Proton trajectory reconstruction for Proton Computed Tomography with machine learning algorithms

GPU DAY 2024
2024.05.30-31

Speaker: Dudás Bence
Collaborators: Dr. Papp Gábor, Dr. Bíró Gábor
Bergen pCT collaboration

Nemzeti Kutatási, Fejlesztési
és Innovációs Hivatal

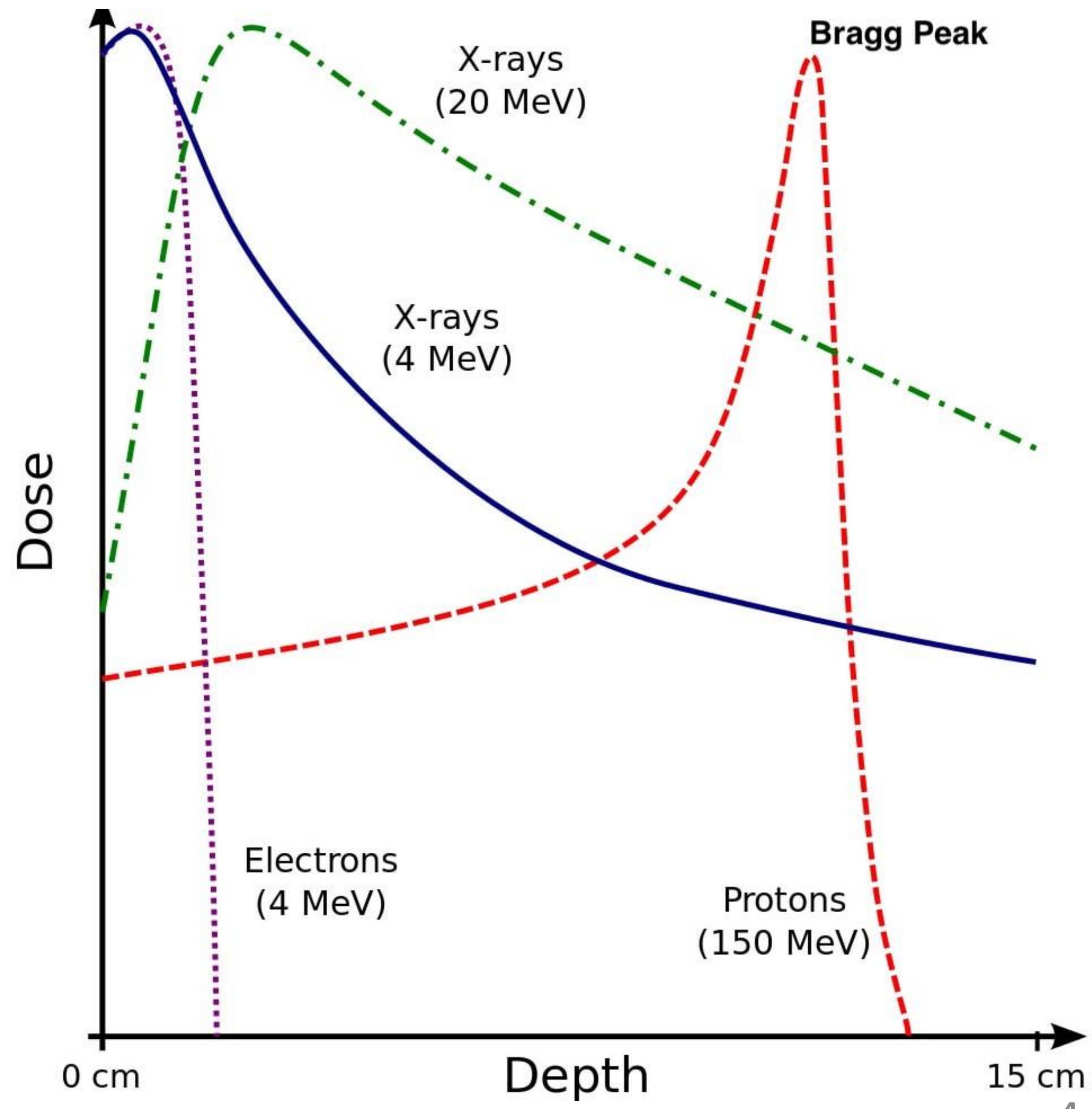
Outline of my talk

- Reminder on Hadron Therapy
- Proton Computed tomography
- Processing pCT detector signals
- Results

