New Margin- and Evidence-Based Approaches for EEG Signal Classification

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Suzanne Martens
Jason Farquhar, Jeremy Hill
Bernhard Schölkopf

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Develop systems which completely paralysed people (such as late-stage sufferers of Amyotrophic Lateral Sclerosis, ALS) can use to communicate, without relying on:

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- peripheral nerves
- (vision)
- (motor cortex)

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  - Manipulation of stimulus type.
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- *Algorithm development.*

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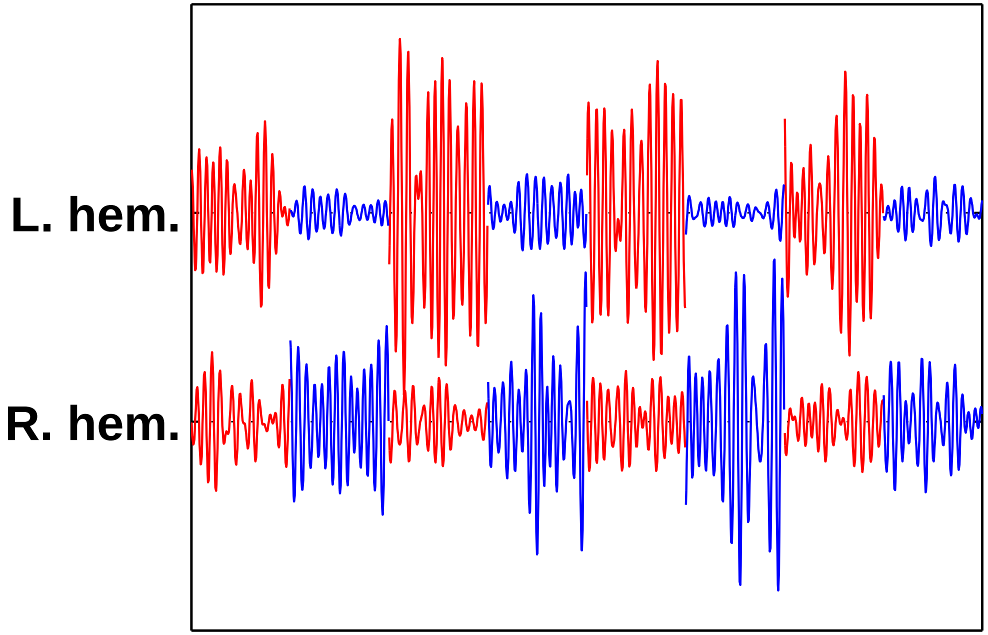
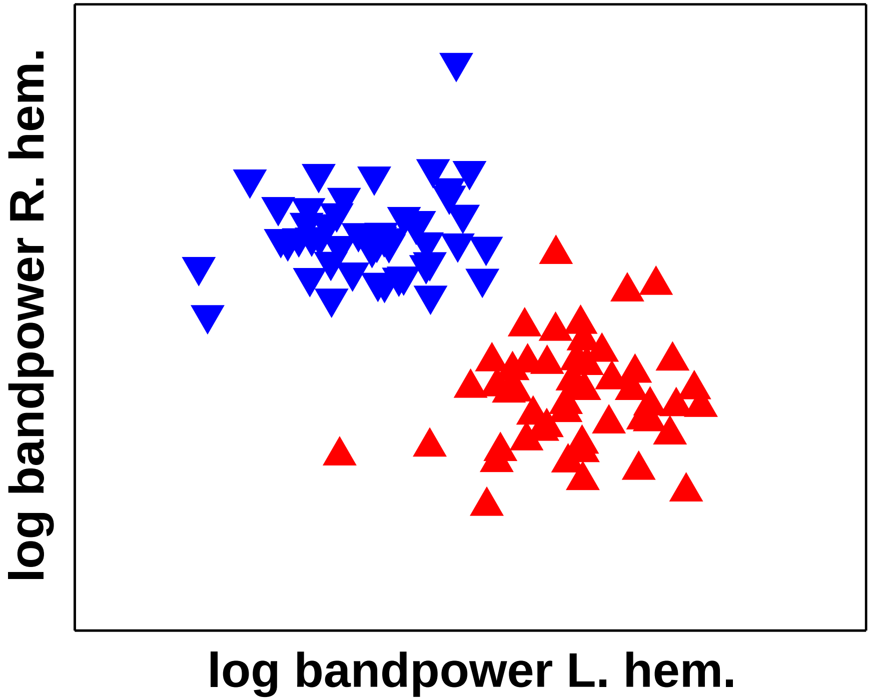
- Let the system run itself:

  No intervention from experts.

Example BCI setting

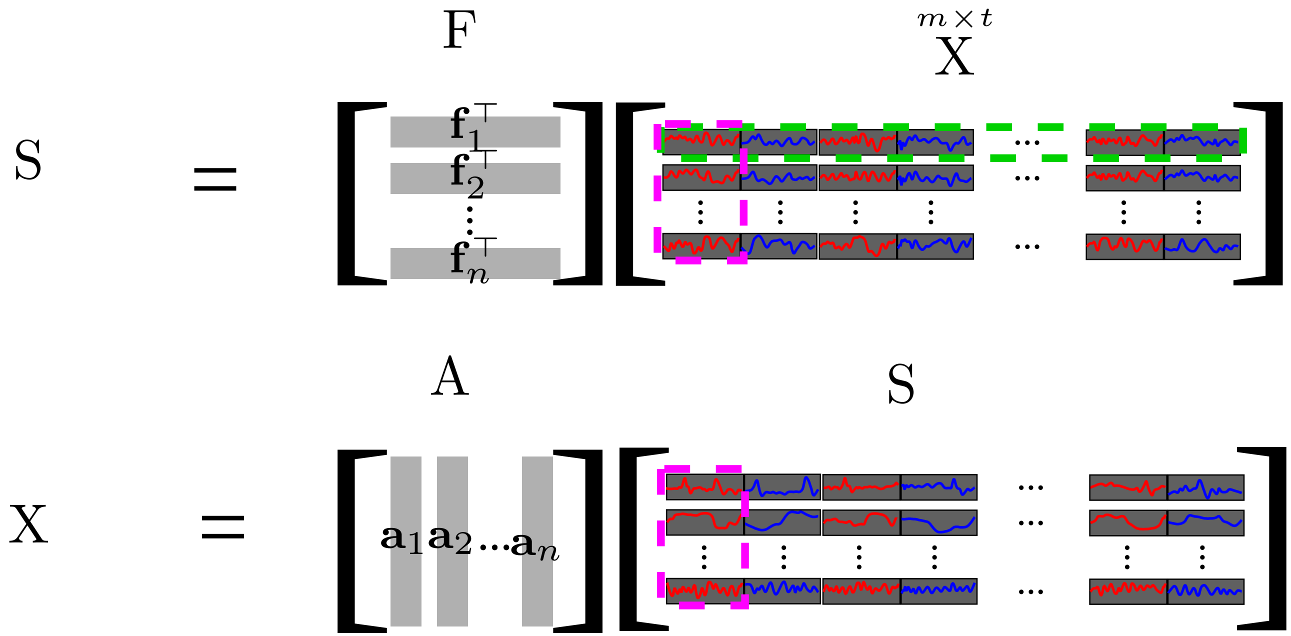
Event-Related Desynchronization in motor imagery: classify imagined left hand movement vs. imagined right hand movement based on α-band power of estimated pre-motor cortex sources in the left and right hemispheres.





Spatial Filtering

Given multichannel time-series X, we want appropriately spatially filtered time-series S = FX that contain only task-relevant information.

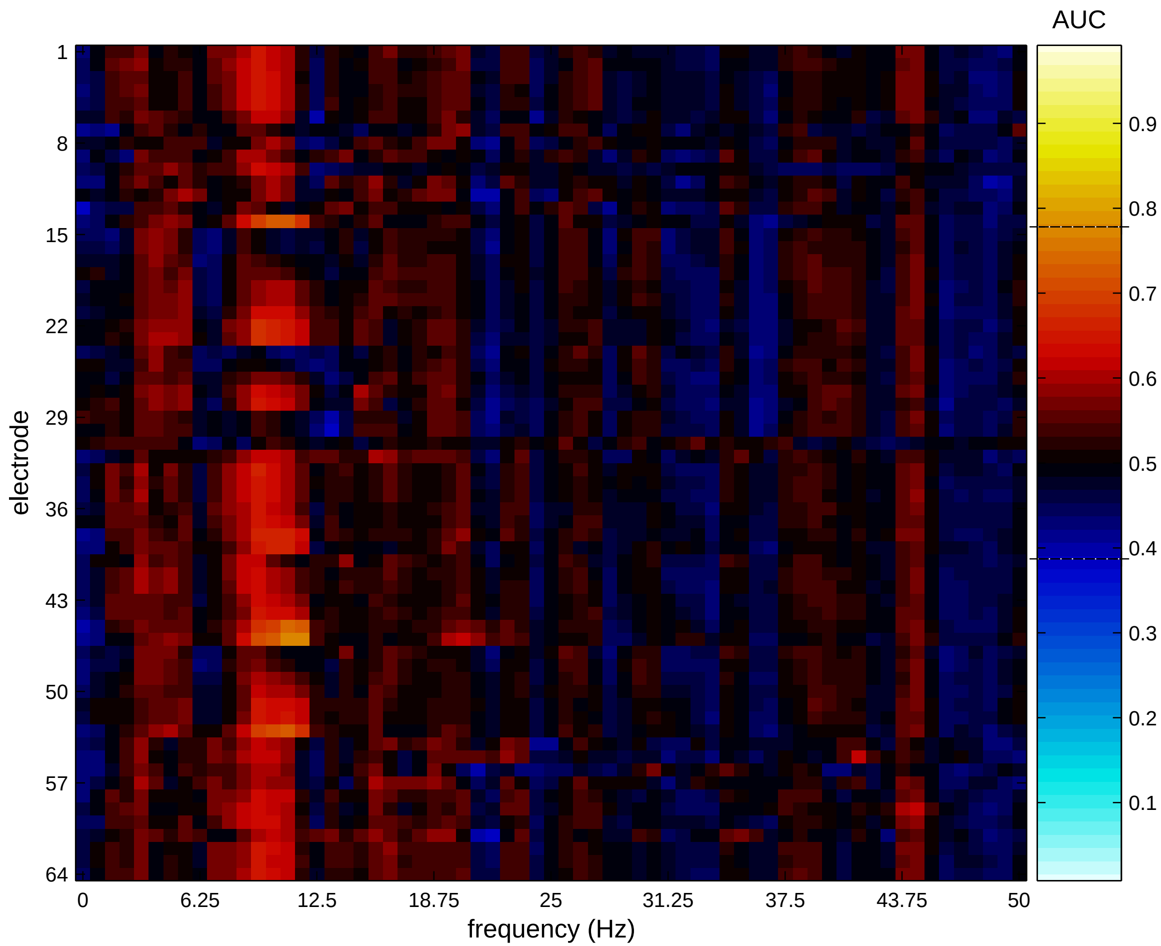


e.g.

- Independent Component Analysis (ICA)
- Common Spatial Pattern (CSP) — Koles 1991.

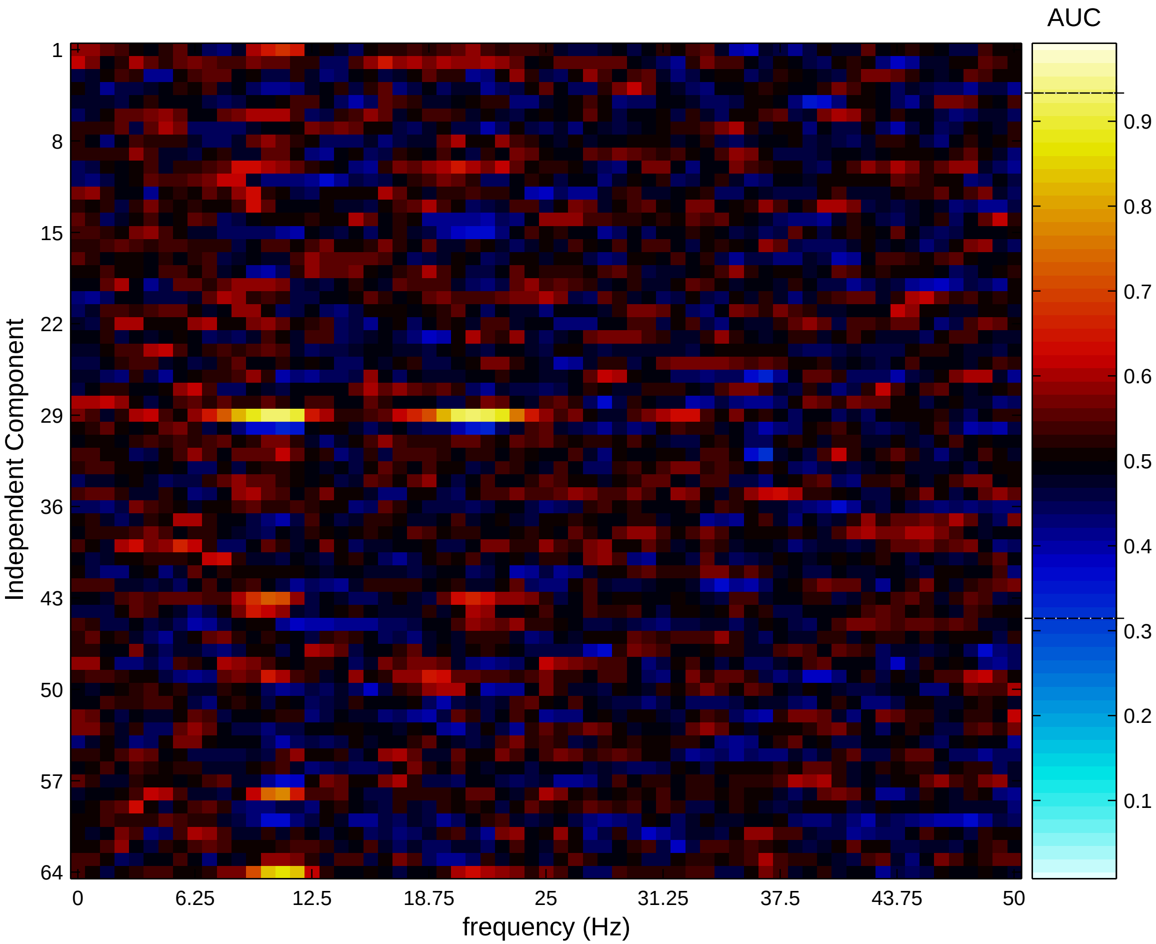
EEG Example

Amplitude spectra of raw EEG signals:

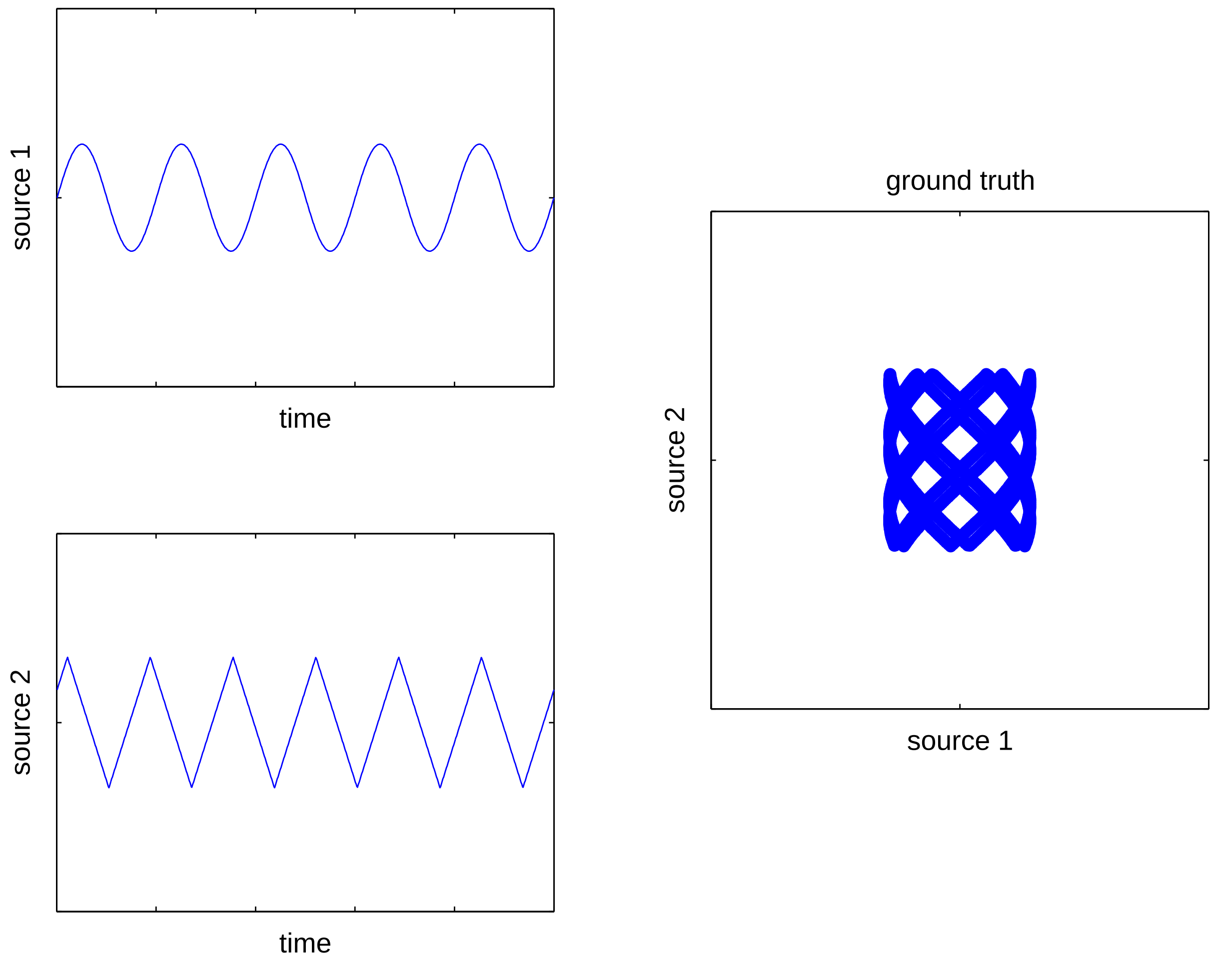


EEG Example

Amplitude spectra of sources estimated by Independent Component Analysis:



Whitening and rotation



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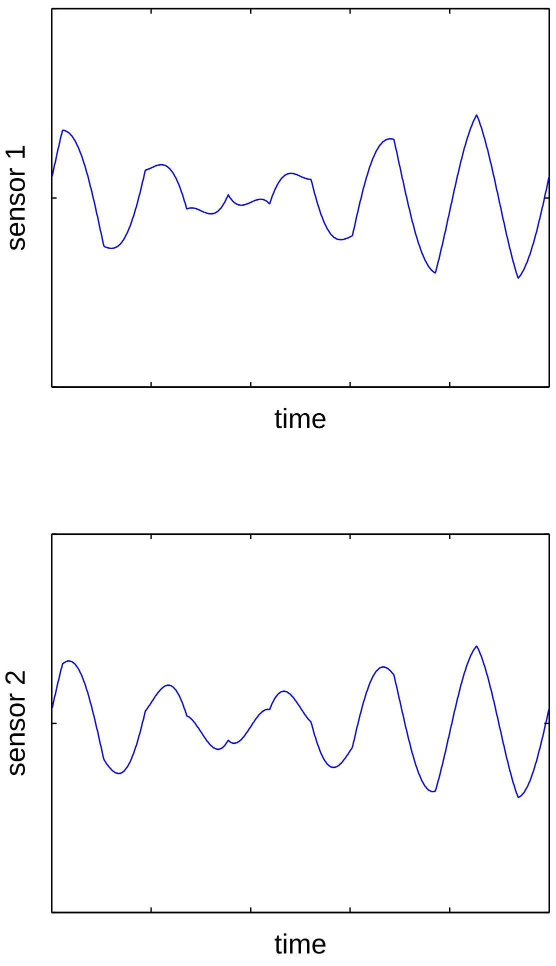

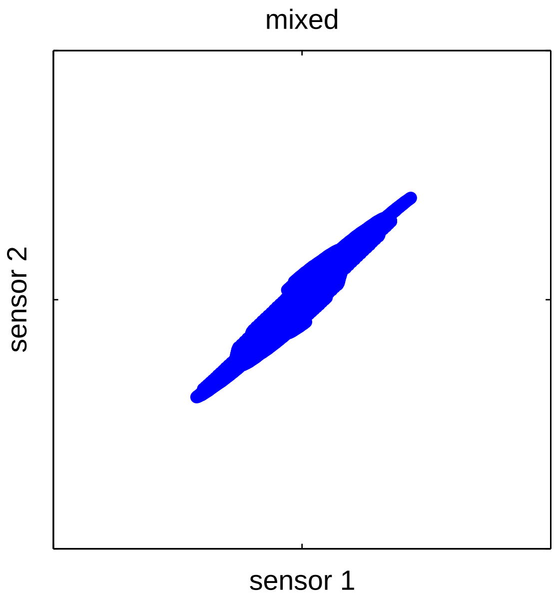

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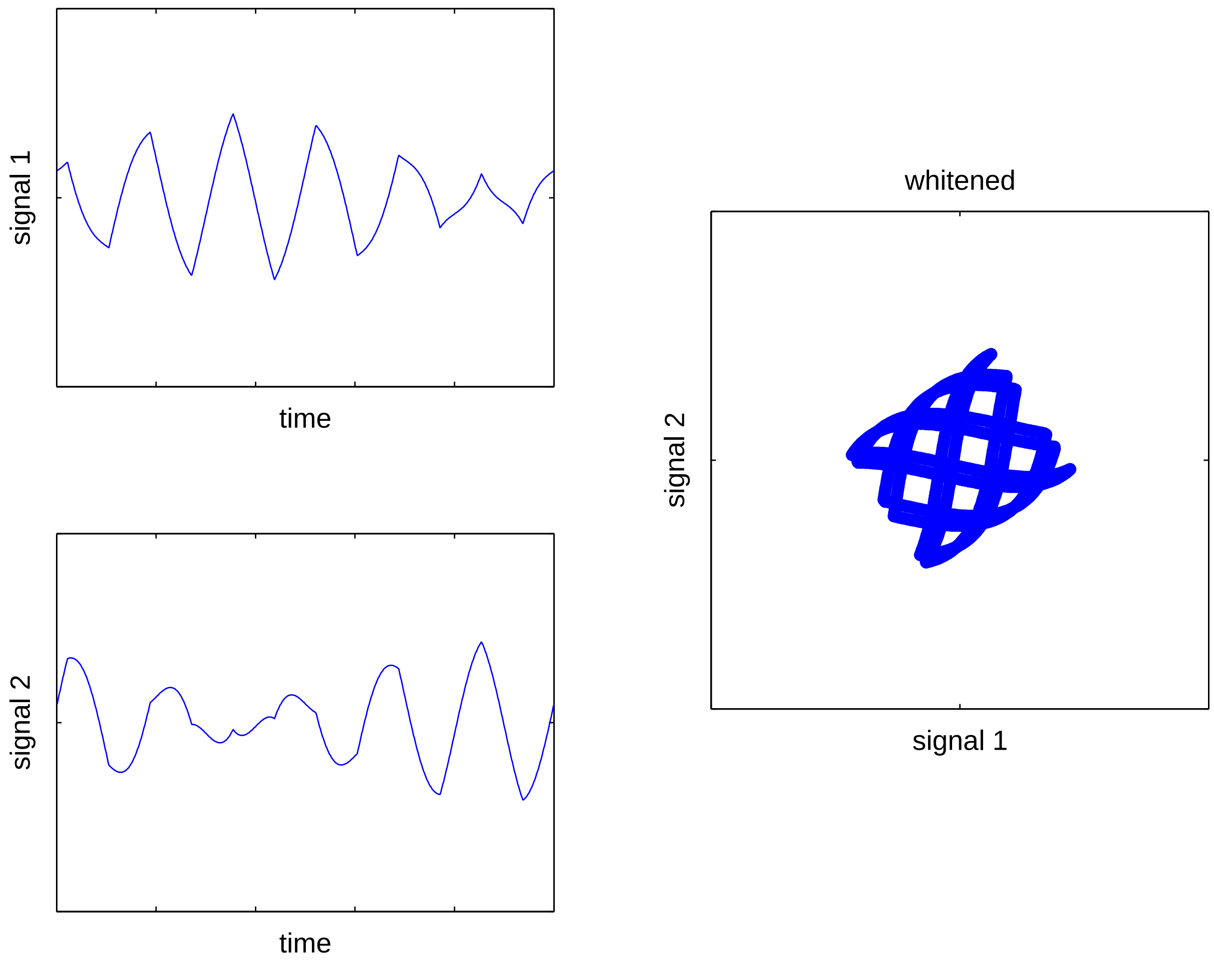

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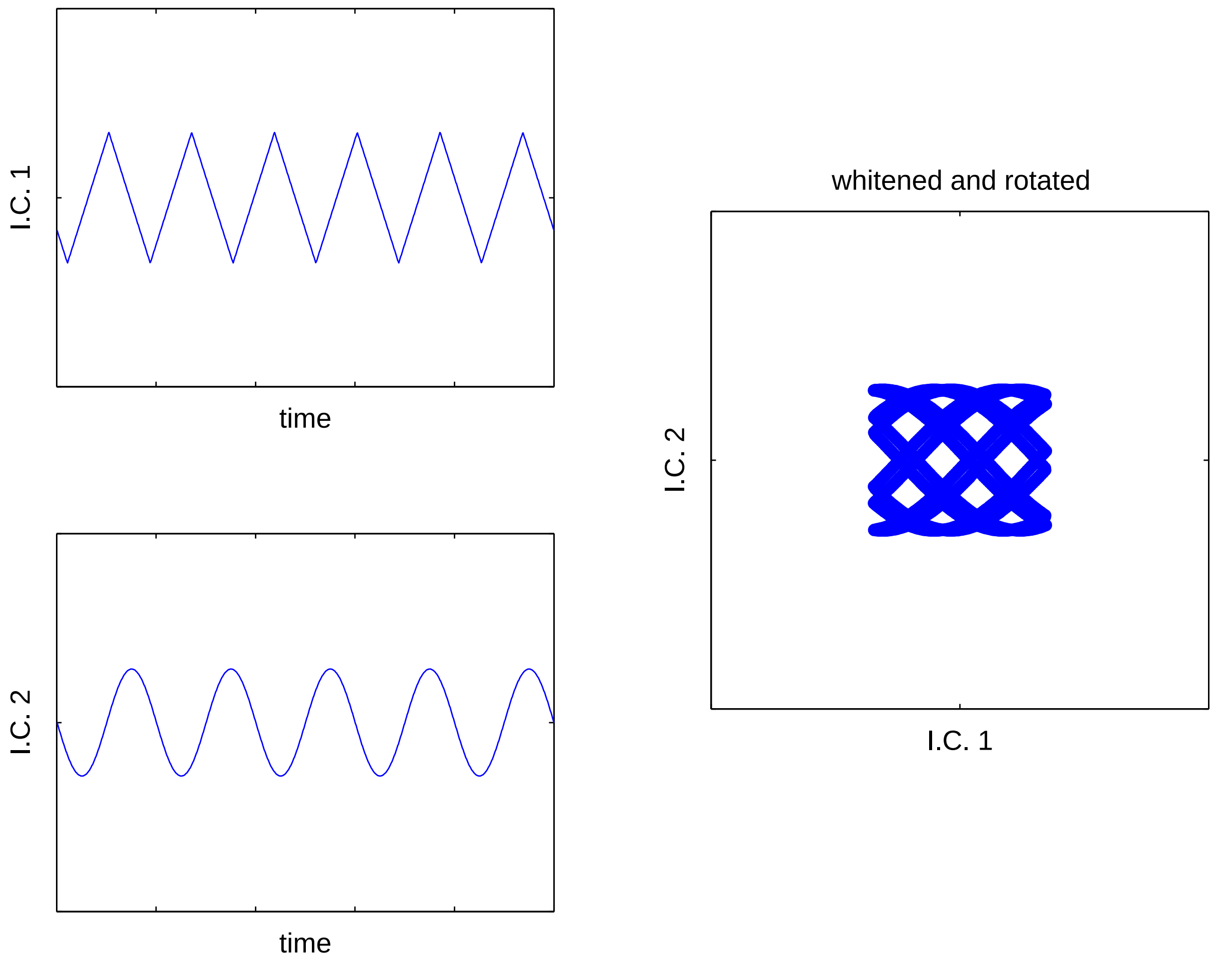

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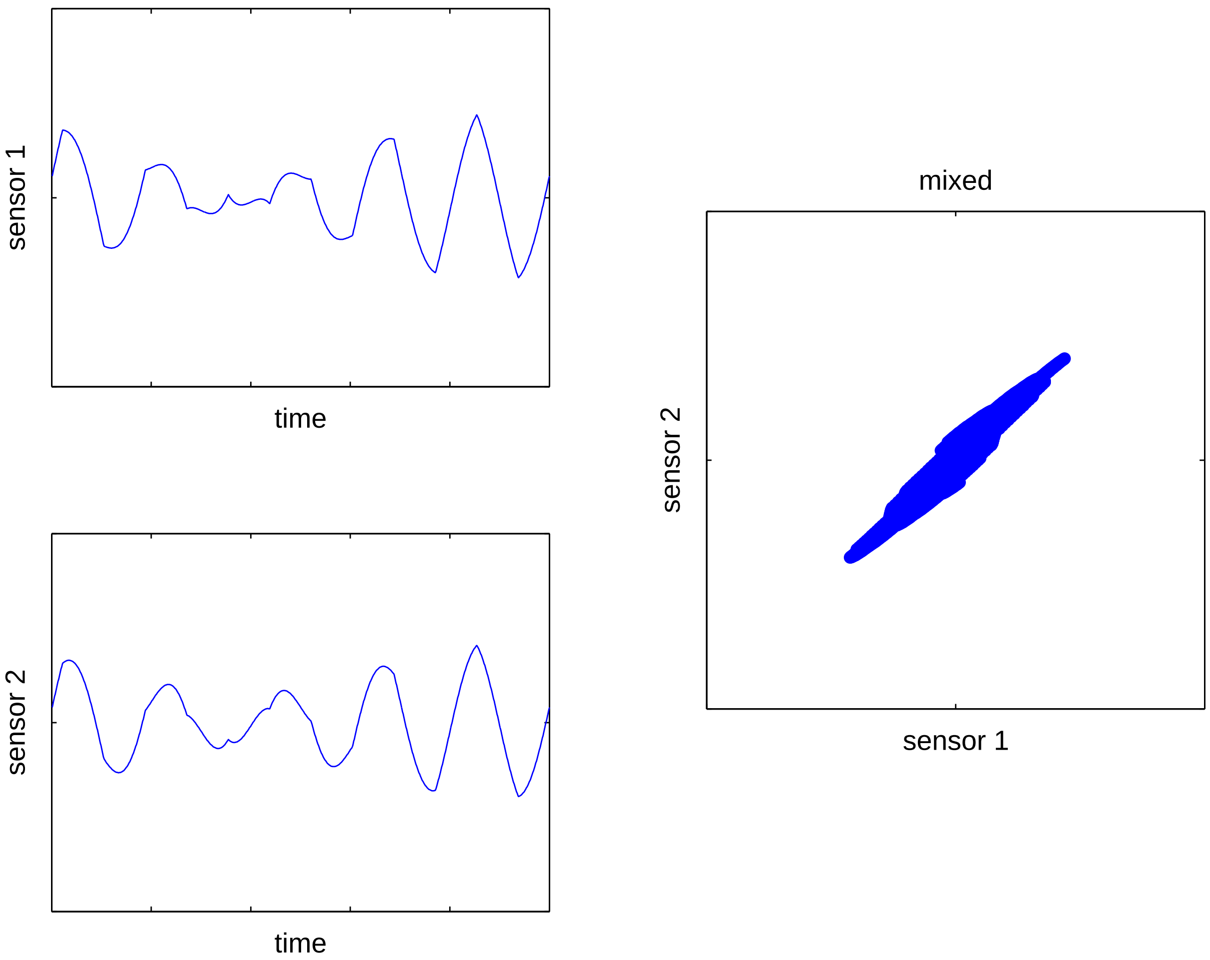
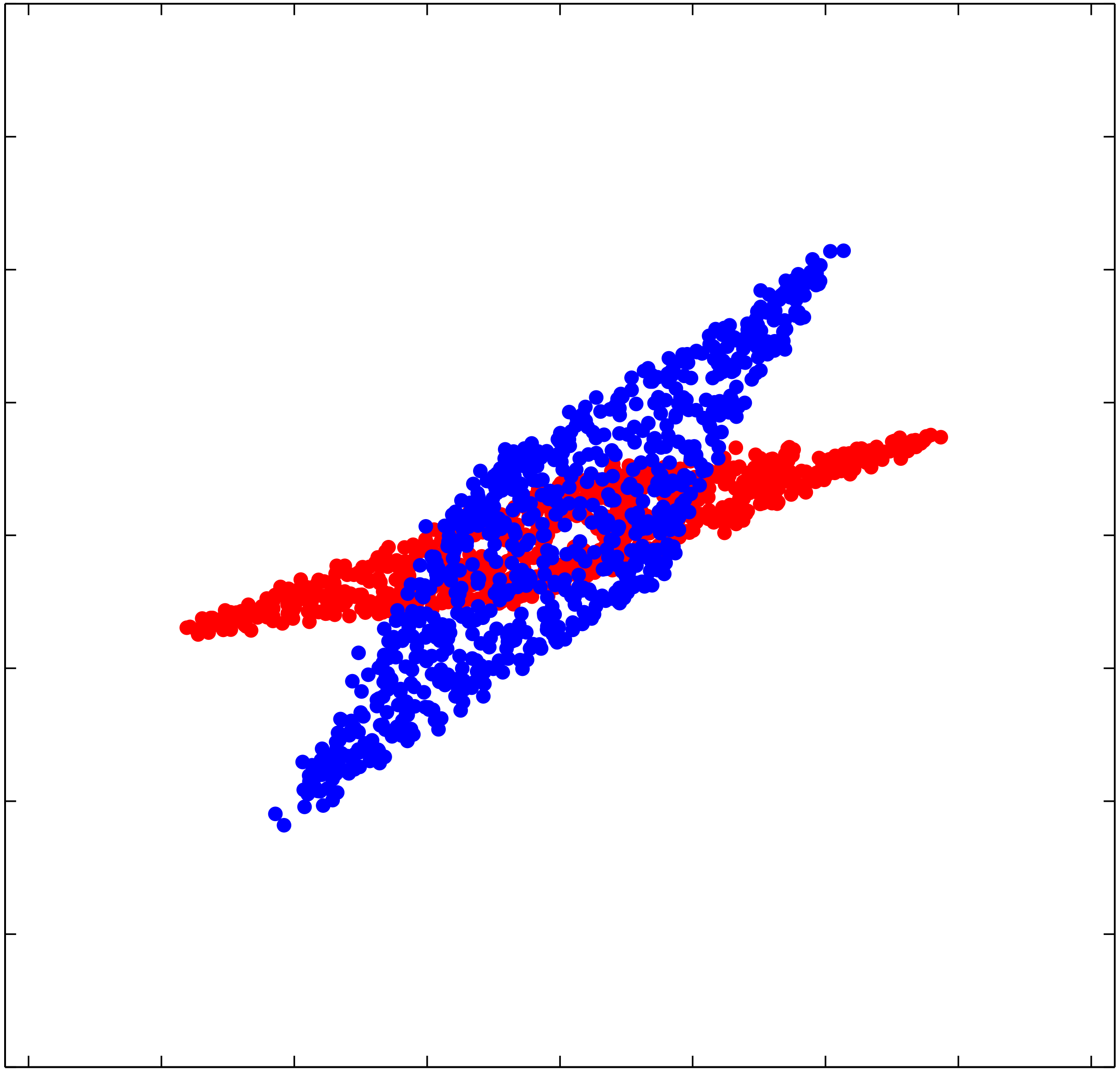


