Fast emulation of deposited dose distributions by means of Deep Learning

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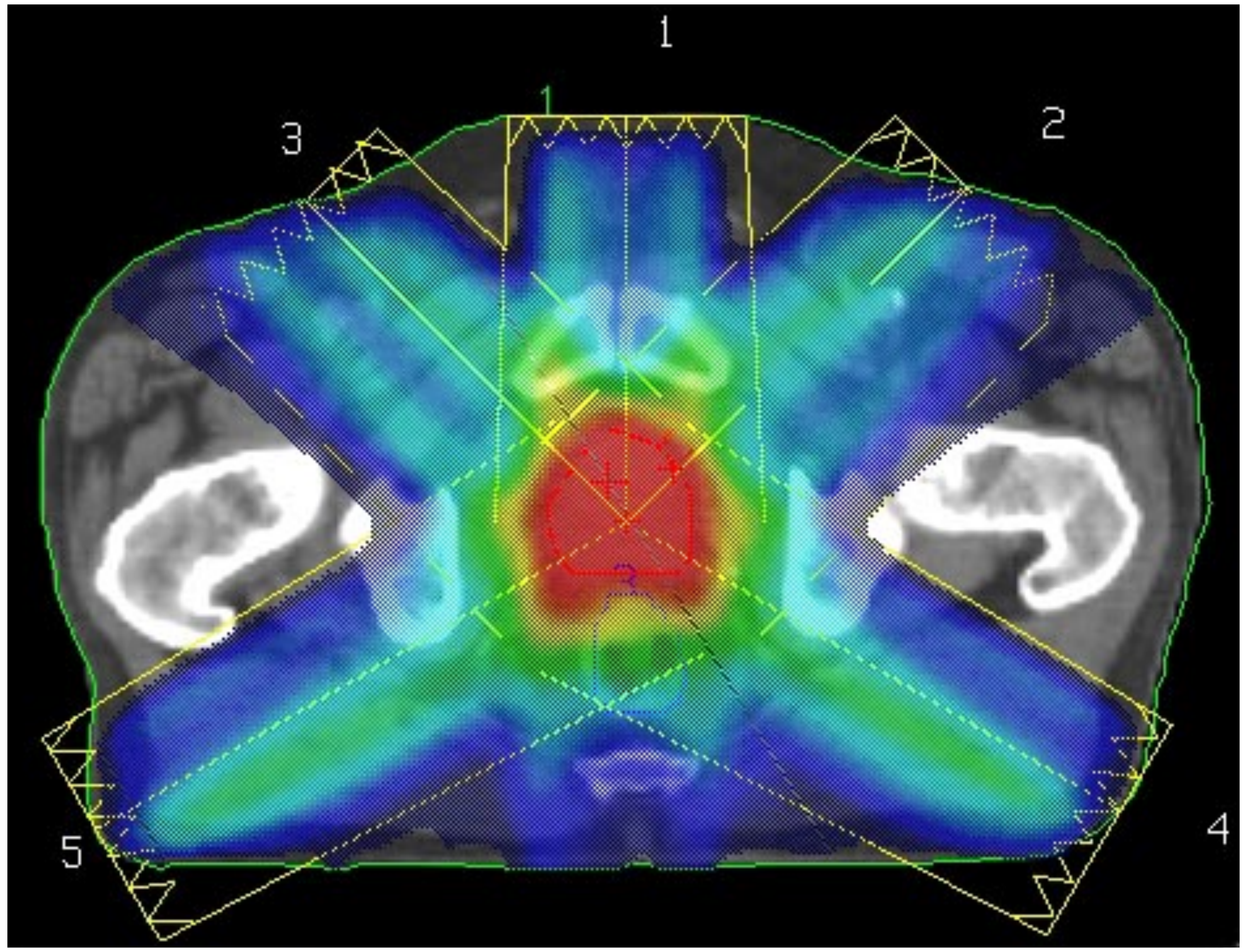
IV Geant4 International User Conference at the physics-medicine-biology frontier

Treatment plan optimization

Choice of angles, energies and intensities of the beamlets

to

Fit dose medical prescription



Now:

2 steps

Energy optimisation   Fluency optimisation

Traditional sequential algorithms

Room for improvement

Today

VMAT
Volumetric Modulated Arc Therapy

Tomorrow

FLASH radiotherapy

Complex optimisation!

Opportunity to choose entry angle from continuous

<u>Sub-optimal optimisation:</u>

- New angles added in steps
- Trade off between quality and time

<u>Clinical unmet need for Treatment Planning System (TPS)</u>

Our Goal

Writing the Dose to each organ as a function of beam parameters

CT scan
Organs' density
Prescribed dose

DL algorithm

Optimised treatment plan

2 Phases

Energy Deposition Emulation	**Treatment Plan Optimisation**
with	starting with
Deep Neural Network generative model	Emulated energy deposition distributions

Energy Deposition Emulation

- Simulation of energy deposition of electrons passing through matter, using Geant4

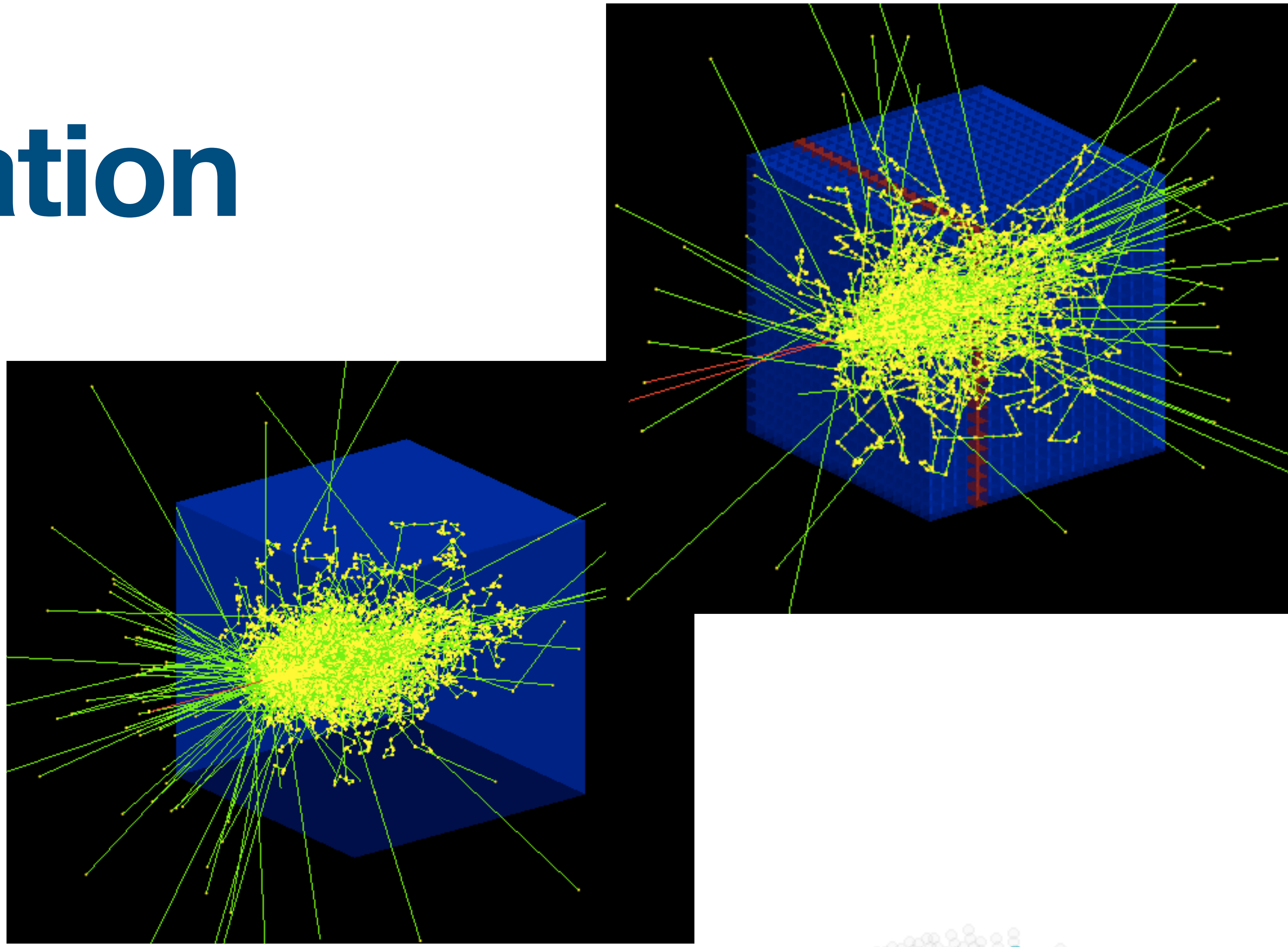
- 2 Geometry settings:

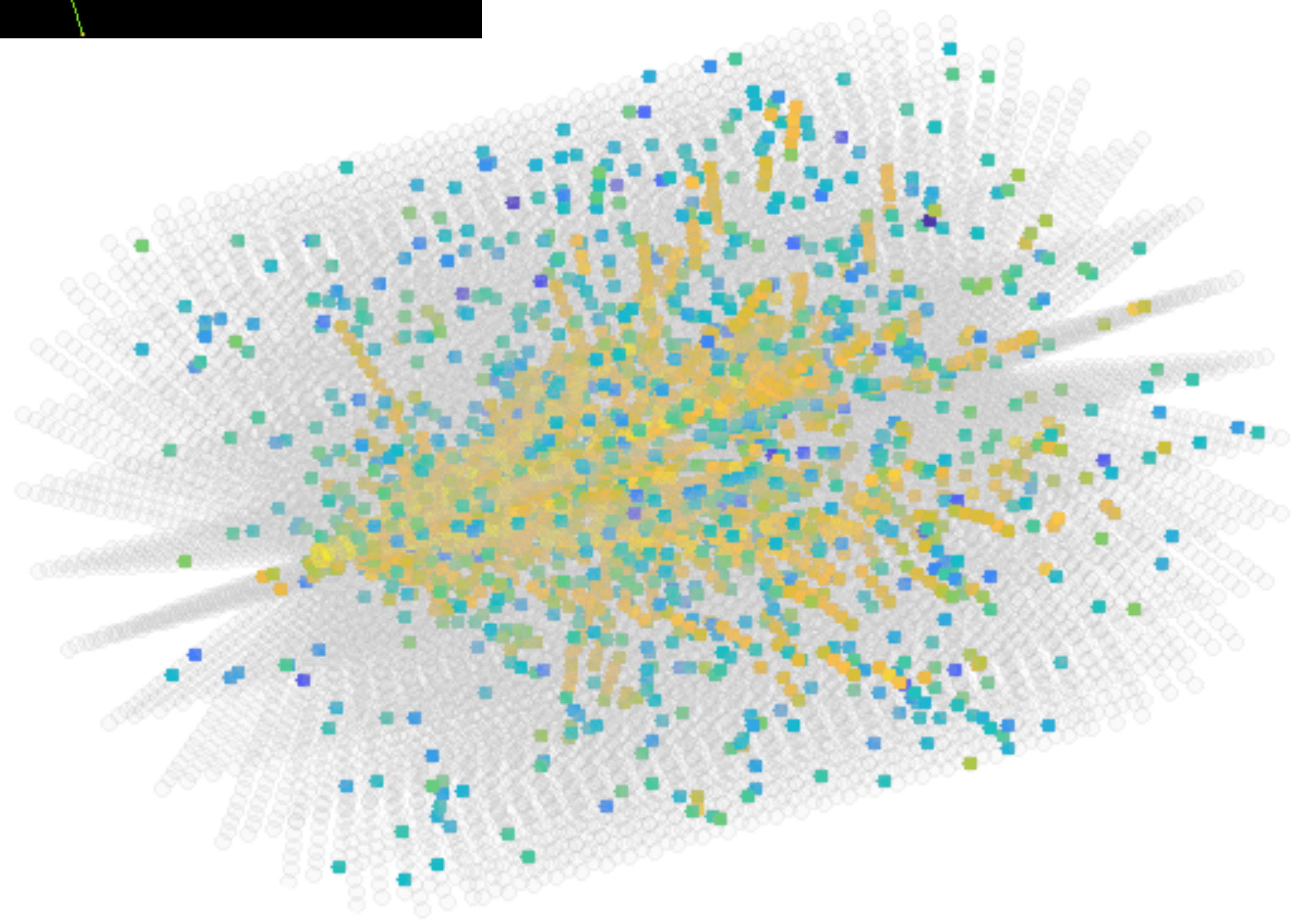
  1. Water volume

  2. Water volume + slice with variable density $d \in [0,\ 5]\ g/cm^3$

- In all cases $E_0 \in [50,\ 100]\ MeV$

- Data collected in a cylindrical scorer made up by 28 x 28 x 28 voxels in r, θ and z



