Probabilistic Recovery of Missing Images in Contrast-Enhanced CT

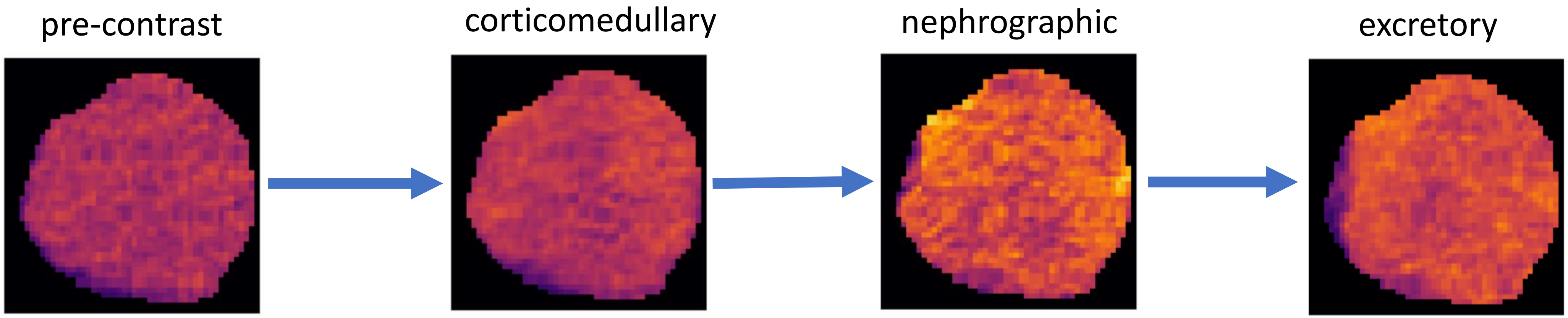
Dhruv Patel, Chiao-chih (George) Hsu, Bino Varghese, Steven Cen, Darryl Hwang, Inderbir Gill, Vinay Duddalwar, Assad Oberai

University of Southern California

Contrast-enhanced Computed Tomography

- Most effective and preferred imaging technique for detection and diagnosis of renal cancer.

- Intravenous contrast agent is injected into the subject and then CT images are taken during four distinct time points - resulting in four images:



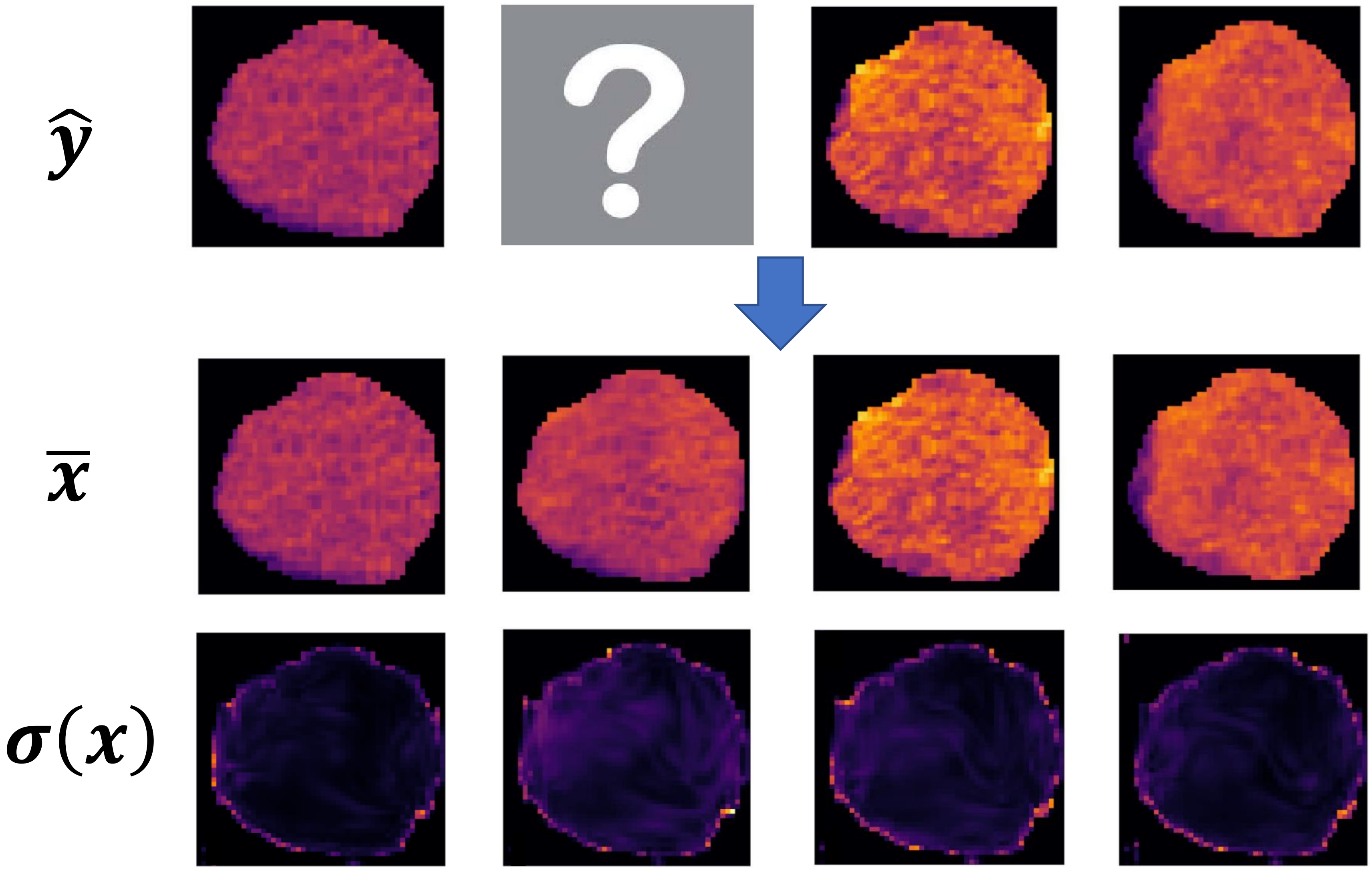
- Pattern of enhancement is an important indicator of malignancy of tumor.

Practical challenges with CECT

- Access to all four images crucial for diagnosis and treatment planning.
- Missing data
    - change in imaging equipment and/or related protocols.
    - deteriorating patient health
    - data management and logistic issues
- Corrupt data
    - low resolution imaging
    - inaccurate imaging technique
    - image-post processing

Goal: Recover missing or corrupt image(s) in a CECT sequence and also quantify corresponding uncertainty.

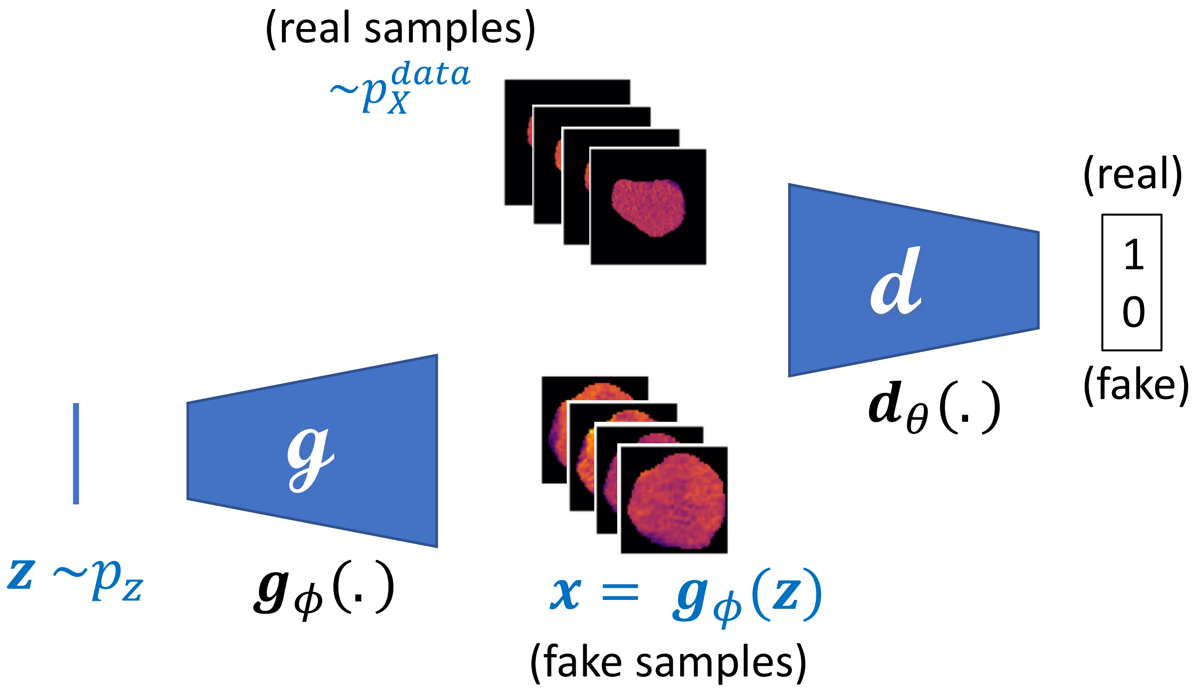
Image recovery



- Complex and High dimensional data
- Presence of fine-scale feature

Probabilistic image imputation

Key idea: Use the distribution learned by GAN as a prior in Bayesian inference and reformulate the posterior inference problem in the low-dimensional latent space of the GAN.



Step 1: Train a GAN using a set $\mathbb{S}$ containing 4-phased CECT images:

$$\mathbb{S} := \{x_i\}_{i=1}^{N}$$

where $\boldsymbol{x_i} \in \mathbb{R}^{n_x \times n_y \times 4}$

$$p^{prior}(\boldsymbol{x}) = p(\boldsymbol{g}(\boldsymbol{z})) \approx p^{data}(\boldsymbol{x}).$$

Probabilistic image imputation

Step 2: Given a CECT sequence with missing/corrupt image(s), $\hat{\boldsymbol{y}}$

compute the required statistics w.r.t. posterior $p^{post}(x|\hat{y})$.

- From the weak convergence of GAN[1]...

$$\mathop{\mathbb{E}}_{\boldsymbol{x}\sim p_X^{post}(\boldsymbol{x}|\hat{\boldsymbol{y}})}[s(\boldsymbol{x})] = \mathop{\mathbb{E}}_{\boldsymbol{z}\sim p_Z^{post}(\boldsymbol{z}|\hat{\boldsymbol{y}})}[s(\boldsymbol{g}(\boldsymbol{z}))]$$

Probe the posterior (using MCMC) to get desired quantity of interest.

1: Patel et al. (2020): GAN-based priors for quantifying uncertainty.

Learning CECT specific fine-scale features

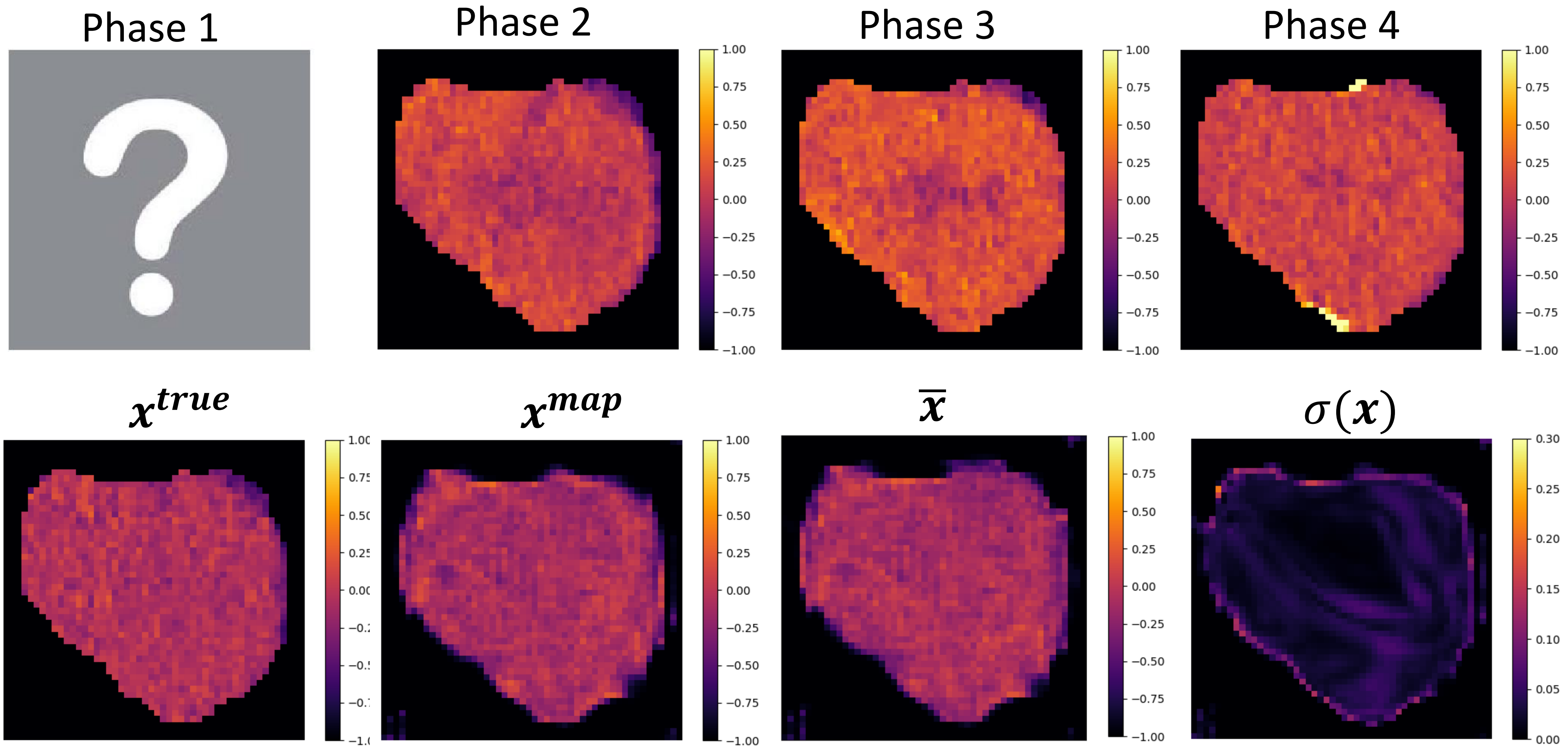
Adversarial loss alone will not ensure capturing fine-scale features unique to CECT imaging.

$$
\begin{aligned}
L &= L_{adv} + L_{style} \\
&= \underbrace{\min_{\boldsymbol{\phi}} \max_{\boldsymbol{\theta}} \mathop{\mathbb{E}}_{\boldsymbol{x} \sim p_X} [\boldsymbol{d}(\boldsymbol{x}; \boldsymbol{\theta})] + \mathop{\mathbb{E}}_{\boldsymbol{z} \sim p_Z} [1 - \boldsymbol{d}(\boldsymbol{g}(\boldsymbol{z}; \boldsymbol{\phi}); \boldsymbol{\theta})]}_{L_{adv}} \\
&+ \underbrace{\sum_{l=1}^{n_{layers}} ||\mathcal{G}^l(\boldsymbol{x}_{\boldsymbol{real}}) - \mathcal{G}(\boldsymbol{x}_{\boldsymbol{fake}})||^2}_{L_{style}}
\end{aligned}
$$

where, $\mathcal{G}^l(\boldsymbol{x}) = \boldsymbol{F}^{\boldsymbol{T}}(\boldsymbol{x}; \boldsymbol{\theta}) \boldsymbol{F}(\boldsymbol{x}; \boldsymbol{\theta})$

Discriminator performs the dual role of classifier and feature extractor.

Results on patient data



Summary

- Algorithm for recovering missing images in CECT sequence with quantified uncertainty estimates;
- Discriminator-driven style loss helps capture fine-scale structure;
- The proposed GAN prior framework can flexibly be extended to variety of medical imaging applications.

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THANK
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