What AI Can Do for HEP Experiment

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Why Physicists care of Machine Learning?

Intelligence

WIKIPEDIA
The Free Encyclopedia

Intelligence has been defined in many ways: the capacity for abstraction, logic, understanding, self-awareness, learning, emotional knowledge, reasoning, planning, creativity, critical thinking, and problem-solving. It can be described as the ability to perceive or infer information; and to retain it as knowledge to be applied to adaptive behaviors within an environment or context.[1]

The term rose to prominence during the early 1900s.[2][3] Most psychologists believe that intelligence can be divided into various domains or competencies.

Intelligence has been long-studied in humans, and across numerous disciplines. It has also been observed in both non-human animals and plants despite controversy as to whether some of these forms of life exhibit intelligence.[4][5] Intelligence in computers or other machines is called artificial intelligence.

"Intelligence" is strongly tailored to the human behaviour

- "Artificial Intelligence" is something like human behaviours, but not in human

Artificial Intelligence

Strong (Generic) AI - behaves like a human intelligence

- can generalize knowledge, apply knowledge from one task to another, plan ahead according to current knowledge, adapt to an environment as changes occur
- We do not have AGI available, however:
  - AlphaGo - AlphaZero - MuZero - moving in that direction
  - GPT-3 - GPT-4 - GPT-4o (May 14, 2024) - moving in that direction

Weak (Specialised, Narrow) AI - ability to perform specific tasks

- Most often better than humans
- Chatbots, smart assistants, navigators, Y.music, self-driving cars, HEP trigger selections, particle ID, background suppression…

Machine Learning

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Machine learning (**ML**) is a field of study in artificial intelligence concerned with the development and study of statistical algorithms that can learn from data and generalize to unseen data, and thus perform tasks without explicit instructions.[1] Recently, generative artificial neural networks have been able to surpass many previous approaches in performance.[2][3]

Machine Learning is a machinery to train AI applications

Under the hood it is almost always building a descriptive model

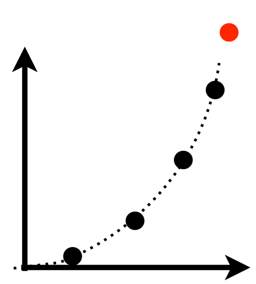
- Function in multi-dimentional space
  - Separation surface for classification
  - Predictive function for regression
  - Policy function for reinforced learning
  - …

Scientific vs Descriptive Models

Scientific Model

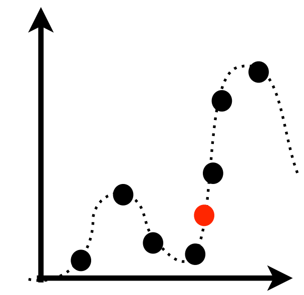
Paradigm: the model predicts data

- Specific dependencies a priori driven by fundamental laws
- Limited number of degrees of freedom
  - Occam’s razor
- Model may be extrapolated beyond the test domain
- Interpretable predictions
- Problems in case of discrepancy between prediction and observation

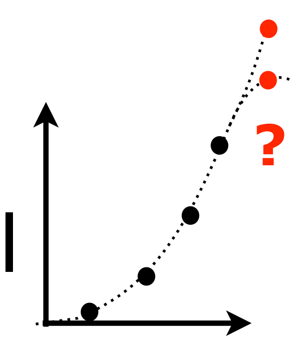


Descriptive Model

Paradigm: the model describes data



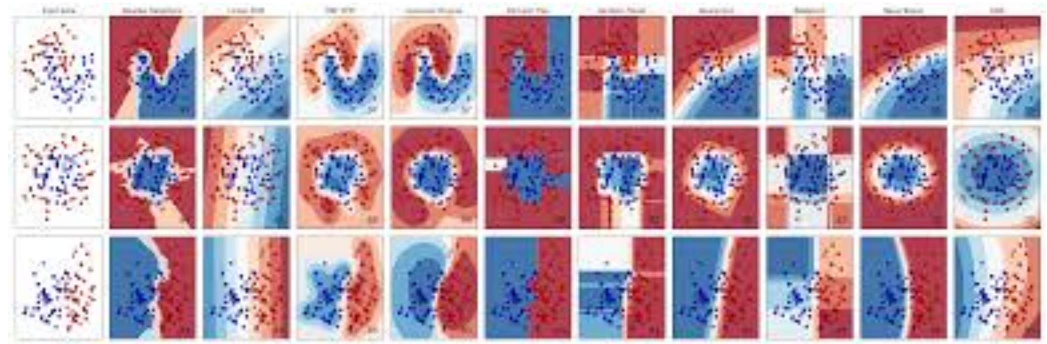
- Data are primary
  - No a priori assumptions about types of dependencies
- Model is universal
- Big number of model parameters
  - Parameters are hardly interpretable
- Can not trust the model extrapolation



Typical ML problems

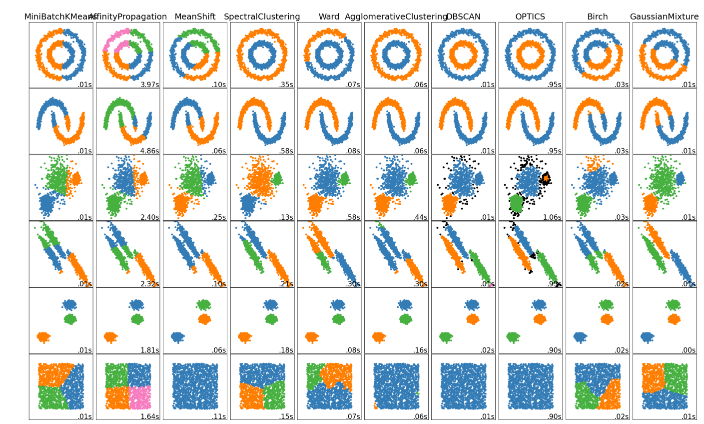
Supervised learning

- “Look on examples and learn how to do the same”



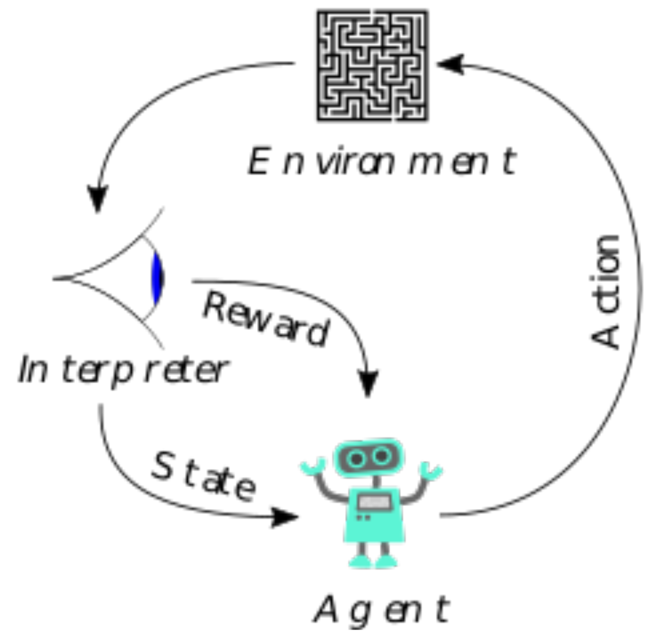
Unsupervised learning

- “Figure out which patterns exist in the data”



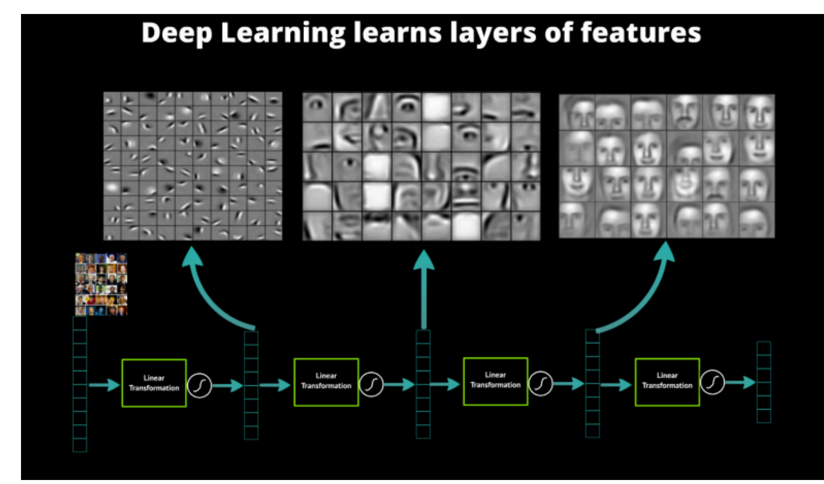
Reinforced learning

- “Train decision-making using the 'carrot and stick' method”



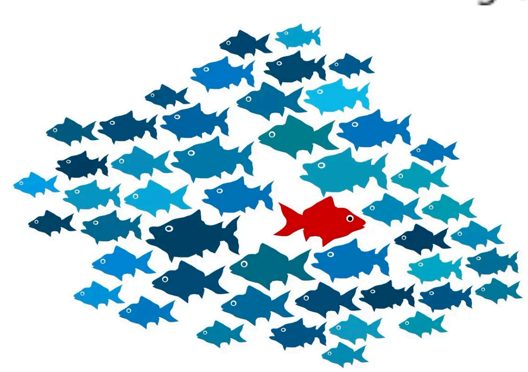
Representation learning

- “What high-level features determine the essential properties of objects”



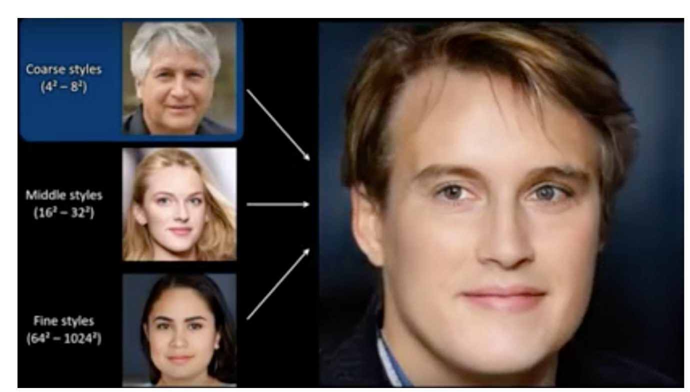
Anomalies detection

- “Find something unusual in the data”



Generative models

- Create a new object similar to the existing ones”



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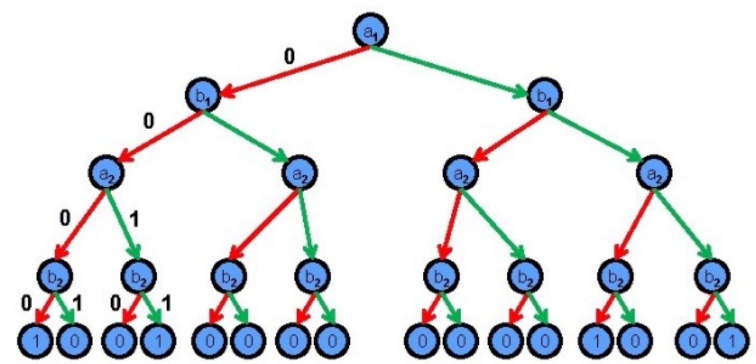
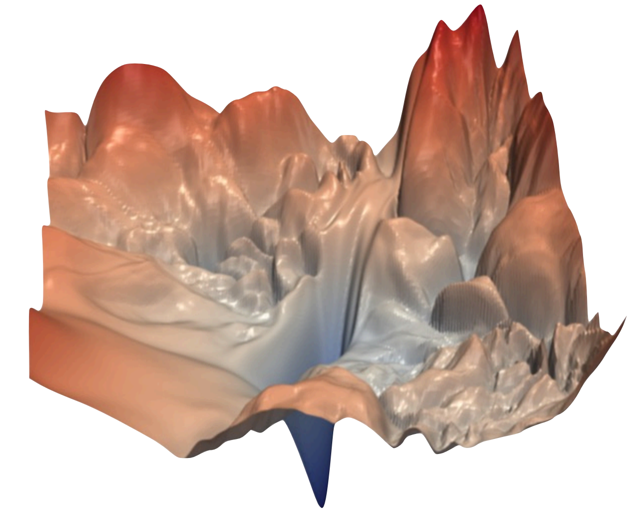
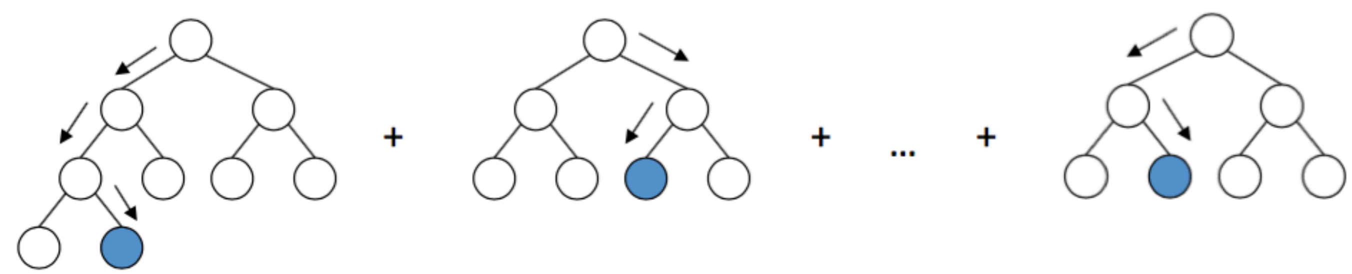
Few types of universal parametric functions

