Università degli Studi di Padova

Physics of Data

Dipartimento di Fisica e Astronomia Galileo Galilei

A deep learning approach for feature extraction from resting state functional connectivity of stroke patients and prediction of neuropsychological scores

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Master Degree in Physics of Data

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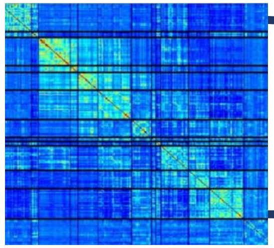
Introduction

absence of any controlled experimental

Resting-state
functional magnetic resonance imaging

spontaneous fluctuations in neural **blood oxygen-level dependent (BOLD)** signal

temporal correlations in the blood oxygen level–dependent (BOLD) signal



Resting-state **functional connectivity**

Neurophysiological scores

Problem: **High dimensionality**

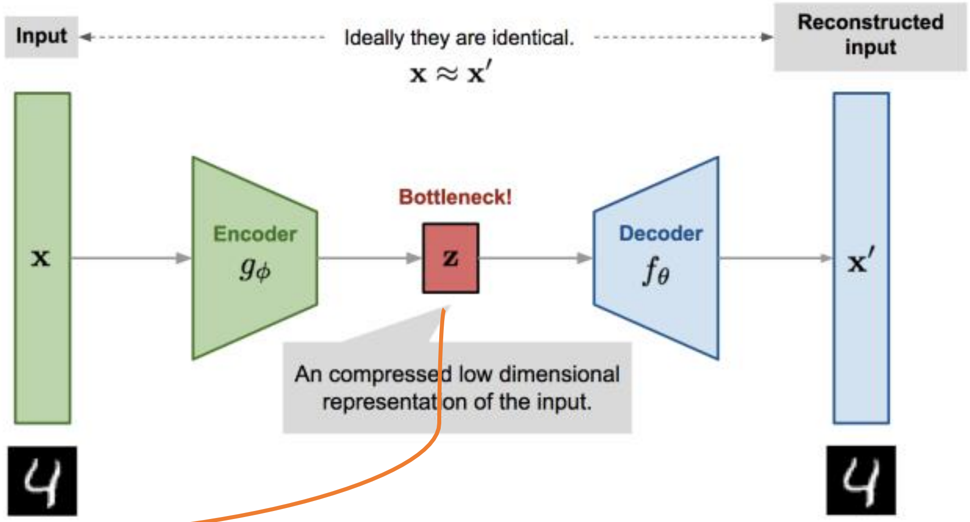
Solution

Linear dimensionality reduction techniques

- Principal Component Analysis (PCA)
- Independent Component Analysis (ICA)
- Sparse coding

Non-linear-dimensionality reduction

- **Deep Autoencoder**



Regularized regression

Materials and methods

Datasets:

132 RSFC matrices from **symptomatic stroke patient [1]**

Neuropsychological scores of 119 subjects: Language, Spatial memory and Verbal memory.

RSFC Pre-processing:

- Matrix of size 324 × 324
- Vectorization
- Null values were converted to zero.

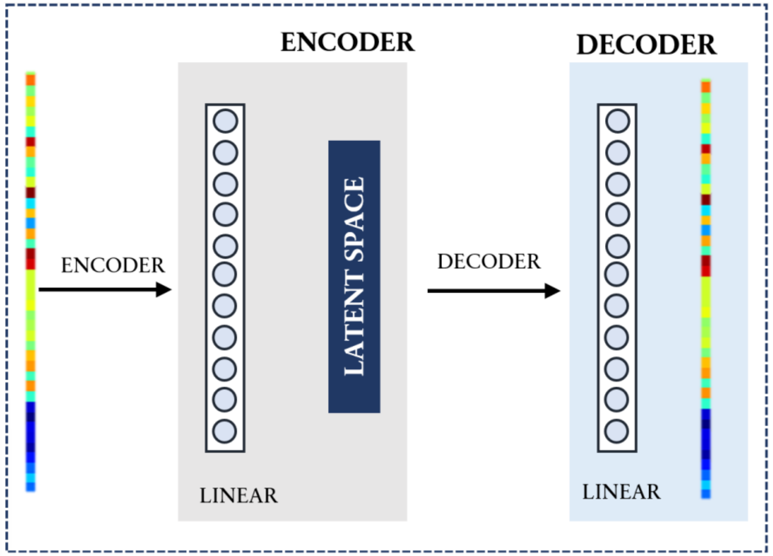
Feature extraction methods:

PCA
Stadarization
(StandardScaler)

