Using Quality-of-Life Scores to Guide Prostate Radiation Therapy Dosing

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THE UNIVERSITY *of* NORTH CAROLINA *at* CHAPEL HILL

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

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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

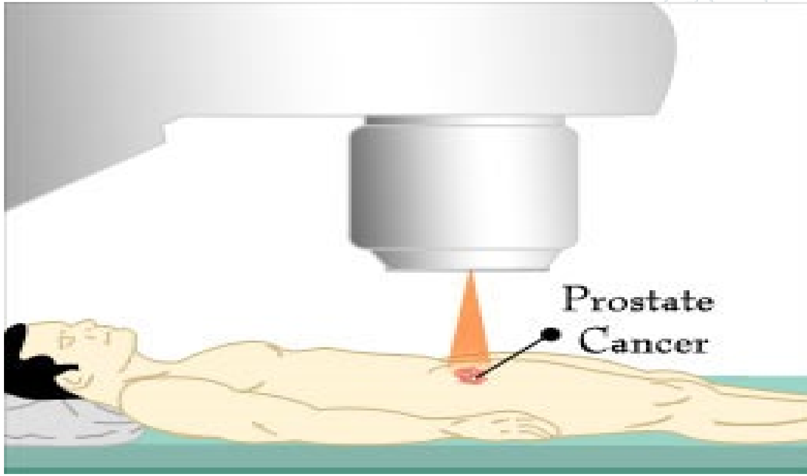
Outline

- **Background**
  - Prostate cancer
  - Data
- **Our Model**
  - Architecture
- **Organ Sensitivity**
  - Statistical analyses
  - Results

Background

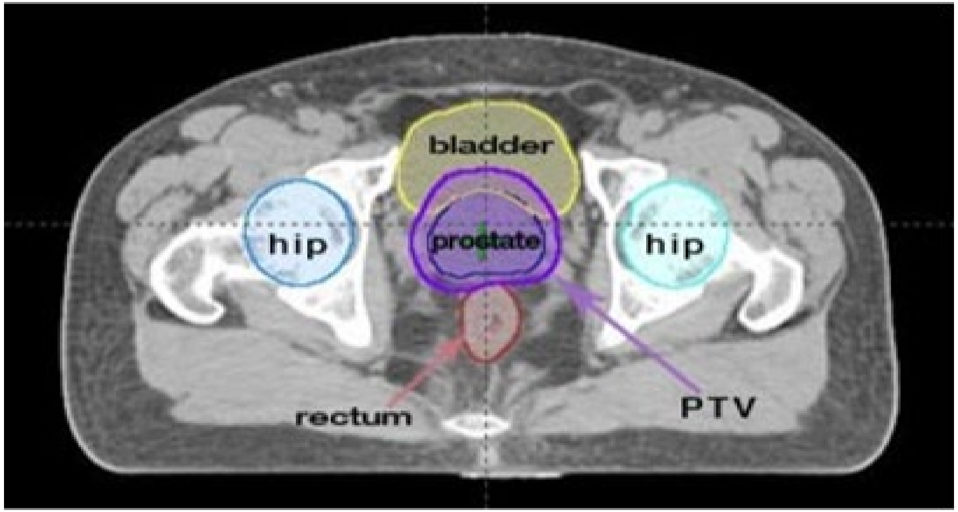
Prostate Cancer & Radiation Therapy (RT)

