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REAL-TIME ANALYSIS FOR SCIENCE AND INDUSTRY

ESR12: Accelerated Anomaly Detection

Pratik Jawahar

Supervisors:
Caterina Doglioni, Jiri Masik, Alex Oh, Maurizio Pierini

Overview:

- Heterogenous Tracking
- AD for DQM
- Knowledge is Overrated - Fast Inference
- Other Activities

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Qualification Task: Heterogenous Track Reconstruction

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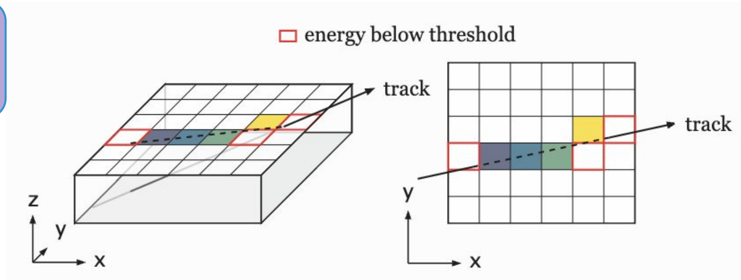
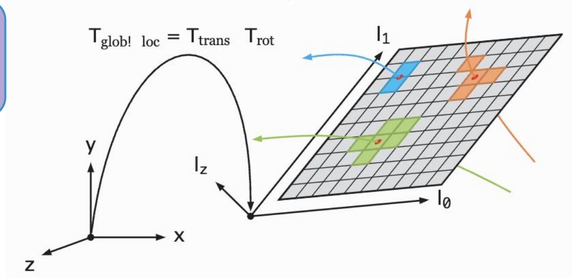
Track Reconstruction

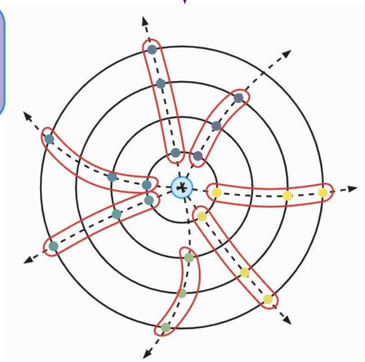
Clusterization



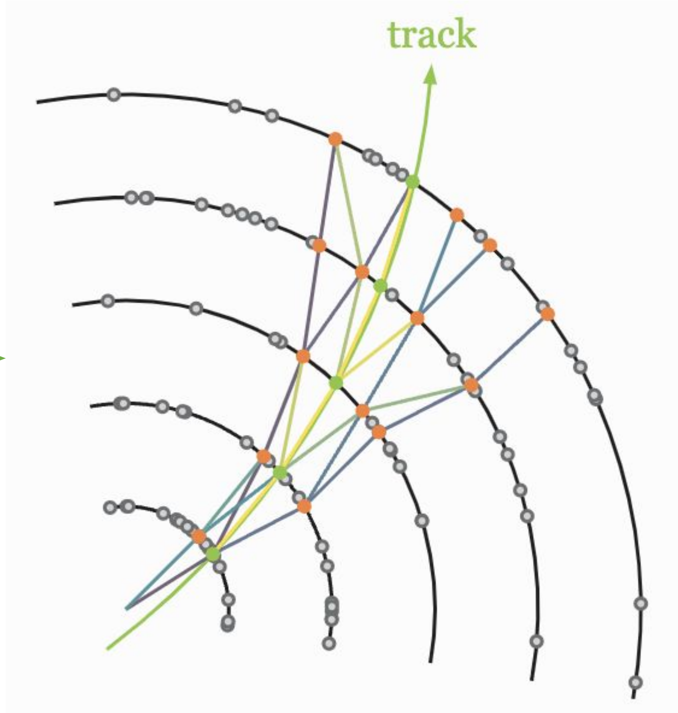
Spacepoints



Seeding



Track Finding



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SMARTHEP Problem(s)!

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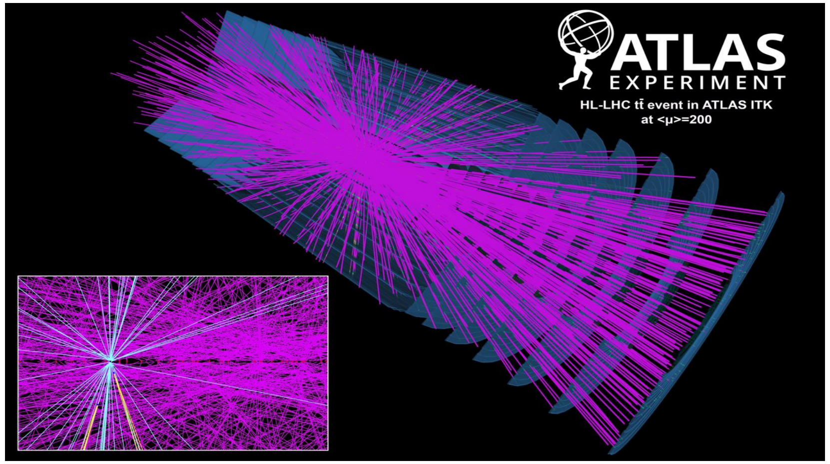
- No. of tracks per event for HL-LHC, expected to increase 2.5x
- Current R&D: Use GPUs for speedup via parallel computation
- However, sequential algorithms like CKF do much better on CPUs than GPUs!
- Heterogenous track reco? (CPU-GPU)



acts

traccc

Demonstrator tracking chain for accelerators.

Computing term for specific purpose architectures (eg. GPU, TPU, IPU etc.)

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Heterogenous Track Reconstruction:

- Step 1: Profiling CPU and GPU code to identify run-time speed-up
    - Ideally without drop in tracking efficiency
- Step 2: Identify bottlenecks
    - Points where one architecture outperforms the other
- Step 3: Calculate data-transfer latencies at bottlenecks
    - Data transfer latencies between host (CPU) and device (GPU) eat up speed-up

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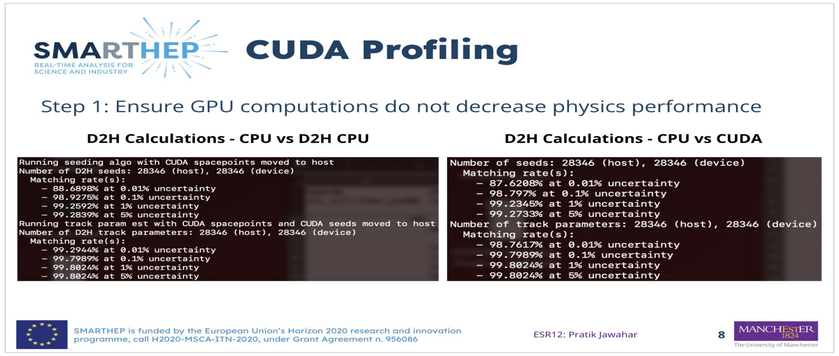
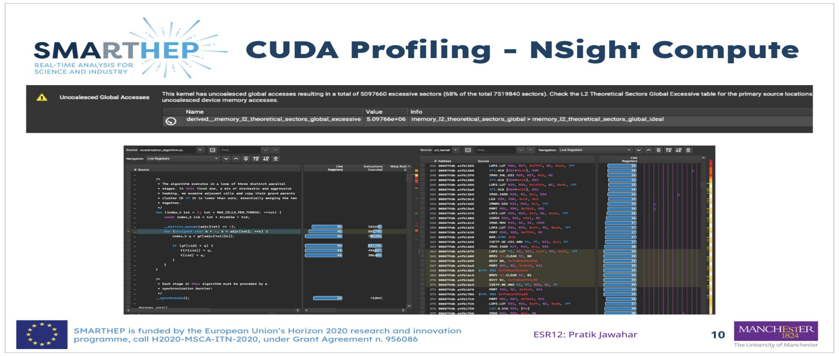
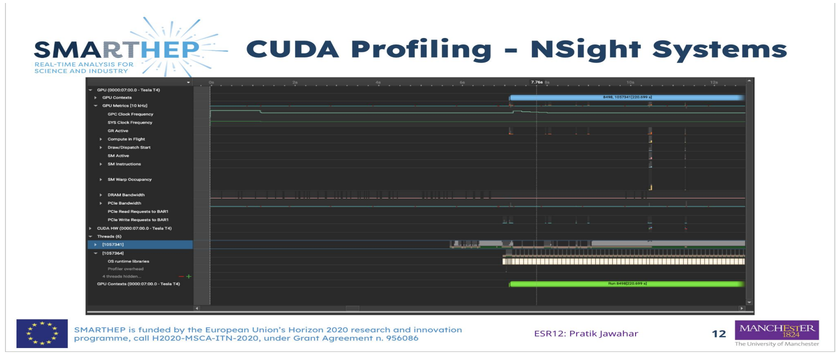
CUDA Profiling (MetaInfo ♞)







