AI and Monte Carlo Particle Transport in Medical Imaging and Radiotherapy

Nils Krah, Holland Proton Therapy Center, Delft, the Netherlands

WMLQ workshop, 2026, Warsaw



HollandPTC
Protonen Therapie Centrum

Consortium of

TU Delft

Erasmus MC
Universitair Medisch Centrum Rotterdam

LUMC Leiden University Medical Center

- Founded in 2013
- First patient treated in Sept 2018
- Final commissioning of beam lines in July 2019

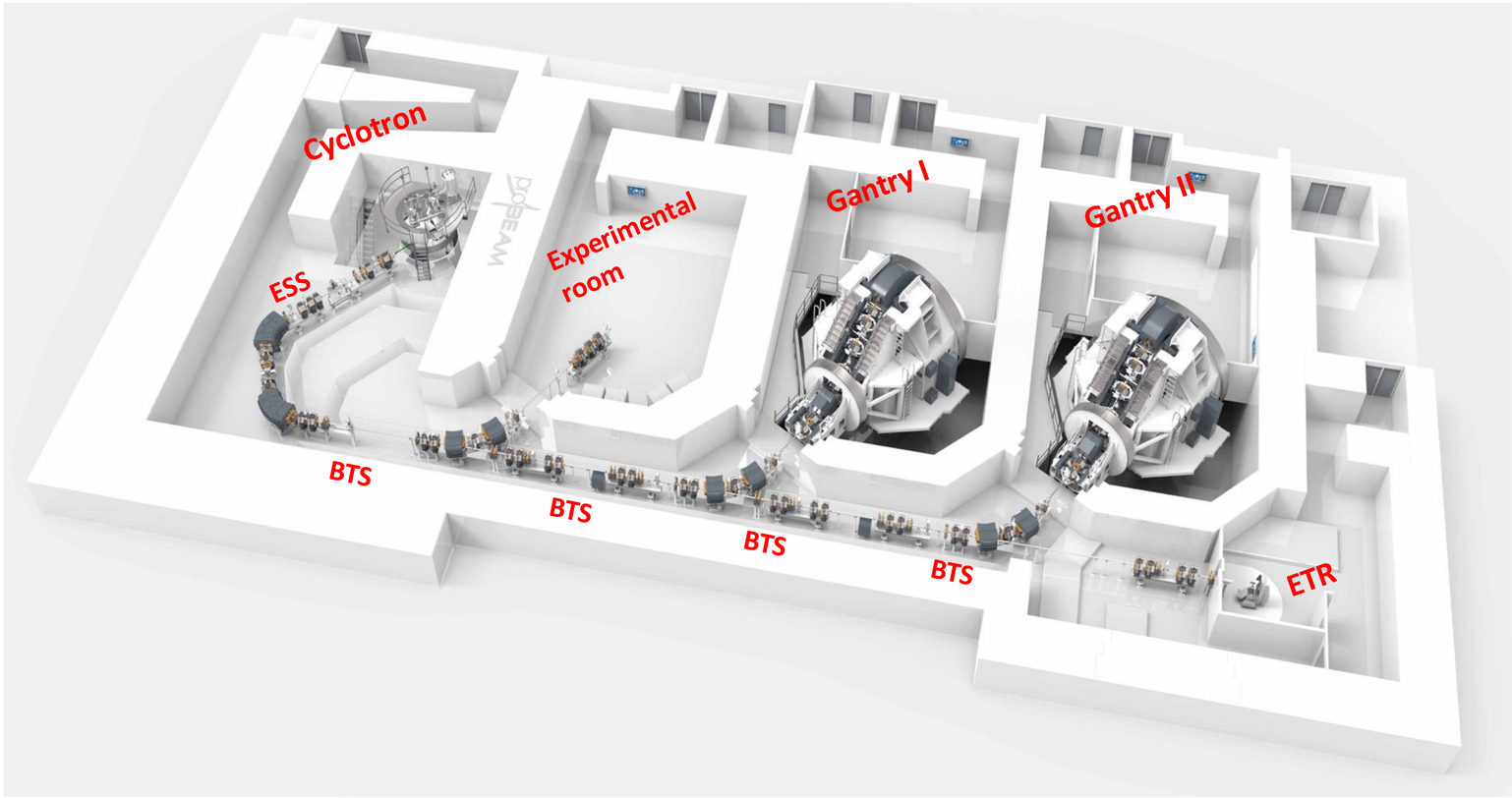
•Assignments:

- •Perform excellent clinical care.
- •Perform R&D from fundamental to clinical research



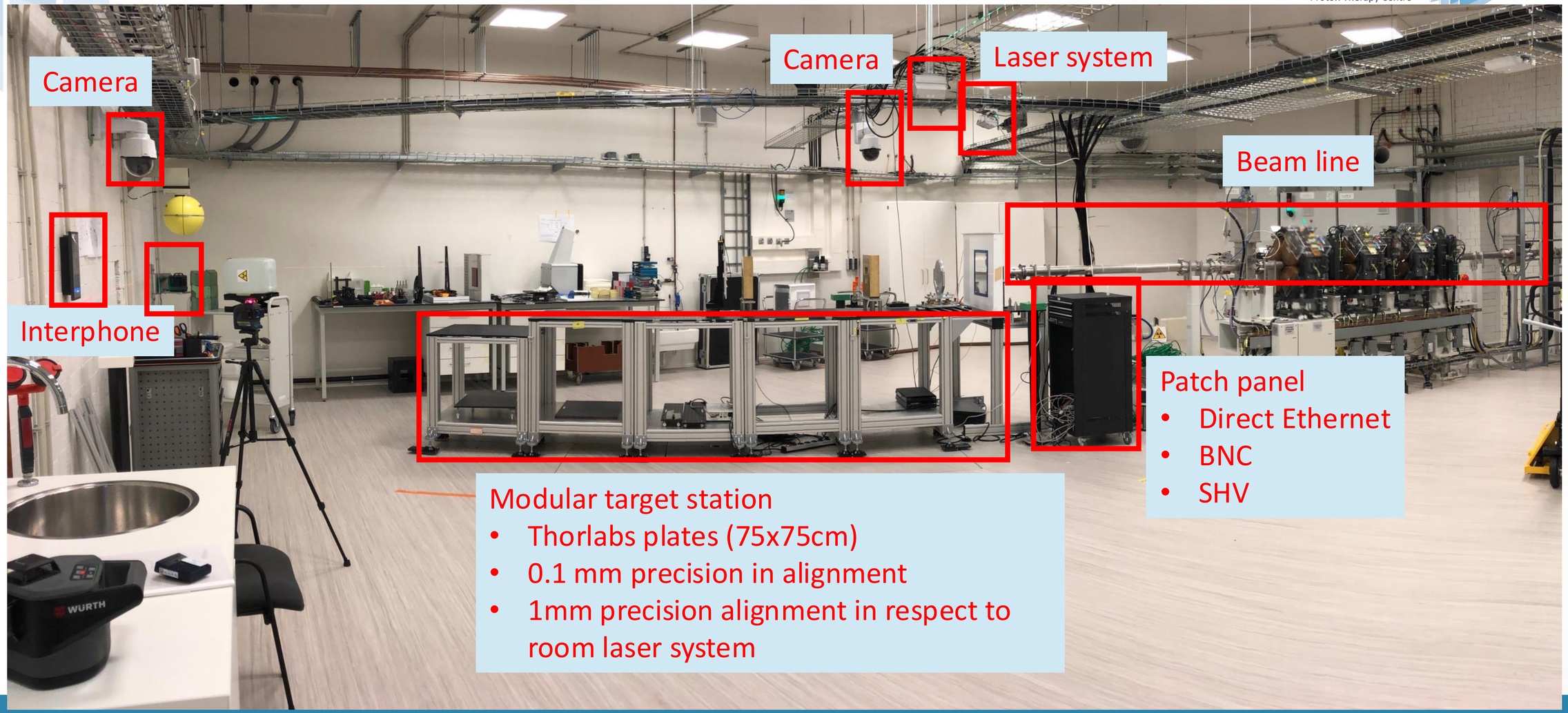
The Holland Proton Therapy Center

- VARIAN Protontherapy Center
- Superconductive Cyclotron ProBeam
- 4 rooms:
  - 2 rotating gantries,
  - 1 eye treatment room
  - 1 R&D room



Experimental beam line

HollandPTC
Proton Therapy Centre

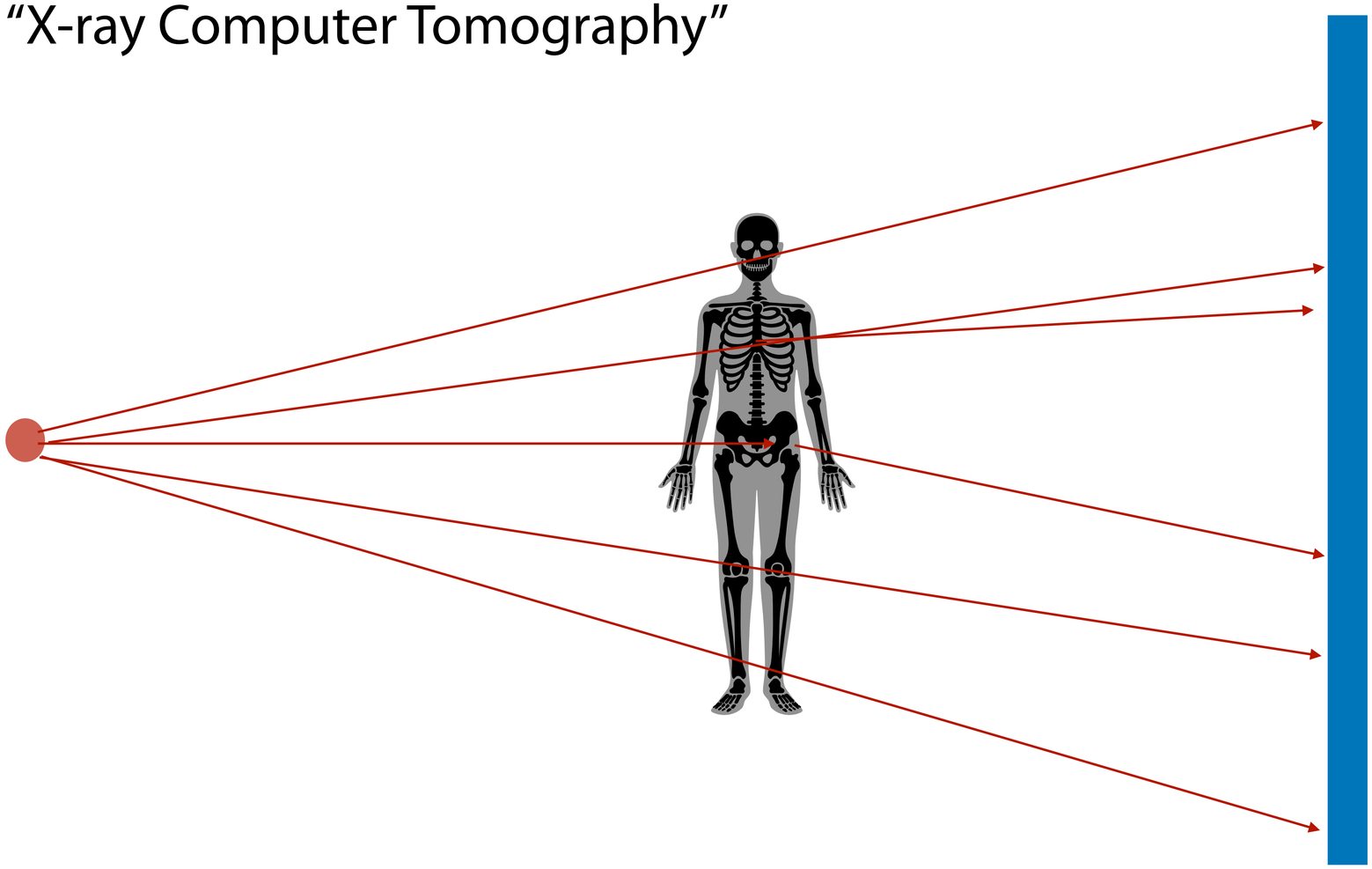


TU Delft
LUMC Leiden University Medical Center
Erasmus MC

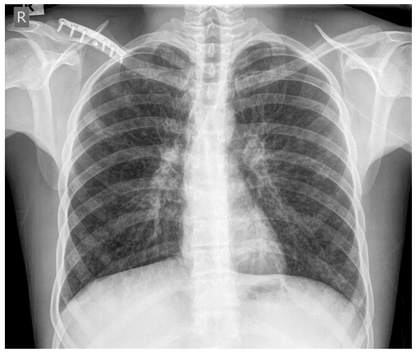
Context: Medical Imaging

Example: x-rays (gammas) traversing a human body

"X-ray Computer Tomography"



