Clinical Background of Knowledge-based Models In IMRT/VMAT Planning

Jackie Wu, PhD, FAAPM
Professor

Duke University Medical Center
Department of Radiation Oncology

DukeMedicine

Jackie Wu PHD

Yaorong Ge PHD

Fang-Fang Yin PHD

Lulin Yuan PHD

Jianfei Liu PHD

Yang Sheng MS

SiMing Lu

Taoran Li PHD

DukeMedicine

Disclosure

- Research Grant: NIH/NCI
- Master Research Grant: Varian Medical System
- Technology License Agreement with Varian.

Motivation

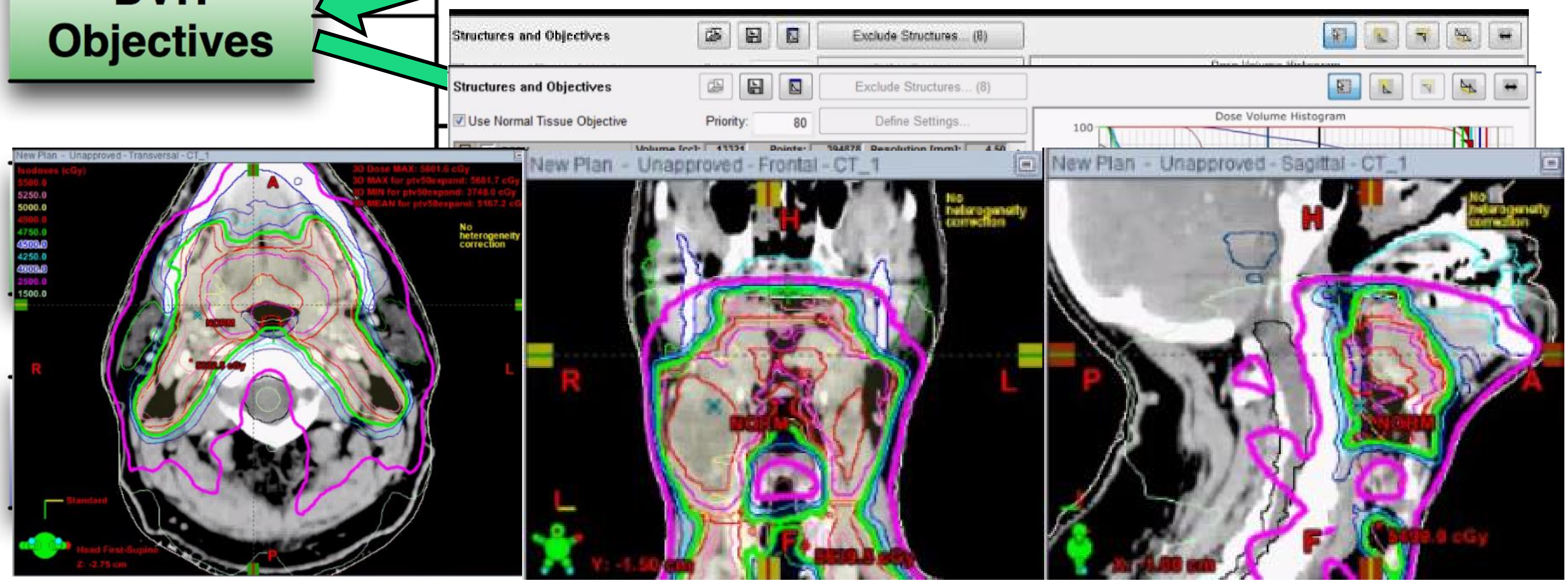
- **Extract human expert's knowledge**
- **Model past planning experience**
- **Reduce, or even automate the planning process**
- **Hypothesis**
  - Past knowledge and experience has always be applied to new patient case
  - We can mathematically extract and model such application of knowledge and experience
  - Knowledge modeling can help us improve the planning efficiency, consistency and quality.

Elements of IMRT/VMAT Treatment Planning

Anatomy

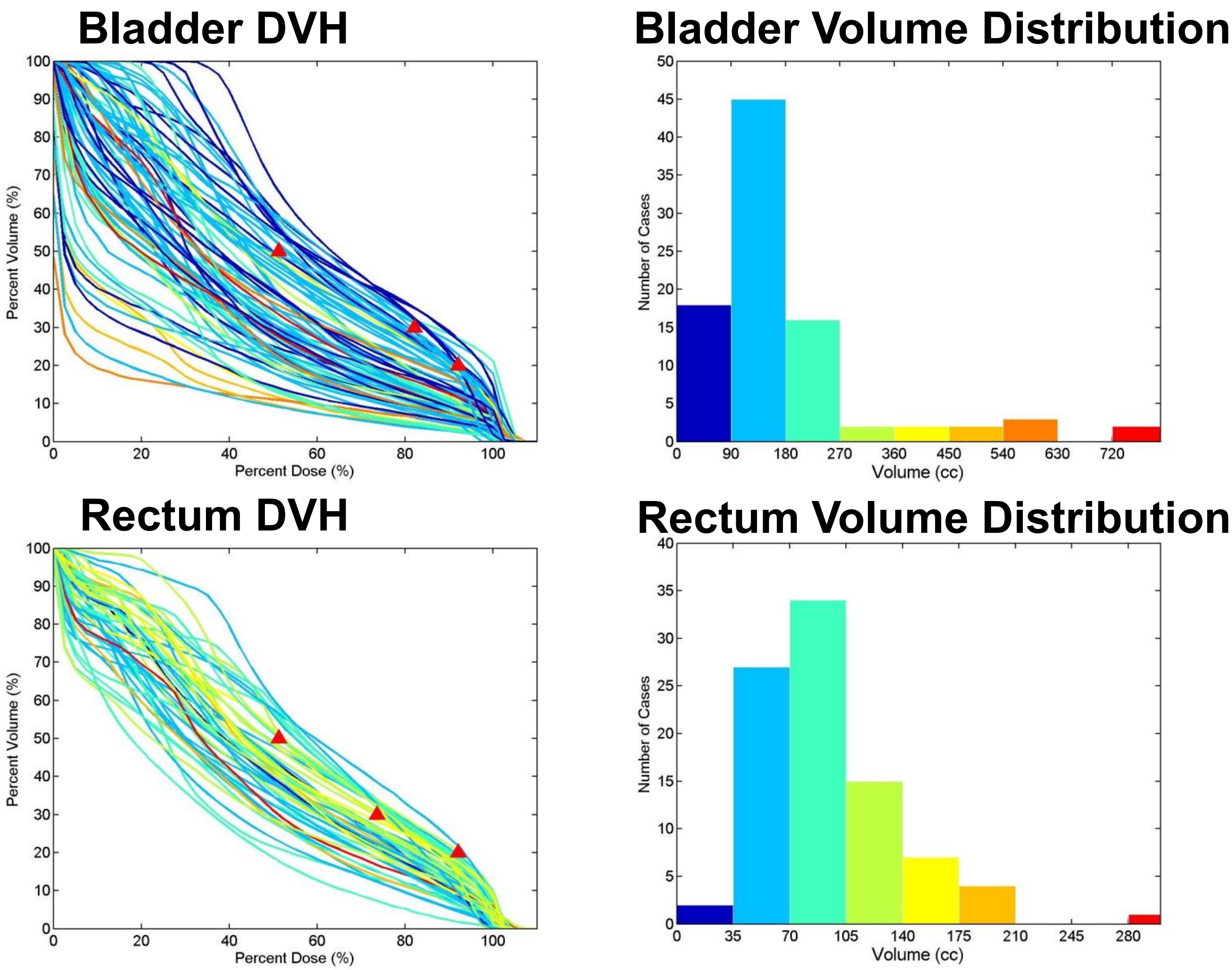
DVH Objectives

how the dose distribution should look like – experience & knowledge

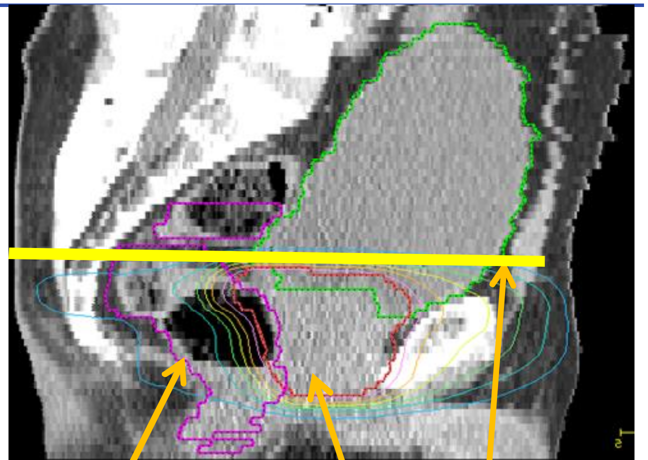


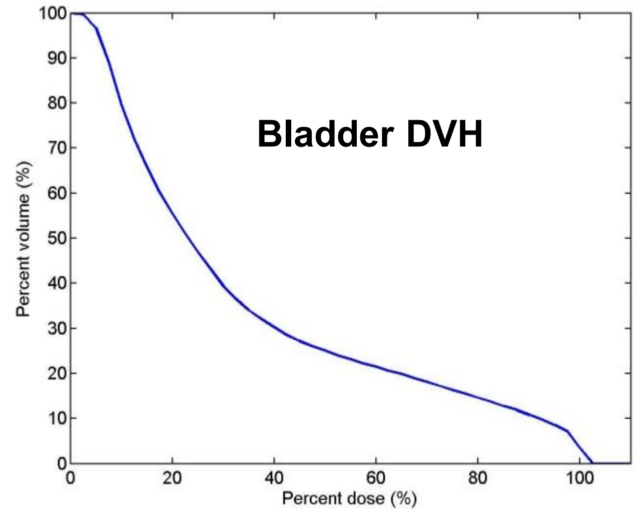
Given | **Limited** | **Variable**

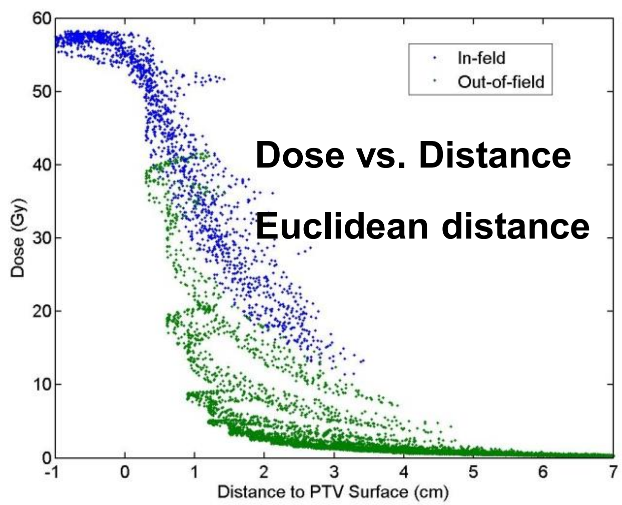
Knowledge Example: Volume vs. Dose

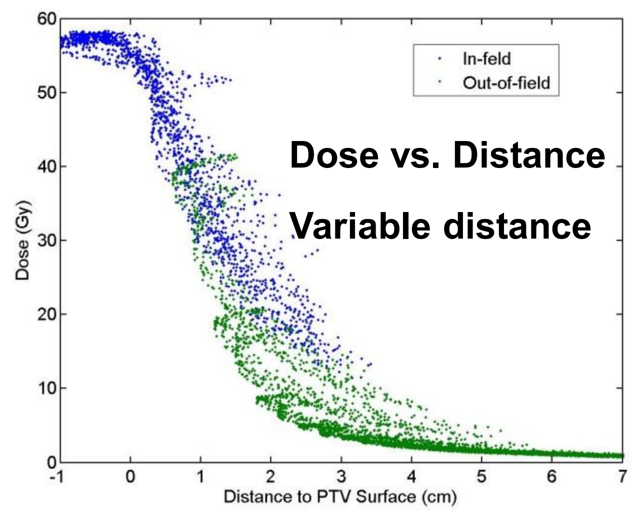


Knowledge Example: Distance vs. Dose









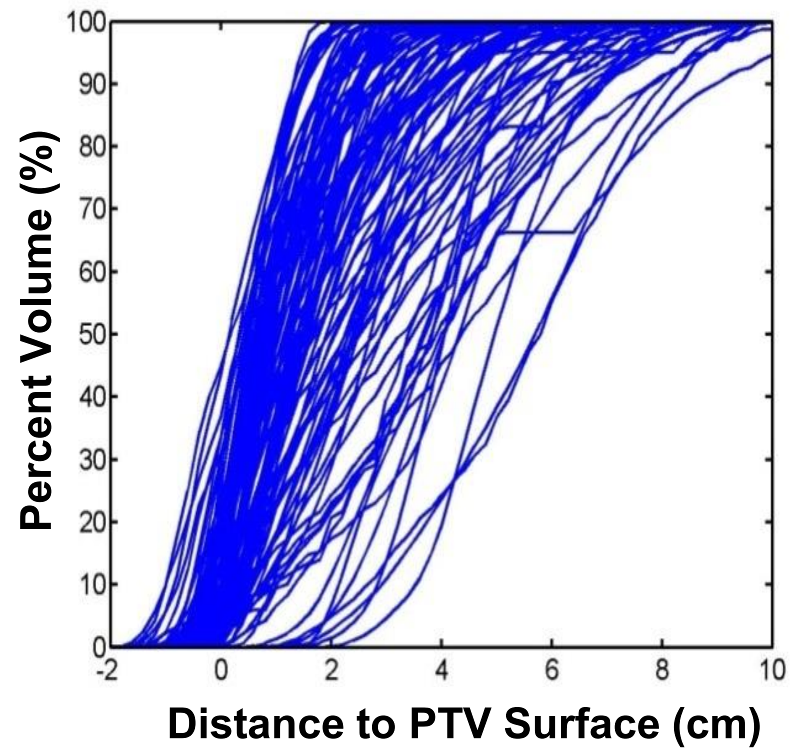
Zhu et al, *Med Phys* 38:719-726, 2011
Yuan et al, *Med Phys* 39:6868-6878, 2012

Knowledge Example: Distance-to-target Histogram (DTH)

- **Signed Distance-to-target histogram (DTH)**

(overlap: negative distance)