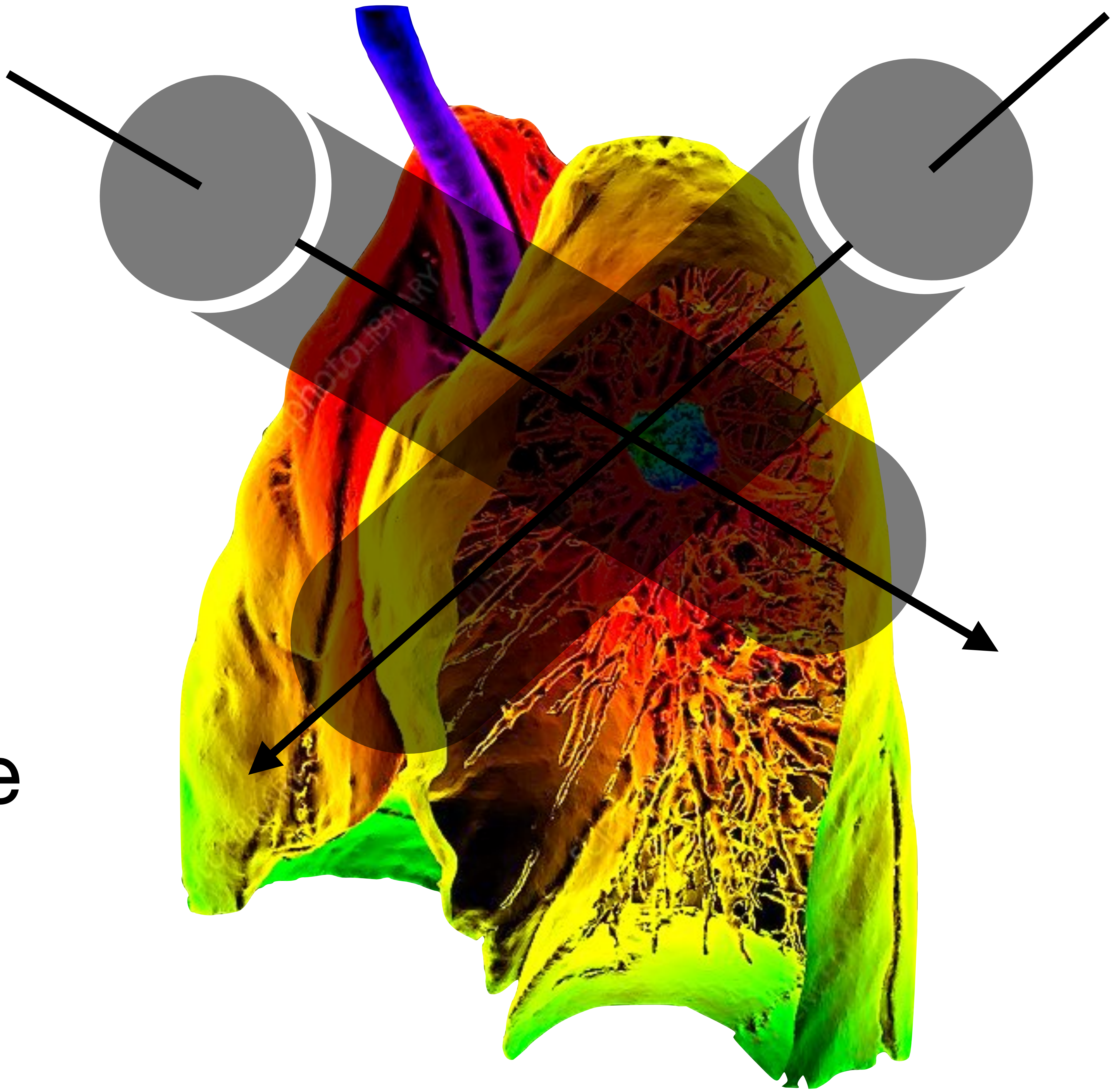


Cylindrical shape

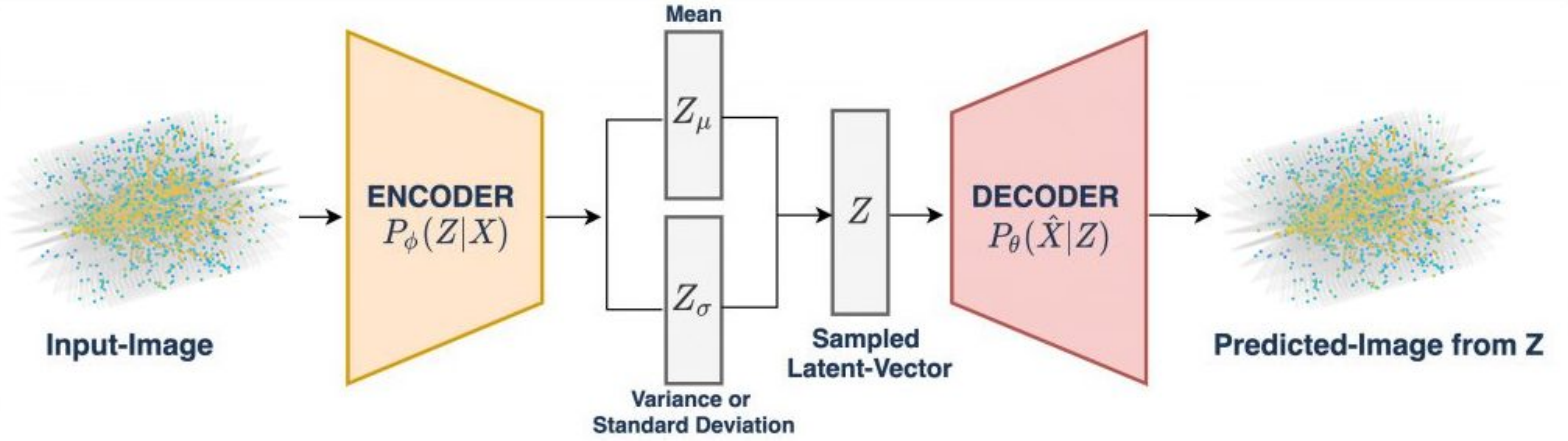
Two main advantages:

- Reduce complexity without loss of generalisation: the cylinder follows the beam

- More precision near the beamline

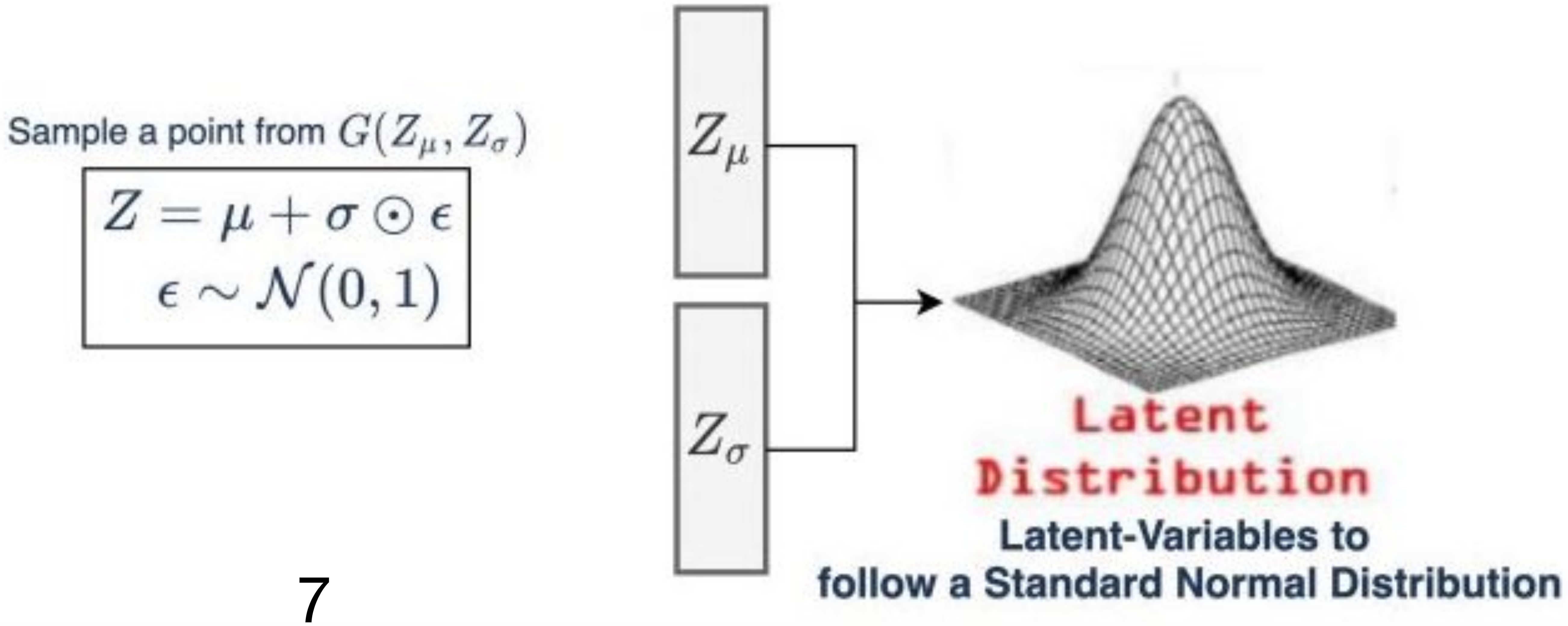


Variational Auto Encoder (VAE)



- Generative Algorithm

- **Encoding and Decoding done with Graph layers**



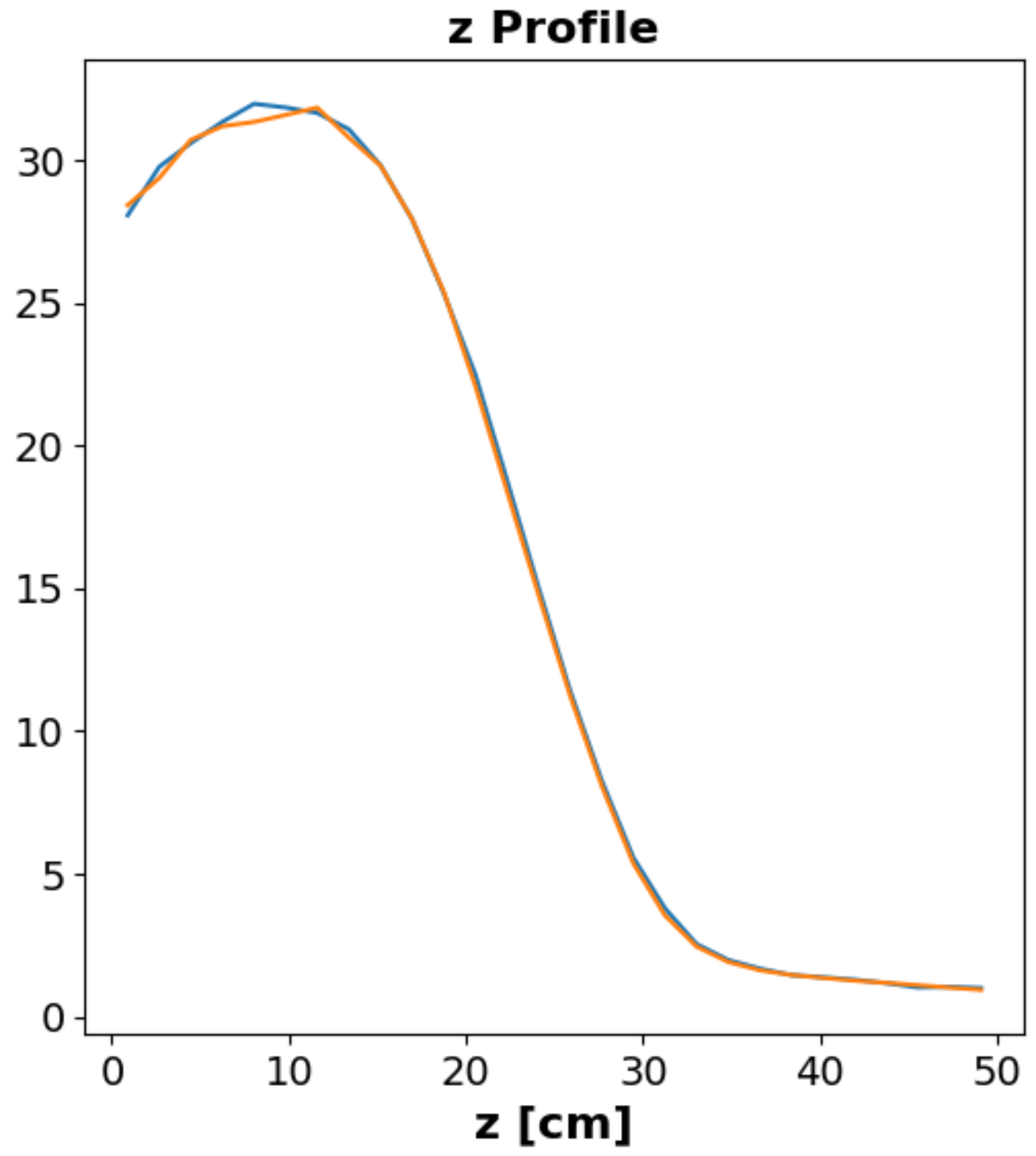

ReNN Graph VAE
Graph Conv
Pooling
Graph Conv
Pooling
Encoding
Sampling
σ
μ
Z
Graph Conv
Un-Pooling
Graph Conv
Un-Pooling
Decoding

