

# Automatic Dose Optimization for Radiotherapy

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# Re-inventing cancer treatment with Artificial Intelligence



**THERAPANACEA**

Reinventing cancer care through AI

# TheraPanacea Overview



Company is spin-off of **Artificial Intelligence research** lab



**Founded in 2017** and based in Paris & Pittsburgh, **70+ employees** to date



Core expertise in **Advanced Mathematics, Medical Imaging and AI**



**ART-Plan** solution for Radiation Oncology 1<sup>st</sup> market launch **in 2019**



**100+ user sites** in Europe, Africa, Middle East and the US



## European and National Science and Innovation Prizes and Awards obtained since 2017:

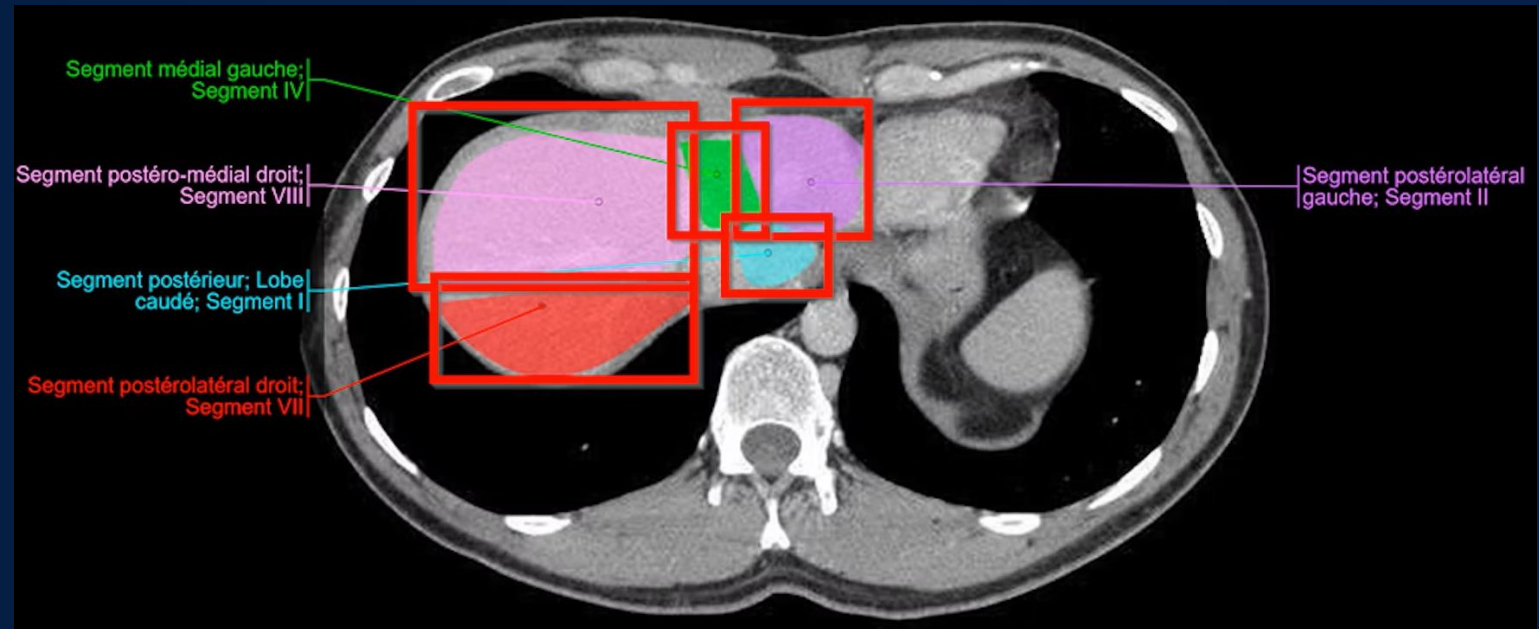


European  
Research  
Council



H2020 ERC POC, Grands Prix d'Innovation de la Ville de Paris, Concours d'innovation numérique, Concours iLab des jeunes entreprises innovantes, Paris Region AI challenge, Prix de l'innovation en imagerie médicale Société Française de Radiologie

