

# Proton Computed Tomography for Hadron Therapy



HUN  
REN



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2025.08.07

Bergen pCT Collaboration

## Talk overview

Cancer

Cancer  
treatments

Hadron  
therapy

pCT

Machine  
learning

Tracking

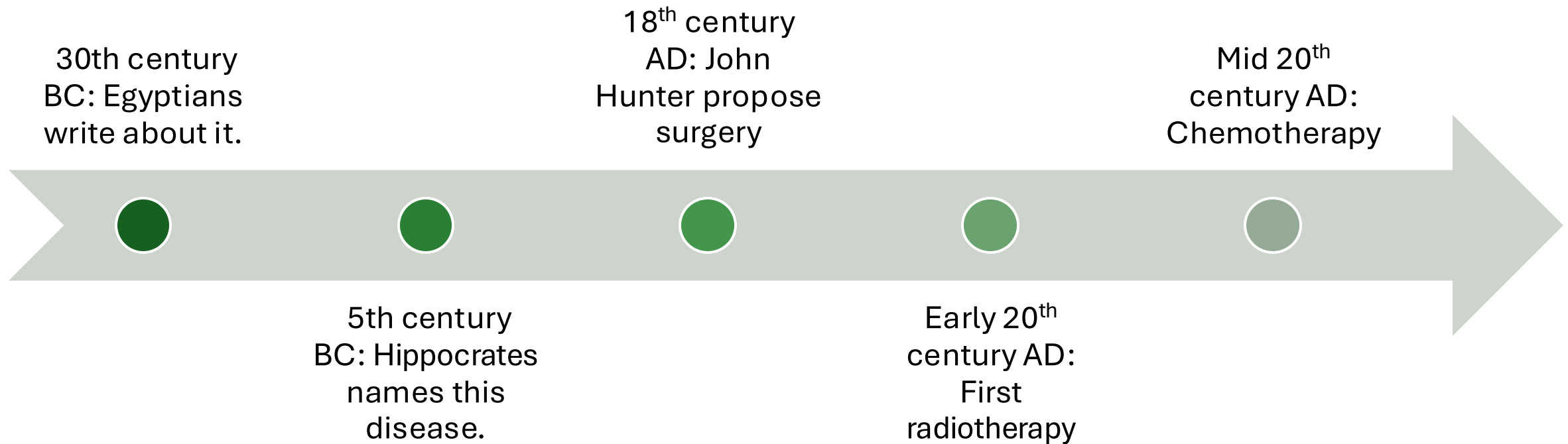
Energy  
prediction

Image  
reconstruction

# Cancer

What we know about it (in short)

## History



## Categories of cancer

### Types

Carcinoma

- Cancer that originates from epithelial tissues. For example: skin

Sarcoma

- Bones and soft tissues

Melanoma

- Starts from the skin

Leukemia

- Cancer in the blood cells

Lymphoma

- Cancer in the immune system

Mix of above

### Stages

Stage one



Stage two



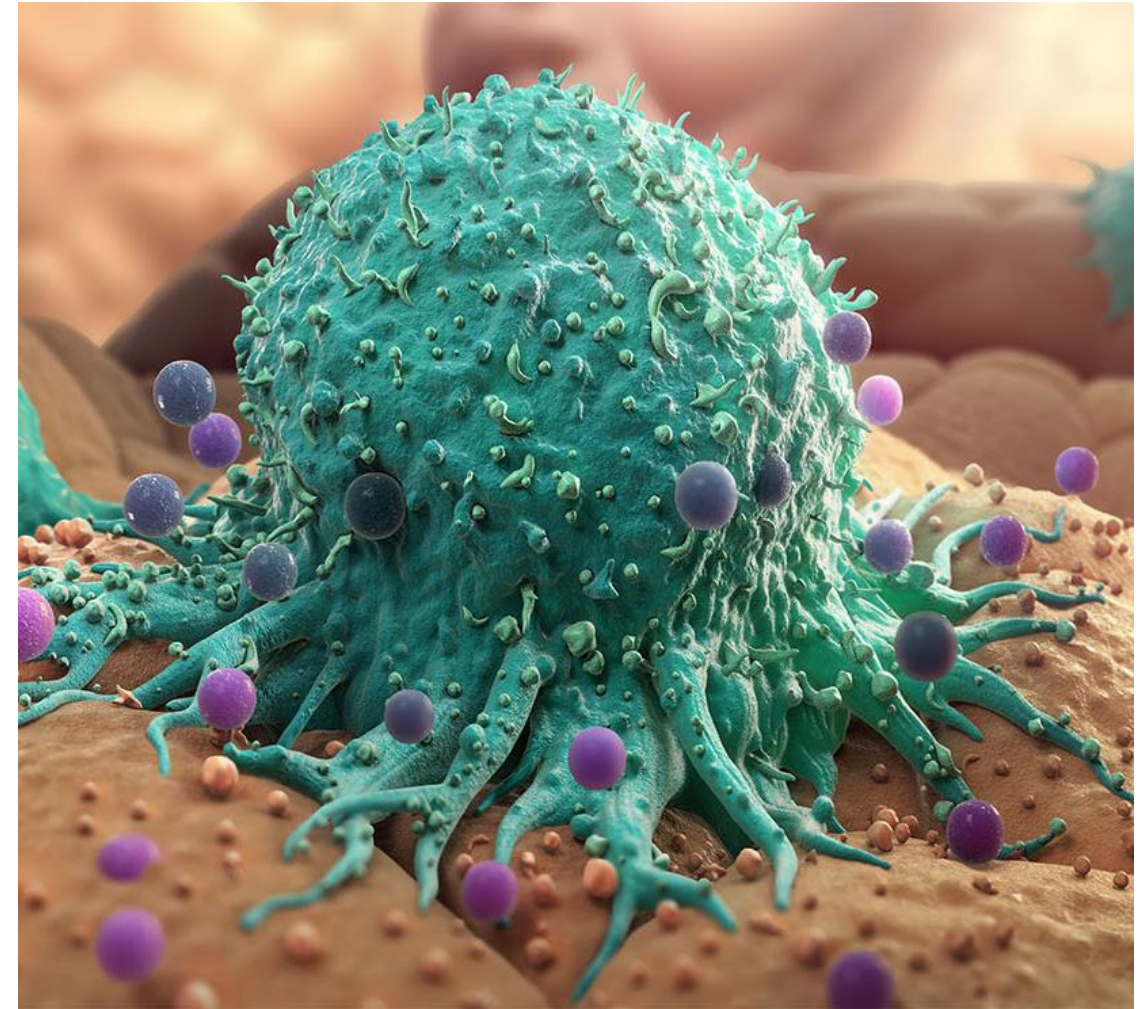
Stage three



Stage four

## What is Cancer

- Mutated/damaged cells.
- Growing constantly, even when they shouldn't.
- Don't stop growing when signaled do to so.
- Spreading through the body.
- Hide from immune system.
- Always grow, eat a lot.

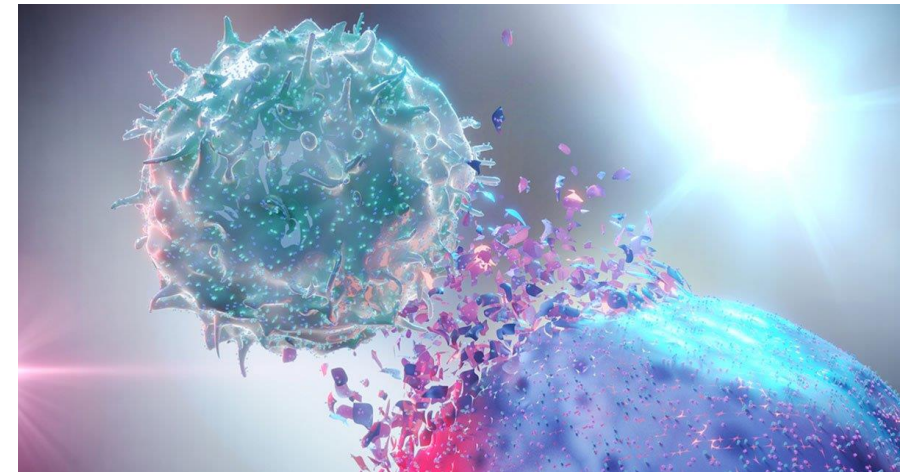


# Cancer treatments

Possible ways to deal with this disease



## Possible treatments



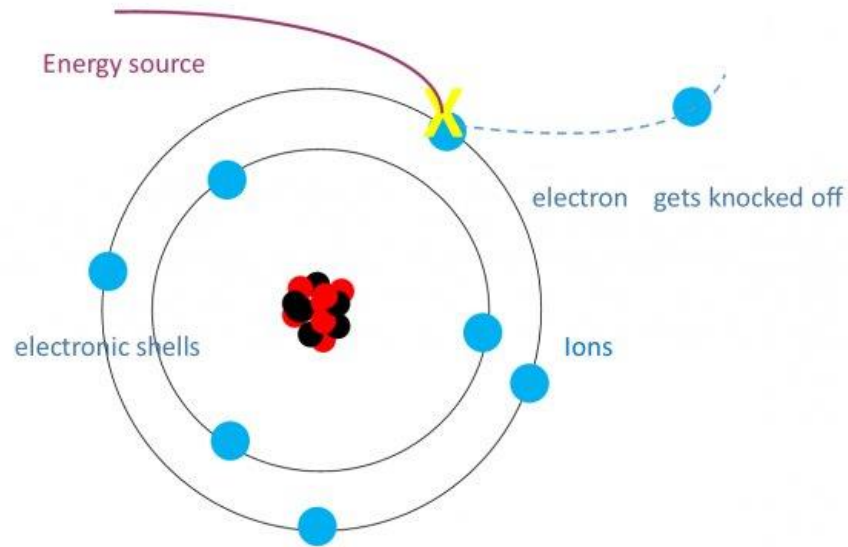


## Radiotherapy

Uses ionizing particles



## Radiotherapy

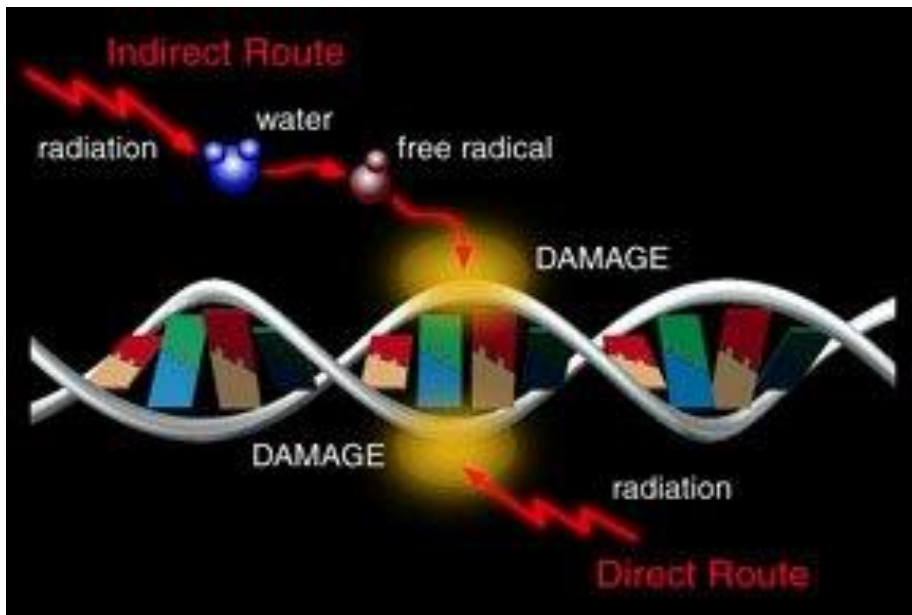


Uses ionizing particles



Ionisation: a particle with sufficient kinetic energy kicks out an electron from an atom so it becomes charged (ionized)

## Radiotherapy



Uses ionizing particles



Ionisation: a particle with sufficient kinetic energy kicks out an electron from an atom so it becomes charged (ionized)



DNA is made of atoms, so ionization changes its structure, it gets damaged

## Radiotherapy

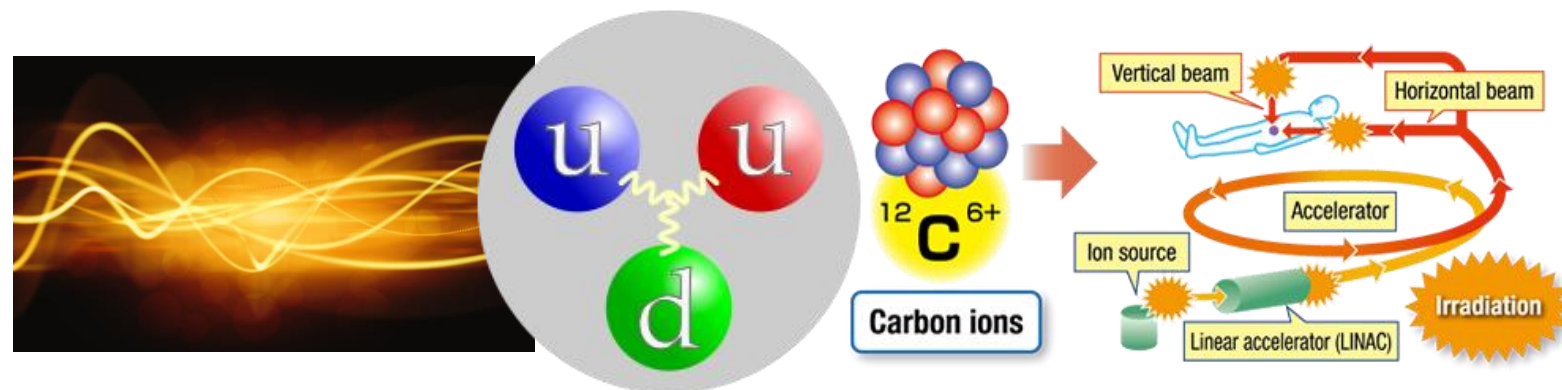


Uses ionizing particles

Photons

Protons

Heavy ions



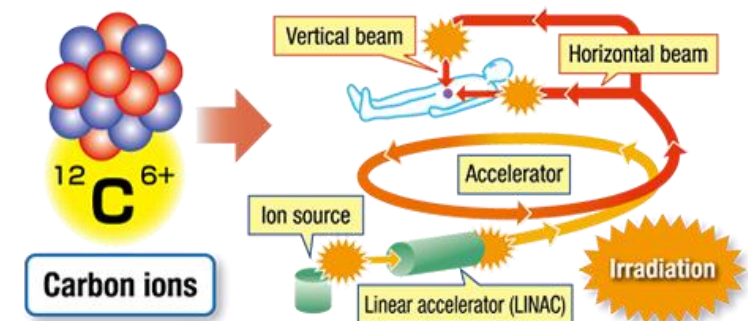
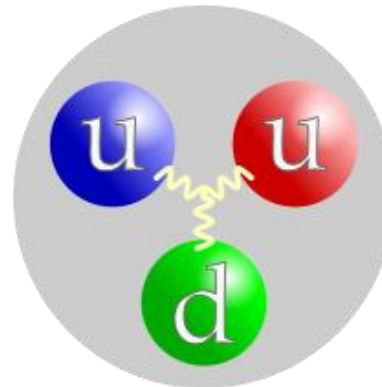
## Radiotherapy



