On the integration of robust AI-based image information for continuous patient stratification

Prof. Olivier Bernard

CREATIS Laboratory, University of Lyon, France

CREATIS; CNRS (UMR 5220); INSERM (U1294); INSA Lyon; University of 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

Robust estimation of existing / new biomarkers

Population representation

Heterogenous data integration

Transformers

Etiology classification
Hypertension characterization

Medical context

Diagnosis from routine modalities

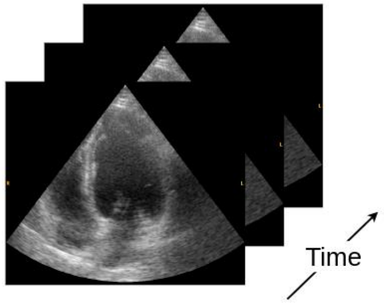
Objective
- ✓ Arterial hypertension characterization

Dataset
- ✓ 239 patients from a French hospital
- ✓ 53 patient descriptors from HER
- ✓ Apical 2 & 4 chamber views per patients

Method
- ✓ Fusion of heterogeneous data using transformers

Multimodal inputs

Video sequences



Electronic Health Records

53 patient descriptors

- General information
- Medical history
- Holter monitor
- Biological exam
- Treatment
- Transtho. echo. measurements

Discrete output

Hypertension Severity Output

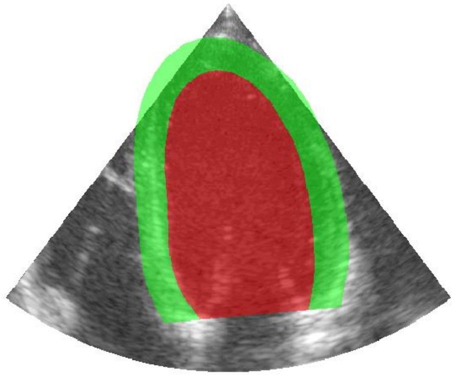
3 classes

- White coat HT	No positive HT diagnosis
- Controlled	Under recommended BP level
- Uncontrolled	Above recommended BP level

CREATIS

Extraction of robust AI-based image from echo. sequences

Quantification of clinical indices to diagnose cardiac pathologies



Automatic segmentation of anatomical structures →

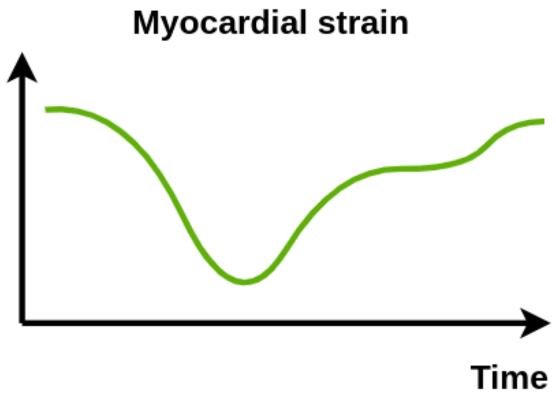
- Scalar descriptors
- Time-series descriptors

Scalar descriptors

- LV volumes
- LV ejection fraction
- Min/max myo. curvature

Time-series descriptors

- LV area
- LV length (base to apex)
- Global strain
- Average myo. Thickness



Segmentation of echocardiographic images

[Leclerc et al., IEEE TMI 2019]

Challenges

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

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

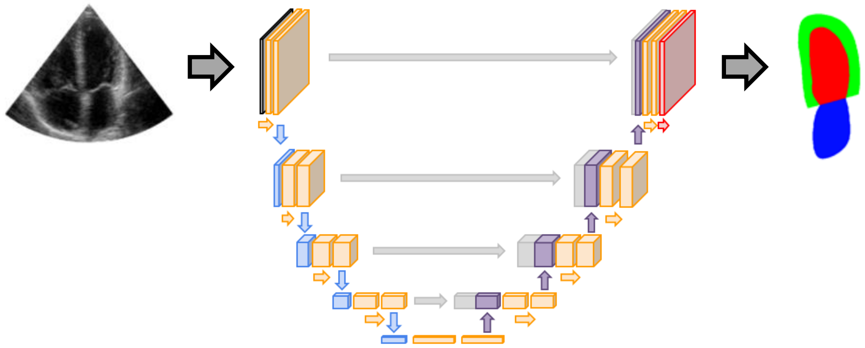
Limited by currently available public datasets!

Static image segmentation 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**
CLAS	CS/CS	.947	.929	4.6	4.6
GUDU		.946	.929	4.7	4.7

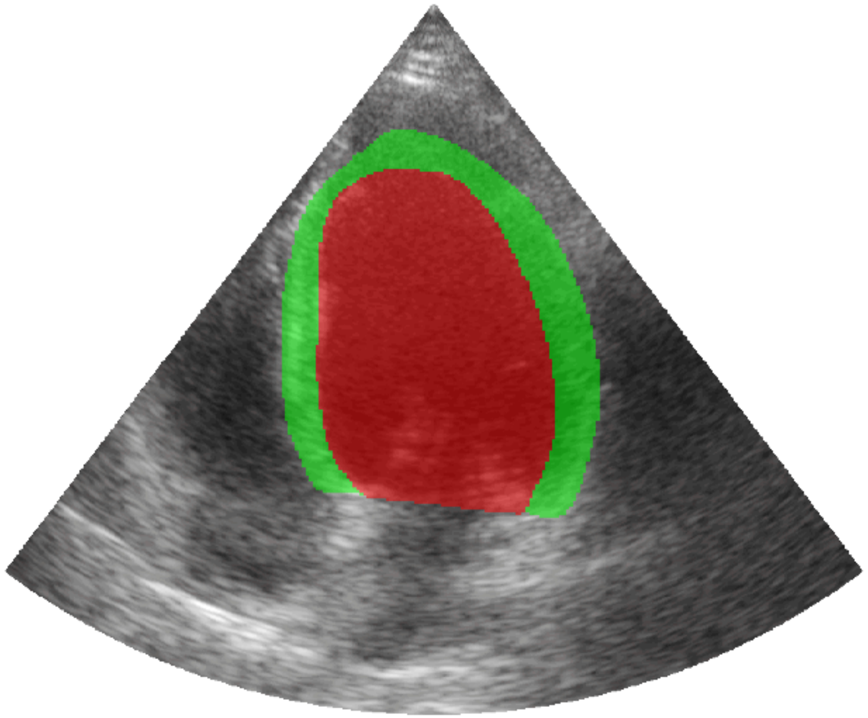
2D nnU-Net architecture



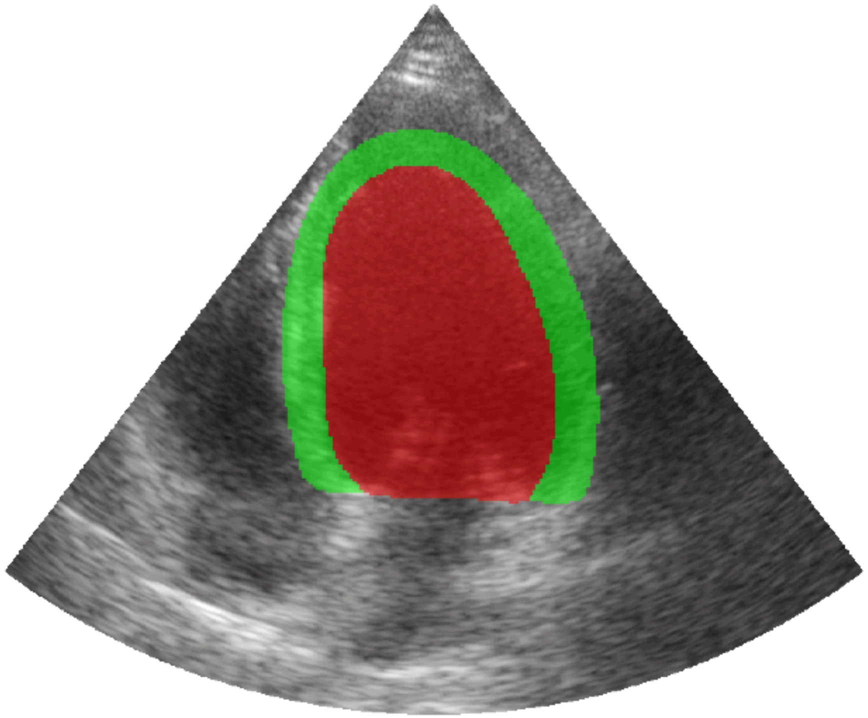
Several engineering tricks

- Resampling to a same resolution
- Automatic architecture choices
- Data augmentation strategies
- Patch approach to preserve resolution