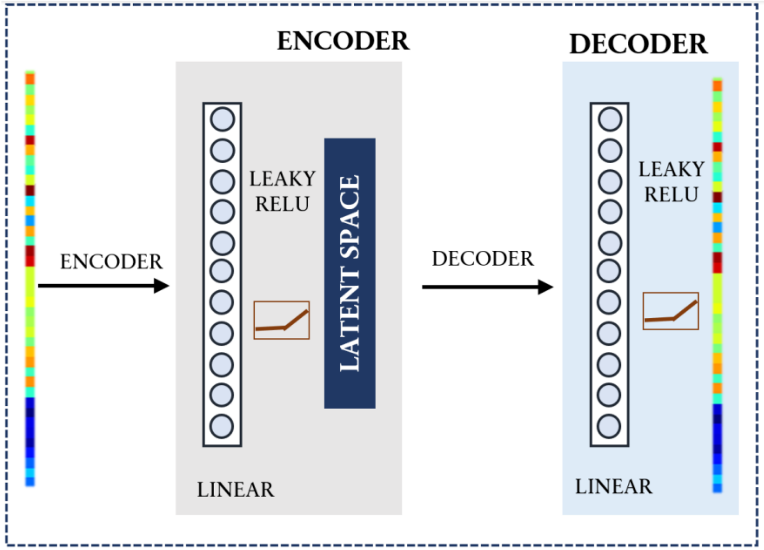
ICA
Stadarization
FASTICA

AUTOENCODERS

Lin AE

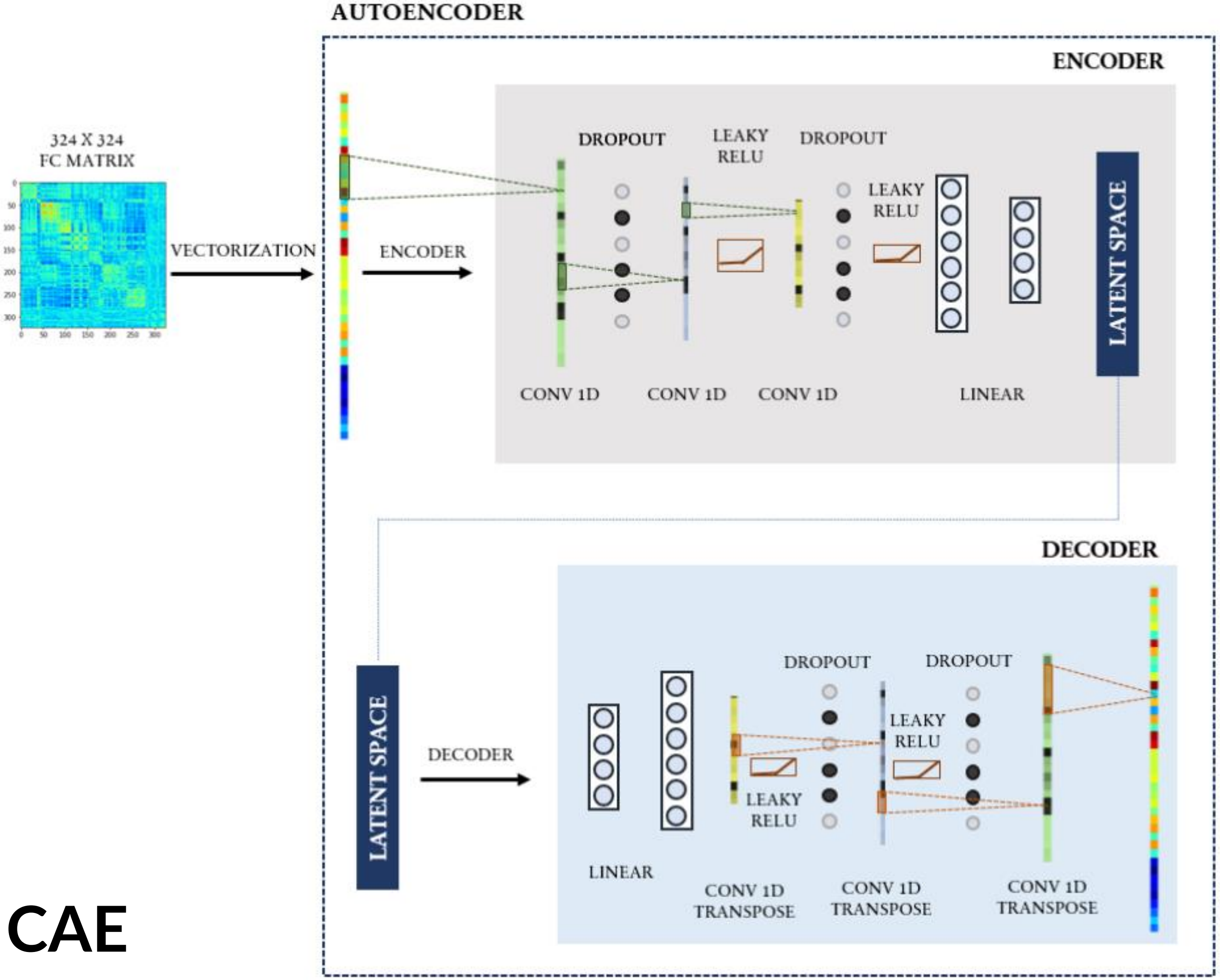


NonLin AE



Latent space: [10-95]

Materials and methods: AUTOENCODER



CAE

Sparse-constraint
(latent space = 200)

→ **CAE (reg):**

Reg:[0.0001,0.001, 0.01,0.1, 1, 4]

→ **CAE(k):**

k :[10, 30, 60, 90]

AUTOENCODER

Curse of dimensionality

Transfer Learning

CAE-TL | The **Human Connectome Project** database is used in order to explore the benefits of TL.

HUMAN Connectome PROJECT

RSFC matrices of 1050 healthy subjects [2]

Mix-up Augmentation

$$\hat{x} = \lambda x_i + (1-\lambda)x_j \quad \Big| \quad \begin{array}{l} \alpha = 0.5 \\ \lambda \sim Beta(\alpha, \alpha) \end{array}$$

CAE-AUG: Original dataset increase ~7500

Regularized regression

ElasticNET

$$\min_{(\beta_0,\beta)} \left(\boldsymbol{y} - \beta_0 - \boldsymbol{X}^T\beta\right)^2 + \lambda\left(\frac{1}{2}(1-\alpha)\,\beta^2 + \alpha\,|\beta|\right)$$