Trees

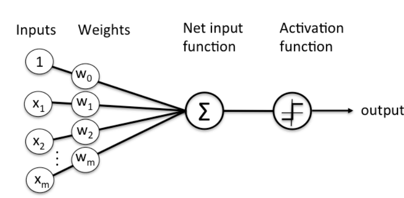


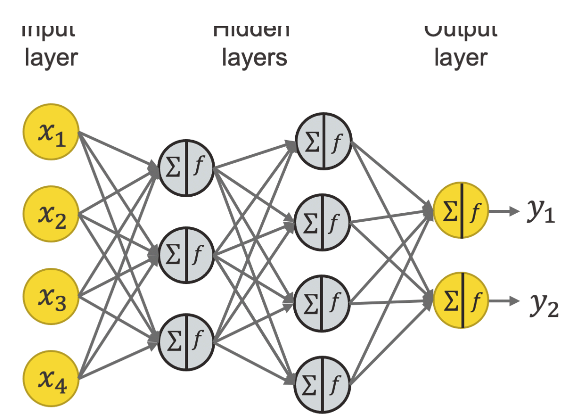


- Ensembles of trees

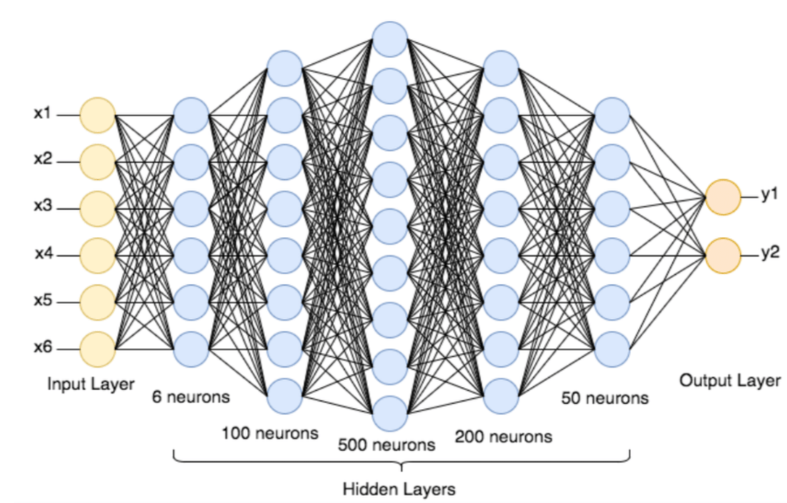


Neural networks





- Deep neural networks



Typical HEP problems addressed by ML

Physical analysis, optimization of signal-background separation (MVA)

Fast event selection in the trigger

Reconstruction in detectors

Particle identification in the detector

Anomaly detection

Technical anomalies: data quality

Physical anomalies: search for new physics

Acceleration of MC generators

Acceleration of detector simulation

Detector optimization

Accelerator control

…

MVA vs Rectangular Cuts

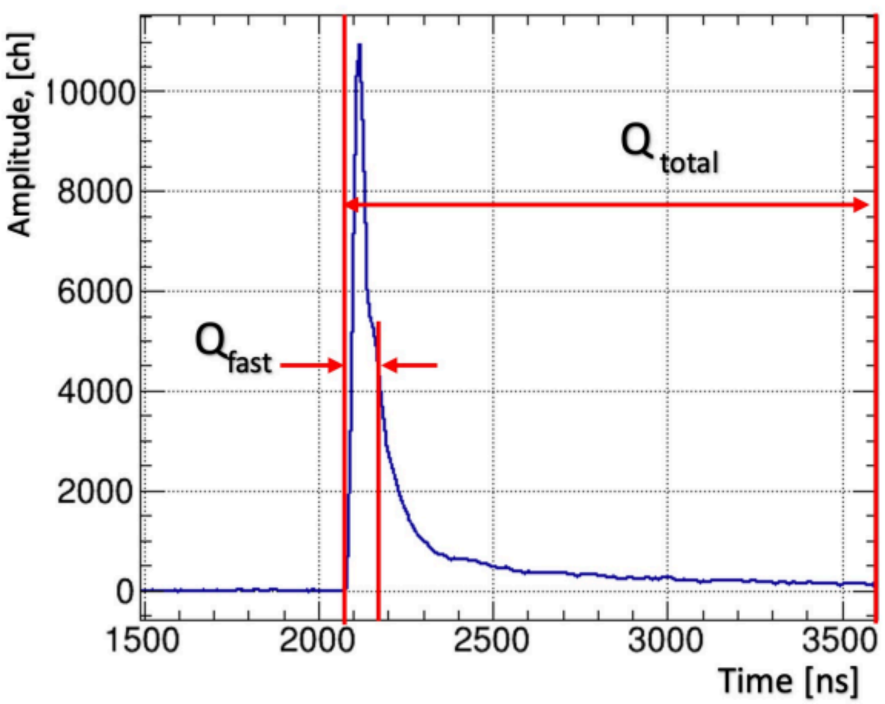
N. Lashmanov et.al

Pulse shape n/γ- discrimination

Quality of pulse shape discrimination:

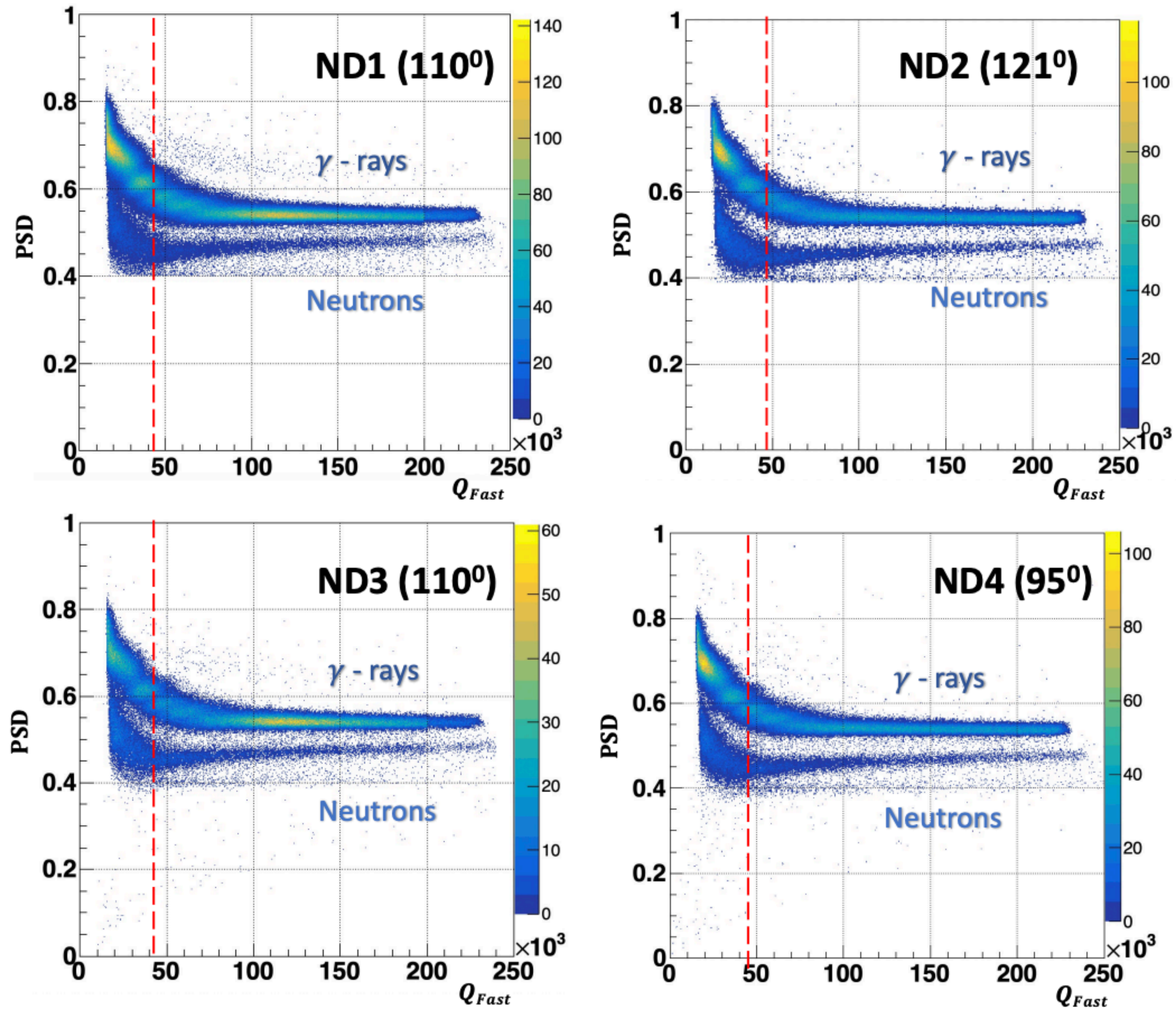
$$PSD = \frac{Q_{fast}}{Q_{total}}$$

Waveform of Neutron Detector (TQDC)



