Machine Learning for Proton Computed Tomography

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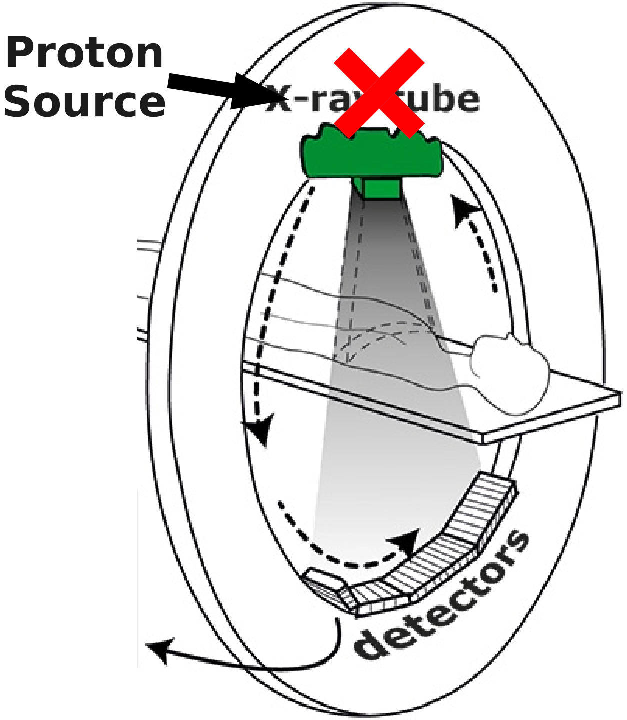
What is pCT…

- Proton Computed Tomography
- Relatively old concept (~1960's)
- Same concept as 'usual' x-ray scanning (xCT)
- Photons → Protons



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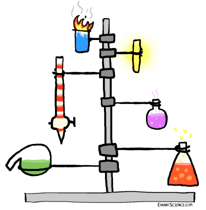
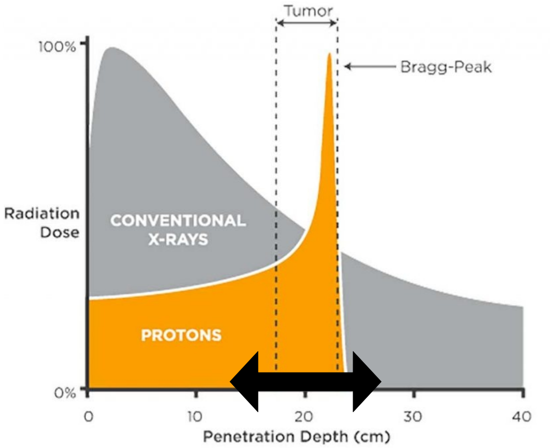
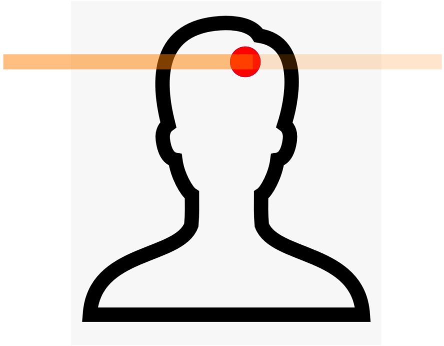
...and why should we care?



- Proton Beam Therapy
- Protons deposit energy in a tight peak, unlike photons (x-rays)
- Relies on lining up the Bragg peek
- Calibration depends on material → RSP map



- Currently measured with x-ray CT
- But introduces an unavoidable minimum error
- pCT measures the RSP directly



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But what's the catch?

- Protons scatter much more than photons
- Mostly small angle MCS
- Paths as straight lines → poor resolution
- But with modern computing, we can do track by track path estimation

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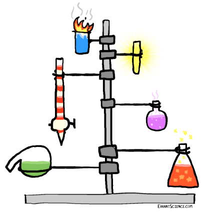
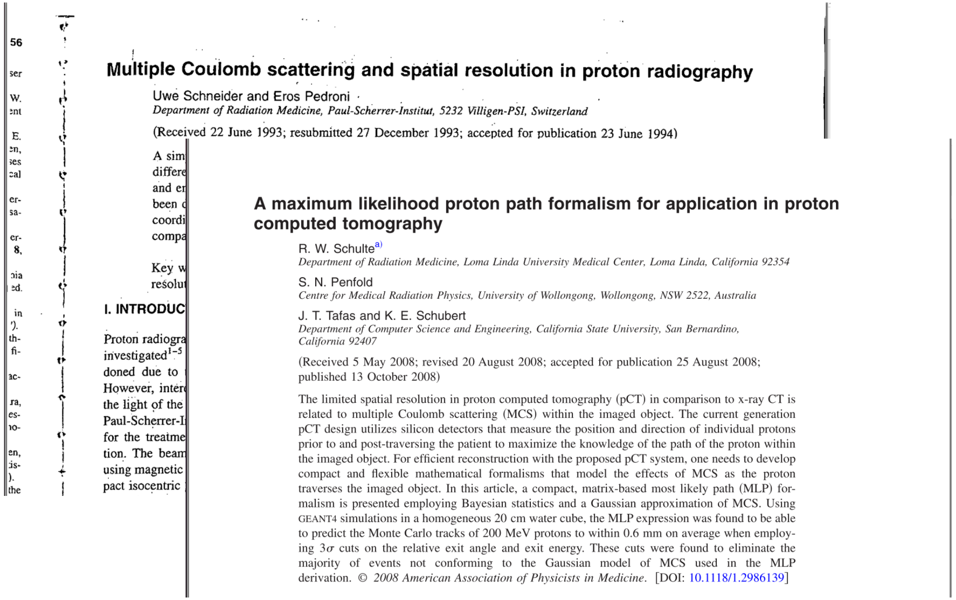
Current methodology



