Generative Models for Intelligent Medical Data Analysis

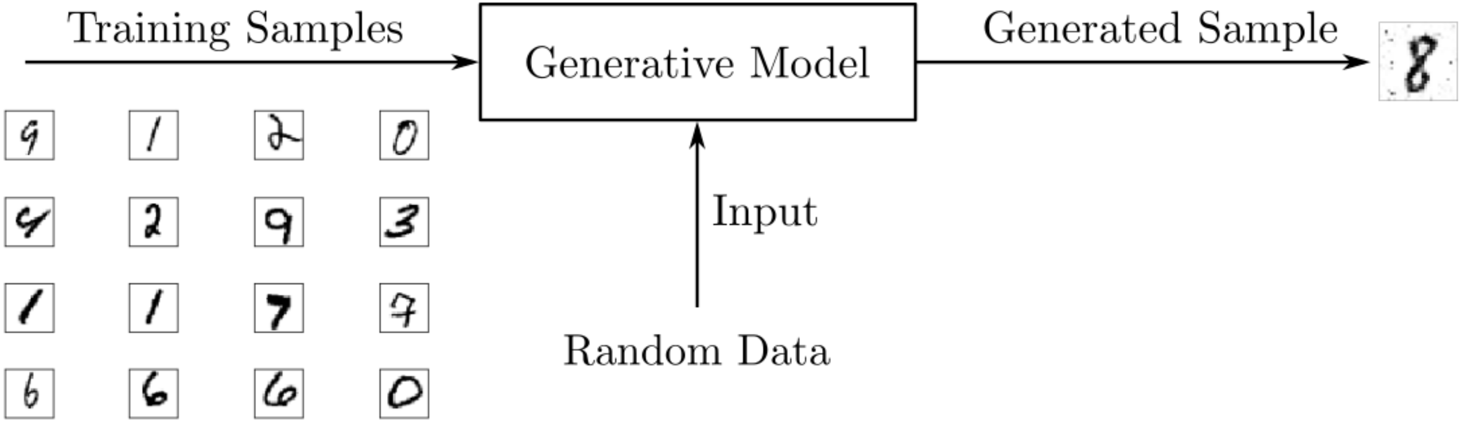
Kamila Kalecińska

& Dose-3D Consortium

Agenda

1. Generative Models
2. Dose-3D Project
3. Medical Data
4. Technologies
5. Intelligent Analysis Towards Improving Treatment Plans
6. Summary

Generative Models



https://realpython.com/generative-adversarial-networks/

➔ Variational Autoencoder (VAE)
➔ Generative Adversarial Networks (GANs)

Dose-3D Project

A reconfigurable detector for measuring the spatial distribution of radiation dose for applications in the preparation of individual patient treatment plans.

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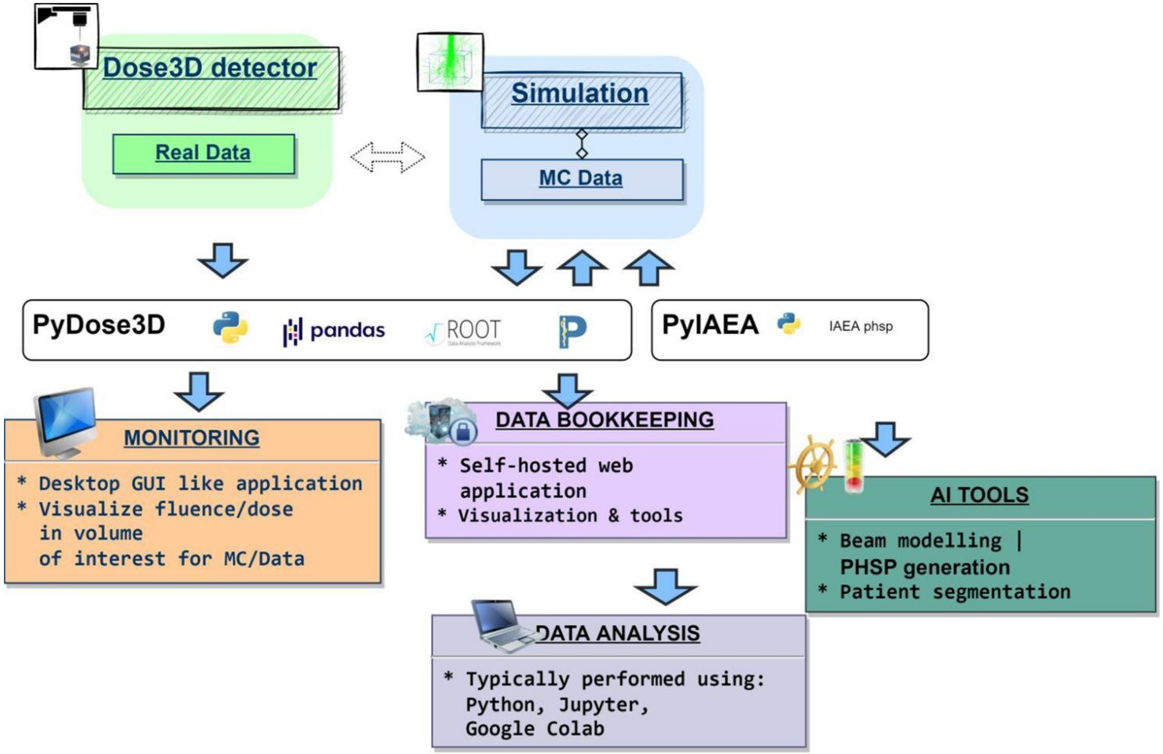
Fundacja na rzecz Nauki Polskiej

