





Parallelized Kalman-Filter-Based Reconstruction of Particle Tracks on Many-Core Architectures

ACAT2017

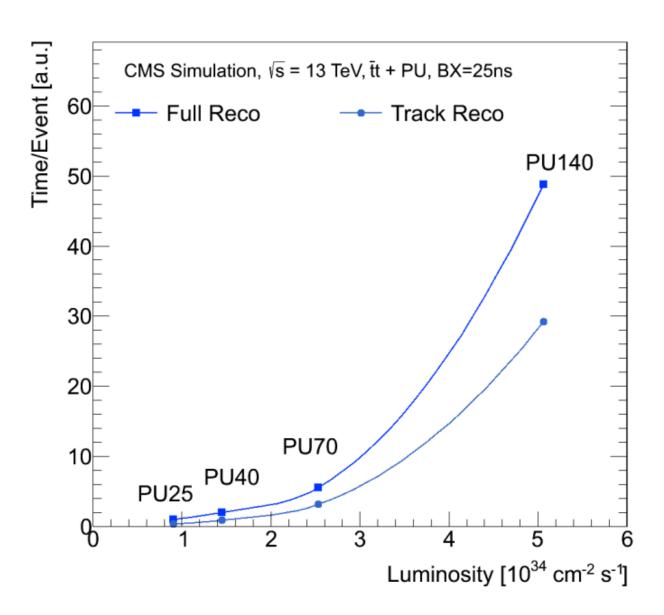
G. Cerati⁴, P. Elmer³, S. Krutelyov¹, S. Lantz², M. Lefebvre³, M. Masciovecchio¹, K. McDermott², D. Riley², M. Tadel¹, P. Wittich², F. Würthwein¹, A. Yagil¹

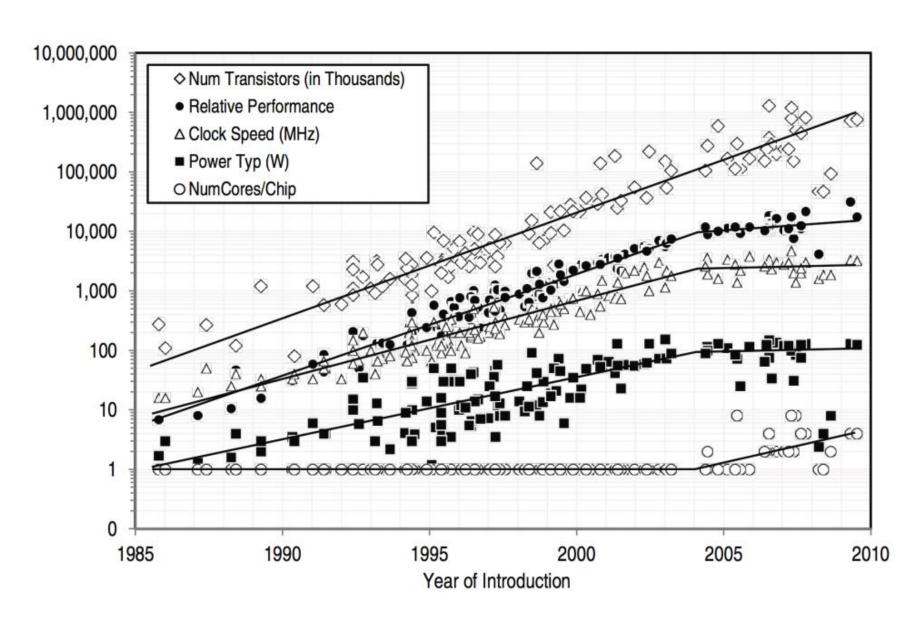
- I. University of California San Diego
- 2. Cornell University
- 3. Princeton University
- 4. Fermi National Accelerator Laboratory





Why Many-Core?