- MLP – ‘Most Likely Path’
- Most statistically precise prediction
- Based on MCS; uses cuts to reduce non MCS interactions

Recent work:

- Faster approximations
- Improved forms for Inhomogeneous media



Multiple Coulomb scattering and spatial resolution in proton radiography

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(Received 22 June 1993; resubmitted 27 December 1993; accepted for publication 23 June 1994)

A maximum likelihood proton path formalism for application in proton computed tomography

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The limited spatial resolution in proton computed tomography (pCT) in comparison to x-ray CT is related to multiple Coulomb scattering (MCS) within the imaged object. The current generation pCT design utilizes silicon detectors that measure the position and direction of individual protons prior to and post-traversing the patient to maximize the knowledge of the path of the proton within the imaged object. For efficient reconstruction with the proposed pCT system, one needs to develop compact and flexible mathematical formalisms that model the effects of MCS as the proton traverses the imaged object. In this article, a compact, matrix-based most likely path (MLP) formalism is presented employing Bayesian statistics and a Gaussian approximation of MCS. Using GEANT4 simulations in a homogeneous 20 cm water cube, the MLP expression was found to be able to predict the Monte Carlo tracks of 200 MeV protons to within 0.6 mm on average when employing 3σ cuts on the relative exit angle and exit energy. These cuts were found to eliminate the majority of events not conforming to the Gaussian model of MCS used in the MLP derivation. © *2008 American Association of Physicists in Medicine.* [DOI: 10.1118/1.2986139]

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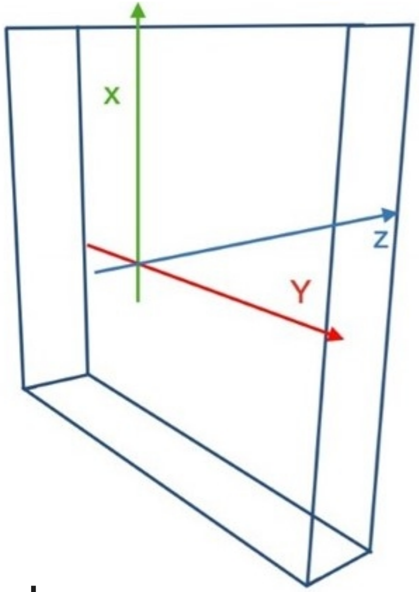
Monte Carlo

- 200MeV Protons
- Discarded partial tracks
- >800’000 tracks per dataset
- Recorded at 1mm intervals



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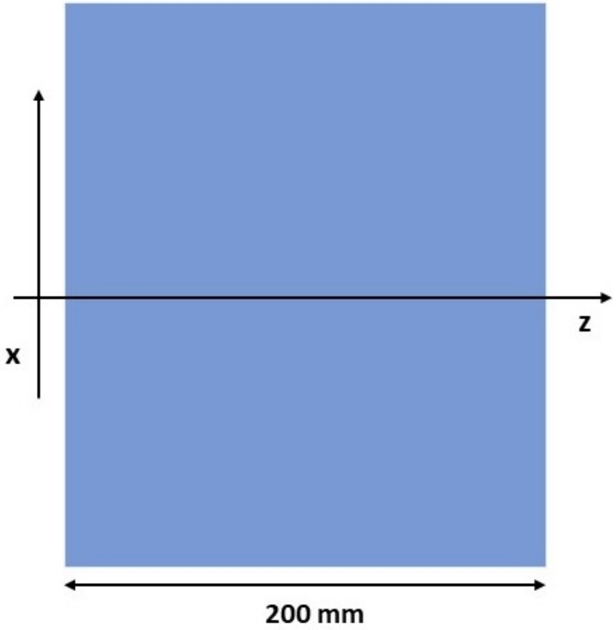

(b)

