Knowledge Based Treatment Planning – Clinical Background and Application

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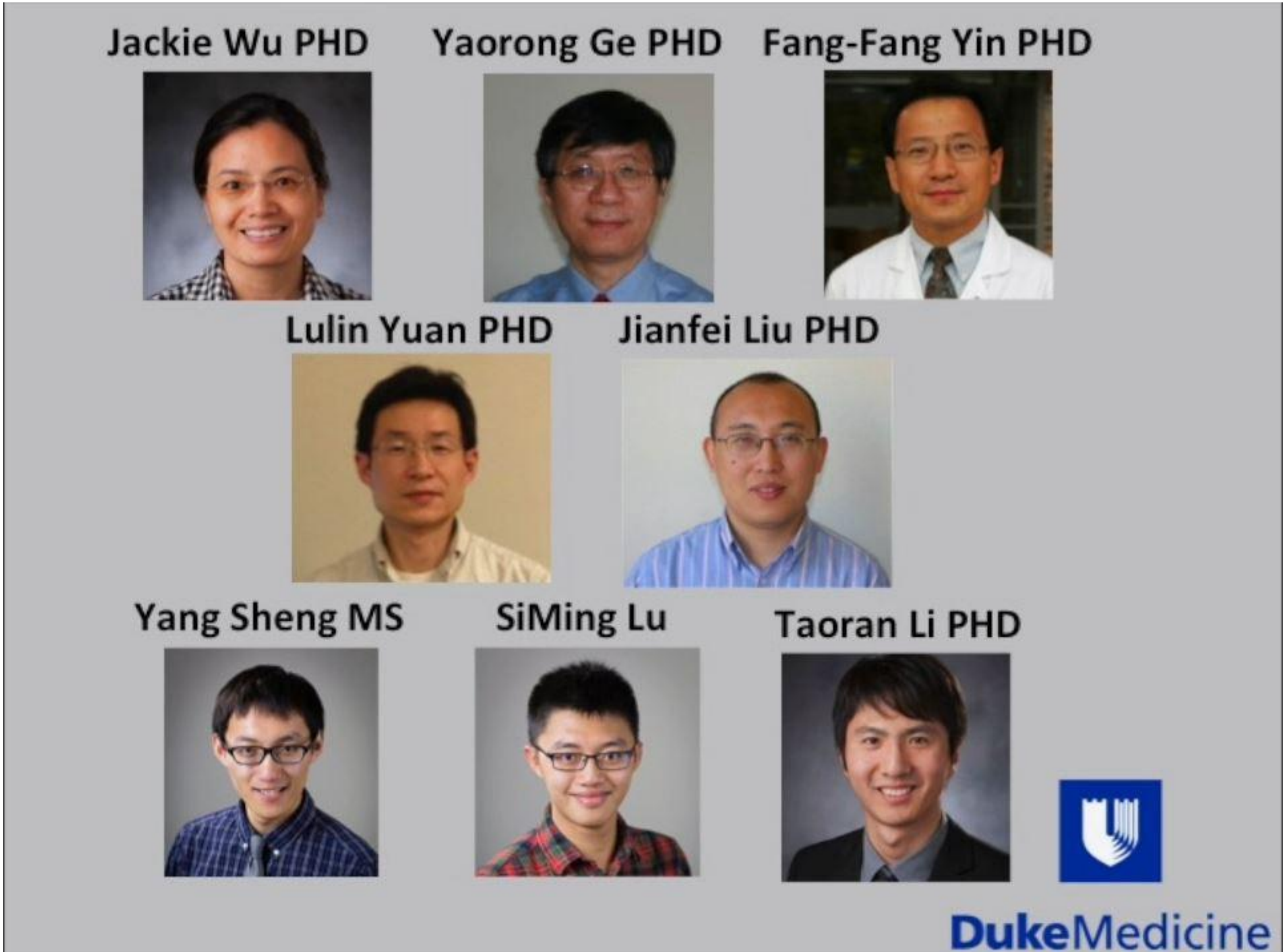
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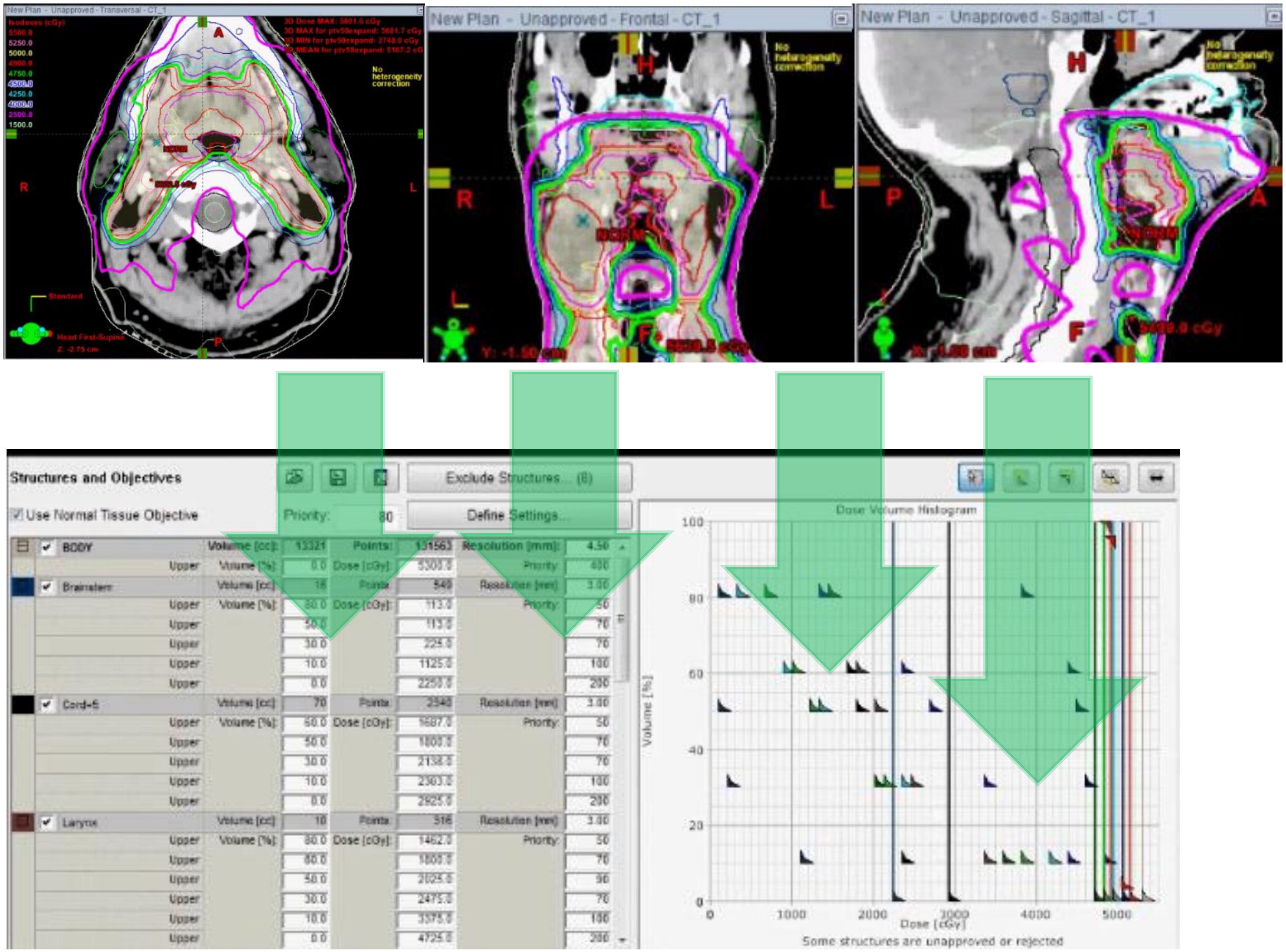
Overview

- How We Started ?
- The Initial Framework
- Going Back to Clinic
- What’s next?

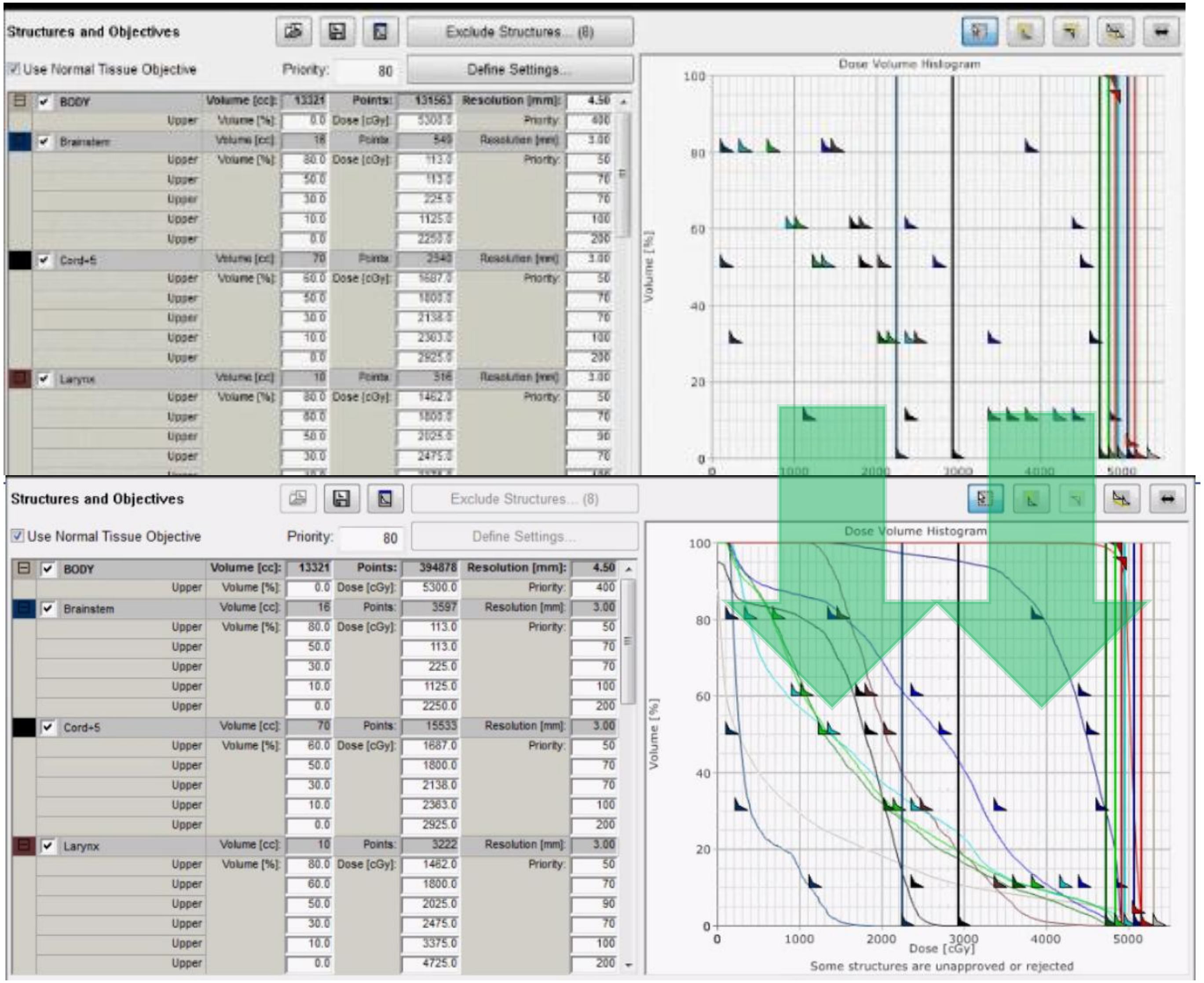
Building Planning Knowledge Models

- How We Started ?
  - Learning Curve, Quality, Consistency
  - Standardization, Automation, Integration
- The Initial Framework
- Going Back to Clinic
- What’s next?

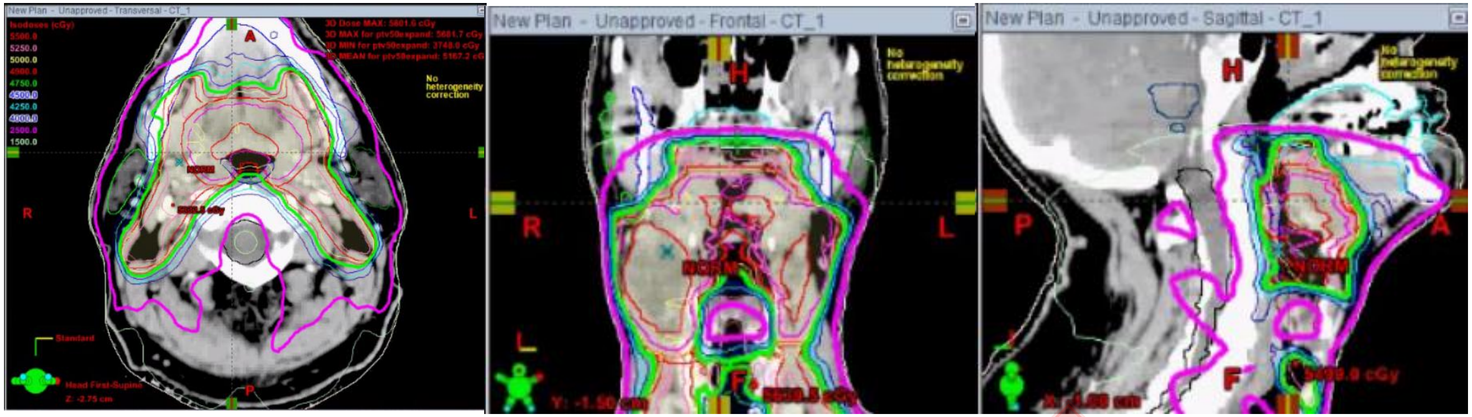
Basics Of Knowledge-Based Planning (KBP)

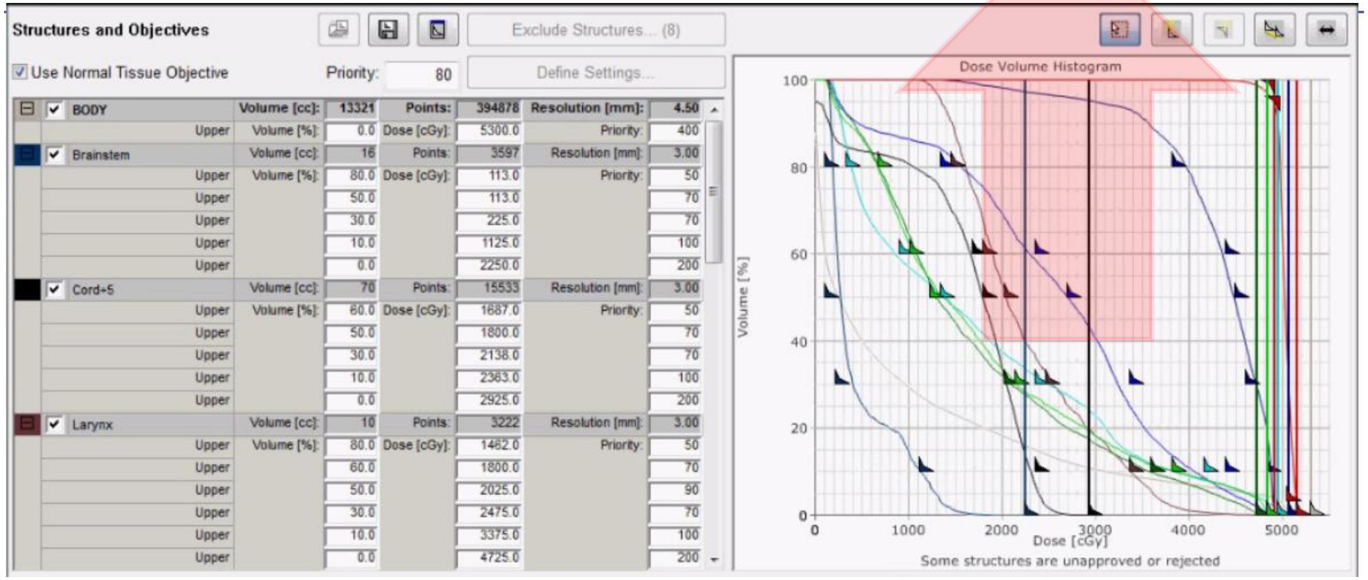


Basics Of Knowledge-Based Planning (KBP)



Basics Of Knowledge-Based Planning (KBP)





BODY		Volume [cc]:	13321	Points:	394878	Resolution [mm]:	4.50
	Upper	Volume [%]:	0.0	Dose [cGy]:	5300.0	Priority:	400
Brainstem		Volume [cc]:	16	Points:	3597	Resolution [mm]:	3.00
	Upper	Volume [%]:	80.0	Dose [cGy]:	113.0	Priority:	50
	Upper		50.0		113.0		70
	Upper		30.0		225.0		70
	Upper		10.0		1125.0		100
	Upper		0.0		2250.0		200
Cord+5		Volume [cc]:	70	Points:	15533	Resolution [mm]:	3.00
	Upper	Volume [%]:	60.0	Dose [cGy]:	1687.0	Priority:	50
	Upper		50.0		1800.0		70
	Upper		30.0		2138.0		70
	Upper		10.0		2363.0		100
	Upper		0.0		2925.0		200
Larynx		Volume [cc]:	10	Points:	3222	Resolution [mm]:	3.00
	Upper	Volume [%]:	80.0	Dose [cGy]:	1462.0	Priority:	50
	Upper		60.0		1800.0		70
	Upper		50.0		2025.0		90
	Upper		30.0		2475.0		70
	Upper		10.0		3375.0		100
	Upper		0.0		4725.0		200

Basics Of Knowledge-Based Planning (KBP)

Volume (%)

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IMRT Constraints

Patient Name	[redacted]	**Patient ID**	[redacted]
Treatment site	Rt pelvis		
Imaging sets		**Fusion (Y/N)**	

