Using Quality of Life Scores to Guide Prostate Radiation Therapy Dosing

Project Manager: Daniel Olszewski
Chujun He
Giulia Pintea
Zhijian Yang

Academic Mentor: Blerta Shtylla, PhD
Sponsors: Ronald Chen, MD/MPH
Tom Chou, PhD
UNC Lineberger Comprehensive Cancer Center & IPAM

- Cancer research & treatment center
- One of the leading centers in the nation
- IPAM: founded as an NSF Mathematical Institute at UCLA
Goal of this Project

- Find relationship between:
  - **Radiation Therapy (RT) dosage** to regions of the bladder and rectum based on **Computed Tomography (CT) images**
  - Prostate cancer patients’ **Quality-of-Life (QoL)** changes
- Using machine learning
  Want to build predictive algorithms
Outline

- **Background**
  - Prostate cancer
  - Data
- **Our Model**
  - Architecture
- **Organ Sensitivity**
  - Statistical analyses
  - Results
Background
Prostate Cancer & Radiation Therapy (RT)

- Affects 200,000 men each year in the U.S.
- Treatment options:
  - Surgically removing prostate
  - Undergoing Radiation Therapy
  - Both
- Radiation Therapy (RT)
  - Beams deliver radiation
  - Over 7 weeks
  - Side effects after radiation
Computed Tomography (CT) Scans

- Cross-sectional image of the body
- Physicians mark organs
- Identify cancer in the body
- Plan the RT
Computed Tomography (CT) Scans
Radiation Therapy (RT) Plan
Data

- 52 Patients
- Post-prostatectomy patients
- Each with a **Computed Tomography (CT) scan** and **Radiation Therapy (RT) Plan**
- Patients took a **QoL survey**
  - Before, during, and after radiation
Goal: Develop deep learning approaches to correlate CT image features and RT dosing to QoL data
Our Model
Prediction Model

- Obtained near-optimal starting points
  - Used autoencoder method on unlabeled augmented images

**Prediction Model:**
- Total patients: 52
  - Training set: 39
  - Testing set: 13
Prediction Model Architecture

- Batchnorm, 3*3 convolution, elu
- Max Pooling
- Fully connect (1024 nodes), relu
- 40% Dropout
- Fully connect(2 nodes), softmax
- Feature Map
- Probability Value
Results

- **Bladder symptoms**: 25% - 60% accuracy
- **Rectal symptoms**: 61.5% - 84.6% accuracy
- Ran multiple times
- Randomized training & testing set
- Sensitivity to training set
Organ Sensitivity
Connection to Specific Organ Areas

- Identified sensitive organ areas
- Used brute force to partition organs
- Found dosage thresholds for each region
Results

- **Organ Sensitivity**
  - Distinct dosage thresholds for the front & back of the rectum
  - Ambiguous for the bladder

- **Our Model**
  - Bladder symptoms: 25% - 60% accuracy
  - Rectal symptoms: 61.5% - 84.6% accuracy
Conclusion

● Connections between spatial dosage and symptoms
  ○ Front and Back of Rectum
● Can get dosage thresholds for each part of the organs
● Further exploration:
  ○ Deep learning applications
  ○ Extending to all QoL scores (1-5)
Special Thanks

● **Mentors**
  ○ Blerta Shtylla, Pomona College
  ○ Ronald Chen, University of North Carolina
  ○ Tom Chou, University of North Carolina
  ○ Jun Lian, University of North Carolina

● Institute for Pure and Applied Mathematics
● NSF Grant DMS-0931852
● Breast Cancer Research Foundation Grant
Questions?
Autoencoder Architecture

• Batchnorm, 3*3 convolution, elu
• Max Pooling
• Batchnorm, 3*3 convolution
• Upsampling
• 1*1 convolution, Sigmoid
• Feature Map
Autoencoder

- Method for transfer learning
- No need for labeled data
- **Target output**: input
- Extract features in hidden layers
Data Augmentation for Autoencoder

- **Curvature-based Interpolation**
  - Fischer-Modersitzki curvature-based interpolation approach
  - Used for CT scans and RT plans
  - Slices of patient A are interpolated with slices of patient B, creating the “fake” patient C

- **Contour Interpolation**
  - Resampling points from patient A and patient B contours
  - Average patient A and patient B’s sampled points
  - Obtain new interpolated contour (patient C)

**Total new images**: 1,520