ILLINOIS

Bioengineering Department
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# Advance DatasetGAN to learn stochastic object model for generating objective segmented images

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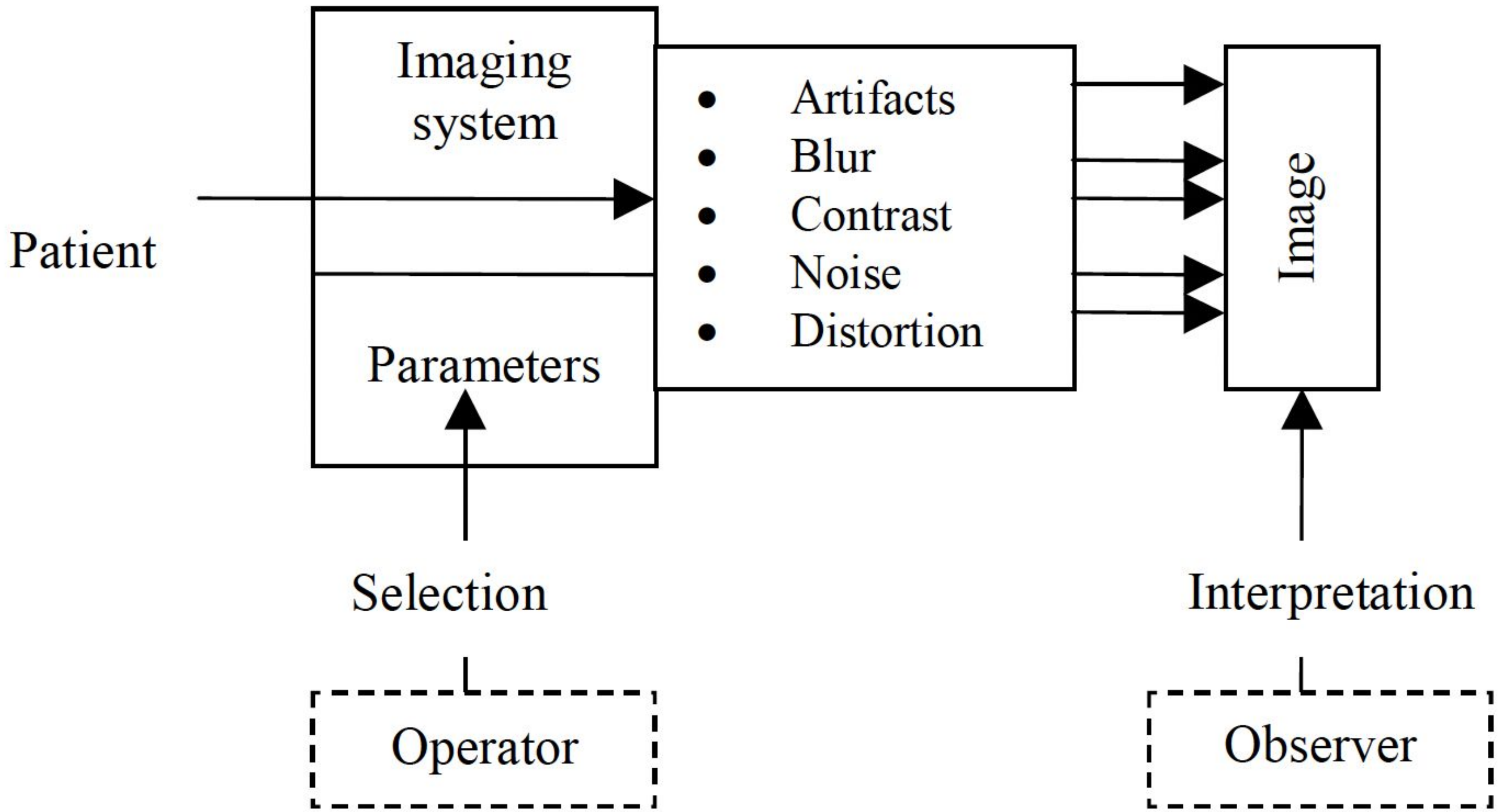
# Outline

- Research background and objectives
- Implementation and revision of DatasetGAN
- Experiment progress & results
- Summary & future work

# Medical imaging process




Simion et al. 2002

# Imaging system needs optimization

- Medical imaging doesn’t produce perfect images.

- Medical imaging system optimization relies on objective measures of image quality (IQ) for a task of interest. It needs a model observer to quantify the performance of the measure.

- For optimization, it’s desired for the observer to extract all the randomness information during the imaging measurement.

