


Building Knowledge Models In RT

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- Master Research Grant: Varian Medical Systems
- License Agreement: Varian Medical Systems
- Speaker Agreement: Varian Medical Systems



Learning Objectives

- Extract Human Planning Knowledge Into Features
- Machine Learning And Modeling Techniques
- Understand Model Parameters and Physics Parameters
- Knowledge Base Refinement and Evolution
- Knowledge Model Guided Treatment Planning

Building Planning Knowledge Models

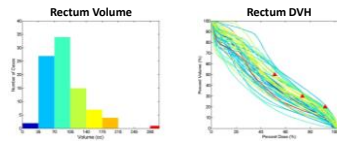
■ Treatment Planning Knowledge

- "Cheat sheet"
- "Tricks" and "Tips"
- "Templates"

Building Planning Knowledge Models

■ Experience and Intuition

- Volume, location, shape, overlap, etc
- Qualitative vs. quantitative vs. descriptive
- Summarized collection vs. individual case memory



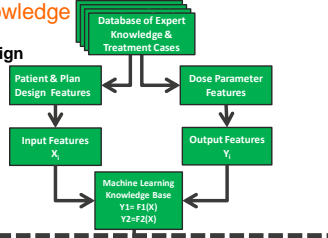
Building Planning Knowledge Models

■ Modeling Experience and Intuition

- Correlate patient anatomy features (input) and PTV/OAR features 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
- Knowledge base evolution and progressive modeling

Building Knowledge

Knowledge Base Training



Knowledge Base Application



Building Knowledge Models

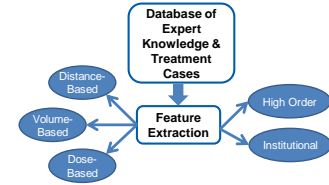
Platform Design

Knowledge Base Application



Building Knowledge Models

Feature Identification and Selection

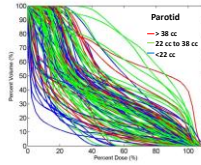


Building Knowledge Models

Data Size

- Adequate number of cases to represent the clinical case spectrum

德国 #1
阿根廷 #2
荷兰 #3
巴西 #4



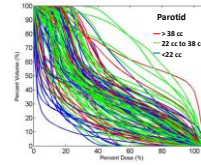
Building Knowledge Models

Data Size

- Adequate number of cases to represent the clinical case spectrum

Data Quality

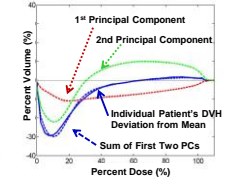
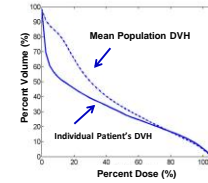
- Reliable feature extraction



Building Planning Knowledge Models

Feature Extraction and Dimension Reduction

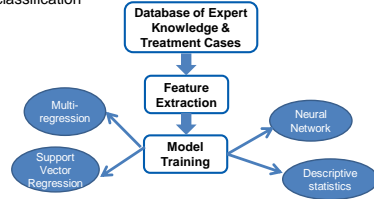
- Large amount data -> features vs. noises
- Principal Component Analysis (PCA)