T_{fast} = 0.12 μs : time window for charge integration Q_{fast}

T_{total} = 1,5 μs. : time window for charge integration Q_{total}



MVA vs Rectangular Cuts

N. Lashmanov et.al

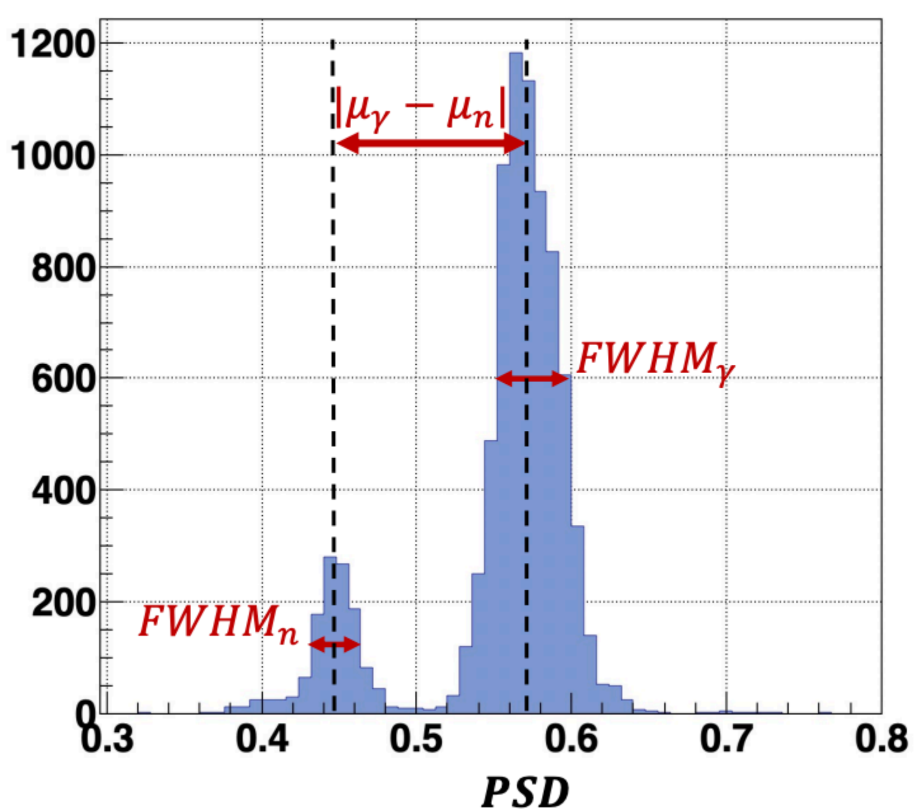
Pulse shape n/γ- discrimination

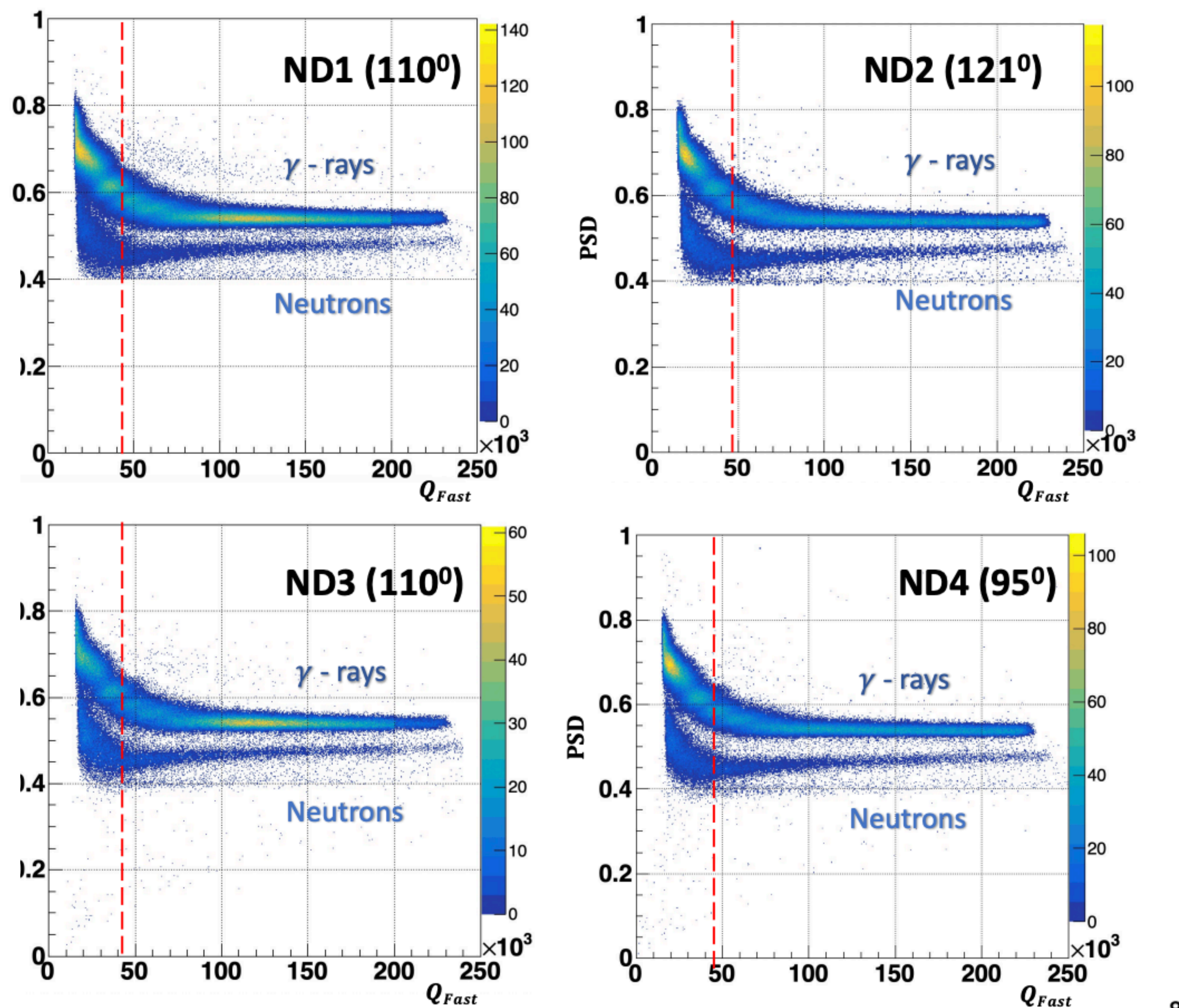
Quality of pulse shape discrimination:

$$PSD = \frac{Q_{fast}}{Q_{total}}$$

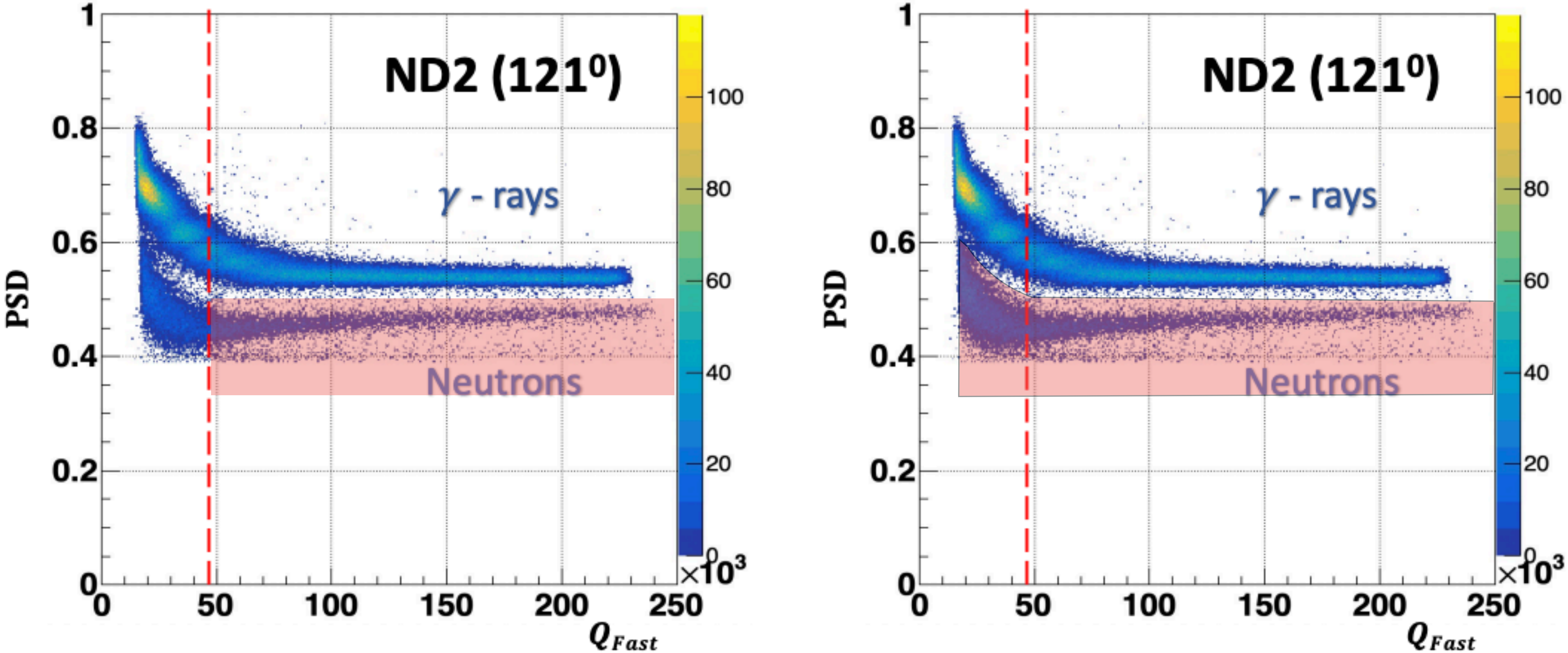
Figure of Merit:

$$FOM = \frac{|\mu_\gamma - \mu_n|}{FWHM_\gamma + FWHM_n}$$





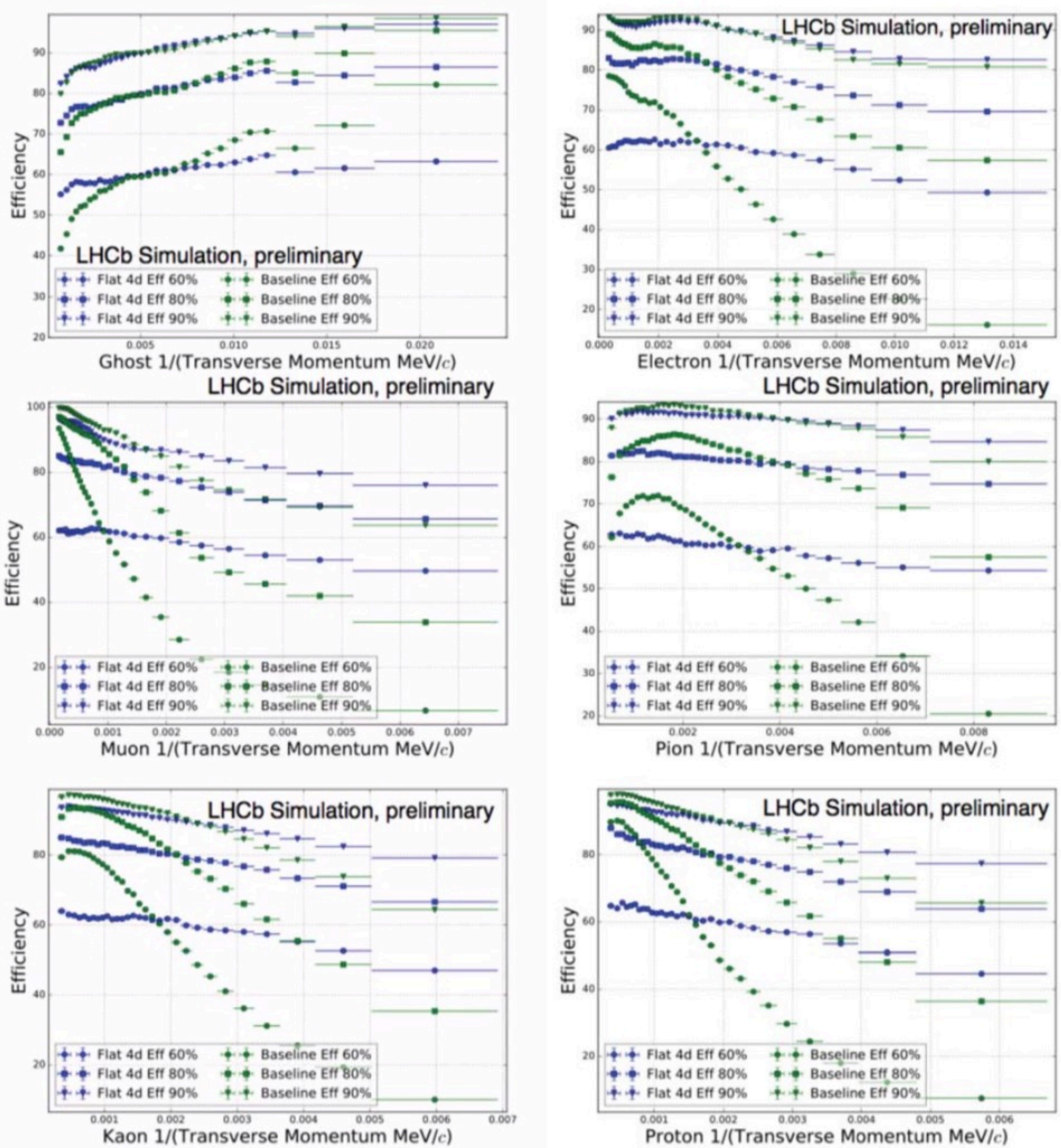
MVA vs Rectangular Cuts



2-D MVA could allows optimising discrimination to better performance

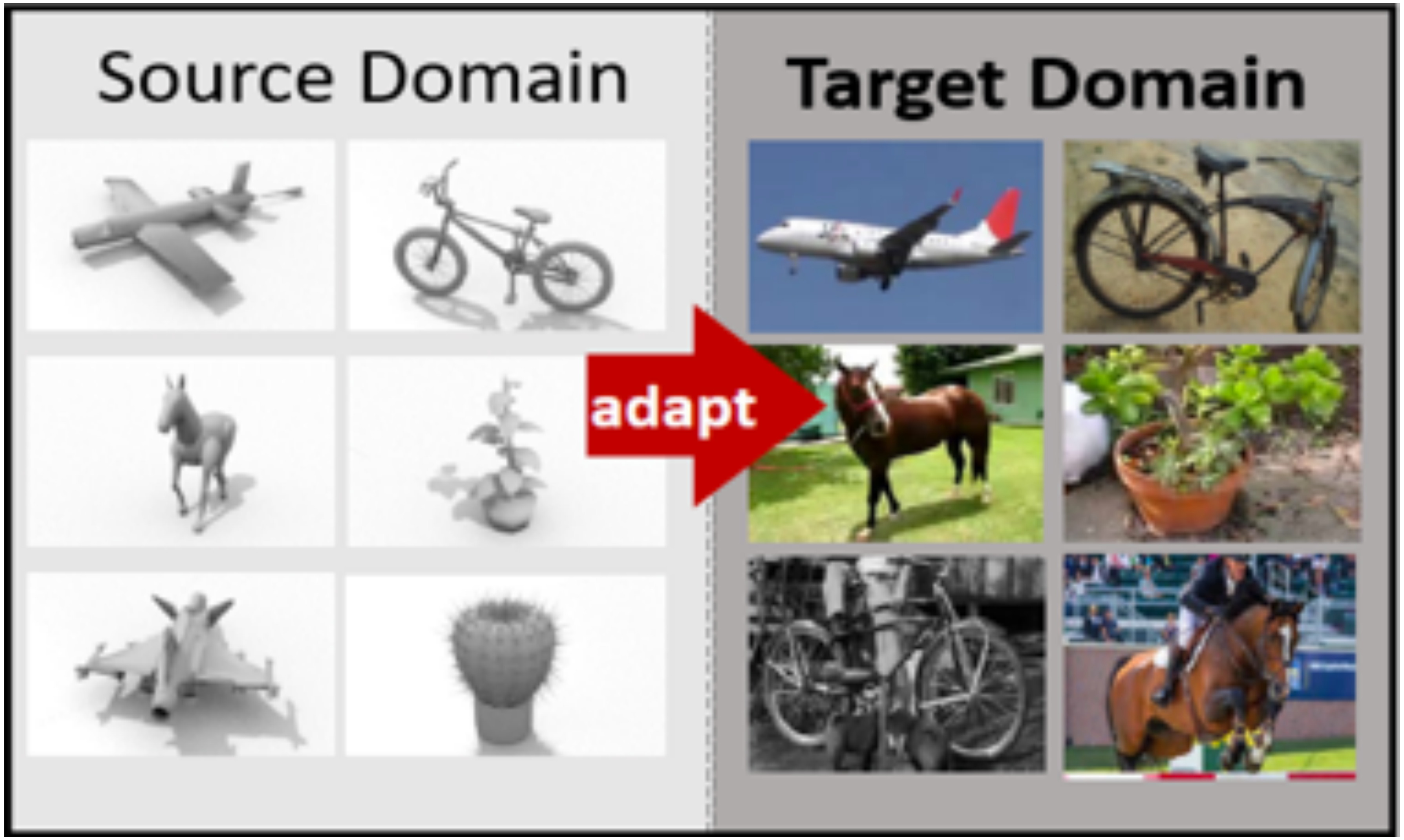
3-D MVA (TOF, PSD, Q_{Fast}) could provide even better discrimination

Imposing of Specific Requirements



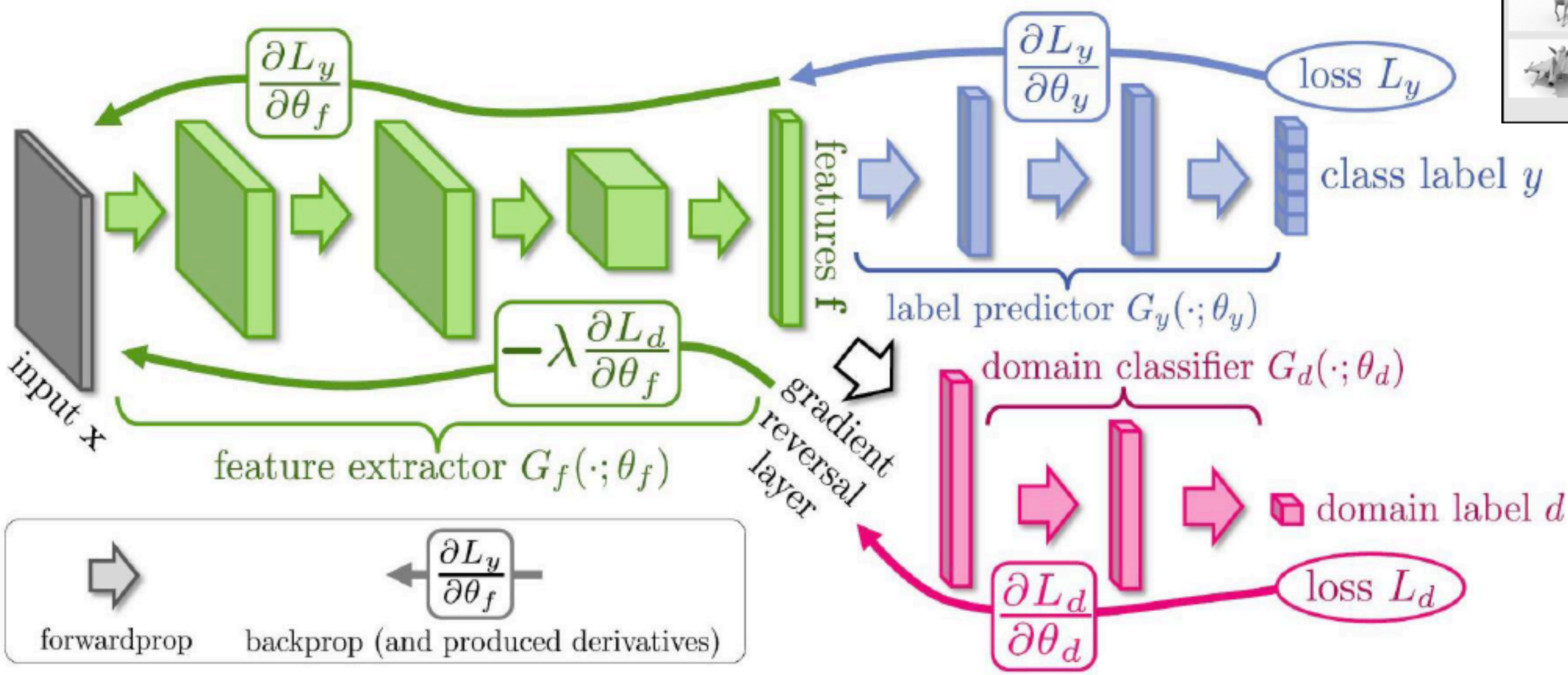
Would like to flatten the PID efficiency dependencies

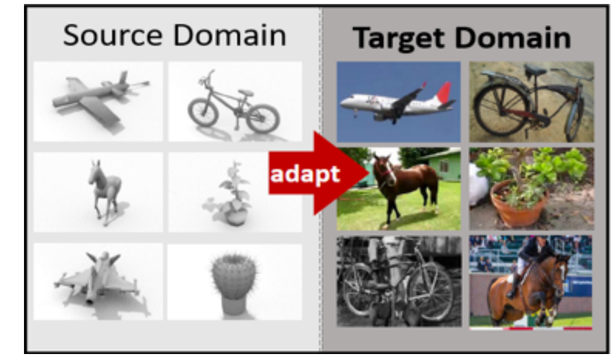
Domen Adaptation



Make the algorithm dependent on the essential properties of objects, but insensitive to the details of the training data set

Domen Adaptation





Make the algorithm dependent on the essential properties of objects, but insensitive to the details of the training data set

