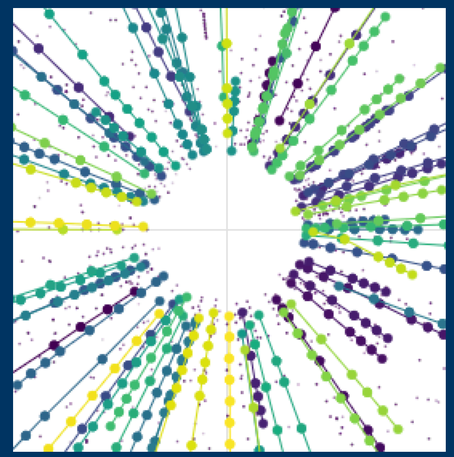
Graph Neural Network for Track Finding at LHCb

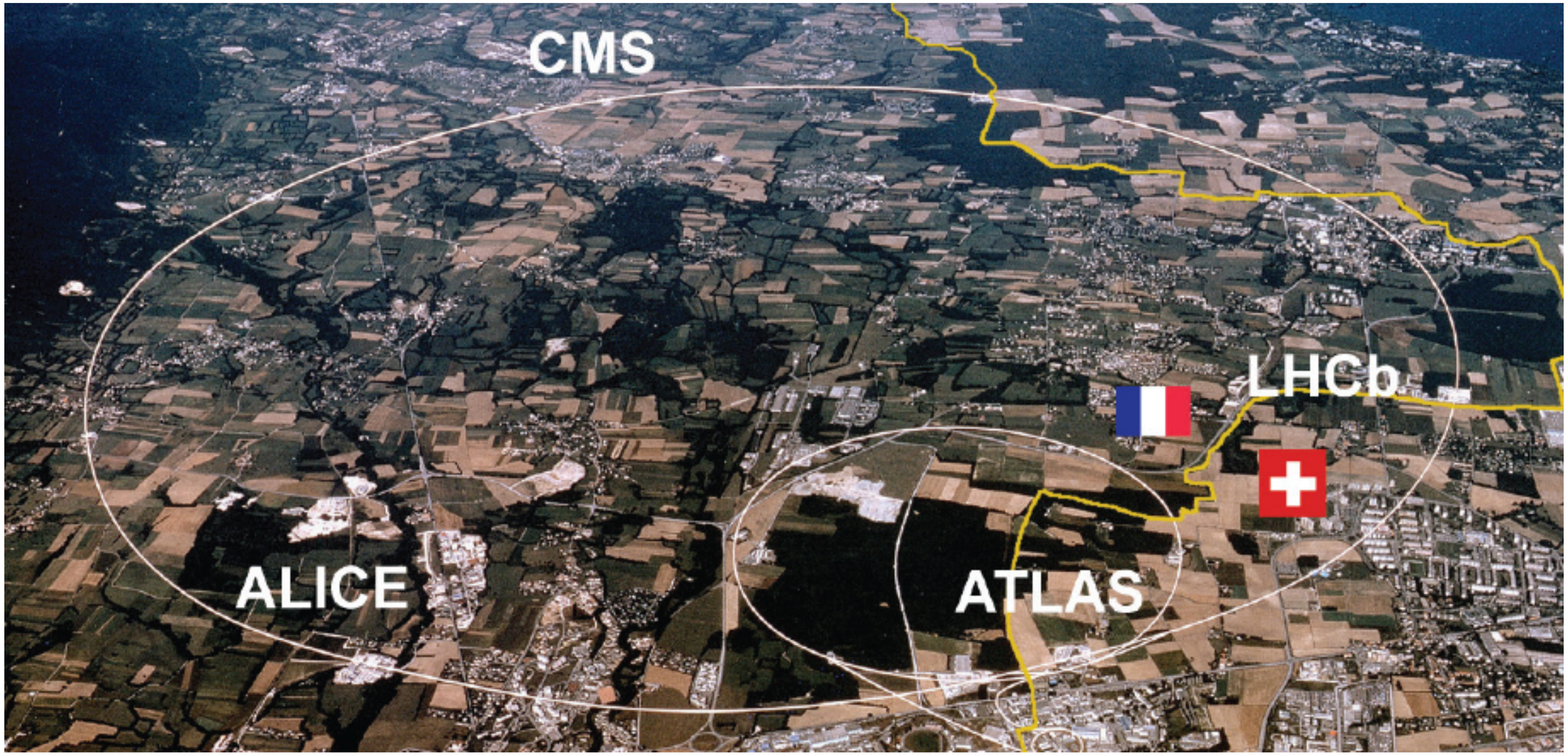
Journées de Rencontre Jeunes Chercheurs
Saint-Jean-de-Monts, France, October 23, 2023

Fotis Giasemis, Anthony Correia, Nabil Garroum, Vladimir Vava Gligorov



CERN

The Large Hadron Collider and LHCb



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CERN

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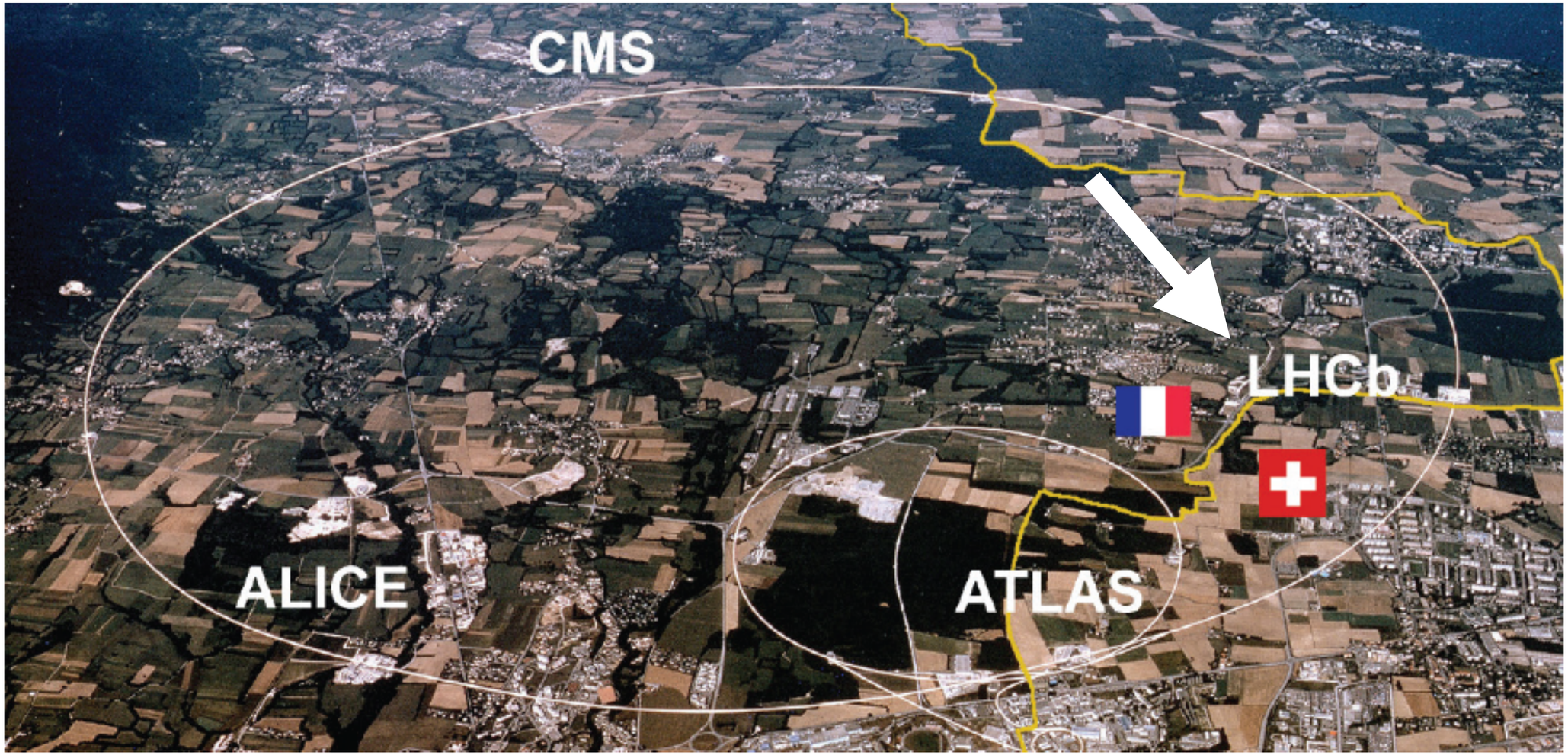

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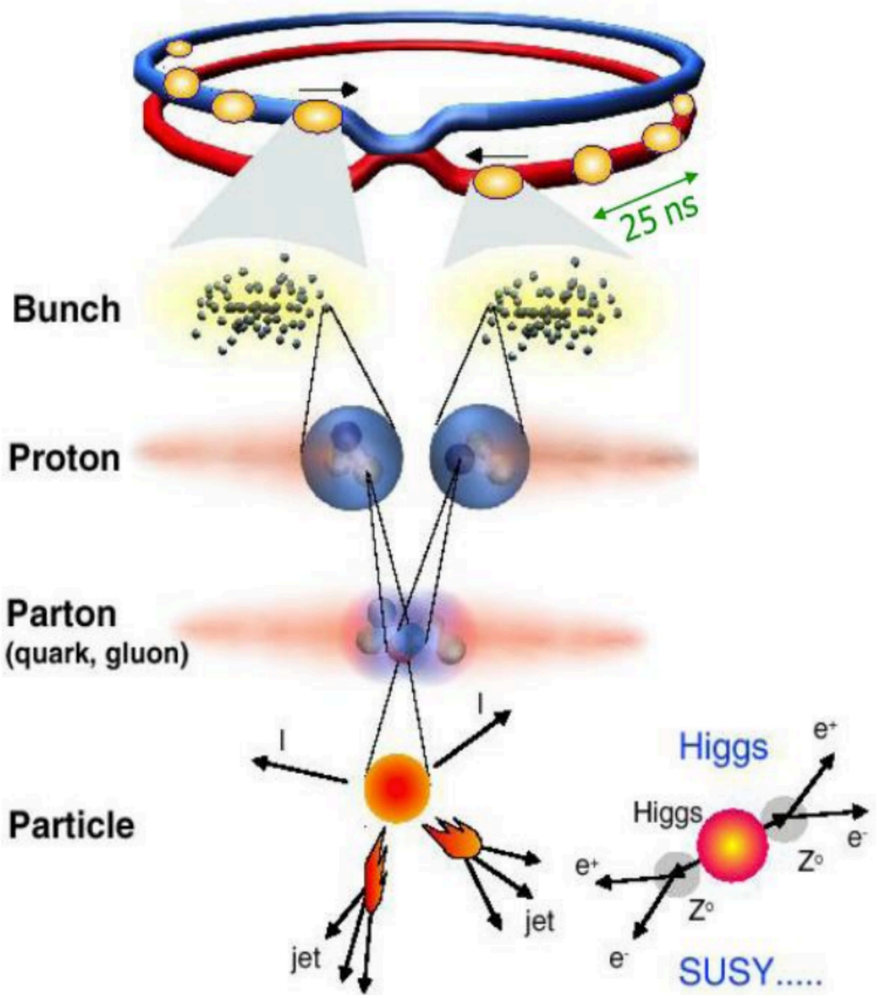
The Large Hadron Collider

Collisions at the LHC



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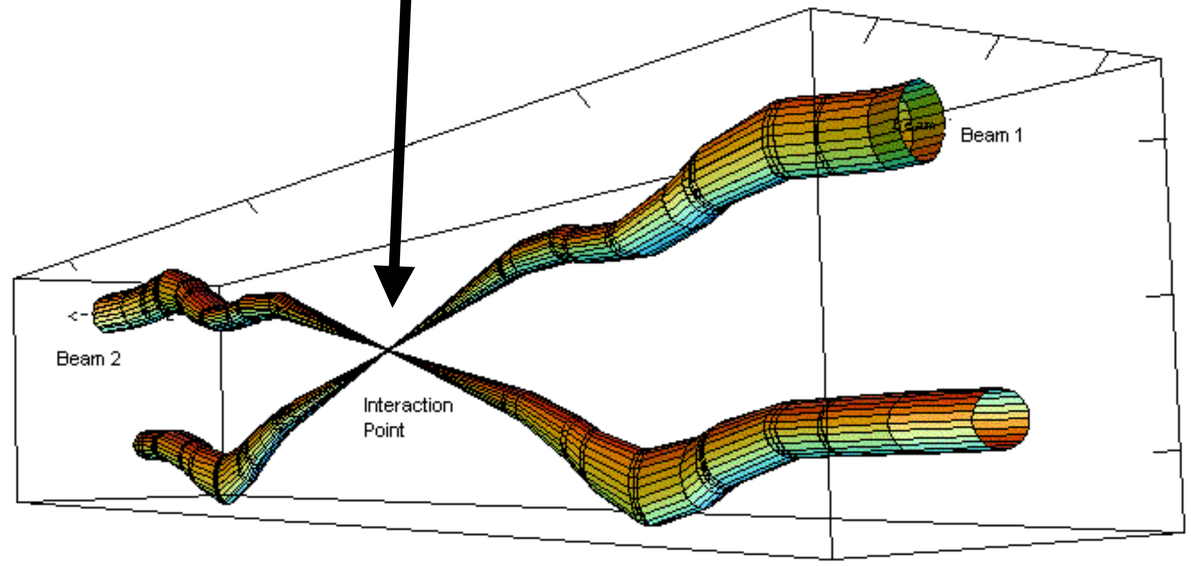
Protons colliding at 0.99999999 the speed of light

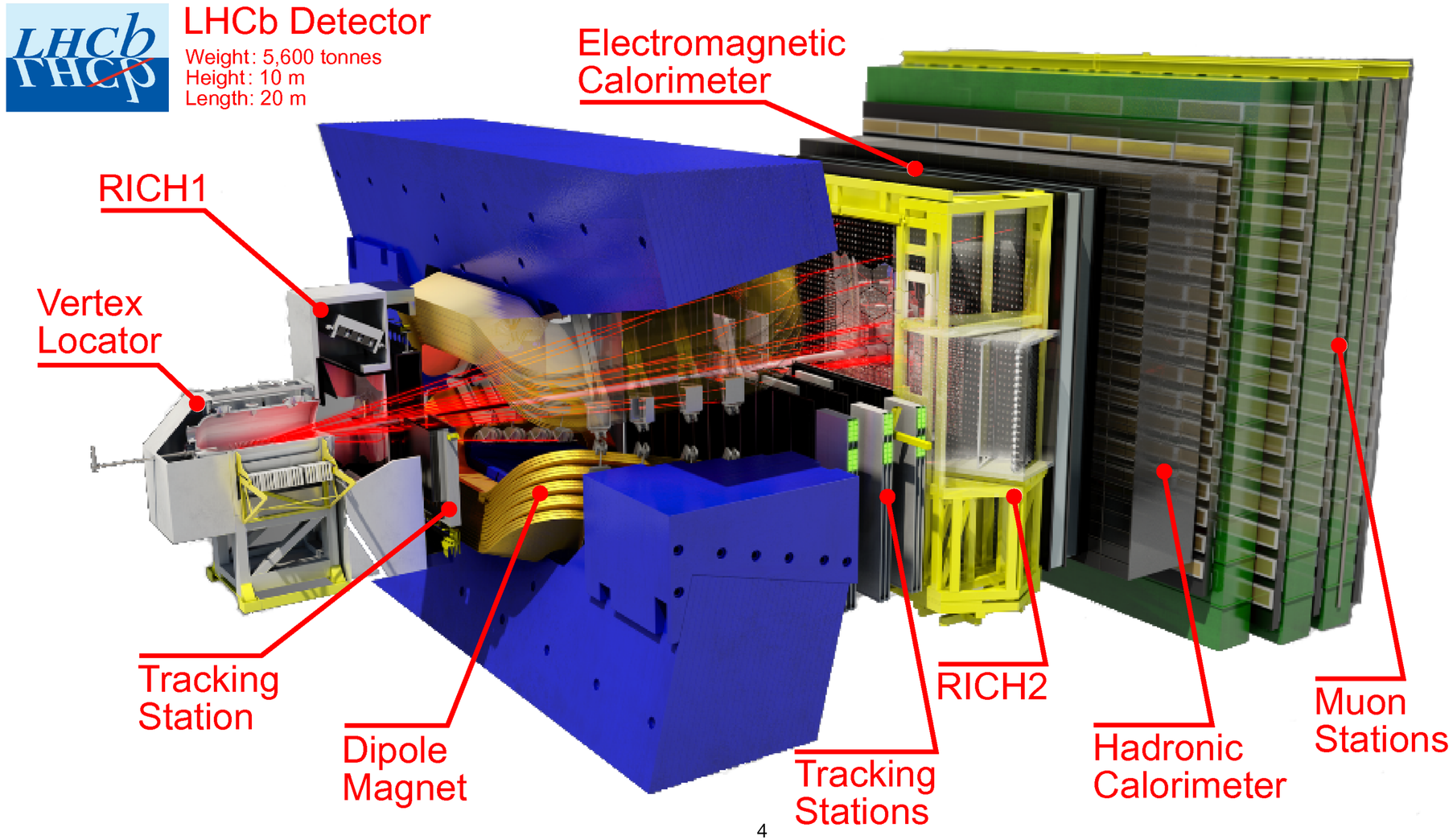


Relative beam sizes around IP1 (Atlas) in collision

source

LHCb

The experiment and the detector



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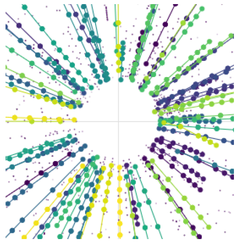
Triggering

