Deep Learning Methods and Software for Reconstruction of The Elementary Particles’ Trajectories

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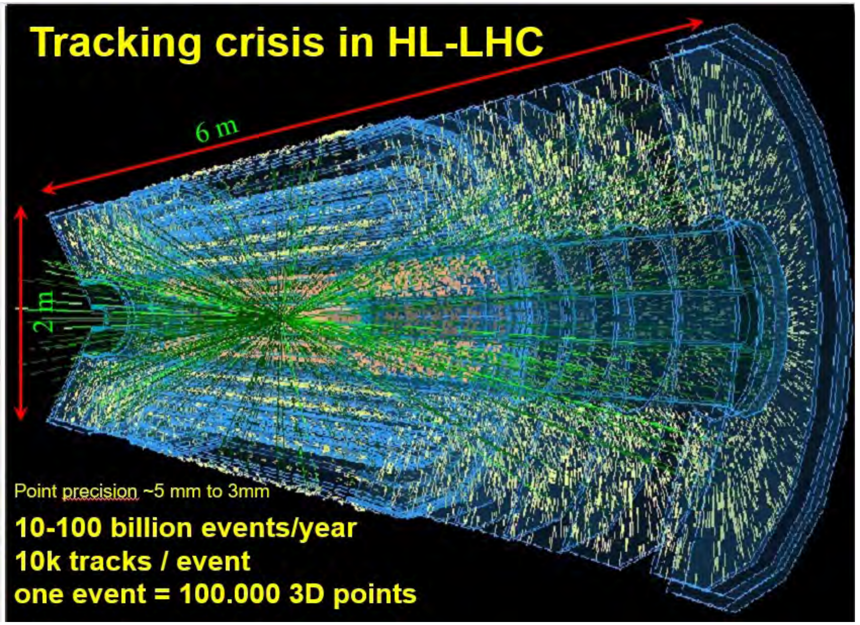
Deep neural networks to face the tracking crisis challenge

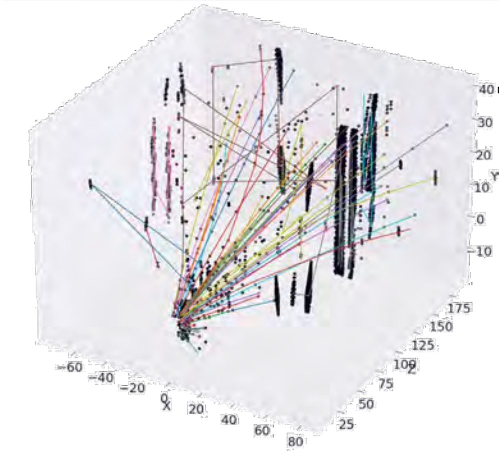
Motivation

- **Particle track reconstruction in dense environments such** as the Run-4 detectors of the High Luminosity Large Hadron Collider (HL-LHC) and of MPD NICA is a **challenging pattern recognition problem**.
- Current algorithms for tracking are highly performant physics-wise and scale badly computation-wise



Machine learning algorithms bring a lot of potential to the tracking problem, thanks to

- their capability to model complex non-linear data dependencies,
- learn effective representations of high-dimensional data through training
- parallelize easily on high-throughput architectures such as GPUs

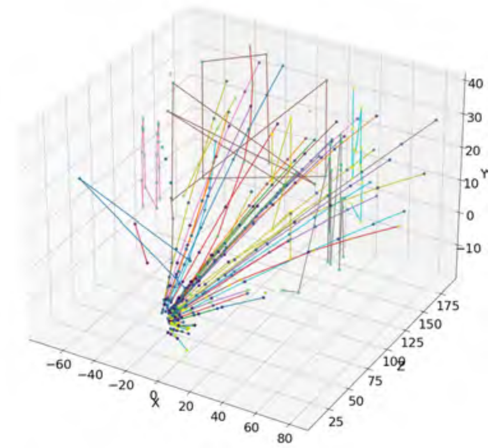


Neural network (online)