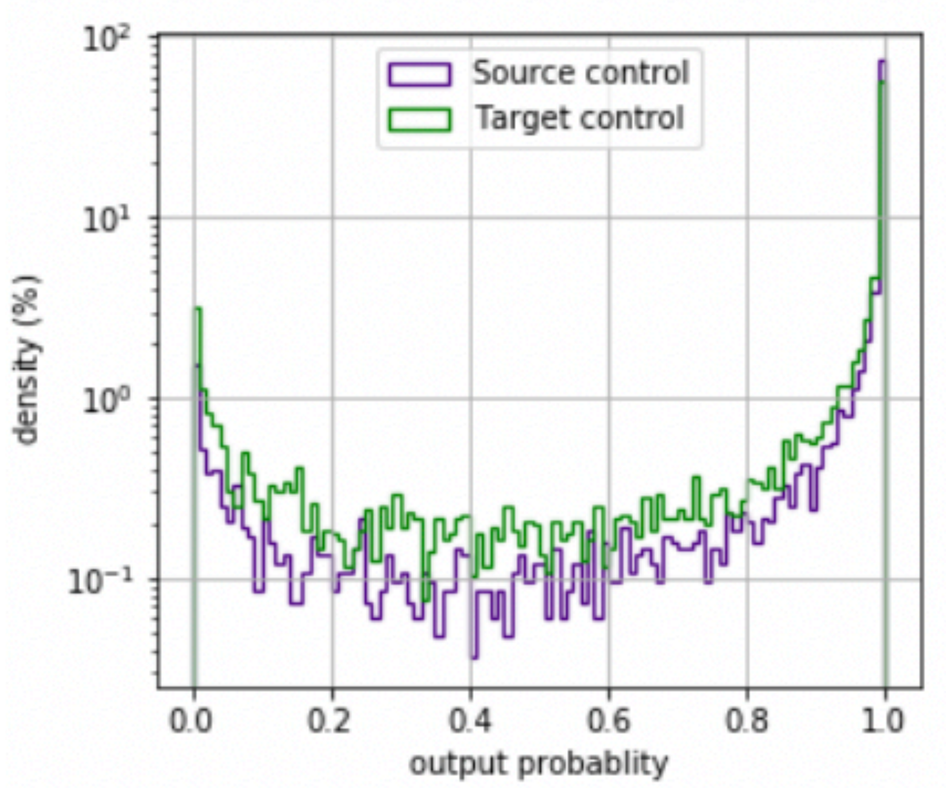
Domen Adaptation in HEP

arXiv:1912.08001

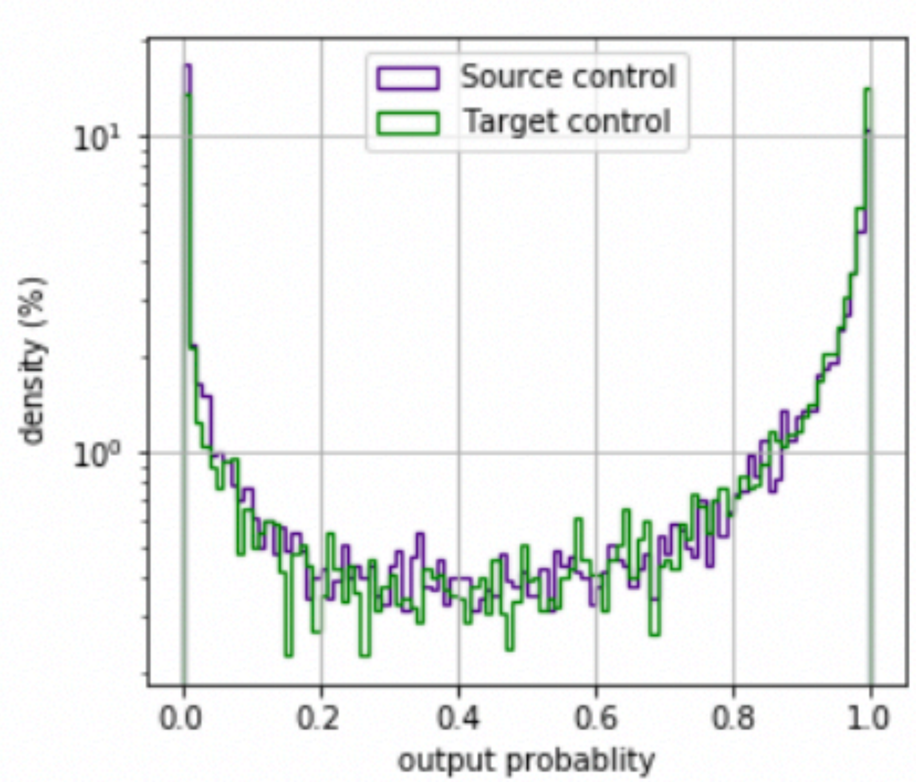
Signal: $\tau \to 3\mu$ MC

Background: $''\tau'' \to 3\mu$ real data beyond τ mass

Control data: $D_s \to \phi\pi \to 3\mu$

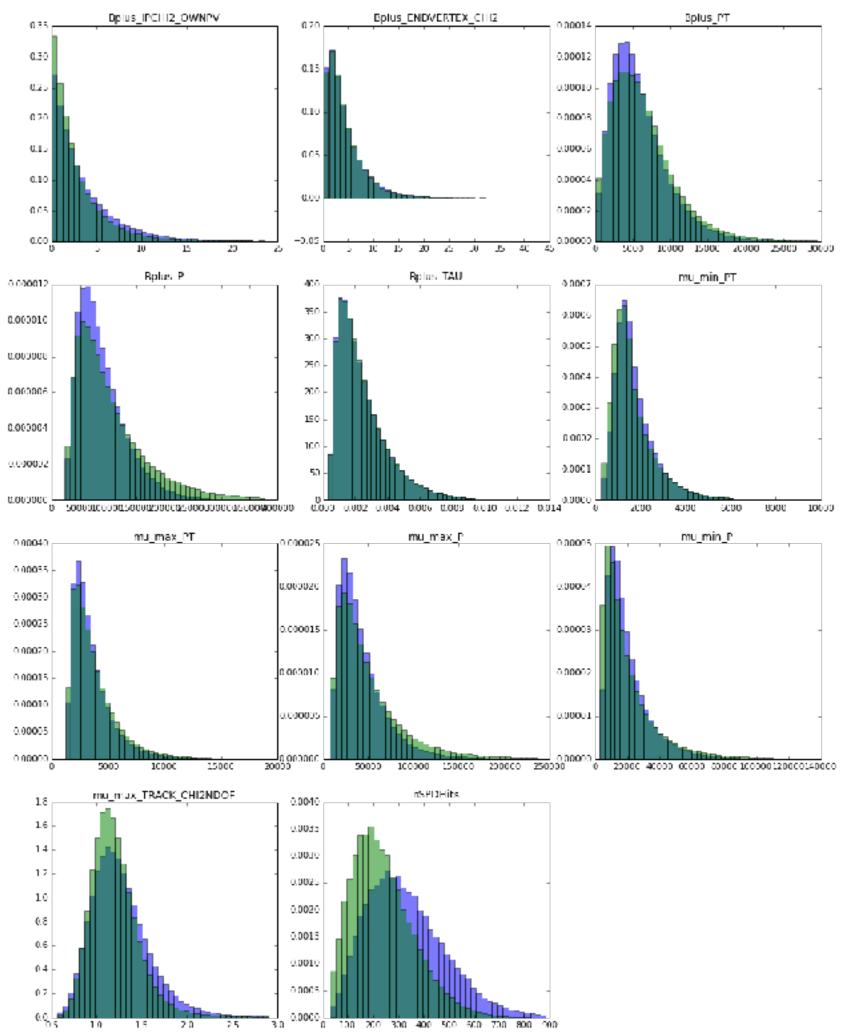


Without DA



With DA

Reweighting MC to Data



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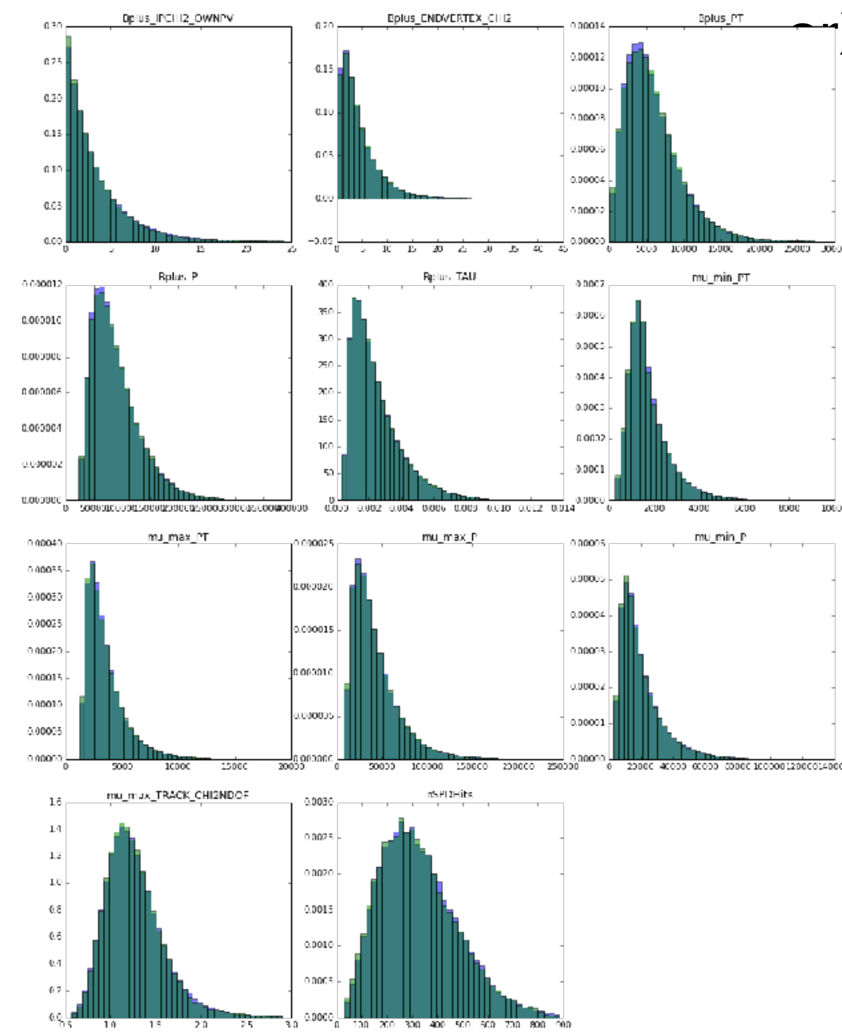


arXiv:1608.05806

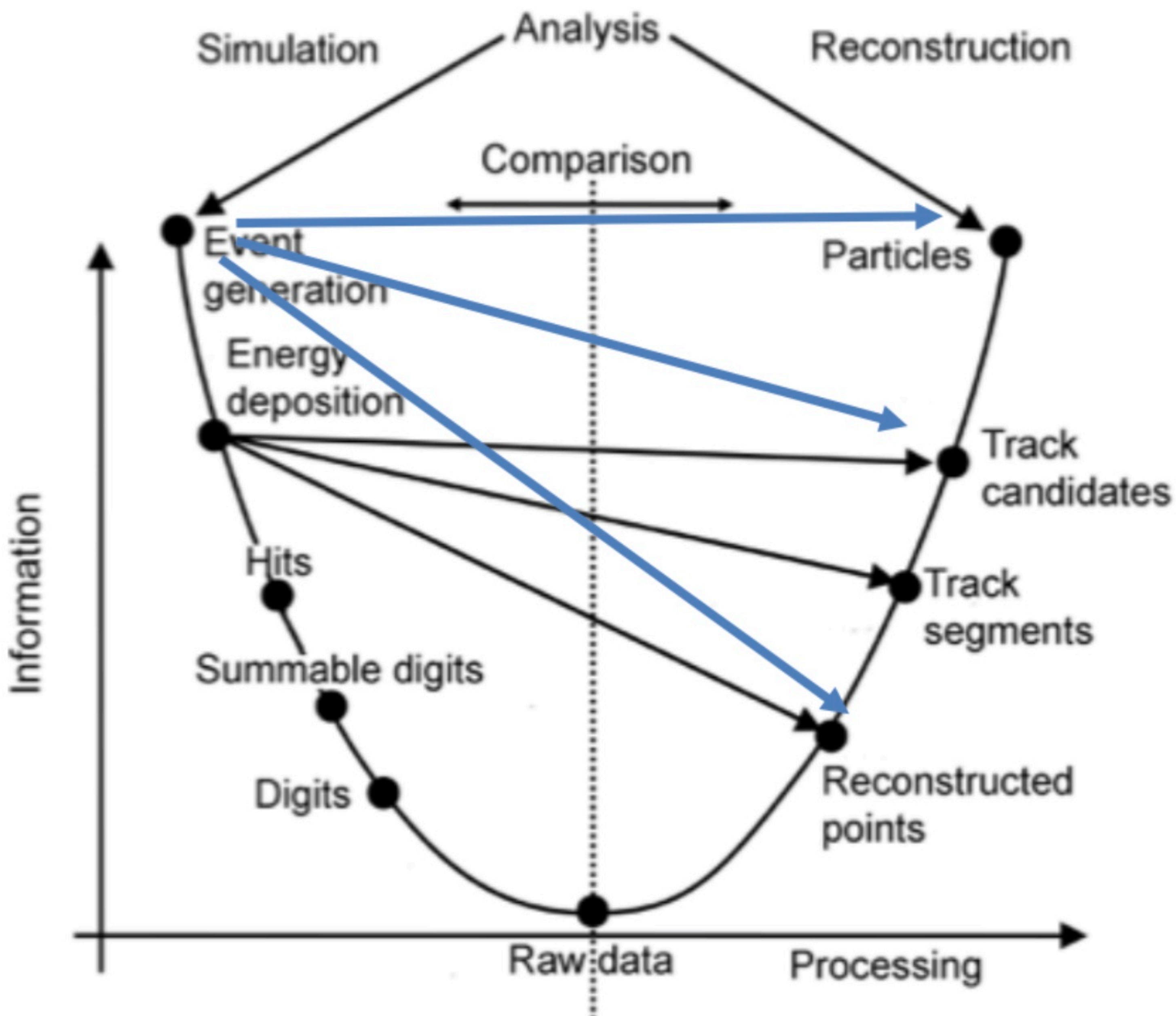
Task: Re-weight simulation events to reproduce certain distributions in the real data

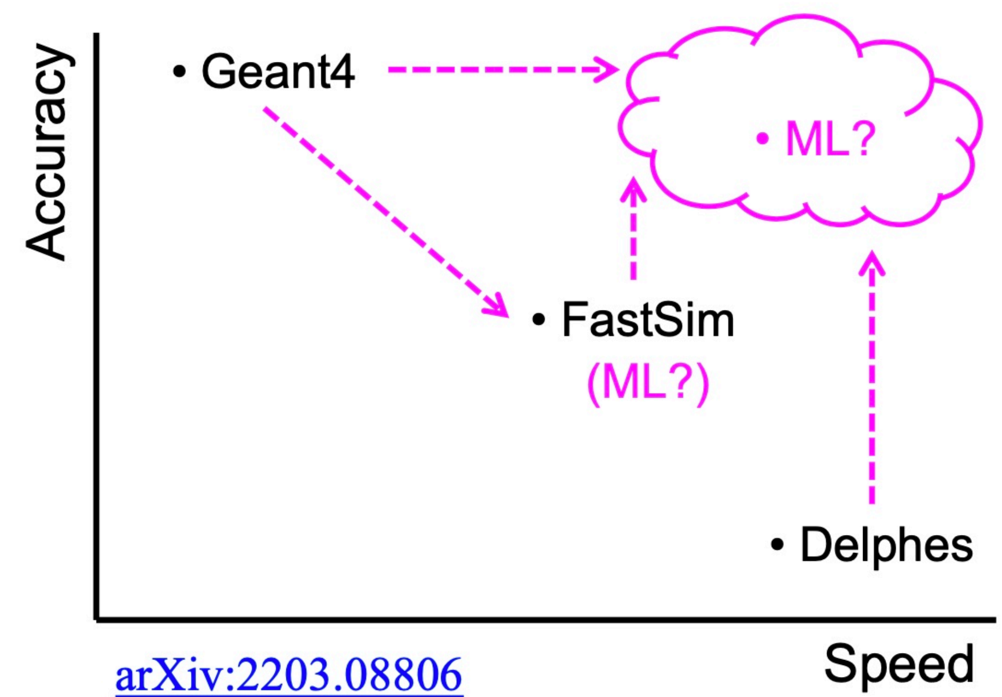
- Straightforward for 1D
- Not easy in many dimensions with limited statistics

Very natural task for ML:

- re-weight to make distributions indistinguishable by the classifier.