- Instantaneous luminosity of the LHC is expected to continue increasing the High Luminosity era
- Higher detector occupancy means more time spent in event reconstruction
- Clock speed has stopped scaling (power consumption, heat dissipation, etc.)
- Number of transistors is still increasing
- More cores/chip, more SIMD







Kalman Filter

Kalman Filter two-step:

- Produce an estimate of the current state (prediction)
- Update the state with the next measurement

Why use it for tracking:

- · Robust handling of multiple scattering, energy loss, and other material effects
- Widely used in the field
- Demonstrated physics performance

Our goals for Kalman Filter (KF) track building on many-core architectures

- Make effective use of parallel and vector architectures
- Maintain physics performance
- Preserve consistent systematics across platforms

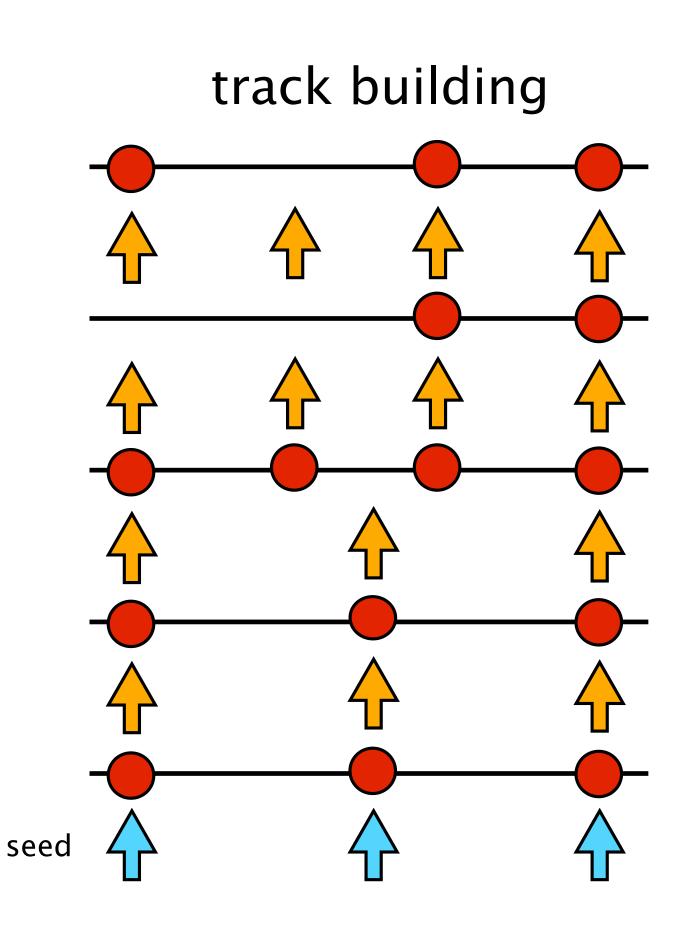




Track Building Basics

Algorithm (for a single seed):

- Start with a seed track from 3 or more measurements
 - Seed finding is currently out of scope for us
- Estimate the track state from the seed track
- Propagate the track state to the next detector layer
- Find candidate detector response "hits" near the projected intersection point(s) of the track with the detector
- Evaluate the goodness of fit of each hit wrt the track
- Select the best fit track/hit combinations as track candidates
- Update the estimated state of all track candidates with the new hit
- · Propagate all track candidates to the next layer and iterate









Track Building Challenges

Good efficiency requires considering multiple hypotheses

- In a dense detector, many tracks will find hit candidates that are the best local fit but lead to a globally poor fit
- Acceptable efficiency typically requires considering ~6 or more track hypotheses for every seed depending on detector occupancy

Track building involves multiple branch points

- Selecting candidate hits at each layer
- Evaluating a variable number of track candidate/hit candidate combinations
- Selecting the best combinations for propagation to the next layer
- · Many seeds turn out to be false leads, dying out after a few layers

Branch points lead to irregular work loads and memory access patterns





Our Approach

Start simple:

- Knights Corner (KNC) Xeon PHI and Sandy Bridge (SNB) Xeon
- Regular cylindrical geometry
- Lots of tracks per event, uniformly distributed in η, simplifying work distribution
- Tracks seeds from Monte Carlo "truth"
- · Track fitting (all hits known) as a warm up exercise before track building
- Develop measurement and validation tools, techniques and intuition

Then add complications—this is where we are now:

- · Realistic geometry with endcaps and transition regions
- Realistic events from CMS simulation
- Seeds from CMS track finding
- Additional platforms: Knights Landing, GPGPU





Data structure: Matriplex

"Matrix-major" matrix representation designed to fill a vector unit with **n** small matrices operated on in synch

Use vector-unit width on Xeons

- With or without intrinsics
- Shorter vector sizes w/o intrinsics
- For GPUs, use the same layout with very large vector width