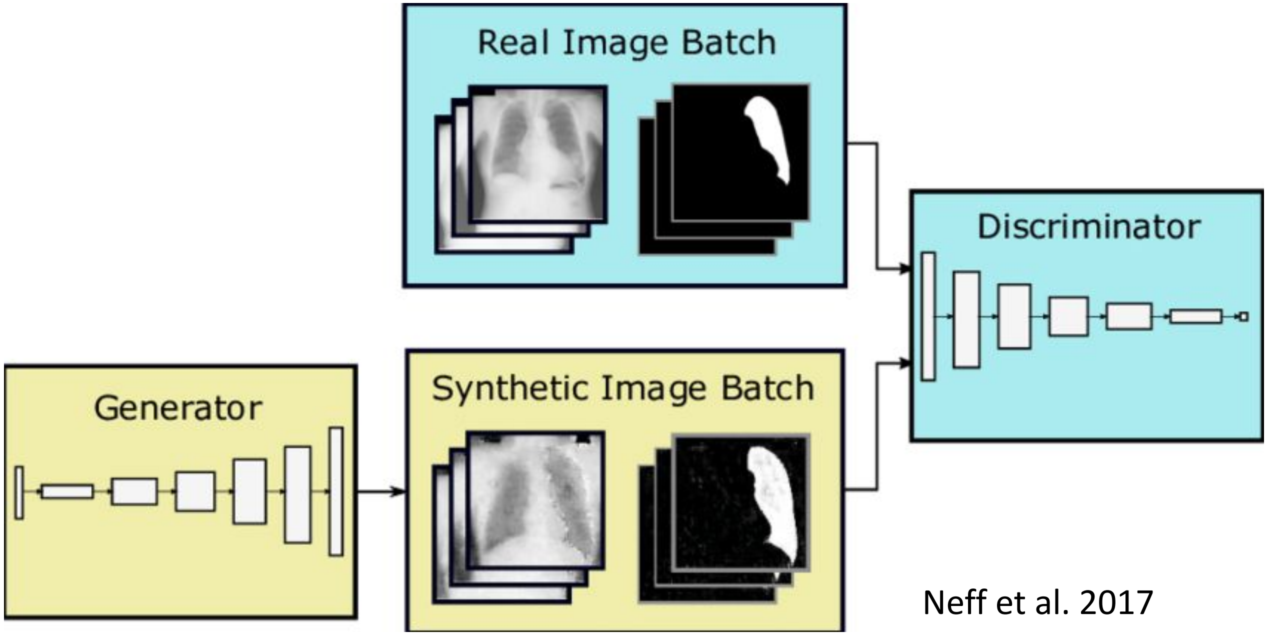
# SOMs describe randomness of objects

- One important randomness source is the variability within class objects. Stochastic object model (SOM) is to describe such variability.

- SOMs need to learn realistic variability via experiment data, rather than non-data-driven methods.

# GANs have potential for learning SOMs

- Generative adversarial networks (GANs) are powerful generative models that could accurately approximate unknown data distributions of training data.




Neff et al. 2017

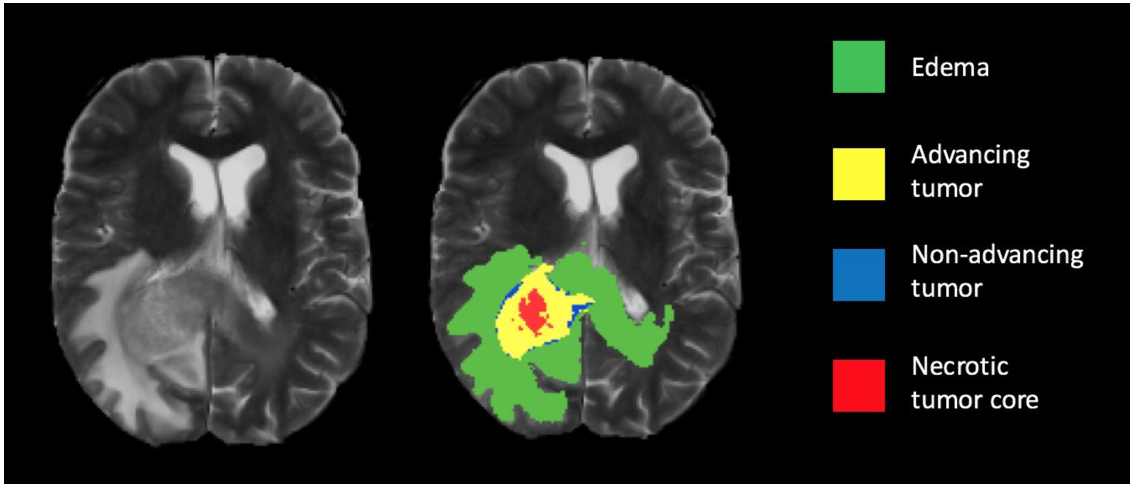
# Augmented GAN for learning SOMs

- Traditional GANs cannot estimate SOMs from training image directly.
  - reconstruction process
  - measurement noise

- Augmented GANs have been developed for learning SOMs to model objects by directly learning from noisy measured data via incorporating the measurement process in the GAN.
  - AmbientGAN Bora et al. 2018
  - Progressively-growing AmbientGAN Zhou et al. 2021
  - ...

# Segmentation information is useful

- Objective image with segmentation
  - A kind of complex and realistic Signal-Known-Exactly (SKE) data
  - For evaluating observer of a given task for optimizing imaging system
- Measured image with segmentation
  - For accurate diagnosis
  - For developing and evaluating segmentation methods for human observers.




