Towards the use of self-supervised learning for EEG analysis

victor.delvigne@imt-nord-europe.fr - victor.delvigne@umons.ac.be
http://vdelv.github.io

IMT Nord Europe
École Mines-Télécom
IMT-Université de Lille

ISIA Lab
INFORMATION, SIGNAL, ARTIFICIAL INTELLIGENCE

UCF
Center for Research in Computer Vision
UNIVERSITY OF CENTRAL FLORIDA

Context

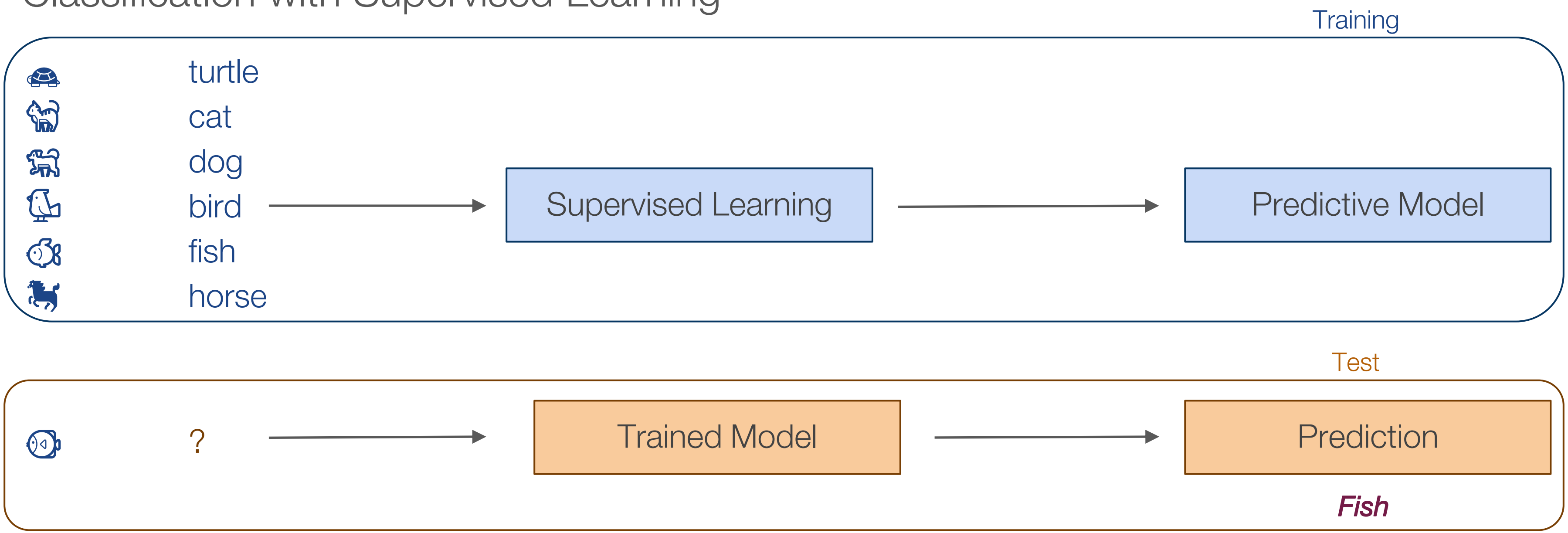
- Joint PhD
  IMT Nord Europe (FR) - University of Mons (BE)

- Pluridisciplinary research project
  Studying attention state in VR (Virtual Reality) with biomedical signals

- Collaboration with University of Central Florida
  Center for Research in Computer Vision (CRCV)

Introduction

Classification with Supervised Learning



Introduction

Challenges & Limitation of Supervised Learning

- Learning with fewer labeled samples?
- Learning to reason?

(a) Texture image		(b) Content image		(c) Texture-shape cue conflict	
81.4%	**Indian elephant**	71.1%	**tabby cat**	63.9%	**Indian elephant**
10.3%	indri	17.3%	grey fox	26.4%	indri
8.2%	black swan	3.3%	Siamese cat	9.6%	black swan

Image taken from Geirhos, Robert, et al. "ImageNet-trained CNNs are biased towards texture; increasing shape bias improves accuracy and robustness." ICLR 2019.