R1			M ¹ (1,1)	M¹(1,2)	 M¹(I,N)	M¹(2,1)	,	M ¹ (N,N)	$M^{n+1}(I,I)$	M ⁿ⁺¹ (1,2)
R2	\	direction	M ² (1,1)	M ² (1,2)	 M ² (1,N)	M ² (2,1)	••••	M ² (N,N)	M ⁿ⁺² (1,1)	M ⁿ⁺² (1,2)
÷		memory di	:	:	:	:		:	÷	:
		fast me								
Rn ector u	nit		M ⁿ (I,I)	M ⁿ (1,2)	 M ⁿ (I,N)	M ⁿ (2,1)		M ⁿ (N,N)	$M^{2n}(I,I)$	M ²ⁿ (1,2)

Interface template common to Xeon and GPU versions







Results from Starting Simple

Results are from a KNC Xeon Phi 7120P

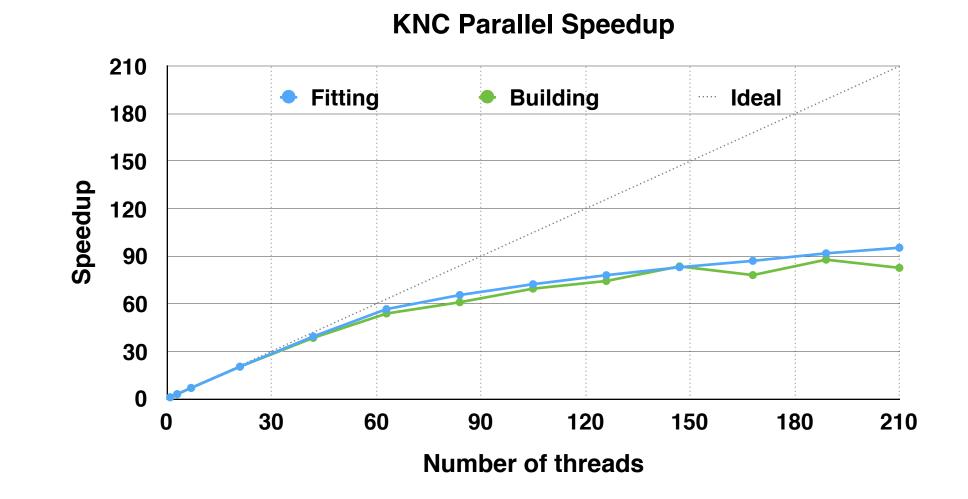
- 61 cores, but needs 122 threads to utilize all clock cycles
- AVX-512 vector width gives 16 single-precision floats
- SNB Xeon results generally better
 - But not as interesting

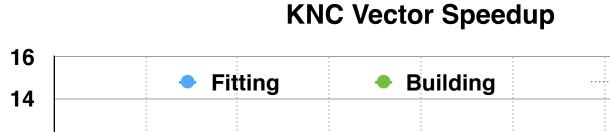
Parallelization:

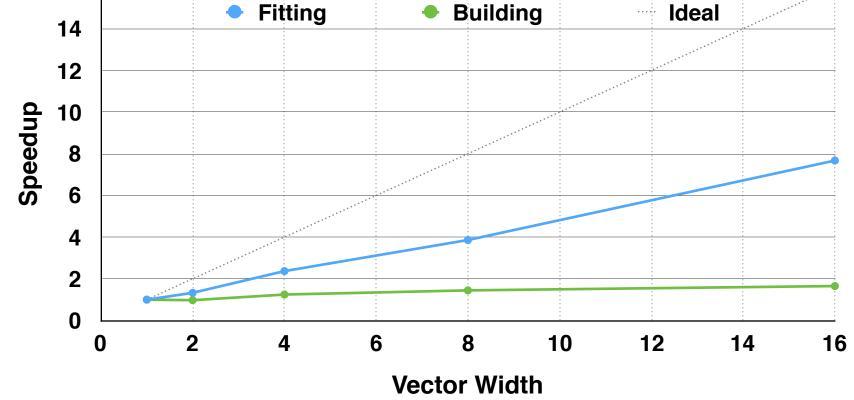
- Matriplexes are assigned to threads via Threading Building Blocks (TBB) tasks
- Near ideal up to the number of physical cores, some resource contention past that

Vectorization:

- Track fitting achieves about half the ideal vector speedup
- Track building vectorization still needs work