CUDA Profiling - TRACCC (mu200)

- POC feasibility example:
  - Clusterization, Spacepoint formation, Seeding are significantly faster on Device
  - Considering Host-Device and Device-Host wall-time overheads,
    - there is still a speedup of ~5800 msec until the seeding step of the chain

Data File	Detector Geometry	No. of Events
tml_full/ttbar_mu200	tml_detector/trackml-detector	10

CPU				GPU		
	Parent process	Duration/ Event [mu-sec]			Parent process	Duration/ Event [mu-sec]
	Container Instantiation	13			Container Instantiation	4
	File reading	3,825,015			File reading	NA
	Clusterization	118,703			Clusterization	NA
	Spacepoint Formation	22,413			Spacepoint Formation	NA
	Clusterization + Spacepoints	141,116			Clusterization + Spacepoints	3,832
	Seeding	5,715,996			Seeding	16,365
	Track param est	32,824			Track param est	365

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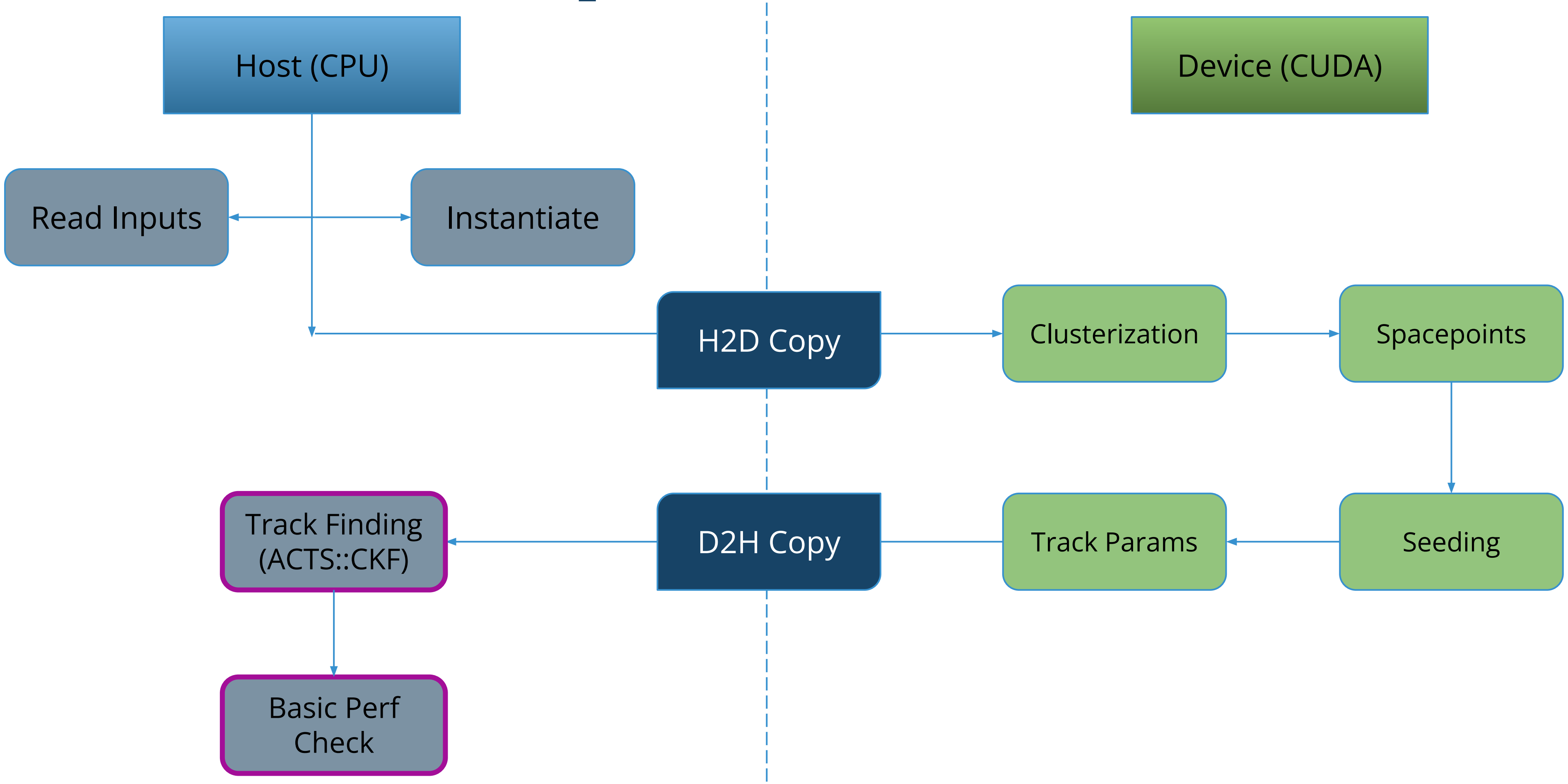
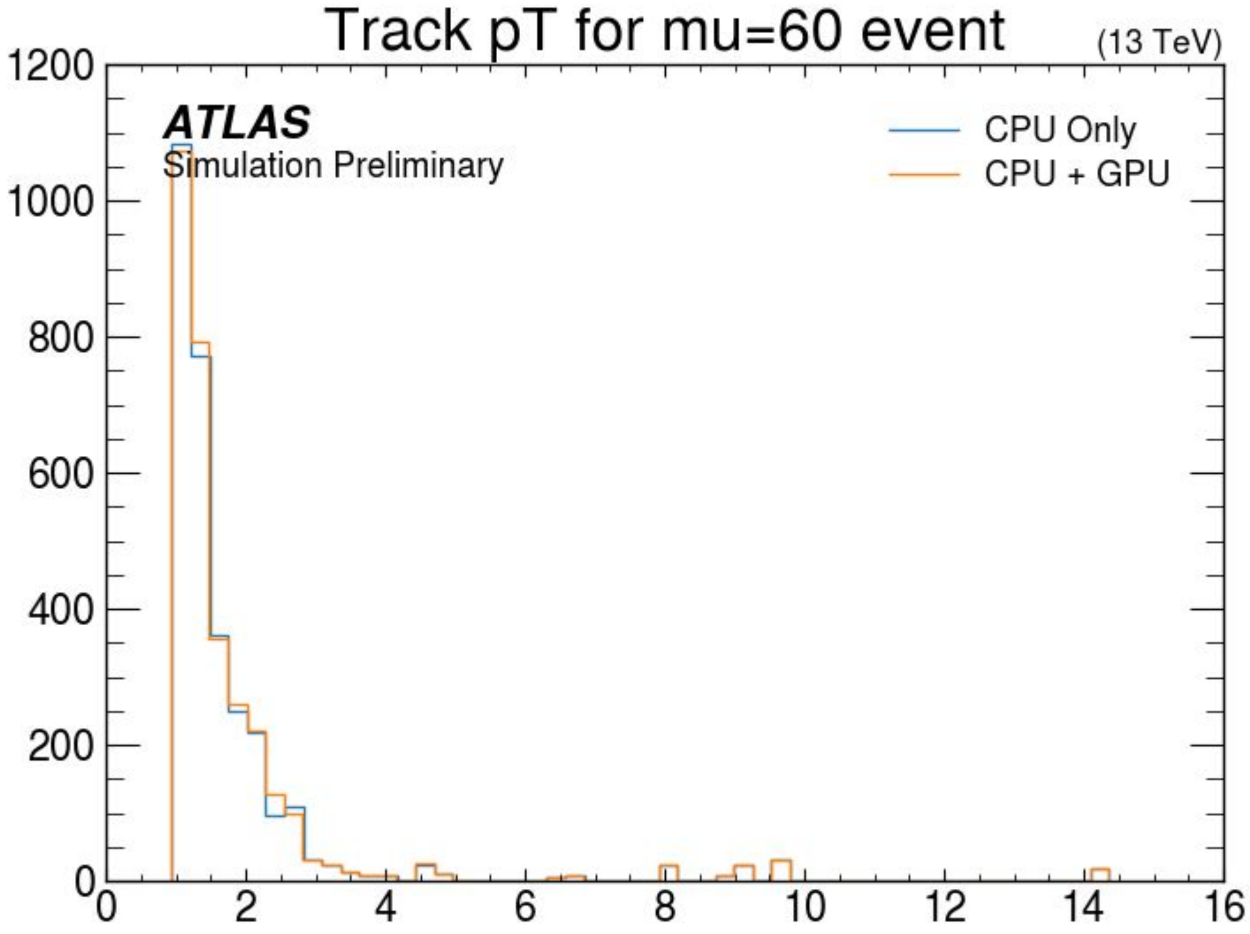
TRACCC + ACTS POC Example



