# Multi-class classification of independent components of EEG

Laura F. Frølich, Tobias Andersen, Morten Mørup
{lff, ta, mm}@imm.dtu.dk

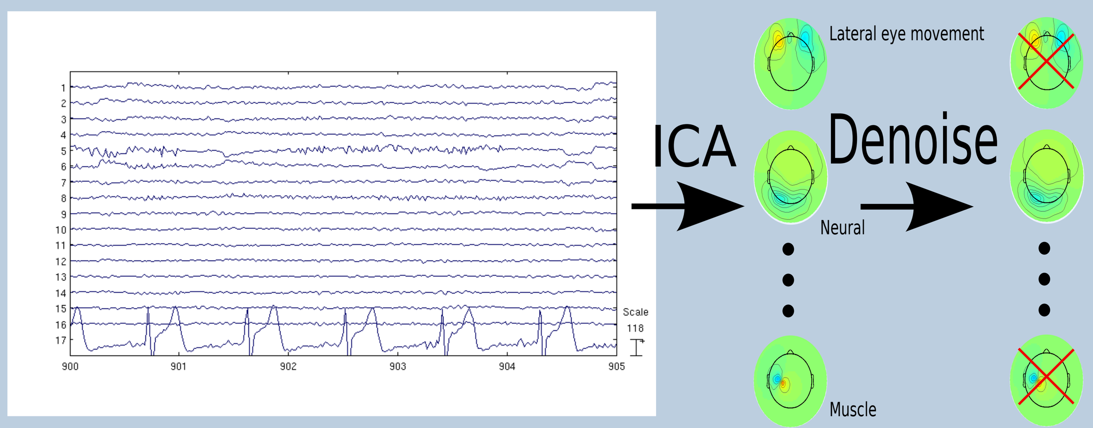
DTU Informatics
Department of Informatics and Mathematical Modelling

## Introduction

Independent components (ICs) of EEG:

- Patterns of brain activity
- Mutually independent

ICs are used both in preprocessing and analysis of EEG data.




- Classification of ICs is necessary before they can be utilized. However, manual classification is time consuming and subjective.
- Binary classification investigated previously. We look at classification at higher resolution, i.e. into more types of ICs.

## Previous work

Neural vs. artifactual classification of ICs

- 2006

**LeVan et. al**

Tree-augmented naïve Bayesian networks used to classify 2s epochs of ICs. Number of epochs of ICs classified as artifactual determine IC classification. Features were mixing matrix, relative band power, dipole fit (fit and residual variance), negentropy, and variance over all channels of each epoch

- 2009

**Tangermann et al.**

Automatic differentiation between neural and artifactual ICs, comparing LDA to SVM. Characteristics of scalp maps and temporal and frequency characteristics of IC activation over time used as features.

**Viola et al.**

Correlation between spatial maps, i.e. mixing matrices, to classify ICs

- 2010

**Mognon et al.**

Automatic differentiation between neural and artifactual ICs, using GMM. Features mostly from scalp map, a few temporal from IC activation time series.

**Bartels et al.**

SVM used to classify ICs from 7s epochs. Features consisted of mixing matrix, power in 5Hz wide bins from 0 to 50 Hz, and 6th order AR coefficients. BSS algorithm "Infomax" used to find EMG ICs and "AMUSE" to find EOG ICs.

- 2011

**Winkler et al.**

Addition and elaboration on the work described in Tangermann et al's 2009 paper.

## References

[1] G. Bartels, Li-Chen Shi, and Bao-Liang Lu. "Automatic artifact removal from EEG - a mixed approach based on double blind source separation and support vector machine". In: *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*. 2010, pp. 5383 –5386. DOI: 10.1109/IEMBS.2010.5626481.

[2] Brain Products GmbH. *Brain Vision Analyzer User Manual, version 1.05*. Tech. rep. Brain Products GmbH, 1999.

[3] K. Gramann, T. Tollner, and H. J. Muller. "Dimension-based attention modulates early visual processing". In: *Psychophysiology* 47 (Sept. 2010), pp. 968–978.

[4] P LeVan, E Urrestarazu, and J Gotman. "A system for automatic artifact removal in ictal scalp EEG based on independent component analysis and Bayesian classification." In: *Clin Neurophysiol* 117.4 (2006), pp. 912–27.

[5] A. Mognon et al. "ADJUST: An Automatic EEG artifact Detector based on the Joint Use of Spatial and Temporal features." In: *Psychophysiology* (2010). DOI: 10.1111/j.1469-8986.2010.01061.x.

