

# 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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CANCER CENTER  
N.C. CANCER HOSPITAL

# 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

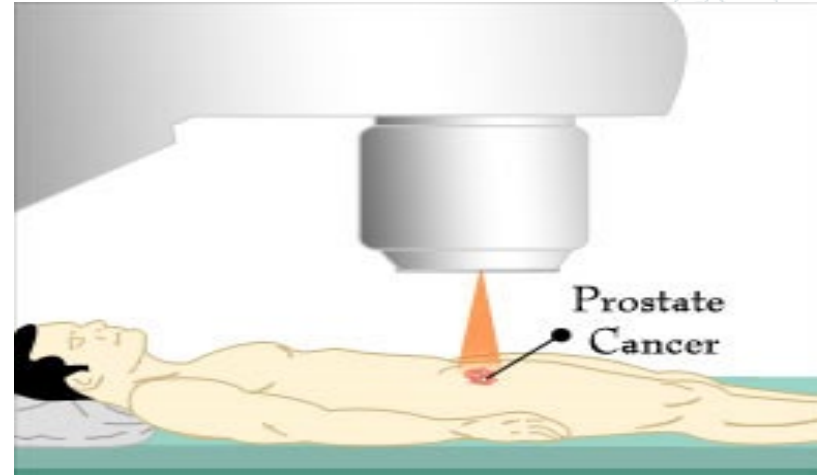


A decorative background featuring a network diagram of nodes and connections. The nodes are represented by circles of varying sizes and colors (gray, blue, and white with a blue outline). They are interconnected by thin lines, forming a complex web-like structure. The diagram is positioned in the corners of the page, with a larger concentration of nodes in the top-left and bottom-right areas.

# Background

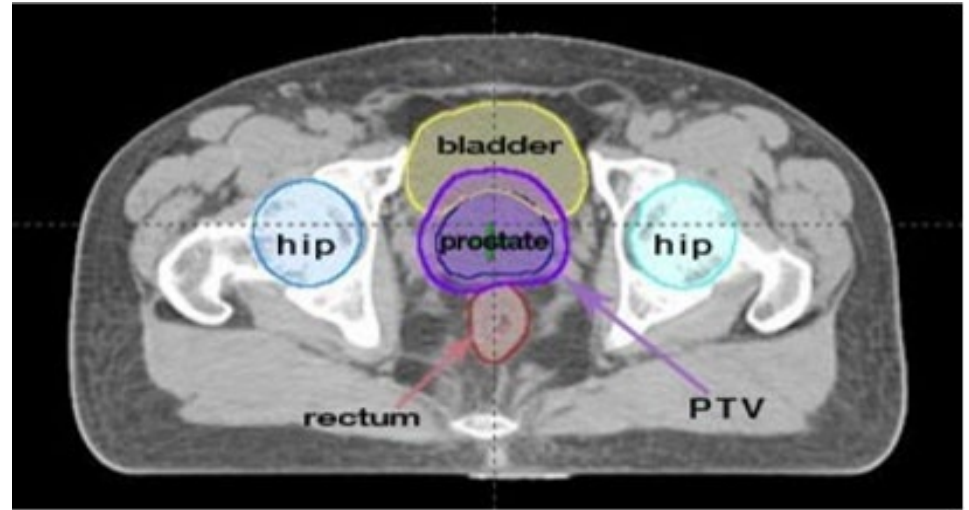
# Prostate Cancer & Radiation Therapy (RT)