Prescription		
Target	**Margin**	**Prescription**
PTV1		1.8 to 54Gy

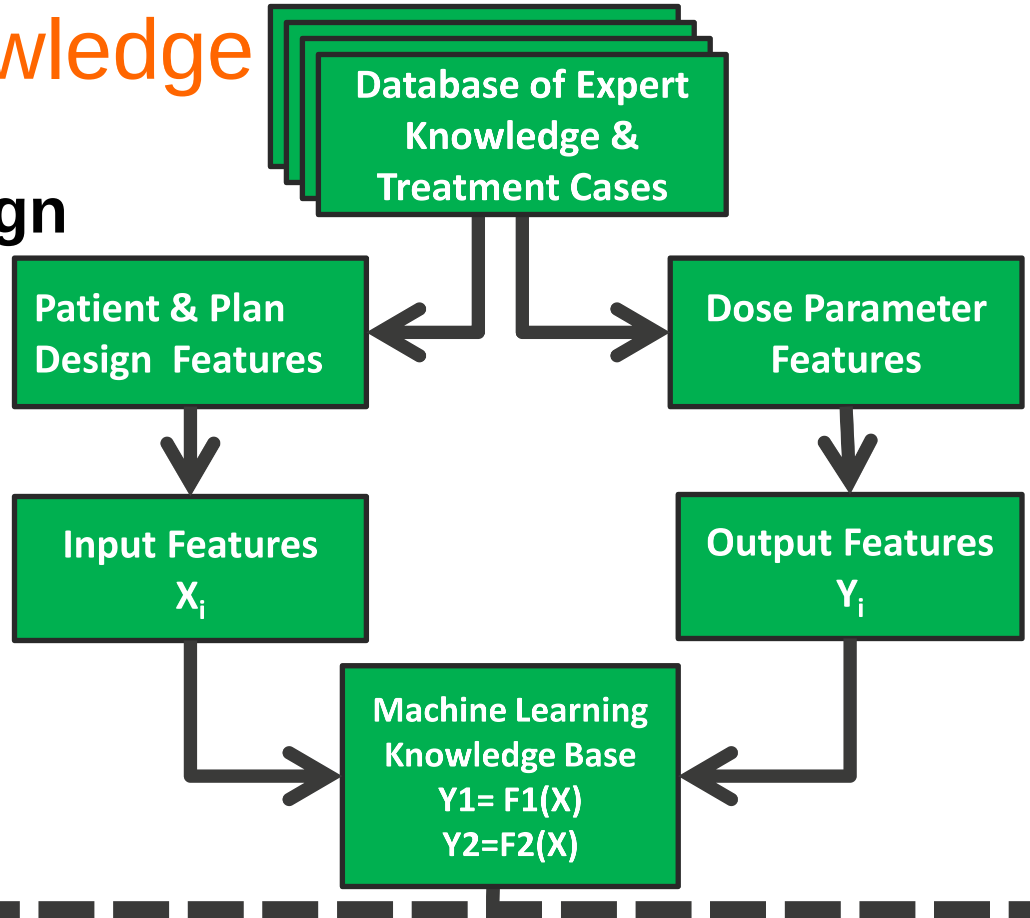
Constraints		
OARs	**Dose**	**Volume (absolute or %)**
ALARA for all		
No hot spots in bladder recturm, small bowel		
Don't push as much on femur- prefer to meet bowel/bladder		

Building Planning Knowledge Models

- How We Started ?
- The Initial Framework
  - Portable: Cases/Plans => Features
  - Systematic: Knowledge =>Machine Learning
- Going Back to Clinic
- What's next?

Building Knowledge

- Knowledge Base Training
  Platform Design



Knowledge Base Application

Building Knowledge Models

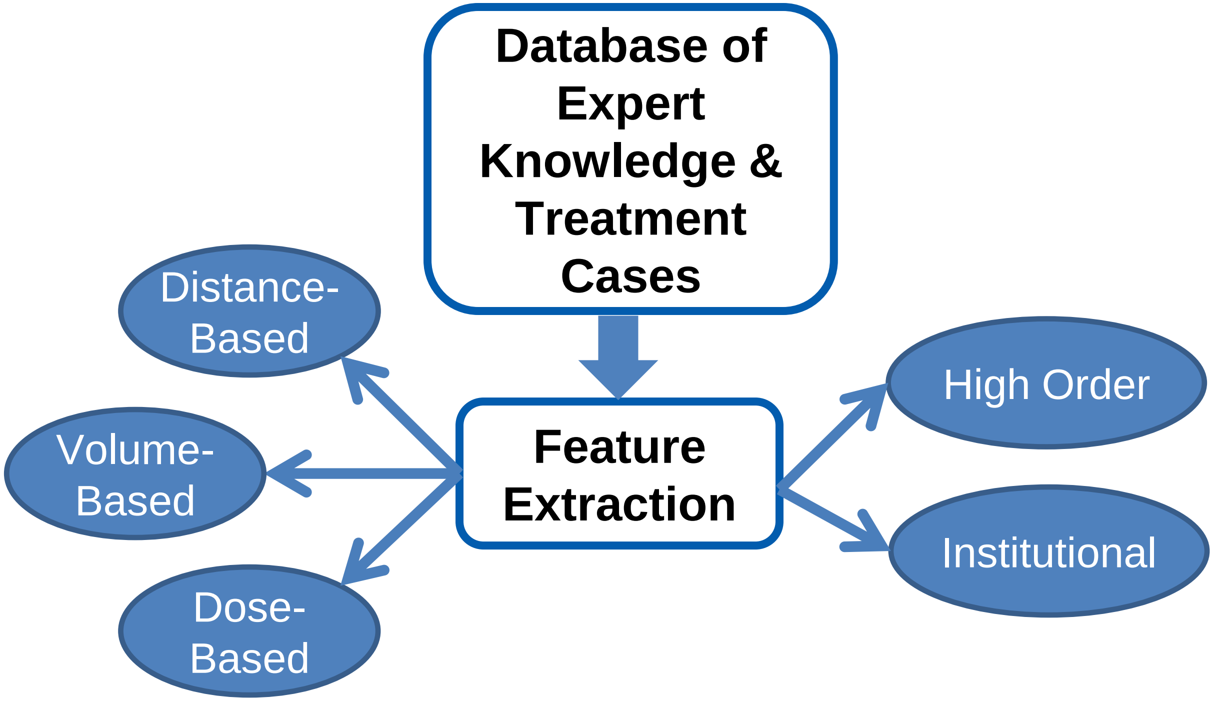
- **Platform Design**

Knowledge Base Application

New Patient → Feature Characterization Xnew → Y=f(X) → Dose Parameter Features Ynew

Building Knowledge Models

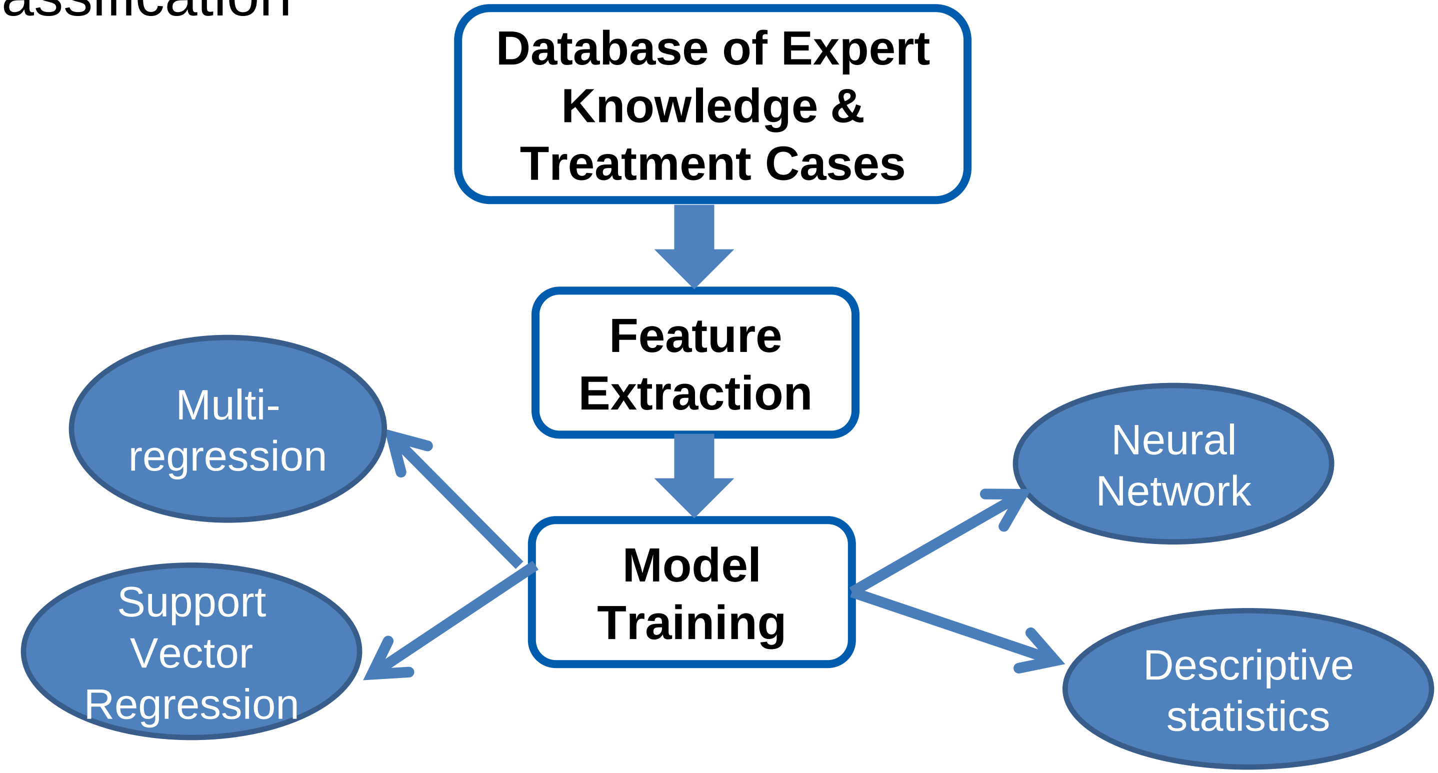
- **Feature Organization**



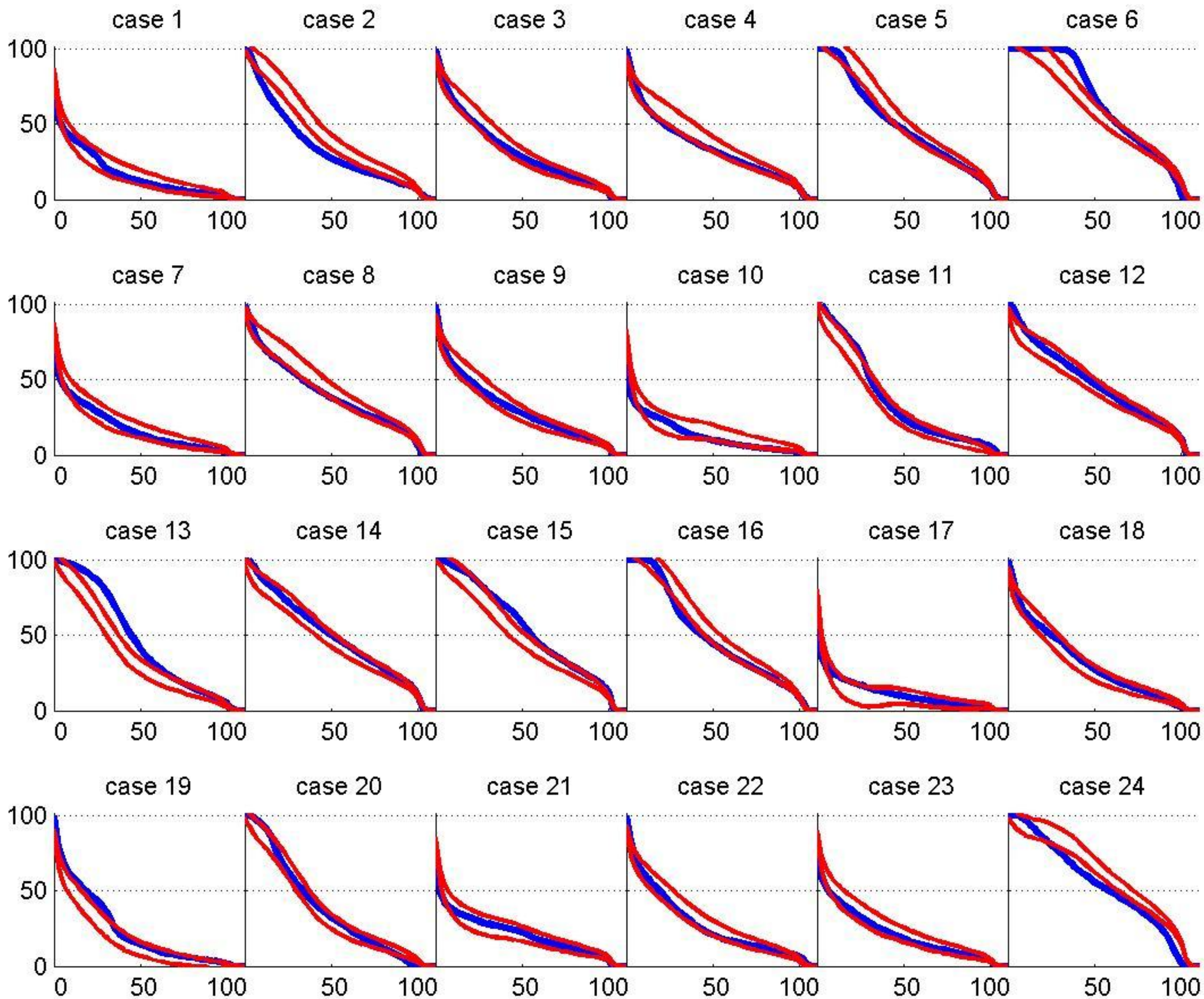
Zhu et al, *Med Phys* 38:719-726, 2011
Yuan et al, *Med Phys* 39:6868-6878, 2012

Building Planning Knowledge Models

- **Systematic Modeling of Knowledge**
  - Machine learning, Descriptive statistics, Pattern classification



Example of Bladder DVH Modeling



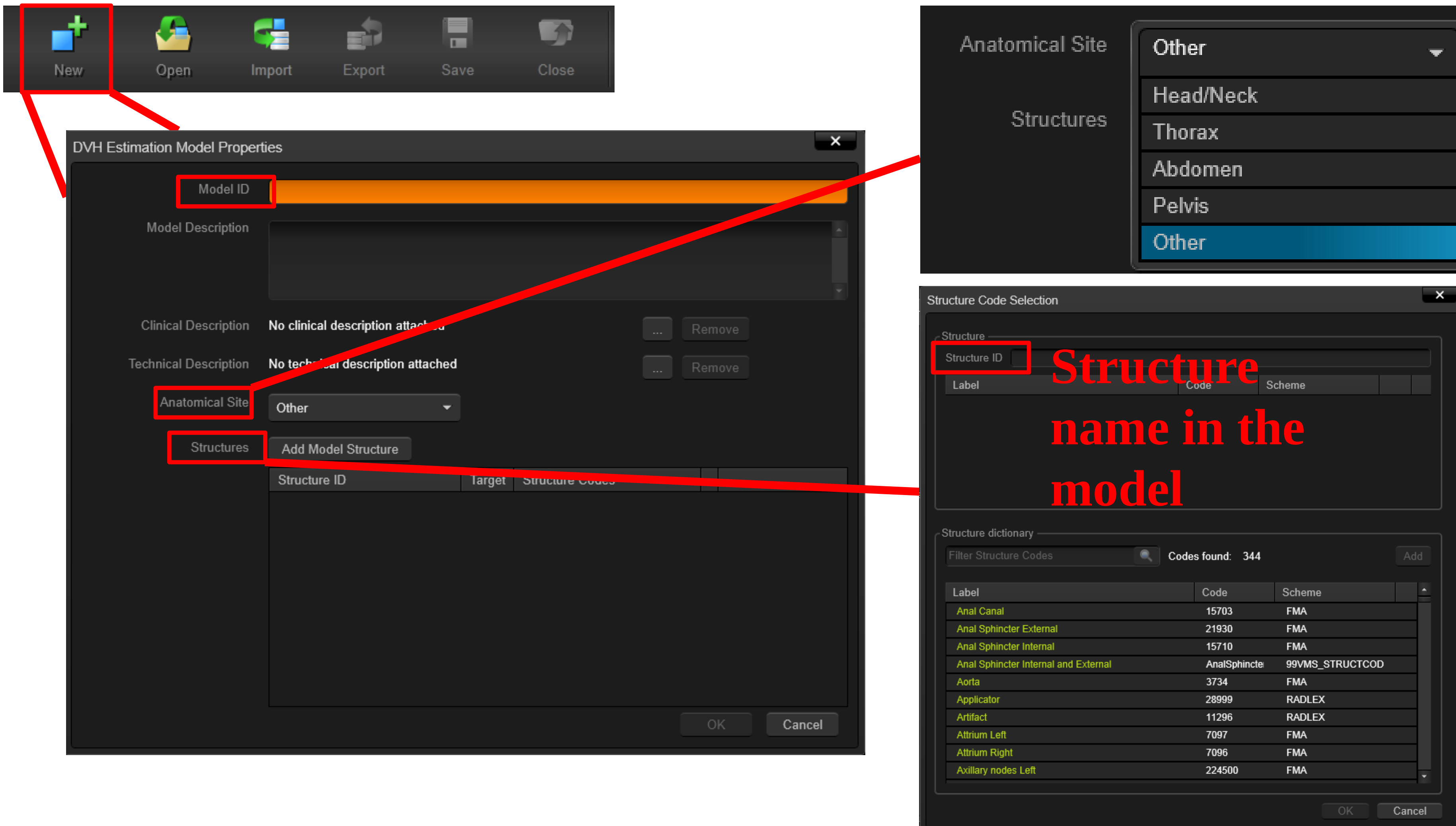
Zhu et al, *Med Phys* 38:719-726, 2011
Yuan et al, *Med Phys* 39:6868-6878, 2012

Building Planning Knowledge Models

- How We Started ?
- The Initial Framework
- Going Back to Clinic
  - Knowledge Model Guided Treatment Planning
- What's next?

