

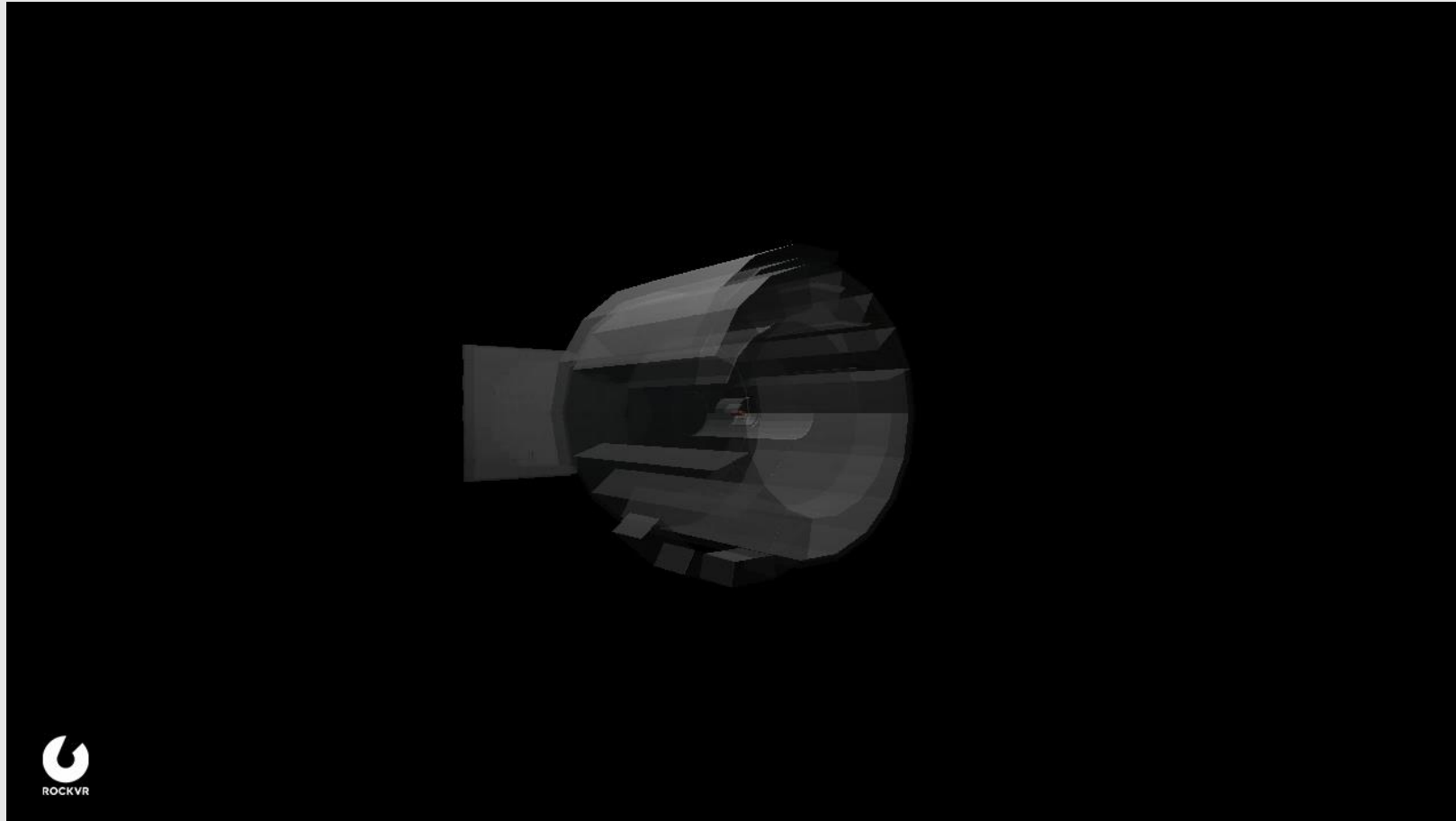
Using Generative Adversarial Networks for Fast Simulation in ALICE Experiment

