Faculty of Physics

WARSAW UNIVERSITY OF TECHNOLOGY

Using Machine Learning methods for improving data quality in ALICE

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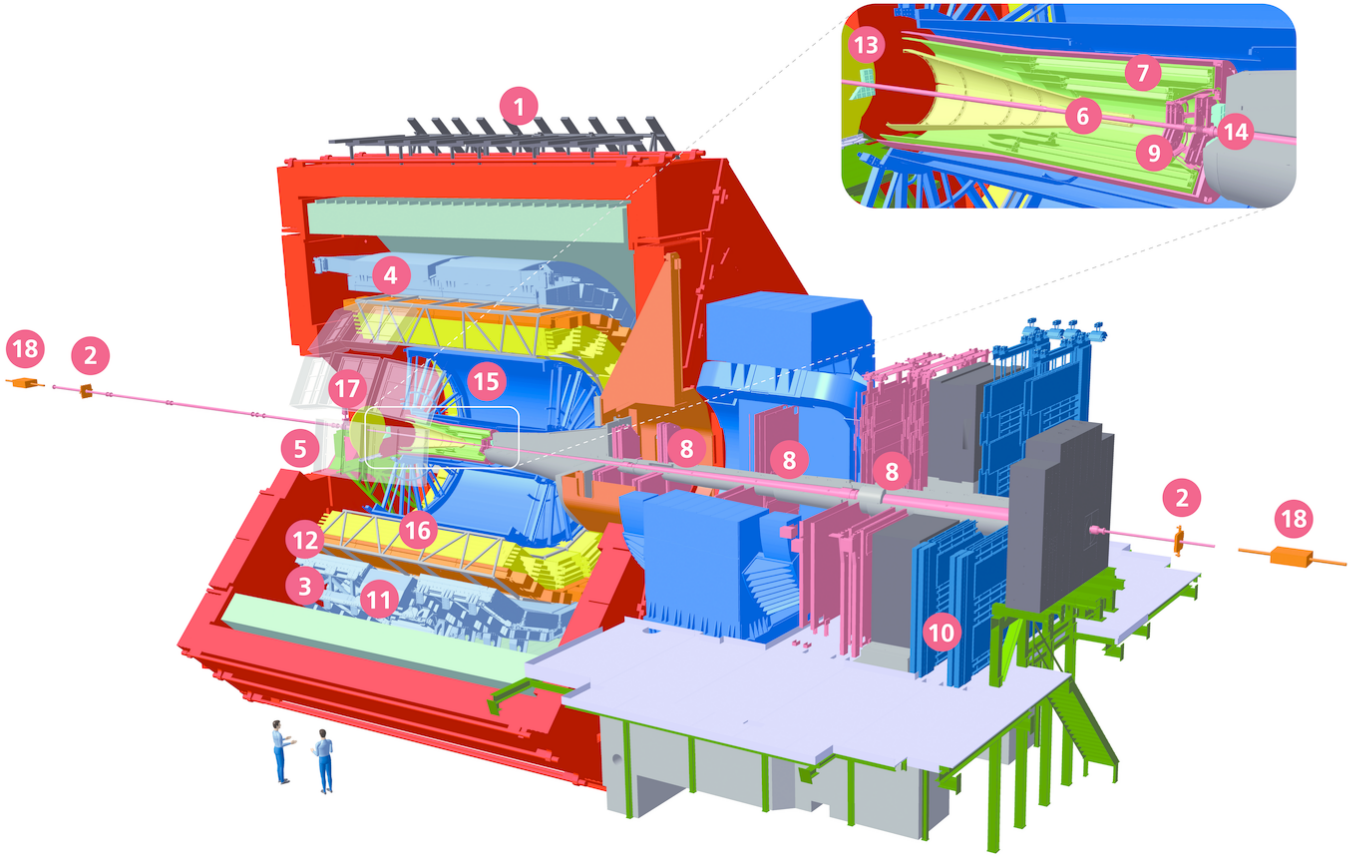
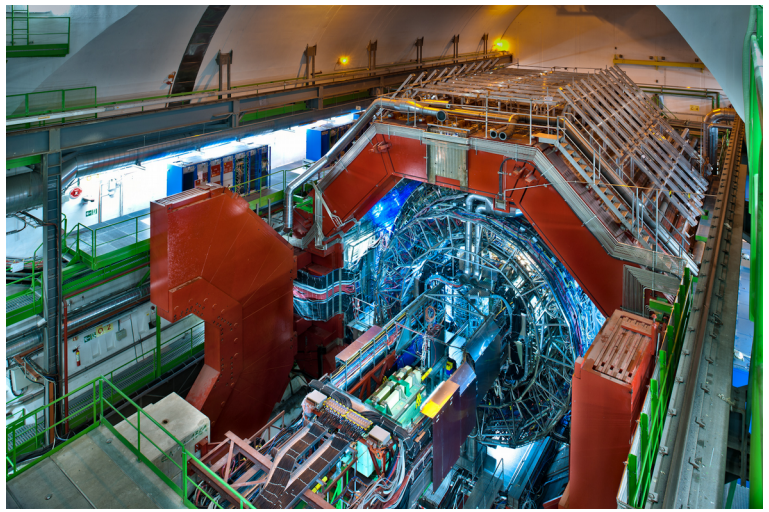
for the ALICE Collaboration

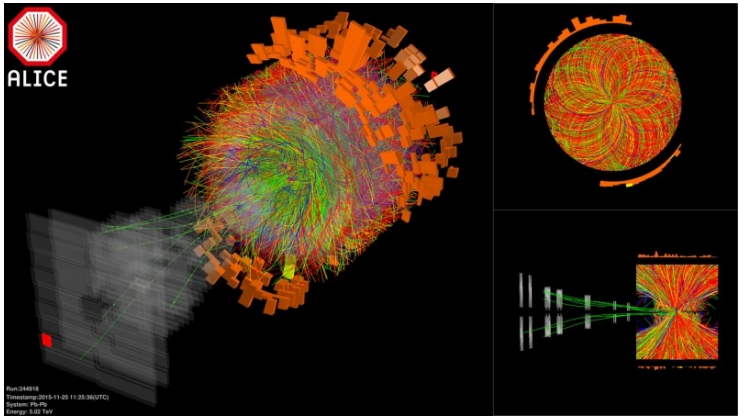
XIII Quark Confinement and the Hadron Spectrum
Maynooth, Ireland
2 August 2018

The ALICE experiment



1. **ACORDE** | ALICE Cosmic Rays Detector
2. **AD** | ALICE Diffractive Detector
3. **DCal** | Di-jet Calorimeter
4. **EMCal** | Electromagnetic Calorimeter
5. **HMPID** | High Momentum Particle Identification Detector
6. **ITS-IB** | Inner Tracking System - Inner Barrel
7. **ITS-OB** | Inner Tracking System - Outer Barrel
8. **MCH** | Muon Tracking Chambers
9. **MFT** | Muon Forward Tracker
10. **MID** | Muon Identifier
11. **PHOS / CPV** | Photon Spectrometer
12. **TOF** | Time Of Flight
13. **T0+A** | Tzero + A
14. **T0+C** | Tzero + C
15. **TPC** | Time Projection Chamber
16. **TRD** | Transition Radiation Detector
17. **V0+** | Vzero + Detector
18. **ZDC** | Zero Degree Calorimeter





Goals

- Use ALICE and its data as a unique environment to advance the Machine Learning field of science
- Identify areas where both ALICE (or HEP in general) and ML communities can mutually benefit
- Focus on Machine Learning research rather than using standard ML tools for ALICE use cases
- Disclaimer:
  - I'm a physicist without a ML expertise – just started my (human) learning of machine learning :)
  - My task is to guide and coordinate the work of WUT ML computer scientists within ALICE

