

InnerEye - The ART of the possible

AI for cancer treatment

Image courtesy of Elekta AB

AI and healthcare – hype vs truth



Prof. Geoff Hinton remarking that
"People should stop training radiologists now"
[@machine learning conference]



Will radiologists be replaced by computers?
Debunking the hype of AI
Prof Eliot Siegel, University of Maryland
[@Carestream blog RSNA16]

Agenda

Why **Radiation Therapy**?

What **AI** is commercially available?

InnerEye, a clinician's perspective

From Precision to **Adaptive Radiotherapy (ART)**



Why radiation therapy?

Huge societal problem for Europe

1 in 2 of us will be diagnosed with cancer

1 in 2 of cancer patients will need radiotherapy

400 K new cancer patients in Europe in 2015



For immediate release [Monday 18 April 2016]

Demand for radiotherapy will rise substantially over next ten years; planning to deal with increase in new cancer cases should start now



“We have shown clearly that the need for radiotherapy across Europe will increase substantially by the year 2025.”

Prof Cai Grau, Aarhus

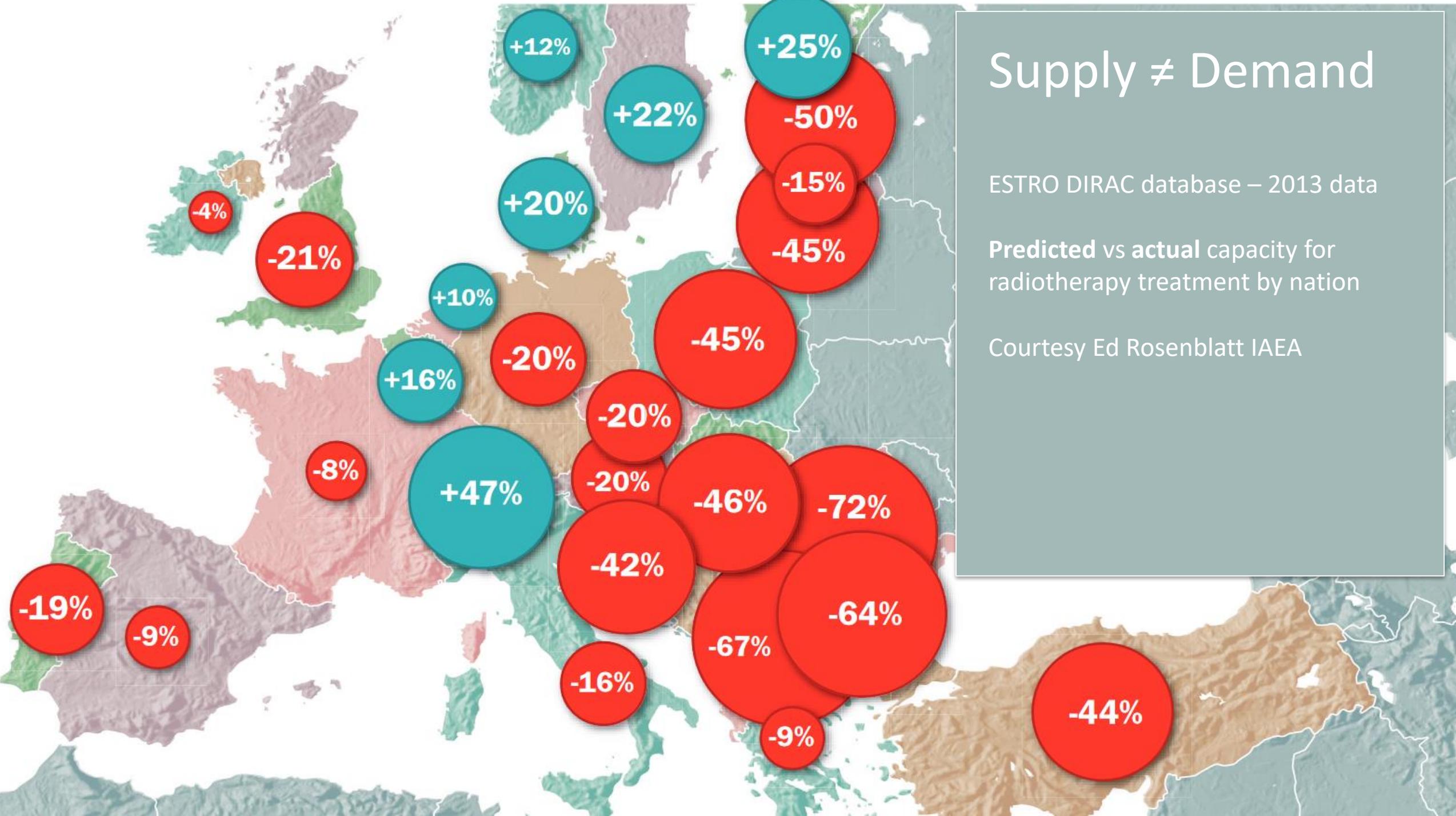


Supply ≠ Demand

ESTRO DIRAC database – 2013 data

Predicted vs actual capacity for radiotherapy treatment by nation

Courtesy Ed Rosenblatt IAEA

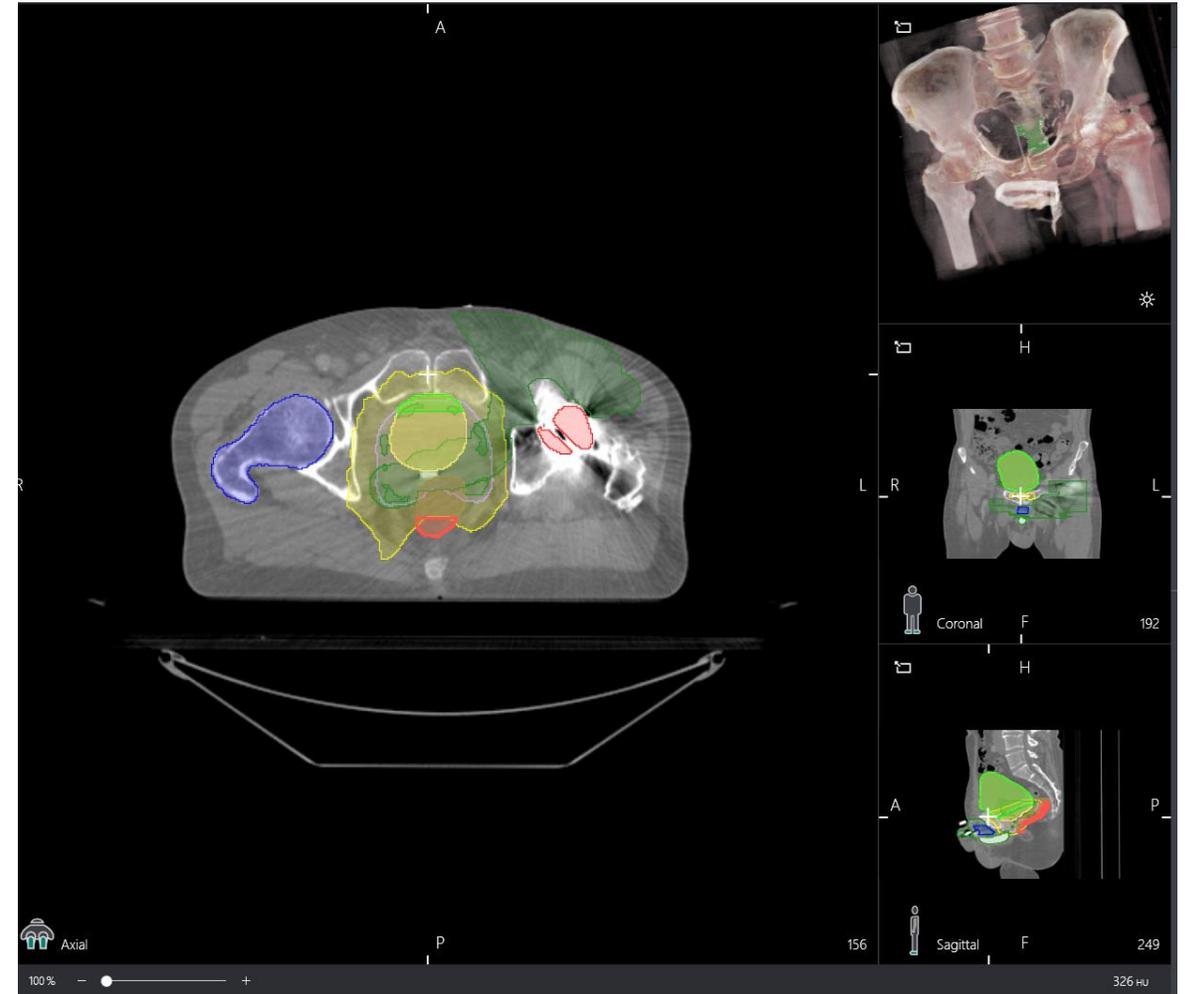


Why “precision” radiation therapy?

Huge unmet **clinical need**

Imaging is at the basis of modern radiotherapy treatment planning

Segmentation of cancer and healthy tissues is extremely slow and expensive





What AI is available commercially ?



Diagnosis: is there cancer?