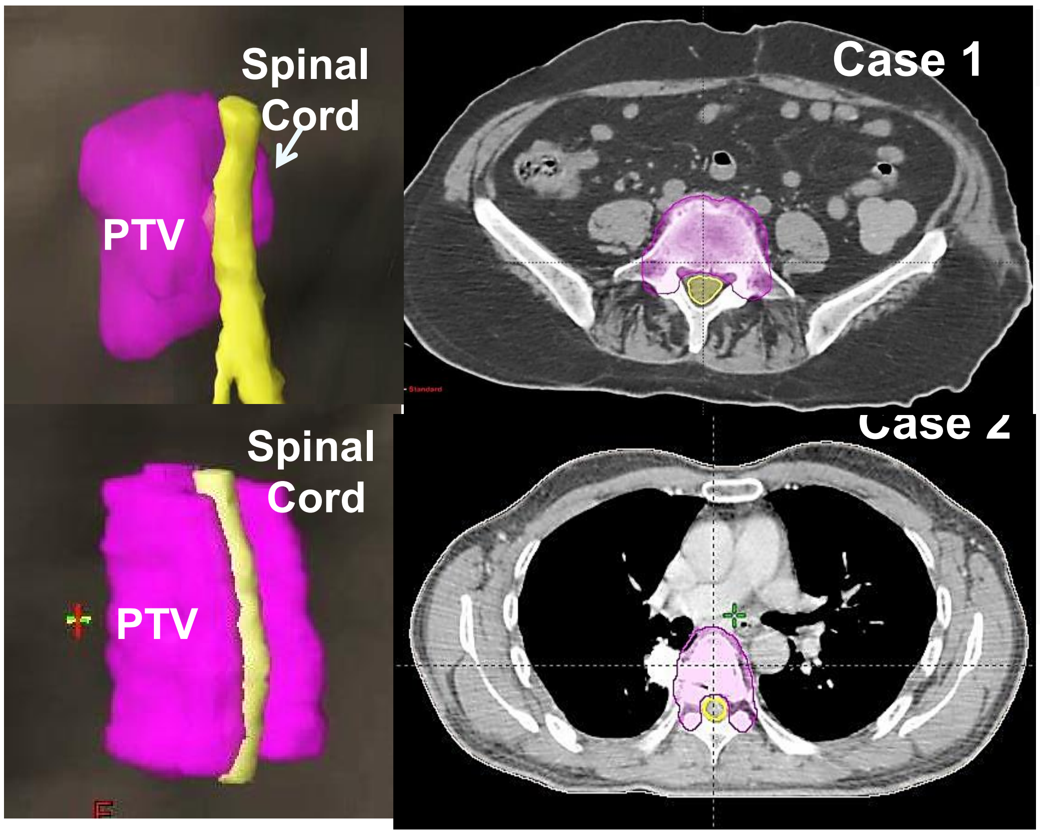
- **Relative geometrical relationships between OAR and PTV**

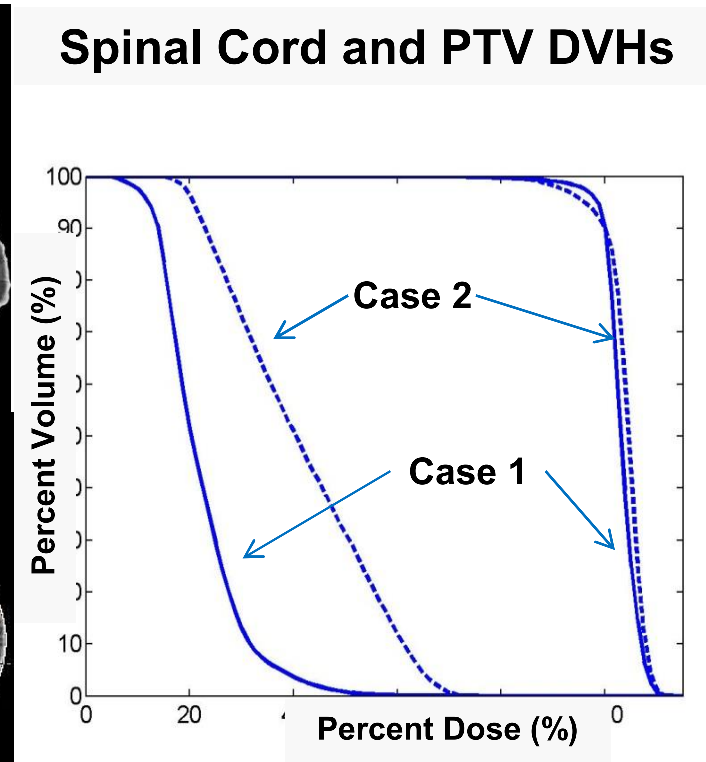


$$\square(\square) = \frac{\cup\{\square_{\square} |\ \square_{\square} \in \square_{\square\square\square} \ \textbf{and}\ \square(\square_{\square}, \square\square\square) \le \square\}}{\cup\{\square_{\square} |\ \square_{\square} \in \square_{\square\square\square}\}}$$

Zhu et al, *Med Phys* 38:719-726, 2011
Yuan et al, *Med Phys* 39:6868-6878, 2012

Knowledge Example: Shape vs. Dose





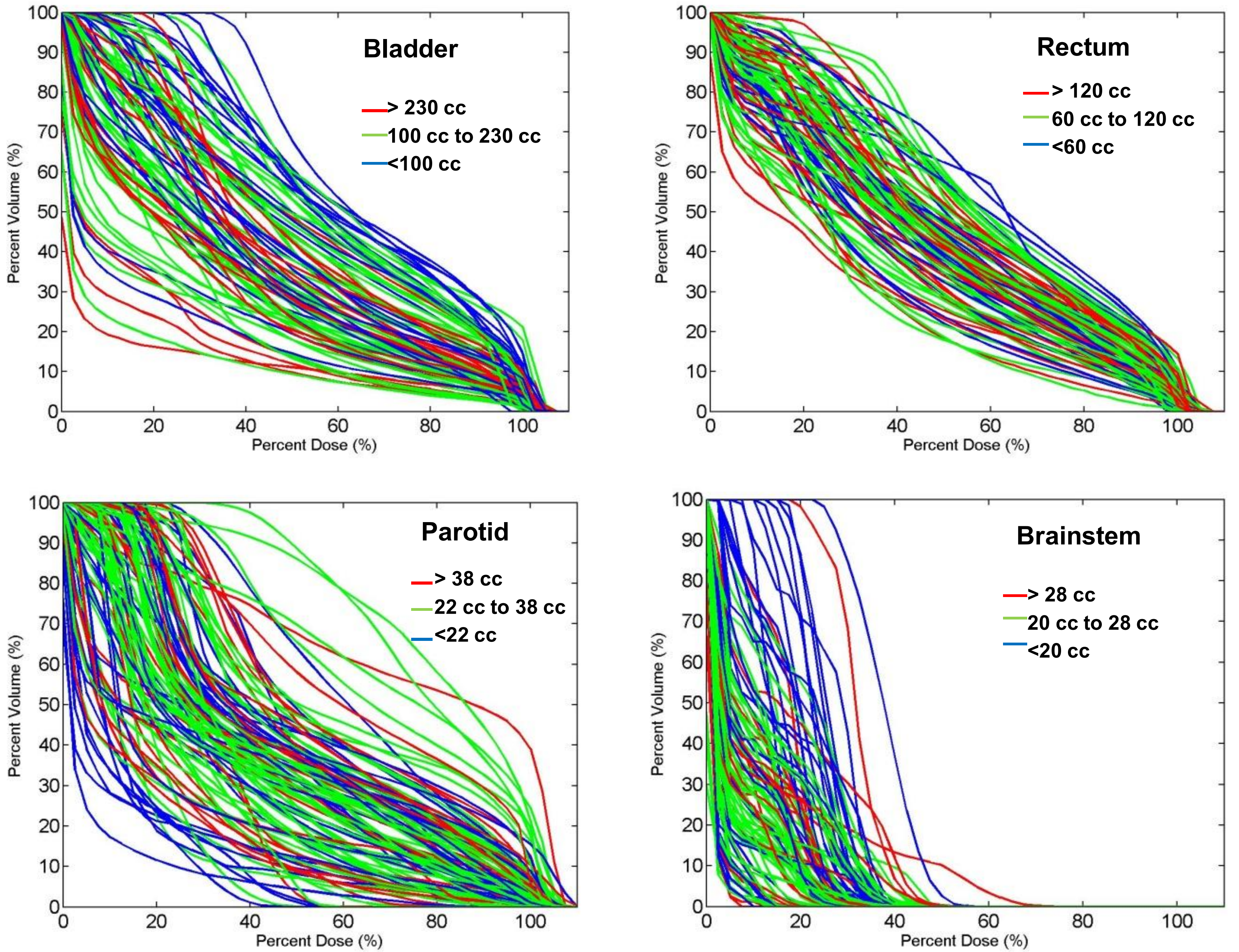
Anatomy and Dose Features Overview

<table>
<tr><th>Site</th><th>OAR</th><th>Anatomical And Dosimetric Features</th></tr>
<tr><td>Prostate</td><td>Rectum
Bladder</td><td rowspan="2">Distance to target histogram (DTH): PCS
Distance to OAR (DOH): PCS

OAR volumes
PTV volume
Fraction of OAR volume overlapping with PTV (overlap volume)
Fraction of OAR volume outside the treatment fields (out-of-field volume)

Tightness of the geometric enclosure of PTV surrounding OAR
Curvature of specific OAR

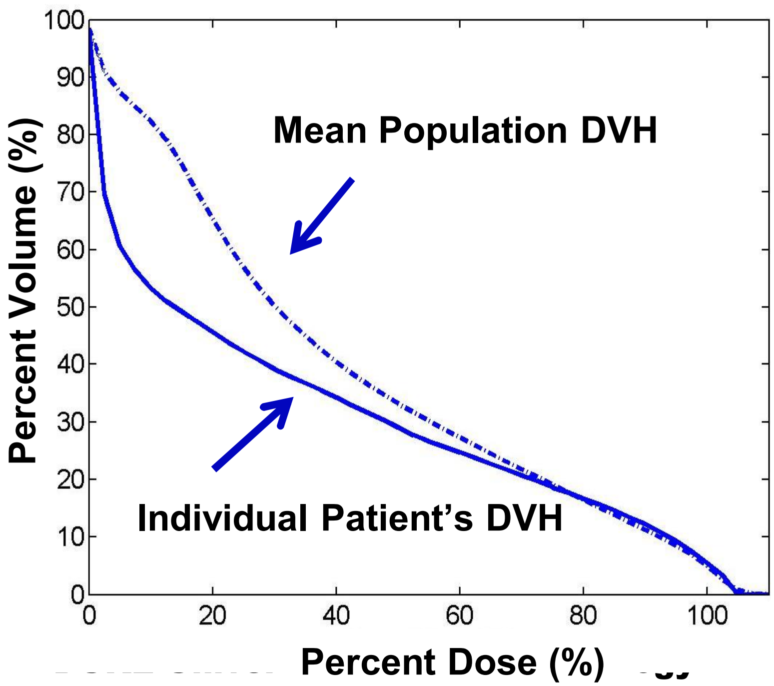
PTV dose homogeneity
PTV hotspot
OAR DVHs</td></tr>
<tr><td>HN</td><td>Parotids
Oral cavity
Larynx
Pharynx
Spinal cord
Brainstem
Mandible</td></tr>
</table>

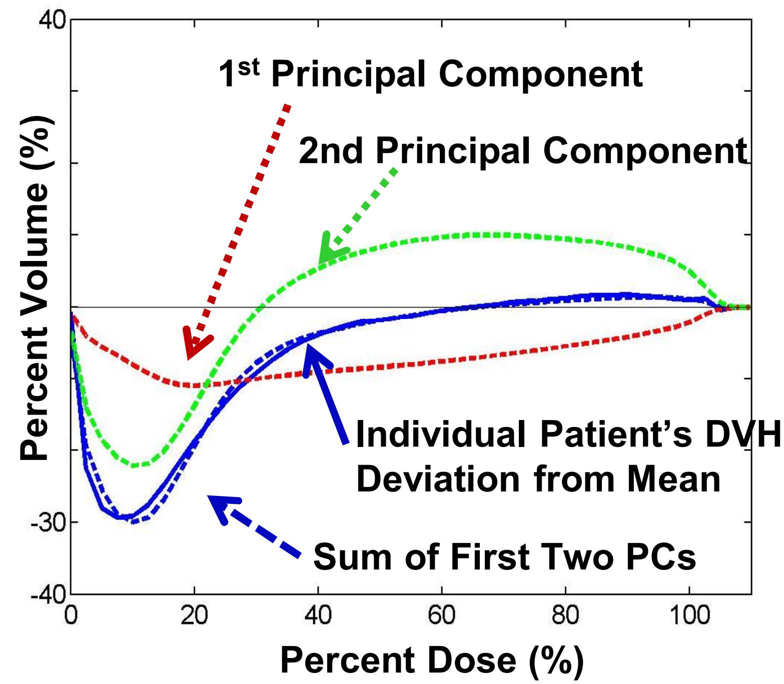


Bladder
> 230 cc
100 cc to 230 cc
<100 cc
Rectum
> 120 cc
60 cc to 120 cc
<60 cc
Parotid
> 38 cc
22 cc to 38 cc
<22 cc
Brainstem
> 28 cc
20 cc to 28 cc
<20 cc
Percent Volume (%)
Percent Dose (%)

Modeling Planning Knowledge

- **DVH/DTH Feature Extraction and Dimension Reduction**
  - Principal Component Analysis (PCA)





Predict Dose/DVH Based on Anatomy Features?

