ML EVENT RECONSTRUCTION TO TEST WITHIN MUonE EXPERIMENT

Miłosz Zdybał on behalf of the MUonE Collaboration

AS SEEN IN

- Zdybał, M., Kucharczyk, M., & Wolter, M. Machine Learning based Event Reconstruction for the MUonE Experiment.
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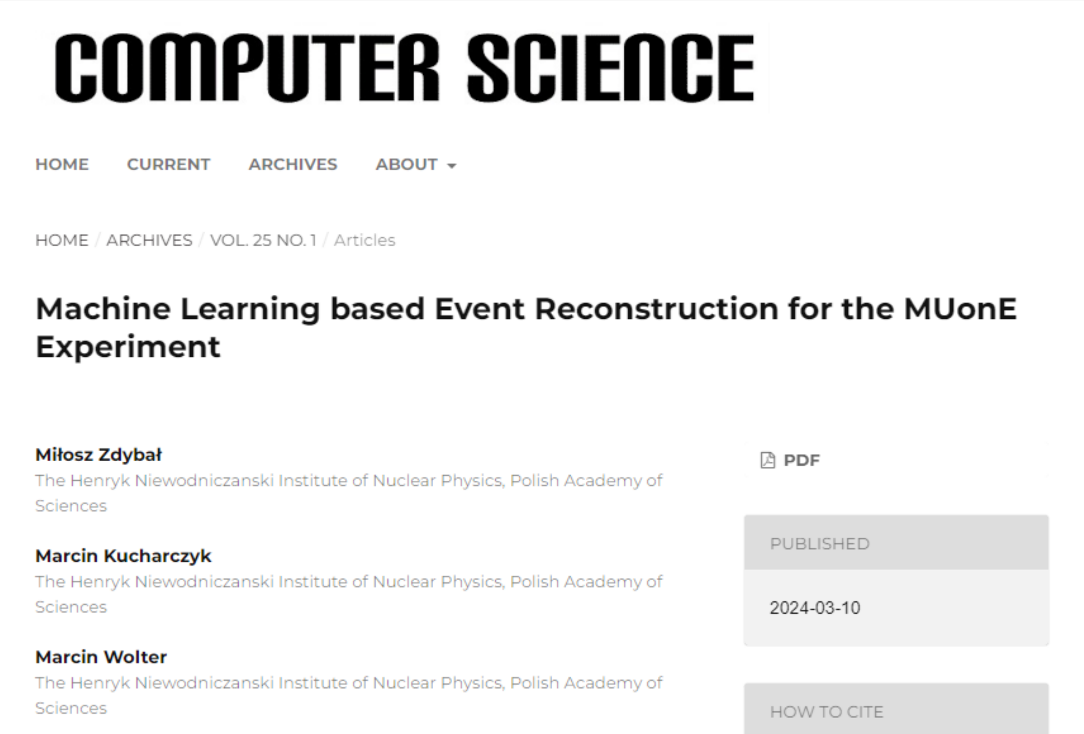

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Machine Learning based Event Reconstruction for the MUonE Experiment

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PDF

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HOW TO CITE

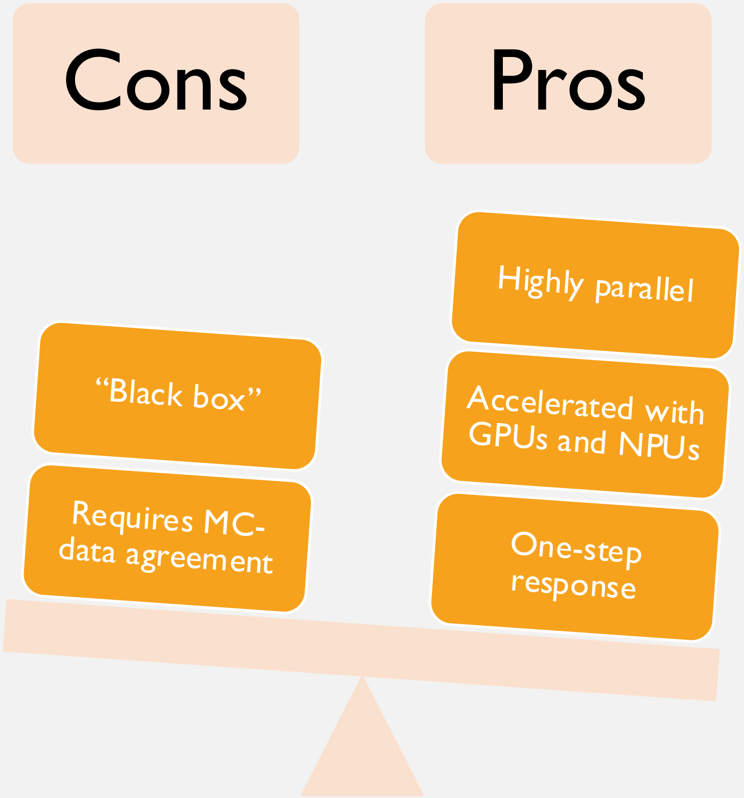
WHY MACHINE LEARNING?

