

# Linear mixed effects models for zero-training BCI

by

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# Introduction to LMM

Lets assume that Juerg, Klaus and me like to run 100m sprints and each one of us runs  $n=50$  sprints a year.

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Explanatory variables (e.g. subject weight, hours of sleep, etc.) for each subject and every sprint are:

$$X_1, X_2, X_3 \in \mathbb{R}^{n \times p}$$

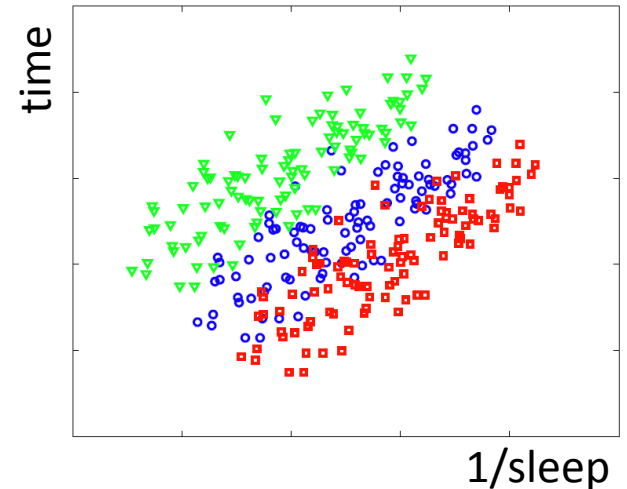
Response variable is the measured times:

$$Y_1, Y_2, Y_3 \in \mathbb{R}^n$$

$$\langle Y_1 \rangle = 10 \pm 1s$$

$$\langle Y_2 \rangle = 12 \pm 1s$$

$$\langle Y_3 \rangle = 15 \pm 1s$$



# Introduction to LMM

Task: find (common) linear projection  $b$  for all three subjects

$$Y = Xb + \epsilon$$

$$X = [X_1 X_2 X_3]$$

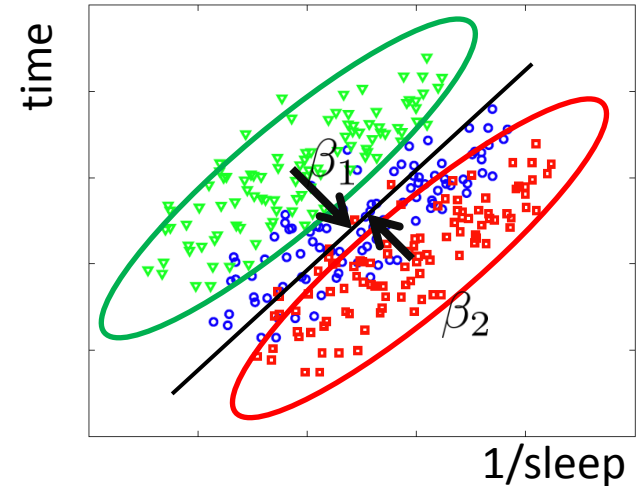
$$Y = [Y_1 Y_2 Y_3]$$

Problem: A requisite for linear regression is that the measurements are independent from each other.

In our case the input signals can have a subject-dependent bias!

Solution: model the bias term as an extra parameter for every group:

$$Y_i = X_i b + \beta_i + \epsilon_i$$



# Introduction to LMM

$$Y_i = X_i b + \beta_i + \epsilon_i$$

common  $b$  for all observations

group-specific deviations  $\beta_i$

noise term  $\epsilon_i$

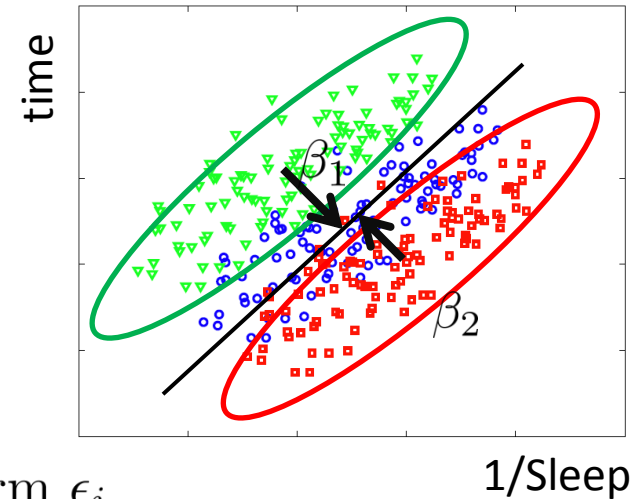
$$\beta_i \sim \mathcal{N}(0, \tau^2)$$

between-group variance  $\tau$

$$\epsilon_i \sim \mathcal{N}(0, \sigma^2)$$

within-group variance  $\sigma$

assumption:  $\epsilon_i$  is independent of  $\beta_i$



# Generation of the data

## ensemble generation

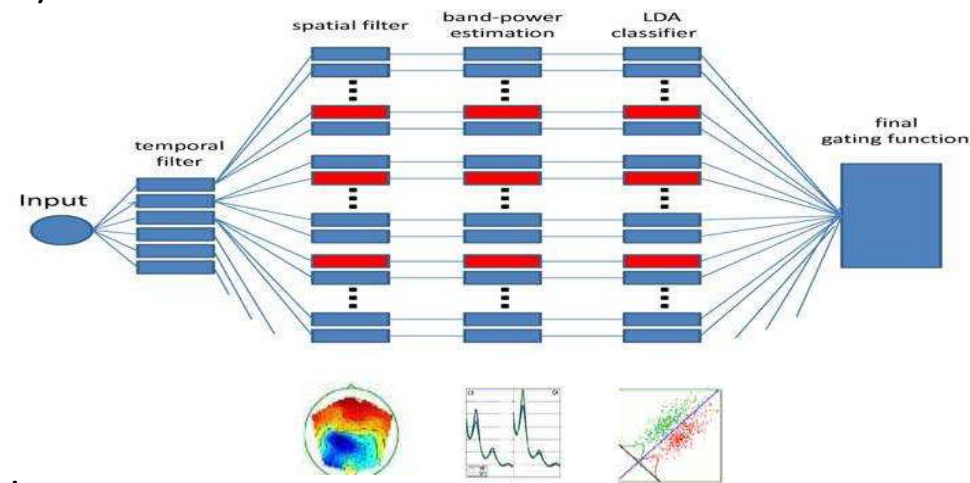
- 18 parallel temporal filters (predefined)
- 80 spatial filters per parallel filter (estimated)
- 80 classifiers per parallel filter (estimated)

$18 \times 80 = 1400$  classifiers in total

## dataset generation

- each dataset has 150 trials
- all trials ( $80 \times 150$ ) are fed into the ensemble (this is the group structure)

