JUSTUS-LIEBIG-UNIVERSITÄT GIESSEN

RICH RING RECONSTRUCTION USING MACHINE LEARNING FOR CBM

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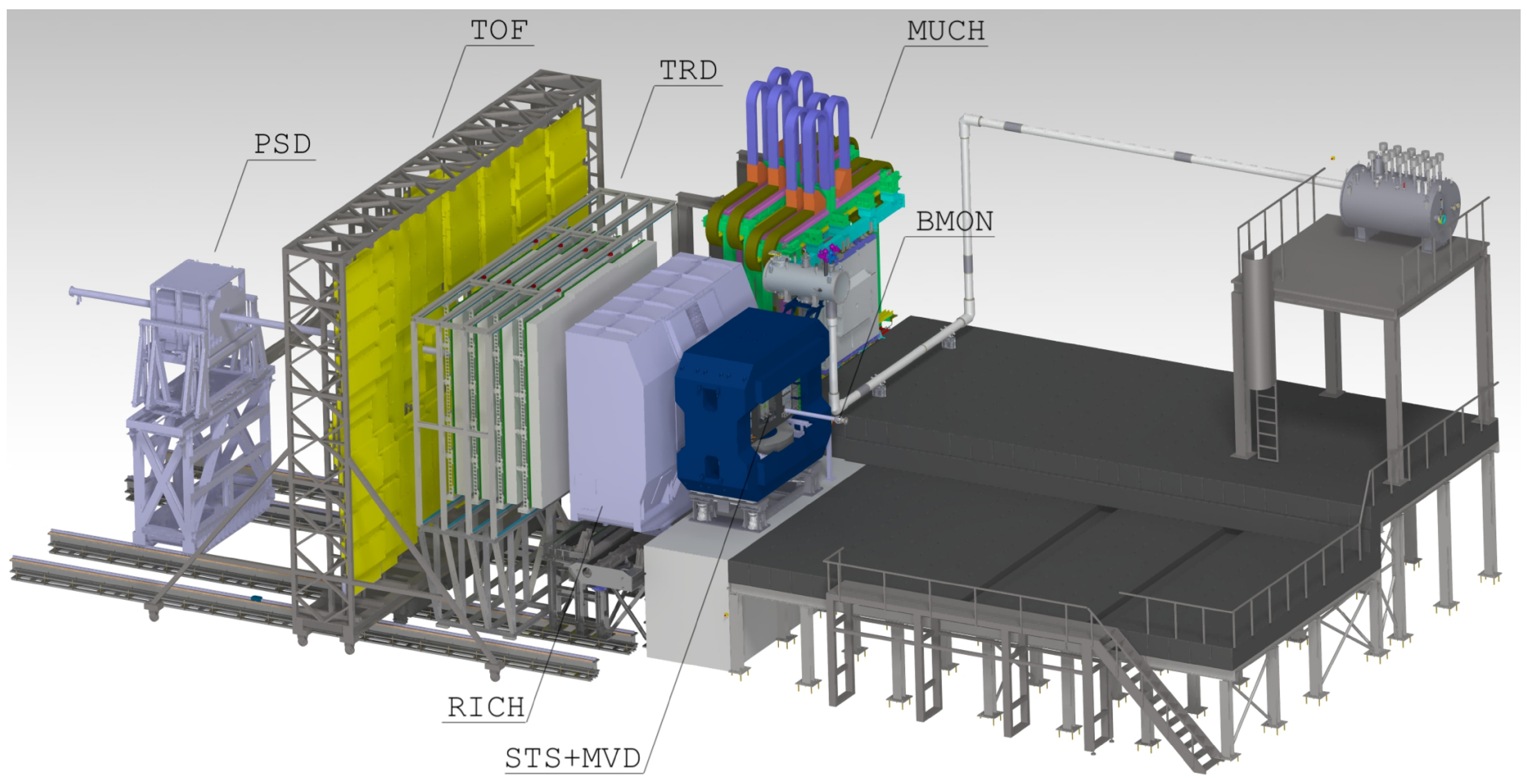
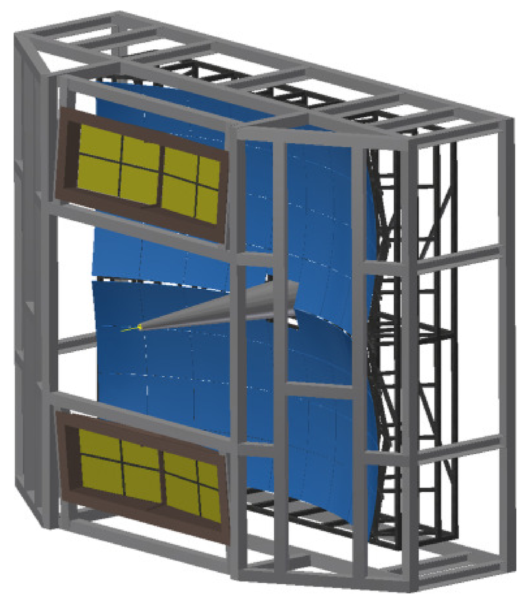
CBM RICH



