XXVIth International Baldin Seminar on High Energy Physics Problems "Relativistic Nuclear Physics and Quantum Chromodynamics«

https://indico.jinr.ru/event/5429/

Addressing heavy ion collision parameters estimation challenges via neural network techniques

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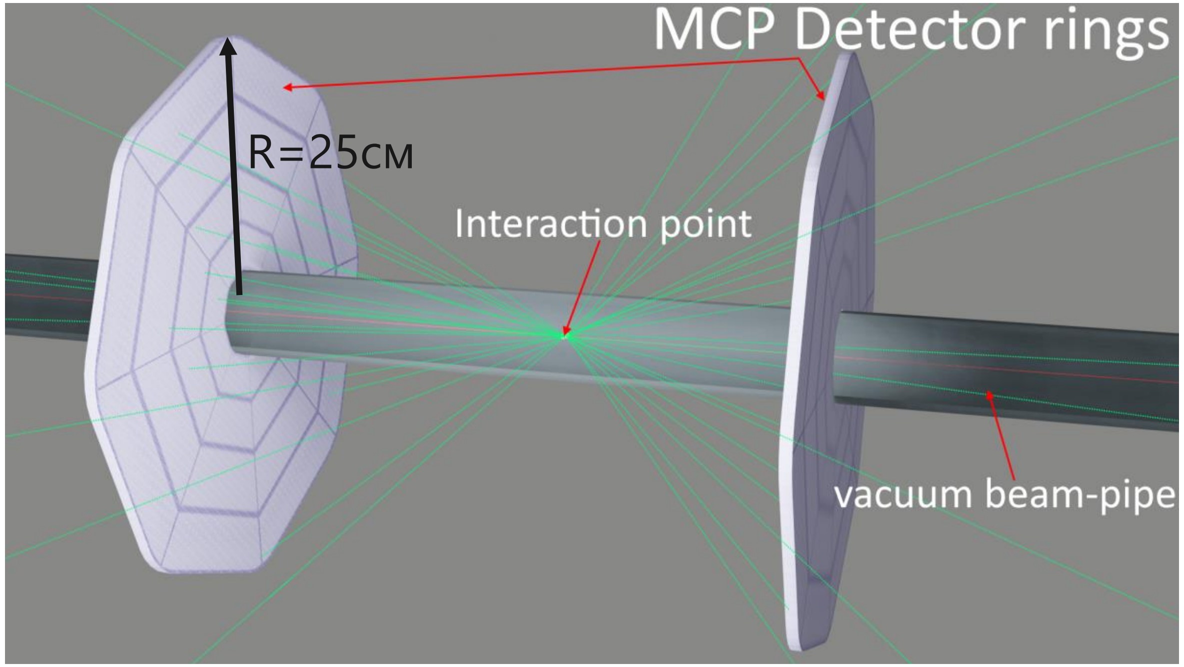
The authors acknowledge Saint-Petersburg State University for a research project 103821868

19th September 2025

The problems of event parameters estimation

Studied problems

- Event-wise estimation of the impact parameter value
- Select head-on collisions (small impact parameter)
- Event-wise estimation of the participants number



Scheme of investigated detectors geometry

Hits information that was used for feature engineering:

- Coordinate of cell, which registered hit
- Particle time of flight (~50ps accuracy)

We used MC generated data of Au+Au collisions at energies $\sqrt{s_{NN}} \approx 11$ GeV, which consists of three datasets:

- 200 000 events generated by **QGSM[1]** model
- 360 000 events generated by **EPOS[2]** model
- 50 000 events generated by **PHQMD[3]** model

[1] Amelin N. S., Gudima K. K., Toneev V. D. Ultrarelativistic nucleus-nucleus collisions within a dynamical model of independent quark - gluon strings // Sov. J. Nucl. Phys. 1990. V. 51(6), P. 1730-1743

[2] Werner, Klaus and Liu, Fu-Ming and Pierog, Tanguy Parton ladder splitting and the rapidity dependence of transverse momentum spectra in deuteron-gold collisions at the BNL Relativistic Heavy Ion Collider
// Physical Review C 2006, V. 74

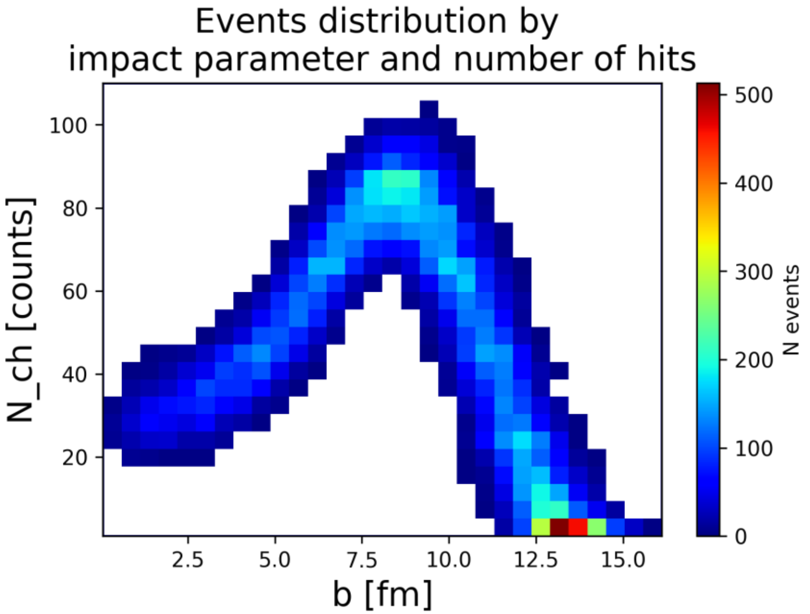
[3] Aichelin, J. and Bratkovskaya, E. and Le Fèvre, A. and Kireyeu, V. and Kolesnikov, V. and Leifels, Y. and Voronyuk, V. and Coci, G., Physical Review C 2020, V. 101

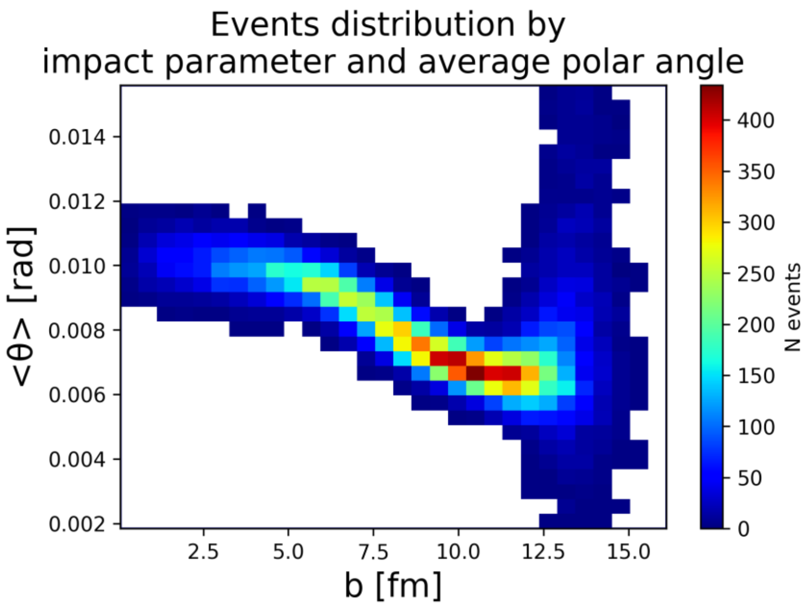
Examples of input data: Multiplicity of charged particles and their average angle

Multiplicity of charged particles

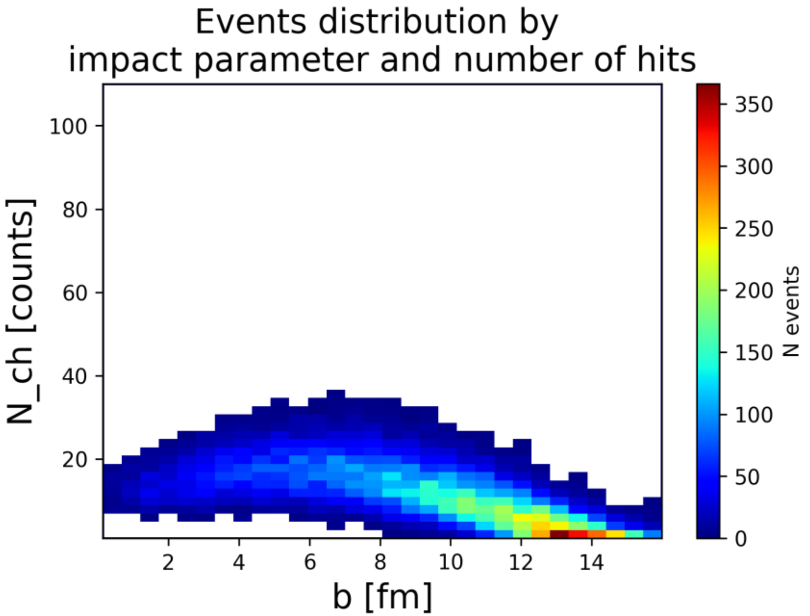
Average polar angle of particles

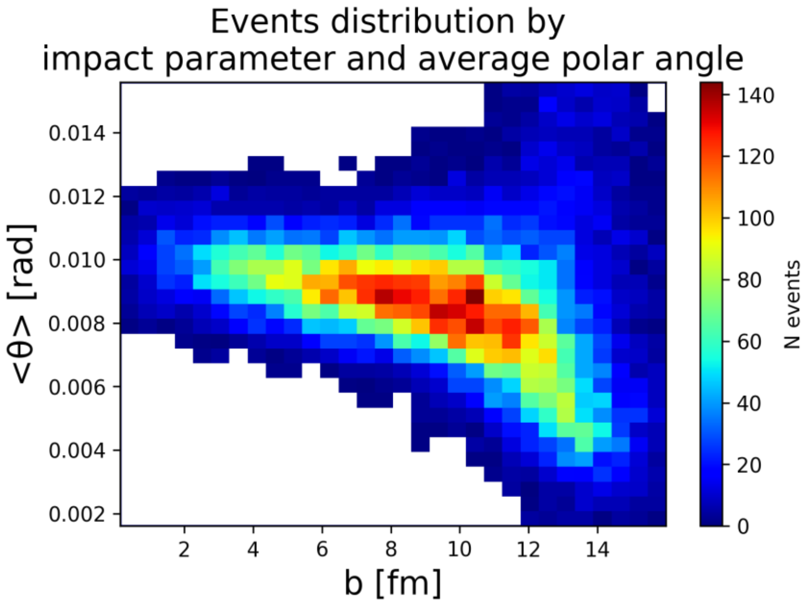
QGSM:





EPOS:





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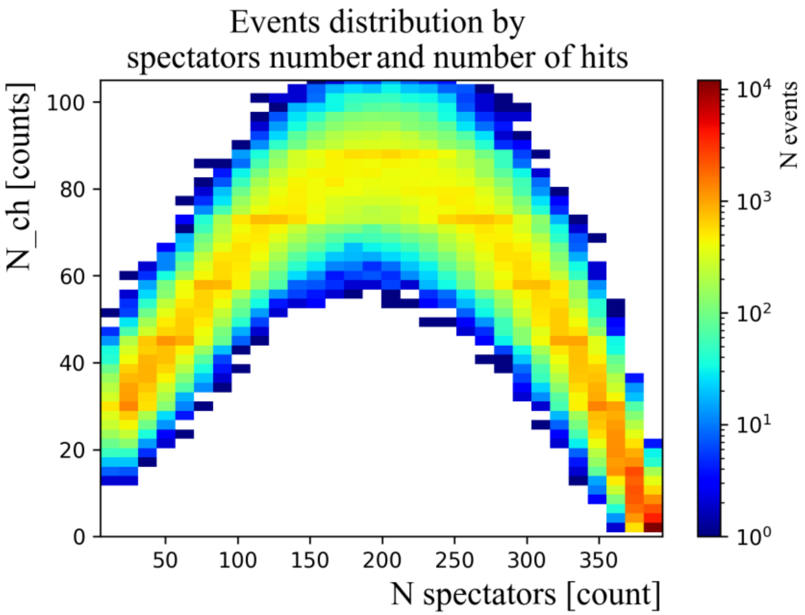
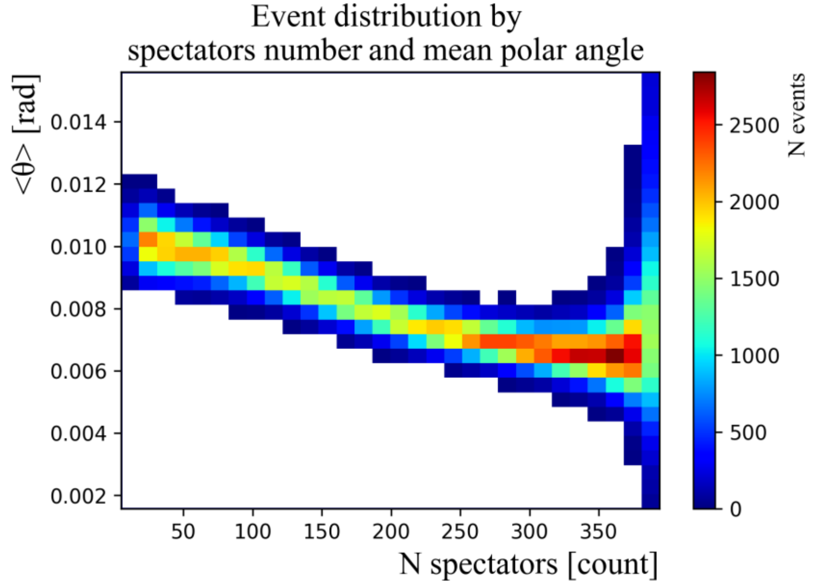
Multiplicity of charged particles

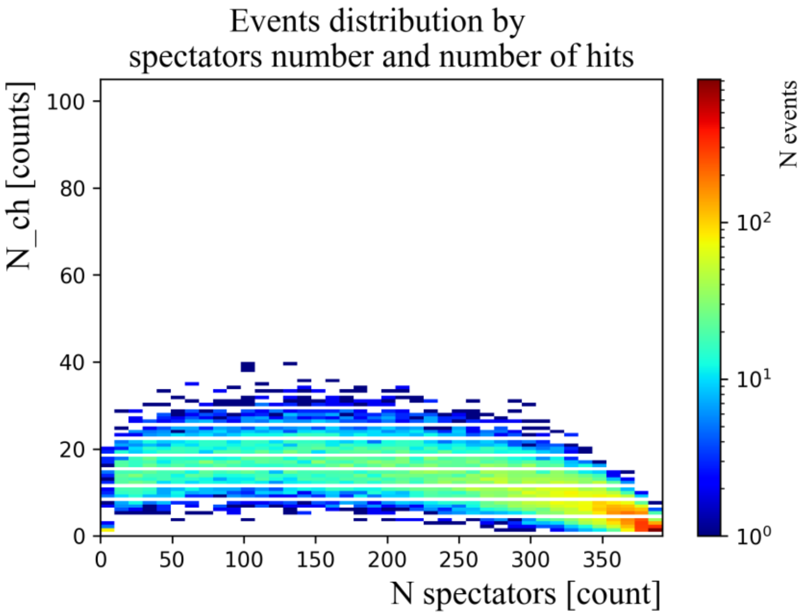
Average polar angle of particles

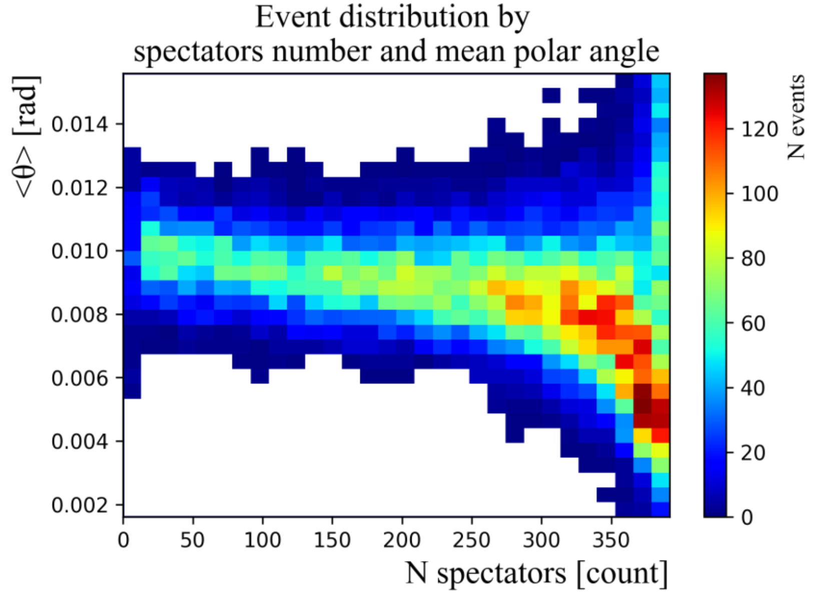
QGSM:



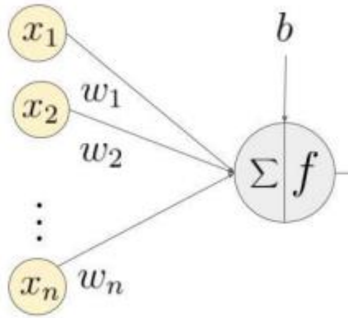


EPOS:

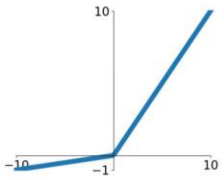




Used artificial neural networks



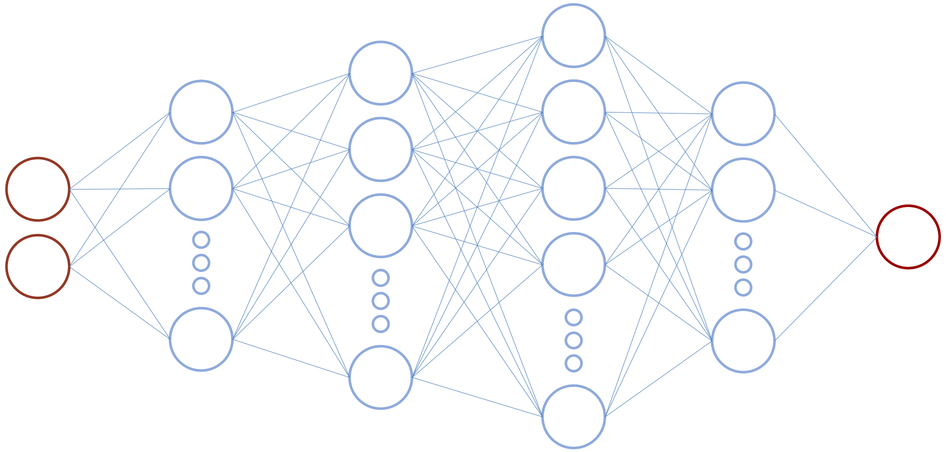
$$f\left(b+\sum_{i=1}^{n} x_i w_i\right)$$

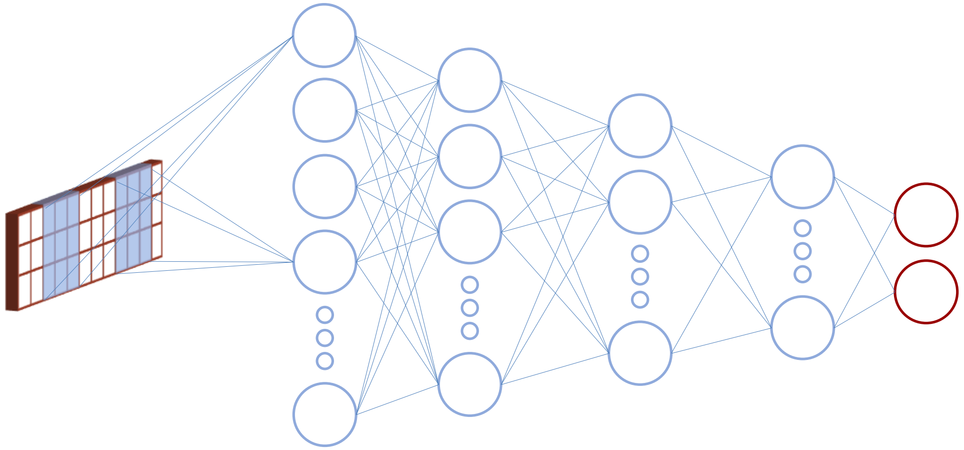


Leaky ReLU

$f(x) = \max(0.01x, x)$

Scheme of an artificial neuron model





Example of used dense neural network with convolutional layer, solving classification problem.

Input – Table of particles information (3x150 features), convolutional layer (16 filters 3x6), 3 hidden layers (128, 64, 32 neurons), output – 2 neurons – probabilities of an event belonging to each class.

Example of used dense neural network architecture, solving regression problem.

Input – 2 event features, 4 hidden layers (4, 8, 16, 4 neurons), output – 1 neuron – estimated impact parameter value

Leaky ReLU activation function. Optimizer – Adam. Optimized functions – mean squared error, binary cross entropy.

Table of NN performance on separate dataset training

Here we train model on one dataset at a time and used detector system consisting of pair of rings with R=25cm, r=2.5cm, L=4m, Δt=50ps, 352 cells.

Event features (Number of features)	Binary classificatory threshold [fm]	QGSM			EPOS		
		RMSE [fm] (lower is better)	TPR [%] (higher is better)	FPR [%] (lower is better)	RMSE [fm] (lower is better)	TPR [%] (higher is better)	FPR [%] (lower is better)
Multiplicity + angle (2)	5	0,77	97,7	5,8	2,06	88,1	38,1
Multiplicity + angle (2)	1		98,9	8,8		77,2	21,1
Time of flight (3x150) (full info)	5	**0,68**	**98,6**	**4,3**	**1,53**	**91,7**	**16,4**
Time of flight (3x150) (full info)	1		90,3	6,2		94,0	17,8

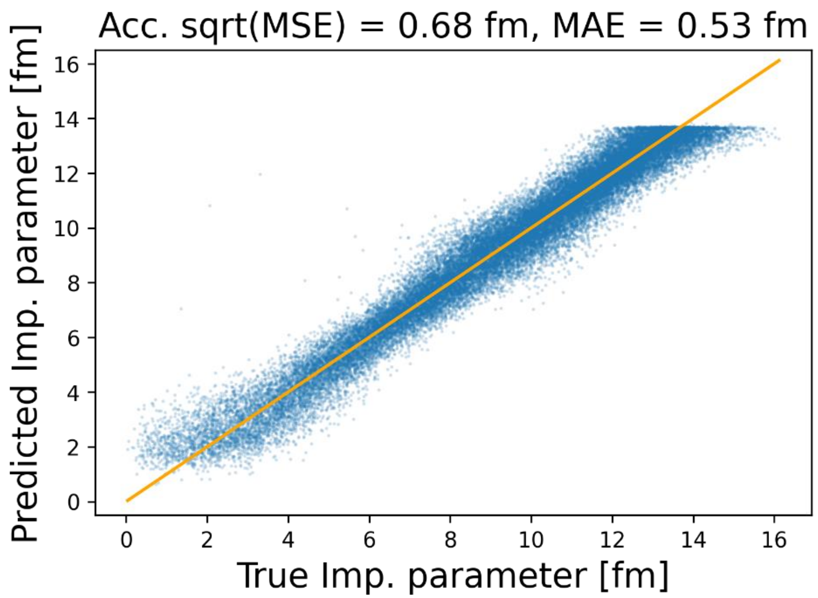
Results demonstrate, that using table of registered particles with information about their spatial and temporal distributions shows better result than simple features. While trained on separate datasets network learns to estimate impact parameter only on data from exactly that dataset.