Model cross validation set-up

→ *Leave one out CV*

Biased model performance

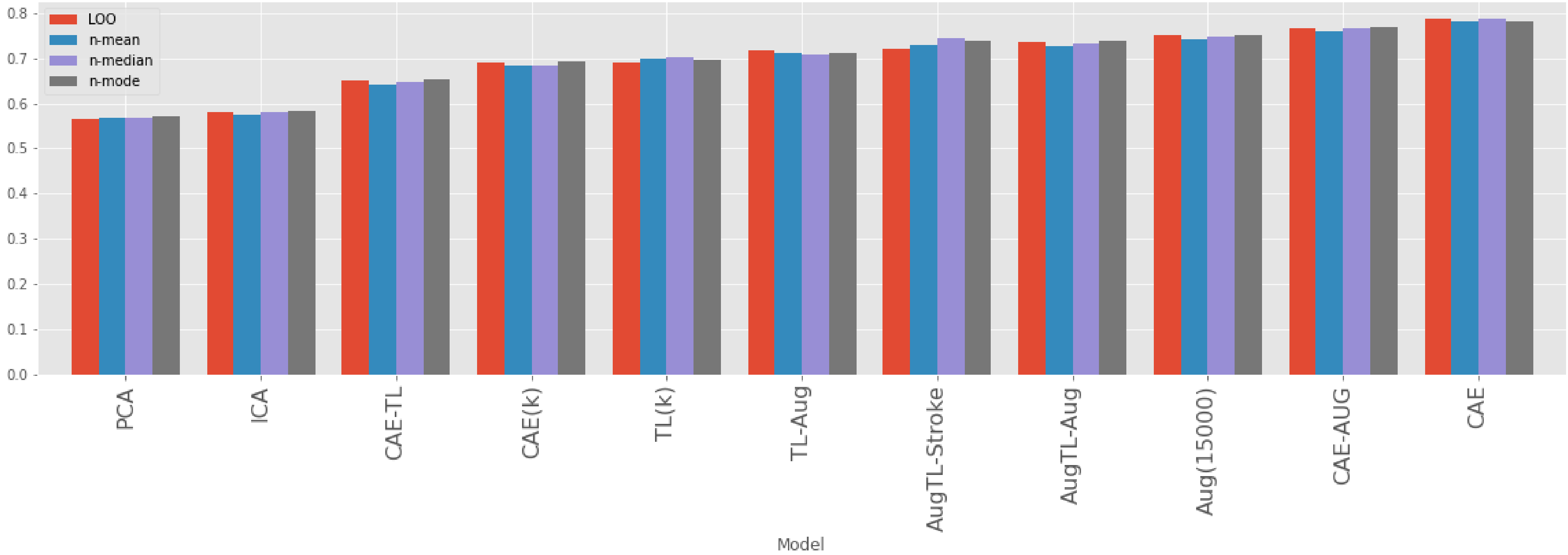
→ *Nested CV*

Results: Cross validation set-up

n-mode condition is leading to the same values as LOOCV.

A slightly variance in the mean value obtained in the n-mean and n-median case can be found in contrast to the LOOCV-scheme.

Results consistent with the ones obtained by Calesella, Testolin, De Filippo De Grazia, and Zorzi [3].



MSE differences across the CV schemes for each feature extraction method in the spatial domain

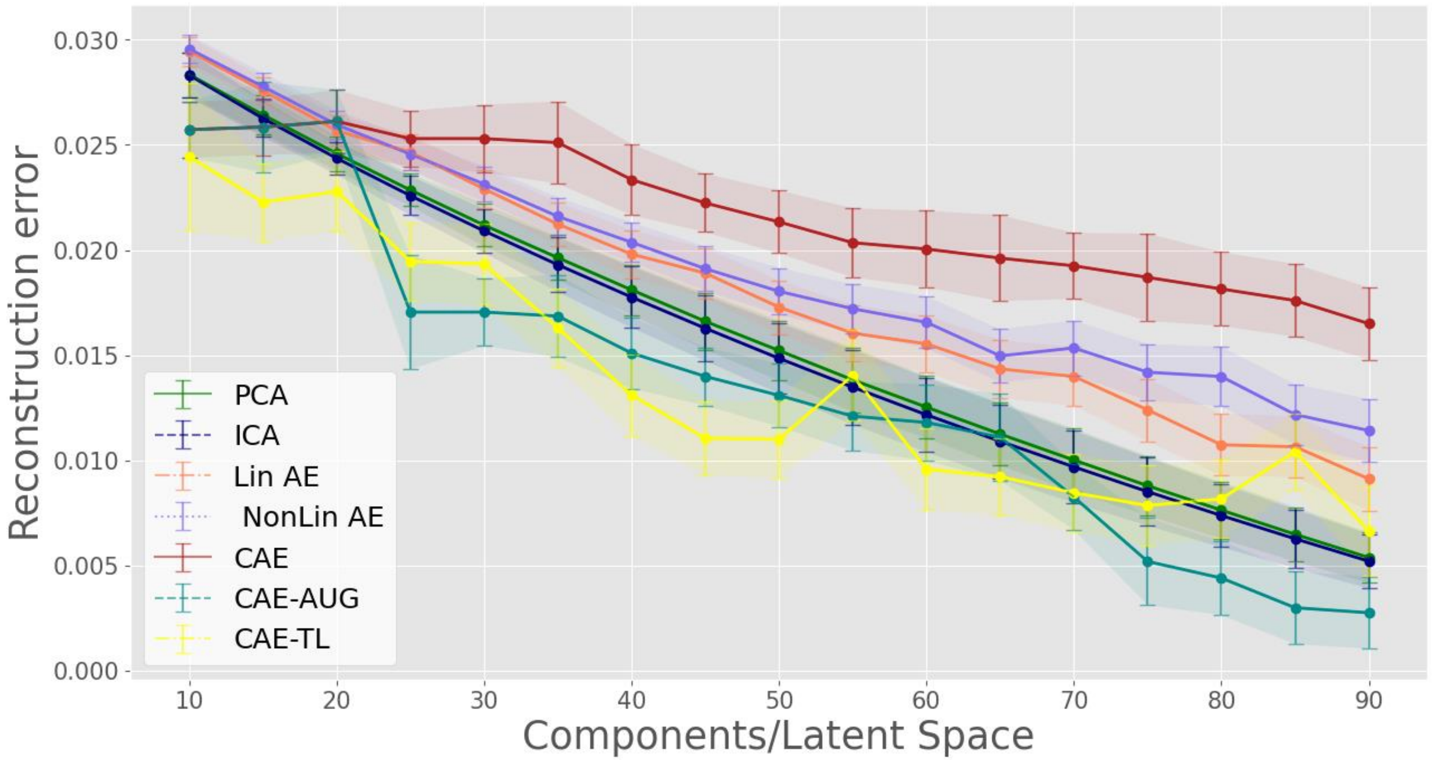
Results

Feature extraction

- All dataset was used (n=132)

+ The **larger** the number of components/latent space, the **better** the reconstruction error.

