

# Celeritas: scientific software for HEP simulation

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Scalable Engineering Applications*



CELERITAS

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U.S. DEPARTMENT OF  
**ENERGY**

**HSF-India**  
**1 August, 2024**

**Background**

Methods

Results

Future work



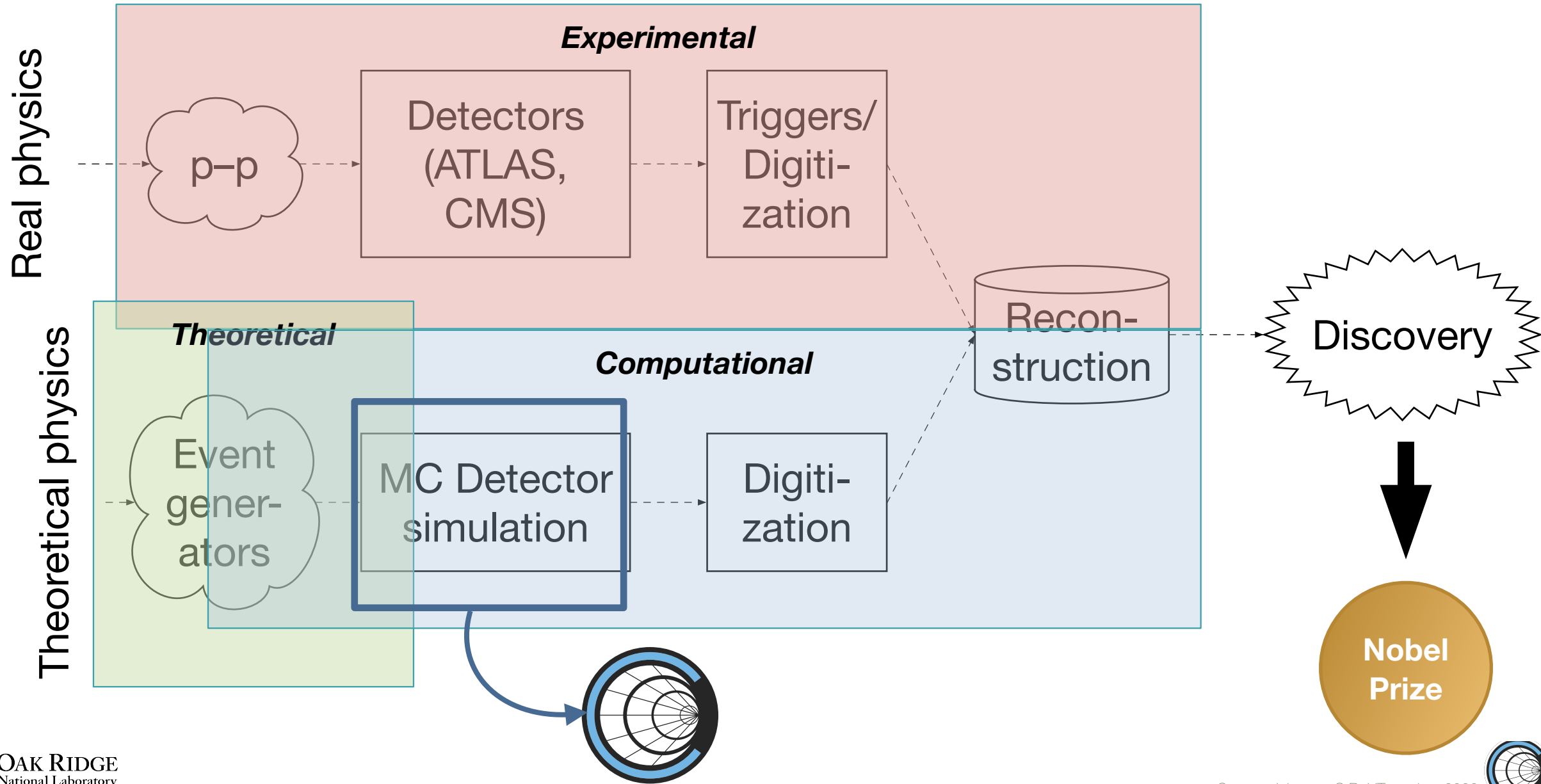
# The Large Hadron Collider

- **What:** particle collider (Ø 8.5km)
- **Where:** Geneva, Switzerland
- **Why:** study fundamental questions about the nature of the universe
- **Who:** CERN and international science collaborations
- **How:** massive radiation detectors (*CMS*, *ATLAS*, ...) around collision sites



LHC Beamline ©CERN

# LHC physics in a nutshell (gross simplification)





# LHC detector simulation

Note magnetic fields

1m

Silicon Tracker

Electromagnetic Calorimeter

Hadron Calorimeter Superconducting Solenoid

Magnetic

with muon chambers

2T

- 100B events
- × 1M tracks
- × 1K steps

— Muon

— Electron

— Charged hadron (e.g. pion)

- - - Neutral hadron (e.g. neutron)

- - - Photon

<https://cds.cern.ch/record/2120661>

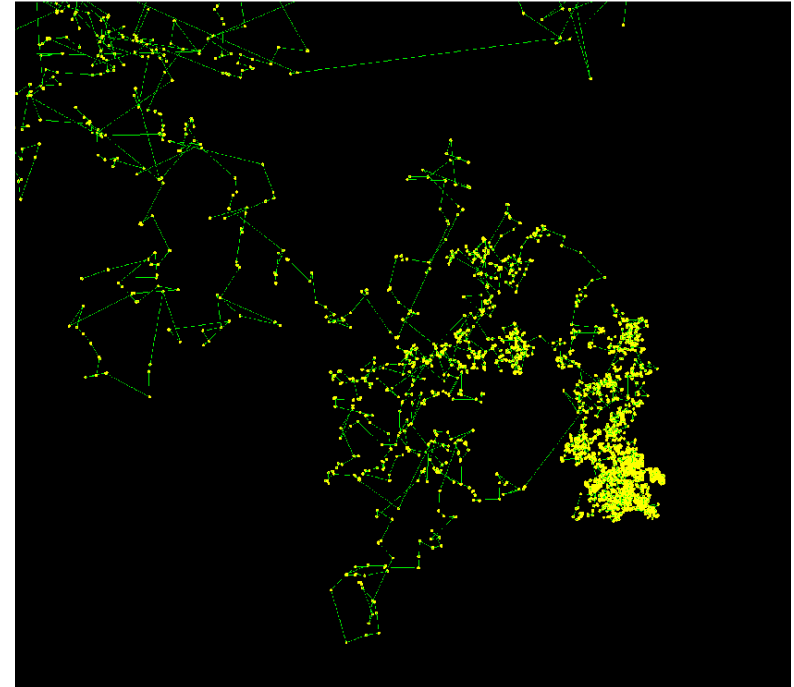
© 2016 CERN, for the benefit of the CMS Collaboration (License: CC BY-NC)

Source: Johnson, S.R. UT seminar 2022



# Monte Carlo detector simulation

- Each **event** inputs a list of **primaries** (starting point for a particle track)
- Each **track** samples physical processes and may produce **secondary** particles
- Each interaction in a “sensitive detector” generates a **hit** to record output
- $\sim 3\times$  number of actual events (140 PB of data!) must be simulated to reduce statistical effects

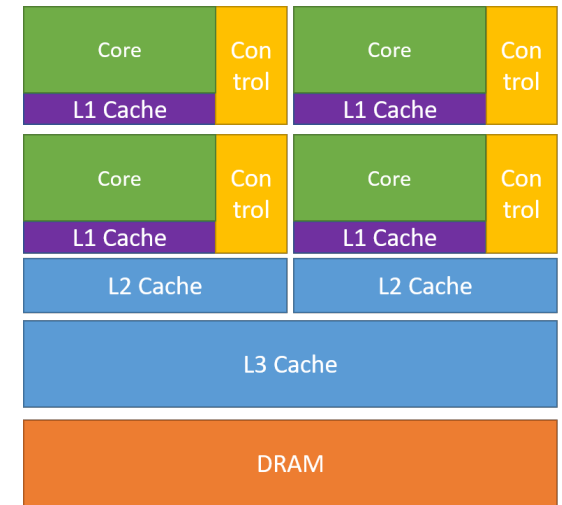


In this kind of MC, each history is an analog physical realization

# GPUs for scientific software

- General Purpose Graphics Processing Units (*GP-GPU*)
  - Conceptualized in early '00s
  - Very fast and power efficient for “graphics”-like applications
- “Many-core”: massively multithreaded
  - Programming models require much more care
  - Not good at flexible/dynamic operations
- Performant when:
  - Lots of similar work is being done at the same time
  - Lots of floating point operations per datum

Hardware characteristics determine programming paradigm



*CPU*



*GPU*



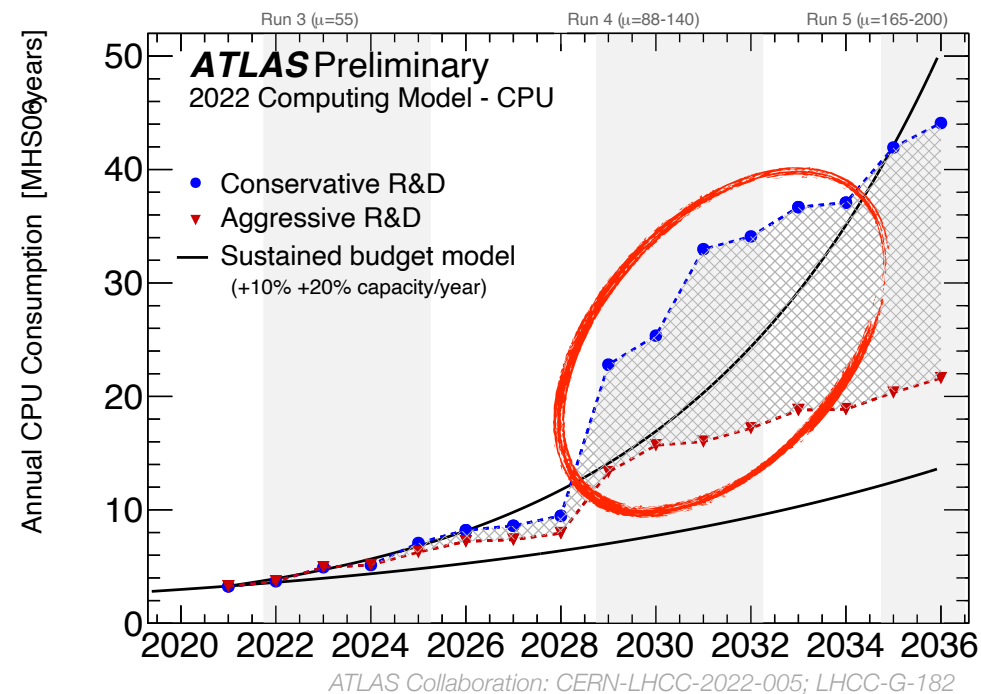
# Intersection of MC + GPU

- HEP demand is rapidly increasing

- Large Hadron Collider High Luminosity upgrade requires  $\geq 10\times$  computational throughput for detector simulation
- AI/ML based “fast simulation” methods need lots of training data on GPU

- HPC supply is fundamentally changing

- “Heterogeneous” architectures are increasingly common in high performance computing
- Scientific codes can run more efficiently on GPU  
*e.g., Perlmutter reports 5x average energy efficiency\**
- Demand for AI/ML training and models **will accelerate** this trend



## Top500 coprocessor brand





# Goal and approach

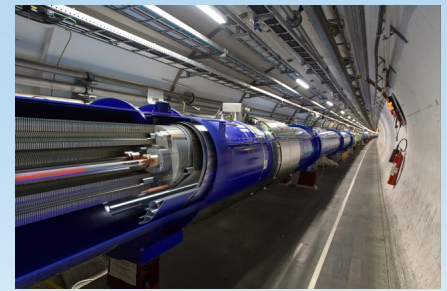
## Enable scientific discovery in HEP

by improving **throughput** and **energy efficiency**  
using **GPU**-based Monte Carlo detector simulation

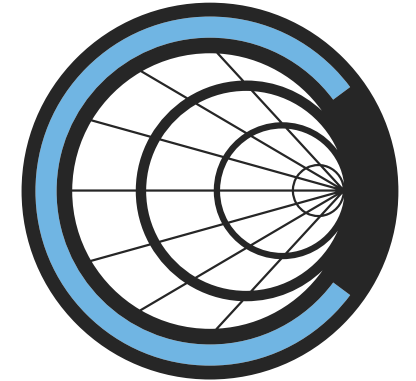
- **Research and develop** novel algorithms
- **Implement** production-quality code
- **Integrate** collaboratively with experiments
- **Deploy** on DOE LCF resources



