ILLINOIS Carle

Bioengineering Department
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Artificial Intelligence in Medical Imaging

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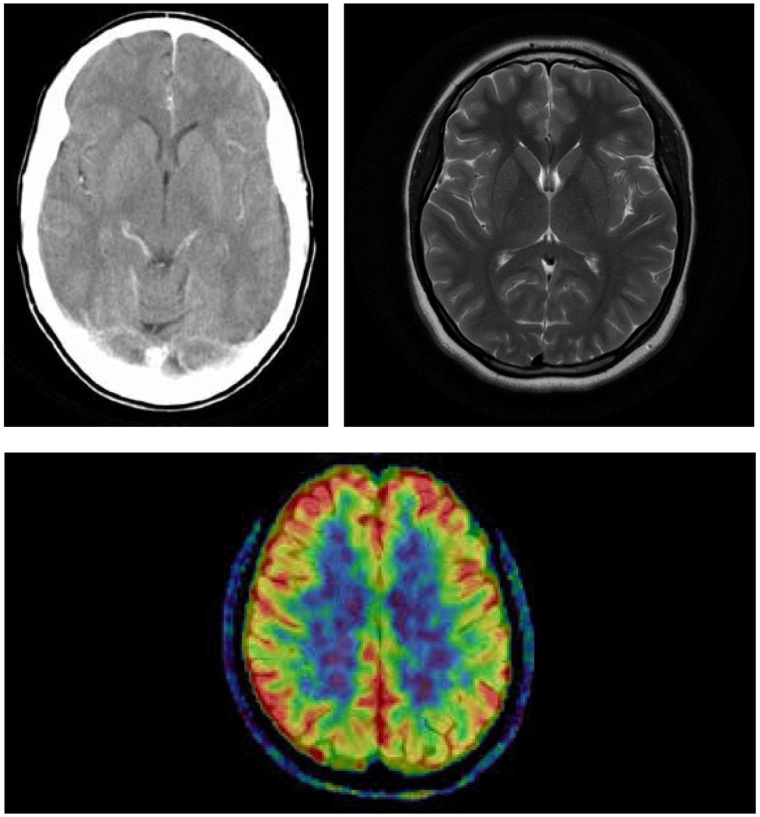
What makes a good medical image?



Background

- Image quality (IQ) should be assessed for medical applications

- Machine learning (ML) methods are widely employed in modern imaging applications

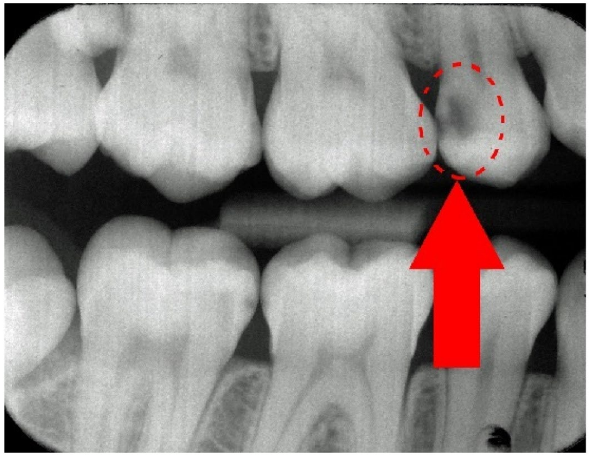
- Less explored is the use of ML for assessing imaging quality and guiding system/algorithm design and optimization for specific tasks.

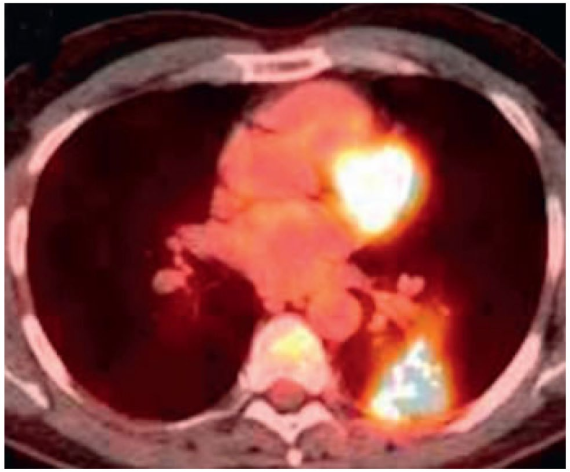
Outline

- Objective image quality (IQ) assessment for specific tasks
- Machine learning-based tools for imaging system/algorithm optimization
  - Learning stochastic object model (SOM) to characterize anatomical variations using geometric attribute distribution models and organ contours in radiation therapy
  - Learning stochastic object model (SOM) from imaging measurements using AmbientGANs

IQ assessment: diagnostic imaging tasks

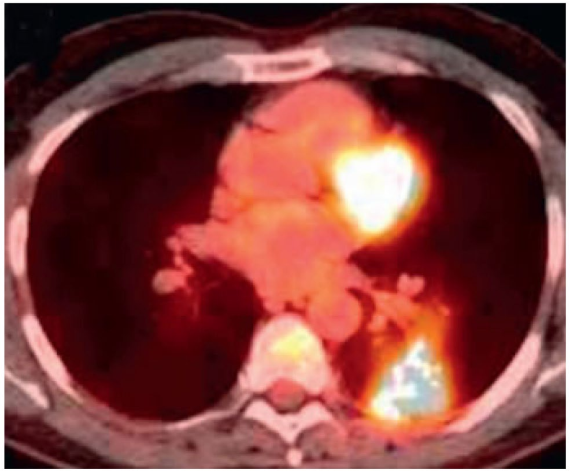
- Does the patient have any cavities in their teeth?
- Do they have a broken bone?
- Do they have cancer?





IQ assessment: radiation therapy tasks

- Tumor/OAR segmentation
  - how exactly the tumor size is?
  - Segmentation uncertainty?
- RT treatment plan quality
- Treatment outcome
- …



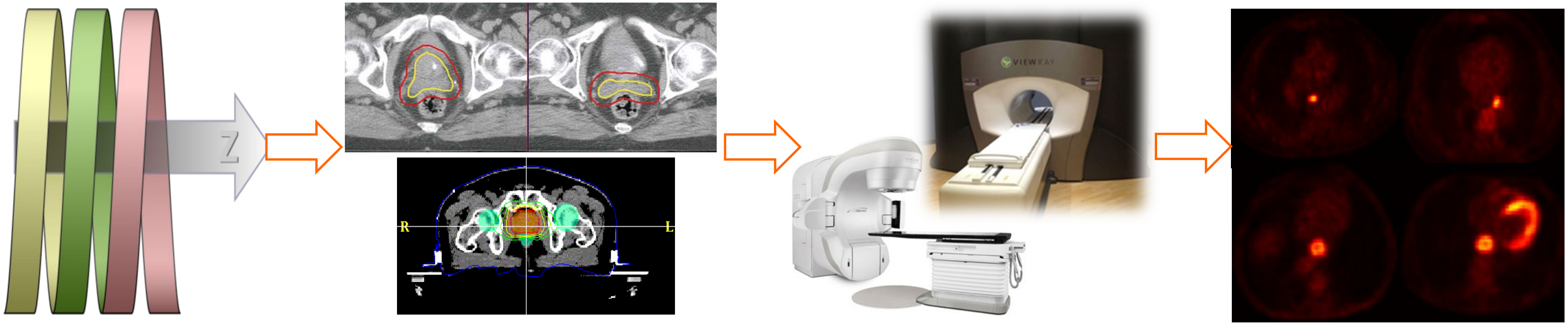


Image quality assessment (IQA)