www.opengatecollaboration.org
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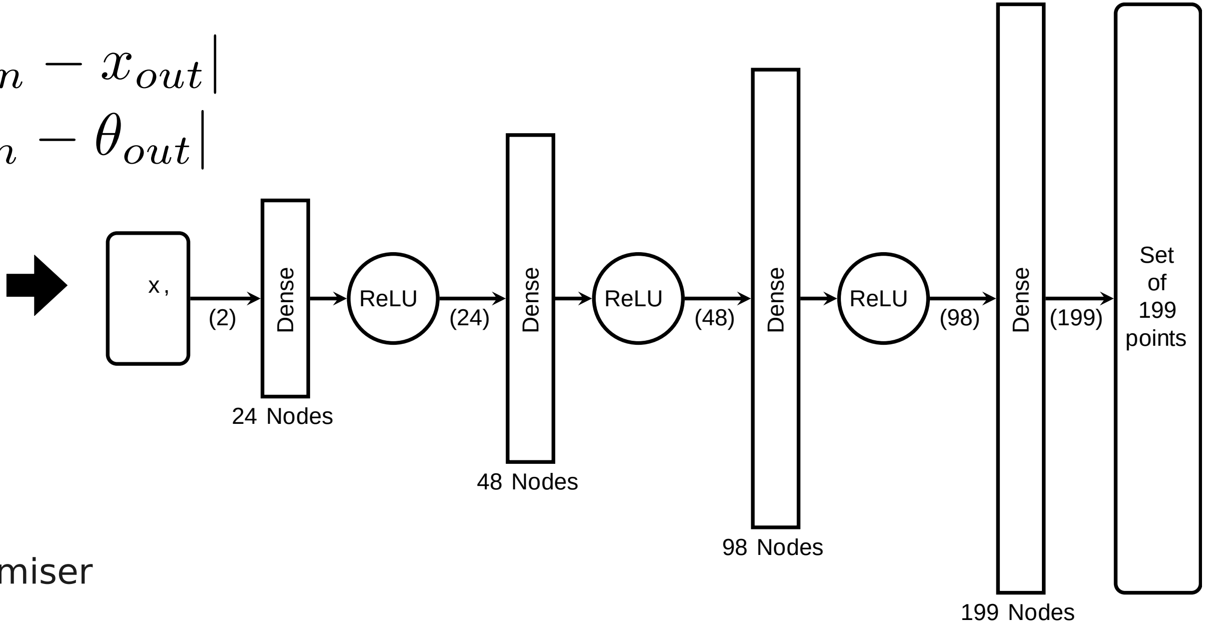
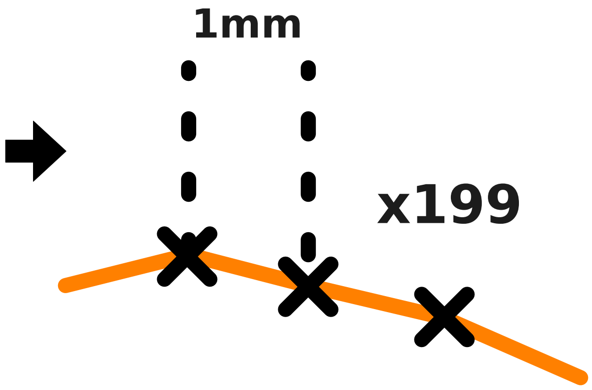
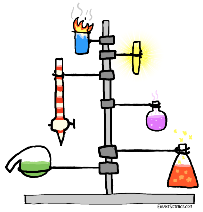
The ‘Proton Path Neural Network’

$$\Delta x = |x_{in} - x_{out}|$$
$$\Delta \theta = |\theta_{in} - \theta_{out}|$$







Training:

- MSE loss
- ADAM optimiser
- Lr = 1e-5
- 1000 epochs

*(In later versions: $x_{in}, x_{out}, \theta_{in}, \theta_{out}$)

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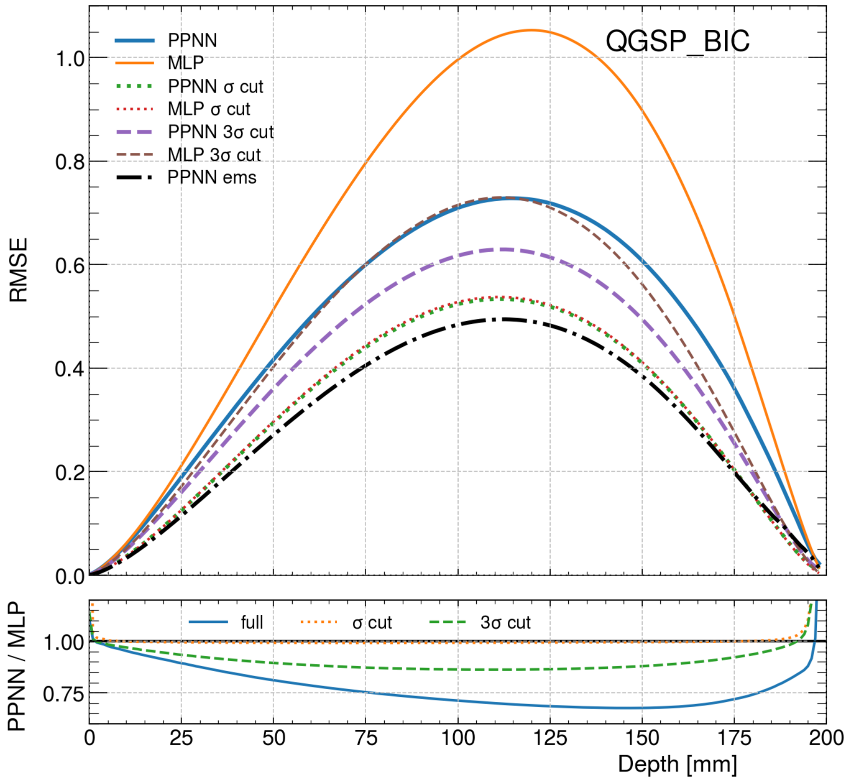
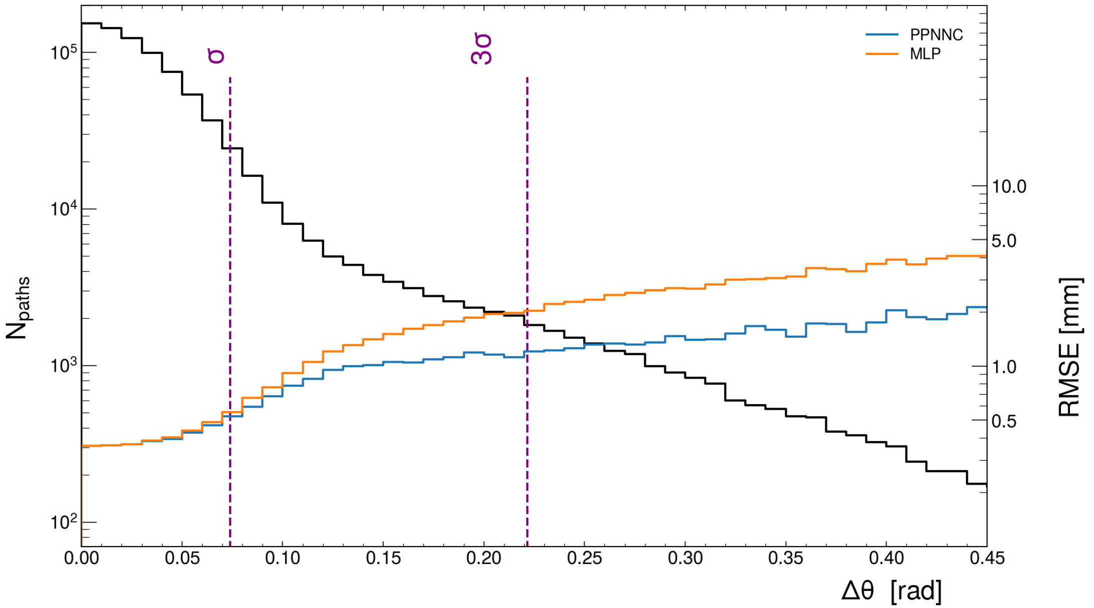
Root Mean Square Error





