

# Mid-PhD Defense

Paul Dubois

TheraPanacea  
MICS, CentraleSupélec  
Institut du Cancer de Montpellier

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Radiotherapy

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Radiotherapy workflow

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## 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

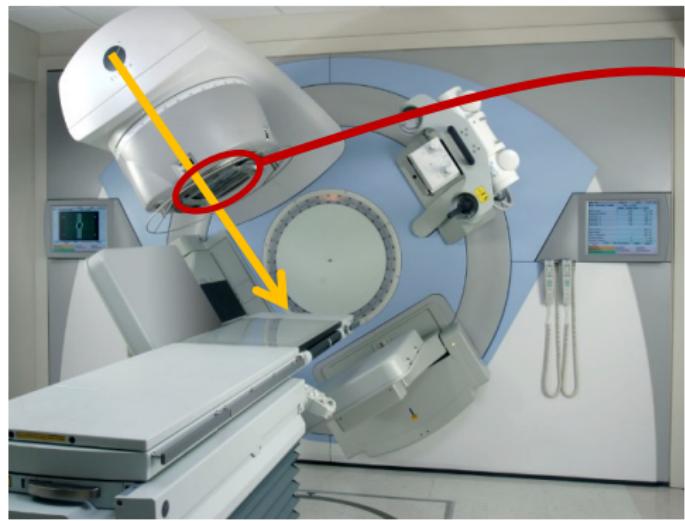
Chemotherapy



Medicine on all the body

does not need to be localized

# Multi-Leaf Collimator



# V-MAT Irradiation Technique

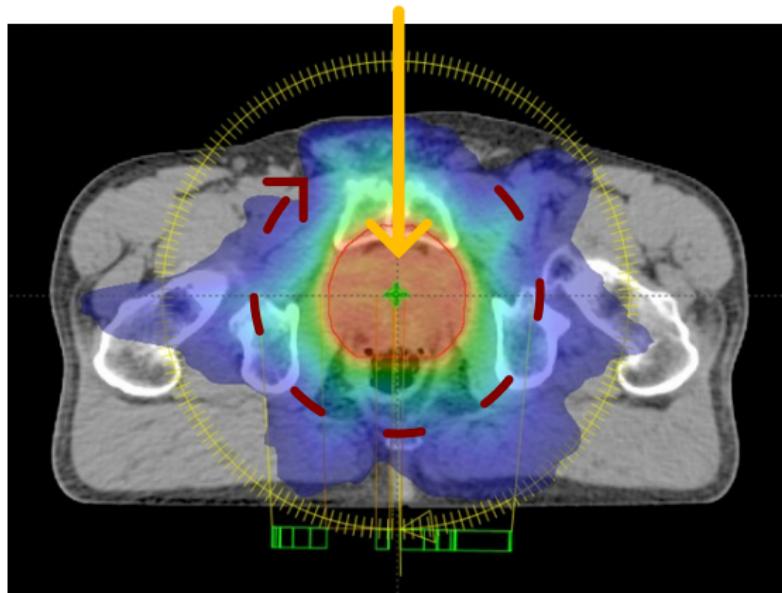


Figure: Typical V-Mat dose slice.

