BIOT: Biosignal Transformer for Cross-data Learning in the Wild

NeurIPS 2023, New Orleans, LA

Chaoqi Yang[1], M. Brandon Westover[2,3], Jimeng Sun[1]

[1]*University of Illinois Urbana-Champaign*

[2]*Harvard Medical School*

[3]*Beth Israel Deaconess Medical Center*

Motivation

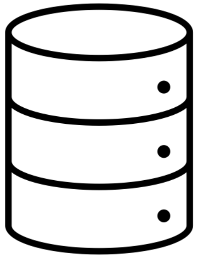
Same contexts, different formats, how to combine them in model training?

- variable length, different sampling rates, different channels

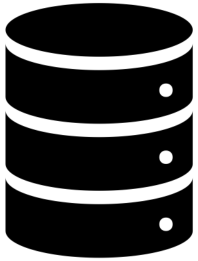
Previously

separate models for training/test

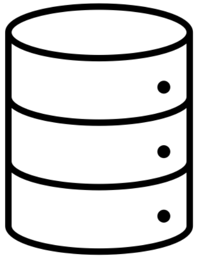
Name: MGH sleep EEG
Tasks: Sleep staging
Duration: 30 seconds
Rate: 500 Hz
Channels: 16 channels



Name: Harvard seizure EEG
Tasks: Seizure detection
Duration: 10 seconds
Rate: 250 Hz
Channels: 8 channels

