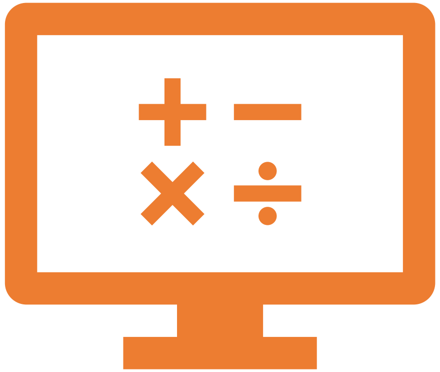
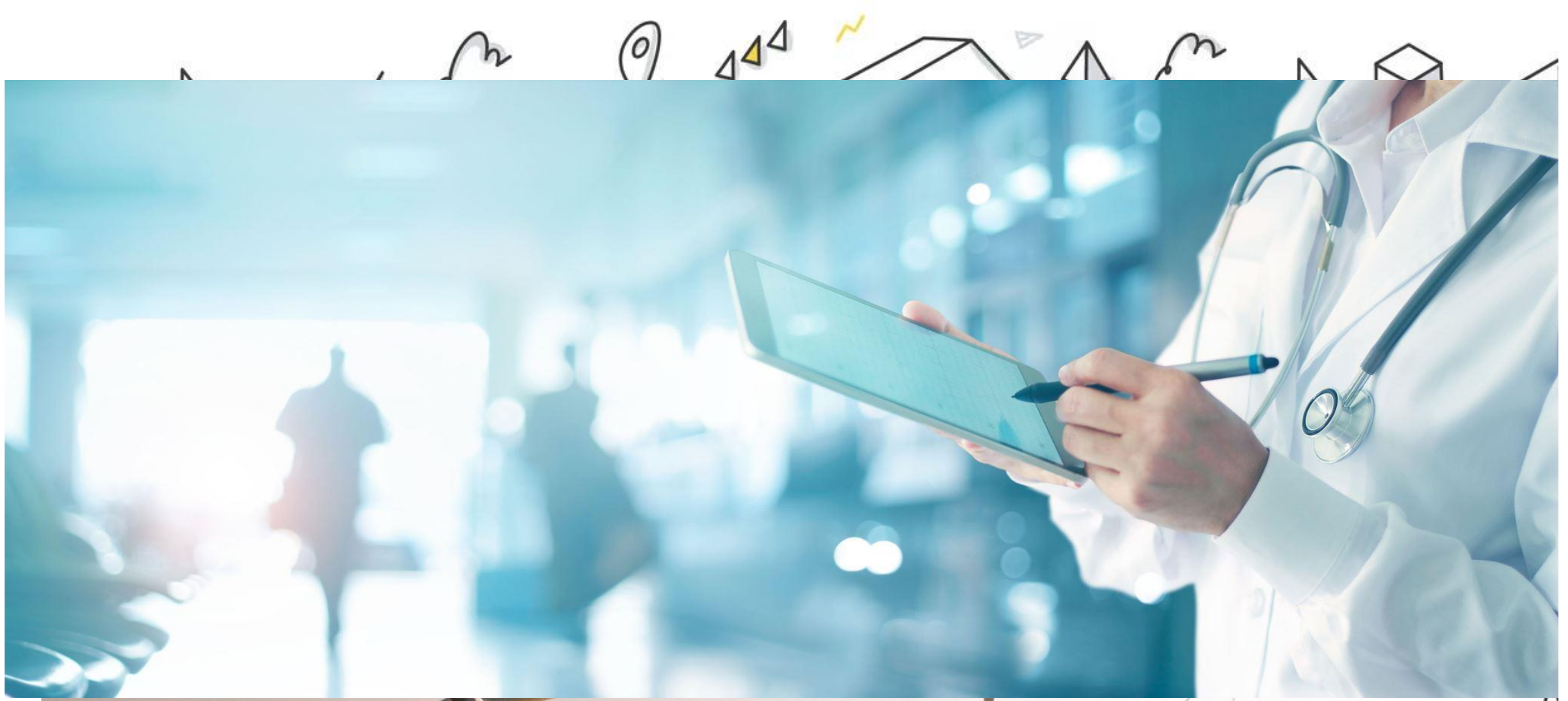


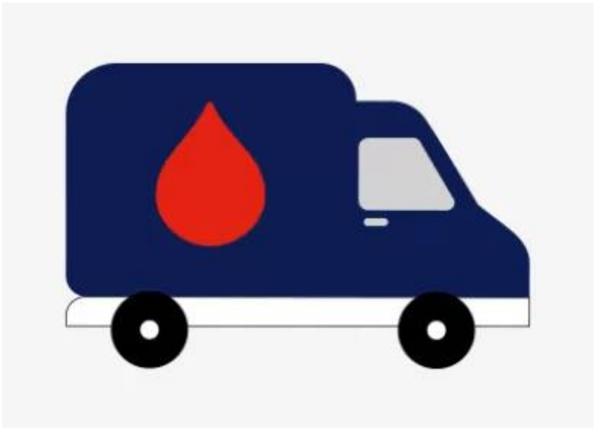

Radiotherapy Treatment Planning

The Role of Operations Research and Multidisciplinary Collaboration

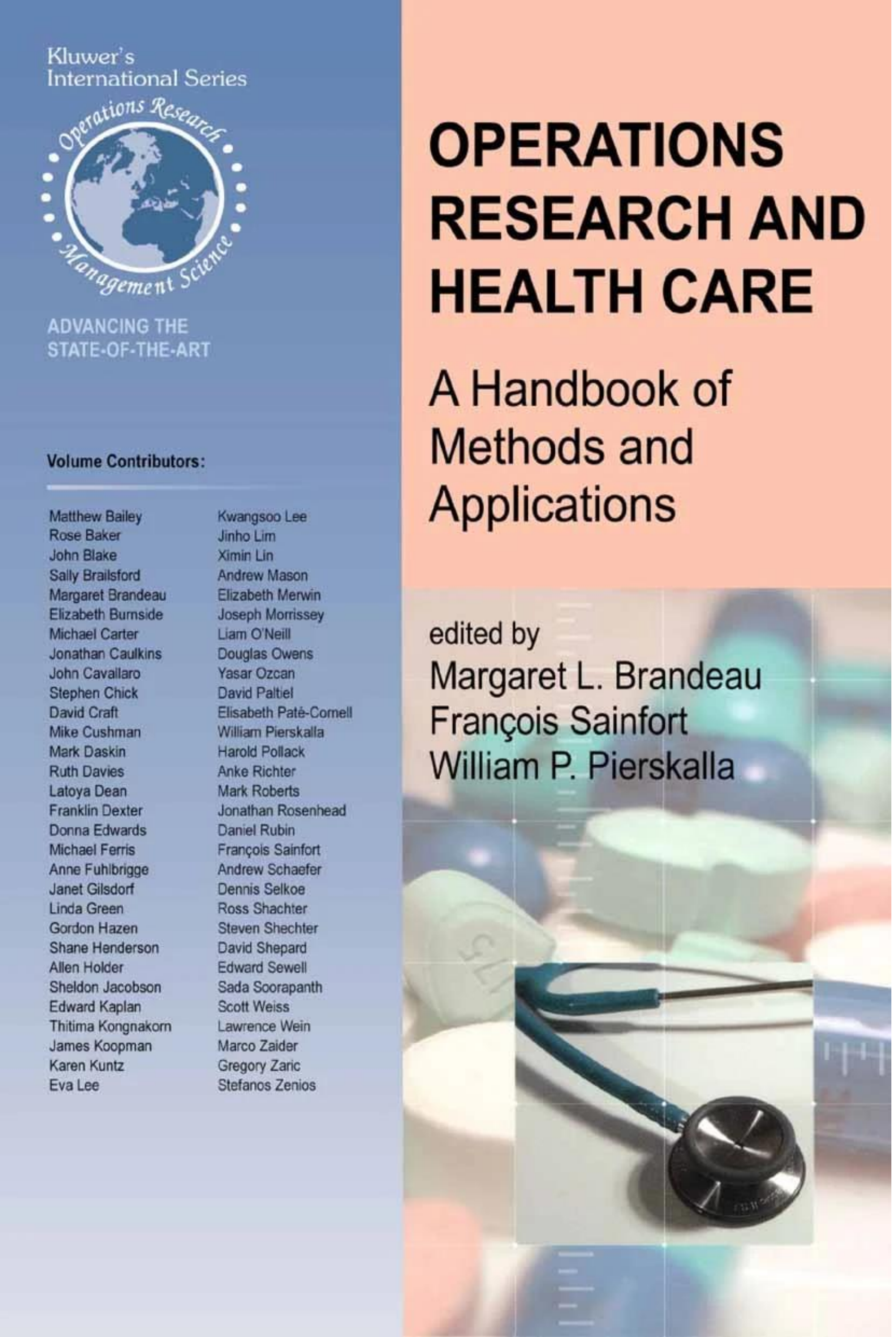
INESCC
Institute for Systems Engineering and Computers at Coimbra