Introduction

Challenges & Limitation of Supervised Learning

- Learning with fewer labeled samples?
- Learning to reason?

> "How do human and animal babies learn?"
>
> Y. Le Cun (Facebook AI Research)

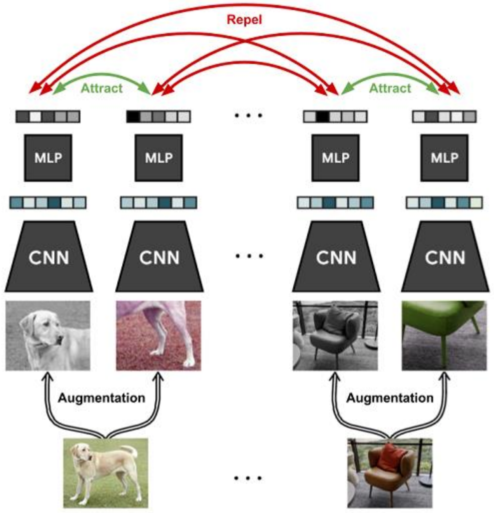
(a) Texture image		(b) Content image		(c) Texture-shape cue conflict	
81.4%	**Indian elephant**	71.1%	**tabby cat**	63.9%	**Indian elephant**
10.3%	indri	17.3%	grey fox	26.4%	indri
8.2%	black swan	3.3%	Siamese cat	9.6%	black swan

Image taken from Geirhos, Robert, et al. "ImageNet-trained CNNs are biased towards texture; increasing shape bias improves accuracy and robustness." ICLR 2019.

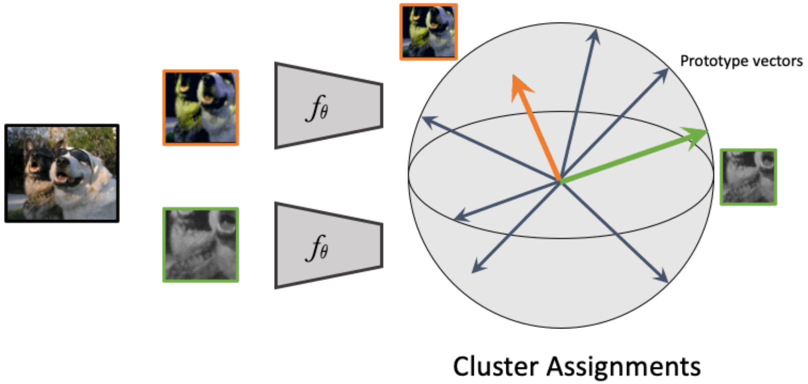
Introduction

Self-Supervised Learning

”Learning how to process instead of how to classify images”