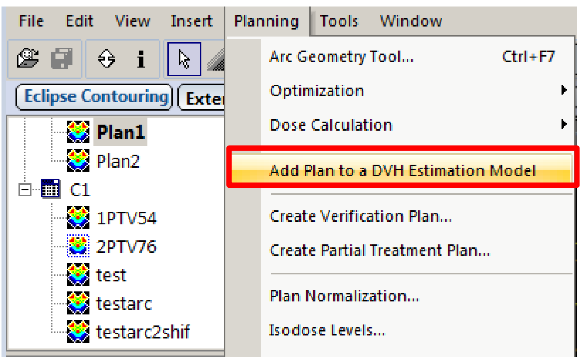
1. Generate a new model

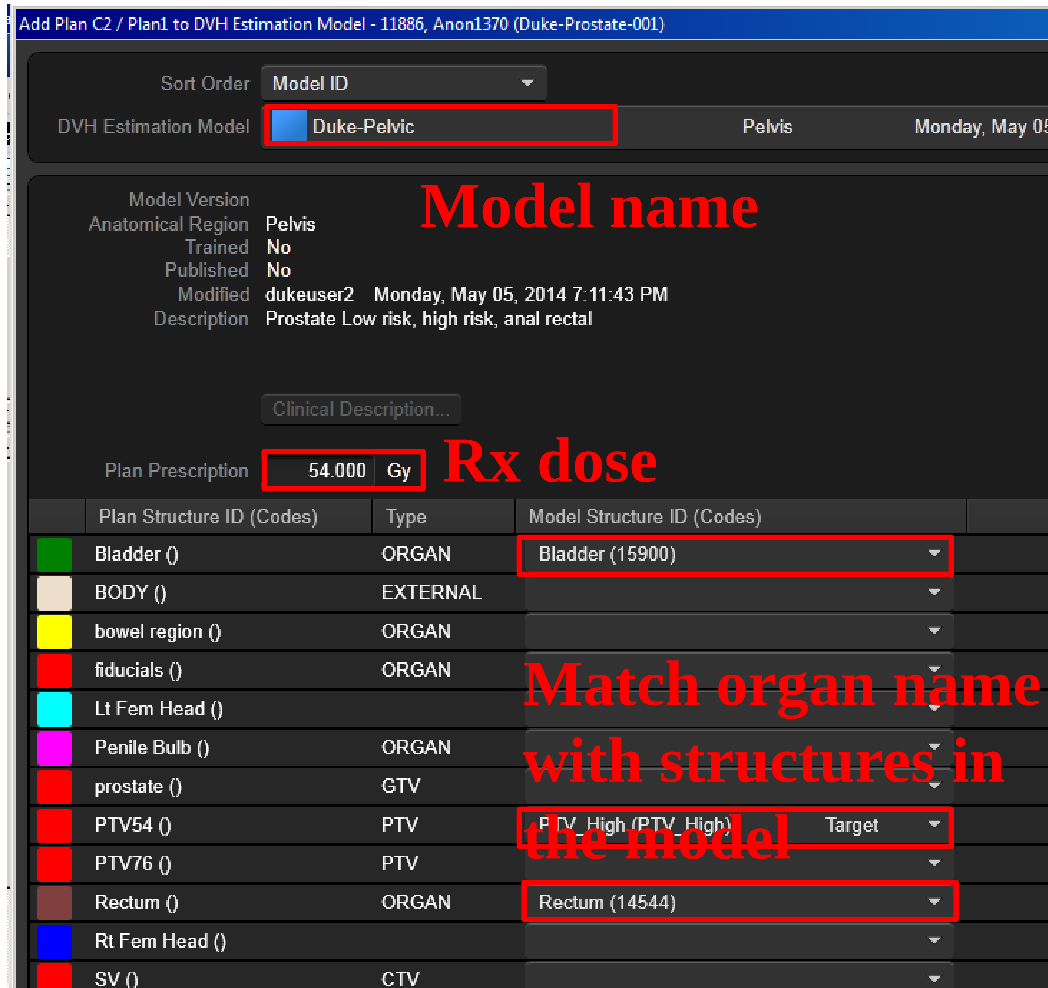
- Generate a new model in “Model Configuration”



2. Add plans to the model

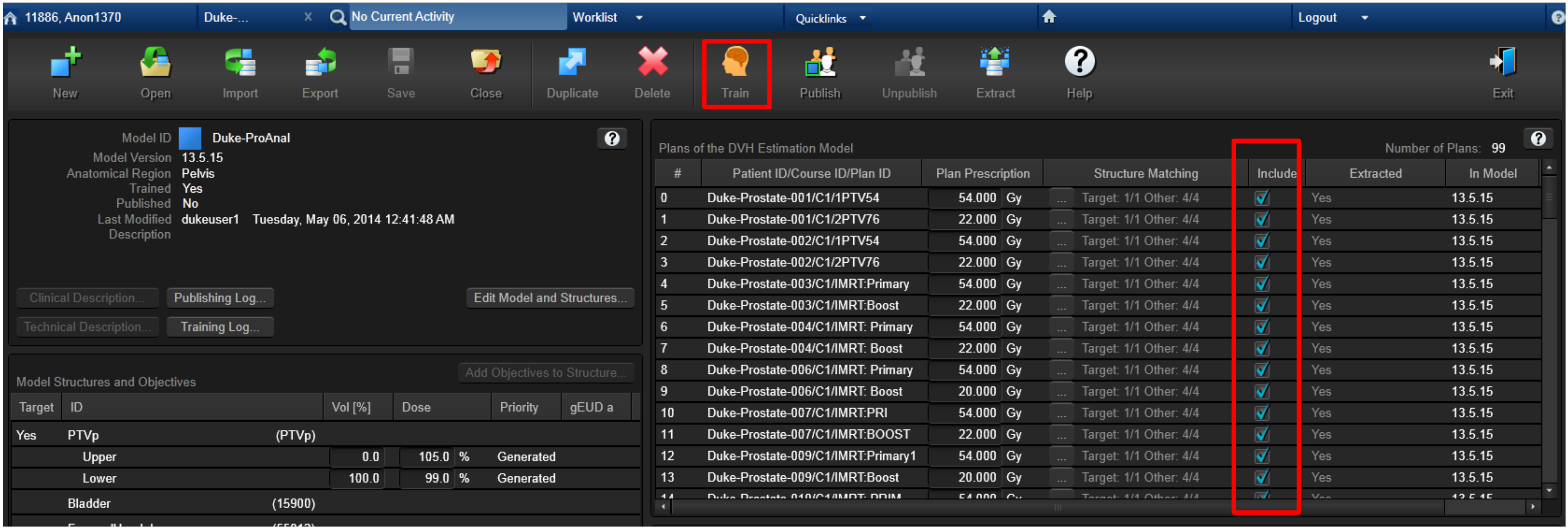
- Extract high quality plans into the model in "External Beam Planning"





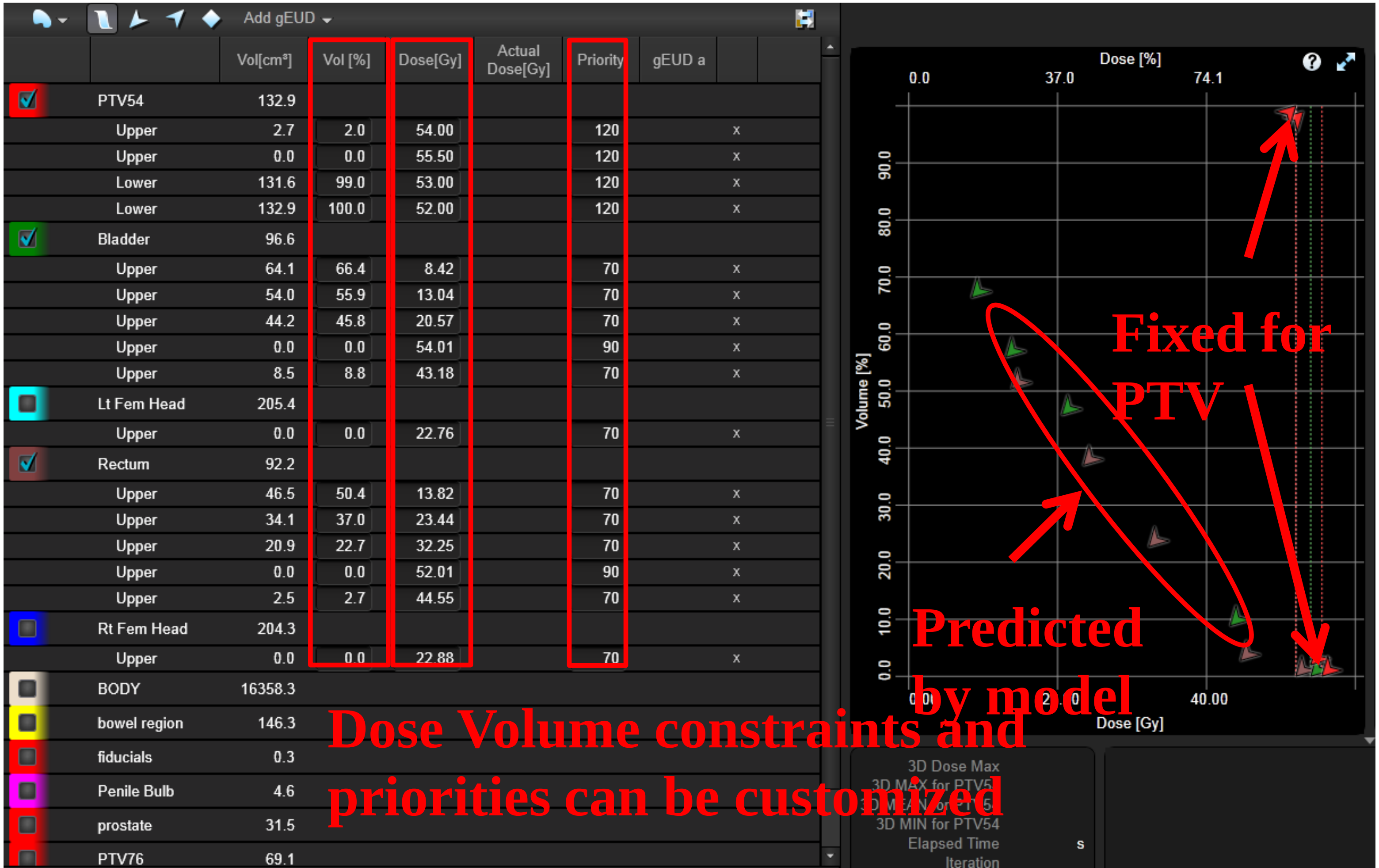
3. Model training

- In “Model Configuration”, select the plan to include in the training and then click “Train”.

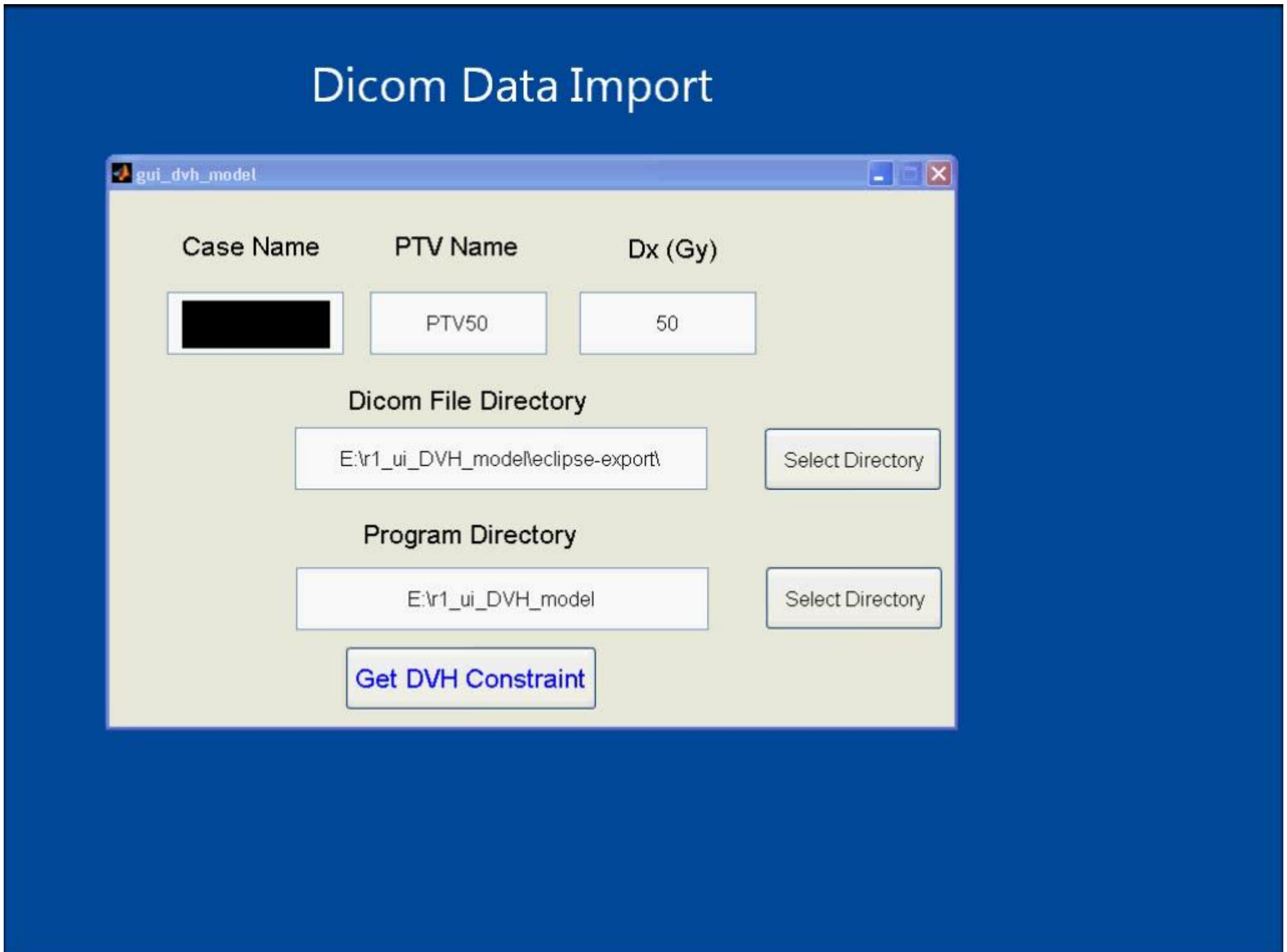


4. DVH Estimation

- In “Optimization” panel, “DVH Estimation” can be invoked to generate DVH estimates.



Knowledge Model-based HN Planning



Using IMRT Knowledge Model For VMAT

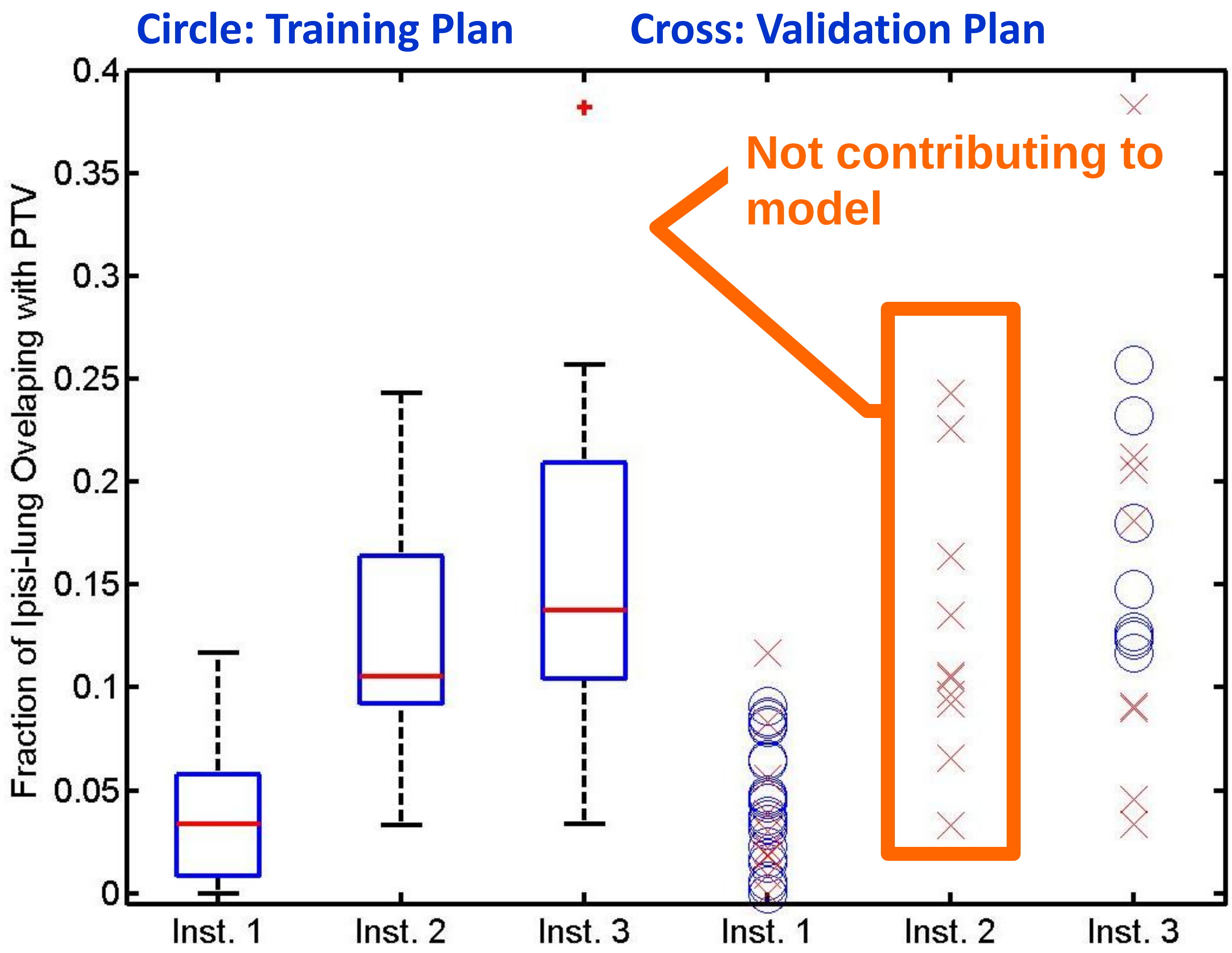
Clinical Application of Knowledge Models - Integration