OR impacts the world everyday





OR impacts HEALTH



Health operations management

Public Policy and Economic Analysis

Clinical Applications

29 RADIOTHERAPY TREATMENT DESIGN AND LINEAR PROGRAMMING

Allen Holder

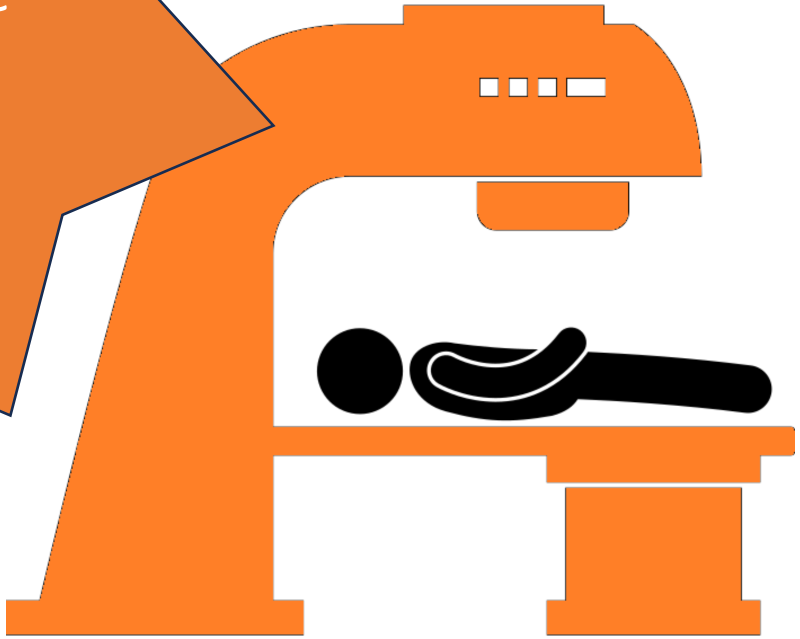
30 OPTIMIZATION TOOLS FOR RADIATION TREATMENT PLANNING IN MATLAB

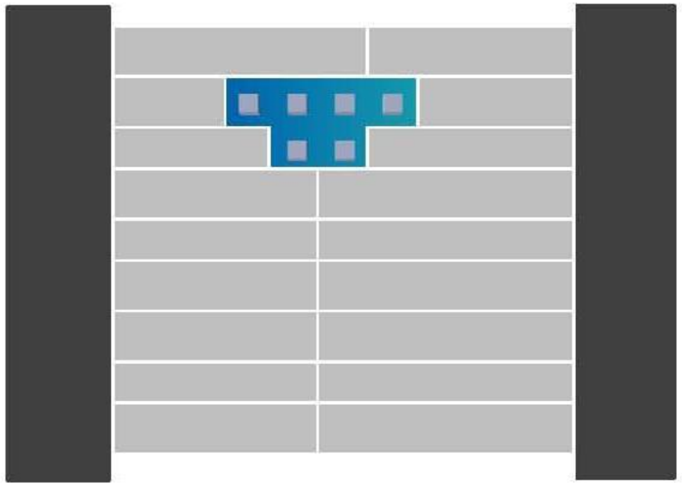
Michael C. Ferris[1], Jinho Lim[2] and David M. Shepard[3]

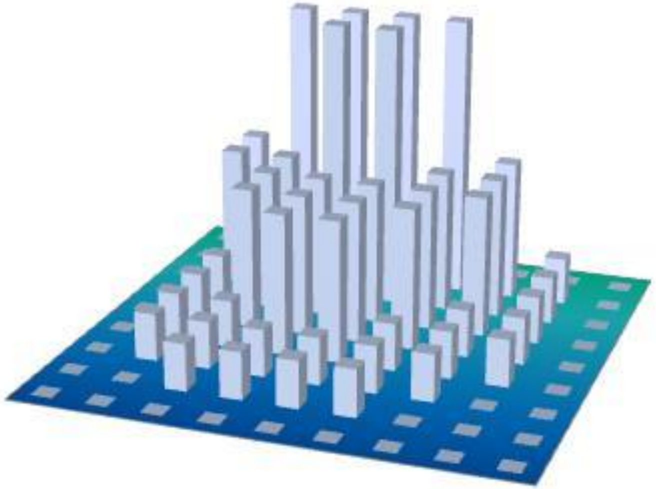
Radiotherapy

- Used for cancer patients, with curat intent
- At least 50% of all the cancer patients wil submitted to radiotherapy treatments
- **In Europe alone, near 2 million patients are treated per year**
- There are different treatment modalities:
    - Intensity Modulated Radiation Therapy (IMRT)
    - Volumetric Modulated Arc Therapy (VMAT)
    - Protons
    - Brachytherapy
    - …

OR impacts every patient, because OR is in the core of radiotherapy treatment planning!