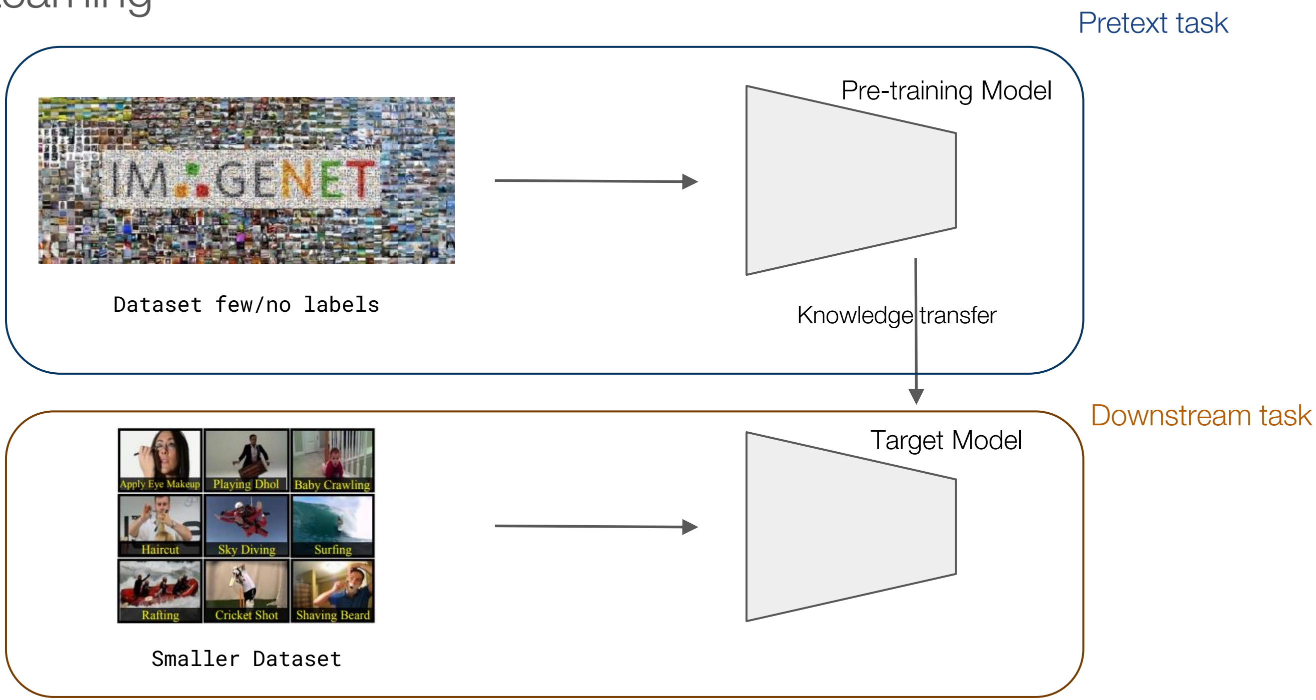
SimCLR - Google ICML 2021.



SwAV - Facebook Neurips 2020.

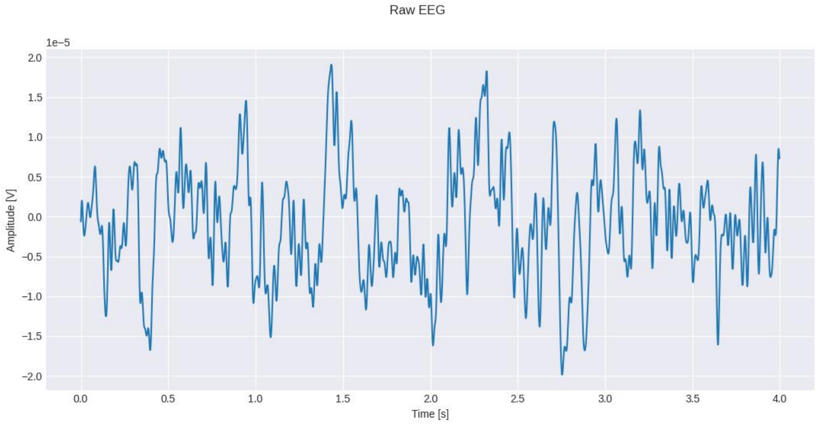
Introduction

Self-Supervised Learning



Deep Learning & EEG

- Electrical activity of the brain
- Temporal series
- Electrodes placed on the scalp



Example of signal from a single electrode.