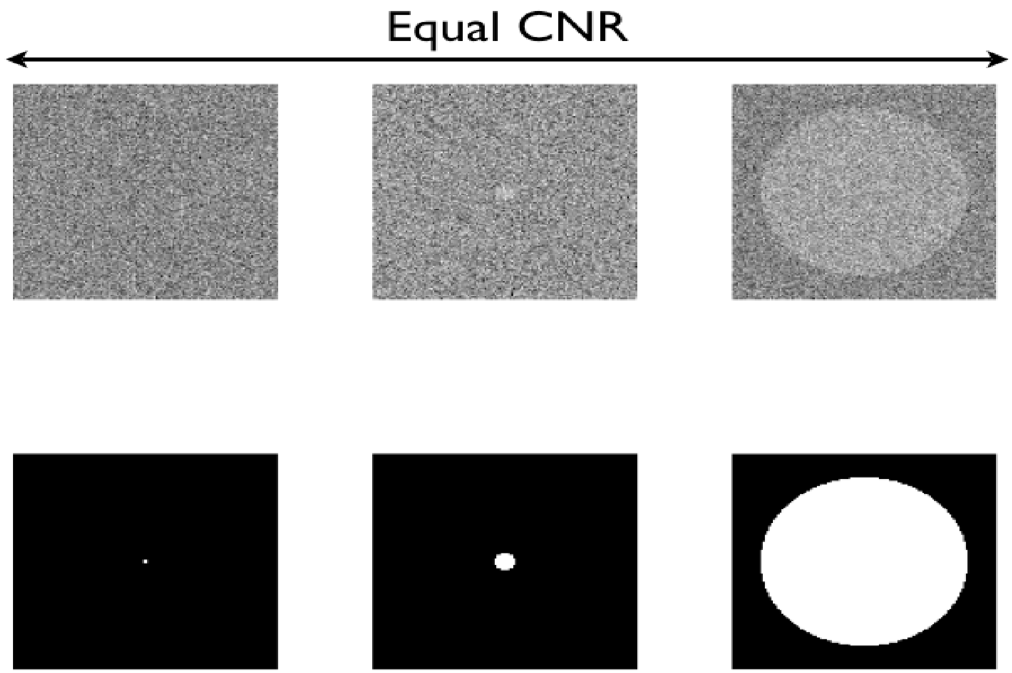
- In order to optimize the performance of imaging systems/algorithms, figures-of-merit (FOMs) that describe IQ are required.

- IQ metrics also permit the comparison of information contained in images acquired by different imaging modalities

- IQ metrics can be divided into two broad classes:
  - Physical-based IQ measures (resolution, SNR, CNR, etc)
  - Objective, or task-based, IQ measures

Limitations of physical-based IQ measures

- Physical measures, such as the CNR, do not always correlate with signal detectability or other task-based measures.



Courtesy of Prof. Matthew Kupinski, U Arizona

Task-based IQA

- Computer-simulation is an important tool used in task-based IQA
- Objective IQ assessment requires knowledge of all sources of randomness in the measured image data.
- Sources of randomness in image data include:
  - Randomness in the imaging system
  - Measurement noise
  - <u>Variations in the object to-be-imaged</u>
- Ideally, objective IQ measures are averaged over all sources of randomness in the measured data to form figures of merit (FOMs).
- ROC curve is one example of a task-based IQA metric for diagnostic imaging

Task-based IQ assessment in Radiation Therapy

- First theory developed for <u>task-based IQ</u> assessment in RT based on therapeutic outcomes:

Objective assessment of image quality VI: imaging in radiation therapy

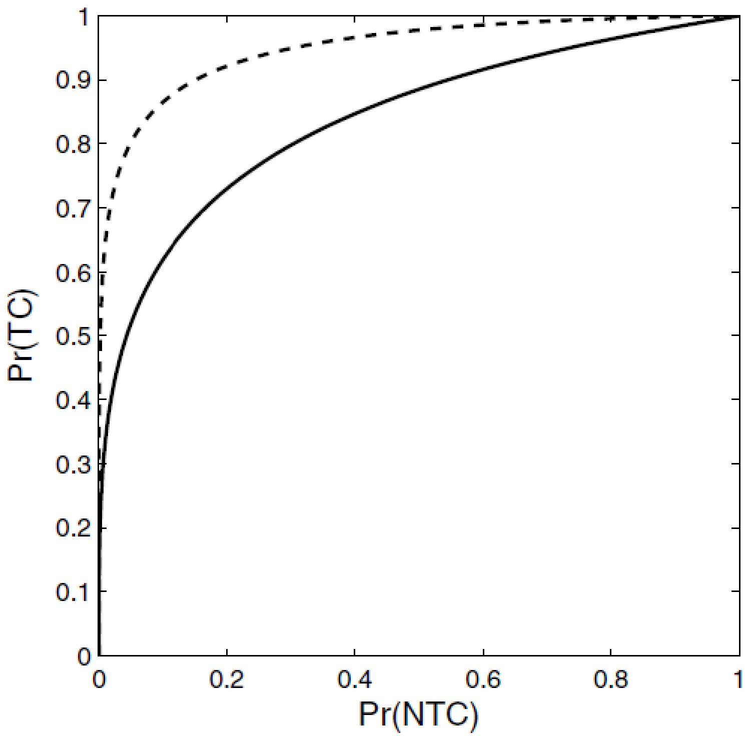
Harrison H Barrett[1,2], Matthew A Kupinski[1,2], Stefan Müeller[3], Howard J Halpern[4], John C Morris III[5] and Roisin Dwyer[6]

Phys. Med. Biol. 58 (2013) 8197–8213

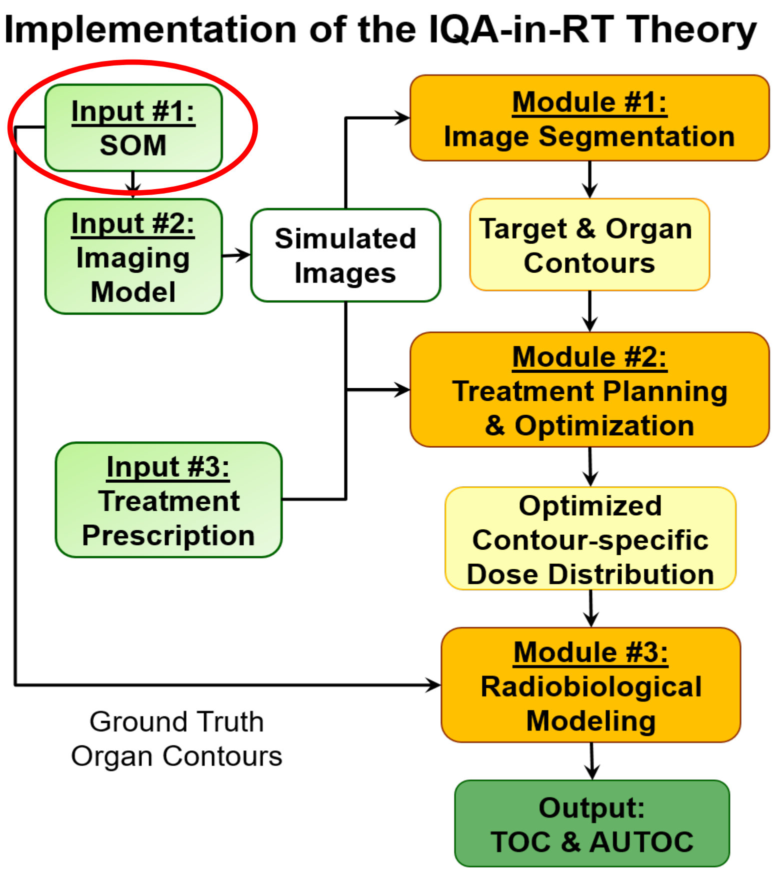
- IQ Figure-of-Merit (FOM):
  - AUTOC: the area under the therapy operating characteristic (TOC) curve