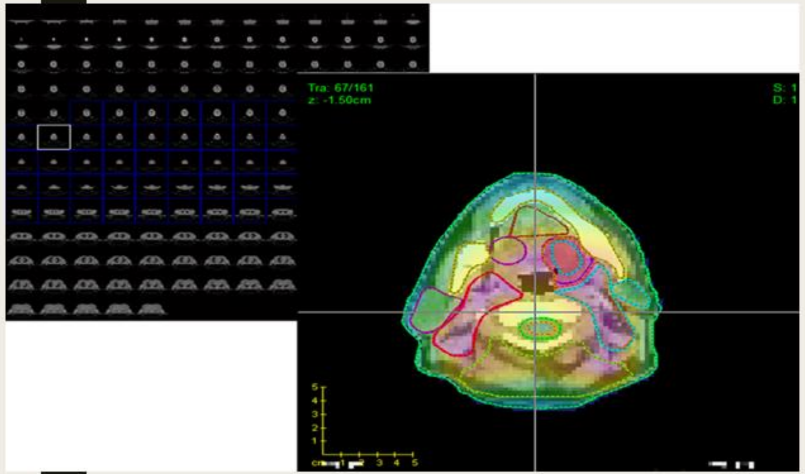


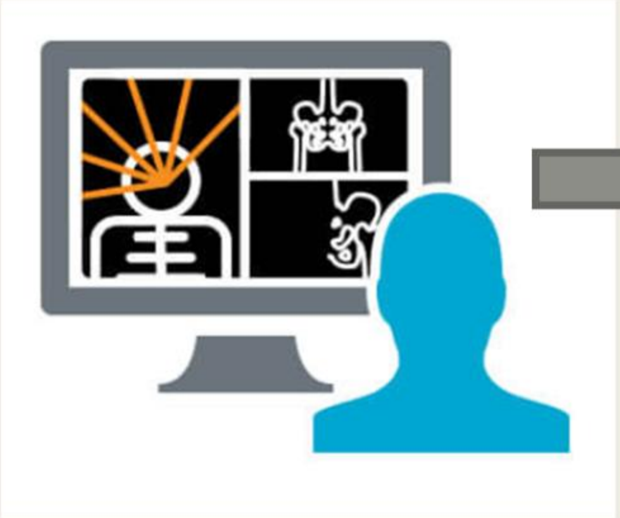
Problem description

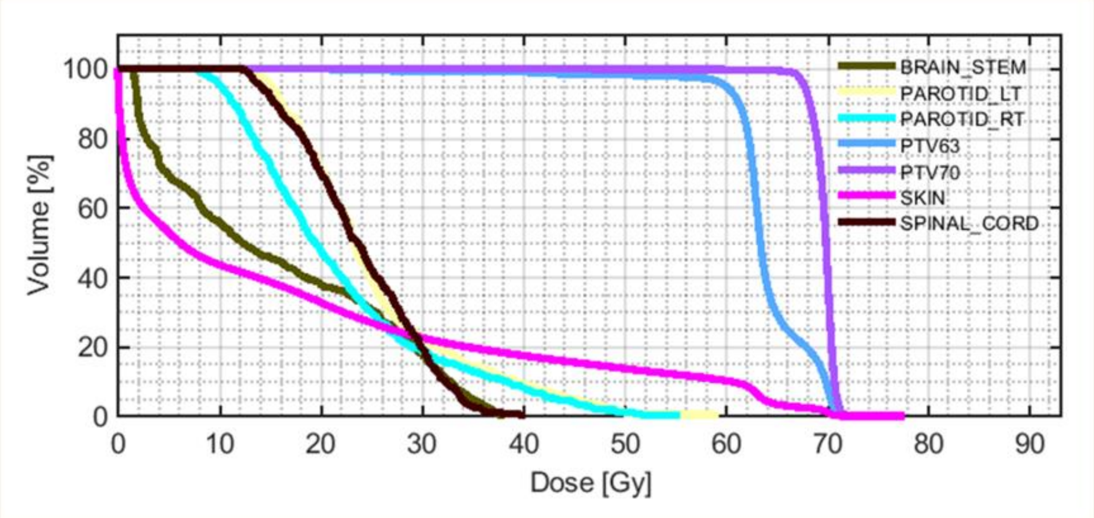
What are the angles/arcs that should be used? What should be the patient couch position?

What should be the radiation intensities (fluence maps)?

What should be the leaf sequencing? How should the leaves move so that the desired fluence maps are obtained?


Tra: 67/161
z: -1.50cm



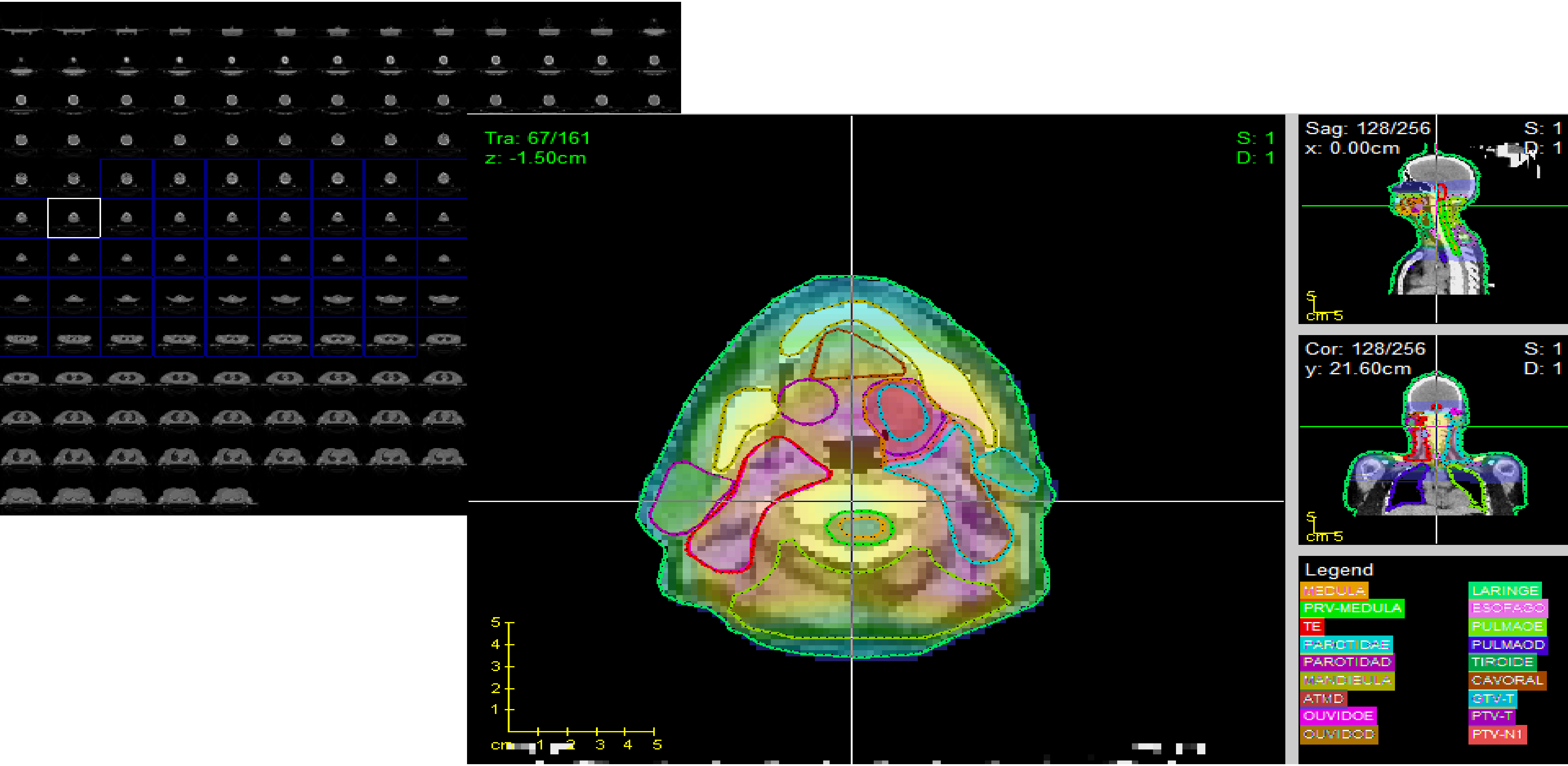

BRAIN_STEM
PAROTID_LT
PAROTID_RT
PTV63
PTV70
SKIN
SPINAL_CORD
Volume [%]
Dose [Gy]
0
20
40
60
80
100
0
10
20
30
40
50
60
70
80
90