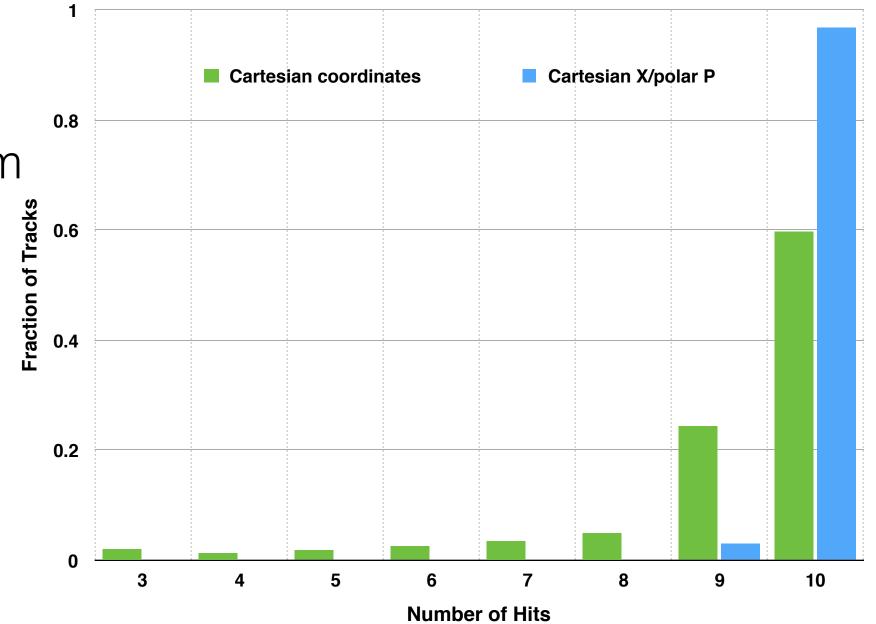
Lessons from the Simple Version

Physics performance lessons:

- Coordinate system choice matters
 - We eventually adopted spatial Cartesian, polar momentum
 - Error matrix is more complex
 - Better prediction performance speeds up track finding

Computing performance:

- Keep data structures and memory allocations minimal
- Data locality is critical
- Reduce tail effects in the work distribution via TBB work stealing
- Pay attention to vectorization reports
 - Avoid unaligned accesses and type conversions
 - Use prefetching, scatter/gather
 - Use 'const' and minimize the scope of variables



Track Building Performance: Hits Found







Adding Complications

Realistic detector geometry

- Endcaps and transition region present new challenges
- Real detectors can have very complex geometries
 - Contributes to memory pressure, takes time to navigate

Realistic events

- Real events may have lower occupancy and less uniform distribution than our simplified events
 - New issues with even distribution of work

New platforms

- KNL: similar to KNC, but new memory organization & CPU micro-architecture
- GPU: different programming model, how well can our code adapt?