POC Track Quality

- Compare POC tracks with tracks produced by ACTS for
  - same detector geometry
  - similar config options
- Plot shows track pT distributions after the track finding step before resolving ambiguities for 1 event
- Distributions checked for 10 example events
  - Distributions roughly correspond
    - POC example produces comparable tracks before ambiguity resolution
- Possible reasons for differences:
  - ACTS methods and TRACCC Device methods do not have 1-1 correspondence
    - Measurements, Seeds, Params are slightly different between the two
  - Minor differences in Config option setups b/w ACTS and TRACCC



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Wall Time Values for POC (mu200)

- POC example runs via a single executable
  - Easier to profile
- ACTS::TrackFinding is the most compute intensive step as expected
- TRACCC::TrackFinding on Device is faster BUT this result is not for the same event or detector geometry
  - TRACCC::TrackFinding measurement comes from a toy example
  - Only meant as a ball-park (placeholder) comparison until TRACCC has a full chain implementation

Data File	Detector Geometry	No. of Events
tml_full/ttbar_mu200	tml_detector/trackml-detector	10

CPU			GPU	
	Parent process	Duration/Event [mu-sec]		Duration/Event [mu-sec]
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	Clusterization + Spacepoints	141,116		3,832
	Seeding	5,715,996		16,365
	Track param est	32,824		365
	ACTS::TrackFinding (CKF)	13,501,182		
	TRACCC::TrackFinding (CKF)			NA

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Conclusions

- Profiling tools can provide a lot of useful metrics - Tools are consistently improving
- Apples-Apples comparison of performance of this work requires a corresponding TRACCC::TrackFinding implementation within the full chain example
  - Caveat: ACTS and TRACCC are not 1-1 replicas for Host nor Device implementations
- Case:
  - TrackFinding on Device is slower: A heterogeneous solution could be considered
    - With performance opitmizations
    - Better build integration between TRACCC-ACTS as opposed to brute-forcing the build
  - TrackFinding on Device is faster: The heterogeneous solution could still provide flexibility downstream in terms of net throughput optimization
- Overall, track reconstruction on Device is promising. Heterogeneous operation is a potential solution to consider for further development

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Anomaly Detection for Data Quality Monitoring

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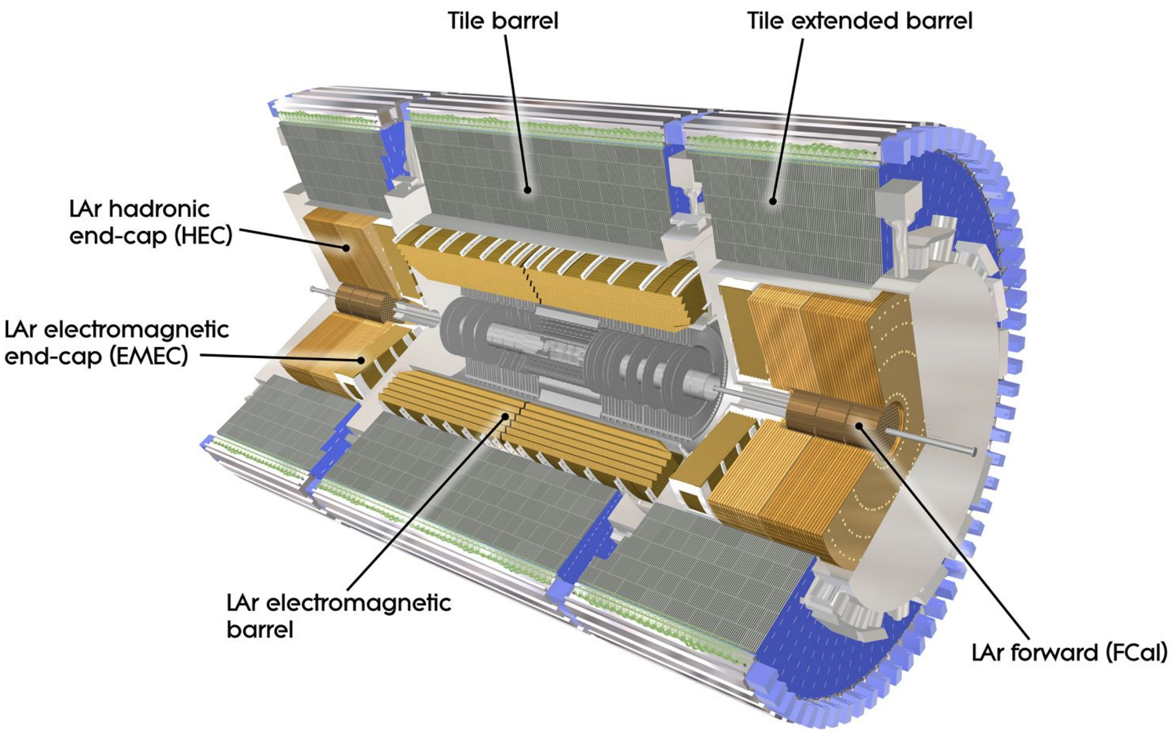
Liquid Argon (LAr) Calorimeter

- Particles passing through the LAr create electromagnetic showers, inducing ionization in the liquid argon, which is collected by electrodes under high voltage
- Structure:
  - Divided into four main sections:
    - Electromagnetic Barrel **(EMB)**: Covers $|\eta| < 1.5$.
    - Electromagnetic Endcap Calorimeters **(EMEC)**: Covers $1.4 < |\eta| < 3.2$.
    - Hadronic Endcap Calorimeter **(HEC)**: Covers $1.5 < |\eta| < 3.2$ and uses copper as passive material.
    - Forward Calorimeter **(FCal)**: Covers the high pseudorapidity region ($3.1 < |\eta| < 4.9$), using copper and tungsten.



