The application of MVPA to event-related potentials

(part 1)

Stefan Bode

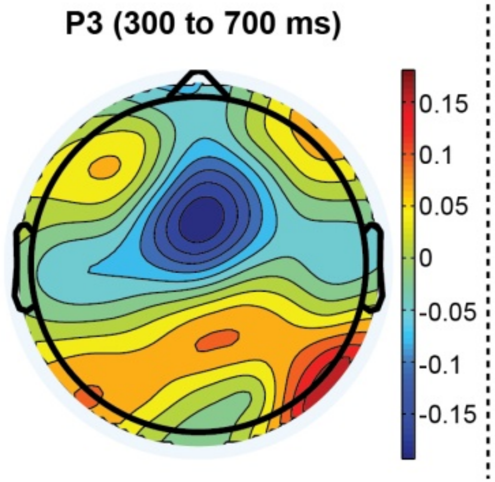
Decision Neuroscience Laboratory
Melbourne School of Psychological Sciences
The University of Melbourne, Australia

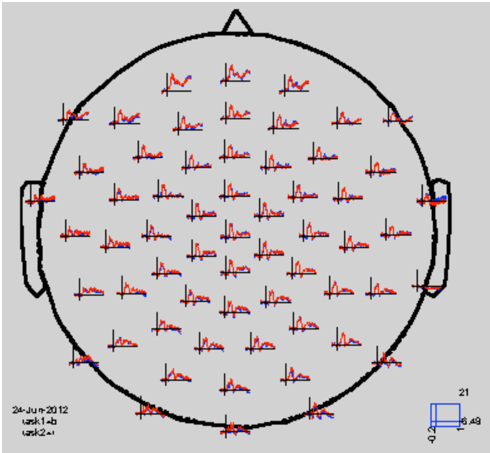
POSTERA CRESCAM LAUDE
THE UNIVERSITY OF
MELBOURNE

Electroencephalography (EEG)

- First described by Berger (1929), the EEG can be used to measure neural activity and relate it to behaviour
- Recording of electrical activity along the scalp that reflects small but meaningful voltage fluctuations resulting from ionic current flows within neurons
- EEG has a very good temporal resolution, and can be characterised by various features, including frequencies and latency and amplitudes of component of the event-related potentials (ERPs).
- Advantages: cheap, easy to use, very good temporal resolution (500 Hz to 4000 Hz possible for most systems), paradigms can be paced fast (more repetitions), etc.
- Disadvantages: Artefacts (eye blinks, muscle activity), noisy, poor spatial resolution, the “inverse problem”, not all brain activity equally represented in the signal.

Electroencephalography (EEG)





- Most components of the ERP are only described for specific electrode locations

➔ What about the temporal dynamics at other channels?

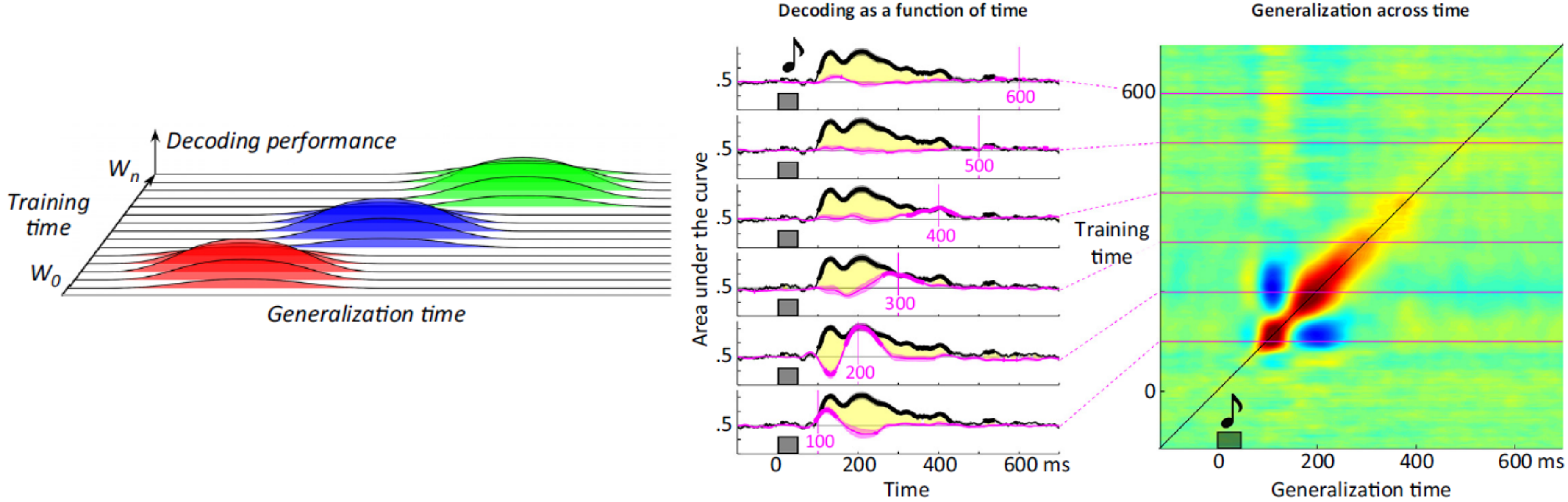
- Most EEG studies do not make use of the multivariate nature of the signal (but see: Das et al., 2010, Neuroimage; Philiastides et al., 2006, J Neurosci; Philiastides & Sajda, 2006, Cerb Cortex; King & Dehaene, 2014, J Neurosci)