Hadron therapy

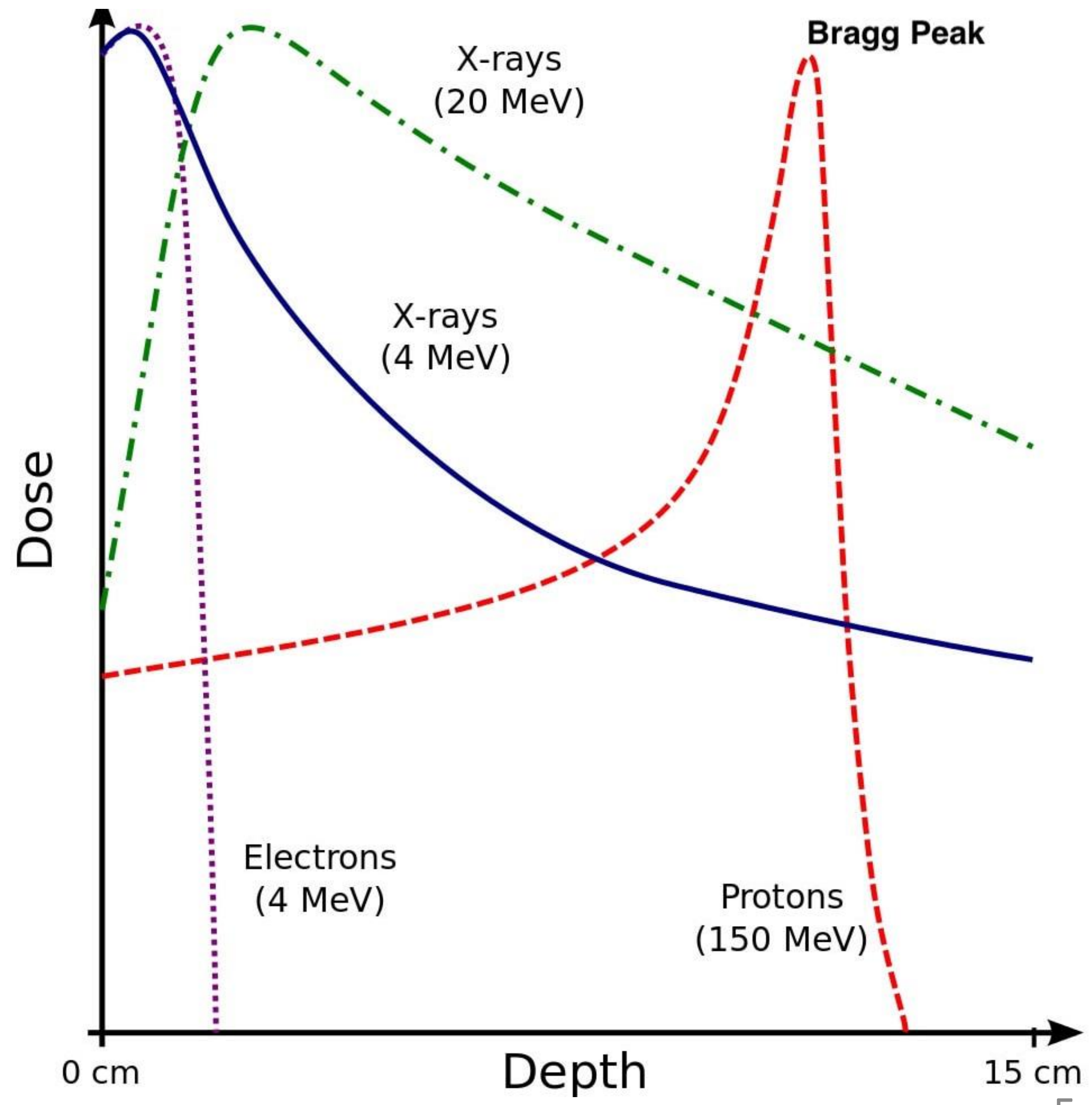
Hadron(proton) therapy

- Cancer therapy
- Using radiation
- Utilize the Bragg peak of proton
- Ambulant treatment