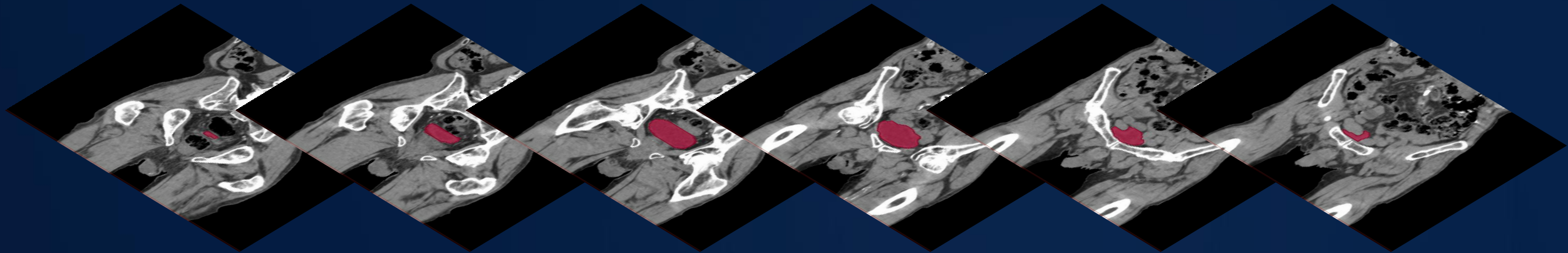
# Annotation



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# Annotation



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# Annotate

## AI-powered contouring tool



In clinical use since 2019



150 + structures (OAR and LN) on CT

→ Sub structures of the heart

→ SBRT Thorax

70 + structures on MR



3-4 minutes contouring



Plug and play



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# MR Box

## Synthetic CT for MR-guided workflow



Automatic delineation on MR



Generate a pseudo-CT from MR images

- Avoid registrations errors
- Accelerate adaptive routines
- Less machine time



Brain T1, Pelvis T2, Pelvis/Abdo Truefisp (ViewRay)  
And more under development



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ART-Plan™ AdaptBox

# Advantages

Accelerate, automatize and simplify adaptive radiation therapy.



Reduce the burdens of multiple manual iterations.



Save time and optimize the resources of your department.



Take earlier and easier re-planning decision.



# Cancer treatments

Surgery



Chemotherapy



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



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

# Cancer treatments

Surgery



Radiotherapy



Chemotherapy



+ : Safe  
- : Tumor needs to be localized

+ : Relatively safe (most tissues are spared)  
- : Tumor needs to be (relatively) localized

Chemotherapy on all the body  
Tumor does **not** need to be localized

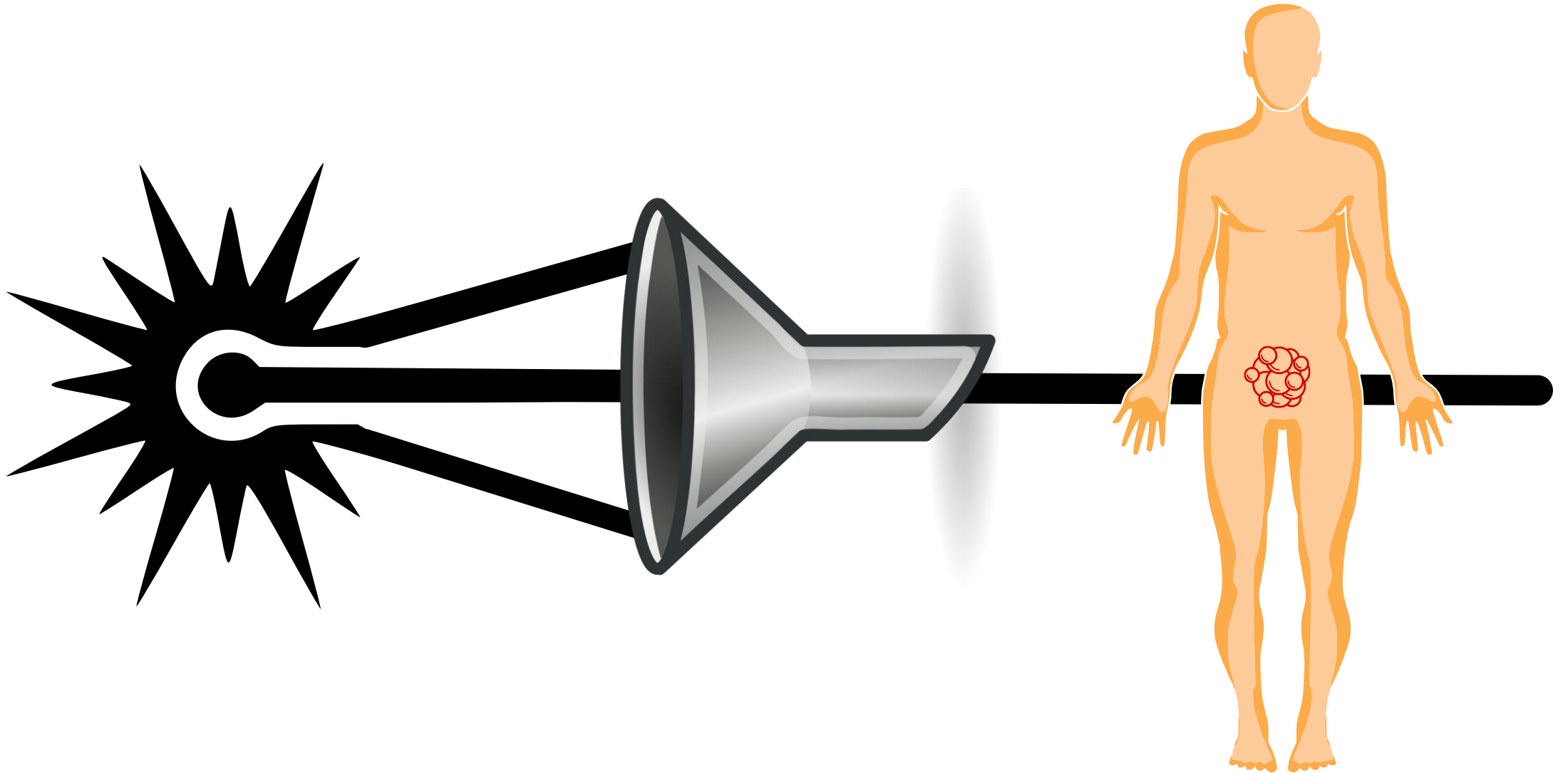
Waves are...