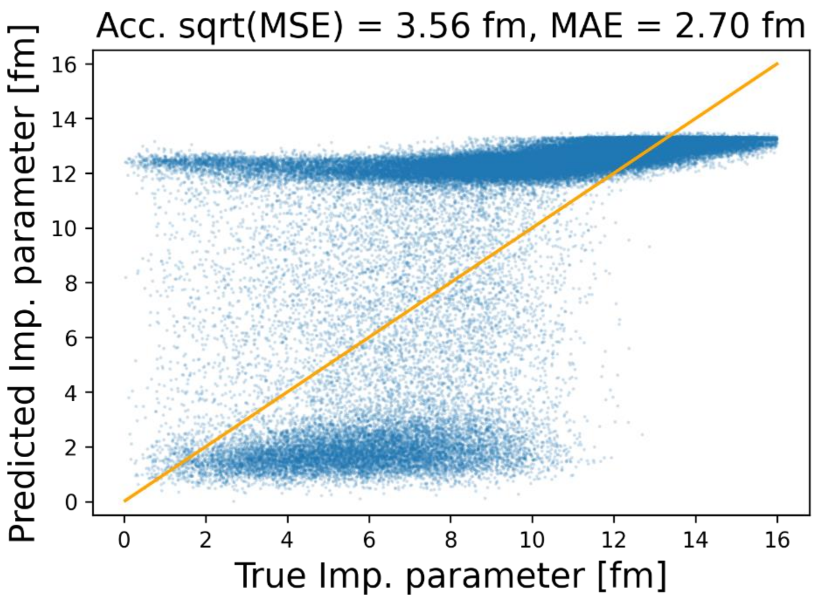
RMSE – root of mean squared error, TPR – true positive rate, FPR – false positive rate.

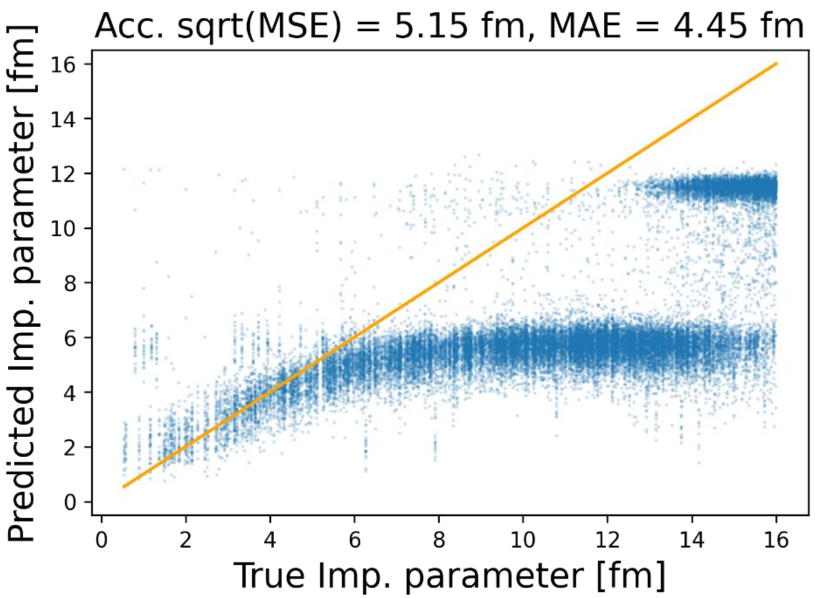
Simple network trained on QGSM dataset

Here we trained the model on QGSM dataset, and performed tests on the three datasets available: QGSM, EPOS and PHQMD.

Tests on: QGSM EPOS PHQMD







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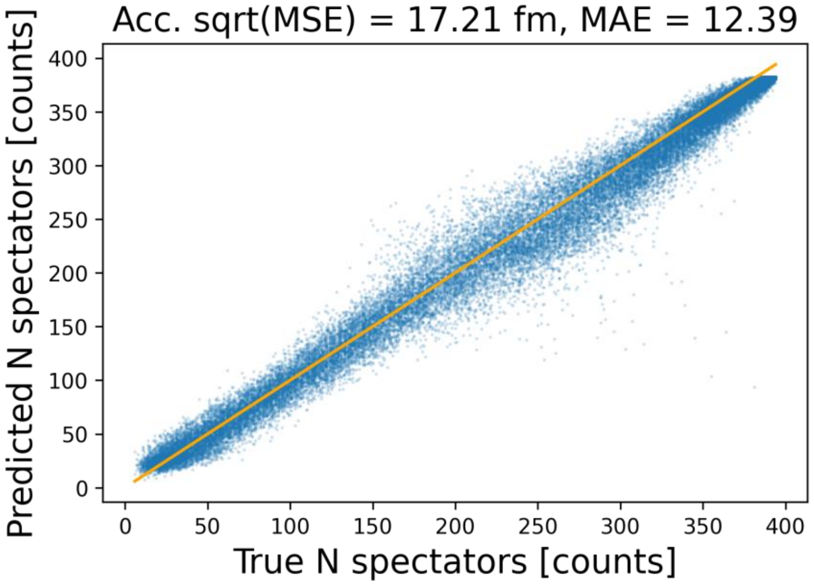
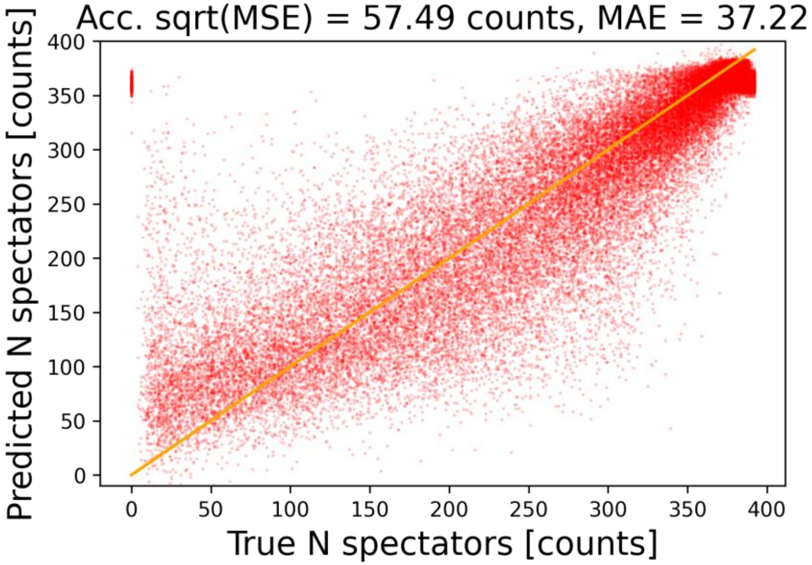


EPOS

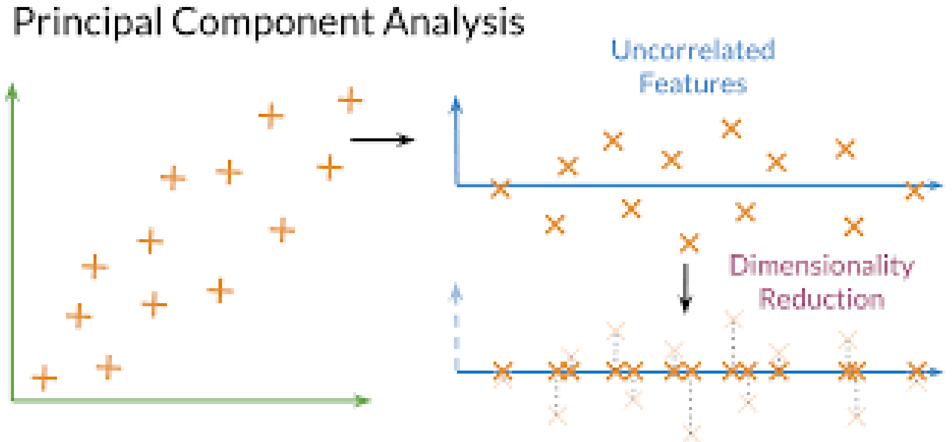


Search for universal event characteristics

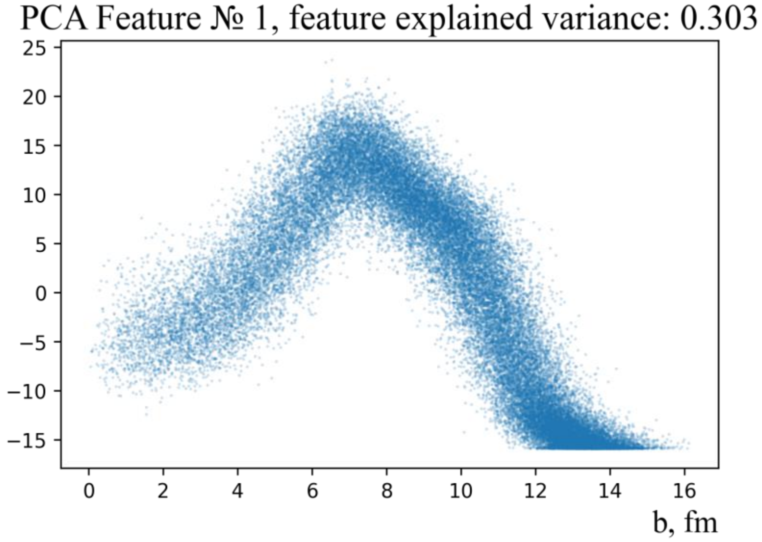
Here we create algorithms to extract features from datasets individually.
Extracted features are useful for impact parameter estimation, but do not solve generator-dependence problem

PCA:

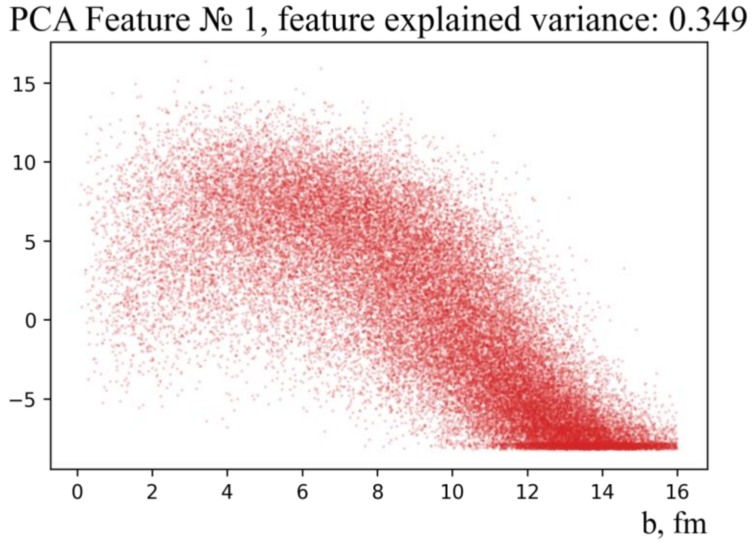
The idea of method



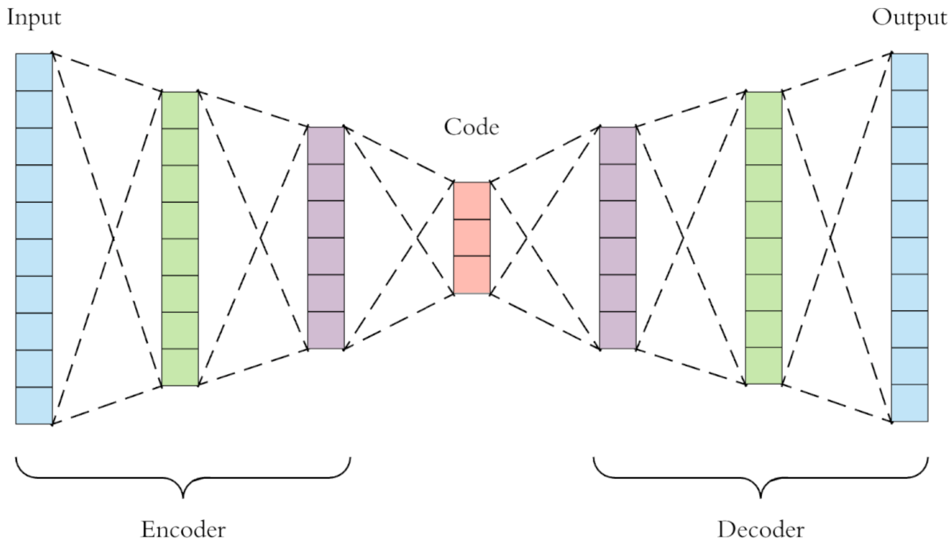
QGSM:

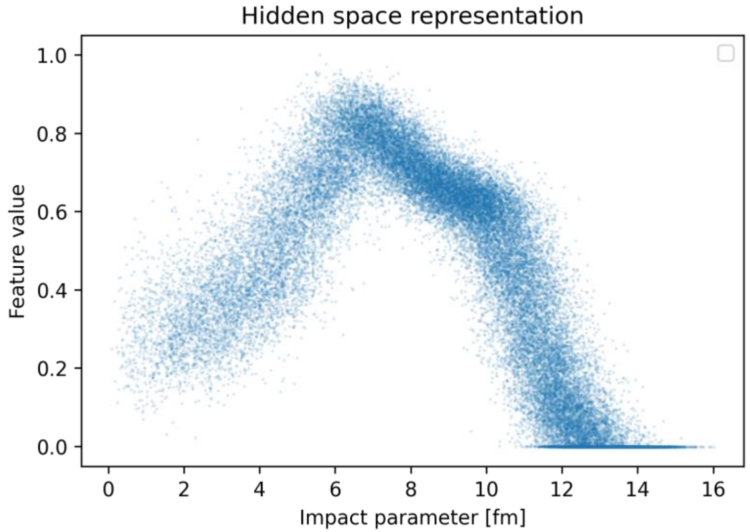


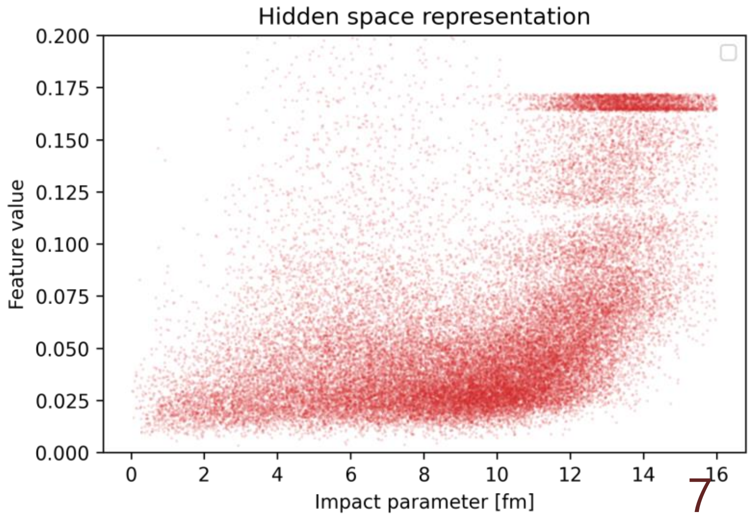
EPOS:



Auto-encoder:



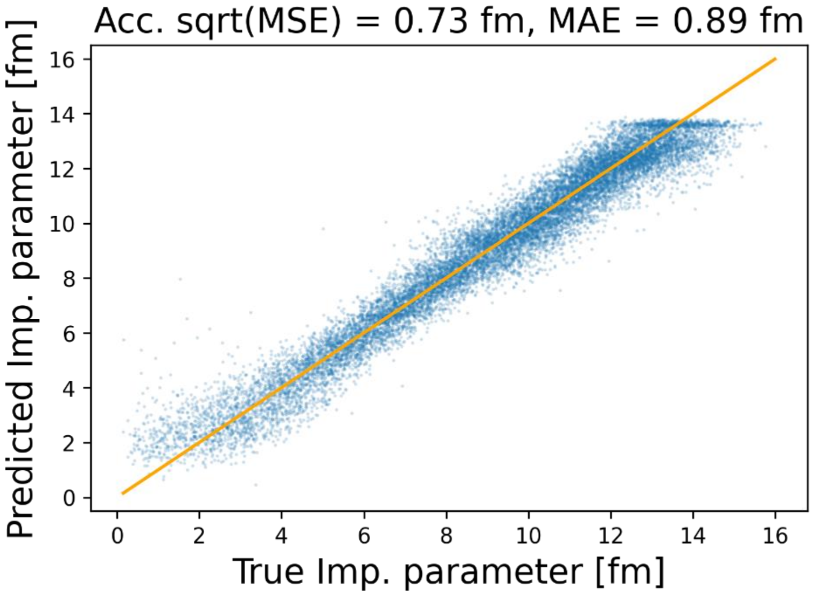




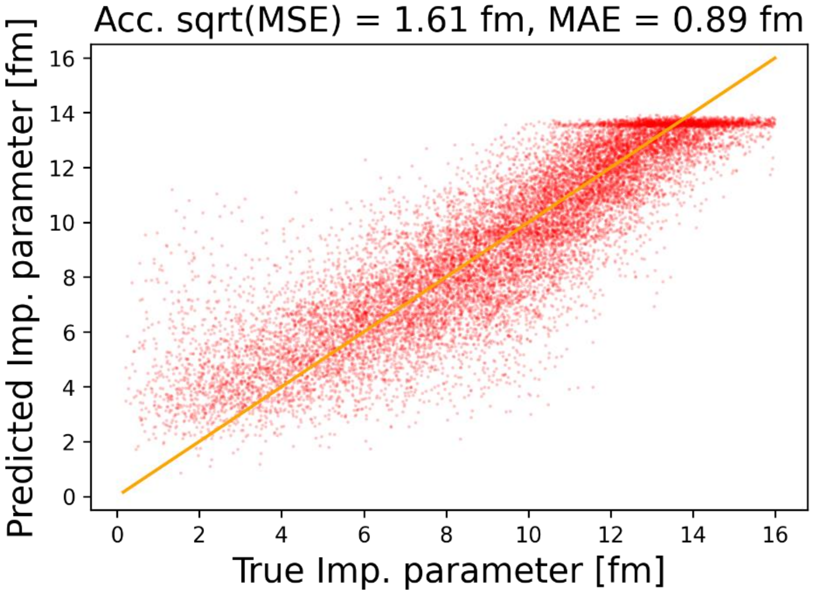
Simple network trained on QGSM+EPOS mixed dataset

Here we trained the model on mixed 1:1 QGSM and EPOS dataset, and performed tests on the three datasets available: QGSM, EPOS and PHQMD.

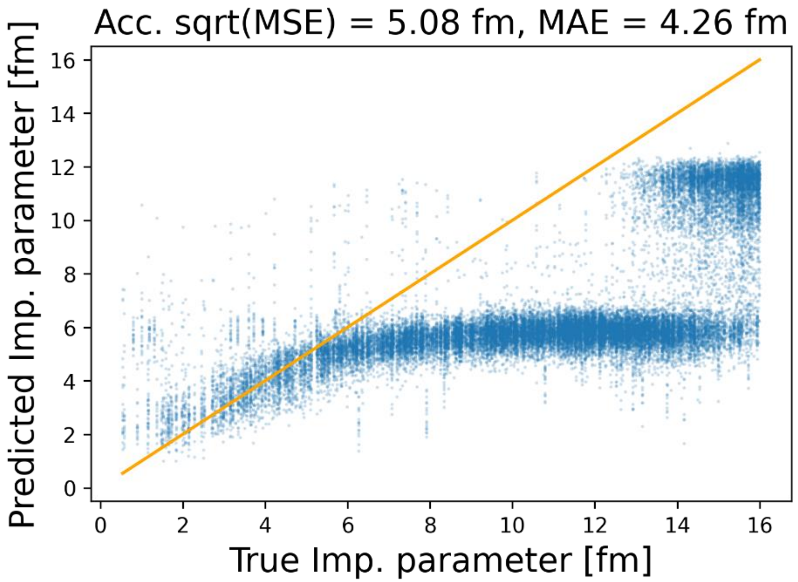
Tests on: QGSM



EPOS



PHQMD



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St Petersburg University

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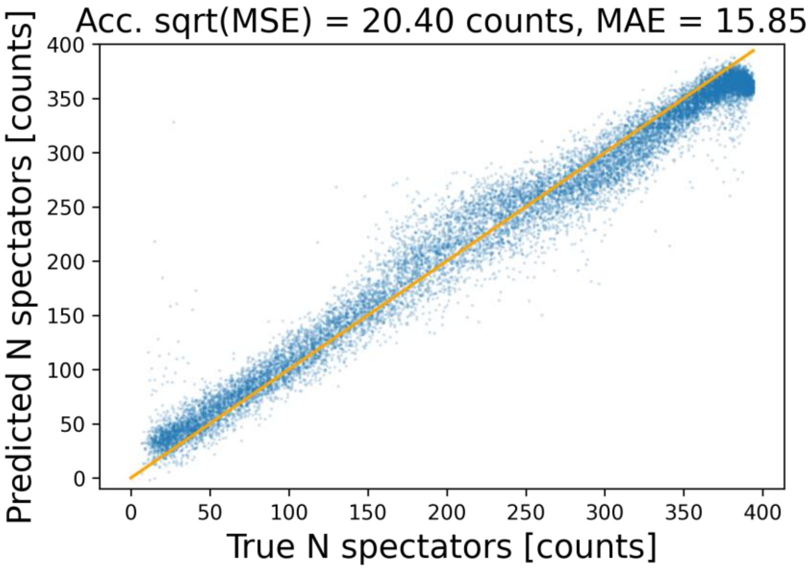
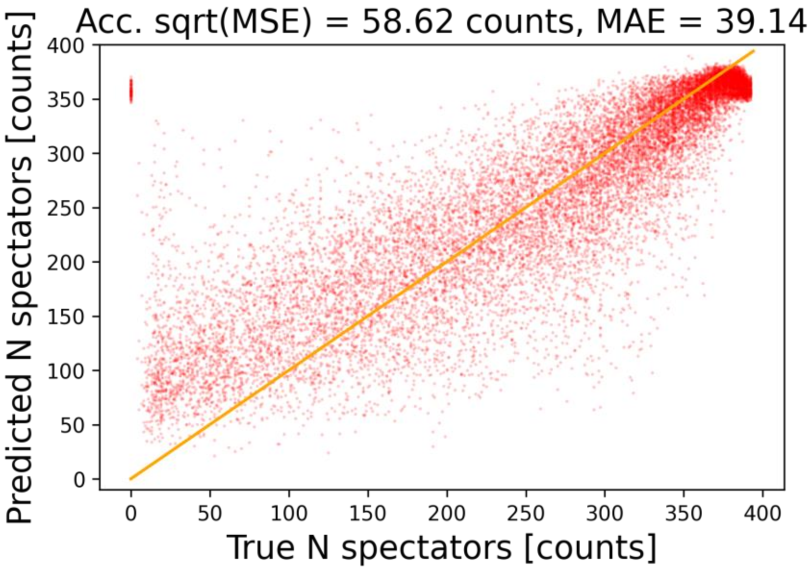
Tests on: QGSM

