Fast simulation of Time Projection Chamber response at MPD using GANs

VI-th Collaboration Meeting of the MPD Experiment at the NICA Facility,

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Outline of the talk

- About us
- Introduction to Generative Adversarial Networks (GANs)
- Our approach to fast simulating TPC using GANs
- Preliminary results

About us

- People involved:
  - Artem Maevskiy (NRU HSE)
  - Fedor Ratnikov (NRU HSE)
  - Alexander Zinchenko (JINR)

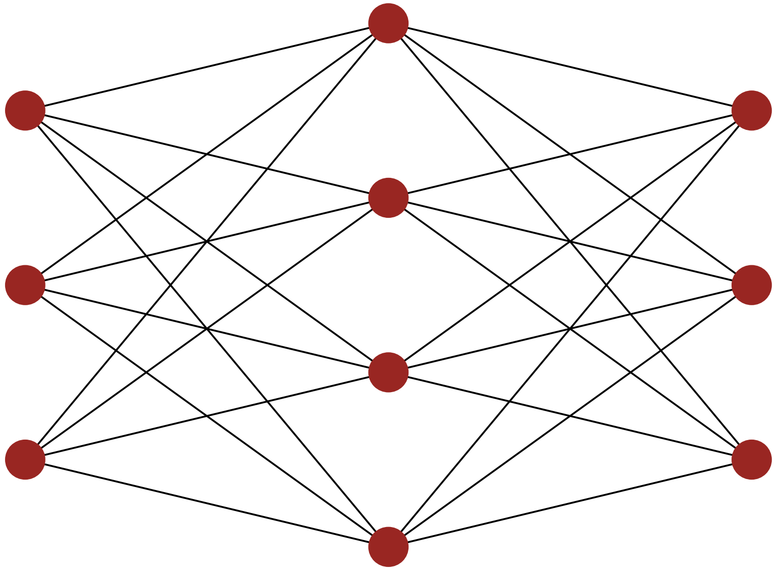
Members of the Lambda laboratory (https://cs.hse.ru/en/lambda/)

Our lab specializes in the applications of **machine learning** techniques to high energy physics problems.

We have similar projects in the LHCb experiment — developing **fast simulation models** for the Cherenkov detectors and the electromagneric calorimeter

Generative Adversarial Networks

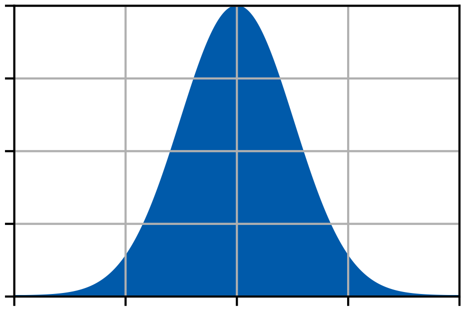
How can a neural network generate data?



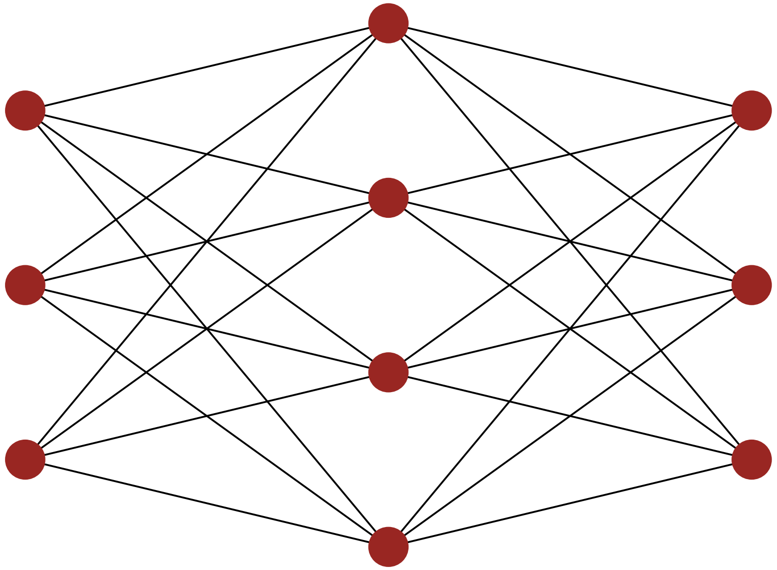
Neural network

Cat image attribution: https://pixabay.com/users/chiemsee2016-1892688/

How can a neural network generate data?



Random noize
e.g. multivariate normal



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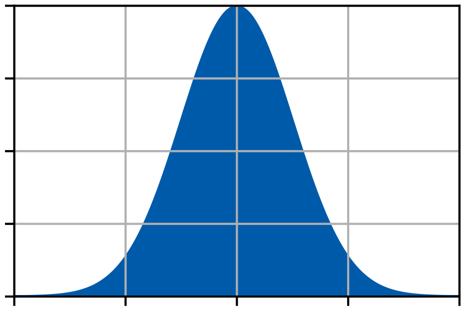

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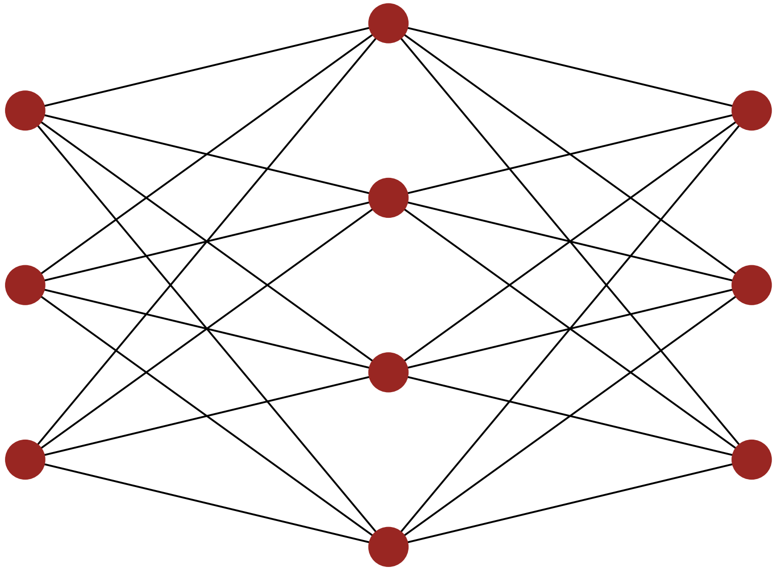

Neural network

Generated data

- This makes the generated object being a **differentiable function** of the network parameters

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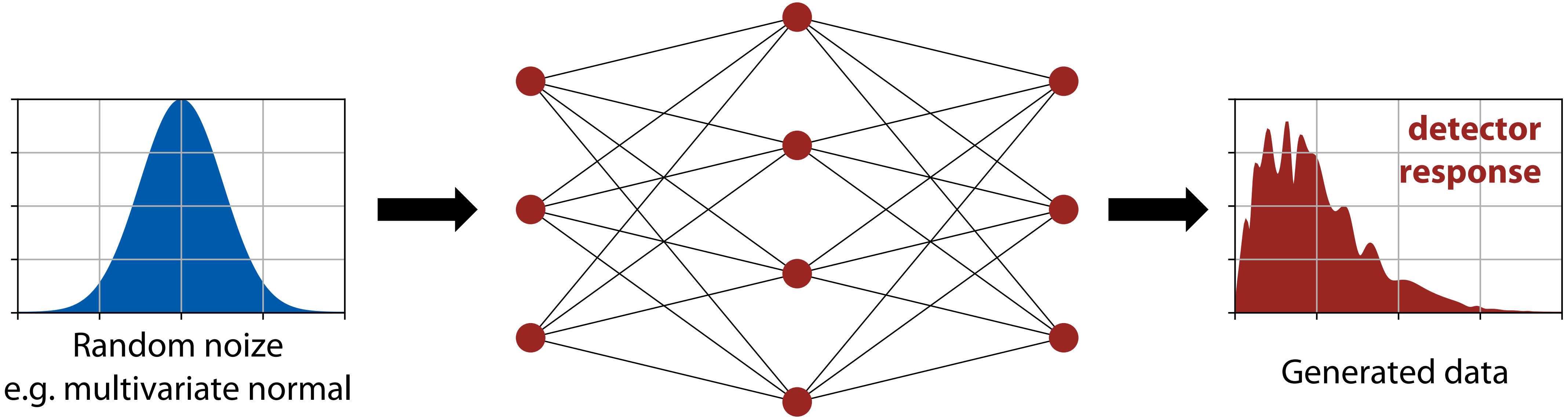


