

Mid-PhD Defense

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Outline

Introduction

Cancer treatments

Radiotherapy

Multi-Leaf Collimator

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IMRT Scheme

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Sliding-windows

Radiotherapy Workflow

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Optimization

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Dose Clustering

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Teaching

Doctoral Training

References

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

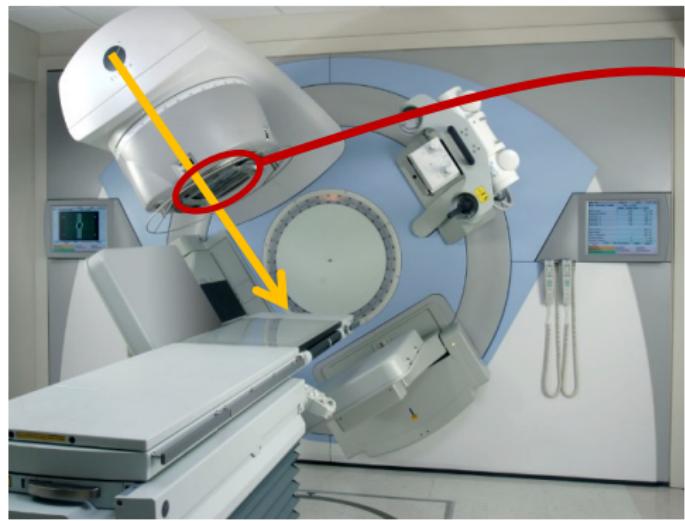
Chemotherapy



Medicine on all the body

does not need to be localized

Multi-Leaf Collimator



V-MAT Irradiation Technique

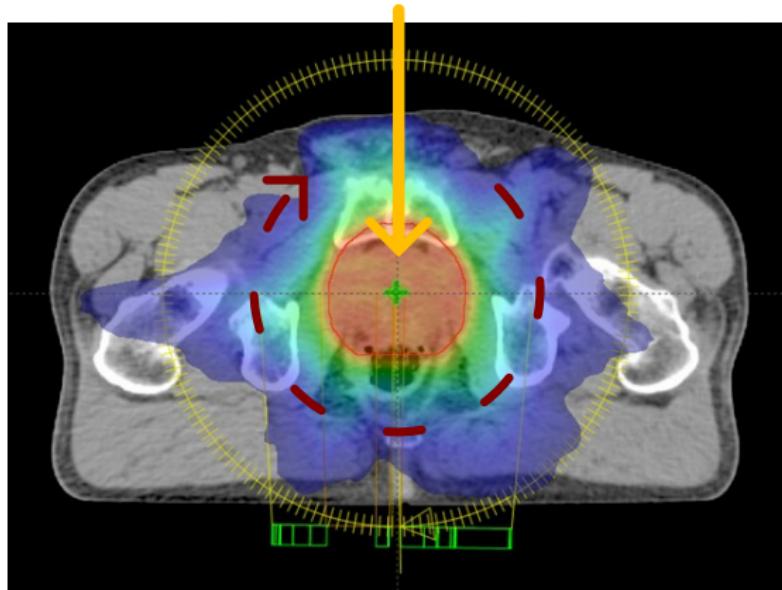


Figure: Typical V-Mat dose slice.

