Fast calibration with Deep Learning

Workshop 6: Learning from small datasets

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Introduction

Deep learning is desirable for BCI.

Obstacles:

1. Long training time of the models;
2. Large amounts of training data required.

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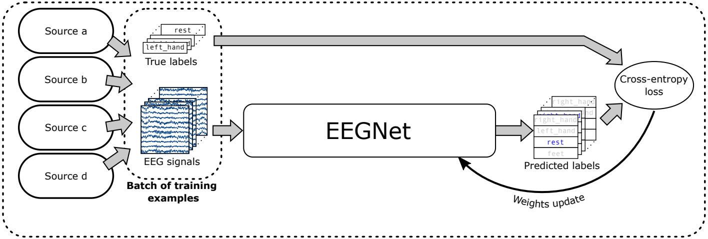
A promising direction: **transfer learning**,
i.e. re-use pre-trained models.

Plan:

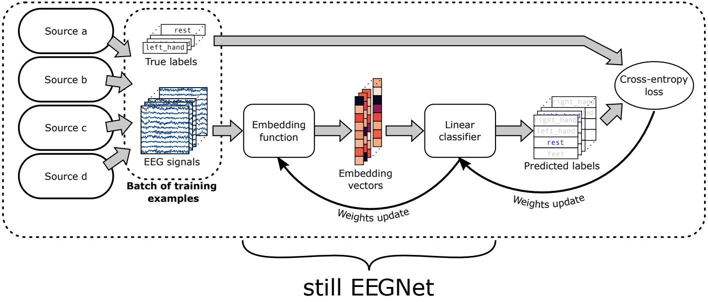
1. A simple strategy for cross-dataset transfer with calibration;
2. Tutorial for re-using pre-trained models, technically.

A simple and fast calibration strategy



- **Phase**: 1/2 pre-training;
- **Example domains**: sessions, subjects (c.f. Analysis 1), datasets (c.f. Analysis 2), paradigms.

A simple and fast calibration strategy



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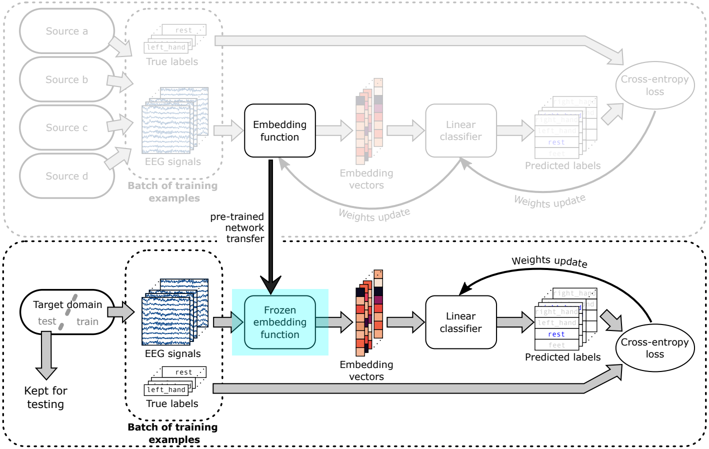
A simple and fast calibration strategy



- **Phase**: 2/2 calibration;
- **Example domains**: sessions, subjects (c.f. Analysis 1), datasets (c.f. Analysis 2), paradigms.

Analysis 1: Cross-subject

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[Guetschel et. al, *2022 IEEE MetroXRAINE*]

- High Gamma Dataset [Schirrmeister et. al (2017) *Hum. Brain Mapp.*];
- 14 subjects, 4 classes, 120-260 trials;
- **Pre-training**: leave-one-subject-out cross-validation;
- **Calibration**: within-session cross-validation (variable #trials).

Analysis 1: Cross-subject | Example embedding space

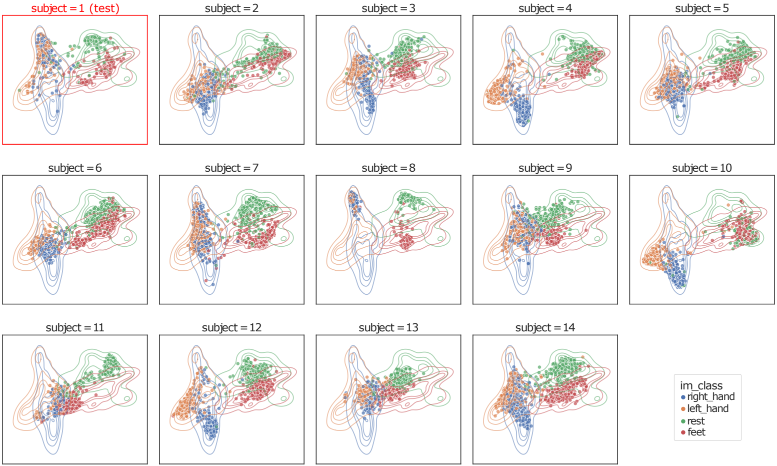

Figure: Embeddings projected by UMAP

[Guetschel et. al, *2022 IEEE MetroXRAINE*]