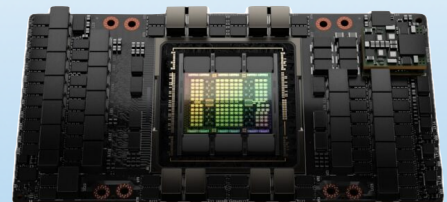
Informal collaborators



LHC beamline ©CERN



CELERITAS



Nvidia H100 GPU @Nvidia

Background

**Methods**

Results

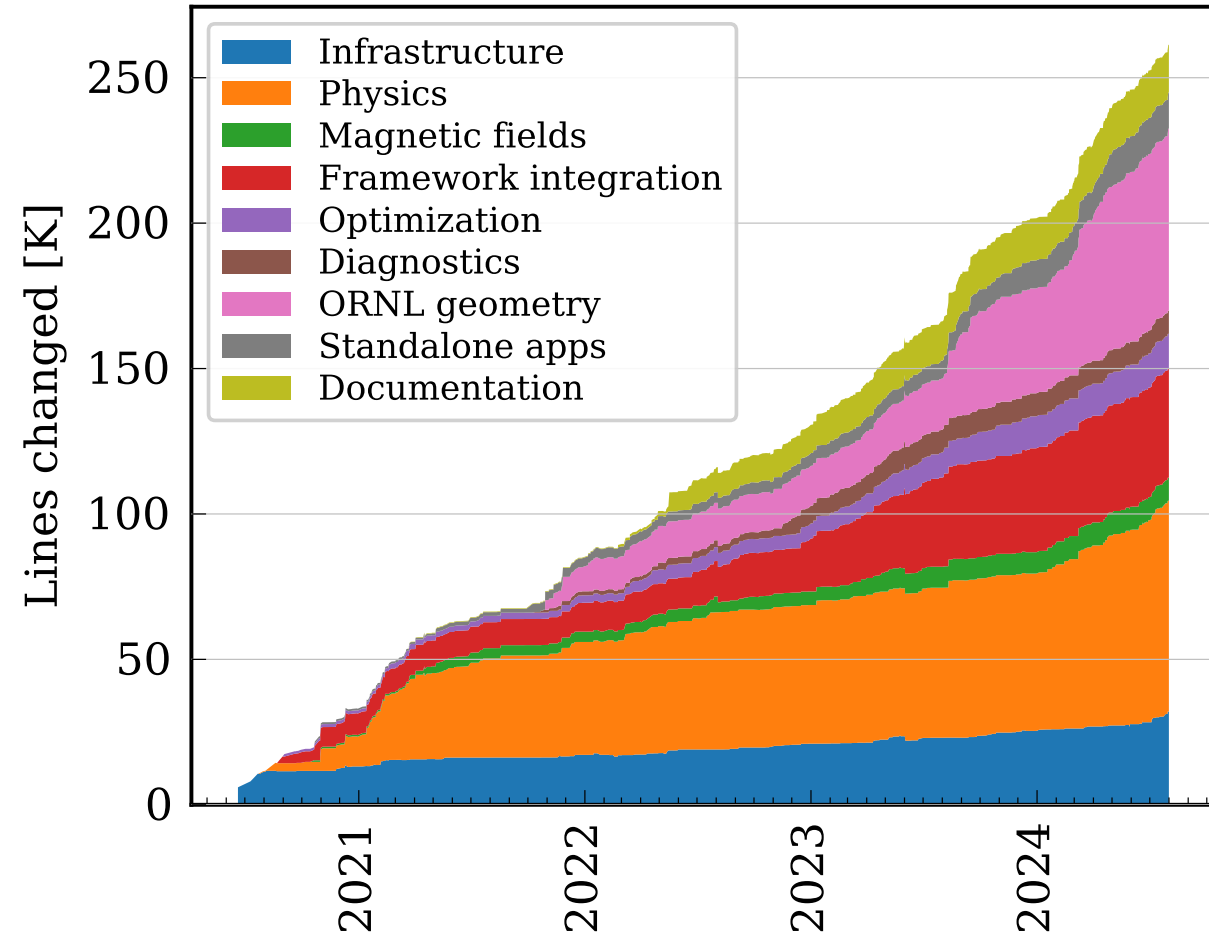
Future work



# Code development

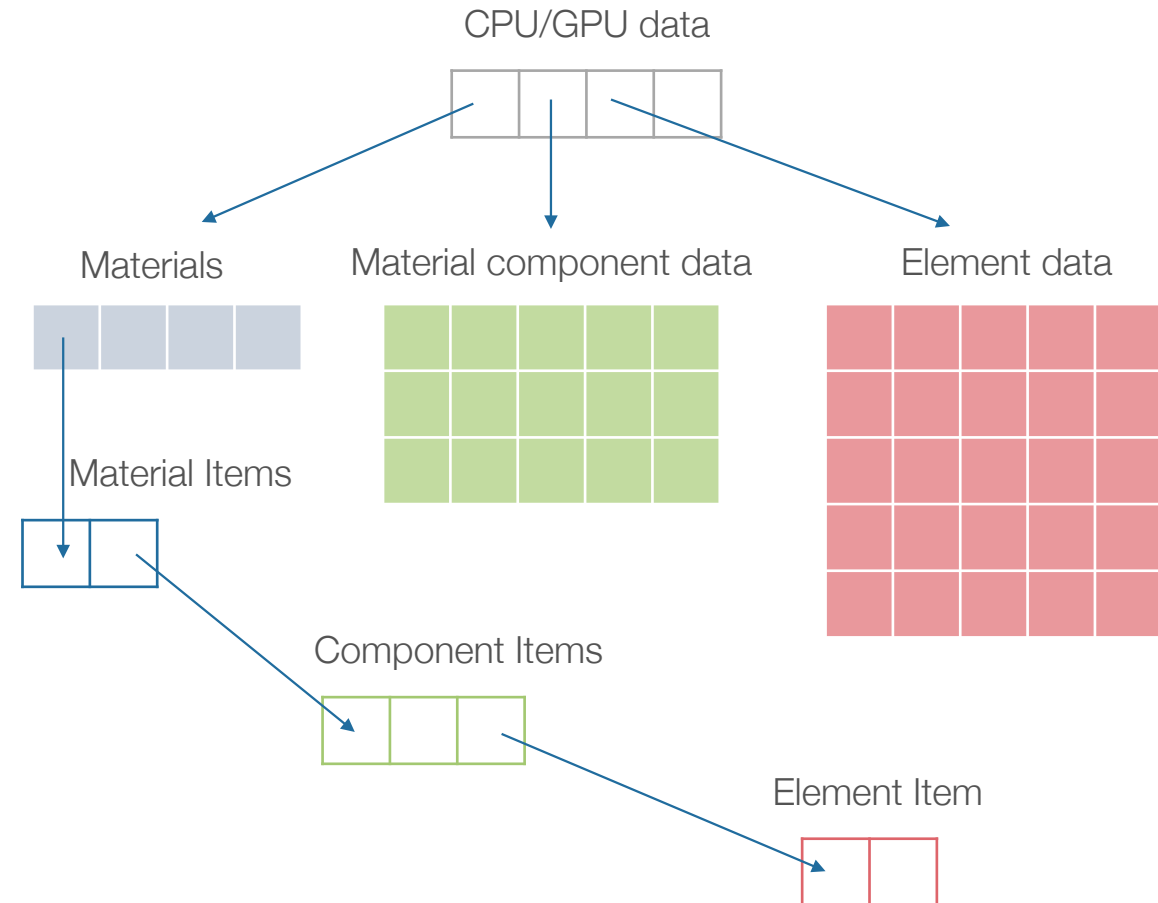
*Production-focused open source scientific software*

- **90%** of source code is reusable library code
- **1:2** ratio of lines of documentation to code
- **50k** lines of test code
- CI and rigorous review before merge



# Data management

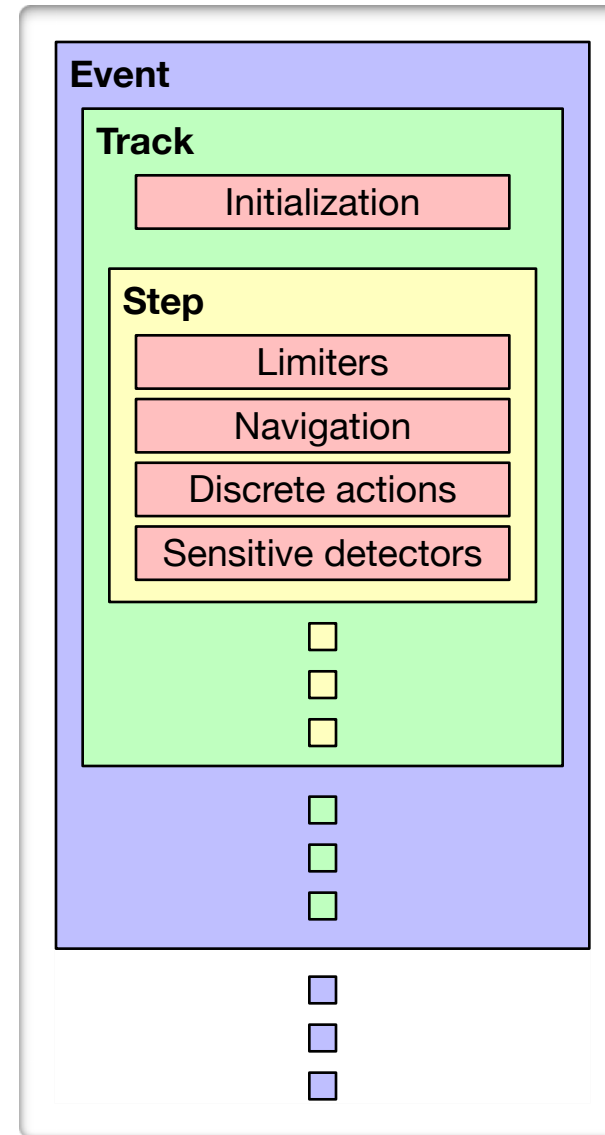
- Traditional GPU data uses:
  - Highly structured, dense, regular arrays
  - Lots of host/device transfers
- Physics data is:
  - “Awkward,” hierarchical, sometimes sparse structures
  - Mostly constant after problem setup
- Celeritas data structures:
  - Run on CPU, Nvidia, AMD, ...
  - Are constructed on CPU with standard C++



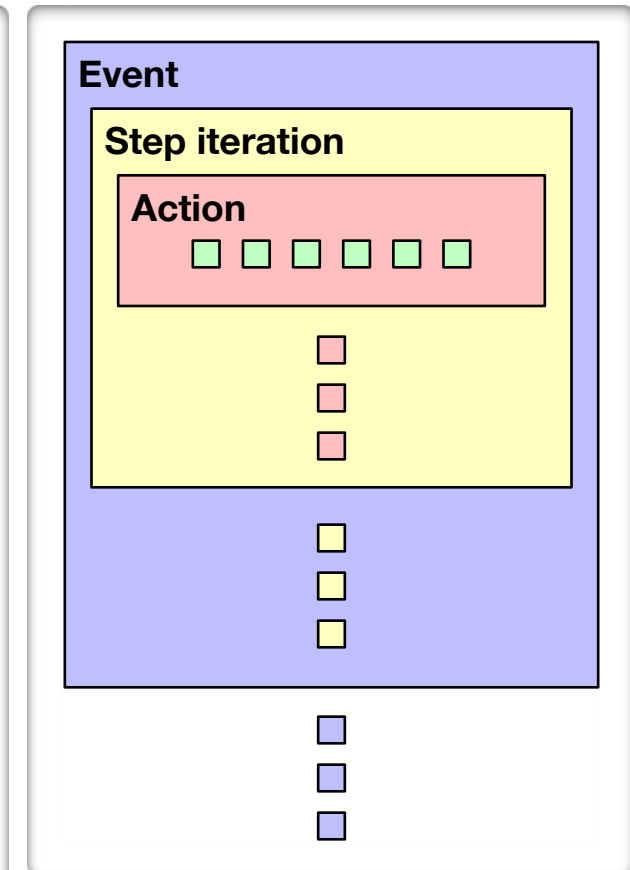


# Core algorithm for simulation: stepping loop

- External synchronization point at each “event” ( $p-p$  collision)
- Dependency between steps and independence of tracks allows *loop interchange*
- Instead of polymorphic functions operating on a single track, they launch a kernel over *many* tracks



CPU (Geant4)

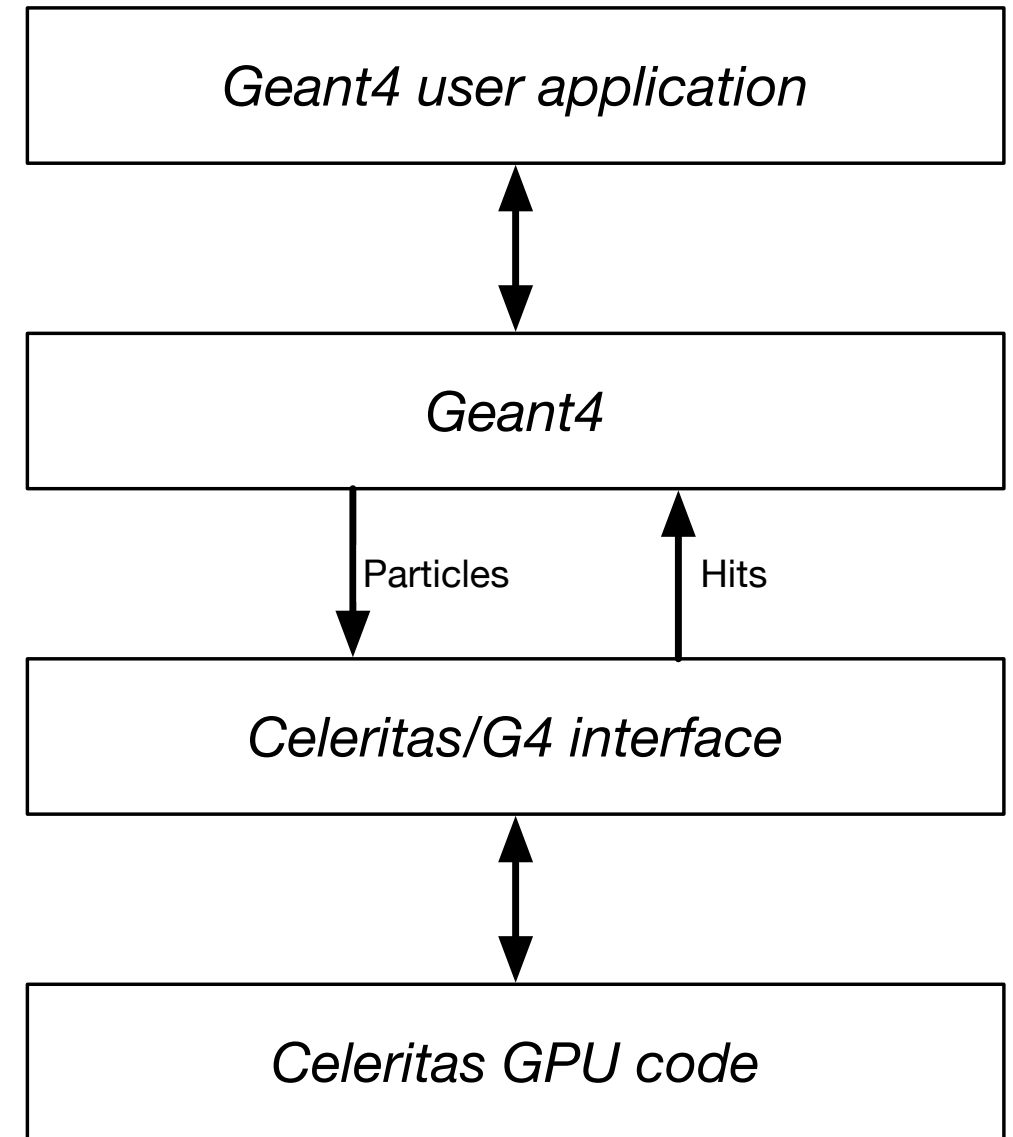


GPU (Celeritas)



