

# Exa.TrkX & GPU Acceleration with Inference as-a-Service

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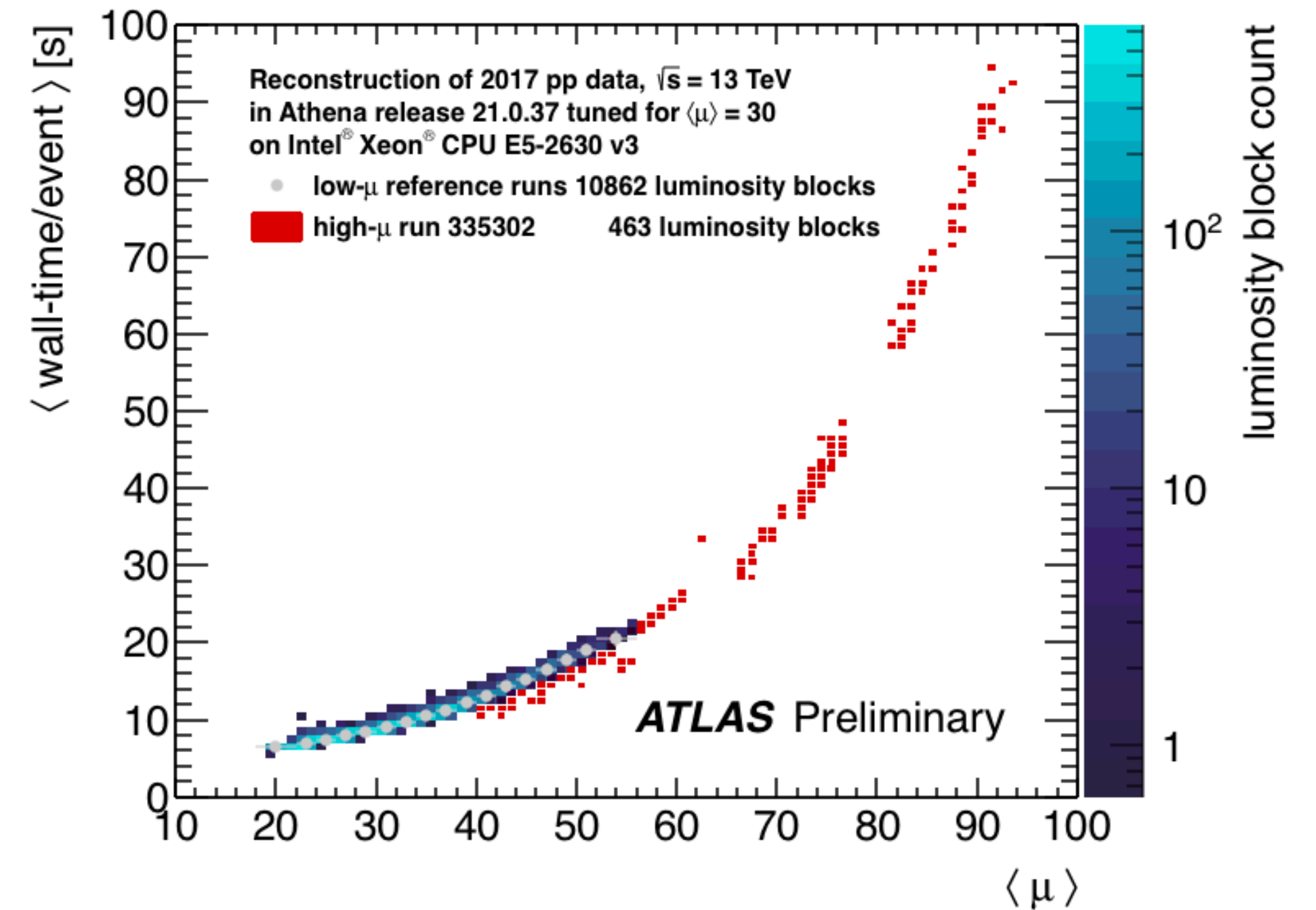
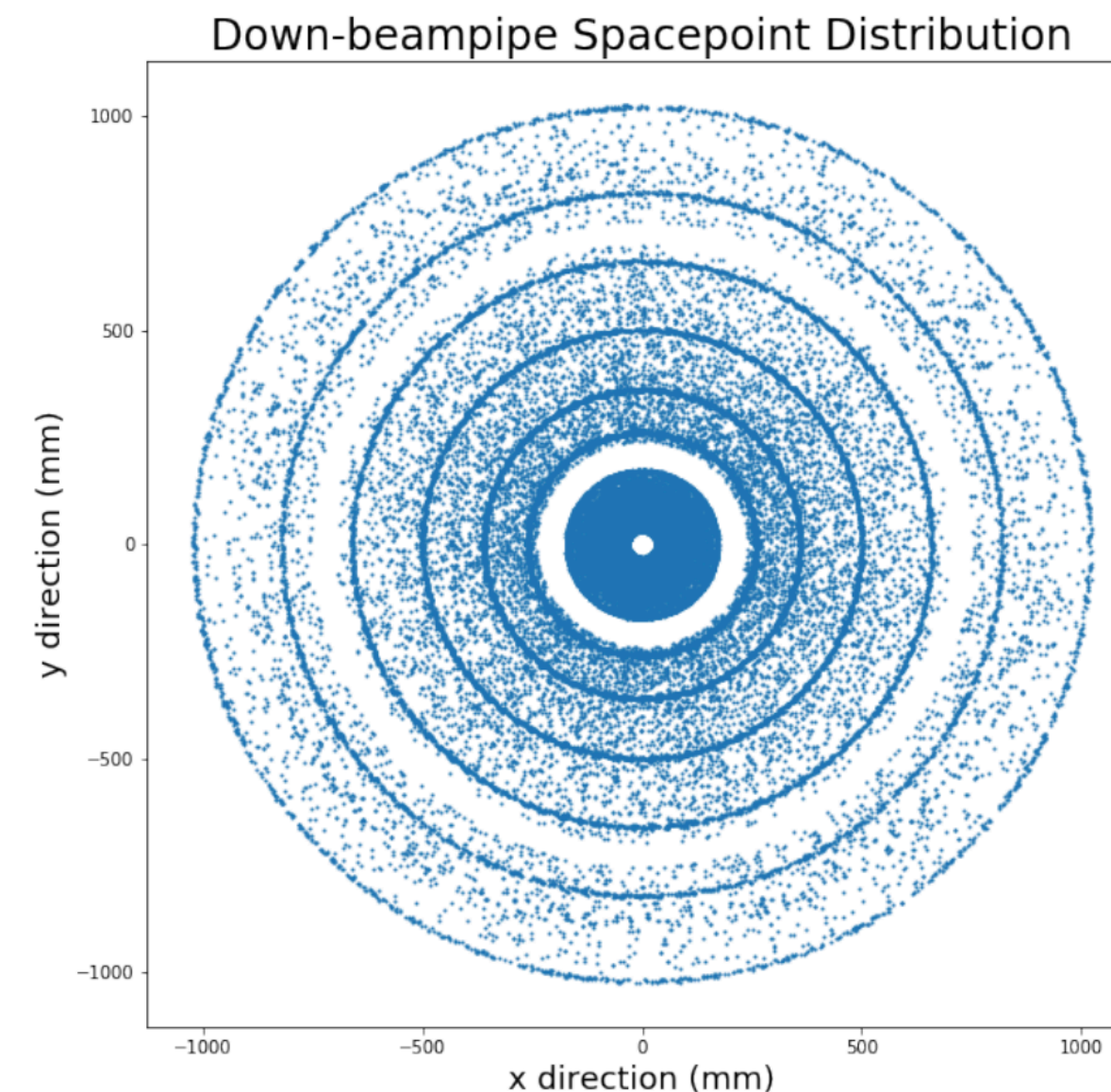
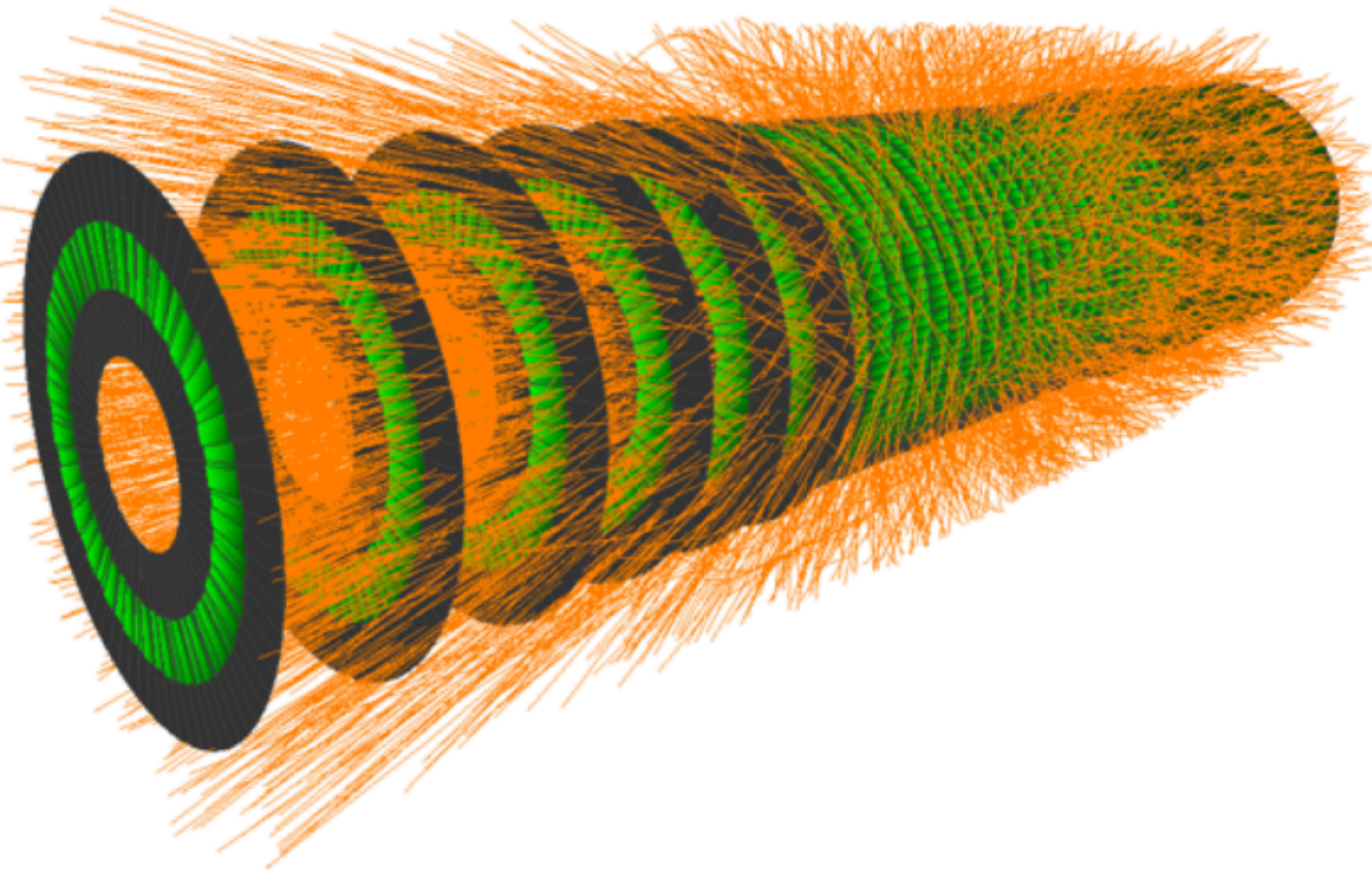
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2022 Fast Machine Learning Workshop