Filtering the enormous amount of data produced

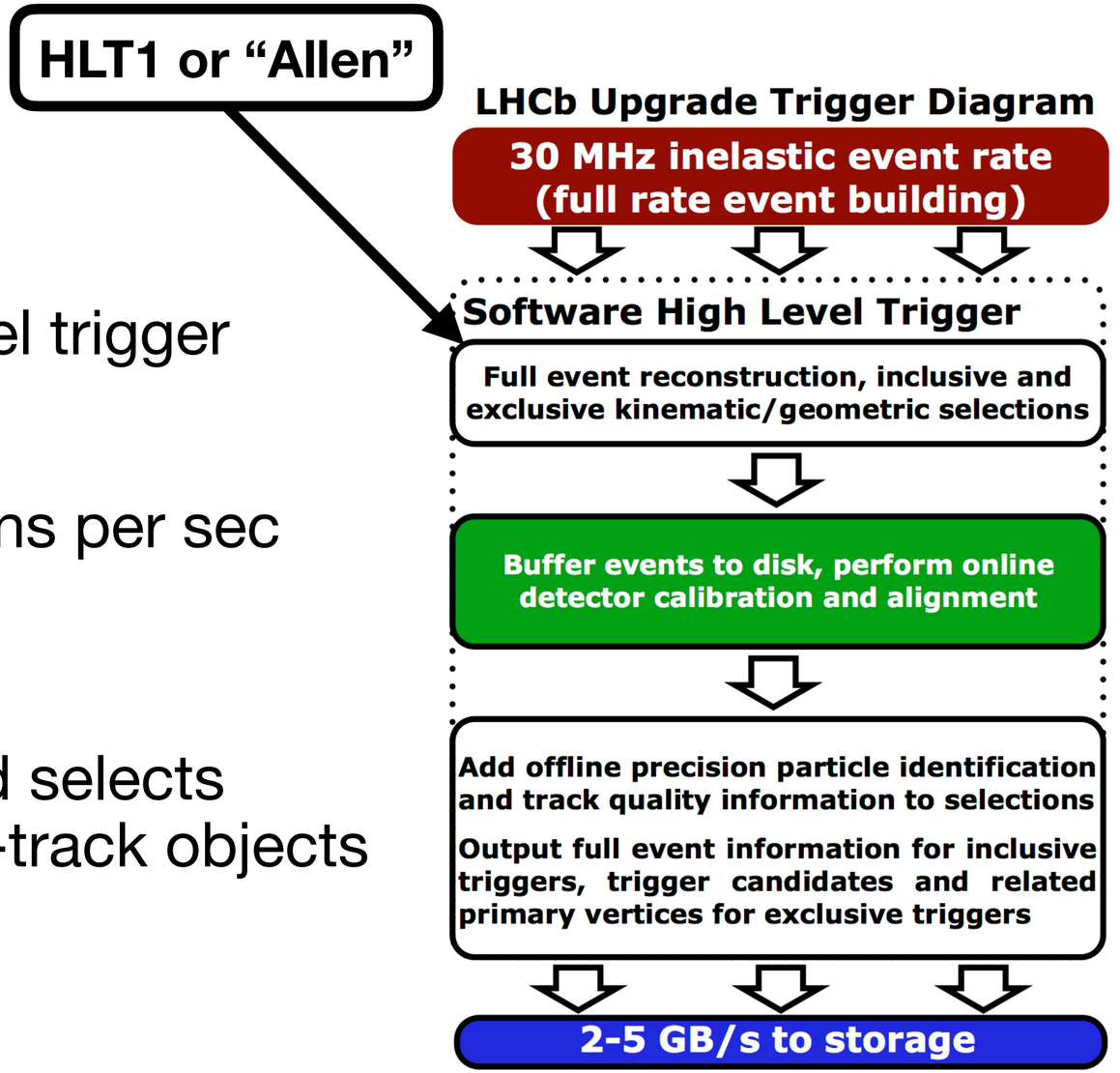


- ~5 TB/s produced at LHCb
- Cannot be stored
- Keep only the “interesting” events → **triggering**
- To decide you need information about
  - particles involved and
  - their trajectories
- LHCb trigger?

The LHCb trigger and Allen

The Software Trigger of LHCb

- Software high level trigger: 2 levels
- Allen is the level 1 of the LHCb high-level trigger (HLT1) running on **GPUs**
- Filters an input rate of 30 million collisions per sec
- **High throughput constraint**
- Performs fast **track reconstruction** and selects collision events based on one- and two-track objects on GPUs



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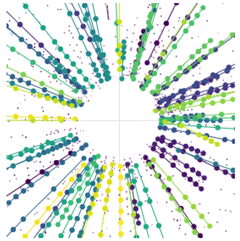
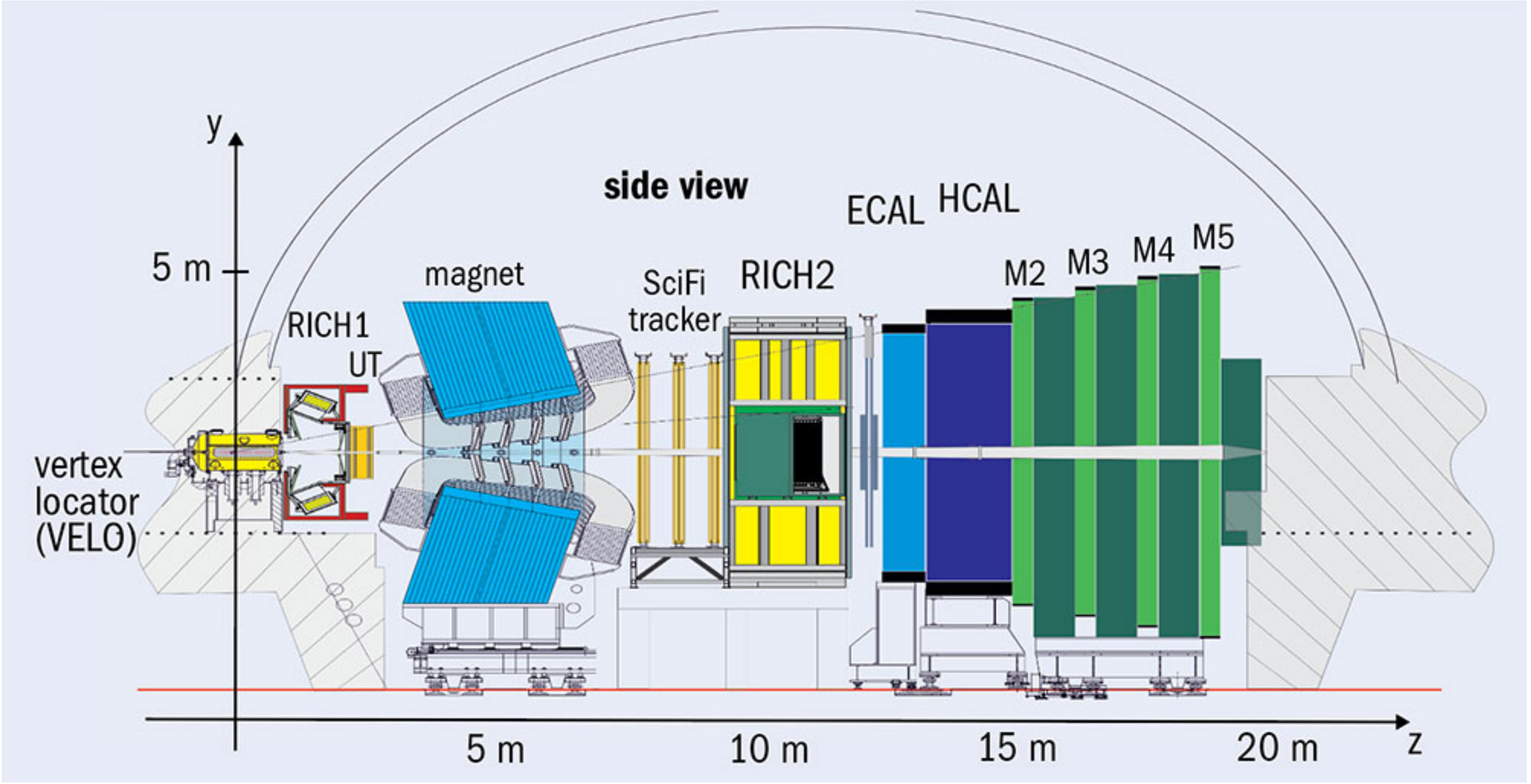
Track Finding

Also called
“track reconstruction”, or
“tracking”



Finding tracks from the hits in the detector



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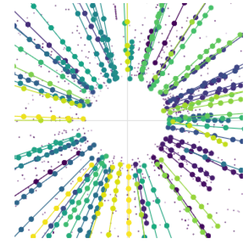

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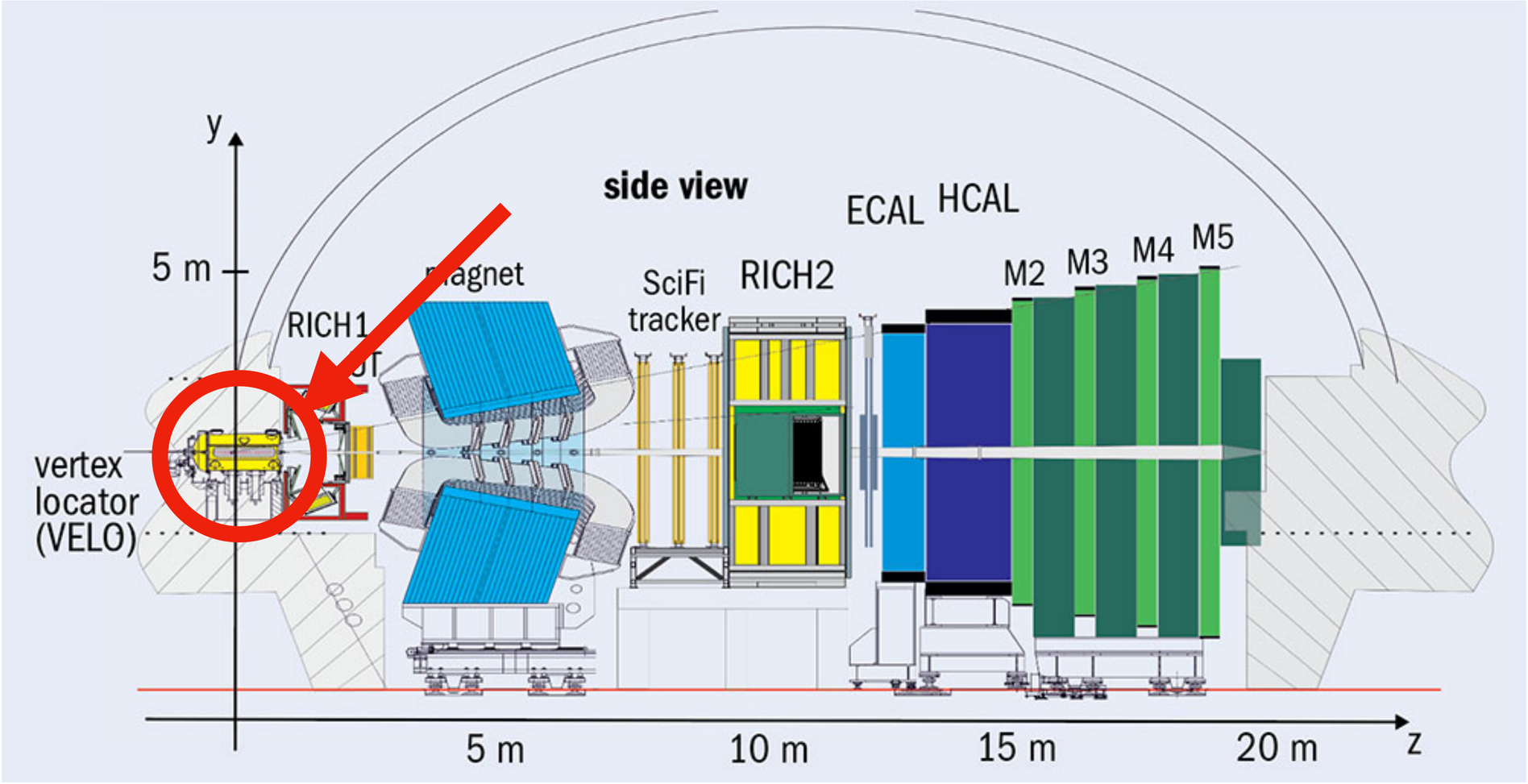

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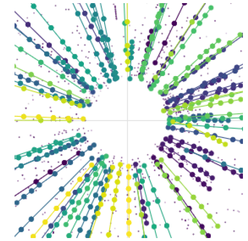

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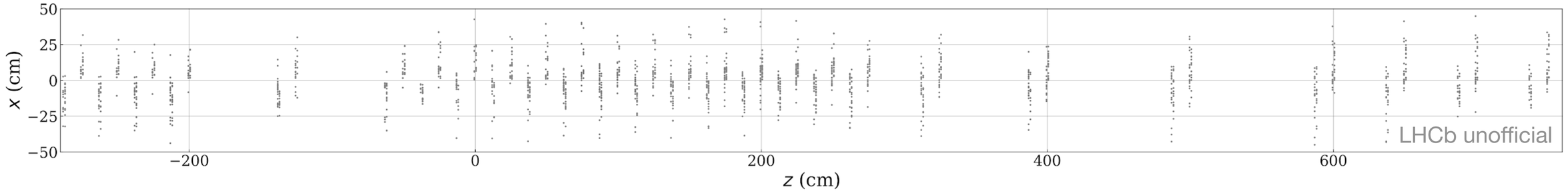