- 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



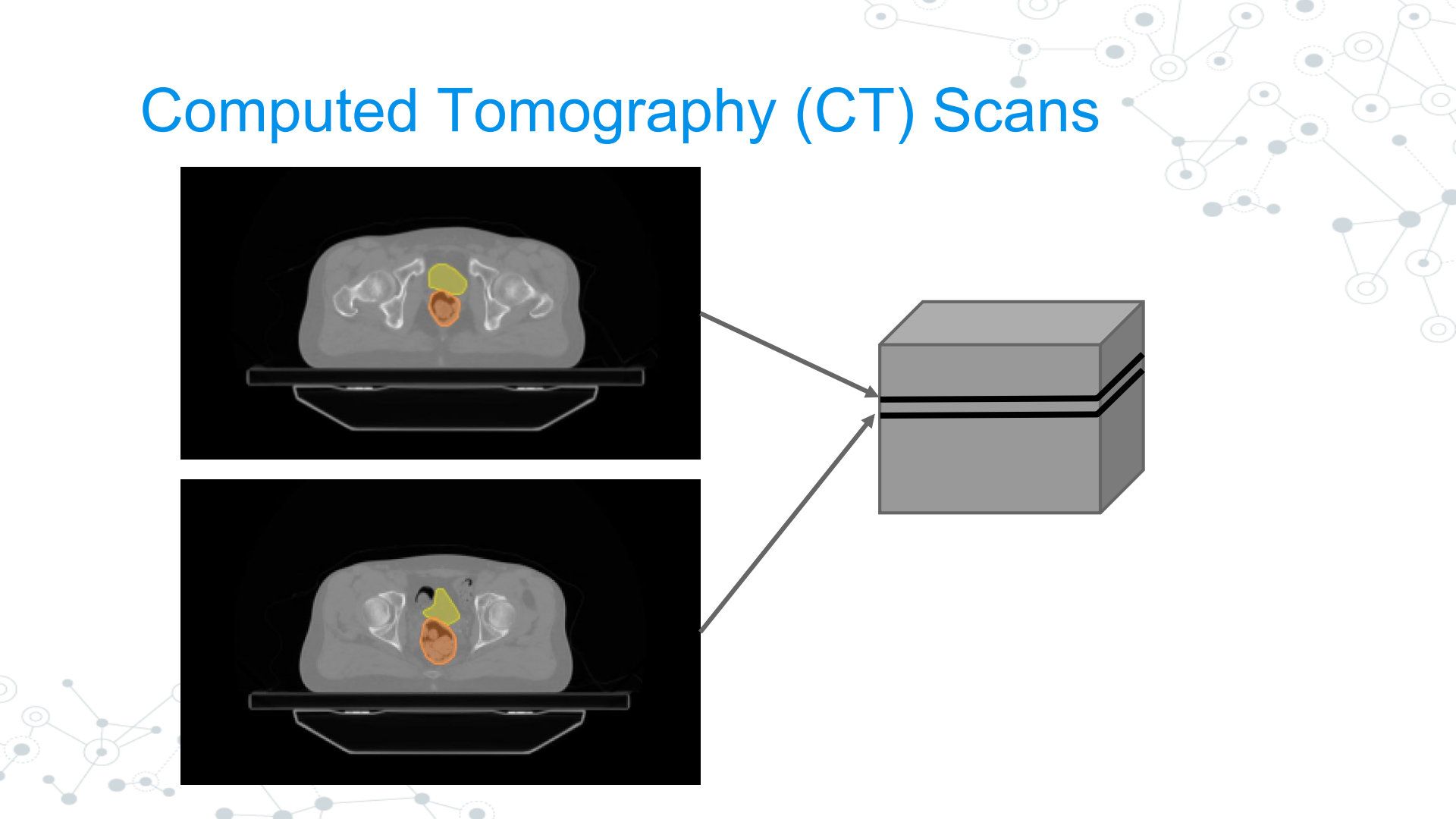
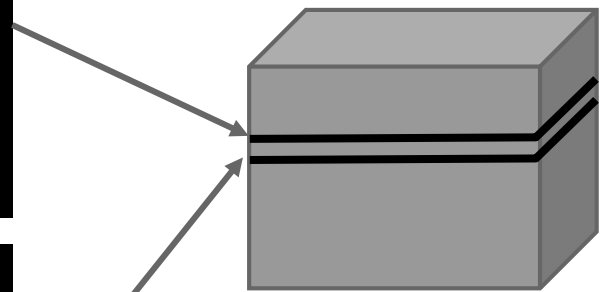
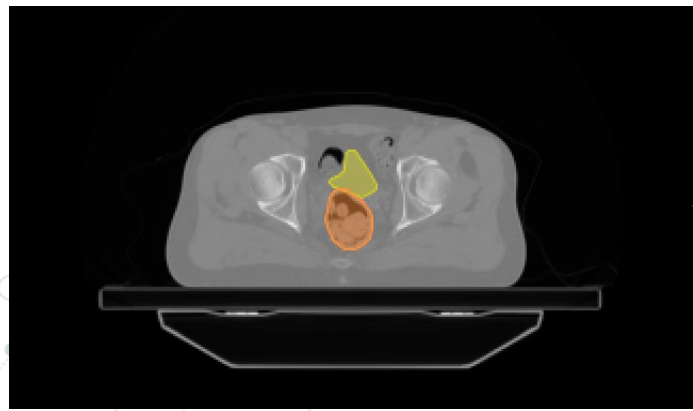
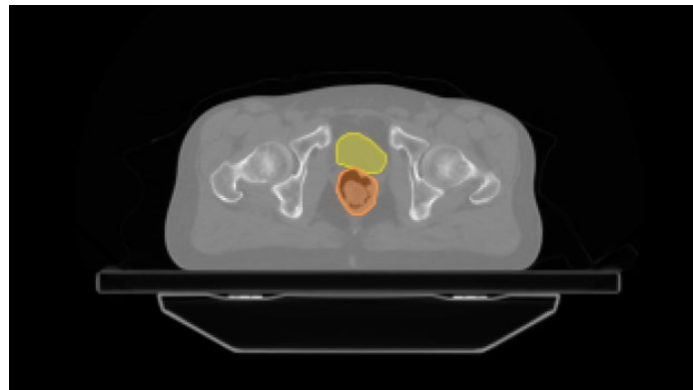
# Computed Tomography (CT) Scans