− CAE is the leading the worst reconstruction errors

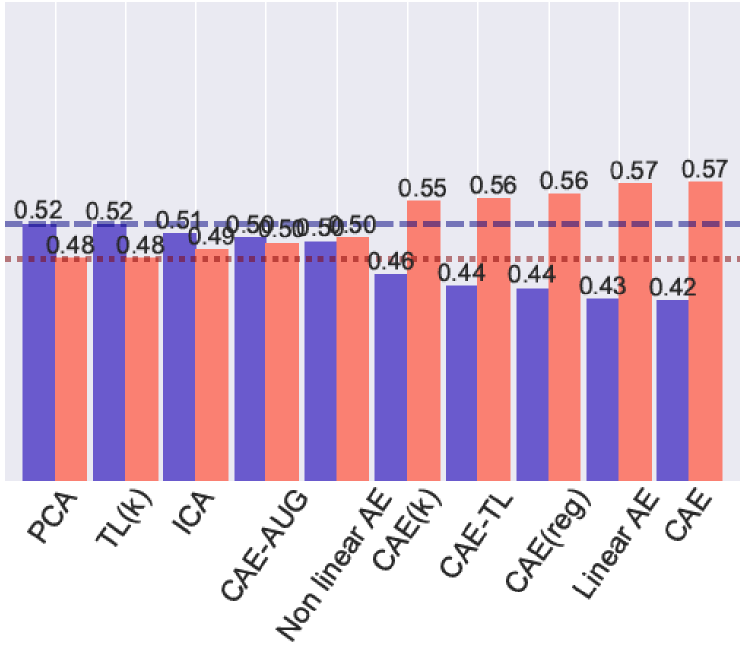


- *Reconstruction error obtained for the several models against the latent space/number of components.*