Dallas, Texas

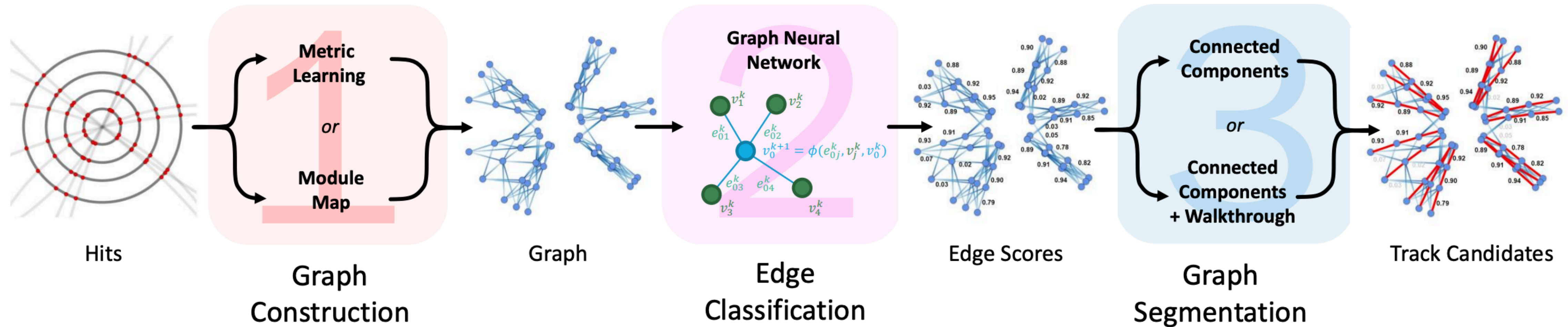
October 3rd, 2022

# Track Reconstruction at the HL-LHC

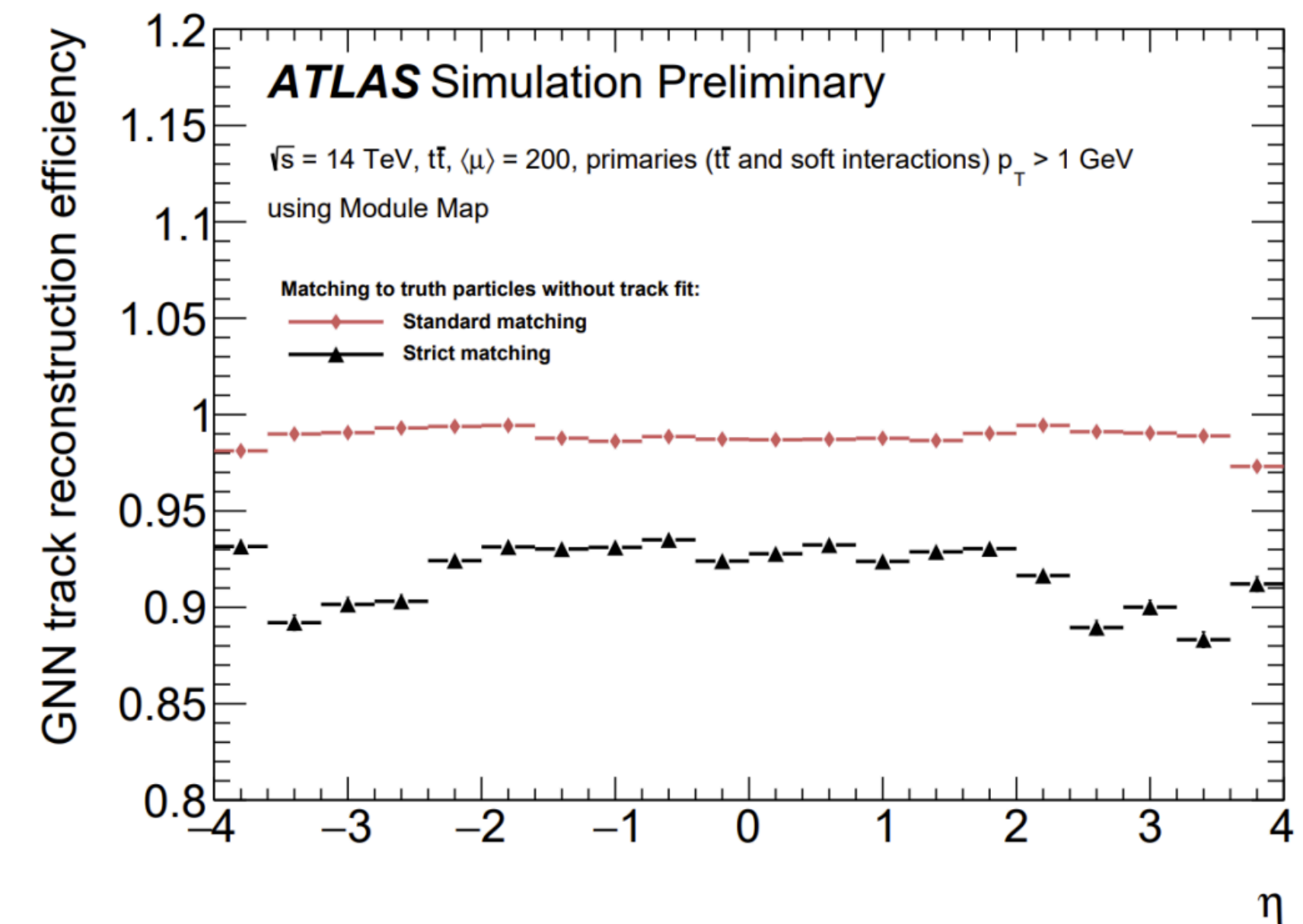


- Track reconstruction is expected to be very challenging in the future, especially at the HL-LHC:
  - ✿ A  $t\bar{t}b\bar{b}$  event with 150-200 pileup at the HL-LHC will produce  $O(5K)$  charged particles, and  $O(100K)$  spacepoints
- Computing cost does not scale linearly with number of pileup. Track reconstruction takes the major fraction of time among all the reconstruction steps