Havaei et al. 2015

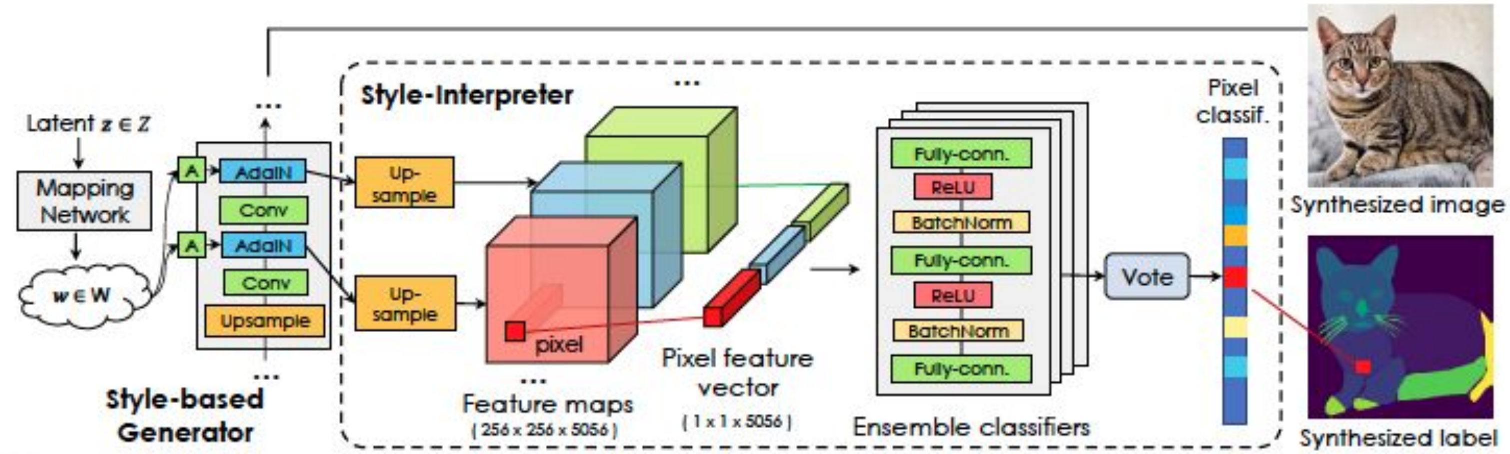
# Problems of obtaining segmentation information

- Manual annotation:
  - It usually needs expertise knowledge to segment the region of interests (ROIs). E.g. tumor, lesion, …
  - It consumes large amounts of time and effort.
  - It suffers the effect of reader “jitter”.

- Automatic annotation:
  - Non-data driven methods have limited performance.
  - Deep learning based methods needs large amounts of annotated data. (Chicken-and-egg problem)

# DatasetGAN could synthesize segmented images

- DatasetGAN is a StyleGAN-based framework. It could synthesize semantically segmented natural image dataset with minimal human intervention.




*Zhang et al. 2020*

1. *Zhang, Yuxuan et al.* "DatasetGAN: Efficient Labeled Data Factory with Minimal Human Effort." CVPR (2021).
2. *Karras, Tero et al.* "A Style-Based Generator Architecture for Generative Adversarial Networks." 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (2019): 4396-4405.

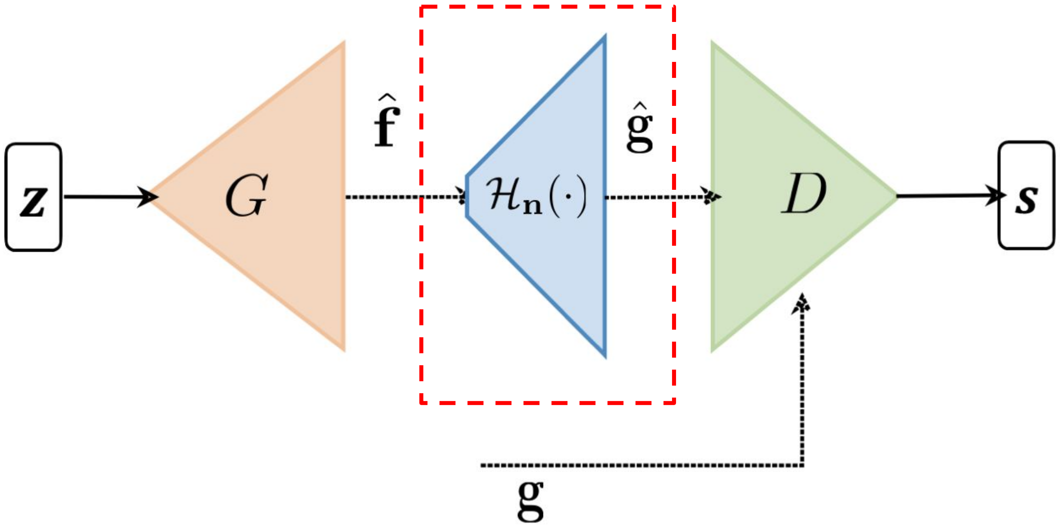
# Research objective

- How to advance DatasetGAN together with idea from AmbientGAN to develop a GAN that could generate realistic objective image with segmentation by directly learning from noisy measured data?

- **Research significance:** Generate an objective segmented dataset for evaluating and optimizing:
    - Hardware: imaging system
    - Software: segmentation techniques

# Idea of AmbientGAN

Network architecture of AmbientGAN




Bora et al. 2018

Imaging process: $\mathbf{g} = H\mathbf{f} + \mathbf{n}, \mathbf{g} \in \mathbb{R}^N, \mathbf{f} \in \mathbb{R}^M, H \in \mathbb{R}^{N \times M} \mathbf{n} \in \mathbb{R}^N$

