

Mid-PhD Defense

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Outline

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Radiotherapy

Multi-Leaf Collimator

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IMRT Scheme

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Sliding-windows

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Cancer treatments

Surgery



- +: Safe (little damage to healthy tissues)
- : Tumor needs to be localized & accessible

Chemotherapy



- : Heavy medicine on all the body
- +: Tumor does **not** need to be localized

Cancer treatments

Surgery



+: Safe

-: Tumor needs to be localized

Radiotherapy



+: Relatively safe (most tissues are spared)

-: Tumor needs to be (relatively) localized

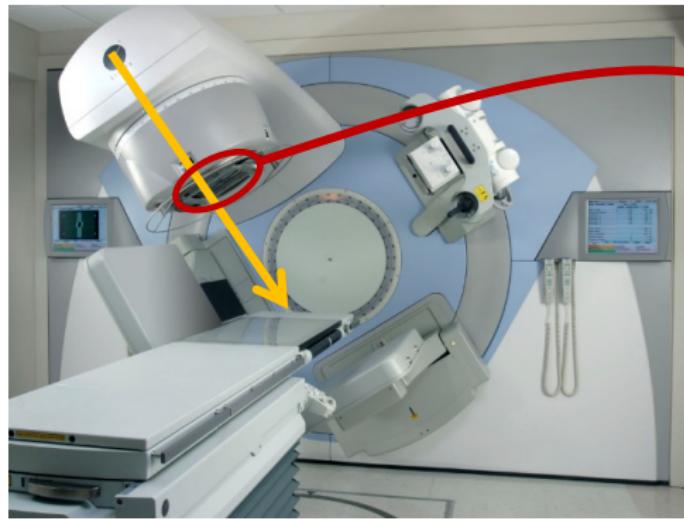
Chemotherapy



Medicine on all the body

does not need to be localized

Multi-Leaf Collimator



V-MAT Irradiation Technique

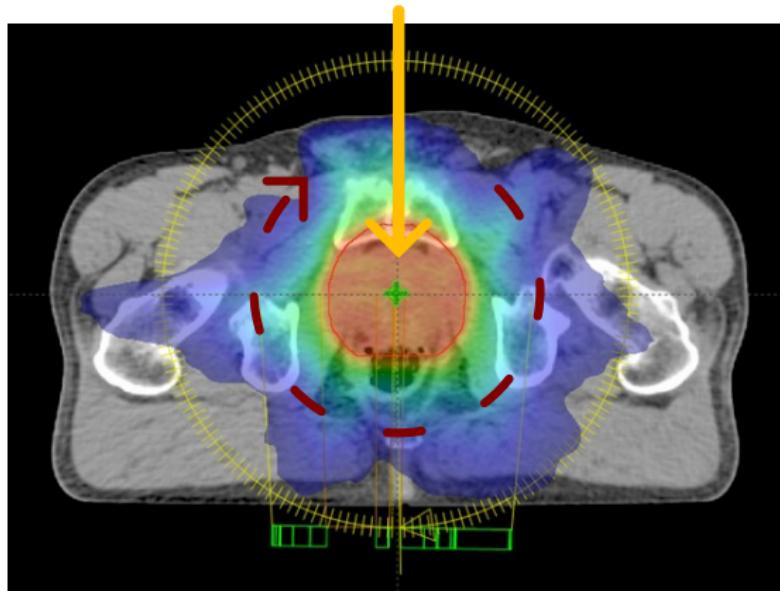


Figure: Typical V-Mat dose slice.