Challanges for Hadron therapy

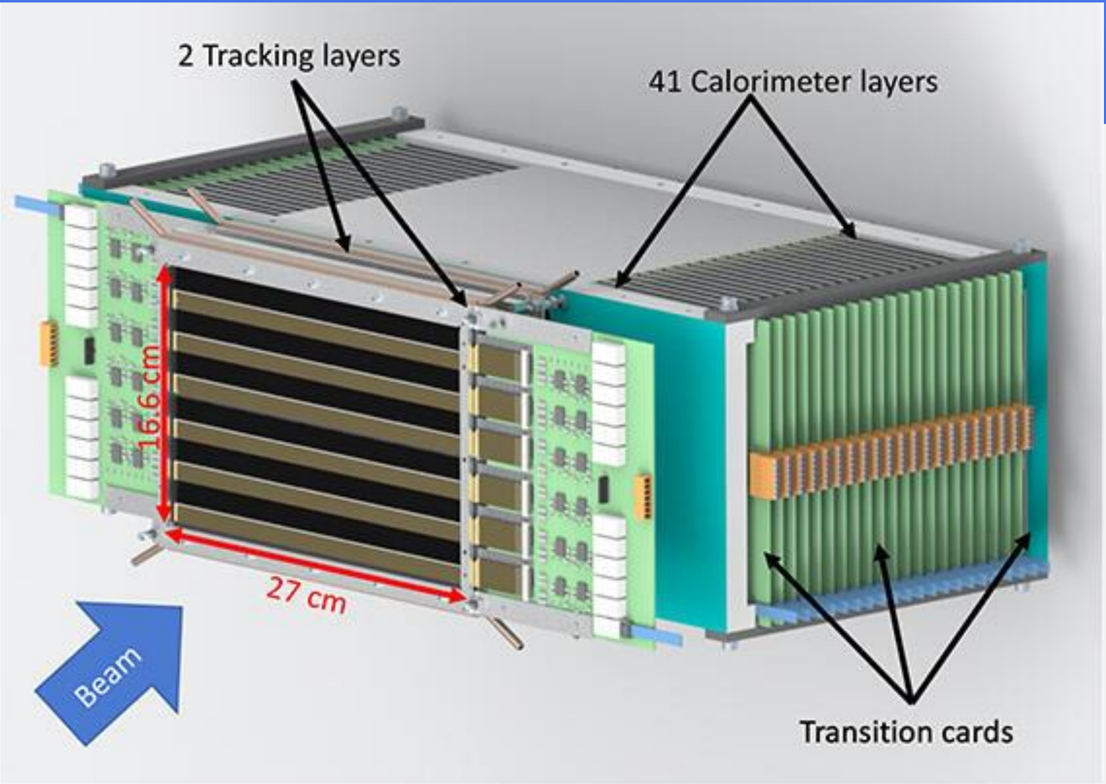
- Traditional tomography was not made for protons
- Hadron therapy needs map of stopping power
- Data processing needs to be fast for ambulant treatment



Proton Computed Tomography

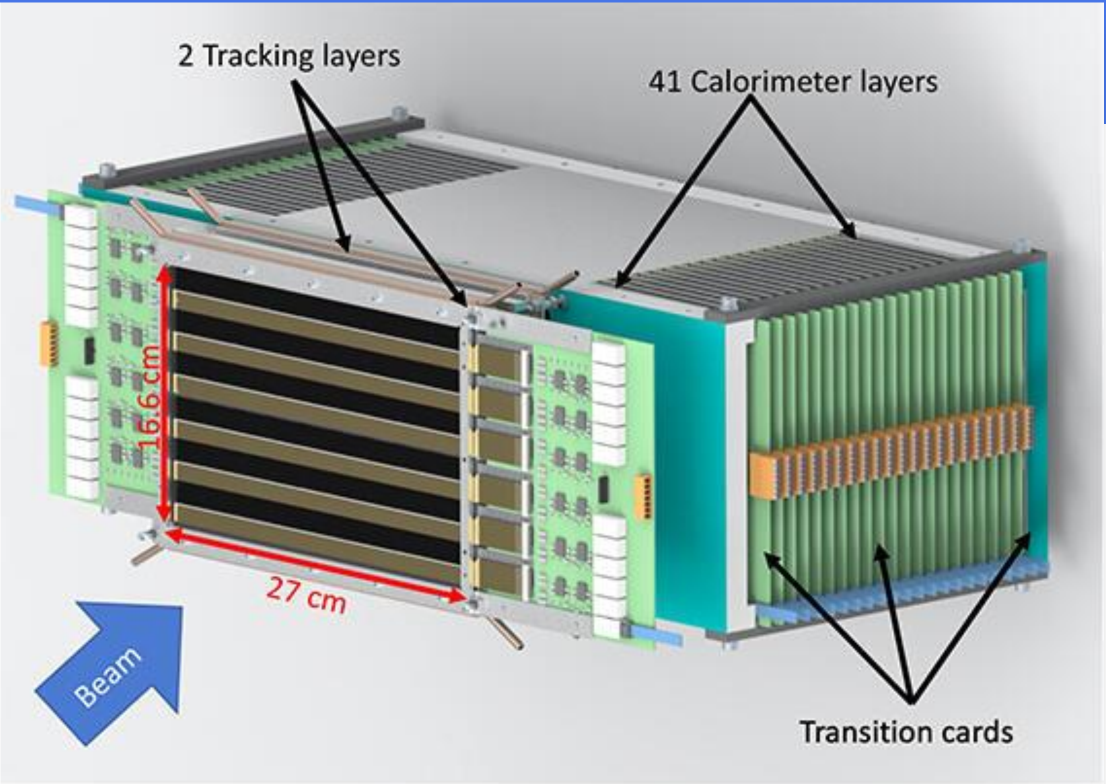
Proton computed tomography(PCT)

