Generative Adversarial Networks for the fast simulation of the Time Projection Chamber responses at the MPD detector

TPC tracker of the MPD experiment

- Main tracker of the central barrel
- Provides PID through dE/dx
- Fast simulation model is very much wanted
- Computational bottleneck in the electron drift simulation
- Our goal: accelerate TPC response simulation with a high-fidelity and physically acceptable generative surrogate

Fast simulation approach

- How can we use a GAN to produce raw pad responses?
- Output space too large:



- Factorize the problem: split the track into segments that contribute to a single row of pads each Ignore inter-row correlations
- Utilize the spatial and temporal localization of the signal from a single segment
 - Only small fraction of pads from a row is hit, in a small fraction of time intervals
- Output size reduced:
- from 30M to 128 = 8 pads \times 16 time bins
- Input parameterized by the segment's location and direction



- Training data from detailed simulation
- Pion tracks flat in angles and coordinates, constant $p_{\rm T}$

Architecture – key features:

- Custom generator activation at output to simulate the noise threshold in a differentiable manner
- Convolutional discriminator, but fully-connected generator (faster at inference time, without loss in quality)









Input image (batch_size, 8, 16)

Reshape (batch_size, 8, 16, 1

(batch_size, 8, 16, 6)

(batch_size, 8, 16, 16)

Conv2D, ELU, Dropout(0.02) kernel: 3x3 filters: 16 padding: same

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kernel: 3x3 filters: 16 padding: same

conv2D, ELU, Dropout(0.02) kernel: 3x3 filters: 32 padding: same

Conv2D, ELU, Dropout(0.02)

kernel: 3x3 filters: 32 padding: same

Maxpool 2x2

onv2D, ELU, Dropout(0.02)

kernel: 3x3 filters: 64 padding: valid

conv2D, ELU, Dropout(0.02)

kernel: 2x2 filters: 64 padding: valid

Reshape (batch_size, 64)

(batch_size, 69)

Concatenate

Dense, 128, ELU

Dense, 1

(batch_size, 8, 8, 32)

(batch_size, 4, 4, 32)

(batch_size, 2, 2, 64)

(batch_size, 1, 1, 64)

(batch_size, 8, 16, 16)

(batch_size, 8, 8, 32)

Maxpool 1x2 (batch_size, 8, 8, 16)

Input features (batch_size, 5)

Reshape (batch_size, 1, 1, 5)

Tile (1, 8, 16, 1)

Model validation

- Two levels of quality assessment:
 - At raw signal level, for prompt checks and model selection At reconstruction level, after having implemented our best
 - model into the MPD simulation pipeline

Raw signal level validation

- Describe individual signals (2D images in pad-time plane) using their integral amplitude along with 1st and 2nd order moments:

 - Barycenter (center of mass) location, widths & covariance – Total: 6 numbers per image
- Compare distributions of these moments between GAN and the detailed sim
- As the function of track segment parameters (each moment vs each parameter)

Reconstruction level validation

- Comparing coordinate resolution, reconstruction efficiencies and more (see the paper)
- Most characteristics are spot on! (srsly, see the paper!)
- Inconsistencies are well-understood and will be fixed at the next iteration (haven't you seen the paper yet?)



Model speed

TPC digitization sped-up by a factor of 12 for the expected-occupancy events (running on CPU)



20th International Workshop on Advanced Computing and Analysis **Techniques in Physics Research**

29 Nov 2021 – 3 Dec 2021

Alternative approach [WIP]: generating moments

KEY RESULT 12x acceleration achieved for TPC with physically acceptable quality



- Optimize the raw metrics directly
- Convert the metrics (5 moments + amplitude) into raw signal image
- Not a trivial operation: getting biased image by evaluating 2D-Gaussian at discrete grid nodes
- Learning to account for these biases by generating adjusted moments in the first place
- Training not stable, looking for improvements



Input parameters



Example signals

For more details, see our EPJC paper



Eur. Phys. J. C 81, 599 (2021)