IMRT Irradiation Technique

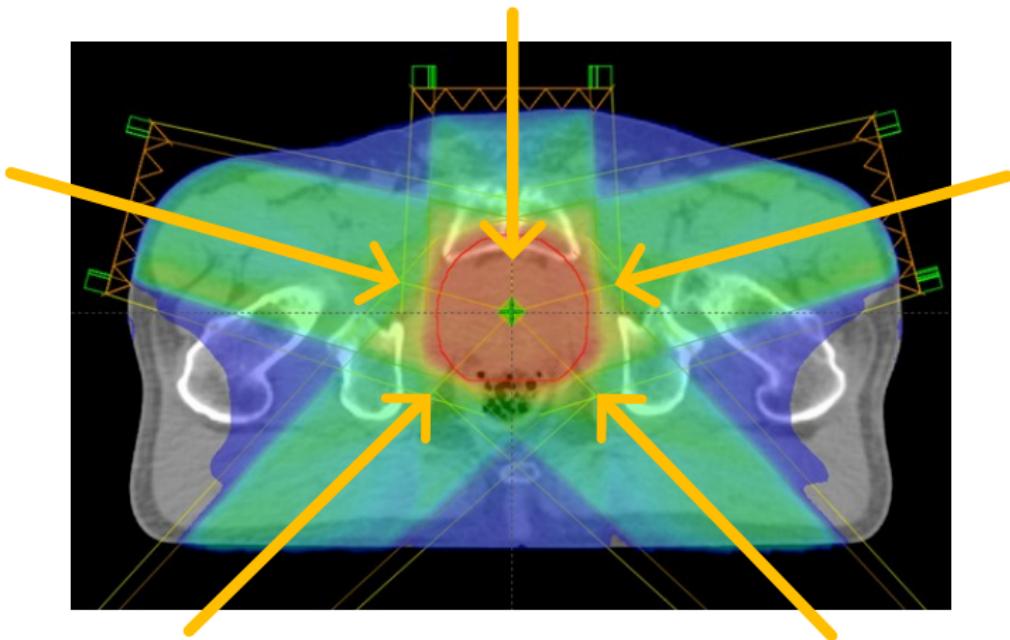


Figure: Typical 5 beams IMRT dose slice.

Step-and-Shoot (1/3)

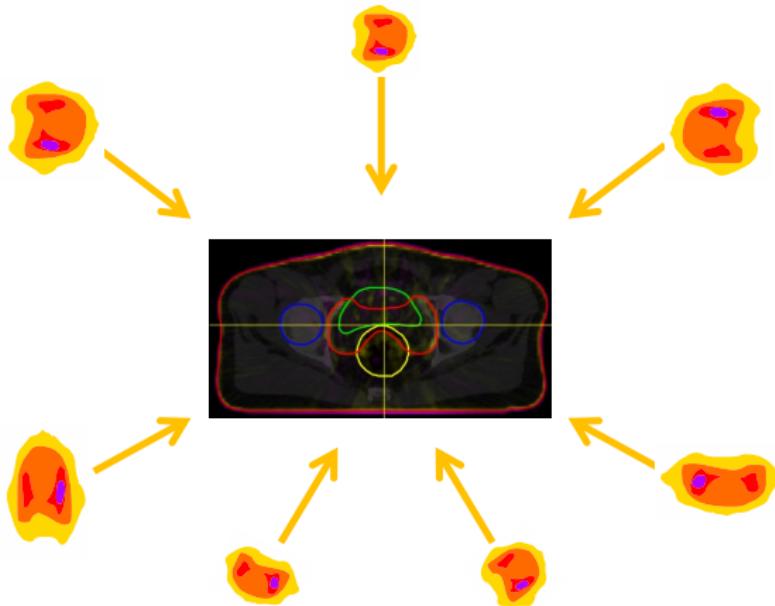


Figure: Optimal Continuous Fluence.