Treatment planning

Objective:

achieving fully automated radiotherapy treatment plans

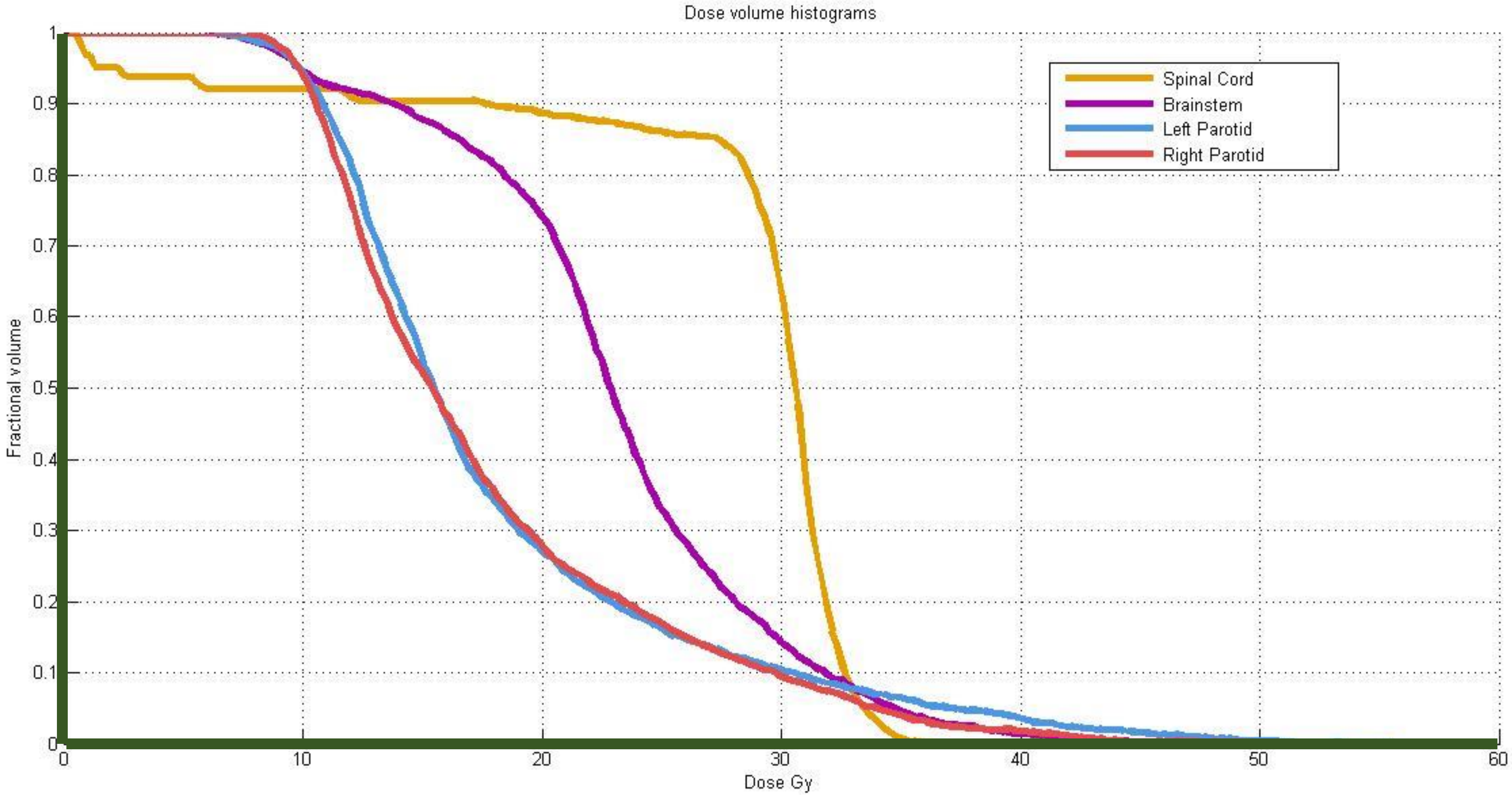
- Trial and error procedure
- Lengthy process
- The quality is highly dependent on the planner’s time availability and experience.

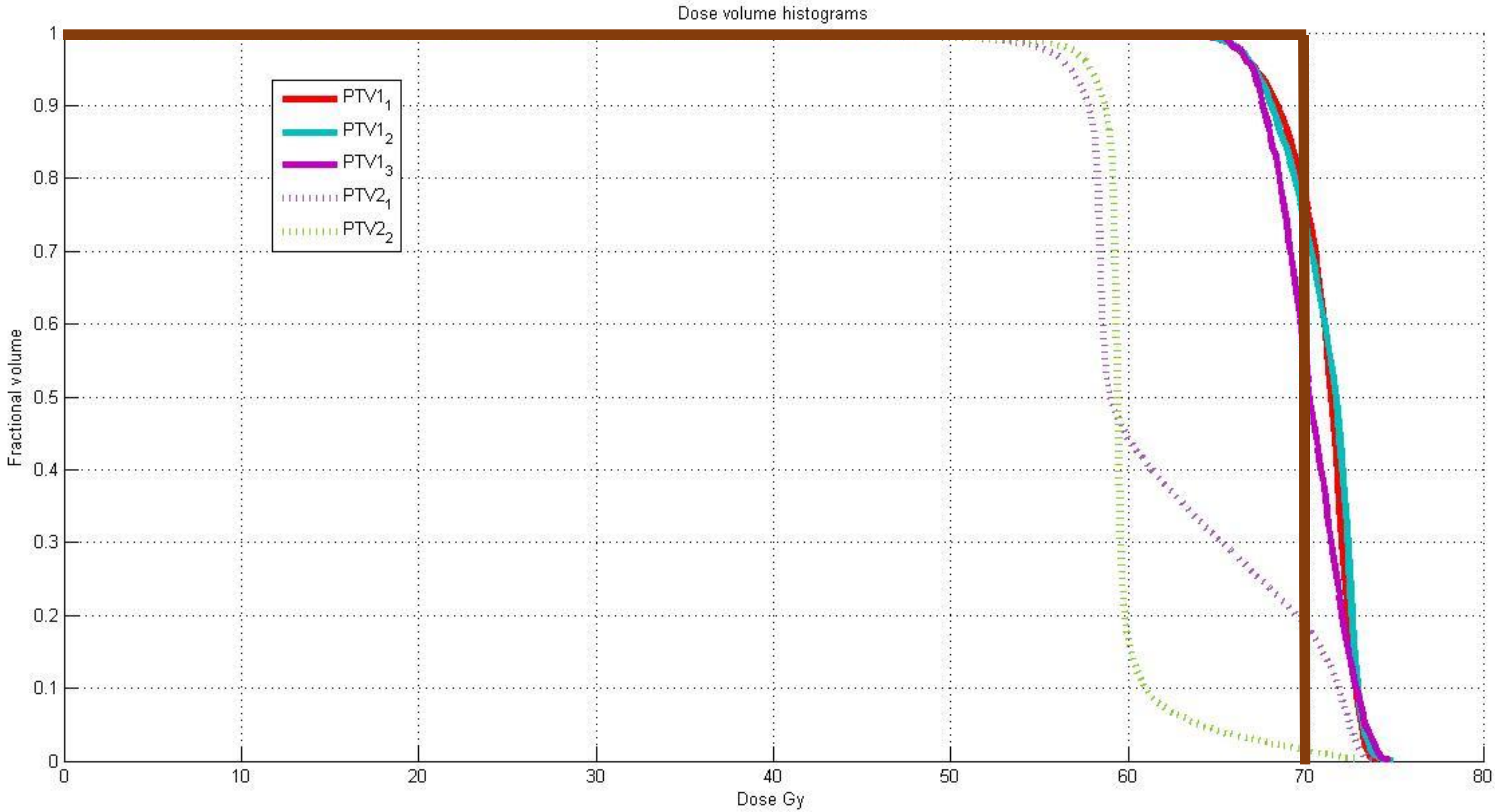

Tra: 67/161
z: -1.50cm
S: 1
D: 1
Sag: 128/256
x: 0.00cm
Cor: 128/256
y: 21.60cm
Legend
MEDULA
PRV-MEDULA
TE
PAROTIDAE
PAROTIDAD
MANDIBULA
ATMD
OUVIDOE
OUVIDOD
LARINGE
ESOFAGO
PULMAOE
PULMAOD
TIROIDE
CAVORAL
GTV-T
PTV-T
PTV-N1

