

Track 2 Summary

ACAT 2024

Lukas Heinrich, TUM

Track 2: Data Analysis - Algorithms and Tools

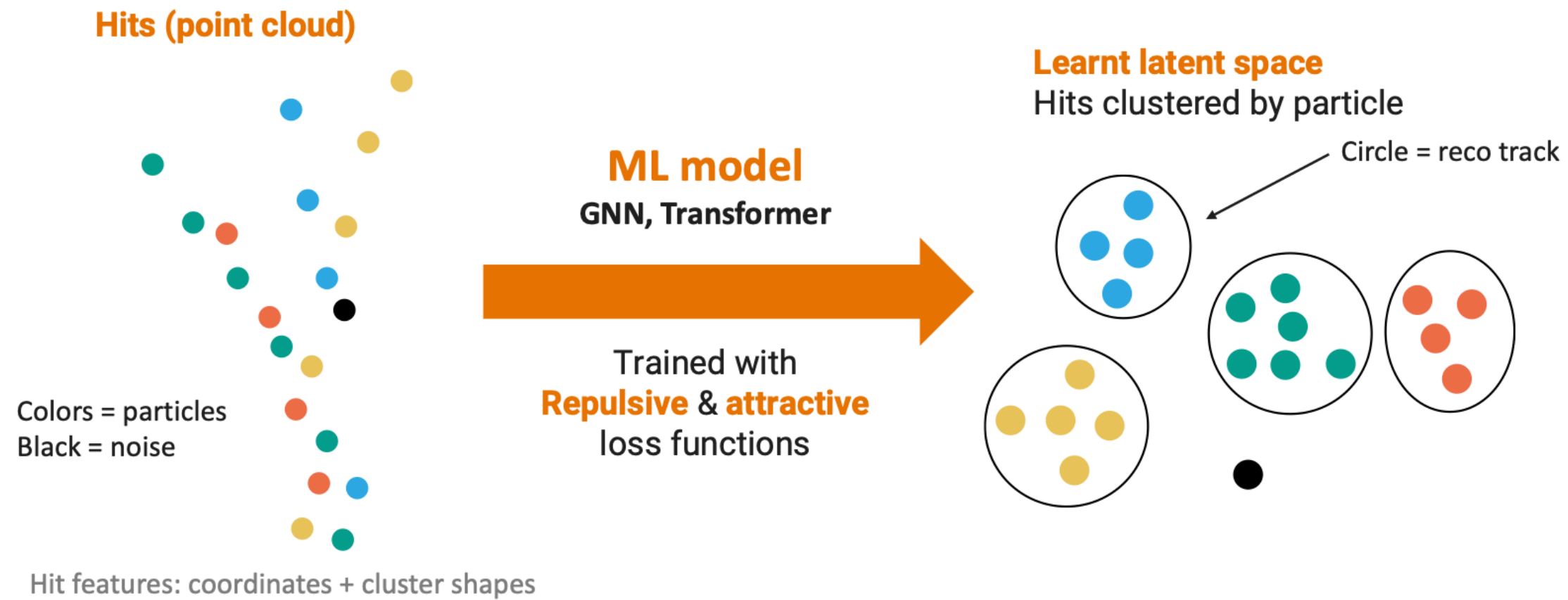
Track to discuss latest developments in reconstruction and analysis tools.

32 Talks. Lots of ML but also great talks that go beyond it incl. online systems, data management, statistics ...

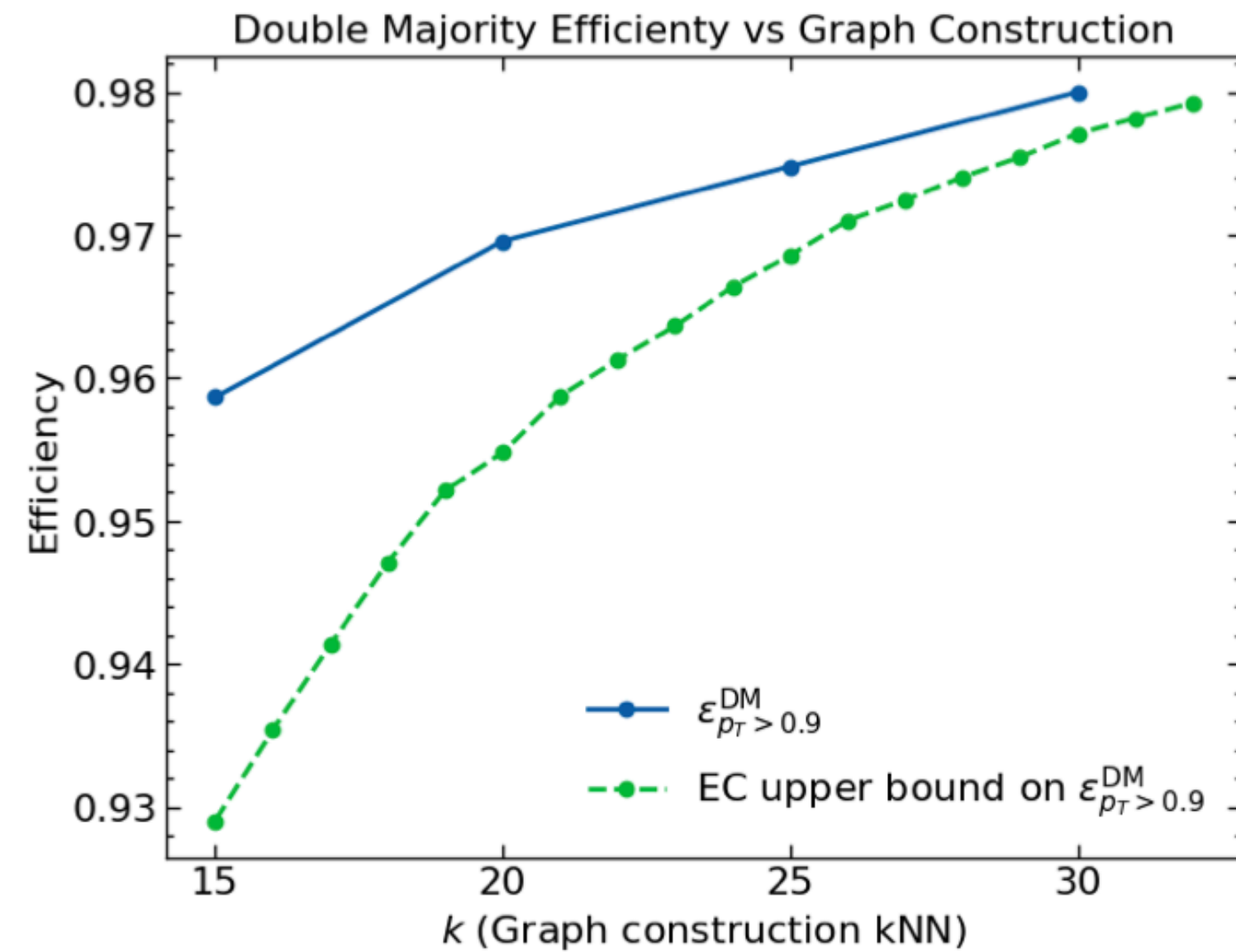
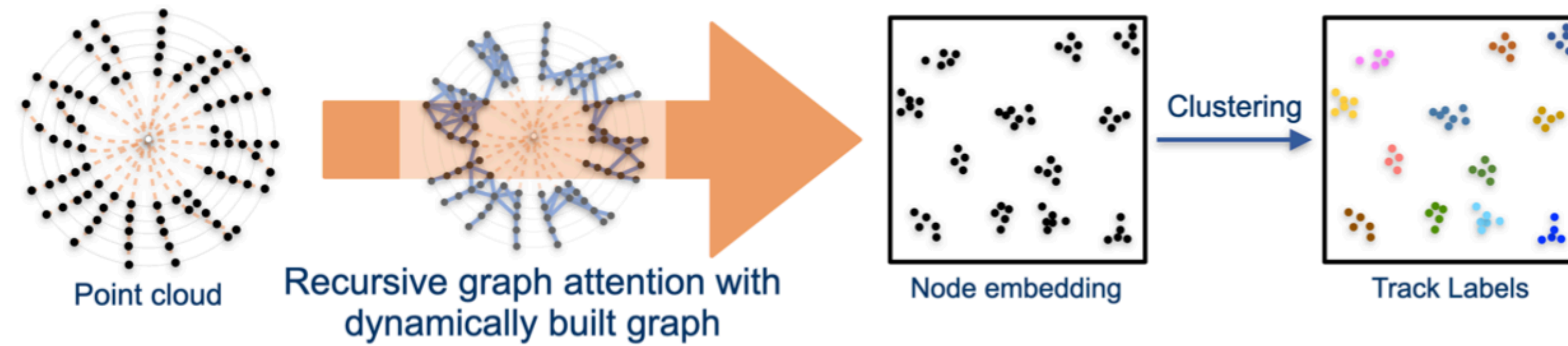
Impossible to summarize everything, but short lightning overview & some high-level thoughts

Single Shot Tracking

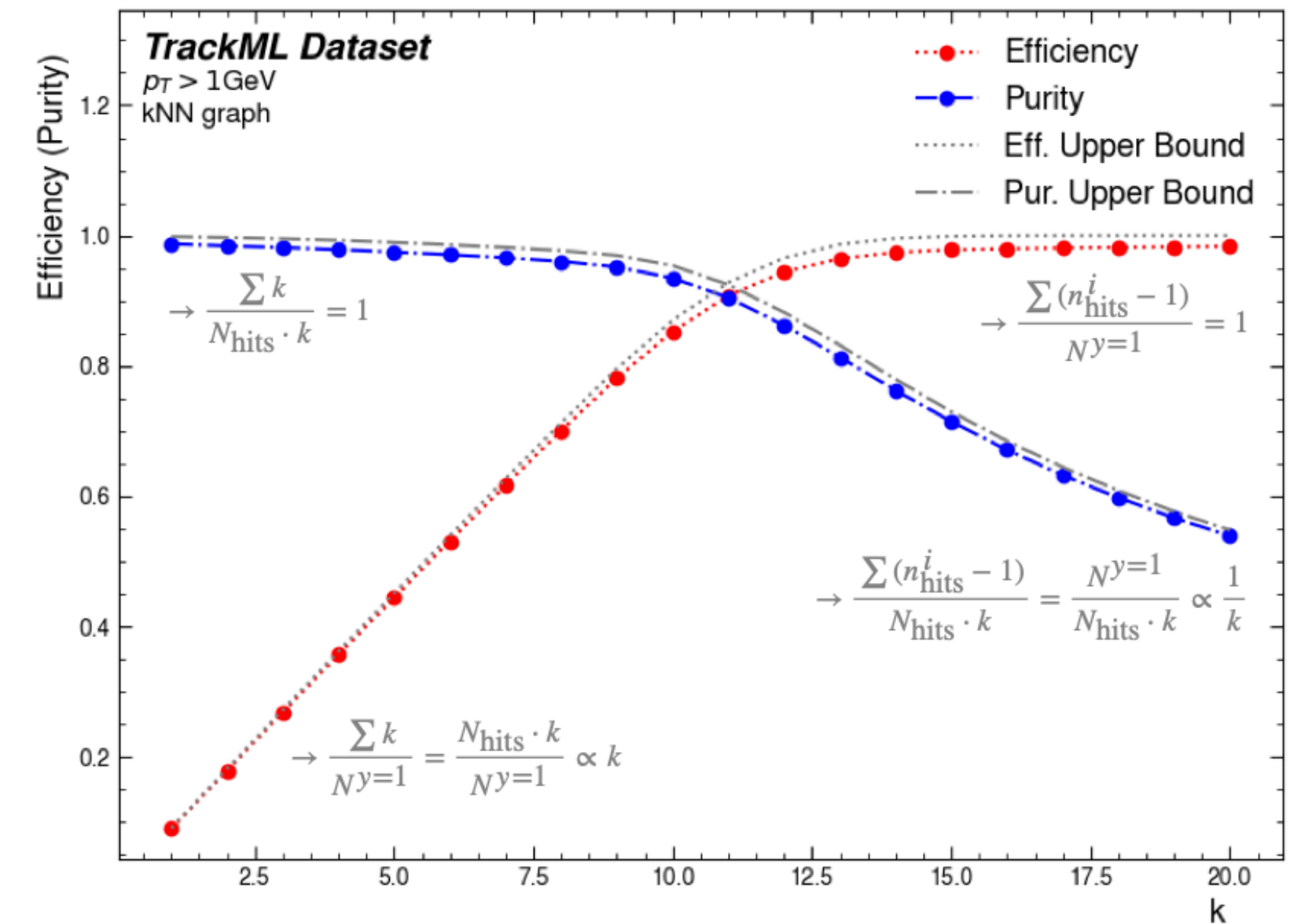
Kilian Lieret



Jay Chan



GNN + Object Condensation



Recursive Graph Attention + DBSCAN

Online Tracking Algorithms

Online Environment is special. Generally not the place for gigantic models, but tailored solution.

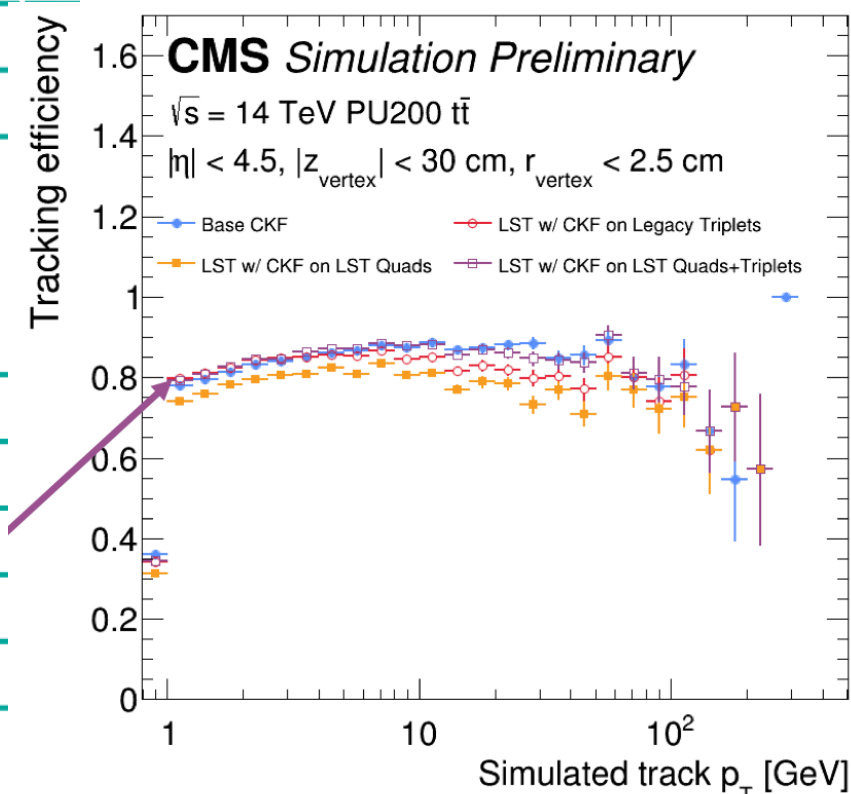
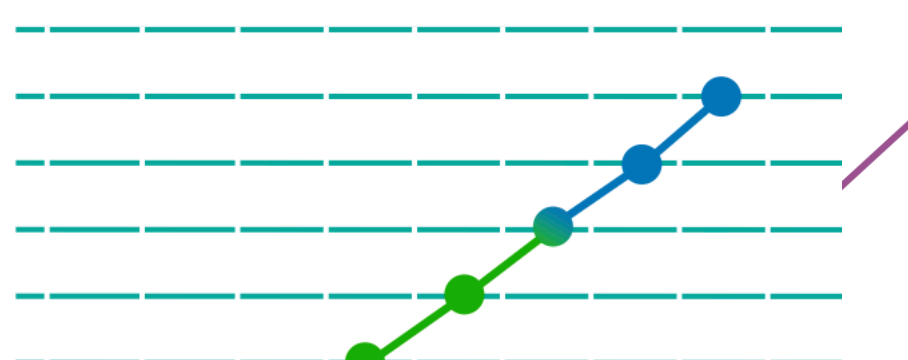
MD + MD = LS



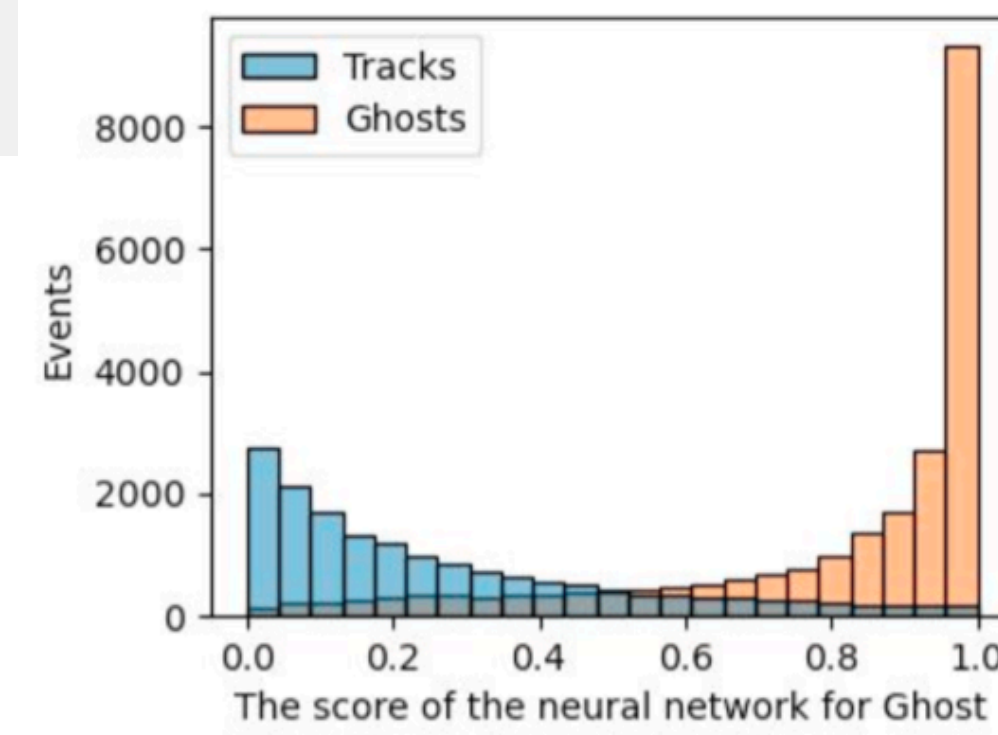
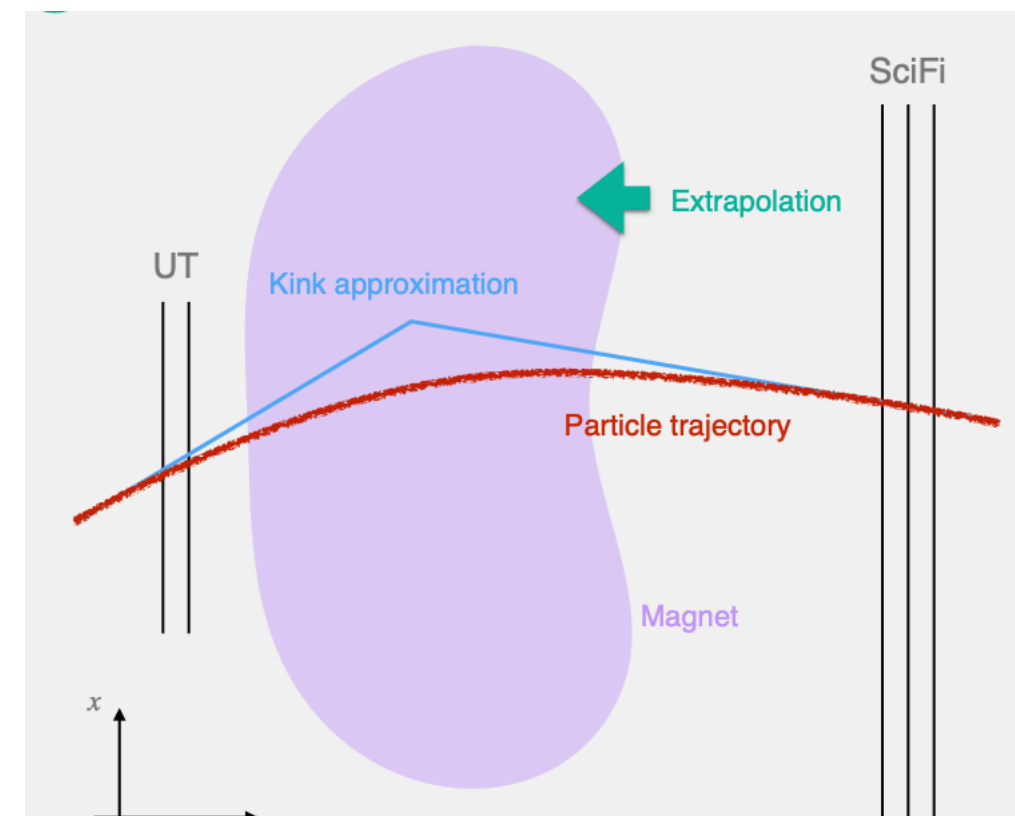
LS + LS = T3