IMRT Irradiation Technique

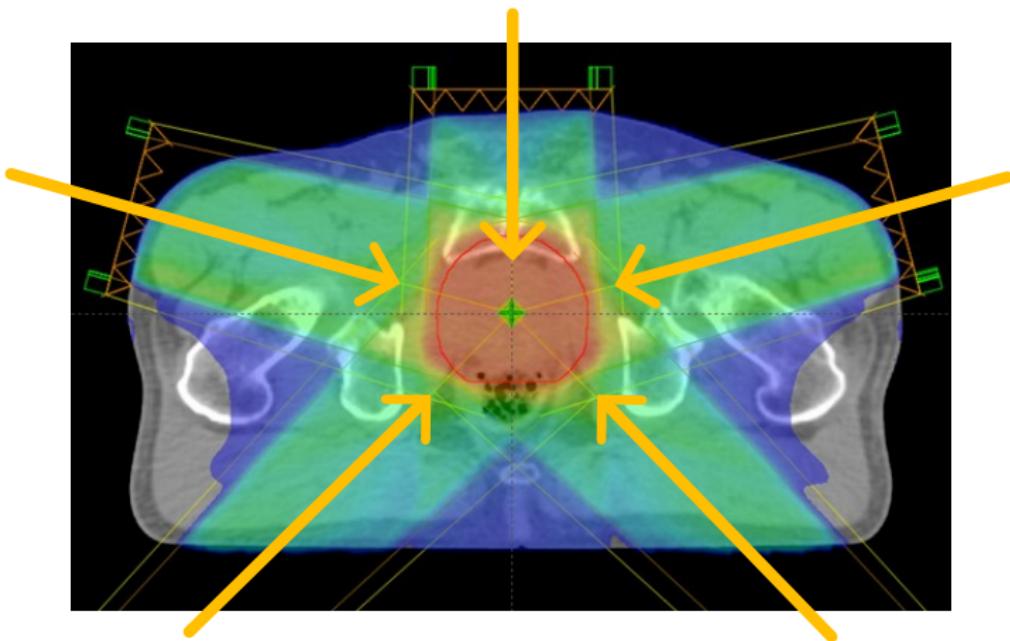


Figure: Typical 5 beams IMRT dose slice.

Step-and-Shoot (1/3)

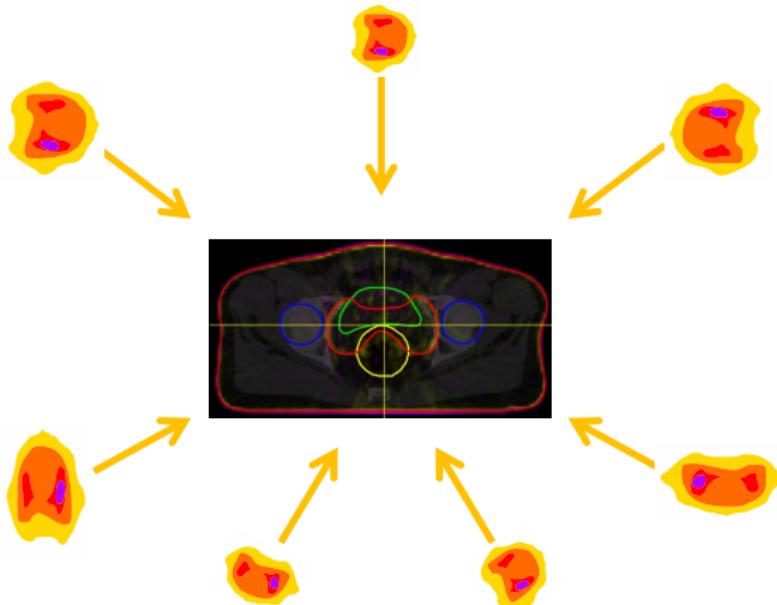


Figure: Optimal Continuous Fluence.

Step-and-Shoot (2/3)

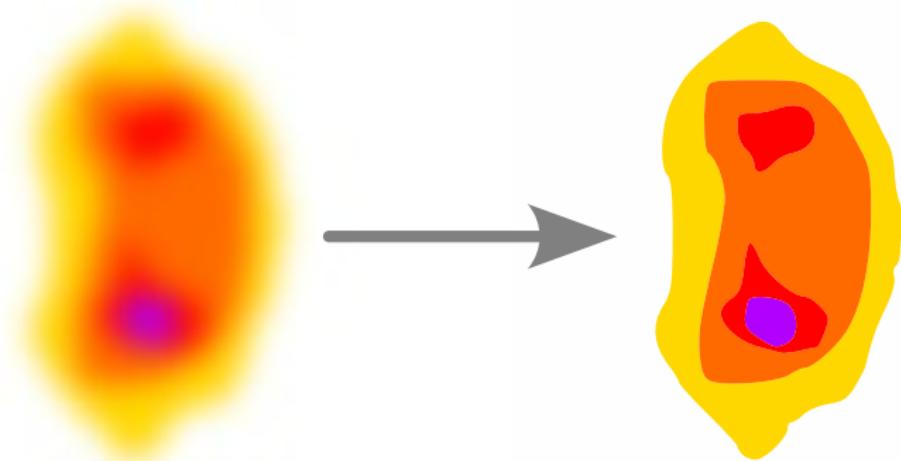


Figure: Discretizing the Fluence.