This is work in progress, so the rest of the talk will be more anecdotal





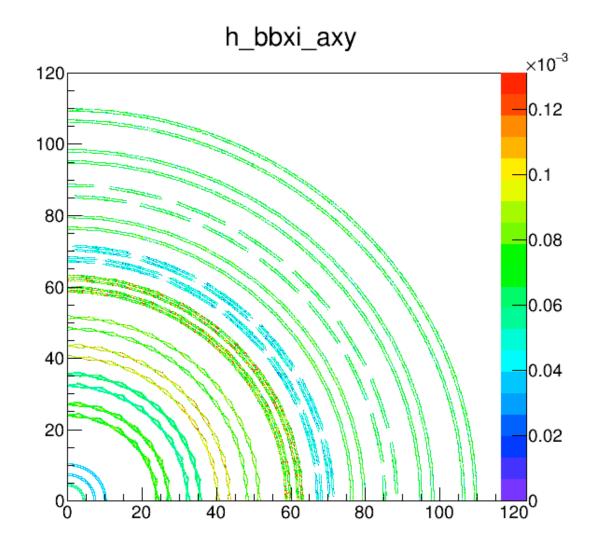
Realistic Geometry

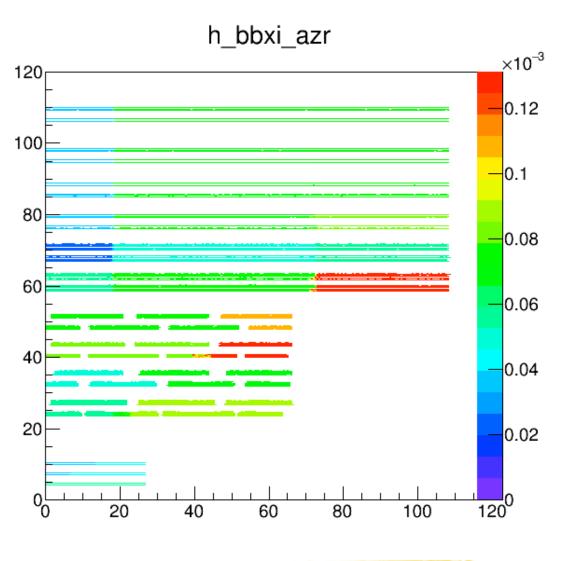
Adding two new geometries:

- · "Cylinder with lids" adds endcaps to our idealized geometry
 - Use for algorithm development for endcaps and transition region
- CMS geometry using CMS data
 - Propagate tracks to average radius of the layer
 - Find hits in the compatibility window
 - Propagate to each hit location and compute the χ^2
 - Advantage: work with a simplified geometry
 - Disadvantage: have to inflate the search window

Status:

- Barrel and endcaps implemented, still working on transition region
- Performance has not been tuned or tested
 - Doing physics validation first











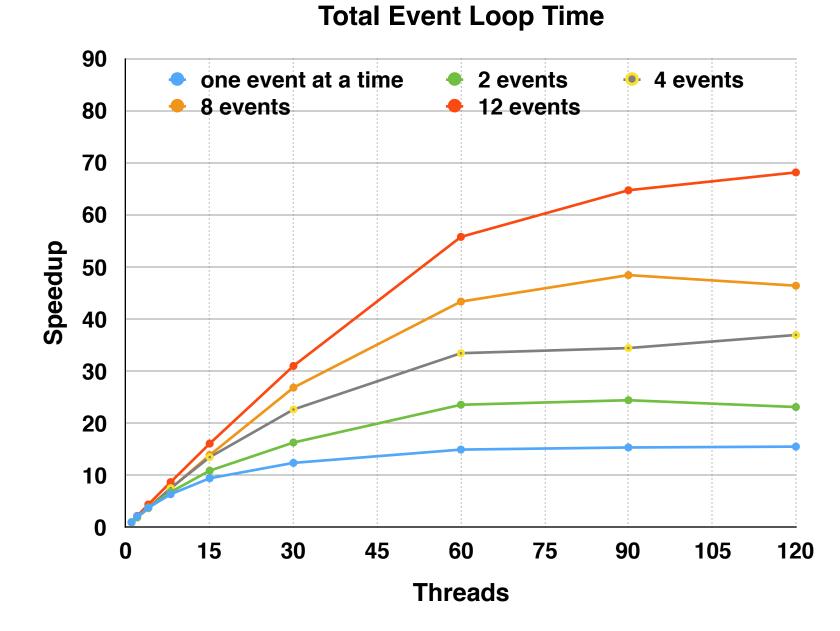
Compensating for Variable Occupancy

CMS events often have fewer good tracks than the simulated events in our simple setup

 Lower occupancy causes difficulties keeping the processors busy and vector units full

Process multiple events at the same time

- Multiple events can fill in gaps in parallelism due to varying levels of parallelism within an event
- · Still scaling limits due to per event data structures
 - Tradeoffs due to granularity vs. memory usage of the binning structure used for finding candidate hits
 - At very low occupancy k-d trees can be effective