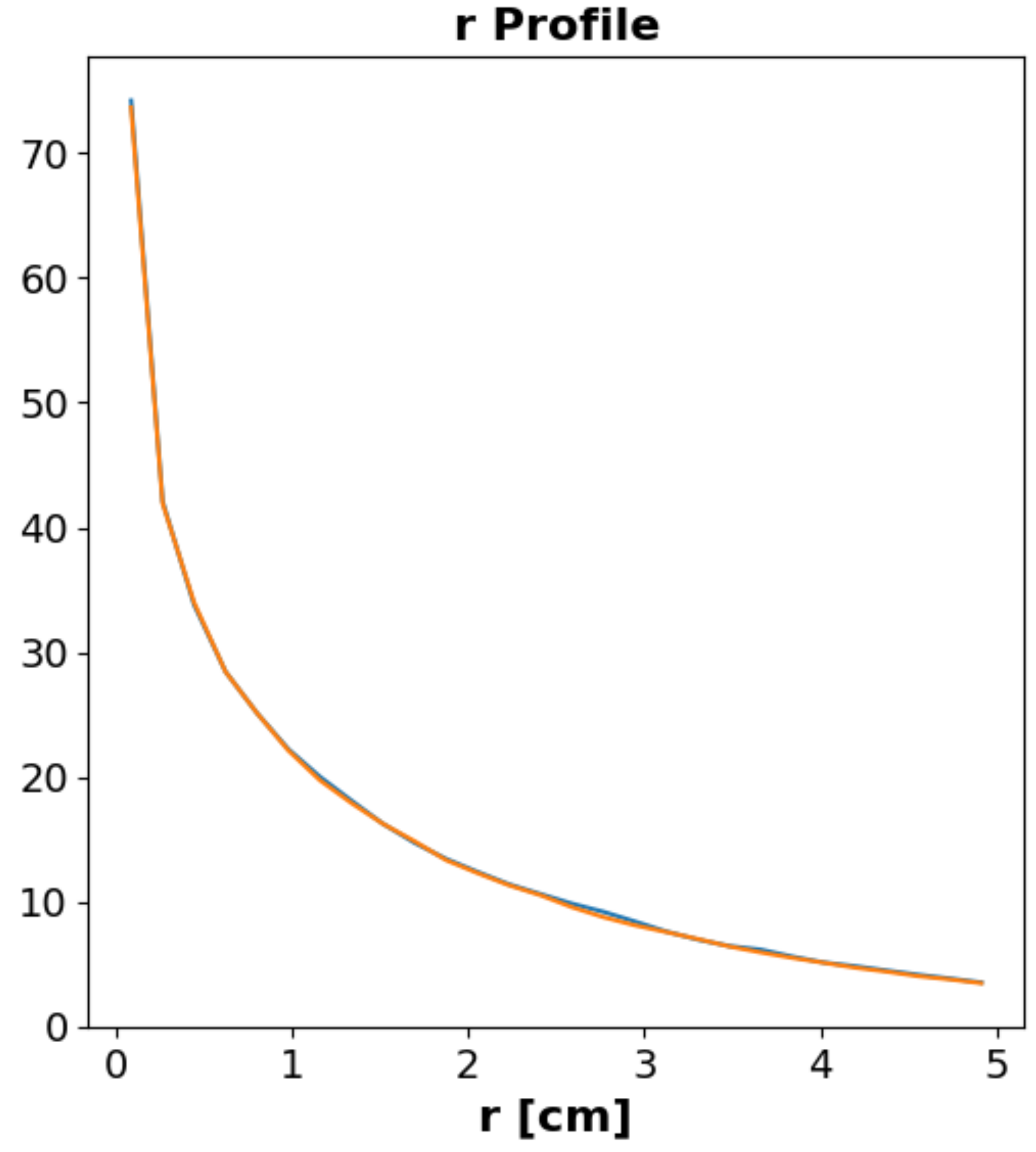
Results

- Energy profiles
- Voxel reconstruction

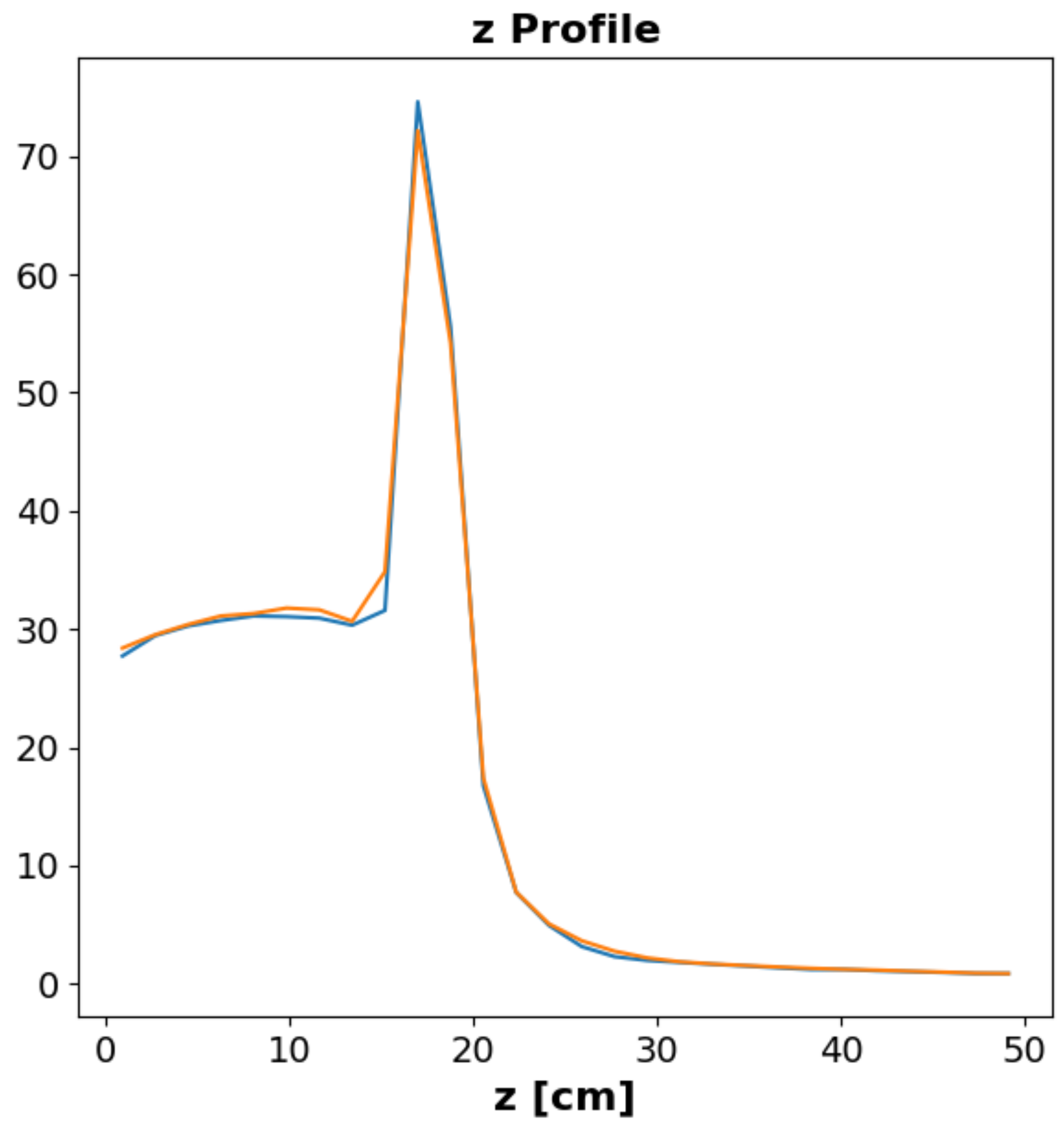
$$\delta = \left\langle \frac{|D_{real} - D_{reco}|}{max(D_{real})} \right\rangle$$

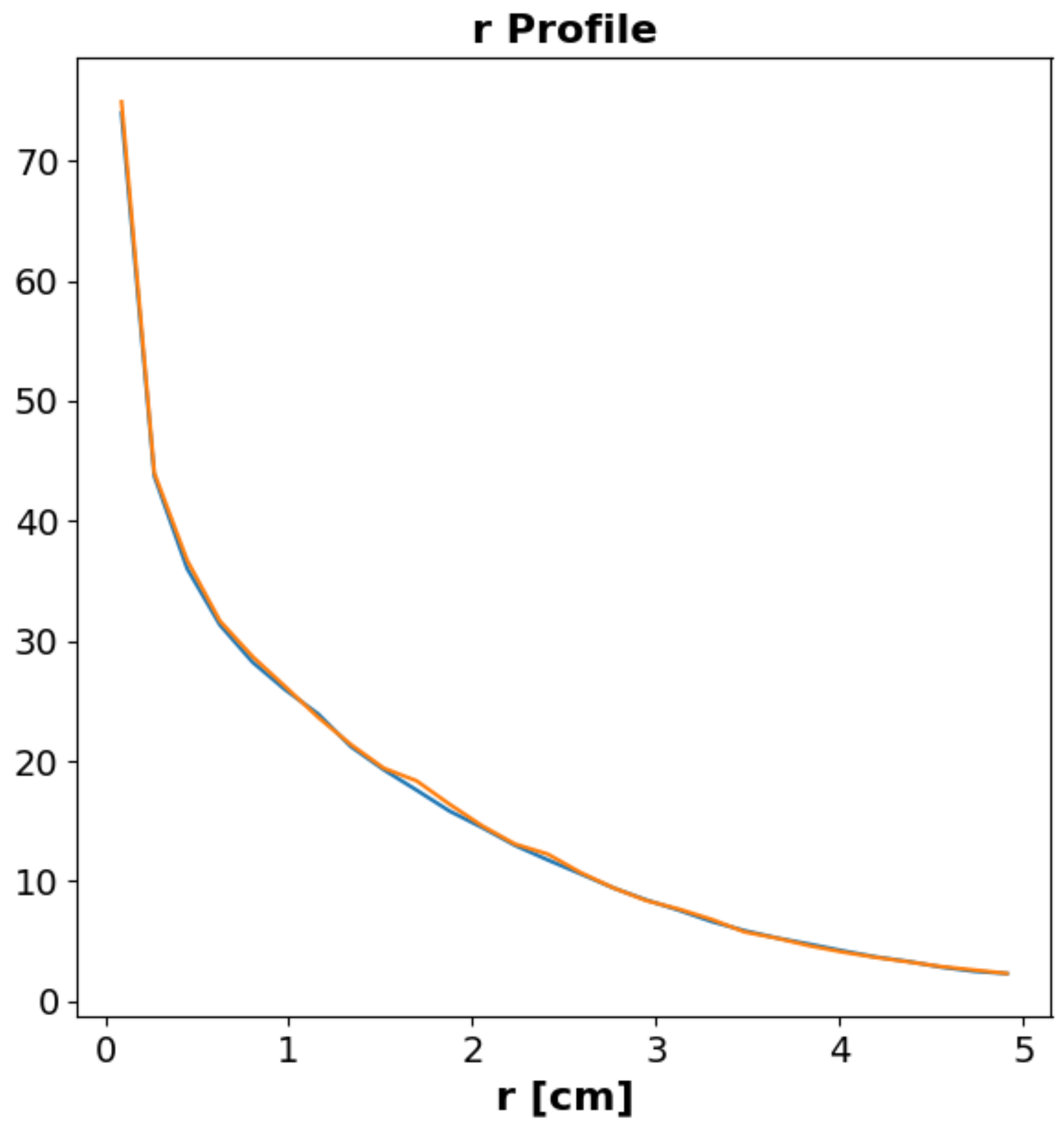
Water Volume





Water Volume + Slice





	ε_z	ε_r	ε_E	$\delta < 3\,\%$
Water	5%	3%	2%	99.4%
Water + Slice	7%	4%	2%	98.4%

Latent Space: Water Volume

Sampling from Latent Space

=

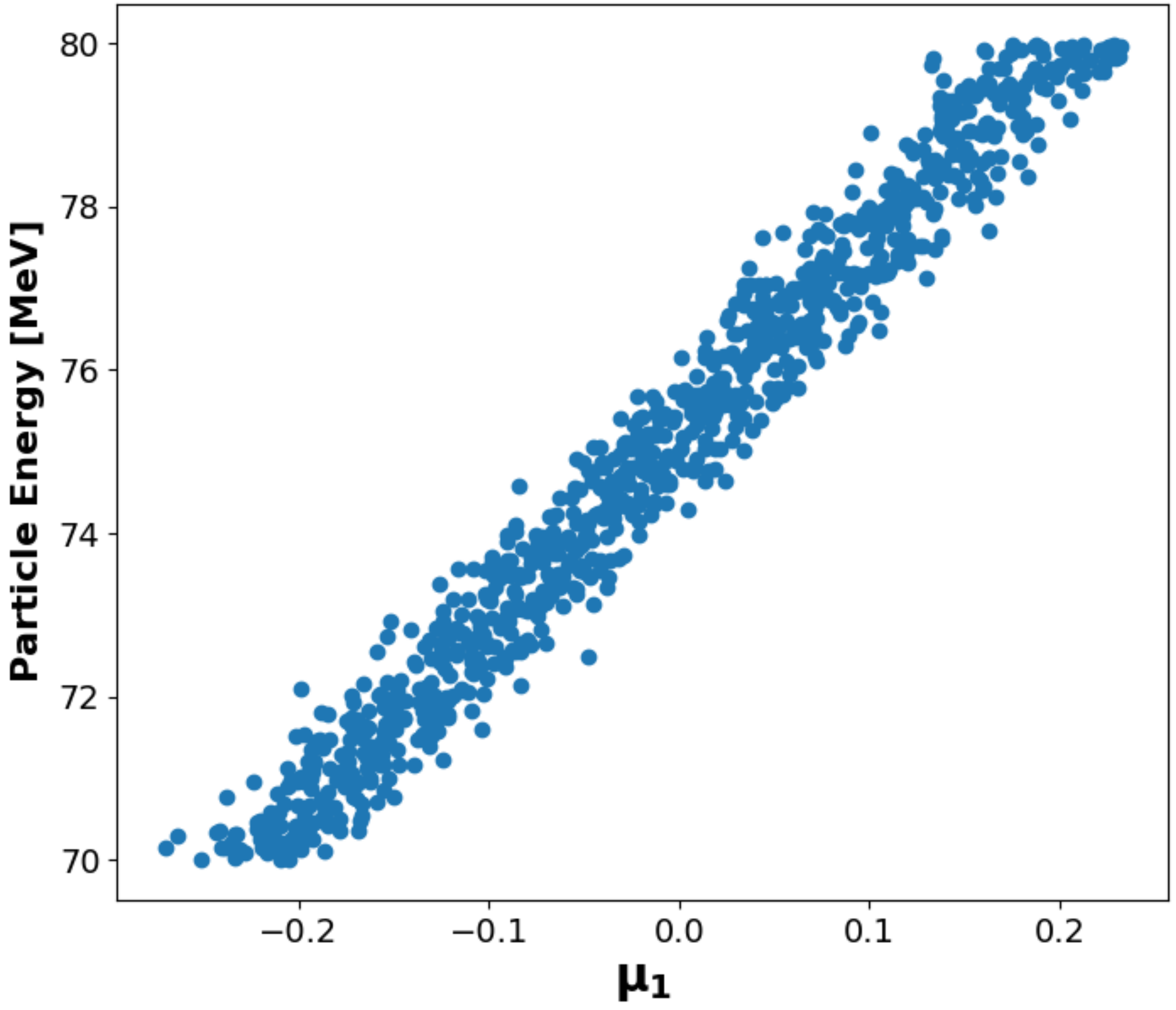
Generating according to beam parameters
(and more)

- <u>In this simple case</u>:

  z is linearly correlated with Particle Energy

- <u>In more complex cases</u>:
  - increase latent space dimensionality
  - latent space conditioning

