Imperial College London

Klinikum rechts der Isar
Technische Universität München

Learning robust segmentations for cardiac MRI

Daniel Rueckert, FREng, FMedSci, FIEEE

Alexander von Humboldt Professor of AI for Medicine and Healthcare
Faculty of Medicine and Informatics, TU Munich, Germany

and

Biomedical Image Analysis Group
Department of Computing, Imperial College London, UK

No conflicts of interests

AI/ML in Medicine

smartheart


23,216 views | Apr 30, 2017, 12:10pm

AI In Medicine: Rise Of The Machines

Paul Hsieh Contributor

I cover health care and economics from a free-market perspective.

THE NEW YORKER

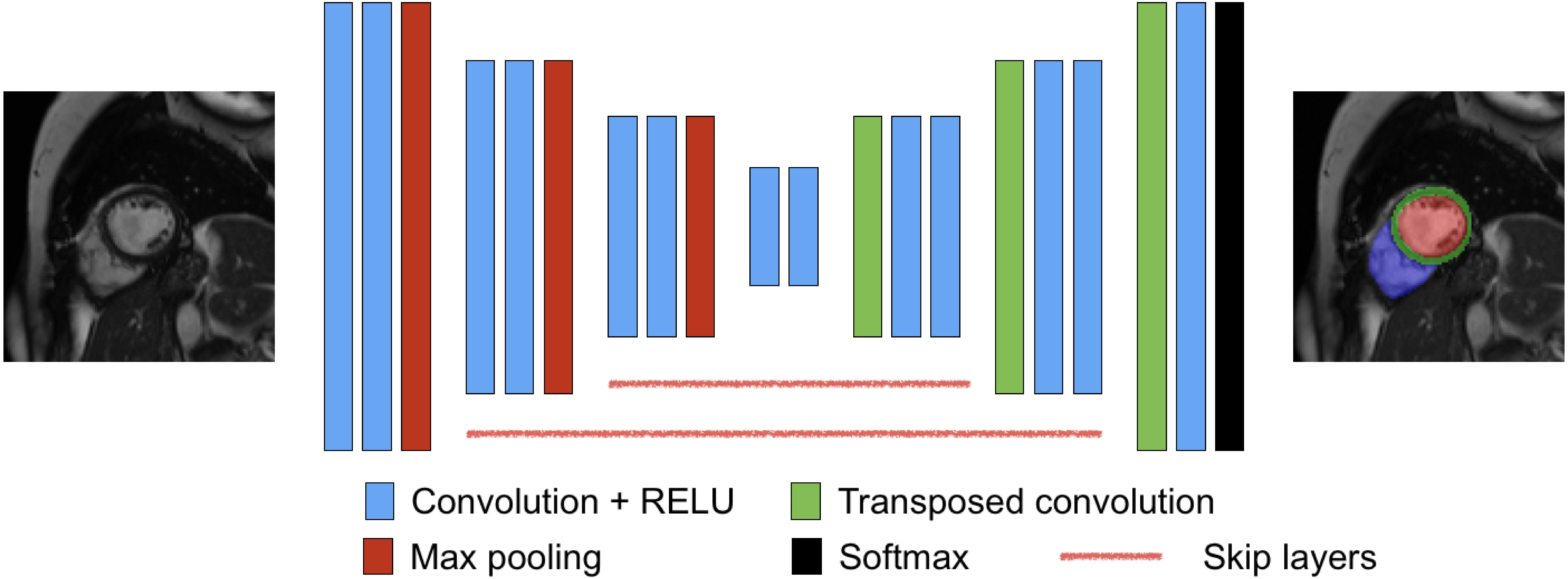
APRIL 3, 2017 ISSUE

A.I. VERSUS M.D.

What happens when diagnosis is automated?

