Self-Supervised Learning for Sleep Staging

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Contents

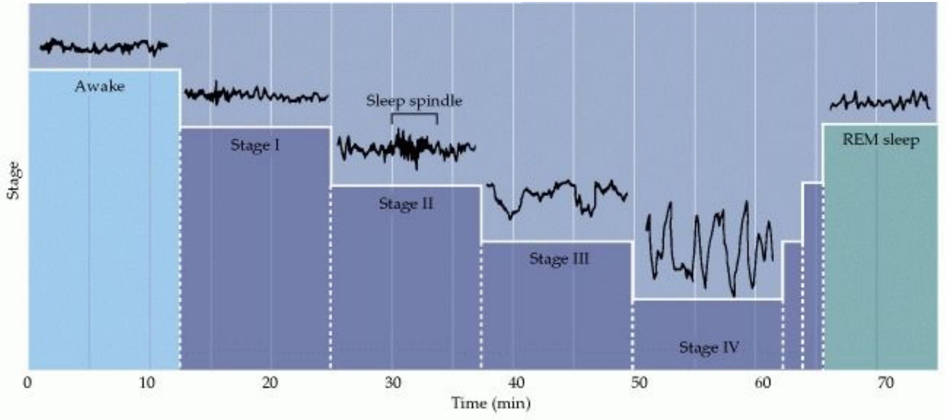
Introduction

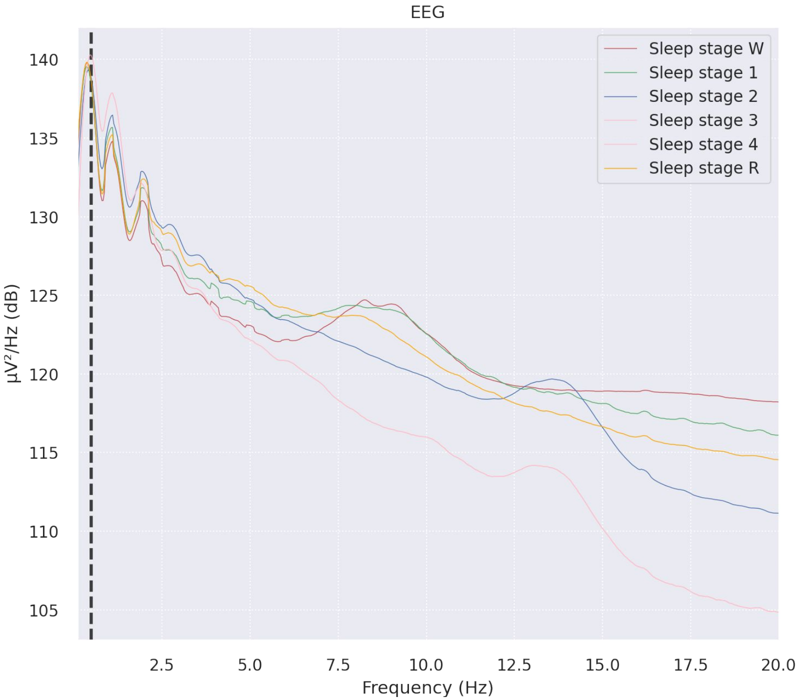
- Supervised learning
  - High performance
  - Requires lots of labeled data
  - Costly
- Unsupervised learning
  - Has access to lots of unlabeled data + some labeled data
  - Difficult
  - Not as good as supervised learning (but can be better if data >>>> 1)
- Self-supervised learning
  - Supervised learning objective from unlabeled data
  - Learn a representation to be provided to the downstream task as an inductive bias
  - Requires labels only for downstream task

Background

- Electroencephalograms & Sleep
- Self-Supervised Learning
- Application to Sleep Staging

Electroencephalograms





Awake: beta activity, high-frequency (15–60 Hz), low-amplitude activity (~30 μV).

Stage I: Theta waves (4–8 Hz) and increasing amplitude (50–100 μV).

Stage II: Spindles (10–15 Hz) oscillations (50–150 μV) during a few seconds.

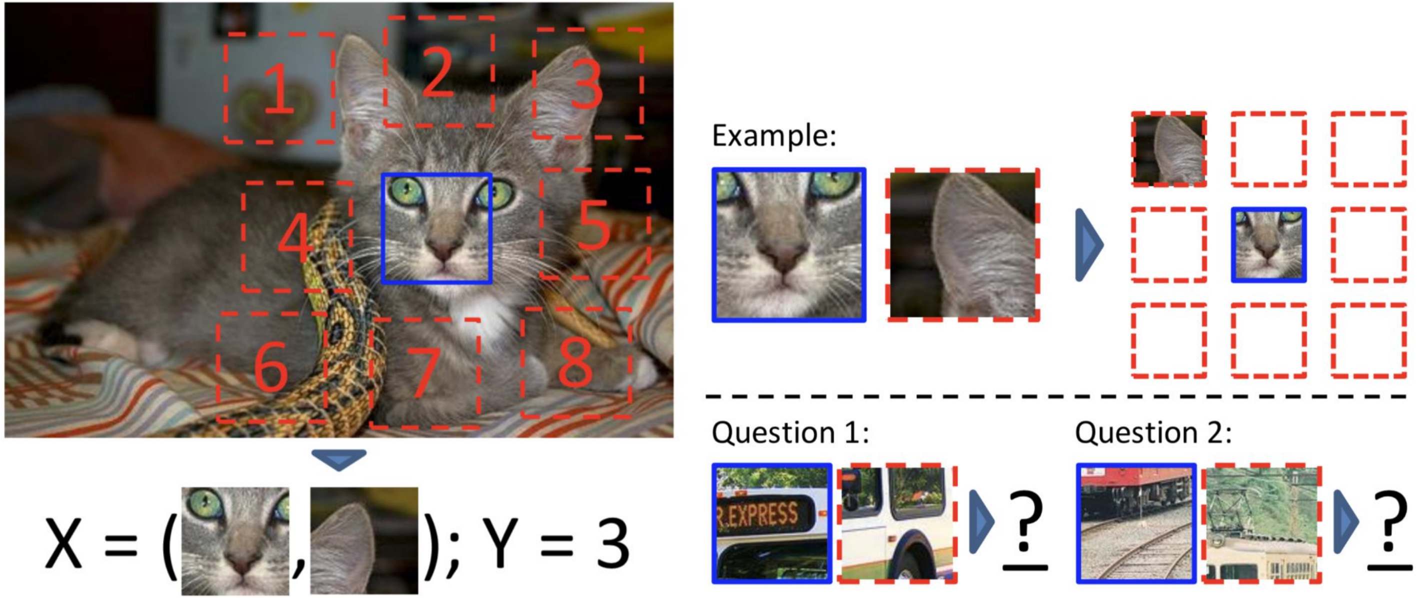
Stage III-IV: delta waves 0.5–4 Hz (100–150 μV).

REM: similar to the EEG activity of individuals who are awake

From Neuroscience. 2nd edition. Purves D, Augustine GJ, Fitzpatrick D, et al., 2001

Self-Supervised Learning

- Learn representations of the data and its intrinsic biases
- Train on a pretext task built from unlabeled data



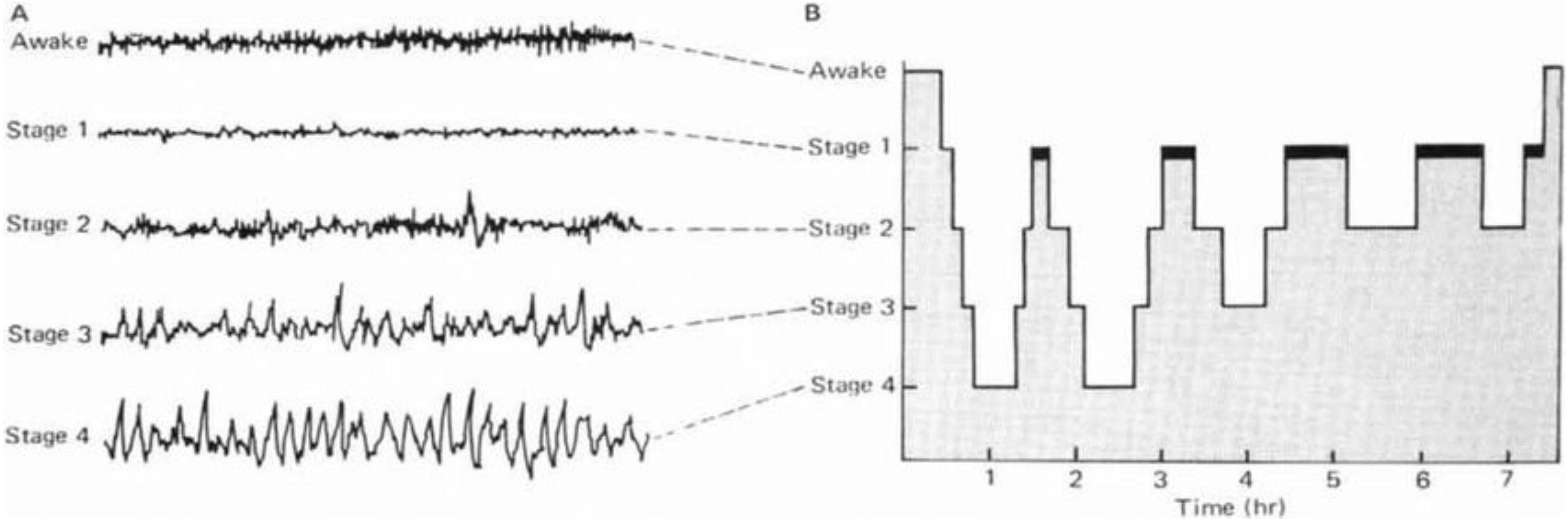
From Doersch et al., 2015

Related Works - Self-Supervised Learning

- Images
  - Prediction of positions of random patches selected from an image [Doersch et al., 2015]
  - Prediction of image rotation [Gidaris et al., 2018]
- Videos
  - Ordering of video frames [Misra et al., 2016]
- Time series
  - Classifying whether windows are sampled from the same temporal context [Banville et al., 2019]
  - Recovering relative position of sampled windows [Banville et al., 2020]
  - Recovering whether windows are chronologically ordered [Banville et al., 2020]

Application to Sleep Staging

- Downstream task: sleep staging classification
- Useful in low (labeled) data regime



From Wikipedia

Related Works - Sleep Stage Detection

- **H. Phan et al.**, Seqsleepnet: End-to-end hierarchical recurrent neural network for sequence-to-sequence automatic sleep staging. *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* **2019**.
- **Jens Stephansen et al.**, Neural network analysis of sleep stages enables efficient diagnosis of narcolepsy. *Nature Communications,* **2018**.
- **Mathias Perslev et al.**, U-time: A fully convolutional network for time series segmentation applied to sleep staging, **2019**.
- **Antoine Guillot and Valentin Thorey**. Robustsleepnet: Transfer learning for automated sleep staging at scale, **2021**.

