CSLP-AE: A Contrastive Split-Latent Permutation Autoencoder Framework for Zero-Shot Electroencephalography Signal Conversion

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Summary

Problem statement

- EEG data is noisy and variable across subjects, making it difficult to extract generalizable signals[1].
- A key aim in EEG analysis is to extract the underlying neural activation (content) while accounting for individual subject variability (style).
- We hypothesize that the auxiliary task of optimizing EEG signal conversion between tasks and subjects requires the learning of latent representations explicitly accounting for content and style.

Method

- A novel contrastive split-latent permutation autoencoder (CSLP-AE) framework is proposed that directly optimizes for EEG conversion.
- The split-latent representations are guided using contrastive learning to promote the latent splits to explicitly represent subject and task.

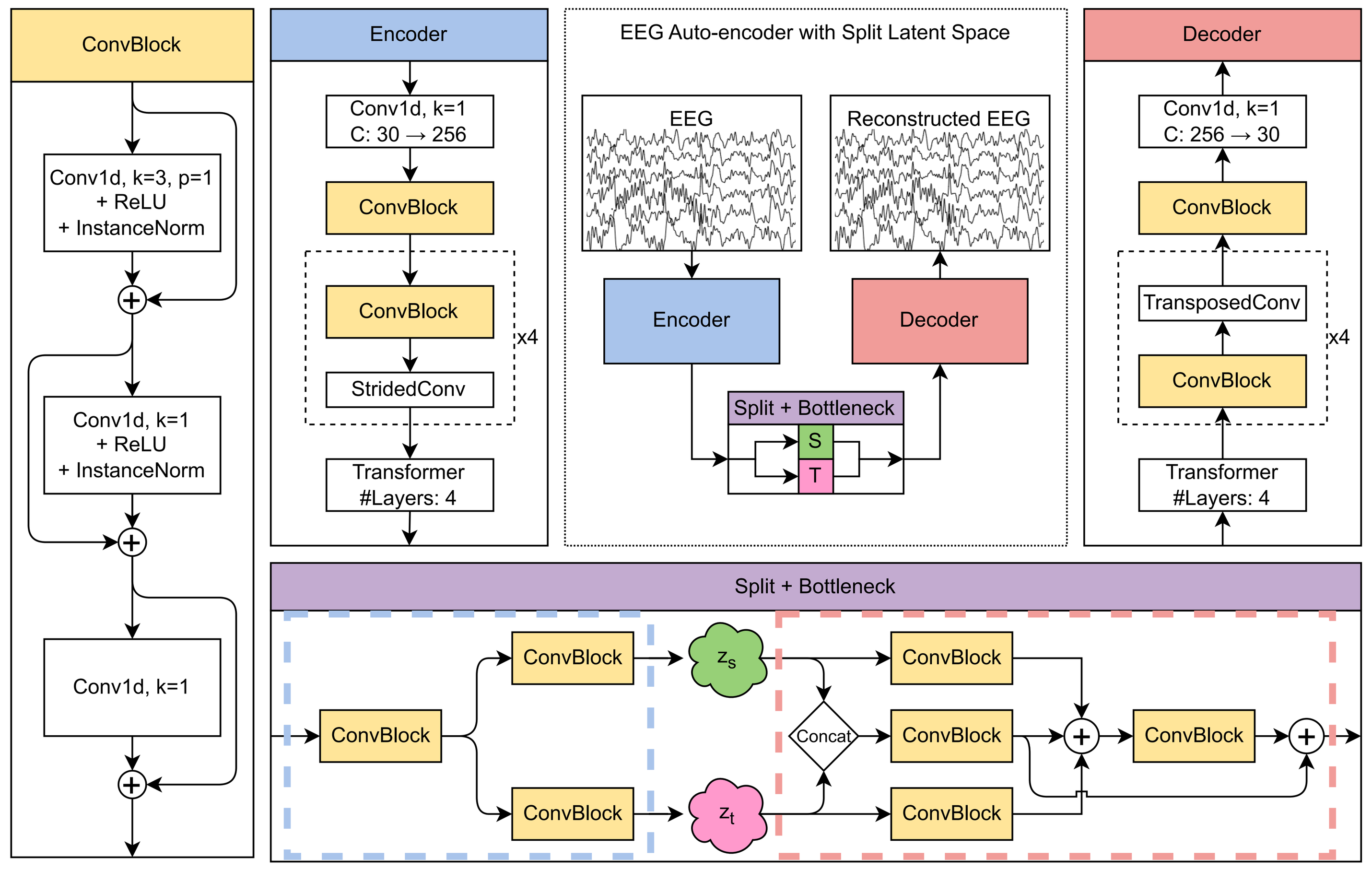
Main conclusions

- CSLP-AE provides favourable generalizable subject and task characterizations compared to supervised, unsupervised and self-supervised (contrastive) learning frameworks.
- The procedure also enables zero-shot conversion between unseen subjects.
- The proposed CSLP-AE provides a general framework for signal conversion and extraction of content (task activation) and style (subject variability) components.

CSLP-AE model architecture

CNN/Transformer-based autoencoder with split latent space:

- Latent space split into subject ($z^{\mathcal{S}}$) and task ($z^{\mathcal{T}}$) spaces.