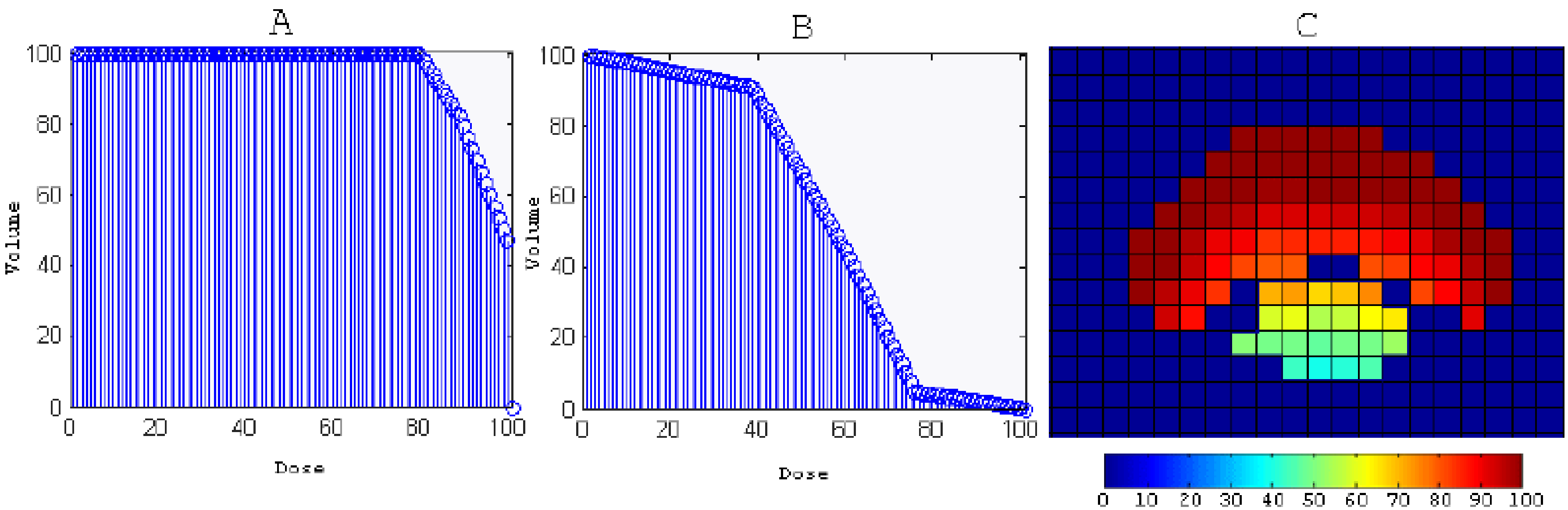


Figure 17 A) A example of a DVH of the target B) An example of DVH of the OAR C)

The prescribed dose based on the given DVHs and voxel position

Multiobjective Approach To Morphology-based Radiation Treatment Planning

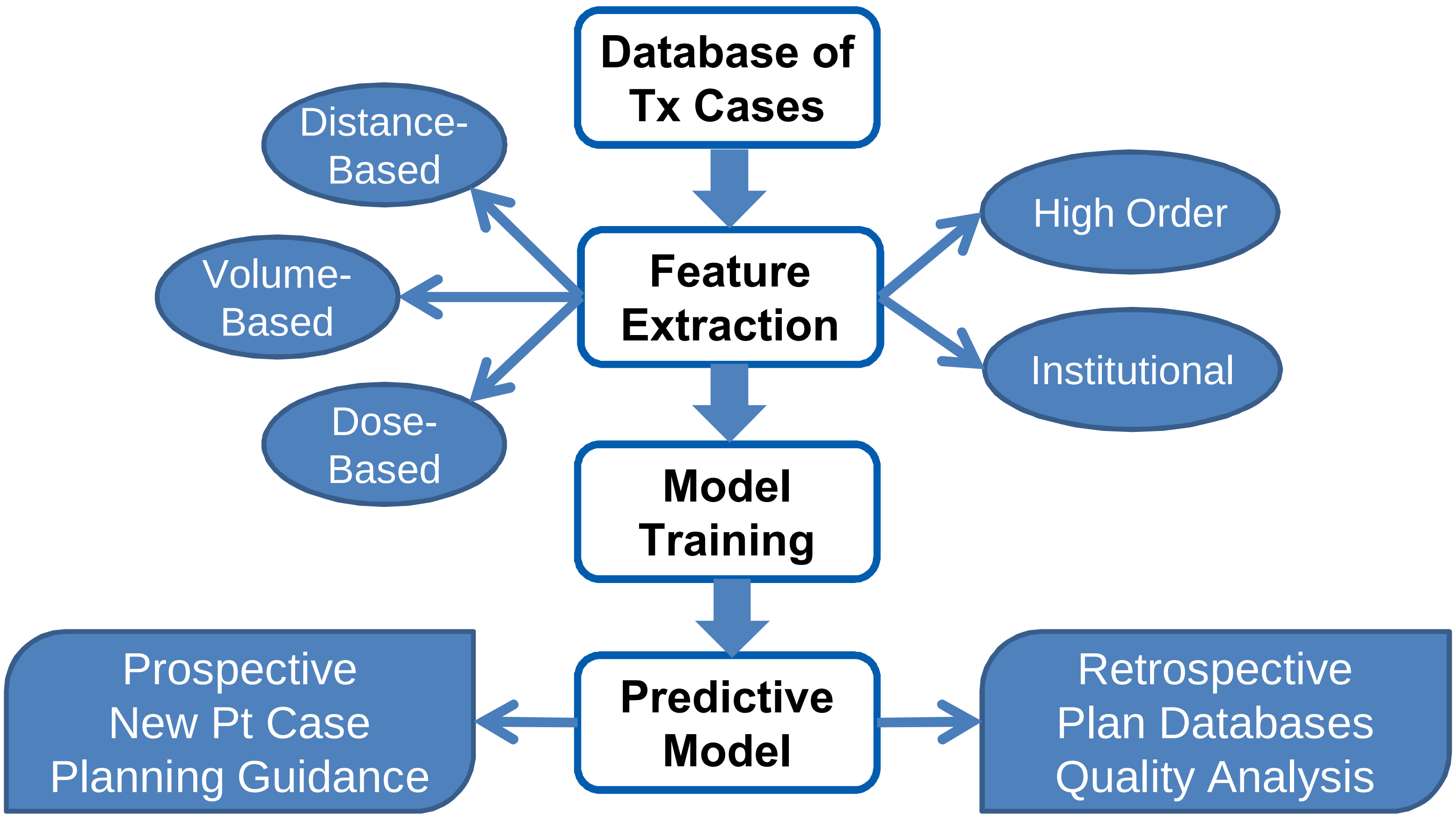
Boonyanit Mathayomachan , PHD Thesis 2005

Case Western Reserve University

Modeling Planning Knowledge

- Correlate patient anatomy features (input) with dose distribution features (output)
- Correlate plan design features (input) with dose distribution features (output)
- Understand and translate the knowledge model parameters to the physics/dose parameters
- Extend and refine the Knowledge base with progressive modeling and rapid learning technologies

Modeling Planning Knowledge



A planning quality evaluation tool for prostate adaptive IMRT based on machine learning
Medical Physics 38, 719,2011

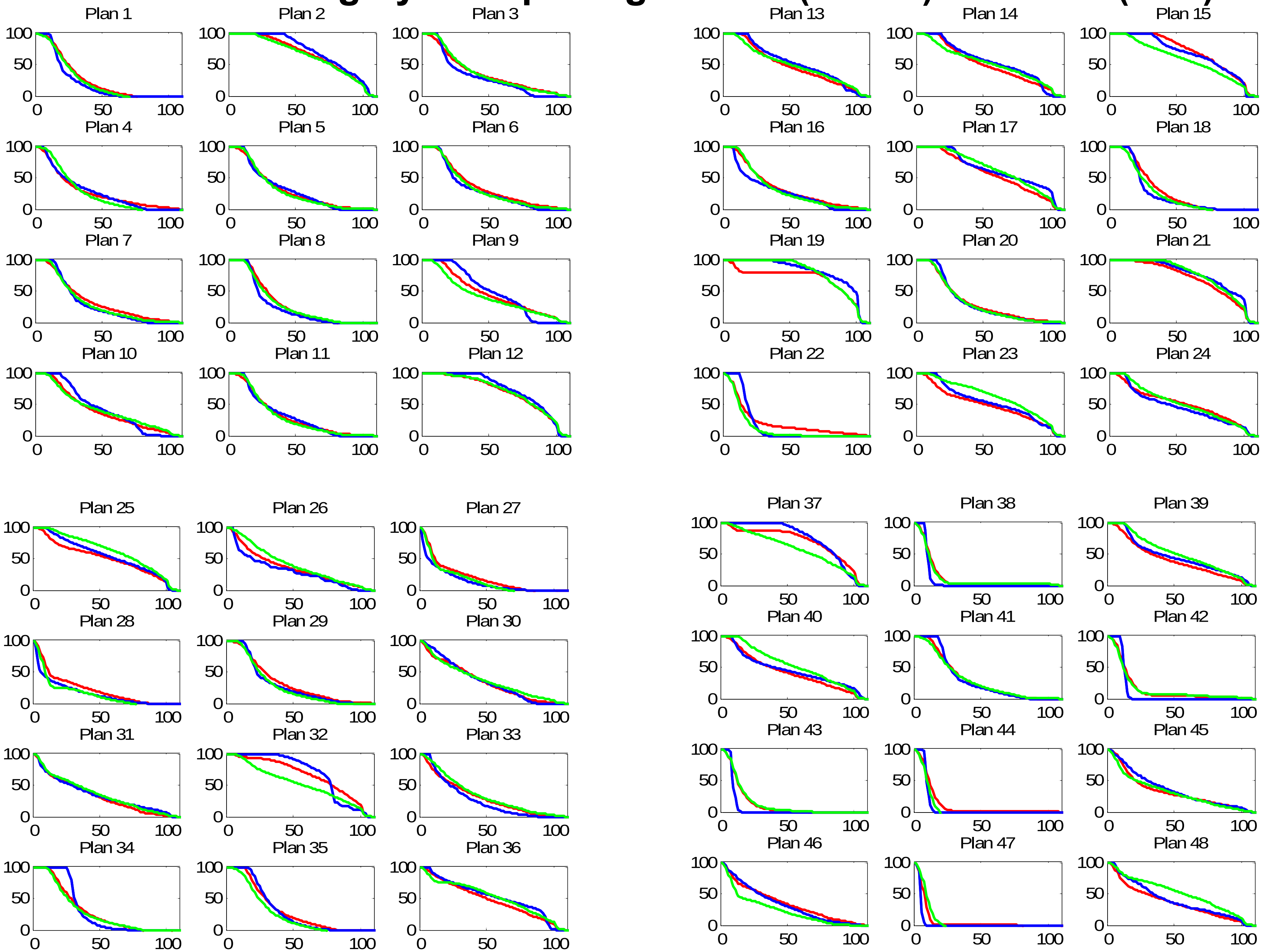
Quantitative analysis of the factors which affect the interpatient organ-at-risk dose sparing variation in IMRT plans.
Medical Physics 39, 6868,2012

Modeling Planning Knowledge

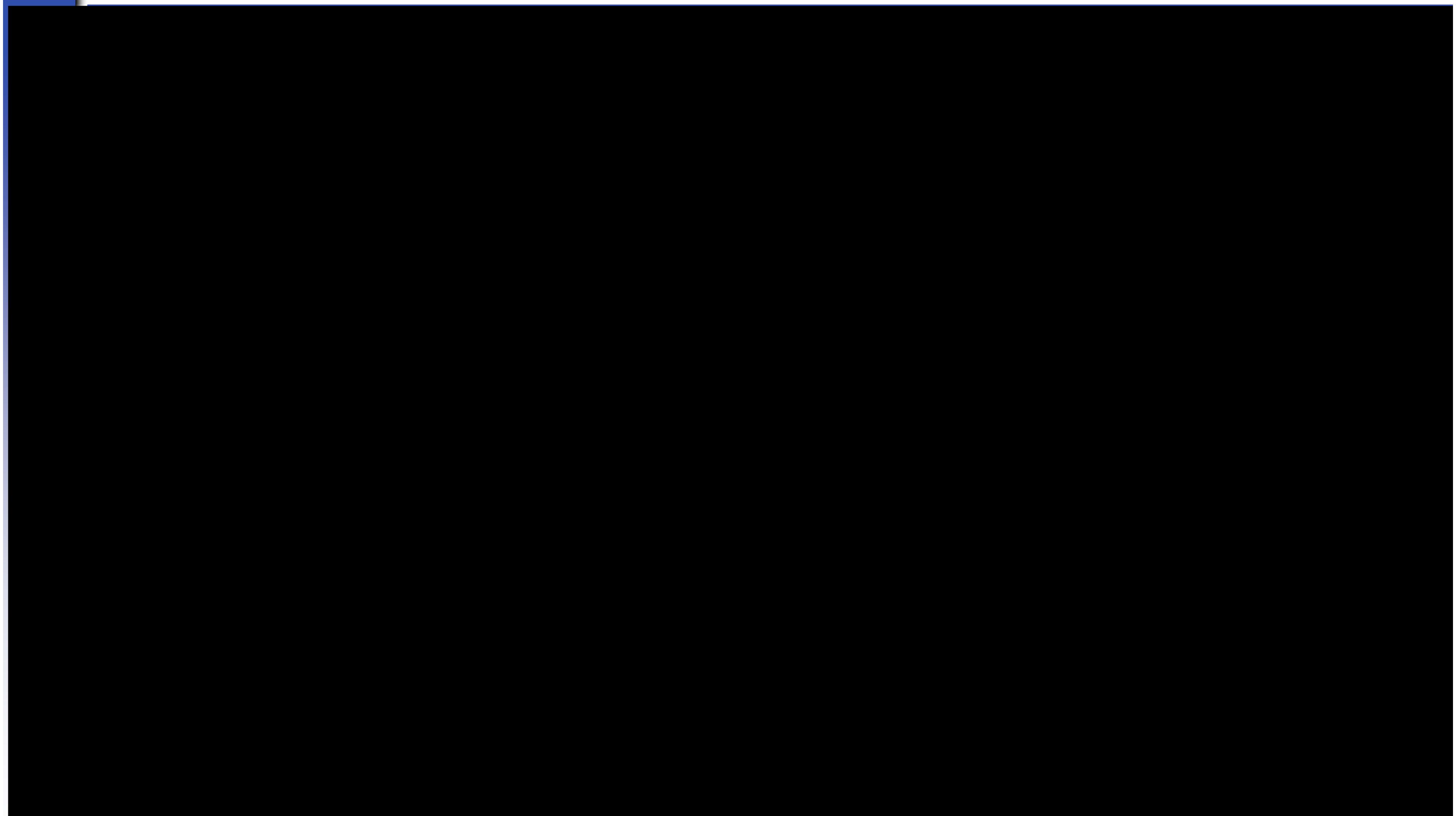
- **Machine Learning of Treatment Planning Knowledge**
  - Knowing X1, X2, ,,,,Xm, and Y1, Y2,,,,,, Yn,

    Solve: Y(1,2,,,,n) = **F**(X1,2,,,,m)
  - Multi-regression learning
  - Support vector learning
  - Neural Network learning
  - Many other methods