Protons

Heavy ions

**HADRONS**



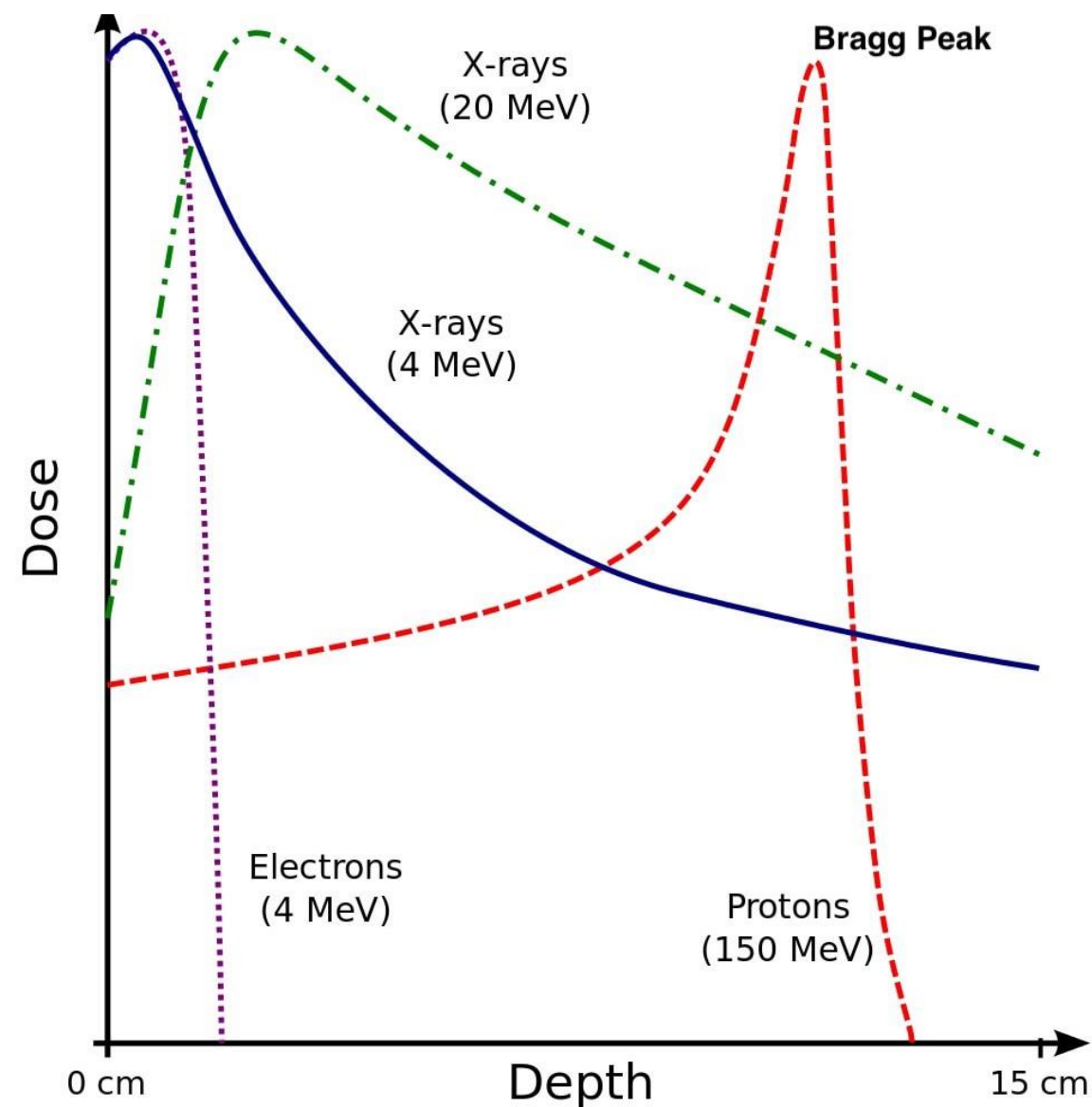
# Hadron therapy

A special version of radiotherapy



## Properties

- Radiation based cancer therapy.
- Using charged particles for more concentrated dose (compared to X-ray) - Bragg peak.
- Ambulant treatment.
- Current medical devices were not made for charged particles (protons in our case).
- Medical imaging needs to be fast to optimal treatment.



# pCT

## Medical Imaging, Proton Computed Tomography

## Why do we need imaging?

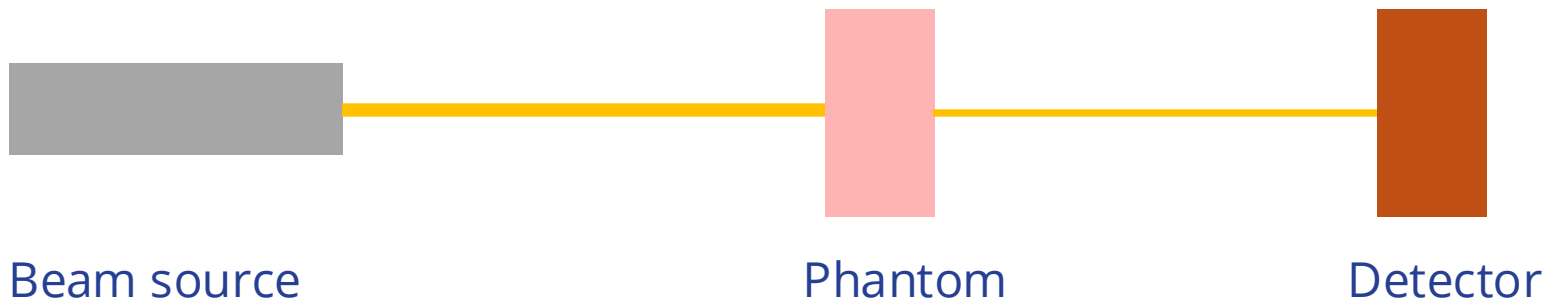
- Before the treatment, we need information of the patient's anatomy
- Contouring, dosage planning
- Currently: mostly (X-ray) CT imaging before the treatment
- Our goal: as accurate and fast imaging as possible (better imaging = better treatment)



Fun fact: to test imaging systems, we use so-called **phantoms**  
(this is a very advanced, Erler-Zimmer head phantom)

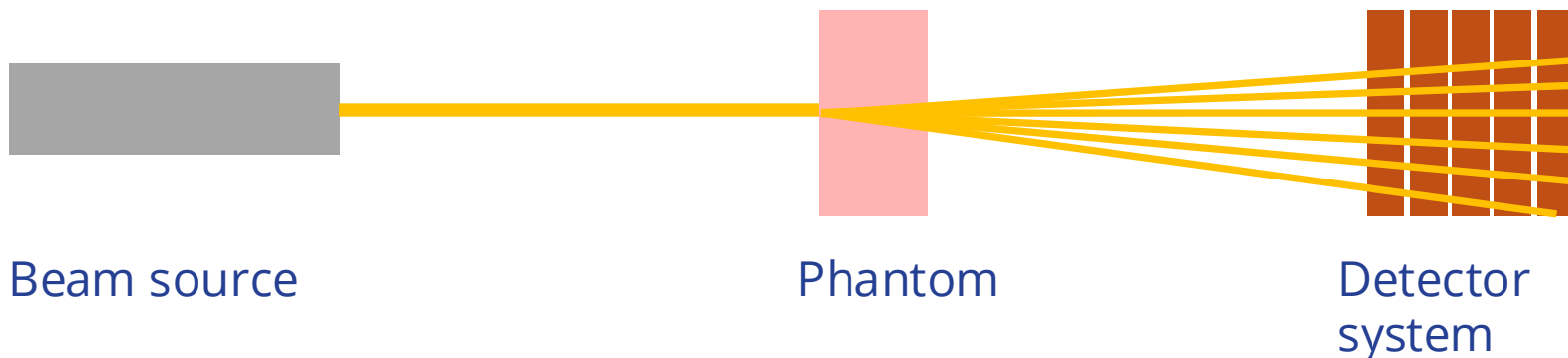
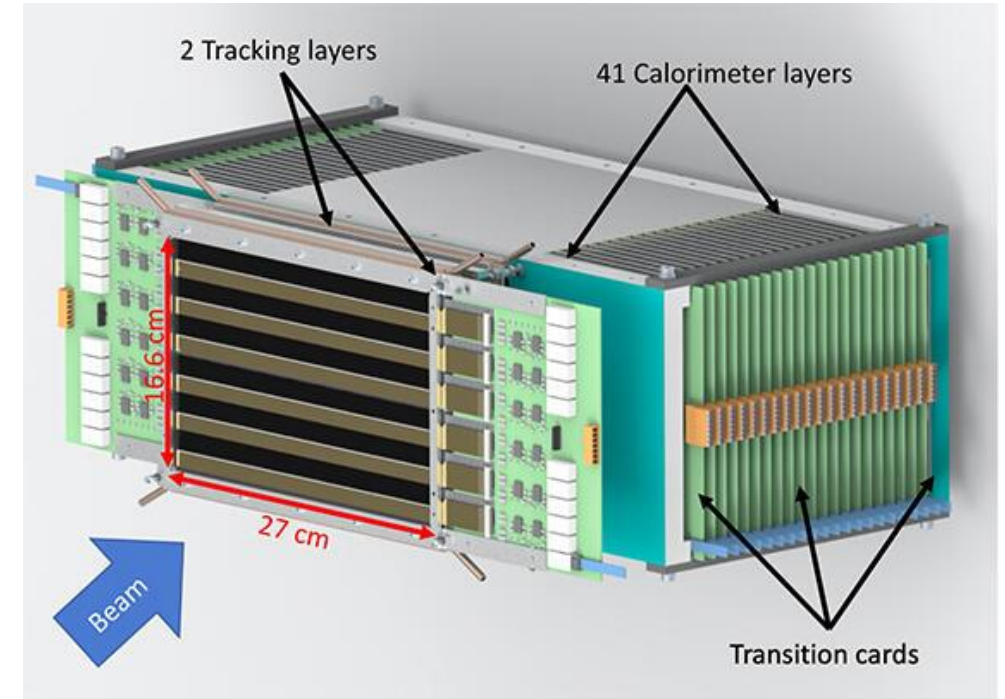
## Computed Tomography

- Rotating X-ray around the patient.
- Detector in the other side.
- Measuring incoming beam intensity.
- Not designed for protons.
- Can't calculate proton stopping power.

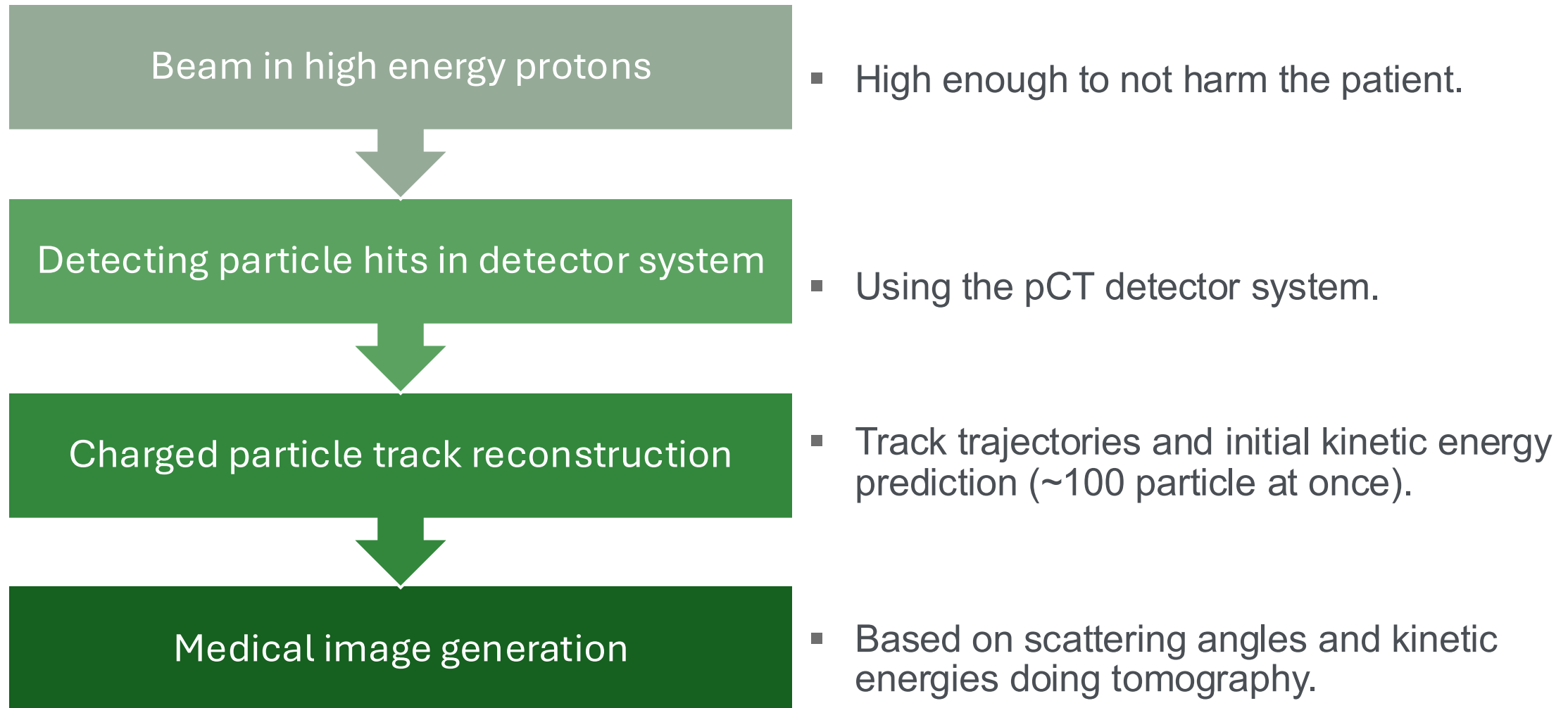


# Proton CT

- Beam in protons.
- High energy protons (not to hurt patient).
- Measure proton scattering (need more detector).
- Need to reconstruct particle trajectories.
- We can calculate scattering angles and energies.
- Rotating around detector system to have 3D image.