More complicated detectors, extreme luminosities

More data to be processed

Stricter time constraints

WHY MACHINE LEARNING?

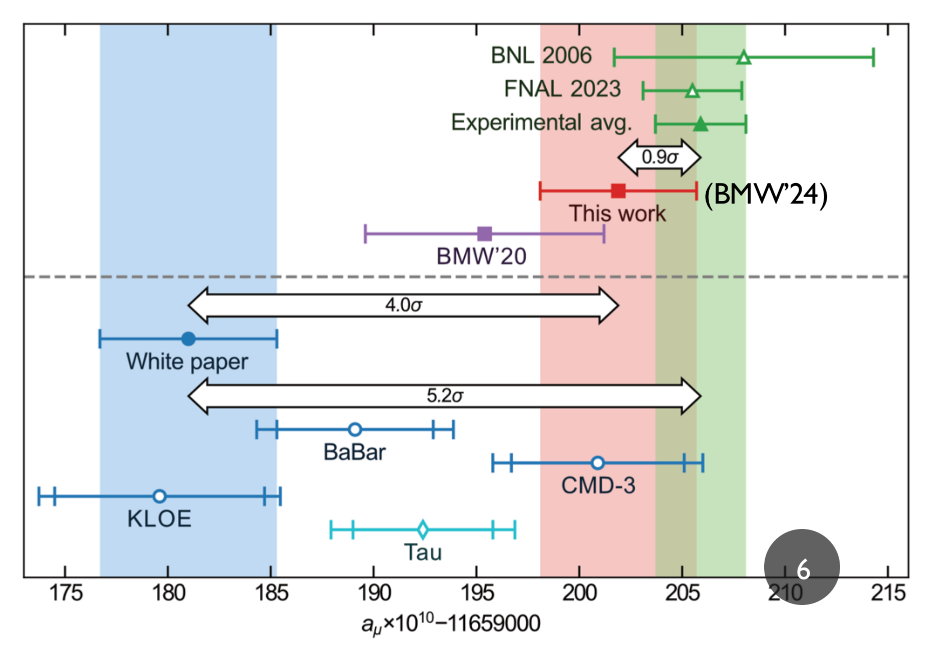


ARTIFICIAL NEURAL NETWORK
TRAINING

- Generalize the model, so it can perform a task using data not seen before,
- Supervised training:
  - Uses *training dataset* (labelled data, ground truth),
  - Responses compared with the labels by the *loss function* (cost function),
- Unsupervised training:
  - No labelled dataset,
  - Network expected to find patterns in the data,
- Reinforcement training:
  - Agents are scored for their actions,
  - Can be used in situation where there is no mathematical model of the problem.

DEVELOPED TO BE USED IN MUonE

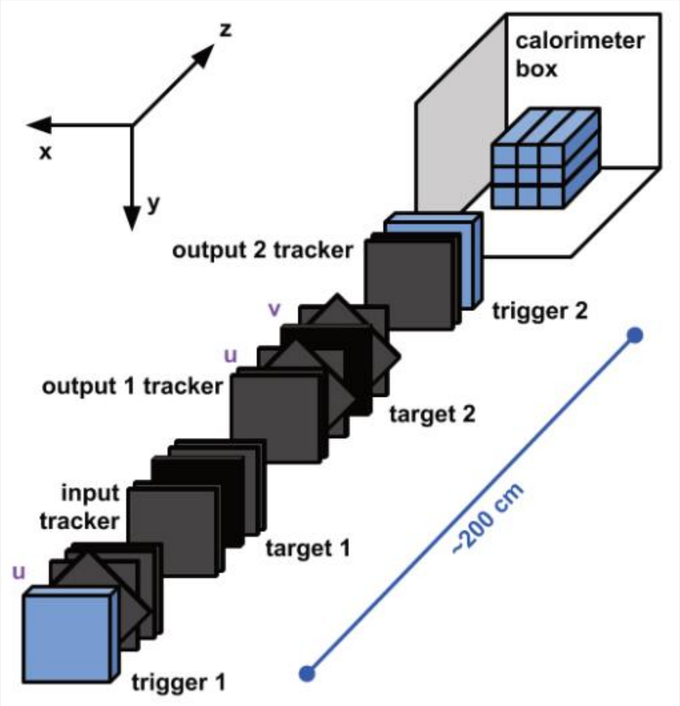
- Looking for signs of the New Physics in determination of the leading hadronic contribution to the muon anomalous magnetic moment a_μ ,
- Elastic scattering of muons on the atomic electrons in the target,
- Previous measurements of a_μ deviate from Standard Model by 5.2σ
- Chance to improve the significance to 7σ by lowering the theoretical error coming from the hadronic vacuum polarization $a_\mu^{HVP,LO}$.