- High energy (200 MeV) protons beamed through a phantom
- These are scattered on the particles of the phantom
- The detector measures position of the hits and energy deposition (by the clusters of the hits)
- Detector layers are ALICE ALPIDE chips
- 9216 pixel in X axis, 6144 pixel in Y axis



Proton computed tomography(PCT)

- The detector signals processed
- Reconstruct the trajectories based on the position and energy deposit of the hits
- Extract initial angles and kinetic energy
- Rotate and translate the system around the phantom
- Get a 3D map



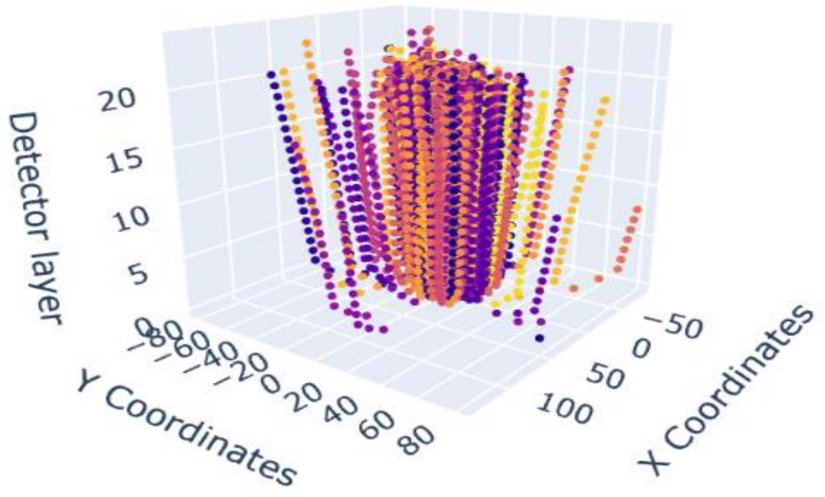
Data processing with machine learning

- To predict angle we need to reconstruct the trajectories
- For the image reconstruction:
  - Scattering angles
  - Initial kinetic energy
- Reconstructing particle path with traditional algorithms takes too much computational time

- Deep Neural Networks can evaluate fast
- Learn complex connections between data

Data structure

- Using data simulated from openGate(Geant4 medical extension)
  - Therefore tracking information is available
  - Large number (O(1e5)) of events may be generated
- Measurment is done in frames with 100-200 primaries (event)
- For every detector layer:
  - middle of every hit (X,Y coordinate)
  - size (energy deposition)



Matching

Sinkhorn algorithm

- We want to connect elements of X with elements of Y
- The Sinkhorn operator:

$$S(X,Y)_{i,j} = e^{\frac{-\sqrt{(X_i - Y_j)^2}}{T}}$$

- T is a constant parameter, often called temperature

Normalize the operator

- $S(X,Y)_{i,j}$ operator gives us transformed distances
- We need to convert this to probability
- $P(X,Y)_i = \sum_j S(X,Y)_{i,j} \cong 1$
- After normalizing the rows the sum of columns will not be 1

Normalize the operator

3.813014	1.1846079	1.1926202
9.104467	4.32391	5.296152
4.1251545	5.4451103	7.04003

- $S(X,Y)_{i,j}$ operator gives us transformed distances
- We need to convert this to probability
- $P(X,Y)_i = \sum_j S(X,Y)_{i,j} \cong 1$
- After normalizing the rows the sum of columns will not be 1