High recall, **low precision**
Very fast

Kalman filter (offline)

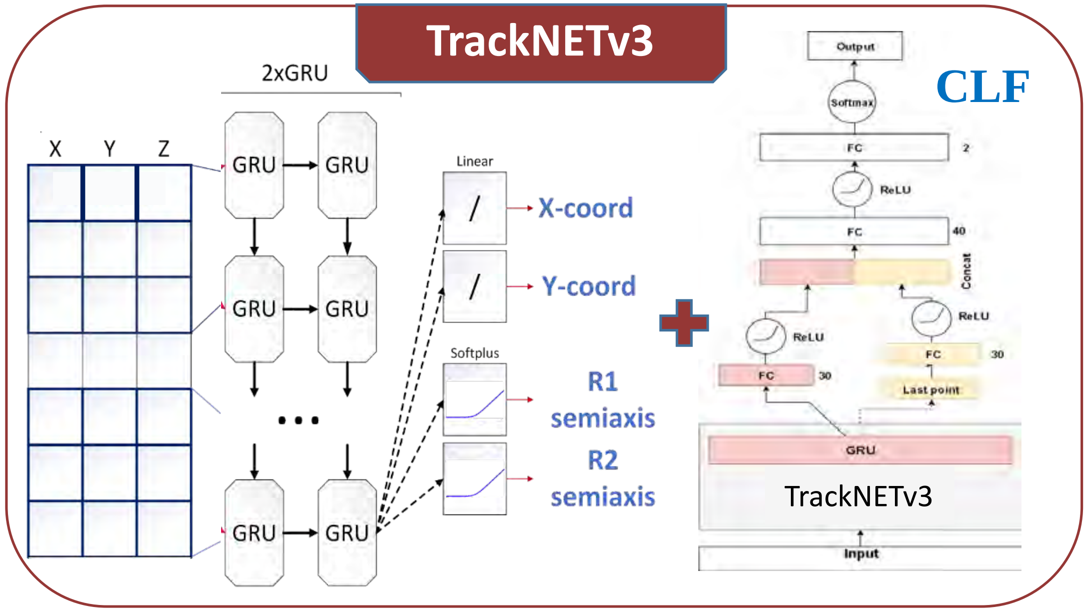
High recall,
high precision
Too slow



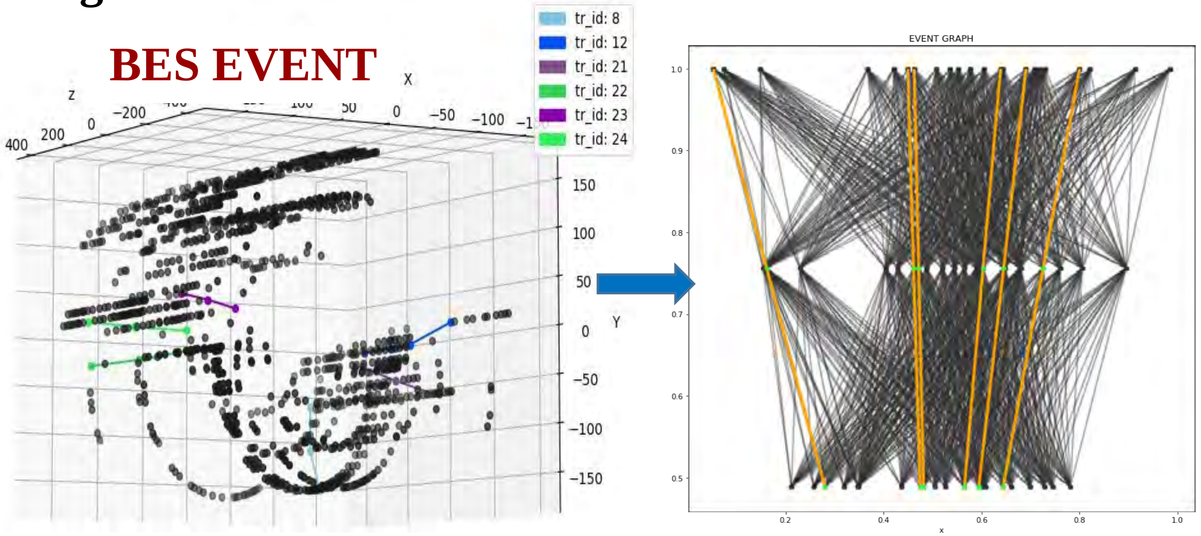
Reconstructed event

TrackNETv3 and RDGraphNet models for track reconstruction

TrackNETv3: a local approach that can be treated as **Kalman Filter “analogue”** powered by neural networks



RDGraphNet: a global approach, works with **event as a graph**. Hits are nodes and they are fully-connected between adjacent stations. The goal of the network is to **predict which edges are belong to true tracks.**