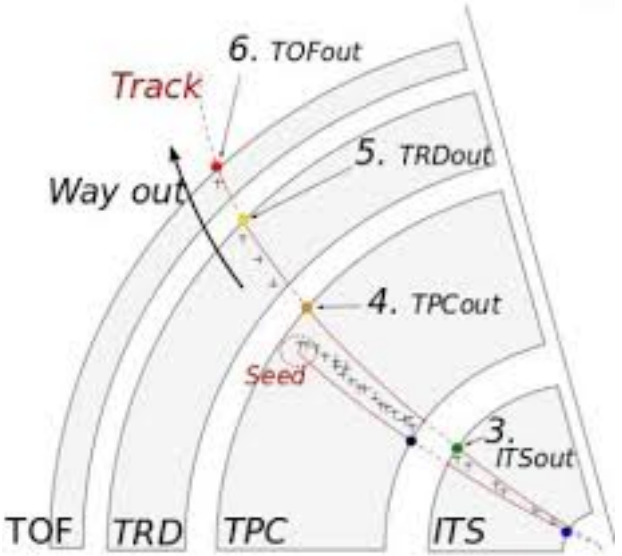
Three areas of research

- Data Quality Assurance – prediction of detector quality label assignment
  - not covered in this talk
- Simulation of TPC clusters in Monte Carlo data using generative networks
- Development of more precise particle identification (PID)

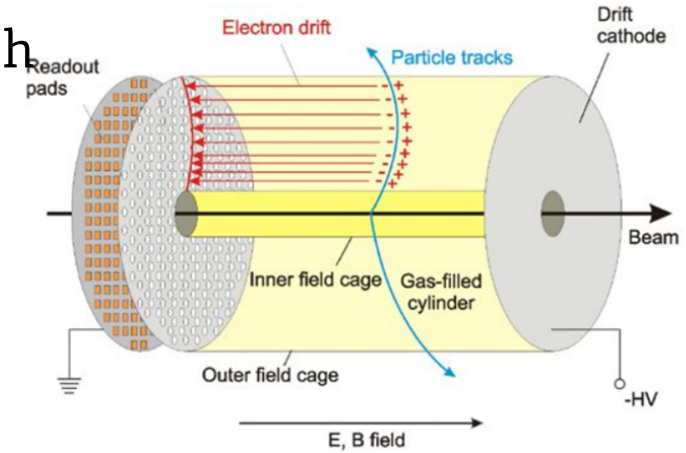
Simulation of TPC clusters in Monte Carlo data using generative networks

Time Projection Chamber

- Tracking in ALICE is performed by ITS, TPC, TRD and TOF
- First attempts – focus on the TPC only:
  - main tracking device
  - located from 0.8 m (inner radius) to 2.5 m (outer radius) from the beam and extending ~2.5 m in each direction along the beam axis
  - volume of 95 m^3
  - filled with Ne-CO_2 gas mixture (90%-10%)
  - **clusters** - points in 3D space, together with the energy loss, which were presumably generated by a particle traveling through
  - provides up to 159 clusters per track



ALICE Data Preparation Group

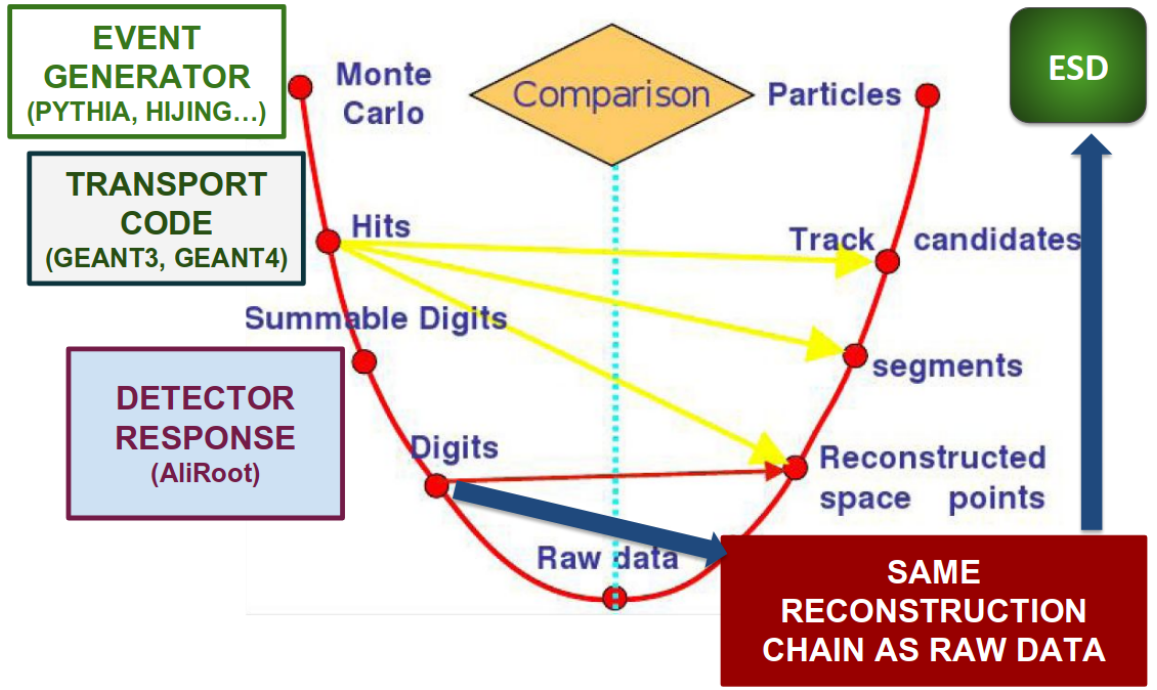


I.Konorov, Front-end electronics for Time Projection chamber

Simulation and reconstruction

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

Collision generator → Particle propagation → Electronic signals (digits) → Digits to Clusters → Tracking

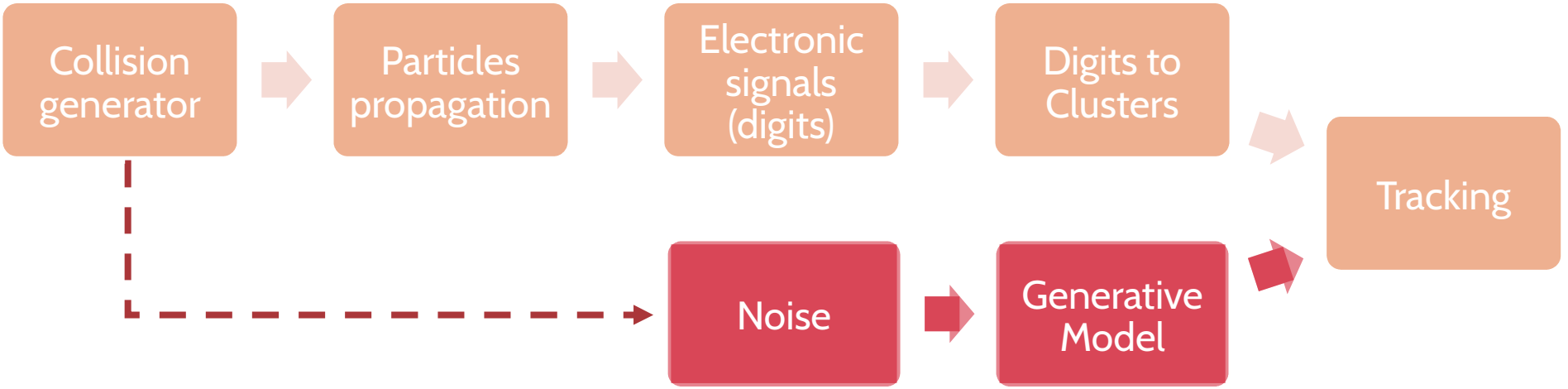


Monte Carlo simulation

Real data

ALICE Data Preparation Group

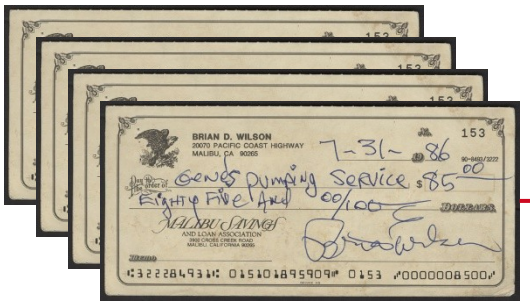
Simulation and reconstruction



- **Generative solution for cluster simulation:**
  - substitute the detector simulation and check for the speed-up
  - full simulation **still needed** to generate training samples
  - **immediate drawback:** quality of such MC data can be either comparable or lower than the full detector simulation – limits potential applications

