Methods for automatization of radiotherapy dosimetry.

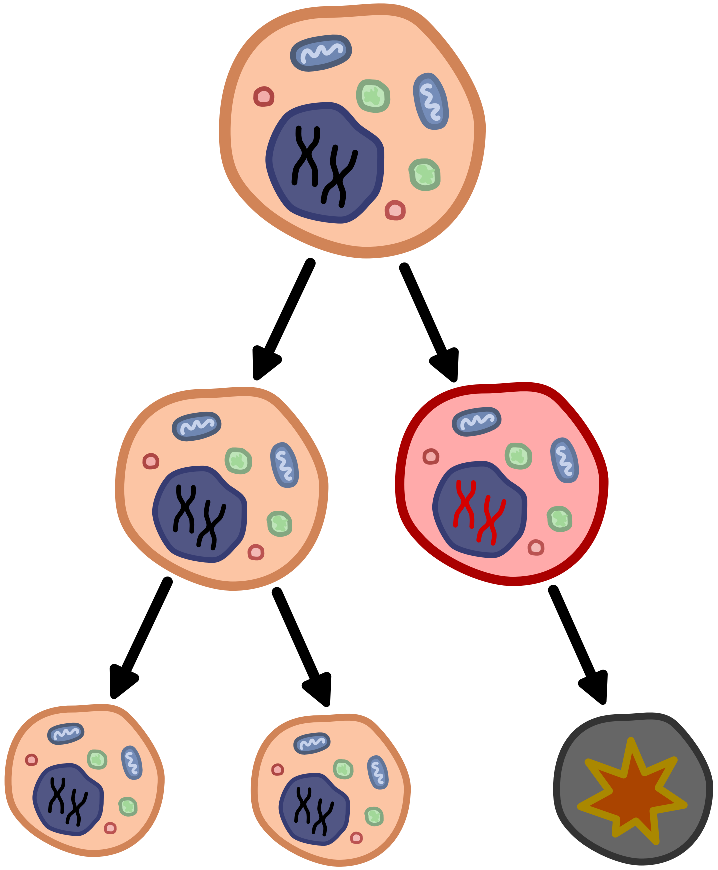
Candidate: Paul Dubois

Directors: Prof. Nikos Paragios
Prof. Paul-Henry Cournède

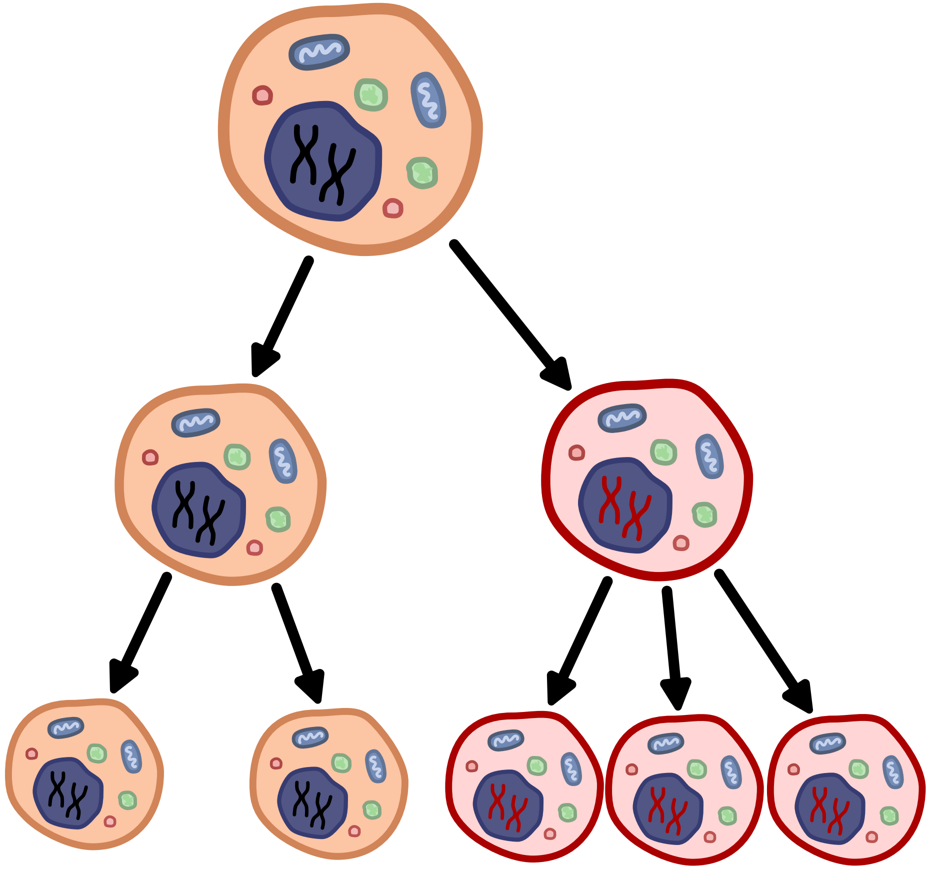
Jury: Prof. David Azria
Prof. Daniela Thorwarth
Prof. Vincent Lepetit
Dr. Pascal Fenoglietto

What is cancer?

Normal cell division



Abnormal cell division



Cancer treatments

Surgery

Radiotherapy

Chemotherapy

+: Safe

-: Tumor needs to be loc

ine on all the body

not need to be localized

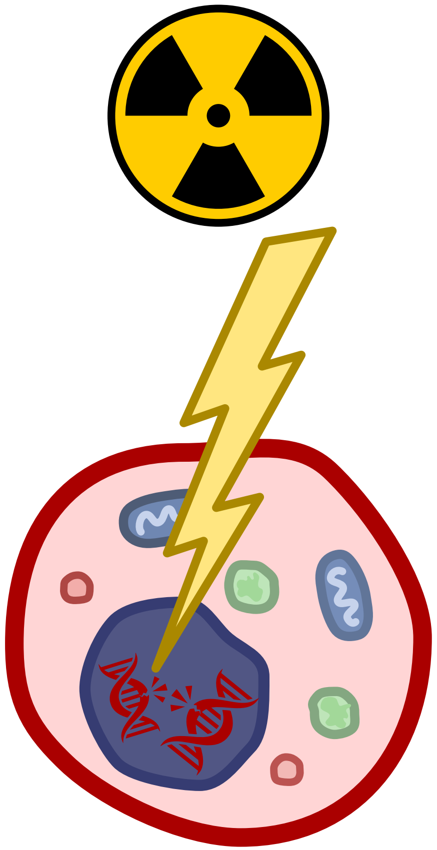
+: Relatively safe (most organs are spared)

-: Tumor needs to be (relatively) localized

Public

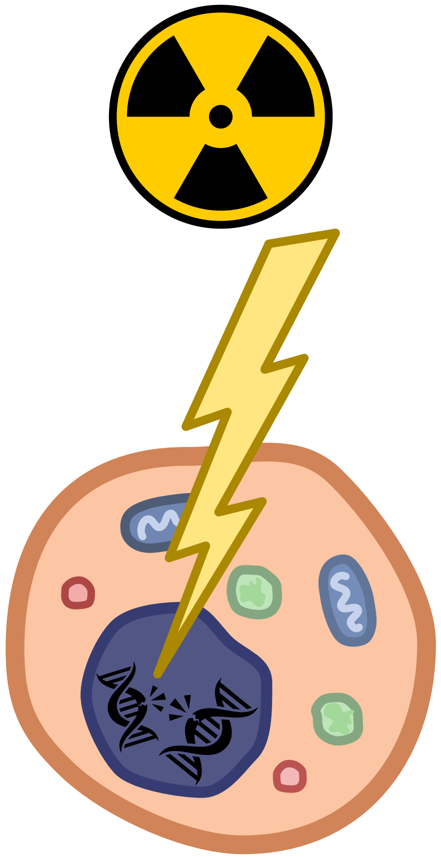
Radiation effects on cells

Cancerous cell irradiation



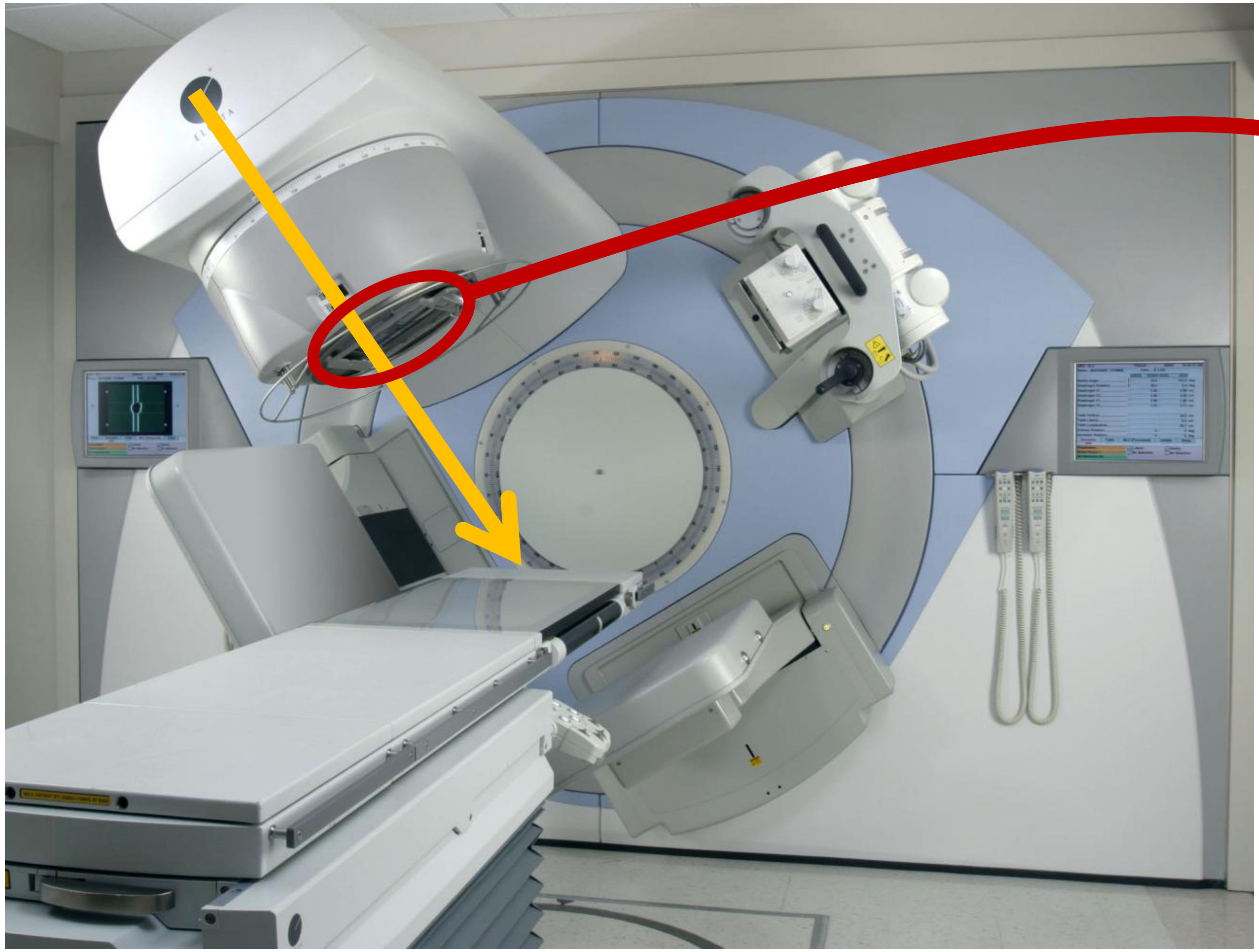
← *Radiation damages DNA* →

Normal cell irradiation



Guo et al. Mitochondrial Damage Response and Fate of Normal Cells Exposed to FLASH Irradiation with Protons. *Radiat Res*. 2022 Jun 1;197(6):569-582. doi: 10.1667/RADE-21-00181.1

MLC LINAC

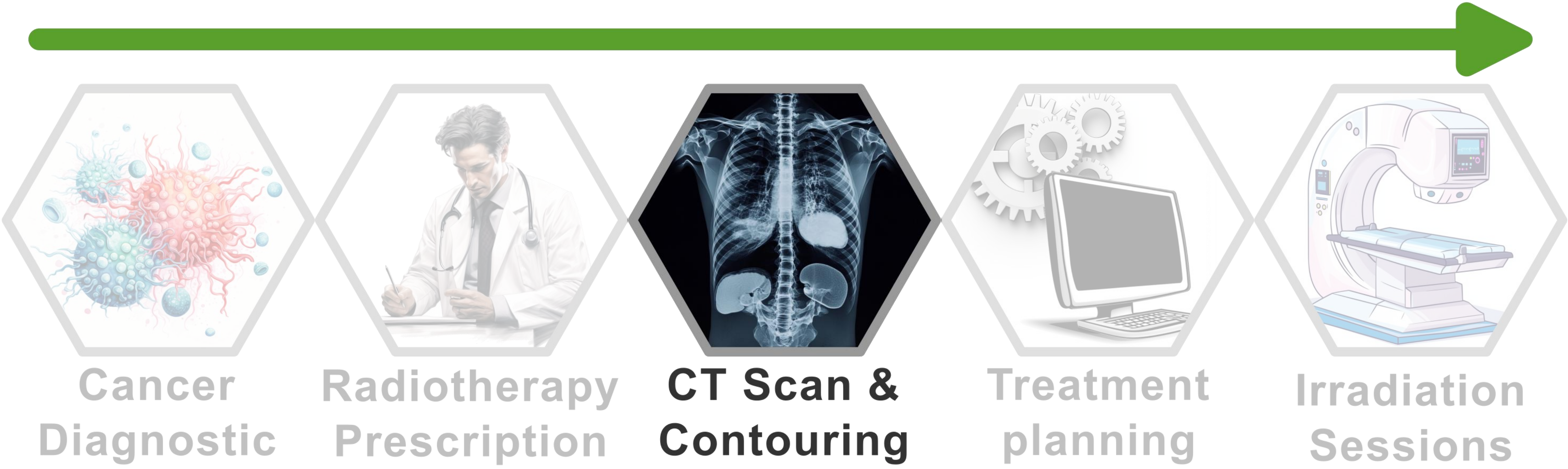


*MLC: **M**ulti **L**eaf **C**ollimator*

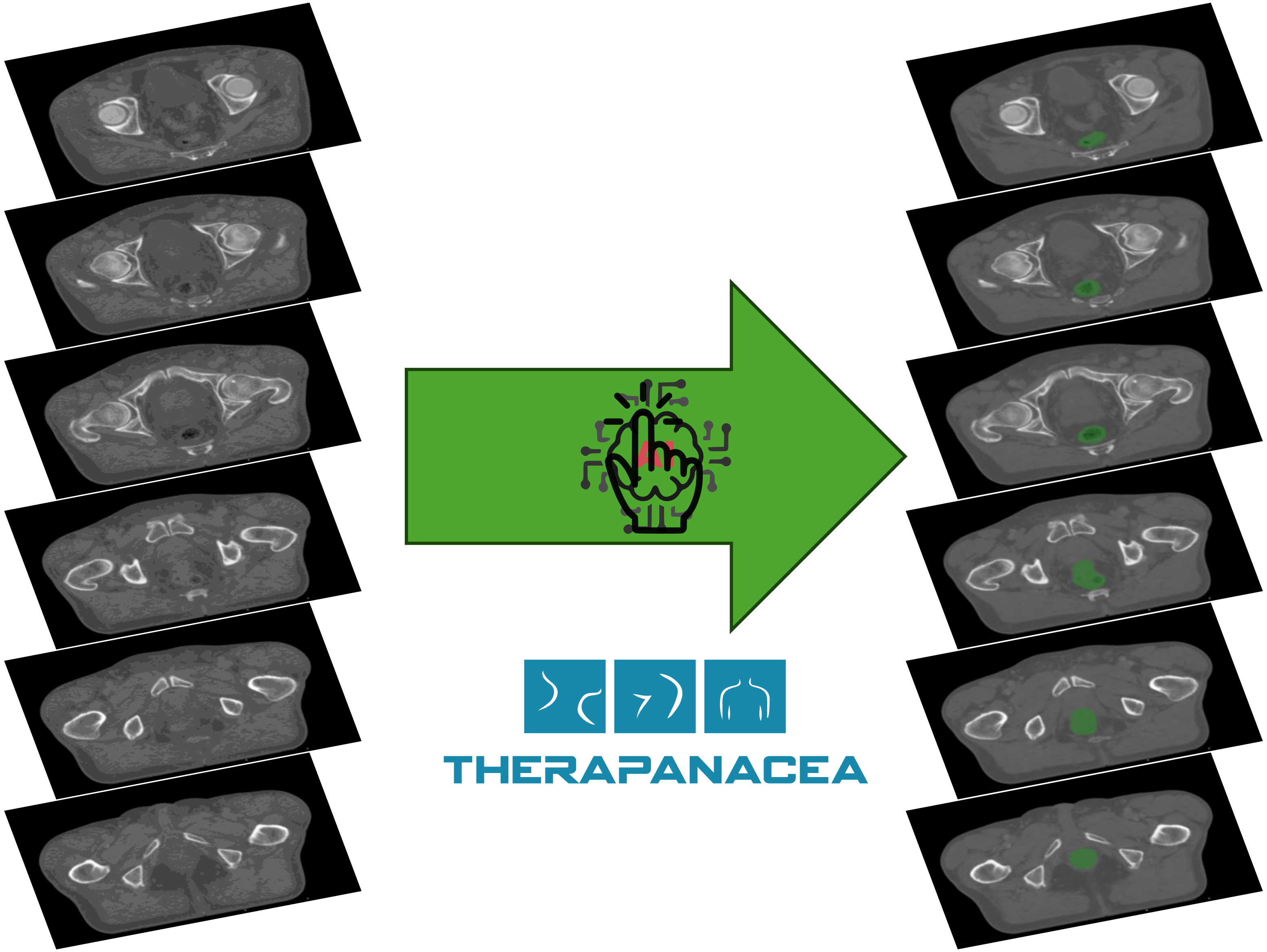
*LINAC: **Lin**ear **Ac**celerator*

L R Holsti. Development of clinical radiotherapy since 1896. *Acta Oncol*, 34(8): 995–1003, 1995

Typical radiotherapy patient path

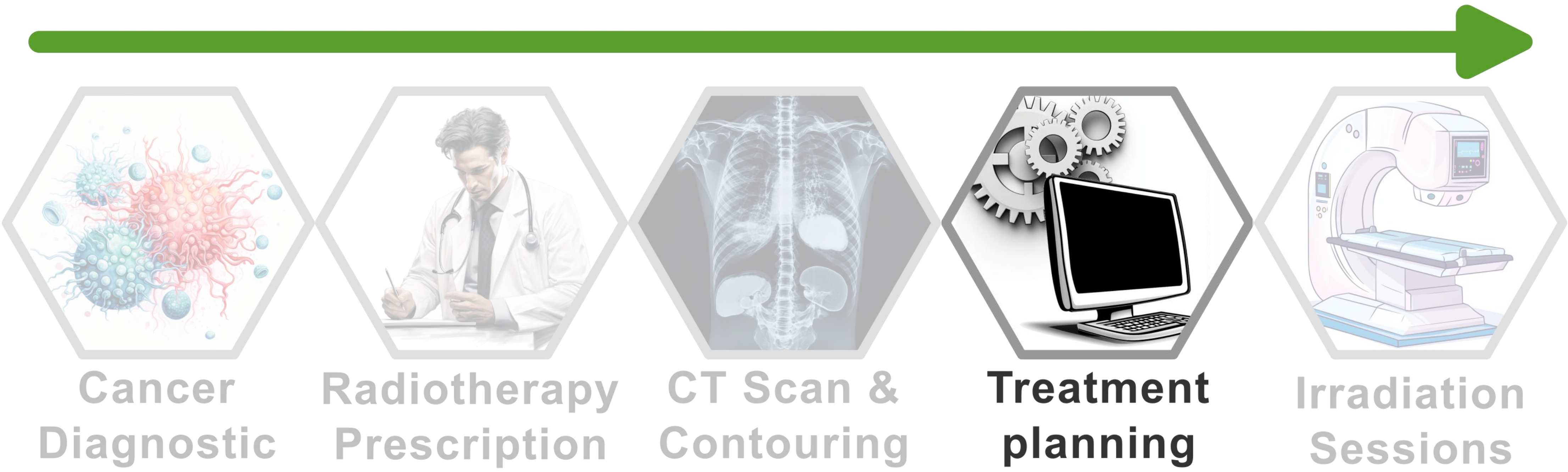


Automatic contouring of organs



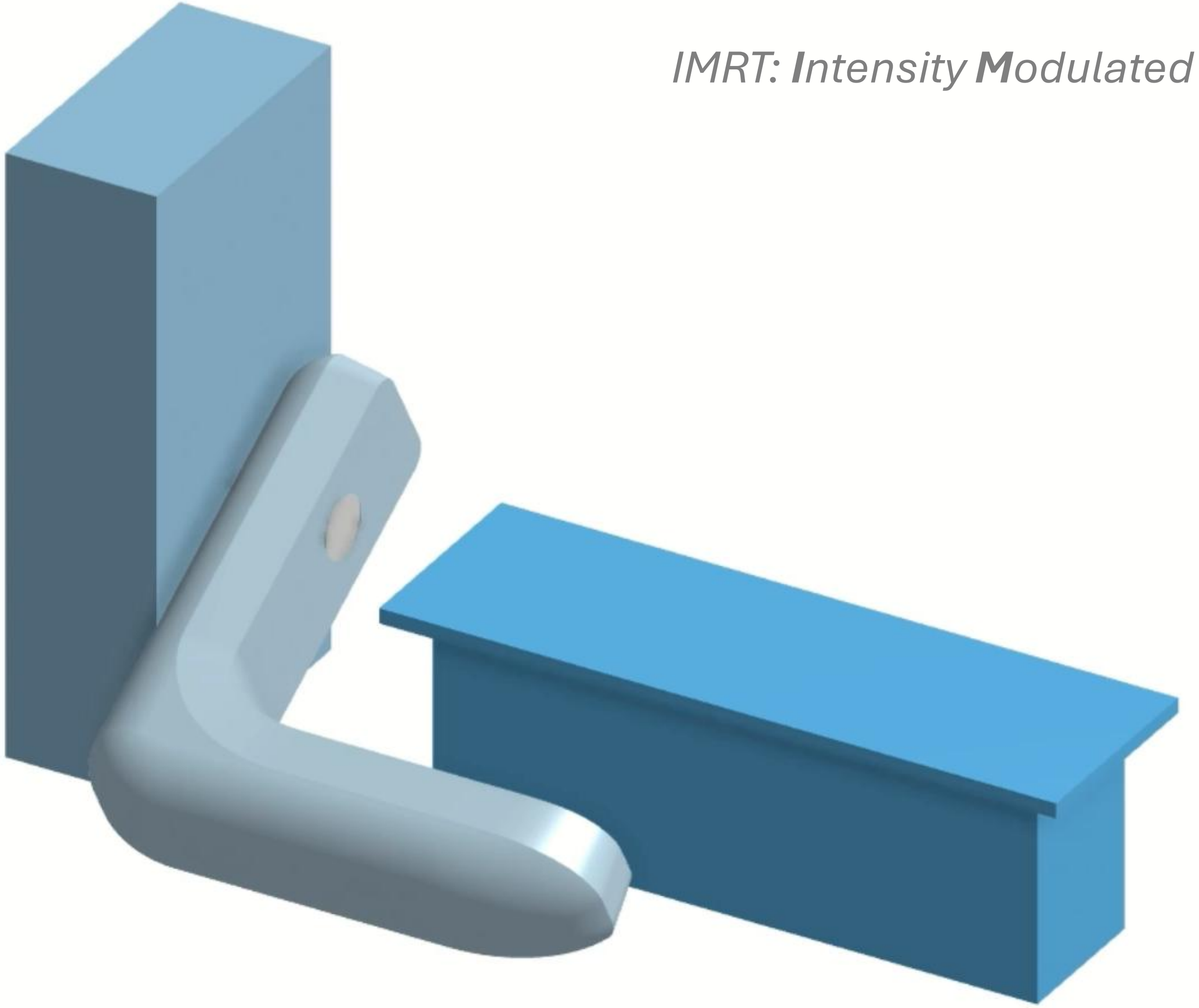
Luis A, et al. Feasibility evaluation of novel ai-based deep-learning contouring algorithm for radiotherapy. *Journal of Applied Clinical Medical Physics*, 24(11):e14090, 2023.

Typical radiotherapy patient path



IMRT

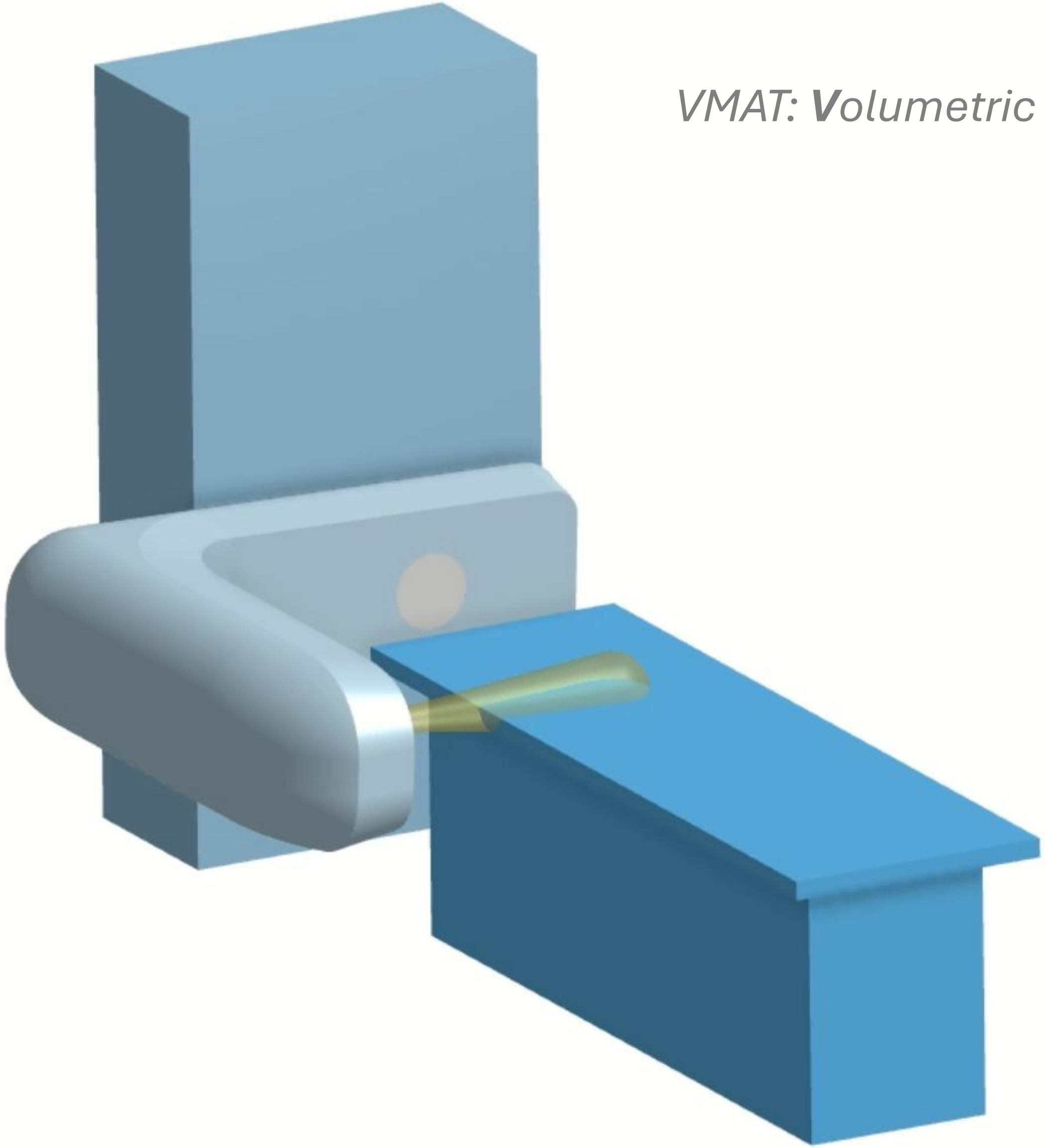
*IMRT: **I**ntensity **M**odulated **R**adio**t**herapy*



Francois Eschwège, Maurice Tubiana. Conformal radiotherapy and intensity modulated radiotherapy: Clinical data. *Acta Oncologica*, 39(5):555–567, 2000.

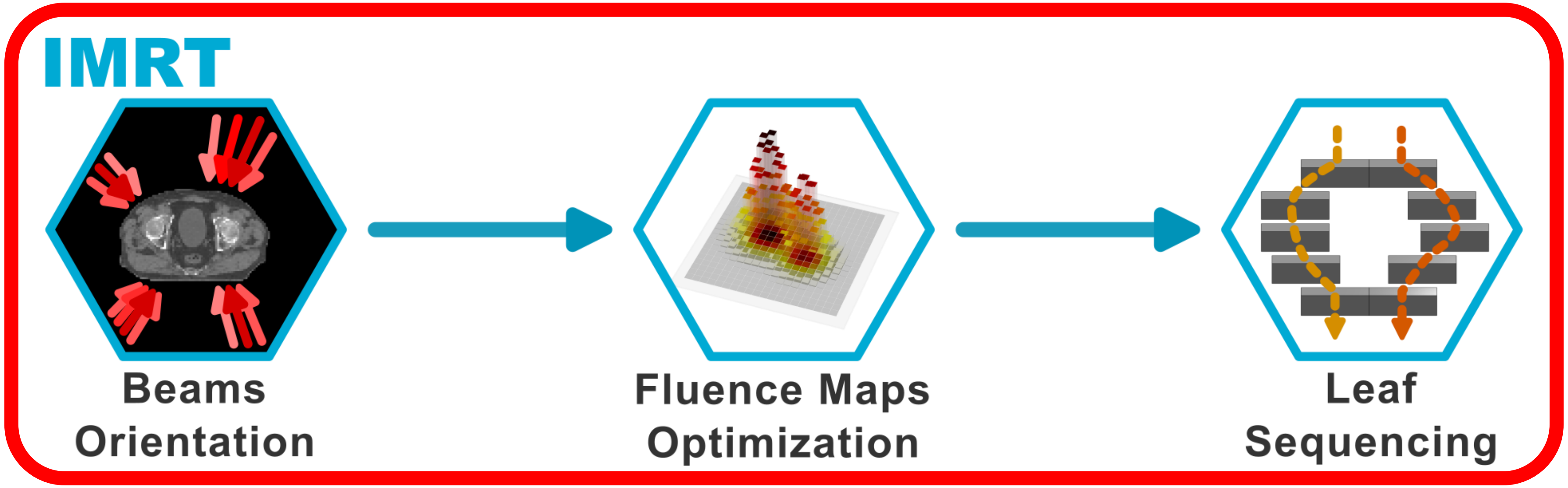
VMAT

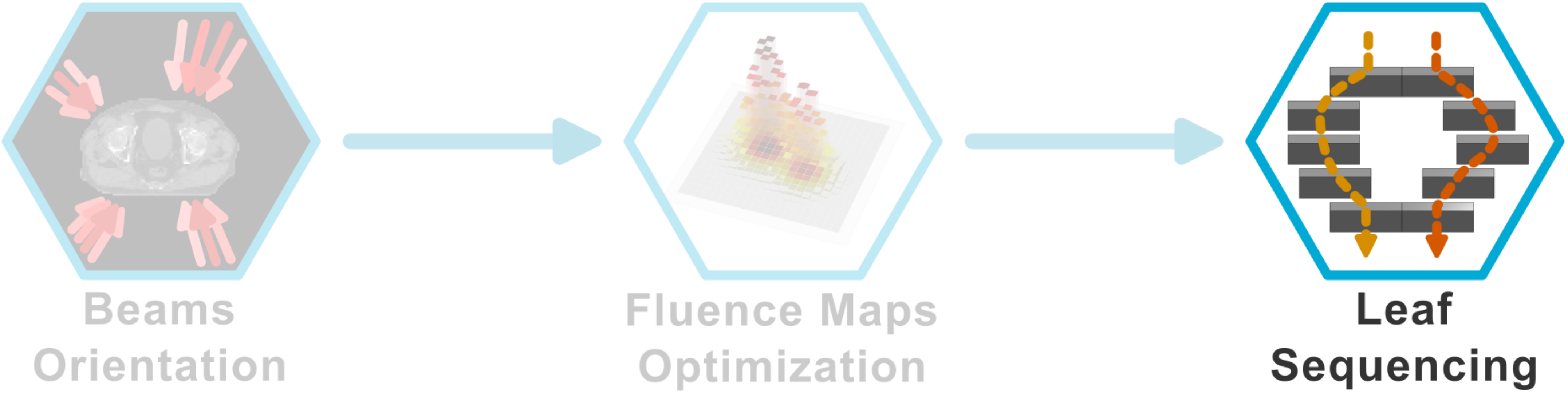
*VMAT: **V**olumetric **m**odulated **a**rc **t**herapy*



Enzhuo M. Quan et al. A comprehensive comparison of imrt and vmat plan quality for prostate cancer treatment. *International Journal of Radiation Oncology Biology Physics*, 2012.

Treatment planning steps



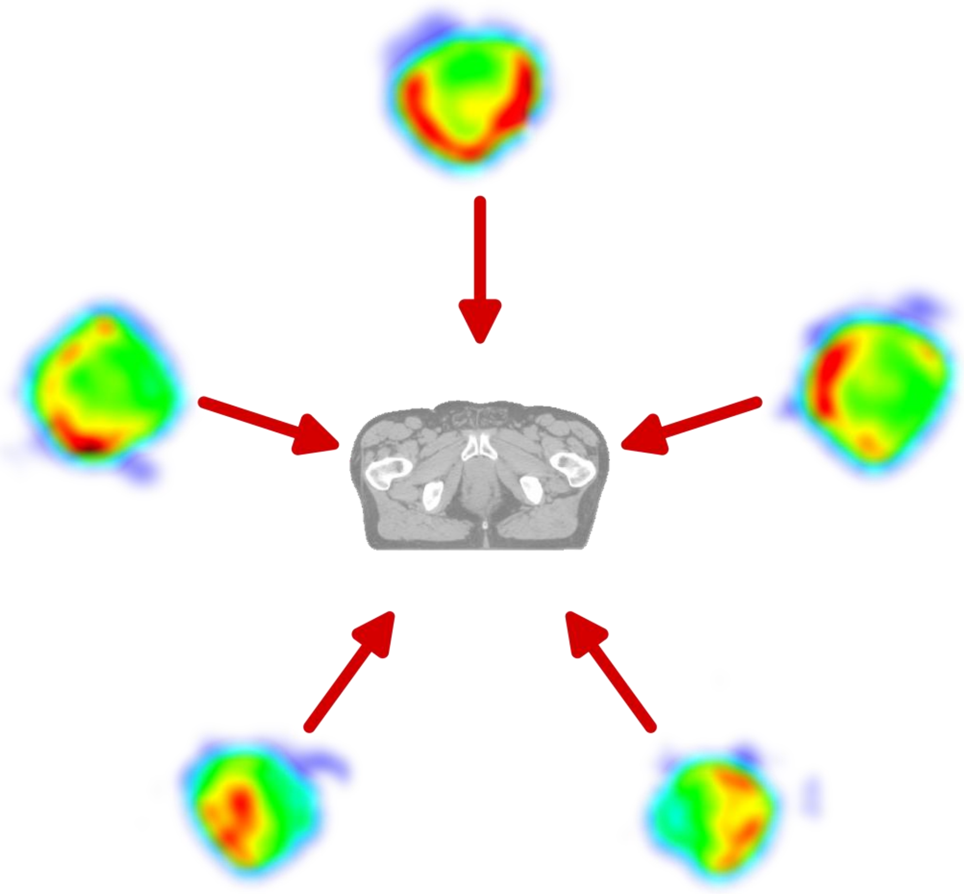


Sliding Window

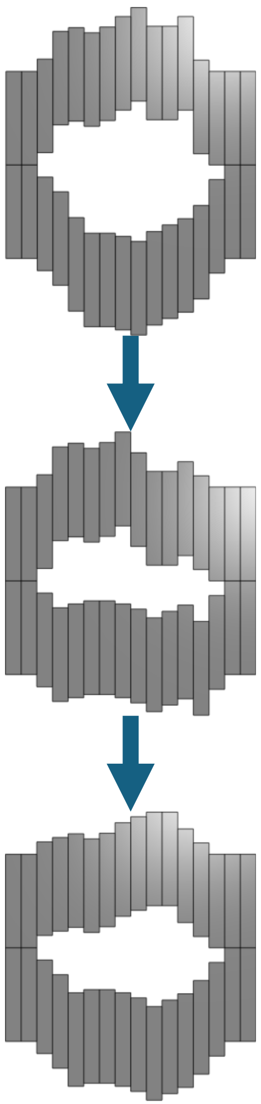
An advanced algorithm

Liming XU Ning GE, Fuci CHEN. Comparison between sliding window and step and shoot, *Chinese Medical Equipment Journal*; (6) 2003.