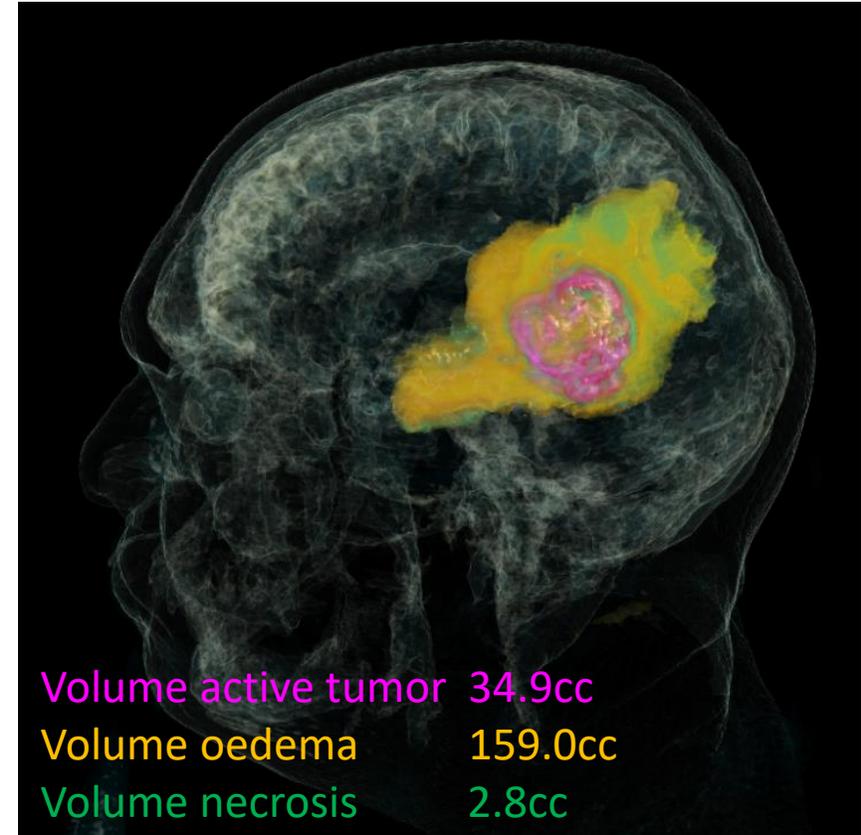
(do we need AI? Humans are good at this)



Segmentation / targeting

No existing AI solution for radiotherapy.
(ABAS is not AI and it does not get used)

Where is the cancer?
Where are the healthy tissues?
What is their extent?



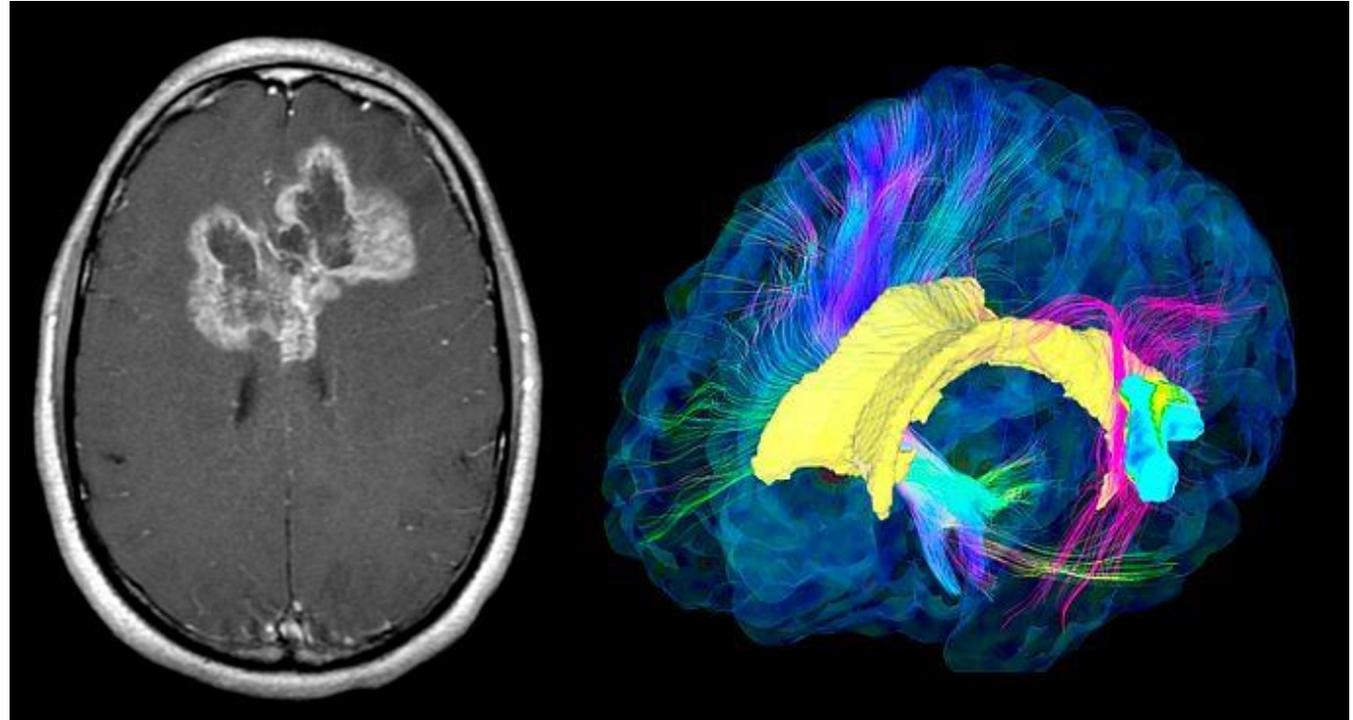


Workflow acceleration – a neuro-oncologist perspective

In neuro-oncology preparing radiotherapy takes **60-90 minutes** for each patient

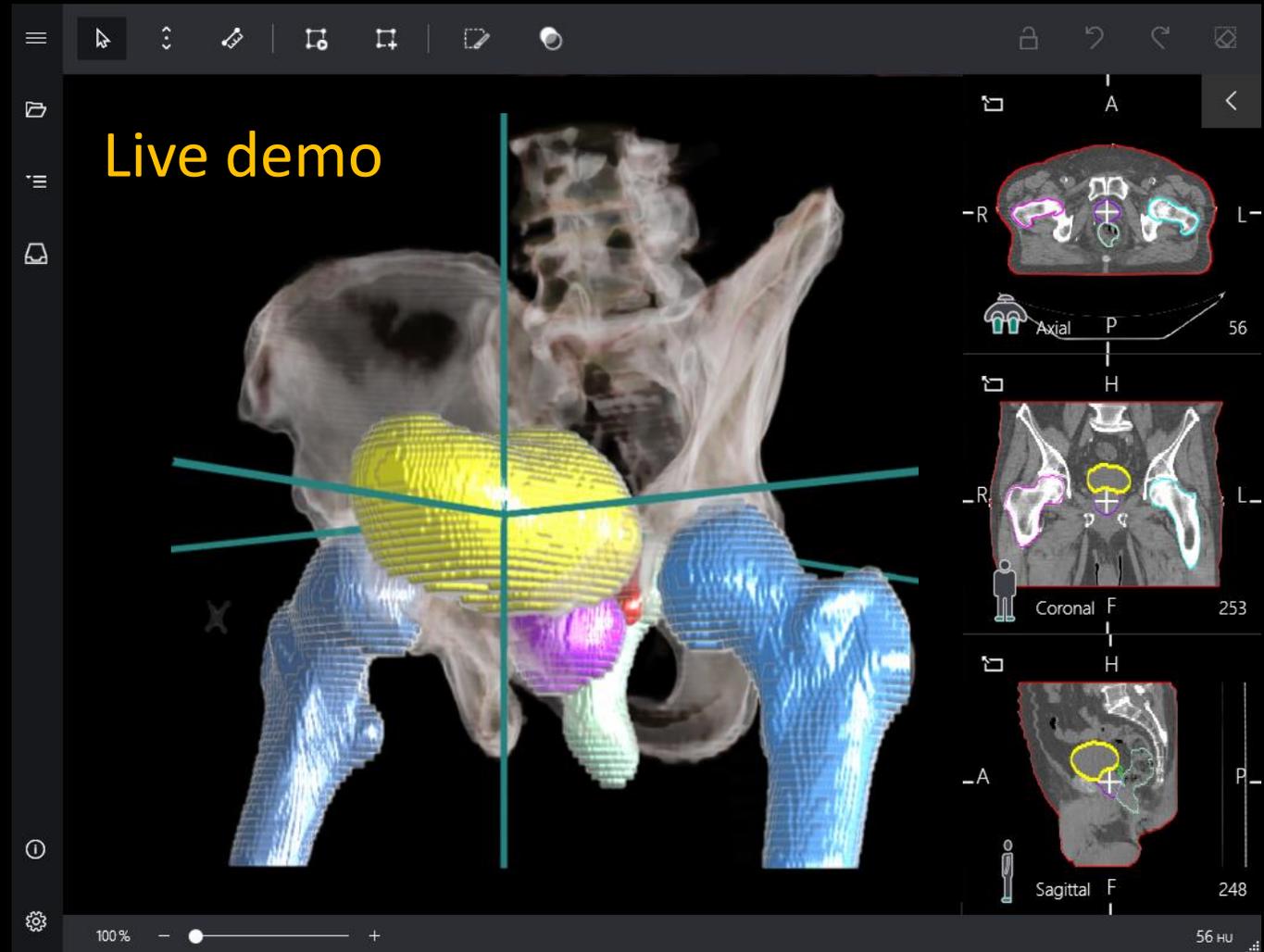
With InnerEye technology it will take **~5 minutes**