Need for temporal consistency



Segmentation with a 2D nnU-Net



Manual annotation

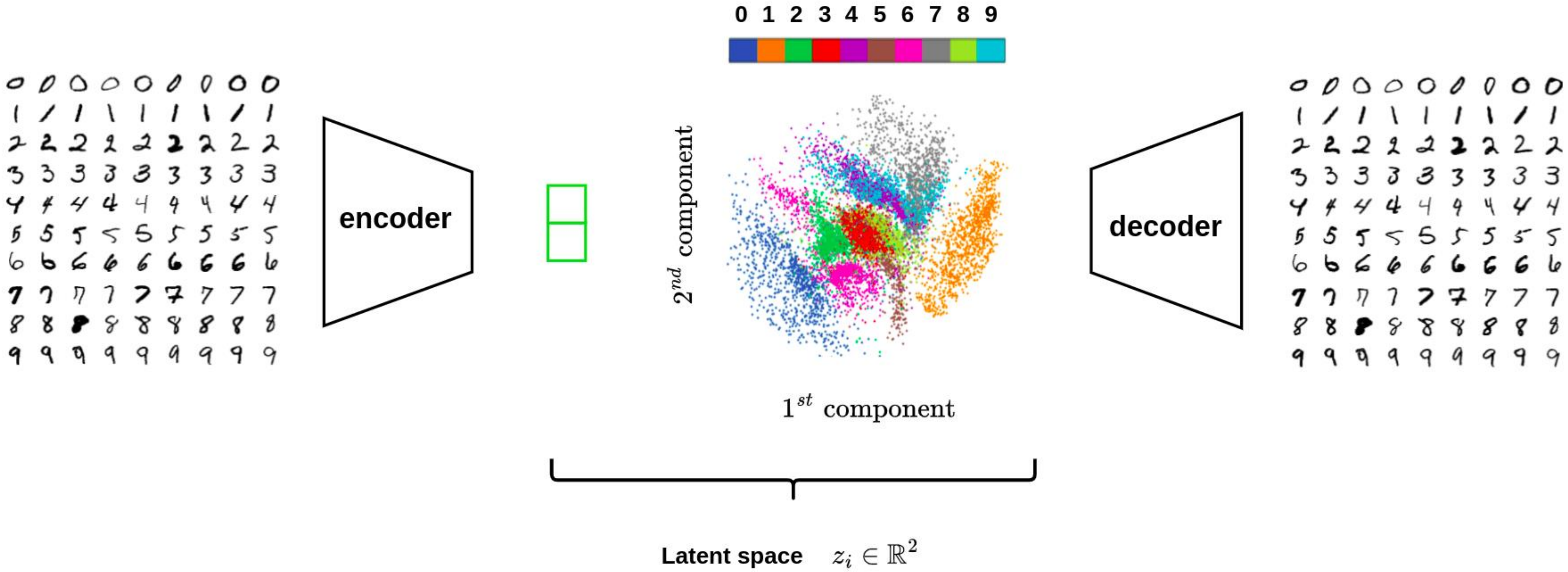
How to guarantee temporal consistency ?

[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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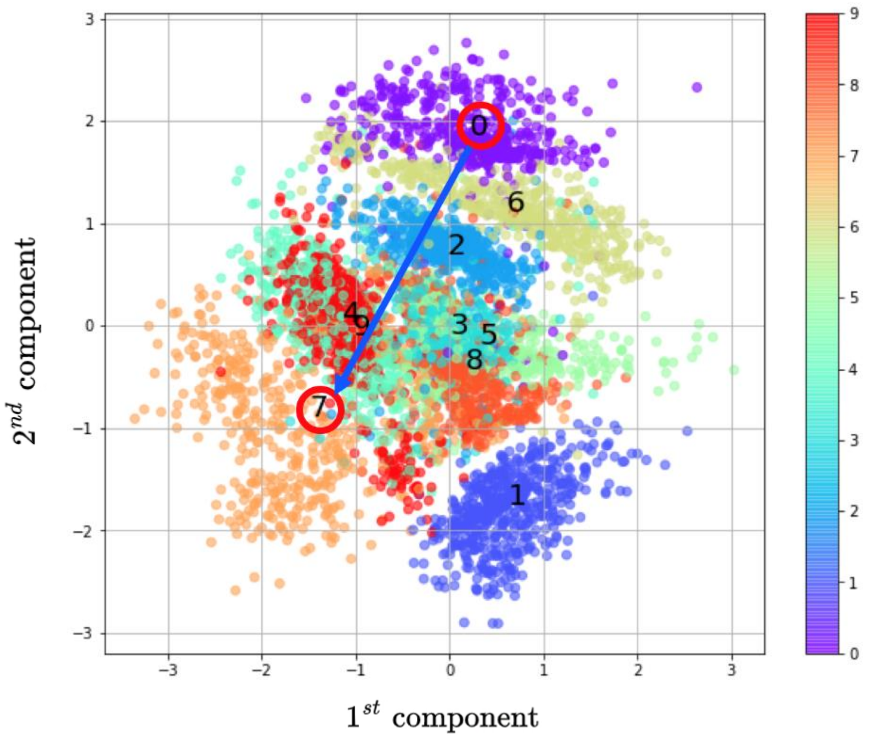
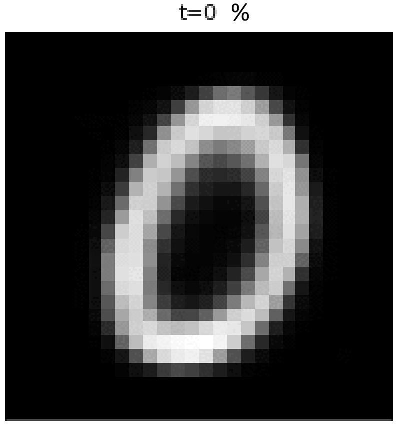


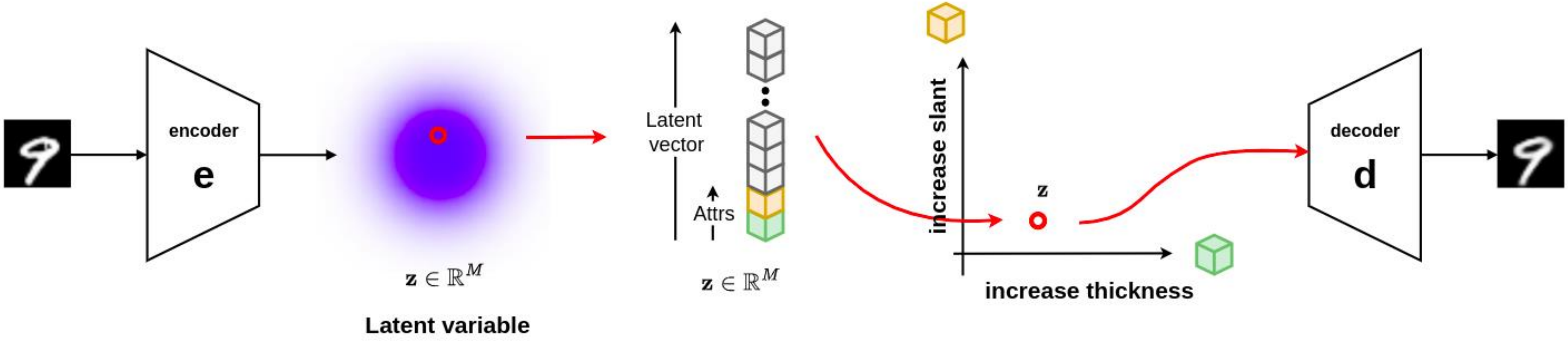
Linear interpolation in the latent space

