SOM-CPC: Unsupervised Contrastive Learning with Self-Organizing Maps for Structured Representations of High-Rate Time Series

23-29 JULY 2023

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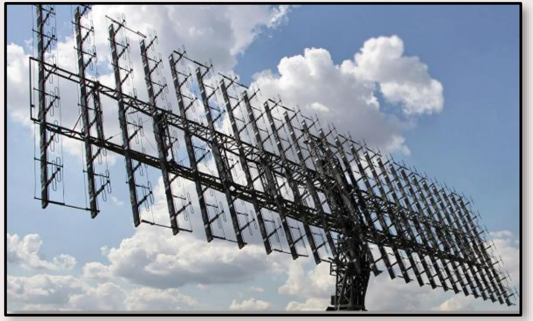
High-rate data streams are everywhere



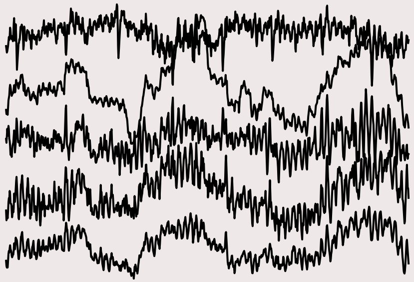
https://circuitcellar.com

https://kiosseslab.weill.cornell.edu

https://www.fau.edu/newsdesk/
articles/autonomous-vehicles-patent

TU/e

Interpreting these data

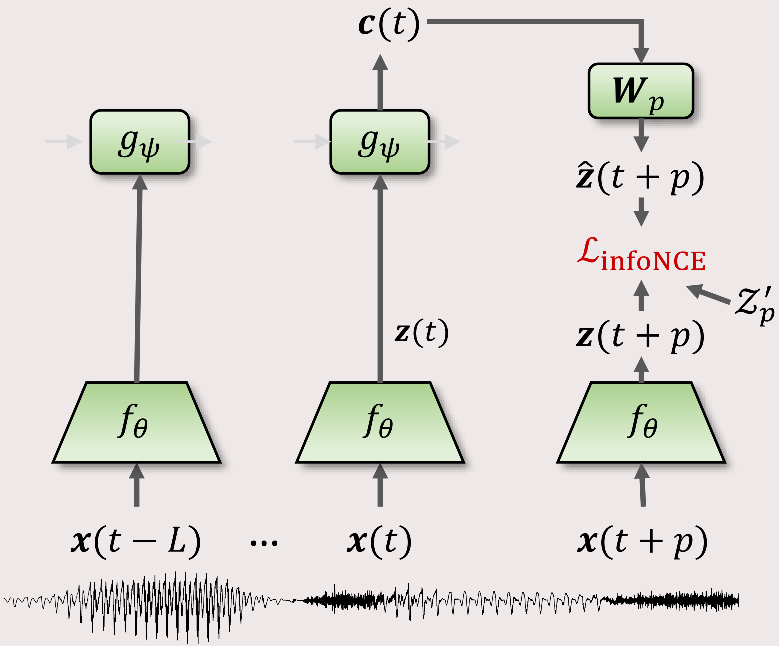


Assign a class for the full stream

Seek temporally-changing patterns

Unsupervised representation learning problem

Window-based embeddings with contrastive learning



Contrastive Predictive Coding (van den Oord et al., 2019)

Maximizes mutual information between $\boldsymbol{c}(t)$ and $\boldsymbol{z}(t+p)$

Therefore encodes slowly-changing features

Van den Oord *et al.*, 2019. Representation learning with contrastive predictive coding.