Step-and-Shoot (2/3)

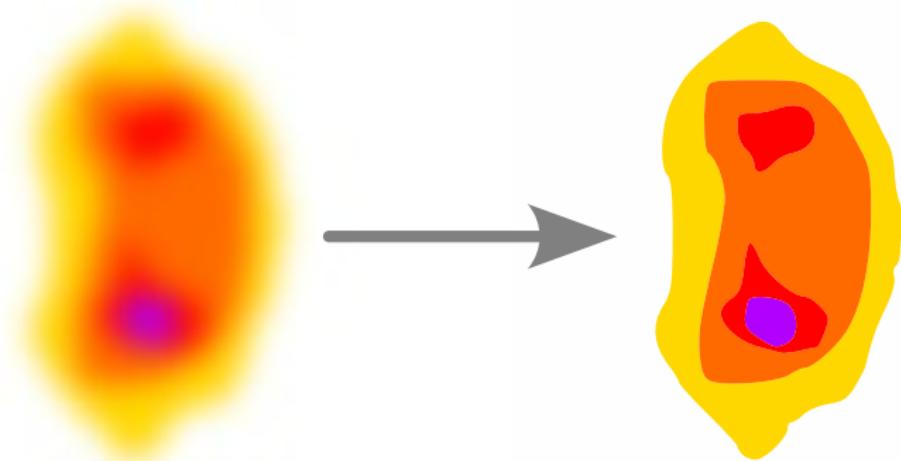


Figure: Discretizing the Fluence.

Step-and-Shoot (3/3)

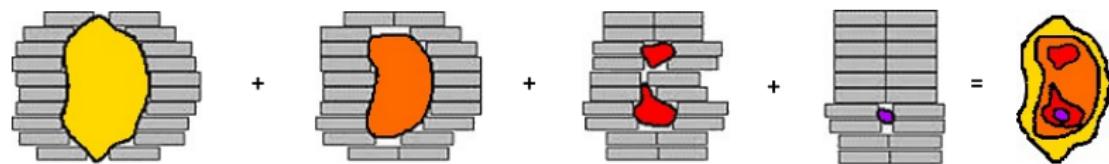


Figure: Delivering Discrete Fluence.

Sliding-Windows (1/3)



Figure: Continuous Fluence to Bixel Fluence.

Sliding-Windows (2/3)

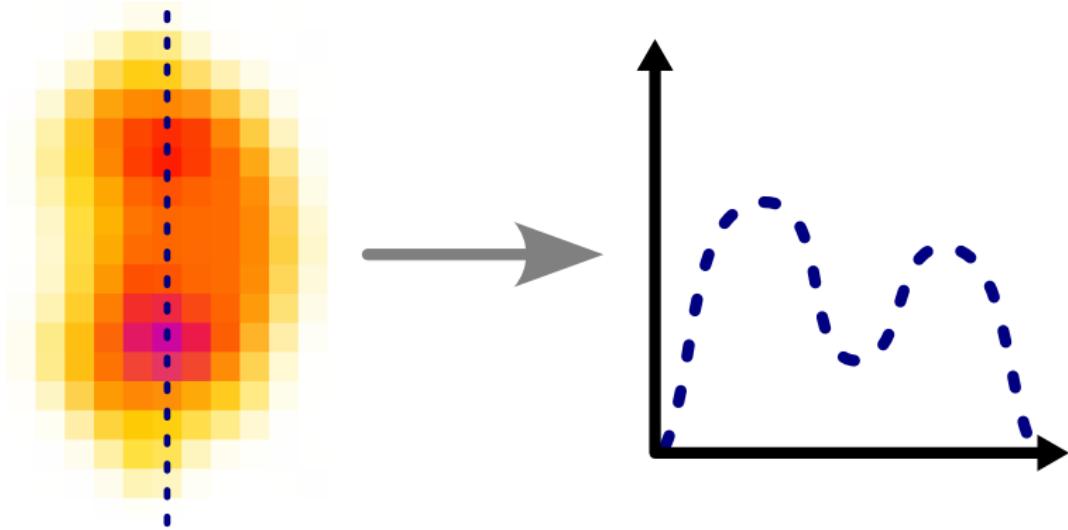


Figure: Bixel Fluence to Row/Column Curves.

Sliding-Windows (3/3)

Convert rows/columns fluence curves to leafs motions.