Poison!

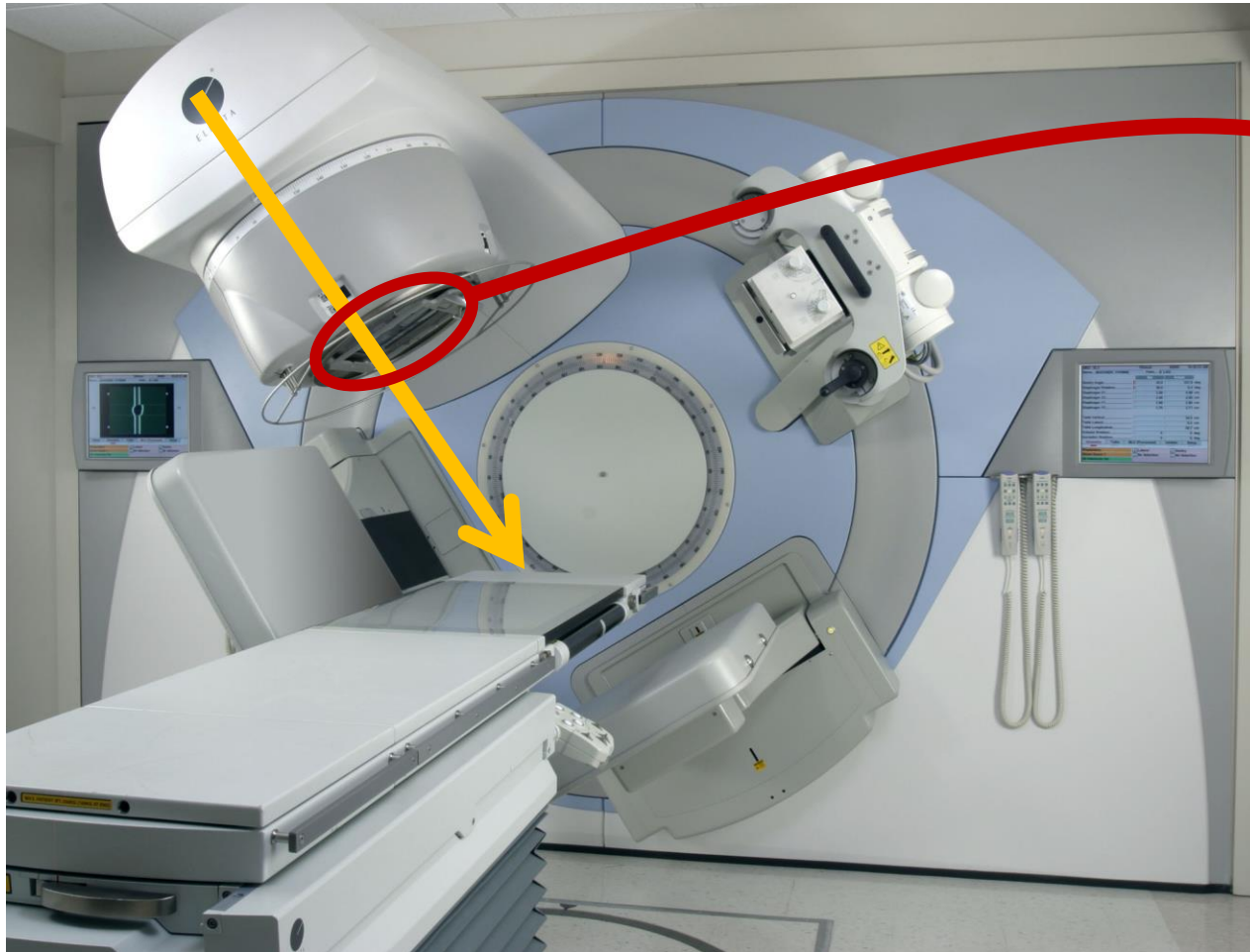


# Targeting the tumor



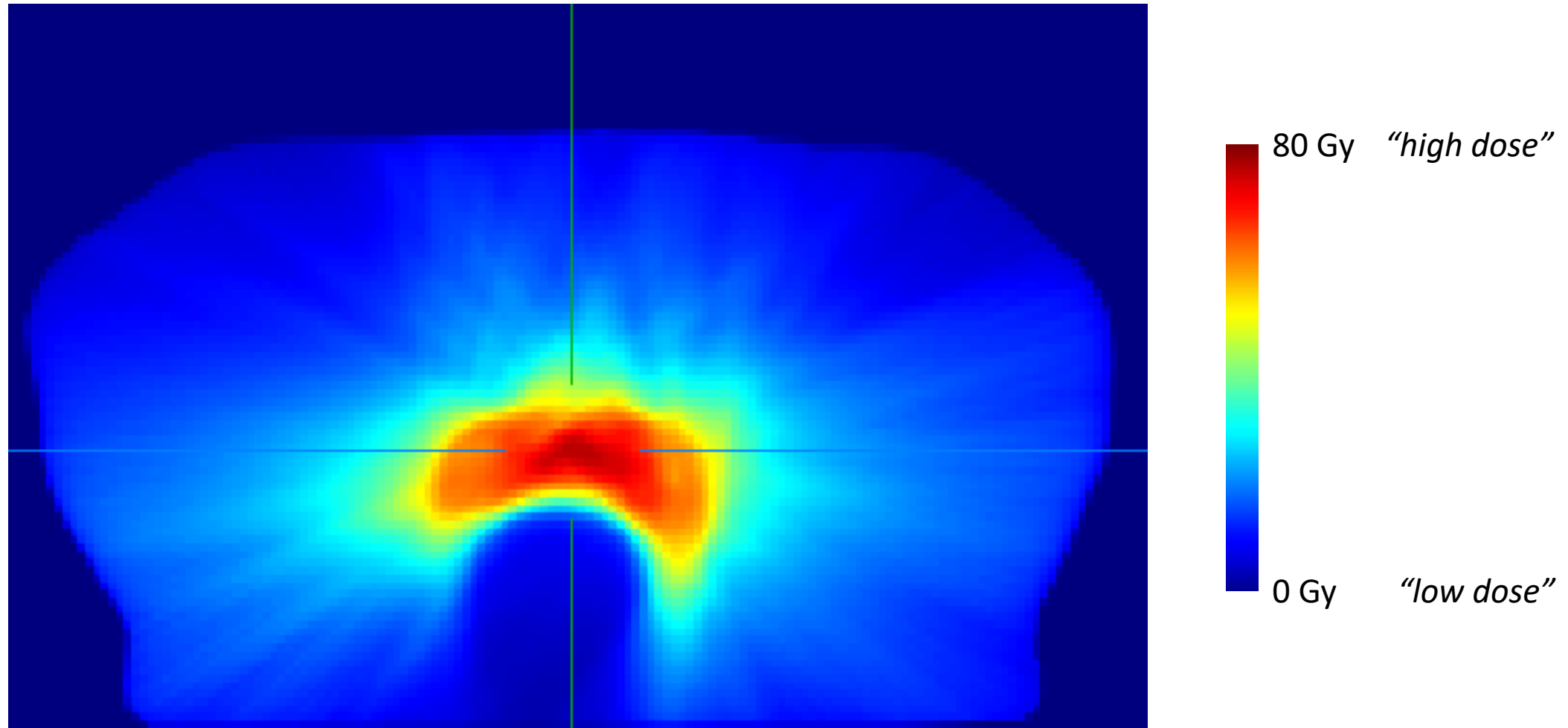


# Multi-Leaf Collimator

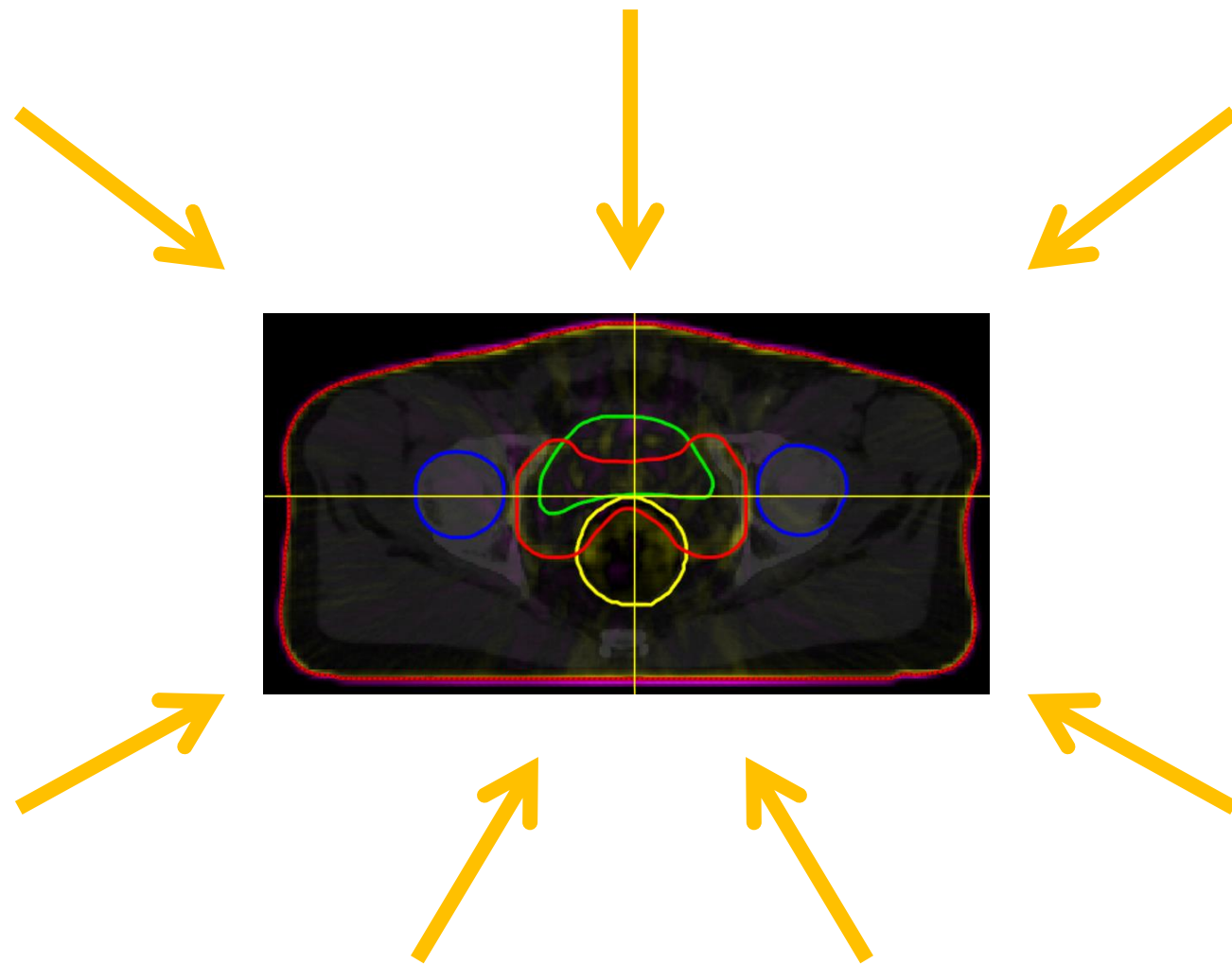




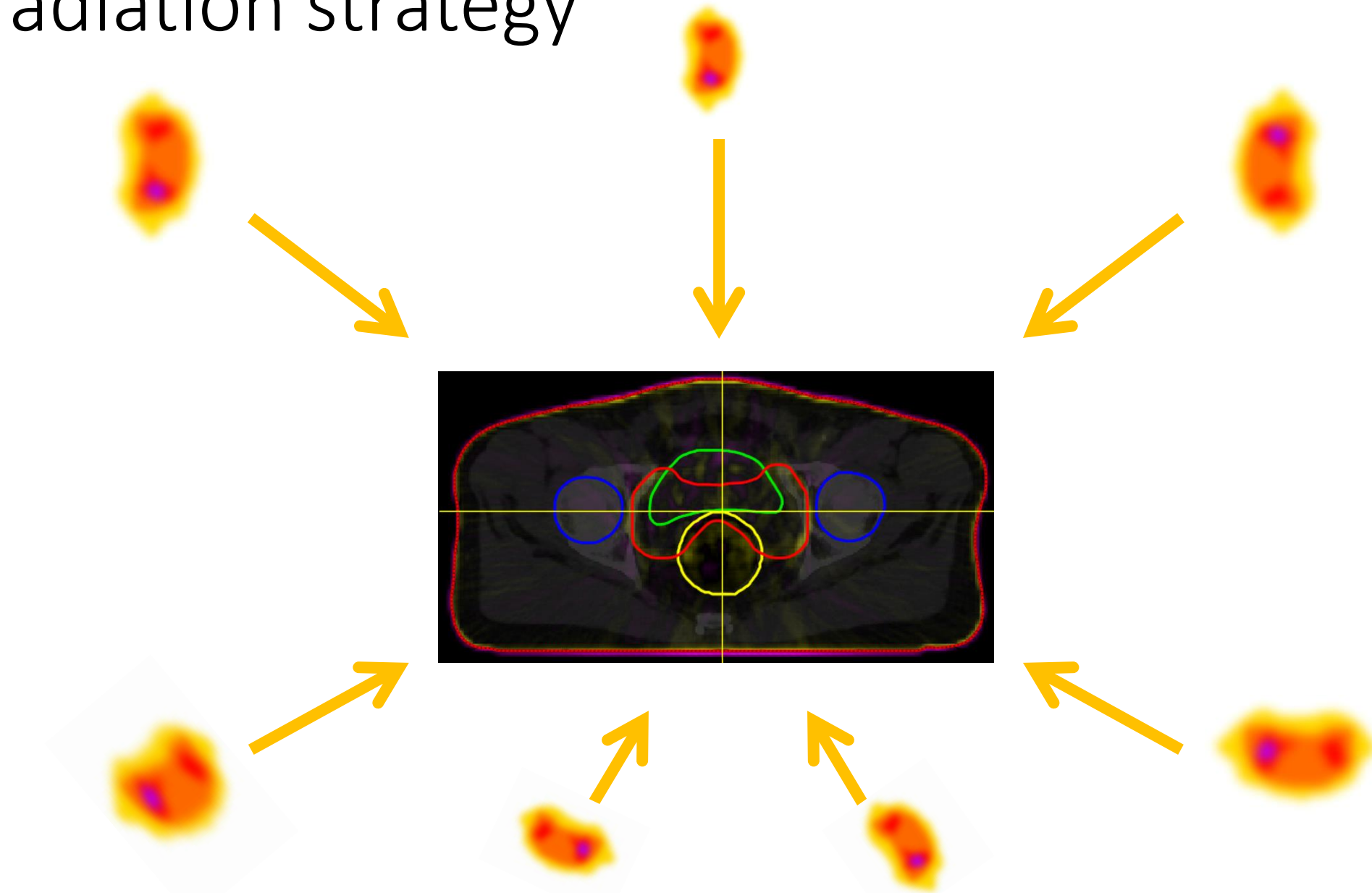
# Dose Spread



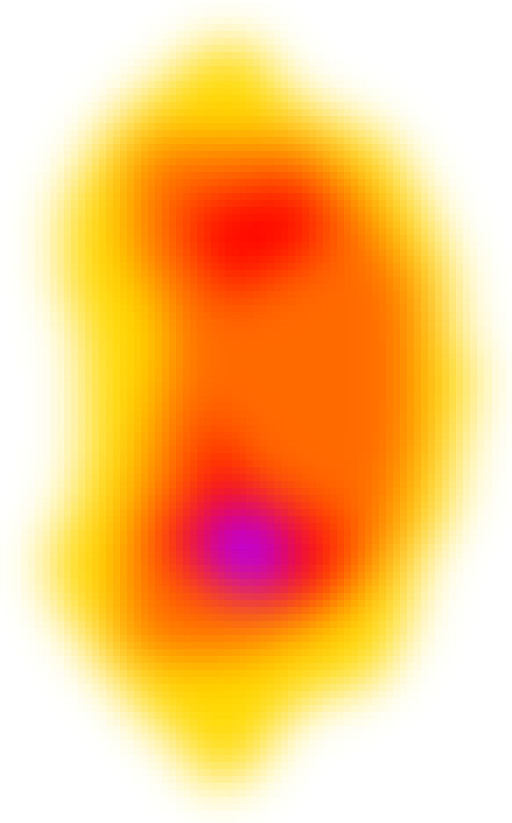