PPNN 0.47 ± 0.01 sec
MLP 7.11 ± 0.08 sec

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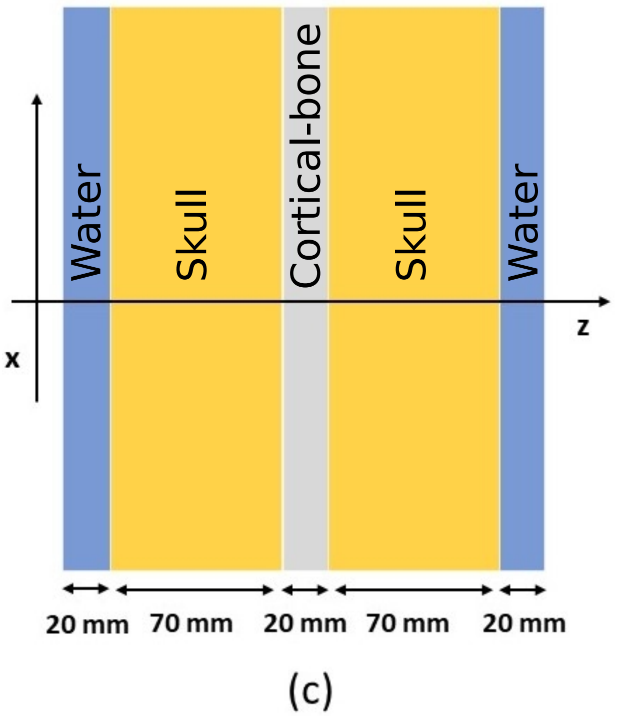
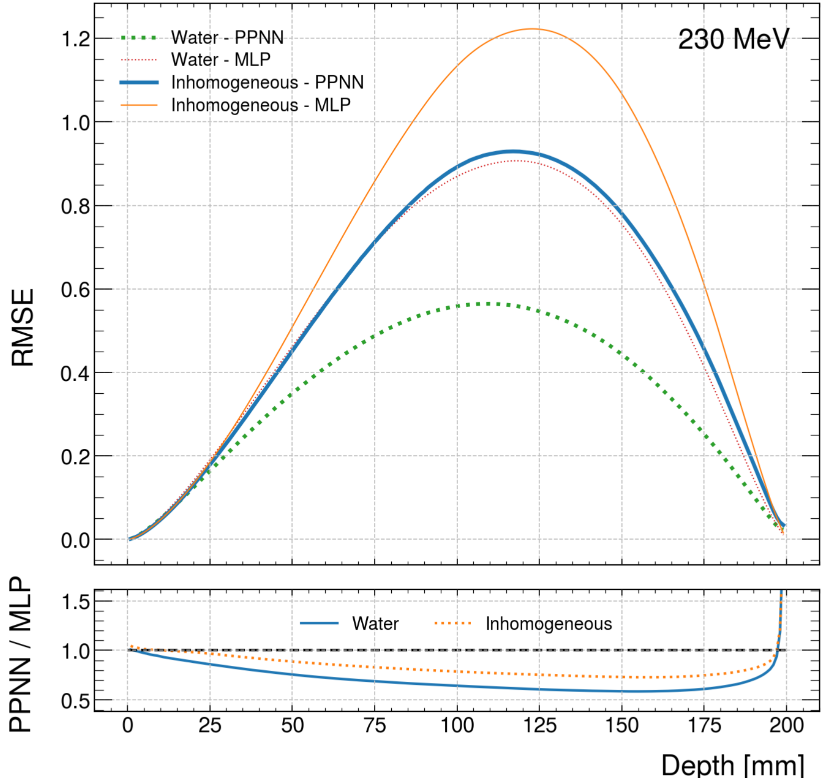
Inhomogeneous Phantom

Both methods trained/calibrated on water at 230MeV.





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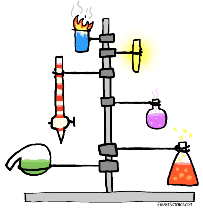
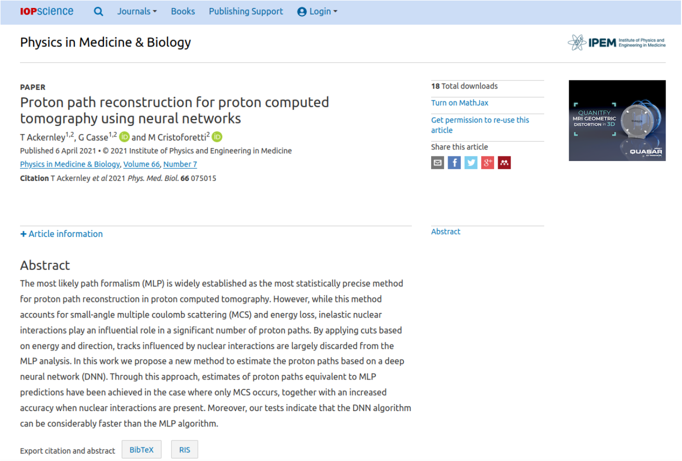
Summary