Intensity mage

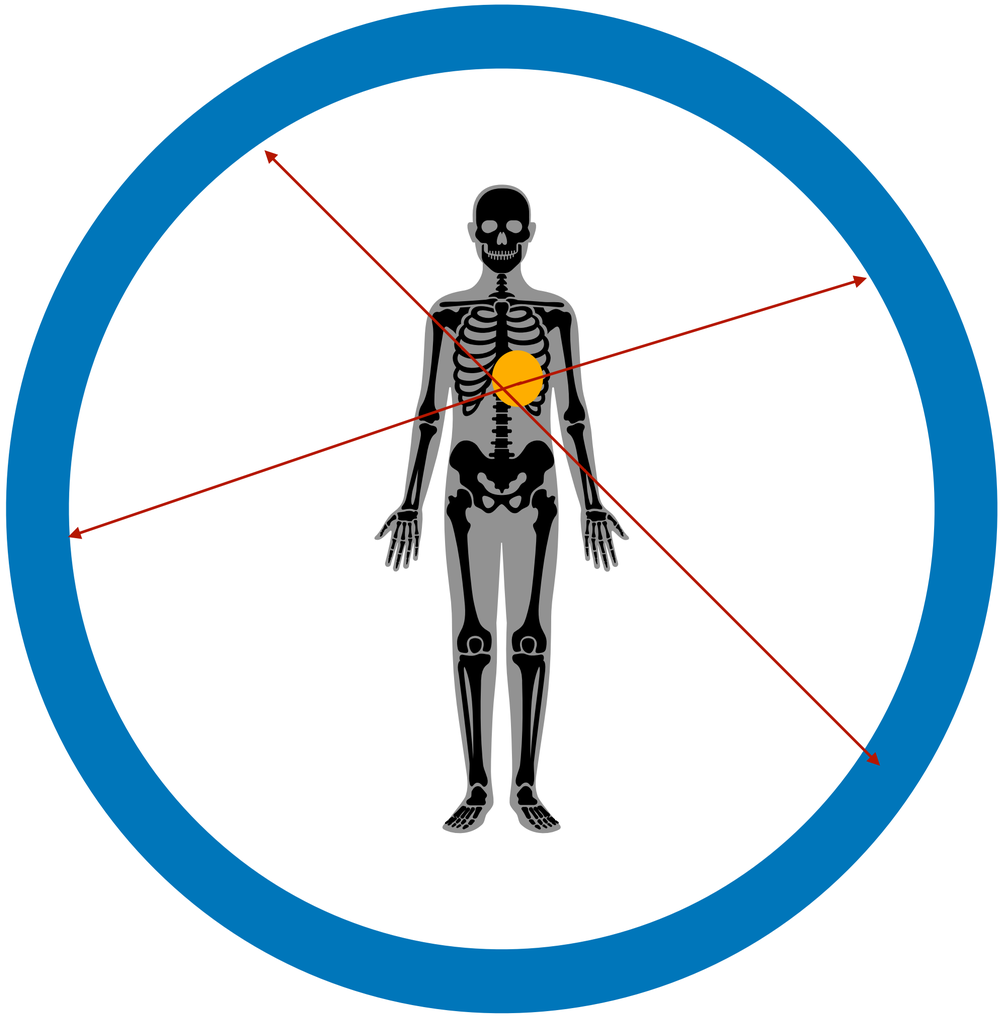


Reconstruct volumetric map of the attenuation coefficient

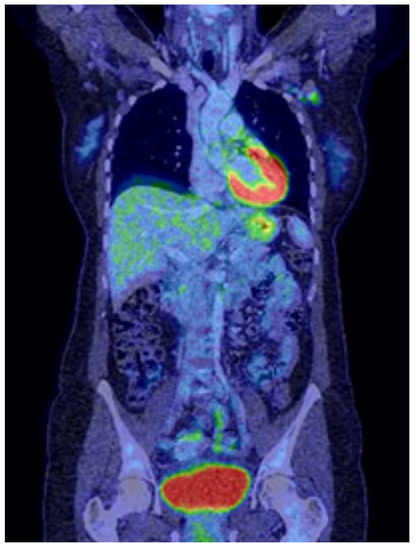


Context: Medical Imaging

- Example: gammas emitted from a body



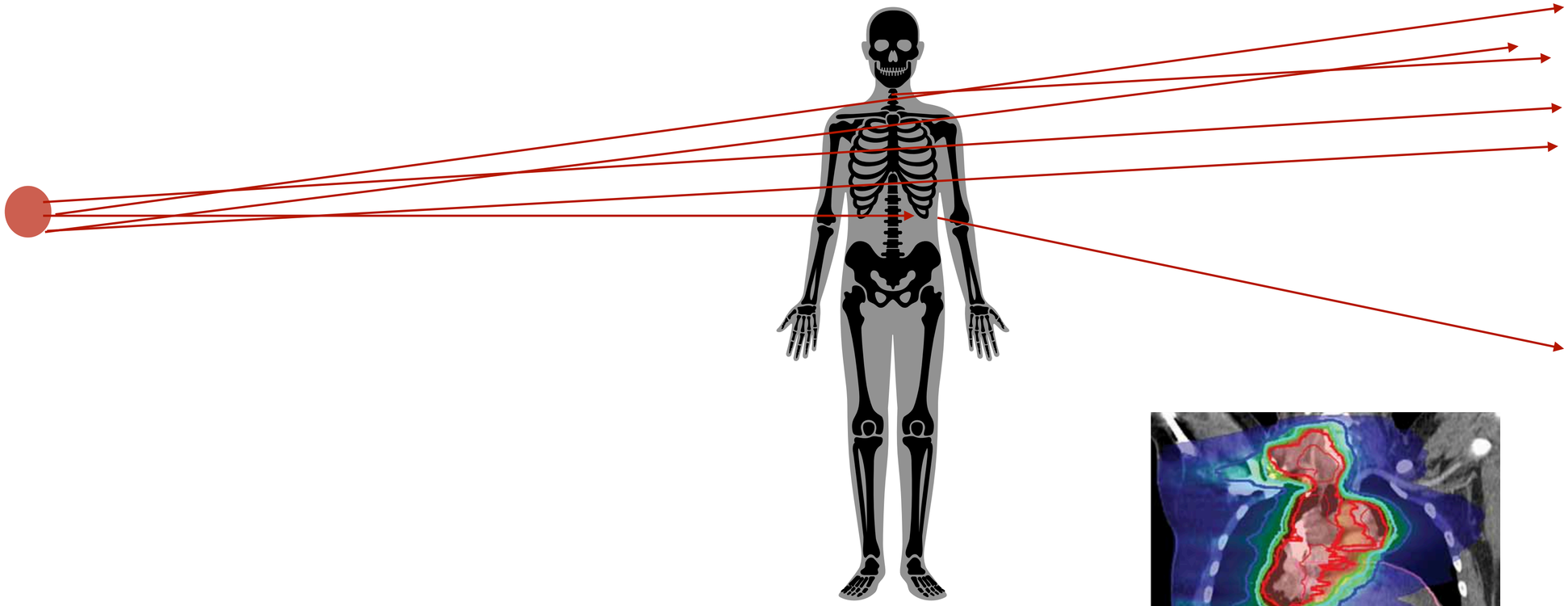
- Positron Emission Tomography (PET)
- Single Photon Emission Computed Tomography (SPECT)



Reconstruction:
Source distribution

Context: External Radiotherapy

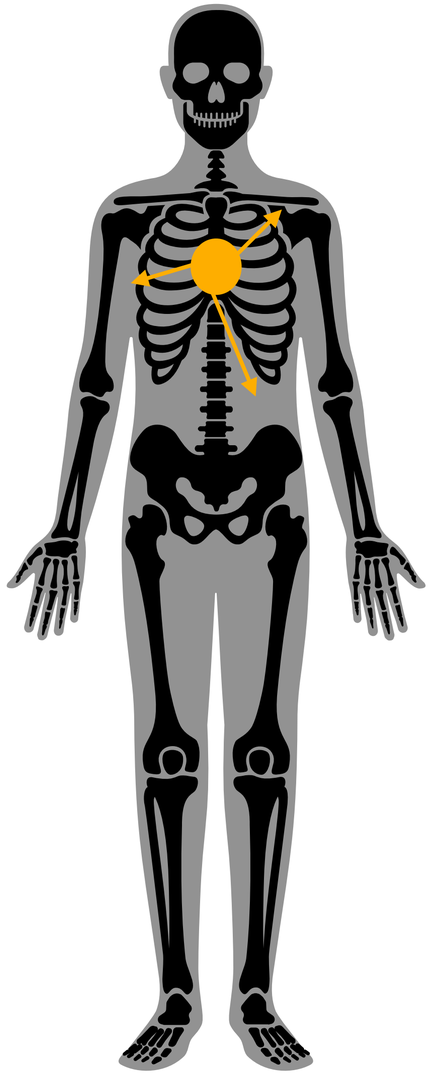
Ionizing radiation penetrating through/into a human body



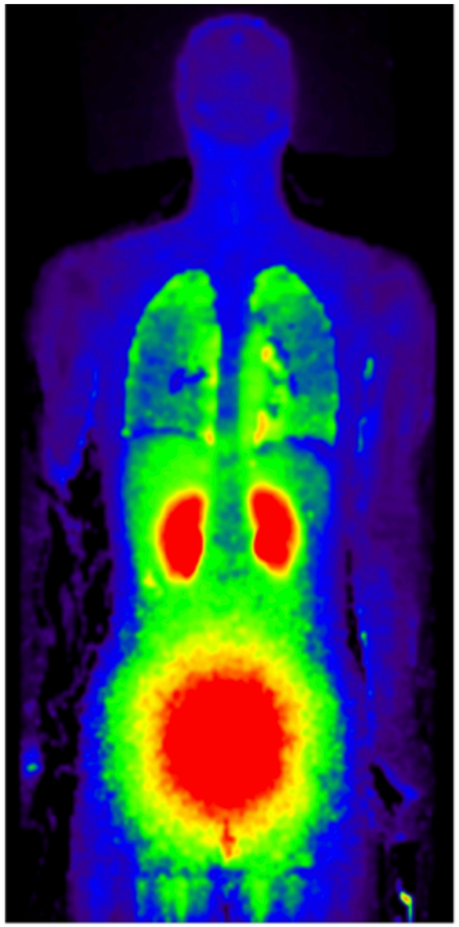
Goal: expose tumor to high dose, but spare healthy tissue as much as possible.

Context: Nuclear Medicine

- Ionizing radiation created inside a human body



Expose organs/cells affected by cancer to radiation dose.



Examples of Monte Carlo codes

Multi-purpose:

- **Geant4, FLUKA, MCNP, …**

Applications built on top of Geant4:

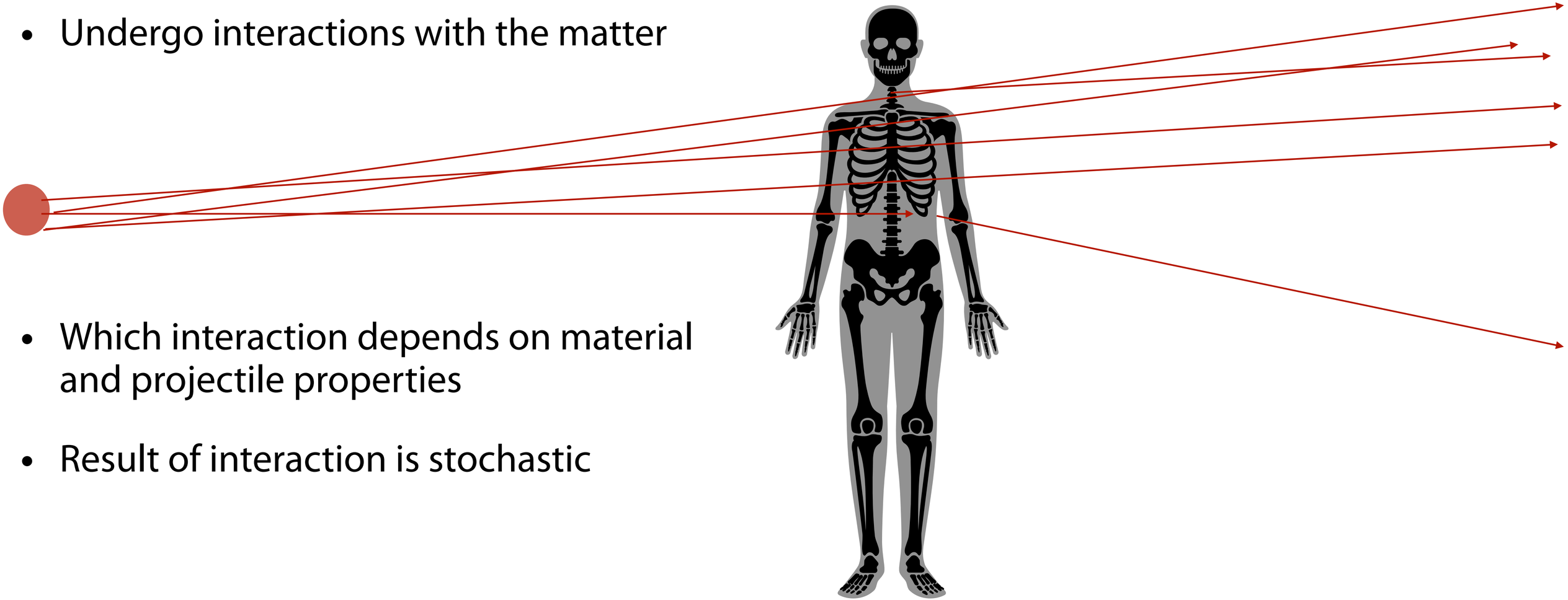
- **TOPAS**
- **GATE version 9.x**
- **new GATE 10**

Application/physics specific:

- **EGS (Electron, photon)**
- **Penelope (electron, photon)**
- **MCsquare (proton therapy)**
- **FRED (mainly fast dose calculation)**
- **GGEMS**
- **…**

Physics perspective

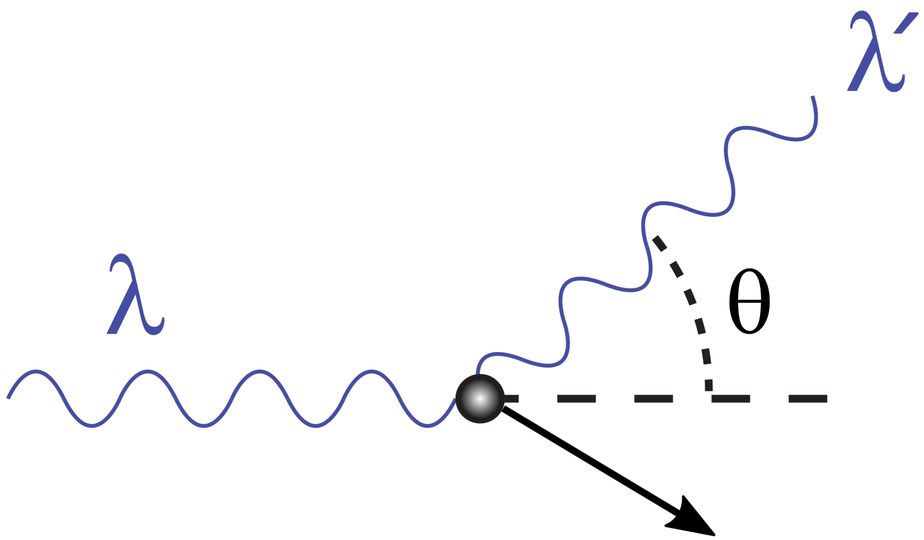
- Particles traveling across a heterogeneous distribution of matter
- Undergo interactions with the matter



- Which interaction depends on material and projectile properties
- Result of interaction is stochastic