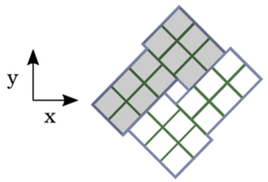

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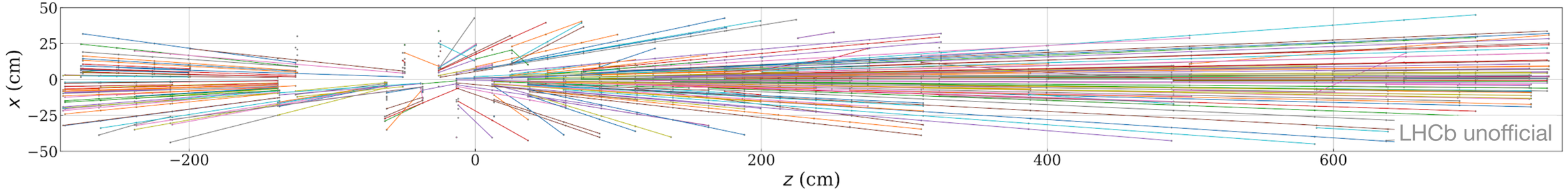
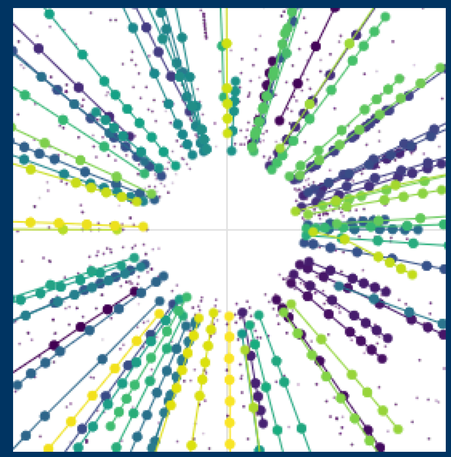


Graph Neural Network for Track Finding at LHCb



Main objectives

- Find a NN for tracking at LHCb that achieves state-of-the-art performance

- Optimise network enough in order to meet high throughput constraint

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- Optimise network enough in order to meet high throughput constraint

etx4velo

GNN-based pipeline for track finding in the Velo at LHCb,
talk@CTD2023

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Exa.TrkX

LHCb subdetector

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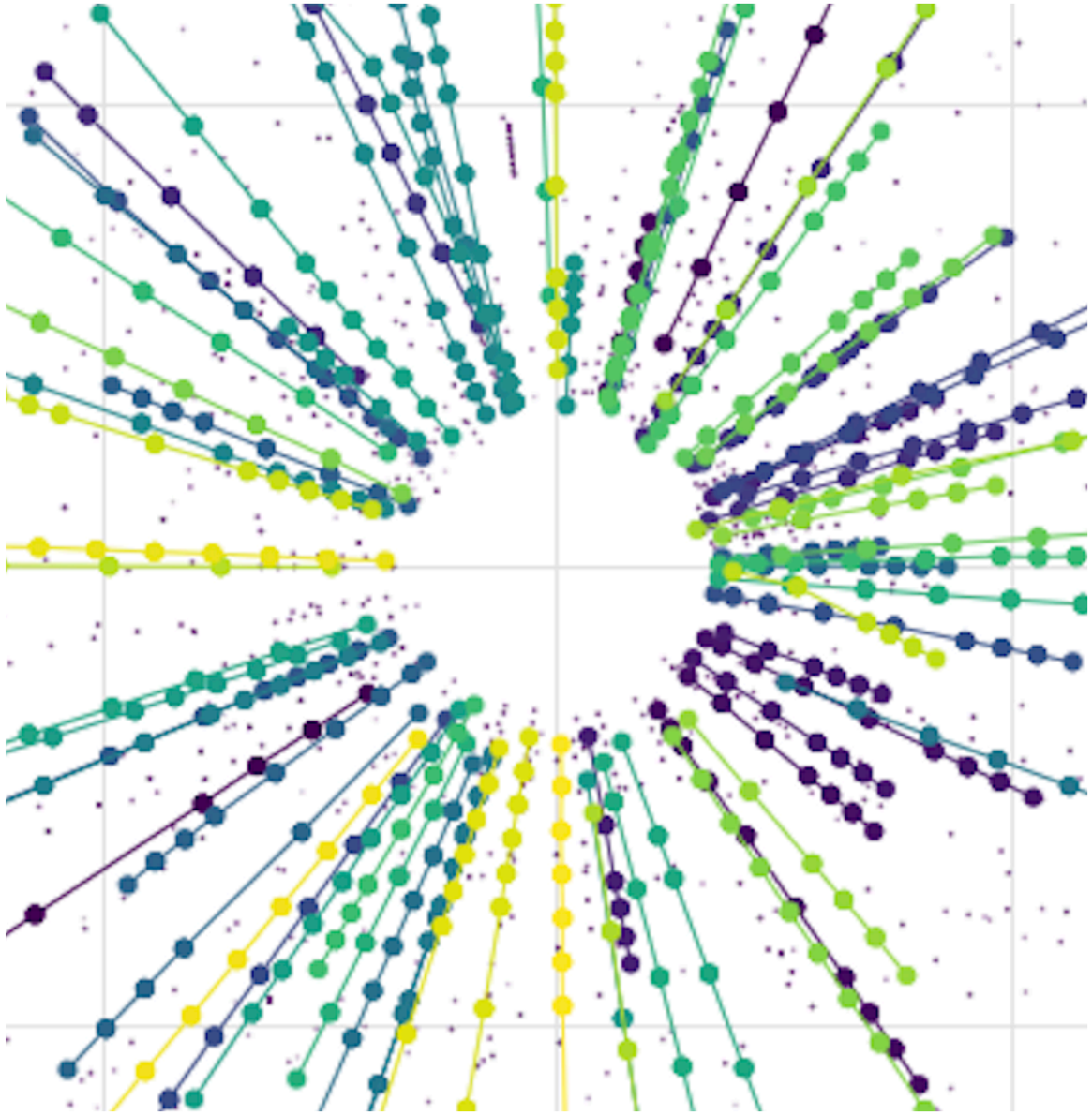

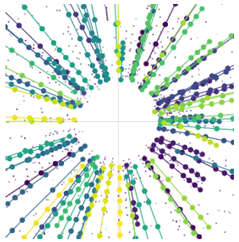

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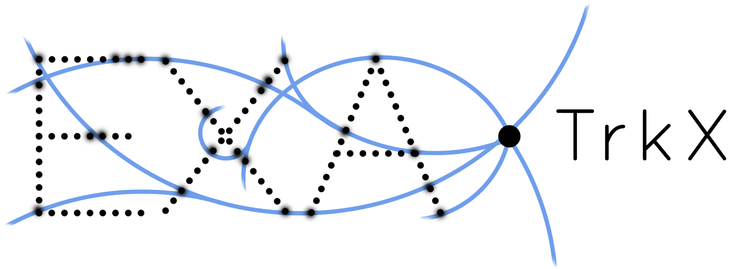
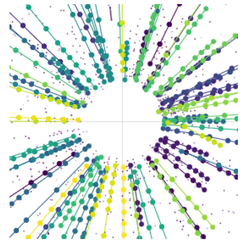
Graph neural network for track finding in the Velo

- Why?: Will ML allow a more **efficient** use of computing resources?
- Expected increase in luminosity, next generation of detectors
- Inference time close to **linear** on # hits vs classical **worse-than-quadratic**
- Comparative studies with classical approaches

- Where do we start?: Exa.TrkX collaboration
- exatrkx.github.io, talk@CHEP2021

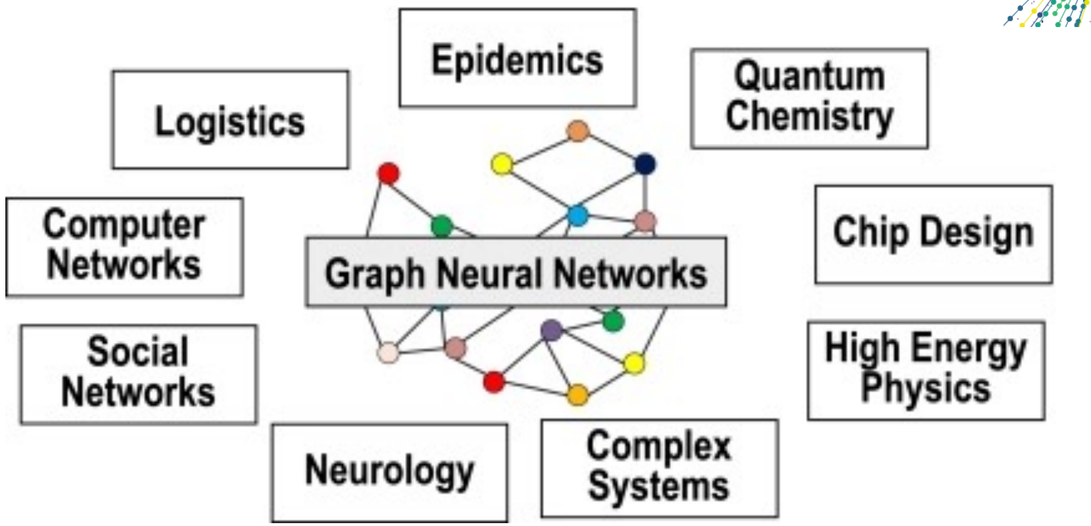




Graph Neural Networks

Why GNNs?

- Why graphs?
  - To take **connectivity** between data into account
- Why GNNs?
  - Modern DL only for structured data (sequences, grids etc.)
  - Develop NNs that are much more broadly applicable
  - Graphs can have **arbitrary shape and size**



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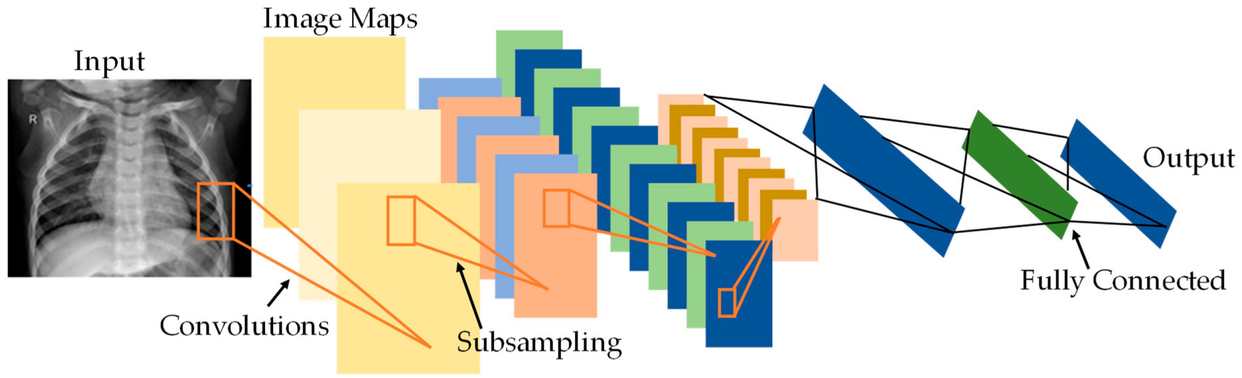

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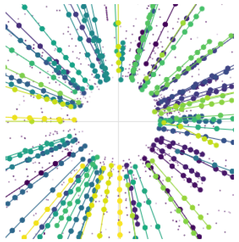
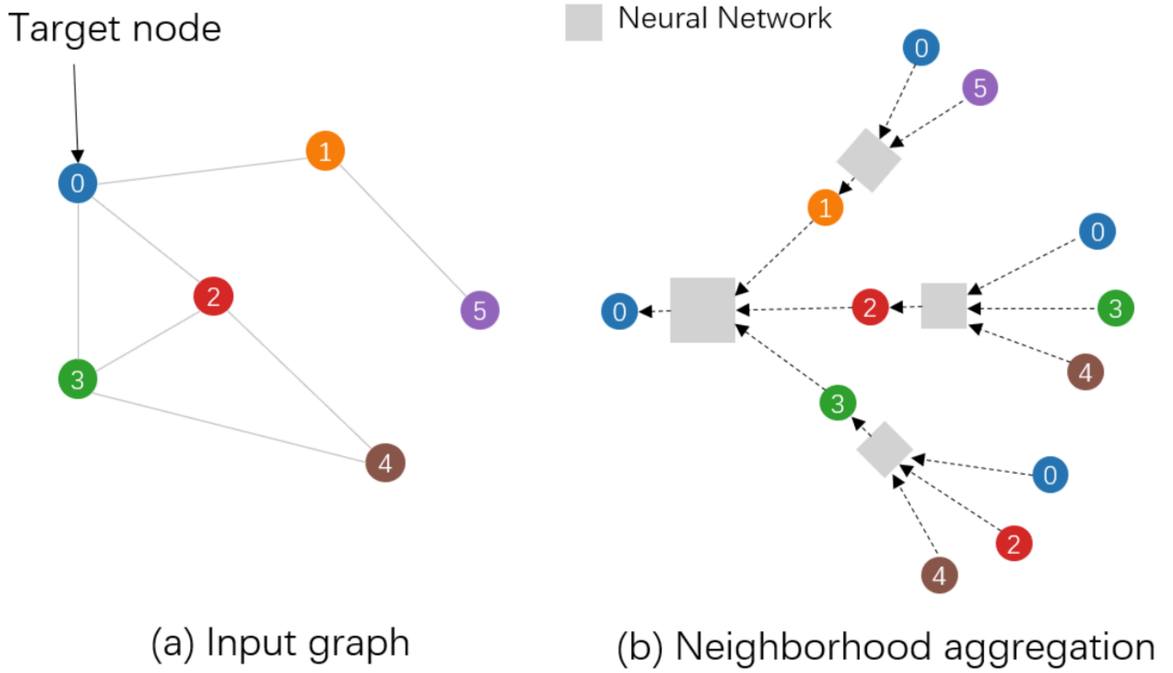
Graph Neural Networks



How?

- How do you learn the structure of the data?
  - ~~Normal convolution, as in CNNs~~
  - **“Graph Convolution”**
- Graph Convolution via a computation graph:
  - Node features
  - Aggregation
  - Message passing



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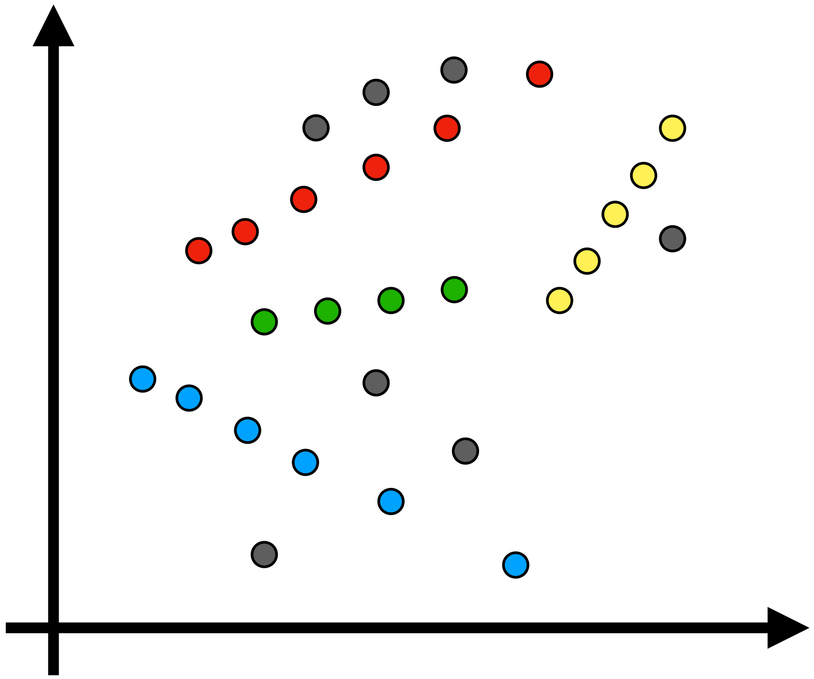
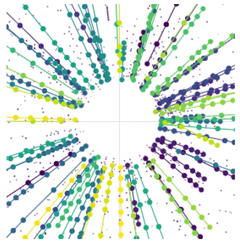
How do we get a graph from the hits?