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

Clinical Application of Knowledge Models - Integration

		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

Clinical Application of Knowledge Models - Integration



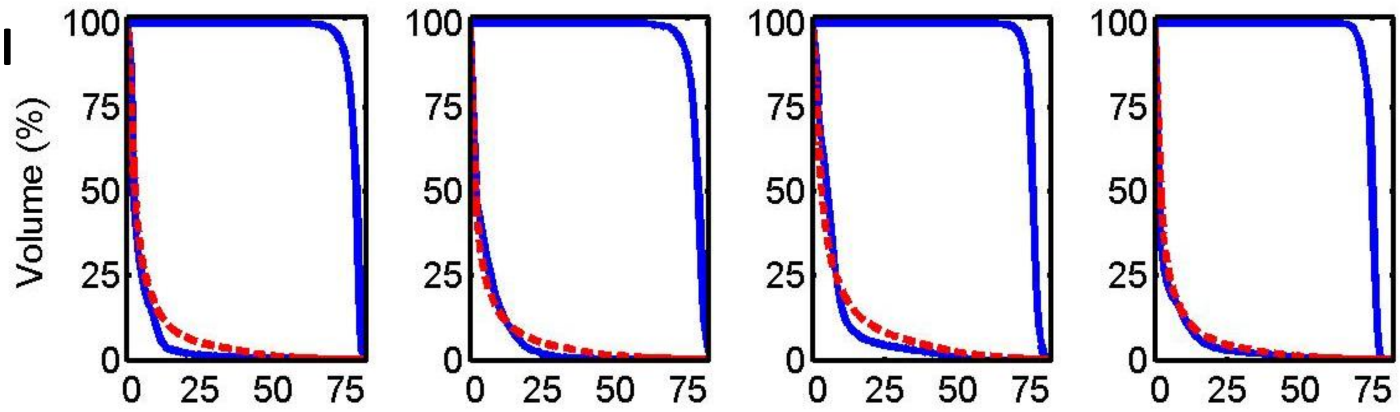
Clinical Application of Knowledge Models - Integration

Contralateral Lung DVH

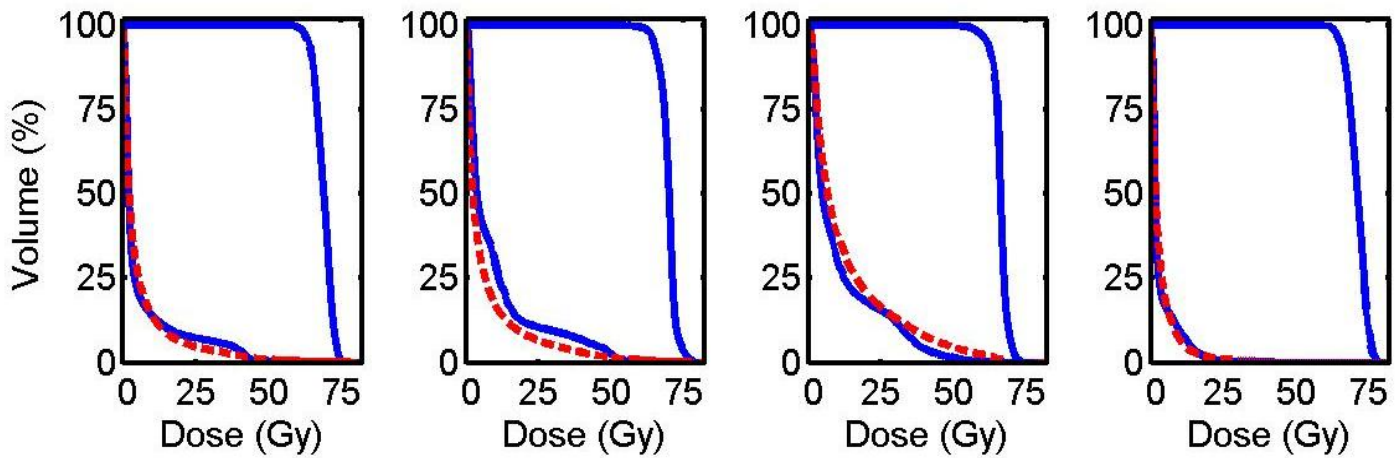
Model

Plan

Institution 2 Not contributing to model



Institution 3 Contributing to model



Cross-Modality Knowledge Base

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

Institution A

- 7-8 min delivery time
- Delivery system: Varian IMRT
- Planning system: Eclipse
- Sequential Boost
  - Multiple plans (one plan for 1 PTV)
  - 40-50 Gy and 60-70 Gy
- ~60 head-and-neck cases

Institution B

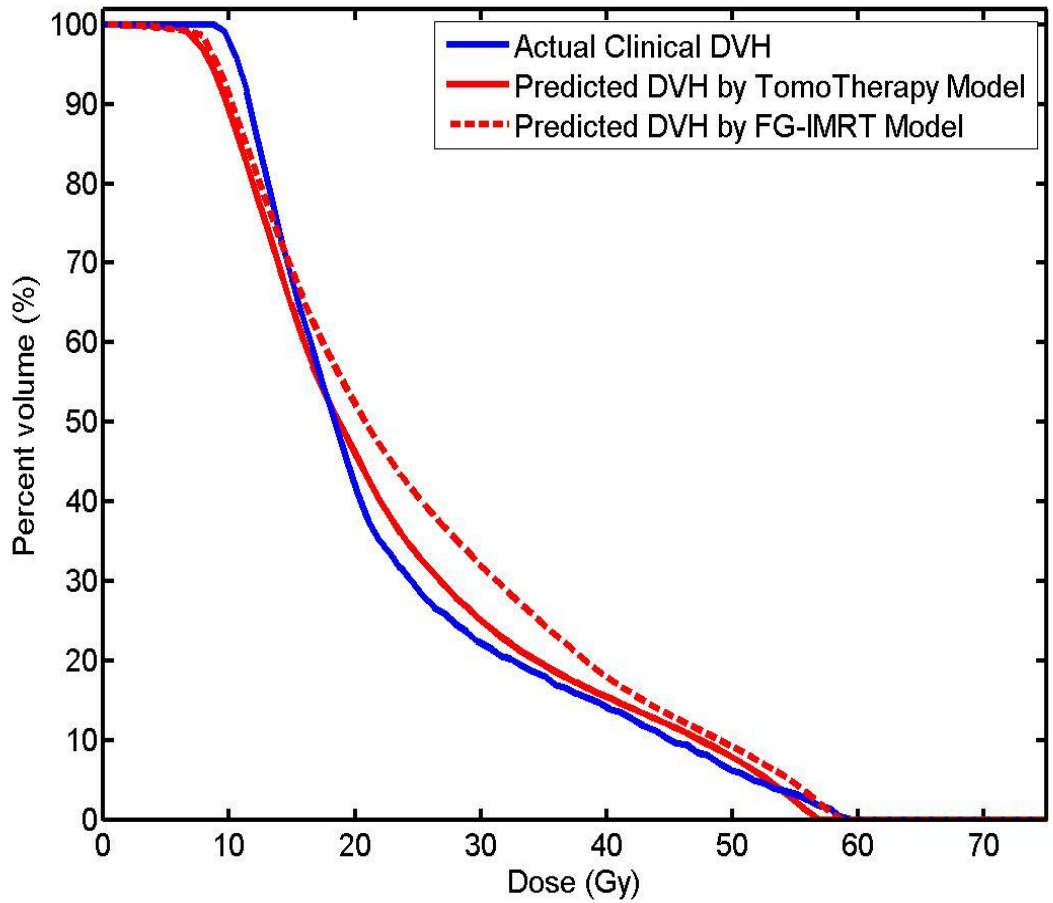
- 7-8 min delivery time
- Delivery system: Tomotherapy
- Planning system: Tomotherapy
- SIB
  - 1 plan (one plan cover all PTVs with diff. daily doses)
  - 54.25 Gy and 70 Gy
- ~60 head-and-neck cases

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

Cross-Institution Knowledge Base

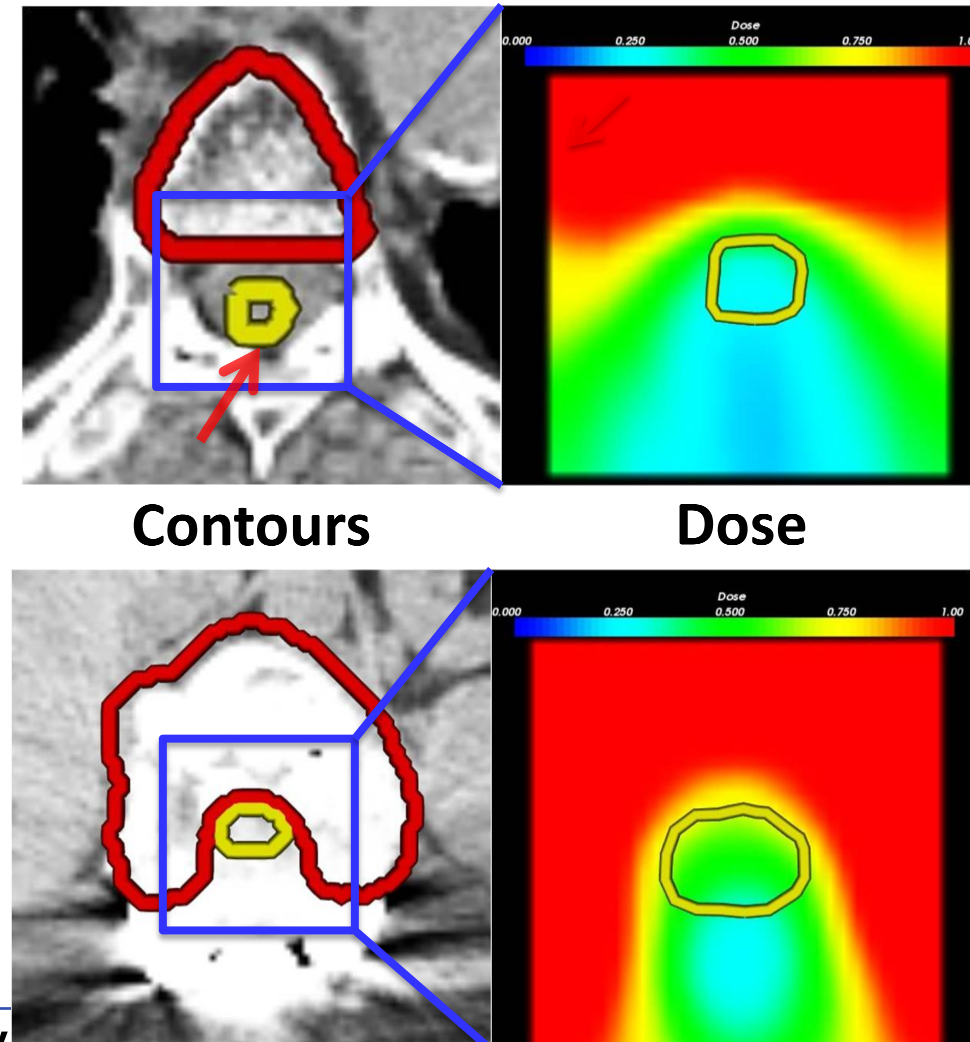
Tomotherapy Model
vs. IMRT Model
vs. Actual Plan DVH

Parotid DVH



Other Knowledge Models: Dose Models

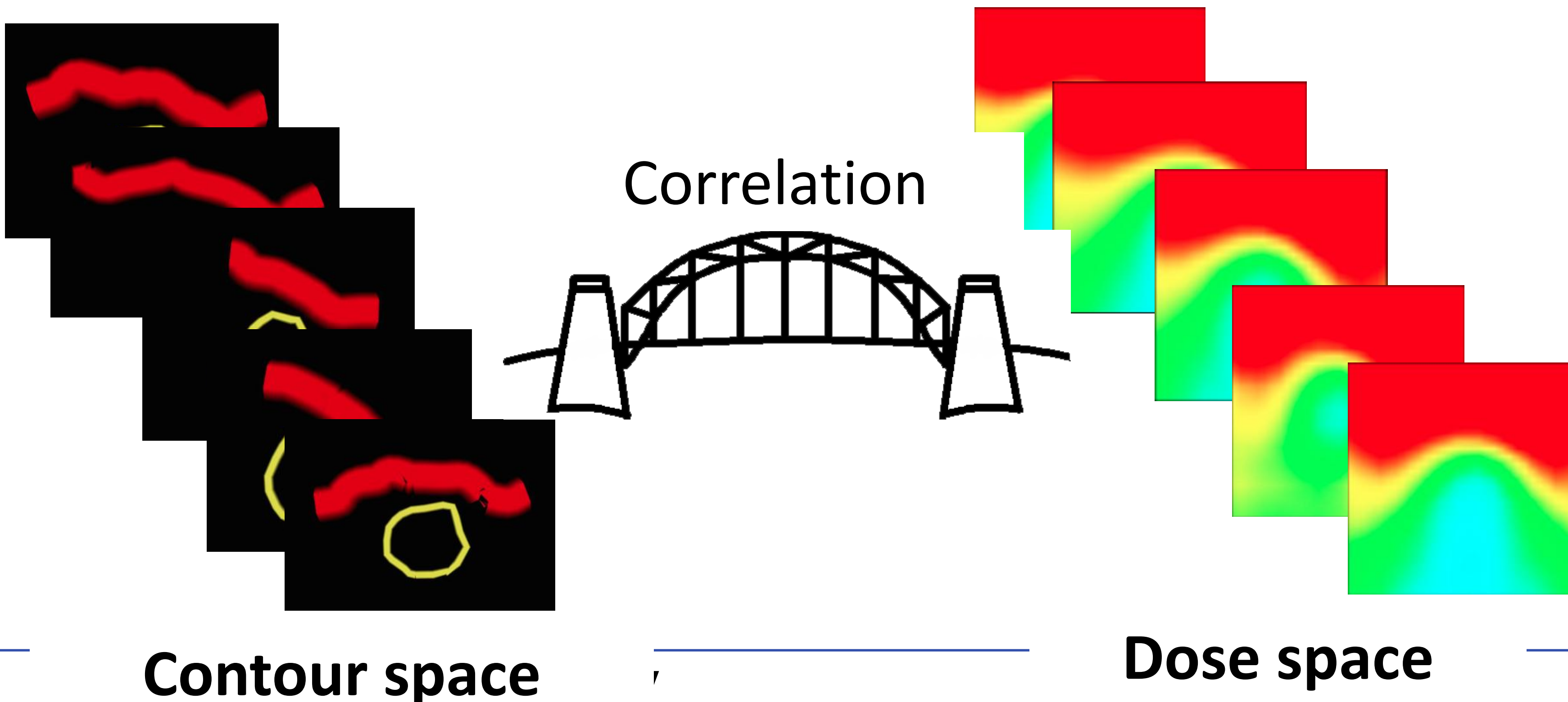
- In Spine SBRT, dose distributions in cord are highly correlated with tumor contour shapes