Step-and-Shoot (3/3)

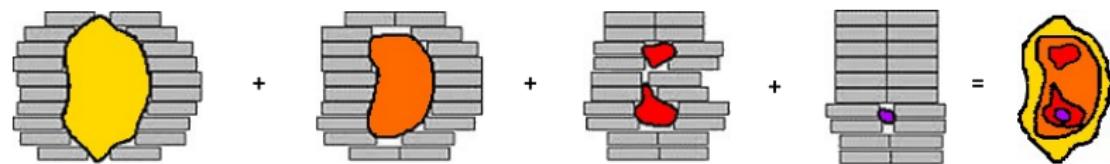


Figure: Delivering Discrete Fluence.

Sliding-Windows (1/3)



Figure: Continuous Fluence to Bixel Fluence.

Sliding-Windows (2/3)

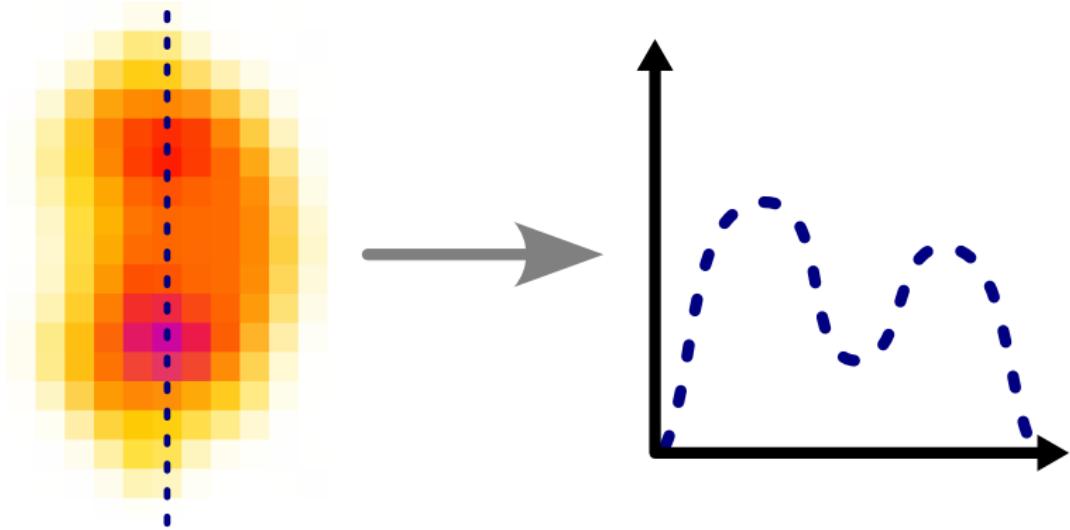


Figure: Bixel Fluence to Row/Column Curves.

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:

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

usually concatenated to a single bixels-value vector x .

Dose calculation:

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

¹20x20 is a typical bixel discretization

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

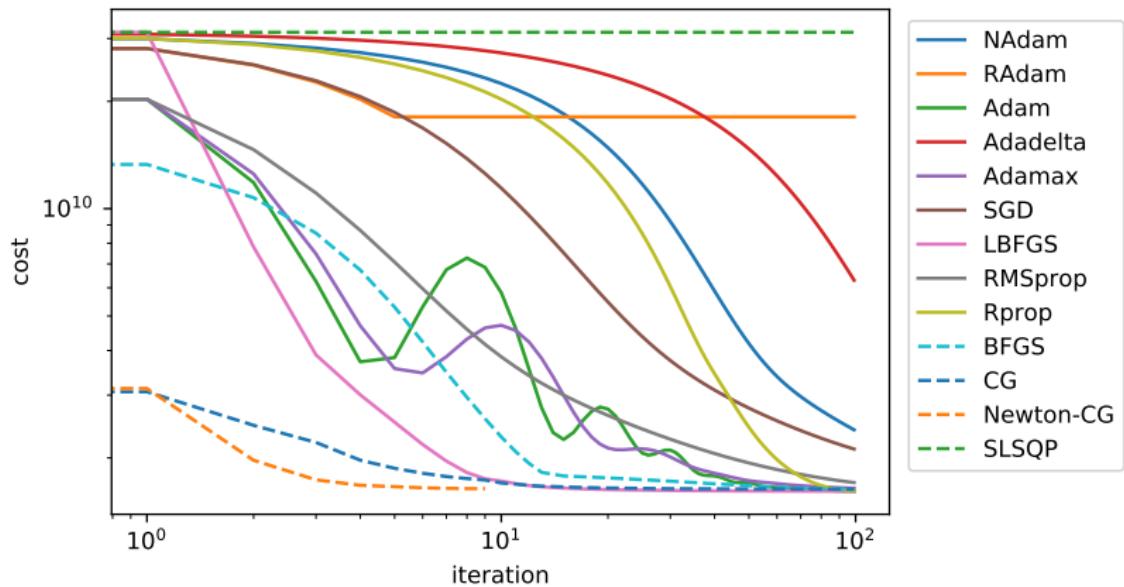


Figure: Typical prostate case.

<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

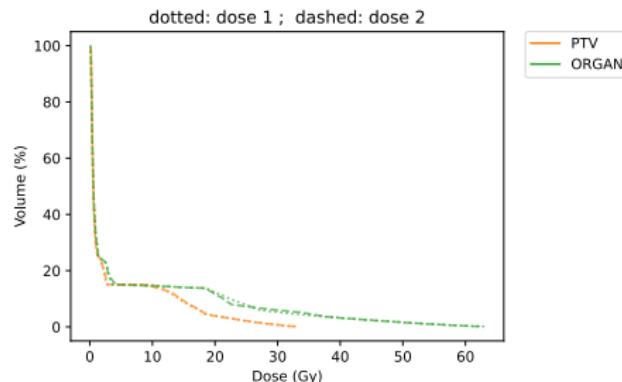
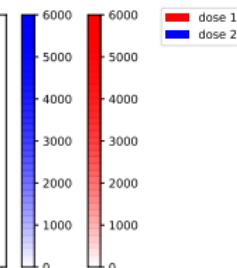
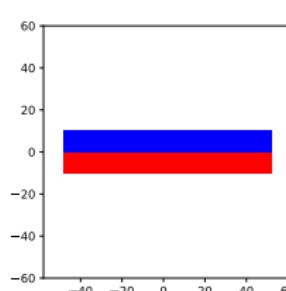
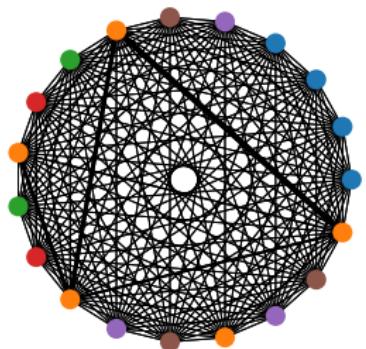
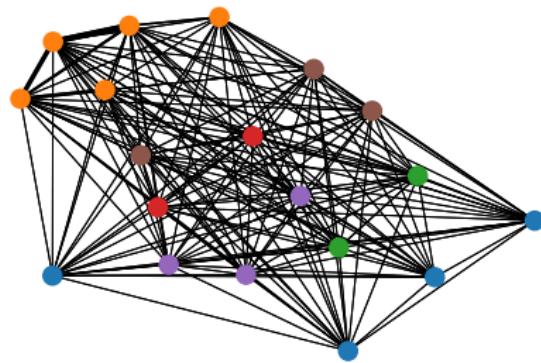


Figure: Example of two doses that have the same clinical effect (measured from the DVHs), but very different voxel-wise dose values.

