c-VEP Decoding
Reconvolution & Zero-Training

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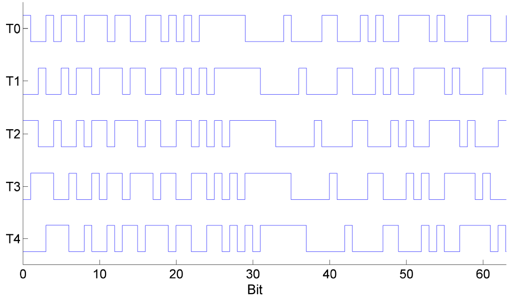
Standard c-VEP stimulus protocol

Symbols encoded with a time-lagged m-sequence

A

23	24	25	26	27	28	29	30	31	0
31	0	1	2	3	4	5	6	7	8
7	8	9	10	11	12	13	14	15	16
15	16	17	18	19	20	21	22	23	24
23	24	25	26	27	28	29	30	31	0
31	0	1	2	3	4	5	6	7	8

B



[Spüler et al. (2012) **PLOS ONE**]

Standard c-VEP classification

Average K synchronized trials (lag 0) to obtain template $\mathbf{T}_0 \in \mathbb{R}^{C \times T}$

$$\mathbf{T}_0 = \frac{1}{K} \sum_{j}^{K} \mathbf{X}_j$$

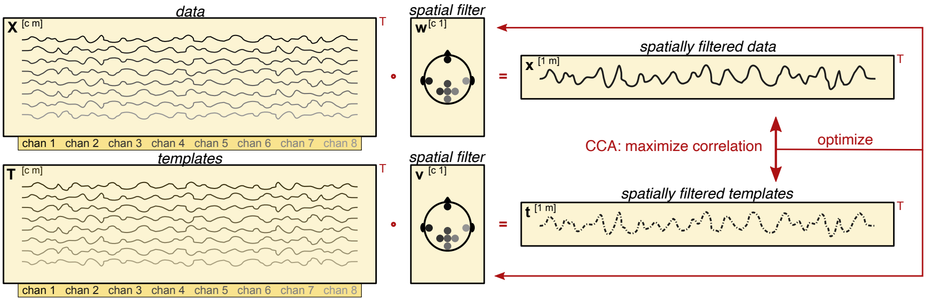
Obtain other templates $\mathbf{T}_i$ by adding time-lag equal to stimulus lag
Classify spatially filtered trials with spatial filter $\mathbf{w} \in \mathbb{R}^{C}$

$$\hat{y} = \arg\max_{i} \rho(\mathbf{w}^\top \mathbf{X}, \mathbf{w}^\top \mathbf{T}_i)$$

[Martinez-Cagigal et al. (2021) **J Neural Eng**]

Canonical correlation analysis (CCA)

$$\mathbf{t}_i = \mathbf{w}^\top \mathbf{T}_i$$



[Hotelling (1936) **Biometrica**] [Spüler et al. (2012) **ESANN**] [Spüler et al. (2013) **IEEE T Neur Sys Reh**]

Downside of the standard classification

Requires a large training dataset!

- Depends on averaging trials to obtain templates
- Even worse when there is no relation between classes (i.e., sequences)

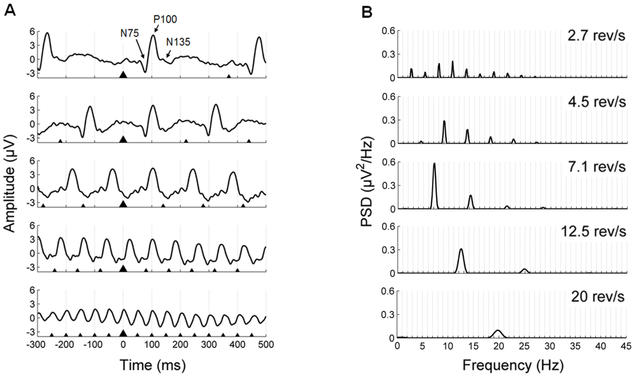
How can one reduce the required amount of calibration data?