Embeddings on their own are not interpretable

Additional steps are needed like:

- PCA + K-means
- t-SNE (Hinton & Roweis, 2002)
- Classifier
- Self-Organizing Map (Kohonen, 1990)

- Only keeps data that is reflected in the principle components
- New data during inference cannot be projected on same space as training set
- Needs labels
- Keeps data in higher dimensions
- New data during inference can be projected on same space as training set
- Does not need labels

Hinton & Roweis, 2002. Stochastic neighbor embedding
Kohonen, 1990. The Self-organizing Map

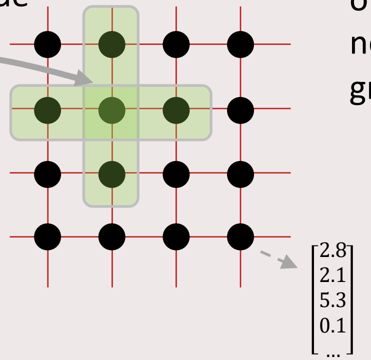
Self-Organizing Maps

Given:

- ✓ A feature vector
- ✓ nodes/clusters that are represented each by a trainable codebook/quantization vector
- ✓ A neighborhood relation (e.g. a plus shape)

Vector quantizer: select winning node

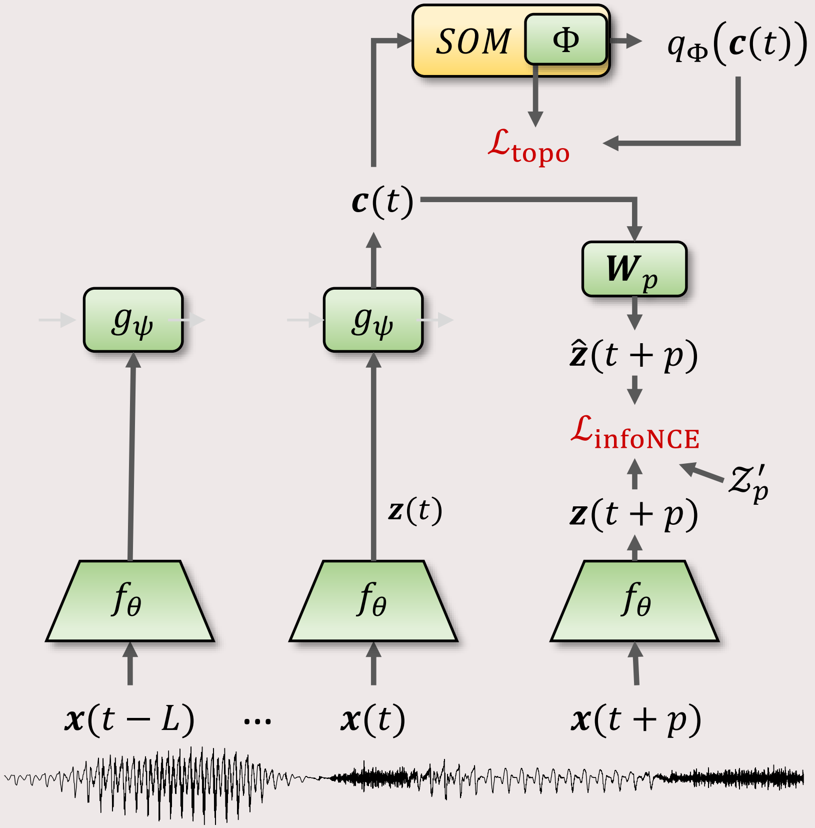
$$\begin{bmatrix} 3.1 \\ 2.7 \\ -0.4 \\ 1.5 \\ \dots \end{bmatrix}$$



Update quantization vector of winning node and the neighbors in 2D using gradient descent with $\mathcal{L}_{\text{topo}}$