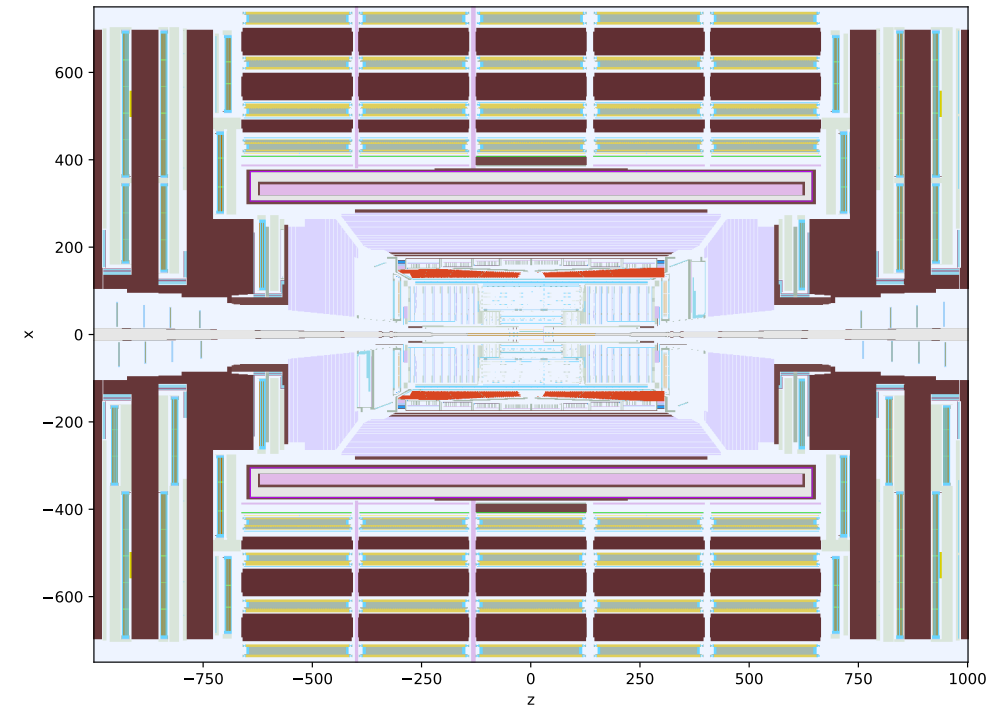
# Geant4 integration

- Geant4 is the *experiment-validated* MC simulation code used in HEP and beyond (*medical physics, dosimetry, ...*)
- Celeritas *directly imports geometry, physics data*
- $e^-$ ,  $e^+$ ,  $\gamma$  sent to Celeritas (GPU)
- Reconstructed “hits” (*energy deposition plus metadata*) sent back to user-defined detectors



# High-level capabilities targeting LHC simulation

- Equivalent to `G4EmStandardPhysics`
- Full-featured Geant4 detector geometries using VecGeom 1.x
- Runtime selectable processes, physics options, field definition
- Execution on CUDA (Nvidia), HIP\* (AMD), *and CPU* devices



*GPU-traced rasterization of CMS 2018*

*\*VecGeom currently requires CUDA:  
ORANGE navigation required for HIP*

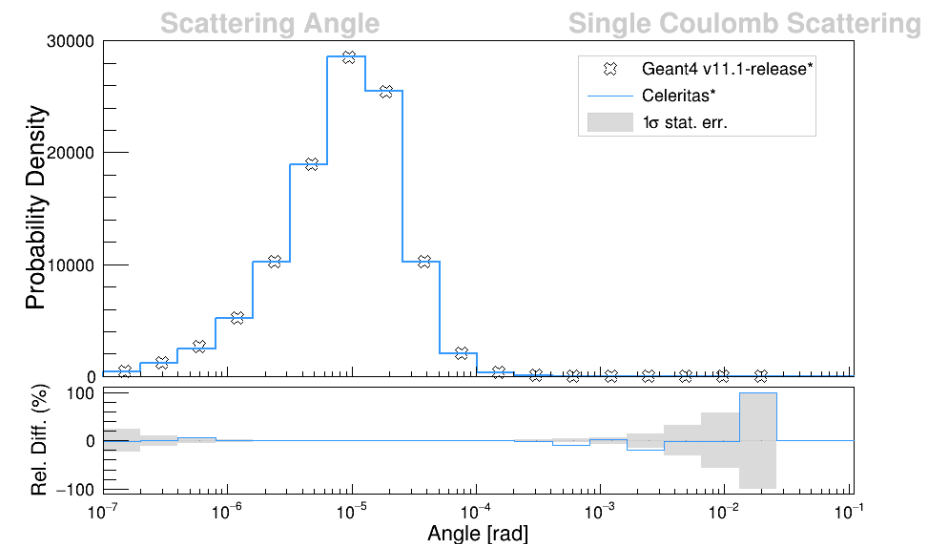
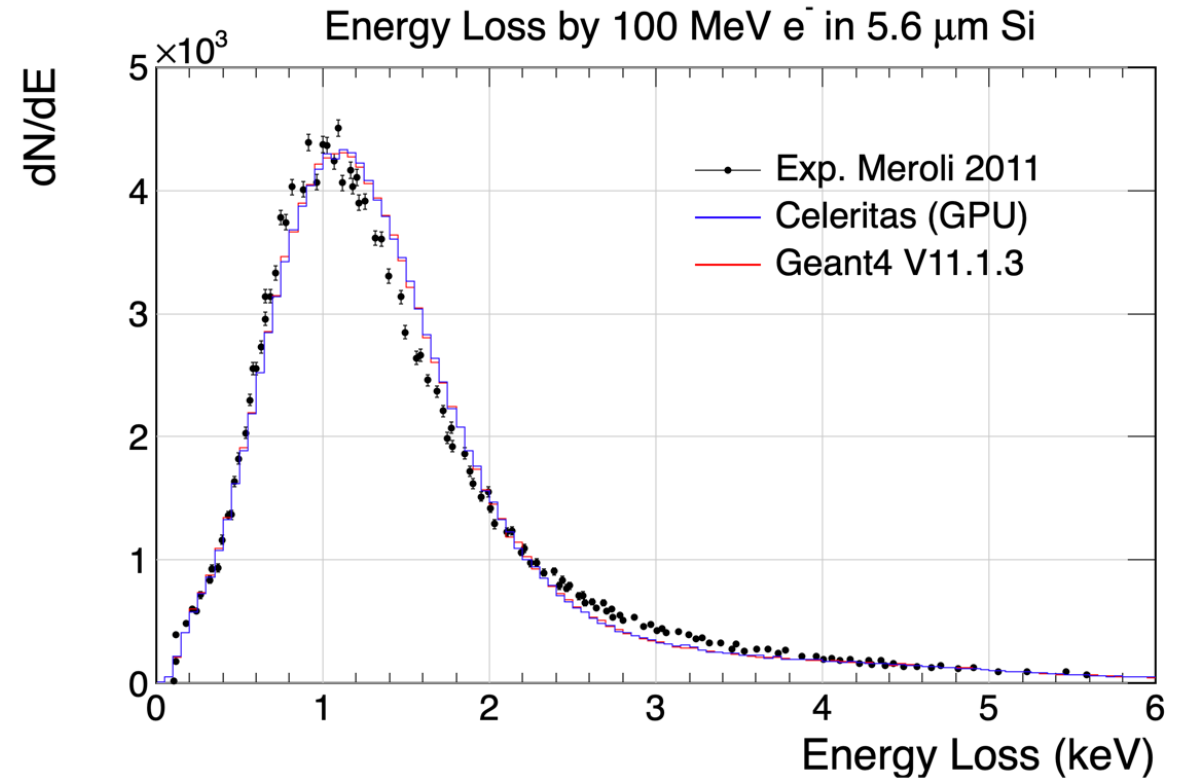
Background  
Methods  
**Results**  
Future work





# EM physics validation

- Established good agreement with Geant4 for:
  - Energy loss fluctuations
  - Multiple scattering (azimuthal angle distribution)
  - Single Coulomb scattering
- Experiment-specific validation required for acceptance



# Standalone EM performance

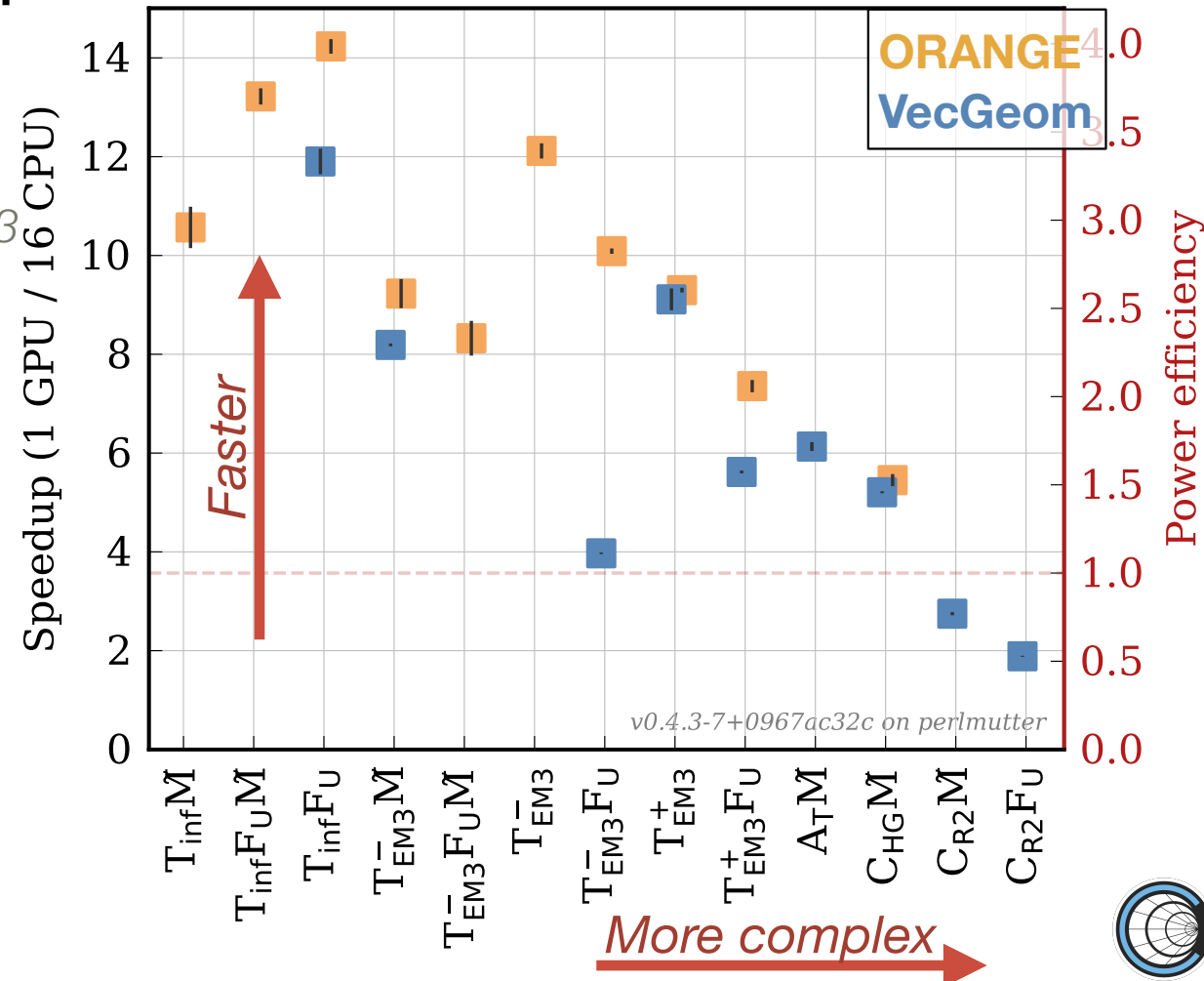
- LHC-scale simulations on DOE LCF

- 1300 × 10 GeV e<sup>-</sup>, 16 events
- ¼ Perlmutter node (NERSC)  
*1 × Nvidia A100 GPU, ¼ × 64-core AMD EPYC 7763*
- Celeritas GPU vs CPU  
*CUDA (1 CPU thread) vs OpenMP (16 CPU threads)*