Normalize the operator

- $S(X,Y)_{i,j}$ operator gives us transformed distances
- We need to convert this to probability
- $P(X,Y)_i = \sum_j S(X,Y)_{i,j} \cong 1$
- After normalizing the rows the sum of columns will not be 1

3.813014	1.1846079	1.1926202
9.104467	4.32391	5.296152
4.1251545	5.4451103	7.04003

0.8733873	0.06305282	0.06356005
0.9703301	0.00814235	0.02152728
0.04312247	0.16141844	0.79545933

Normalize the operator

- $S(X,Y)_{i,j}$ operator gives us transformed distances
- We need to convert this to probability
- $P(X,Y)_i = \sum_j S(X,Y)_{i,j} \cong 1$
- After normalizing the rows the sum of columns will not be 1
- Repeat iterations until the sum of rows is 1 and the sum of columns is 1 also

0.8733873	0.06305282	0.06356005
0.9703301	0.00814235	0.02152728
0.04312247	0.16141844	0.79545933

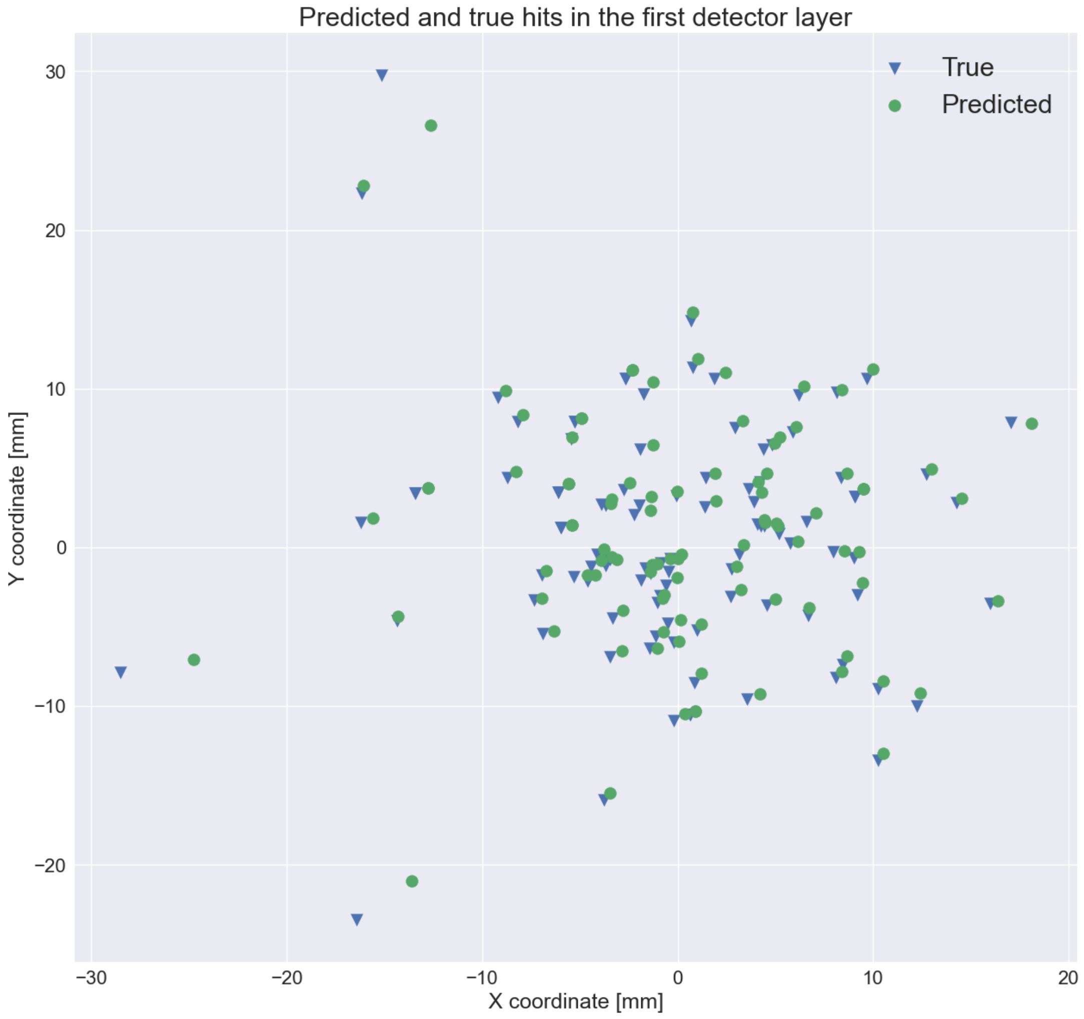
0.2894971	0.5115175	0.19898538
0.70675534	0.14515041	0.14809425
0.00374754	0.34333208	0.6529203