Data Flows for Simulation and Reconstruction



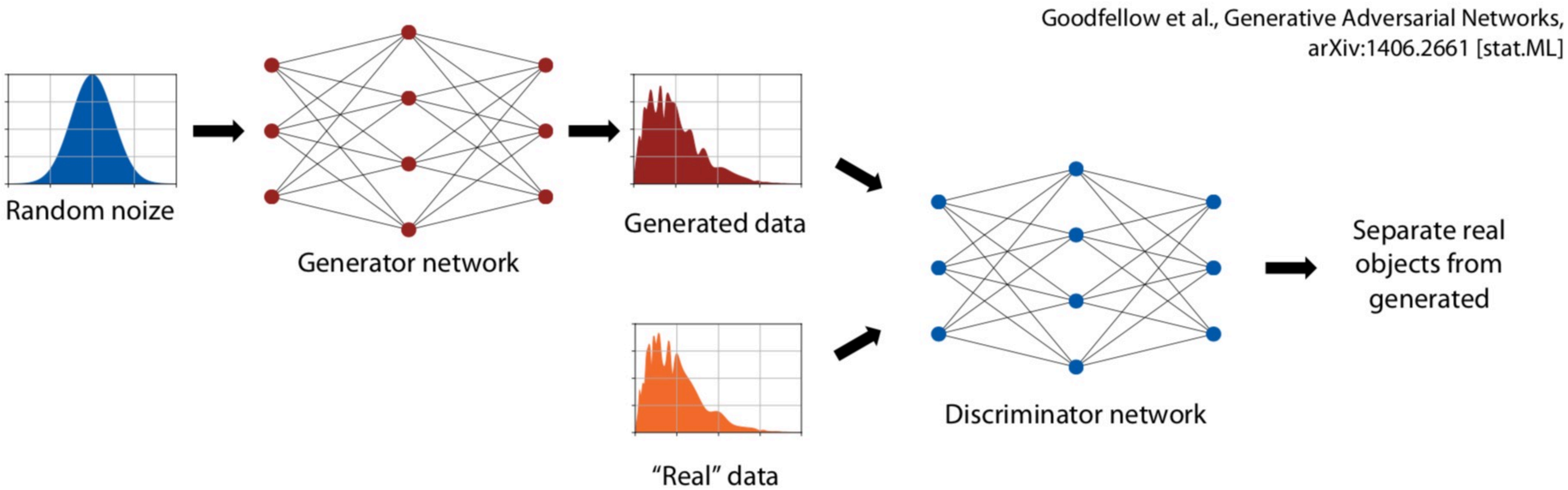


arXiv:2203.08806

mia parabola" Figure by Federico Carminati, independent parallel inventions by Vincenzo Innocente & K.C.

- Surrogate generative models allow simulating final objects without diverting resources to detailed simulation of internal processes

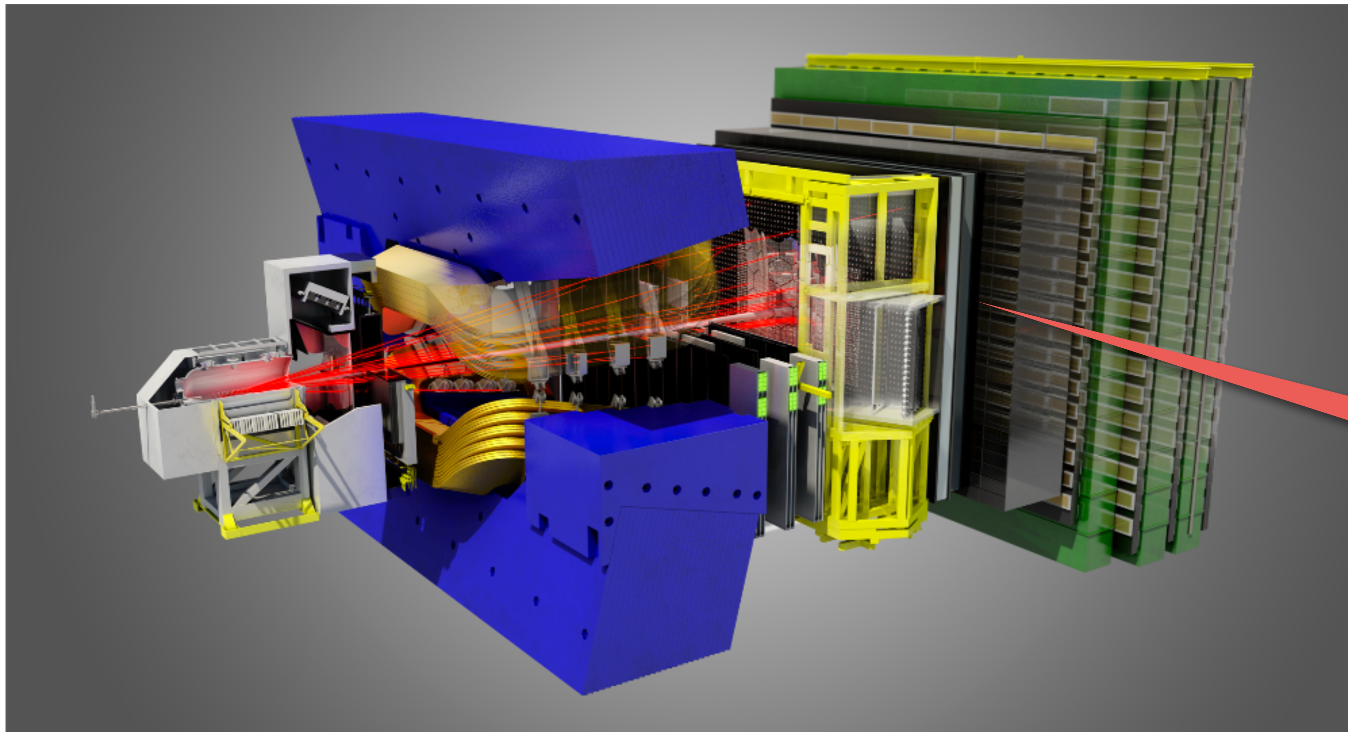
Adversarial Approach (GAN)



The quality metric of a generator network is how well another network (discriminator) can distinguish generated data from real data