AGH

Narodowy Instytut Onkologii im. Marii Skłodowskiej-Curie Państwowy Instytut Badawczy

Dose-3D Project

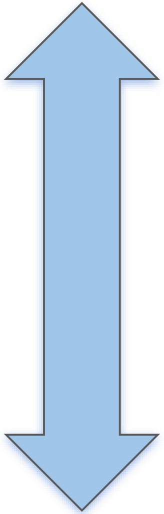


Intelligent Data Analysis Towards Improving Treatment Plans

- ➔ Medical Data Segmentation for Detector Geometry
- ➔ Medical Image Data Augmentation
- ➔ Patient - Detector Resolution Scaling
- ➔ Photon Beam Generation

Medical Data

- variety of data
- variety of formats
- complexity of data
- privacy issues



DICOM & DICOM RT

HDF5

MINC

NIFTI

RAW

https://www.scnsoft.com/blog/health-data-analytics-overview

Medical Data

- **DICOM** (Digital Imaging and Communications in Medicine)
- **DICOM-RT** (DICOM for Radiotherapy)
- **NIfTI** (Neuroimaging Informatics Technology Initiative)

Standard format

Technologies

- acceleration with NVIDIA’s GPU
- modern deep learning frameworks: **Monai**, **Clara**

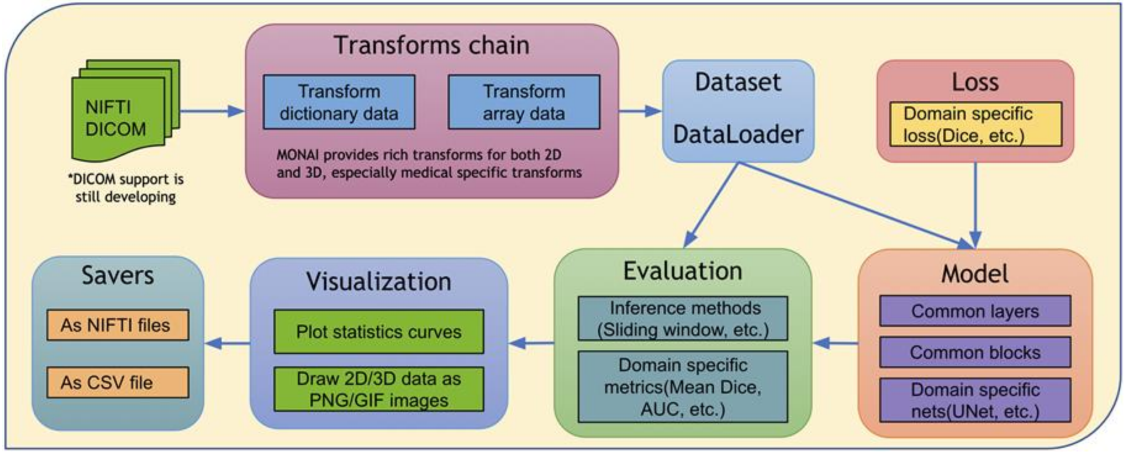
Technologies - Clara Train SDK

- ➔ state of the art pre-trained models
- ➔ training performance increased by up to 50x with domain-specific GPU optimization for 3D Imaging model
- ➔ powerful techniques like AutoML, that enable automatic parameter tuning and make iterative experimentation faster
- ➔ Federated Learning - ML technique that trains an algorithm across multiple devices/servers holding data samples without exchanging them
- ➔ Monai on backend