Compressed Baryonic Matter (CBM) experiment

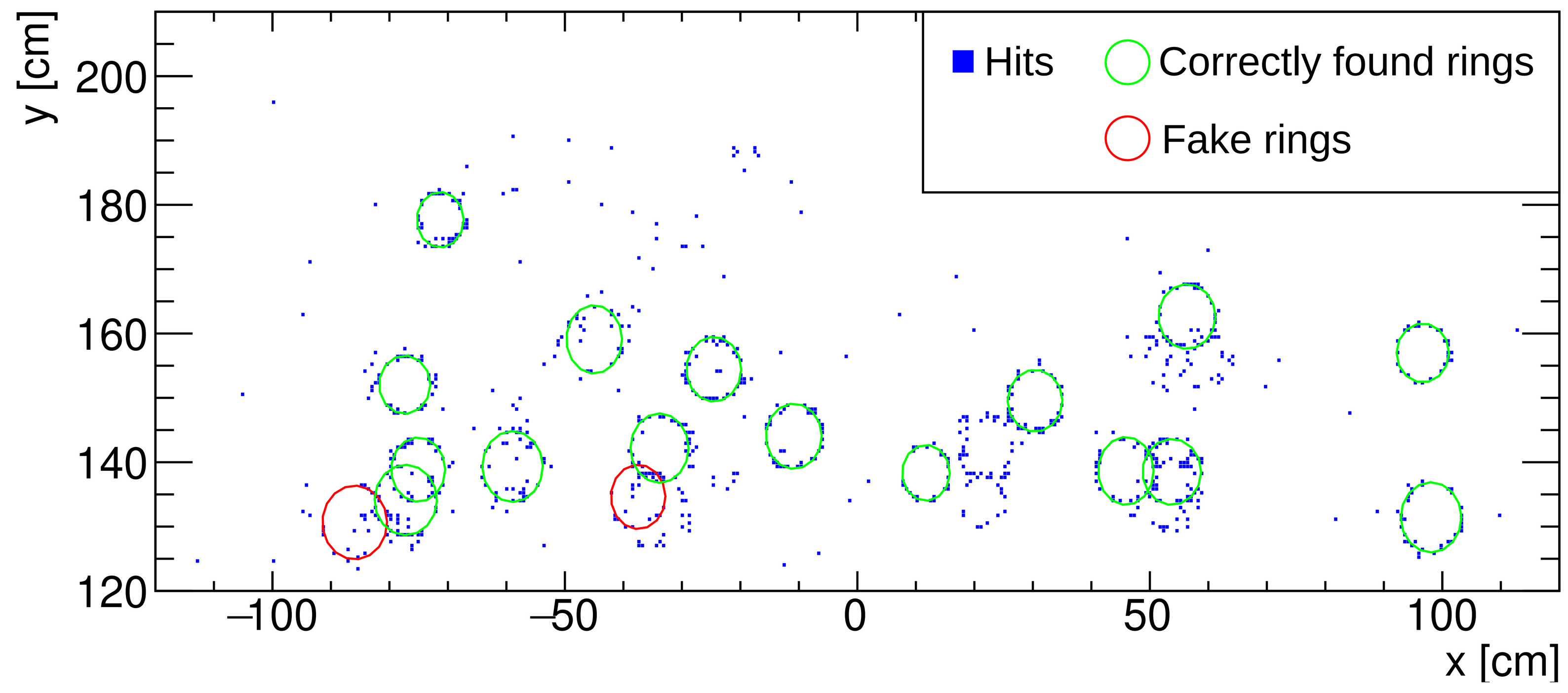
- High statistics heavy-ion fixed target experiment
- Interaction rates up to 10 MHz with SIS100 beam at FAIR energy range: Au from 2 to 11 AGeV, protons from 3 to 29 AGeV
- Data acquisition via triggerless free-steaming readout
- Event selection in software by online reconstruction and trigger