Experiments

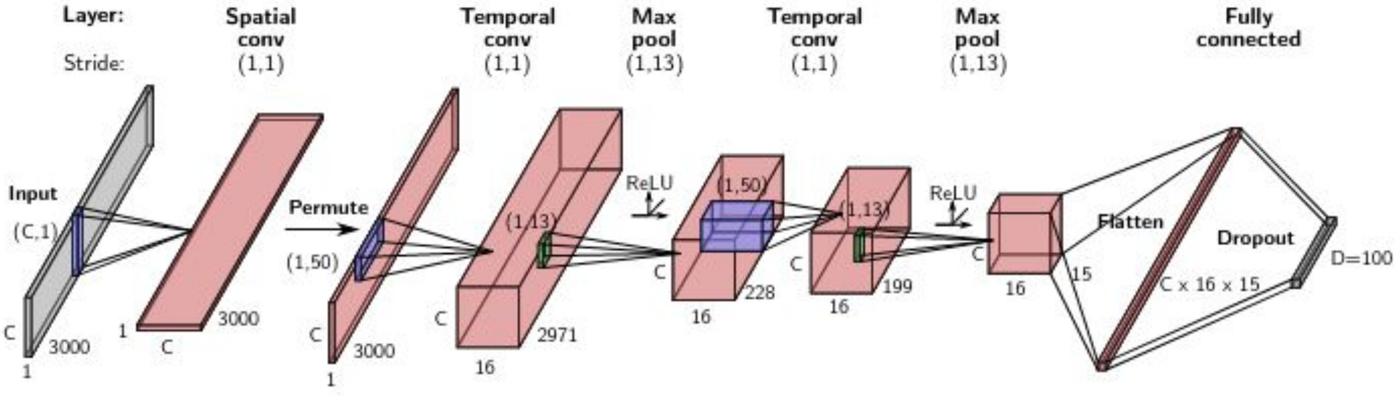
→ Reproduce results from *Uncovering the structure of clinical EEG signals with self-supervised learning, Banville et al., 2020.*

- Model Architecture
- Dataset
- Pretext Task (SSL)
- Downstream Task
- Pre-training Size
- Embeddings Analysis

Model Architecture

→ Modified StagerNet (Banville et al., 2020; Chambon et al., 2018)

- 3-layer CNN
- Relu
- Batchnorm
- Maxpool
- Dropout



From Banville et al., 2020

Dataset

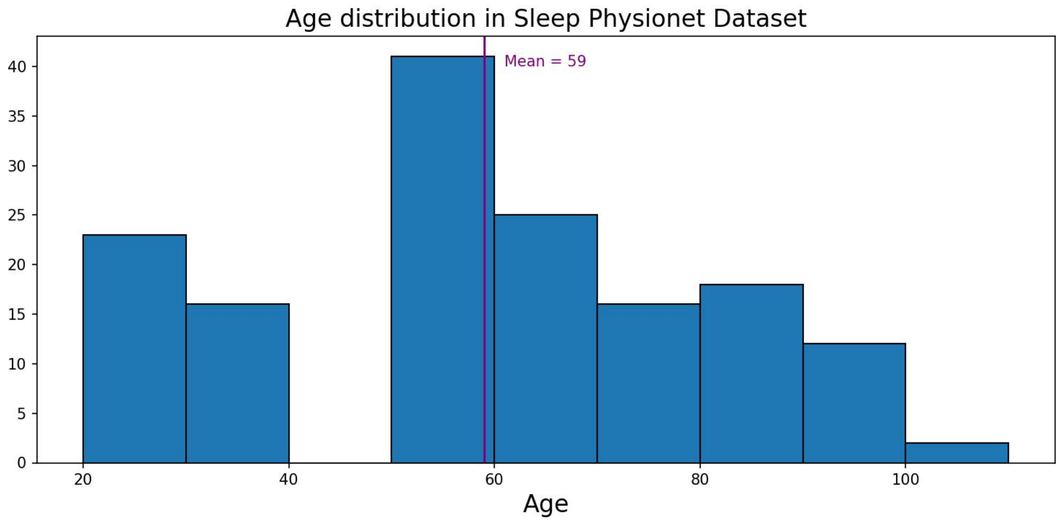
Sleep Physionet Dataset (Goldberget et al., 2000)

- 30-s windows
- 2 EEG channels
- 83 patients
- 2 nights per patient
- First 30-min wake removed

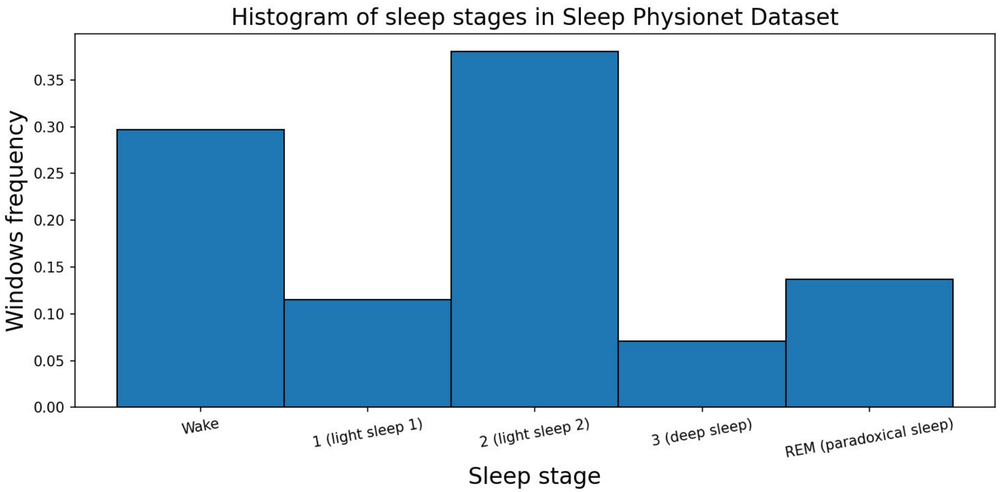
Dataset

Statistics:

- Age
  - Mean: 59
  - Std: 22



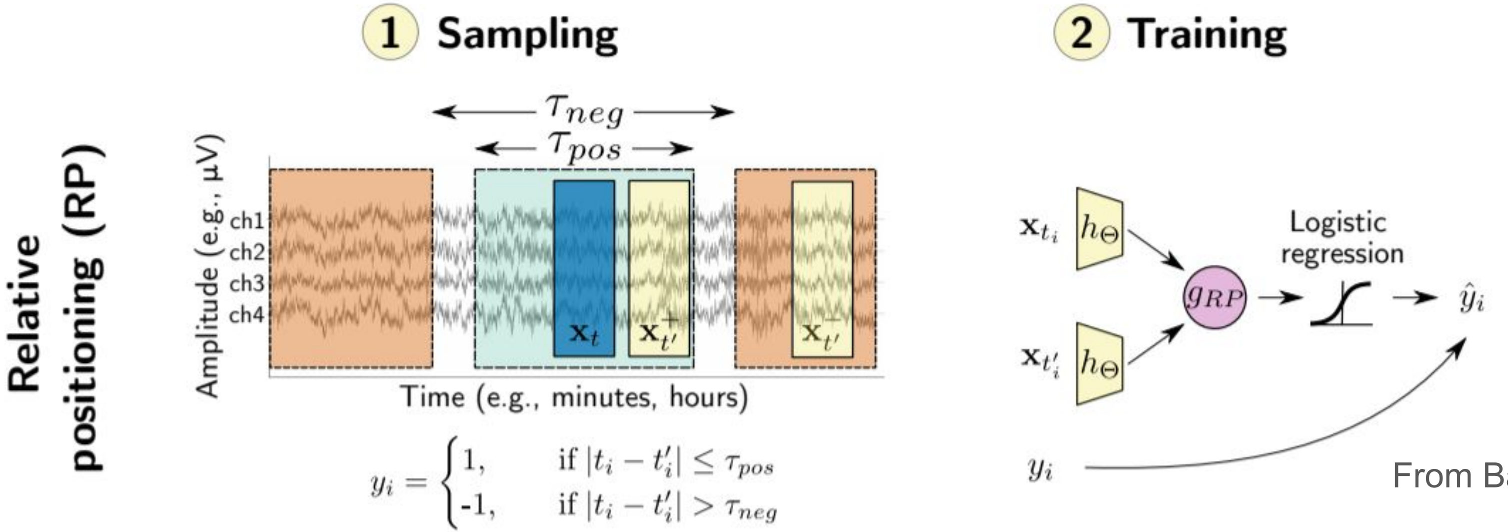
- Sleep stages



Pretext Task (SSL Pre-training)

Contrastive task

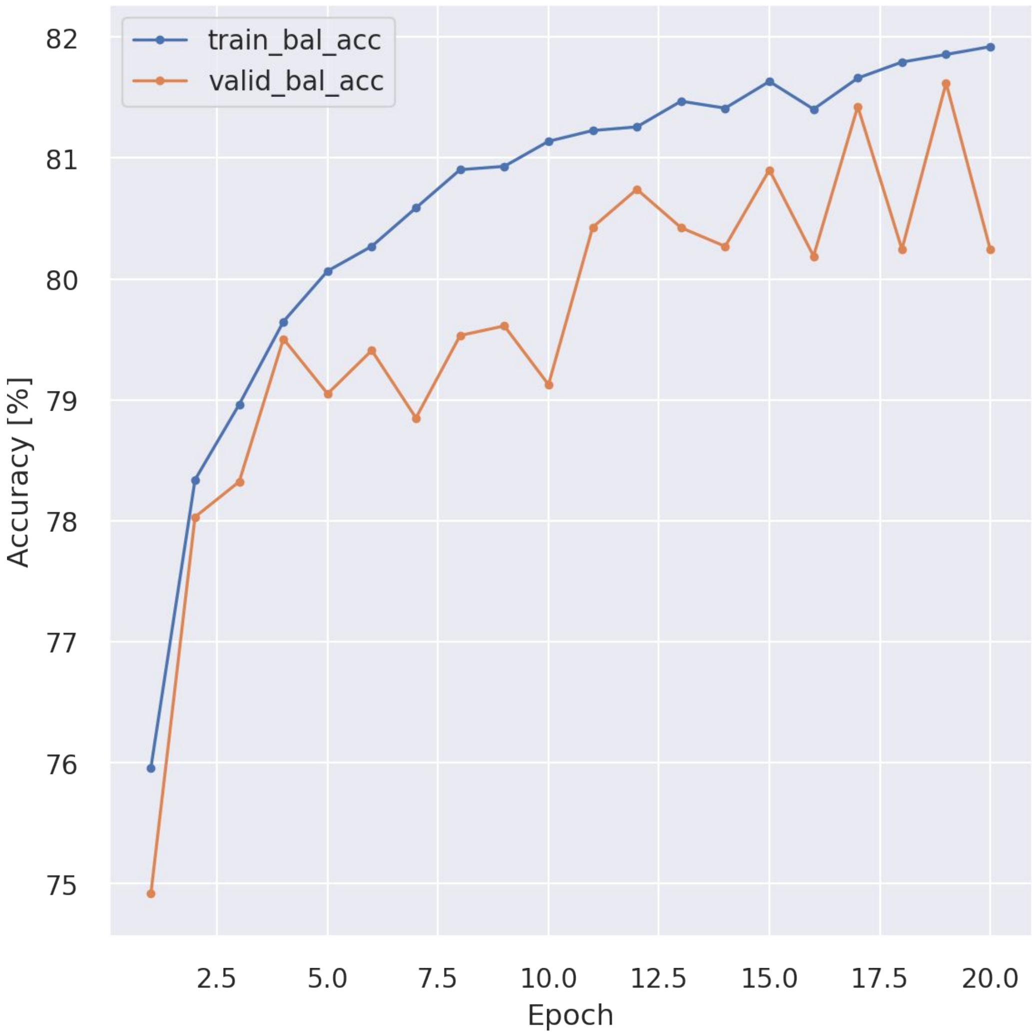
- Sample positive / negative pairs
- Tau_pos = 10 windows / Tau_neg = 100 windows