- Consists of ConvBlocks and a Transformer bottleneck.



Dual-component loss objective balancing reconstruction and contrastive learning

$$L(\mathbf{X},\mathbf{Z}) = \left[L_{\mathrm{LP}}(\mathcal{T};\mathbf{X}^a,\mathbf{X}^b) + L_{\mathrm{LP}}(\mathcal{S};\mathbf{X}^a,\mathbf{X}^b)\right] + \alpha\left[L_{\mathrm{CLIP}}(\mathbf{Z}^{(\mathcal{S},a)},\mathbf{Z}^{(\mathcal{S},b)}) + L_{\mathrm{CLIP}}(\mathbf{Z}^{(\mathcal{T},a)},\mathbf{Z}^{(\mathcal{T},b)})\right]$$

- MSE-based latent permutation loss for both subject ($\mathcal{S}$) and task ($\mathcal{T}$) permutation.

$$L_{\mathrm{LP}}(\mathcal{L};\mathbf{X}^a,\mathbf{X}^b) = \frac{1}{N}\sum_{j=1}^{N}\left(\left\|\mathbf{X}_j^a - \hat{\mathbf{X}}_j^{(\mathcal{L},a)}\right\|_2^2 + \left\|\mathbf{X}_j^b - \hat{\mathbf{X}}_j^{(\mathcal{L},b)}\right\|_2^2\right)$$

- Contrastive learning using multi-class N-pair temperature-scaled symmetrical cross-entropy loss.

$$L_{\mathrm{NT\text{-}Xent}}(\mathbf{Z}',\mathbf{Z}'',k) = -\log\frac{\exp(\mathrm{sim}(\mathbf{z}_k',\mathbf{z}_k'')/\tau)}{\sum_{i=1}^{K}\mathbb{1}_{[i\neq k]}\exp(\mathrm{sim}(\mathbf{z}_k',\mathbf{z}_i'')/\tau)}$$

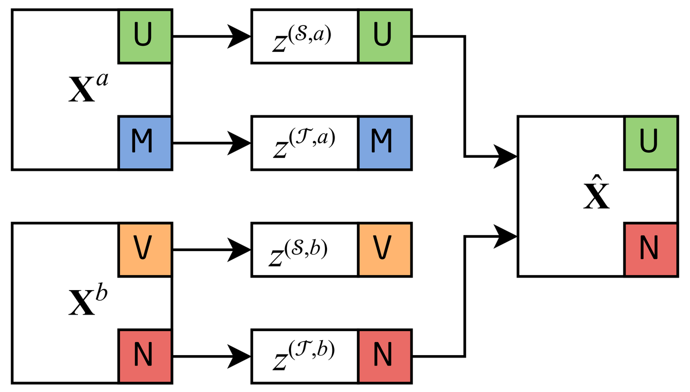
$$L_{\mathrm{CLIP}}(\mathbf{Z}^A,\mathbf{Z}^B) = \frac{1}{K}\sum_{k}^{K}\left(L_{\mathrm{NT\text{-}Xent}}(\mathbf{Z}^A,\mathbf{Z}^B,k) + L_{\mathrm{NT\text{-}Xent}}(\mathbf{Z}^B,\mathbf{Z}^A,k)\right)$$

- Parameter α controls the trade-off between optimizing for conversion or specialization of the latent space. Here, we focus on the case of $\alpha = 0$ (pure permutation loss, SLP-AE) and $\alpha = 1$ (equal contribution).

