



ISBI 2025

2025 IEEE International Symposium on Biomedical Imaging
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Weakly-supervised semantic space structuring : cardiac cycle position for cerebral emboli visualization using contrastive learning

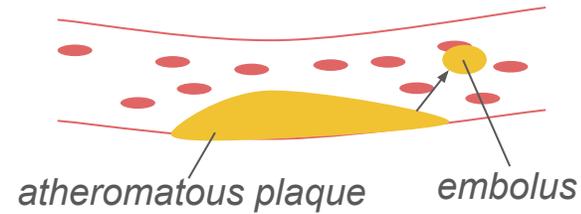
Mathilde Dupouy, Yamil Vindas, Marilyns Almar, Blaise Kévin Guépié, Philippe Delachartre

CREATIS, INSA Lyon, Lyon, France

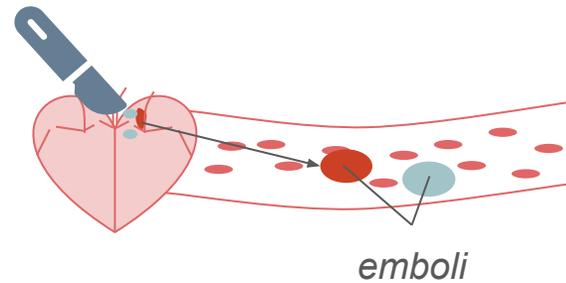
Cerebral emboli

Cerebral emboli are solid or gaseous material in the cerebral blood flow, and are one of the main risk of stroke.

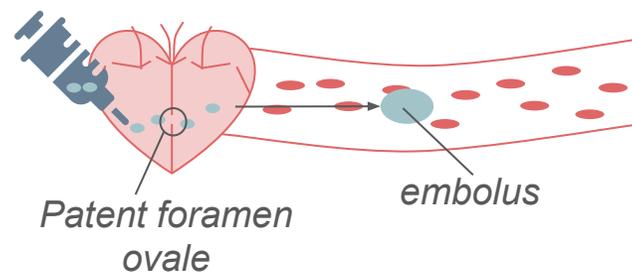
Pathology
(Atherosclerosis)



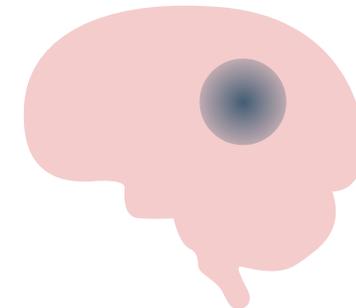
Surgical operation
(TAVI)



Micro-bubbles injection procedure
(PFO detection)



Solid or gaseous emboli circulating in cerebral blood flow



Potential ischemic stroke

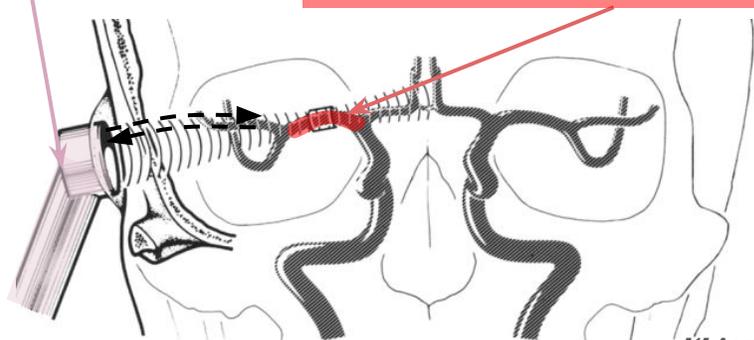
Emboli detection

Transcranial Doppler is a unique non-invasive modality to monitor emboli, detected as high intensity transient signals.

Transcranial Doppler (TCD)

ultrasound probe

right cerebral middle artery



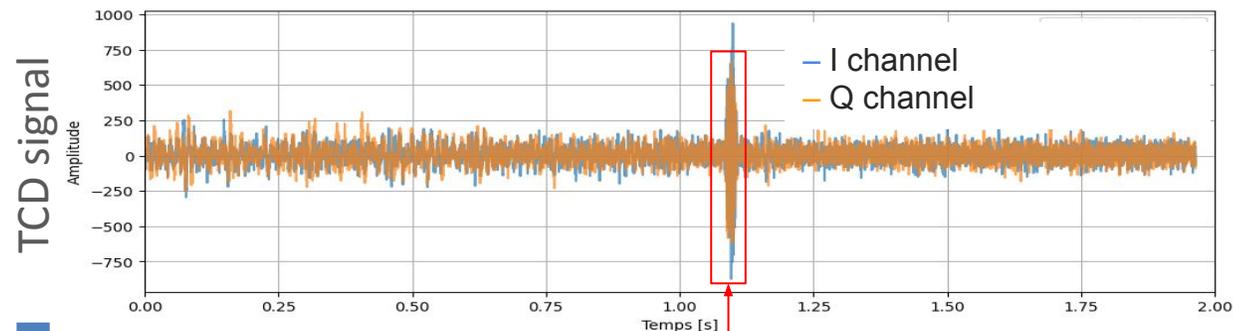
[1] Aaslid et al., JNS, 1982

Portable TCD



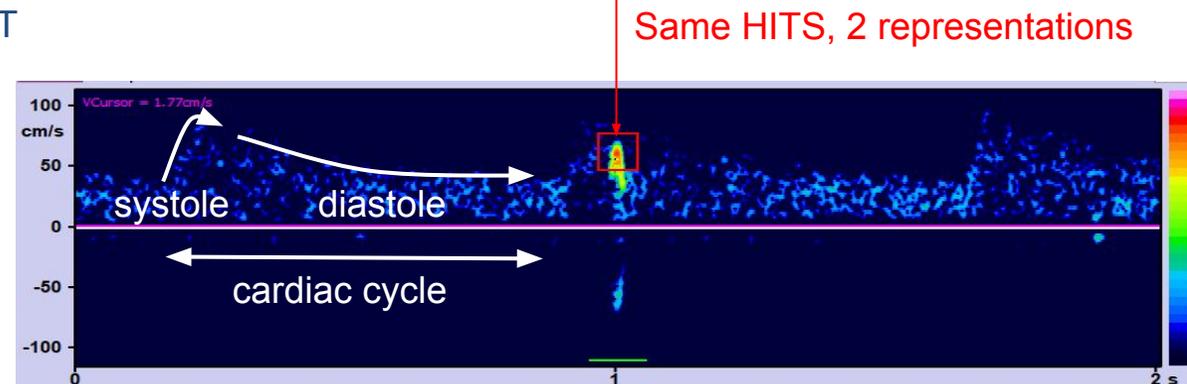
Longer recordings with low constraints for the patient [2]

High Intensity Transient Signal (HITS)