Tomasz Trzcinski, Kamil Deja, Łukasz Graczykowski
for the ALICE Collaboration



ALICE

ALICE Experiment

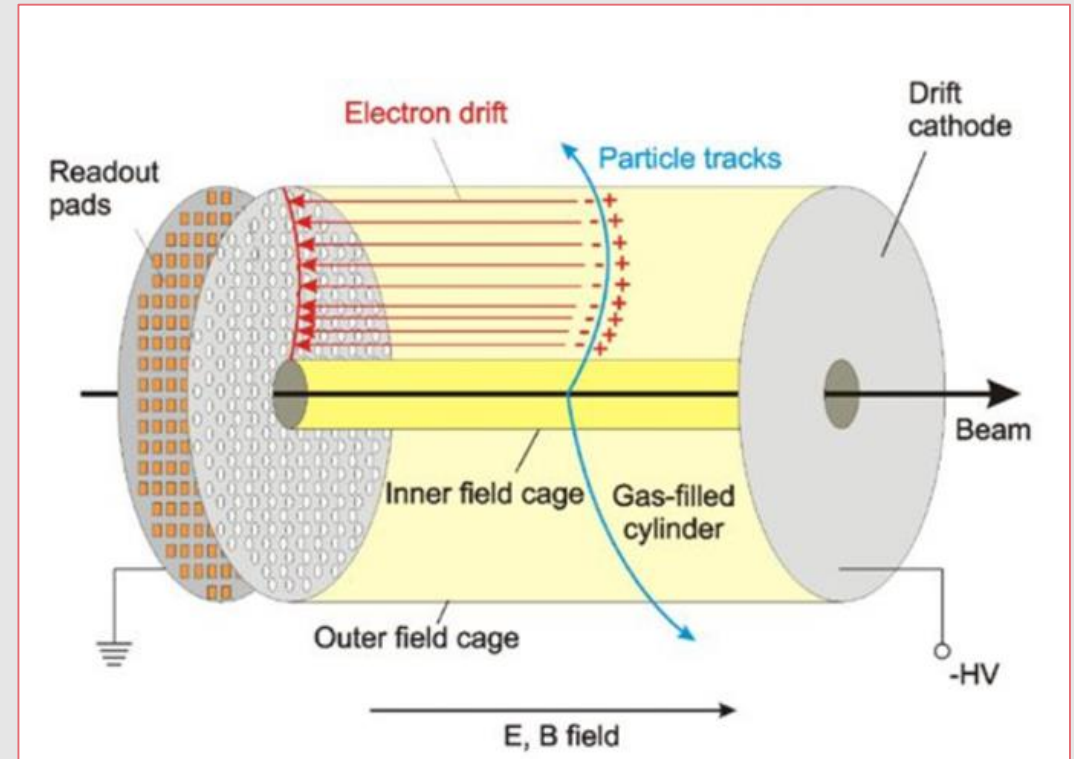


J.Ramatowski, Visualization of data from ALICE experiment in virtual reality



Particle clusters in TPC

- Points in **3-dimensional space**, together with the energy loss, which were presumably generated by a particle crossing by.
- Input for particle tracks generation
- Up to **159 points per particle**
- Possible values **restricted** by the detector size $\sim 5\text{m} \times 5\text{m} \times 5\text{m}$
- **No clusters** in the inner field cage