- How much information about cognitive processes can be decoded from patterns of event-related potentials?

Classification-based EEG/ERP analysis

Why should we use MVPA for ERPs?

1) Signal might contain more information than single ERPs
2) No ERP component known for particular problem
3) We might be interested in *when* information becomes available
4) *Generalisation of representations* can be tested across *time* and across *content*



King & Dehaene, 2014, TICS

Classification-based EEG/ERP analysis

Data input: many options - ERPs, wavelet coefficients, PCA factor weights, etc.

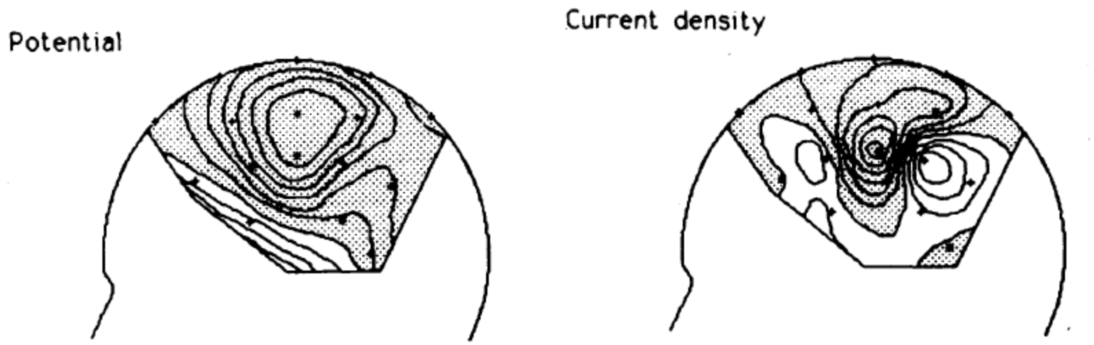
- for ERPs: either block-averaged ERPs (less noise) (Bode et al., 2012, J Neurosci) or single-trials (more exemplars) (Bode & Stahl, 2014, Biol Psychol) can be used.

- Preprocessing requires standard artefact rejection and sorting data into conditions

- Current source density (CSD) is beneficial. CSD maps represent the magnitude of the radial (transcranial) current flow entering (sources) and leaving (sinks) the scalp

(Kayser & Tenke, 2005; Tenke & Kayser, 2006; Perrin et al., 1987, 1989; Pernier et al.,1988)

➔ reference-free, spatially enhanced representation of the direction, location, and intensity of current generators that underlie an ERP topography, reduces signal redundancies in neighbouring channels