<u>Latent Space in 1 dimension</u>

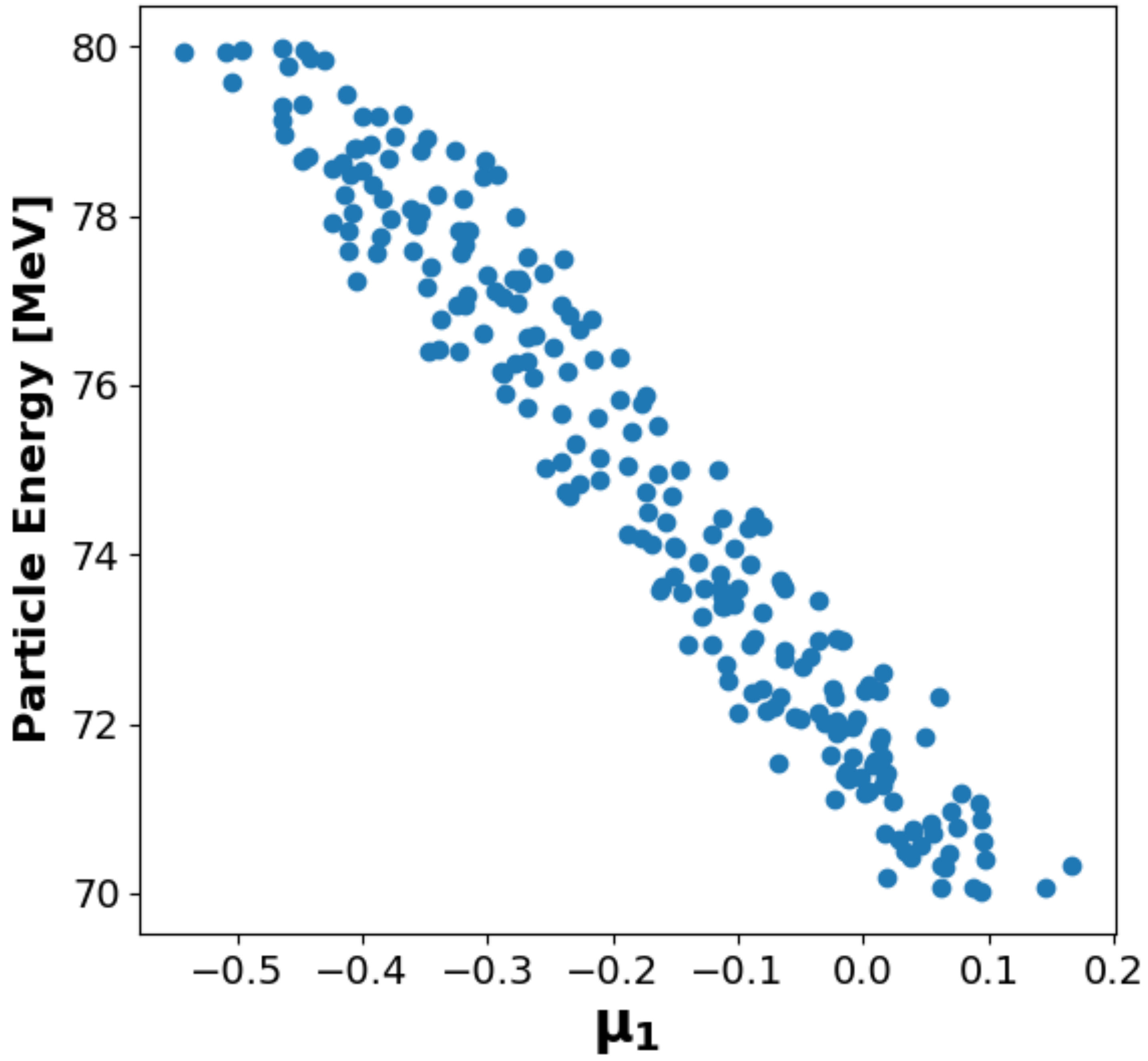


Latent Space: Water + Slice with variable density

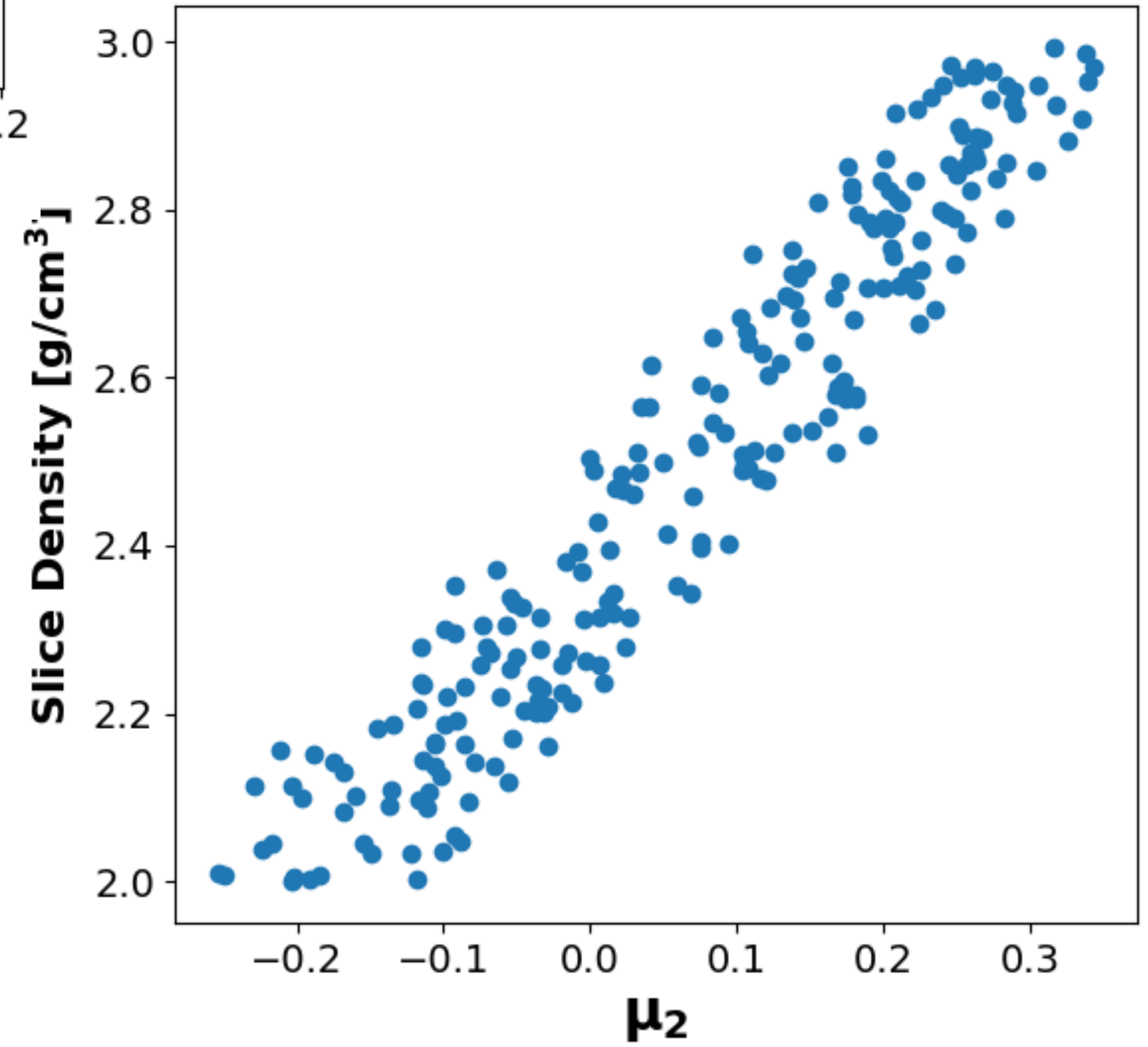
<u>Latent Space in 2 dimensions</u>

μ_1 and μ_2 highly correlated with:

- Particle Energy
- Slice's density



The Network recognizes essential parameters in the simulation



Generation time

Physical Parameters → Predictor → Latent Space → Decoder → Generated Dose Distribution

	Geant4 10'000 primaries	Graph VAE
Generation time (CPU)	82 s	0.02 s

Further advantages of Deep Learning approach:

- Generation time is independent of number of primaries
- Generation time can be further reduced using GPUs

Up to x10^6 faster than MC

Conclusions

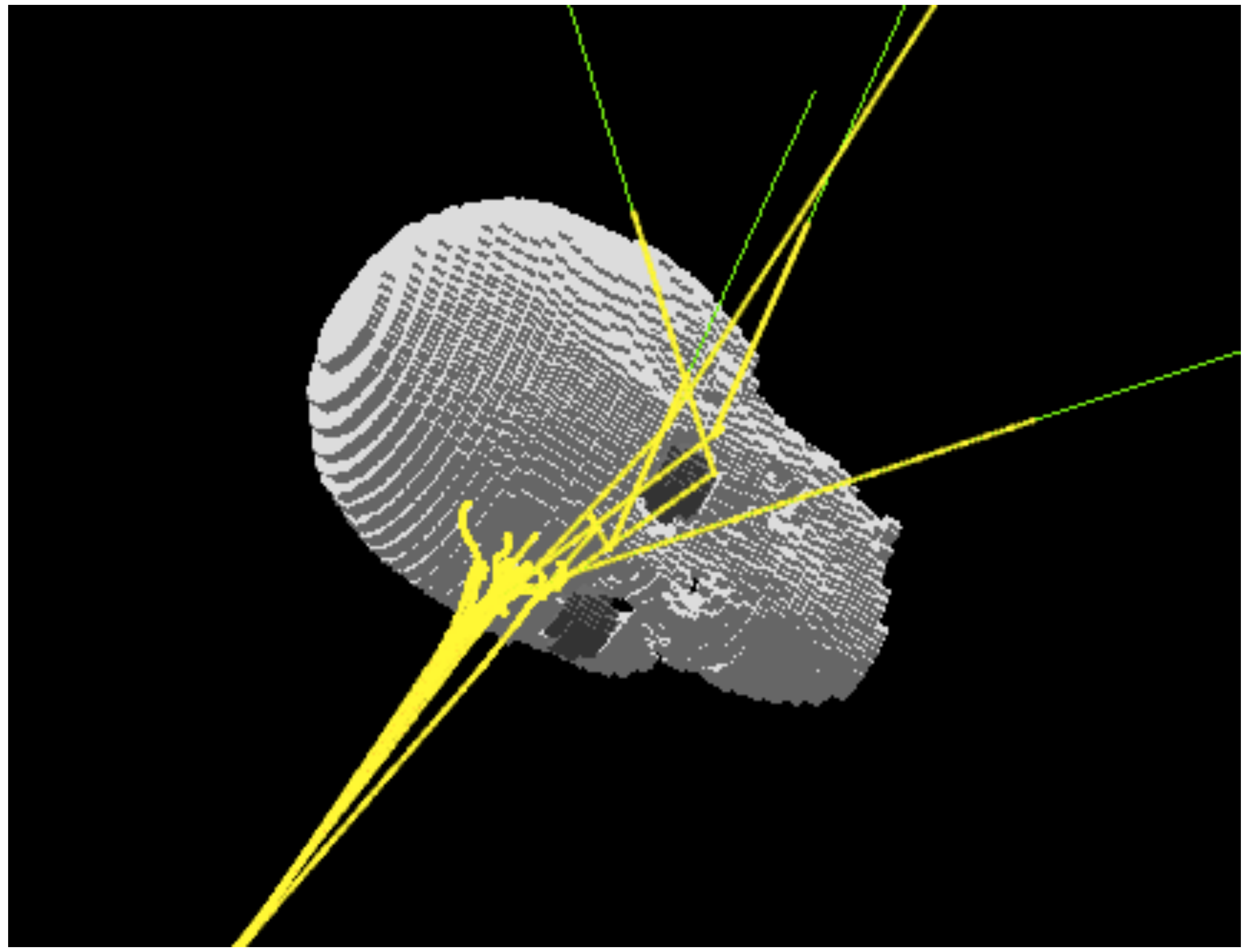
This was a proof-of-concept → Deep Learning can have a huge impact on today's and future's Radiotherapy

Today → Better and faster optimization for VMAT

Tomorrow → Optimized treatments with FLASH therapy

Next steps:

- Increasing the complexity of the medium
- Phase 2: optimisation of treatment plan



Thank you for your attention!

- Clinical unmet need for FLASH e- TPS and for better and faster way to optimize VMAT treatment plans
- Potential huge impact on today's and future's Radiotherapy
- Our Graph VAE emulates well dose distributions:
  - Encoding and Decoding with graph layers
  - Nearest Neighbours Pooling
- Generation is >1000x faster than Geant4

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Outline

- Clinical unmet demand for TPS for VMAT and FLASH e-
- Generative Deep Learning approach
  - Dataset
  - Architecture: Graph Encoding and Decoding
- Results
- Perpectives

Radiotherapy

- Globally, 18 million cases of cancer diagnosed in 2020
- Approximately 50% of all cancer patients should receive radiation

Today 99.9% of treatments are done with photons

	PhotonTherapy	HadronTherapy
Equipments	~15.000	~100
Centers	~7.600	~100
Countries	156	20

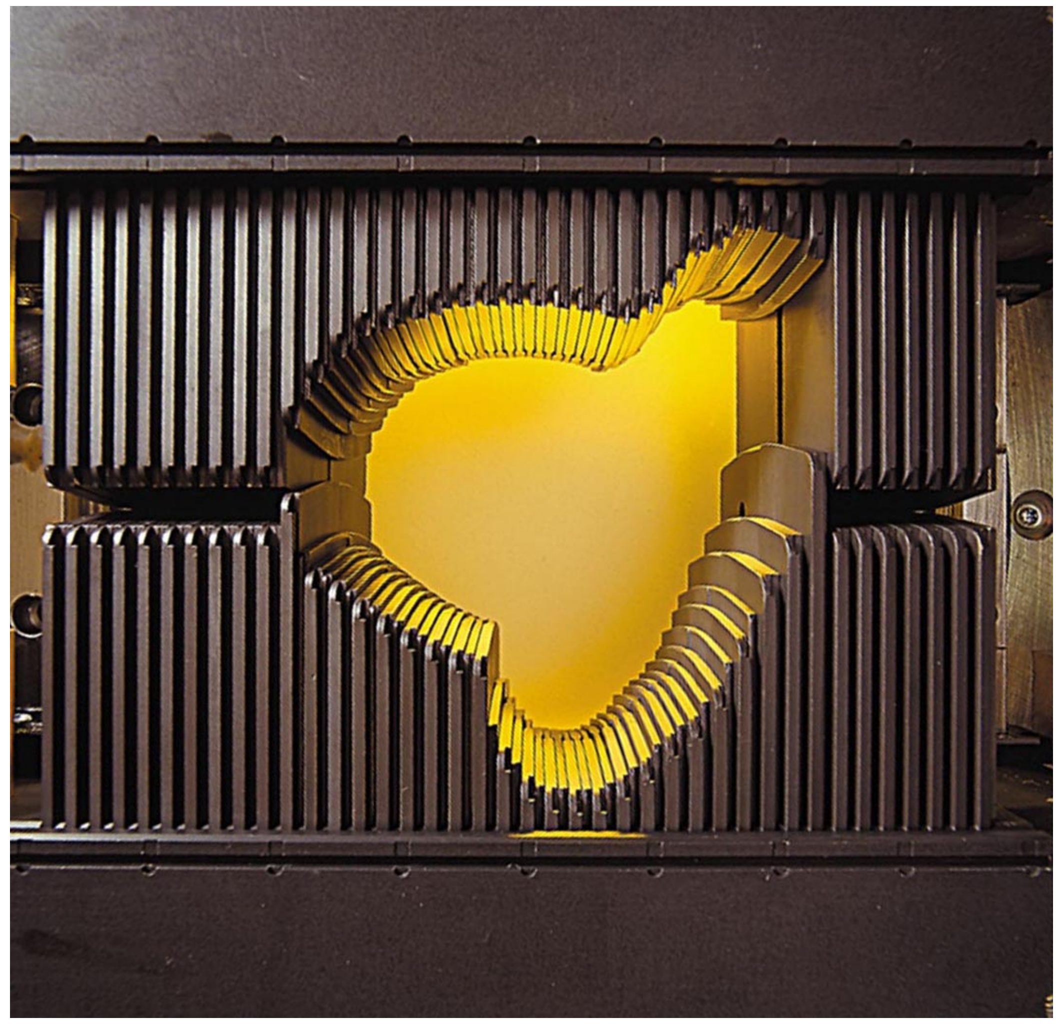
References:

https://www.wcrf.org/cancer-trends/worldwide-cancer-data/

https://dirac.iaea.org

Delaney, G., Jacob, S., Featherstone, C. and Barton, M. (2005), The role of radiotherapy in cancer treatment. Cancer, 104: 1129-1137. https://doi.org/10.1002/cncr.21324

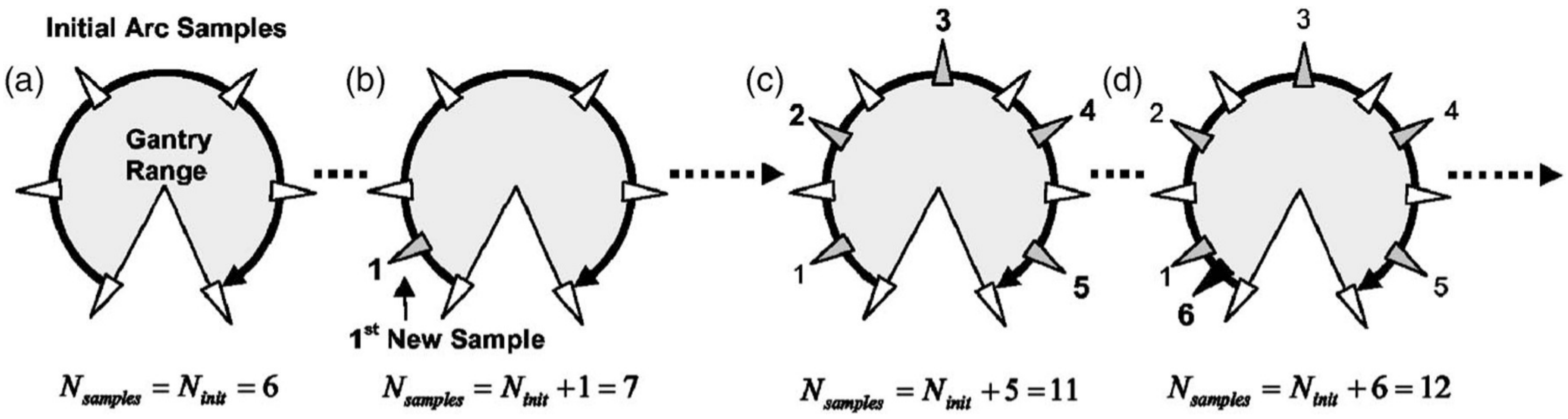
Current Radiotherapy



VMAT: Volumetric Modulated Arc Therapy

- Sophisticated therapy with photons used worldwide
- Opportunity to choose entry angle from continuous of 360°

BUT STILL → <u>Sub-optimal optimisation:</u>



- New angles added in steps
- Trade off between quality and time

Otto K. Volumetric modulated arc therapy: IMRT in a single gantry arc. Med Phys. 2008 Jan;35(1):310-7. doi: 10.1118/1.2818738. PMID: 18293586.