# Spreading rays



# Irradiation strategy



# Delivering irradiation

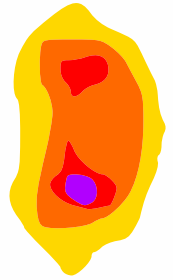


Ideal heatmap

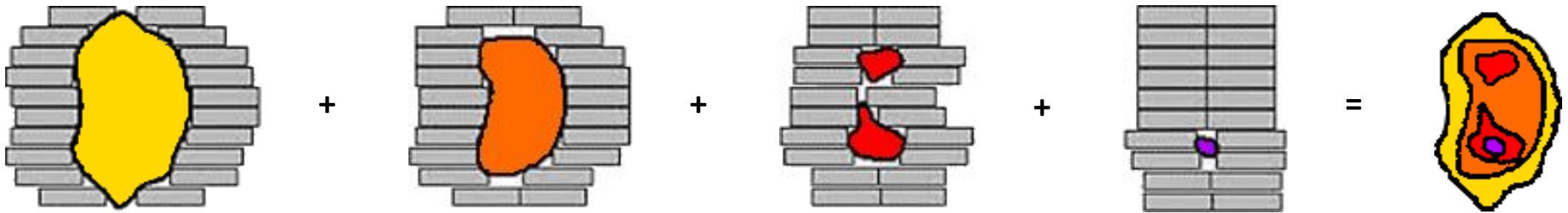


Discretized heatmap

# Delivering discretized dose



*dose to deliver*





# Problem statement



% of the volume	Name	Dose
<b>PTV constraints:</b>		
