Fast simulation, CERN activities

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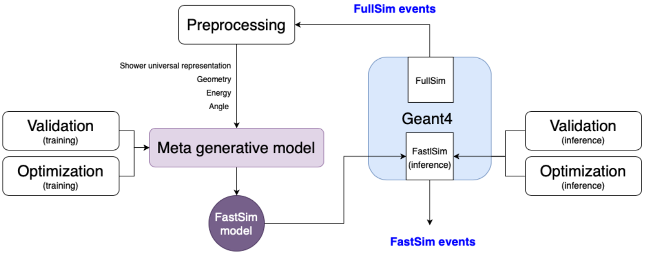
Integration of ML models

Integration of Machine Learning (ML) models into standard simulation toolkit (Geant4)

- Demonstration of ML inference in `C++` framework
- available in Geant4 11.0 release, but can be also used with 10.7
- Incorporation of few libraries: ONNX Runtime, LWTNN, Torch

- Implemented as a Geant4 example Par04, includes a trained model: Variational Autoencoder (VAE)



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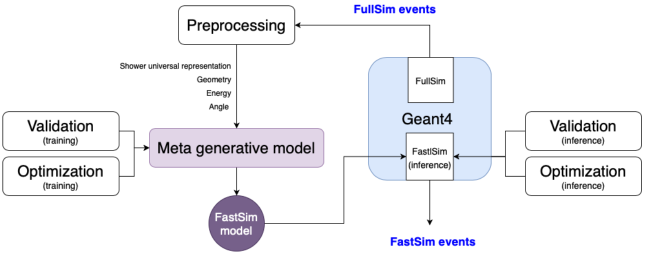

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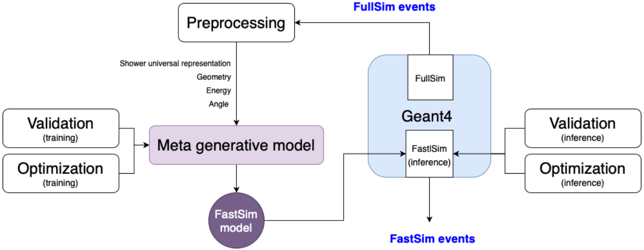
- Described in AIDAinnova milestone report



Calo Challenge and Open Data Detector

calochallenge.github.io/homepage

CaloChallenge

- A challenge compares a variety of models on the same datasets (3 datasets with increasing complexity)
- Workshop organized in Frascati at the end of May will conclude the cahllenge and compare the submitted contributions.

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Both topics will presented in two CHEP 2023 presentations.

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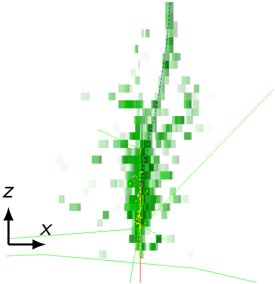
- Reuse an existing and a pretrained model to new detectors.
- A pre-trained model can adapt quickly to new detectors.



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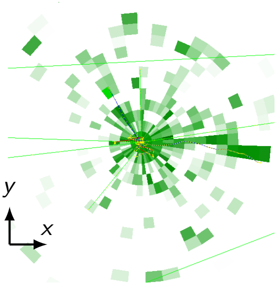

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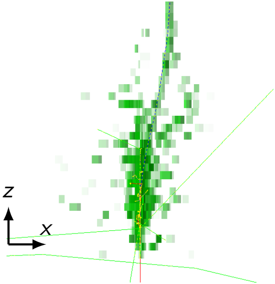
- Substantially decreases time needed to design and train a model.



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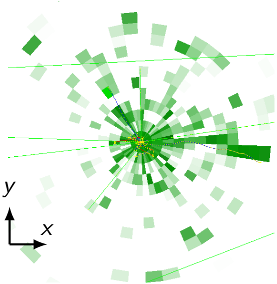

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Training	Steps	Convergence time
Traditional	400	20 min
Traditional	3900	3h 15min
Adaptation	400	20.5 s

527 speed-up

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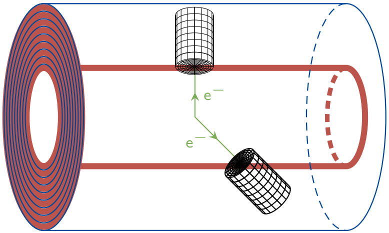

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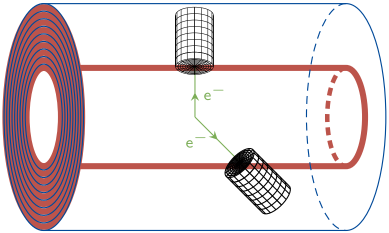

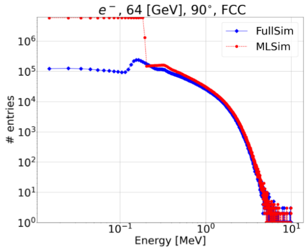

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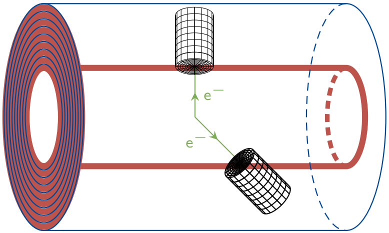
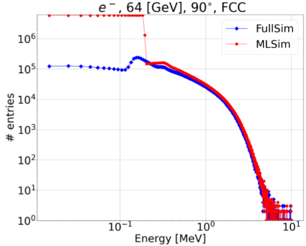
- Work presented at ACAT 2022





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- Generative ML model with transformers:
  - Vector Quantised VAE (VQ-VAE) plus an autoregressive (AR) model - exploring sequences in showers
  - Diffusion models - at early design stage, no results yet

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- Generative model will be presented at CHEP 2023

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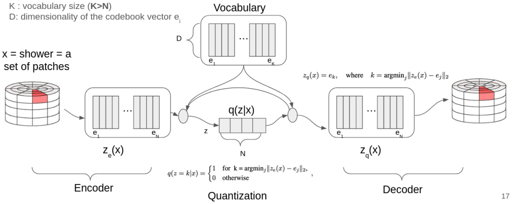
VQ-VAE

- VQ-VAE was first introduced in the "Neural Discrete Representation Learning" paper in 2017 by DeepMind
- It is a combination of a variational autoencoder (to learn lower representation of the input data) and then discretizes this representation using a vector quantization step to map it to a finite set of discrete codes

- z: discrete latent variable
- Latent embedding space e Ɛ R^{NxD}
- N: number of codebook vectors to represent a shower
- K : vocabulary size (**K>N**)
- D: dimensionality of the codebook vector e_i



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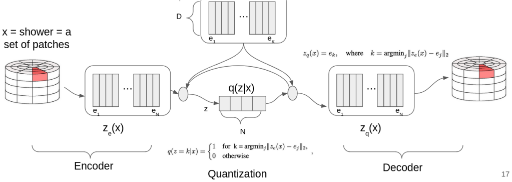

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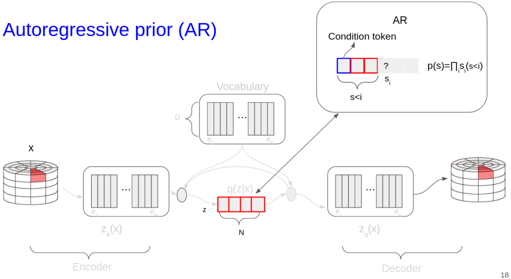
Autoregressive prior (AR)



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Summary and outlook

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- Finalisation of the Open Deta Detector calorimeter implementation and production of the dataset