## Process of pCT



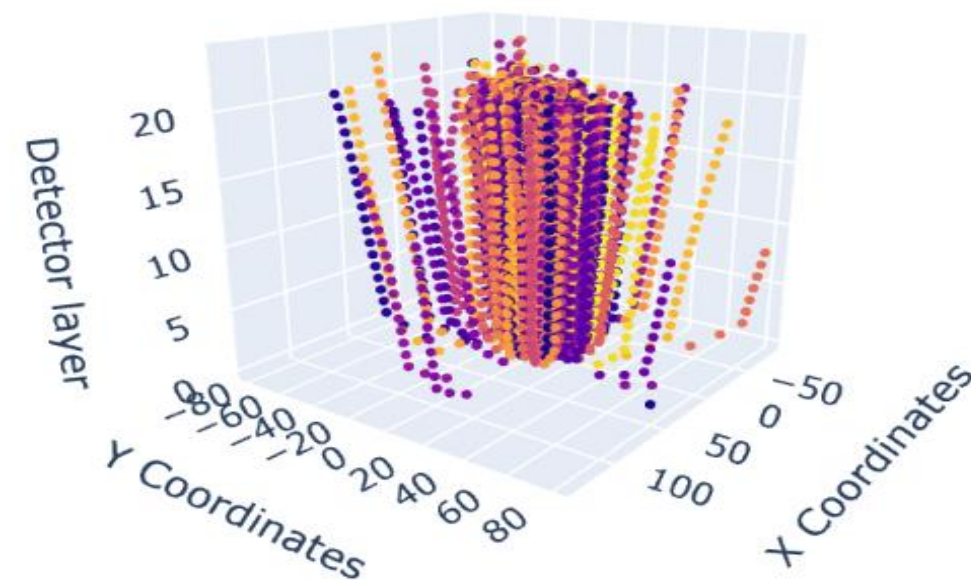


# Tracking

Reconstruction of particle paths

## Explain the problem

- Have to reconstruct particle path in detector system.
- There are a lot of particles very close to each other.
  - Hard to find based on distance.
- Particles can cross each others' path.
  - Crossing track can confuse algorithms.
- There are existing methods in HEP.
  - Too computational heavy/too slow.
- We have to process data quickly for medical imaging.



# Machine learning

Curing cancer with AI

## History

1955: John  
McCarthy  
„Artificial  
Intelligence”

1974-1980:  
AI winter

1998: Yann  
LeCunn  
Deep  
Learning

2022:  
OpenAI  
ChatGPT

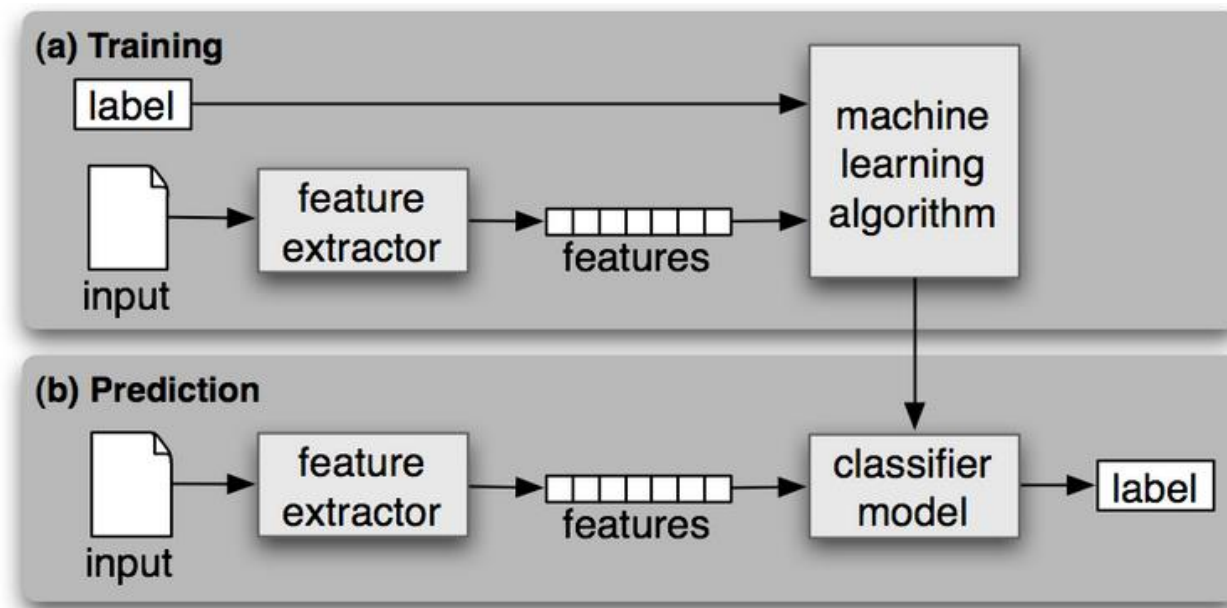
1958:  
Perceptron  
model

1986: Multi  
layer  
perceptron

2017:  
Attention Is  
All You Need

## Fundamentals

- There is a relation between some features and a target.
  - House prices, computer electricity consumption, etc...
- We can approximate it with a defined model.
  - Universal Approximation theory
- Model parameters are tuned.
  - Objective function.
  - Gradient descent etc.



## Why ML?

- What if we can't define this rule?
- Or it is too complicated to define?
- How to find differences?
- Machine learning is not about explicit rule definition.
  - It's about learning the rules that gives us the connection.

How to write a program that defines cats and dogs?



How to write a program as recognize all of this as car?





## Why we want it?

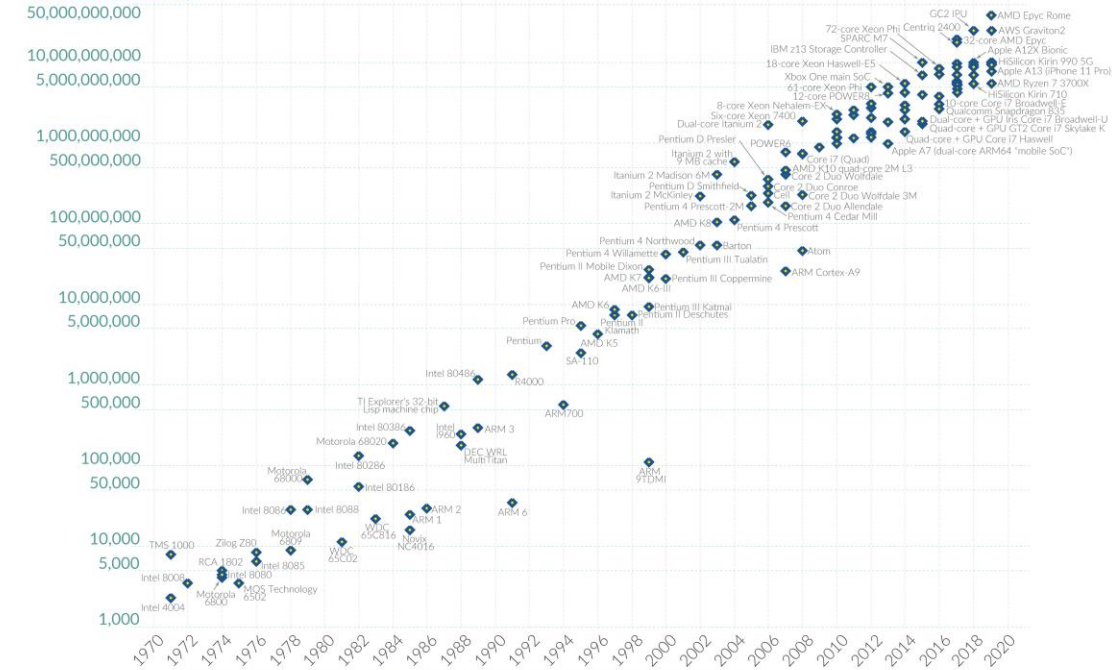
- By nature these evaluate fast.
  - GPU property.
  - Paralellized.
  - Needs to run in medical device.
- pCT medical imaging – iterative reconstruction methods can be used.
  - Can be sped up with ML.
- pCT tracking must be very fast.
  - Traditional particle track reconstruction is slow.
  - And we can't really define rules of matching.

**Moore's Law:** The number of transistors on microchips doubles every two years

Moore's law describes the empirical regularity that the number of transistors on integrated circuits doubles approximately every two years. This advancement is important for other aspects of technological progress in computing – such as processing speed or the price of computers.

Our World in Data

Transistor count



Data source: Wikipedia (wikipedia.org/wiki/Transistor\_count)  
OurWorldinData.org – Research and data to make progress against the world's largest problems. Licensed under CC-BY by the authors Hannah Ritchie and Max Roser.