FFT

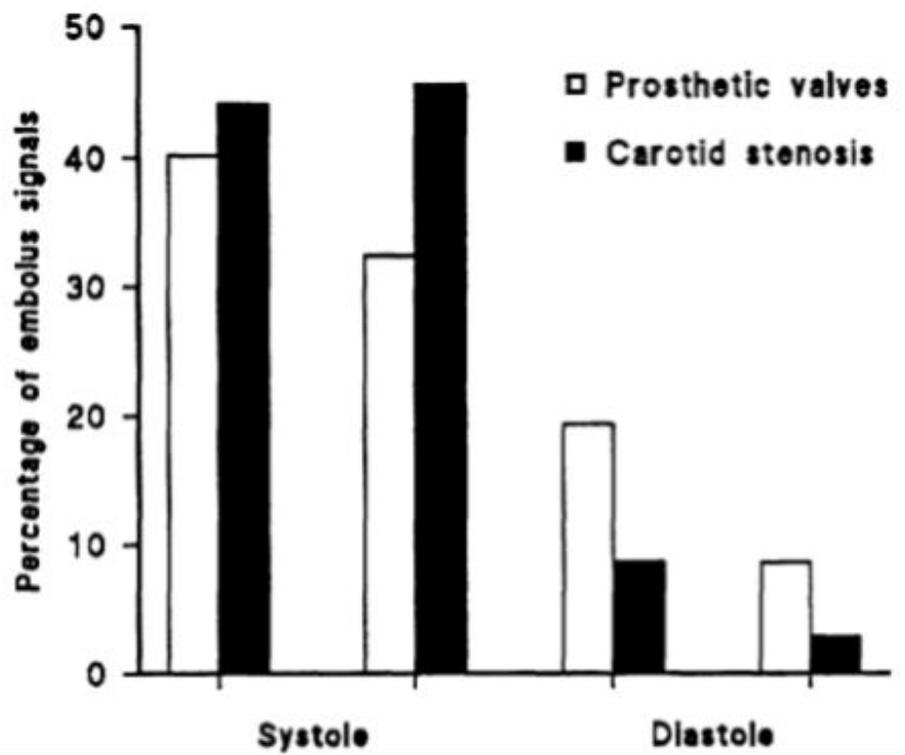
Spectrogram



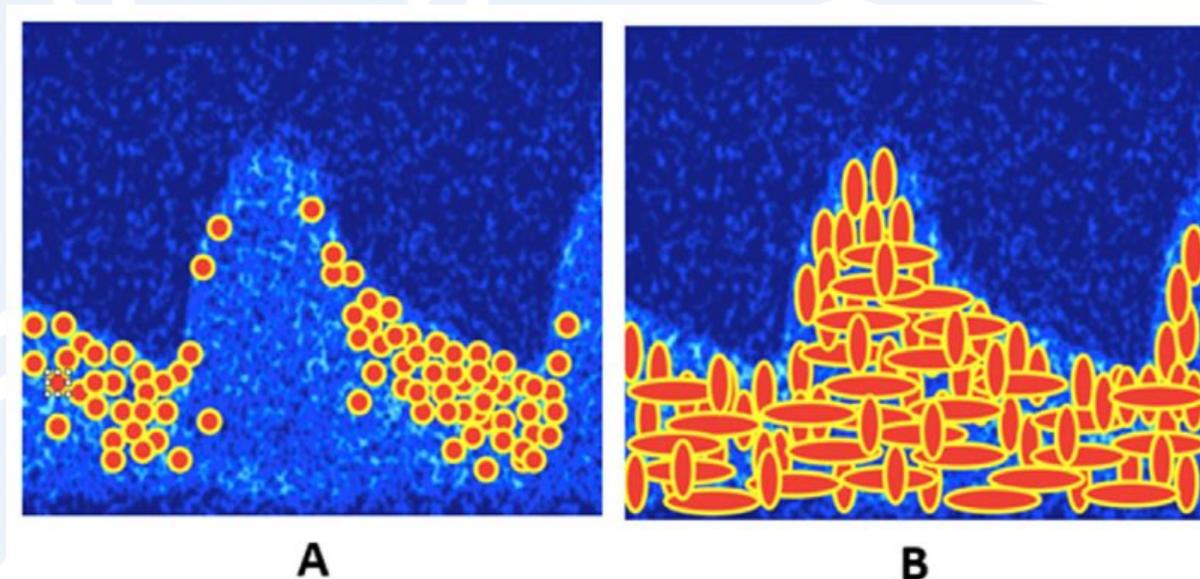
Same HITS, 2 representations

Emboli and cardiac cycle

Some papers identify a link between the nature or source of emboli and their position in the cardiac cycle.



Emboli distribution for four positions in the cardiac cycle between two sources [3]



Solid (A) and gaseous (B) emboli distributions in the cardiac cycle [4]

Keunen et al., UMB, 2023 [3] Diagnostic accuracy of an algorithm for discriminating presumed solid and gaseous microembolic signals during TCD examinations

Image details: A - patient post carotid endarterectomy; B - patient with positive PFO exams

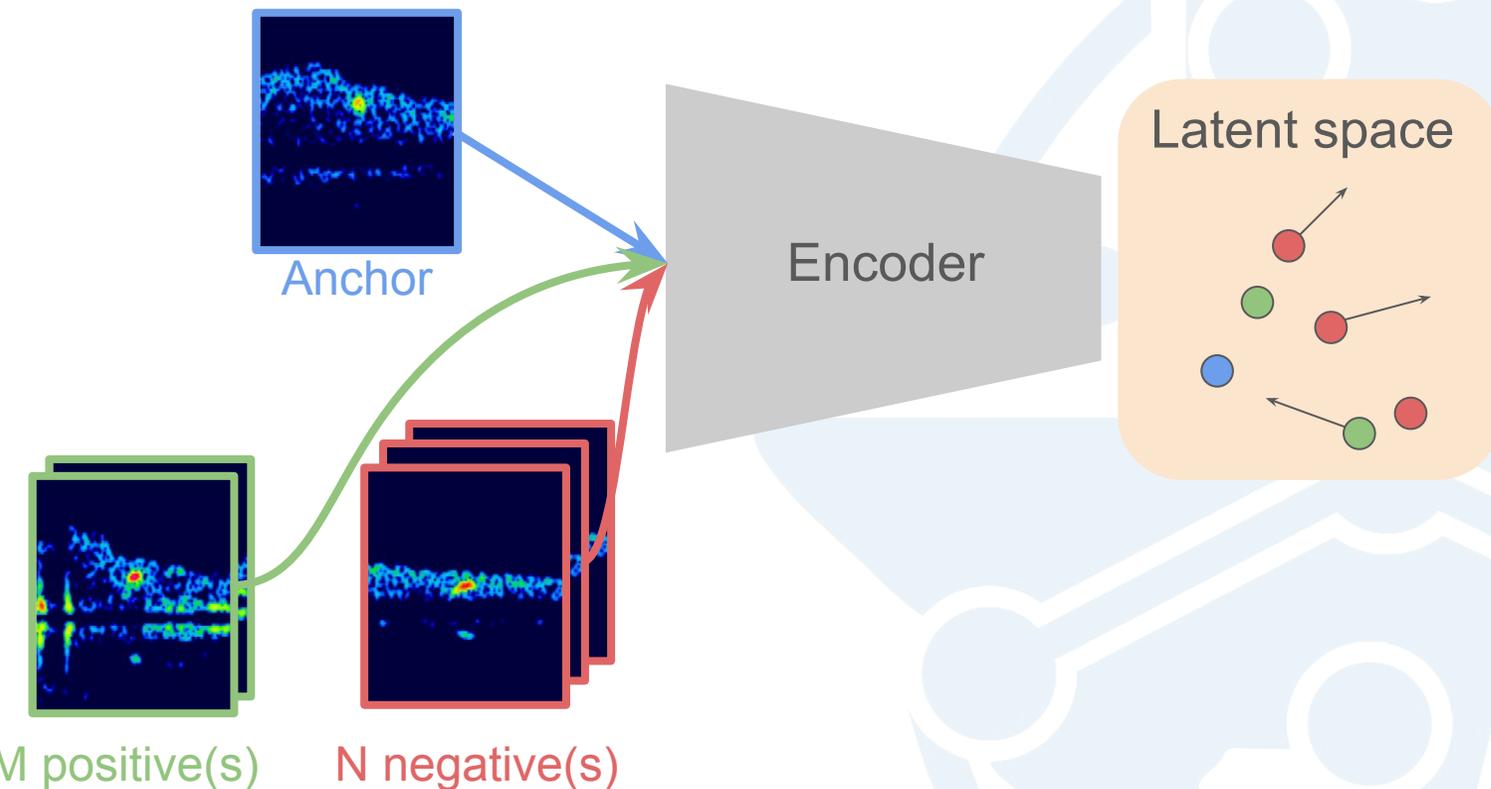
Grosset et al., Stroke, 1993 [4] Quantification of ultrasound emboli signals in patients with cardiac and carotid disease 4

Image details: 80 patients with prosthetic cardiac valves and 20 patients with internal carotid artery stenosis. 30 minutes exams.