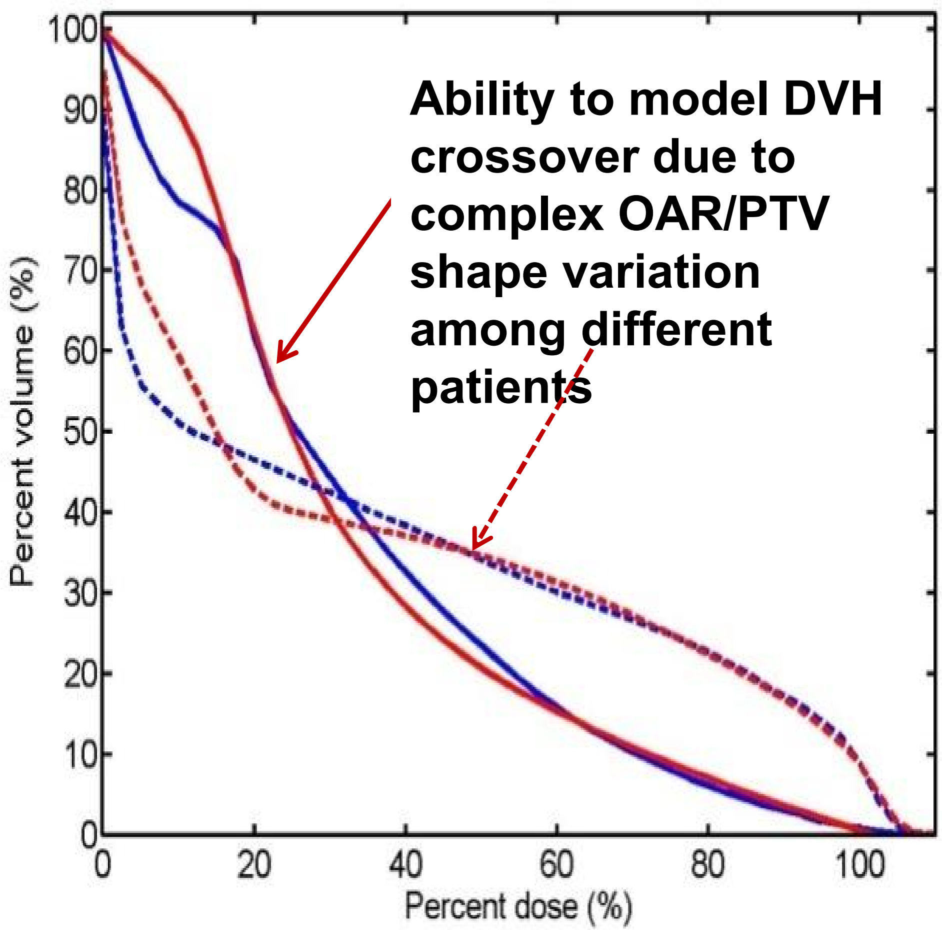
Parotids modeling by multiple regression (Green) and SVR (Red)



