

# Neural network transfer learning with fast calibration for mental imagery decoding

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## INTRODUCTION

### Problem setting

In this work, we use deep learning for cross-dataset transfer learning in mental imagery decoding tasks. We investigate which datasets are well suited for transfer, both as donors and as receivers. Additionally, we discuss the technical aspects of our work and how models can be re-used.

### Challenges

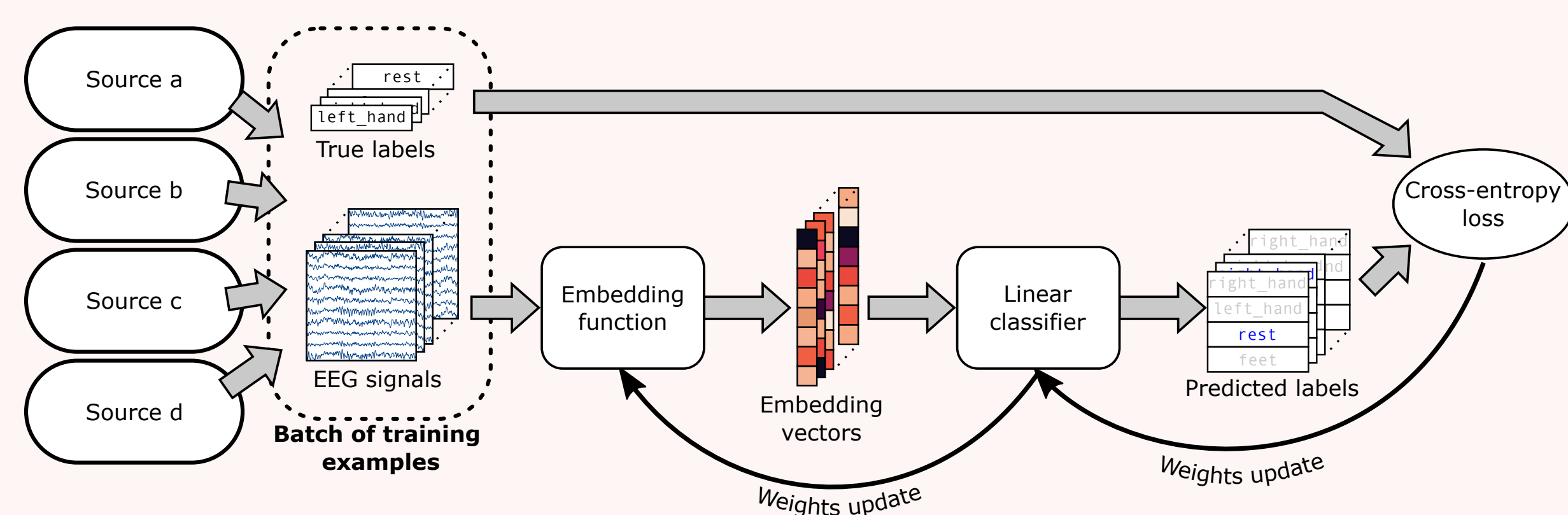
Deep learning models typically require long training times and are data-hungry. These make their use for BCI difficult because of the time needed to record examples and the constraints induced by experiments involving human subjects. A solution to both issues is transfer learning but it comes with its own challenges which are the compatibility between data sources for the transfer and the technical difficulties of re-using models.