Leaf sequencing task

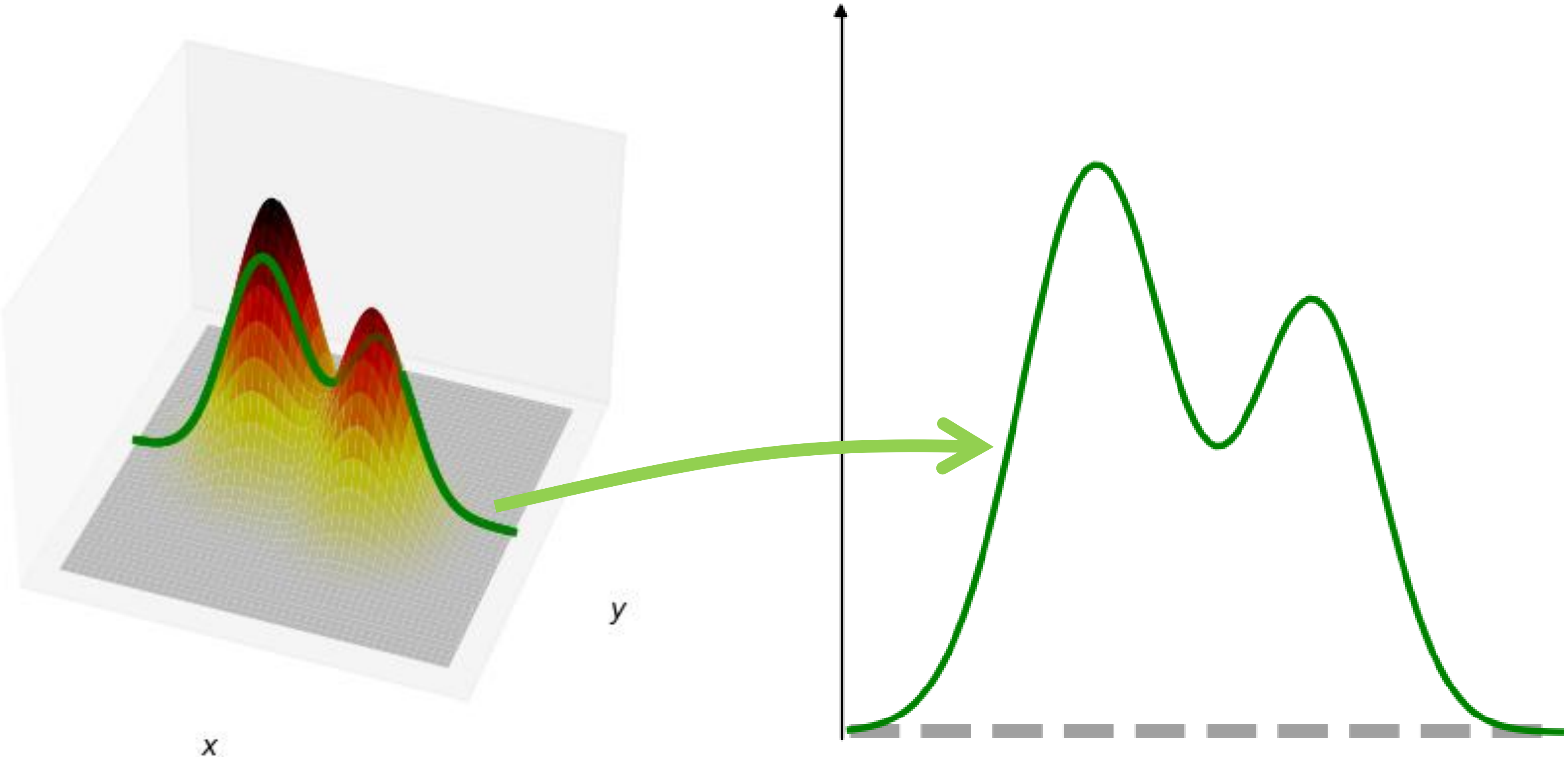


Optimal fluence from each angle



Leaves motion ("RT plan")

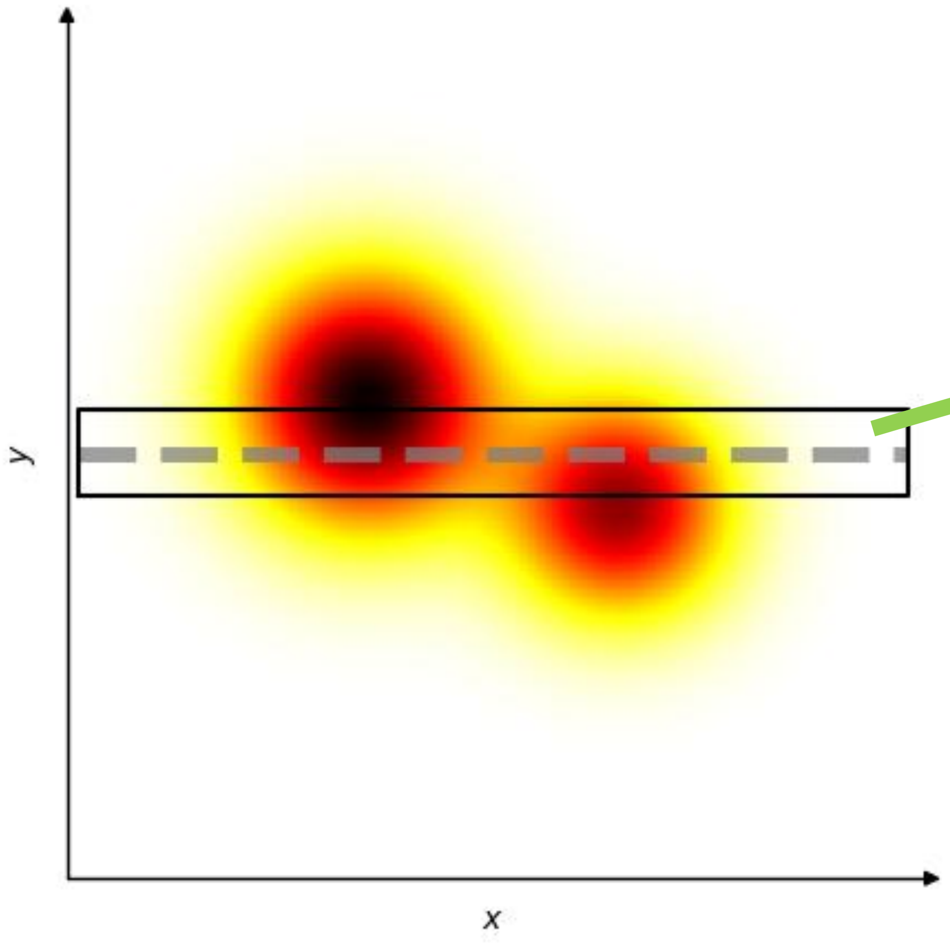
Fluence map on a leaf pair axis



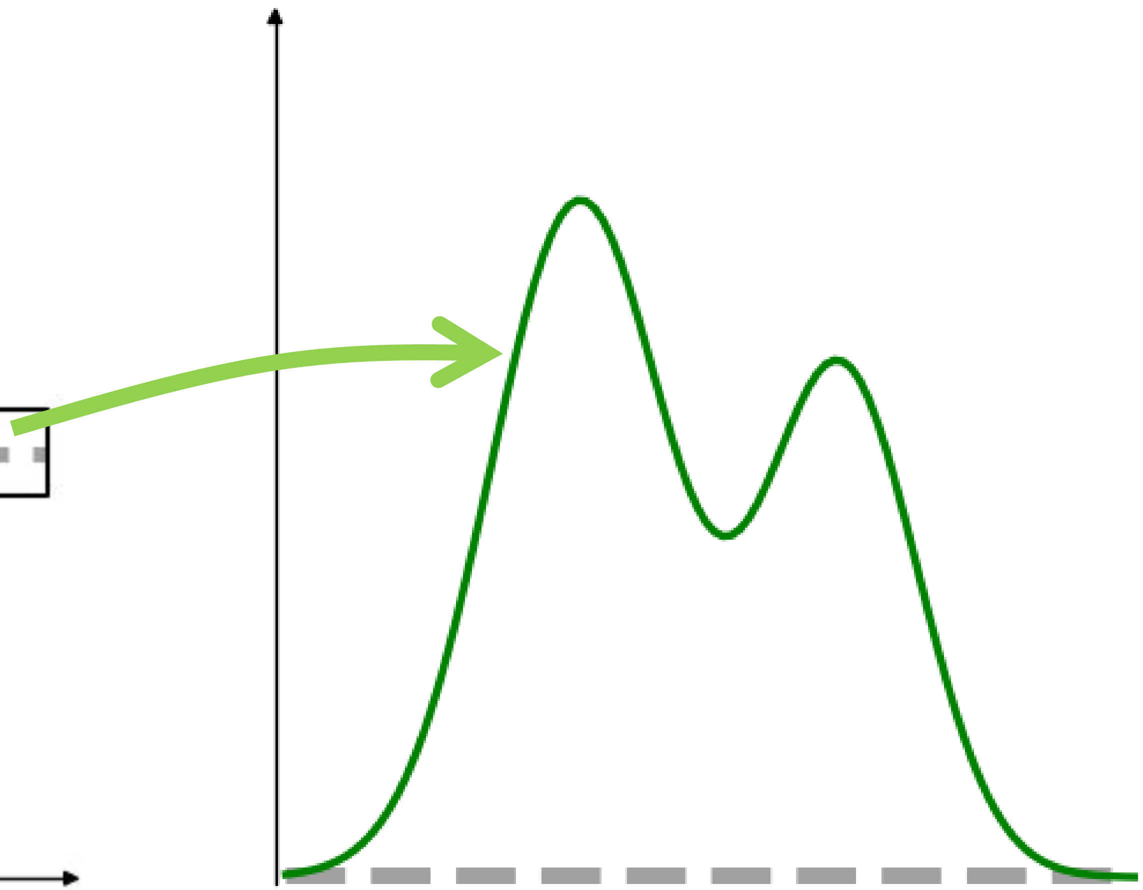
2D fluence map

Fluence map on a leaf pair axis

Fluence map segmentation on a leaf pair axis

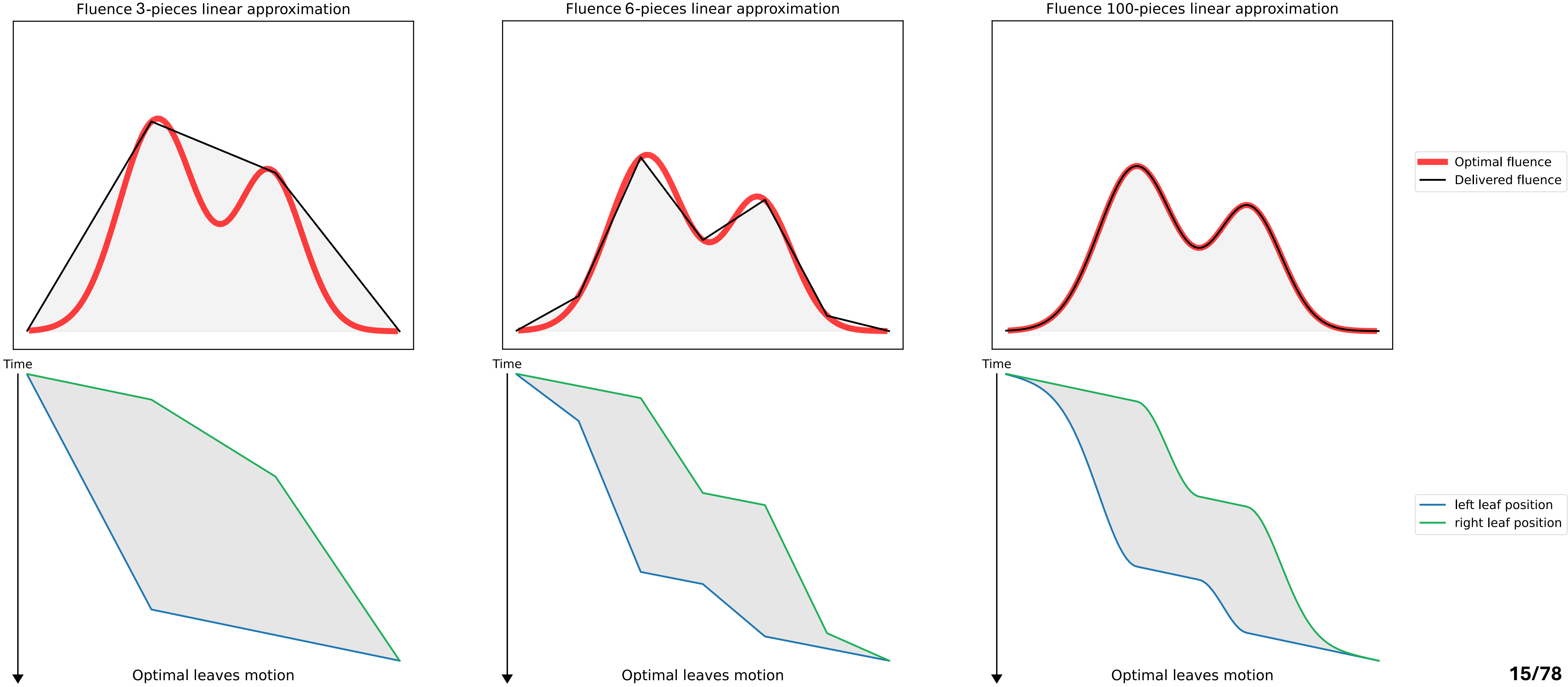


2D fluence map

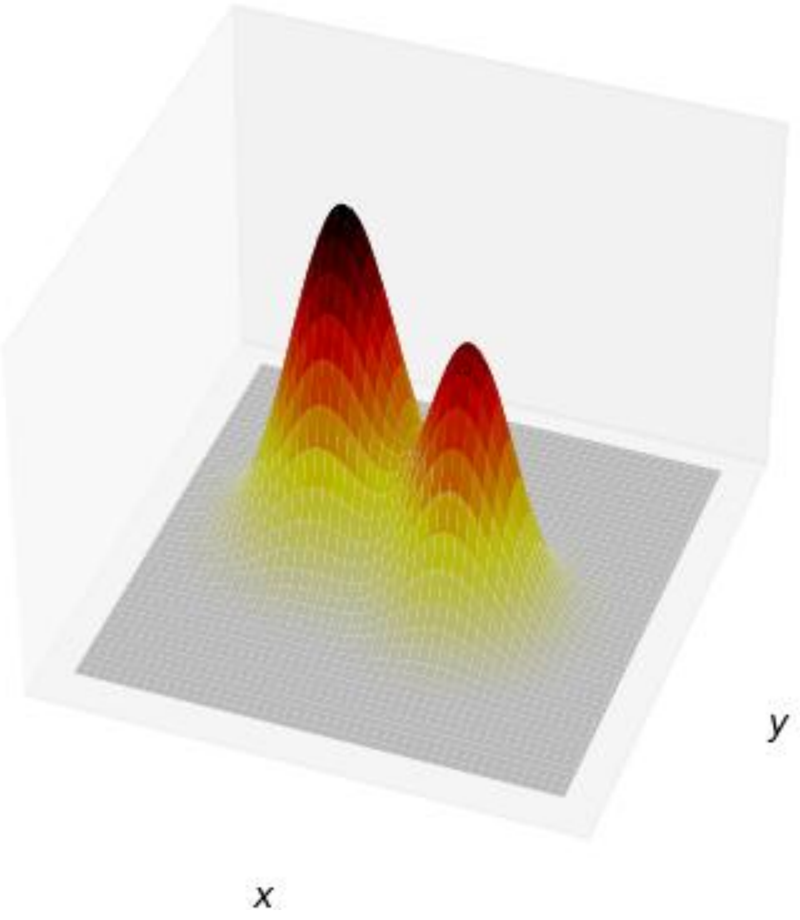


Fluence map on a leaf pair axis

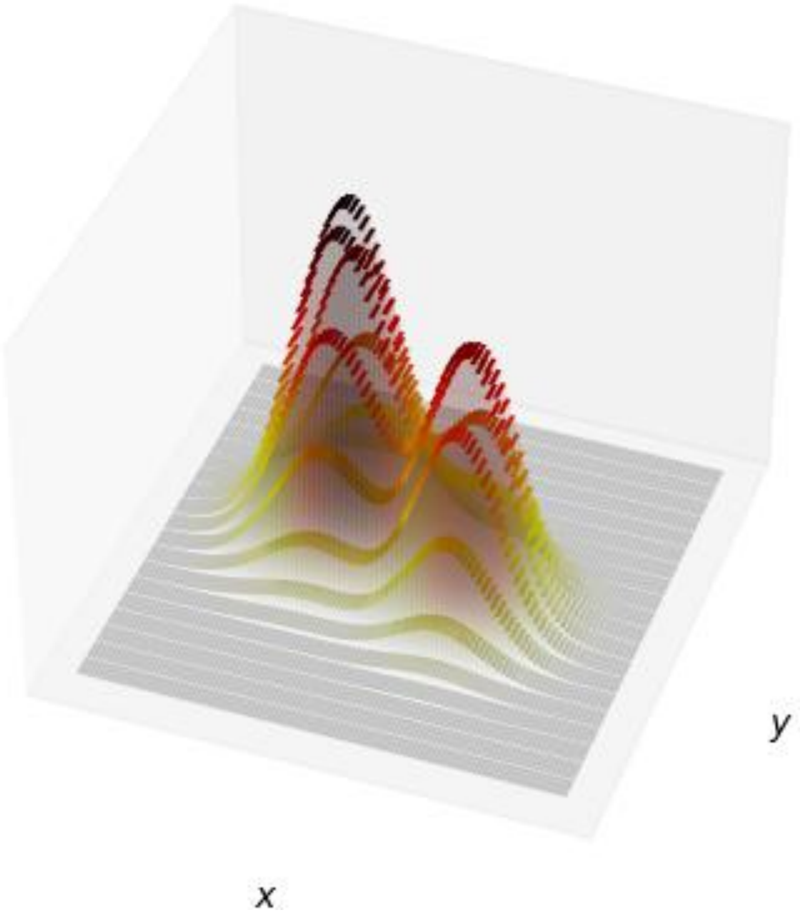
Arbitrary approximation of a fluence curve



Sliding window effective fluence

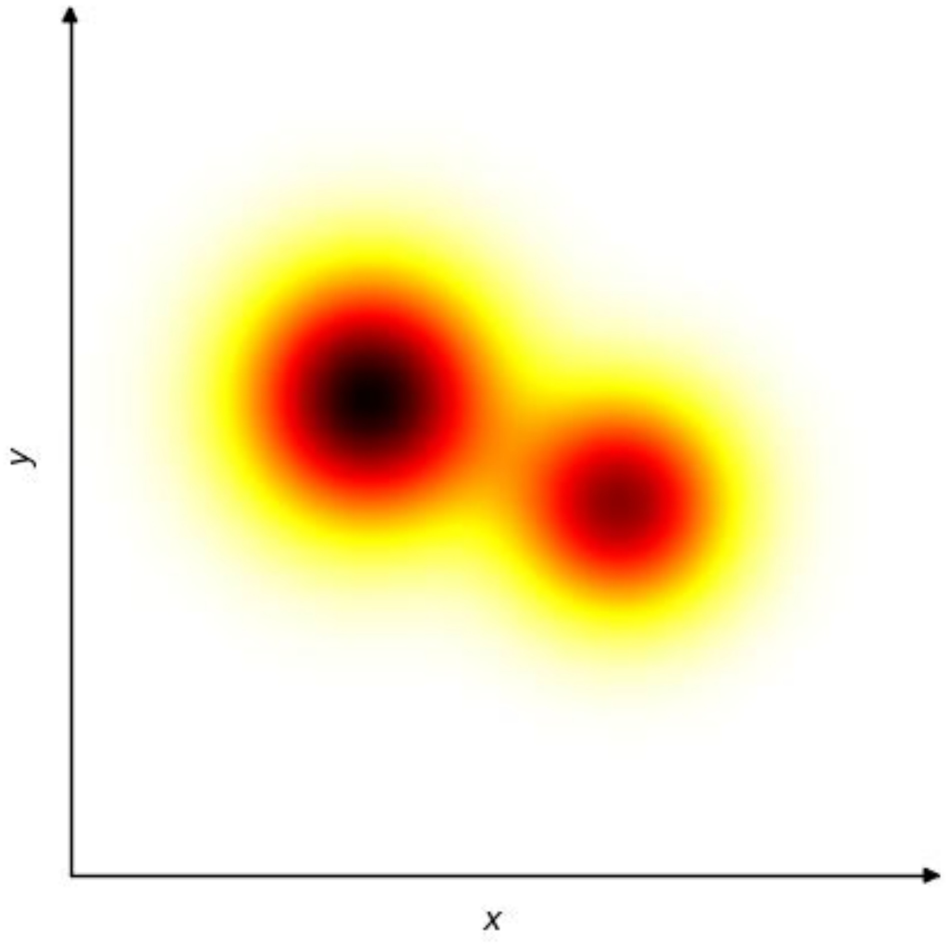


Ideal continuous fluence map

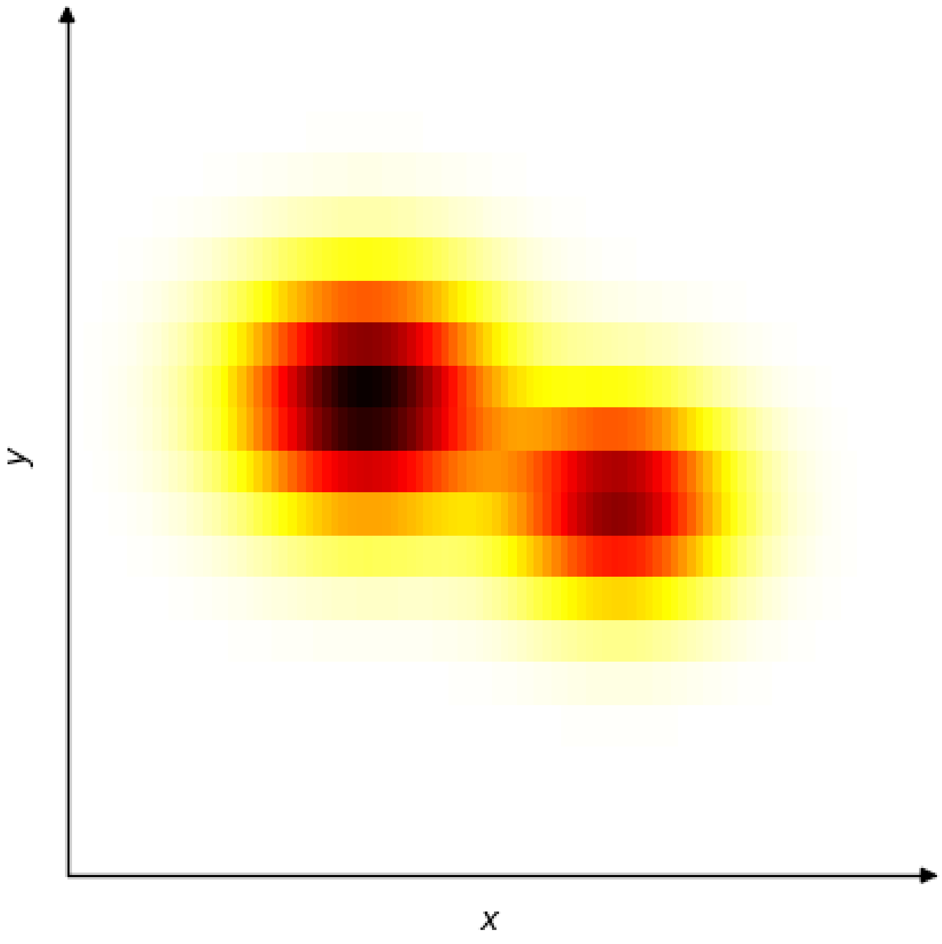


MLC delivered fluence map

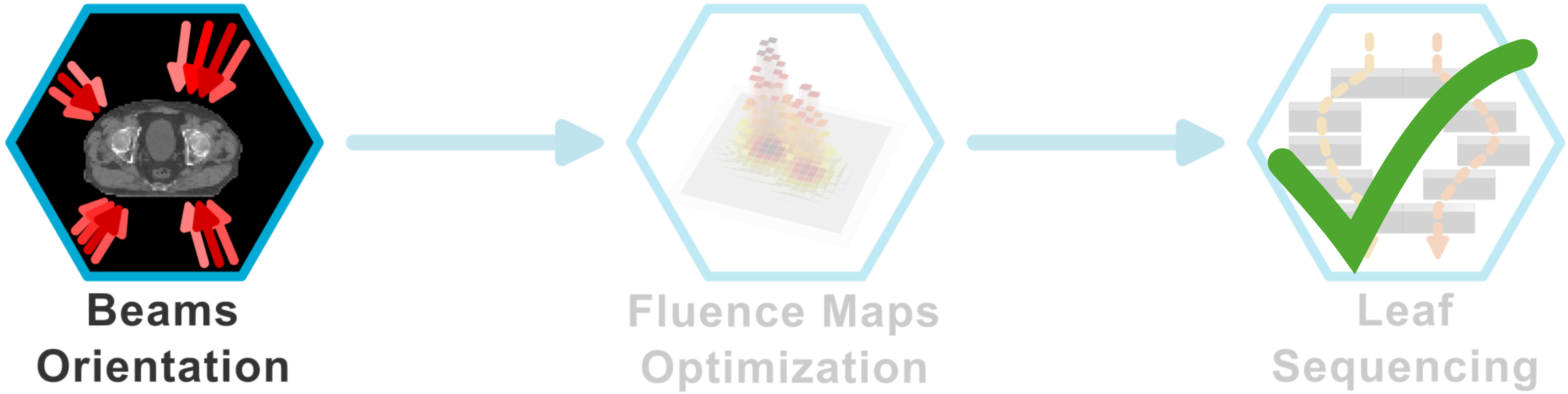
Sliding window effective fluence



Ideal continuous fluence map



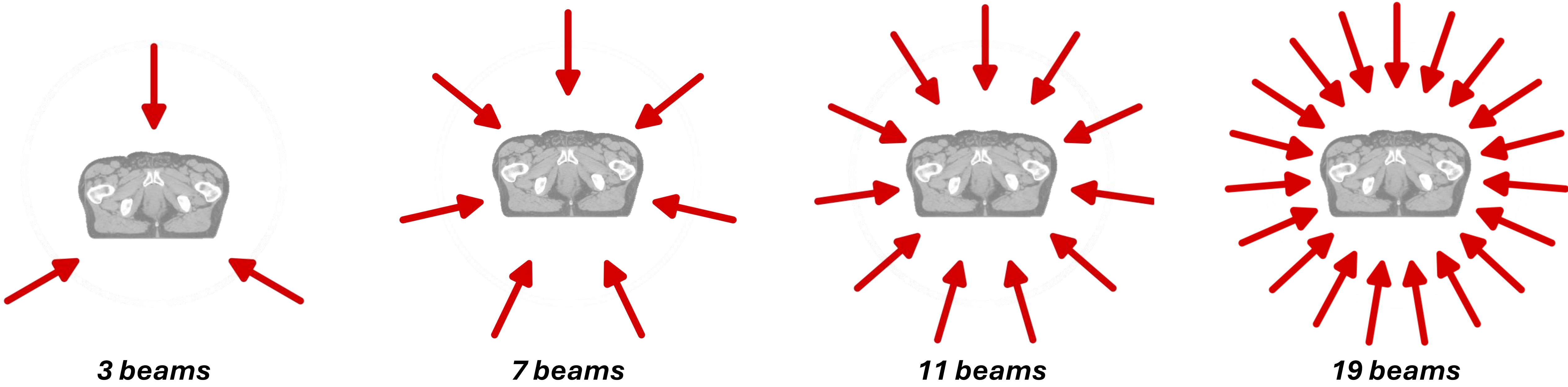
MLC delivered fluence map



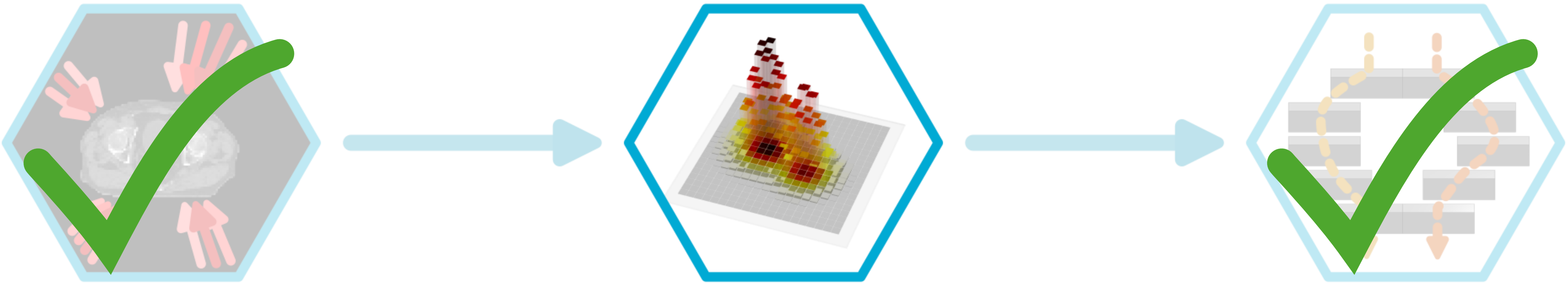
Beams Orientation Optimization

First step of treatment planning

Beams angles templates



Thomas Bortfeld. The number of beams in IMRT. *Physics in Medicine & Biology*, 55(1):83, nov. 2009.
Humberto Rocha, et al. Beam angle optimization in IMRT: are we really optimizing what matters? *International Transactions in Operational Research*, 26(3):908–928, 2019.

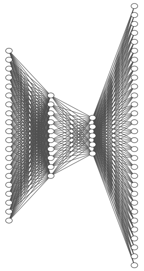


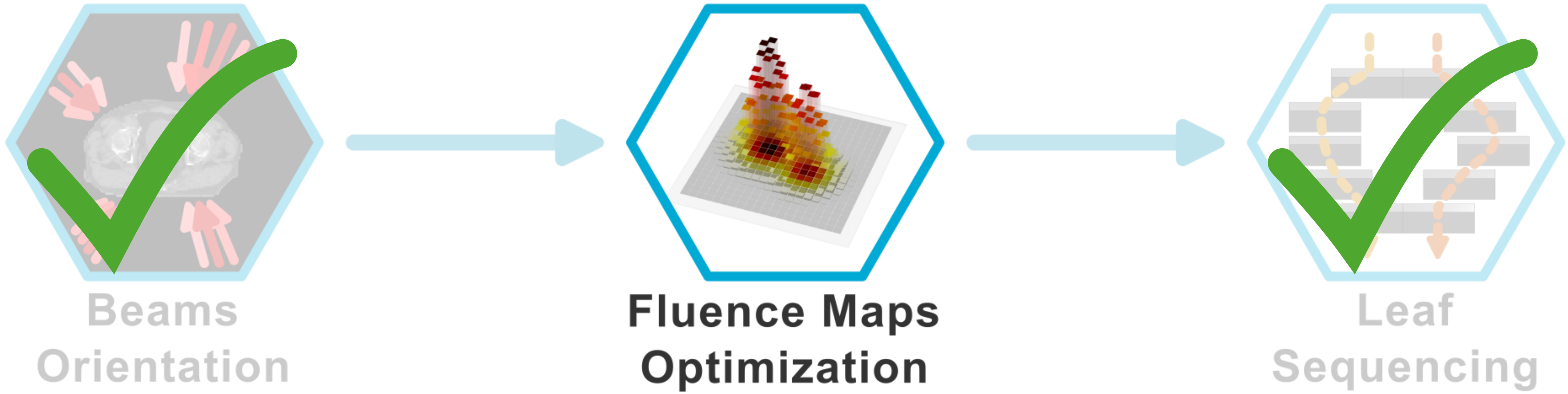
Beams Orientation

Fluence Maps Optimization

Leaf Sequencing

Content

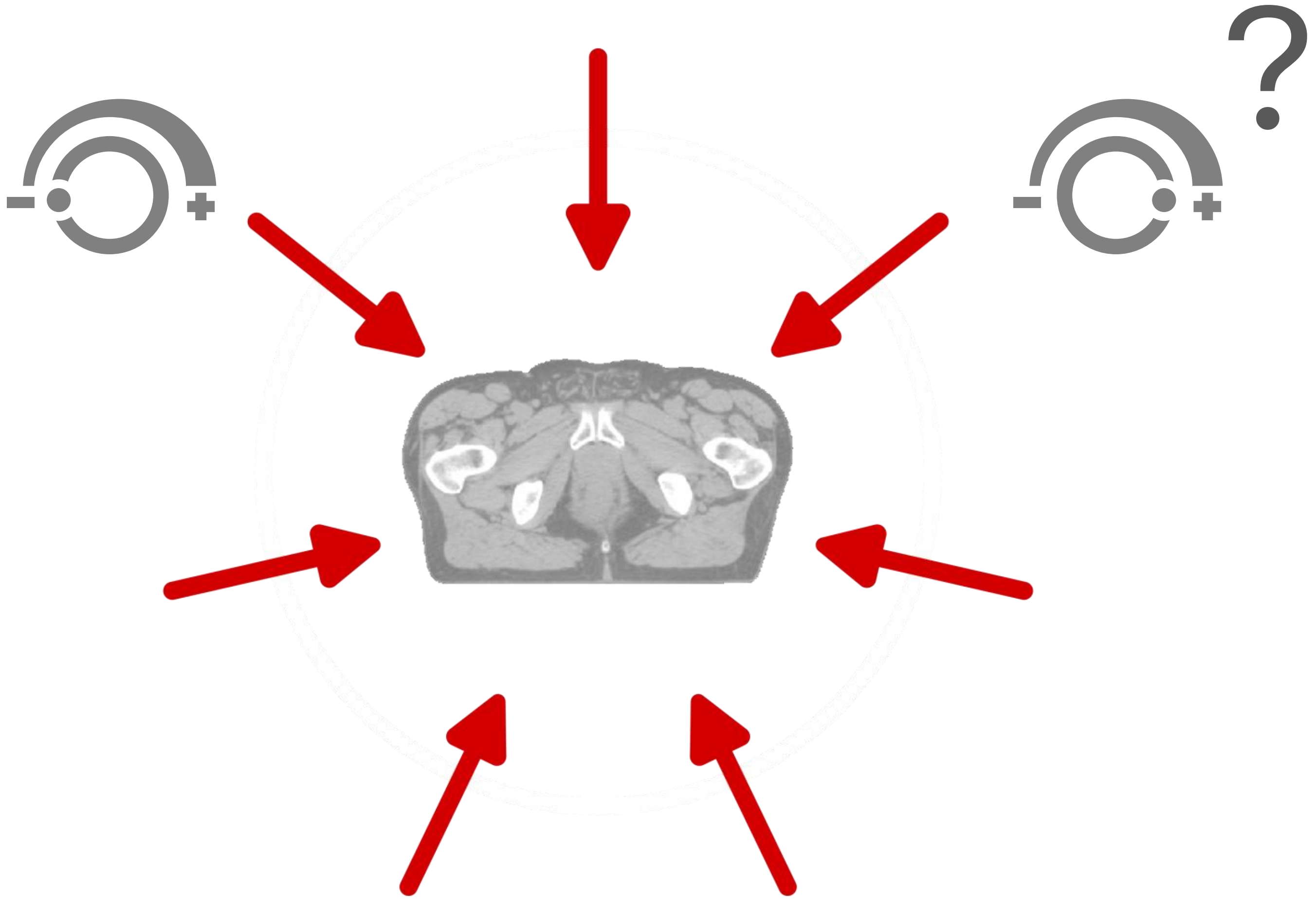
1. Manual treatment planning
2. Network of treatment plans 
3. Constraints based dosimetry full automation 
4. Automated dosimetry via dose mimicking



Problem Formulation

Translating clinical needs to mathematical objectives

What power from each angle?



Irradiation constraints

Structure	Constraint
Rectum (OAR*)	$D_{1\%} < 76\ Gy$
Rectum (OAR)	$D_{25\%} < 72\ Gy$
Rectum (OAR)	$D_{50\%} < 60\ Gy$
Bladder (OAR)	$D_{1\%} < 80\ Gy$
Bladder (OAR)	$D_{25\%} < 74\ Gy$
Bladder (OAR)	$D_{50\%} < 70\ Gy$
Femoral heads (OAR)	$D_{50\%} < 55\ Gy$
Femoral heads (OAR)	$V_{50Gy} < 5\%$

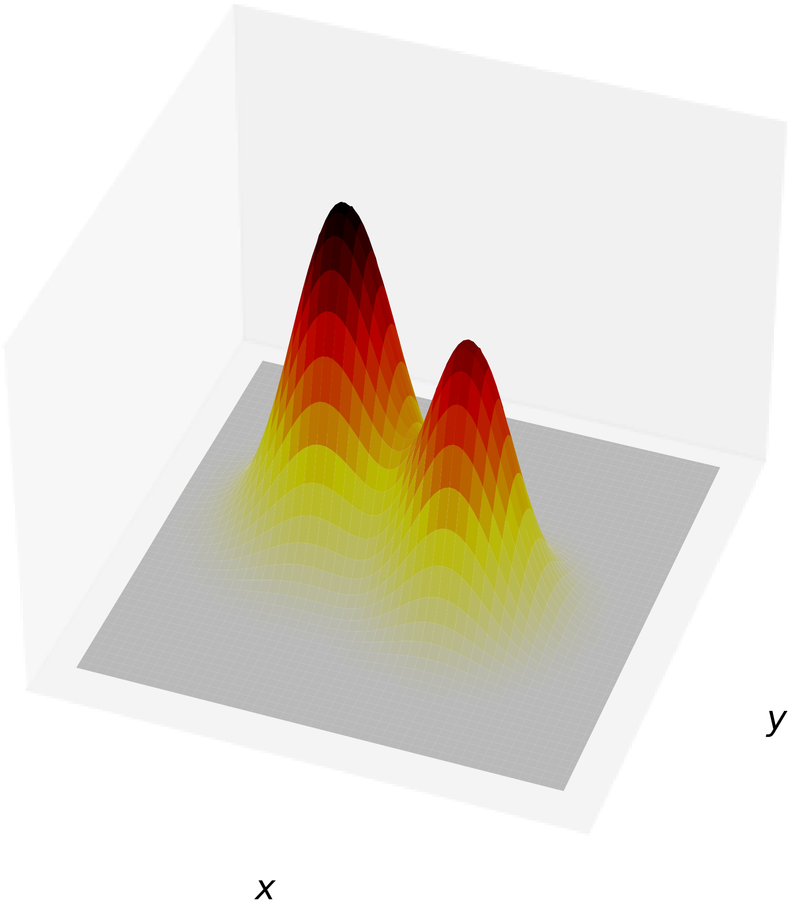
Structure	Constraint
PTV*	$D_{98\%} > 72\ Gy$
PTV	$D_{95\%} > 76\ Gy$
PTV	$D_{2\%} < 107\ Gy$

Example of constraints for a prostate treatment.