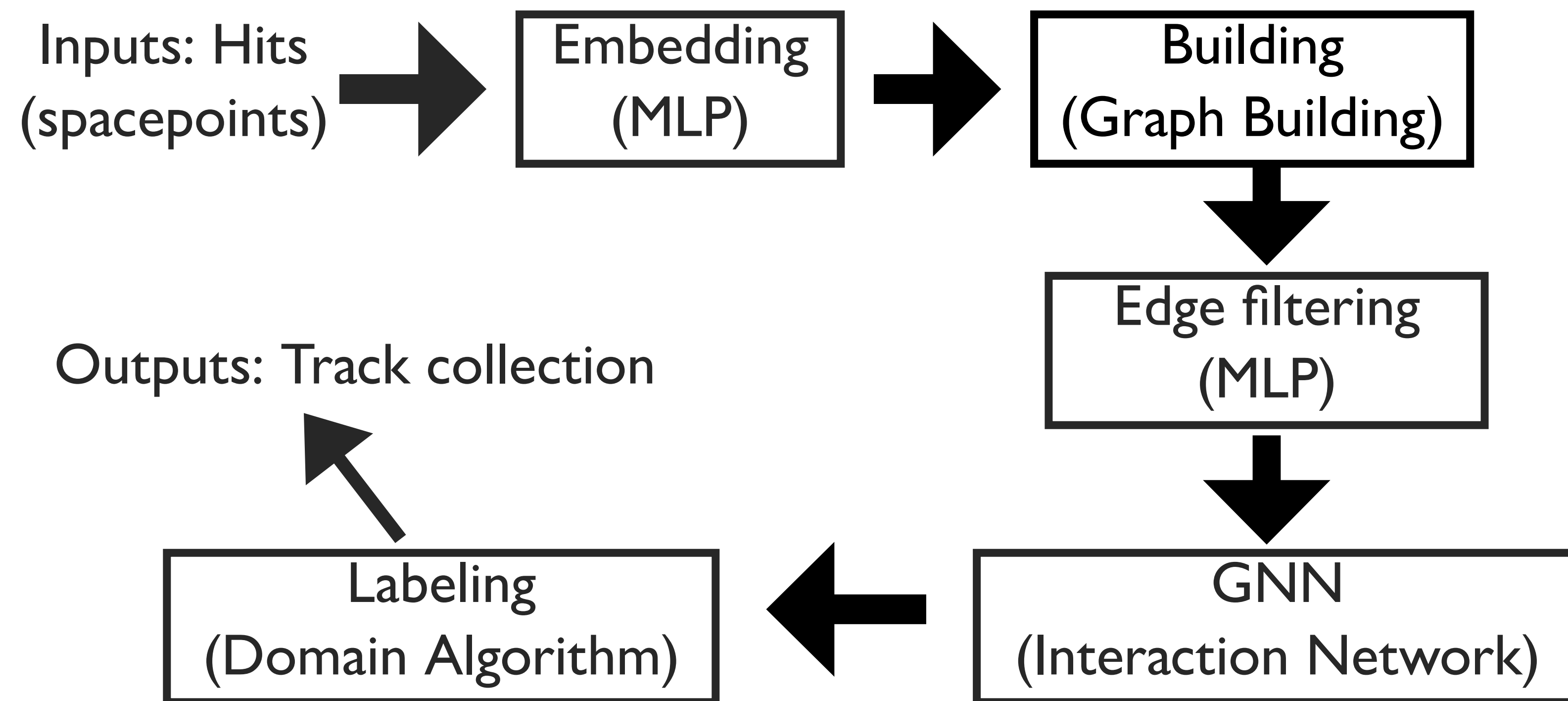
# ML-based Track Reconstruction



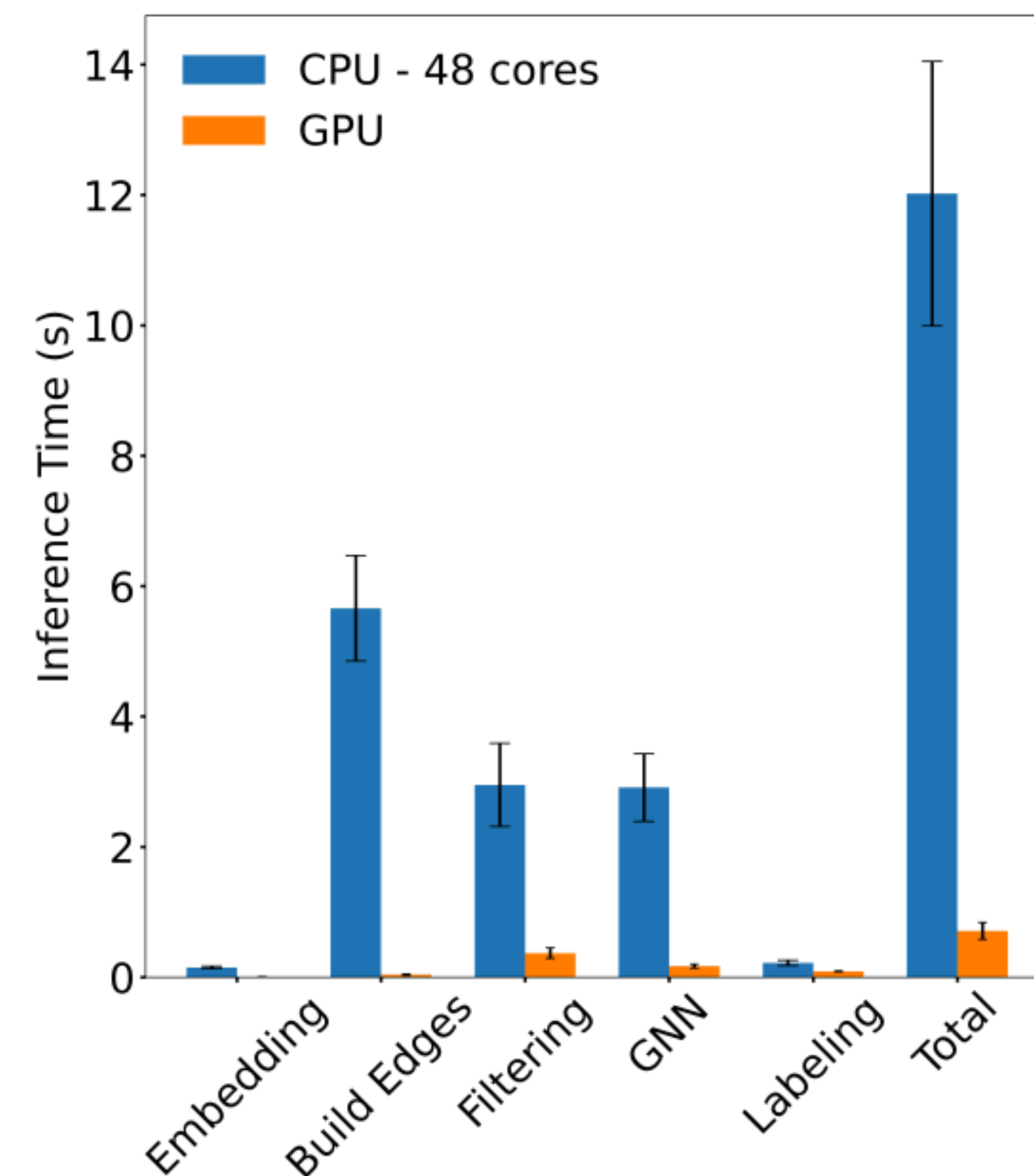
- ML-based track reconstruction with GraphNN could be a promising solution:
  - ✿ ML algorithms can run fast, easy to optimize, and easily accelerated on different coprocessors to get faster
- Good performances on the 200 pileup simulation datasets: similar efficiency as the classical algorithm, and  $O(10^{-3})$  fake rates