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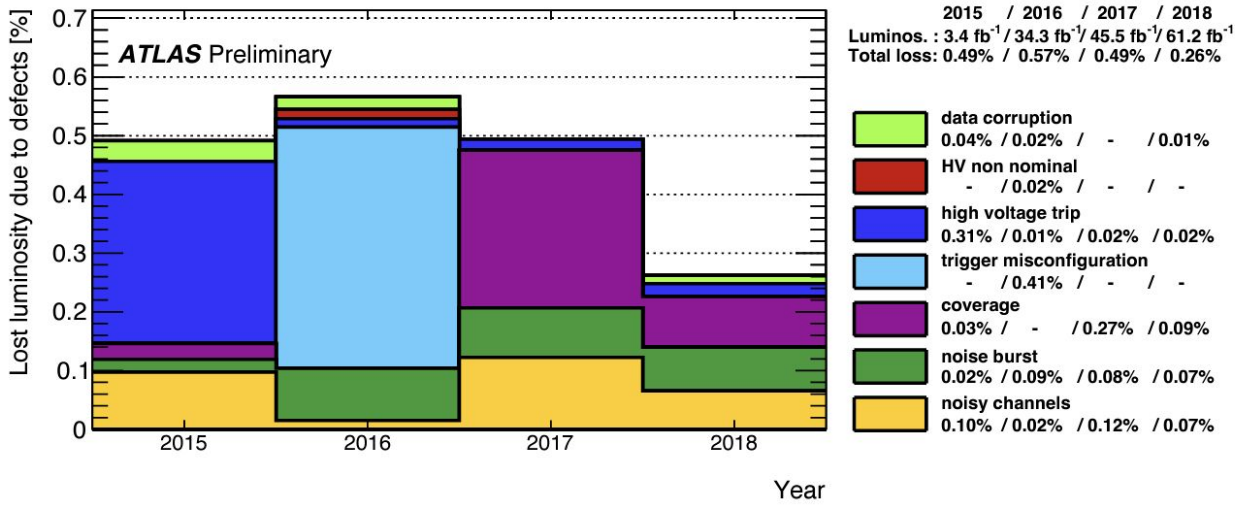
LAr Data Quality Issues

- High Voltage (HV) Trips:
  - Sudden voltage drops, affecting signal collection.
- Data Corruption:
  - Desynchronization errors between FEB and clocks.
- Noisy Channels:
  - Identified during calibration, corrected using neighboring cells.
- Noise Bursts:
  - Correlated with luminosity, detected using LArNoisyRO algorithm.
- Trigger and Coverage Misconfigurations:
  - Misconfigurations leading to reduced data quality.



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LAr Data Quality Issues

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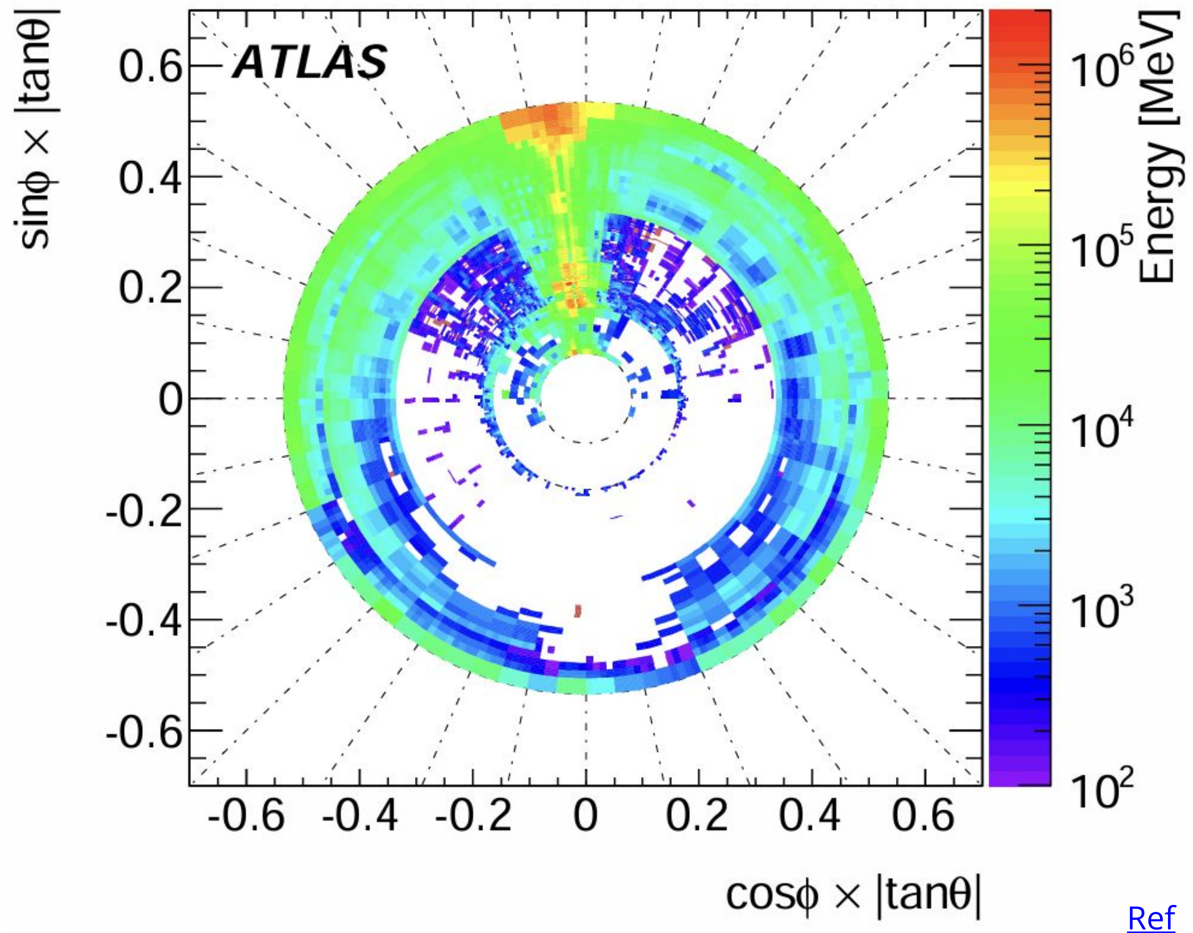
- **Noise Bursts:**
  - Correlated with luminosity, detected using LArNoisyRO algorithm.
- Trigger and Coverage Misconfigurations:
  - Misconfigurations leading to reduced data quality.
- However, there could be other unlabelled detector effects that affect the LArs



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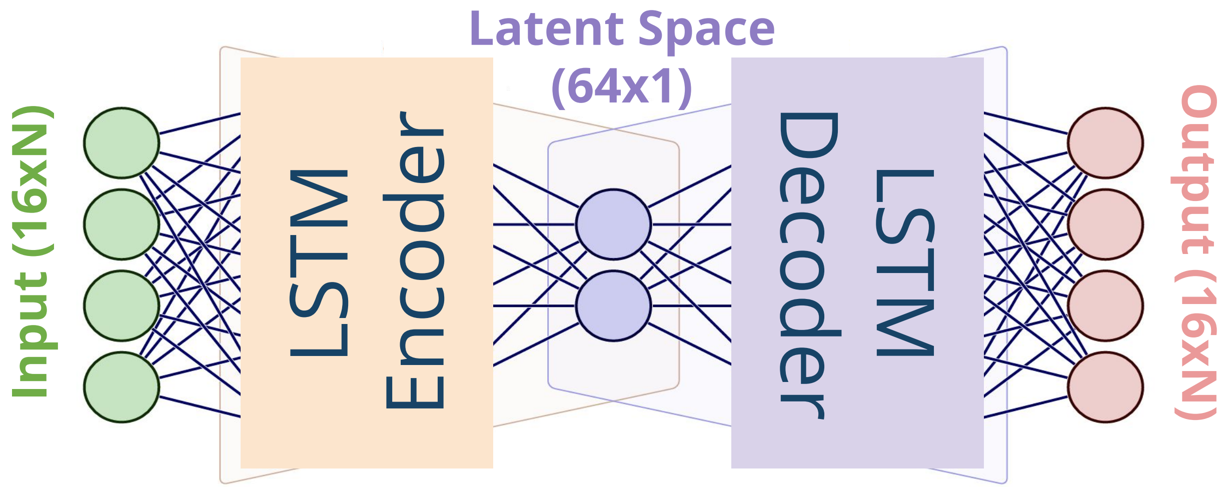
Unsupervised AD