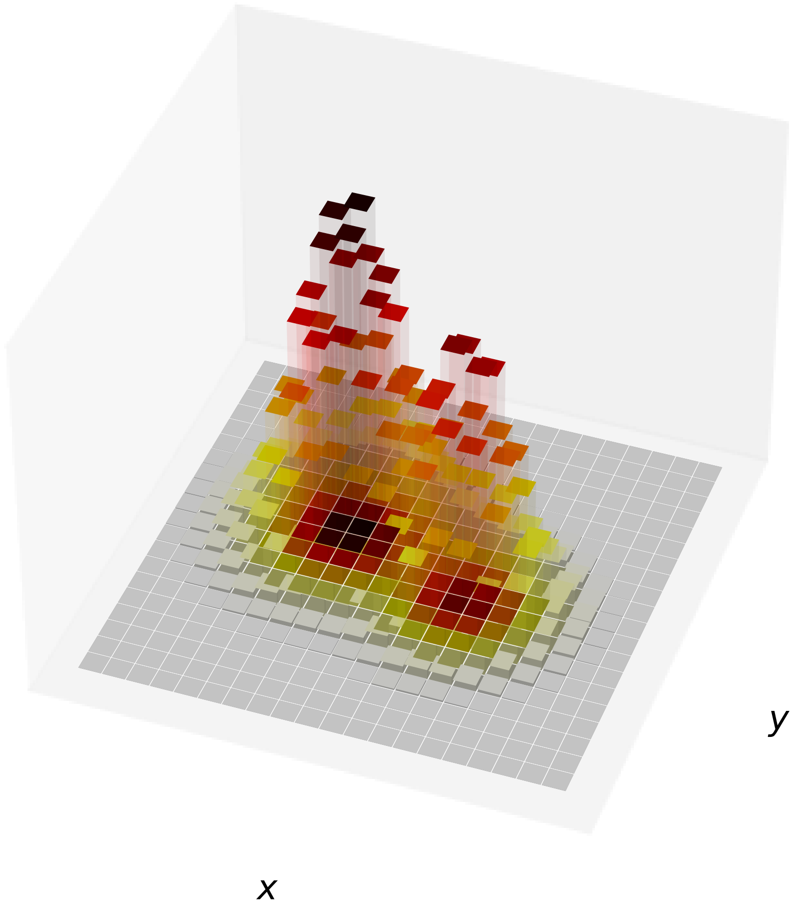
OAR: **O**rgan **A**t **R**isk*

PTV: **P**rincipal **T**arget **V**olume*

Fluence discretization

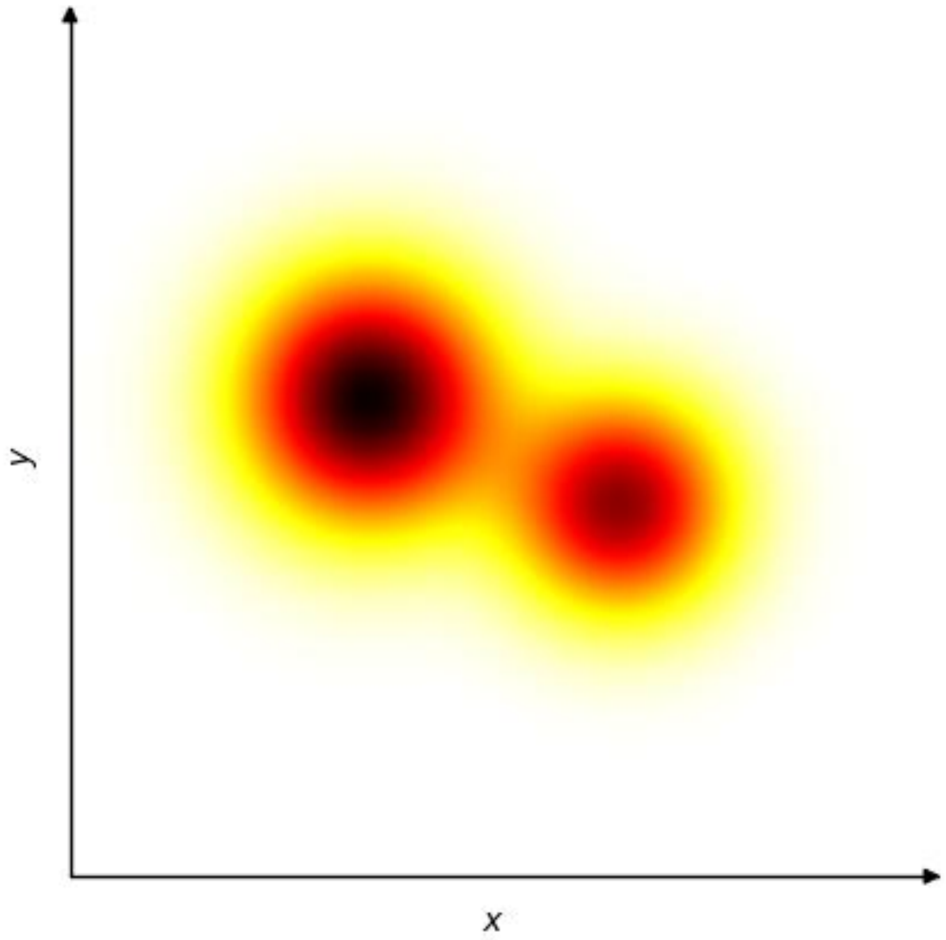


Continuous fluence

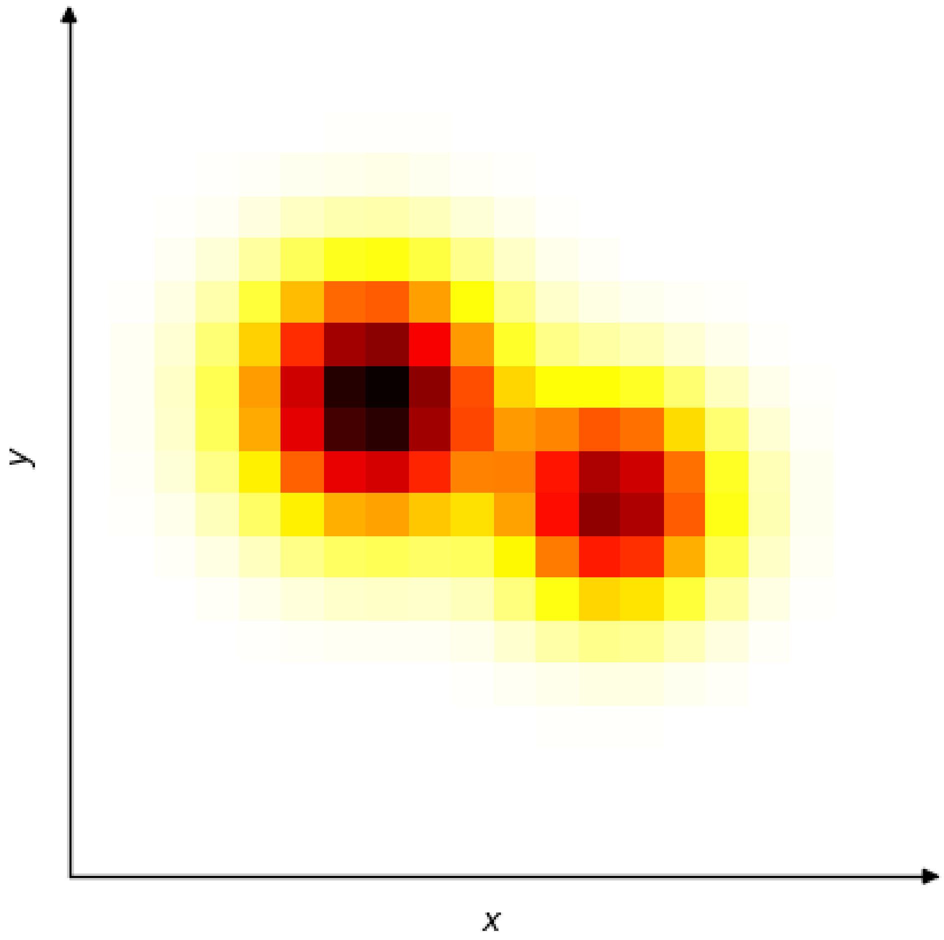


Discretized fluence

Fluence discretization

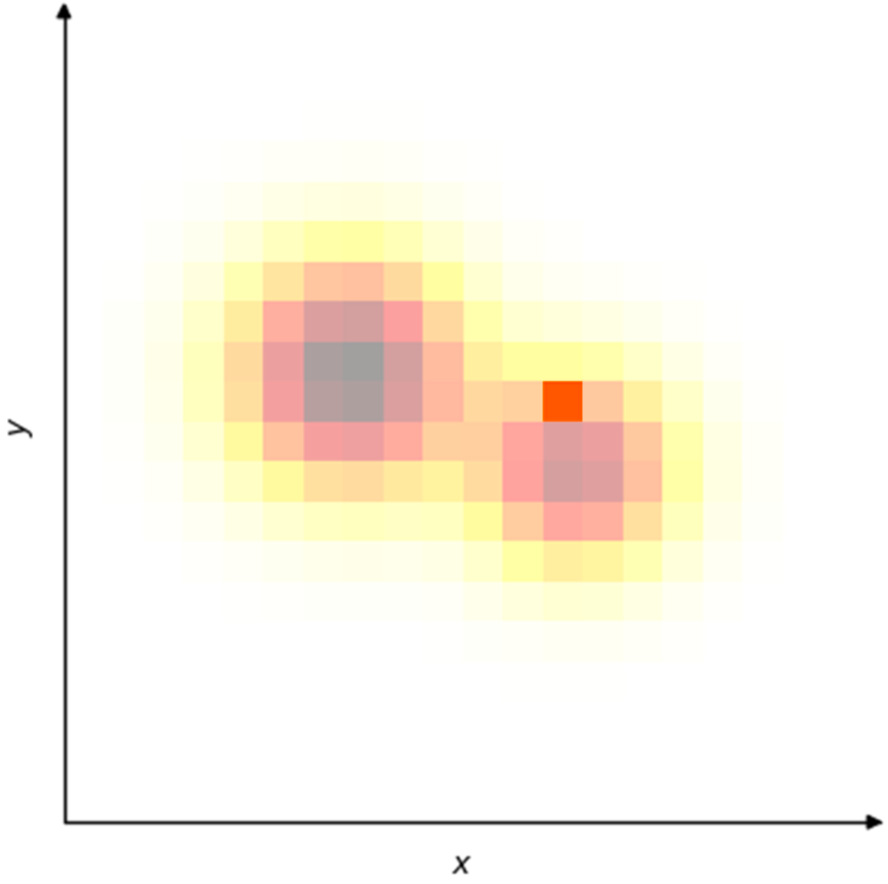


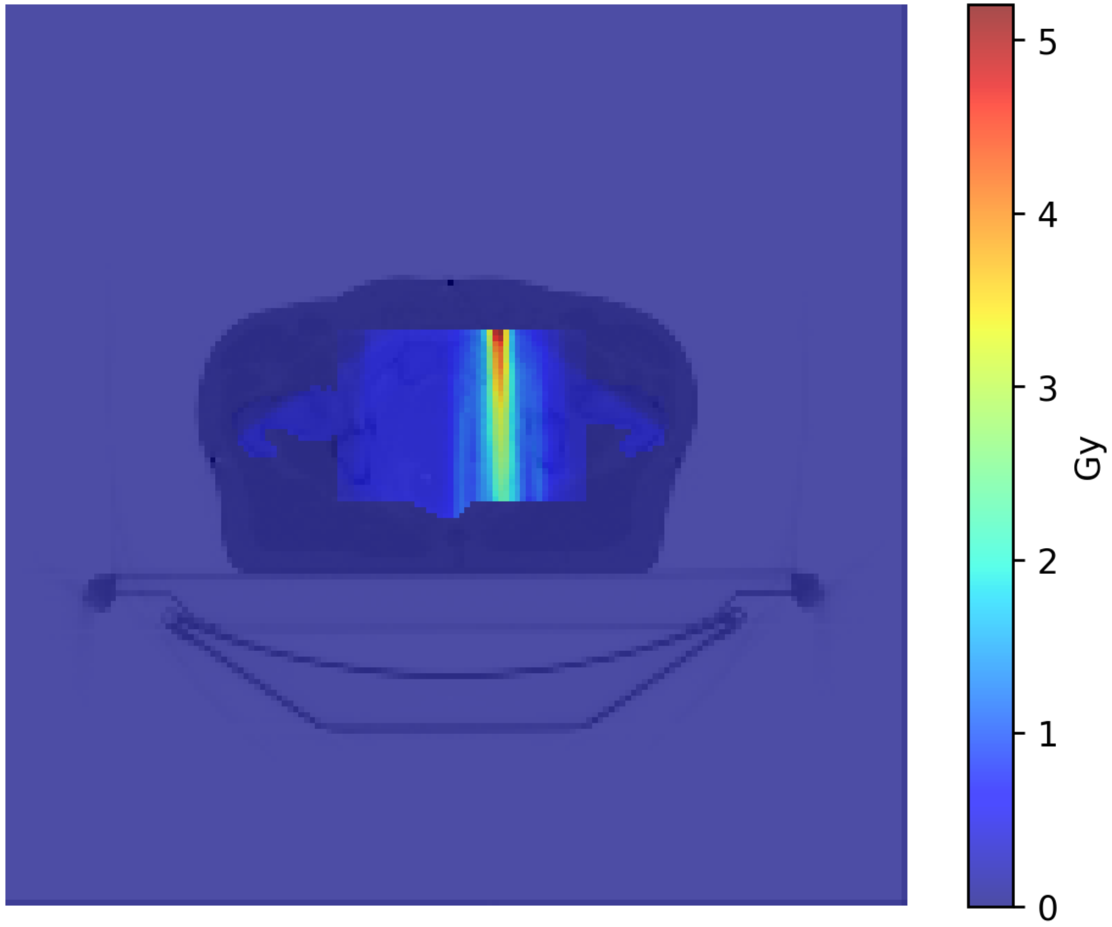
Continuous fluence



Discretized fluence

From bixels* to voxels*

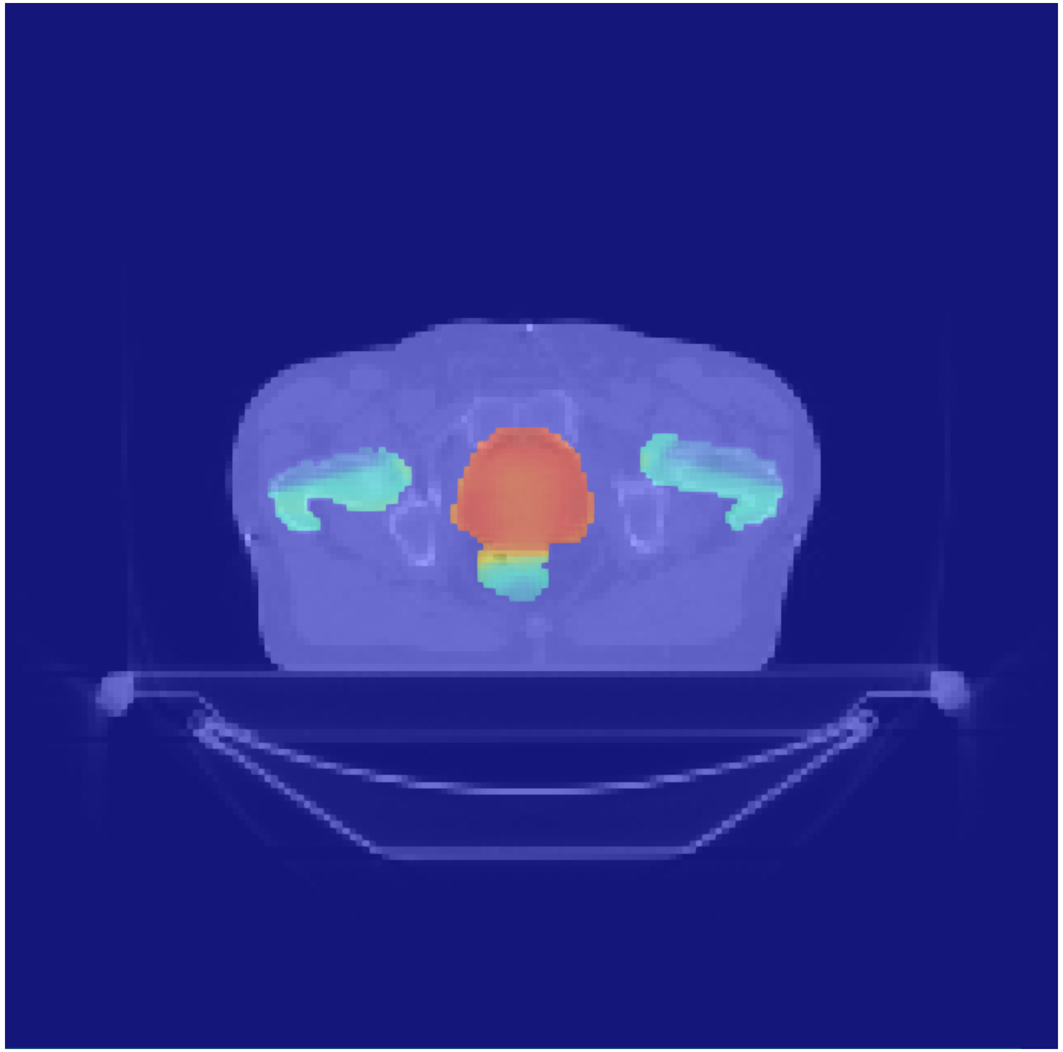




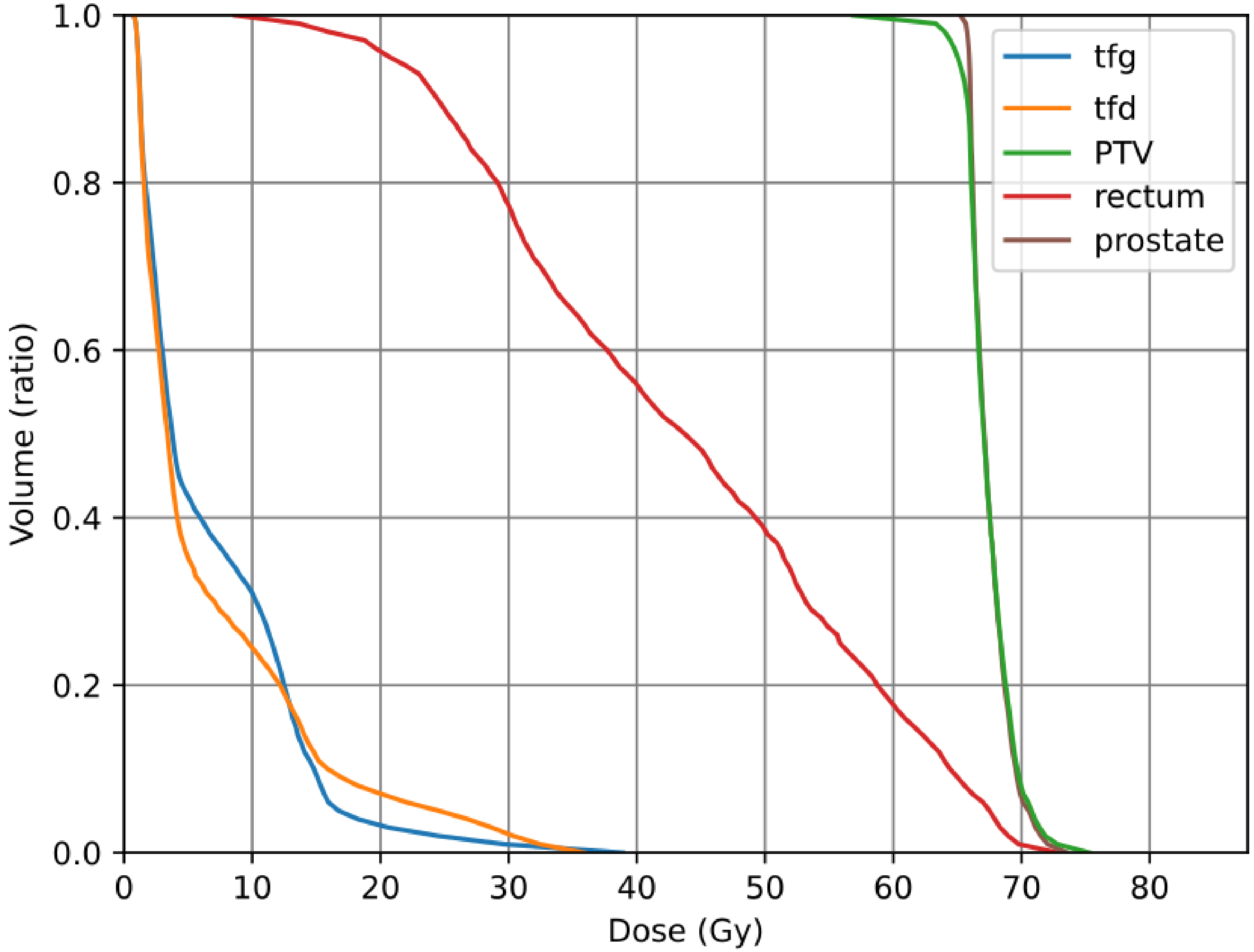
Bixel: **Beam** **El**ement*

Voxel: **Vo**lume **El**ement*

From 3D dose to DVHs



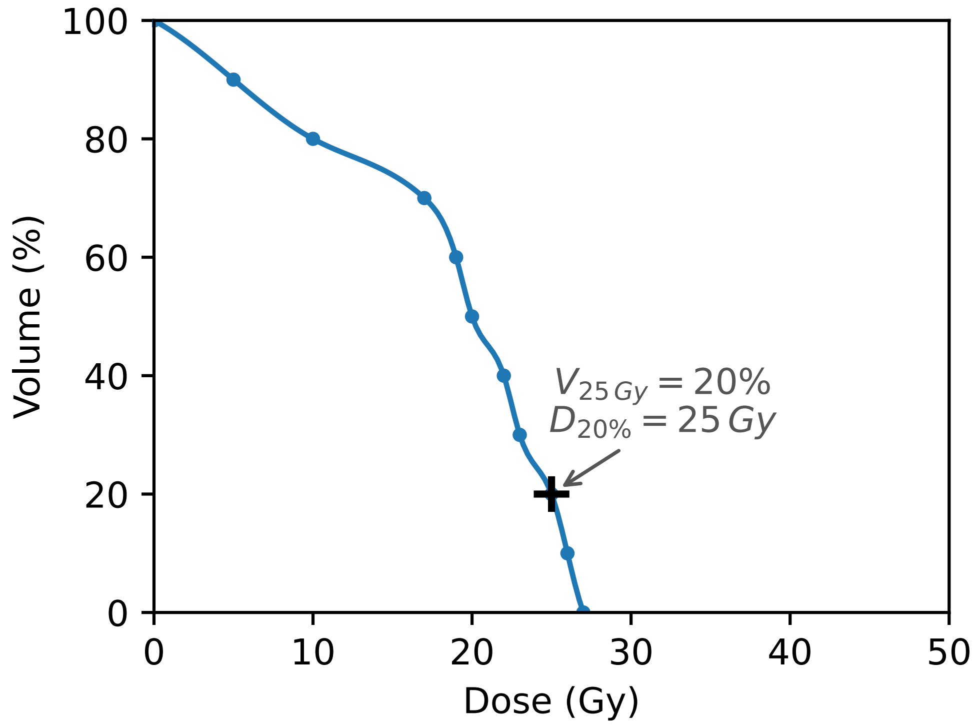
3D dose



*DVH(s): **D**ose **V**olume **H**istogram(s)*

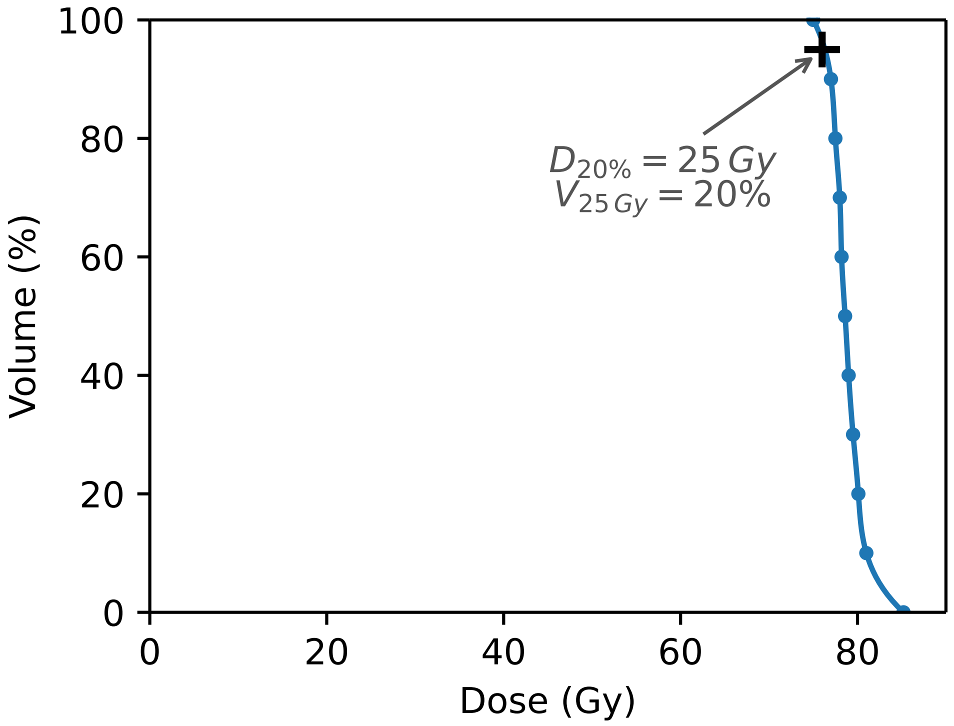
Dose constraints

$D_{20\%} < 25\ Gy$ $V_{25Gy} < 20\%$



Maximal dose constraint *(achieved)*

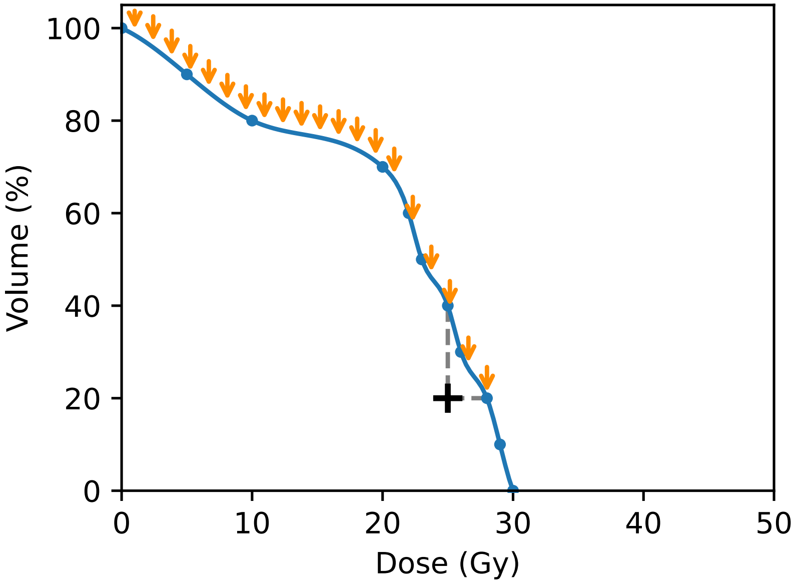
$D_{95\%} > 76\ Gy$ $V_{76Gy} > 95\%$



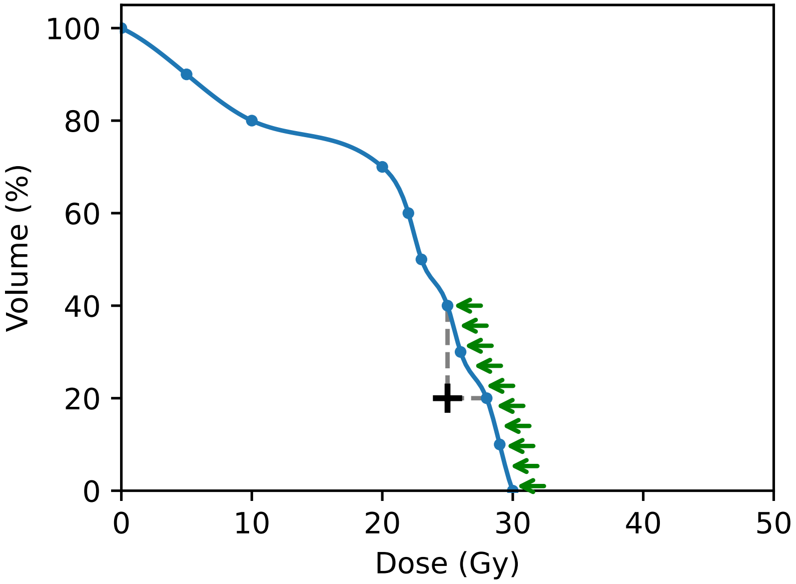
Minimal dose constraint *(achieved)*

Dose constraints penalizations

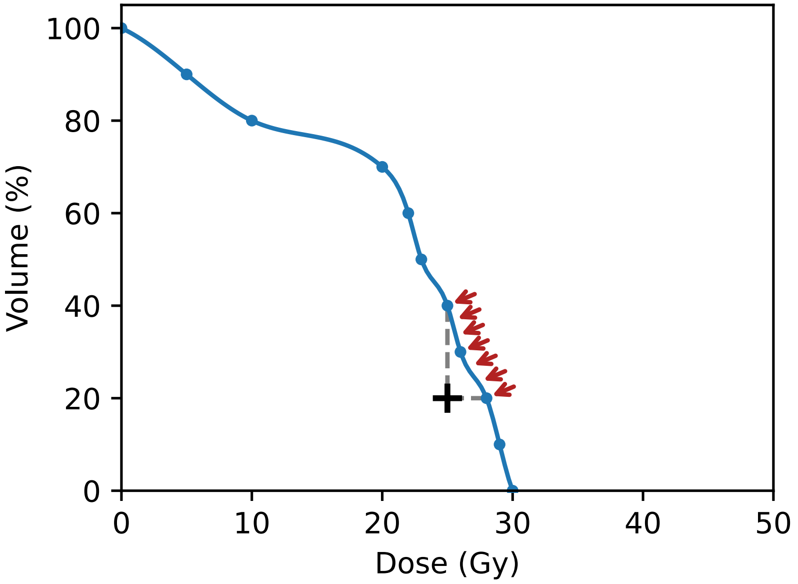
$D_{20\%} < 25\ Gy$ $\qquad$ $V_{25Gy} < 20\%$



Penalizing the
***lower 80%** dose voxels*



Penalizing voxels with dose
greater than 25Gy



Penalizing the
***lower 80%** dose voxels*
*with dose **greater than 25Gy***

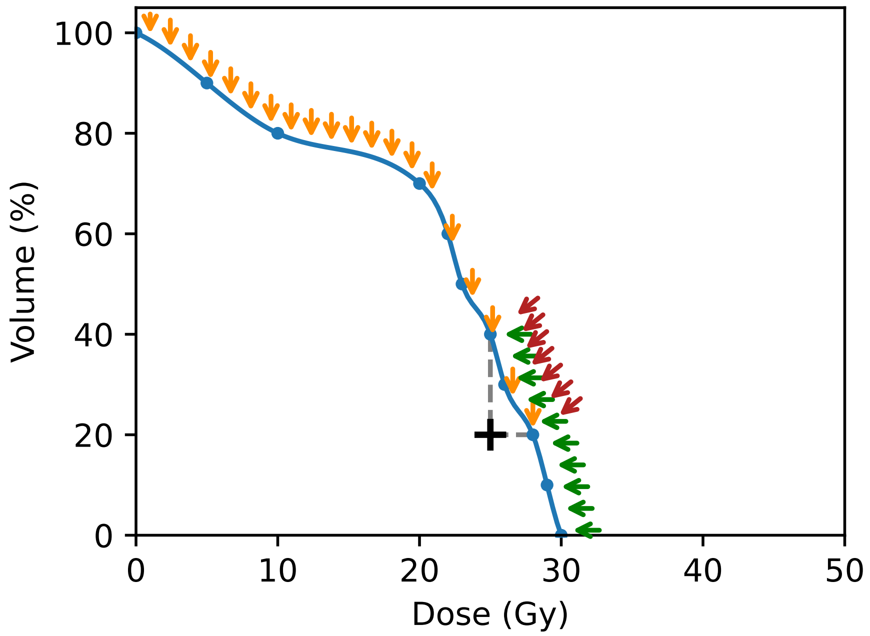
Dose constraints penalizations

Penalize voxels with dose ≥ 25 Gy

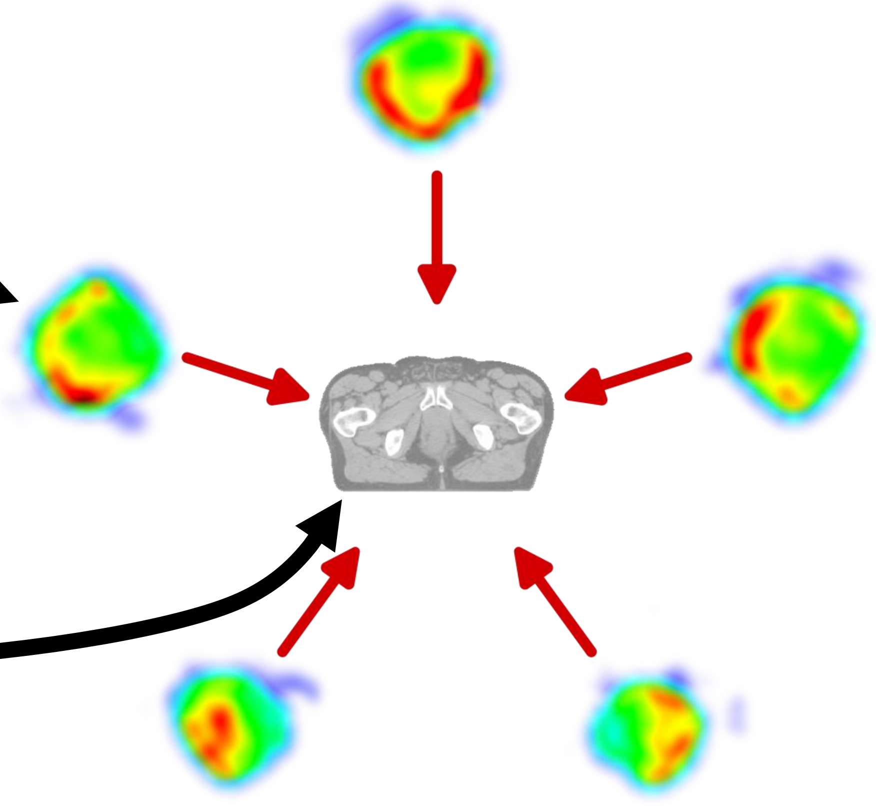
$$d_{OAR} = [\,5\,;\,10\,;\,20\,;\,22\,;\,23\,;\,25\,;\,26\,;\,28\,;\,29\,;\,30\,]$$

Penalize 80% lower dose voxels

Penalize voxels both within 80% lower dose and with dose ≥ 25 Gy



Mathematical formulation



Optimize: $\boldsymbol{x}_{i,j}^{(\theta)}$ with $1 \leq i, j \leq N_\theta$ (the irradiation window) and $\theta \in \Theta$ (the list of irradiation angles)

Such that: $\boldsymbol{x}_{i,j}^{(\theta)} \geq 0$ (as we can not emit negative energy beams)

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

Minimize $$\boldsymbol{g}(\boldsymbol{x}) = \sum_{\boldsymbol{c} \in \boldsymbol{\mathcal{C}}} \boldsymbol{w_c} \frac{\mathbf{1}}{|\boldsymbol{V_c}|} \sum_{\boldsymbol{v} \in \boldsymbol{V_c}} \{\boldsymbol{y}(\boldsymbol{x})_{\boldsymbol{v}} - \boldsymbol{d_c} \mid \boldsymbol{d_c} - \boldsymbol{y}(\boldsymbol{x})_{\boldsymbol{v}}\}_+^{\boldsymbol{p}}$$

Constraints based optimization

Minimize $$f(x) = |\boldsymbol{y}(\boldsymbol{x}) - \boldsymbol{y_{opt}}|^p$$

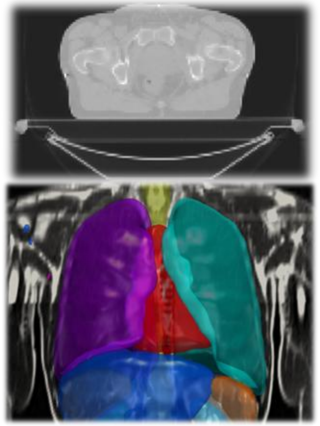
Dose mimicking

$\mathcal{C}$: set of constraints V_c: Voxels of constraint c d_c: dose min/max of c

Current Workflow

N-clicks solution

Patient data
- CT scan
- OARs & PTV contours
- Doctors' objectives



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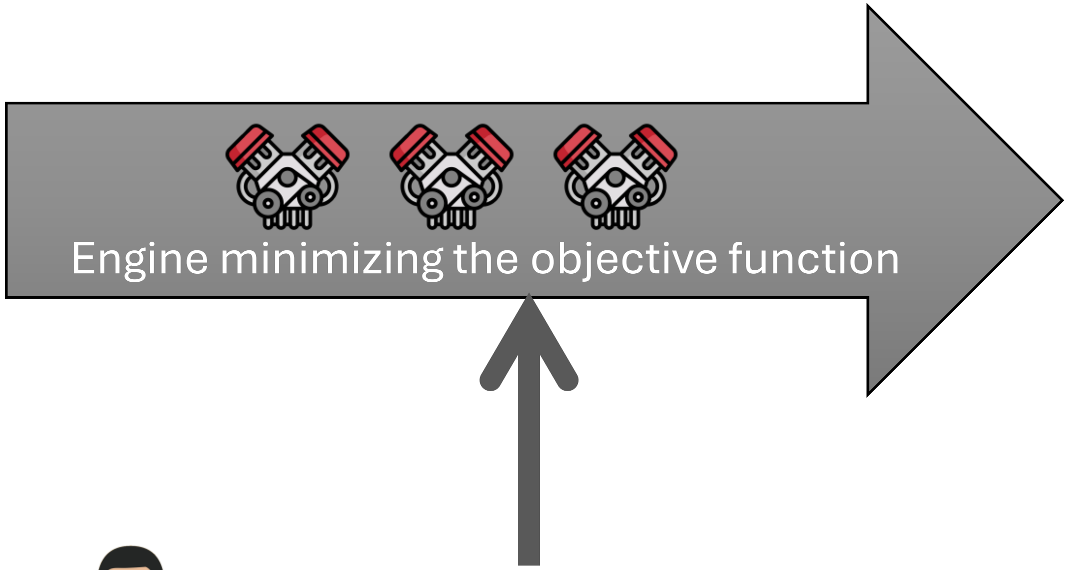


Treatment plan
- ➢ Fluences
- ➢ Leaf motions

Input from dosimetrist
- Weights of each objective

State of the art

Research

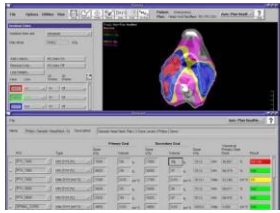
- Automated rule implementation and reasoning [1] *("if-then")*
- Knowledge-based radiotherapy planning [2,3]
- Conventional techniques (Hierarchical constrained optimization, Lagrangian methods) [4]
- A priori multi criteria optimization [5]
- Pareto surface narrowing [6]
- Pareto surface exploration [7]

1. Delphine Rossille, Jean-François Laurent, and Anita Burgun. Modelling a decision support system for oncology using rule-based and case-based reasoning methodologies. *International Journal of Medical Informatics*, 74(2):299–306, 2005. MIE 2003.
2. Obioma Nwankwo, Dwi Seno K Sihono, Frank Schneider, and Frederik Wenz. A global quality assurance system for personalized radiation therapy treatment planning for the prostate (or other sites). *Physics in Medicine & Biology*, 59(18):5575, aug 2014.
3. Antonella Fogliata, Francesca Belosi, Alessandro Clivio, Piera Navarria, Giorgia Nicolini, Marta Scorsetti, Eugenio Vanetti, and Luca Cozzi. On the pre-clinical validation of a commercial model-based optimisation engine: Application to volumetric modulated arc therapy for patients with lung or prostate cancer. *Radiotherapy and Oncology*, 113(3):385–391, Dec 2014.
4. Masoud Zarepisheh, Linda Hong, Ying Zhou, Qijie Huang, Jie Yang, Gourav Jhanwar, Hai D. Pham, Pınar Dursun, Pengpeng Zhang, Margie A. Hunt, Gig S. Mageras, Jonathan T. Yang, Yoshiya (Josh) Yamada, and Joseph O. Deasy. Automated and clinically optimal treatment planning for cancer radiotherapy. *INFORMS Journal on Applied Analytics*, 52(1):69–89, 2022.
5. Michael Lahanas, Eduard Schreibmann, and Dimos Baltas. Multiobjective inverse planning for intensity modulated radiotherapy with constraint-free gradient-based optimization algorithms. *Physics in Medicine & Biology*, 48(17):2843, 2003.
6. David Craft and Thomas Bortfeld. How many plans are needed in an imrt multiobjective plan database? *Physics in Medicine & Biology*, 53(11):2785, 2008
7. David Craft et al. An approach for practical multiobjective imrt treatment planning. *International Journal of Radiation Oncology Biology Physics*, 69(5):1600–1607, 2007.

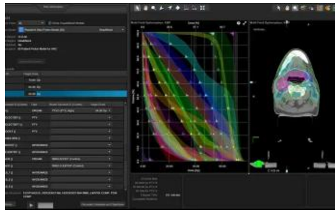
State of the art

Commercial

- Philips Pinnacle: AutoPlanning – prescription based [1] (knowledge-based planning)

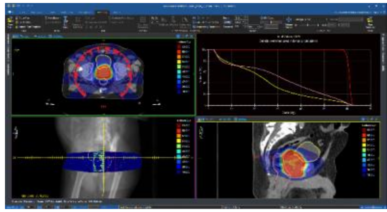


- Varian Eclipse: "*RapidPlan*" - statistical recognition & scripts [2] (knowledge-based planning)



- RaySearch Raystation: Autoplanning – "IronPython" scripts [3] (automated rules and reasoning)

- Elekta ONE: *mCycle* - API SmartFlow & C# scripts [4] (a priori multi criteria optimization)

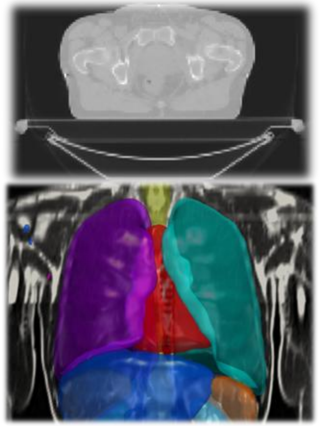


1. Anne Richter, Florian Exner, Klaus Bratengeier, Bülent Polat, Michael Flentje, and Stefan Weick. Impact of beam configuration on vmat plan quality for pinnacle3autoplanning for head and neck cases. *Radiation Oncology*, 14(1):12, Jan 2019
2. P. Meyer, M.-C. Biston, C. Khamphan, T. Marghani, J. Mazurier, V. Bodez, L. Fezzani, P.A. Rigaud, G. Sidorski, L. Simon, and C. Robert. Automation in radiotherapy treatment planning: Examples of use in clinical practice and future trends for a complete automated workflow. *Cancer/Radiothérapie*, 25(6):617–622, 2021. 32e Congrès national de la Société française de radiothérapie oncologique.
3. Yiwei Yang, Kainan Shao, Jie Zhang, Ming Chen, Yuanyuan Chen, and Guoping Shan. Automatic planning for nasopharyngeal carcinoma based on progressive optimization in raystation treatment planning system. *Technology in Cancer Research & Treatment*, 19:1533033820915710, 2020. PMID: 32552600.
4. P. Meyer, M.-C. Biston, C. Khamphan, T. Marghani, J. Mazurier, V. Bodez, L. Fezzani, P.A. Rigaud, G. Sidorski, L. Simon, and C. Robert. Automation in radiotherapy treatment planning: Examples of use in clinical practice and future trends for a complete automated workflow. *Cancer/Radiothérapie*, 25(6):617–622, 2021. 32e Congrès national de la Société française de radiothérapie oncologique.