Analysis 1: Cross-subject | Classification accuracy

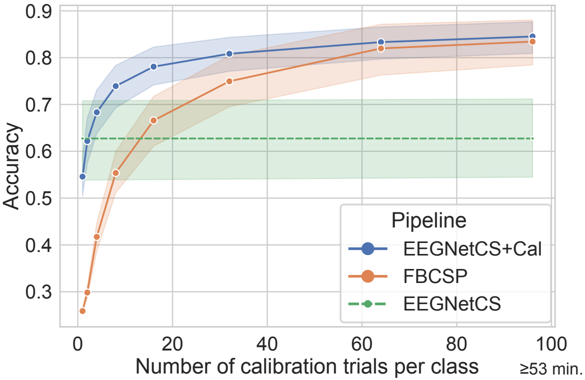

Figure: Classification accuracy averaged across subjects
[Guetschel et. al, *2022 IEEE MetroXRAINE*]

Analysis 2: Cross-dataset

Analysis 2: Cross-dataset

- 12 mental imagery datasets of MOABB;
- **Pre-training**: One whole dataset;
- **Calibration**: within-session cross-validation (variable #trials);
- **Calibration configurations**: `f-rh`, `lh-rh`, and `all`.

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
Schirrmeister2017	14	120	f,lh,r,rh
Weibo2014	10	80	bh,f,lh,lhrf, r,rh,rhlf
Zhou2016	4	480	f,lh,rh

- **bh**: hands
- **f**: feet
- **lh**: left hand
- **lhrf**: 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

Analysis 2: Cross-dataset | Results table

Test classes

Feet vs right hand

Pretraining dataset \ Test dataset	AlexMI	BNCI2014001	BNCI2015001	BNCI2015004	PhysionetMI(I)	Schirrmeister2017	Weibo2014	Zhou2016
AlexMI	60	62	56	51	56	77	52	58
BNCI2014001	70	**82**	68	52	64	90	67	87
BNCI2014004	70	66	65	**54**	60	84	66	81
BNCI2015001	70	74	**76**	53	64	89	**77**	87
BNCI2015004	50	61	55	50	54	72	51	57
Cho2017	52	58	55	50	59	66	51	62
Lee2019_MI	71	71	68	51	66	84	74	88
Ofner2017(I)	50	50	50	50	50	50	50	50
PhysionetMI(I,E)	**73**	78	70	53	**69**	90	72	85
Schirrmeister2017	72	75	71	50	64	**94**	73	88
Weibo2014	71	73	65	**54**	64	86	65	81
Zhou2016	68	71	71	52	64	86	73	**94**

Left hand vs right hand

Pretraining dataset \ Test dataset	BNCI2014001	BNCI2014004	Cho2017	Lee2019_MI	PhysionetMI(I)	Schirrmeister2017	Weibo2014	Zhou2016
AlexMI	57	62	61	55	61	60	50	54
BNCI2014001	**78**	70	64	64	68	61	59	80
BNCI2014004	68	**85**	62	67	63	65	65	84
BNCI2015001	68	70	63	63	62	59	61	72
BNCI2015004	56	62	60	53	60	61	48	55
Cho2017	63	69	**71**	58	67	59	52	62
Lee2019_MI	77	79	66	**74**	**73**	**68**	**73**	90
Ofner2017(I)	50	50	50	50	50	50	50	50
PhysionetMI(I,E)	68	67	62	65	70	60	60	74
Schirrmeister2017	69	68	62	66	64	64	62	78
Weibo2014	65	66	64	60	68	61	54	61
Zhou2016	72	74	65	69	66	66	68	**91**