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



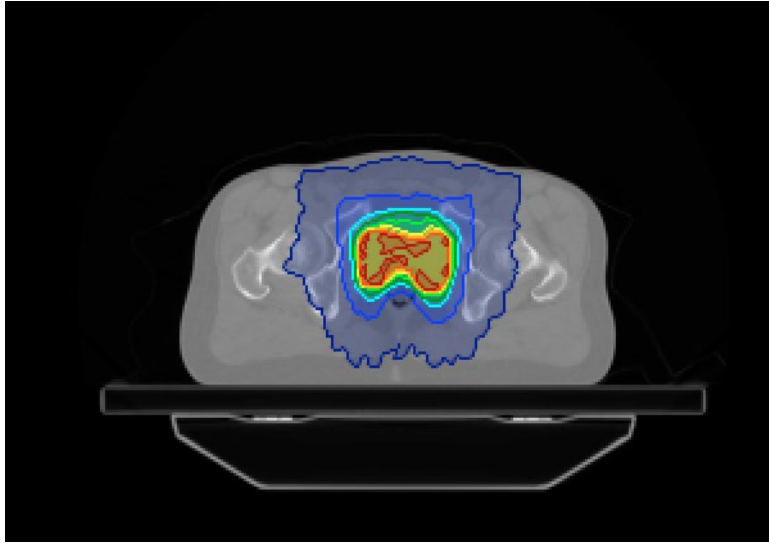
**CT image with demarcated organs**

# Computed Tomography (CT) Scans

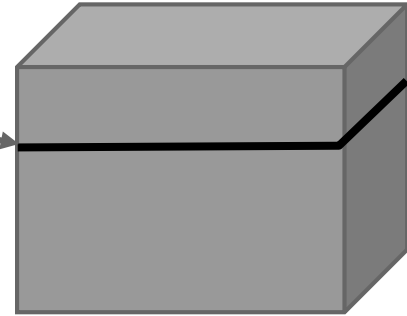




# Radiation Therapy (RT) Plan



**Radiation Therapy Plan**

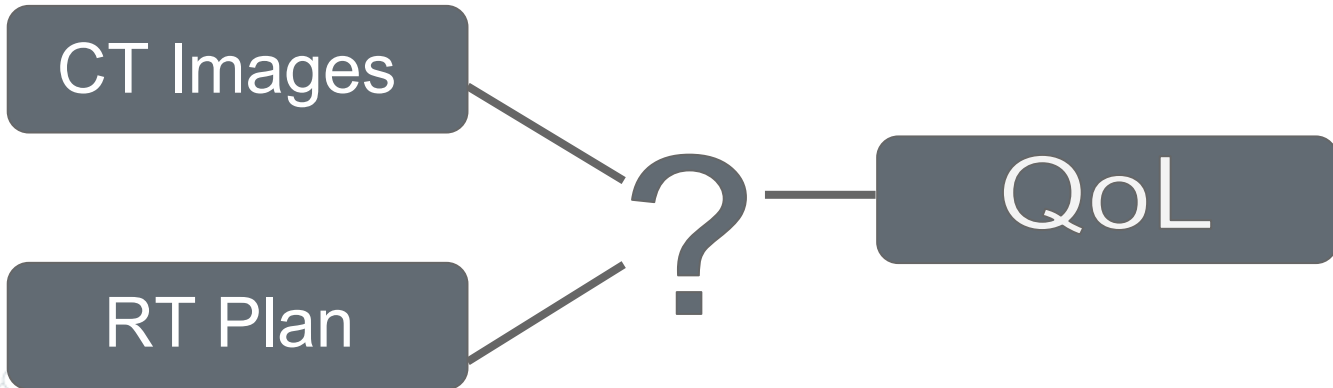


# Data

- 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



A decorative network diagram in the top-left corner, consisting of a complex web of interconnected nodes and edges. The nodes are represented by small circles, some of which are highlighted with a blue outline or filled with a solid blue color. The edges are thin lines connecting the nodes, creating a dense, interconnected structure.

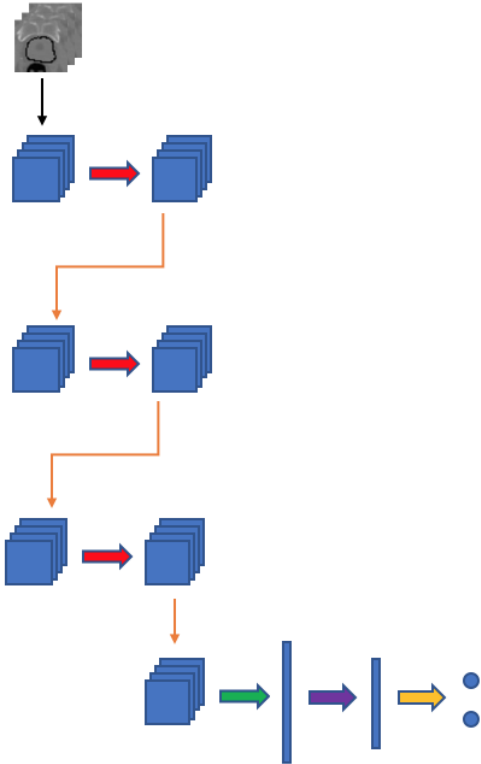