“Interaction”: Physics perspective

Example of interaction: Photon scattering off an electron - Compton scattering

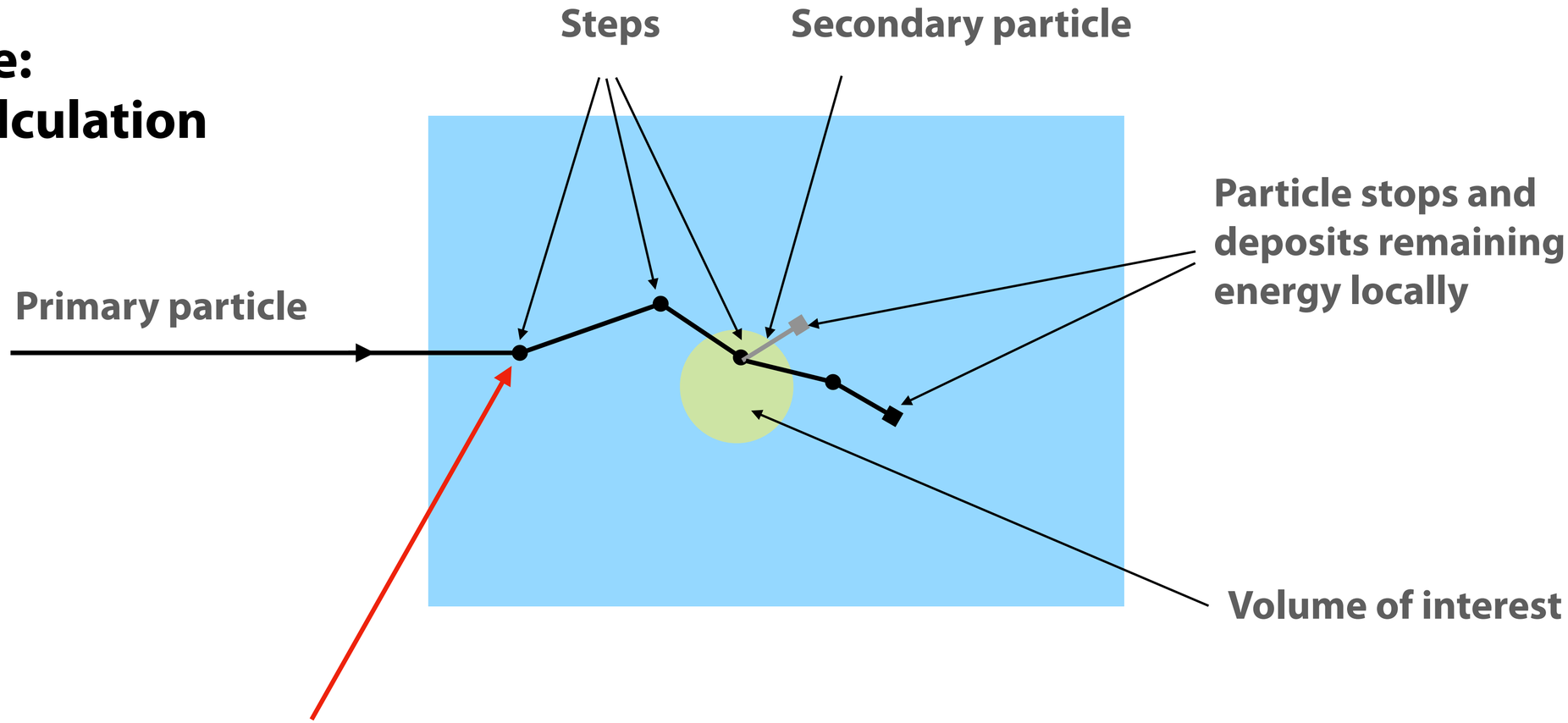


- Photon changes energy (wavelength) and direction
- Transfers some energy to target

Particle transport simulation

Step-wise propagation of a particle across a medium (condensed history)

Example:
Dose calculation

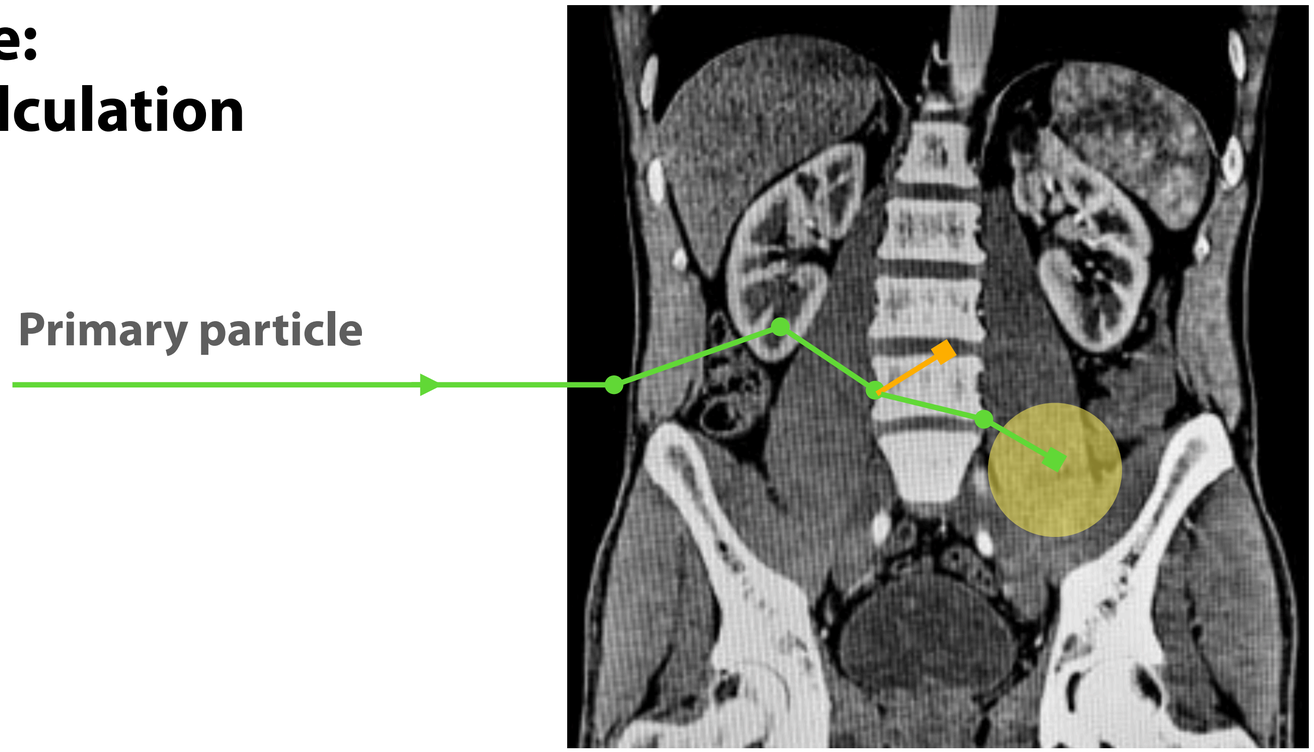


At each step: Evaluate and apply interaction models

Particle transport simulation

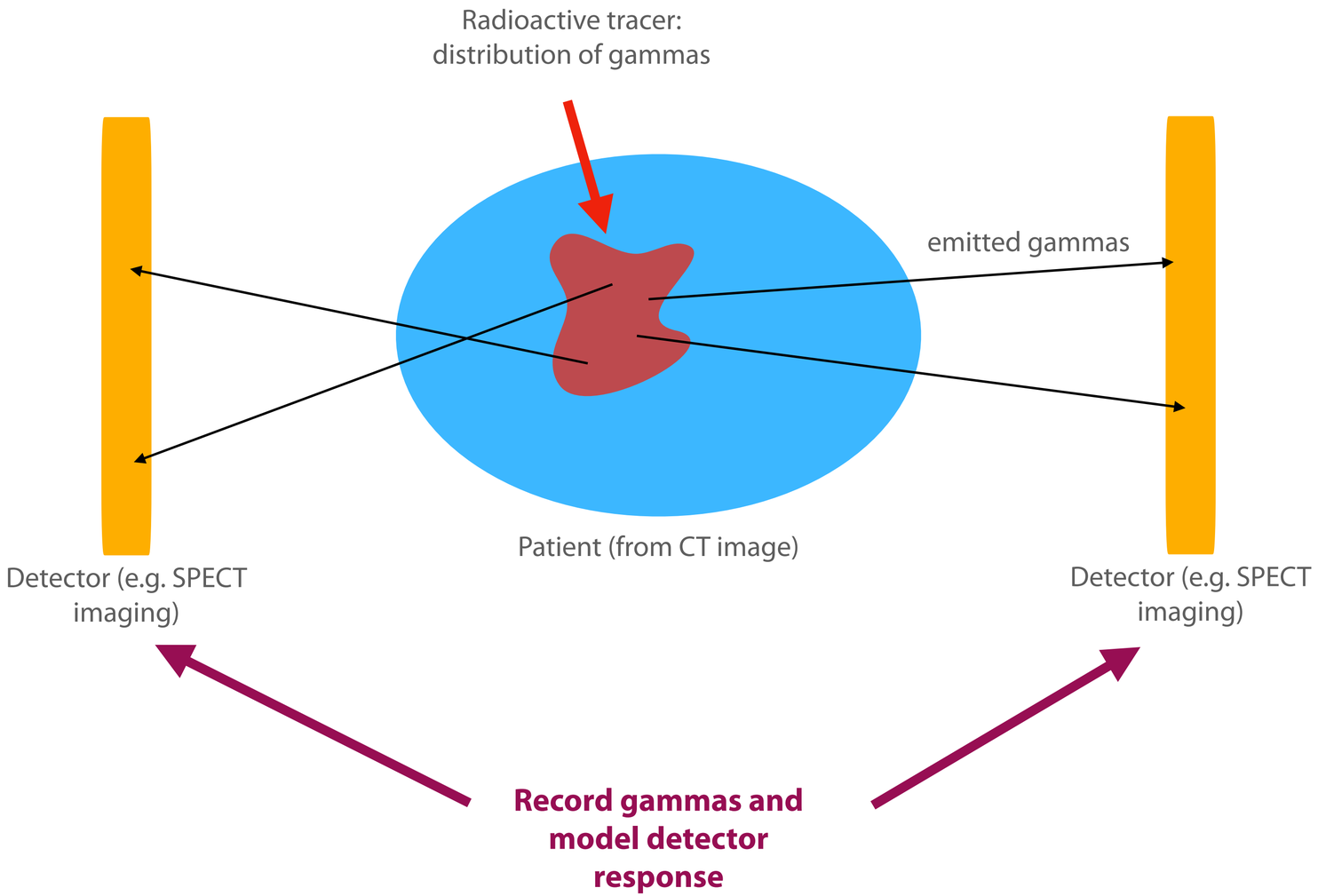
Patient = complex heterogeneous geometry

Example:
Dose calculation

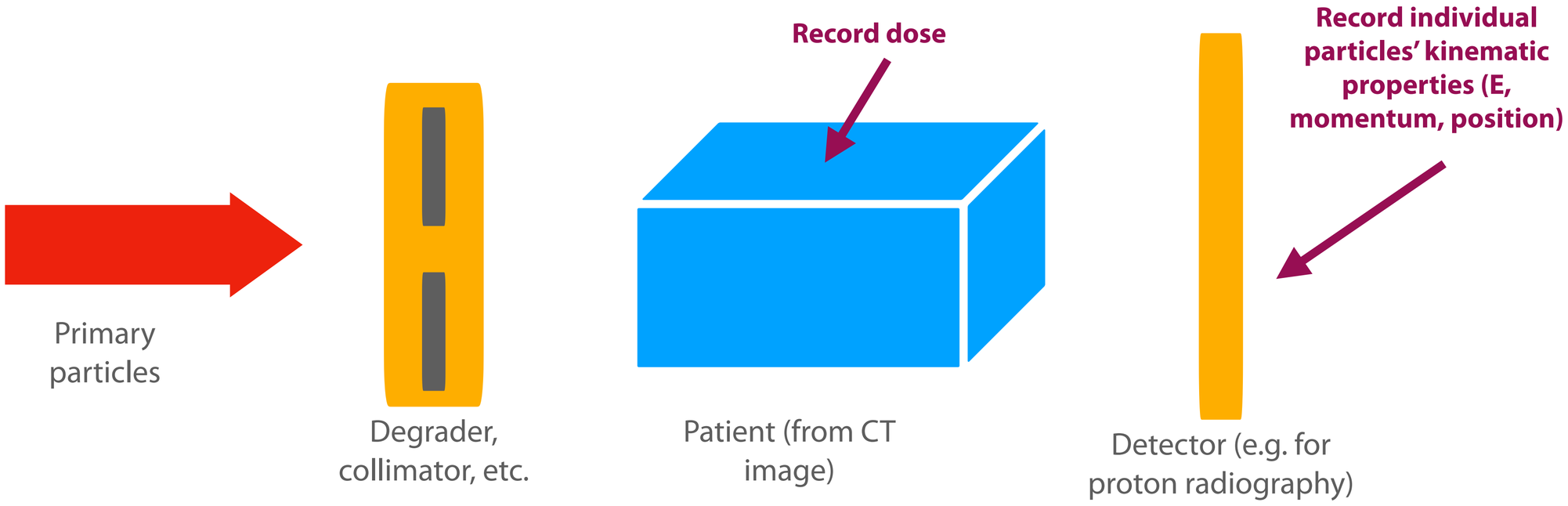


Patient geometry usually parametrized via 3D discretized image: x-ray CT image

Schematic example of "Monte Carlo Simulation" …

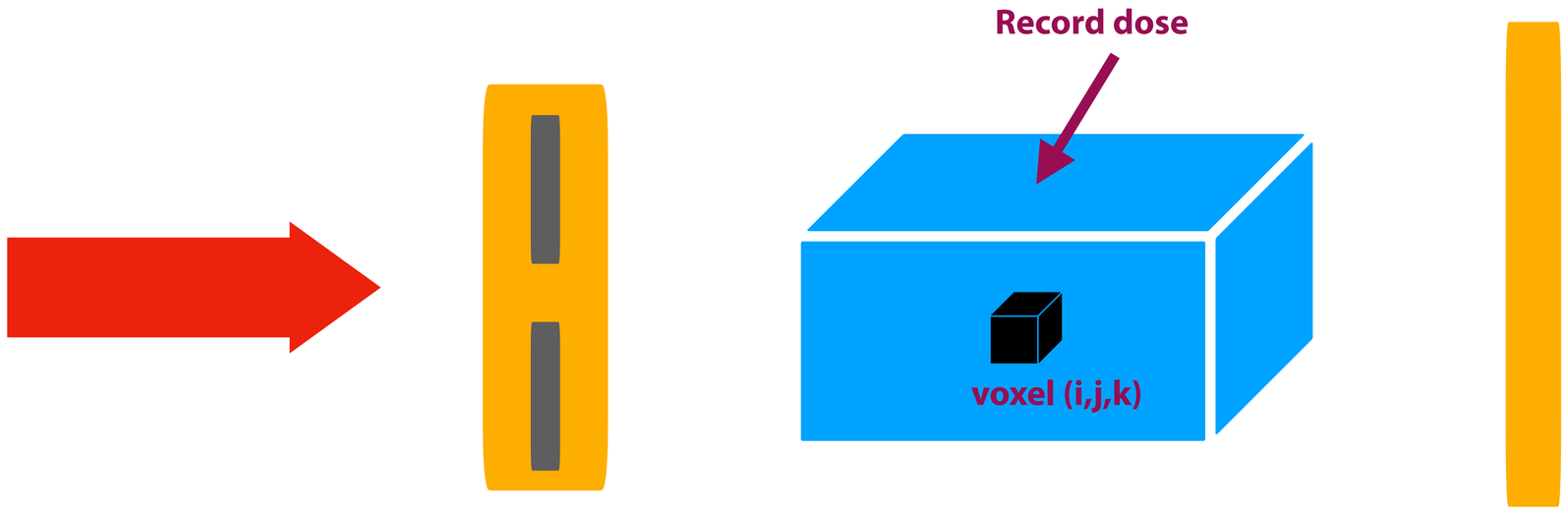


Example of "Monte Carlo Simulation" …



Monte Carlo simulations
(in medical physics/imaging)
are used to
sample probability distributions.