Ring-imaging Cherenkov (RICH) detector

- Mirror focusing setup with 2 photon detectors
- 8x8 channel multi-anode photomultiplier tubes (MAPMT) ➔ in total $\sim$ 65.000 pixels
- CO_2 as radiator gas
- Provides electron/pion separation from lowest momenta up to 8 - 10 GeV/c
- Pion threshold of 4.65 GeV/c

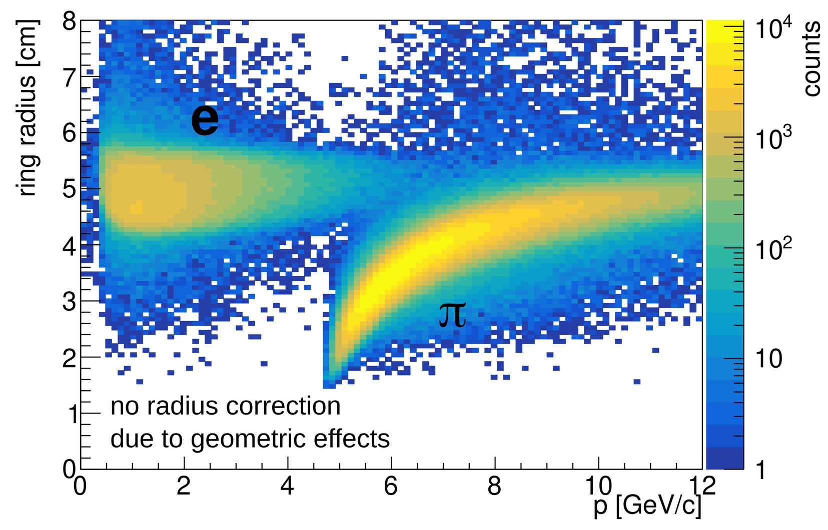
RICH ring reconstruction challenges

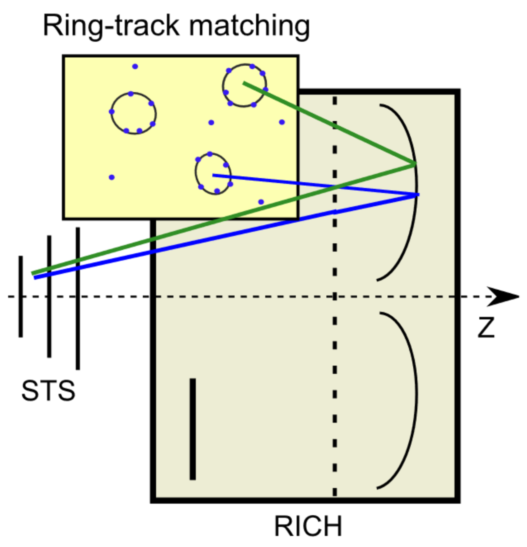


CBM RICH single-event-display of upper photo camera @ 11 AGeV Au+Au mbias

Ring reconstruction difficulties

- Rings with different sizes and number of hits
- Often with slightly elliptical ring structure
- Overlapping rings and noise
- Partial and smeared ring recognition
- Very crowded central region, with most pion rings located there
- Minimization of fake rings to reduce particle miss-identification
- Taking into account hit times