# Our Model








A decorative network diagram in the bottom-right corner, similar to the one in the top-left. It features a complex web of interconnected nodes and edges. Some nodes are highlighted with a blue outline or filled with a solid blue color, while others are grey or white. The edges are thin lines connecting the nodes, creating a dense, interconnected structure.

# 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

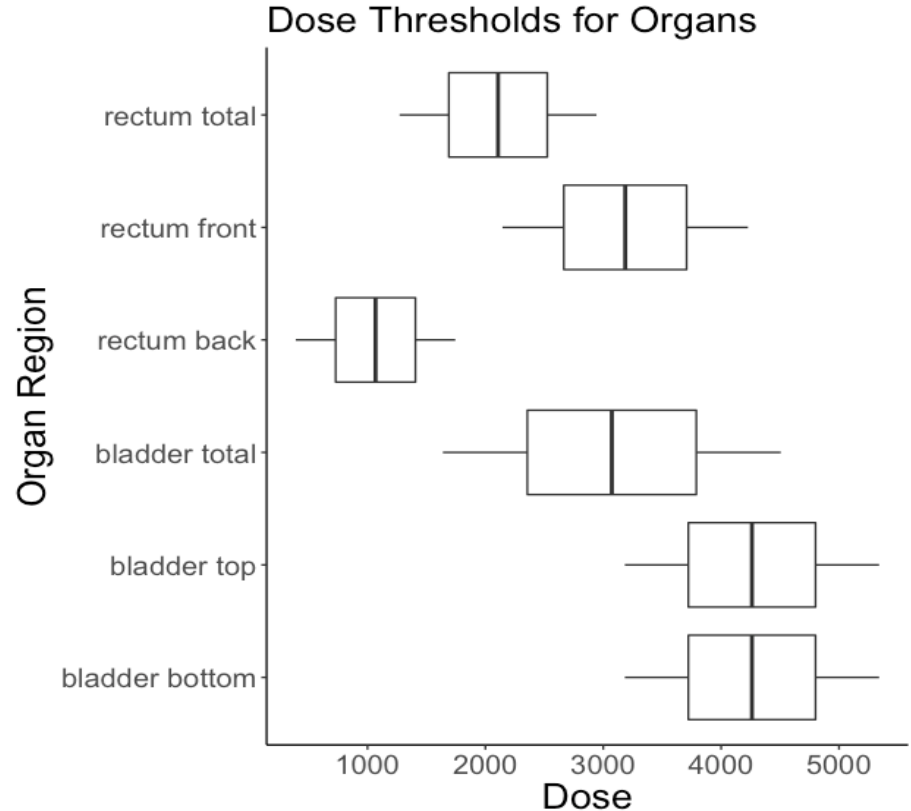
A decorative graphic consisting of a network of nodes and connections. The nodes are represented by small circles, some of which are highlighted in blue. The connections are thin lines, some solid and some dashed, forming a complex web-like structure. This graphic is positioned in the corners of the page, framing the central text.