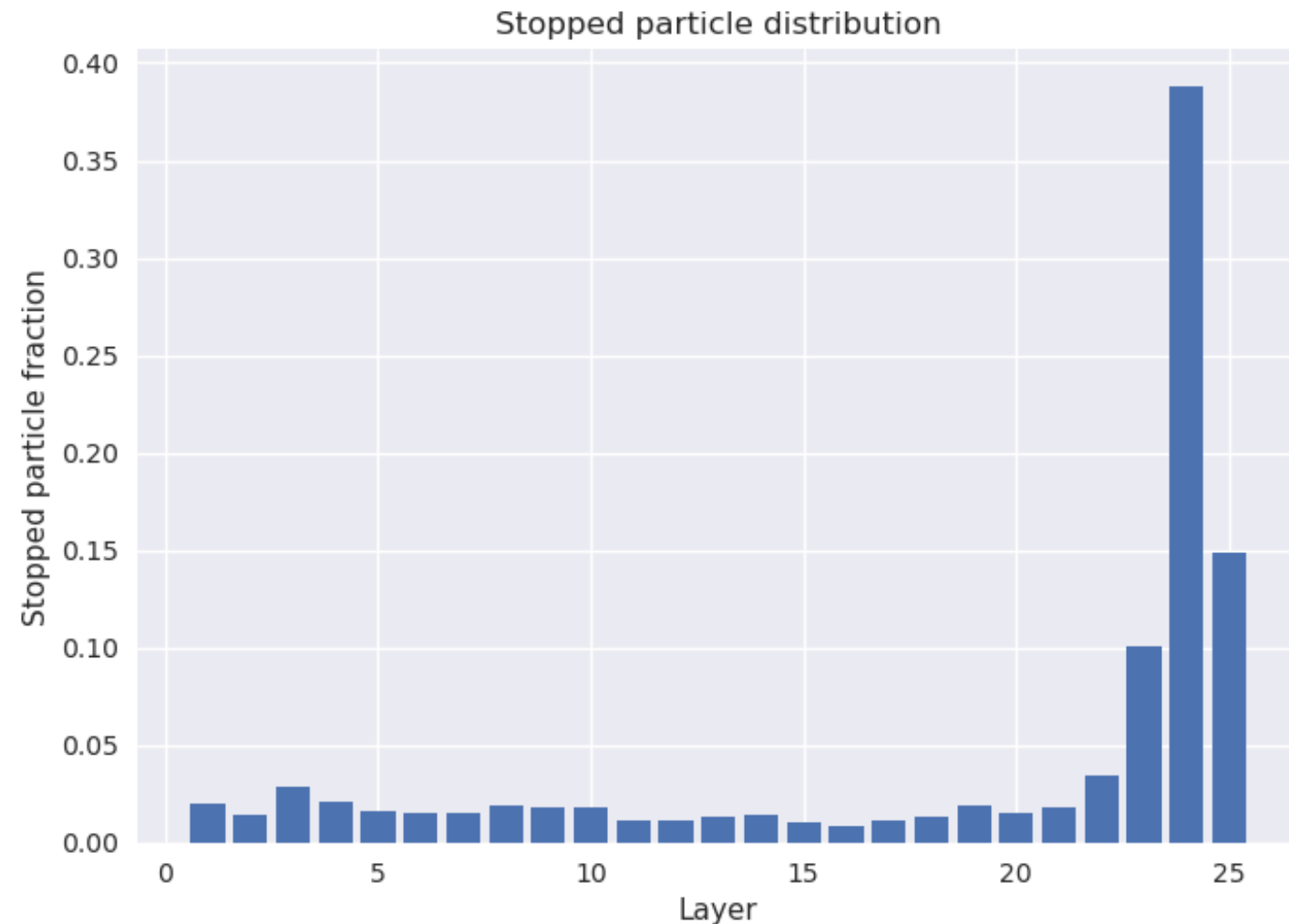
TECHPOWERUP

# Tracking - Energy prediction

This is the easiest part, can be done by simple machine learning algorithms

## Energy prediction

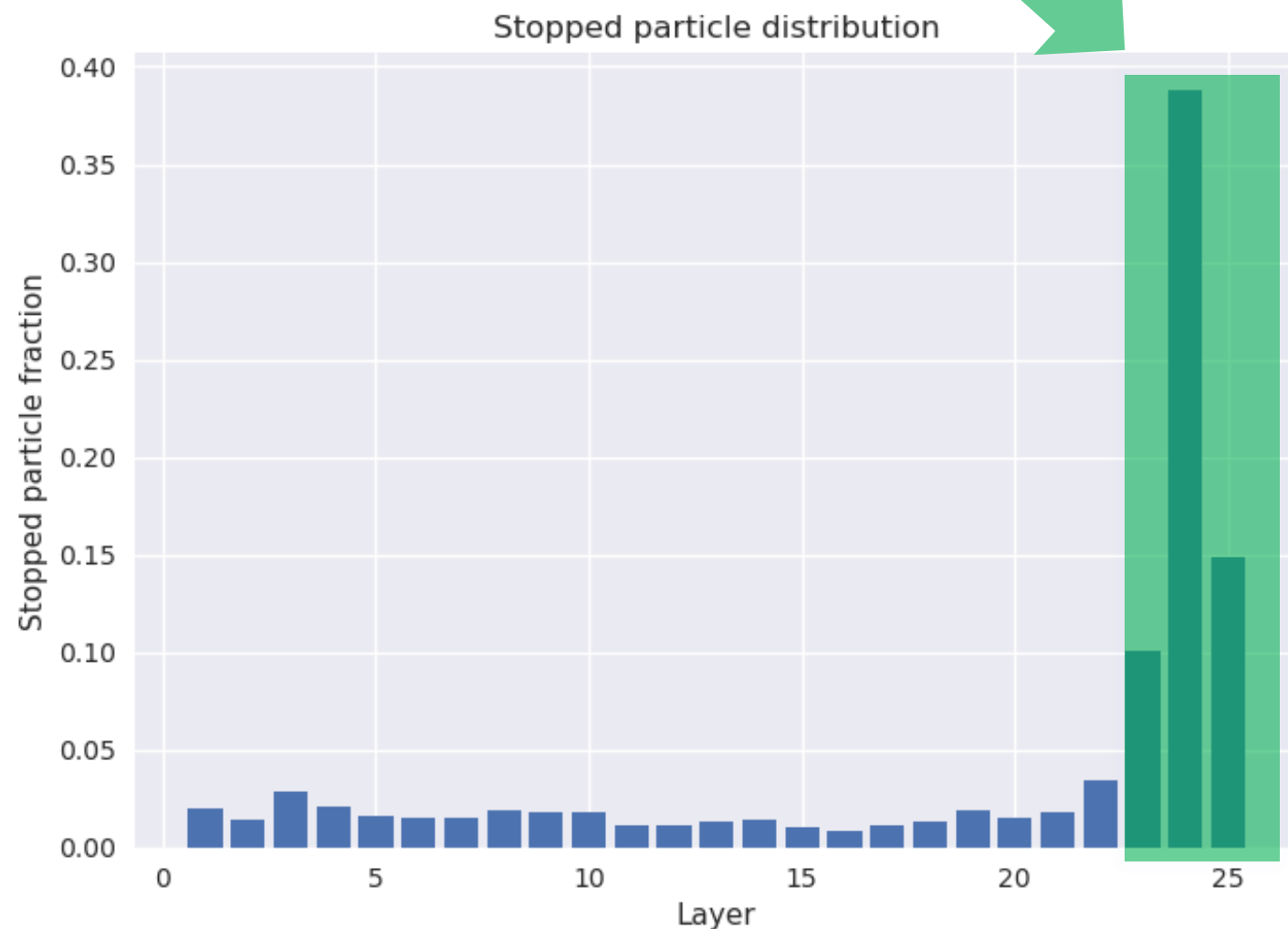
- Small neural network to approximate energies.
- Filter data around expected Bragg peak.
- In evaluation, we don't know expected.



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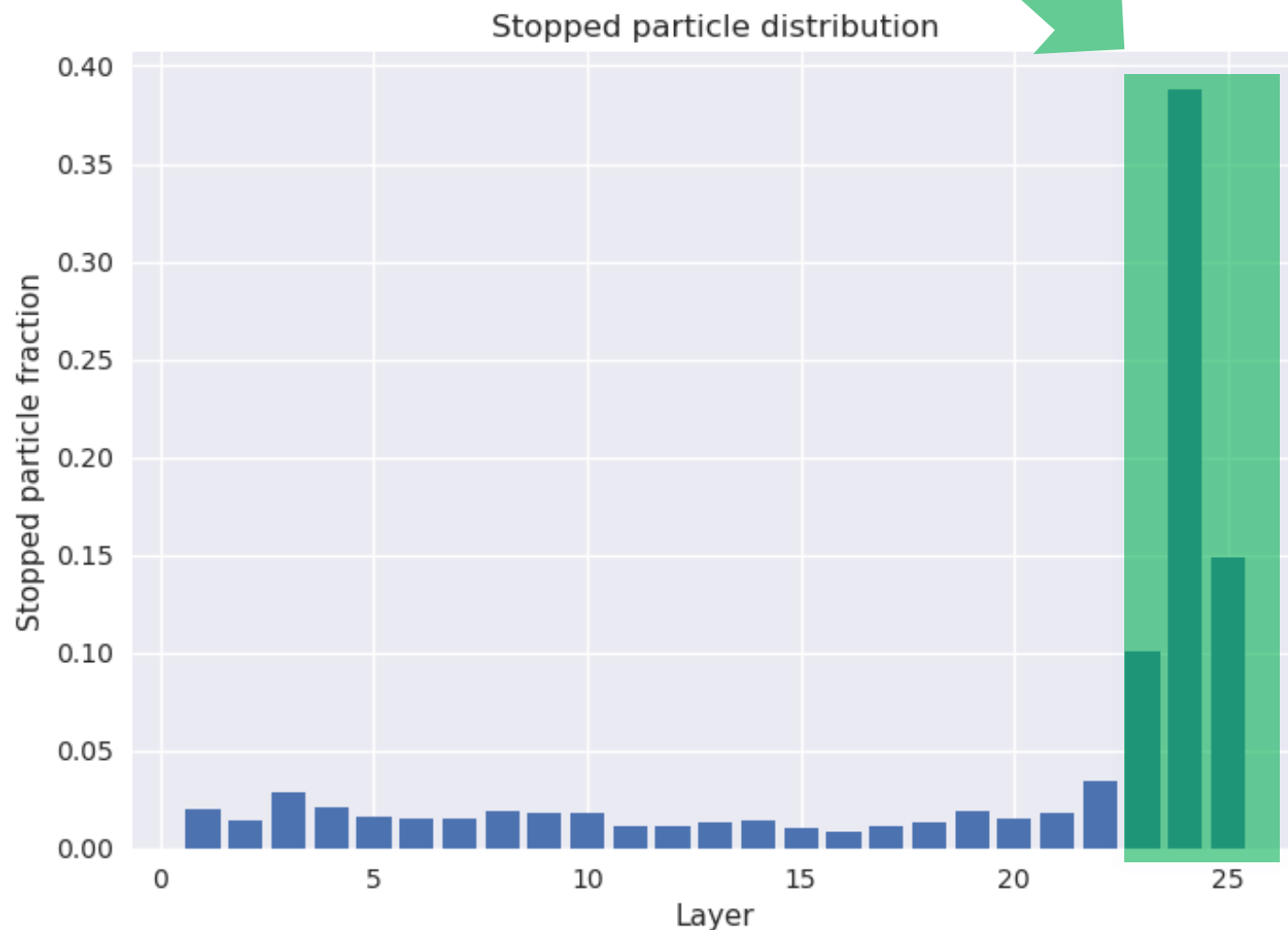
We want to work with these!



## Energy prediction

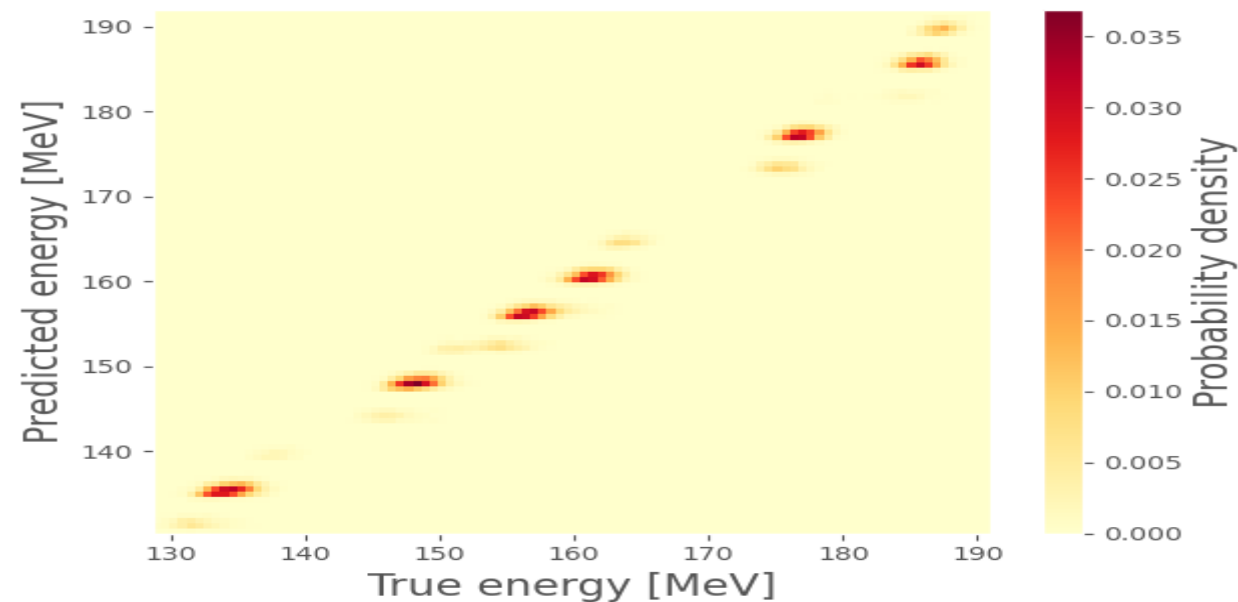
- Approximated from already reconstructed tracks.
- Last particle with not 0 energy.
- This will be our „expected Bragg peak”.
- Particles leaving the detector system are uniformly occurred everywhere.
- These usually make the prediction worse.
- With the maximum position we can make an assumption on the initial beam energy.

We want to work with these!

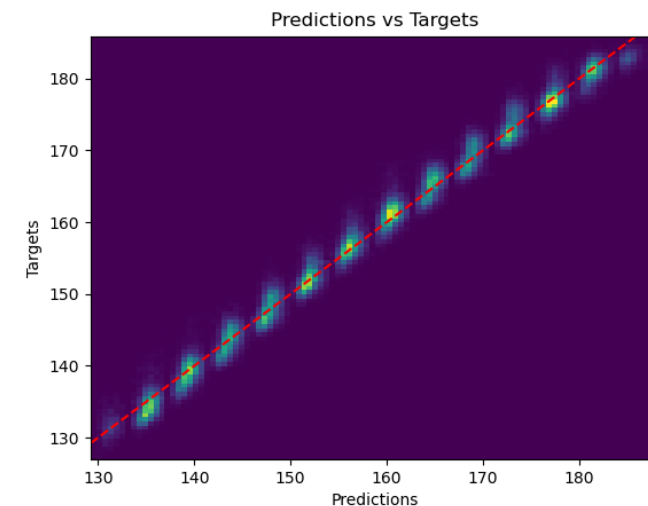
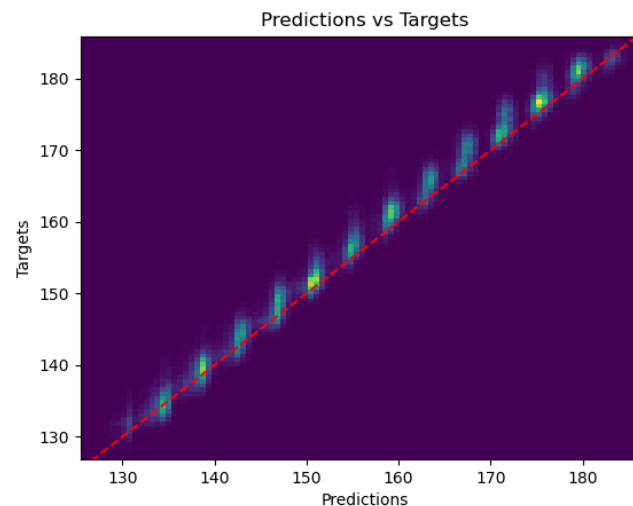


## Energy prediction

- Small neural network to approximate energies.
  - Originally linear regression was very close.
  - Deep neural nets slightly better.
  - Possible to merge NN with other subtasks.
- Input of the model is:
 
$$\hat{X} = (L_B, E_{B-1}/E_B, E_{b+1}/E_B)$$
- Where  $E_B$  is the energy deposition on the „expected” Bragg peak,  $L_B$  the normalized position of the Bragg peak.
  - Some embedding might improve.
  - But currently this is enough for reconstruction.