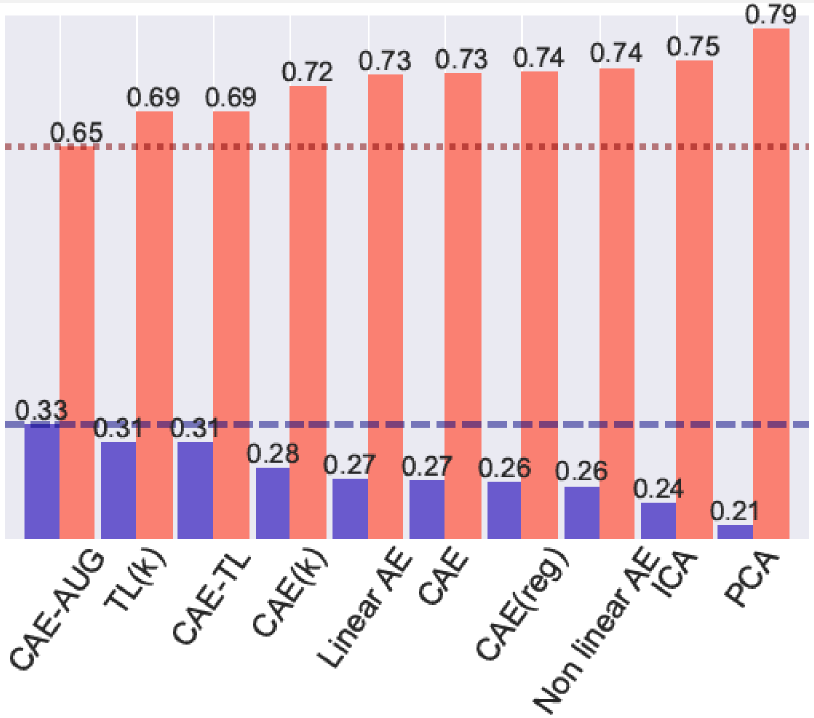
Results: regularized regression

MSE and R^2

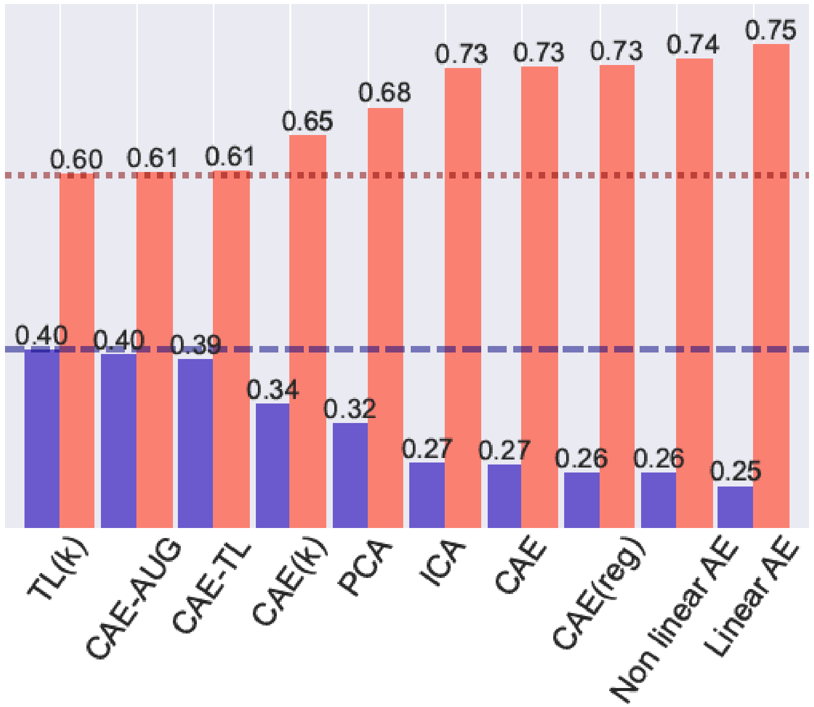
① Language Score



② Spatial memory Score



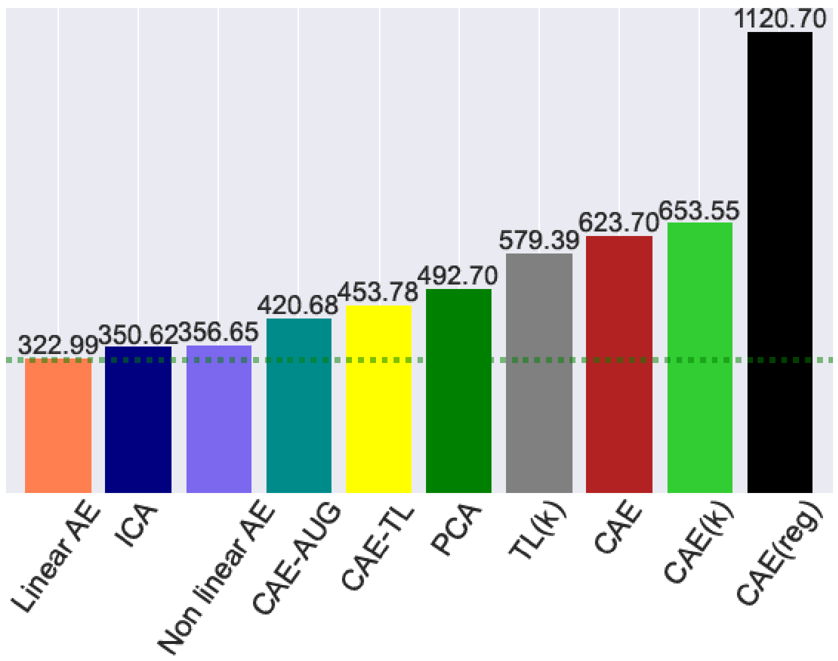
③ Verbal memory Score



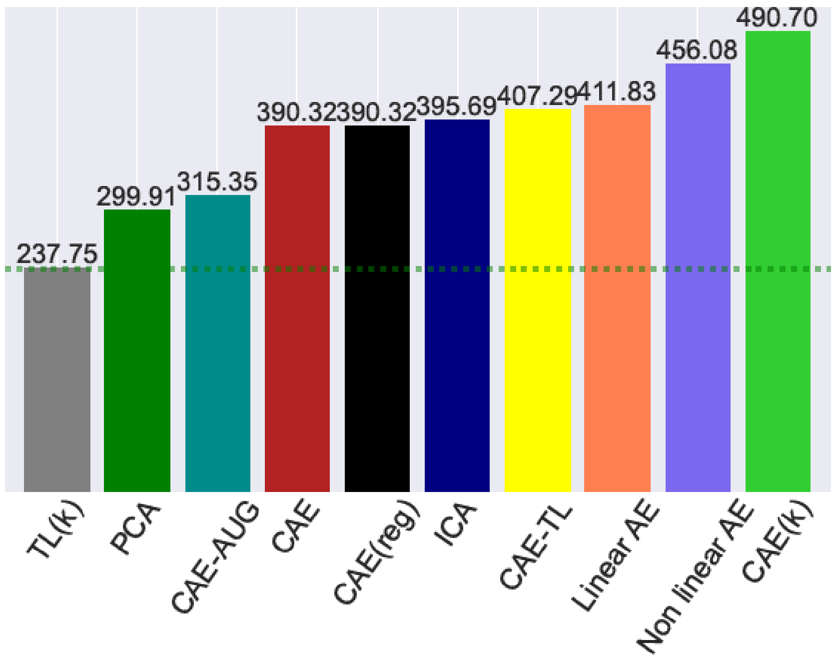
Results: regularized regression

BIC

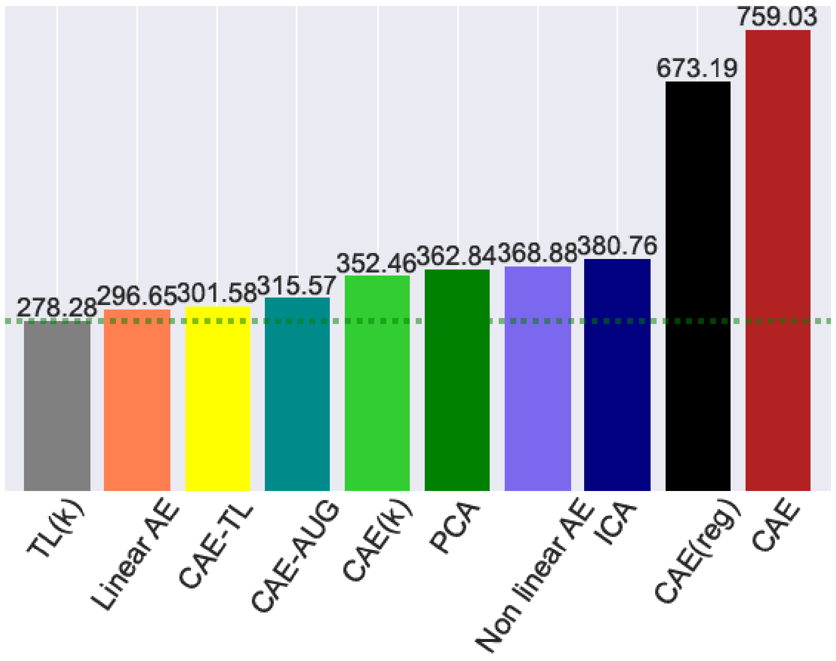
① Language Score



② Spatial memory Score



③ Verbal memory Score



Min BIC BIC

Getting deeper on Augmentation techniques

AugTL-Aug: The CAE is trained over synthetic HCP dataset (~6000) and also trained on the initial augmented stroke dataset