$\leq 1\%$	of Ext_Tumor receives	$\geq 70\text{Gy}$
$\geq 95\%$	of Tumor receives	$\geq 63\text{Gy}$
<b>OAR constraints:</b>		
$\leq 1\%$	of Spinal_Cord receives	$\geq 43\text{Gy}$
$\leq 15\%$	of Heart receives	$\geq 30\text{Gy}$
$\leq 20\%$	of Esophagus receives	$\geq 10\text{Gy}$
$\leq 2\%$	of Lt_Lung receives	$\geq 20\text{Gy}$
$\leq 8\%$	of Lt_Lung receives	$\geq 10\text{Gy}$

List of “objectives”

# Mathematical formulation

Parameters to optimize

$$x_{i,j}^{(\theta)} \text{ with } 1 \leq i, j \leq N_{leaf\_pairs}$$
$$\theta \in \Theta \text{ (the list of angles chosen for this case)}$$

Parameters constraints

We cannot send negative dose, i.e.:

$$x_{i,j}^{(\theta)} \geq 0$$

however, the angles are completely free.

Dose calculation

The dose on each voxel of the body  $y_v$  is approximated by:

$$y = \sum_{\theta \in \Theta} L^{(\theta)} x^{(\theta)}$$

We want to find the best dose distribution  $y$ .