Sinkhor algorithm with deep learning

- Project points on the detector layer:
- Connect the projected points with the true points

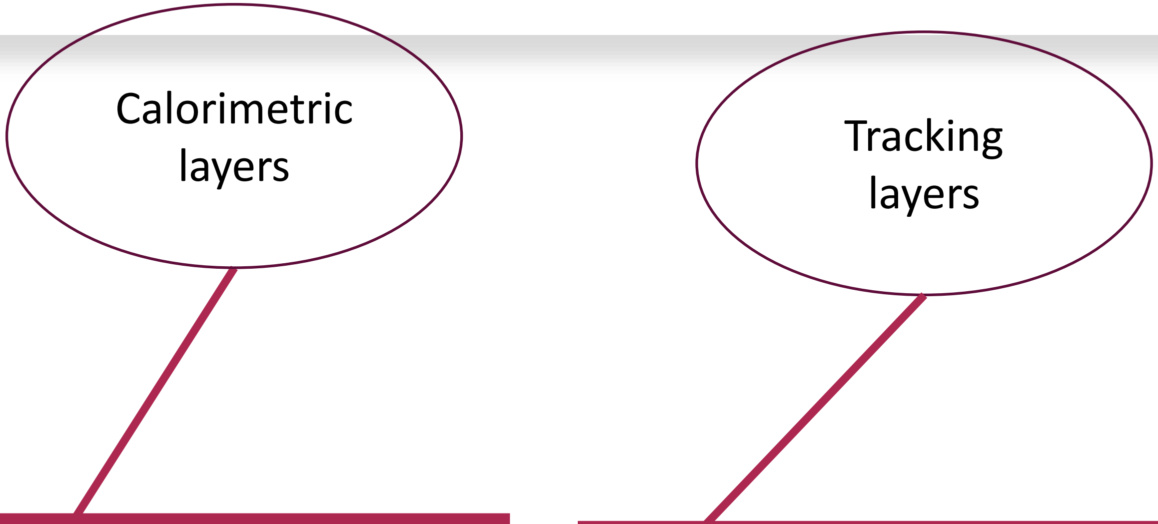
$$X_L^p = h(X_{L-1}, X_{L-2})$$

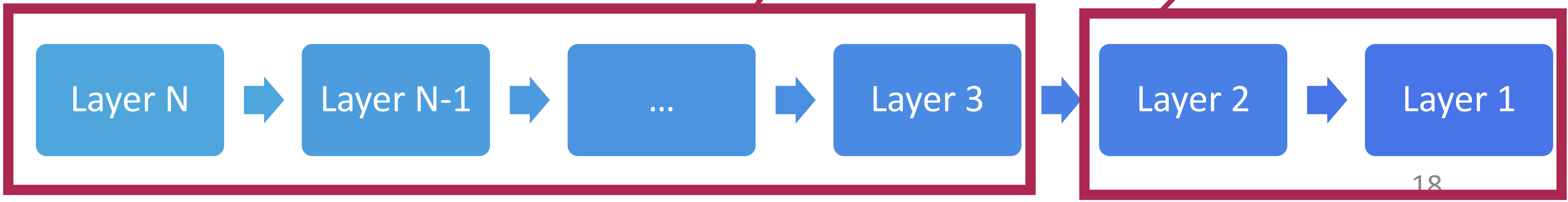
$$S(X_L^p, X_L^t)_{i,j} = e^{\frac{-\sqrt{(X_{L,i}^P - X_{L,j}^t)^2}}{T}}$$



Data flow

- Connecting points in between detector layers
- Between calorimetric layers only Sinkhorn matching is enough
- For the tracking layers we use previous momentum of reconstructed track