- Exploit the repeating structure in the data
- Average events within and across trials (i.e., sequences)

Linear superposition hypothesis

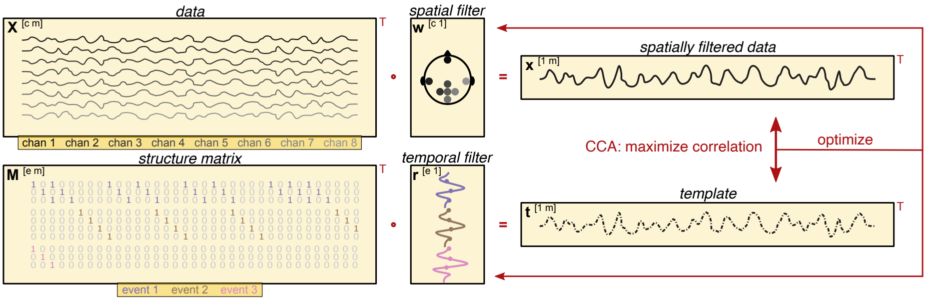
The response to a sequence of events is the addition of the responses to the individual events.

$$x(t) = \sum_i \sum_\tau l_i(t) r_i(t - \tau)$$



[Capilla et al. (2011) **PLOS ONE**]

$$\mathbf{t}_i = \mathbf{r}^\top \mathbf{M}_i$$



[Thielen et al. (2015) **PLOS ONE**] [Thielen et al. (2021) **J Neural Eng**]

From supervised to semi-supervised with reconvolution

Calibrated (supervised): [Thielen et al. (2015) **PLOS ONE**]

$$\max_{\mathbf{w},\mathbf{r}} \rho(\mathbf{w}^\top \mathbf{X}, \mathbf{r}^\top \mathbf{M}_i)$$

$$\hat{y} = \arg\max_i \rho(\mathbf{w}^\top \mathbf{X}, \mathbf{r}^\top \mathbf{M}_i)$$

Calibration-free (instantaneous): [Thielen et al. (2021) **J Neural Eng**] [Thielen et al. (2024) **arXiv**]

$$\max_{\mathbf{w}_i,\mathbf{r}_i} \rho(\mathbf{w}_i^\top \mathbf{X}, \mathbf{r}_i^\top \mathbf{M}_i)$$

$$\hat{y} = \arg\max_i \rho(\mathbf{w}_i^\top \mathbf{X}, \mathbf{r}_i^\top \mathbf{M}_i)$$

Calibration-free (cumulative): [Thielen et al. (2021) **J Neural Eng**] [Thielen et al. (2024) **arXiv**]

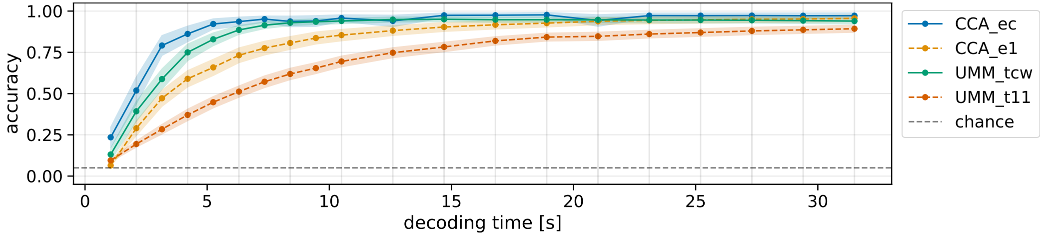
$$\mathbf{X} = [\mathbf{X}_0, ..., \mathbf{X}_k]$$

$$\mathbf{M}_i = [\mathbf{M}_{\hat{y}_0}, ..., \mathbf{M}_{\hat{y}_{k-1}}, \mathbf{M}_i]$$