- 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



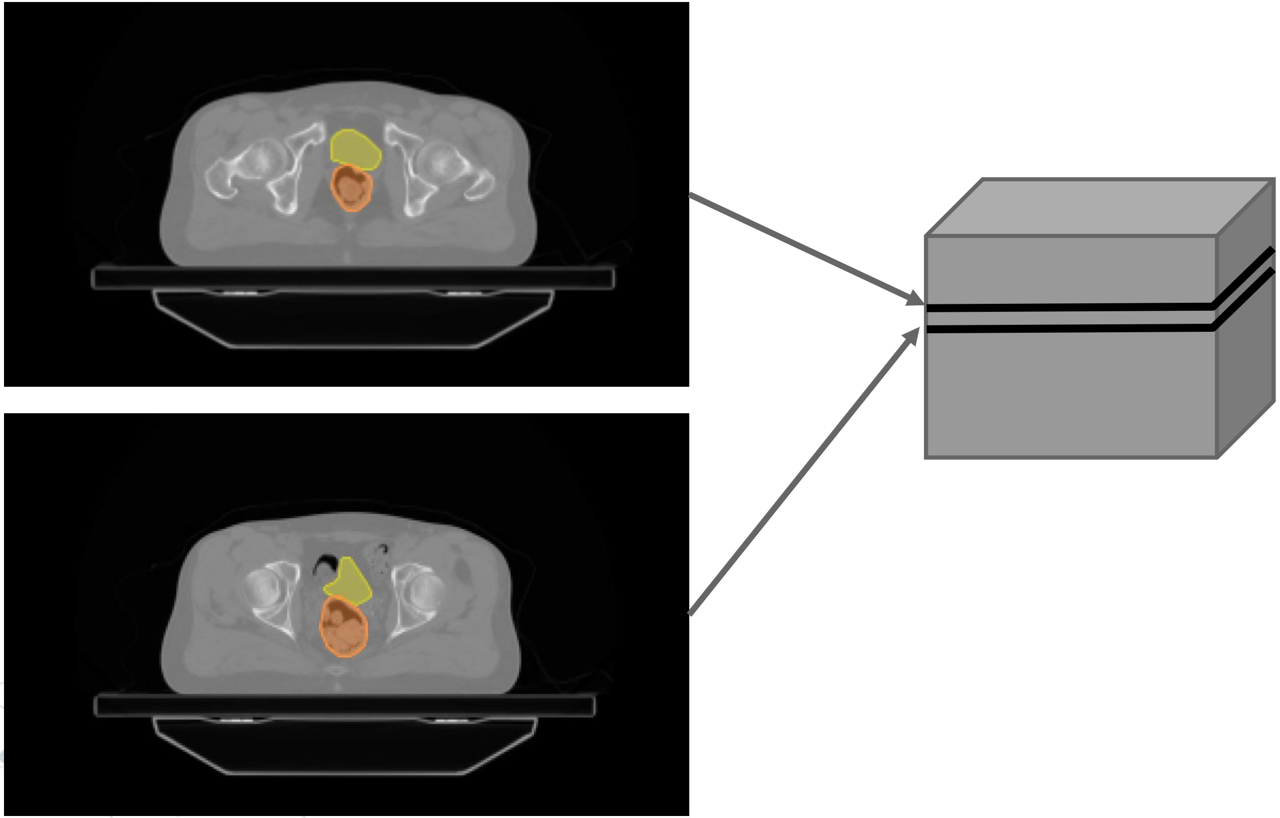
Computed Tomography (CT) Scans

- Cross-sectional image of the body
- Physicians mark organs
- Identify cancer in the body
- Plan the RT