Generative Adversarial Networks

- Generative Adversarial Network (GAN) is a neural network architecture of two networks competing with each other (playing a min-max game)
  - **"Generator"** is trained to produce fake data resembling the real data
  - **"Discriminator"** predicts whether an example data is real or fake

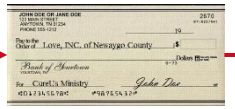


https://33milesinnewaygocounty.files.wordpress.com

Discriminator

https://thechive.files.wordpress.com

Generator

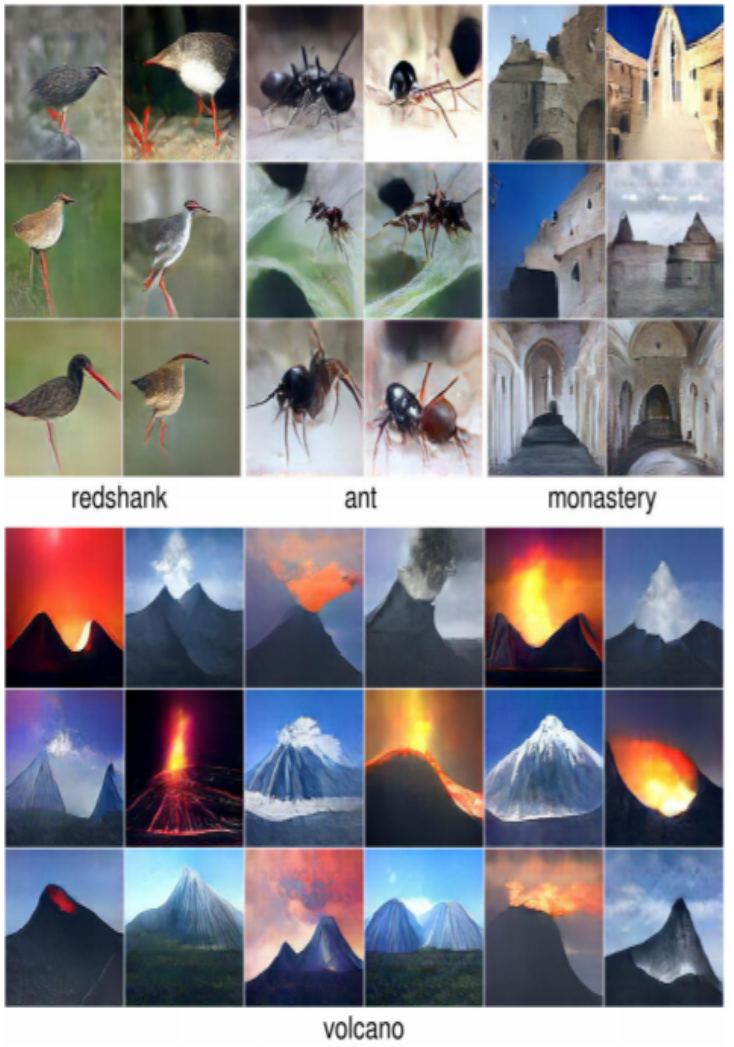


https://giphy.com/gifs/leonardo-dicaprio-catch-me-if-you-can-5leocharacters-t1h4nnWEWKfn2

Generative Adversarial Networks

- Typical use cases:
  - mainly generation of photo quality fake images (i.e. of celebrities)

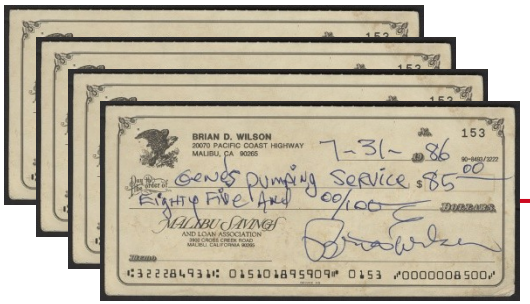
https://arxiv.org/abs/1710.10196



https://arxiv.org/pdf/1612.00005v1.pdf

Generative Adversarial Networks

- **Extending the GAN architecture – provide a set of initial parameters for the generator and discriminator:**
  - generator would not generate a random output, but a customized one
  - in our case: initial momenta of Monte Carlo particles



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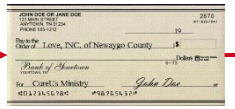
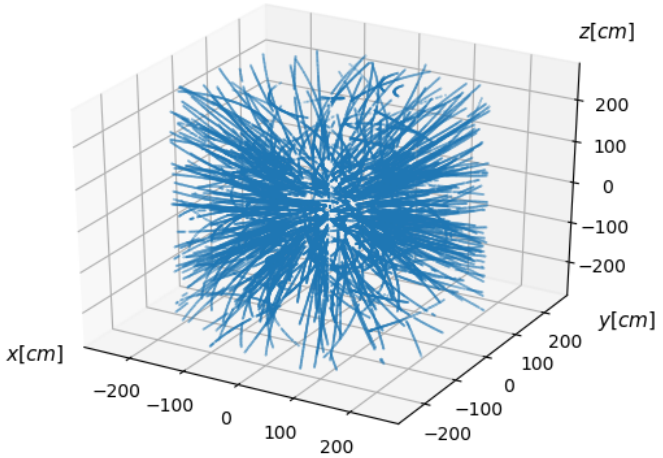
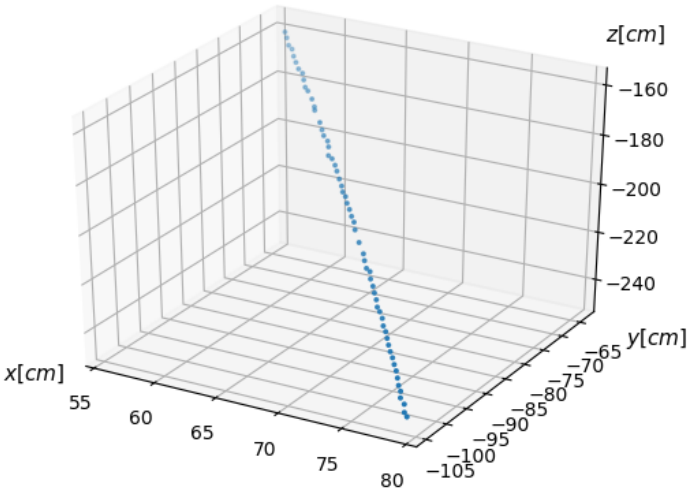


Initial Parameters

TPC clusters with GANs

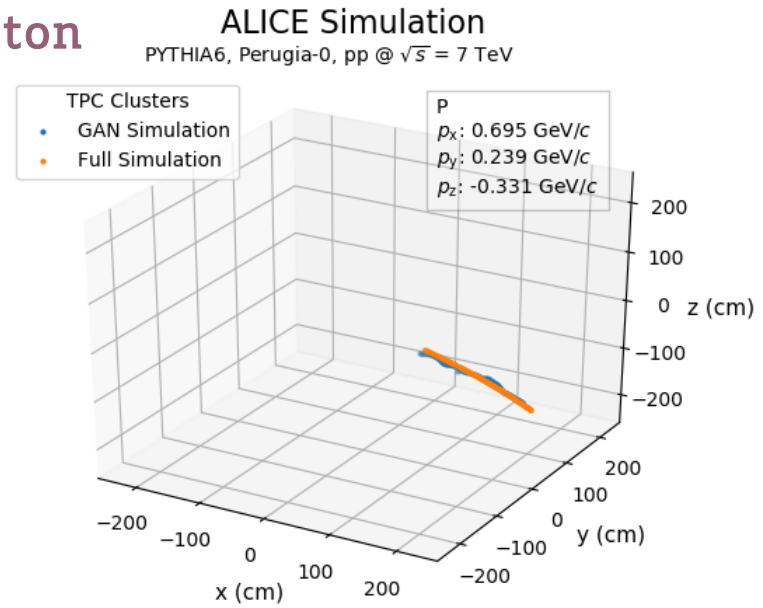
- It is not (yet!) possible to generate the full 3D image of the event at once (especially in the Pb-Pb event)
- Our solution is to:
  - generate clusters for single particles
  - two separate flows for spatial coordinates (x,y,z) and the energy
  - in the beginning focus only on 3D coordinates
  - merge generated samples (individual particles) into full images
  - training of the GAN on original full simulations