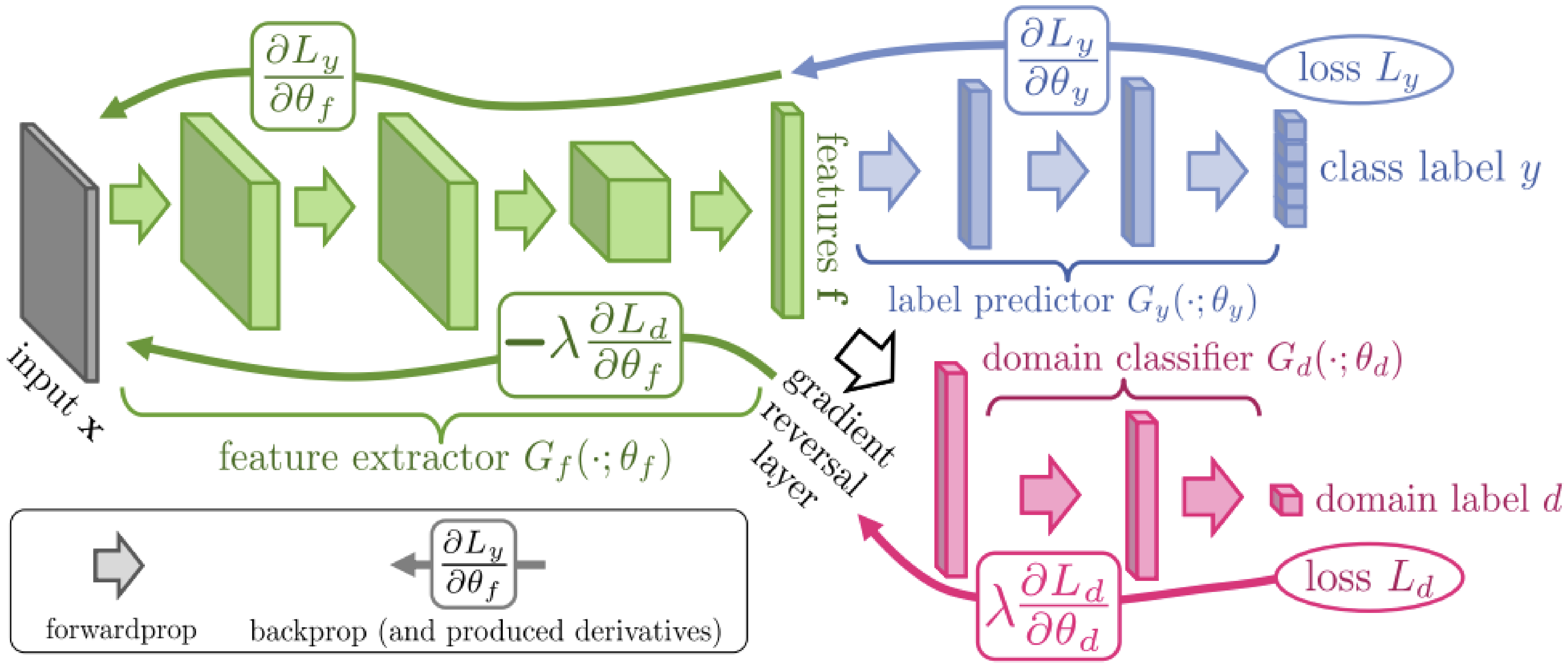


EPOS



Domain adaptation: Domain-adversarial neural network[1]

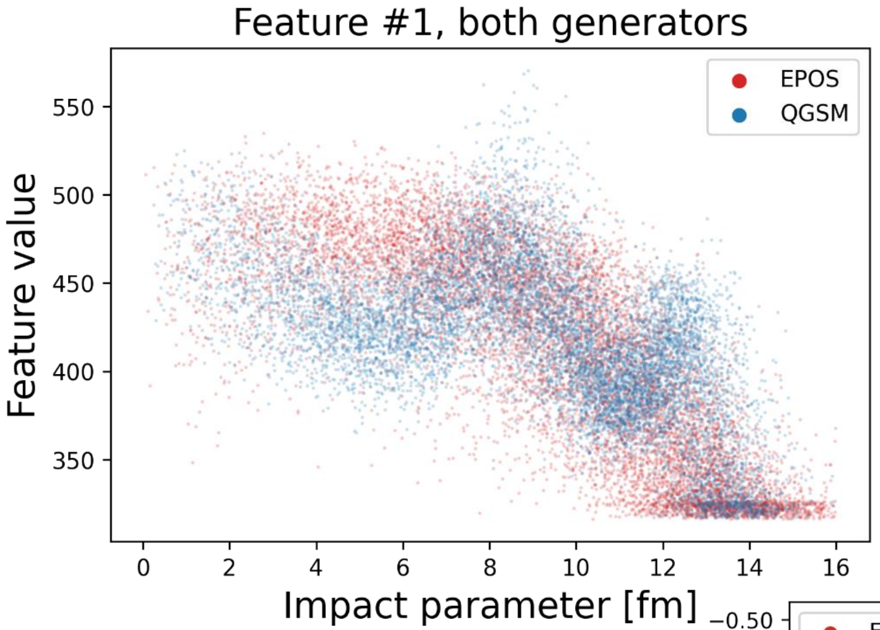
The idea is to train a neural network on a mixed dataset that can simultaneously estimate the impact parameter and not distinguish which generator the event came from.

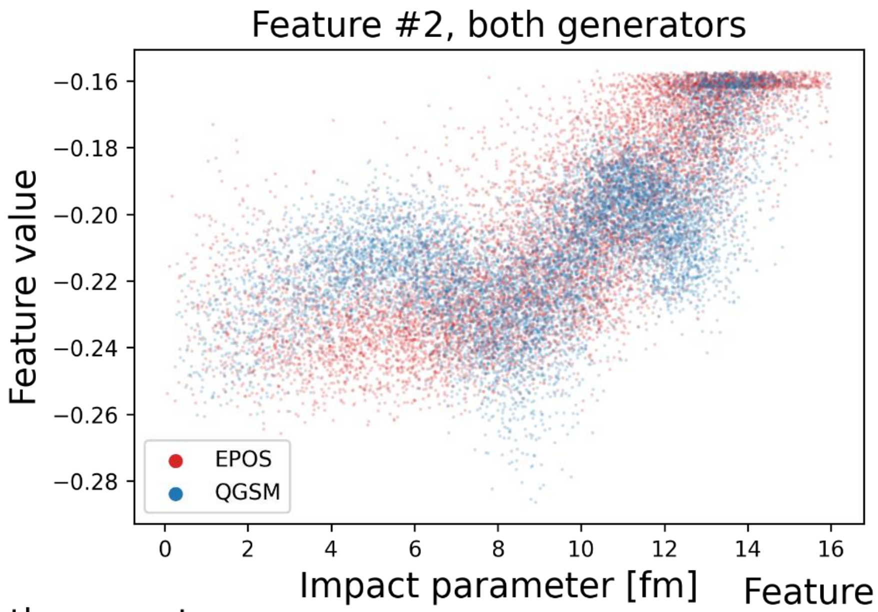


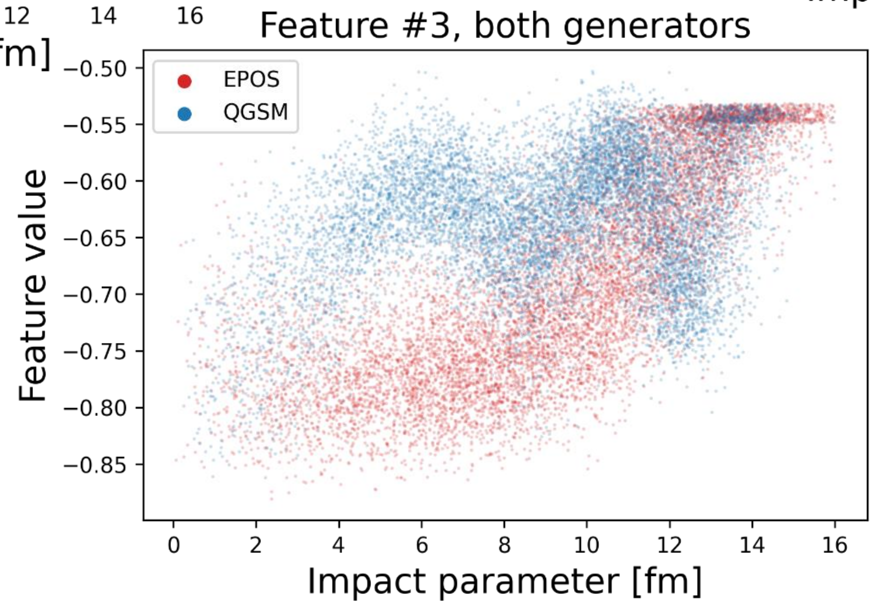
[1] Mei Wang, Weihong Deng, "Deep visual domain adaptation: A survey", Neurocomputing, 2018, V. 312, P. 135-153, https://doi.org/10.1016/j.neucom.2018.05.083

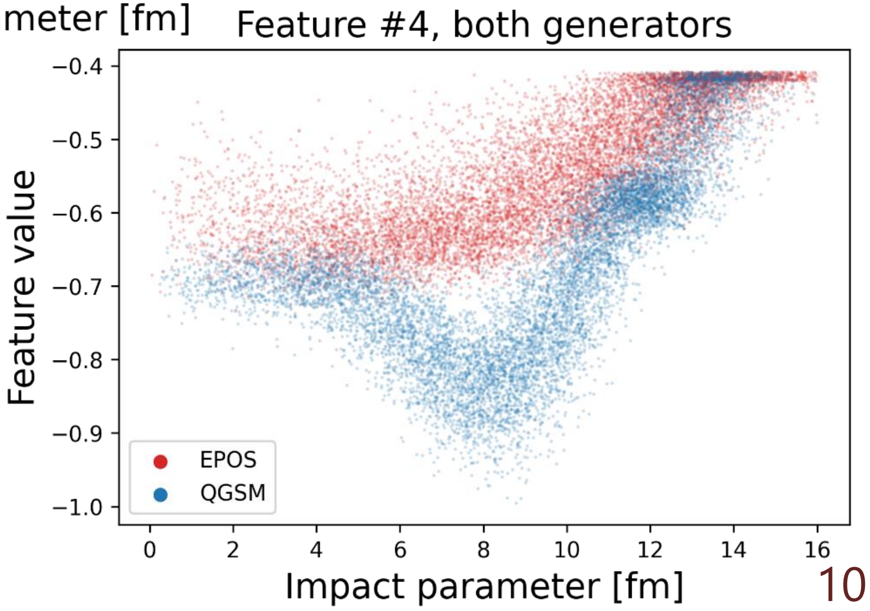
Domain-adversarial neural network, extracted features

Extracted features for two datasets do blend, however impact parameter estimation is worse than for simple mixed dataset training, so it is not enough.