I.Konorov, Front-end electronics for Time Projection chamber

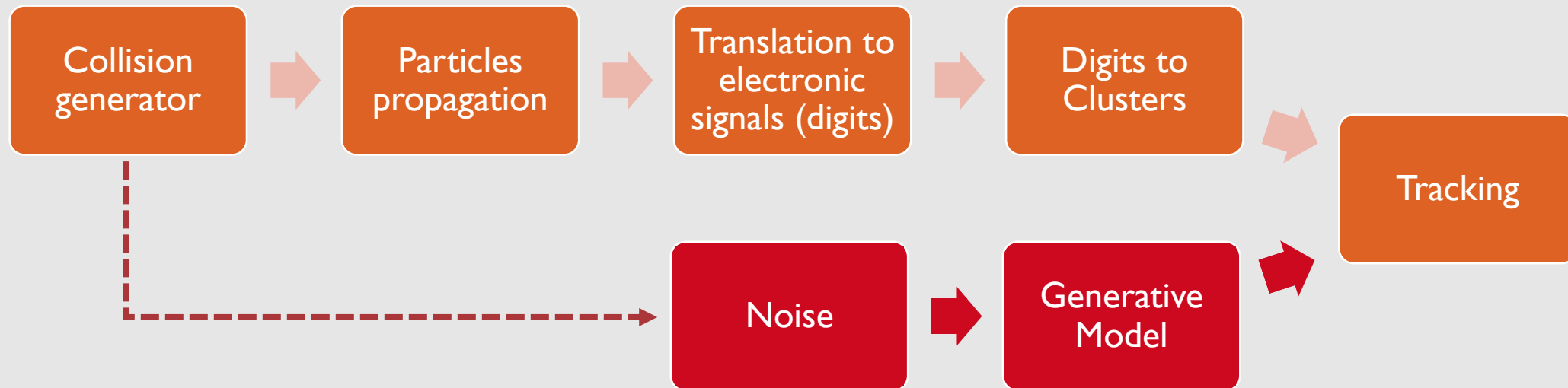
Simulation and reconstruction

- Current process relies **on 5 independent modules**
- The computationally most expensive module is **particle propagation** through detector's matter



Simulation and reconstruction

Generative solution for cluster simulation

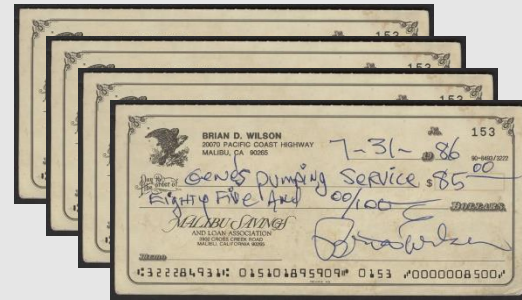




ALICE

Generative Models

Generative Adversarial Networks

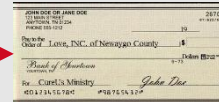


<https://33milesinnewayogounty.files.wordpress.com>

Generator



<https://giphy.com/gifs/leonardo-dicaprio-catch-me-if-you-can-5lecharacters-t1h4nnWEWKfn2>