From Banville et al., 2020

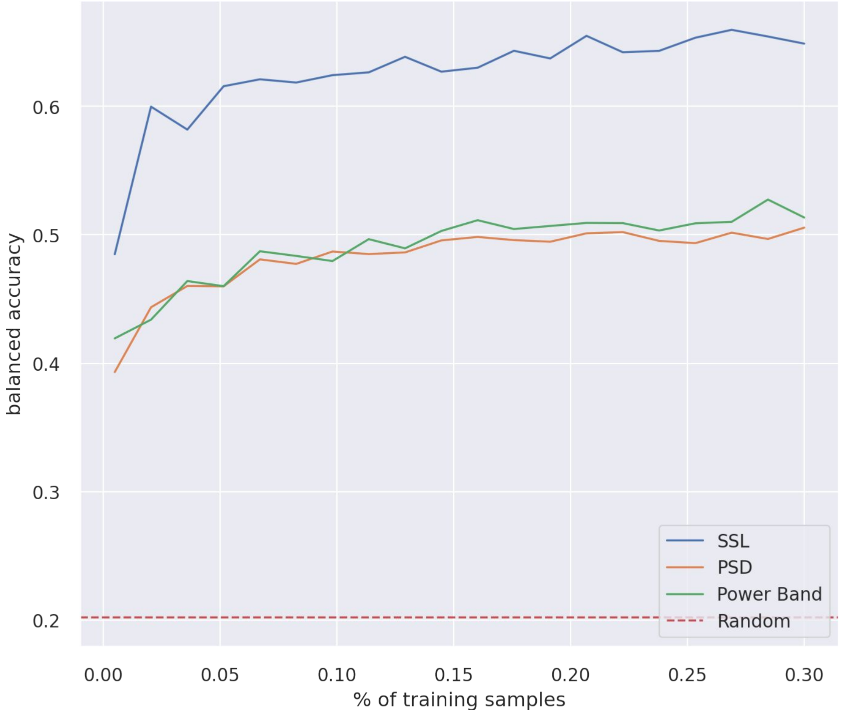
Pretext Task - Training

- Trains successfully in a few epochs
- Reaches 81% validation accuracy

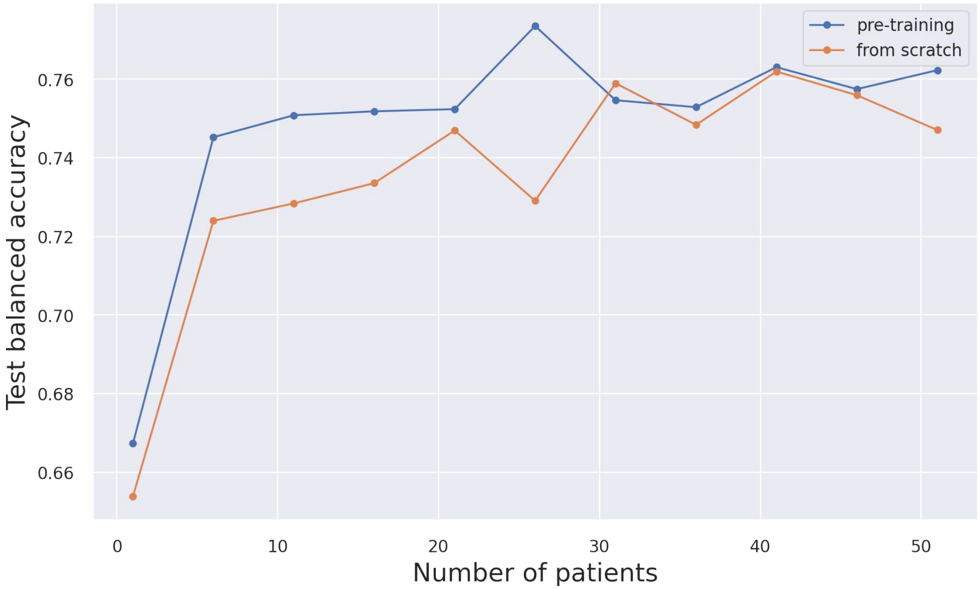


Proof Of Concept - Sleep Stages

SSL compared to baseline with a k-NN trained on the embeddings (k=10, cross validated)

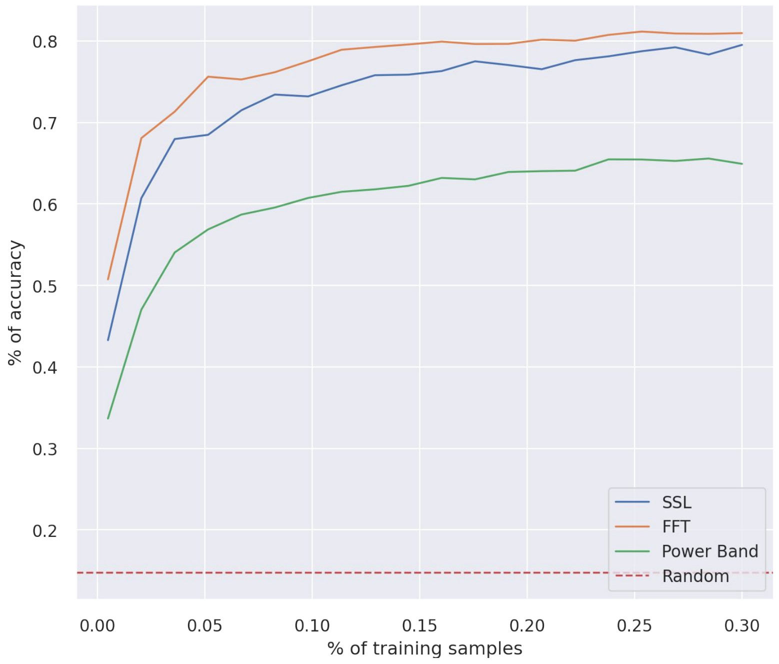


Impact of pre-training with 70% unlabeled data and then fine-tuning with a MLP VS training from scratch