Technologies - Monai

➔ open-source framework for deep learning in healthcare imaging

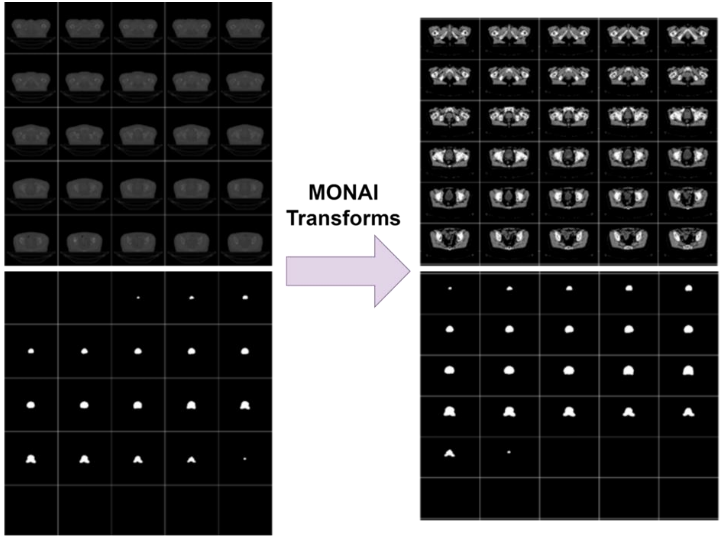
➔ Provides set of tools for medical data transformations



https://monai.io/docs.html

Technologies - Preprocessing Monai Transforms

- **LoadImage**: Load medical specific formats file from provided path
- **Spacing**: Resample input image into the specified pixel diimensions
- **Orientation**: Change the image’s orientation into the specified axcodes
- **RandGaussianNoise**: Perturb image intensities by adding statistical noises
- **NormalizeIntensity**: Intensity Normalization based on mean and standard deviation
- **Rand2DElastic**: Random elastic deformation and affine in 2D
- **Rand3DElastic**: Random elastic deformation and affine in 3D



Technologies – Post-processing Monai Transforms

(a) Original image (b) Segmentation result (c) Keep largest connected (d) Contour of regions (e) Map contour to image

https://docs.monai.io/en/stable/highlights.html

Intelligent Data Analysis Towards Improving Treatment Plans

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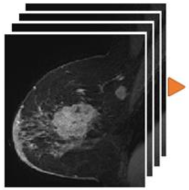
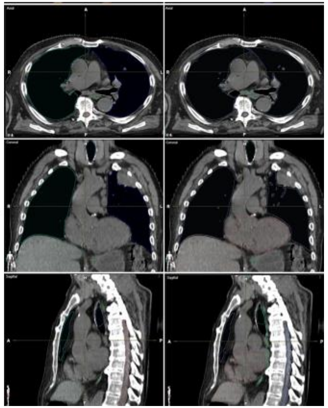
- ➔ Patient - Detector Resolution Scaling
- ➔ Photon Beam Generation

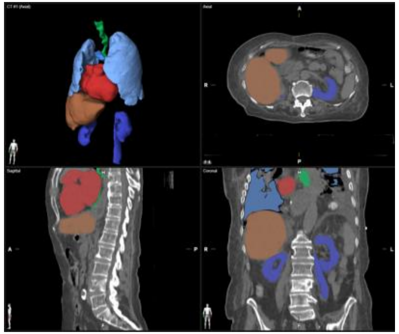
Medical Data Segmentation for Detector Geometry





3D DICOM
images

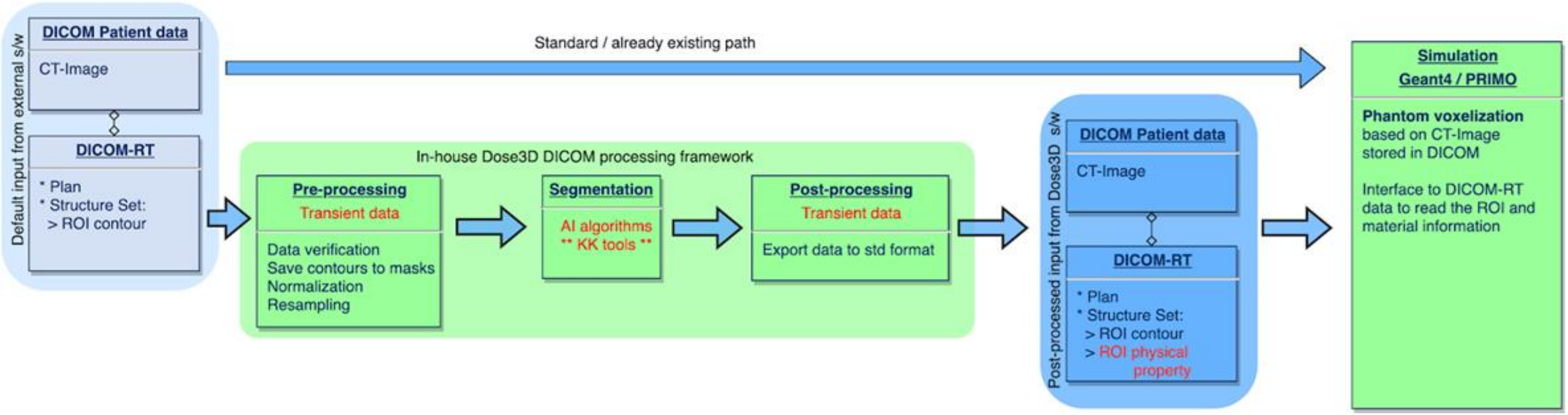
"intelligent analysis"



images + contours
(DICOM + DICOM
RT Structures)