Generative Models for Calorimeters

arXiv:1812.01319

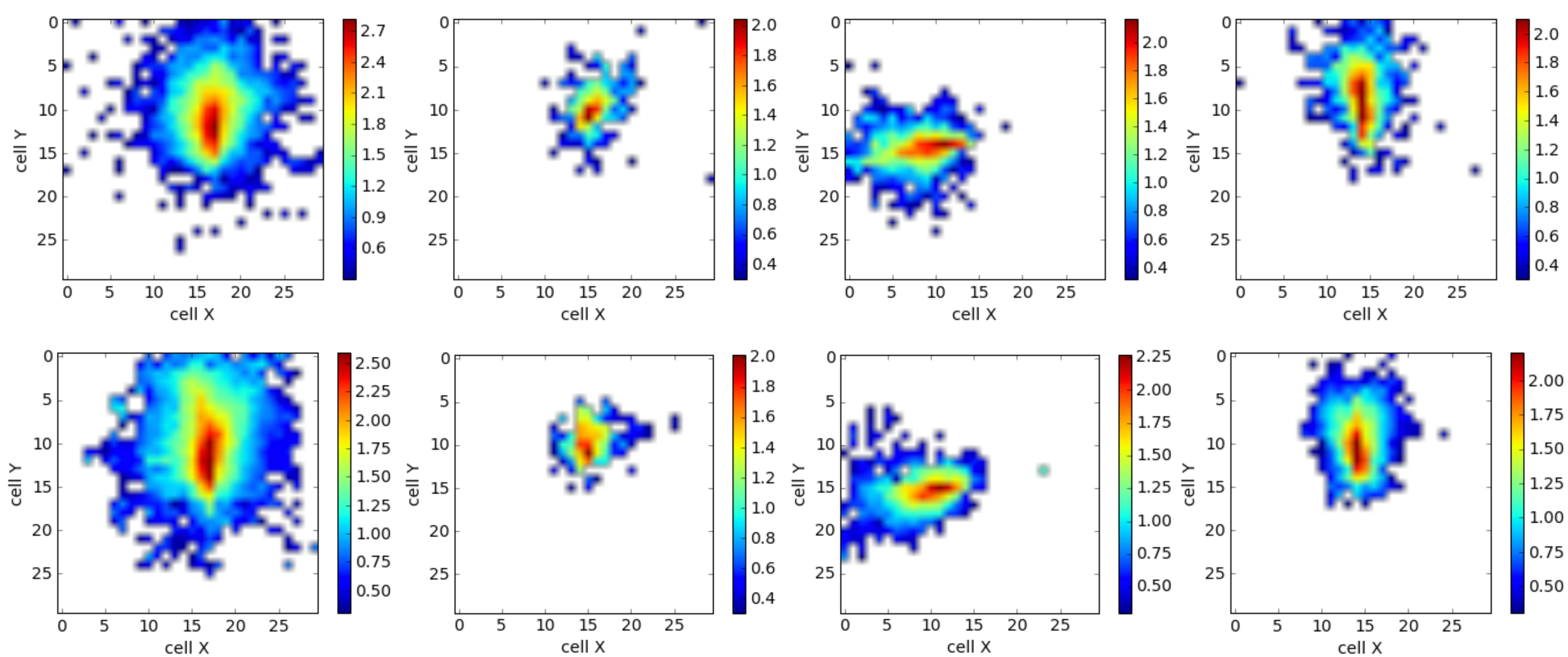


E-M Calorimeter LHCb

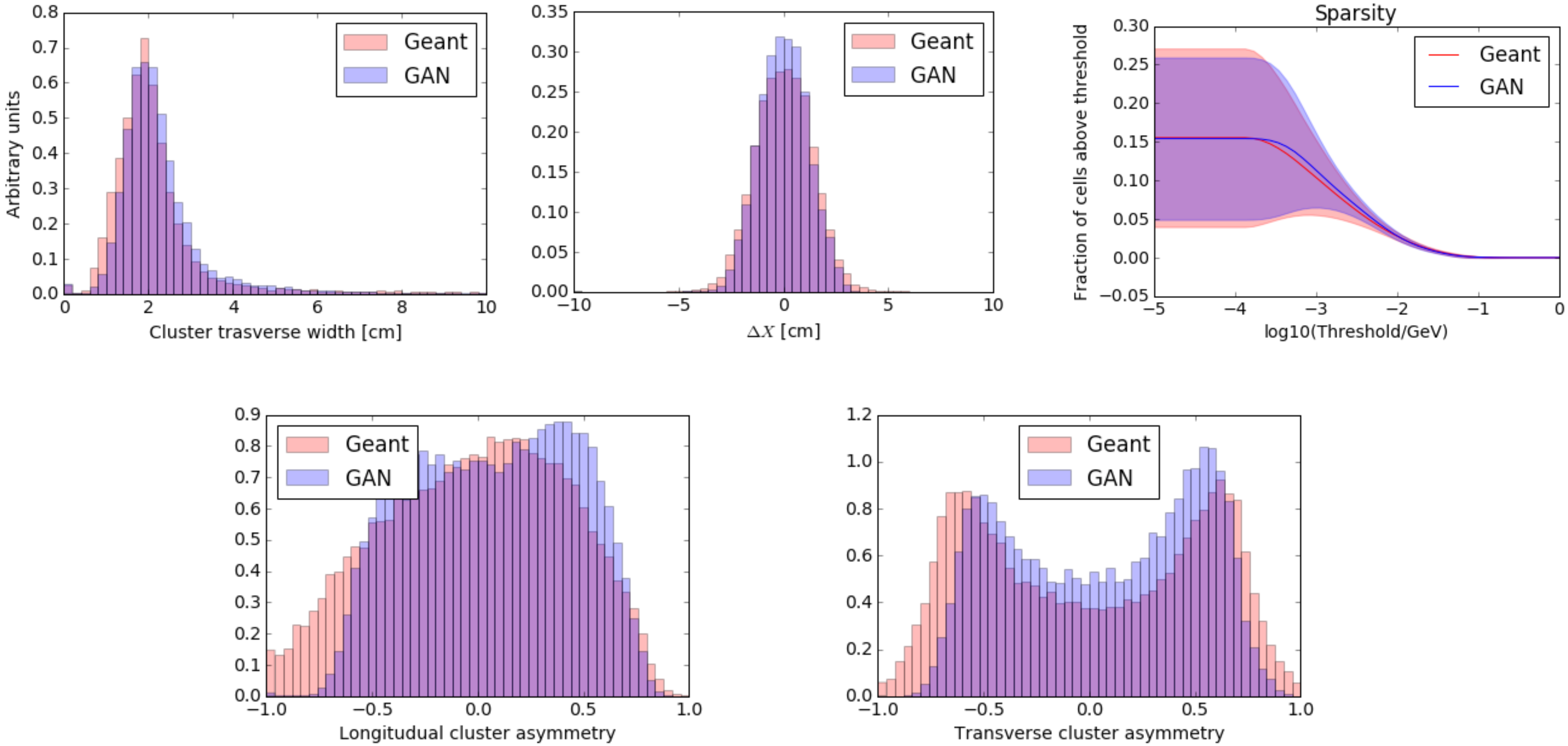
GEANT Simulated

$\log_{10}$(cell energy)

GAN Generated



Generative models

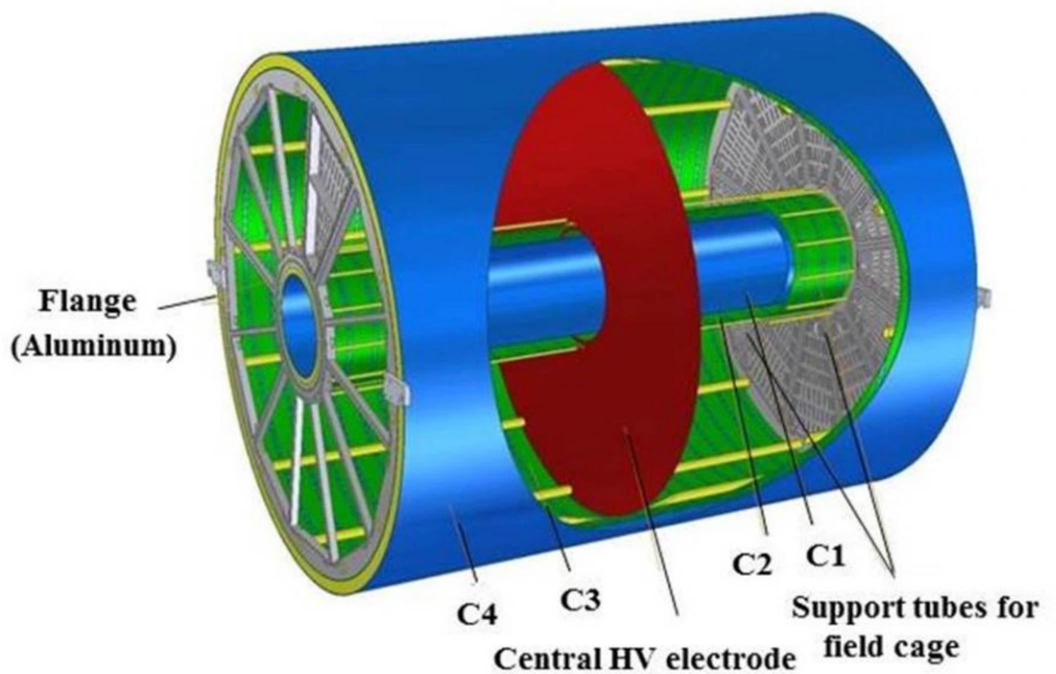


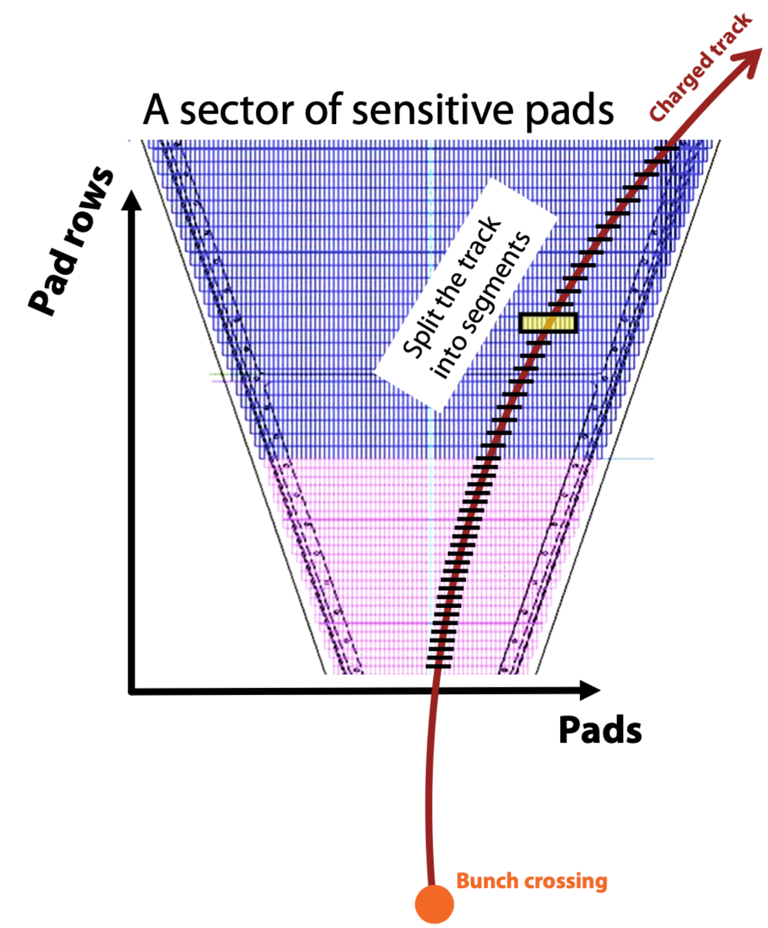
Generating responses that look similar is not difficult.

The challenge lies in reproducing marginal distributions

- especially if their list is not known *a priori*.

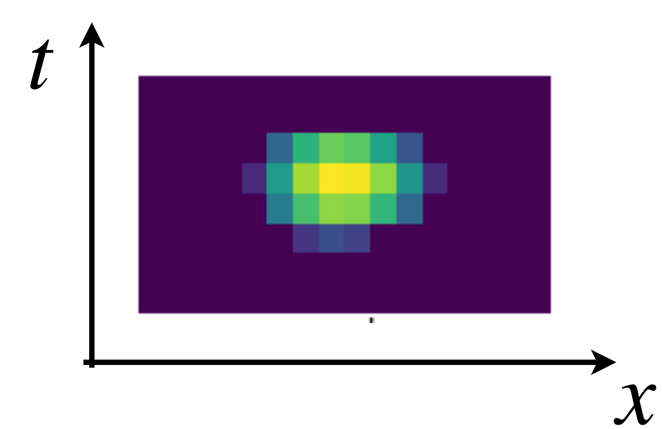
Precision for the Generative Model (TPC@MPD)