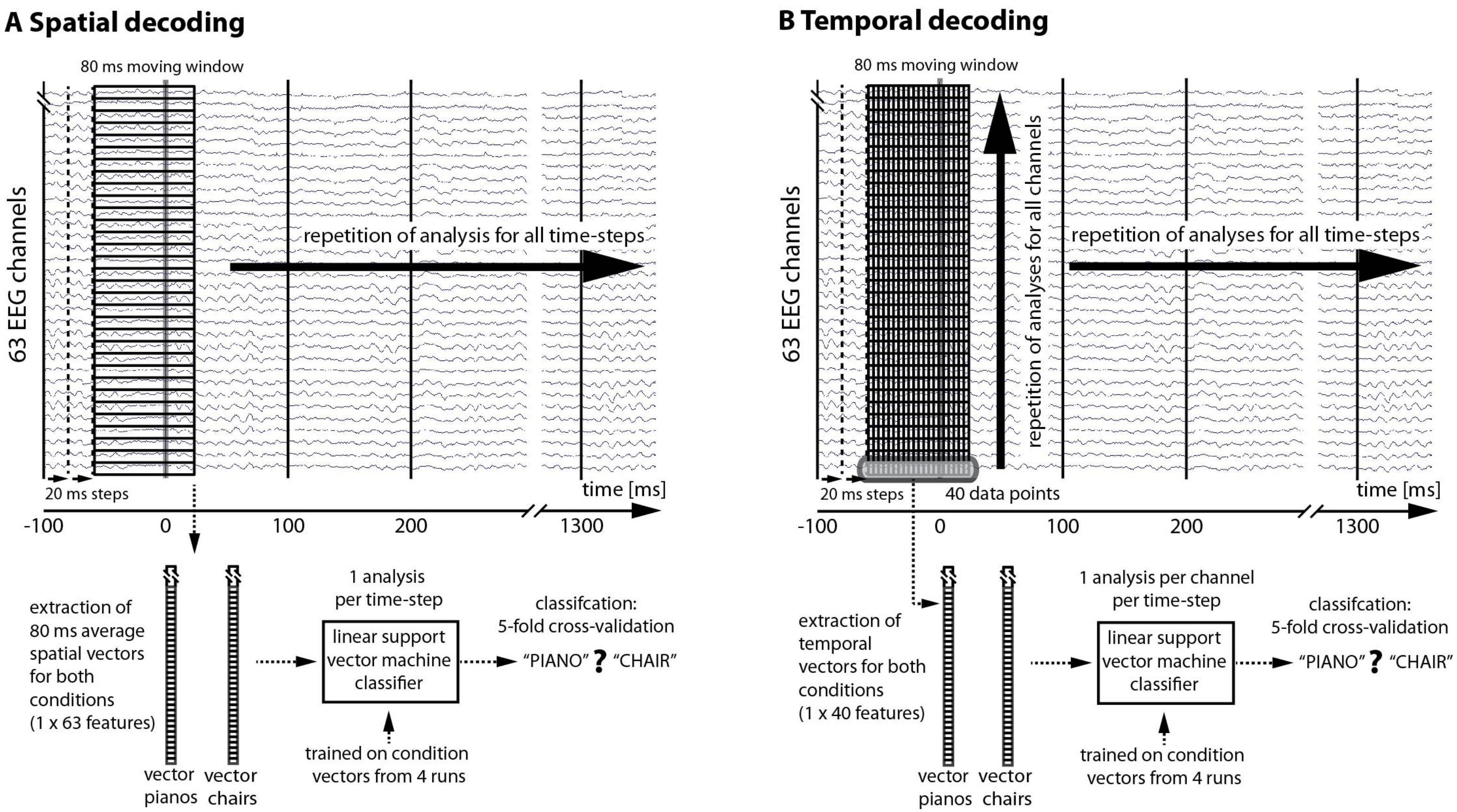


Perrin et al., 1987, IEEE Trans Biomed Eng

Classification-based EEG/ERP analysis

<u>Classifiers</u>: same as for fMRI. Linear SVM classifiers work well

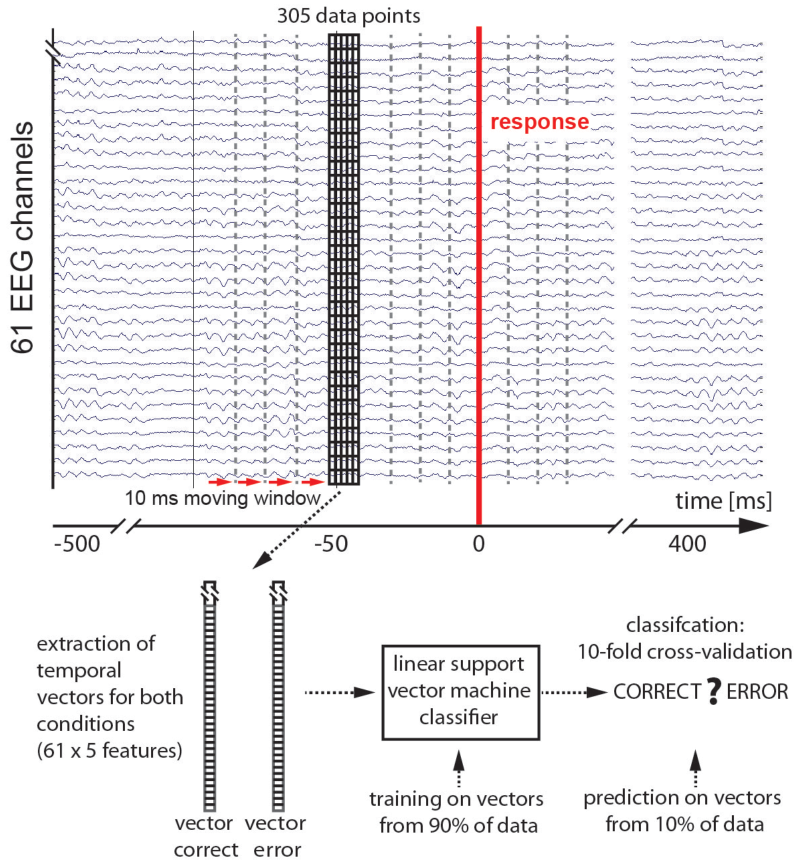
(Bai et al., 2007, Clin Neurophysiol; Das et al., 2012, Neuroimage)