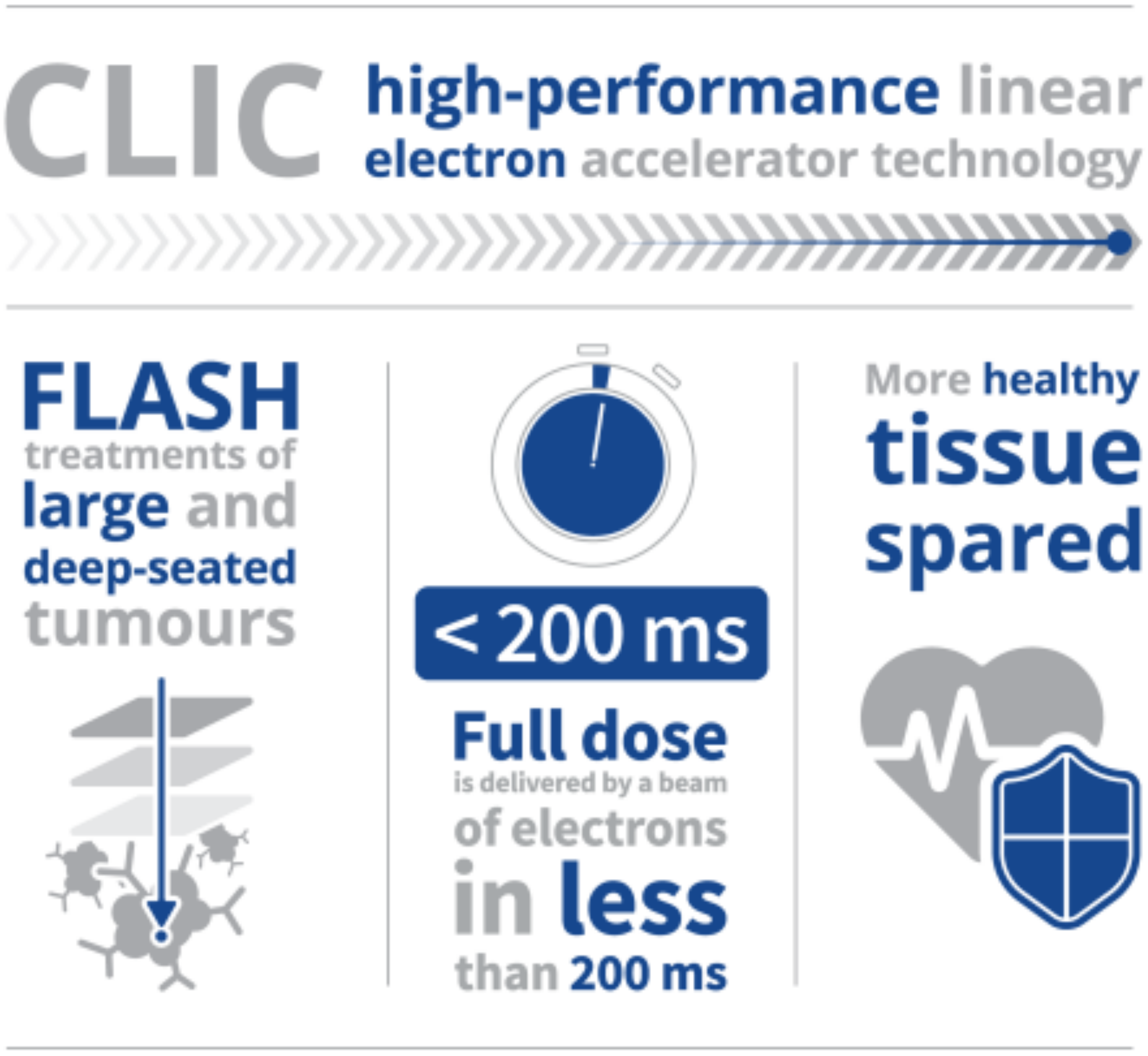
Future perspectives

FLASH radiotherapy

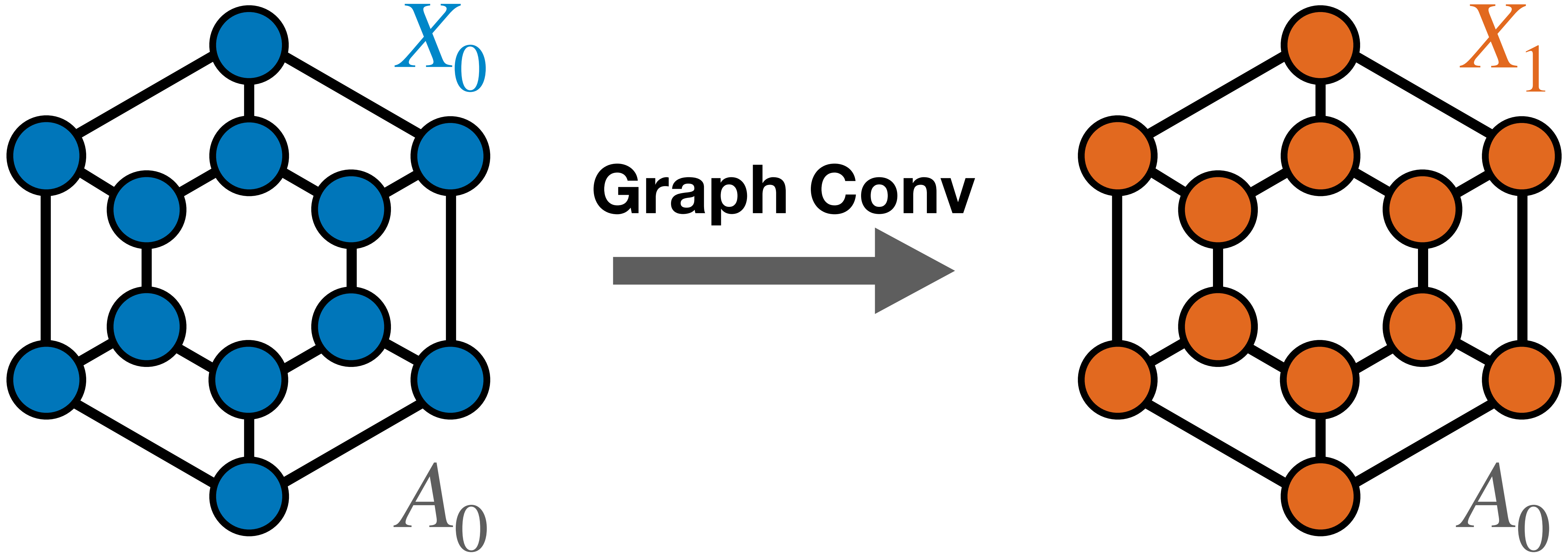
Best candidates for it are
electrons, in particular VHEE

↓

Opportunity to choose gantry from
the entire solid angle



Clinical unmet need for Treatment Planning System (TPS)

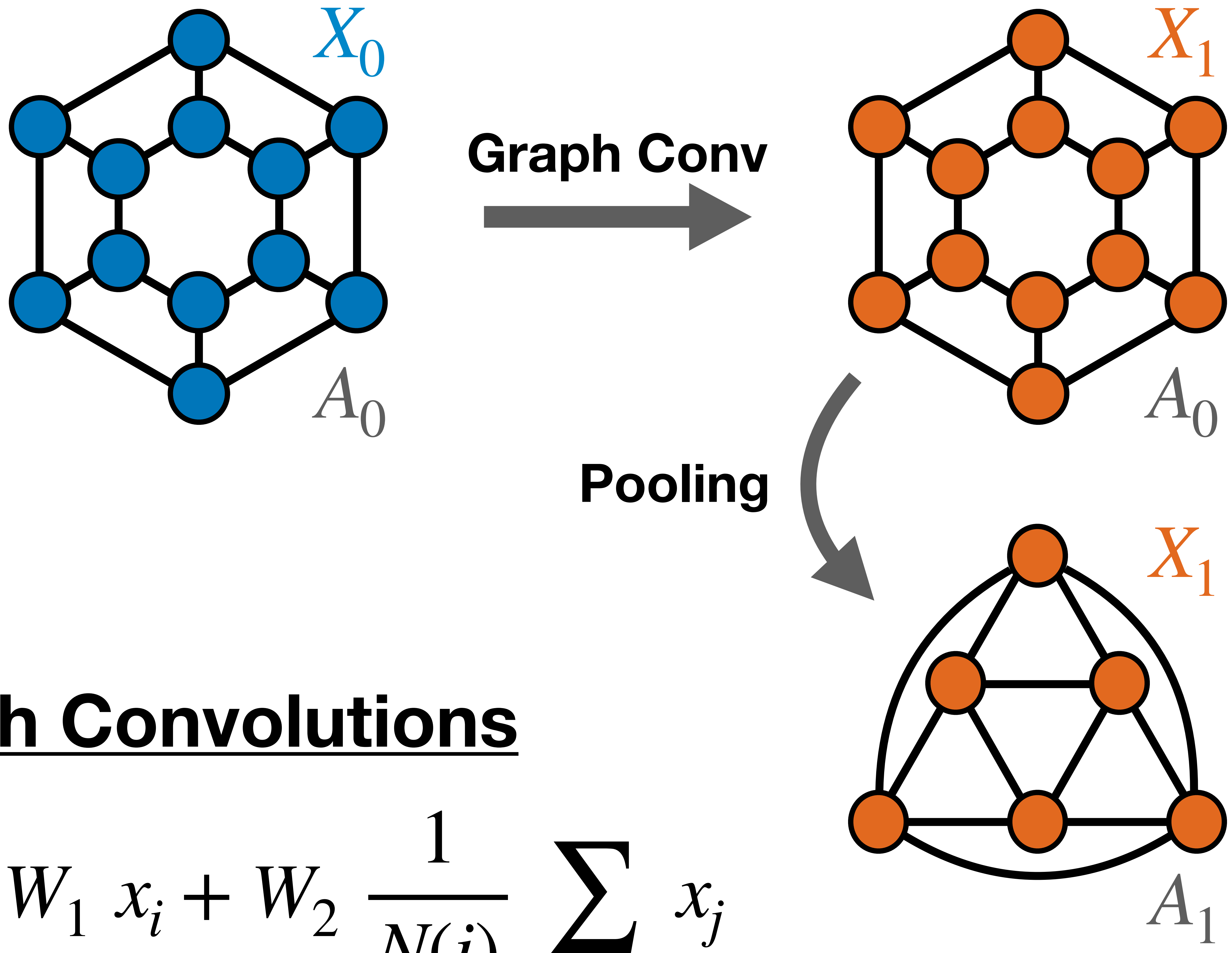


Encoding

Graph Convolutions

$$x_i' = W_1 \; x_i + W_2 \; \frac{1}{N(i)} \sum_{j \in N(i)} x_j$$

Encoding



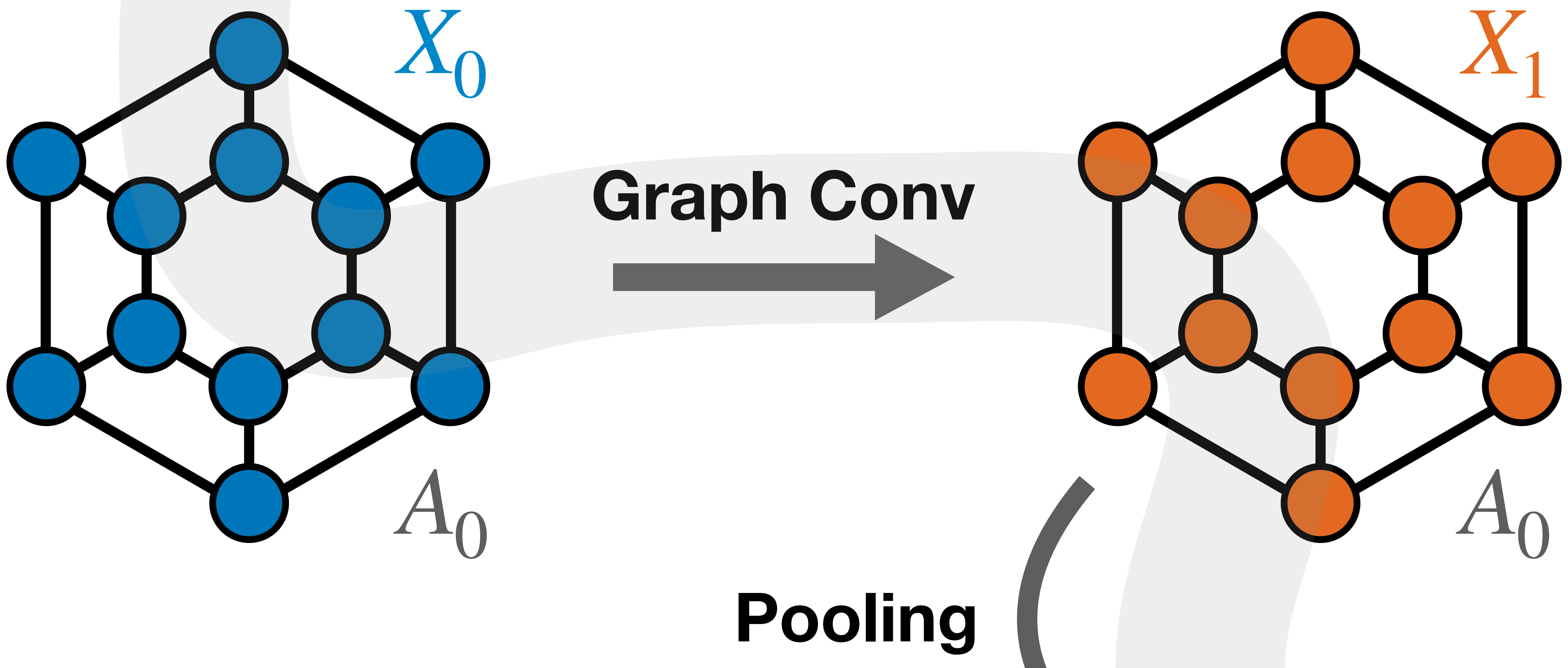
Graph Convolutions

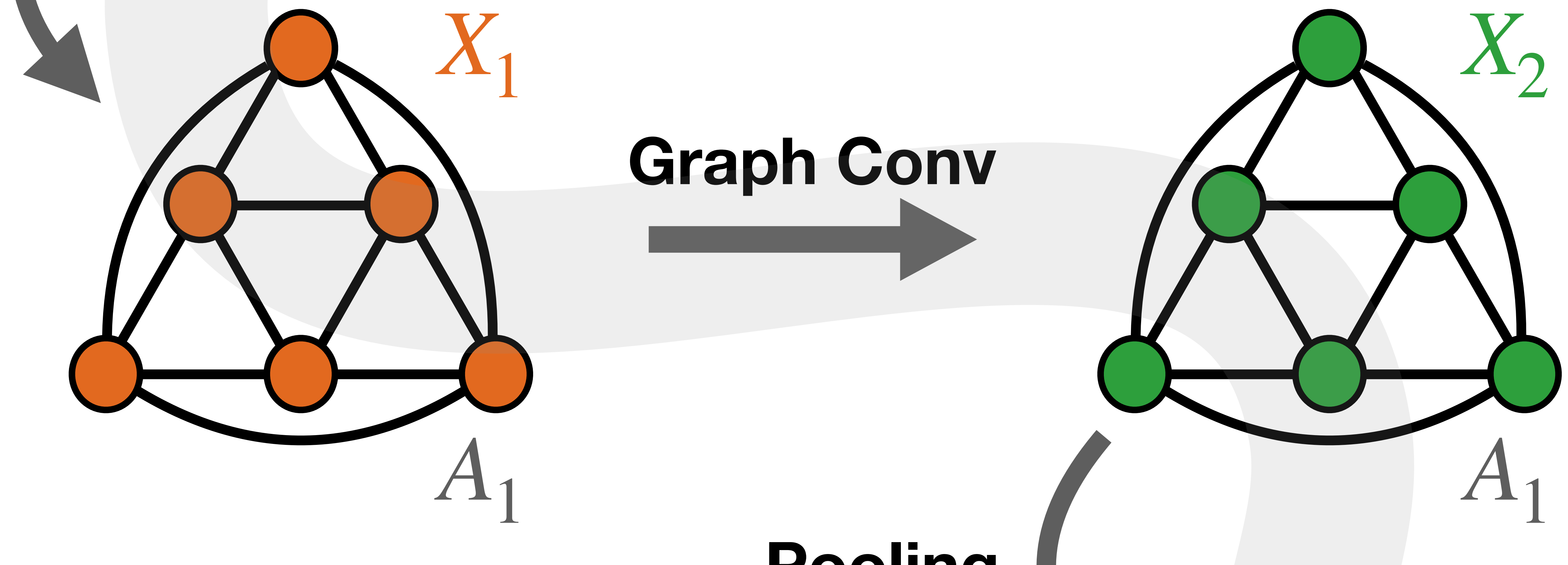
$$x_i' = W_1\, x_i + W_2\, \frac{1}{N(i)} \sum_{j \in N(i)} x_j$$