T3 + T3 = T5



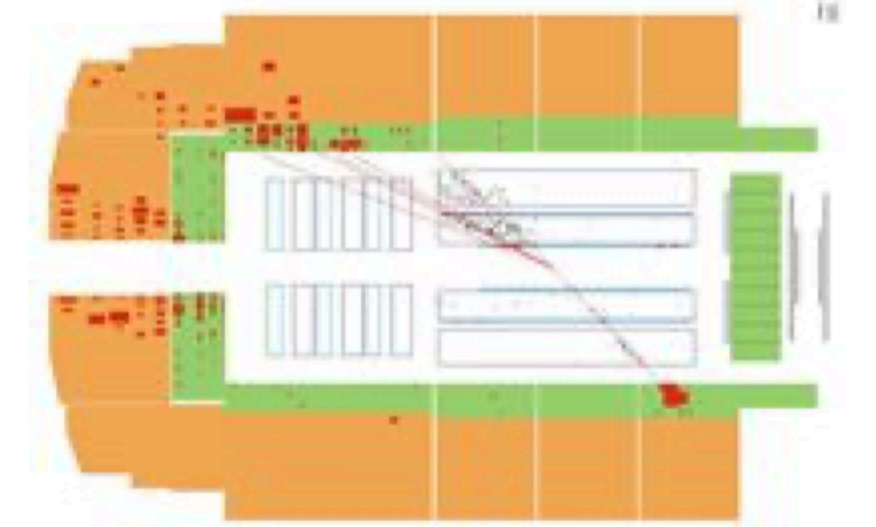
Fast and Parallelizable Tracking for CMS Trigger



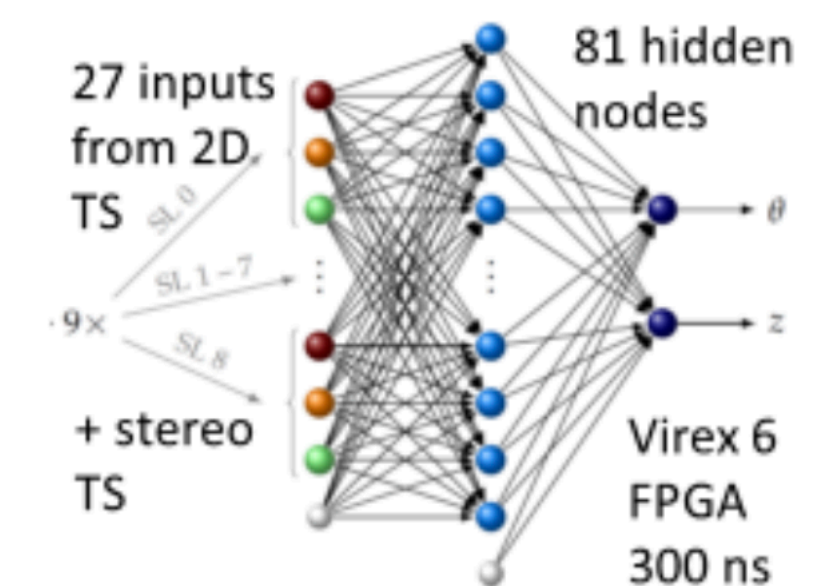
Downstream Tracking in LHCb Trigger

AINHEP 1999

H1 @HERA ep Collider:
First Neural Trigger in HEP
in active production mode



↓ ACAT 2024



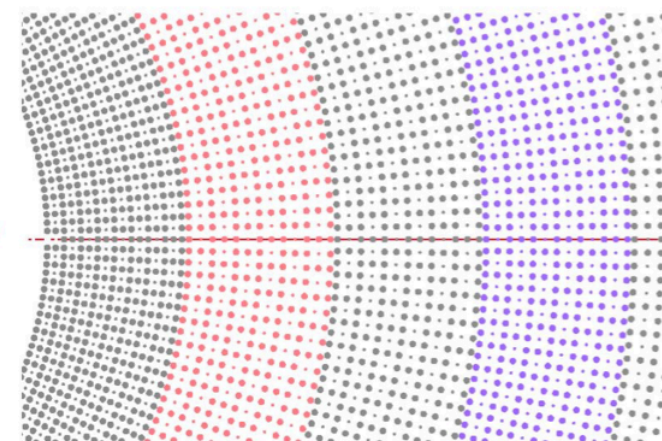
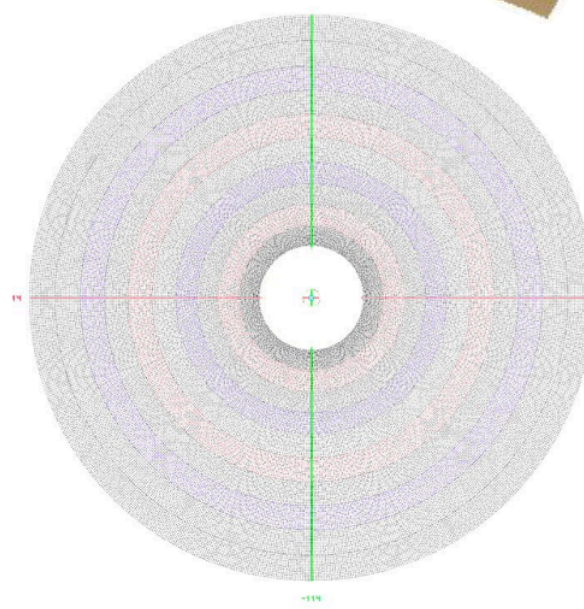
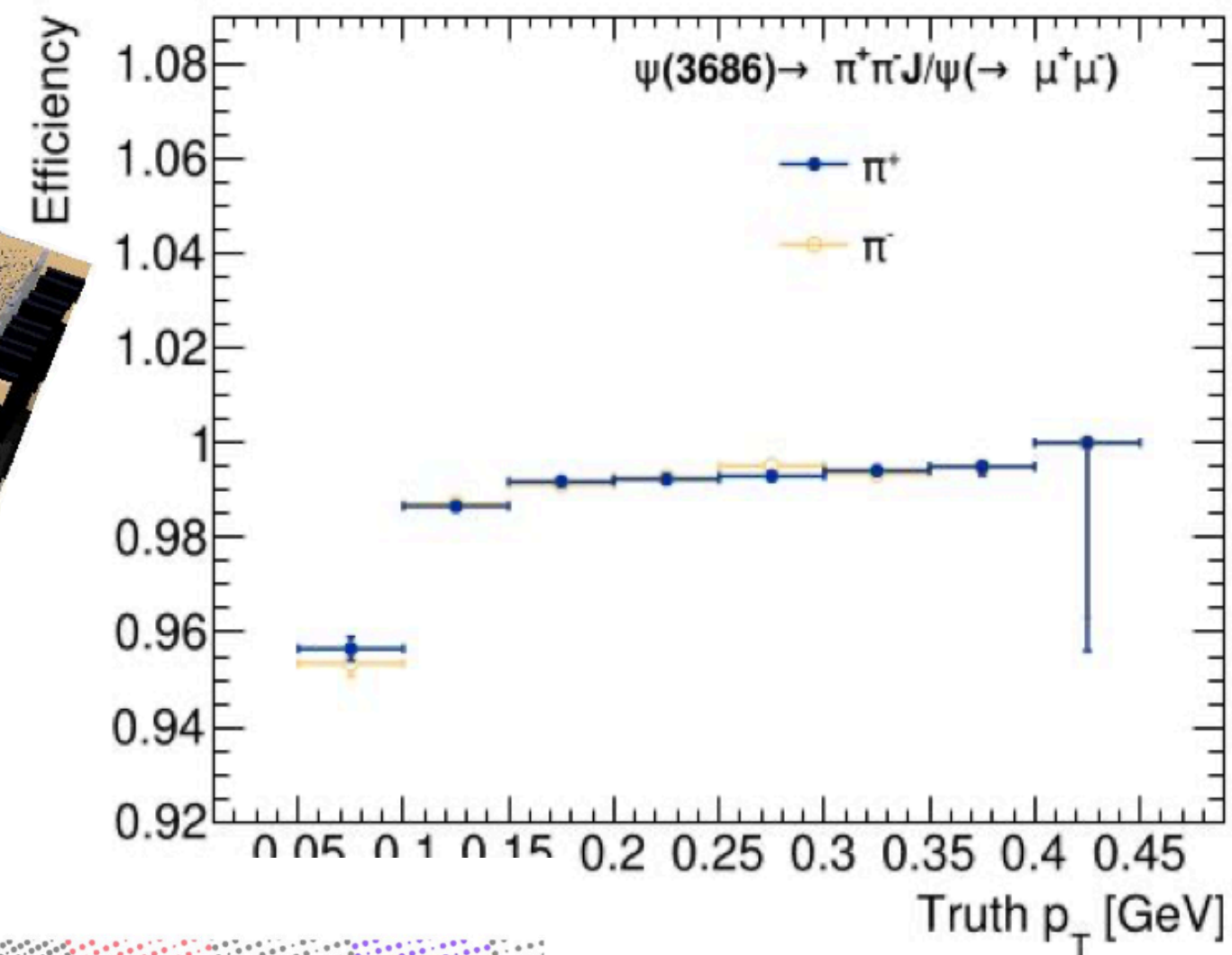
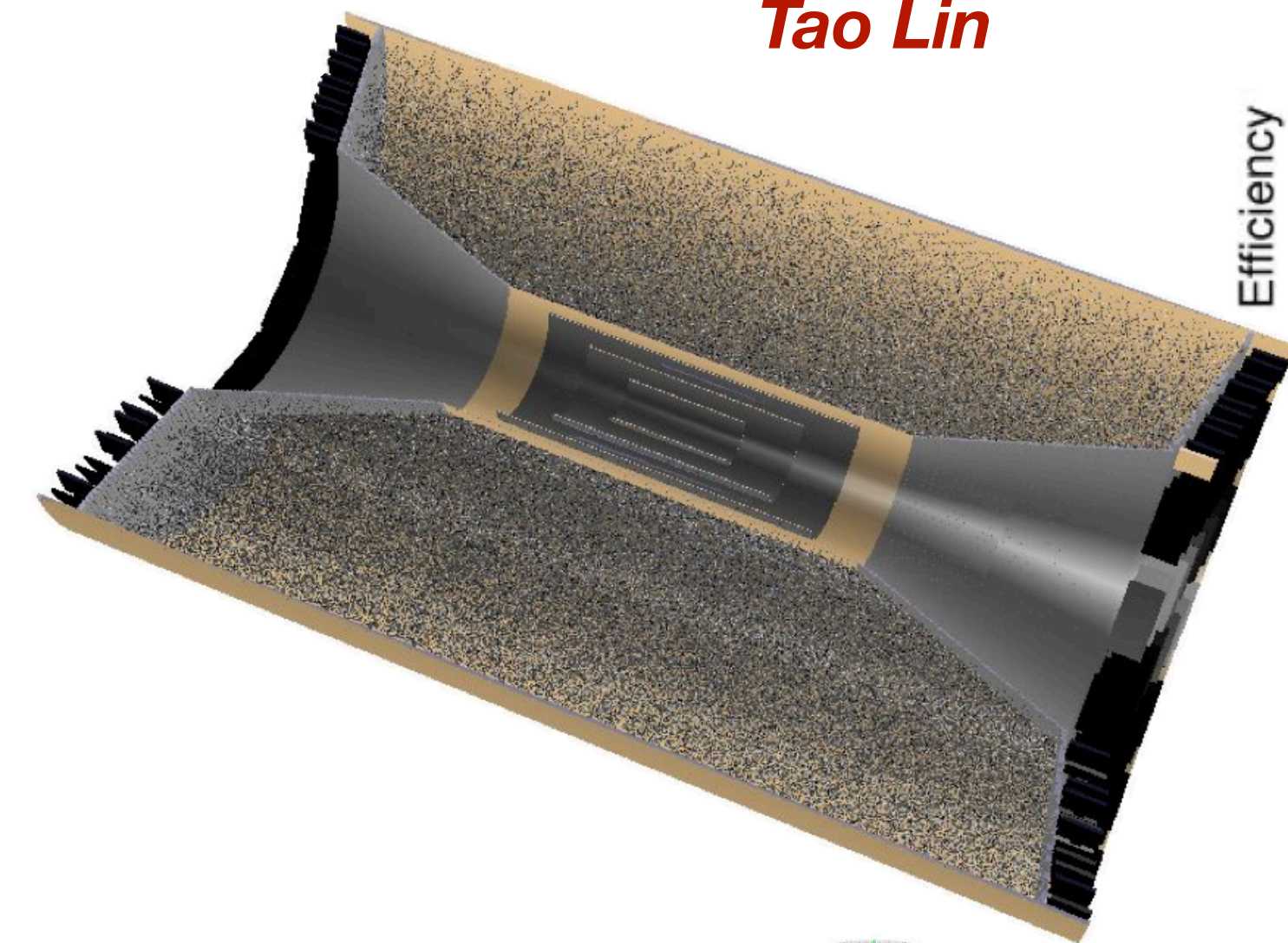
Neural Network Trigger at Belle II

Tracking beyond LHC & Silicon

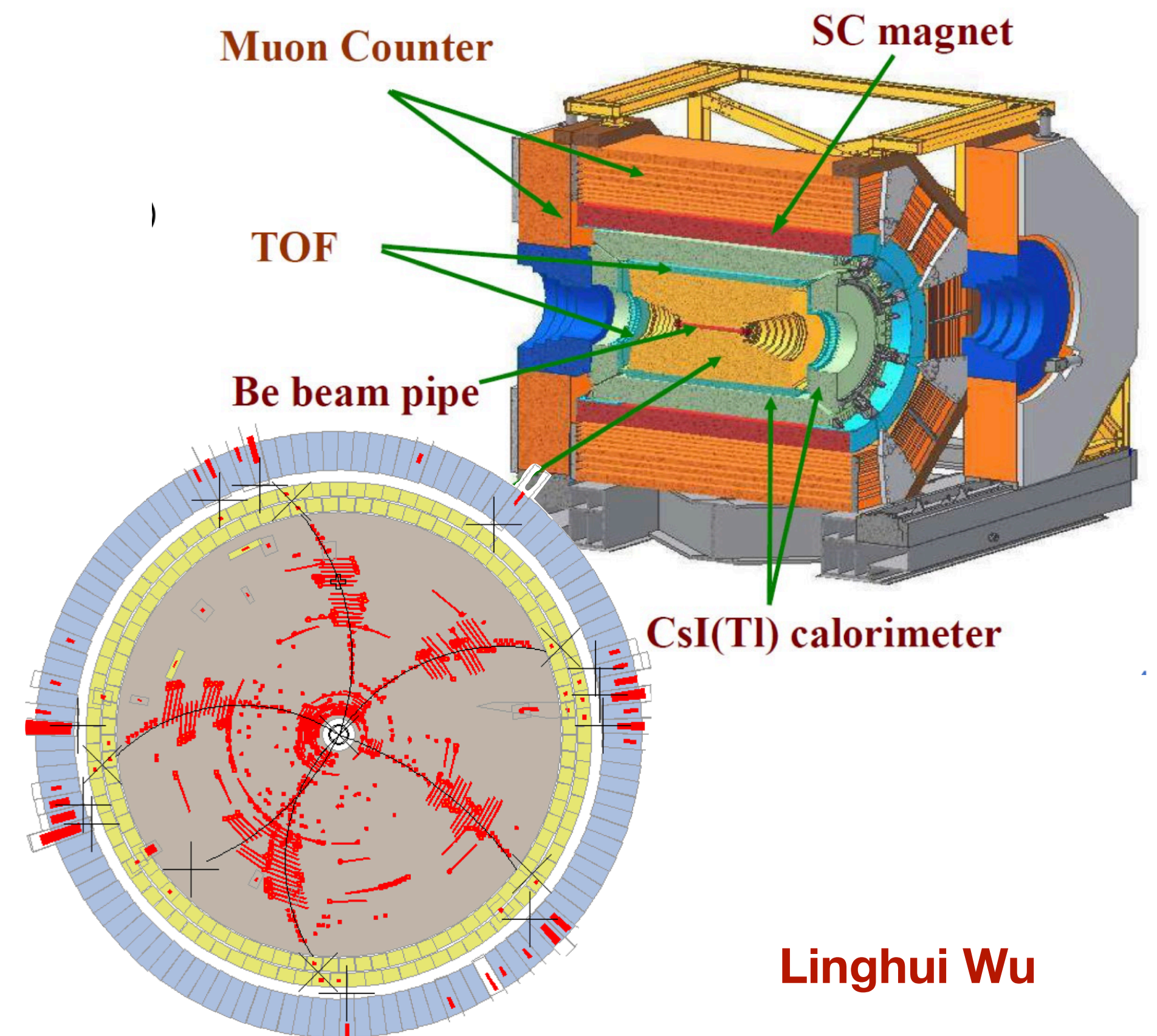
Not everything is the LHC. Unique challenges & Solutions

More in [talk at CHEP2023](#)
and [JINST 18 P07026](#)

Tao Lin



A: grey; U: red; V: blue



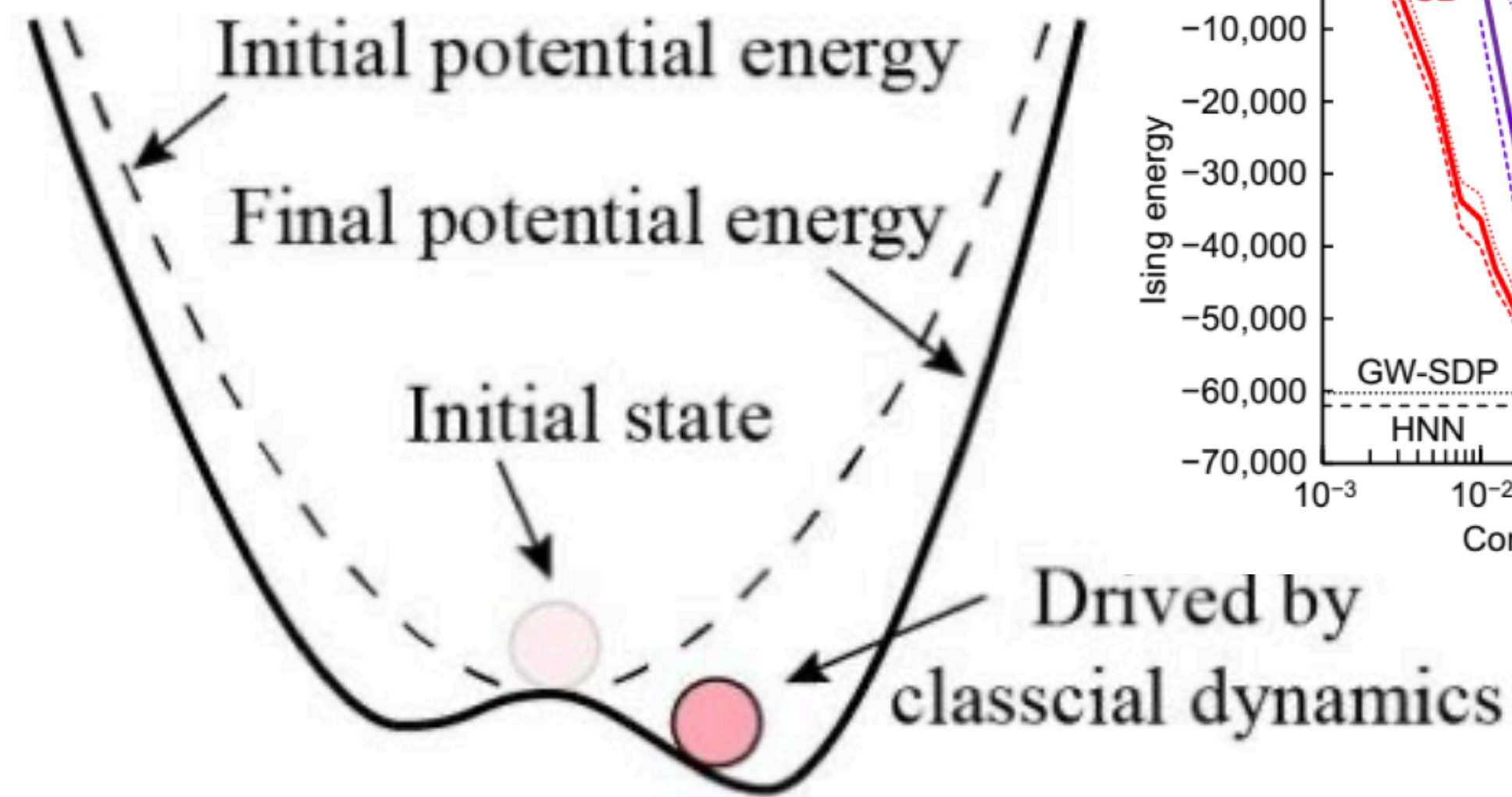
Linghui Wu

ACTS for Gaseous Detectors (
Extending Community Tools & Open Source!