- Key metrics favor GPU**

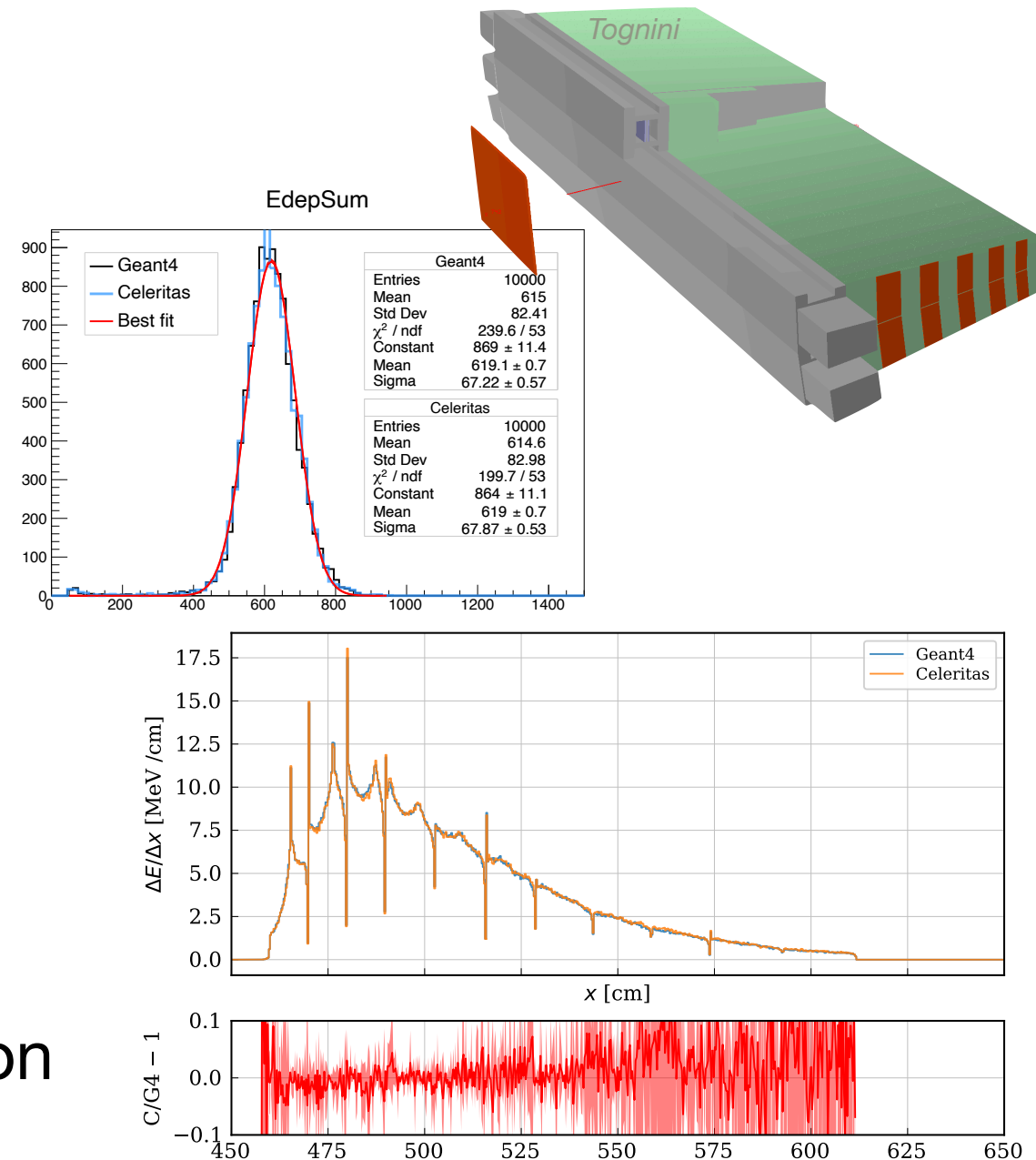
- Capacity*: **50–94% loss** if GPUs are ignored
- Efficiency*: up to **4x** performance per watt

Problem definition		Modifier	
T <sub>inf</sub>	“Infinite” medium	F <sub>U</sub>	uniform
T <sub>EM3</sub>	Idealized calorimeter		1T field
A <sub>TC</sub>	ATLAS TileCal	M̃	no MSC
C <sub>HG</sub>	CMS HGCal		
C <sub>R2</sub>	CMS Run 2 (2018)		



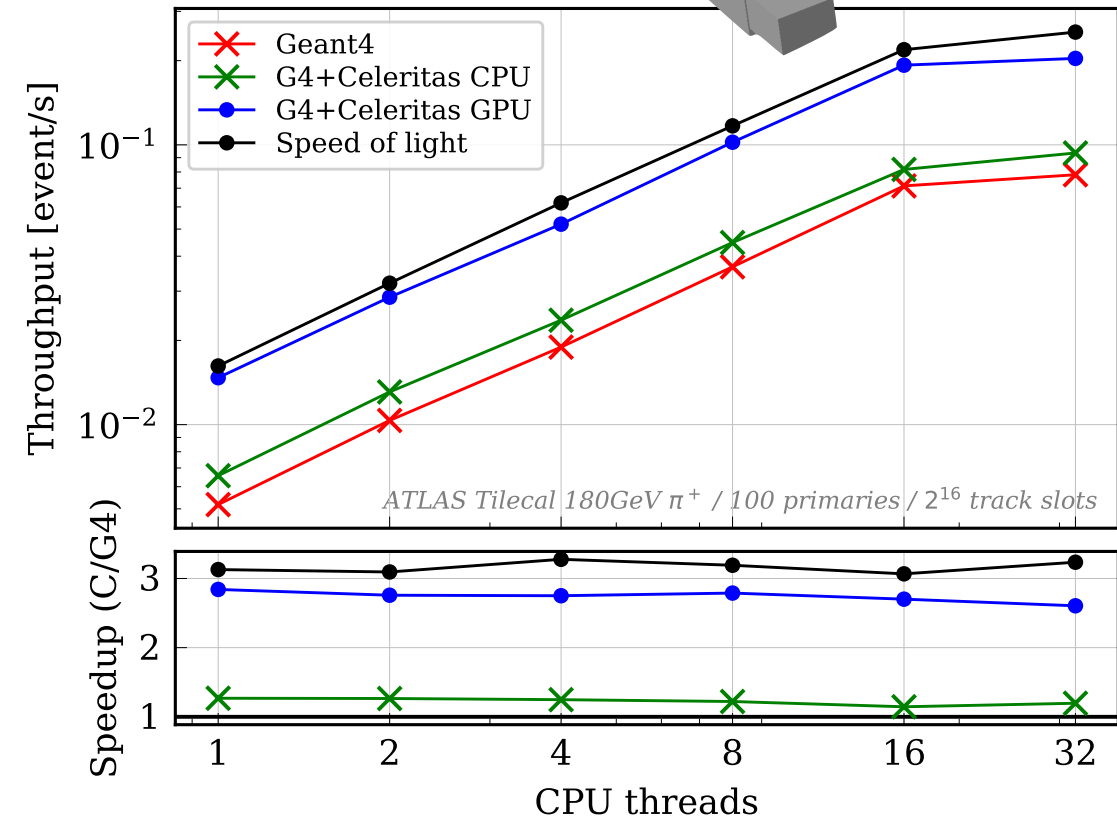
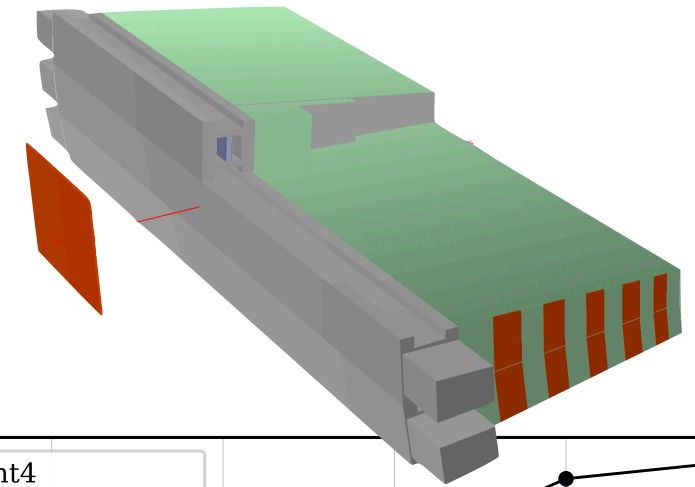
# EM offloading with FullSimLight

- ATLAS FullSimLight: hadronic tile calorimeter module segment
  - 64 segments in full ATLAS, 2 in this test beam
  - 18 GeV  $\pi^+$  beam, no field
  - FTFP\_BERT (default) physics list  
(includes standard EM)
- **~100 lines of code to integrate**
  - Offload  $e^-$ ,  $e^+$ ,  $\gamma$  to Celeritas
  - Celeritas reconstructs hits and sends to user-defined G4VSensitiveDetector
- **Good agreement** in energy deposition



# Offload performance results

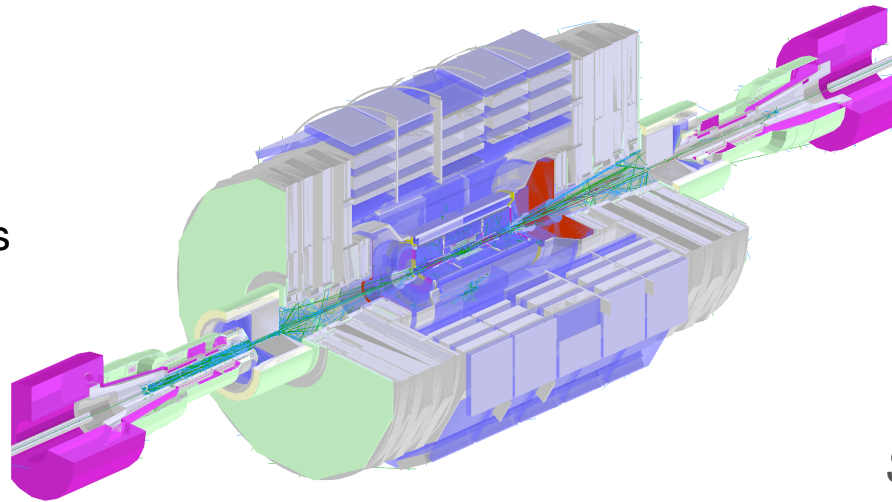
- 1/4 of a Perlmutter (NERSC) GPU node  
16 cores of AMD EPYC, 1 Nvidia A100
- Time **includes** startup overhead, Geant4 hadronic physics, track reconstruction, and SD callback
- GPU speedup: **2.6–2.8x** at full occupancy  
Using all CPU cores with a single GPU
- CPU-only speedup: **1.1–1.3x**
- Theoretical maximum speedup: **3.0–3.3x**  
Instantly killing e<sup>-</sup>, e<sup>+</sup>, γ when born
- **LHC-scale energy per event (>1 TeV)  
is needed for GPU to be effective**
- **One GPU is effective with many-CPU Geant4**



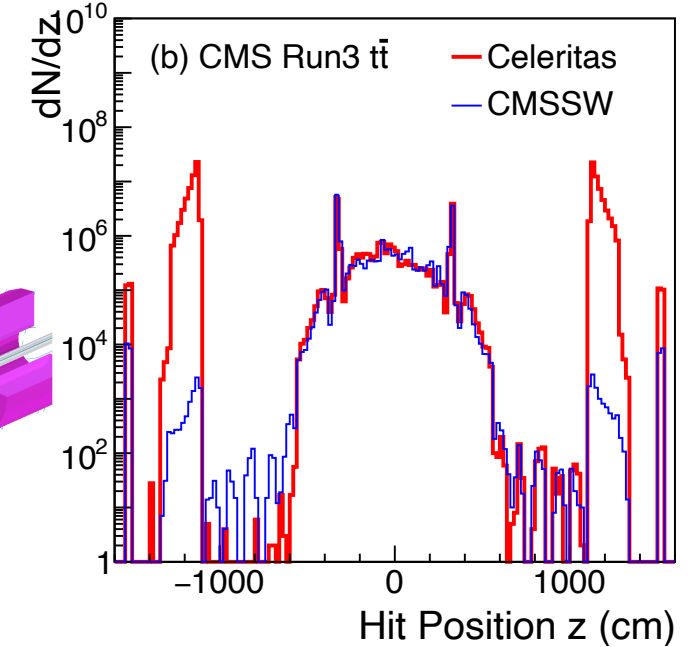


# CMS Run 3&4 Standalone Simulations

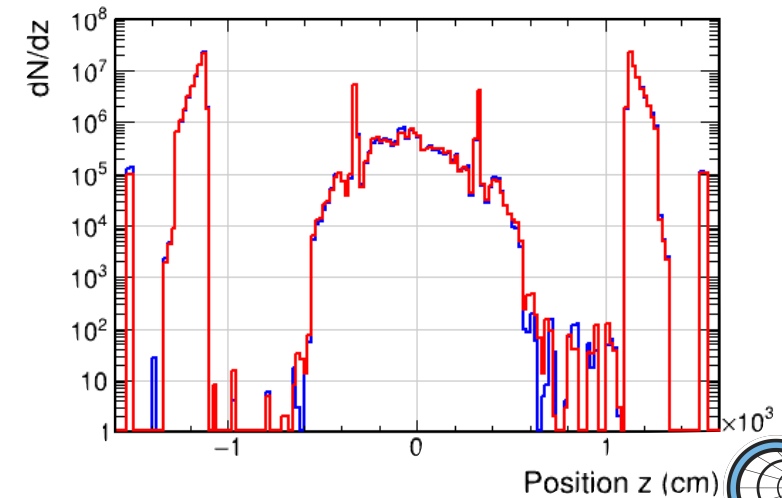
- Standalone Geant4 app celer-g4
- 32  $t\bar{t}$  events from Pythia
- FTFP\_BERT physics
  - Geant4 simulates hadronics
  - All EM tracks offloaded to Celeritas
  - Lepto-nuclear reactions neglected
- Multiple field options
  - No magnetic field
  - Uniform 4T field
  - Discretized+interpolated RZ field (901×481 points)
- CMSSW/Geant4 throughput: **8×**  
*(we're simulating a harder problem than necessary, but we now have an equivalent test problem)*