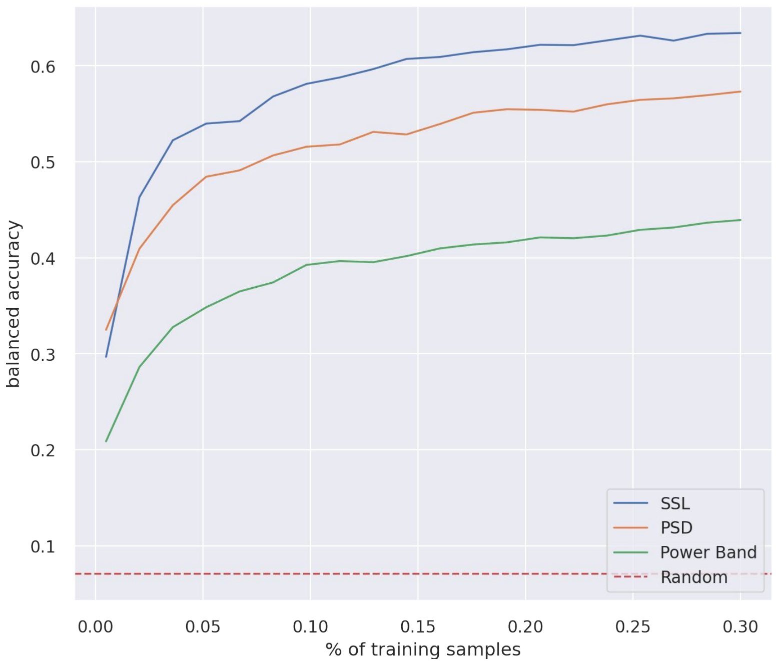


Proof Of Concept - Learned Biases

Patient age

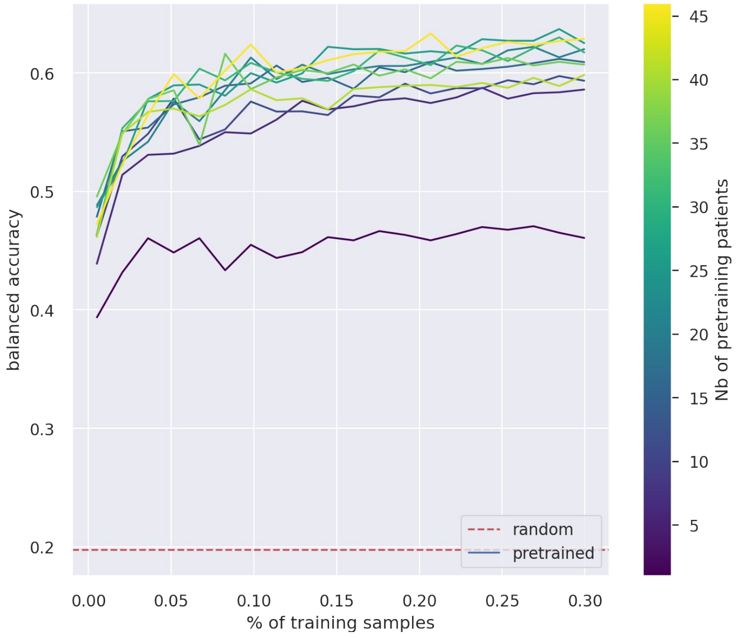


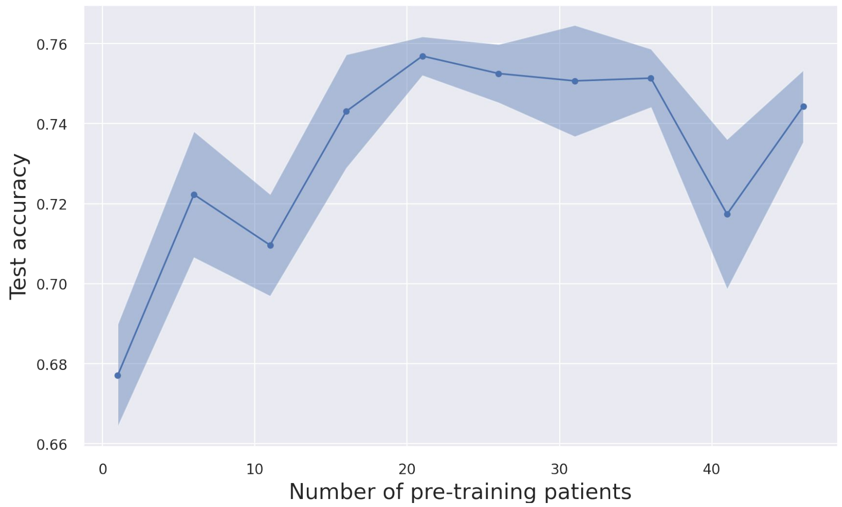
Patient ID



Pre-training Size - Sleep Stages

- Downstream task

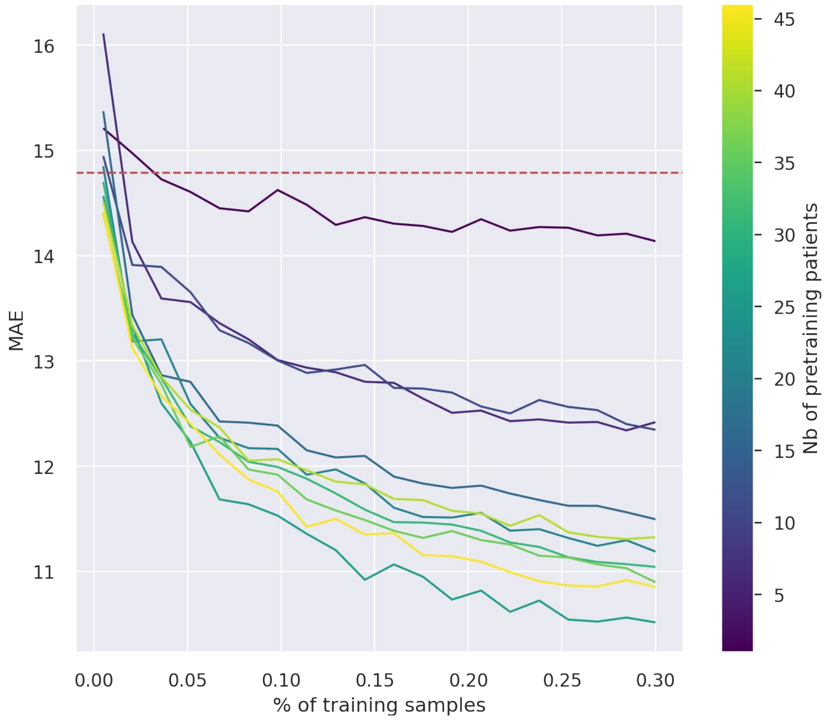




Increasing sets of pre-training patients
(folds not independent)

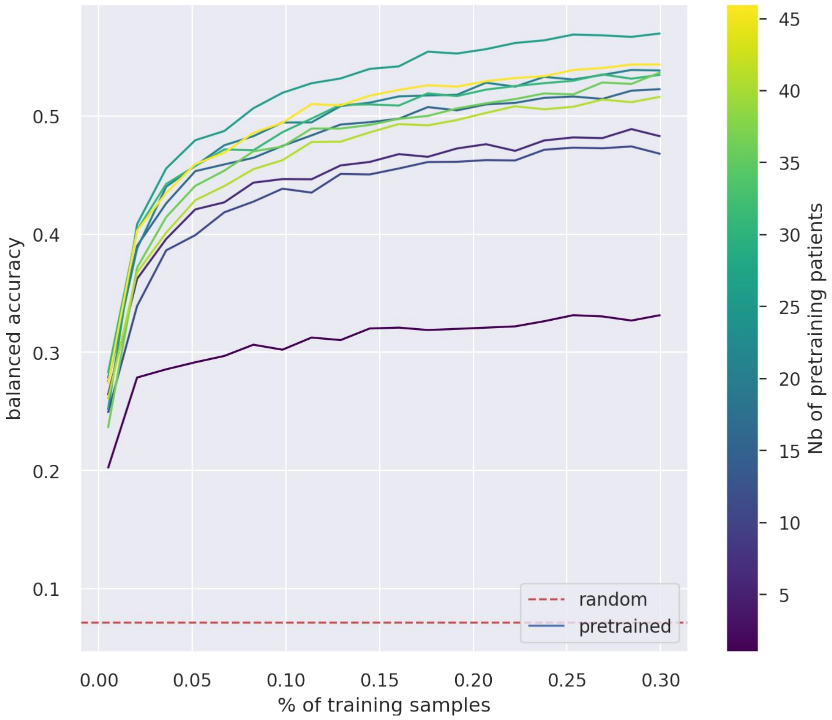
Pre-training Size - Learned Unwanted Features