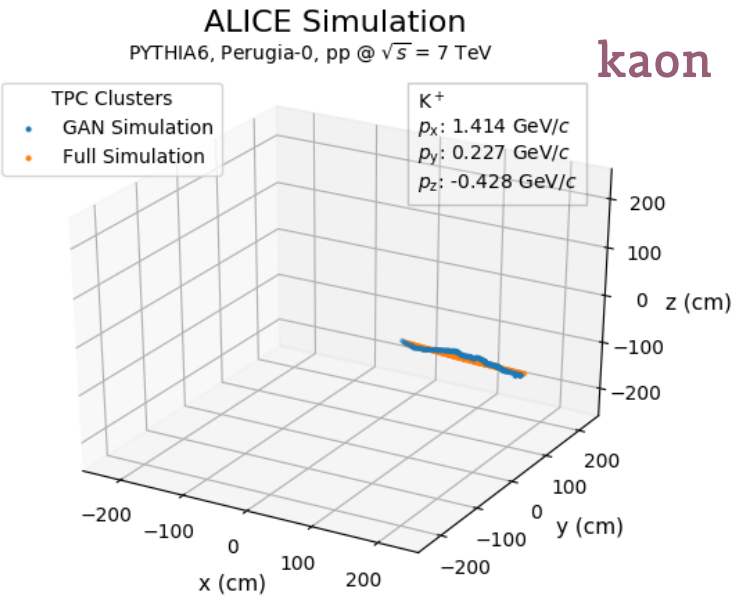


Example results

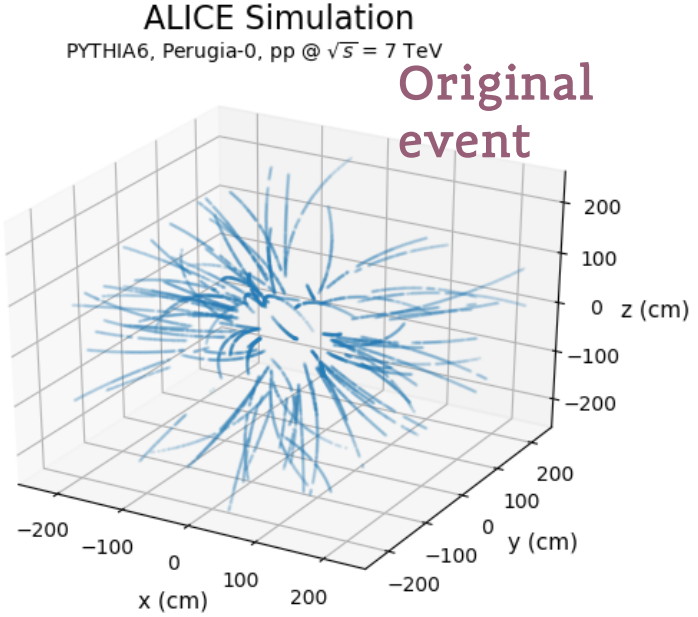
proton



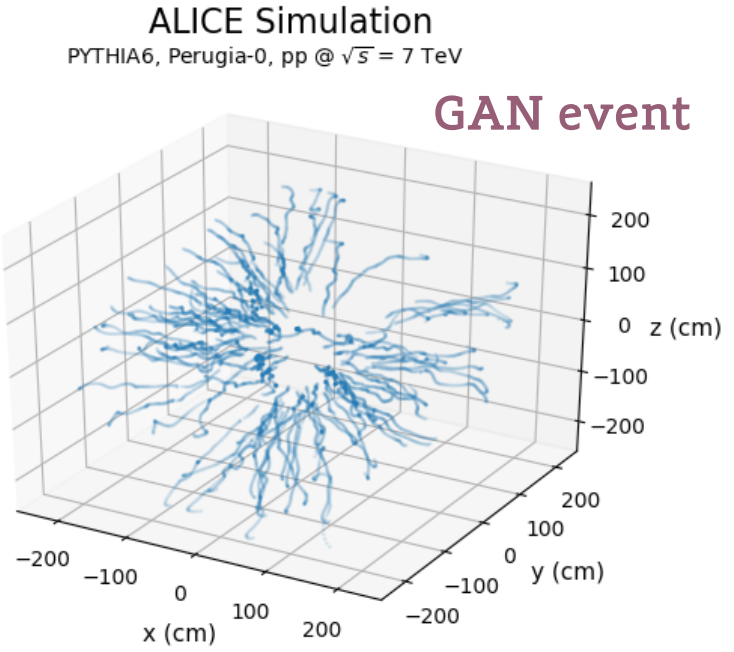
kaon



Original event



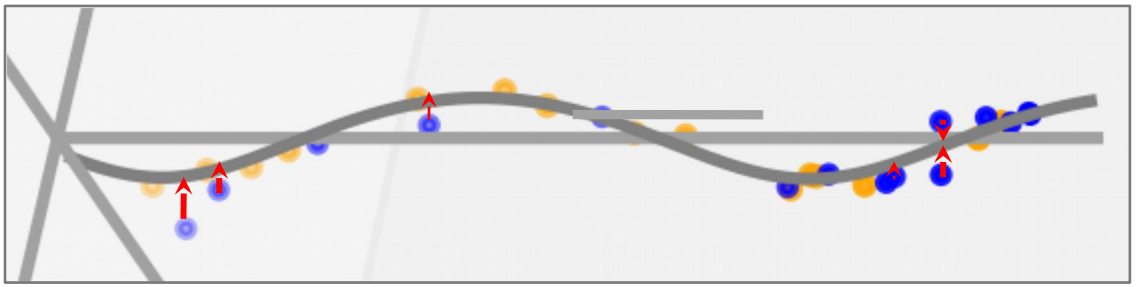
GAN event



Results

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

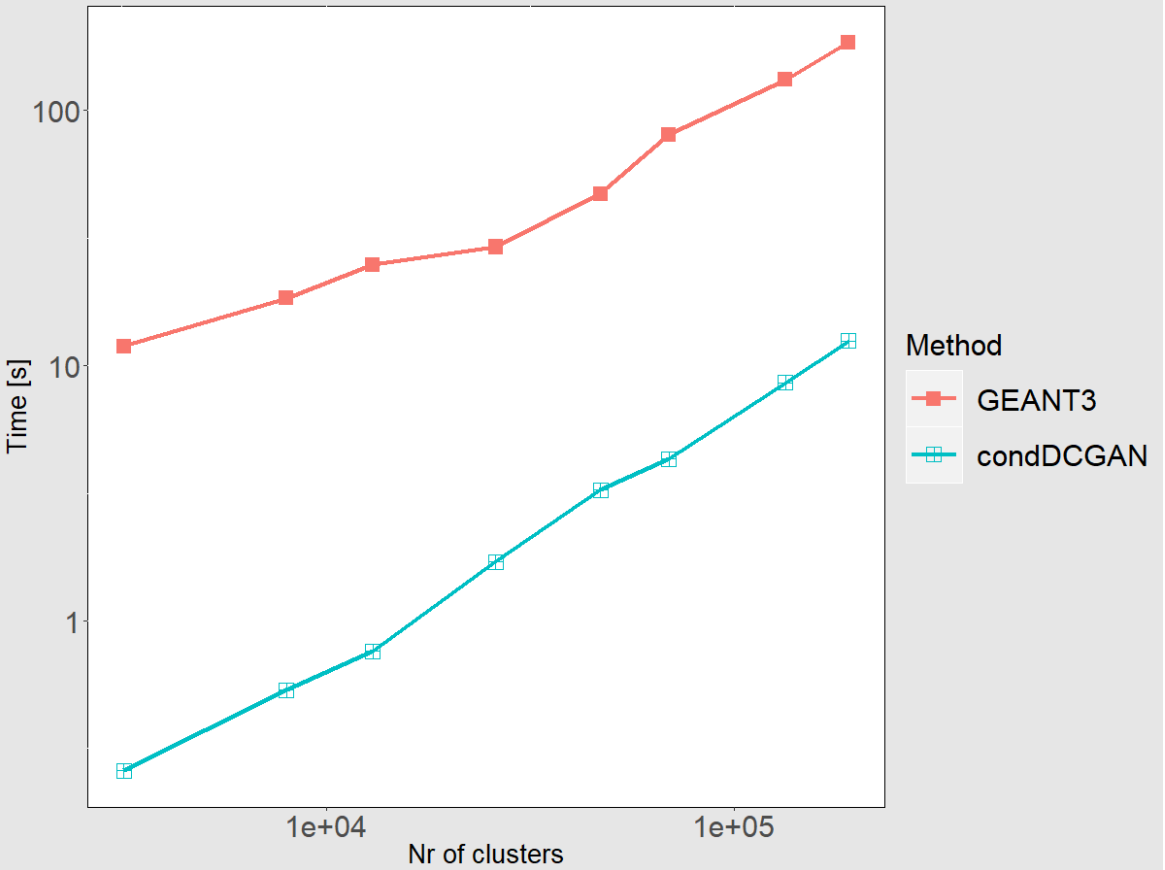
MSE visualisation:
Red - error
Grey- ideal helix
Orange – original clusters
Blue – generated clusters



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**	

Computational cost

- Performance test conducted on the standalone machine with Intel Core i7-6850K (3.60 GHz) CPU using single core and no GPU
- Additional order of magnitude speed-up for GAN models with nVidia Titan Xp GPU

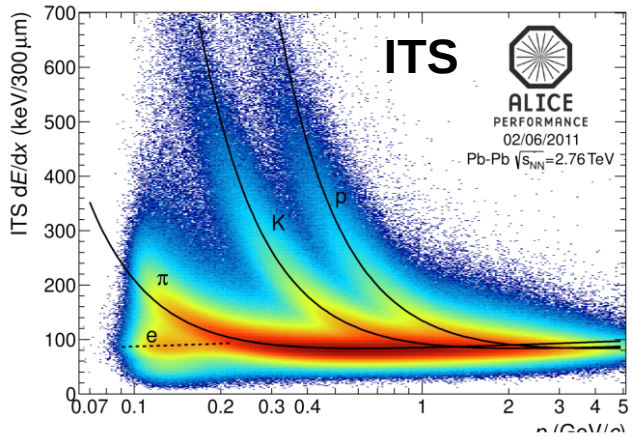