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

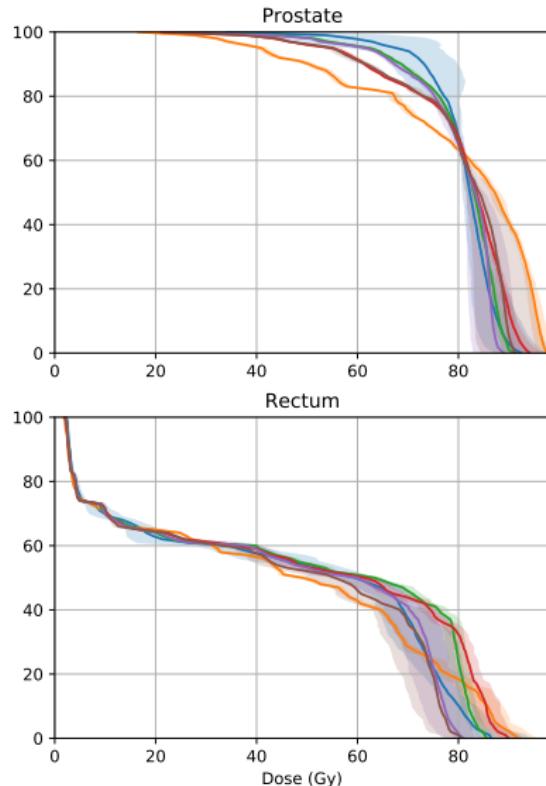
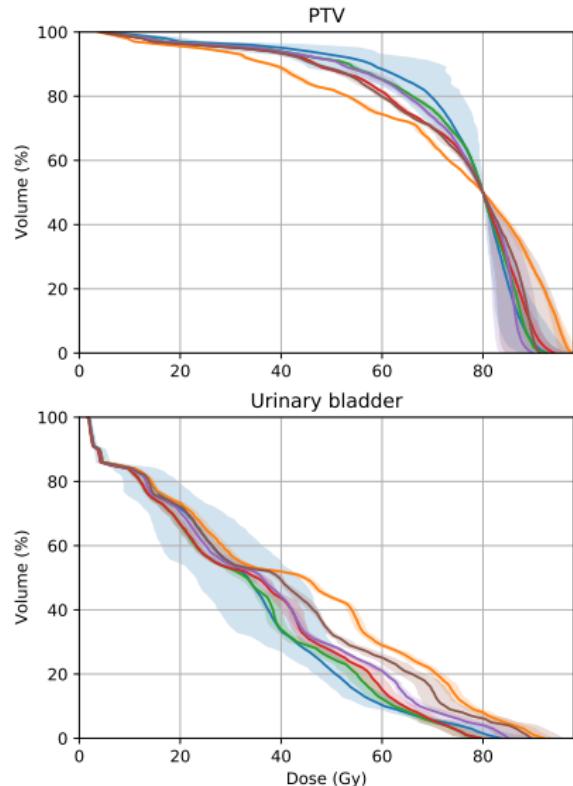
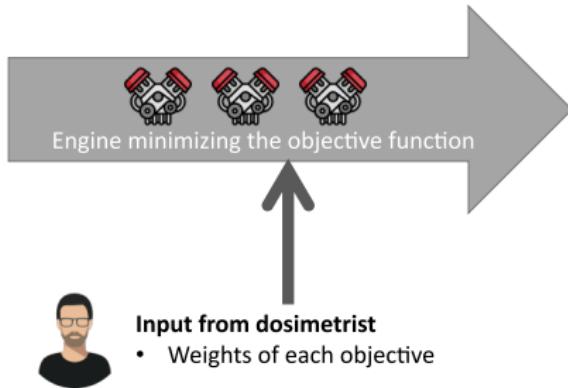


Figure: Dose-Volume Histogram Standard Deviation per Community

Current Workflow

Patient data

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



Treatment plan

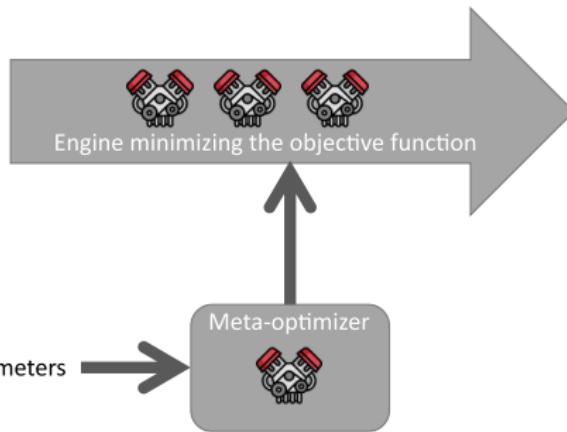
- Fluences
- Leaf movements
- Dose per organ