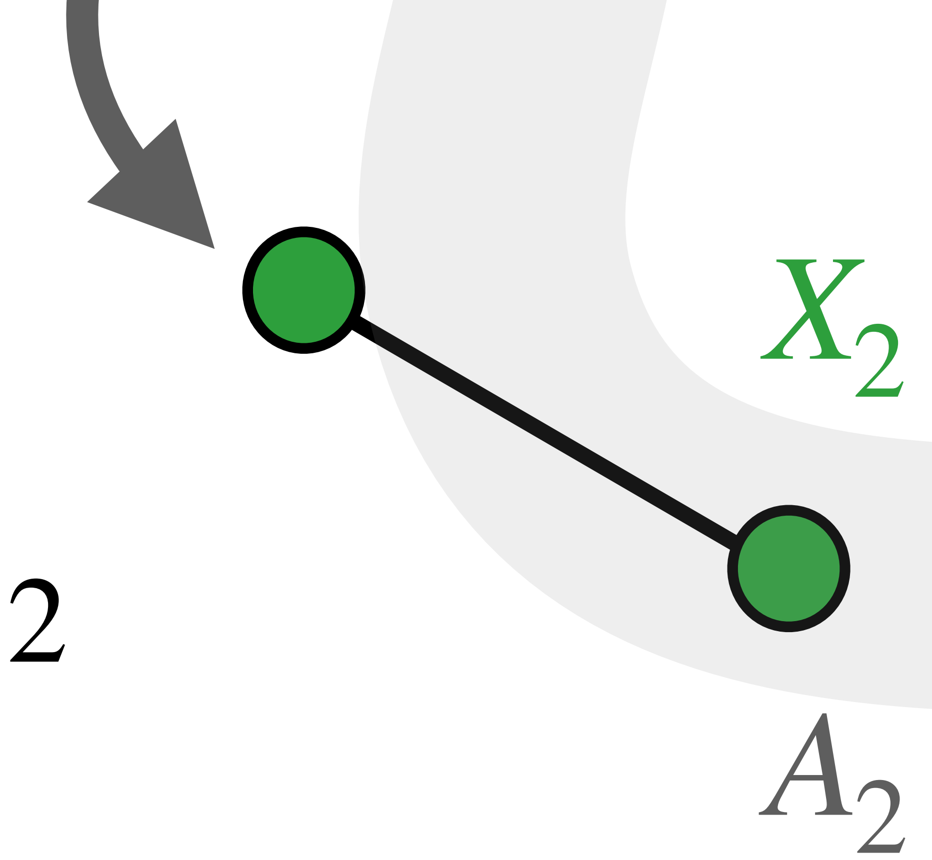
Recursive Nearest Neighbors Pooling

Recursively drop nearest neighbours and choose: $A' = A^2$

Encoding







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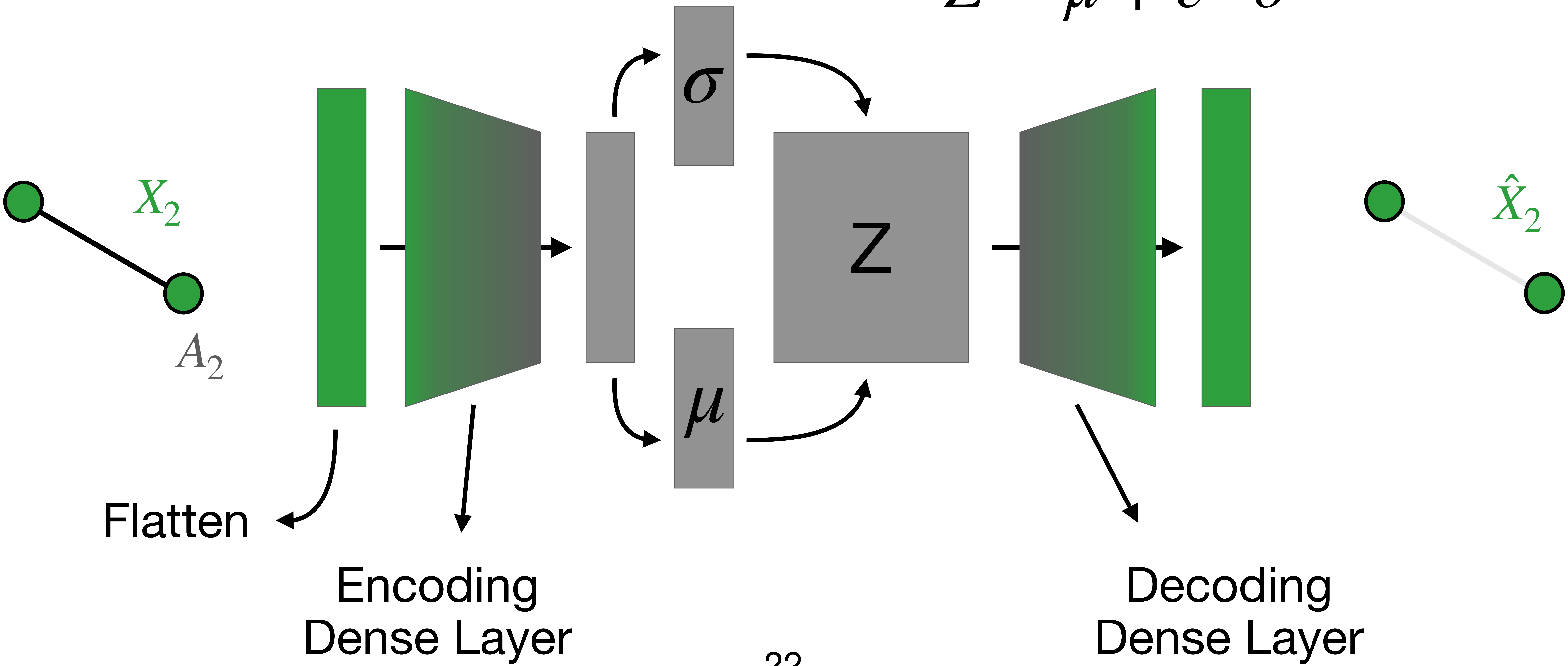
Recursive Nearest Neighbors Pooling