Hits in the detector



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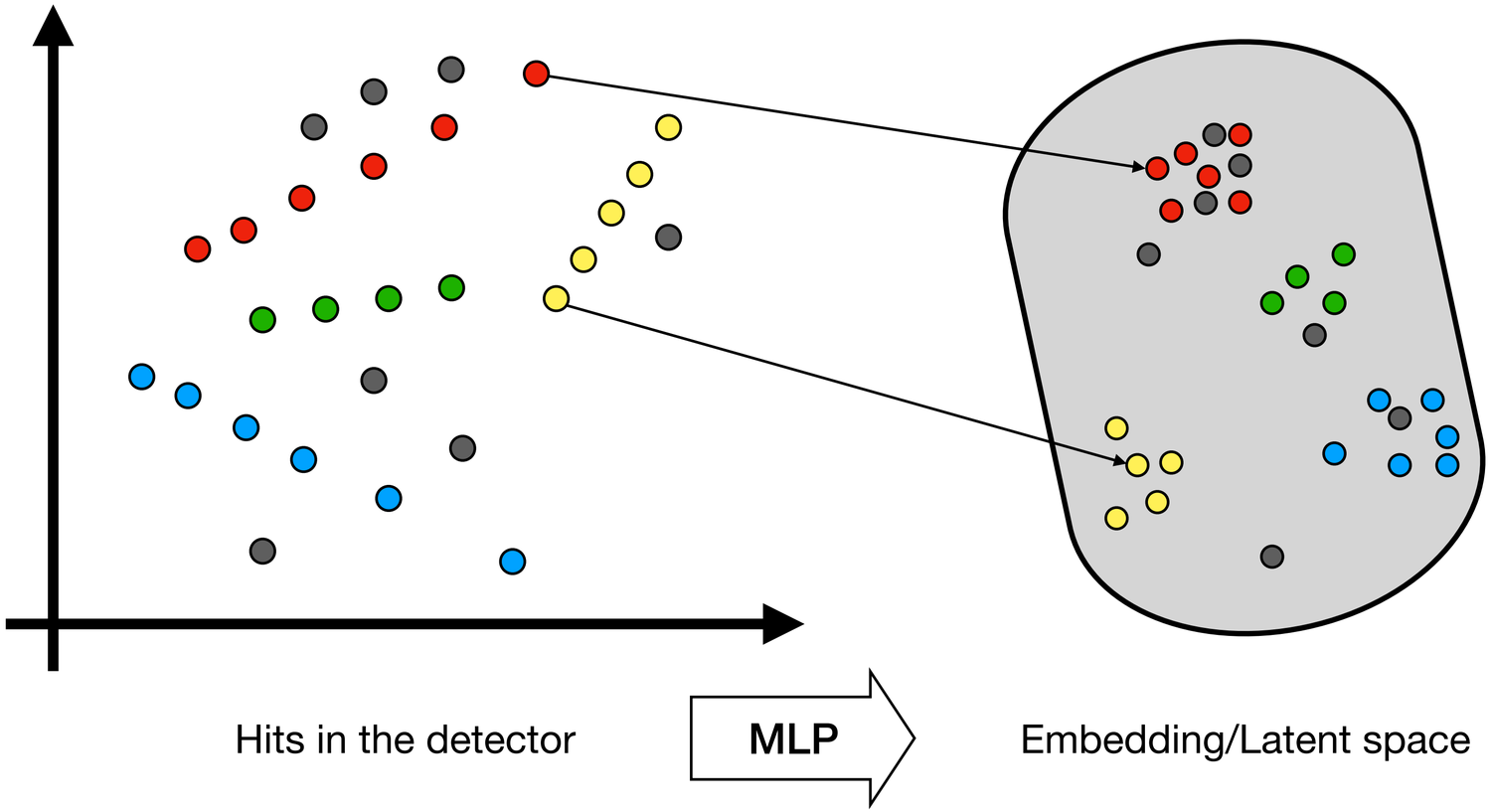

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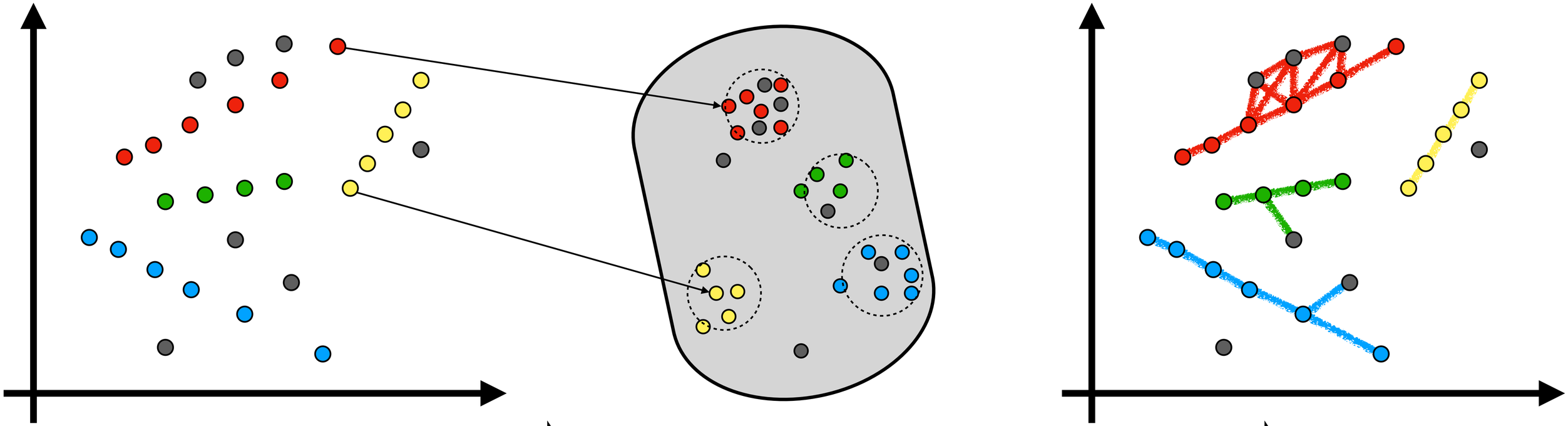

Hits in the detector

MLP

Embedding/Latent space

Graph construction

Graph

etx4velo

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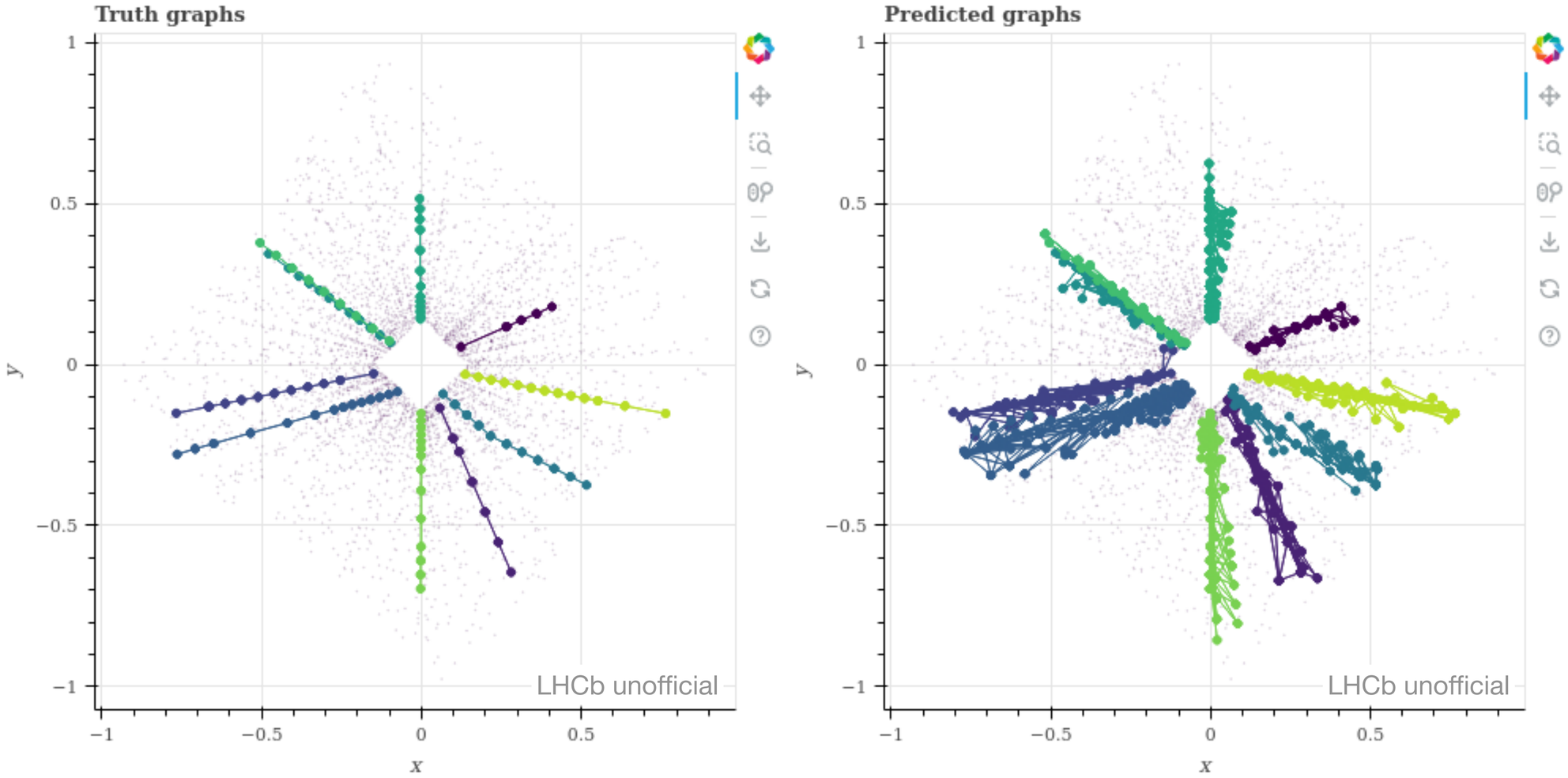

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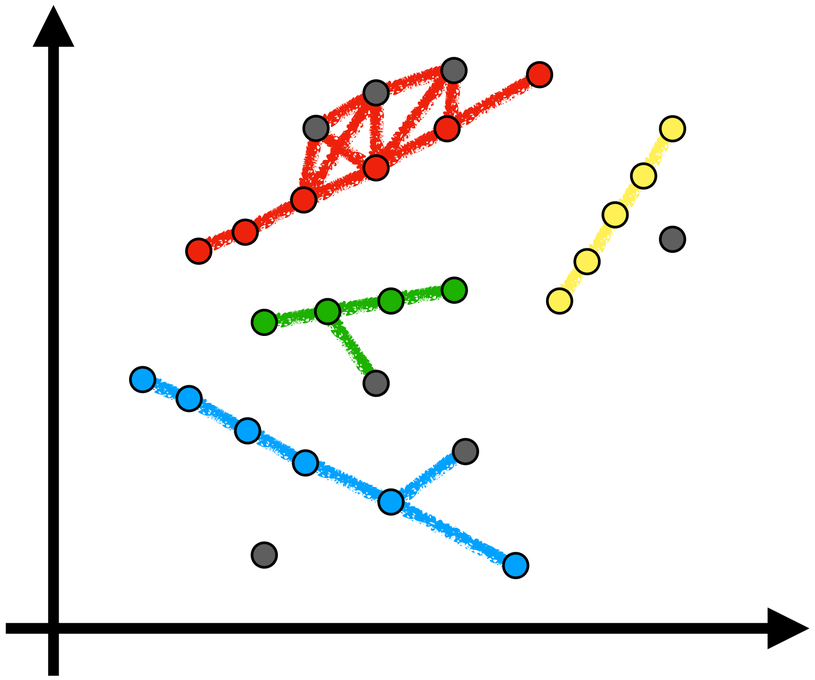
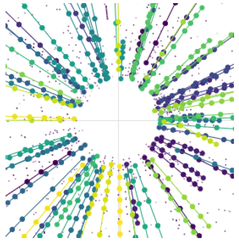
How do we get tracks?



Graph



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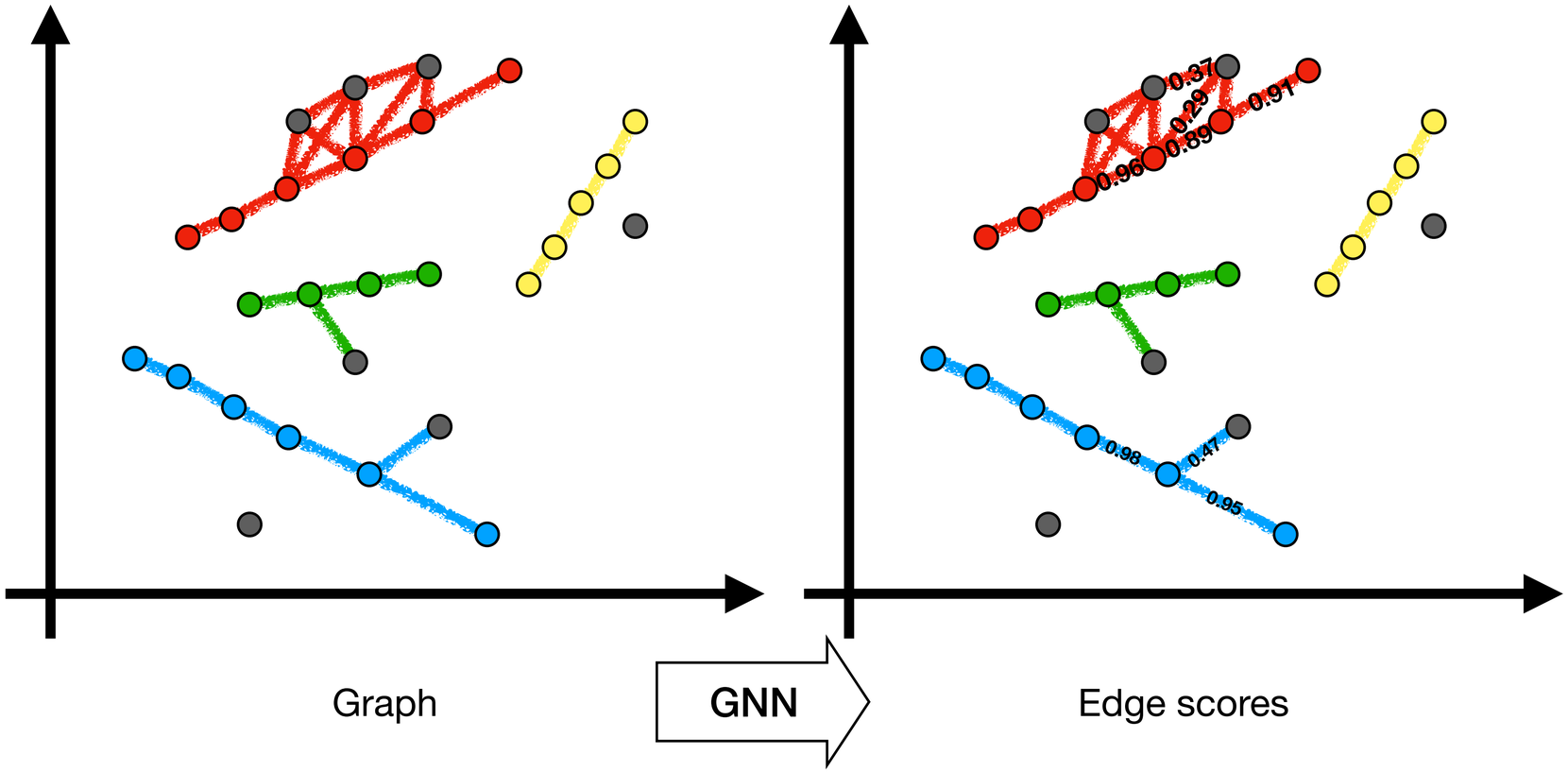