### Approach

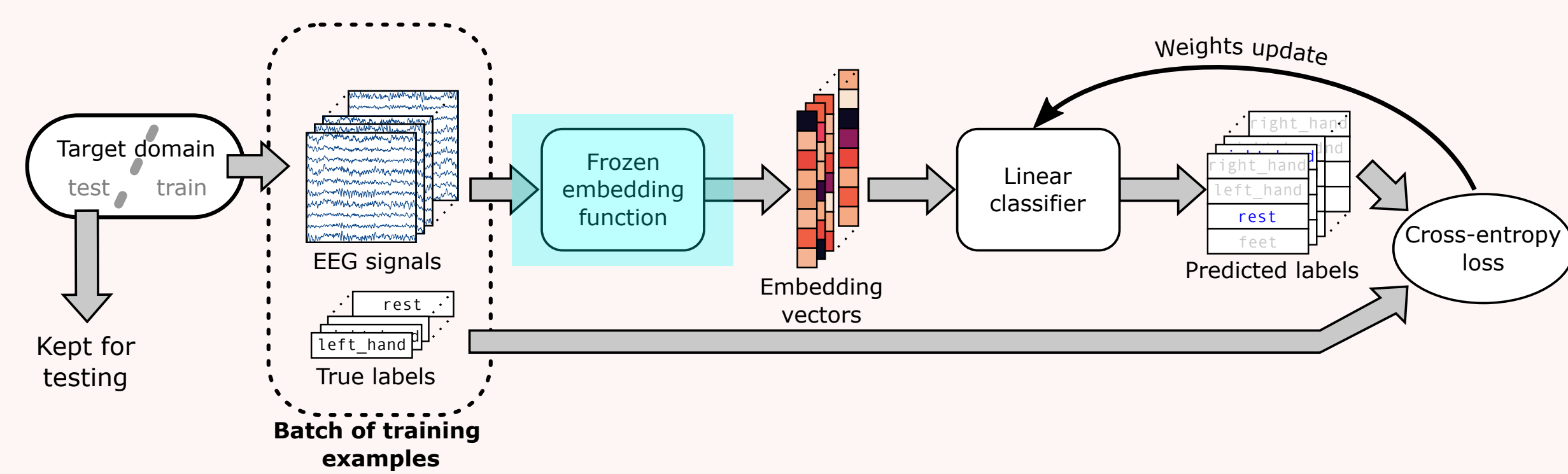
Our transfer cross-validation procedure is: for every pre-training dataset and test dataset pair, first, train a model on the pre-training dataset, then train only a new classification layer on a few trials from the test dataset and test on other trials from the same session of the test dataset [1]. We explain our workflow and how our pre-trained models can easily be loaded for future use.

## METHODS

### A. Pre-training phase - on the pre-training dataset



### B. Calibration phase - on the test dataset



## MATERIALS

### DATASETS

Dataset	#subjects	#trials	classes
AlexMI	8	20	f,r,rh
BNCI2014001	10	288	f,lh,rh,t
BNCI2014004	10	1800	lh,rh
BNCI2015001	13	400	f,rh
BNCI2015004	10	160	f,n,rh,s,wa
Cho2017	53	100	lh,rh
Lee2019_MI	55	200	lh,rh
Ofner2017	15	60	r,ree,ref, rhc,rho,rp,rs
PhysionetMI	109	23	bh,f,lh,r,rh
Schirmmeister2017	14	120	f,lh,r,rh
Weibo2014	10	80	bh,f,lh,rhlf, r,rh,rhlf
Zhou2016	4	480	f,lh,rh

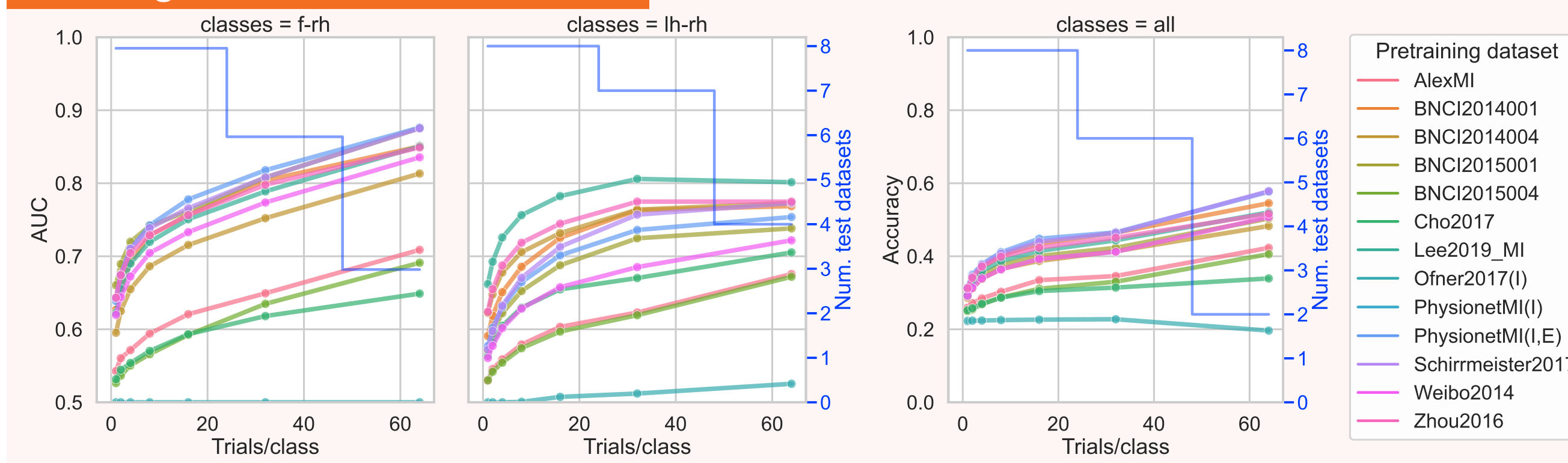
- Neural network architecture: **EEGNet** [2];
- Training and testing on 12 mental imagery datasets from the **MOABB** library [3].