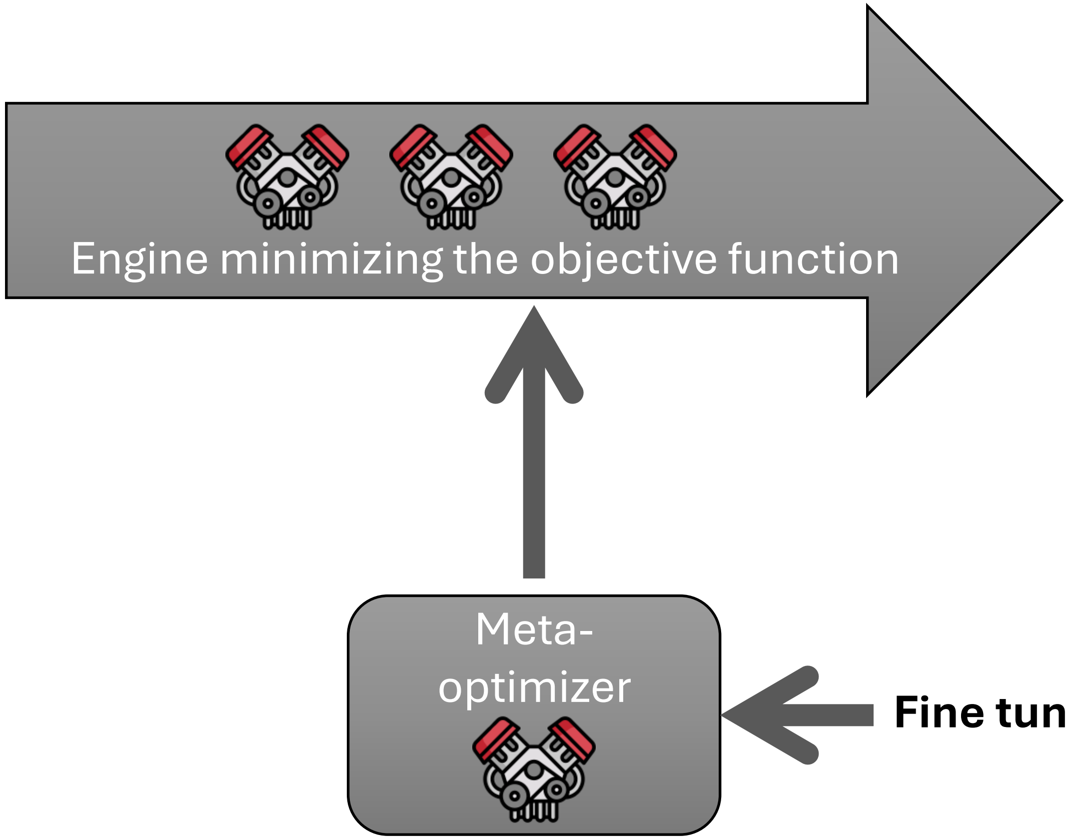
Meta Optimization

[Not general]

Patient data
- CT scan
- OARs & PTV contours
- Doctors' objectives



Structure	Constraint
Rectum	$D_{1\%} < 76\ Gy$
Rectum	$D_{25\%} < 72\ Gy$
Rectum	$D_{50\%} < 60\ Gy$
Bladder	$D_{1\%} < 80\ Gy$
Bladder	$D_{25\%} < 74\ Gy$



Treatment plan
- Fluences
- Leaf motions

Fine tuning of hyper parameters

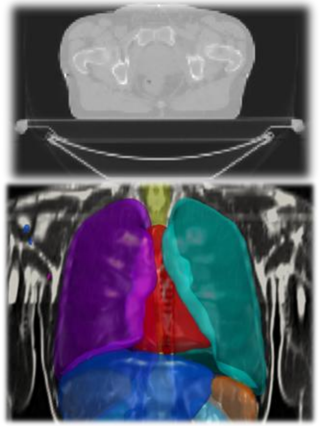
Dose clustering

Semi-automatic technique

Batch optimization & Dose Clustering

Patient data

- CT scan
- OARs & PTV contours
- Doctors' objectives



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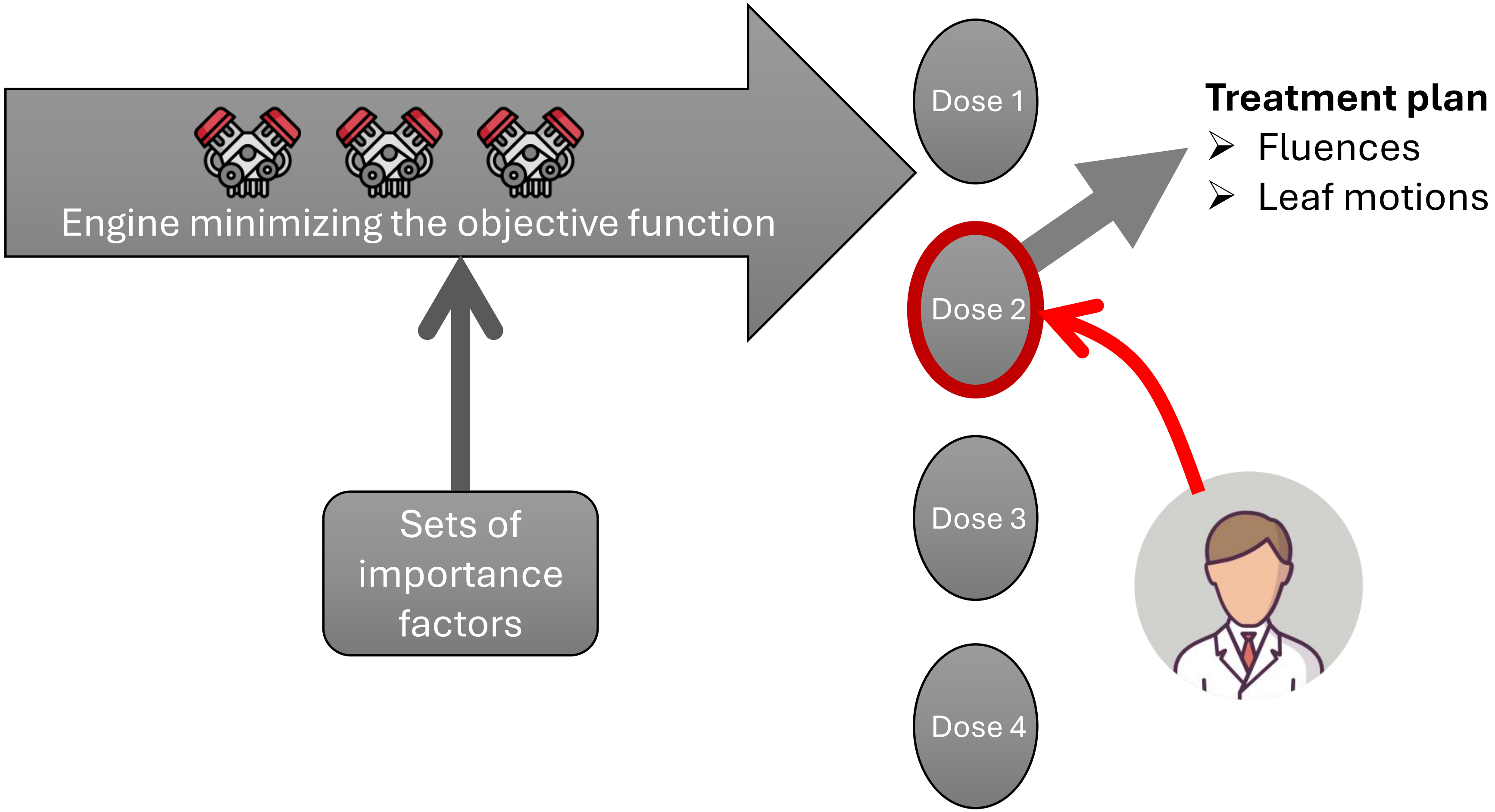
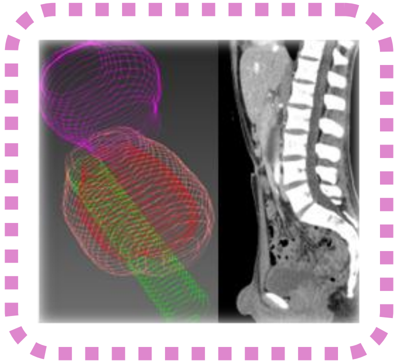
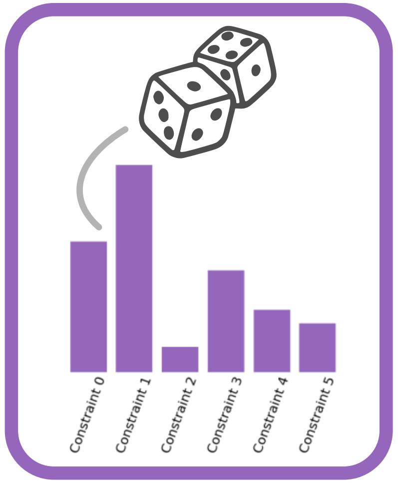


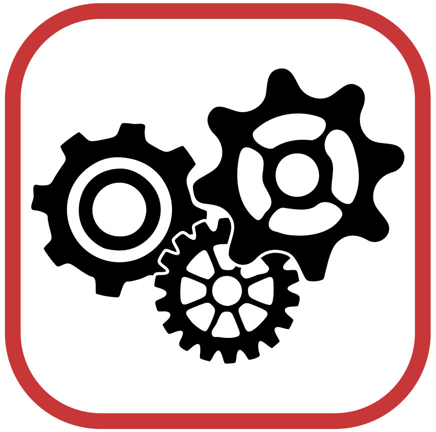
Batch optimize with random weights



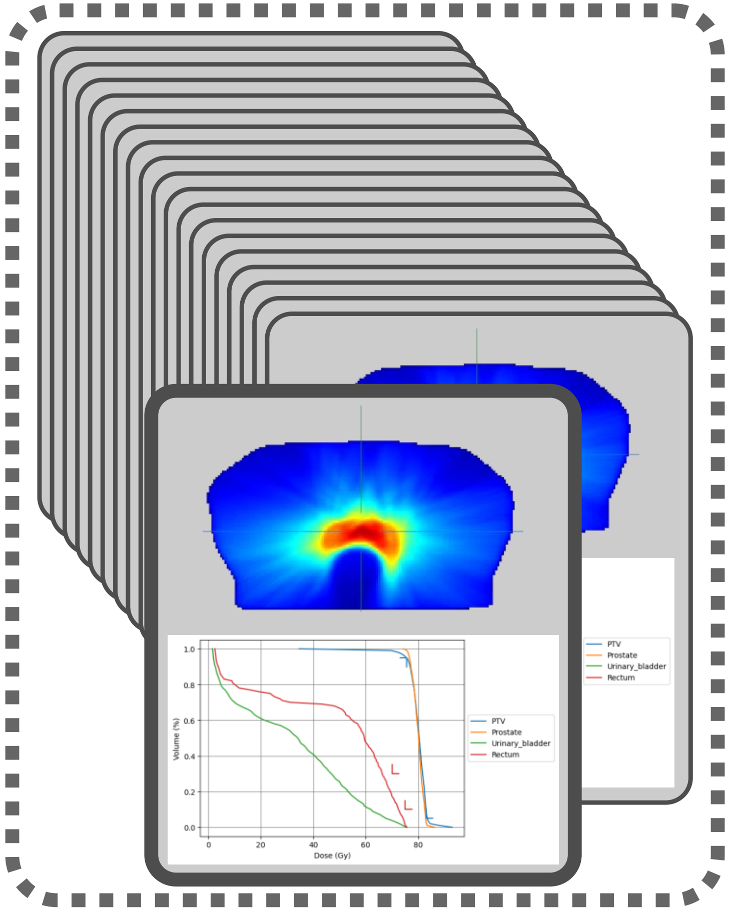
Patient data



Multi-objective criteria perturbation models

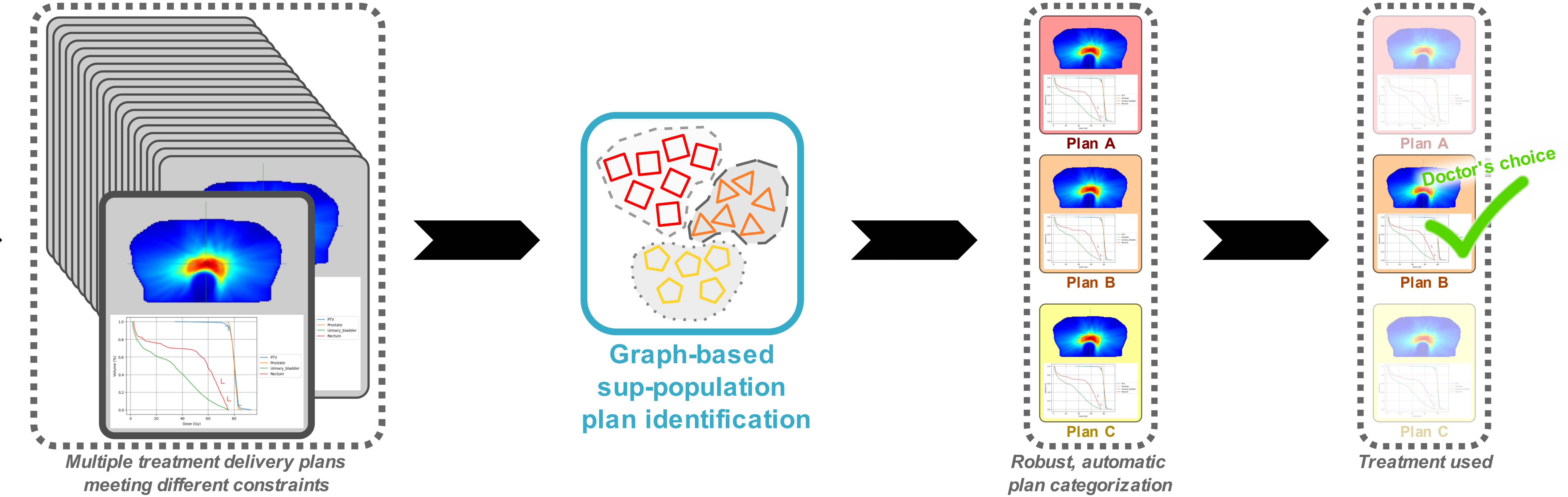


Optimization engine

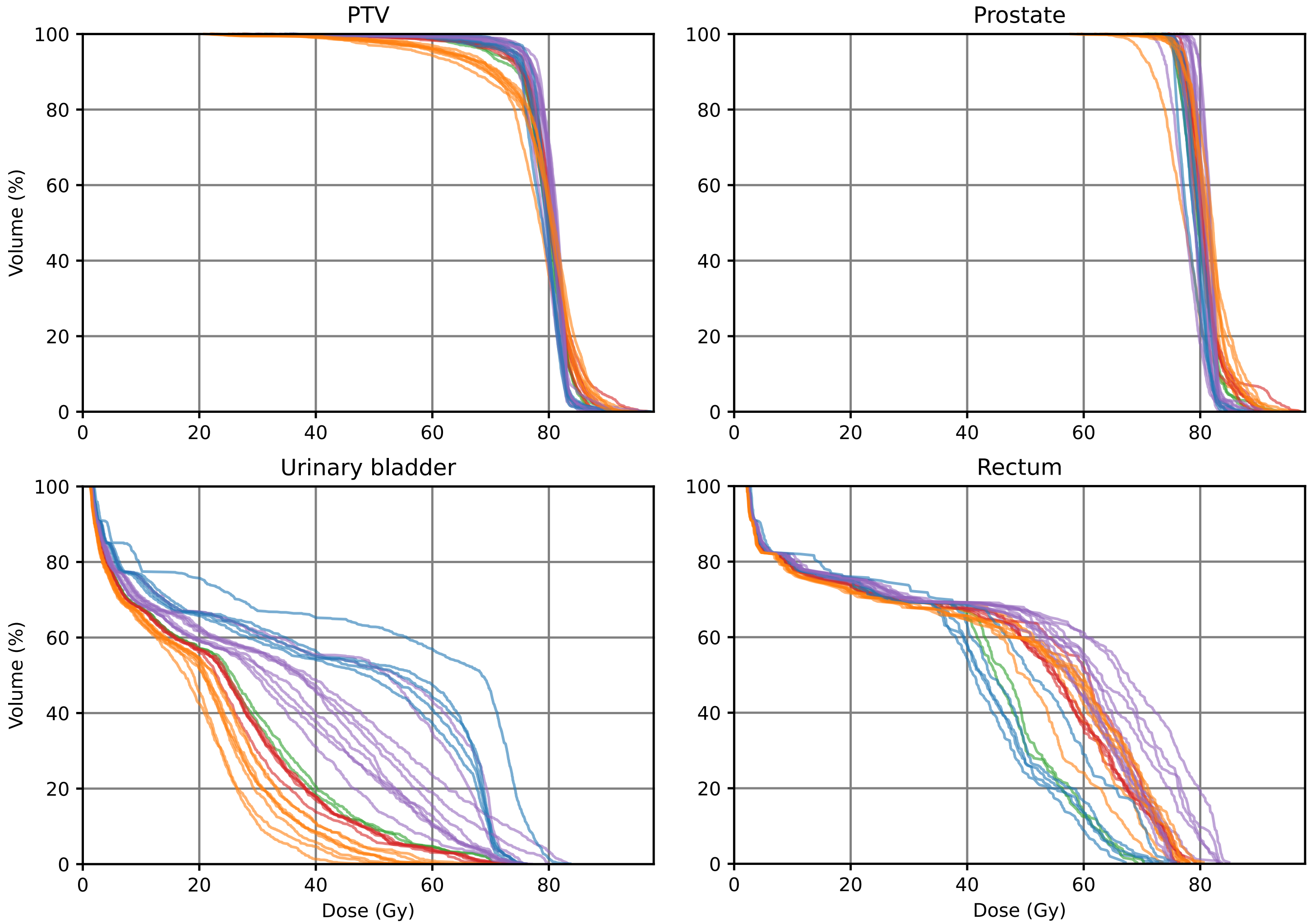


Multiple treatment delivery plans meeting different constraints

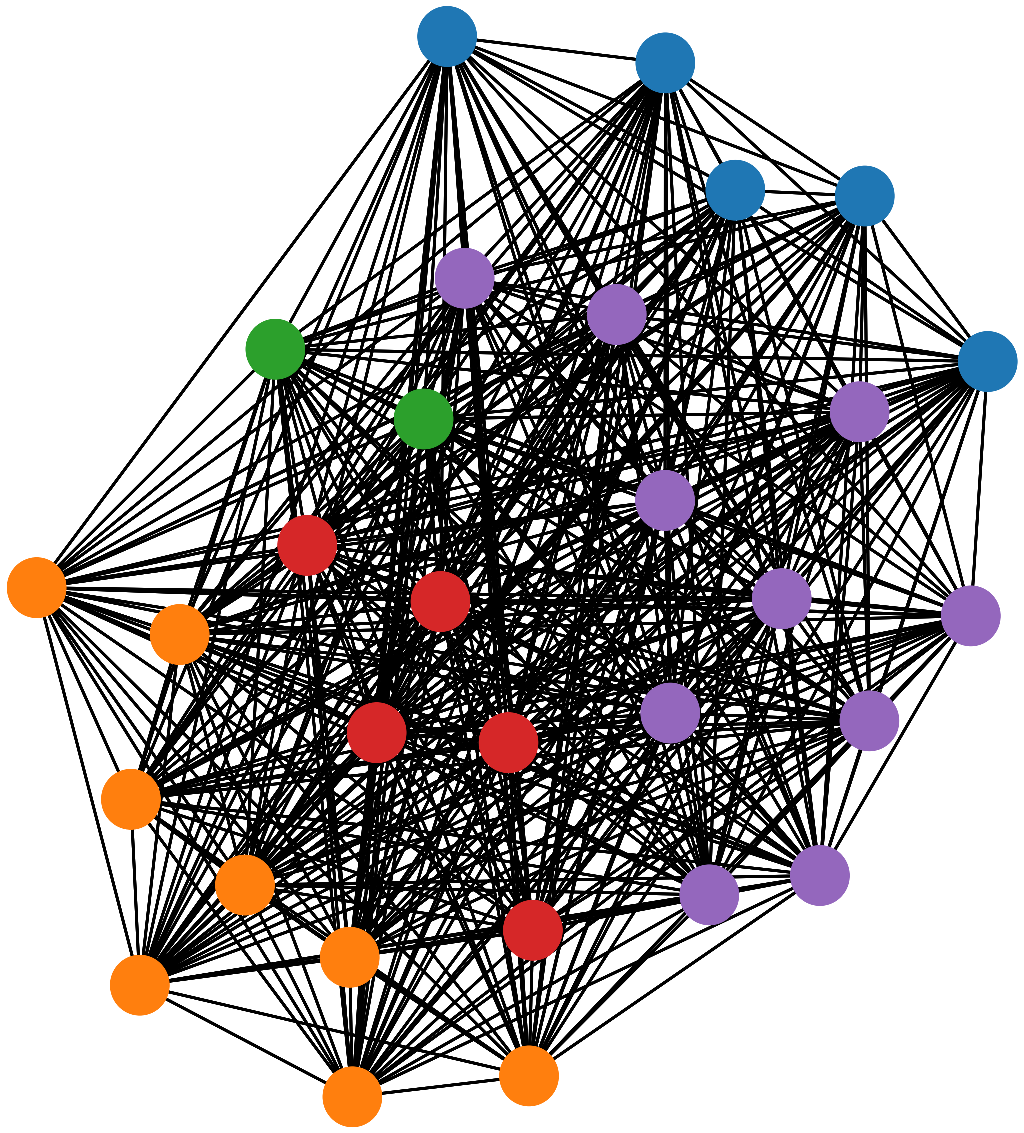
Cluster optimized plan



Clinically meaningful clusters



Spring view of the graph

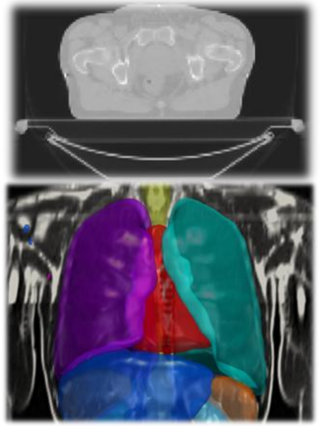


Batch optimization & Dose Clustering

3-clicks solution

Patient data

- CT scan
- OARs & PTV contours
- Doctors' objectives



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Bladder	$D_{1\%} < 80\ Gy$
Bladder	$D_{25\%} < 74\ Gy$

Engine minimizing the objective function

Sets of importance factors

Dose 1

Dose 2

Dose 3

Dose 4

Treatment plan

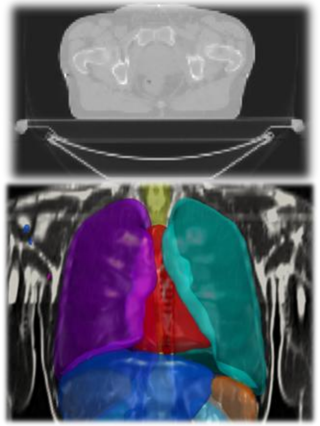
- ➢ Fluences
- ➢ Leaf motions

Reinforcement Learning
& *Constraints based optimization*

Fully automatic technique

Reinforcement Learning

Patient data
- CT scan
- OARs & PTV contours
- Doctors' objectives



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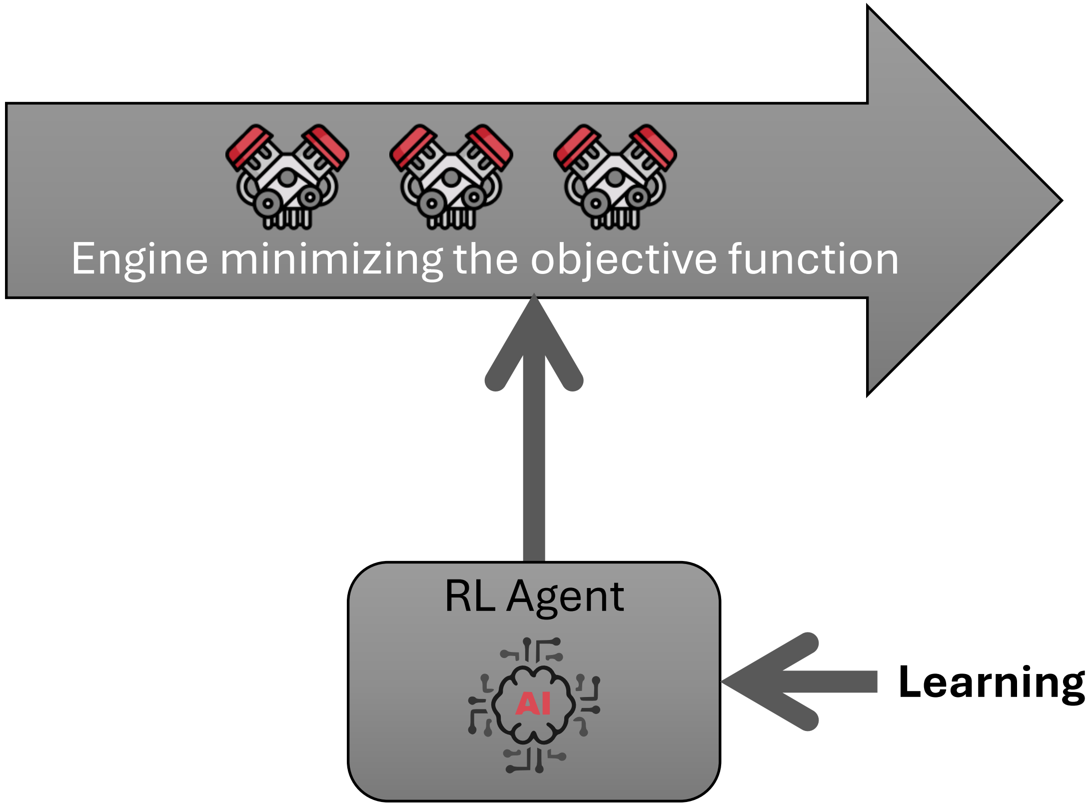
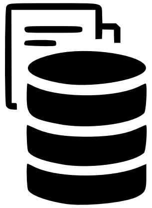
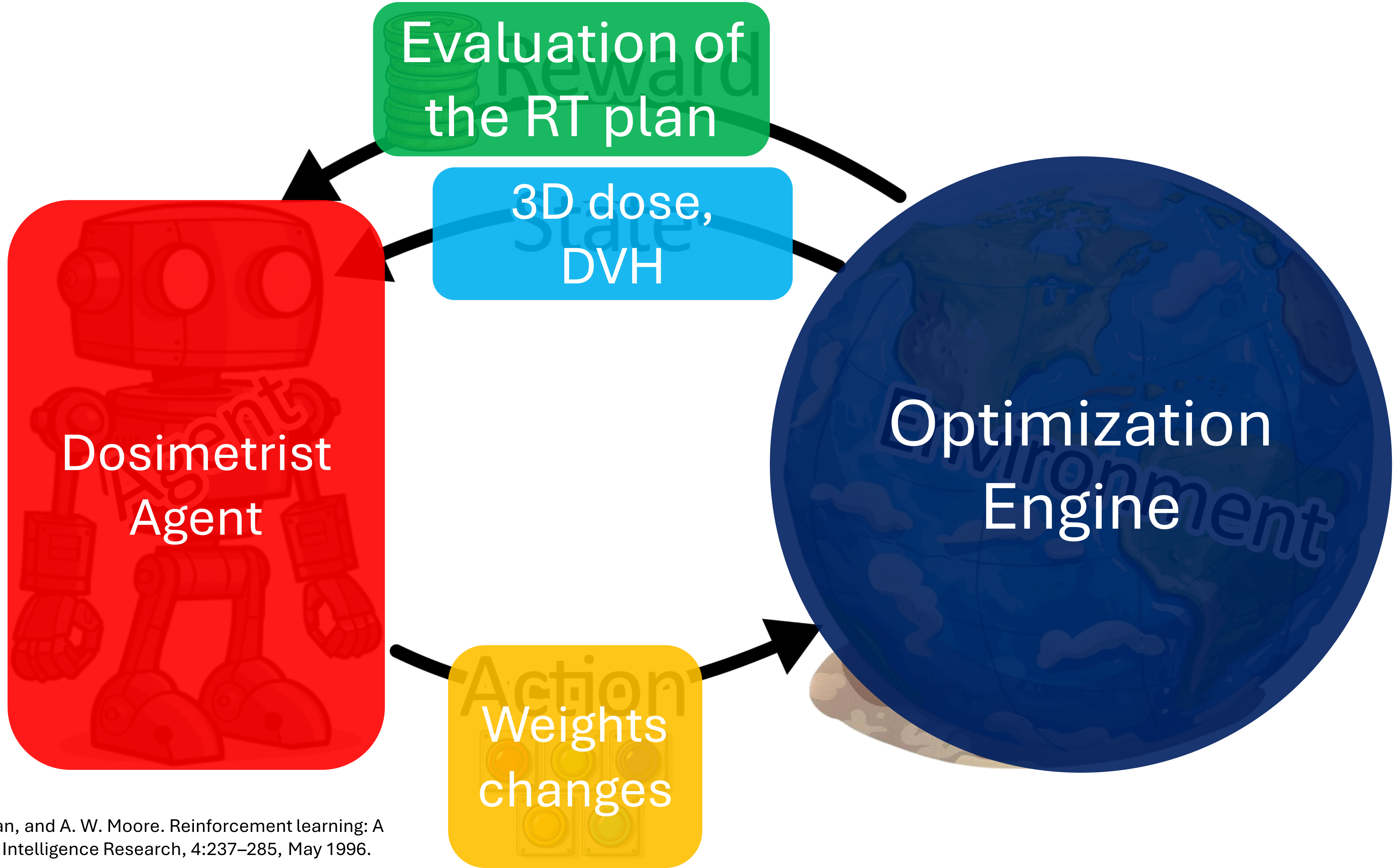


Treatment plan
- ➢ Fluences
- ➢ Leaf motions

Learning based on previous cases

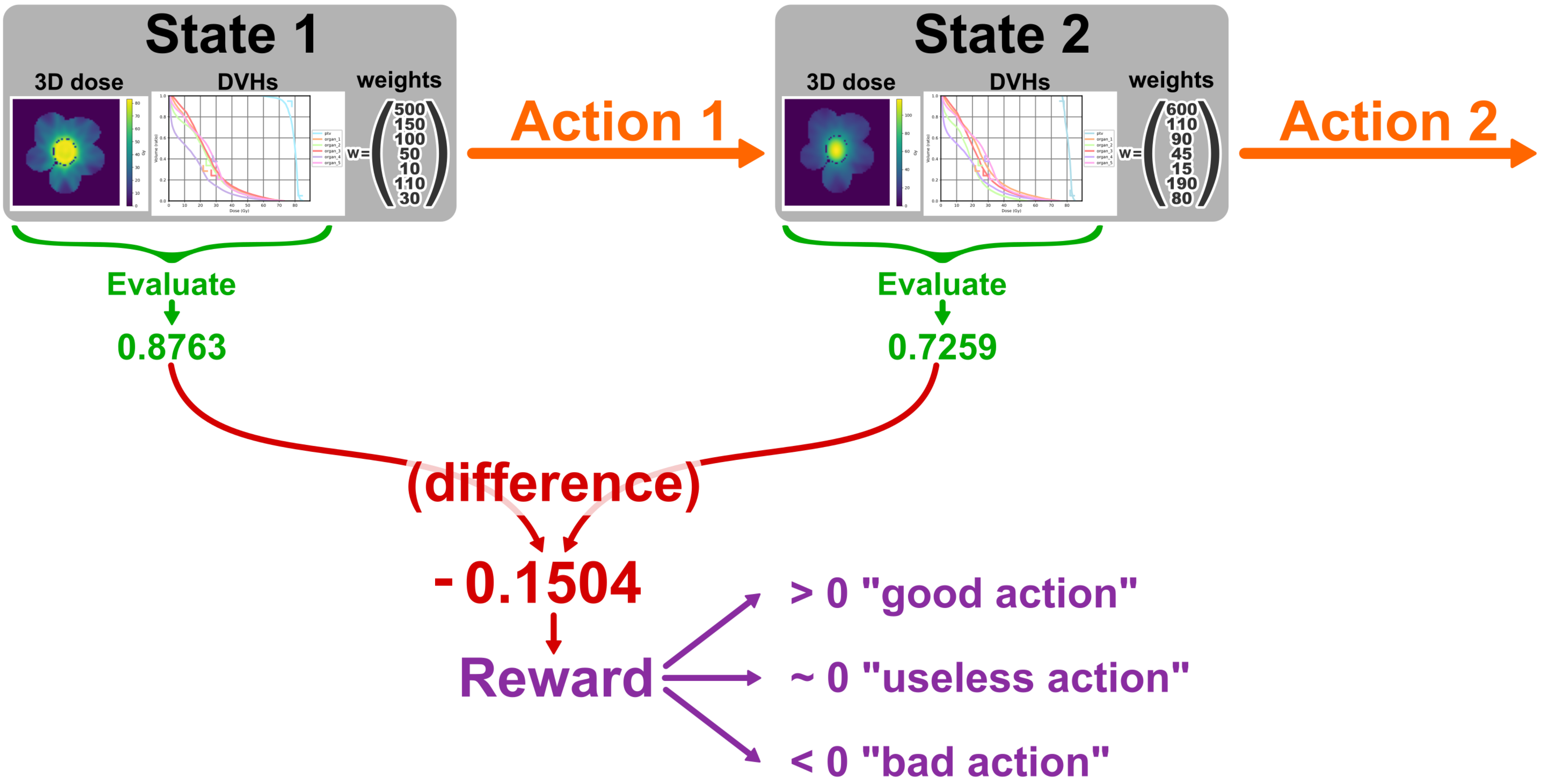


Reinforcement Learning Paradigm

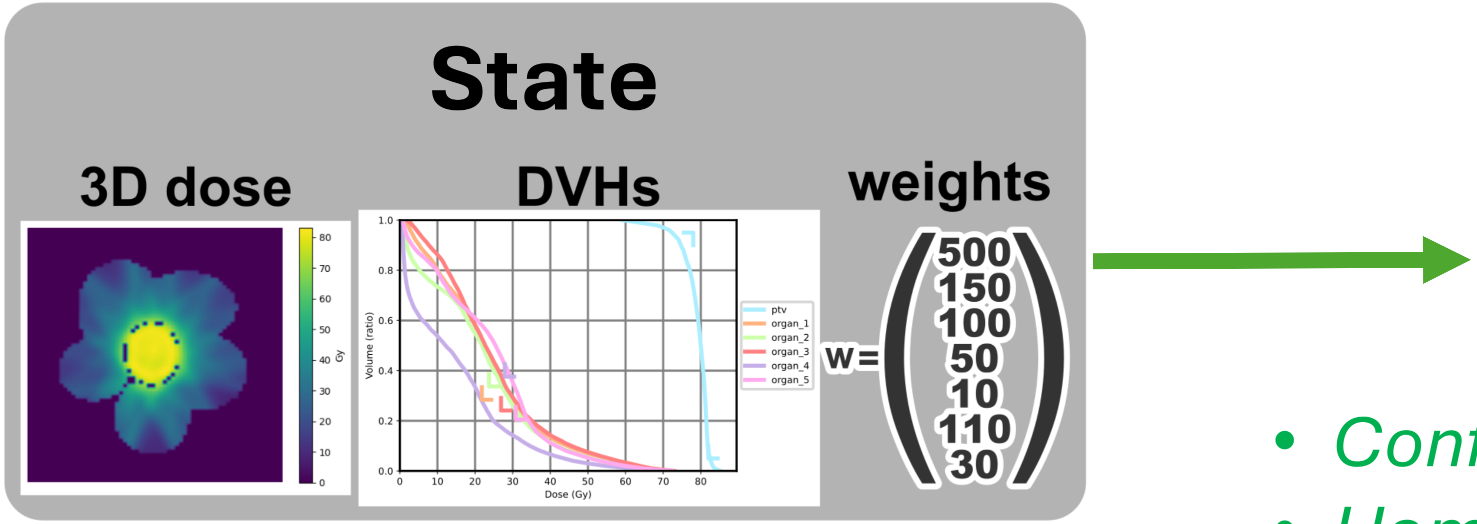


L. P. Kaelbling, M. L. Littman, and A. W. Moore. Reinforcement learning: A survey. Journal of Artificial Intelligence Research, 4:237–285, May 1996.

Reinforcement Learning Paradigm



Evaluating a State



0.5679

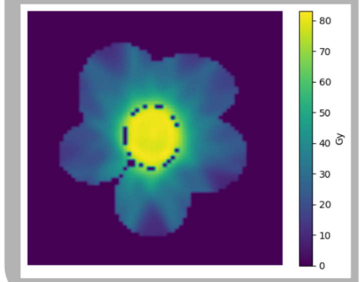
- *Conformity index*
- *Homogeneity index*
- *Gradient index*
- …

- Chenyang Shen, Liyuan Chen, and Xun Jia. A hierarchical deep reinforcement learning framework for intelligent automatic treatment planning of prostate cancer intensity modulated radiation therapy. *Physics in Medicine & Biology*, 66(13):134002, July 2021.
- Chenyang Shen, Yesenia Gonzalez, Peter Klages, Nan Qin, Hyunuk Jung, Liyuan Chen, Dan Nguyen, Steve B. Jiang, and Xun Jia. Intelligent Inverse Treatment Planning via Deep Reinforcement Learning, a Proof-of-Principle Study in High Dose-rate Brachytherapy for Cervical Cancer. *Physics in Medicine & Biology*, 64(11):115013, May 2019. arXiv:1811.10102 [physics].
- Grégoire Moreau, Vincent François-Lavet, Paul Desbordes, and Benoît Macq. Reinforcement Learning for Radiotherapy Dose Fractioning Automation. *Biomedicines*, 9(2):214, February 2021.

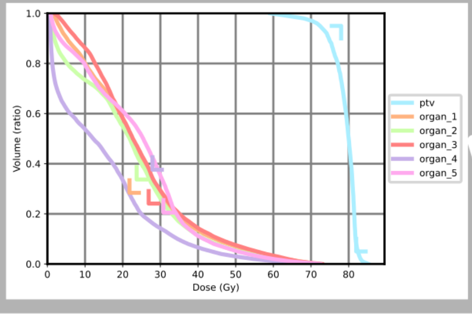
Evaluating a State

State

3D dose



DVHs

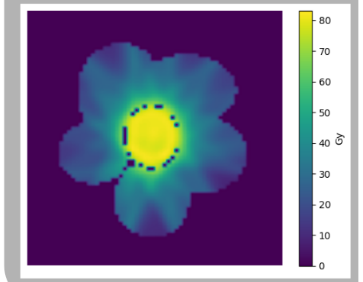


weights

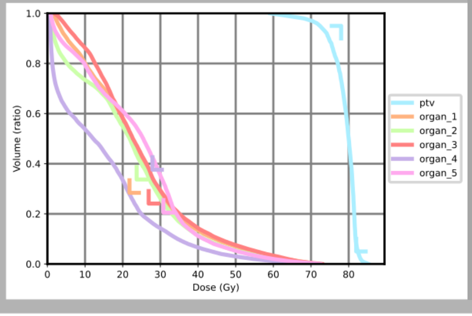
$$w = \begin{pmatrix} 500 \\ 150 \\ 100 \\ 50 \\ 10 \\ 110 \\ 30 \end{pmatrix}$$

Clinical Dose

3D dose

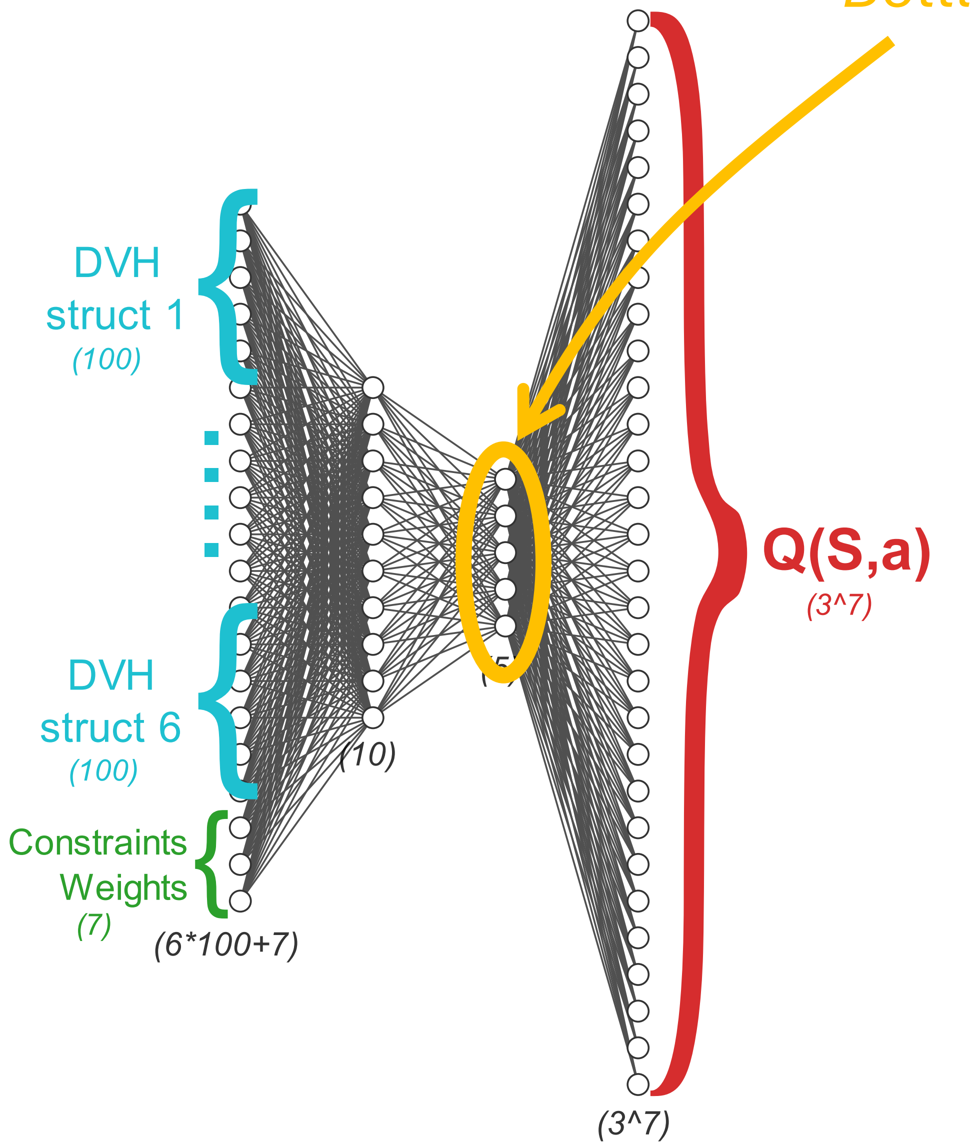


DVHs

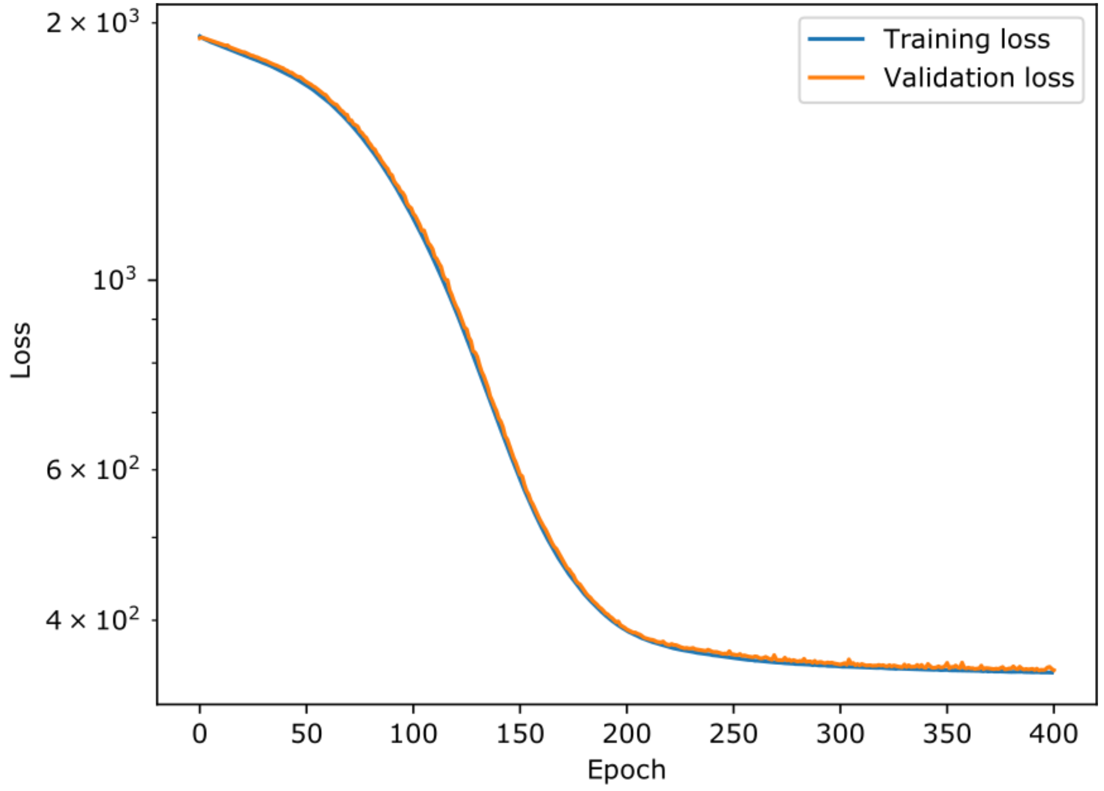


0.4683 *(DVH distance)*

Architecture



Dosimetrist agent architecture



Training & Evaluation losses

Numerical results

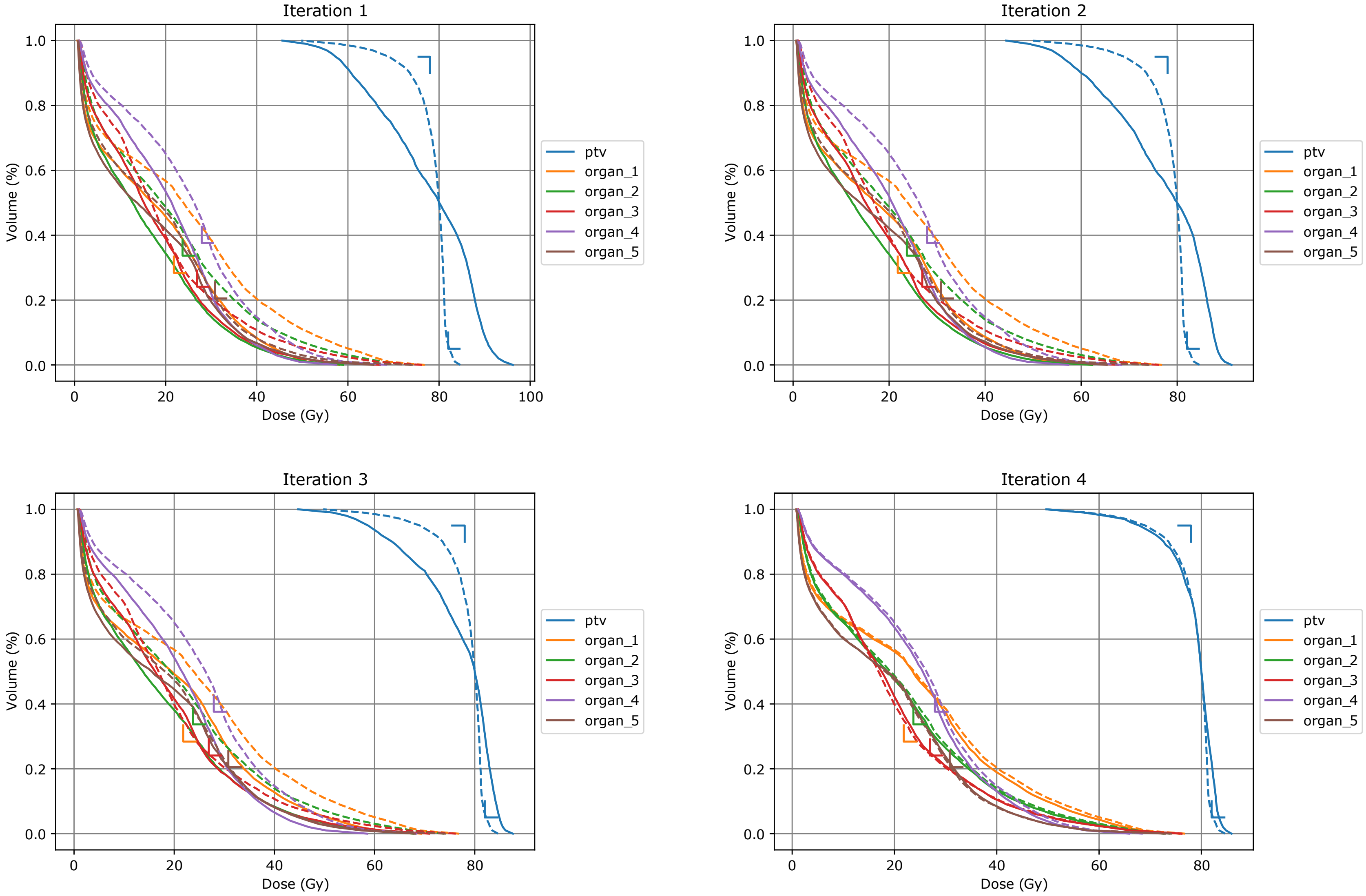
Agent \ Metric	Mean Final Distance (*)	Homogeneity Score (¤)	Conformity Score (¤)
RL Distance	**0.612**	1.871	0.406
RL Homogeneity	2.012	**4.387**	0.567
RL Conformity	1.770	4.017	0.507
Meta-optimization	N/A	4.117	**0.610**
Clinical doses	*0*	*1.541*	*0.580*

Scores of final RL agents plan and clinical plan.