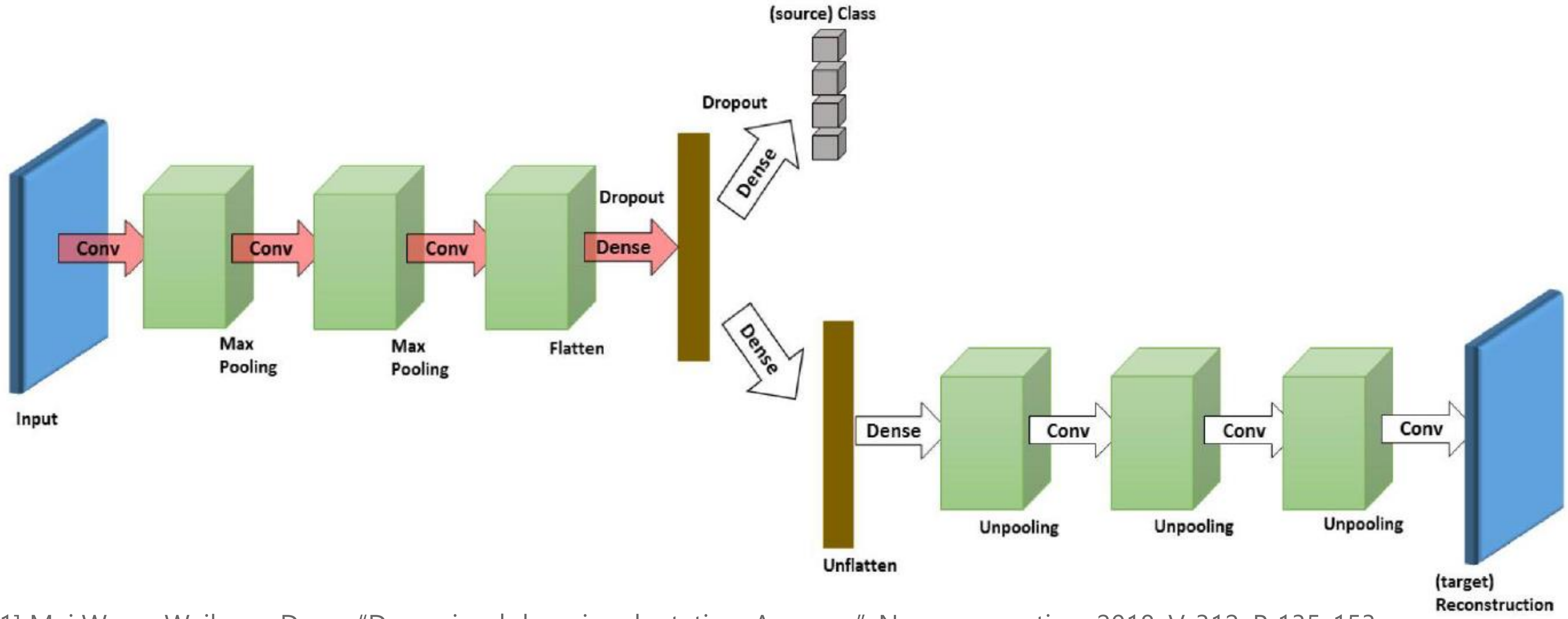






The deep reconstruction neural network (DRNN)[1]

The idea is to train a neural network on a mixed dataset that can simultaneously estimate the impact parameter and reconstruct the input data to preserve most important information.

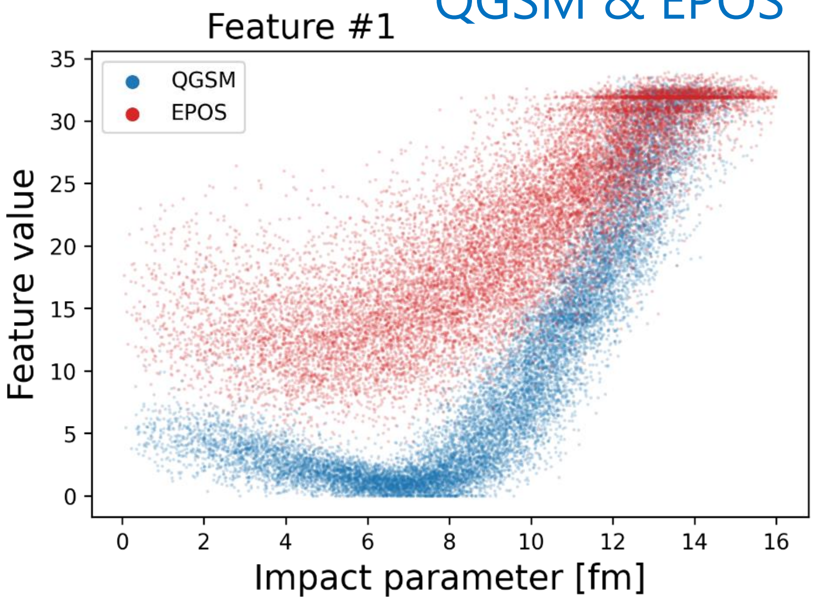


[1] Mei Wang, Weihong Deng, “Deep visual domain adaptation: A survey”, Neurocomputing, 2018, V. 312, P. 135-153,
https://doi.org/10.1016/j.neucom.2018.05.083

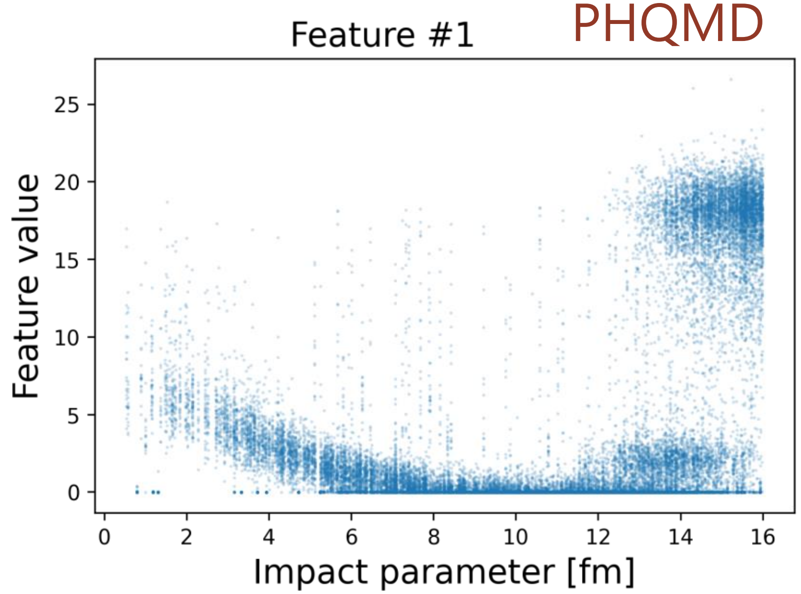
The deep reconstruction neural network. New features.

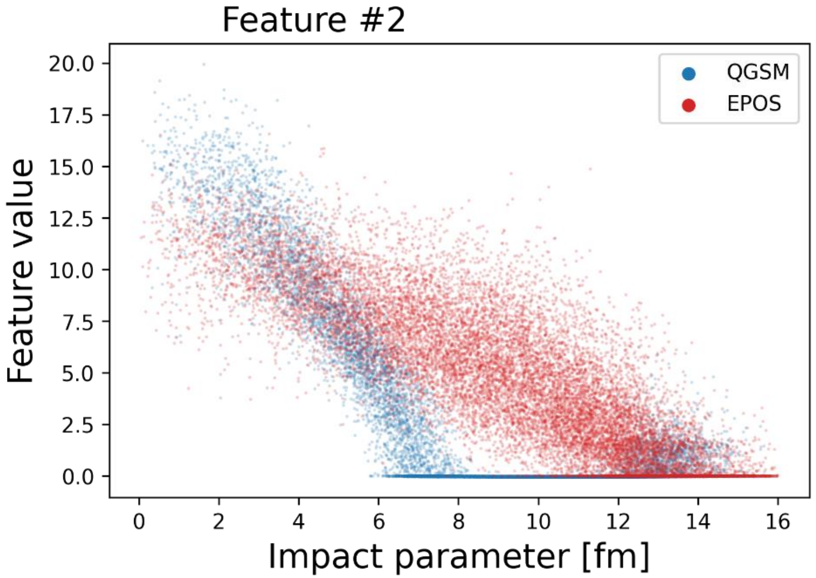
Extracted features look more simple but impact parameter dependence is much more obvious.

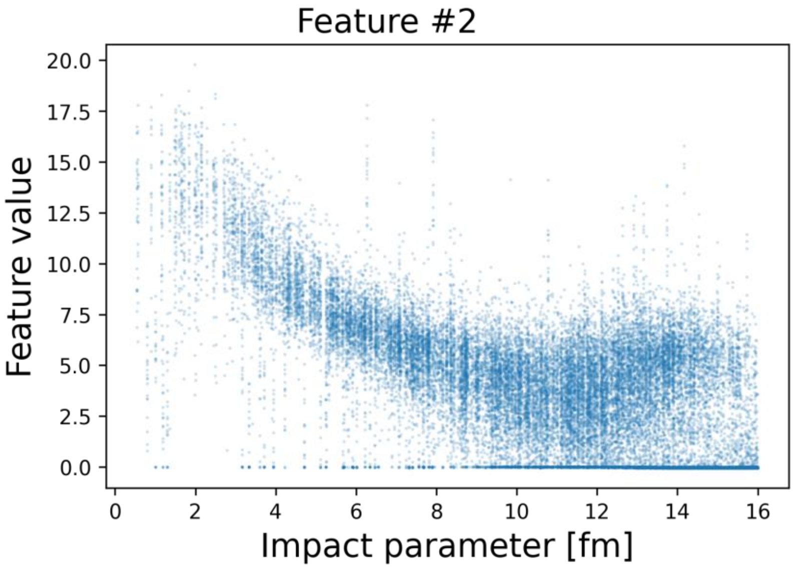
QGSM & EPOS



PHQMD





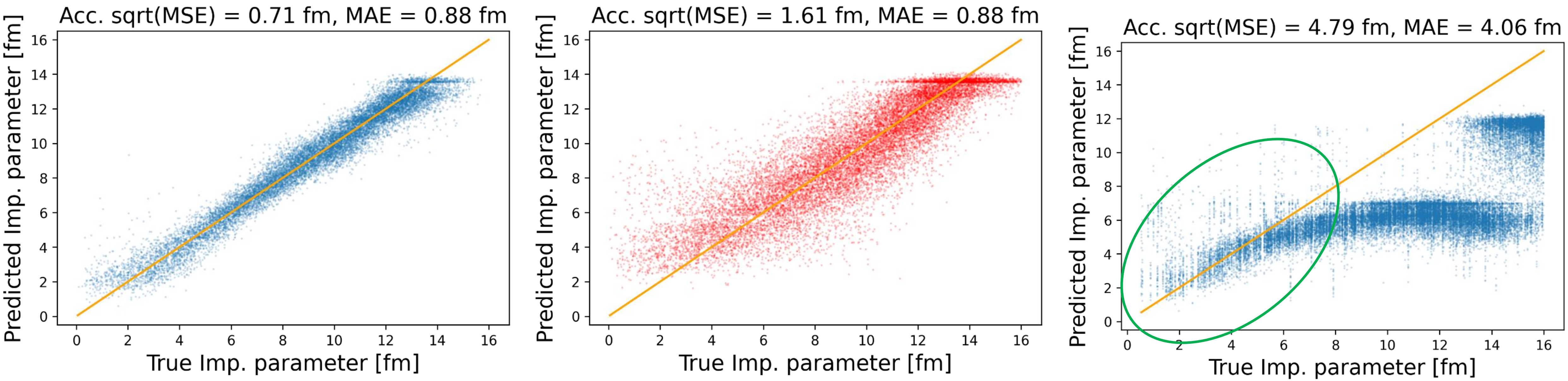


The deep reconstruction neural network. Results.

Here we trained the DRNN model on mixed QGSM and EPOS dataset, and performed tests on the three datasets available: QGSM, EPOS and PHQMD.

The results show better accuracy, especially for the regions of small impact parameter, less than 7 fm.