[M. Aehle et al, Reconstruction of proton relative stopping power with a granular calorimeter detector model]

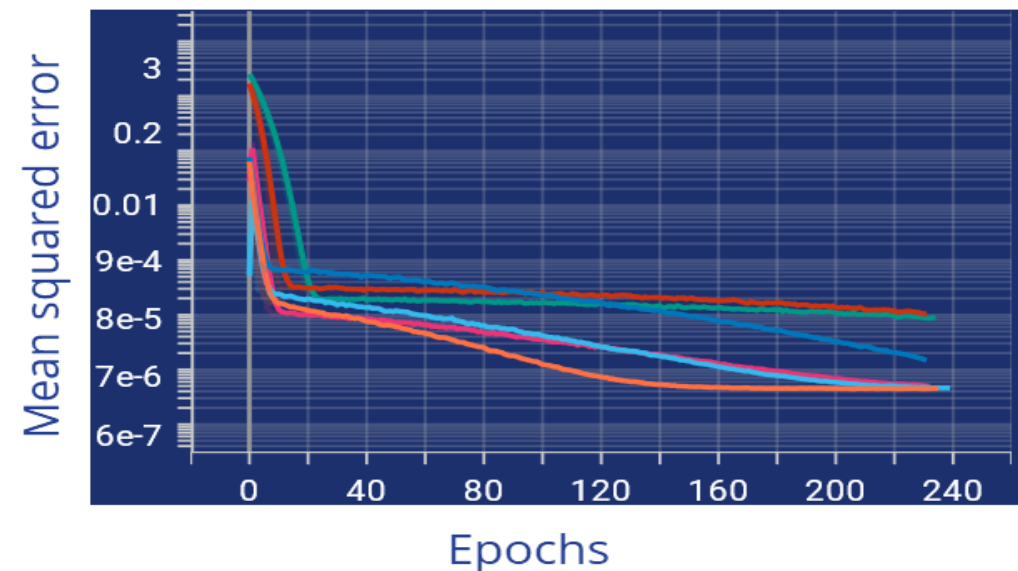




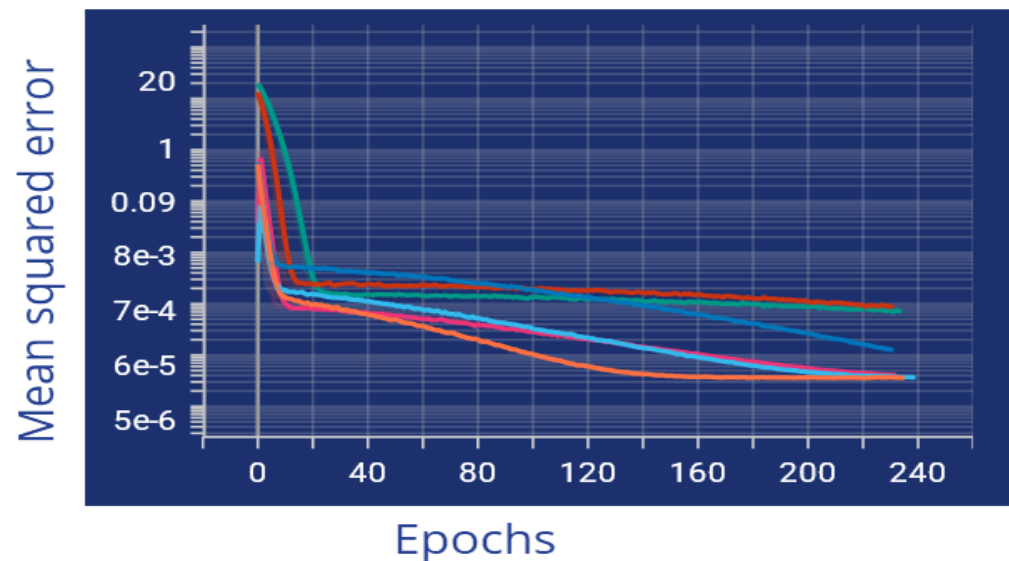
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  - Some embedding might improve.
  - But currently this is enough for reconstruction.
- We obtain around 1MeV precision.
- Colors indicate hyperparameter configs

Training loss of different runs



Validation loss of different runs

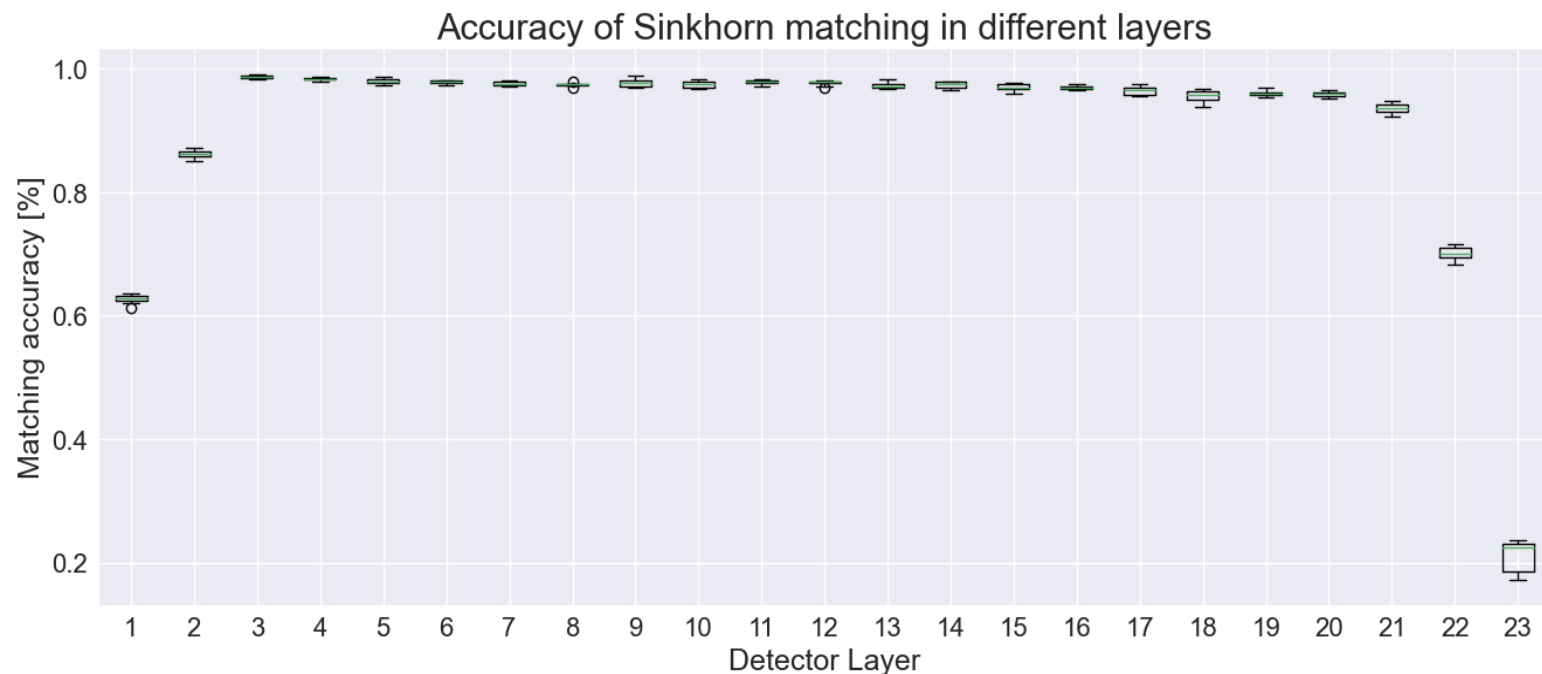


# Tracking – Particle matching

I have 2 proposed system for particle trajectory reconstruction. One is to help traditional algorithms, one is to replace them

## Particle matching

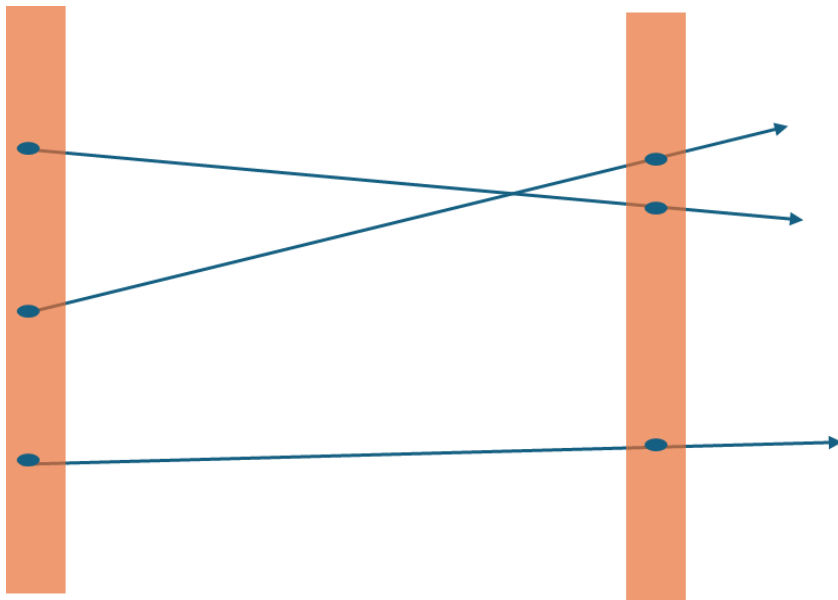
- Need match particles to recreate trajectories.
- Matching in the calorimetric layers is very efficient.
  - For technical reasons we pad the trajectories.
  - This leads to small accuracy later.
  - This can be filtered in track reconstruction.
- We have 2 approaches to this problem.
  - Position correction.
  - Matching Neural Network.



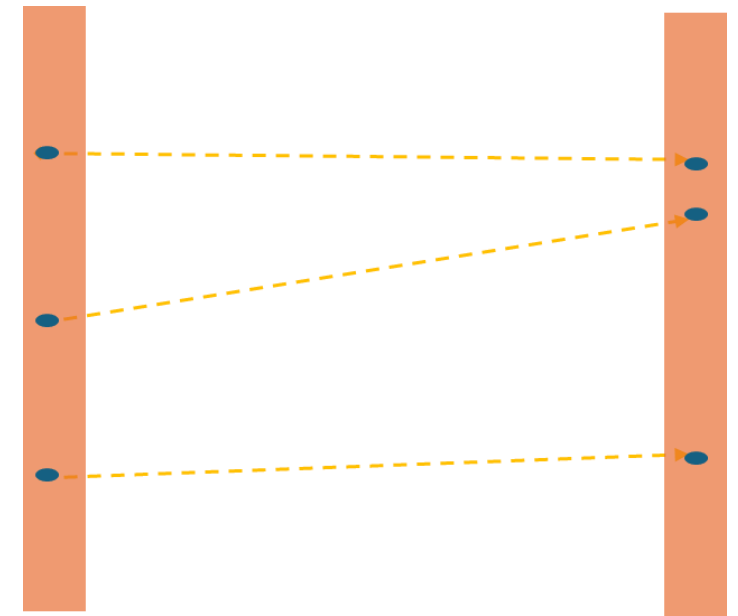
- Closest particle matching around: 54%
- Sinkhorn matching is around: 65%
- The whole track reconstruction is even worse.

## Position projection

- Scattering and path crossing is very common.
- Distance based algorithms can't correct this.
- We created a neural network that predicts expected position.



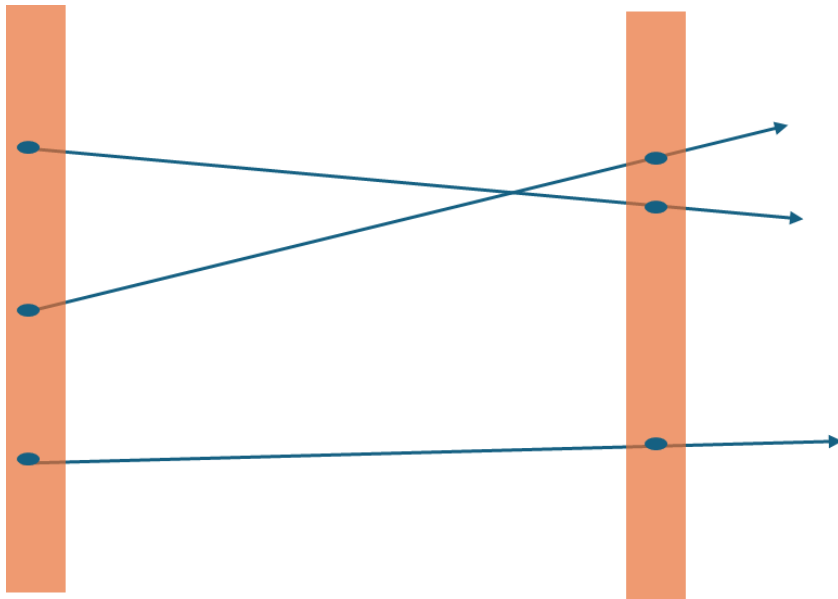
Real trajectories



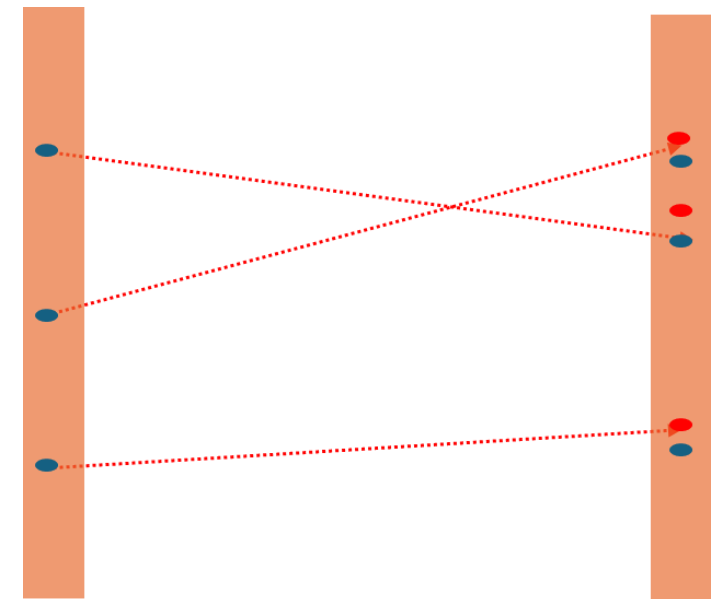
Reconstructed

## Position projection

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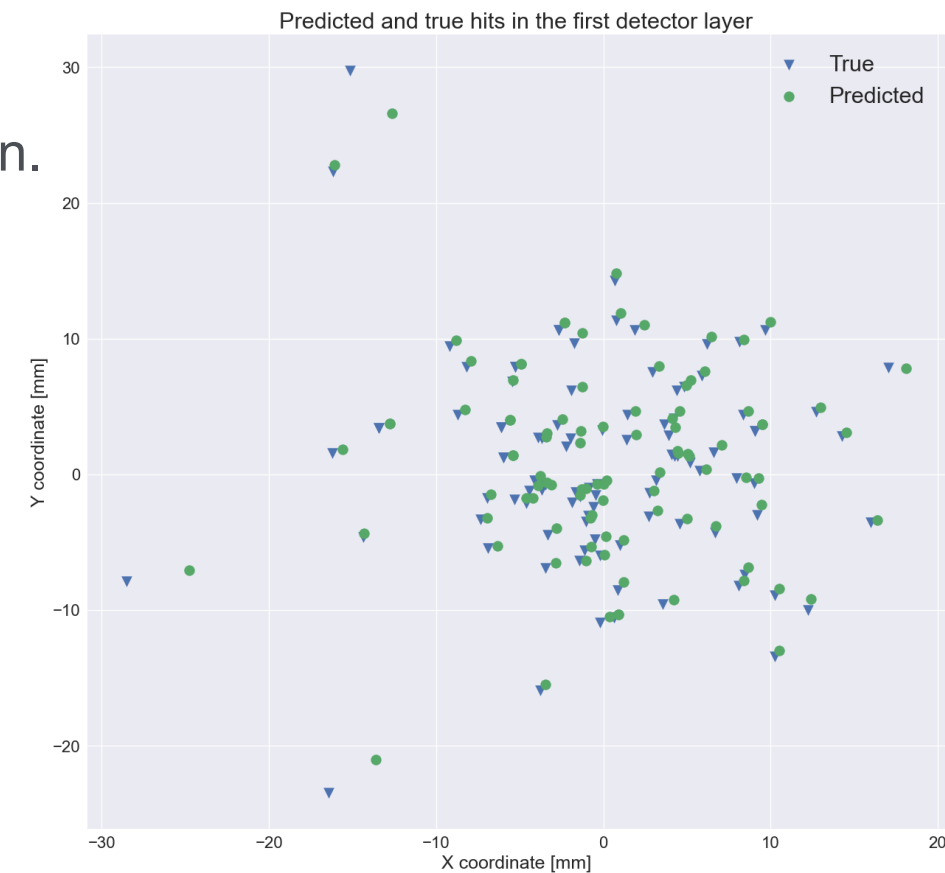
Real trajectories