Patient age



Age distribution: 59 +/- 22

Patient ID



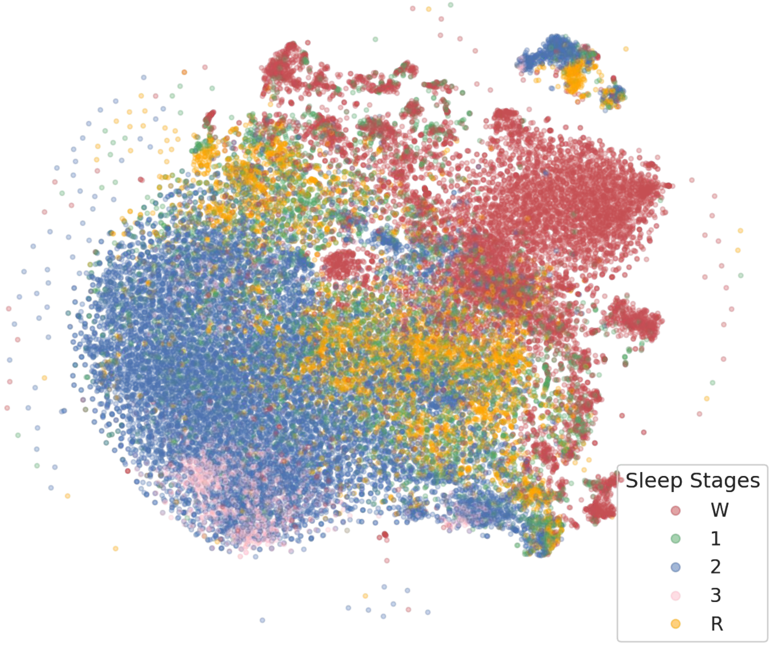
Test on 14 patients

Embeddings Analysis

PSD Embeddings Analysis

PCA

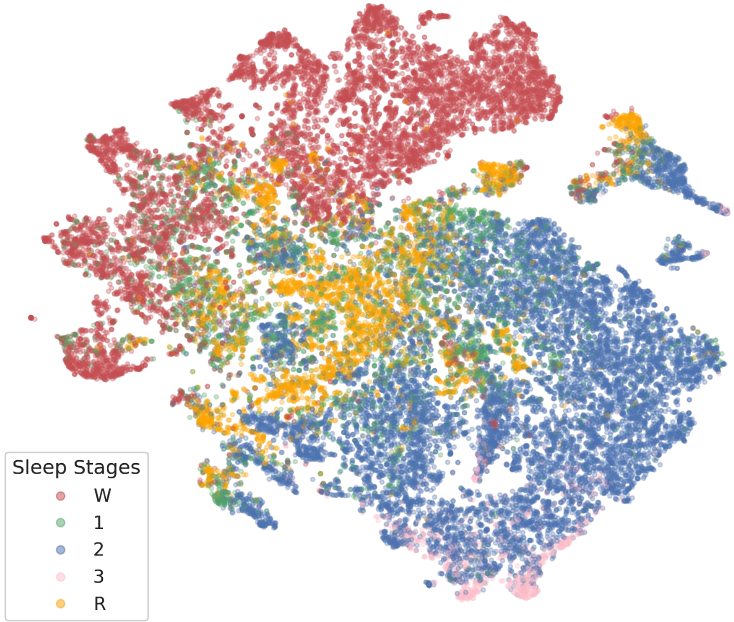
T-SNE



SSL Embeddings Analysis - Sleep Stages

PCA

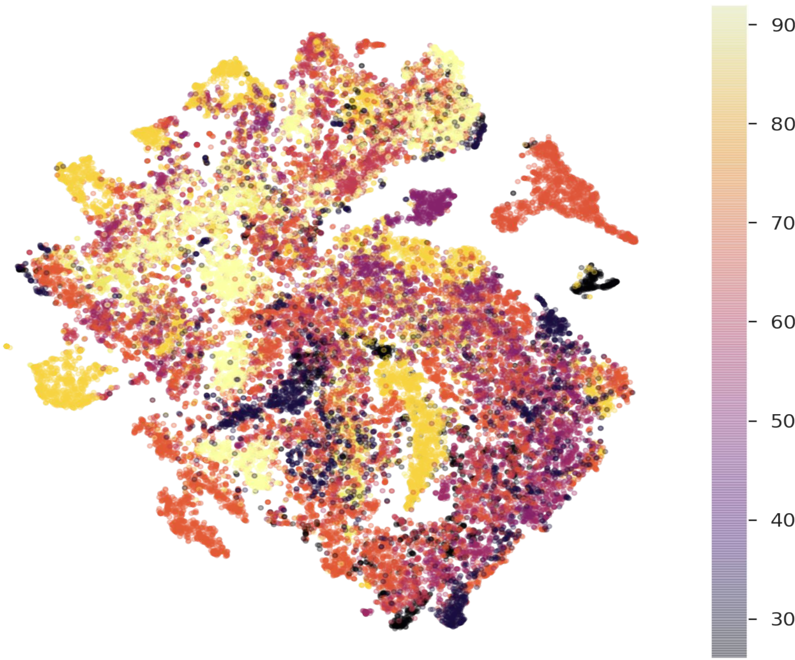
T-SNE



SSL Embeddings Analysis - Patient Age

PCA

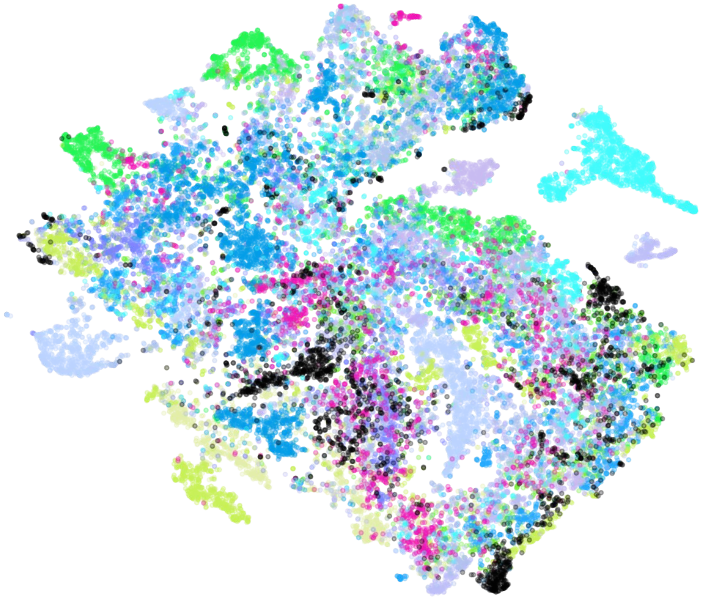
T-SNE



SSL Embeddings Analysis - Patient ID

PCA

T-SNE

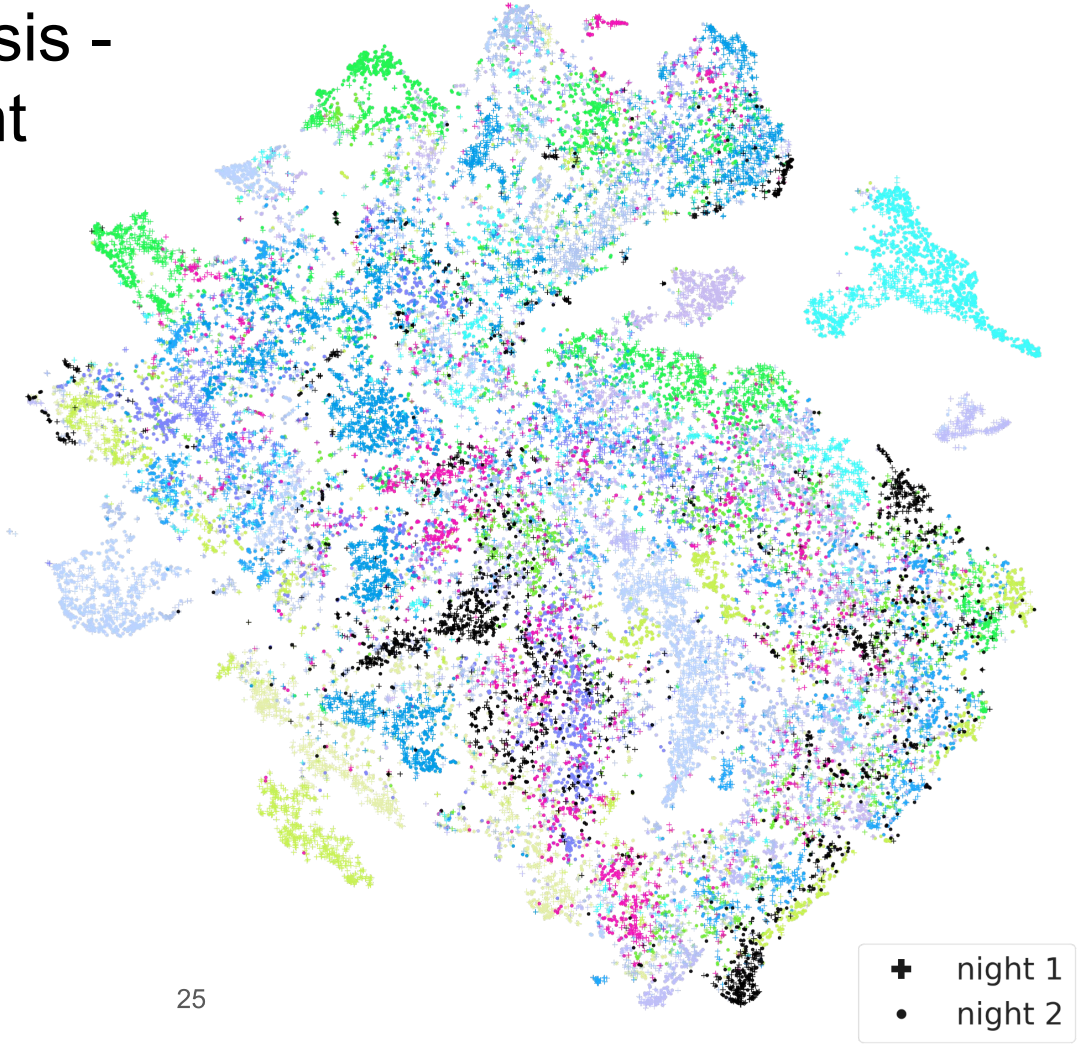


SSL Embeddings Analysis - Patient ID + patient night

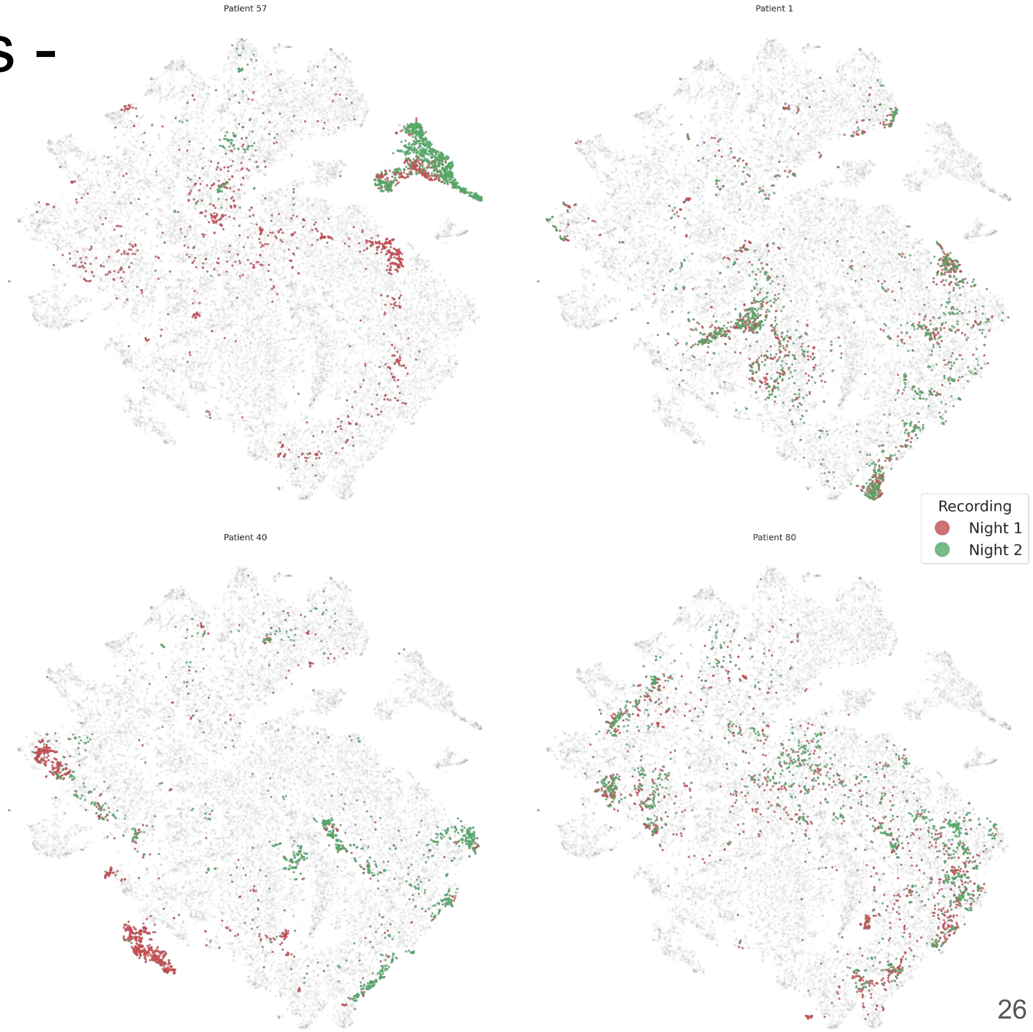
A lot of patient are clustered alone !

But the network nether saw them…

Must be some bias somewhere



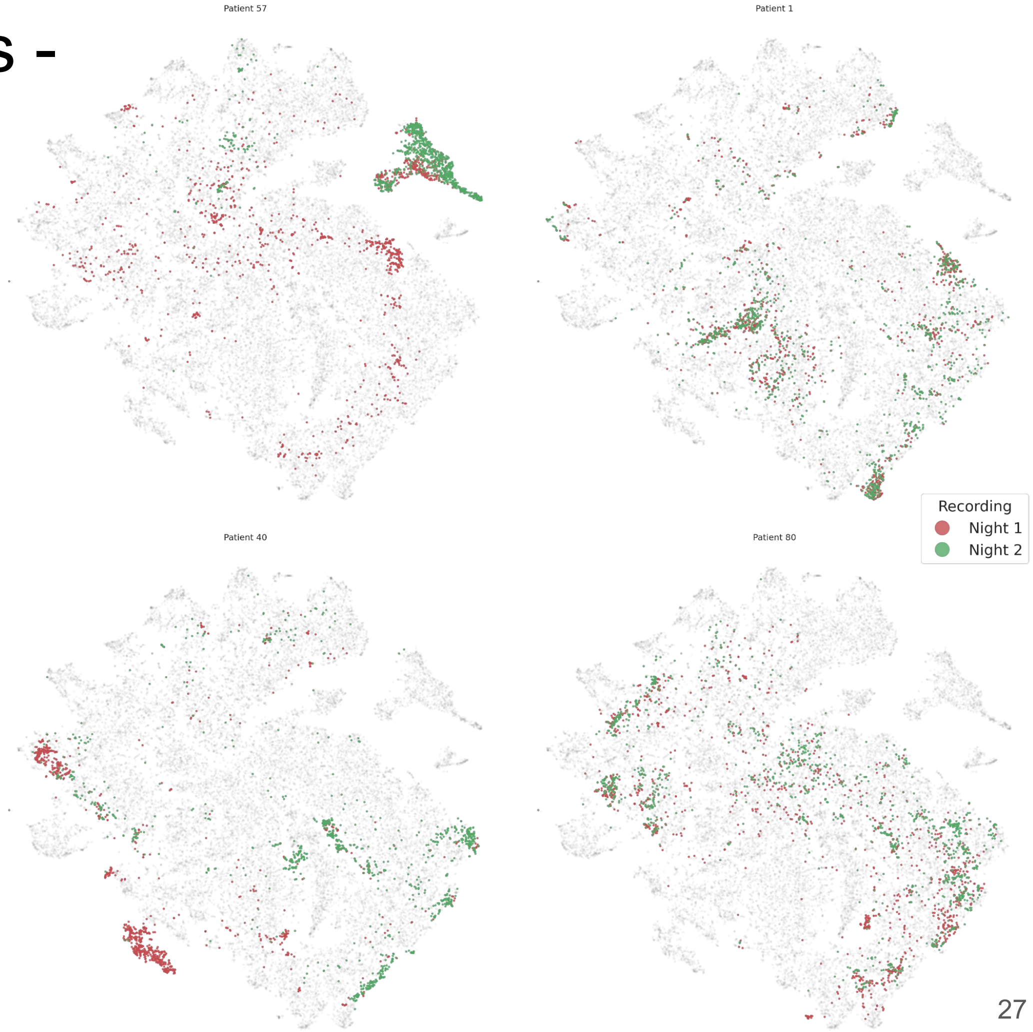
SSL Embeddings Analysis - Patient ID + patient night