A **12-18 X speed-up factor**



The 3D image segmentation app

Efficient segmentation
of anatomy and pathology

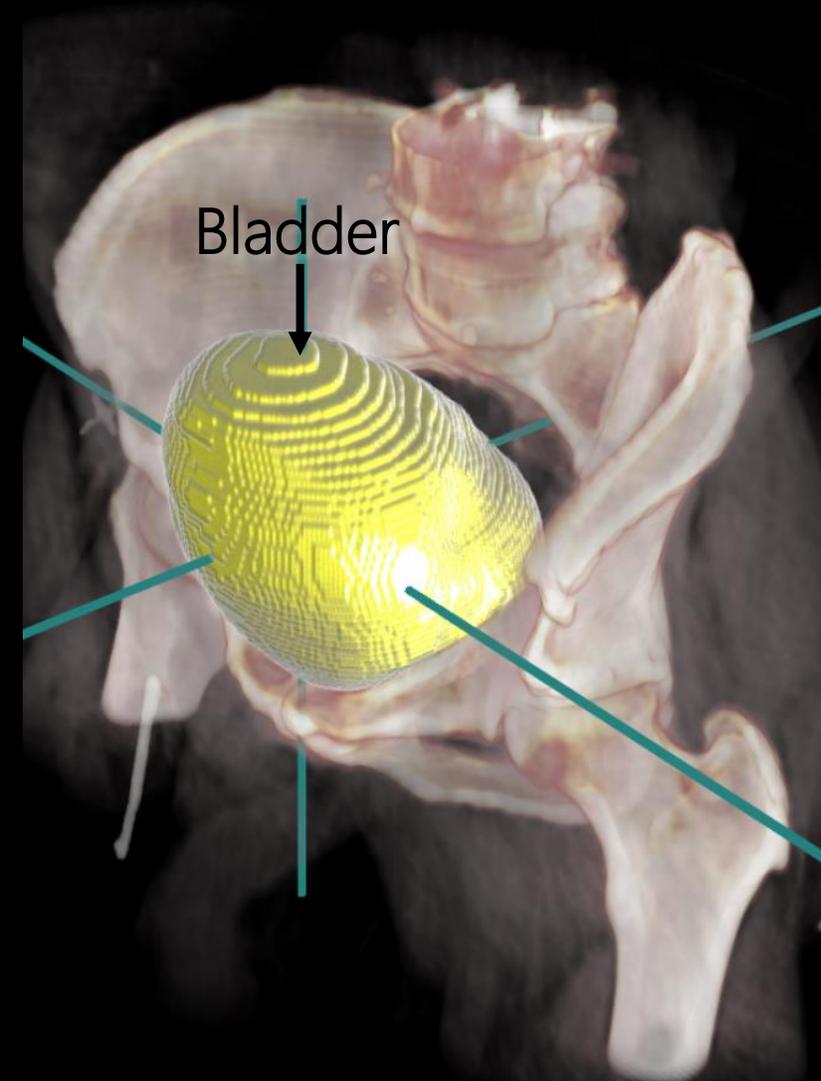
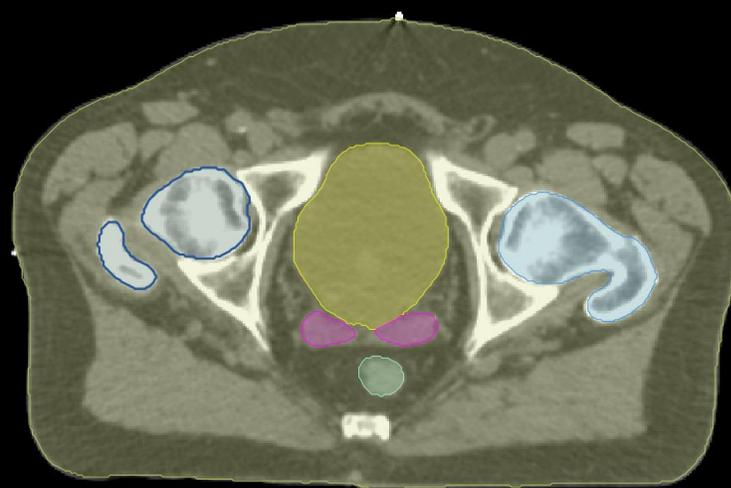
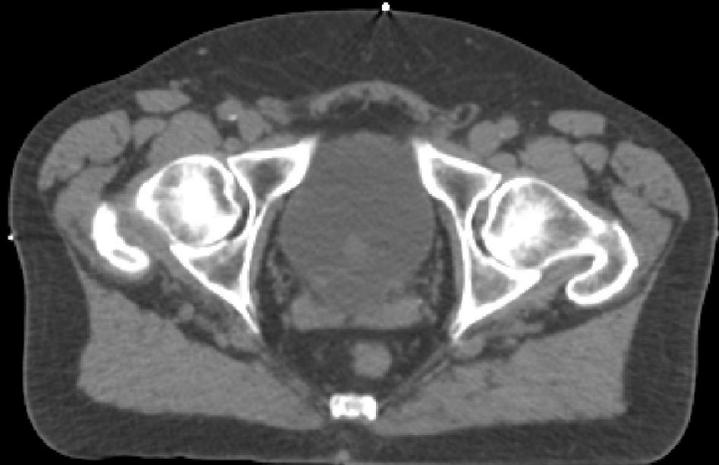