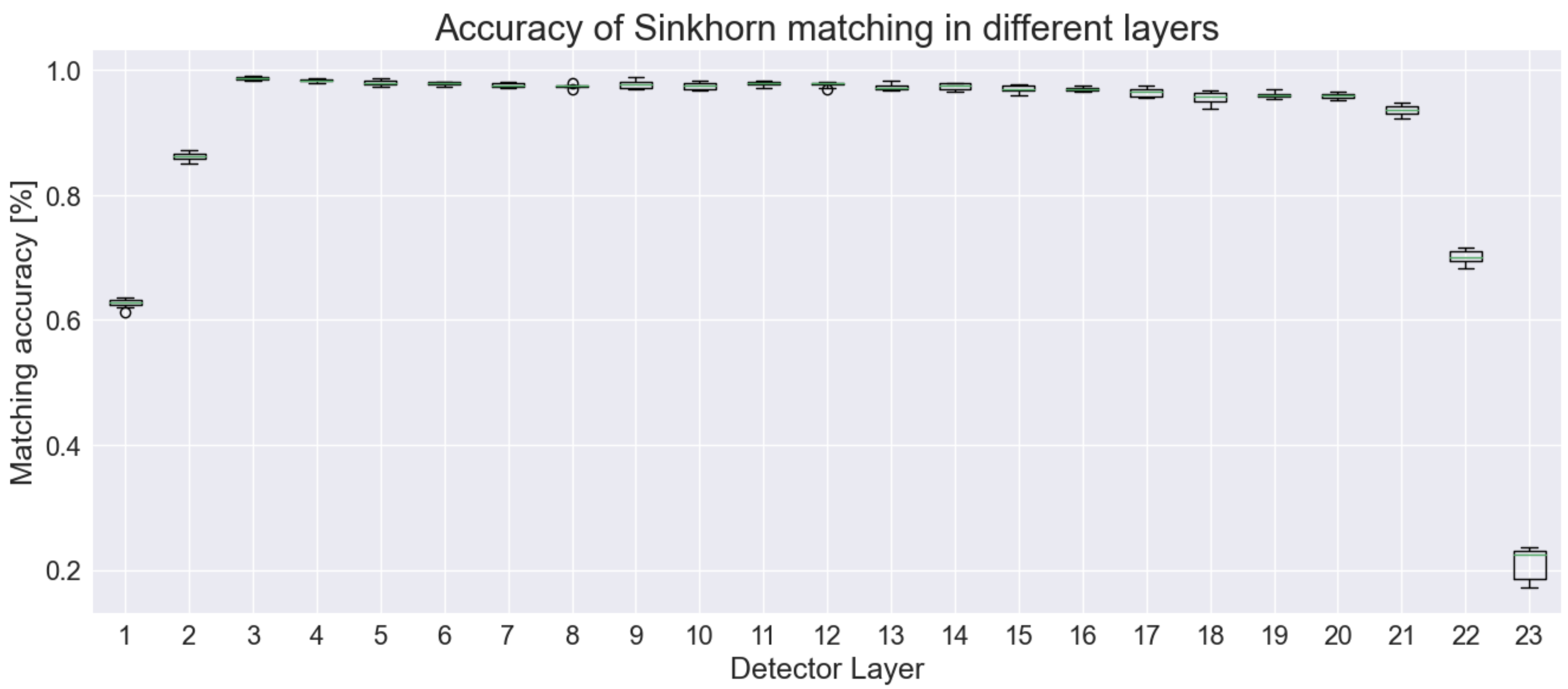




Results

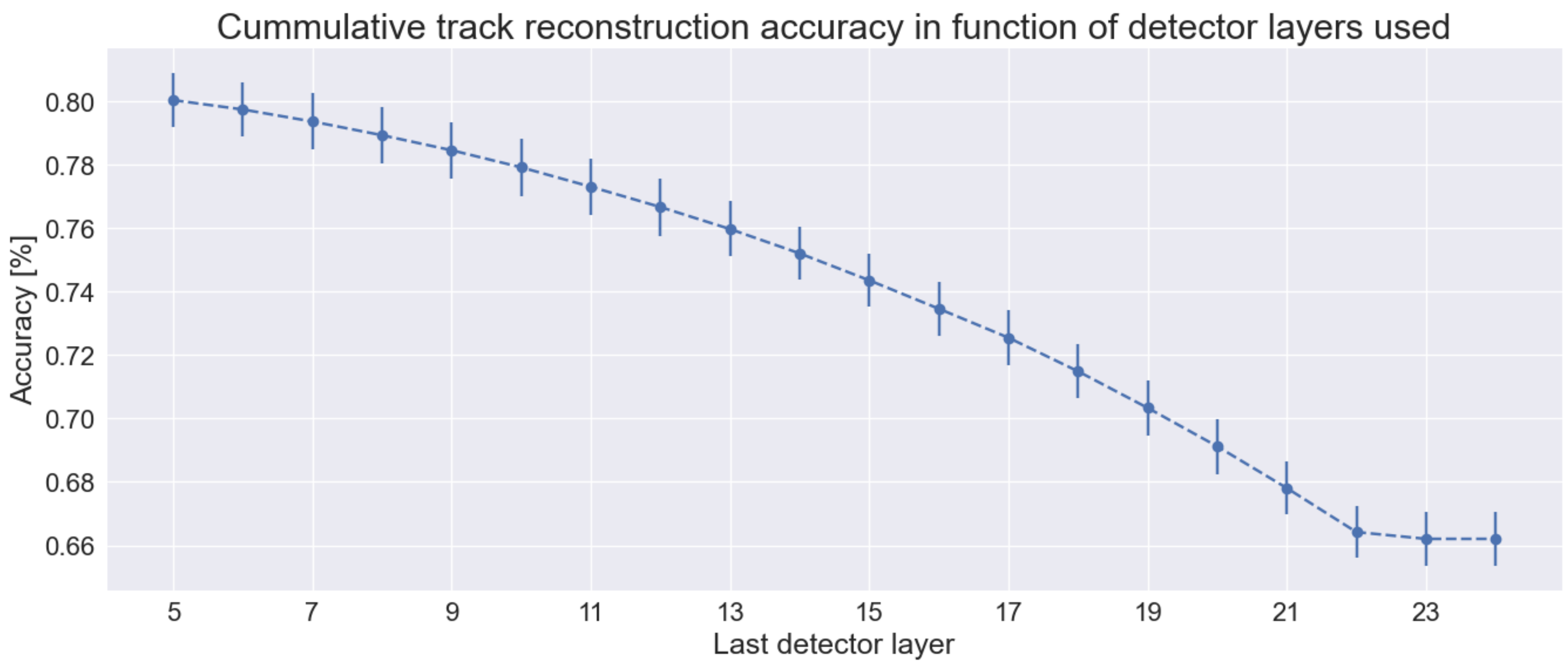
Results

- Accuracy is very high in the calorimetric layers
- When most of the particles stop the accuracy go down significantly
- Drops at the end can be handled easily



Results

- Accuracy has some decrease in it
- Mean of O(1e4) number of events
- Around layer 23 all the particles are stopped
- This is why results are not decrease from there



Results

- Large number of events for testing O(1e4)
- Maximum time for track reconstruction: 2-6 ms
- One particle track reconstruction time: 0.8 ms

Summary & outlook

The application of deep learning algorithms in the pCT track reconstruction yields good results. The Bergen pCT machine learning approach gives better results, but took significantly more time to reconstruct trajectories.

- Writing a publication
- Integrate into the Bergen pCT collaboration

Supporters:

- Hungarian Artificial Intelligence Laboratory, under the ID: RFF-2.3.1-21-2022-00004
- OTKA K135515
- SUPPORTED BY THE DKOP-23 DOCTORAL EXCELLENCE PROGRAM OF THE MINISTRY FOR CULTURE AND INNOVATIONFROM THE SOURCE OF THE NATIONAL RESEARCH, DEVELOPMENT AND INNOVATION FUND.