**further analysis
(simulations)
&
detector
geometry input**

Medical Data Segmentation for Detector Geometry



Medical Data Segmentation for Detector Geometry

Inside the “black box” of intelligent analysis:

- **data preprocessing** - preparing training dataset: creating ground truth segmentation masks, resolution resampling, format conversion, data augmentation
  Python, 3D Slicer, Monai

- **segmentatiation & classification** - developing an 3d deep learning model able to automatically classify each voxel to a class (e.g. cancer, surrounding organs)
  NVIDIA Clara, Monai, Pytorch

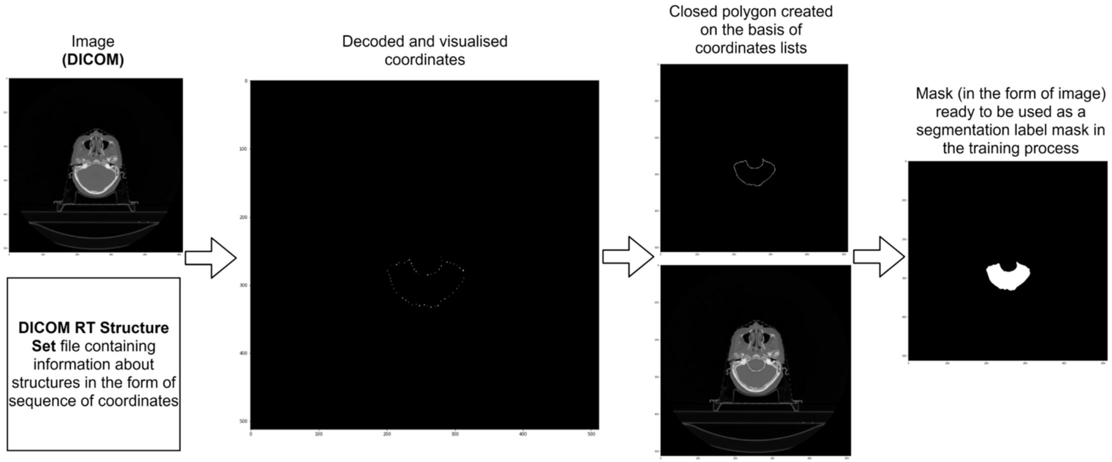
- **data post-processing** - export data to DICOM format
  Python, 3D Slicer

Data Preprocessing for Segmentation

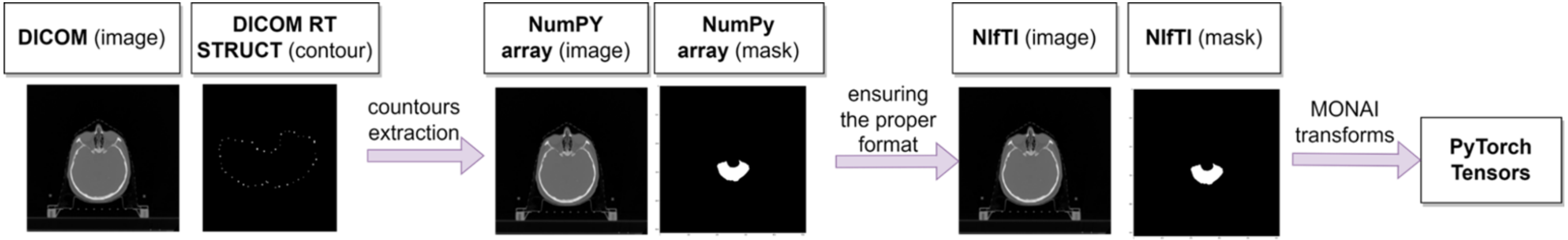
Preparing training data for segmentation:

- decoding from input format
- normalizing and scaling
- resampling
- cleaning from outliers