### CLASSES

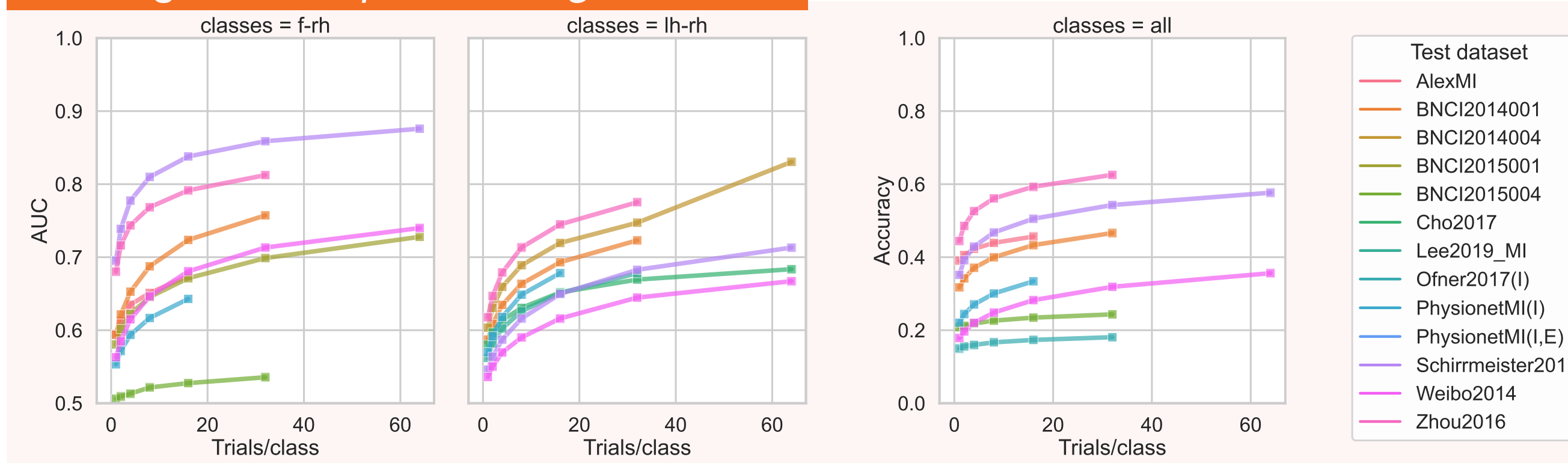
- bh**: hands
- f**: feet
- lh**: left hand
- lhlf**: left hand right foot
- n**: navigation
- r**: rest
- ree**: right elbow extension
- ref**: right elbow flexion
- rh**: right hand
- rhc**: right hand close
- rhlf**: right hand left foot
- rho**: right hand open
- rp**: right pronation
- rs**: right supination
- s**: subtraction
- t**: tongue
- wa**: word ass