Cheap supervised rotation with CSP



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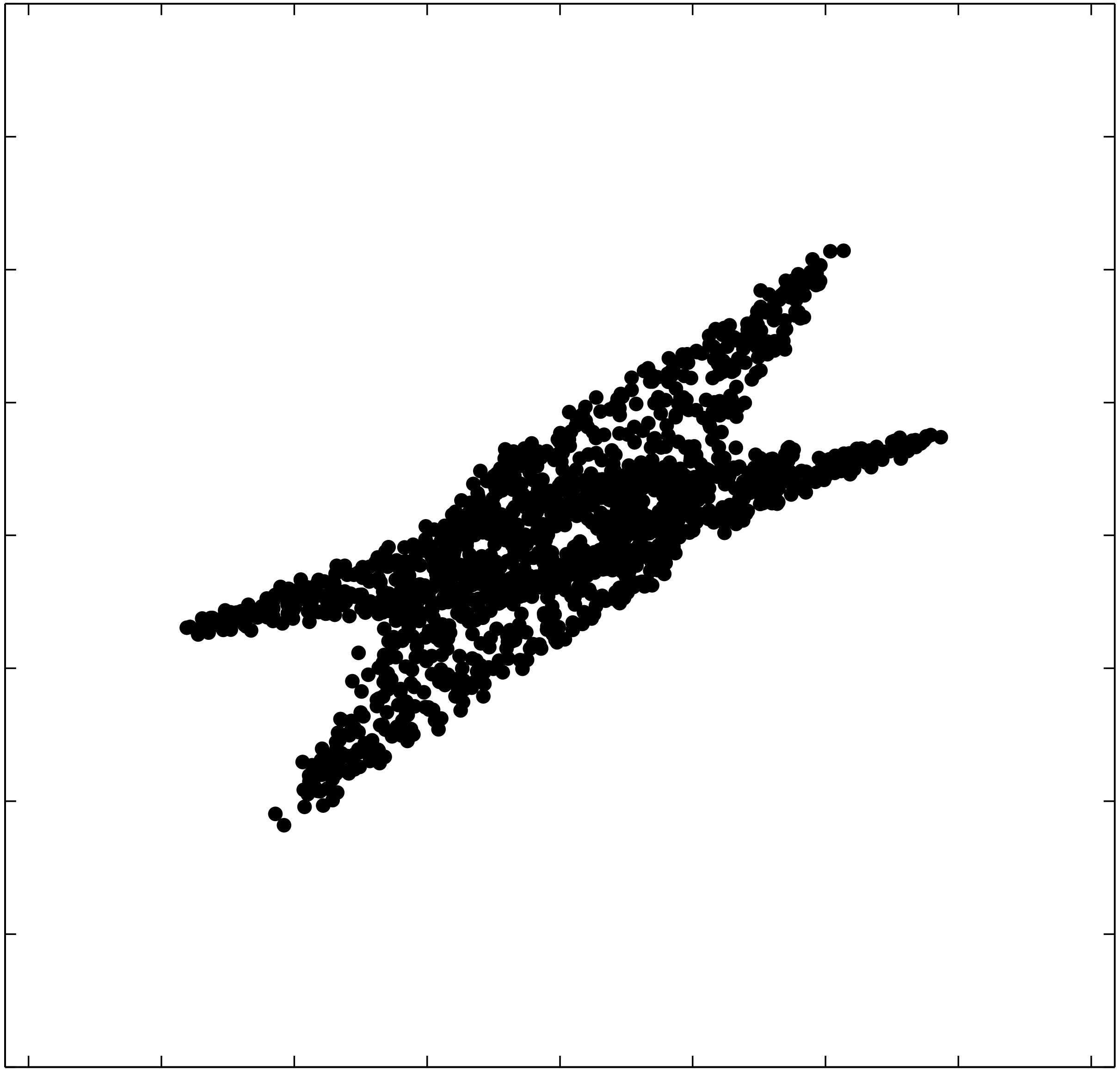

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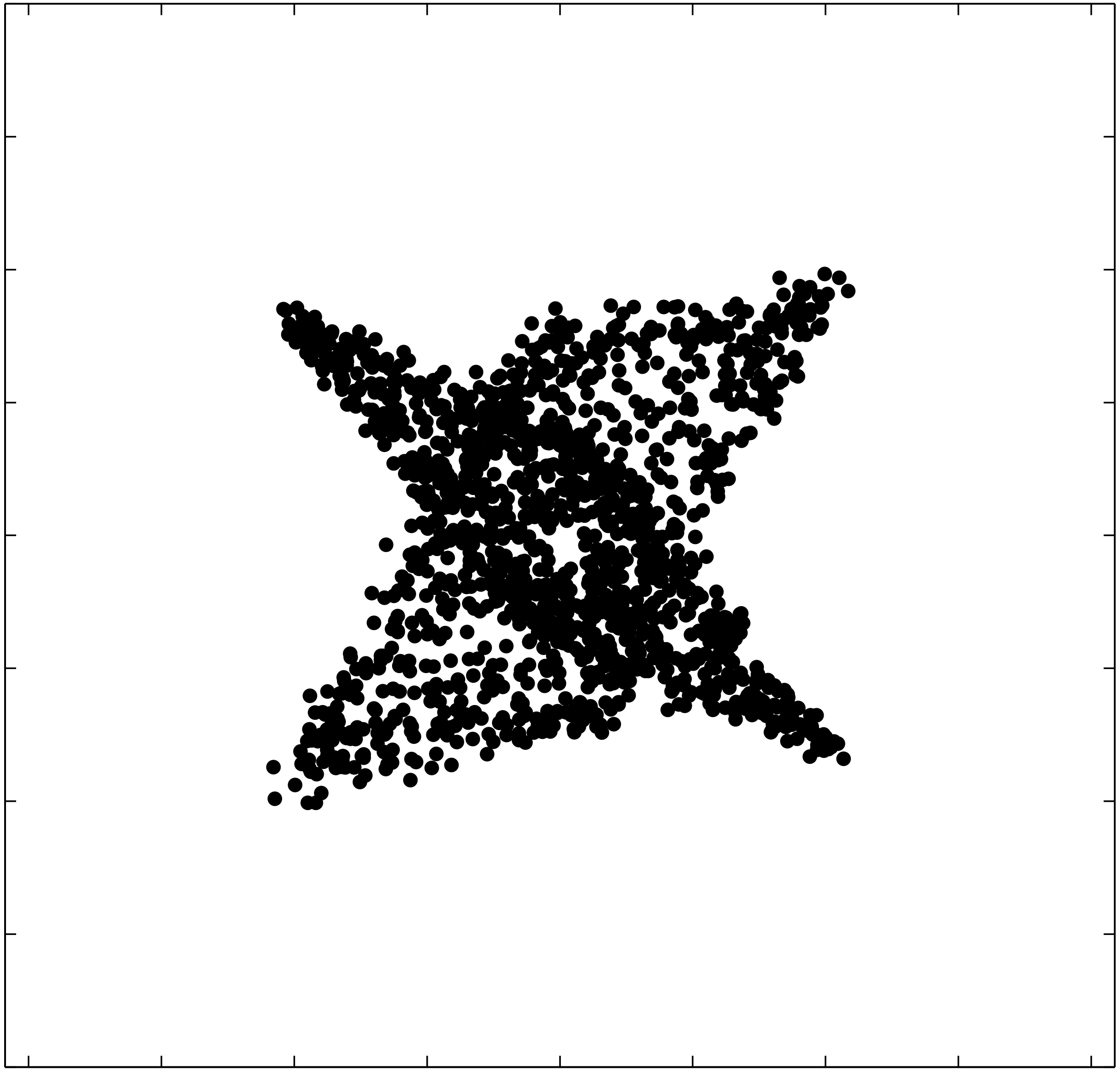

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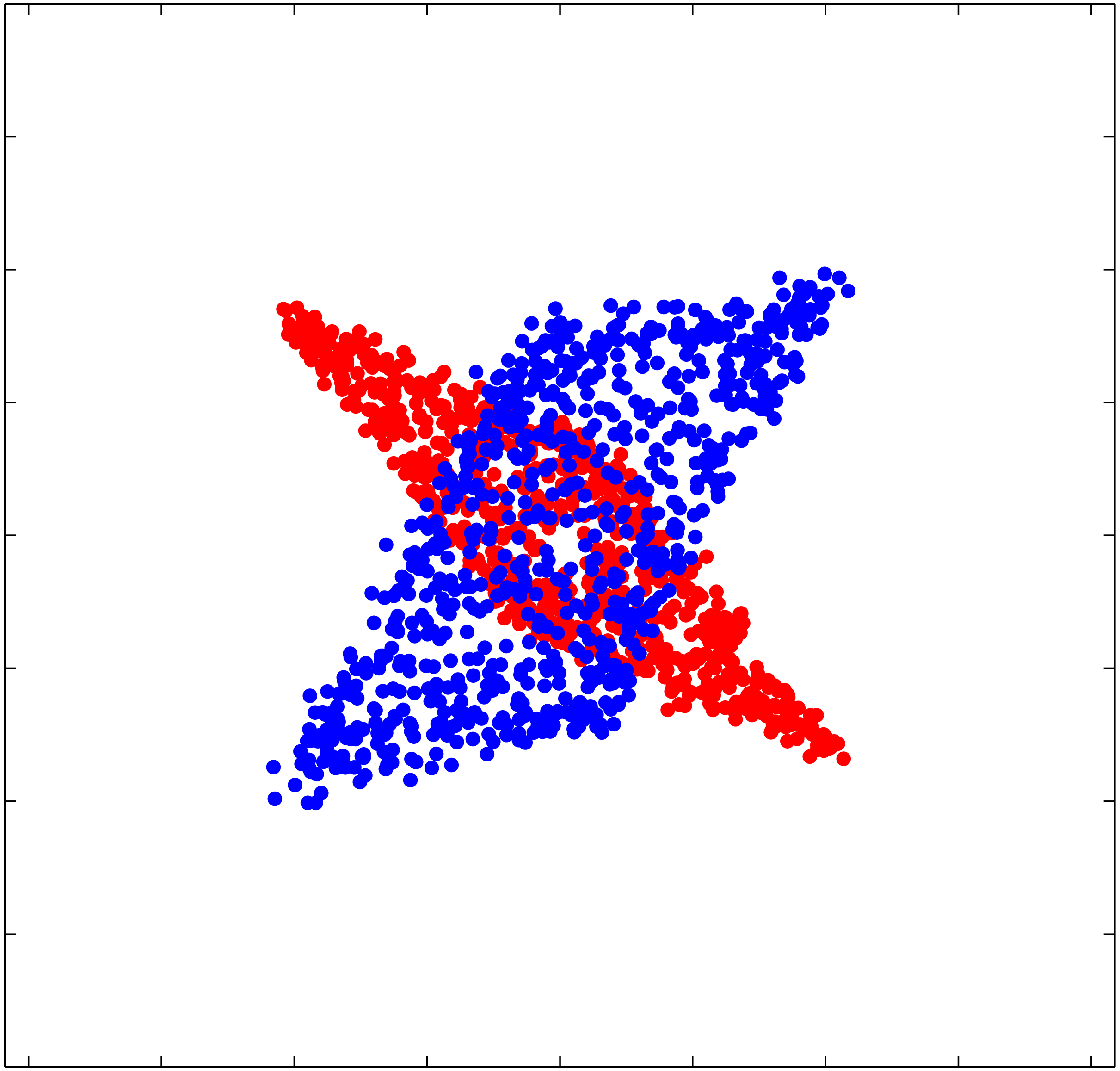

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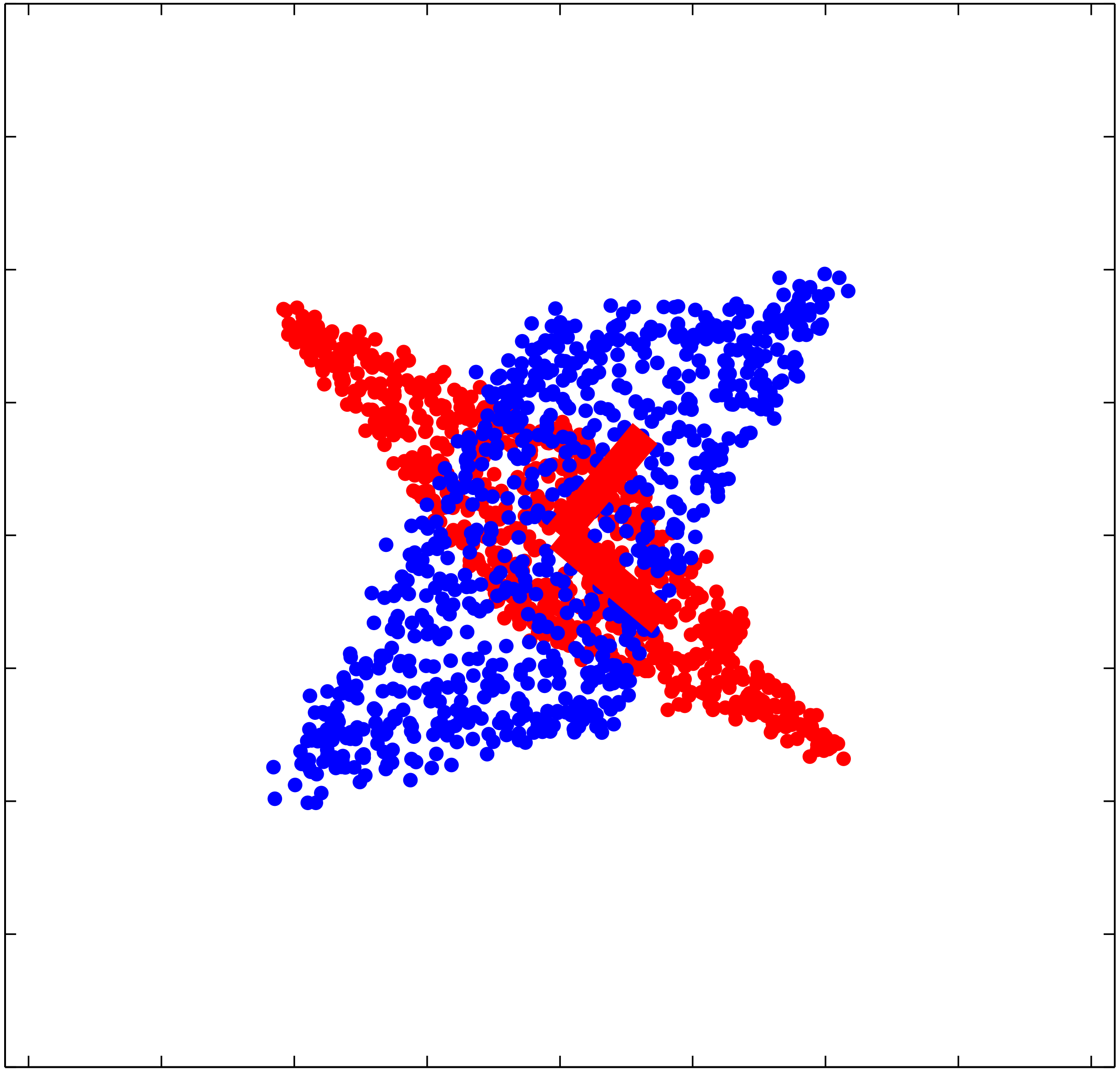

