ML-based digitization for CEPC vertex detector

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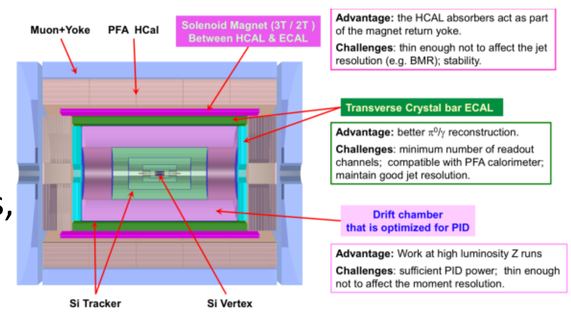
1. CEPC Vertex Detector

The Circular Electron Positron Collider (CEPC)[1] is a large international scientific facility proposed to explore the aforementioned physics program.

The Vertex Detector is an important sub-detector of CEPC, and its main purpose is to measure position and angles of charged particle tracks to sufficient precision.

The CEPC Vertex Detector has three layers, with detector units on both sides of each layer.

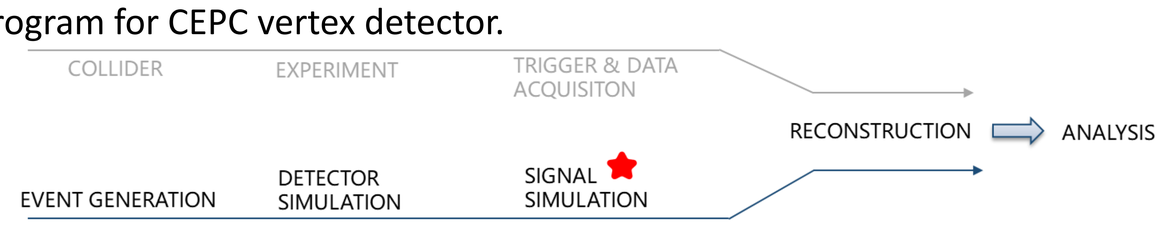


2. Digitization

The simulation path of the HEP experiments includes Event Generation, Detector Simulation, Signal Simulation, Reconstruction and Analysis.

Signal Simulation, which can also be called as Digitization, is the process of converting from analog to digital form.

The main purpose of this project is to develop a ML-based Digitization program for CEPC vertex detector.



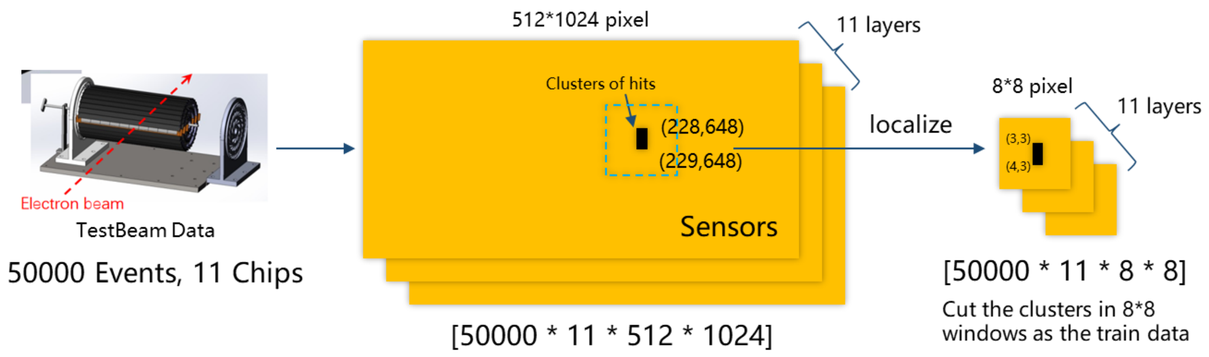
HEP simulation path

3. Methods

(1) Dataset

To meet the specific requirements of CEPC vertex detector, the MOST2 project was launched to develop a fully functional pixel sensor.