- A single algorithm sensitive to all known and unknown LAr issues
- Events do not need to be tagged in most cases since they are usually discarded if any DQM check is not met
- Autoencoder approach:
  - Train on "good" events
    - LumiBlocks with no known flagged issues
  - During inference, detector issues result in high reconstruction loss
    - MSE between AE input and output
- Current setup uses LSTM networks in the encoder and decoder
  - Enables time-series feature extraction



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Input Data

- Source of Input Data:
  - The data comes from topocluster moments, which are aggregated features of clusters of calorimeter cells.
  - The two primary topocluster properties used are:
    - Q-factor: Indicates how well the signal pulse shape matches the expected ideal shape.
    - Timing (τ): Refers to the timing of the signal relative to the event, helping detect out-of-time signals or anomalies.
  - For each of these properties, we consider the mean and std. dev as the AE inputs
- Two regions considered for both Barrel and End Cap resp.:
  - Barrel C: $-1.5 \leq \eta \leq 0$
  - Barrel A: $0 < \eta \leq 1.5$
  - Endcap C: $-3.2 \leq \eta < -1.5$
  - Endcap A: $1.5 < \eta \leq 3.2$
- As a result each input point to the AE is 16 dimensional considering p-p collisions

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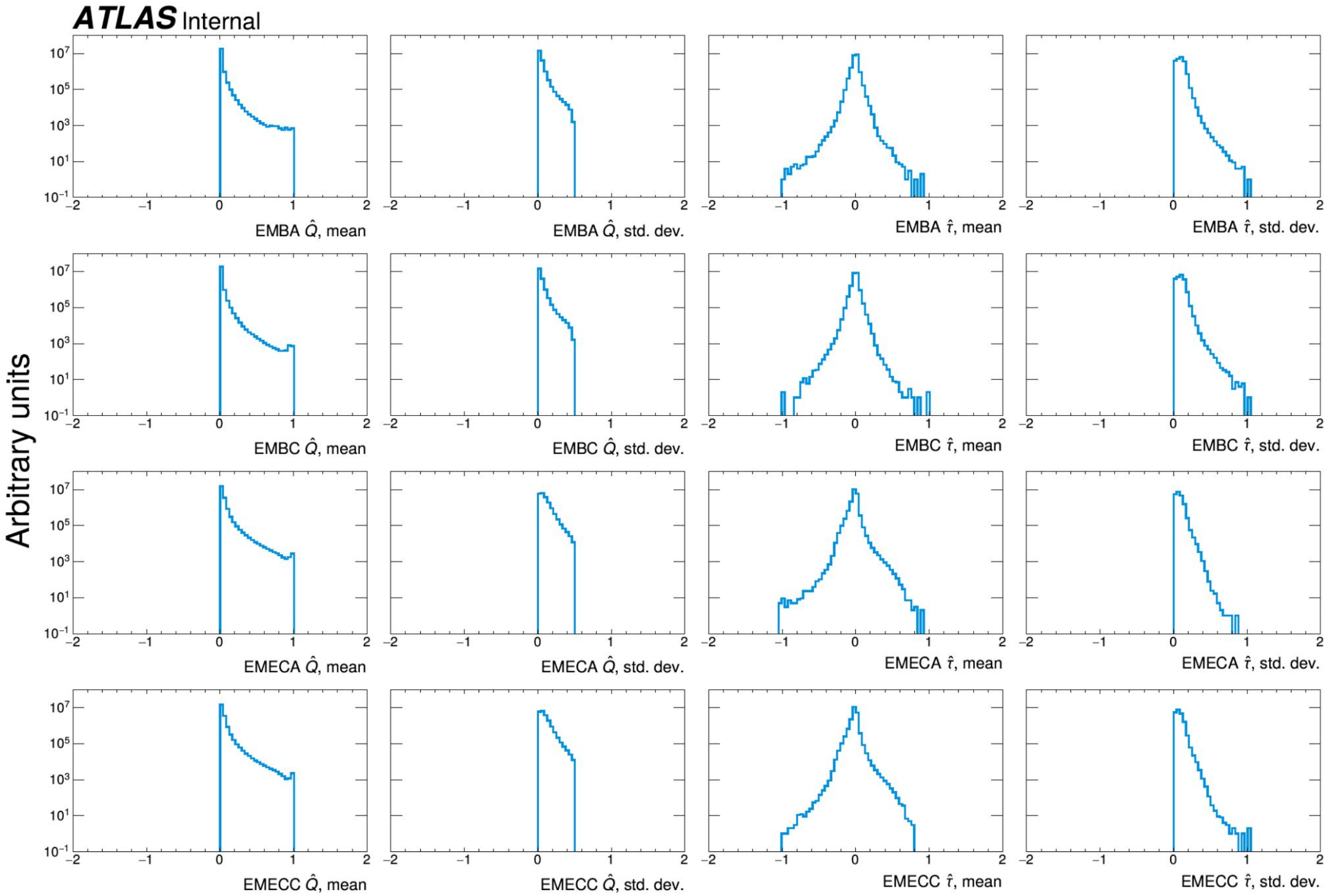

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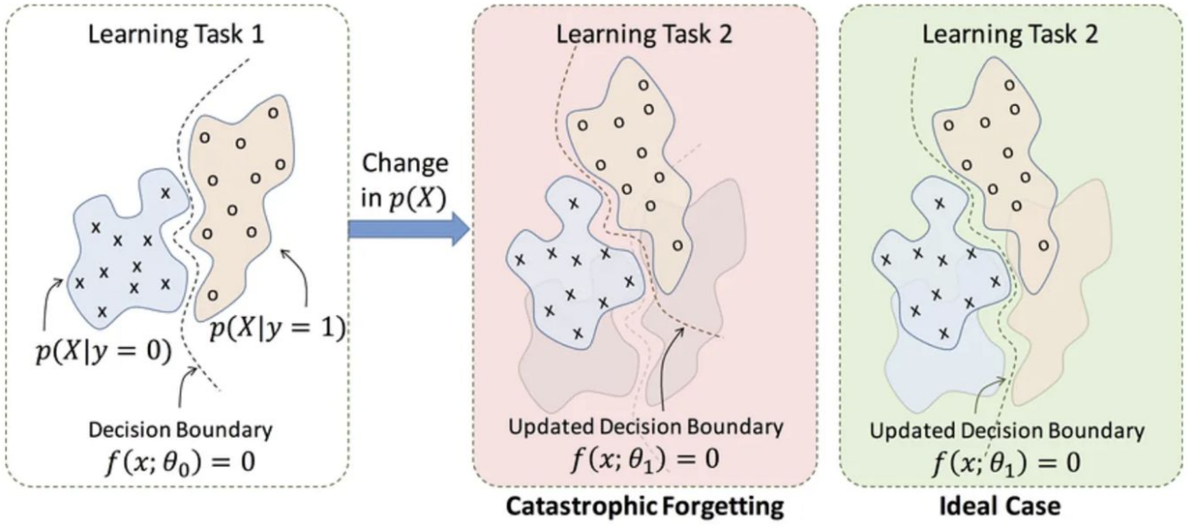
Problems with LSTMs