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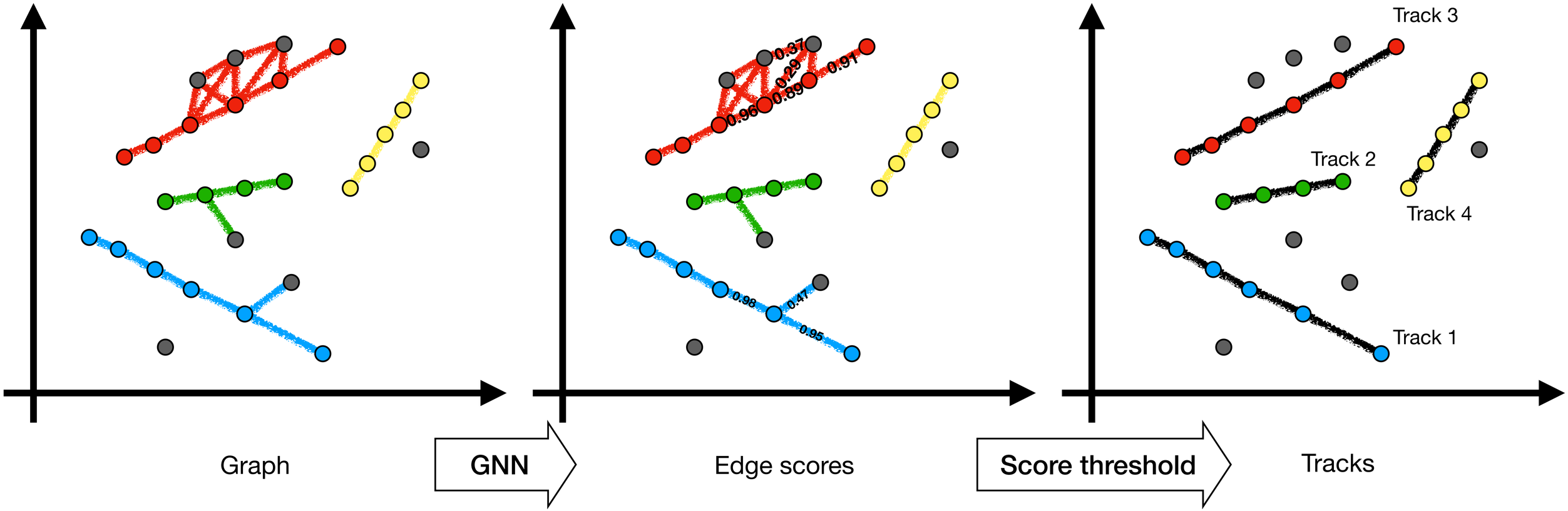

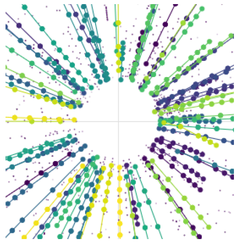

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Refinements

- Performance close to the state of the art

- Problem with electrons:
  - ~ 55% electrons share hits with another electron
  - The 2 electrons share ≥ 1 hit before splitting up
  - Electrons with “long tracks” = **“long electrons”**
  - Important for the LHCb physics program

```
TrackChecker output                    :     38049/  1117828   3.40% ghosts
01_velo                                :    491643/   520515  94.45% ( 95.11%),
02_long                                :    286719/   296345  96.75% ( 97.22%),
03_long_P>5GeV                         :    185866/   189727  97.96% ( 98.30%),
04_long_strange                        :     13654/    15243  89.58% ( 90.68%),
05_long_strange_P>5GeV                 :      6606/     7229  91.38% ( 92.00%),
06_long_fromB                          :       497/      513  96.88% ( 96.86%),
07_long_fromB_P>5GeV                   :       335/      343  97.67% ( 97.82%),
08_long_electrons                      :     16634/    21330  77.98% ( 78.93%),
09_long_fromB_electrons                :        41/       58  70.69% ( 76.42%),
10_long_fromB_electrons_P>5GeV         :        30/       38  78.95% ( 81.18%),

*** Benchmark score:  94.01

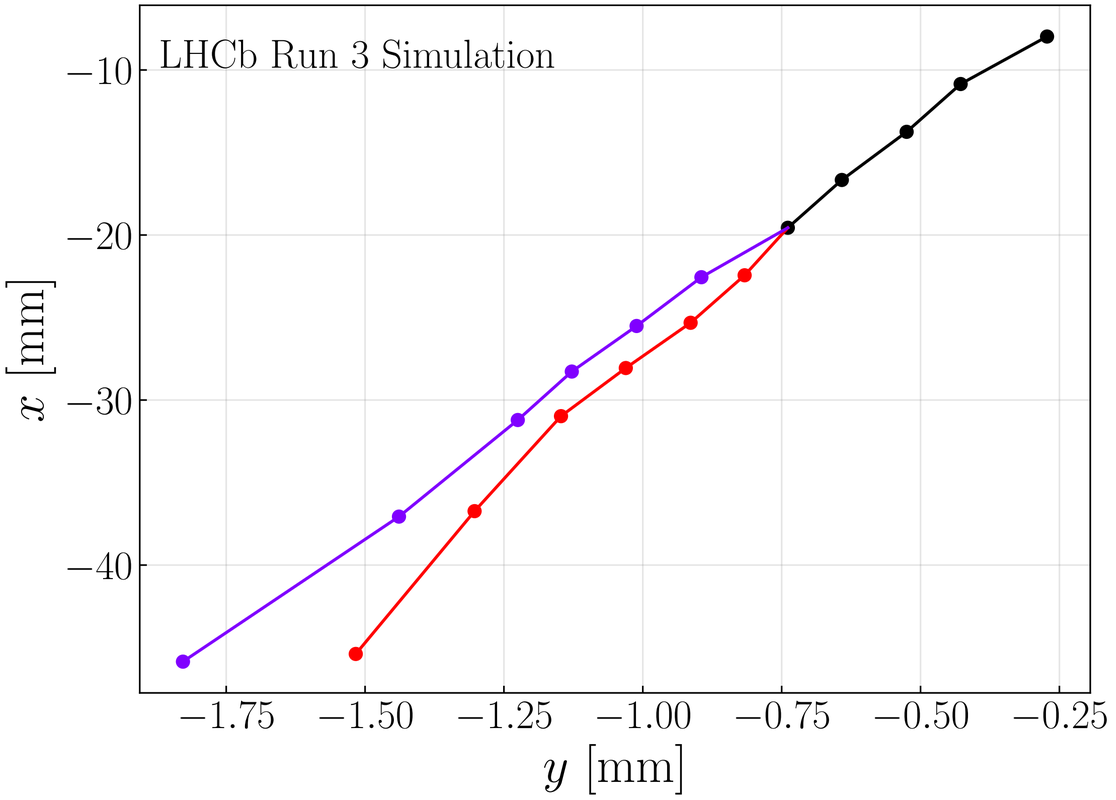
| Categories           | Efficiency   | Average efficiency   | % clones   | Average hit pur
|:---------------------|:-------------|:---------------------|:-----------|:---------------
| Velo                 | 90.37%       | 91.08%               | 1.41%      | 99.03%
| Long                 | 95.49%       | 95.97%               | 0.97%      | 99.33%
| Velo, no electrons   | 94.45%       | 95.11%               | 0.89%      | 99.30%
| Velo, only electrons | 69.30%       | 69.84%               | 4.91%      | 97.15%
| Long, only electrons | 77.98%       | 78.93%               | 3.54%      | 97.36%

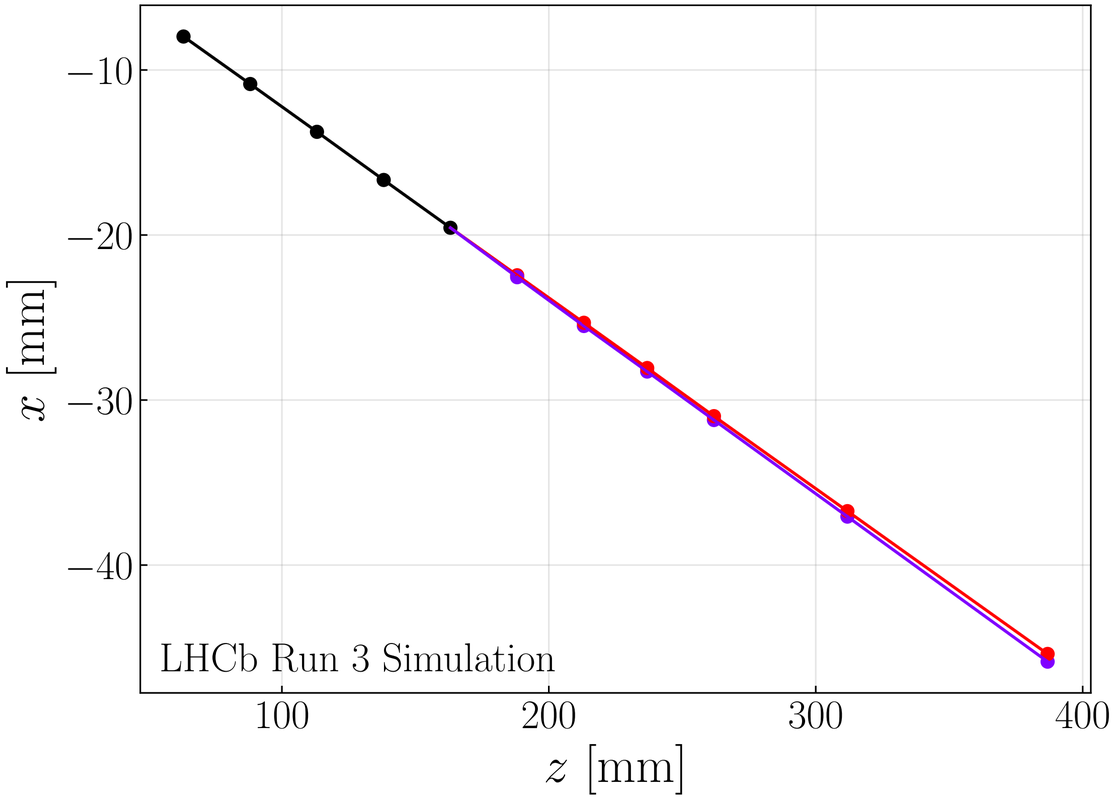
| Categories   | # ghosts   | # tracks   | % ghosts   |
|:-------------|:-----------|:-----------|:-----------|
| Everything   | 38,049     | 1,117,828  | 3.40%      |
```

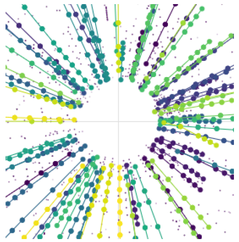
LHCb unofficial

etx4velo

Problem with electrons: shared hits







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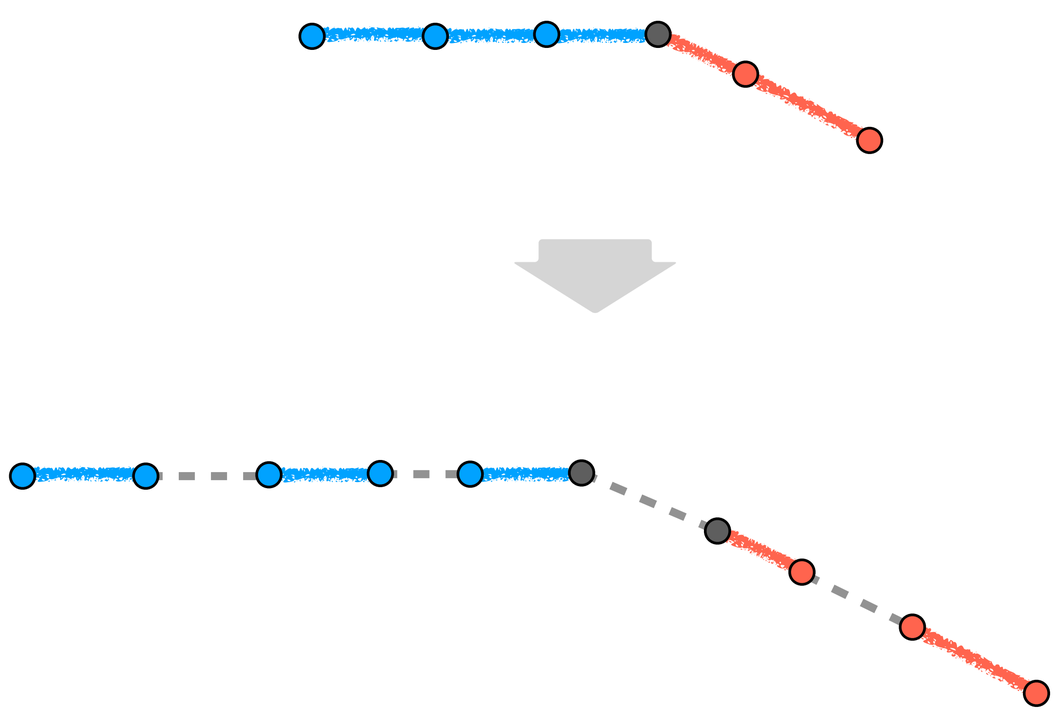
Problem with electrons: the solution

- Problem with electrons:
  - Pipeline cannot separate particle with shared edges
  - Hit-hit connections are not enough
  - Solution:
  - Use edge-edge connections (triplets)
  - Use GNN again on triplets



etx4velo

Already outperforming the state of the art

```
TrackChecker output                    :     1736/   254023   0.68% ghosts
01_velo                                :   102725/   104345  98.45% ( 98.48%),      1059 (  1.02%) clones, pur  99.81%, hit eff  98.66%
02_long                                :    58771/    59167  99.33% ( 99.30%),       566 (  0.95%) clones, pur  99.89%, hit eff  98.93%
03_long_P>5GeV                         :    38035/    38150  99.70% ( 99.65%),       296 (  0.77%) clones, pur  99.91%, hit eff  99.21%
04_long_strange                        :     3066/     3142  97.58% ( 97.64%),        41 (  1.32%) clones, pur  99.48%, hit eff  98.55%
05_long_strange_P>5GeV                 :     1485/     1521  97.63% ( 97.45%),        10 (  0.67%) clones, pur  99.38%, hit eff  99.46%
06_long_fromB                          :      120/      120 100.00% (100.00%),         0 (  0.00%) clones, pur 100.00%, hit eff 100.00%
07_long_fromB_P>5GeV                   :       87/       87 100.00% (100.00%),         0 (  0.00%) clones, pur 100.00%, hit eff 100.00%
08_long_electrons                      :     4169/     4198  99.31% ( 99.44%),       379 (  8.33%) clones, pur  98.39%, hit eff  96.38%
09_long_fromB_electrons                :       10/       10 100.00% (100.00%),         0 (  0.00%) clones, pur 100.00%, hit eff 100.00%
10_long_fromB_electrons_P>5GeV         :        7/        7 100.00% (100.00%),         0 (  0.00%) clones, pur 100.00%, hit eff 100.00%
```

LHCb unofficial

GDL4HEP › etx4velo

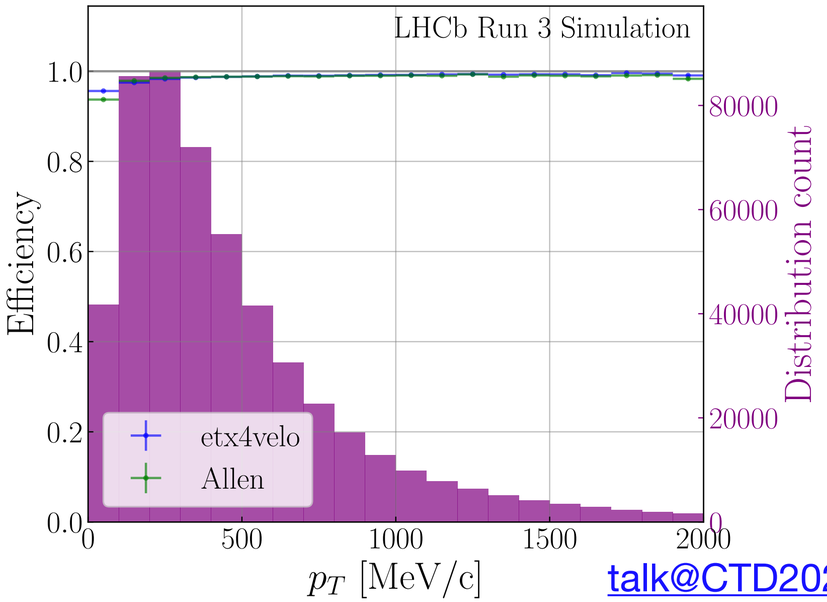
etx4velo

Project ID: 154495

738 Commits **13** Branches **4** Tags **1.1 GiB** Project Storage **1** Release **1** Environment

Topics: LHCb python Tracking + 2 more

Track reconstruction in Velo, using the tools of Exa.TrkX.