Modeling Planning Knowledge



Complex OAR Sparing Knowledge Modeling

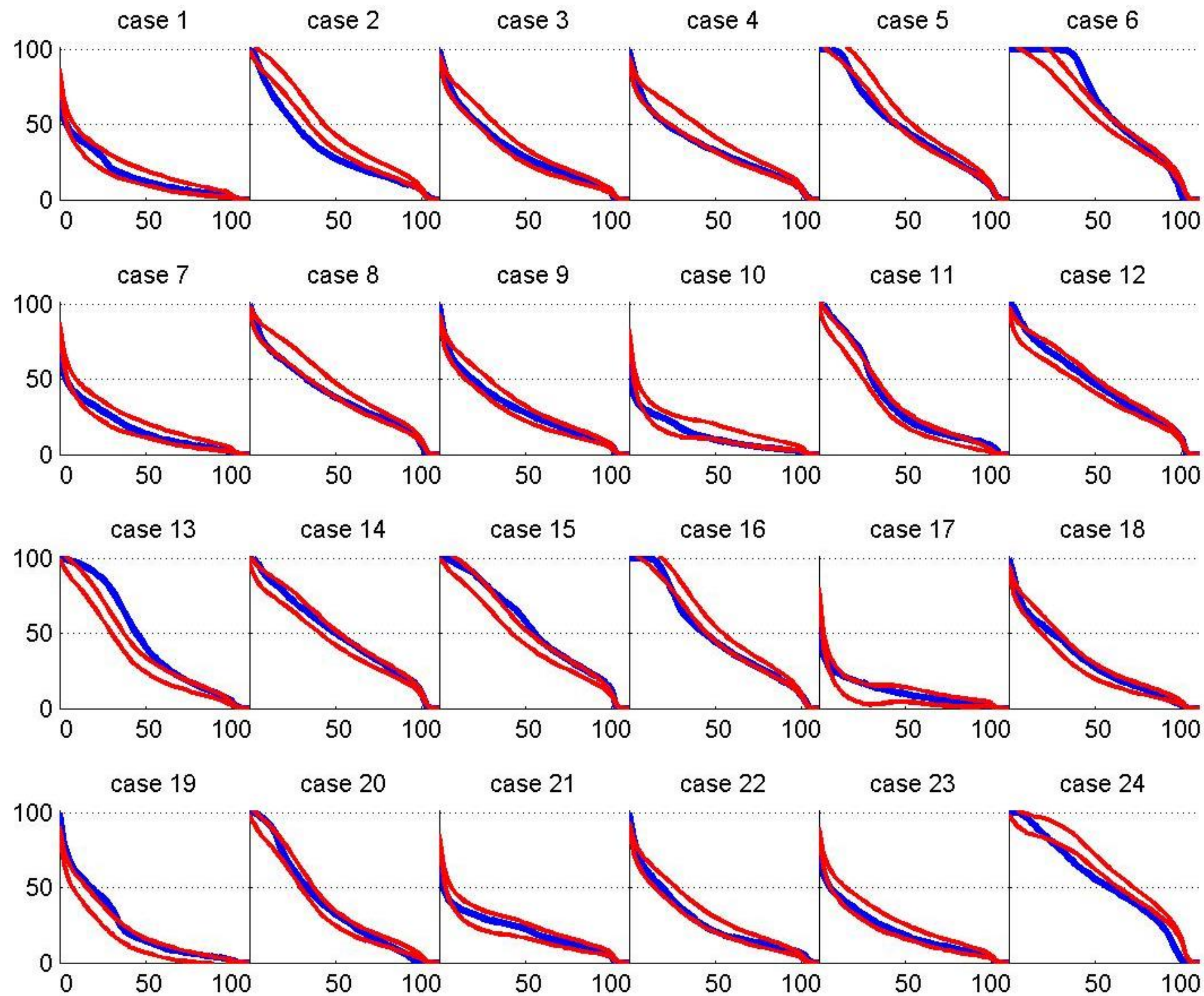


— Actual Parotid DVH

— Modeled Parotid DVH

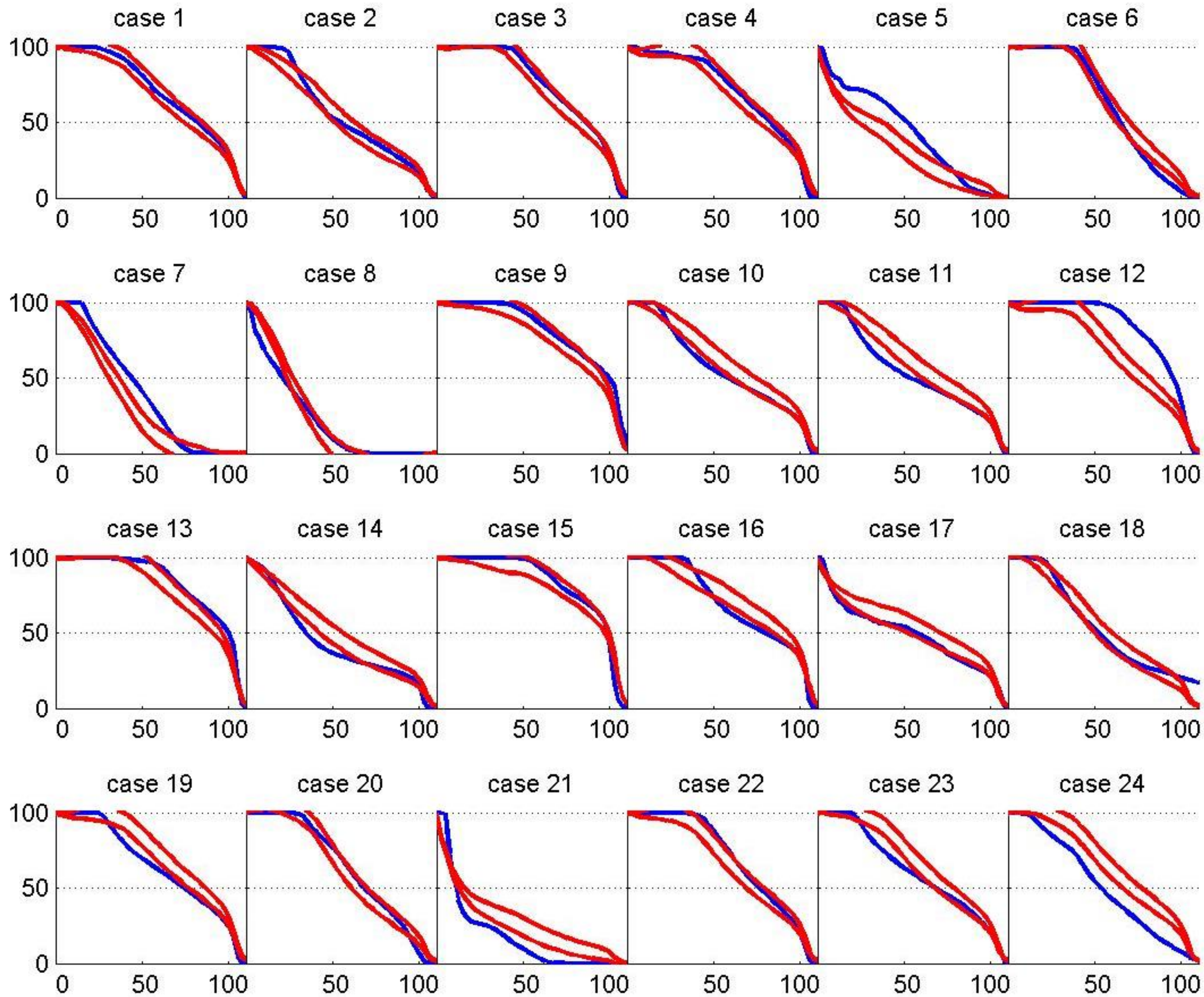
Example of Bladder DVH Modeling

Prostate Cases

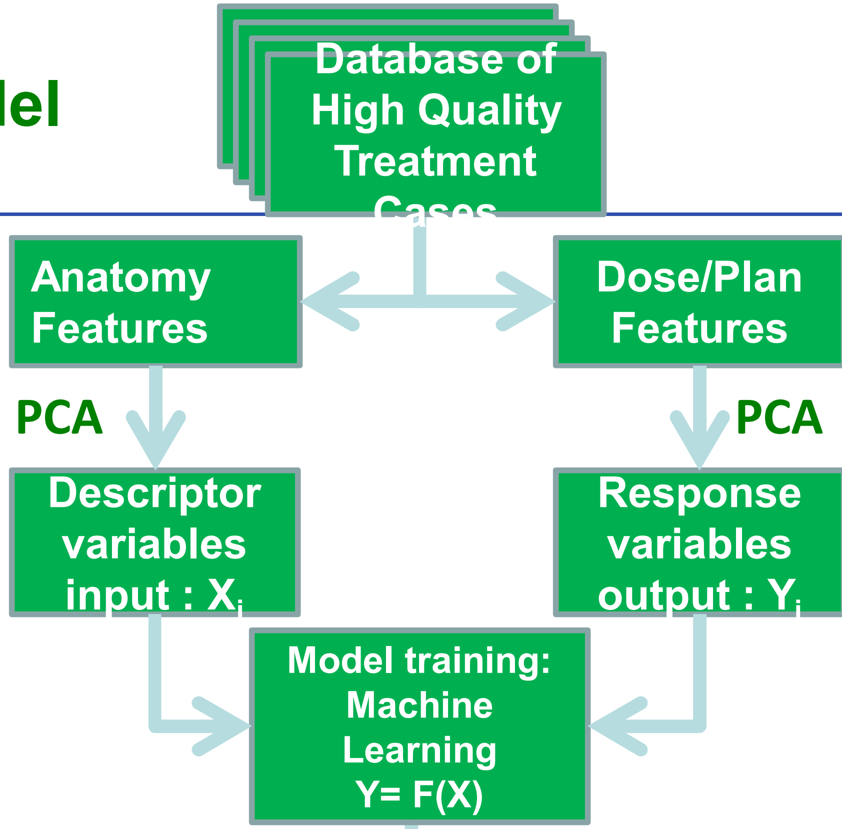


Example of Bladder DVH Modeling

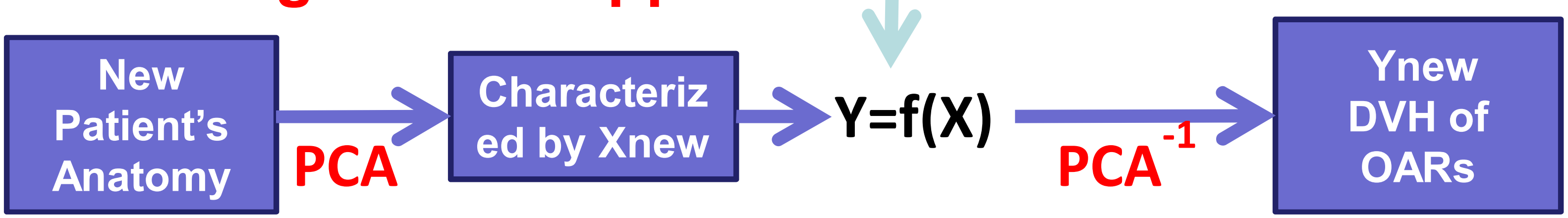
Anal-rectal Cases



Knowledge Model Training

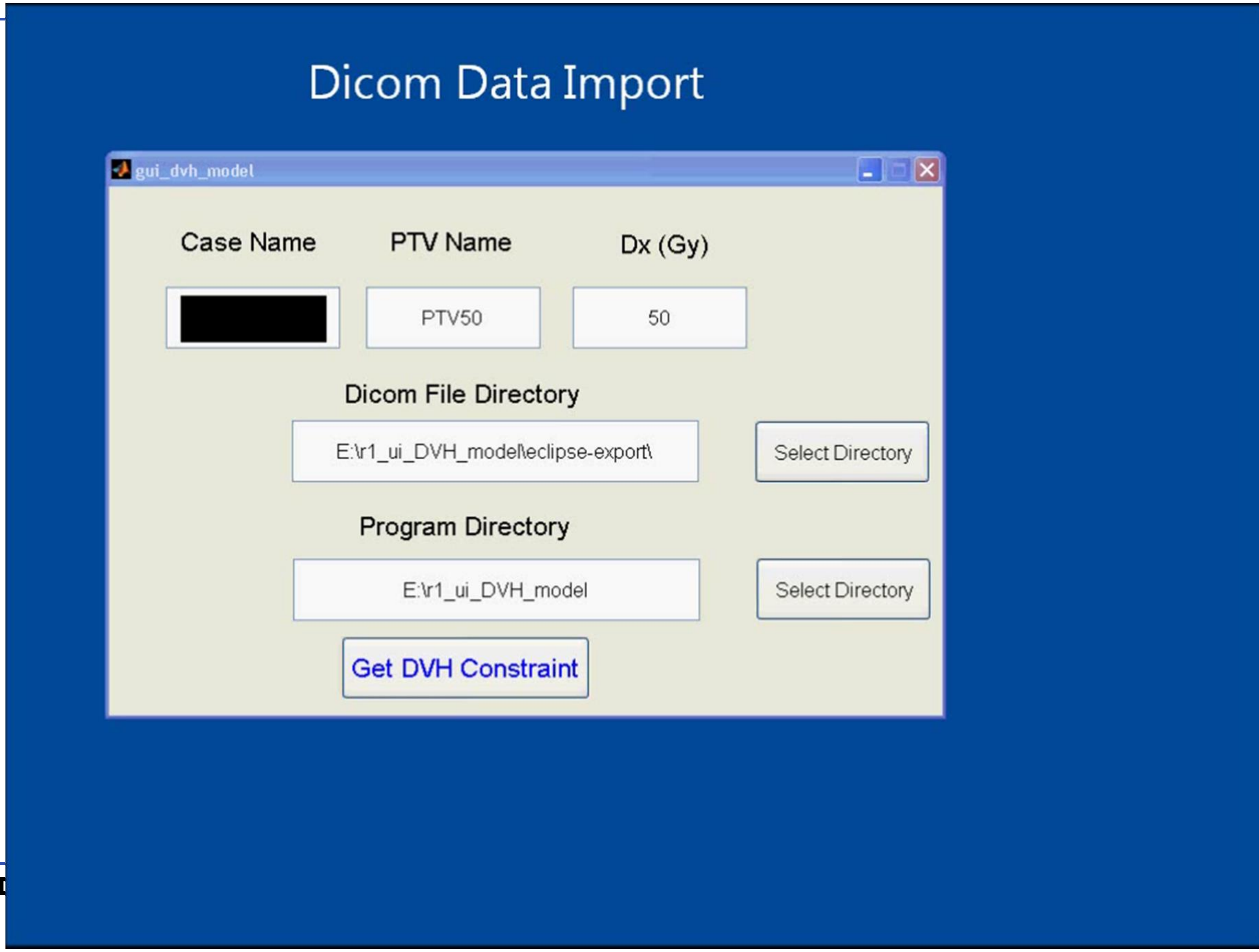


Knowledge Model Application

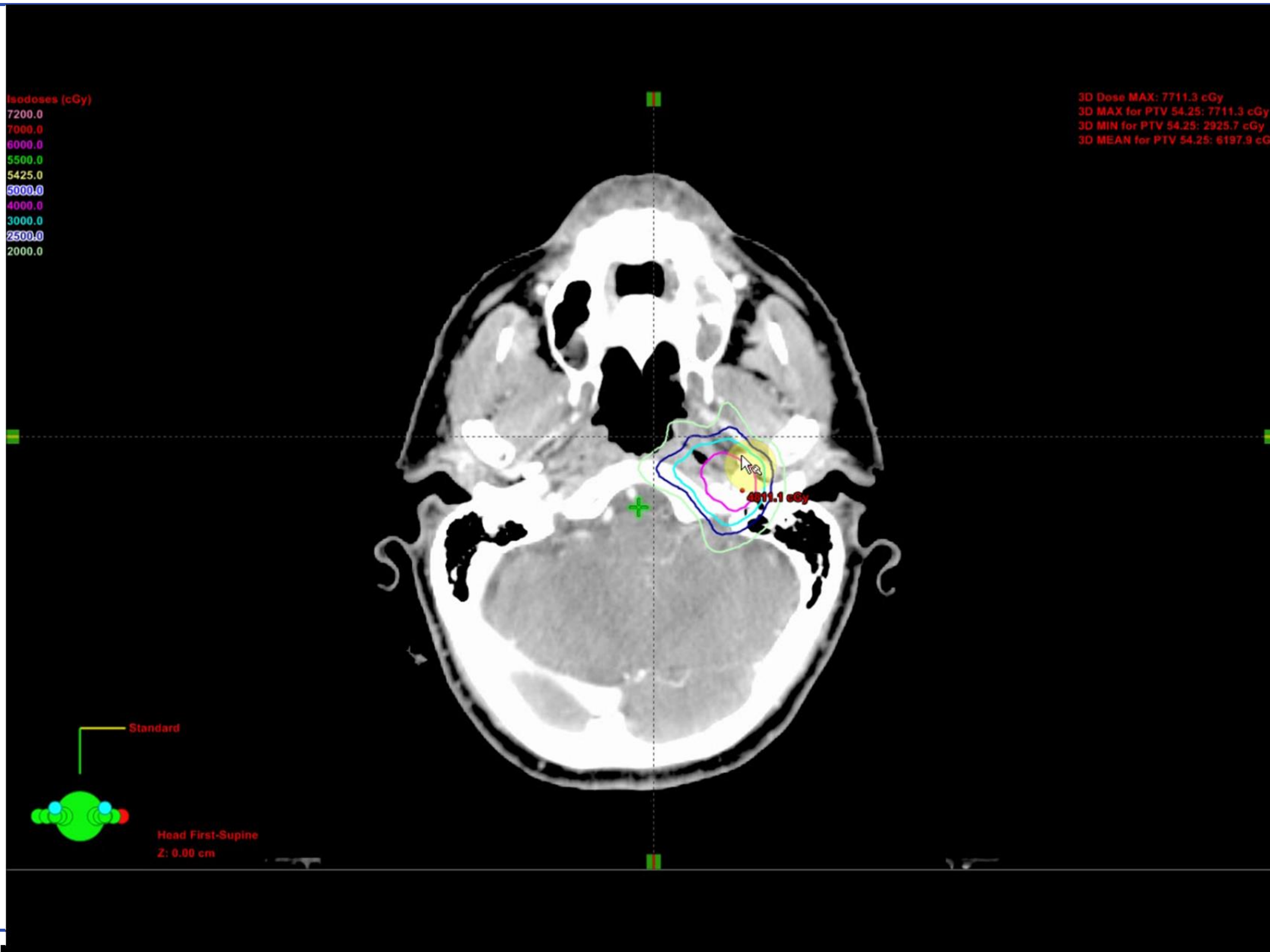


Zhu et al, *Med Phys* 38:719-726, 2011
Yuan et al, *Med Phys* 39:6868-6878, 2012

From Models To Planning



From Models To Planning



Cross-Institution Knowledge Base

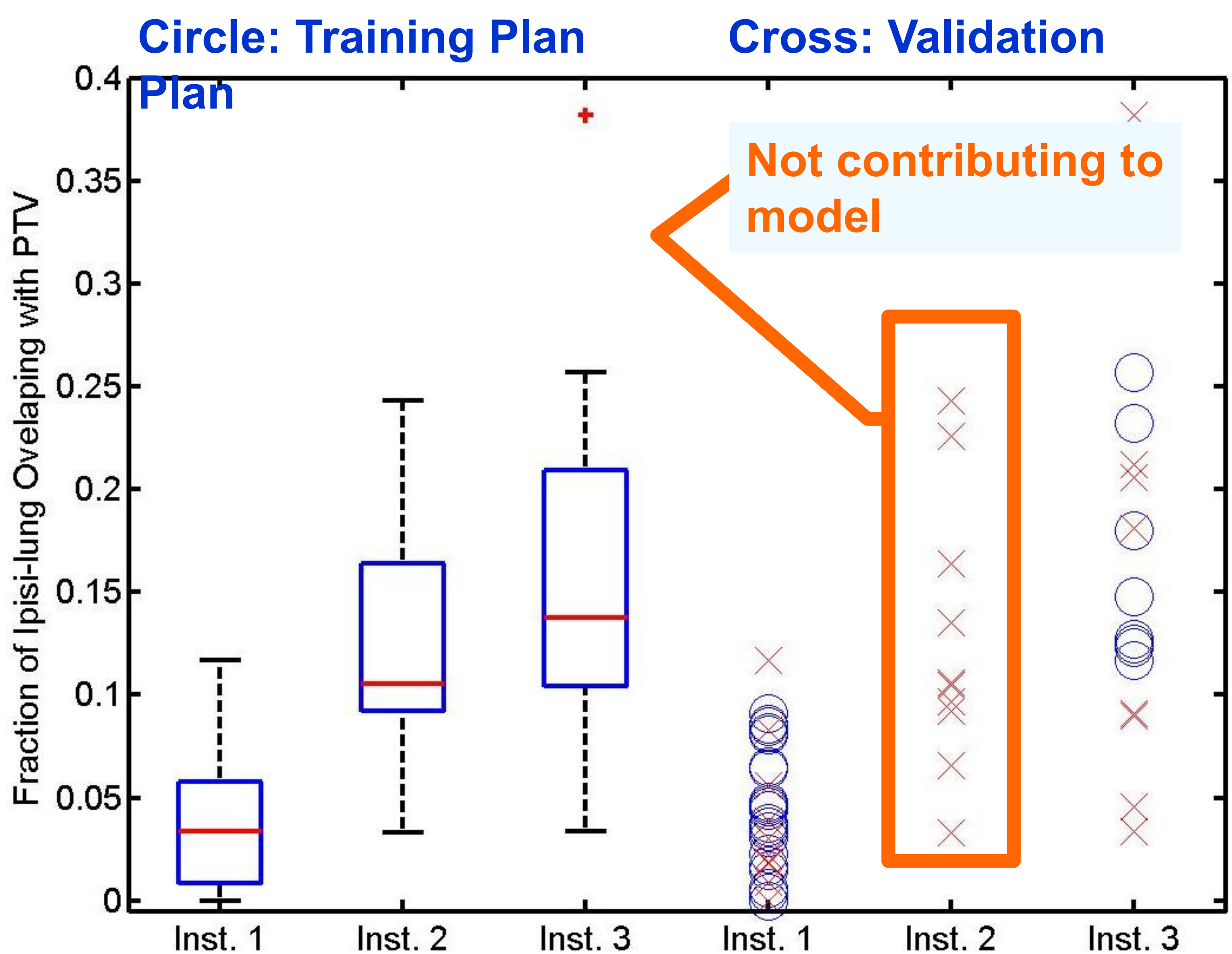
- Cross-institution Knowledge
  - If we believe best planning knowledge is shared among all planners
  - LUNG IMRT Pilot Study By RTOG/NRG
    - **71 Cases**
    - **3 Institutions**

Cross-Institution Knowledge Base

		Mean	Median	Min	Max
Prescriptions (Gy)		67	64	40	74

		Institution 1	Institution 2	Institution 3
Volume (cm^3)	mean	421	595	512
	median	343	519	379
	min. max	62. 1132	76. 1132	175. 1161
Location (side)	Total	45	10	16
	Left/Left-Medial	18	4	5
	Right/Right-Medial	21	6	10
	Medial	6	0	1

Cross-Institution Knowledge Base

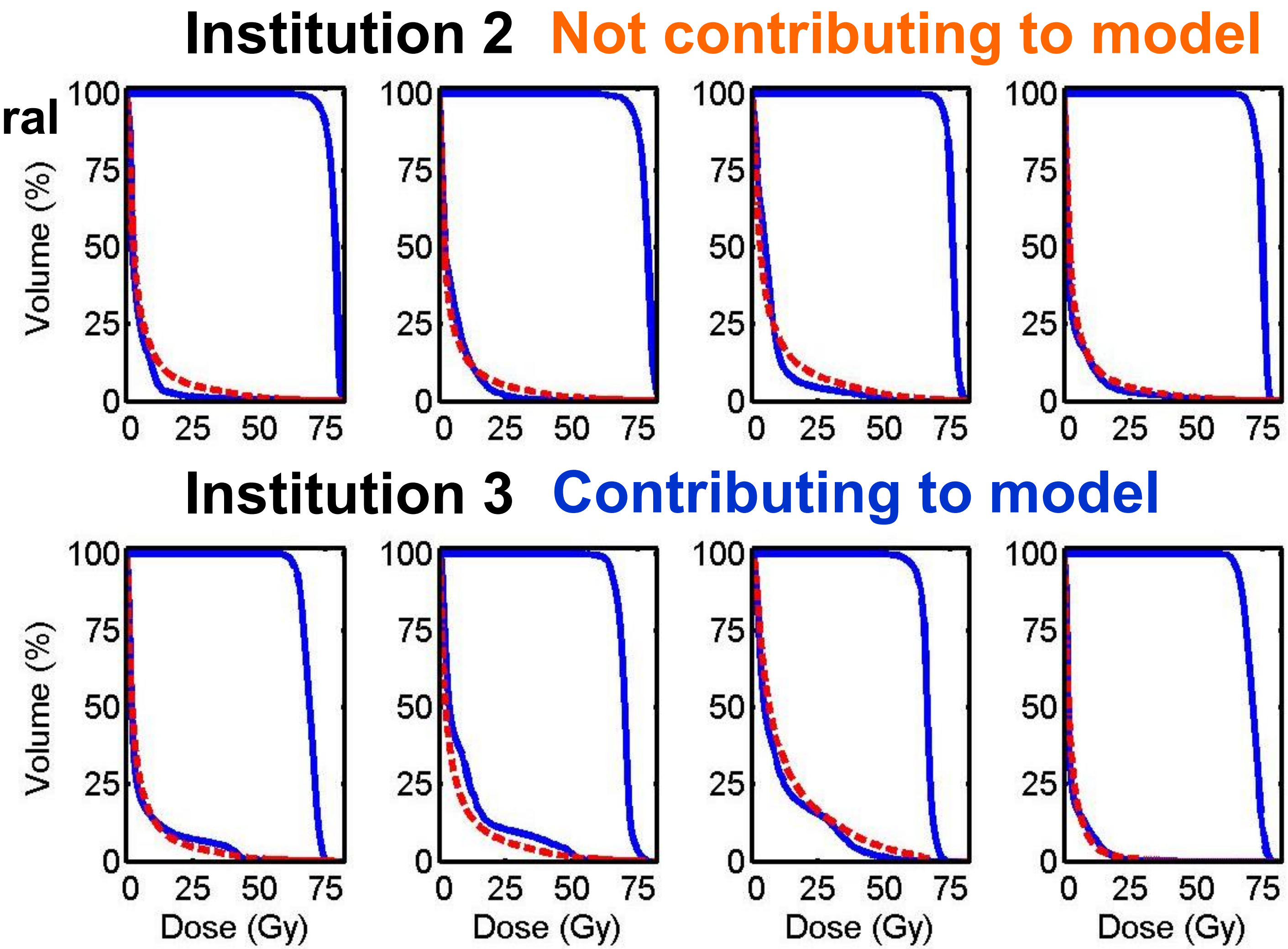


Cross-Institution Knowledge Base

Contralateral Lung DVH

Model

Plan



Cross-Modality Knowledge Base

- Cross-Modality Knowledge
  - If you believe best planning knowledge is independent of treatment modality

Institution A

Å 7-8 min delivery time

Å Delivery system: Varian IMRT

Å Planning system: Eclipse

Å Sequential Boost

ï Multiple plans (one plan for 1 PTV)