SSL Embeddings Analysis - Patient ID + patient night

Spread out → less bias

Tightly clustered → more bias



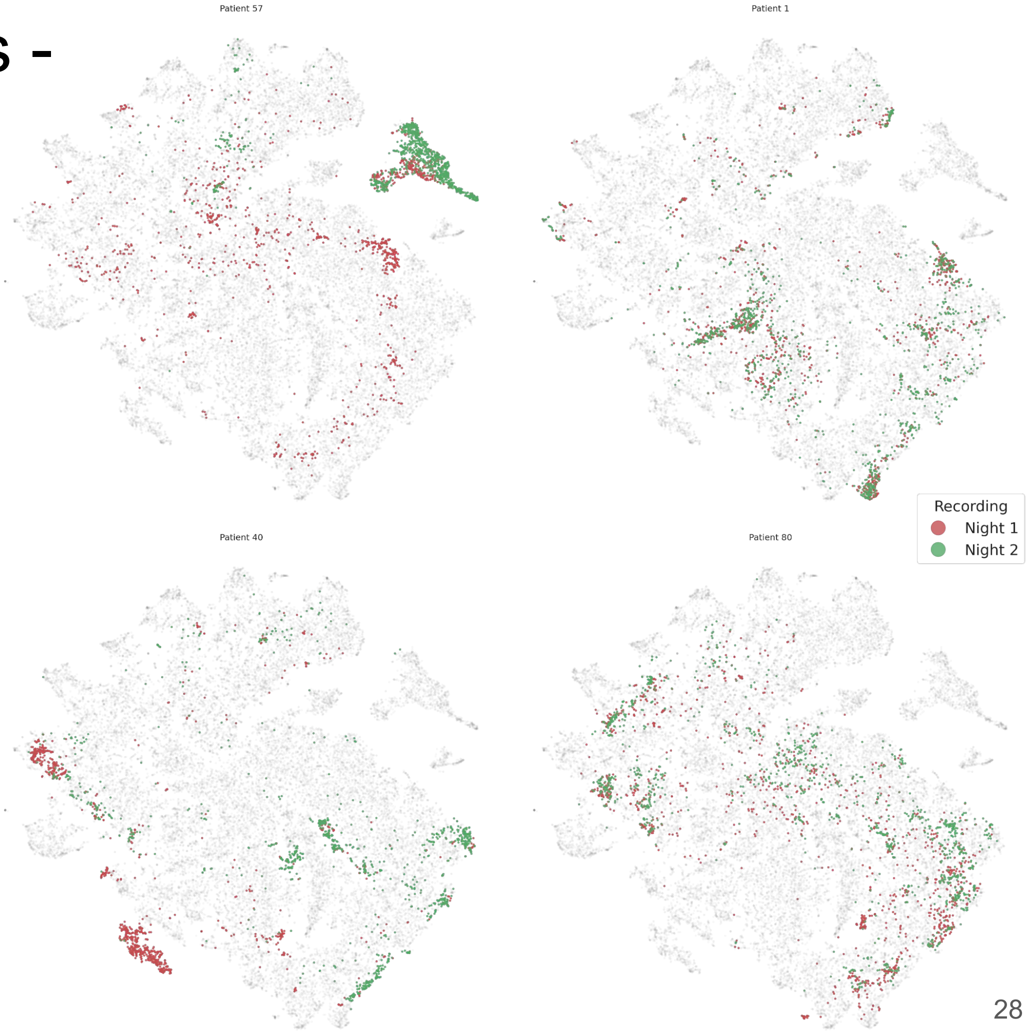
SSL Embeddings Analysis - Patient ID + patient night

Spread out → less bias

Tightly clustered → more bias

Observations :

- If night 1 is tightly clustered, then night 2 is also likely to be tightly clustered.
- If night 1 is spread out, night 2 may also be spread out.



SSL Embeddings Analysis - Patient ID + patient night

To get a quantitative metric of the spreading :

1. Take only certain points (filter on patient, night, sleep stage...).
2. Compute the distance to k-NN for each point (k=20% of # points).
3. Aggregate by patient, night and/or sleep stage.

SSL Embeddings Analysis - Patient ID + patient night

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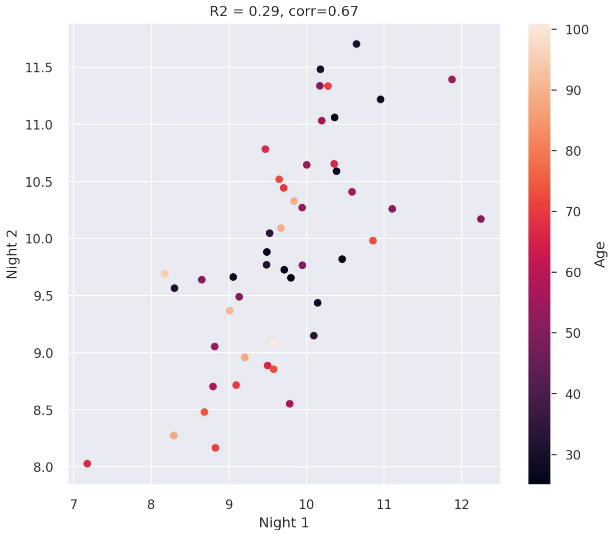
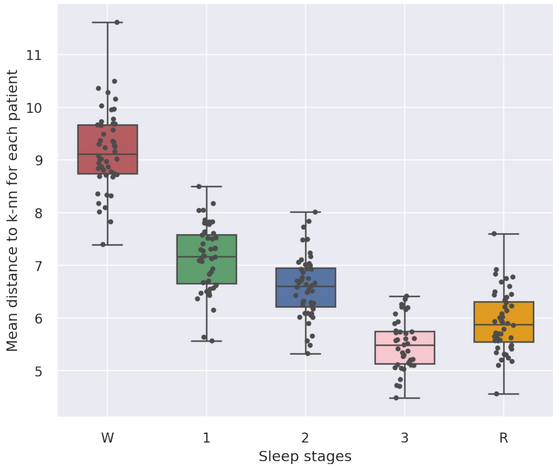




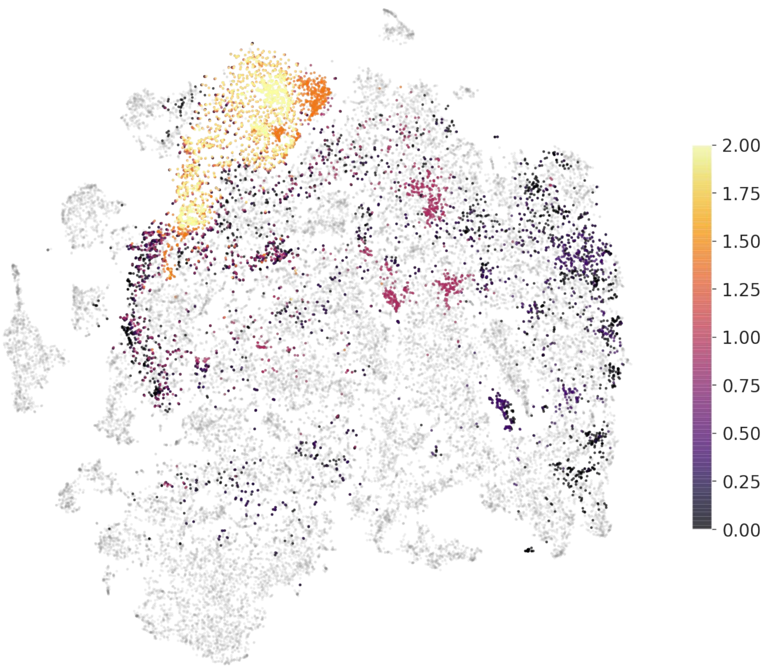
Night 1 and Night 2 correlated (67%)

SSL Embeddings Analysis - Adding controlled noise

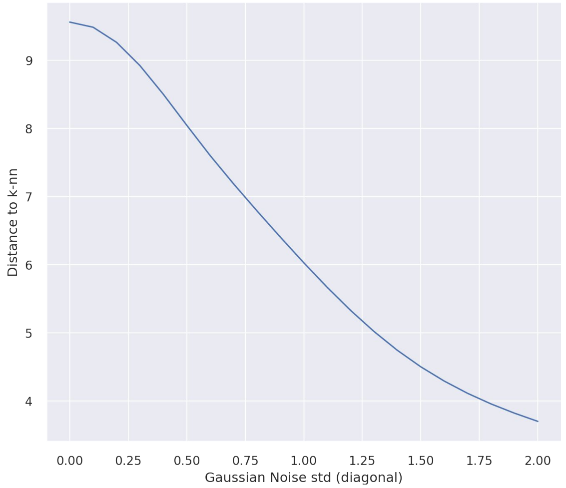
Add a Gaussian noise with std in [0, 2] and fixed seed.

Embed it using the pre-trained encoder to see the evolution of the spreading.