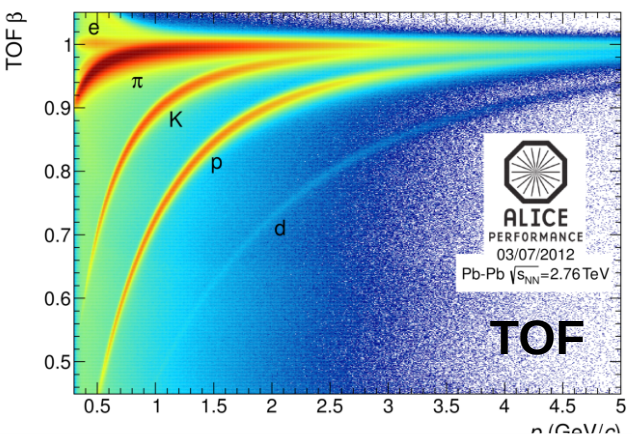
PID with Machine Learning

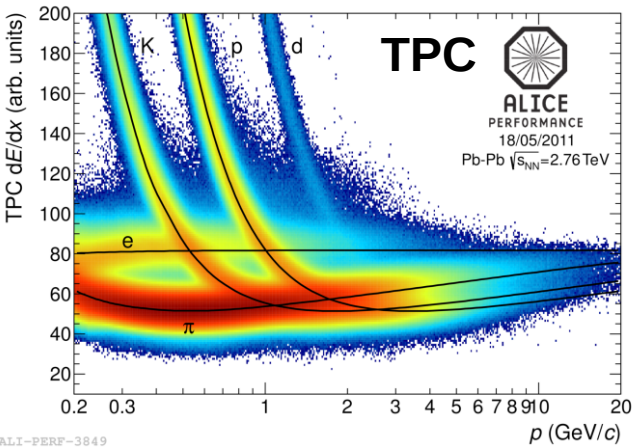
Particle identification

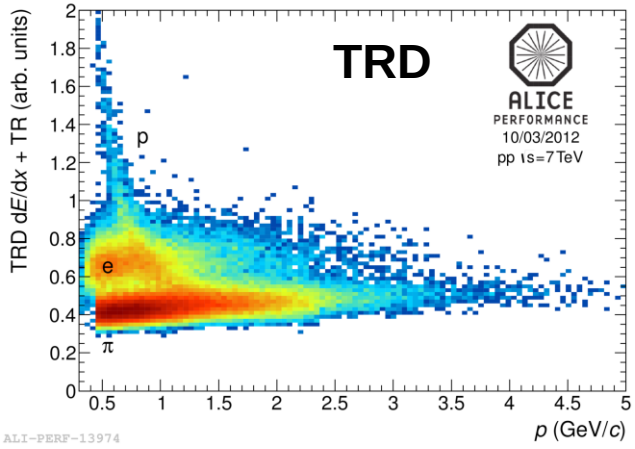
- Particle identification (PID) is one of the most important steps in many physics analyses
- Crucial for Quark-Gluon Plasma measurements
- PID is one of the strongest advantages of ALICE:
  - practically all known techniques used (dE/dx energy loss, time-of-flight, Cherenkov radiation for hadrons and transition radiation for electrons)
  - possibility to identify (anti-)nuclei
  - very good separation of pions, kaons, protons, electrons over a wide momentum range
  - separation of signals of charged hadrons and electrons for very low momenta (down to 0.1 GeV/c)