ï 40-50 Gy and 60-70 Gy

Å ~60 head-and-neck cases

Institution B

Å 7-8 min delivery time

Å Delivery system: Tomotherapy

Å Planning system: Tomotherapy

Å SIB

ï 1 plan (one plan cover all PTVs with diff. daily doses)

ï 54.25 Gy and 70 Gy

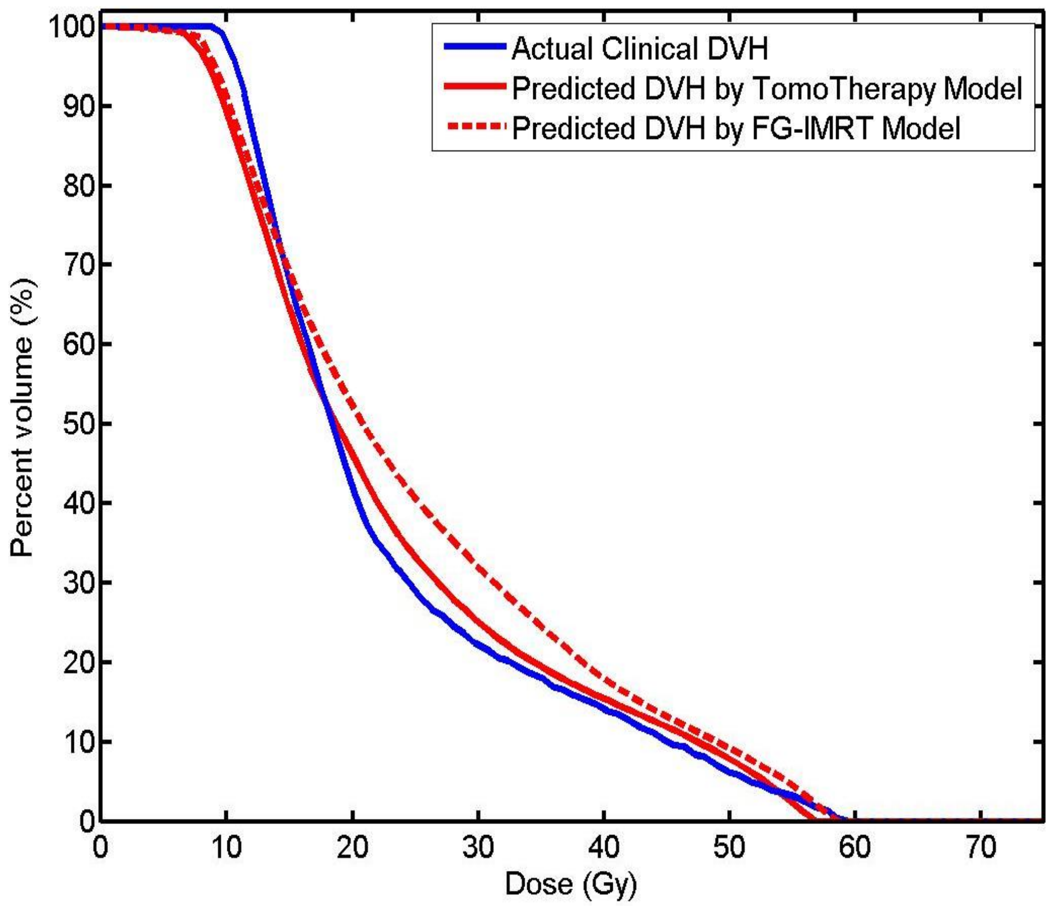
Å ~60 head-and-neck cases

Lian et al, *Med Phys* 40:121704, 2013

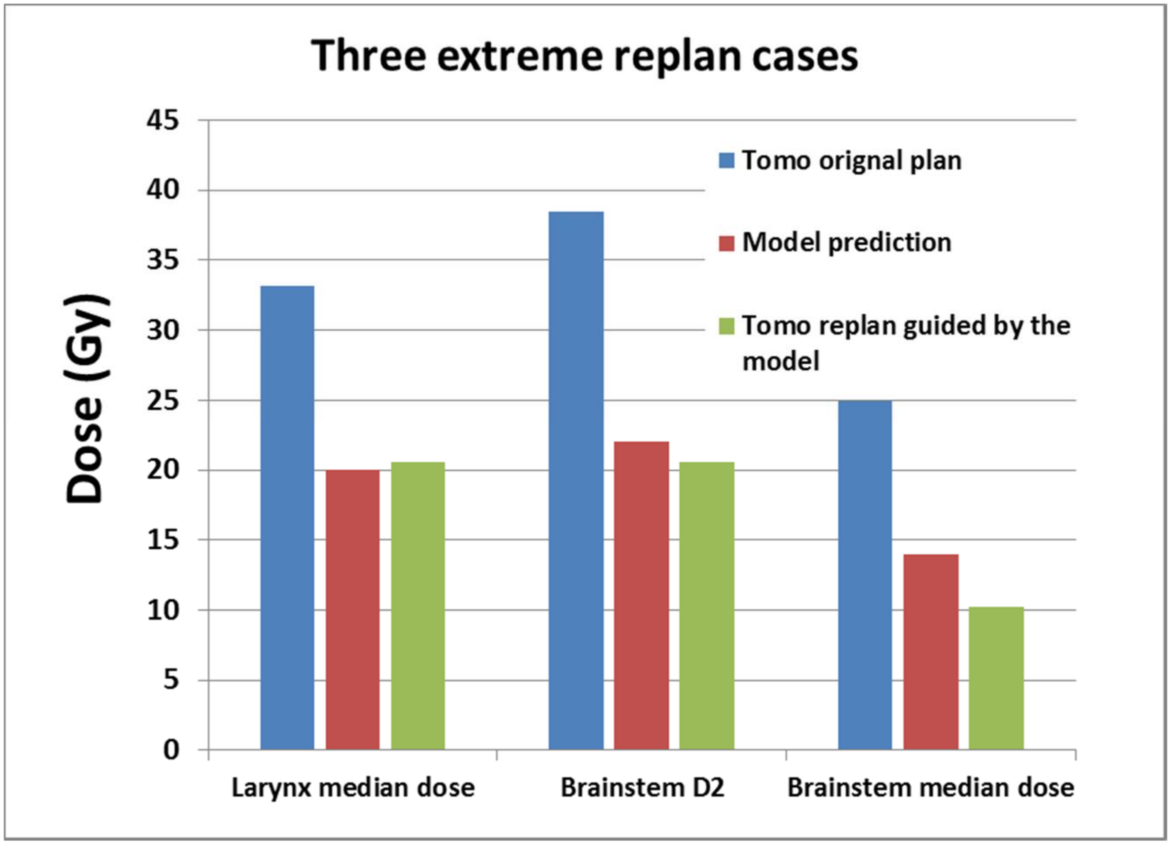
Cross-Institution Knowledge Base

Tomotherapy Model
vs. IMRT Model
vs. Actual Plan DVH

Parotid DVH

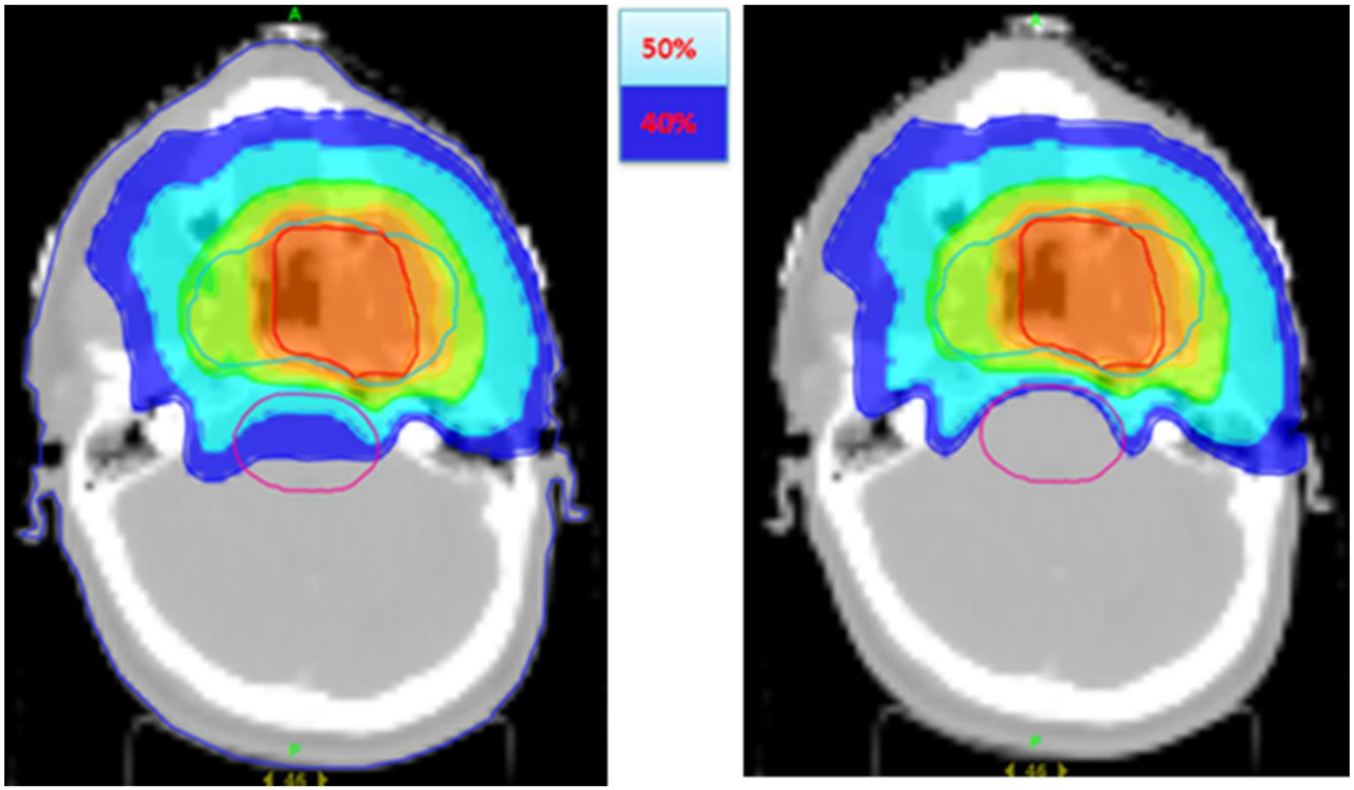


Knowledge Model Improves Plan Quality



Knowledge Model Improves Plan Quality

Original Clinical Plan Knowledge-Model Guided Plan



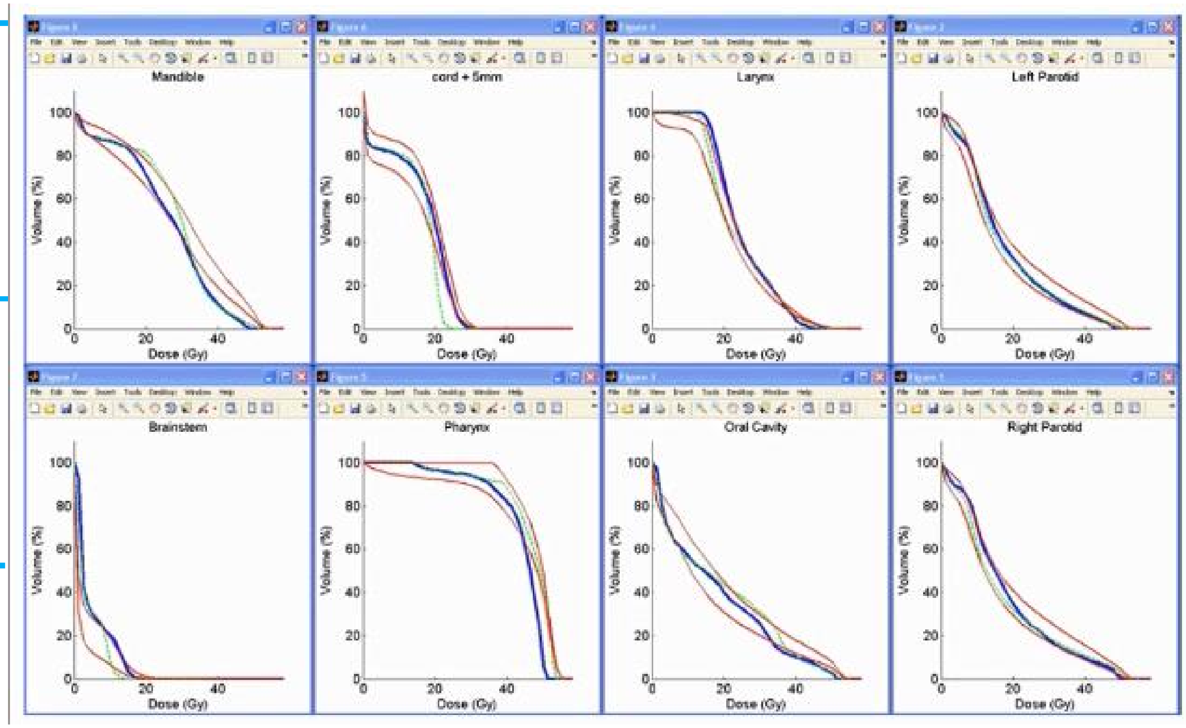
Summary: What Knowledge Modeling May Help