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

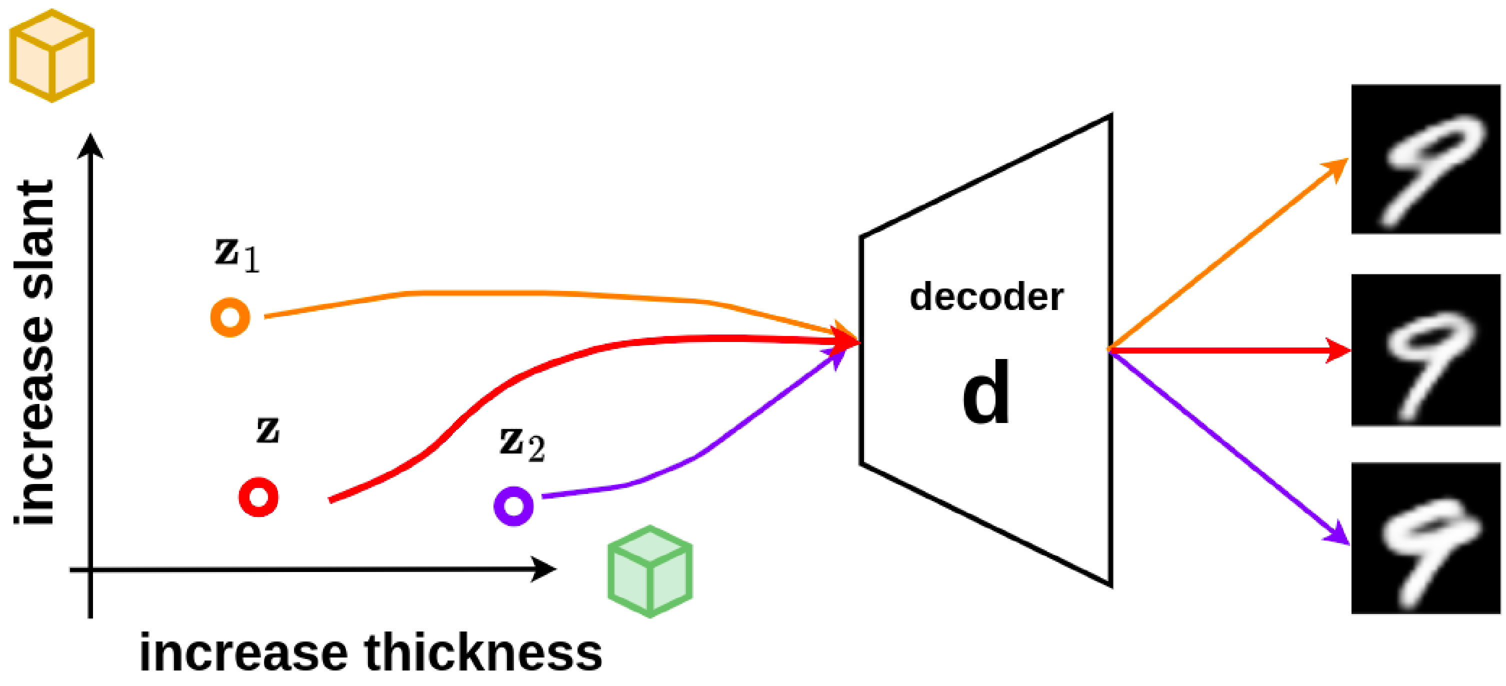


Generation of a structured latent space

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

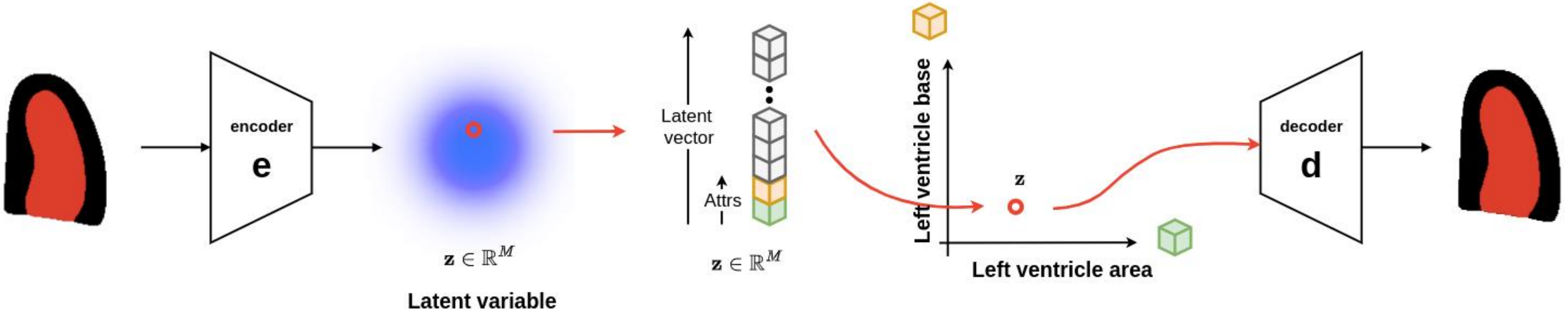


Sampling of the structured latent space

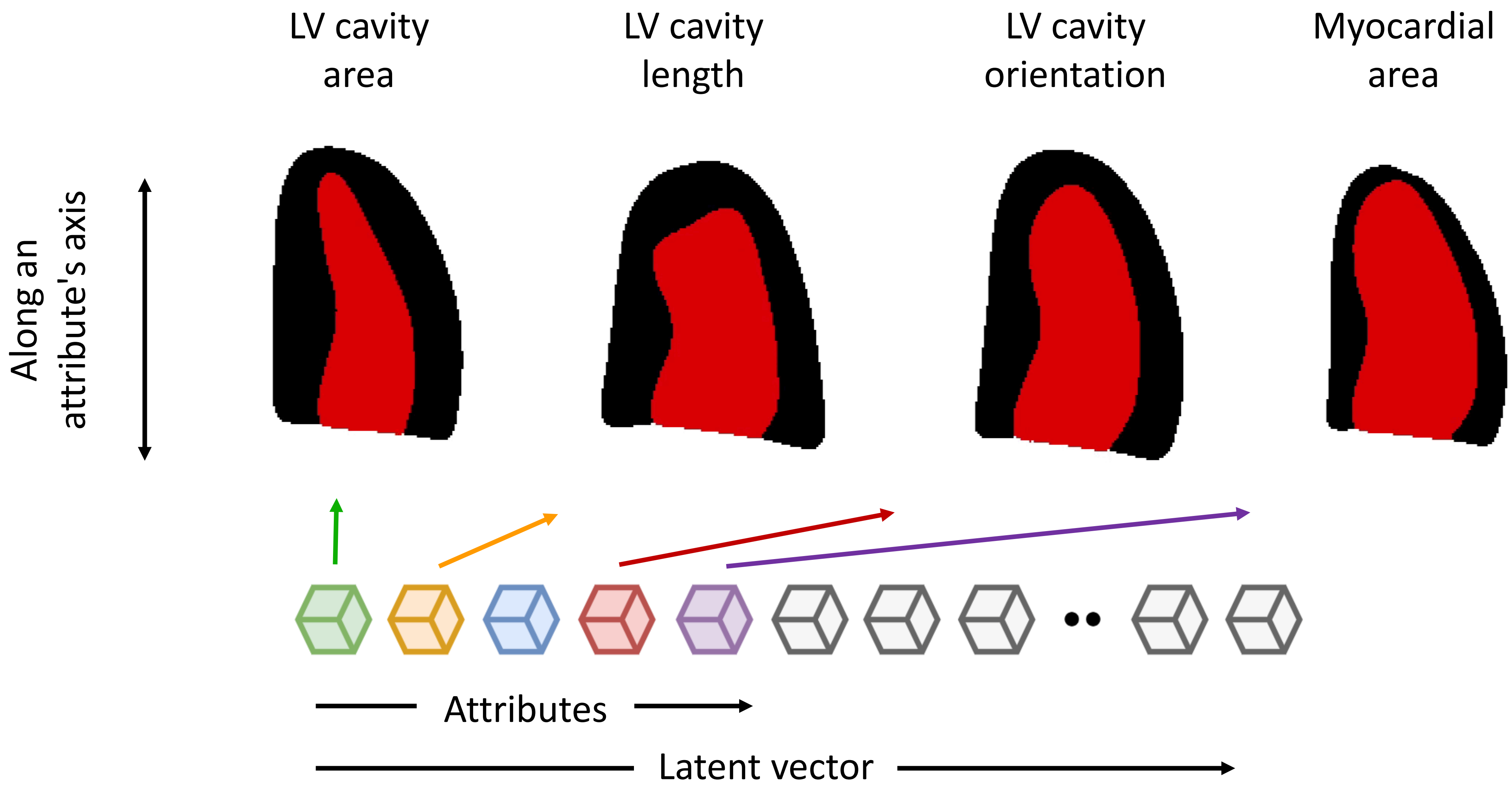


Generation of structured latent space according to specific attributes

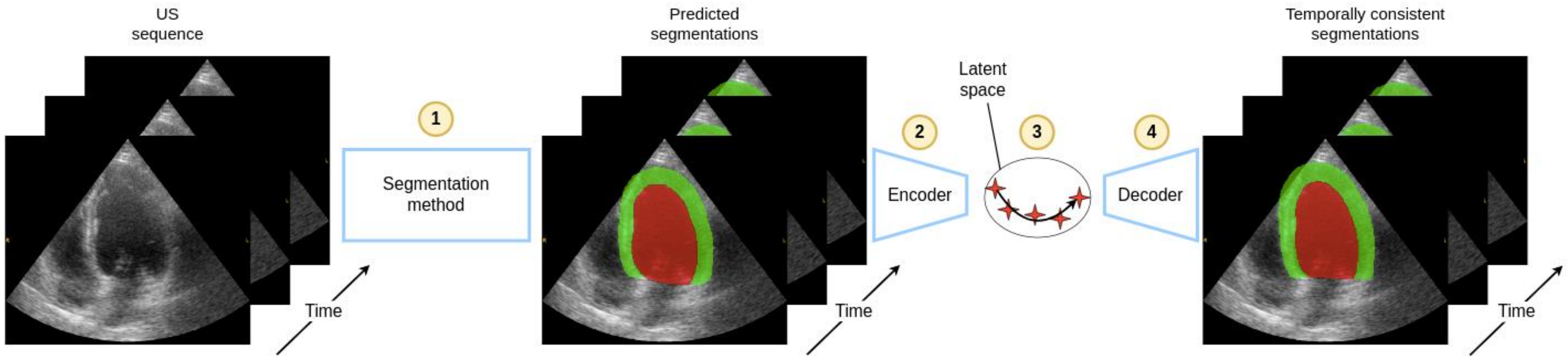
- ✓ Left ventricle (LV) cavity: area, length, basal width, orientation
- ✓ Myocardial area
- ✓ Epicardial center