Data Quality for Tracking in MDC (BESIII)

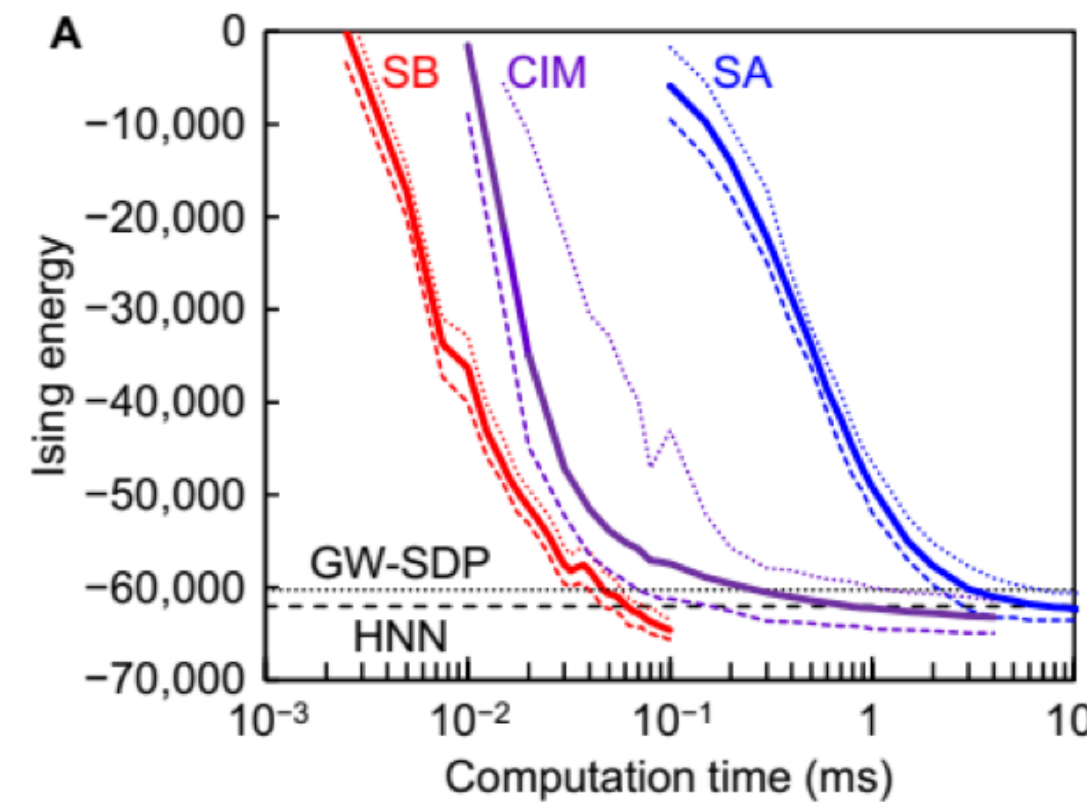
Future Tracking Technologies

Xiangyang Ju

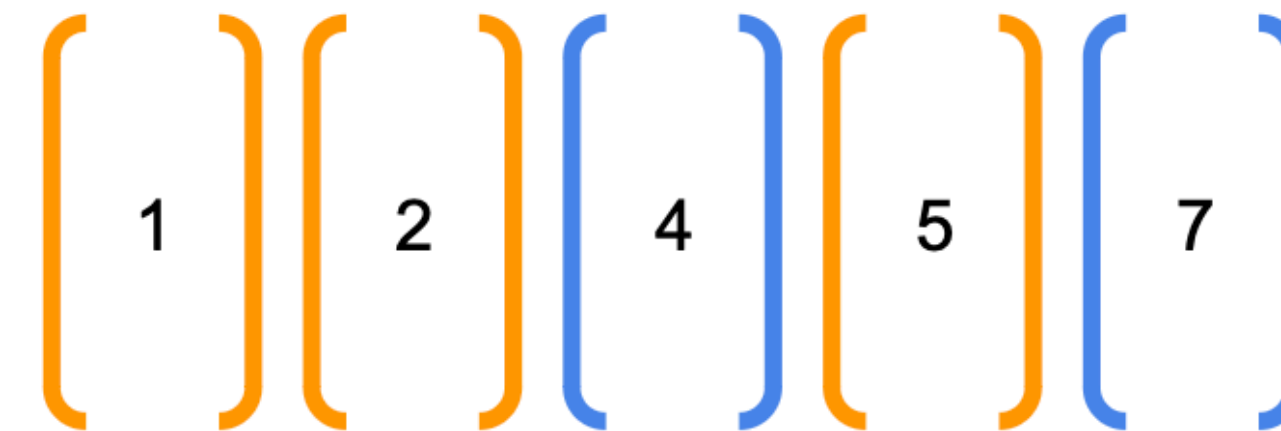


Quantum inspired algorithm

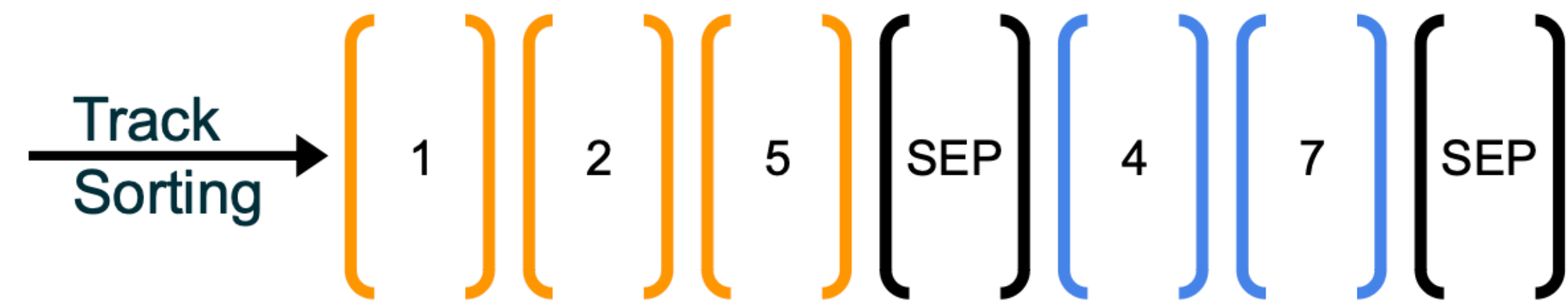
Hideki Okawa



Hit vectors sorted by r in input sequence



Hit vectors in output sequence



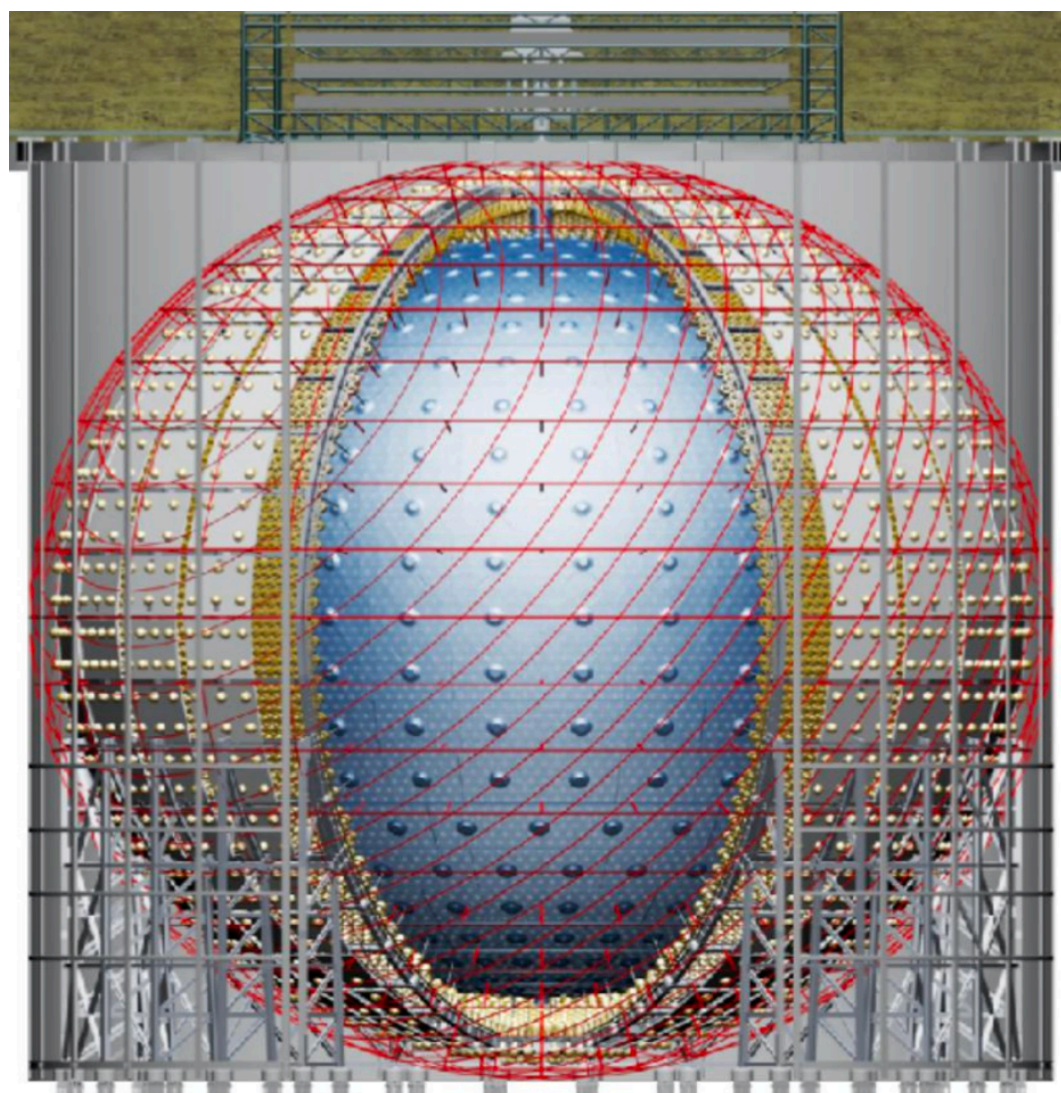
Analogy between HEP and NLP

Detector elements	Words
All detector elements	Vocabulary
Trajectories or showers	Sentences
Collision Events	Paragraphs

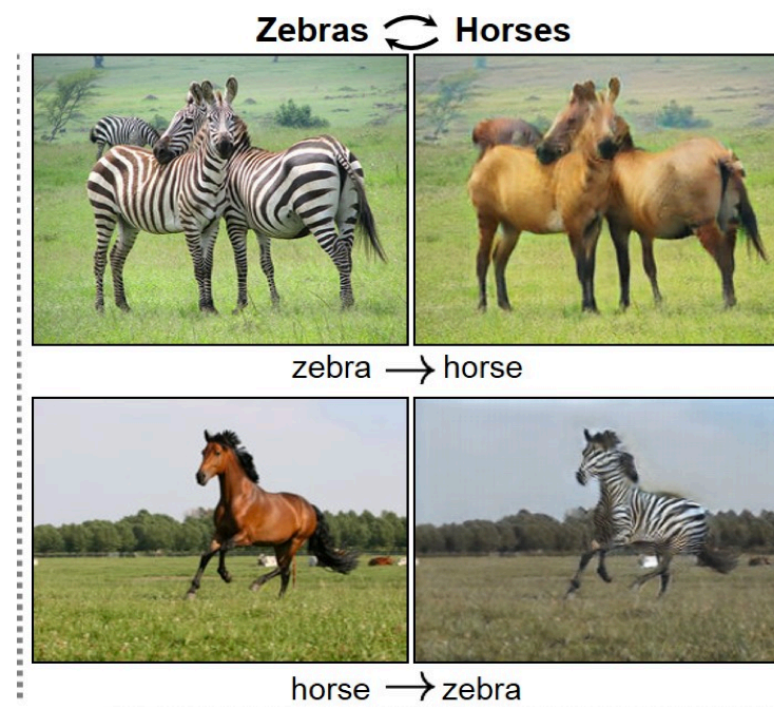
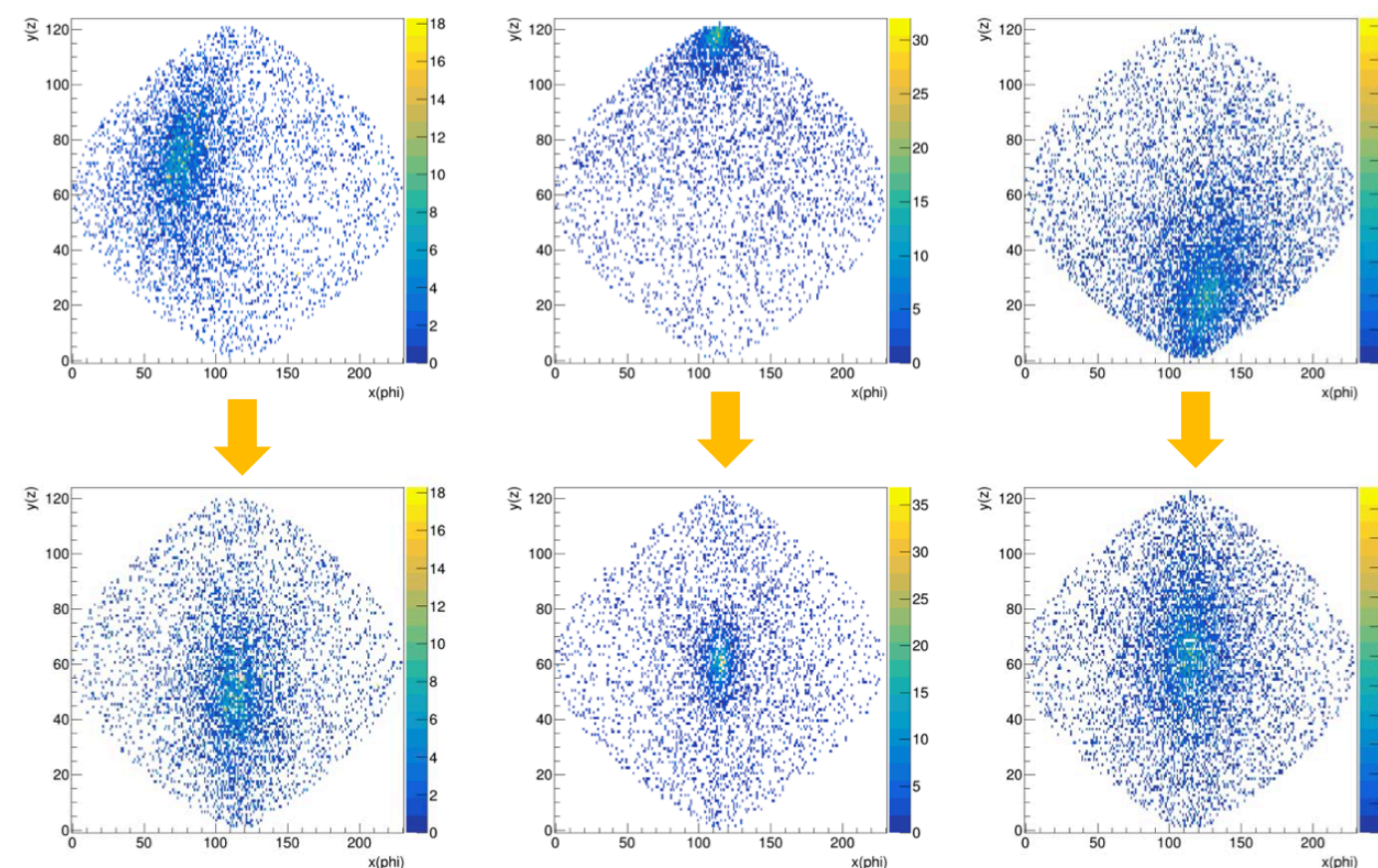
Language models

Reconstruction at Neutrinos

Not everything is the LHC. Unique challenges & Solutions

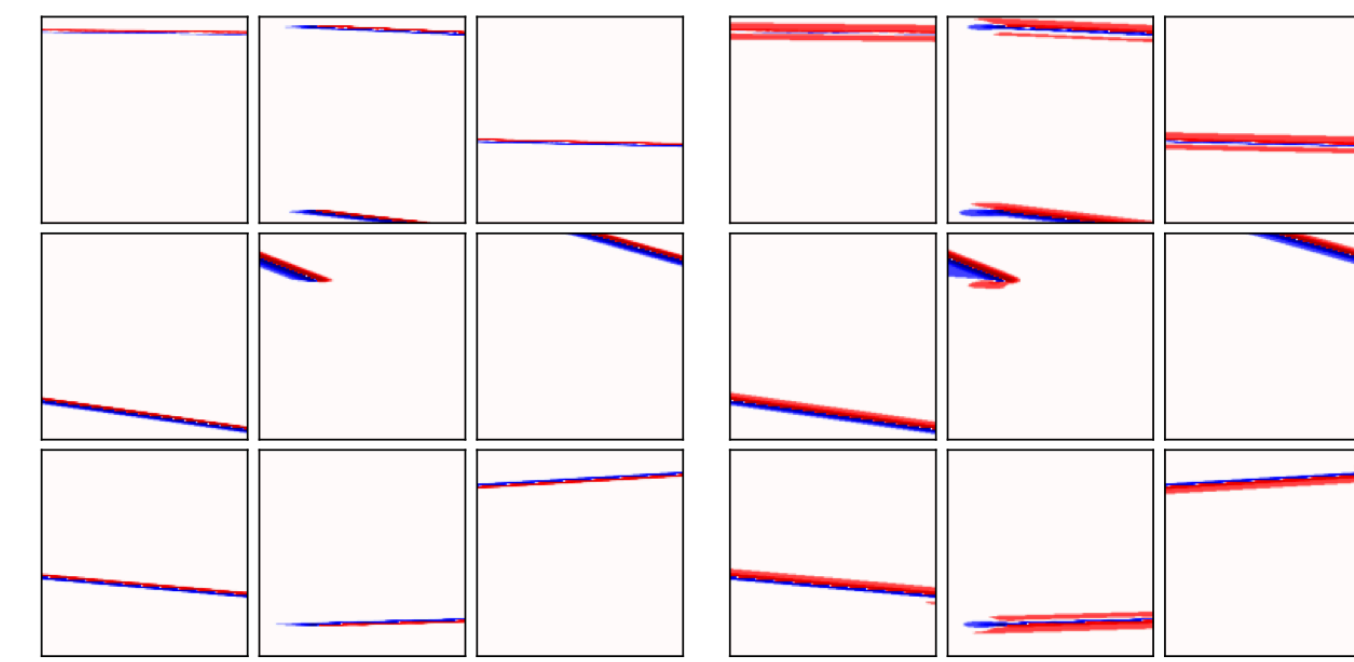


Wenxing Fang



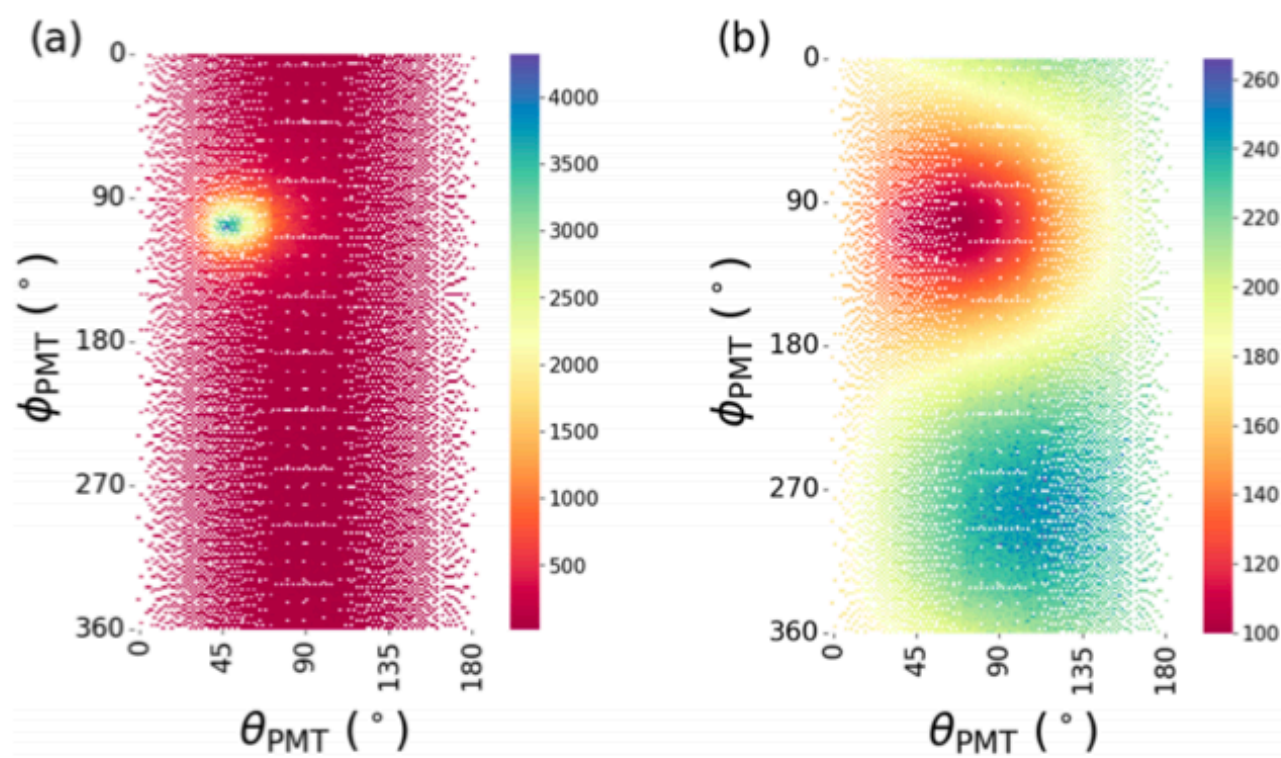
DUNE

Dmitrii Torbunov

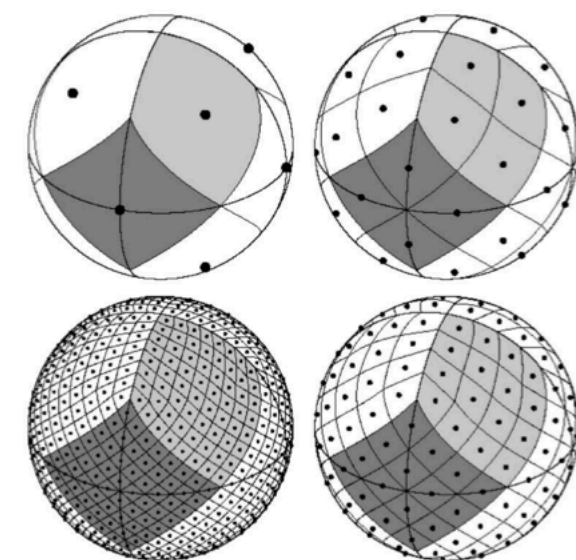


(a) Domain A (low-quality simulation)