[arXiv:2407.10913]

INITIAL TEST ON FIRST MUonE PROTOTYPE IN 2018

- Simulation based on the 2018 beam test of muon-electron elastic scattering at CERN [JINST 16 (2021) P06005],
- ~132 000 events,
- 2D hits: z + measured value,
- Ground truth:
  - Track parameters:
    - Slope,
    - Intercept,
  - Particle type.

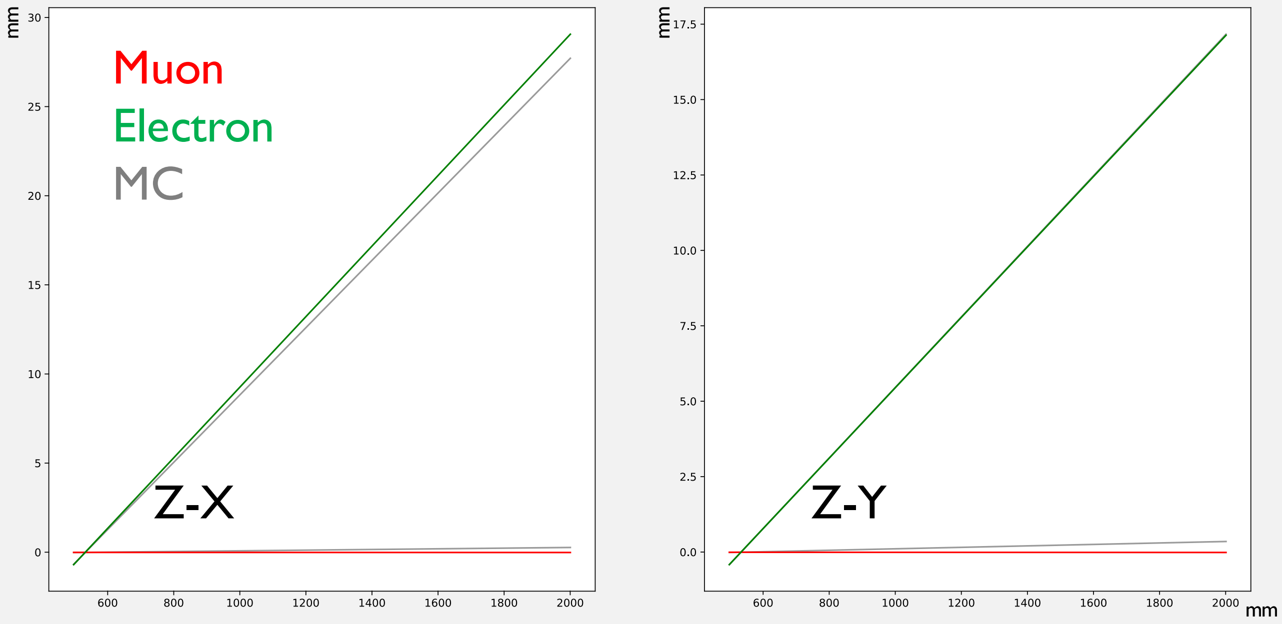


IMPLEMENTED NETWORK

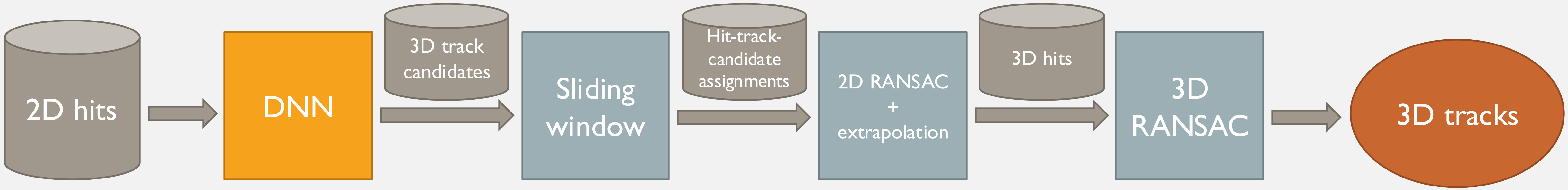
- Multi Layer Perceptron (MLP):
  - PyTorch,
  - Deep neural network: 4 linear layers, 1000 neurons each,
  - Activation function: ReLU,
  - Loss function: MSELoss (Mean Square Error Loss).
- Input: 2D hit coordinates,
- Output: slopes and intercepts of two 3D tracks.