Clustering when adding more and more noise



Spreading when adding noise

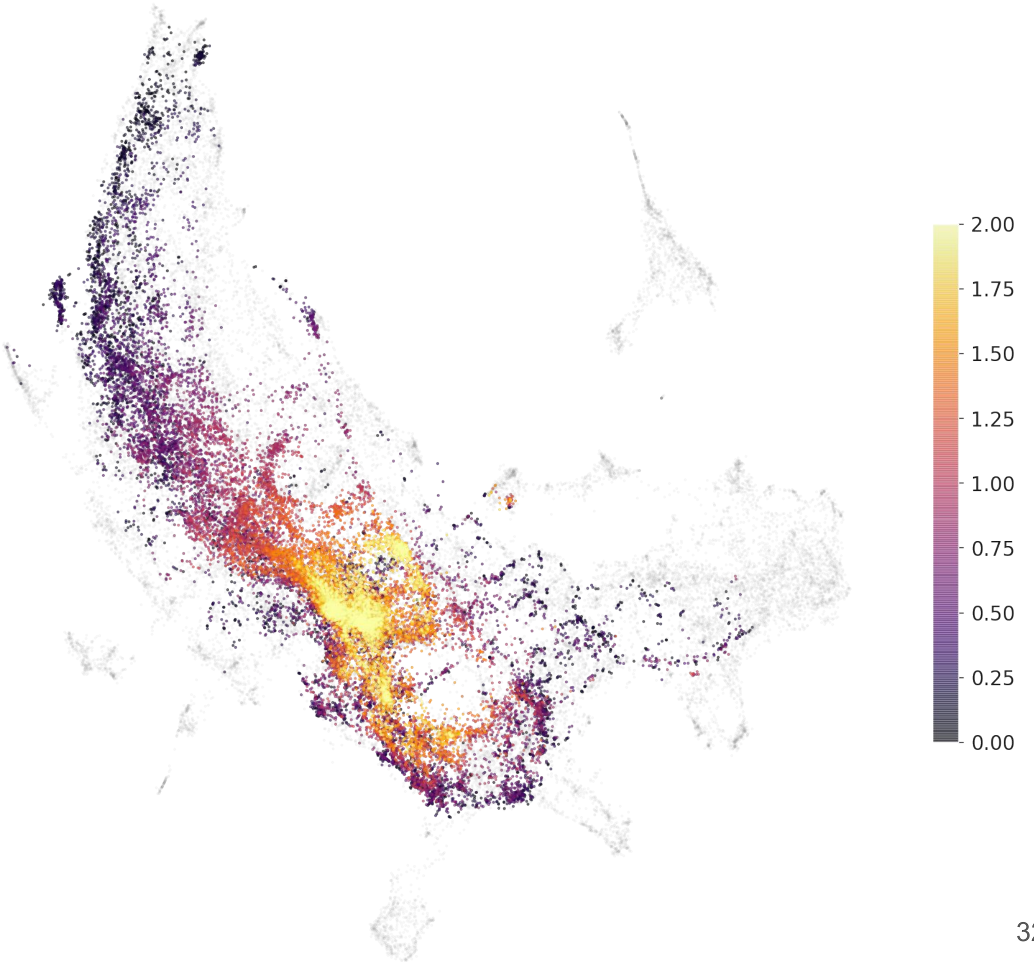


SSL Embeddings Analysis - Adding controlled noise

Add a Gaussian noise with std in [0, 2] and fixed seed.

Embed it using the pre-trained encoder to see the evolution of the spreading.

UMAP of embeddings when adding more and more noise



Conclusion

- Self-supervised learning → pre-train for sleep stage classification
- Main issue → patient-specific features, biases, clusters of patients
- Study of the pre-training size: diminishing returns to scale, plateau
- Limited robustness of the learned embeddings
- SSL may help perform well on EEG data in low-data regimes

→ Analyze biases provided by pretext task

Opening - What To Do Next ?

- Find a way to pre-train RNN along the encoder (as in SoTA architectures)
- Find new data augmentations to reduce patient-specific bias
- Study learned biases from a dataset to another or from different cohorts

References

Code shared at: *https://github.com/TheoMoutakanni/TCC-EEG*

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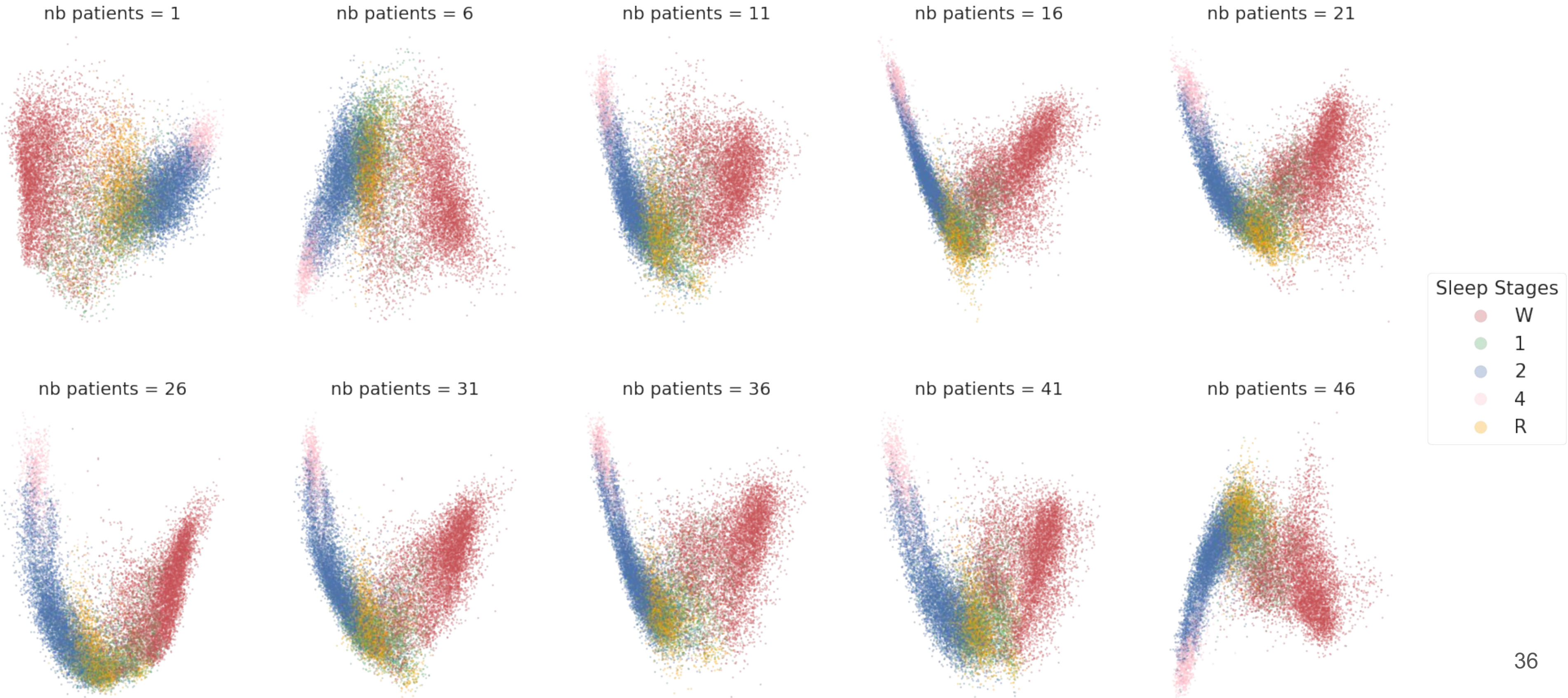
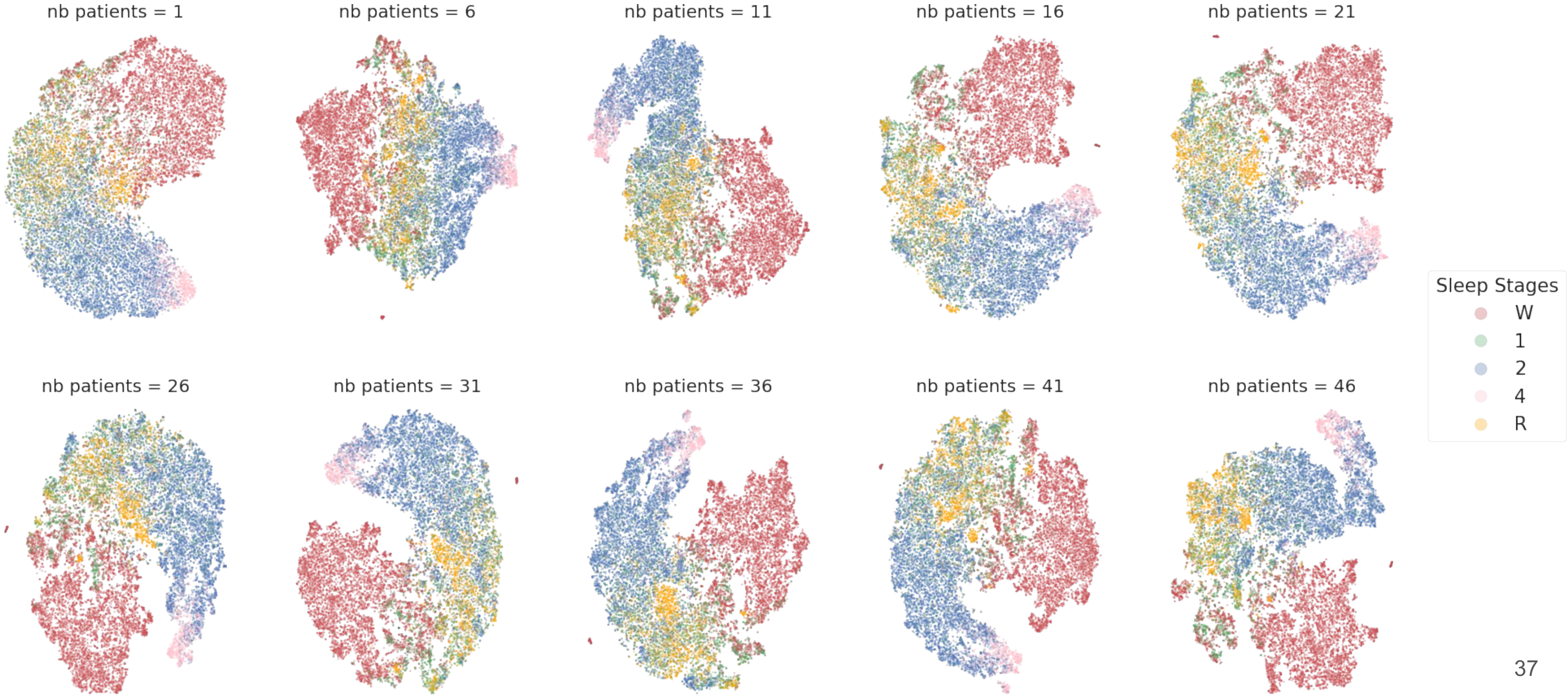
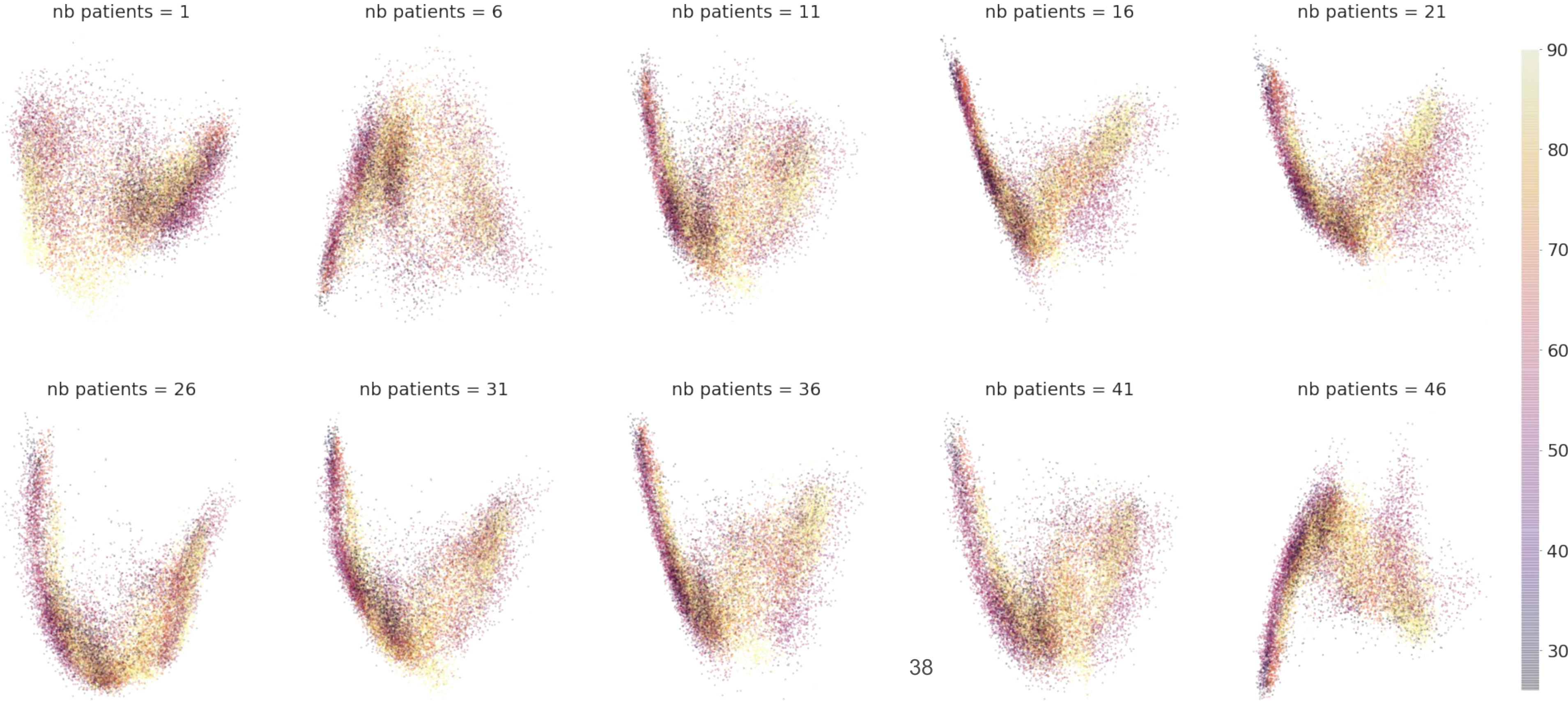
Evolution of Sleep Stages Embeddings - PCA