Calibration-free (cumulative, adaptive): [Thielen et al. (2021) **J Neural Eng**]

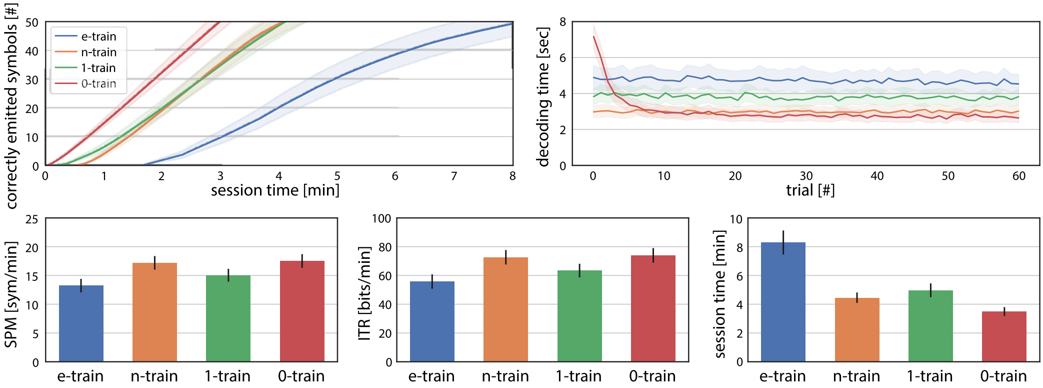
Calibration-free instantaneous and cumulative decoding

CCA: [Thielen et al. (2015) **PLOS ONE**] [Thielen et al. (2021) **J Neural Eng**]
UMM: [Sosulski & Tangermann (2022) **J Neural Eng**] [Sosulski & Tangermann (2023) **arXiv**]



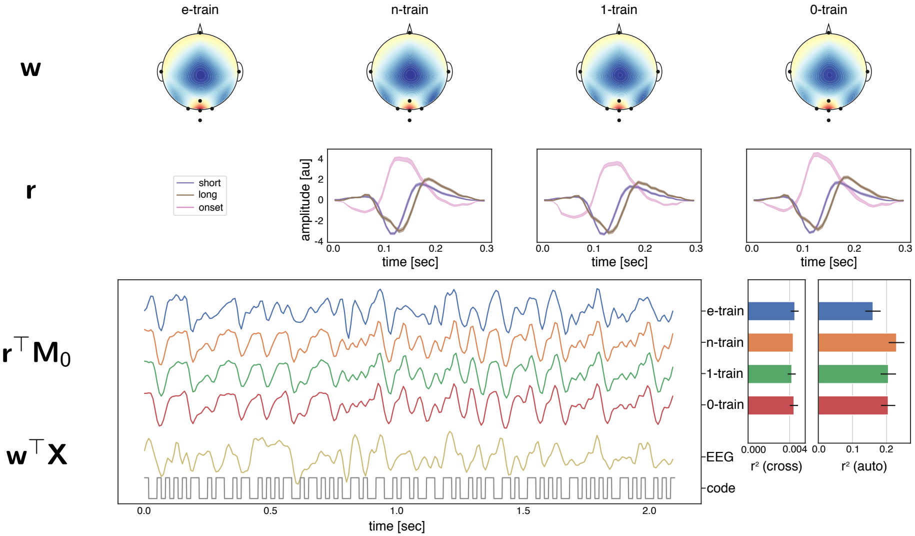
[Thielen et al. (2024) **arXiv**]

Calibration-free adaptive cumulative and supervised



[Thielen et al. (2021) **J Neural Eng**]

Calibration-free converges to a calibrated model



[Thielen et al. (2021) **J Neural Eng**]

Conclusion

Exploiting **structure in neural data**

- Forward model assuming linear superposition hypothesis
  - Decreases number of model parameters
  - Increases number of repetitions per parameter
- Limits as well as eliminates the need for training data
  - Achieves high explained variance and BCI performance
  - Generalizes to unseen data/sequences
  - Realizes instantaneous, cumulative, and adaptive decoding

Reconvolution CCA (rCCA)

- Tutorial/demo at the end of the workshop
- Python Noise-Tagging BCI: `https://github.com/thijor/pyntbci`

Acknowledgements

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- Michael Tangermann
- Sara Ahmadi
- Jan Sosulski

BCI lab

- Peter Desain
- Jason Farquhar
- Pieter Marsman
- Philip van den Broek

Join the Data-Driven Neurotechnology Lab @ Donders Institute!