FIRST RESULTS

- Promising, but experiment requires high precision,
- Response from the network may be used as a part of the algorithm.



RECONSTRUCTION ALGORITHM



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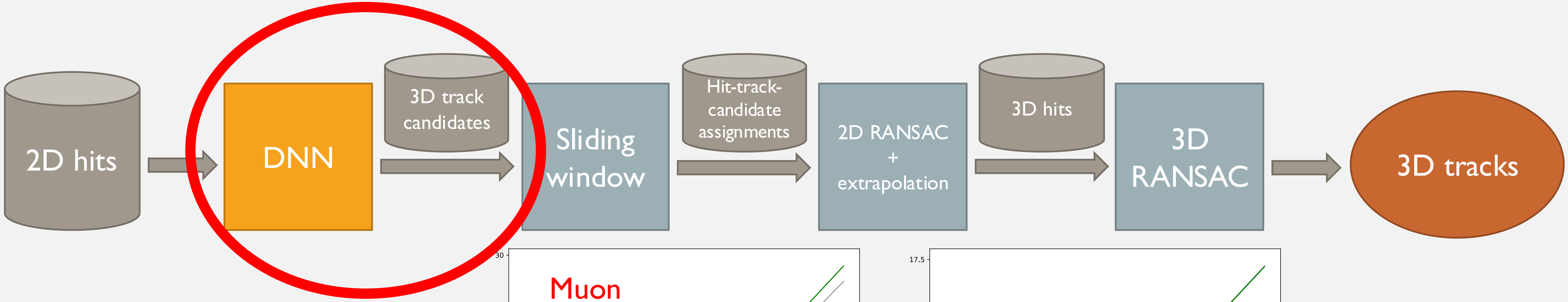