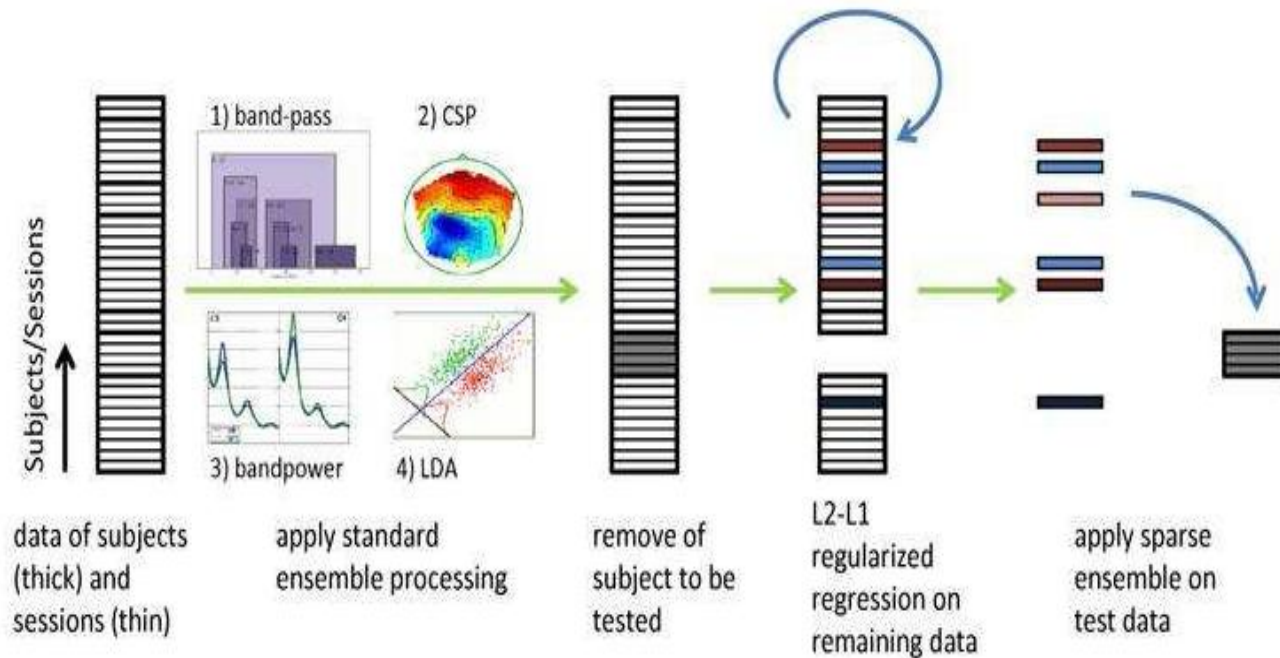
Thus our data set has **1400 features x 12450 trials**





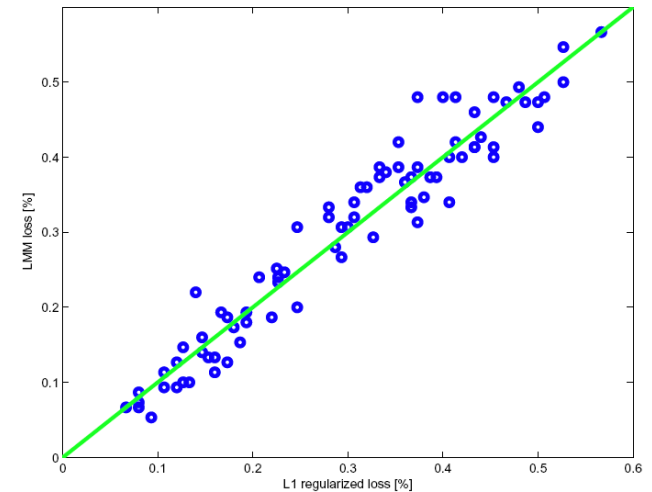
# Leave-one-subject-out-cross-validation

..of course we are not allowed to use all features, but must exclude those, which stem from the subject itself..



# Results -prediction

training data	model	
	LMM	L1-LSR
10%	29.8	29.52
20%	29.24	29.3
30%	29.21	29.44
40%	28.91	28.81



LMM does not outperform our original approach, percentage-wise...

# Results – model interpretation

- surprisingly the estimated between-group variance low  $\hat{\tau} \approx 0.1$  ,  
as compared to the within-group variance is large  $\hat{\sigma} \approx 0.9$

$$\frac{\tau^2}{\tau^2 + \sigma^2} = 0.012$$

- i.e. **98.8%** of total variability is explained by **within-group variance**

->  $\beta_i$  has a very small effect => set  $\beta_i = 0$  brings us back to LSR