- Demonstrated a proof of concept proton trajectory prediction using a neural network based method
- Achieved a significant speed increase over MLP, and accuracy increase when data cut is neglected
- Similar behaviour on a sample inhomogeneous phantom
- Now published in Physics in Medicine & Biology



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Physics in Medicine & Biology

PAPER

Proton path reconstruction for proton computed tomography using neural networks

T Ackernley[1,2], G Casse[1,2] and M Cristoforetti[2]

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Citation T Ackernley *et al* 2021 *Phys. Med. Biol.* **66** 075015

+ Article information

Abstract

Abstract

The most likely path formalism (MLP) is widely established as the most statistically precise method for proton path reconstruction in proton computed tomography. However, while this method accounts for small-angle multiple coulomb scattering (MCS) and energy loss, inelastic nuclear interactions play an influential role in a significant number of proton paths. By applying cuts based on energy and direction, tracks influenced by nuclear interactions are largely discarded from the MLP analysis. In this work we propose a new method to estimate the proton paths based on a deep neural network (DNN). Through this approach, estimates of proton paths equivalent to MLP predictions have been achieved in the case where only MCS occurs, together with an increased accuracy when nuclear interactions are present. Moreover, our tests indicate that the DNN algorithm can be considerably faster than the MLP algorithm.

Export citation and abstract BibTeX RIS

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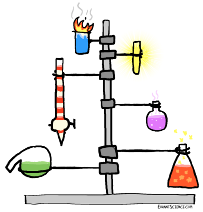
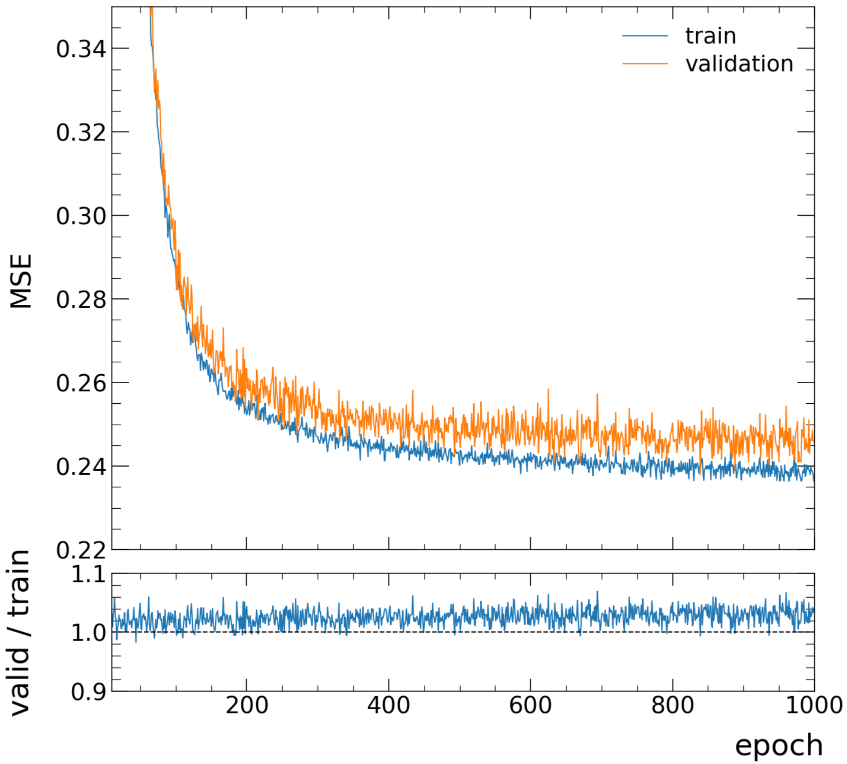
Backup Slides