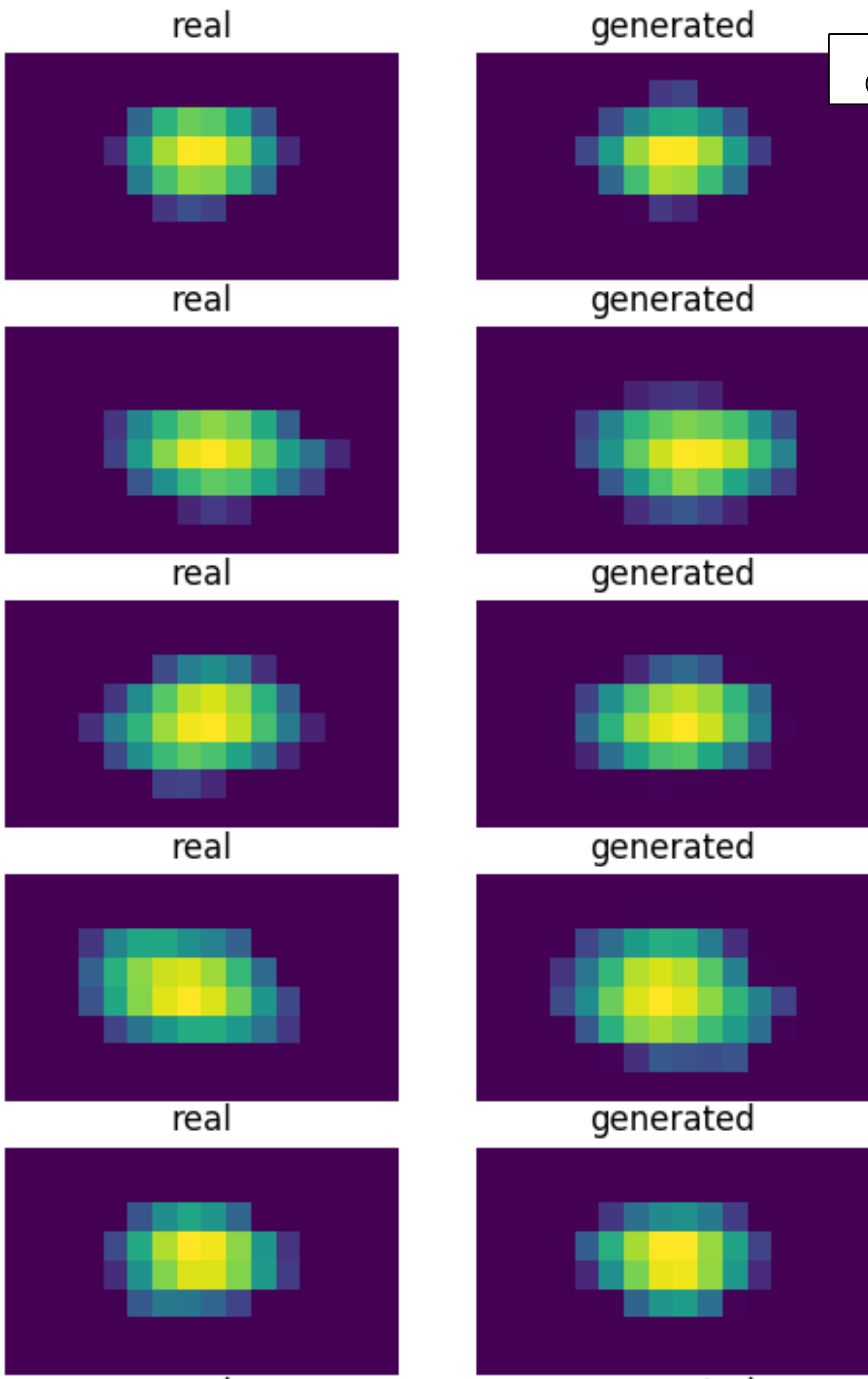


Generative model

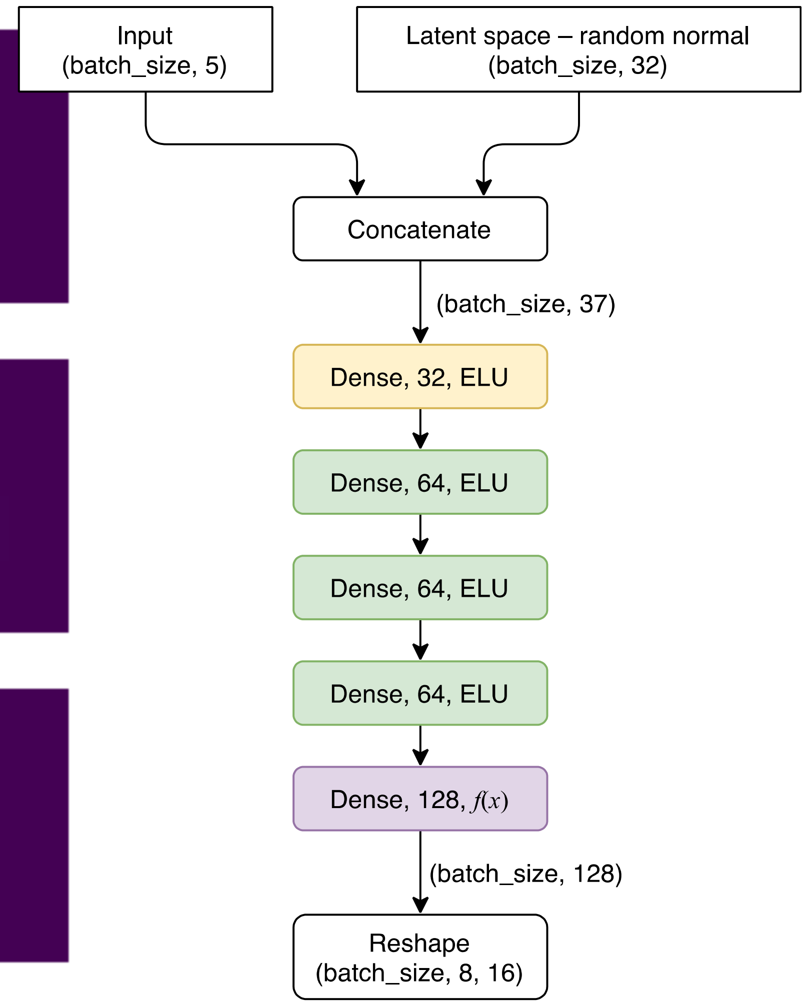
- in: 6 track parameters
- out: stochastic response
  - 8 (pads) × 16 (time slices) response for every pads row



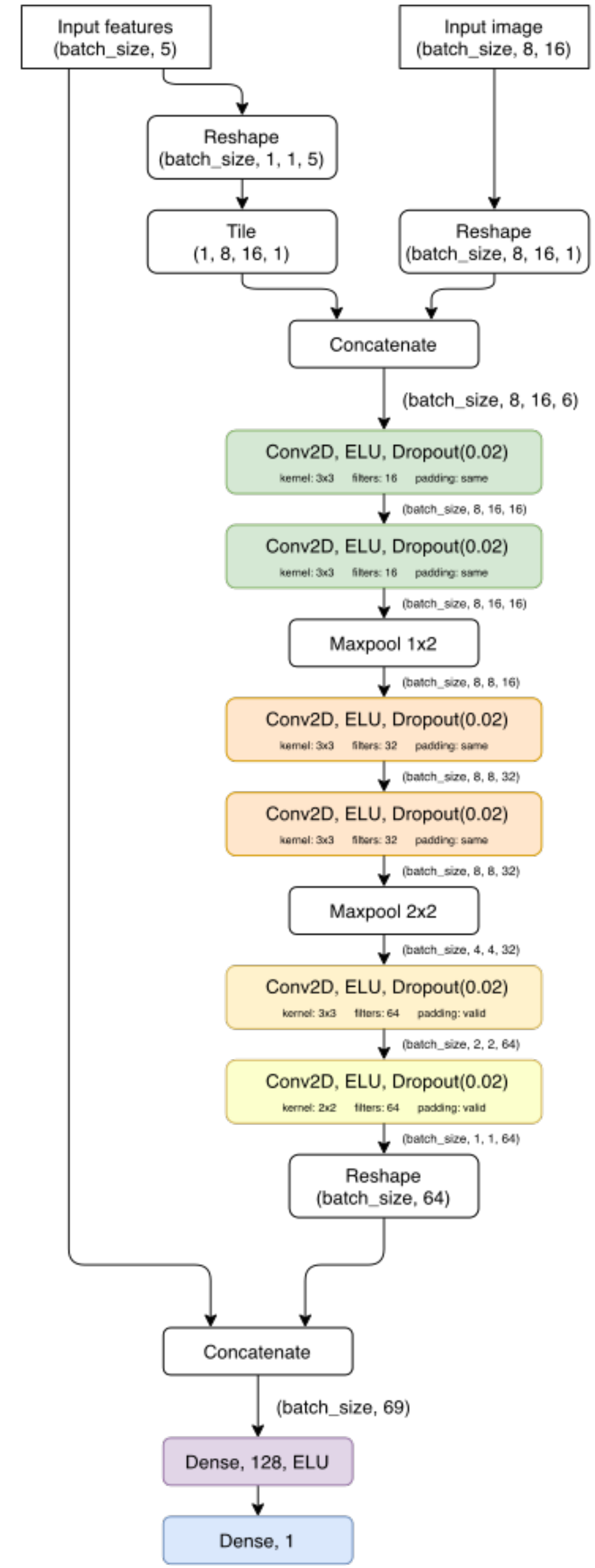
Generating TPC responses



Generator



Discriminator



Low Level and High Level Validation

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

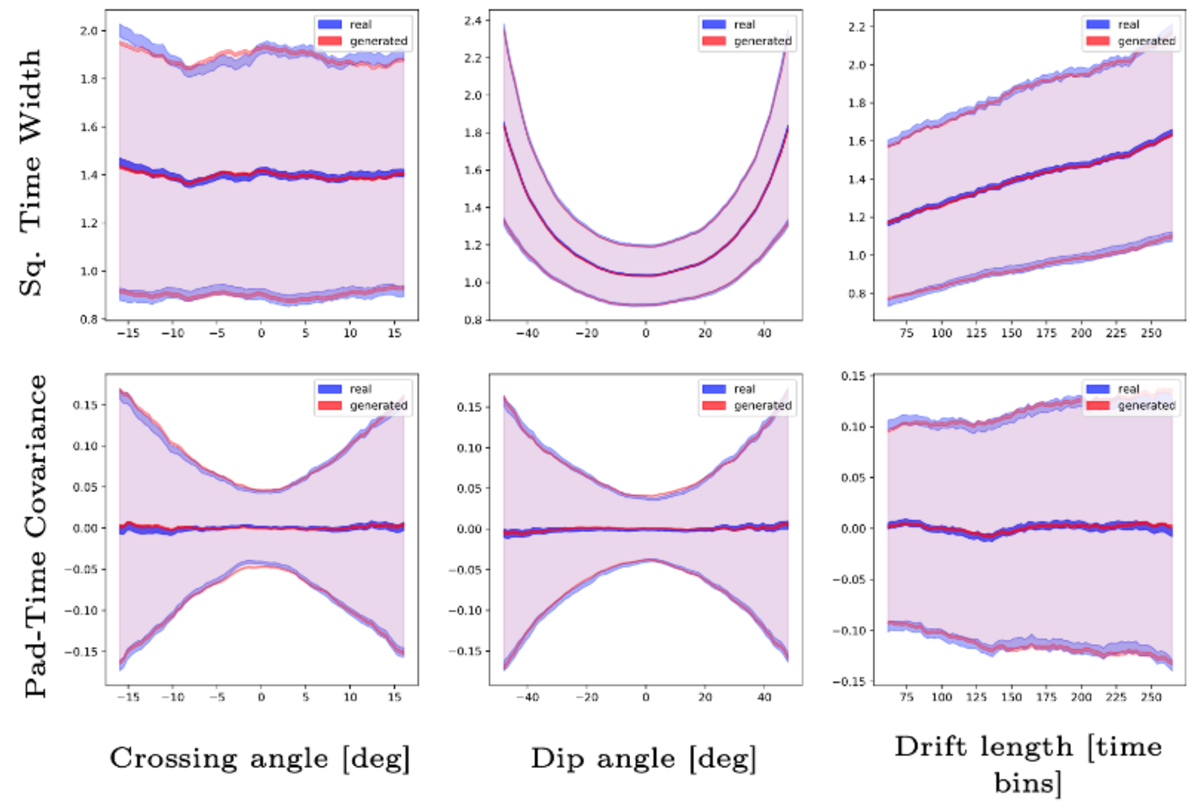
Low level:

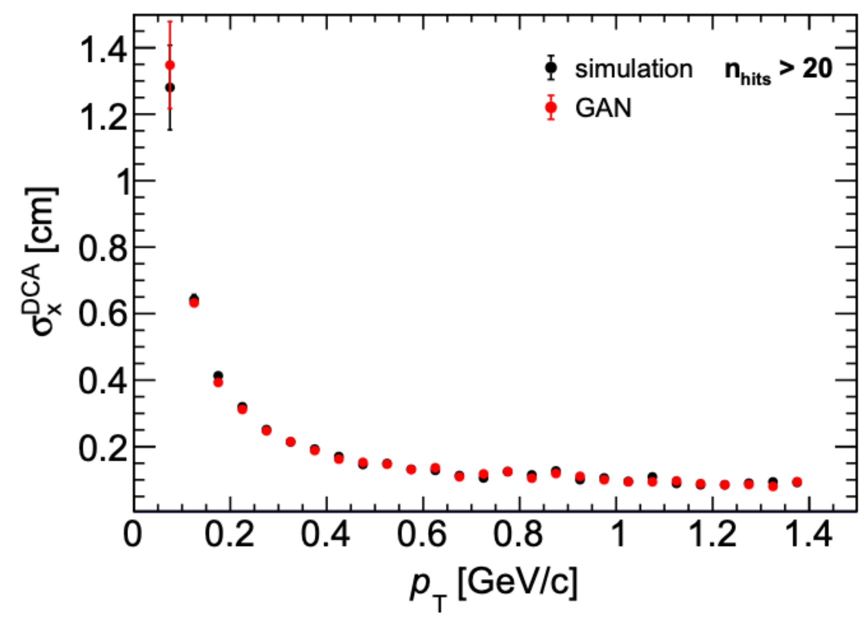
Estimate the first and second moments of the signal cluster.

- Evaluate the difference between these moments for original and generated signals across different parameter values.

High Level

- Integrate the model into the detector simulation software stack
  - compare the quality of reconstructions.





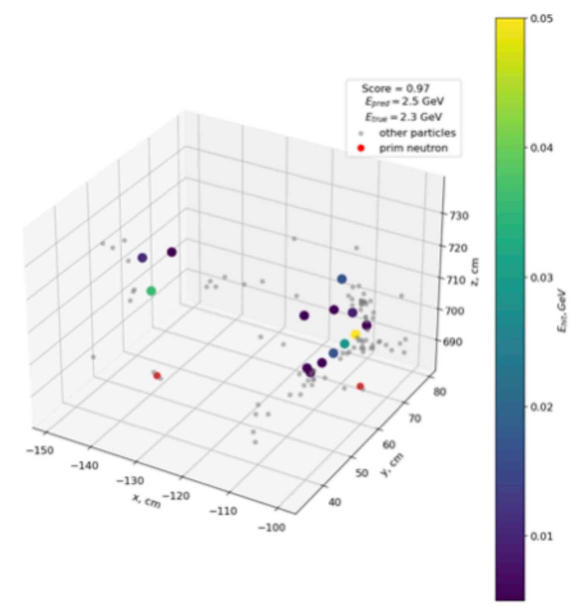
(a) Distance of closest approach resolution along x

Contributing to BM@N

ML-based neutron reconstruction in the HGND at the BM@N experiment

BM@N 12th Collaboration Meeting,

Vladimir Bocharnikov, HSE University
on behalf of HGND group



HSE MEPhI BM@N LAMBDA • HSE

@ 18:00 today

Conclusions

The machine learning, artificial intelligence, and big data analysis significantly influence the development of modern civilization.

Development made in these fields are readily adapted and employed in modern high-energy physics.

Proficiency in using machine learning has become a crucial for success of physical programs in modern high-energy physics experiments.

Our experience demonstrates that the joint efforts of ML expert and physics expert are the most effective for both the mutual education and for effective result

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Physical anomalies: search for new physics

Acceleration of MC generators

Acceleration of detector simulation

Detector optimization

Accelerator control

…

OpenAI Gamers