All classes

Pretraining dataset \ Test dataset	AlexMI	BNCI2014001	BNCI2015004	Ofner2017(I)	PhysionetMI(I)	Schirrmeister2017	Weibo2014	Zhou2016
AlexMI	39	33	22	15	30	41	20	38
BNCI2014001	47	**52**	**24**	**17**	34	54	28	63
BNCI2014004	46	37	23	15	28	49	26	64
BNCI2015001	48	43	23	**17**	31	49	27	59
BNCI2015004	33	31	22	15	29	38	19	38
Cho2017	35	32	20	15	28	34	18	43
Lee2019_MI	47	43	21	**17**	30	49	28	70
Ofner2017(I)	33	24	20	16	12	25	14	33
PhysionetMI(I,E)	**51**	47	**24**	16	**38**	56	**30**	62
Schirrmeister2017	50	46	22	16	31	**62**	28	66
Weibo2014	45	41	22	**17**	33	49	26	53
Zhou2016	47	43	23	**17**	31	50	28	**77**

- Number of calibration trials per class: **8**;
- **Blue**: AUC score (colour range: 50-100%);
- **Green**: Accuracy score (colour range: 0-100%);
- **Bold**: best of the column.

Analysis 2: Cross-dataset | Results table

Test classes

Feet vs right hand

Pretraining dataset \ Test dataset	AlexMI	BNCI2014001	BNCI2015001	BNCI2015004	PhysionetMI(I)	Schirrmeister2017	Weibo2014	Zhou2016
AlexMI	63	66	57	51	60	81	54	60
BNCI2014001	73	**85**	71	53	67	92	72	89
BNCI2014004	72	70	67	55	63	86	71	85
BNCI2015001	70	77	**79**	53	67	90	**80**	89
BNCI2015004	52	65	57	52	56	76	51	60
Cho2017	56	61	57	49	61	70	51	65
Lee2019_MI	74	75	71	51	70	88	78	90
Ofner2017(I)	50	50	50	50	50	50	50	50
PhysionetMI(I,E)	**78**	82	73	**56**	**71**	92	77	88
Schirrmeister2017	74	80	75	51	67	**96**	77	91
Weibo2014	71	78	69	54	67	89	72	83
Zhou2016	71	75	74	53	67	88	78	**95**

Left hand vs right hand

Pretraining dataset \ Test dataset	BNCI2014001	BNCI2014004	Cho2017	Lee2019_MI	PhysionetMI(I)	Schirrmeister2017	Weibo2014	Zhou2016
AlexMI	61	64	62	56	65	64	51	56
BNCI2014001	**81**	75	66	69	72	65	64	83
BNCI2014004	71	**87**	64	70	66	68	69	86
BNCI2015001	72	73	64	66	66	63	64	78
BNCI2015004	58	65	62	55	63	64	50	57
Cho2017	66	72	**74**	60	70	62	52	65
Lee2019_MI	79	82	68	**77**	**75**	**72**	**77**	91
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Schirrmeister2017	74	73	64	70	68	69	66	84
Weibo2014	68	69	65	63	71	64	57	66
Zhou2016	75	78	66	72	69	70	70	**93**

All classes

Pretraining dataset \ Test dataset	AlexMI	BNCI2014001	BNCI2015004	Ofner2017(I)	PhysionetMI(I)	Schirrmeister2017	Weibo2014	Zhou2016
AlexMI	43	37	23	17	34	46	23	41
BNCI2014001	49	**56**	**25**	**18**	38	58	32	68
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BNCI2015001	48	47	23	**18**	34	53	30	63
BNCI2015004	34	34	23	16	32	43	22	41
Cho2017	36	34	21	16	31	37	20	46
Lee2019_MI	48	47	23	17	33	53	32	74
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PhysionetMI(I,E)	**56**	51	**25**	17	**43**	60	**36**	67
Schirrmeister2017	54	50	23	17	35	**66**	33	69
Weibo2014	46	46	23	**18**	38	54	31	55
Zhou2016	49	46	24	17	34	54	32	**80**

- Number of calibration trials per class: **16**;
- **Blue**: AUC score (colour range: 50-100%);
- **Green**: Accuracy score (colour range: 0-100%);
- **Bold**: best of the column.