(<https://mics-lab.github.io/PresentationJuin2023MICS/demo>)

Radiotherapy Workflow



Radiotherapy Workflow



Automatic Dose Optimization for Radiotherapy



Problem Formulation

IMRT

Bixel values:

$$x_{i,j}^{\theta} \geq 0, \text{ for } \theta \in \Theta \text{ and } 1 \leq i \leq 20, 1 \leq j \leq \text{nb_leafs_involved}$$

usually concatenated to a single bixels-value vector \mathbf{x} .

Dose calculation:

$$\mathbf{y} = L\mathbf{x} \text{ with } L \text{ (pre-calculated) dose-influence (DI) matrix}$$

Problem Formulation

IMRT (bis)

Objective for *maximum* constraint c on structure s , dose d :

$$f_c(\mathbf{y}) = \frac{1}{|\mathcal{V}|} \sum_{v \in \mathcal{V}} (\mathbf{y}_v - d)_+^2$$

(reverse sign for minimal constraint).

Final objective:

$$f(\mathbf{y}) = \sum_{c \in \mathcal{C}} w_c f_c(\mathbf{y})$$

with w_c the weight of constraint c .

Problem Optimization

Optimizer review



Figure: Typical prostate case.

<https://arxiv.org/abs/2305.18014>

Problem Optimization

Optimizer review (bis)



Figure: Typical prostate case.

<https://arxiv.org/abs/2305.18014>

Meta-Optimization

Usual optimization

$$\min_{\mathbf{x}} f(\mathbf{x}, w) \text{ s.t. } \mathbf{x} > 0$$

... and fine-tune w until the dose is clinically acceptable.

Meta optimization

$$\min_w \left\{ \min_{\mathbf{x}} f(\mathbf{x}, w) \text{ s.t. } \mathbf{x} > 0 \right\}$$

... still need to fine-tune the parameters (learning rate, momentum, etc...) of the meta-optimizer.

Dose Distances

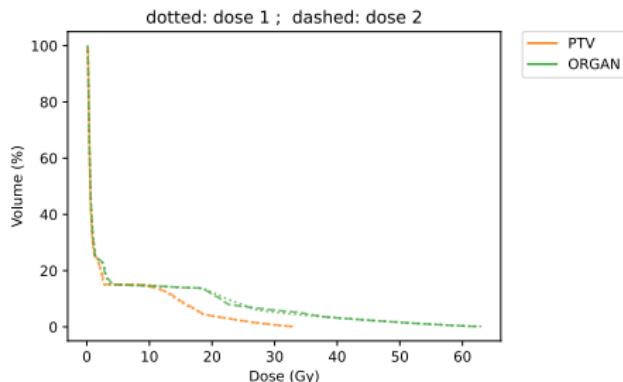
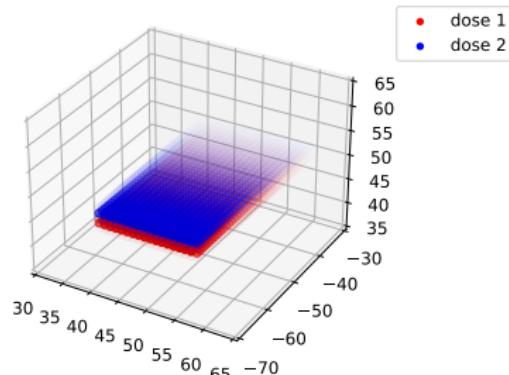
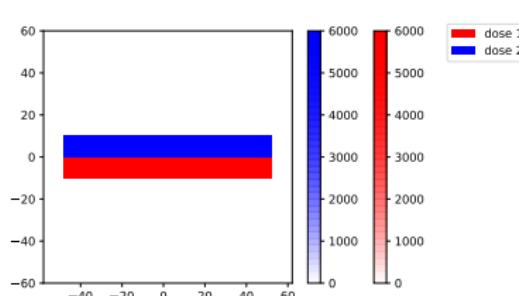
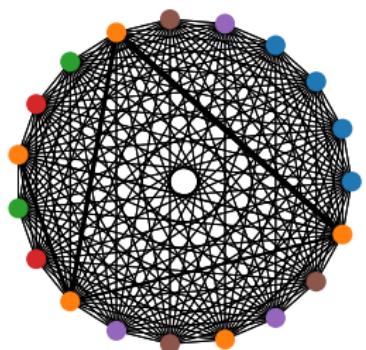
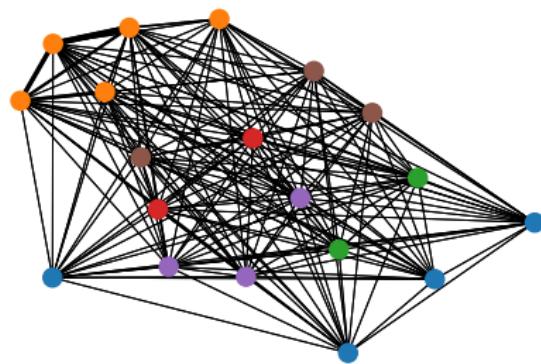