(*) : Lower is better *(¤) : Higher is better*

Qualitative Results

Dotted lines: Clinical plan
Solid lines: RL plan



Clinically-Dependence of RL agents

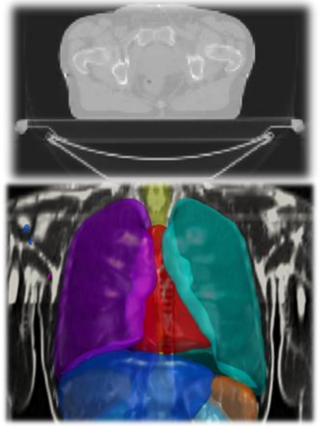
Agent \ Distance	To Clinic A	To Clinic B	To Clinic C
RL on clinic A	**1.6**	2.2	5.1
RL on clinic B	2.3	**1.3**	2.3
RL on clinic C	2.7	2.5	**1.6**

Average distance between final RL agent plan and clinical plan.

Reinforcement Learning

1-click solution

Patient data
- CT scan
- OARs & PTVs contours
- Doctors' objectives



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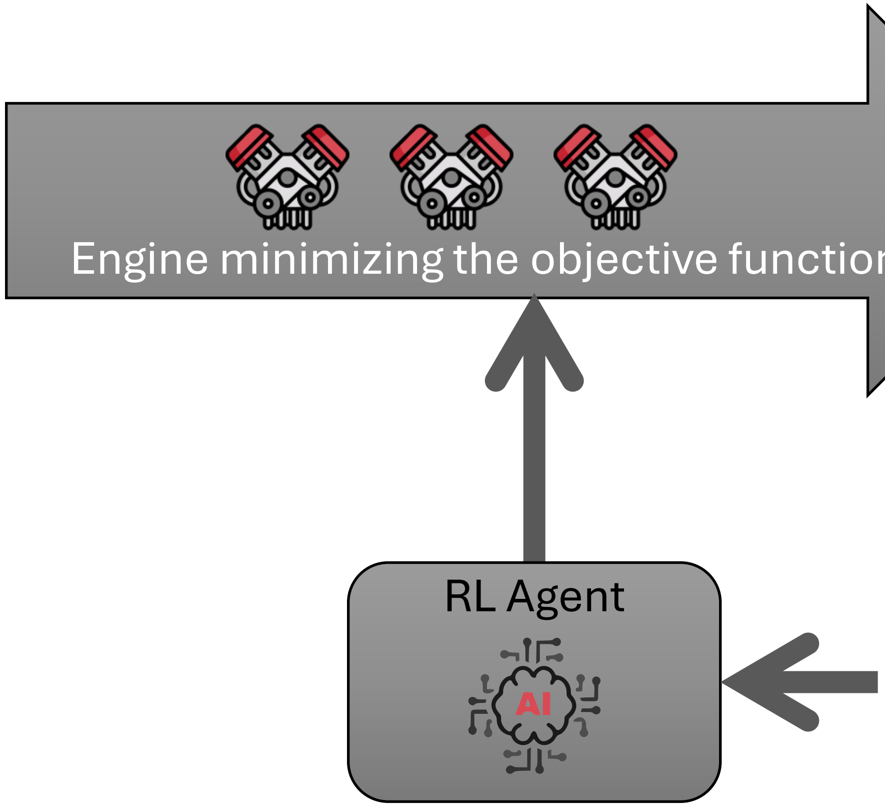
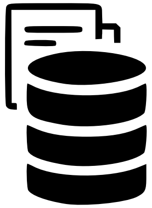


Treatment plan
- ➢ Fluences
- ➢ Leaf motions

Learning based on previous cases

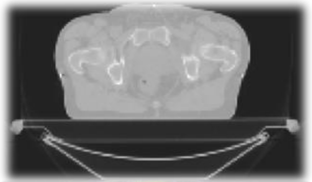


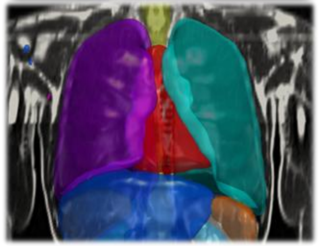
Target DVH Deep Dose & *Dose Mimicking*

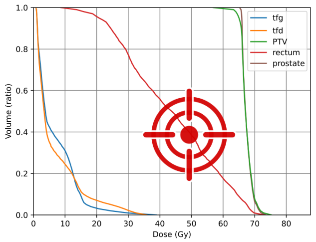
Fully automatic technique with adjustability

Dose prediction & mimicking

Patient data
- CT scan
- OARs & PTVs contours
- Target DVH







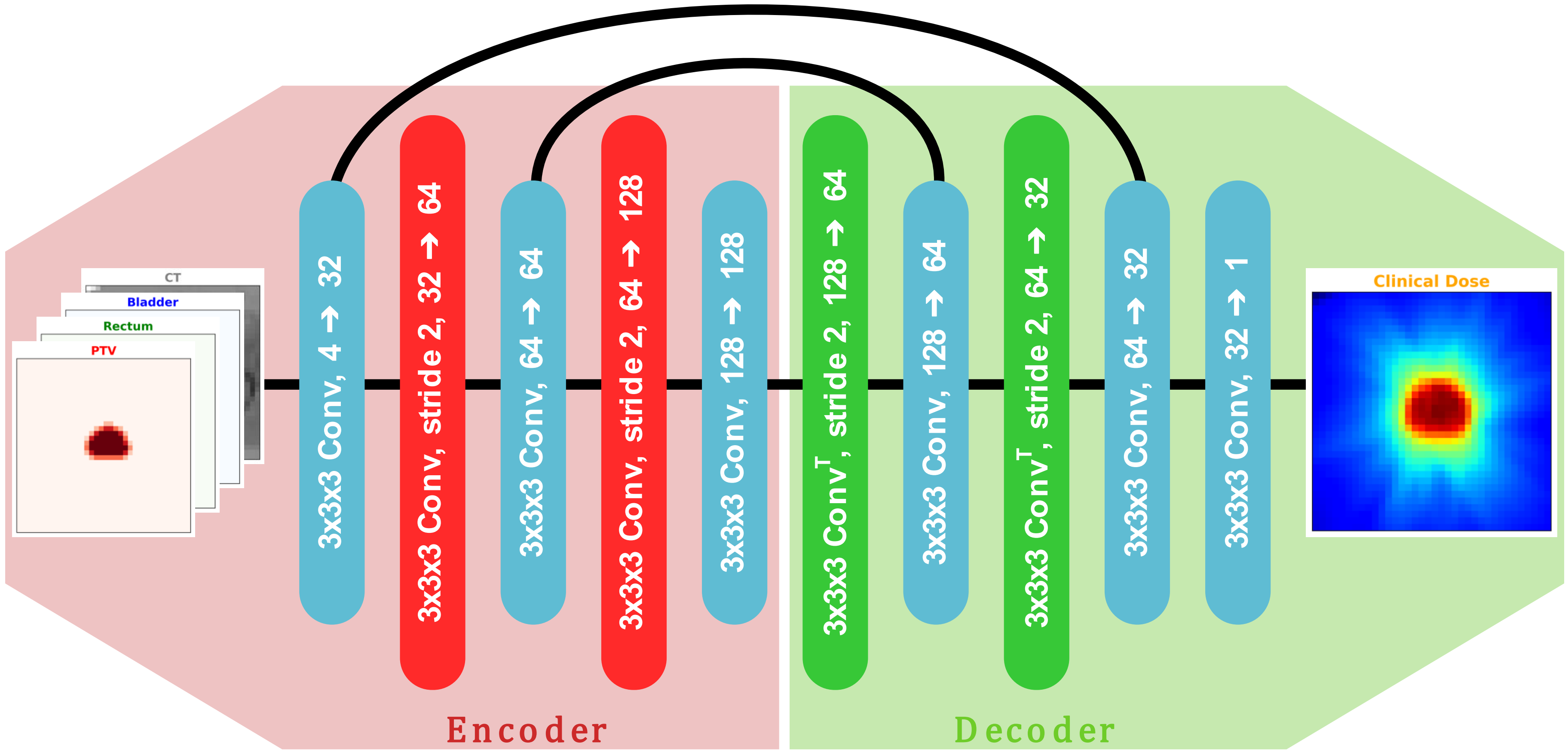
3D dose prediction

Dose mimicking Engine

Learning based on previous cases

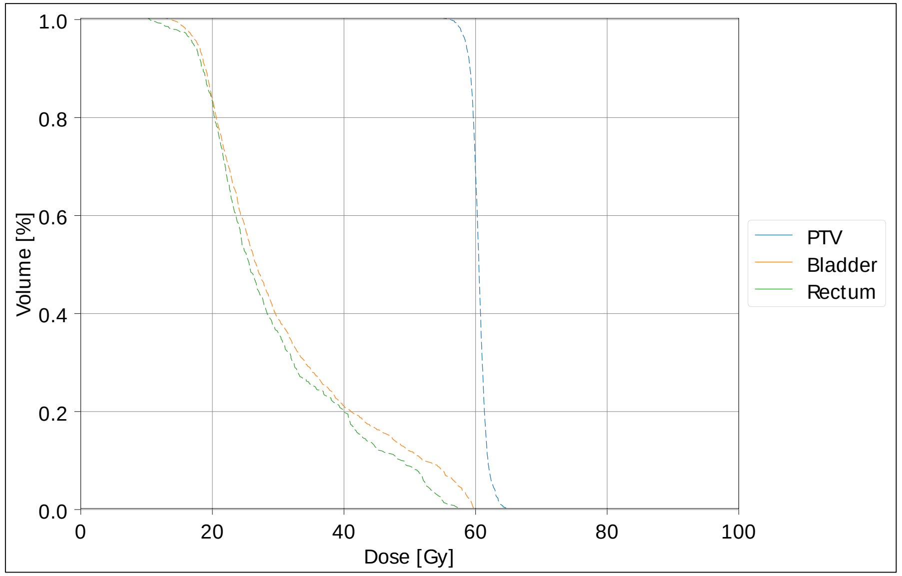
Treatment plan
- Fluences
- Leaf motions

3D Dose Prediction



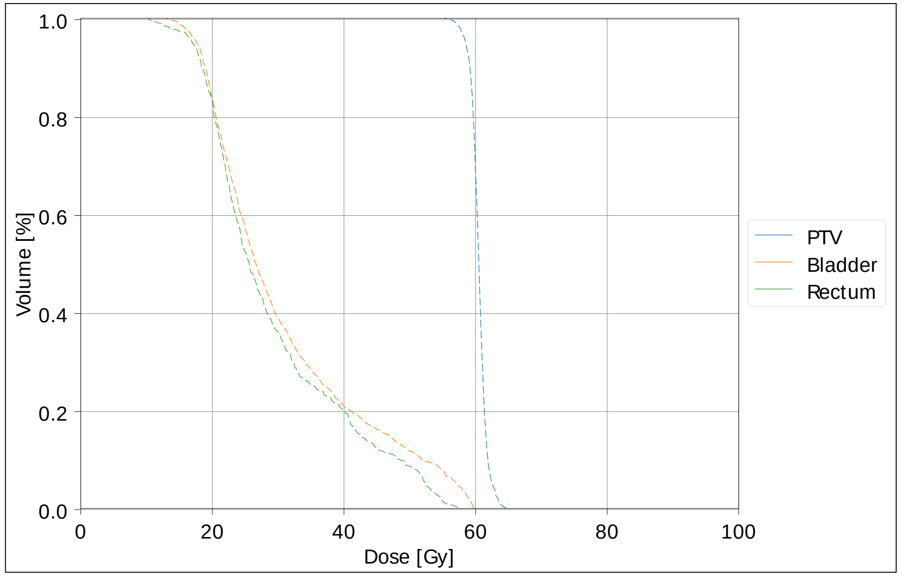
Model "Classic"

Processing DVHs data



U-Net

Processing DVHs data

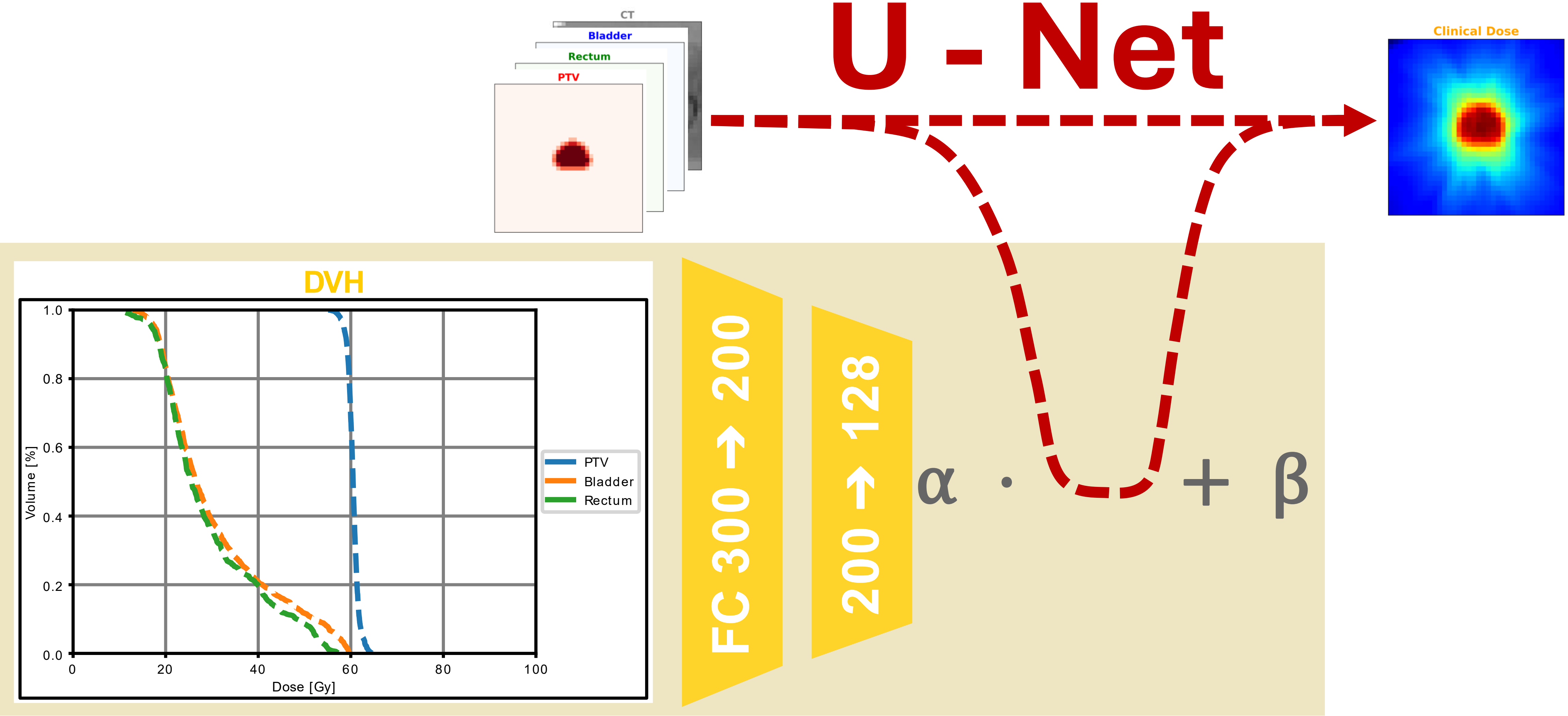


Dynamic Affine Features Transform

U-Net

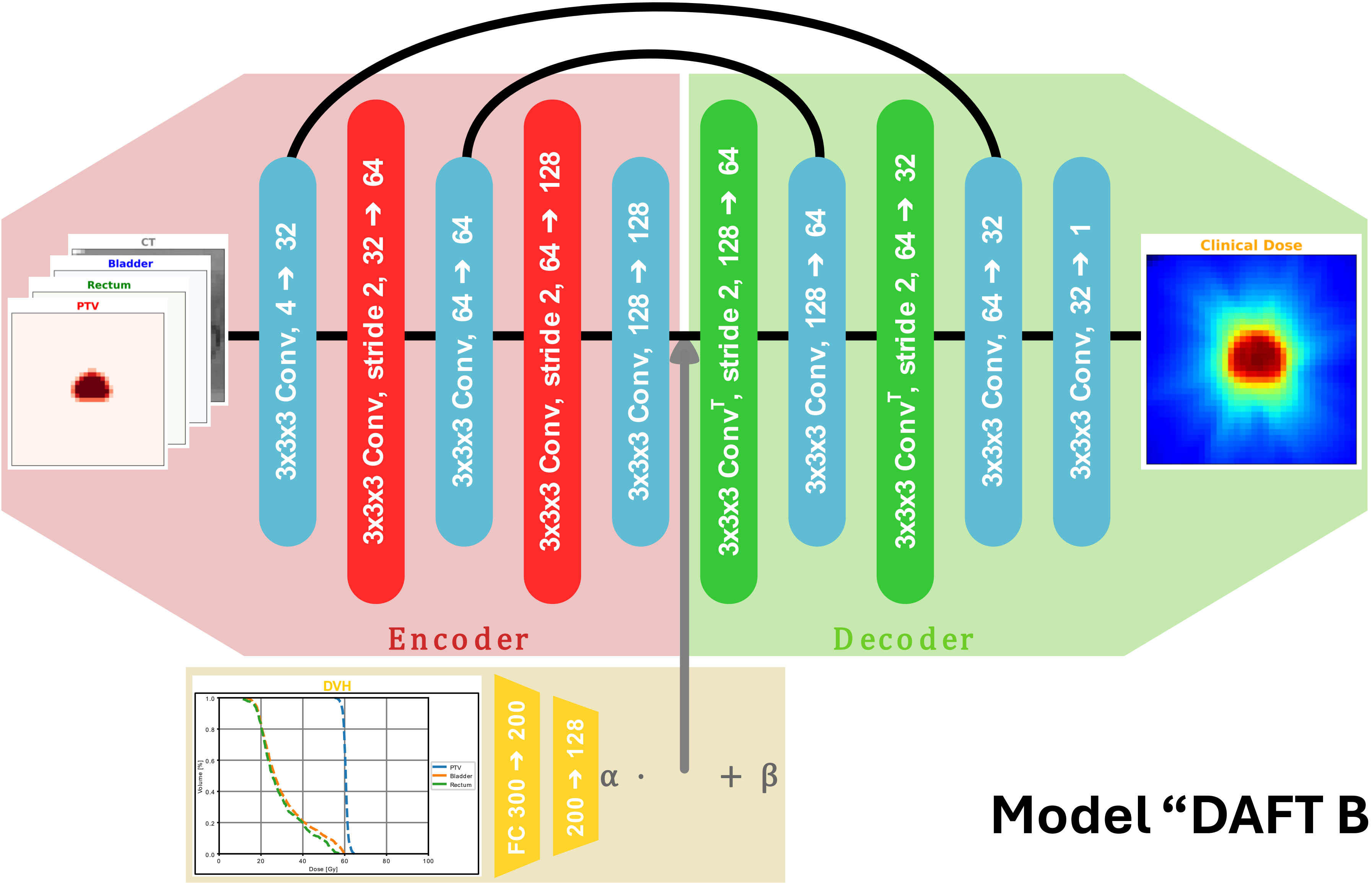
Sebastian Pölsterl, Tom Nuno Wolf, and Christian Wachinger. Combining 3D Image and Tabular Data via the Dynamic Affine Feature Map Transform, page 688–698. *Springer International Publishing*, 2021

Processing DVHs data



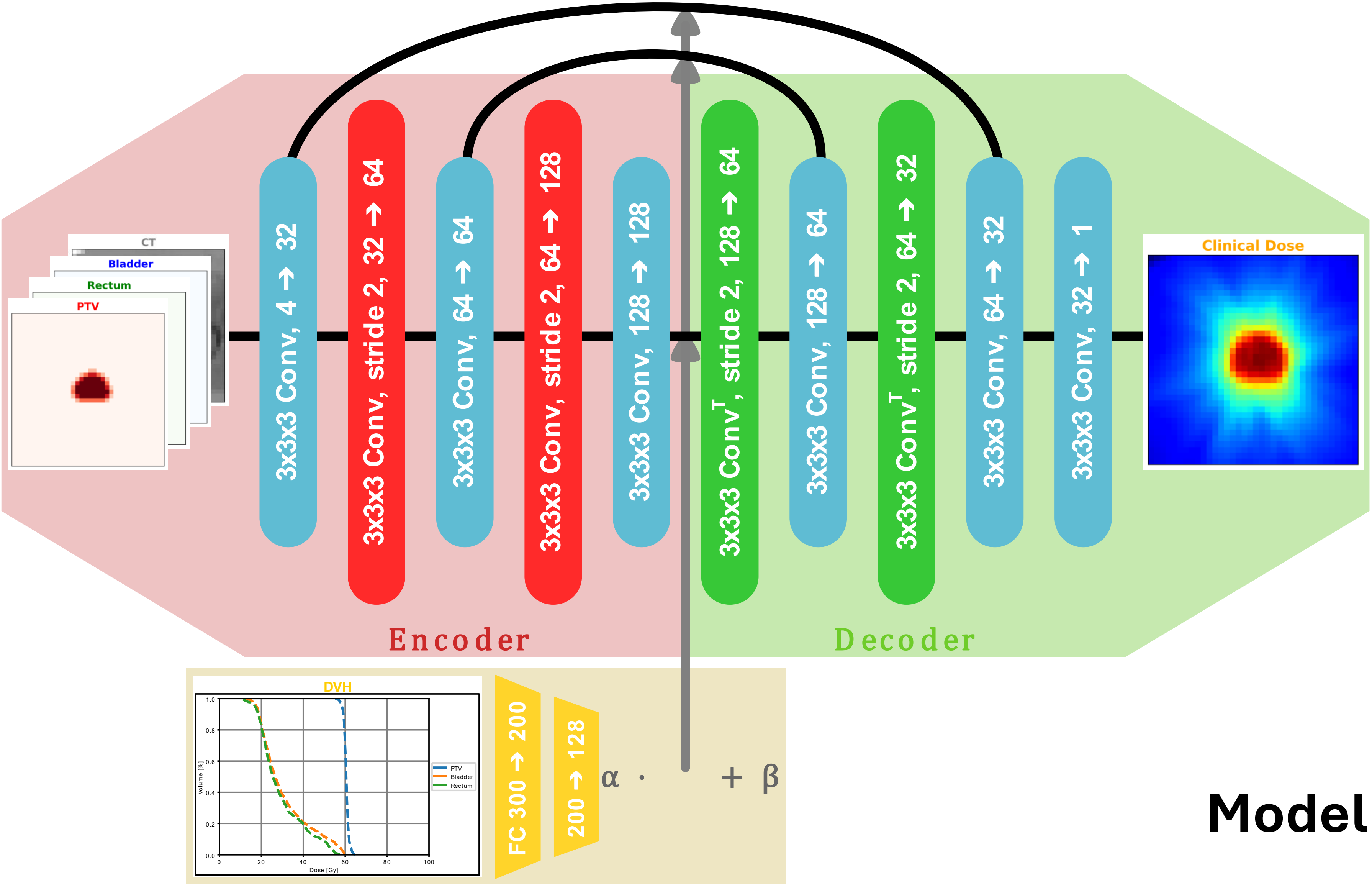
Sebastian Pölsterl, Tom Nuno Wolf, and Christian Wachinger. Combining 3D Image and Tabular Data via the Dynamic Affine Feature Map Transform, page 688–698. *Springer International Publishing*, 2021

3D Dose Prediction with DVH information



Model "DAFT Bottleneck"

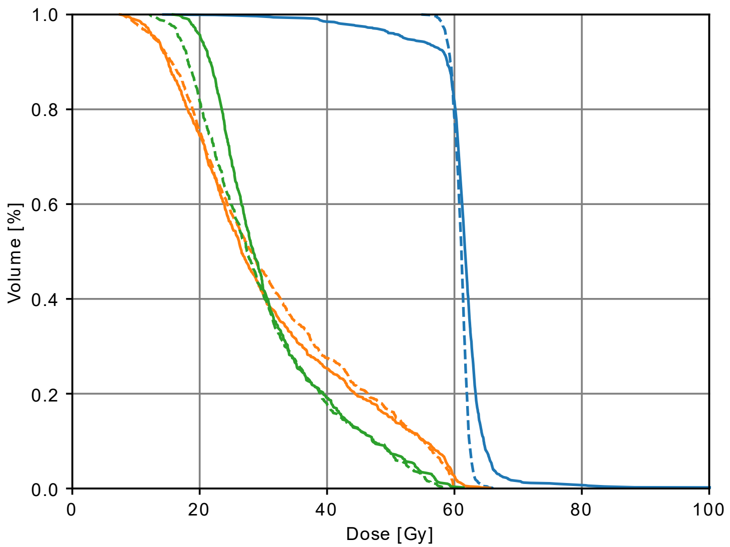
3D Dose Prediction with DVH information (bis)



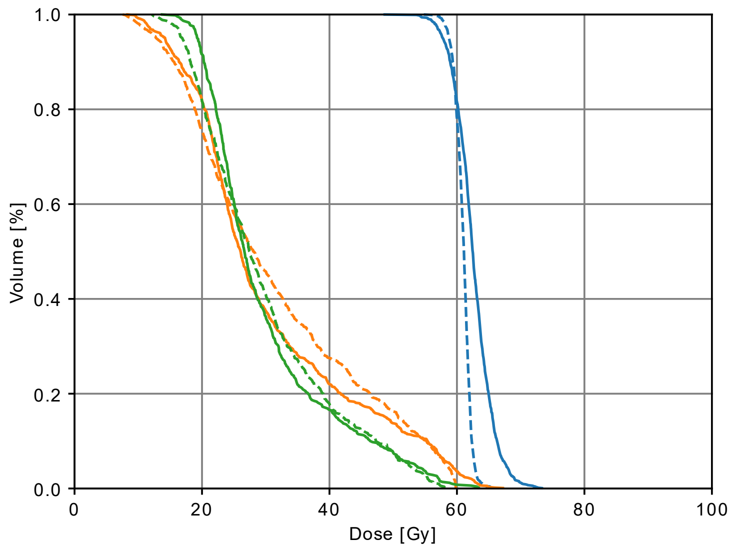
Model "DAFT All"

Performances comparison

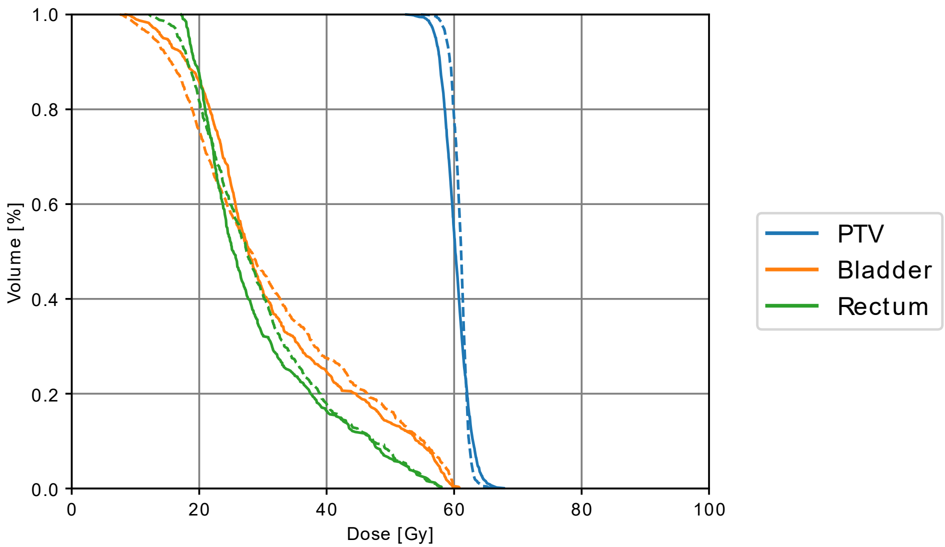
<u>Patient 1:</u> DVHs of the dose predicted by each model; dotted is clinical target dose.



"Classic"
(no DVH information)



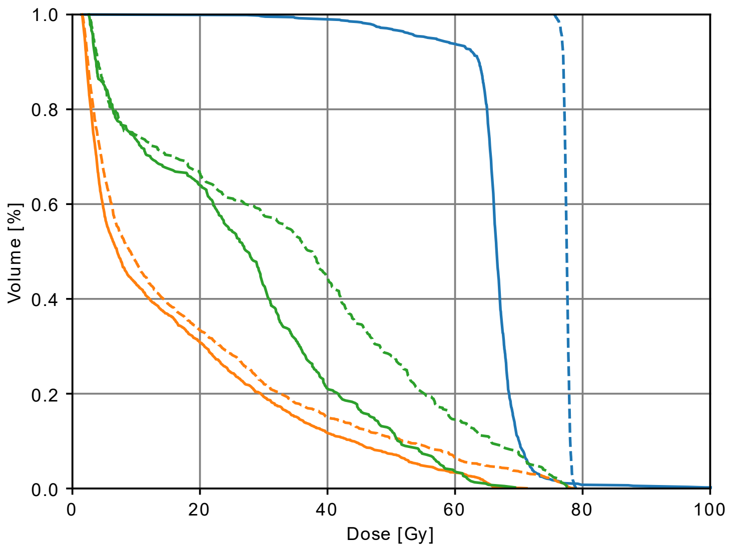
"DAFT Bottleneck"
(DVH information on bottleneck)



"DAFT All"
(DVH information on all connections)

Performances comparison

<u>Patient 2:</u> DVHs of the dose predicted by each model; dotted is clinical target dose.



“Classic”
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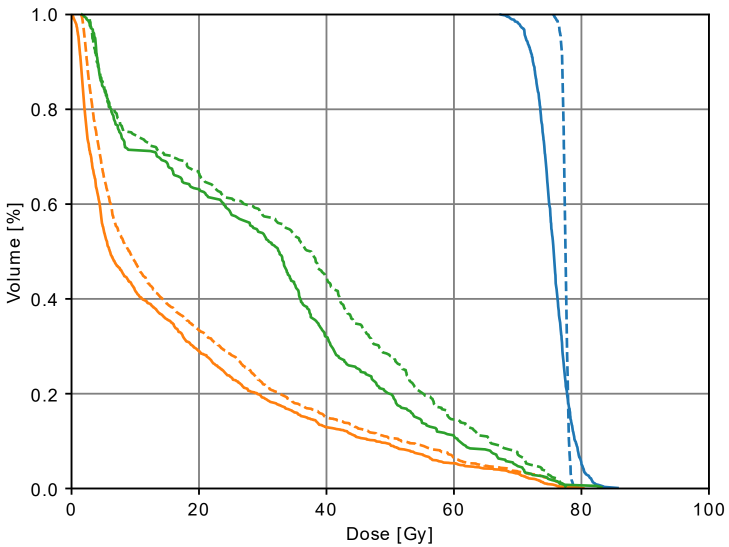

“DAFT Bottleneck”
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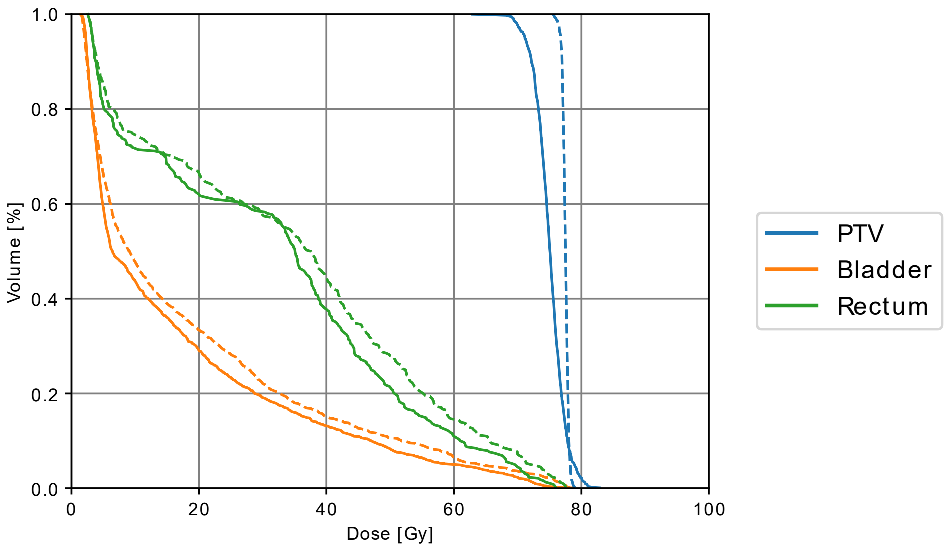
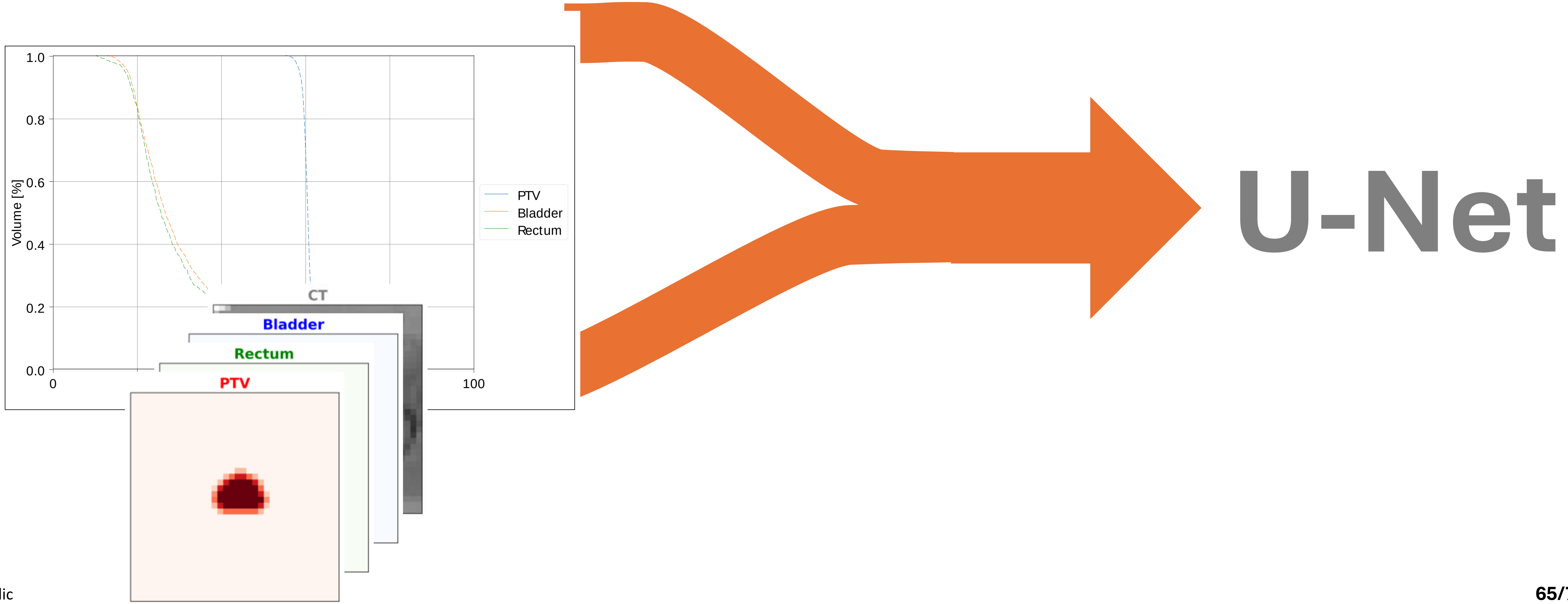
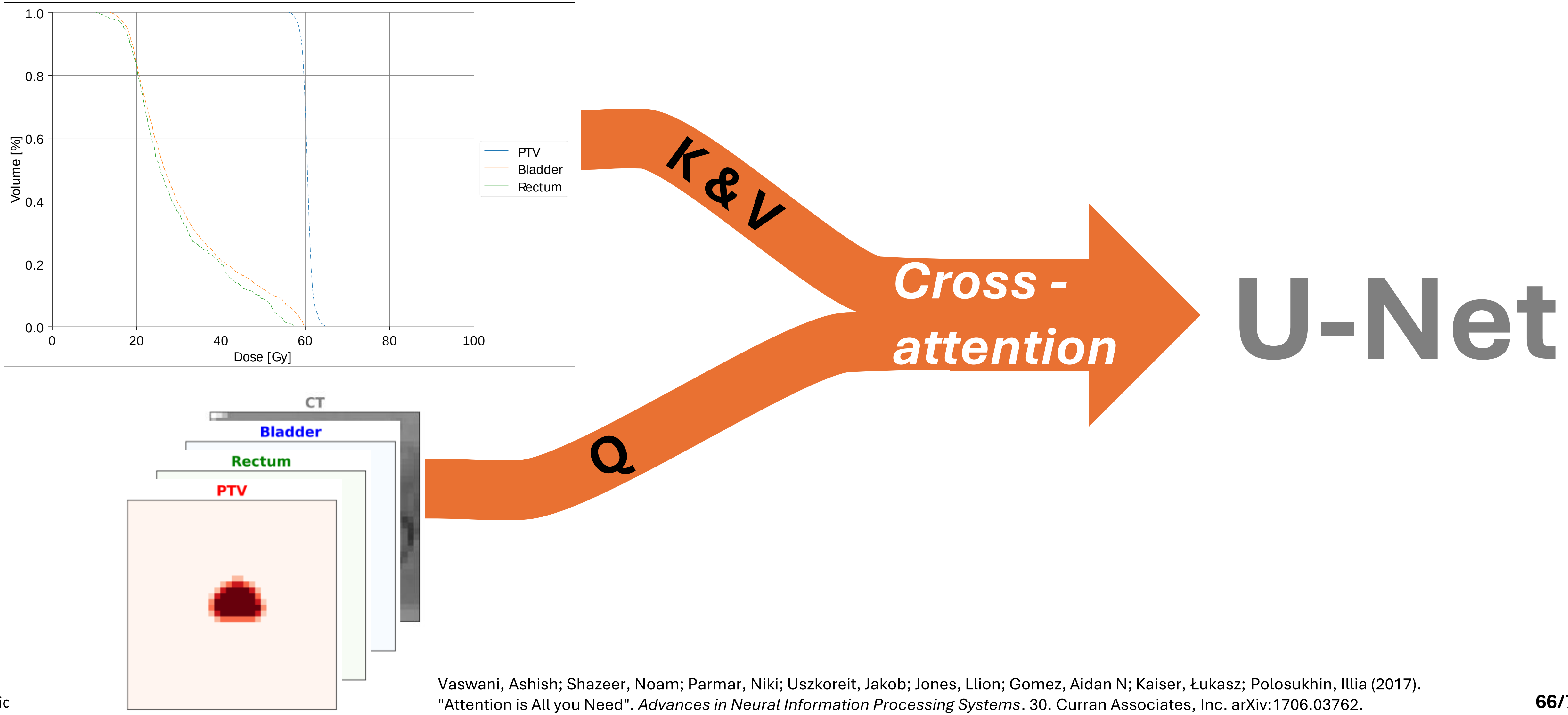


“DAFT All”
(DVH information on all connections)

Processing DVHs data better

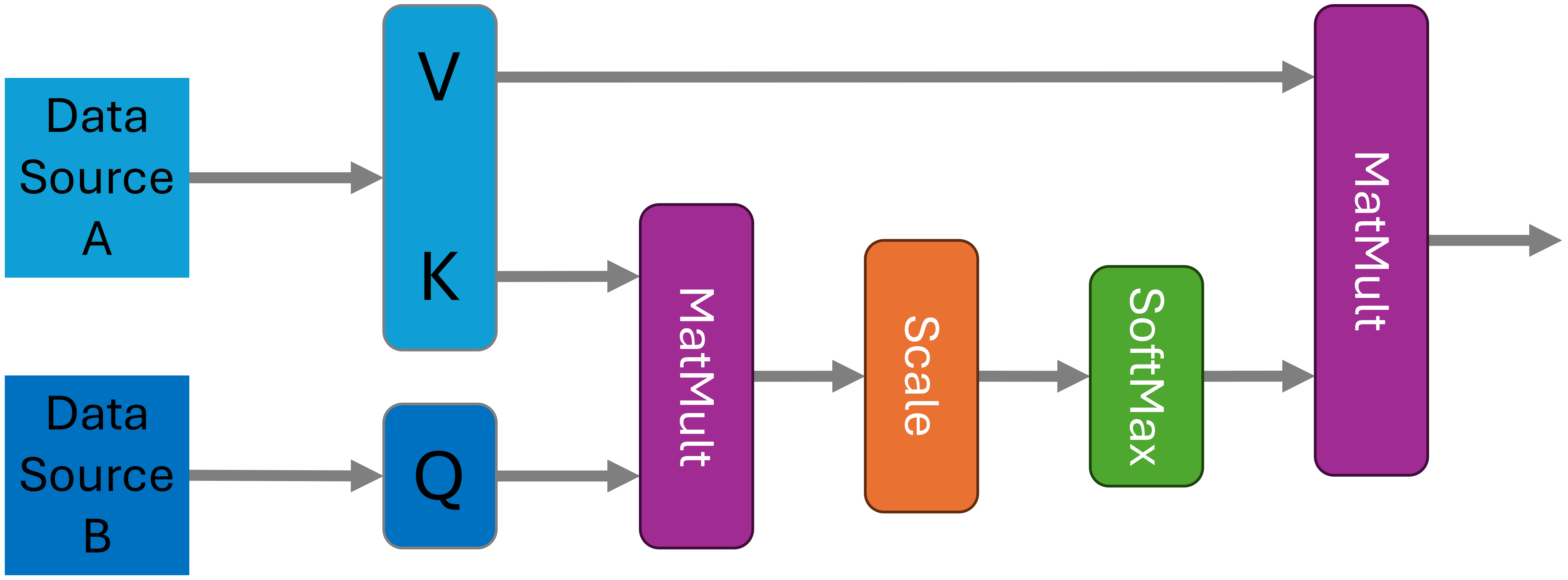


Processing DVHs data better



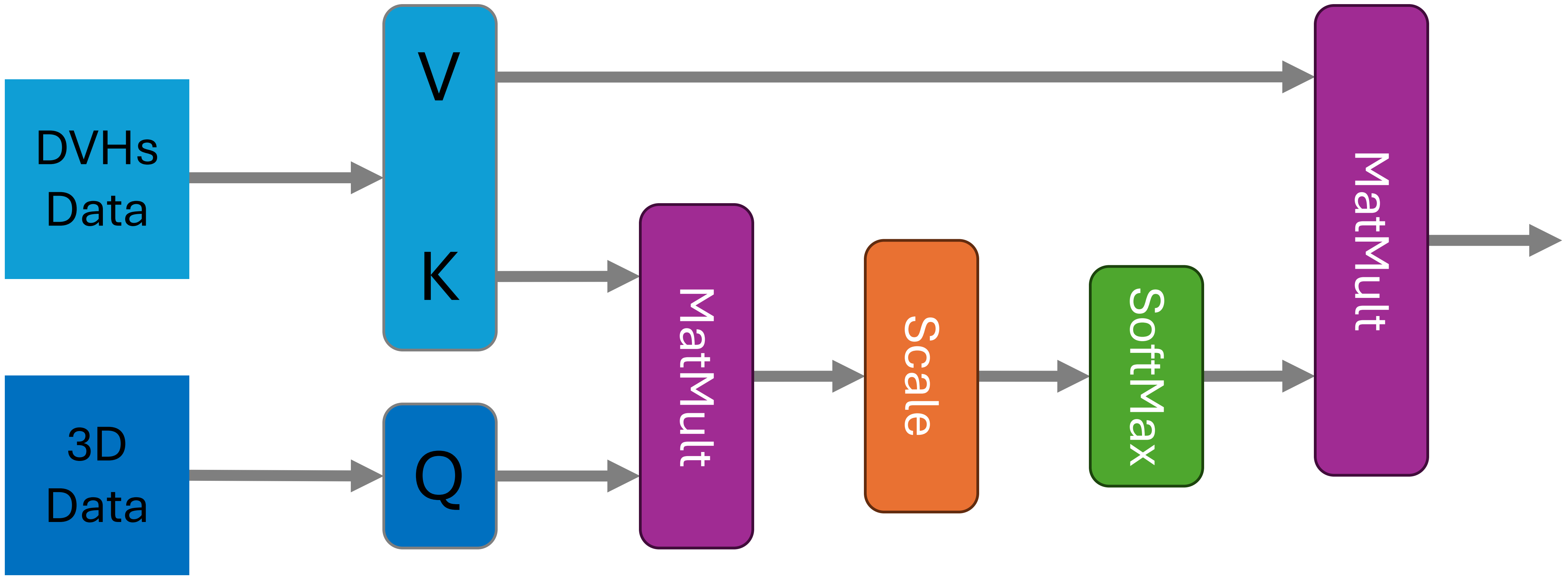
Vaswani, Ashish; Shazeer, Noam; Parmar, Niki; Uszkoreit, Jakob; Jones, Llion; Gomez, Aidan N; Kaiser, Łukasz; Polosukhin, Illia (2017). "Attention is All you Need". *Advances in Neural Information Processing Systems*. 30. Curran Associates, Inc. arXiv:1706.03762.