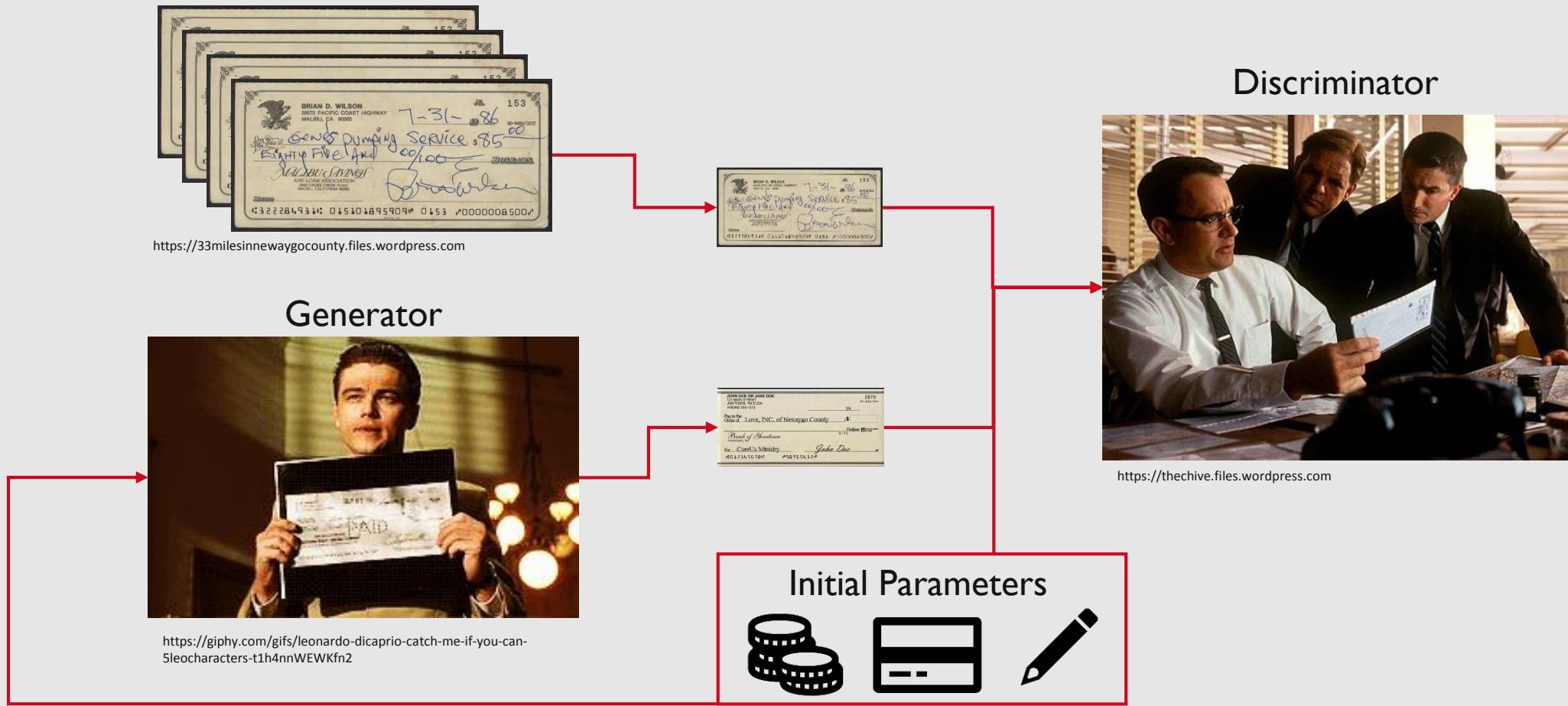


Discriminator



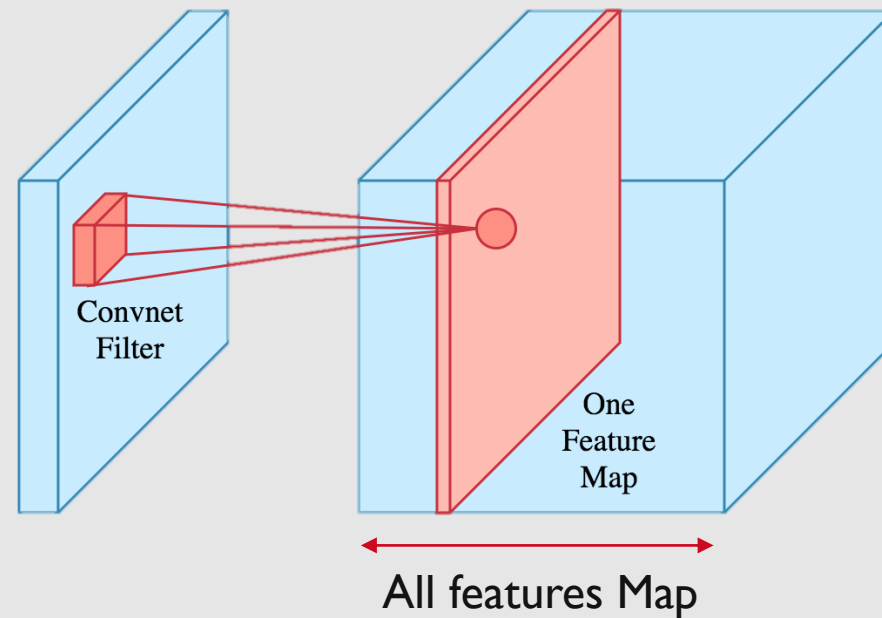
<https://thehive.files.wordpress.com>

Conditional Generative Adversarial Networks



Deep Convolutional GAN

- Class of architectures which use the convolutional and deconvolutional layers – mostly used with images