Figure: Example of two doses that have the same clinical effect (measured from the DVHs), but very different voxel-wise dose values.

Dose Clustering



(a) (Circular Layout)



(b) (Spring Layout)

Figure: Doses Network

edges width \propto edge weight $\propto 1/\text{distance}$

node's color reflects community attribution

Dose Clustering



Figure: Dose-Volume Histogram

Dose Clustering

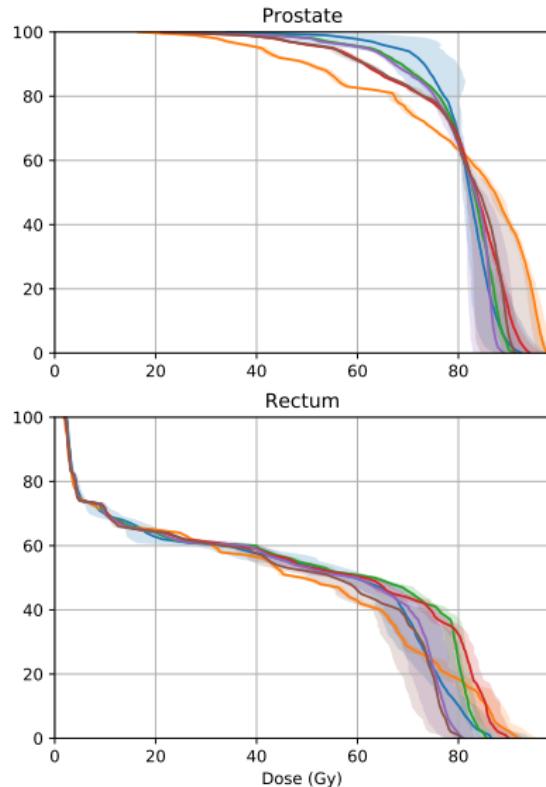
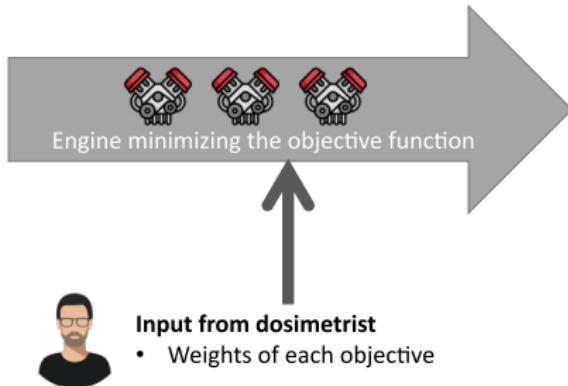