# IMRT Irradiation Technique

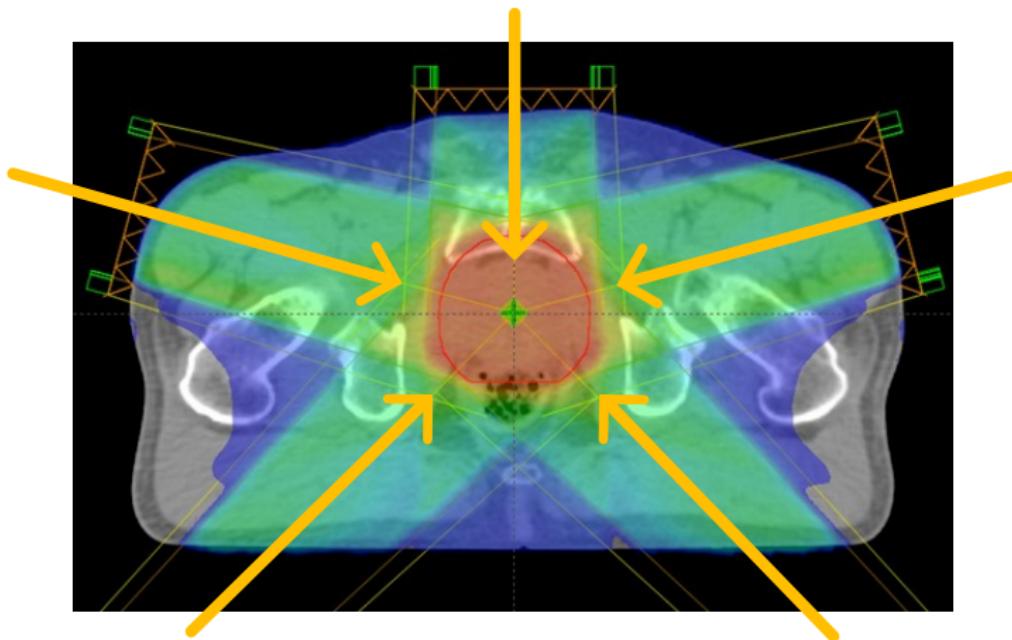
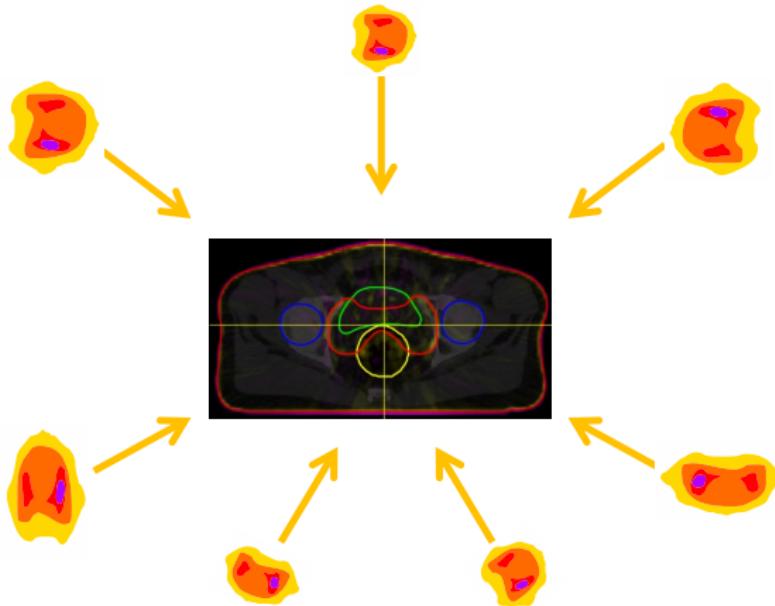


Figure: Typical 5 beams IMRT dose slice.

## Step-and-Shoot (1/3)



**Figure:** Optimal Continuous Fluence.

## Step-and-Shoot (2/3)

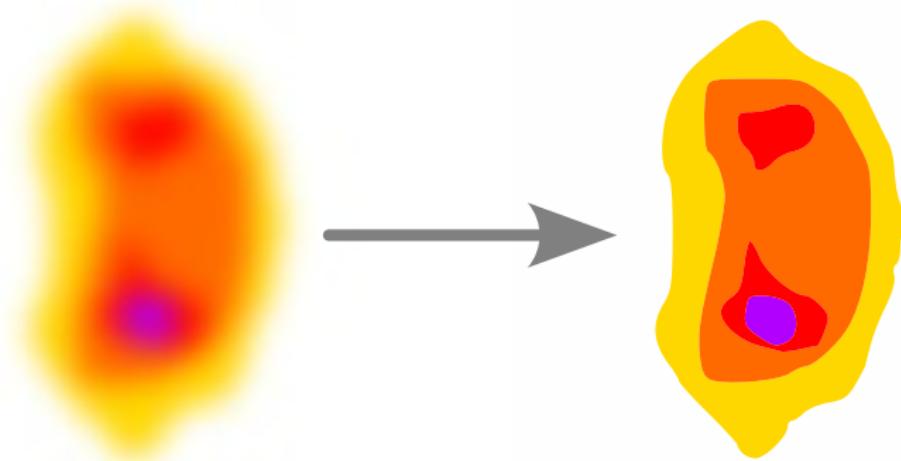


Figure: Discretizing the Fluence.