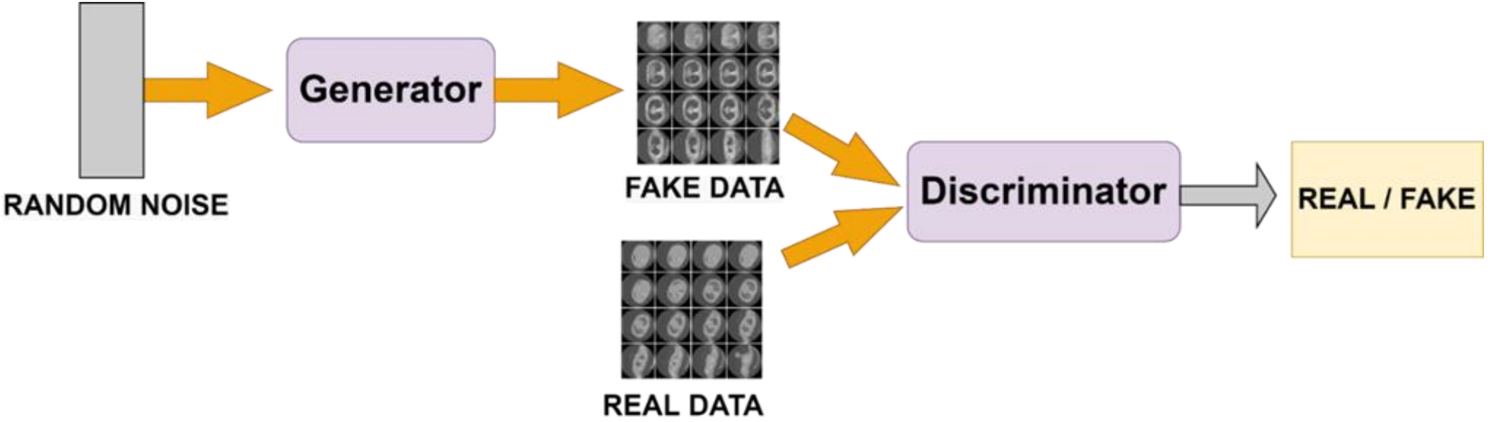
Decoding and visualization of DICOM RT Structure Set and creation of mask that can be then saved in any image format and used in the training process