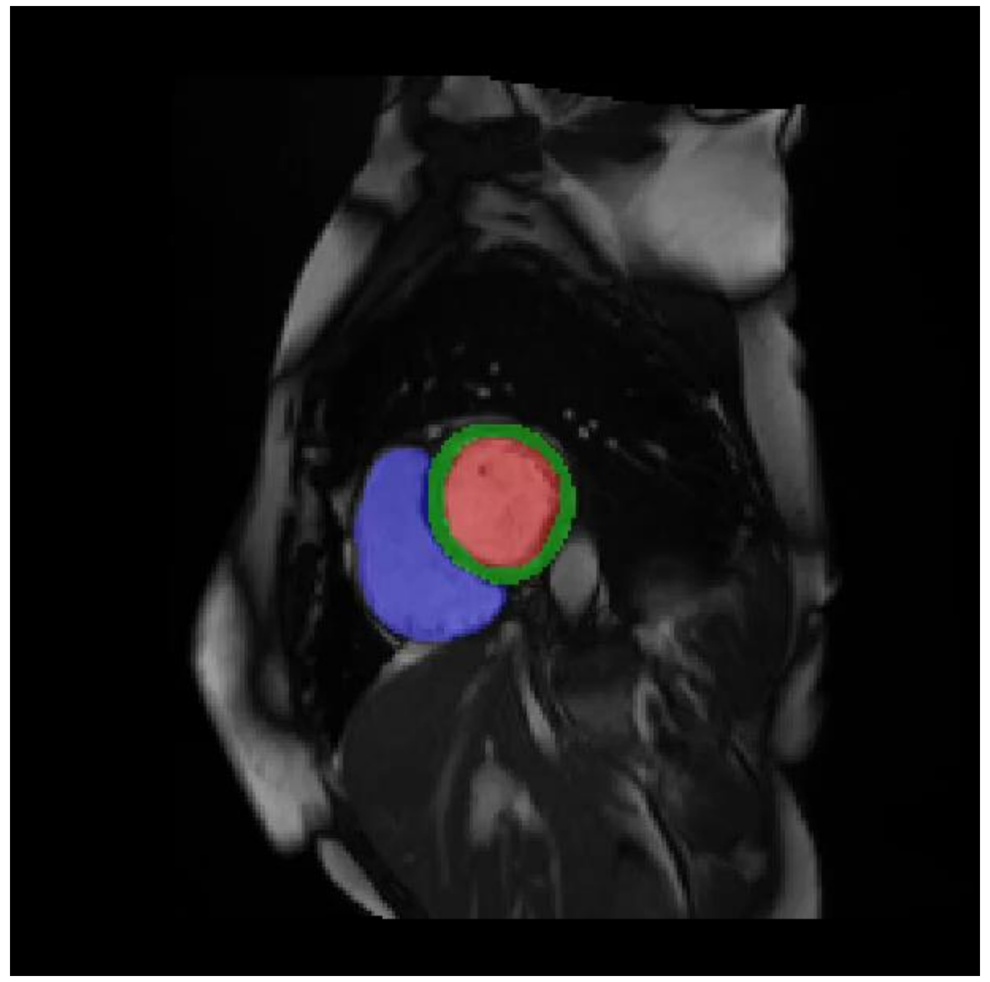
By Siddhartha Mukherjee

Deep learning for image segmentation

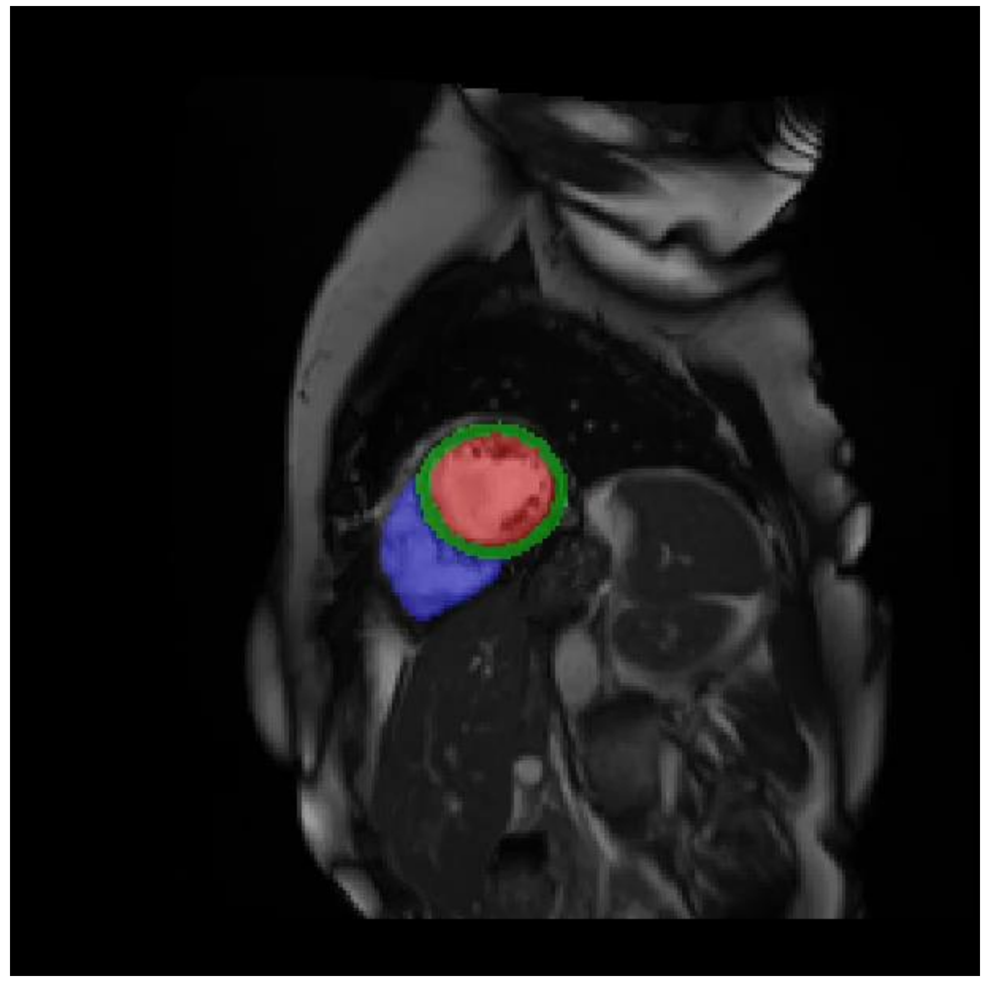


Bai et al., JCMR 2018

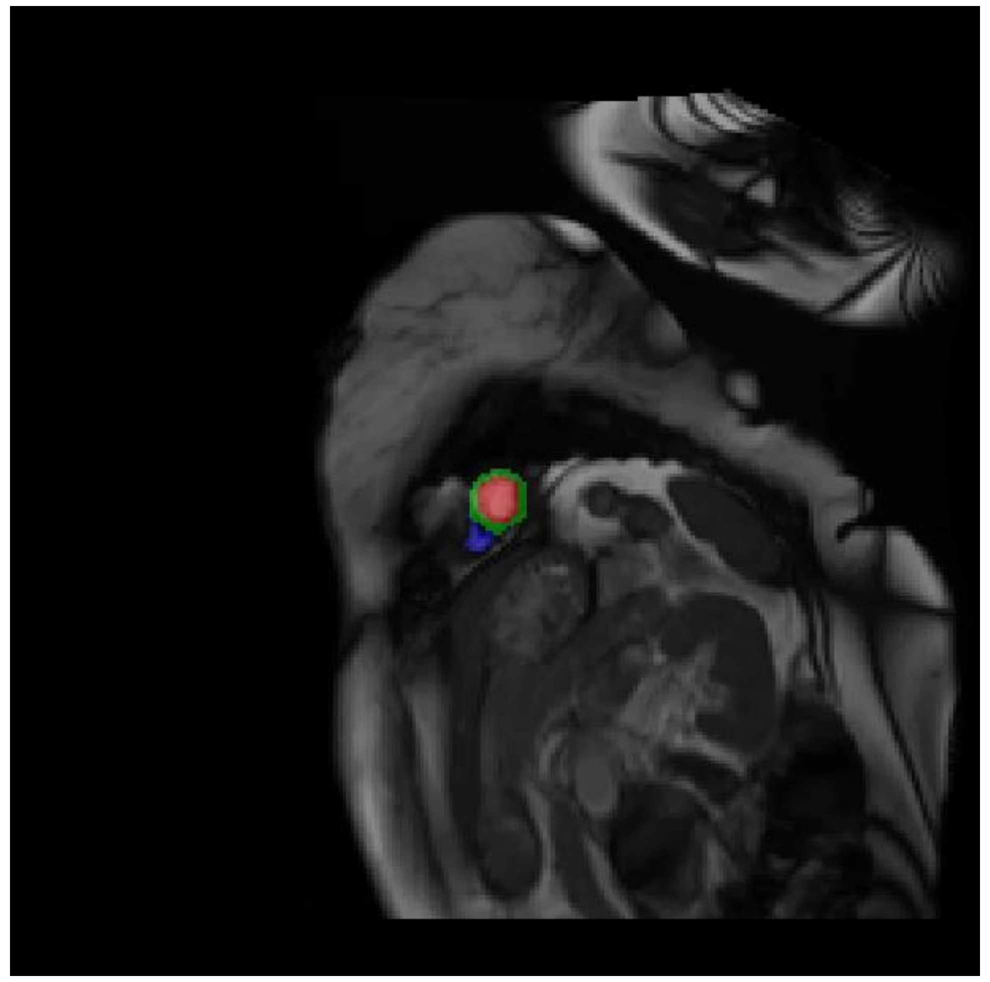
Deep learning for image segmentation



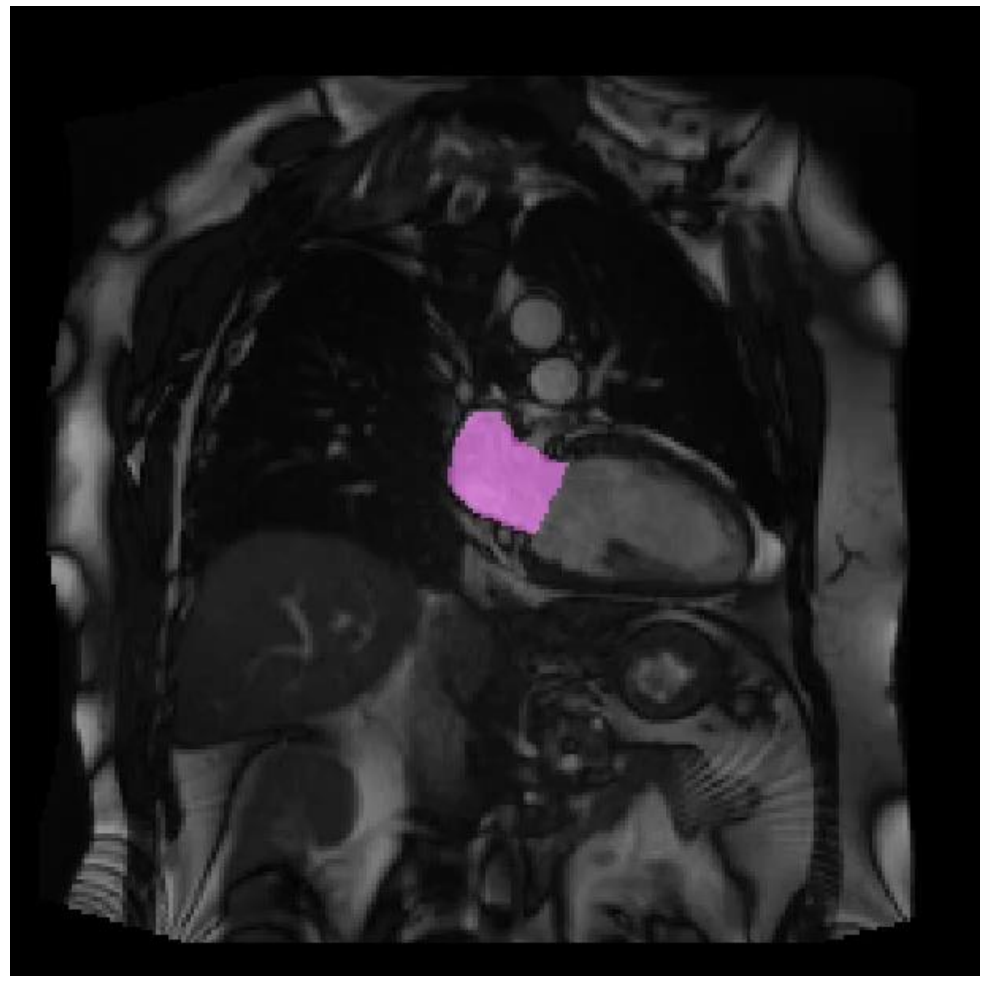
SA, basal



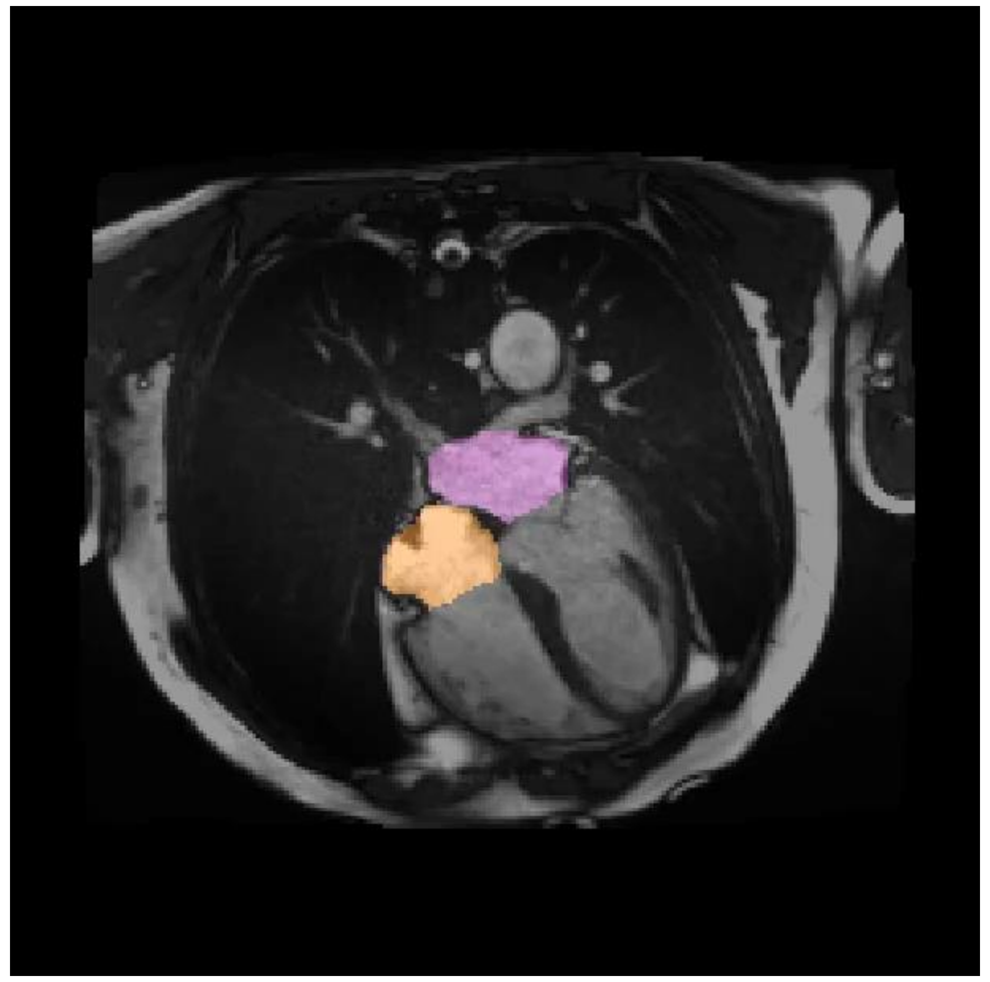
SA, mid-ventricular



SA, apical



LA, 2 chamber



LA, 4 chamber

Bai et al., JCMR 2018

Evaluation of segmentation accuracy
Comparison to expert observers

smartheart

(a) Absolute difference

	Auto vs Man (n = 600)	O1 vs O2 (n = 50)	O2 vs O3 (n = 50)	O3 vs O1 (n = 50)
LVEDV (mL)	$6.1_{\pm 5.3}$	$6.1_{\pm 4.4}$	$8.8_{\pm 4.8}$	[illegible]
LVESV (mL)	$5.3_{\pm 4.9}$	$4.1_{\pm 4.2}$	[illegible]	[illegible]
LVM (gram)	$6.9_{\pm 5.5}$	$4.2_{\pm 3.2}$	[illegible]	[illegible]
RVEDV (mL)	$8.5_{\pm 7.1}$	[illegible]	[illegible]	$8.7_{\pm 5.8}$
RVESV (mL)	$7.2_{\pm 6.8}$	[illegible]	[illegible]	$11.7_{\pm 6.9}$

	[illegible]	O1 vs O2 (n = 50)	O2 vs O3 (n = 50)	O3 vs O1 (n = 50)
[illegible]	[illegible]	$4.2_{\pm 3.1}$	$6.3_{\pm 3.3}$	$3.4_{\pm 2.2}$
[illegible]	$9.5_{\pm 9.5}$	$6.8_{\pm 7.5}$	$12.5_{\pm 8.5}$	$11.7_{\pm 5.1}$
[illegible]	$8.3_{\pm 7.6}$	$4.4_{\pm 3.3}$	$6.0_{\pm 3.7}$	$6.7_{\pm 4.6}$
[illegible] (%)	$5.6_{\pm 4.6}$	$8.0_{\pm 5.0}$	$4.2_{\pm 3.1}$	$5.7_{\pm 3.6}$
RVESV (%)	$11.8_{\pm 12.2}$	$30.6_{\pm 15.5}$	$10.9_{\pm 8.3}$	$16.9_{\pm 9.2}$

Computer performs as well as different expert observers

Automated

Manual

W. Bai et al., JCMR 2018

AI/ML in Medicine

smartheart

MIT Technology Review

Artificial intelligence / Machine learning

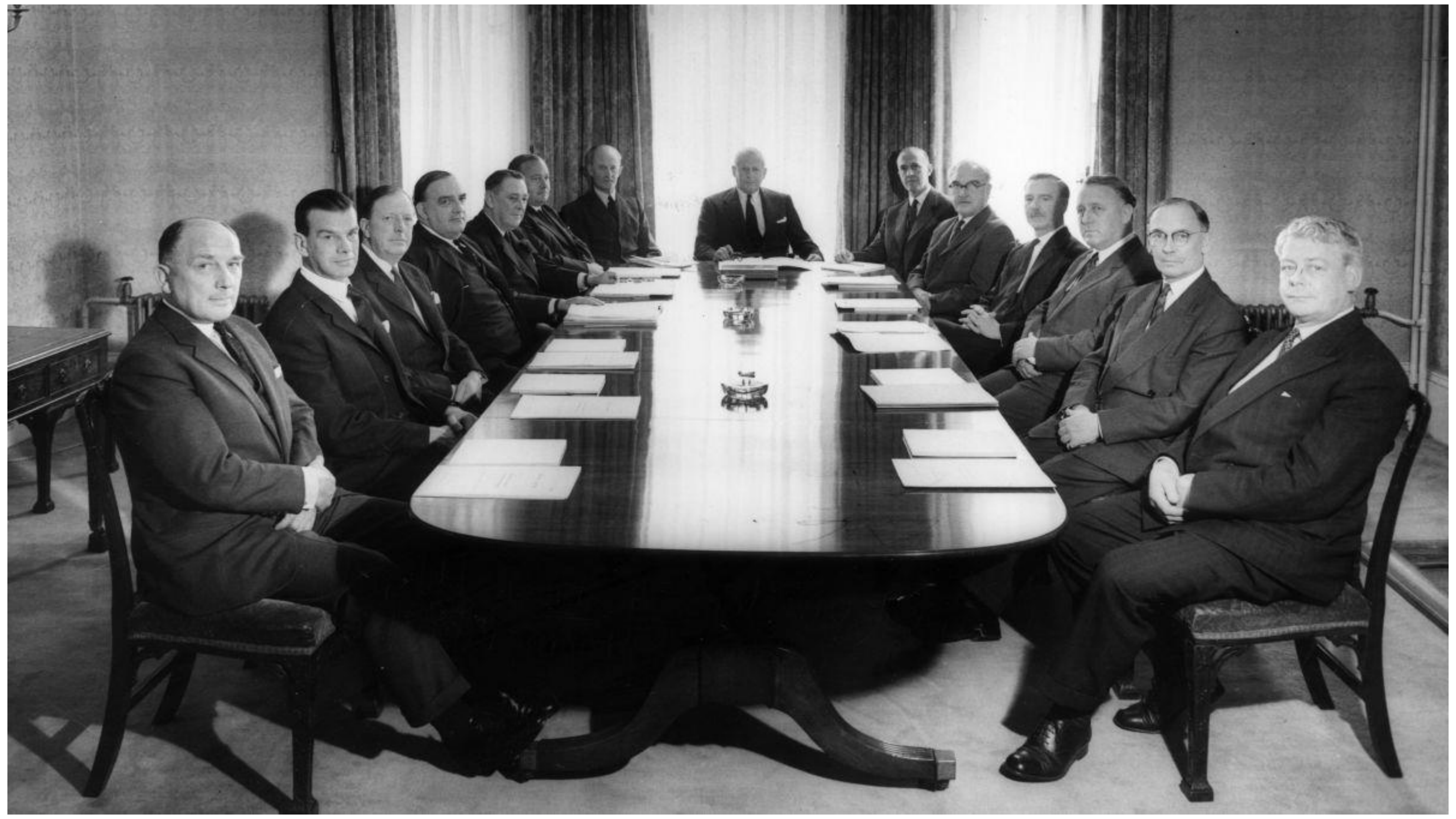
Hundreds of AI tools have been built to catch covid. None of them helped.