How can we integrate cardiac cycle position in the latent space structure, so that the latent space holds a semantic meaning ?

Contrastive learning

Contrastive learning is a metric learning strategy that brings similar samples closer and pushes dissimilar ones apart.



Contrastive loss [6]

$$\mathcal{L}^C(\mathbf{x}, \mathbf{x}^+, \mathbf{x}^-; \theta) = -\frac{1}{M} \sum_{i=1}^M \log \left(\frac{\exp(\mathbf{z} \cdot \mathbf{z}_i^+)}{\sum_{p=1}^M \exp(\mathbf{z} \cdot \mathbf{z}_p^+) + \sum_{j=1}^N \exp(\mathbf{z} \cdot \mathbf{z}_j^-)} \right)$$

Triplet loss case $M = N = 1$

- + Similarity criterion flexibility (unsupervised [5] or supervised [6, 7])
 - + Local and interpretable structuration
 - + “Low” supervision
- ! significant choice
 - ! global structure
 - ! no guarantee on learned similarities

Chen et al., ICML, 2020 [5] A simple framework for contrastive learning of visual representations

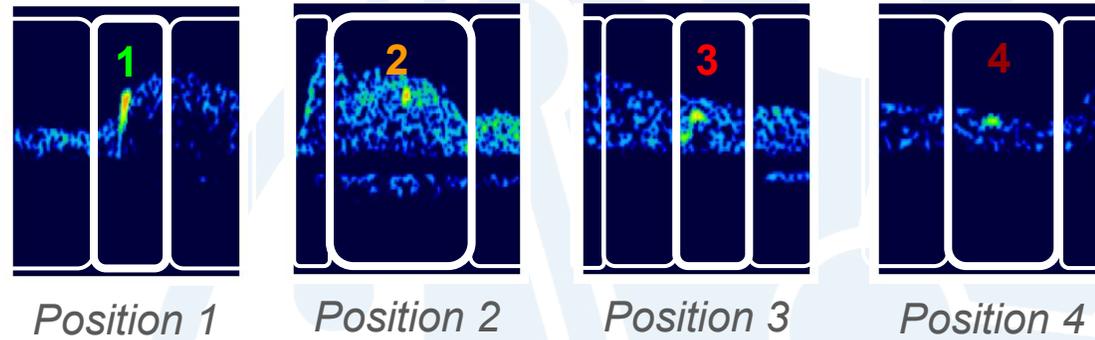
Khosla et al., NeurIPS, 2020 [6] Supervised contrastive learning

Ferrand et al., IEEE J. Sel. Areas Commun., 2021 [7] Triplet-based wireless channel charting: Architecture and experiments

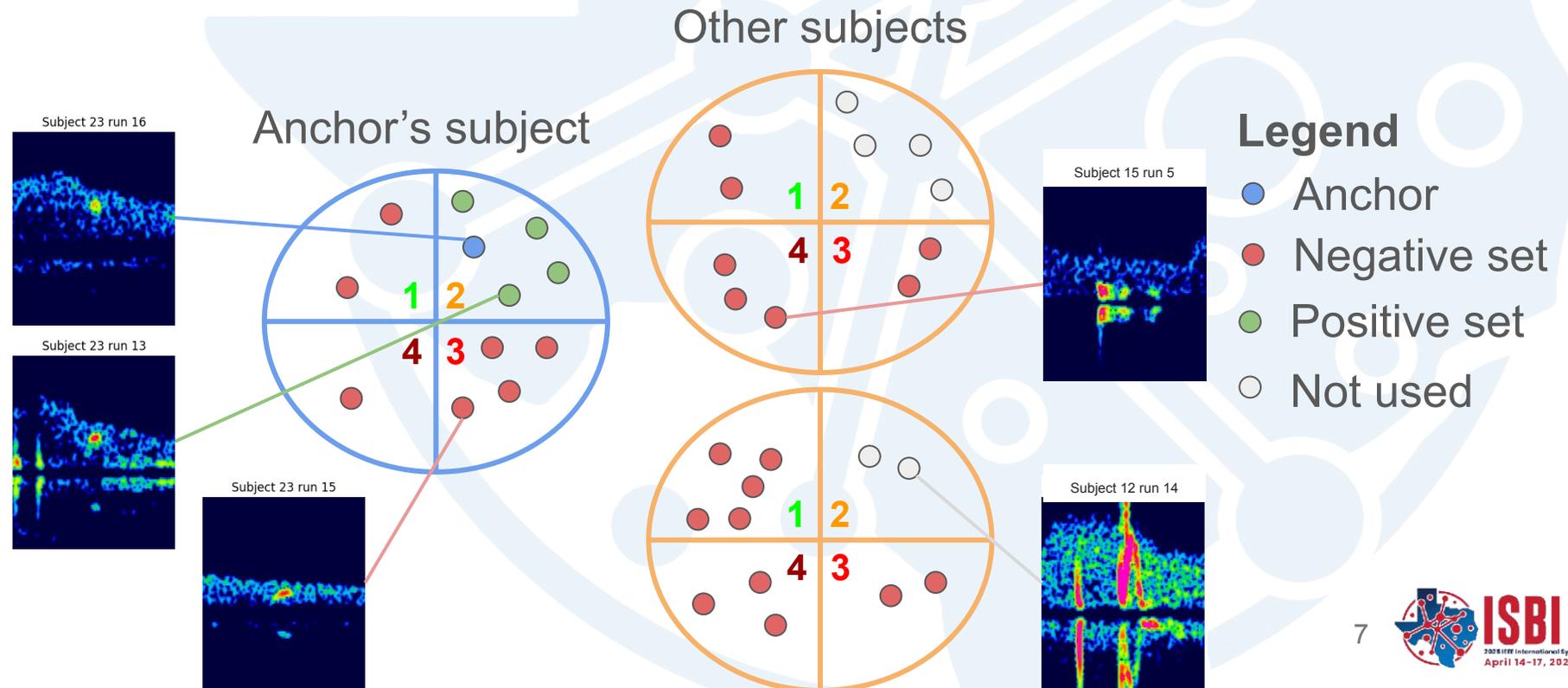
Similarity criterion

We chose that samples from same position and subject are similar, and dissimilar to other positions.

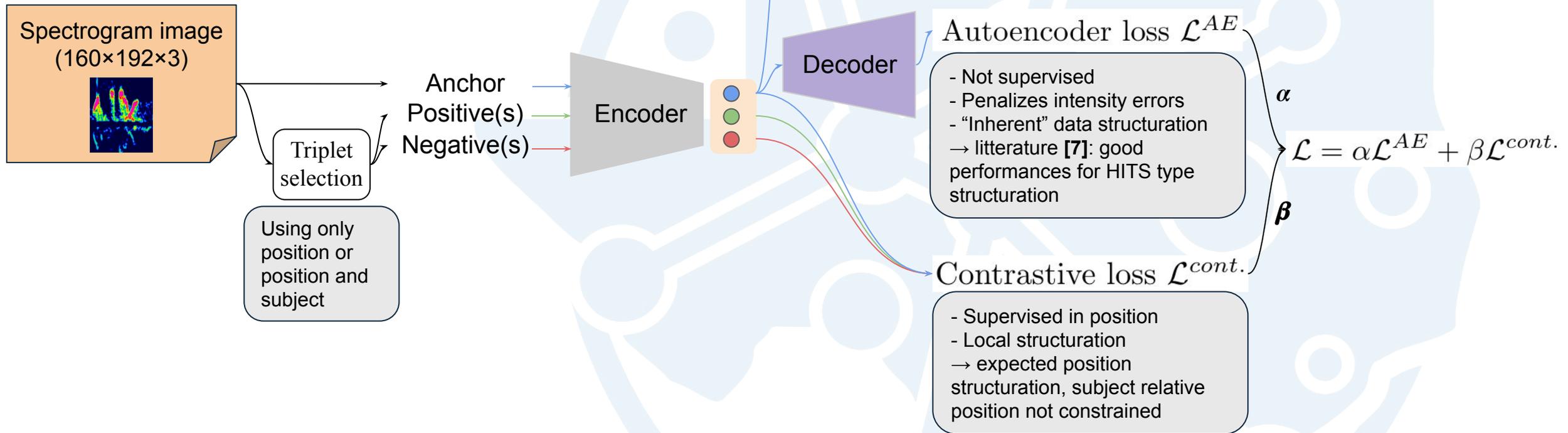
Four annotated positions:



Similarity criteria:



Training



Evaluation

Structuration is evaluated with a “category continuity” metric, that evaluates local continuity of a category across K neighbors.