Physician Prescription

IMRT/VMAT Planning

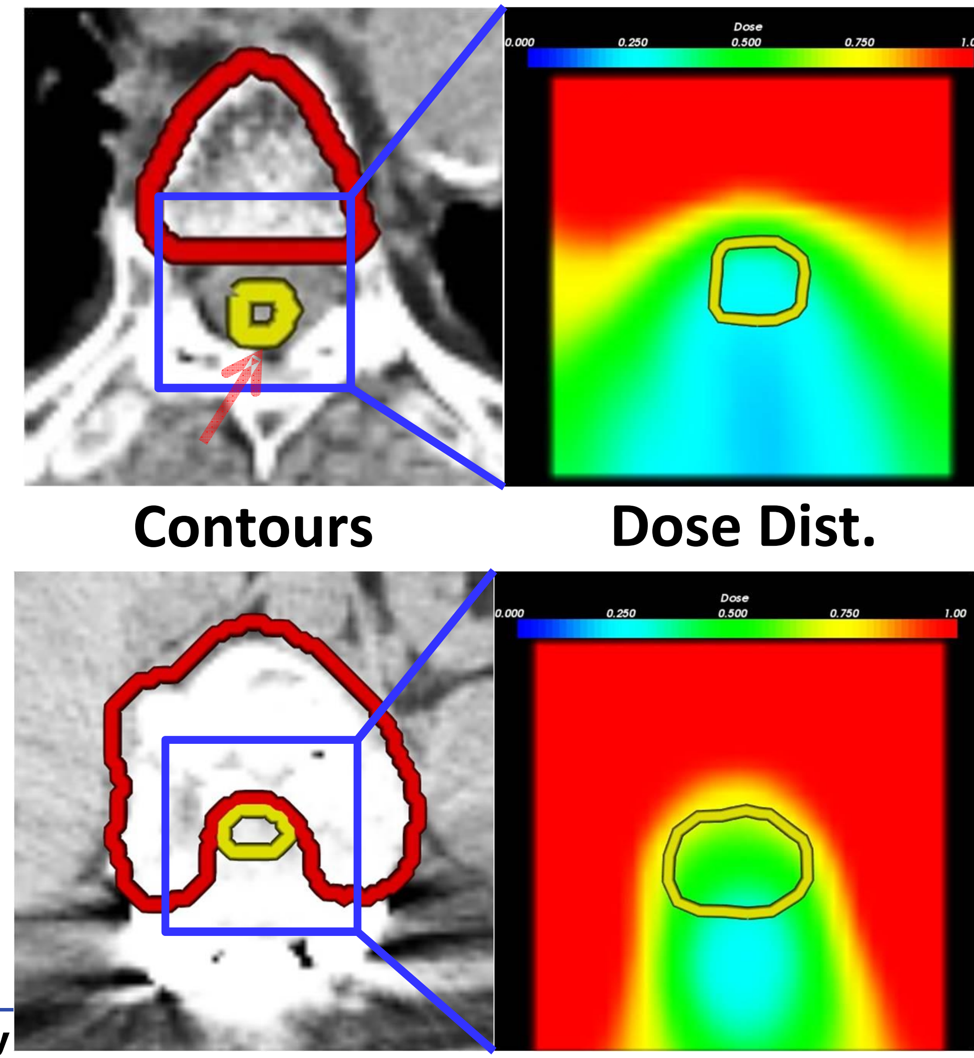
Plan Evaluation

Planned vs. Modeled



Other Knowledge Models: Dose Models

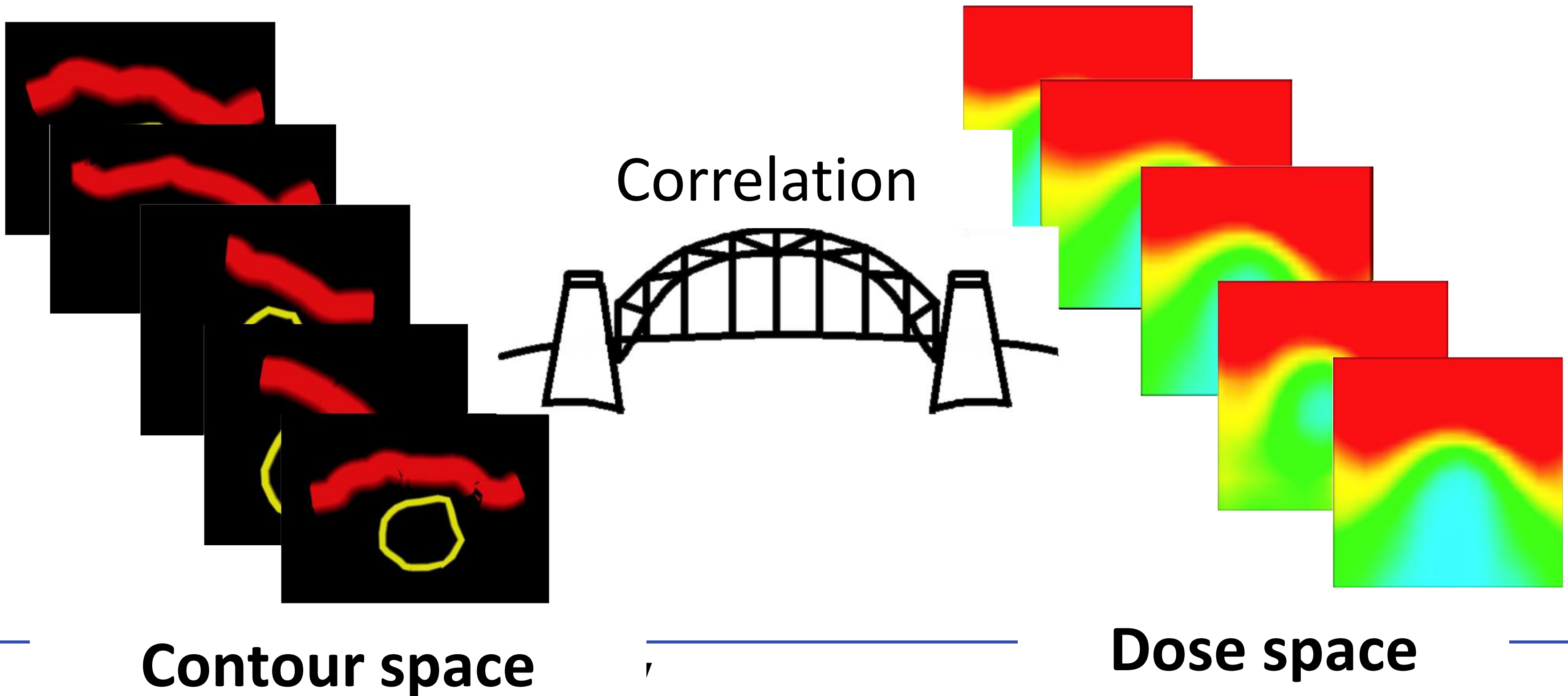
- In Spine SBRT, dose distributions in cord are highly correlated with tumor contour shapes



Liu et al, *PMB* 60:N83-N92, 2015

Other Knowledge Models: Dose Models

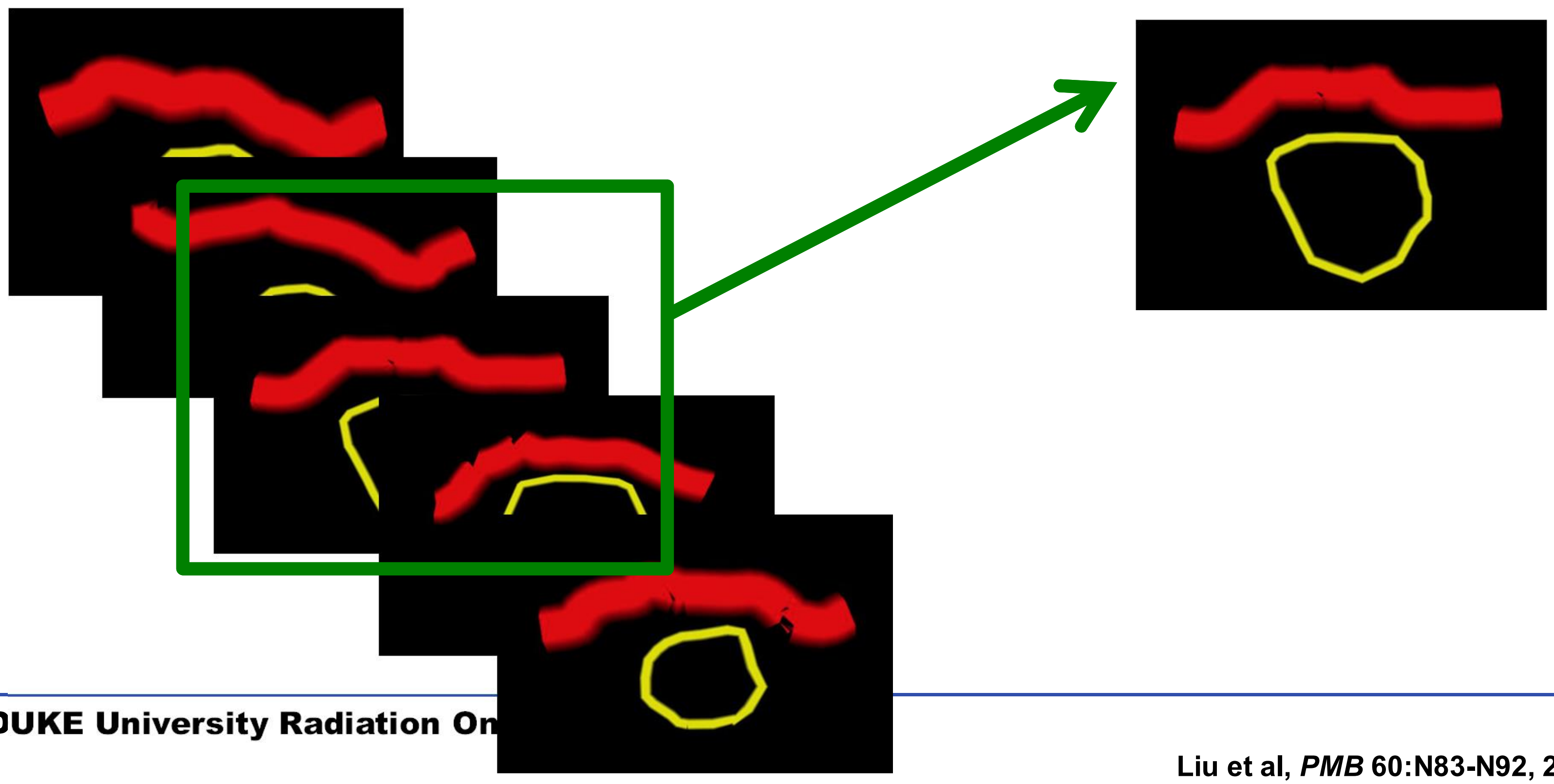
- Compute correlation between tumor contour shapes and cord dose distributions
- Use learned correlations to predict voxel-level dose distributions



Liu et al, *PMB* 60:N83-N92, 2015

Other Knowledge Models: Dose Models

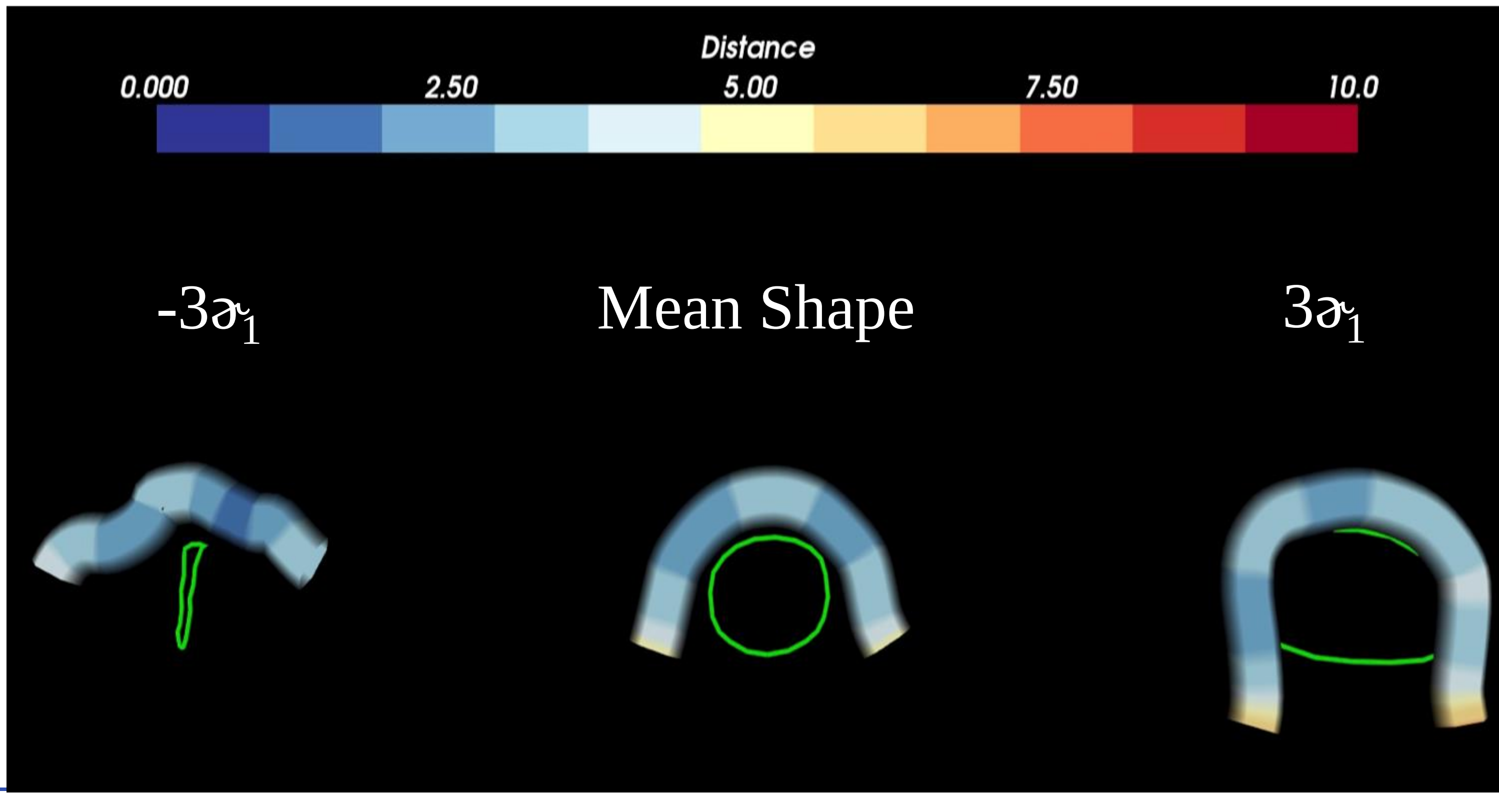
- **Active Shape Model**
  - Align the reference tumor contours and all other contours using the iterative closest point (ICP) algorithm



Liu et al, *PMB* 60:N83-N92, 2015

Other Knowledge Models: Dose Models

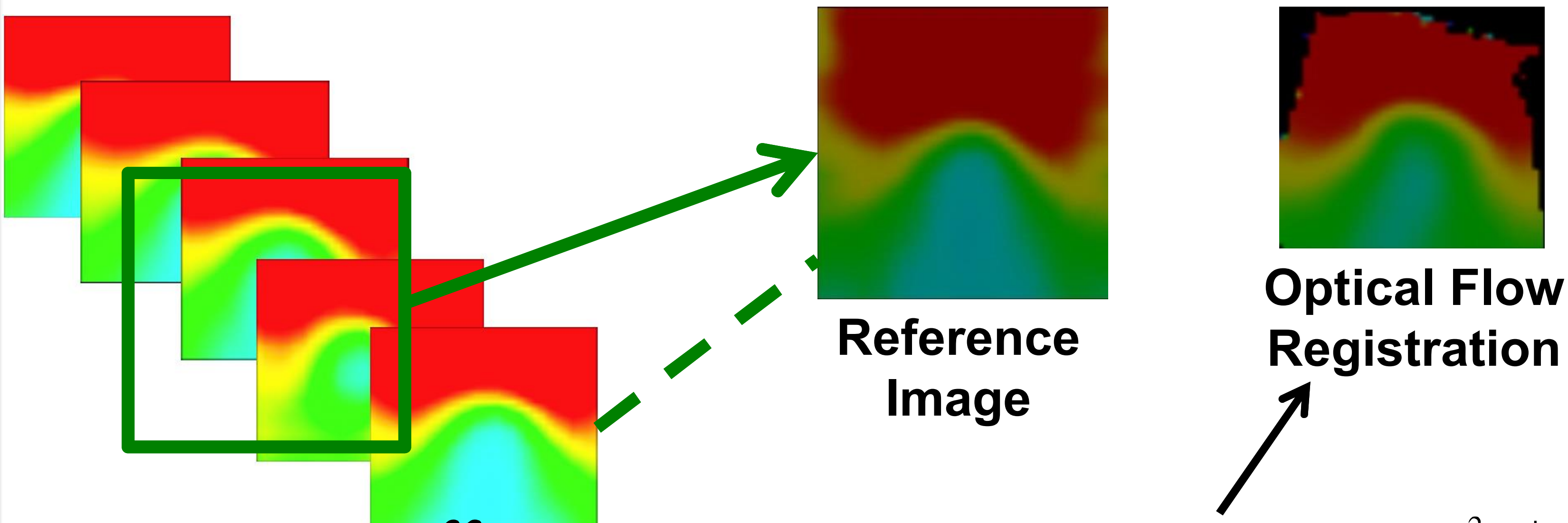
- **Active shape models**
  - PCA analysis of a set of aligned tumor contours