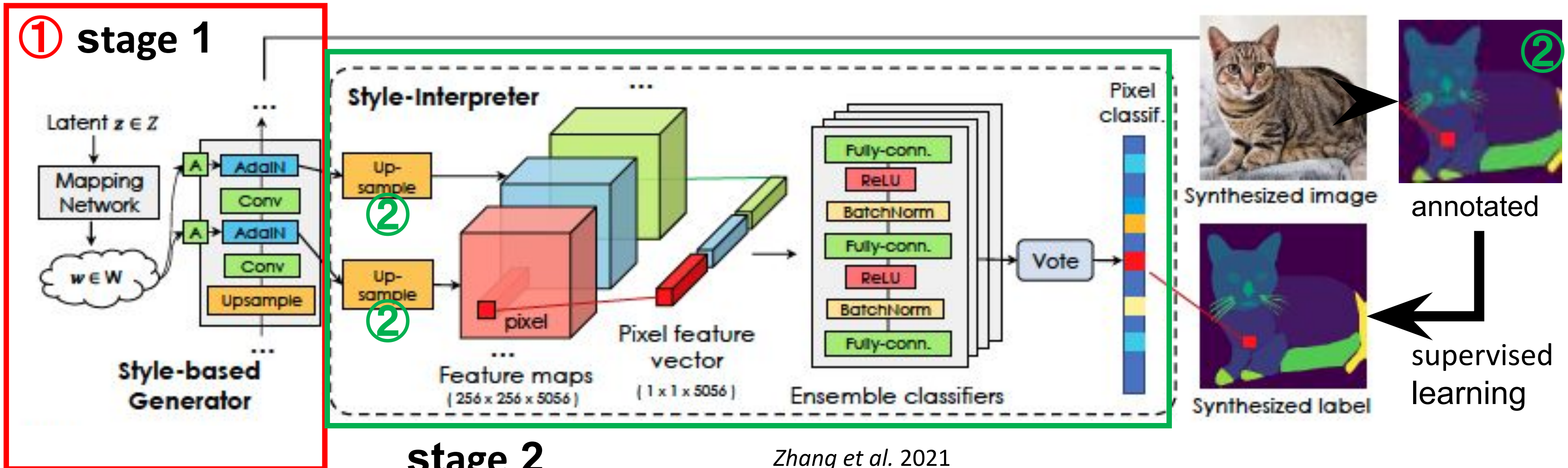
1. For G: map latent $\mathbf{z} \in \mathbb{R}^k$ to generated image $\hat{\mathbf{f}} \in \mathbb{R}^M$ $\quad \hat{\mathbf{f}} = G(\mathbf{z}, \Theta_G)$

2.Simulate measurement data $\hat{\mathbf{g}} \in \mathbb{R}^N$ via measurement operator $\mathcal{H}_n$ $\quad \hat{\mathbf{g}} = \mathcal{H}_n(\hat{\mathbf{f}})$

3.For D: distinguish experiment measurement $\mathbf{g} \in \mathbb{R}^N$ and simulated measurement $\hat{\mathbf{g}} \in \mathbb{R}^N$ by mapping $\mathbb{R}^N \to \mathbb{R}$

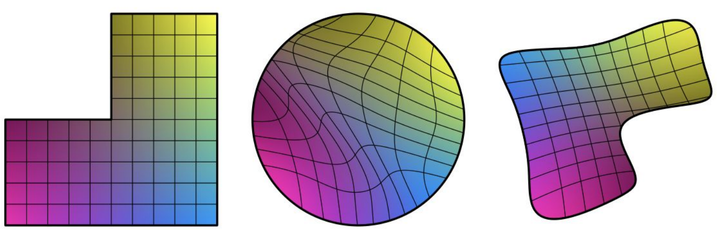
$$\min_{\Theta_G} \max_{\Theta_D} E_{\mathbf{g} \sim p_g}[l\left(D(\mathbf{g}; \Theta_D)\right)] + E_{\mathbf{z} \sim p_z}[l(1 - D\left(\hat{\mathbf{g}}; \Theta_D\right))],$$

# Idea of DatasetGAN




**stage 2**

*Zhang et al.* 2021



(a) Distribution of features in training set

(b) Mapping from $\mathcal{Z}$ to features

(c) Mapping from $\mathcal{W}$ to features

*Karras et al.* 2019

**Image generator: (FOM: FID)**

Learn style vector w: $\mathbf{w} = M(z, \Theta_M), \mathbb{R}^k \rightarrow \mathbb{R}^j$