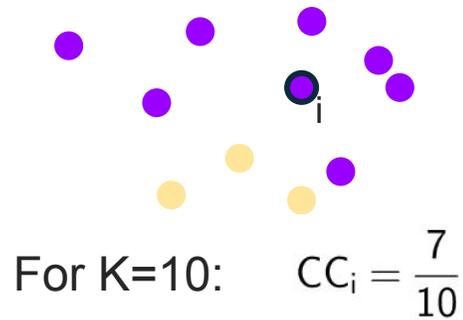
Sample i: $CC_i = \frac{N_{c_i}}{K} \in [0, 1]$

Number of neighbors with the same category as sample i

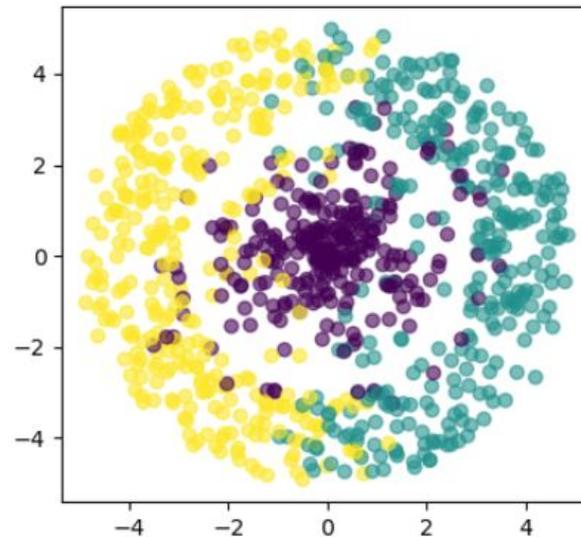
- More local than silhouette score
 - Derived from NN-norm [8]
- Pauwels et al., CVIU, 1998 [8] Finding Salient Regions in Images*

Global: $CC = \frac{1}{N} \sum_{i=1}^N CC_i \in [0, 1]$

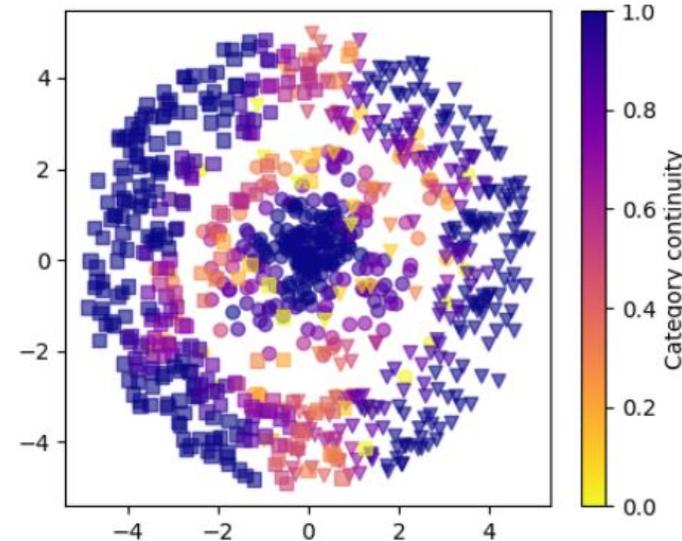
Examples



Category labels



Category continuity (CC_i) for each sample (K=10)



Global category continuity $CC=0.807$ for $K = 10$

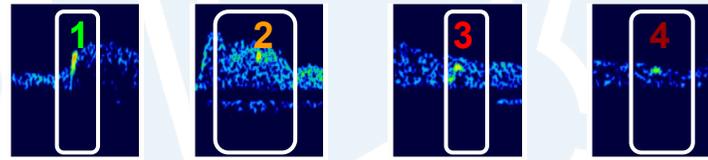
Dataset

We used a private dataset of HITS spectrogram images from heterogeneous sources.

Dataset
Spectrograms (400 ms)
1320 RGB images
(160×192×3)

 36 subjects
 10 hospital sources
 various examinations

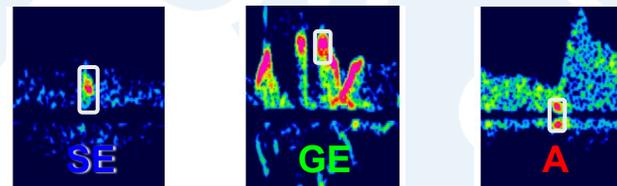
Annotated positions



Position 1 Position 2 Position 3 Position 4

Annotated HITS type

→ *Evaluation purpose*

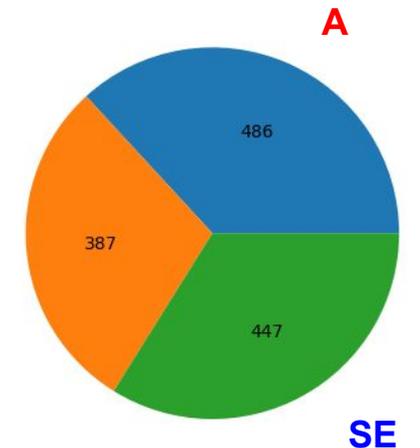
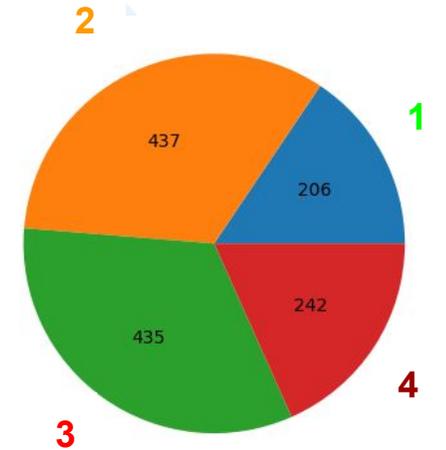


Solid embolus

Gaseous embolus

Artifact

GE

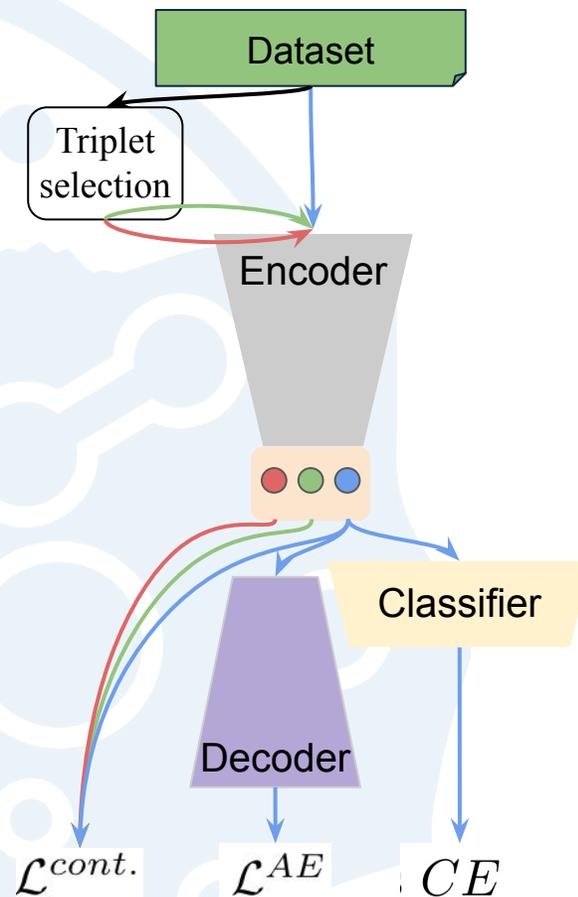


Contrastive performances

Mean and standard deviation (%) of CC for K=10 in the latent space (10 trainings)