(b) Domain B (high-quality simulation)



Wing Yan Ma



Jiaxi Liu JUNO

TPC simulation
noise filtering
signal processing

3D imaging
clustering
charge-light matching

3D trajectory & dQ/dx fitting
cosmic muon tagger

multi-track fitting
DL-3D vertexing
particle identification

DNN ROI finding with multiple input channel

input: waveform frame → output: tagged ROI

[JINST 12 P08003 \(2017\)](#)
[JINST 13 P07006 \(2018\)](#)
[JINST 13 P07007 \(2018\)](#)
[JINST 16 P01036 \(2020\)](#)

[JINST 13 P05032 \(2018\)](#)
[JINST 16 P06043 \(2021\)](#)

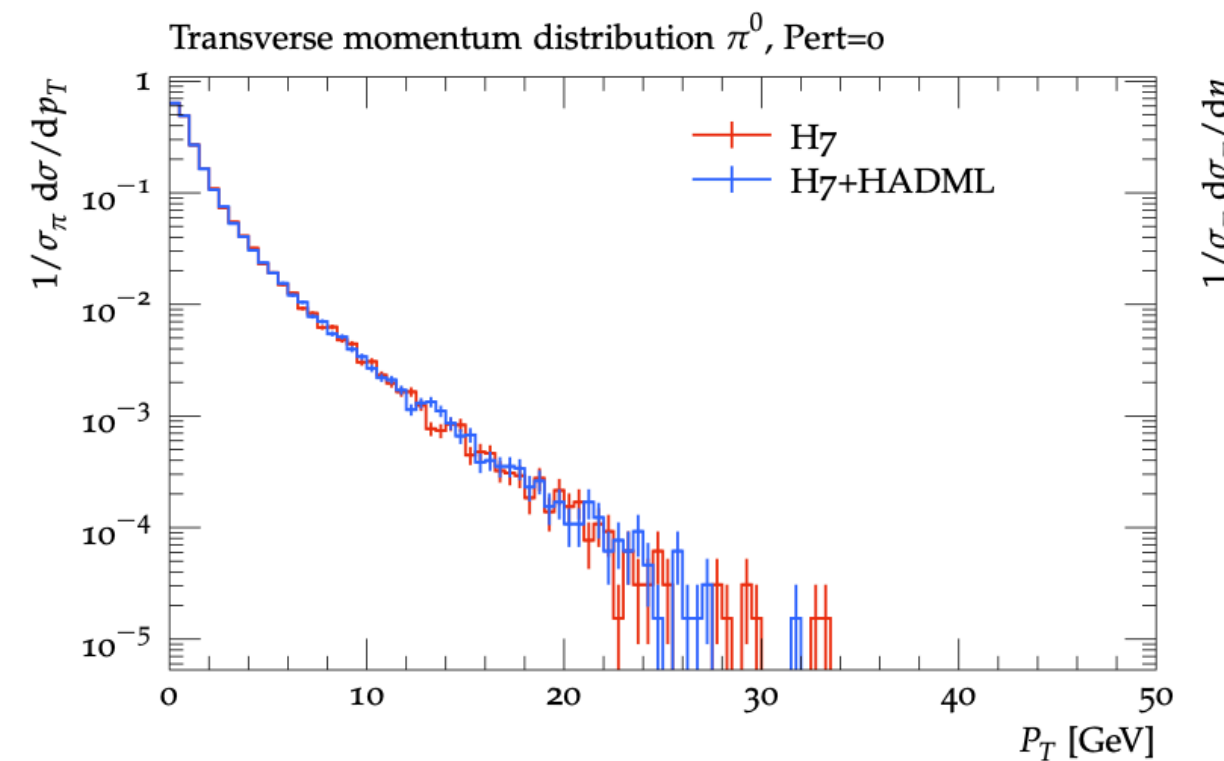
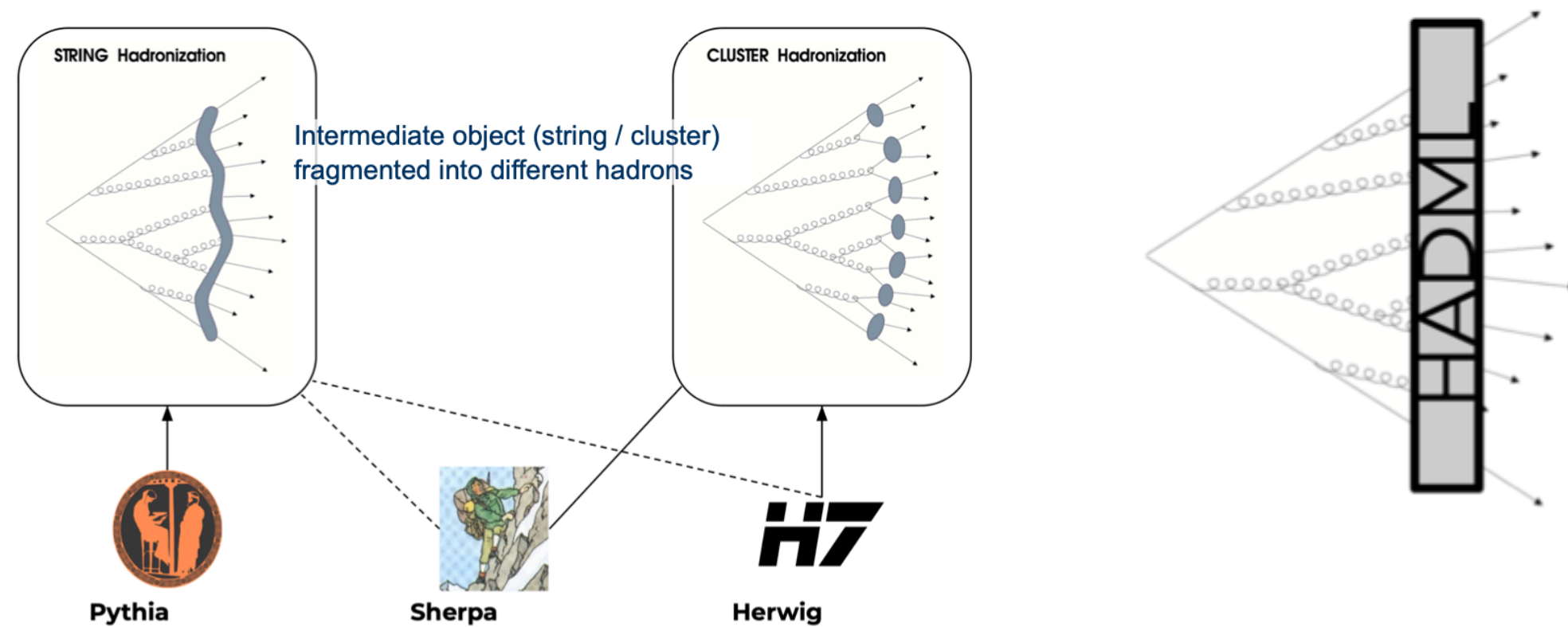
[Phys. Rev. Applied 15, 064071 \(2021\)](#)

[JINST 17 P0](#)

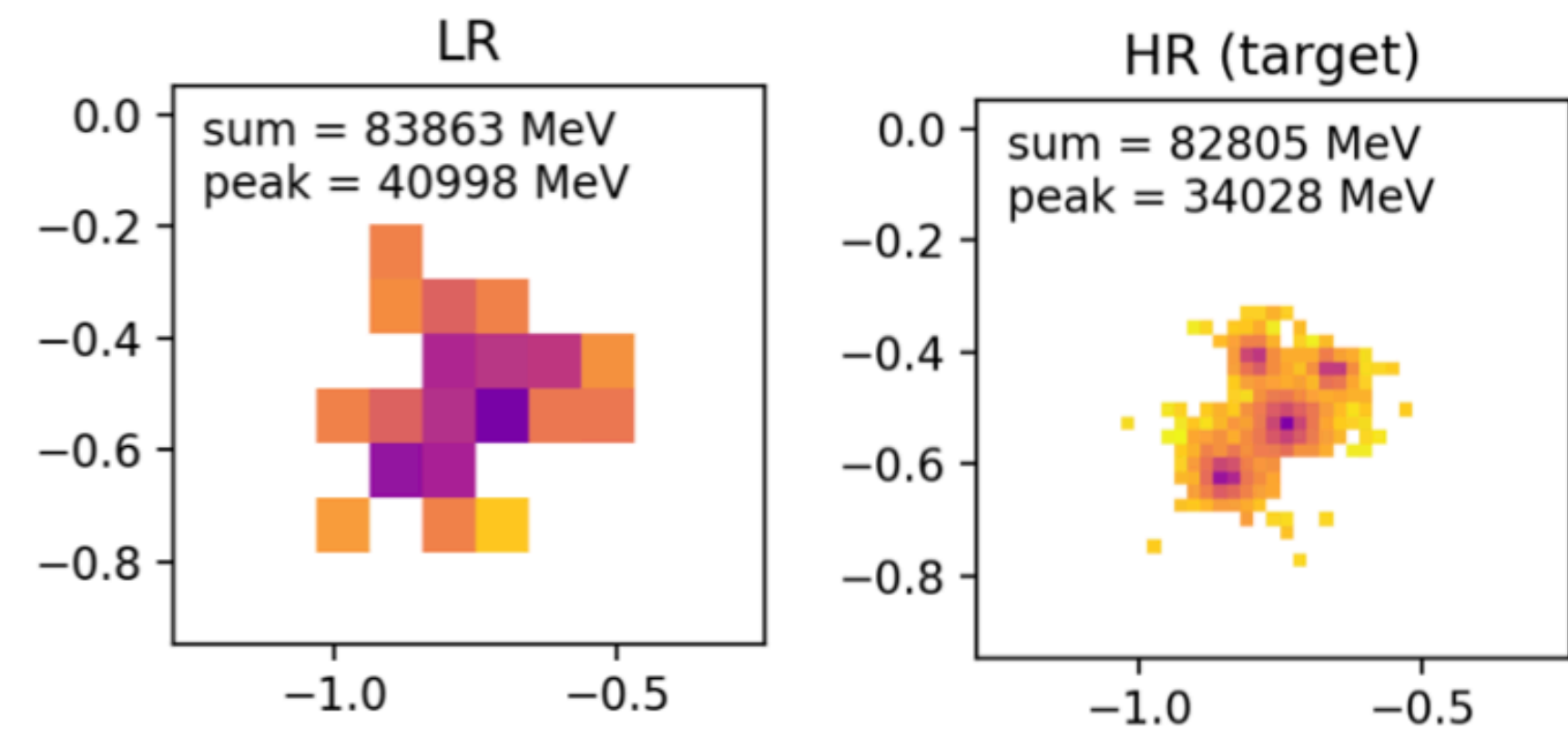
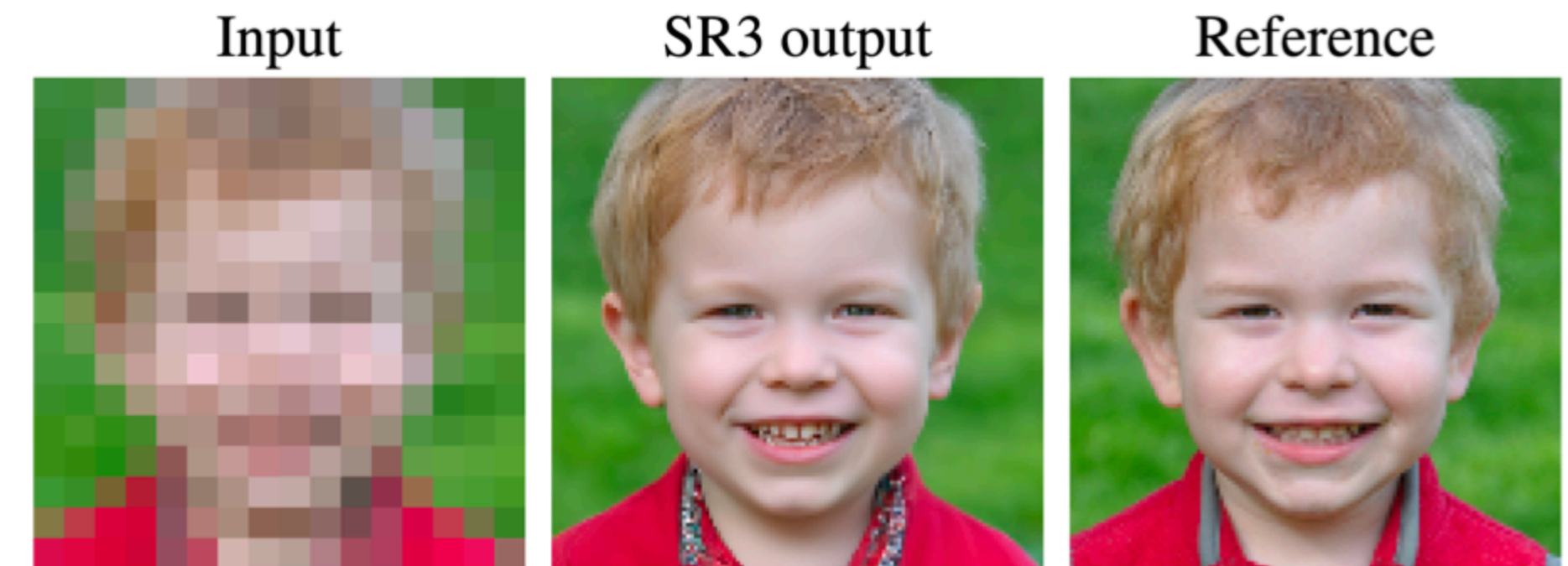
Haiwang Yu

Generative Models

We're not done yet with Generative Models. Both on the Simulation as well as Reconstruction side.



Jay Chan



Nilotpal Kakati

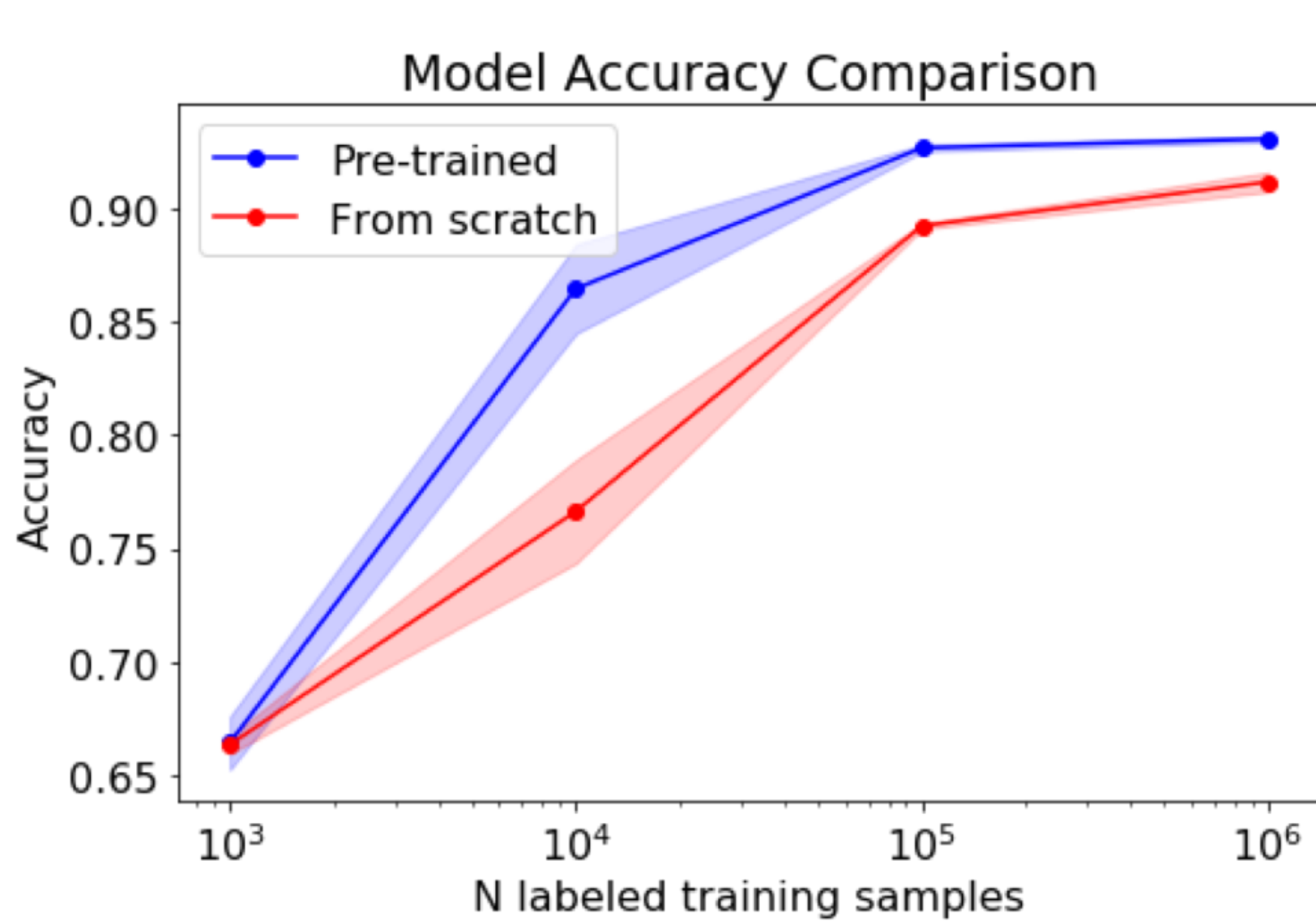
Foundation Models

Foundation Models are about data efficiency & finetuning.
Get used to seeing this plot more often in the future