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

Other Knowledge Models: Dose Models

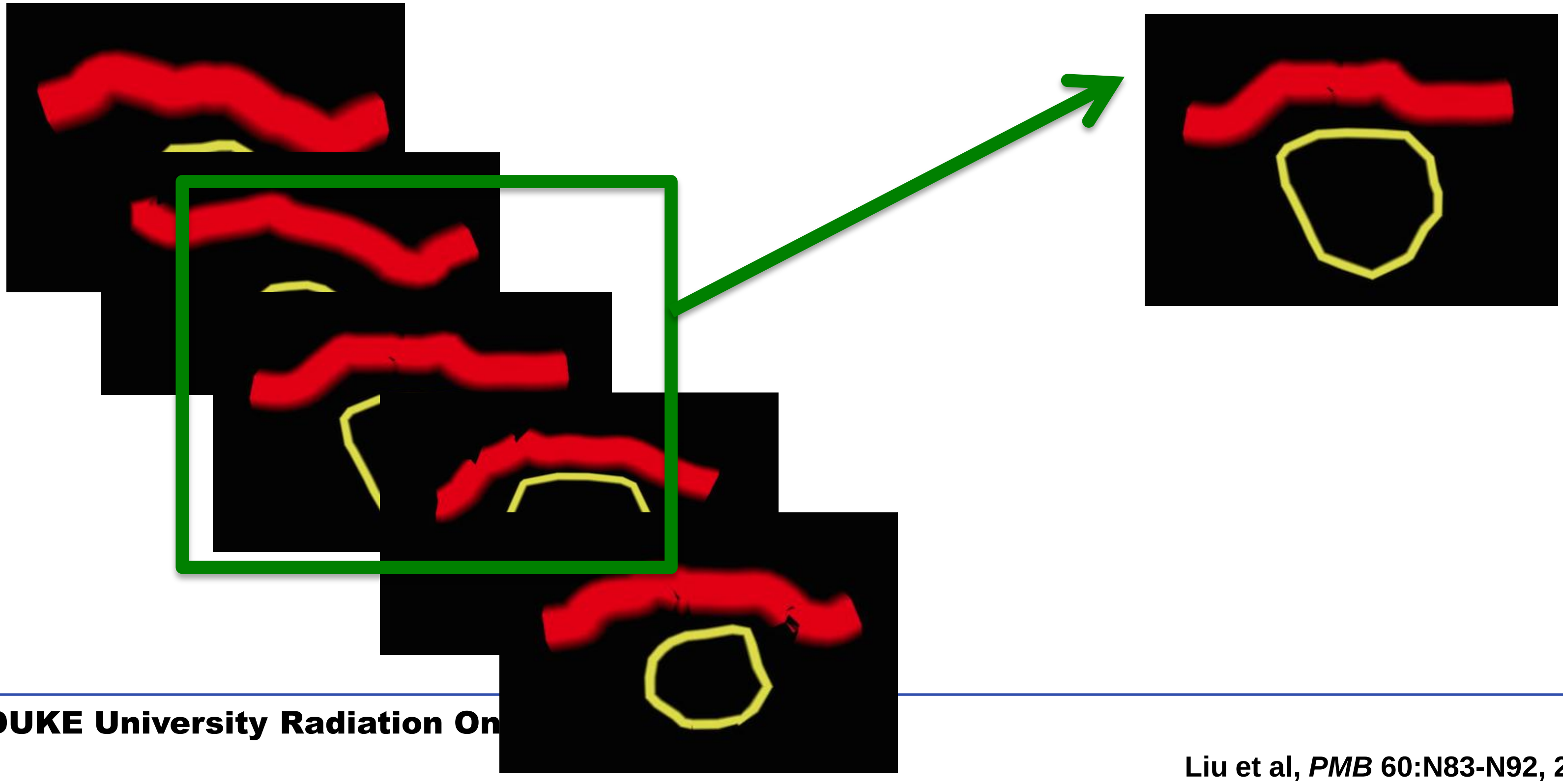
- Compute correlation between tumor contour shapes and cord dose distributions
- Use learned correlations to predict voxel-level dose distributions



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

Other Knowledge Models: Dose Models

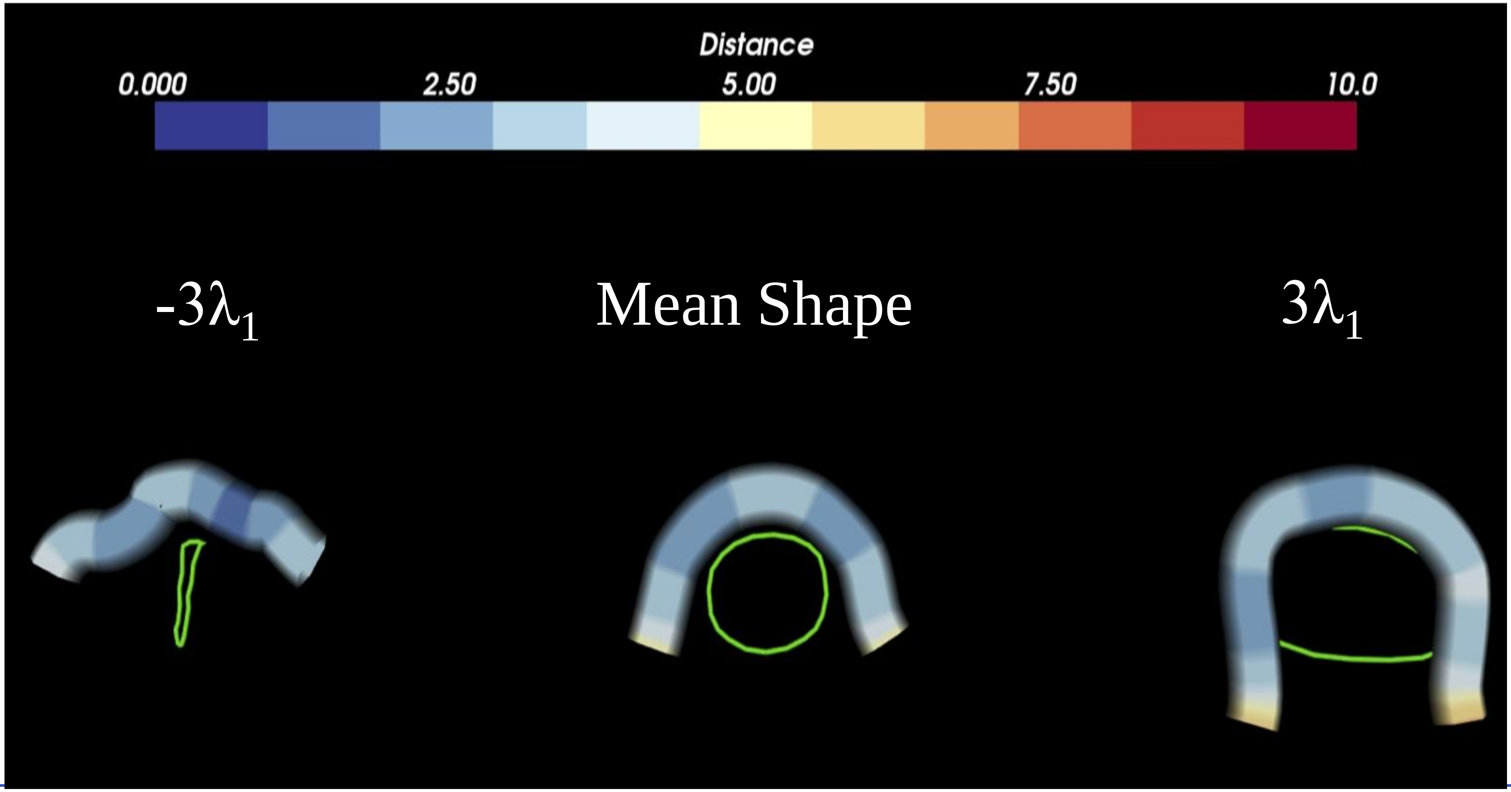
- **Active Shape Model**
  - Align the reference tumor contours and all other contours using the iterative closest point (ICP) algorithm



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

Other Knowledge Models: Dose Models

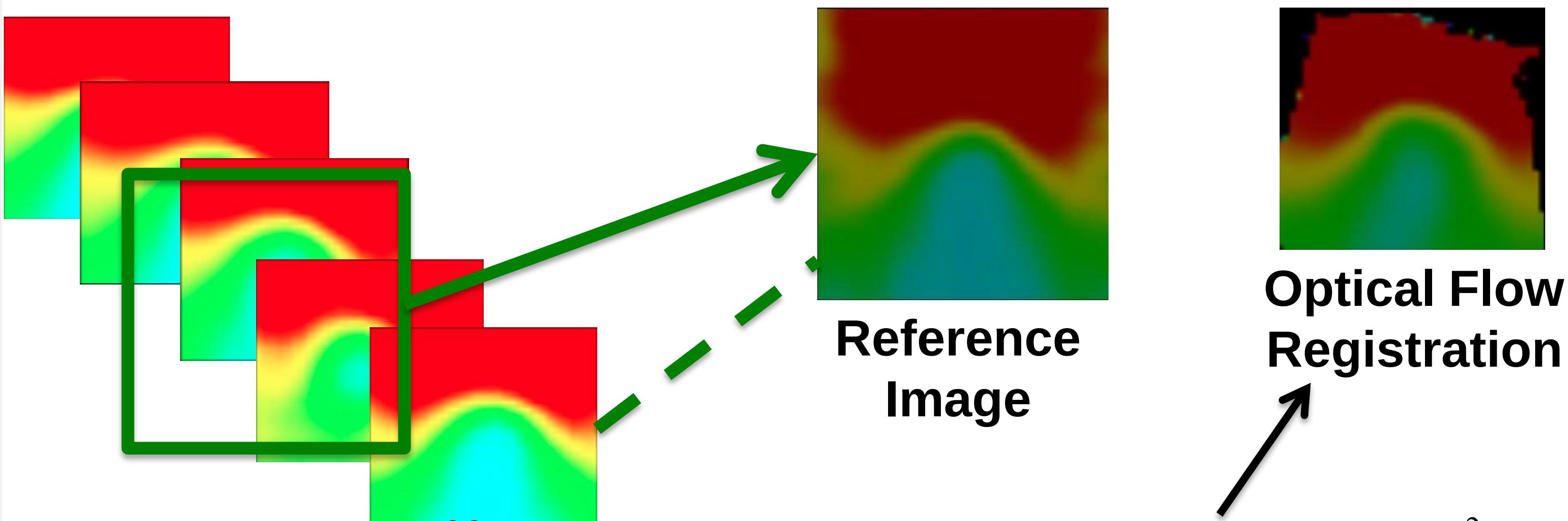
- **Active shape models**
  - PCA analysis of a set of aligned tumor contours



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

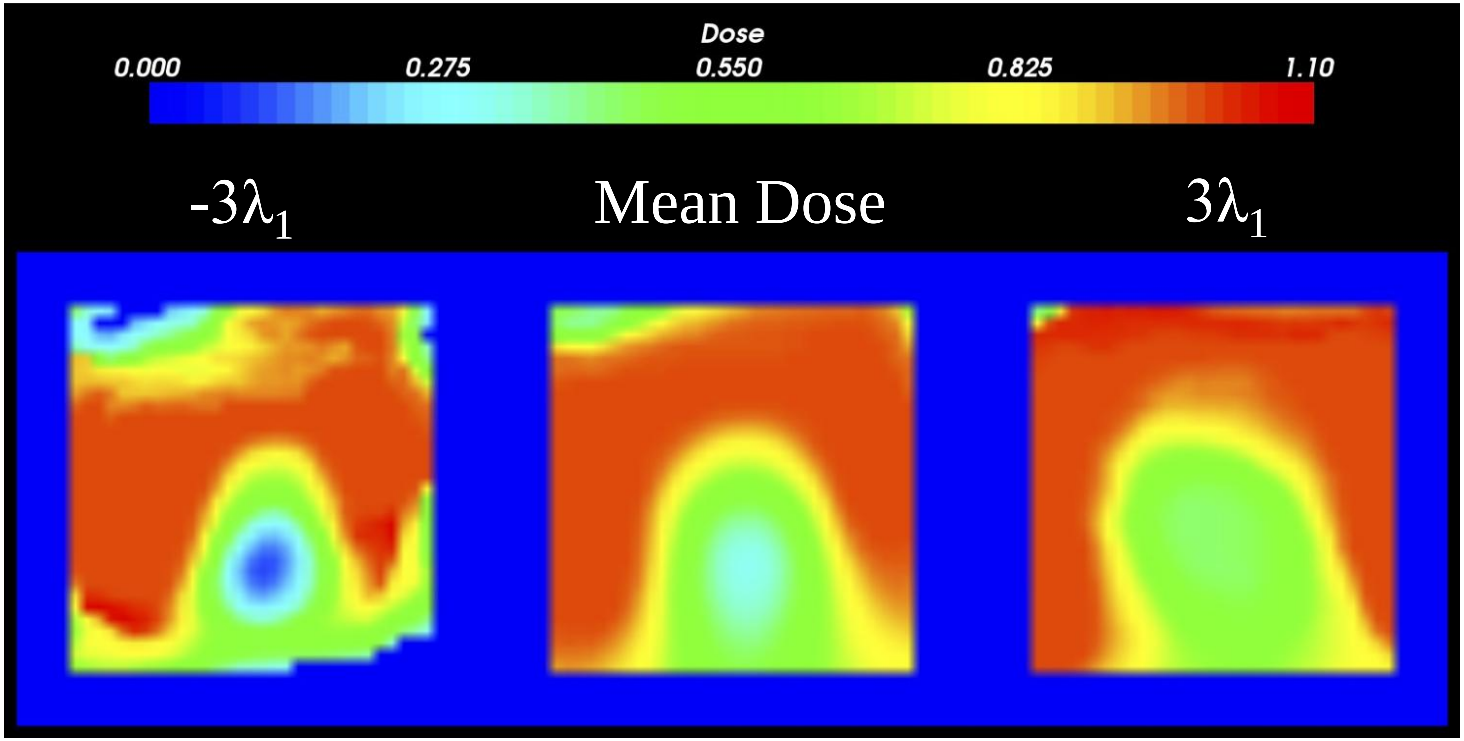


$$E(u_x,u_y)=\iint \Psi(\underbrace{(I(x+u_x,y+u_y,t+1)-I(x,y,t))^2}_{\text{Intensity constraint}}+\beta\Psi(\underbrace{\left|\nabla u_x\right|^2+\left|\nabla u_y\right|^2}_{\text{Smoothness constraint}})$$

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

Other Knowledge Models: Dose Models

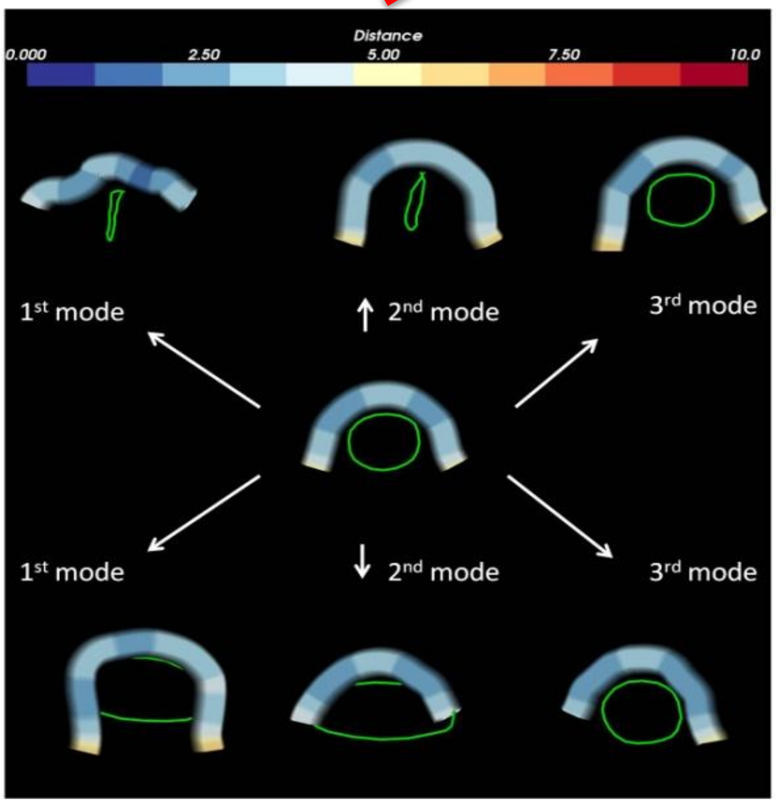
- **Active optical flow dose distribution model**
  - PCA analysis of a sequence of optical flow fields