## RESULTS

### Average across test datasets



### Average across pre-training datasets



### Right-hand vs feet - AUC score

Test dataset	AlexMI	BNCI2014001	BNCI2015001	BNCI2015004	PhysionetMI(I)	Schirmmeister2017	Weibo2014	Zhou2016
Pretraining dataset	1	2	4	8	16	32	64	128
AlexMI	58	57	56	60	63	55	57	60
BNCI2014001	62	62	66	70	73	67	72	77
BNCI2014004	60	64	67	70	72	56	59	62
BNCI2015001	65	67	70	70	65	68	71	74
BNCI2015004	50	51	50	52	53	55	56	57
Cho2017	53	54	51	52	56	58	61	64
Lee2019_MI	59	64	68	71	74	65	70	75
Ofner2017(I)	50	50	50	50	50	50	50	50
PhysionetMI(LE)	64	68	73	73	65	69	73	78
Schirmmeister2017	64	66	71	74	64	67	71	75
Weibo2014	64	65	69	71	64	68	73	78
Zhou2016	60	64	68	71	64	67	71	75

### Right-hand vs left hand - AUC score

Test dataset	BNCI2014001	BNCI2014004	Cho2017	Lee2019_MI	PhysionetMI(I)	Schirmmeister2017	Weibo2014	Zhou2016
Pretraining dataset	1	2	4	8	16	32	64	128
AlexMI	51	53	55	57	61	64	55	56
BNCI2014001	65	69	73	78	81	85	59	62
BNCI2014004	61	62	65	68	71	73	66	67
BNCI2015001	60	62	65	68	72	75	60	63
BNCI2015004	53	53	56	58	62	65	58	61
Cho2017	56	57	60	63	66	69	60	63
Lee2019_MI	68	72	77	82	87	91	64	68
Ofner2017(I)	50	50	50	50	50	50	50	50
PhysionetMI(LE)	58	61	64	68	72	75	60	63
Schirmmeister2017	59	62	65	68	71	74	66	69
Weibo2014	56	58	62	65	68	72	57	60
Zhou2016	63	65	69	72	75	77	64	67

### All classes - Accuracy score

Test dataset	AlexMI	BNCI2014001	BNCI2015004	Ofner2017(I)	PhysionetMI(I)	Schirmmeister2017	Weibo2014	Zhou2016
Pretraining dataset	1	2	4	8	16	32	64	128
AlexMI	38	39	38	39	43	28	29	31
BNCI2014001	41	43	45	47	49	36	41	47
BNCI2014004	38	41	42	46	45	29	32	37
BNCI2015001	40	43	46	48	48	34	37	40
BNCI2015004	34	32	33	34	27	28	29	31
Cho2017	35	33	35	36	27	28	30	32
Lee2019_MI	37	39	44	47	48	33	37	41
Ofner2017(I)	33	33	33	33	24	24	24	24
PhysionetMI(LE)	44	49	49	51	50	35	39	43
Schirmmeister2017	41	44	48	50	34	38	42	46
Weibo2014	42	43	45	46	33	38	41	45
Zhou2016	40	42	45	47	33	36	40	43