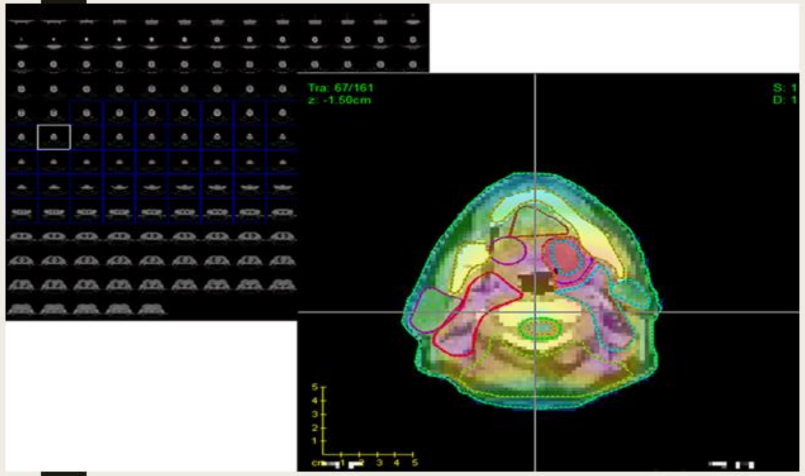
Medical prescription

- Doses that should be delivered to the volumes to treat (PTV –Planning Target Volume)
- Dose limits for the OARs - organs at risk

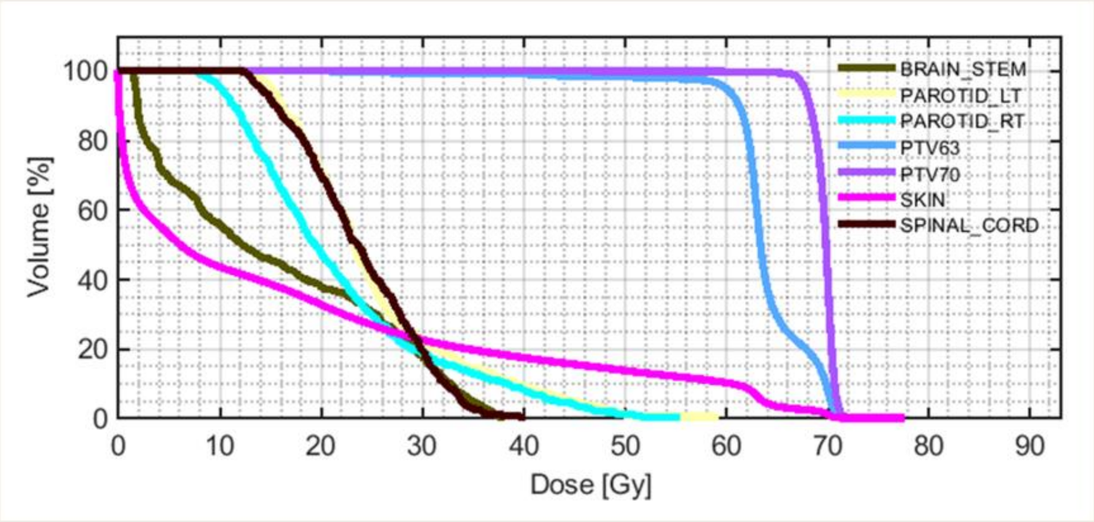
Structure	Type of constraint		Limit
Spinal cord	Maximum dose	Lower than	45 Gy
Brainstem	Maximum dose	Lower than	54 Gy
Left parotid	Mean dose	Lower than	26 Gy
Right parotid	Mean dose	Lower than	26 Gy
PTV_{70}	$D_{95\%}$	Greater than	66.5 Gy
PTV_{70}	Maximum dose	Lower than	74.9 Gy
PTV_{59}	$D_{95\%}$	Greater than	56.4 Gy
PTV_{59}	$V_{107\%}$	Lower than	Percentage of PTV_{70} volume inside PTV_{59} plus a 10% margin
Body	Maximum dose	Lower than	80 Gy


Dose volume histograms
Spinal Cord
Brainstem
Left Parotid
Right Parotid
Fractional volume
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
10
20
30
40
50
60
Dose Gy


Dose volume histograms
PTV1$_1$
PTV1$_2$
PTV1$_3$
PTV2$_1$
PTV2$_2$
Fractional volume
Dose Gy
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
10
20
30
40
50
60
70
80



Where is OR?


BRAIN_STEM
PAROTID_LT
PAROTID_RT
PTV63
PTV70
SKIN
SPINAL_CORD
Volume [%]
100
80
60
40
20
0
0
10
20
30
40
50
60
70
80
90
Dose [Gy]

Treatment Planning System

- Mathematical Optimisation
- Dose computation

Medical prescription

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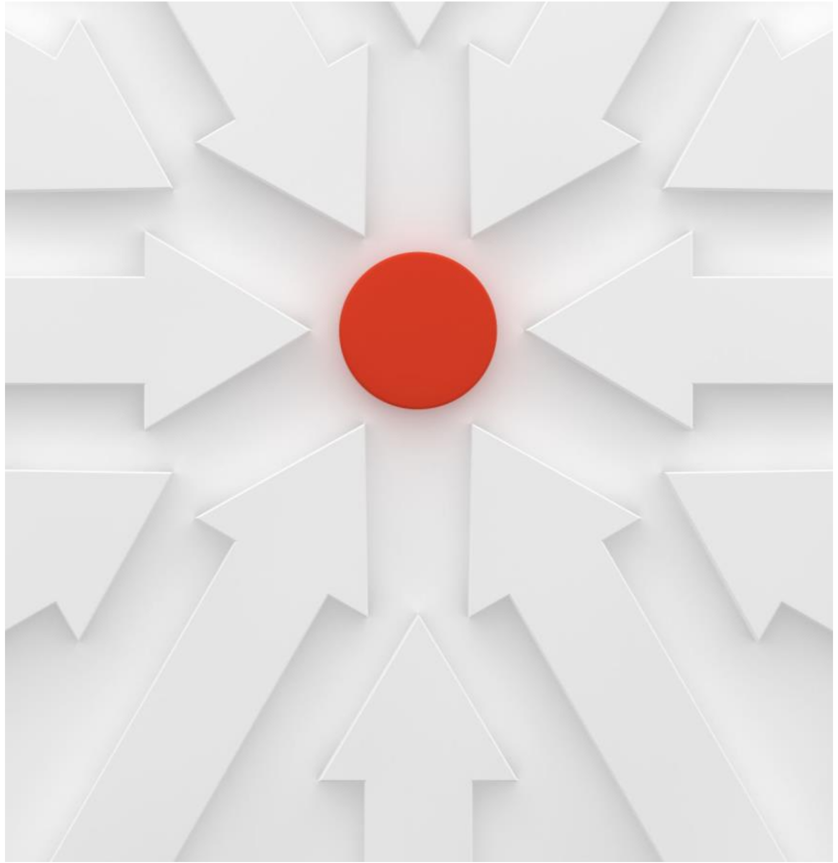
Body	Maximum dose	Lower than	80 Gy

Optimal or admissible? Inverse Optimisation!

- We know what we want to achieve: compliance with the medical prescription.
- We are unsure of the path to reach this goal.
- Therefore, we are seeking an admissible solution for a highly constrained problem, but...
- If possible, we aim to exceed the established constraints!




We are thrilled!! We were able to improve the value of our objective function around 10%!!!
So what???

Non-linearities in constraints and objectives.

Several and conflicting objectives.

Uncertainties: robust optimization.

Very large problems, very large matrixes.

All the ingredients for a very difficult problem

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Remote planning Services

What is Mercurius Connect ® and how does it impact radiation therapy?

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ASSOCIAÇÃO PARA A INOVAÇÃO
E DESENVOLVIMENTO EM CIÊNCIA E TECNOLOGIA

IPO COIMBRA

THE UNIVERSITY OF TEXAS
MD Anderson ~~Cancer~~ Center

C

PATIENTS & FAMILY · PREVENTION & SCREENING · DONORS & VOLUNTEERS

Radiation Physics

UTAustin Portugal

Non-linearities in constraints and objectives.

Several and conflicting objectives.

Uncertainties: robust optimization.

Very large problems, very large matrixes.

