Disclosure

- Research Grant: NIH/NCI
- 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”

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

- **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 Models

- Feature Identification and Selection

Building Knowledge Models

- Platform Design

Building Knowledge

- Platform Design
- Training

Knowledge Base Application

- New Patient
- Feature Characterization
- Dose Parameter
  - Features

Knowledge Base Application

- New Patient
- Feature Characterization
- Dose Parameter
  - Features
Building Knowledge Models

- **Data Size**
  - Adequate number of cases to represent the clinical case spectrum

- **Data Quality**
  - Reliable feature extraction

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Building Planning Knowledge Models

- **Feature Extraction and Dimension Reduction**
  - Large amount data -> features vs. noises
  - Principal Component Analysis (PCA)

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Graphs showing individual patient's DVH deviation from mean and percent dose vs. percent volume.
### Building Planning Knowledge Models

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

- **Database of Expert Knowledge & Treatment Cases**
  - Feature Extraction
  - Model Training
  - Neural Network
  - Support Vector Regression
  - Multi-regression
  - Descriptive statistics

### Building Knowledge Models

- **Plan Standardization**

#### Understand The Knowledge Models

<table>
<thead>
<tr>
<th>Significant Factors</th>
<th>R²</th>
<th>Significant Factors</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bladder DVH PCS1 (Median Dose)</td>
<td>0.81</td>
<td>Rectum DVH PCS1 (Median Dose)</td>
<td>0.59</td>
</tr>
<tr>
<td>Bladder DTH PCS1 (Median Distance)</td>
<td>0.22</td>
<td>Volume of Rectum</td>
<td>0.12</td>
</tr>
<tr>
<td>Overlap Volume</td>
<td>0.08</td>
<td>Combined</td>
<td>0.88</td>
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<tr>
<td>Bladder DVH PCS2 (DVH Slope)</td>
<td>0.50</td>
<td>Rectum DTH PCS2 (DVH Slope)</td>
<td>0.32</td>
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<tr>
<td>Out-of-field Volume</td>
<td>0.50</td>
<td>Overlap Volume</td>
<td>0.33</td>
</tr>
<tr>
<td>Bladder DTH PCS2 (gradient)</td>
<td>0.30</td>
<td>Rectum DTH PCS2 (gradient)</td>
<td>0.32</td>
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<tr>
<td>Overlap Volume</td>
<td>0.12</td>
<td>Combined</td>
<td>0.68</td>
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<tr>
<td>Rectum DTH PCS3</td>
<td>0.12</td>
<td>Rectum DTH PCS3</td>
<td>0.12</td>
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#### Model Parameter

<table>
<thead>
<tr>
<th>Physics Parameter</th>
<th>R²</th>
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<tr>
<td>Beam On Time</td>
<td>0.99</td>
</tr>
<tr>
<td>Setup Margin</td>
<td>0.99</td>
</tr>
<tr>
<td>Dose</td>
<td>0.99</td>
</tr>
<tr>
<td>Percentage Volume</td>
<td>0.99</td>
</tr>
<tr>
<td>Normalized Dose</td>
<td>0.99</td>
</tr>
<tr>
<td>Transverse Magnitude</td>
<td>0.99</td>
</tr>
<tr>
<td>Longitudinal Magnitude</td>
<td>0.99</td>
</tr>
<tr>
<td>Caudal Medial Magnitude</td>
<td>0.99</td>
</tr>
<tr>
<td>Rectum DVH PCS1 (Median Dose)</td>
<td>0.99</td>
</tr>
<tr>
<td>Rectum DVH PCS2 (DVH Slope)</td>
<td>0.99</td>
</tr>
</tbody>
</table>

#### Physics Parameter

<table>
<thead>
<tr>
<th>Control Parameter</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beam On Time</td>
<td>0.99</td>
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<tr>
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<tr>
<td>Dose</td>
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<td>0.99</td>
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</tbody>
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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

