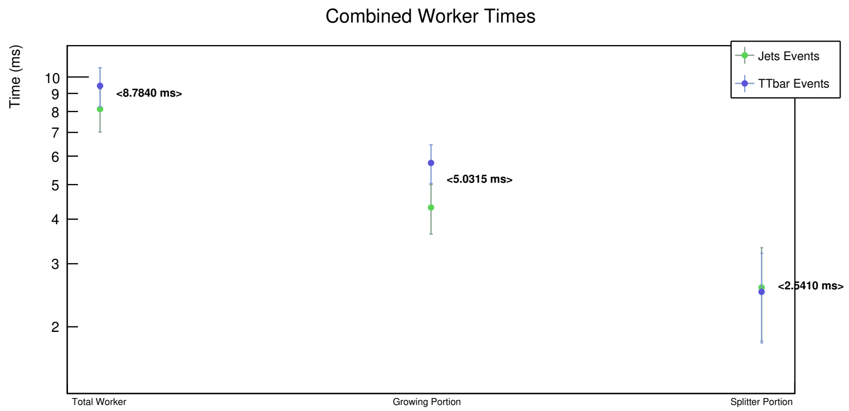
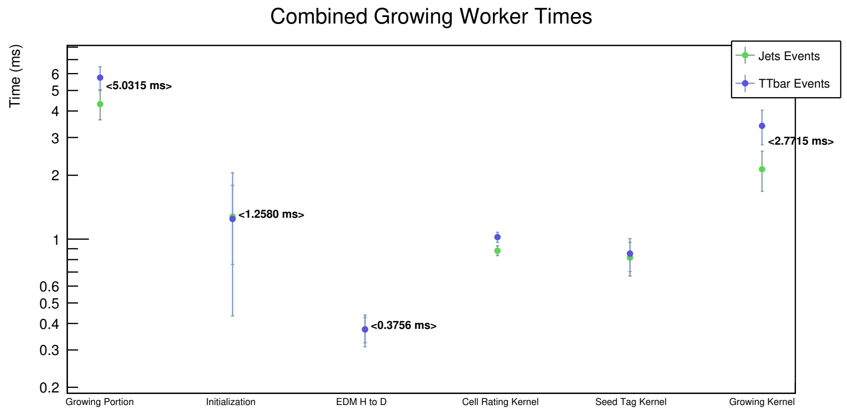
- Sometimes threads execute the loop over Q, with the wrong length causing the whole process to hang.
- Solution: `__syncthreads()` before the loop
- This made code slower as we now have to wait for all threads.

Combined Condensed Results



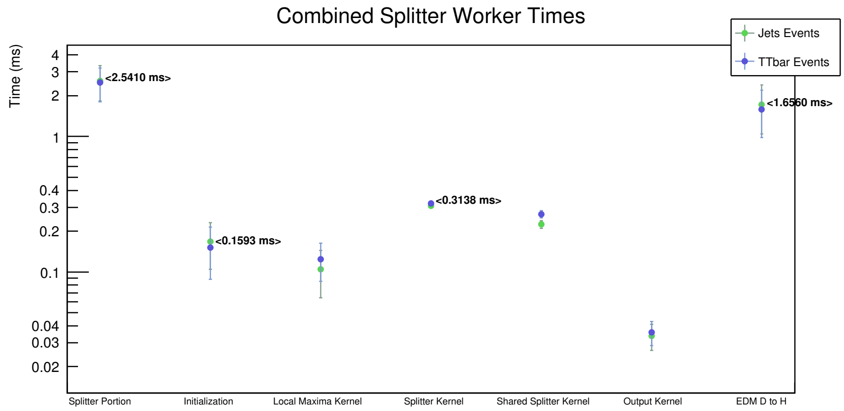
- Splitter V2 used.
- Total time is much lower than the sum of the separate growing and splitting stage

Combined Growing Condensed Results



- Total time decreased
- Note the absence of data copies from the device

Combined Splitter Condensed Results



- Total time decreased about 50%
- Again, no copies to the device, data is already there.
- Most of the time is spent copying data rather than processing

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- Comparing times for CPU only execution, around 10 fold improvement is achieved.
- There's a problem: data conversion to and from the GPU as well as data transfer accounts for a significant portion of the time spent.
- GPGPU's show a promising improve in terms of accelerating processing tasks, while providing less power consumption and physical footprint.