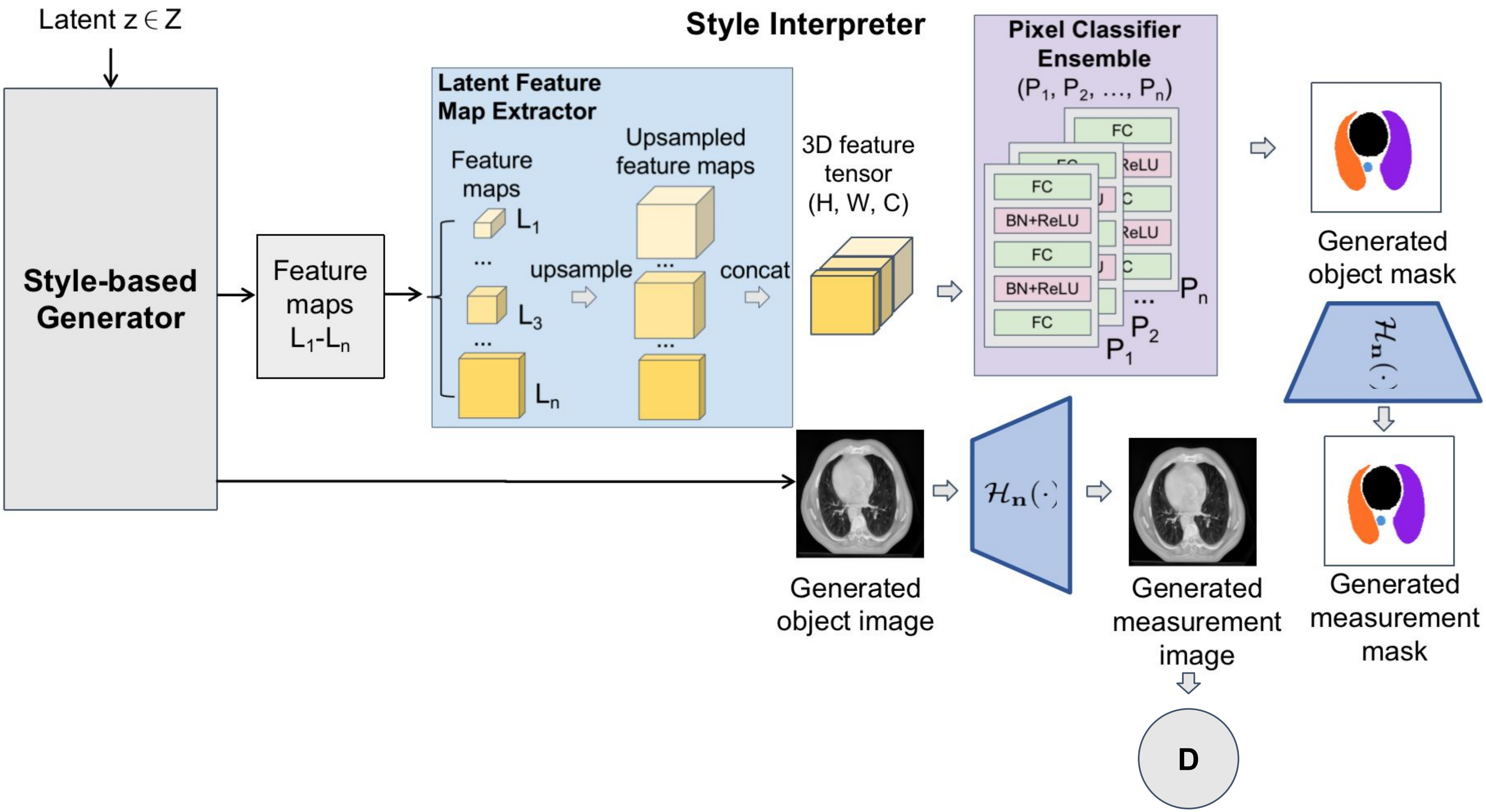
Map w to image g: $\hat{\mathbf{g}} = G(w, n, \Theta_G), \mathbb{R}^j \rightarrow \mathbb{R}^N$

**Segmentation generator: (FOM: CE)**

Extract intermediate features from trained G: $\hat{\mathbf{f}} = \{\hat{f}_1, \hat{f}_2, .., \hat{f}_n\}, \hat{f}_i \in \mathbb{R}^{N/2^i}$

Classify each pixel label c from pixel vector $P_i = C(\mathbf{f}_i, \Theta_C), \mathbb{R}^c \rightarrow \mathbb{R}$