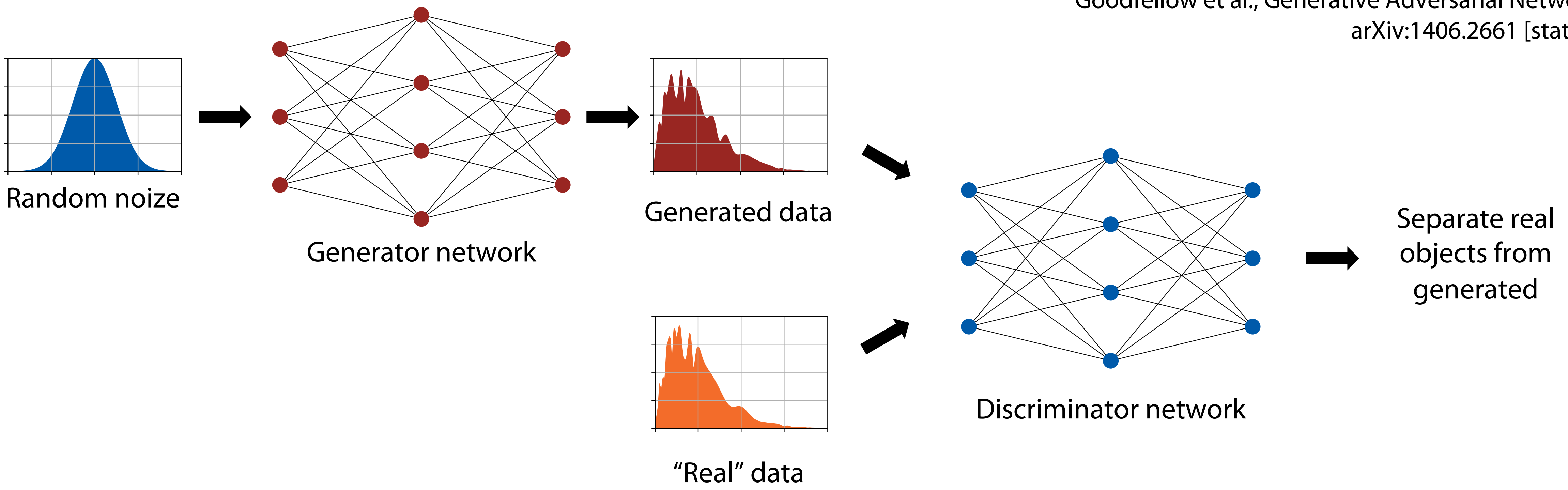
- This makes the generated object being a **differentiable function** of the network parameters

How to train such a generator?

- Generated object is a differentiable function of the network parameters
- Need a differentiable **measure of similarity** between the generated objects and real ones
  - Can optimize with gradient descent
- How to find such a measure?

Adversarial approach

Goodfellow et al., Generative Adversarial Networks,
arXiv:1406.2661 [stat.ML]



- Measure of similarity: how well can another neural network (discriminator) tell the generated objects apart from the real ones

GANs for fast simulation

K. Matchev, P. Shyamsundar, Uncertainties associated with GAN-generated datasets in high energy physics, arXiv:2002.06307 [hep-ph]

- Quite a developing field!

- Important note: one cannot increase the statistics with GANs
- GANs rather memorize and interpolate the available data

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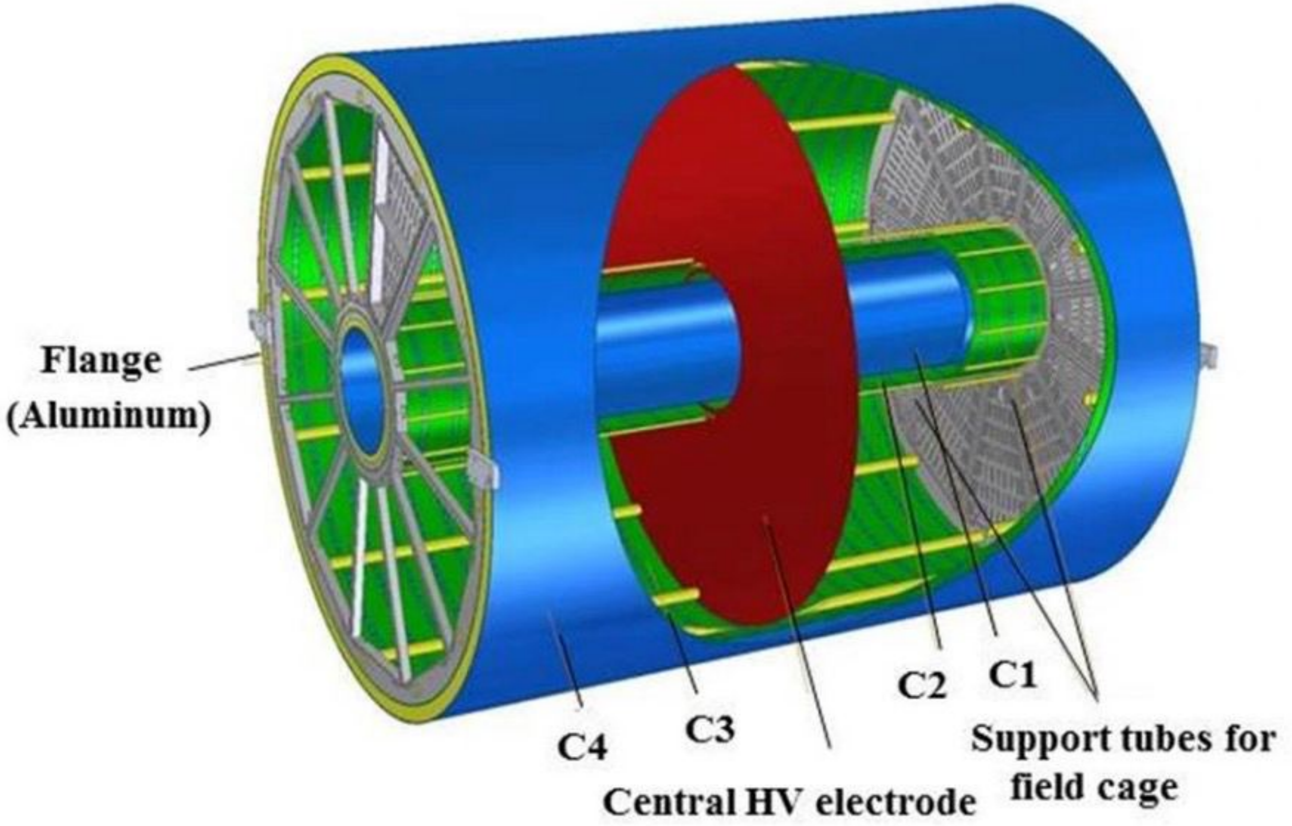
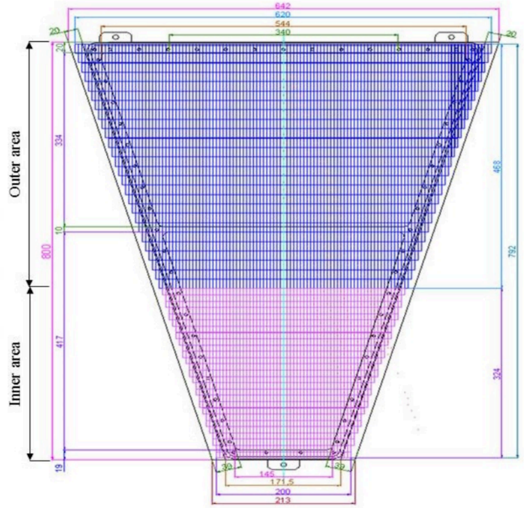
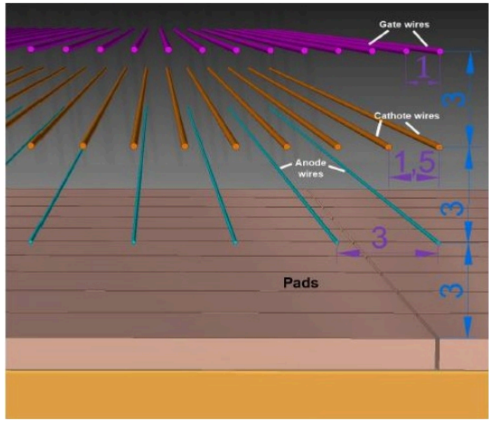
Simulating TPC with a GAN