Liu et al, *PMB* 60:N83-N92, 2015

Other Knowledge Models: Dose Models

- **Optical Flow Dose Distribution Model**
  - measures dose variance between a reference image and any other images within the training dataset

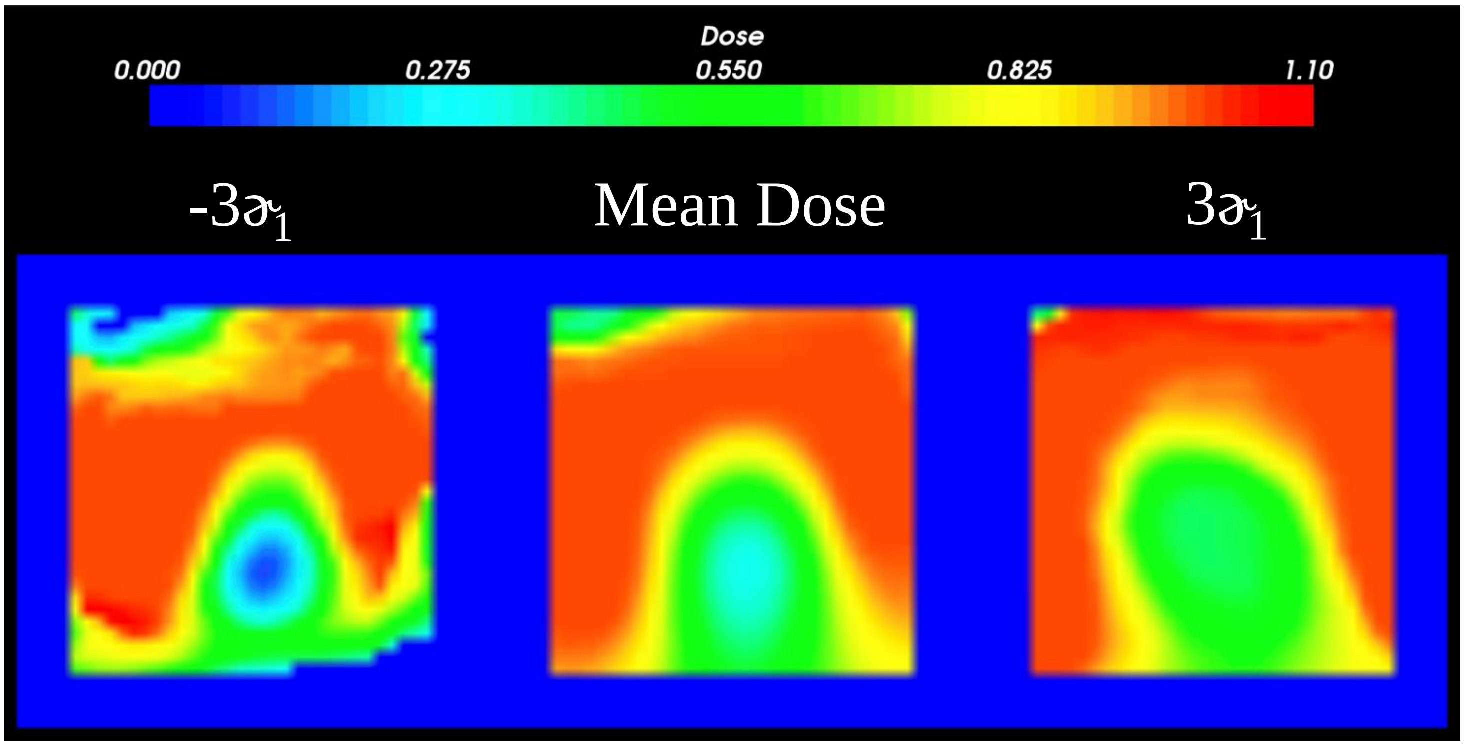


$$E(u_x,u_y) = \iint \Psi\Big(\underbrace{(I(x+u_x,y+u_y,t+1) - I(x,y,t))^2}_{\text{Intensity constraint}} + \beta\Psi\big(\underbrace{\left|\nabla u_x\right|^2 + \left|\nabla u_y\right|^2}_{\text{Smoothness constraint}}\big)$$

$$+\alpha\underbrace{(\nabla I(x+u_x,y+u_y,t+1) - \nabla I(x,y,t))^2}_{\text{Intensity constraint}}\,dxdy$$

Other Knowledge Models: Dose Models

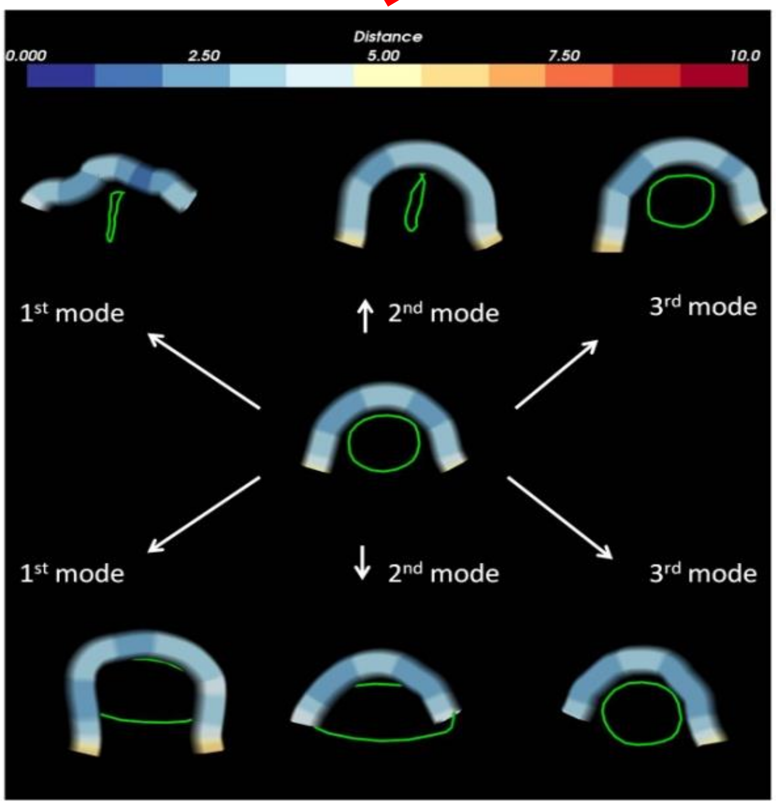
- **Active optical flow dose distribution model**
  - PCA analysis of a sequence of optical flow fields

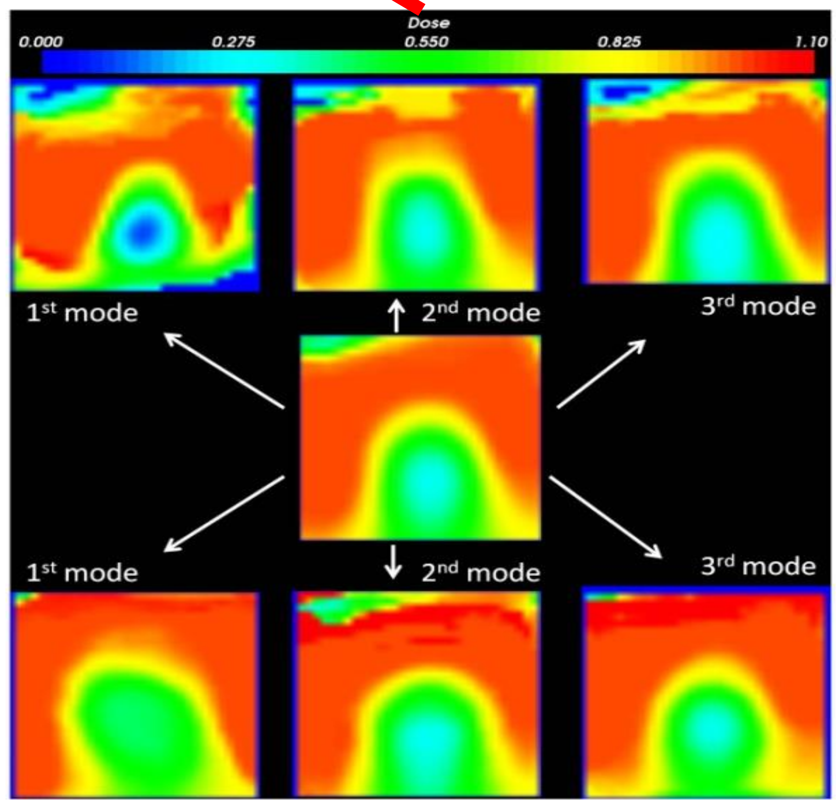


Liu et al, *PMB* 60:N83-N92, 2015

Other Knowledge Models: Dose Models

- **Machine Learning**
  - PTV contour space ↔ cord dose space





Liu et al, *PMB* 60:N83-N92, 2015

Other Knowledge Models: Dose Models

Index	$D_{2\%}$ (Gy)		$D_{5\%}$ (Gy)		$D_{10\%}$ (Gy)		$D_{0.1cc}$ (Gy)	
	Clinic.	Pred.	Clinic.	Pred.	Clinic.	Pred.	Clinic.	Pred.
1	10.1	11.6	9.3	10.7	8.6	9.7	9.3	10.7
2	12.1	11.7	11.8	11.4	11.3	11.1	12.0	11.7
3	14.1	13.7	13.1	12.5	12.1	11.7	13.1	12.5
4	8.9	9.0	8.3	8.3	7.7	7.7	7.8	7.7
5	10.7	9.6	9.6	9.0	8.7	8.3	10.4	9.5
6	9.9	10.5	9.4	10.0	9.0	9.5	9.3	9.8
7	10.7	10.7	10.0	10.0	9.3	9.6	10.9	10.8
8	14.0	14.1	12.6	12.8	11.6	11.9	14.2	14.4
9	10.8	11.3	10.2	10.1	9.6	8.5	9.1	8.1
10	14.1	14.8	13.0	13.1	11.9	12.0	14.4	15.3
11	11.9	11.7	10.6	11.0	9.5	10.3	11.3	11.3
12	10.3	10.1	9.9	9.1	9.5	8.3	9.9	9.0
13	12.4	12.2	11.7*	14.5*	11.1	10.7	11.1	10.7
14	14.3	13.9	13.9	13.6	13.4	13.3	14.1	14.0
15	11.5	11.5	10.3	9.7	9.0	8.6	10.6	10.3
Mean ±std.	11.7 ±1.7	11.8 ±1.7	10.9 ±1.7	11.1 ±1.9	10.2 ±1.6	10.1 ±1.7	11.2 ±2.0	11.1 ±2.2

Summary

- Modeling clinic treatment planning knowledge is feasible
- Various sources of knowledge can be combined
- Multi-center, multi-modality knowledge modeling will help clinical practice in large and small centers and clinical trials
- Knowledge models can assist physicians, physicists and planners
- Knowledge modeling can help to improve plan quality, consistency, as well as efficiency

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- Liyong Lin PHD (U Penn)
- Jeffery D. Bradley MD (Wash U)

Thank You

Treatment planning knowledge models are

20%	1.	**Confined to a single institution**
20%	2.	**Applicable to multiple modalities**
20%	3.	**Useful for only IMRT**
20%	4.	**Physician Specific**
20%	5.	**Useable only with Monte Carlo-based dose calculation algorithms26**

Treatment planning knowledge models are

0%	1.	Confined to a single institution
0%	2.	Applicable to multiple modalities
0%	3.	Useful for only IMRT
0%	4.	Physician Specific
0%	5.	Useable only with Monte Carlo-based dose calculation algorithms

Treatment planning knowledge models are

- Answer:
- 2

- Reference:

Lian et al, Modeling the dosimetry of organ-at-risk in head and neck IMRT planning: An inter-technique and inter-institutional study, Medical Physics 2013, 40(12)

Machine learning of the knowledge models is useful

20%
20%
20%
20%
20%

1. In quantifying the influence of anatomy features to t dose sparing in the OARs
2. In defining linac performance
3. In predicting dose prescription
4. In collecting past cases as database
5. In detecting planning errors

Machine learning of the knowledge models is useful

0%	1.	In quantifying the influence of anatomy features to the dose sparing in the OARs
0%	2.	In defining linac performance
0%	3.	In predicting dose prescription
0%	4.	In collecting past cases as database
0%	5.	In detecting planning errors

Machine learning of the knowledge models is useful

- Answer:
- 1

- Reference:

Yuan et al, Quantitative analysis of the factors which affect the inter-patient organ-at-risk dose sparing variation in IMRT plans, Medical Physics 2012, 39(11)

The organ sparing capability predicted by the knowledge model is

20%	1.	The average value of the sparing in the database
20%	2.	Interpolated among a few similar cases
20%	3.	Independent of prescription dose
20%	4.	Only valid for maximum dose
20%	5.	Patient specific, based his/her anatomy and physician's prescription

The organ sparing capability predicted by the knowledge model is

0% 1. The average value of the sparing in the database

0% 2. Interpolated among a few similar cases

0% 3. Independent of prescription dose

0% 4. Only valid for maximum dose

0% 5. Patient specific, based his/her anatomy and physicianâs prescription

The organ sparing capability predicted by the knowledge model is

- Answer:
- 5

- Reference:

Yuan et al, Quantitative analysis of the factors which affect the inter-patient organ-at-risk dose sparing variation in IMRT plans, Medical Physics 2012, 39(11)

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Jackie Wu, PhD, FAAPM
Professor

Duke University Medical Center
Department of Radiation Oncology

DukeMedicine