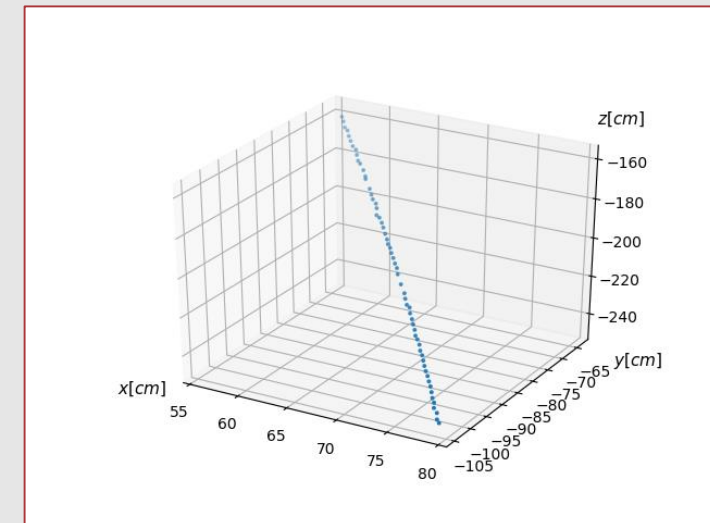
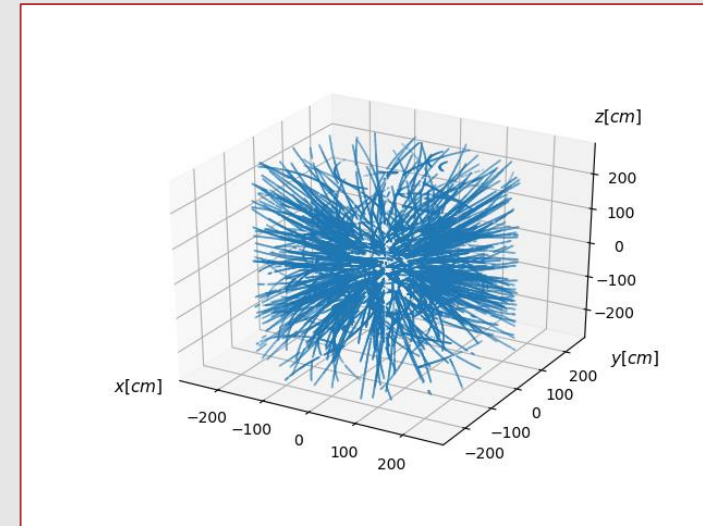


ALICE

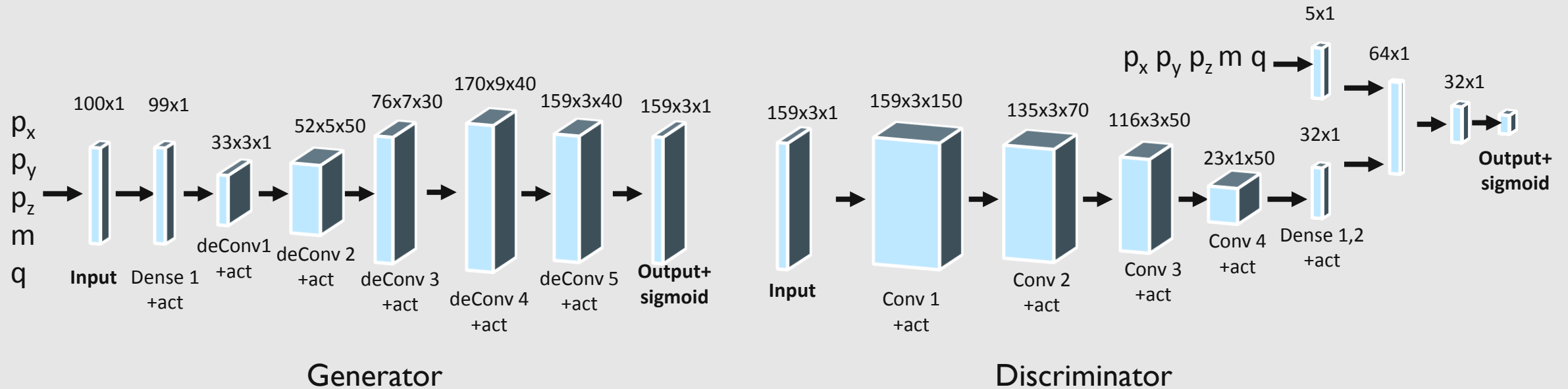
Cluster Simulation with Generative Models