Time projection chamber







Pad and wire planes

95 232 pads

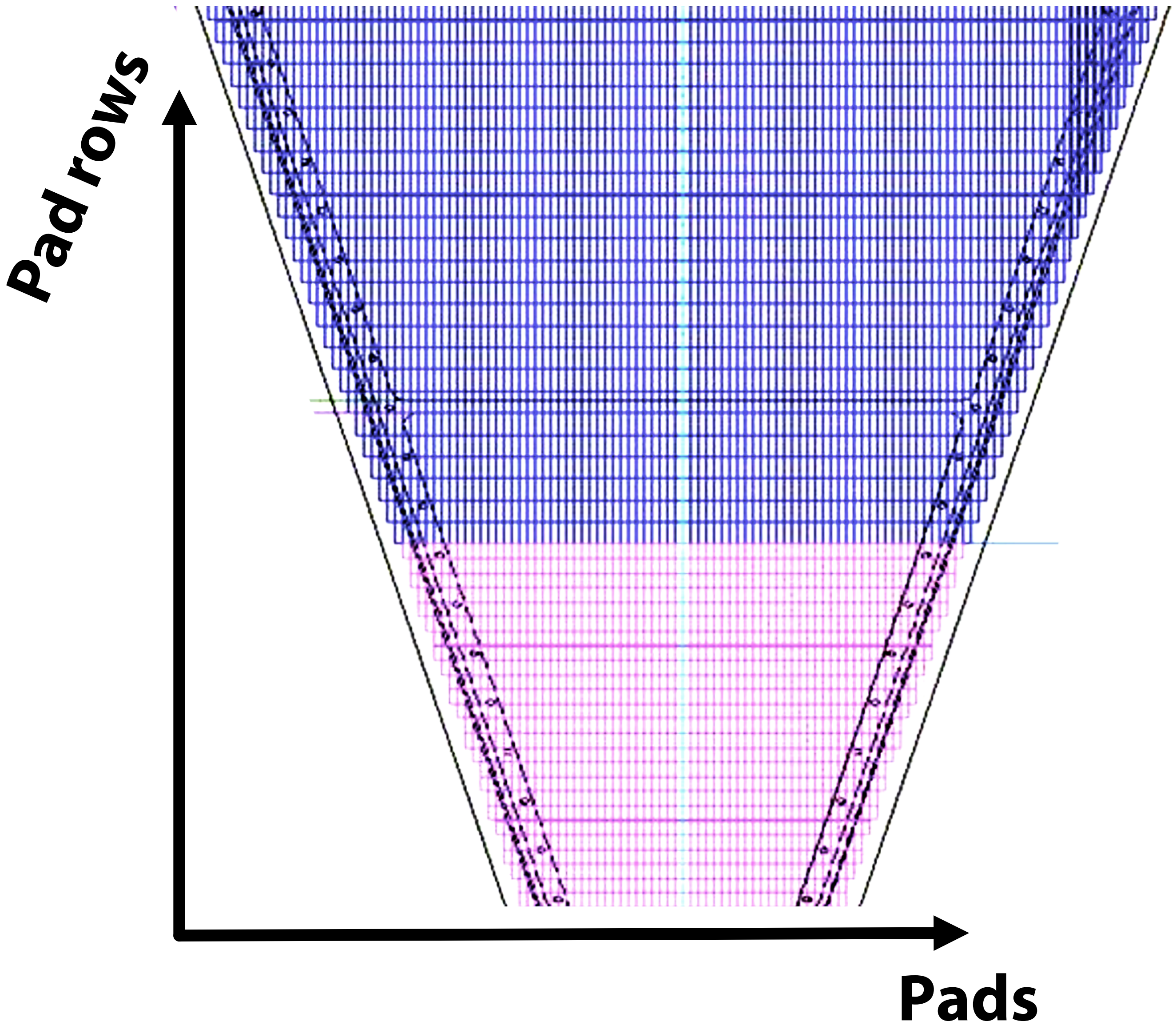
310 time buckets

Simulation time: ~25 sec/event

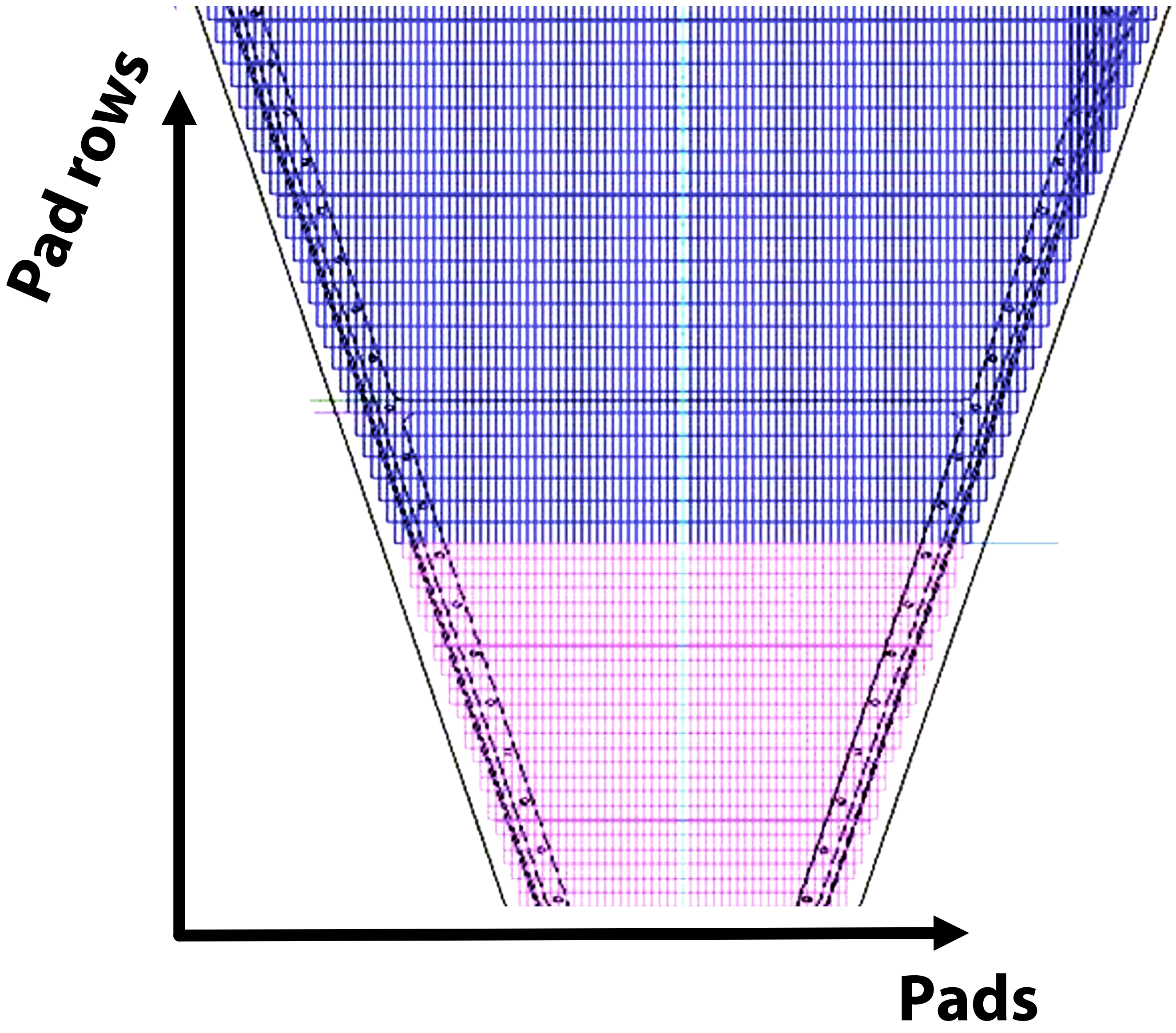
http://mpd.jinr.ru/wp-content/uploads/2019/01/TpcTdr-v07.pdf

Objective

- For each event need to generate the signal for:
  - $95\,232 \cdot 310$ elements (pads x time buckets)
  - Conditioned on the track parameters for the whole event
- Very large output space
- Input of varying dimensionality
- Need to simplify somehow!