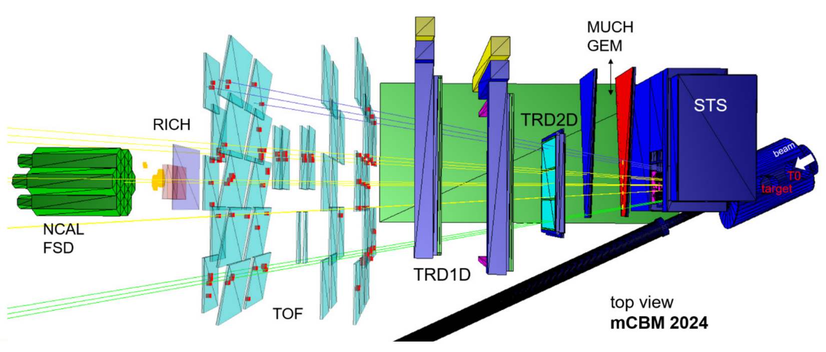
RICH particle identification

- Ring track matching by closest distance
  ➔ Contribution to overall particle identification by ring size
  ➔ Requires precise ring centers and ellipse fit parameters
- Average numbers for 11 AGeV Au+Au mbias collisions:
  – 40 secondary electrons (mostly without STS tracks)
  – 9 pions
  – 350 track projections
  – < 1 primary electrons (i.e. electrons from primary vertex)

mRICH noise removal using a CNN

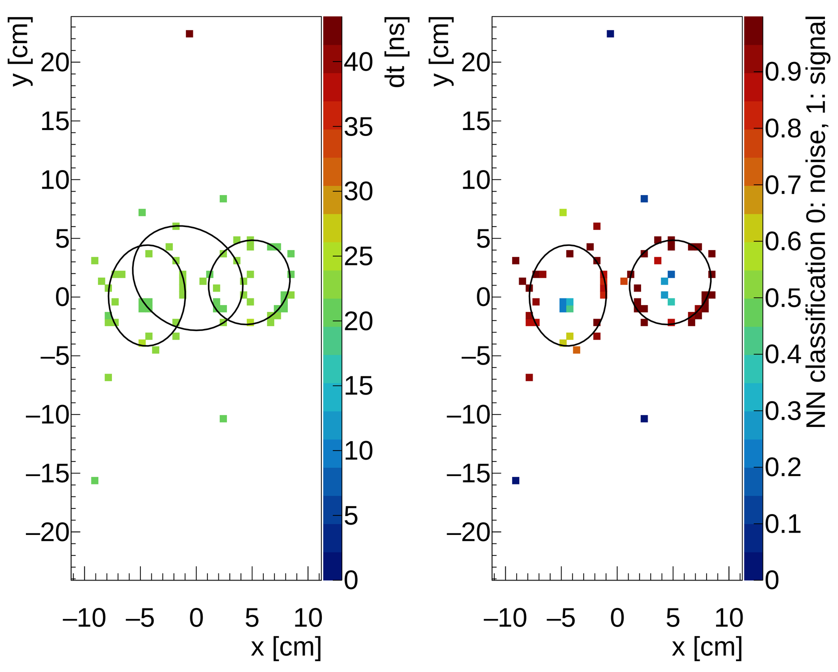
mini-RICH (mRICH) detector in the mini-CBM (mCBM) experiment

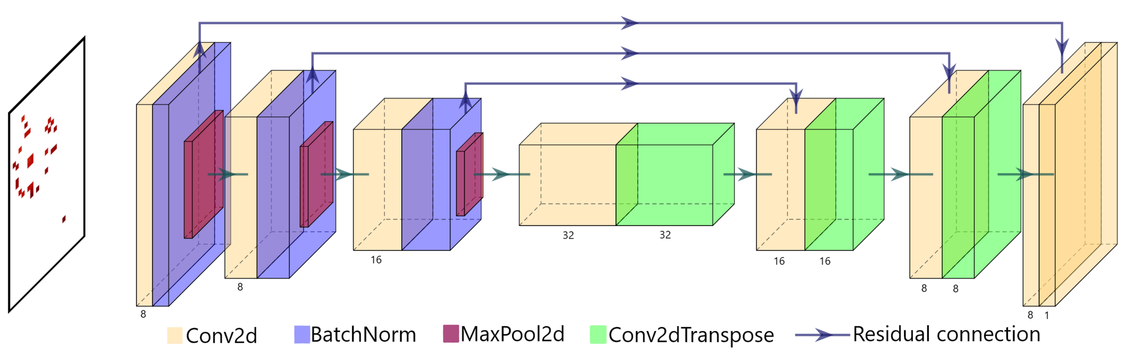
- Prototype version of CBM operated at GSI
- Test-bench for soft- and hardware
- mRICH is a proximity-focusing design equipped with 36 (4x9) MAPMTs
  Downside: Additional clusters due to charged particles passing through MAPMTs
  ➔ More fake rings