Description of the cardiac shapes



Proposed temporal pipeline



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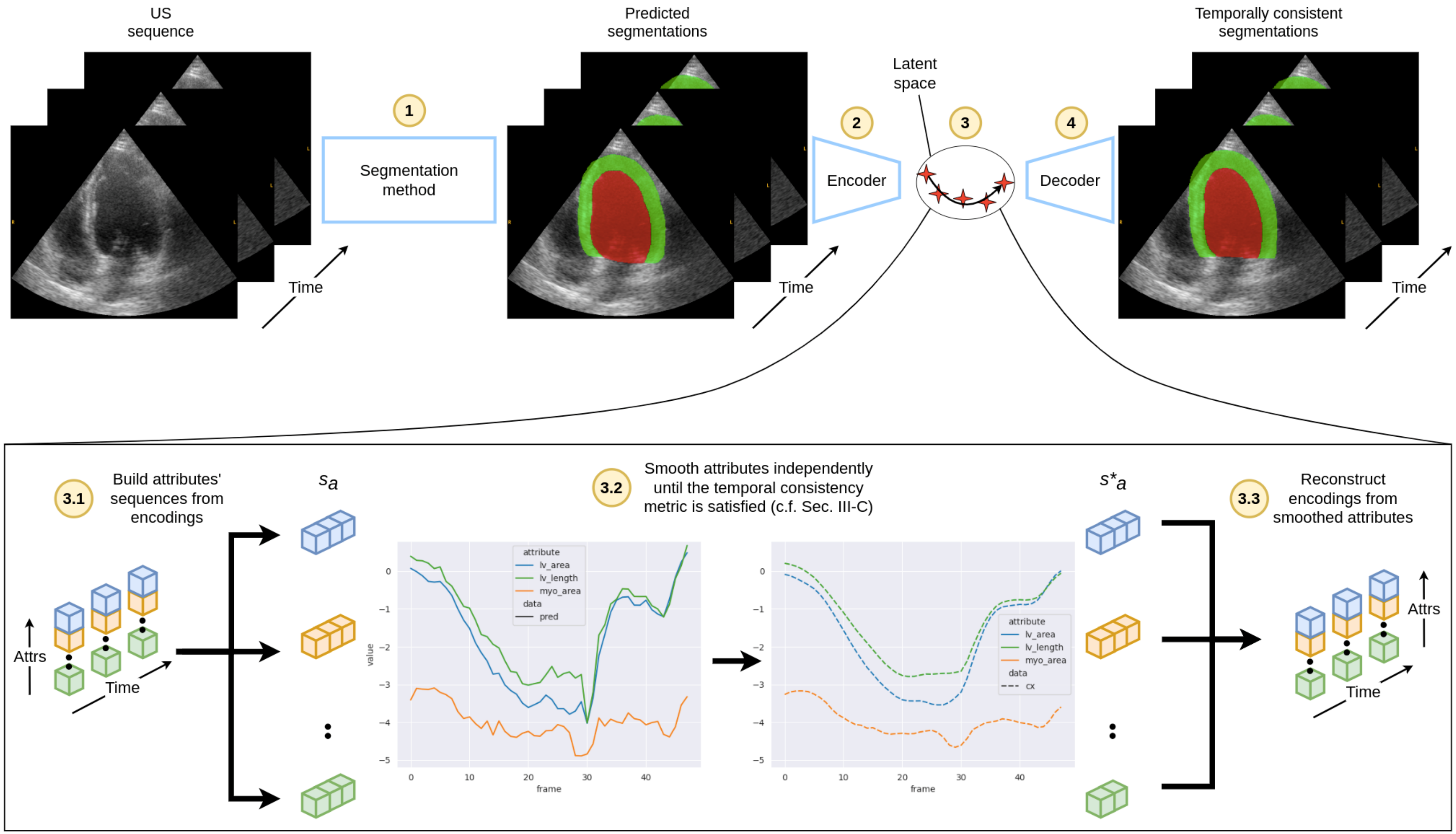
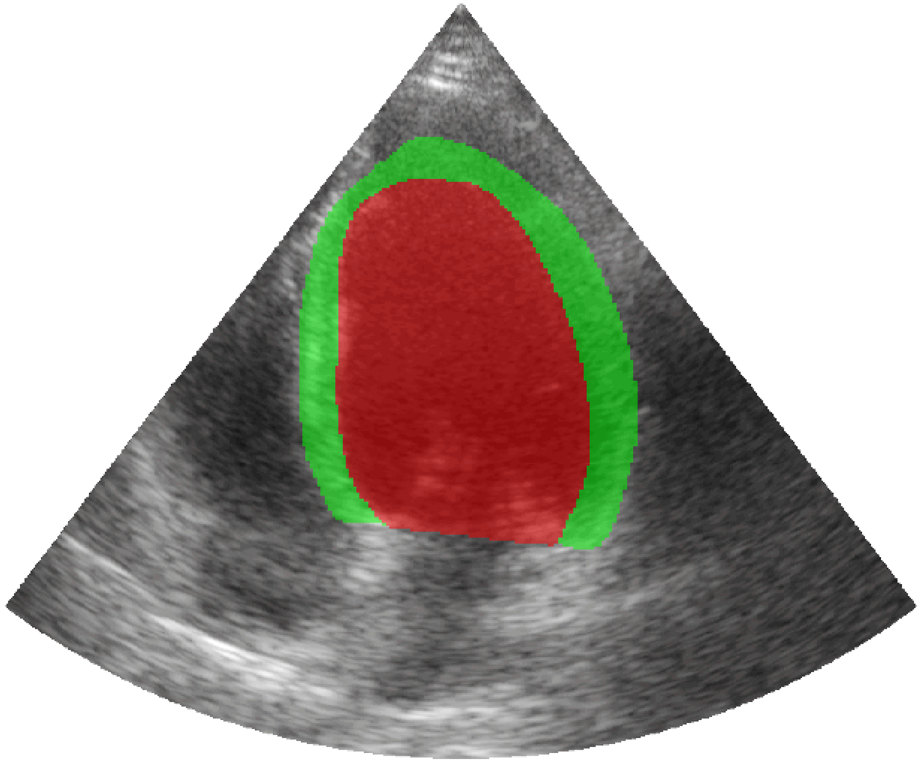
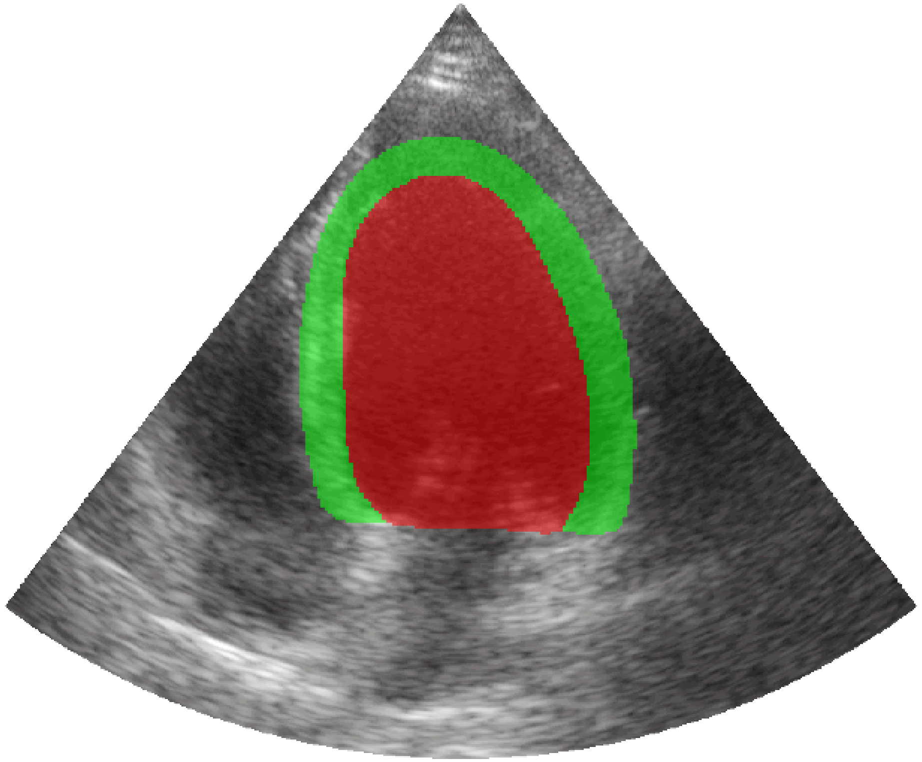