Task-based IQA in Radiation Therapy

- TOC curve:
  - Plots of the probability of tumor control (TCP) vs. the probability of normal tissue complications (NTCP) as the overall dose level of a radiation treatment is varied
  - Analogy to receiver operating characteristic (ROC) curves and their variants
- TOC can be defined for a single patient and for a population of patients



General framework of the IQA-in-RT



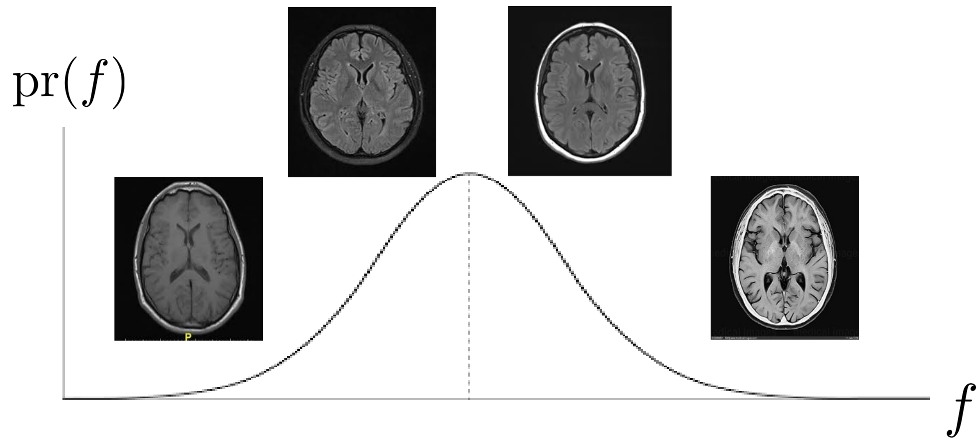
- Medical image simulation
  - CT, MRI, etc.
- Image Segmentation
  - Automatic, manual, or any other algorithms
- RT Treatment planning & optimization
  - IMRT, SBRT, etc.
- Radiobiological modeling
  - Equivalent uniform dose (EUD)
  - …
- TOC & AUTOC calculation

Steven Dolly, Yang Lou, Mark Anastasio, Hua Li, “Task-Based Image Quality Assessment in Radiation Therapy: Initial Characterization and Demonstration with Computer-Simulation Study”, Physics in Medicine and Biology, 2019.*

SOM: describing object randomness

- Direct estimation of $\mathrm{pr}(f)$ is rarely tractable.

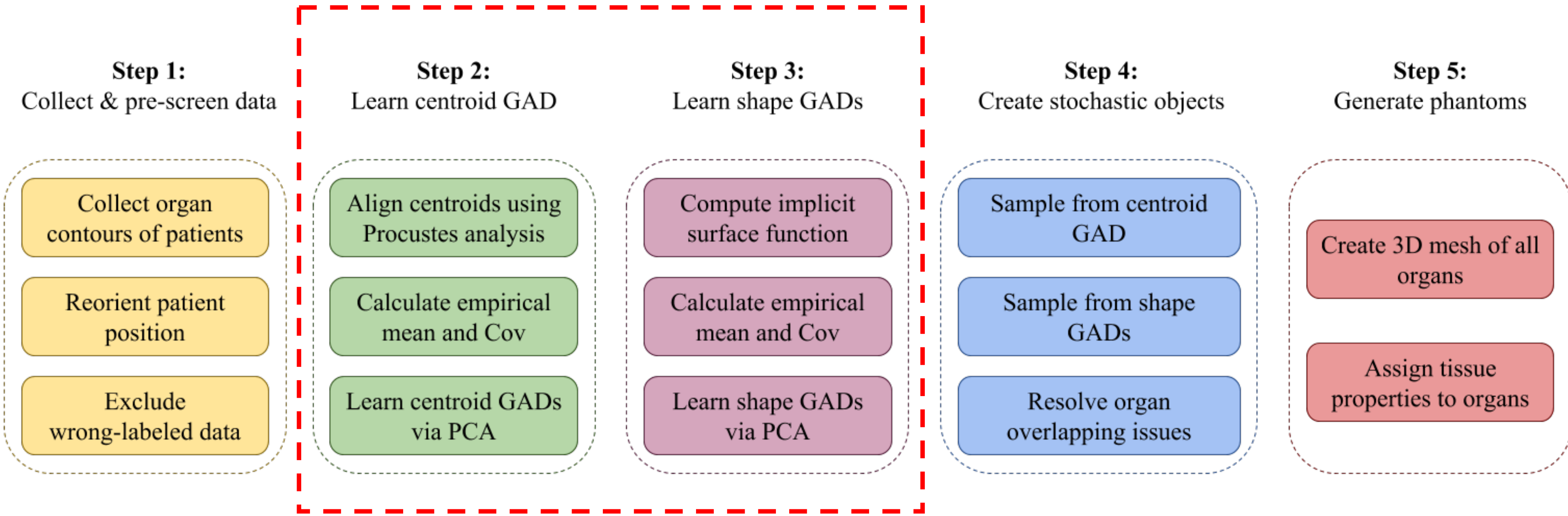
The objects to-be-imaged are samples from an (unknown) probability density function



- Stochastic object model (**SOM**) enables the simulation of object ensembles with prescribed statistical properties for use in simulation.

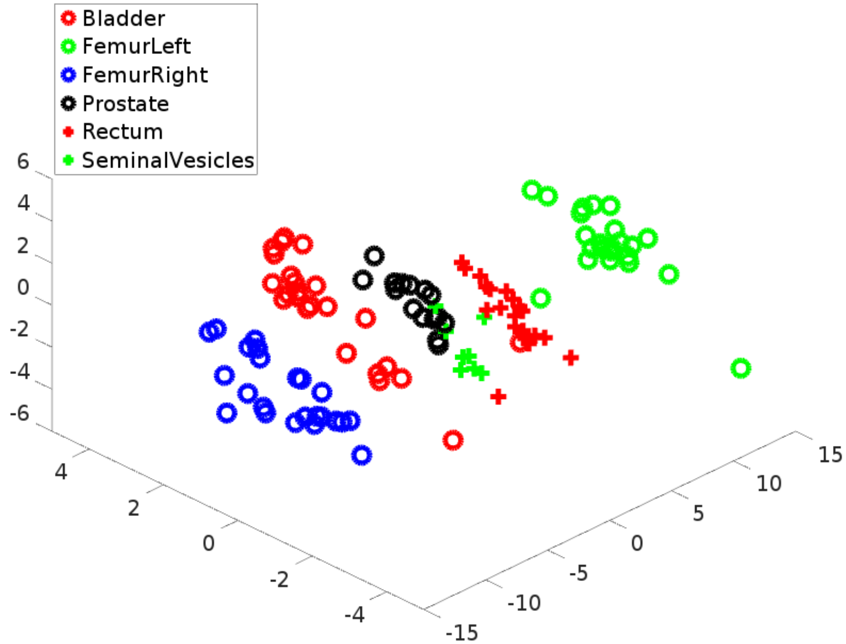
Learning SOMs for characterizing anatomical variations