MC samples a probability distribution



Dose D in voxel i,j,k is:

$$D_{i,j,k} \propto \int p(\epsilon, \vec{x}_{i,j,k}) \epsilon \mathrm{d}\epsilon$$

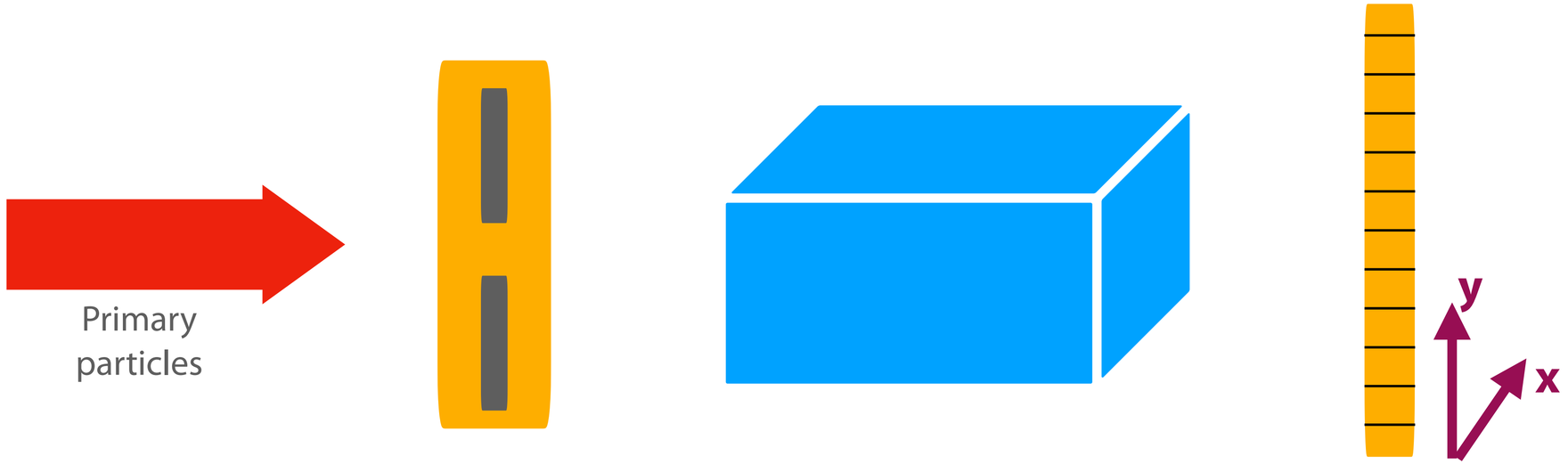
with ϵ deposited energy

Sampled by transporting N primary particles

→ **Precision of D improves with 1/sqrt(N)**

→ **More particles = lower noise**

MC samples a probability distribution



Projected image is obtained by binning:

$$I(x,y) \propto \int p(E,x,y)\, w(E)\, \mathrm{d}E$$

with E the particle's energy

and $w(E)$ the detector response

Sampled by transporting N primary particles

More particles = lower noise

Simulated images are spatially discretized probability distributions

where

1 image represents 1 distribution

Pros and cons of (multi-purpose) Monte Carlo

Accurate and “complete” physics

Versatile applications



Computationally intensive

Monte Carlo simulations can generate training datasets (images)

How to get around the “slowness”?

- Strip down and simplify physics (models, cuts)
- Implement task-specific optimized code
- Use parallel hardware; GPU
- Replace parts of the tracking by fast simulation
- Replace Monte Carlo completely by effective model
- Enhance low-statistics Monte Carlo output

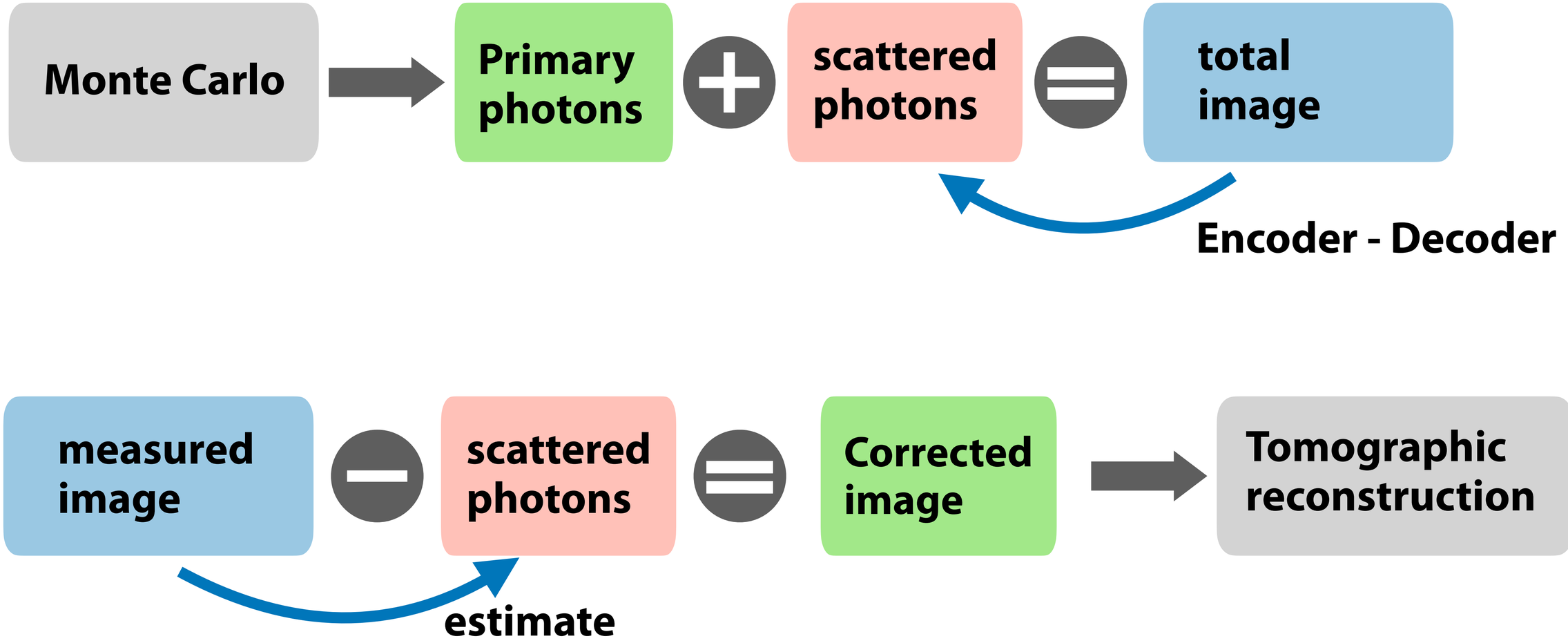


this talk

Scatter estimation/removal

- Scatter contribution in projections reduces image quality in SPECT, PET, CBCT
- Scatter can be simulated via Monte Carlo, but it is slow
- Idea: Train network to estimate scatter images from projections
- … and replace the Monte Carlo simulation

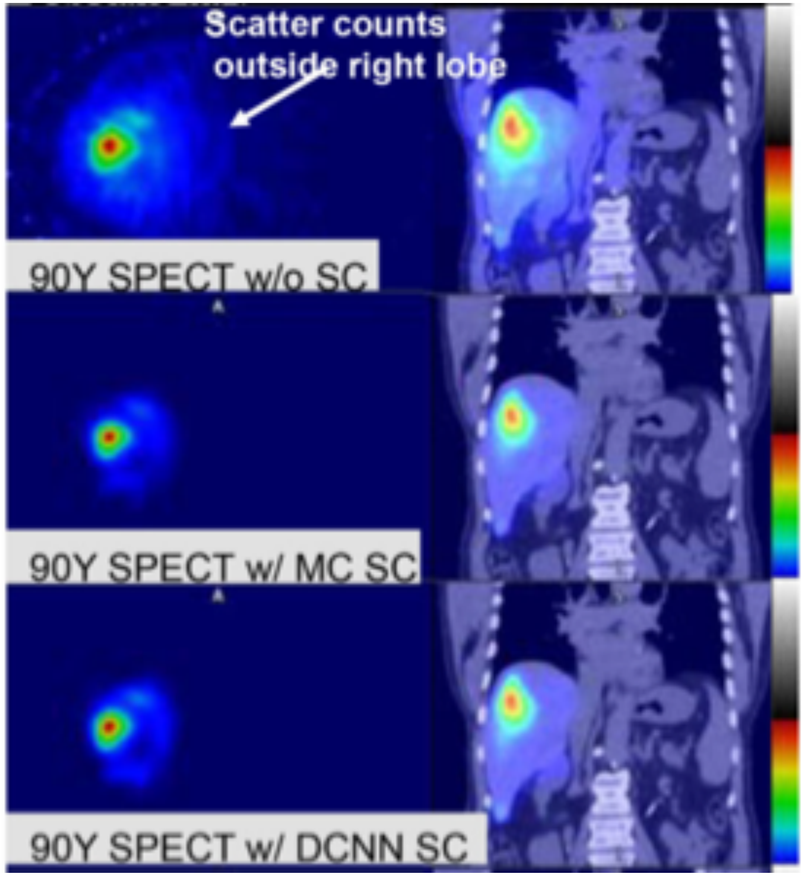
Scatter estimation/removal



Scatter estimation/removal

Examples:

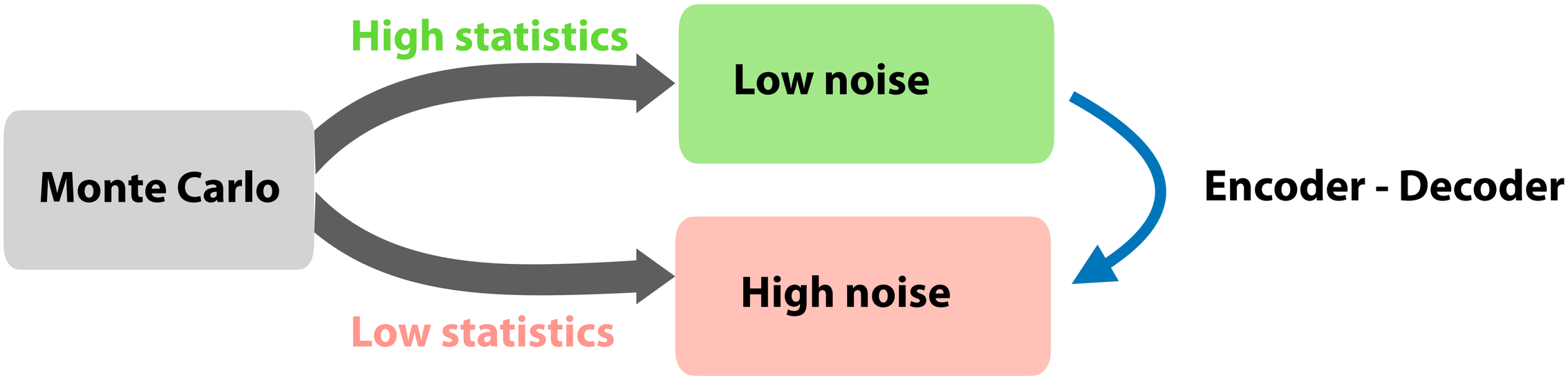
- Xiang et al, 2020, “A deep neural network for fast and accurate scatter estimation in quantitative SPECT/CT under challenging scatter conditions”
- Heyden et al., 2020, “Monte Carlo Based Scatter Removal Method for Non-isocentric Cone-Beam CT Acquisitions Using a Deep Convolutional Autoencoder”

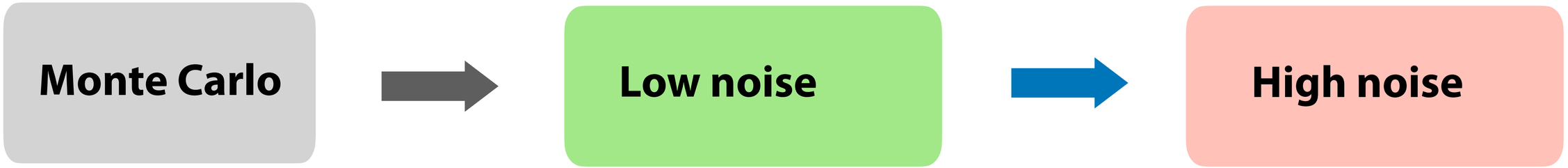


[Xiang2020]

[Lalonde2020]
[Lee2019]
[Maier2019]
[van der Heyden2020]
[Xiang2020]

Enhance low-statistics Monte Carlo output





Enhance low-statistics Monte Carlo output

- Post-processing, CNN-based denoising
- Training dataset: pairs of high-noise/low-noise distributions
- Data: dose maps, SPECT/PET images
- 10–100 times fewer particles
- Dose gradients preserving?

[Fornander2019]
[Neph2019]
[Peng2019]
[Javaid2019]
[Reymann2019]
[Kontaxis2020]
[Javaid2021]
[Bai2021]

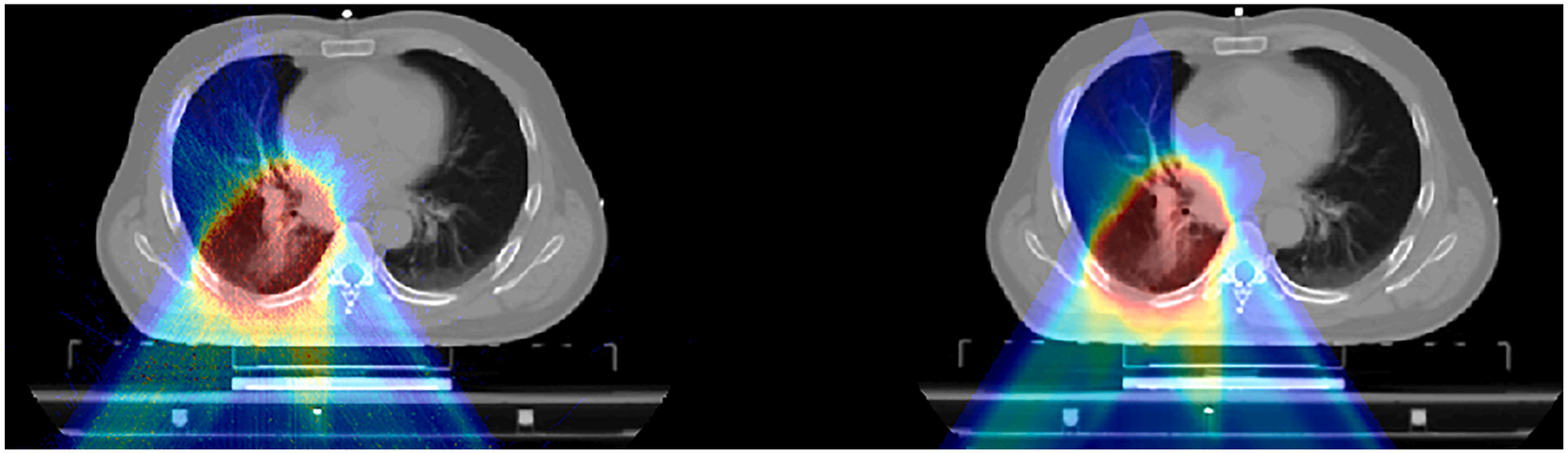


Fig. 3. A dose distribution on a sample lung test case. *Left* is the noisy dose distribution (MC simulation with 1×10^6 protons) and *right* is the reference dose distribution computed with 1×10^9 protons.