The goal of automatic 3D segmentation

Two axial slices of the same CT scan

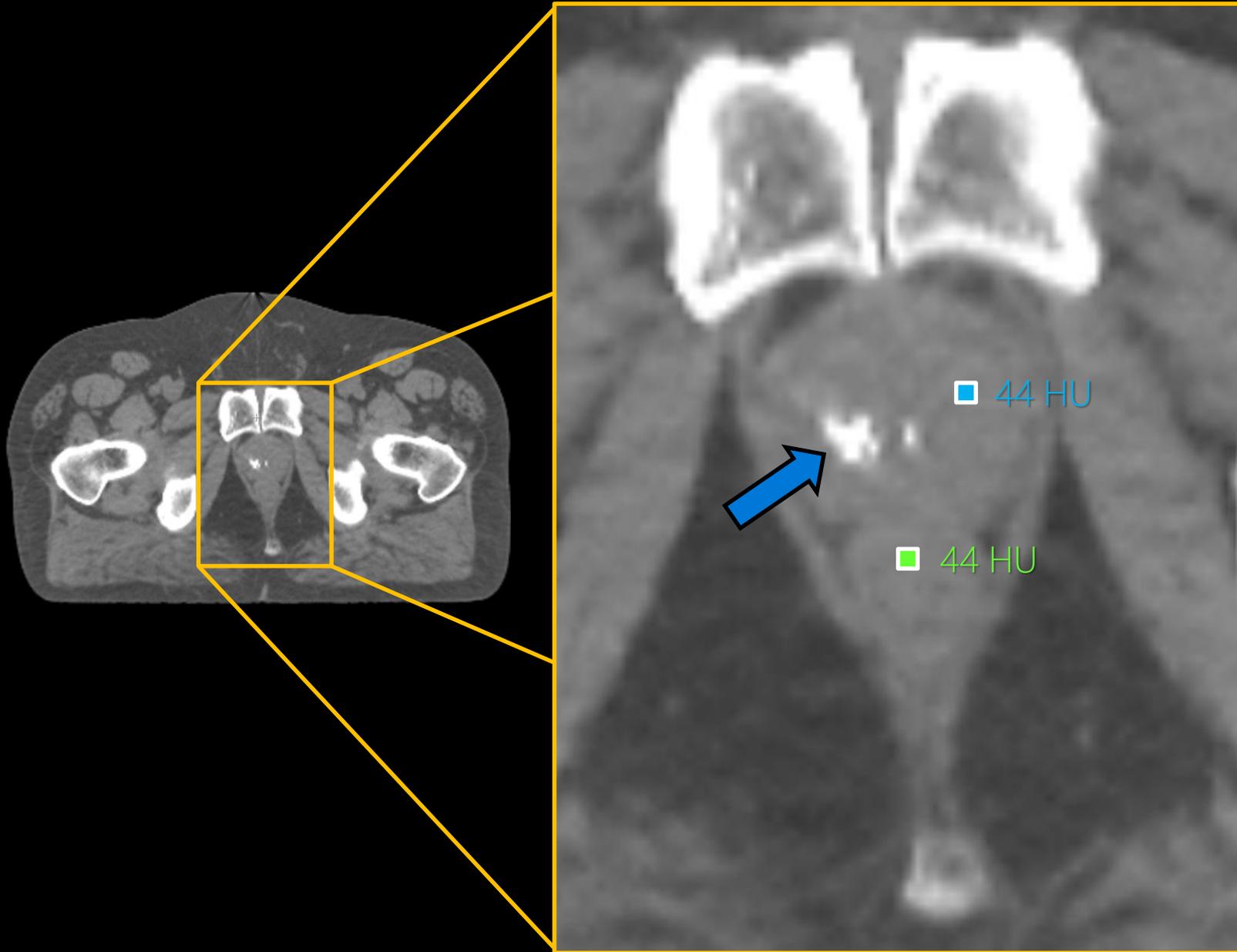
Overlaid axial segmentations

Natively 3D segmentation



Prostate, seminal vesicles, rectum, bladder, left femur, right femur, skin

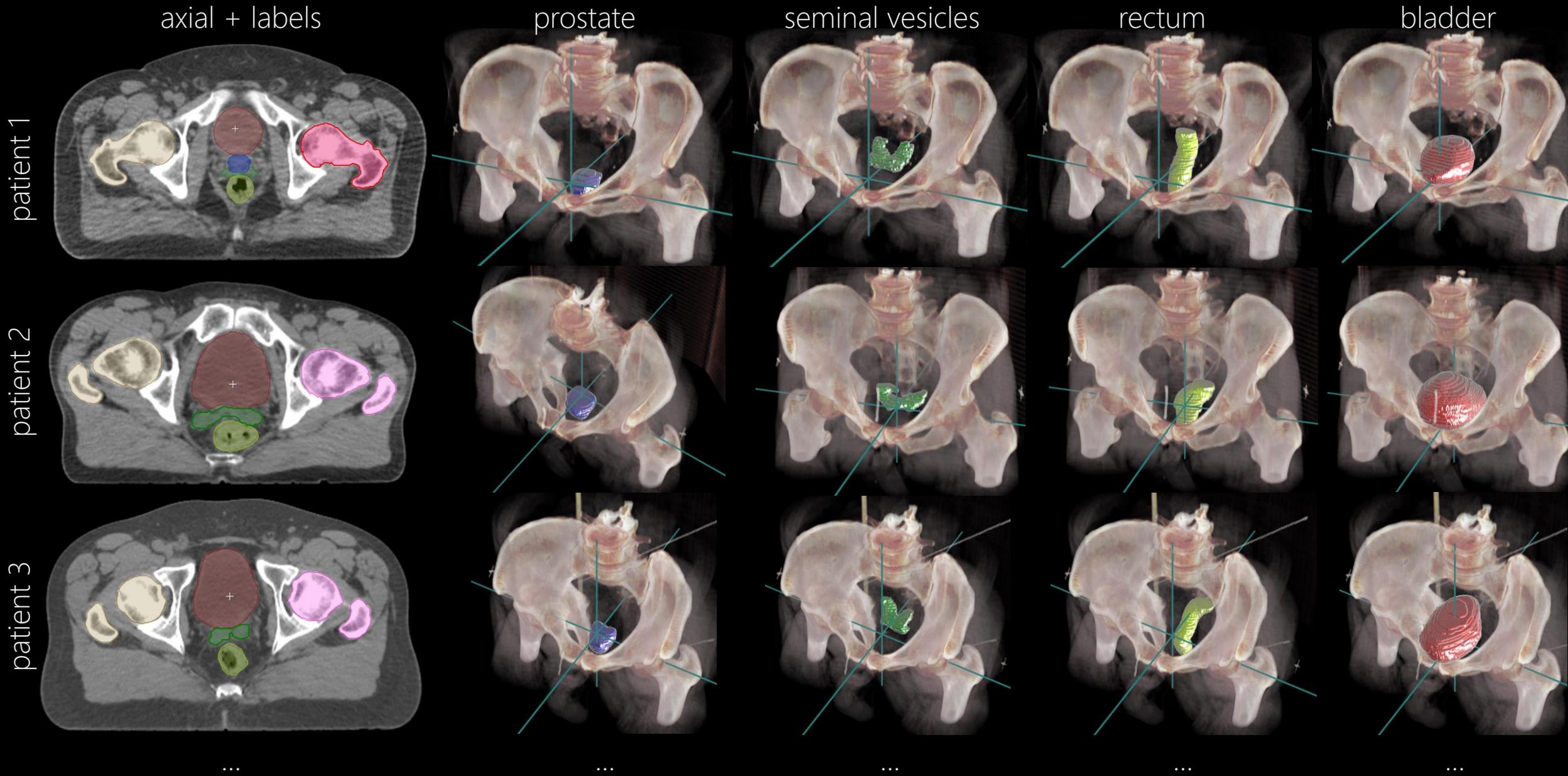
Why is voxel-wise semantic segmentation hard?



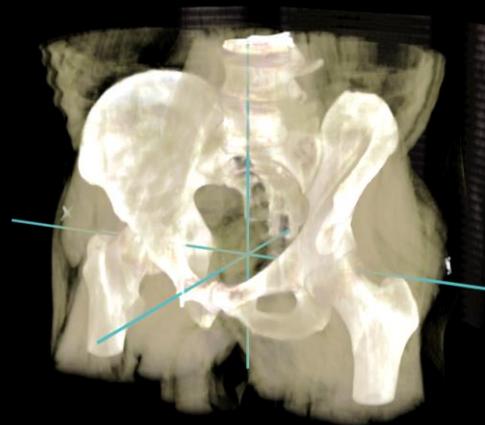
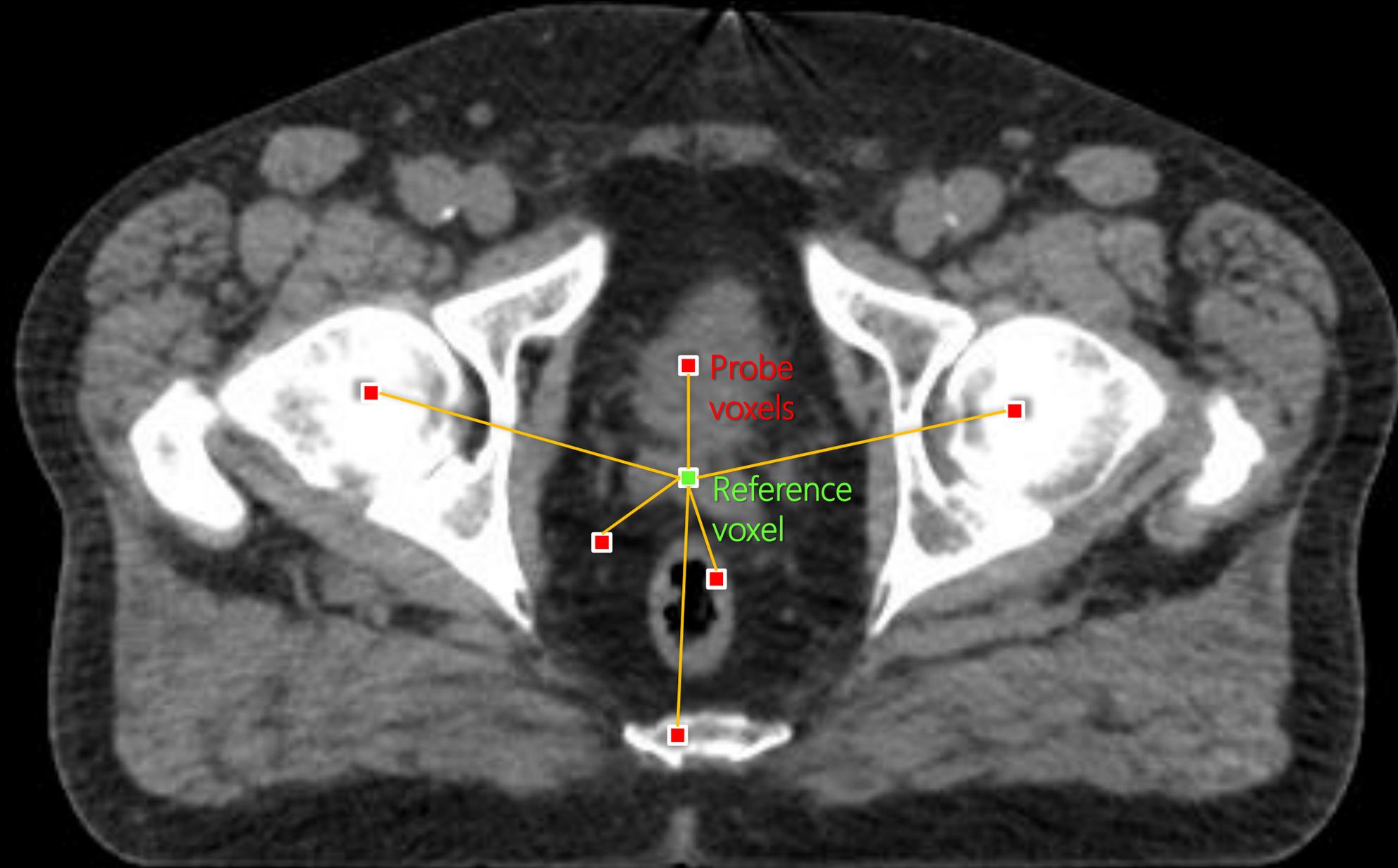
The challenge

- Same HU value for different anatomies
- Large deformations
- Implants
- Beam-hardening artefacts
- Different image resolution
- Image noise
- Presence/absence of contrast medium
- Different patient preparation
- ...

Our "ground-truth" labelled image dataset – hundreds of patients



Modeling context via learned neighborhood patterns

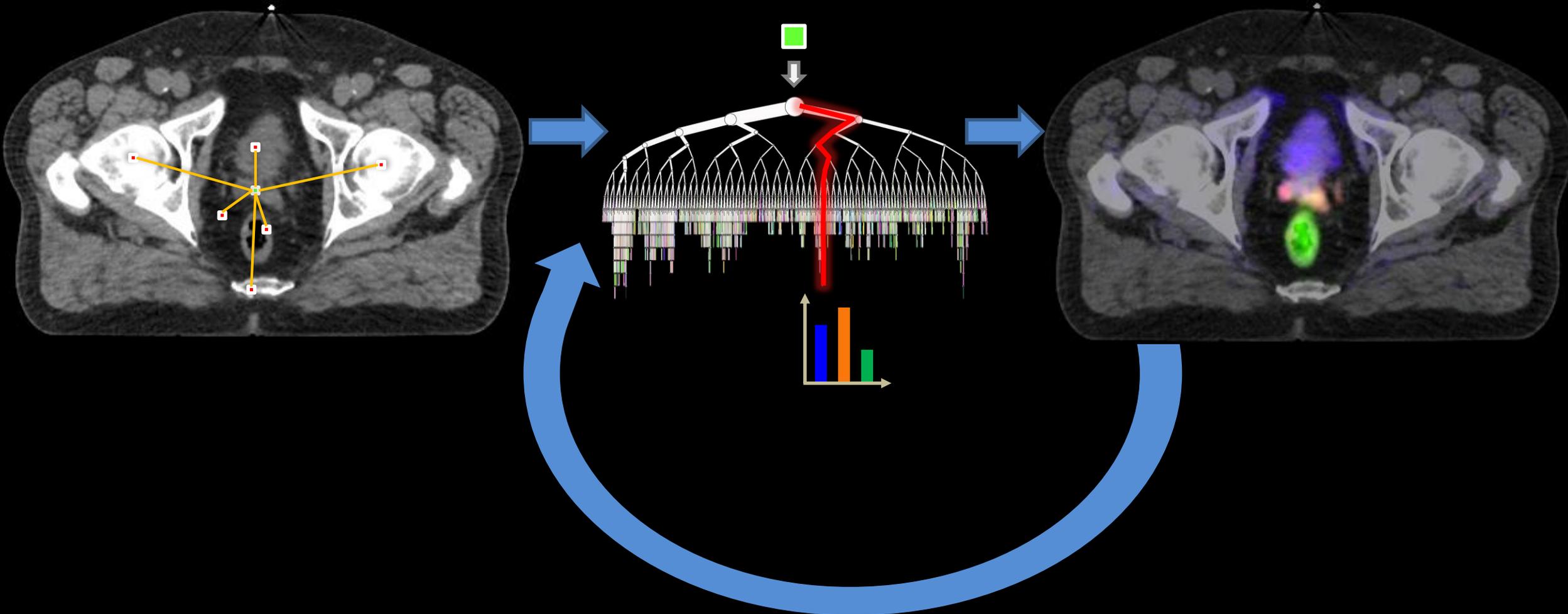


Deep Decision Forests for semantic segmentation - training

Input CT image

For each input voxel
(and all its context features)