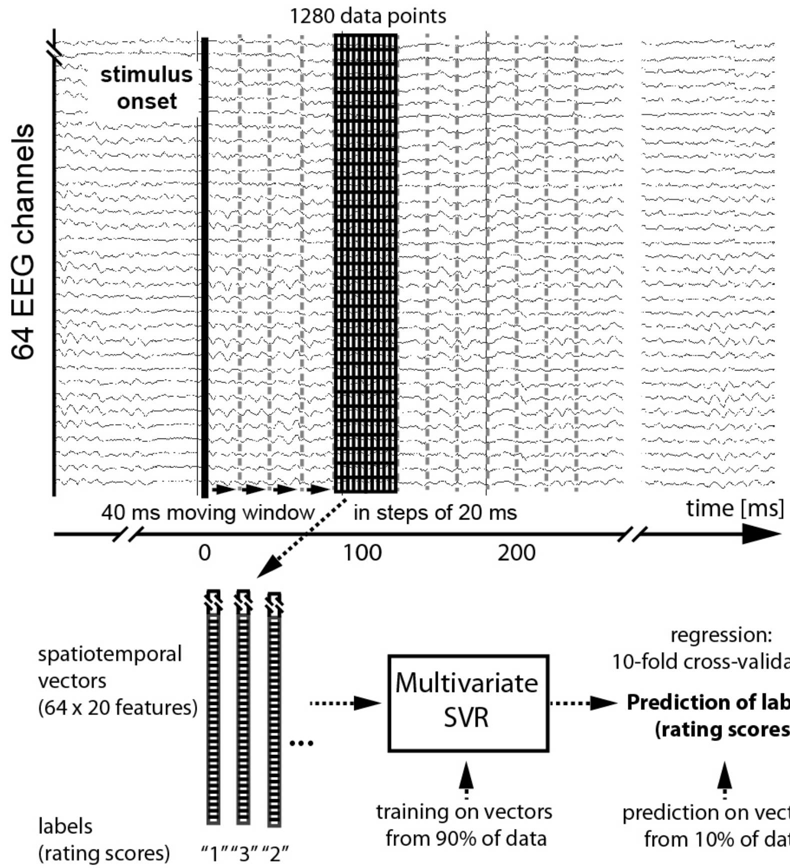


Bode, Sewell, Lilburn, Forte, Smith & Stahl, 2012, J Neurosci

Classification-based EEG/ERP analysis

Other approaches: spatio-temporal decoding increases precision, support-vector regression (SVR) for continuous variables





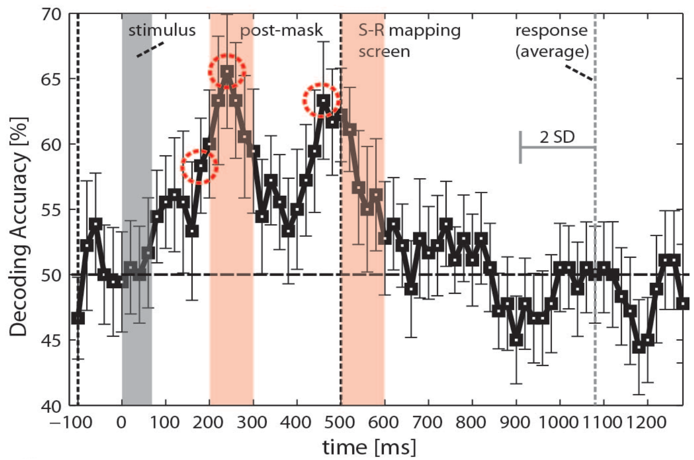
Classification-based EEG/ERP analysis

<u>Group-level analysis</u>:

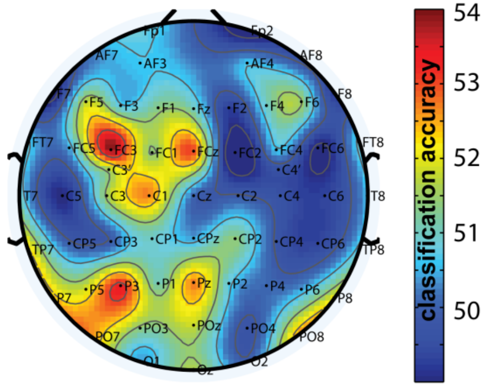
1) Compute group-level statistics for *information time-courses* (spatial decoding) ➔ problem of multiple comparisons (number of tests / time windows, shuffled labels analysis, area under the curve, time series analyses)
2) Compute group-level statistics for single channels (temporal decoding)
3) Feature weights? But these might reflect other sources than true information