What is “Cross-Attention” ?



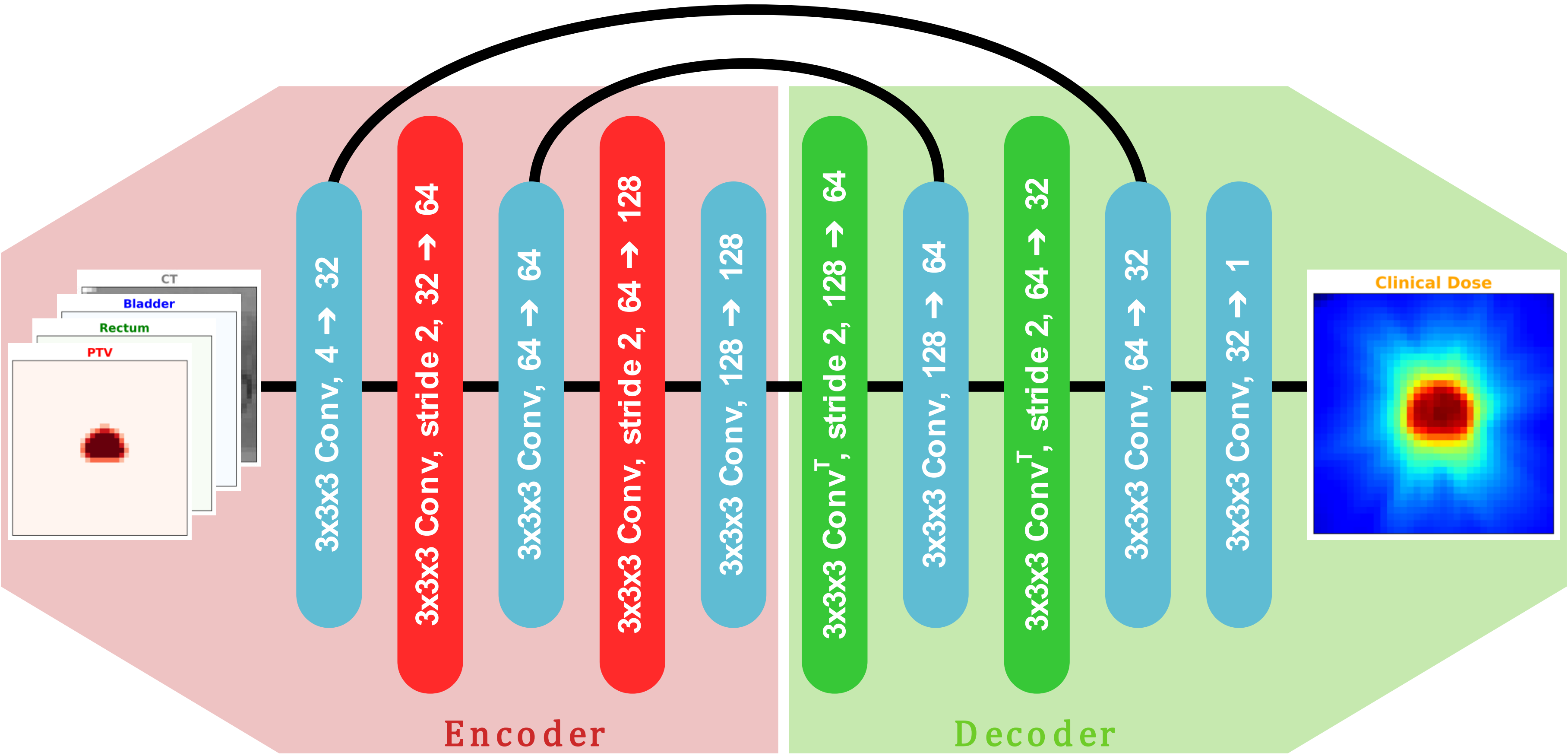
Vaswani, Ashish et al. "Attention is All you Need". *arXiv:1706.03762*.

Cross-Attention mixing DVHs & 3D data



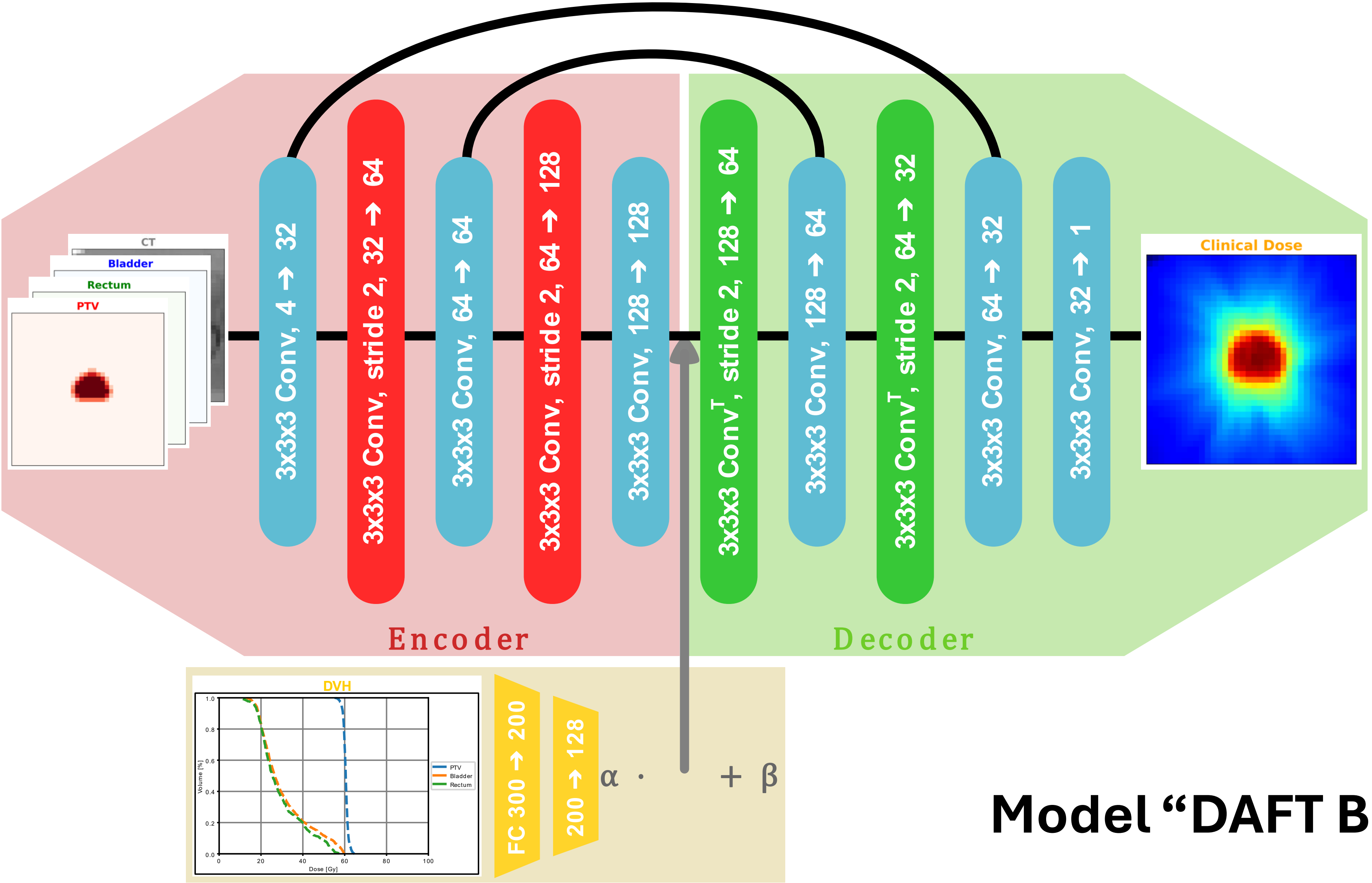
Vaswani, Ashish et al. "Attention is All you Need". *arXiv:1706.03762*.

3D Dose Prediction



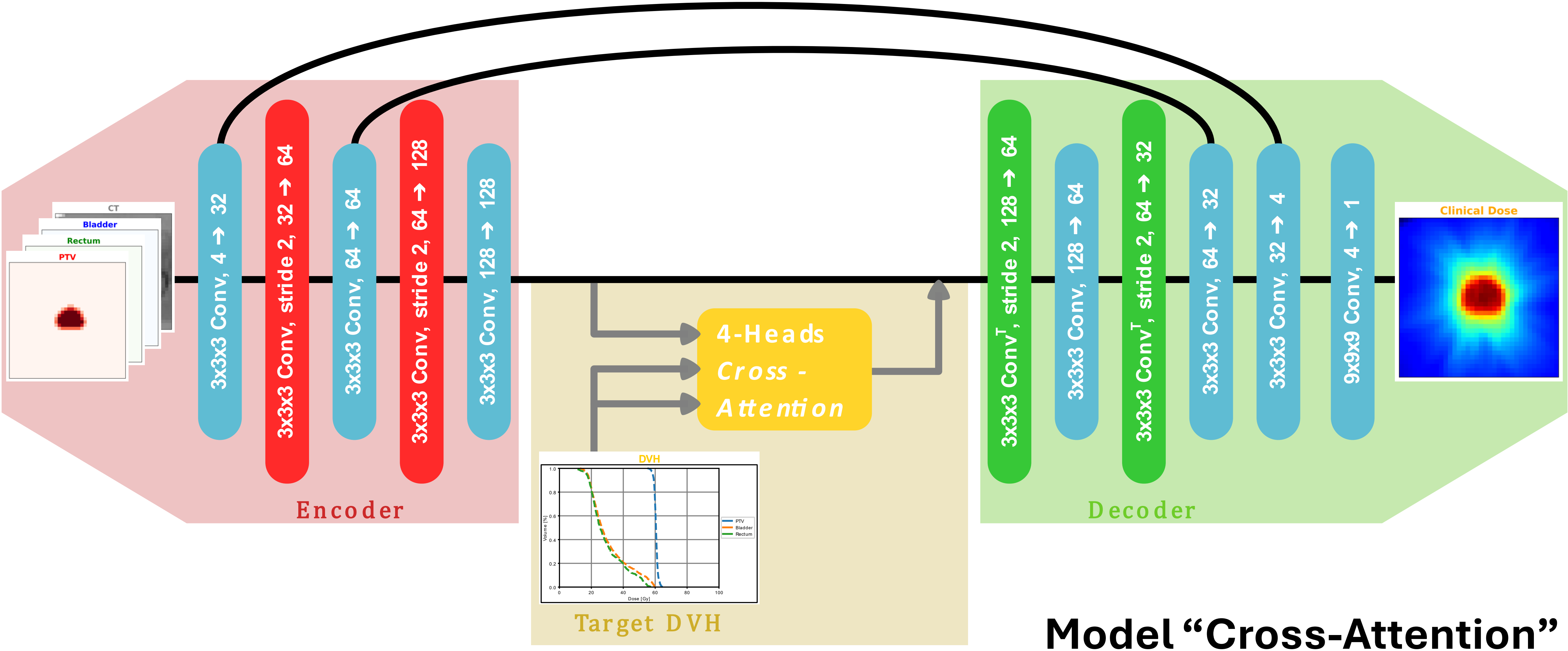
Model "Classic"

3D Dose Prediction with DVH information



Model "DAFT Bottleneck"

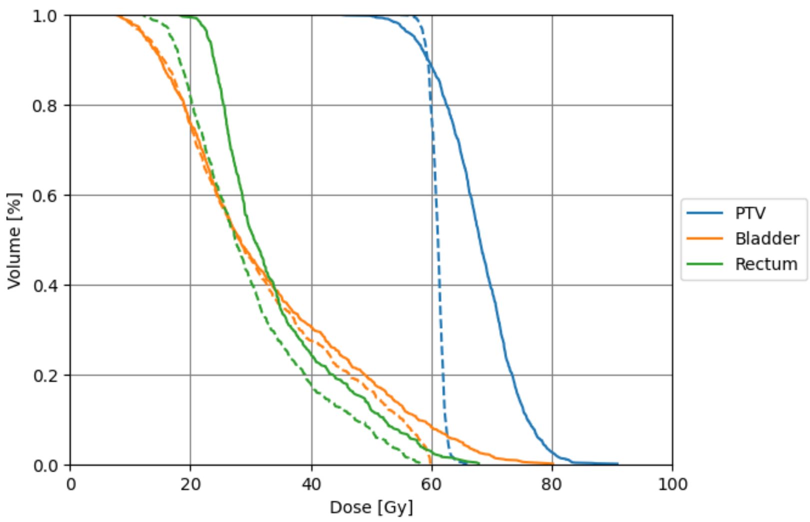
3D Dose Prediction with DVH information



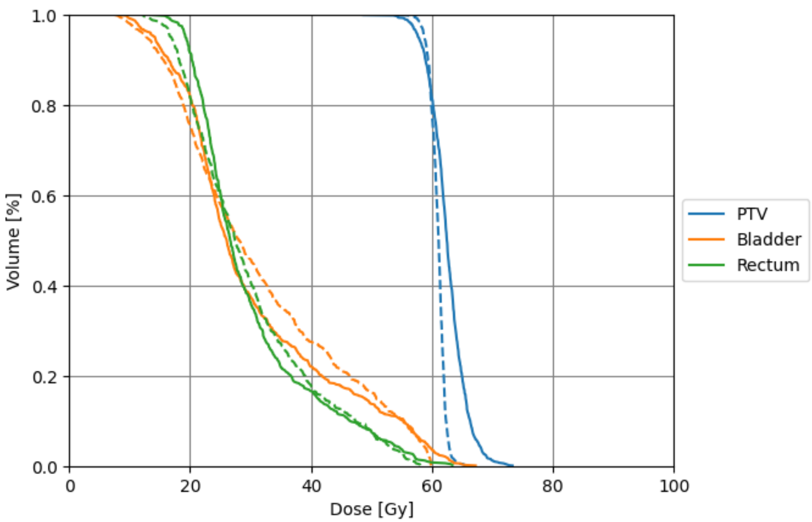
Model "Cross-Attention"

Results

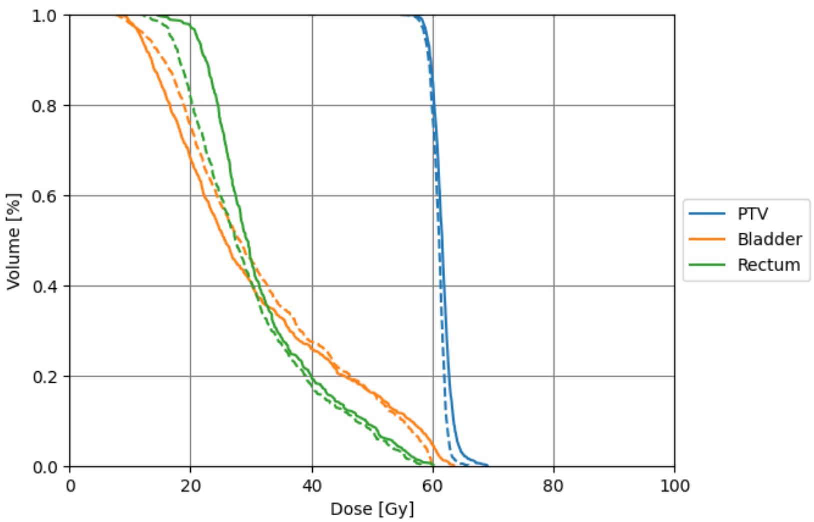
<u>Patient 1:</u> DVHs of the dose predicted by each model; dotted is clinical target dose.



"Classic"
(no DVH information)



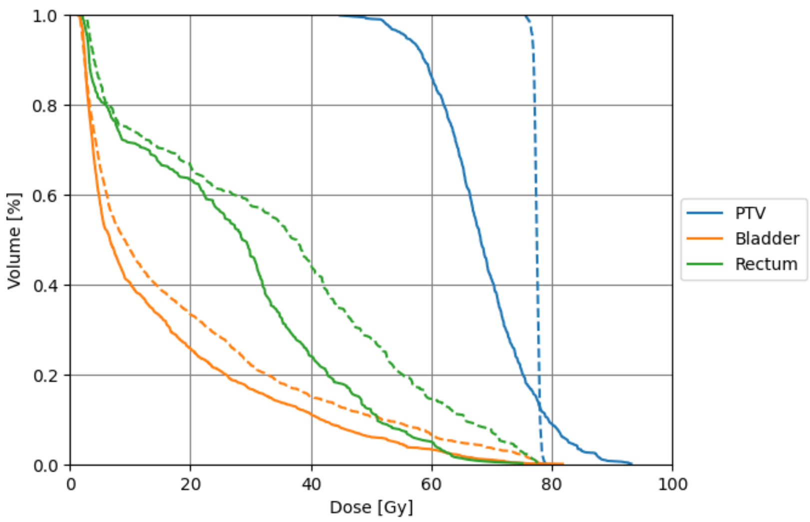
"DAFT Bottleneck"
(DVH information via DAFT)



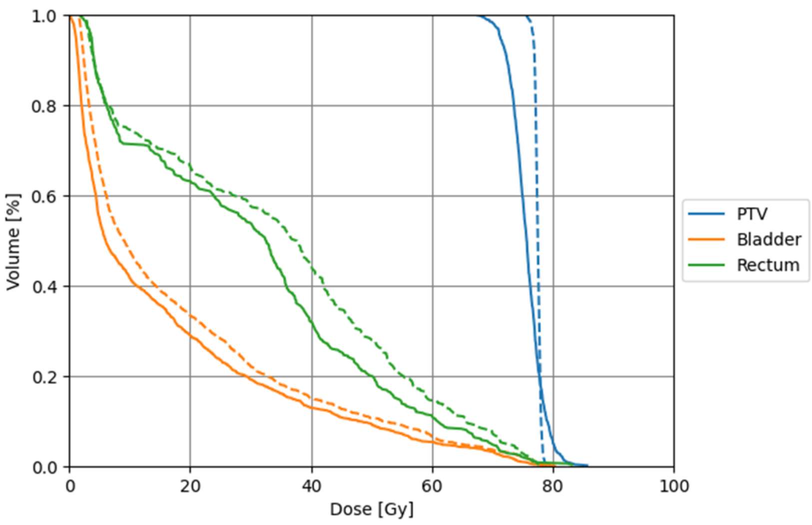
"Cross-Attention"
(DVH information via cross-attention)

Results (bis)

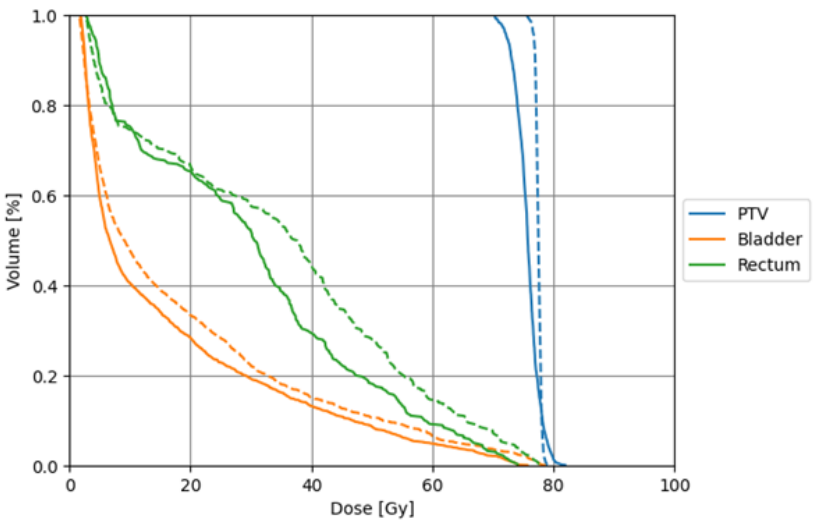
<u>Patient 2:</u> DVHs of the dose predicted by each model; dotted is clinical target dose.



"Classic"
(no DVH information)



"DAFT Bottleneck"
(DVH information via DAFT)



"Cross-Attention"
(DVH information via cross-attention)

Performance Comparison of the Models

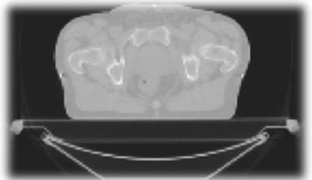
Model	**N°1 (No DVH)**	**N°2 (DAFT Bottleneck)**	**N°3 (Cross-Attention)**
3D dose MAE	3.093 Gy	2.254 Gy	2.210 Gy
DVH MAE	1.942 Gy	1.051 Gy	0.930 Gy

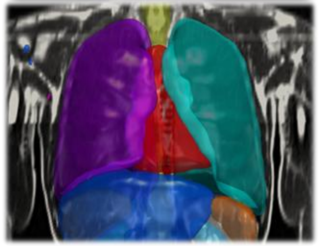
Performances of the models on two metrics of interest

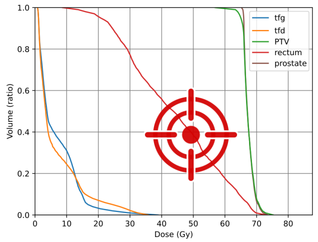
Dose prediction & mimicking

Adjustable
1-click solution

Patient data
- CT scan
- OARs & PTVs contours
- Target DVH







3D dose prediction

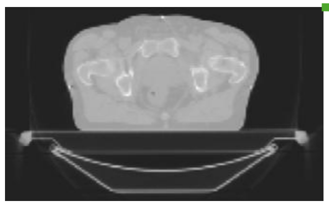
Dose mimicking Engine

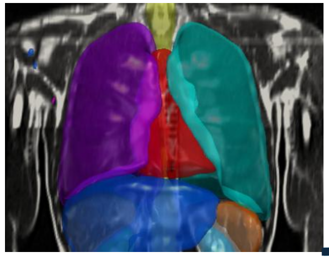
Learning based on previous cases

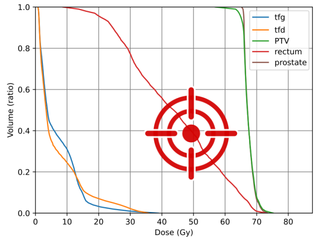
Treatment plan
- Fluences
- Leaf motions

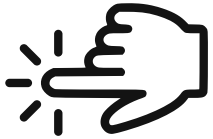
Summary

Structure	Constraint
Rectum	$D_{1\%} < 76\ Gy$
Rectum	$D_{25\%} < 72\ Gy$
Rectum	$D_{50\%} < 60\ Gy$
Bladder	$D_{1\%} < 80\ Gy$
Bladder	$D_{25\%} < 74\ Gy$







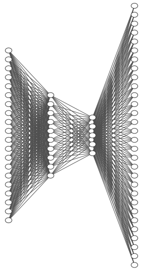


Manual dosimetry

N-clicks solution

Graph based technique

3-clicks solution



Reinforcement Learning

1-click solution

Target DVH

Adjustable
1-click solution

Acknowledgements

Prof. Nikos Paragios
Prof. Paul-Henry Cournède

Prof. David Azria
Prof. Daniela Thorwarth
Prof. Vincent Lepetit
Dr. Pascal Fenoglietto

List of Contributions

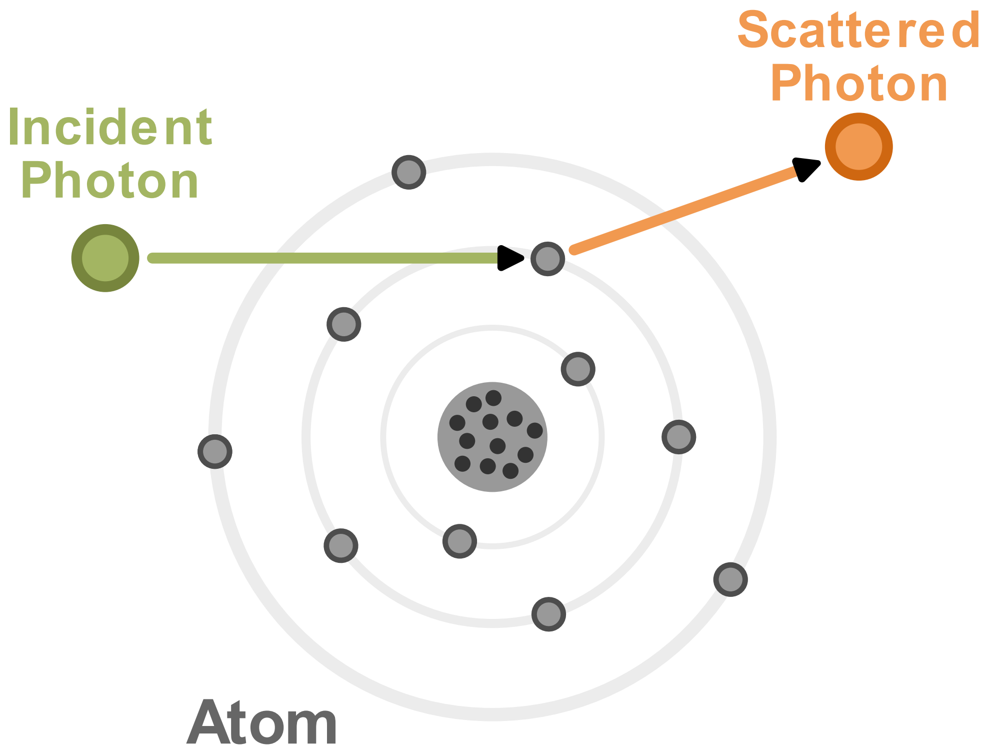
1. Novel Framework for Multi-Objective Optimization and Robust Plan Selection Using Graph Theory, *European Society for Radiotherapy and Oncology (ESTRO)*
2. Radiotherapy Dose Optimization via Clinical Knowledge Based Reinforcement Learning, *Artificial Intelligence in Medicine (AIME)*
3. Clinically Dependent Fully Automatic Treatment Planning System, *American Society for Radiation Oncology (ASTRO)*
4. Dose Volume Histograms Guided Deep Dose Predictions, *Société Française de Physique Médicale (SFPM)*
5. Attention mechanism on dose-volume histograms for deep dose predictions, *Société Française de Radio Oncologie (SFRO)*

Appendix

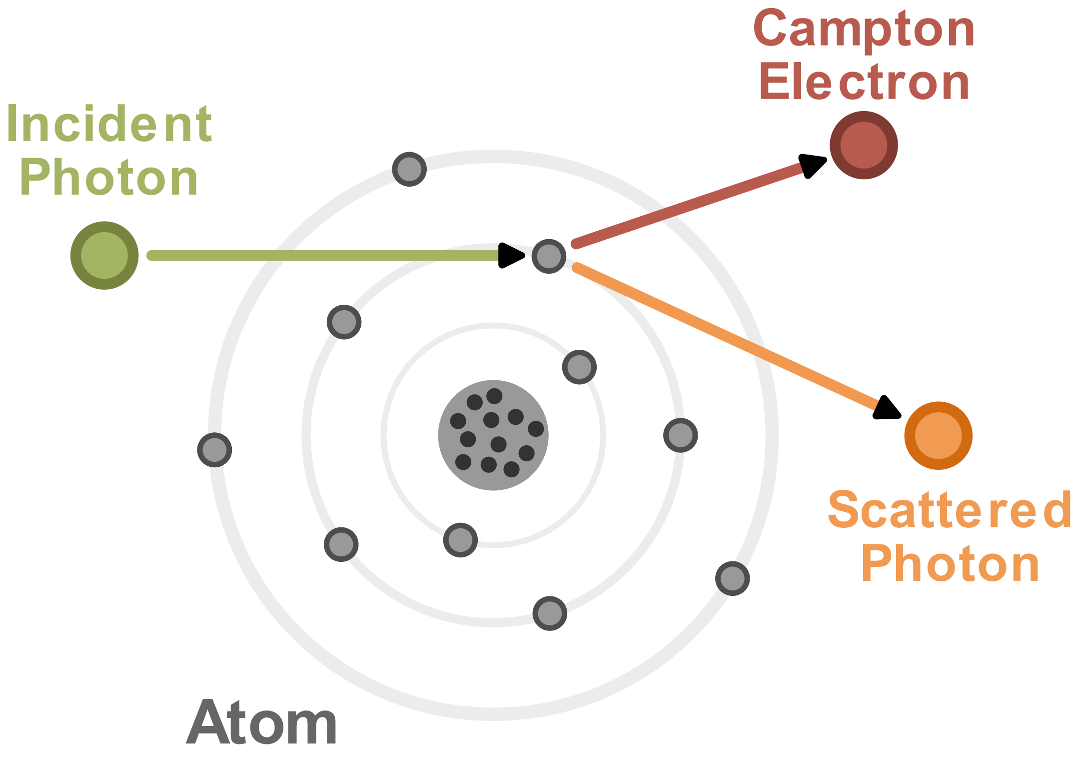
Extra material

Photon interactions with matter (1/2)

Rayleigh Diffusion



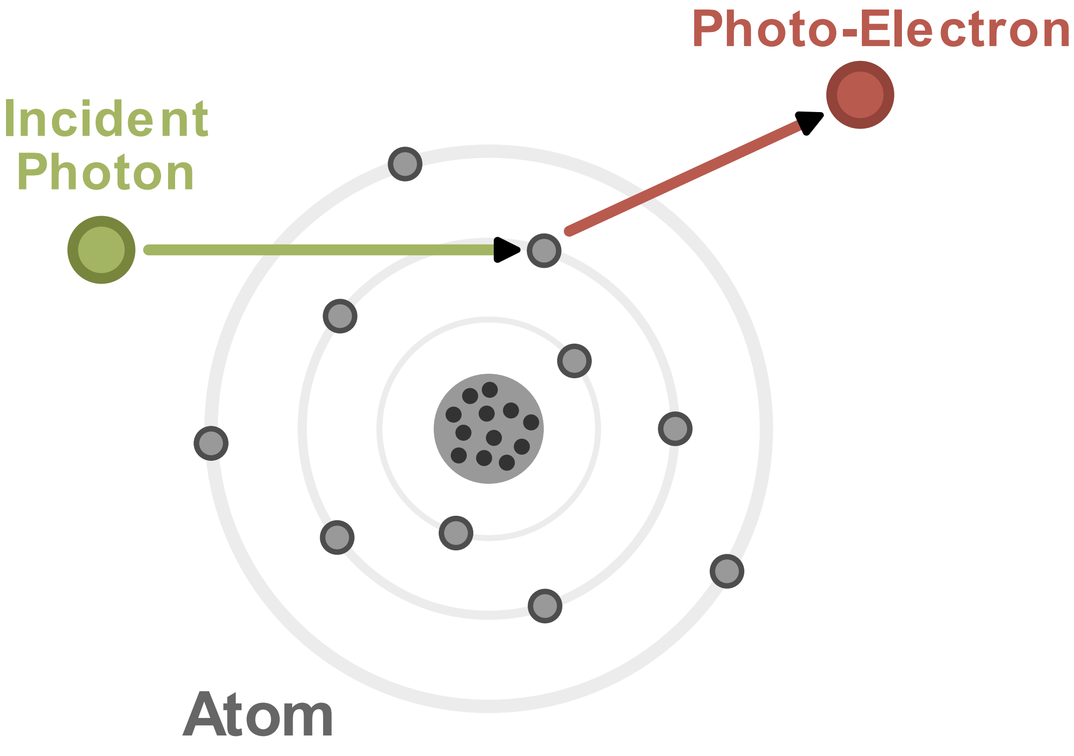
Campton Scattering



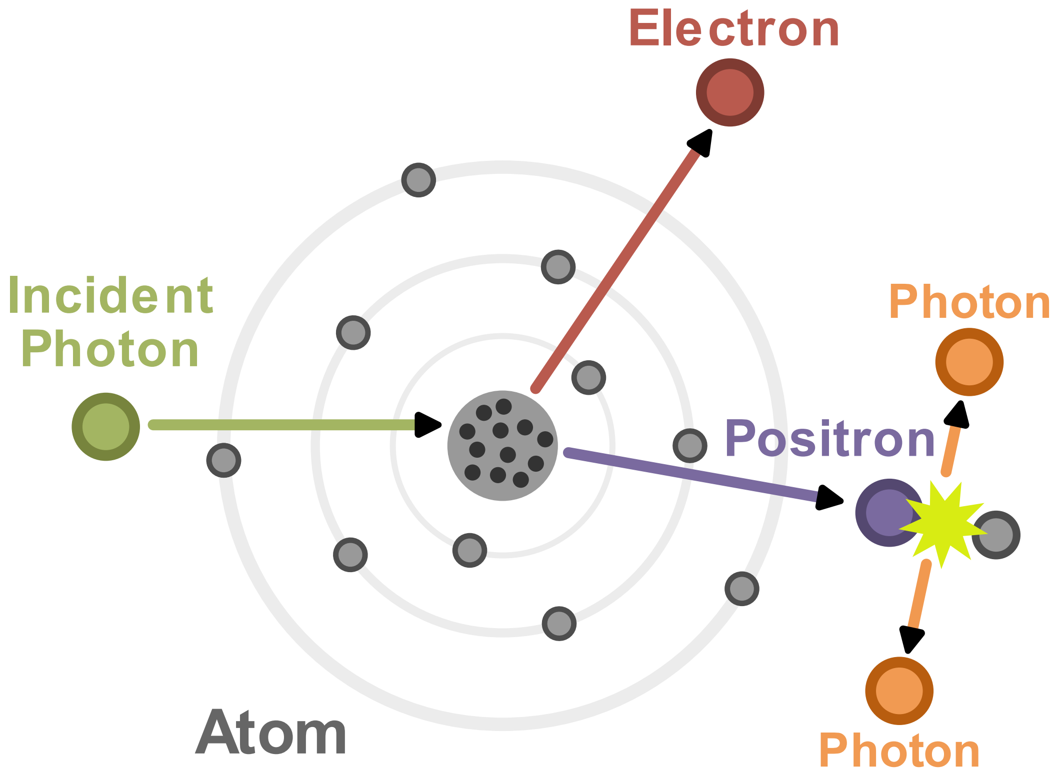
Robley D. Evans. Compton Effect, pages 218–298. Springer Berlin Heidelberg, Berlin, Heidelberg, 1958

Photon interactions with matter (2/2)

Photoelectric Absorption

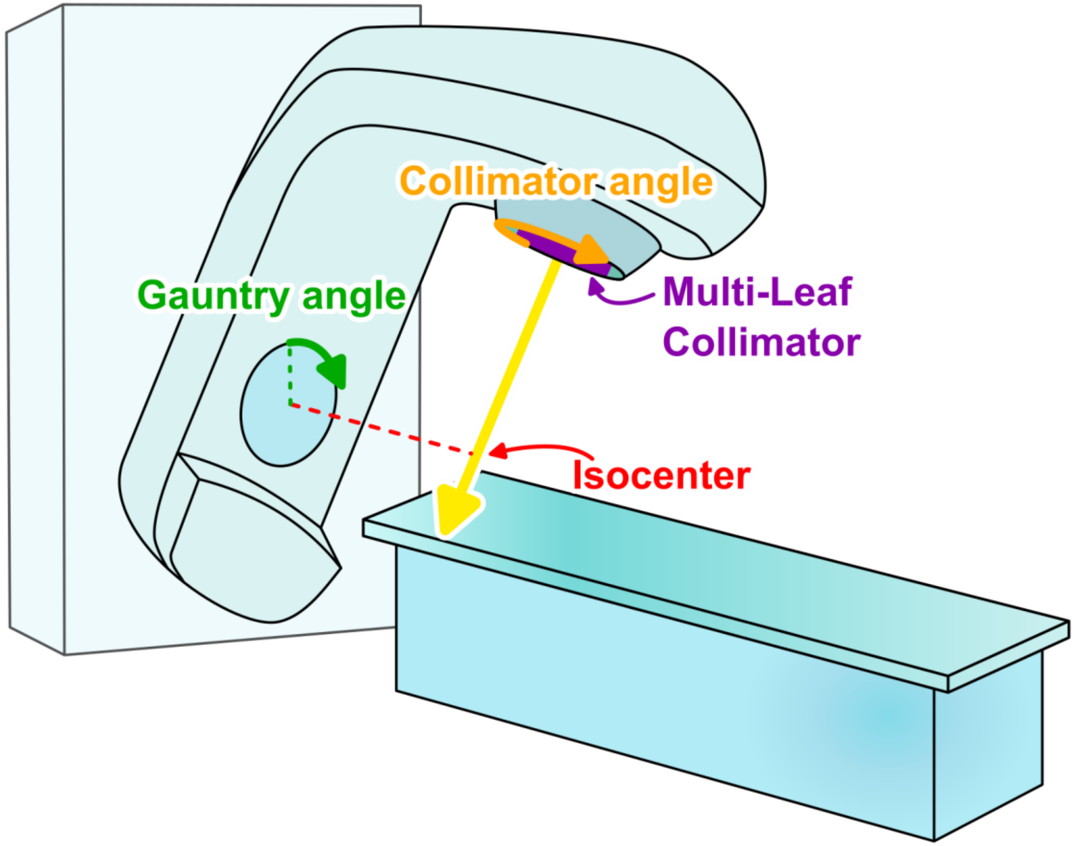


Pair Production

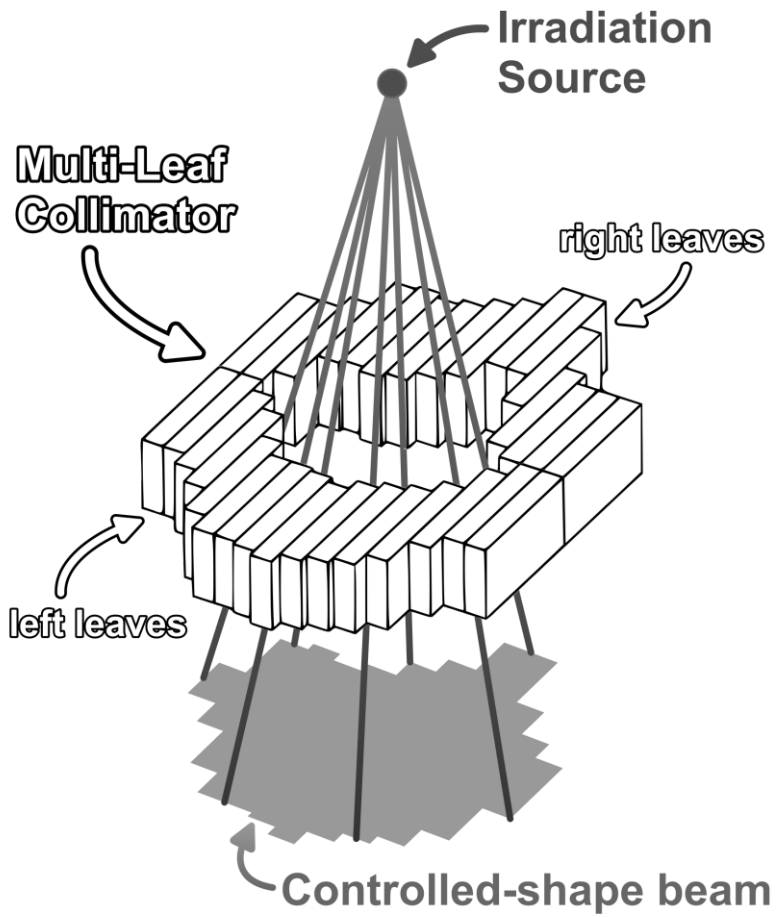


Robley D. Evans. Compton Effect, pages 218–298. Springer Berlin Heidelberg, Berlin, Heidelberg, 1958