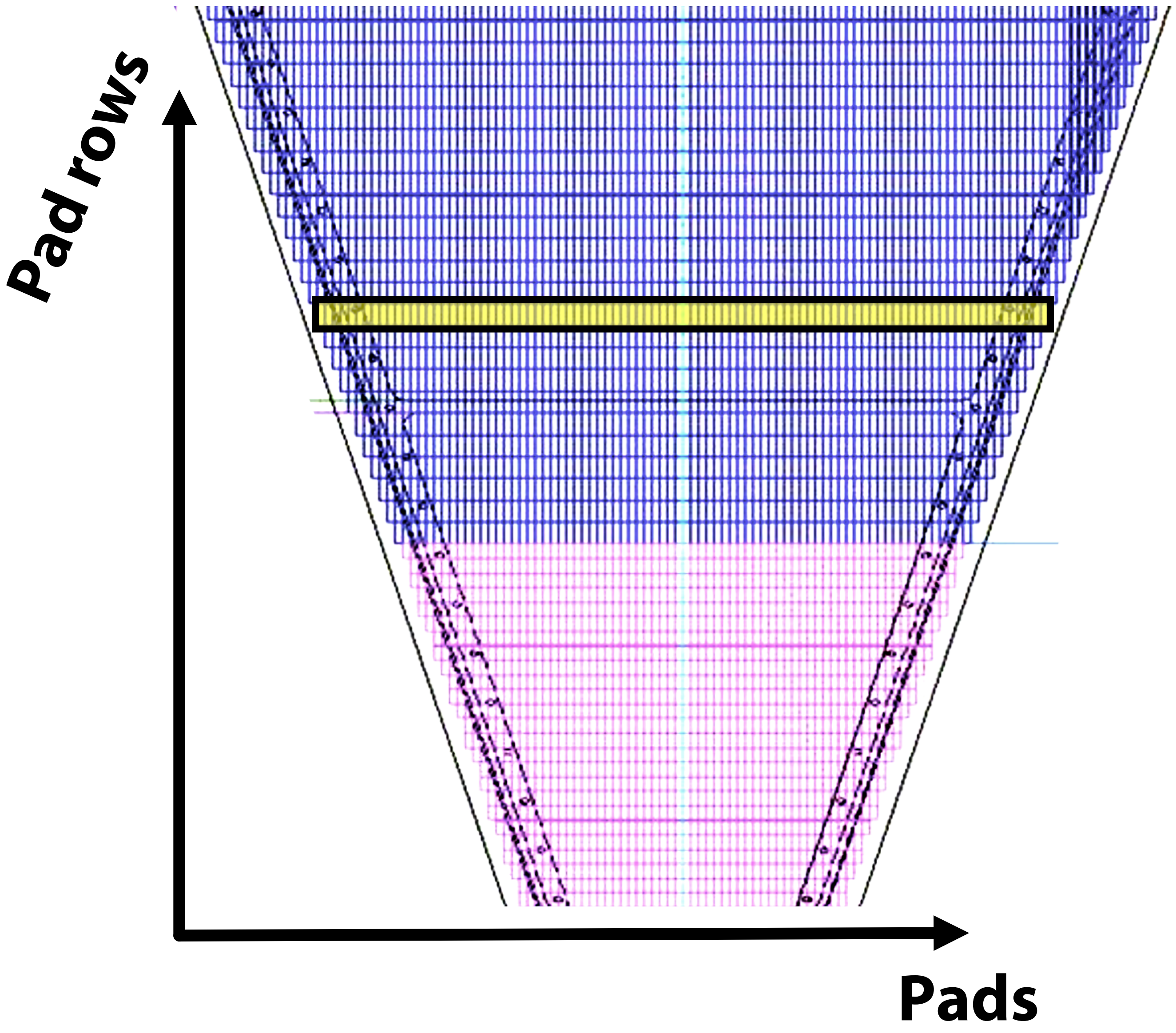


Assumptions for fast simulation



Assumptions for fast simulation

- Factorizing the pad rows
  - dividing tracks to segments, each contributing to a particular pad row
  - can model such contributions **independently**!



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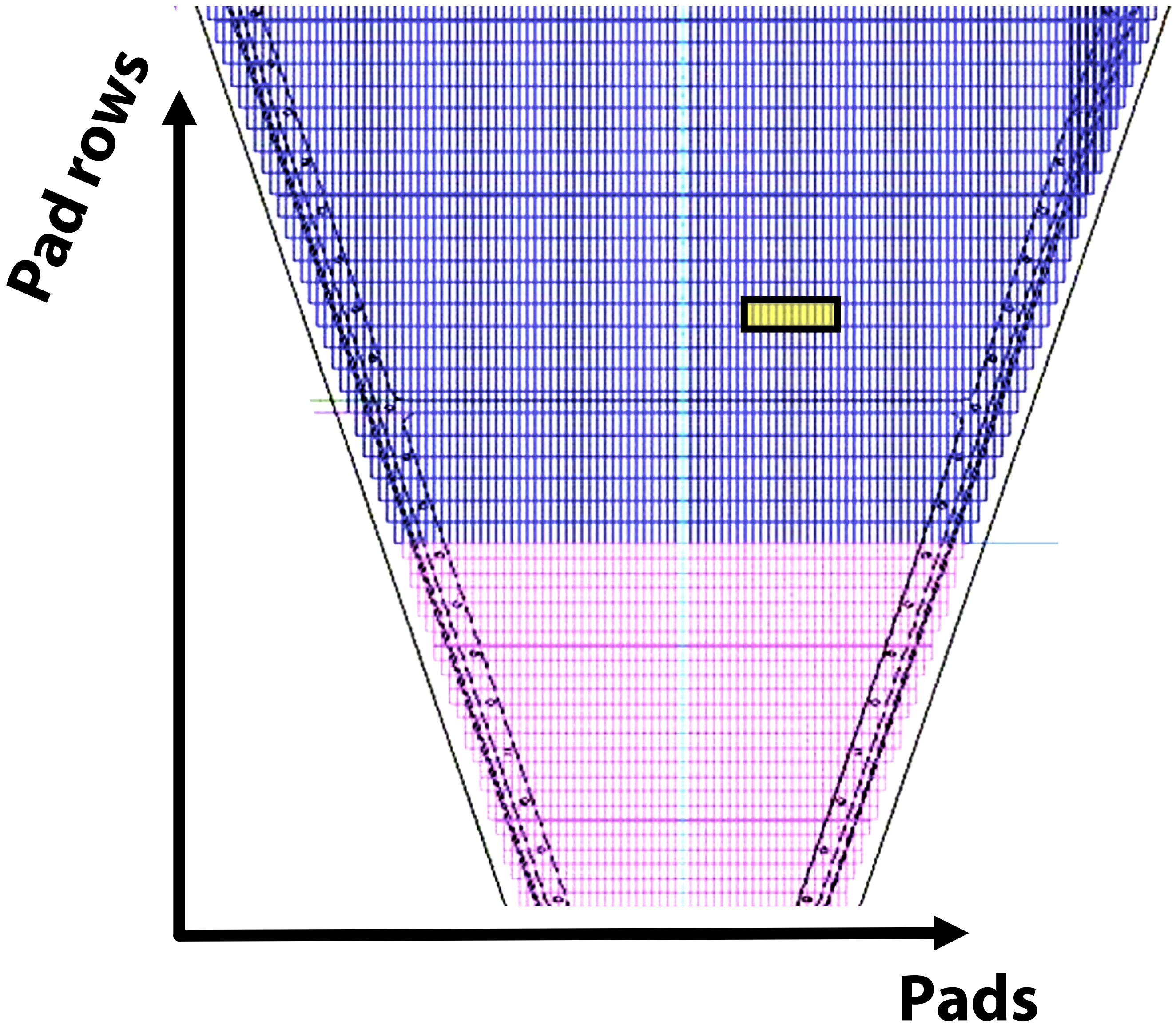
- Signal localization (both space & time)
  - model only a **small area** instead of the full row
  - model only a **few time buckets**