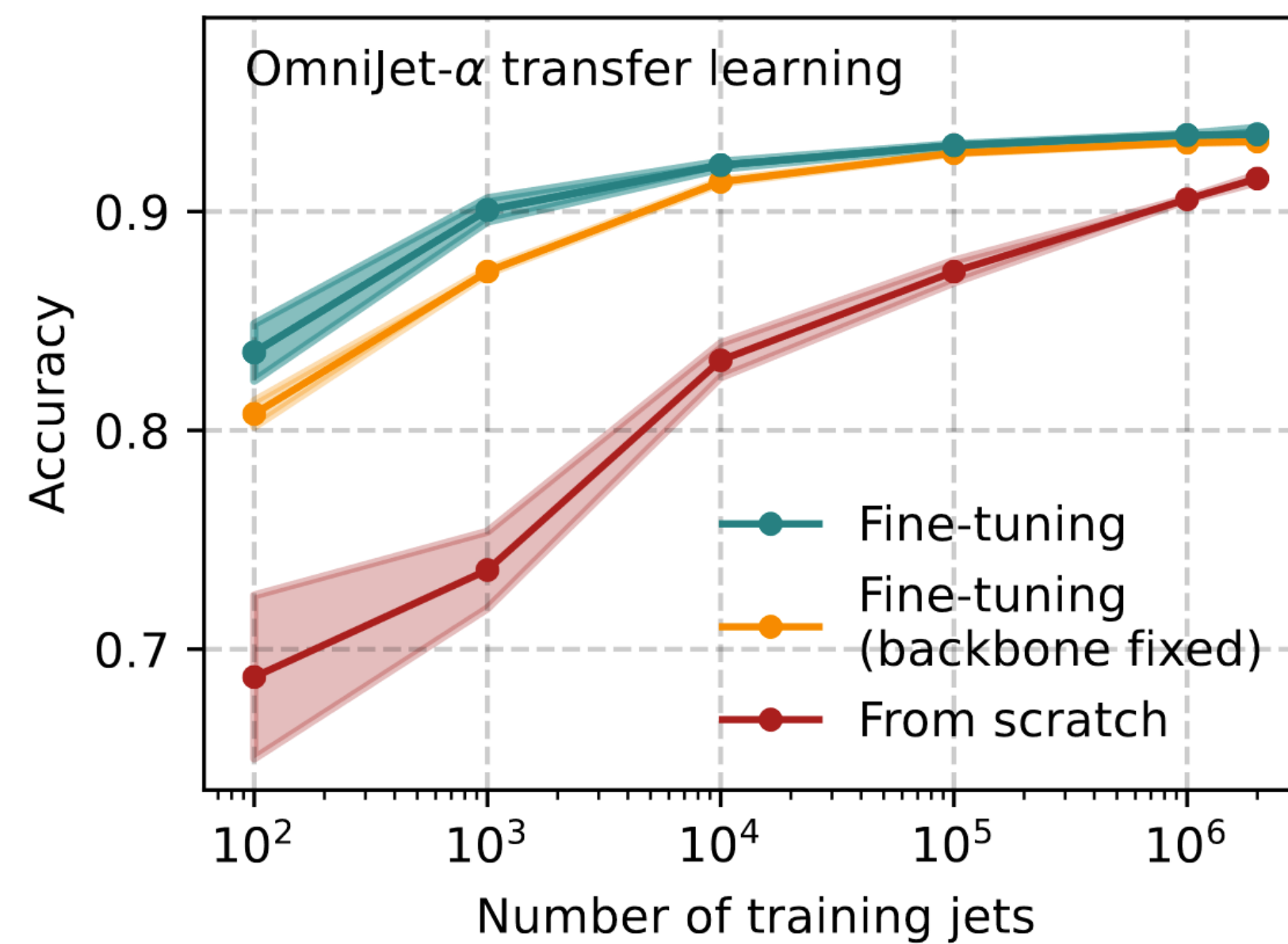
Self-supervised

Self-supervised

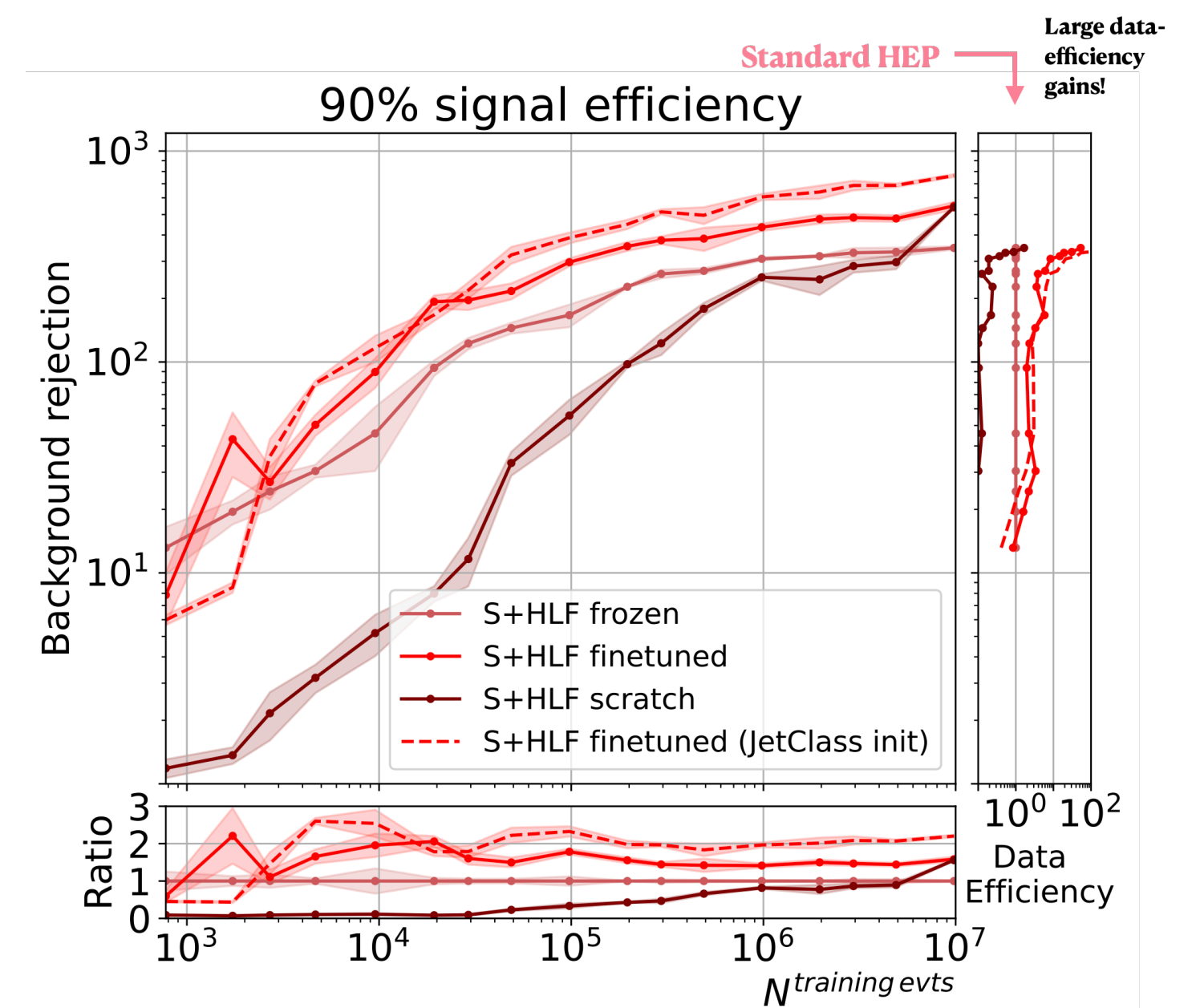
Supervised



Zihan Zhao



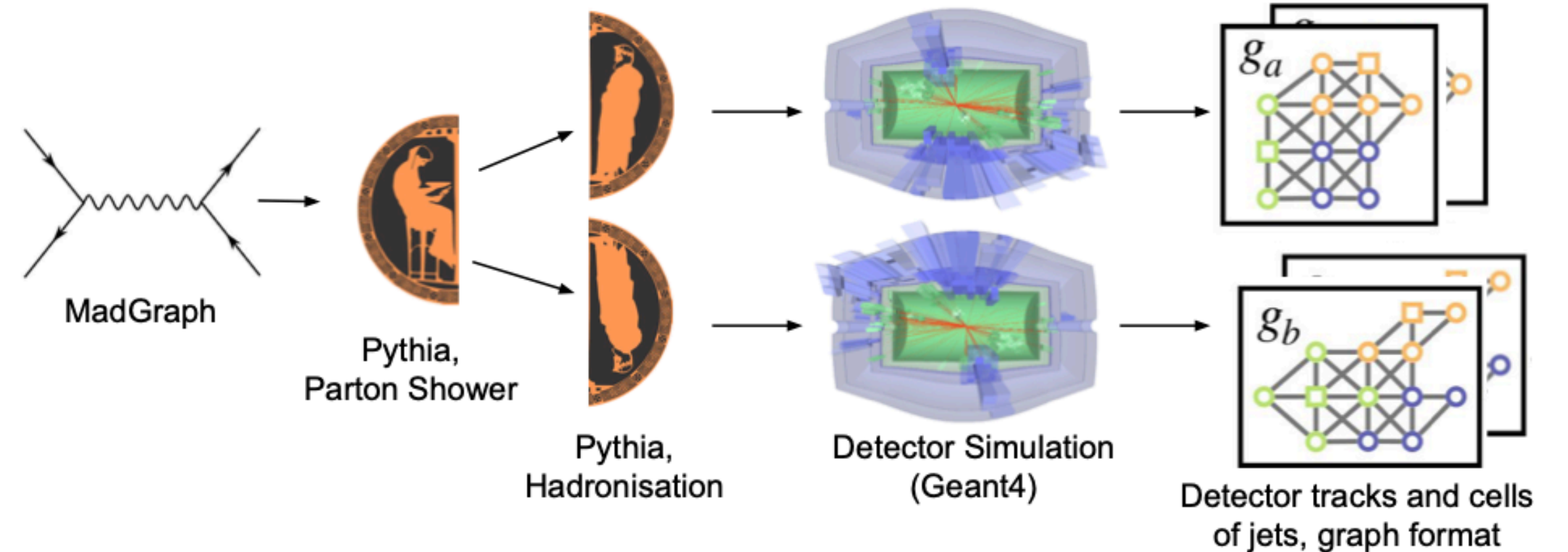
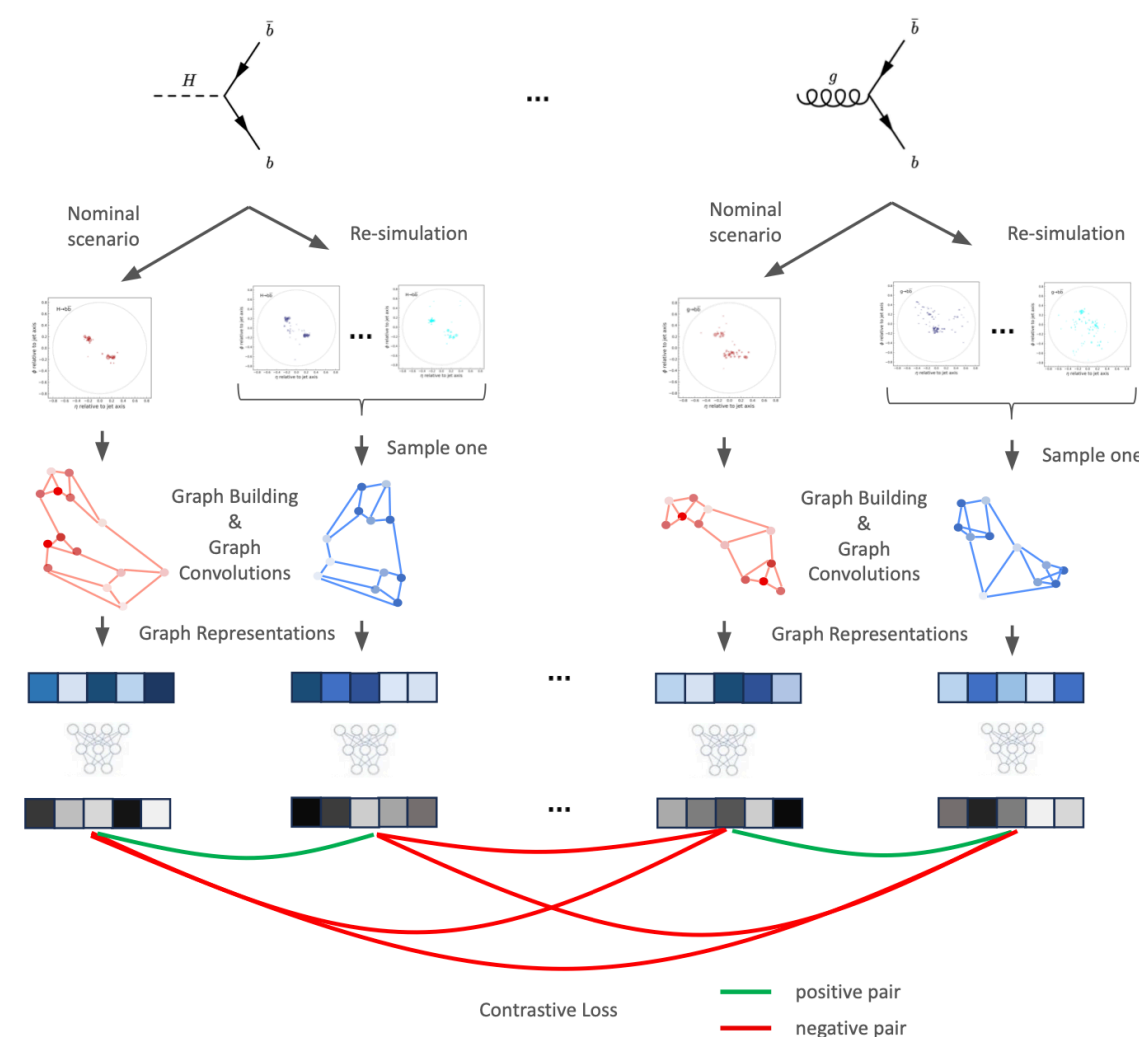
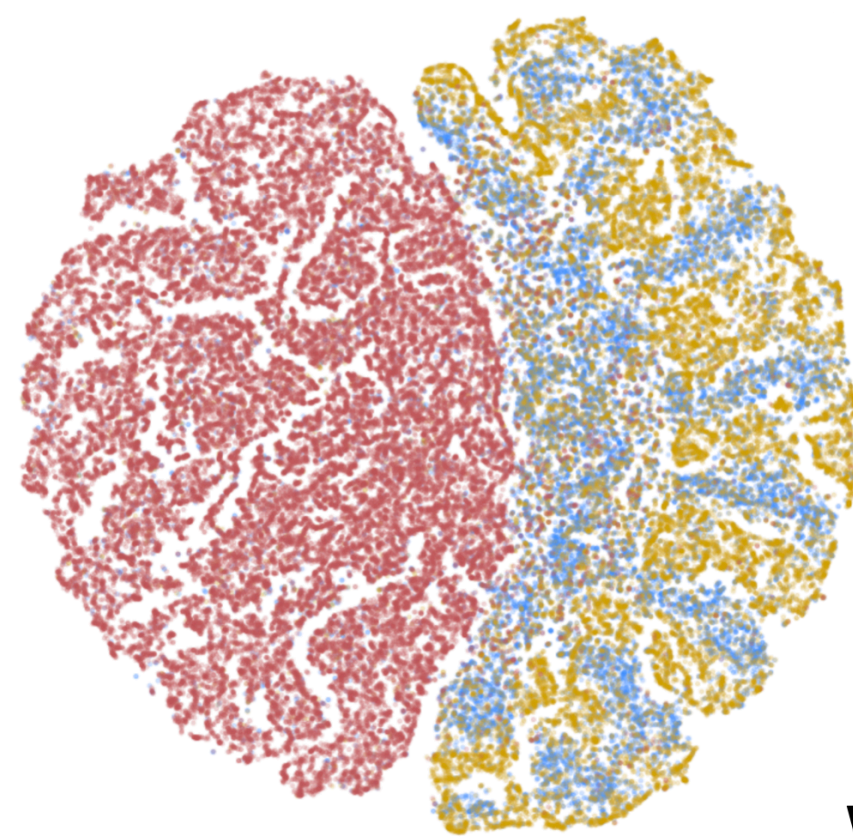
Anna Hallin



Matthias Vigl

Foundation Models II

Representation Learning & Joint Embedding: Use Simulator to reflect what we actually value & what we consider noise

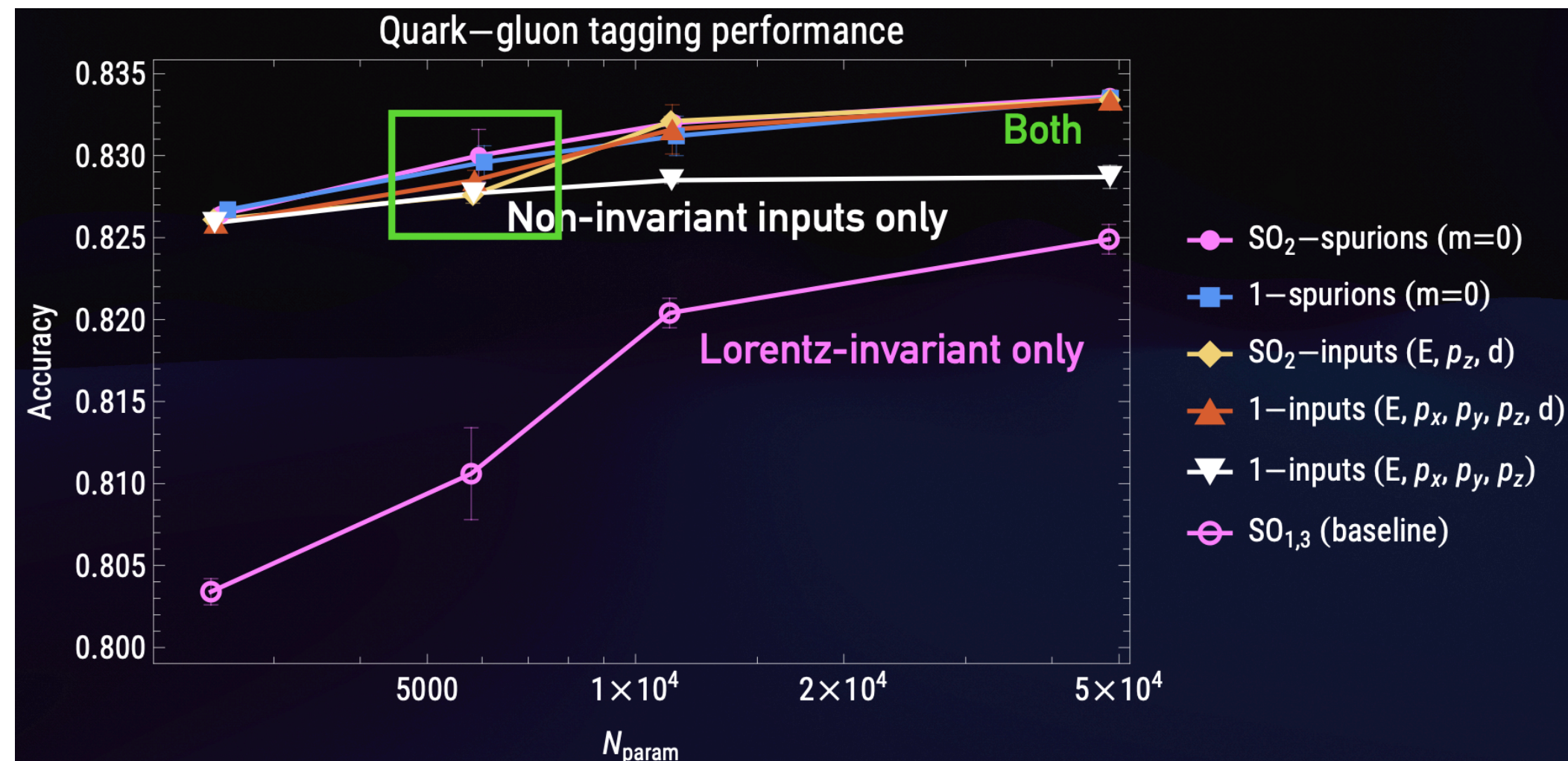


Phil Harris

Patrick Rieck

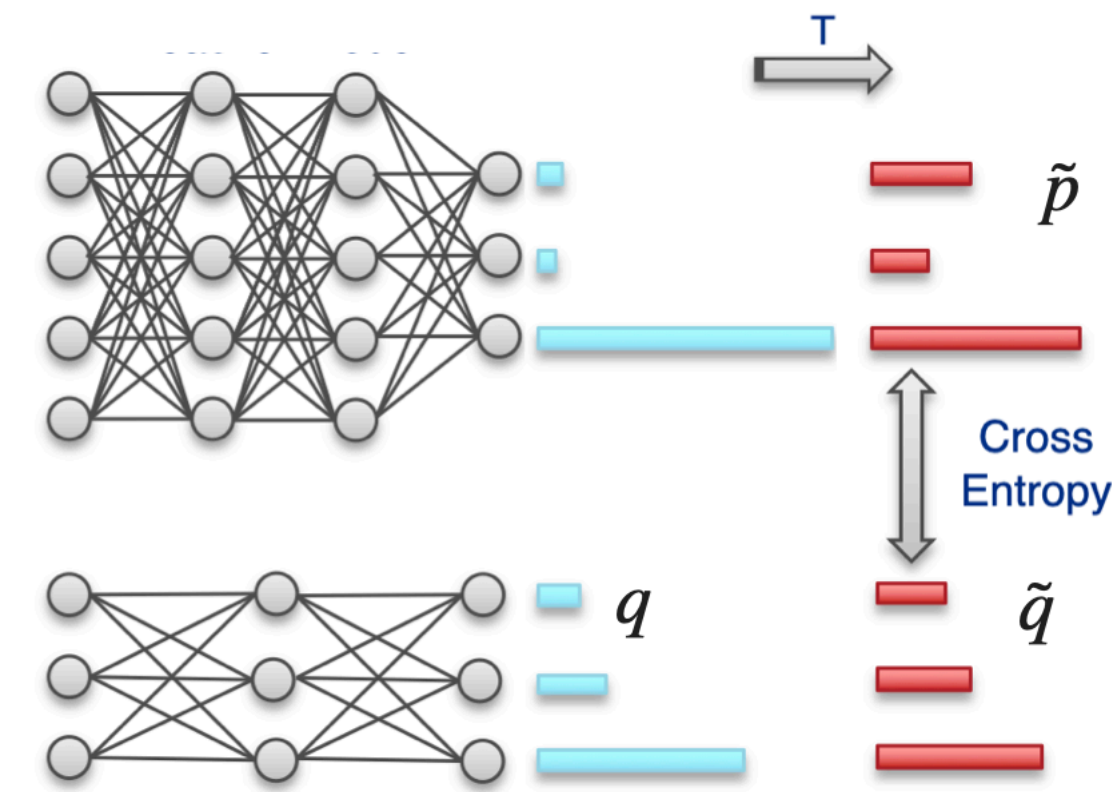
Robustness & Inductive Bias

Inductive Bias is still important, but can also slow down complicate neural networks. Can we resolve this tension?