Expected positions

## Position projection

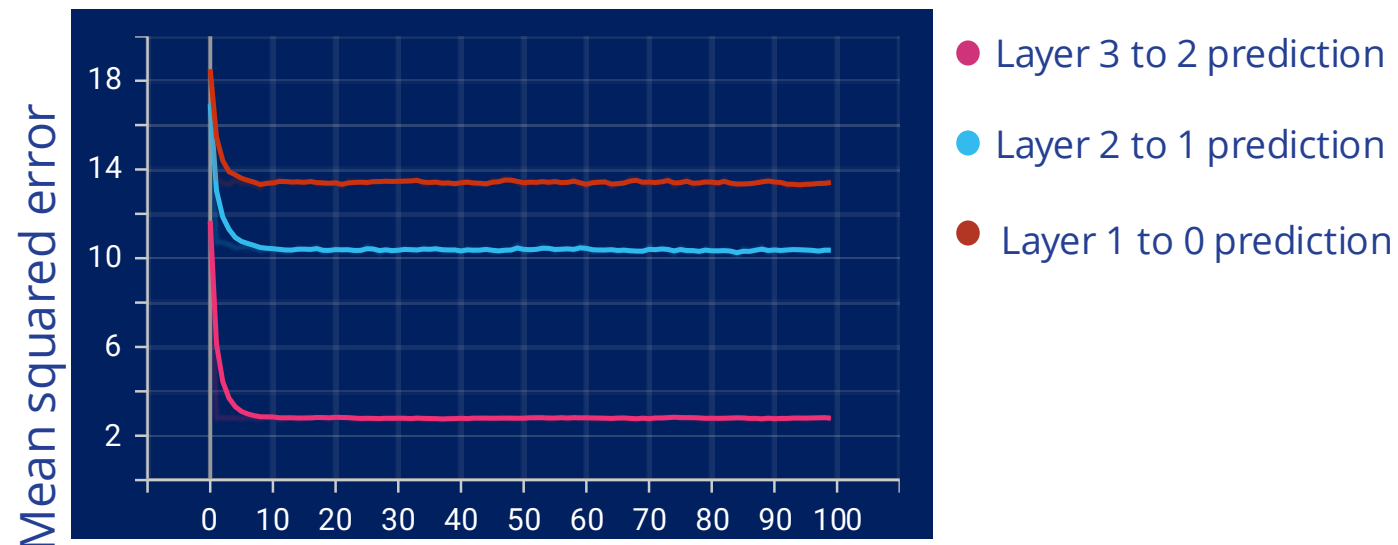
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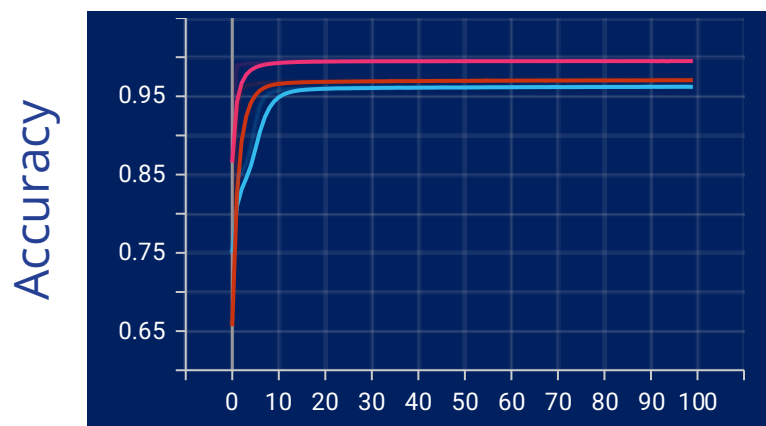
## Position projection

- We start from the end of the detector system.
  - Few particles, that are very easy to match.
  - In calorimetric layers we can do very good matching.
- Based on previous position we predict an expected position.
- We want to match expected position with the real one.
- One-one model for the first 3 layers.

Training loss for position prediction

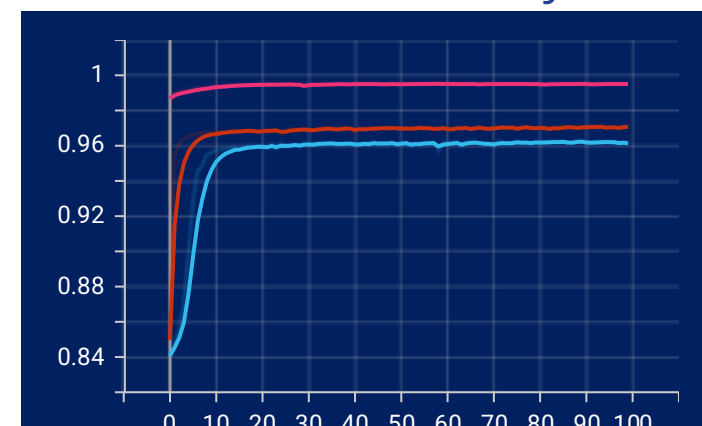


Training accuracy



Epochs

Validation accuracy



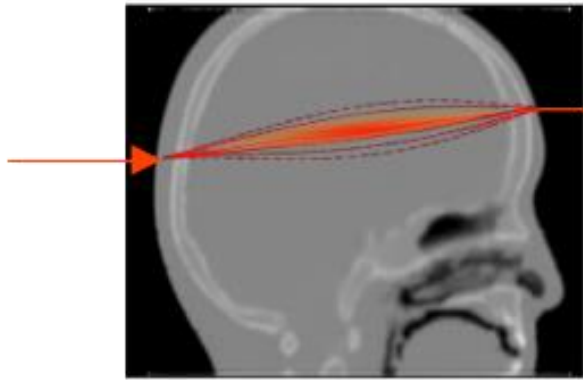
Epochs



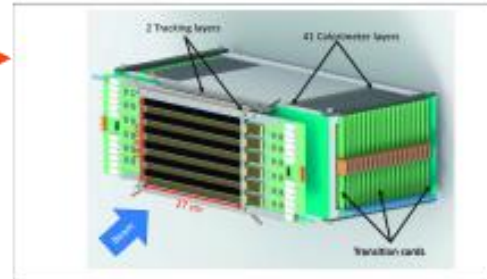
# Image Reconstruction

We already developed an algorithm that can reconstruct Relative Stopping Power maps. We are currently developing an AI based system, for more accuracy and less computational time.

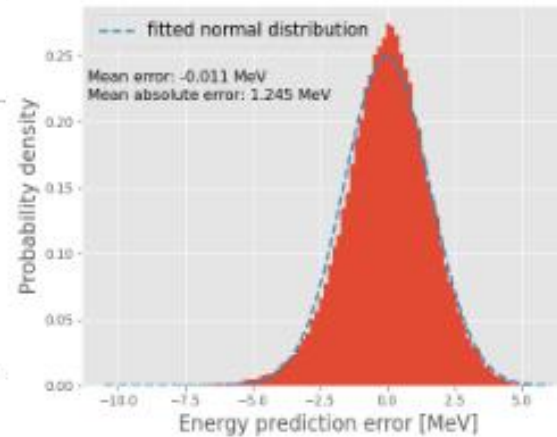
## Recall - how did we get the picture?



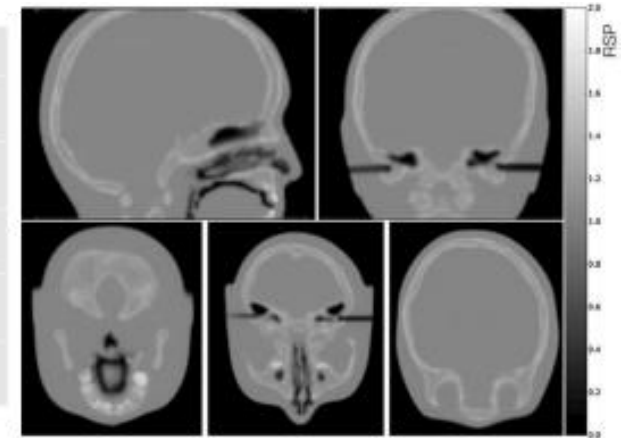
Irradiating phantom with high energy ( $\sim 100$  MeV) protons



Detector system senses the signals



Processing the signals (reconstructing trajectories from hits + predicting energies)



Reconstructing the image (some kind of image reconstruction algorithm needed)

## Image reconstruction methods

Integral transformations (Radon, Inverse Radon)

- Easy, but cannot be used for protons

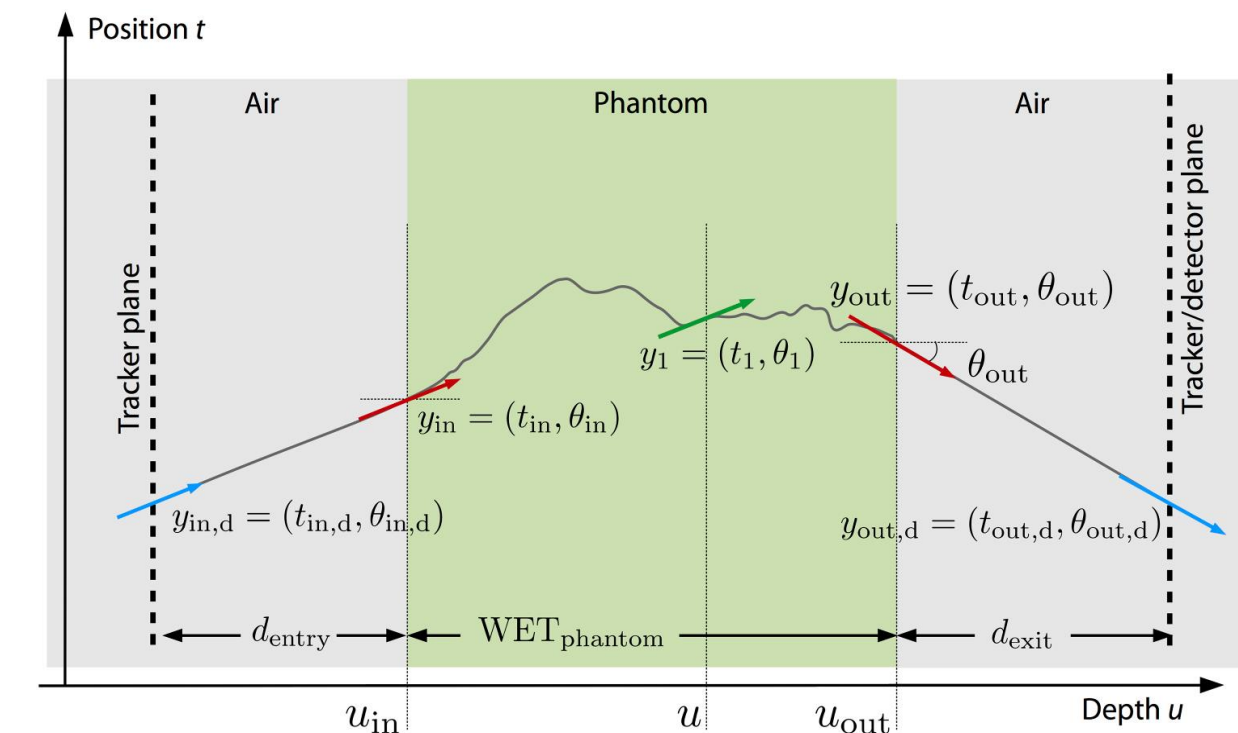
Iterative reconstruction methods

- Solving a linear equation system

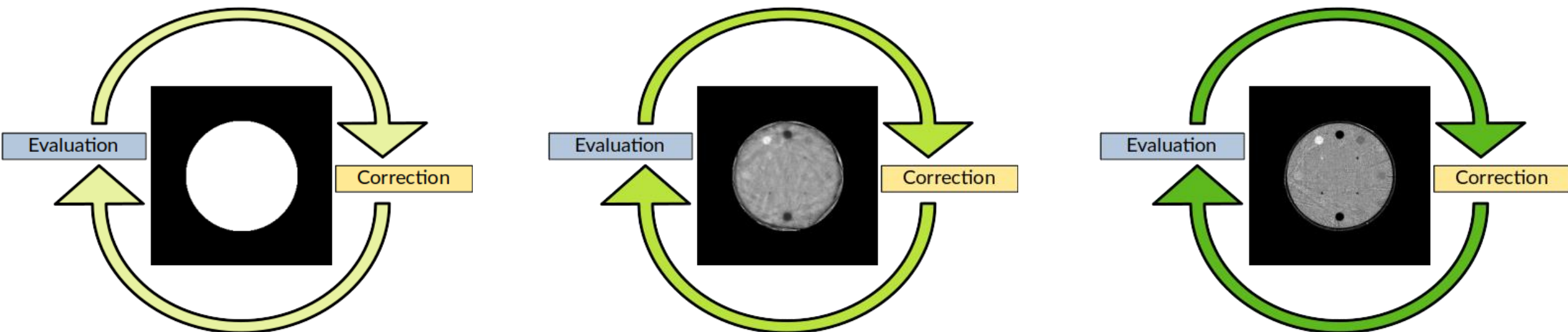
$$\mathbf{A} \times \mathbf{x} = \mathbf{y}$$