Kohonen, 1990. The Self-organizing Map

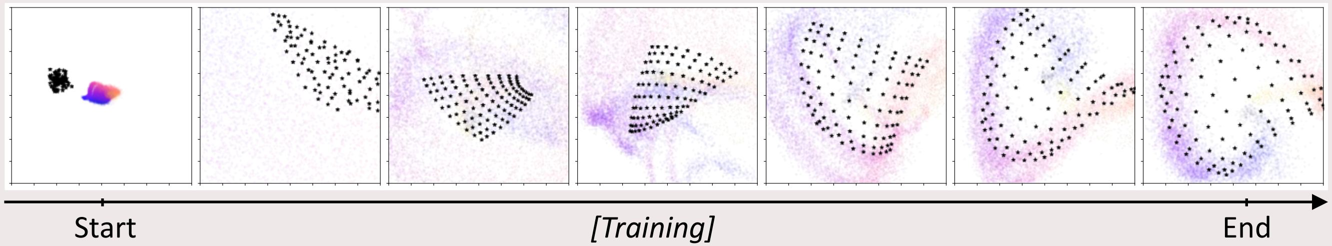
SOM-CPC



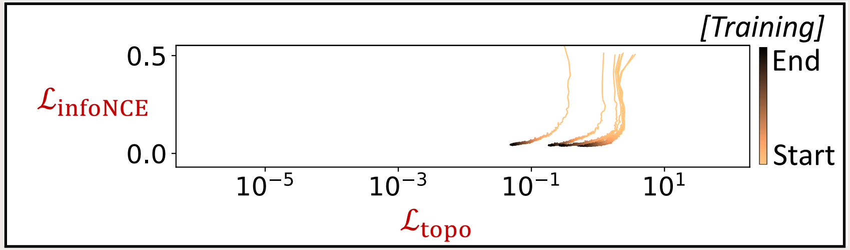
SOM
Φ
$q_\Phi(\boldsymbol{c}(t))$
$\mathcal{L}_{\text{topo}}$
$\boldsymbol{c}(t)$
$\boldsymbol{W}_p$
g_ψ
g_ψ
$\hat{\boldsymbol{z}}(t+p)$
$\mathcal{L}_{\text{infoNCE}}$
$\mathcal{Z}'_p$
$\boldsymbol{z}(t)$
$\boldsymbol{z}(t+p)$
f_θ
f_θ
f_θ
$\boldsymbol{x}(t-L)$ …
$\boldsymbol{x}(t)$
$\boldsymbol{x}(t+p)$

Training dynamics

The codebook vectors of the SOM (black) learn to non-uniformly quantize the data space (color) throughout training.



For various loss trade-offs both losses converge smoothly to a minimum

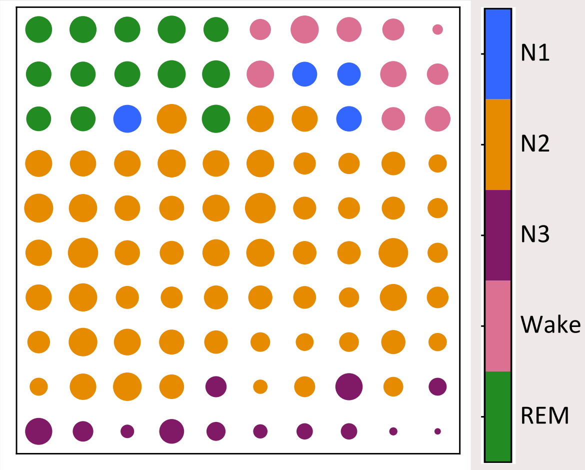


Real-world data

SOM-CPC outperforms all baselines on clustering, classification and temporal smoothness metrics.

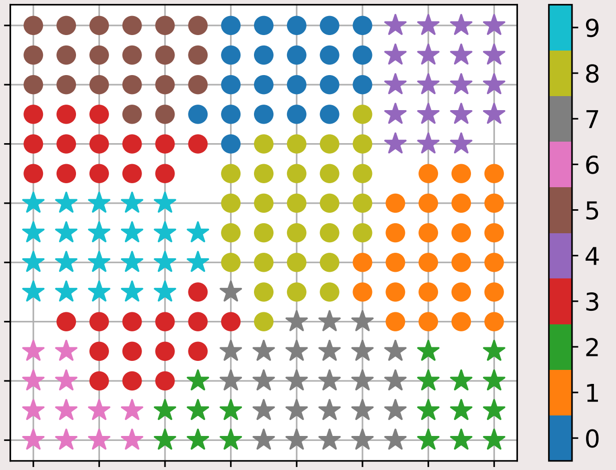
Biophysiological measurements

Different states of sleep
are grouped together and deep sleep (N3) is
well separated from light sleep (N1) and Wake



Audio

Recordings of the same
speaker are grouped



Take aways

- SOM-CPC visualizes time series in 2D, but keeps information in a codebook in higher dimensions
- It enables recognition of patterns that change over time
- New streams can be projected onto the learned space
- It can be used for any raw (multi-channel) time series data

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