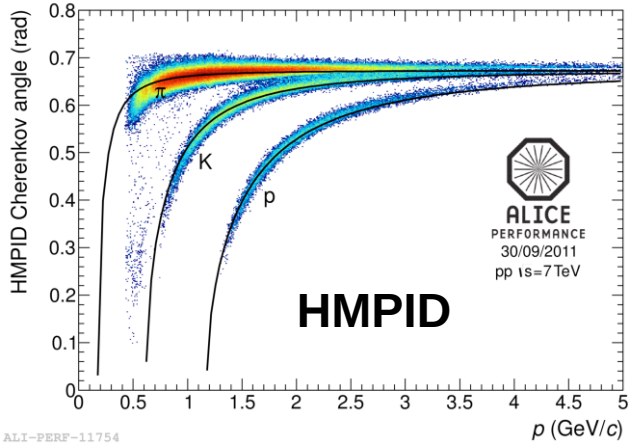
Particle identification

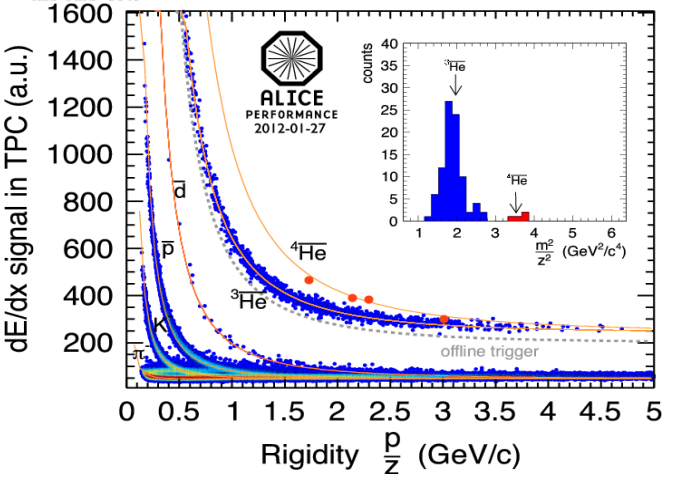


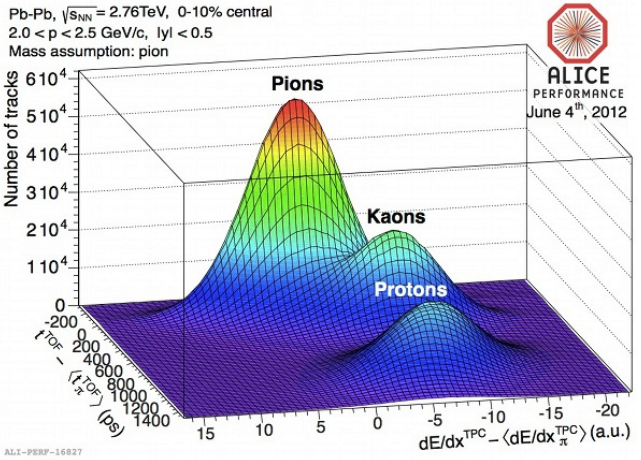






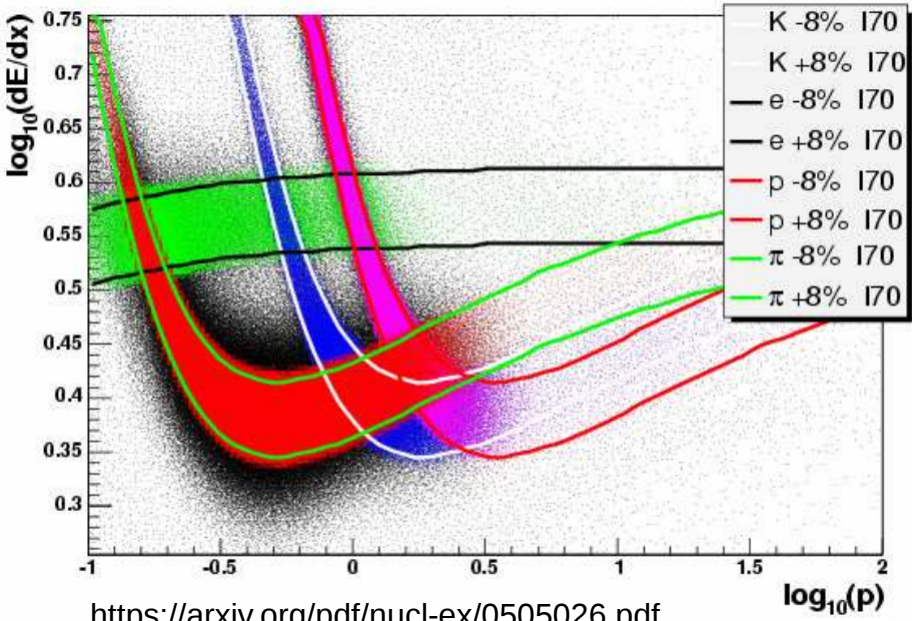






Traditional vs ML PID

- **Traditional PID:**
  - a typical analyzer selects particles "manually" by cutting on certain quantities, like the number of standard deviations of a signal from the expected value
  - most limitations come in the regions where signals from different particle species cross
  - "cut" optimization is a time-consuming task

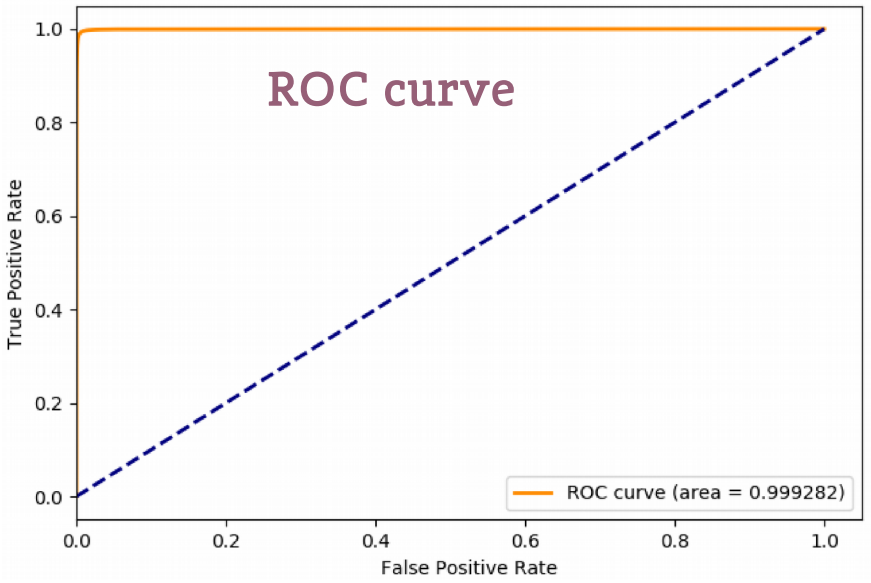


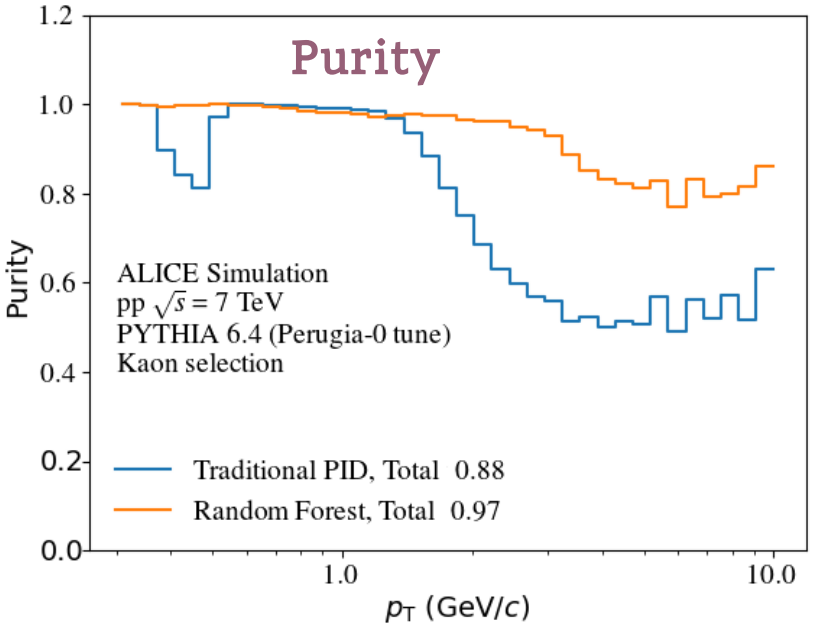
https://arxiv.org/pdf/nucl-ex/0505026.pdf

