Interpretable Representation Learning of Cardiac MRI via Attribute Regularization

Maxime Di Folco[1,2], Cosmin I. Bercea[1,2,3], Emily Chan[1,2], and Julia A. Schnabel[1,2,3,4]

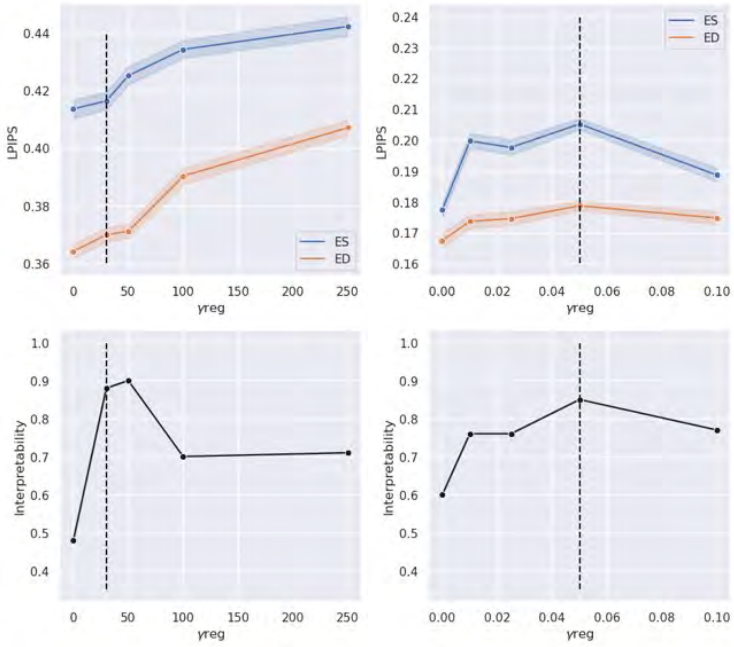
[1] Institute of Machine Learning in Biomedical Imaging, Helmholtz Munich, Germany
[2] School of Computation, Information and Technology, Technical University of Munich, Germany
[3] Helmholtz AI, Helmholtz Munich, Germany
[4] School of Biomedical Engineering & Imaging Sciences, King's College London, UK
maxime.difolco@helmholtz-munich.de

A Hyperparameters selection

β-VAE:	β	2.0
Attri-VAE:	γ_{reg}	30.0
	δ	10.0
SIVAE:	β_{rec}	0.8
	β_{KL}	1
	β_{neg}	1024
	η	1e-8
	α_{pl}	100.0
AR-SIVAE:	γ_{reg}	0.05
	δ	1.0

Table 1: Hyperparameters for the experiments

B Interpretability scores



(a) Attri-VAE (b) AR-SIVAE

Fig. A.1: Study of the trade-off between reconstruction and interpretability performance for (a) Attri-VAE and (b) AR-SIVAE. γ_{reg} is the hyperparameter that controls the importance given to the attribute regularization. The dashed line represents the selected value. For LPIPS (top row) the lower the better and for the *Interpretabilty* score (bottom row) the higher the better.

	ED			ES		
	LV	**RV**	**Myo**	**LV**	**RV**	**Myo**
β-VAE	0.53	0.48	0.52	0.43	0.44	0.49
Attri-VAE	0.87	**0.90**	**0.91**	0.85	**0.88**	0.88
SIVAE	0.66	0.64	0.56	0.62	0.60	0.54
AR-SIVAE	**0.93**	0.90	0.82	**0.90**	0.66	**0.90**

Table 2: Interpretability scores for all of the attributes at End-Diastole (ED) and End-Systole (ES). Score between 0 and 1, with 1 being the best performance