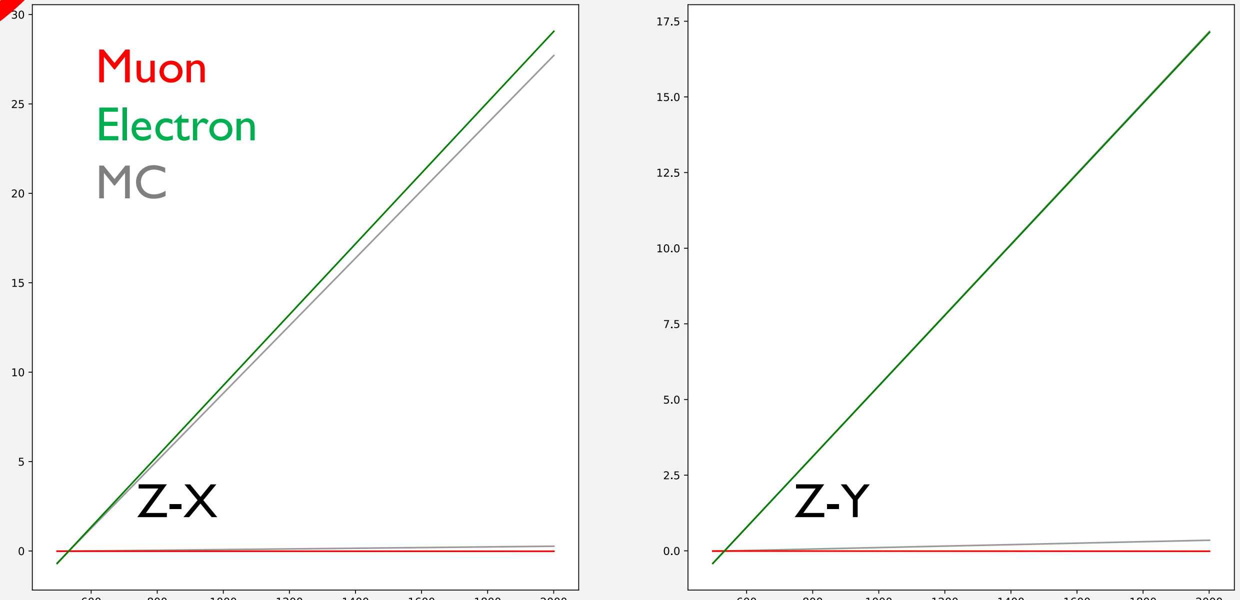

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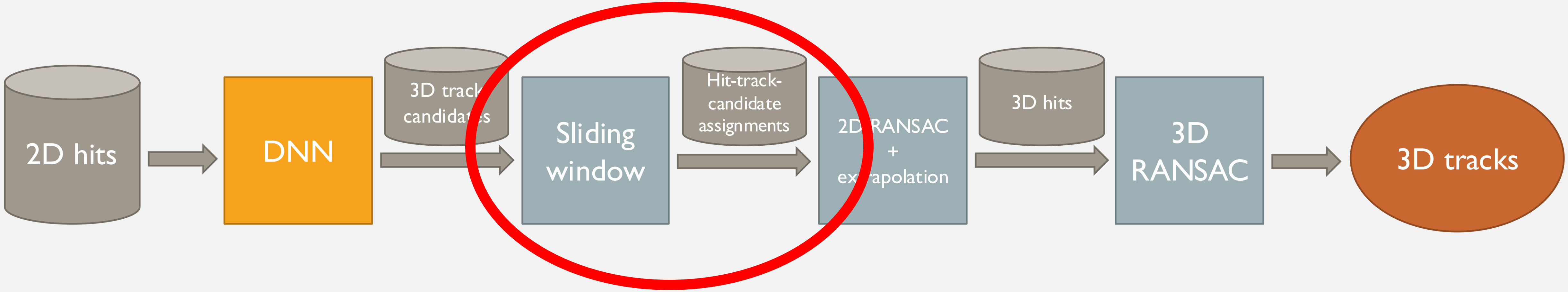