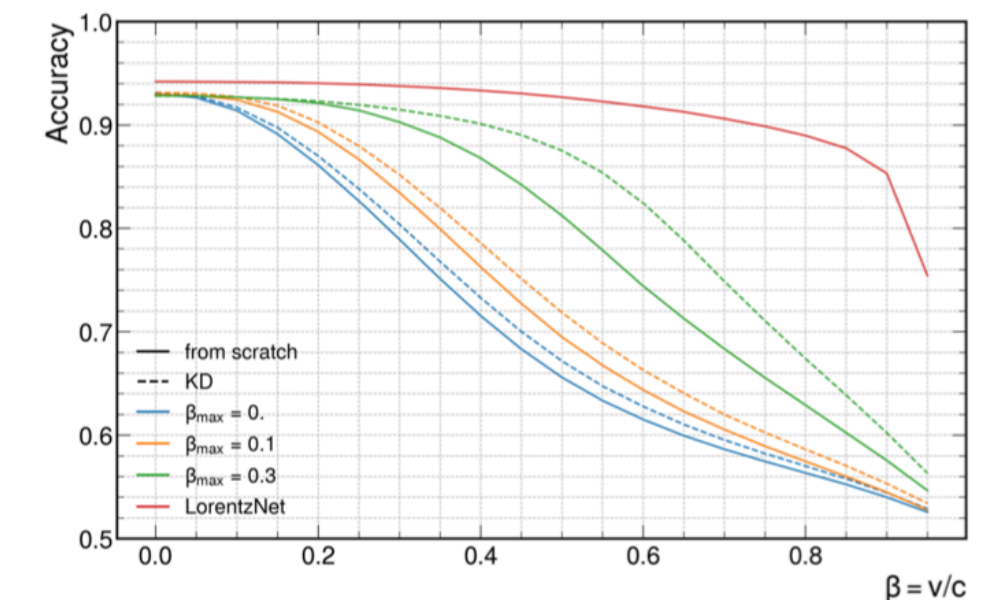


Alexander Bogatskiy

Inductive Bias Impact



Abhijith Gandrakota

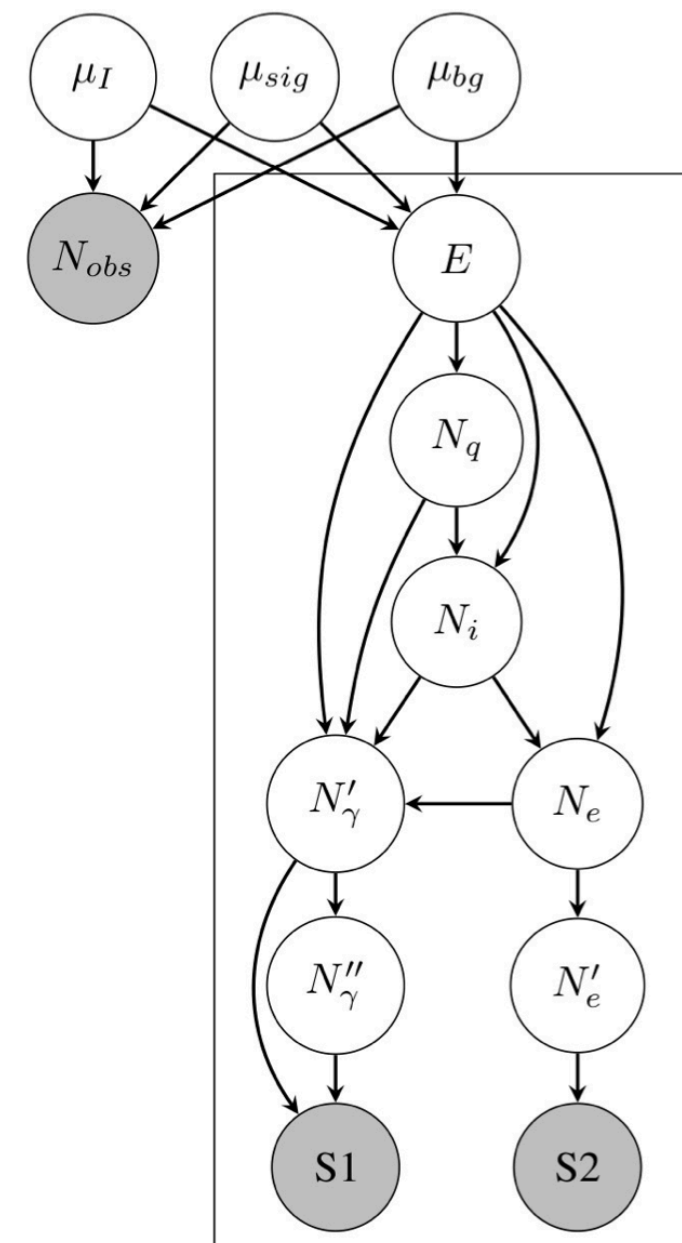
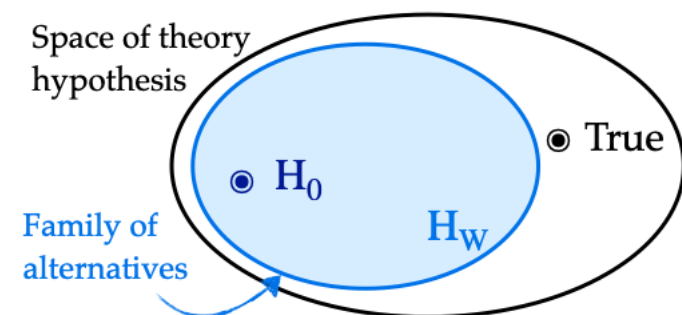
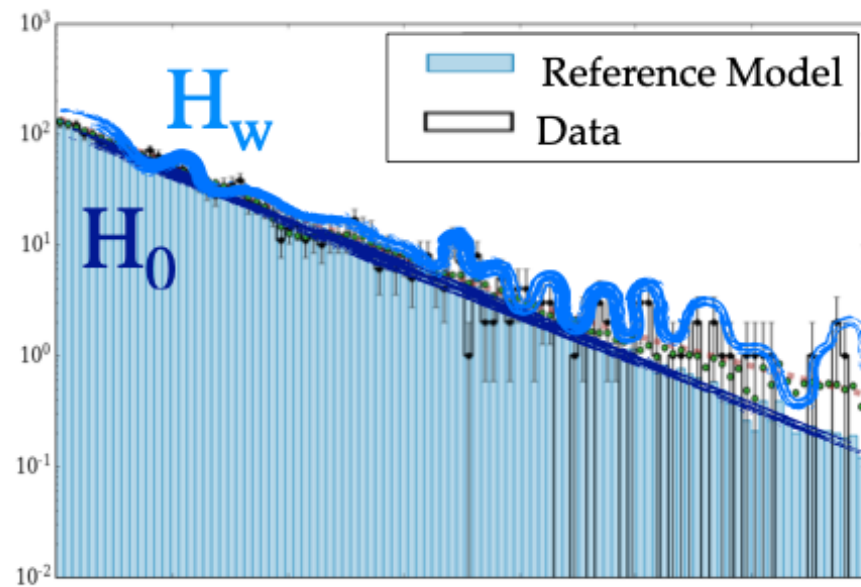


Knowledge Distillation

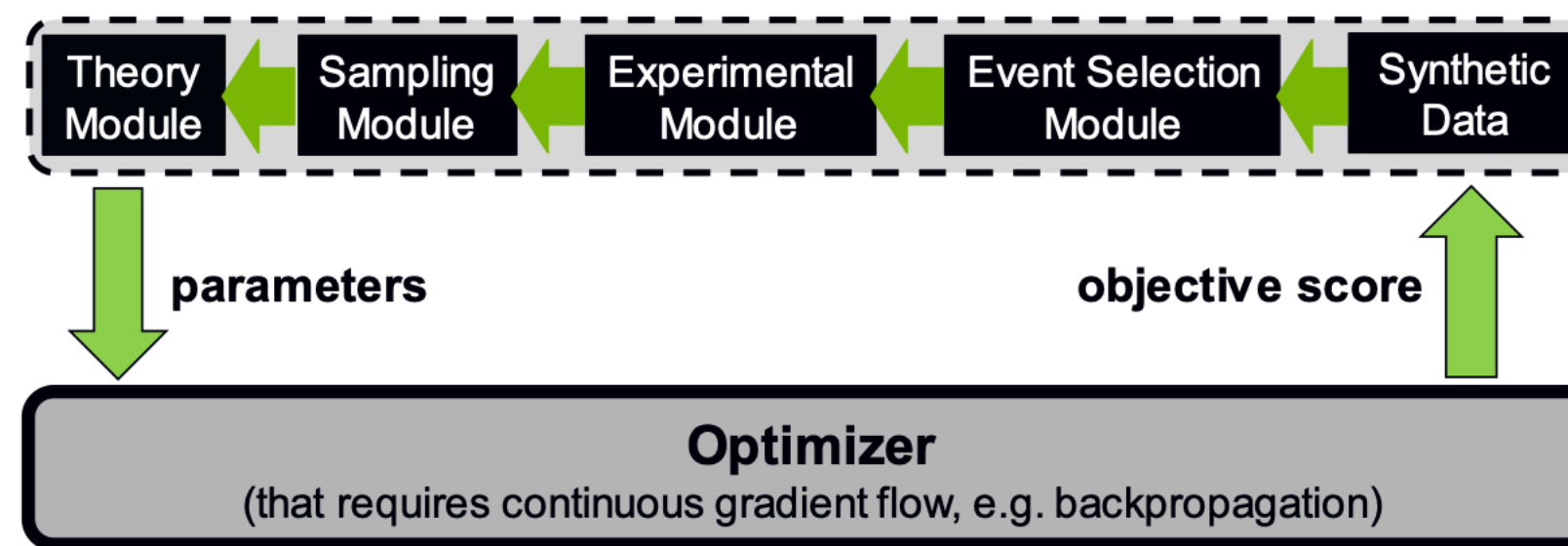
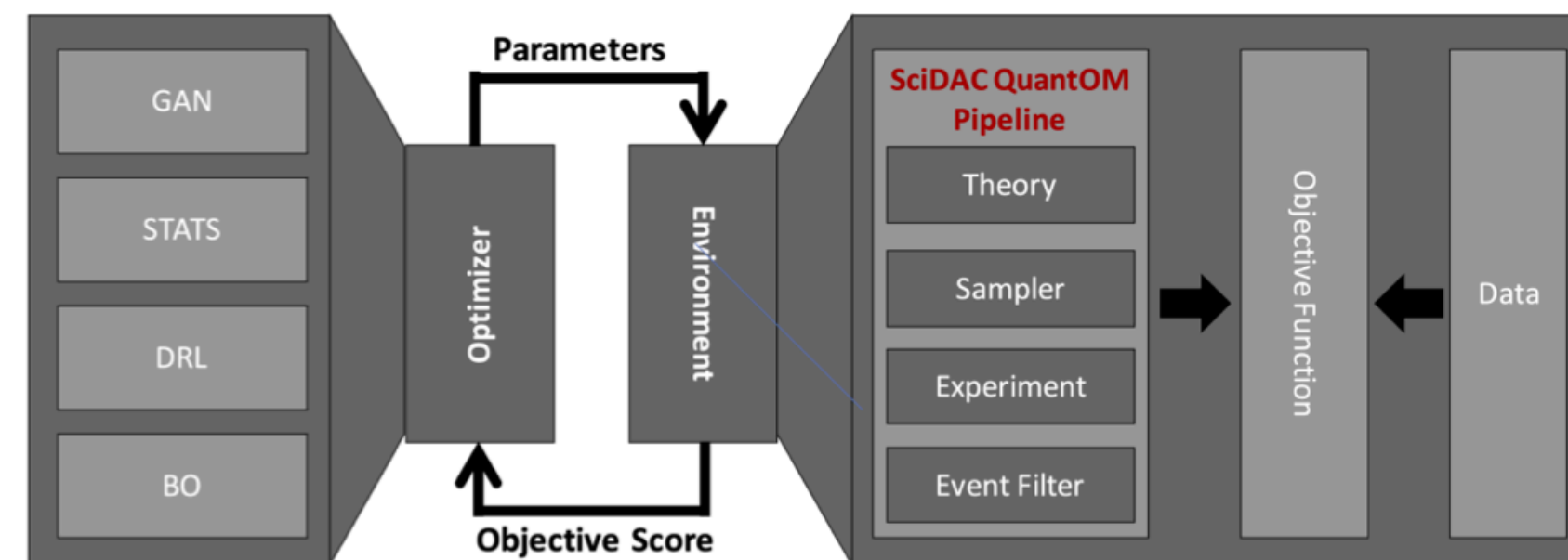
Advanced Inference Methods

Uptake of new Techniques. Probabilistic & Differentiable Programming, Likelihood Ratio Learning, Bayesian Opt. ...

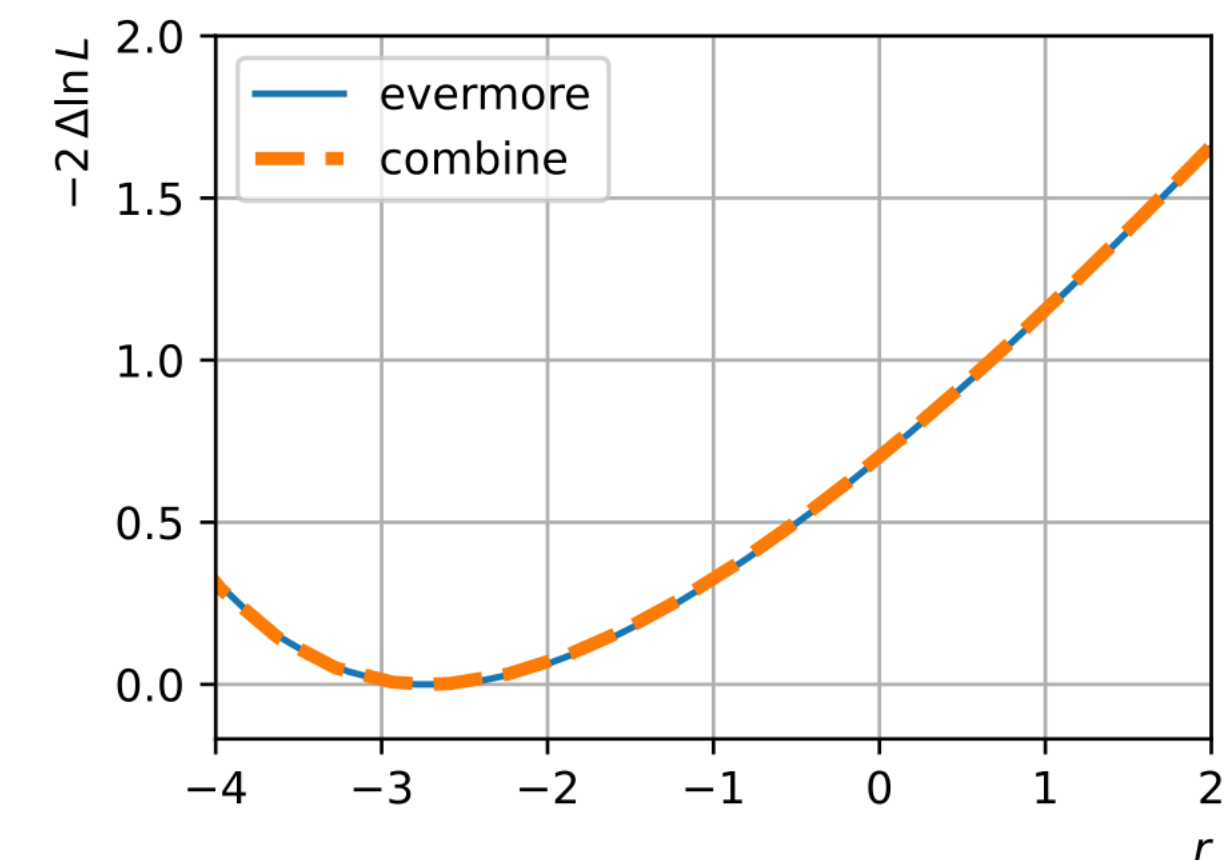
Gaia Grosso



Daniel Lersch

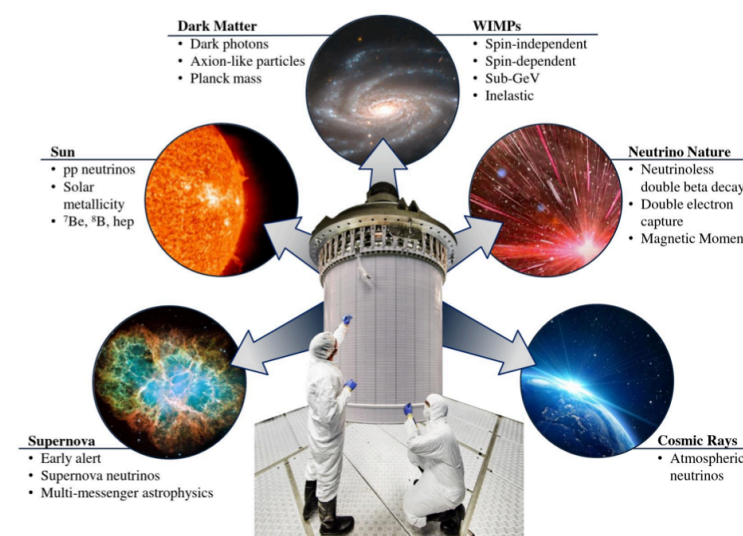


evermore



Peter Fackeldey

Juehang Qin

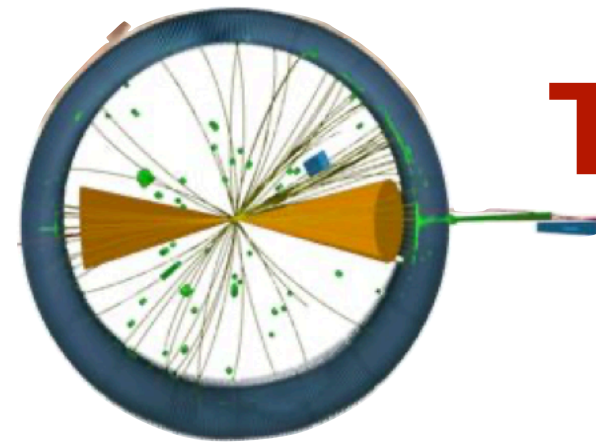
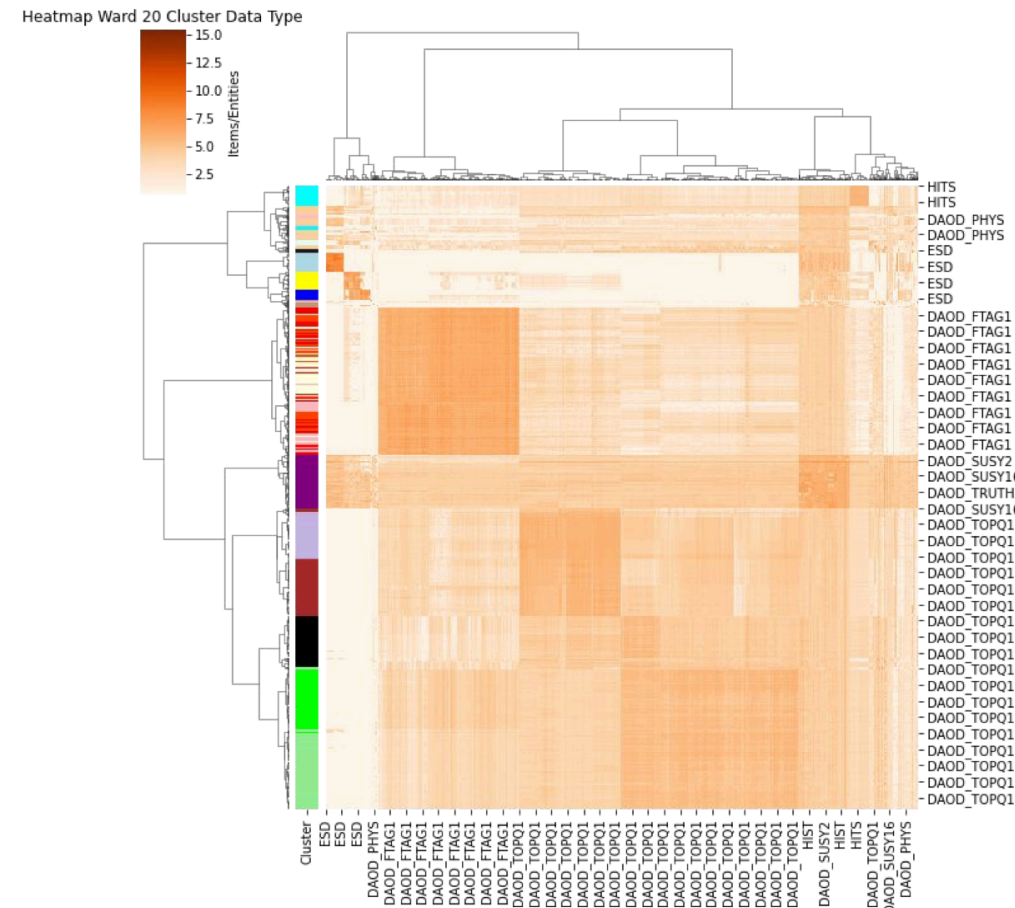