1st Automatization try “baseline”

Patient data

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

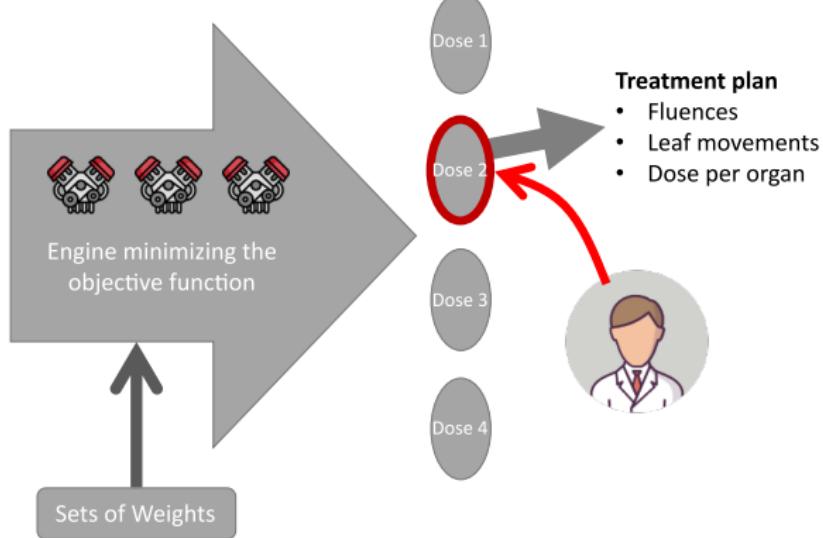
Fine tuning of hyper parameters



1st (bis) Automatization try

Patient data

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

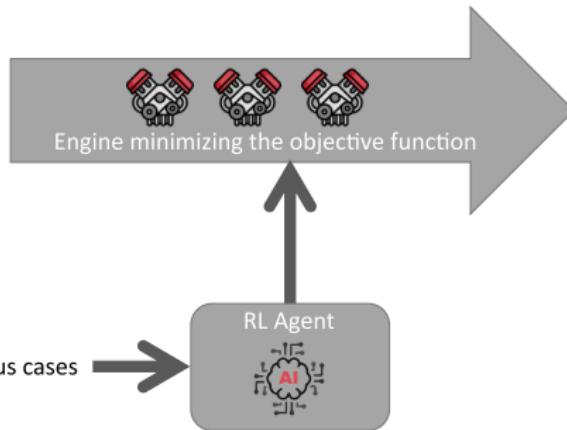


2nd Automatization try (*work in progress*)

Patient data

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

Learning based on previous cases



Treatment plan

- Fluences
- Leaf movements
- Dose per organ

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 le 12 janvier 2023 (14 décembre 2022 - 14 décembre 2022) Théâtre Rousseau, bâtiment Bouygues, Rue Joliot Curie
- ▶ Math On Mars (06 mai 2022 - 6 mai 2022) Info@lèze; à Lagardelle-sur-èze (31)
- ▶ Asymmetric Cryptography (23 septembre 2022 - 23 septembre 2022) Info@lèze; à Lagardelle sur lèze (31)
- ▶ Genetic Algorithms (10 juin 2022) Info @ lèze; à Lagardelle sur lèze (31)
- ▶ Math With Jupyter (18 décembre 2021) Info@lèze; à Lagardelle-sur-èze (31)
- ▶ Writing skills in Science ADVANCED [Eng] (10 mai 2022)
- ▶ AI 4 Health (10 janvier 2022 - 14 janvier 2022) Emmanuel Bacry - online
- ▶ Writing skills in Science ADVANCED [Eng] (10 mai 2022 - 12 juillet 2022) 10 heures

Total participation : 109 heures / 7 modules

Total des Crédits/Points de Thèse : 22

References