- LSTMs are known to suffer from the catastrophic forgetting phenomenon
  - Evident when network trained on p-p collisions is then trained on Heavy Ion data
    - Fixed by small tweak in the code disconnecting mem gates for both tasks
- Sequence length suitable for LSTM-AE is considerably small
- LSTMs are also very memory heavy
  - Intermediate contexts need to be stored for backprop.
- LSTMs are hard to parallelize



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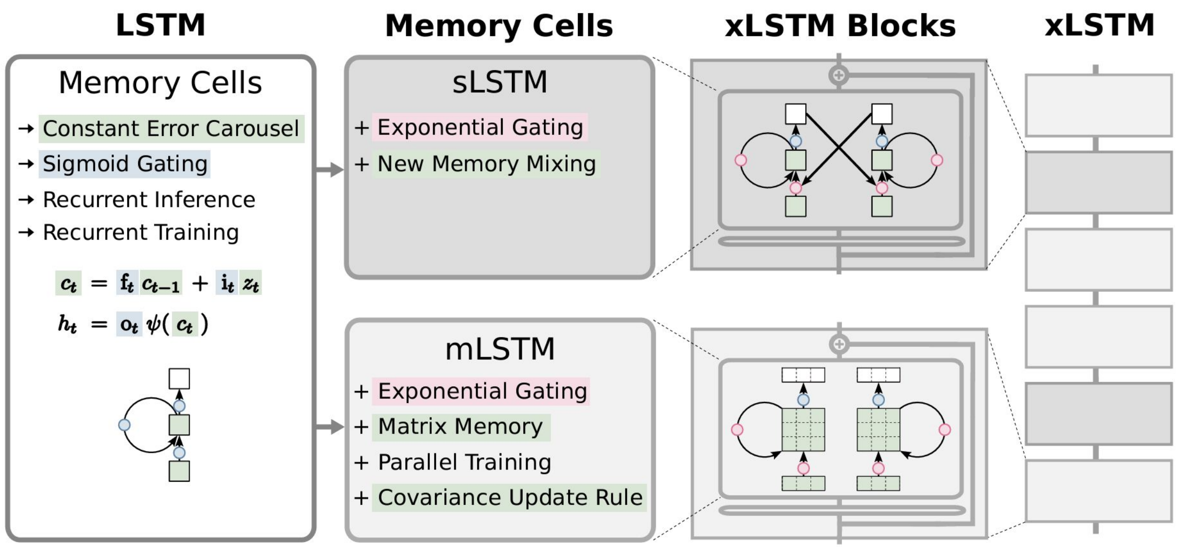
xLSTM

- Motivation: solves catastrophic forgetting
  - Specialized memory handling
- Produces richer hidden representations of much longer sequences
  - More sensitive to harder to find detector issues
- Still memory intensive and non-parallelizable
  - Train a student network to predict xLSTM loss
  - Accuracy gained over the baseline LSTM is traded off in the student network for speed
- Current status: xLSTM implementation and code testing done
  - Repeat tests using same dataset
  - Merge events from dataset to form larger input sequences and compare LSTM-xLSTM



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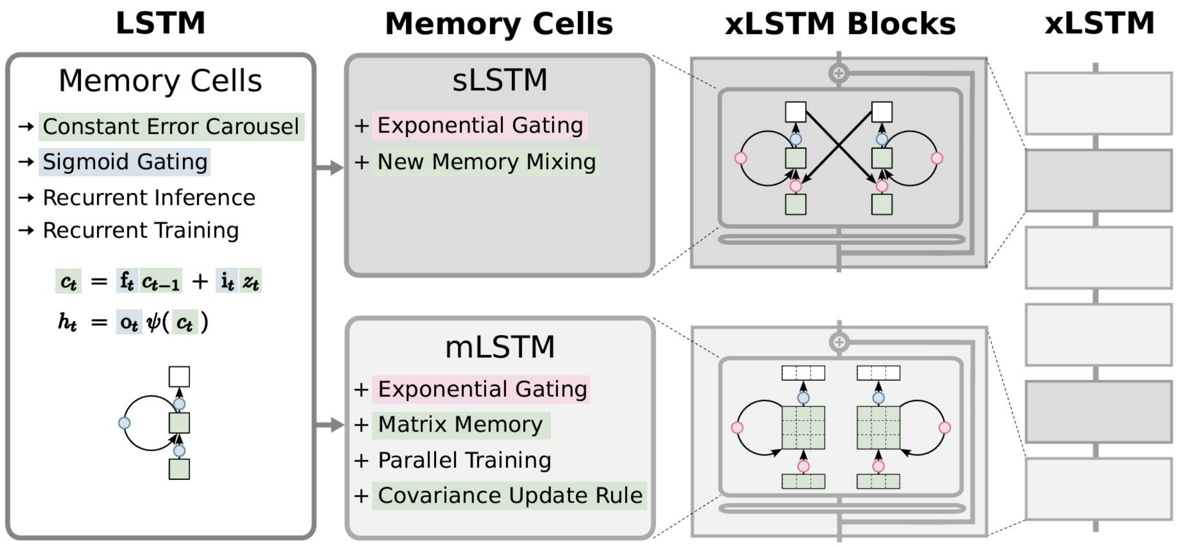
xLSTM

- xLSTM is a better 1-1 comparison to attention based models such as transformers
  - (potentially what Laura might look at with the same dataset)
- Better memory management
  - The architecture of XLSTM allows it to allocate memory more effectively, improving performance on tasks that require long-term sequence retention.
  - It can selectively forget less useful information while preserving key details for future use.
- However xLSTM inference is much more compute intensive than LSTM
  - KD is essential!



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Secondment: Knowledge is Overrated

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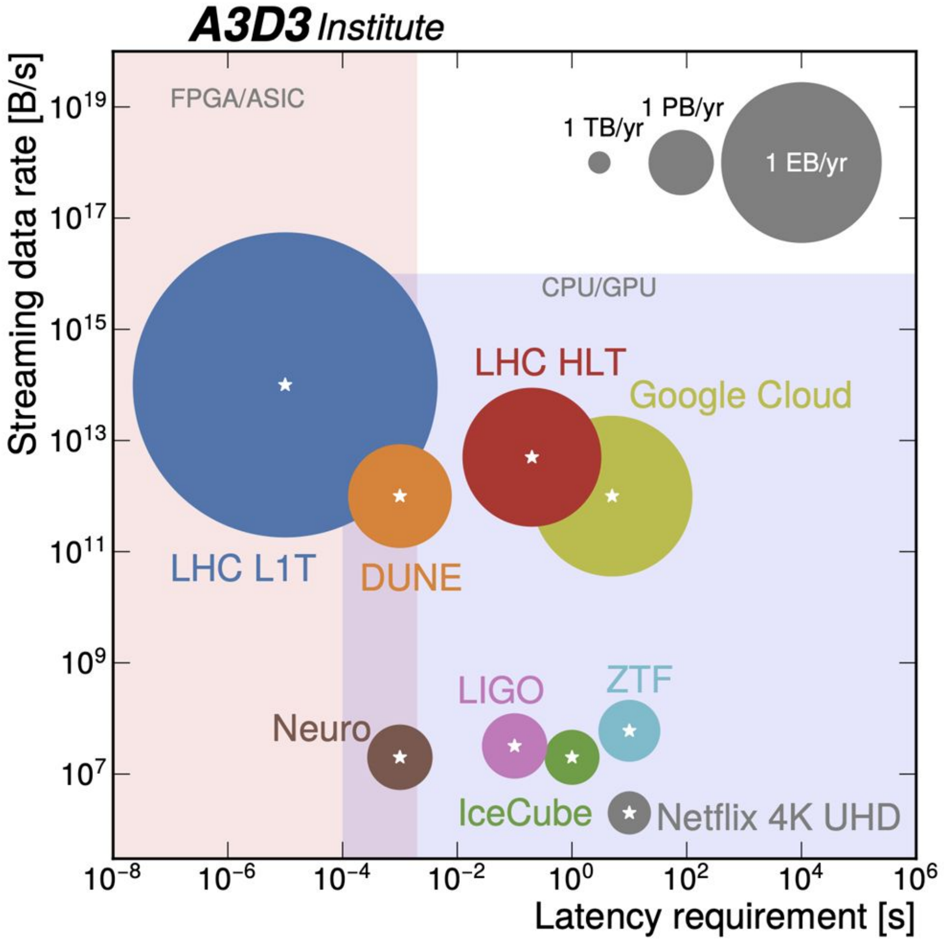
Fast Inference (EdgeML '24)