# Mathematical formulation

Ideal problem

$$\begin{aligned} & \text{minimize } \sum_{s \in \mathcal{O}} \frac{1}{|\mathcal{V}_s|} \sum_{v \in \mathcal{V}_s} y_v^2 \\ & \text{s.t. DVH are respected, } y = Lx \text{ and } x \geq 0 \end{aligned}$$

% of the volume	Name	Dose
<b>PTV constraints:</b>		
≤ 1%	of Ext_Tumor receives	≥ 70Gy
≥ 95%	of Tumor receives	≥ 63Gy
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≤ 8%	of Lt_Lung receives	≥ 10Gy

Objective function



$$f_s(y) = \sum_{v \in \mathcal{V}_s} \frac{1}{|\mathcal{V}_s|} \left( \overline{w}_s (y_v - \overline{t}_s)_+^p + \underline{w}_s (-y_v + \underline{t}_s)_+^p \right)$$

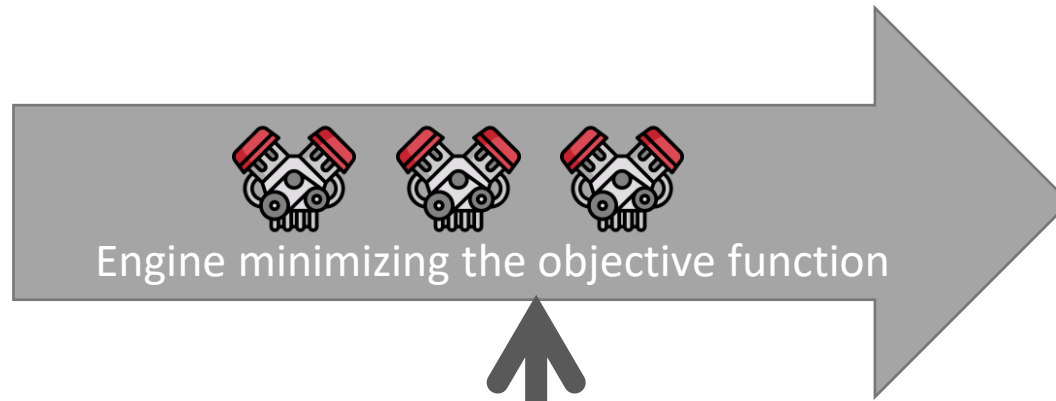
$$f(y) = \sum_{s \in \mathcal{S}} f_s(y)$$

*if constraint is not satisfied for structure  $s$ , else  $f_s(y) = 0$*

# Current Workflow

## Patient data

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



## Treatment plan

- Fluences
- Leaf movements
- Dose per organ



## Input from dosimetrist

- Weights of each objective

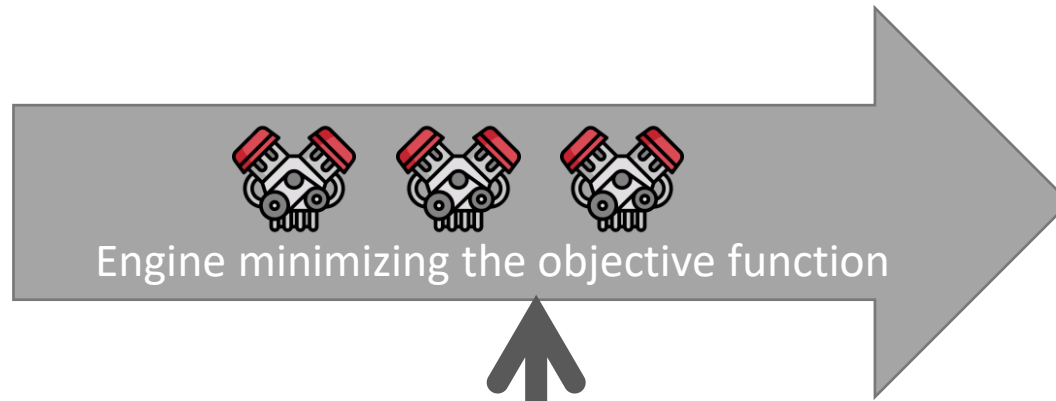
# Automatization (*work in progress*)

## Patient data

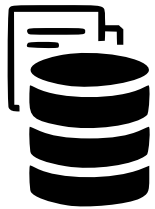
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## Treatment plan

- Fluences
- Leaf movements
- Dose per organ



Learning based on previous cases







# Thank You