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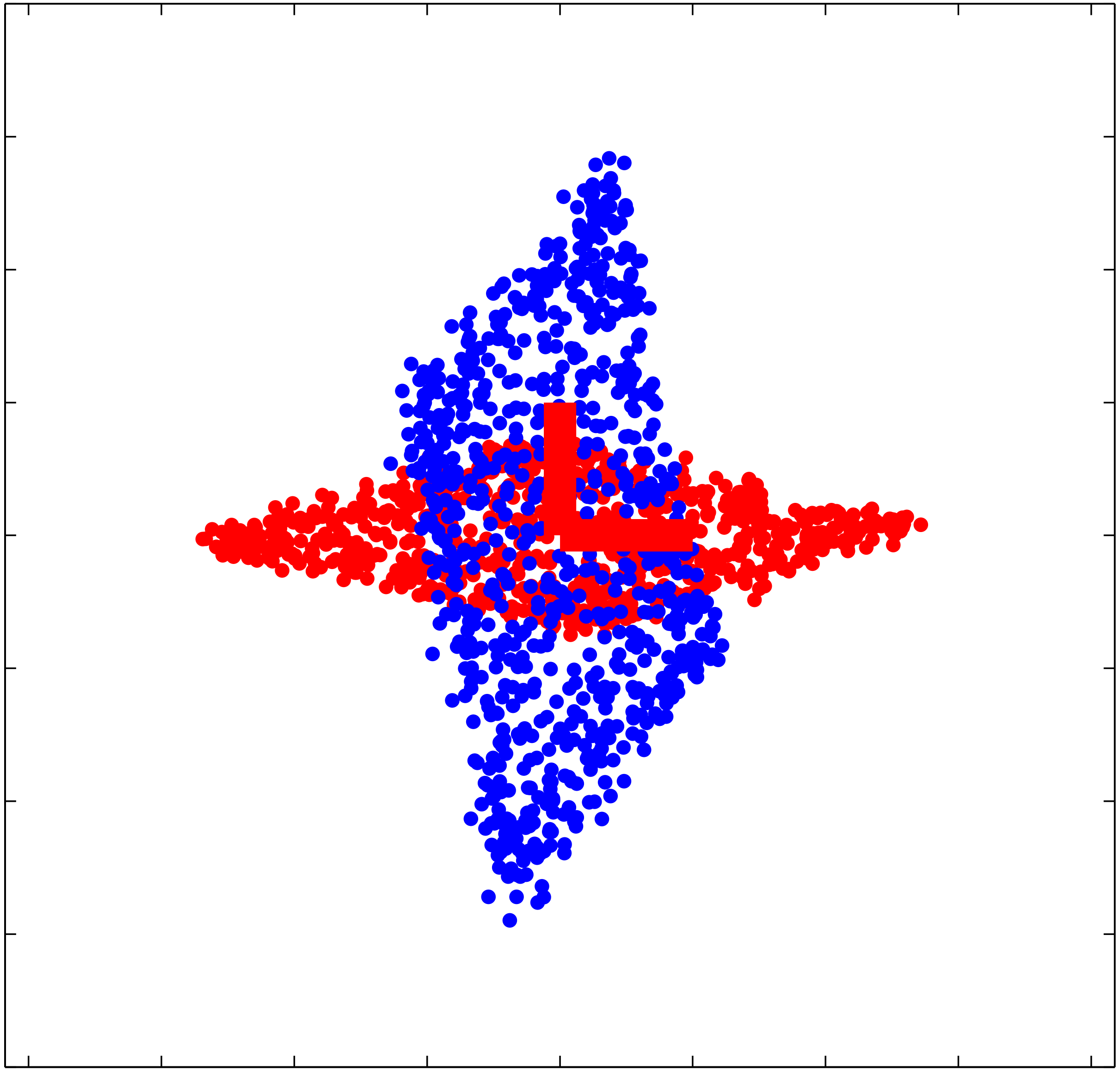
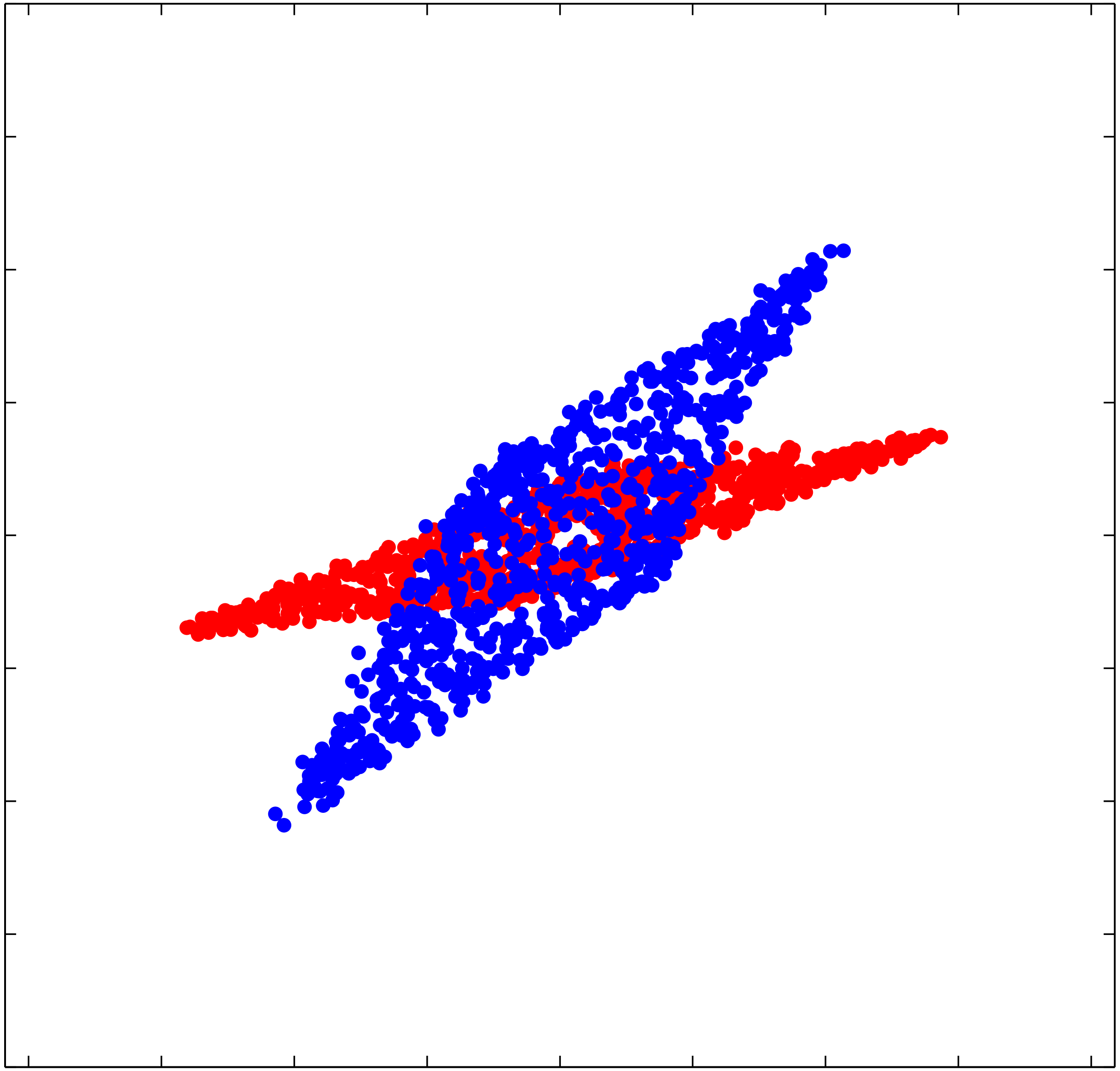
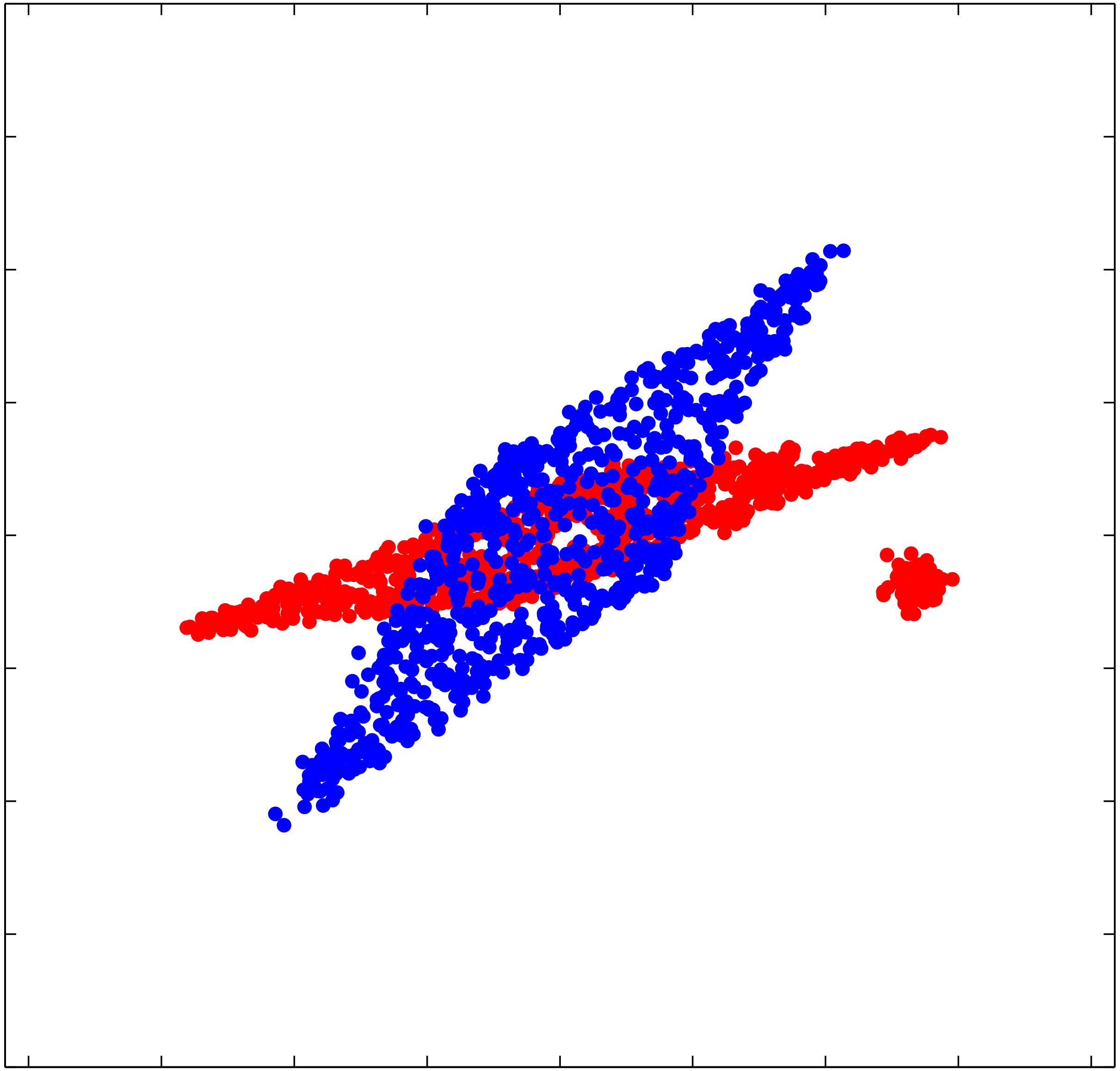




CSP: outlier- (artifact-) sensitivity



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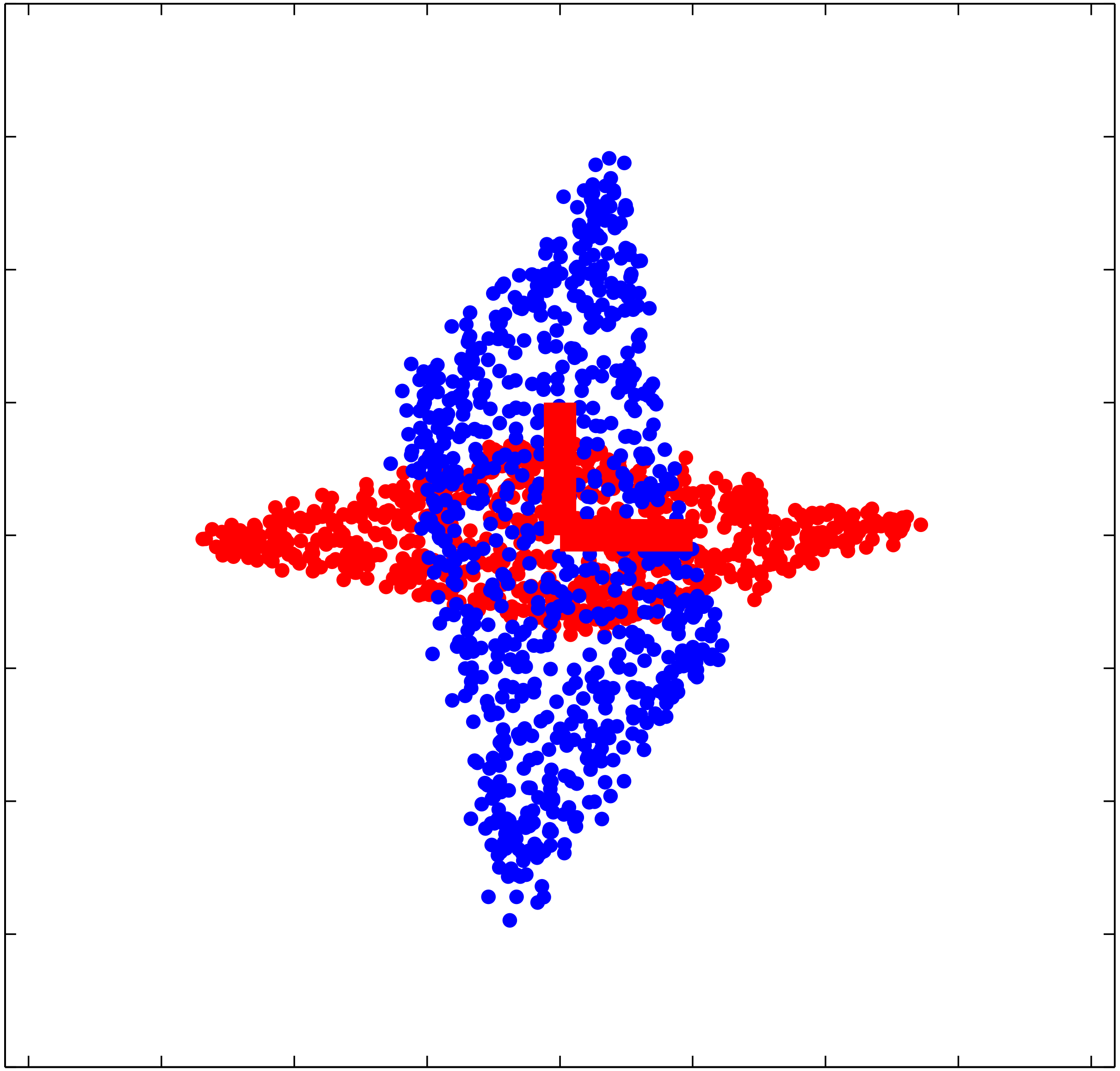