The sensor was characterized at the DESY test beam facility on Dec. 2022 and Apr. 2023. A beam telescope composed of 11 CMOS-based sensor chips (TaichuPix-3) was tested by 4Gev electron beam in these experiments.[2]

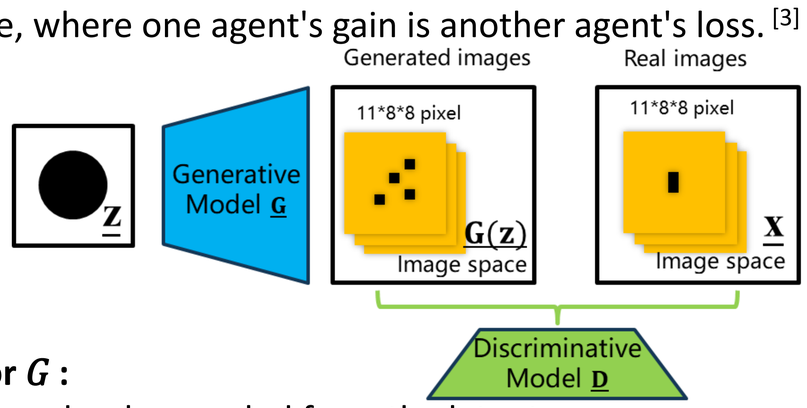


- The sensor size is 12.8mm*25.6mm, the pixel size of which is 25μm*25μm.
- Localization: Collect the clusters of hits using a 8*8 pixels window, which is used as the training dataset in the following NN model training.

(2) Model & Training

We developed a generative adversarial network (GAN) capable of digitization for CEPC vertex detector.

In a GAN, two neural networks contest with each other in the form of a zero-sum game, where one agent's gain is another agent's loss.[3]

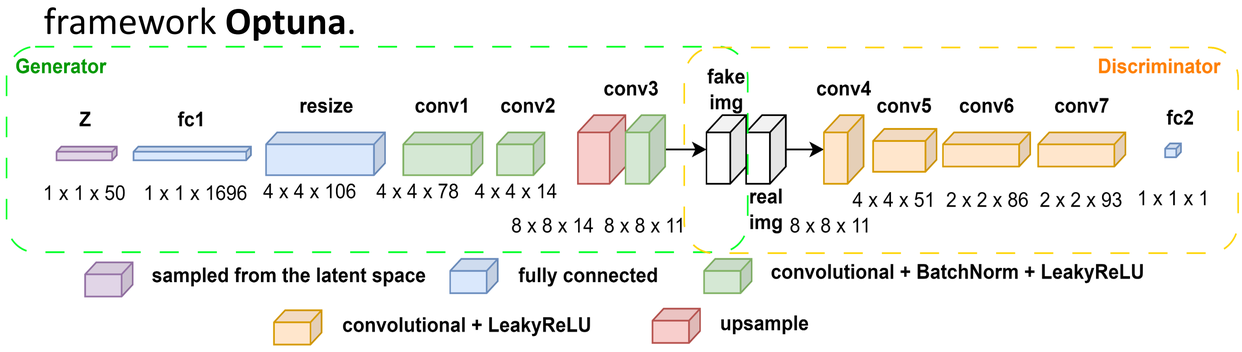


Generator G :
Input Z : randomly sampled from the latent space
Goal: try to make output resemble real samples (train data) as much as possible.
Discriminator D :
Input: real sample or the output of G
Output: the possibility that input is a real sample

- For every 10 times the discriminator is trained, the generator is trained once.
- Loss Function: Wasserstein Distance
- Metric: relative entropy of real and generated samples

(3) Optimization

- Generator\discriminator with different network models (fully connected neural network, CNN ...)
- Optimize the model with automatic hyperparameter optimization software framework **Optuna**.

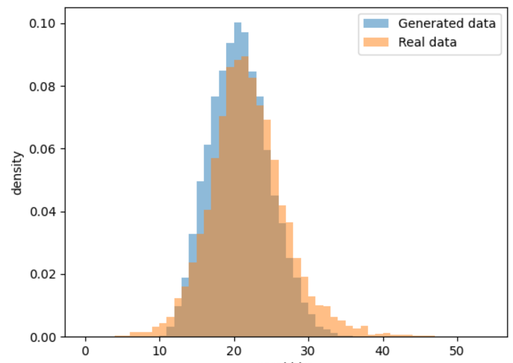


Optimized network architectures for the best performance is shown above.
The relative entropy of real and generated samples is considered as the metric of the performance, which of the different models is shown below.