Tests on: QGSM EPOS PHQMD



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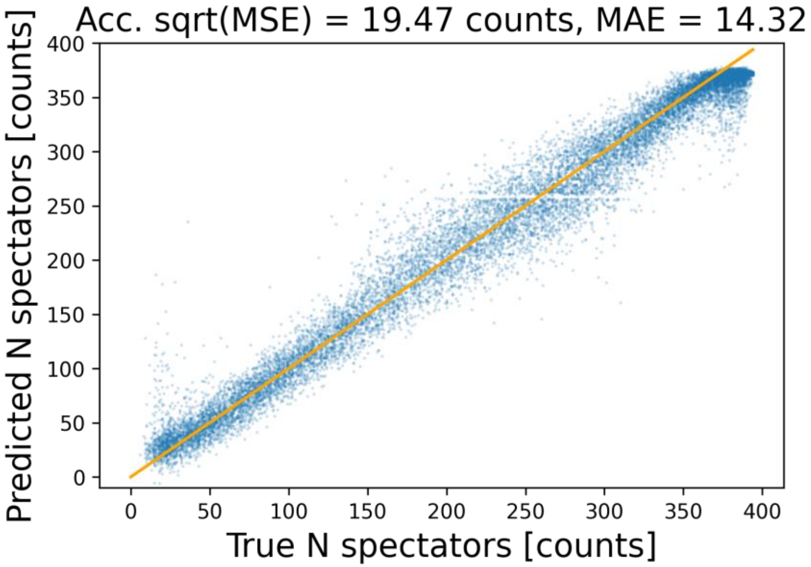
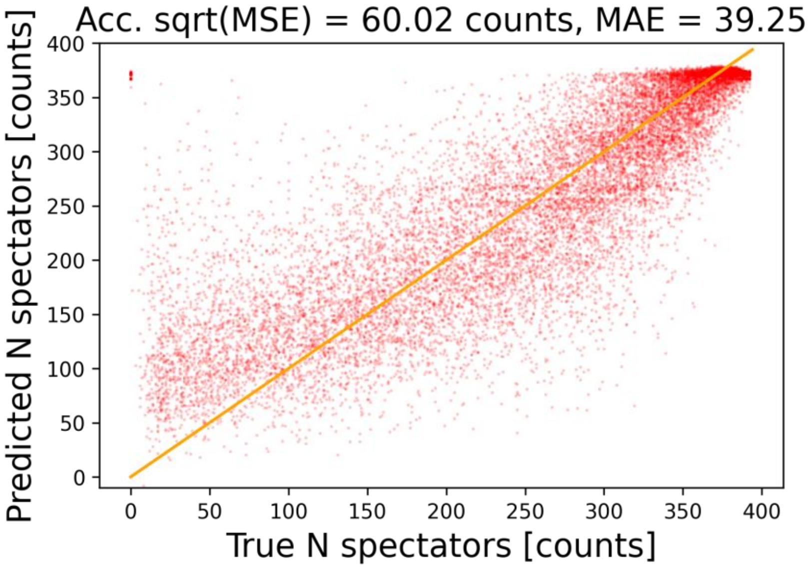
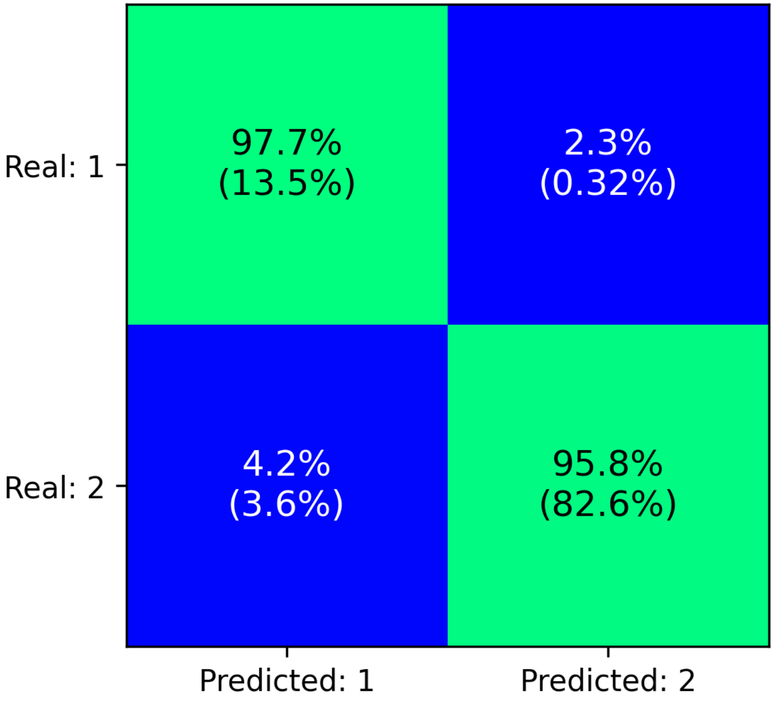




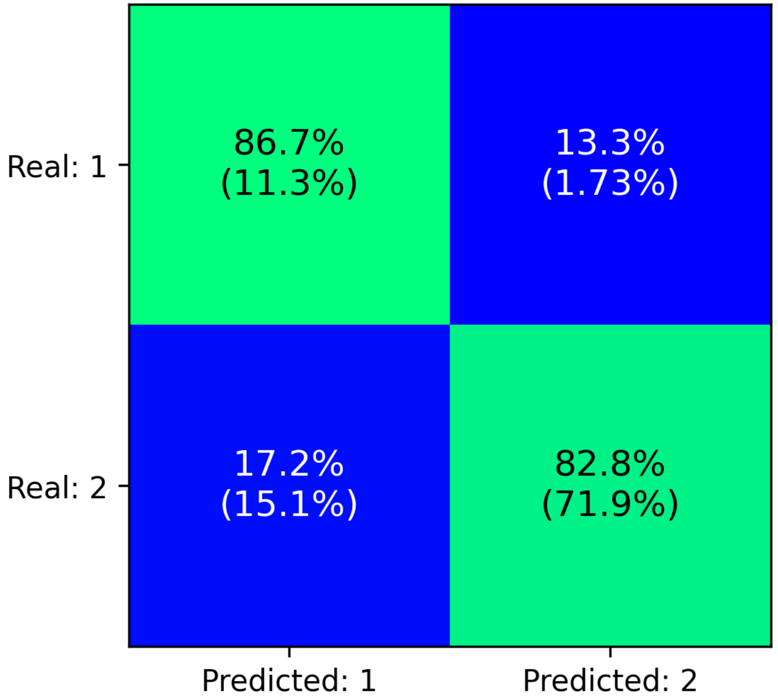
The deep reconstruction neural network. Results for the classification problem.

Here we trained the DRNN model on mixed QGSM and EPOS dataset to label the events with impact parameter **<u><5 fm</u>** (binary classification problem), and performed tests on the three datasets available: QGSM, EPOS and PHQMD.

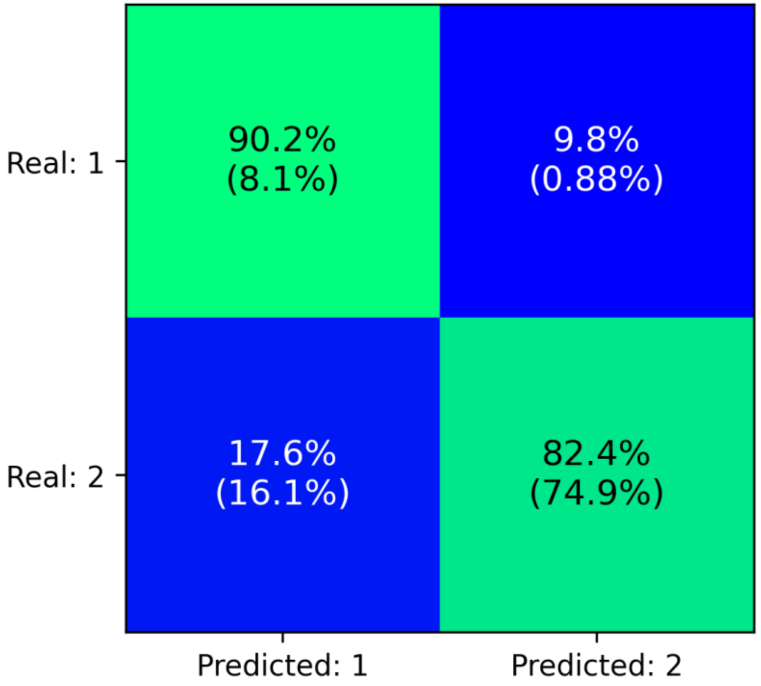
Tests on: QGSM



EPOS



PHQMD



Conclusions

1. Hidden dependencies — With the help of artificial neural networks, it has become possible to extract hidden patterns in data from different sources.

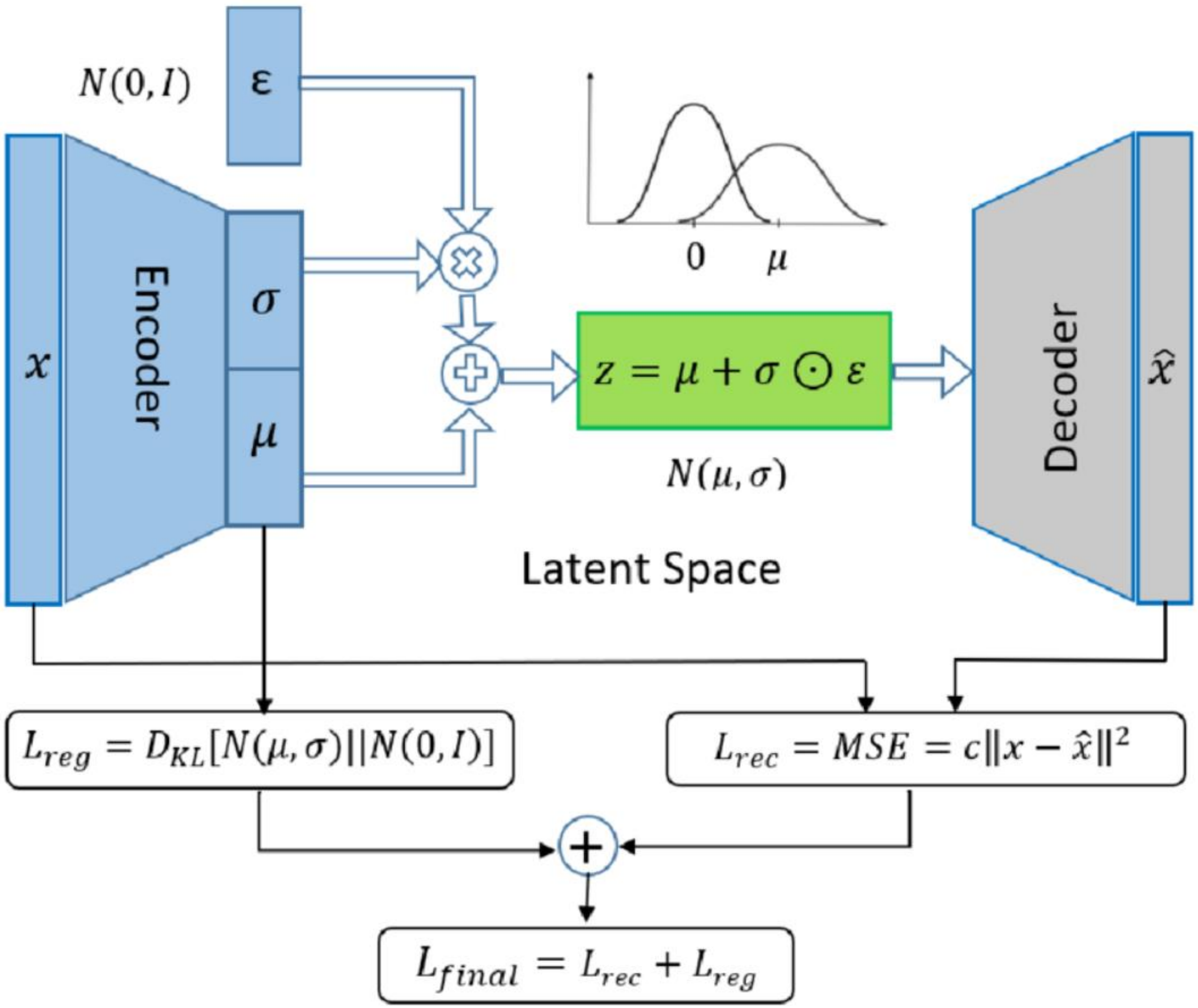
2. Domain adaptation — Several domain adaptation techniques we investigated. While some of them showed results worse than for simple mixed dataset training, the “Deep reconstruction neural network” outperformed other approaches, demonstrating good generalization on new dataset for collisions with small impact parameter.