CMSSW Run 3 hit distribution



Standalone Run 3 hit distribution



# CMS Run 3&4 Standalone Results

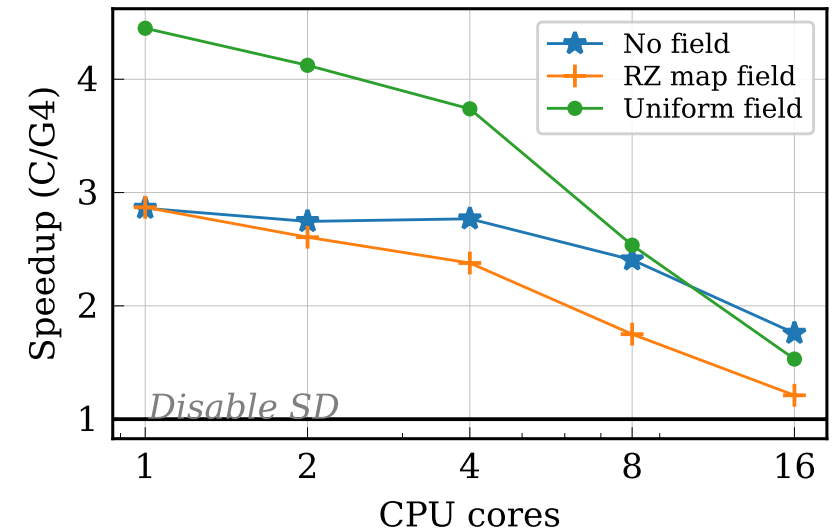
- Promising performance

- SD reconstruction adds <15% overhead
- Initial comparison of hits shows good agreement
- With task-based framework we might see better (due to less GPU contention)

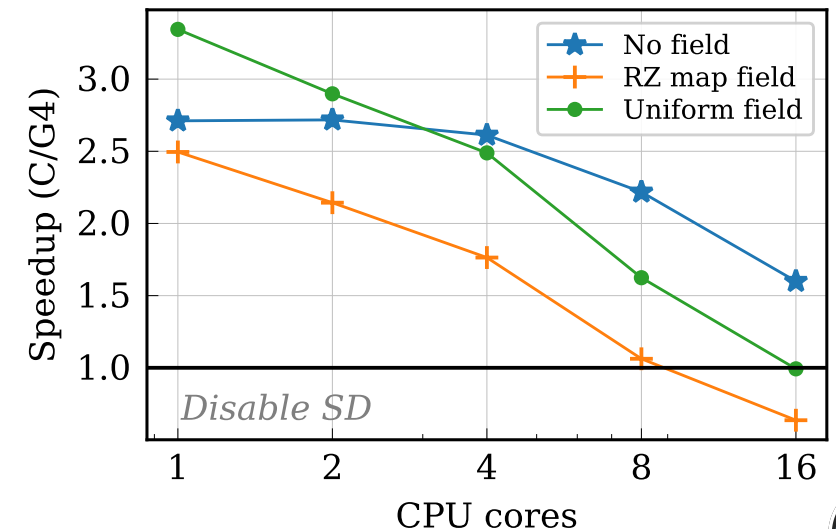
- Possible future improvements:

- Magnetic field propagation
- Activating track sorting to get smaller kernel grid sizes
- Single-precision? (Especially on consumer cards)

Run 3; Nvidia A100



Run 4 (HL-LHC); Nvidia A100



Nvidia A100 vs AMD 7532 EPYC

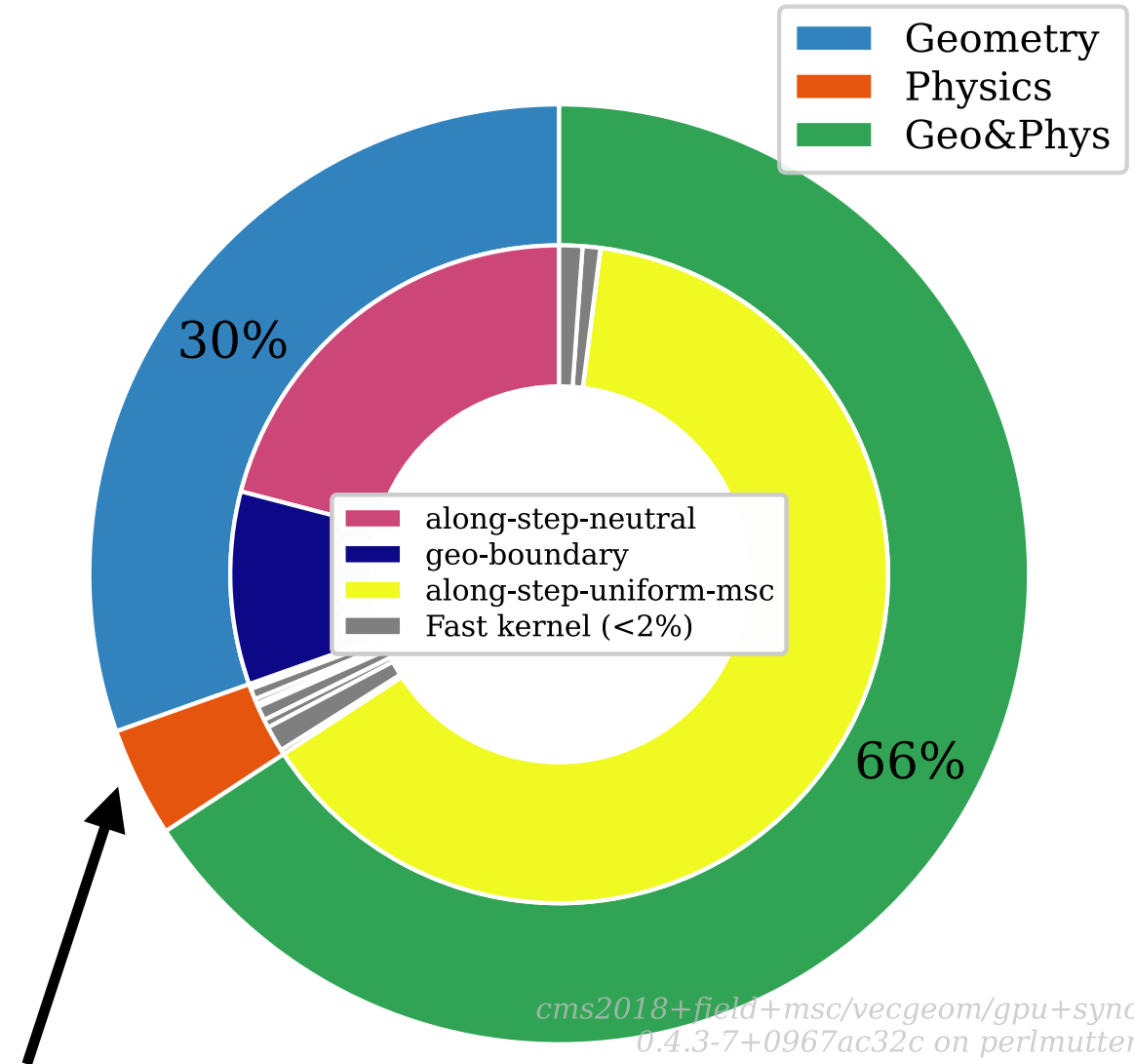


# Primary bottleneck: geometry

- Each step\* may require 100 “distance to boundary” evaluation

*\* remember, ~1B steps per simulation!*

- Up to  $\sim 10^5$  distinct geometric elements per detector model
- Current geometry implementation is *not* optimized for GPU
- CERN (VecGeom) and ORNL (ORANGE via HEP-CCE2) both implementing solutions

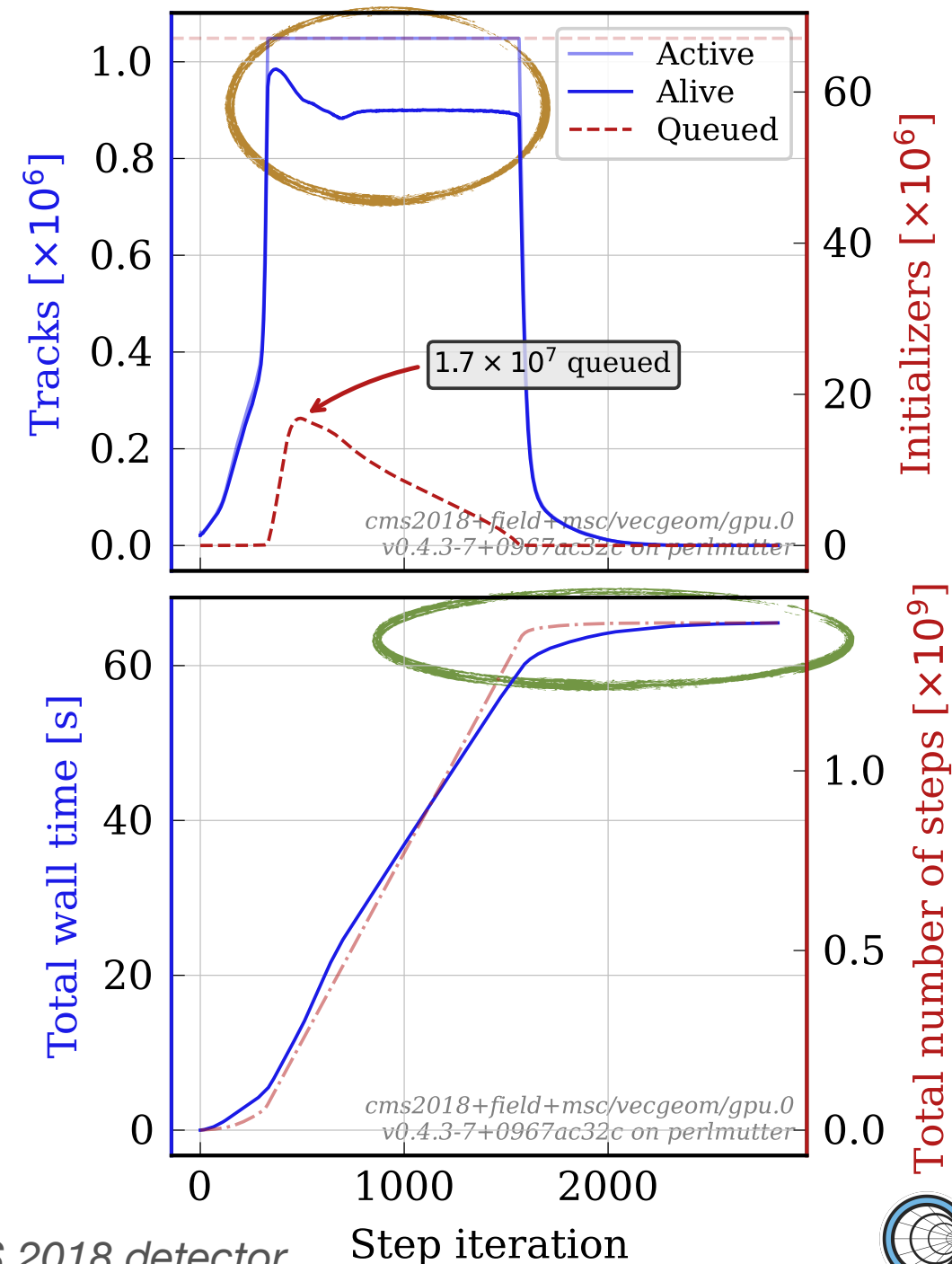


*Physics is 4% on GPU,  
but 19% on CPU*

*cms2018+field+msc/vecgeom/gpu+sync  
0.4.3-7+0967ac32c on perlmutter*

# Step-dependent behavior

- Number of active particle tracks changes drastically due to EM shower
- Saturated GPU takes the most time but <50% of step iterations  
*Despite using masking instead of sorting!*
- Converting the tail of long-lived tracks does *not* kill us