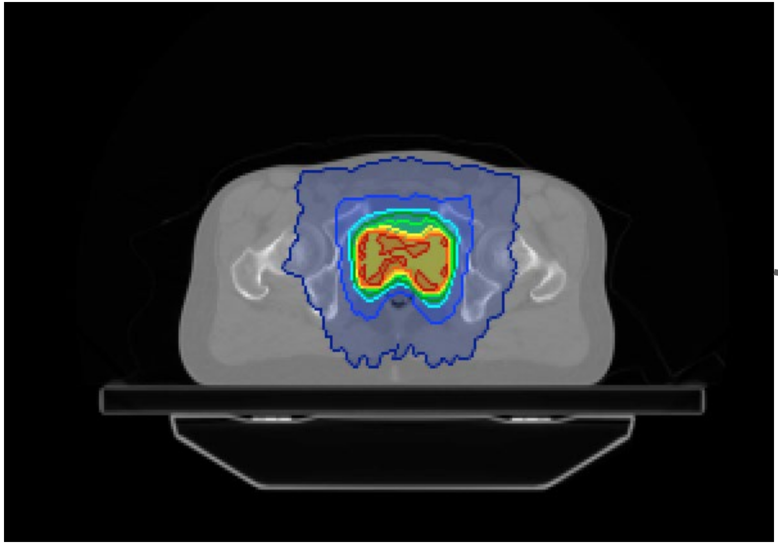


CT image with demarcated organs

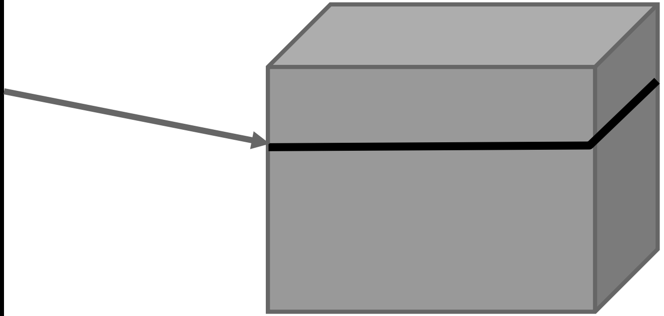
Computed Tomography (CT) Scans



Radiation Therapy (RT) Plan



Radiation Therapy Plan

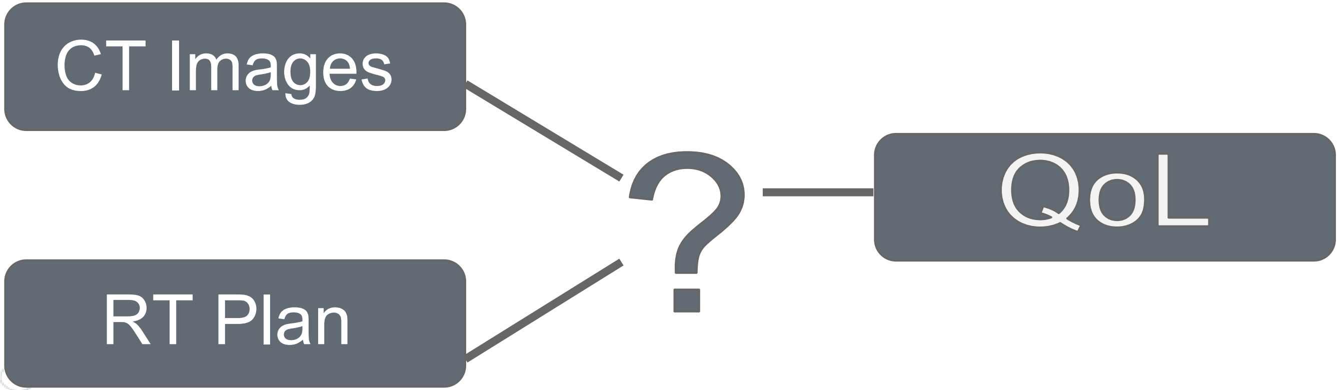


Data

- 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

Connection

- Goal: Develop deep learning approaches to correlate CT image features and RT dosing to QoL data