- High demand in HEP and many other fields for:
  - Fast execution of algorithms
    - Low latency
    - Low compute
    - Low power
    - Low memory
- Ideally without losing performance on the task
- Something that wasn't spoken about in much detail:
  - Fast yet **SUSTAINABLE!**
    - Low power IS fast (FastML '23)



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Fast ML Inference (EdgeML '24)

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- Use specialized hardware
  - GPUs
  - FPGAs
    - Requires special model management driven by hardware specs
      - Pruning
      - Quantization
  - ASICs
  - NPUs
- Knowledge Distillation
  - A large network is trained on the required task
  - A much smaller network is trained to predict the loss of the larger one
  - Only the smaller network is deployed on the Edge device

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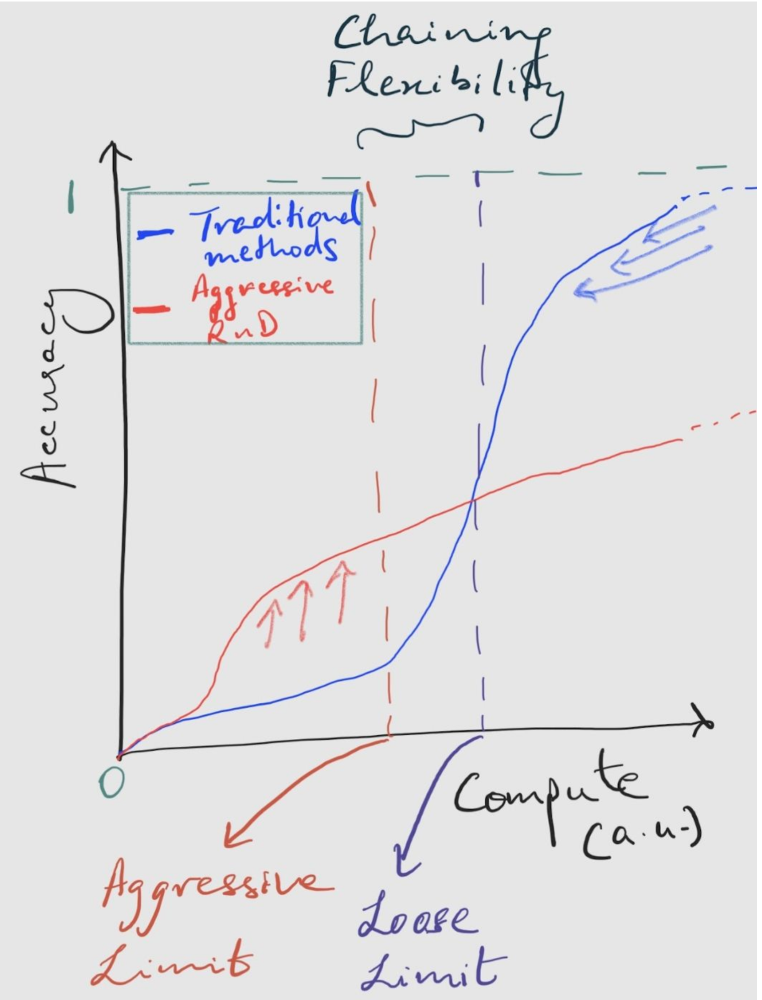
What if…

- We could distill a larger network like in KD but regress to:
  - An arbitrary metric as opposed to loss of a complicated network (loss landscapes can be extremely complex high-dimensional manifolds themselves)
    - Would enable significantly larger inference-size reduction
  - While being:
    - Verifiable
    - Scalable
- Trade off some more performance for… speeeeeed
  - Quantize not just weights but also inputs
- The pareto line still lies at the {accuracy lost - speedup line}
  - But now instead of
    - pushing the line down with resistance from accuracy loss
  - We are:
    - pushing the line up with resistance from loss in speedup



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Project Title Proposals

- Project Status:
  - Built codebase with toy MNIST examples
  - Identified ways of calculating net amount of computations required for inference
    - Needs improving
  - Need to design tests using HEP data and tasks
- “Knowledge is overrated: Fast ML Inference”
  - Knowledge: richness of the learned prior
    - i.e. how descriptive the algo is
      - NNs are designed to give as rich prior approximations as possible
  - Over {Rated} : rate of compute
    - We don't want a high compute rate
  - So we are trading away knowledge for lower compute rates (high speed)
- “DUMBHEP ”
  - Trading away knowledge makes the algorithm inherently “dumb”

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Other Activities

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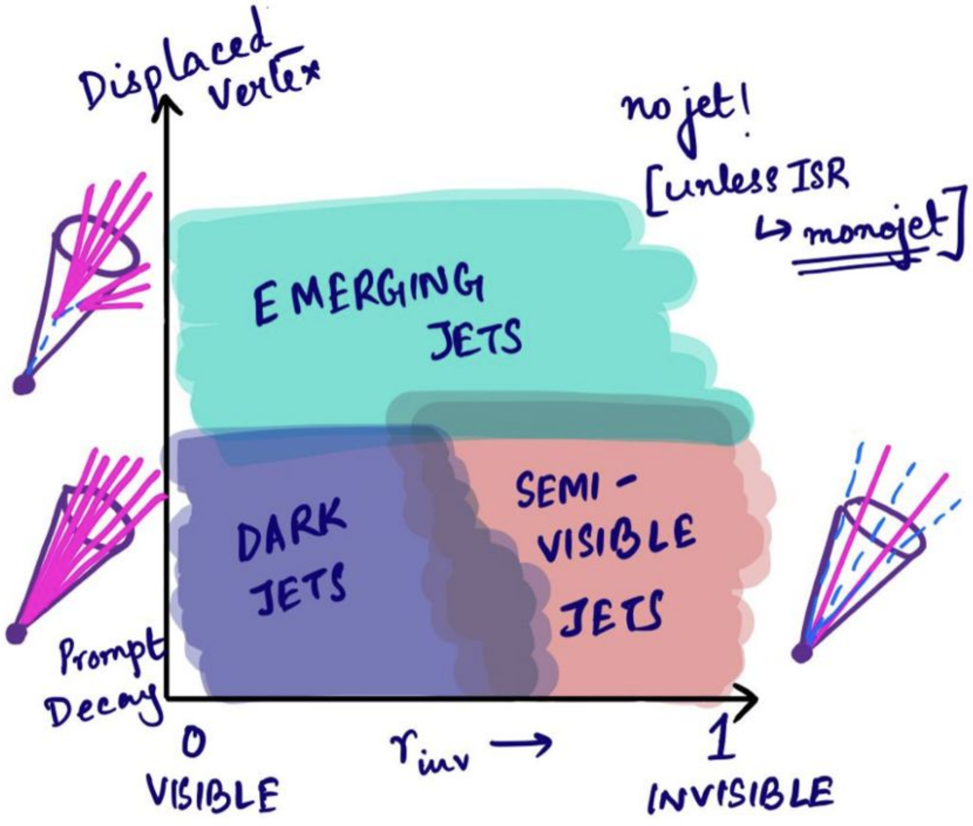
Quests