Analysis 2: Cross-dataset | Learning curve 1/2

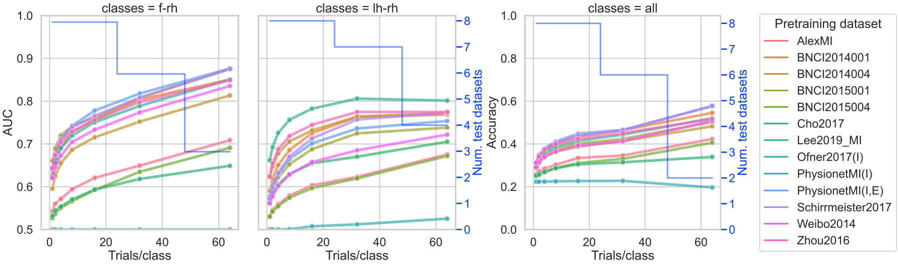


Figure: Scores wrt. num. of calibration trials per class (from test dataset); averaged over test datasets.

Best donors (pre-training datasets):

- **f-rh**: No clear winner, still BNCI2015001 best if few trials and PhysionetMI best if more trials;
- **lh-rh**: Lee2019 by a large margin (many subjects: 55).

Analysis 2: Cross-dataset | Learning curve 2/2

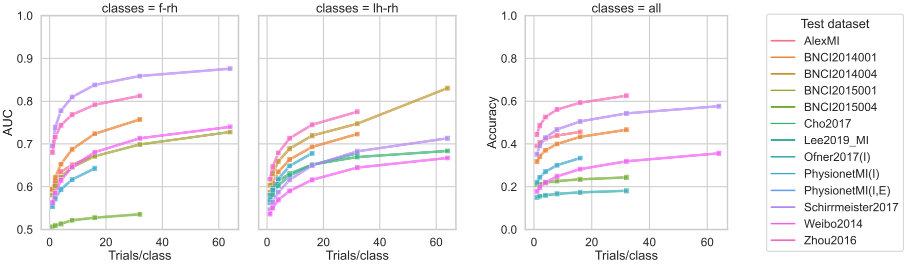


Figure: Scores wrt. num. of calibration trials per class (from test dataset); averaged over pre-training datasets.

Best receivers (test datasets):

- **f-rh**: Schirrmeister2017 (probably simpler because executed movements);
- **lh-rh**: Zhou2016 if few trials, BNCI2014004 if more trials.

(Re)Usability / Reproducibility

(Re)Usability / Reproducibility

Cross BCI dataset transfer works well with deep learning.

- C.f. previous results;
- Top 3 at BEETL competition (2021) all used DL.

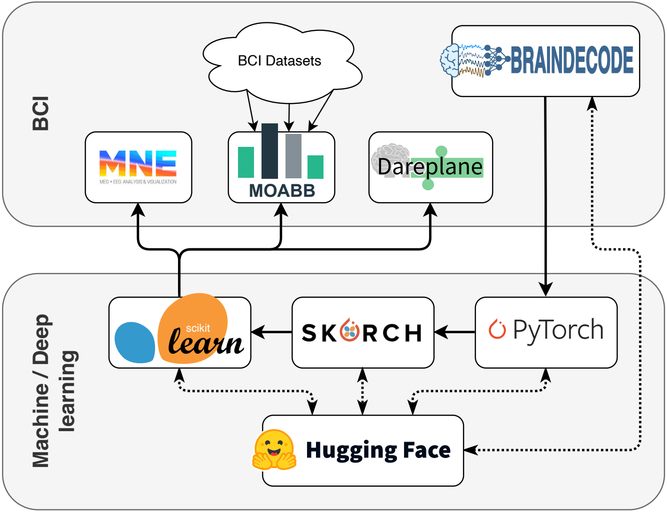
Why is cross-dataset transfer relevant?

- To reuse pre-trained models.

How can we re-use/share models?

- It can appear challenging technically;
- Tutorial $\rightarrow$

Libraries - open-source constellation / ecosystem



If you are interested, come and talk to me at the end of the session or poster 2-F-48.

But concretely... the code

Load a pre-trained model in 3 lines!

```
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.pkl')
net = EEGNetv4(3, 2, 385).eval()
net.load_state_dict(torch.load(path, map_location='cpu'))
```

Full Notebook:

Explains how to:

- Download pre-trained models;
- Integrate into classification pipelines;
- Share your own models.

Take home message

- Cross-mental-imagery-dataset transfer works well using deep learning, even with simple pipelines;
- The infrastructures are there to *effortlessly* share and reuse models;
- We should 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 (less data needed);
- Both our method and workflow could be used on other paradigms than mental imagery and other types of transfer than cross-dataset.

Full Notebook:

Poster

Come and chat tomorrow (session 2), spot 2-F-48.