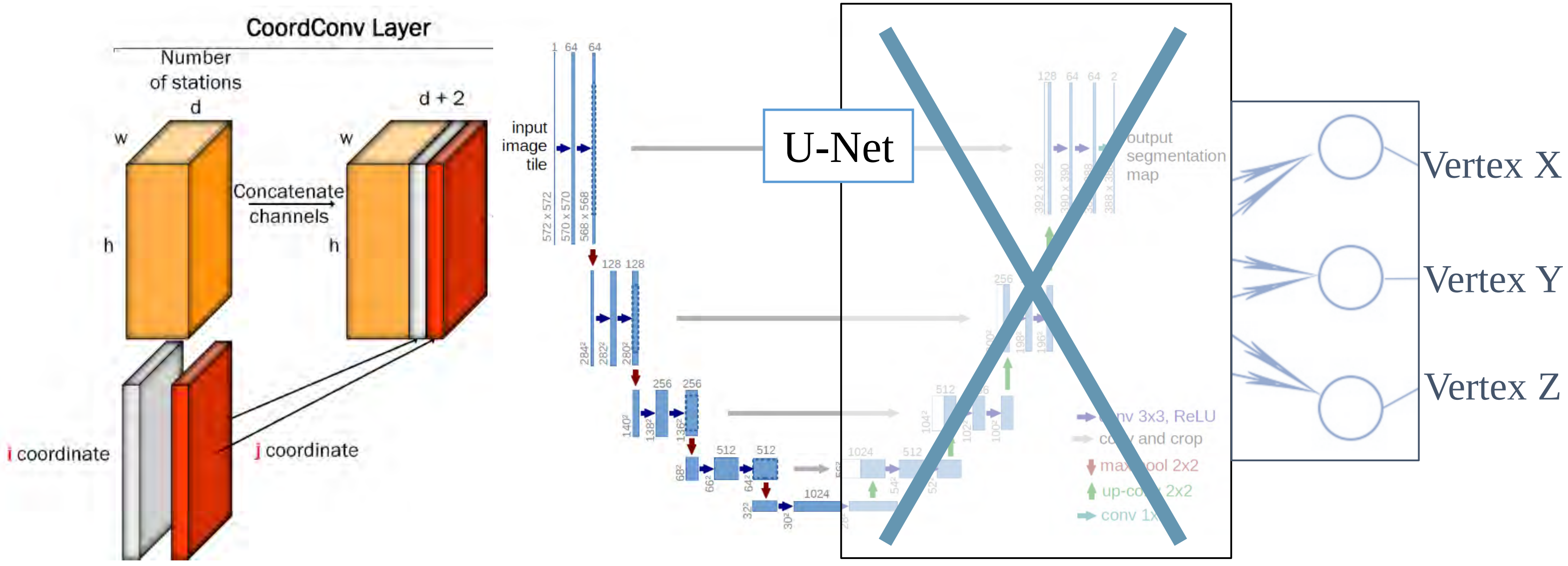


	BESIII Inner Tracker			BM@N RUN6		BM@N RUN7
	TrackNETv3	RDGraphNet	Kalman filter	TrackNETv2	RDGraphNet	TrackNETv3 (no clf)
Efficiency	0.9475	0.9548	0.9223	0.9593	0.87	0.9830
Ghost rate	0.2406	0.2596	0.0477	-	-	0.9791
Speed (events/sec)	74.17 (GPU)	283.70 (GPU)	0.2382 (CPU)			0.4545 (CPU)

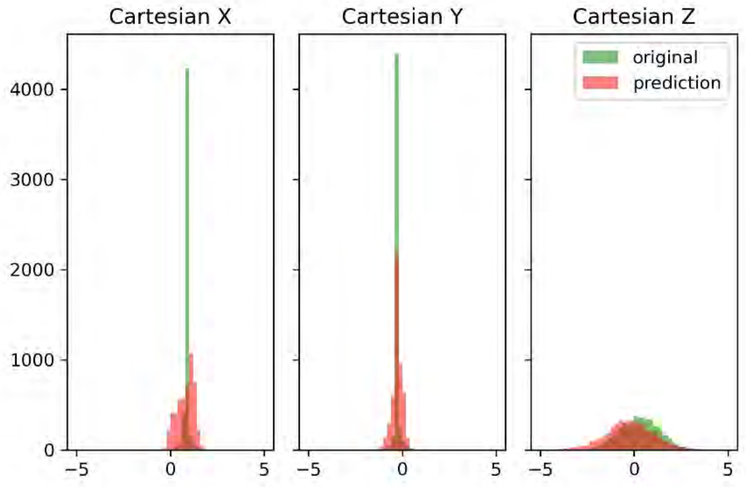
LOOT model for primary vertex prediction