LITTLE BINS
FOR LITTLE HANDS

Training

- Pytorch
- MSE loss
- ADAM optimiser
- 1000 epochs
- Learning rate 1e-5



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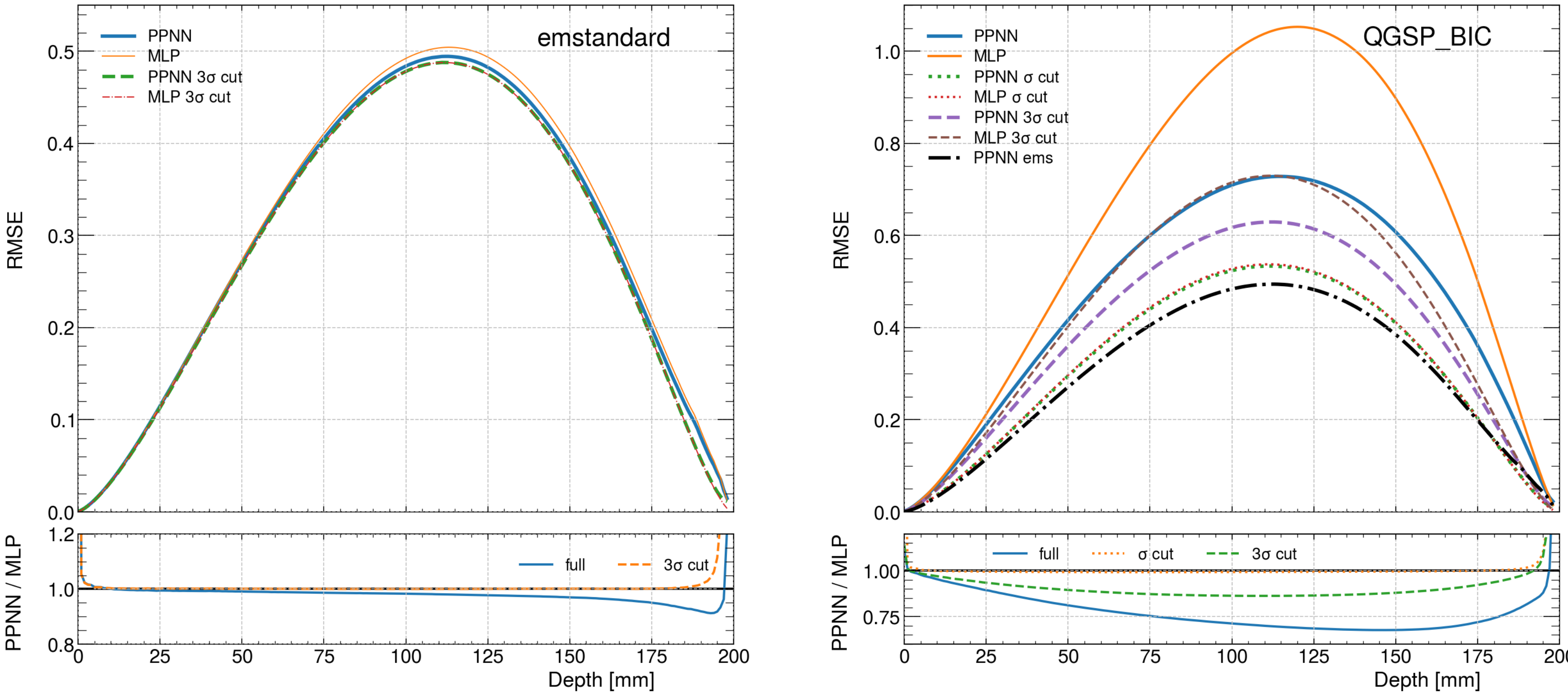
Root Mean Square Error



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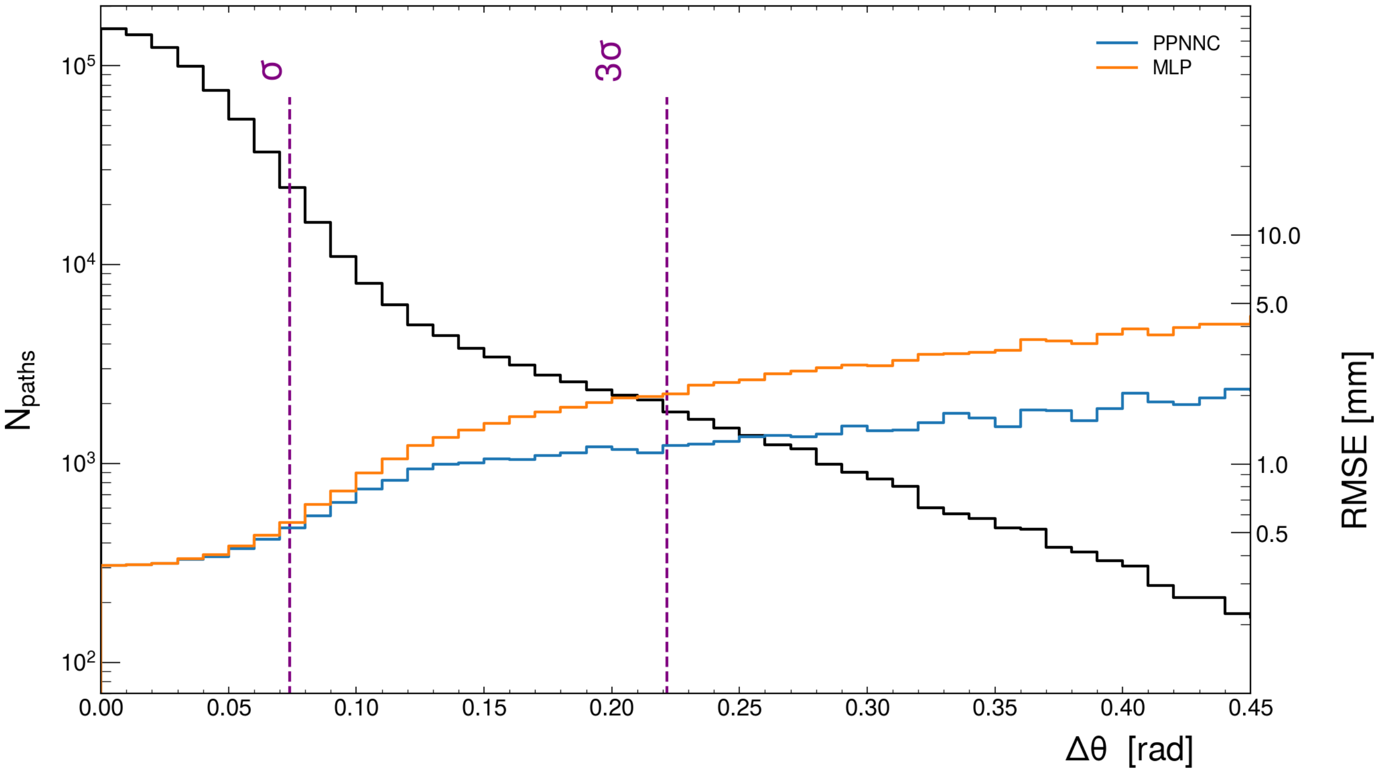
Breakdown by angular change