# Advance DatasetGAN with AmbientGAN



# Replicate DatasetGAN on medical imaging

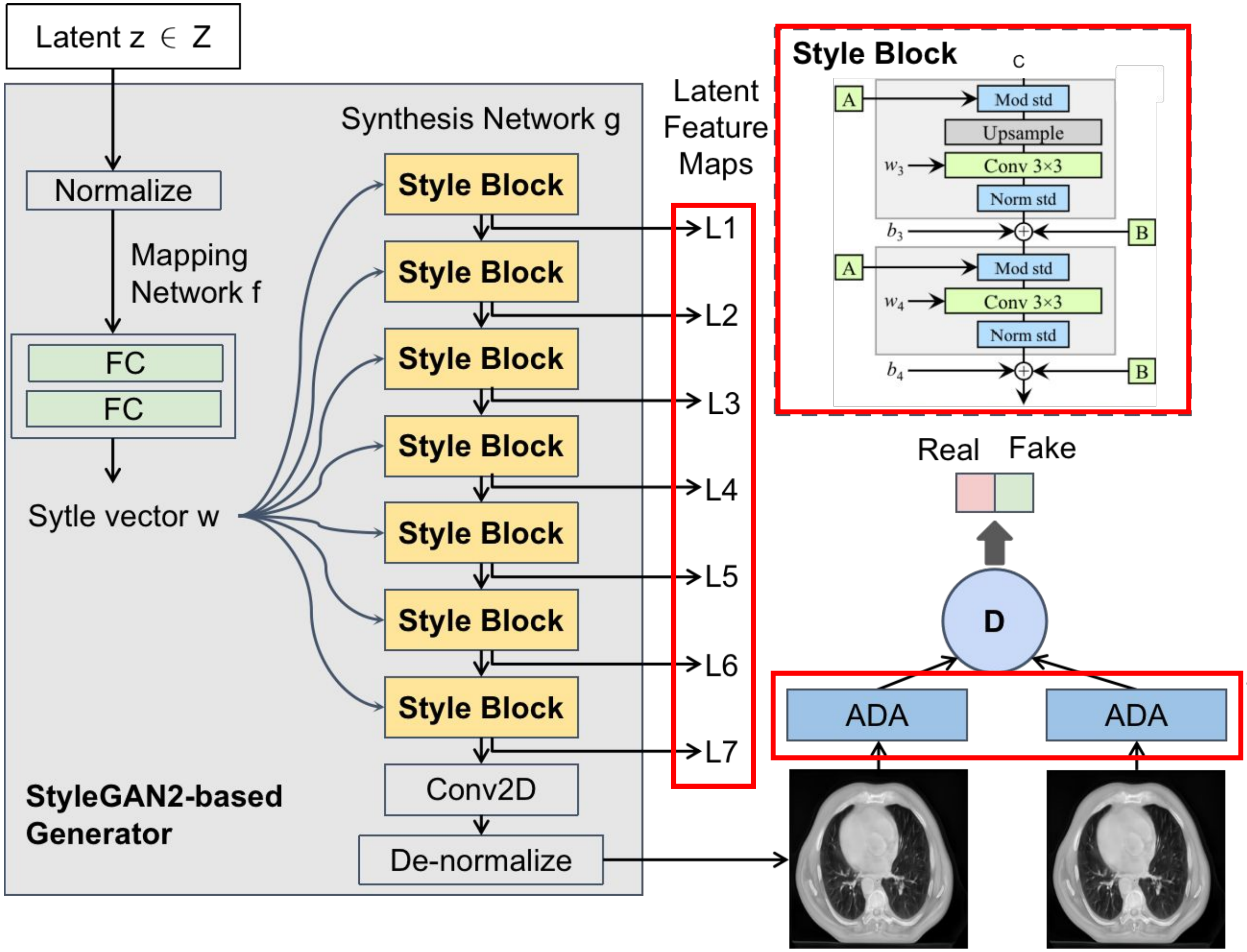
**Potential problems:**

1. DatasetGAN highly depends on StyleGAN generator.

2. Training a high-quality GAN generator usually needs $10^5$ to $10^6$ images to avoid overfitting on unseen data.

3. Current intermediate feature maps probably contain highly redundant information for decoding class label of pixel.

# Revised style-based generator of DatasetGAN




**3 revisions:**

1. use **StyleGAN2** instead of StyleGAN

2. use **adaptive discriminator augmentation** strategy[1] during training discriminator

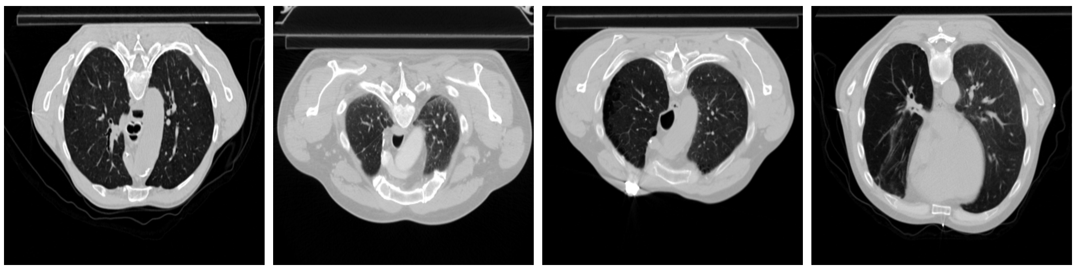
3. optimize latent feature map extraction to get from the output of style block rather than AdaIN layers.

1. *Karras, Tero et al.* "Training Generative Adversarial Networks with Limited Data." ArXiv abs/2006.06676 (2020): n. pag.

# Training Dataset

## 1. StyleGAN2 generator training dataset

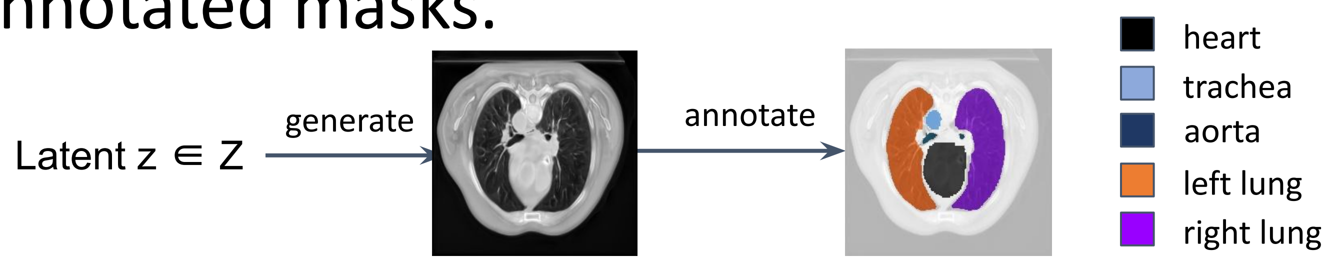
2377 SegTHOR chest CT images with image size as 256×256 pixels



Lambert, Zoé et al. "SegTHOR: Segmentation of Thoracic Organs at Risk in CT images." 2020 Tenth International Conference on Image Processing Theory, Tools and Applications (IPTA) (2020): 1-6.

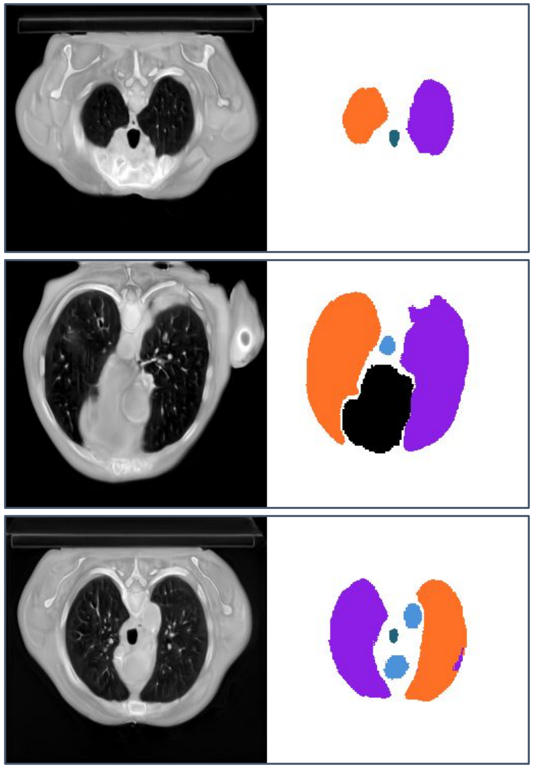
## 2. Style interpreter training data

N intermediate feature maps and corresponding annotated masks.