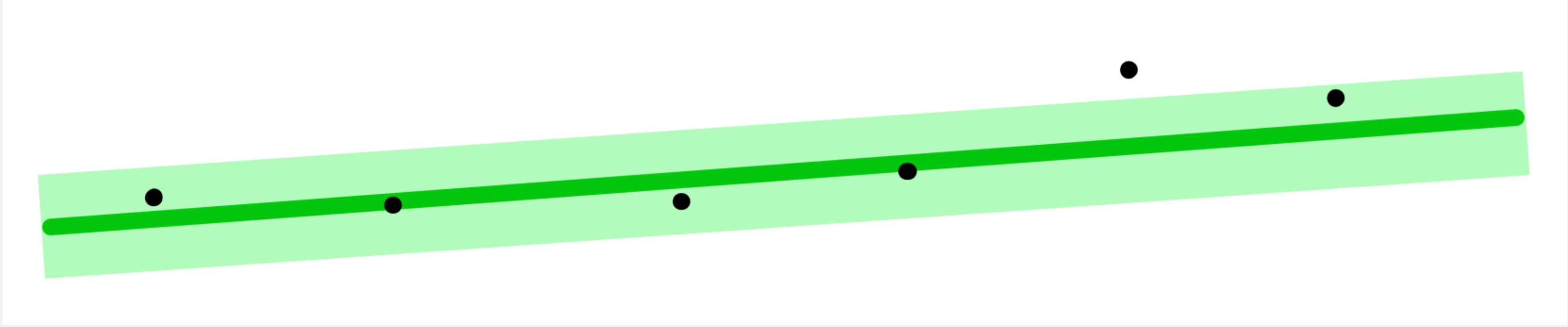

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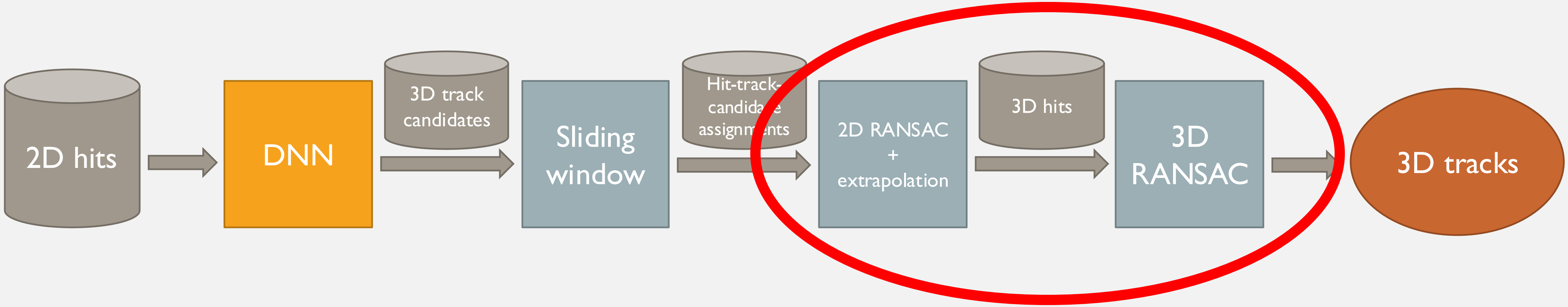
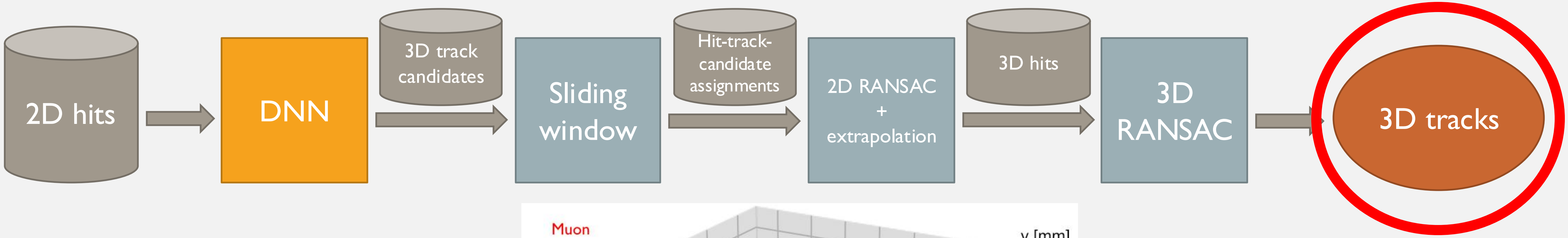
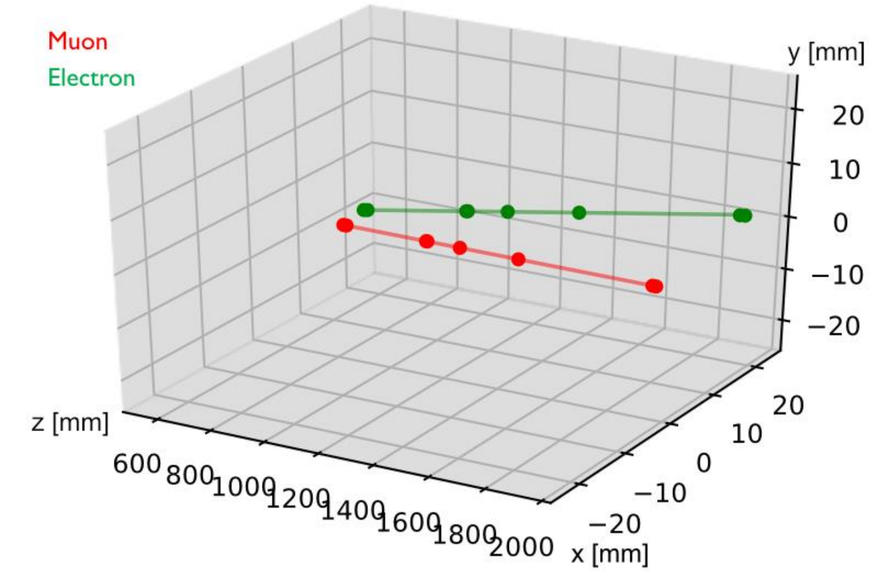


- RANSAC:
  - **RAN**dom **SA**mple **C**onsensus,
  - Robust linear fit algorithm insensitive to outliers.