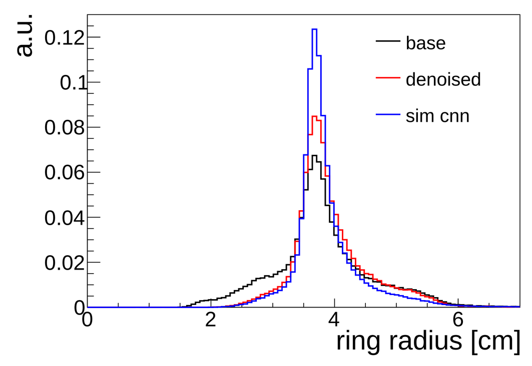


Noise removal via convolutional neural network (CNN)

- U-Net trained to classify noise (center clusters + noise)
- Hidden activation: ReLU
  Output activation: Sigmoid
- Supervised learning on simulated data
- Include time via sliding time windows
  Input: $(0,1)^{72\times32}$ ➔ Output: $(0,1)^{72\times32}$
- Reaches > 92% accuracy (0.5 threshold)
- Model deployed into the CBM C++ codebase using ONNX Runtime
- Tested and in operation on real data



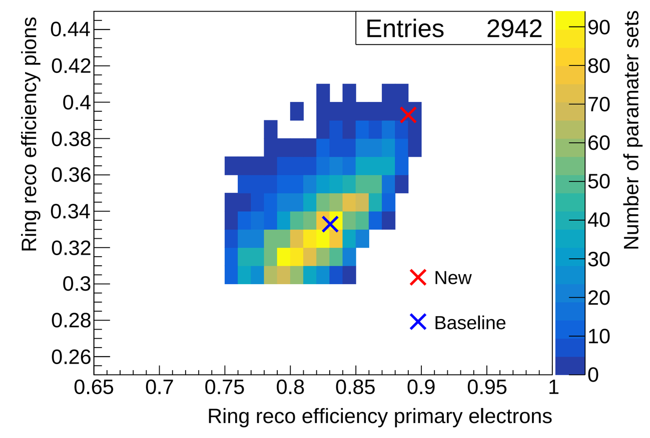




HT ringfinder

HT ringfinder parameter optimization

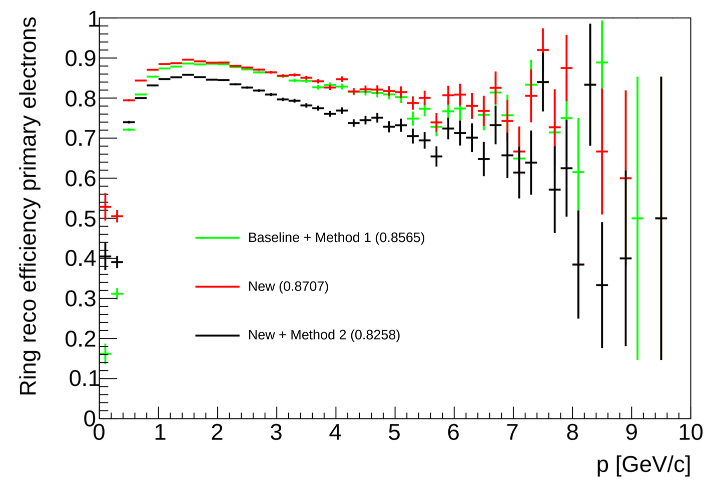
- Current ringfinder based on a circular Hough transform (HT)
- Optimize ringfinder algorithm parameters to maximize ring finding efficiency and purity
- Usage of a random search approach
  ➔ Primary electron and pion efficiency increases while keeping ring purity the same