Some post-processing examples

Original nnU-Net



Post-processed nnU-Net

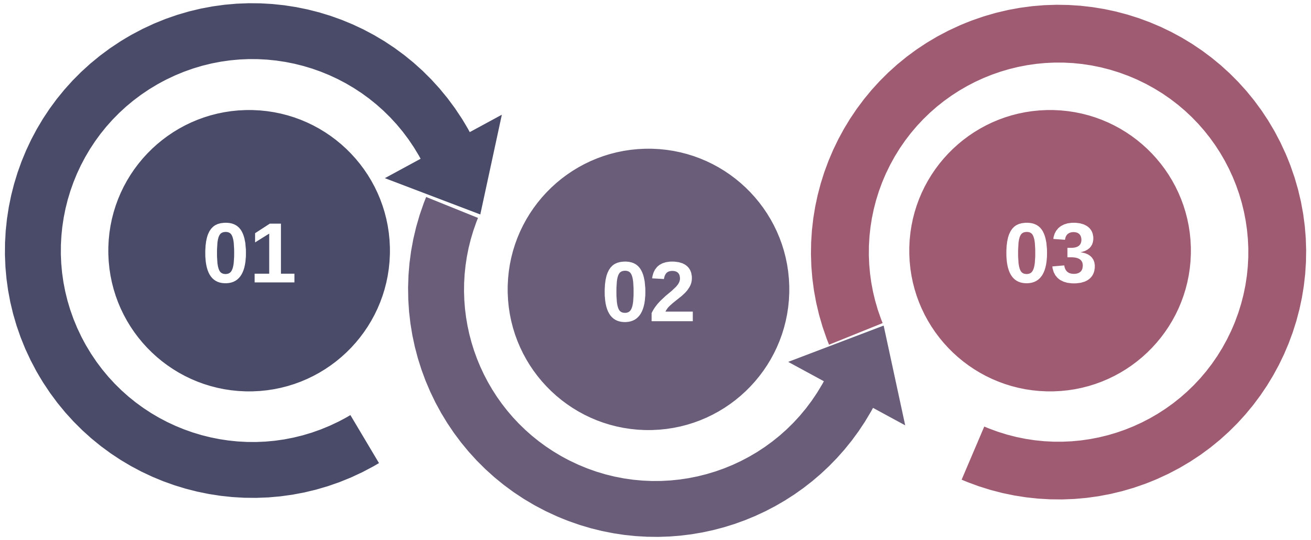


Segmentation of echocardiographic images with temporal consistency

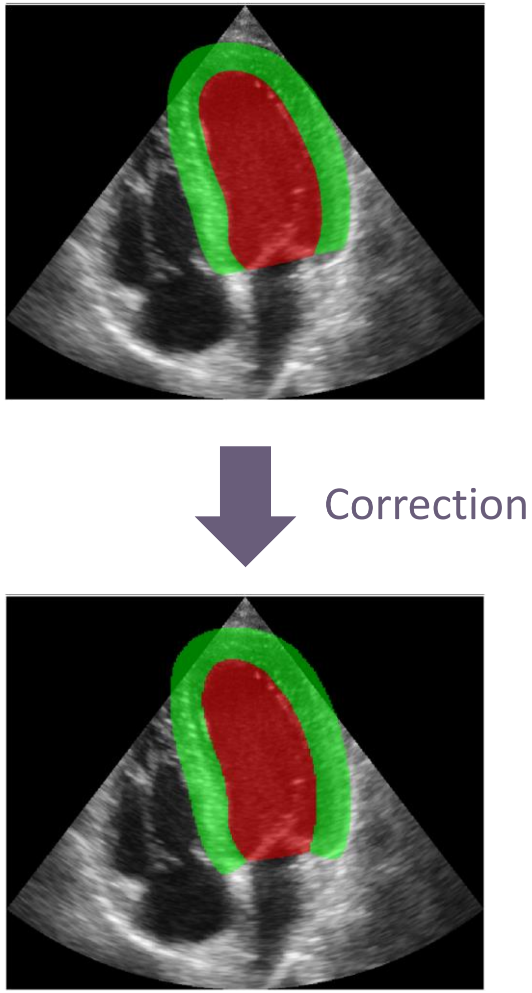
[Ling et al., FIMH 2023]

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

Trained 3D nnU-Net on CARDINAL with GOLD STANDARD (378 sequences)

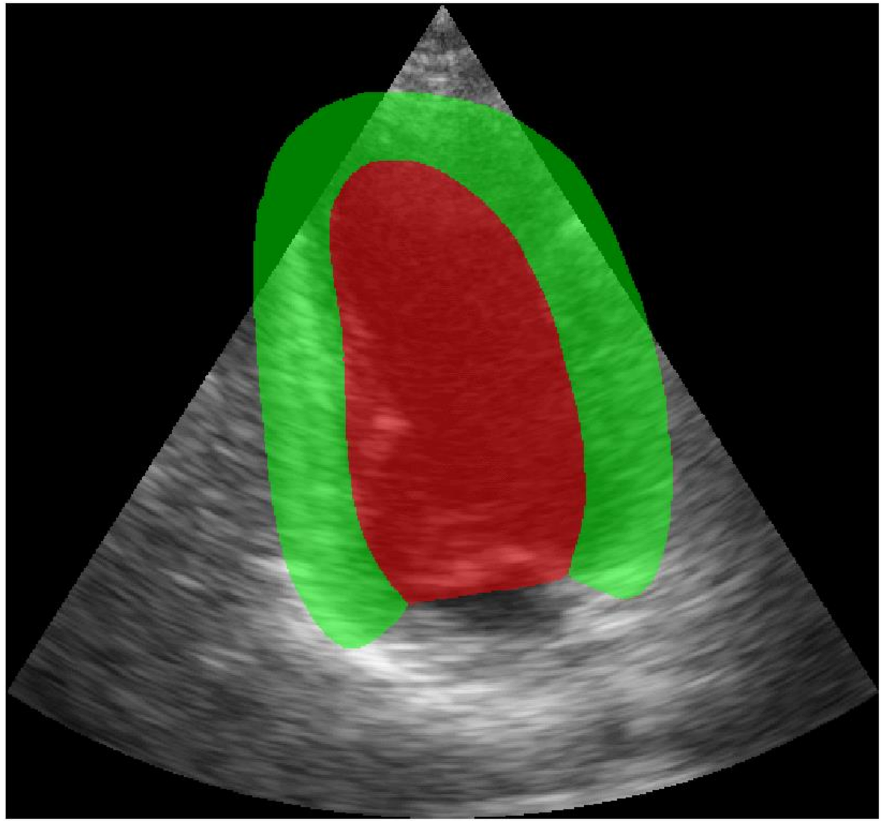


Applied trained models on CARDINAL and postprocessed
predictions using Painchaud et al. model to correct temporal inconsistency
-> GOLD STANDARD