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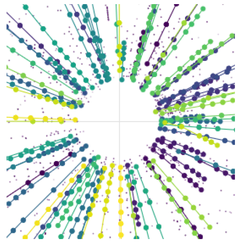

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04_long_strange                        :     3066/     3142  97.58% ( 97.64%),        41 (  1.32%) clones, pur  99.48%, hit eff  98.55%
05_long_strange_P>5GeV                 :     1485/     1521  97.63% ( 97.45%),        10 (  0.67%) clones, pur  99.38%, hit eff  99.46%
06_long_fromB                          :      120/      120 100.00% (100.00%),         0 (  0.00%) clones, pur 100.00%, hit eff 100.00%
07_long_fromB_P>5GeV                   :       87/       87 100.00% (100.00%),         0 (  0.00%) clones, pur 100.00%, hit eff 100.00%
08_long_electrons                      :     4169/     4198  99.31% ( 99.44%),       379 (  8.33%) clones, pur  98.39%, hit eff  96.38%
09_long_fromB_electrons                :       10/       10 100.00% (100.00%),         0 (  0.00%) clones, pur 100.00%, hit eff 100.00%
10_long_fromB_electrons_P>5GeV         :        7/        7 100.00% (100.00%),         0 (  0.00%) clones, pur 100.00%, hit eff 100.00%
```

LHCb unofficial

GDL4HEP › etx4velo

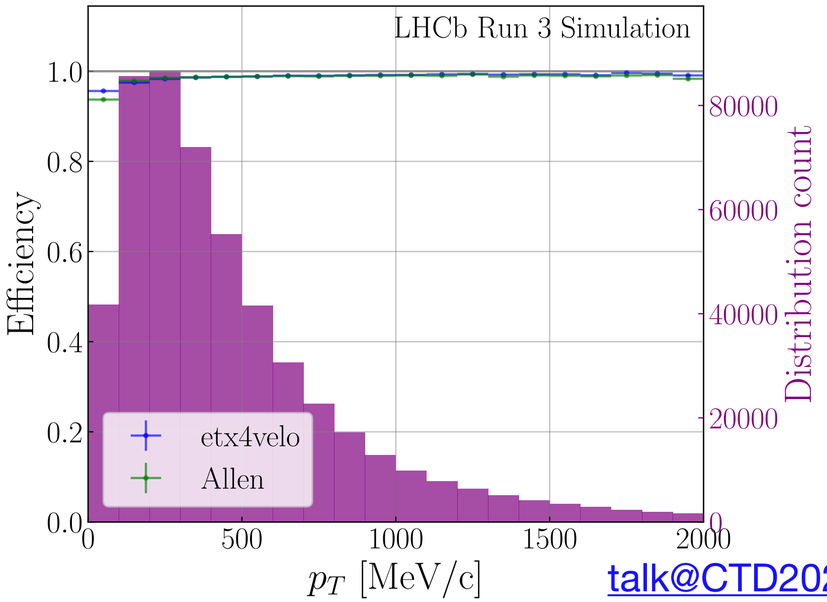
etx4velo

Project ID: 154495

738 Commits **13** Branches **4** Tags **1.1 GiB** Project Storage **1** Release **1** Environment

Topics: LHCb python Tracking + 2 more

Track reconstruction in Velo, using the tools of Exa.TrkX.



[talk@CTD2023]

Main objectives

- **Find a NN for tracking at LHCb that achieves state-of-the-art performance**

- Optimise network enough in order to meet high throughput constraint

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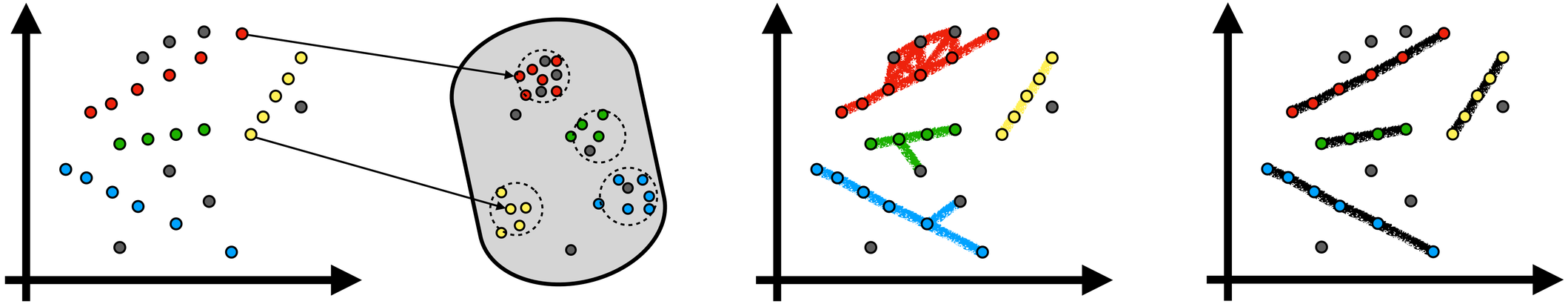
Switch from Python to C++/CUDA

etx4velo inference

What is slowing us down



Hits in the detector → **MLP** → Embedding/Latent space → **Graph construction** → Graph

Graph → **GNN** → Edge scores → **Score threshold** → Tracks

etx4velo inference

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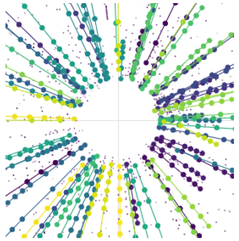

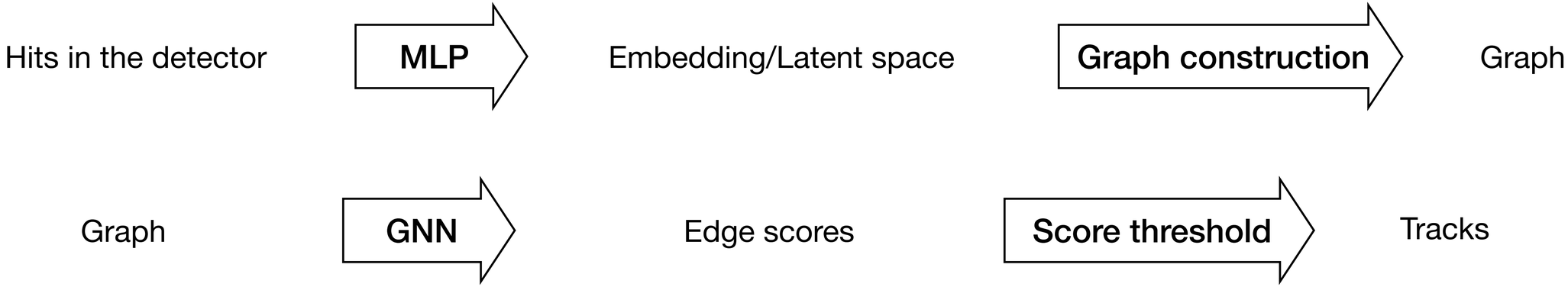

etx4velo inference

What is slowing us down

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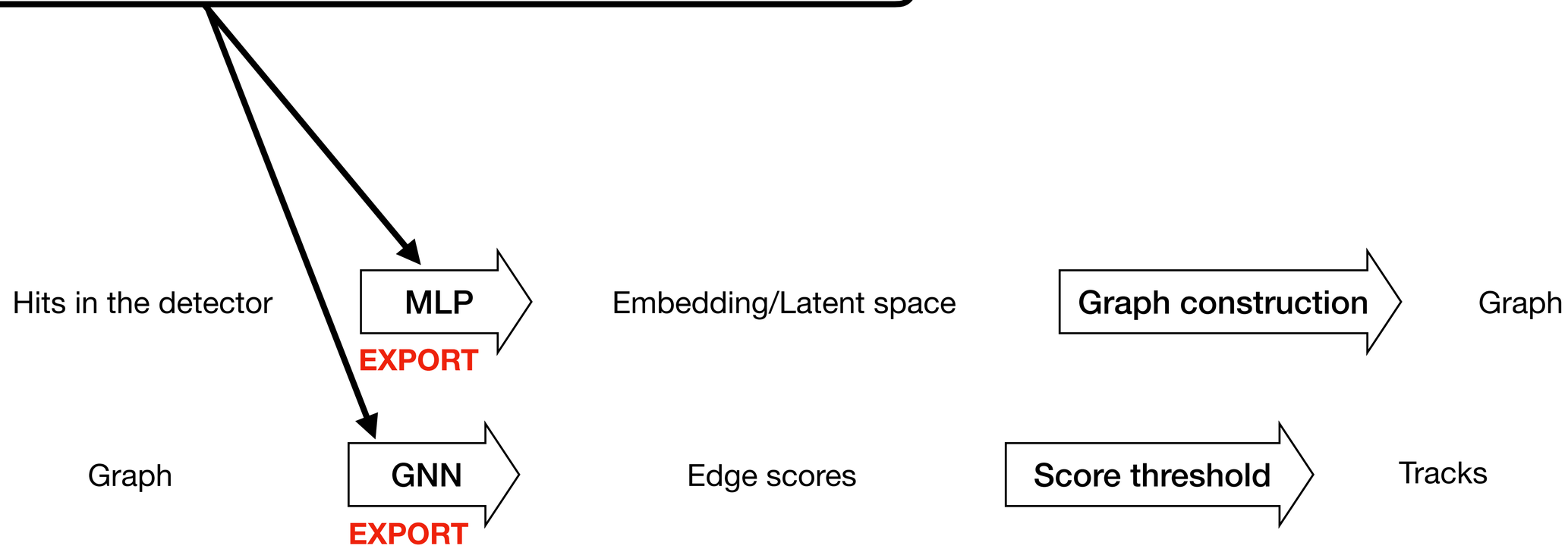
- Can use tools for inference on GPU: TensorRT, ONNX runtime, libTorch



- **EXPORT: ONNX or PyTorch**
- **IMPLEMENT: C++/CUDA**

etx4velo inference

