let de l'

Eidgenössische Technische Hochschule Zürich Swiss Federal Institute of Technology Zurich

Jürg Schelldorfer 1 , Siamac Fazli 2 , Márton Danóczy 2 , Klaus-Robert Müller 2

 ℓ_1 -penalized Linear Mixed-Effects Models for zero-training

Brain Computer Interfacing

¹ETH Zürich, Switzerland ²Technical University Berlin, Germany

Introduction

• use large set of BCI data to obtain a subject-independent classifier [1]

• novel statistical approach differentiates *within-subject* and *between-subject variability* [3]

• find a unifying model that (inherently) takes care of possible shifts in the input space

Figure 1: 2 Flowcharts of the ensemble method. The red patches in the top panel illustrate the inactive nodes of the ensemble after sparsification.

Statistical Model

1.1 Model Setup

Let $i = 1, ..., N$ be the number of subjects, $j = 1, ..., n_i$ the number of observations per subject and $N_T = \sum_{i=1}^N n_i$ the total number of observations. For each subject we observe an n_i -dimensional response vector y_i . Moreover, let X_i and Z_i be $n_i \times p$ and $n_i \times q$ covariate matrices, where X_i contains the fixed-effects covariates and Z_i the corresponding random-effects covariates. Denote by $b \in \mathbb{R}^p$ the *p*-dimensional fixed-effects vector and by β_i , $i = 1, ..., N$ the q -dimensional random-effects vectors. Then the linear mixed-effects model can be written as $([2])$

$$
y_i = X_i b + Z_i \beta_i + \varepsilon_i \quad i = 1, \dots, N \quad , \tag{1}
$$

where we assume that $i)$ $\beta_i \sim \mathcal{N}_q(0, \tau^2 I_q)$, $ii)$ $\varepsilon_i \sim \mathcal{N}_{n_i}(0, \sigma^2 I_{n_i})$ and $iii)$ that the errors ε_i are mutually independent of the random effects β_i .

1.2 Available Data and Experiments

• 83 BCI datasets (45 EEG channels), each consisting of 150 trials ($t = 3s$, $f = 100Hz$)

• preprocess each dataset by 18 predefined temporal filters in parallel (see Figure 2)

Figure 4: four figures show loss, averages over 83 subjects for L1-LSR, and LMM-LSR as well as L1-logistic regression and LMM logistic regression. two top figures are not bias corrected, while two lower ones are.

- calculate a corresponding spatial filter and linear classifier for every band-pass filtered dataset to obtain a large number of subject-dependent BCI filters/classifiers (see Figure 1)
- process every dataset by this large set of basis functions
- perform a ℓ_1 -regularized logistic regression LMM (and classic ℓ_1 logistic regression) on each classifier's output to obtain an optimal combination of basis functions
- our method is validated by leave-one-subject-out cross-validation

Figure 2: 18 temporal filters, used to generate the data

active features − L1 regularized logisitc regression

- [1] S. Fazli, C. Grozea, M. Danoczy, B. Blankertz, F. Popescu, and K.-R. Müller. Subject independent eeg-based bci decoding. In Y. Bengio, D. Schuurmans, J. Lafferty, C. K. I. Williams, and A. Culotta, editors, *Advances in Neural Information Processing Systems 22*, pages 513–521. 2009.
- [2] José C. Pinheiro and Douglas M. Bates. *Mixed-Effects Models in S and S-Plus*. Springer, New York, 2000.
- [3] J. Schelldorfer and P. Buhlmann. Estimation for high-dimensional linear mixed-effects models using ℓ_1 -penalization. *arXiv preprint 1002.3784*, 2010.

10

20

Figure 3: selected features in white, inactive features in black. top: L1 logreg , bottom: LMM logreg, both at ideal L1 regularization constant

2 Results

Preliminary analysis of the data indicates that a so called random-intercept is appropriate for this data:

$$
y_{ij} = x_{ij}^T b + \beta_{i1} + \varepsilon_{ij} \quad i = 1, ..., N, \quad j = 1, ..., n_i
$$
 (2)

Figure 5: shows that LMM rather chooses features, that had a good 'self prediction', and needs less features in total

3 Conclusion

- solution is sparser, as compared to classical L1
- LMM helps in achieving lower overall error
- chosen features have a lower self-prediction error
- method is suitable for finding features, common to multiple subject data

References