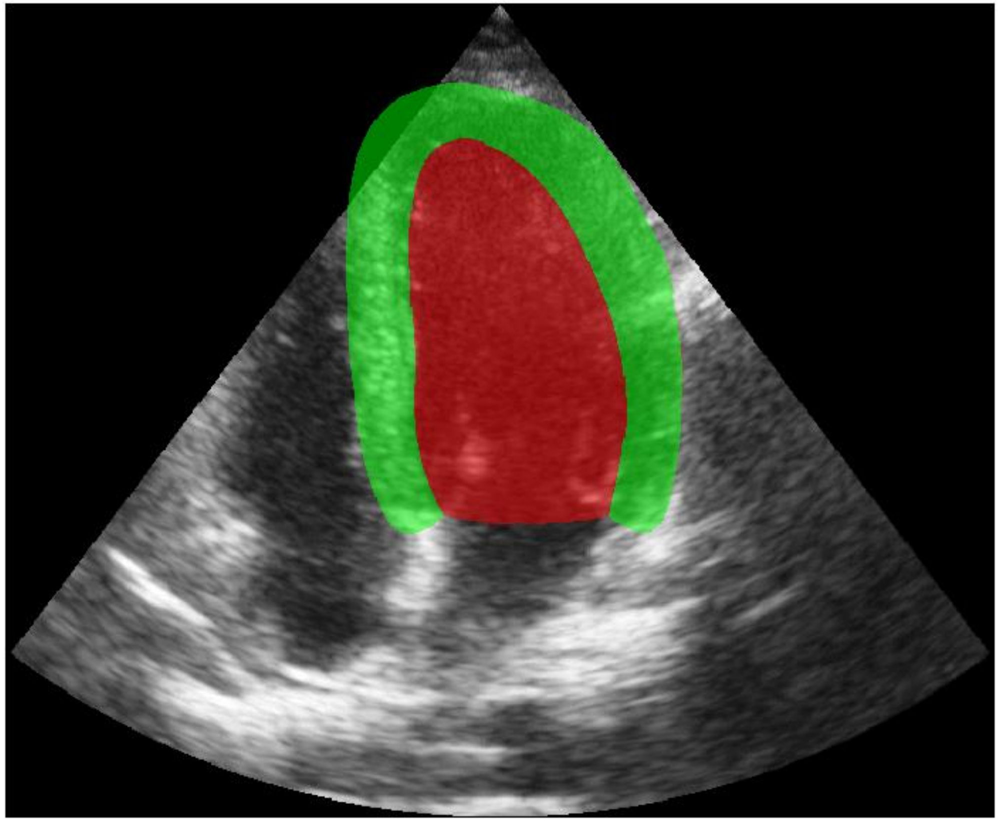


Visualization – temporal consistency

3D nnU-Net prediction on CAMUS

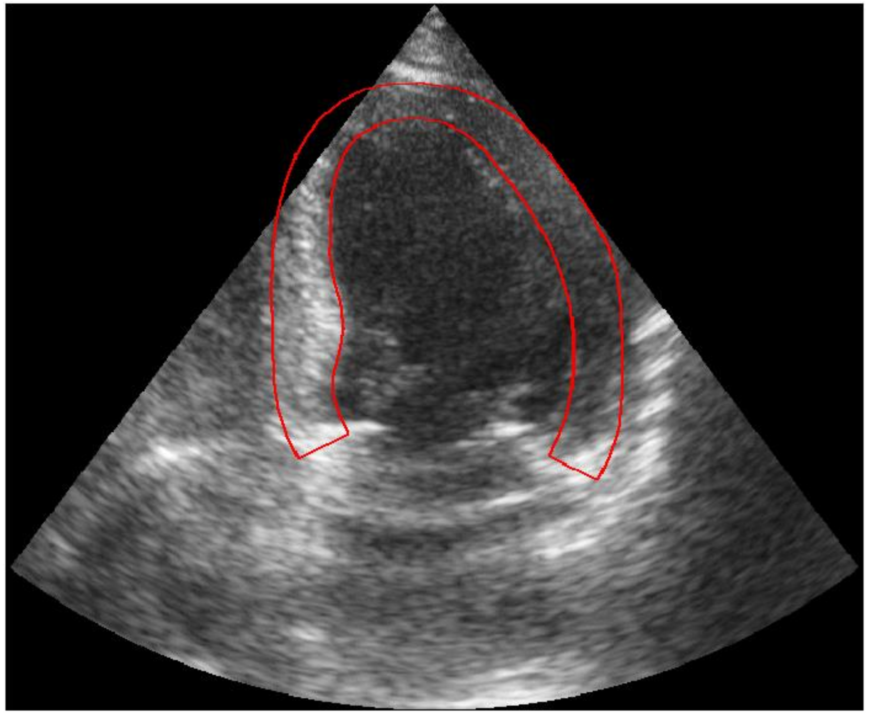


3D nnU-Net prediction on CARDINAL



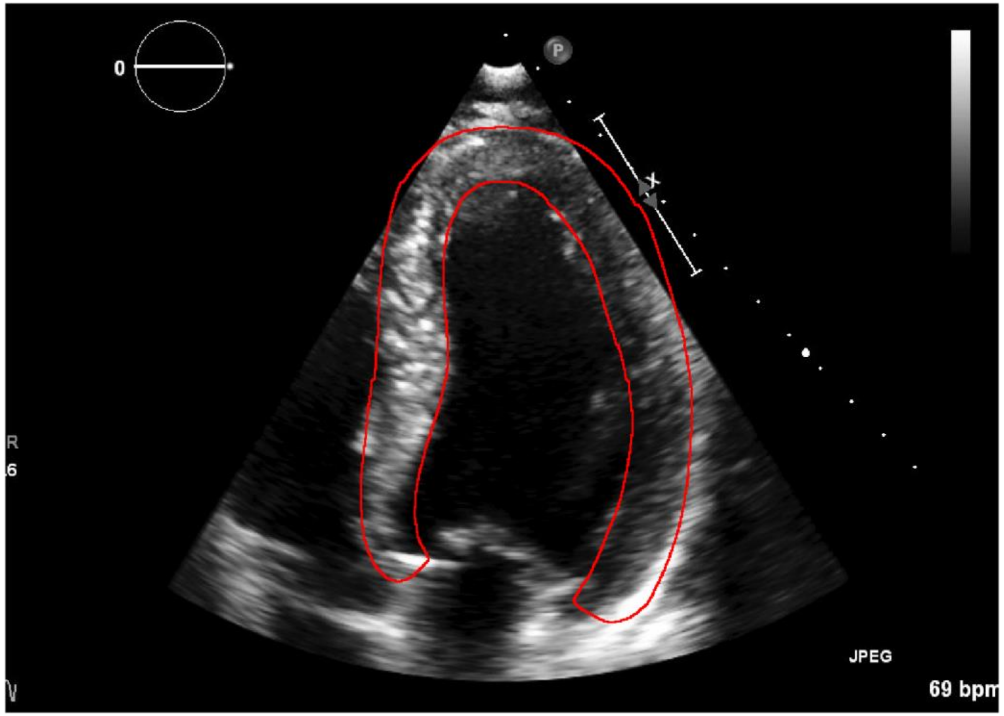
Visualization – GE vs Philips

CAMUS annotator (CAMUS)



Vendor 1

3D nnU-Net prediction



Vendor 2

On the continuous stratification of patient with hypertension

[Painchaud et al., arxiv 2024]

Diagnosis from routine modalities

Objective

- ✓ Arterial hypertension characterization

Dataset

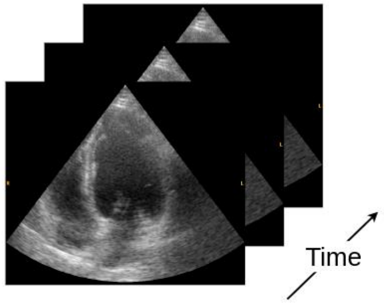
- ✓ 239 patients from a French hospital
- ✓ 53 patient descriptors from HER
- ✓ Apical 2 & 4 chamber views per patients

Method

- ✓ Fusion of heterogeneous data using transformers

Multimodal inputs

Video sequences



Electronic Health Records

53 patient descriptors

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Discrete output

Hypertension Severity Output

3 classes

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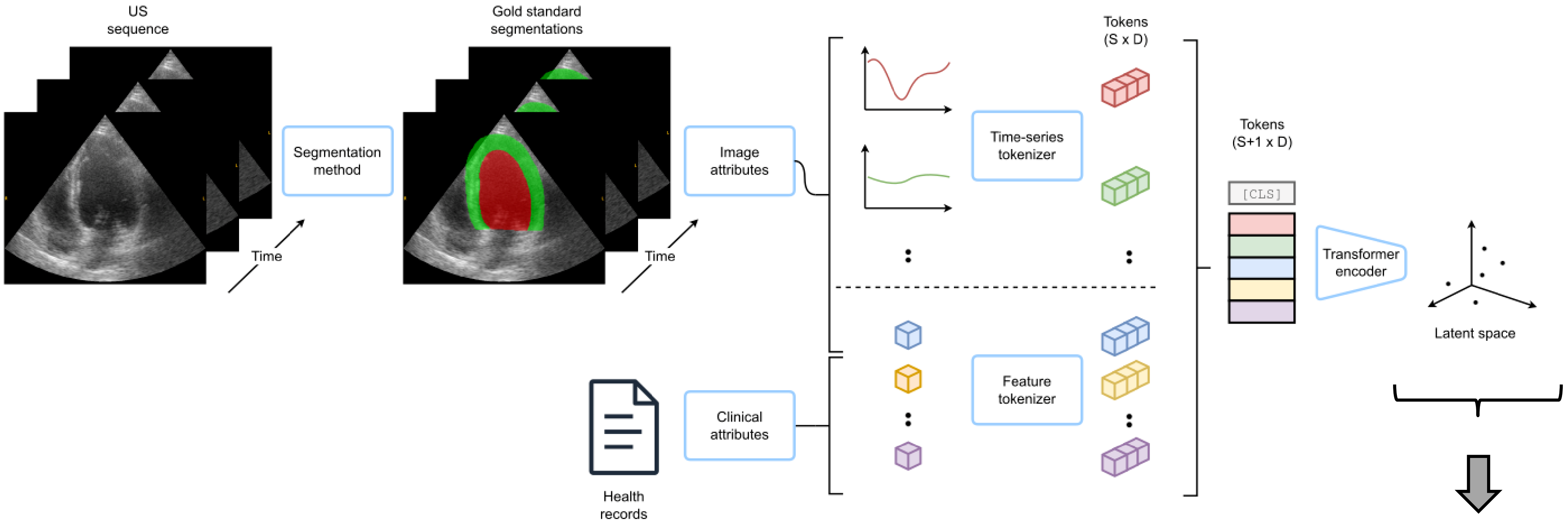
Fusion of heterogeneous data

Method

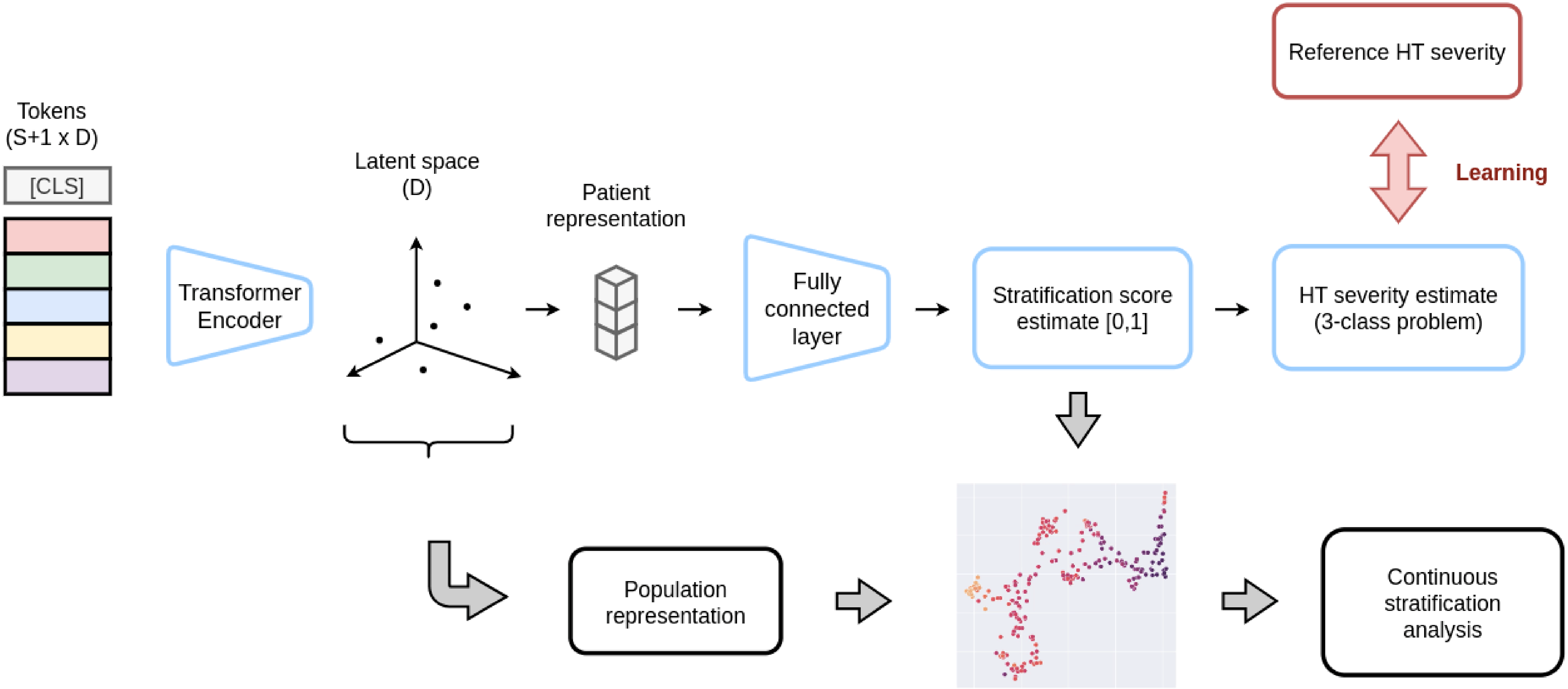
- ✓ Transformer paradigm
- ✓ Multimodal information fusion