EEG conversion

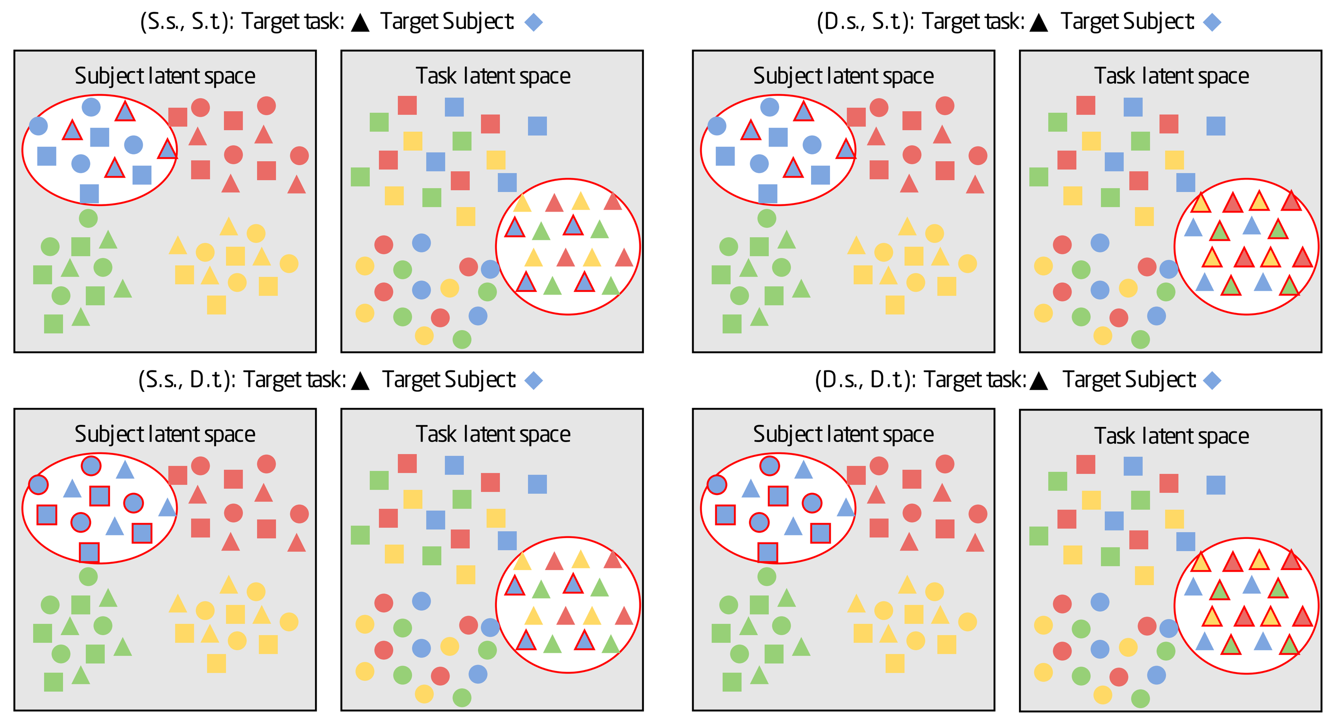
Ideal conversion

- Latent representations contain specialized information about subjects and tasks. Conversion is possible by switching respective latents from samples a and b.
- A successful conversion (illustrated for task conversion) is decoded from subject latent U and task latent N yielding a converted signal $\hat{\mathbf{X}}$ representing subject U performing task N.