	Category		
	position	(position, HITS type)	
Baselines	Autoencoder	50.51 ± 1.27	43.22 ± 0.97
	Position classifier	65.08 ± 1.69	44.18 ± 1.71
Two similarity criteria	Triplet* by position	52.55 ± 1.95	30.75 ± 1.83
	Triplet* by position, subject	62.14 ± 2.01	49.14 ± 1.45

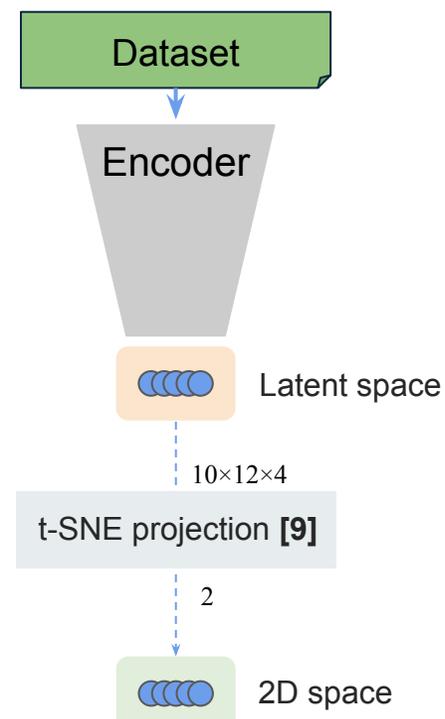
- Performance similar to strongly supervised setting (~3% lower)
- Consistency with the inherent data structure (HITS type) (~5% better)
- Joint training (varying β) does not enable to overtake separate training performances



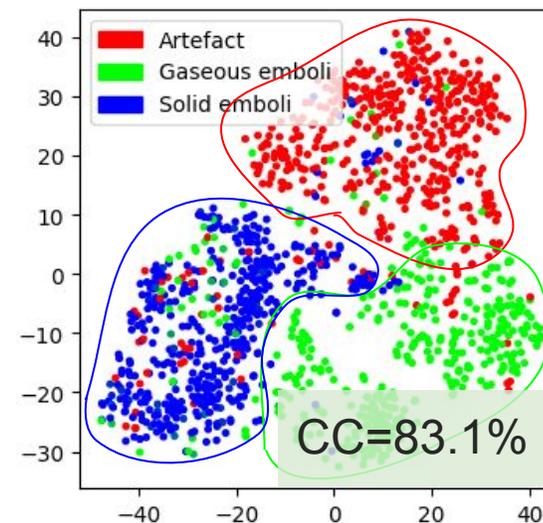
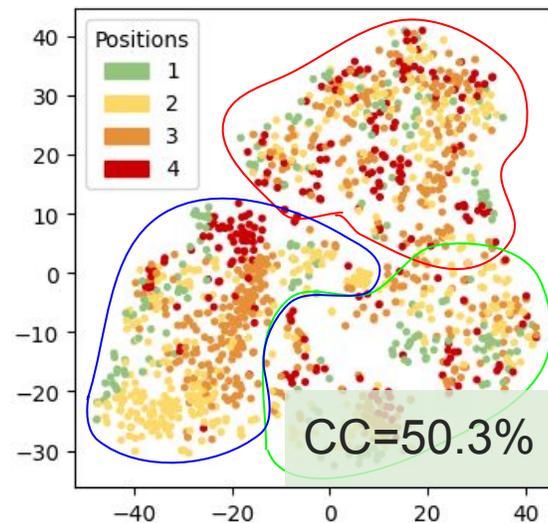
$$\mathcal{L} = \alpha \mathcal{L}^{AE} + \beta \mathcal{L}^{cont.}$$

Qualitative evaluation

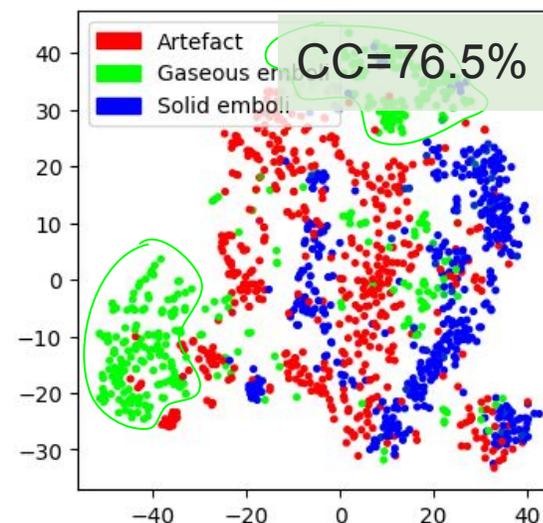
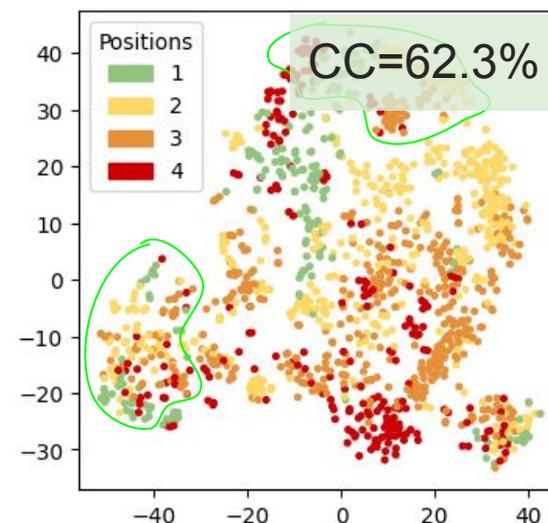
Compromise between position and HITS type is seen in the corresponding 2D spaces.



AE
 $\alpha = 1, \beta = 0$



Triplet
 $\alpha = 0, \beta = 1$



Cardiac cycle position

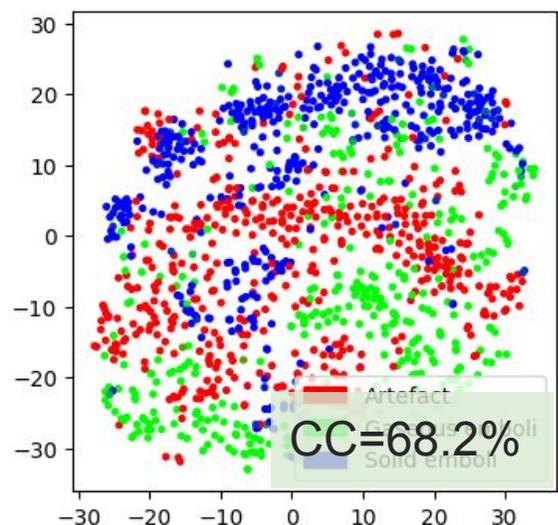
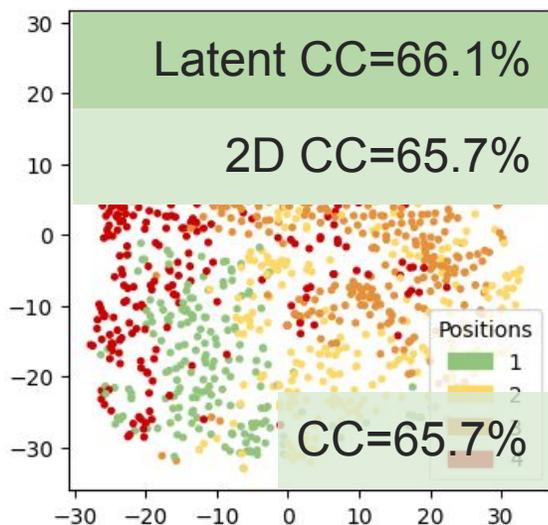
HITS type