Figure: Dose-Volume Histogram Standard Deviation per Community

Current Workflow

Patient data

- CT scan
- OARs & PTVs contours
- doctors' objectives



Treatment plan

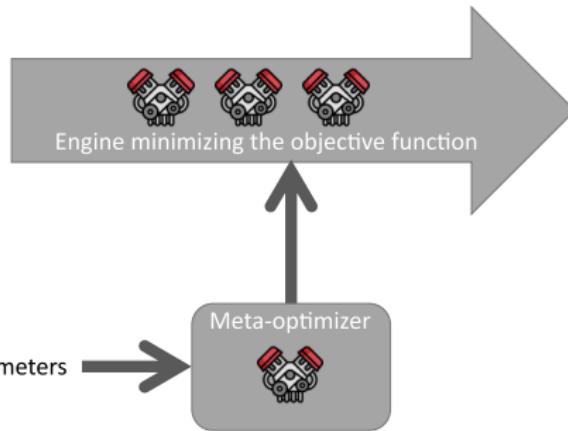
- Fluences
- Leaf movements
- Dose per organ

1st Automatization try “baseline”

Patient data

- CT scan
- OARs & PTVs contours
- doctors' objectives

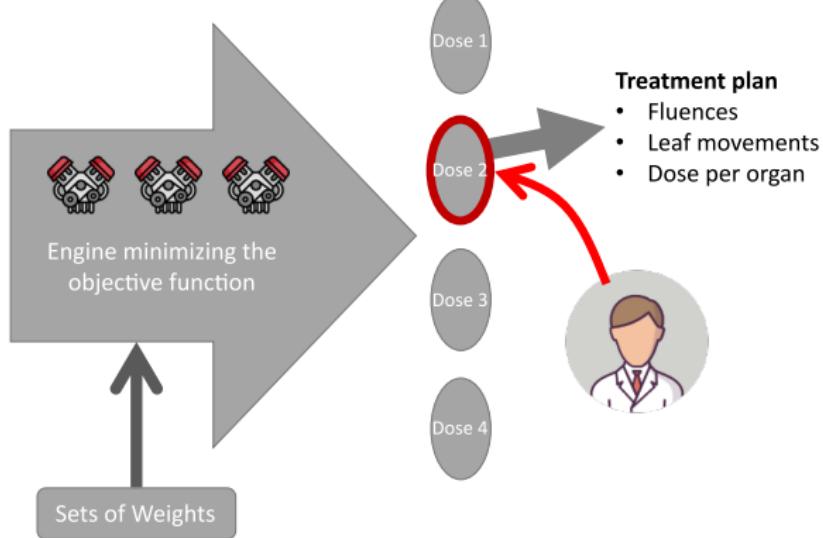
Fine tuning of hyper parameters



1st (bis) Automatization try

Patient data

- CT scan
- OARs & PTVs contours
- doctors' objectives

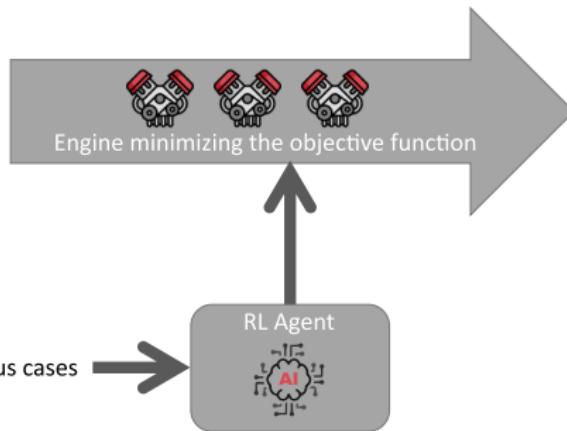


2nd Automatization try (*work in progress*)

Patient data

- CT scan
- OARs & PTVs contours
- doctors' objectives

Learning based on previous cases



Treatment plan

- Fluences
- Leaf movements
- Dose per organ

Reinforcement Learning Setup

Agent A network.

Environment The current dose/weights, the CT scan, structures contours.