All the ingredients for a very difficult problem

OR toolbox

- Mathematical Modelling
- Exact optimization approaches
- Heuristics/Metaheuristics
- Simulation
- Statistics
- Machine Learning
- …

CEJOR (2014) 22:431–455
DOI 10.1007/s10100-013-0289-4

ORIGINAL PAPER

A genetic algorithm with neural network fitness function evaluation for IMRT beam angle optimization

**Joana Dias · Humberto Rocha ·
Brígida Ferreira · Maria do Carmo Lopes**

Machine Learning vs with OR?
OR!

- Neural networks can be used as function approximators when dealing with expensive objective functions
- Machine learning can make optimization algorithms run faster (parameter optimization, initial solution...).
- Machine learning can help in the algorithmic choice.

Problem description

What are the angles/arcs that should be used? What should be the patient couch position?

What should be the radiation intensities (fluence maps)?

What should be the leaf sequencing? How should the leaves move so that the desired fluence maps are obtained?

Fluence Map Optimisation

$$f(w) = Min_w \sum_{i=1}^{V} \left[\boxed{\underline{\lambda}_i} \left(\boxed{L_i} - \sum_{j=1}^{N} D_{ij} w_j \right)_+^2 + \boxed{\overline{\lambda}_i} \left(\sum_{j=1}^{N} D_{ij} w_j - \boxed{U_i} \right)_+^2 \right]$$

- Minimise the squared deviations from the desired dosimetric values for each structure of volume.
- A considerable number of parameters that must be tuned.

MEDICAL PHYSICS
The International Journal of Medical Physics Research and Practice

Therapeutic interventions

Automated fluence map optimization based on fuzzy inf
systems

Joana Dias, Humberto Rocha, Tiago Ventura, Brígida Ferreira, Maria do Carmo Lopes

First published: 05 February 2016 | https://doi.org/10.1118/1.4941007

Fluence Map Optimization

Quadratic Programming Optimization Problem

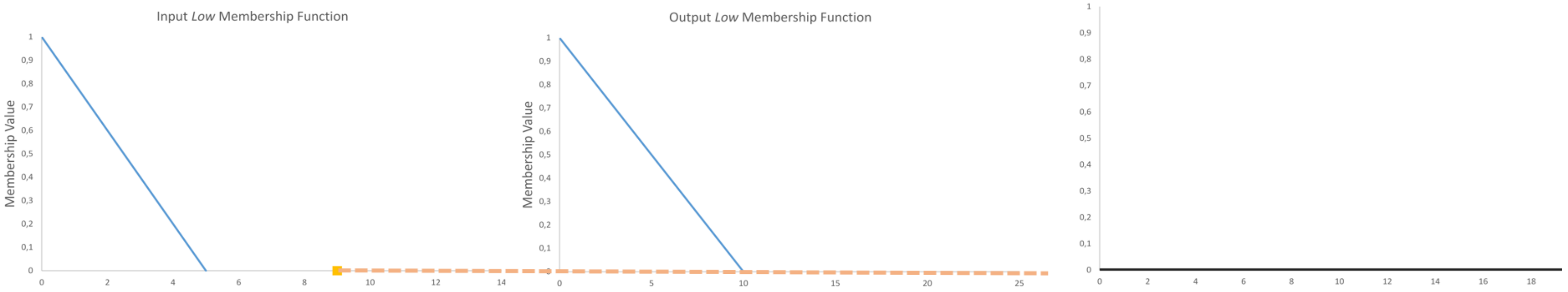
Fuzzy Inference Systems

Fluence Map Optimization

Quadratic Programming Optimization Problem

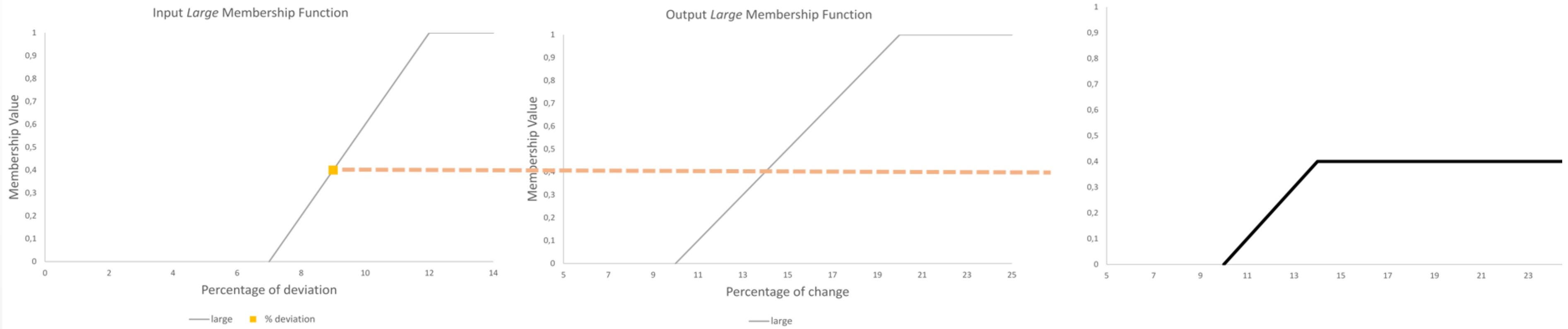
Fuzzy Inference Systems

Reinforcement learning to learn the best fuzzy rules



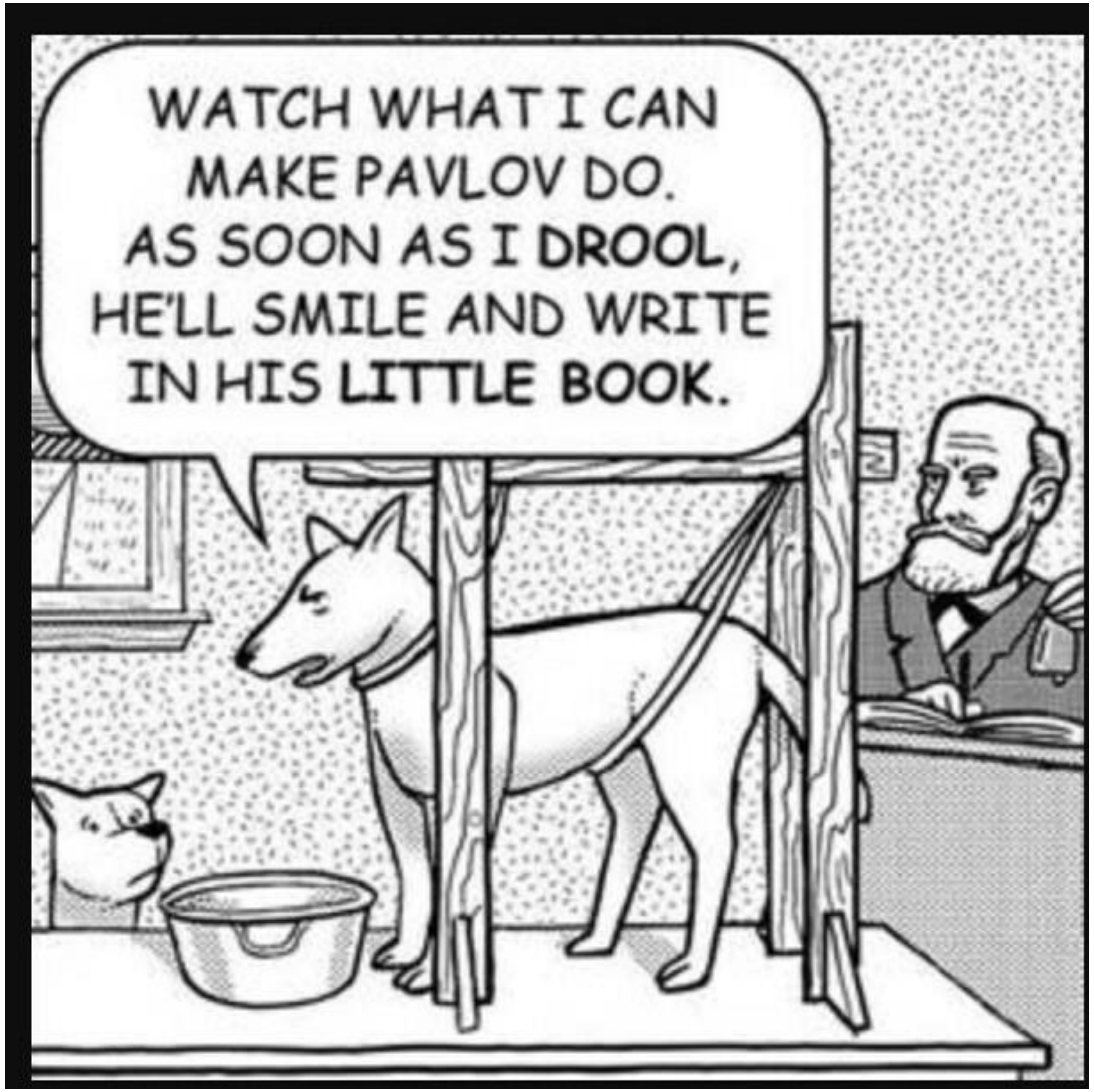
Instead of predefining the membership functions that represent these concepts, these functions can be optimized and dinamically changed as the optimization algorithm progresses!