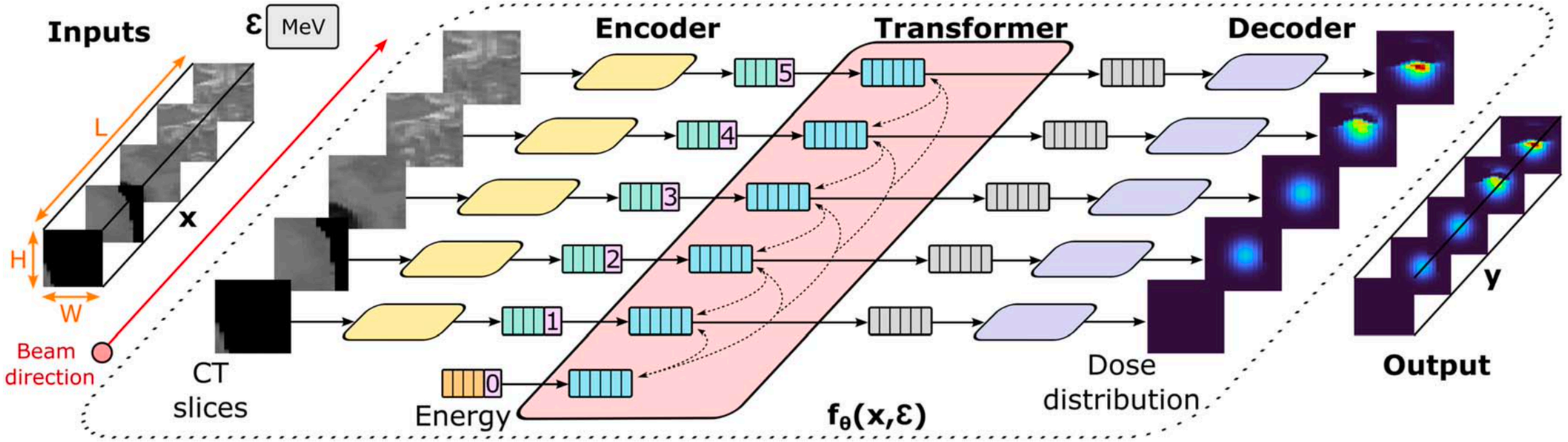
Javaid U. et al., 2021, https://doi.org/10.1002/mp.13856

Deep learning based dose estimation

Example: Proton beam therapy

- Predict stack of 2D dose distribution along the beam

Training data: Monte Carlo

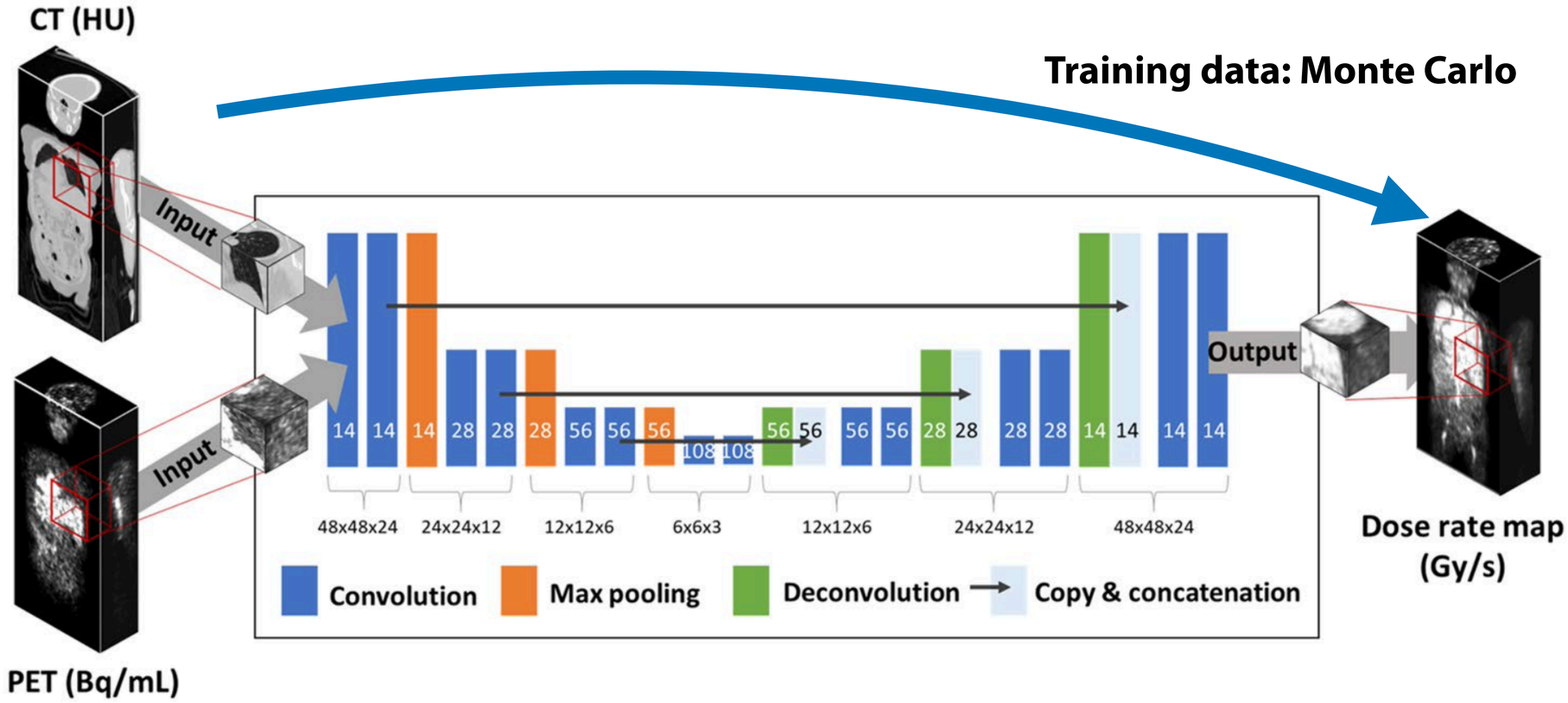


Pastor-Serrano, O., & Perkó, Z. (2022). https://doi.org/10.1088/1361-6560/ac692e

Deep learning based dose estimation

Example: Nuclear medicine

- Predict 3D dose distribution given CT and PET images



Lee, M. S. et al., (2019). https://doi.org/10.1038/s41598-019-46620-y

AI-predicted dose and deliverable treatment plans

A plausible dose map does not establish that a linac can deliver it

1 Dose prediction

Anatomy and prescription provide the input

AI proposes a desired 3D dose distribution

2 Dose mimicking

Optimize beam settings to reproduce that dose

MLC apertures and motion plus monitor-unit settings constrain the achievable dose

3 Dose verification

Recalculate dose from the actual machine settings

Evaluate clinical objectives and delivery performance

If the prediction is infeasible, conversion must change the dose

Dose mimicking may include MLC optimization, or be followed by a separate leaf-sequencing step

Babier et al. (2020), doi:10.1016/j.ejmp.2020.03.016. Prunaretty et al. (2024), doi:10.3390/cancers16223735

Erasmus MC: fast prediction, constrained conversion

Prostate photon plans

Van Genderingen, Breedveld et al. (2025)

1.2 s

for 3D dose prediction

1,250 patients
Erasmus-iCycle reference plans

Final conversion to true VMAT was outside this study

Head-and-neck proton plans

Nomer, Knuth, Breedveld et al. (ESTRO 2026)

6.8 min

mean time for constrained dose mimicking

150 test patients
Clinical and delivery constraints met
No manual fine-tuning

Conference abstract
Robustness within specified scenarios

Different cohorts, modalities and processing stages. These times are not a direct comparison.

Van Genderingen et al., doi:10.1016/j.radonc.2024.110662. Nomer et al., ESTRO 2026, poster 1719

Models to synthetically generate (pseudo) images

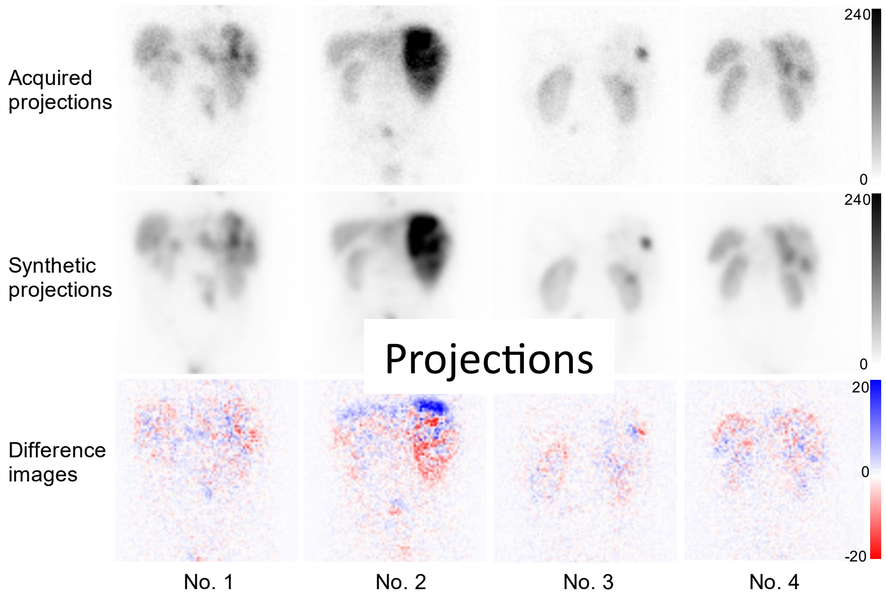
(not strictly Monte Carlo, but medical imaging)

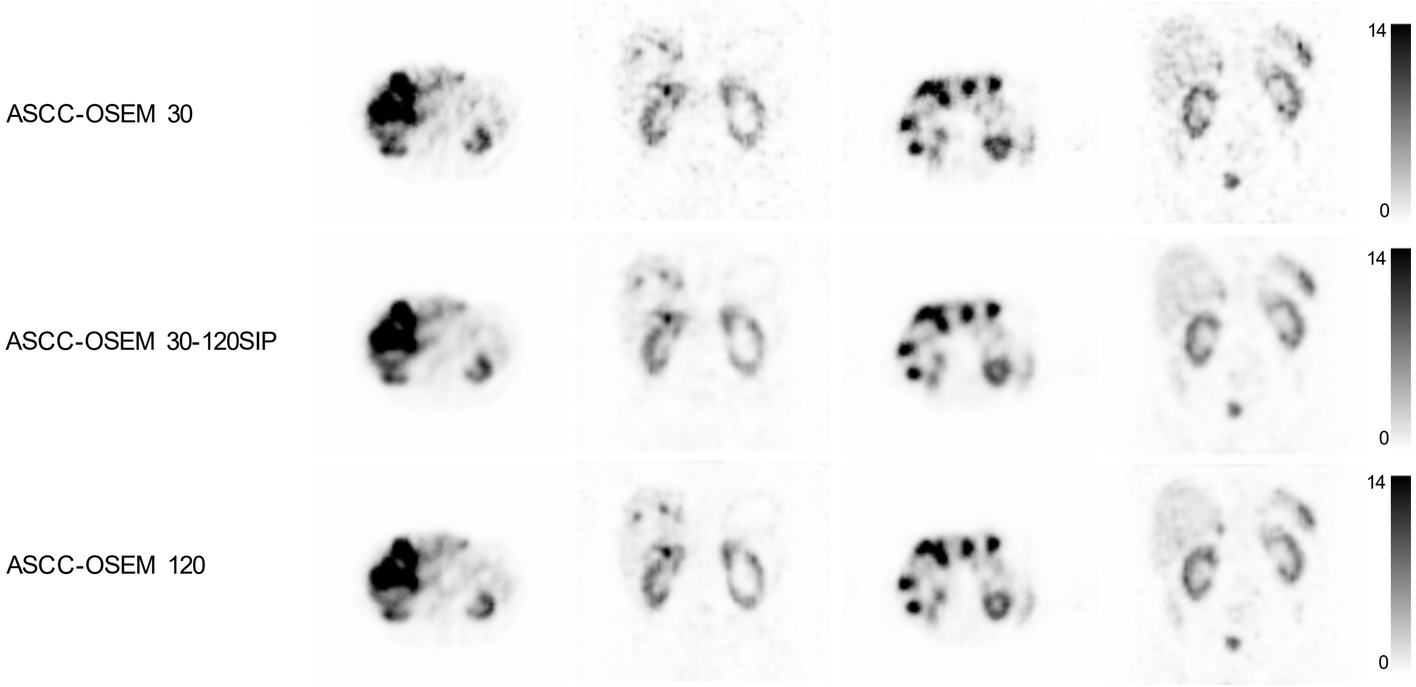
Generative intermediate SPECT projections

Long 3D SPECT acquisition with rotation gantry, around 120 angles

Rydén et al, 2020: Synthetic intermediate projections

… to be used during the reconstruction

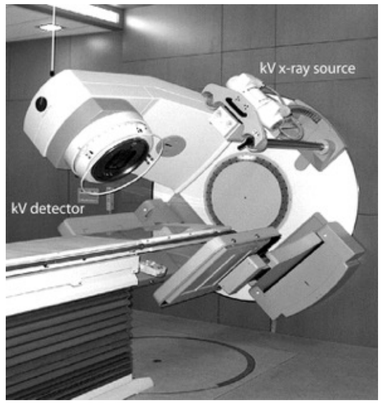




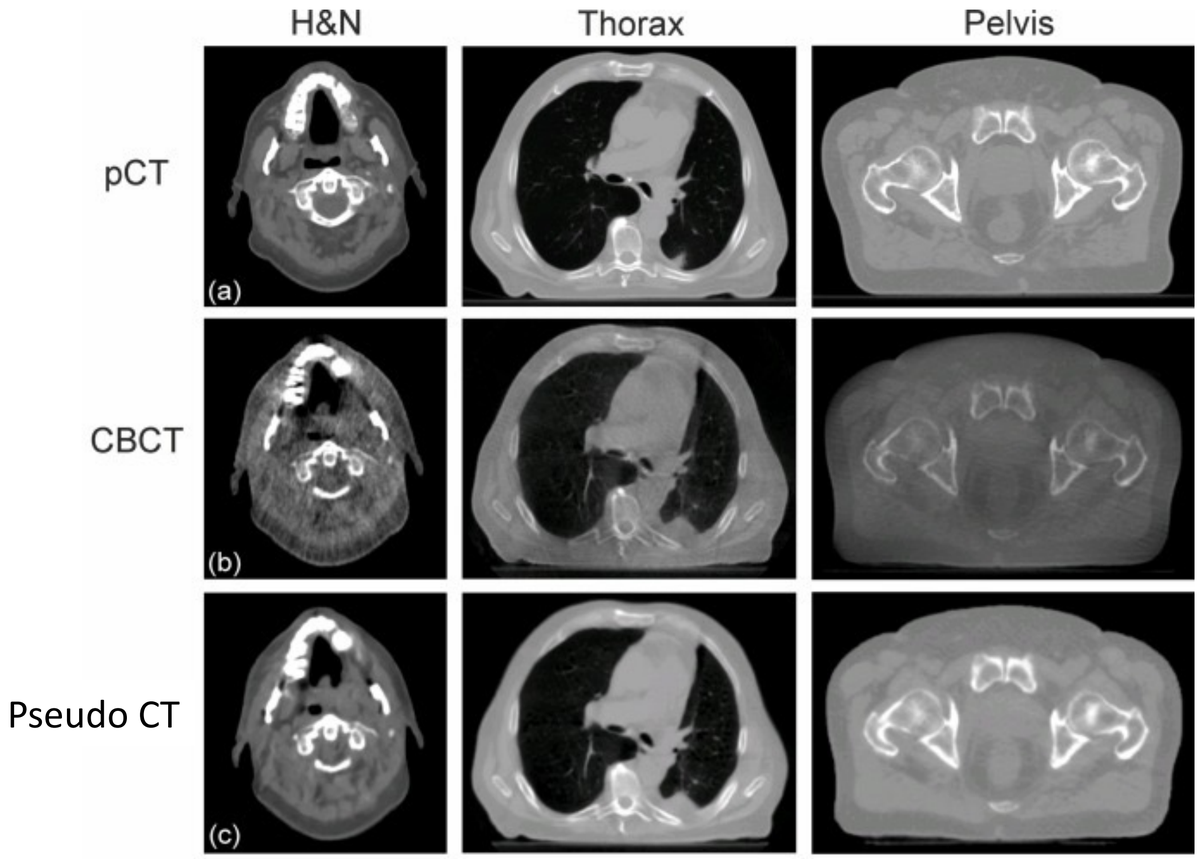
GAN for pseudoCT from cone beam CT



conventional (fan beam) x-ray CT



cone beam x-ray CT



[Liang2019], [Kinda2020]: CycleGAN

GAN for pseudoCT from Magnetic Resonance Imaging (MRI)