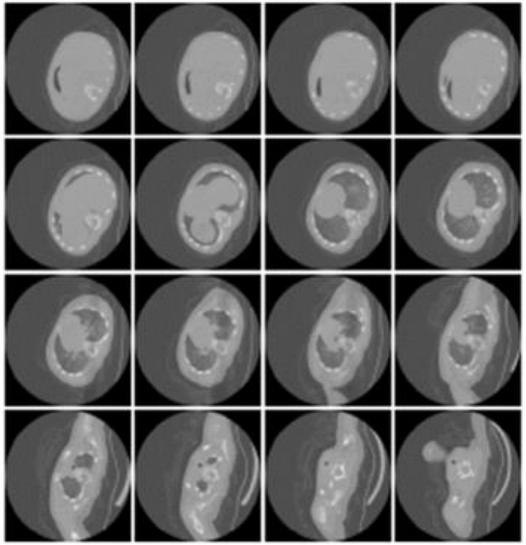
Data Preprocessing for Segmentation

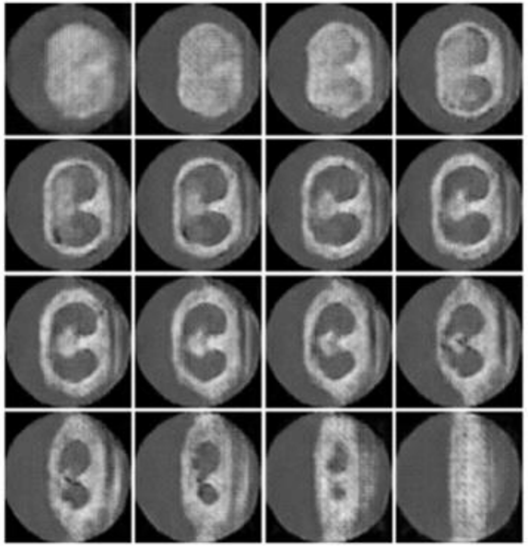


Medical Image Data Augmentation with GANs



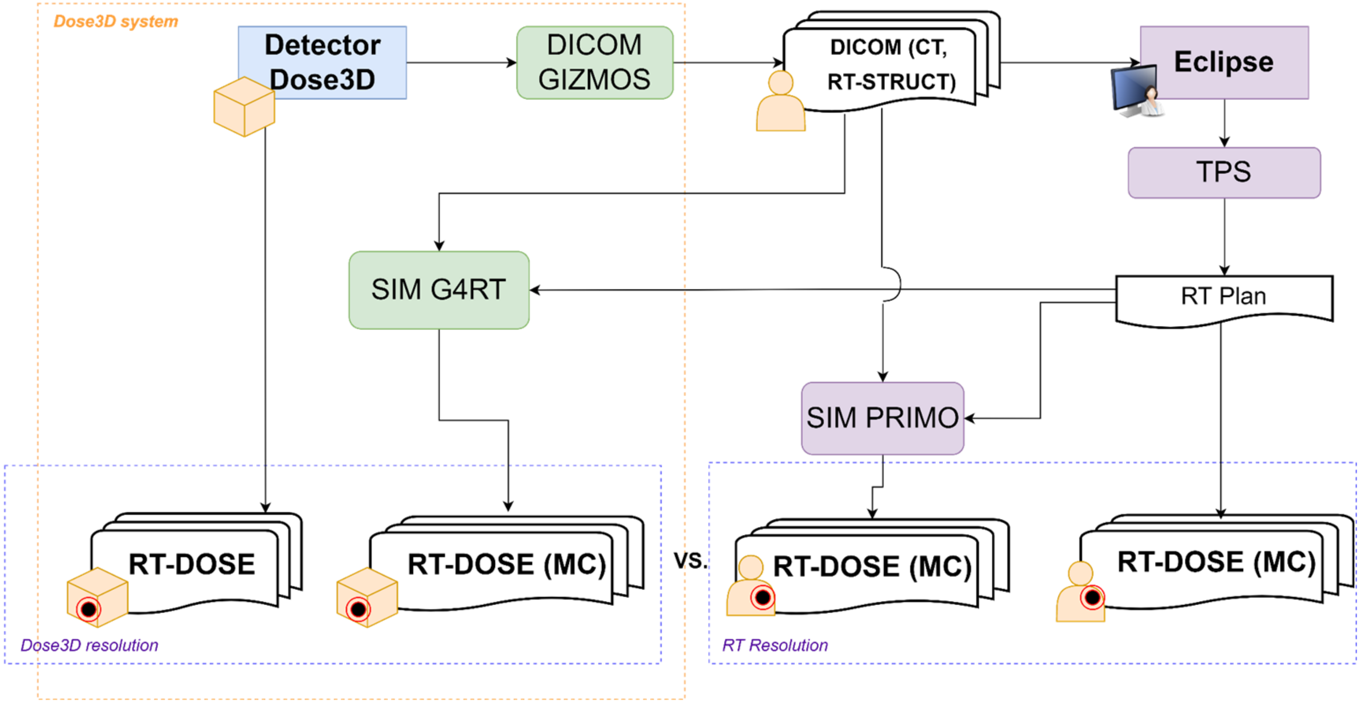
Medical Image Data Augmentation with GANs



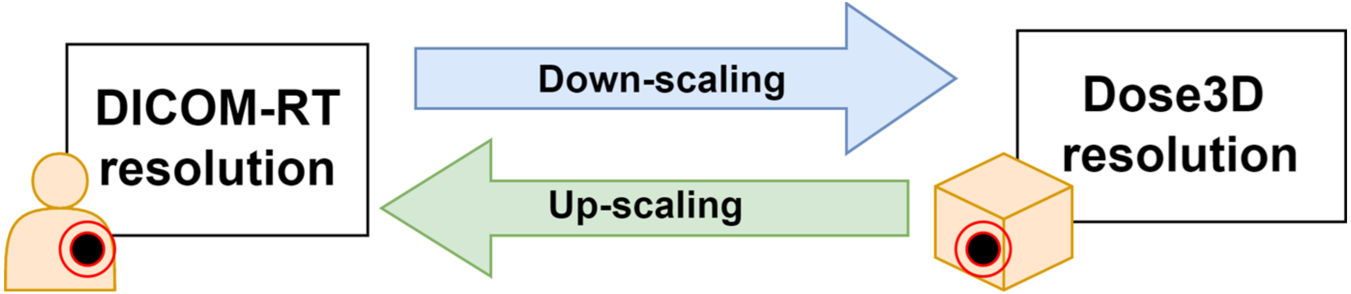


Original (real) data samples from a public database [2] (left) data generated (fake) by generative GANs model built and trained using MONAI.