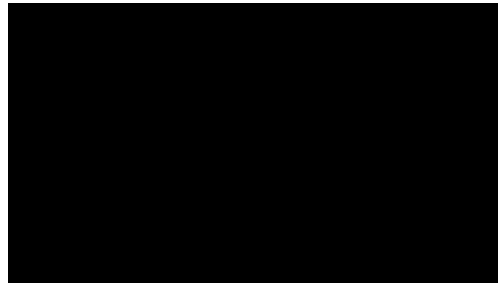
Building Planning Knowledge Models

Systematic Modeling of Knowledge

- Machine learning, Descriptive statistics, Pattern classification



Building Knowledge Models



Understand The Knowledge Models

Model Parameter ↔ Physics Parameter

Bladder DVH PCS1 (Median Dose)		Rectum DVH PCS1 (Median Dose)	
Significant Factors	R²	Significant Factors	R²
Bladder DTH PCS1 (Median Distance)	0.81	Rectum DTH PCS1 (Median Distance)	0.59
2 nd Order of Bladder DTH PCS1	0.22	Volume of Rectum	0.12
Combined	0.88	Overlap Volume	0.08
		Combined	0.68
Bladder DVH PCS2 (DVH Slope)		Rectum DVH PCS2 (DVH Slope)	
Significant Factors	R²	Significant Factors	R²
Out-of-field Volume	0.50	Rectum DTH PCS2 (gradient)	0.32
Overlap Volume	0.33	Out-of-field Volume	0.32
Bladder DTH PCS2 (gradient)	0.30	Overlap Volume	0.12
Combined	0.85	Rectum DTH PCS3	0.12
		Combined	0.69

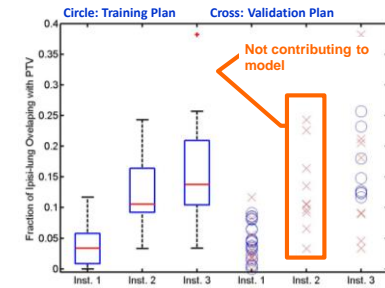
Understand The Knowledge Models

- 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

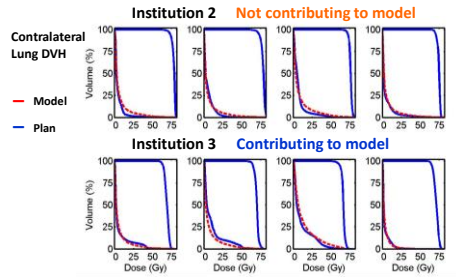
Cross-Institution Knowledge Models

	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 Models



Cross-Institution Knowledge Models



Cross-Modality Knowledge Models

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

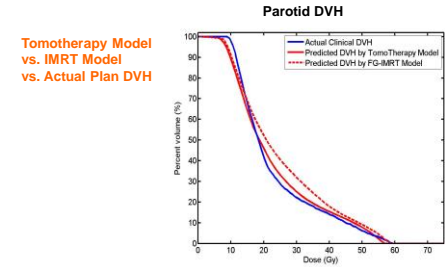
Institution A

- 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

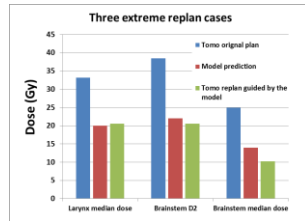
Institution B

- 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

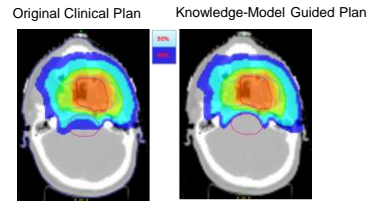
Cross-Institution Knowledge Models



Knowledge Model Guided Tomotherapy Planning



Knowledge Model Guided Tomotherapy Planning

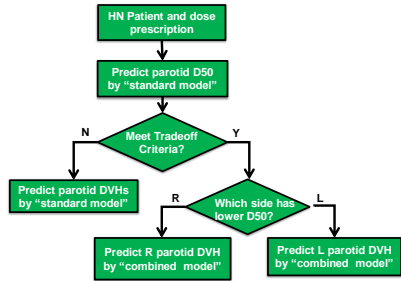


Knowledge Model Refinement

Trade-off Modeling

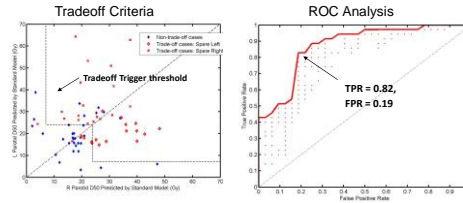
- > Clinical tradeoff among different OARs or between OAR and PTV is common
- > Pareto-front planning (T. Borfeld@MGH, etc)
- > Different models may be needed to represent trade-off options