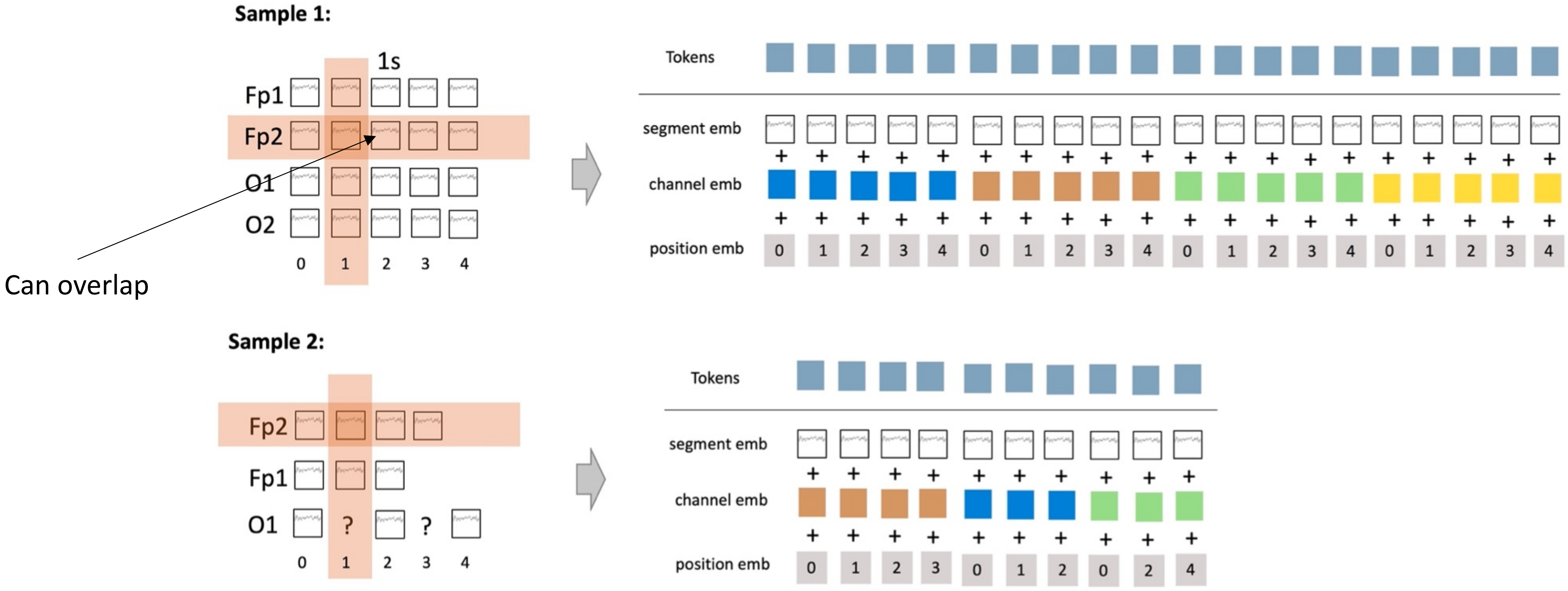


Name: SleepEDF EEG data
Tasks: Sleep staging
Duration: 10 seconds
Rate: 256 Hz
Channels: 16 channels



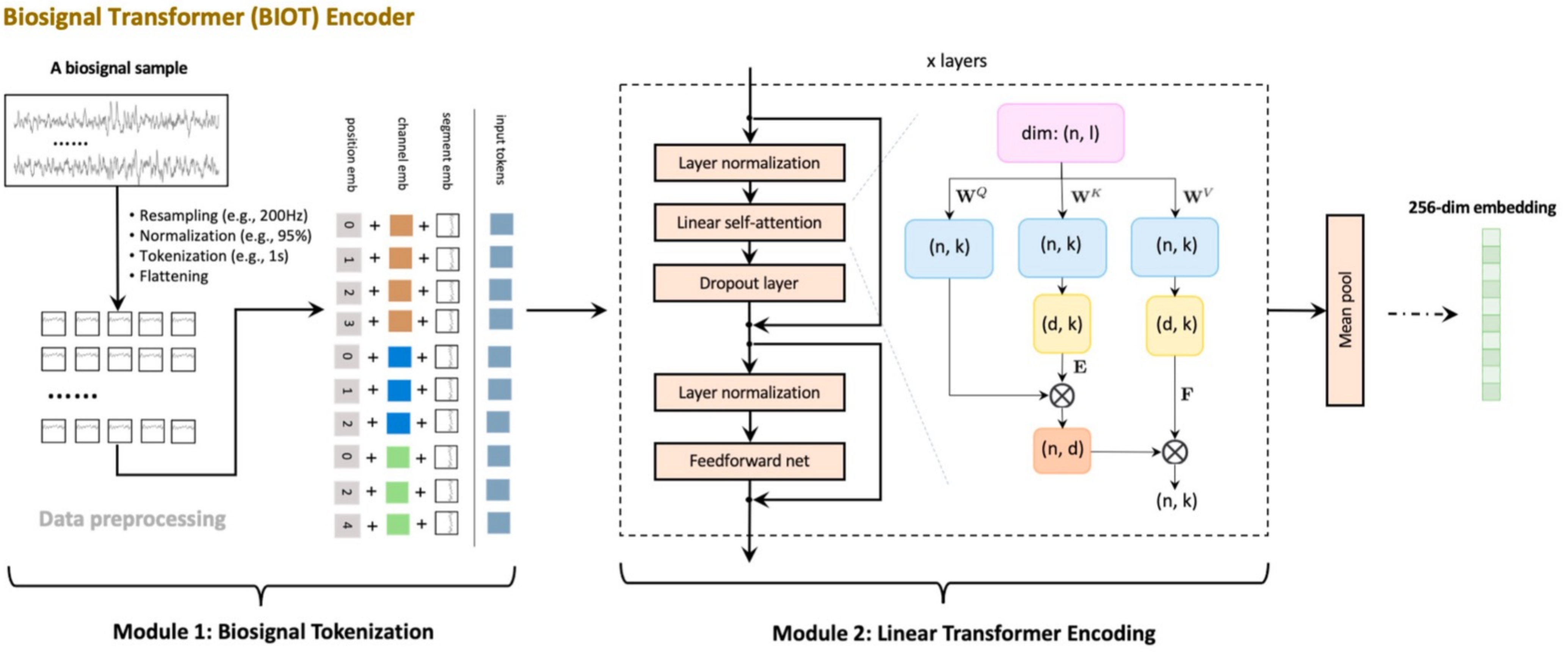
BIOT: A unified biosignal transformer encoder

We transform different biosignals into consistent sentence structures.