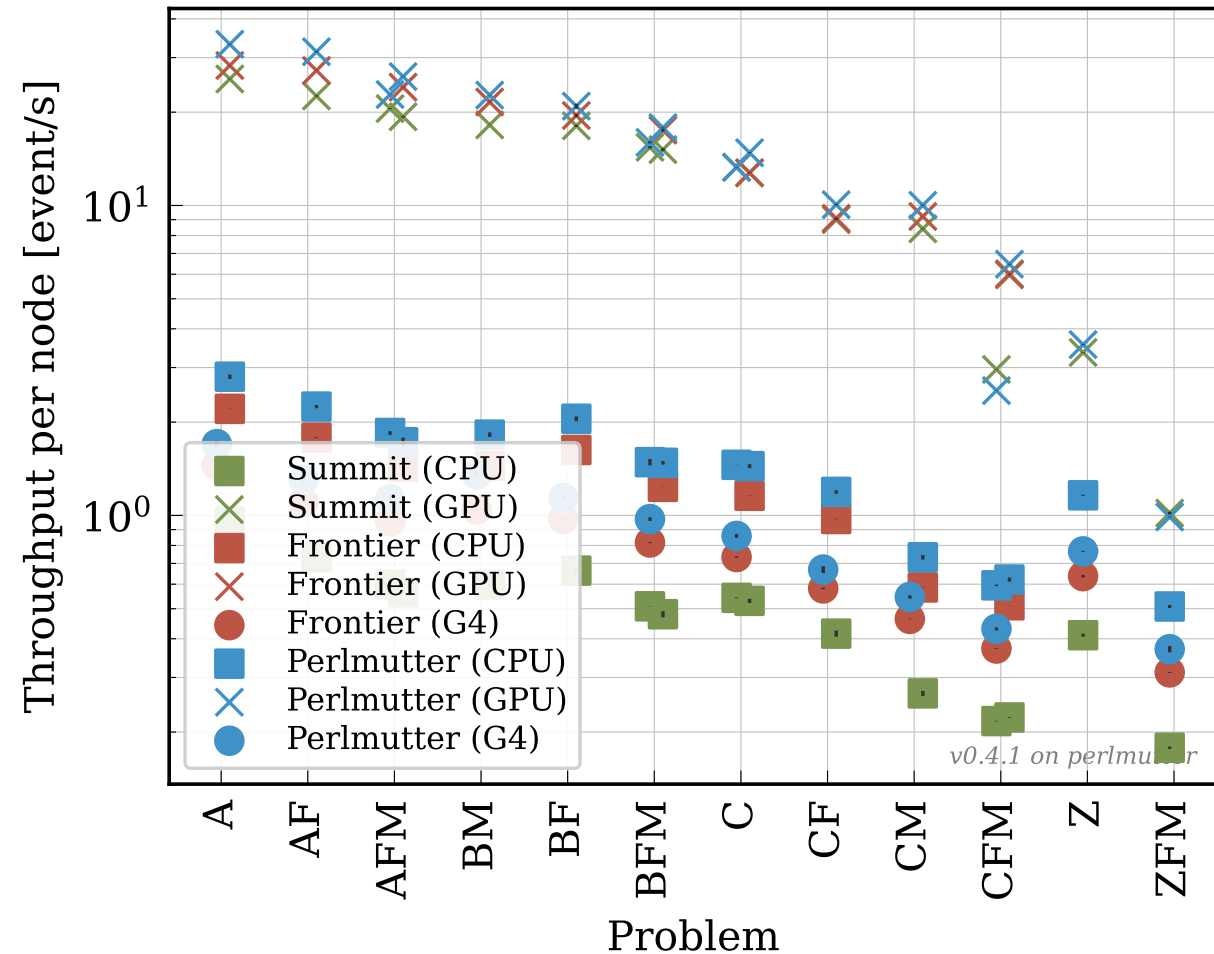


# Figure of merit: throughput

- GPUs *cannot* be ignored if present
- AI/ML “revolution” guarantees more coprocessors at all scales

Per-node stats for DOE supercomputers

Machine	Arch	Card	TDP (W)	Cores*	Cards
Summit	CPU	IBM Power9	190	‡22	2
	GPU	Nvidia V100	250	80	6
Perlmutter	CPU	AMD EPYC 7763	280	64	1
	GPU	Nvidia A100	250	108	4
Frontier	CPU	AMD EPYC 7453	225	‡64	1
	GPU	AMD MI250x	500	‡220	‡4





\*or SMs;

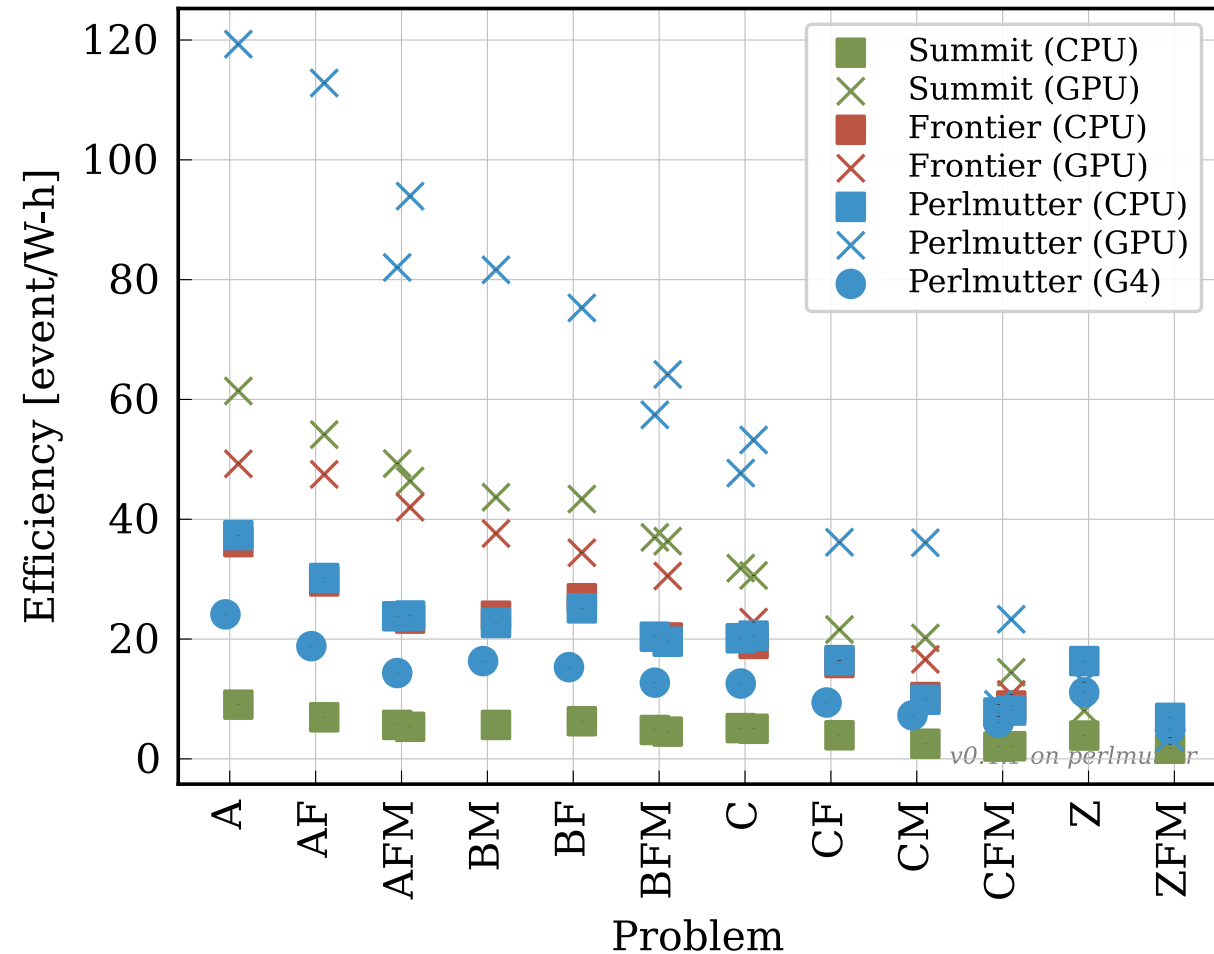
‡Each card has 2 GPUs

‡One core reserved per GPU



# Figure of merit: **efficiency**

- Estimated using reported Thermal Design Power (TDP)\* and Celeritas throughput
- GPU consistently shows higher energy efficiency 
  - Reduced operating costs
  - Higher compute density (fewer nodes, smaller data centers)
- A100:EPYC price is ~4x 



# Results: impact by the numbers

**100** lines of code

to integrate Celeritas into a FullSimLight tile calorimeter test application, with no modifications to Geant4

**2.8x** full-simulation speedup

including hadronics and SD hits, by using 1 Nvidia A100 with 16 AMD EPYC cores for the ATLAS test beam application *[NERSC Perlmutter]*

**2–20x** throughput

when using Celeritas on GPU (compared to Geant4 MT CPU) for EM test problems *[NERSC Perlmutter]*

**4x** performance per watt

for TestEM3 (ORANGE geometry) using Celeritas GPU instead of Geant4 CPU *[NERSC Perlmutter]*





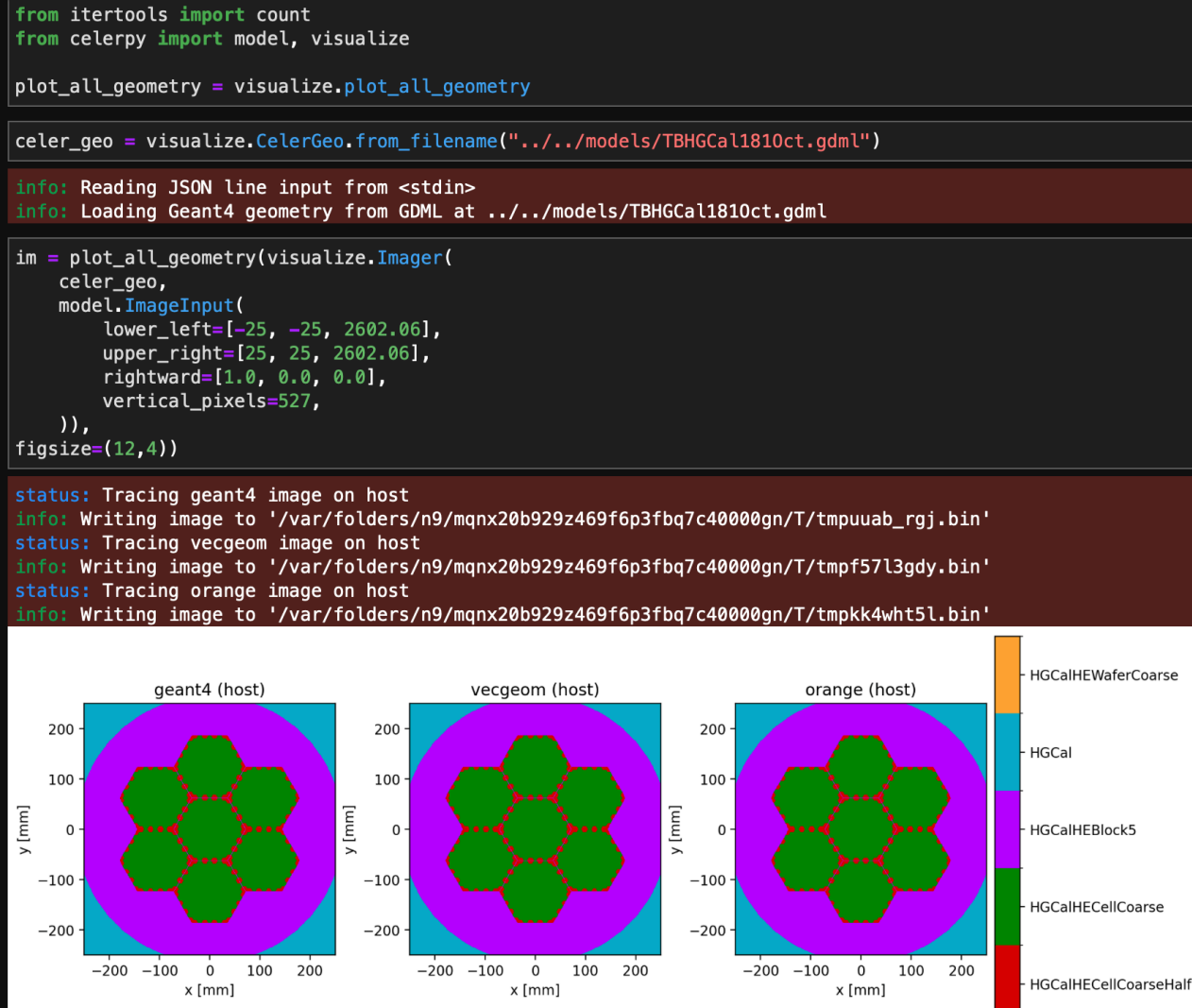
Background  
Methods  
Results  
**Future work**



# Python/REST interface

**Challenge:** generic integration with next-generation experiment frameworks

- JSON I/O in C++
  - Integrates cleanly with containers
  - Quickly “spin up” interactive notebooks for student exploration
- Current capability: rasterization for geometry validation