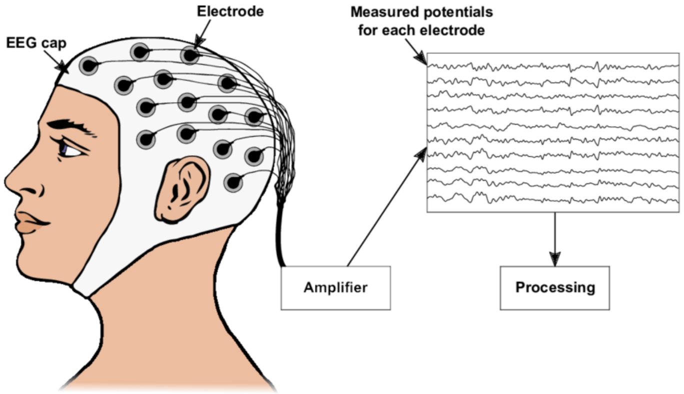
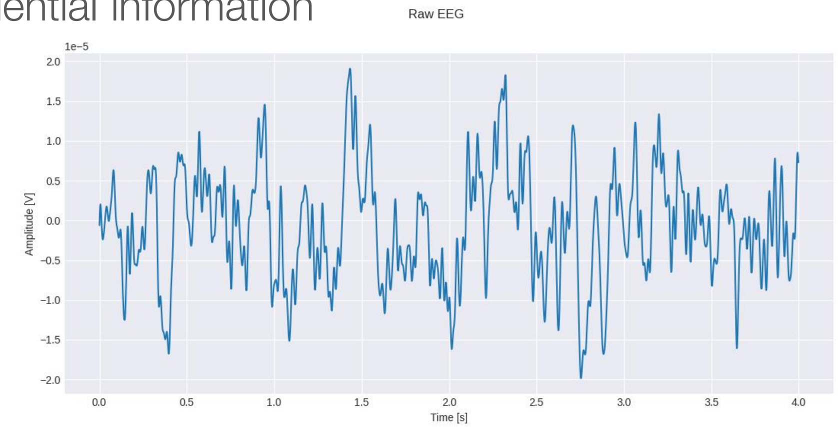


Image taken from link.

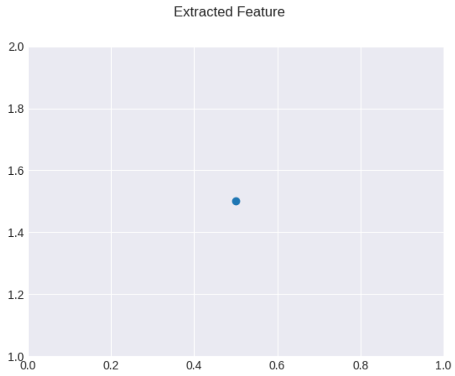
Deep Learning & EEG

Extracting features from EEG representing

- Statistical information
- Temporal information
- Frequential information
- etc



Example of signal from a single electrode.



Example of extracted feature of signal from a single electrode.

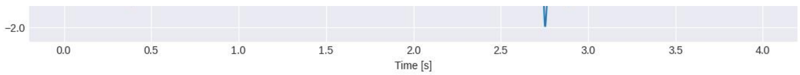
Deep Learning & EEG

Extracting features from EEG representing

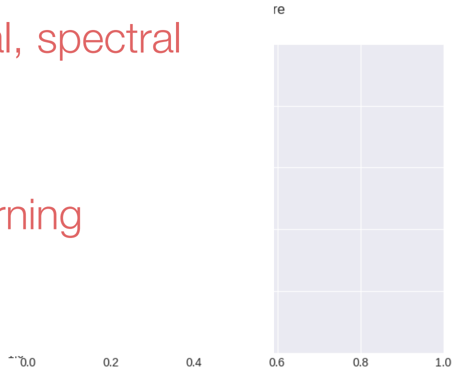
- Statisti
- Tempo
- Freque
- etc

Limitations:

- Although from scientific knowledge, not generalisable
- Not taking into account all the signal aspect (spatial, spectral and temporal)
- Not working for each paradigm
- … seems naïve with the advanced in Machine Learning



Example of signal from a single electrode.



Example of extracted feature of signal from a single electrode.

Deep Learning & EEG

Several models consider the raw signals instead of extracted features based on

- CNN
- RNN
- GANs
- Autoencoders
- etc

… but trained in most of the case with supervised learning

Deep Learning & EEG

Several models consider the raw signals instead of extracted features based on

- CNN
- RNN
- GANs
- Autoen
- etc

… but traine

Limitations:

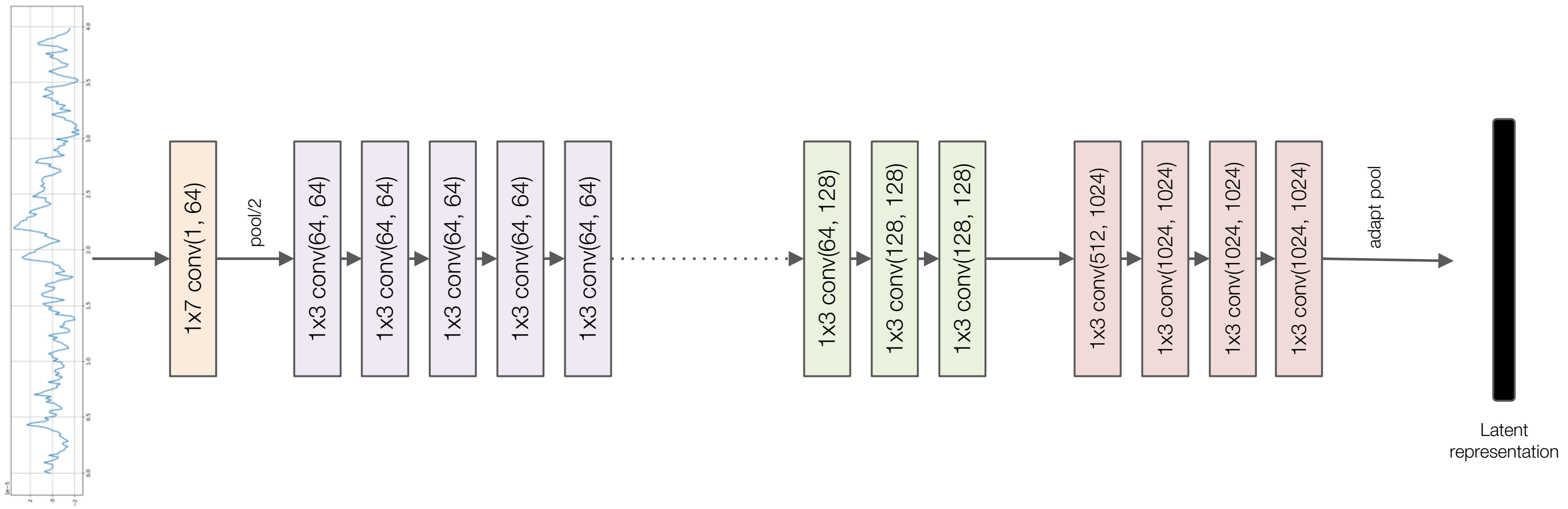
- Knowledge not transferable from a method to another
- Not working with smaller dataset
- No way to ensure that the model is actually learning, which is a **necessity** (cf. issues with Pneumonia) in medical domain
- Huge set of data unused (systematic EEG recordings)

Self-Supervised learning approach for EEG

- Considering a general pipeline reusable for every type of EEG segments
- Trained on a huge corpus of EEG signals
- Trained to proceed specific self-supervised tasks
    - Time dependent
    - Frequency dependent
    - Spatial dependent
- Helping for classification task on smaller datasets

Self-Supervised learning approach for EEG

1. Considering a general pipeline reusable for every type of EEG segments



VGG inspired approach for the backone feature extractor.

Self-Supervised learning approach for EEG

2. Trained on a huge corpus of EEG signals

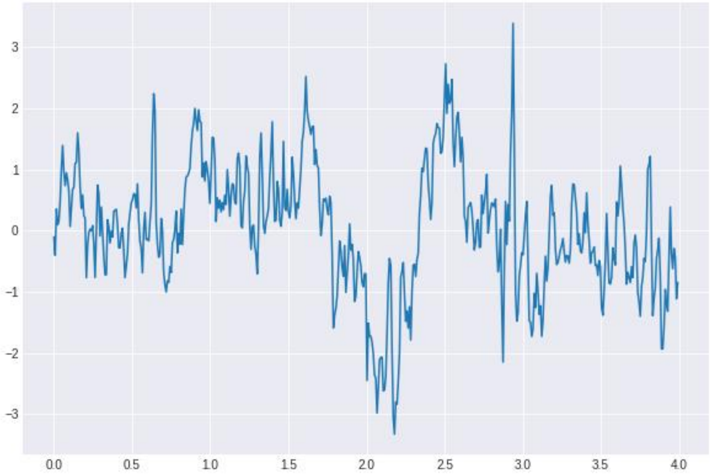
- “The Temple University Hospital EEG Data Corpus”[1] with set of unlabeled/poorly labeled signals of **more than 1 years** of recordings in total
- Different types of events recorded listed on the dataset, e.g. seizure, noise, etc.
- Corpus very diverse covering a lot of possible situations/context

[1]Obeid, Iyad, and Joseph Picone. "The temple university hospital EEG data corpus." Frontiers in neuroscience 10 (2016): 196.