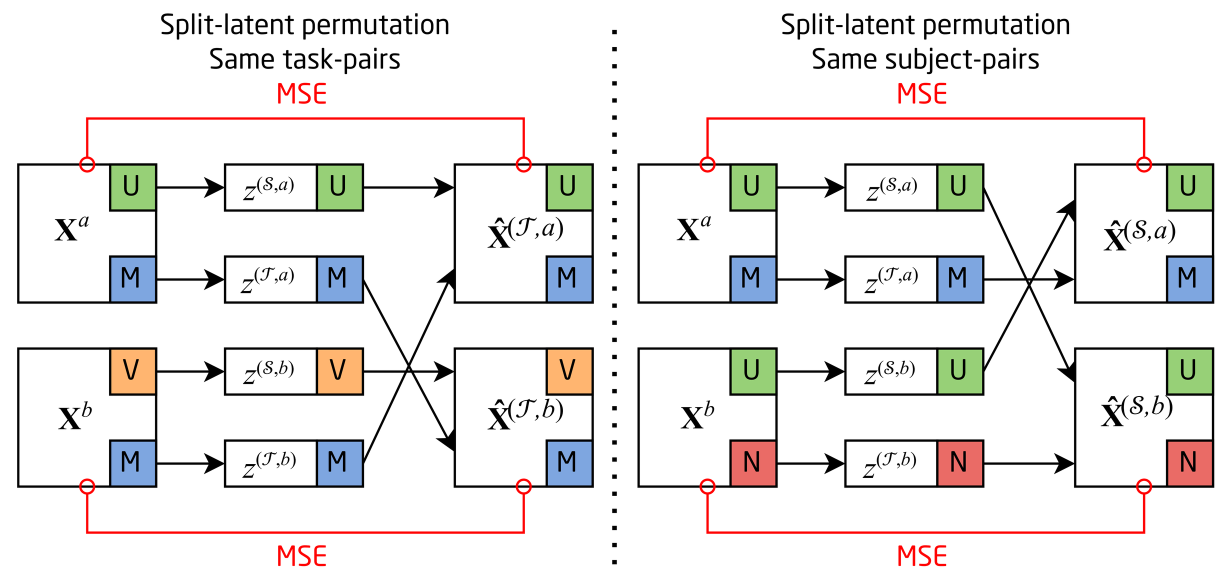
Conversion schemes

- We define four conversion schemes denoting which latent representations are used for the conversion.
  - S.s. and D.s. denote same and different subject, respectively.
  - S.t. and D.t. denote same and different task, respectively.
  - Subjects are shown as colors and tasks are shown as shapes.



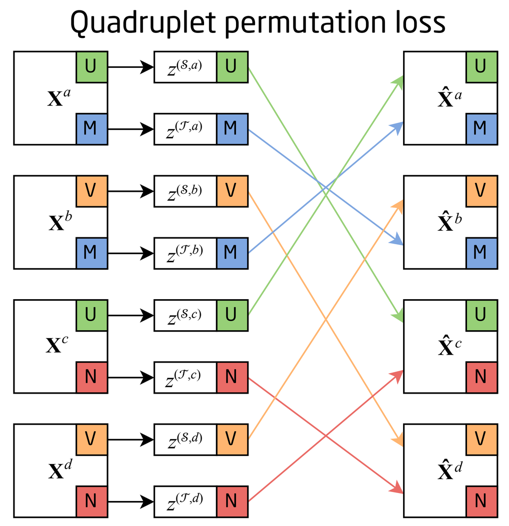
Split-latent permutation

- Sampling is performed such that each batch contains a pair of samples for each subject and for each task.
- For same-task pairs the task latent representations are swapped during training, while for same-subject pairs the subject latent representations are swapped.



Quadruplet permutation

- The batch is sampled to contain four samples each with a combination of tasks M and N and subjects U and V.
- No direct pathway from conversion (output) to sample (input).
- Quadruplet loss consists of four terms for each latent space.



$$L_{\mathrm{QP}}(\mathcal{L};\mathbf{X}^a,\mathbf{X}^b,\mathbf{X}^c,\mathbf{X}^d) = \frac{1}{4N}\sum_{j=1}^{N}\left(\left\|\mathbf{X}_j^a - \hat{\mathbf{X}}_j^{(\mathcal{L},a)}\right\|_2^2 + \left\|\mathbf{X}_j^b - \hat{\mathbf{X}}_j^{(\mathcal{L},b)}\right\|_2^2 + \left\|\mathbf{X}_j^c - \hat{\mathbf{X}}_j^{(\mathcal{L},c)}\right\|_2^2 + \left\|\mathbf{X}_j^d - \hat{\mathbf{X}}_j^{(\mathcal{L},d)}\right\|_2^2\right)$$