GPU: Choice of Memory Layout

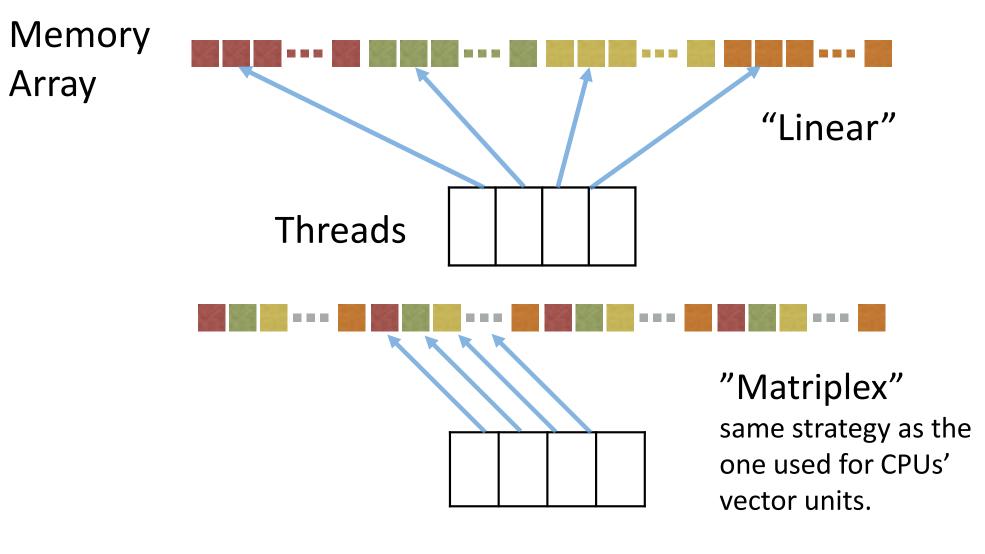
Array

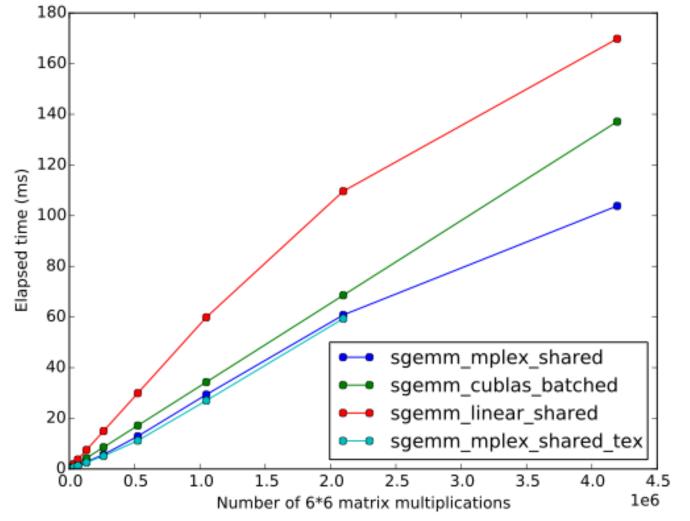
Linear vs. Matriplex

 For multiplying lots of 6x6 matrices, the Matriplex layout gave better performance than the obvious alternatives

Use a very large Matriplex-style structure

- · GPlex: same interface as Matriplex, but customized for GPU/CUDA
- Opens the possibility of templating many of the core Kalman routines to accept either