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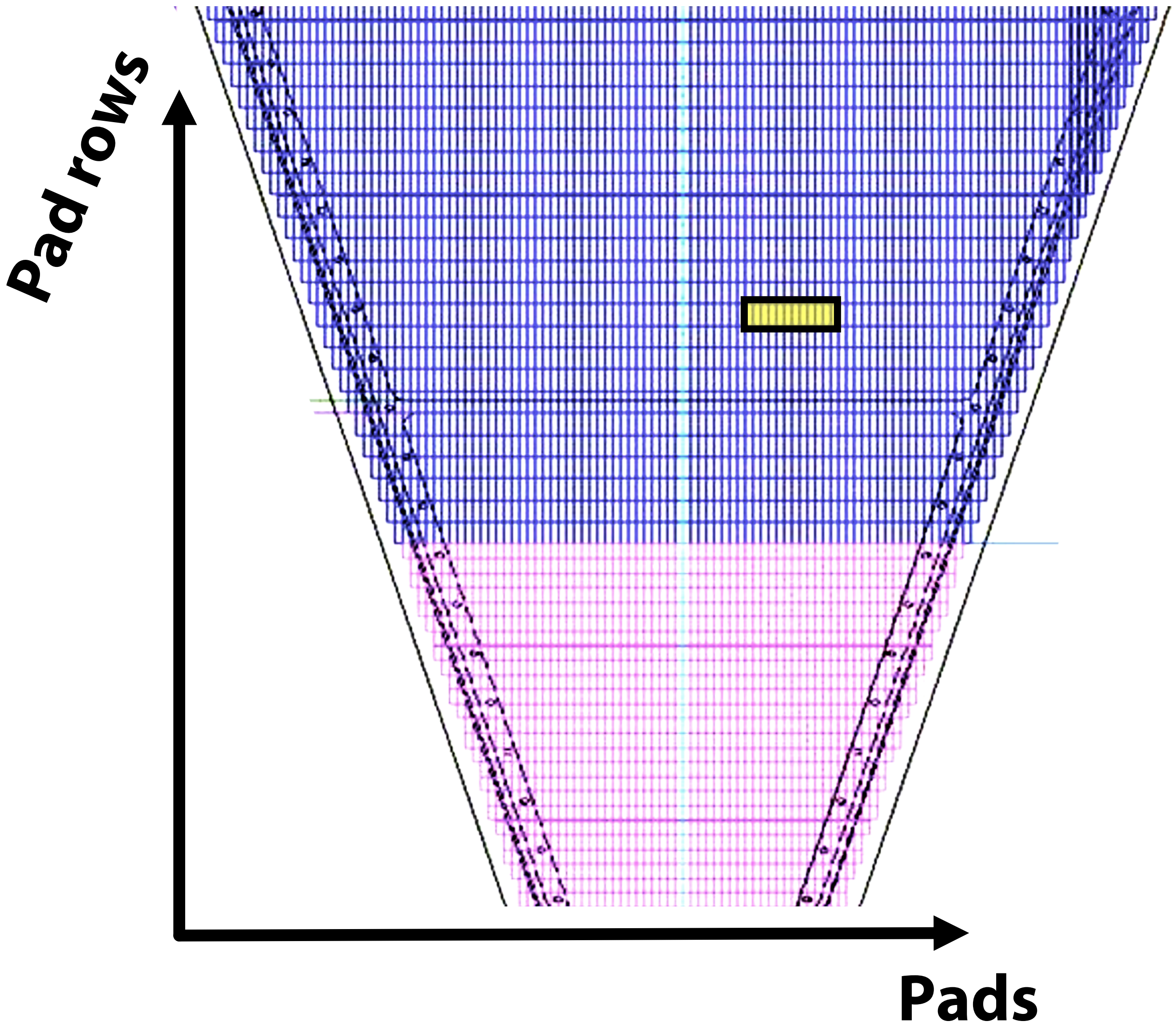
- Target dimensionality:
  8 pads x 16 time buckets



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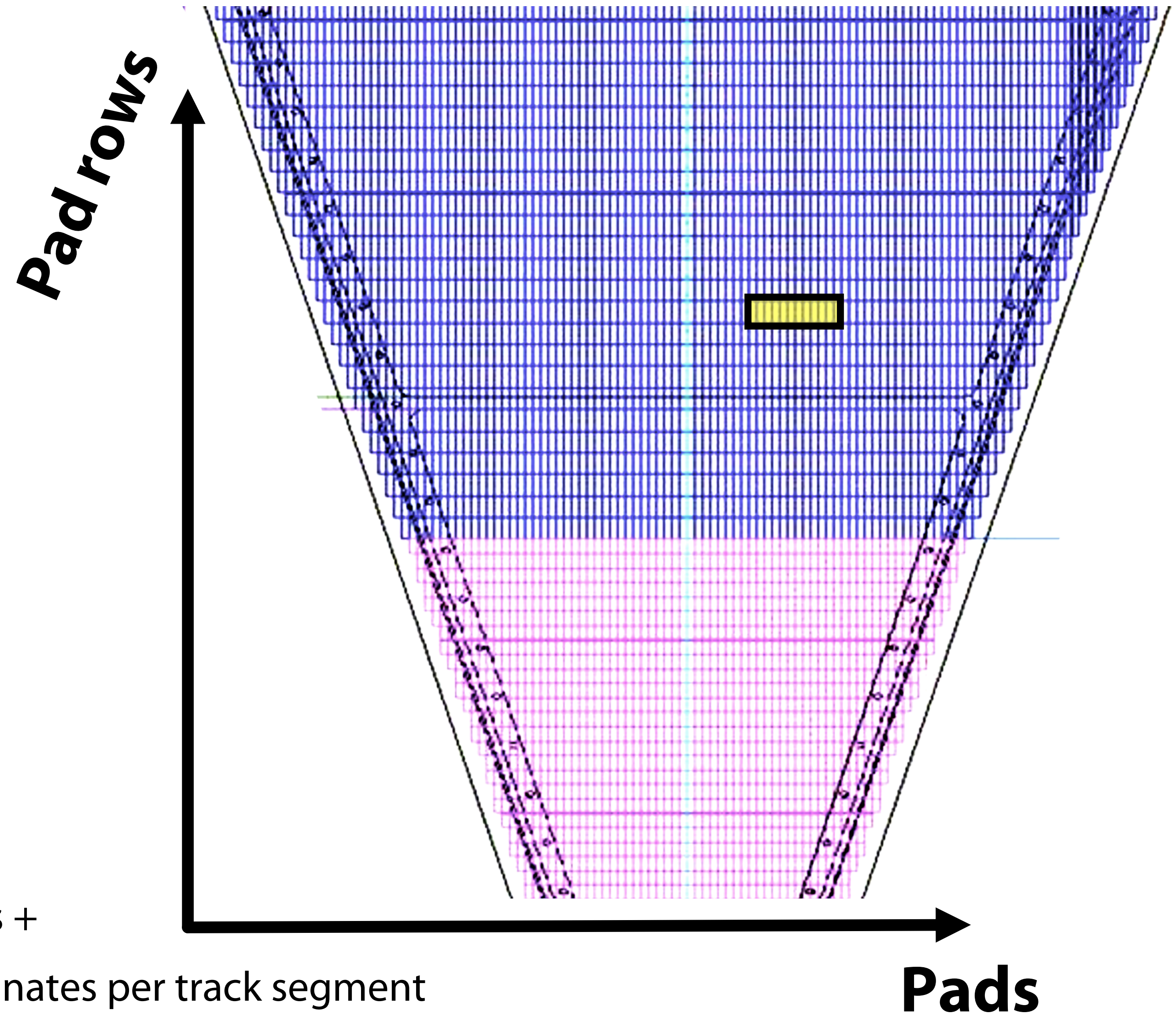
Input:

2 angles +

3 coordinates per track segment



Model details

- Model: WGAN-GP (arXiv:1704.00028 [cs.LG])
- Generator:
  - Fully connected
  - ELU activations
  - 5 layers
- Discriminator:
  - Deep convolutional NN
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Convolutional layers are too slow on CPU

Results

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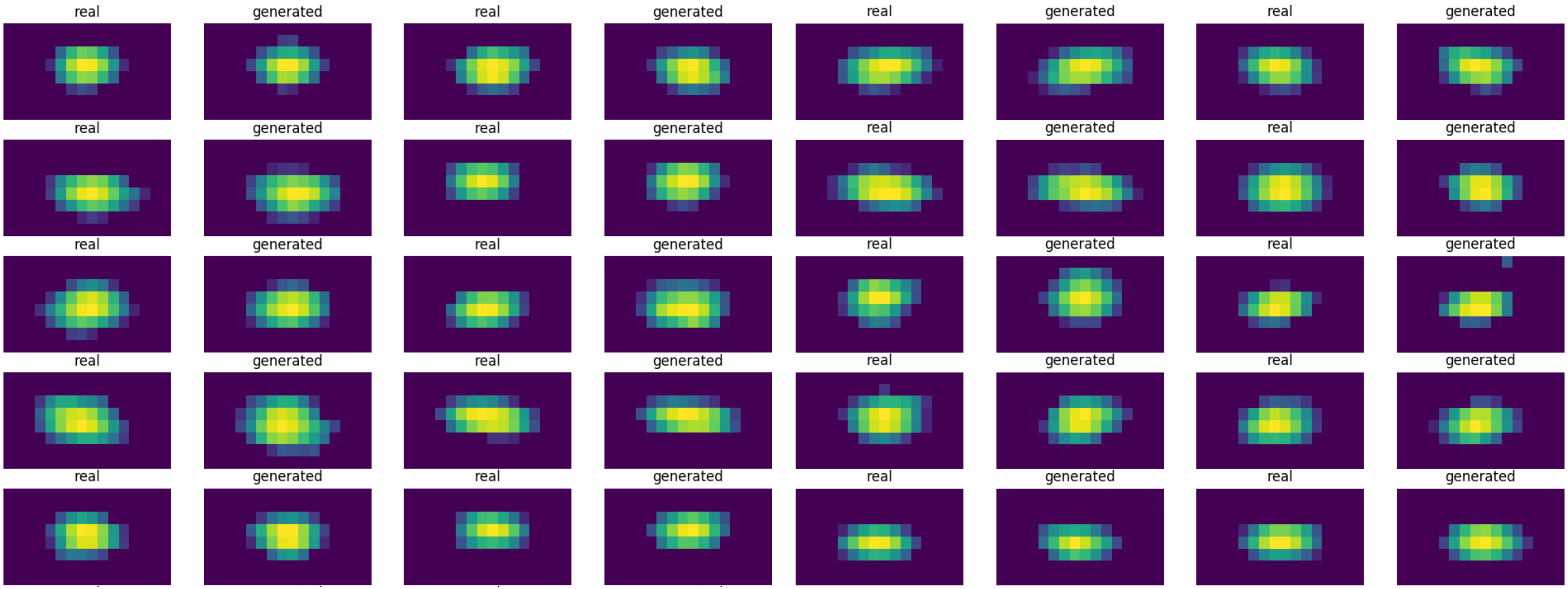
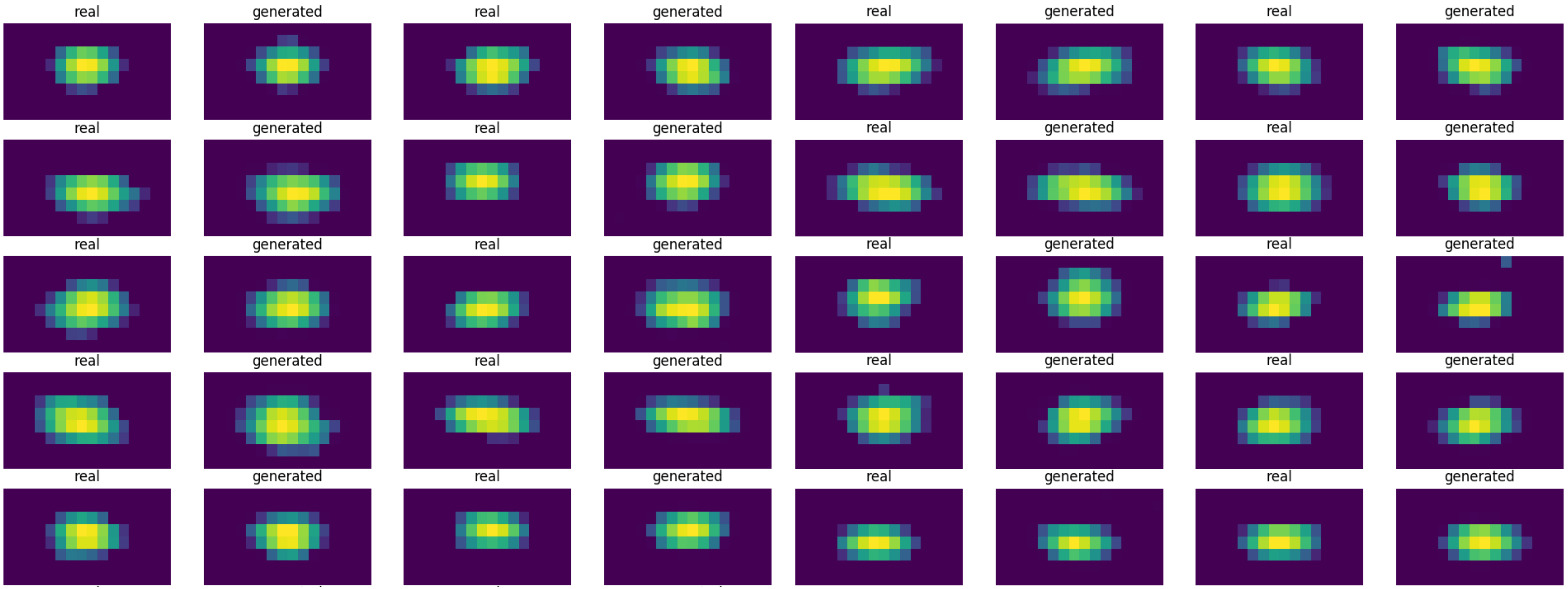


Real **Generated** **Real** **Generated** **Real** **Generated** **Real** **Generated**