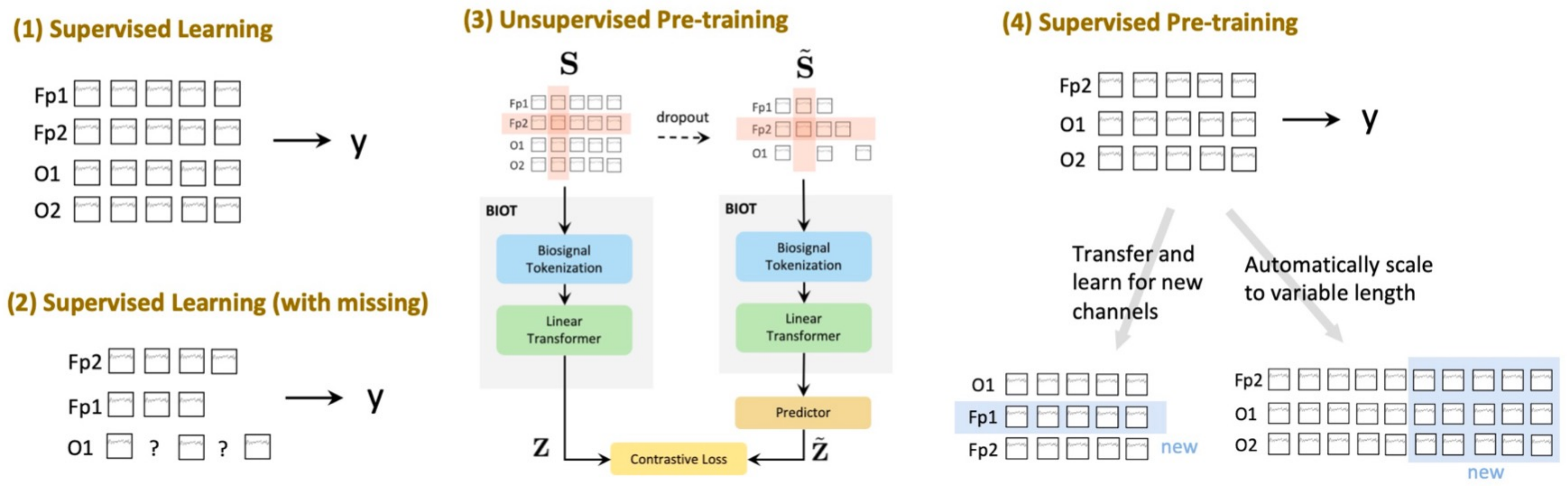
BIOT: A unified biosignal transformer encoder

Sentence structure + Linear complexity transformer.



BIOT: A unified biosignal transformer encoder

The BIOT model can be used in various settings.



Experiments

Datasets: EEG, ECG, HAR

Settings: supervised learning, unsupervised pre-training and then finetuning.

Datasets	Type (subtype)	# Recordings	Rate	Channels	Duration	# Sample	Tasks
SHHS	EEG (sleep)	5,445	125Hz	C3-A2, C4-A1	30 seconds	5,093,522	Unsupervised pre-training
PREST	EEG (resting)	6,478	200Hz	16 montages	10 seconds	5,110,992	Unsupervised pre-training
Cardiology	ECG	21,264	500Hz	6 or 12 ECG leads	10 seconds	495,970	Unsupervised pre-training
CHB-MIT	EEG (resting)	686	256Hz	16 montages	10 seconds	326,993	Binary (seizure or not)
IIIC Seizure	EEG (resting)	2,702	200Hz	16 montages	10 seconds	165,309	Multi-class (6 seizure types)
TUAB	EEG (unknown)	2,339	256Hz	16 montages	10 seconds	409,455	Binary (abnormal or not)
TUEV	EEG (sleep and resting)	11,914	256Hz	16 montages	5 seconds	112,491	Multi-class (6 event types)
PTB-XL	ECG	21,911	500Hz	12 ECG leads	5 seconds	65,511	Binary (arrhythmias or not)
HAR	Wearable sensors	10,299	50Hz	9 coordinates	2.56 seconds	10,299	Multi-class (6 actions)