- Good structuring by types
- No structure by position, except SE
- Better structure by positions
- Same structuring performances by type
- Subject influence

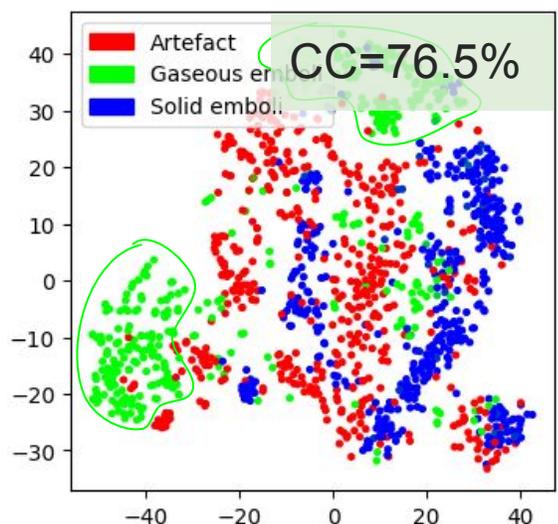
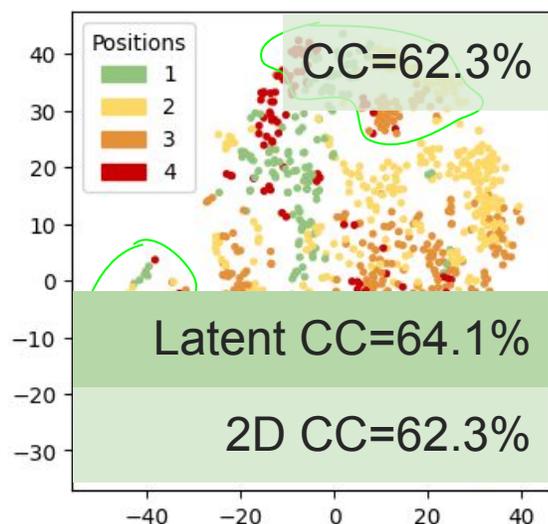
Qualitative evaluation

Compromise between position and HITS type is seen in the corresponding 2D spaces.

Position classifier



Triplet
 $\alpha = 0, \beta = 1$



Cardiac cycle position

HITS type

- Good structuring by positions
- Less structured by type

Latent vs. 2D

→ structure complexity not fully captured by 2D projection

Conclusion

- Position integration in HITS data visualization
- “Low” supervision with contrastive learning: a promising approach
 - Performance similar to strongly supervised setting (~3% lower)
 - Consistency with the inherent data structure (HITS type here) maintained (~5% better)

Perspectives

- Metadata integration
 - Improve HITS characterization in a non-supervised manner
 - Compare structuring with respect to different metadata (clinical data, features, etc.)
- “Low” supervision
 - Explore robustness to label noise with “low” vs. “hard” supervision

Thanks for your attention, any question ?

Contributions

- Position integration in HITS data visualization
- “Low” supervision with contrastive learning: a promising approach
 - Performance similar to fully supervised setting (~3% lower)
 - Consistency with the inherent data structure (HITS type here) maintained (~5% better)

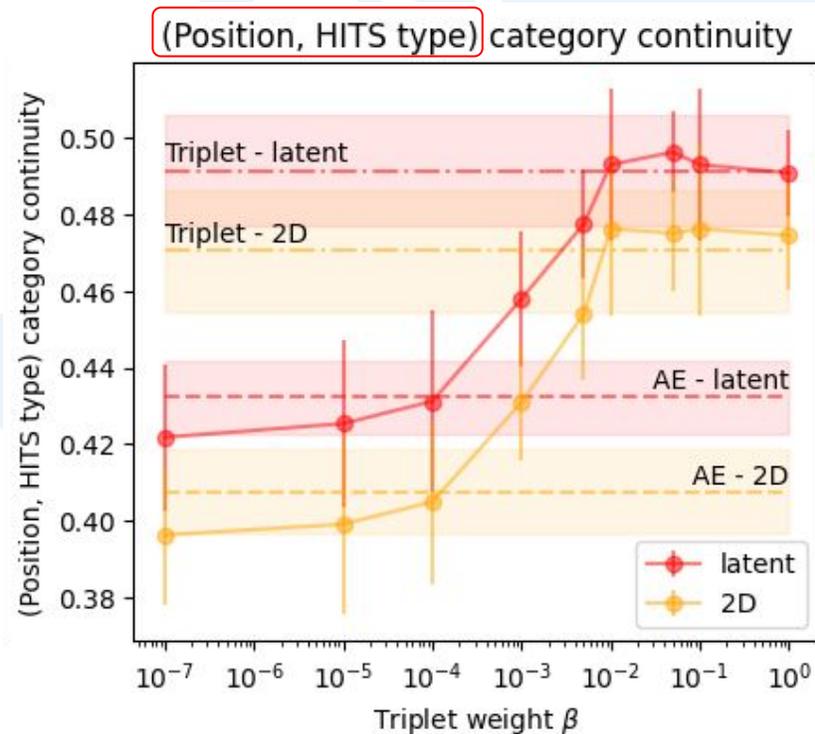
INSTITUT NATIONAL
DES SCIENCES
APPLIQUÉES
LYONContact: mathilde.dupouy@creatis.insa-lyon.fr

Loss weight influence

The contrastive loss weight allows a compromise between HITS type structure and position structure.