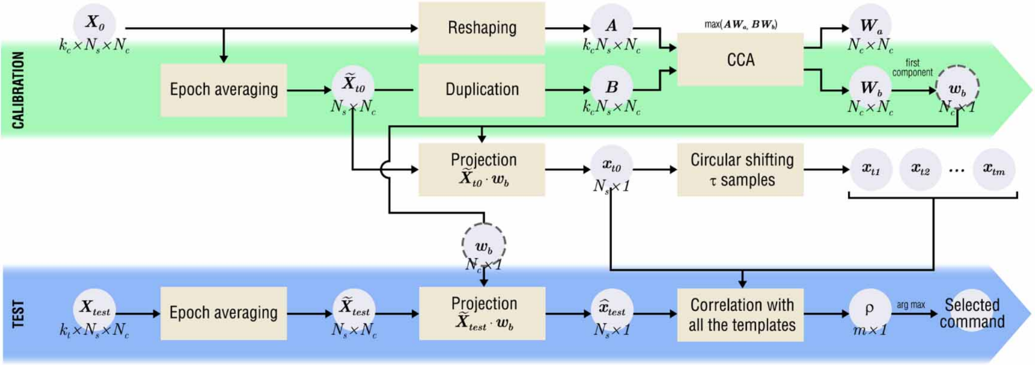
If you are interested in BCI and the psychology of learning and self-introspection,

then join our team and the European Doctoral Network DONUT as **PhD candidate**!

Primer on posters:

- 64 (Tue): Towards gaze-independent c-VEP BCI: A pilot study
- 61 (Thu): Exploring new territory: Calibration-free decoding for c-VEP BCI
- 63 (Thu): Towards auditory attention decoding with noise-tagging: A pilot study

Reference c-VEP pipeline



$$\hat{y} = \arg\max_i \rho(\mathbf{w}^\top \mathbf{X}, \mathbf{w}^\top \mathbf{T}_i)$$

[Martinez-Cagigal et al. (2021) **J Neural Eng**]

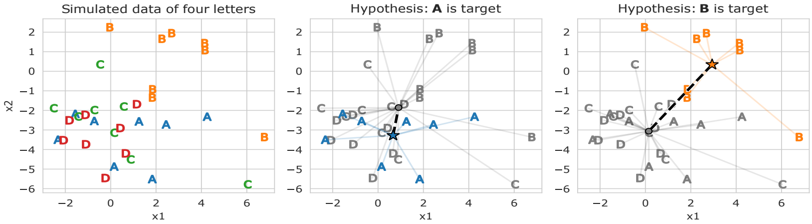
Unsupervised Mean-Difference Maximization

Slice trial into K epochs $\mathbf{x} \in \mathbb{R}^D$

Assume symbol i is target defines target (A_i^+) and non-target epochs (A_i^-)

$$\Delta\boldsymbol{\mu}_i = \frac{1}{|A_i^+|}\sum_{j\in A_i^+}\mathbf{x}_j - \frac{1}{|A_i^-|}\sum_{j\in A_i^-}\mathbf{x}_j$$

$$\hat{y} = \arg\max_i (\Delta\boldsymbol{\mu}_i)\boldsymbol{\Sigma}^{-1}(\Delta\boldsymbol{\mu}_i)$$



[Sosulski & Tangermann (2022) **J Neural Eng**] [Sosulski & Tangermann (2023) **arXiv**]