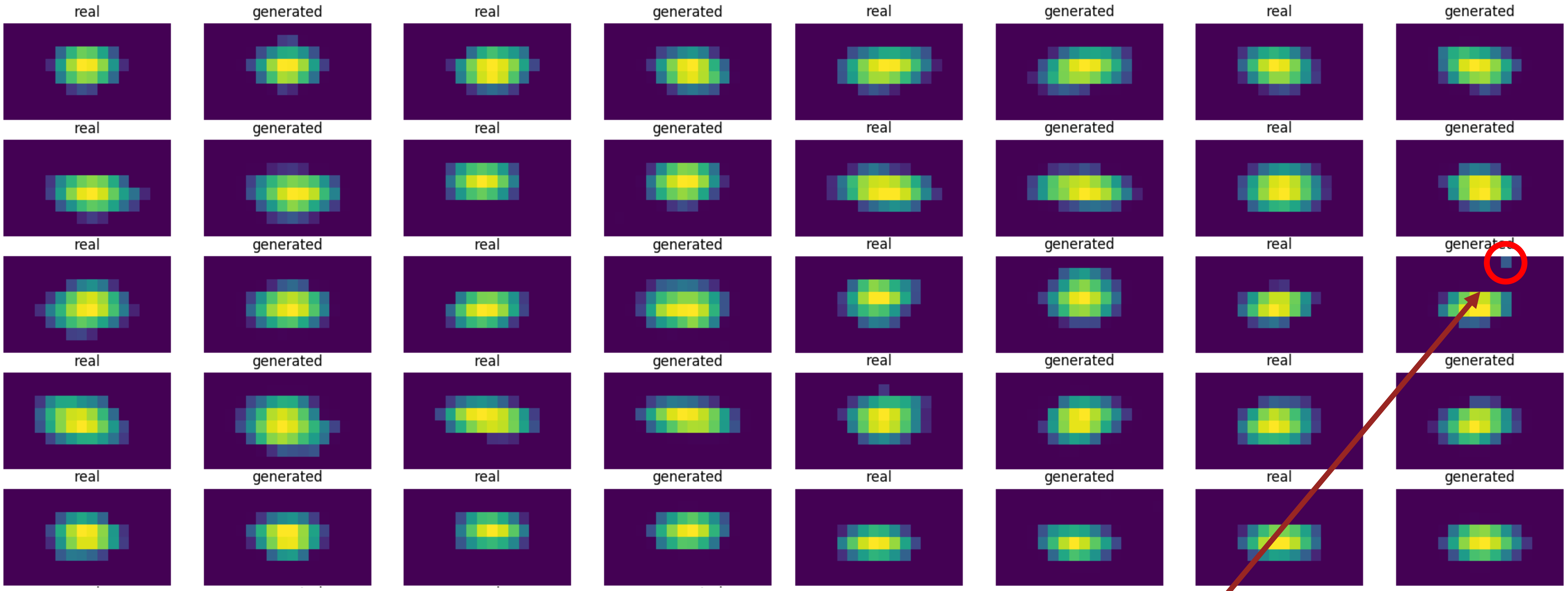
Results



Real Generated Real Generated Real Generated Real Generated

Visually similar!

Results



Real **Generated** **Real** **Generated** **Real** **Generated** **Real** **Generated**

Visually similar!

With minor artifacts

Metrics

- Model not yet integrated into the MPD software
- So far, no direct way of measuring the quality from e.g. tracking performance

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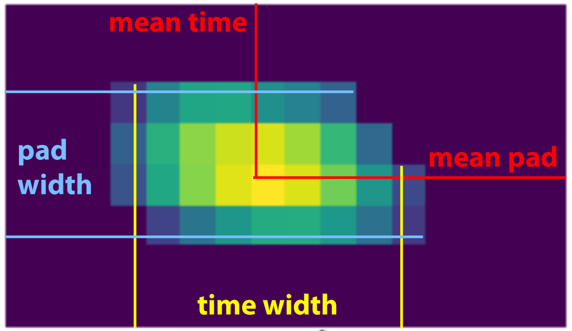
- Instead (as a preliminary metric): we compare the 1st & 2nd order moments of the signal images, i.e.:
  - the location of the signal in pads and time bins
  - the widths of the signal in pads and time bins
  - the tilt of the signal in the pad-time matrix



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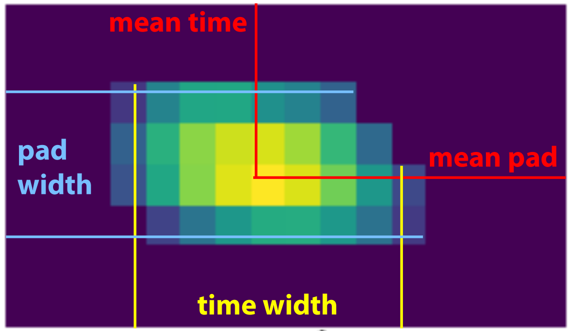
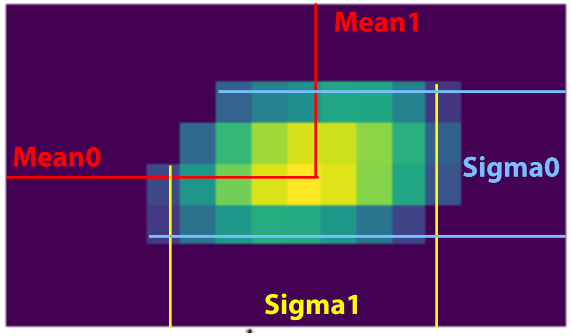
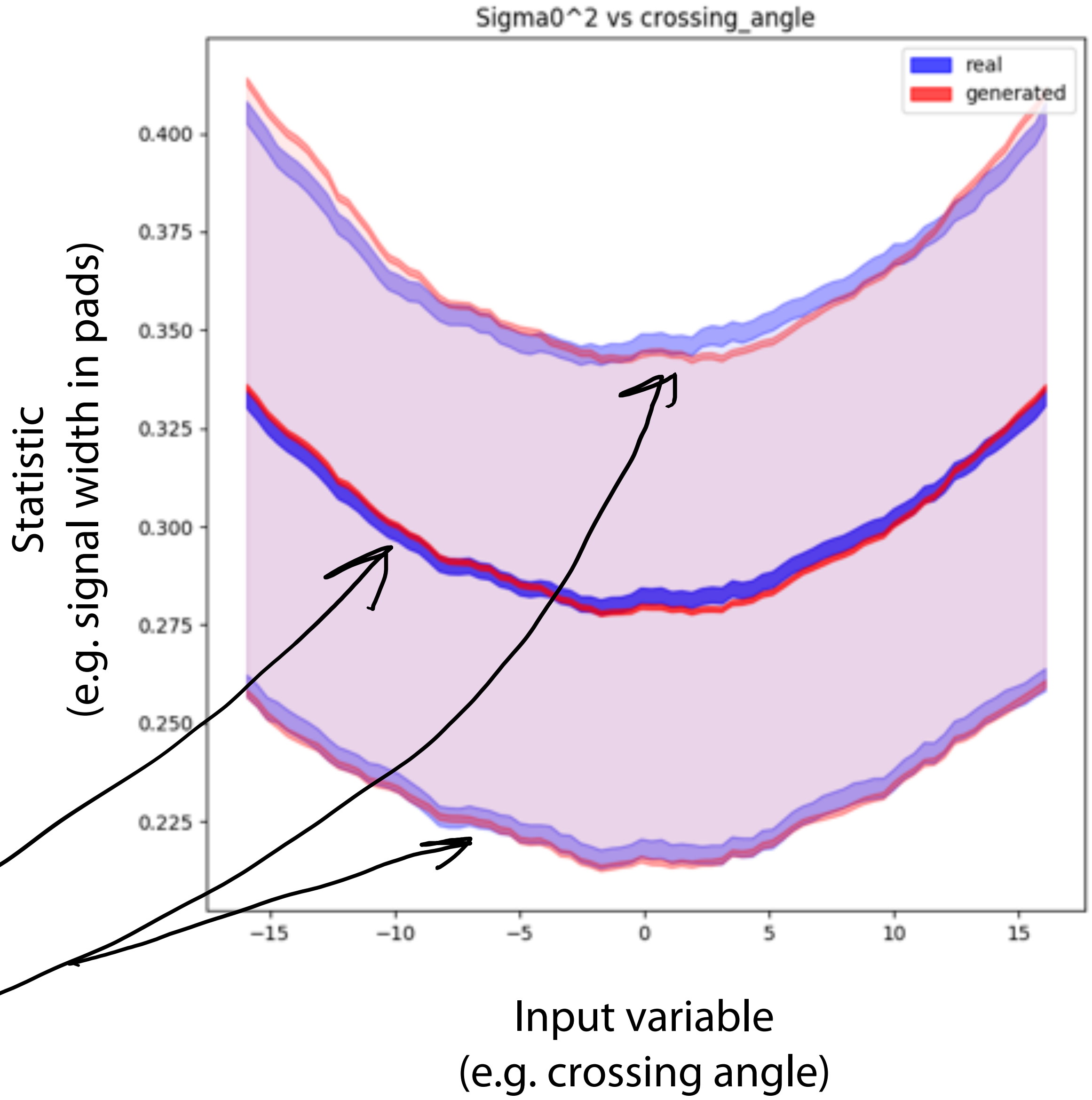