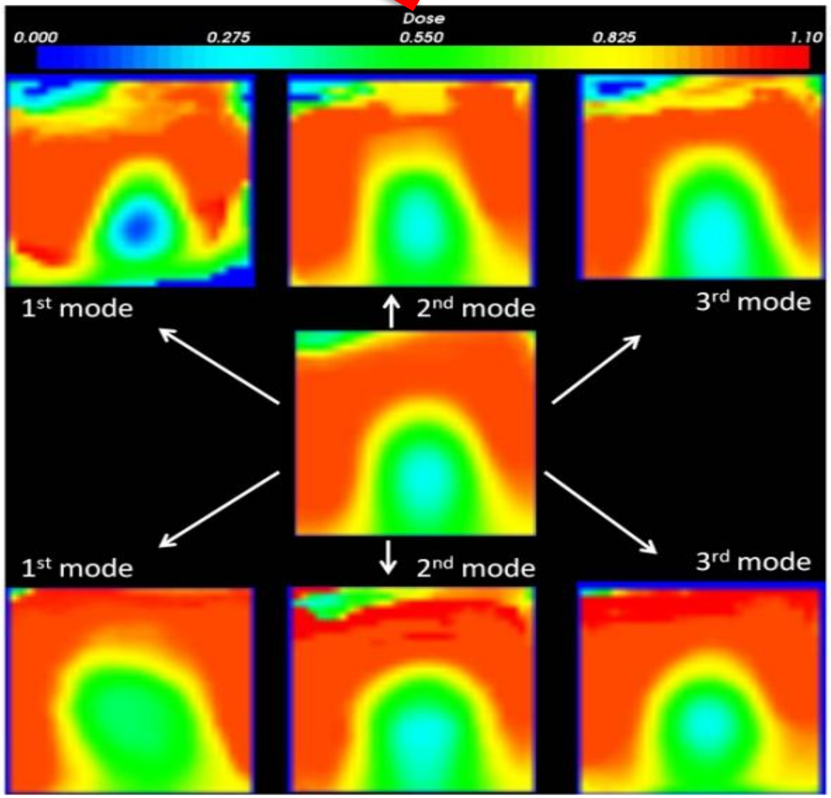


Liu et al, *PMB* 60:N83-N92, 2015

Other Knowledge Models: Dose Models

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

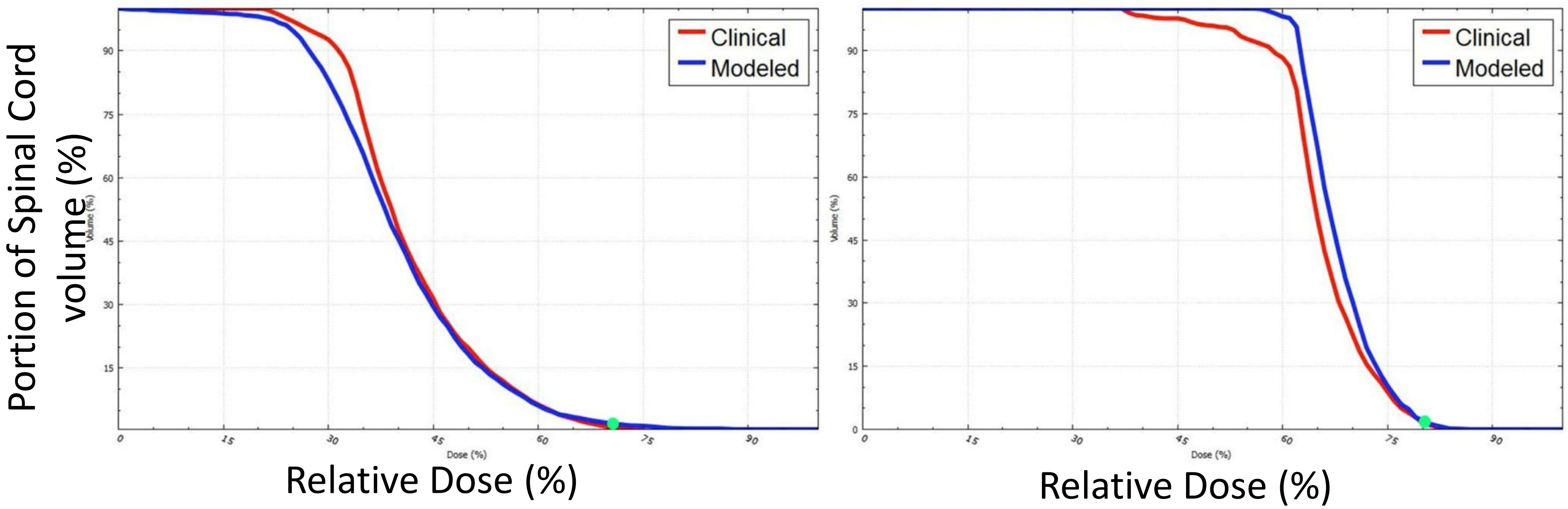




Liu et al, *PMB* 60:N83-N92, 2015

Other Knowledge Models: Dose Models

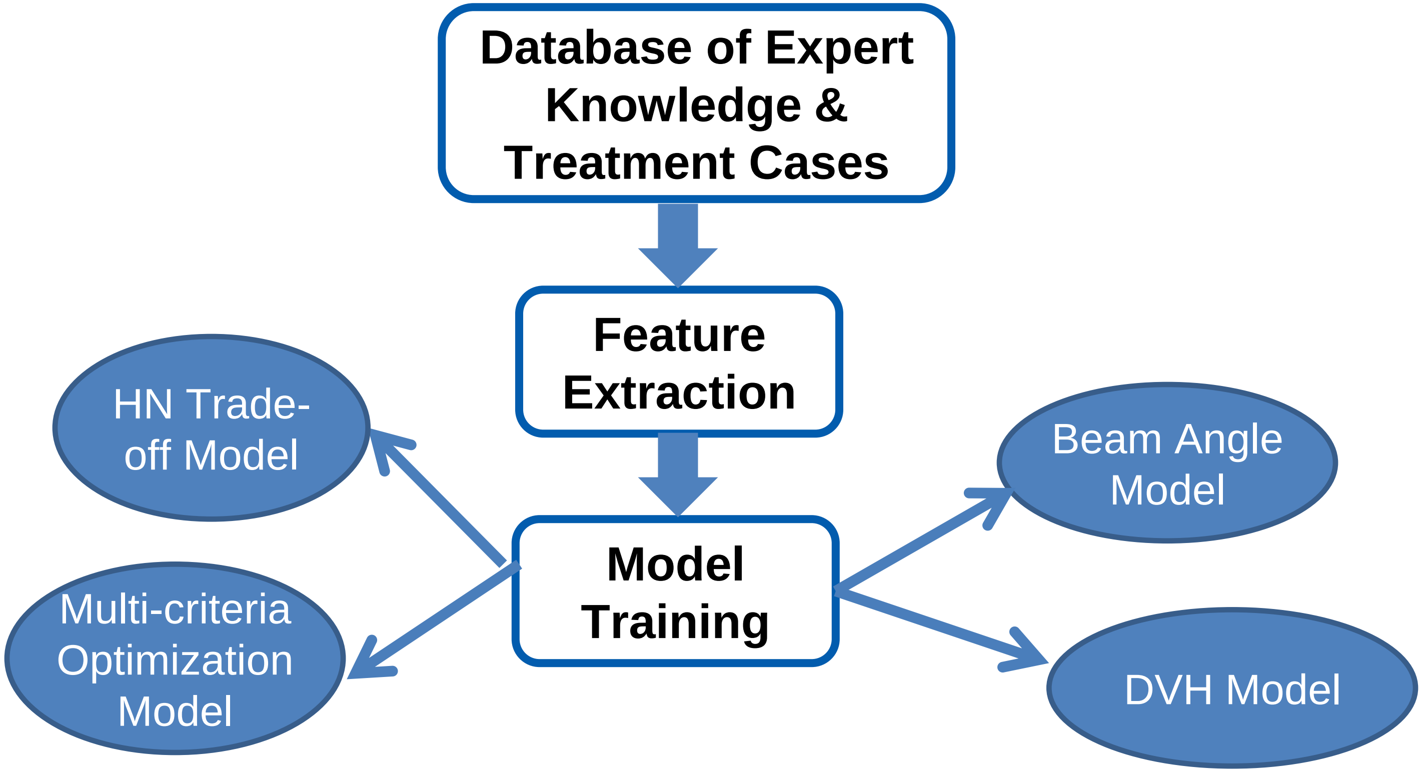
- Modeled vs clinical plan DVH



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

Clinical Application of Knowledge Models - Integration

- Rapid Learning Framework
- Multiple Knowledge Resources



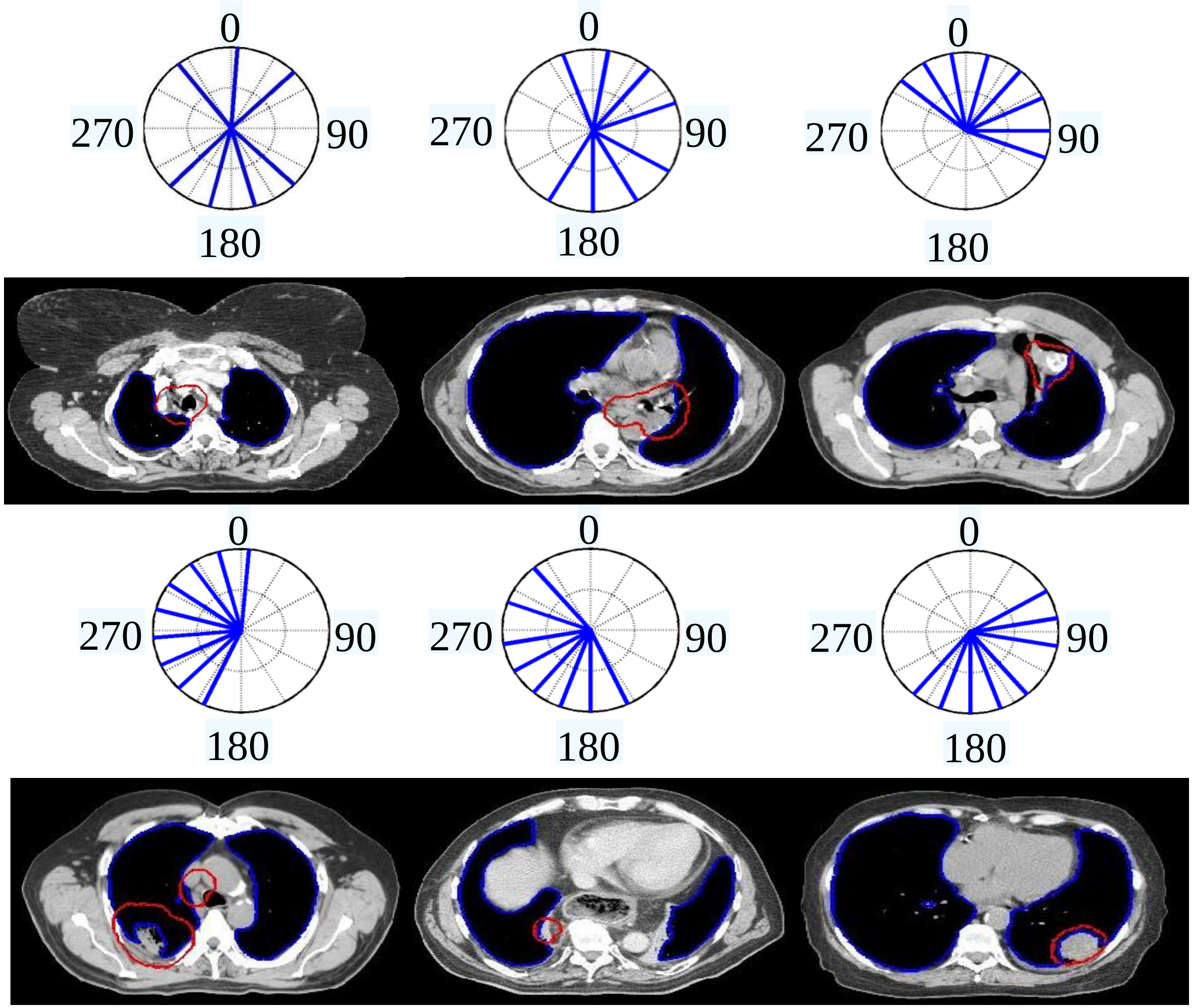
Clinical Application of Knowledge Models - Integration

- **<u>Lung IMRT Model as A Rapid-learning Show Case</u>**
  - DVH Model + Beam Angle Model
    - **100 Lung Cases**
    - **All co-planar beams (best clinical knowledge)**
    - **Ignore non-planar plans (clinical knowledge sparse)**

Phase 1 : Class Solution

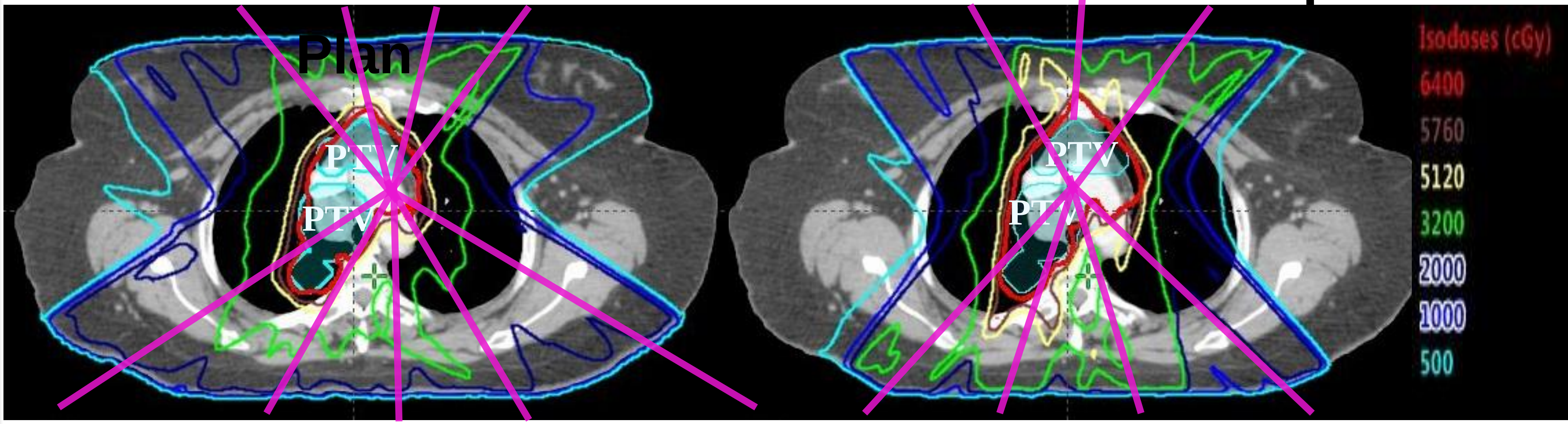
- Step1: Define distance between two beam bouquets
- Step2: Classify beam configuration using clustering analysis
- Step 3: Extract standard bouquets

Phase 1: Class Solution - Beam Bouquet Atlas

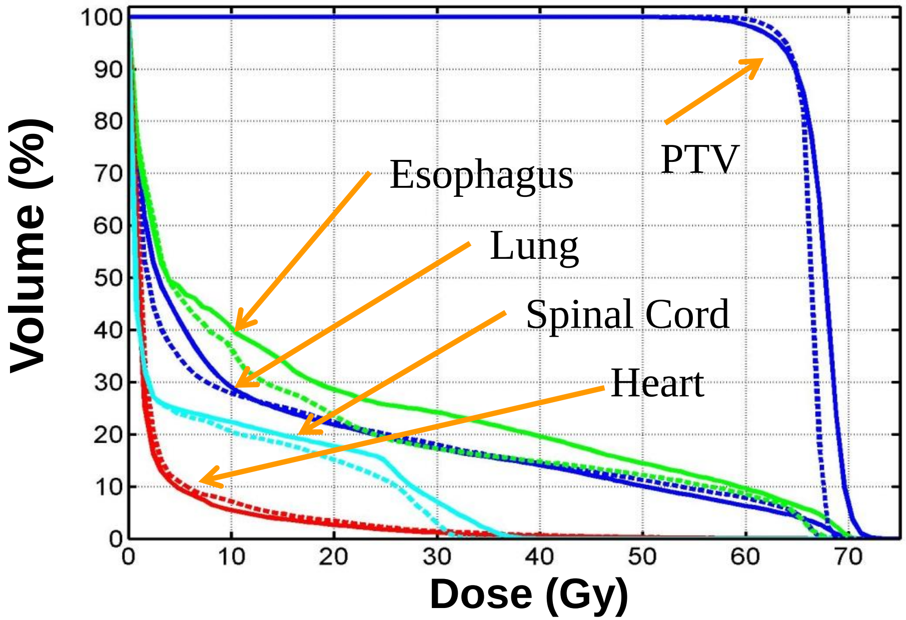


Clinical Plan

Class Solution Bouquets



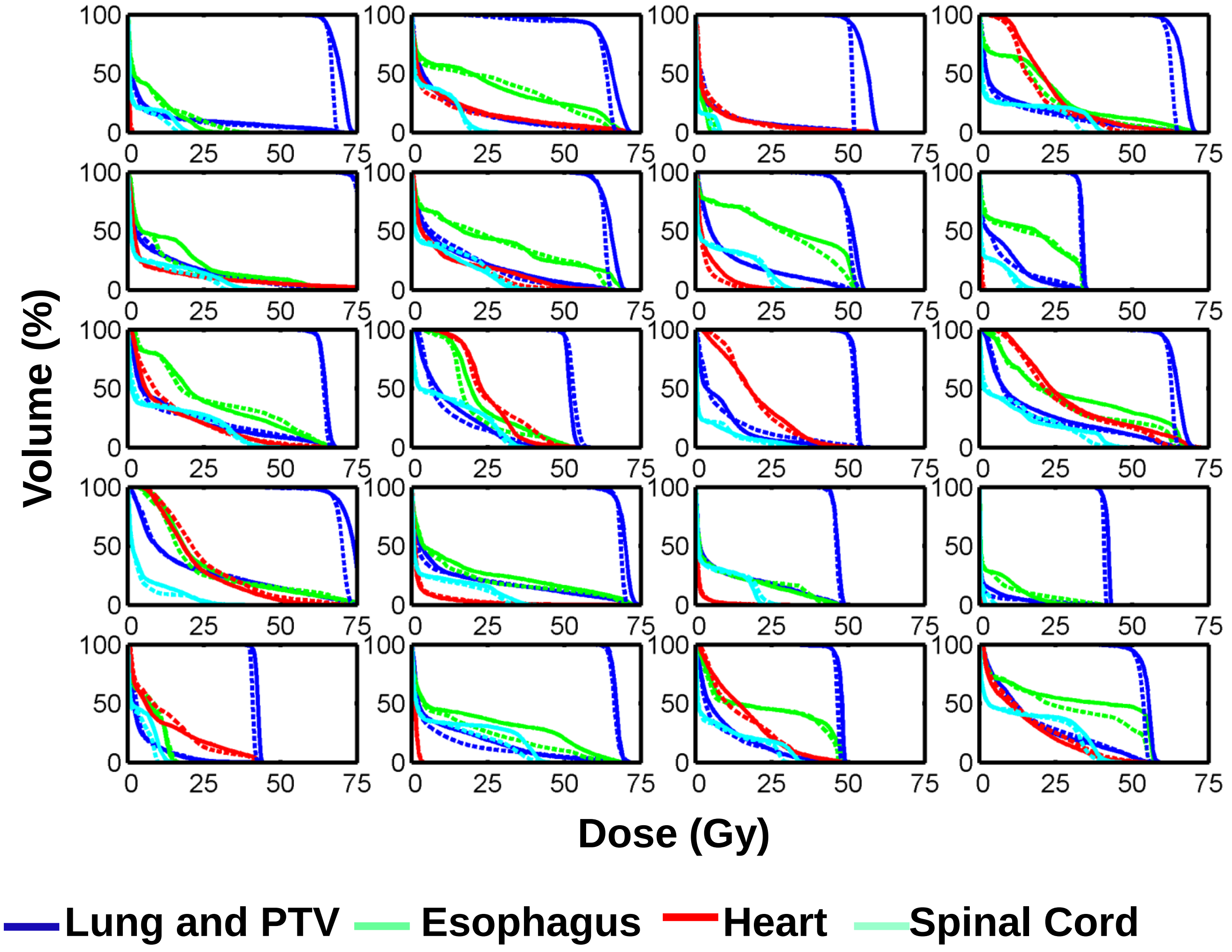
Case #12 DVHs



Clinical plan: ***solid***

Beam Bouquet plan: ***dashed***

Phase 1 : Class Solution Plans Using Beam Bouquets VS. Clinical Plans for 20 Validation cases