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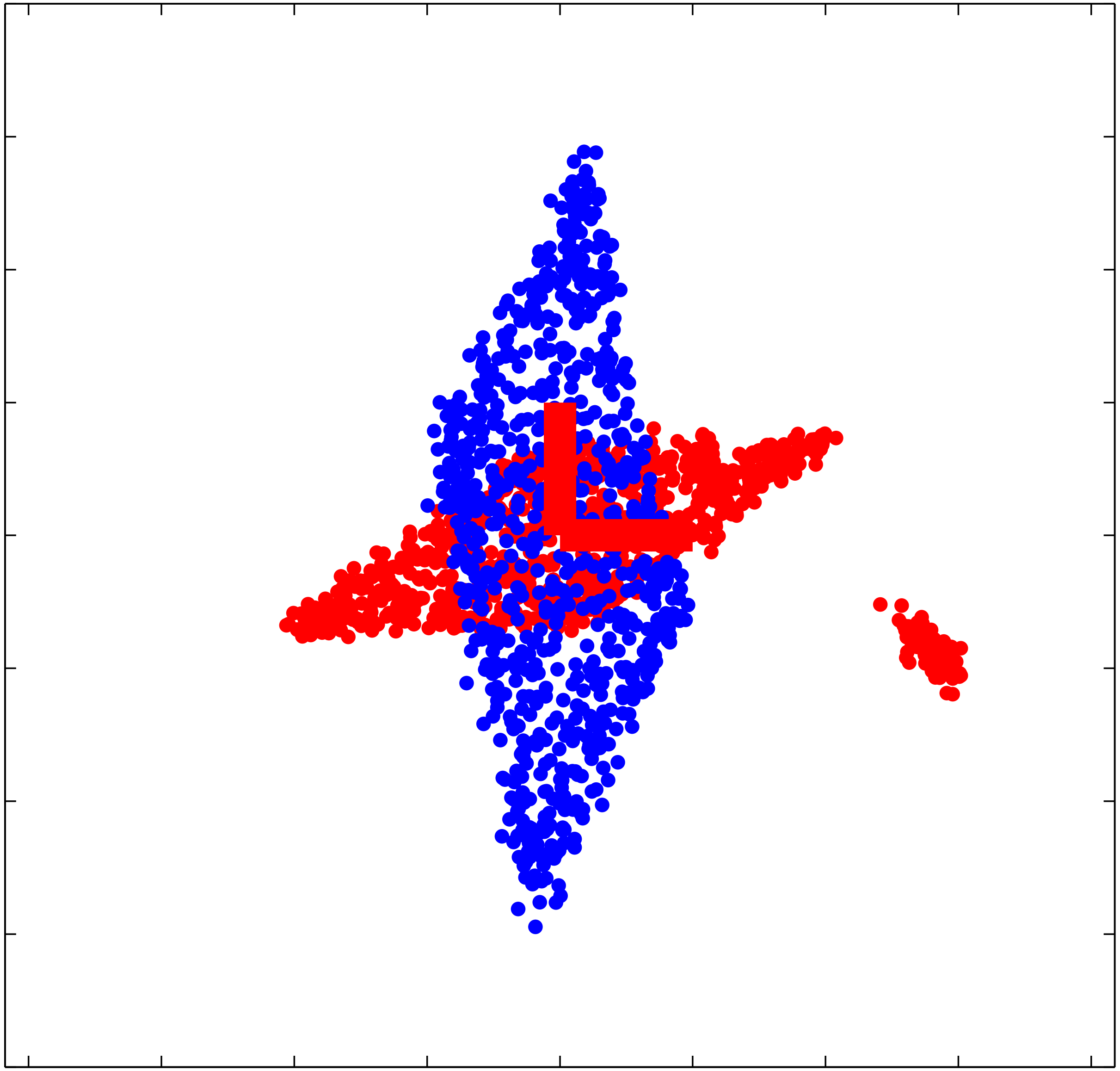
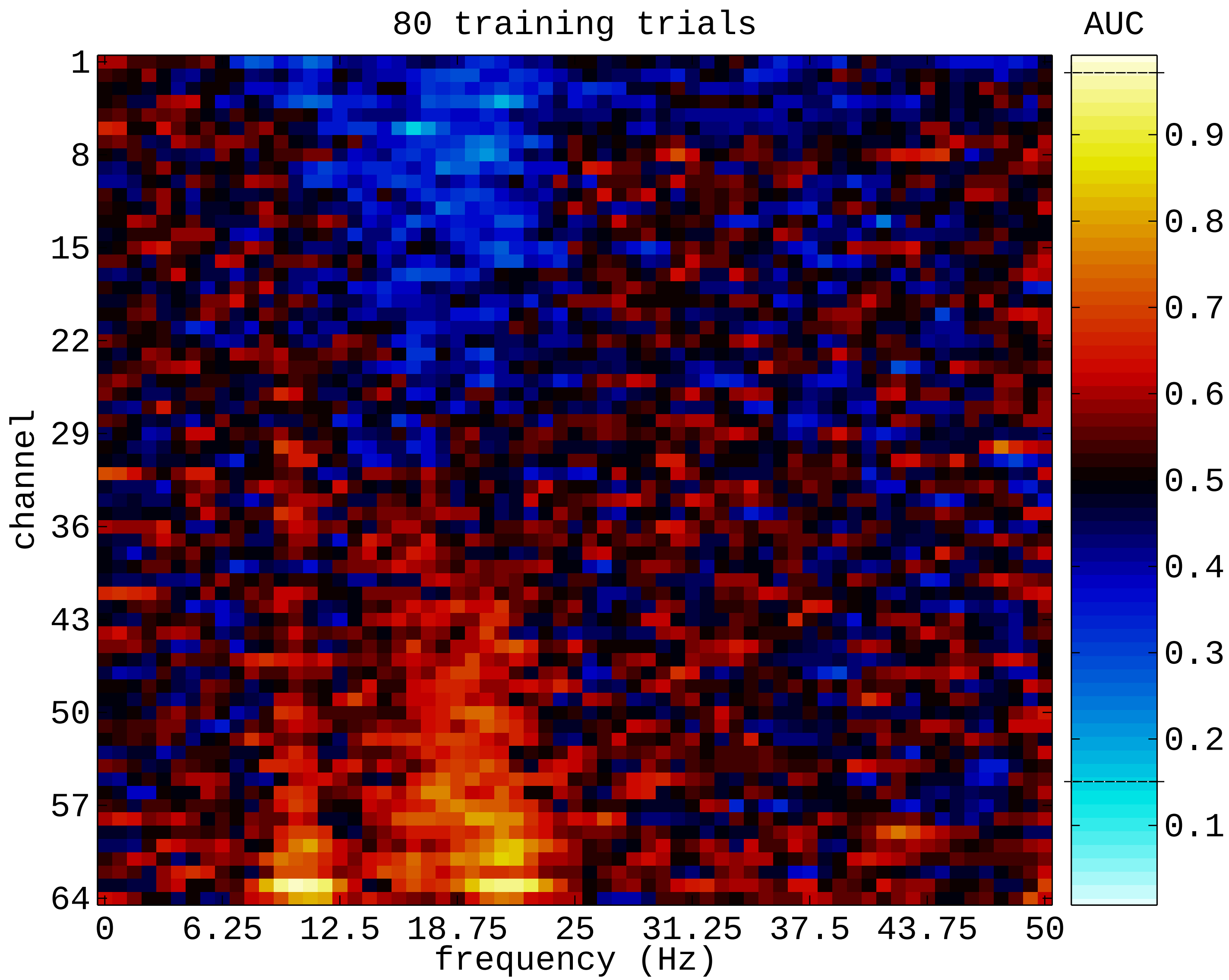


CSP: overfitting



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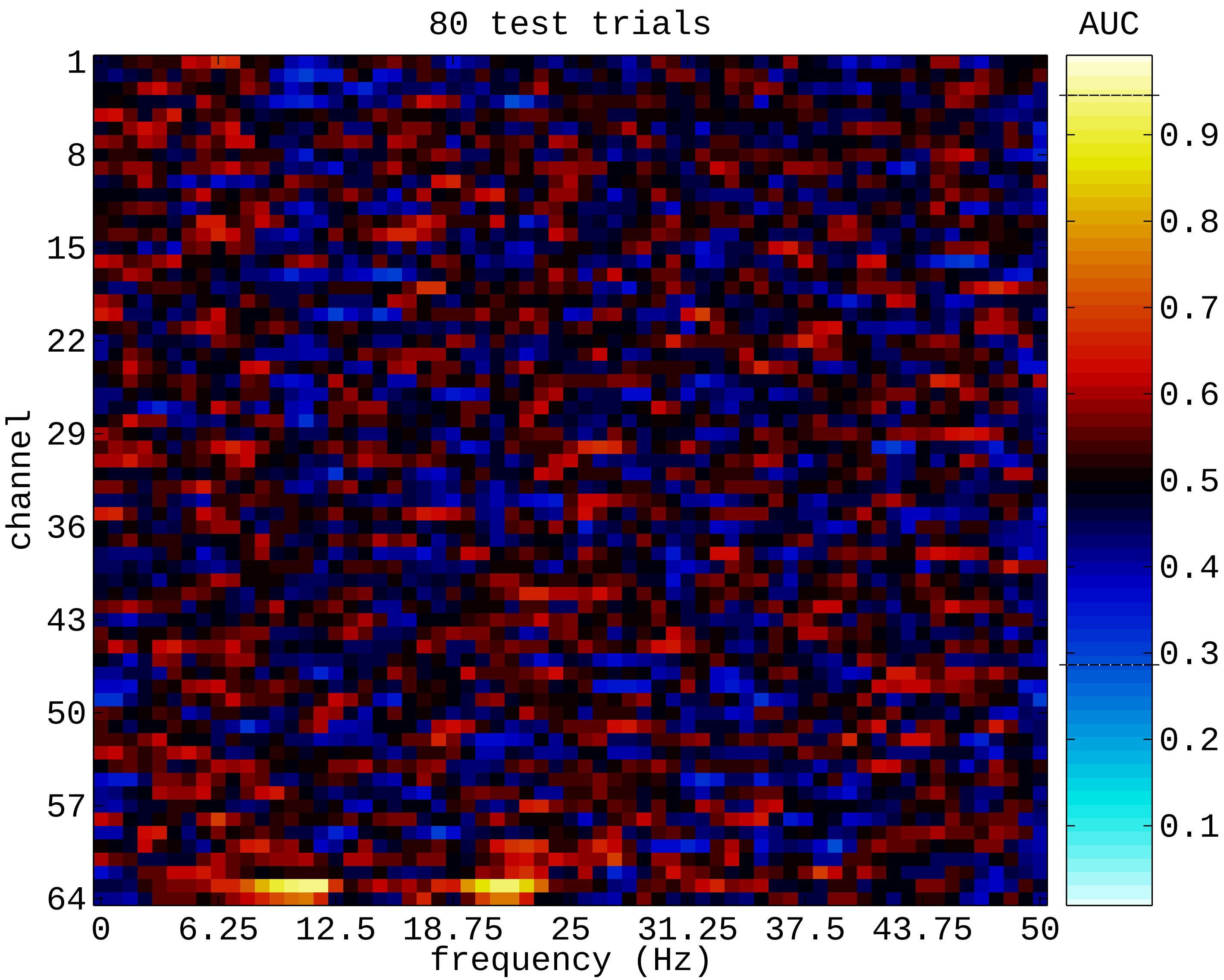

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The exact frequency of sensory-motor rhythms varies between individuals.

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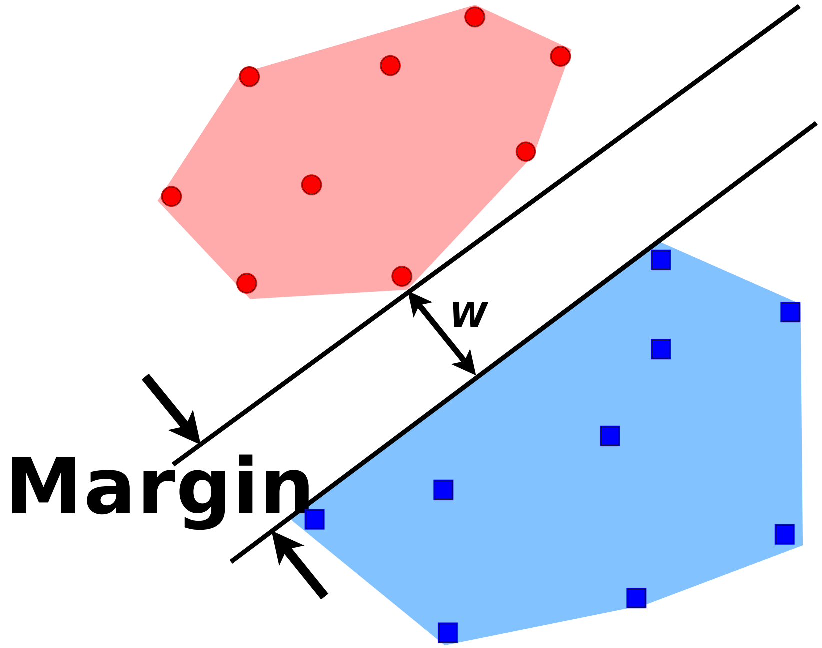
The exact frequency of sensory-motor rhythms varies between individuals.

In practice, component / band / time-window selection is often best performed by hand. The ideal BCI algorithm would be a “glass box” requiring no such intervention.

Get a better objective (I)

Approach #1: Margin Maximization (à la Support Vector Machine)



Maximize the margin in the space of log bandpower features $\psi(\mathrm{X}; \mathrm{F})$.

$$\psi(\mathrm{X}_i; \mathrm{F}) = \log \operatorname{diag} \left(\mathrm{F} \mathrm{X}_i \mathrm{X}_i^\top \mathrm{F}^\top \right)$$

Get a better objective (I)

Approach #1: Margin Maximization (à la Support Vector Machine)

Given time-series X_i and class labels y_i, simultaneously optimize

- spatial filtering coefficients F
- classifier weight-vector $\mathbf{w}$ in log-bandpower space
- classifier bias b in log-bandpower space

to minimize the SVM-like objective function:

$$\lambda \mathbf{w}^\top \mathbf{w} + \sum_i \max(0,\ 1 - y_i(\psi(\mathrm{X}_i; \mathrm{F})^\top \mathbf{w} + b))$$

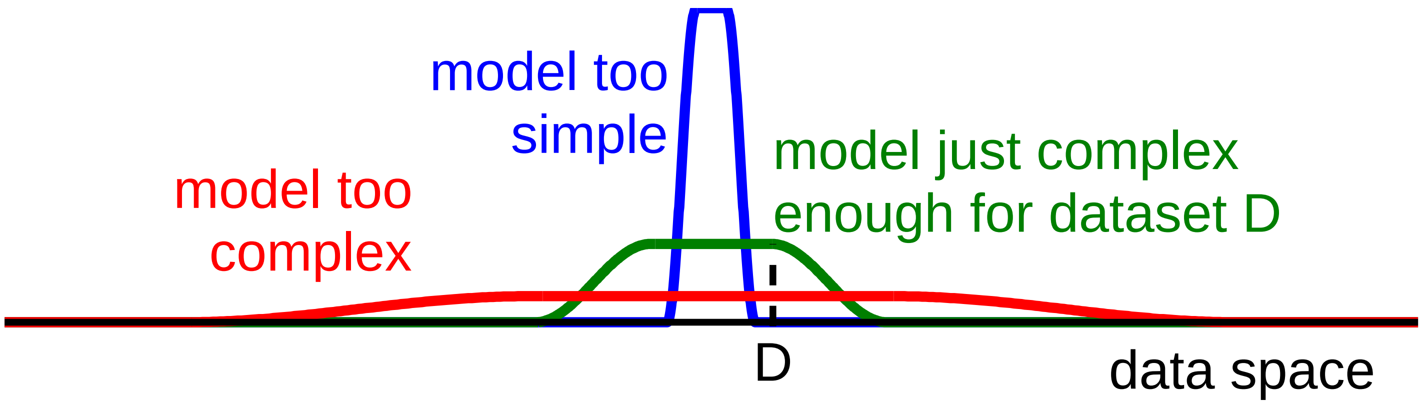
Regularization parameter λ can be found by cross-validation.

Approach #2: "Evidence" Maximization (using Gaussian Process classifiers)

The *marginal likelihood* or *evidence* of a probabilistic model with hyperparameters F is given by integrating the lower-level parameters (e.g. a classifier's weight vector $\mathbf{w}$) out of the likelihood for data D:

$$P(D|\mathrm{F}) = \int \mathrm{Pr}(D|\mathbf{w}, \mathrm{F})\mathrm{Pr}(\mathbf{w}|\mathrm{F})\mathrm{d}\mathbf{w}$$

It is a probability density function, so it normalizes over the space of possible datasets. Maximizing evidence can be an effective means of complexity control and hence model selection:



Get a better objective (II)

Approach #2: "Evidence" Maximization (using Gaussian Process classifiers)

- Define a *covariance function* in the log-bandpower space, e.g. a linear covariance function

$$k(\mathrm{X}_i, \mathrm{X}_j) = 1 + \psi(\mathrm{X}_i; \mathrm{F})^\top \psi(\mathrm{X}_j; \mathrm{F})$$

  or some other function of ψ for non-linear classification.

- Plug this into a Gaussian Process Classifier

  (using Probit likelihood, and the Expectation-Propagation algorithm to approximate it—see Kuss & Rasmussen 2005, Journal of Machine Learning Research 6).

- The Gaussian Process framework yields an expression for the evidence, which is easily differentiable with respect to F.
- So optimize F by conjugate gradient descent.

Experiments

Both methods were tested on motor-imagery EEG data from 15 subjects:

- 9 from BCI competitions (Comp 2:IIa, Comp 3:IVa,IVc)
- 6 recorded at the MPI (Lal et al 2004, IEEE Trans. Biomed. Eng. 51)

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Preprocessing:

- select time-windows 0.5–4 sec after stimulus presentation
- band-pass filtered in the broad 8–25Hz band.