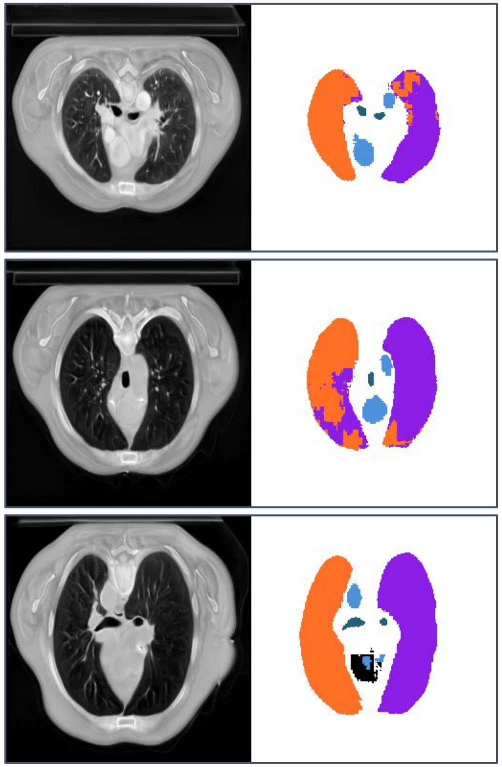


# Example of the synthesized segmented images

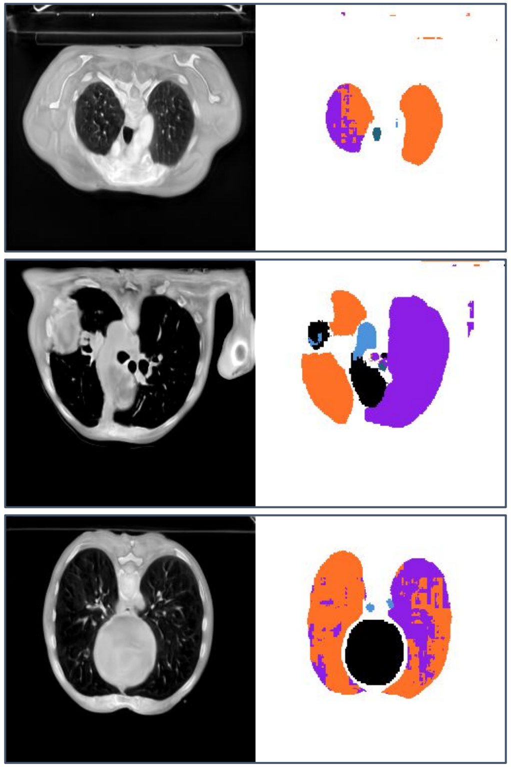
Good cases: few pixels are misclassified (**< 1%**)



Partial-bad cases: small percentage of pixels are misclassified (**1% - 25%**)



Bad cases: large percentage of pixels are misclassified (**>25%**)



# Effect of size of style interpreter training data

Use N=30, 50,100 annotated images when training style-interpreter.

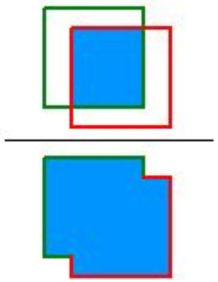
| Training images | N=30 | N=50 | N=100 |
|---|---|---|---|
| # good case | 74 | 76 | 80 |
| # partial-bad case | 15 | 12 | 11 |
| # bad case | 11 | 12 | 9 |

1. Generated data contains noise.
2. It's a tradeoff to use a proper number of annotated images.

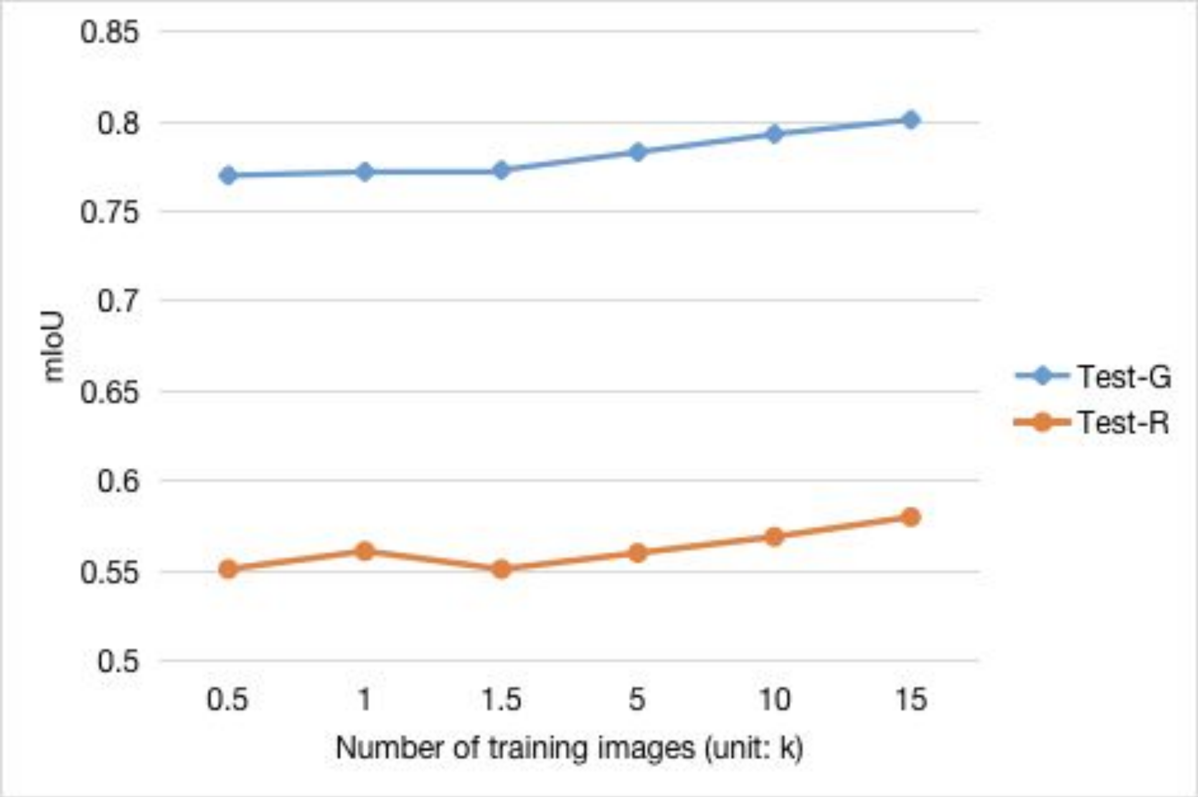
# Performance of a pre-defined image segmentation method using generated data