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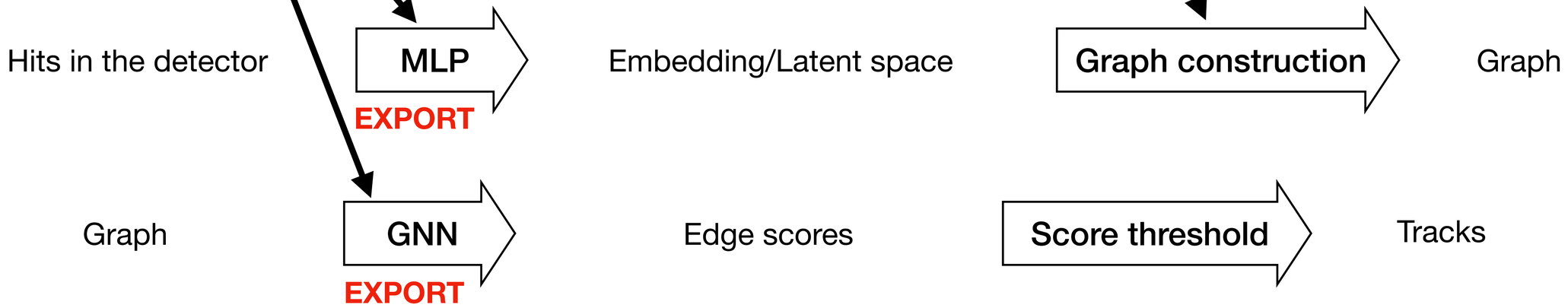
IMPLEMENT

"k nearest neighbours (kNN)" algorithm: computationally expensive



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EXPORT

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EXPORT

IMPLEMENT

"Weakly connected components (WCC)" algorithm

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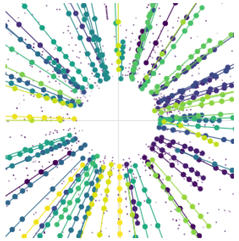
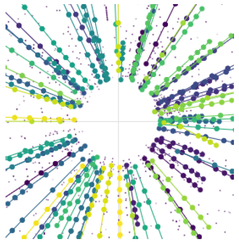
etx4velo inference

Throughput considerations



- Currently, Allen throughput, on 1 GPU **~100 kHz**
- First implementation using the Exa.TrkX repository, talk@ACAT2021, arXiv:2202.06929
- First estimates of current out-of-the-box etx4velo throughput **~1 Hz** (!)
- **Optimizations** to do:
  - Parallelise kNN and WCC across the events
  - Infer MLP and GNN in large batches
  - Optimize data transfers between host and device
  - Reduce neural network size or change architecture, pruning
  - Write custom implementations
  - Accelerate parts of the pipeline on FPGAs

Conclusion



Track finding with etx4velo

- Comparable or superior performance to current state of the art
- Excellent electron reconstruction

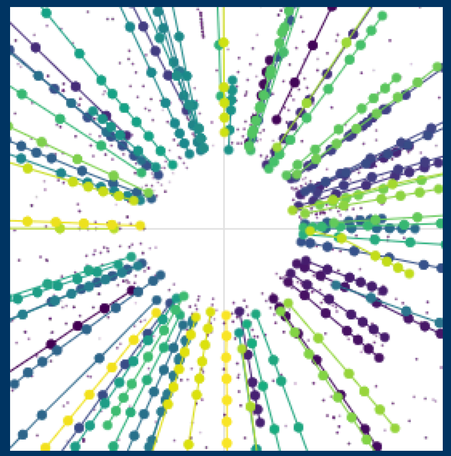
Ongoing work

- Implementation in LHCb framework (Allen)
  - Optimise throughput of the pipeline
  - Compare the optimal throughput with current implementation
- Extension to other LHCb tracking detectors, starting from SciFi

Thank you!

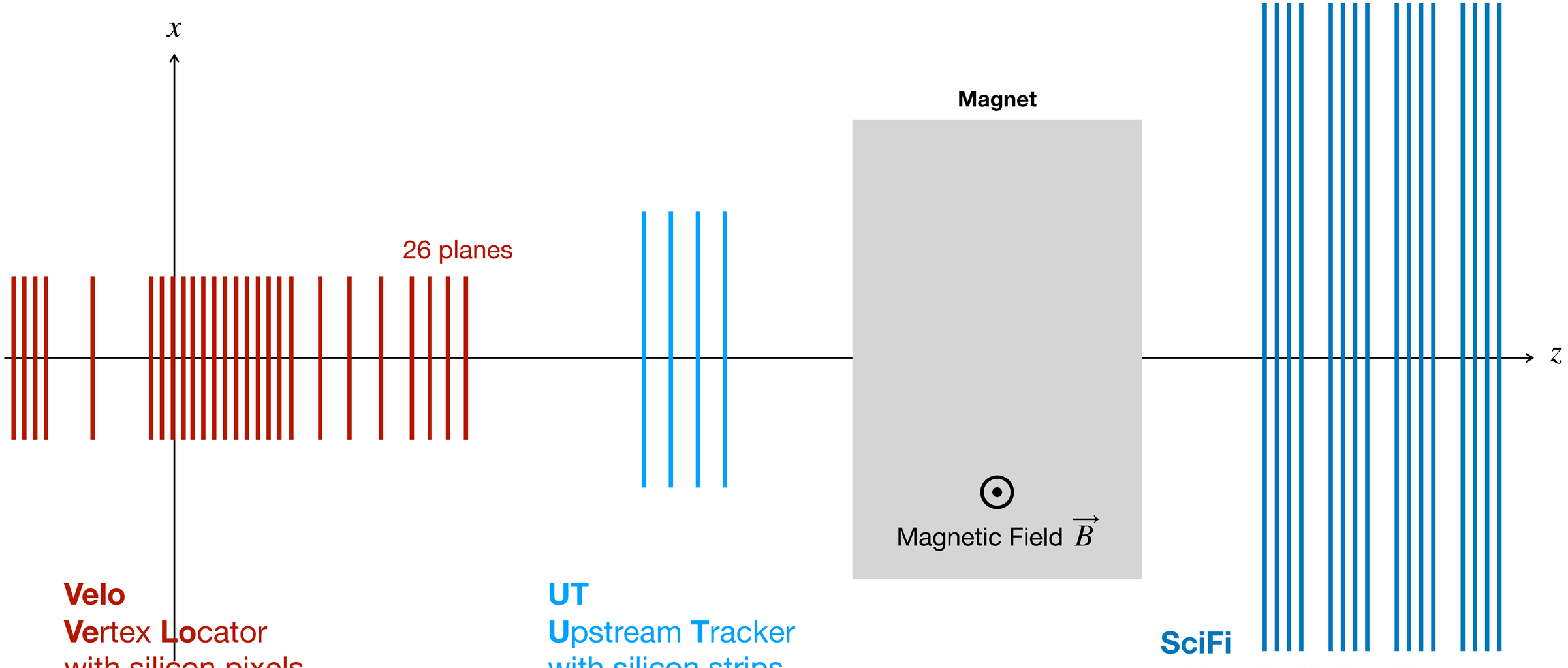
This work is part of the SMARTHEP network and it is funded by the European Union's Horizon 2020 research and innovation programme, call H2020-MSCA-ITN-2020, under Grant Agreement n. 956086.

Backup



Tracks in LHCb

Long tracks



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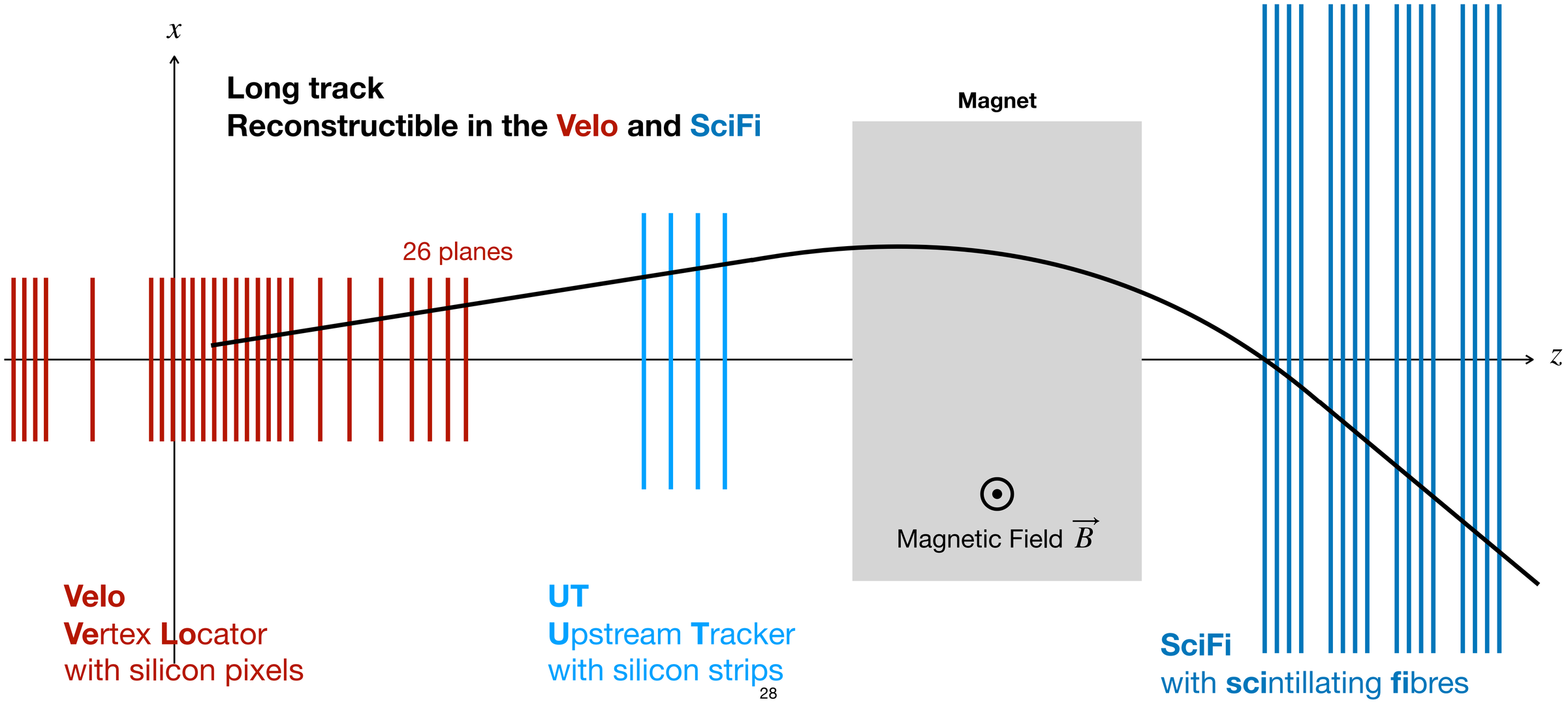

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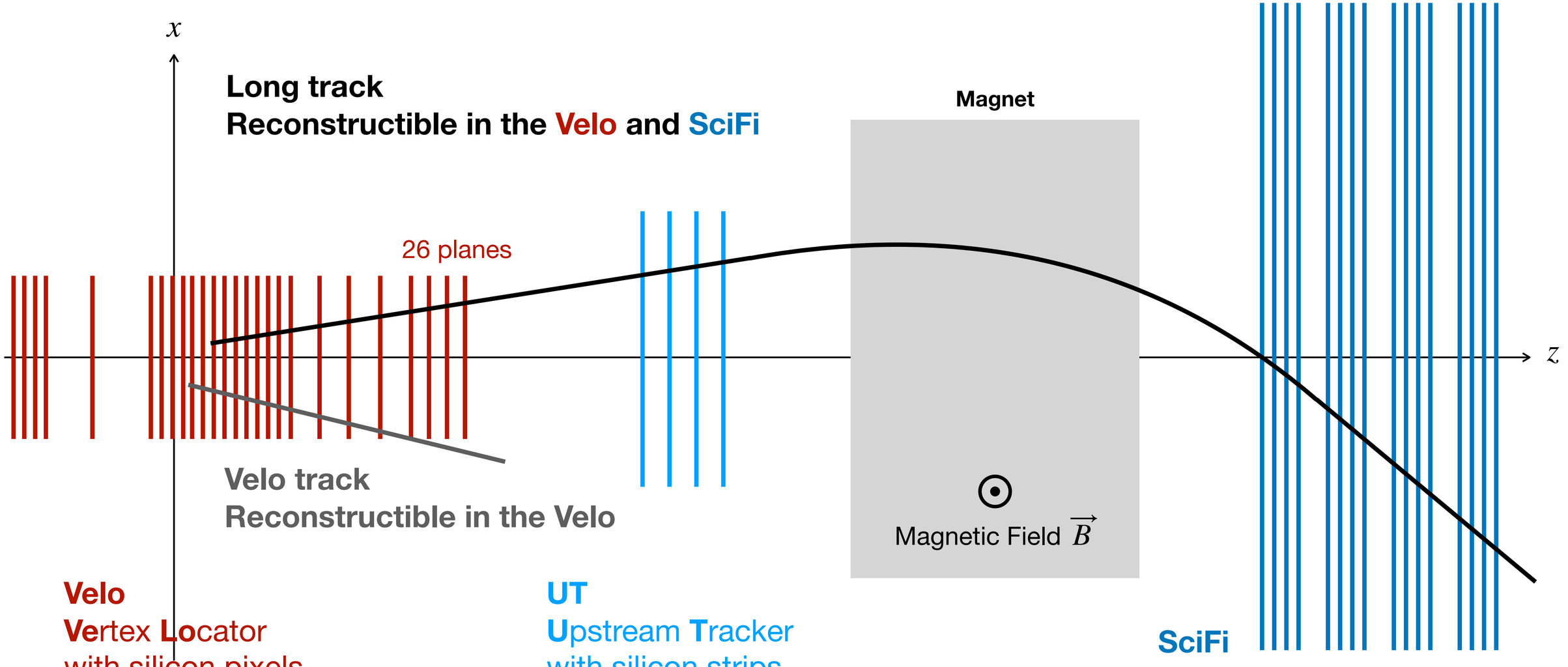
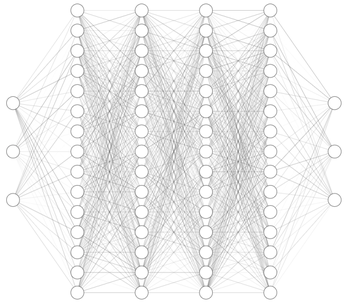
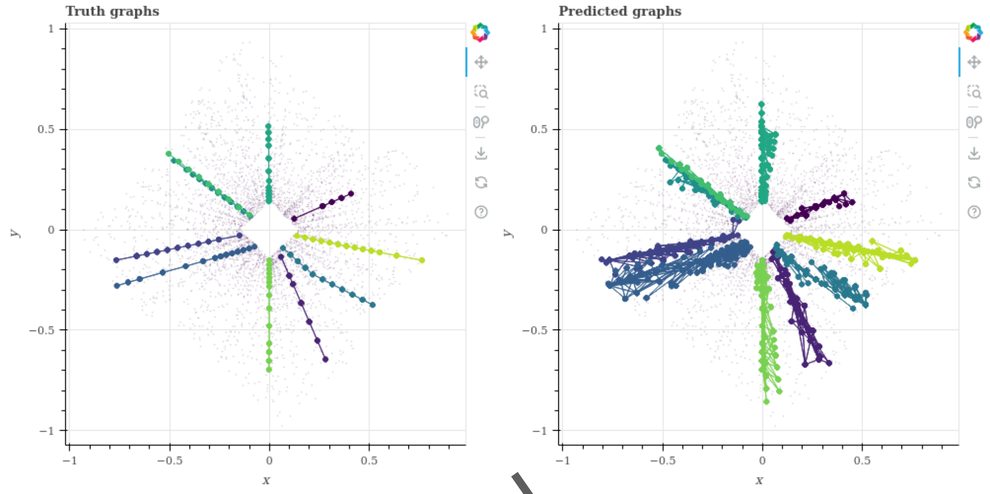
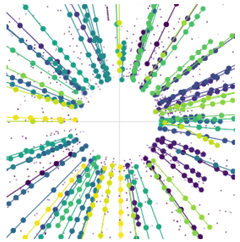


etx4velo

Training pipeline







Processing

Metric Learning Training

Metric Learning Inference

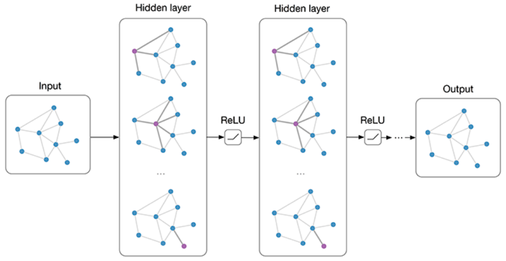
Graph Construction

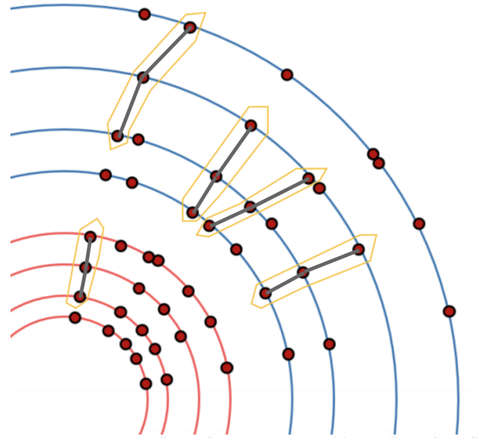
GNN Training

GNN Inference

Track Building

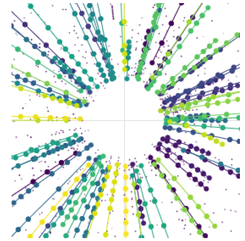
Evaluation





etx4velo

Inference pipeline