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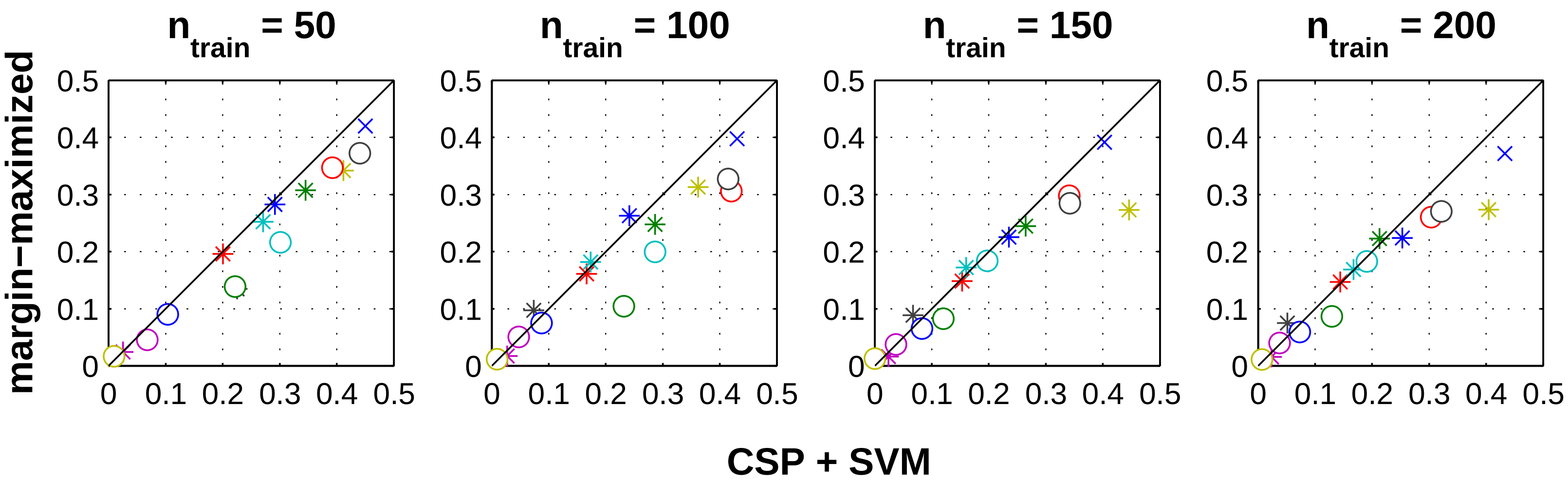
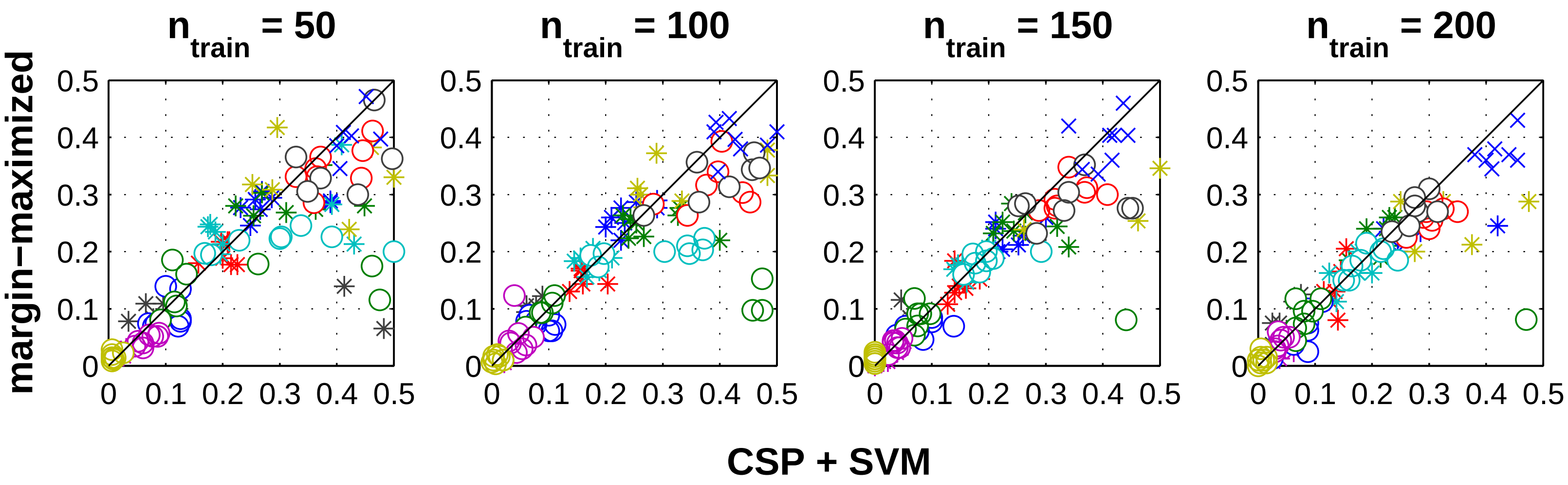
Design:

- Two spatial filters were optimized in each case.
- Performance was assessed as a function of training set size, $n_{\text{train}} \in \{50, 100, 150, 200\}$.
- Each assessment was repeated using 8 random training subsets.



Binary classification error rates:
new approach vs. traditional two-stage CSP + classifier approach.

Results (I)

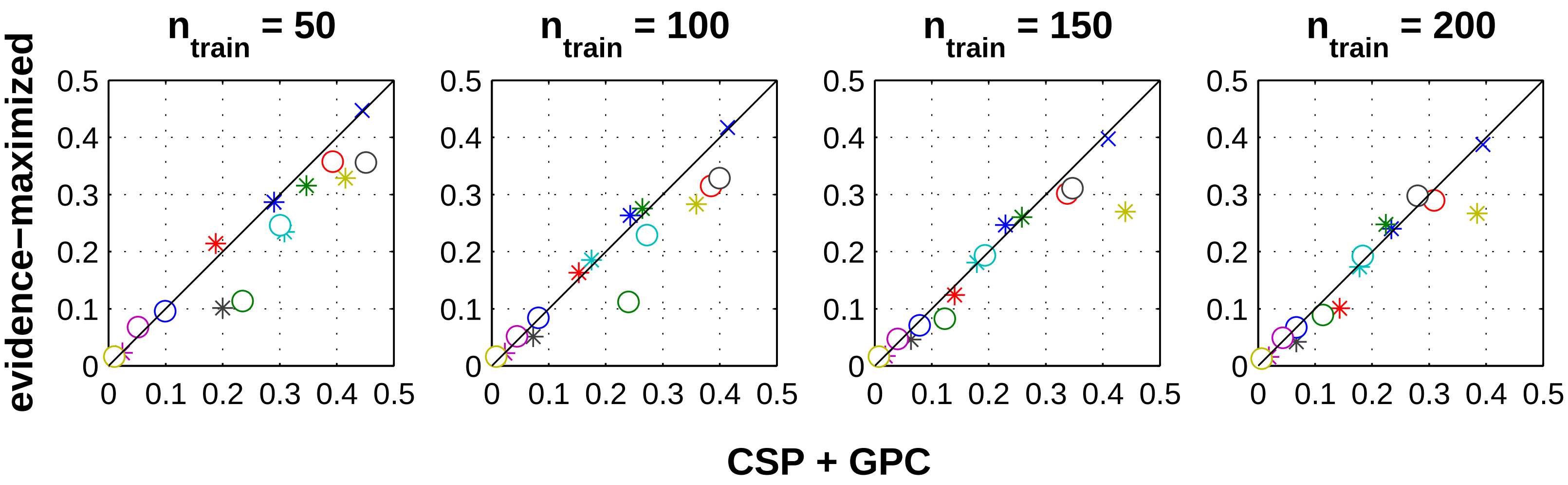


Note the consistent improvement, most markedly when we have:

- poor subject performance;
- small numbers of training trials.

This is encouraging from a clinical viewpoint.

Results (II)



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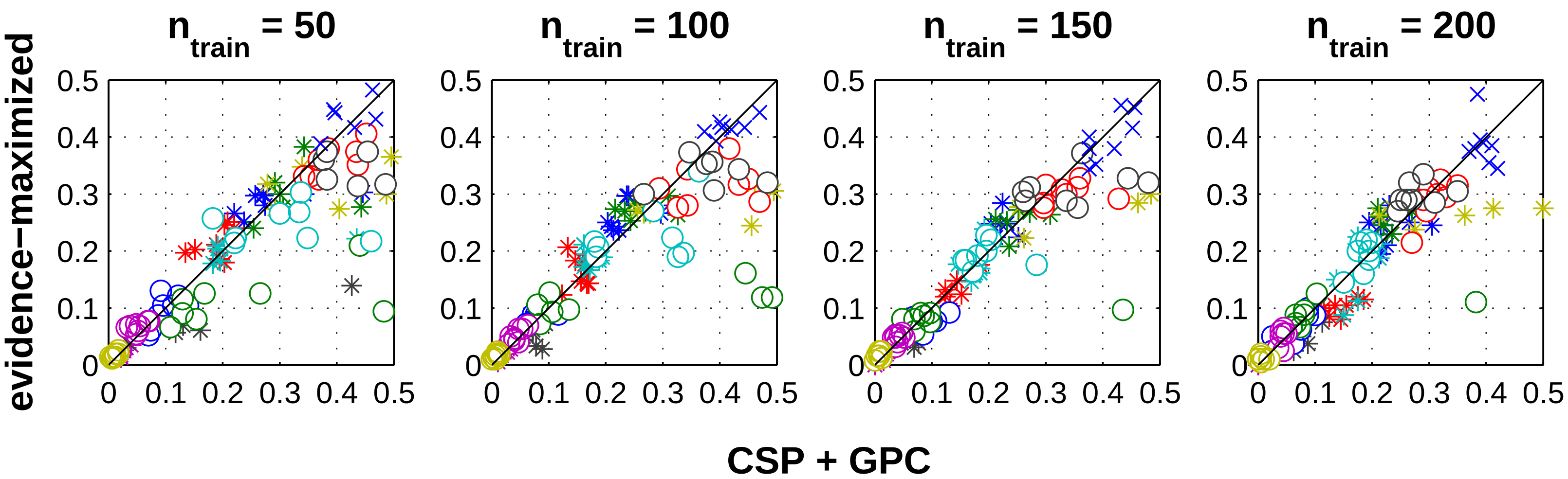

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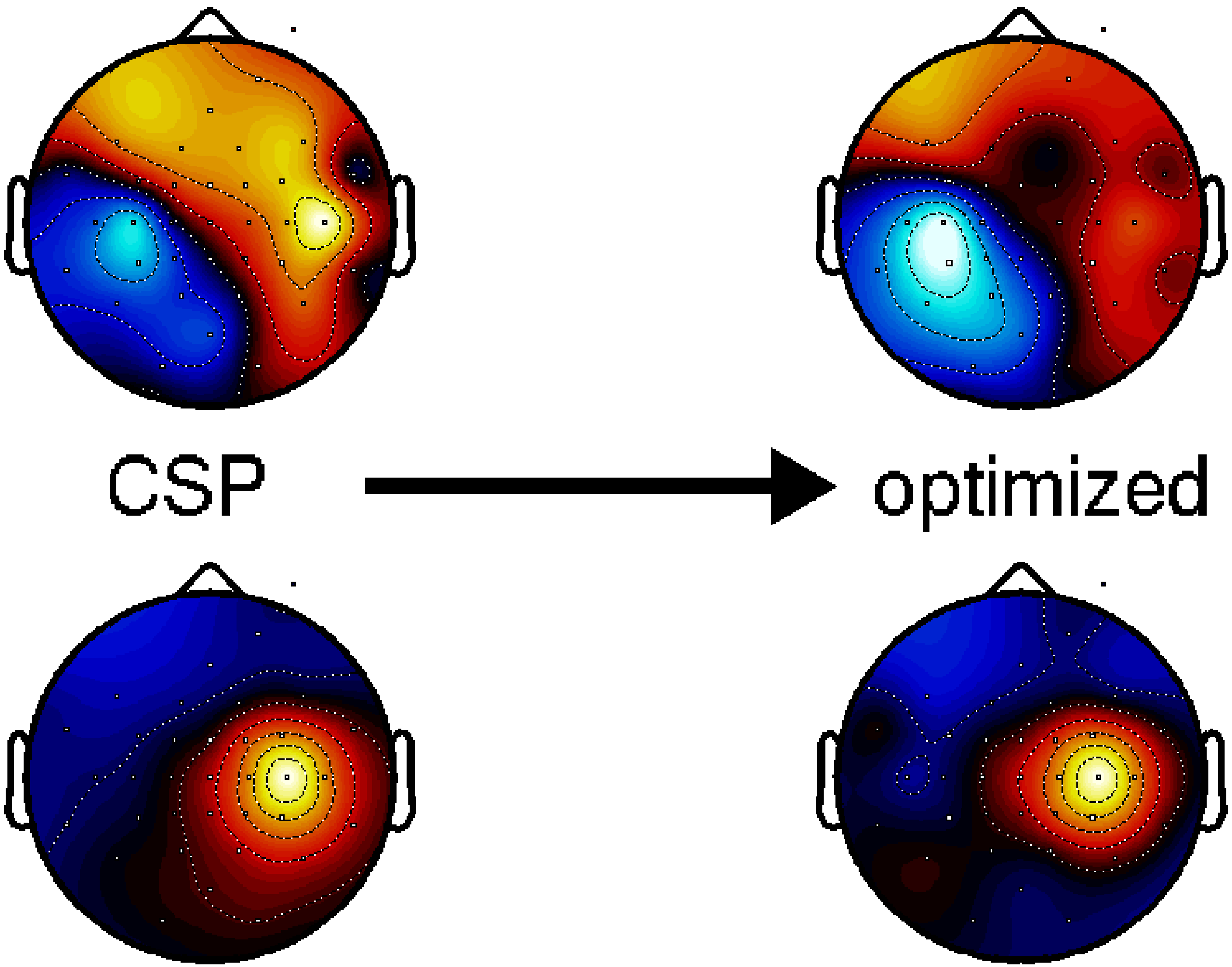
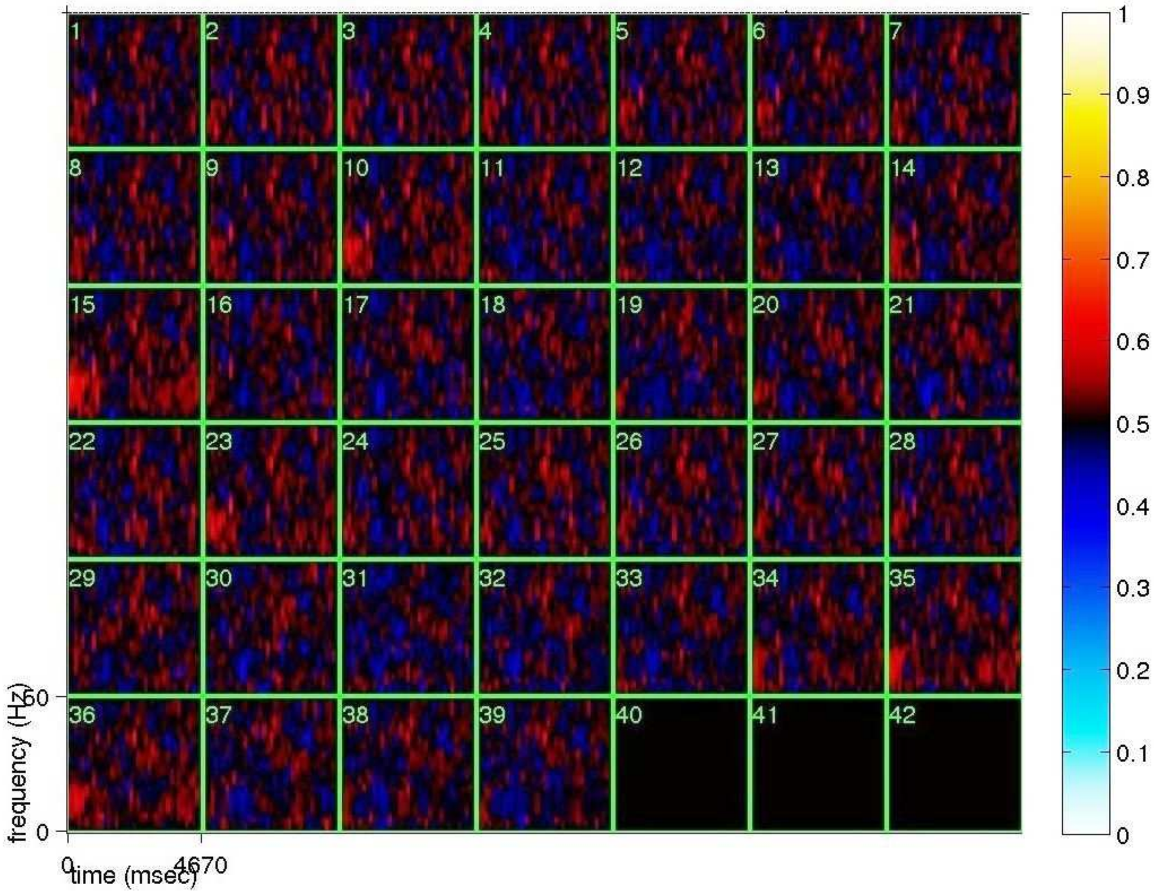
Example of spatial patterns “fixed” by evidence-maximization:



Spatial, temporal, spectral. . .