- Segmentation network: DeepLab-V3
- Training data:
  - DatasetGAN generated images
- Loss: Cross-entropy
- Testing data:
  - **Test-G: 100** DatasetGAN generated images
  - **Test-R: 100** real SegTHOR images and real masks.
- Testing method: mean IoU with 5-fold cross-validatic

$$IOU = \frac{\text{area of overlap}}{\text{area of union}} =$$



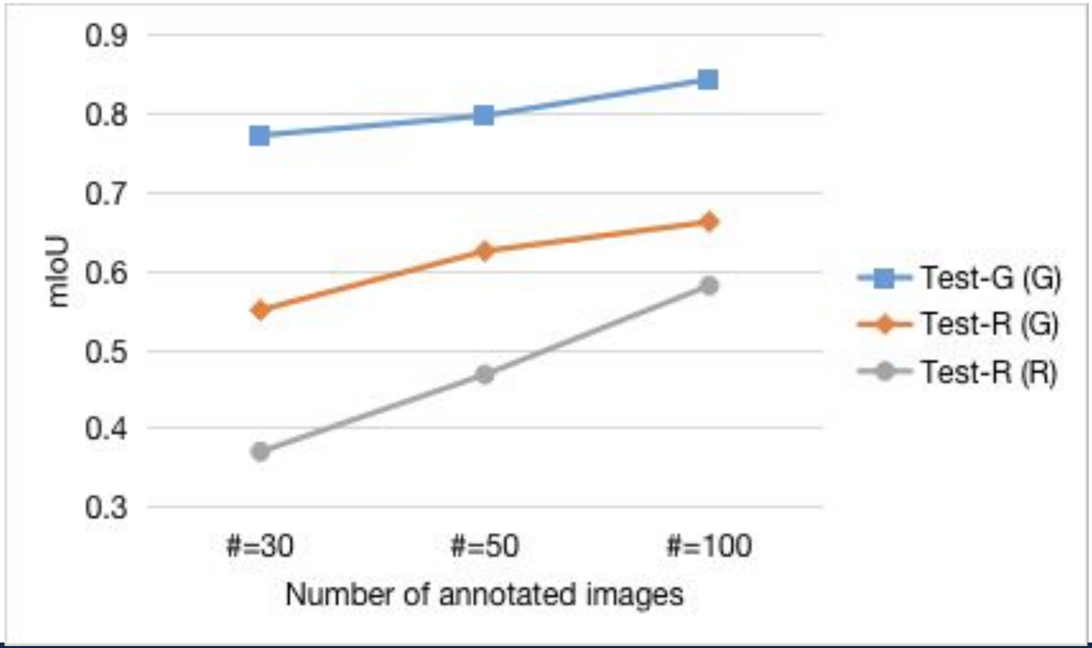
# Effect of segmentation training data size




1. Performance gap exists.
2. Small datasets still comprehensively represent target distribution, even biased.

# Using more annotated images improves performance

1. train style interpreter with N=30, 50, 100 annotated images.
2. train DeepLab-v3 with 1500 generated images and test on:
   a) Test-G (Test-G(G))
   b) Test-R (Test-R(G))
3. compared to DeepLab-v3 on small real dataset (30, 50, 100) and test on Test-R (Test-R(R))



# Key takeaways

1. DatasetGAN shows high potential to be applied in medical imaging for segmented data synthesis. It also indicates the possibility to be combined with AmbientGAN for learning SOMs for objective segmented image generation.

2. Weakness: Generated segmented data contain still certain noise and are biased from the target dataset.

# Future work

1. Employ AmbientGAN's measurement operator process with DatasetGAN.

2. Further investigate the DatasetGAN for segmentation tasks, like:
   a. How does the generated noisy data affect the performance of following segmentation tasks?
   b. Whether the method could be generalized to other datasets? Like MRI or phantom data?

3. ....

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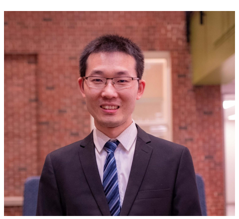
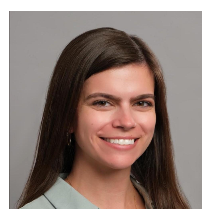
  - CCIL Seed grant



- Collaborators:
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  - Wang Group, UIC,
  - Ruan Group, Univ. of Rouen, France
  - Lam Group, UIUC
  - Song Group, UIUC
  - Radiation Oncology Department, WashU
  - …




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