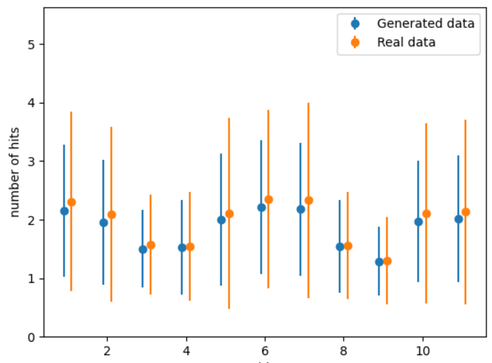
Model	NN	NN_Optuna	CNN	CNN_Optuna
Metric(relative entropy)	2.7548	2.1639	0.2393	0.0497

4. Evaluation

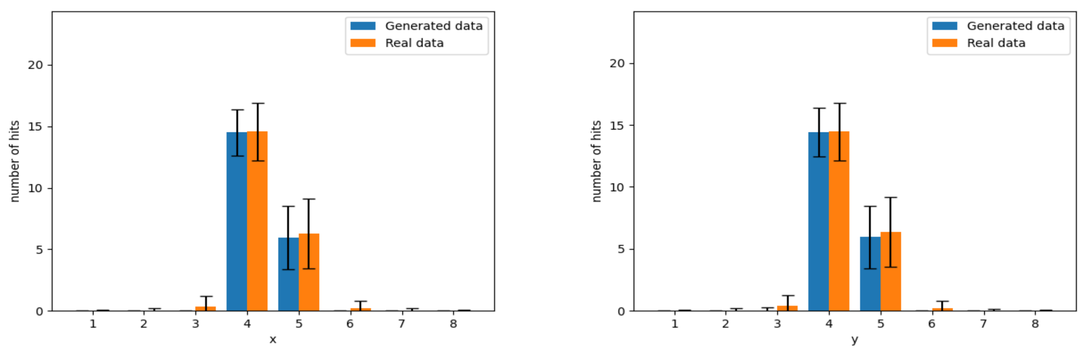
(a) Distribution of total clusters size per event



(b) Mean cluster size for each chip



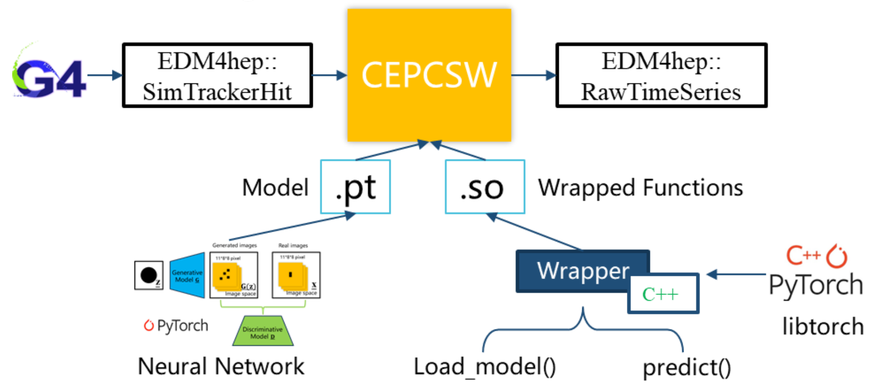
(c) Mean cluster size projected on X-direction/Y-direction



The distribution of digitization generated by the current model is generally as expected.

5. Application

The model has been integrated in CEPCSW.



The simulation path for CEPC vertex detector:

- GEANT4 generates simulate track hit.
- Digitization Algorithm use trained ML model to generates clusters of hits and stores them in EDM4hep::RawTimeSeries format.

We wrapped some features of libtorch in a .so file due to the conflict between ROOT and libtorch. The wrapped function can load the trained generator model and generates clusters.

6. Code

https://github.com/stch-zhangyzh/VDX_digitization

7. Reference

[1] CEPC Study Group. "CEPC Conceptual Design Report: Volume 2-Physics & Detector." arXiv preprint arXiv:1811.10545 (2018).
[2] Wang, Wei, et al. "Characterization of a CMOS Pixel Sensor prototype for the CEPC vertex detector." Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment 1056 (2023).
[3] Schlegl T, Seeböck P, Waldstein S M, et al. f-anogan: Fast unsupervised anomaly detection with generative adversarial networks[J]. Medical image analysis, 2019, 54: 30-44.