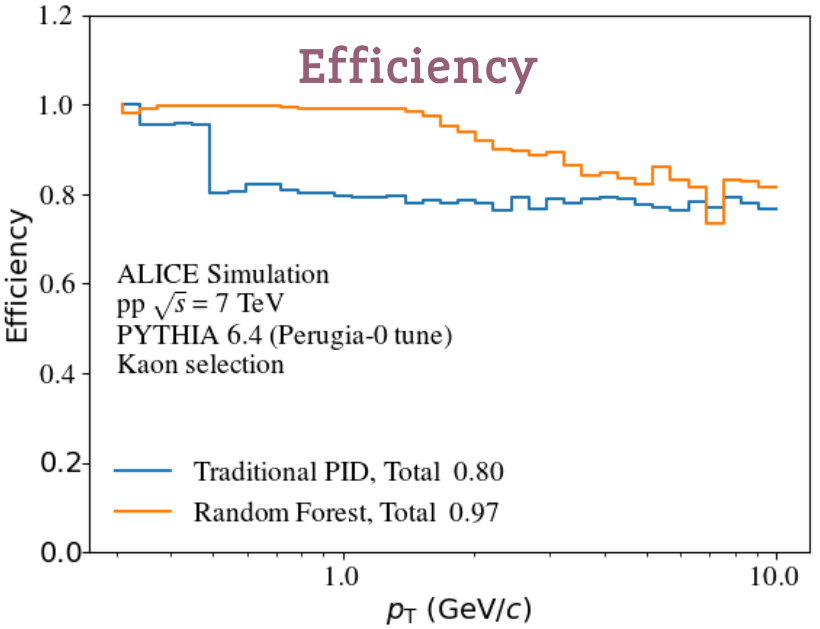
- **Machine learning PID:**
  - perfect task for machine learning
  - can learn non-trivial relations between different track parameters and PID
  - no "trial and error" approach

Results

- **Test data sample:**
  - pp @ 7 TeV, Pythia 6 Perugia-0
- **Traditional PID:**
  - $n^2_{\sigma,TPC} < 2$, for $p \leq 0.5$ GeV/c
  - $\sqrt{n^2_{\sigma,TPC} + n^2_{\sigma,TOF}} < 2$, for $p > 0.5$ GeV/c
- **Machine Learning PID:**
  - Random Forest classifier







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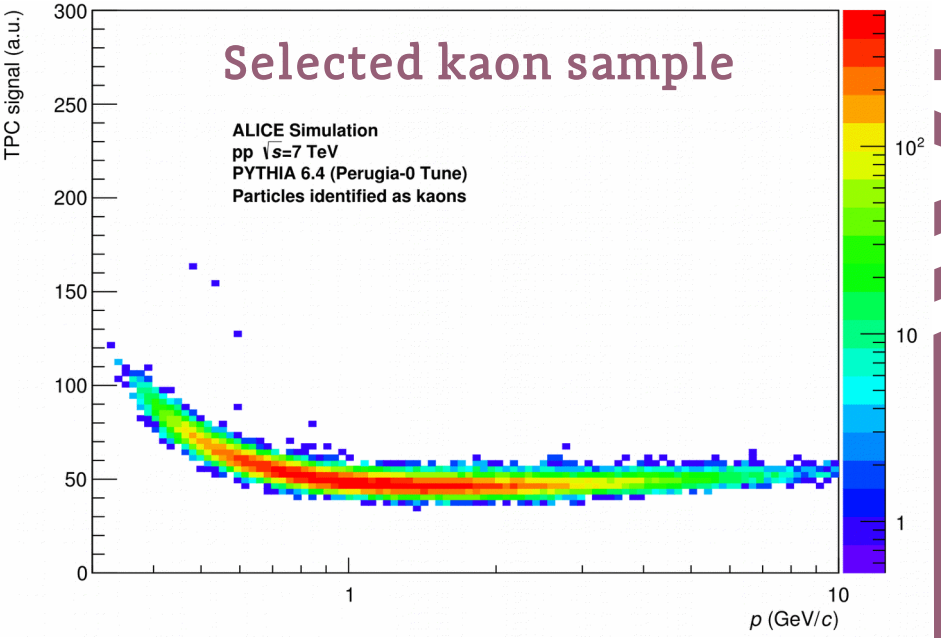
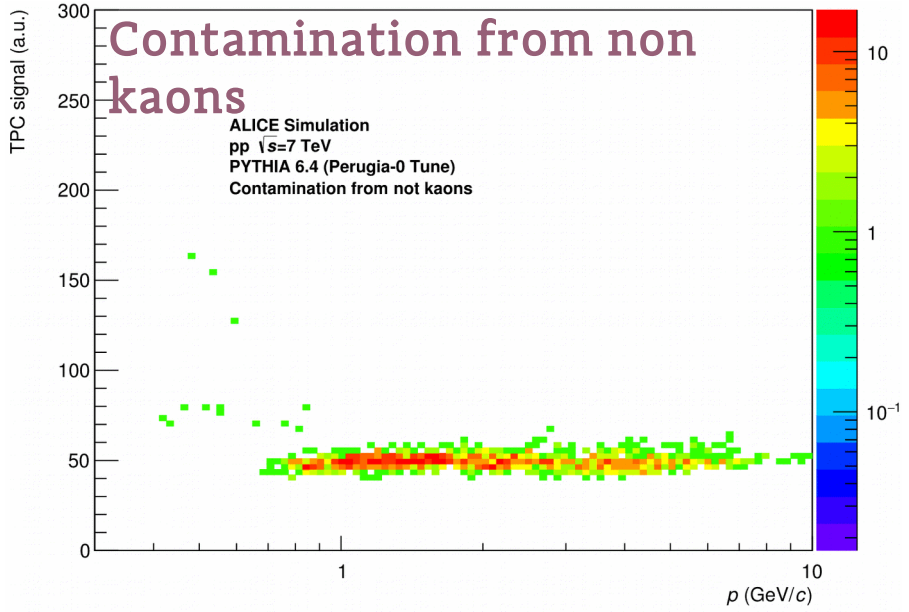
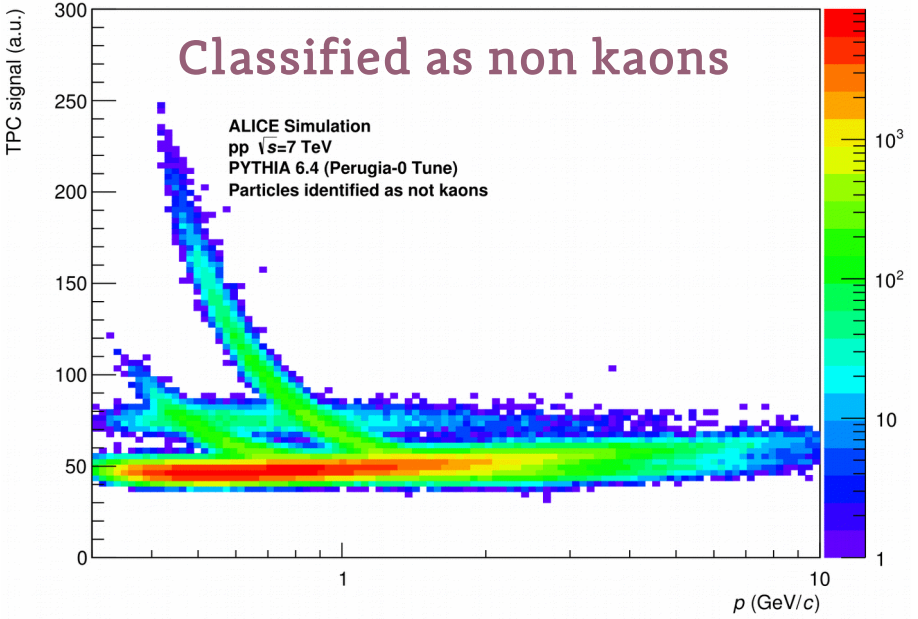