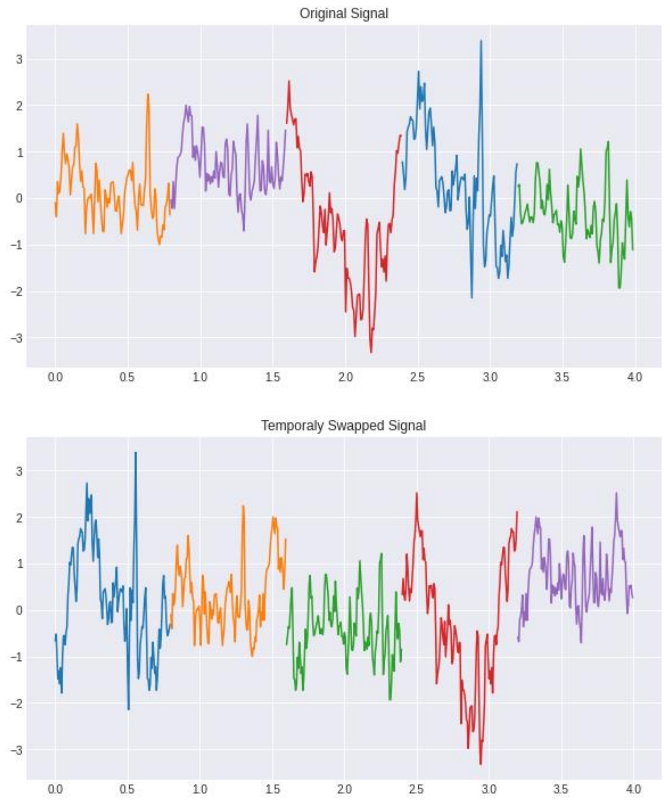
Self-Supervised learning approach for EEG

3. Trained to proceed specific self-supervised tasks

Time dependent - *Jigsaw EEG*



Self-Supervised learning approach for EEG



Aims at reconstructing the signal

- Finding the right order
  (i.e. one combination correspond to one of the possible combinations)
  ⇒ Cross Entropy Loss

- Promoting the retrieval of sequence trend
  e.g. if the swap order is *[3, 0, 4, 2, 1]*, predicting is a *[0, 4, 2, 1, 3]* is a similar sequence.
  ⇒ Similarity Loss

Self-Supervised learning approach for EEG

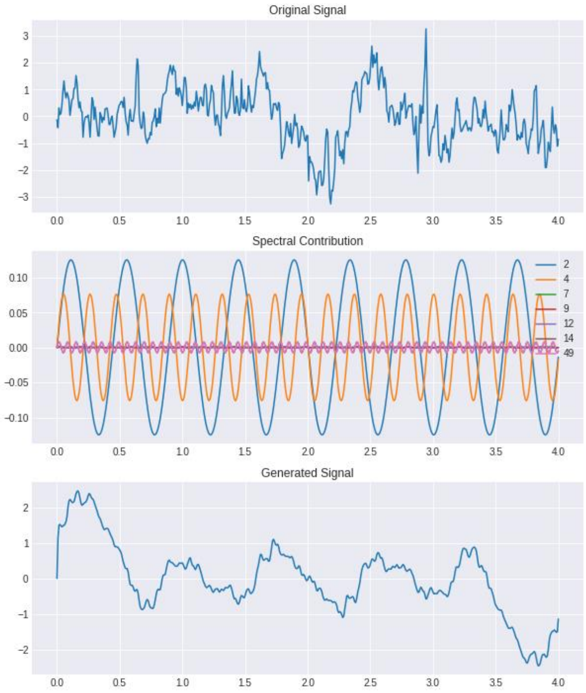
3. Trained to proceed specific self-supervised tasks