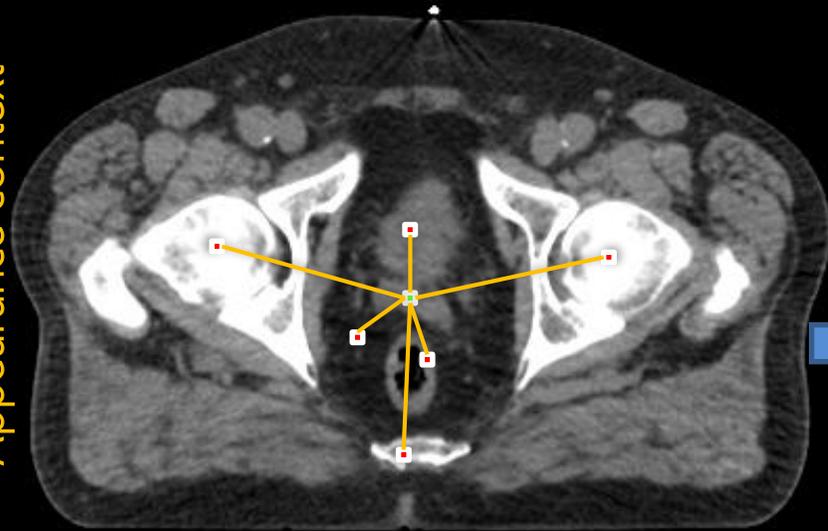
Output - probabilities @ layer 0



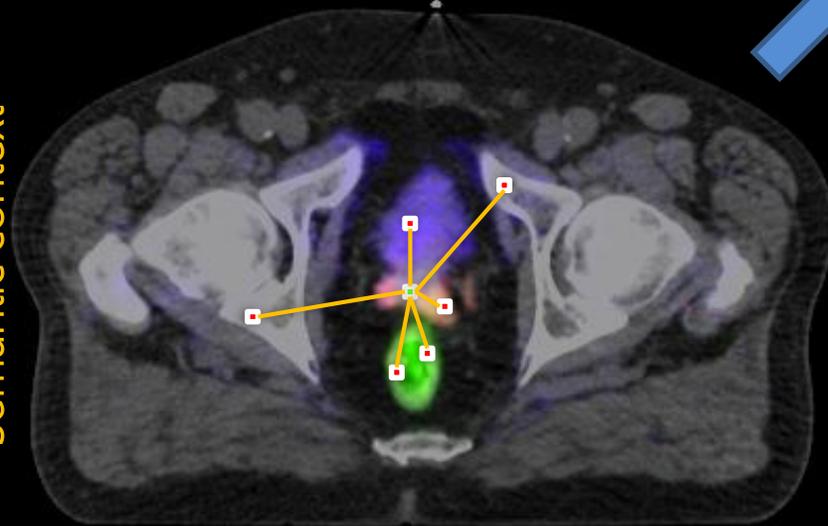
Deep Decision Forests for semantic segmentation - training

Appearance context

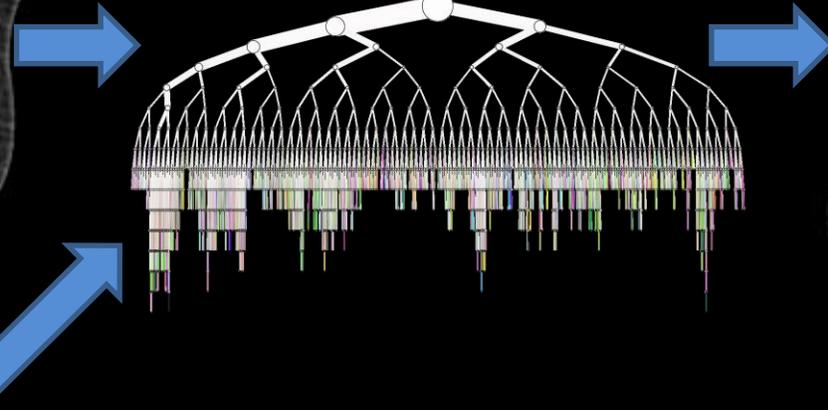
Input CT image



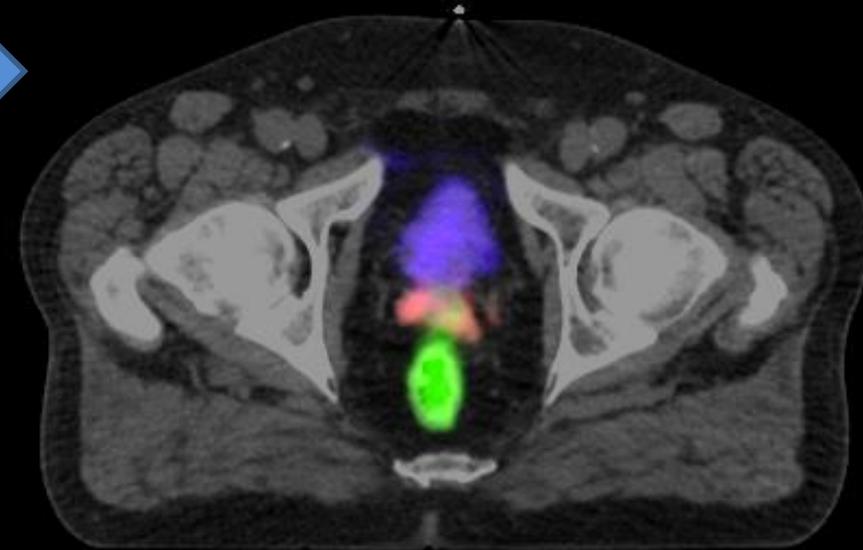
Input - probabilities @ layer 0



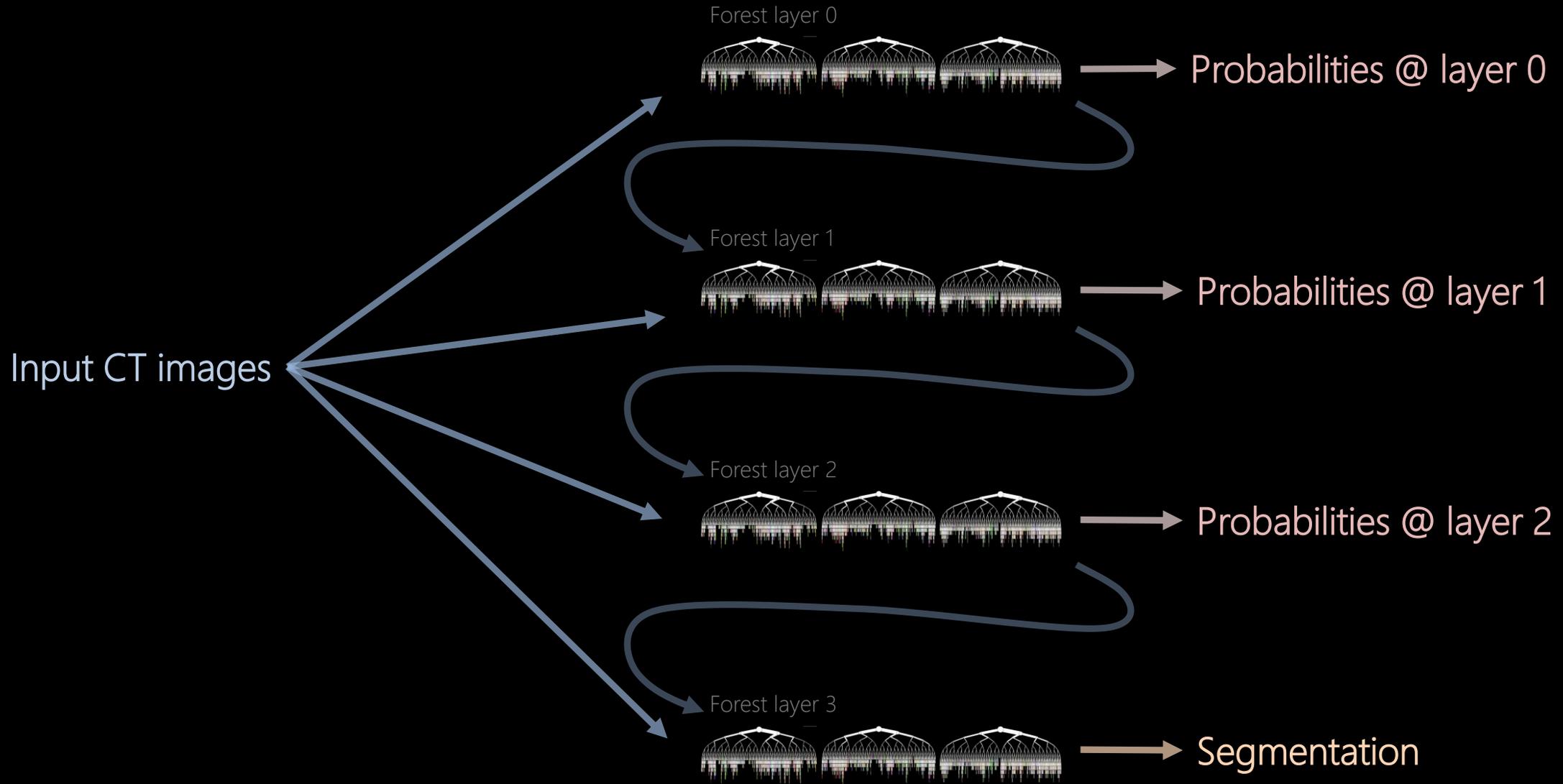
Semantic context



Output - probabilities @ layer 1



Our trained Deep Decision Forest model



M. Fiterau, A. Criminisi, S. Rota Bulò, P. Kotschieder, *Deep Neural Decision Forests [Winner of the David Marr Prize]*. ICCV 2015

Y. Ioannou, D. Robertson, R. Cipolla, A. Criminisi, *Deep Roots: Improving CNN Efficiency with Hierarchical Filter Groups*. CVPR 2017

Y. Ioannou, D. Robertson, D. Zikic, P. Kotschieder, J. Shotton, M. Brown, A. Criminisi, *Decision Forests, Convolutional Networks and the Models in Between*. ArXiv and Microsoft Tech Report 2015.