Matrix containing interaction coefficients between protons and pixels

Estimated Relative Stopping Power values



## Iterative reconstruction techniques



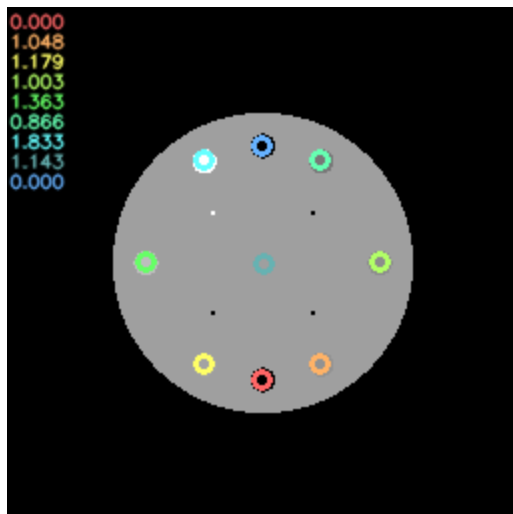
Currently being developed and used: Richardson-Lucy algorithm

- Originally used in optics, not for medical imaging
- Technical challenge (~millions of proton trajectories)
- Currently sped up with GPU, but there is room for further improvement (AI)

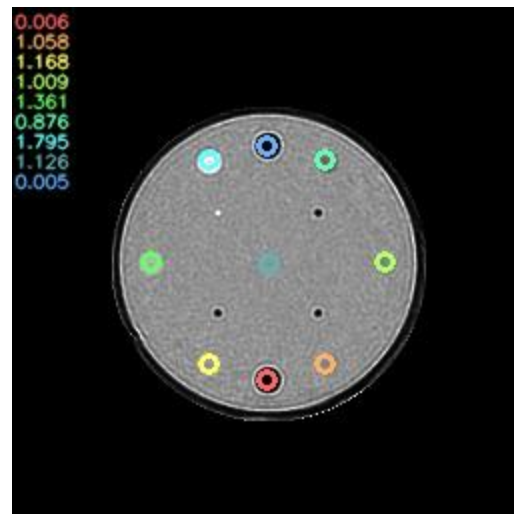
## Some of our latest results

CTP404 phantom:

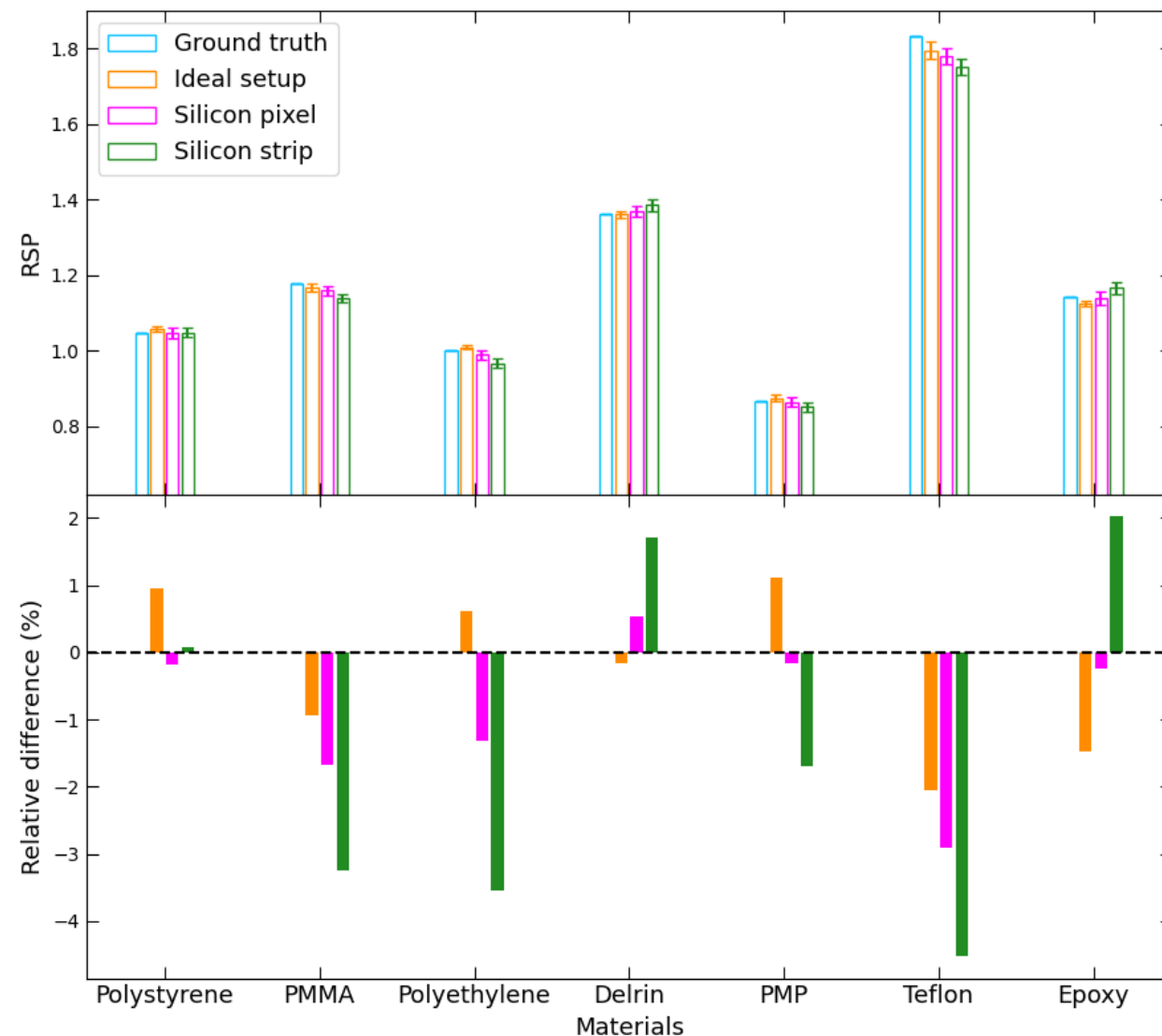
- Used for testing proton RSP reconstruction accuracy (basically density reconstruction)
- Has 8 inserts made of materials with different density
- 3 different setups tested, ~4% relative difference achieved between ground truth and reconstructed values



"Ground truth" image



Reconstructed image



## Proton Computed Tomography

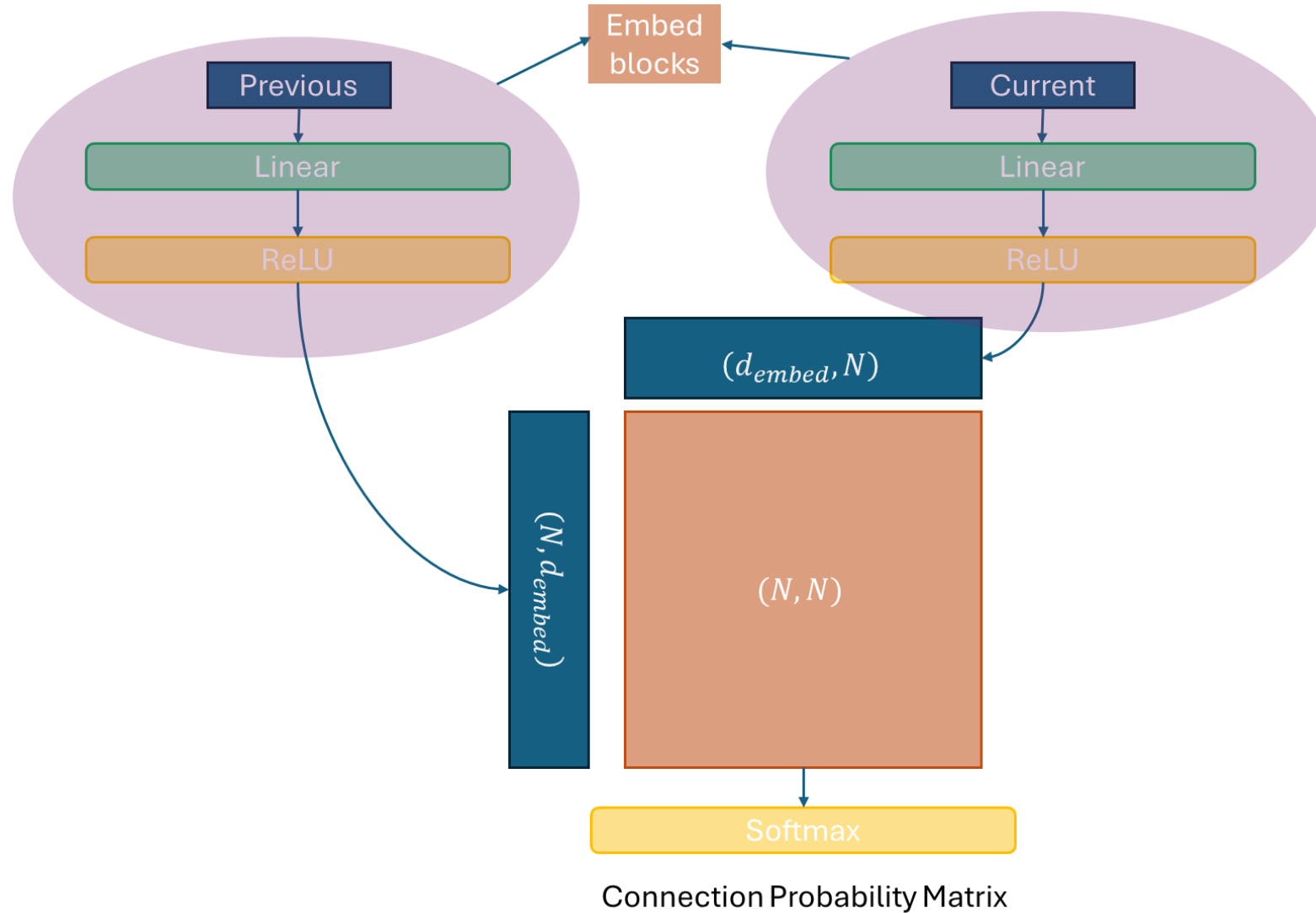
- Hadron therapy is an outstanding way to treat cancer...
- But it requires very specific imaging.
- Proton Computed Tomography is a promising method.
- Machine learning could be implemented at many parts of the imaging process.
  - Charged particle tracking in pCT detector system.
  - Medical image generation.

Thank you for your attention!

# Backup

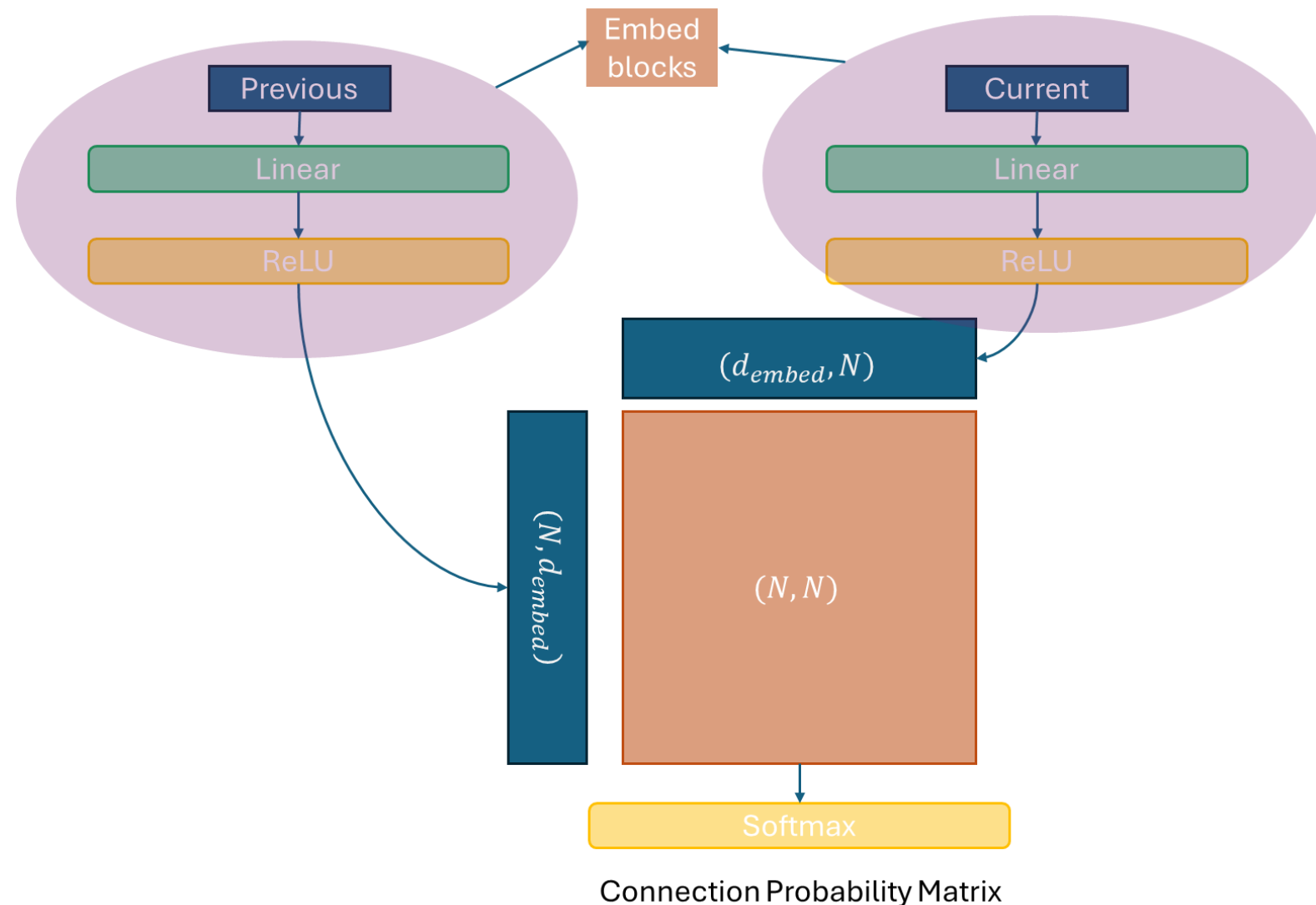


# Deep particle matching



# Deep particle matching

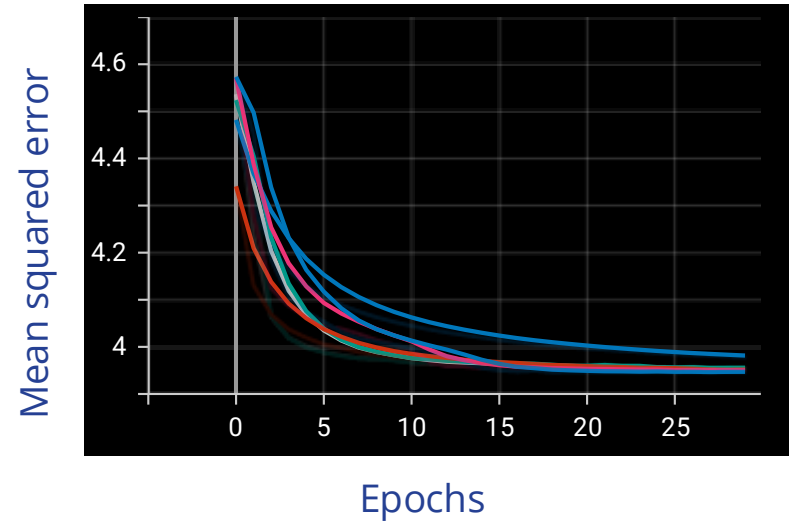
- Normalize input before giving it to the model.
- Creating a high dimensionel embeddig from input.
- Shallow linear block don't break normalization.
- Multiply them with each other.
  - The closer they are the bigger the matrix element value.
  - Similar to attention.



