4th Inter-experiment Machine Learning Workshop

Argonne NATIONAL LABORATORY

Pre-Learning a Geometry Using Machine Learning To Accelerate High Energy Physics Detector Simulations

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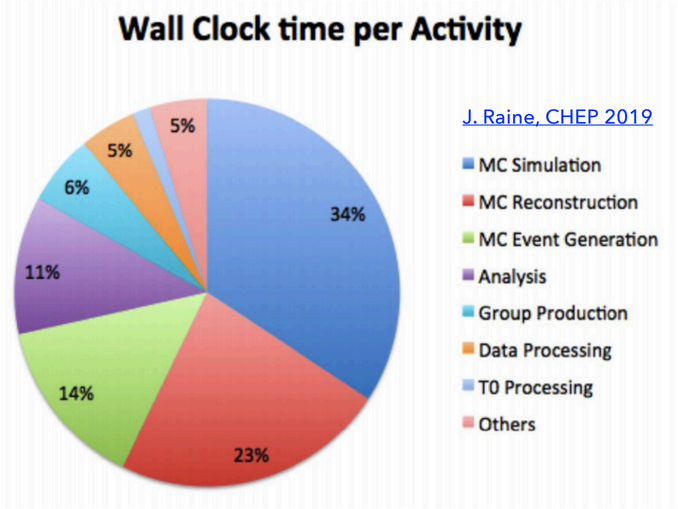
HEP Detector Simulations

The ATLAS detector paradigm

Facts

1. Detector simulation the largest CPU consumer.
2. EM calorimeters dominate the simulation load (steps).

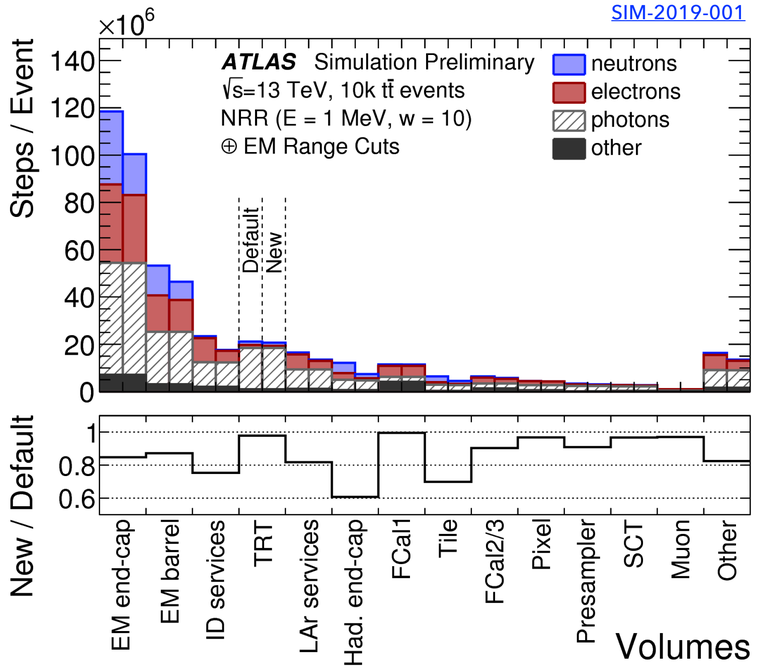


Geant4 Profile: photons on end-cap

Callees	CPU Time: Total
G4SteppingManager::Stepping	100.0%
G4SteppingManager::DefinePhysicalStepLength	66.7%
G4VProcess::AlongStepGPIL	58.2%
G4Transportation::AlongStepGetPhysicalInteractionLength	51.7%
G4Navigator::ComputeStep	34.1%
G4NormalNavigation::ComputeStep	20.9%
G4VoxelNavigation::ComputeStep	10.8%

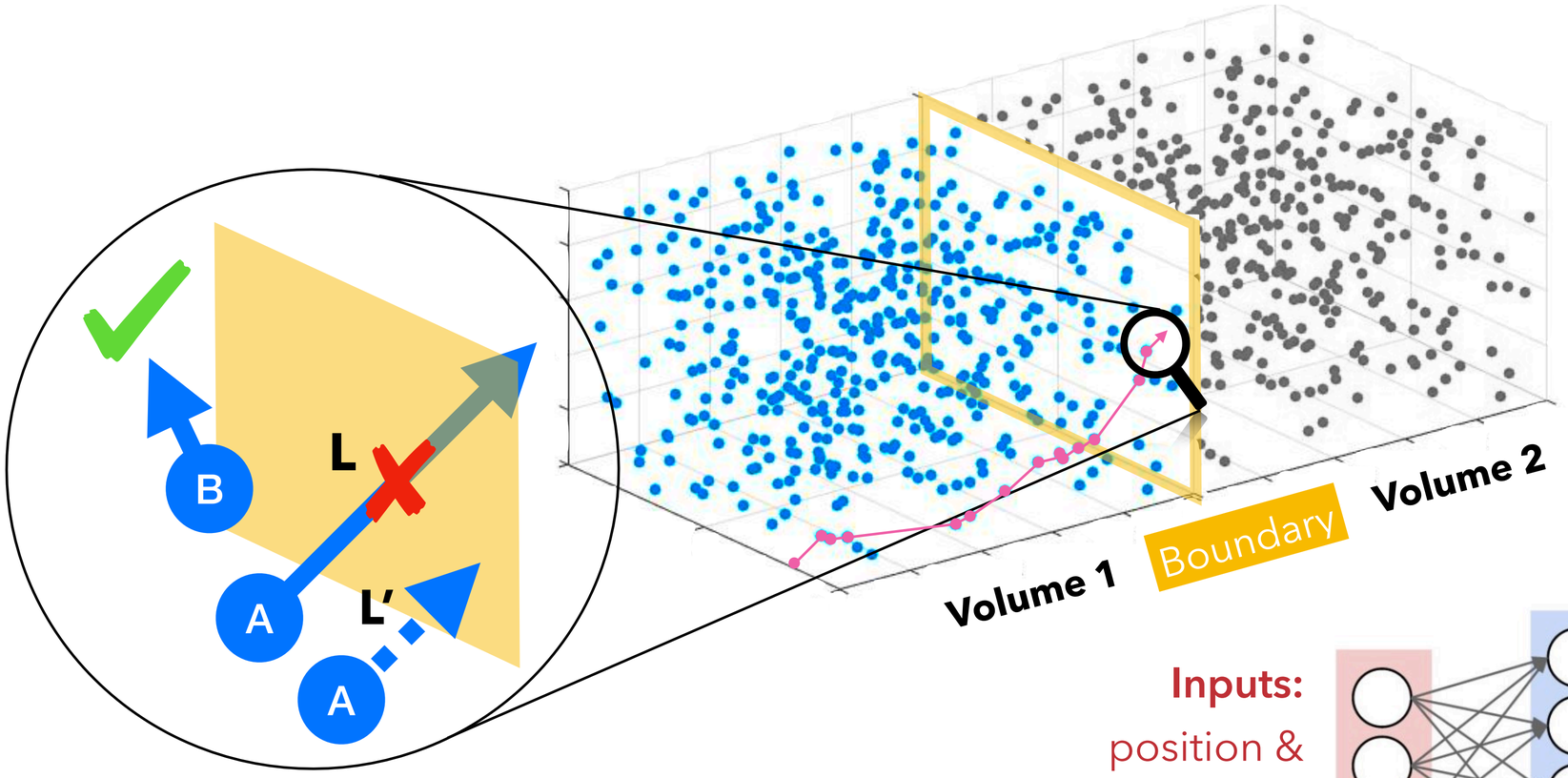
The point: methods exploring the geometry* are taking significant amount of the simulation time.

* Locate position into geometry tree and calculate distance to next boundary in order to limit step.



The Idea

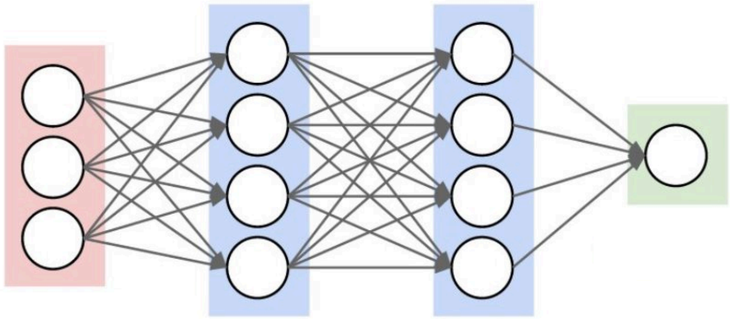
Surrogate modeling within Geant4: *Could we speed-up the geometry exploration by using a* pre-defined/learned map instead of algorithmic calculations *in each step?*



Machine learning regression technique trained for a particular geometry (e.g. ATLAS EMEC)

Hardware transparent industrial libraries optimized for different hardware architectures (CPU or GPU)

Inputs: position & direction

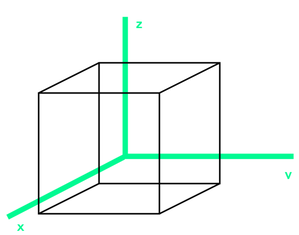


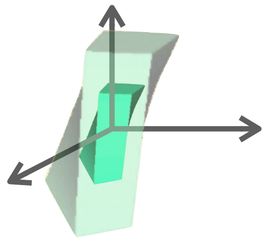
Output: Geometrically safe step length

Fully connected NNs, Point-nets, …

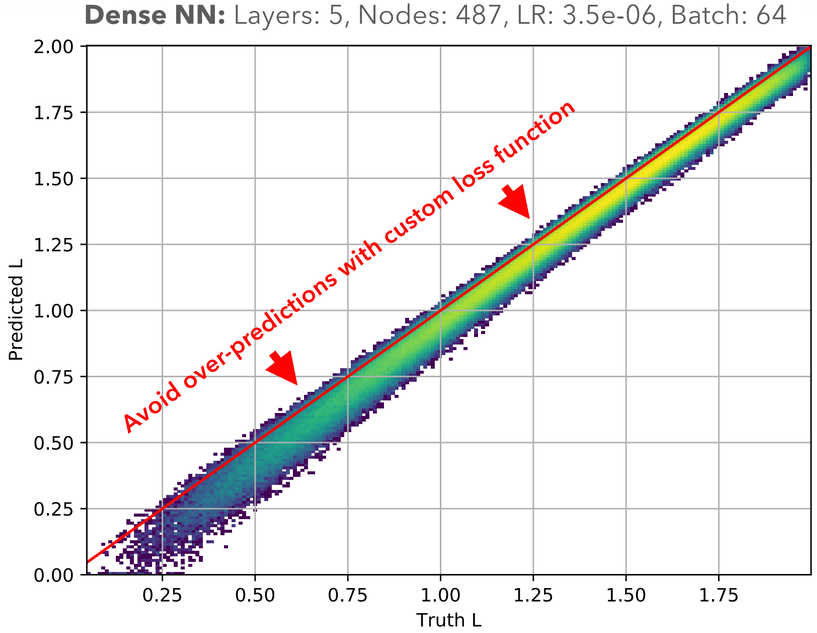
Results

Explore the idea in simplified geometries:





Training data collection via Geant4 application



How long Geant4 takes to explore the geometry vs ML inference?*

	Geometry	Time [μs]
Geant4	ATLAS EMEC	~ 5
	(nested) Twisted Trapezoids	50 - 100
Dense NN evaluation	-	~ 1000

Strong Remarks!

- No batch evaluation
- Evaluation on CPU
- Naive model structure
- Tests in Python

* Locate position into geometry tree and calculate distance to next boundary in order to limit step.