Tooling, Tooling, Tooling

People Management

Hardware Management

Data Management



Tomasso Tedeschi

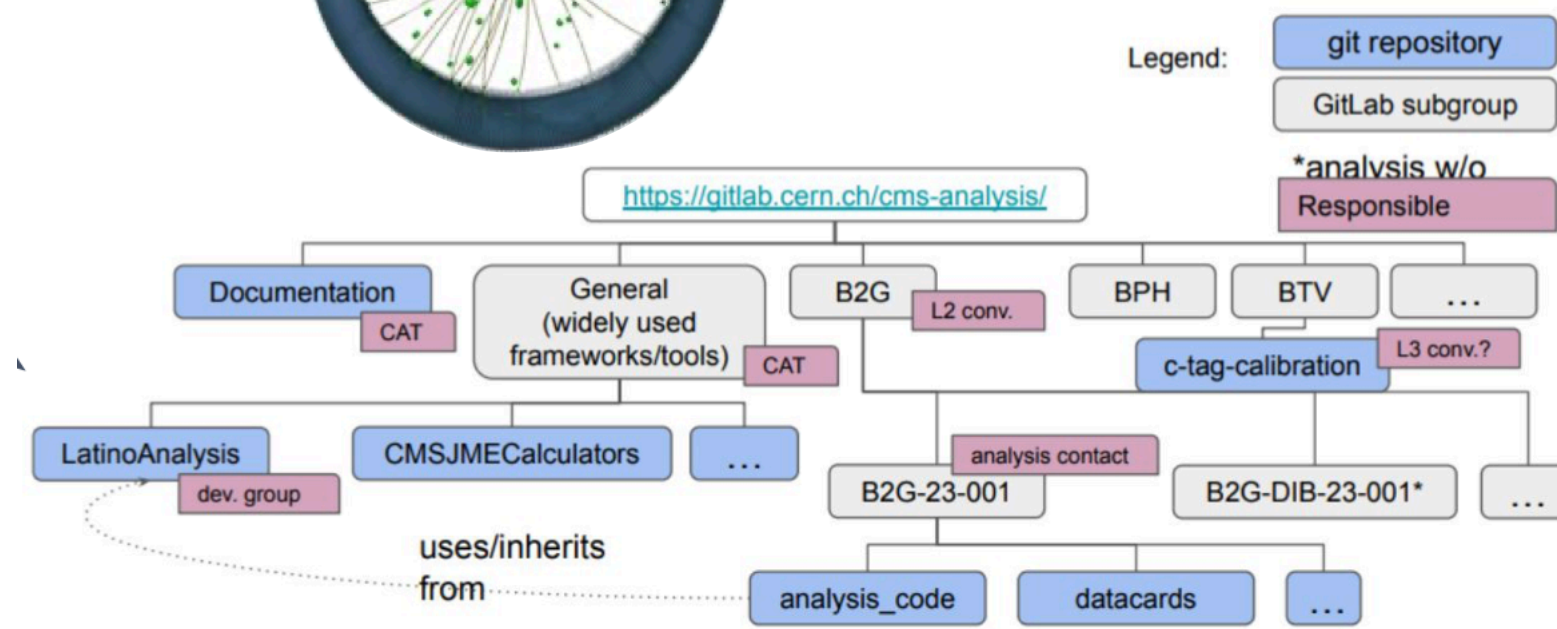
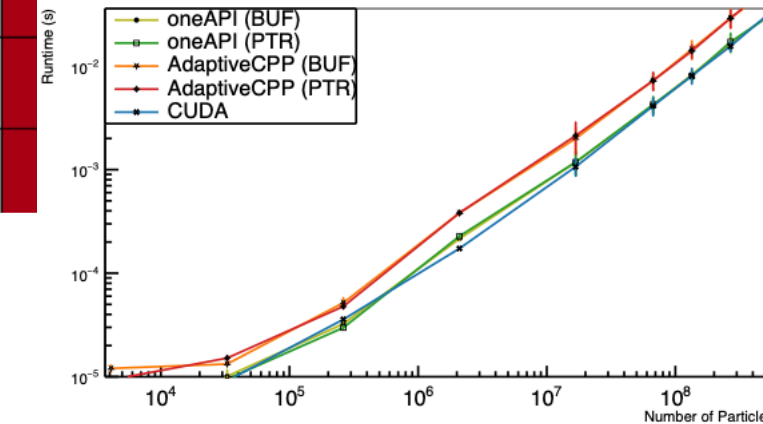


Figure: Hardware support of portability layers¹

	CUDA	HIP	OpenMP Offload	Kokkos	dpc++ / SYCL	alpaka	std::par
NVidia GPU	✓	✓	✓	✓	✓	✓	nvc++
AMD GPU	✓	✓	✓	✓	✓	hip 4.0.1 / clang	
Intel GPU	✓	✓	✓	✓	✓	prototype	oneAPI::dpl
multicore CPU	✓	✓	✓	✓	✓	✓	g++ & tbb
FPGA	✓	✓	✓	✓	✓	via SYCL	

Figure: A100

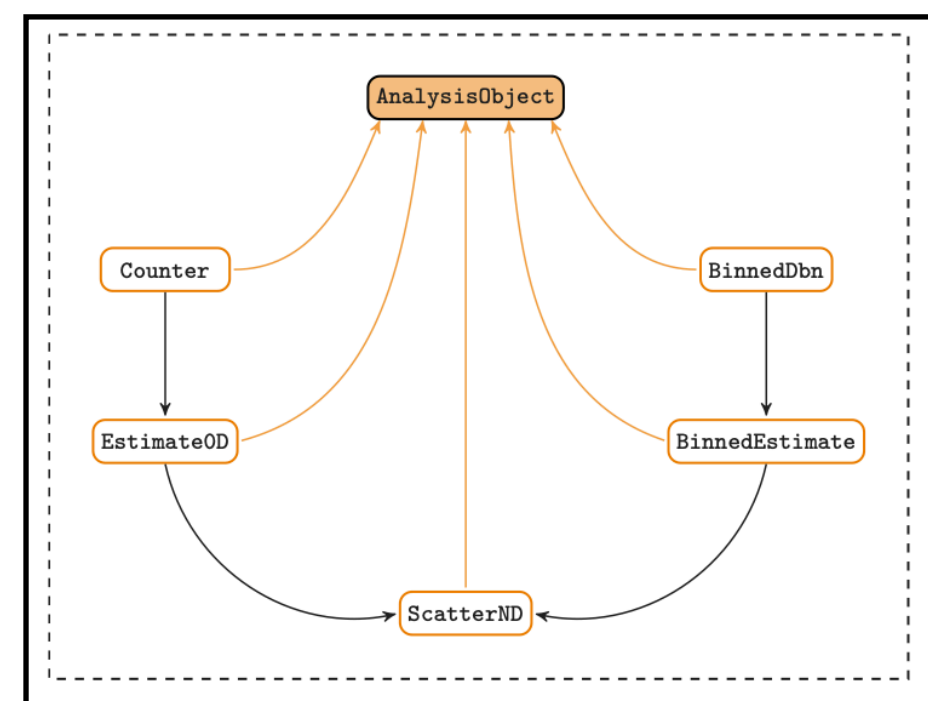


Qiulan Huang

Histograms

Declarative Languages

Christian Gütschow



```

topo_clusters = (ds_jz2_exot15
    .SelectMany(lambda e: e.Jets())
    .SelectMany(lambda j: j.getConstituents())
    .Select(lambda tc: tc.pt())
    .AsAwkwardArray('JetClusterPt')
    .value()
)
    
```

Gordon Watts

High Level Thoughts

ML is absolutely everywhere. Even in the smallest nooks & crannies. **Simple General-Purpose Tool.**

The level of **sophistication and speed** at which ideas from ML research are integrated is impressive.

Diverse Physics exposes us to **different problems and connection points** to ML research.

ML is not everything. At the end of the day the work should make contact with the real world and actually be deployed. **Tools and Engineering Matter and should get rewarded.**

About Foundation Models..

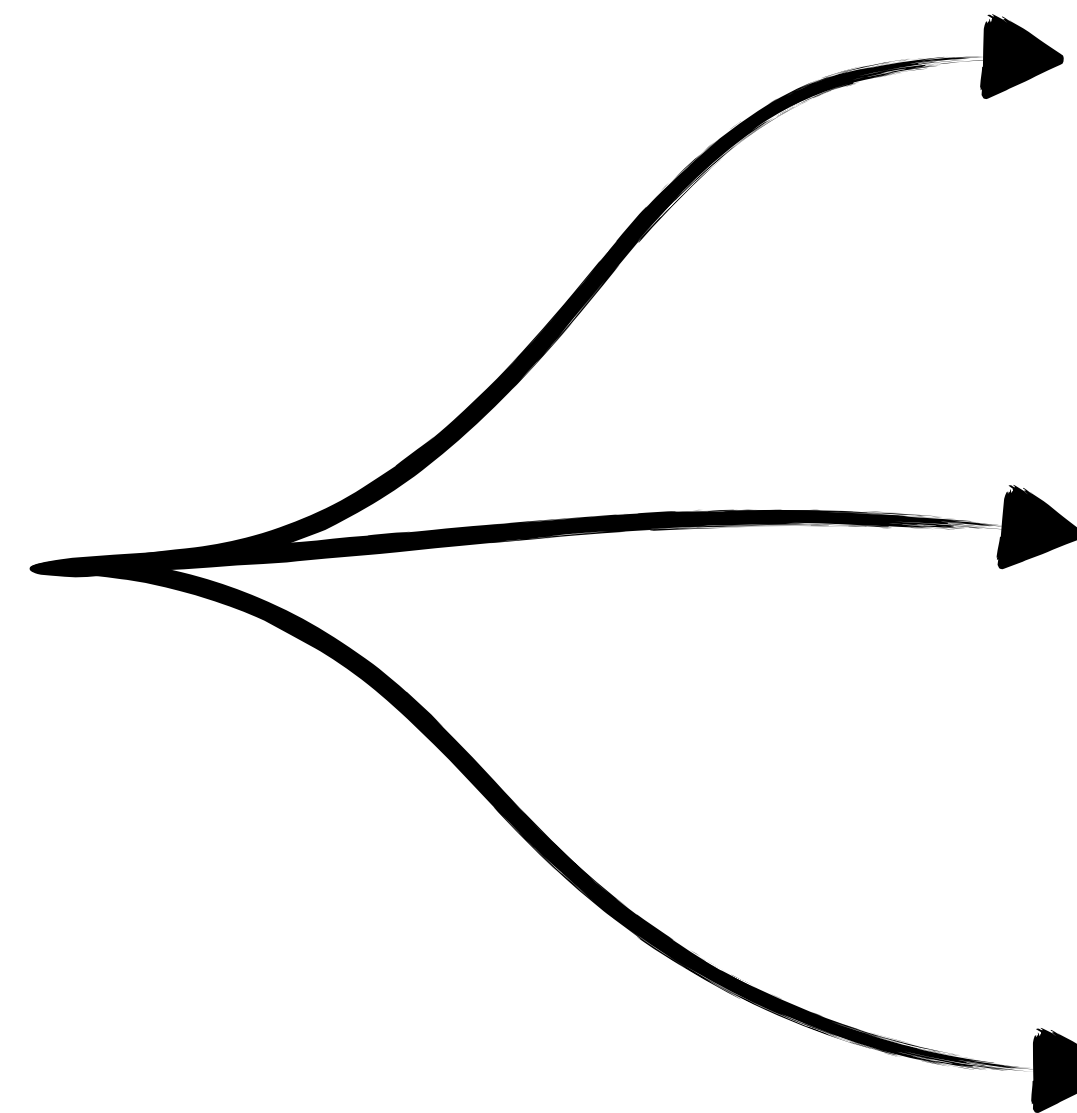
Modality 1

Modality 2

Modality 3



Joint
Embedding /
Representation

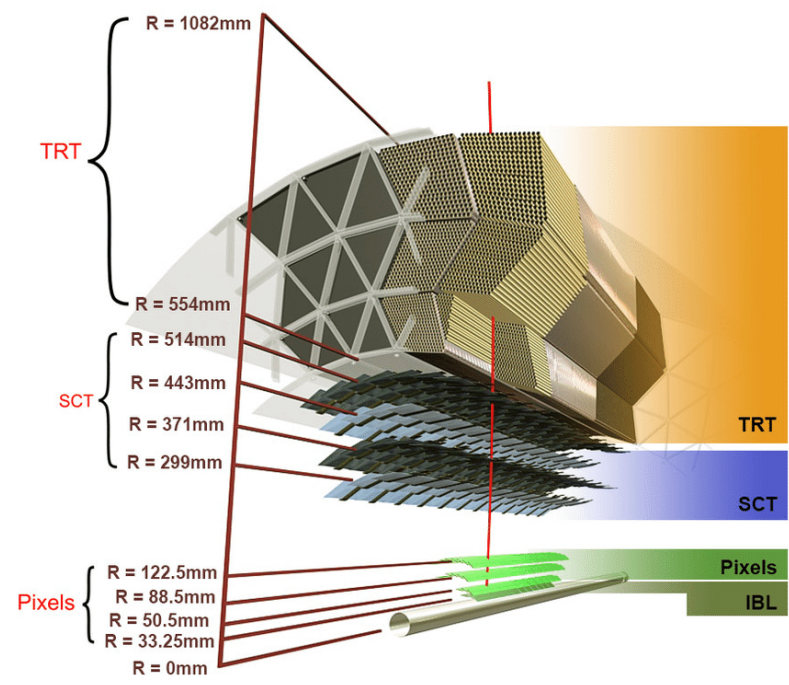


Use Case 1

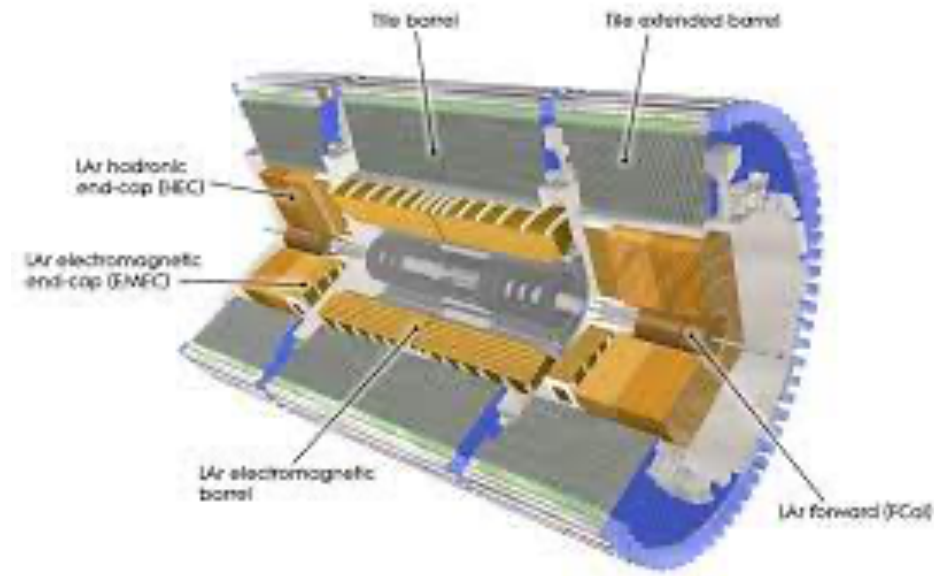
Use Case 2

Use Case 3

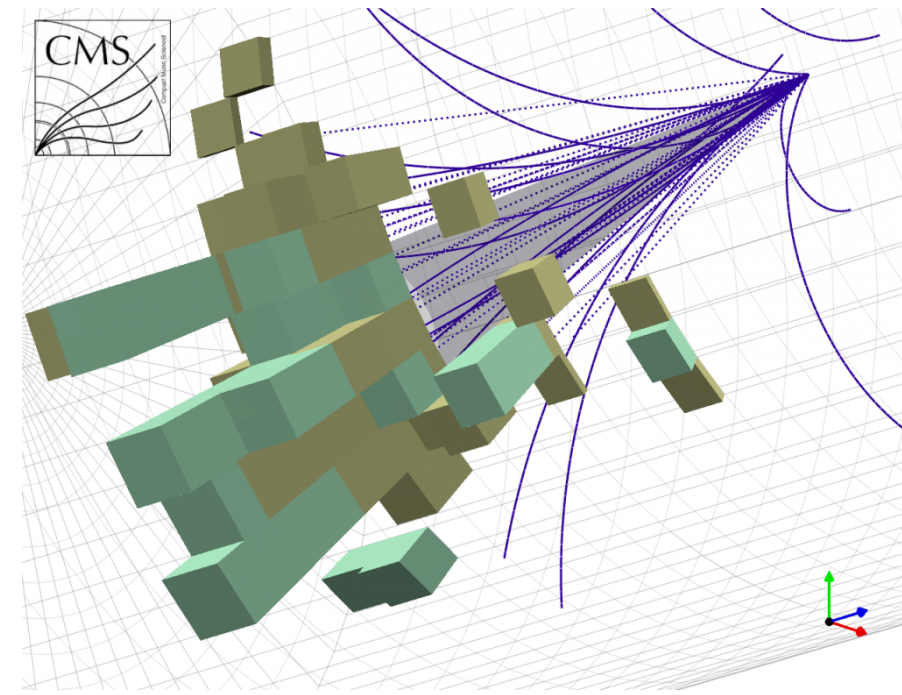
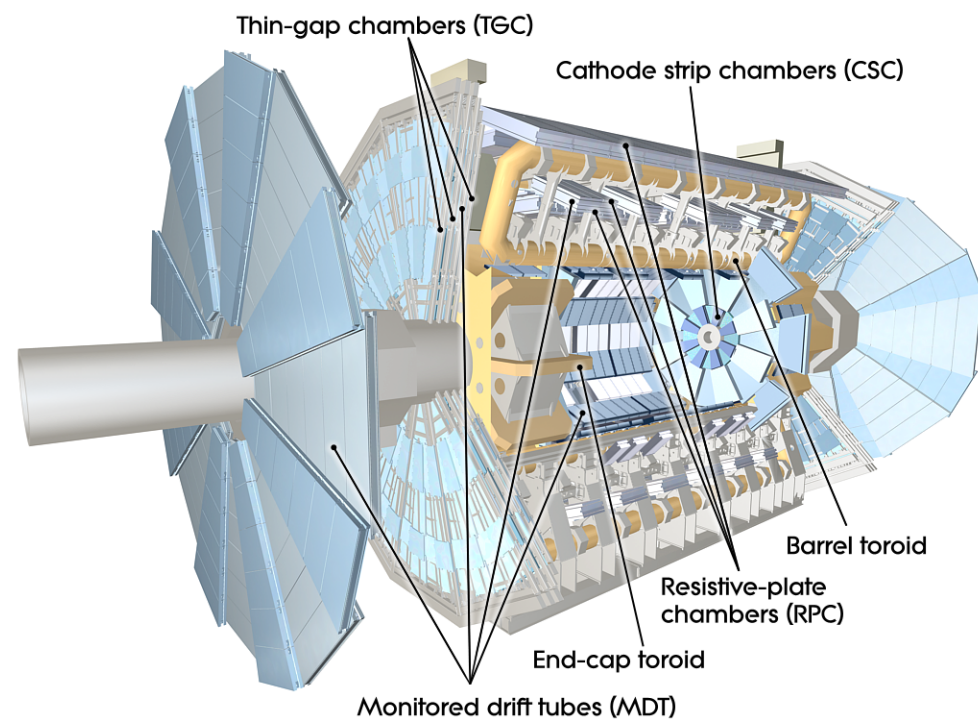
Tracking Data