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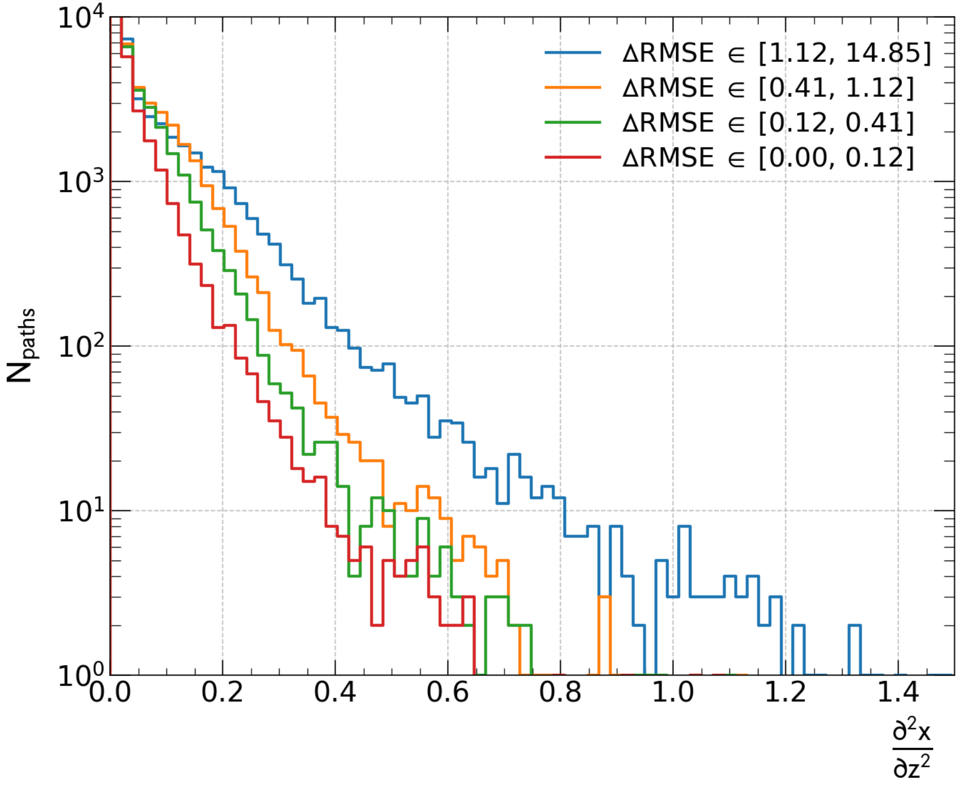
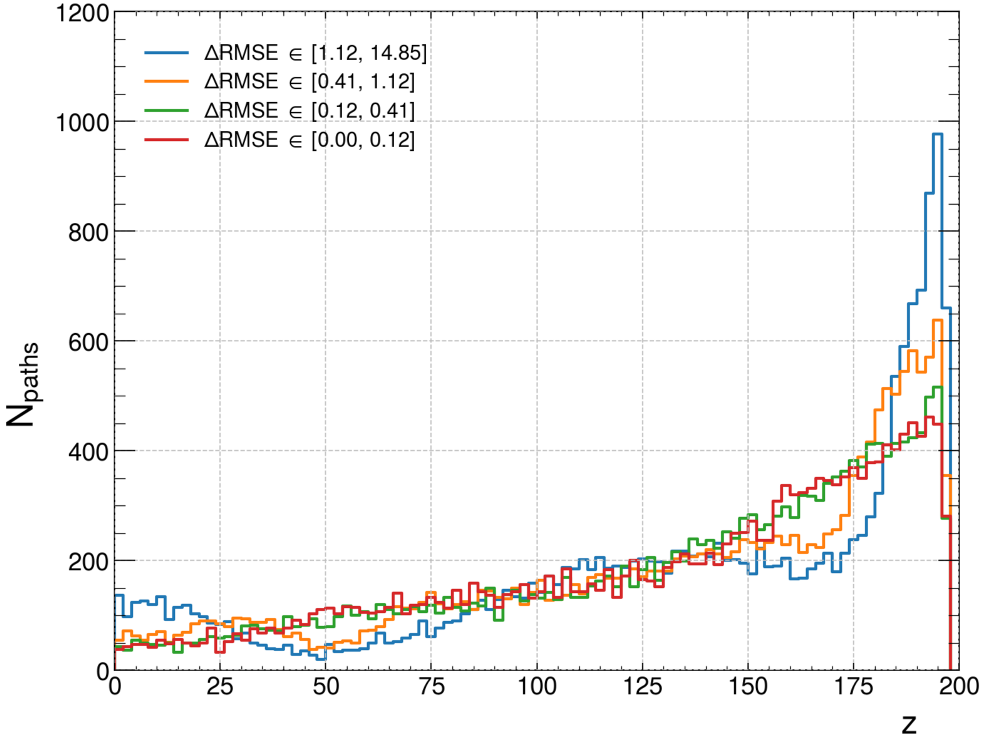
Maximum change