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
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<tbody>
<tr>
<td>Prescriptions (Gy)</td>
<td>67</td>
<td>64</td>
<td>48</td>
<td>74</td>
</tr>
<tr>
<td>Volume (cm³)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mean</td>
<td>421</td>
<td>595</td>
<td>512</td>
<td></td>
</tr>
<tr>
<td>median</td>
<td>343</td>
<td>539</td>
<td>379</td>
<td></td>
</tr>
<tr>
<td>min, max</td>
<td>62, 1132</td>
<td>75, 1132</td>
<td>17%, 1151</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Location [side]</th>
<th>Total</th>
<th>Left/Left-Medial</th>
<th>Right/Right-Medial</th>
<th>Medial</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>45</td>
<td>18</td>
<td>21</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>4</td>
<td>6</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>16</td>
<td>5</td>
<td>10</td>
<td>1</td>
</tr>
</tbody>
</table>

Circle: Training Plan
Cross: Validation Plan

Not contributing to model
### Cross-Institution Knowledge Models

- **Contralateral Lung DVH**
  - **Institution 2** (Not contributing to model)
  - **Institution 3** (Contributing to model)

### Cross-Modality Knowledge Models

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

<table>
<thead>
<tr>
<th>Institution A</th>
<th>Institution B</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>7-8 min delivery time</strong></td>
<td><strong>7-8 min delivery time</strong></td>
</tr>
<tr>
<td><strong>Delivery system:</strong> Varian IMRT</td>
<td><strong>Delivery system:</strong> Tomotherapy</td>
</tr>
<tr>
<td><strong>Planning system:</strong> Eclipse</td>
<td><strong>Planning system:</strong> Tomotherapy</td>
</tr>
<tr>
<td><strong>Sequential Boost</strong></td>
<td><strong>SIB</strong></td>
</tr>
</tbody>
</table>
| - Multiple plans (one plan for 1 PTV)  
  - 40-50 Gy and 60-70 Gy | - 1 plan (one plan cover all PTVs with 3 off, daily doses)  
  - 54-60 Gy and 70 Gy |
| **~60 head-and-neck cases** | **~60 head-and-neck cases** |

### Cross-Institution Knowledge Models

- **Tomotherapy Model vs. IMRT Model vs. Actual Plan DVH**

- **Parotid DVH**
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

- Predict parotid D50 by "standard model"
- Predict parotid DVHs by "standard model"
- Meet Tradeoff Criteria?
- Predict parotid D50 by "combined model"
- Which side has lower D50?
- Predict R parotid DVH by "combined model"
- Predict L parotid DVH by "combined model"

Parotid Tradeoff Model

- TPR = 0.82, FPR = 0.19

ROC Analysis

Tradeoff Criteria

Shape Pattern As New Features

Machine Learning

X = F(Y)

Active shape model X, Active optical flow model Y.

Spine SBRT Treatment Cases

Spine SBRT

Knowledge Model Refinement

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Spine SBRT Treatment Cases

Spine SBRT
Knowledge Model Refinement

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

Knowledge Model Refinement and Evolution

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

\[
E(u_1, u_2) = \int \int \nabla \cdot \mathbf{u}_1 \cdot \mathbf{u}_2 \, dxdy + \beta \int \left( \mathbf{v}_1 - \mathbf{v}_2 \right)^2 \, dxdy
\]

- **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

Basic Anatomy Case

Additional Anatomy Case

Type 1: Low-intermediate risk prostate
Type 2: High risk prostate
Type 2: Anal rectal

Model Training

New Case

Prediction Error

Bladder Model: gEUD prediction error

Add. Case 1
Add. Case 2
Add. Case 3
Add. Case 4
Add. Case 5
Add. Case 6

Expanded Model 1
Expanded Model 2
Expanded Model 3
Expanded Model 4
Expanded Model 5
Expanded Model 6
Summary: Knowledge-Model Guided Planning

- Planned vs. Modeled

References

- 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

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