### BEST DONORS

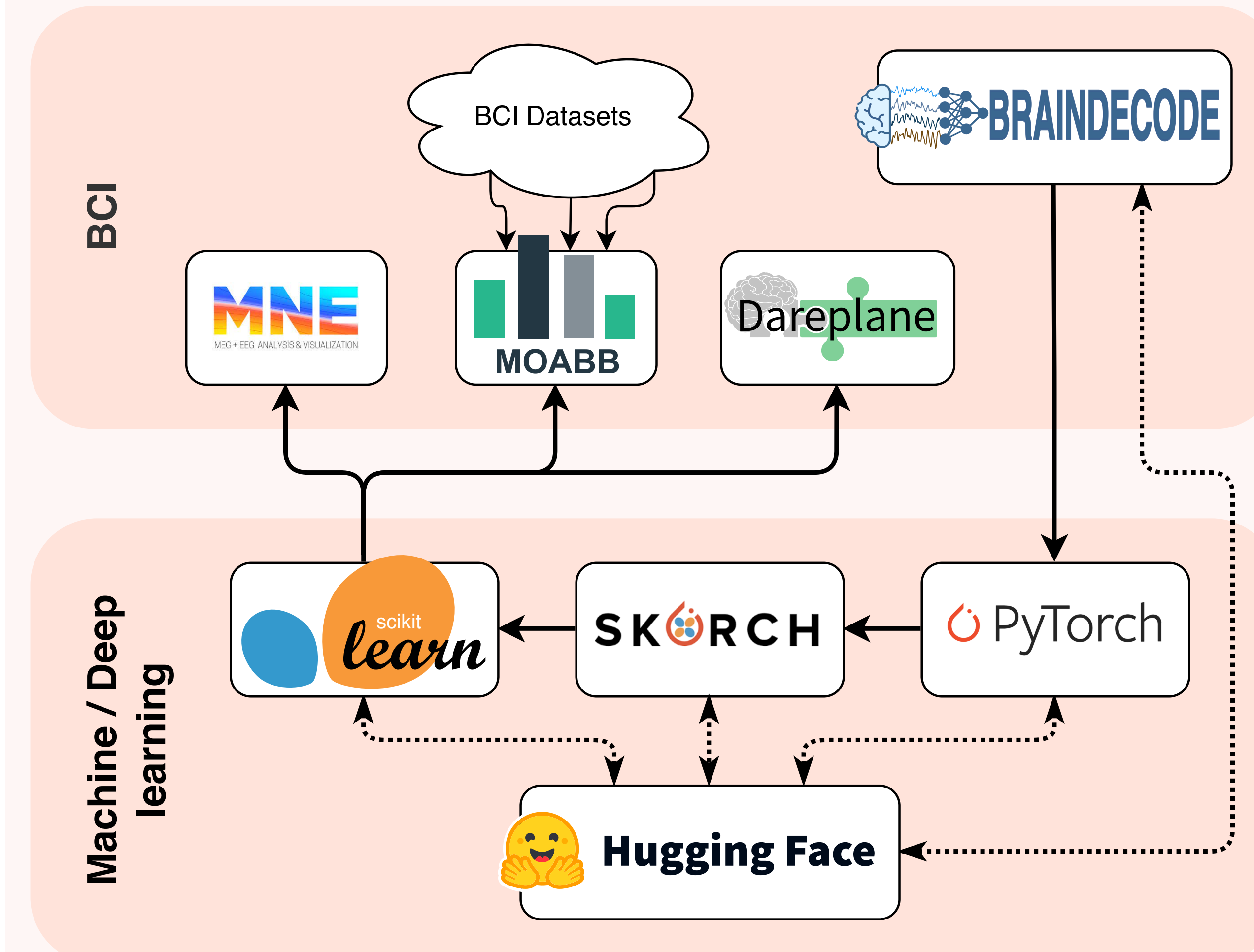
- f-rh**: No clear winner, still BNCI2015001 best if few trials and PhysionetMI best if more trials;
- lh-rh**: Lee2019 by a large margin.

### BEST RECEIVERS

- f-rh**: Schirmmeister2017 (probably simpler because executed movements);
- lh-rh**: Zhou2016 if few trials, BNCI2014004 if more trials.

## FRAMEWORK

### Open-source libraries ecosystem



## DISCUSSION

- Deep learning-based cross-mental-imagery-dataset transfer works well, even simple pipelines;
- The infrastructures are there to *effortlessly* share and reuse models;
- We must make it a standard practice within the BCI community to share our pre-trained models;
- Using pre-trained models allows for fast prototyping;
- Using pre-trained models lowers the threshold for new studies (data size needed);
- Both our method and workflow can be used on other paradigms than mental imagery and other types of transfer than cross-dataset.

### USE MY PRE-TRAINED MODELS

```
import torch
from huggingface_hub import hf_hub_download
from braindecode.models import EEGNetv4

path = hf_hub_download(
    repo_id='PierreGtch/EEGNetv4',
    filename='EEGNetv4_Lee2019_MI/model-params.pk1')
net = EEGNetv4(3, 2, 385).eval()
net.load_state_dict(torch.load(path, map_location='cpu'))
```

Full notebook:



## REFERENCES

- Guetschel et al. 2022 *IEEE MetroXRaine* doi:10.1109/metroxraine54828.2022.9967496
- Lawhern et al. (2018) *J Neural Eng* doi:10.1088/1741-2552/aace8c
- Jayaram & Barachant (2018) *J Neural Eng* doi:10.1088/1741-2552/aadea0