Results (only show CHB-MIT, IIIC-seizure tables)

Conclusions:

- BIOT performs better than previous biosignal classification models.
- BIOT pre-training from other datasets can benefit the supervised tasks on new datasets.

Models	CHB-MIT (seizure detection)			IIIC Seizure (seizure type classification)		
	Balanced Acc.	AUC-PR	AUROC	Balanced Acc.	Cohen's Kappa	Weighted F1
SPaRCNet (Jing et al., 2023)	0.5876 ± 0.0191	0.1247 ± 0.0119	0.8143 ± 0.0148	0.5546 ± 0.0161	0.4679 ± 0.0228	0.5569 ± 0.0184
ContraWR (Yang et al., 2021)	0.6344 ± 0.0002	0.2264 ± 0.0174	0.8097 ± 0.0114	0.5519 ± 0.0058	0.4623 ± 0.0148	0.5486 ± 0.0137
CNN-Transformer (Peh et al., 2022)	0.6389 ± 0.0067	0.2479 ± 0.0227	**0.8662** ± 0.0082	0.5476 ± 0.0103	0.4481 ± 0.0139	0.5346 ± 0.0127
FFCL (Li et al., 2022)	0.6262 ± 0.0104	0.2049 ± 0.0346	0.8271 ± 0.0051	0.5617 ± 0.0117	0.4704 ± 0.0130	0.5617 ± 0.0171
ST-Transformer (Song et al., 2021)	0.5915 ± 0.0195	0.1422 ± 0.0094	0.8237 ± 0.0491	0.5423 ± 0.0056	0.4492 ± 0.0056	0.5440 ± 0.0014
(Vanilla) BIOT	**0.6640 ± 0.0037**	**0.2573 ± 0.0088**	0.8646 ± 0.0030	**0.5762 ± 0.0034**	**0.4932 ± 0.0046**	**0.5773 ± 0.0031**
Pretrained BIOT (PREST)	0.6942 ± 0.0431	0.3072 ± 0.1187	0.8679 ± 0.0106	0.5787 ± 0.0066	0.4980 ± 0.0054	0.5828 ± 0.0049
Pretrained BIOT (PREST+SHHS)	0.6788 ± 0.0036	0.3090 ± 0.0003	0.8752 ± 0.0022	$\boxed{0.5800 \pm 0.0004}$	$\boxed{0.5040 \pm 0.0041}$	$\boxed{0.5878 \pm 0.0015}$
Pretrained BIOT (6 EEG datasets)	$\boxed{0.7068 \pm 0.0457}$	$\boxed{0.3277 \pm 0.0460}$	$\boxed{0.8761 \pm 0.0284}$	0.5779 ± 0.0087	0.4949 ± 0.0103	0.5737 ± 0.0088

1. All models use the same training set of the task, while the pre-trained BIOT models are initially pre-trained on other data sources (see Section 3.4, 3.6).
2. **Bold** for the best model (trained from scratch) and $\boxed{\text{box}}$ for the best pre-trained models. Running time comparison is in Appendix C.4.

BIOT: Biosignal Transformer for Cross-data Learning in the Wild

NeurIPS 2023, New Orleans, LA

Chaoqi Yang[1], M. Brandon Westover[2,3], Jimeng Sun[1]

[1]*University of Illinois Urbana-Champaign*

[2]*Harvard Medical School*

[3]*Beth Israel Deaconess Medical Center*

Thanks for your attention!

Chaoqi Yang
chaoqiy2@illinois.edu
https://github.com/ycq091044/BIOT