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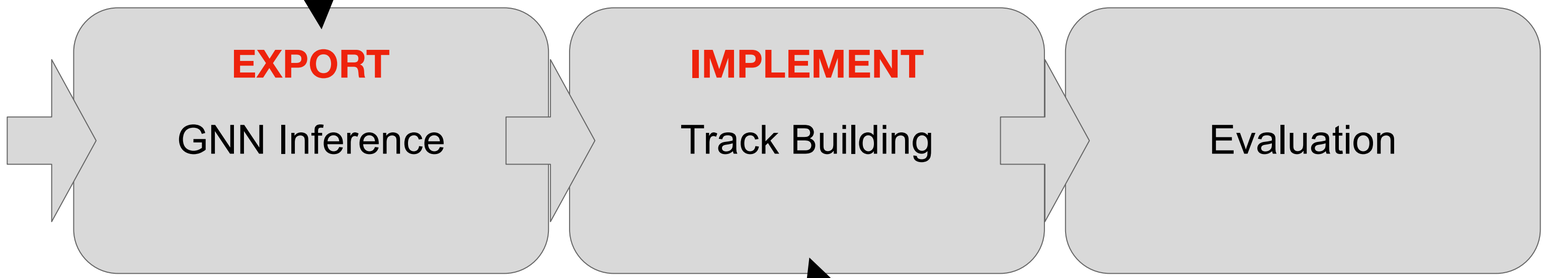

"Weakly connected components" algorithm

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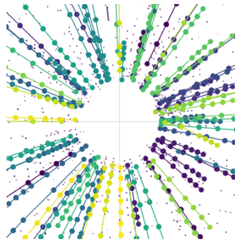
- **IMPLEMENT: C++/CUDA**

etx4velo

Processing



- Split data by event
- Selection on data / cuts
- Transform the data from Cartesian to cylindrical coordinates
- Calculate true edges of the graph
  - Find all the hits with the same mcid
  - Order them wrt the distance from the origin vertex
  - True edges are between these ordered successive hits
- Store data into torch tensors

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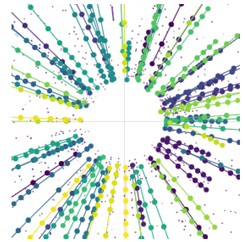
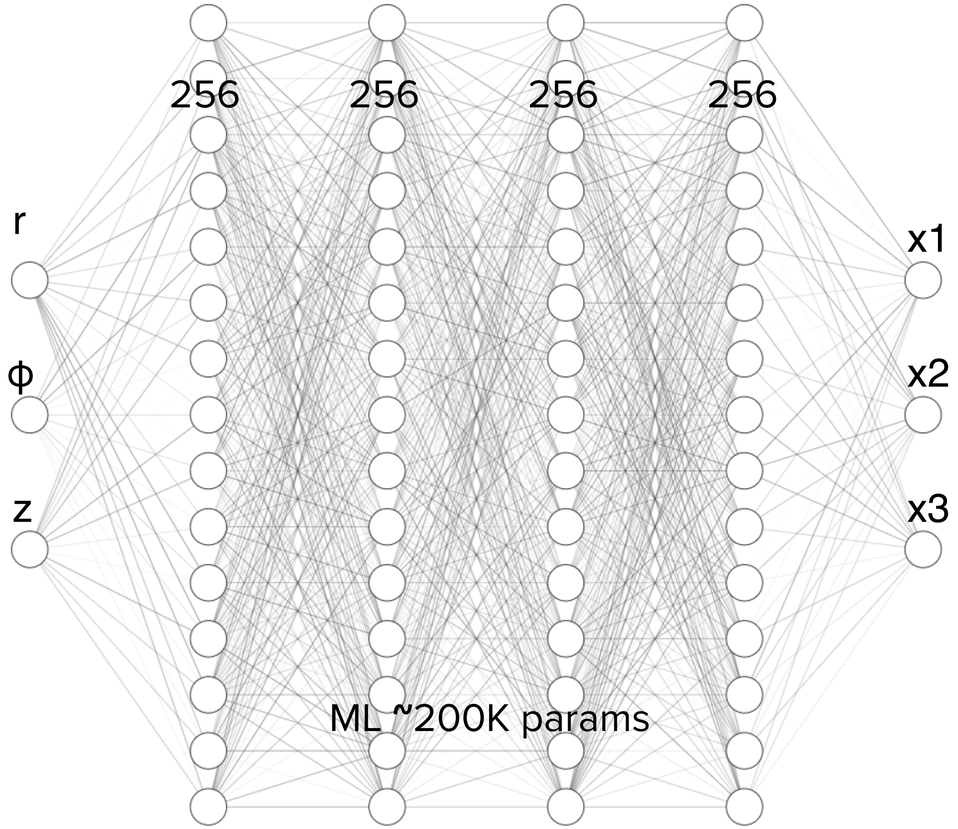
Metric Learning



- **Metric Learning Training**
  - Train an MLP to map the features to an embedding space
  - **Distance is reduced for successive hits** (same edge)
  - Distance is amplified if not successive
  - Create the graph for the event
    - For each hit in the embedding space
    - Create hypersphere around it
    - Connect target hit with all hits inside hypersphere
    - **faiss.knn_gpu** github.com/facebookresearch/faiss
- **Metric Learning Inference**
  - With the now trained network, **generate the graphs** for each of the events

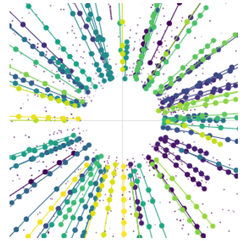


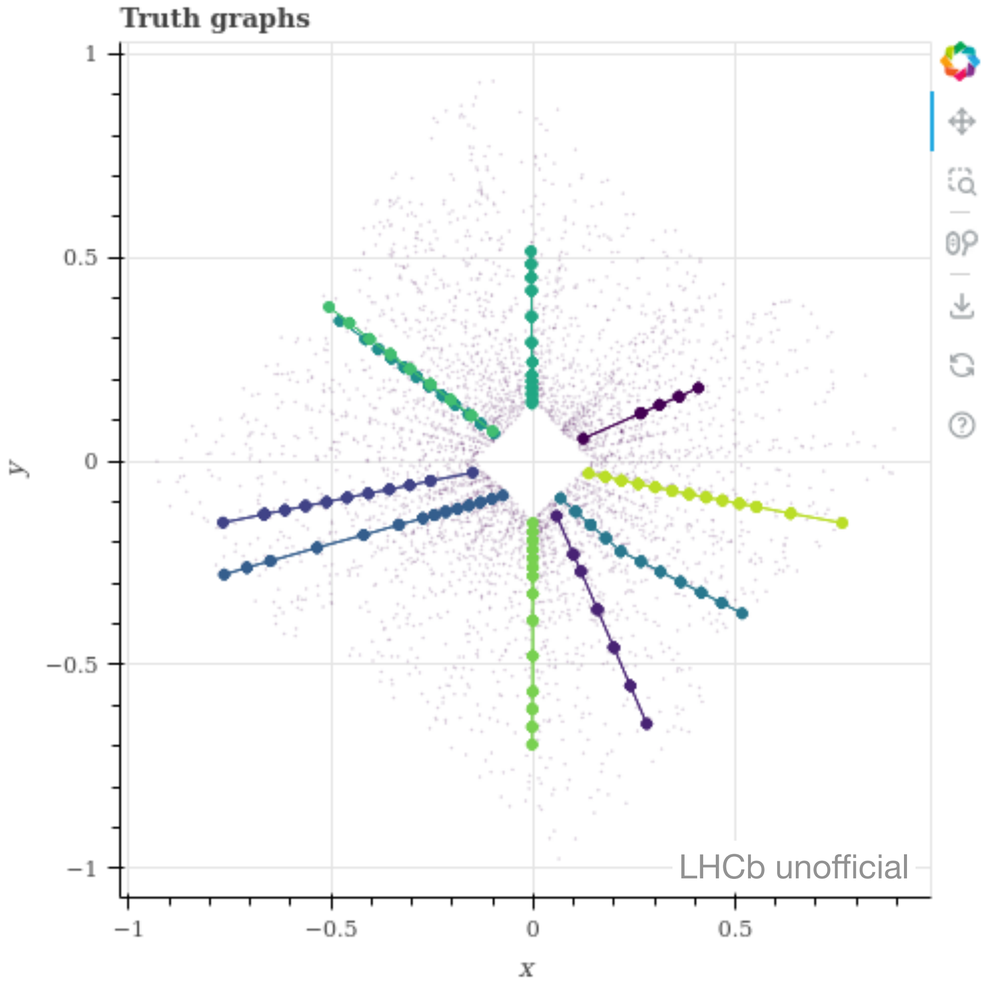
source

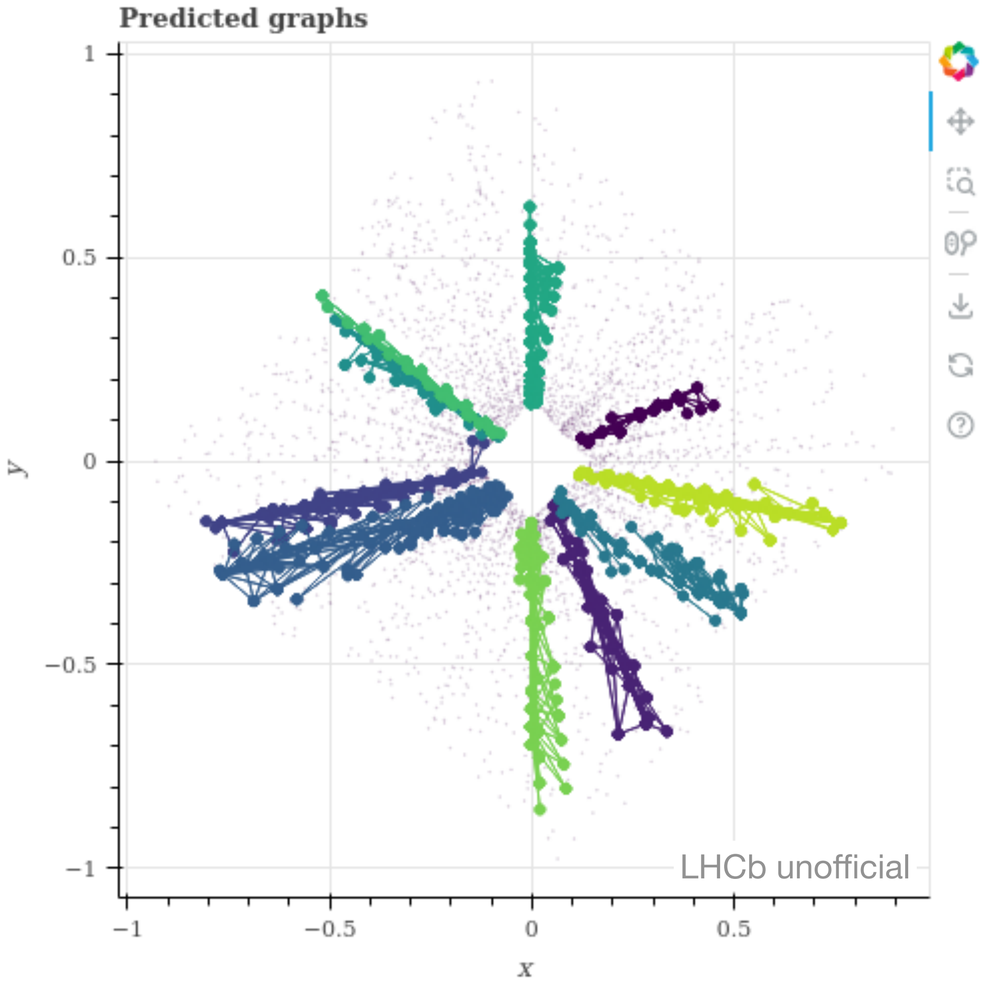
etx4velo

Metric Learning

Hits → Embedding → Graph

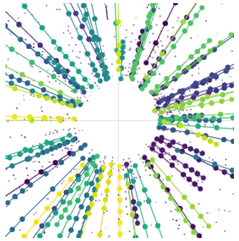






etx4velo

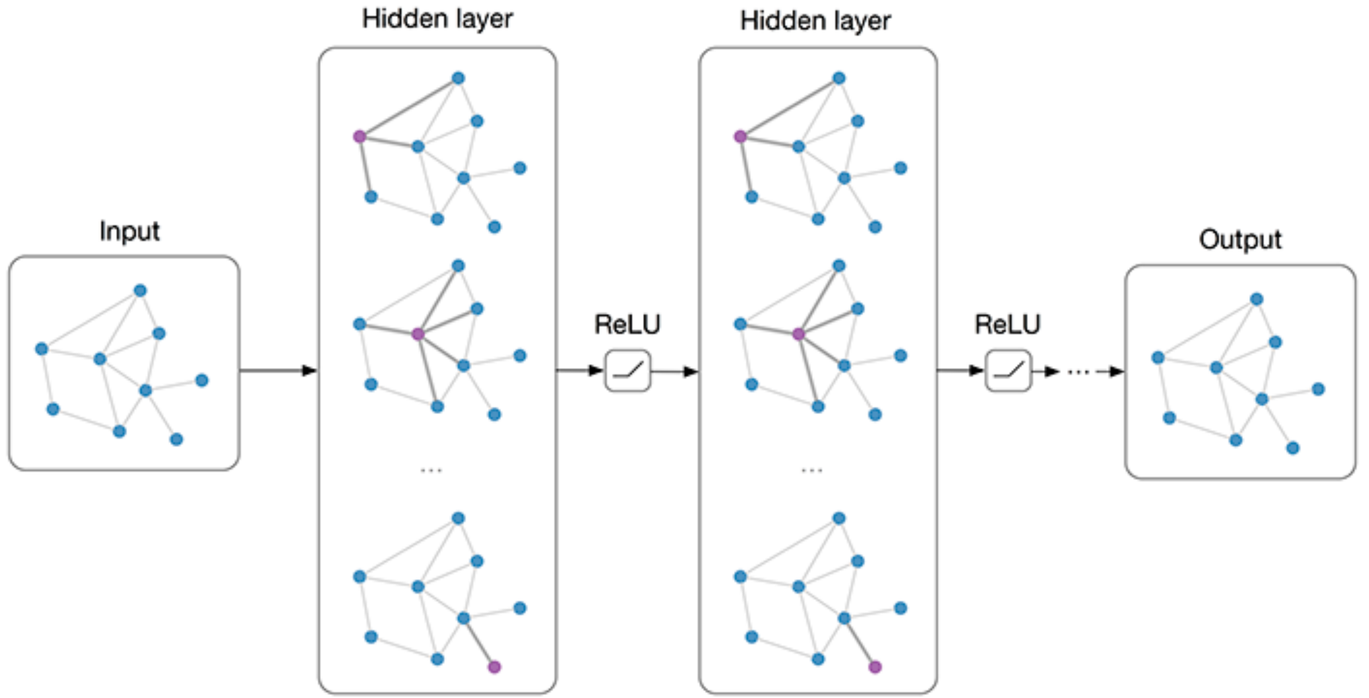
GNN



Graph → Edge scores

- **GNN Training**
  - With the generated graphs, train the GNN to give scores to each edge
  - True edge score = 1
  - GNN: Interaction network, Battaglia et al. “Interaction Networks for Learning about Objects, Relations and Physics”, arXiv:1612.00222
- **GNN Inference**
  - For each generated graph for the events, give scores to all the edges

GNN ~2M params (no pruning yet)



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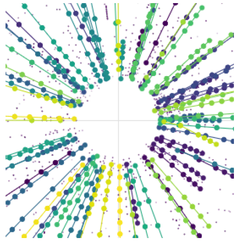
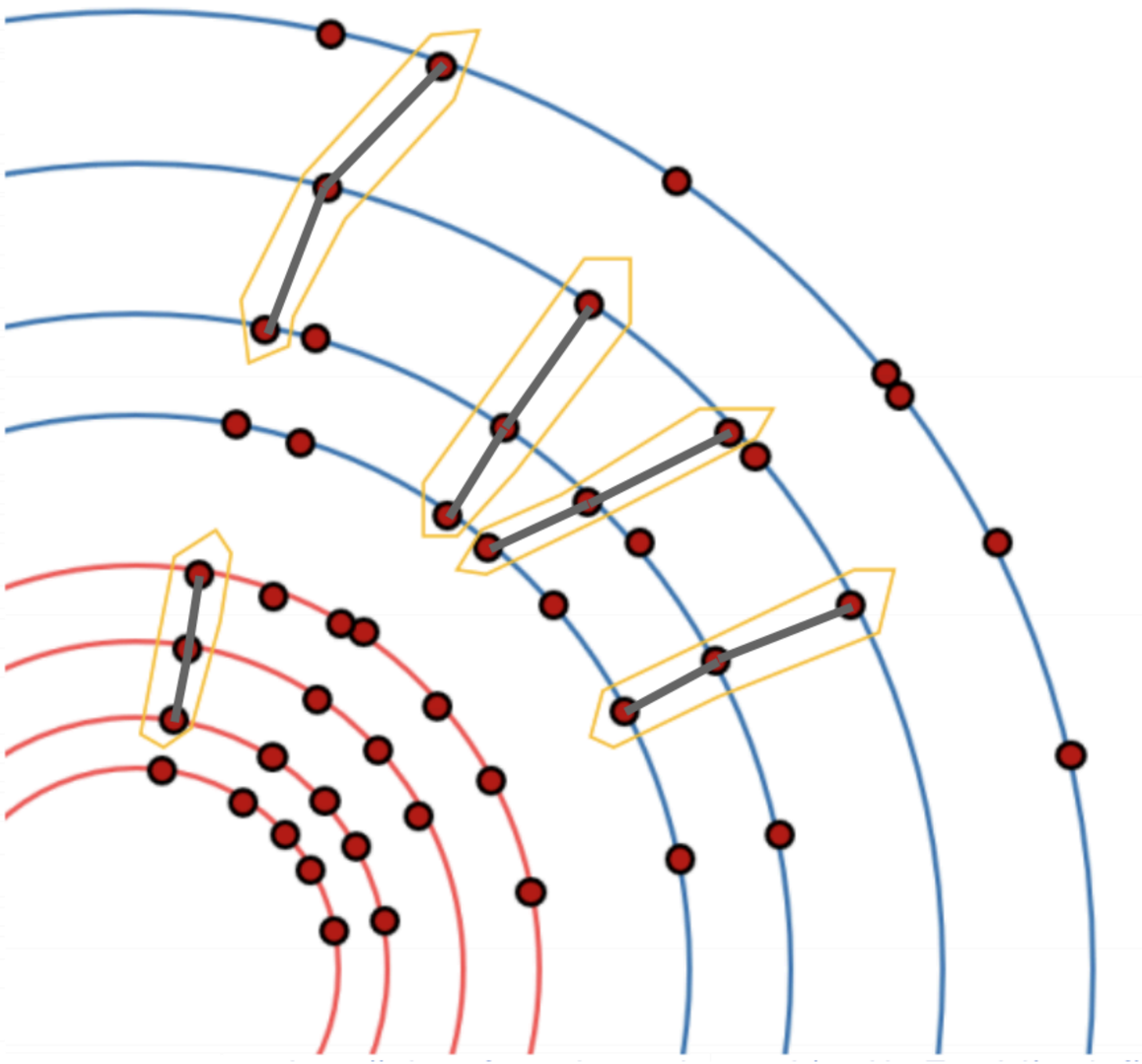
etx4velo

Track building



- Graph: sparse
- Choose score cut, e.g. 0.9
- If edge score < 0.9: remove edge
- Graph with disconnected components
- Break graph down to its connected components, [scipy.sparse.csgraph.connected_components]
- → Track candidates



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