Recursively drop nearest neighbours and choose: $A' = A^2$

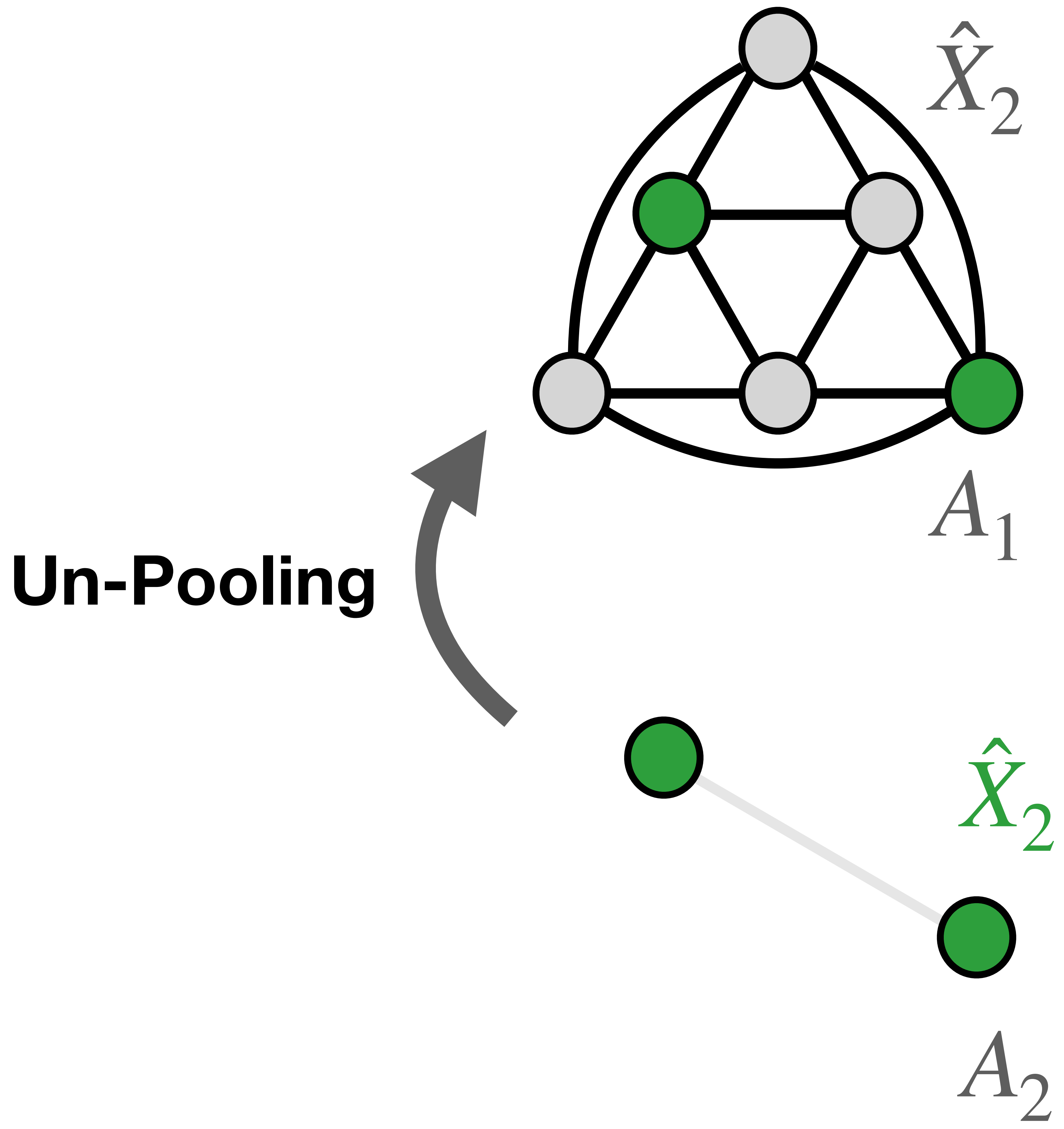
Sampling

Reparametrisation trick

$$Z = \mu + \epsilon \cdot \sigma$$



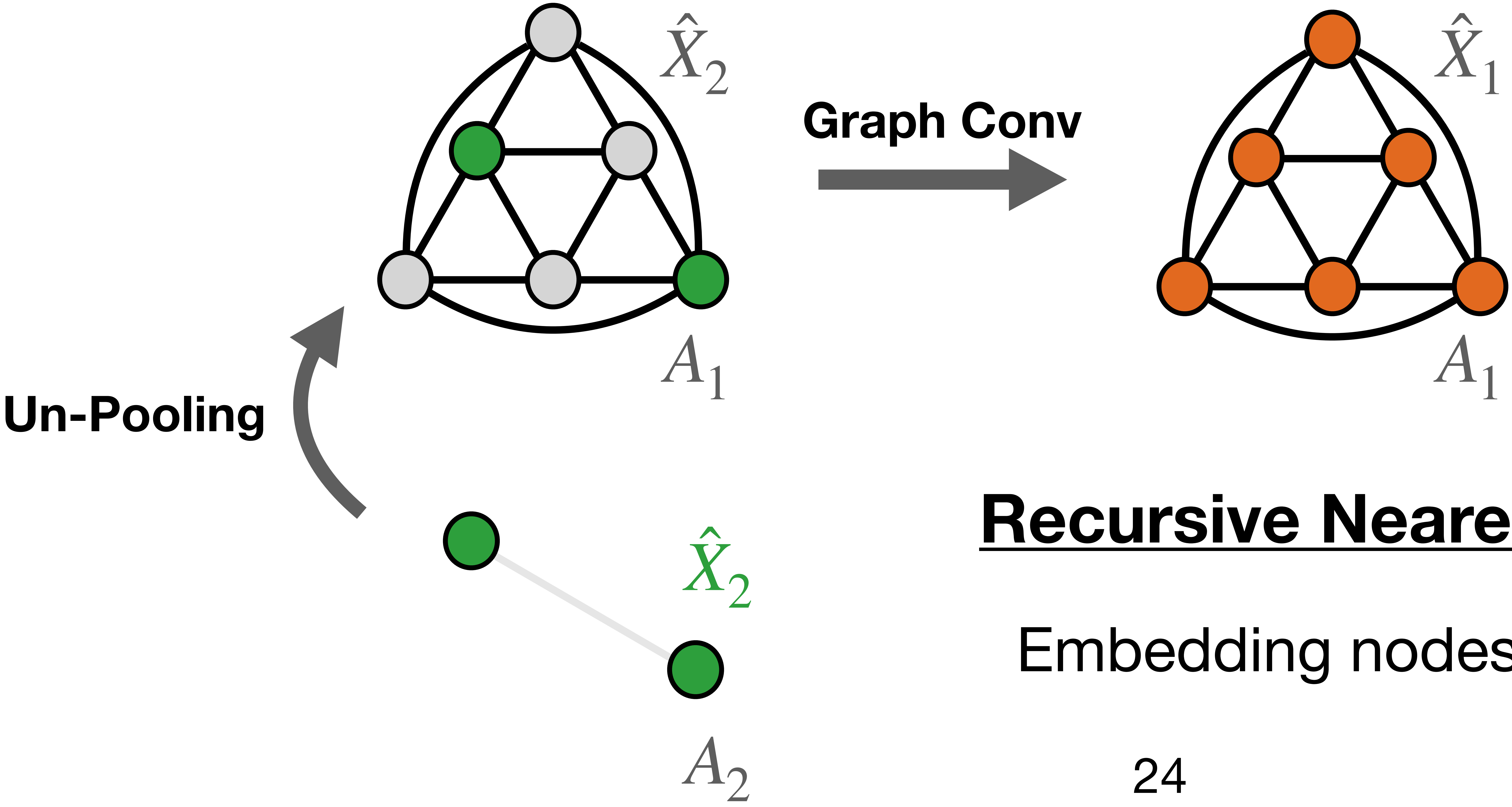
Decoding



Recursive Nearest Neighbors Un-Pooling

Embedding nodes in the previous bigger graph

Decoding



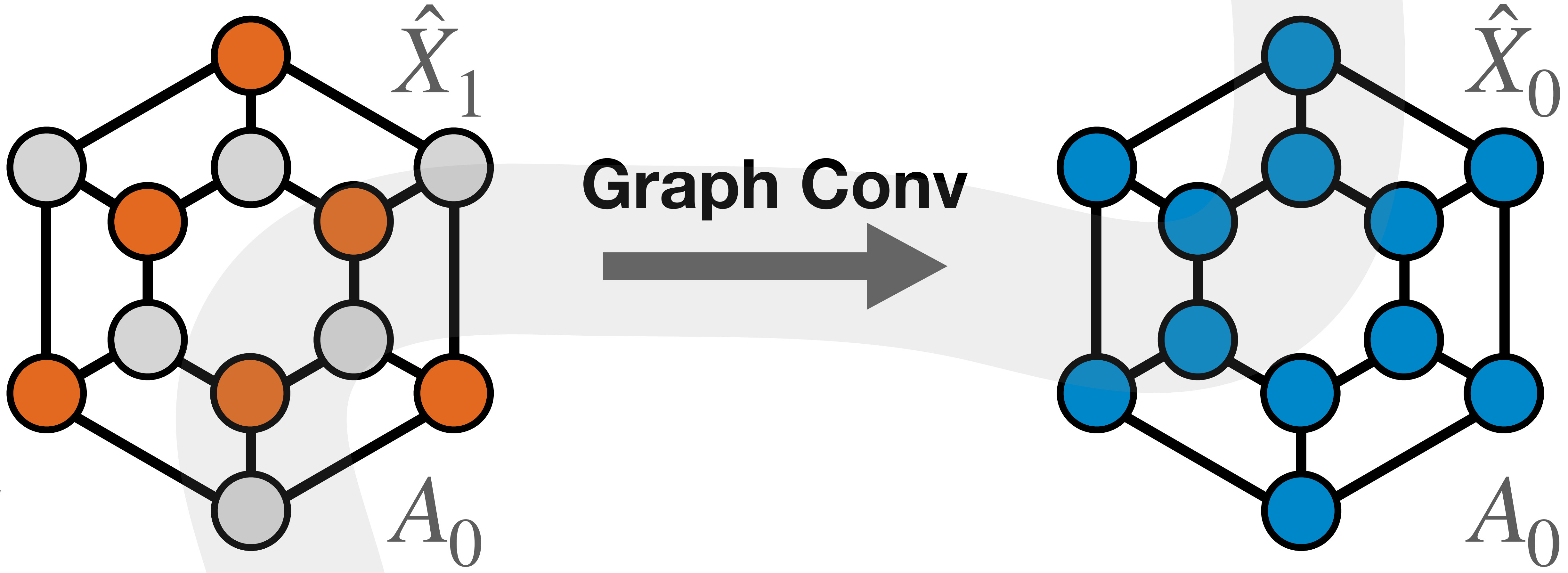
Graph Convolutions

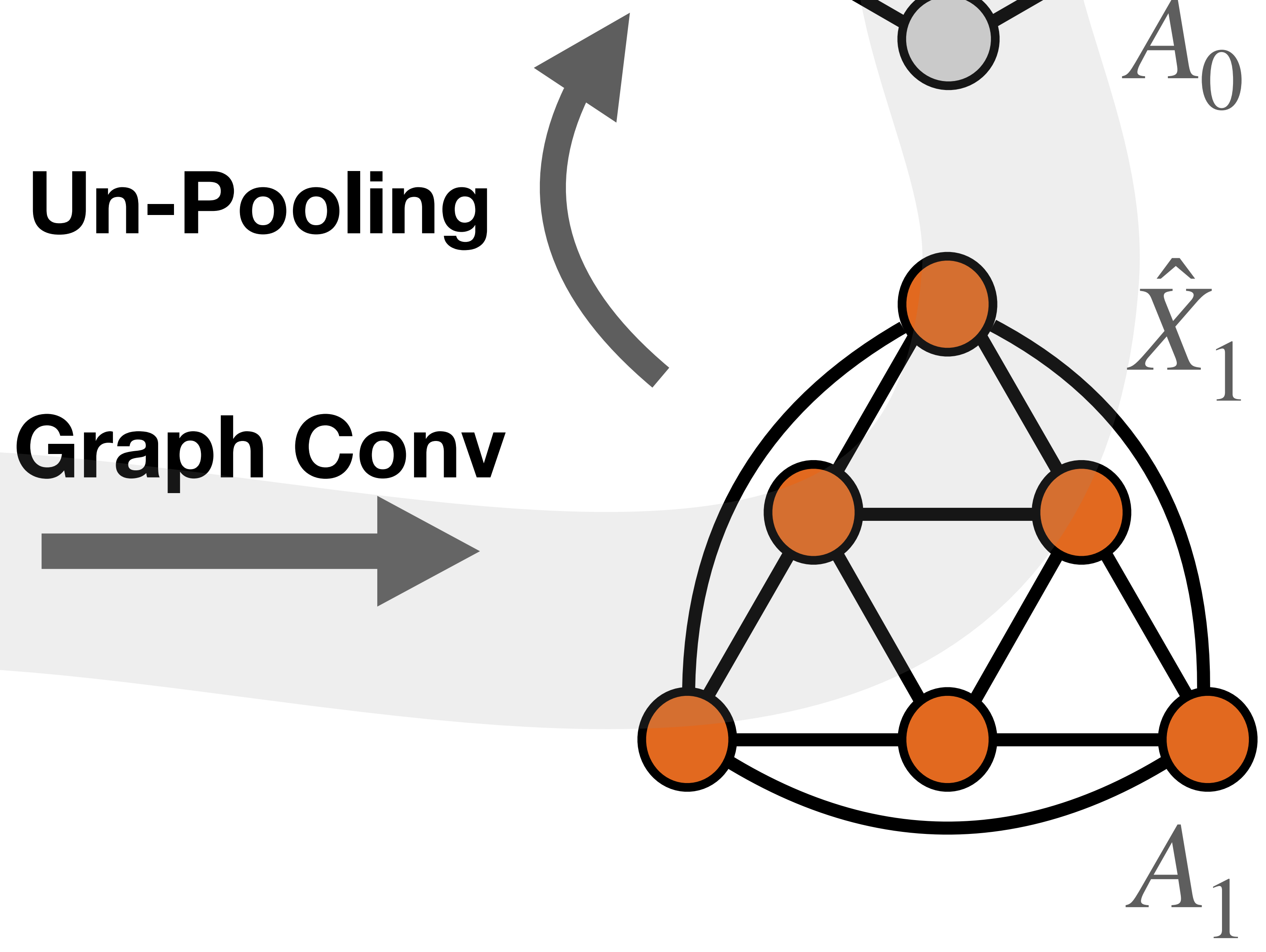
Same as in the encoding

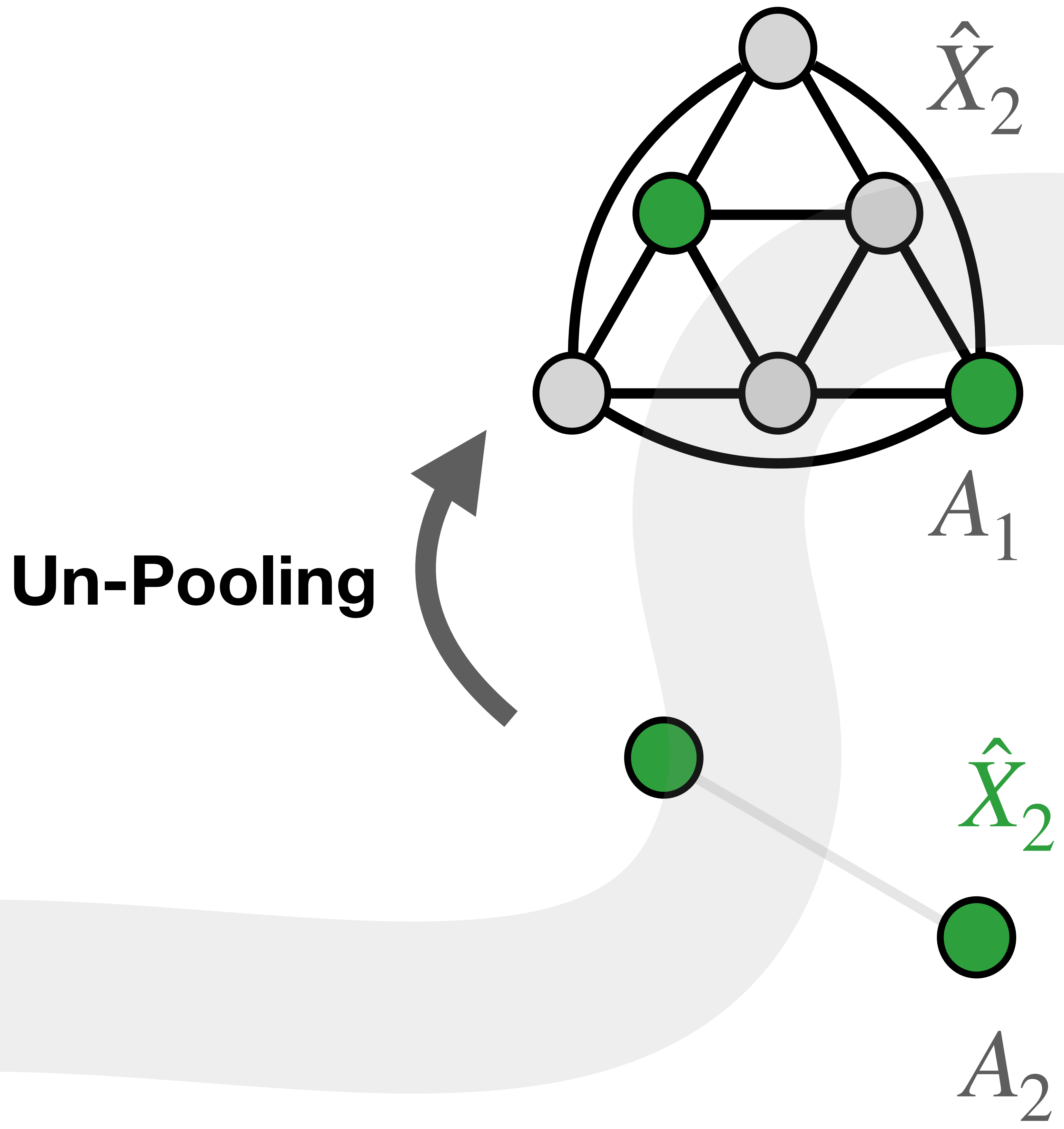
Recursive Nearest Neighbors Un-Pooling

Embedding nodes in the previous bigger graph

Decoding







Graph Convolutions

Same as in the encoding

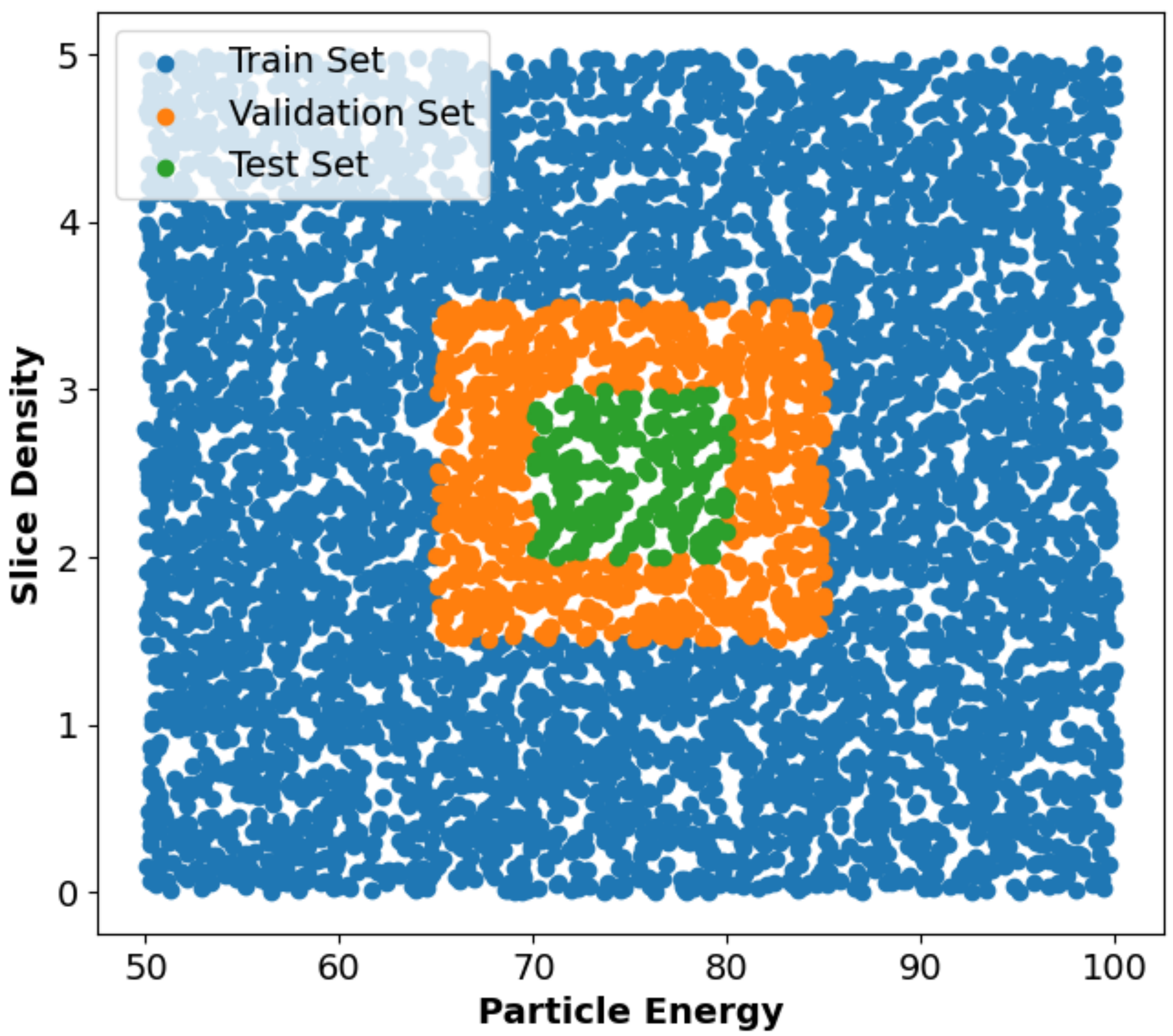
Recursive Nearest Neighbors Un-Pooling

Embedding nodes in the previous bigger graph

Training specifications

$$Loss = \underbrace{BCE(X,\hat{X})}_{\text{Reconstruction}} + \underbrace{KL(\mathcal{N}(\mu,\sigma)\,|\,\mathcal{N}(0,1))}_{\text{Regularisation}}$$