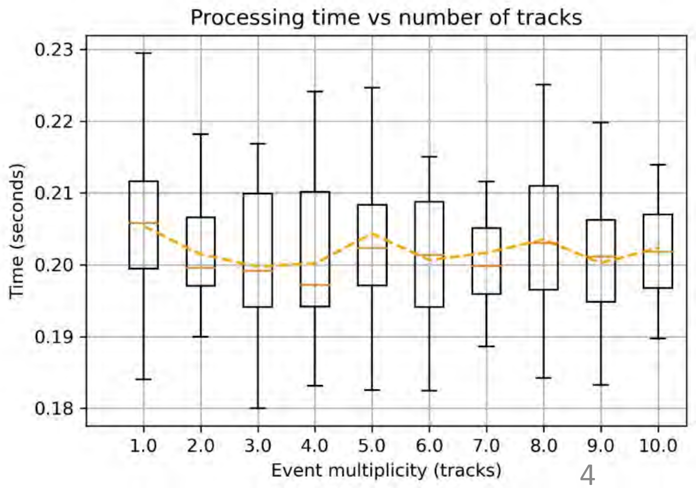
Due to the too-high expected rate of data receipt in the SPD experiment, there is a **pileup effect** when more than one event sticks together, so it is necessary to find all primary vertices for all these events to disentangle them.

To address this problem we introduce **LOOT** – a convolutional neural network that processes all event hits at once, like a three-dimensional image.