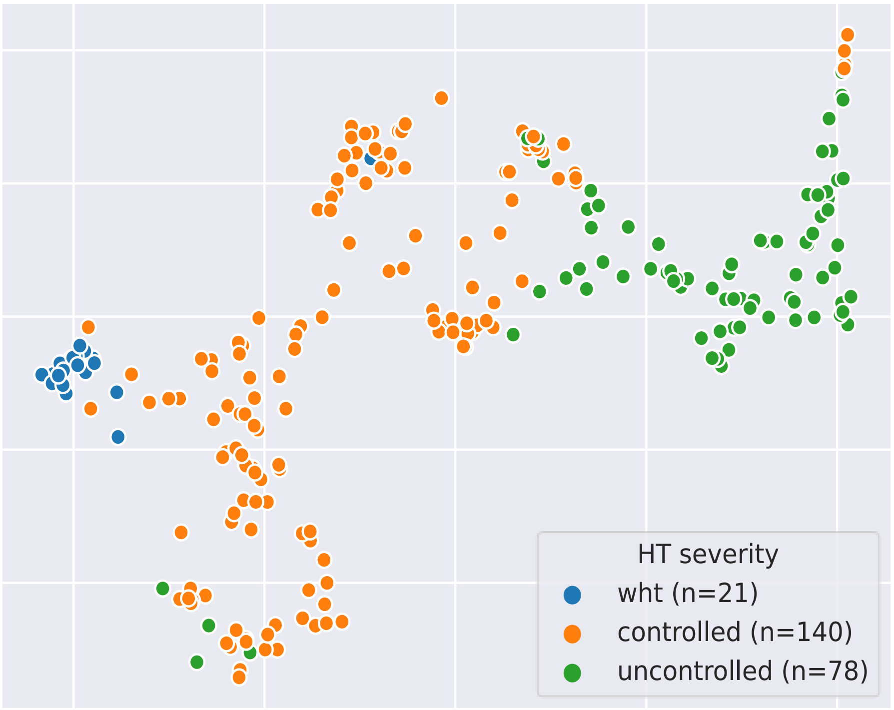
Population representation in a dedicated space

Method

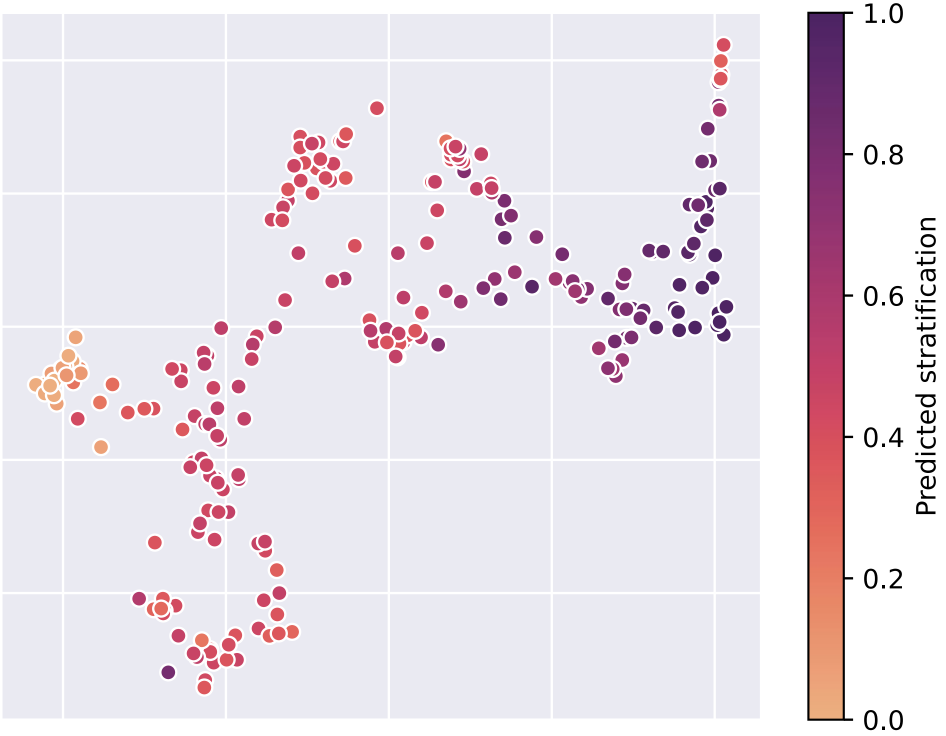
✓ Stratification estimation



Target labels versus continuous stratification



Population representation: coloration according to HT severity



Population representation: coloration according to predicted stratification

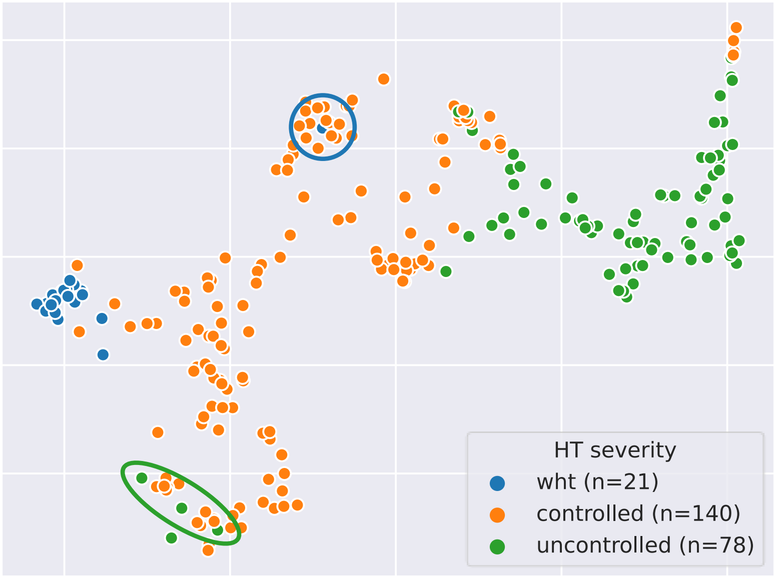
Population representation

Results

- ✓ Automatic classification of HT severity (3-class problem)
- ✓ Training on 191 patients, testing on 48 patients
- ✓ Mean ± standard deviation over 10 trainings

Transformer	tabular+time-series
Accuracy (%)	**83.3 ± 2.8**

Classification accuracy using the 64 tabular descriptors + 14 time-series descriptors



Population representation: coloration according to HT severity

Population representation

Results

- ✓ The more data, the better !
- ✓ Unusual results

More data ↓

Input descriptors	Nb of descriptors	Accuracy (%)
tab-13	13	71.3 ± 3.8
tab-13+time-series	27	74.4 ± 3.8
records	30	80.6 ± 4.2
tabular	64	**83.5 ± 4.8**
tabular+time-series	78	83.3 ± 2.8

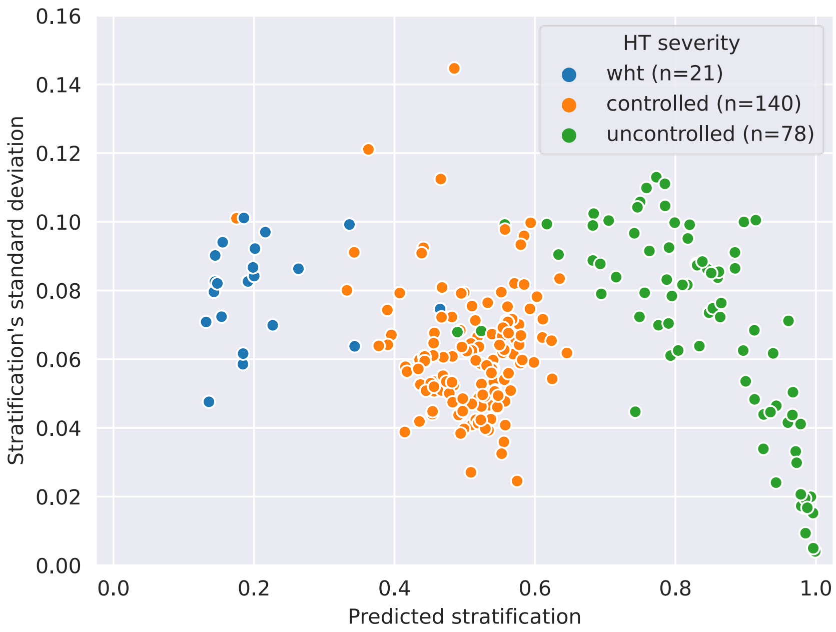
Training on 191 patients, testing on 48 patients, average values from 10 different experiments