Aug(15000): Original dataset increase ~15000

AugTL-Stroke: The CAE is trained over synthetic HCP dataset (~6000) and also trained on the initial original stroke datase

Tl-Aug: The CAE is trained over the HCP dataset and also trained on the initial augmented stroke dataset

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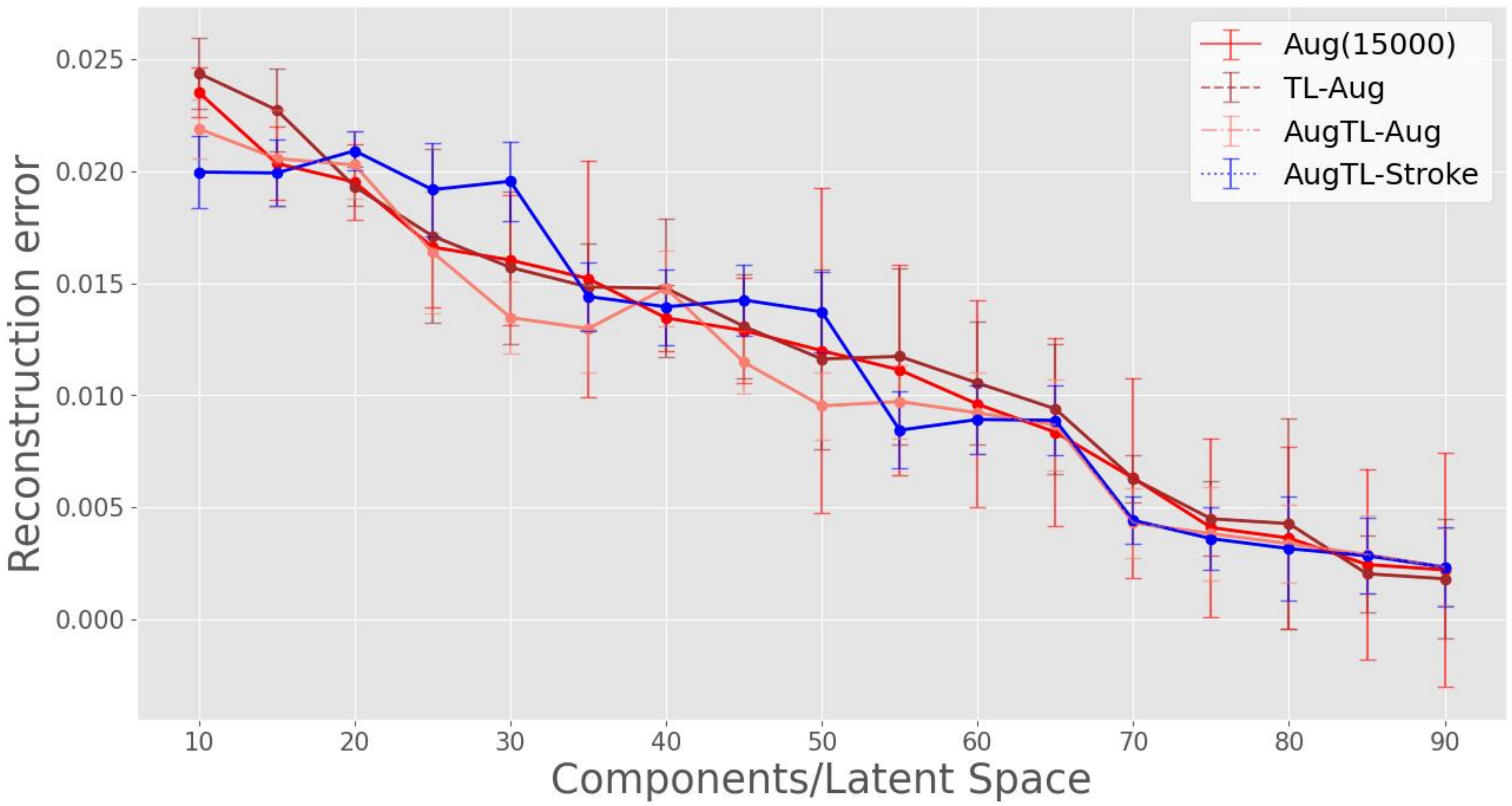
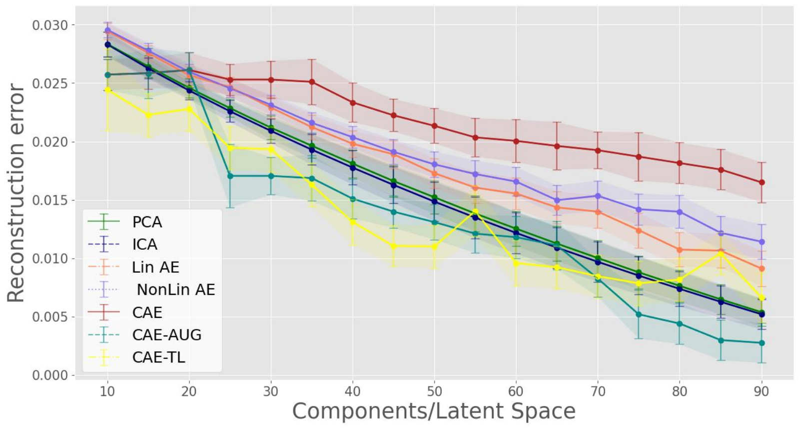
Results: Augmentation techniques