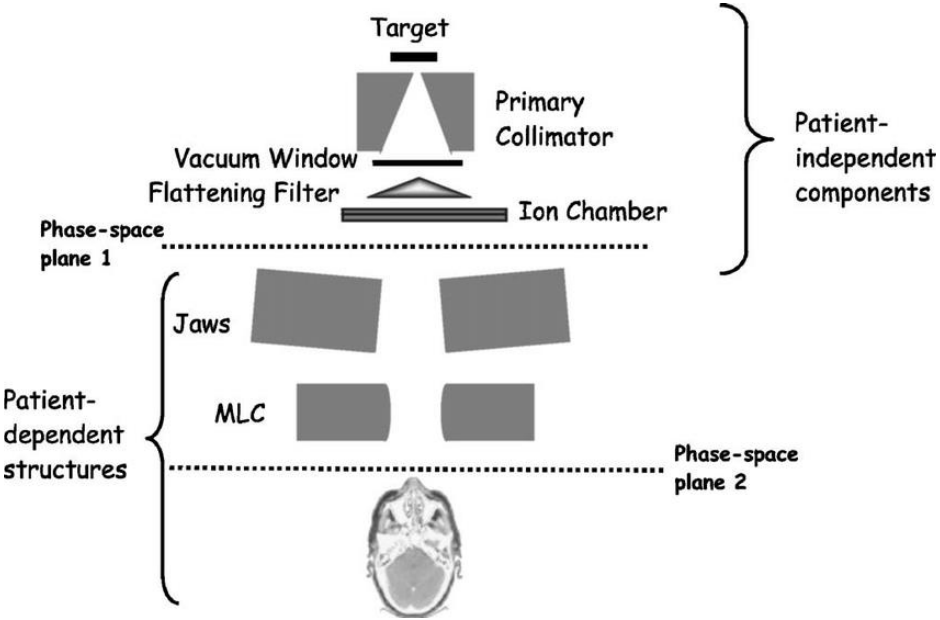
Patient - Detector Resolution Scaling



Patient - Detector Resolution Scaling



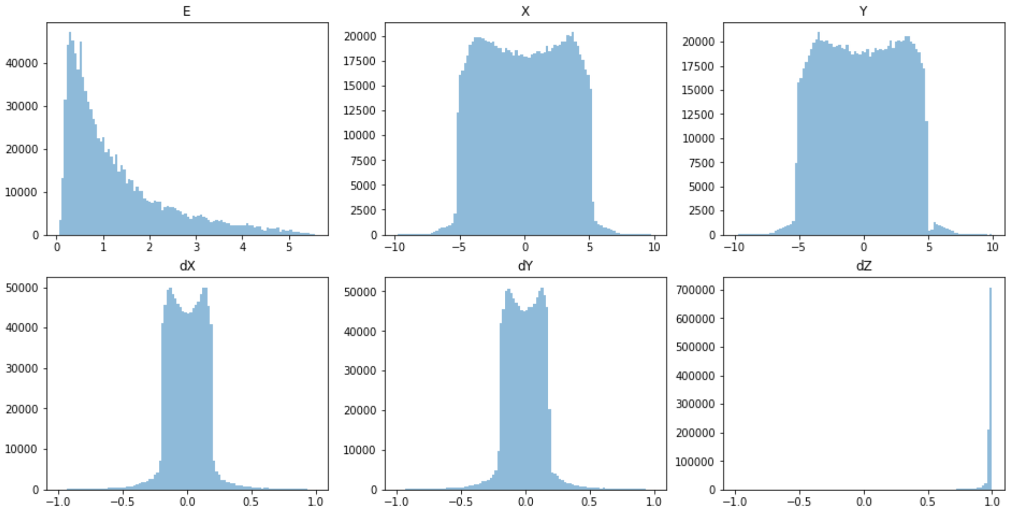
Photon Beam Generation



https://www.researchgate.net/figure/Illustration-of-the-components-of-a-typical-Varian-linear-accelerator-treatment-head-in_fig8_5654346

- ➔ Monte Carlo simulation of photon beam therapy (PBT)
- ➔ Goal: obtain phase spaces (Photons data) with **generative models** instead of time consuming simulations
- ➔ Variational Autoencoders (VAE)

Photon Beam Generation



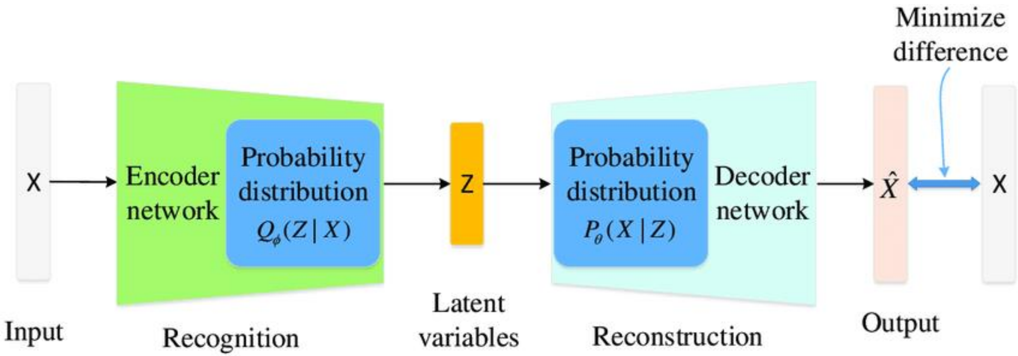
Photons in a phase space are described by six parameters: position coordinates X, Y in the plane perpendicular to the beam axis, direction of momentum (dX, dY, dZ) which is a unit vector and energy of the photon.

The VAE model is trained to learn 6D probability distribution of the above six photon parameters.