Influence of loss weights

$$\mathcal{L} = \alpha \mathcal{L}^{AE} + \beta \mathcal{L}^{cont.}$$

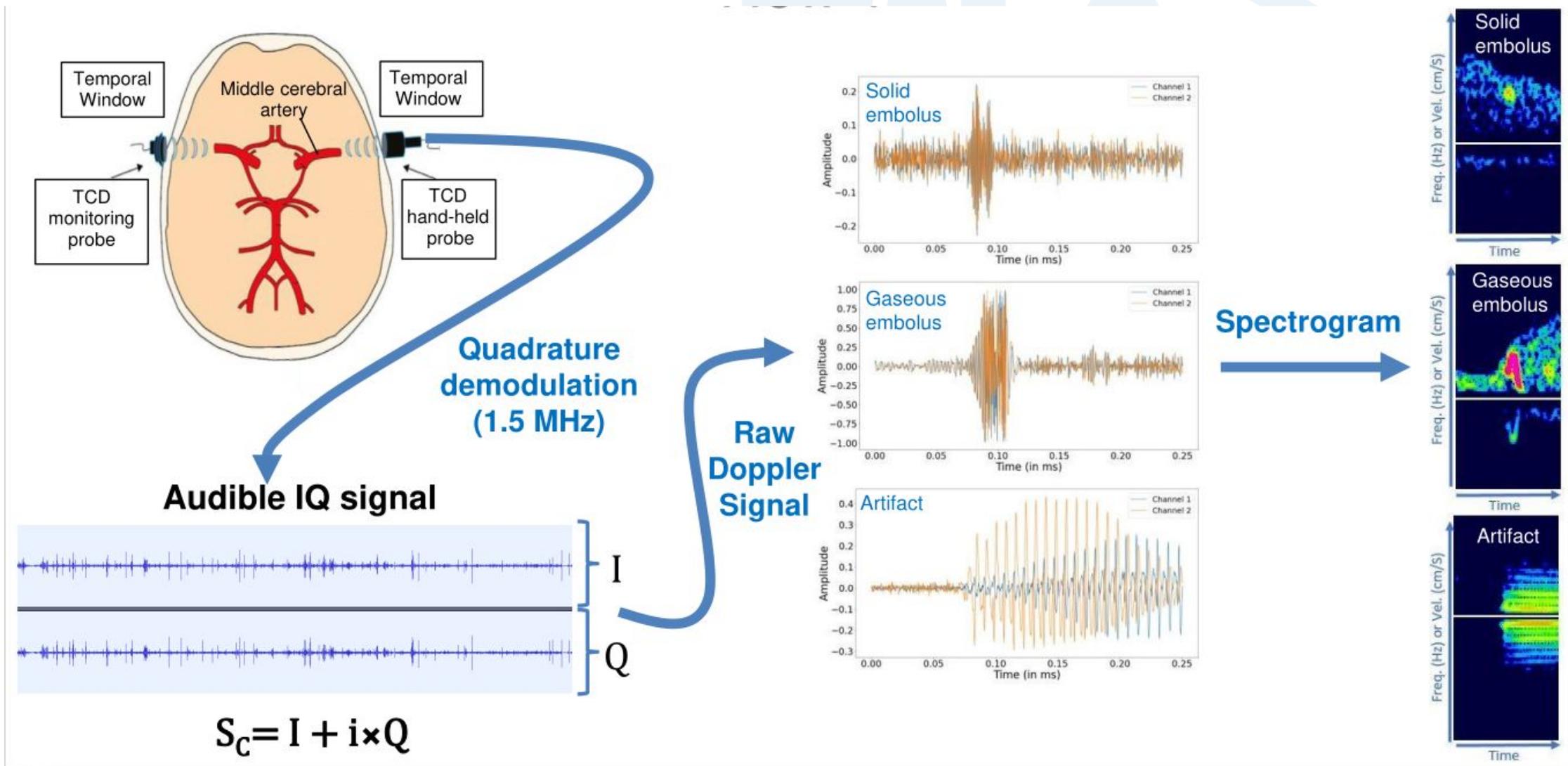


Triplet by position, subject
 $\alpha = 0, \beta = 1$

AE
 $\alpha = 1, \beta = 0$

$\alpha = 1, \beta$

- joint training does not enable to overtake separate training performances
- structure complexity not fully captured by 2D projection
- performance appears bounded in this set up



Evaluation

Silhouette score

→ Distance from a point to its group compared with distance to closest neighbouring group

- Hypothesis: one cluster by group
- Favour ball-shaped groups
- Difficult to interpret gaps (distinct clusters ≠ distant clusters)
- Silhouette score by category is an adaptation

$$s_{sil}(i) = \frac{b(i) - a(i)}{\max(a(i), b(i))}$$

a(i) mean distance from a sample to its group

b(i) mean distance from a point to the closest other group

$$S_{sil} = \frac{1}{|C|} \sum_{c \in C} \frac{1}{|I_c|} \sum_{i \in I_c} s_{sil}(i)$$

NN-norm

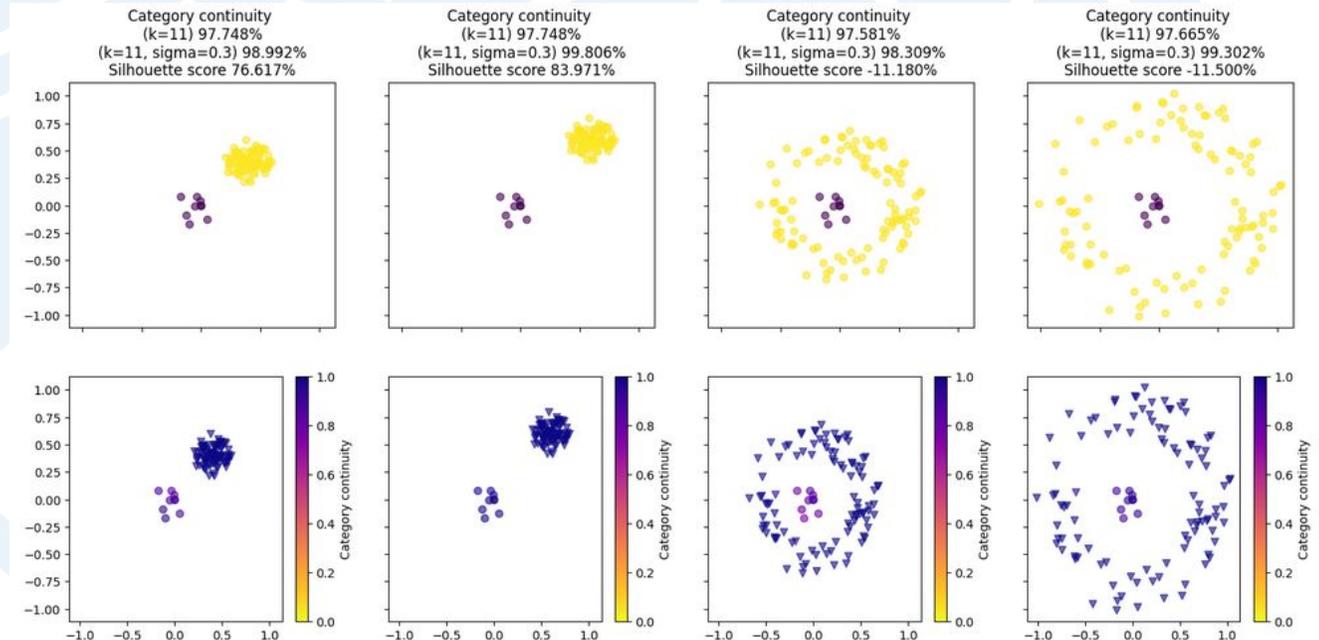
→ Number of neighbours over K neighbours from the same cluster

- Linked to density-based clustering methods
- Not used in practice (E.J. Pauwels)

⇒ Category continuity is an adaptation in terms of categories

Continuity

→ Penalizes samples that are neighbors in the reference space but not in the latent space.