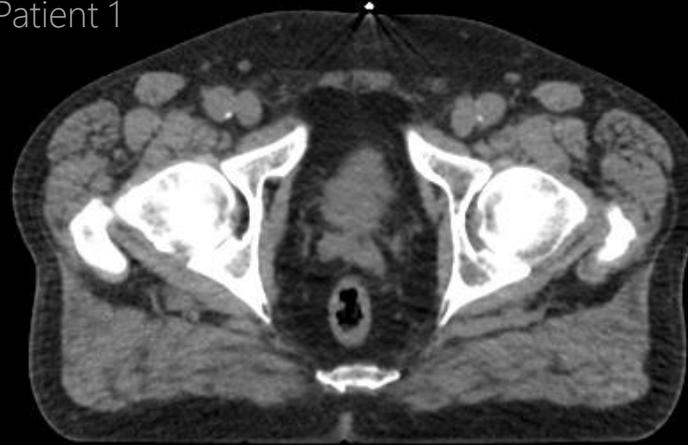
L. Le Folgoc, A. Nori, S. Ancha, A. Criminisi, *Lifted Auto-Context Forests for Brain Tumour Segmentation*. MICCAI 2016. BRATS workshop.

Deep Decision Forests for semantic segmentation - runtime

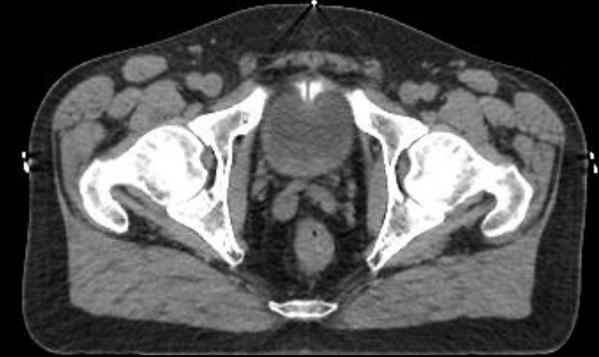
@ runtime

Input CT image

Patient 1



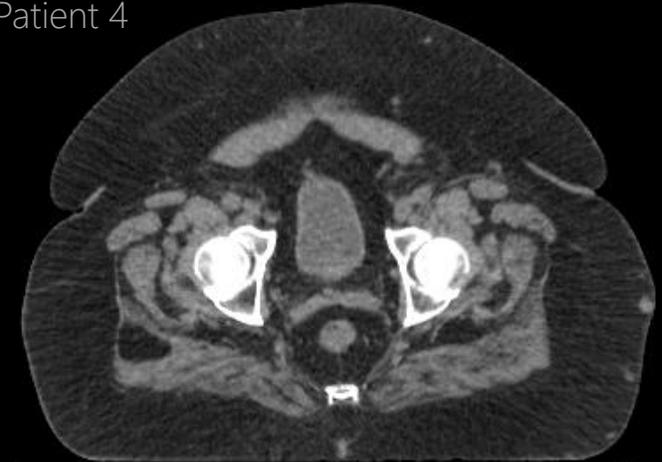
Patient 2



Patient 3



Patient 4



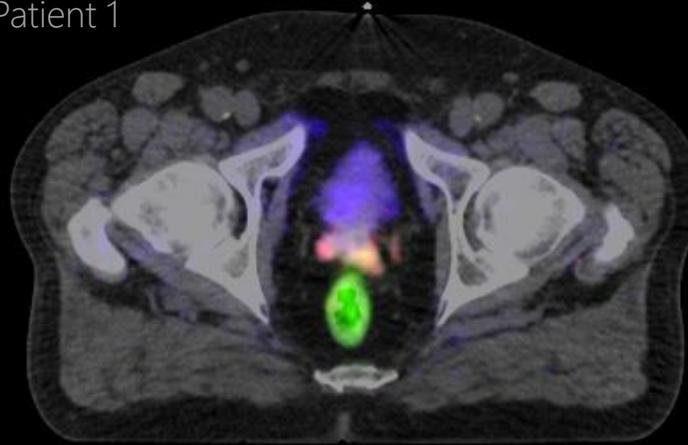
Deep Decision Forests for semantic segmentation - runtime