RECONSTRUCTION ALGORITHM



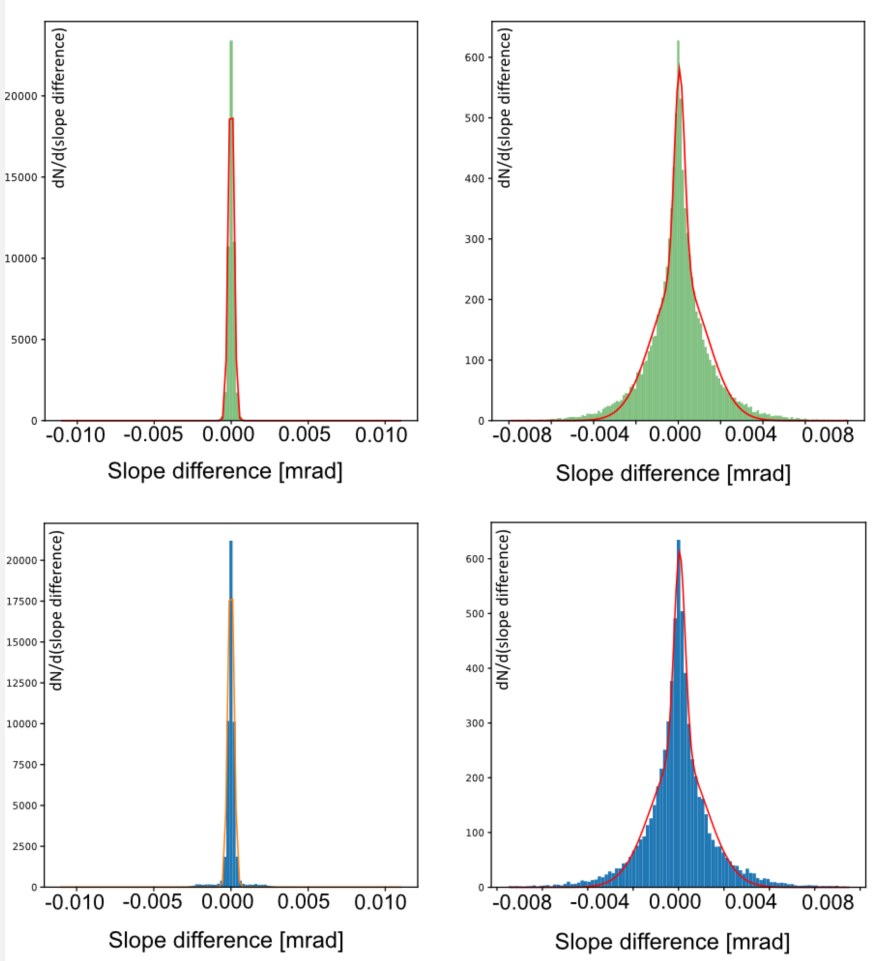


RESULTS

- Track 1: muon, Track 2: electron
- Top: ML-based algorithm
- Bottom: "conventional" reconstruction

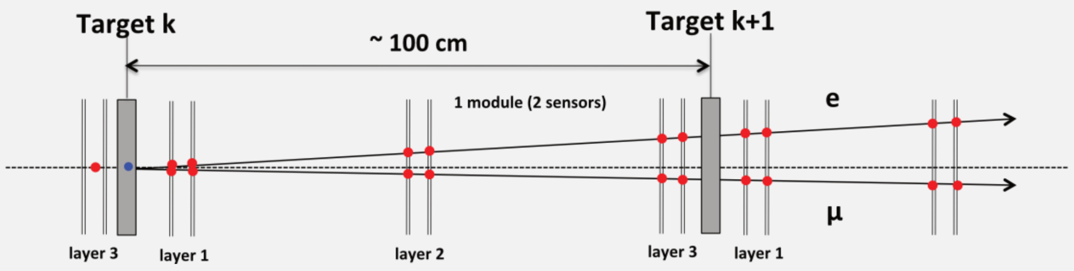
Resolution:

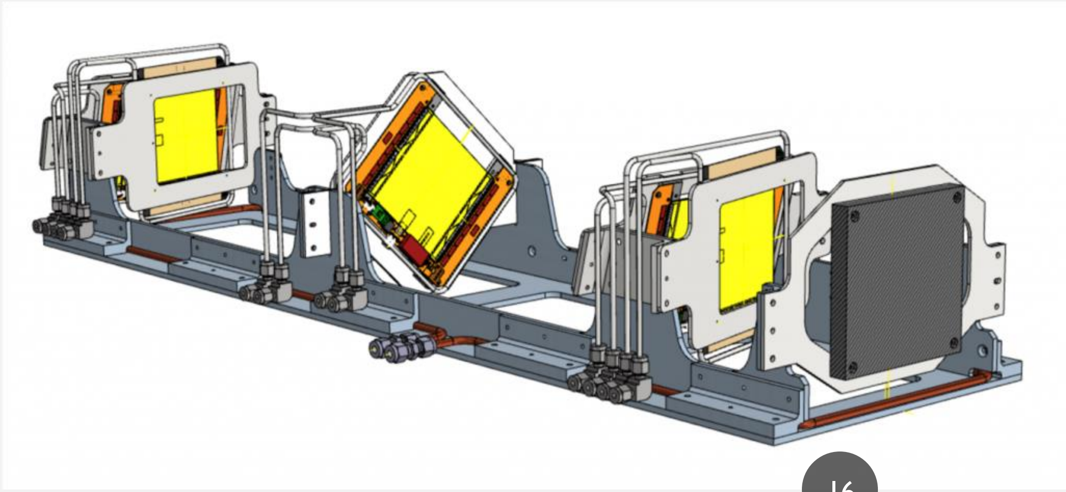
Particle	ML-based	Conventional
Muon	σ = 0.000018 mrad	σ = 0.000019 mrad
Electron	σ_1 = 1.290 mrad, σ_2 = 0.245 mrad	σ_1 = 1.230 mrad, σ_2 = 0.244 mrad