Execution Time Trails

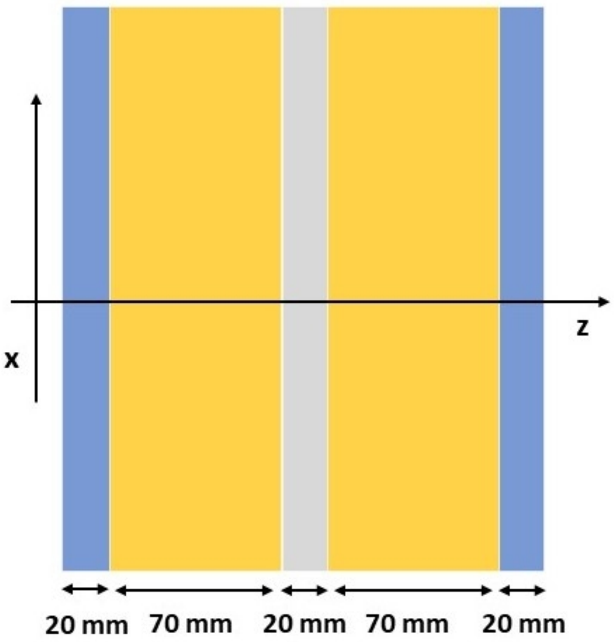
- Standard NC6 Microsoft Azure machine (CPU)
- 1,600,000 trajectories
- 10 times, unique batch combinations

PPNN	0.47 ± 0.01 sec
MLP	7.11 ± 0.08 sec

~sixteen times faster

Inhomogeneous Phantom

- 20mm Water
- 70mm Skull
- 20mm Cortical-bone
- 70mm Skull
- 20mm Water

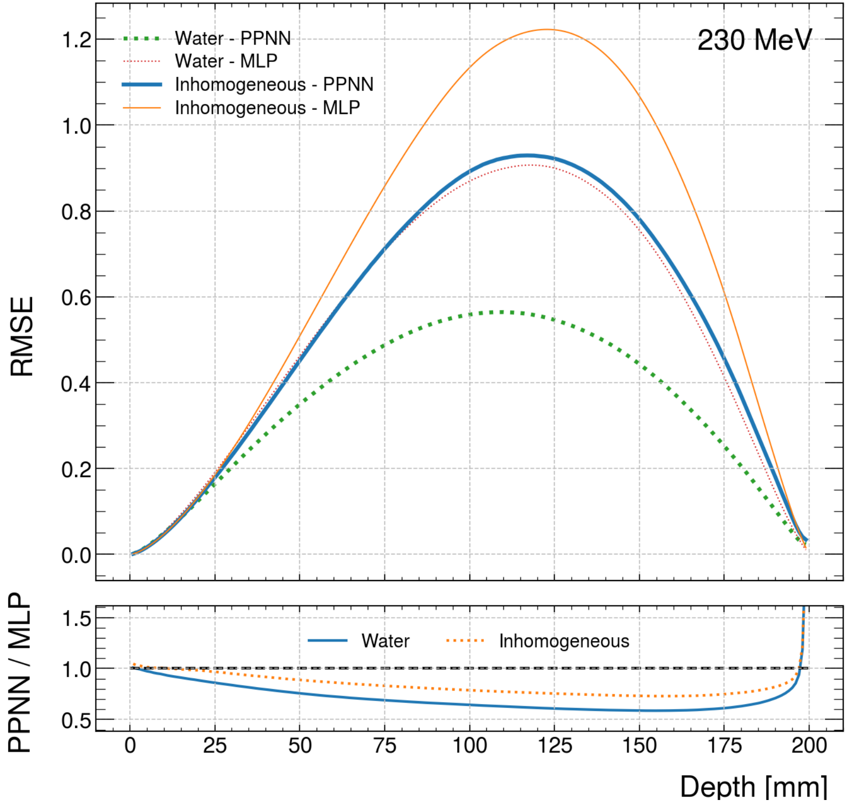


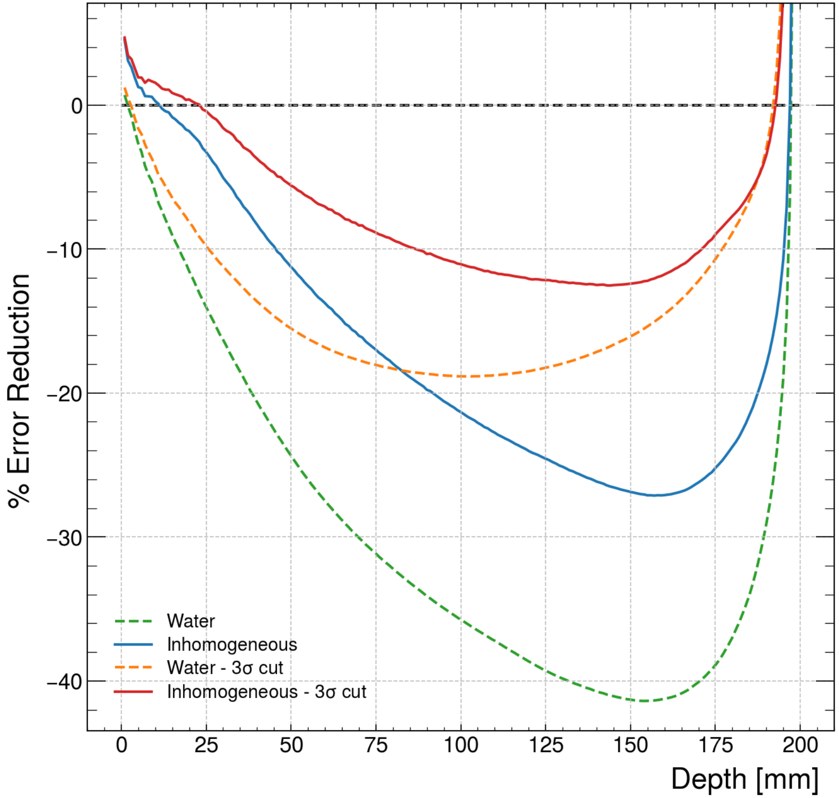
(c)

Increased stopping power → 230MeV

- PPNN; trained on 230MeV water phantom
- MLP; ‘momentum velocity ratio’ recalculated using 230MeV water phantom

Inhomogeneous Phantom RMSE





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