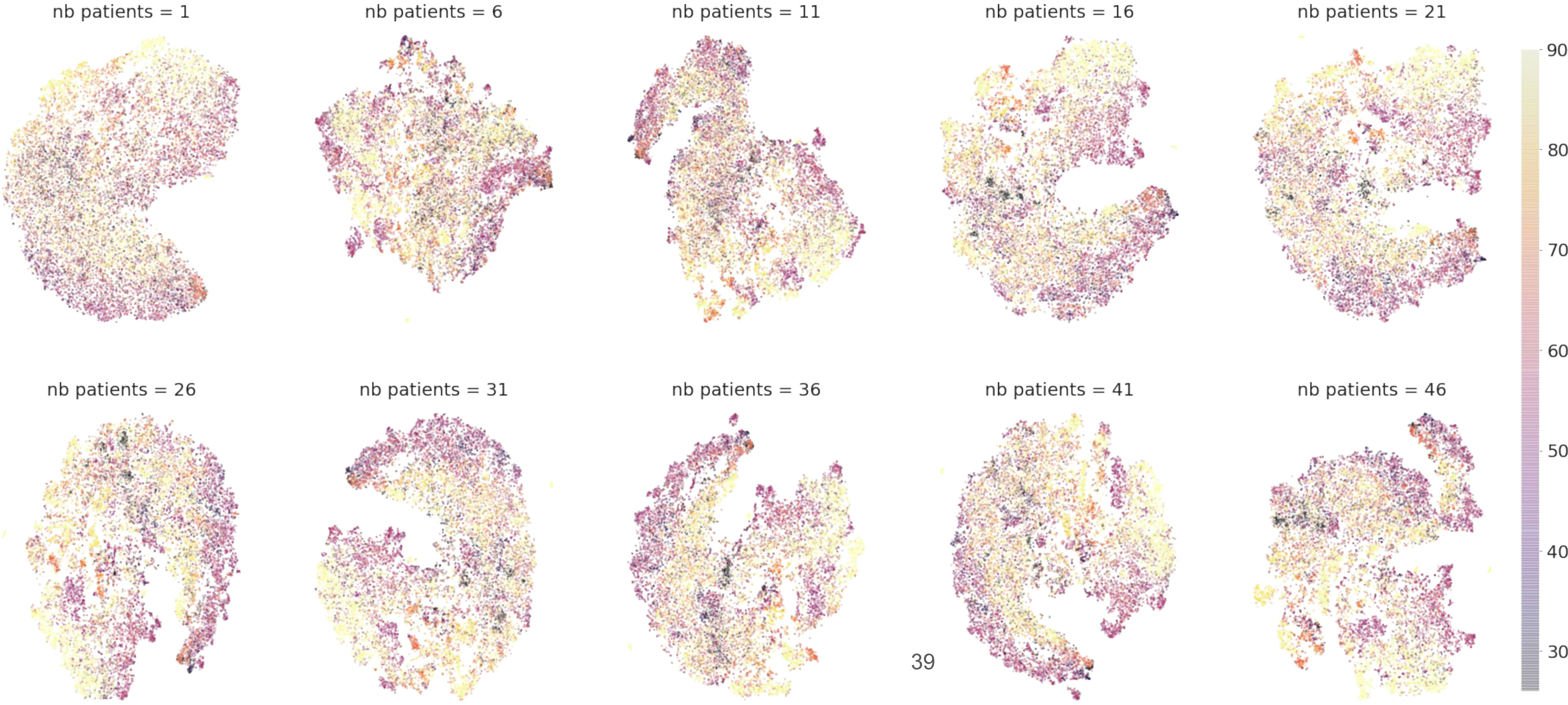
Evolution of Sleep Stages Embeddings - T-SNE



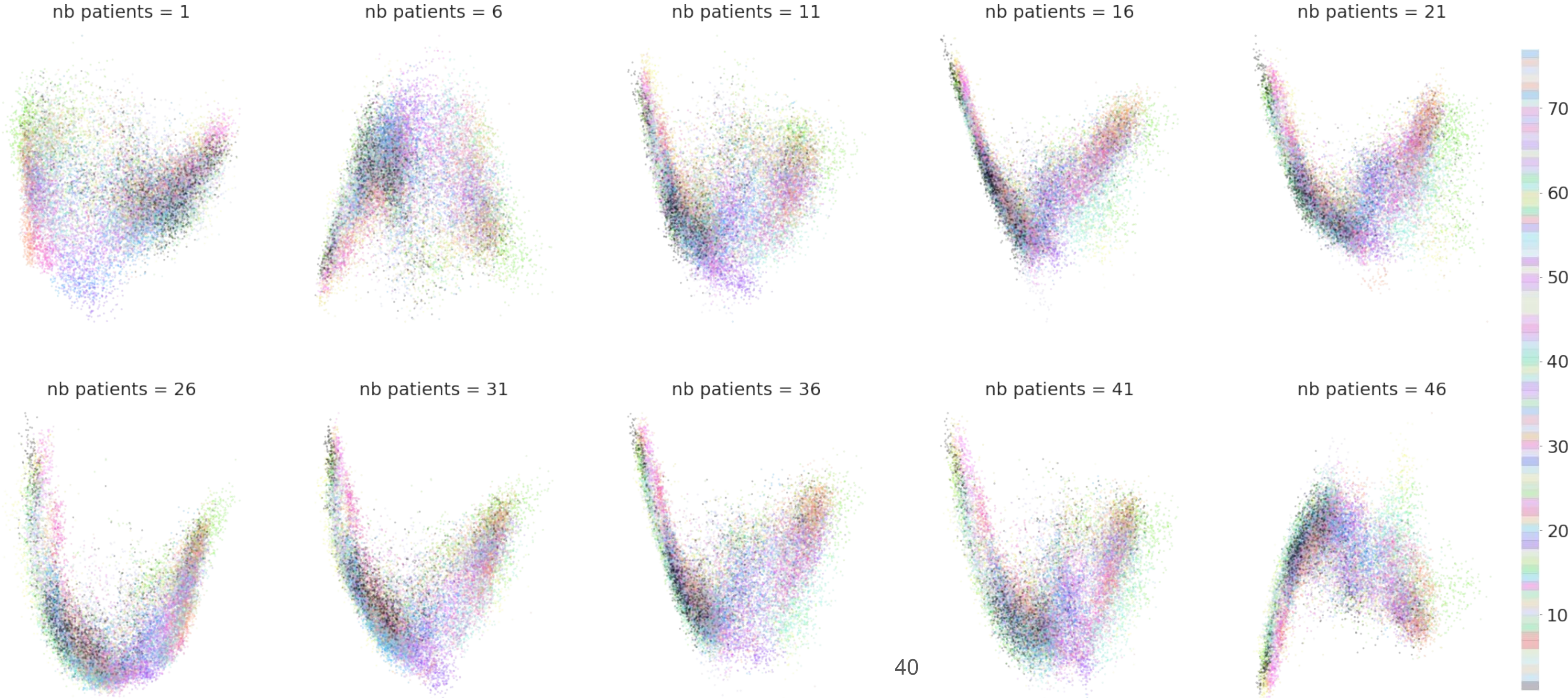
Evolution of Patient Ages Embeddings - PCA



Evolution of Patient Ages Embeddings - T-SNE



Evolution of Patient ID Embeddings - PCA



Evolution of Patient ID Embeddings - T-SNE