- Motivation: available databases of high-quality volumetric images and organ contours in RT
- Learn geometric attribute distribution (GAD) models

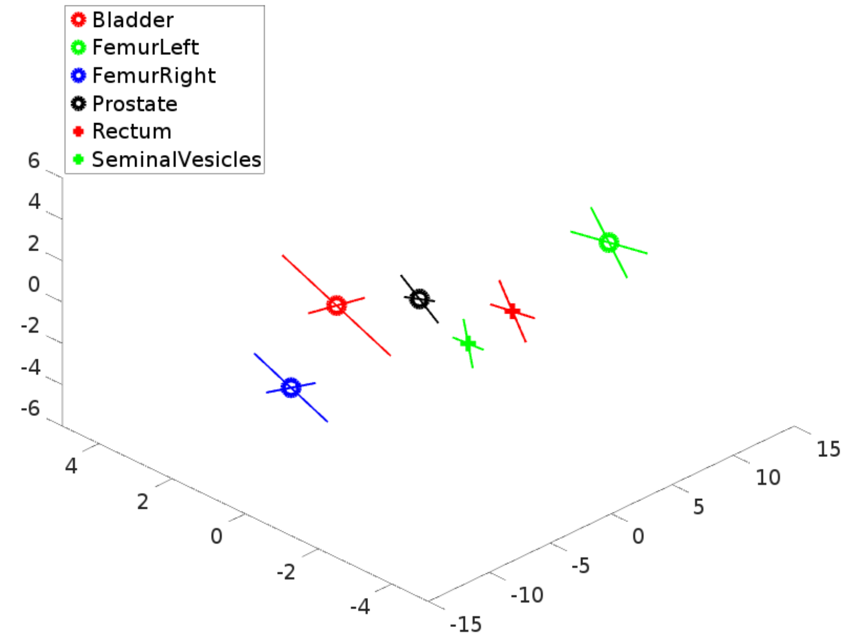


*Steven Dolly, Yang Lou, Mark Anastasio, **Hua Li***, "Learning-based Stochastic Object Models for Characterizing Anatomical Variations", Physics in Medicine and Biology, 2018.*

Learning inter-structural centroid GAD of multiple organs



Centroid training data



Mean centroid and centroid distribution

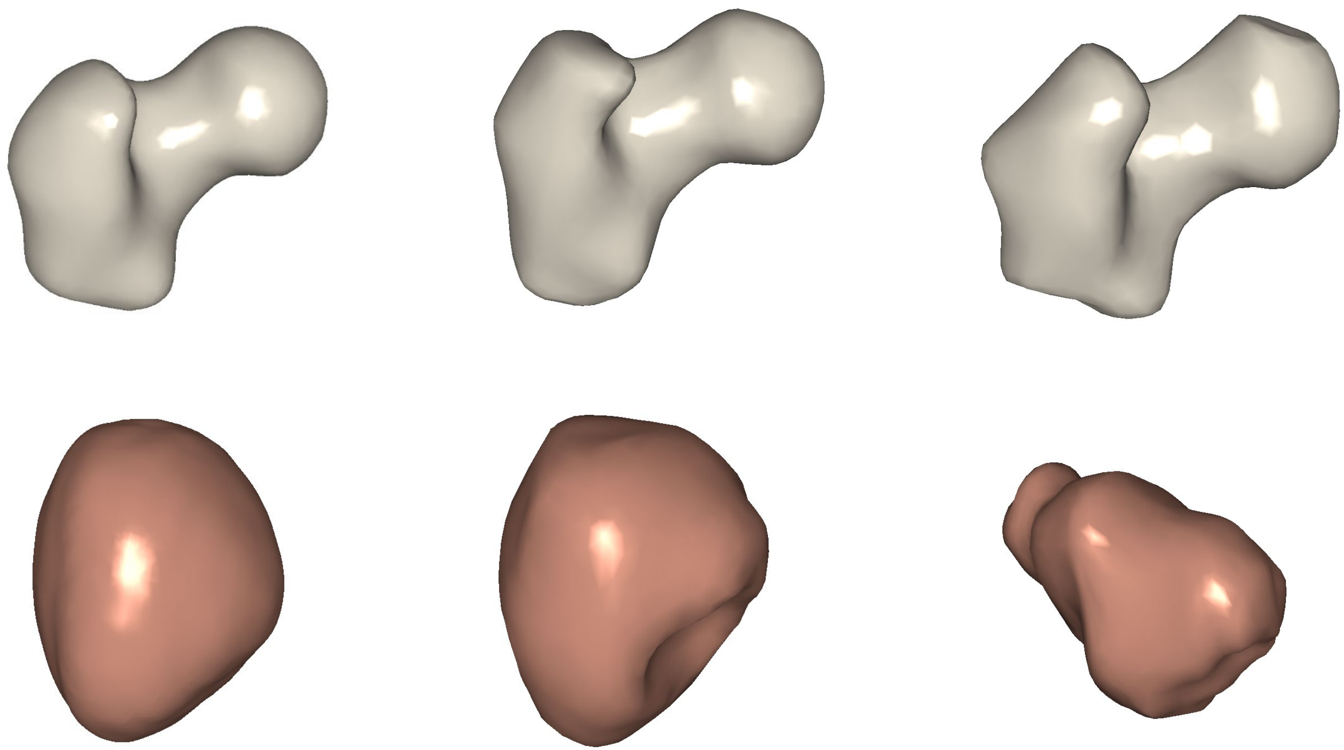
$$\hat{\mathbf{G}} = \bar{\mathbf{G}} + \sum_{k=1}^{K_G} \alpha_k \sqrt{\lambda_k^G}\,\mathbf{e}_k^G$$