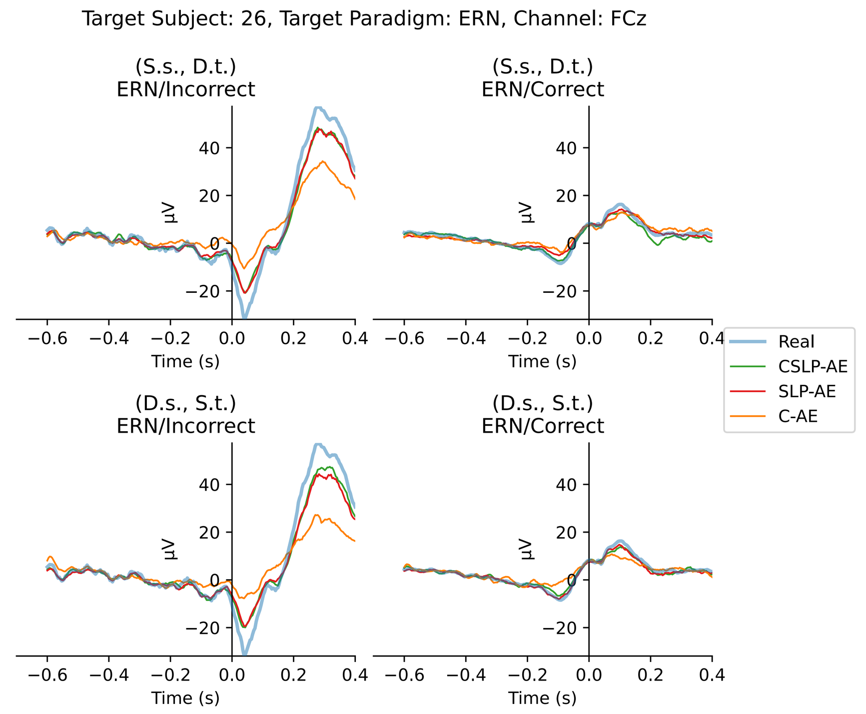
Experimental results

Superior performance in EEG analysis on unseen subjects

- High classification accuracies in both subject and task classification from EEG data.
- Effective zero-shot EEG conversion across various scenarios.
- Quadruplet permutation without contrastive learning obtains highest task classification accuracy and (D.s., D.t.) conversion.

Model	S.acc%	T⊢S.acc%	T.acc%	S⊢T.acc%	(S.s.,S.t.)	(D.s.,D.t.)	(D.s.,S.t.)	(S.s.,D.t.)
CSQLP-AE	76.10±0.76	43.36±0.46	46.17±0.25	76.47±0.46	1.91±0.08	6.90±0.05	3.43±0.05	3.94±0.16
SQLP-AE	69.26±0.50	46.86±1.35	44.80±0.77	69.60±0.25	**1.48±0.05**	**6.44±0.03**	**2.87±0.10**	**2.97±0.05**
CSQP-AE	73.04±0.50	35.89±0.42	44.83±0.21	71.56±0.64	6.20±0.12	7.00±0.08	6.60±0.11	6.59±0.10
SQP-AE	73.44±0.33	43.92±0.29	**48.88±0.13**	70.42±0.39	5.58±0.07	6.49±0.04	6.07±0.04	5.99±0.06
CSLP-AE	**80.32±0.28**	45.41±0.37	48.48±0.34	79.64±0.37	4.21±0.12	20.06±0.10	5.80±0.15	6.65±0.23
SLP-AE	74.63±0.74	47.23±0.31	47.00±0.32	74.70±0.73	3.82±0.04	19.92±0.10	6.12±0.09	5.02±0.08
C-AE	79.42±0.48	37.34±0.45	46.59±0.23	73.27±0.25	4.28±0.06	20.28±0.07	11.33±0.47	10.64±0.30
AE	60.68±0.16	31.62±0.27	31.43±0.28	61.08±0.38	3.54±0.12	20.82±0.07	11.20±0.32	10.74±0.48
CL	78.82±0.46	37.65±0.54	45.36±0.37	71.70±0.55	-	-	-	-
CE	79.25±0.37	35.52±0.38	45.22±0.23	64.73±0.44	-	-	-	-
CE(t)	-	-	45.80±0.24	44.27±0.59	-	-	-	-
CSP	-	-	35.22±0.11	69.89±0.10	-	-	-	-