(see Haufe et al., 2014, Neuroimage)

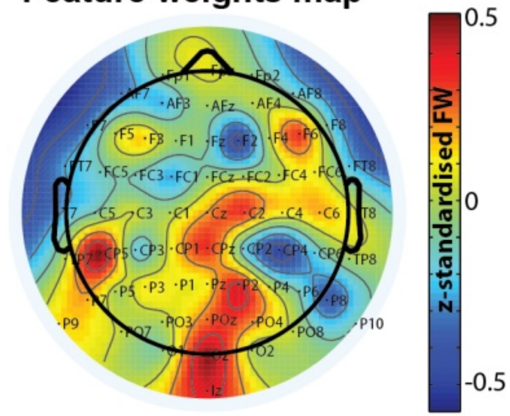
spatial decoding



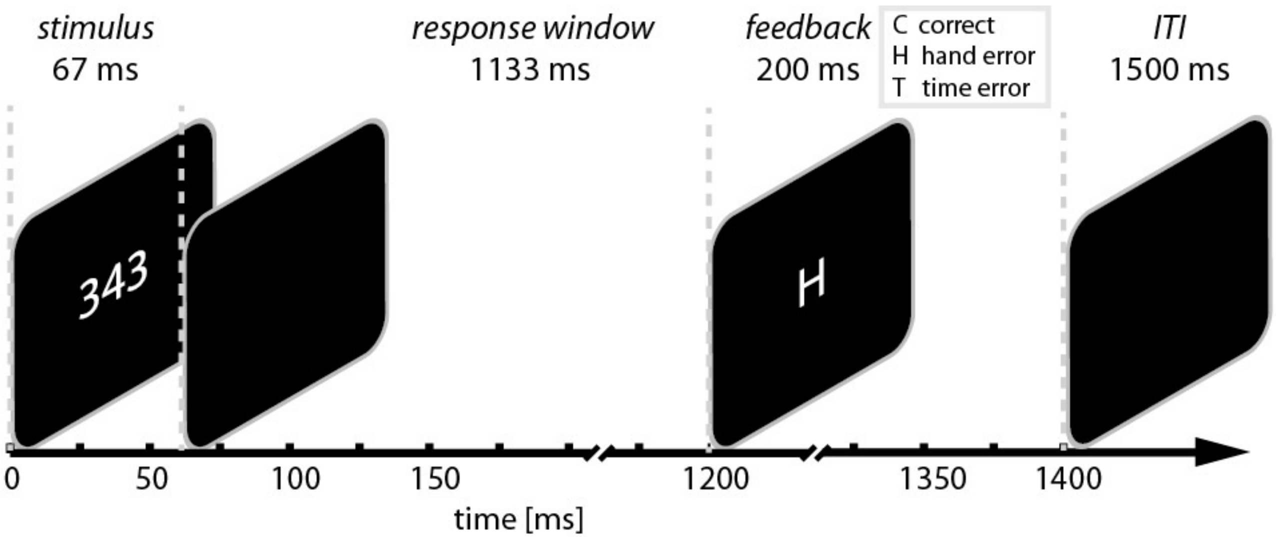
temporal decoding



Feature weights map



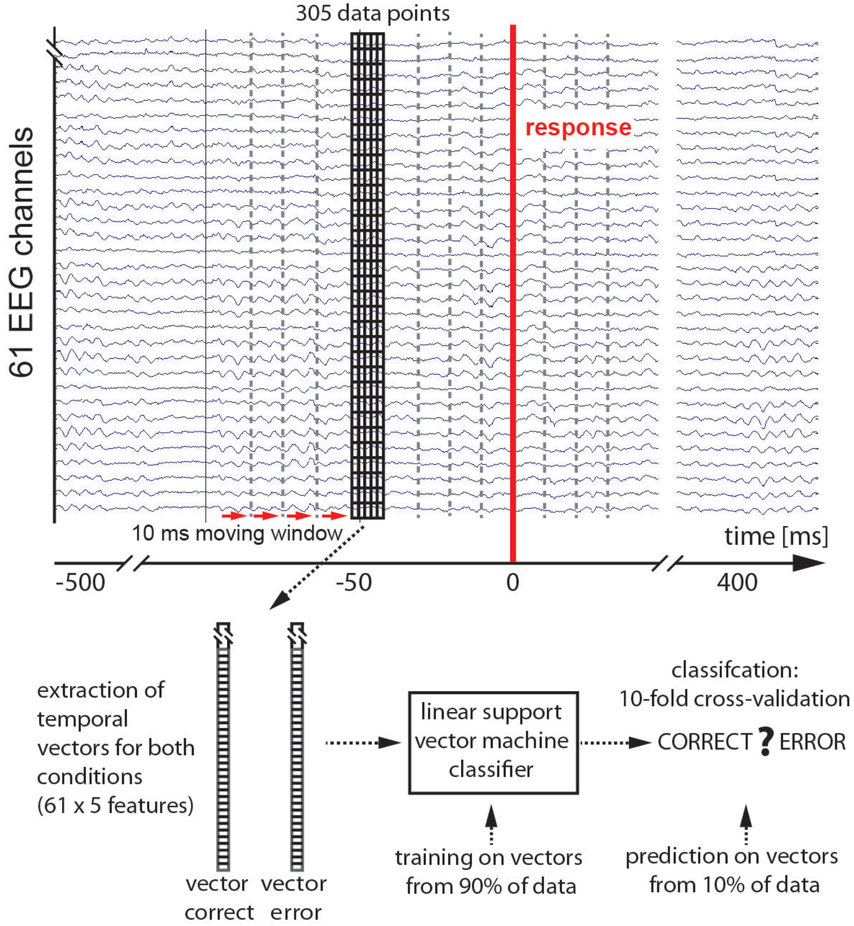
Predicting errors from patterns of single-trial ERPs