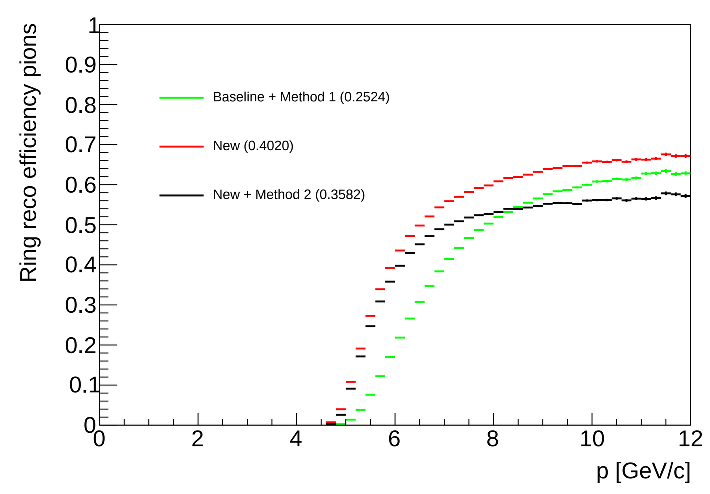


Ring selection using machine learning

- HT ringfinder itself only archives around 70% ring purity
- Remove fake rings by ML classification on ring parameters and structure, 2 approaches:
  Method 1: Classify ring candidates in the internal part of the HT algorithm
  ➔ Slows down the algorithm too much
  Method 2: Do fake rejection after ring finding
  ➔ Can not reach the same primary electron efficiency as the first approach, but significantly faster
- Trade-off between efficiency, purity and latency
- In both cases the classification only reaches 80% accuracy (0.5 threshold)

Setting	PrimEl Eff.	Pion Eff.	Purity	Latency / event
Baseline	0.8118	0.3258	0.7041	**6ms**
Baseline + Method 1	0.8565	0.2524	**0.8570**	650ms
New	**0.8707**	**0.4020**	0.7016	10ms
New + Method 2	0.8258	0.3582	0.8562	11ms





Future plans

Towards graph neural network (GNN) applications

Improvements over CNNs:

- More efficient operation on sparse data
- Handling of time data ➔ No need for sliding time windows

To be investigated:

- Structural awareness of rings using GNNs
- Under-reaching
  – Local, global transformation of hit positions
  – Graph creation, e.g. kNN in embedding space

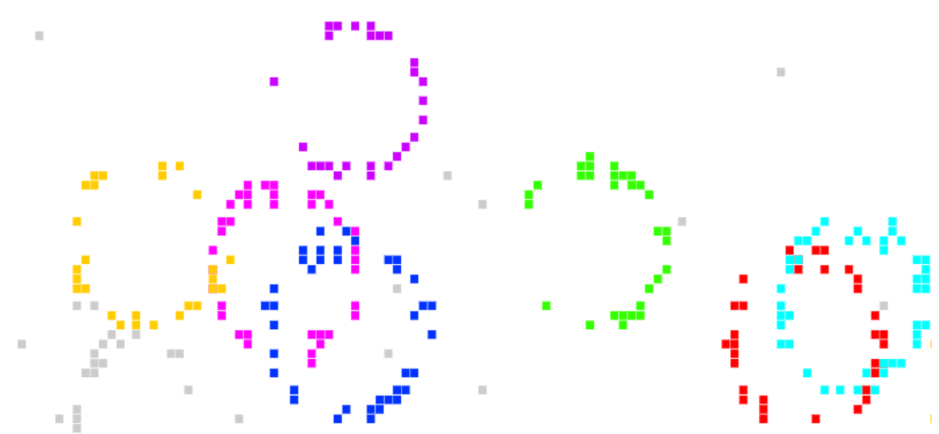
Downstream task approaches

Link prediction:

- Predict whether pairs of hits belong together based on their respective position, time and surrounding structure
- Find individual rings using the HT ringfinder taking into account pair predictions

Instance segmentation/clustering:

- Find ring instances as the downstream task directly
- Followed up by an outlier stable ellipse fitter



Funded by HGS-HiRE, GSI Helmholtzzentrum für Schwerionenforschung, Helmholtz Forschungsakademie Hessen für FAIR, BMBF (No. 05P24RG6)