- Wigner Scientific Computer Laboratory

Thank you for your attention

Resources

- https://www.uwa.edu.au/study/courses/master-of-surgery
- https://www.timesofisrael.com/major-israeli-hospital-admits-giving-cancer-patients-expired-chemotherapy-drugs/
- https://www.saferradiationtherapy.com/radiation-therapy-2/
- https://builtin.com/artificial-intelligence/transformer-neural-network
- https://study.com/academy/lesson/bipartite-graph-definition-applications-examples.html
- Johan Alme et all, *A High-Granularity Digital Tracking Calorimeter Optimized for Proton CT*, Frontiers in Physics (2020), doi: 10.3389/fphy.2020.568243
- Robert P Johnson, *Review of medical radiography and tomography with proton beams,* Rep. Prog. Phys. **(81)** (2018) 016701, doi: 10.1088/1361-6633/aa8b1d.
- M. Mager et all, *ALPIDE, the Monolithic Active Pixel Sensor for the ALICE ITS upgrade,* Elsevier **434-438** (2016), doi 10.1016/j.nima.2015.09.057
- H.E.S. Pettersen et all, *Design optimization of pixel-based range telescope for proton computed tomography,* Physica Medica **87-97** (2019) doi:https://doi.org/10.1016/j.ejmp.2019.05.026