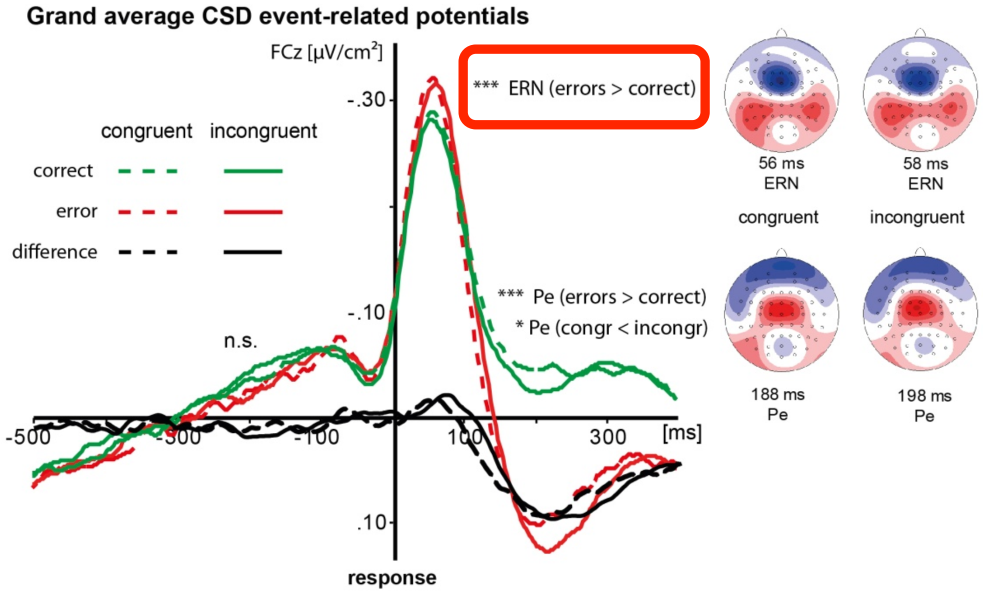


- Digit flanker task (Stahl, 2010, Int J Psychophysiol) with speed instruction
- Response to central digit (odd or even) with congruent or incongruent flankers

111 subjects (58 female, mean age 25.2 ± 5.8 SD years)
recording with 61 channel EEG system; active Ag/AgCl electrodes (actiCAP, Brain Products)
sampling rate of 500 Hz, on-line 70 Hz band-pass filtering; ± 100 µV artefact rejection