Clinical plans: solid   Plans using templates: dashed

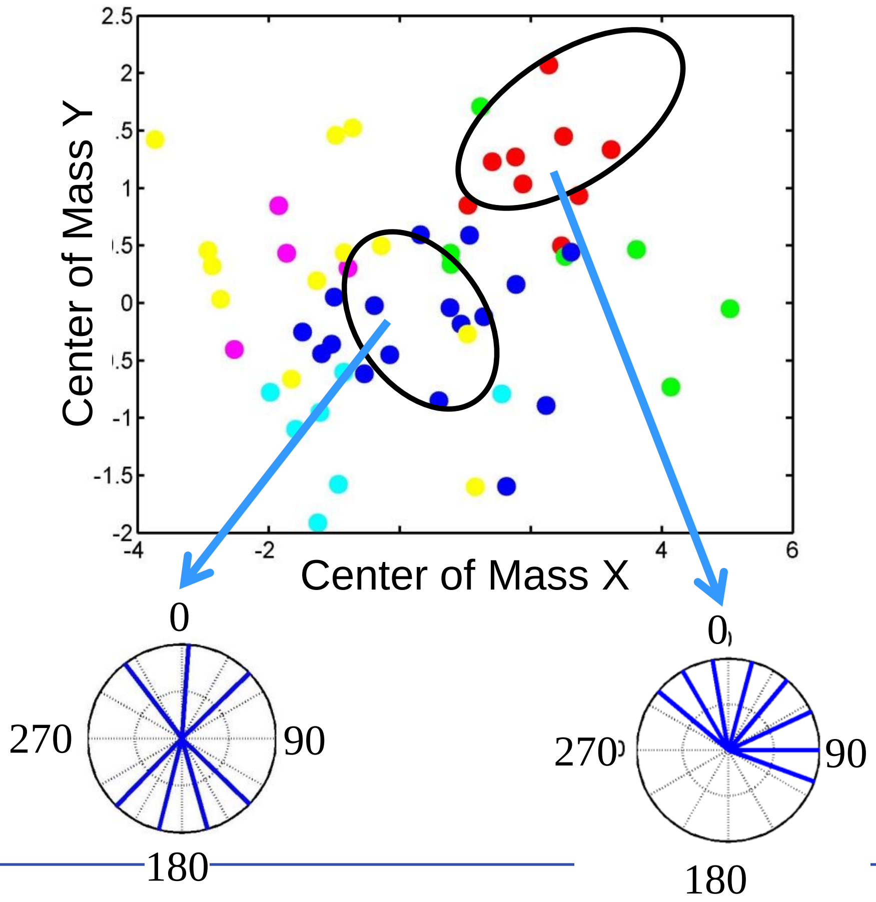
Phase 2: From Class Solution to Patient Specific Solution

- Anatomy variation always happens in clinical treatment planning
- Reflects clinical application of knowledge
- Natural progression of knowledge application

Clinical Application of Knowledge Models - Integration

- Correlation between the anatomical features and beam angle configurations learned by supervised classification method

Anatomical Features and Beam Configuration Correlation



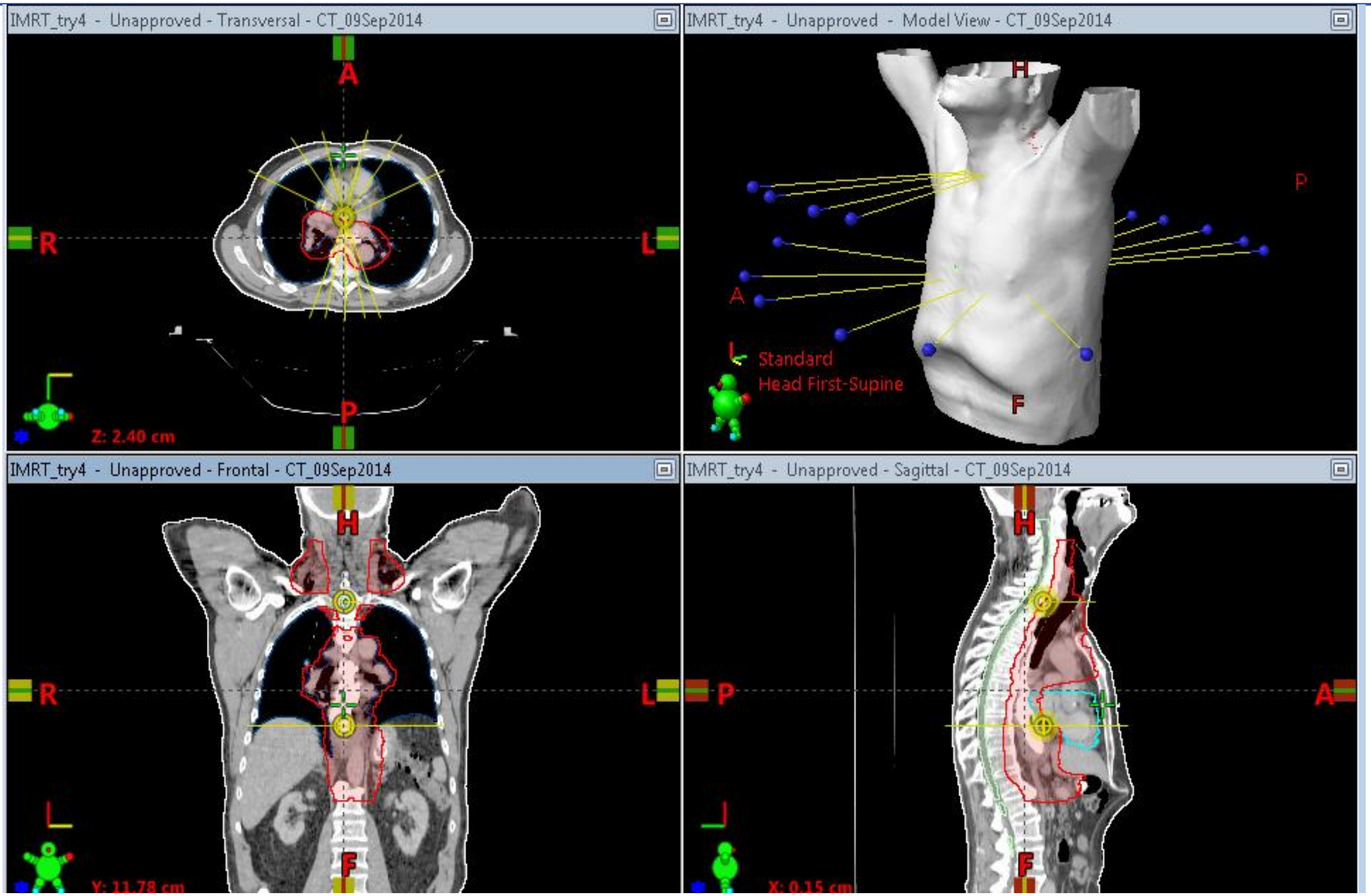
Clinical Application of Knowledge Models - Integration

- **<u>Lung IMRT Model as A Rapid-learning Show Case</u>**
  - DVH Model + Beam Angle Model
    - **100 Lung Cases**
    - **All co-planar beams (best clinical knowledge)**
    - **Ignore non-planar plans (clinical knowledge sparse)**
  - Extend Knowledge Models to Other Thorax Cases (large esophageal case)

Phase 2: From Class Solution to Patient Specific Solution

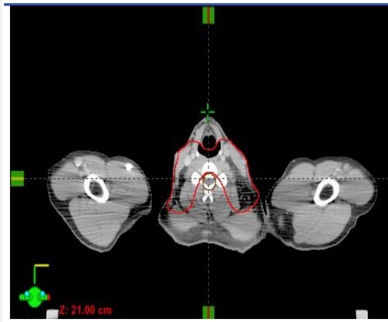
- Example case: esophagus tumor extending from neck to abdomen
- Separate fields, even isocenters, may be needed to treat different parts of the tumor in superior-inferior direction
- Multiple beam configurations in one plan

Phase 2: From Class Solution to Patient Specific Solution



Axial CT Slices

Z=-21



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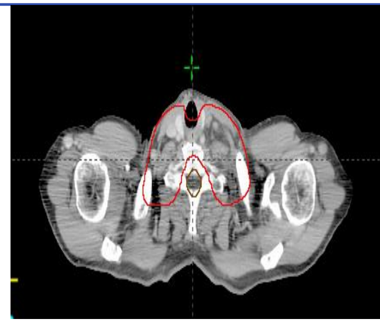

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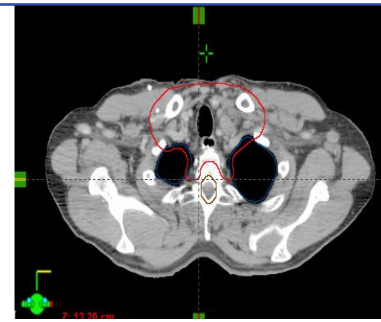

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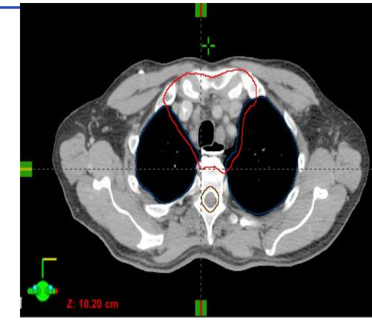

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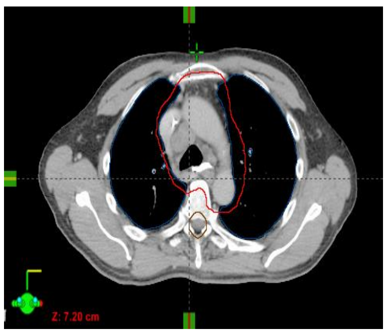

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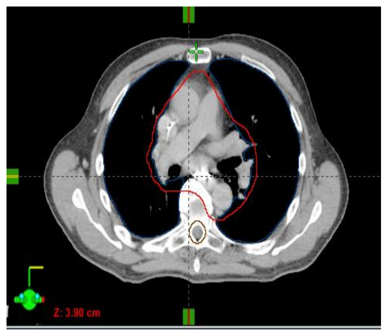

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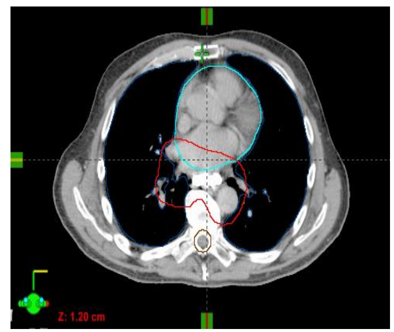

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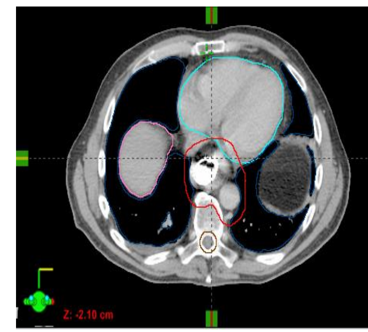

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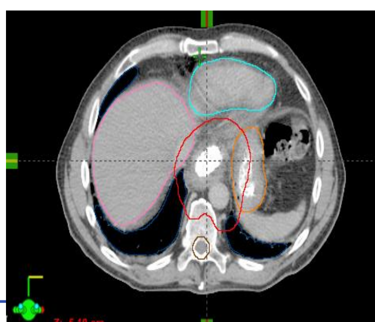

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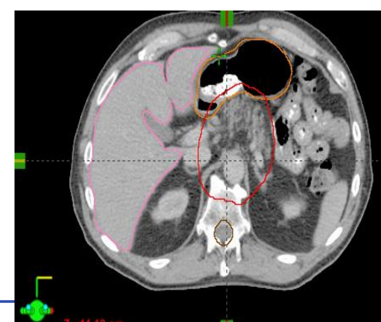

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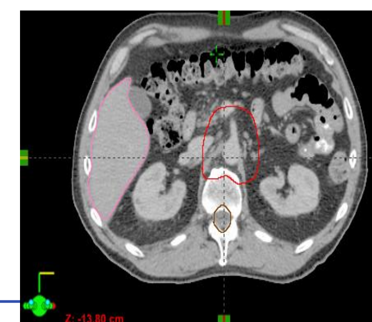


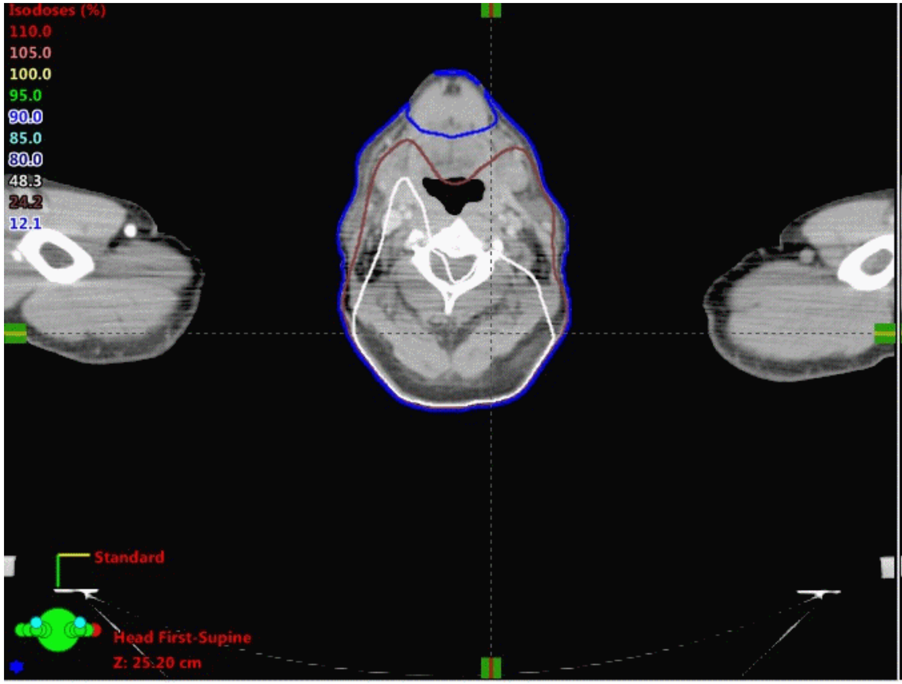
Phase 2: From Class Solution to Patient Specific Solution