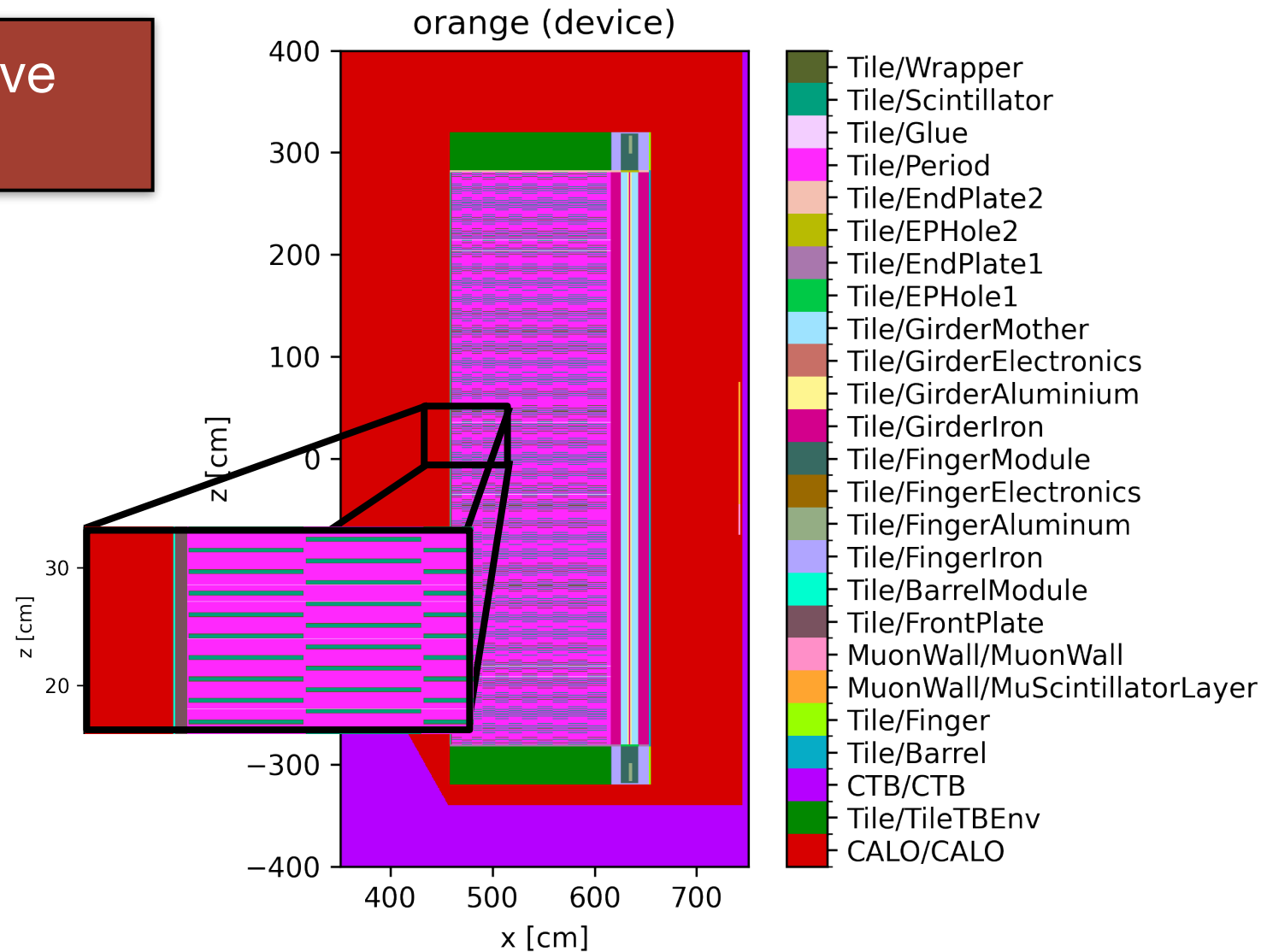
# Platform-portable surface-based geometry

**Challenge:** most compute intensive aspect of EM simulation on GPU

- ✓ Model conversion
- ✓ Robust surface construction
- ➔ Model verification
- ➔ Performance optimization
- × Safety calculation

## *Initial targeted geometry*

- ATLAS TileCal
- CMS HGCal
- ATLAS EMEC



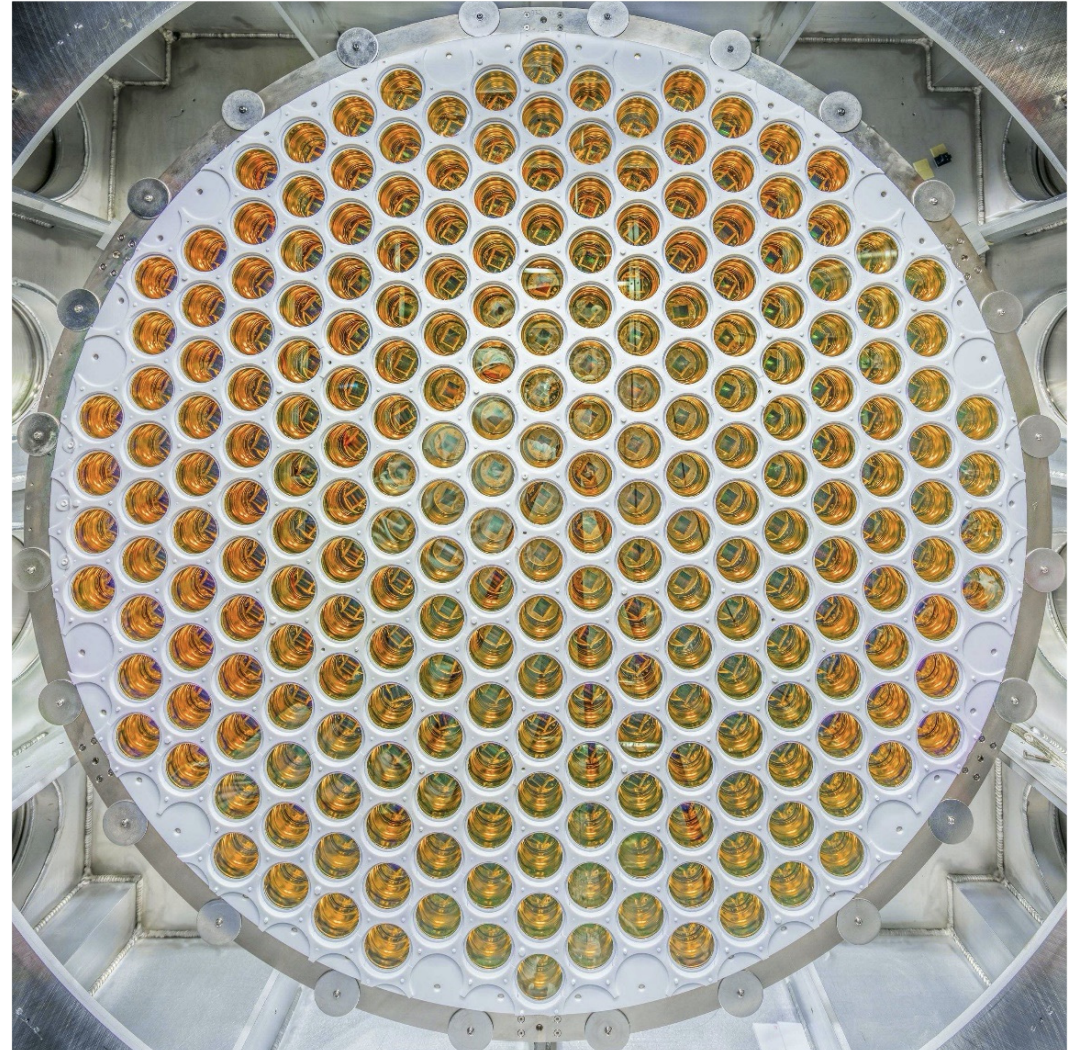
GPU ORANGE raytrace of ATLAS tile calorimeter



# Optical photon transport for Calvision

**Challenge:** thousands of optical photons can be emitted per track per step, leading to long run times

- **Initial goal:** integrated optical tracking loop with absorption by end of summer
- ✓ Geant4 optical data import
- ✓ Scintillation production
- ✓ Cerenkov production



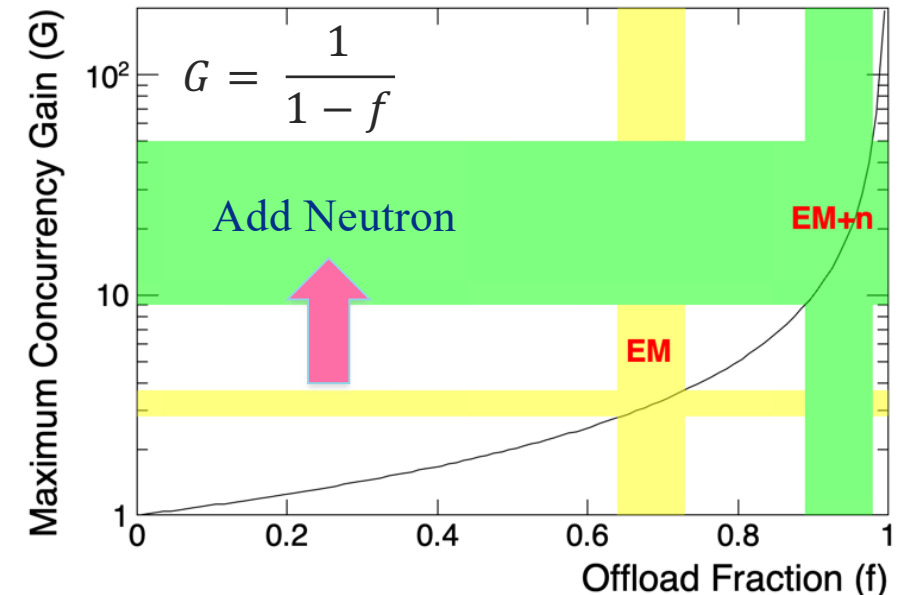
PMT array ©LZ

# Neutron physics

**Challenge:** offloading more work to GPU

- Critical for muon beam background simulations  
(AI/ML training: see K. Pedro ECA proposal)
- **Technically feasible** due to early investment and design decisions

cms2018@LHC Max Gain by GPU		
Process	EM	EM+n
QCD( $p_T^{min}=1\text{TeV}$ )	2.9	21.1
W+Jets	2.8	22.2
Z+Jets	3.0	22.7
$t\bar{t}$	2.8	21.0
Higgs	2.8	21.1
MSSM	3.4	20.2
Stop	2.8	20.9

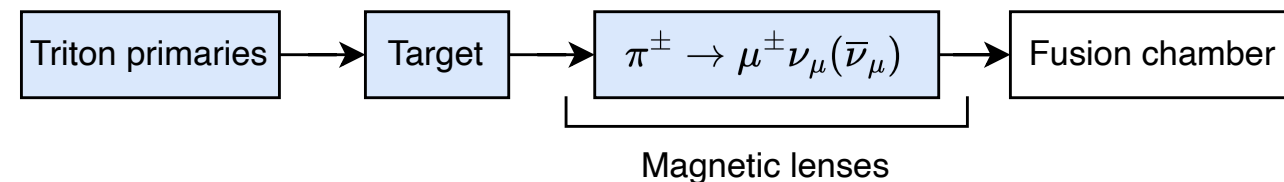
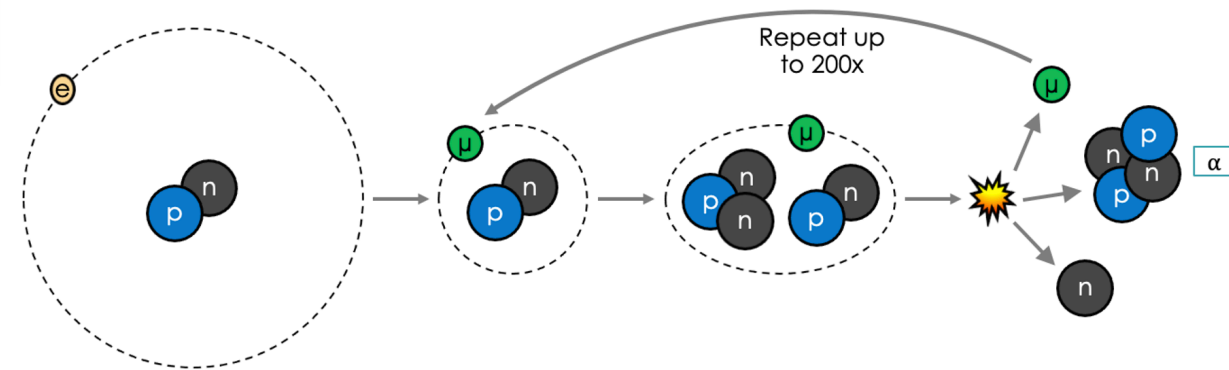




# Physics for muon-confined fusion

**Challenge:** improving beam simulation throughput for design optimization

- Design optimization and to validation of theoretical models against experimental data
- R&D to address the feasibility of  $\mu$ CF as an energy source



*$\mu$ CF takes advantage of the reduced size of d-t muonic molecules to achieve fusion at low temperature regimes*

# Continuing collaborations

- Experiments for integrating
- Institutions for strategizing
- Codes for knowledge sharing
- Vendors for performance benchmarking

Any and all contributors and collaborators are welcome!