Knowledge Model Refinement



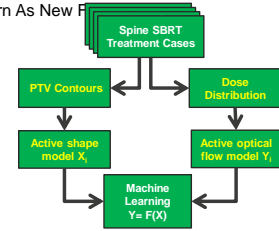
Knowledge Model Refinement

Parotid Tradeoff Model



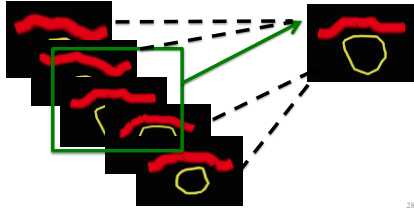
Knowledge Model Refinement

Shape Pattern As New Feature Spine SBRT Tradeoff Model



Knowledge Model Refinement

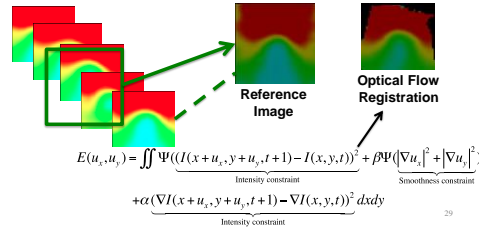
- **Active Shape Model:** iterative closest point (ICP) algorithm to align PTV contours



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Knowledge Model Refinement and Evolution

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

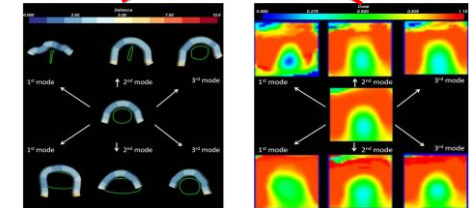


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Knowledge Model Refinement and Evolution

- **Machine Learning**

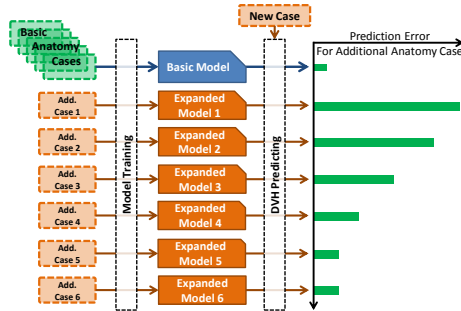
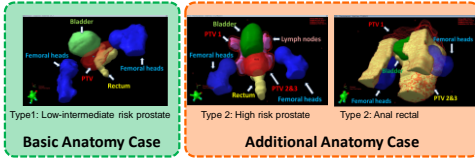
PTV contour space ↔ cord dose space



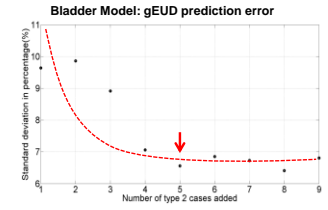
Knowledge Model Evolution

Progressive Learning: Knowledge Update and Adaptation

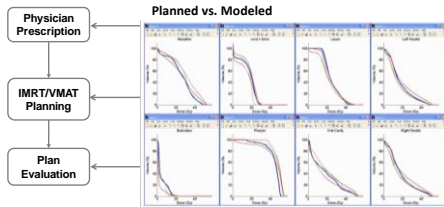
- Build single knowledge model for multiple cancer types in the pelvic region



Knowledge Model Evolution



Summary: Knowledge-Model Guided Planning



References

- **AAPM2014: SU-F-BRD-9:** Yuan et al, Lung IMRT Planning Using Standardized Beam Bouquet Templates
- **AAPM2014: SU-E-T-49:** Yuan et al, Automatic Beam Angle Determination for Lung IMRT Planning Using a Beam Configuration Atlas
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- **AAPM2014: MO-C-17A-7:** Sheng et al, Building Atlas for Automatic Prostate IMRT Planning: Anatomical Feature Parameterization and Classification
- **AAPM2014: TU-C-17A-11:** Lu et al, Progressive Knowledge Modeling for Pelvic IMRT/VMAT Treatment Planning
- **AAPM2014: TH-A-9A-1:** Liu et al, Active Optical Flow Model: Predicting Voxel-Level Dose Prediction in Spine SBRT
- **AAPM 2014: SU-E-T-527:** Lian et al, Prior Knowledge Guided TomoTherapy Treatment Planning

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