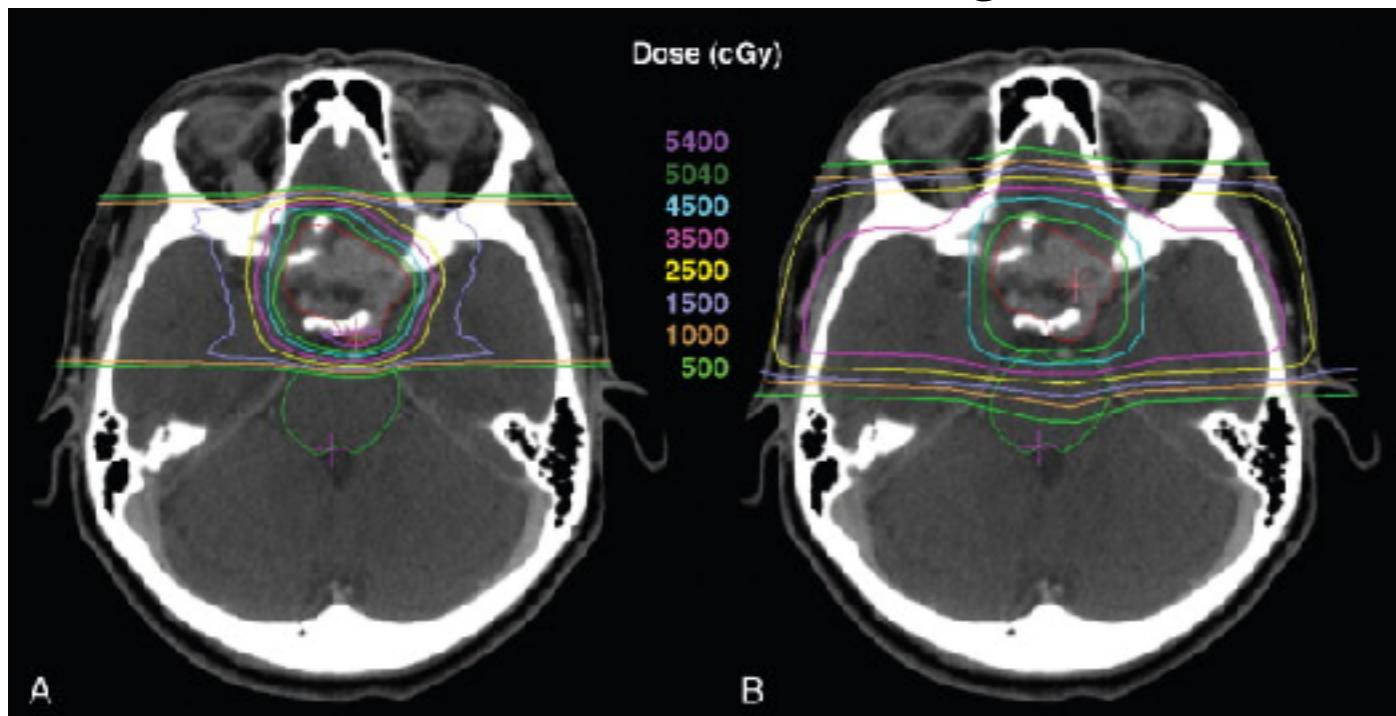


Structure-Aware Shape Analysis in Medical Imaging

Elena Balashova Sizikova
Princeton University

Introduction

Treatment Planning



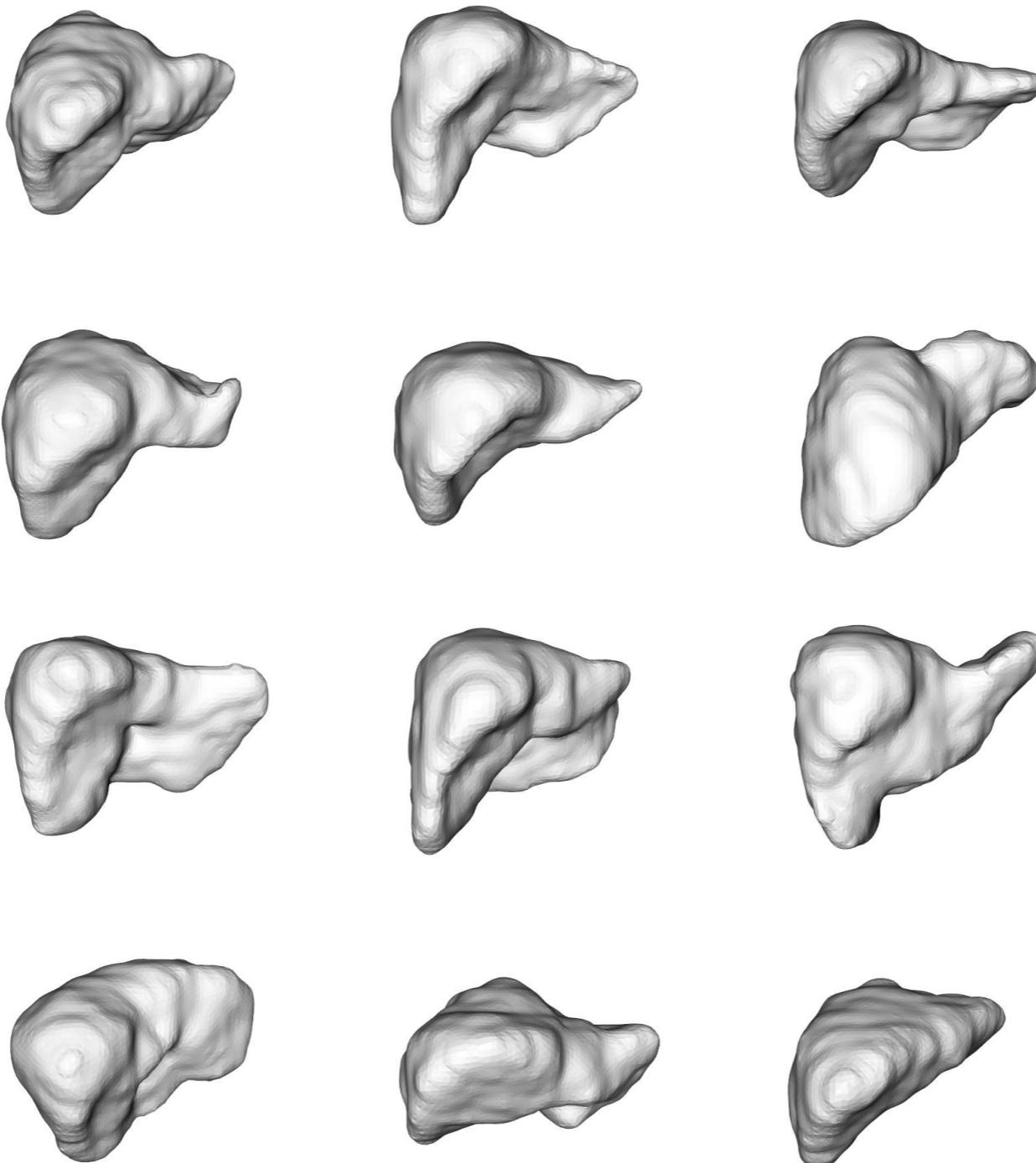
[Shih '10]

Post Operative Followup



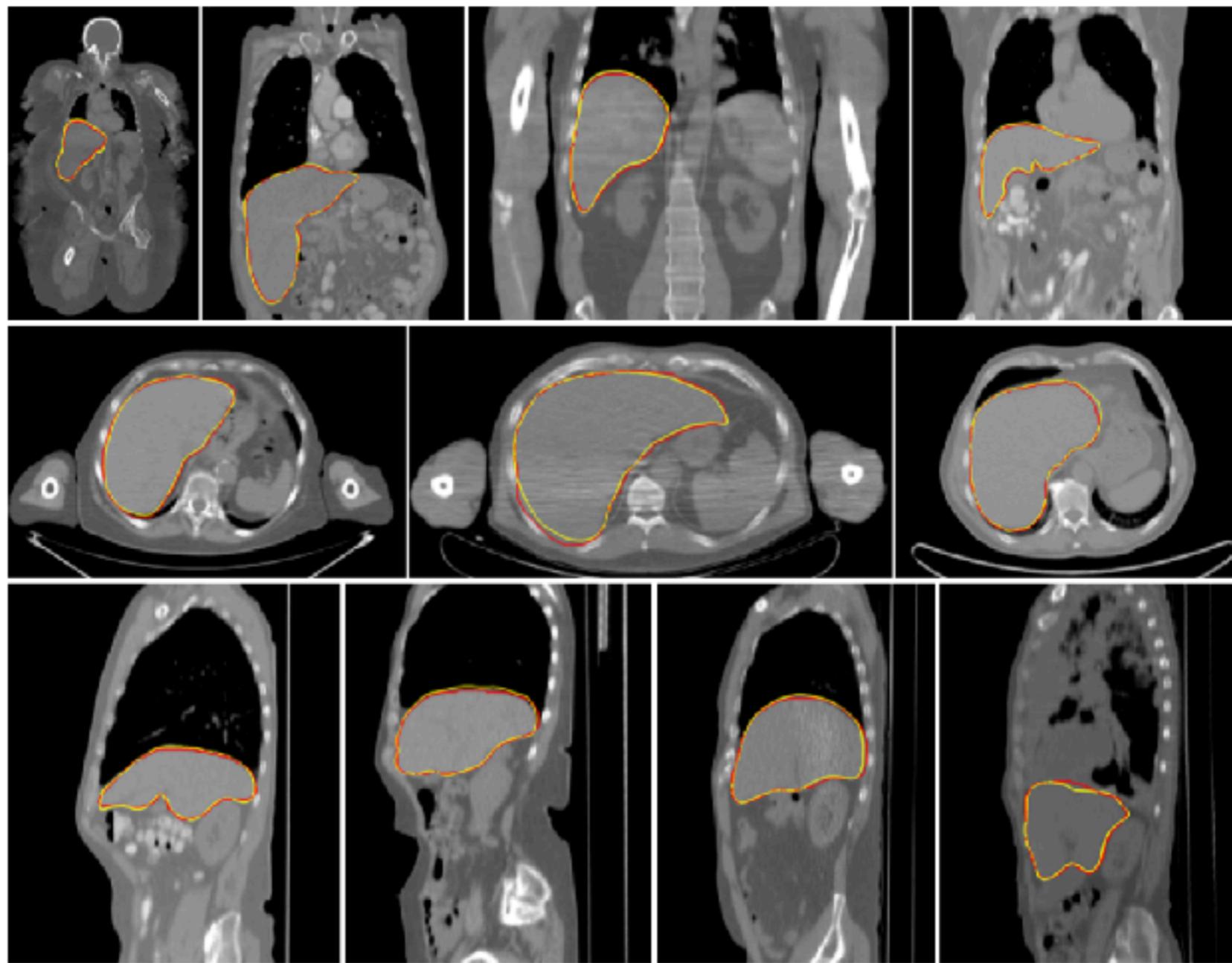
[Cincinnati Children's]

Introduction



High Degree of Shape Variation

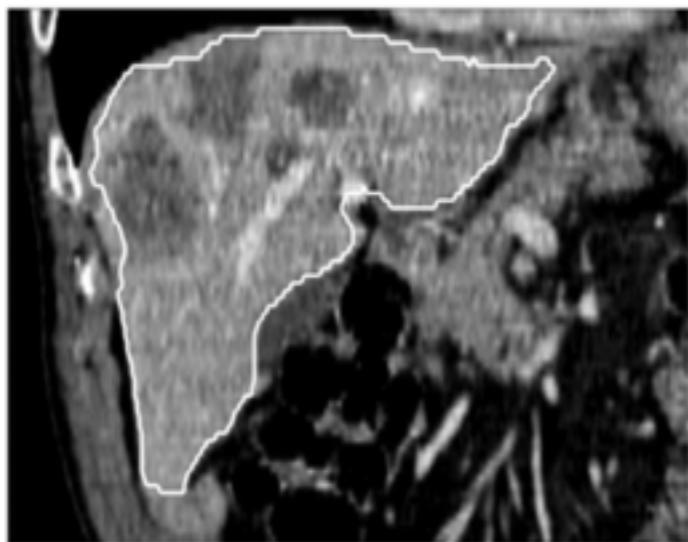
Background



[Yang '17]

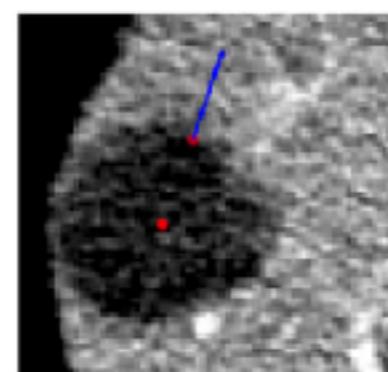
Background

Statistical Shape Model



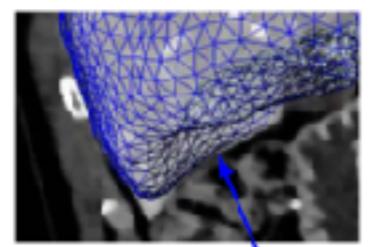
[Heimann '09]

Sigmoid Edge Model

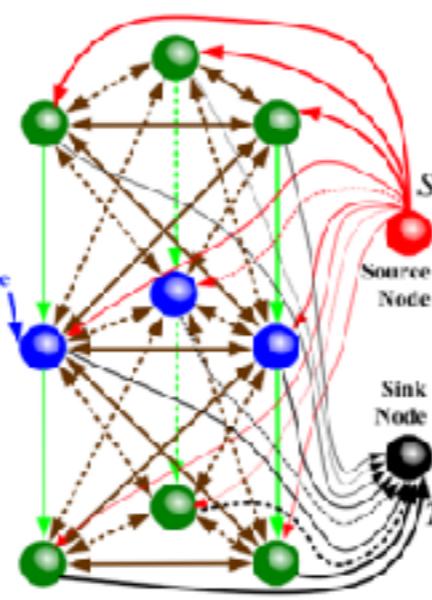


[Foruzan '15]

Graph Cut

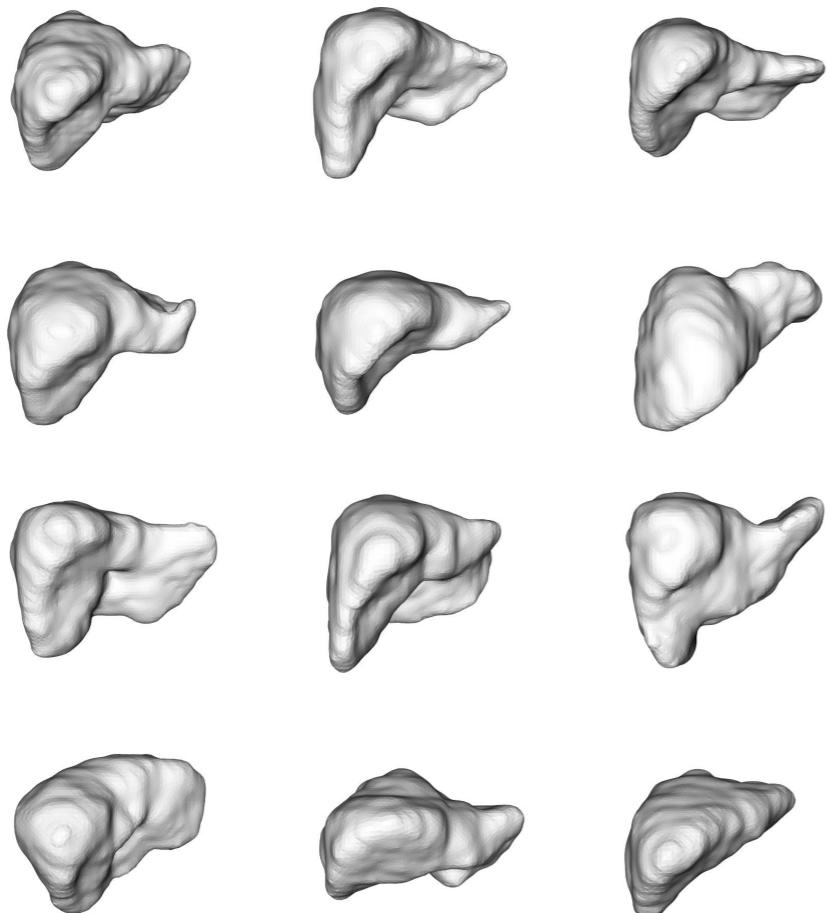


- E_a : Intra-Column Arc
- ↔ E_r : Inter-Column Arc
- E_s : Source Arc
- E_t : Sink Arc
- N : Node



[Li '15]

Challenge

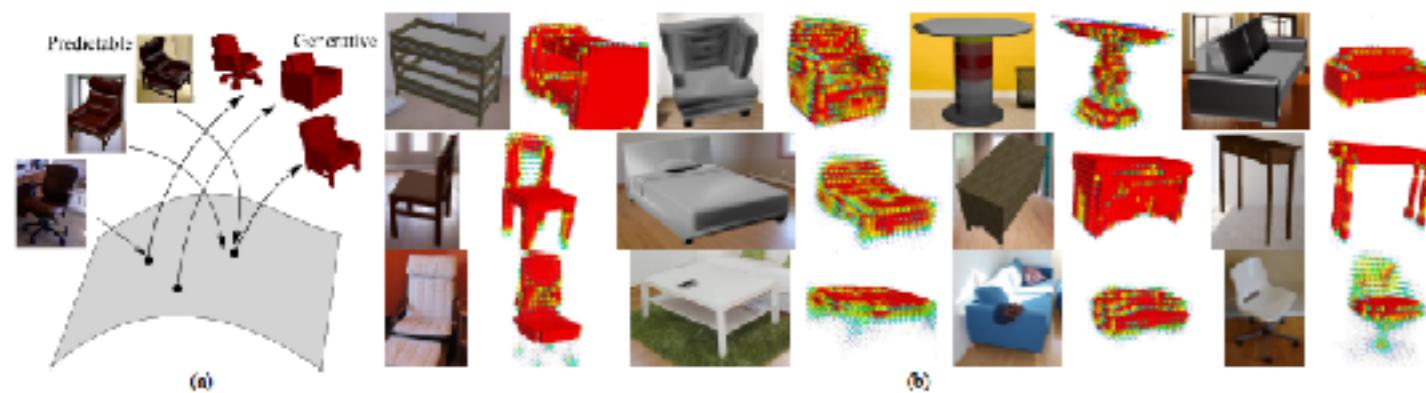


Model

Neural Manifolds

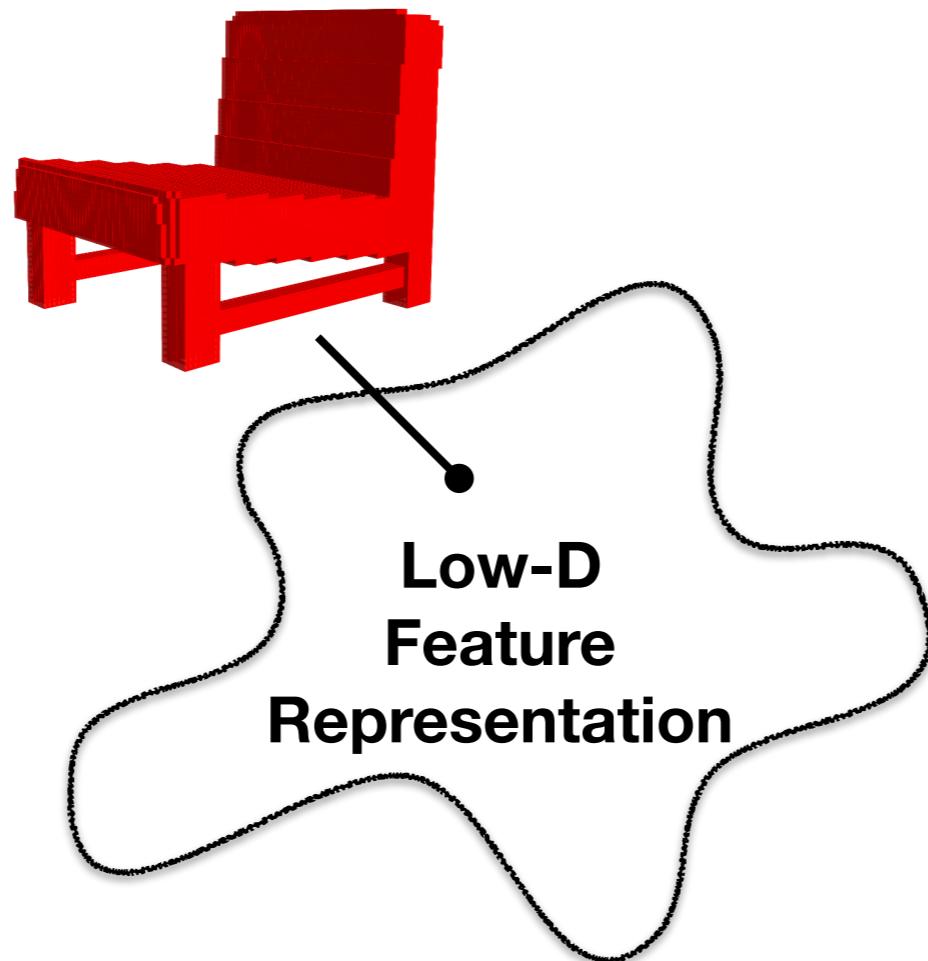


[Wu '16] aka 3D-GAN

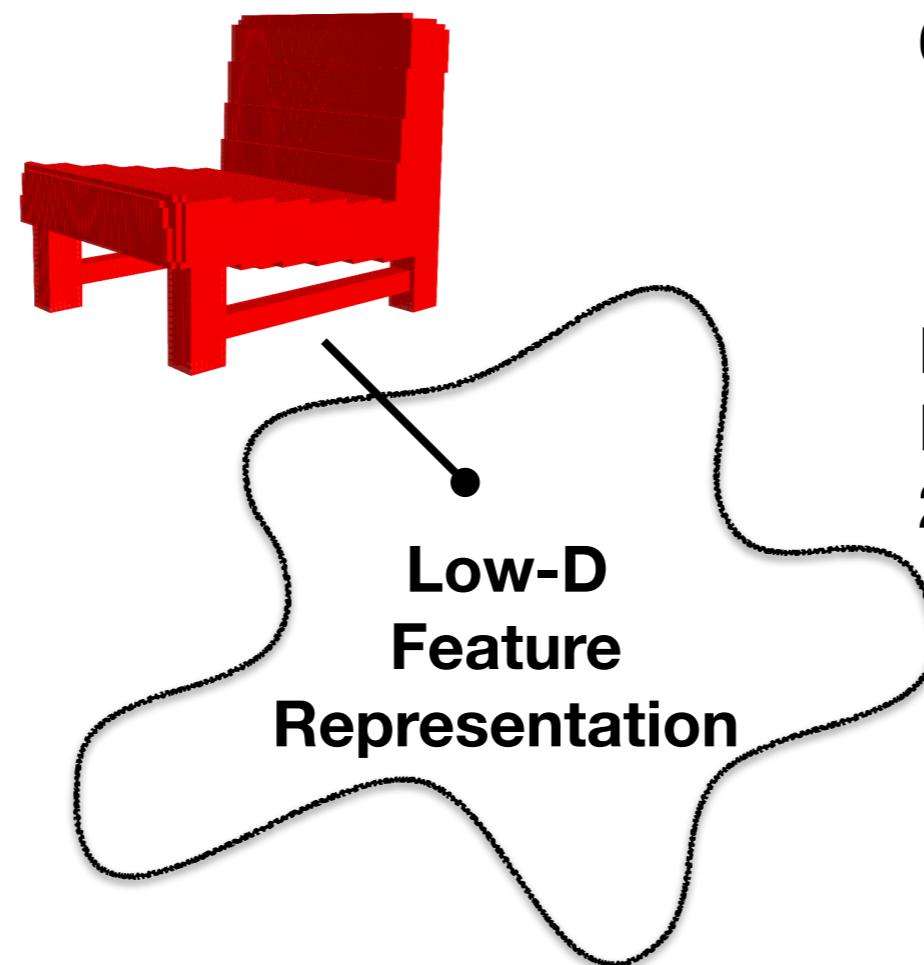


[Girdhar '16] aka TL Network

Neural Manifolds



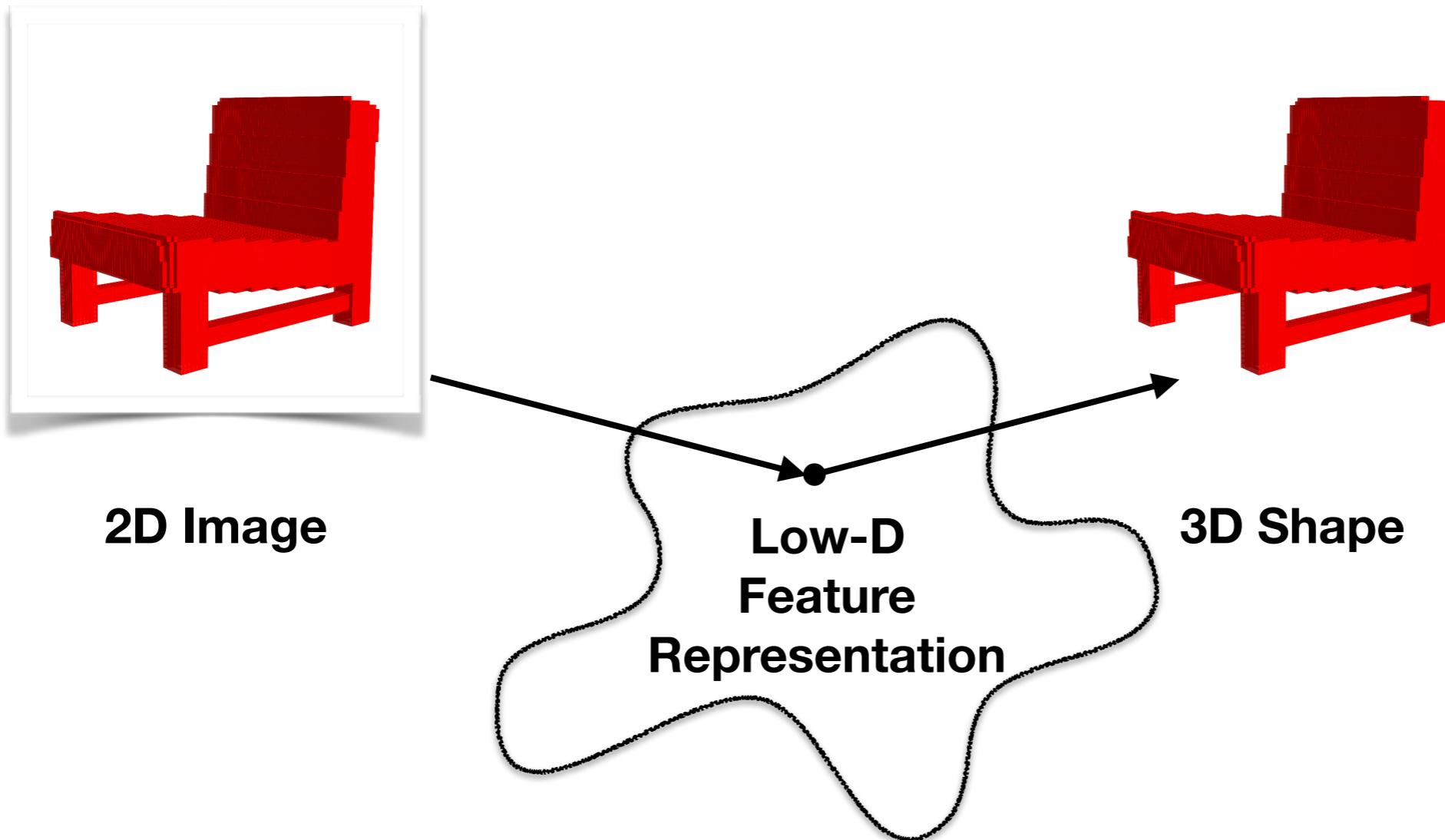
Neural Manifolds



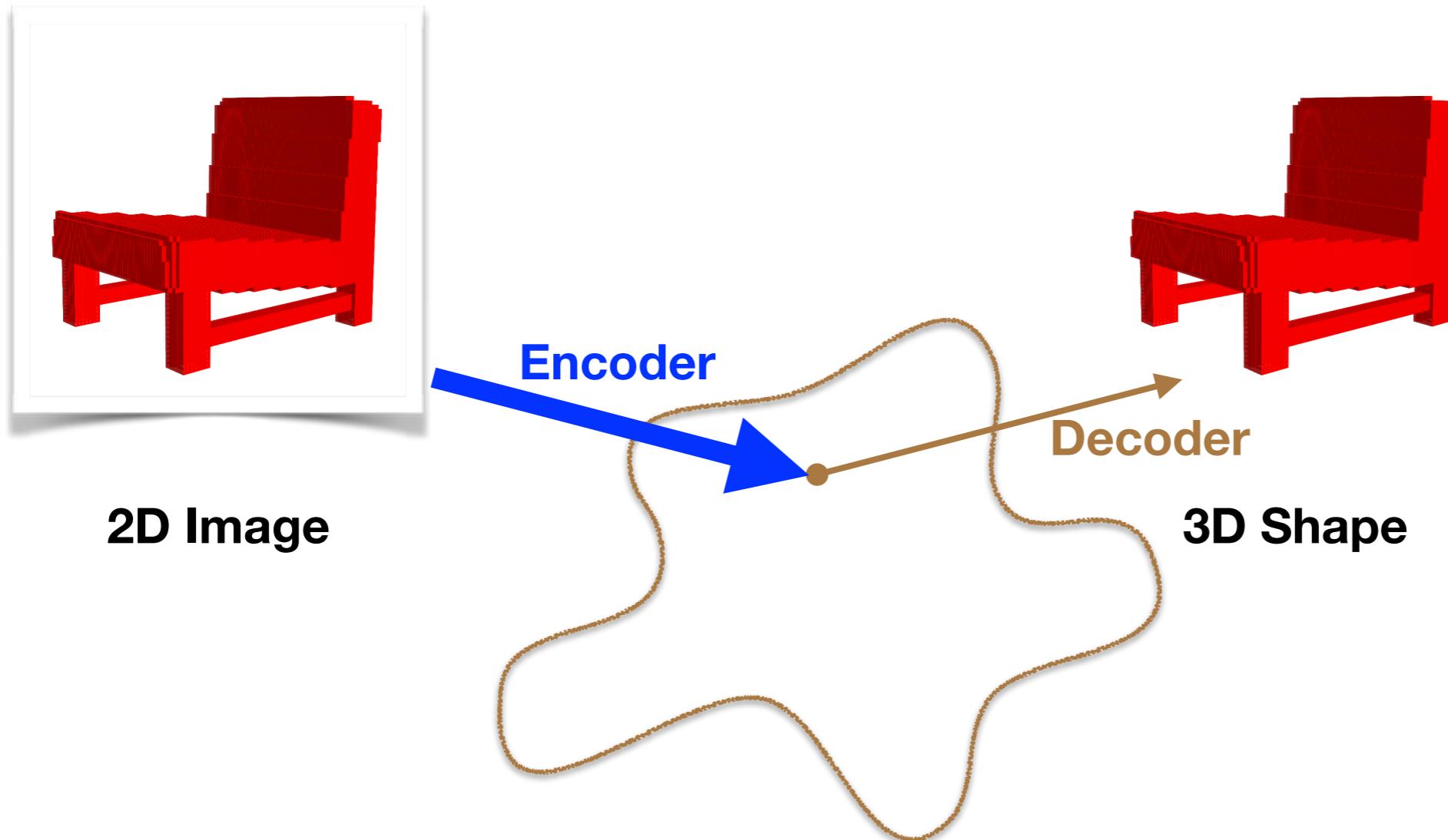
Voxel Grid Shape Representation:
64x64x64 = 262,144 parameters

Low-Dimensional Feature
Representation:
200 parameters

3D Reconstruction

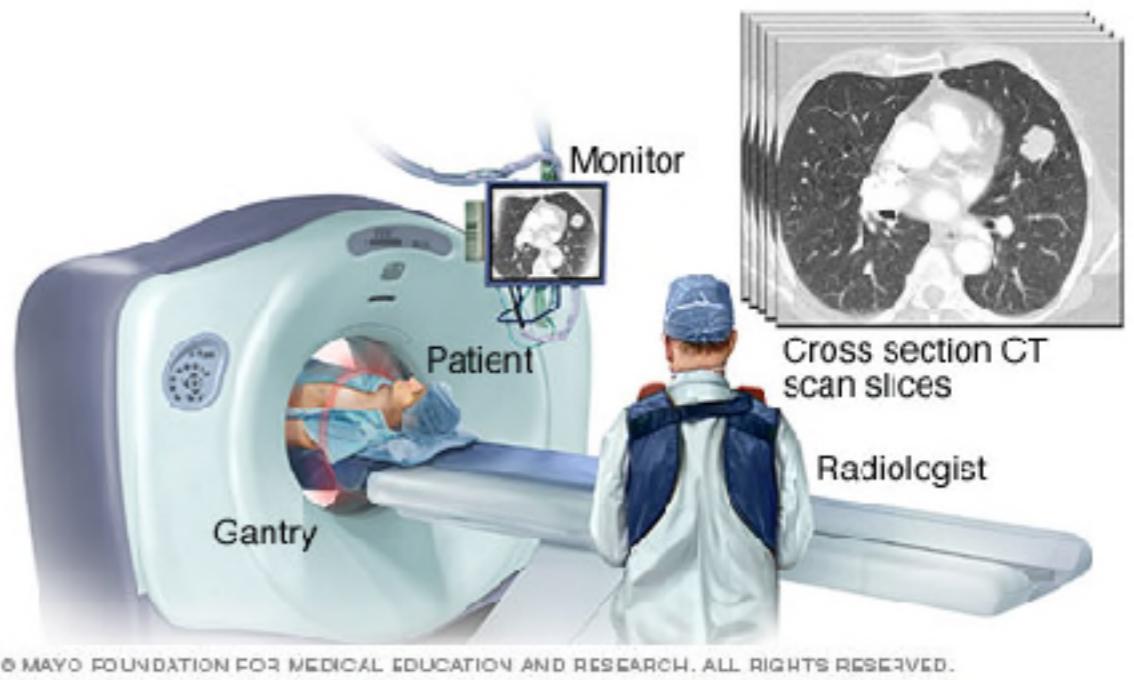


3D Reconstruction



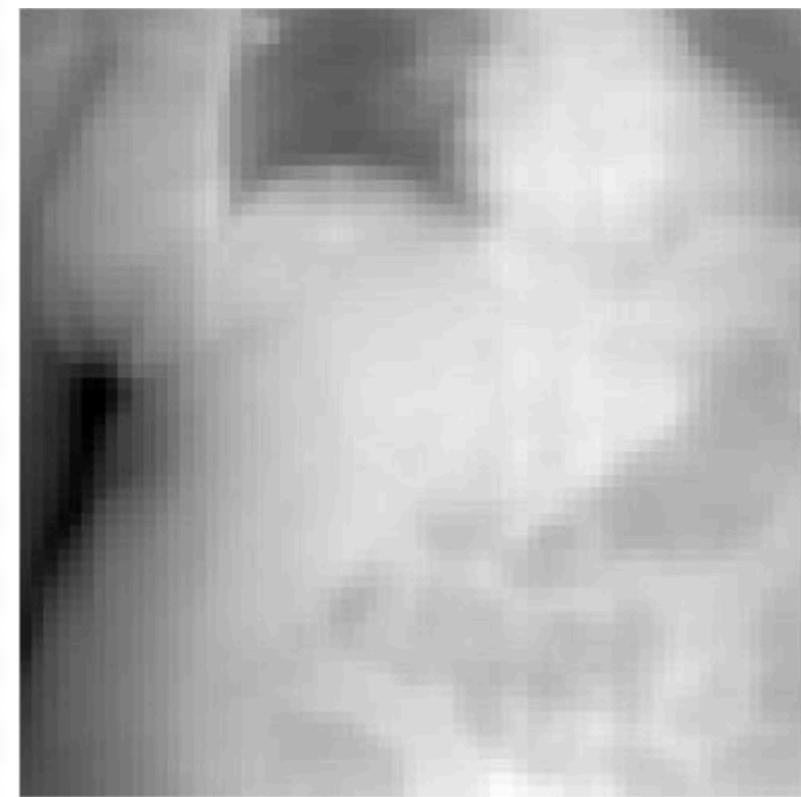
Application: 3D Liver Reconstruction

Application: 3D Liver Reconstruction

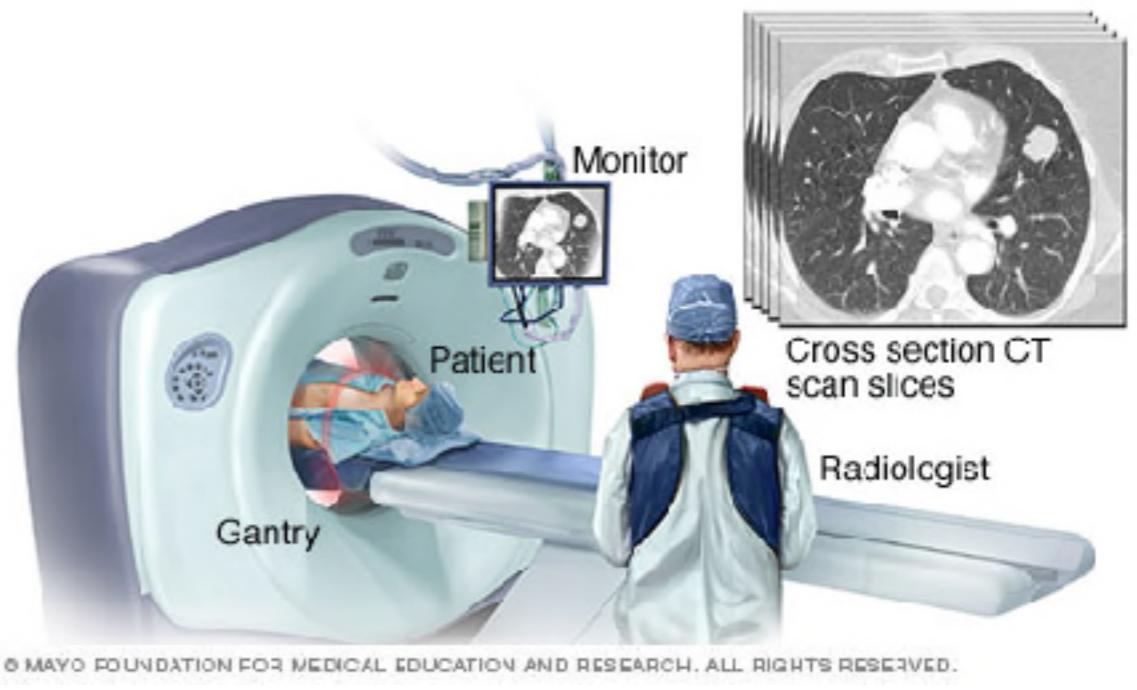


CT Scan

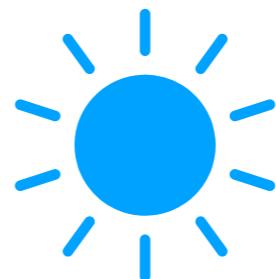
Application: 3D Liver Reconstruction



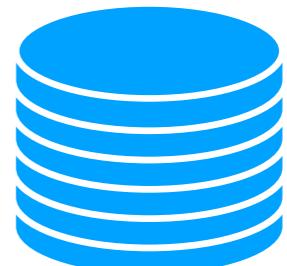
Topogram Scan



CT Scan

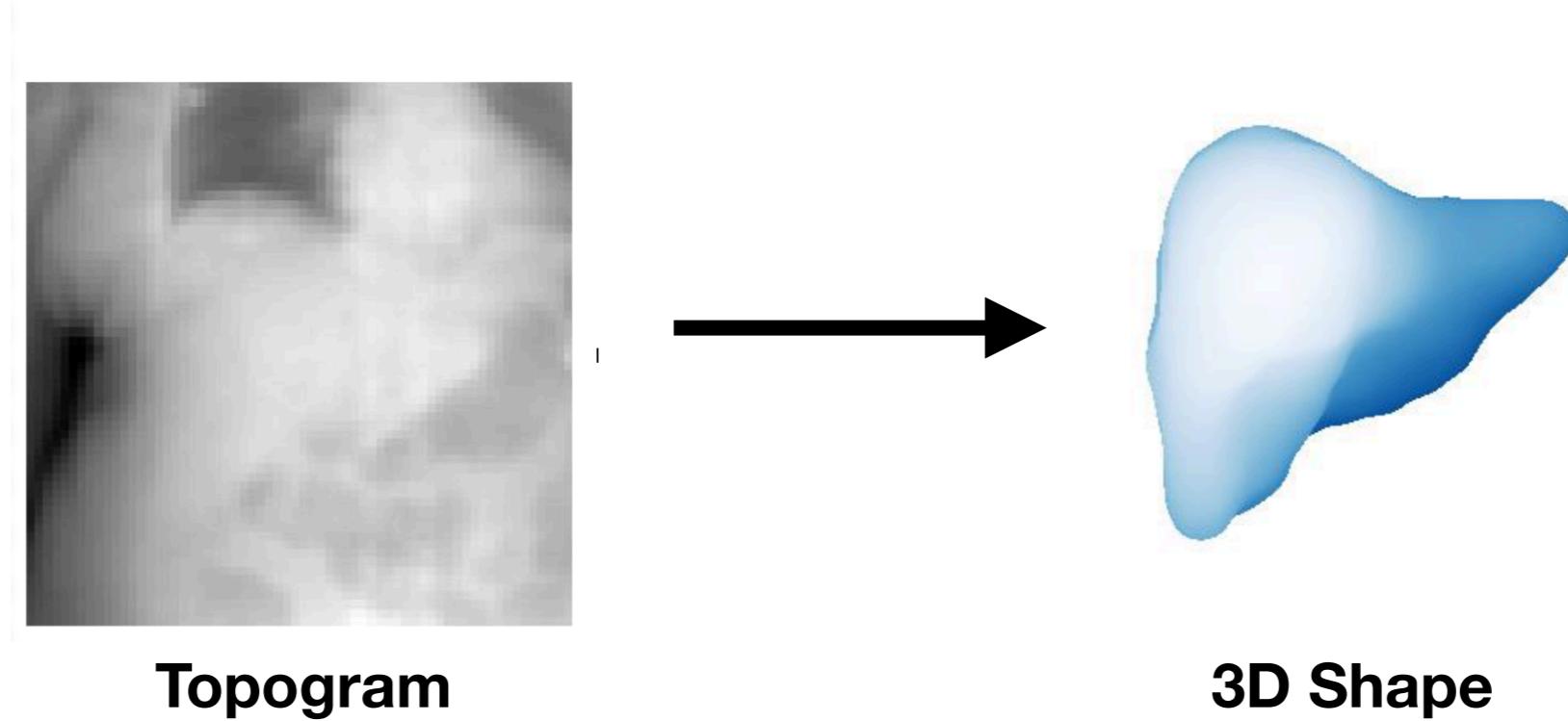


Higher radiation
exposure!

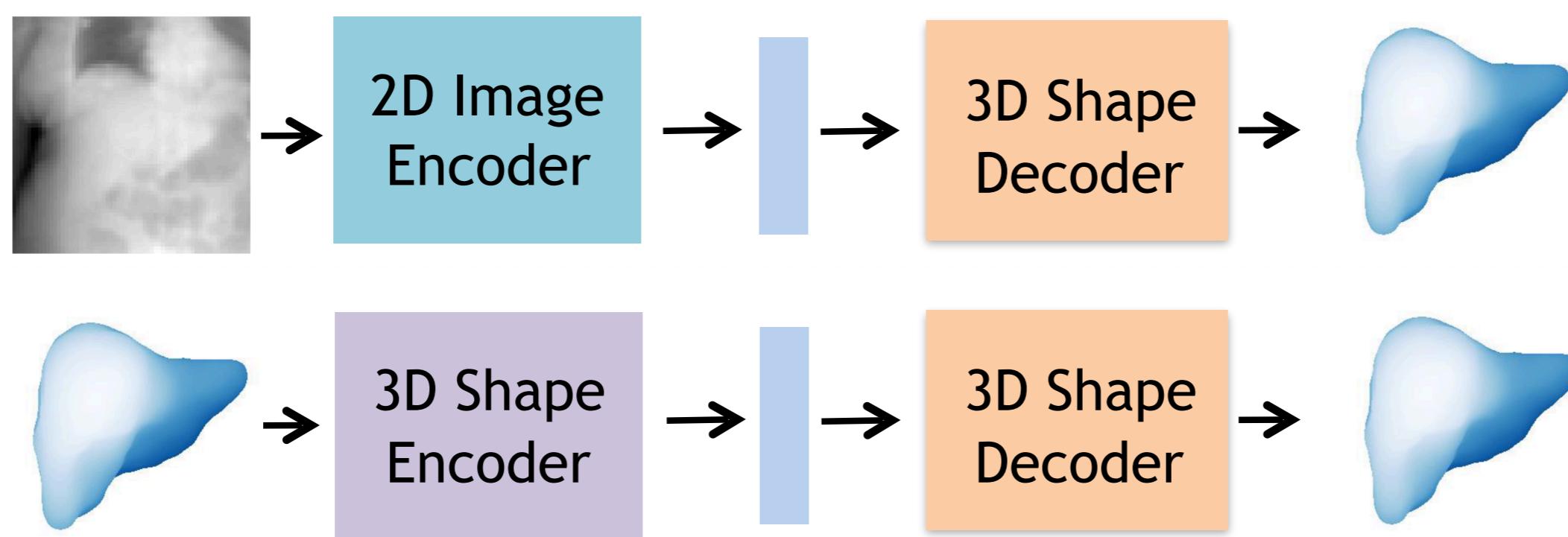


More Expensive!

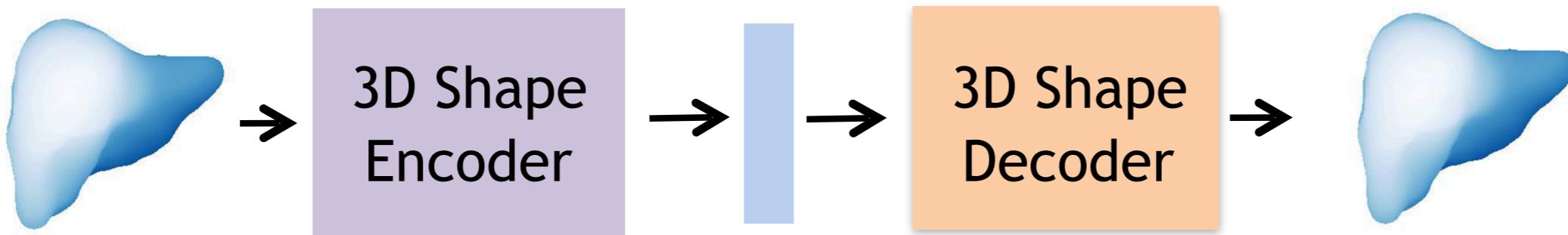
Application: 3D Liver Reconstruction



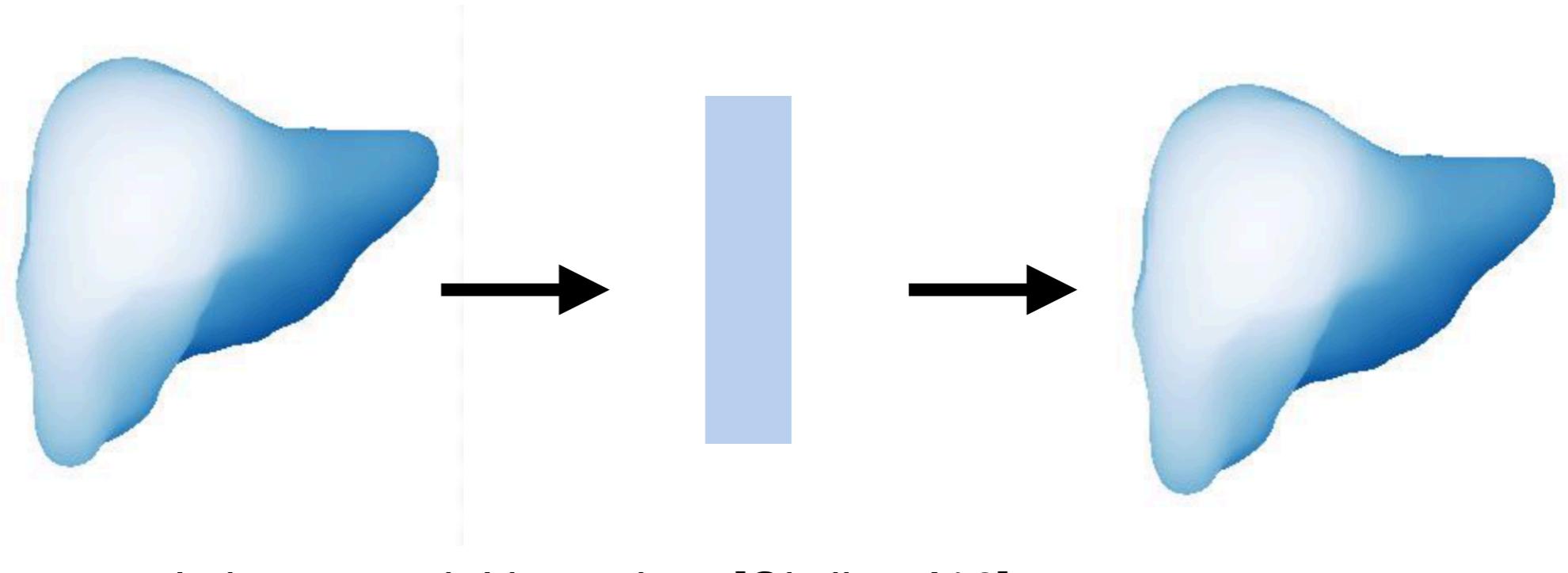
Model



Model

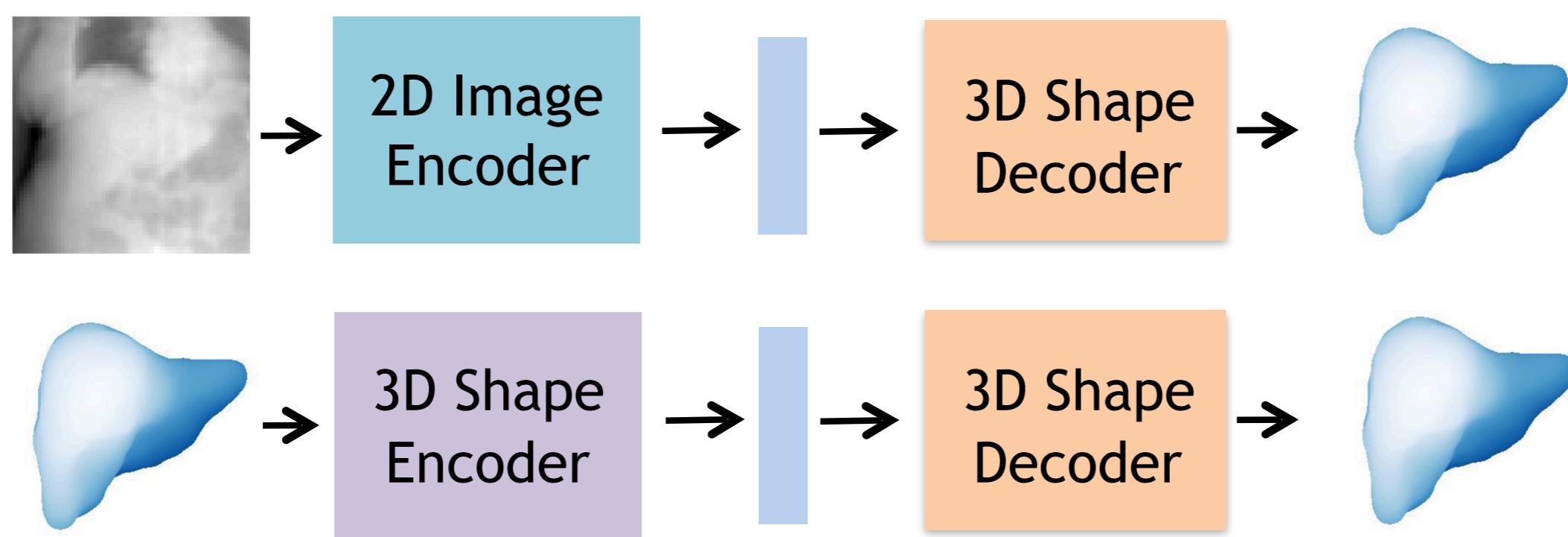


3D Shape Model



Learn a neural shape model based on [Girdhar '16]

Model



Objective

We optimize the networks using a combination loss function L :

$$L = \alpha_1 L_{rec}(s, s') + \alpha_2 L_{KL} + \alpha_3 L_{rec}(s, G(\bar{z}))$$

Shape Model Loss **Image Loss**

Kullback
Leibler divergence Encoder Output

$$L_{rec}(s, s') = -\frac{1}{N} \sum_{n=1}^N s_n \log s'_n + (1 - s_n) \log (1 - s'_n)$$

GT Shape Pred. Shape BCE Loss

Reconstruction Loss

$\alpha_1, \alpha_2, \alpha_3$

- Sub-Component weights

Results

Input Topogram

Ground Truth Shape

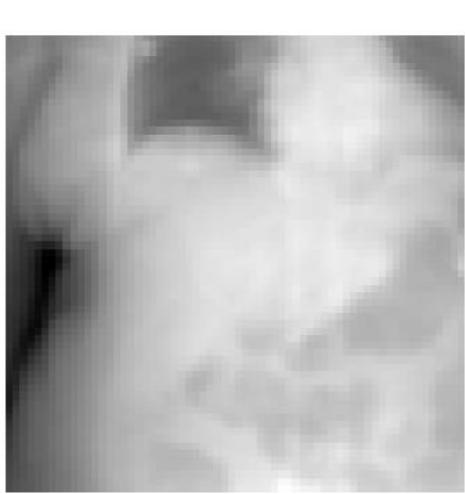
Topogram Only
Shape Prediction

Example 1

Example 2

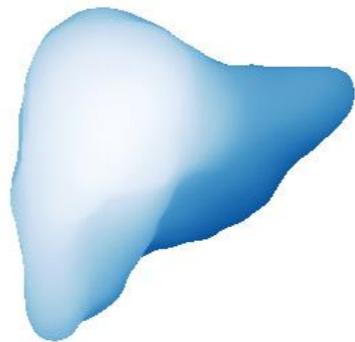
Results

Example 1

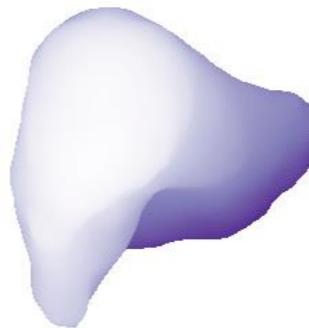


Input Topogram

Ground Truth Shape

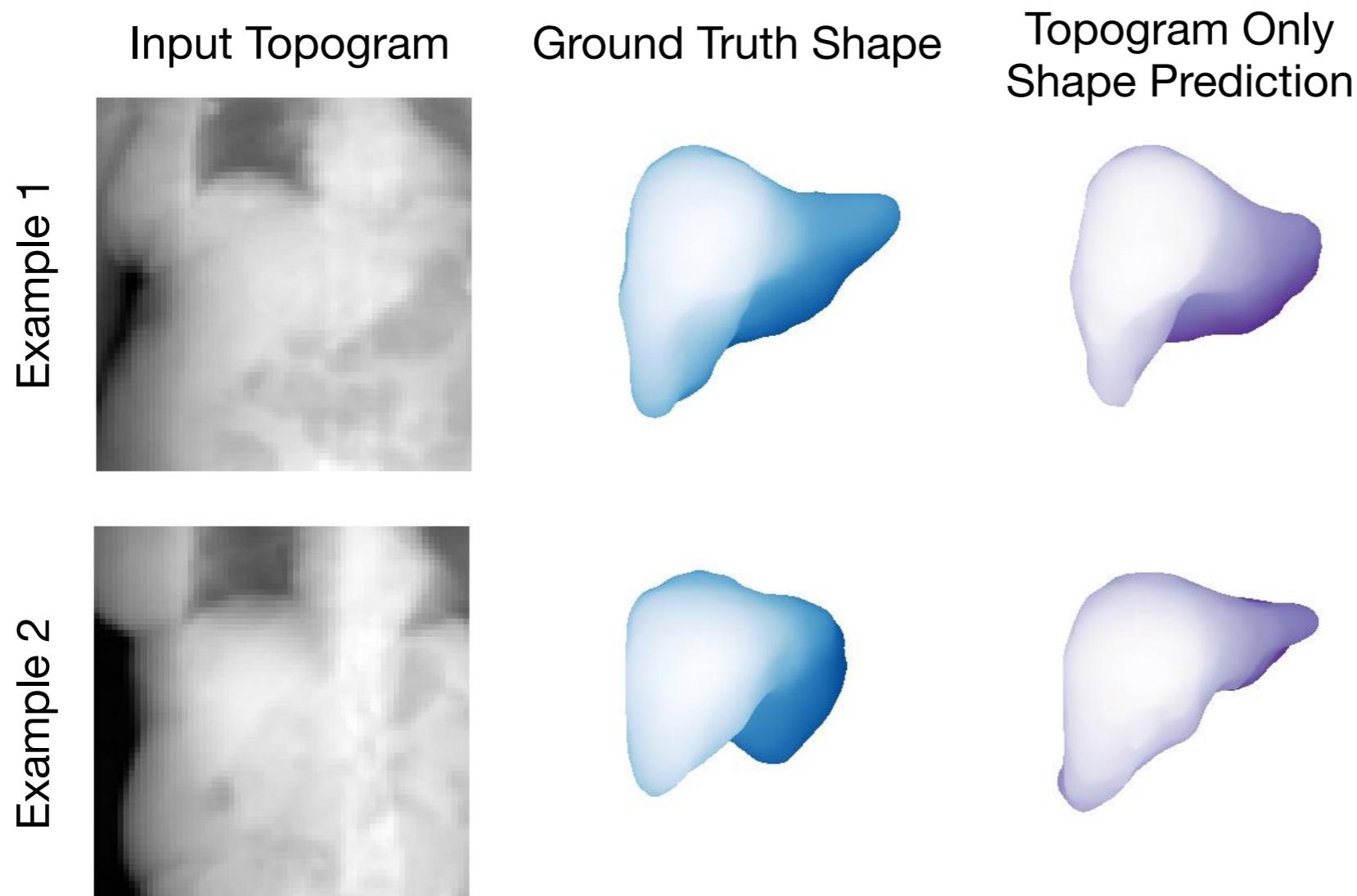


Topogram Only
Shape Prediction



Example 2

Results



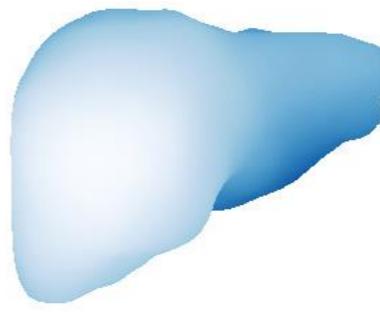
Results

Example 3

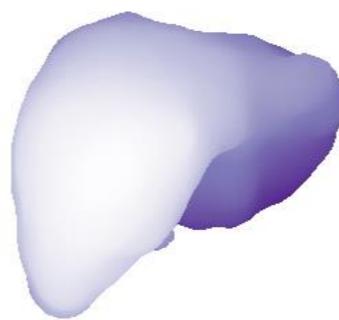


Input Topogram

Ground Truth Shape

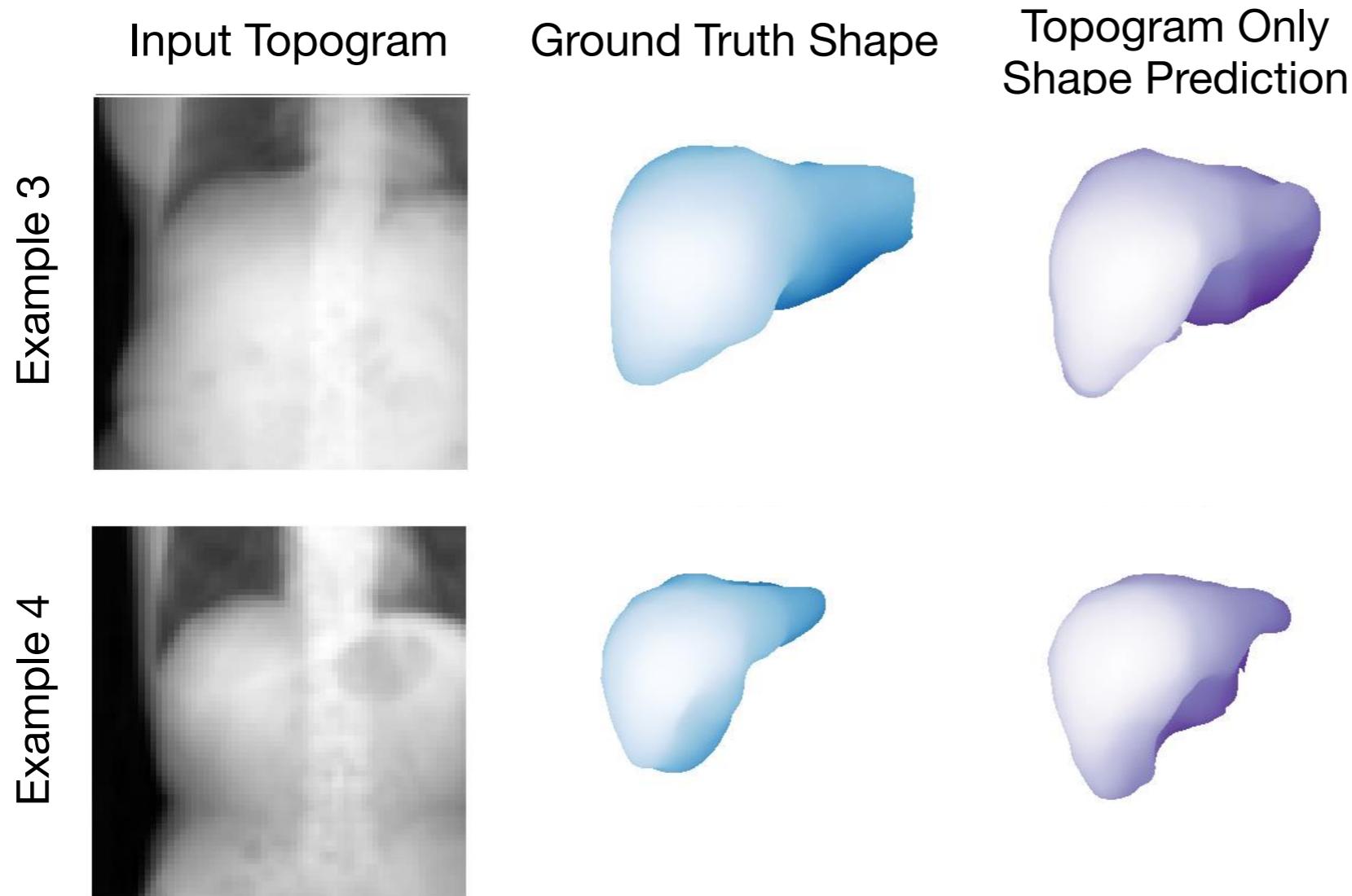


Topogram Only
Shape Prediction



Example 4

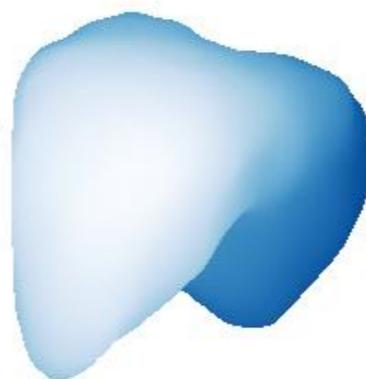
Results



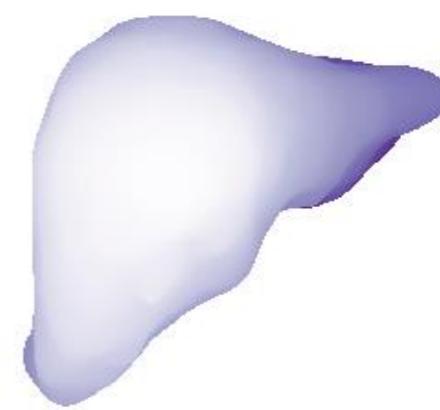
Improve Accuracy?



Ground Truth Shape



Shape Prediction

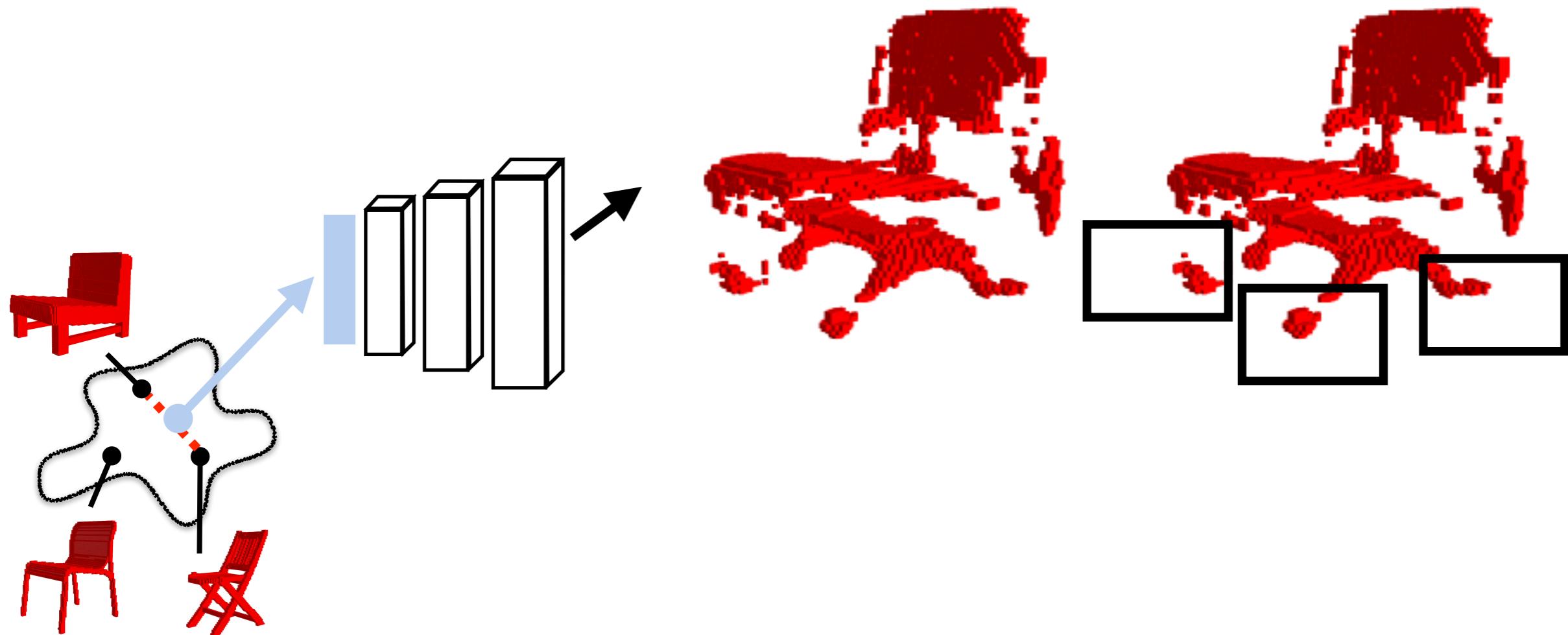


Structure-Aware Shape Synthesis

[E. Balashova, V. Singh, B. Teixeira, J. Wang, T. Chen, T. Funkhouser](#)
Structure-Aware Shape Synthesis
International Conference on 3D Vision (3DV) 2018.

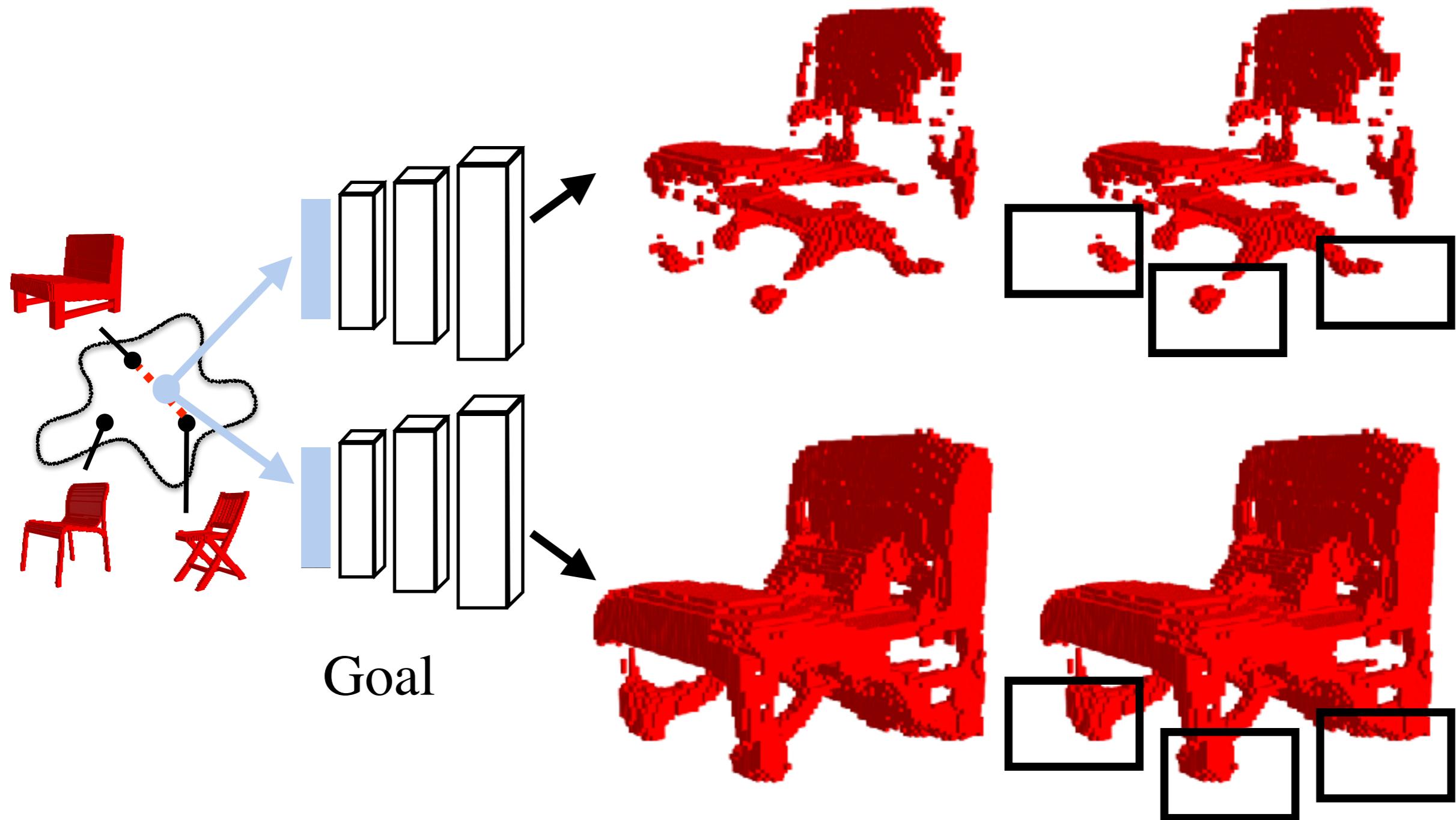


Challenge





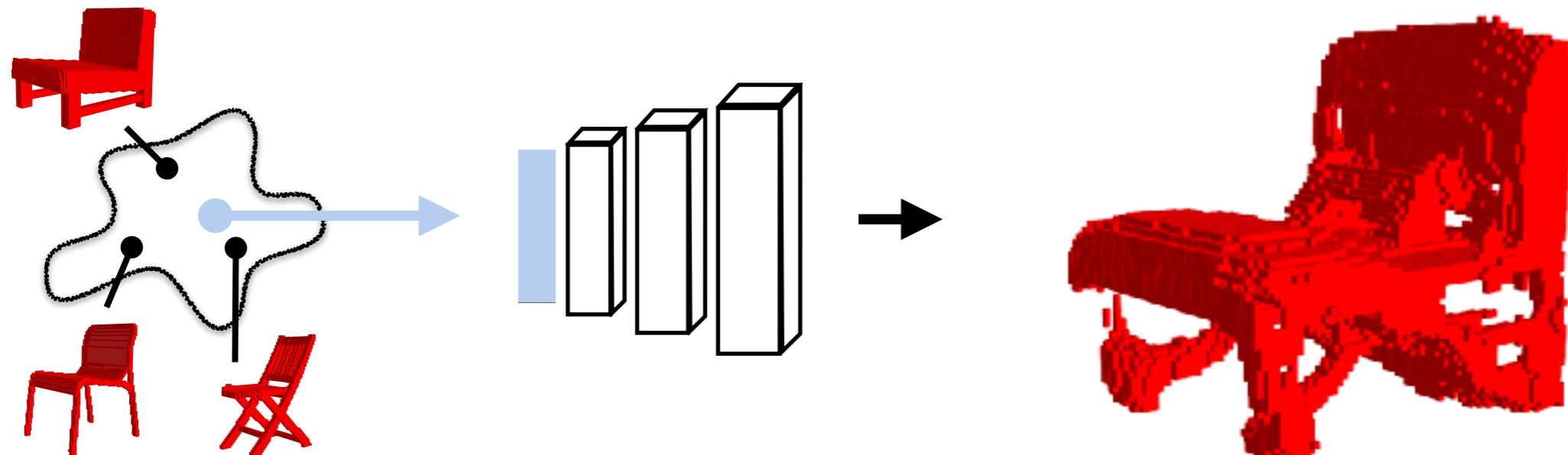
Structure-Aware Synthesis





Goal

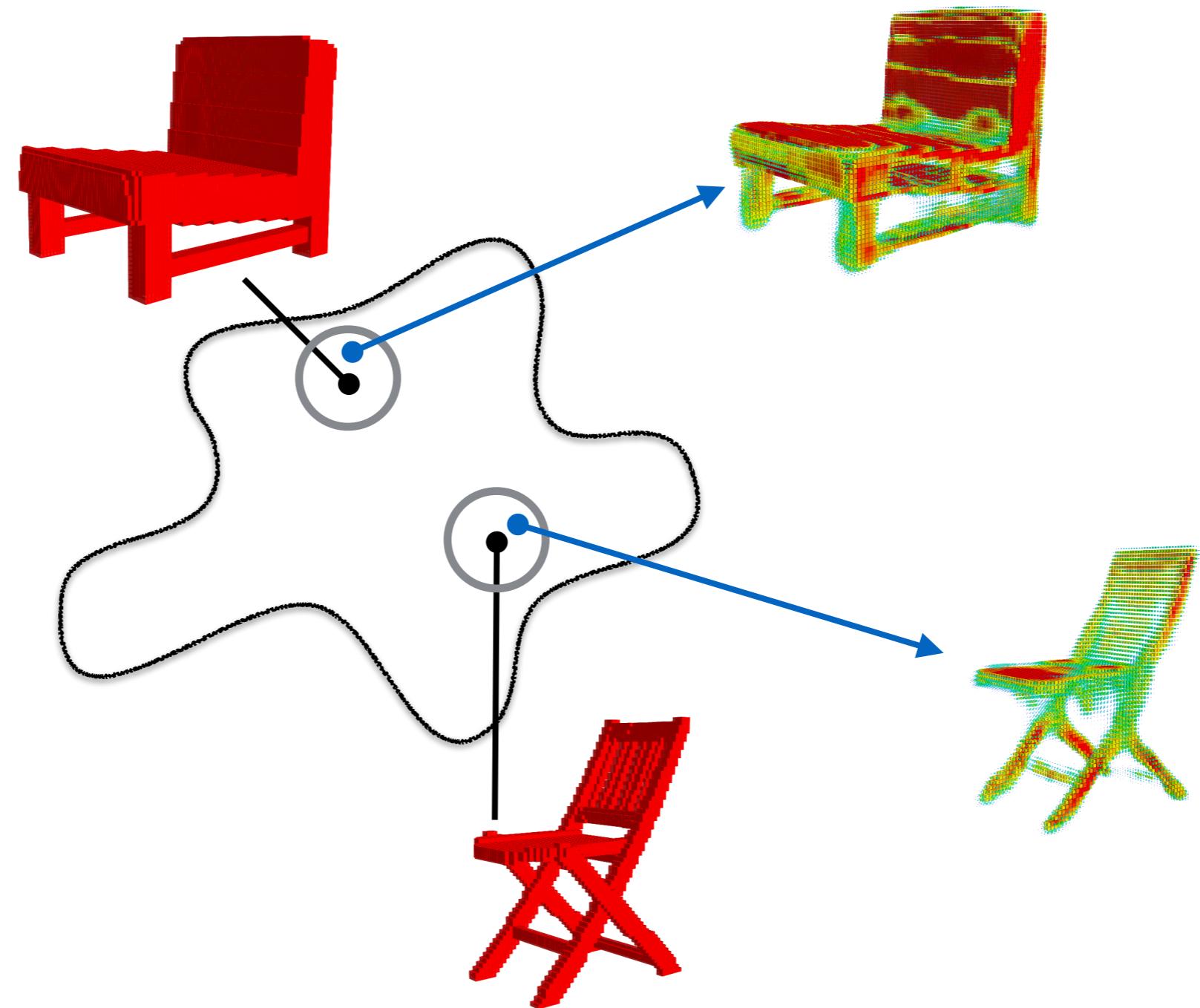
Any Manifold Point



Structurally Correct Example

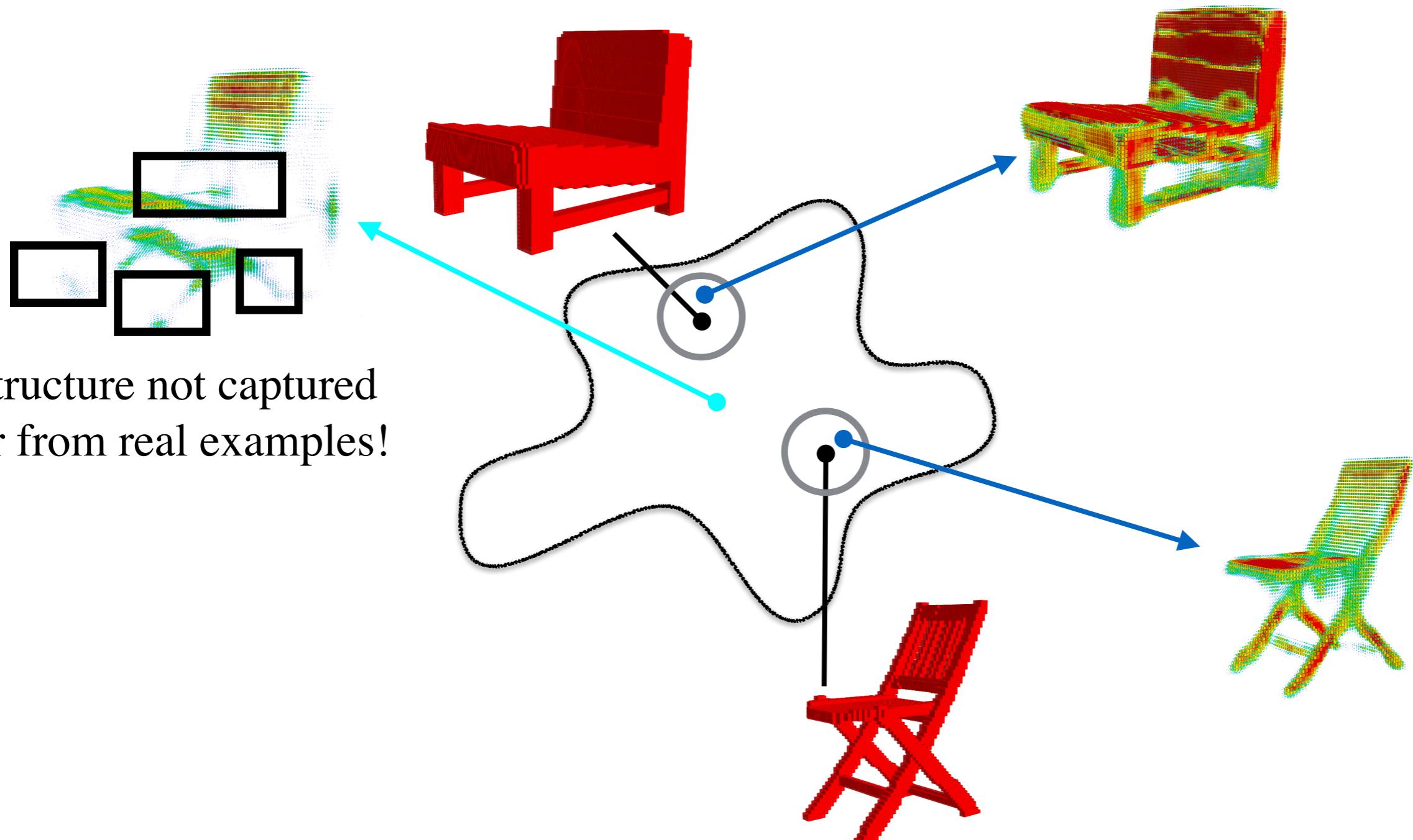


Manifold Learning



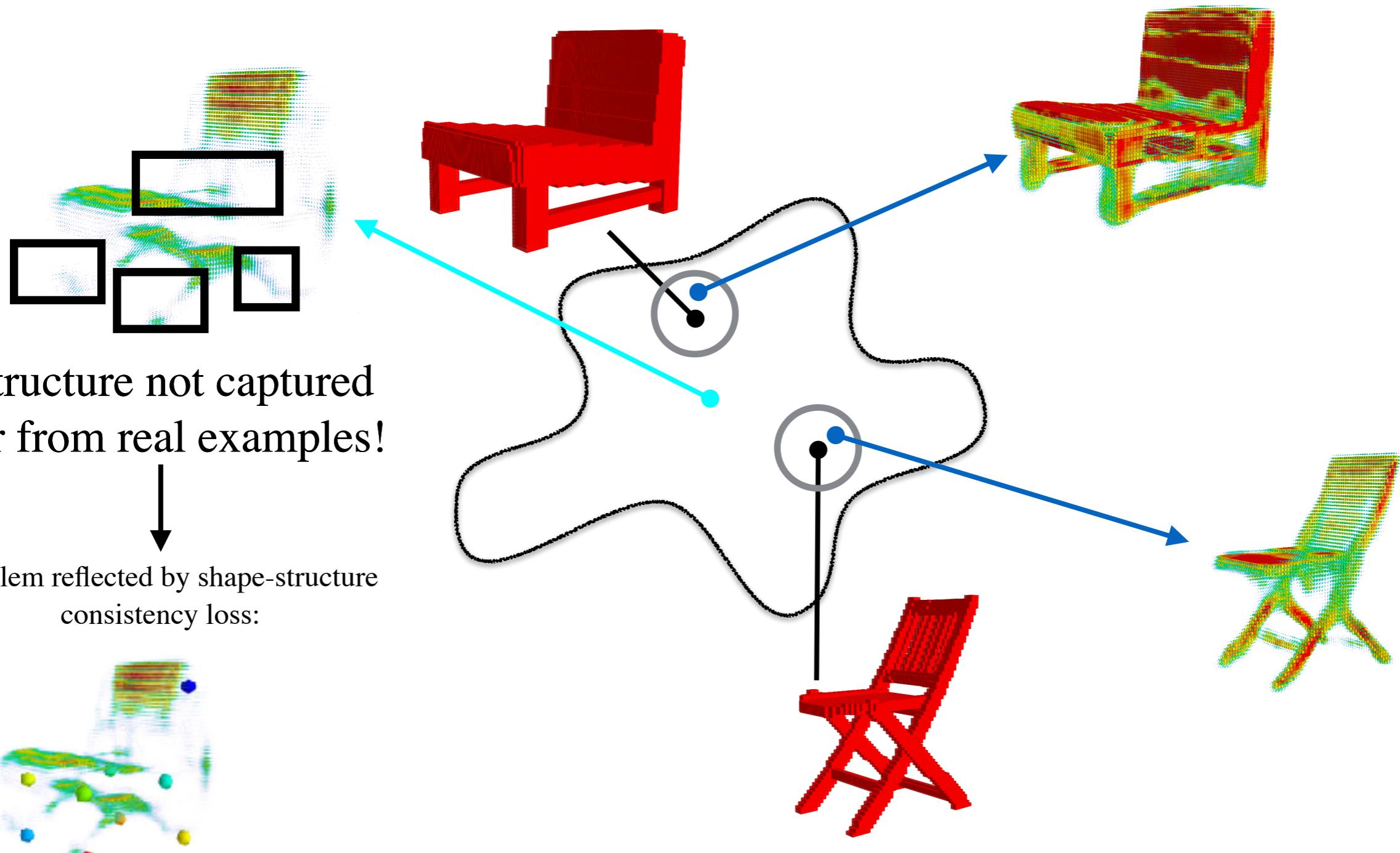


Manifold Learning



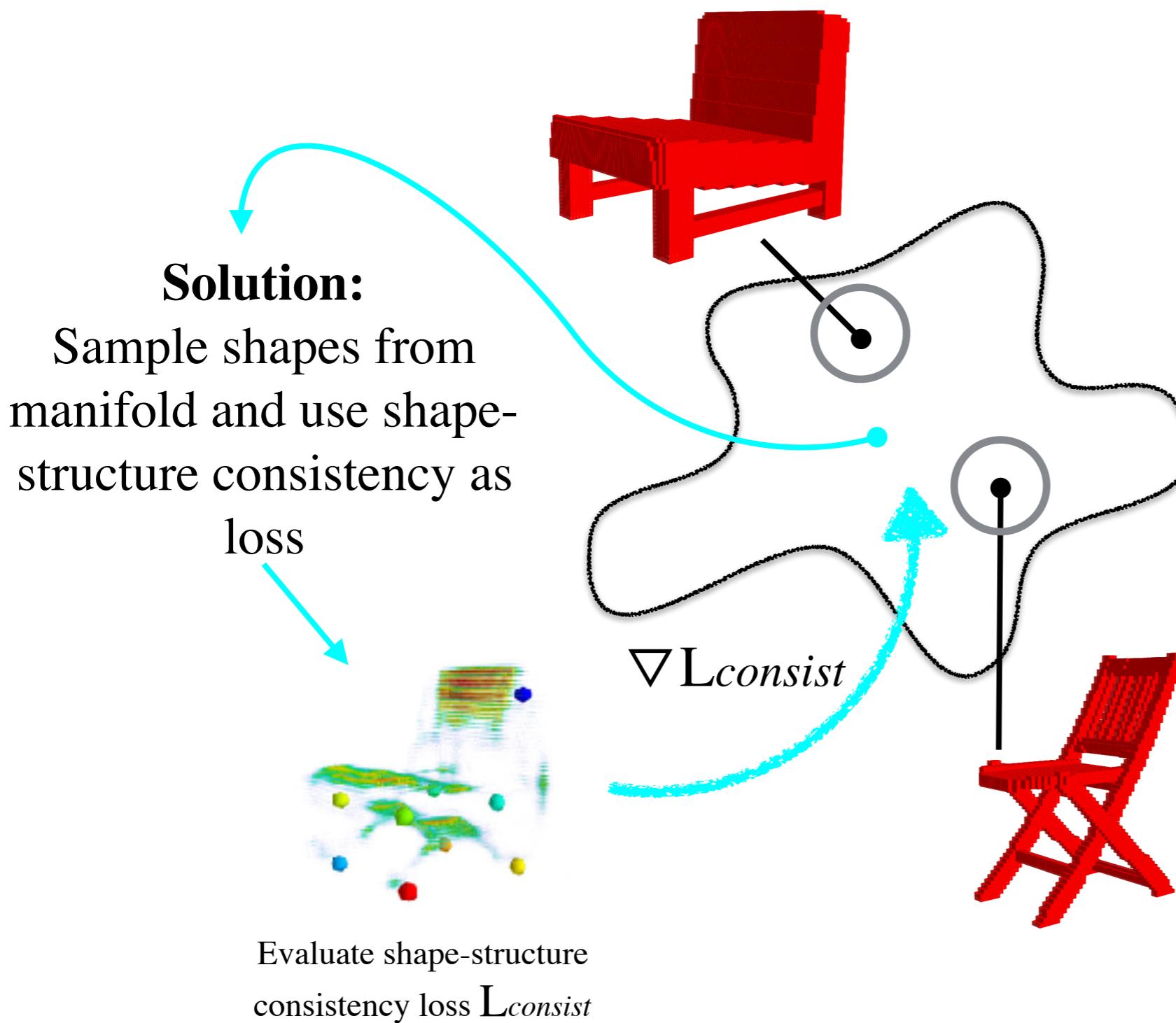


Manifold Learning



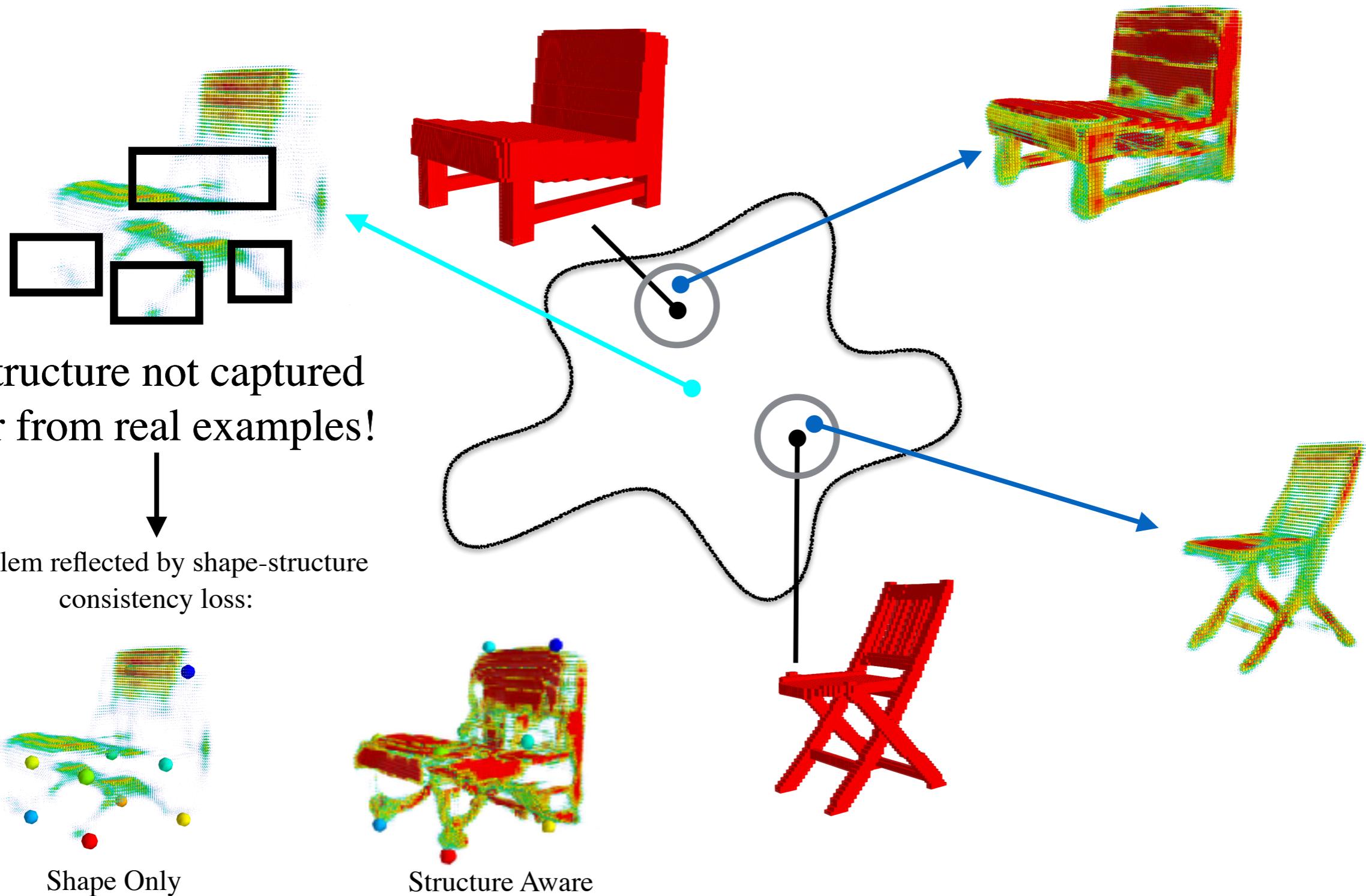


Manifold Learning





Manifold Learning



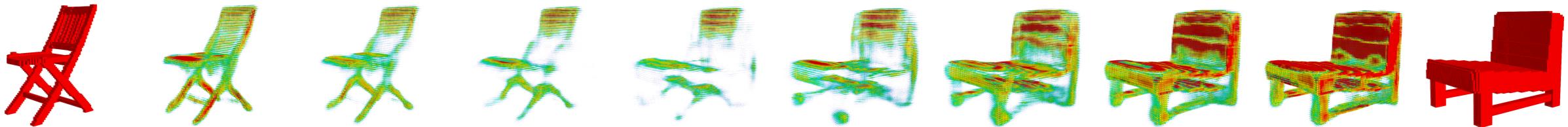


Interpolation

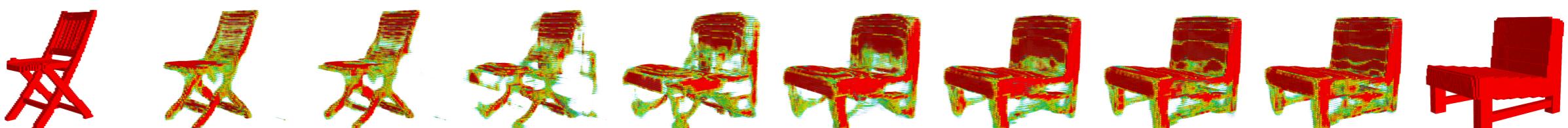


Interpolation

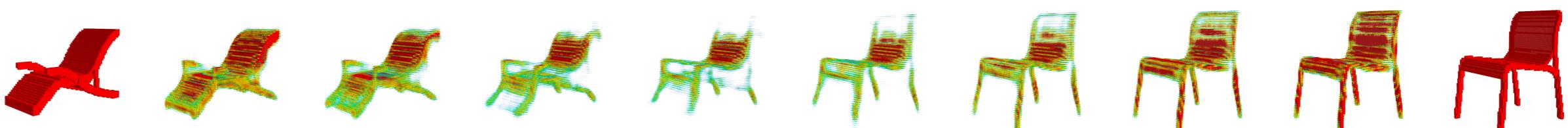
Shape
Only



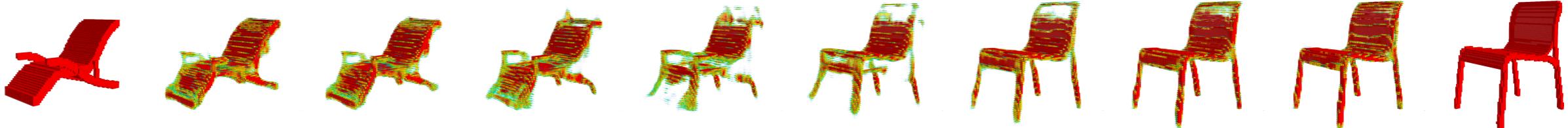
Structure
Aware



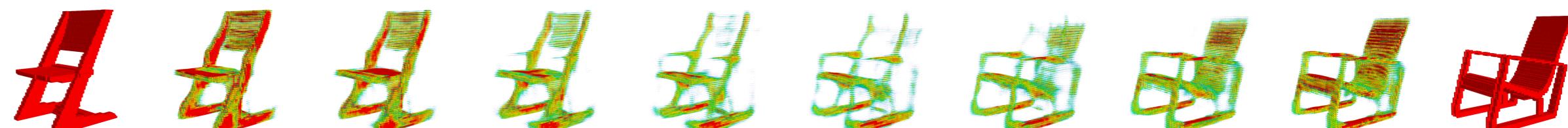
Shape
Only



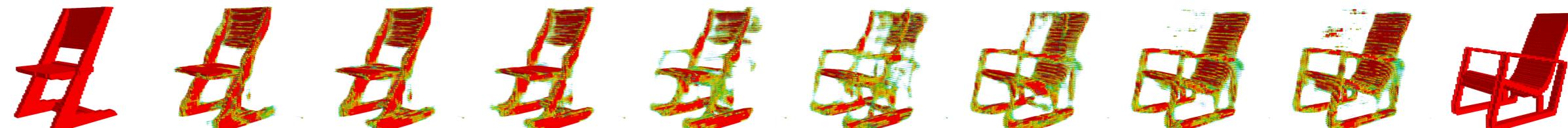
Structure
Aware



Shape
Only



Structure
Aware





Interpolation

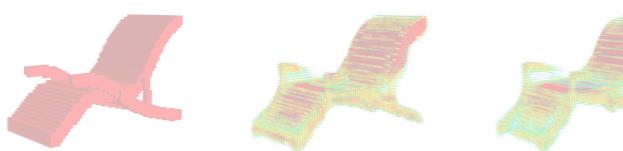
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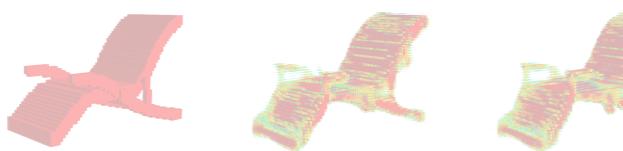
Structure Aware



Shape Only



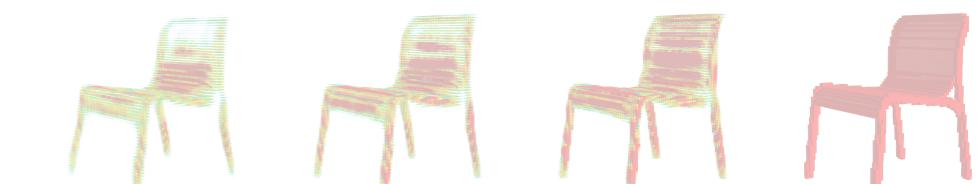
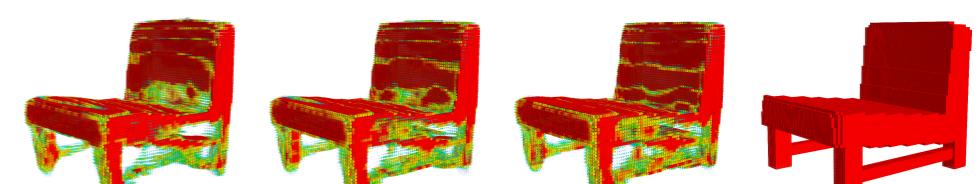
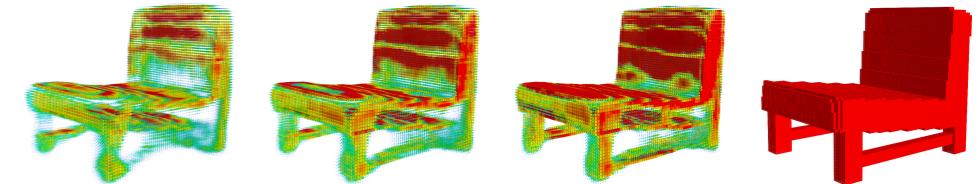
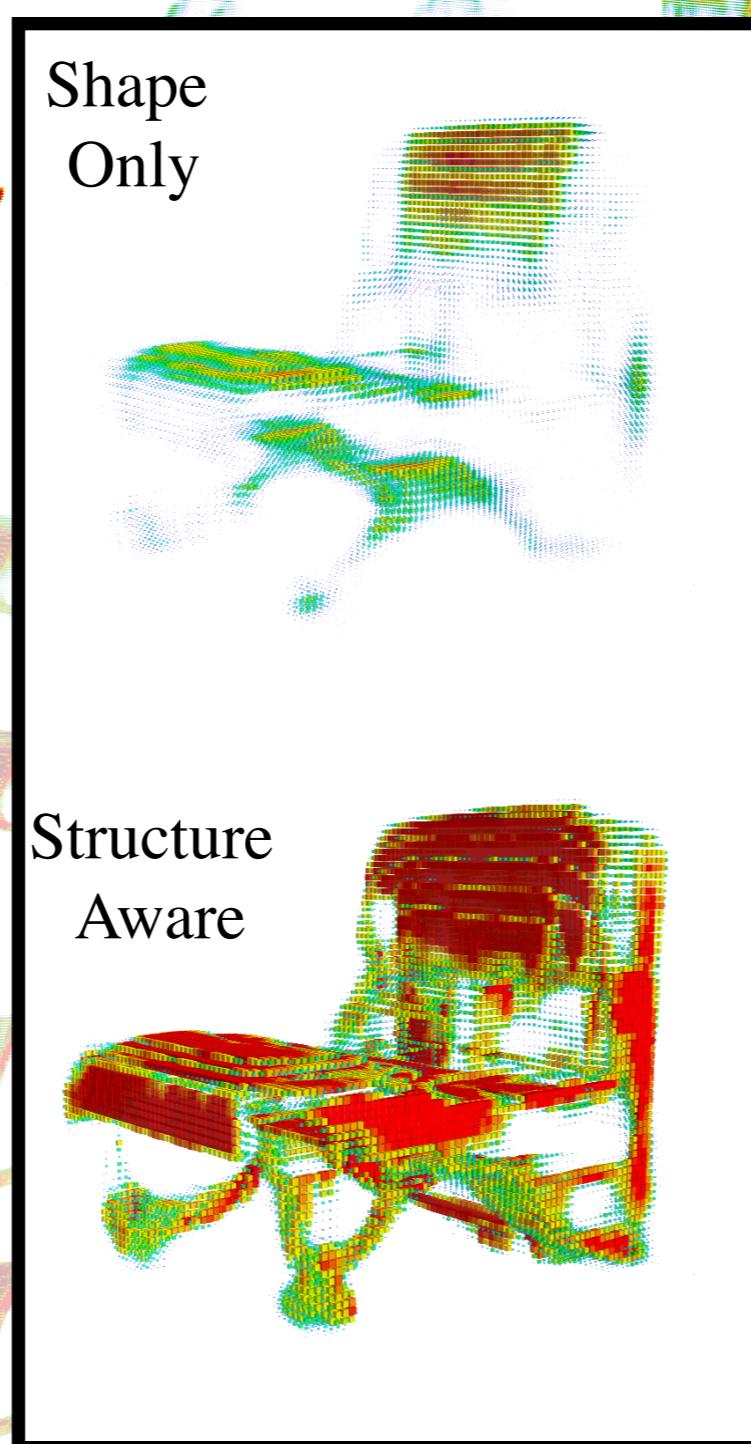
Structure Aware



Shape Only



Structure Aware



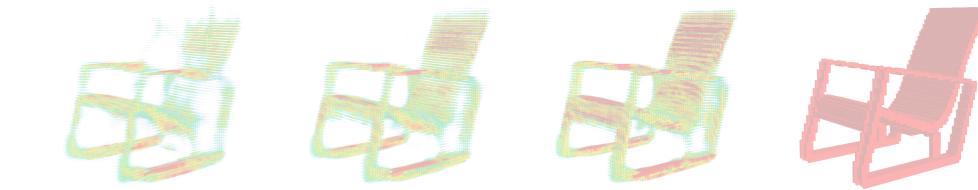
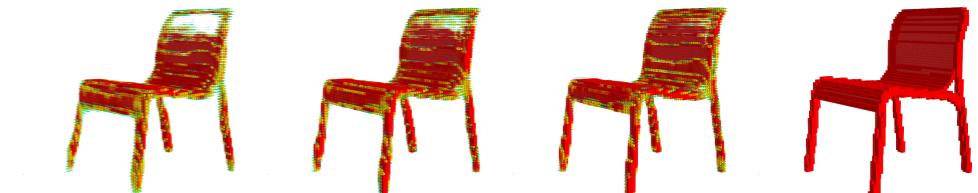
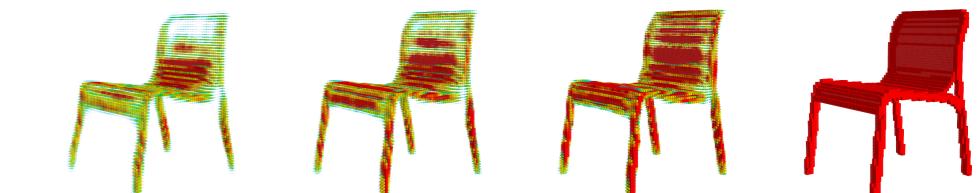
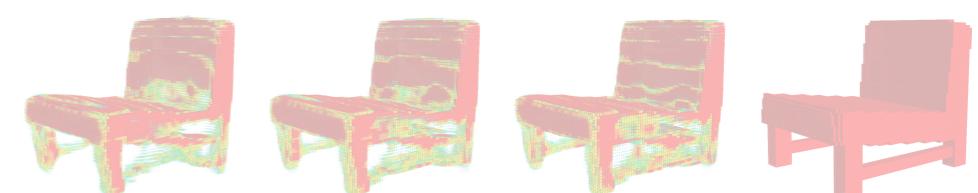
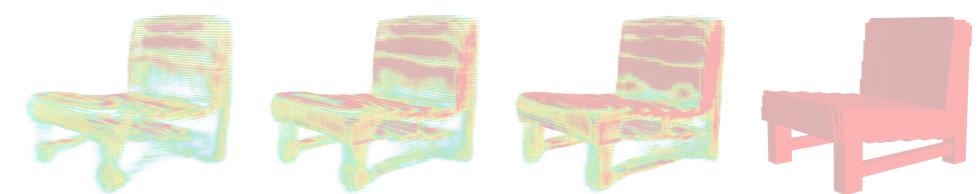
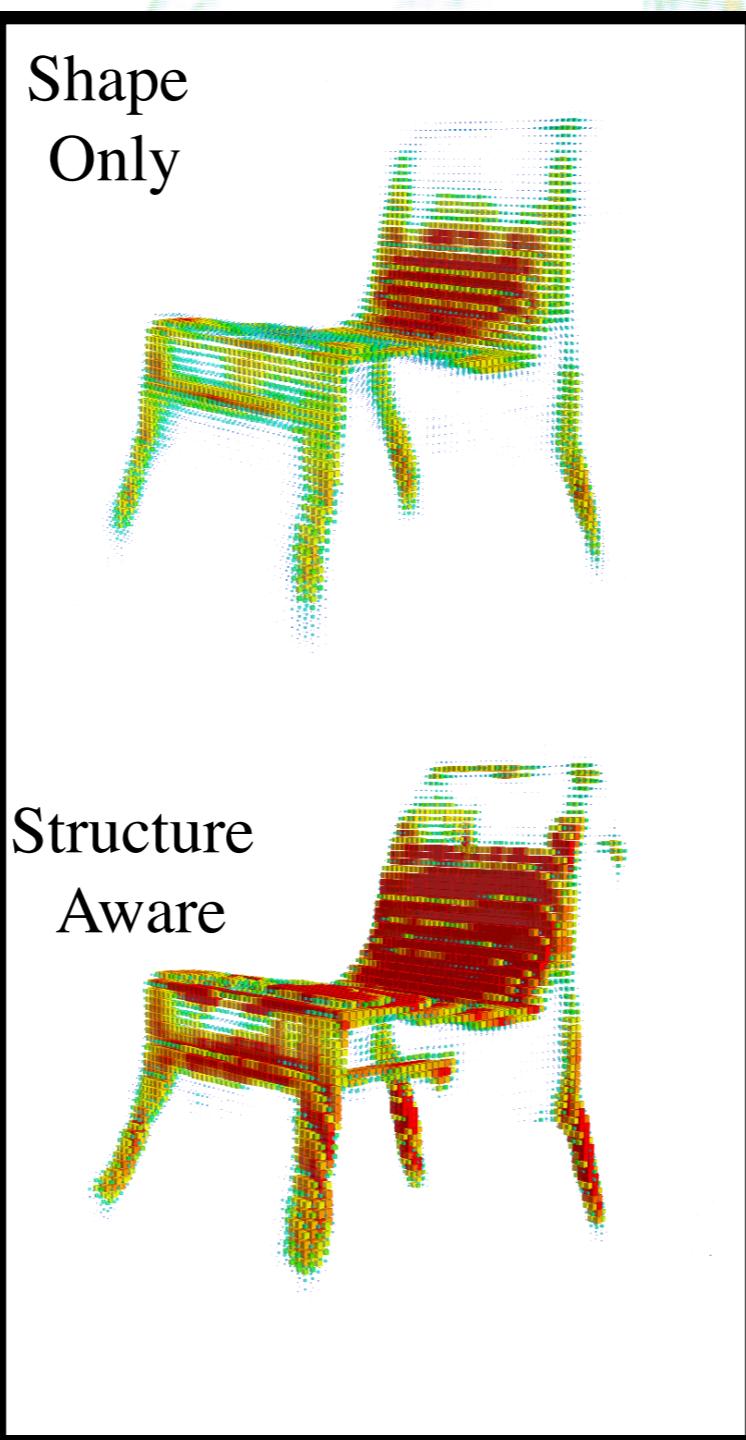


Interpolation

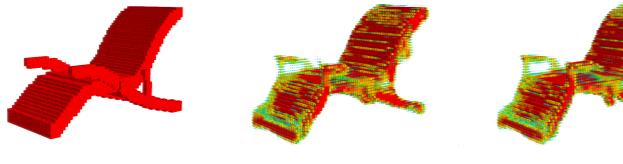
Shape Only



Structure Aware



Structure Aware



Shape Only



Structure Aware





Interpolation

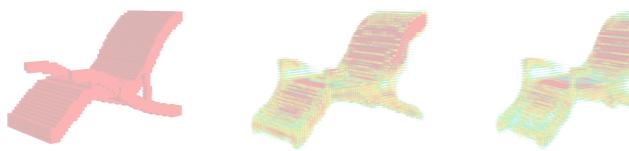
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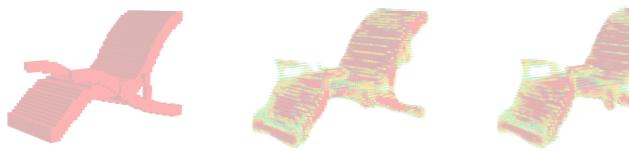
Structure
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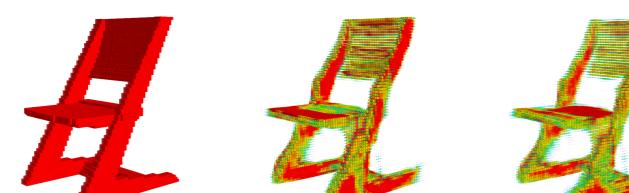
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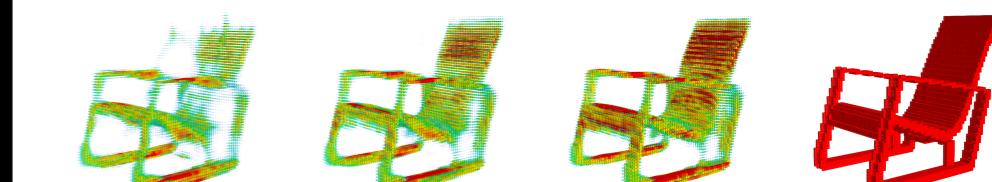
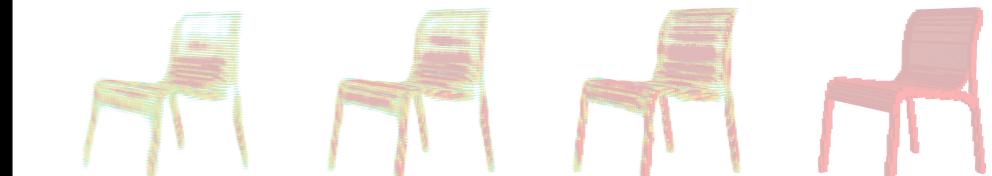
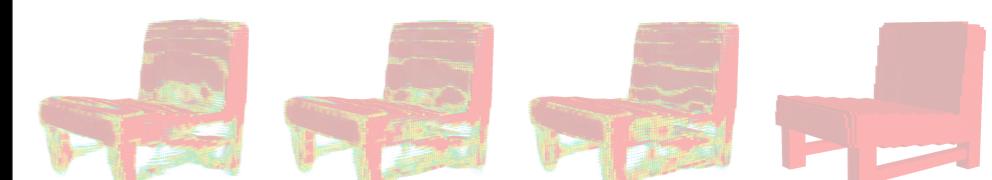
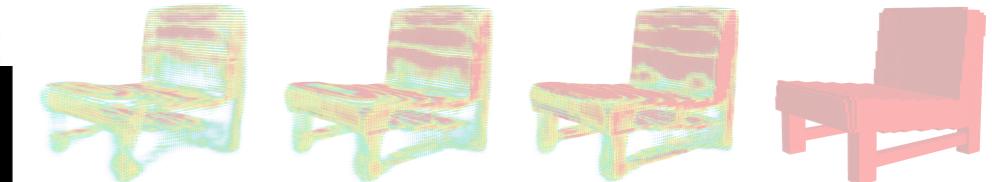
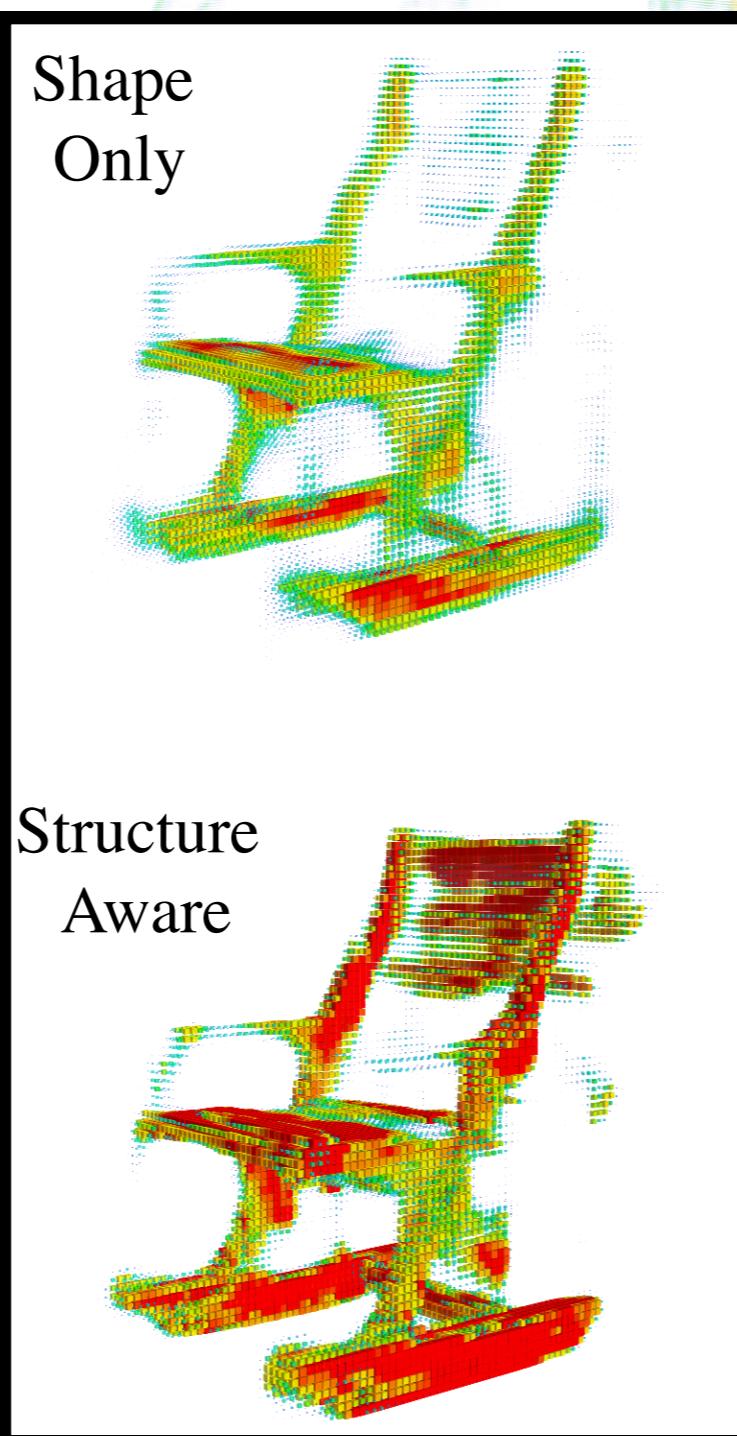
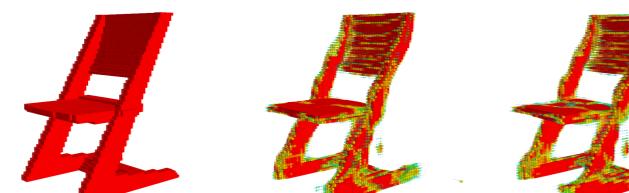
Structure
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Shape
Only



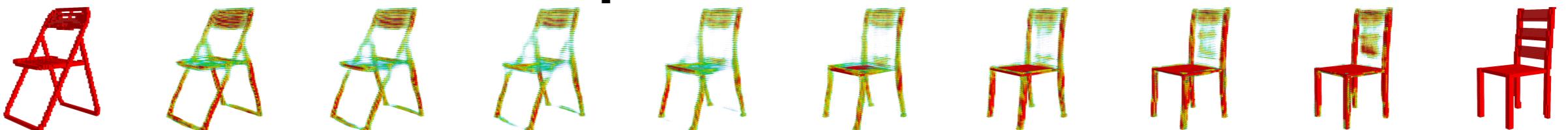
Structure
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Interpolation

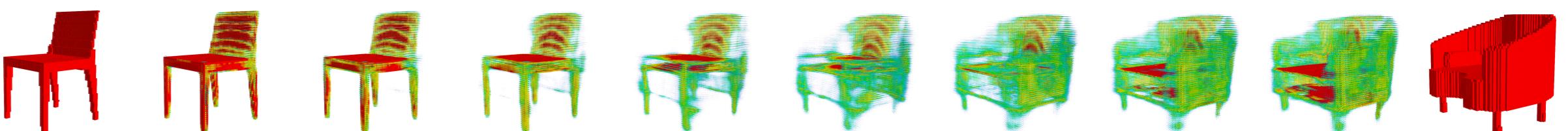
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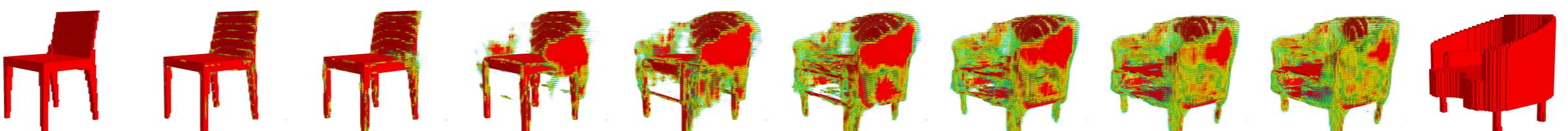
Structure
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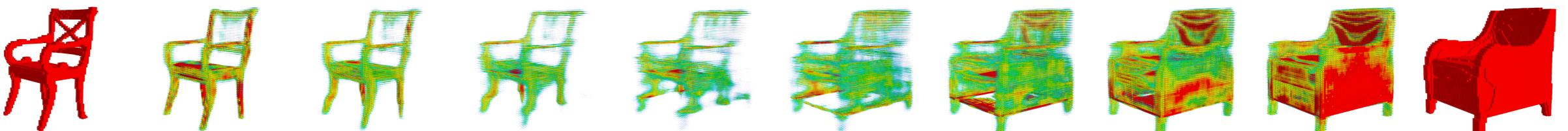
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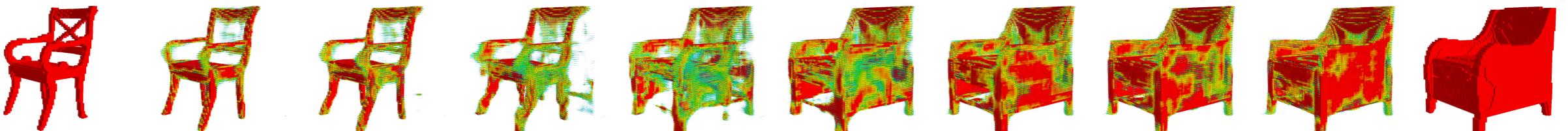
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Shape
Only



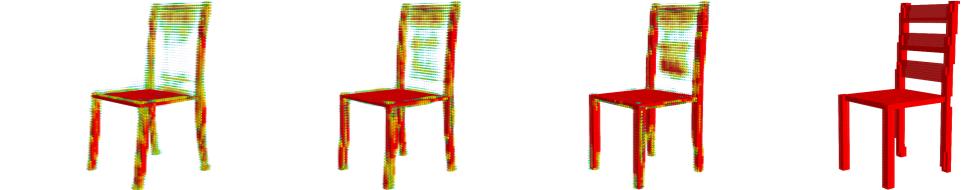
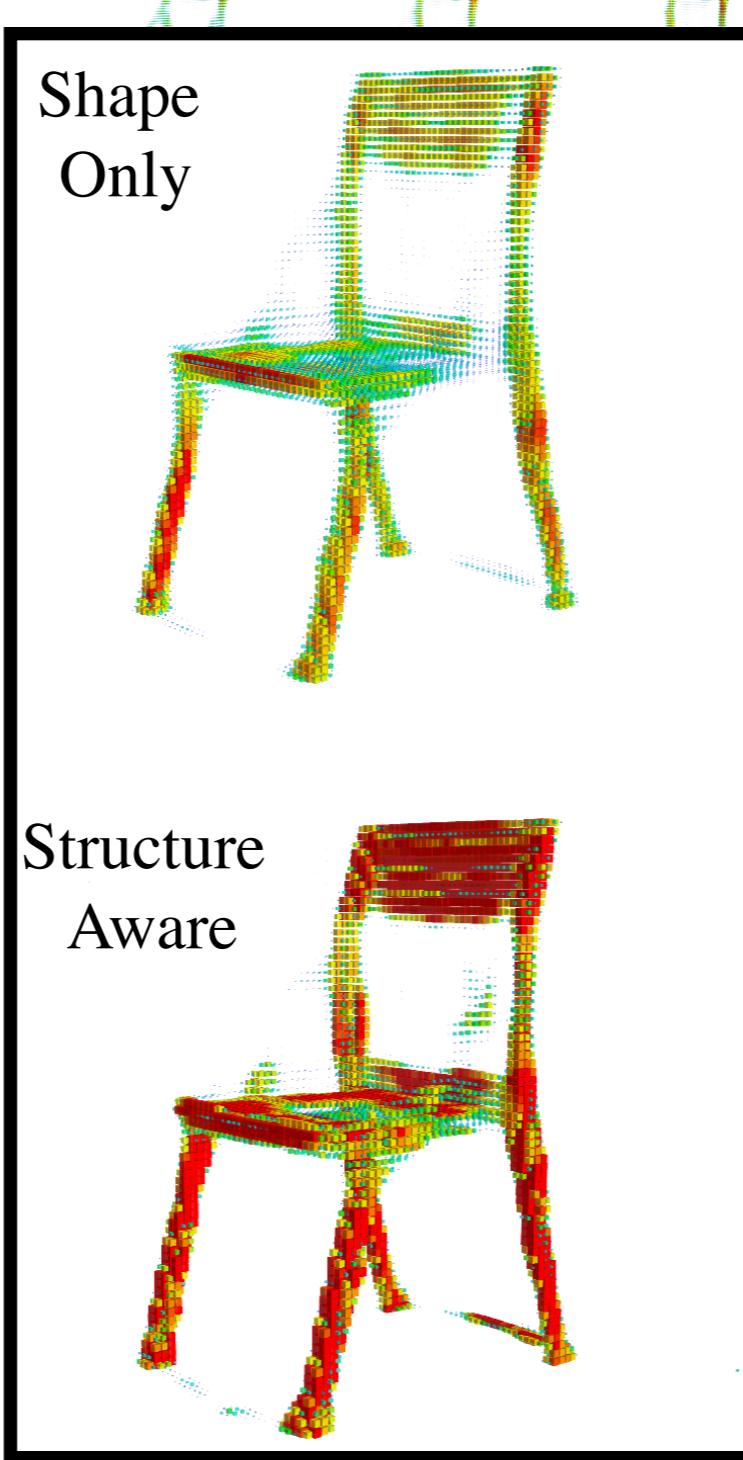
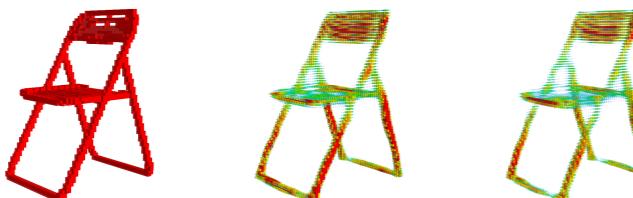
Structure
Aware



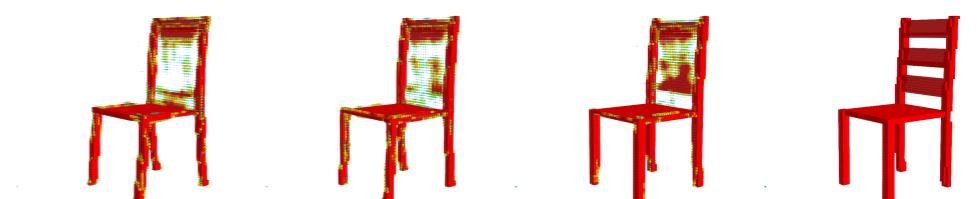
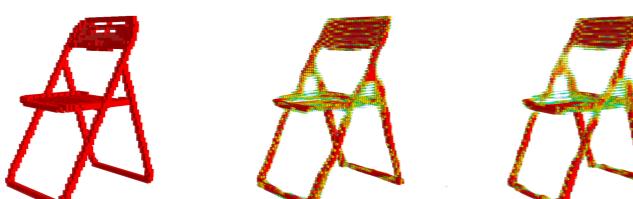


Interpolation

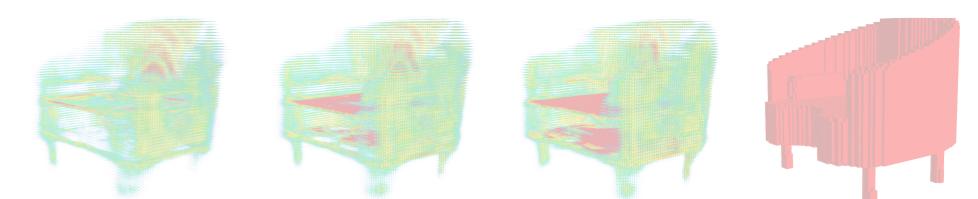
Shape Only



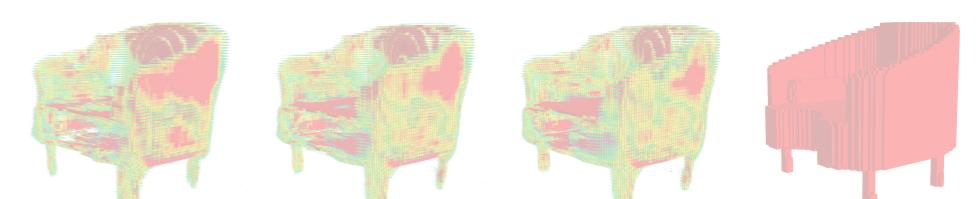
Structure Aware



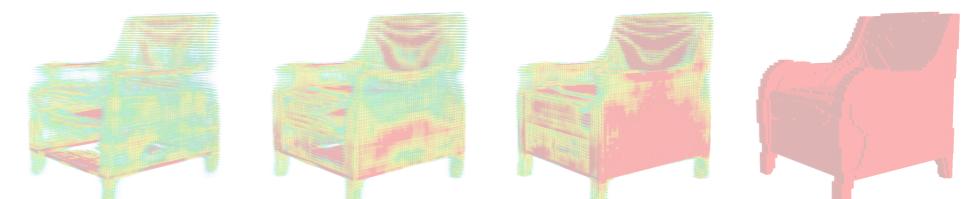
Shape Only



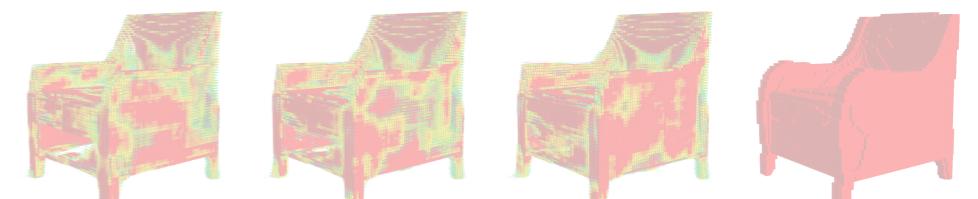
Structure Aware



Shape Only



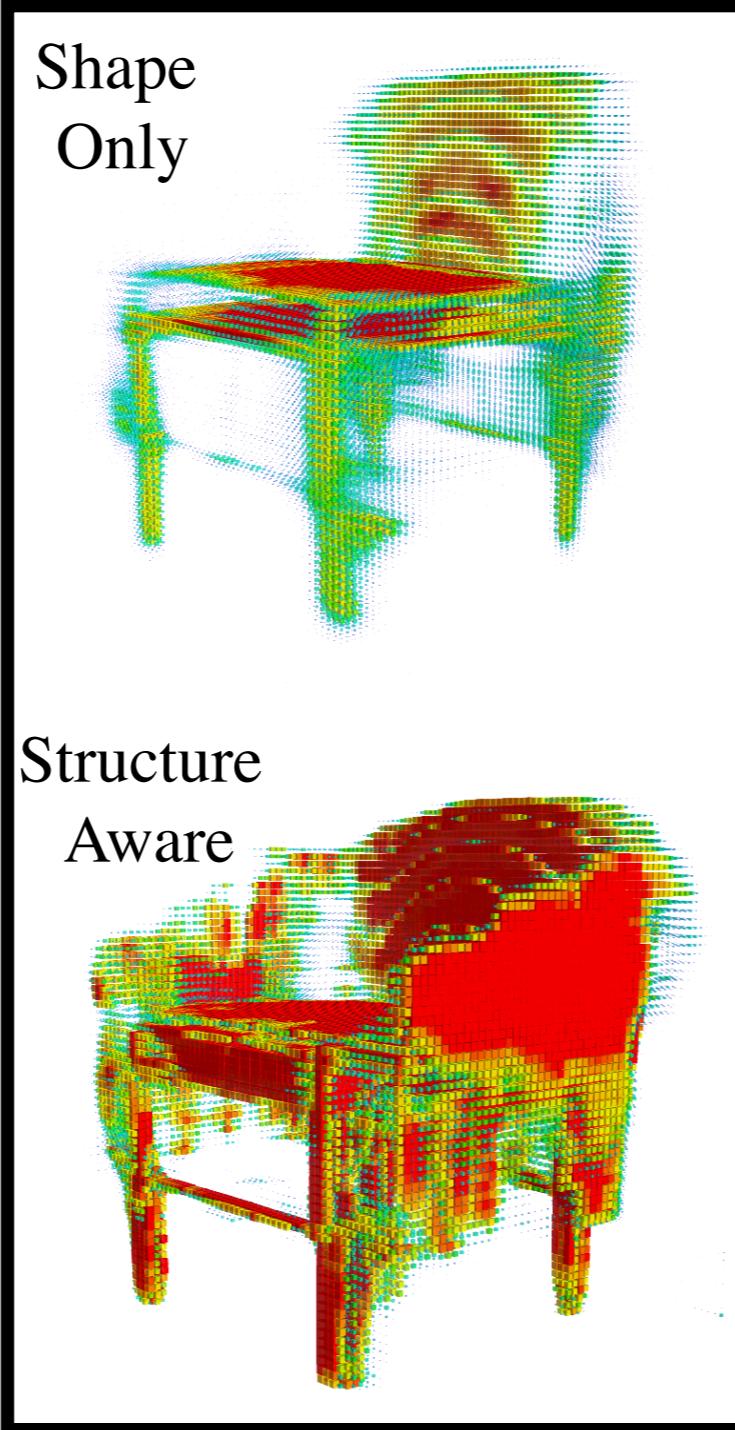
Structure Aware





Interpolation

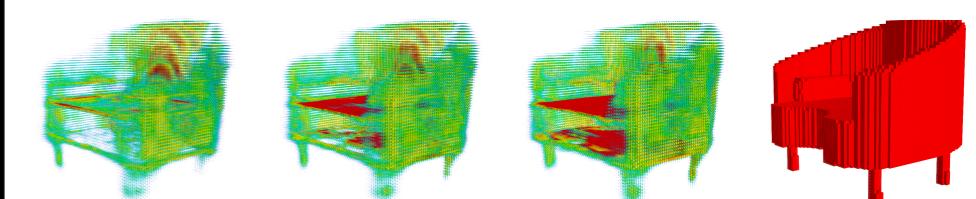
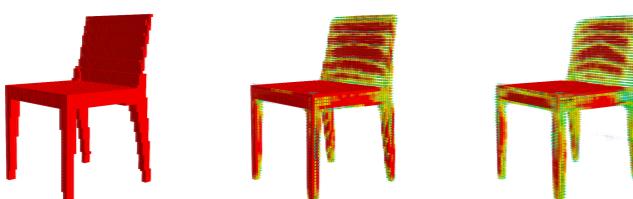
Shape
Only



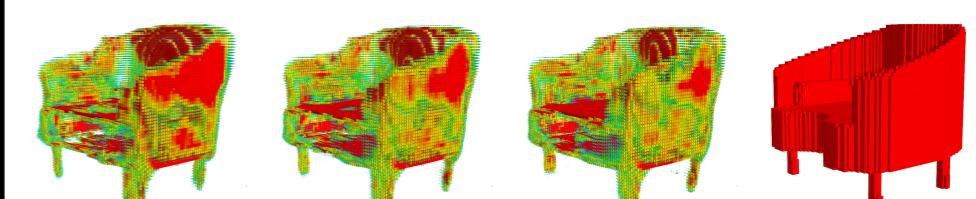
Structure
Aware



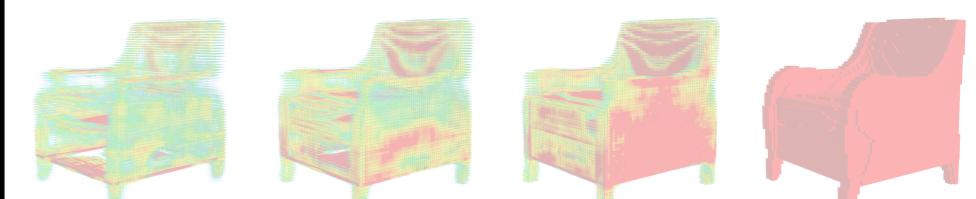
Shape
Only



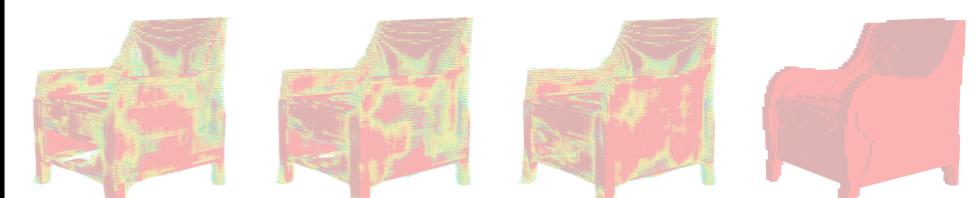
Structure
Aware



Shape
Only



Structure
Aware





Interpolation

Shape Only



Structure Aware



Shape Only



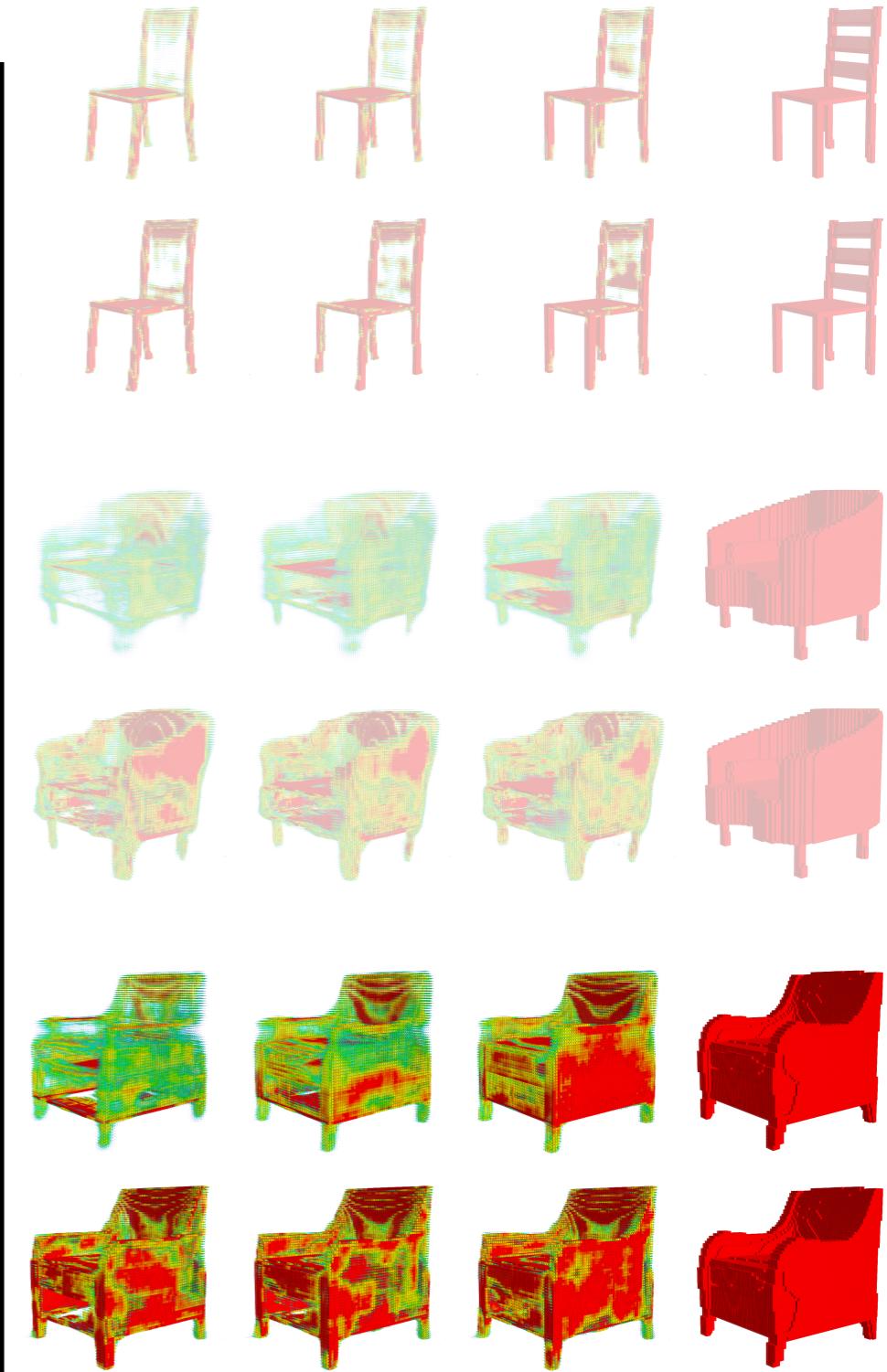
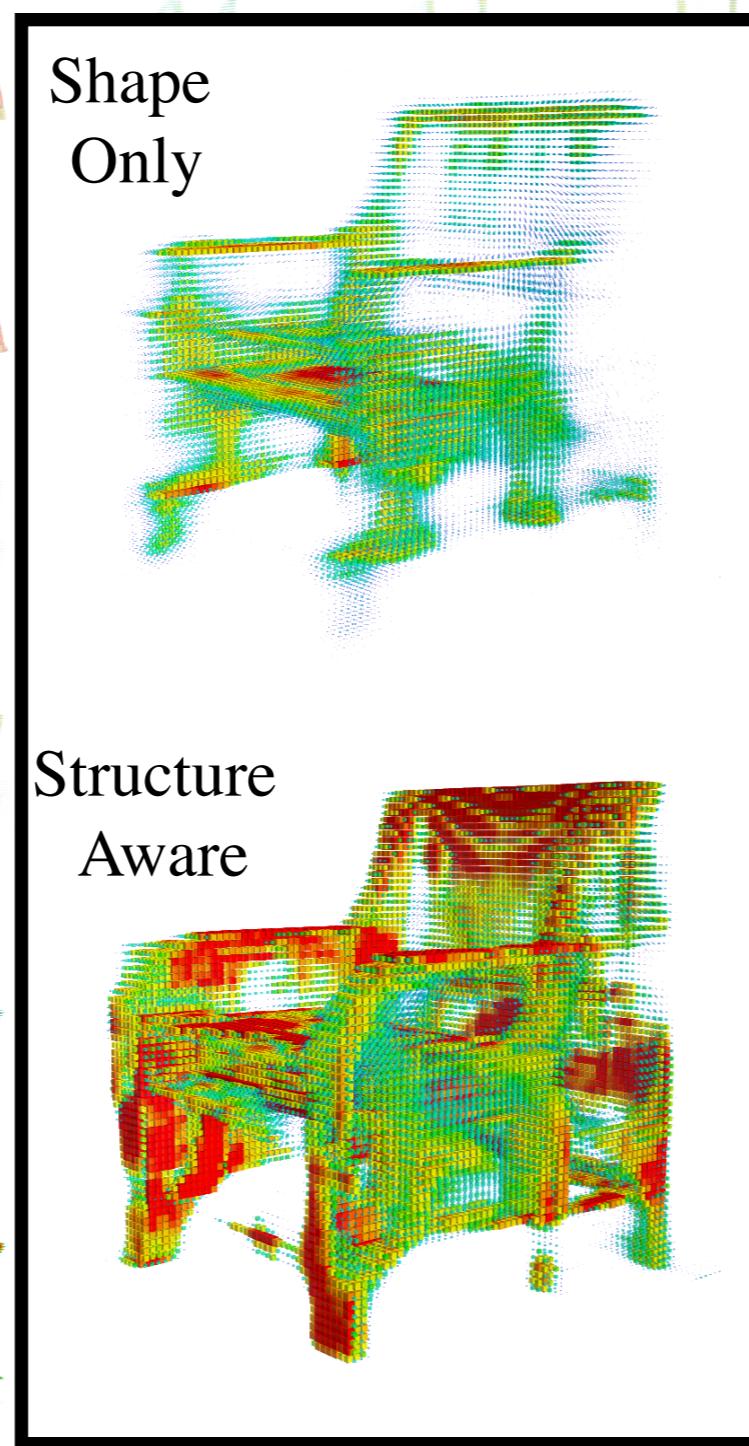
Structure Aware



Shape Only

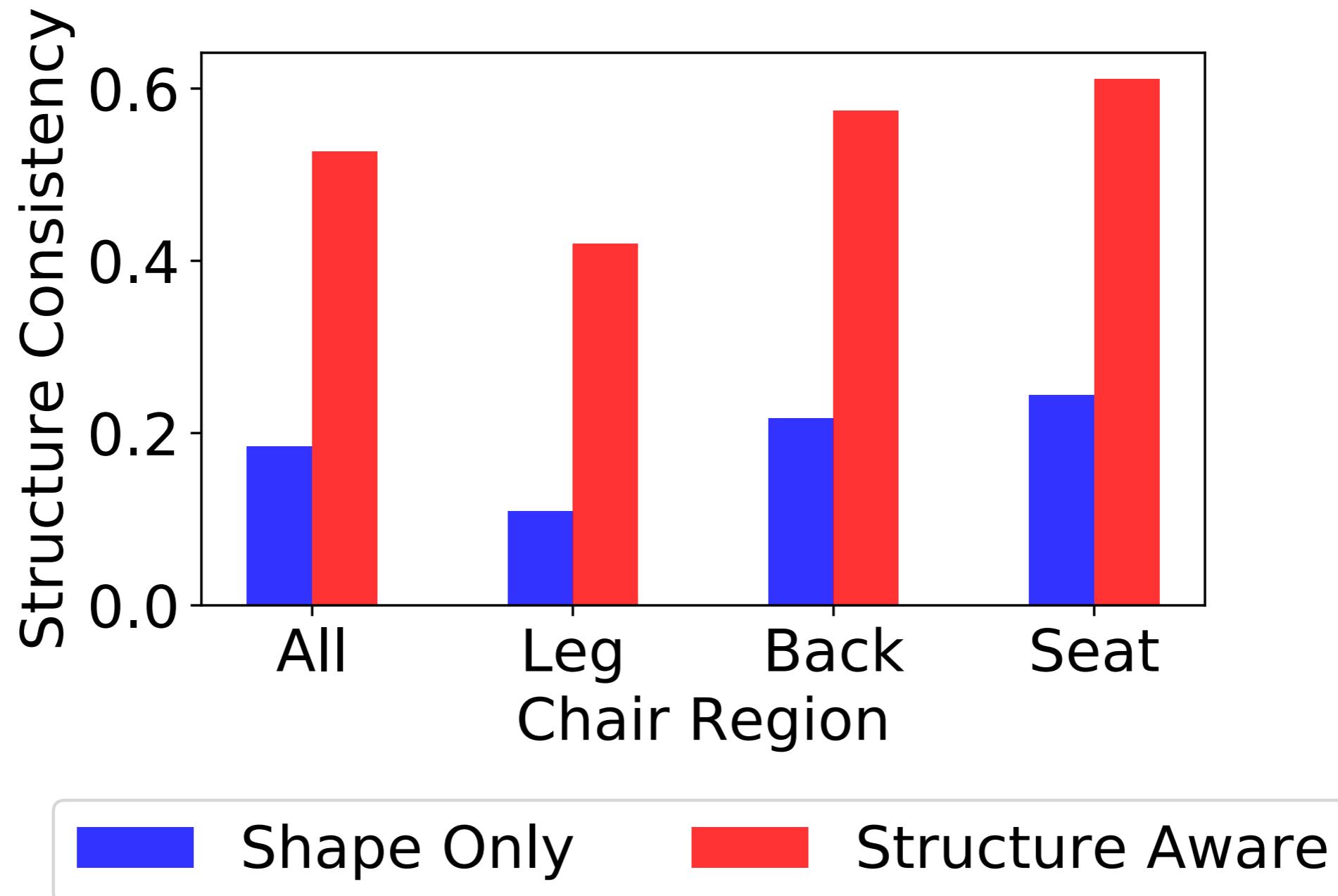


Structure Aware

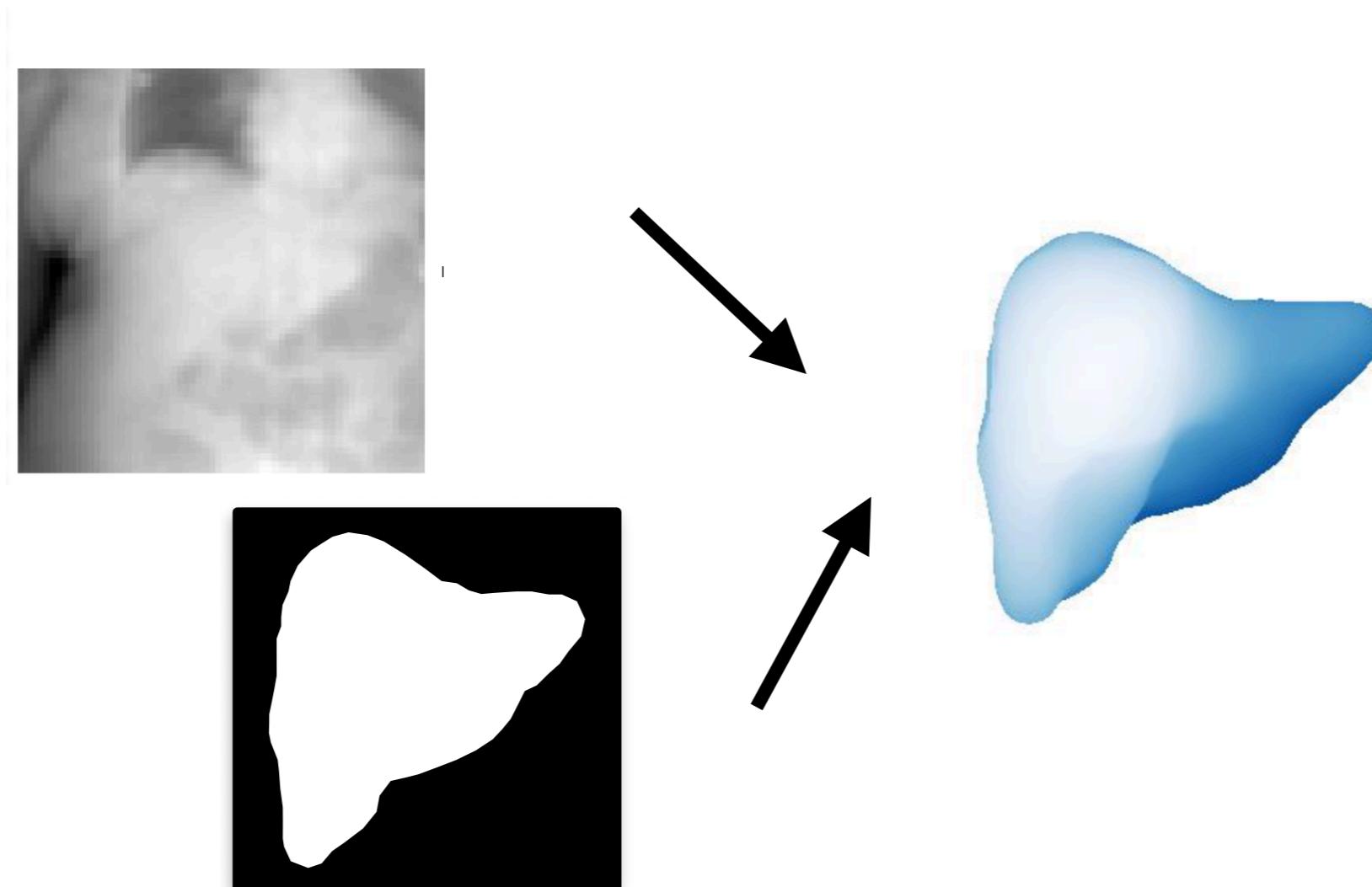




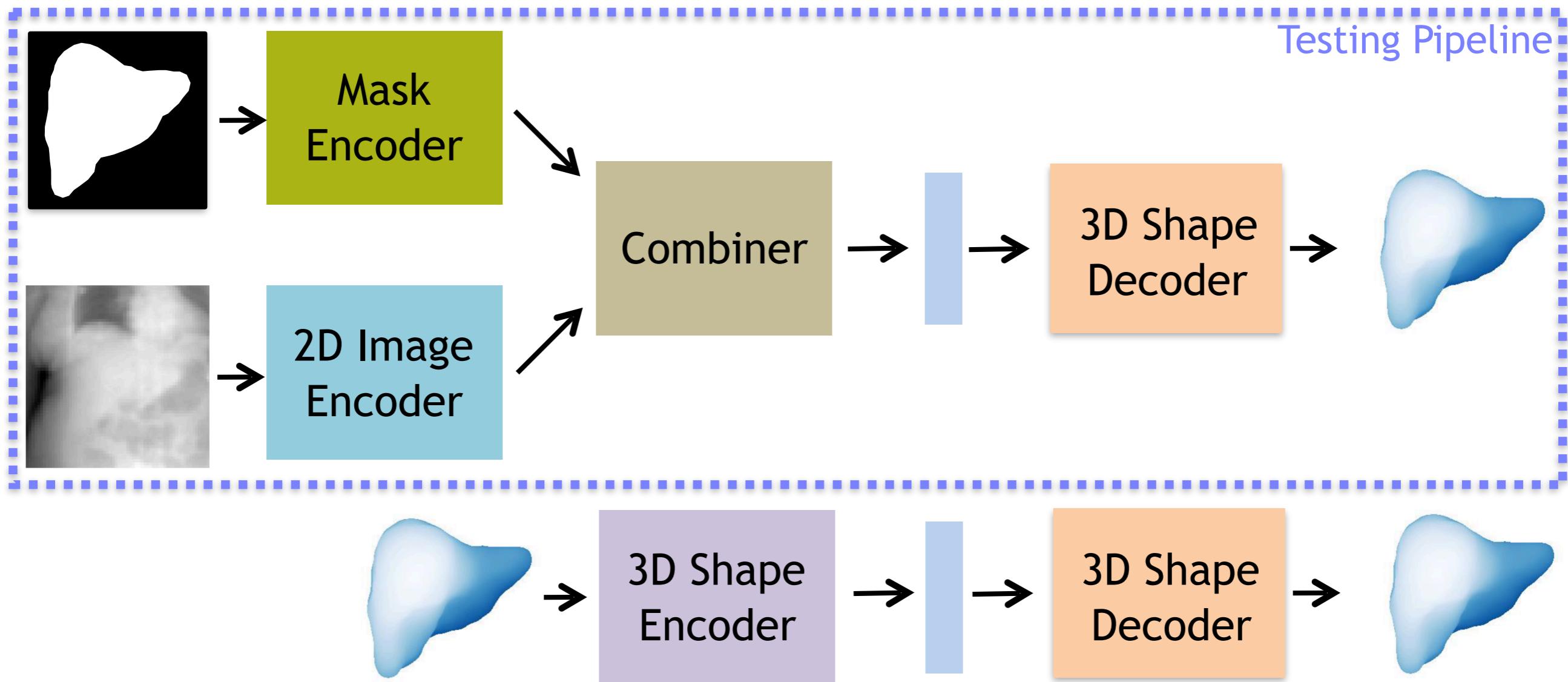
Landmark Consistency



Structure-Aware Liver Reconstruction



Structure-Aware Liver Reconstruction



Objective

We optimize the networks using a combination loss function L :

$$L = \alpha_1 L_{rec}(s, s') + \alpha_2 L_{KL} + \alpha_3 L_{rec}(s, G(\bar{z})) + \alpha_4 L_{mask}(k, \tilde{k}),$$

Kullback
Leibler divergence Encoder Output

$$L_{mask}(k, \tilde{k}) = - \sum_{n=1}^N k_n \log \tilde{k}_n + (1 - k_n) \log (1 - \tilde{k}_n).$$

Mask Loss BCE Loss
GT Mask Pred. Mask

$$L_{rec}(s, s') = - \frac{1}{N} \sum_{n=1}^N s_n \log s'_n + (1 - s_n) \log (1 - s'_n)$$

BCE Loss
Reconstruction Loss

$\alpha_1, \alpha_2, \alpha_3, \alpha_4$ - Sub-Component weights

Results

Input Topogram

Ground Truth Shape

Topogram Only
Shape Prediction

Topogram + Mask
Shape Prediction

Example 1

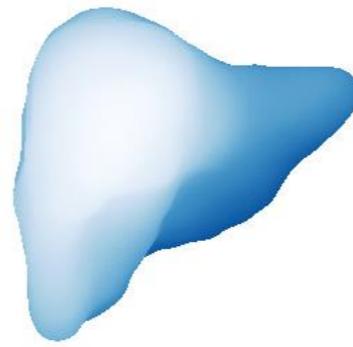
Example 2

Results

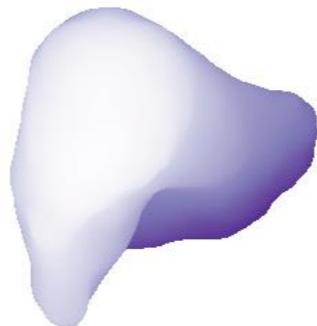
Example 1



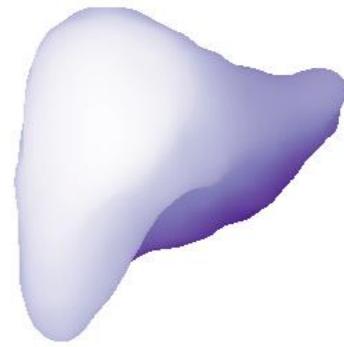
Ground Truth Shape



Topogram Only
Shape Prediction

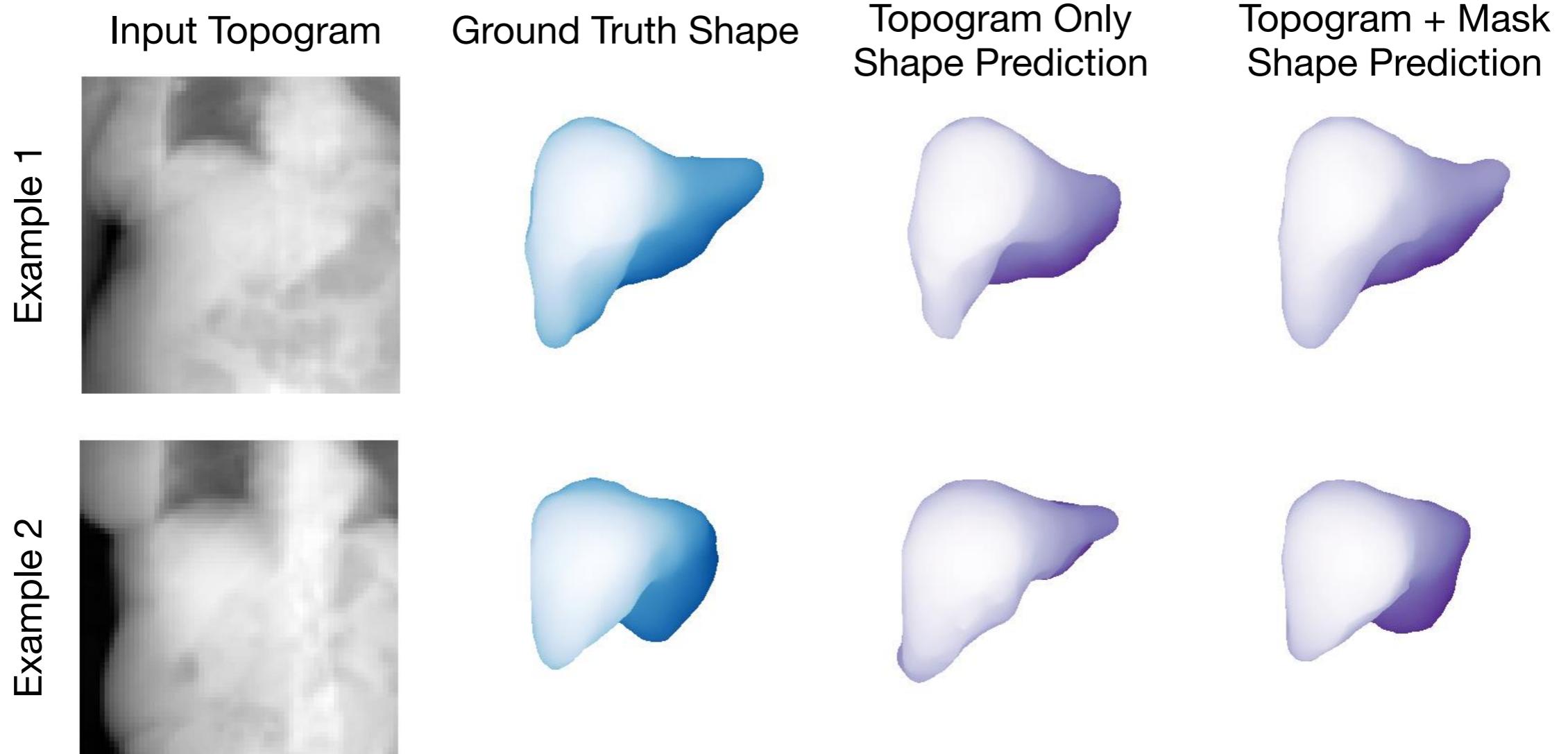


Topogram + Mask
Shape Prediction



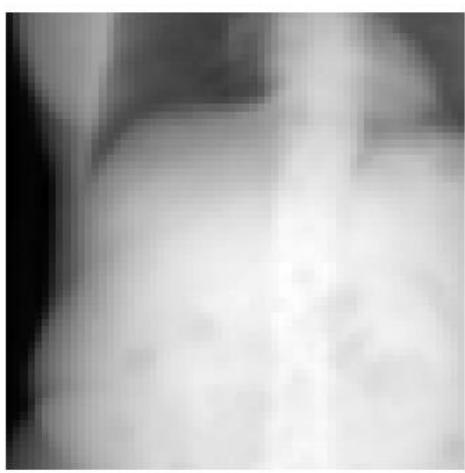
Example 2

Results



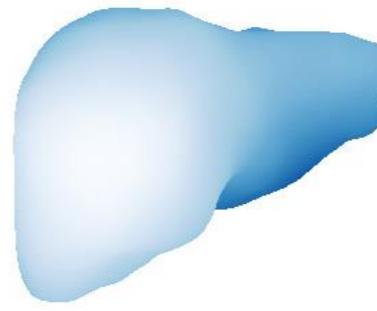
Results

Example 3

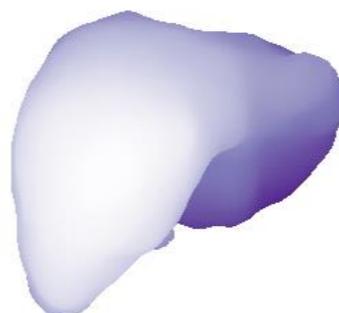


Input Topogram

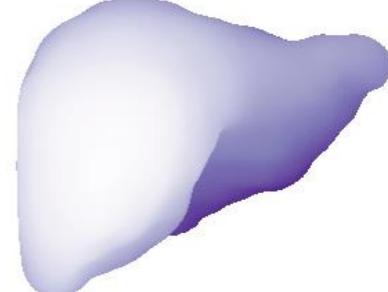
Ground Truth Shape



Topogram Only
Shape Prediction

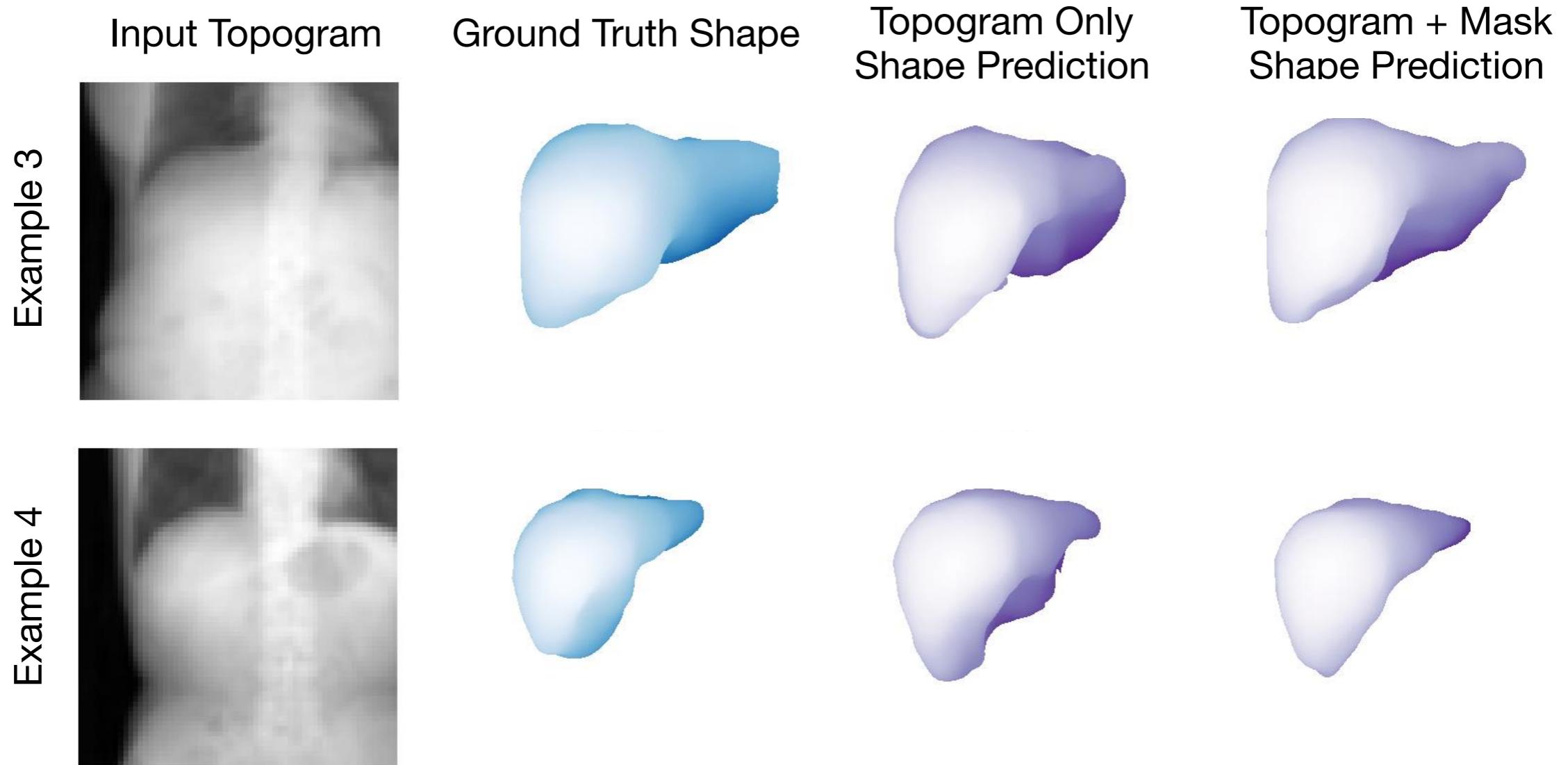


Topogram + Mask
Shape Prediction



Example 4

Results



Results

Example (1)

Example (2)

Example (3)

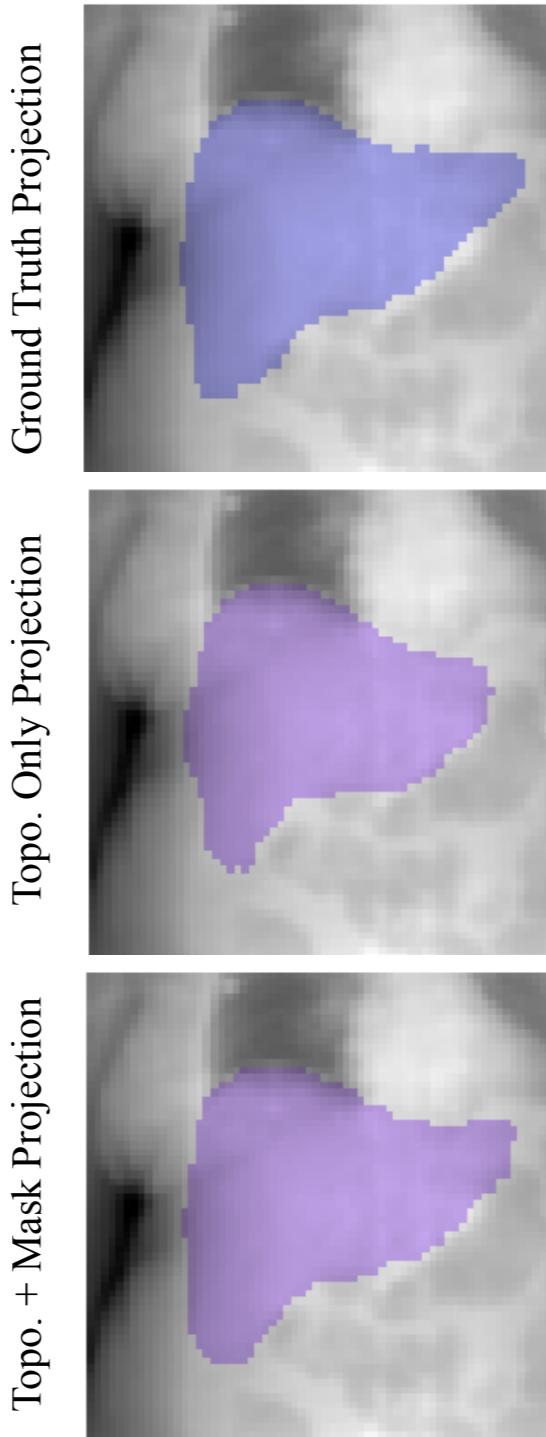
Topo. Only Projection

Topo. + Mask Projection

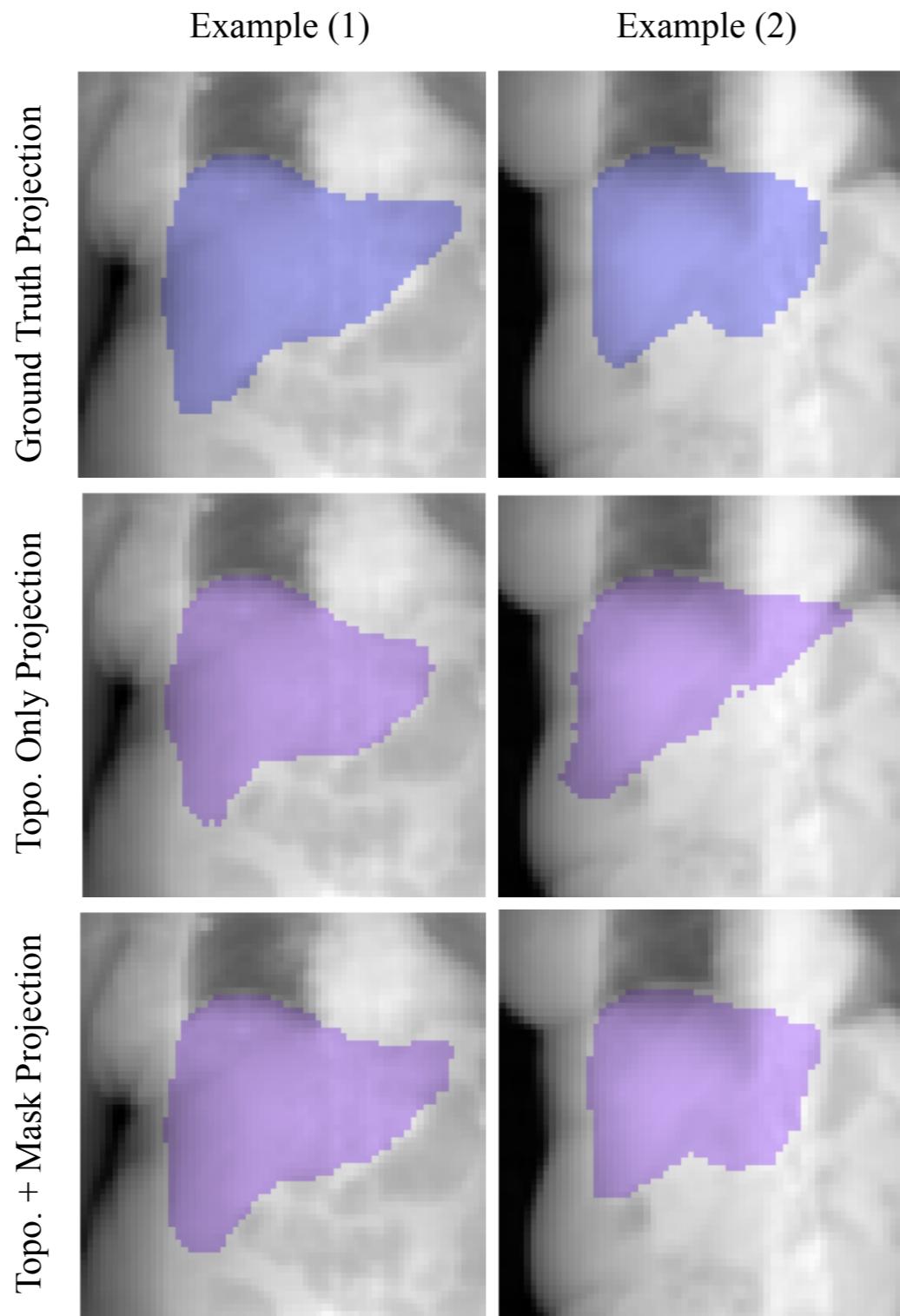
Ground Truth Projection

Results

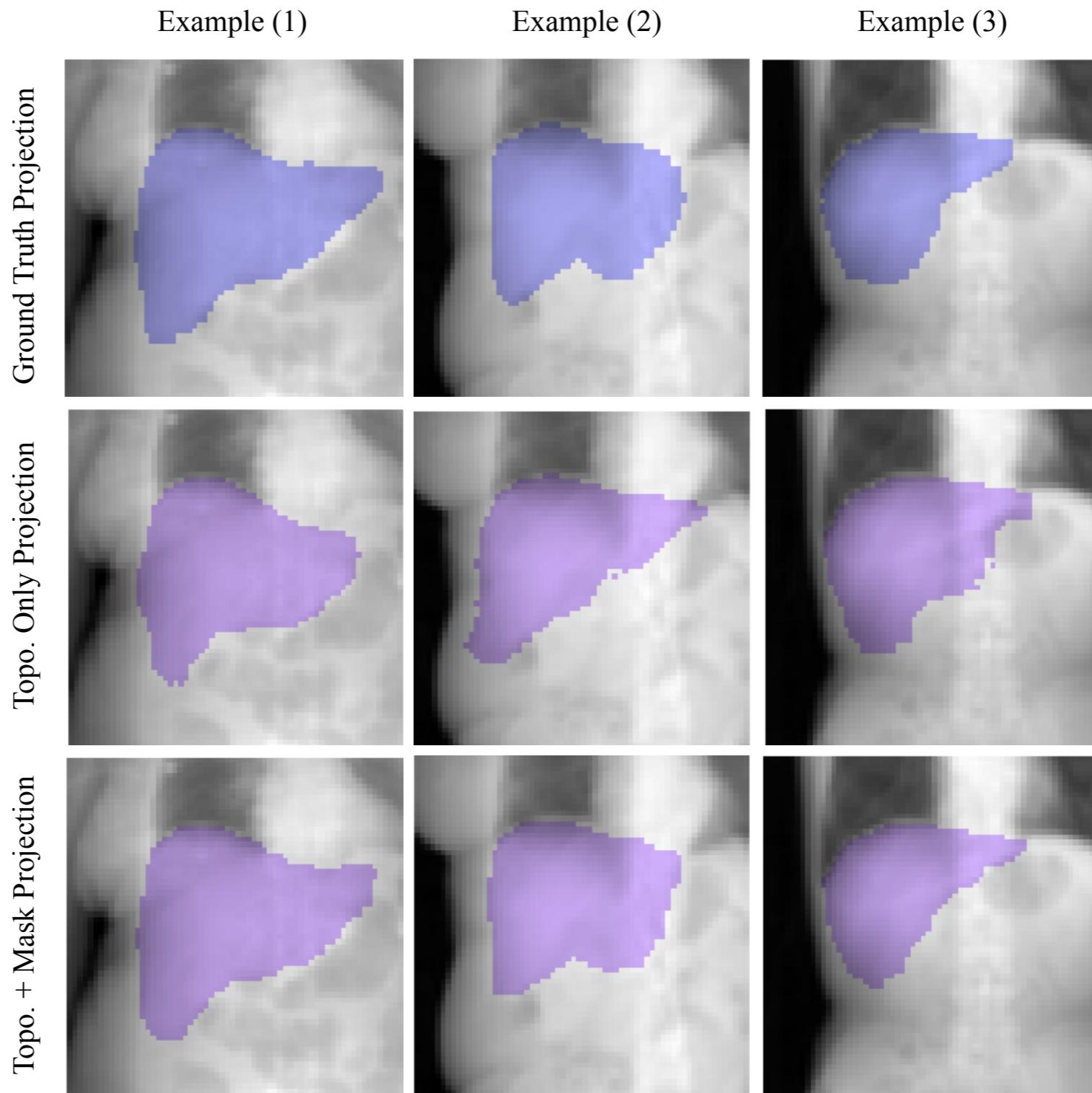
Example (1)



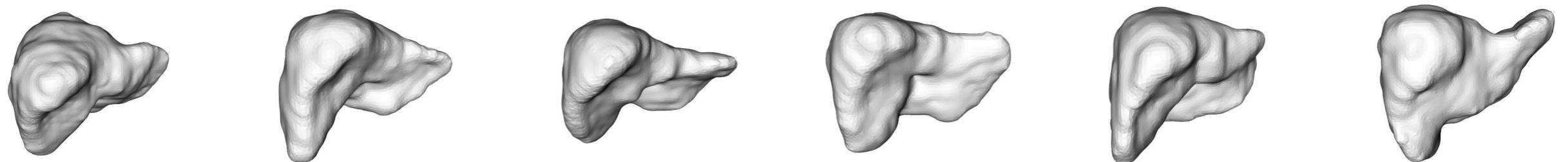
Results



Results



Volume Prediction

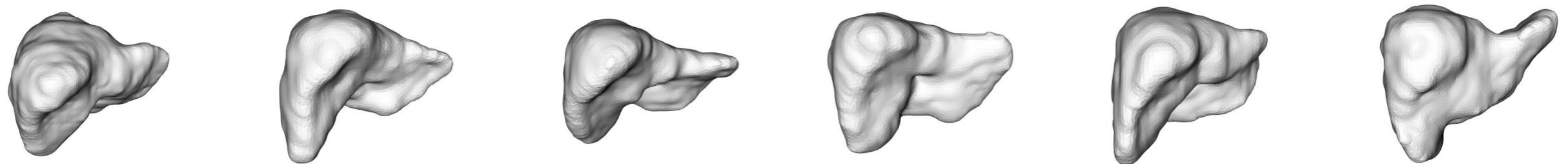


V_{gt} - ground truth volume

V_{pred} - predicted volume

$$V_f = \|V_{pred} - V_{gt}\|/V_{gt}$$

Volume Prediction



Metric	Topogram Only	Topogram + Mask
Volume Error (V_f)	0.10	0.06

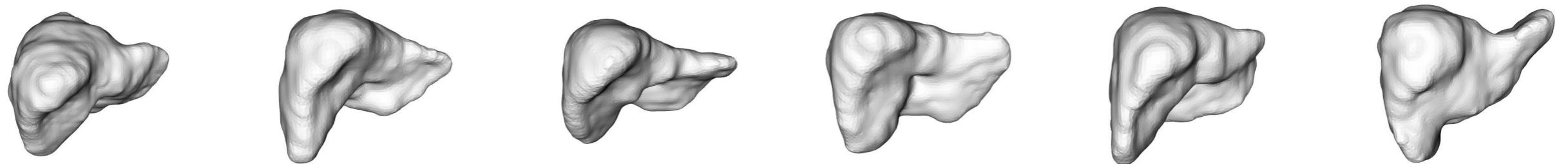
Mean Volume Error evaluation and comparison.

V_{gt} - ground truth volume

V_{pred} - predicted volume

$$V_f = \|V_{pred} - V_{gt}\| / V_{gt}$$

Volume Prediction



Metric	Mask Only	Topogram Only	Topogram + Mask
Volume Error (V_f)	0.34	0.10	0.06

Mean Volume Error evaluation and comparison.

V_{gt} - ground truth volume

V_{pred} - predicted volume

$$V_f = \|V_{pred} - V_{gt}\| / V_{gt}$$

Quantitative Evaluation

	Volume Prediction	Shape Reconstruction		
	Volume Error (V_f)	IoU	Dice	Hausdorff
Variational Autoencoder (VAE) (without/with mask)	0.10/ 0.06	0.78/ 0.82	0.87/ 0.90	7.10/ 5.00

Comparison of the variational auto-encoder (VAE) (with and without mask).

Quantitative Evaluation

	Volume Prediction	Shape Reconstruction		
	Volume Error (V_f)	IoU	Dice	Hausdorff
Variational Autoencoder (VAE) (without/with mask)	0.10/ 0.06	0.78/ 0.82	0.87/ 0.90	7.10/ 5.00
Adversarial (3D-GAN) [29]	0.21	0.61	0.75	10.50

Comparison of the variational auto-encoder (VAE) (with and without mask), and generative adversarial network (GAN) -based approaches on volume prediction and shape reconstruction tasks.

Quantitative Evaluation

	Volume Prediction	Shape Reconstruction		
	Volume Error (V_f)	IoU	Dice	Hausdorff
Variational Autoencoder (VAE) (without/with mask)	0.10/ 0.06	0.78/ 0.82	0.87/ 0.90	7.10/ 5.00
Adversarial (3D-GAN) [29]	0.21	0.61	0.75	10.50
Performance Difference	109% / 250%	22% / 26%	14% / 17%	48% / 110%

Comparison of the variational auto-encoder (VAE) (with and without mask), and generative adversarial network (GAN) -based approaches on volume prediction and shape reconstruction tasks.

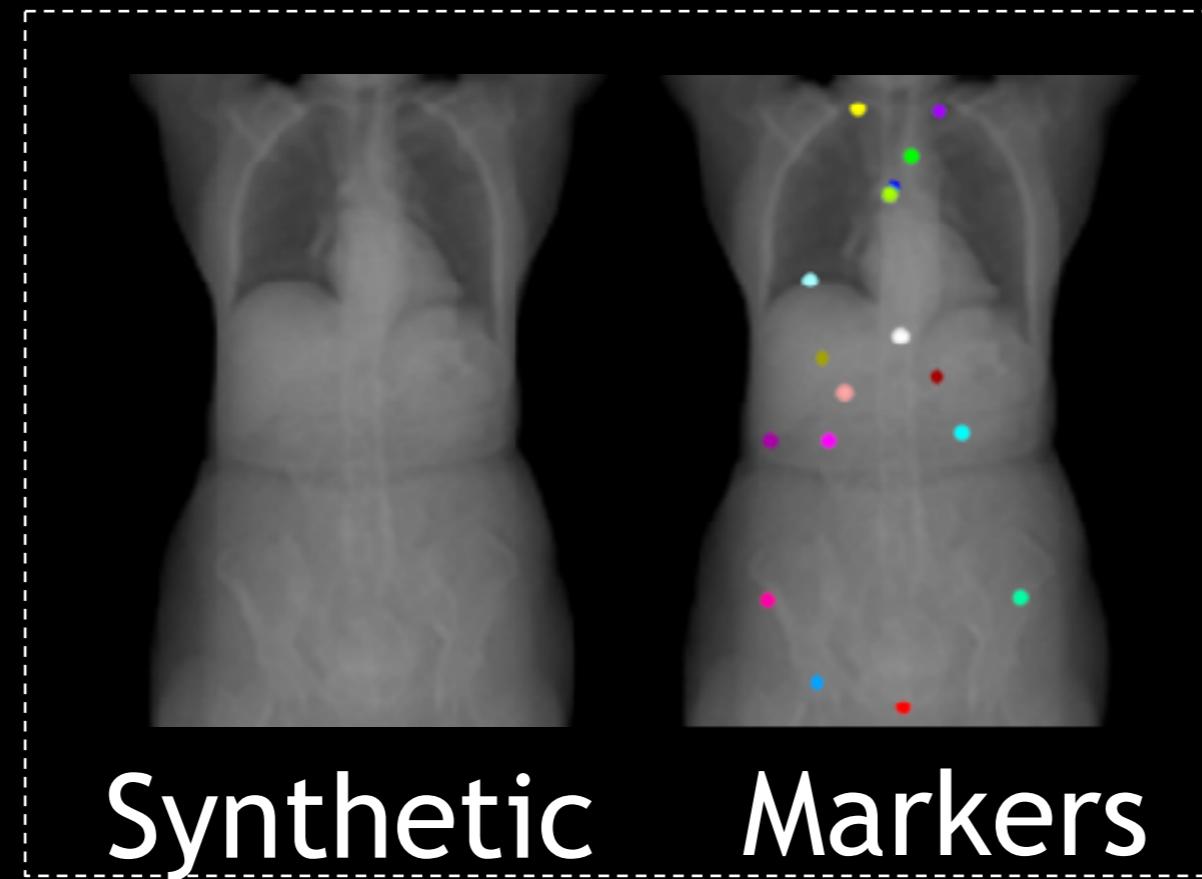
Interactive Techniques

[B Teixeira, V. Singh, K. Ma, B. Tumeroy, T. Chen, Y. Wu, E. Balashova, D. Comaniciu](#)
Generating Synthetic X-Ray Images of a Person from Surface Geometry
Conference on Computer Vision and Pattern Recognition (CVPR) 2018.

Parametrized Synthetic X-ray

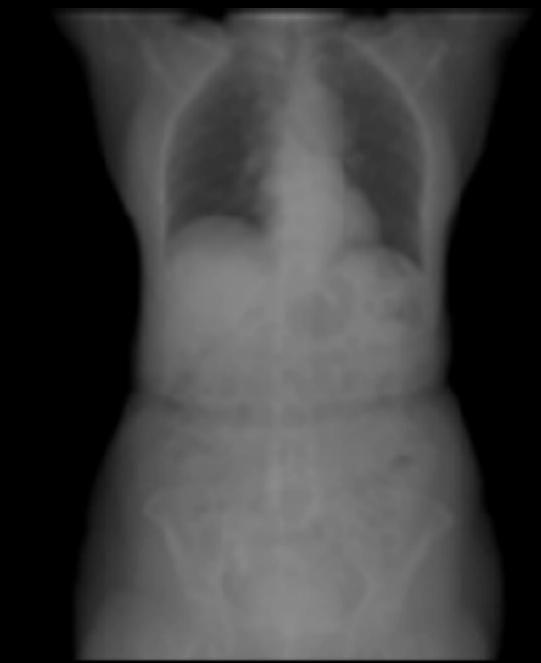


3D Surface
Mesh



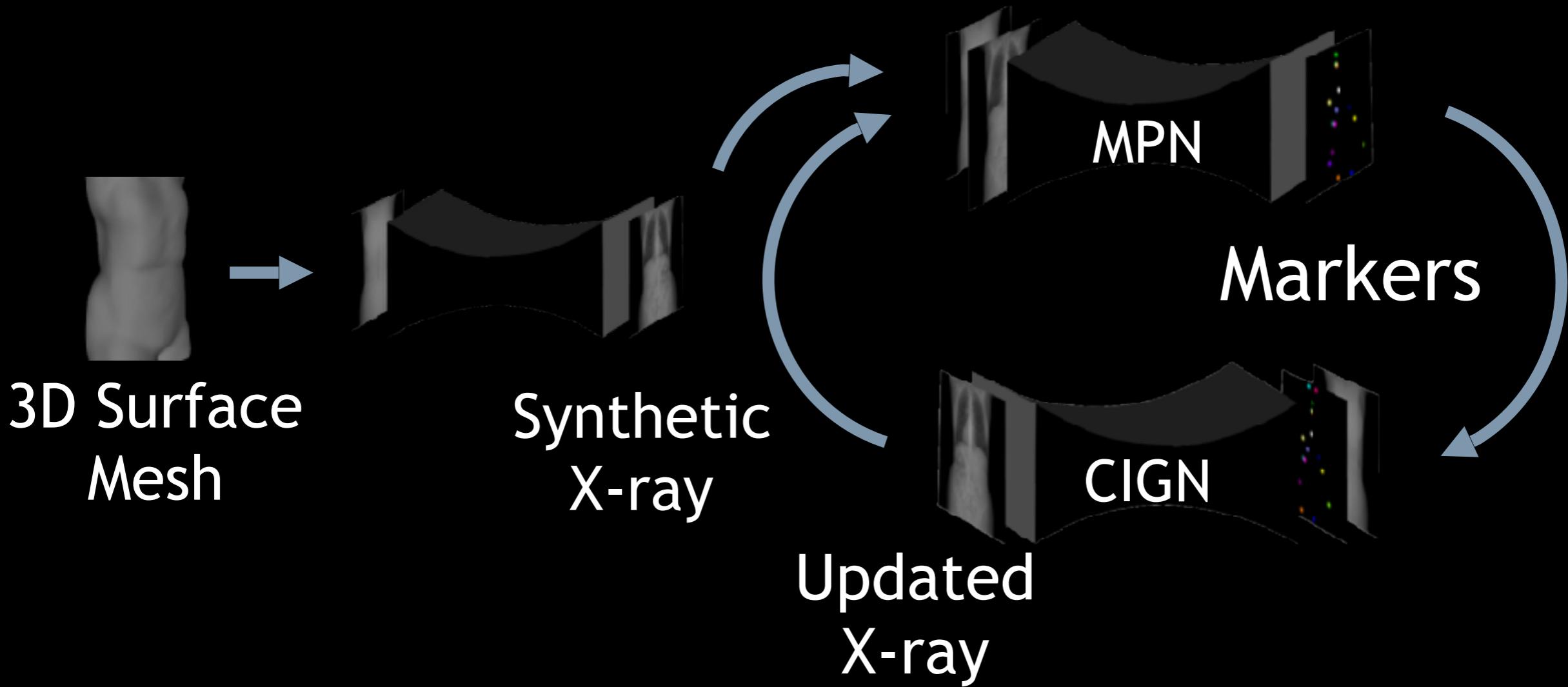
Synthetic
X-ray

Markers

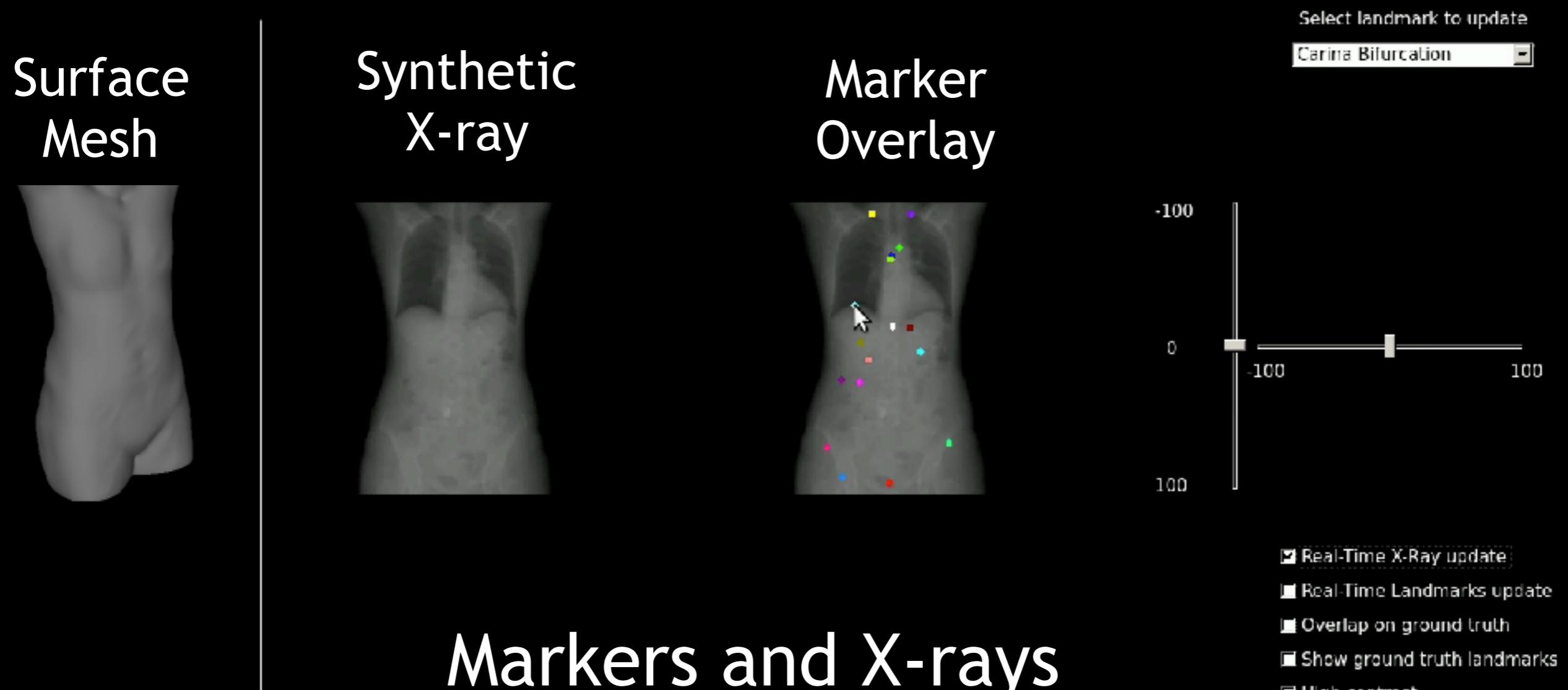


Real X-ray
(For
comparison)

Approach Overview



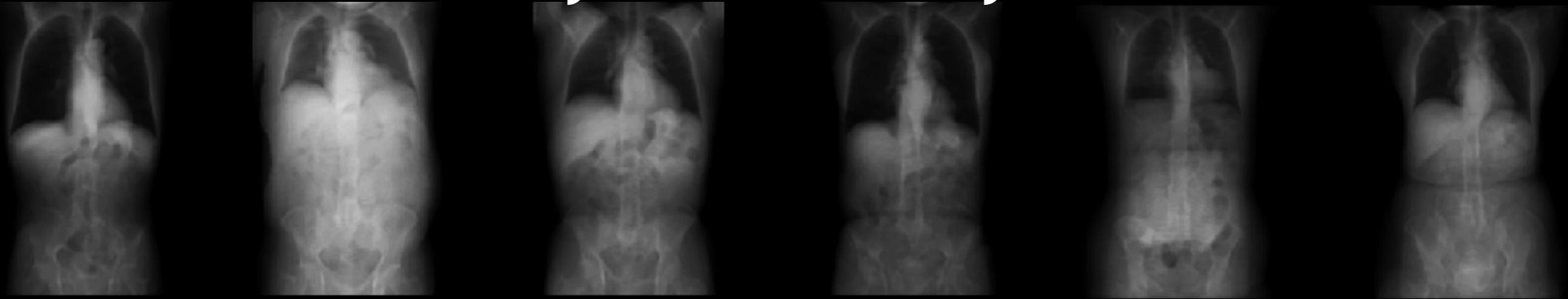
Markers as Parametrization for Synthetic X-ray



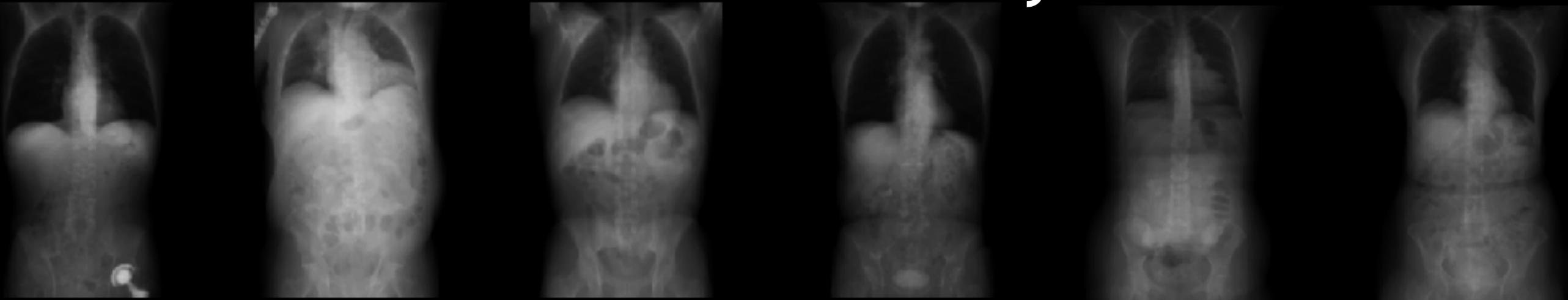
Markers and X-rays converge to a steady state where both are consistent

Results on Testing Set

Synthetic X-rays

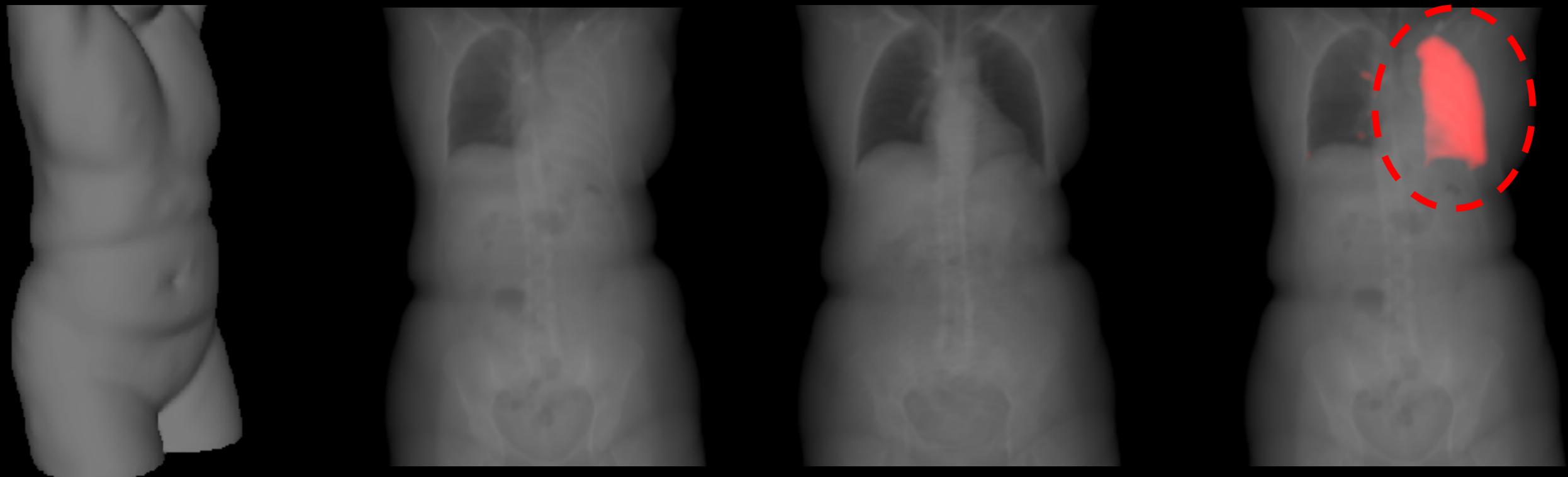


Ground Truth X-rays



Synthetic X-ray to Detect Pathologies

Trauma Patient Data with no Left Lung



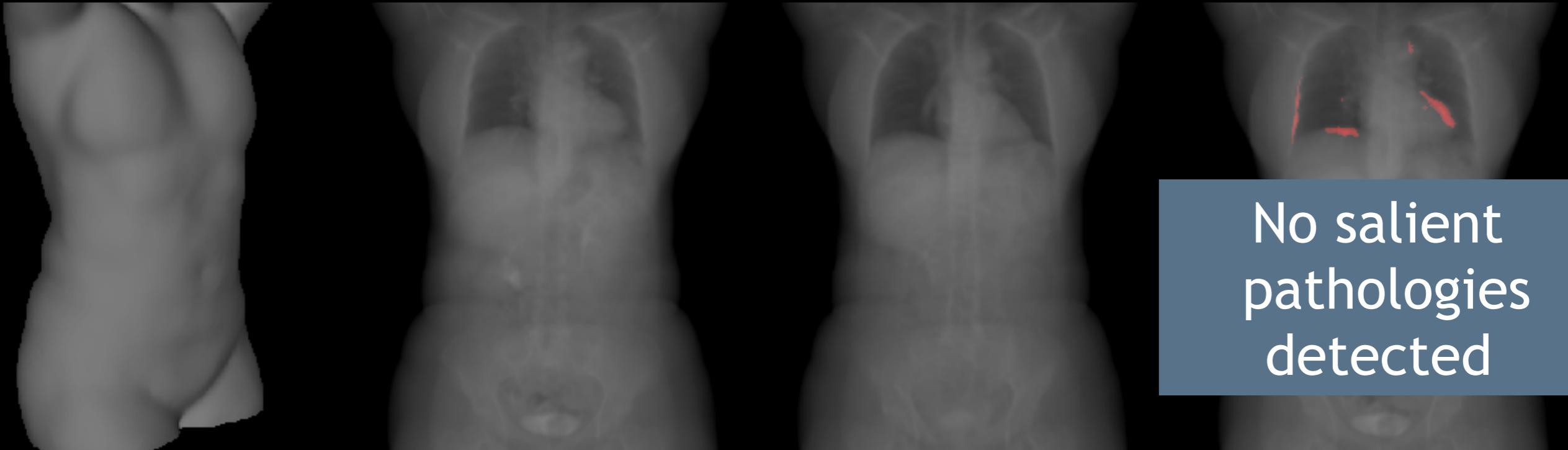
3D Surface Mesh

Real X-ray

Synthetic X-ray Difference Overlay

Synthetic X-ray to Detect Pathologies

Patient with no visual salient pathologies



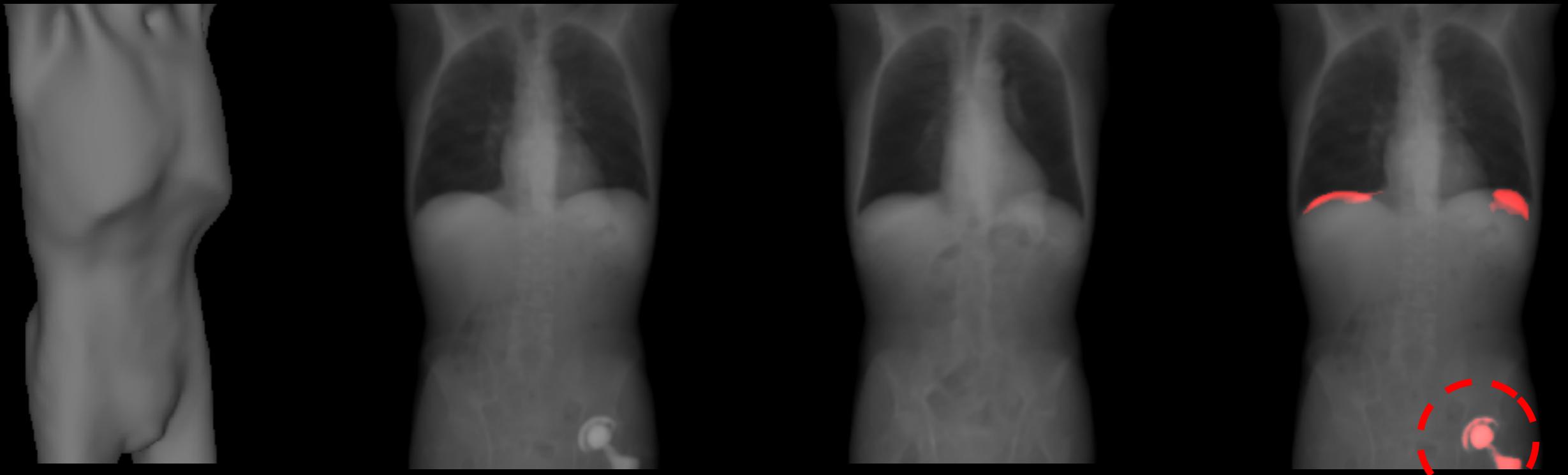
3D Surface Mesh

Real X-ray

Synthetic X-ray Difference Overlay

Synthetic X-ray to Detect Implants

Patient with metallic implant in the left leg



3D Surface Mesh

Real X-ray

Synthetic X-ray Difference Overlay

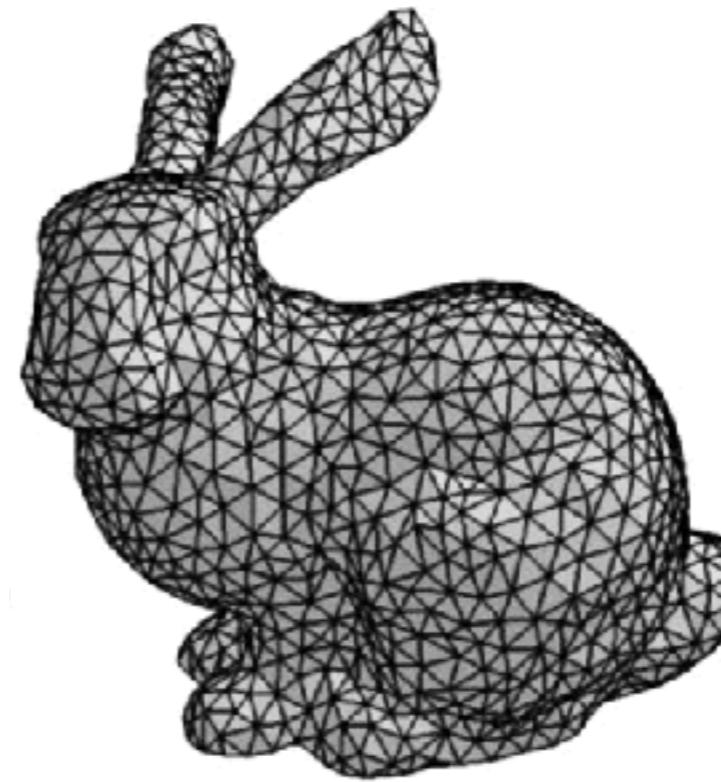
Future Work

Other Organs



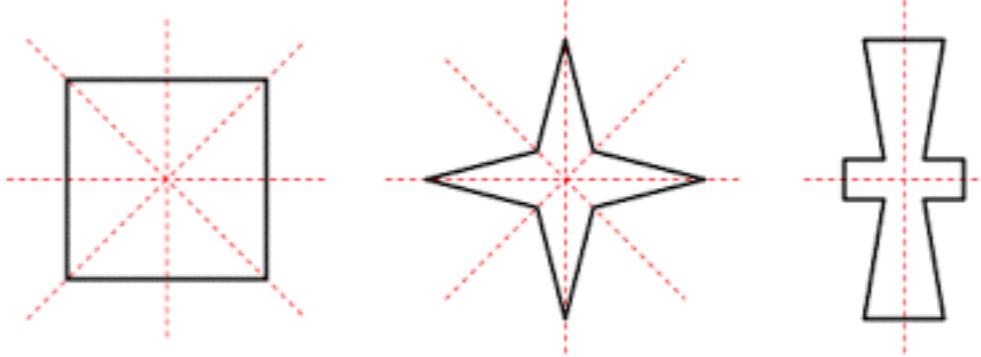
[www.123rf.com]

Different Shape Representations



[Predrag Novakovic]

Different Structures



[www.math.cmu.edu]

Acknowledgements



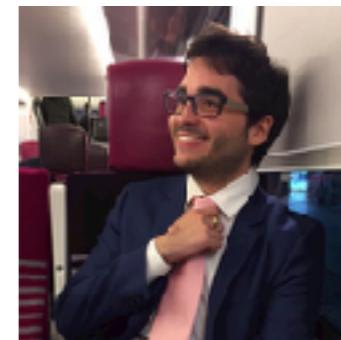
Jiangping Wang



Vivek Singh



Bogdan Georgescu



Brian Teixeira



Thomas Funkhouser



Terrence Chen



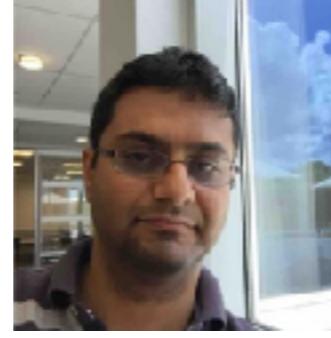
Kai Ma



Birgi Tumeroy



Dorin Comaniciu



Ankur Kapoor



Yifan Wu

Daguang Xu, Sungheon Gene Kim, Linda Moy, Krzysztof Geras, Kyunghyun Cho,
Support: Siemens Healthcare and NSF-GRFP

**Thank you!
Questions?**