Dataset

- It is not possible (yet) to generate the full 3D image of the event at once
- (5000 x 5000 x 5000 resolution)
- Our solution is to:
 - Generate clusters for single particle
 - Two separate flows for x, y, z and q, q_{\max}
 - Currently we focus on 3D coordinates
 - Merge generated samples
- Training on the original reconstructions



condDCGAN: Conditional DCGAN



- Deep Conditional Convolutional GAN
- 2D Convolutional/ Deconvolutional Layers
- Leaky ReLU Activation

- Dropout
- Batch Normalization
- Sigmoid activation on output

condDCGAN+: combined loss

- Training only on the real examples from dataset
- Preparing the noise from initial parameters of real examples
- Comparing the generated samples with original ones
- Combining original conditional GAN loss with the results of comparison

$$\mathcal{L}_G(m, X) = \mathbb{E}_{z \sim p_z(z|m)} [\alpha \log(1 - D(G(z))) + \beta \frac{1}{n} \sum_{i=1}^n (X_i - G(\hat{z})_i)^2]$$

m - initial parameters (particle momenta),

X - original value corresponding to m ,

$p(z|m)$ - distribution of a noise vector under initial parameters m

z - input into a generator

G and D - generator and discriminator

n - the number of produced clusters

Additional parameters α and β are used to weight the share of individual losses.

Best performing values are $\alpha = 0.6$ and $\beta = 0.8$

Results

- Mean Squared Error (MSE) from the original helix as a quality measure
- Evaluation conducted on the separate test-set with ~15000 examples

Method	Mean MSE (mm)	Median MSE (mm)	Speed-up
GEANT3	1.20	1.12	1
Random (estimated)	2500	2500	N/A
condLSTM GAN	2093.69	2070.32	100
condLSTM GAN+	221.78	190.17	
condDCGAN	795.08	738.71	25
condDCGAN+	136.84	82.72	

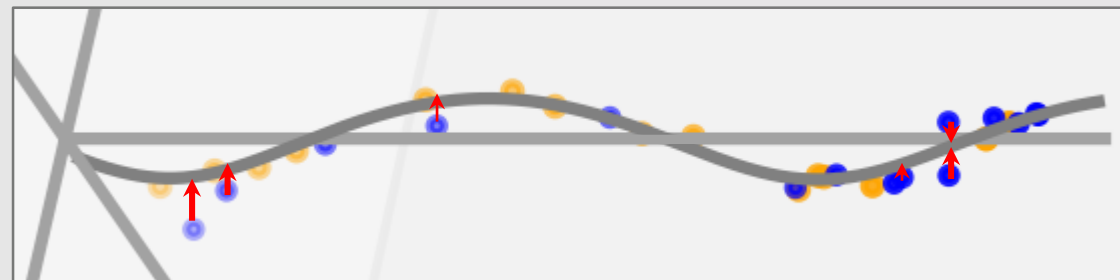
MSE visualisation:

Red - error

Grey- ideal helix

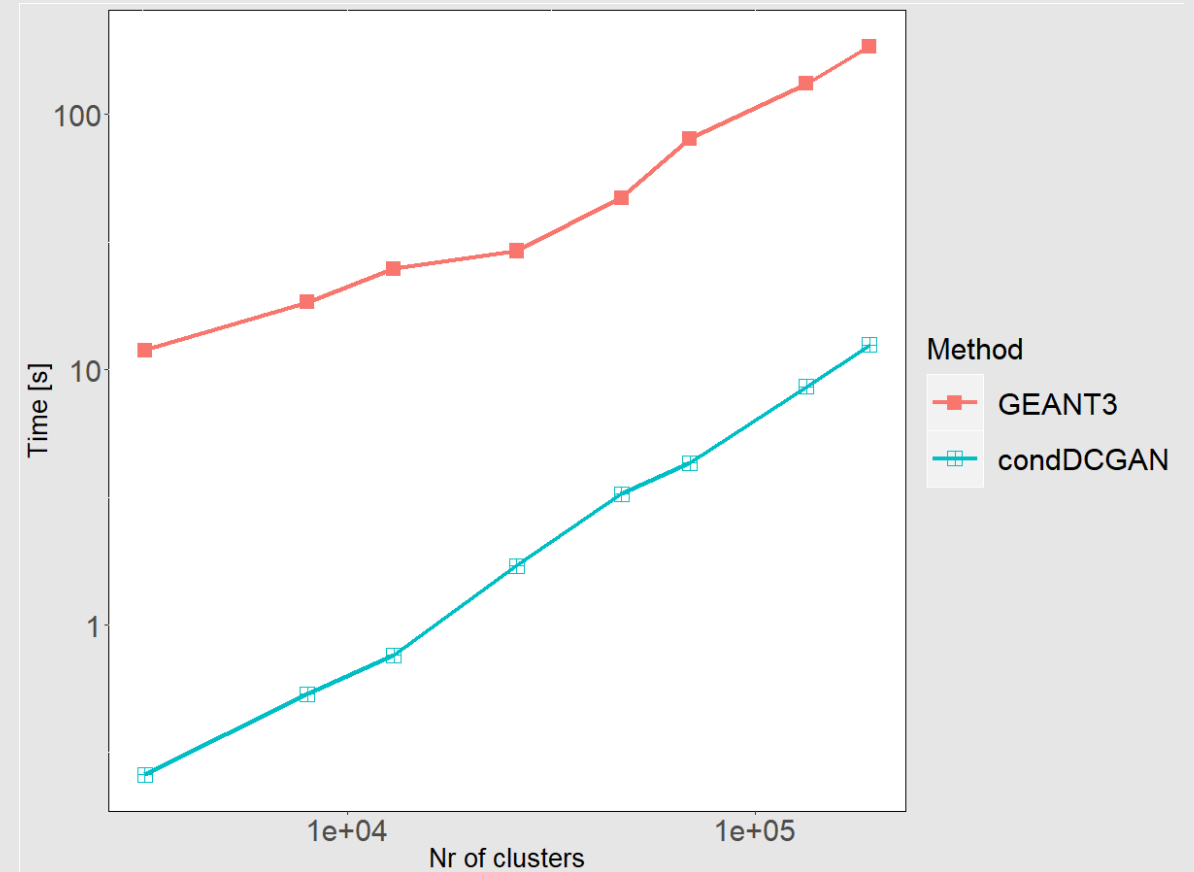
Orange – original clusters

Blue – generated clusters



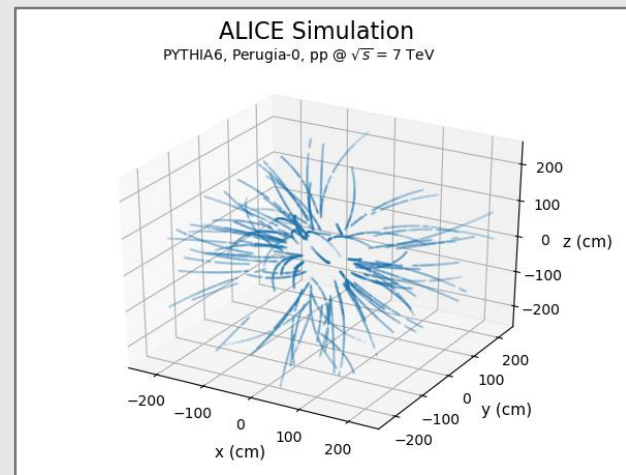
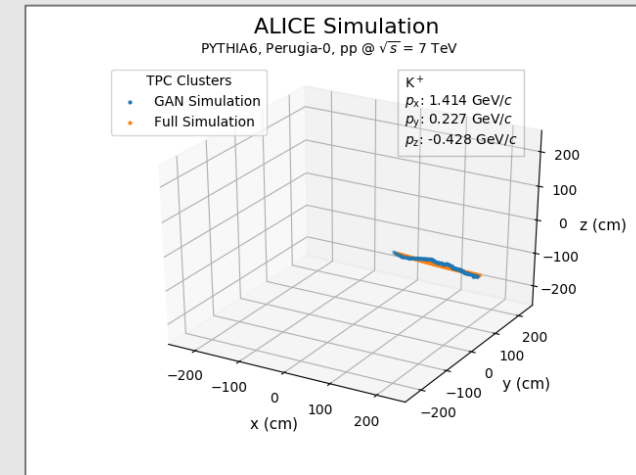
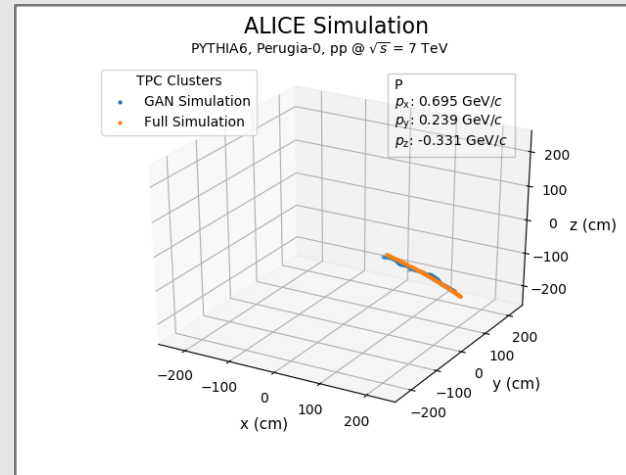
Computational costs

- Performance test conducted on the standalone machine with Intel Core i7-6850K (3.60GHz) CPU (using single core, no GPU acceleration)
- Additional order of magnitude speedup for Generative models with Nvidia Titan Xp

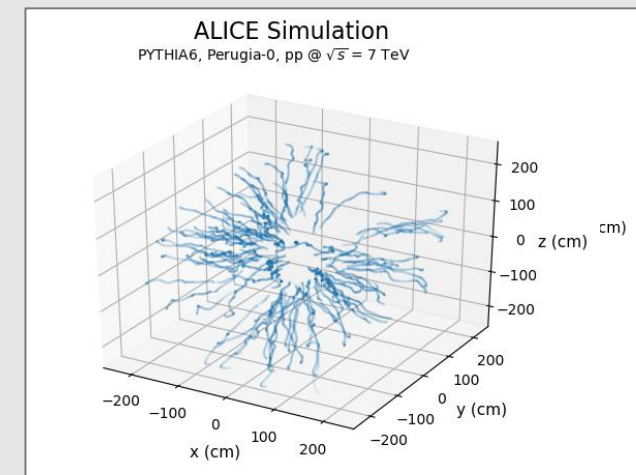


Examples

for the conditional
cluster simulation:



Original event



Generated event

Summary

- Quality not yet equal to this observed with full simulation
- Massive speed-up 25 (CPU) or 250 (GPU) comparing to standard simulation methods
- First step toward semi-real time anomaly detection tool

Limitations:

- Multi-track generation
- 2 flows for 3D coordinates and energy
- Error estimation based on a helix

Acknowledgments

- The authors acknowledge the support from the Polish National Science Centre grant no. UMO-2016/21/D/ST6/01946.
- The GPUs used in this work were funded by the grant of the Dean of the Faculty of Electronics and Information Technology at Warsaw University of Technology (project II/2017/GD/I).



National Science
Centre Poland



Faculty of Electronics and
Information Technology
Warsaw University of Technology