Reconstruction error for each augmentated dimensionality reduction method as a function of the number of extracted features



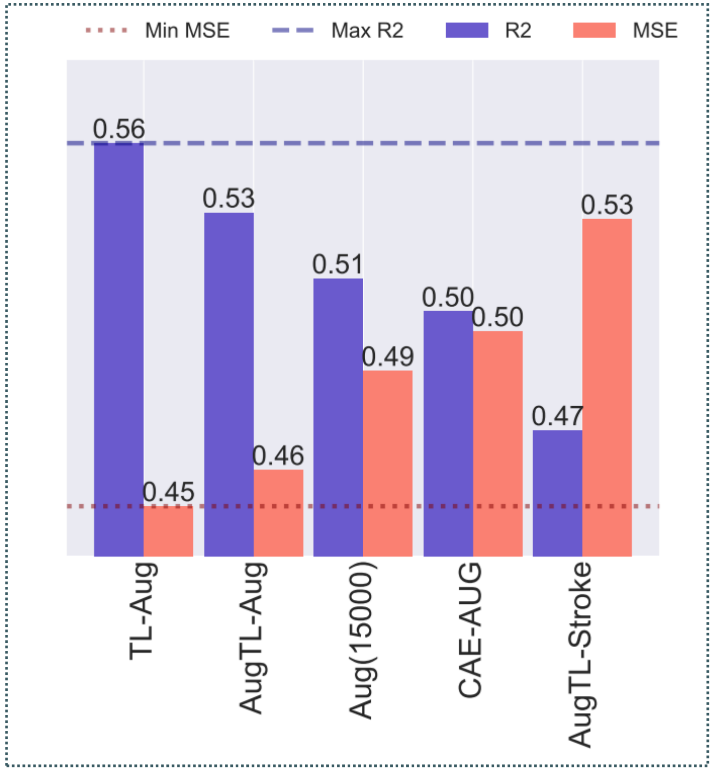


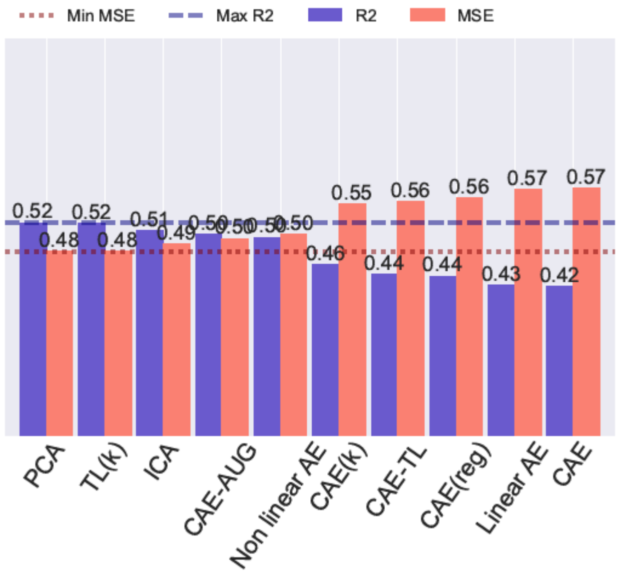
Results: Augmentation techniques

① Language score

- MSE improved 7% respect to PCA
- R2 improved 7% respect to PCA

	Method	R^2	MSE	BIC	Optimal α	Optimal λ	Fold	NZ
Language Score	TL- Aug	0.555	0.445	283.634	0.001	0.031	20	20
	Aug(15000)	0.514	0.486	420.68	0.5	0.06	50	43
	AugTL-Stroke	0.468	0.532	432.587	1	0.016	60	46
	AugTL-Aug	0.534	0.456	420.68	0.5	0.06	50	43





Before

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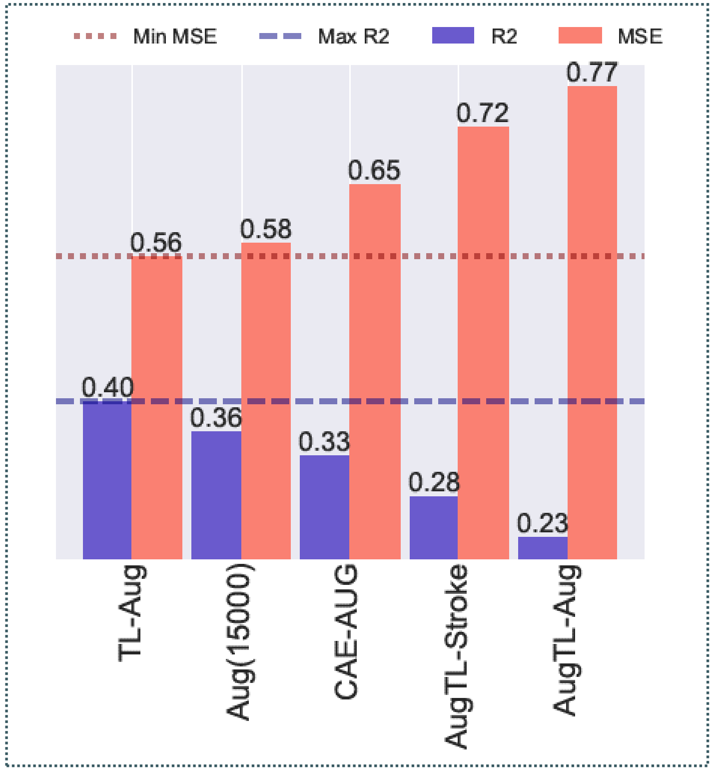
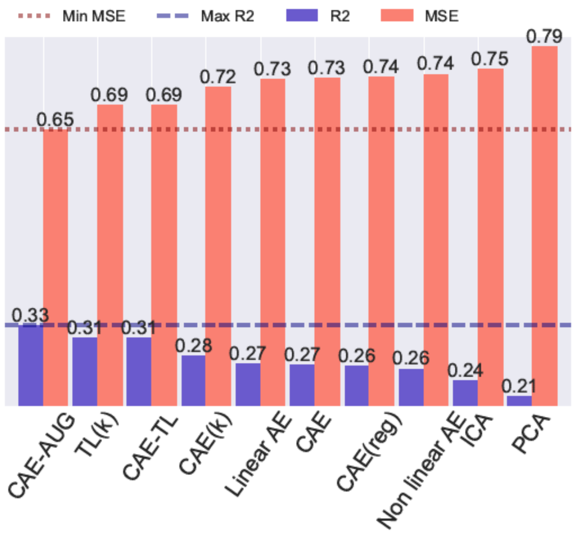
Results: Augmentation techniques