## Step-and-Shoot (3/3)

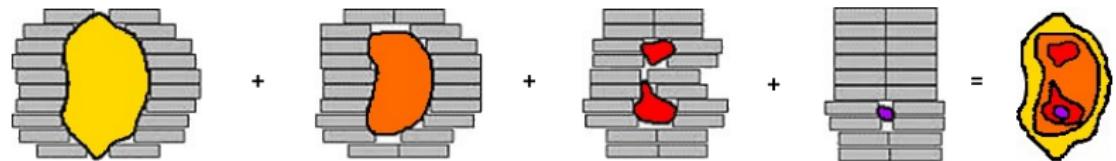
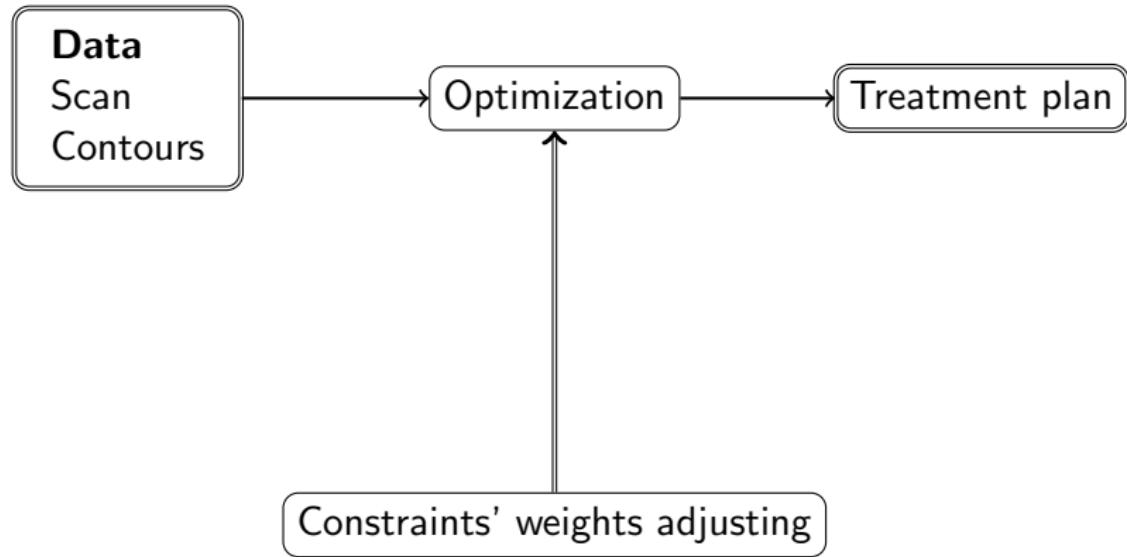


Figure: Delivering Discrete Fluence.

# 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:

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

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<sup>1</sup>20x20 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

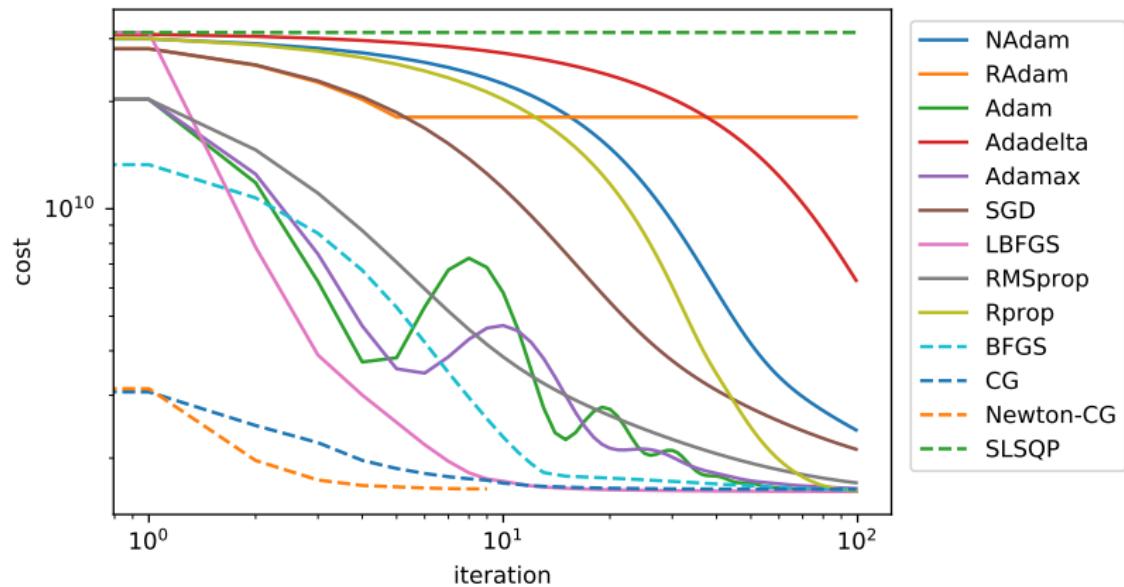


Figure: Typical prostate case.