Learning intra-structural shape GAD of single organ

Mean Shape | Realization #1 | Realization #2

Left Femoral Head

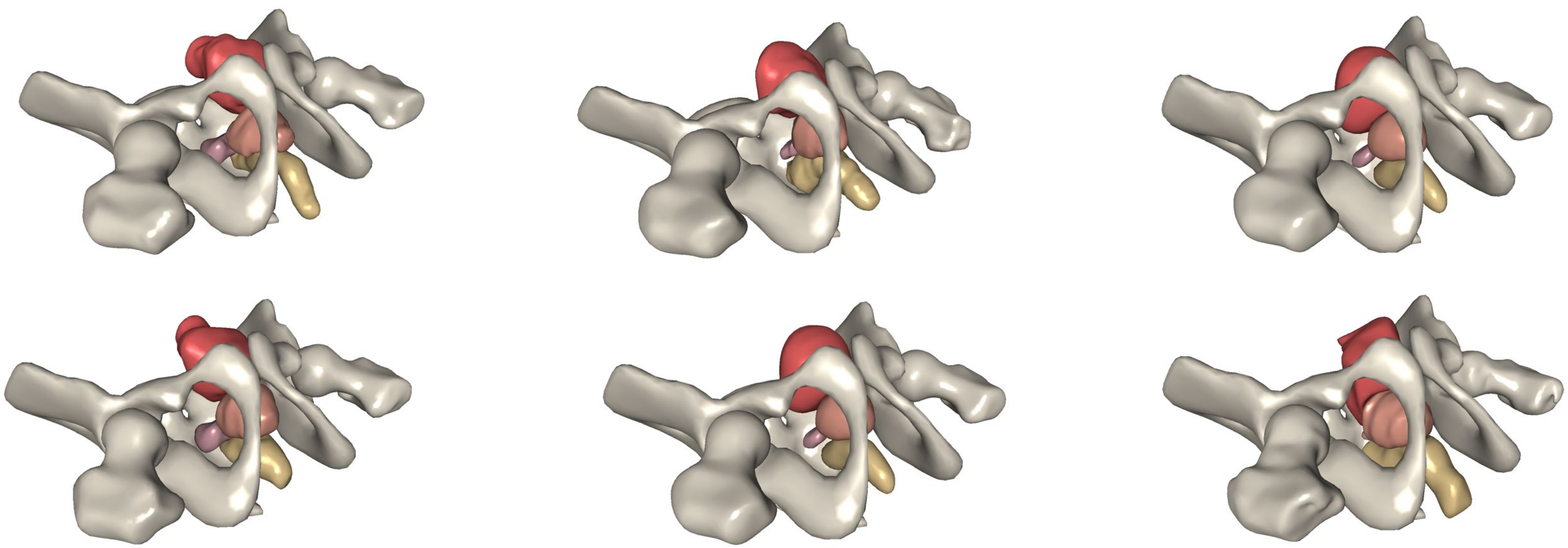
Bladder



$$\hat{\boldsymbol{\Psi}}_n = \bar{\boldsymbol{\Psi}}_n + \sum_{k=1}^{K_{\Psi_n}} \beta_{k,n}\sqrt{\lambda_{k,n}^{\Psi_n}}\,\mathbf{e}_{k,n}^{\Psi_n}$$

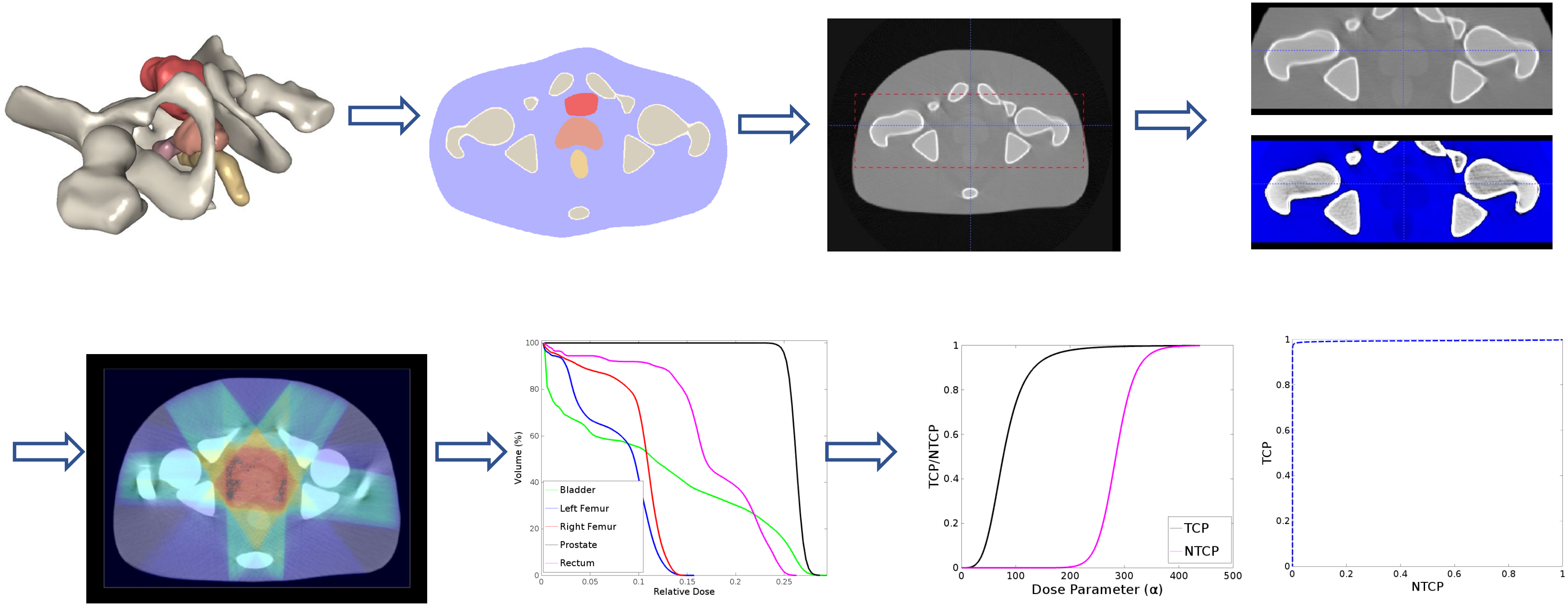
Create randomly-generated objects based on learned GADs

- Sampling the GADs: $\hat{\mathbf{G}} = \bar{\mathbf{G}} + \sum_{k=1}^{K_G} \alpha_k \sqrt{\lambda_k^G} \mathbf{e}_k^G$ $\quad \hat{\Psi}_n = \bar{\Psi}_n + \sum_{k=1}^{K_{\Psi_n}} \beta_{k,n} \sqrt{\lambda_{k,n}^{\Psi_n}} \mathbf{e}_{k,n}^{\Psi_n}$

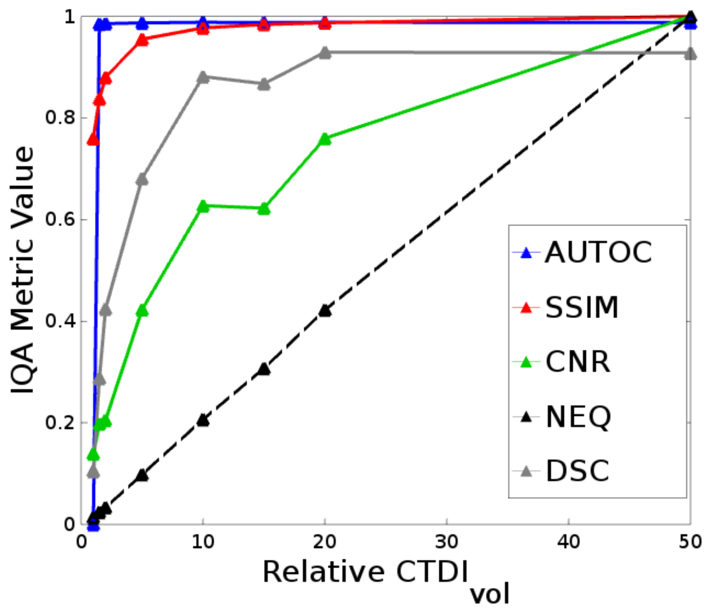


Organ models: prostate, bladder, rectum, femoral heads, pelvic bone, and seminal vesicles