- Also looking at the integrated amplitudes
- All this as a function of track segment parameters (2 angles + 3 coordinates)

Explaining the profiles

Widths of the shaded lines correspond to the statistical uncertainties

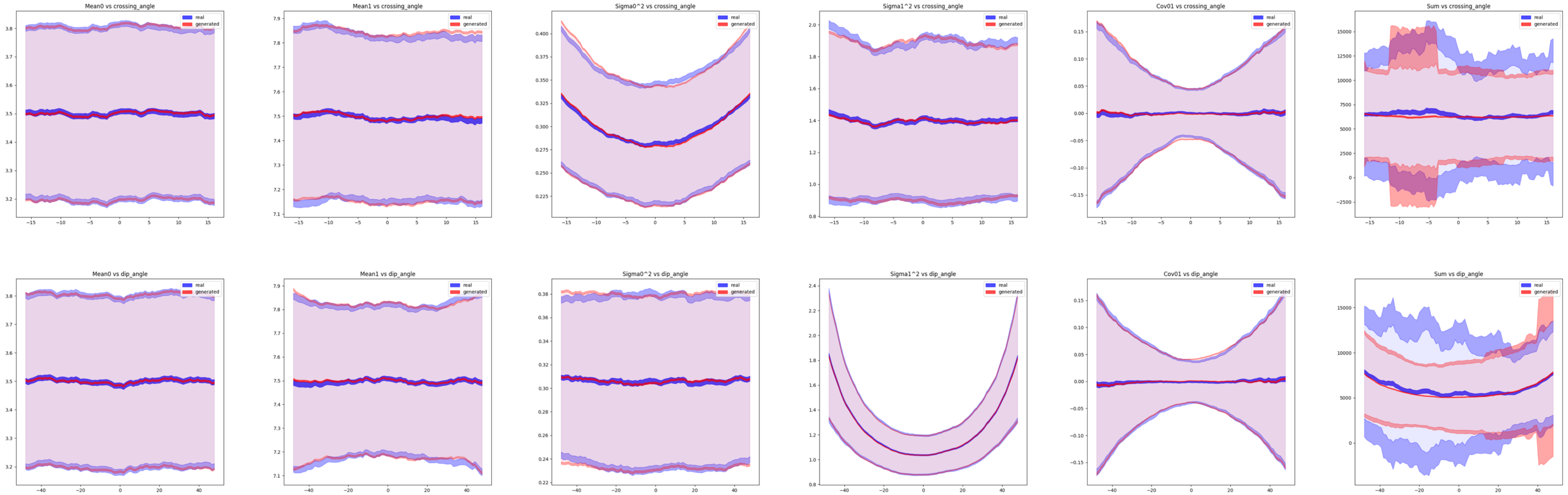




Mean of the statistic

Mean ± 1 standard deviation

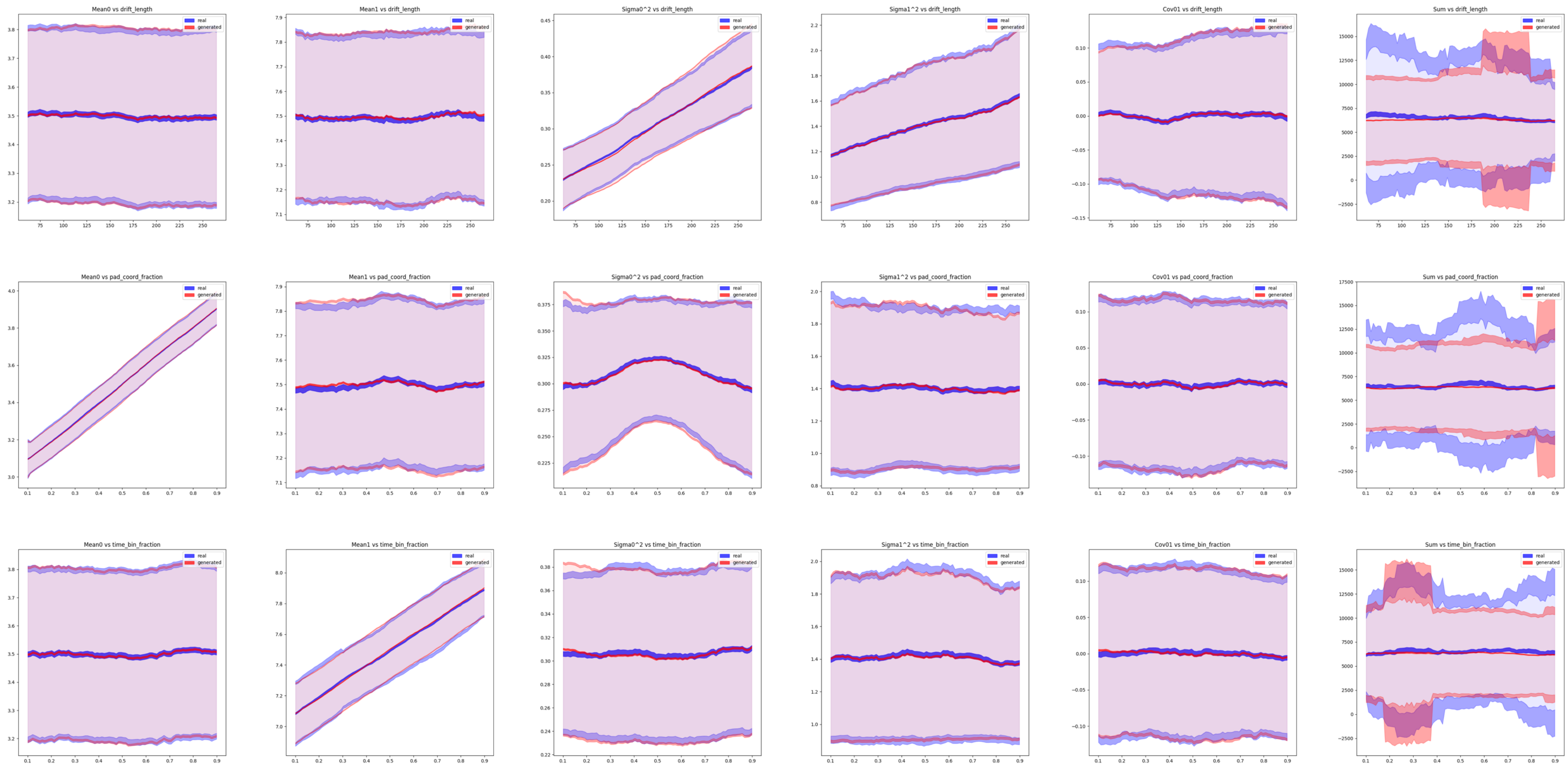
Results (profiles)



location (pad) | location (time) | width (pad) | width (time) | tilt | amplitude

- 6 metrics vs the 2 angles

“Real”
Generated



location (pad) | location (time) | width (pad) | width (time) | tilt | amplitude

- 6 metrics vs the 3 coordinates

"Real"
Generated

Summary

- Promising results
  - Reasonable quality according to the proposed metric
- About 30x improvement in speed
  - preliminary number, not yet estimated on the target platform

- Major TODOs:
  - Integrate our model into the MPD software stack
  - Validate the tracking and dE/dx performance from full reconstruction

Thank you!