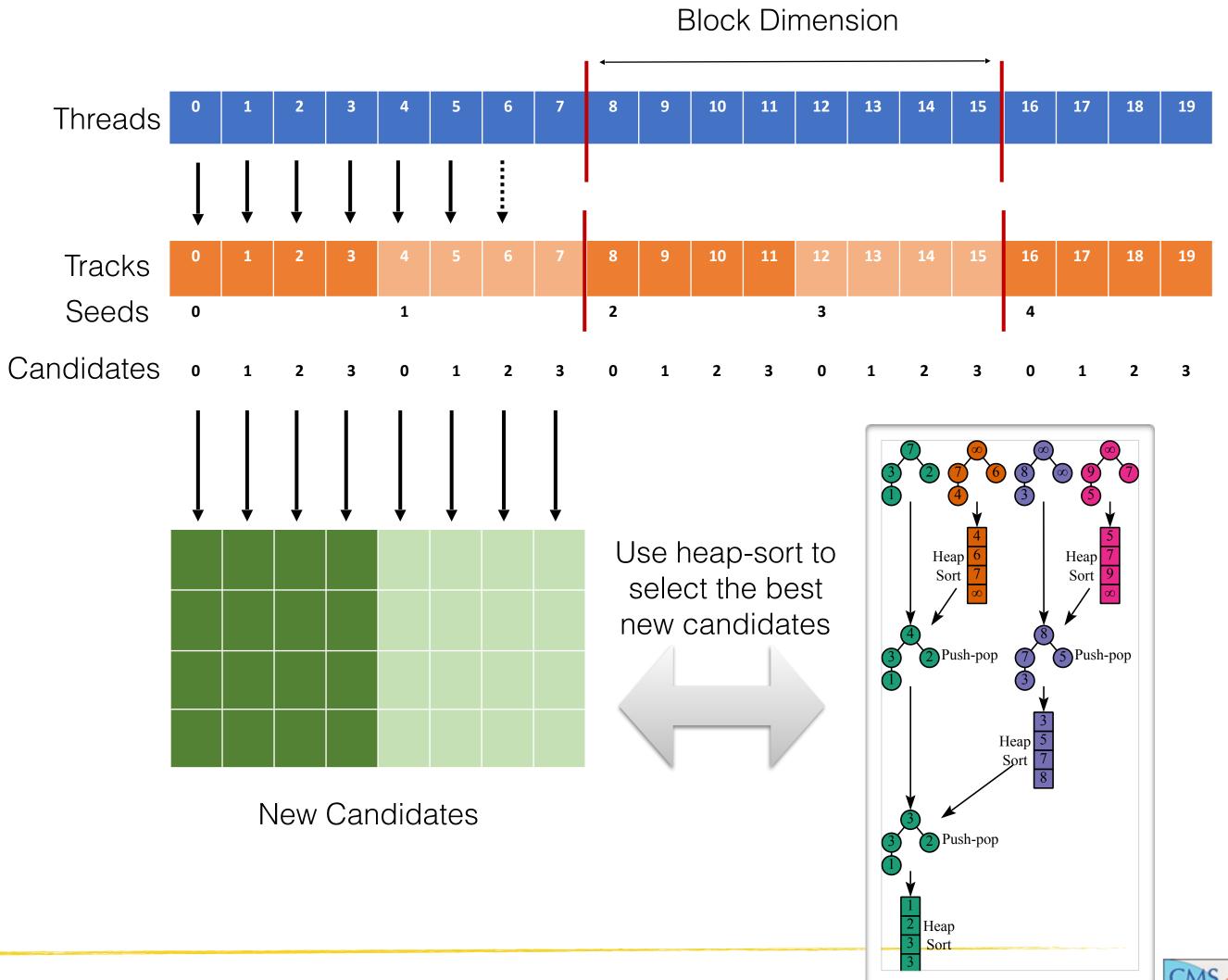




GPU: Handling Branching

Moving tracks in global memory is prohibitively expensive

- For parallelization, one GPU thread per candidate
- Heap-sort the new candidate list to select the best new candidates







CPU: Track Building Vectorization

How can we improve track building vectorization on CPUs?

- Most of the non-vector sections are moving track candidates around in memory
 - Considering copying the GPU approach of fixed assignments of vector units to seed candidates
- Finding candidate hits to add to the track, naively implemented, vectorizes poorly
 - Search window varies, number of hits found per track candidate varies
 - Split into three loops, two out of three can vectorize
 - Smarter data structure choices?

```
calculate z, φ windows
find bins in z, φ windows

for zBin: zBins

for phiBin: phiBins

for hit: hits[zBin][phiBin]

calculate hit-track dphi, dz

if ok(dz) && ok(dphi) && track.candidates < candMax

add hit.hitid to track.candidates
```





Perspective

The "start simple" plan has worked well for us

- · Achieved good parallelization and (mostly) good vectorization on KNC
- · Having a baseline for comparison has been a great help as we tackle the complications

Complications are on track

- · Realistic geometry and events are nearing completion
- Lessons learned seem to be carrying over well to new architectures
- Progress is being made on the GPU front

Lessons learned on architecture can be valuable on others

- CPU choices of data structures influenced the GPU version
- Some sharing of low level code (but steering logic differs)
- Lessons learned from GPU are starting to be applied back to the CPU version





Backup Slides

Splitting vector vs. non-vector loops

Overview:

- First loop calculates the search windows;
 this trivially vectorizes
- Second loop make a list of hits within the search windows
- Third loop is reorganized to check every hit against every track
 - the loop over tracks vectorizes

Problems:

- There's only a benefit if the track candidates have many candidate hits in common
 - This should be true if the candidate tracks are mostly from the same seed

```
for track: tracks calculate vector of \mathbf{z}, \boldsymbol{\phi} windows find vector of bins in \mathbf{z}, \boldsymbol{\phi} windows
```

```
for track: tracks
for zBin: zBins
for phiBin: phiBins
add z/phi bin to bins
```

```
for bin : bins
  for hit : bin.hits
  clear hitmask

for track : tracks
  calculate hit-track dphi, dz
  hitmask[track] = ok(dz) && ok(dphi)

for track : tracks
  if hitmask[track] && track.candidates < candMax</pre>
```

add hit.hitid to track.candidates