Some have been used in hospitals, despite not being properly tested. But the pandemic could help make medical AI better.

by **Will Douglas Heaven**

July 30, 2021

Domain shift: Population bias



EBioMedicine 67 (2021) 103358

Contents lists available at ScienceDirect

EBioMedicine

journal homepage: www.elsevier.com/locate/ebiom

ELSEVIER

Review

Ensuring that biomedical AI benefits diverse populations

James Zou[a], Londa Schiebinger[b,*]

[a] Department of Biomedical Data Science, Stanford University, United States
[b] History of Science, Stanford University, United States

RESEARCH ARTICLE

ECONOMICS

Dissecting racial bias in an algorithm used to manage the health of populations

Ziad Obermeyer[1,2*], Brian Powers[3], Christine Vogeli[4], Sendhil Mullainathan[5*†]

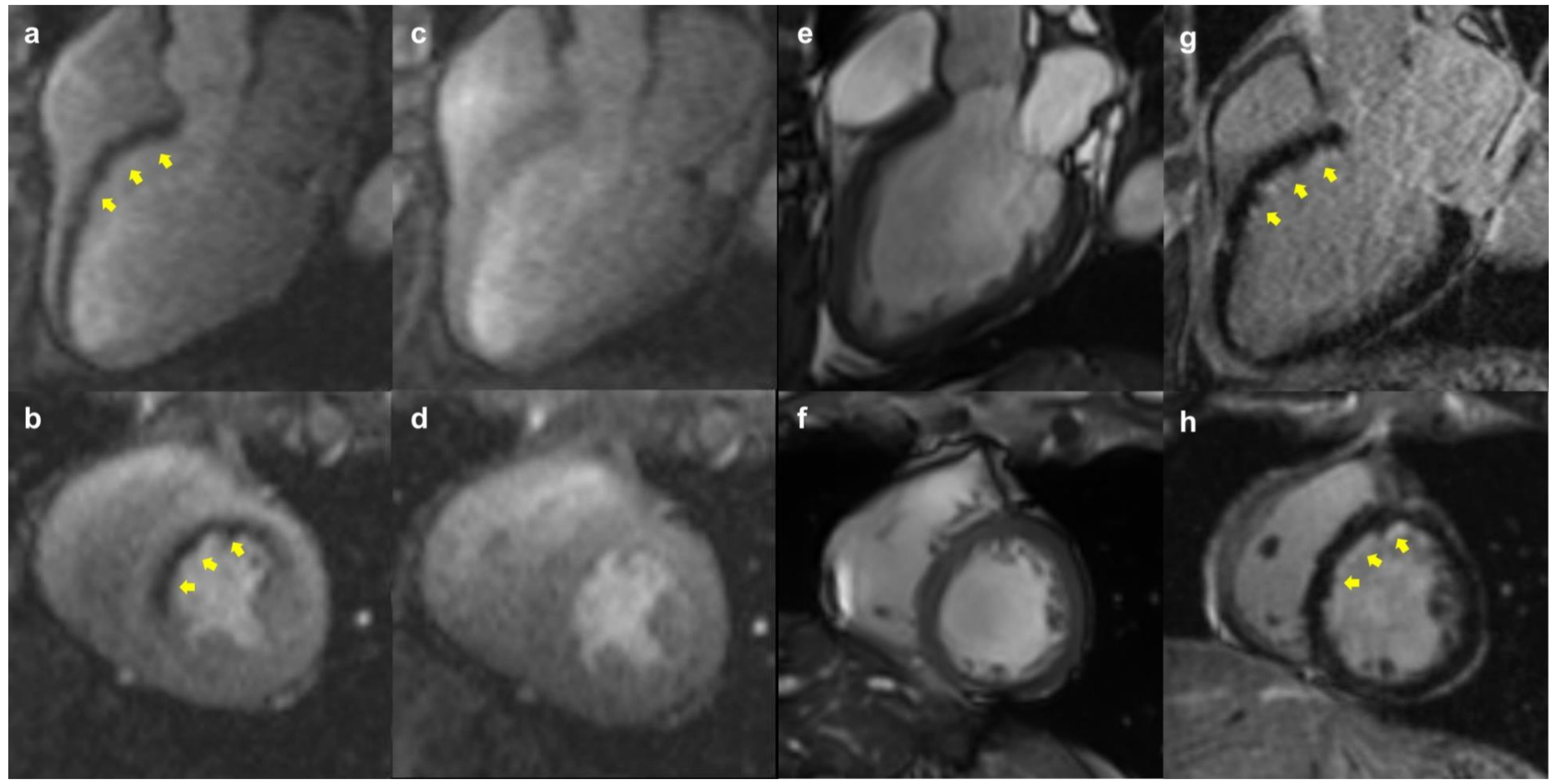
Domain shift: Pathologies

Variation during training

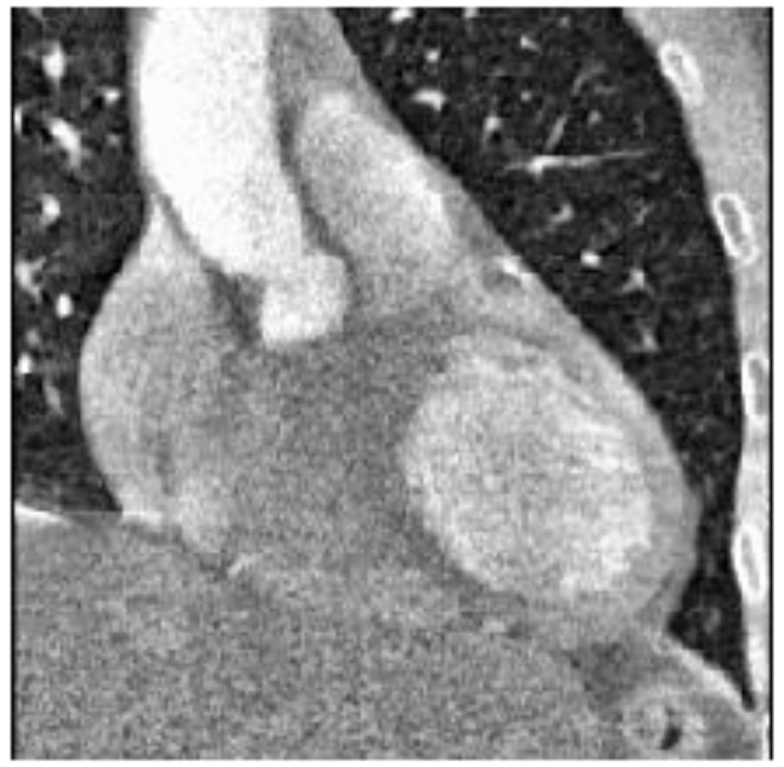
Variation during deployment

Domain shift: Acquisition variations

Different hardware



Stress Rest Cine LGE



CT

MR

Domain shift: What is the problem?

Source (S)

Domain: $D_S = \{\mathcal{X}_S, P(X_S)\}$

Task: $T_S = \{\mathcal{Y}_S, f'_S : \mathcal{X}_S \mapsto \mathcal{Y}_S\}$

Given: (X_S, Y_S)

$X_S = \{x_{S1}, \ldots, x_{Sn}\}, x_{Si} \in \mathcal{X}_S$

$Y_S = \{y_{S1}, \ldots, y_{Sn}\}, y_{Si} \in \mathcal{Y}_S$

Learn: $f_S \approx f'_S$

$f_S(x) \approx P_S(y|x)$

Target (T)

Domain: $D_T = \{\mathcal{X}_T, P(X$

Task: $T_T = \{\mathcal{Y}_T, f'$

<u>Here:</u> $\mathcal{Y}_T = \mathcal{Y}$

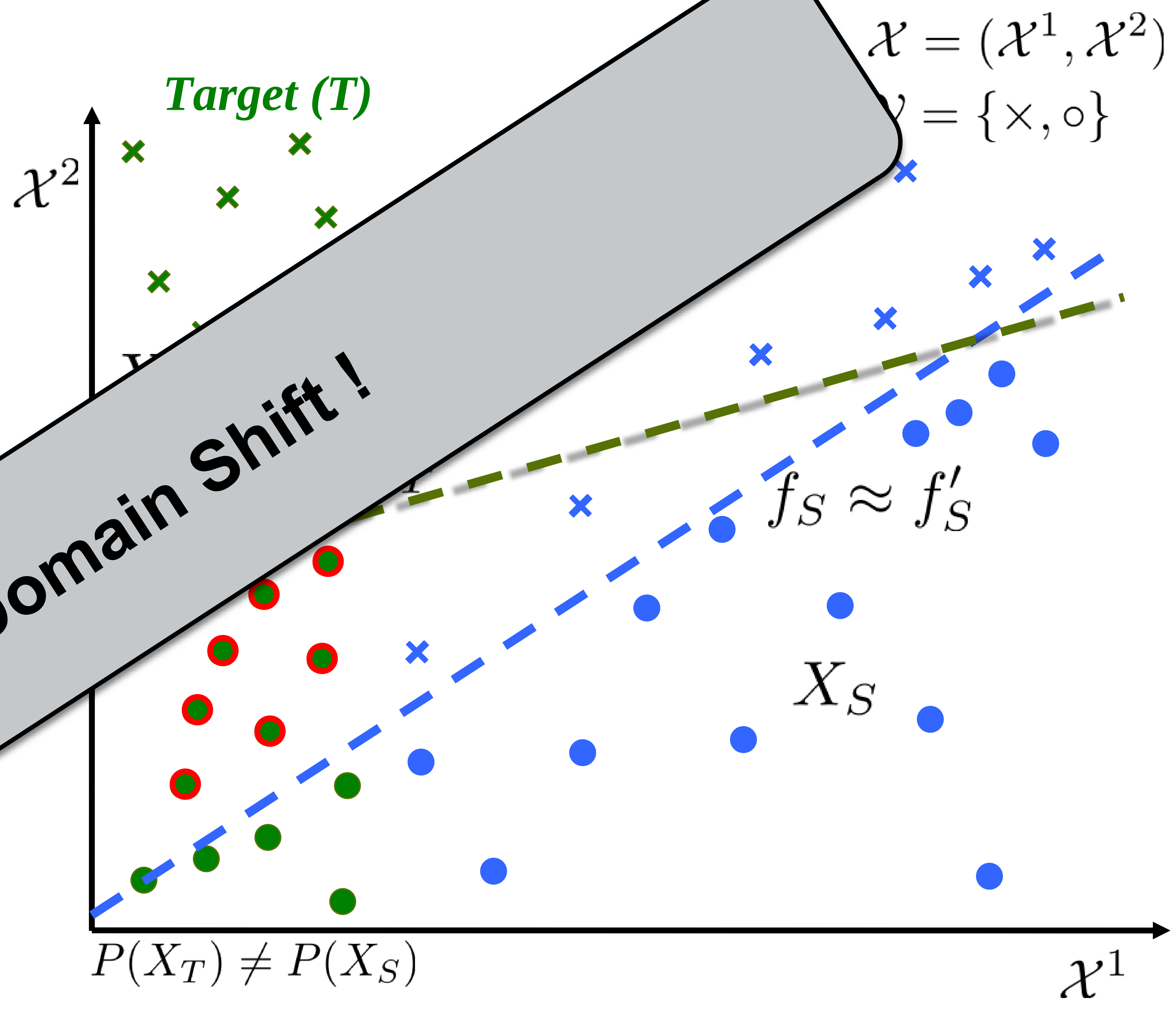
Domain Shift:

$P(X$

$P_T(y|x$ $|x)$

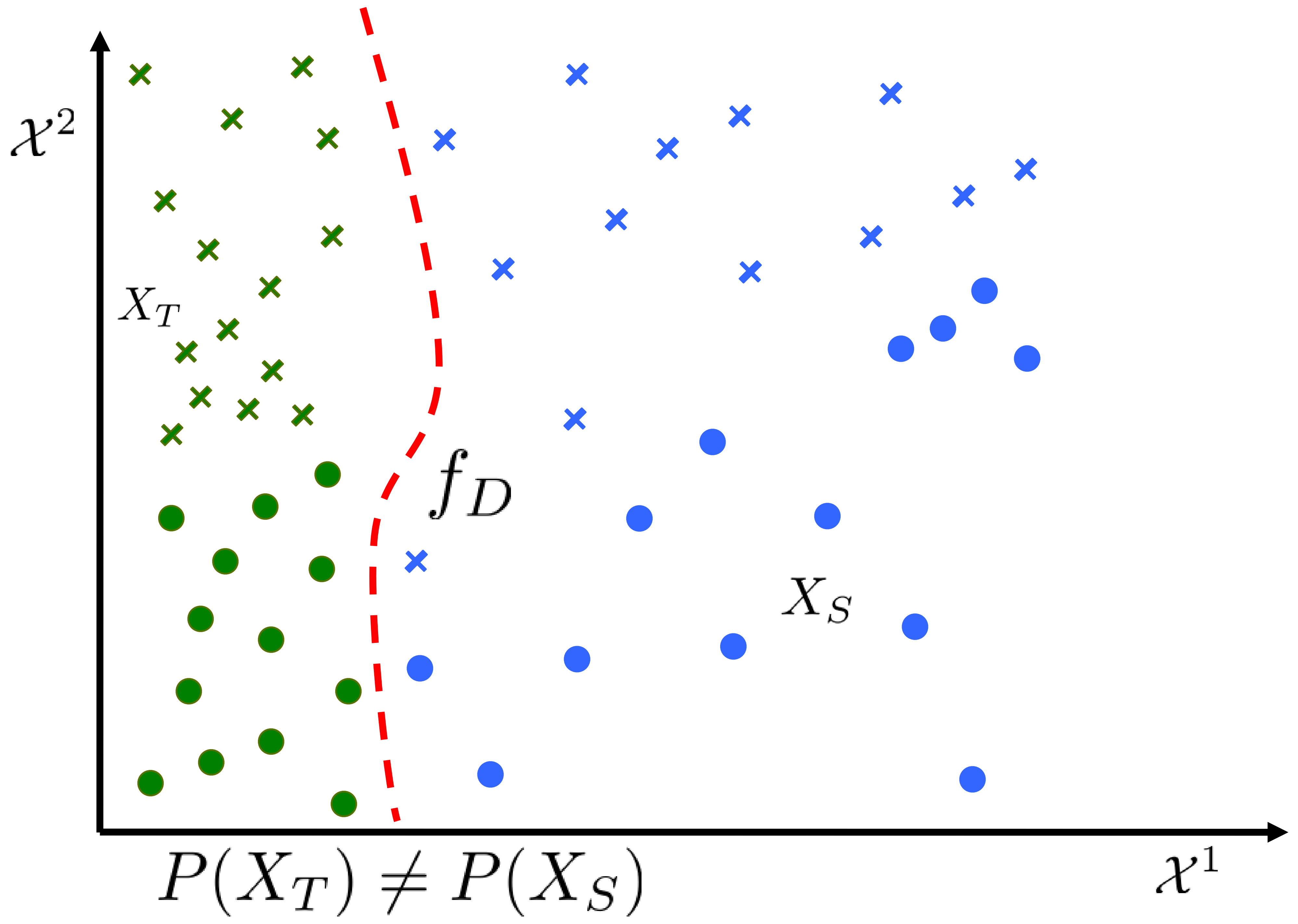
$f'_T \neq f'_S$

Domain Shift !

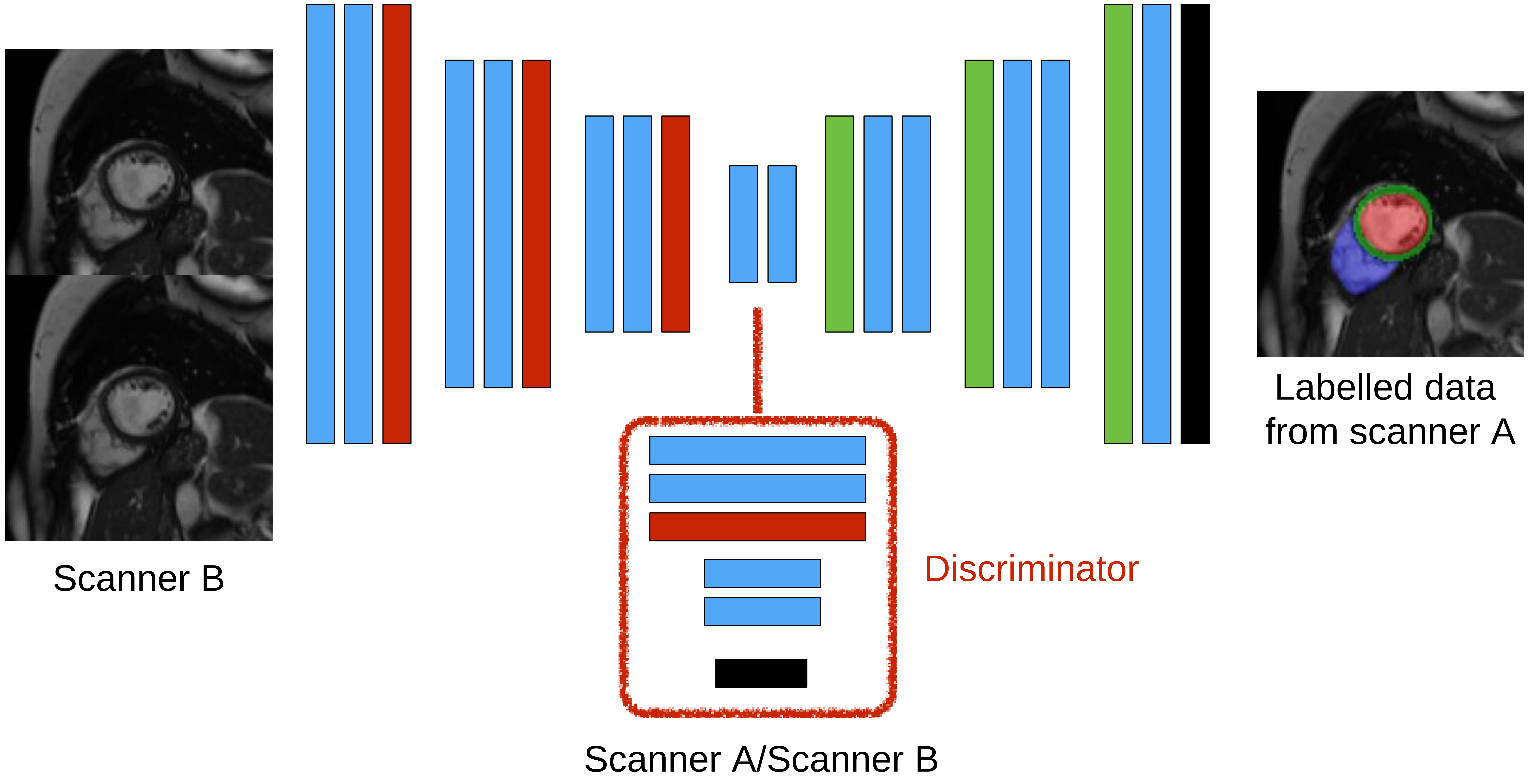


Domain shift: Learning invariant features using adversarial learning

- Learn a domain classifier f_D



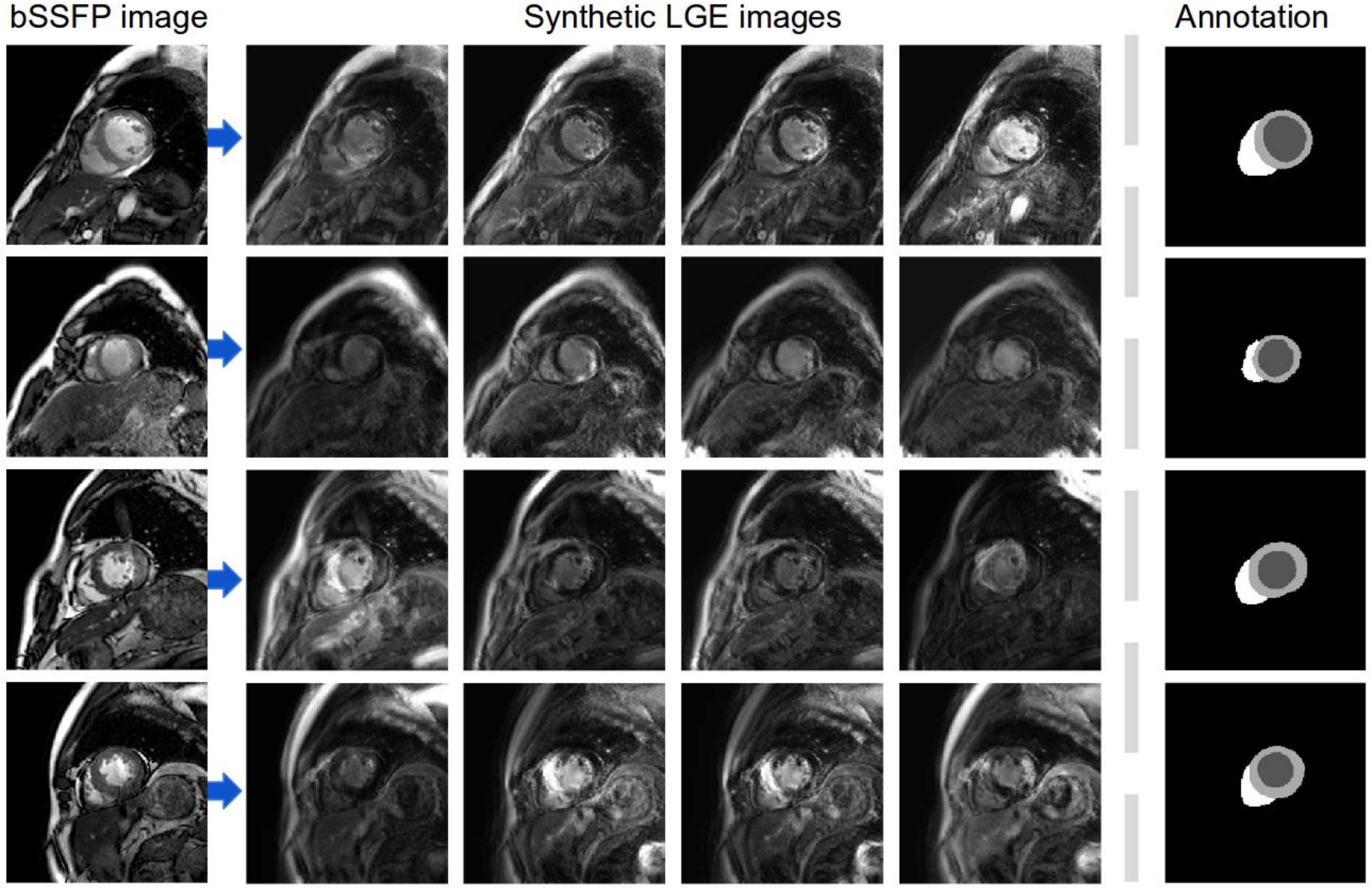
Domain shift: Learning invariant features using adversarial learning



K. Kamnitsas et al. IPMI 2017, arXiv:1612.08894

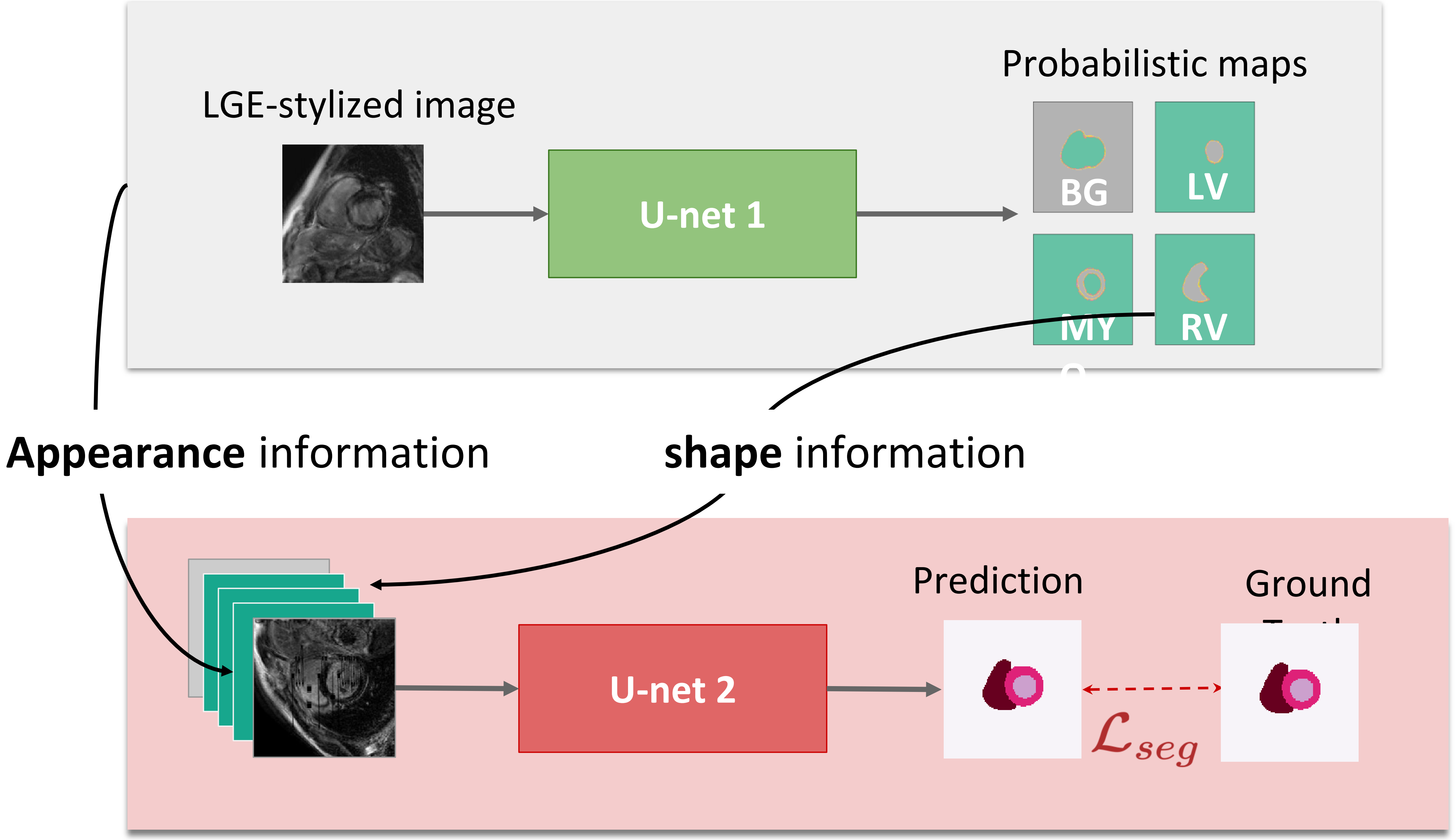
Domain shift: Unsupervised multi-modal style transfer

(Winner of the MS-CMR Segmentation Challenge)



1. Learn an image style translator to translate labelled bSSFP images to be LGE-like images

At training time, only unpaired bSSFP and LGE images are required.

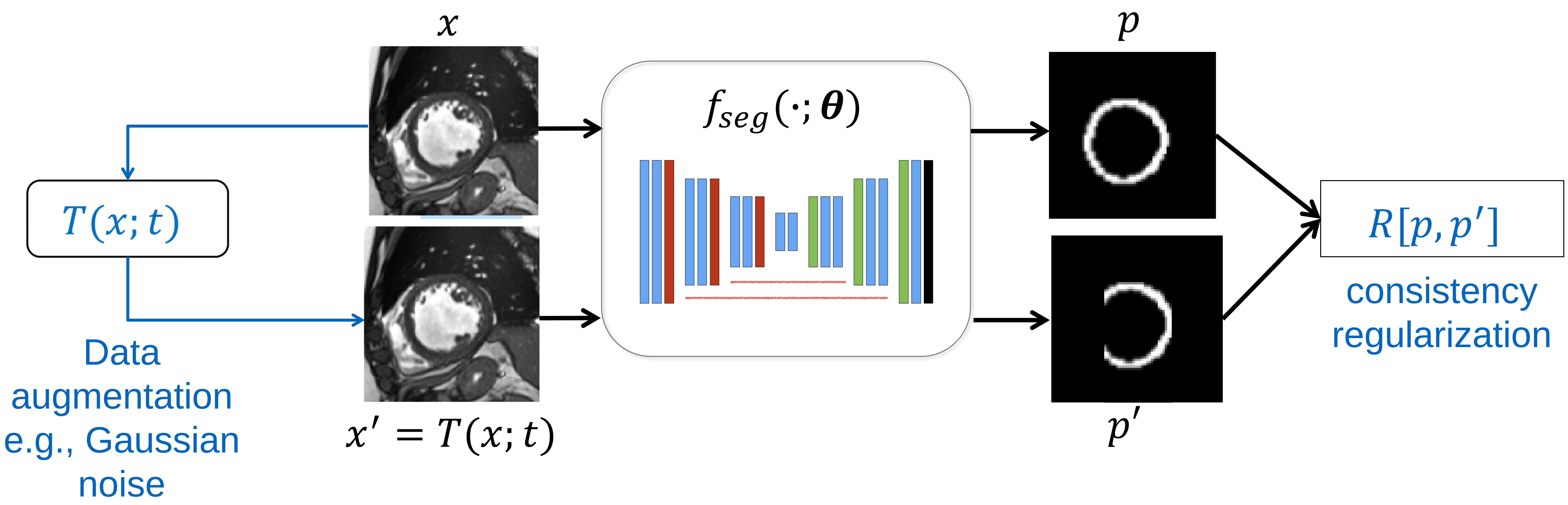


2. Training a cascaded LGE image segmentation network with synthetic images

C. Chen et al., "Unsupervised multi-modal style transfer for cardiac MR segmentation ," in *STACOM'19*

Enforce consistency for domain shift

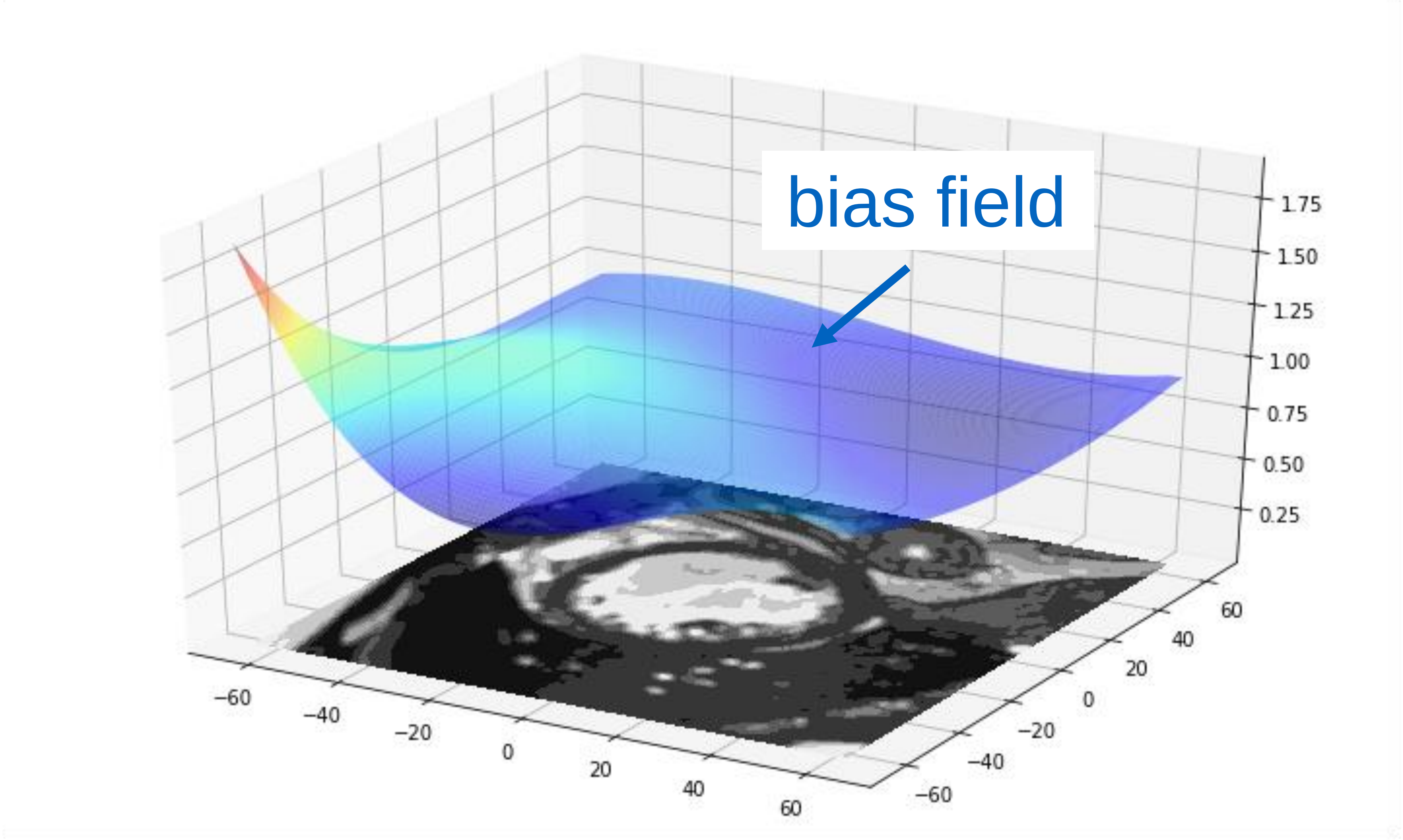
- Produce consistent predictions on the input image and its augmented one with similar semantic attributes.

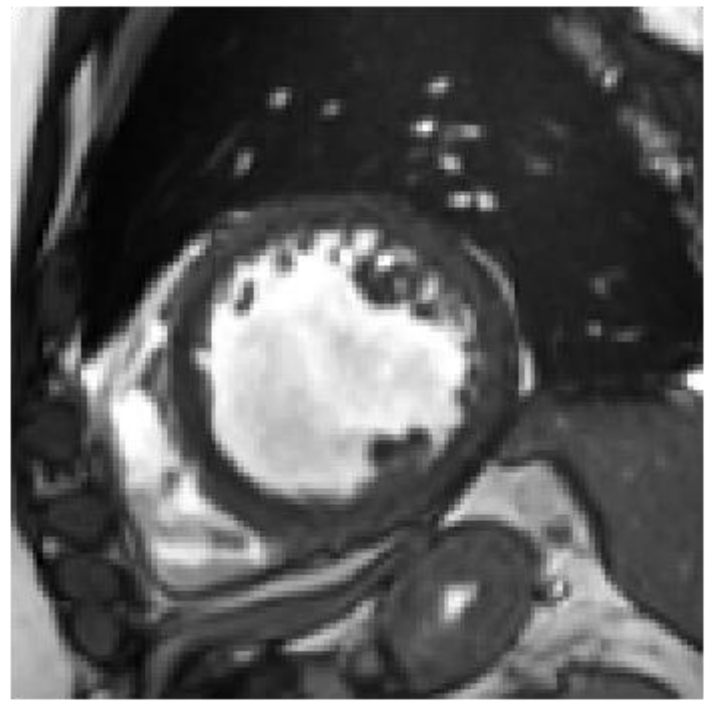


$$\underset{\boldsymbol{\theta}}{\textbf{Minimize}} \quad \mathbb{E}_{(x,y)\sim D_l}\mathcal{L}_S(\mathrm{p},\mathrm{y}) + \lambda\mathbb{E}_{x\sim \boldsymbol{D_l}\cup\boldsymbol{D_u}}\, R(p,p')$$

Data augmentation: Bias field

- Bias field introduces intensity inhomogeneities in the same tissue, which can greatly affect segmentation accuracy





Original image

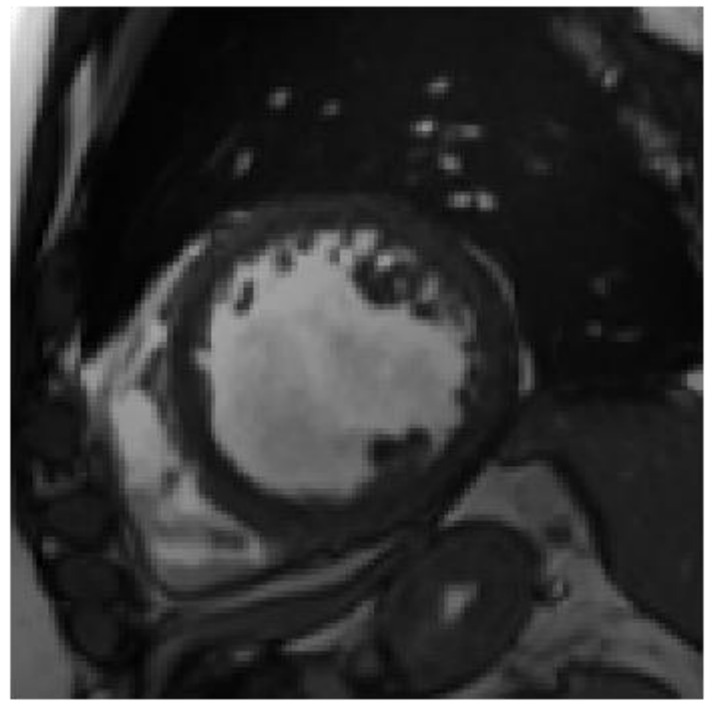
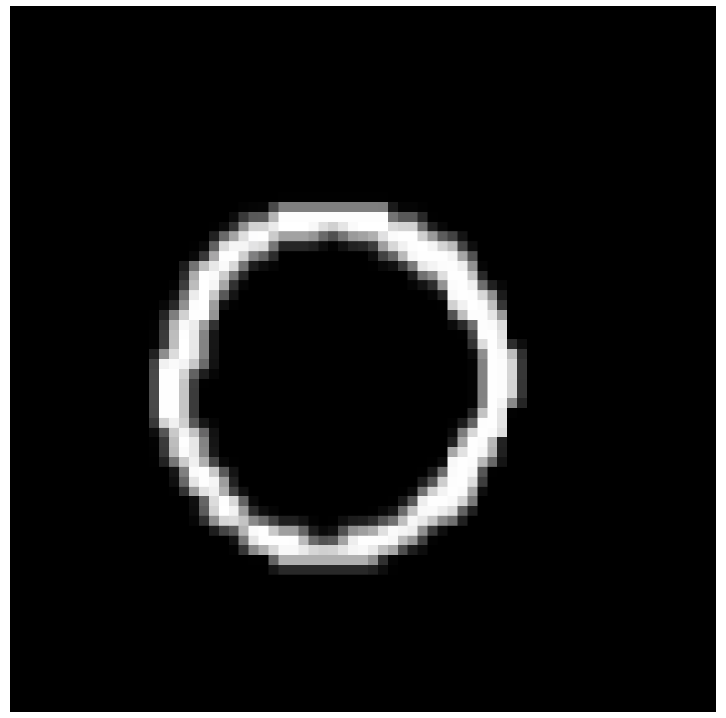


Image with bias field



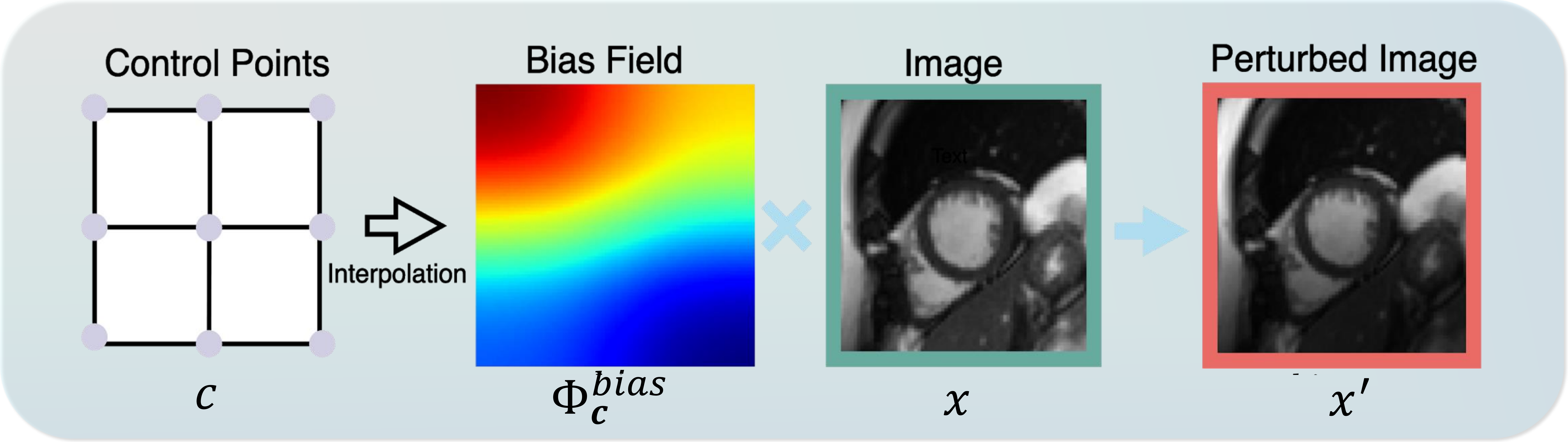
Prediction

Prediction

Data augmentation: Bias Field Generator $\mathcal{G}_{bias}$

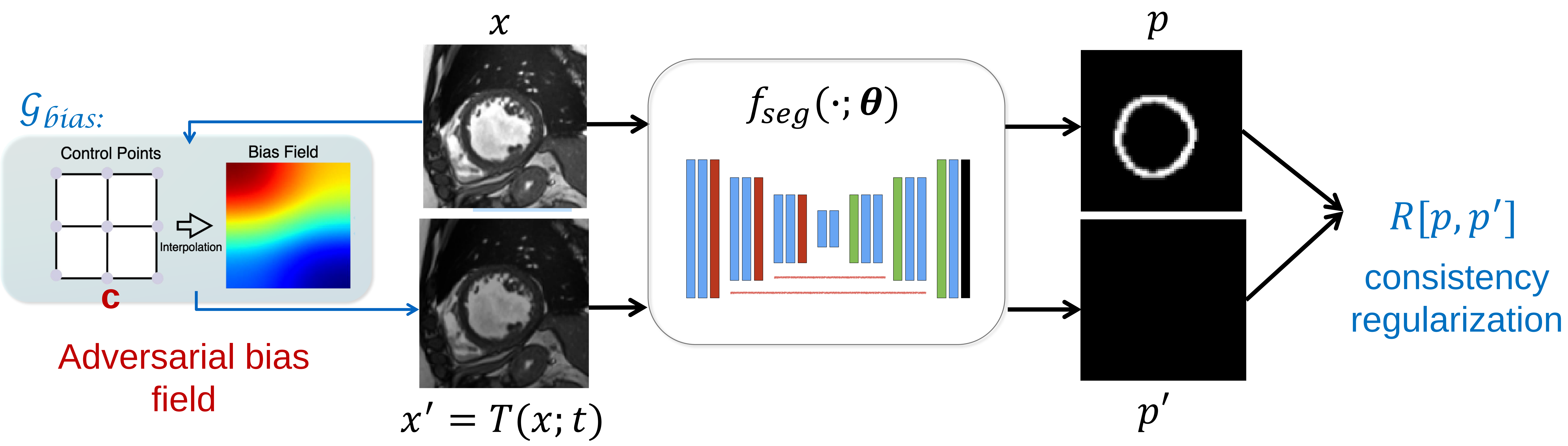
- We model the bias field using a set of control points $\boldsymbol{c}$ uniformly distributed across the image [1]:

$\mathcal{G}_{bias}$:



C. Chen “Realistic Adversarial Data Augmentation for MR Image Segmentation,” in MICCAI 2020

Data augmentation: Bias Field Generator $\mathcal{G}_{bias}$

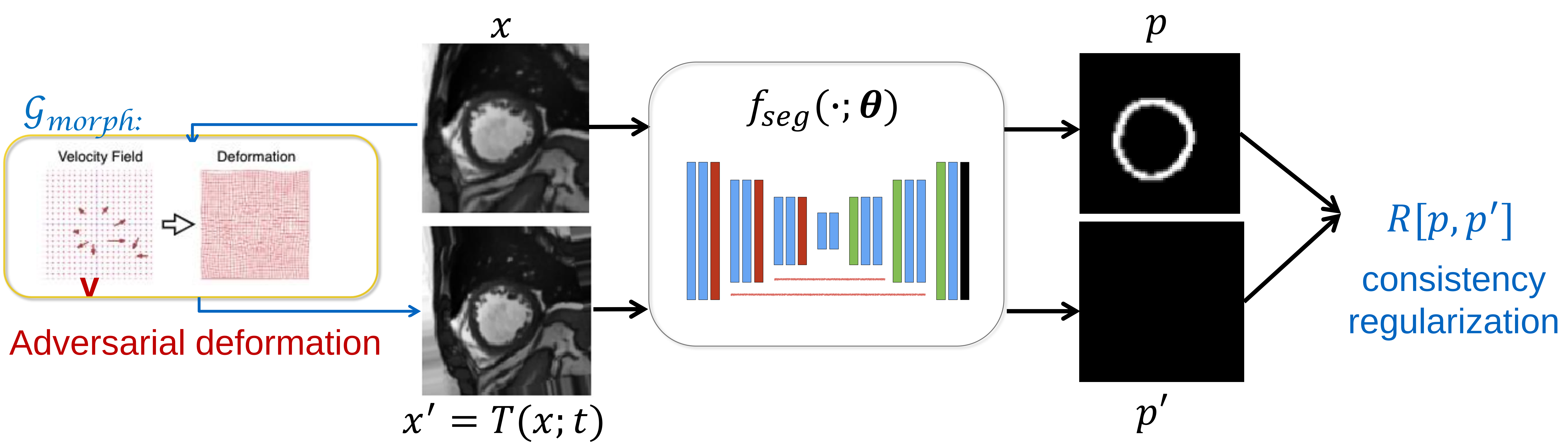


$$\underset{\mathbf{c}}{\textbf{Maximize}} \quad R(p, p')$$

$$\underset{\boldsymbol{\theta}}{\textbf{Minimize}} \quad \mathbb{E}_{(x,y)\sim D_l}\mathcal{L}_S(\mathrm{p}, \mathrm{y}) + \lambda \mathbb{E}_{x\sim \boldsymbol{D_l} \cup \boldsymbol{D_u}} R(p, p')$$

C. Chen “Realistic Adversarial Data Augmentation for MR Image Segmentation,” in MICCAI 2020

Data Augmentation: Warping Generator $\mathcal{G}_{morph}$

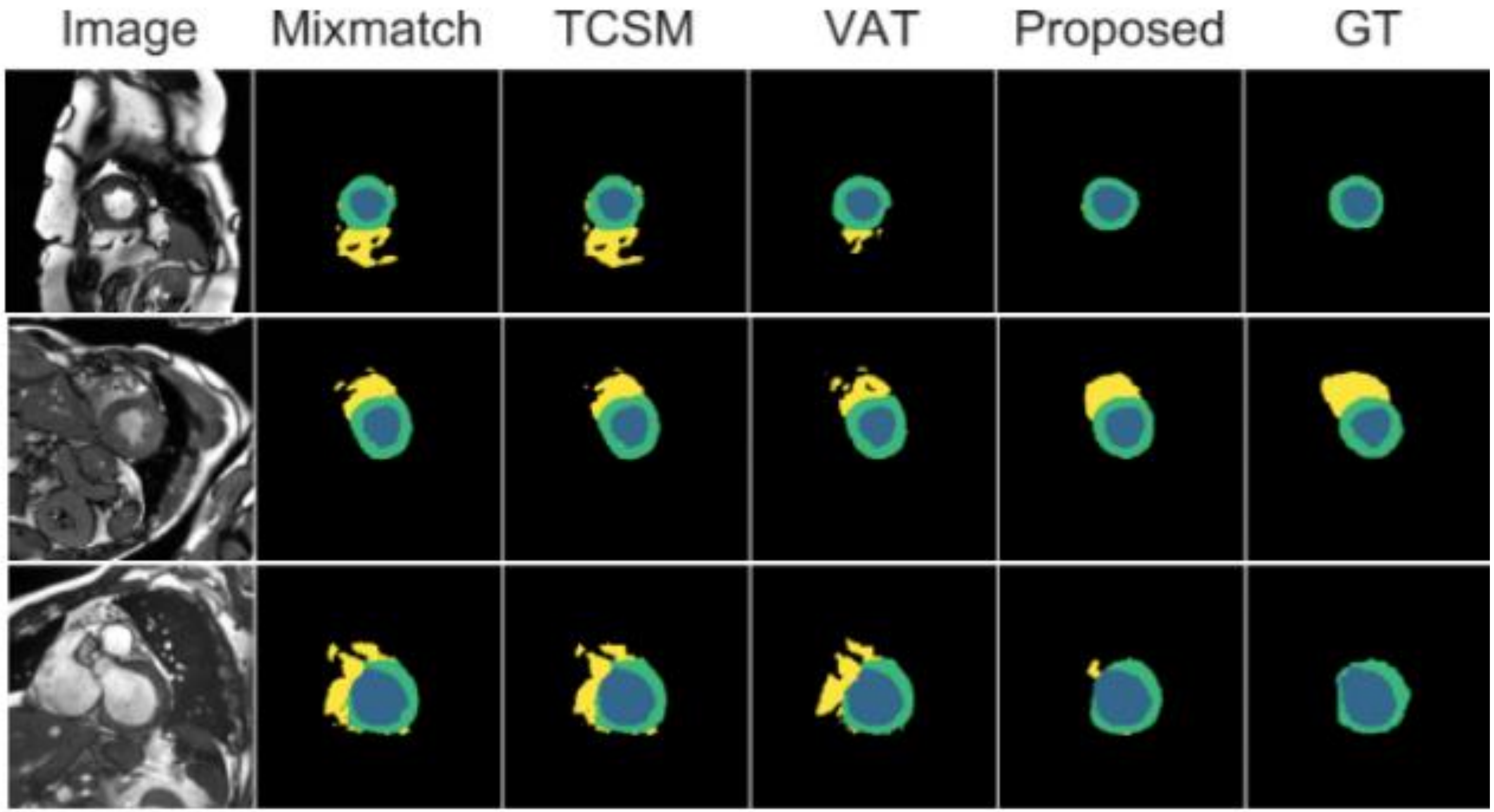


$$\max_{v} \; R(p,p')$$

$$\min_{\boldsymbol{\theta}} \; \mathbb{E}_{(x,y)\sim D_l}\mathcal{L}_S(\mathrm{p},\mathrm{y}) + \lambda\mathbb{E}_{x\sim \boldsymbol{D_l}\cup\boldsymbol{D_u}} R(p,p')$$

C. Chen “Realistic Adversarial Data Augmentation for MR Image Segmentation,” in MICCAI 2020

Segmentation results



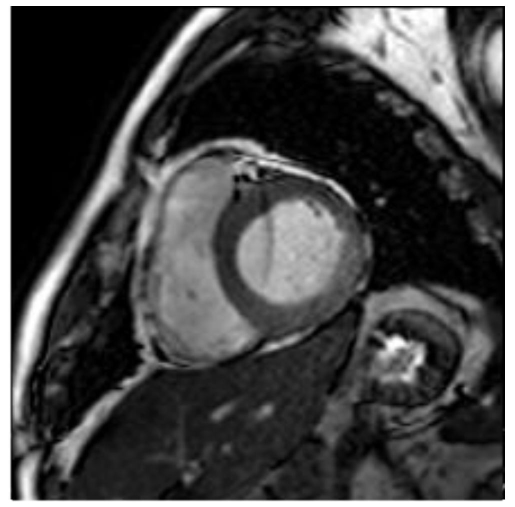
C. Chen "Realistic Adversarial Data Augmentation for MR Image Segmentation," in MICCAI 2020

Data augmentation:
Synthesize infinite novel domains

- A simple appearance-based data augmentation pipeline for single-source domain generalization
- Training on one single source domain, generalizable to multiple target domains.
- Synthesizing infinite novel domains (i.e. types of image appearances) using randomly-weighted shallow convolutional networks.
- Verified on cross-domain segmentations for cardiac, abdominal and prostate images.

Data augmentation:
Synthesize infinite novel domains

1. Synthesizing infinite novel domains using randomly-weighted networks.

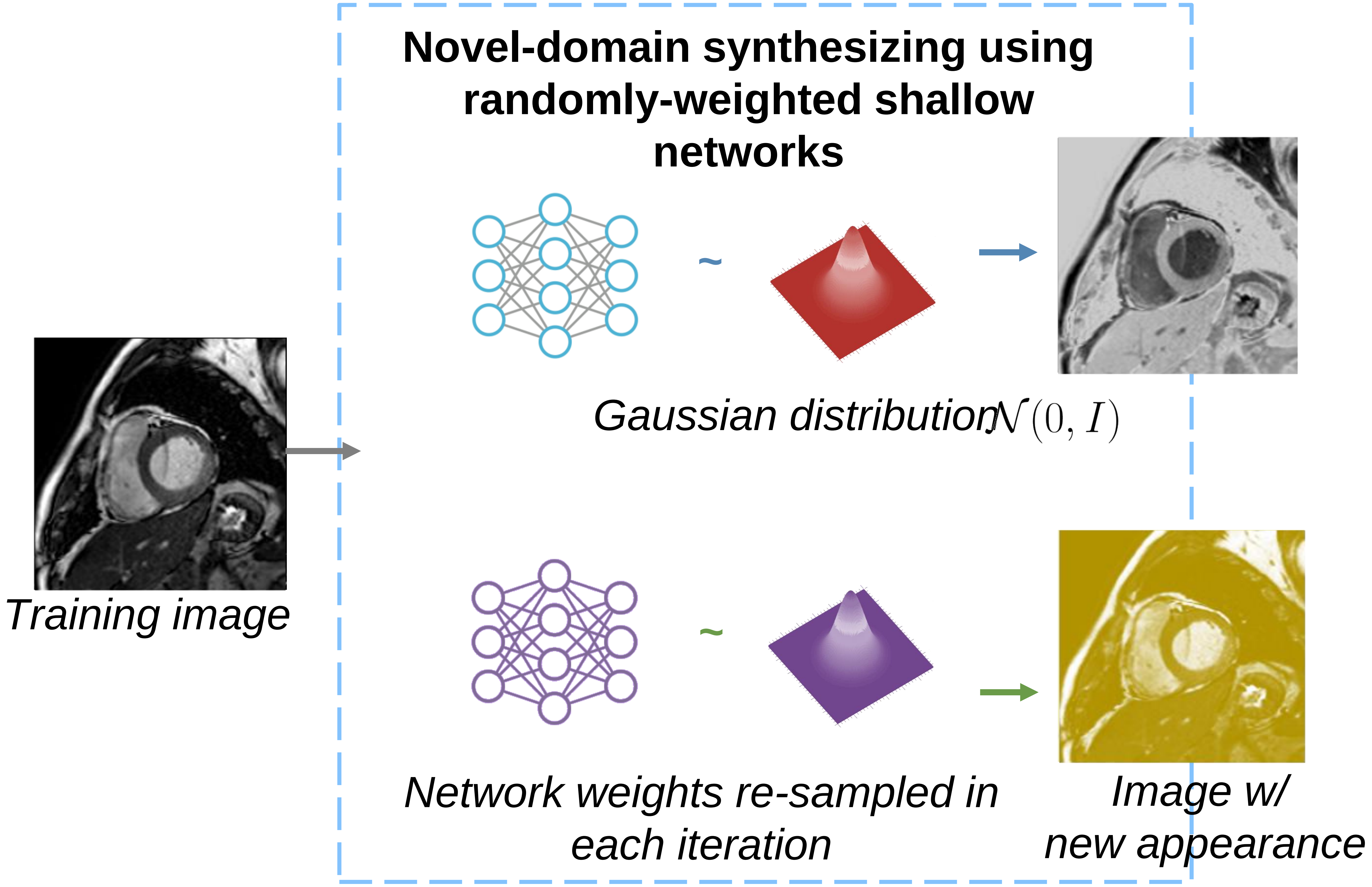


Training image

C. Ouyang et al.: Causality-inspired Single-source Domain Generalization for Medical Image Segmentation. CoRR abs/2111.12525 (2021)

Data augmentation:
Synthesize infinite novel domains

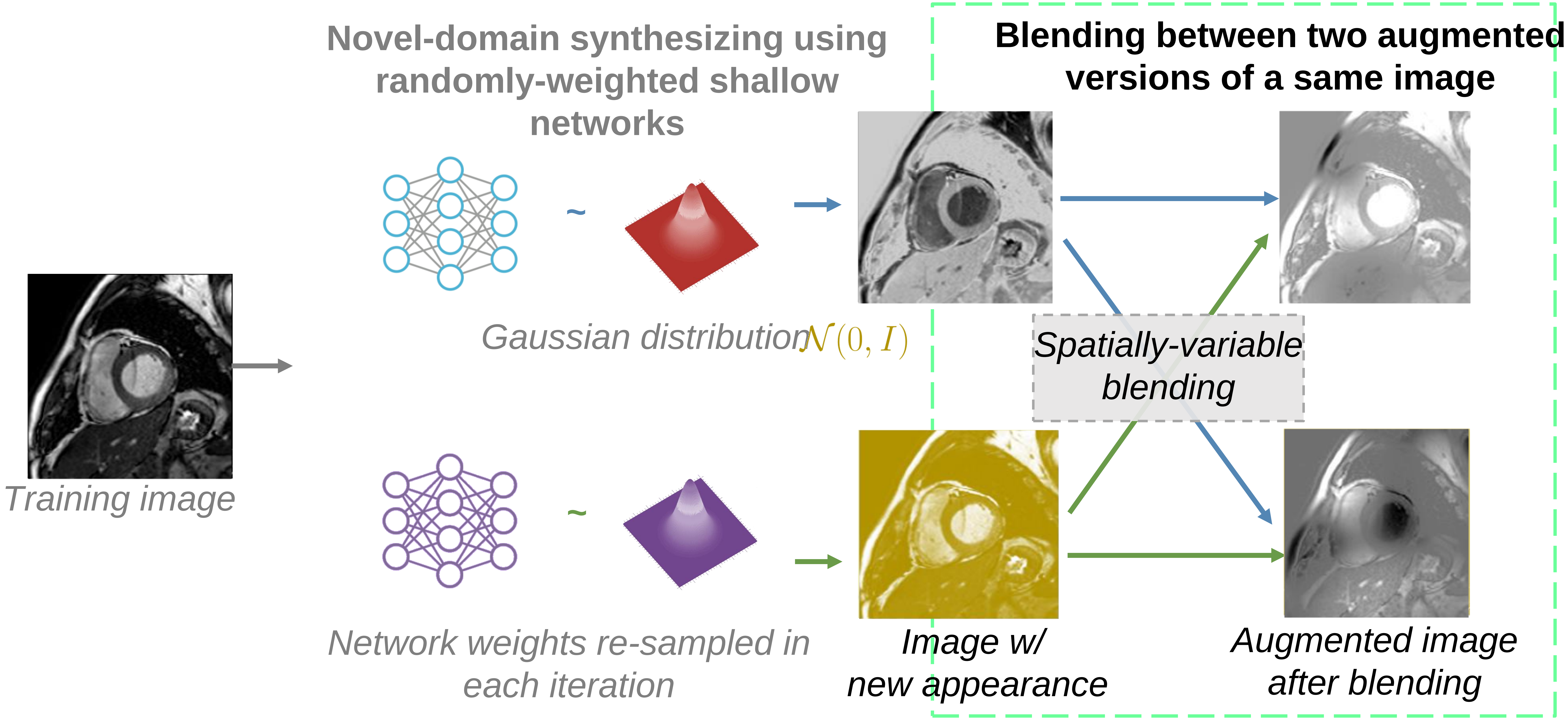
1. Synthesizing infinite novel domains using randomly-weighted networks.



C. Ouyang et al.: Causality-inspired Single-source Domain Generalization for Medical Image Segmentation. CoRR abs/2111.12525 (2021)

Data augmentation:
Synthesize infinite novel domains

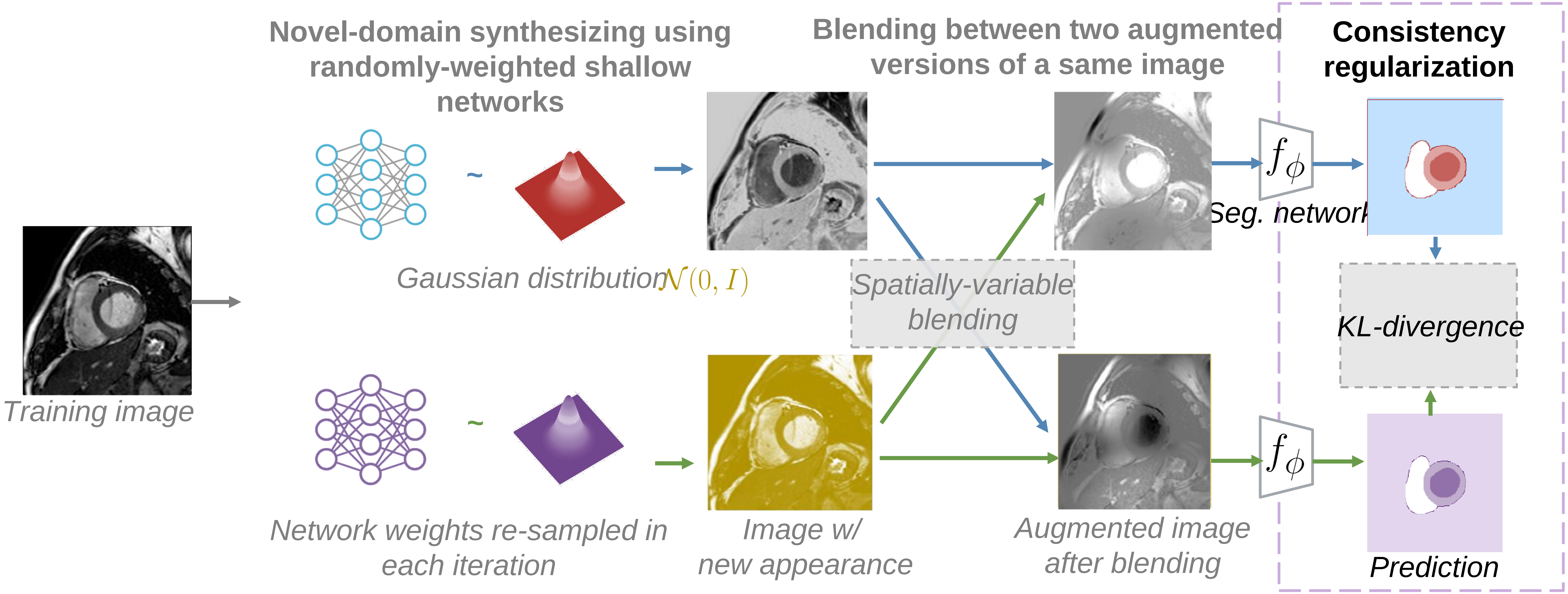
2. Blending network-augmented images in a spatially-variable manner.