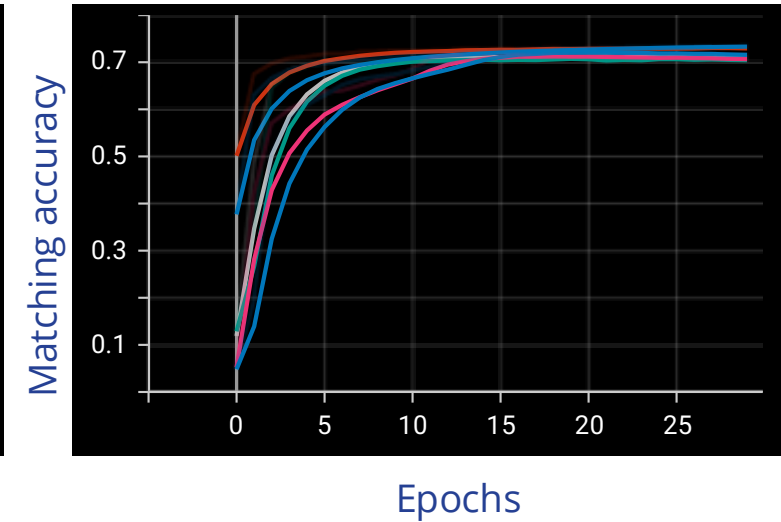
# Deep particle matching

- Connection between two detector layer hits.
- Deep neural nets evaluate quick.
- Currently overperforms every traditional algorithm.
  - 72% compared to 65%
- Colors indicate different hyperparameters.
  - As you can see end up with very similar results.

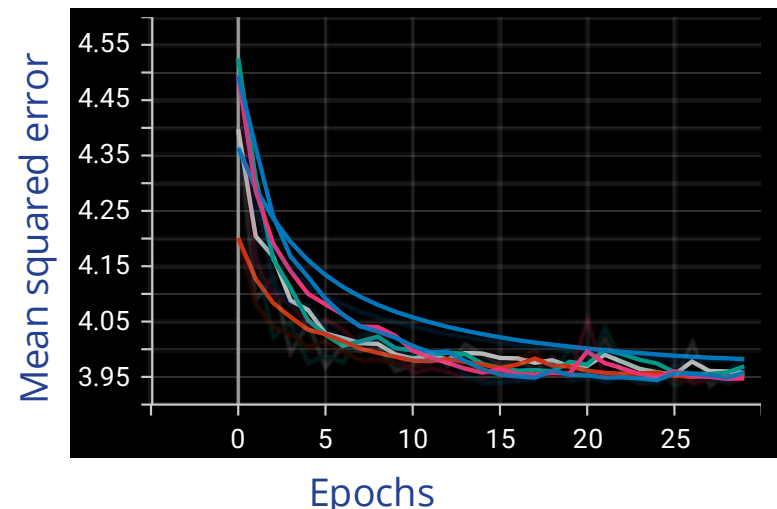
Training loss of different runs



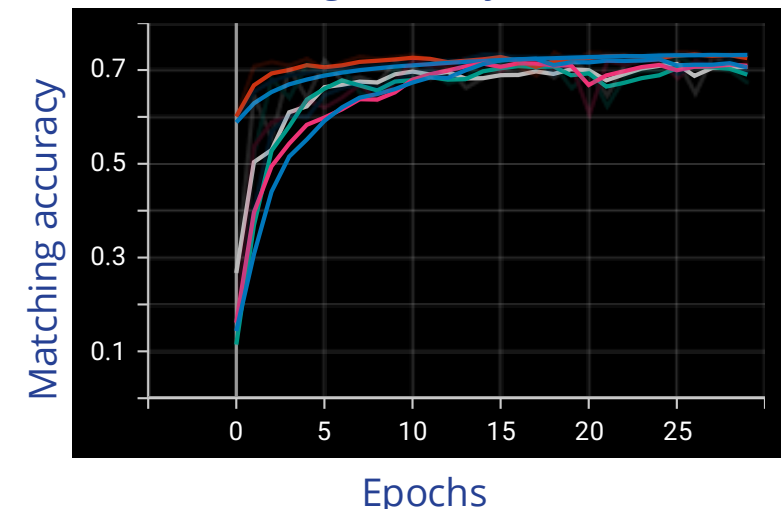
Matching accuracy on training



Validation loss of different runs

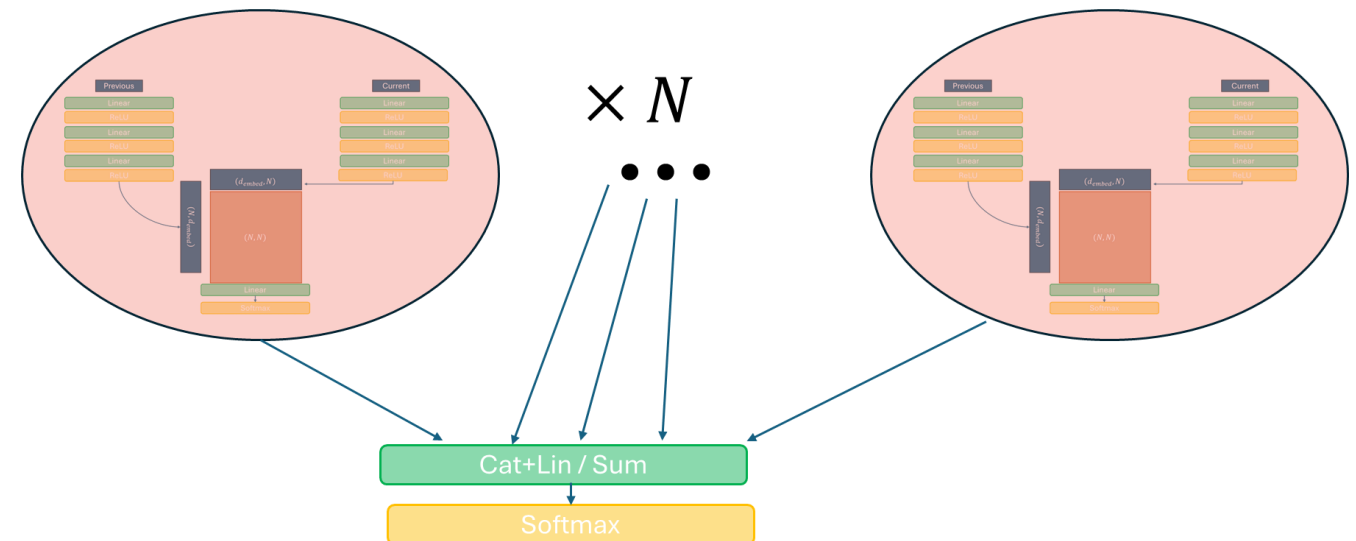
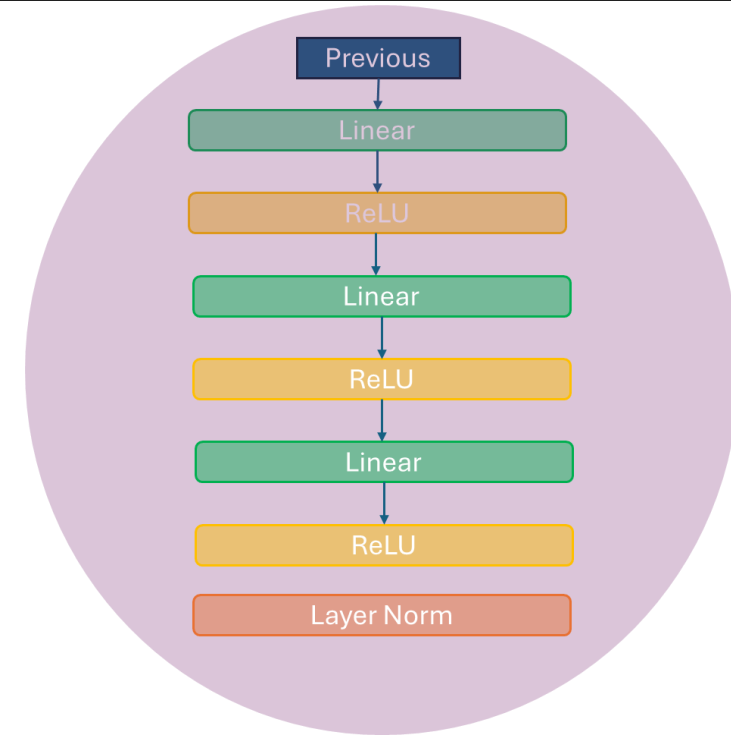


Matching accuracy in validation

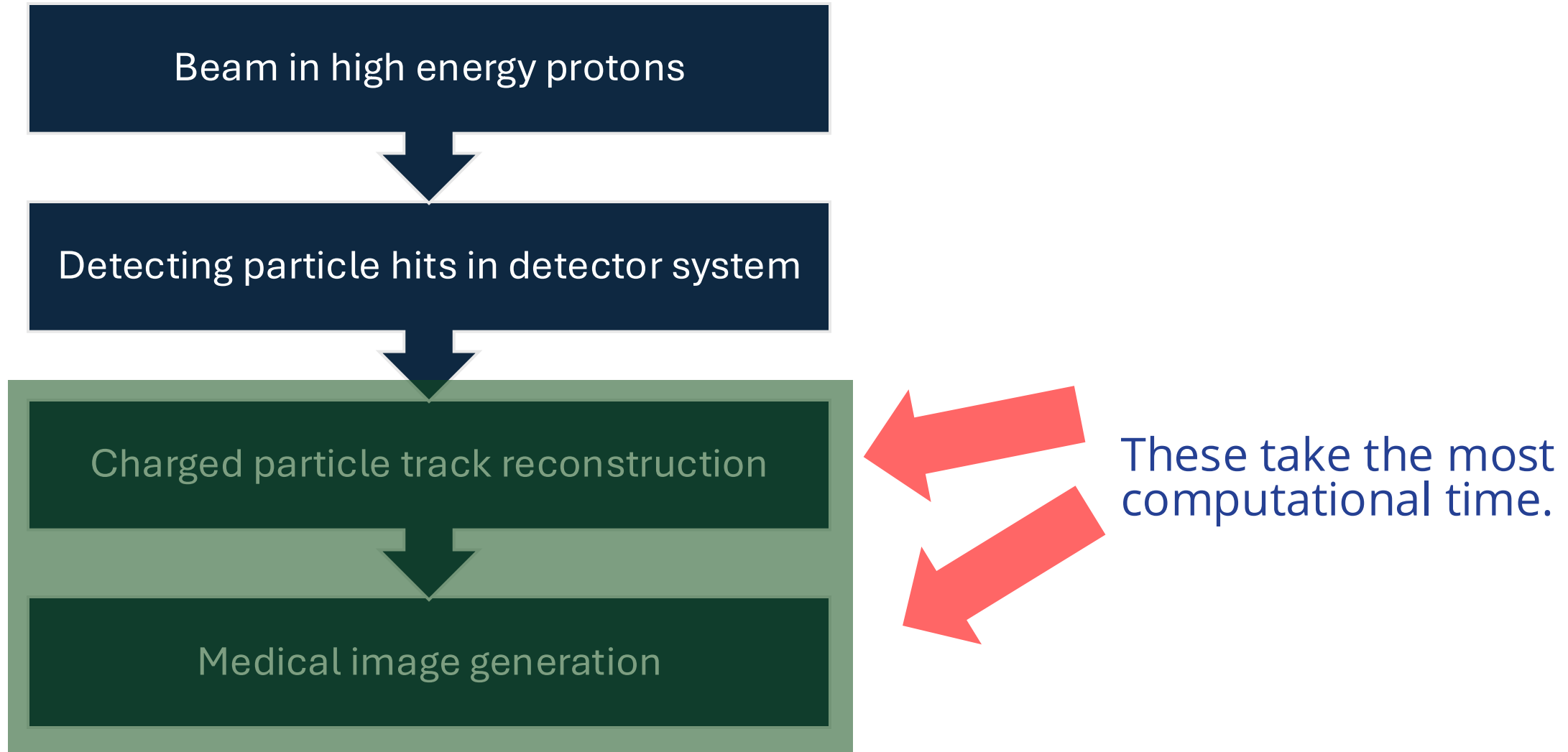


# Possible improvements

- Multi head attention doesn't show improvement.
- Trying to add multiple normalization step to enforce 1-1 matching.
  - The problem is that the gradients are vanishing.
- Deeper embedding blocks are not making improvement.
- Plans to do position projection in latent dimension and apply match block there.



# Process of pCT



# Process of pCT

Beam in high energy protons



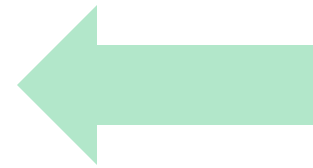
Detecting particle hits in detector system



Charged particle track reconstruction



Medical image generation



I concentrate on this.