Predicting errors from patterns of single-trial ERPs

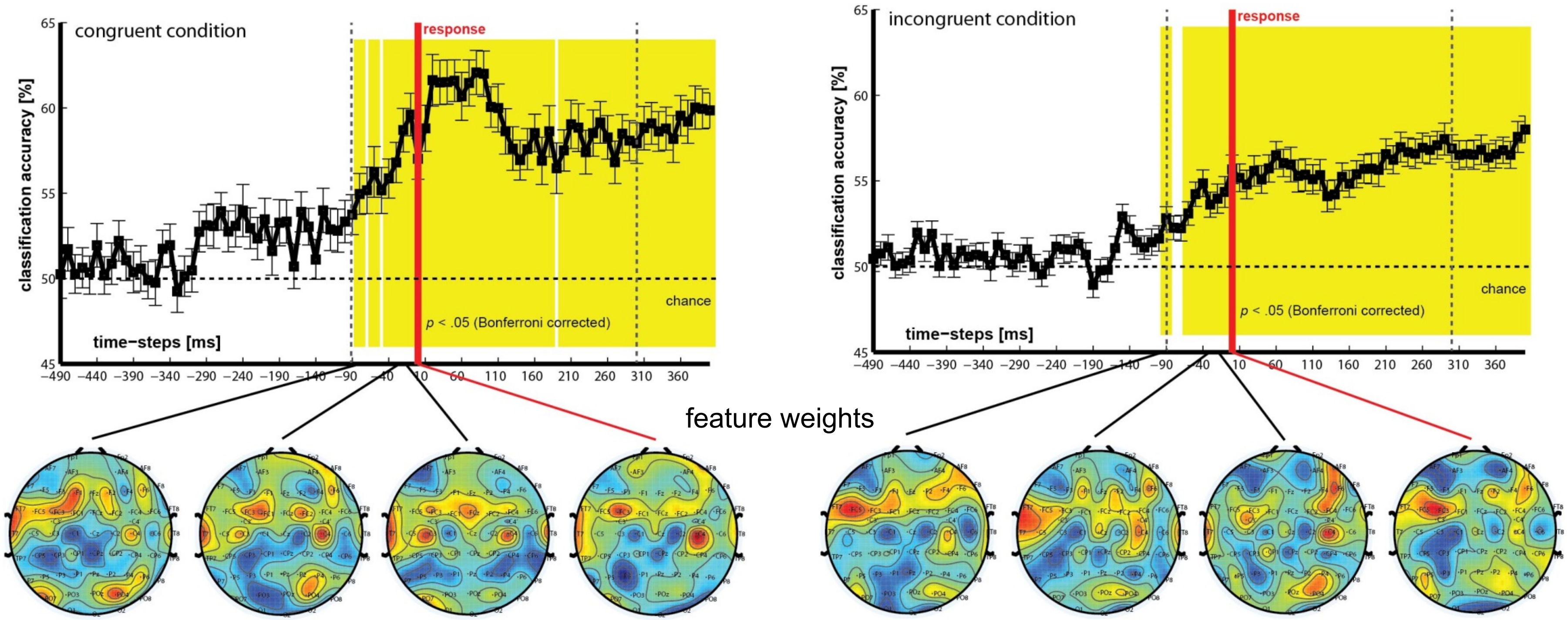




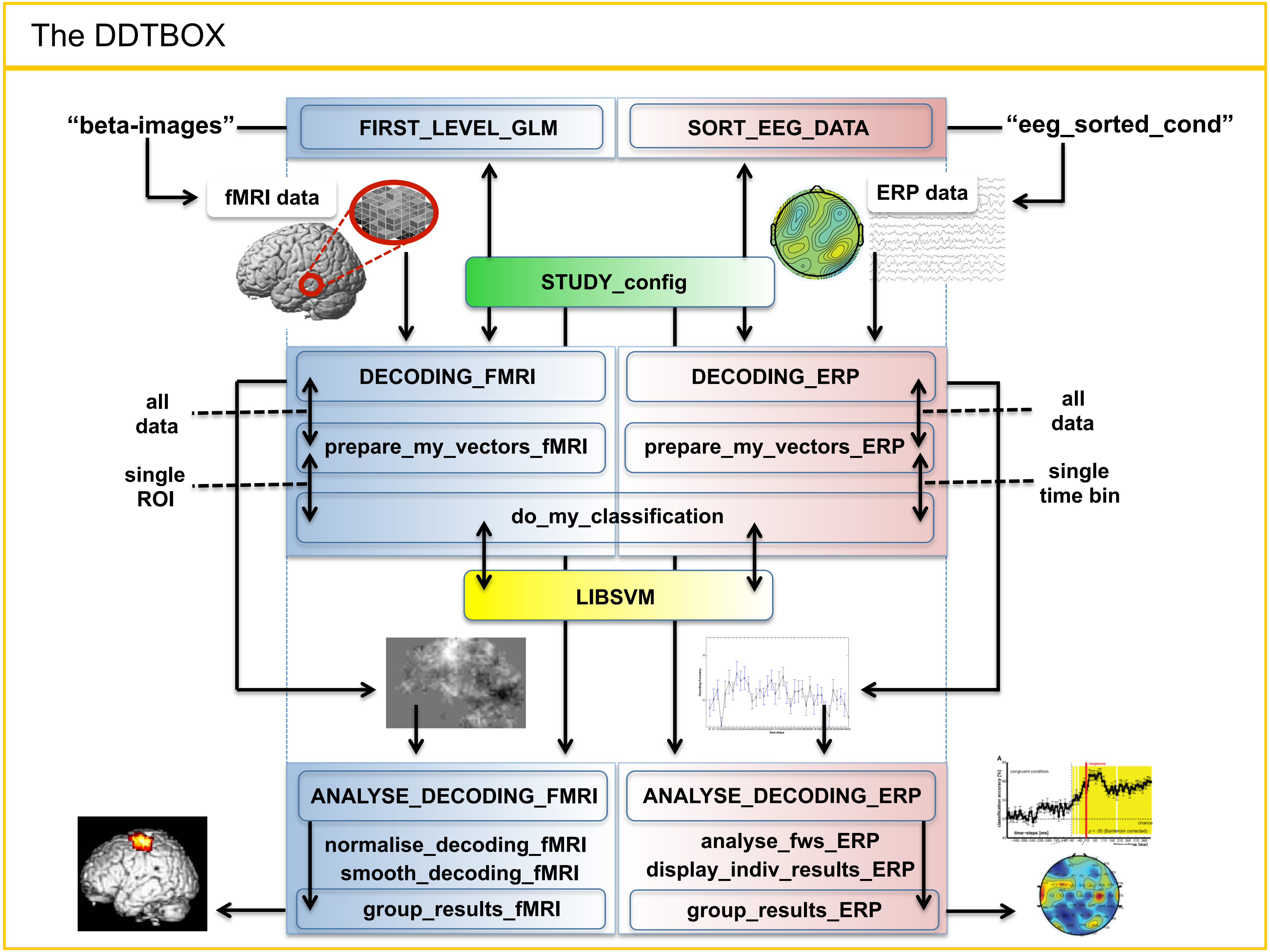
- Ne/ERN after ~80 ms
- No differences in CSD-ERP between conditions preceding overt response
- Are patterns of small pre-response differences in CSD-ERP predictive for errors?