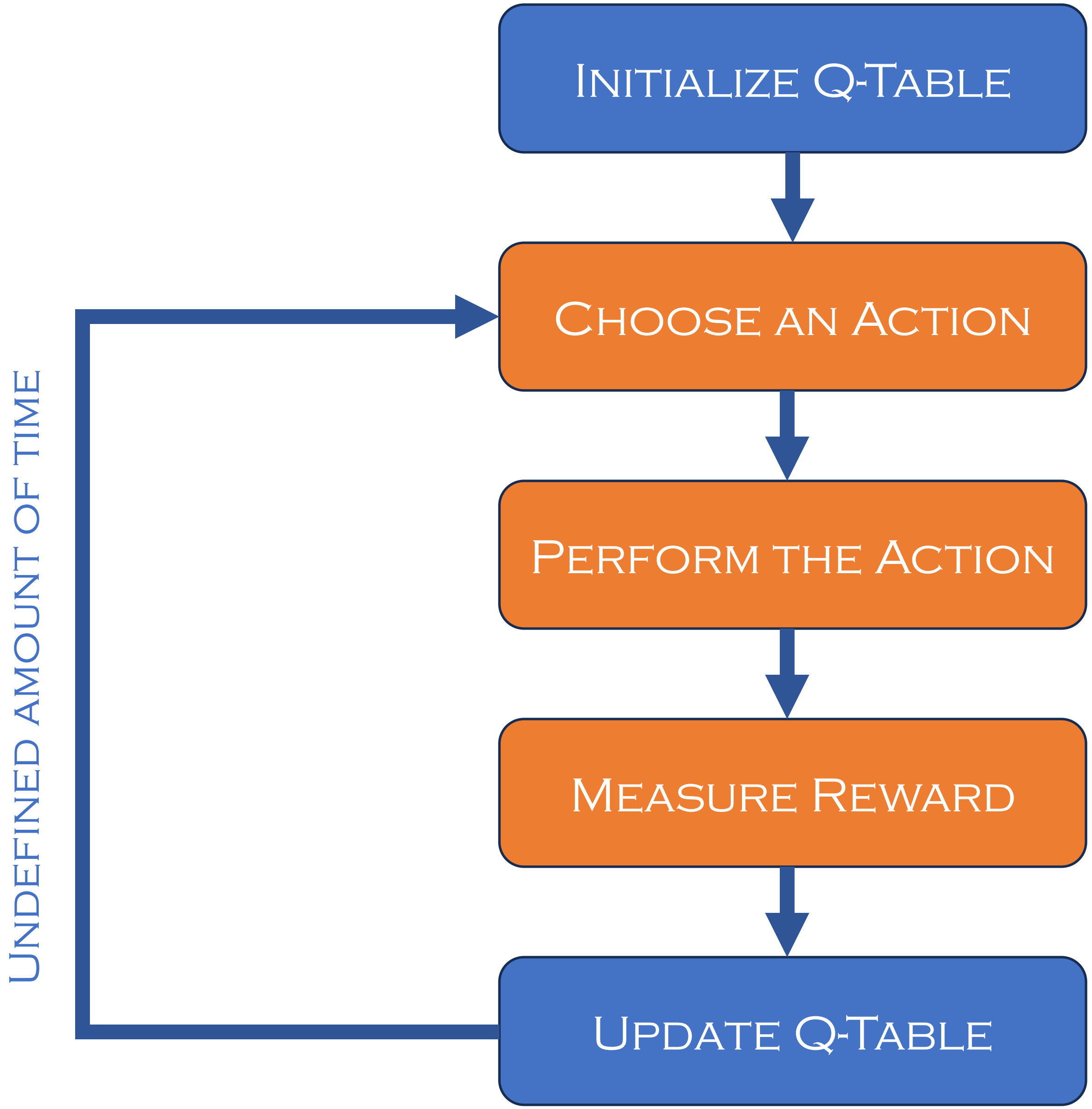
If deviation is *medium* then the change in the bound should be *medium*.



If deviation is *large* then the change in the bound should be *large*.