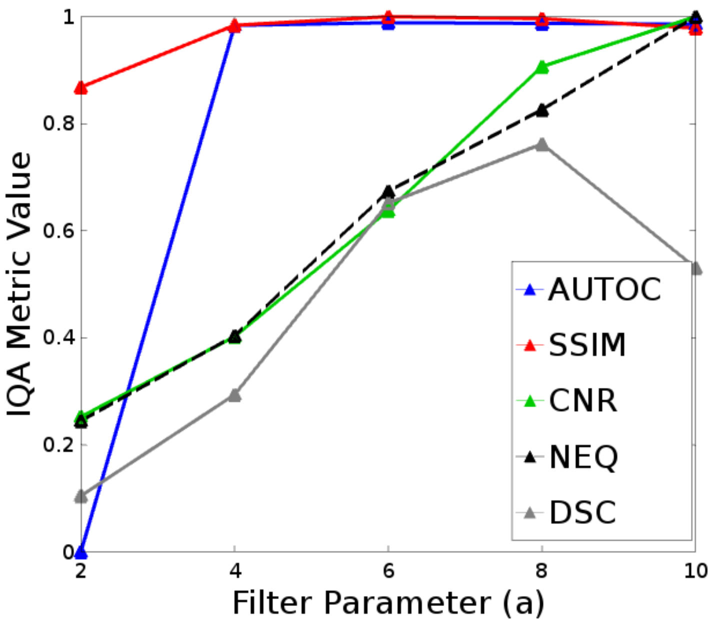
Example Implementation of the IQA-in-RT Framework



IQ Assessment based on AUTOC vs other IQA metrics



Optimizing CT imaging dose



Optimizing FBP reconstruction filter

The AUTOC compared to various IQA metrics for optimizing imaging dose and image reconstructions (the filter parameter)

Learning SOMs using deep generative models

- A generative model defines a process that could have generated the observed data

- Once trained using observed (training) imaging data, a generative model can represent the SOM

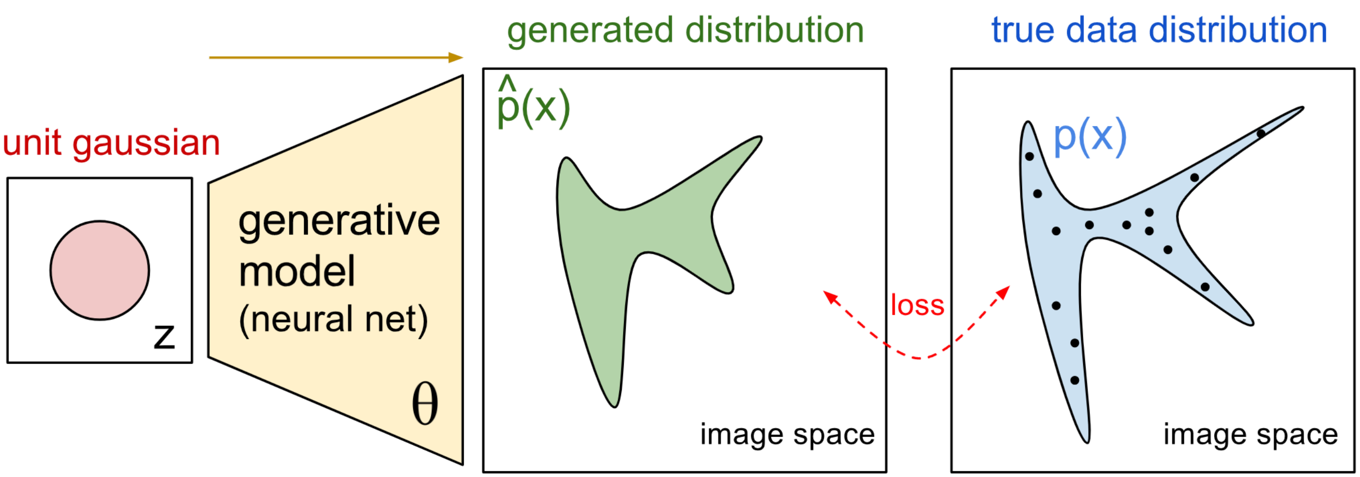
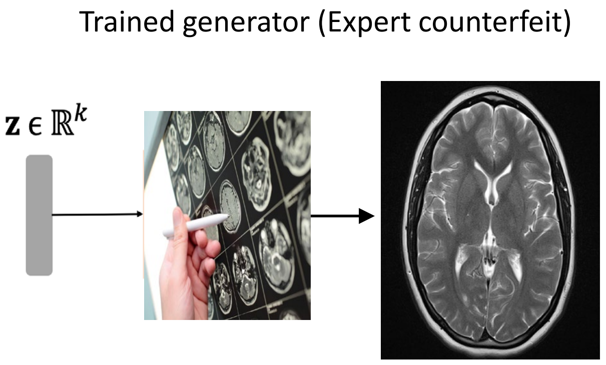


Image credit: https://blog.openai.com/generative-models/

Generative Adversarial Networks (GANs)

- **Generative Adversarial Networks (GANs)** [Goodfellow, I., et al. NIPS. 2014]
  - Generator network $G(z; \theta_G)$ learns by competing against an adversary - a neural network called the **discriminator** $D(x; \theta_D)$**.**
  - The discriminator attempts to distinguish between samples from *real* images and samples produced by the generator, or *fake* images**.**

During training



After training

Image credit: Biomedical Imaging Group, EPFL and Radiopaedia

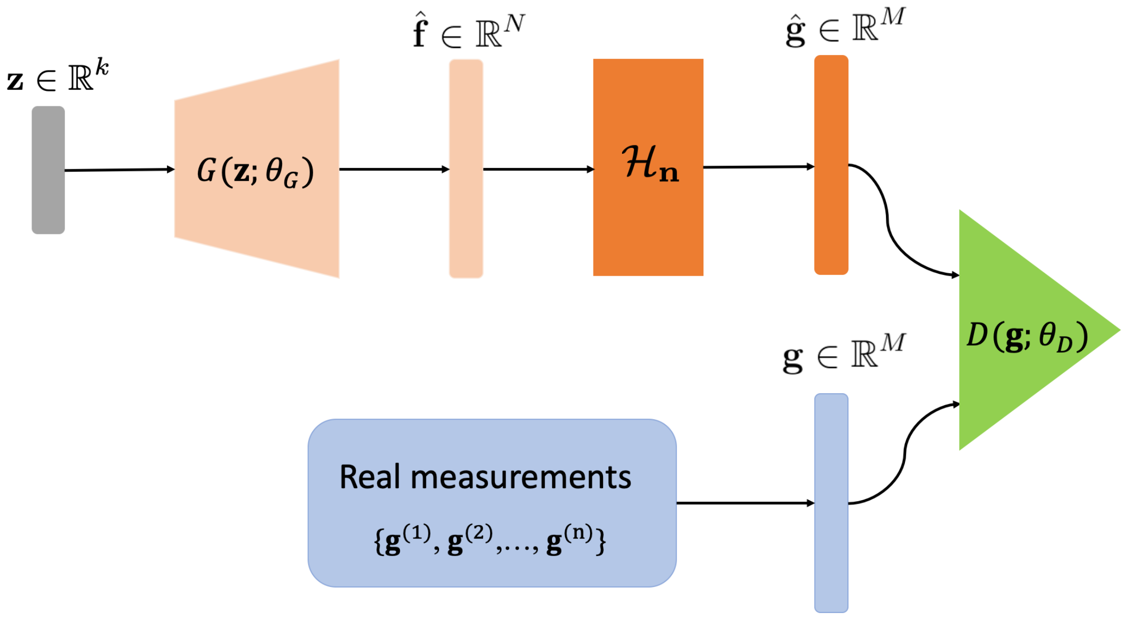
Need for a different type of GAN

- It is desirable to train a GAN on experimental data, so that the learned SOM can produce realistic images that serve as digital phantoms.
- However, conventional GANs are trained on acquired or reconstructed images that contain noise and potentially reconstruction artifacts.
- Ideally, we would like to establish a SOM from experimental measurements.
  - Want to learn object variability, not measurement noise
  - An Ambient GAN can do this!
  - We have developed a progressively-growing Ambient GAN (**ProAmGAN**) that can work with large images