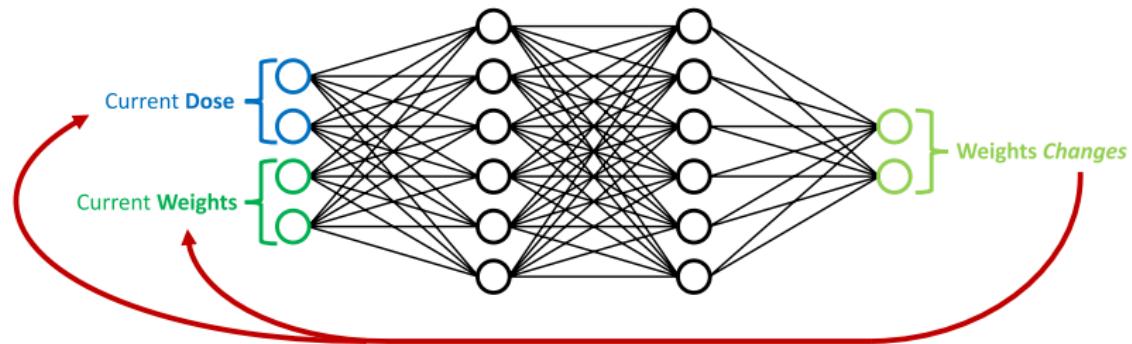
State The agent will only access the the current dose/weights.

Action Changing the set of weights.

Reward The (DVH) distance between the current dose and the one that was actually used.

Policy The value changes of the sets of weights.

Planned Network Architecture



Trick: encode the dose to smaller space

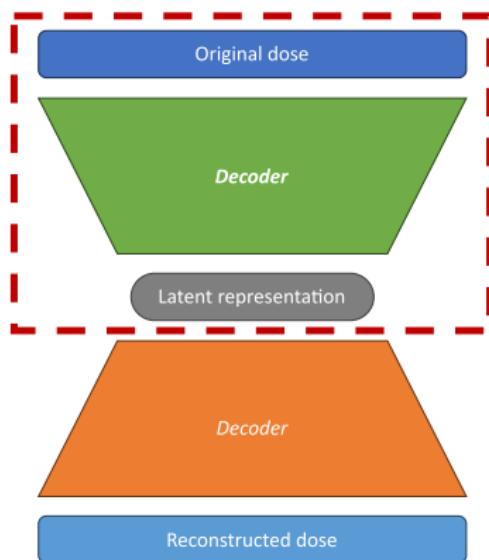


Figure: Dose Auto-Encoder Architecture

Challenges

- ▶ Normalizing the body scan size
- ▶ Normalizing the structures per anatomy
- ▶ Normalizing the constraints per anatomy
- ▶ Training on large data
- ▶ Weights sensitivity

Teaching

Lectures:

- ▶ Mathematics Refresher Course for DSBA (M2 students) 2021
- ▶ Deep Learning for HSB (3rd year students) 2023

TDs:

- ▶ Coding Weeks (1st year) 2021
- ▶ Optimization (1st year) 2021
- ▶ Visual recognition (3rd year) 2022
- ▶ Coding Weeks (1st year) 2022
- ▶ Algorithm and Complexity (2nd year) 2022/2023

Doctoral Training

- ▶ ED INTERFACES - Journée de Rentrée 2022 (12 janvier 2023)
- ▶ Math On Mars (06 mai 2022) Info@lèze
- ▶ Asymmetric Cryptography (23 septembre 2022) Info@lèze
- ▶ Genetic Algorithms (10 juin 2022) Info@lèze
- ▶ Math With Jupyter (18 décembre 2021) Info@lèze
- ▶ Writing skills in Science ADVANCED [Eng] (10 mai 2022)
- ▶ AI 4 Health (10 janvier 2022 - 14 janvier 2022)

Total participation: **109/125** heures; 7 modules

Total des Crédits/Points de Thèse: **22/25**

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