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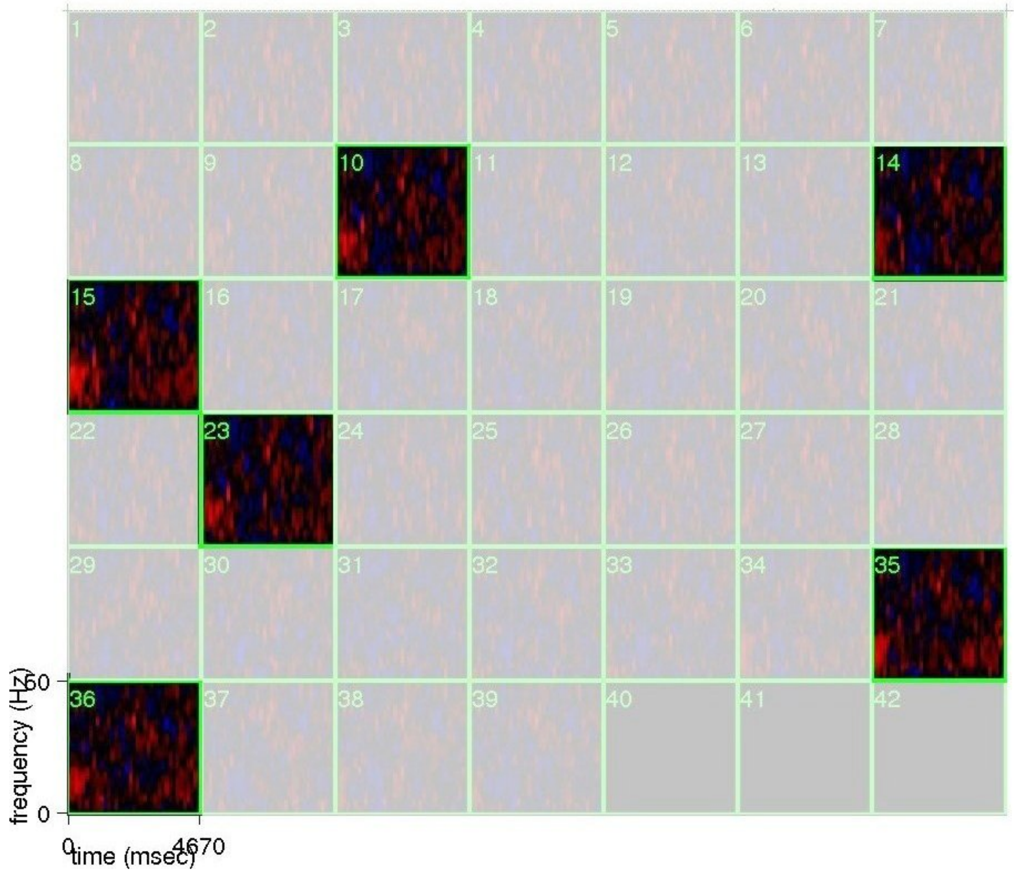

Ideally we want to optimize automatically over space

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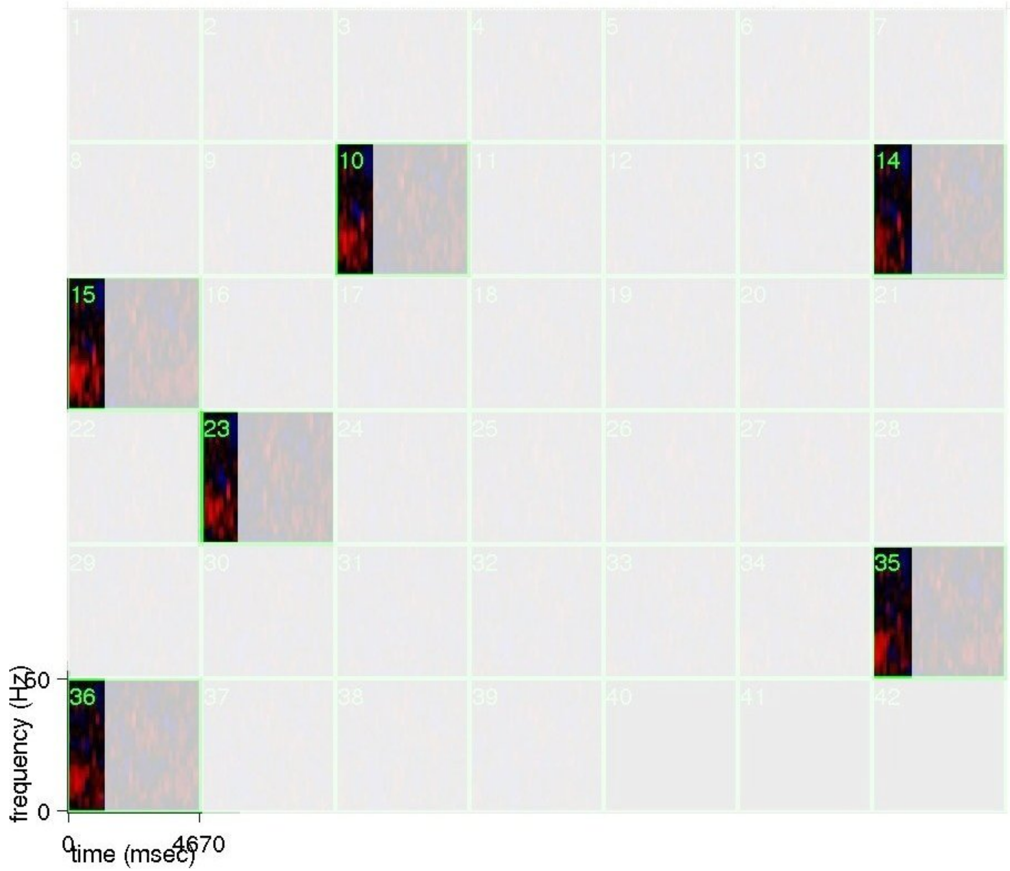

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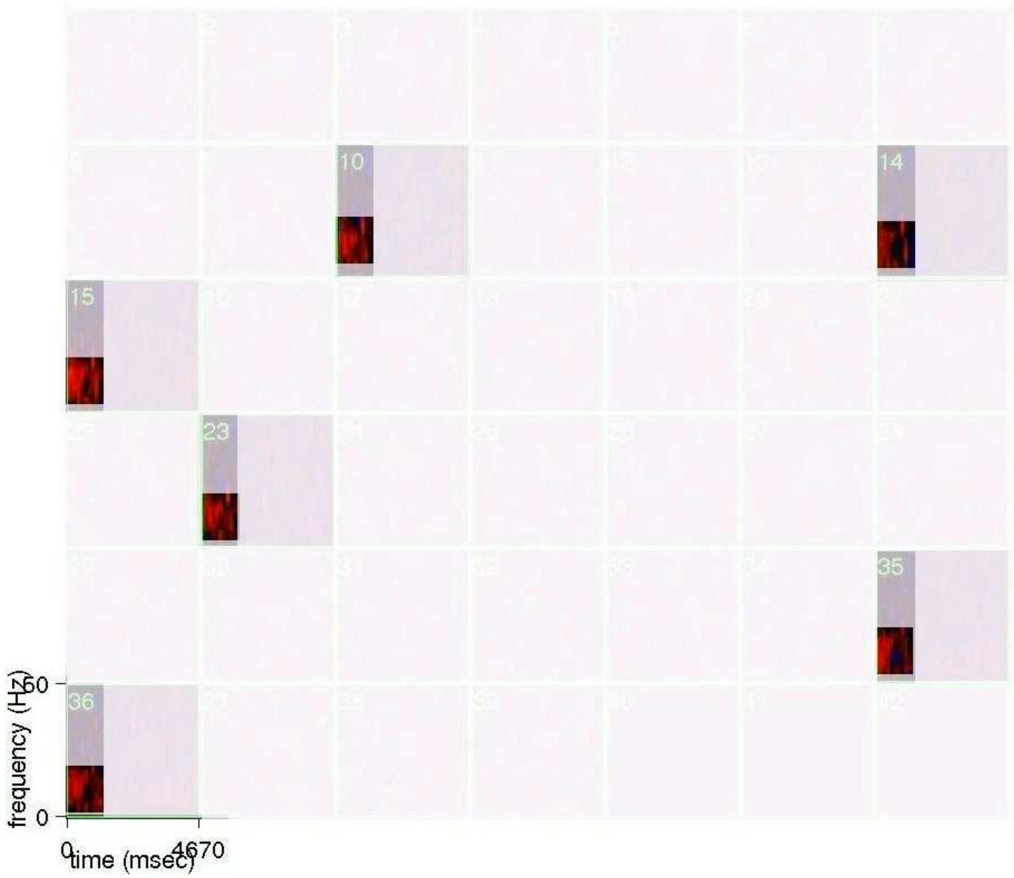

Ideally we want to optimize automatically over space
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Spatial, temporal, spectral...

Weightings over time or frequency can be incorporated into our feature mapping:

$$\psi(\mathrm{X};\ \mathrm{F}) = \log \operatorname{diag}\left(\mathrm{F}\,\mathrm{X}\,\mathrm{X}^\top\,\mathrm{F}^\top \right)$$

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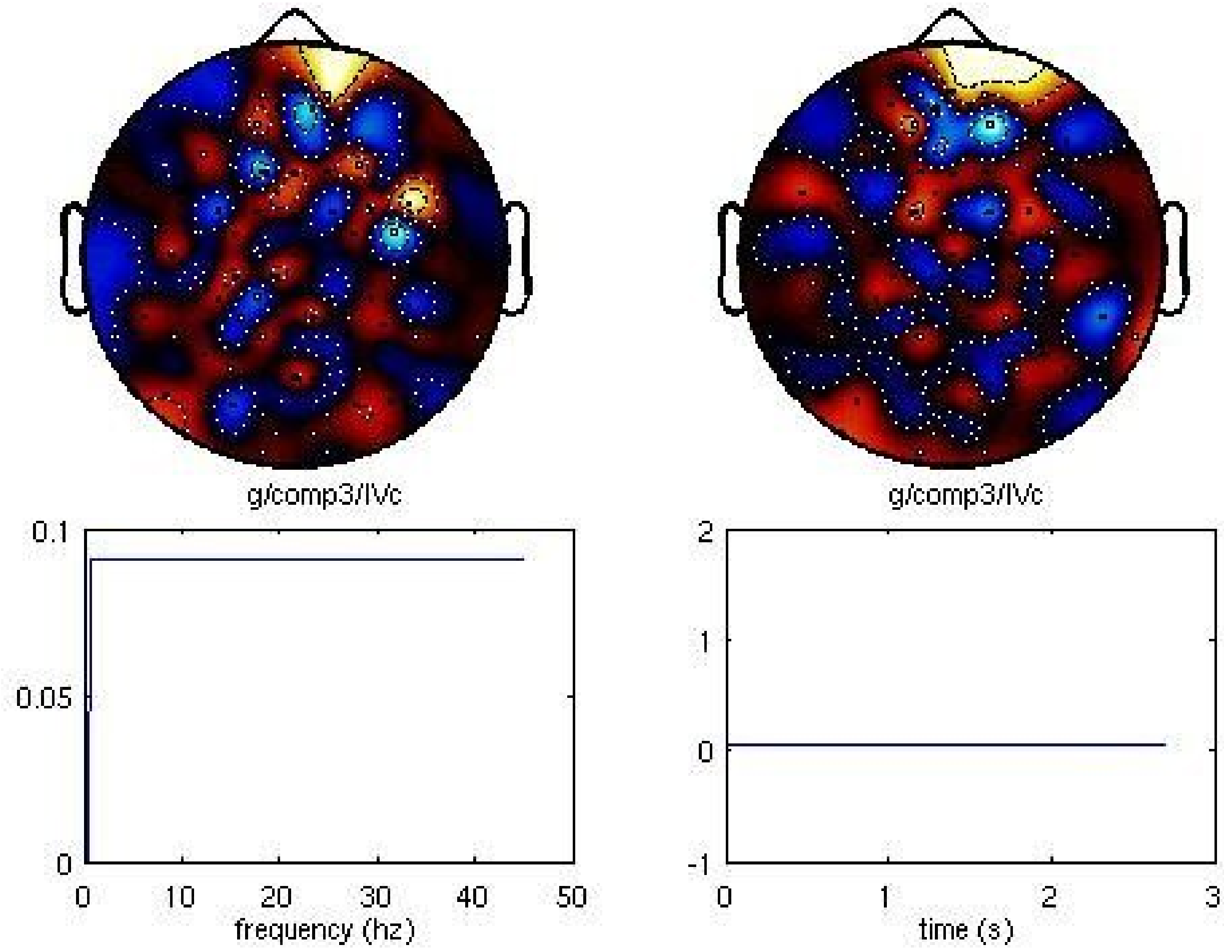

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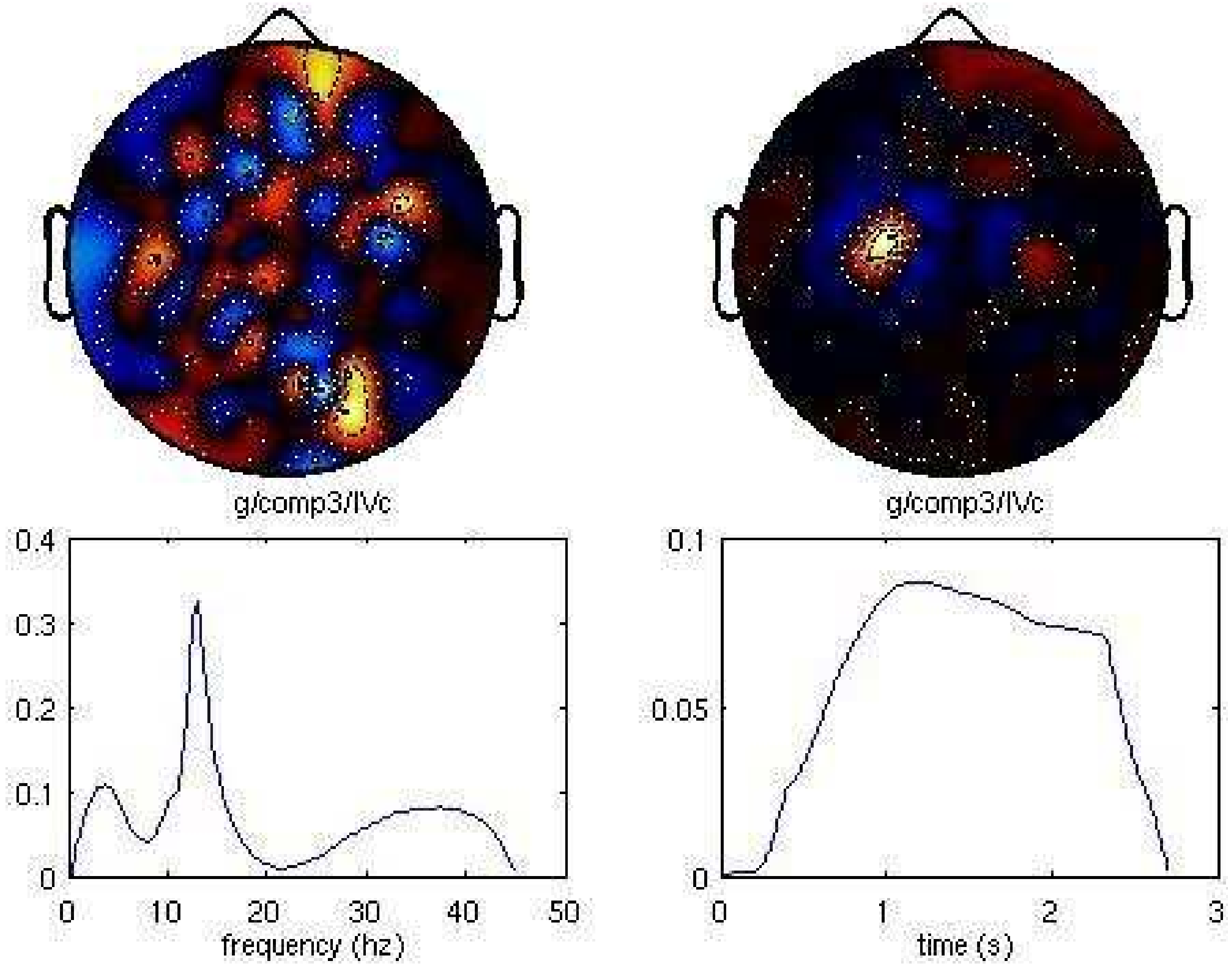