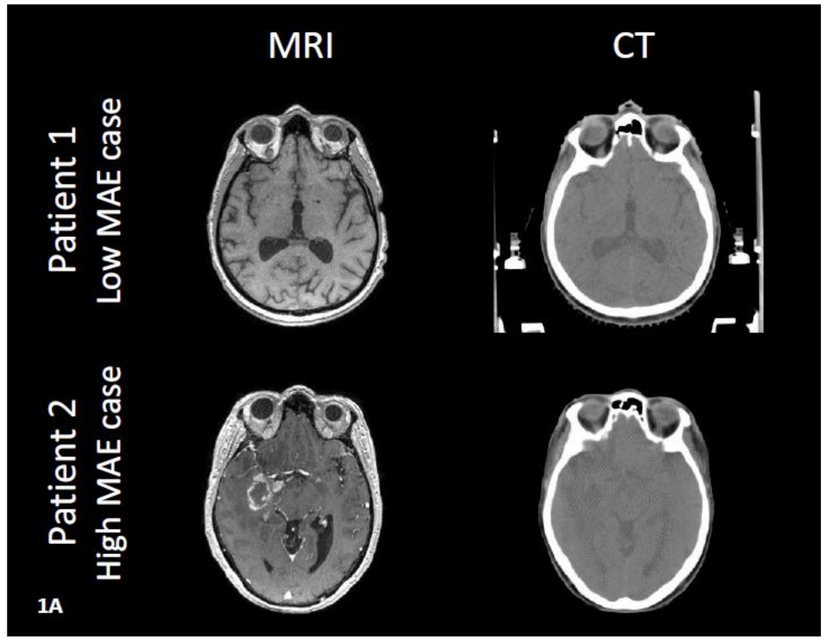
- Use case: input for dose computation in radiotherapy



x-ray CT

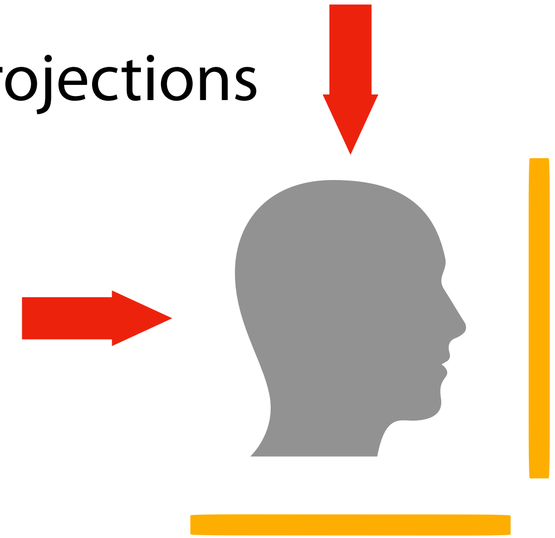


MRI



Heads up when generating images …

2 projections



Generative model
(encoder - decoder)

Reconstructed image
from full CT scan



Now we can get patient CTs from only 2 projections! Awesome.

Would you buy this?

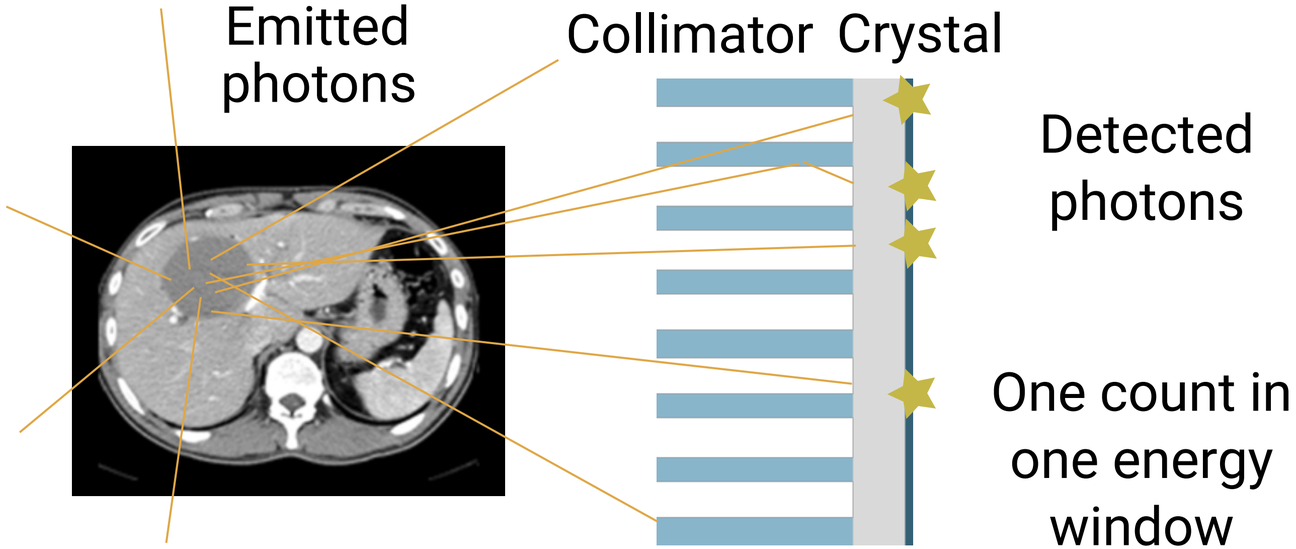
Question: Up to which point is it legitimate to generate images?

Tentative answer: Depends if we transform/convert information or invent it.

Learning the detector response function in Monte Carlo simulation of SPECT imaging

Angular Response Function (ARF)

- SPECT imager usually has a collimator with holes to filter out photons according to their direction.
- Energy windows are applied at the electronic acquisition level.



Detection likelihood

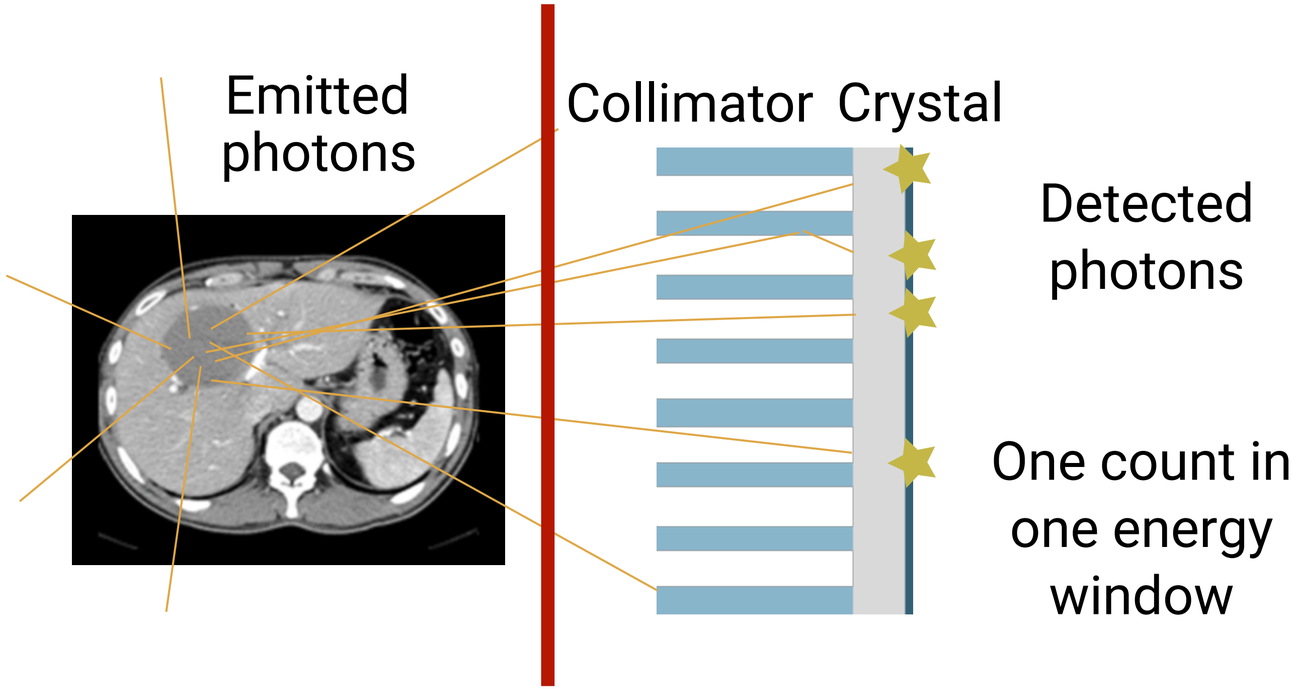
$$p(\theta, \phi, E)$$

Likelihood in window "i"

$$\int_{E_{i,\text{low}}}^{E_{i,\text{high}}} p(\theta, \phi, E)\mathrm{d}E$$

Angular Response Function (ARF)

- Instead of transporting the photons across the detector, we score them according to the likelihood determined from their properties at a virtual plain.



Detection likelihood

$$p(\theta, \phi, E)$$

Likelihood in window "i"

$$\int_{E_{i,\text{low}}}^{E_{i,\text{high}}} p(\theta, \phi, E)\mathrm{d}E$$

Angular Response Function (ARF)

Detection likelihood

$$p(\theta, \phi, E)$$

Likelihood in window "i"

$$p_i(\theta, \phi) = \int_{E_{i,\text{low}}}^{E_{i,\text{high}}} p(\theta, \phi, E)\mathrm{d}E$$

Parametrize as multi-dimensional histogram

Train a neural network to predict p_i from theta and phi

acts as variance reduction technique because network is a smooth non-linear function

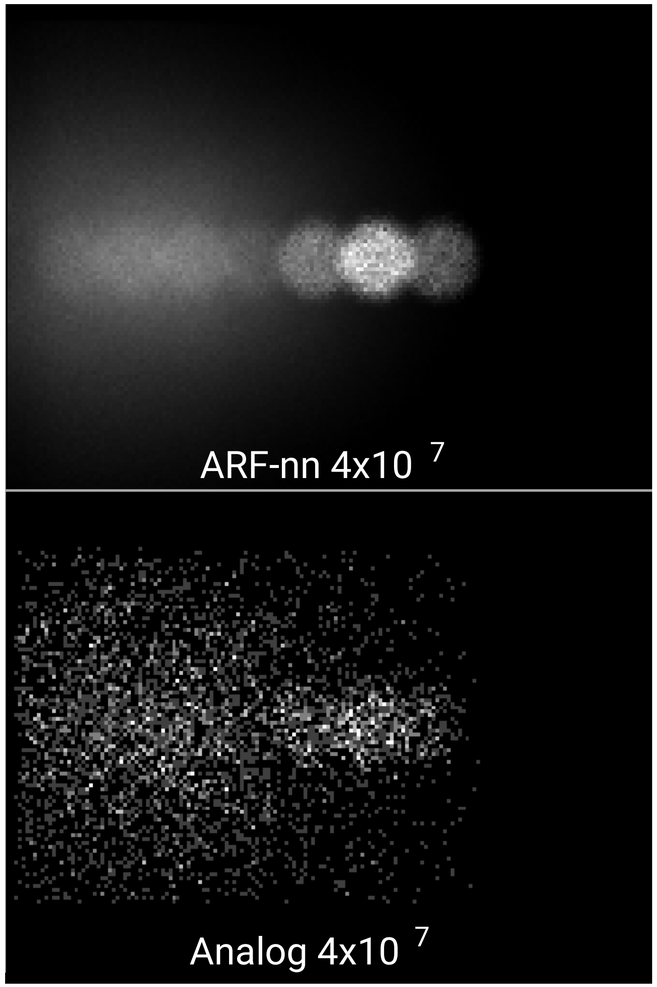
Angular Response Function (ARF)