ML STUDIES FOR CURRENT MUonE LAYOUT

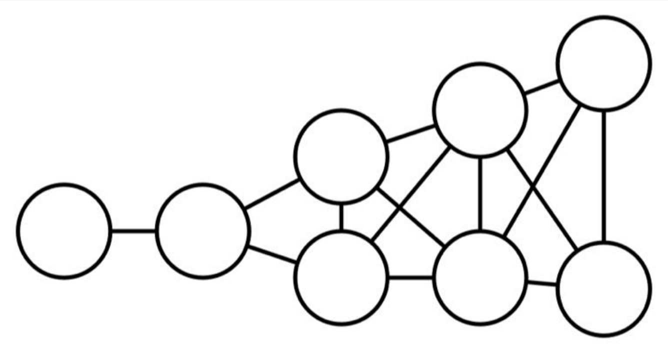
- Will operate at a high energy muon beam at CERN SPS,
- Beryllium or carbon target,
- Pair of outgoing muon and electron will pass through the set of tracking stations with silicon strip sensors,
- Measured coordinates:
  - *x* or *y* (alternatively) in the plane perpendicular to the beam axis,
  - *u* or *v* (*stereo layers*) – like *x* and *y*, but rotated ±45°.
- 40 stations followed by the calorimeter and muon chamber.





CURRENT/FUTURE WORKS

- Graph neural networks (GNN):
  - Growing popularity in HEP,
  - Events represented as graphs:
    - Nodes – hits,
    - Edges – track segment candidates, connections,
  - Flexible at handling missing or additional hits (noise, background).



MACHINE LEARNING TASKS

- Track reconstruction:
  - Graph edges representing track segment candidates,
  - Edge classification,
- Particle identification, event classification:
  - Graph nodes representing hits, graphs representing events,
  - Node classification,
  - Graph classification,
- Software alignment.

CONCLUSIONS

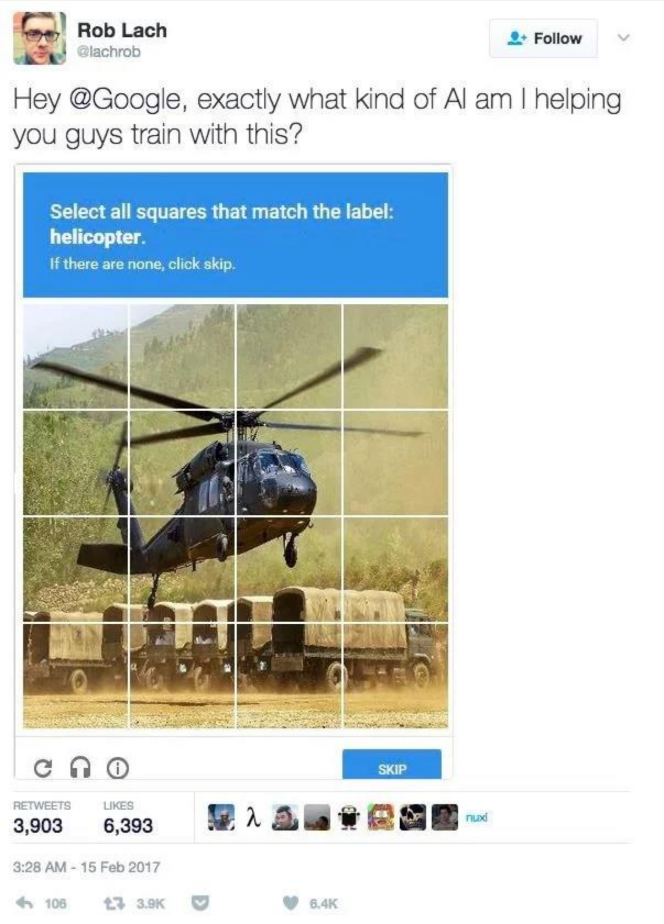
- Machine learning potential for HEP:
  - Good at finding patterns in big datasets,
  - Fast response (no iterations),
  - Highly parallel,
- Practical application:
  - ML-based track reconstruction for a dataset representing a prototype MUonE test,
  - Results on par with the classical method,
- Potential to use also for different tasks for current MUonE layout.

Q&A

BACKUP

SUPERVISED LEARNING

- Labelled dataset:
  - Expected output value assigned to each input,
  - Used for training and testing,
- Loss function:
  - Grades every response from the network,
  - Results used to optimize the model,
- Optimization:
  - Backpropagation algorithm.



BACKPROPAGATION AND OPTIMIZATION

- Backpropagation for feedforward neural networks:
  - Estimation of the gradient of the loss function with respect to the weights,
  - Term often used to refer to the learning algorithm,
- Optimizer:
  - Utilizes calculated gradient (e.g. stochastic gradient descent),
  - Adjusts values of the weights to minimize the value of the loss function.