# Inference Costs

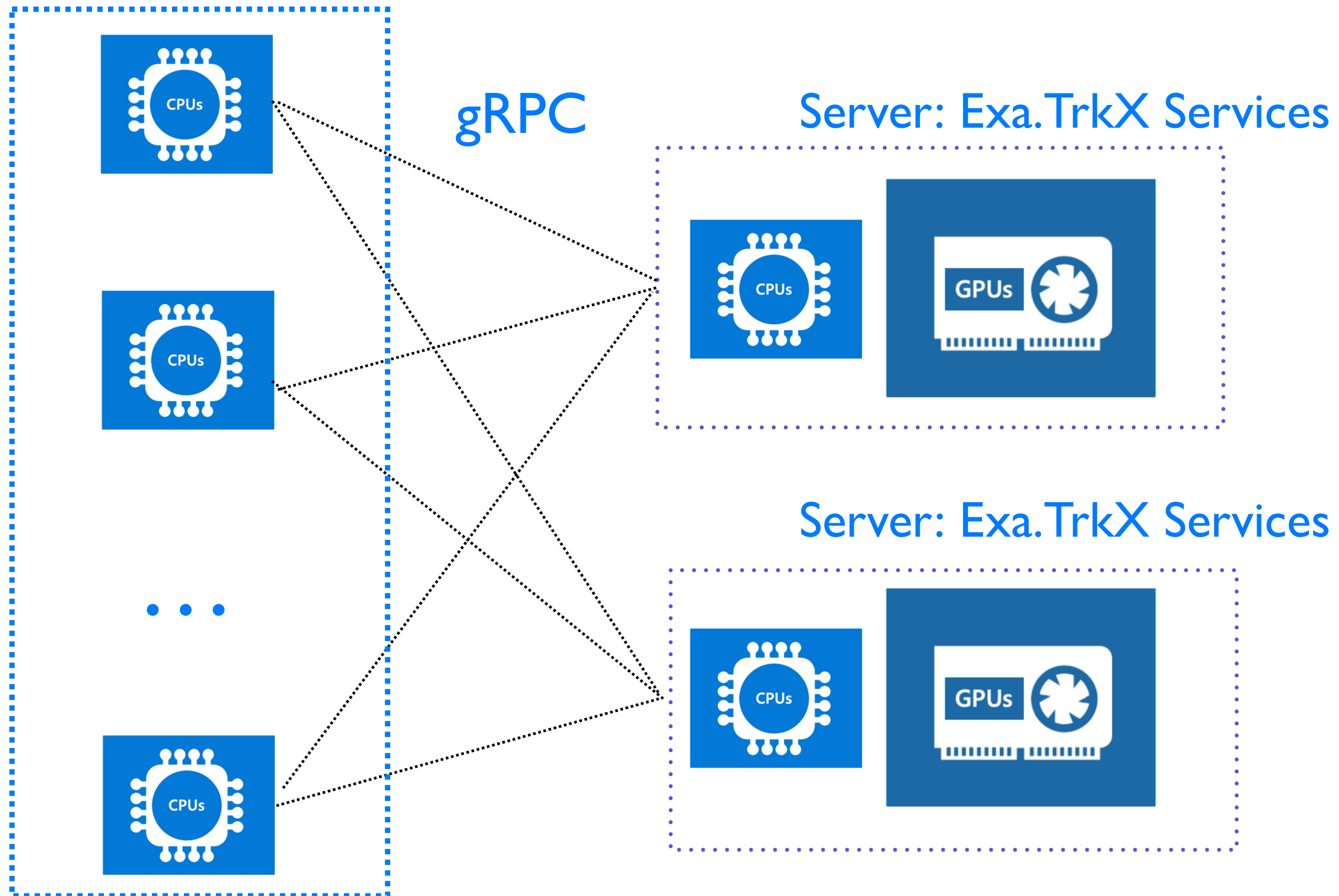


- Workflow runs much faster on GPUs compared with CPUs after optimizations: from  $O(20s)$  on 48-core Intel Xeon 8268s CPUs to  $<1s$  on NVIDIA V100. More details on [Arxiv.2202.06929](https://arxiv.org/abs/2202.06929)



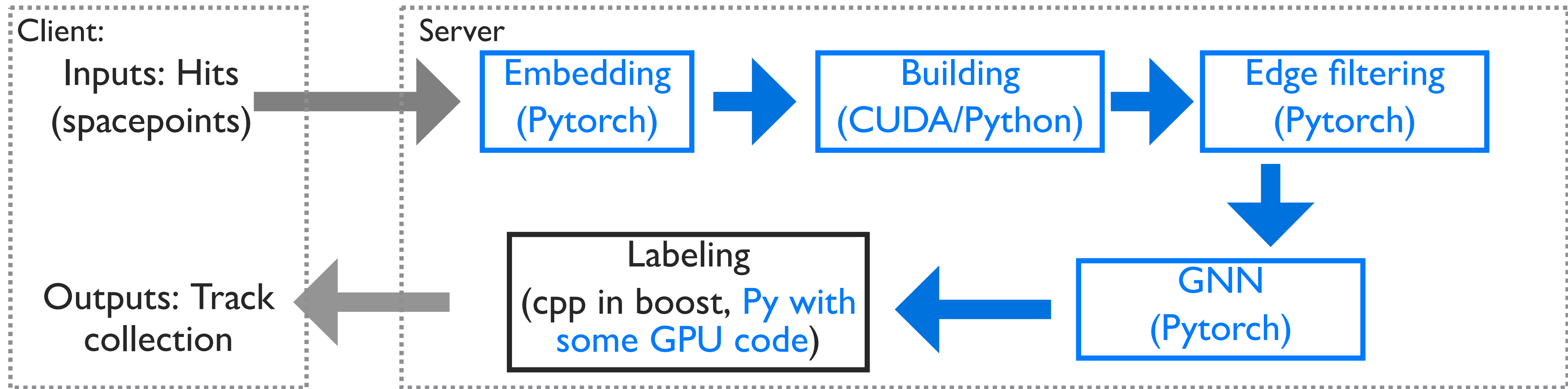
# Inference As-a-Service

Client: Regular Workflow



- Inference as-a-Service provides lots of benefits, e.g.:
  - ❖ Separate ML inferences out of the main software, easy to maintain
  - ❖ Enables access to remote GPUs;
  - ❖ more flexibility of the CPU/GPU ratios;
  - ❖ Easy deployment on different types of coprocessors
  - ❖ Etc
- More in [Patrick's talk](#) and [Dylan's talk](#)

# Current Exa.TrkX Workflow with as-a-Service



- Server side uses NVIDIA Triton Inference server. Various features and benefits:
  - ❖ Supports of different backends: ML including TF, Pytorch, ONNX; domain algorithms: CUDA, Python, Cpp
  - ❖ Ensemble model that can collect the whole inference modules together; reduce the IOs between client and server
- Pytorch models runs out of the box; CUDA and cpp implementations currently done with Python custom backend

# Preliminary Results

Direct Inference	ms/evt
Embedding	0.5
Building	2.2
Filtering	27.6
GNN	31.7
Total	62

As a Service	ms/evt
Embedding	1.7
Building	7.3
Filtering	26.7
GNN	21.3
Total	64.4

- Benchmarked in the 0-PU dataset to start with.
- Time not including the labeling part (domain algorithm code; takes some efforts to prepare a custom backend for it)
- Similar inference time between CPU-GPU directly connected and CPU-Server with aaS:
  - ❖ Also checked the server-side metrics: the fraction of time to handle IOs are small. Most of the time are on computations.

# Summary

- Track reconstruction is expected to be very challenging in the high-density environments. ML-based approaches are naturally nice candidates to solve such problems.
- Current Exa.TrkX models have very promising results, similar to domain algorithms and runs faster. These ML algorithms can easily be deployed on different hardwares and accelerated:
  - ❖ Preliminary results indicates that it can run 20-100 times faster on the GPUs compared with CPUs.
- As-a-Service version of the Exa.TrkX inference workflow implemented. Preliminary results show consistent behaviors with directly-connected, but more flexibilities. More studies and results in the future!



# Back Up