Population representation

Results

✓ Stable prediction of the stratification score [0,1]

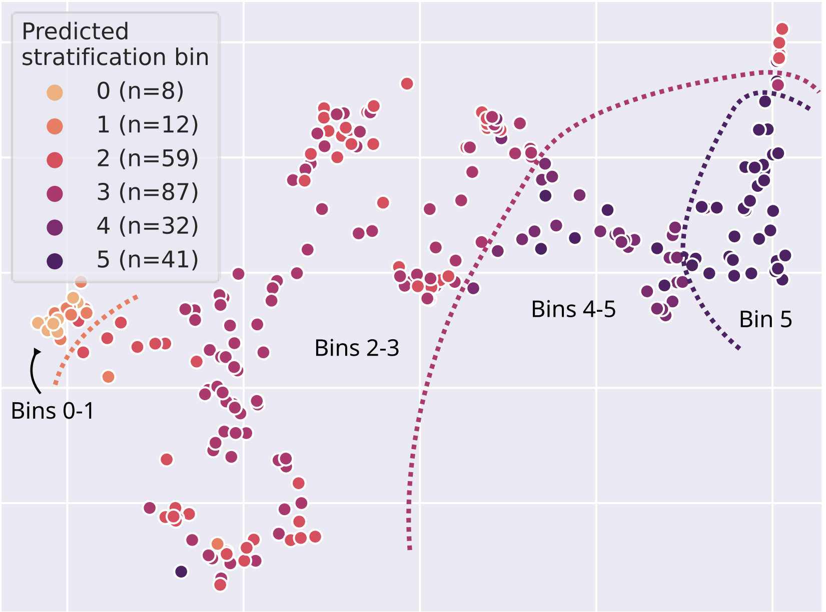
→ Average variability of 0.065 over 10 trainings



Computation of the variability of the stratification estimation over 10 different trainings

Results

✓ Continuous stratification enables a more detailed study of phenogroups

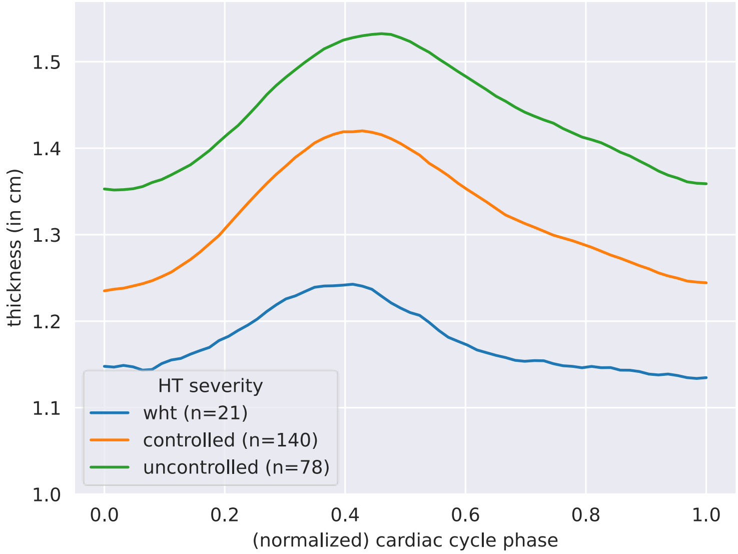


Discretization of the continuous stratification according to bins

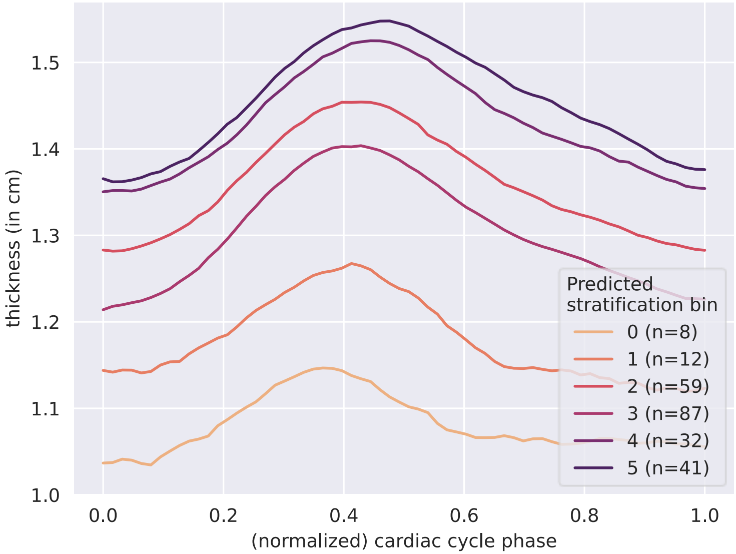
Phenogroups analysis

Results

- ✓ Study of patterns in time-series descriptors
- ✓ Basal Septal Thickness (BST)
  - → Thicker myocardium for HT patients
  - → Shift in peak thickness



Patient groups according to the severity score provided by a cardiologist

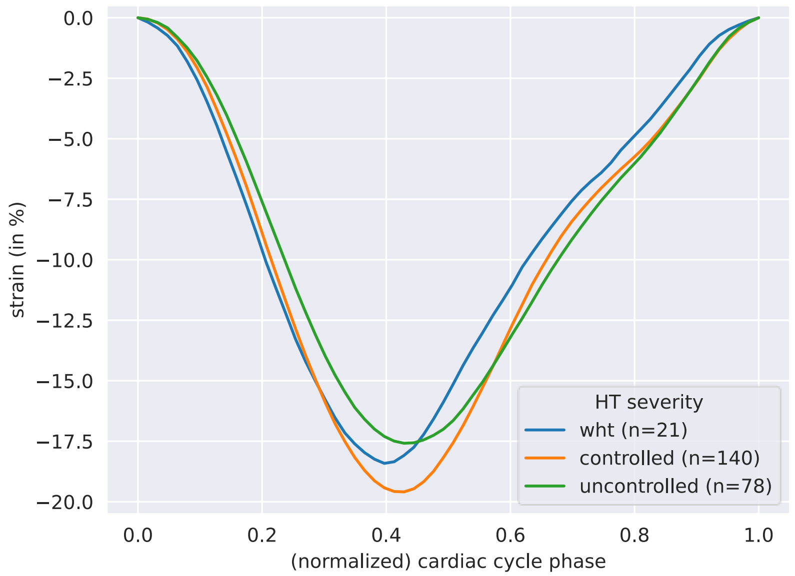


Patient groups according to the stratification bins

Phenogroups analysis

Results

- ✓ Study of patterns in time-series descriptors
- ✓ Global Longitudinal Strain (GLS)
  - → Decrease in peak GLS
  - → Altered post-systolic relaxation



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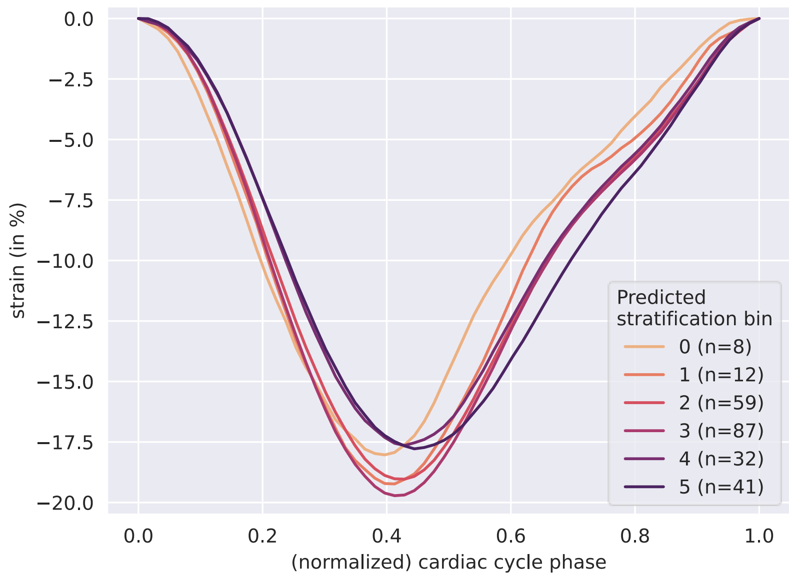

Patient groups according to the stratification bins

Conclusions & Perspectives

Conclusions & perspectives

✓ AI-based framework enables
- Automatic and robust quantification of several clinical indices
- Efficient fusion of heterogenous data

✓ In this pilot study, we investigate
- The continuous stratification of patients with hypertension
- The stability and reproducibility of the results
- The additive value of continuous stratification representation

✓ Perspectives
- Validation on larger dataset
- Perform a more clinical analysis
- Deploy an explainable AI framework for better understanding

Thank you !

Hang Jung Ling

Nathan Painchaud

Nicolas Duchateau

Pierre-Marc Jodoin