# 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)

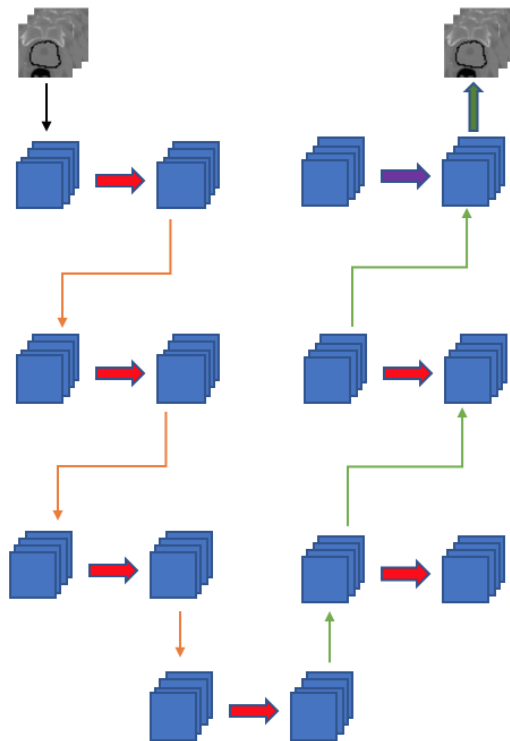
# Special Thanks

A decorative network diagram in the top right corner, consisting of various sized circles (nodes) connected by thin lines (edges). Some nodes are solid grey, while others are hollow white with a grey border. The connections form a complex, branching structure.

- **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
- 
- A decorative network diagram in the bottom left corner, similar to the one in the top right, featuring a cluster of nodes and connecting lines.

Questions?

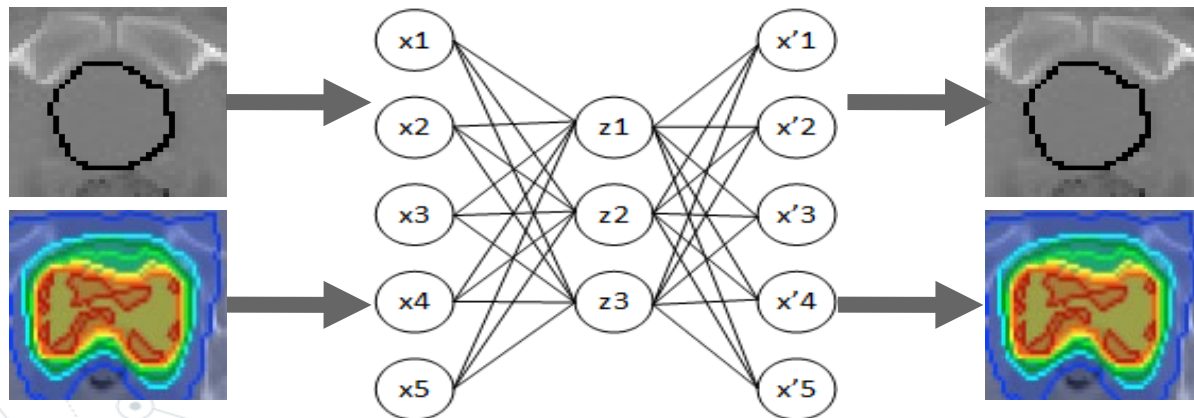
# Autoencoder Architecture



- 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