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

# Problem Optimization

## Optimizer review (bis)

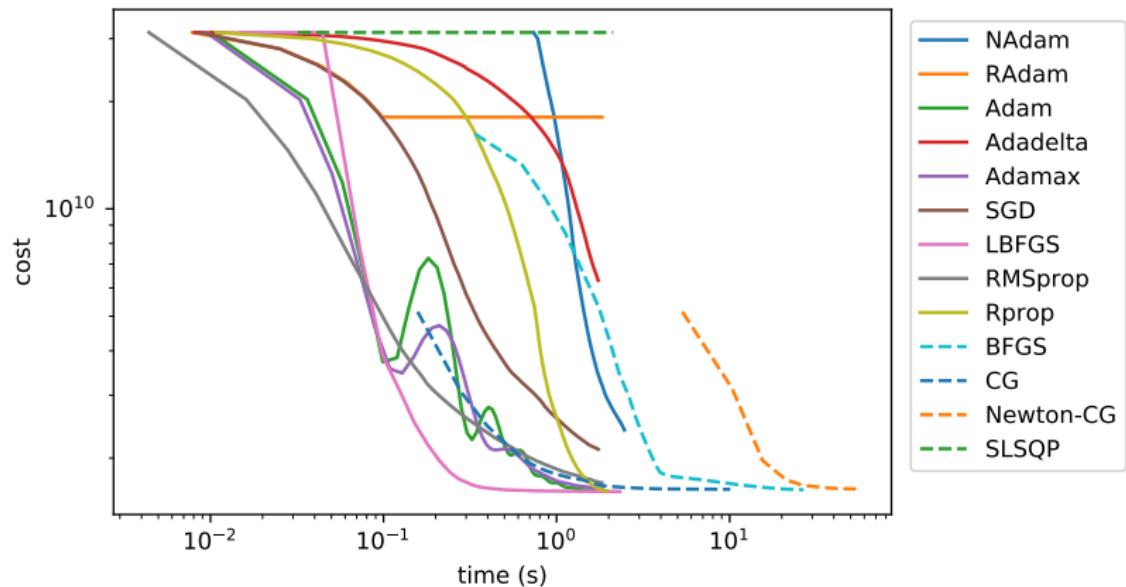


Figure: Typical prostate case.

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

# Meta-Optimization

## Usual optimization

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

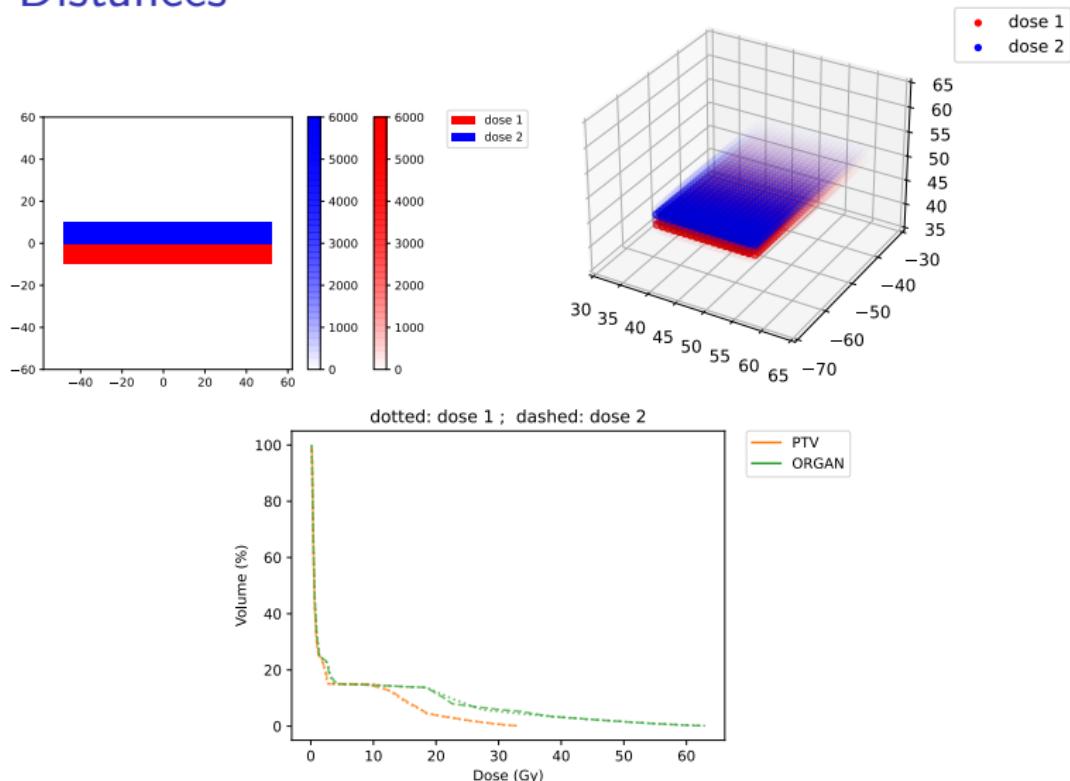
... and fine-tune  $w$  until the dose is clinically acceptable.

## 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.

# References