3. New methods are worth researching — Investigated methods are capable of working simultaneously with data from different event generators, and their performance can be tuned with data from other generators.

4. Detector generalization — We performed computational experiments addressing MCP detectors (For more information on MCP detectors see talk “Малошумящий детектор минимально ионизирующего излучения на основе МКП” by Никодим Макаров, 05.07.2025), but the techniques can be applied to detectors of other types.

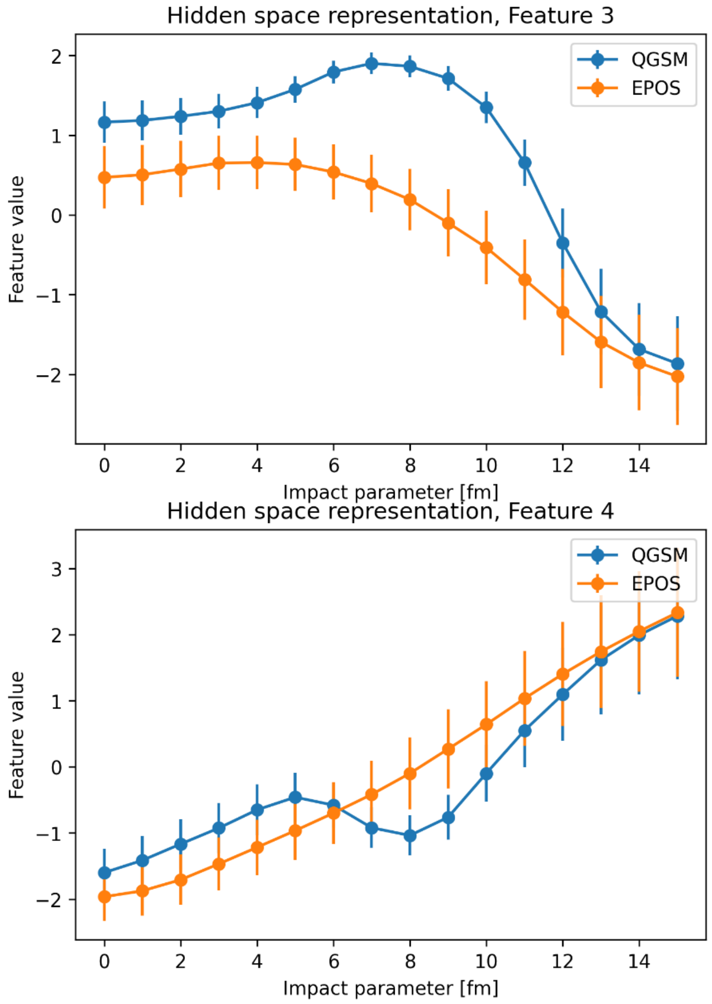
The authors acknowledge Saint-Petersburg State University for a research project 103821868

Using variational autoencoder (VAE) as the domain adaptation technique

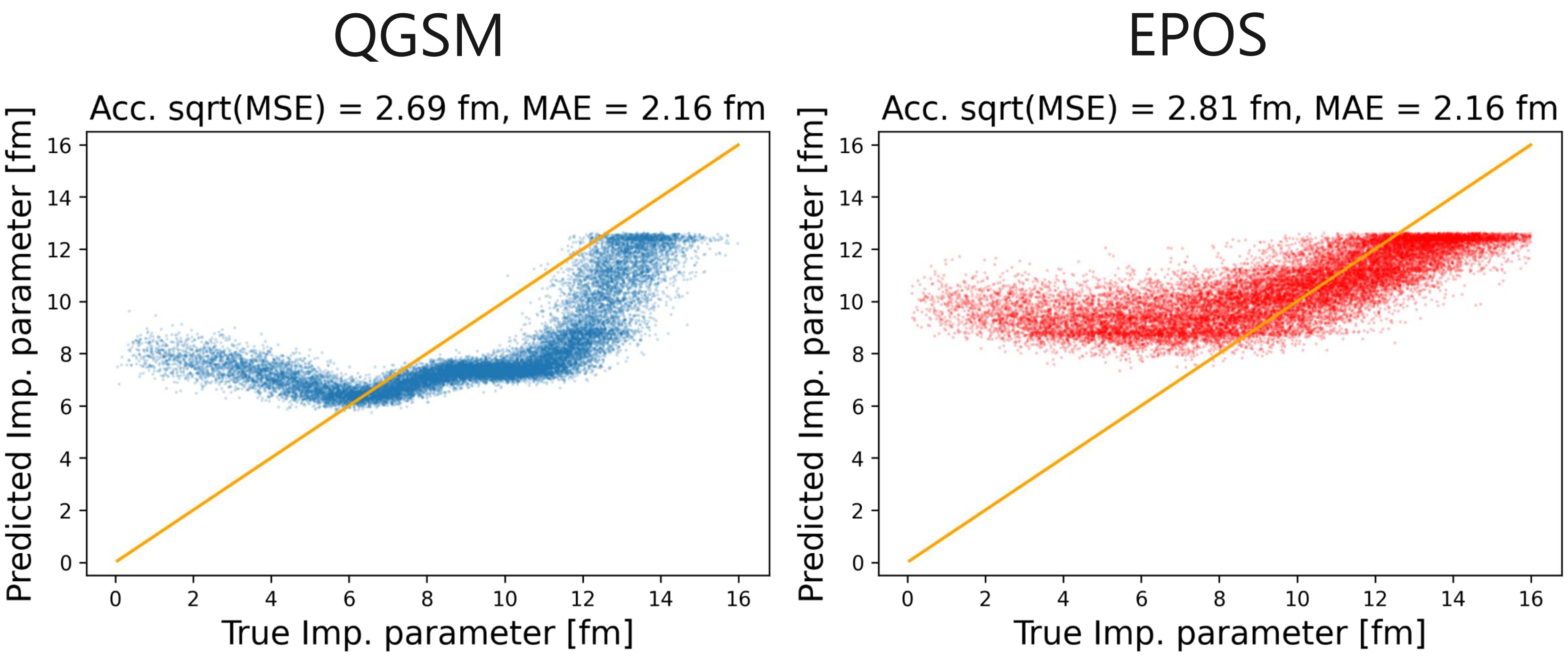


Variational autoencoder results

While the use of variational autoencoders can result in meaningful event features, the results of impact parameter estimation are worse than with other techniques.



VAE features

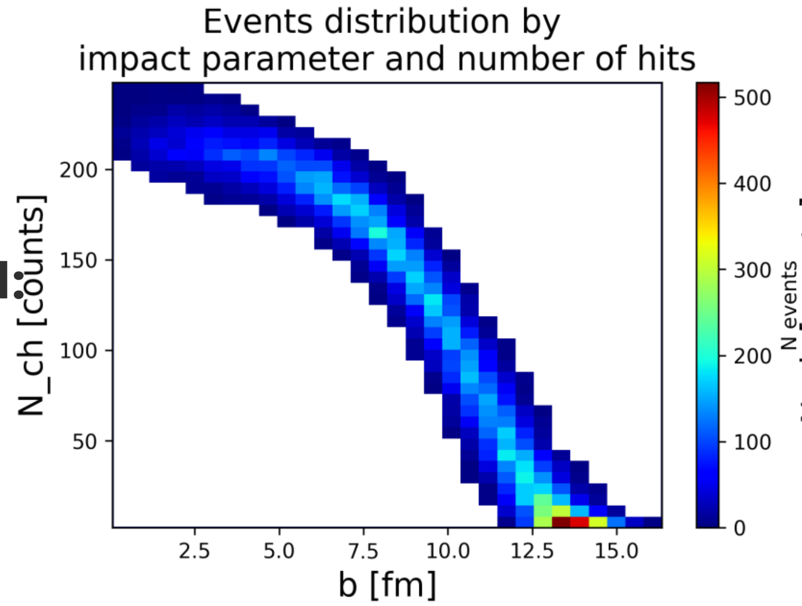


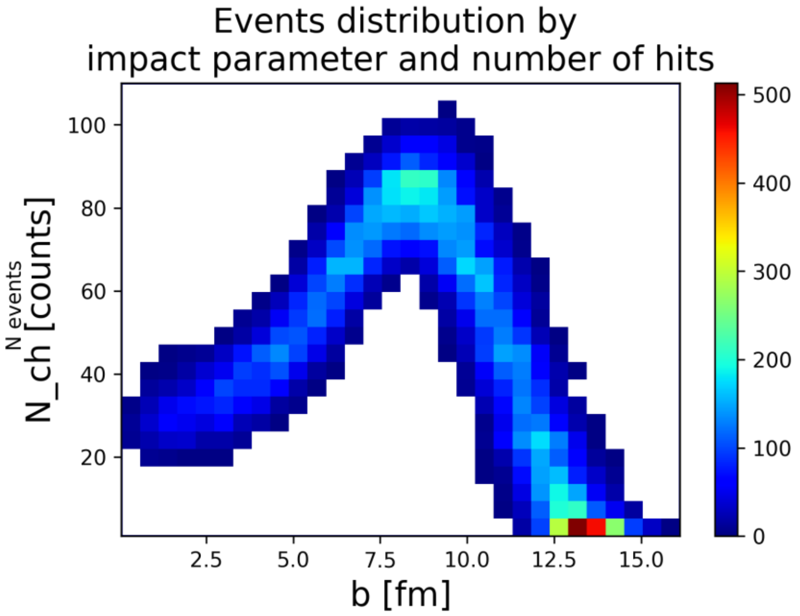
Regression results

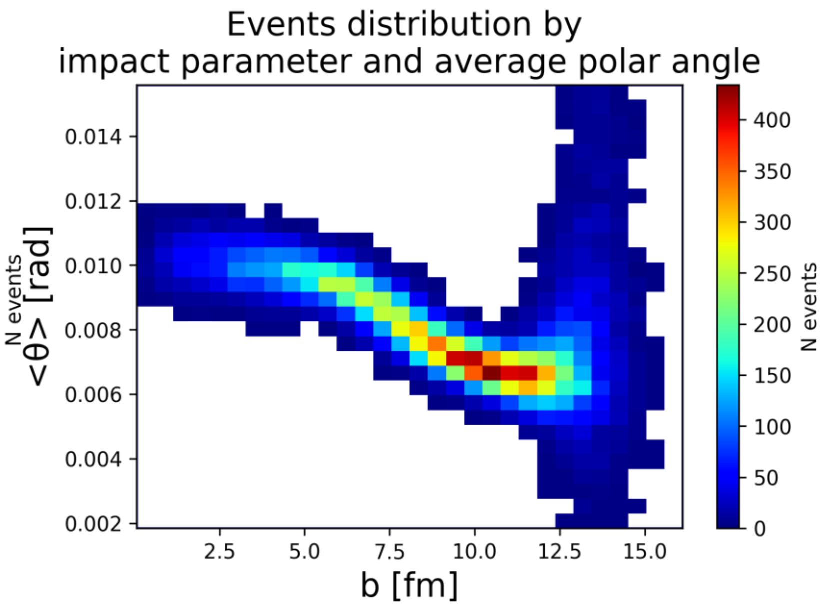
Examples of input data: Multiplicity of charged particles and their average angle

Multiplicity, R=1m | Multiplicity, R=0.25m | Average angle

QGSM:







EPOS: