CREATIS Medical Imaging Research Laboratory
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UNIVERSITÉ JEAN MONNET SAINT-ÉTIENNE

Segmentation in echocardiography: is the problem finally solved ?

by

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September 06, 2023

CREATIS; CNRS (UMR 5220); INSERM (U1294); INSA Lyon; Université de Lyon, France

Resume

AI methods in cardiac image analysis

Acquisition

Ultrafast cardiac imaging

Convolutional NN
Realistic simulations

Image quantification

Segmentation
Tissue motion estimation
Blood flow estimation
Uncertainty modeling

Convolutional NN
Variational Auto-Encoders
Physics informed NN
Diffusion networks

Population representation

Multi-modal fusion
Heterogenous data integration

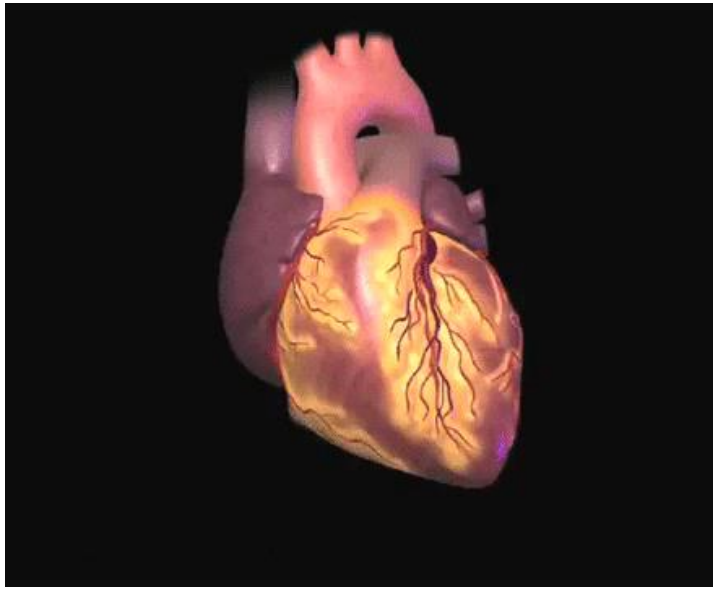
Transformers

Etiology classification
Hypertension characterization

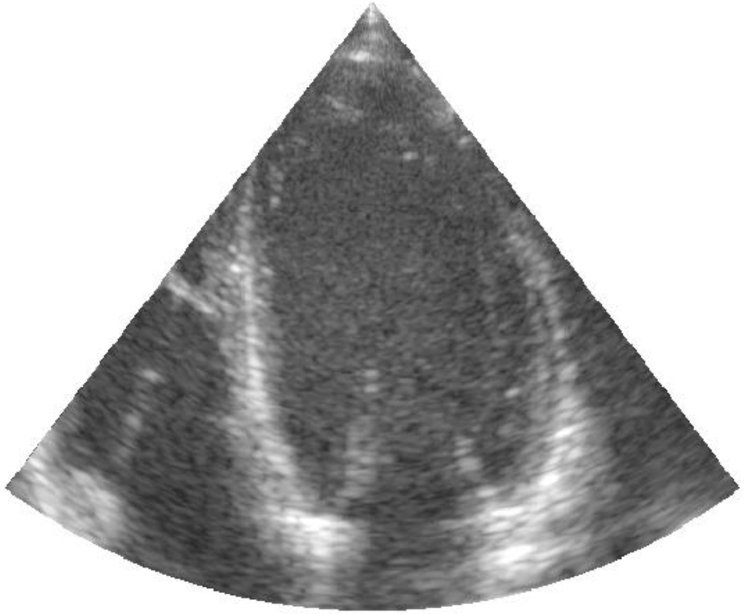
Robust estimation of existing / new biomarkers

Quantification of clinical indices to diagnose cardiac pathologies

- Anatomical imaging

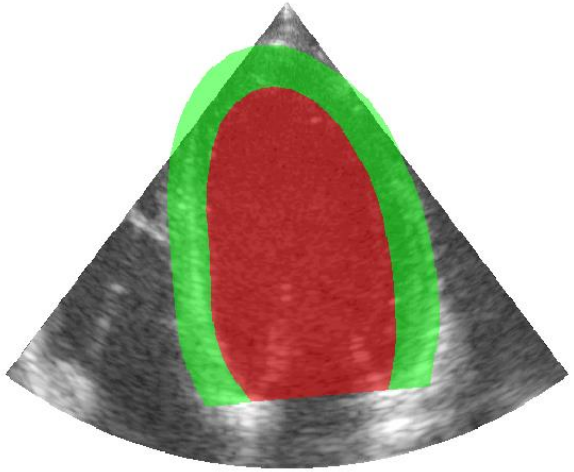


Source: GE Healthcare web site



Echocardiographic imaging

Quantification of clinical indices to diagnose cardiac pathologies



Segmentation of anatomical structures

- Ventricular volumes
- Myocardial mass
- Ejection fraction

Challenges

- How to make the measurements extracted from images automatic, reliable and precise ?

  → Cardiac structure segmentation

  → Tissue motion / blood flow estimation

Segmentation of echocardiographic images

[Leclerc et al., IEEE TMI 2019]

Challenges

1. Precise and accurate 2D segmentation ✓
   - ✓ Intra-observer variability
2. Frame-by-frame temporal consistency ✗
3. Generalization ability across datasets ✗

Limited by currently available public datasets

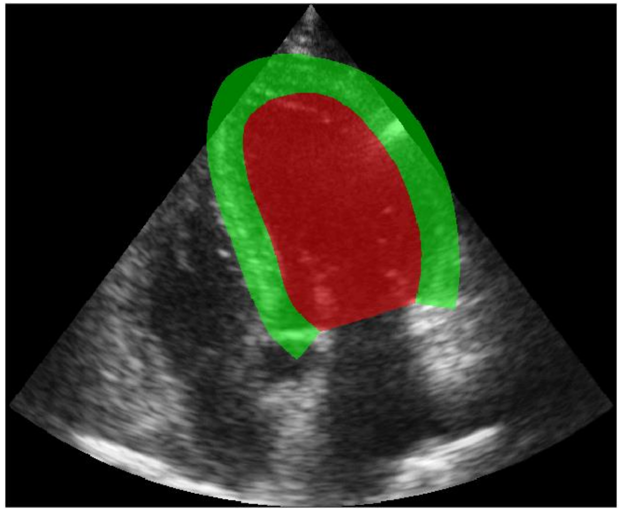
2D Public Echocardiographic Datasets											
Name	Year	Investigators	Nb. Subjects	Ground truth				Views		Characteristics	
				LV_{endo}	*LV_{epi}*	*LA*	*Full cardiac cycle*	*A2C*	*A4C*	*Multi-Center*	*Multi-Vendor*
CAMUS	2019	CREATIS	500	✓	✓	✓	✗	✓	✓	✗	✗
EchoNet	2019	Stanford	10,036	✓	✗	✗	✗	✗	✓	✗	-
HMC-QU	2021	Hamad/Tampere/Qatar	292	✓	✓	✗	✗	✓	✓	✗	✓
TED	2022	CREATIS	98	✓	✓	✗	✓	✗	✓	✗	✗

Echocardiographic datasets

Multi center, multi vendor, multi annotator datasets

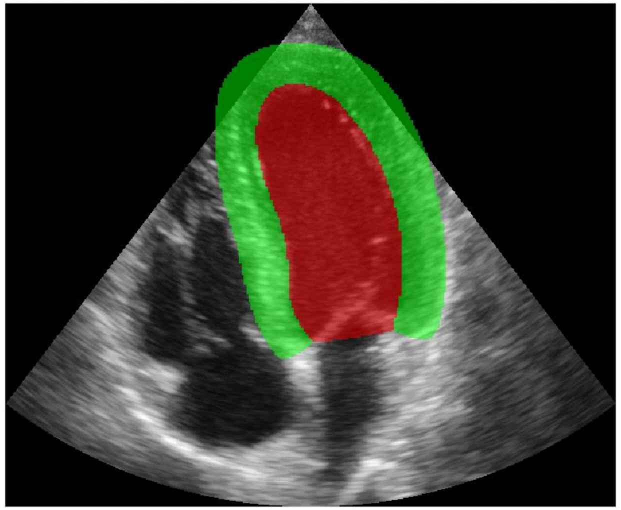
CAMUS

- ✓ Center 1
- ✓ 500 patients
- ✓ **Annotator 1** (images)
- ✓ GE system



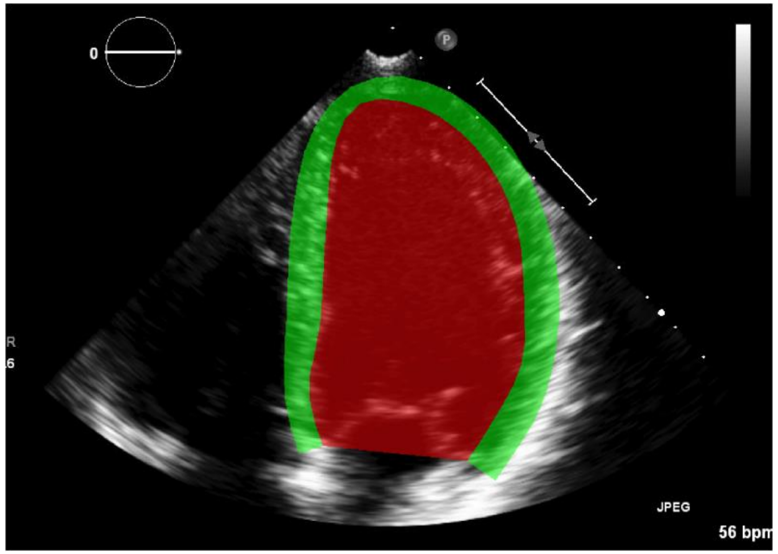
CARDINAL

- ✓ Center 2
- ✓ 240 patients
- ✓ **NO** annotator
- ✓ GE system



US-MR

- ✓ Center 3
- ✓ 30 patients
- ✓ **Annotator 2** (sequences)
- ✓ Philips system



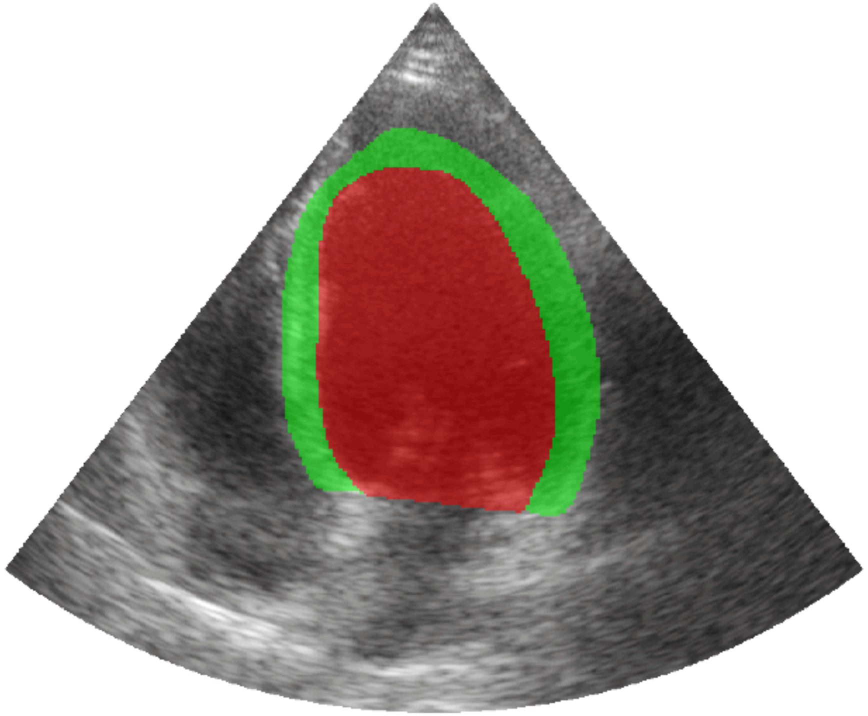
Static image accuracy

(CS:CAMUS)

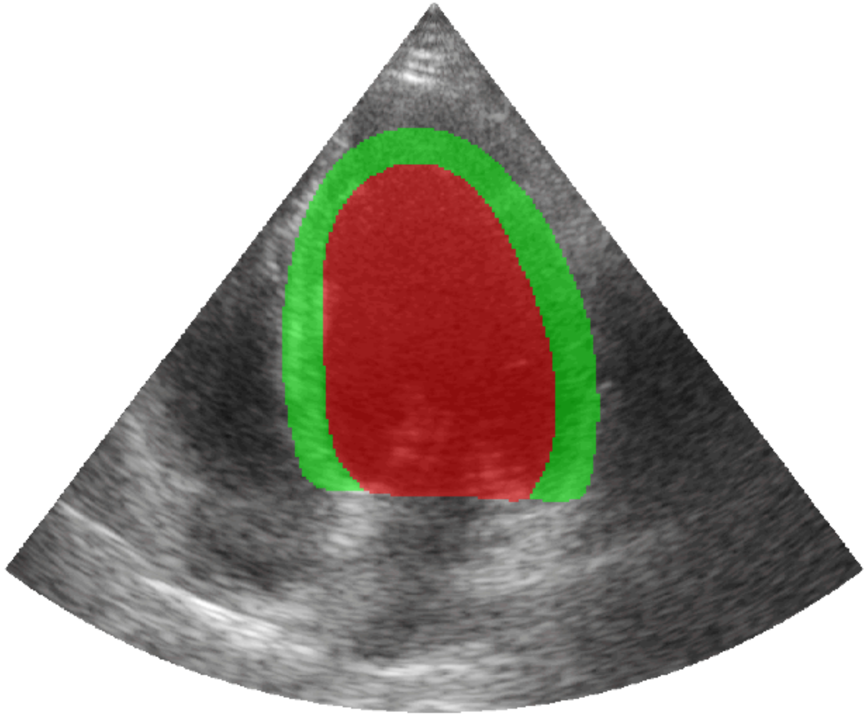
Methods	Train/test	Dice		Hausdorff (mm)	
		ED	ES	ED	ES
Intra-obs.		.945	.930	4.6	4.5
2D nnU-Net	CS/CS	**.952**	**.935**	**4.3**	**4.2**
CLAS		.947	.929	4.6	4.6
GUDU		.946	.929	4.7	4.7

Intra-observer variability can be reached using standard NN architectures with enough data (around 2000 images) on a controlled dataset !

Needs for temporal consistency



Segmentation with a 2D nnU-Net



Manual annotation

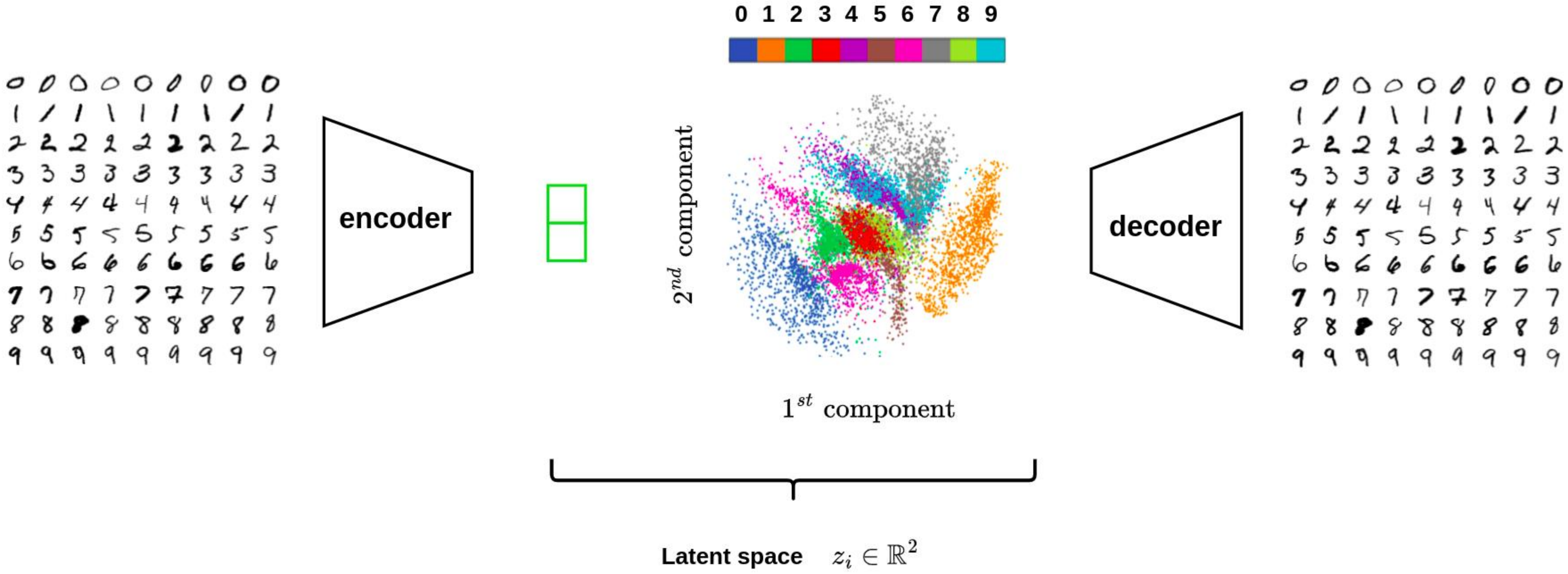
How to guarantee anatomical and temporal consistency ?

[Painchaud et al., IEEE TMI 2020]

[Painchaud et al., IEEE TMI 2022]

Efficient representation of data through a latent space

- ✓ Local continuity
- ✓ Global completeness



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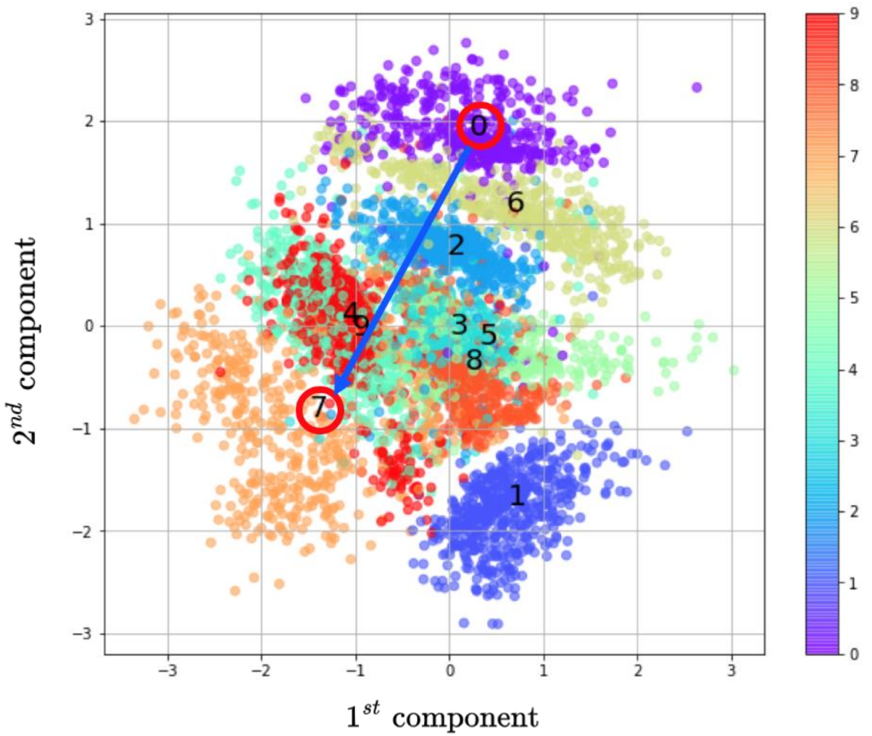
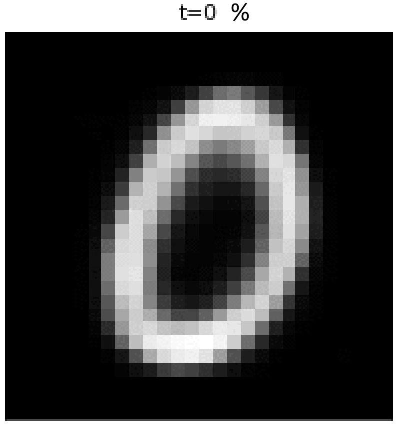


Linear interpolation into the latent space

$$t \cdot z_0 + (1-t) \cdot z_7, \qquad 0 \leq t \leq 1$$



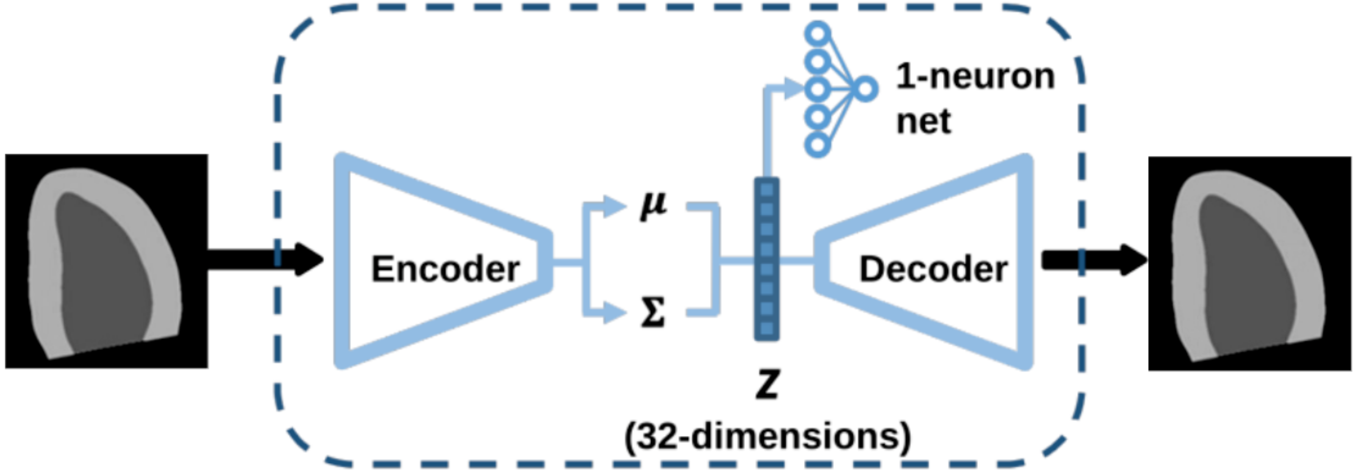
How to guarantee anatomical coherence ?

[Painchaud et al., IEEE TMI 2020]

Reinforcement of the local linearity of a shape latent space

- ✓ Use of a single neuron network with no activation and a regression on its instant on the cardiac phase between 0 (ED) and 1 (ES)

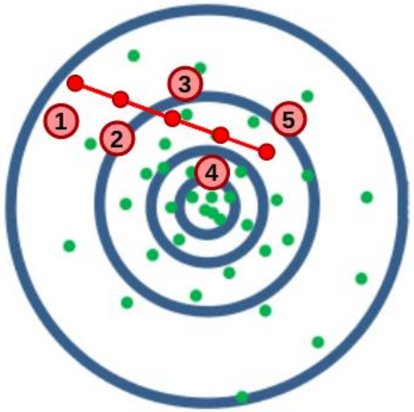
- ✓ Force the encoder to learn a more linear manifold of valid shapes in the latent space

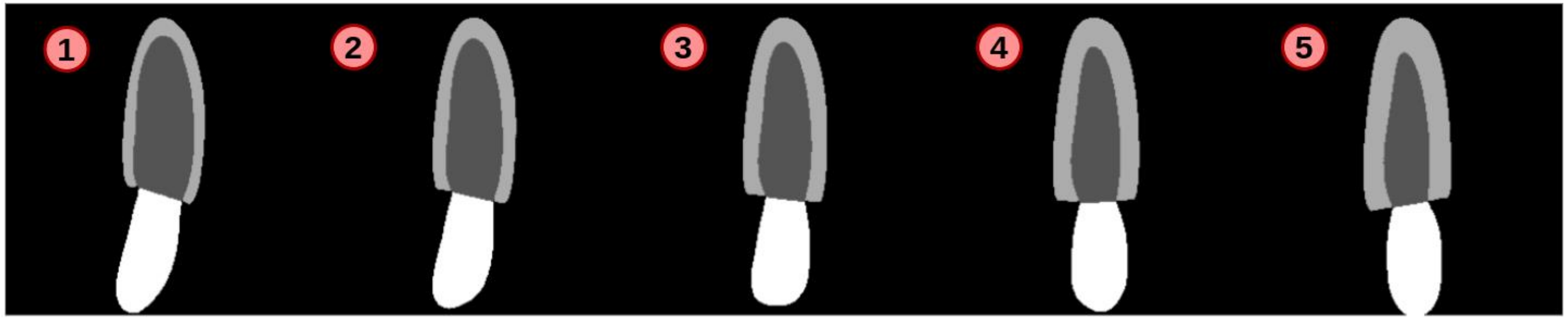


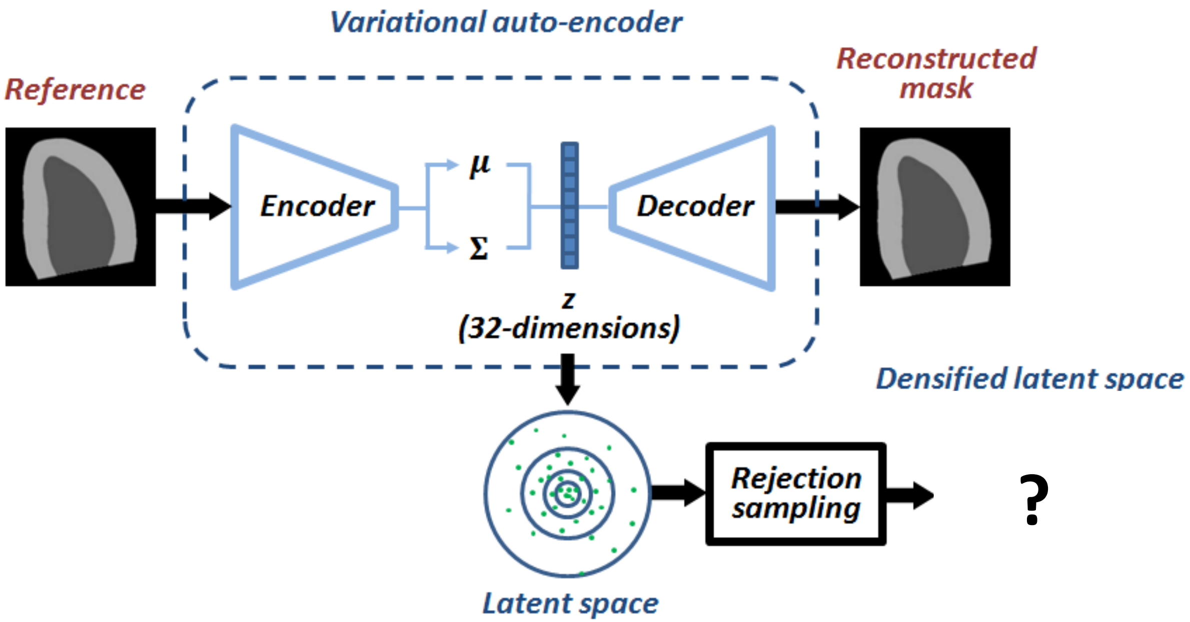
Reinforcement of the local linearity of a shape latent space

✓ Linear interpolation in the latent space make sense

Constrained latent space

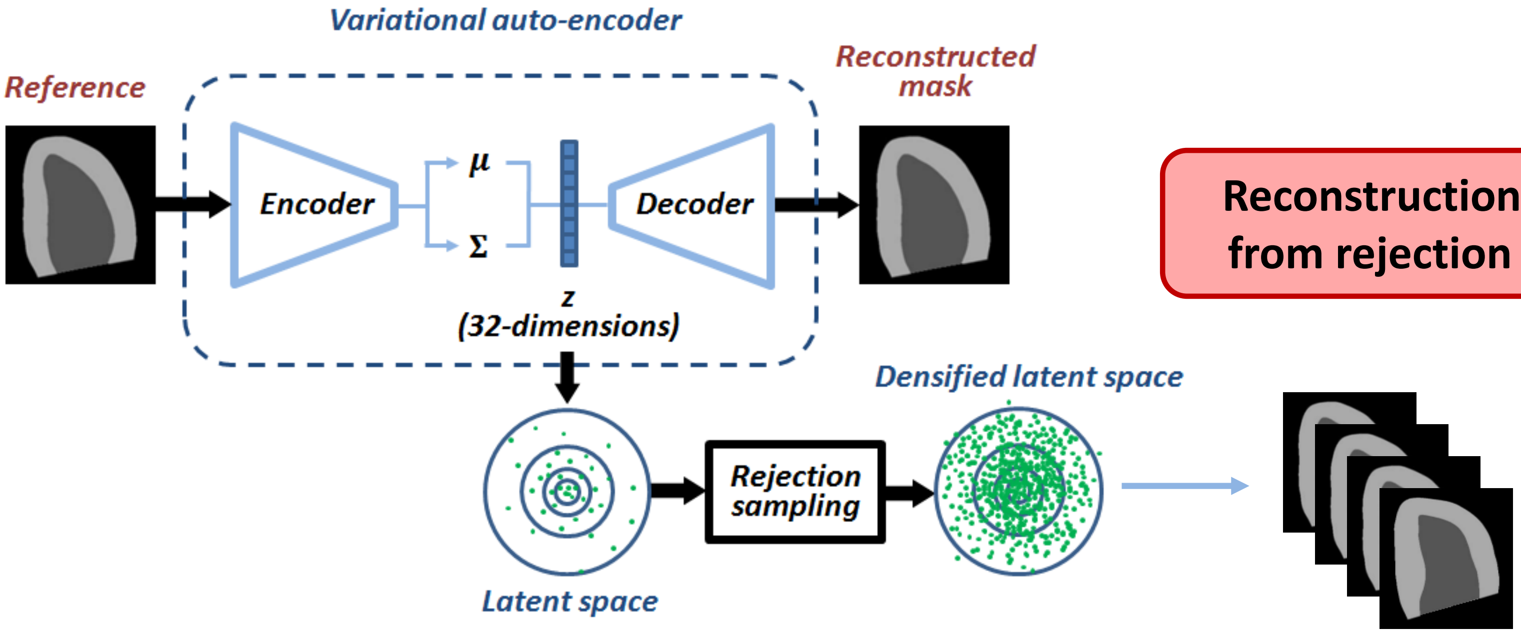






Efficient encoding of anatomical shapes in a latent space

Segmentation with strong anatomical guarantees

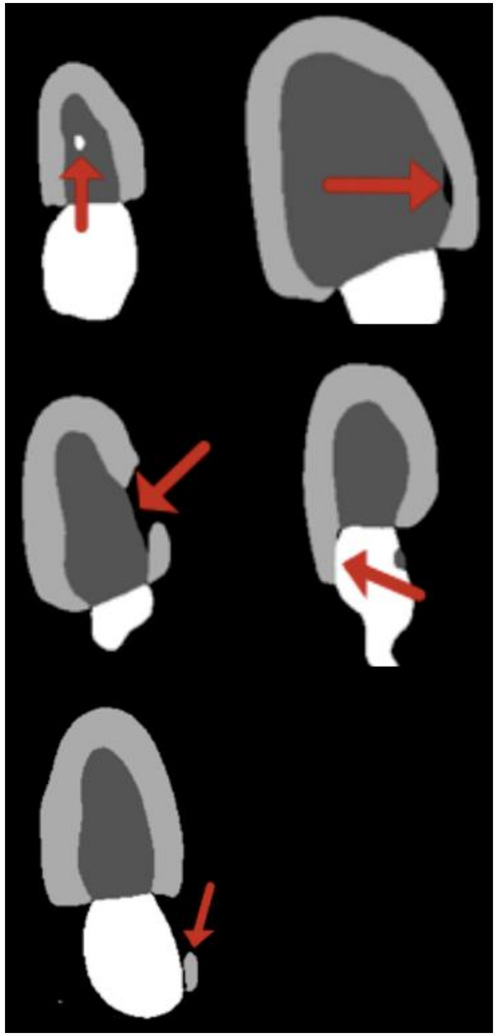


Reconstruction of masks from rejection sampling

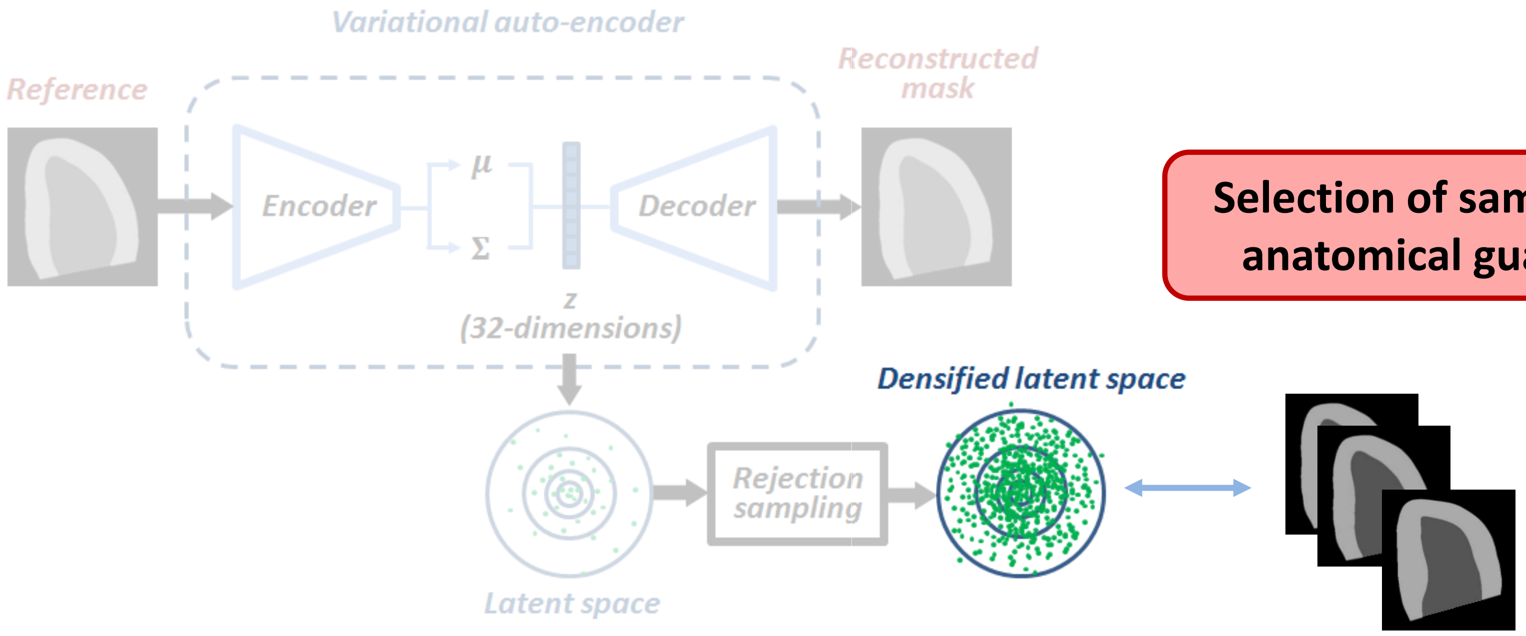
Densified latent space with 5 million points

Definition of 12 anatomical metrics

- ✓ (3 criteria) hole(s) in the LV, RV or LA
- ✓ (2 criteria) hole(s) between LV/MYO or between LV/LA
- ✓ (3 criteria) presence of more than one LV, MYO or LA
- ✓ (2 criteria) size of the area by which the LV touches the background or the MYO touches the LA
- ✓ (1 criterion) ratio between the minimal and maximal thickness of the MYO
- ✓ (1 criterion) ratio between the width of the LV and the average thickness of the MYO



Segmentation with strong anatomical guarantees

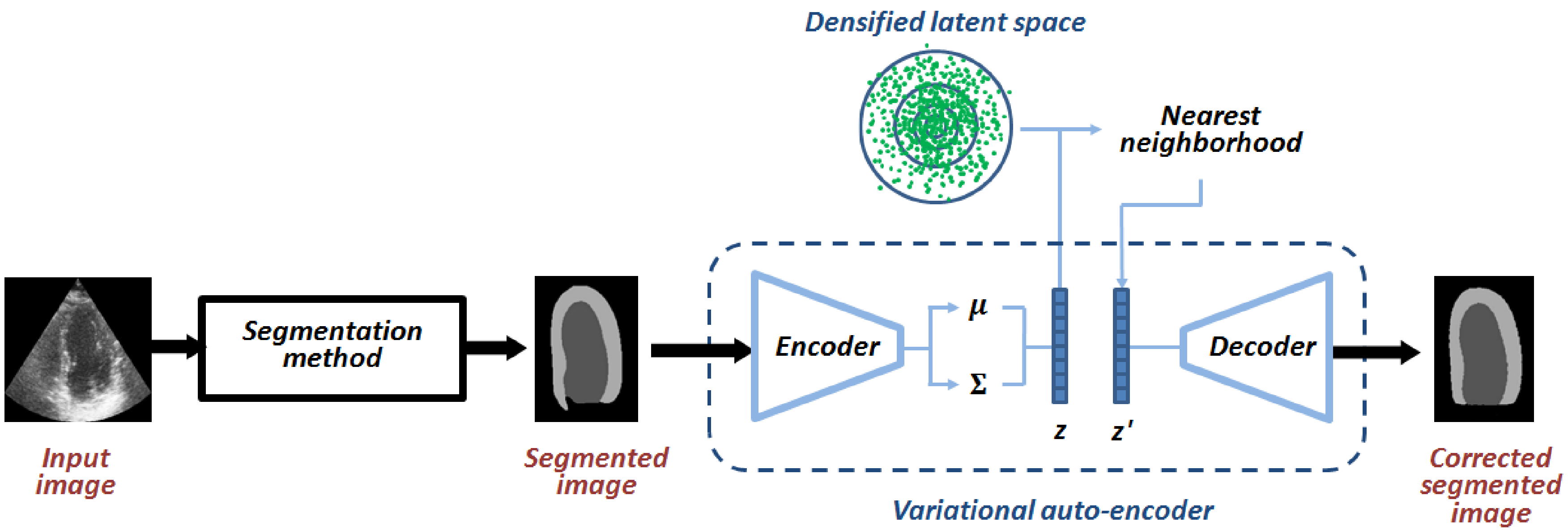


Selection of samples with anatomical guarantees

Densified latent space with 4 million points

Segmentation with strong anatomical guarantees

Correction of segmentation to guarantee the plausibility of anatomical shapes → **Almost same accuracy than the original methods but with correct anatomical shapes**



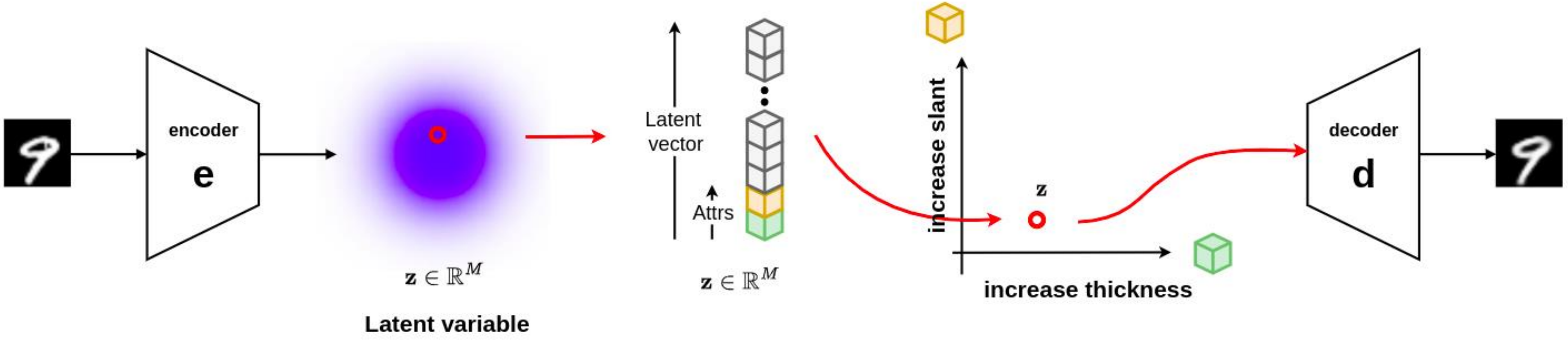
How to guarantee temporal consistency ?

[Painchaud et al., IEEE TMI 2020]

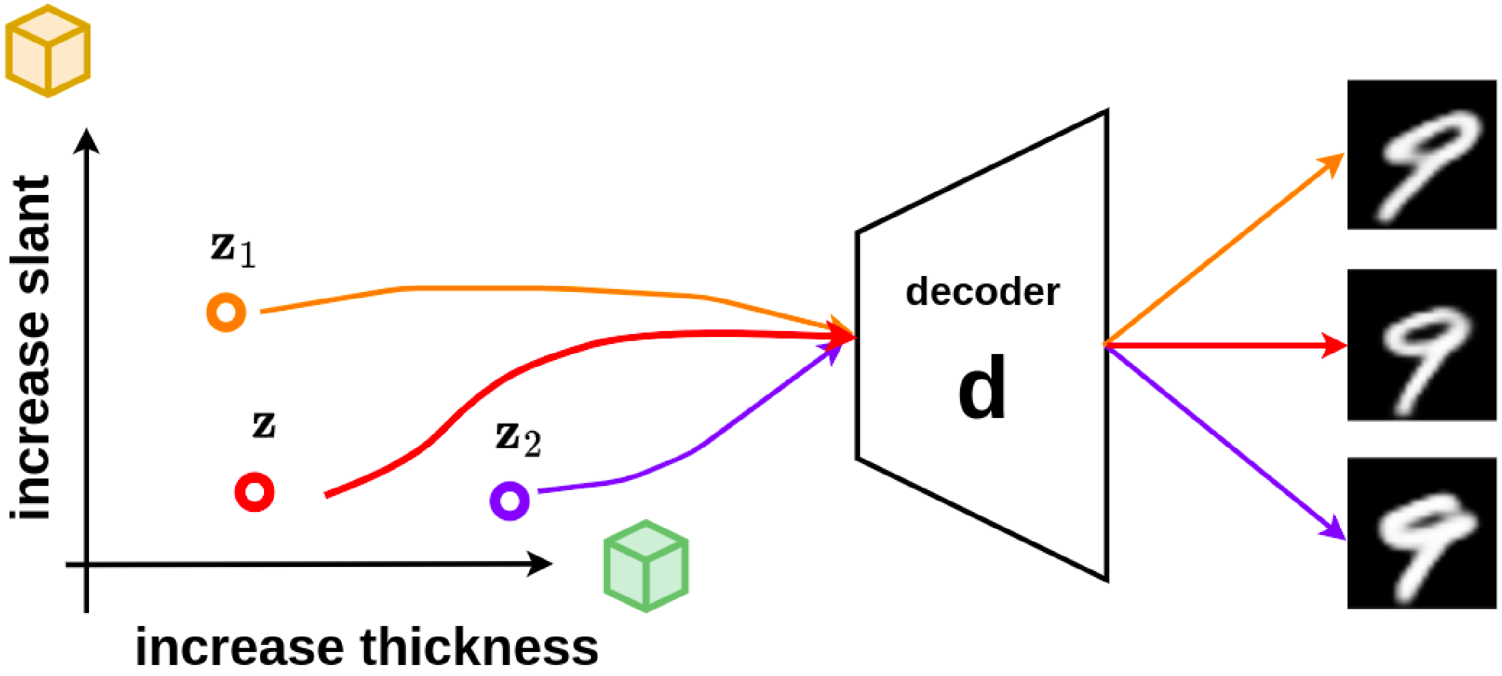
[Painchaud et al., IEEE TMI 2022]

Generation of a structured latent space

- ✓ Specific continuous-valued attributes forced to be encoded along specific dimensions
- ✓ $Loss = VAE\ loss + Attribute\ Regularisation\ Loss$

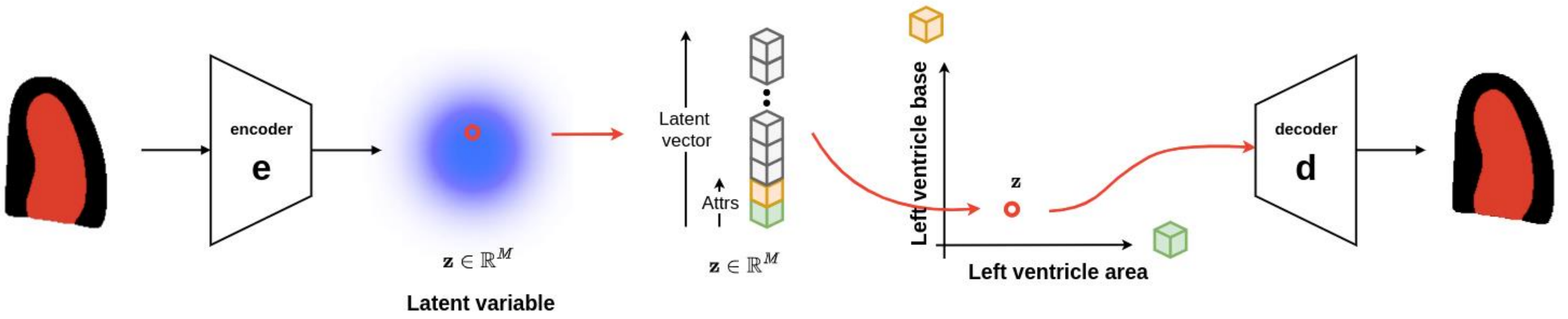


Sampling of the structured latent space

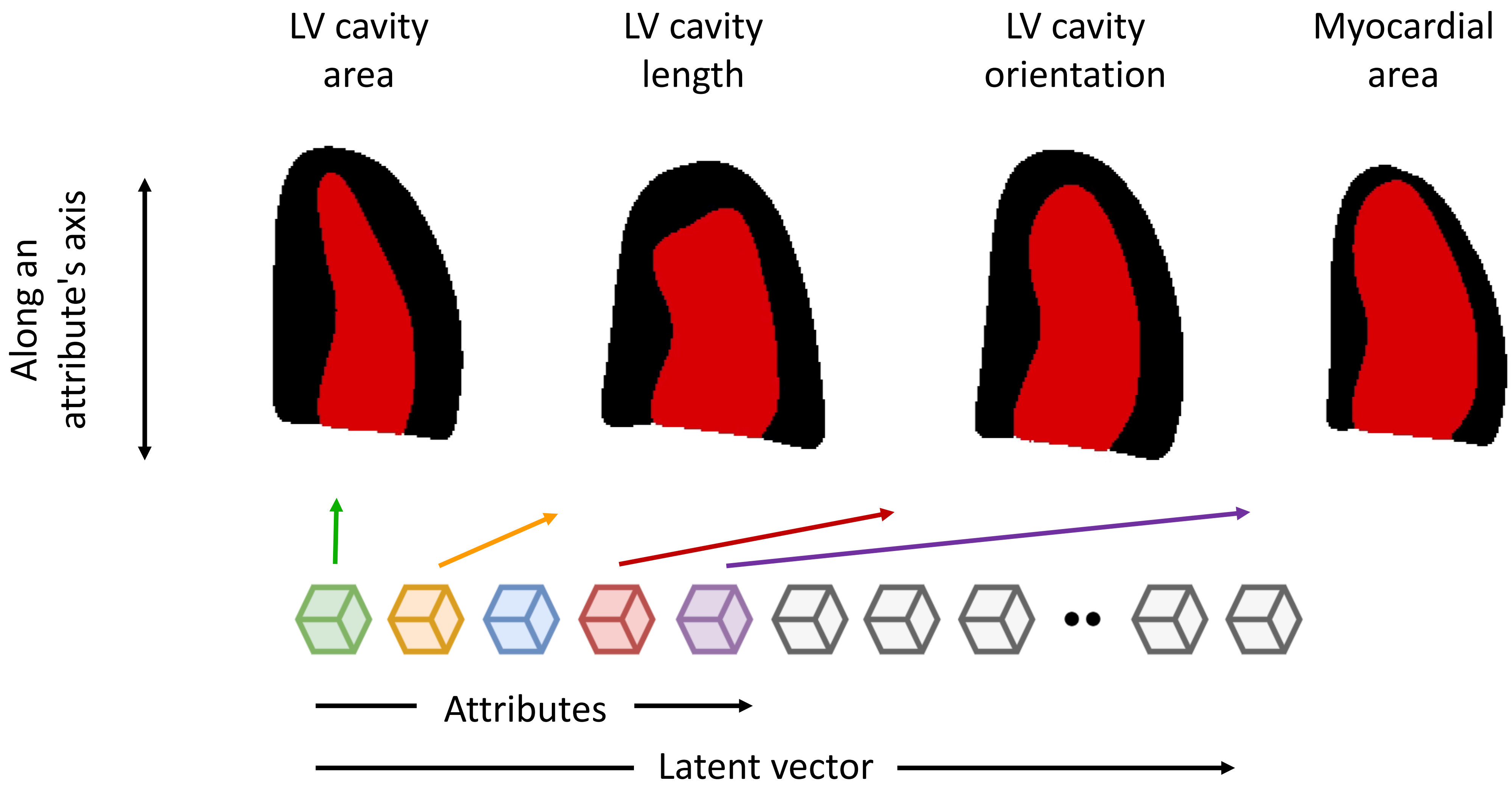


Generation of structured latent space according to specific attributes

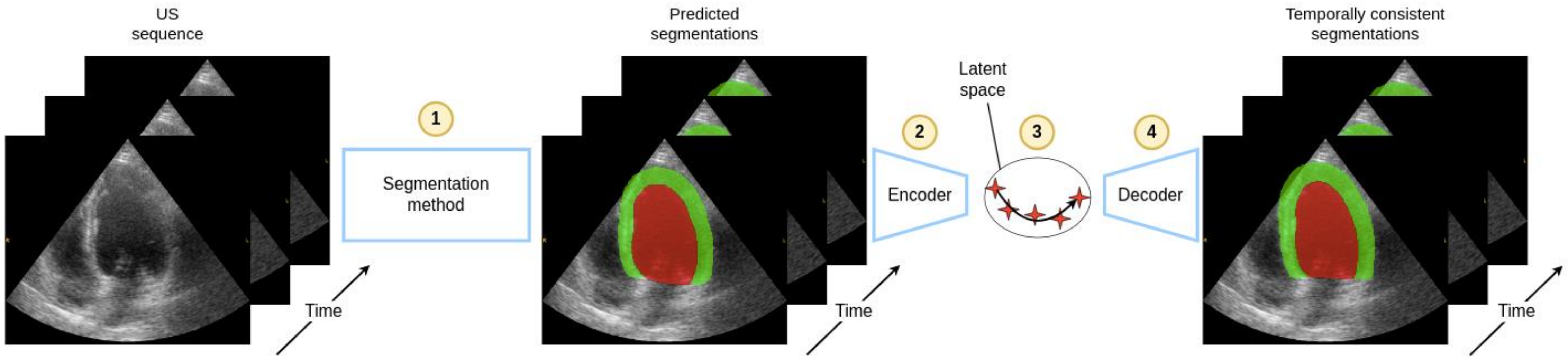
- ✓ Left ventricle (LV) cavity: area, length, basal width, orientation
- ✓ Myocardial area
- ✓ Epicardial center



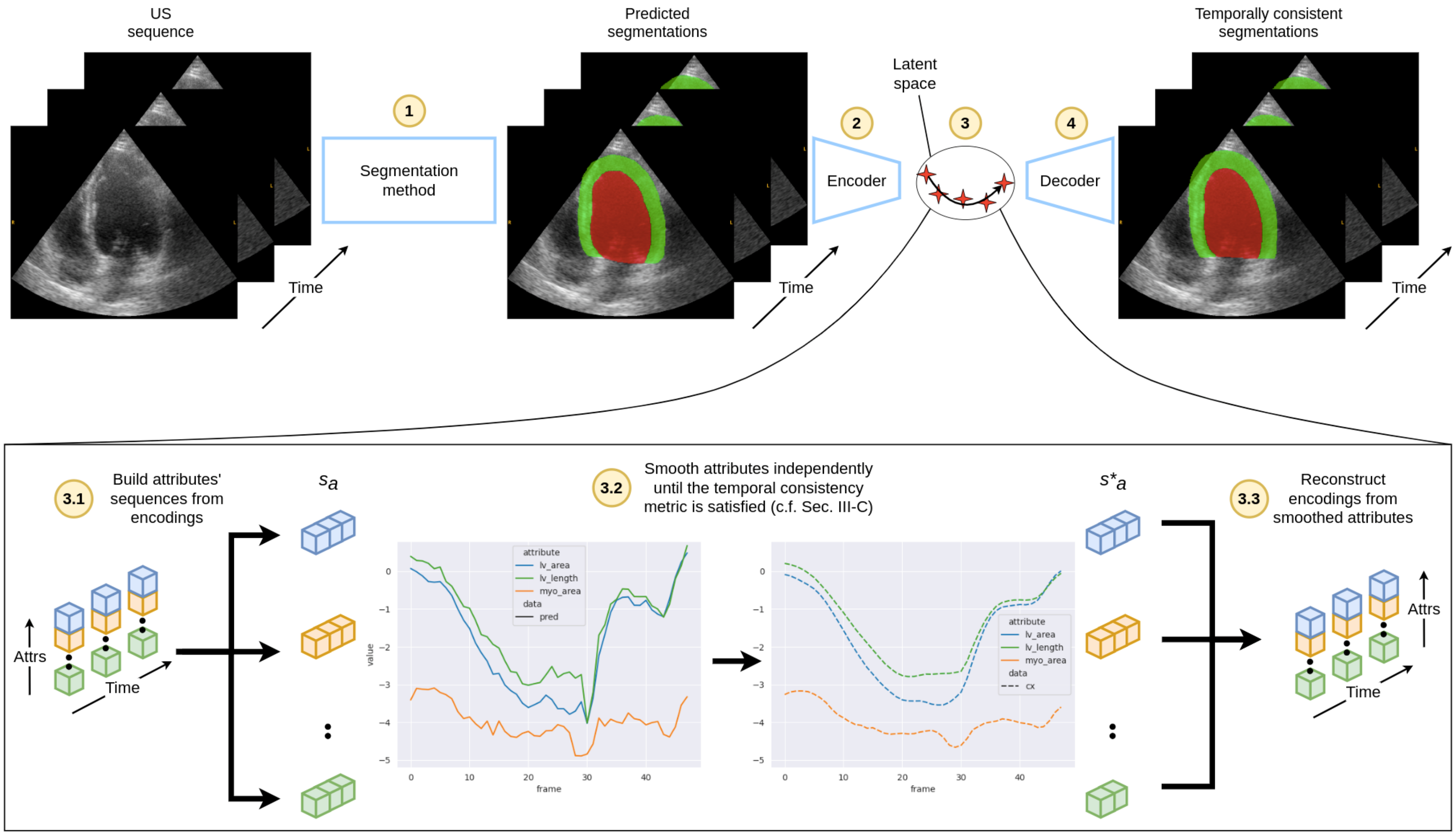
Description of the cardiac shapes



Proposed temporal pipeline

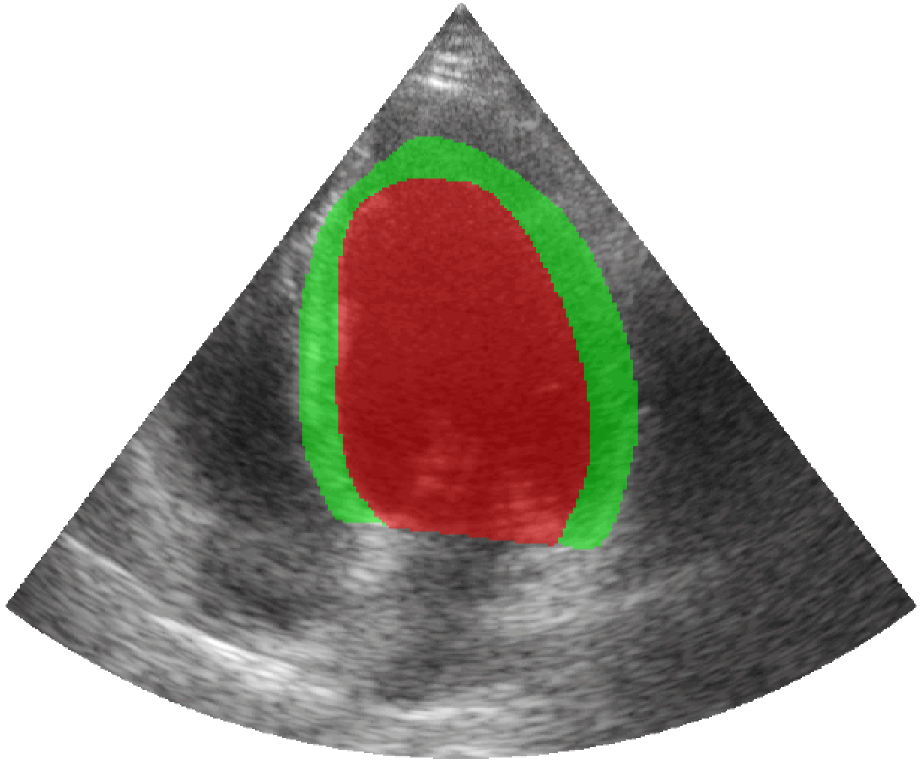


Proposed temporal pipeline

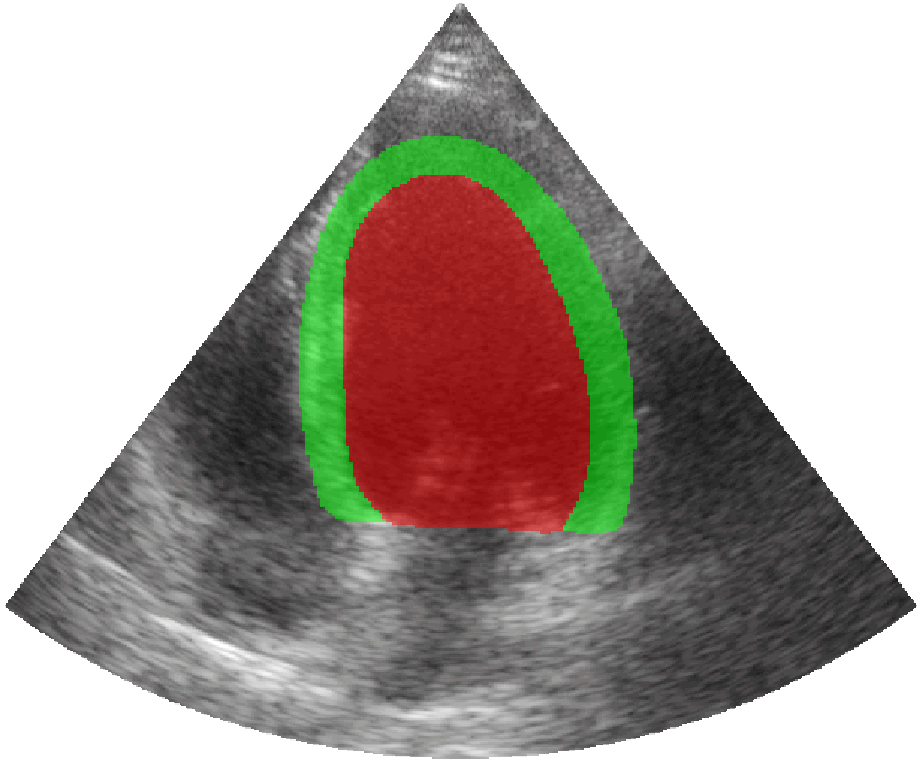


Some post-processing examples

Original nnU-Net

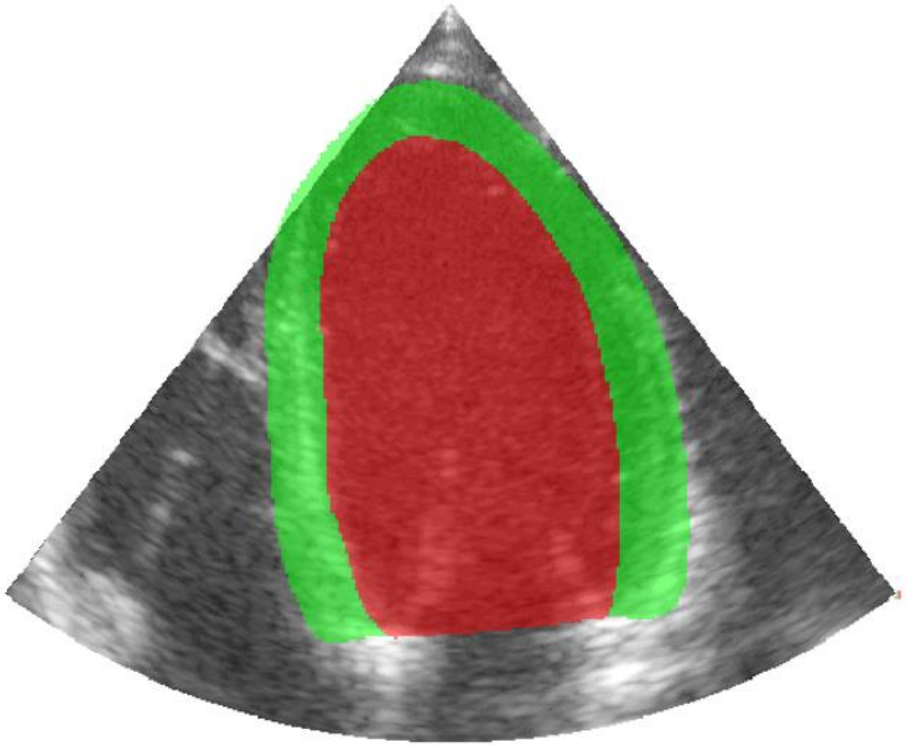


Post-processed nnU-Net

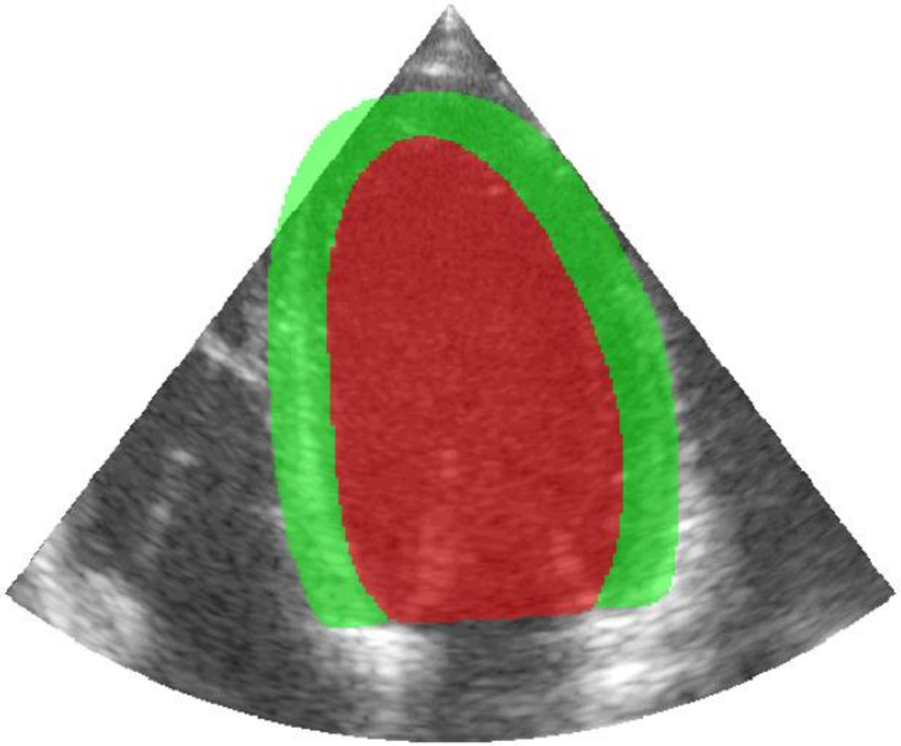


Some post-processing examples

Original nnU-Net



Post-processed nnU-Net



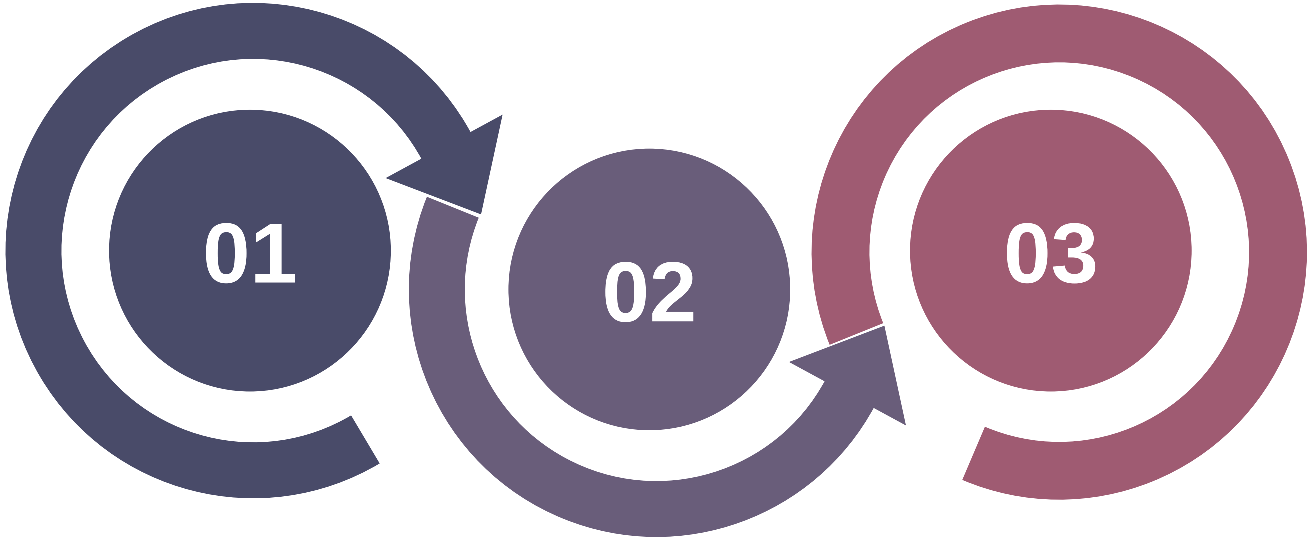
Segmentation of echocardiographic images with temporal consistency

[Ling et al., FIMH 2023]

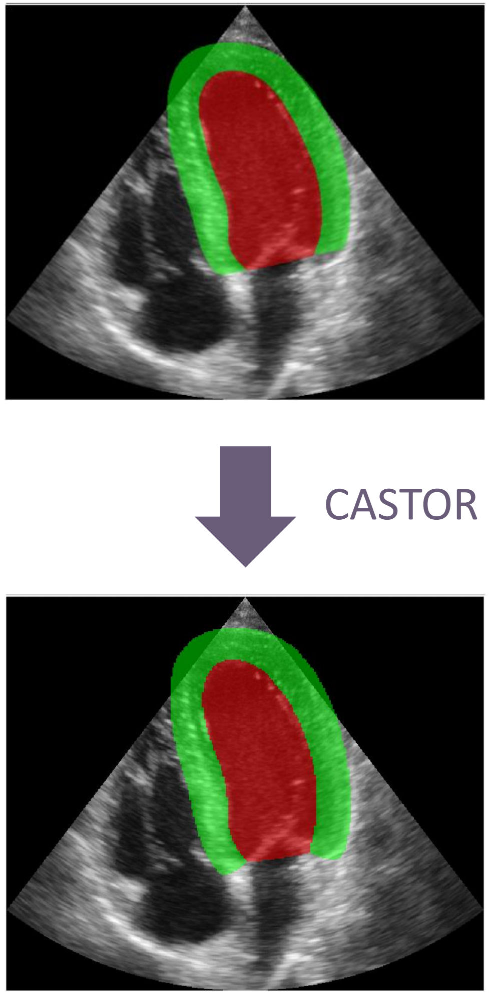
CARDINAL’s gold standard generation pipeline

Trained 2D nnU-Nets on CAMUS annotated A2C/A4C ED/ES frames

Trained DL models on CARDINAL with GOLD STANDARD (378 sequences)



Applied trained models on CARDINAL and postprocessed predictions using CASTOR to correct temporal inconsistency -> GOLD STANDARD



Geometrical accuracy

(CL:CARDINAL, CS:CAMUS)

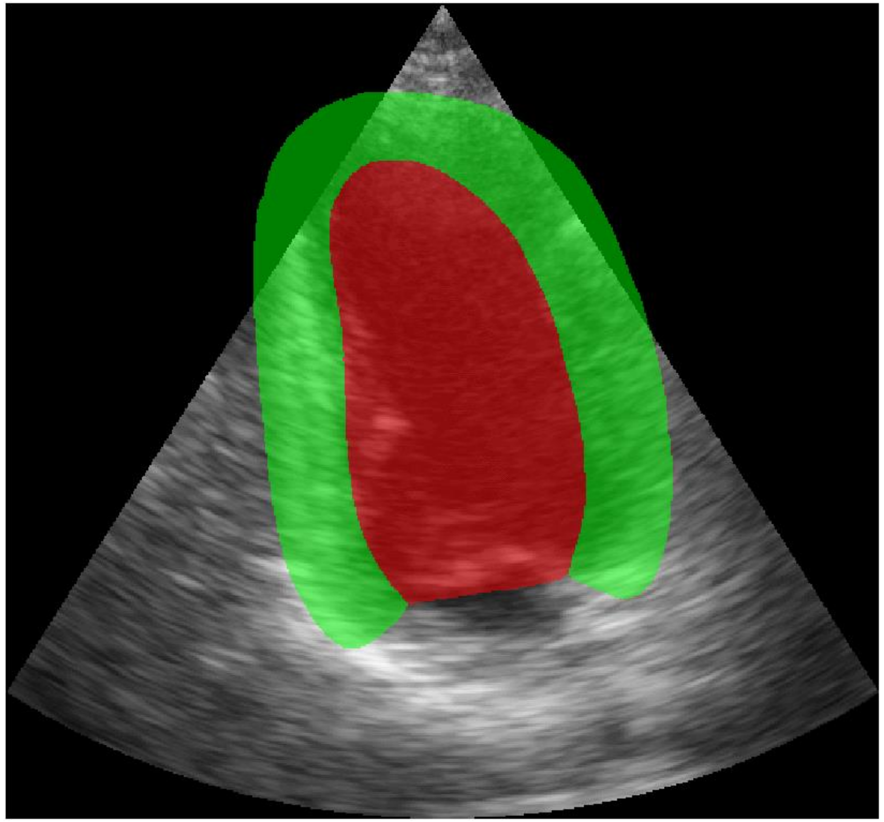
Methods	Train/test	Dice ED	Dice ES	Hausdorff (mm) All	Hausdorff (mm) ED	Hausdorff (mm) ES
Intra-obs.		.945	.930		4.6	4.5
3D nnU-Net	CL/CL	**.968**	**.960**		**2.7**	**2.5**
2D nnU-Net	CL/CL	.961	.942		3.1	3.1
U-Net LSTM	CL/CL	.964	.956		2.8	2.6
3D nnU-Net	CL/CS	**.939**	**.926**	-	5.2	**4.6**
2D nnU-Net	CL/CS	.934	.921	-	**4.9**	4.6
U-Net LSTM	CL/CS	.925	.903	-	6.0	5.8
2D nnU-Net	CS/CS	**.952**	**.935**	-	**4.3**	**4.2**
CLAS	CS/CS	.947	.929	-	4.6	4.6
GUDU	CS/CS	.946	.929	-	4.7	4.7

Clinical accuracy

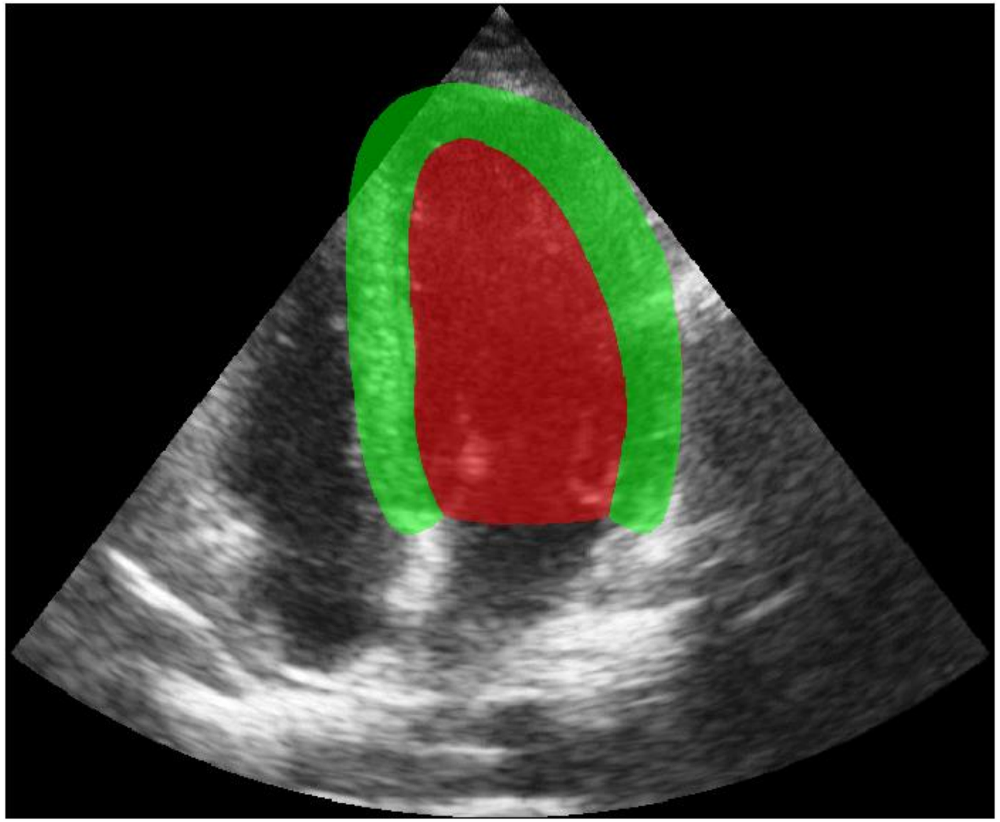
Methods	Train/test	EF		Volume ED		Volume ES	
		Corr.	MAE (%)	Corr.	MAE (ml)	Corr.	MAE (ml)
Intra-obs.		.896	4.7	.978	6.5	.981	4.5
3D nnU-Net	CL/CL	.913	2.9	**.978**	**3.3**	**.974**	**2.7**
2D nnU-Net	CL/CL	.850	3.8	.967	4.4	.957	3.2
U-Net LSTM	CL/CL	**.922**	**2.7**	.973	3.4	.969	2.8
3D nnU-Net	CL/CS	**.869**	**5.3**	**.974**	**9.6**	**.976**	**4.9**
2D nnU-Net	CL/CS	.810	7.0	.970	12.8	.959	6.2
U-Net LSTM	CL/CS	.822	11.1	.879	15.9	.903	8.2
2D nnU-Net	CS/CS	.857	4.7	**.977**	**5.9**	**.987**	**4.0**
CLAS	CS/CS	**.926**	**4.0**	.958	7.7	.979	4.4
GUDU	CS/CS	.897	**4.0**	**.977**	6.7	.981	4.6

Visualization – temporal consistency

CAMUS

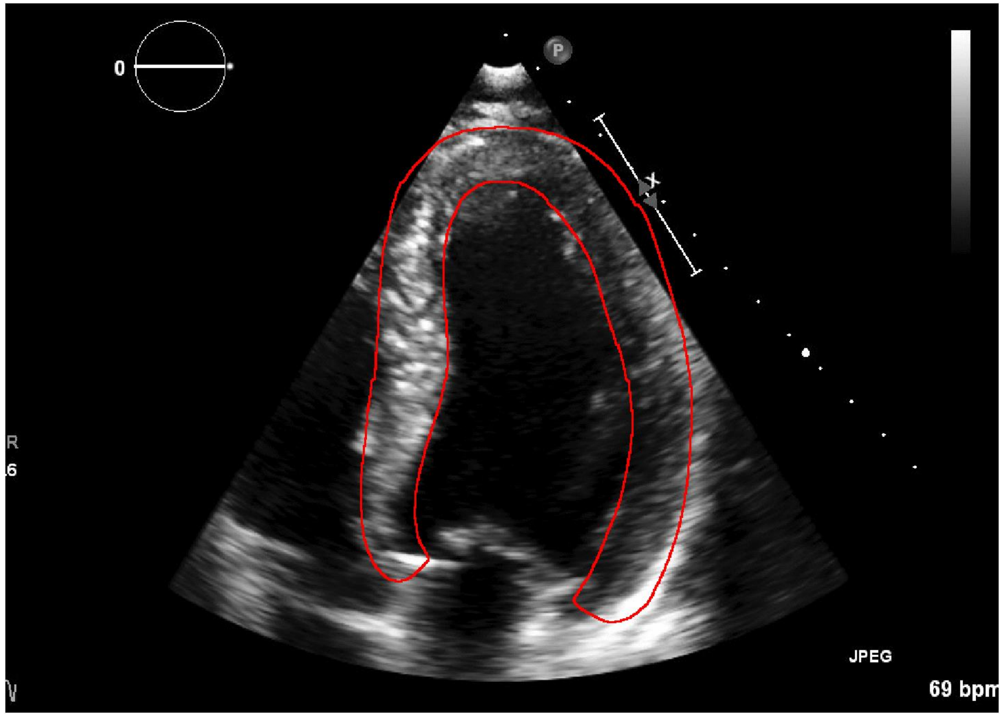


CARDINAL



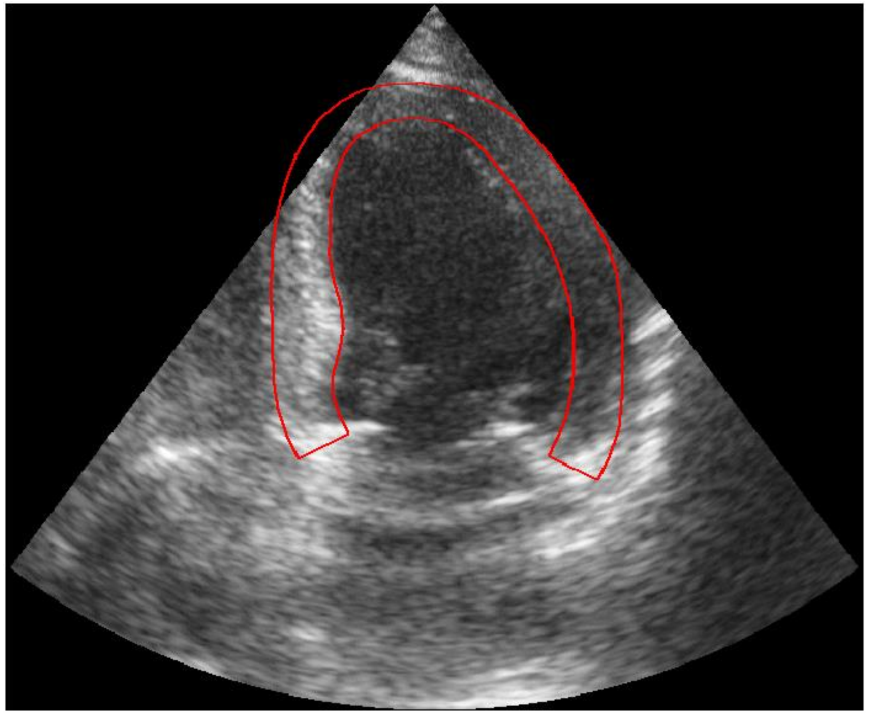
Visualization – GE vs Philips

3D nnU-Net prediction (US-MR)



Philips system

CAMUS annotator (CAMUS)

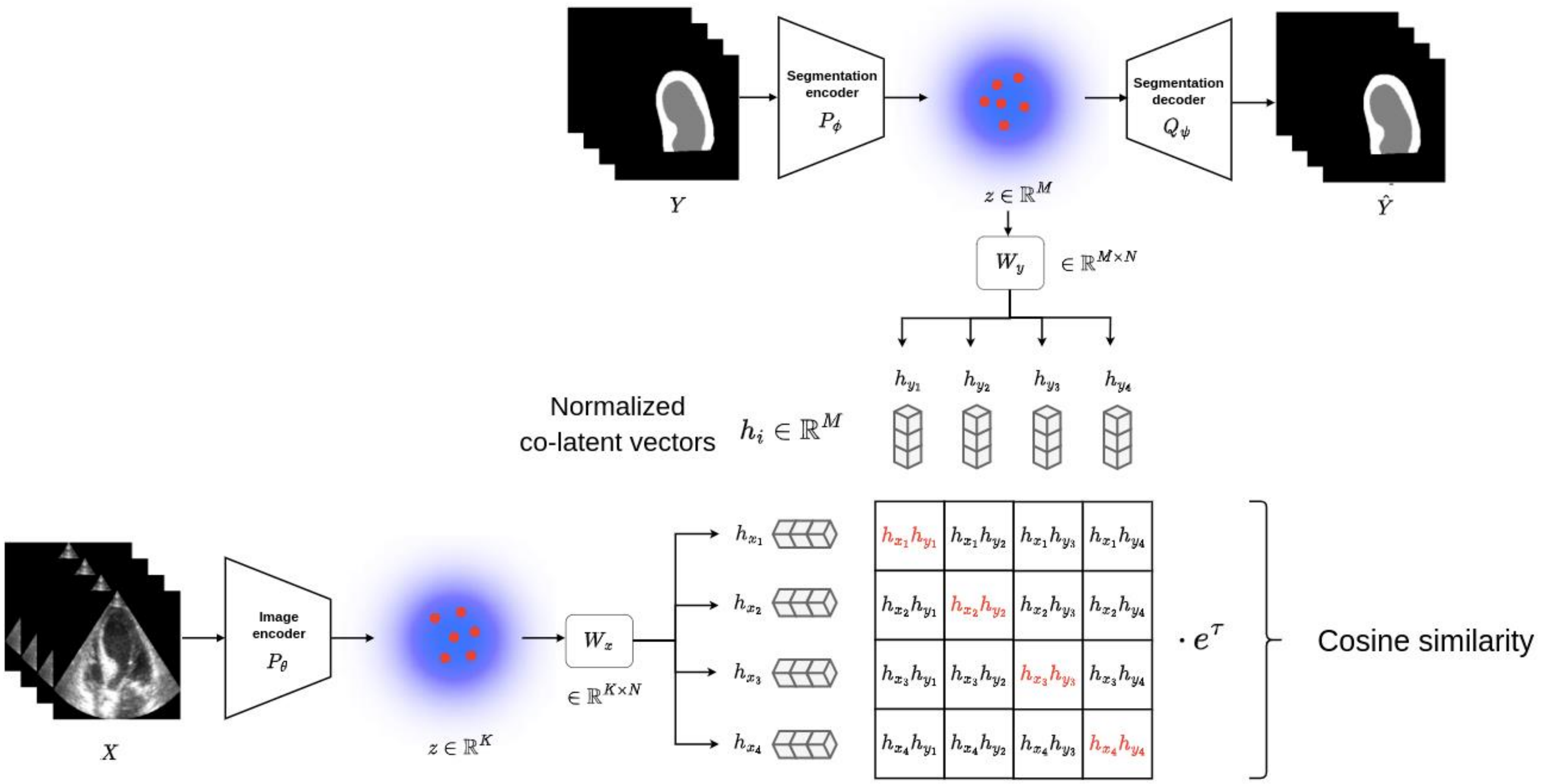


GE system

Uncertainty estimation for cardiac image segmentation

[Judge et al., MICCAI 2022]

Training phase



Inference phase

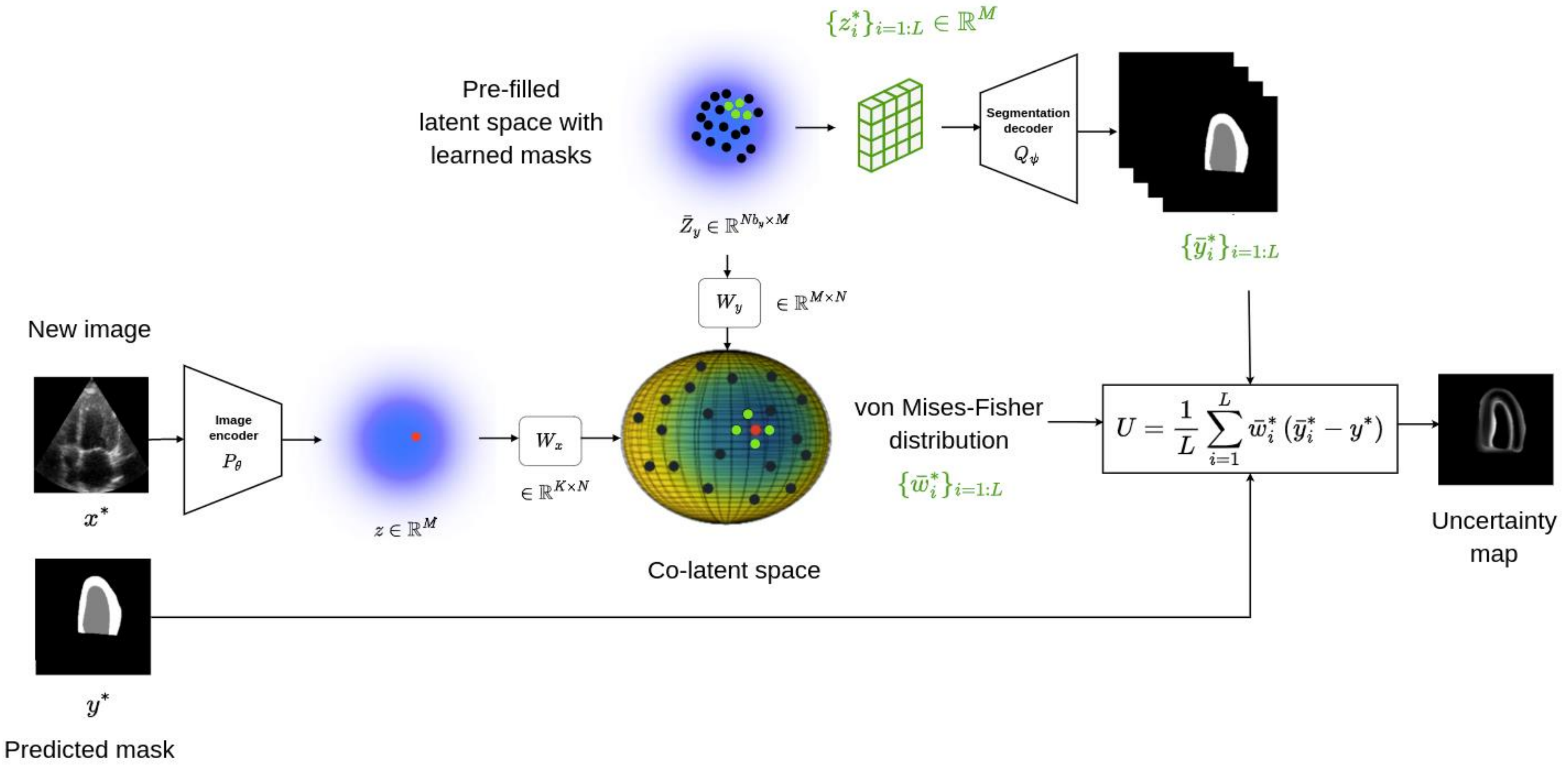
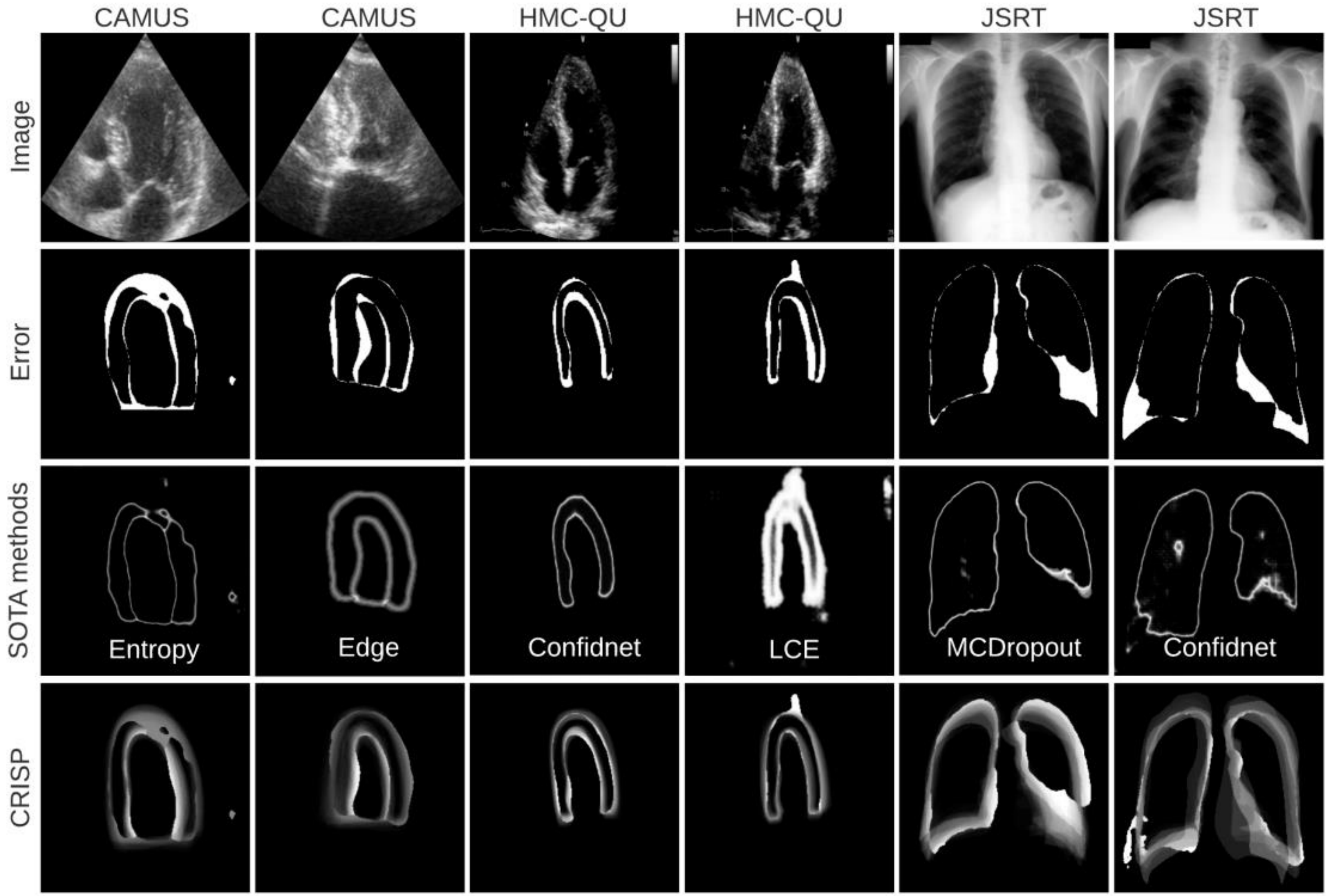


Illustration of uncertainty results

CAMUS

- ✓ $Nb_y = 9000$
- ✓ $L = 150$



Quantitative evaluation

- ✓ Corr: correlation between the sum of the uncertainty values and (1-Dice) score
- ✓ MI: Mutual information between the uncertainty map and the error map

Training data Testing data	CAMUS CAMUS		CAMUS HMC-QU		Shenzen JSRT	
Method	Corr. ↑	MI ↑	Corr. ↑	MI ↑	Corr. ↑	MI ↑
Entropy	0.66	0.02	0.34	0.02	**0.89**	0.02
ConfidNet [1]	0.34	0.04	0.36	0.04	0.69	0.01
CRISP	**0.71**	**0.20**	**0.41**	**0.06**	0.83	**0.11**
McDropout [3]	0.67	0.03	0.26	0.02	**0.82**	0.03
CRISP-MC	**0.78**	**0.26**	**0.29**	**0.06**	**0.82**	**0.08**
LCE [2]	0.58	0.44	**0.35**	0.37	**0.87**	0.06
CRISP-LCE	**0.59**	**0.08**	0.34	**0.13**	0.85	**0.11**

Conclusions & Perspectives

Conclusions & perspectives

▶ Conclusions

✓ VAE framework can be effectively used in medical imaging to

- Guarantee anatomical coherence
- Guarantee temporal consistency
- Estimate uncertainty for image segmentation

▶ Perspectives

✓ Extensive validation on large scale dataset (>100.000 patients)

Thanks

Appendices

Static image accuracy

(CS:CAMUS)

Methods	Train/test	Dice		Hausdorff (mm)	
		ED	ES	ED	ES
Intra-obs.		.945	.930	4.6	4.5
2D nnU-Net		**.952**	**.935**	**4.3**	**4.2**
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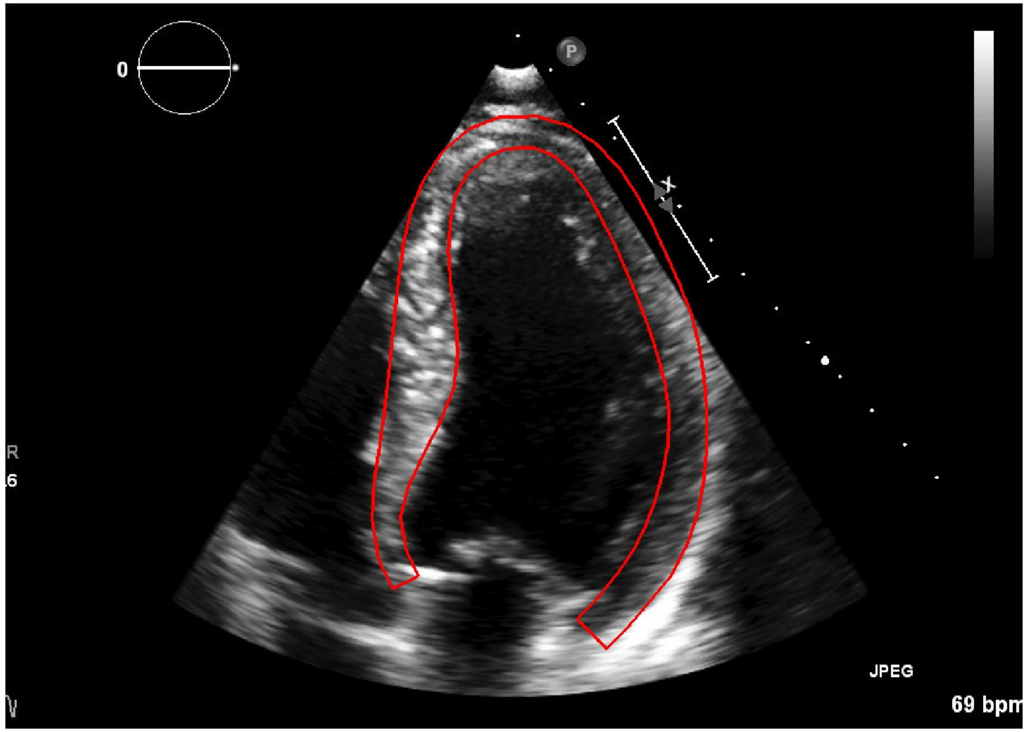
CLAS	CS/CS	**.926**	**4.0**	.958	7.7	.979	4.4
GUDU		.897	**4.0**	**.977**	6.7	.981	4.6

Geometrical accuracy

(CL:CARDINAL, CS: CAMUS, PS:PHILIPS)

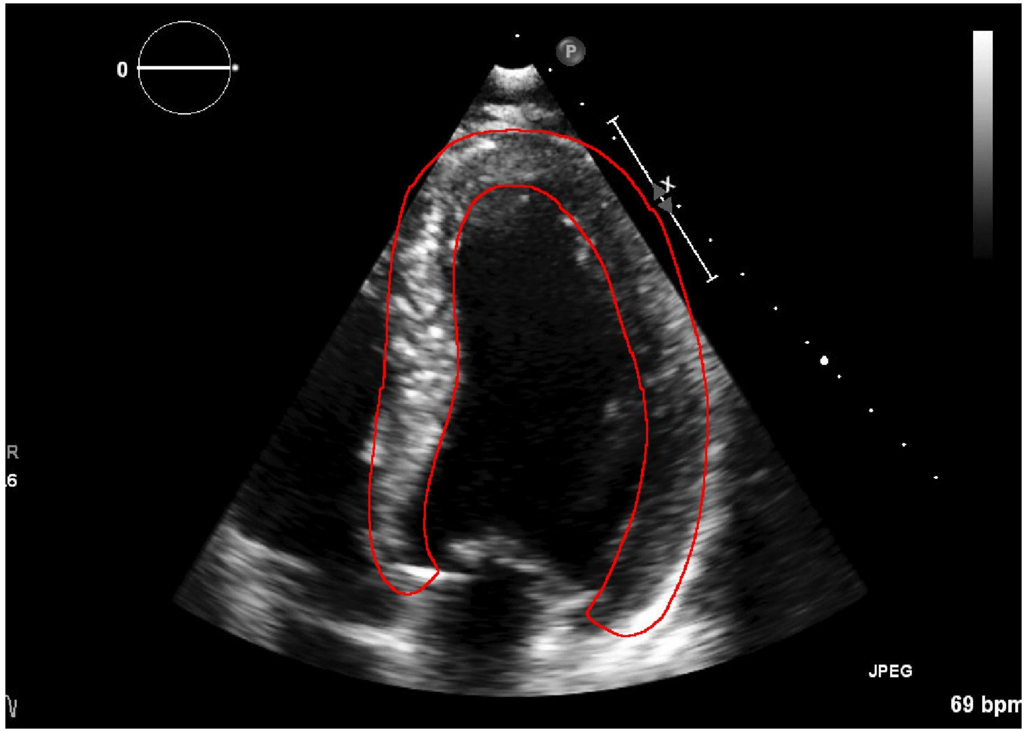
Methods	Train/test	Dice		Hausdorff (mm)		MAD (mm)	
		ED	ES	ED	ES	ED	ES
3D nnU-Net	CL/CL	**.968**	**.960**	**2.7**	**2.5**	**0.8**	**0.7**
3D nnU-Net	CL/CS	.939	.926	5.2	4.6	1.6	1.5
3D nnU-Net	CL/PS	.876	.938	12.1	15.1	3.1	2.6
Inter-observer	-	.885	.914	7.1	7.6	2.9	3.2

Annotator 2



Philips system

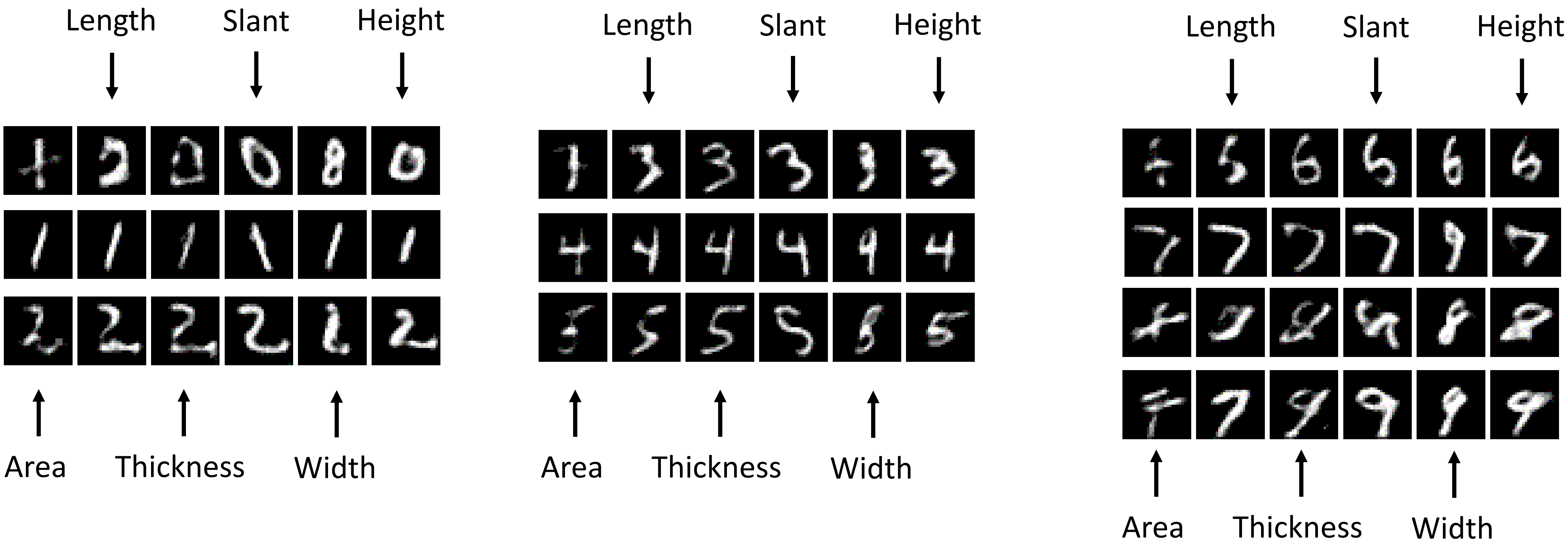
3D nnU-Net prediction
Trained from annotator 1



Philips system

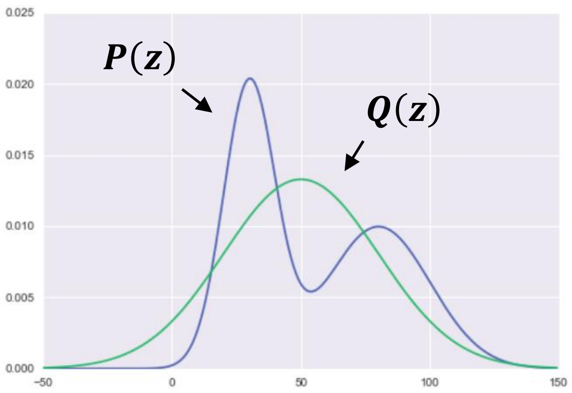
Sampling of the structured latent space

- ✓ Specific attributes: area, length, thickness, slant, width, height
- ✓ Each column corresponds to traversal along a regularized dimension

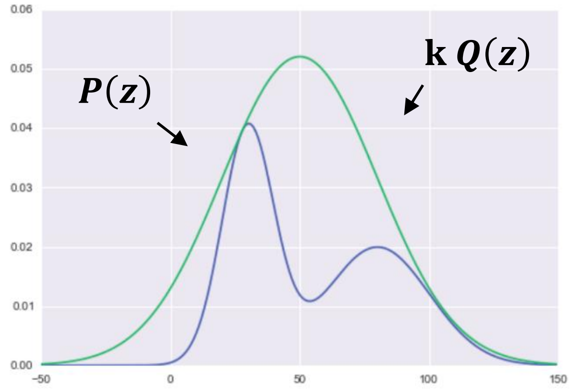


Rejection sampling

- **Targeted distribution $P(z)$**
  - ➔ **Parzen window technique**
- **Proposed distribution $Q(z)$**



- **Constrain $kQ(z) > P(z)$**
  - ➔ **Automatic choice of k**



Rejection sampling

- $\mathbf{z} \sim \boldsymbol{Q}(\boldsymbol{z})$
- $\mathbf{u} \sim \boldsymbol{Unif}(\mathbf{0}, \boldsymbol{kQ}(\boldsymbol{z}))$

- **Computation of $\boldsymbol{P}(\boldsymbol{z})$**

  ➔ **If $\boldsymbol{u} \leq \boldsymbol{P}(\boldsymbol{z})$ then keep $\boldsymbol{z}$**
  ➔ **If $\boldsymbol{u} > \boldsymbol{P}(\boldsymbol{z})$ then reject $\boldsymbol{z}$**

Populated space