Neural network based ARF

ARF acts as variance reduction technique

Explicit (analog) Monte Carlo simulation

Image of spherical sources

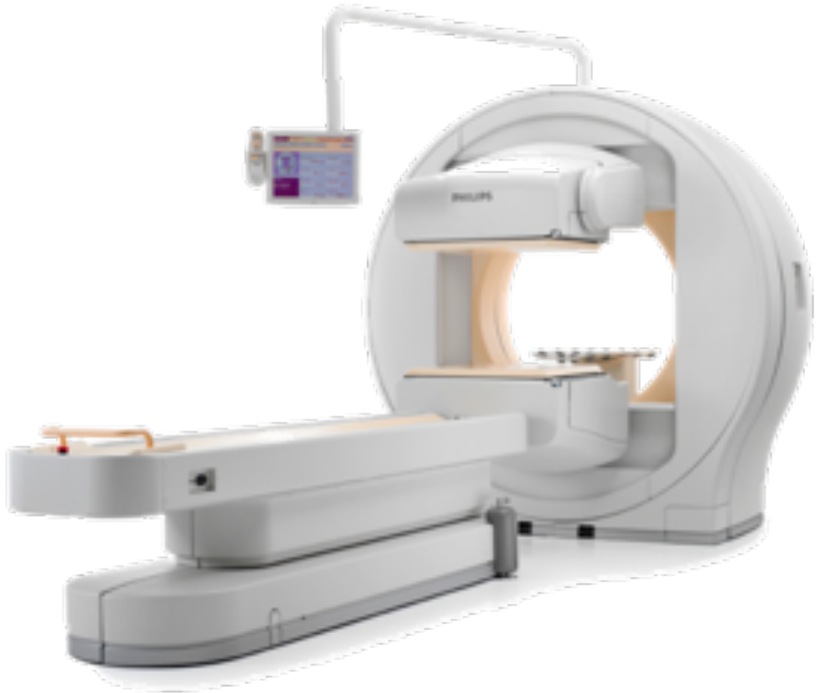


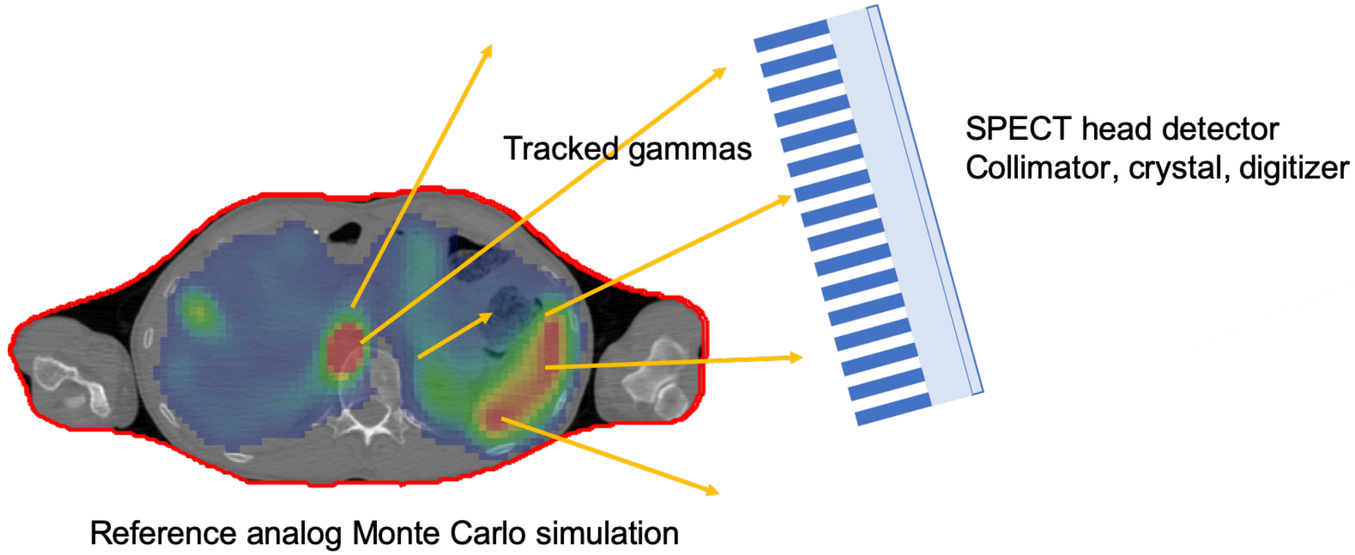
Sarrut, D., Krah, N., et al., 2018, https://doi.org/10.1088/1361-6560/aae331

Learning phase-space distributions for Monte Carlo simulations in nuclear imaging

GAN to accelerate SPECT simulation

- Part1: from emission to patient exiting gamma
- Part2: track gamma inside the detector



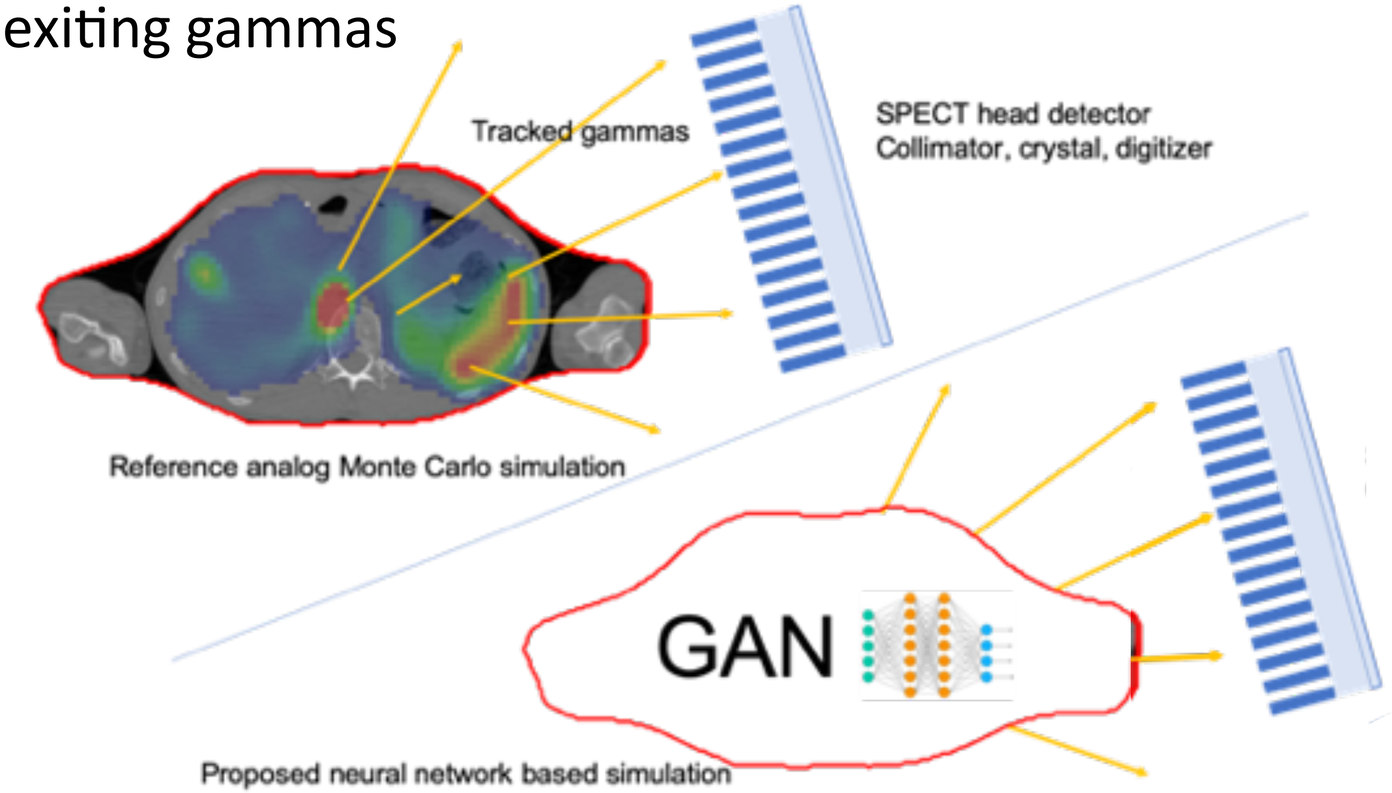


Reference analog Monte Carlo simulation

Training the GAN based on Monte Carlo data

Train a GAN to produce exiting gamma from a given source

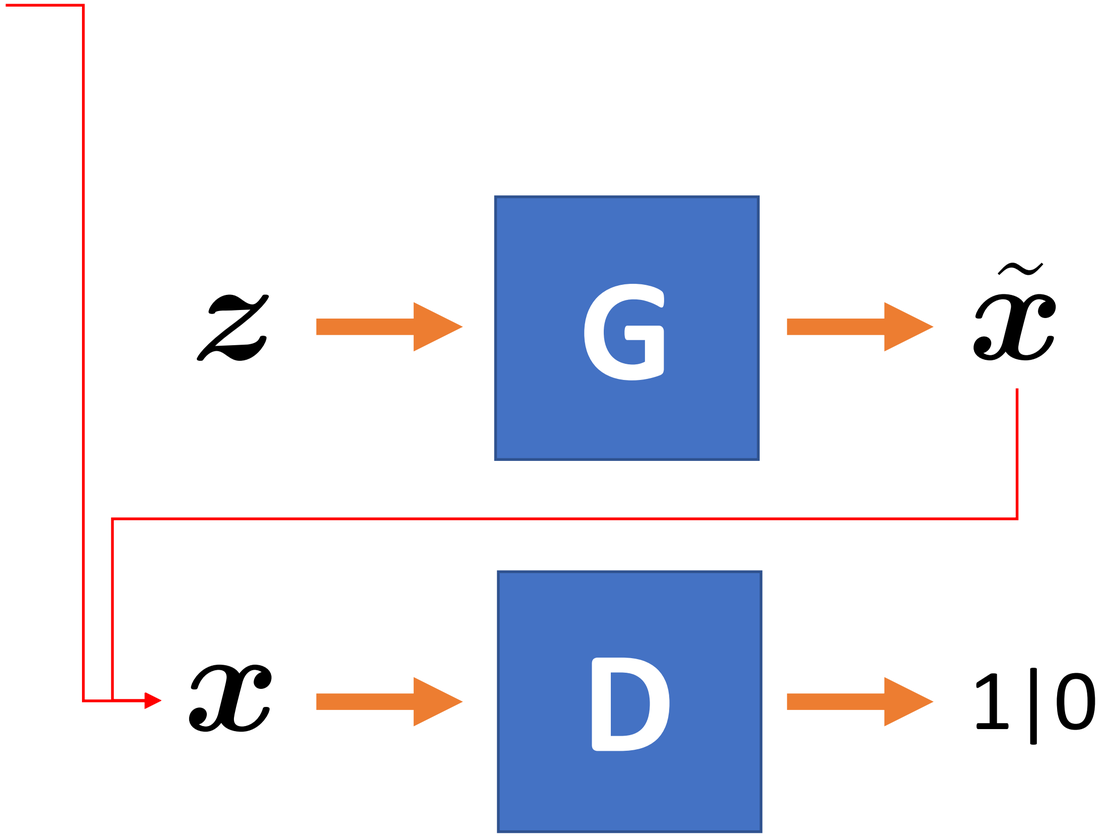
- Step1: run low stats MC, consider exiting gammas
- Step2: train a GAN
- Step3: use GAN a source



Training the GAN based on Monte Carlo data

[Goodfellow et al 2014]

- Training dataset $\boldsymbol{x} \in \mathbb{R}^d$
  - Dimension d=7 (E, X, Y, Z, dX, dY, dZ)
  - Samples of unknown p_{real}
- Generator $G(\boldsymbol{z}; \boldsymbol{\theta}_G)$
- Discriminator $D(\boldsymbol{x}; \boldsymbol{\theta}_D)$



Generalize GAN to arbitrary source distribution: Conditional GAN

Train with one given **phantom** (CT, patient) …

… but with **homogeneous** activity

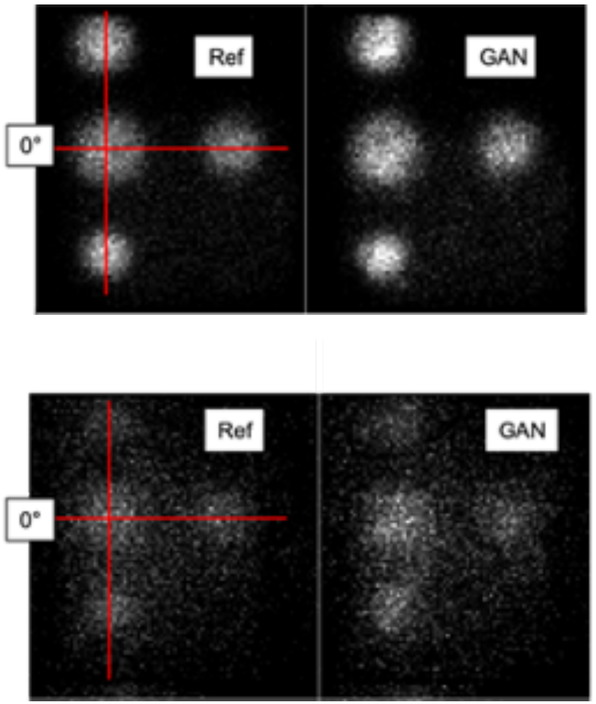
Conditional input activity map.

$$\mathcal{L}_C = \mathbb{E}[C(G(\mathbf{z}|\mathbf{y}))] - \mathbb{E}[C(\mathbf{x}|\mathbf{y})] + \underbrace{\lambda \mathbb{E}[(\left\|\nabla_{\hat{\mathbf{x}}|\mathbf{y}} C(\hat{\mathbf{x}}|\mathbf{y})\right\|_2 - 1)^2]}_{GP \quad regularization}$$

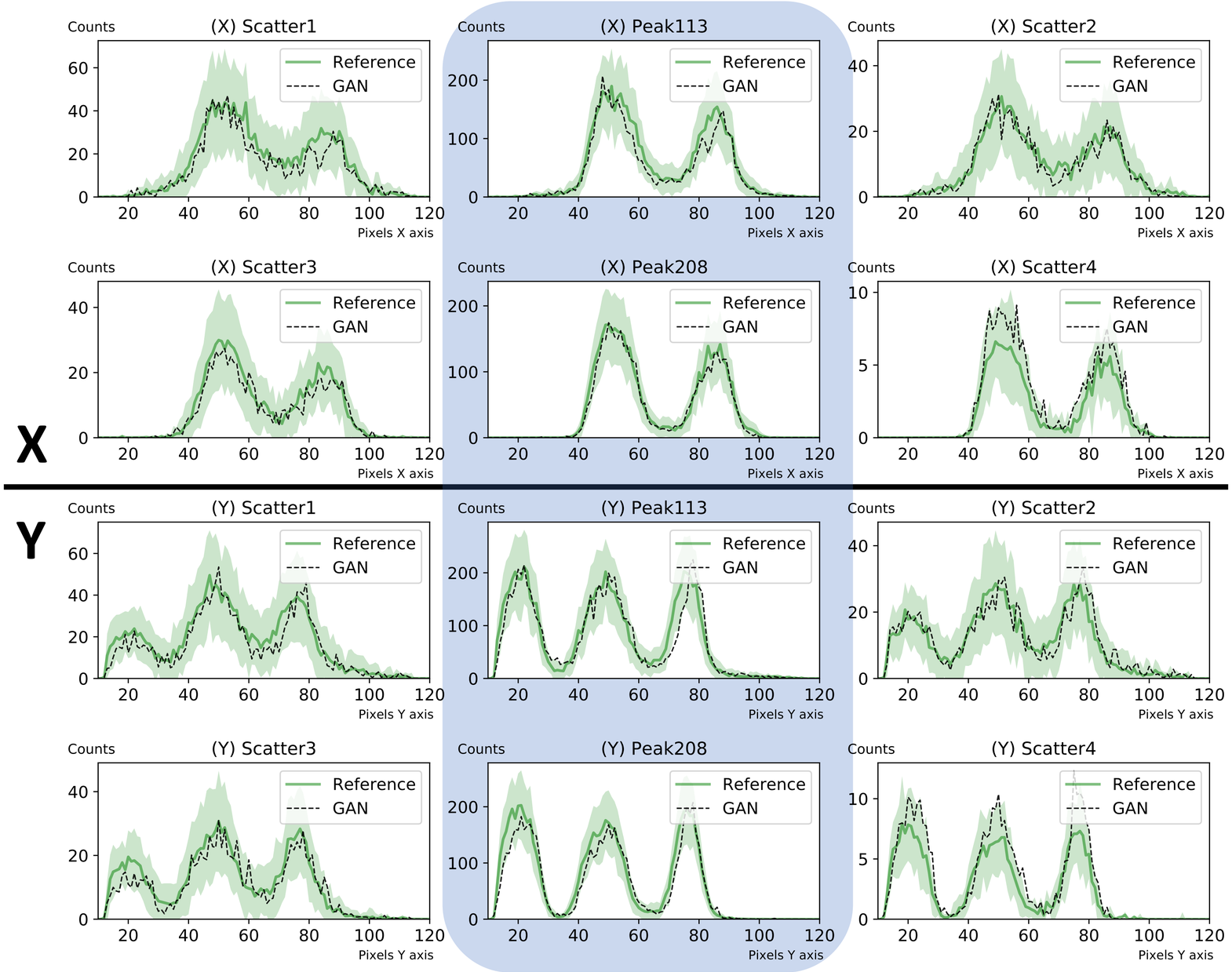
$$\mathcal{L}_G = -\mathbb{E}[C(G(\mathbf{z}|\mathbf{y}))]$$

