



### **Introduction to Patatrack**

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### **Introduction**

- The overall approach
	- Reconstruct pixel-based tracks and vertices on the GPU
	- Leverage existing support in CMSSW for threads and on-demand reconstruction
		- Also explore adding support for heterogeneous computing into the framework
	- Minimize data transfer
- An earlier step was actually a standalone program for the "hit quadruplets"
	- Fully utilizing CPU and GPU, encouraging performance
	- First developed on GPU, then ported to CPU
		- CPU version became the pixel quadruplet/triplet seeding algorithm since 2017 pixel detector upgrade in both HLT and offline reconstruction
- Results were shown in CHEP 2019 <https://indico.cern.ch/event/773049/timetable/?view=standard#76-heterogeneous-online-recons>
- Some material also from Connecting the Dots 2019 <https://indico.cern.ch/event/742793/timetable/?view=standard#93-patatrack-accelerated-pixel>



## **The full workflow**

- Copy the raw data to the GPU (~250 kB/event)
- Run multiple kernels (39) to perform the various steps
	- Decode the raw data
	- Cluster the pixel hits
	- Form hit doublets
	- Form hit ntuplets (triplets/quadruplets) with a Cellular Automaton algorithm
	- Clean up duplicates
	- Vertexing
- Copy only the final results back to the host (optimized SoA format)
	- $-$  ~4 MB/event for tracks, ~90 kB/event for vertices
	- Convert to legacy format if requested



## **Top 5 kernels**

- On a Tesla T4, one CPU thread, one concurrent event
	- 4000 data events with high-pT jets, average time per event, quadruplets only
- 220 μs: kernel find ntuplets() ntuplets
	- Identify ntuplets from the CA connection graph
- 170 μs: getDoubletsFromHisto() doublets
	- Creates doublets from compatible hits in adjacent layers
- 130 μs:  $findClass()$ clusters
	- Produces clusters on each pixel module
- 120 µs: kernelBLFit<4>() pixel tracks
	- Fit 4-hit tracks with General Broken Lines algorithm
- 120 μs: kernel connect() ntuplets
	- Connect hit doublets (create "CA connection graph")

# **In the big picture (HLT)**





## **Performance (legacy)**



### pixel tracks and vertices global reco

#### CPU

- · dual socket Xeon Gold 6130
- $\cdot$  2 × 16 cores (2 x 32 threads)
- throughput measured on a full node
- 4 jobs with 16 threads

throughput (ev/s)



## **Performance (GPU, no output on CPU)**



### pixel tracks and vertices global reco

### **CPU**

- · dual socket Xeon Gold 6130
- $2 \times 16$  cores (2 x 32 threads)
- throughput measured on a full node
- 4 jobs with 16 threads

### **GPU**

- · single NVIDIA Tesla T4
- 2560 CUDA cores
- · single job with 10-16 concurrent events

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## **Performance (backported algorithms)**



### pixel tracks and vertices global reco

### CPU

- · dual socket Xeon Gold 6130
- $\cdot$  2 × 16 cores (2 x 32 threads)
- throughput measured on a full node
- 4 jobs with 16 threads

#### **GPU**

- · single NVIDIA Tesla T4
- · 2560 CUDA cores
- · single job with 10-16 concurrent events

Part of the GPU algorithms were backported to CPU with an ad-hoc "CUDA compatibility" layer.

"Legacy" produces only quadruplets, and has lower efficiency



## **Performance (transfer output to CPU)**



### pixel tracks and vertices global reco

#### CPU

- · dual socket Xeon Gold 6130
- $2 \times 16$  cores (2 x 32 threads)
- throughput measured on a full node
- 4 jobs with 16 threads

#### **GPU**

- · single NVIDIA Tesla T4
- · 2560 CUDA cores
- · single job with 10-16 concurrent events

### transfer from GPU to CPU

- on demand
- · small impact on event throughput



## **Performance (convert SoA to legacy)**



### pixel tracks and vertices global reco

### CPU

- · dual socket Xeon Gold 6130
- $\cdot$  2 × 16 cores (2 x 32 threads)
- throughput measured on a full node
- 4 jobs with 16 threads

#### GPU

- · single NVIDIA Tesla T4
- · 2560 CUDA cores
- · single job with 10-16 concurrent events

### transfer from GPU to CPU

- on demand
- · small impact on event throughput

#### conversion to legacy data formats

- on demand, to be minimised
- · small impact on event throughput
- high cost in CPU usage



### **Technical implementation**

- CUDA streams are used to process multiple events concurrently
	- Data from one event not enough to saturate a GPU
	- One CUDA stream / branch in the module data dependence DAG / concurrent event
- Aim is to utilize both CPU and GPU
	- There are no calls to cuda\*Synchronize()
		- Except one which is mostly a sanity check, we are thinking ways to remove it
	- Instead use callback functions to notify the CMSSW framework when CPU work that waits for GPU work to finish can proceed
		- Allows CPU threads to do other work in the meantime
- Device and pinned-host memory allocations made through a memory pool
	- Currently based on cub::CachingDeviceAllocator
	- Most flexible towards minimizing device memory usage compared to alternatives
- Supports multiple GPUs



## **Standalone program**

- The standalone program in <https://github.com/makortel/pixel-standalone> is essentially a mini-app of the first kernel in  $\vert$  digis  $\vert$  step intended to explore portability technologies
	- Contains data from one event
- Currently has implementations for
	- CPU (naive)
	- CUDA
	- Kokkos
	- Alpaka (both directly and through CUPLA that provides more CUDA-like interface)
	- Data Parallel C++ (oneAPI)



## **Backup**



### **Doublets**

- The local reconstruction produces hits  $\bullet$
- Doublets are created opening a window depending on the tracking region/beamspot and layer-pair  $\bullet$
- The cluster size along the beamline can be required to exceed a minimum value for barrel hits connecting to an endcap layer Hits within the bins are connected to form doublets if they pass further "alignment cuts" based  $\bullet$ position
- In the barrel the compatibility of the cluster size along the beamline between the two hits can be required  $\bullet$
- The cuts above reduce the number of doublets by an order of magnitude and the combinatorics by a factor 50  $\bullet$



## **Cellular Automaton -based Hit Chain Maker**

The CA is a track seeding algorithm designed for parallel architectures

It requires a list of layers and their pairings

- A graph of all the possible connections between layers is created
- Doublets aka Cells are created for each pair of layers, in parallel at the same time
- Fast computation of the compatibility between two connected cells, in parallel  $\bullet$
- No knowledge of the world outside adjacent neighboring cells required, making it easy to parallelize





BPix1

- Better efficiency and fake rejection wrt previous algo
- Since 2017 data-taking has become the default track seeding algorithm for all the pixel-seeded online and offline iterations
- In the following, at least four hits are required, but triplets can be kept to recover efficiency where geometric acceptance lacks one hit

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# **CA compatibility cuts**

- The compatibility between two cells is  $\bullet$ checked only if they share one hit
	- AB and BC share hit B
- In the R-z plane a requirement is  $\bullet$ alignment of the two cells
- In the cross plane the compatibility  $\bullet$ with the beamspot region