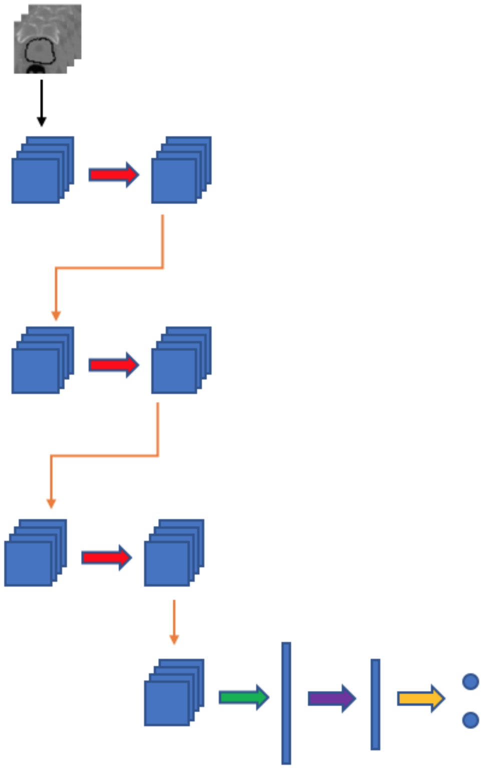


Our Model

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

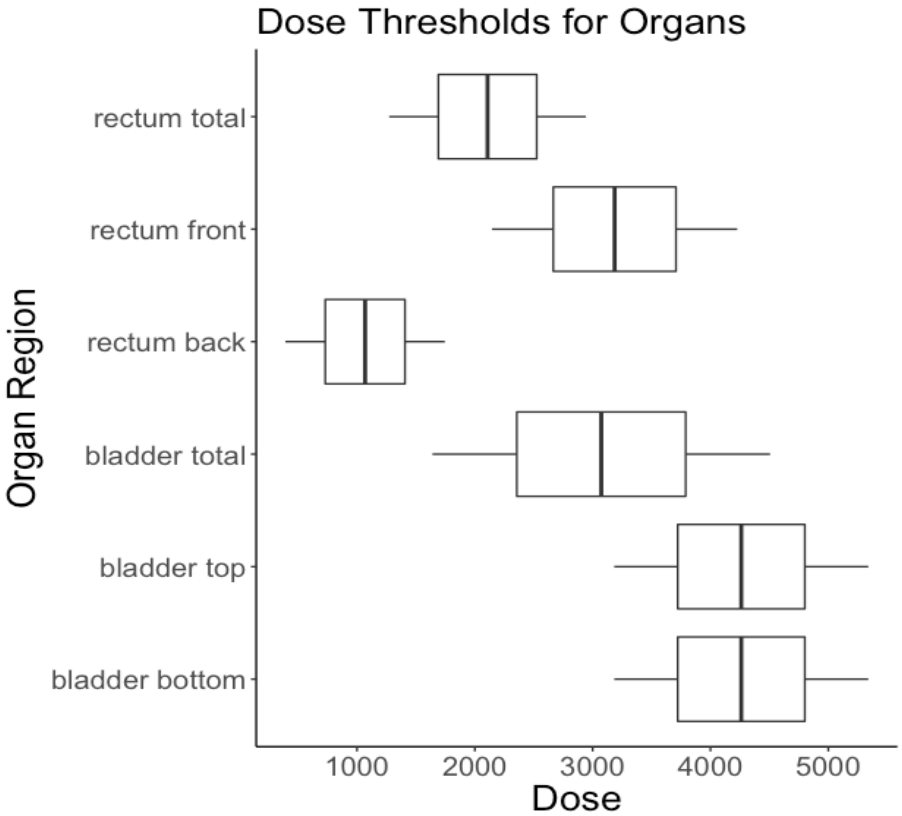
Results

- 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

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  - Jun Lian, University of North Carolina
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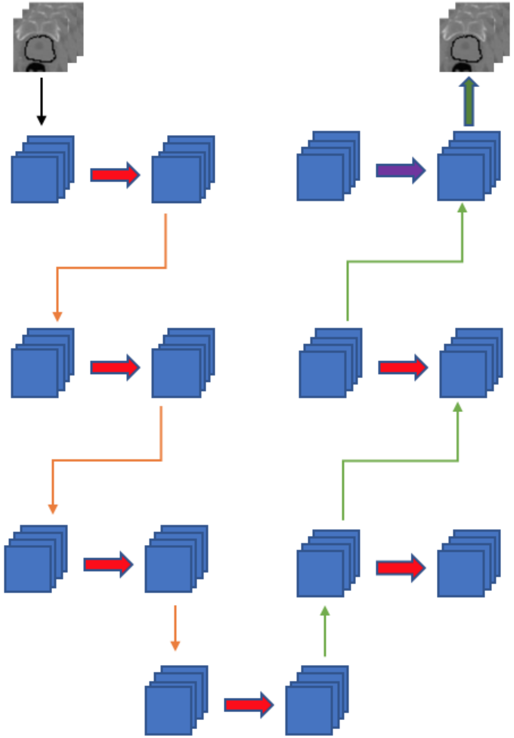
Questions?

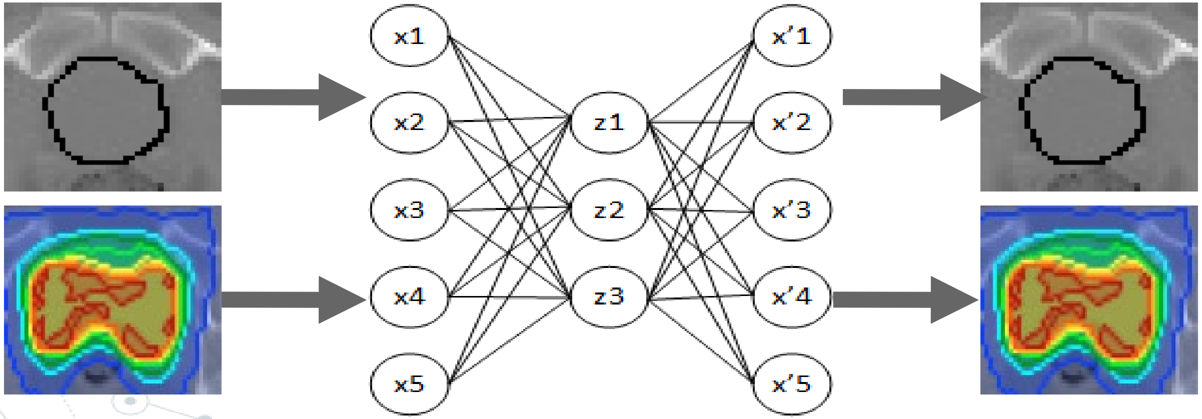
Autoencoder Architecture



- 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
- <u>Target output</u>: 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)
- <u>Total new images</u>: 1,520