Water volume + slice

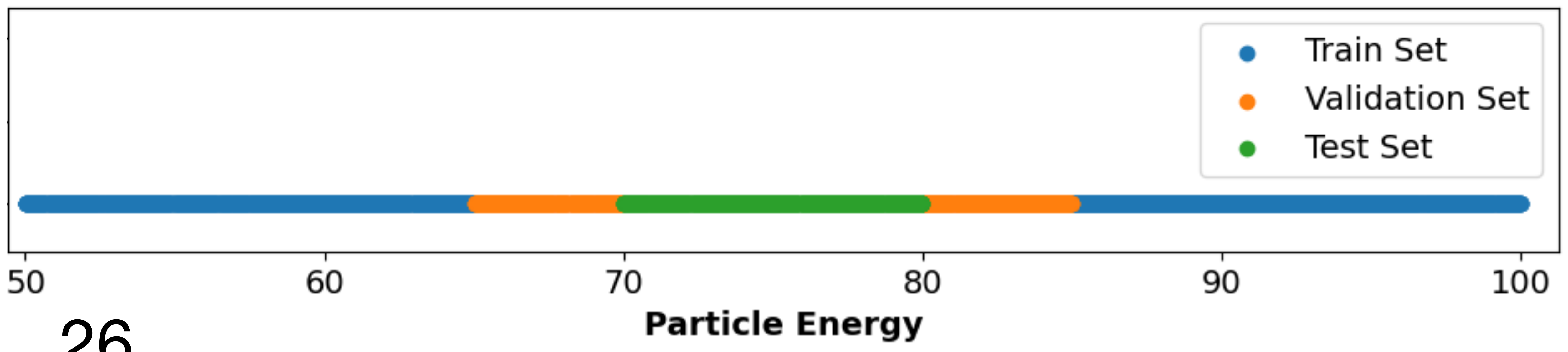


Optimiser: Adam

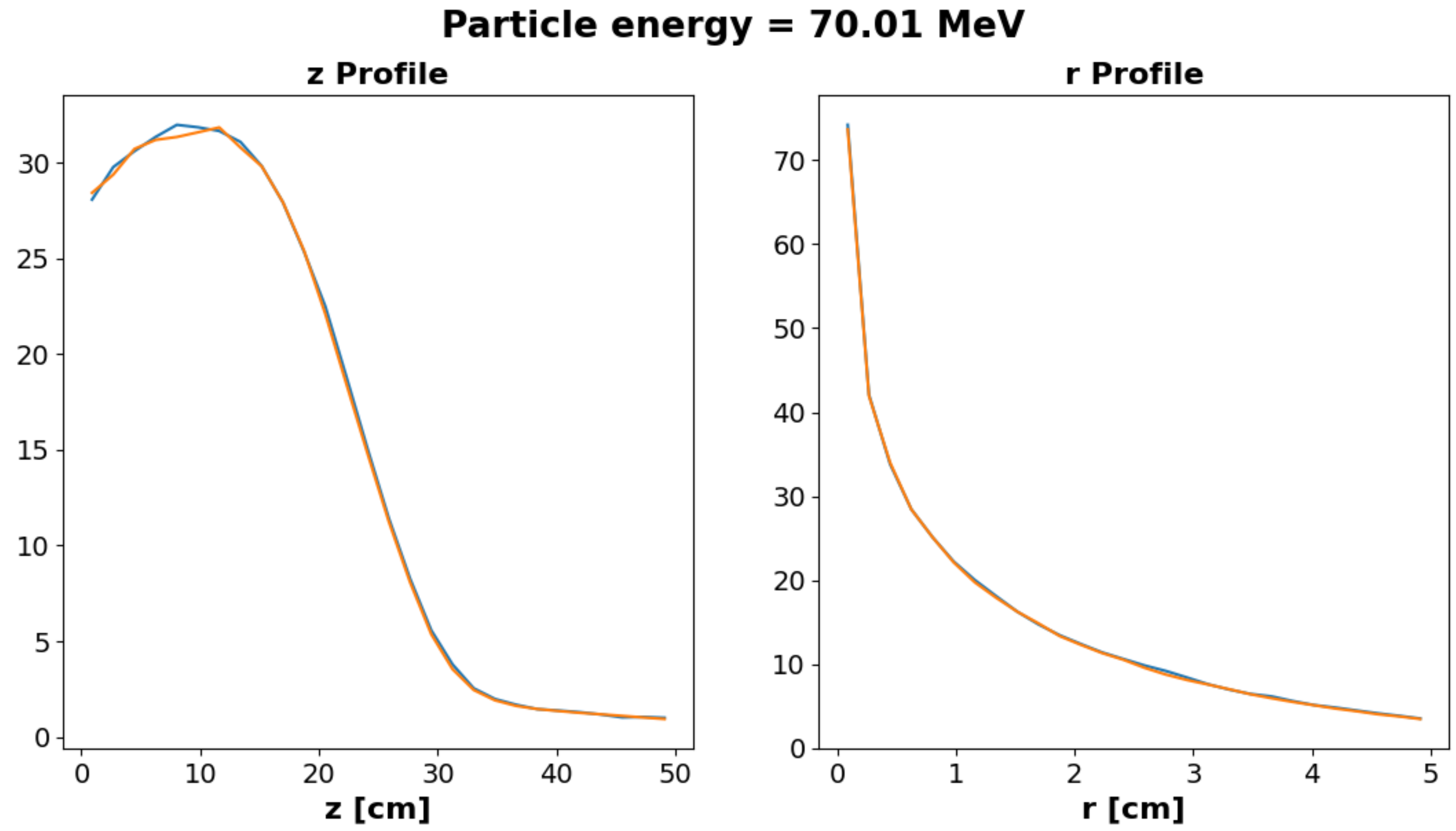
Learning rate: 0.003

Scheduler: exponential $\lambda = 0.9$

Water volume



Results: Water Volume



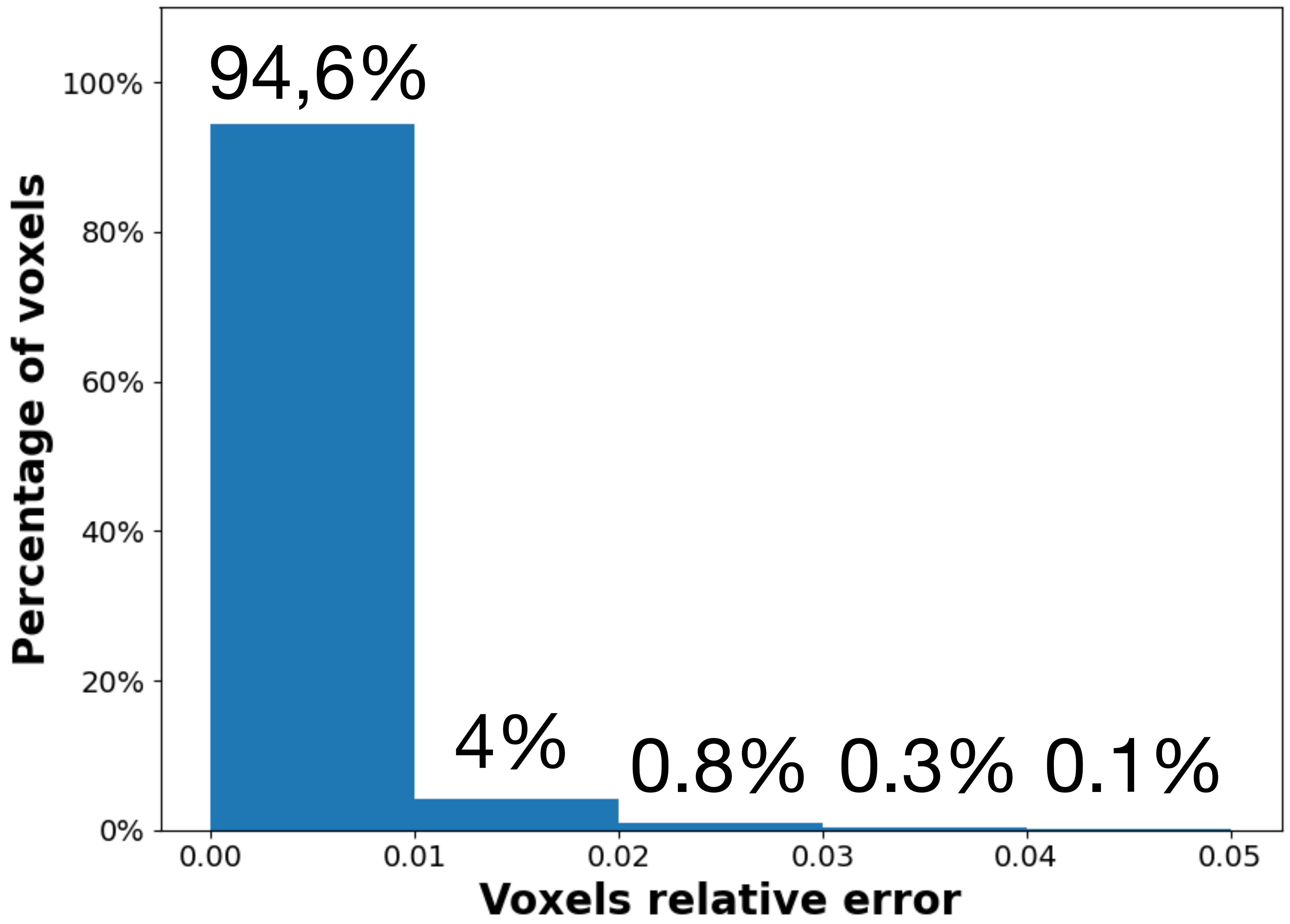
Average results:

- 95% on z profile
- 97% on r profile
- 98% on Energy conservation

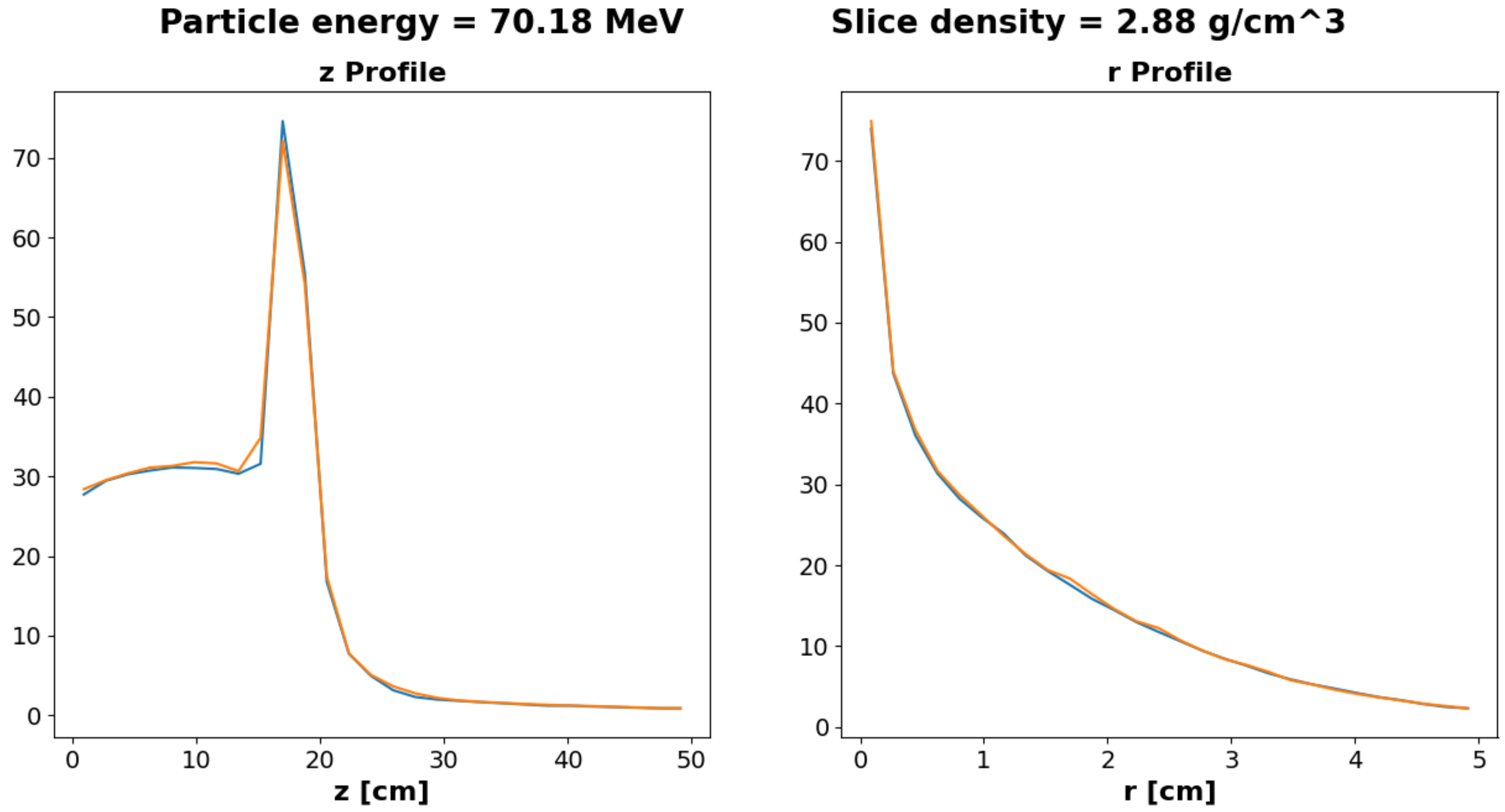
Voxel reconstruction:

$$\delta = \left\langle \frac{|D_{real} - D_{reco}|}{max(D_{real})} \right\rangle$$

99,4% with $\delta < 3\%$



Results: Water + Slice with variable density



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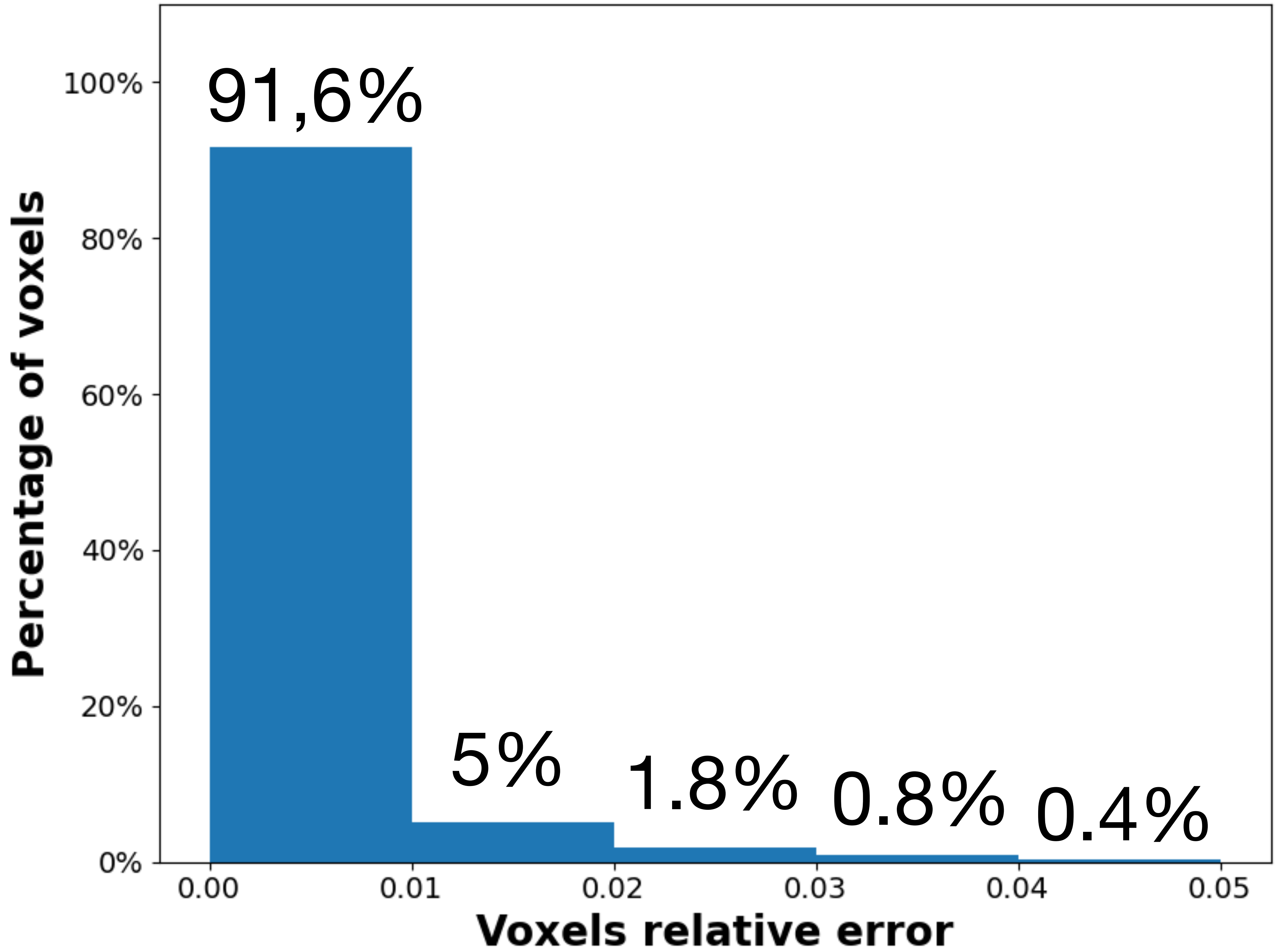

Average results:

- 93% on z profile
- 96% on r profile
- 98% on Energy conservation