Result distribution of the coordinates of the true and the predicted vertex (BESIII Monte-Carlo)

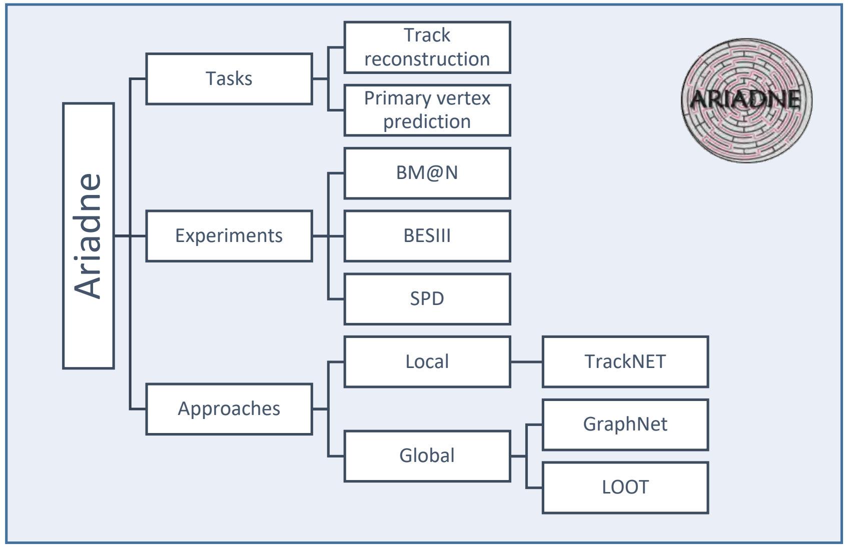


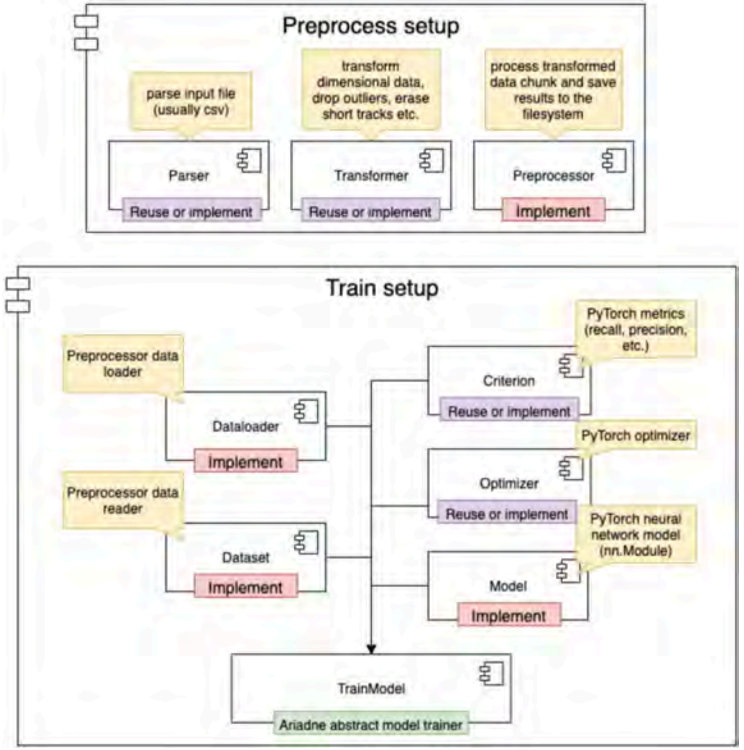


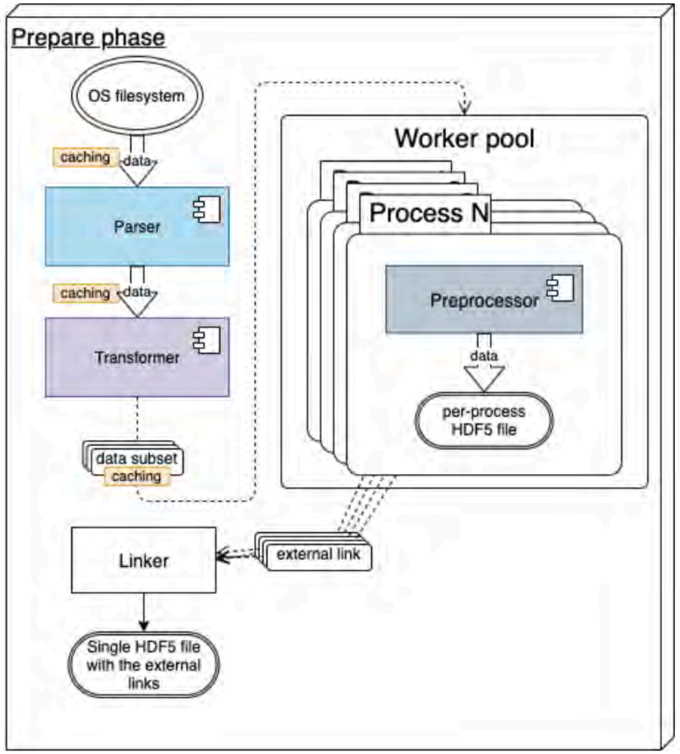
Ariadne: PyTorch Library for Particle Track Reconstruction Using Deep Learning

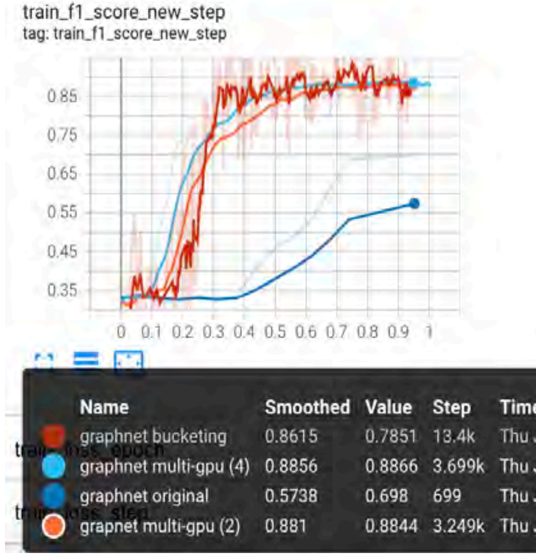
Ariadne – the first library for deep learning tracking on Python:

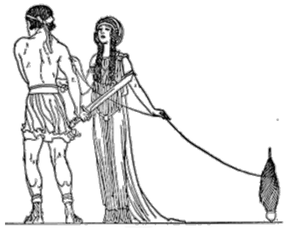
- tracking and vertex reconstruction tasks
- rapid prototyping a new NN model
- metrics logging, multiprocessing for data preparation, multi-GPU training
- open source and fully deterministic (https://github.com/t3hseus/ariadne)











Conclusion and Outlook

Conclusion

- The TrackNETv3 model which operates like a trainable Kalman filter was developed.
- RDGraphNet model that is able to consume the whole event data as a graph was introduced.
- A special convolutional neural network named LOOT was proposed to solve the problem of primary vertex recognition.
- We developed Ariadne – the first library for deep learning tracking on Python.
- With the help of Ariadne, we've trained RDGraphNet, TrackNETv3, and LOOT models on Monte-Carlo data from BESIII and BM@N experiments.
- For the BESIII experiment, we achieved more than 94% of track reconstruction efficiency that is superior to the Kalman filter!
- Each of the proposed deep learning models is more than 100 times faster than the Kalman filter.
- Besides, we've trained the regression part of the TrackNETv3 model on BM@N RUN7 data (Ar+Pb interaction) and achieved the descent tracking efficiency equal to 98.3%.
- The LOOT model was successfully trained on the task of primary vertex recognition in the BESIII experiment and showed sufficient results.

Outlook

- We are going to create the classifier of track candidates for TrackNETv3 required for the BM@N RUN7 data.
- When the full track reconstruction pipeline for BM@N RUN7 is trained, we **will run inference on experimental data!**
- We have to do a lot of refactoring in Ariadne in order to build a production-ready Python package.
- Besides, now we are training our models – LOOT and TrackNETv3 on Monte-Carlo data from SPD.