- Analysis: SVJ+leptons (potential DM signature)
  - Jets with MET aligned along jet axis
- Consulting for AD at the Trigger for new physics
  - VAE based approach inspired by AXOL1TL (CMS)
- Pheno project: AD using richer bkg representations by combining generator tunes



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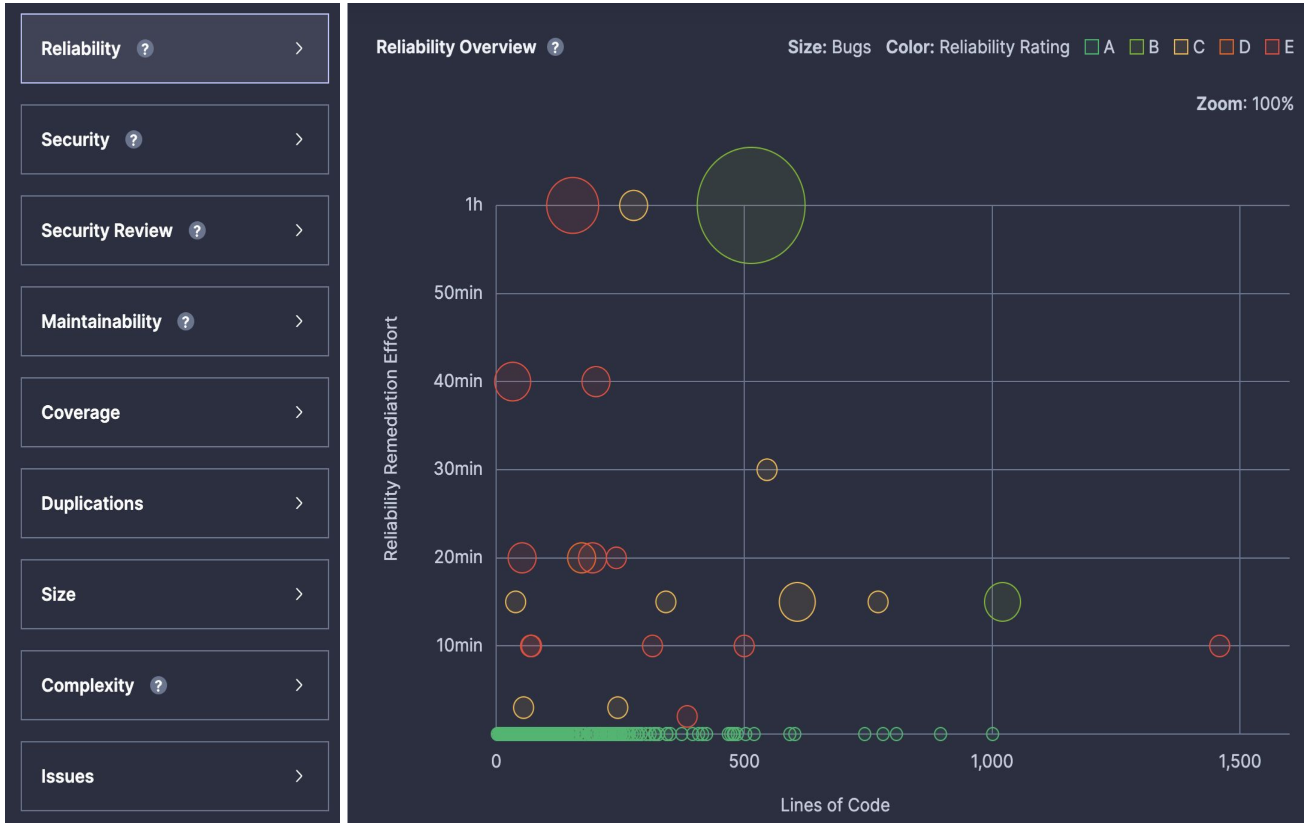
Side Quests

- EVERSE Project: Software sustainability
  - WP4 pilot (ACTS)
    - Used static analysers (SonarCloud) to extract code quality metrics
- Used static analysis to help identify code inefficiencies and reduce cyclomatic complexity in:
  - GAPS: GPU-Amplified Parton Showers
  - Project in UniMan theory Dept.



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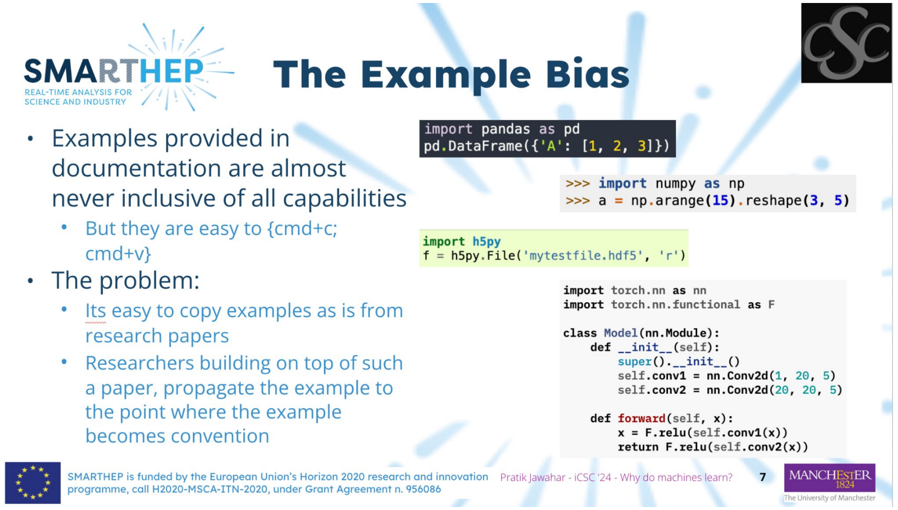
Side Quests

- Taught at the iCSC
  - A fundamentals of ML lecture titled “Why do Machines Learn”
    - Dealt with typical misconceptions at every step of a traditional ML pipeline
    - Introduced a partially new idea called example bias
      - Documentation biases people in the way they perceive code
    - Introduced fundamental theoretical ML research via
      - Geometric DL
      - Categorical DL
      - Search for a “Theory of Everything ML”
- Anthology (10/17) + EP (3/7)

58% 42%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The Example Bias

- Examples provided in documentation are almost never inclusive of all capabilities
  - But they are easy to {cmd+c; cmd+v}
- The problem:
  - Its easy to copy examples as is from research papers
  - Researchers building on top of such a paper, propagate the example to the point where the example becomes convention

```
import pandas as pd
pd.DataFrame({'A': [1, 2, 3]})
```

```
>>> import numpy as np
>>> a = np.arange(15).reshape(3, 5)
```

```
import h5py
f = h5py.File('mytestfile.hdf5', 'r')
```

```
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

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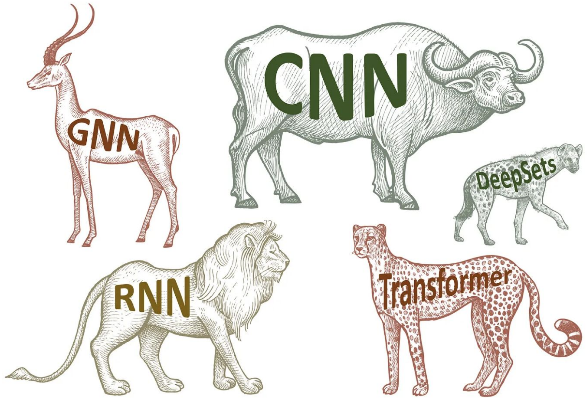

Deep learning today: a zoo of architectures, few unifying principles. Animal images: ShutterStock.

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Thank you!