Clinical Plan

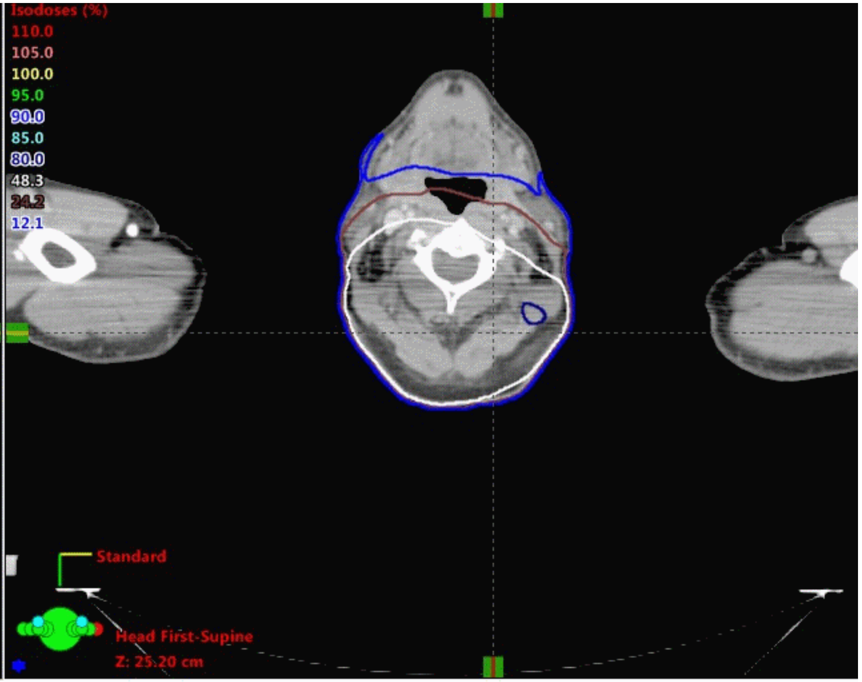
Model Plan

Phase 2: From Class Solution to Patient Specific Solution

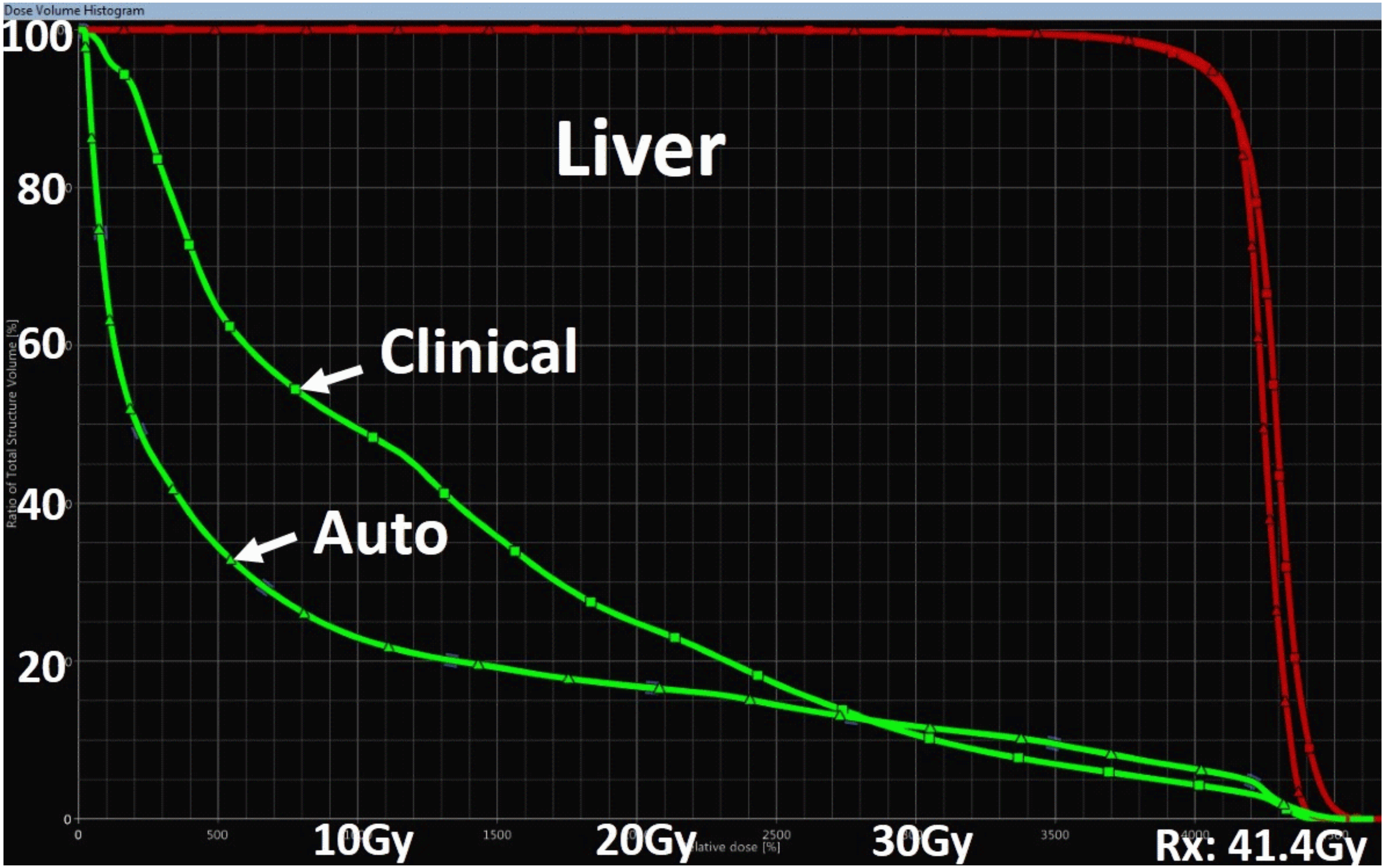
Clinical Plan



Model Plan



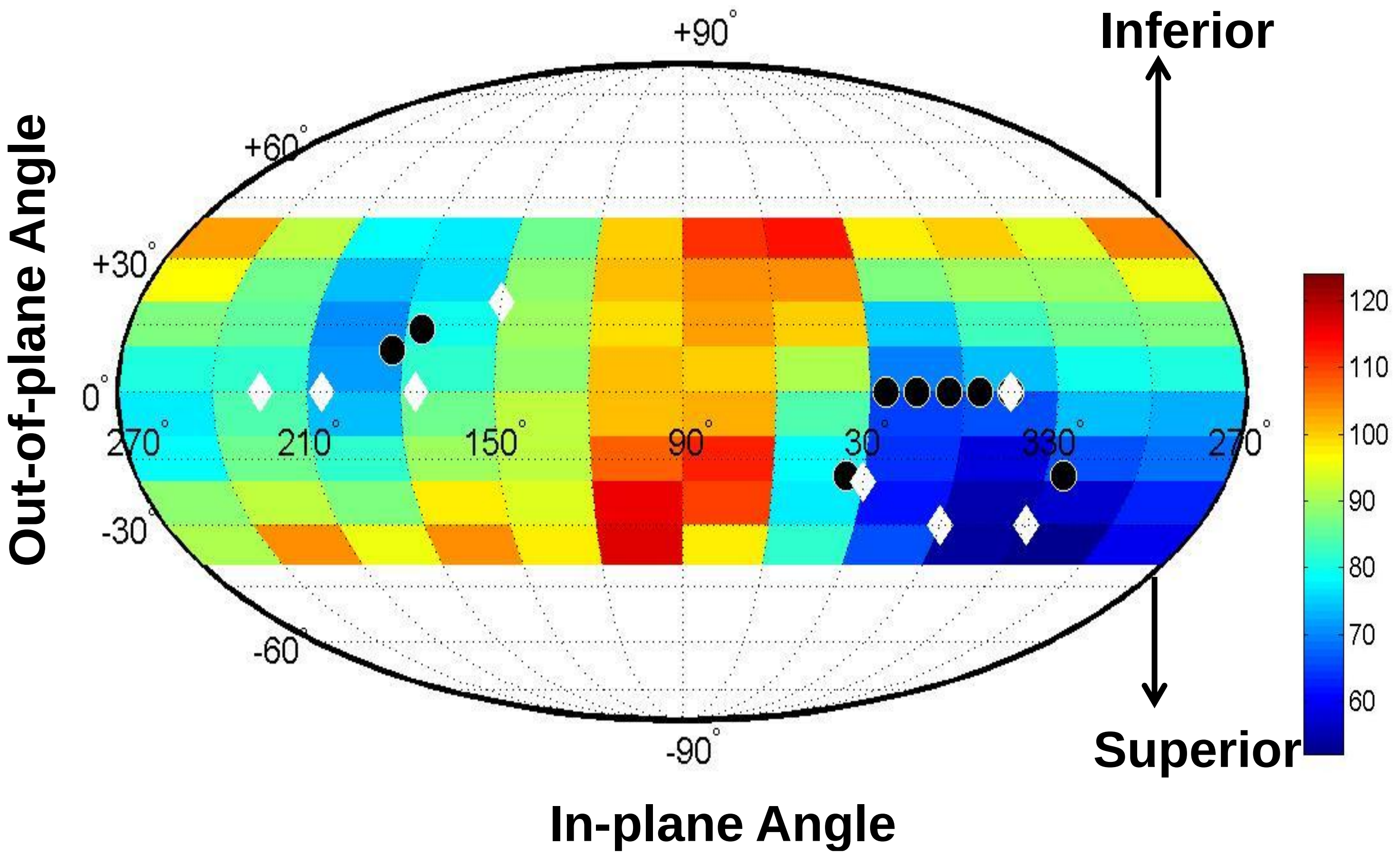
Phase 2: From Class Solution to Patient Specific Solution



Clinical Application of Knowledge Models - Integration

- **<u>Lung IMRT Model as A Rapid-learning Show Case</u>**
  - DVH Model + Beam Angle Model
    - **100 Lung Cases**
    - **All co-planar beams (best clinical knowledge)**
    - **Ignore non-planar plans (clinical knowledge sparse)**
  - Extend Knowledge Models to Other Thorax Cases
  - Extend Knowledge Models to Non-coplanar Cases
    - **Clinical knowledge about non-coplanar beam angles is sparse, immature**
    - **Extend the knowledge learned from co-planar beam to non-coplanar beam**

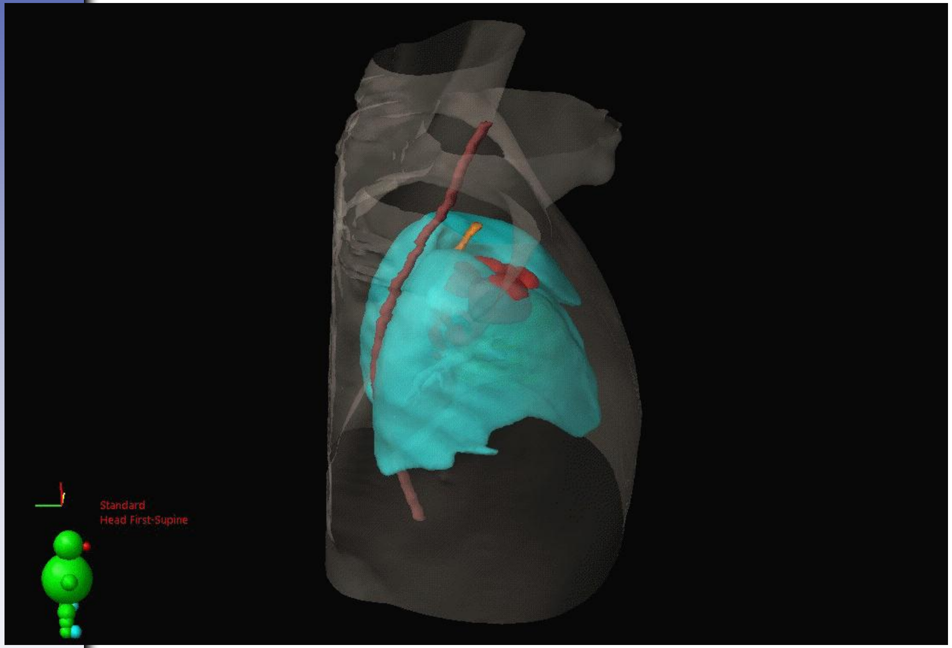
Phase 3: Progressive Modeling
- From Coplanar to Non-coplanar Beams



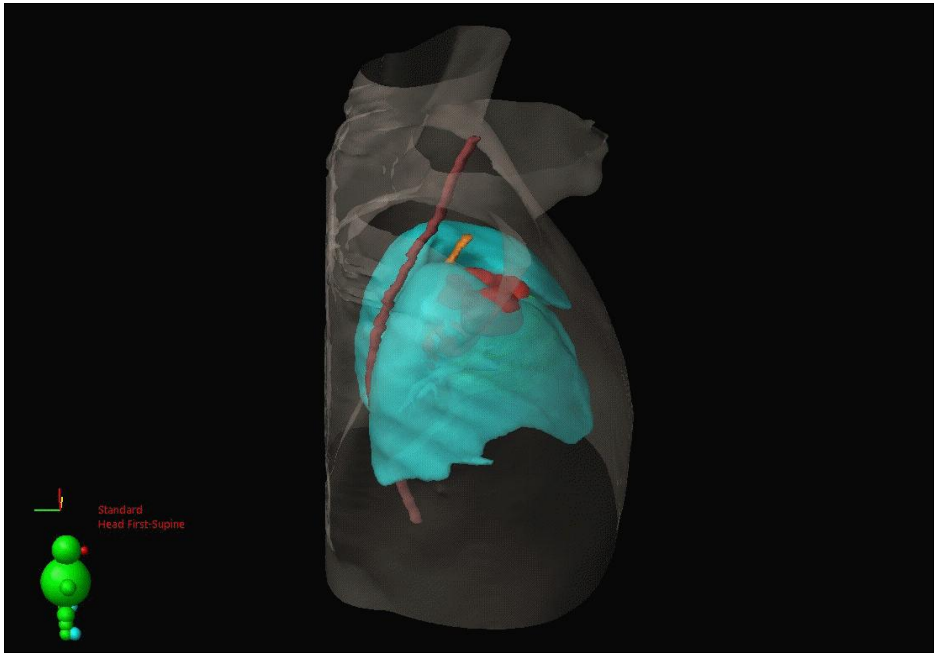
black circle: clinical angles
white diamond: knowledge driven angles

Phase 3: Progressive Modeling
- From Coplanar to Non-coplanar Beams

Clinical Plan

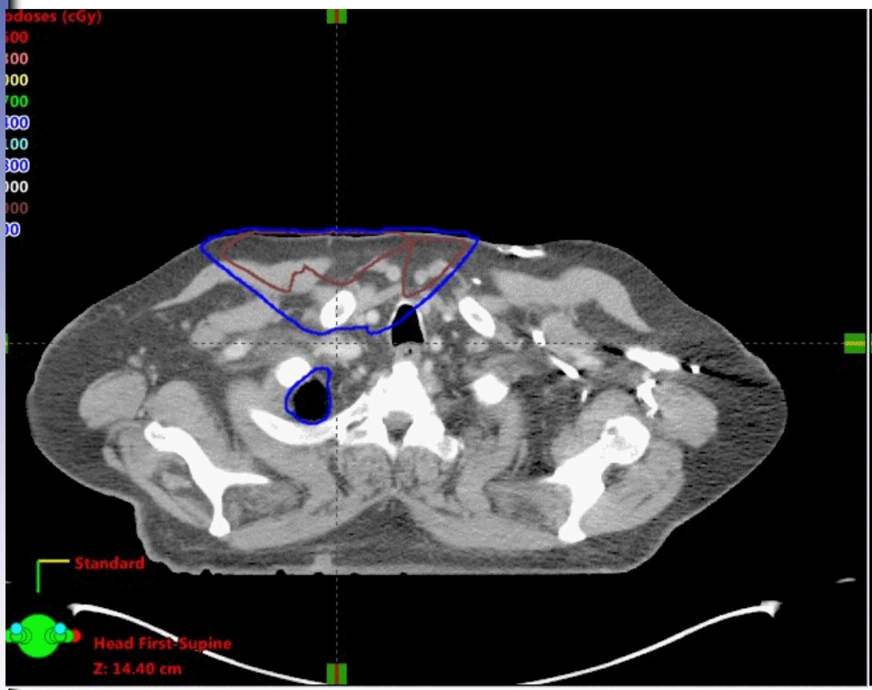


Model Plan

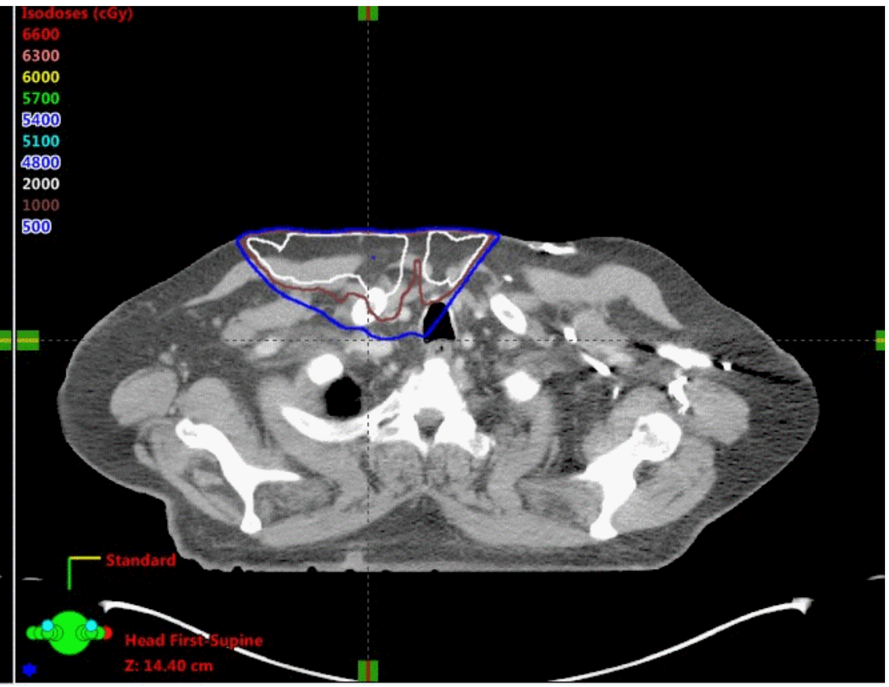


Phase 3: Progressive Modeling
- From Coplanar to Non-coplanar Beams

Clinical Plan



Model Plan



Summary

- Benefits of Knowledge Modeling: Clinical
  - Learning Curve, Quality, Consistency
  - Standardization, Automation, Integration
- Benefits of Knowledge Modeling: Institutional
  - Systematic, Objective
  - Integrated Refinement and Evolution
- Benefits of Knowledge Modeling: Future
  - Feature Based Knowledge for Big Data Research
  - Standardization (Evidence-based) and Optimization (Personalized)

SAM Questions

Treatment planning knowledge models are:

3%	a.	Confined to a single institution
90%	b.	Applicable to multiple modalities
6%	c.	Useful for only IMRT
1%	d.	Physician Specific
0%	e.	Useable only with Monte Carlo-based dose calculation algorithms

SAM Questions

- 1. Treatment planning knowledge models are:

  a. Confined to a single institution
  b. Applicable to multiple modalities
  c. Useful for only IMRT
  d. Physician Specific
  e. Useable only with Monte Carlo-based dose calculation algorithms

- Answer: b
- 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)

SAM Questions

The treatment planning knowledge that we can model include

0%	a.	incident beam angle selection
1%	b.	multiple OAR structures
0%	c.	multiple PTV prescriptions
1%	d.	DVHs of OARs
97%	e.	All the above

SAM Questions

- 2. The treatment planning knowledge that we can model include
  a. incident beam angle selection
  b. multiple OAR structures
  c. multiple PTV prescriptions
  d. DVHs of OARs
  e. All the above

- Answer: e
- Reference:

  - Yuan L, Wu QJ, Yin F, Li Y, Sheng Y, Kelsey CR, Ge Y. Standardized beam bouquets for lung imrt planning. *Physics in medicine and biology* 2015;60:1831-1843.
  - Liu J, Wu QJ, Kirkpatrick JP, Yin FF, Yuan L, Ge Y. From active shape model to active optical flow model: A shape-based approach to predicting voxel-level dose distributions in spine sbrt. *Physics in medicine and biology* 2015;60:N83-N92.
  - Yuan L, Ge Y, Lee WR, Yin FF, Kirkpatrick JP, Wu QJ. Quantitative analysis of the factors which affect the interpatient organ-at-risk dose sparing variation in imrt plans. *Med Phys* 2012;39:6868-6878.

SAM Questions

The organ sparing capability predicted by the knowledge model is

13%	a.	The average value of the sparing in the database
15%	b.	Interpolated among a few similar cases
6%	c.	Independent of prescription dose
1%	d.	Only valid for maximum dose
65%	e.	Patient specific, based his/her anatomy and physician’s prescription

SAM Questions

- 3. The organ sparing capability predicted by the knowledge model is
  a. The average value of the sparing in the database
  b. Interpolated among a few similar cases
  c. Independent of prescription dose
  d. Only valid for maximum dose
  e. Patient specific, based his/her anatomy and physician's prescription

- Answer: e
- Reference:
  - Yuan L, Ge Y, Lee WR, Yin FF, Kirkpatrick JP, Wu QJ. Quantitative analysis of the factors which affect the interpatient organ-at-risk dose sparing variation in imrt plans. *Med Phys* 2012;39:6868-6878.
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Thank you

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