C. Ouyang et al.: Causality-inspired Single-source Domain Generalization for Medical Image Segmentation. CoRR abs/2111.12525 (2021)

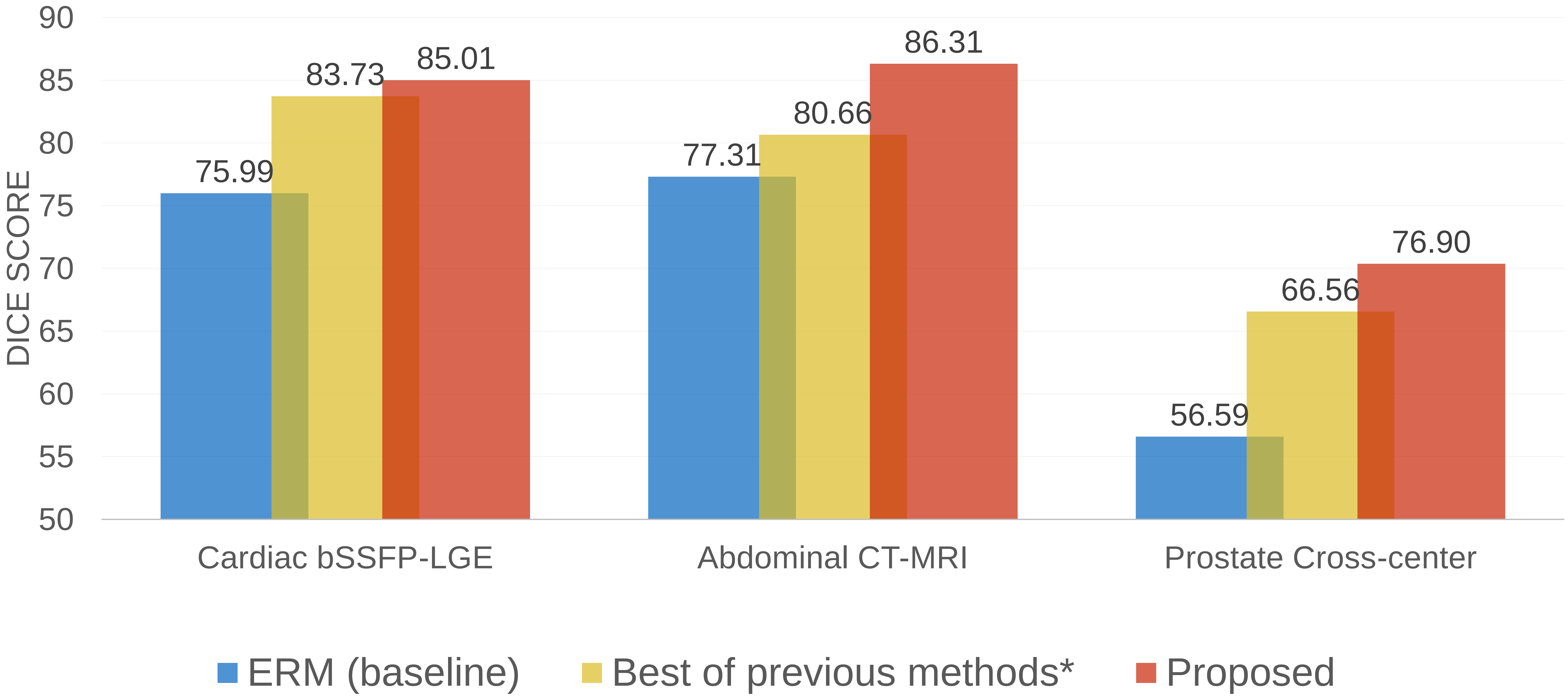
Data augmentation:
Synthesize infinite novel domains

3. Enforcing consistency between predictions under different augmentations.



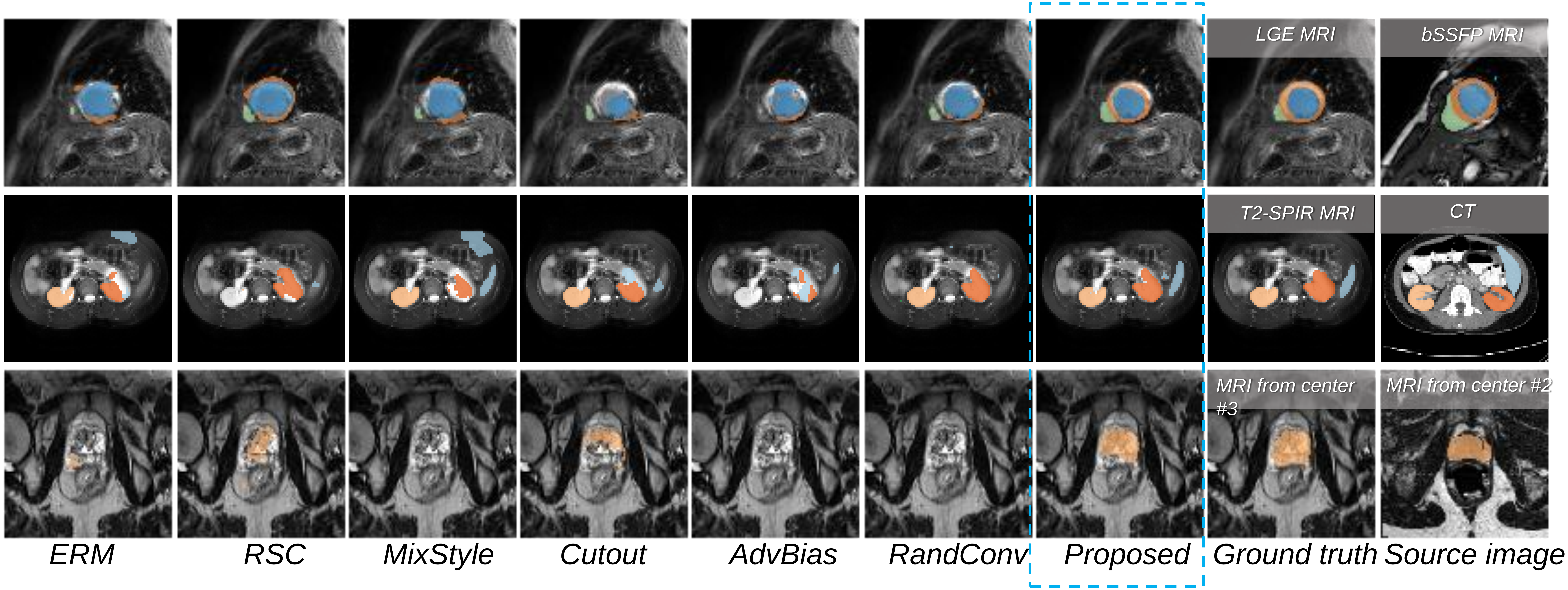
C. Ouyang et al.: Causality-inspired Single-source Domain Generalization for Medical Image Segmentation. CoRR abs/2111.12525 (2021)

Data augmentation:
Synthesize infinite novel domains – Results



C. Ouyang et al.: Causality-inspired Single-source Domain Generalization for Medical Image Segmentation. CoRR abs/2111.12525 (2021)

Data augmentation:
Synthesize infinite novel domains – Results



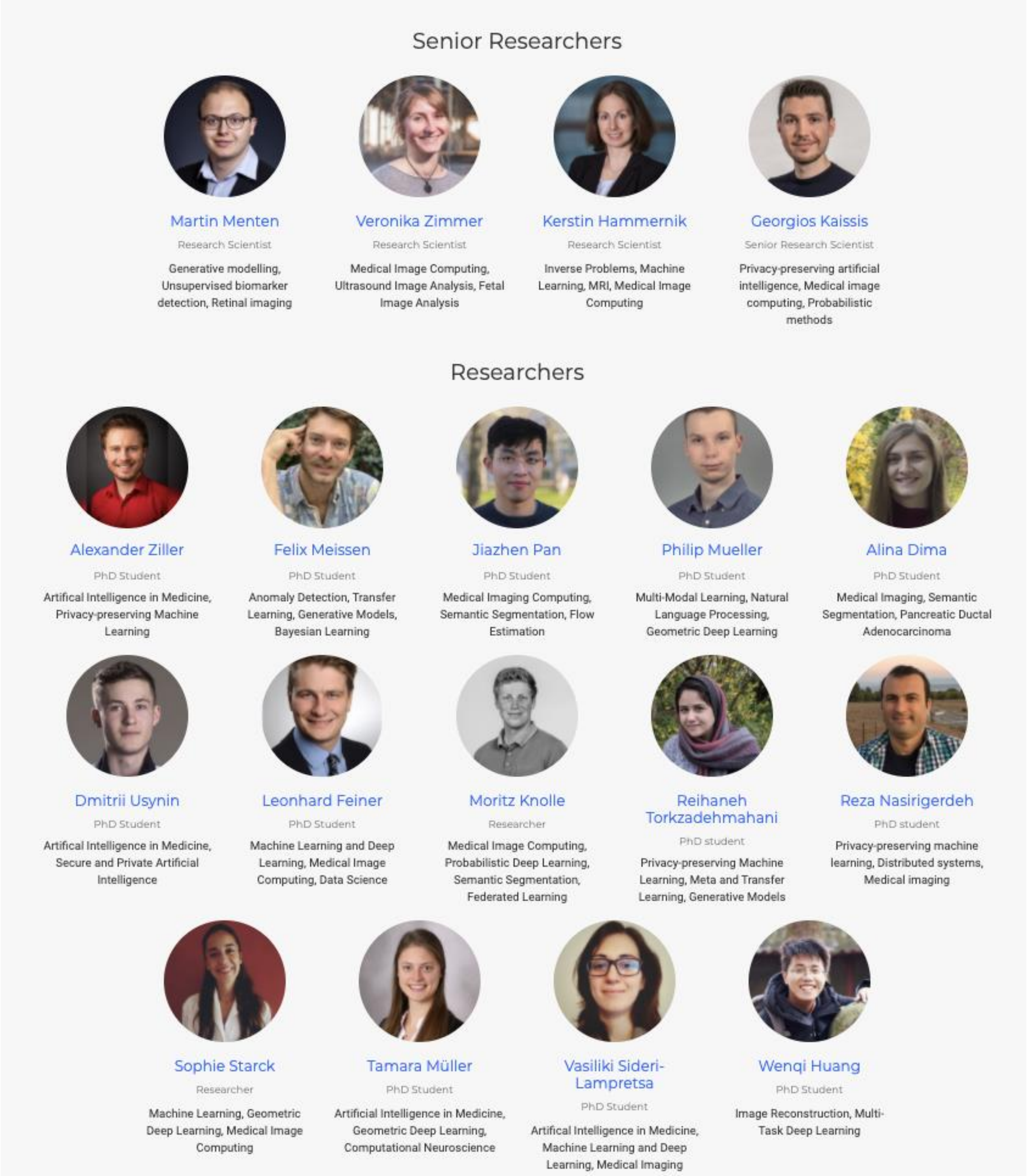
C. Ouyang et al.: Causality-inspired Single-source Domain Generalization for Medical Image Segmentation. CoRR abs/2111.12525 (2021)

Summary and Conclusions

- Domain shift can cause significant deterioration of AI models in real-world data
  - Significant problem for AI models for image analysis
  - Also significant problem in the context of image reconstruction and enhancement
- Domain shift is caused by a variety of reasons
  - Scanner variabilities
  - Population variations and pathologies
- Understanding causes of domain shift is important in developing strategies that can deal with these variations
- Assessing performance during deployment is critical!

Acknowledgements

Lab for AI in Medicine @



https://aim-lab.io/

BioMedIA @ Imperial College London

https://biomedia.doc.ic.ac.uk/

Acknowledgements

smartheart

EPSRC
Engineering and Physical Sciences Research Council

British Heart Foundation

erc

biobank uk
Improving the health of future generations

Alexander von Humboldt
Stiftung / Foundation