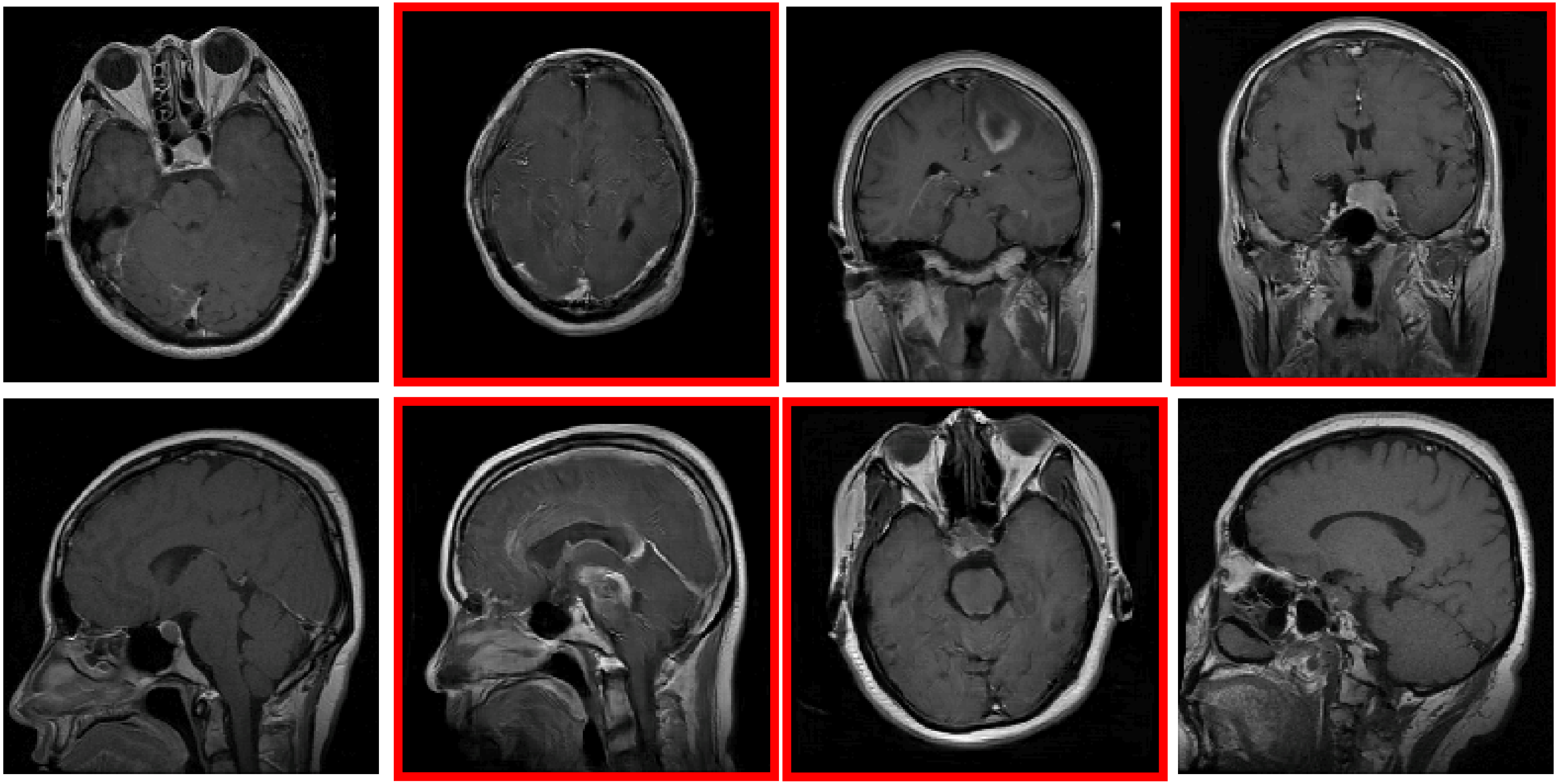
W. Zhou, S. Bhadra, F. Brooks, H. Li, M. Anastasio. "Learning stochastic object models from medical imaging measurements using Progressively-Growing AmbientGANs", https://arxiv.org/abs/2006.00033

AmbientGANs

- **AmbientGAN** [Bora, A., et al. ICLR. 2018]
  - Discriminator distinguishes between *real* and *simulated measurements*
  - We acquire imaging measurements: $\mathbf{g} = \mathcal{H}_{\mathbf{n}}(\mathbf{f}) = \mathbf{Hf} + \mathbf{n}$