2 Spatial score

	Method	R^2	MSE	BIC	Optimal α	Optimal λ	Fold	NZ
Spatial Score	TL-Aug	0.395	0.565	367.205	0.5	0.098	70	42
	Aug(15000)	0.359	0.581	569.703	0.001	0.05	15	85
	AugTL-Stroke	0.282	0.718	380.29	0.001	0.811	40	40
	AugTL-Aug	0.234	0.766	246.493	1	0.159	55	9

- MSE improved 30% respect to PCA
- R2 improved 66% respect to PCA





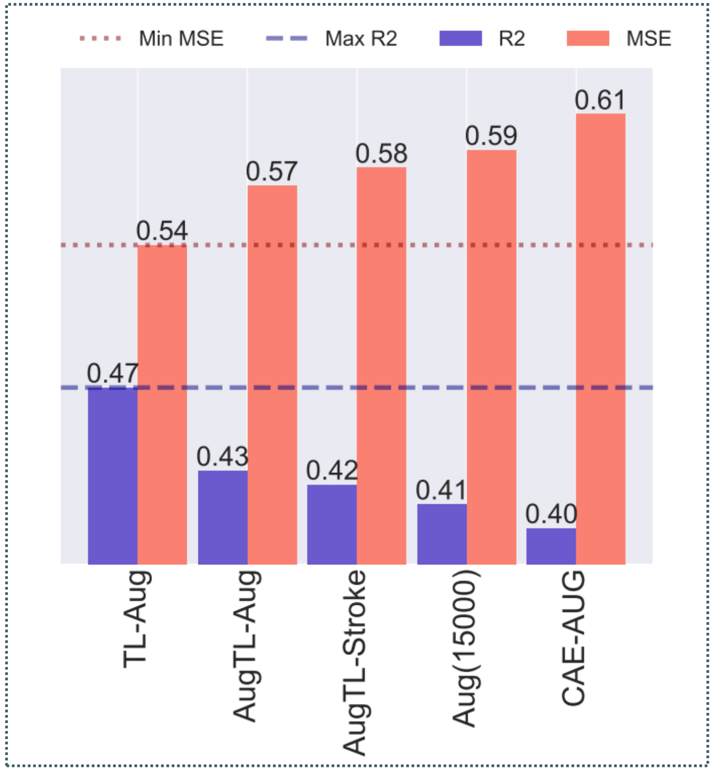
Before

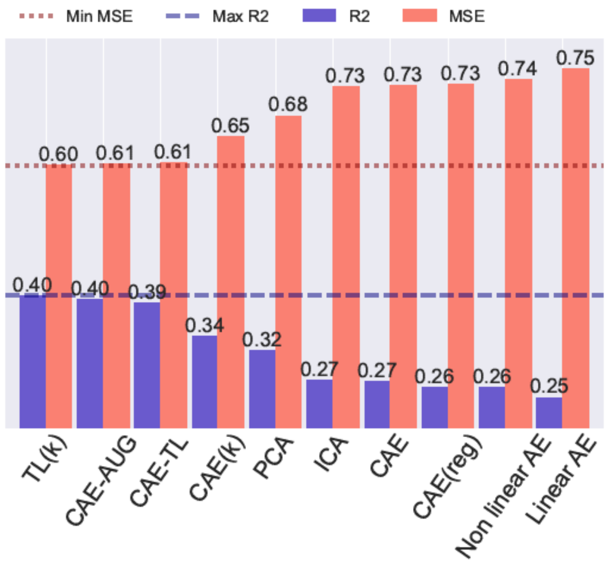
Results: Augmentation techniques

③ Verbal score

	Method	R^2	MSE	BIC	Optimal α	Optimal λ	Fold	NZ
Verbal Score	TL-Aug	0.469	0.541	357.279	0.75	0.083	70	37
	Aug(15000)	0.410	0.589	569.703	0.001	0.05	15	85
	AugTL-Stroke	0.420	0.580	242.202	1	0.159	45	8
	AugTL-Aug	0.427	0.571	238.96	1	0.083	25	8

- MSE improved 20% respect to PCA
- R2 improved 47% respect to PCA





Before

Conclusion

1

All methods achieved similar reconstruction error. Augmentation obtained slightly better accuracy.

2

Results showed that the performance of the basic autoencoders was overall comparable to that of traditional methods (ICA and PCA).

3

Convolutional architectures trained using data augmentation and transfer learning achieved a **much higher performance** with respect to the previously reported state-of-the-art methods [3].

Our results demonstrate the great potential of deep learning models for the analysis of multi-dimensional neuroimaging data even in cases with limited data availability, which is often considered a critical limitation in clinical studies.

4

Future work :

- Performance of DL models on the prediction of other neuropsychological and behavioral scores.
- Design and implement advanced visualization techniques in order to interpret the features extracted by non-linear dimensionality reduction methods

Thanks for your attention

Questions?

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