MLC-LINAC

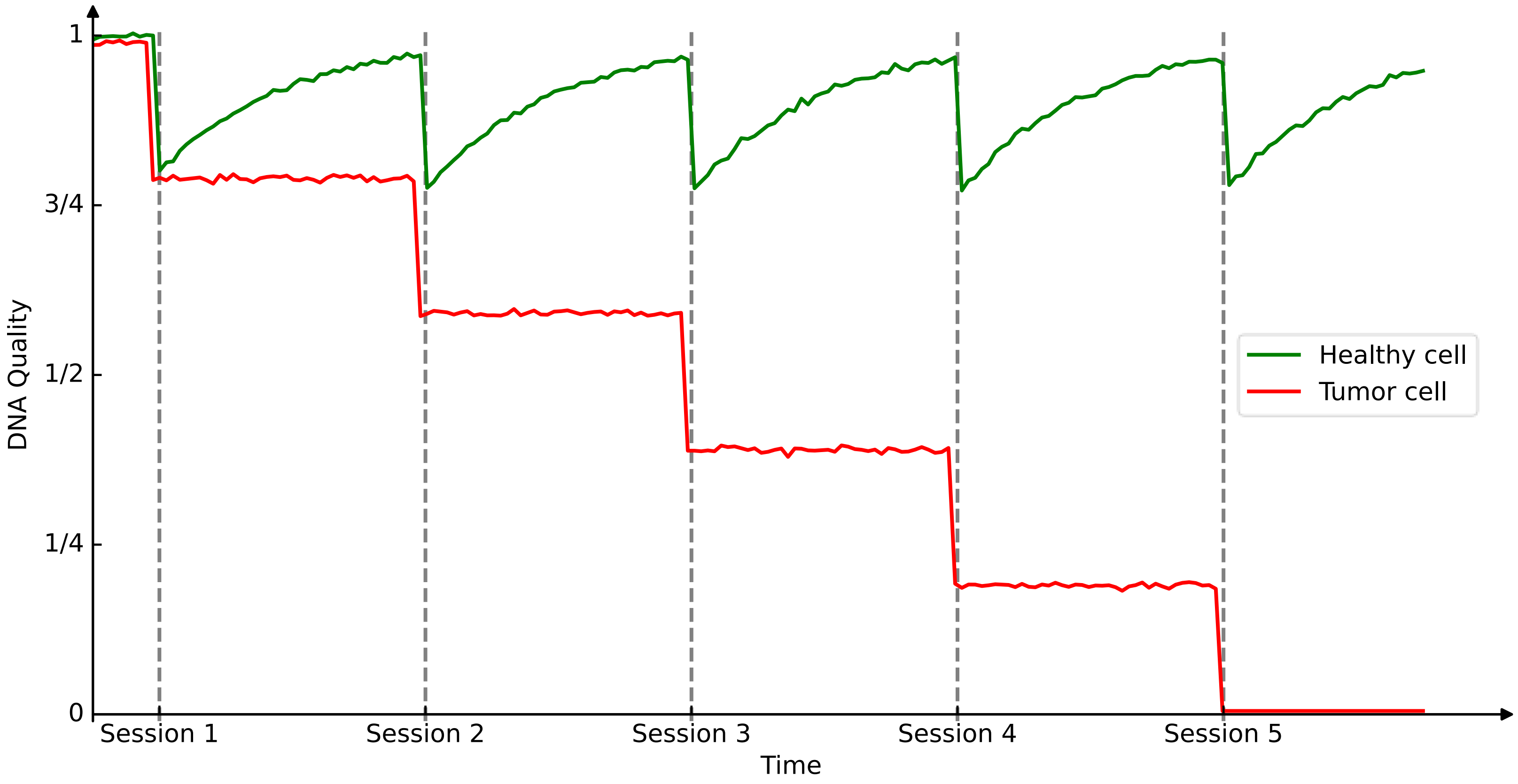


Collimator angle
Gauntry angle
Multi-Leaf
Collimator
Isocenter



Irradiation
Source
Multi-Leaf
Collimator
right leaves
left leaves
Controlled-shape beam

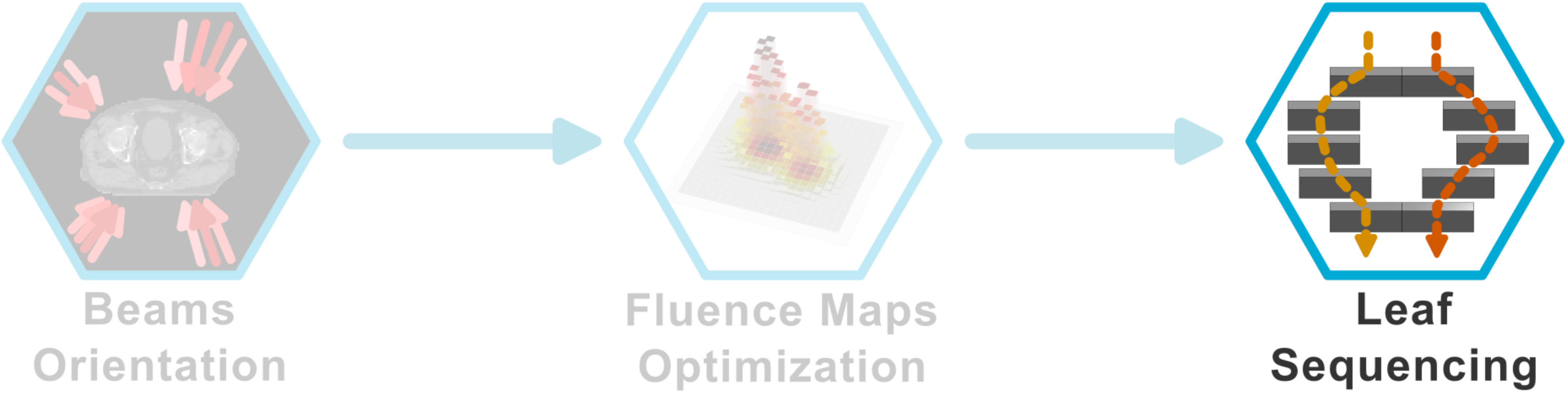
Resilient nature of healthy cells



Quality of the DNA in healthy and tumor cell after radiotherapy sessions.

Hubenak et al. Mechanisms of injury to normal tissue after radiotherapy: a review. *Plast Reconstr Surg*. 2014 Jan;133(1):49e-56e. doi: 10.1097/01.prs.0000440818.23647.0b.

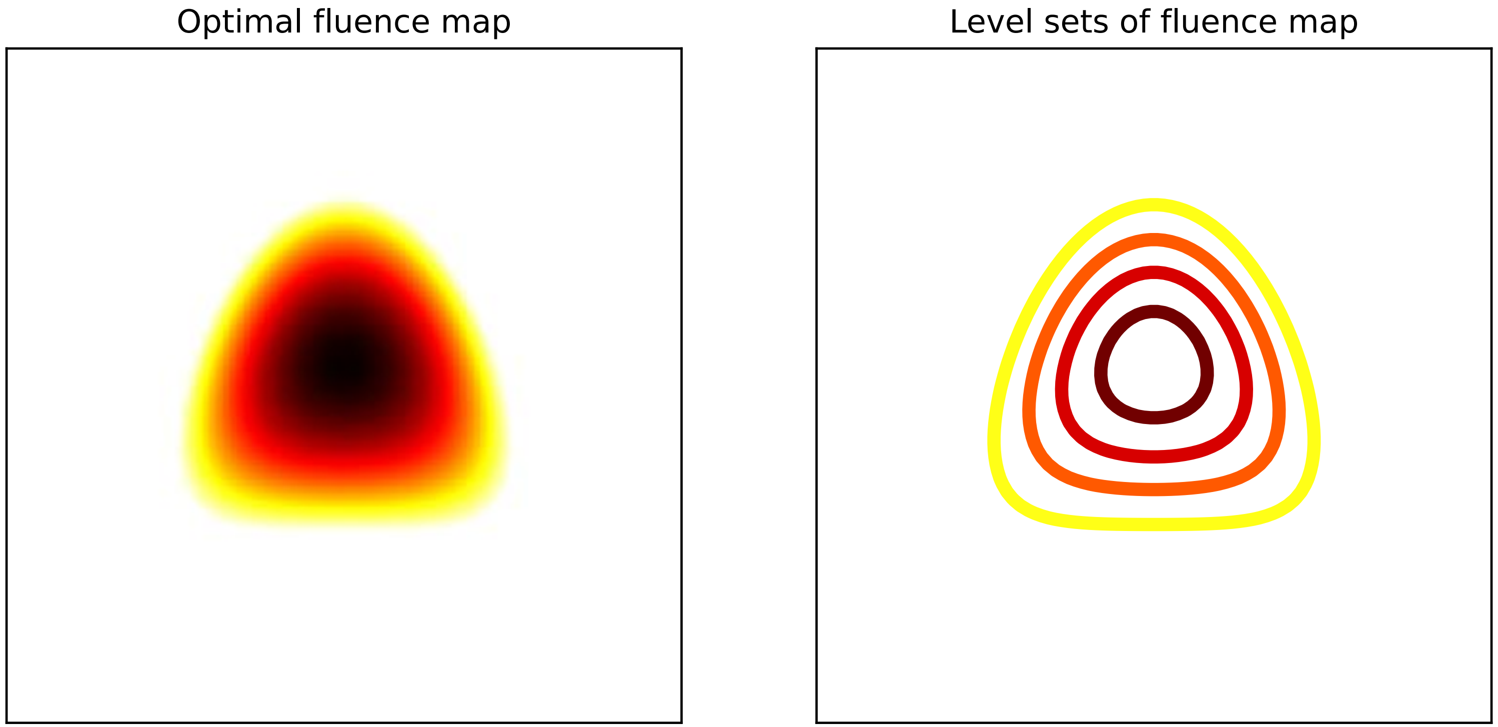
V



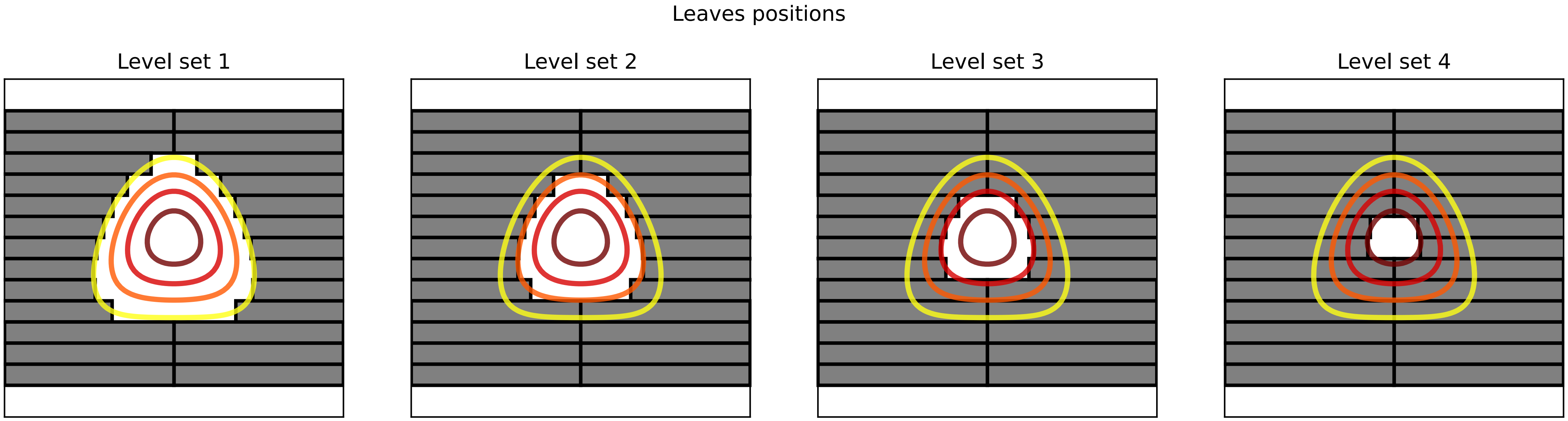
Level-set matching

A naive algorithm

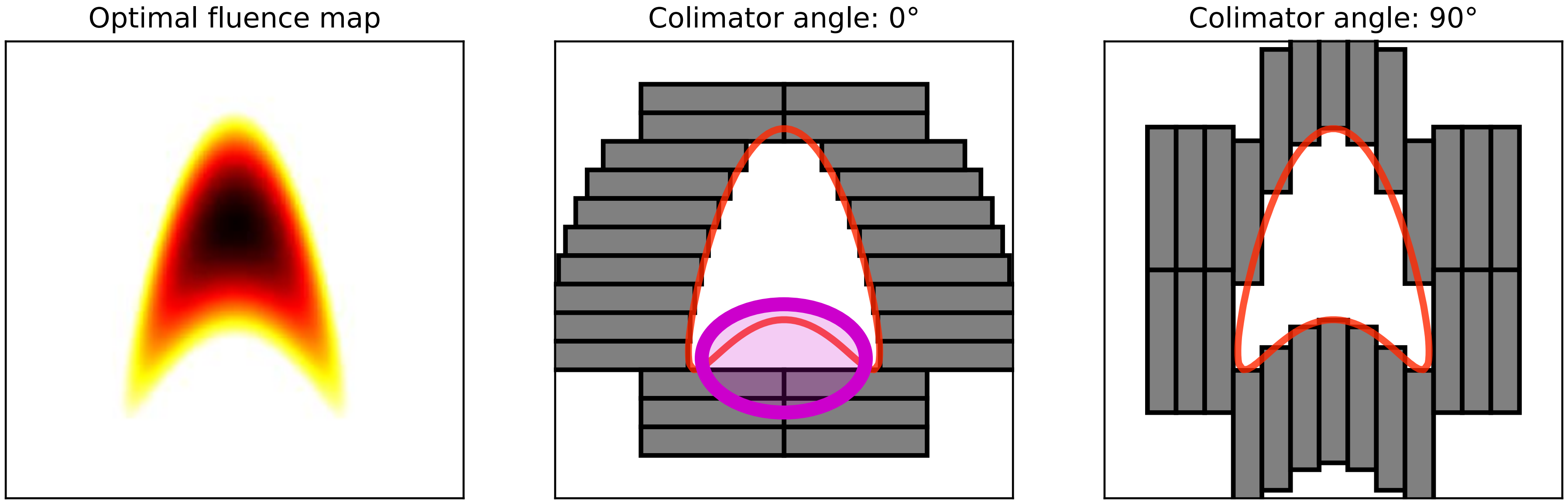
Fluence map discretization



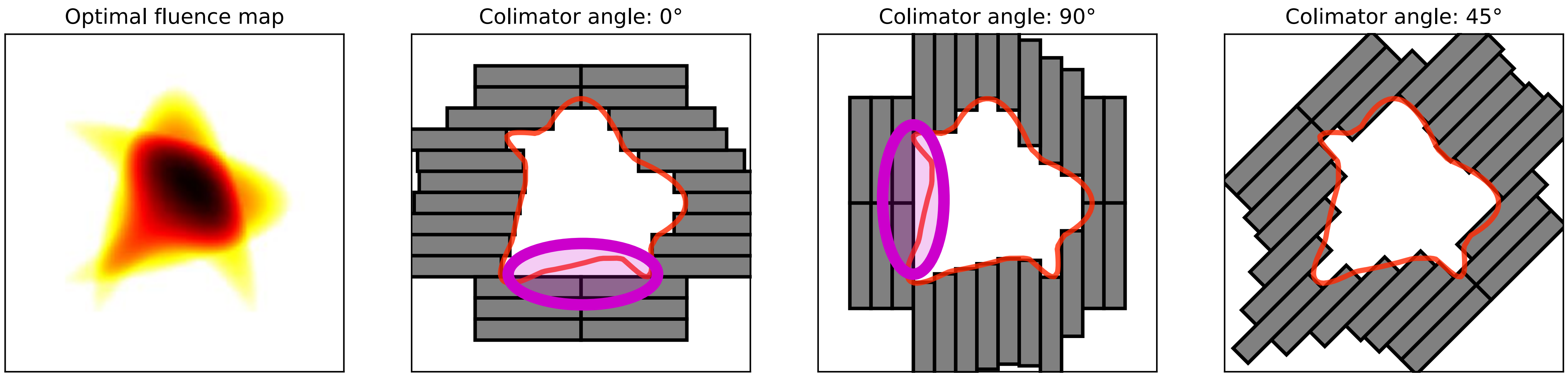
Level sets matching with leaves



Concave level sets matched with leaves

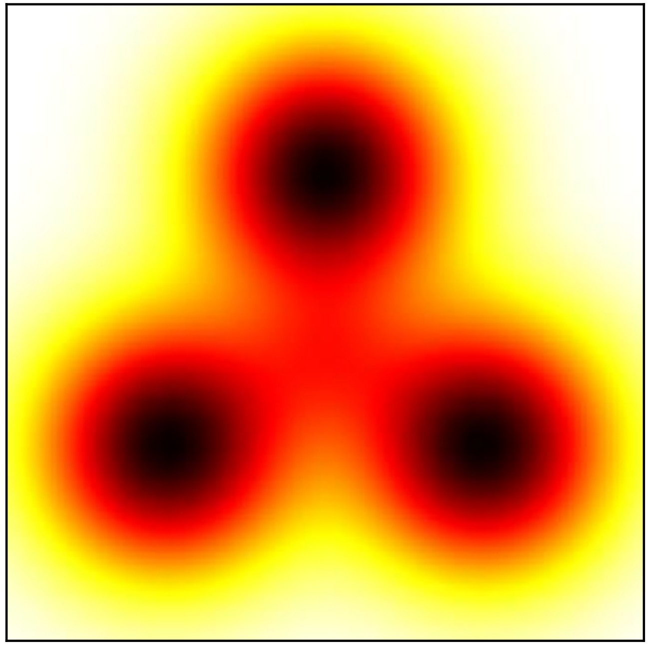


Concave level sets matched with leaves (bis)