@ runtime

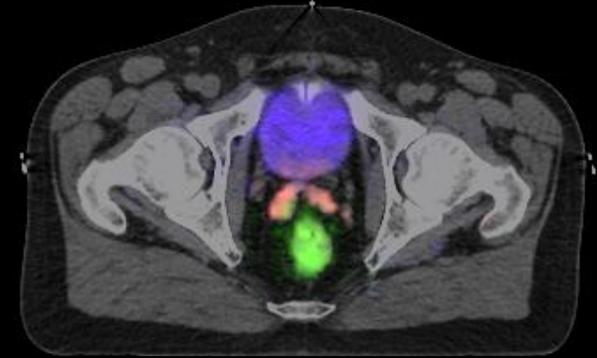
Probabilities @ layer 0

Input CT image

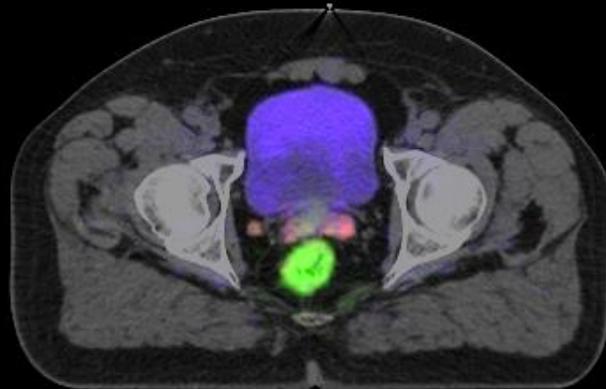
Patient 1



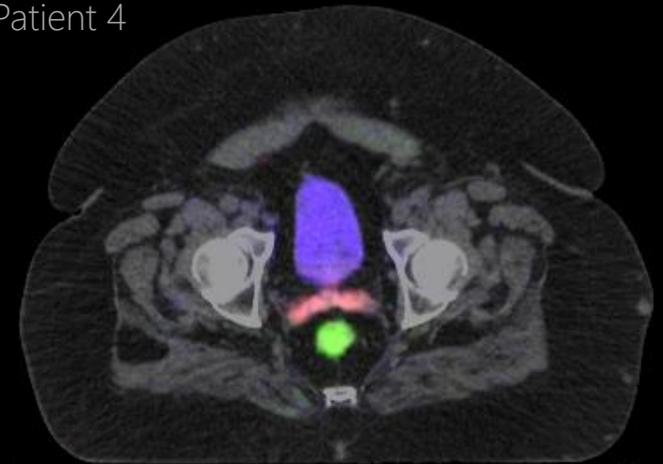
Patient 2



Patient 3



Patient 4



Deep Decision Forests for semantic segmentation - runtime

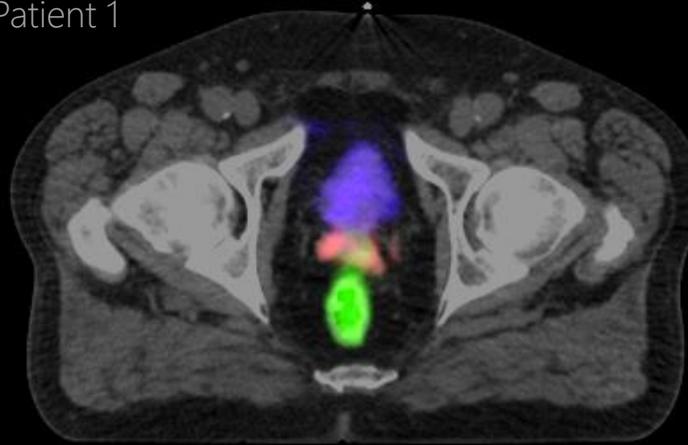
@ runtime

Probabilities @ layer 1

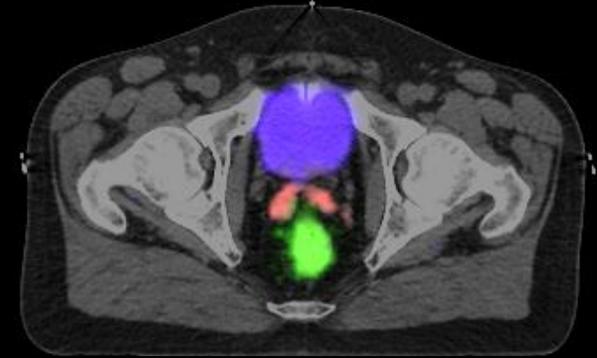
Probabilities @ layer 0

Input CT image

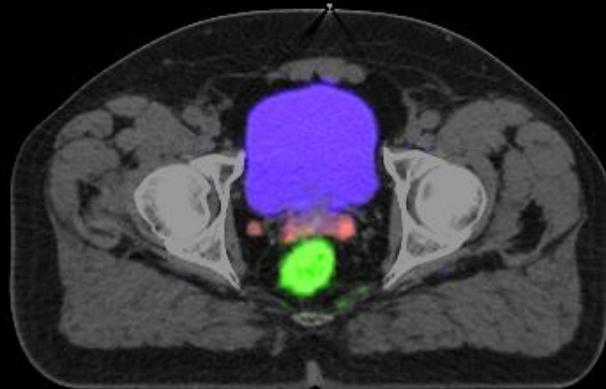
Patient 1



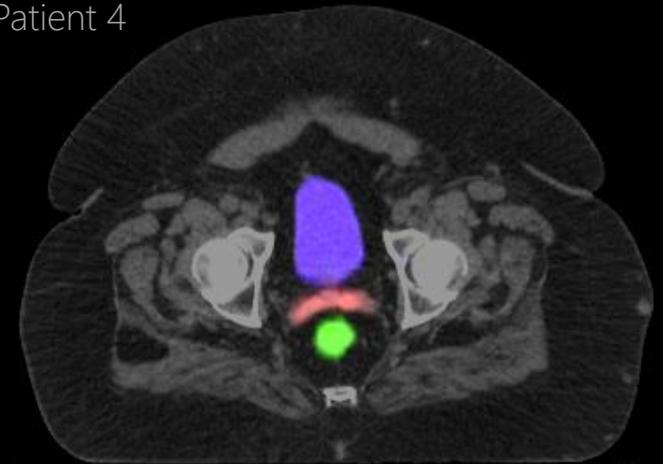
Patient 2



Patient 3



Patient 4



Deep Decision Forests for semantic segmentation - runtime

@ runtime

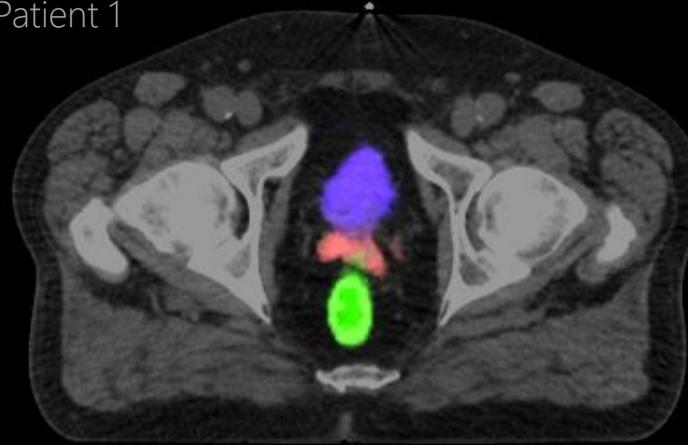
Probabilities @ layer 2

Probabilities @ layer 1

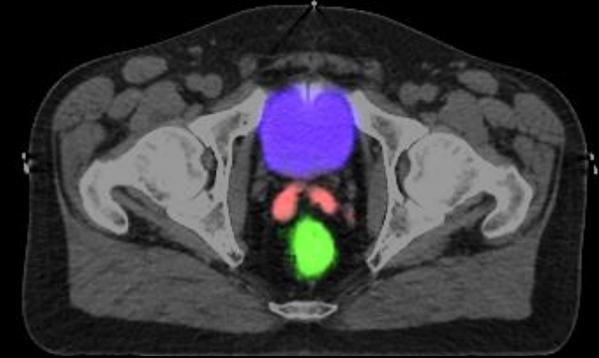
Probabilities @ layer 0

Input CT image

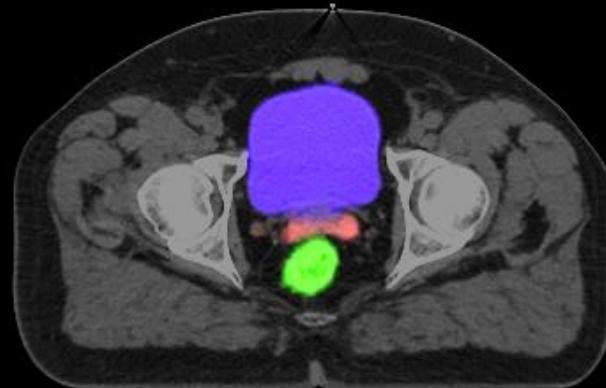
Patient 1



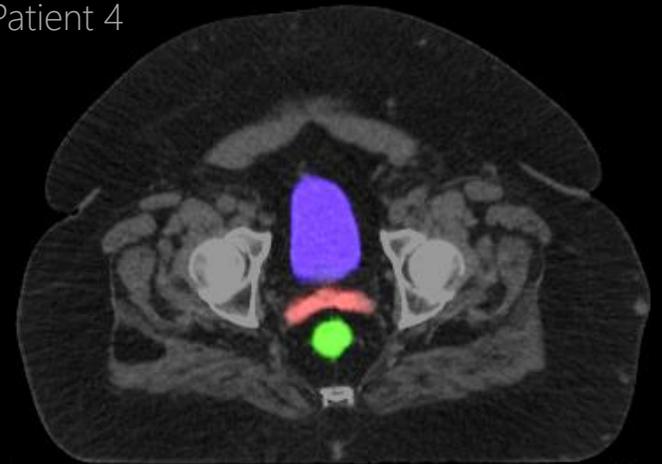
Patient 2



Patient 3



Patient 4



Deep Decision Forests for semantic segmentation - runtime

@ runtime

Segmentation

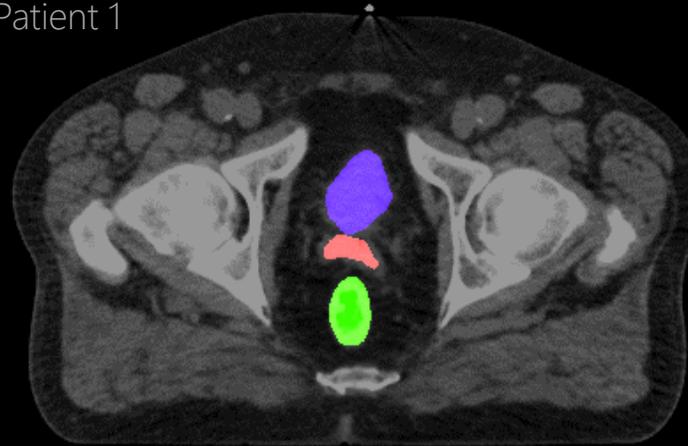
Probabilities @ layer 2

Probabilities @ layer 1

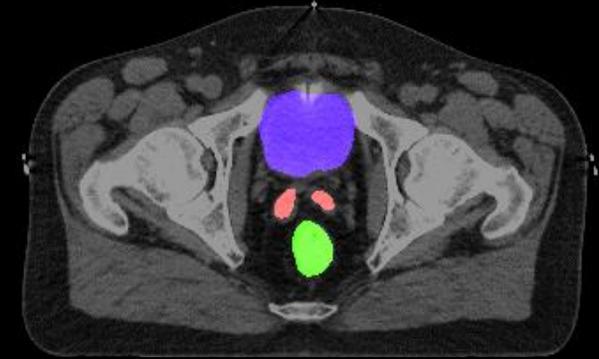
Probabilities @ layer 0

Input CT image

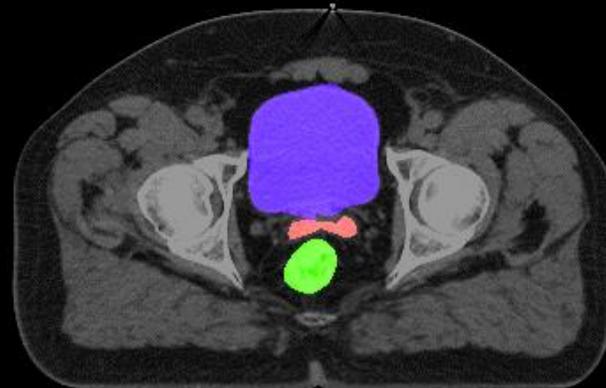
Patient 1



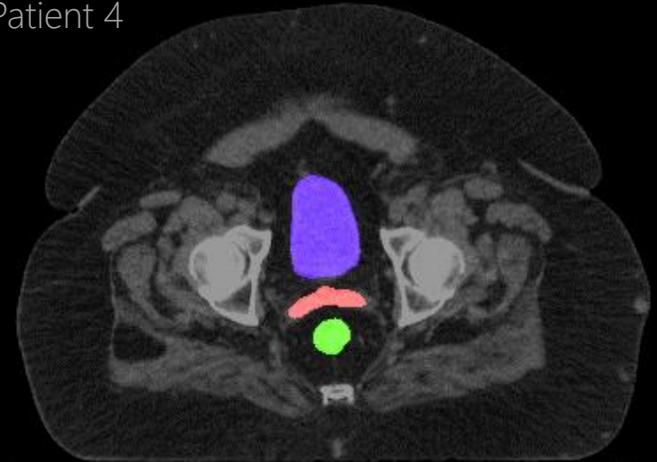
Patient 2



Patient 3



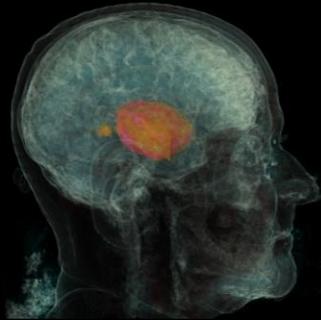
Patient 4



The segmentation works despite anatomical variations. No need for atlases. No need for deformable registration. Probabilistic output (it encodes uncertainty).

The machine learning models we are building

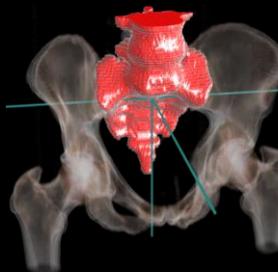
Input: MR
High/low grade gliomas
Oedema
Necrosis
Longitudinal analysis ...