- MVPA with 10 repetitions of 10 cross-validation steps and permutation test

Predicting errors from patterns of single-trial ERPs



- Increasing accuracy between response initiation and response execution
- Early accumulation of error evidence after initial decision, probably based on **ongoing analyses of perceptual input** (Resulaj et al., 2009, Nature) and **motor signals**
- Basis for fast *error correction* processes?



The DDTBOX
"beta-images"
FIRST_LEVEL_GLM
SORT_EEG_DATA
"eeg_sorted_cond"
fMRI data
ERP data
STUDY_config
DECODING_FMRI
DECODING_ERP
all data
prepare_my_vectors_fMRI
prepare_my_vectors_ERP
all data
single ROI
single time bin
do_my_classification
LIBSVM
ANALYSE_DECODING_FMRI
ANALYSE_DECODING_ERP
normalise_decoding_fMRI
smooth_decoding_fMRI
analyse_fws_ERP
display_indiv_results_ERP
group_results_fMRI
group_results_ERP

Recommended papers

Bai O, Lin P, Vorbach S, Li J, Furlani S, et al. (2007). Exploration of computational methods for classification of movement intention during human voluntary movement from single trial EEG. ***Clin Neurophysiol*** ,118, 2637–2655.

Blankertz B, Lemm S, Treder M, Haufe S, Mueller KR (2011). Single-trial analysis and classification of ERP components—A tutorial. ***Neuroimage***, 56, 814–825.

Bode S, Bennett D, Stahl J, Murawski C (2014). Distributed patterns of event-related potentials predict subsequent ratings of abstract stimulus attributes. ***PLoS ONE***, 9(10): e109070.

Bode S, Sewell D, Lilburn S, Forte J, Smith PL, Stahl J (2012). Predicting perceptual decision biases from early brain activity. ***J Neurosci***, 32, 12488–12498.

Bode S, Stahl J (2014). Predicting errors from patterns of event-related potentials preceding an overt response. ***Biol Psychol***, 103, 357-369.

Das K, Giesbrecht B, Eckstein MP (2010). Predicting variations of perceptual performance across individuals from neural activity using pattern classifiers. ***Neuroimage***, 51, 1425–1437.

King JR, Dehaene S (2014). Characterizing the dynamics of mental represen-tations: The temporal generalization method. ***Trends Cogn Sci***, 18,203–210.

Acknowledgements

The University of Melbourne, Melbourne School of Psychological Sciences

Decision Neuroscience Laboratory
Dr. Carsten Murawski
Daniel B. Bennett
Bowen J. Fung
Daniel Rosenblatt
Katharina Voigt
Damien Crone
Hayley Warren
Maja Brydevall
Ariel Goh
William Turner
Philip Johnston
Kathleen De Boer
Pola Held
Tracy Wang

Vision & Attention Laboratory
Prof. Philip Smith
Dr. David Sewell
Dr. Jason Forte
Dr. Elaine Corbett
Simon Lilburn

University of Cologne, Germany
Prof. Jutta Stahl

Thank you for your attention!

Funding sources
ARC DECRA (DE140100350)
University of Melbourne Department of Finance Initiative Project Grant
University of Melbourne Early Career Researcher (ECR) Grant
Melbourne Neuroscience Institutes (MNI) Interdisciplinary Seed Funding Grant