[Saporta et al, PMB 2022]

Results

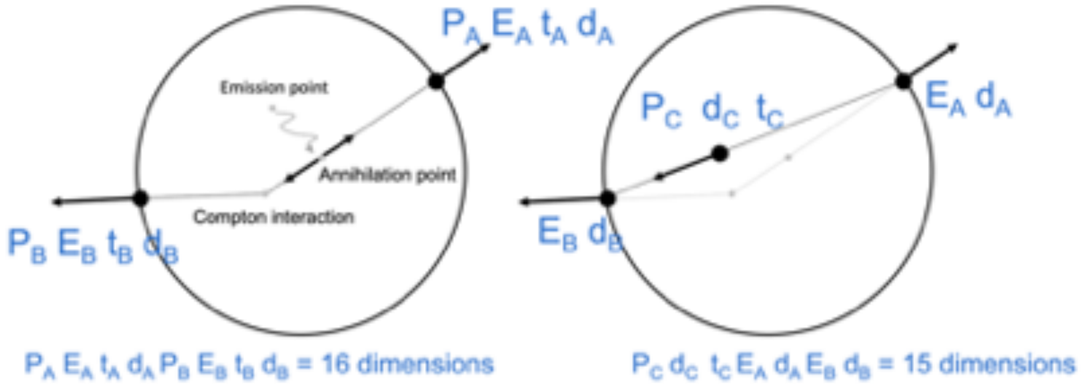


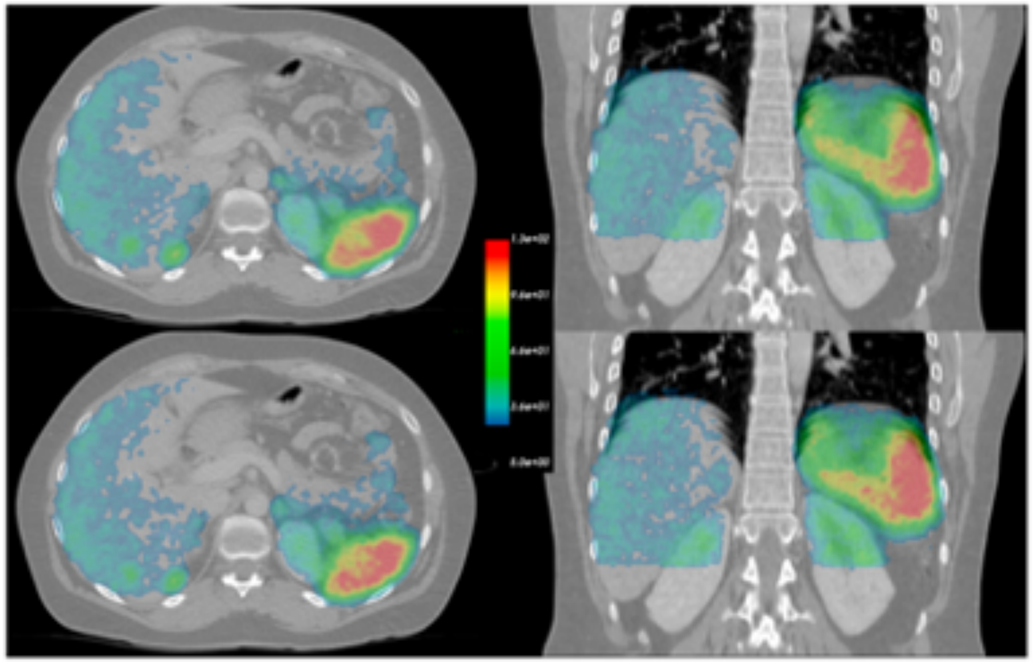
2D projections
Lu177 (1 peak & scatter)



GAN in PET simulation

Back-to-back GAN photon source for PET Monte Carlo simulation

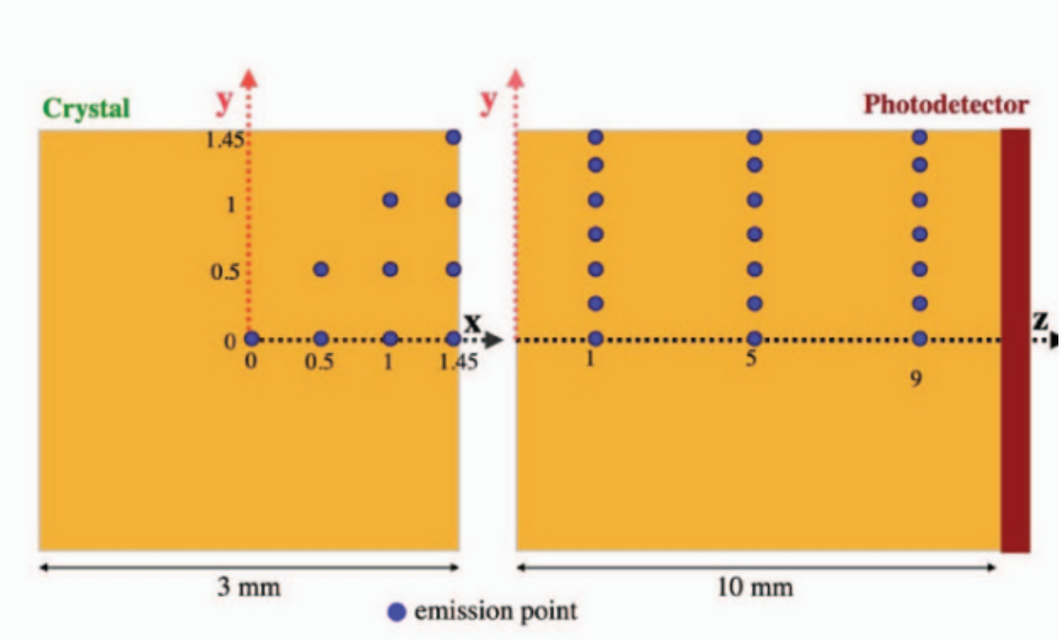




[Sarrut et al, PMB 2023]

Optical photon transport with optiGAN

A conditional GAN samples photons at the photodetector face



BGO crystal: 3 × 3 × 10 mm³

Training: 900,000 photons at 30 emission positions

Conditioning

Emission position (x, y, z)
Photon count supplied by the simulation

Generated photon properties

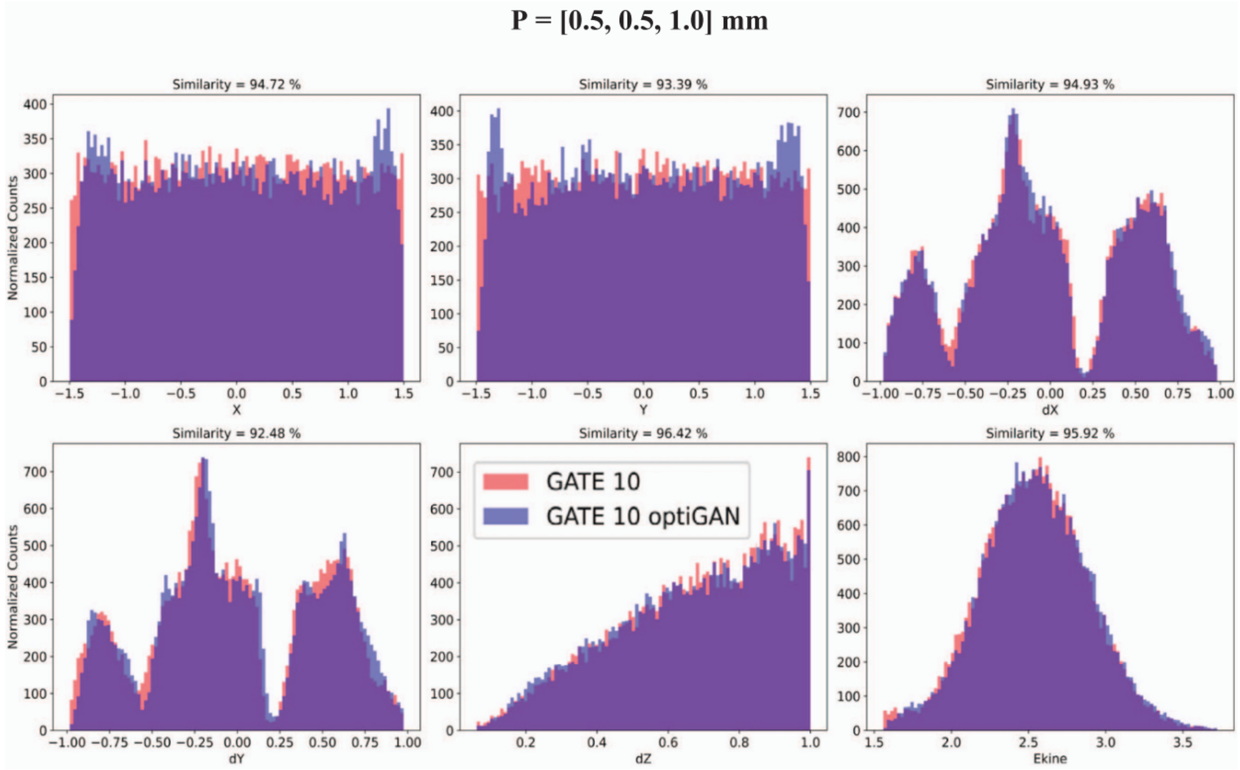
Position (X, Y), direction (dX, dY, dZ)
and energy at the photodetector

Replaces repeated optical transport within the GATE 10 workflow

Mummaneni, Trigila, Krah, Sarrut & Roncali (2025). Phys. Med. Biol. 70, 135009. doi:10.1088/1361-6560/ade2b5

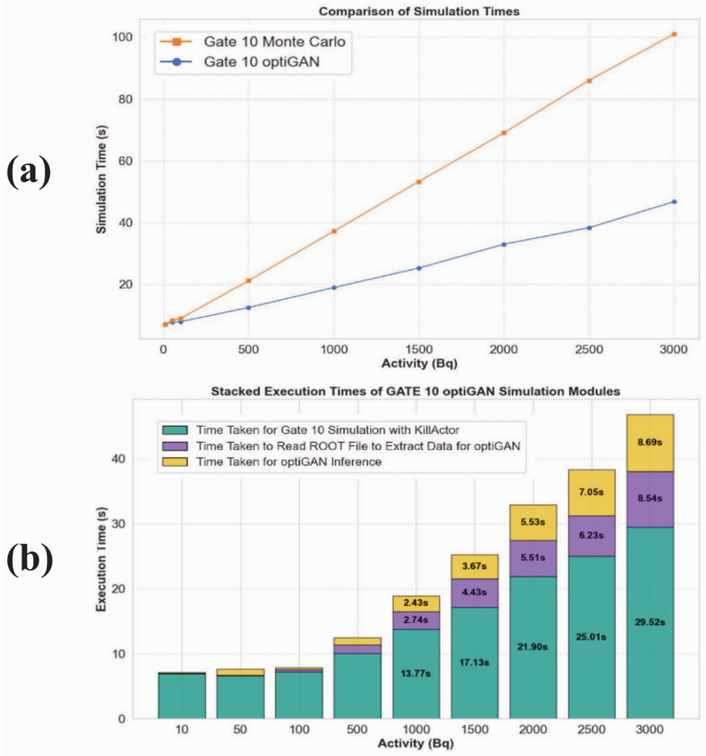
Distribution agreement and simulation time

Photon distributions



Reported mean similarity: about 92–97%
Histogram metric: 1 − Jensen–Shannon distance

About 2× faster overall



Remaining simulation and file handling limit the overall speed gain

Mummaneni, Trigila, Krah, Sarrut & Roncali (2025). Phys. Med. Biol. 70, 135009. doi:10.1088/1361-6560/ade2b5

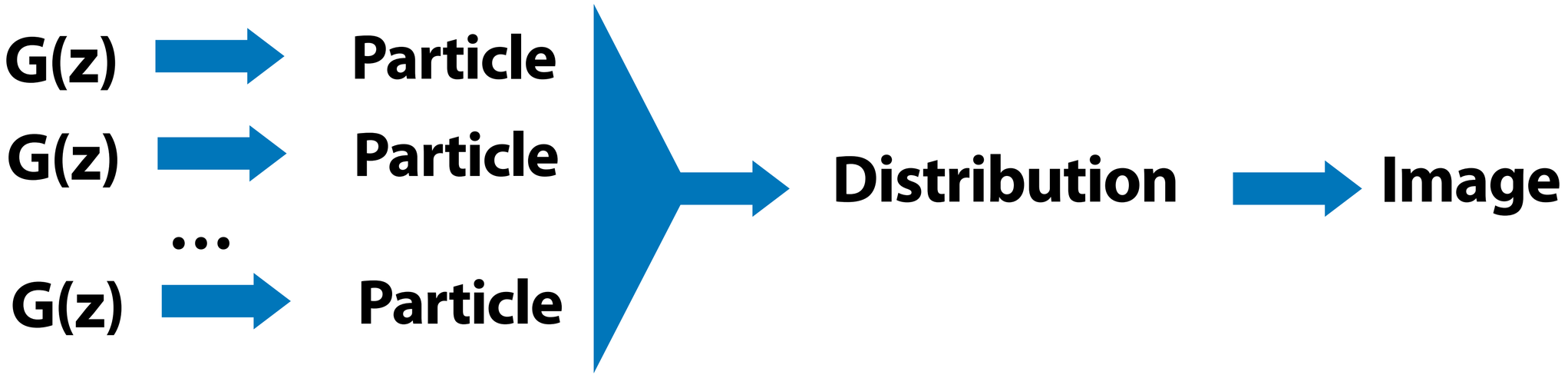
Recall:

Simulated images are spatially discretized probability distributions
where
1 image represents 1 distribution

G(z) → **Image**

Generators produce 1 image from 1 vector z

Different when generating particles in Monte Carlo:



Inaccurate sampling of distribution of G(z) has systematic impact on image (artifacts)

In other words …

G(z) → 

G(z) → 

G(z) → 

G(z) → 

Each horse looks realistic

→ **"G works well"**

although G might slightly overrepresent brown horses ….

… now with particles

G(z) → Particle

G(z) → Particle

G(z) → Particle

G(z) → Particle

Each particle has realistic energy

→ “G works well” (?)

But high energy particles are oversampled

→ Incorrect image

Conclusions

- **Monte Carlo provides both a simulation method and a generator of training data for AI.**
- **AI can accelerate medical imaging and radiotherapy simulations at different levels: predicting accumulated outputs such as dose maps, or sampling individual particle representations in phase space.**
- **With particle generation, images and dose distributions emerge from transporting and accumulating the generated particles.**
- **Validation must assess the resulting distributions and correlations, since sampling errors can introduce systematic artifacts.**
- **Clinical usefulness depends on the complete workflow, including accurate dose calculation and physically deliverable treatment plans.**



Thank you