Calorimeter



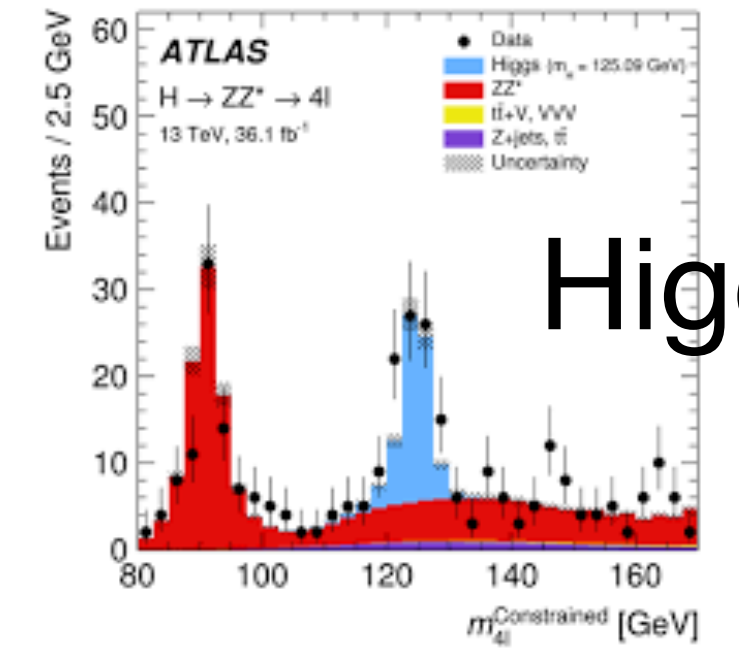
Muon Data



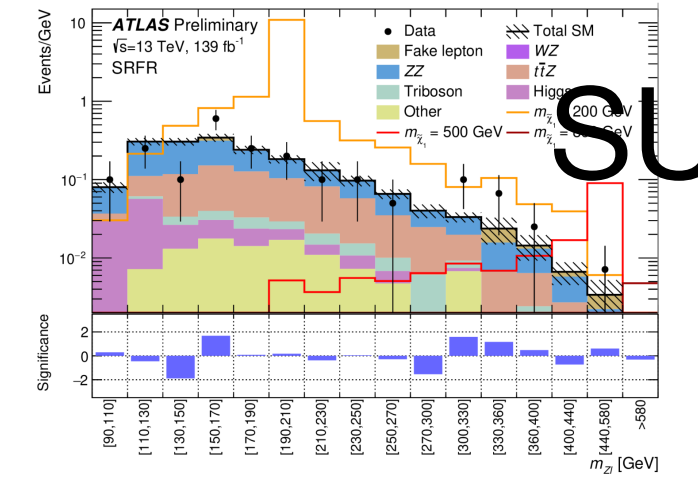
Reco



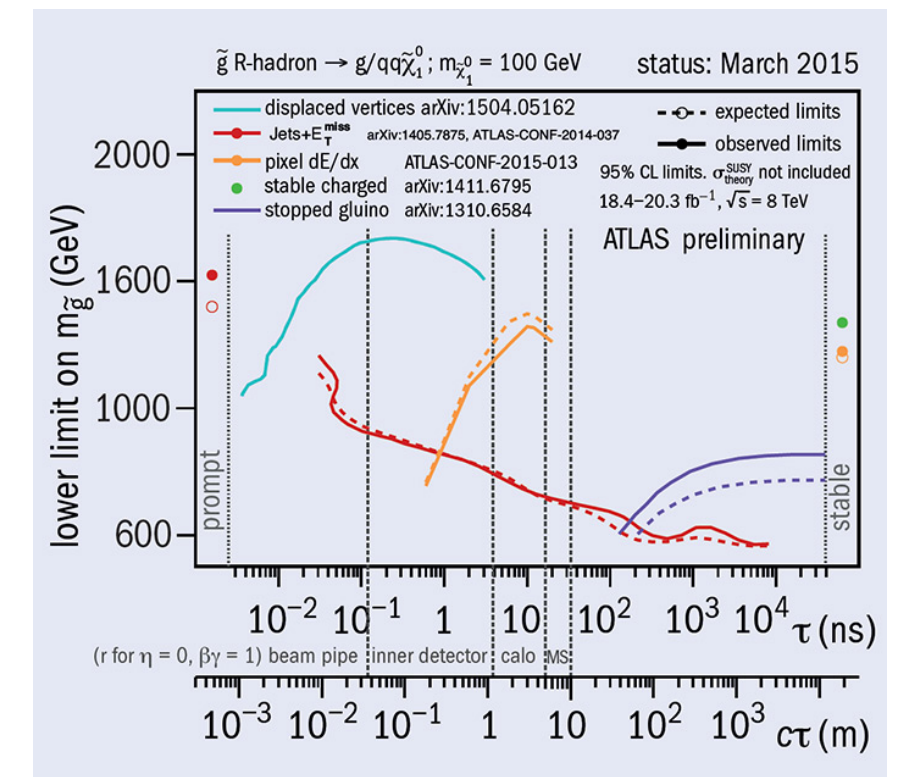
Reconstructed Event



Higgs



SUSY

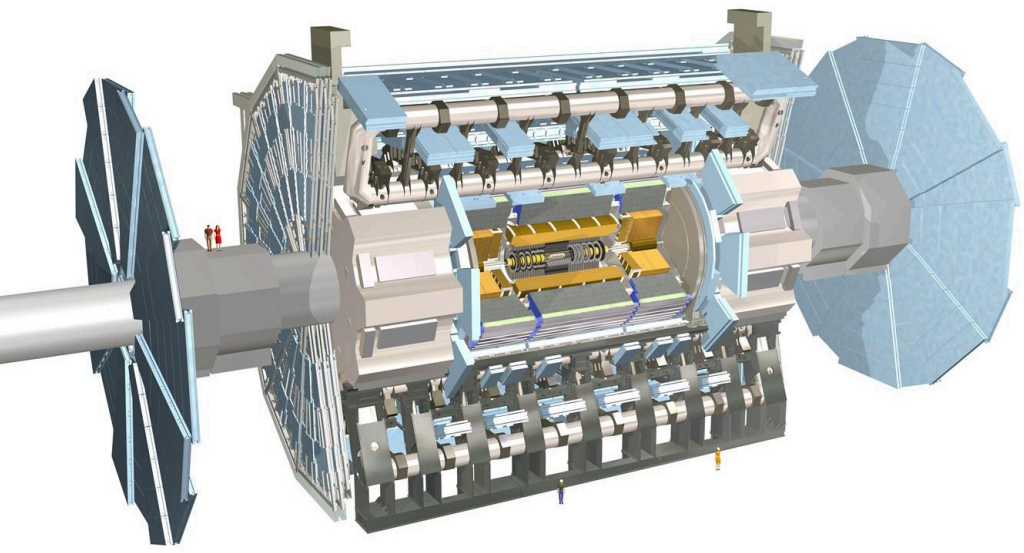


Exotic Particles

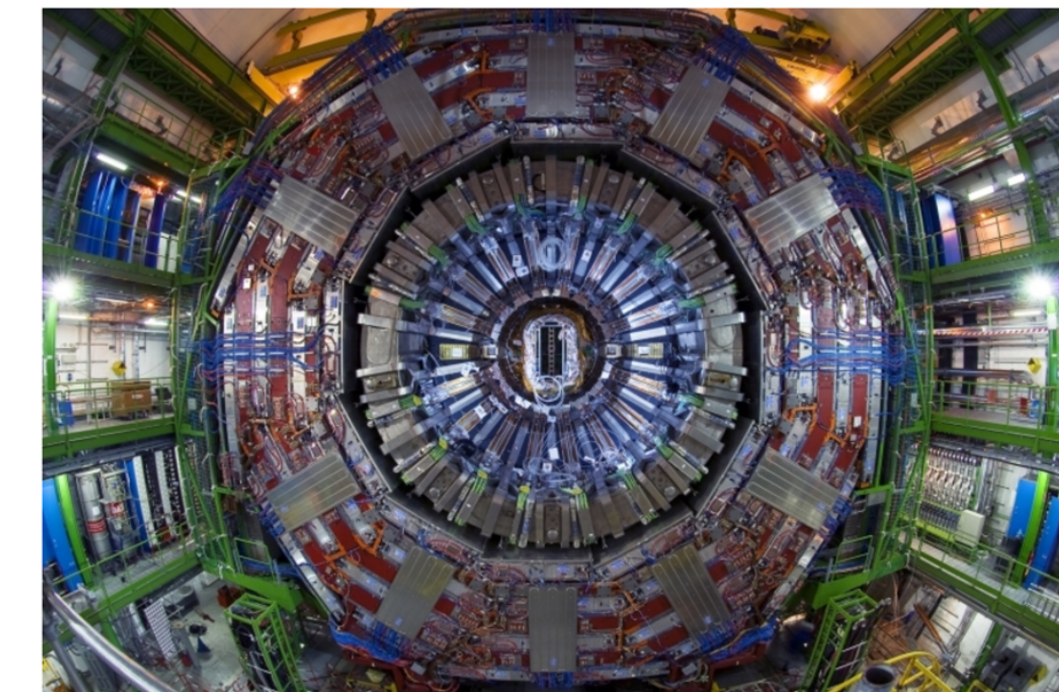
In many ways we've always had a foundation model for general purpose experiments..

Some more detail here: [\[Slides\]](#)

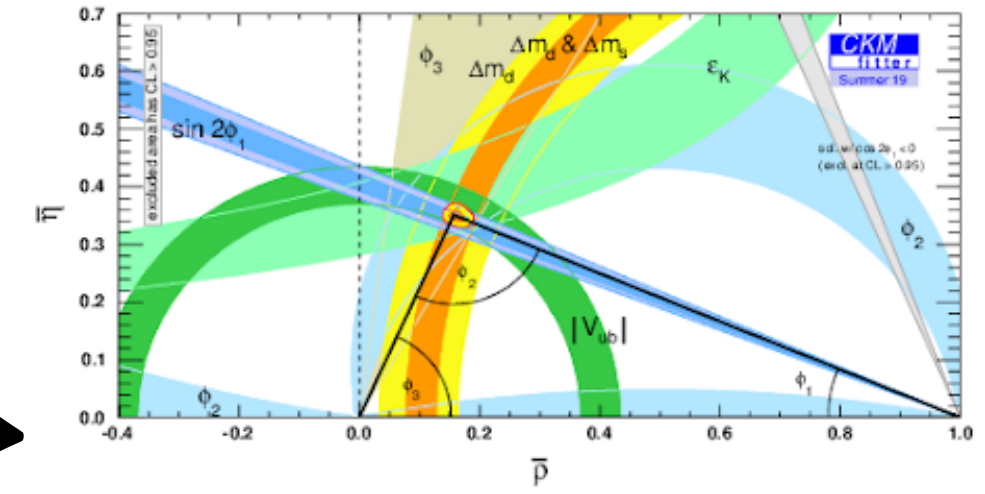
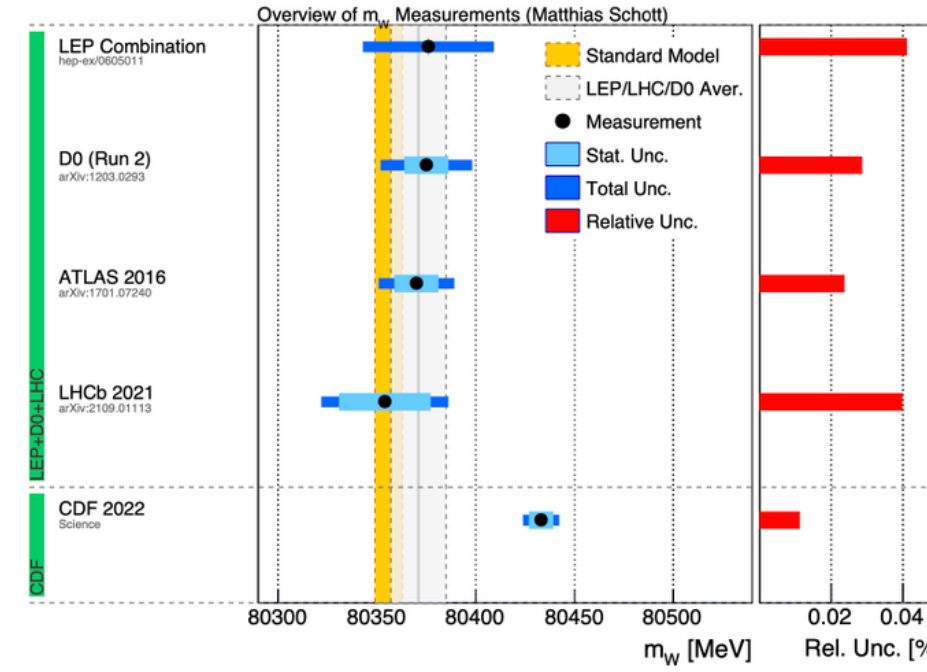
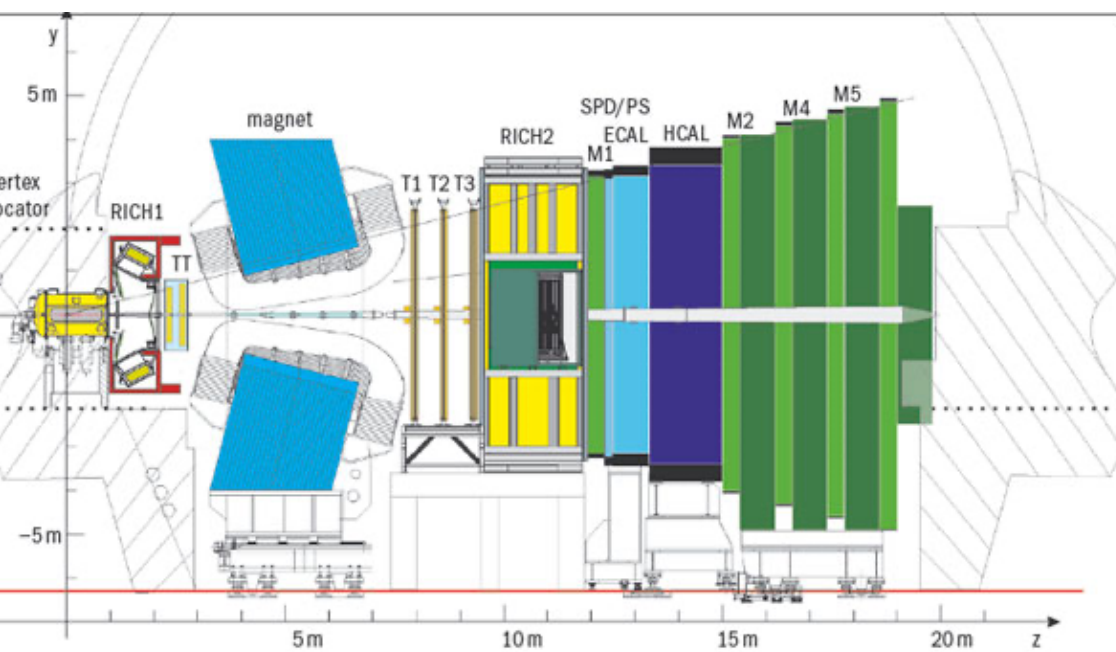
ATLAS



CMS

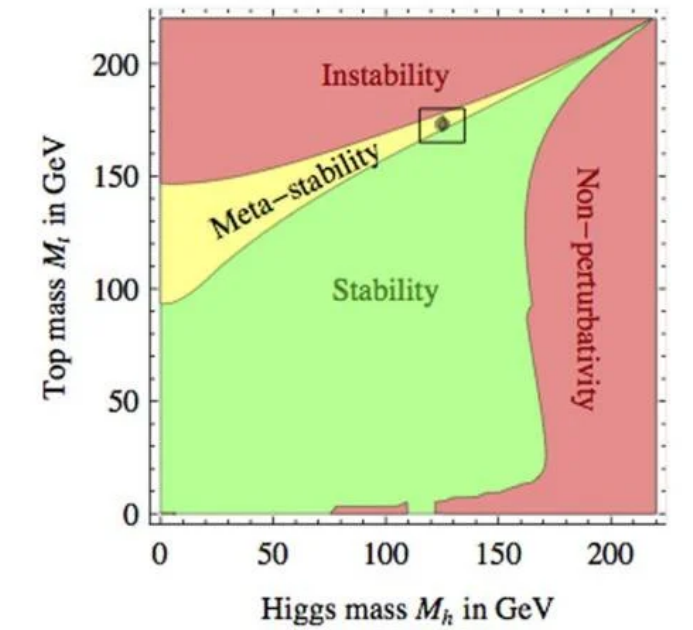
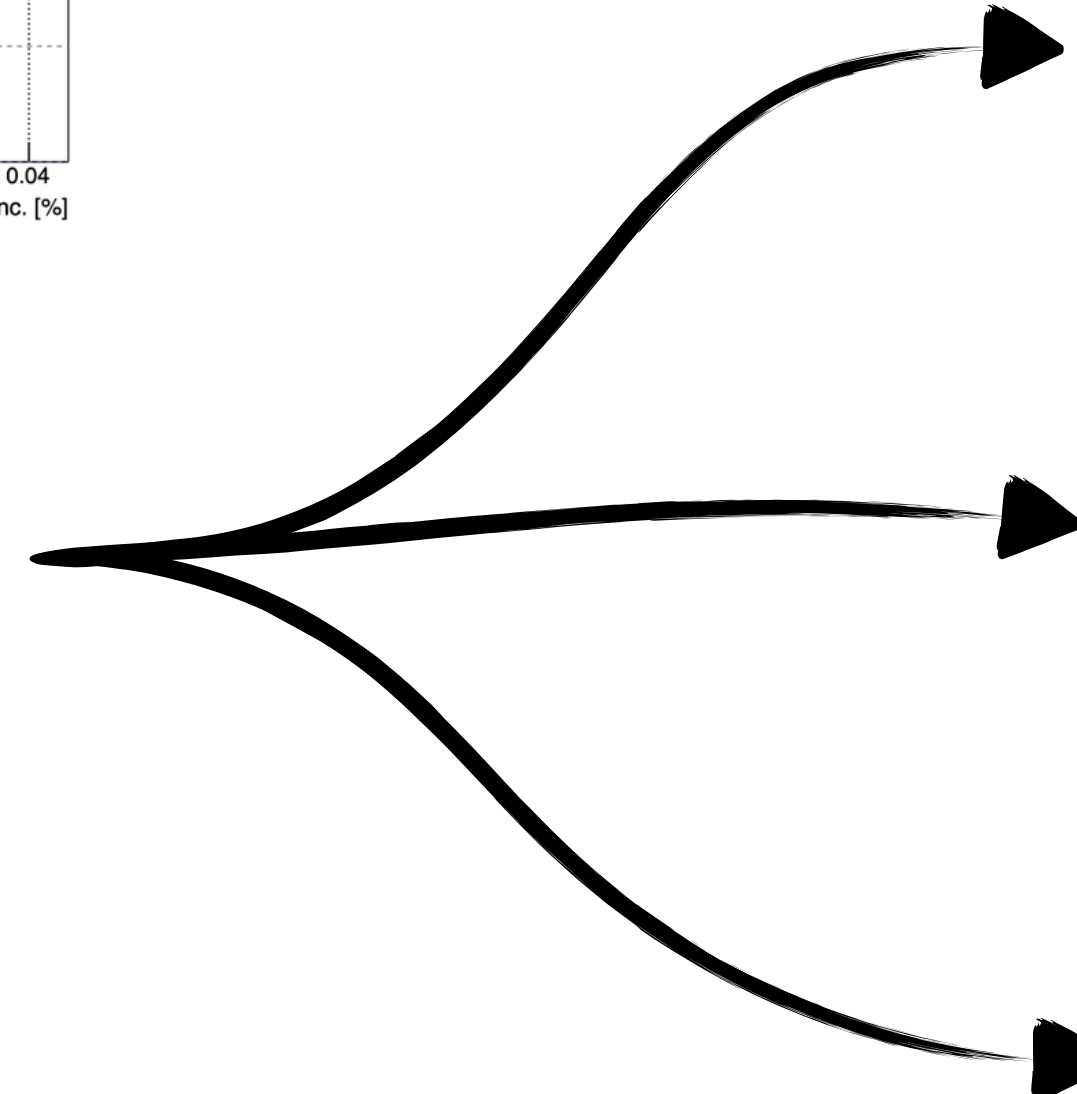


LHCb



Analysis

Particle Theory



Theory is the “joint emedding” space in which we compare different experiments..

What do we mean by Foundation Models

Just a common backbone?

Does it have to trained unsupervised?

How portable should it be?

Fixed Inputs vs open-ended data streams?

Does it have to relate to language models ?

Lots of existing questions. We'll see where it takes us.

What do we mean by Foundation Models

This is not to say we shouldn't work on *new, neural Foundation Models of the current kind* !

The opposite! we see that **the way we've always worked is very much aligned with these new technologies**

→ a lot of opportunities ahead

→ a bit of care needed to make it mean something and not just the buzzword du jour

Outlook

ACAT always a great opportunity to catch up with latest developments in the field and see a glimpse of the future

Thanks to all the speakers for the great talks and discussion!