Frequency dependent

- Attract signals and its corresponding spectral generated from the same electrode

- Repeal signals and reconstruction of same electrodes signals from other batches

⇒ Contrastive Loss



Self-Supervised learning approach for EEG

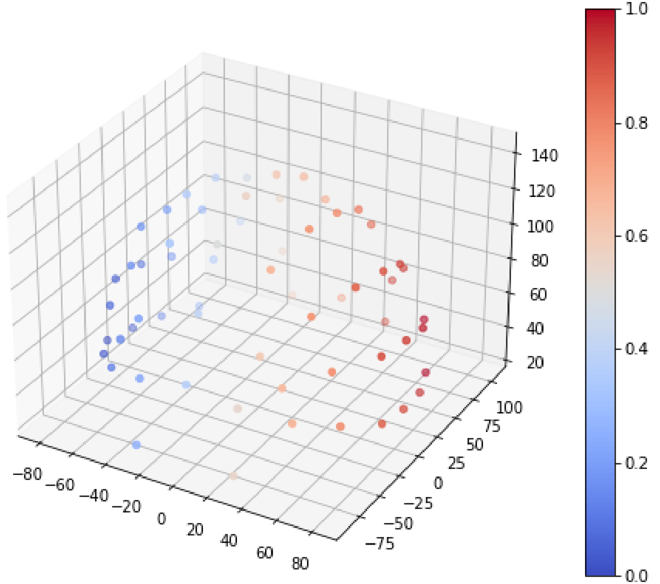
3. Trained to proceed specific self-supervised tasks

Spatial dependent

- Attract neighbors signals proportionally to the electrodes distance

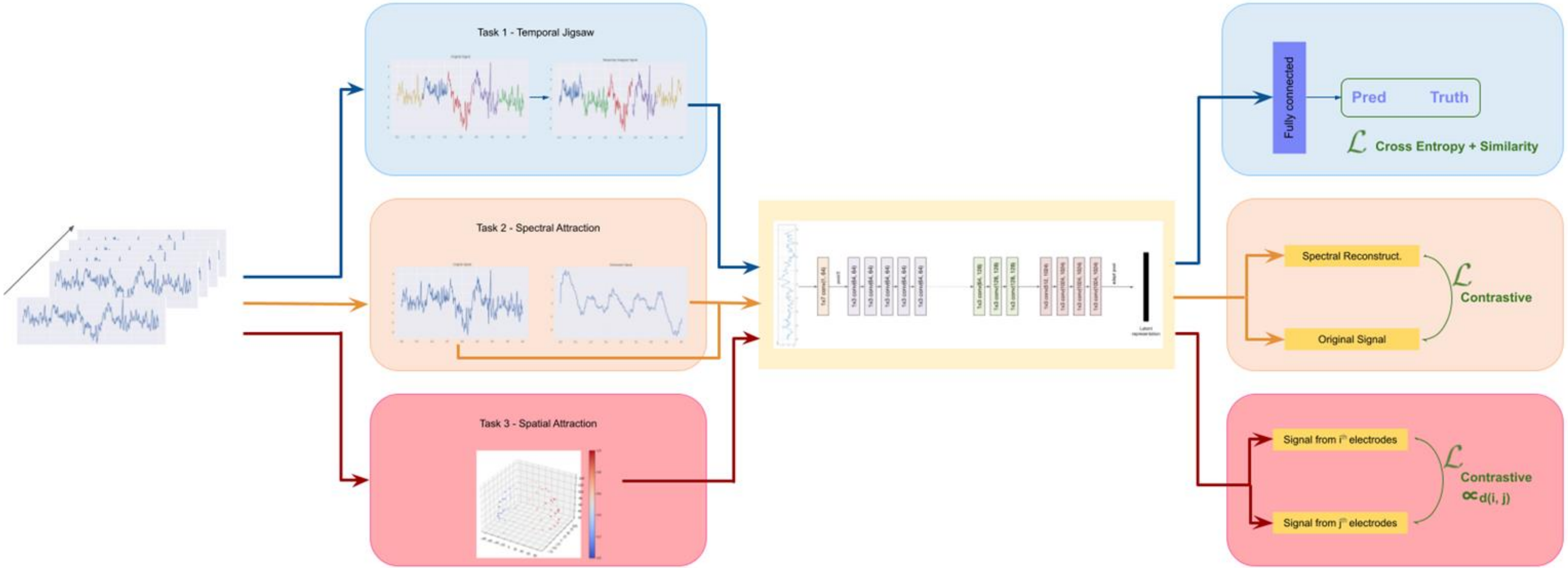
- Repeal signals from other batches with the opposite process