Reinforcement Learning ~Classical conditioning theory





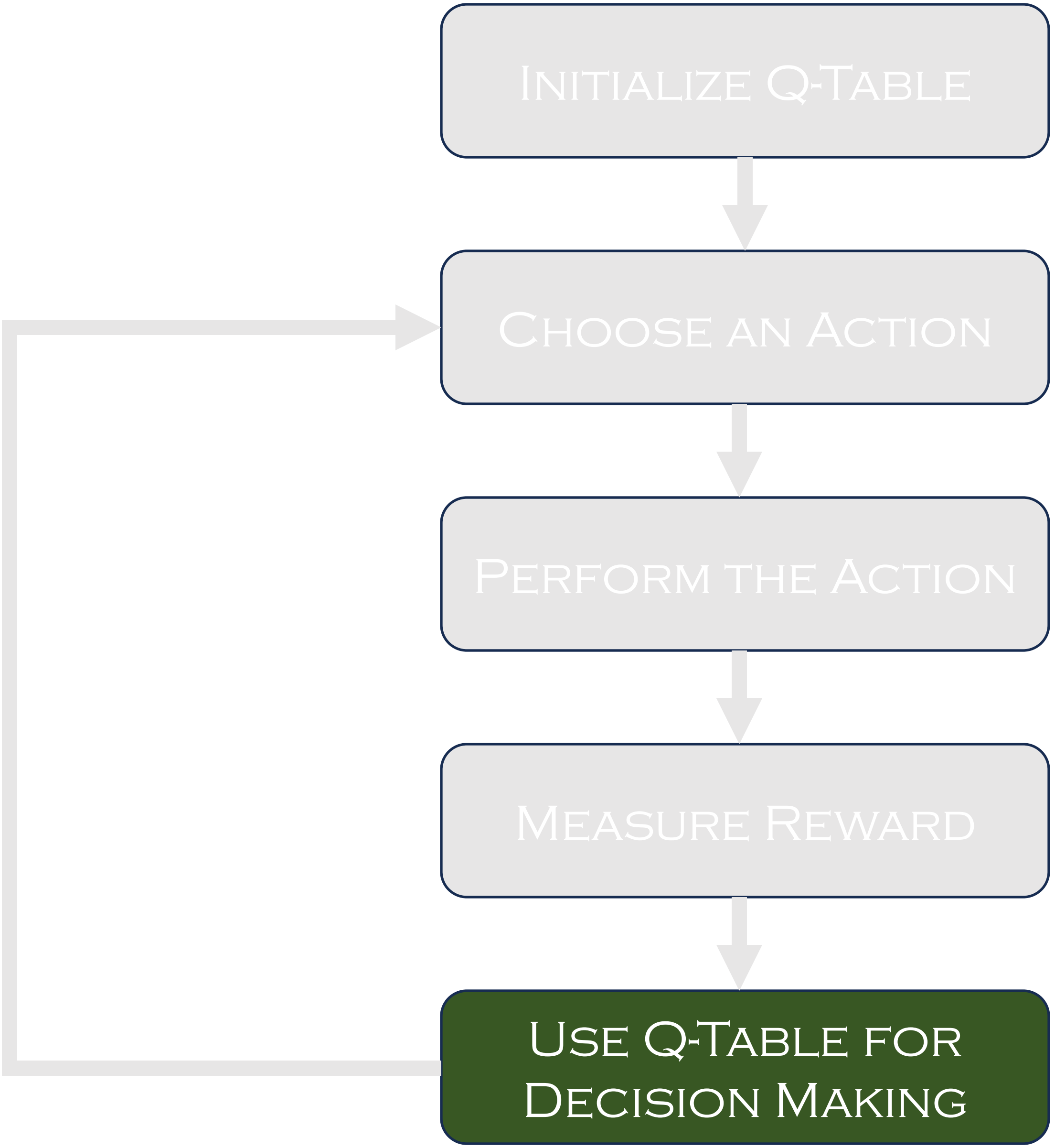
Exploration

- Explore the environment
- Randomly choose an action

Exploitation

- Some knowledge of the environment already exists
- Increased confidence on the current Q-Table
- Choose actions based on Q-table

Q-table	Action 1	Action 2
State 1		
State 2		
State 3		

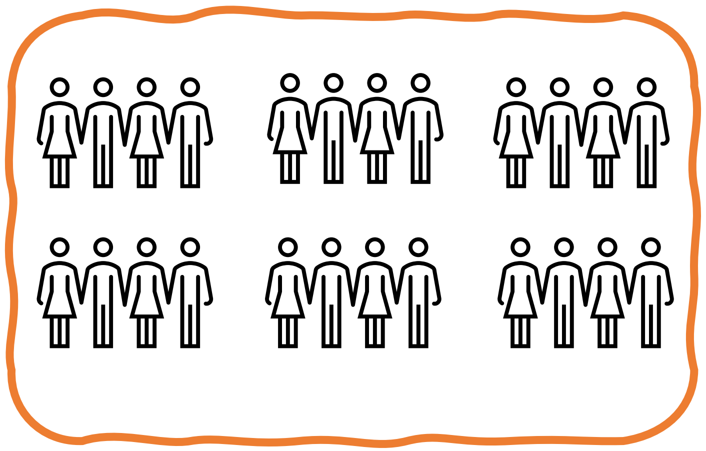

Initialize Q-Table
Choose an Action
Perform the Action
Measure Reward
Use Q-Table for Decision Making

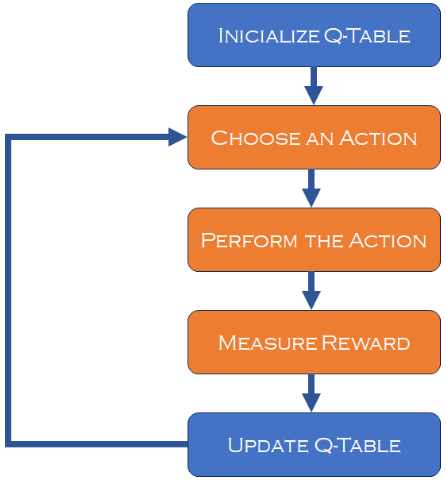
1. The structure is complying with the medical prescription.
2. The structure is not respecting dose constraints by less than 10%.
3. The structure is not respecting dose constraints by more than 10%.

EXISTING STATES

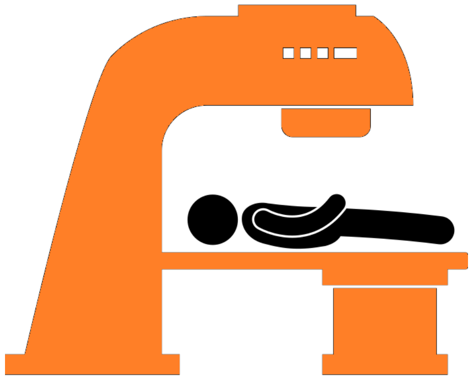
1. Use fuzzy rules defined by set 1 to change the parameters of the FMO model.
2. Use fuzzy rules defined by set 2 to change the parameters of the FMO model.

POSSIBLE ACTIONS





Training



Use Q-Table for Decision Making

Testing

Results: Our original approach had already proven to be able to obtain high quality treatment plans.

WITH THE INCLUSION OF Q-LEARNING, FUZZY RULES ARE DYNAMICALLY CHANGED AS THE ALGORITHM PROGRESSES, INSTEAD OF BEING FIXED.

This has led to a decrease in the total number of iterations needed to reach a treatment plan complying with the medical prescription.

Average values considering Cross Validation show a reduction in the total number of iterations ranging from 50% to 63%.

Conclusion: Automated treatment planning can be achieved by combining ML with optimization models and algorithms.

In this work an ensemble approach joining RL, optimization and fuzzy inference systems is presented for fully automated treatment planning WITHOUT RESORTING TO LARGE TRAINING DATASETS.

Reinforcement learning, as well as other ML approaches, can be naturally integrated with OR models and methods.

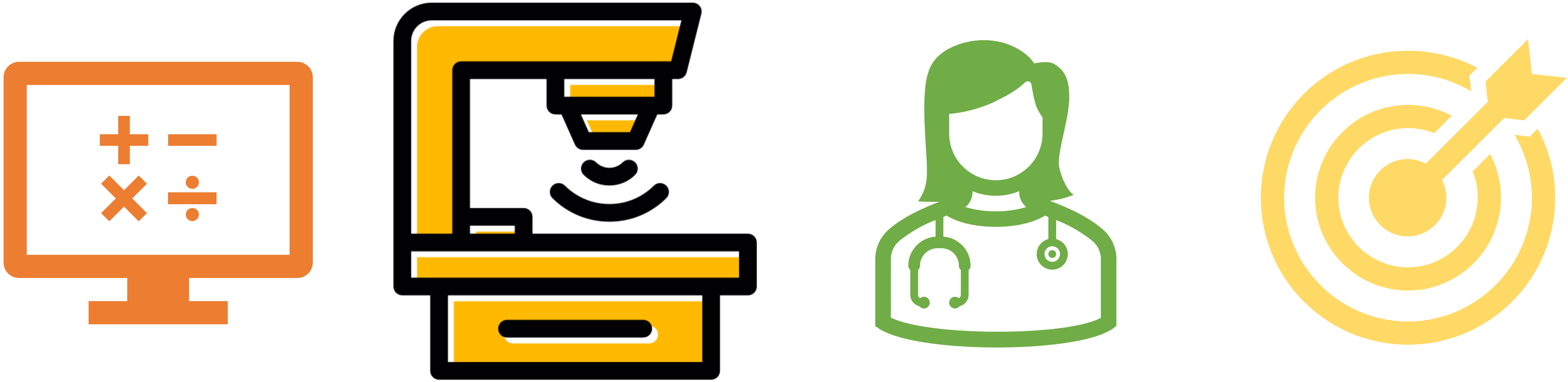
Difficult and interdisciplinary real world problems will gain with the integrated use of different tools.

Machine learning is just one more tool that Operations Researchers can/should use. It is not the holy grail for all existing problems.

So many new avenues for research and for tackling real world problems!

Operations Research and multidisciplinary collaboration in real world applications

- Have an open mind and be willing to learn.
- Step into the others' shoes and understand other points of view.
- Understand what is really important: what will be the results that can make the difference.
- Incorporate existing knowledge into OR way of thinking.
- Be flexible and use the most adequate tools.



Radiotherapy Treatment Planning

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INESCC Institute for Systems Engineering and Computers at Coimbra