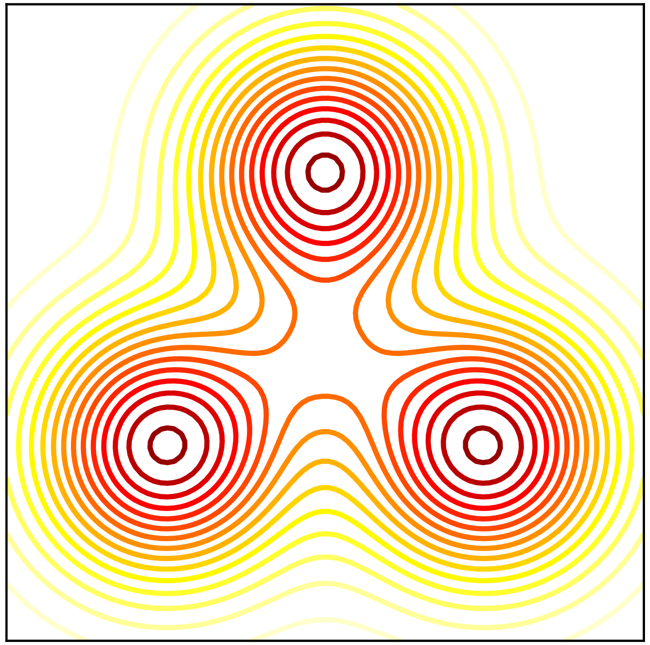


More complex fluence map

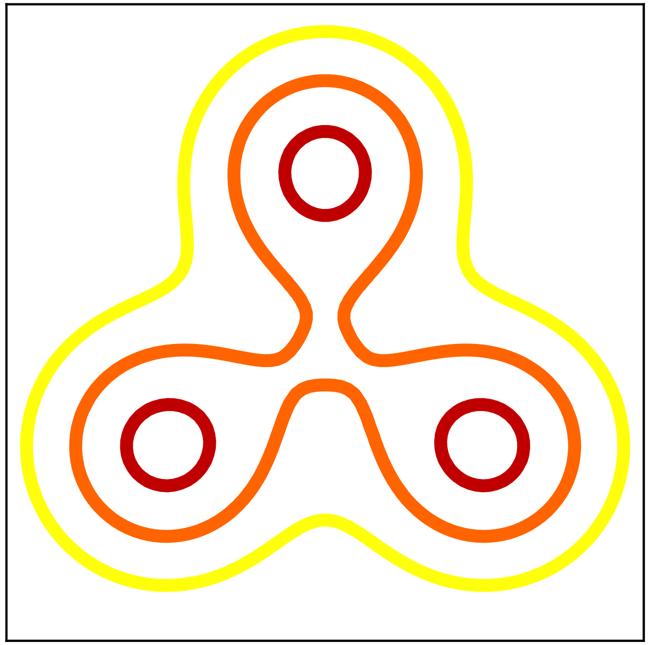
Optimal fluence map



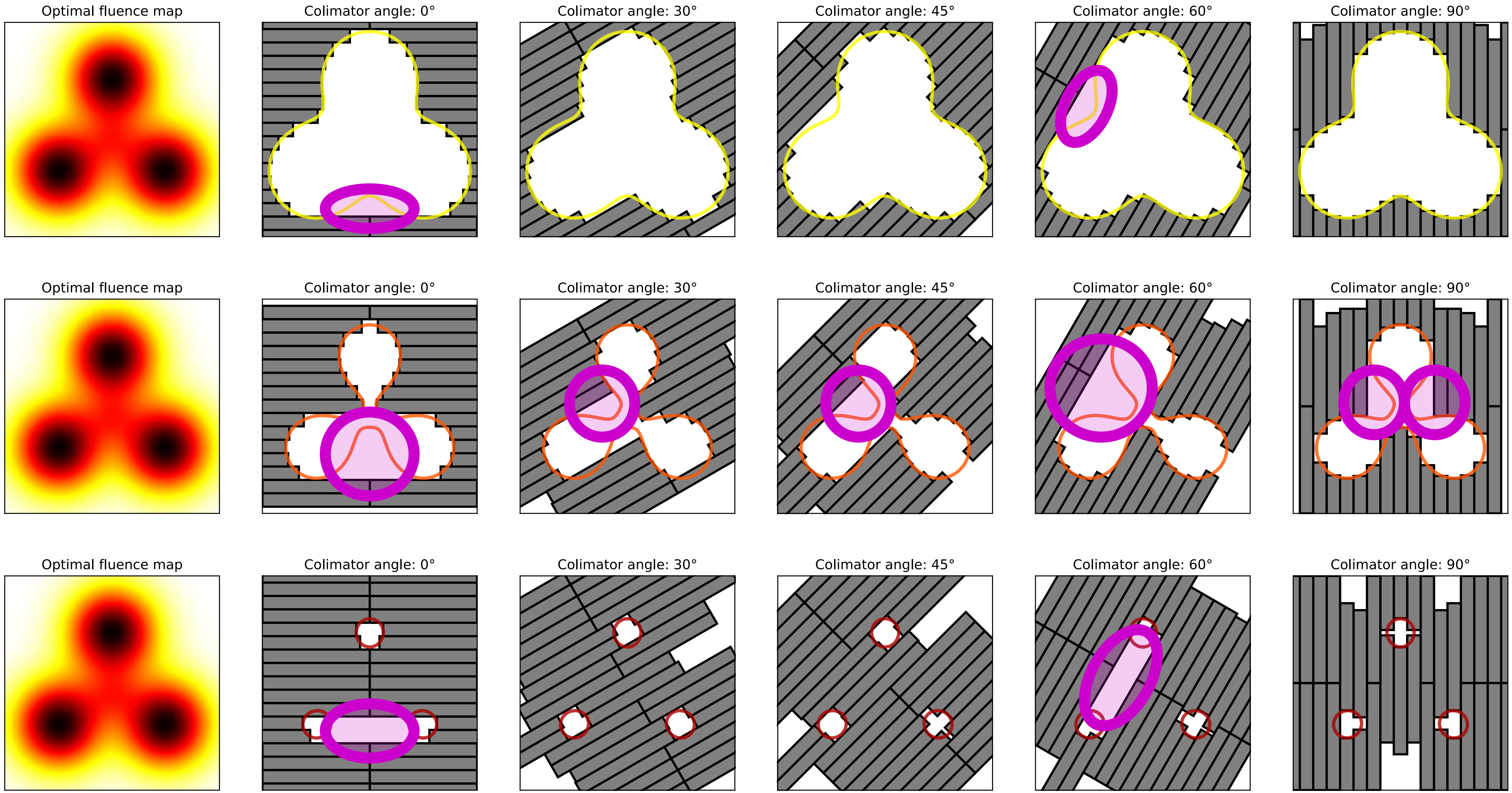
Level sets of the fluence map



Problematic level set of the fluence map



Level sets impossible to match with leaves

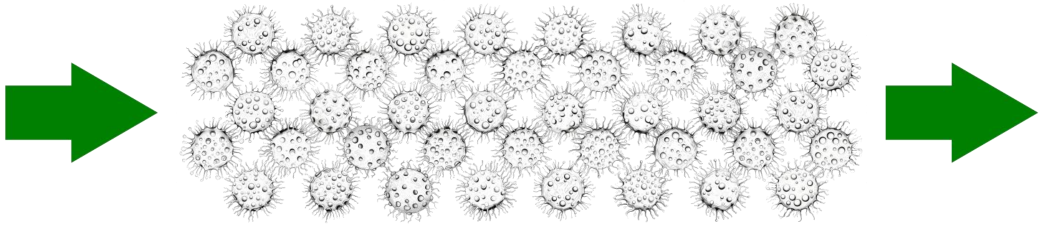


Sliding Window algorithm demo

https://mics-lab.github.io/PresentationJuin2023PRFD/demo

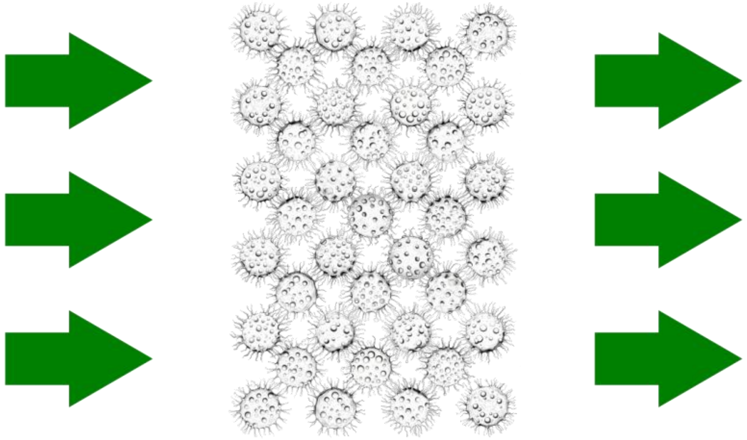
Organ functioning types

Serial-like



e.g.: spinal cord or oesophagus

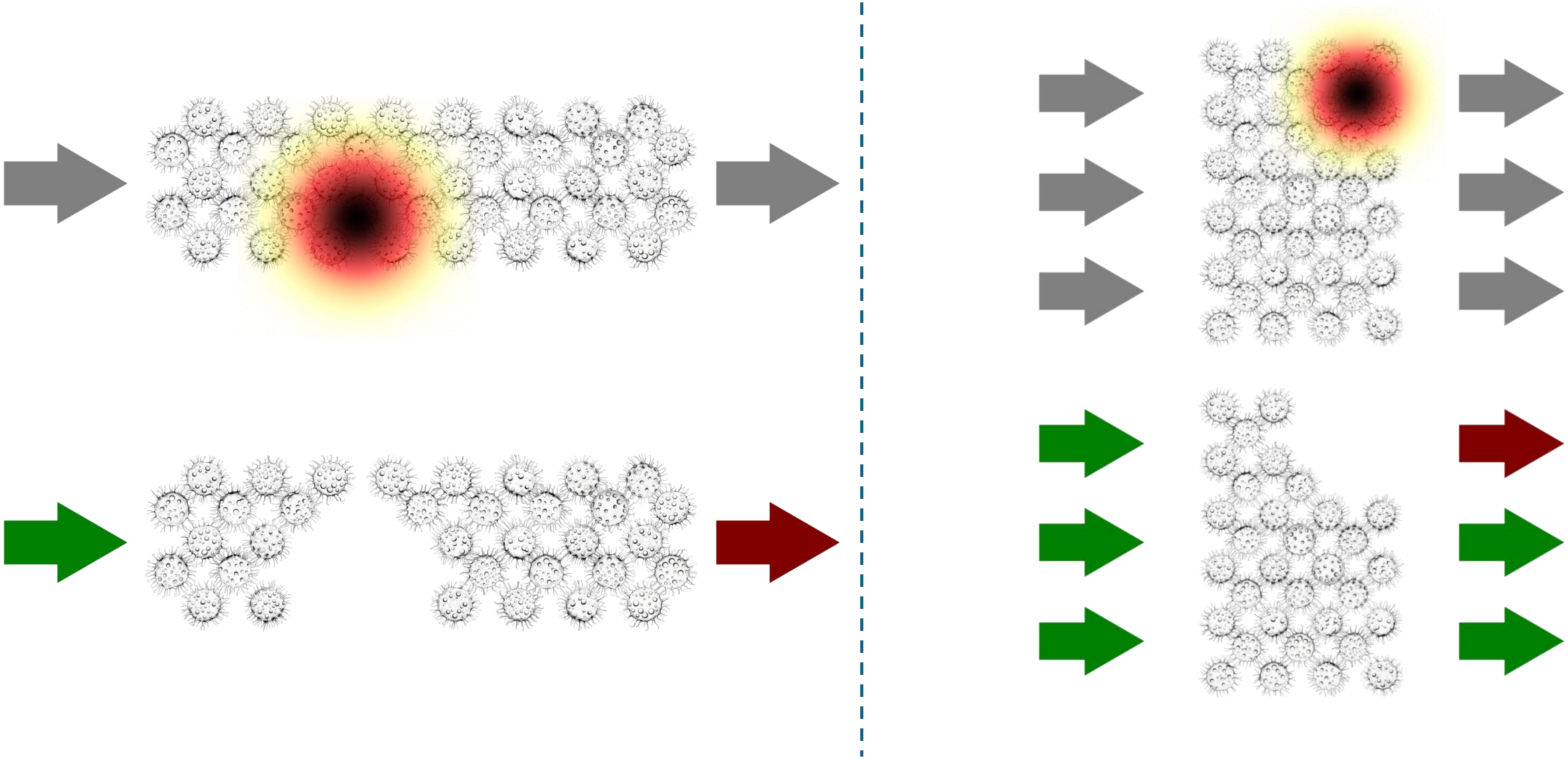
Parallel-like



e.g.: lung or liver

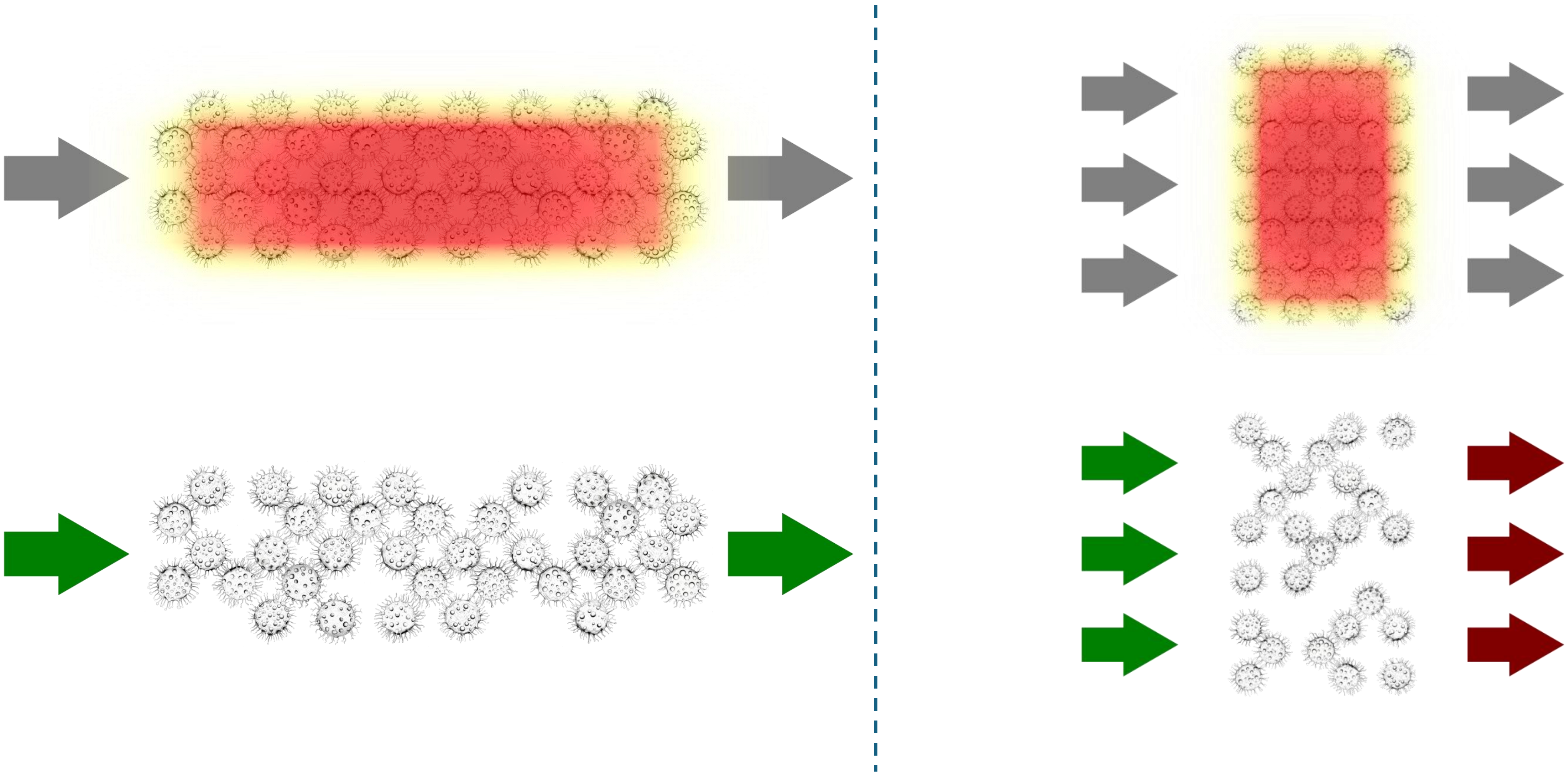
Organ irradiation tolerance

hot point



Organ irradiation tolerance

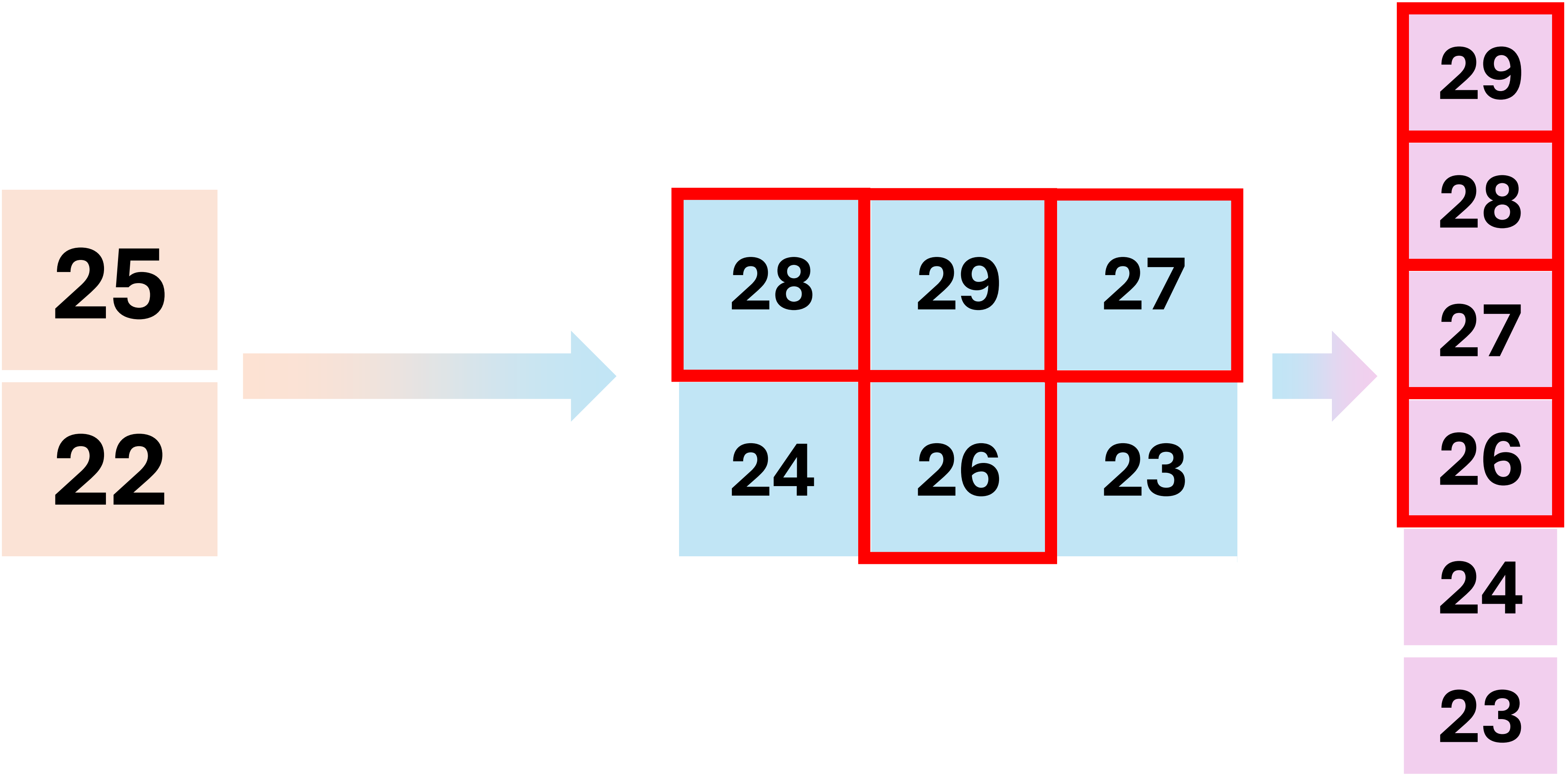
warm zone



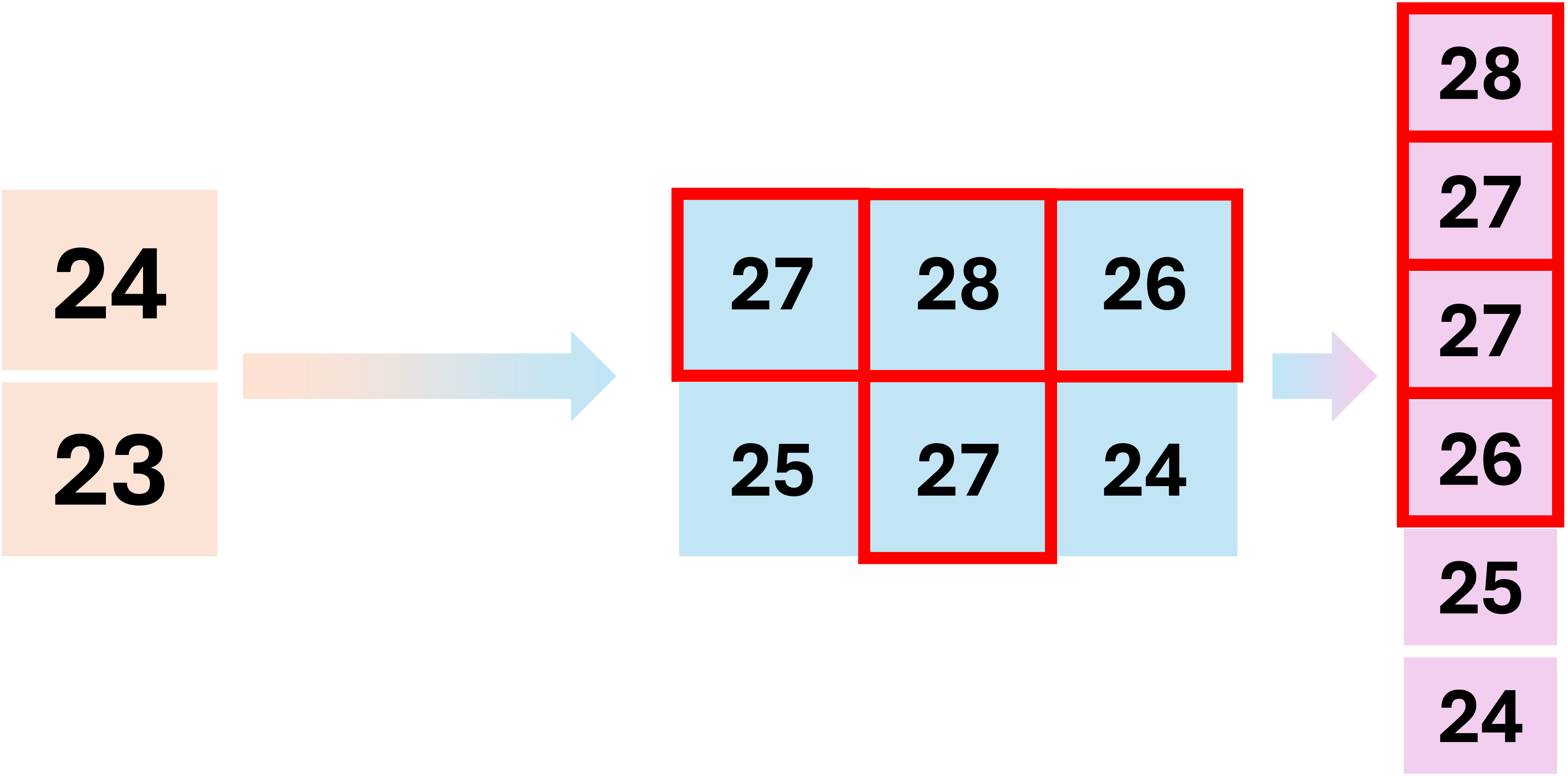
Penalization on DVHs

The problem of sorting / re-ordering

$$D_{50\%} < 25\ Gy$$



$$D_{50\%} < 25\ Gy$$



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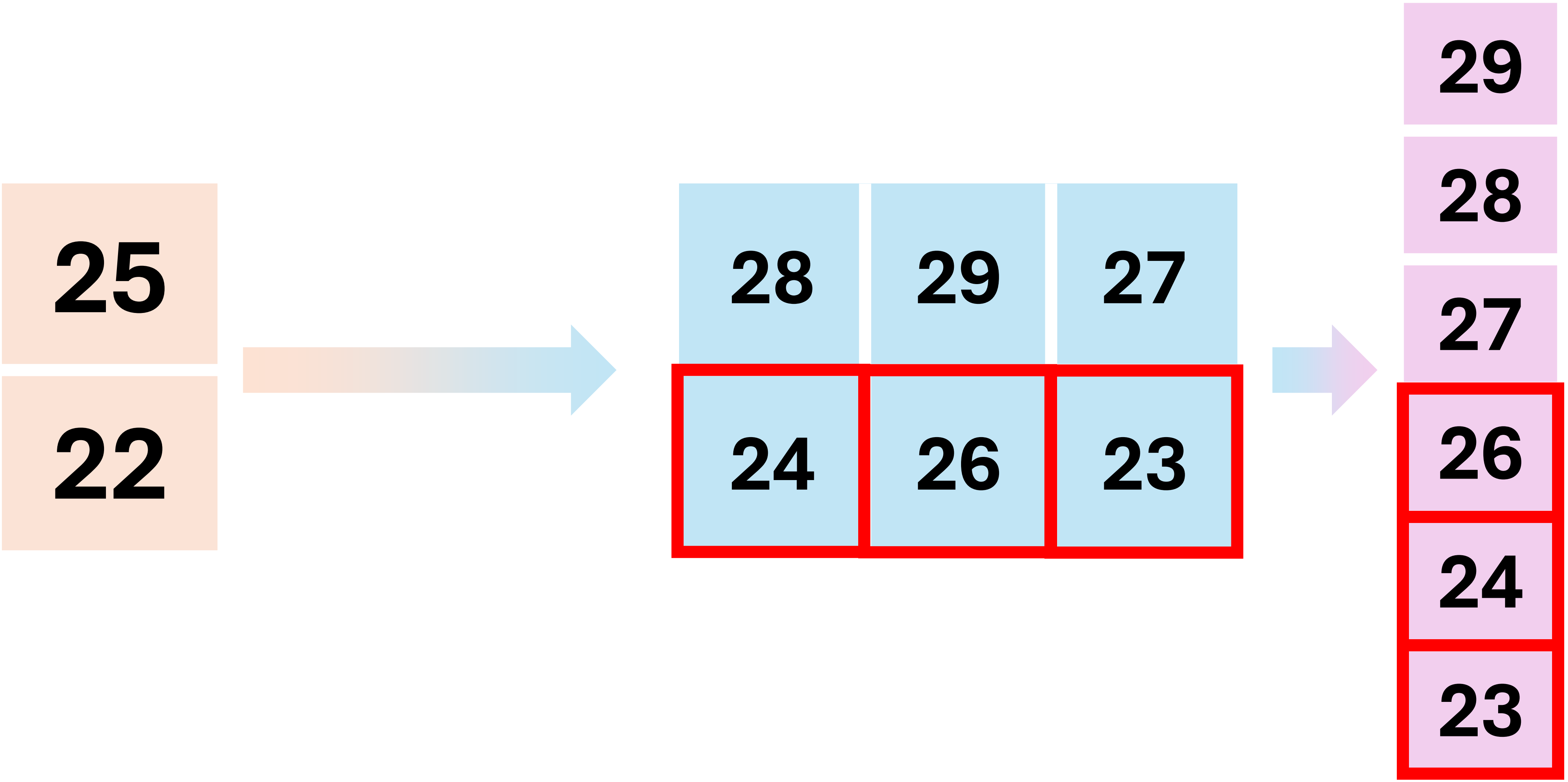
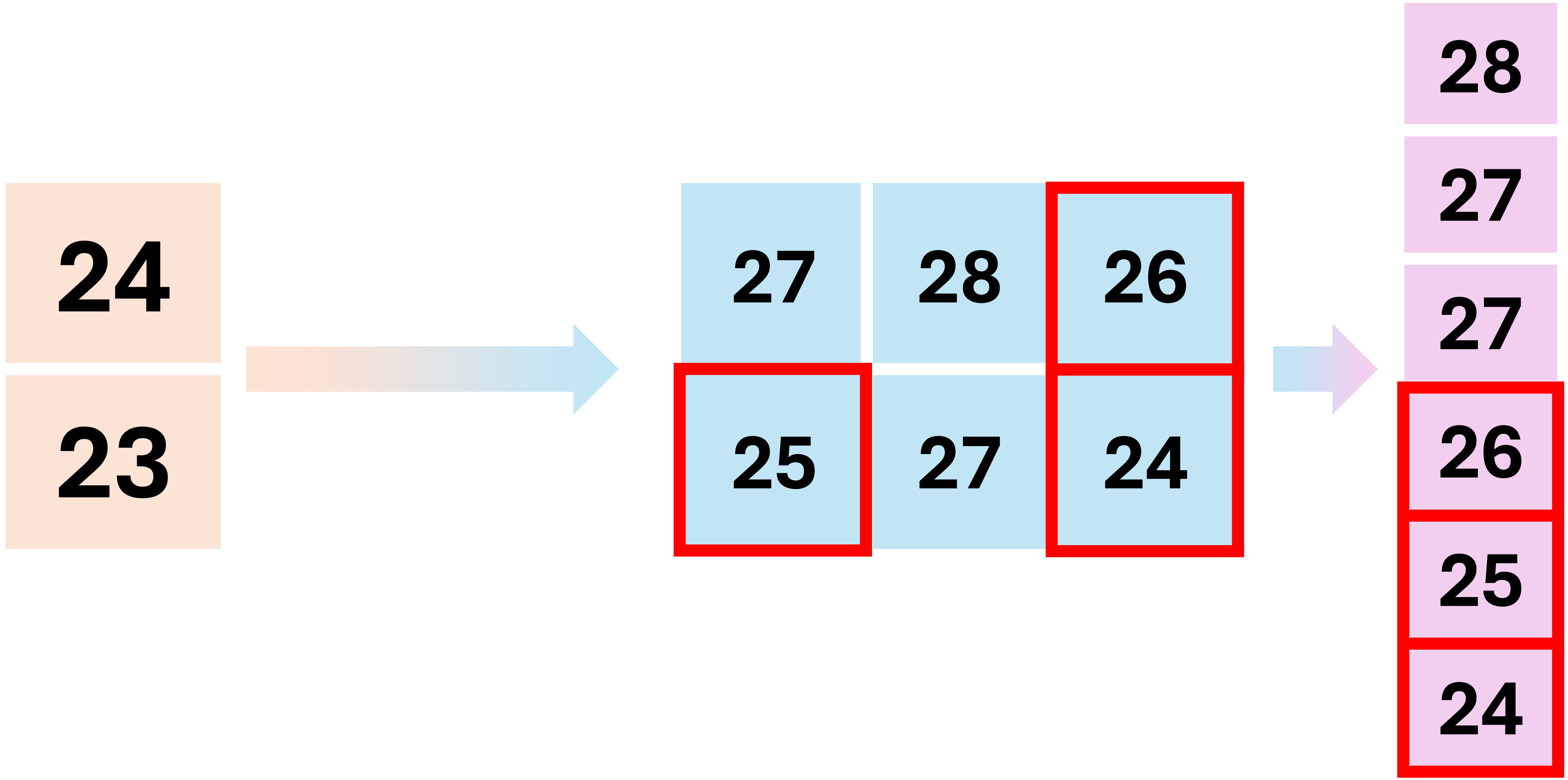
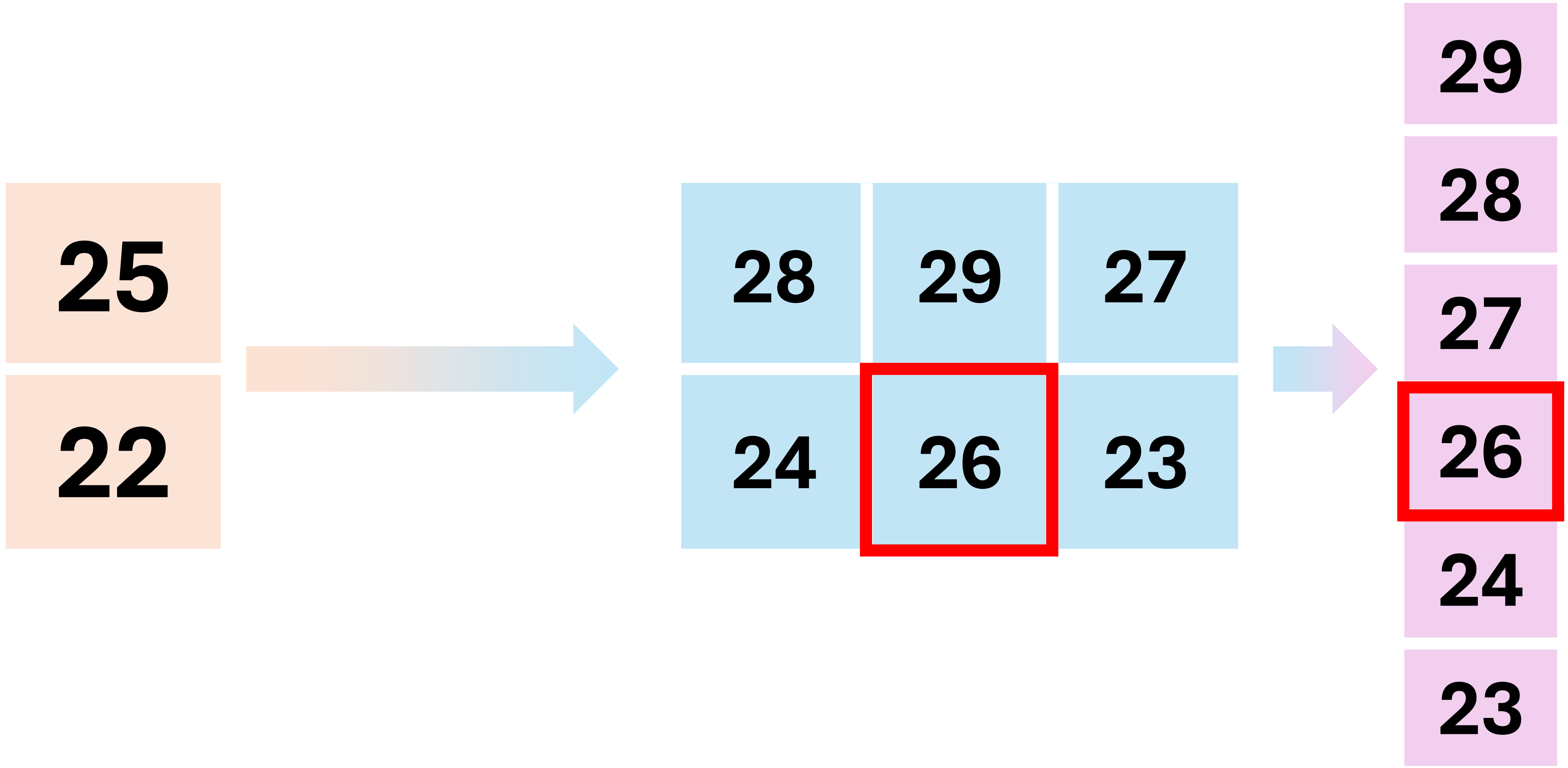


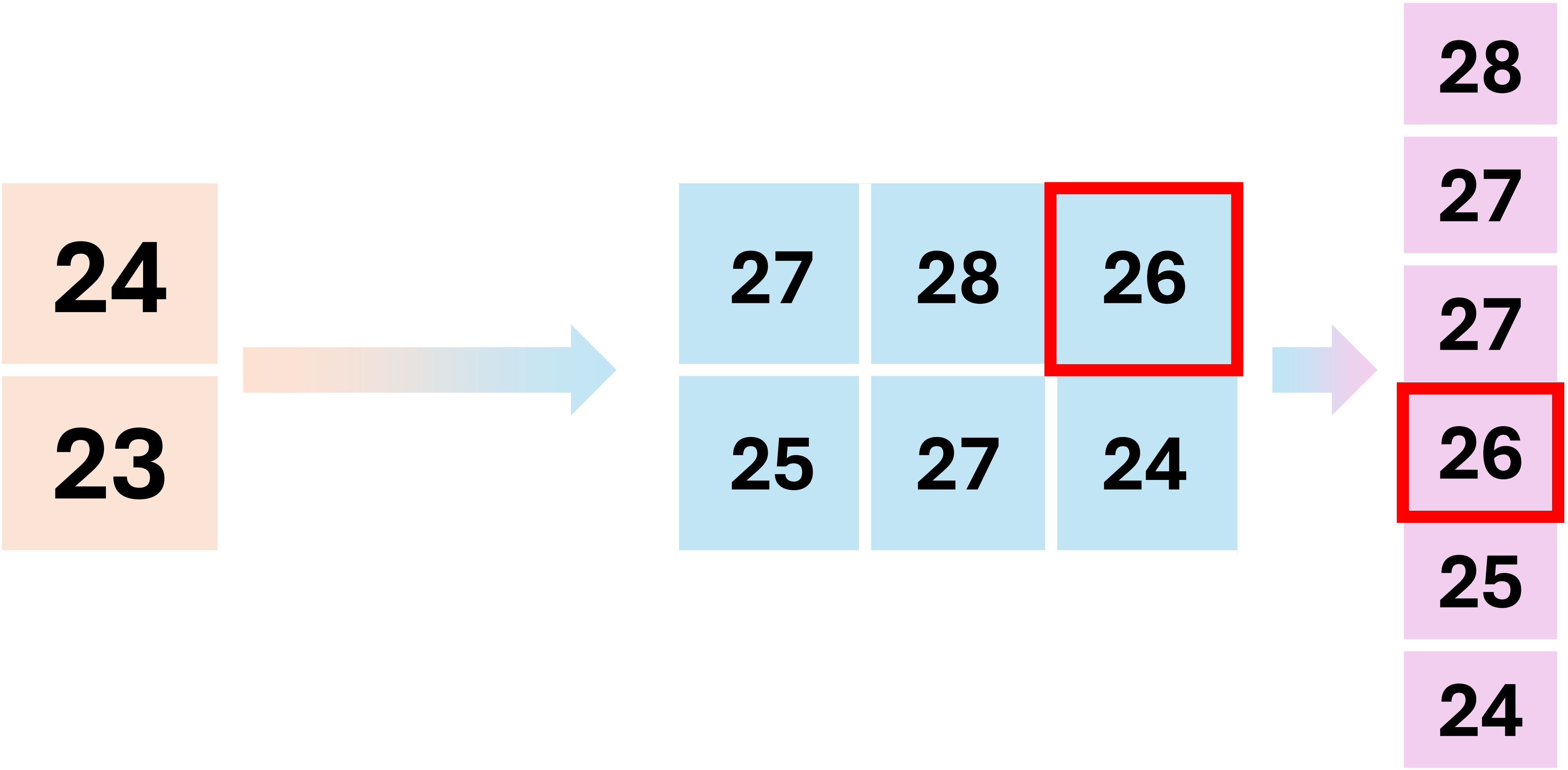
$$D_{50\%} < 25\ Gy$$



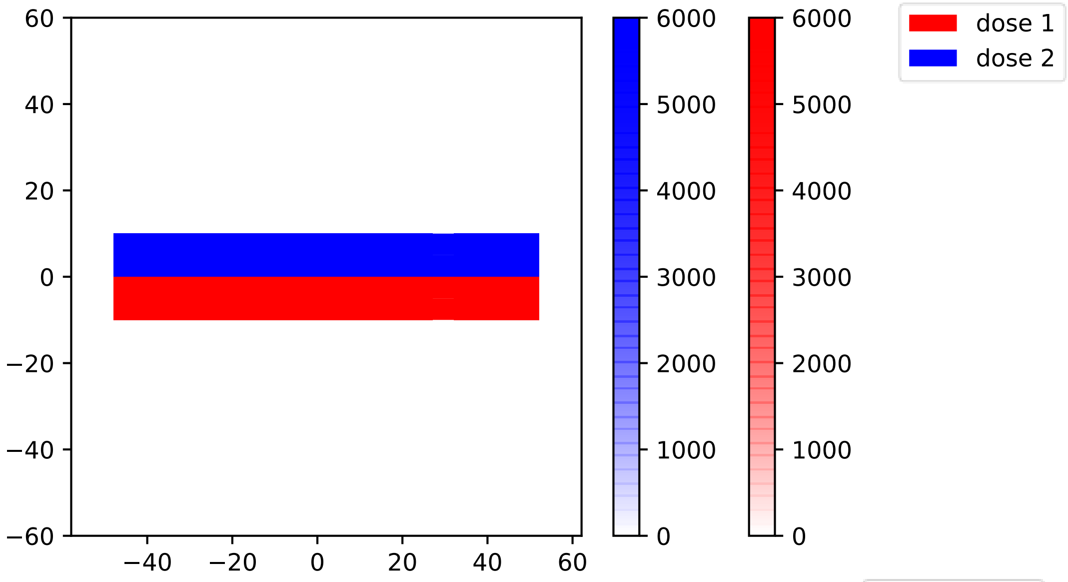
$$D_{50\%} < 25\ Gy$$

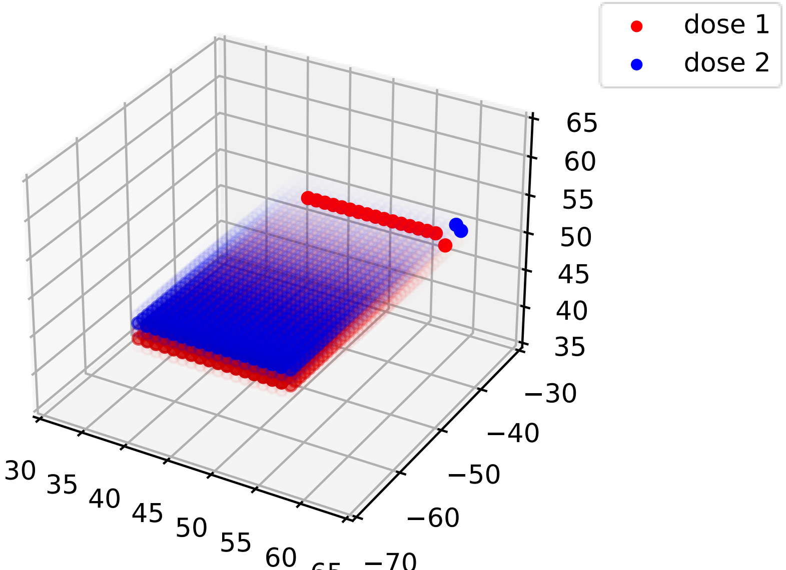


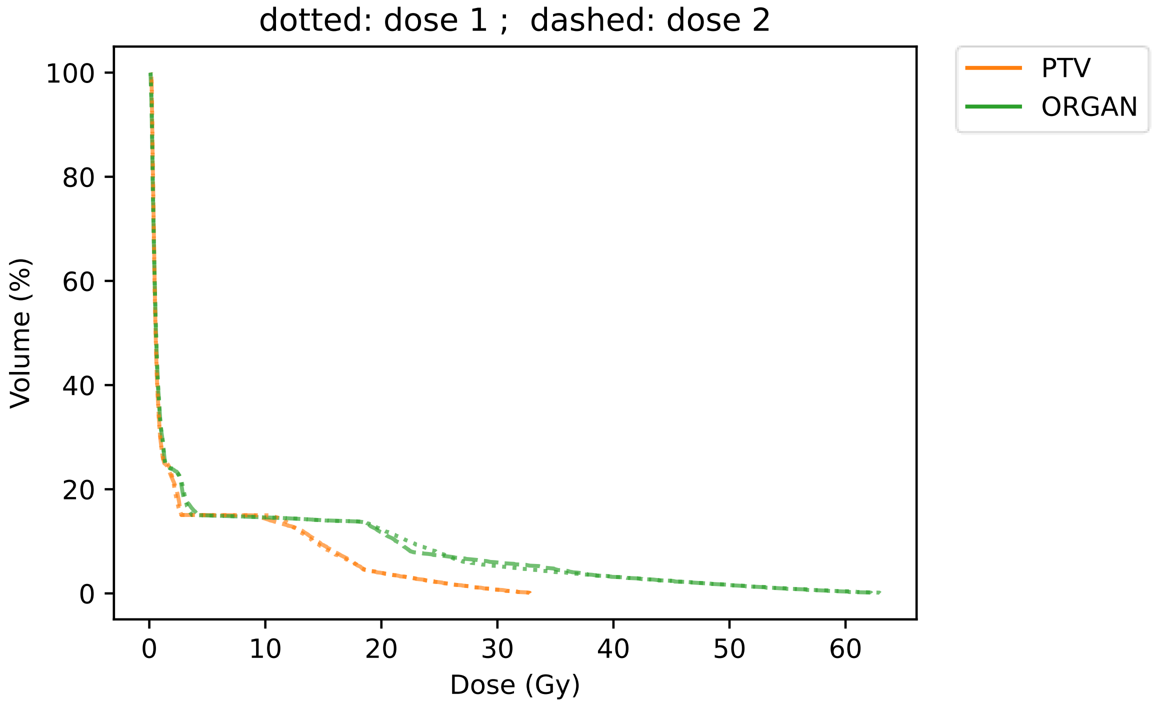
$$D_{50\%} < 25\ Gy$$



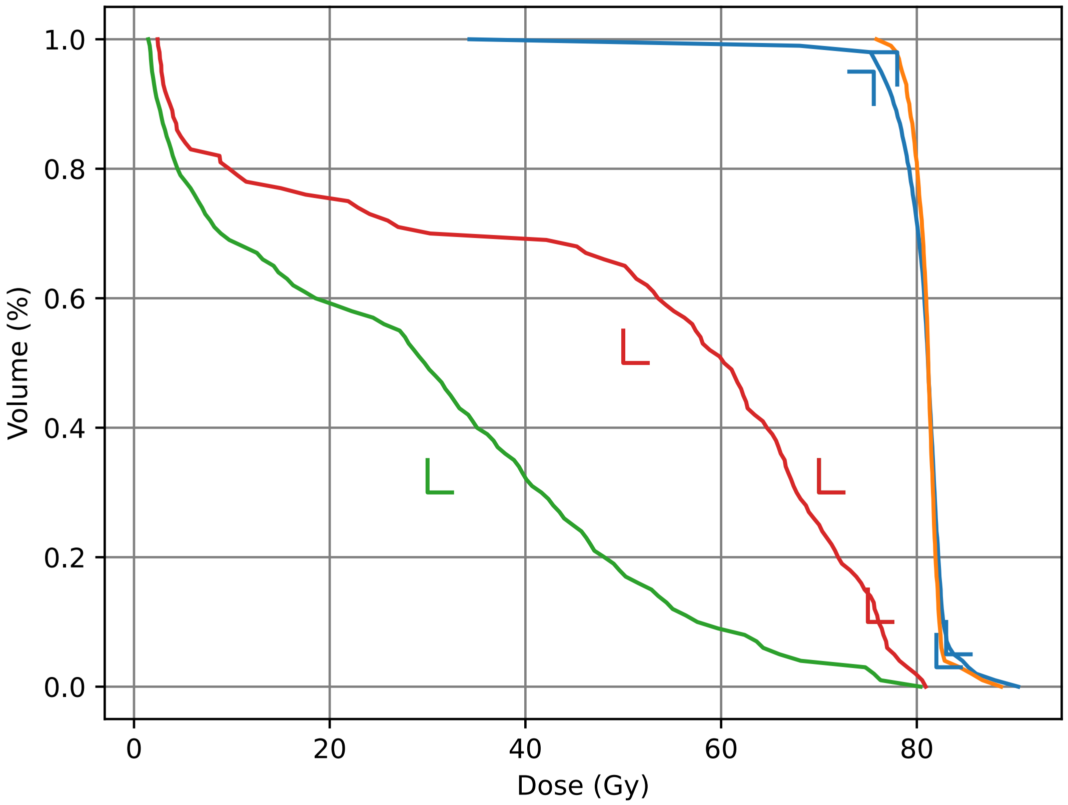
Two doses with similar clinical effect



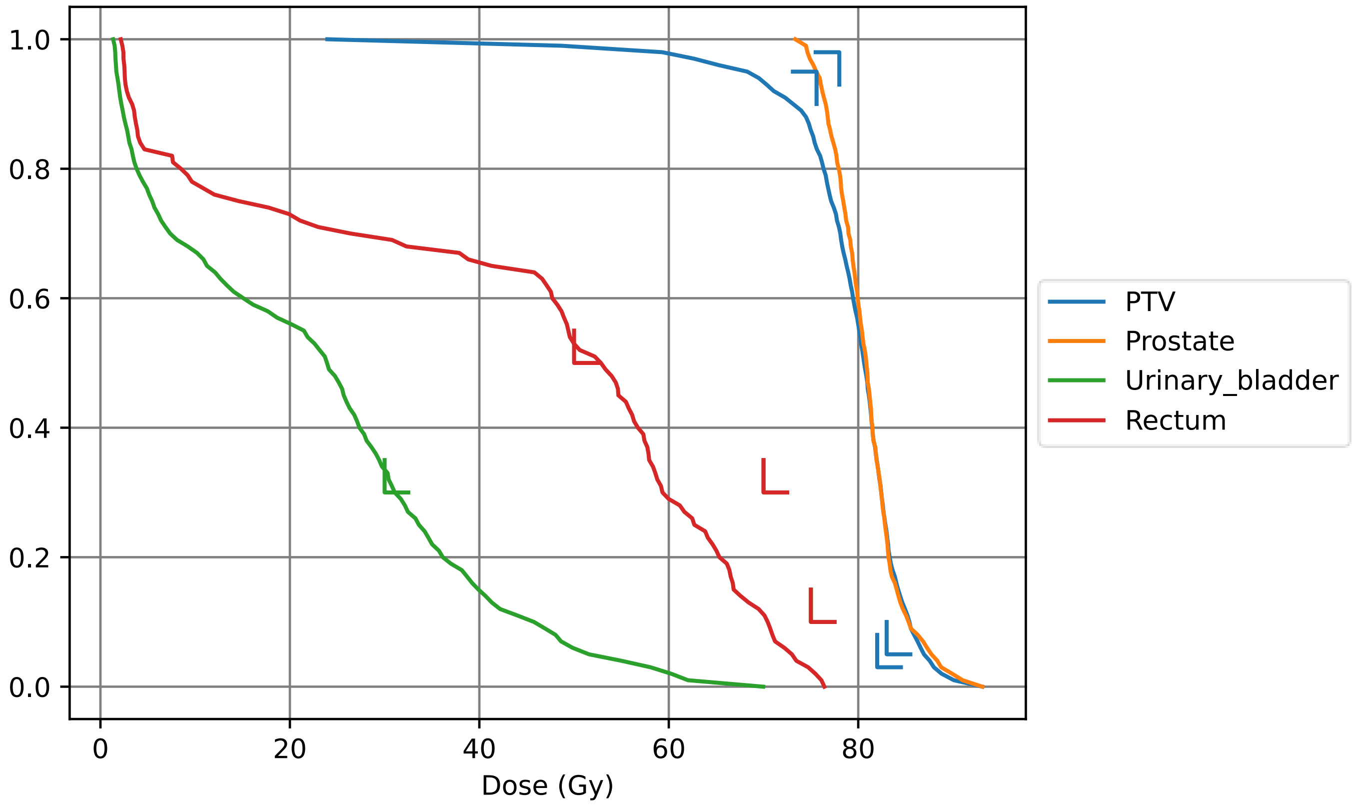




DVH Comparison

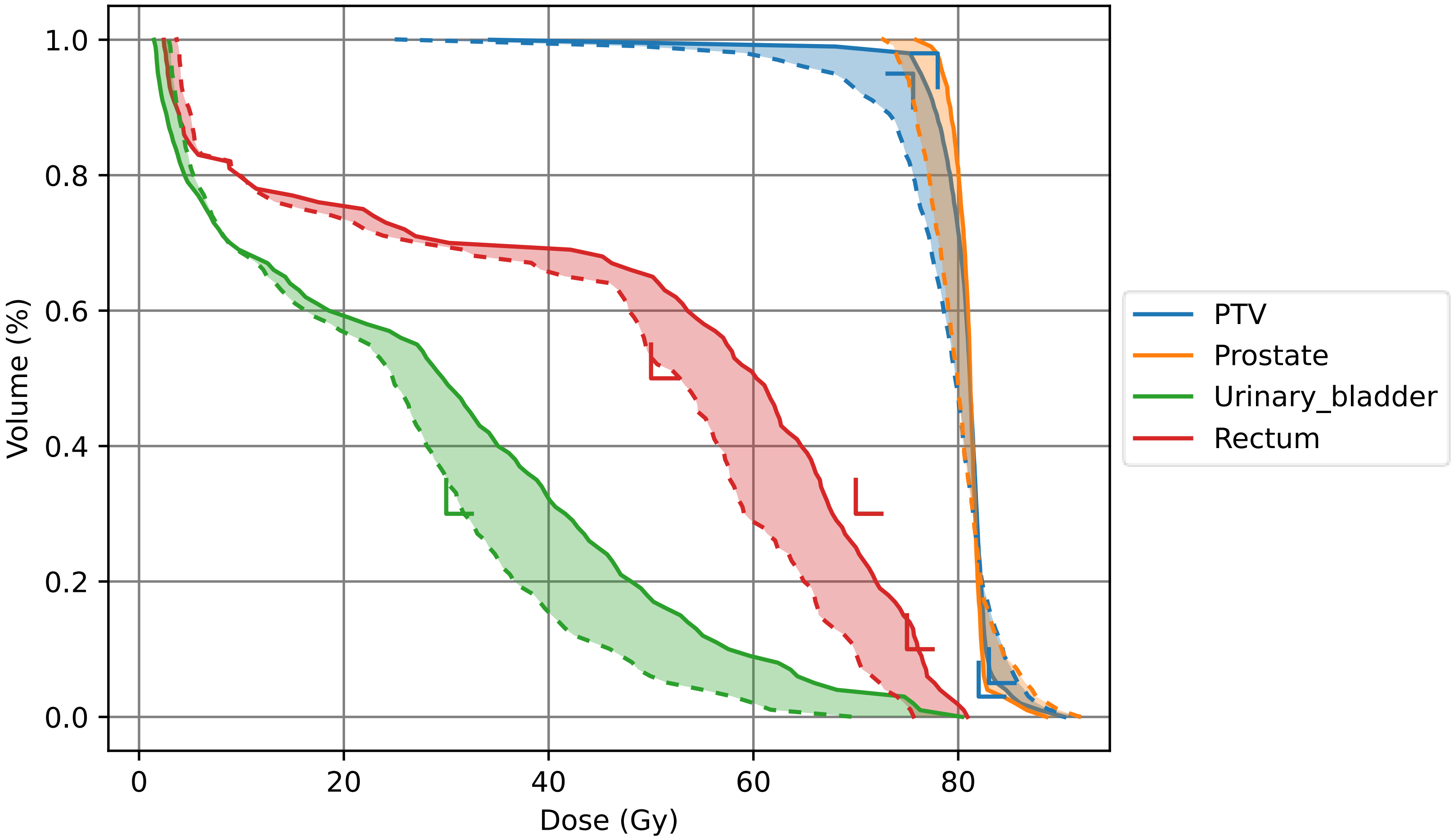


Dose A



Dose B

DVH Comparison



Bellman equation

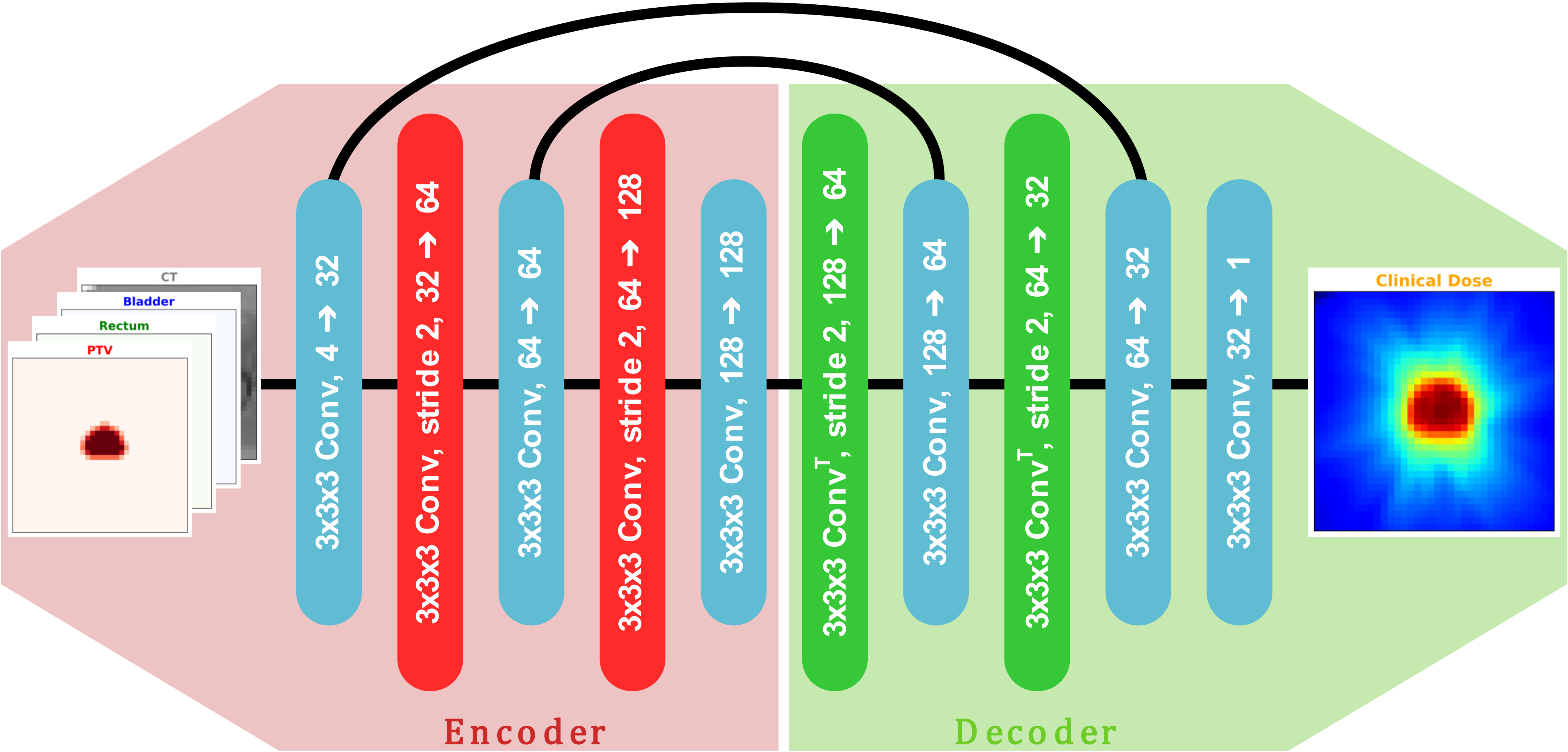
- $V(s) = R(s) + \gamma * \max_{a} \sum_{s'} P(s'|s,a) * V(s')$

- $Q(s,a) = R(s) + \gamma * \sum_{s'} P(s'|s,a) * V(s')$
- $V(s) = \max_{a} Q(s,a)$

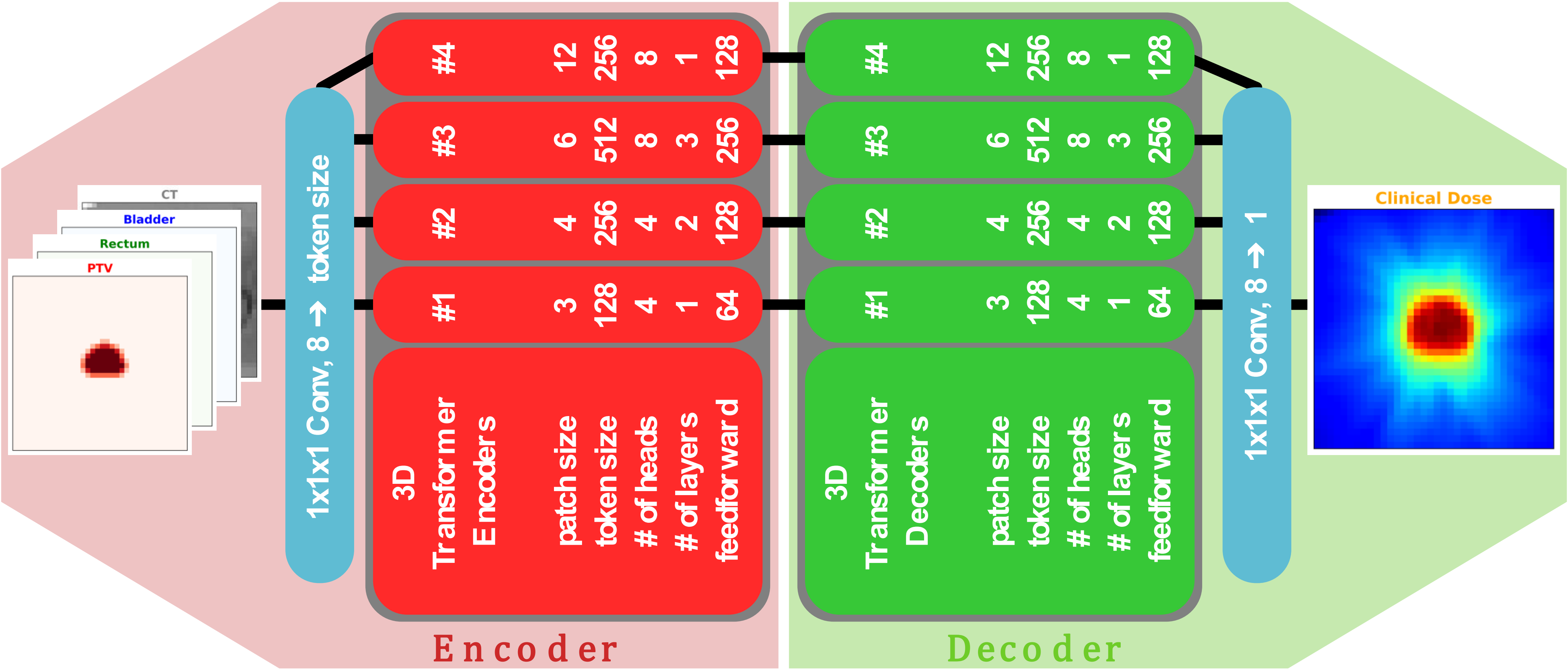
- $Q(s,a) = R(s) + \gamma * \sum_{s'} P(s'|s,a) * \max_{a'} Q(s',a')$
- $Q(s,a) = R(s) + \gamma * \max_{a'} Q(s',a')$

- Update rule (TD): $Q(s,a) = (1-\alpha)Q(s,a) + \alpha[R(s) + \gamma * \max_{a'} Q(s',a')]$
- Update rule (SARSA): $Q(s,a) = (1-\alpha)Q(s,a) + \alpha[R(s) + \gamma * Q(s',a')]$

Convolution Architecture



Transformer Architecture



Performance Comparison of the Models

Metric \ Model	**3D Convolutions**	**3D Transformers**
3D dose MAE	3.141 Gy	3.363 Gy
DVH deviation MAE	1.947 Gy	2.052 Gy

Performances of the models on two metrics of interest