Input: CTA
Left/right parenchymas
Collecting systems
Arteries, Veins
Masses ...



Input: CT
Spine...



Microsoft Azure

InnerEye segmentation services

BrainML.Glioblastoma

BrainML.LowGradeGlioma

HeadNeckML

ThoraxML.Lungs

AbdomenML.Liver

AbdomenML.Kidneys

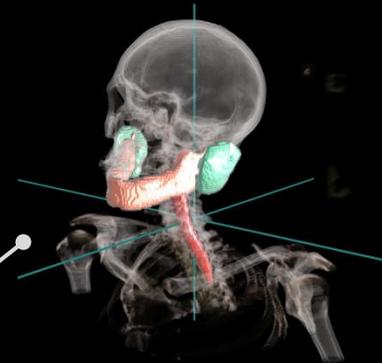
PelvisML.Spine

PelvisML.Prostate

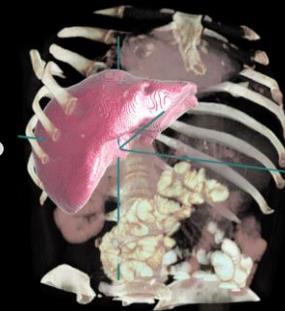
...

Medical components, paid services

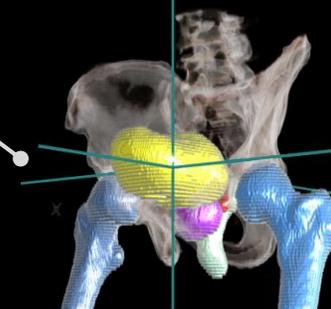
Input: CT
Parotid glands
Spinal cord
Mandible ...

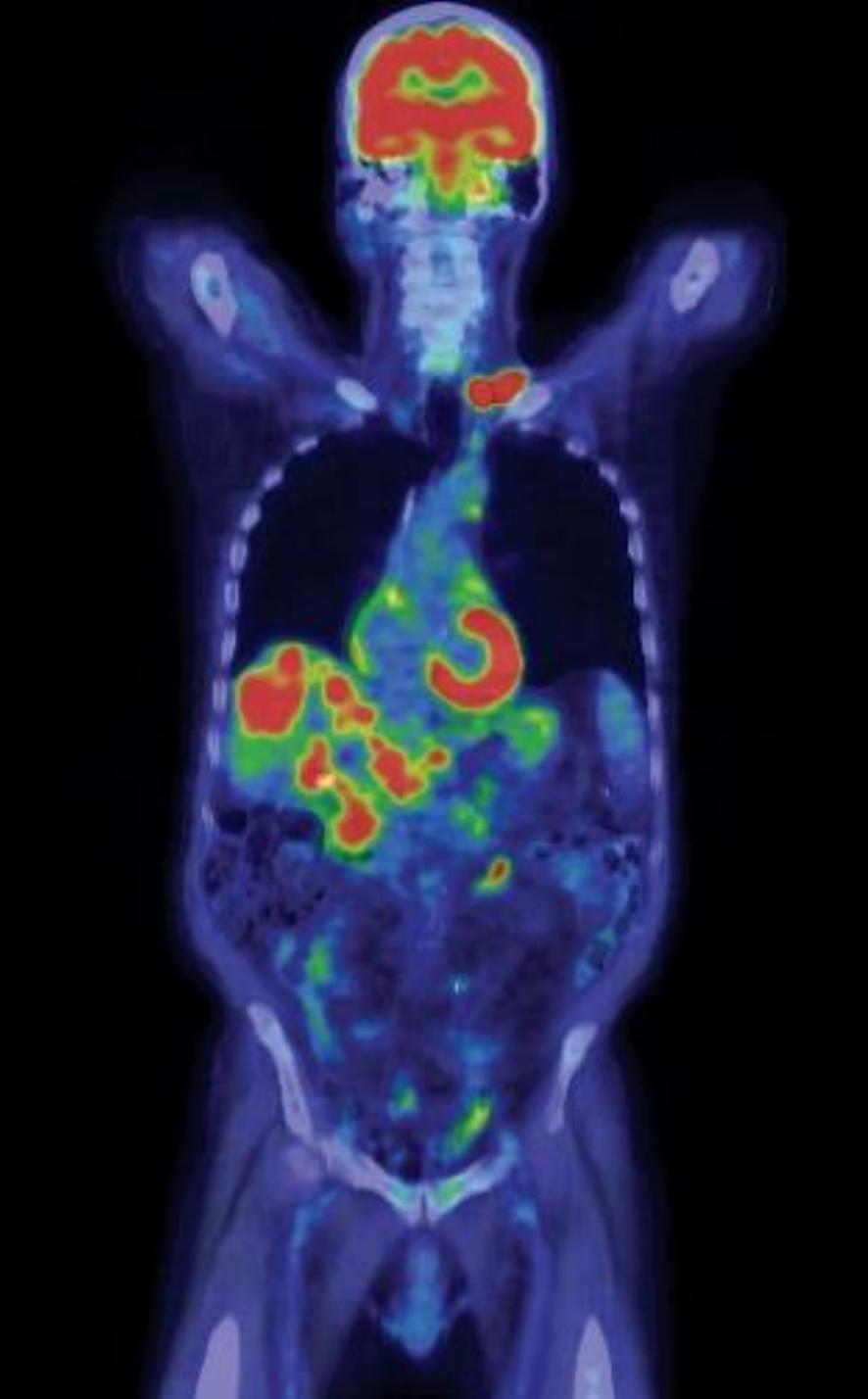


Input: CT
Liver
Masses...



Input: CT
Prostate
Seminal vesicles
Left/right femurs
Rectum
Bladder ...





Hardware enabling ART

Adaptive Radiation Therapy



AI will make ART a reality

Scan, re-identify and track the tumor target as it changes, every day

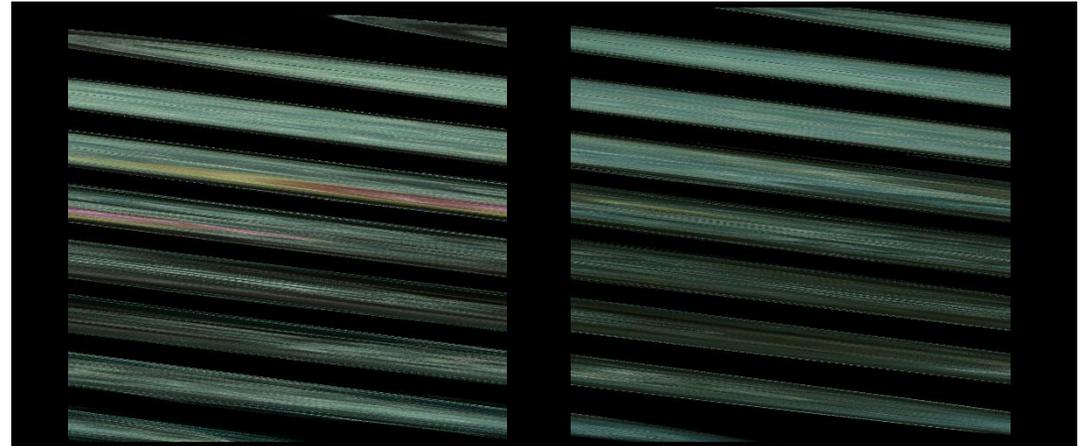
Optimized radiation therapy **targeting**

Fewer radiotherapy **sessions** (a.k.a. fractions)

Fewer **side effects**

Lower **costs**

Only realizable in the clinic through **AI**

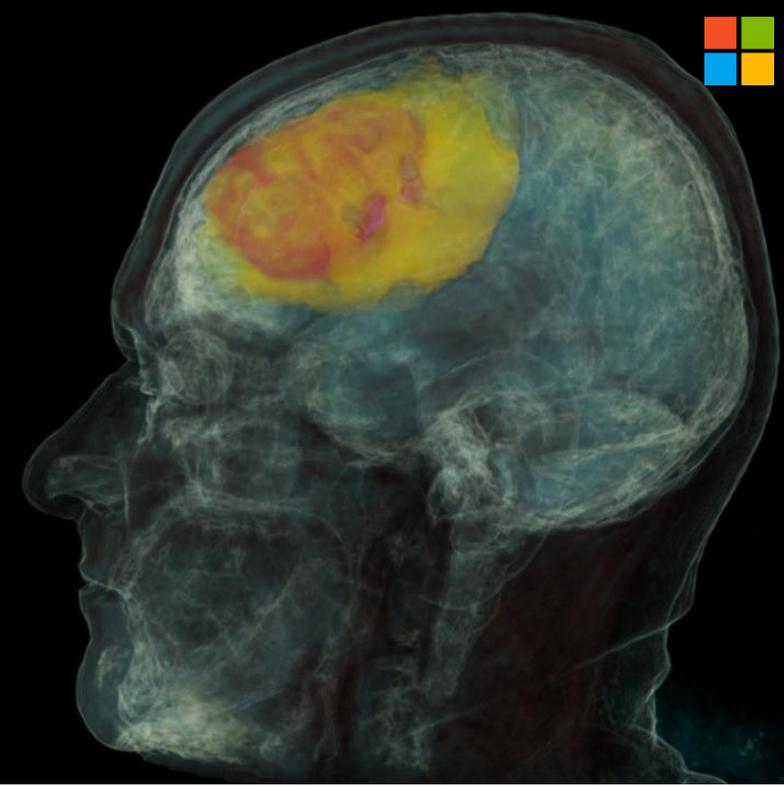


Better **outcomes** for patients

More time to think about **the patient**

Project InnerEye – Medical Imaging AI to Empower Clinicians

Established: October 7, 2008



<https://aka.ms/innereye>

R. Jena.
A. Criminisi.

Dept. Oncology Cambridge University Hospitals
Microsoft Research Cambridge