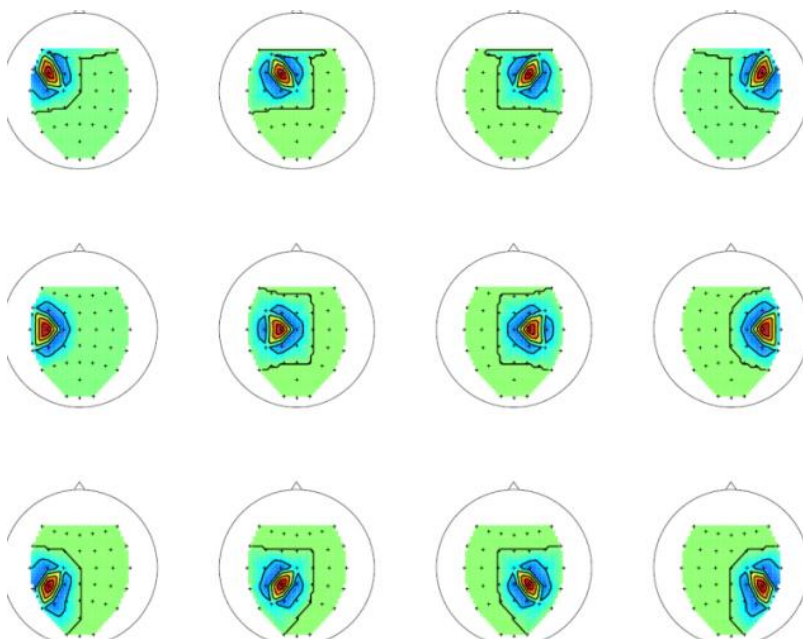
-> it seems our original approach was viable

# Thank you for your time

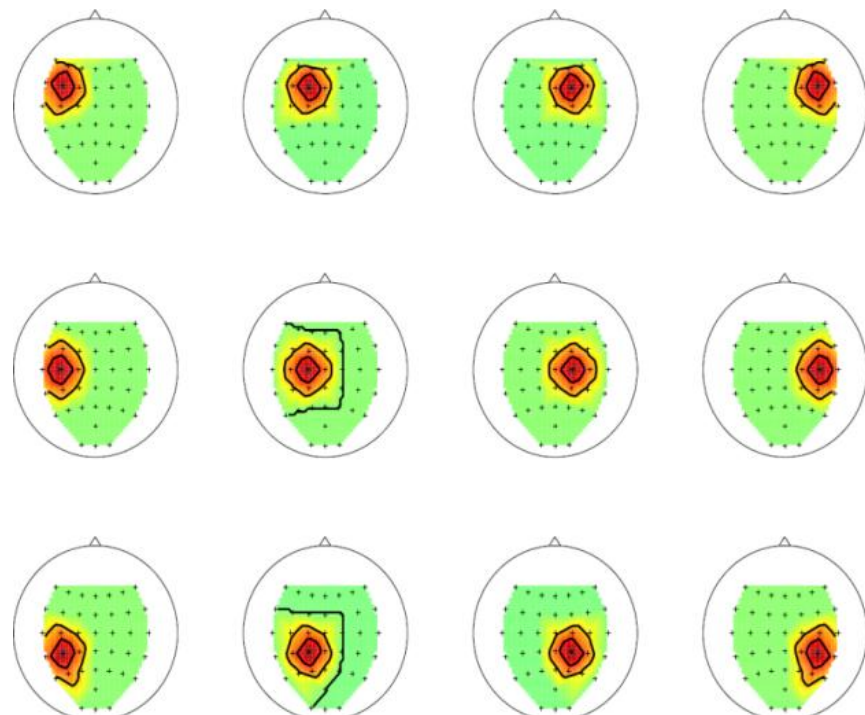


# adding artificial spatial features

'mexican hat'



simple laplacians





# Introduction to LMM

Linear regression

$$Y = Xb + \epsilon$$

In case inputs are grouped and not independent within groups..

$$X_i = X_1, X_2, \dots, X_N \quad i = 1, \dots, N$$

..one can consider a Linear mixed-effects model

$$Y_i = X_i b + \beta_i + \epsilon_i$$