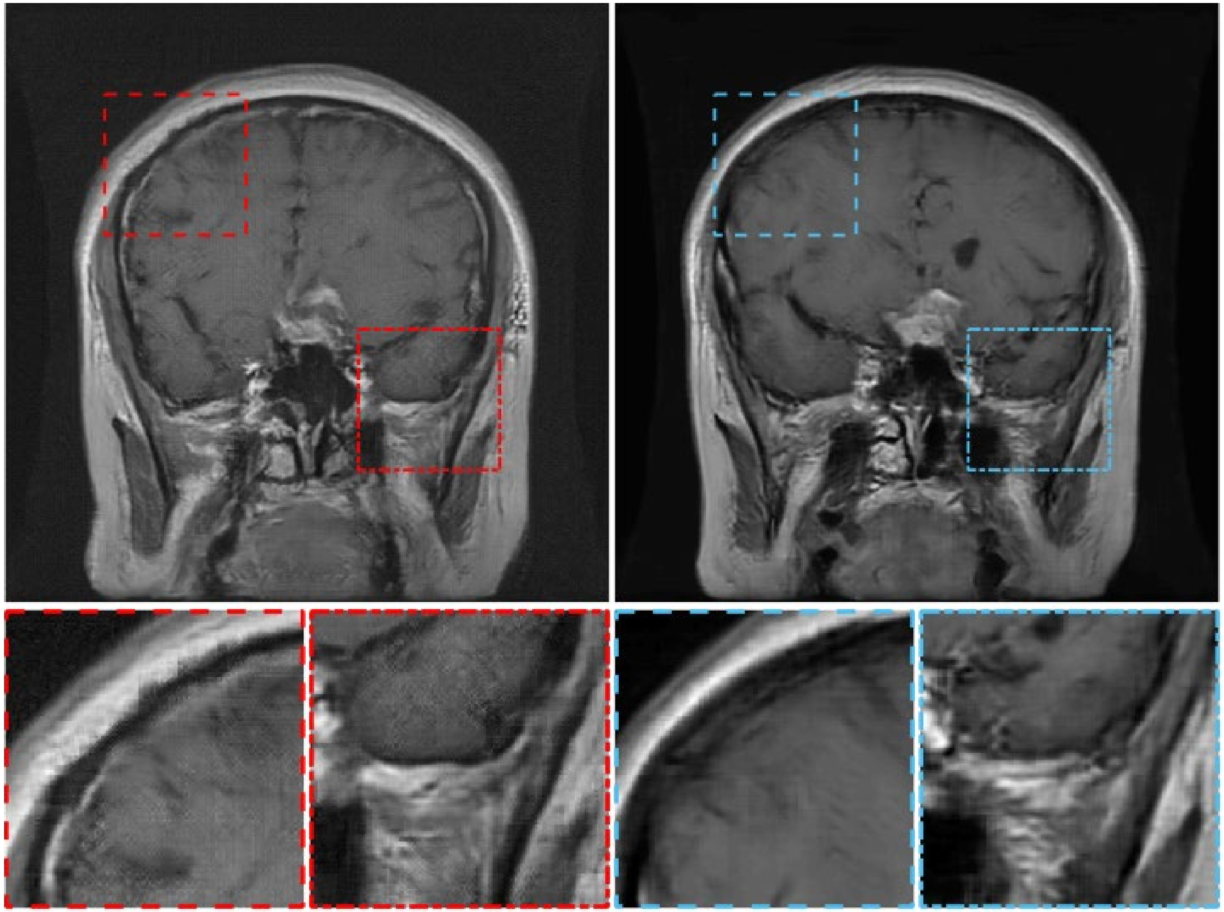
True and ProAmGAN-generated MRI objects



Red boxes: ProAmGAN-produced objects (SOM)

ProAmGAN vs conventional GAN

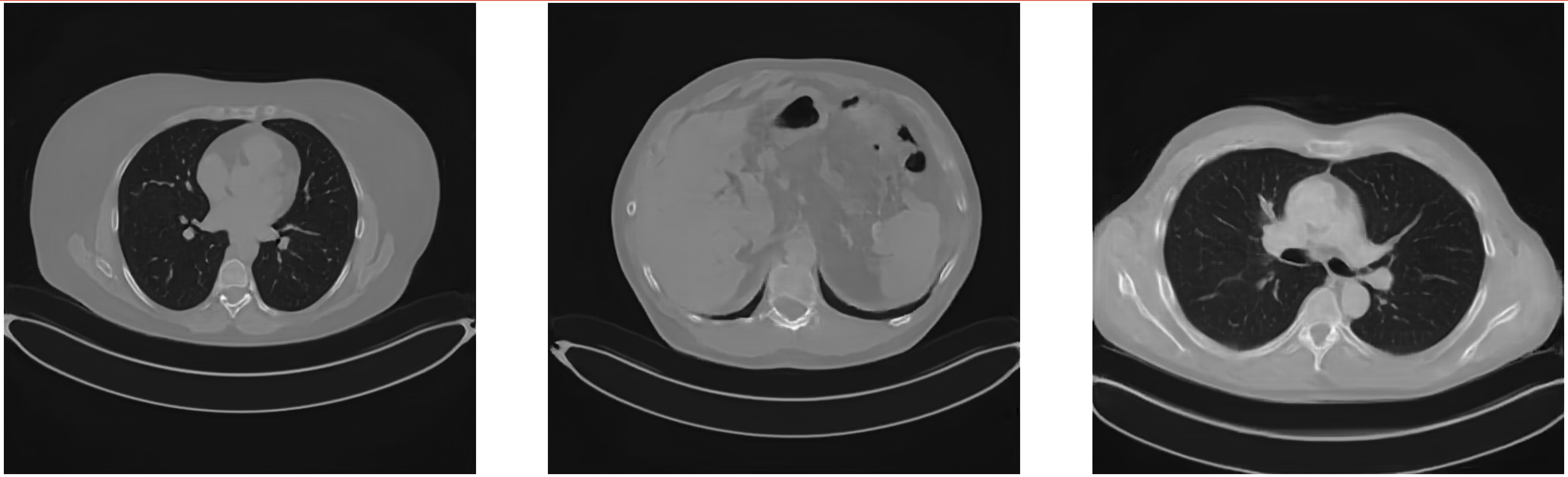
Conventional GAN



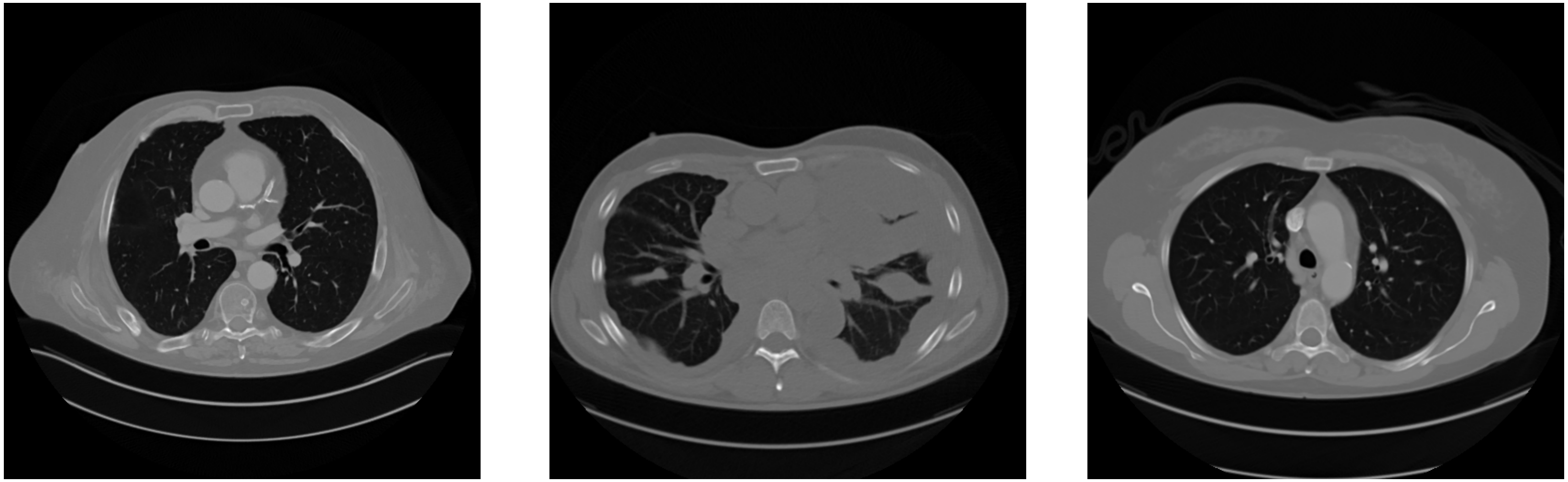
ProAmGAN

ProAmGAN - learns object variability, not noise

True and ProAmGAN-generated CT objects



ProAmGAN-generated objects



True objects

True and ProAmGAN-generated Chest X-ray objects

ProAmGAN-generated objects

True objects

Summary

- When optimizing imaging systems, we need to account for object randomness
- Using GAD models to characterize anatomical variations and establish SOMs from RT contours
- Using an ambientGAN coupled with a measurement model – to establish SOMs from experimental measurements
- By use of the trained SOM, we can sample objects from the unknown PDF of interest and perform simulation studies
- The SOM can then be employed for the optimization of components in the IQA-in-RT workflow

Acknowledgement

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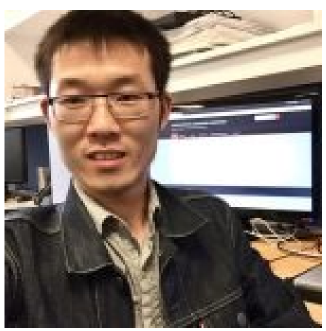

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  - Tao Group, UT Houston,
  - Radiation Oncology Department, WashU

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