Photon Beam Generation

➔ State of art: D Sarrut , N Krah, J M Létang **"Generative adversarial networks (GAN) for compact beam source modelling in Monte Carlo simulations"** (2019)

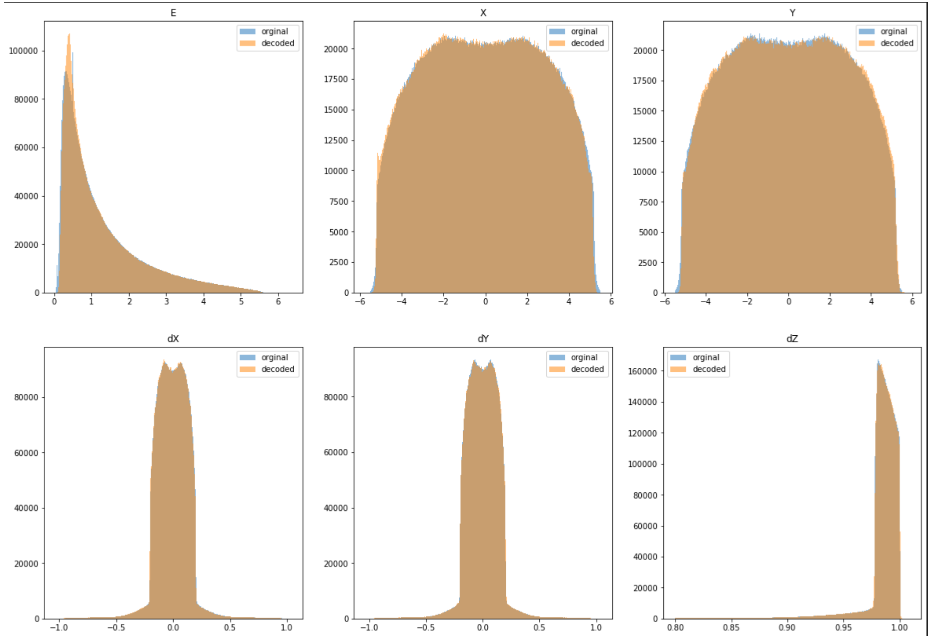
Photon Beam Generation



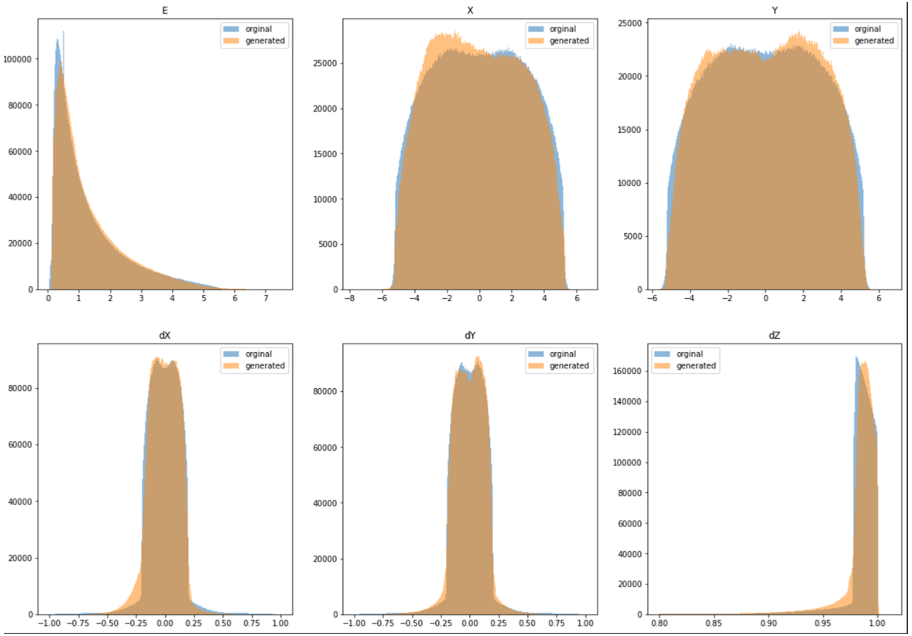
https://www.researchgate.net/figure/Variational-AutoEncoder-VAE-architecture_fig1_333573656

- BetaVAE
  Loss Function = MSE + Beta * KL divergence
- MKMMD_VAE
  Loss Function = MSE + MKMMD LOSS
- MMD_WAE
  Loss Function = MSE + MMD LOSS
- InfoVAE
  Loss Function = MSE + MMD LOSS + KL divergance
  [Zhao et al., 2017]

Photon Beam Generation



MKMMD_VAE: original vs. decoded



MKMMD_VAE: original vs. generated

Summary

- generative models have a huge potential to help with medical data challenges
- we observe the technology development in this direction
- already obtained results are promising
- there are still many areas to be explored

Thank You!