[6] Julie A Onton and Scott Makeig. "High-frequency broadband modulation of electroencephalographic spectra". In: *Frontiers in Human Neuroscience* 0 (2009), p. 12. ISSN: 1662-5161. DOI: 10.3389/neuro.09.061.2009. URL: http://www.frontiersin.org/Journal/Abstract.aspx?s=537&name=humanneuroscience&ART_DOI=10.3389/neuro.09.061.2009.

[7] Michael Tangermann et al. "Classification of artifactual ICA components". In: *Int J Bioelectromagnetism* 11.2 (2009), pp. 110–114.

[8] Filipa Campos Viola et al. "Semi-automatic identification of independent components representing EEG artifact." In: *Clin Neurophysiol* 120.5 (2009), pp. 868–77.

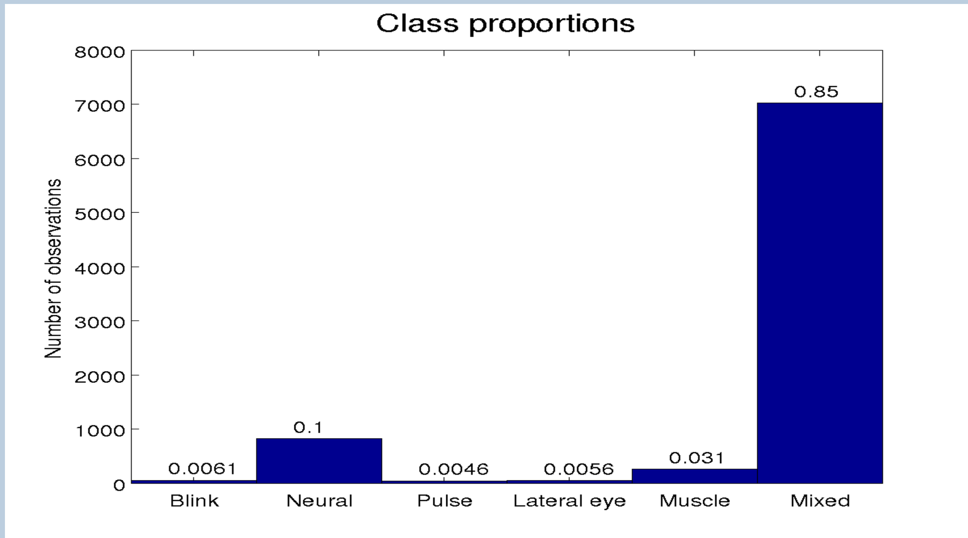
[9] I. Winkler, S. Haufe, and M. Tangermann. "Automatic Classification of Artifactual ICA-Components for Artifact Removal in EEG Signals". In: *Behav Brain Funct* 7 (Aug. 2011), p. 30.

## Data

Data with manually labelled ICs were made available by Julie Onton and Klaus Gramann [6, 3].

| Data | Subjects | Channels | Reference | ICA algorithm |
|---|---|---|---|---|
| [6] | 35 | 250 | Active reference | Extended infomax (*binica* in EEGLab) |
| [3] | 12 | 64 | Referenced to Cz, re-referenced to linked mastoids | Infomax, Brain Vision Analyzer [2] |

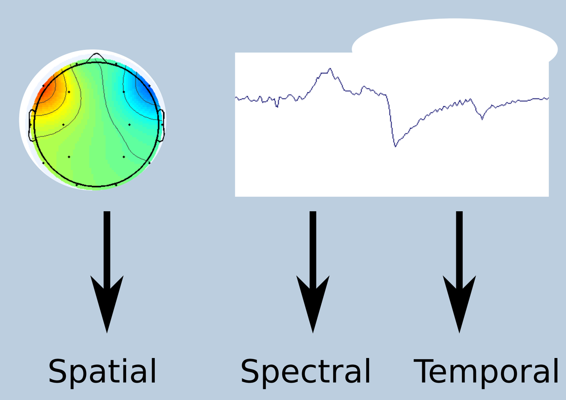
8229 ICs in total in data sets. Types of ICs and class proportions:



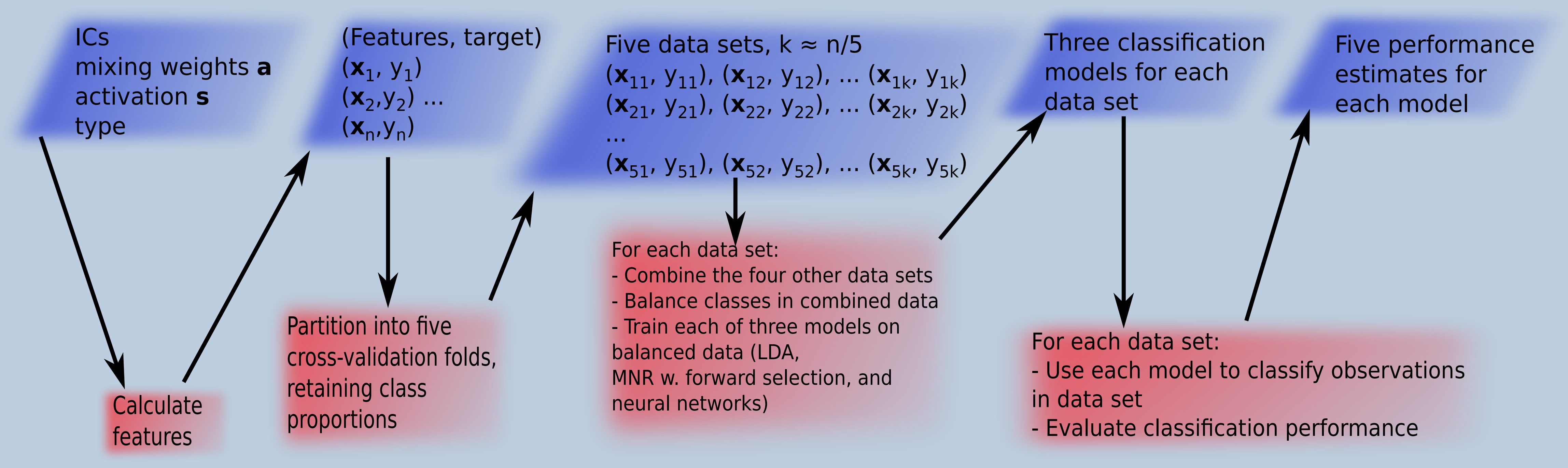

## Methods

### Features

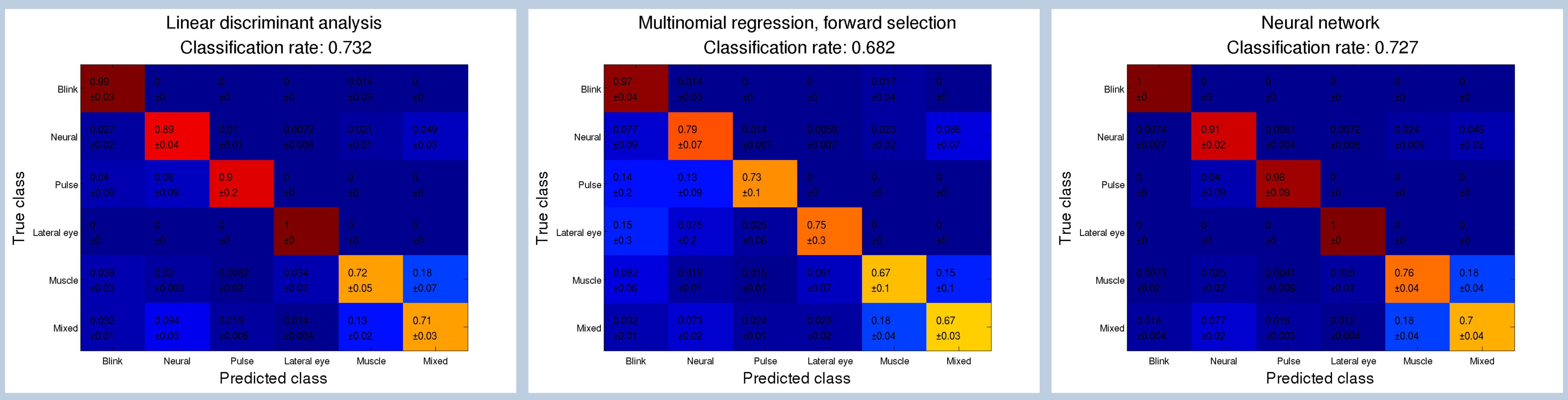
- 43 features, including most from two previous studies on binary classification [5, 9]
- Features quantify spectral, spatial, and temporal properties of ICs




### Classification




## Results




## Conclusions

- Differentiation between multiple classes of ICs is possible
- Classes are linearly separable
- Classification generalizes across studies, electrode setup, and ICA algorithm
- Classification at higher resolution useful for
  - Monitoring of artifact types, possible to instruct subject to minimize certain artifacts
  - Artifacts could be informative, e.g. eye artifacts and drowsiness
  - Classification of non-artifactual types of ICs may be possible

## Future work

- Use developed features and classification methods to investigate classification of general types of ICs
- Incorporate the classification scheme into an automatic data cleaning tool