# Interested?

- Check out our GitHub repository
  - ★ to show interest and get updates
  - Easy installation and thorough documentation
  - Code structure is conducive to student projects
- Standalone “starter” tasks available
  - Physics verification and code-to-code comparisons
  - Geometry development
  - Physics model implementations

[Code](#)



[Documentation](#)



# Acknowledgments

## *Celeritas v0.4 code contributors:*

- Elliott Biondo (@elliottbiondo)
- Philippe Canal (@pcanal)
- Julien Esseiva (@esseivaju)
- Tom Evans (@tmdelellis)
- Pete Heywood (@ptheywood)
- Hayden Hollenbeck (@hhollenb)
- Seth R Johnson (@sethrij)
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- Guilherme Lima (@mrguilima)
- Amanda Lund (@amandalund)
- Ben Morgan (@drbenmorgan)
- Stefano C Tognini (@stognini)

## *Past code contributors:*

- Doaa Deeb (@DoaaDeeb)
- Vincent R Pascuzzi (@vrpascuzzi)
- Paul Romano (@paulromano)

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## Code



## Documentation



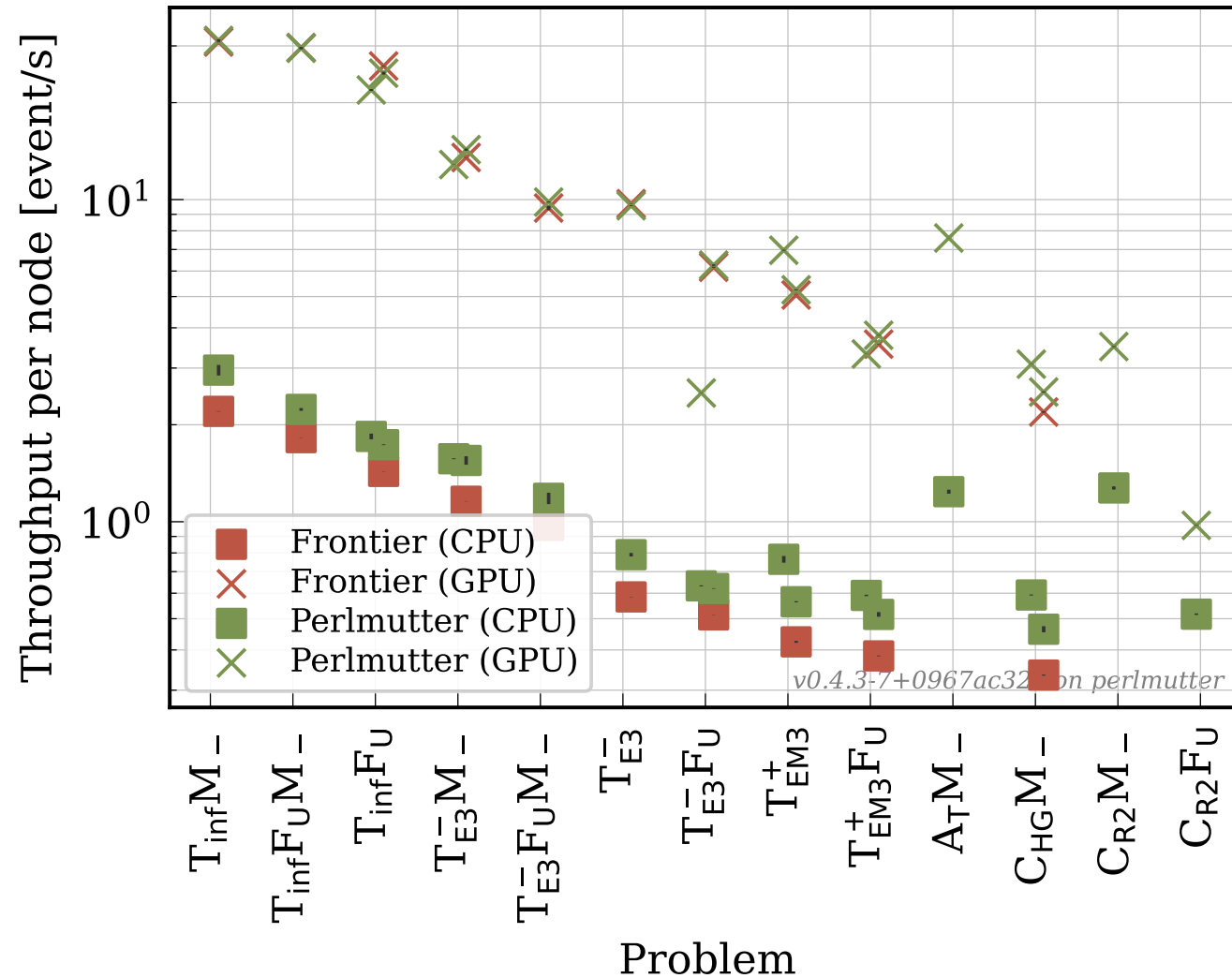
## Publication



# BACKUP SLIDES



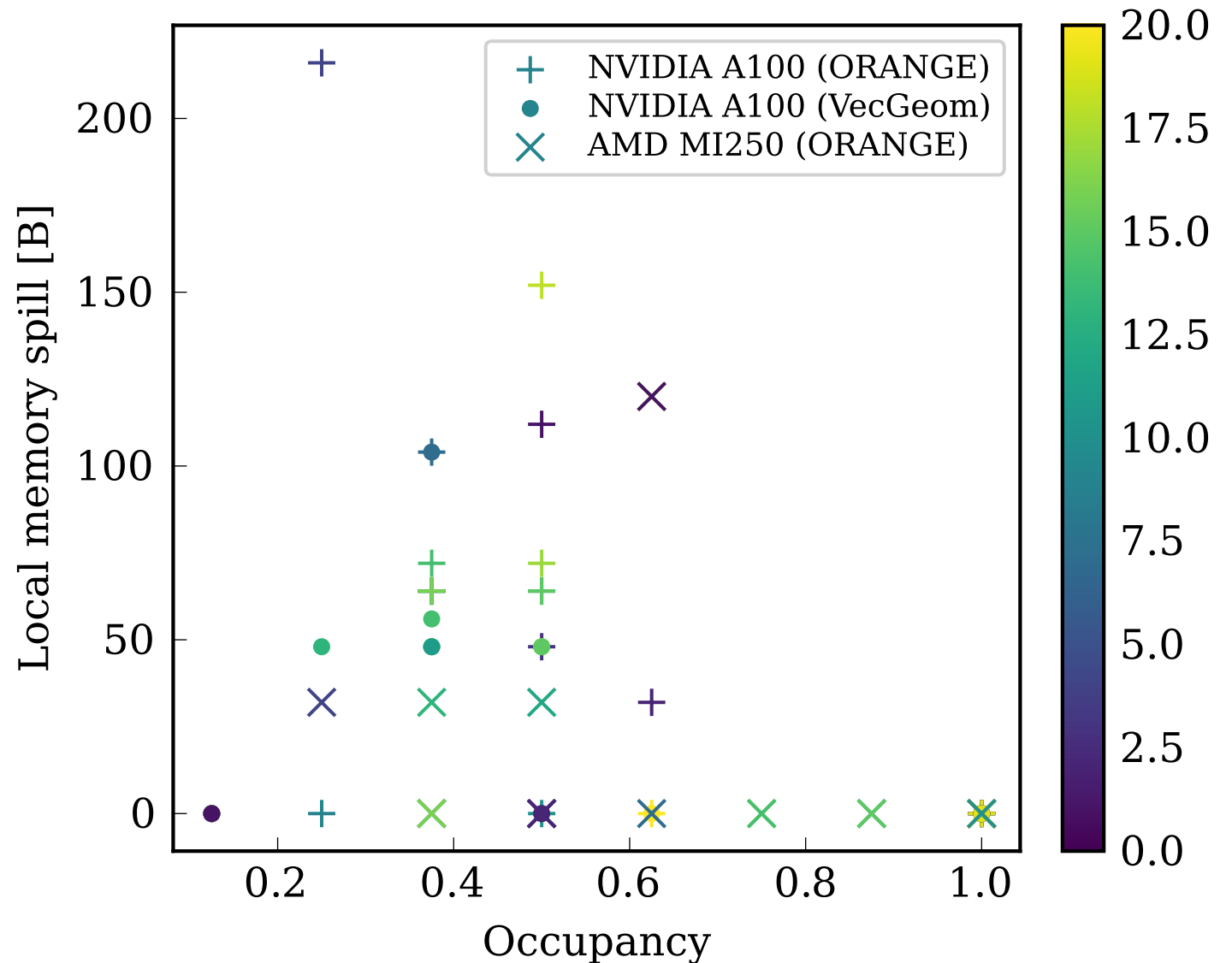
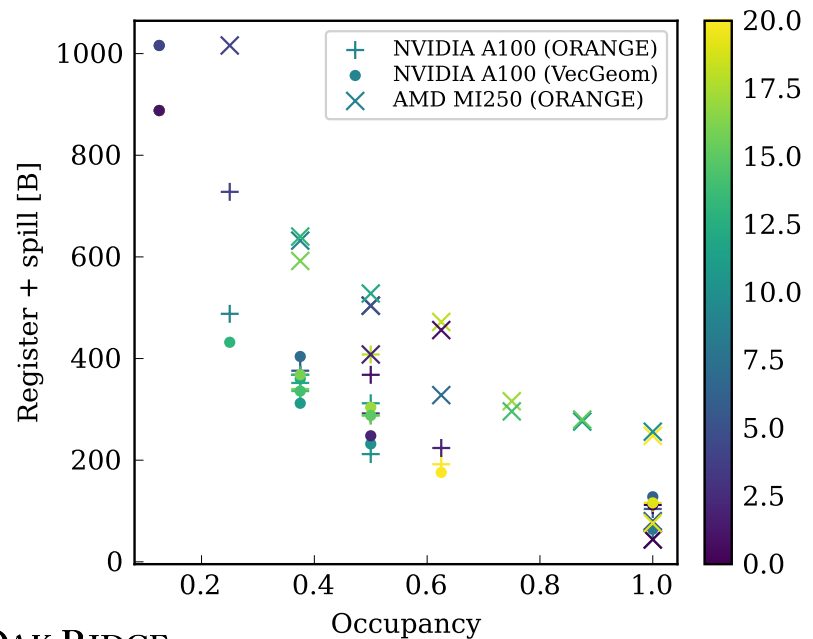
# Computational throughput



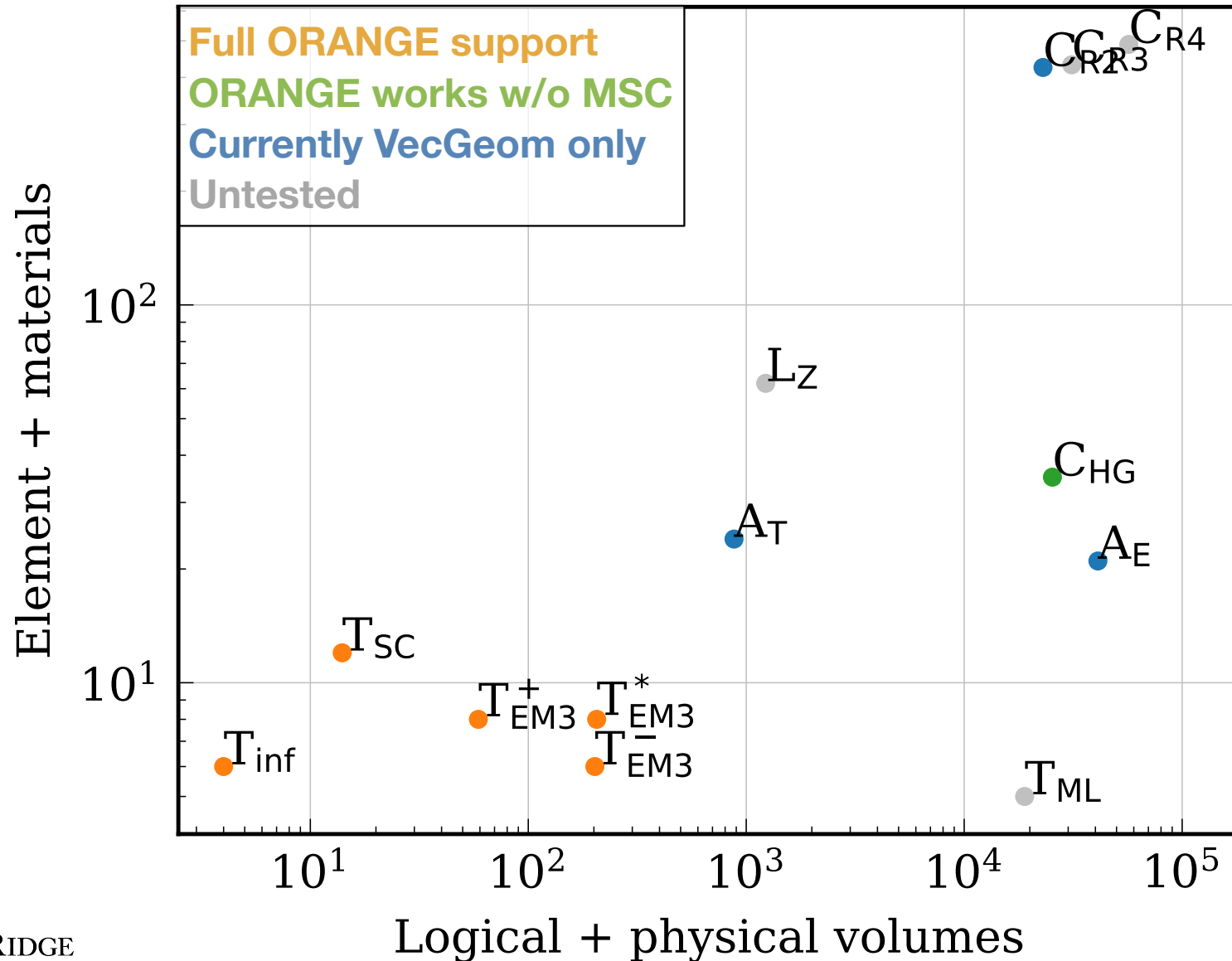
# GPU Kernel occupancy

- Geometry is register-intensive
- VecGeom requires additional dynamic stack

(up to 32KB/thread!)



# Test problem complexity



name	label
Infinite	$T_{inf}$
TestEM3 (flat)	$T_{EM3}^-$
TestEm3 (composite)	$T_{EM3}^+$
TestEm3 (expanded)	$T_{EM3}^*$
Simple CMS	$T_{SC}$
ATLAS EMEC	$A_E$
ATLAS TileCal	$A_T$
CMS HGCal	$C_{HG}$
CMS Run 2 (2018)	$C_{R2}$
CMS Run 3 (2022)	$C_{R3}$
CMS Run 4 (HL)	$C_{R4}$
TrackML	$T_{ML}$
ALICE ZDC	$L_Z$