Summary

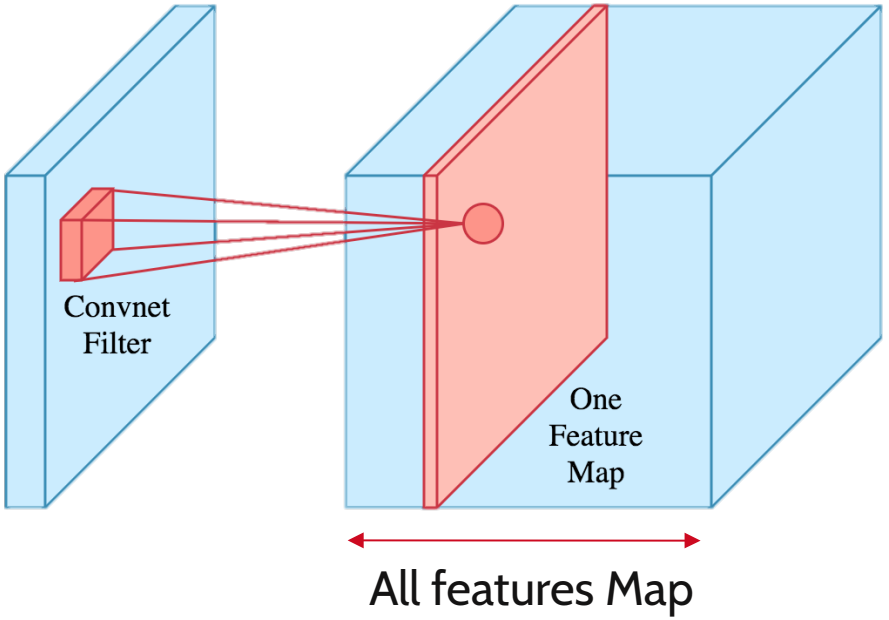
- GANs for TPC cluster simulation
  - Quality not yet equal to the full simulation
  - Massive speed-up of 25x (CPU) or 250x (GPU) wrt standard simulation
  - First step towards semi-real time anomaly detection tool
- PID
  - ML-based PID outperforms traditional PID, especially in the low momentum region
  - training needed only once for each data set – no need for manual cut optimizations
  - Quality of final classification more vulnerable to discrepancies between MC and real data

Thank you!

Backup

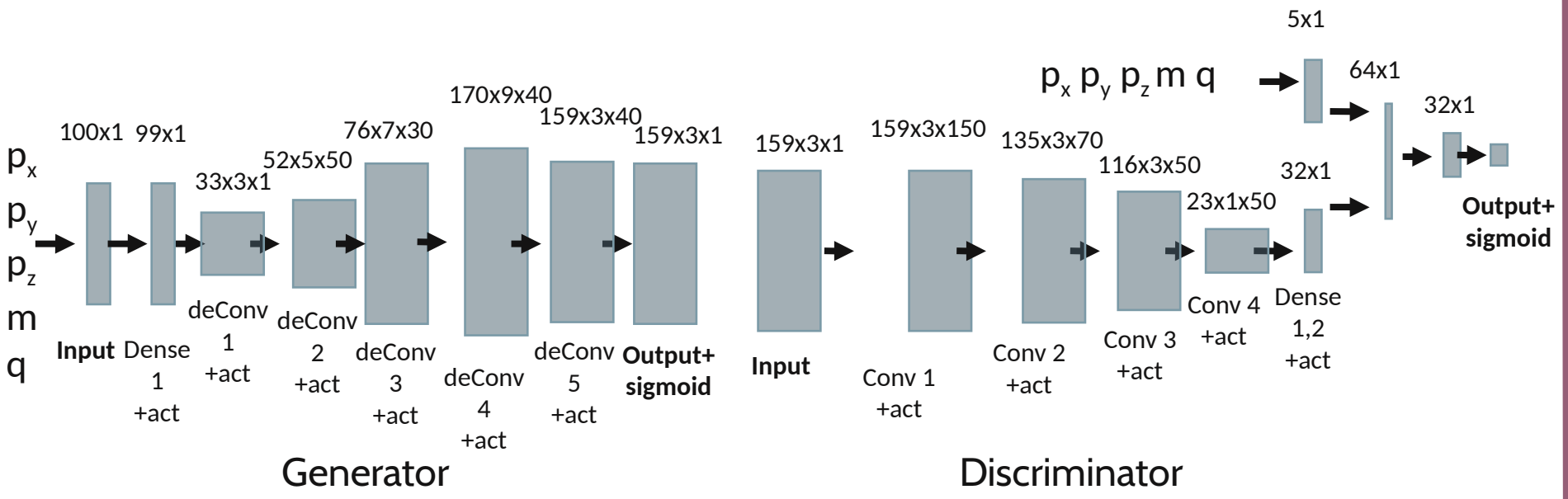
Deep Convolutional GAN

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



condDCGAN: Conditional DCGAN

- Generator – deconvolutional layers
- Discriminator – convolutional layers
- Network conditioned on particle momenta, mass, and charge
- Output classification – sigmoid function

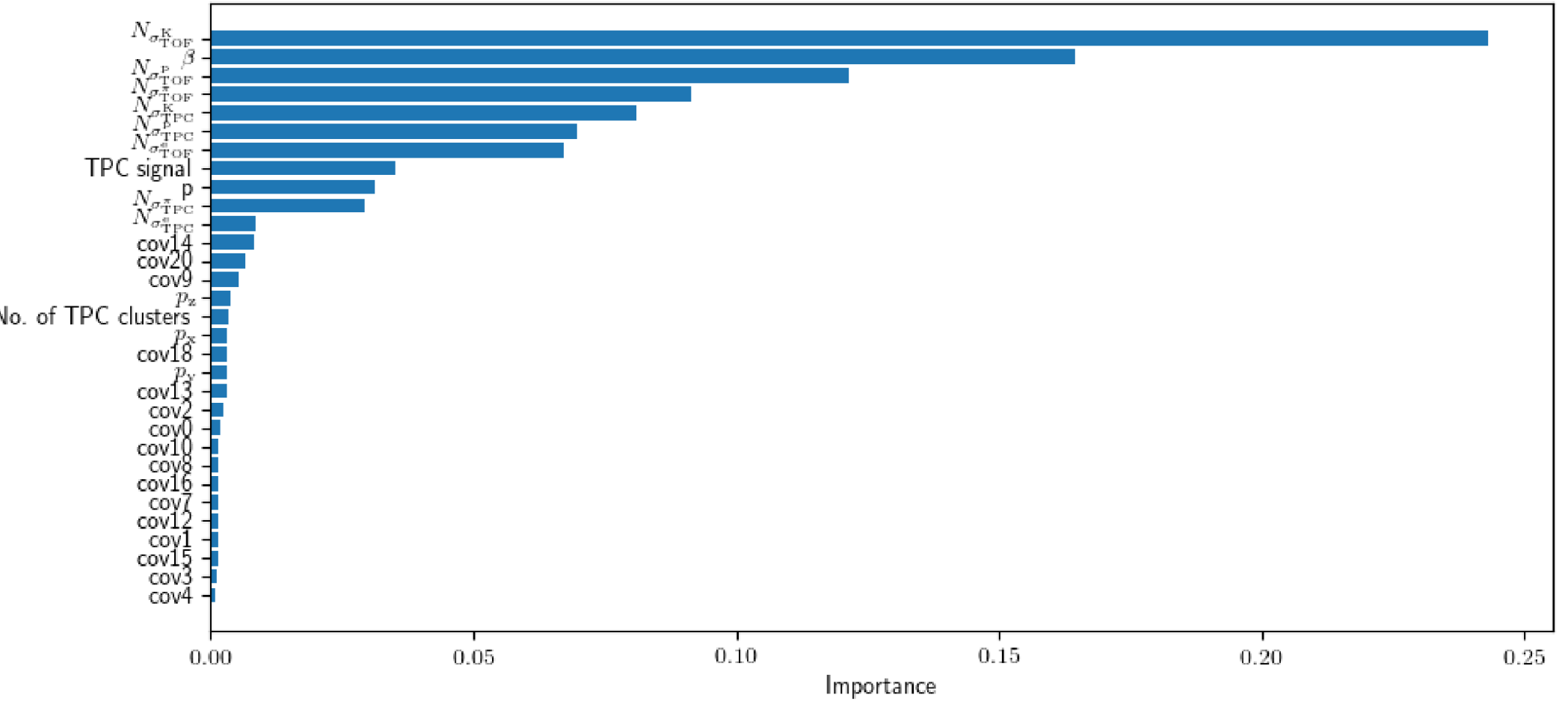


condDCGAN+: combined loss

- Training on on the full MC simulations
- Preparing the noise from initial parameters of MC simulations
- Comparing the generated samples with original ones
- Combining origininal 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 α = 0.6 and β = 0.8

PID parameter importance