⇒ Contrastive Loss



Self-Supervised learning approach for EEG

In brief



Self-Supervised learning approach for EEG

4. Helping for classification task on smaller datasets

After focusing on the pretext tasks, the downstream tasks will be tested on

- Classification of motor movements
  - BCI dataset (9 participants / ~ 6 hours)
  - MMI dataset (109 participants / ~ 40 hours)
- Sleeping stage classification
  - SSC dataset (78 participants / ~ 1500 hours)

Self-Supervised learning approach for EEG

Results

Dataset	Supervised Standalone	Dual Supervised and Self-Supervised with TUEG			
		Temporal	Spectral	Spatial	Combined
BCI 4 classes	32.81/1.26	41.54/3.7	42.82/4.1	39.50/5.1	**43.96/5.2**
MMI 3 classes	66.92/5.68	70.66/7.04	72.54/2.5	68.03/7.68	**74.42/4.9**
SSC 5 classes	38.59/8.34	42.80/6.62	43.37/6.39	40.72/6.08	**45.28/6.04**

Self-Supervised learning approach for EEG

Discussion

- Self-Supervised Learning promotes better results
- Spatial tasks seems to perform poorly compared to other tasks
- Knowledge transfer from a dataset to another

Conclusion

- Baseline and preliminary works
- *“Hot Topic”* for the moment
- Existing methods in computer vision can be transposed
- Other tasks could also be considered

References

1. Geirhos, R., Rubisch, P., Michaelis, C., Bethge, M., Wichmann, F. A., & Brendel, W. (2018). ImageNet-trained CNNs are biased towards texture; increasing shape bias improves accuracy and robustness. arXiv preprint arXiv:1811.12231.
2. Chen, Ting, et al. "A simple framework for contrastive learning of visual representations." *International conference on machine learning*. PMLR, 2020.
3. Caron, Mathilde, et al. "Unsupervised learning of visual features by contrasting cluster assignments." *Advances in Neural Information Processing Systems* 33 (2020): 9912-9924.
4. Obeid, I., & Picone, J. (2016). The temple university hospital EEG data corpus. *Frontiers in neuroscience*, *10*, 196.
5. Schneider, S., Baevski, A., Collobert, R., & Auli, M. (2019). wav2vec: Unsupervised pre-training for speech recognition. *arXiv preprint arXiv:1904.05862*.
6. Banville, Hubert, et al. "Uncovering the structure of clinical EEG signals with self-supervised learning." *Journal of Neural Engineering* 18.4 (2021): 046020.
7. Hsu, Wei-Ning, et al. "Hubert: Self-supervised speech representation learning by masked prediction of hidden units." *IEEE/ACM Transactions on Audio, Speech, and Language Processing* 29 (2021): 3451-3460.

Thank you for your attention !

Towards the use of self-supervised learning for EEG analysis

victor.delvigne@imt-nord-europe.fr - victor.delvigne@umons.ac.be
http://vdelv.github.io

IMT Nord Europe
École Mines-Télécom
IMT-Université de Lille

ISIA Lab
INFORMATION, SIGNAL, ARTIFICIAL INTELLIGENCE

UCF
Center for Research in Computer Vision
UNIVERSITY OF CENTRAL FLORIDA