Generalizable EEG conversion for unseen subjects

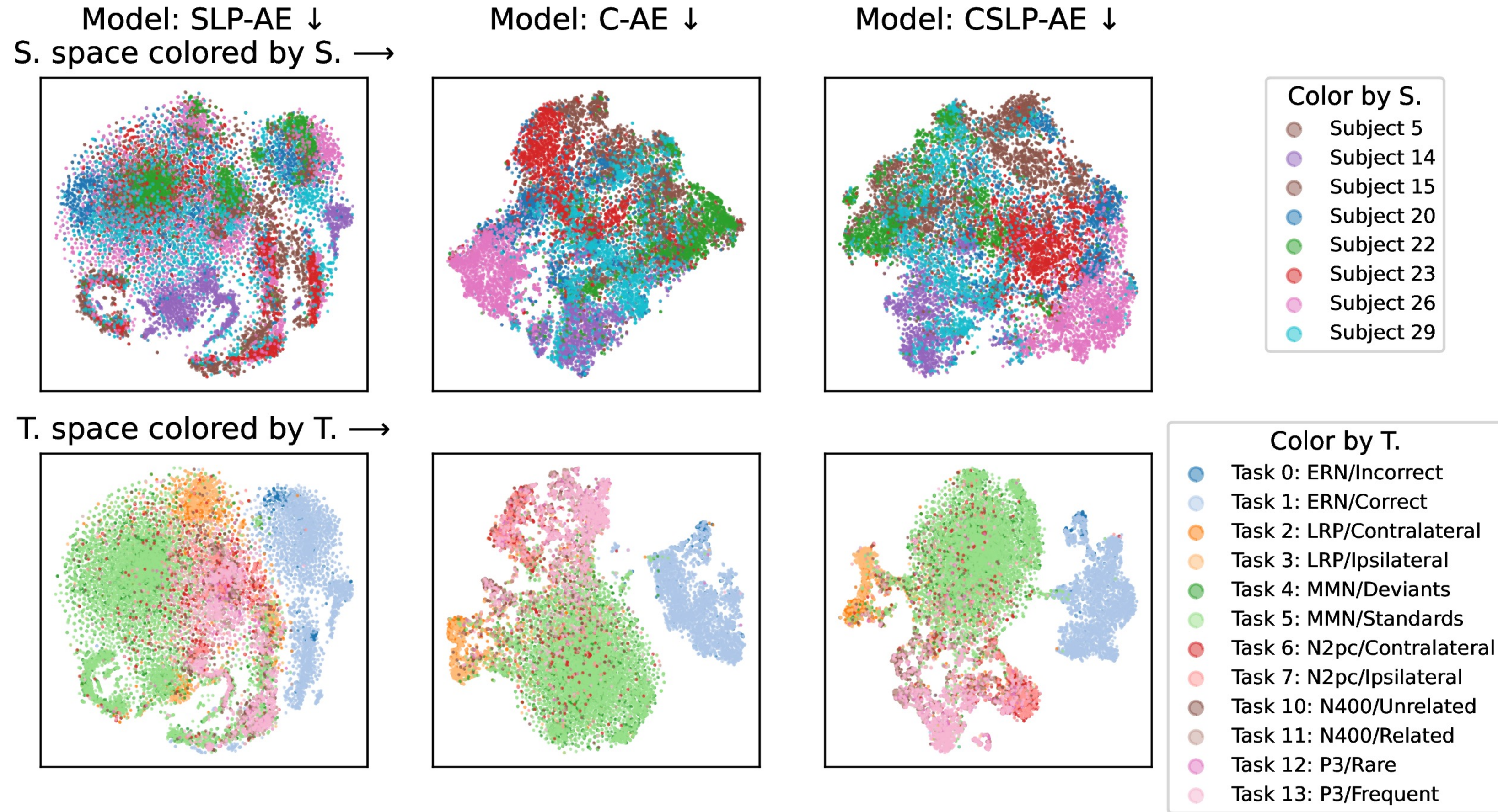


Competitive out-of-domain performance with only slight degradation in continuous domains

Model	EEGMMI	SleepEDFx
CSLP-AE (this work)	64.28±0.16	75.16±0.95
C-AE (this work)	61.89±0.41	75.16±0.86
SLP-AE (this work)	57.93±0.56	70.59±1.18
EEGNet (Wang et al.[2])	65.07	-
f-Ctrans (Xie et al.[3])	64.22	-
CNN (Dose et al.[4])	58.59	-
XSleepNet2 (Phan et al.[5])	-	84
Zhu et al.[6]	-	82.8
SeqSleepNet (Phan et al.[7])	-	82.6
SleepTransformer (Phan et al.[8])	-	81.4
AttnSleep (Eldele et al.[9])	-	81.3
SleepEEGNet (Mousavi et al.[10])	-	80

Contrastive learning is required for specialized latent spaces

- Structural encoding in duplicated latent spaces.
- Quadruplet permutation loss is an alternative to contrastive learning.



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