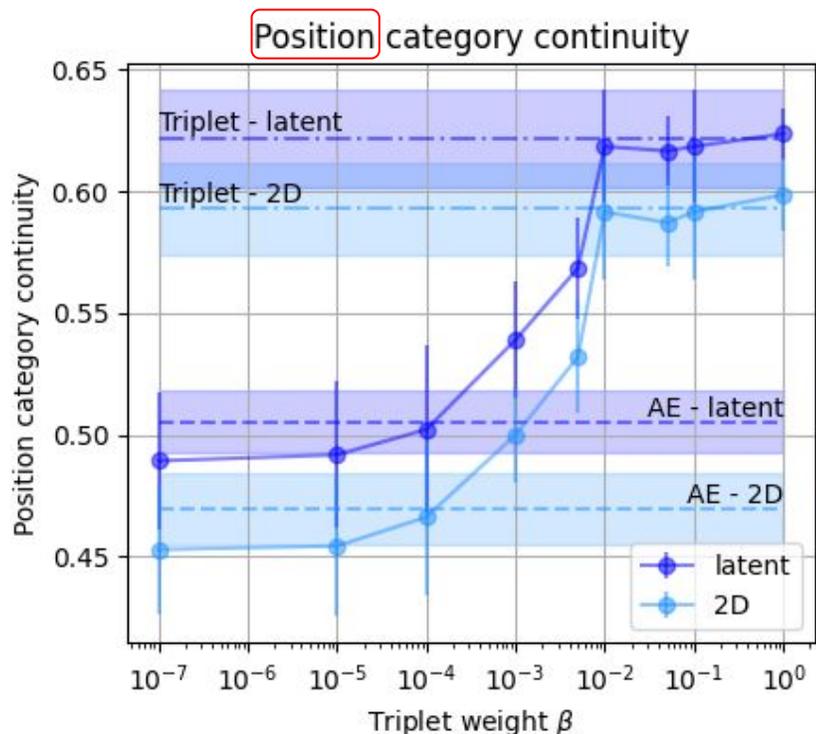


Loss weight influence

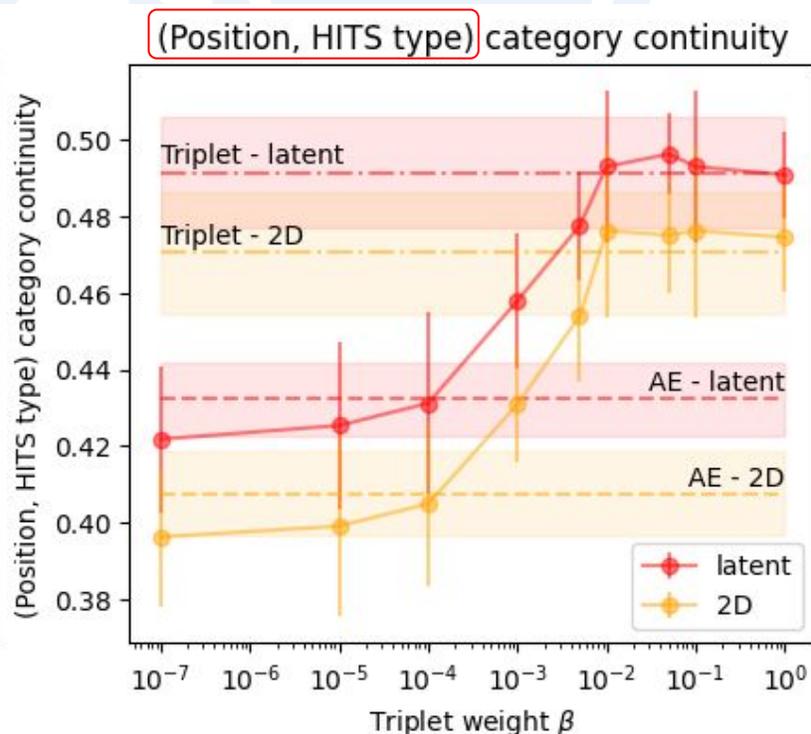
The contrastive loss weight allows a compromise between HITS type structure and position structure.

Influence of loss weights

$$\mathcal{L} = \alpha \mathcal{L}^{AE} + \beta \mathcal{L}^{cont.}$$



$\alpha = 1, \beta$



$\alpha = 1, \beta$

Triplet by position,
subject: $\alpha = 0, \beta = 1$

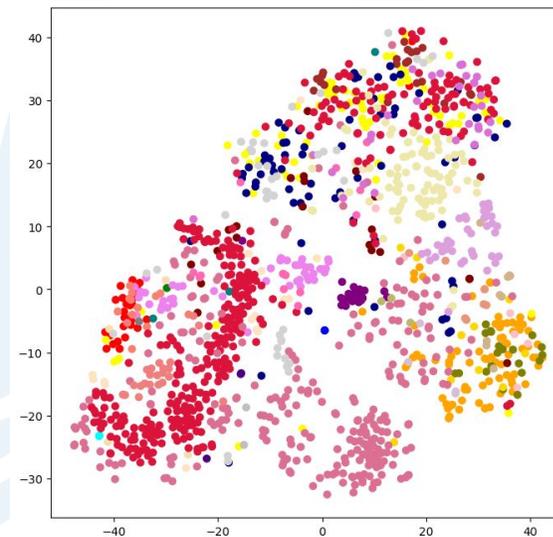
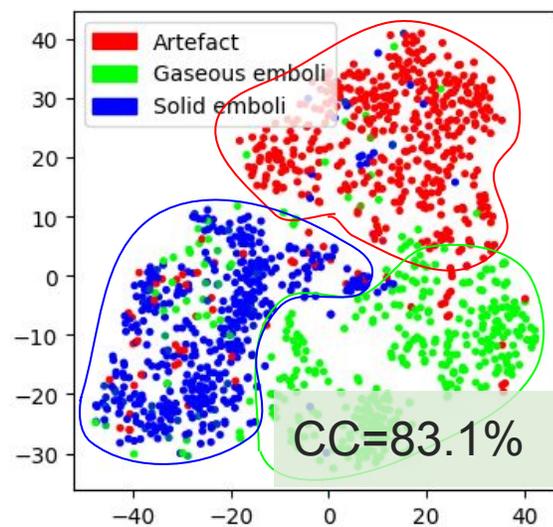
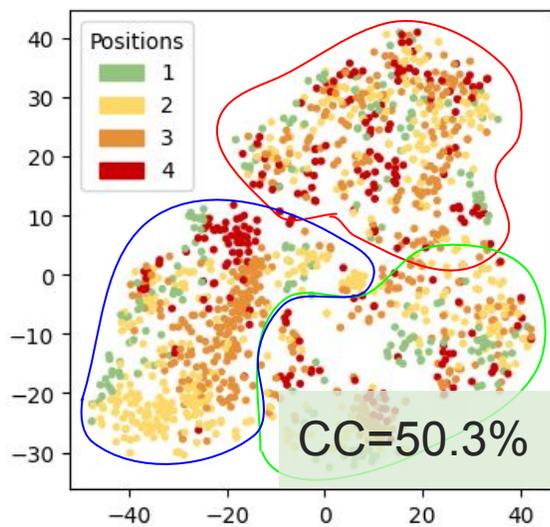
AE: $\alpha = 1, \beta = 0$

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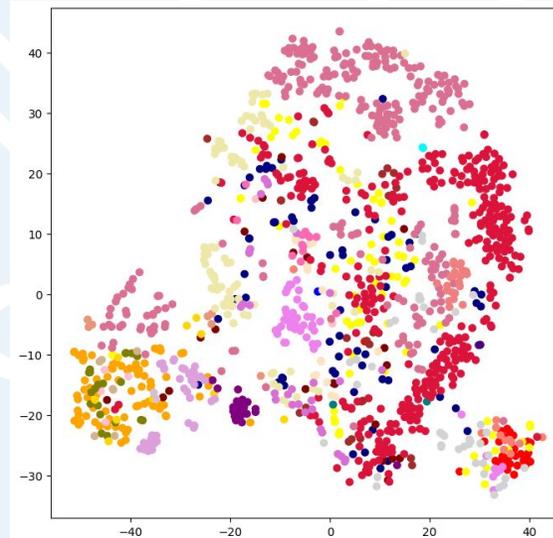
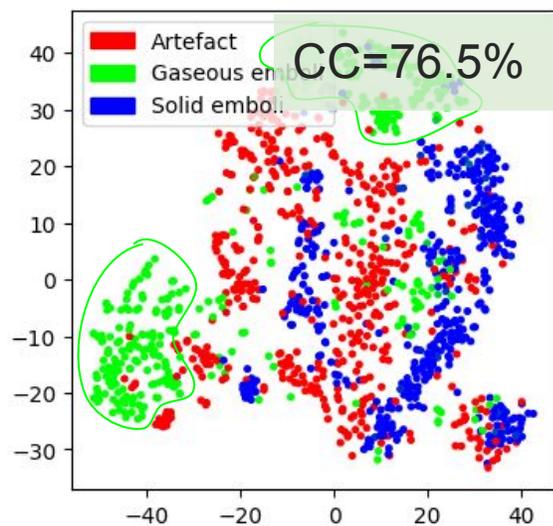
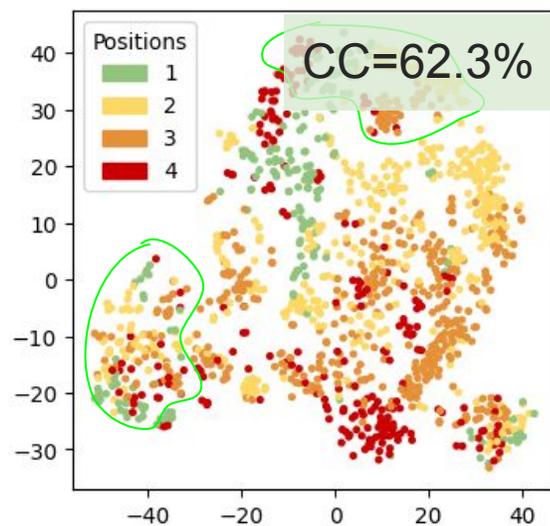
Qualitative evaluation

Compromise between position and HITS type is seen in the corresponding 2D spaces.

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 $\alpha = 1, \beta = 0$



Triplet
 $\alpha = 0, \beta = 1$



Cardiac cycle position

HITS type

Subject