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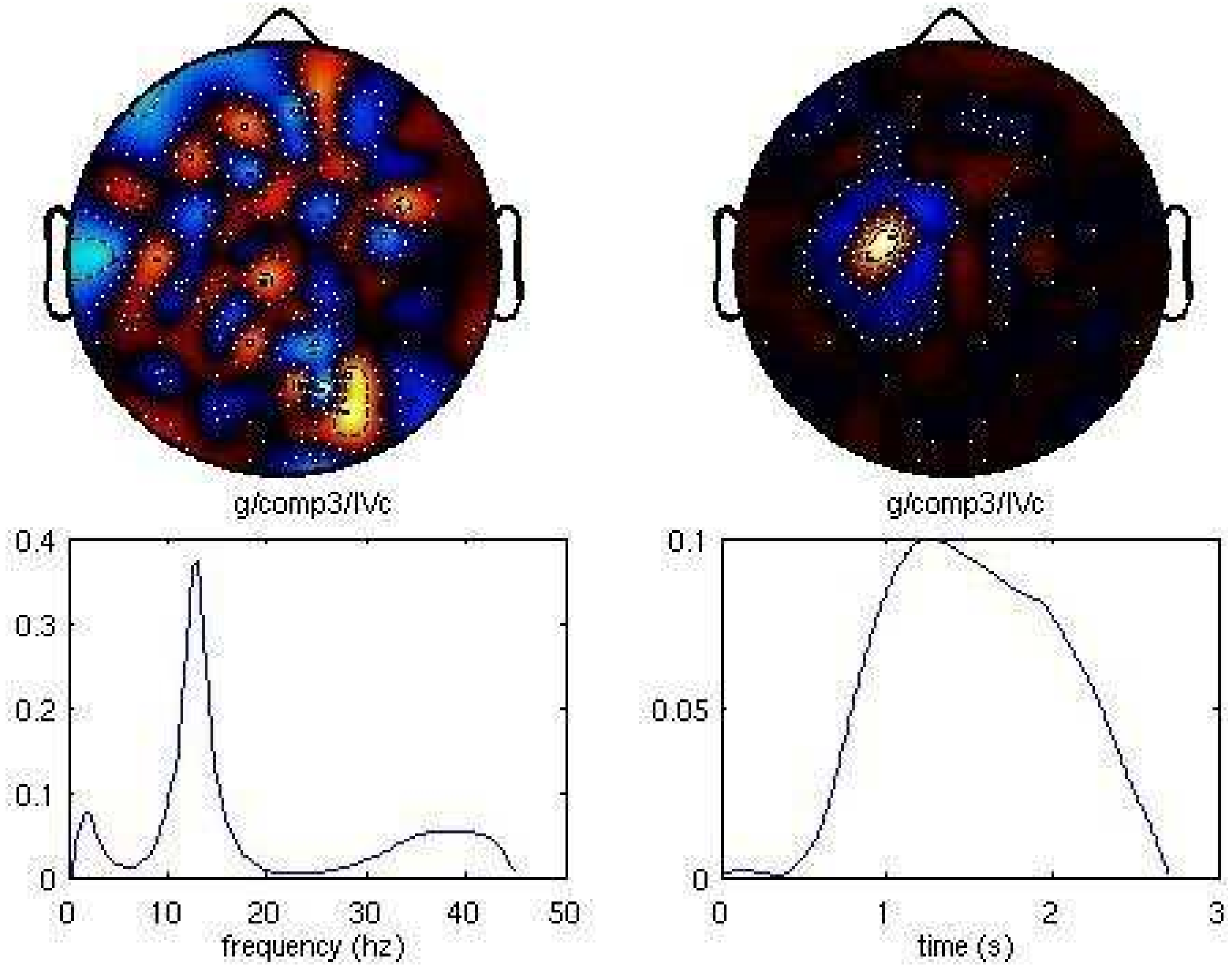

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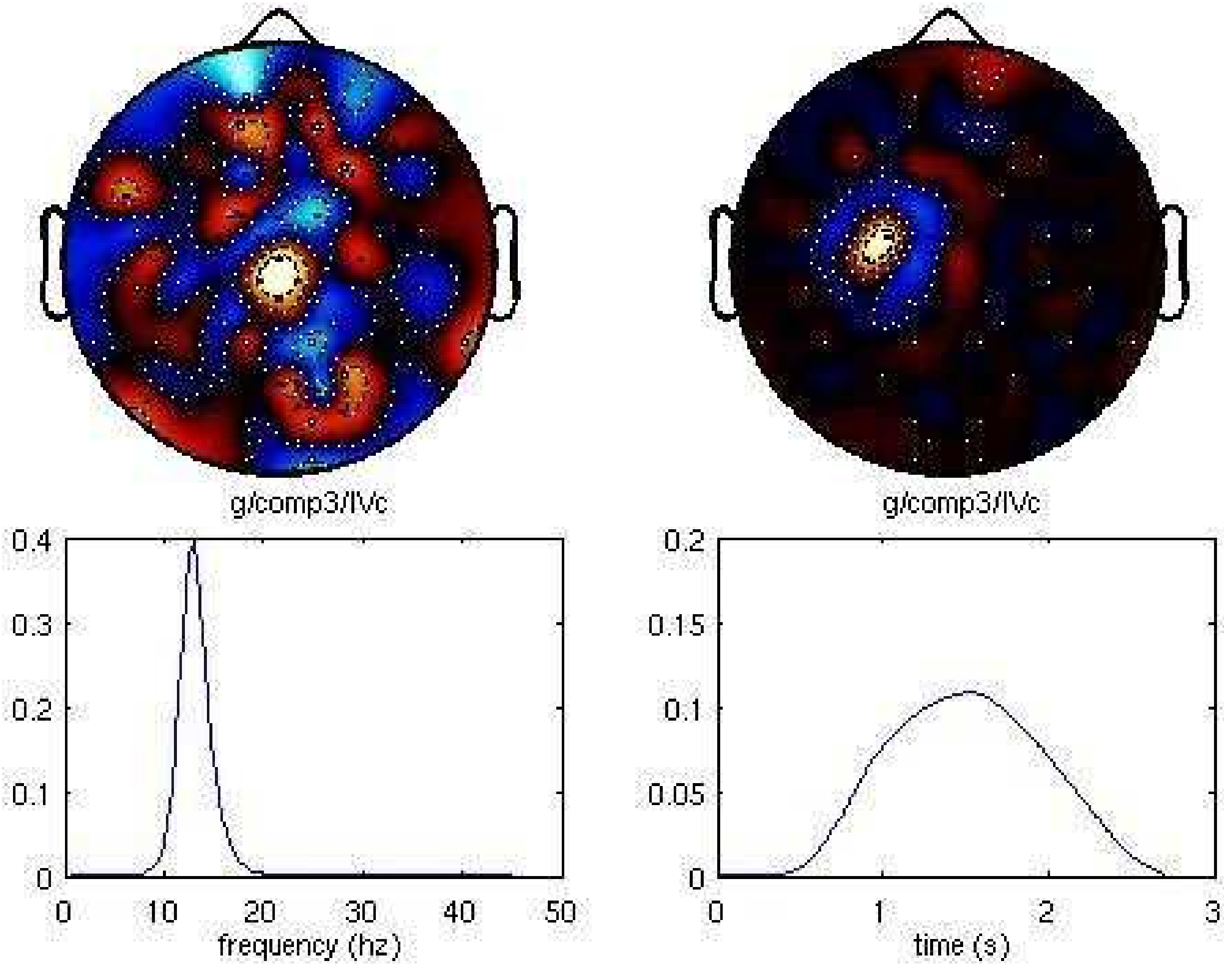

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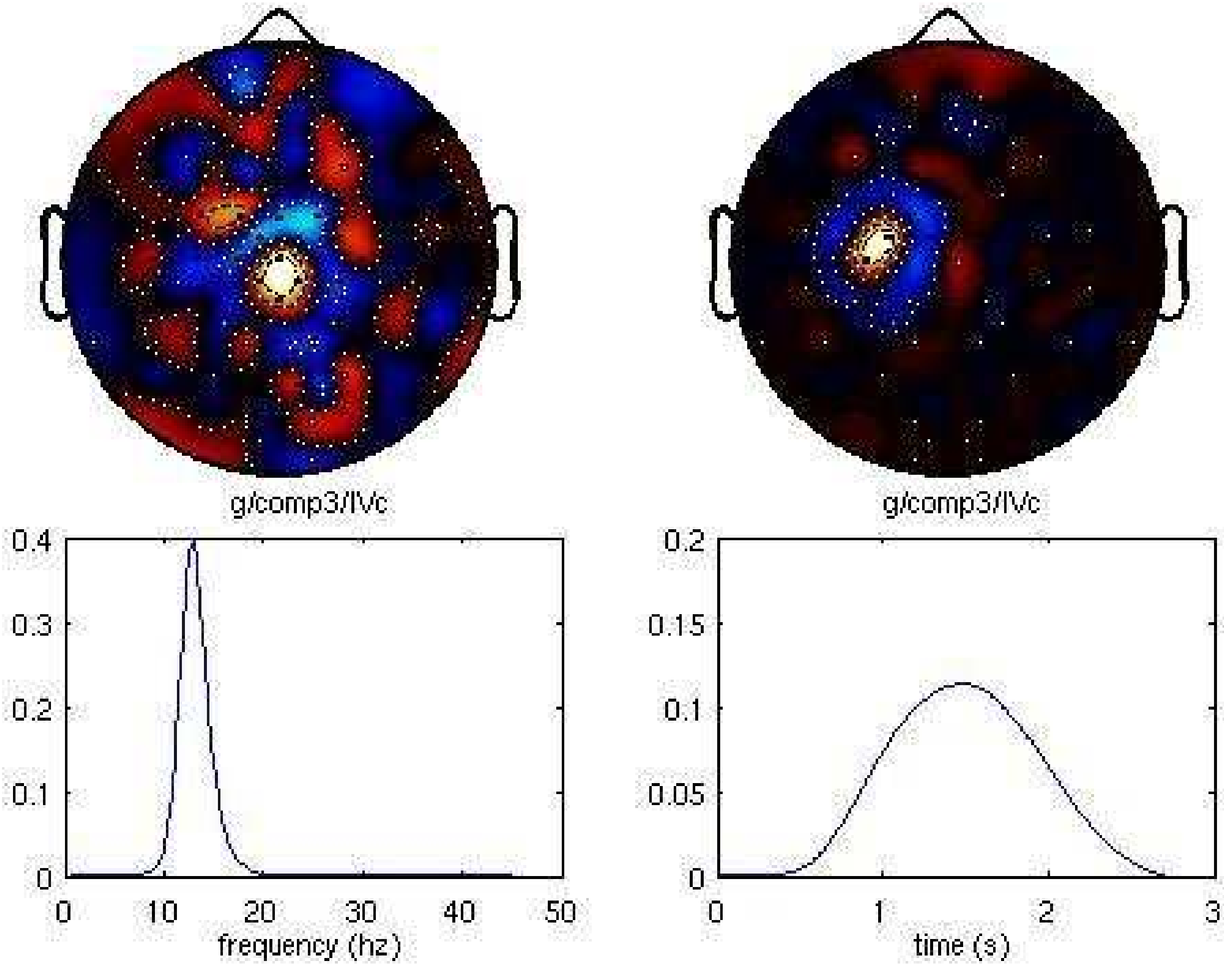

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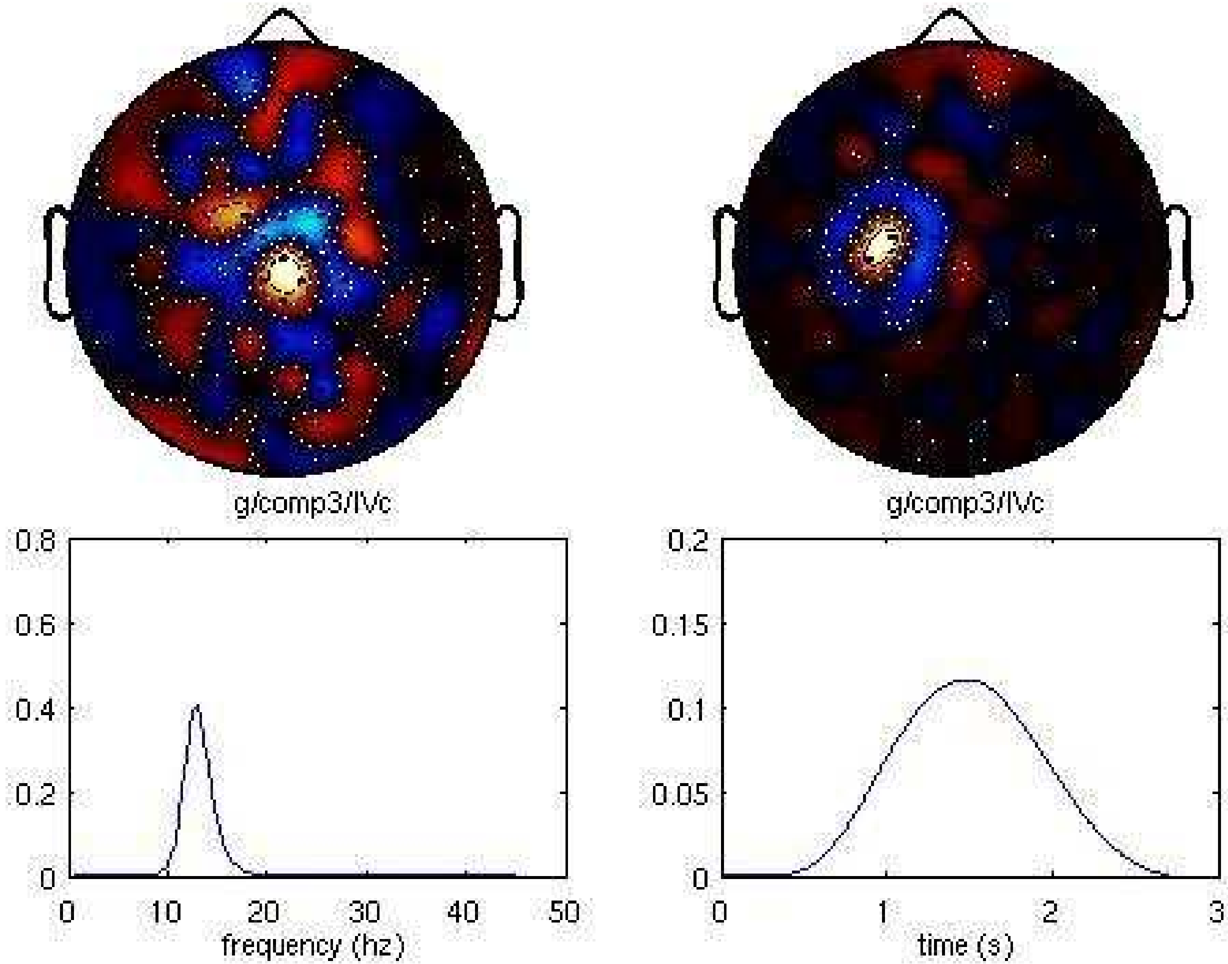

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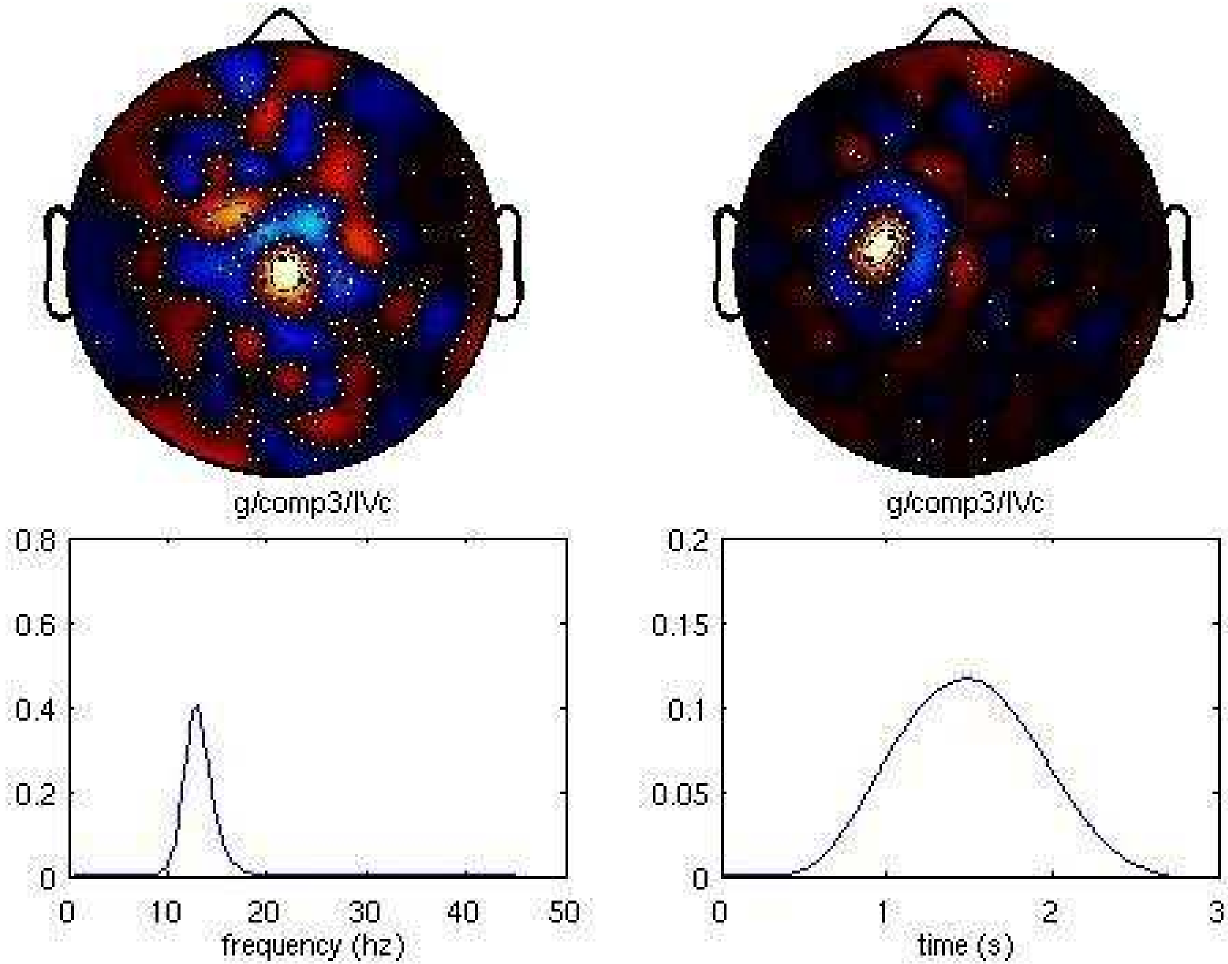

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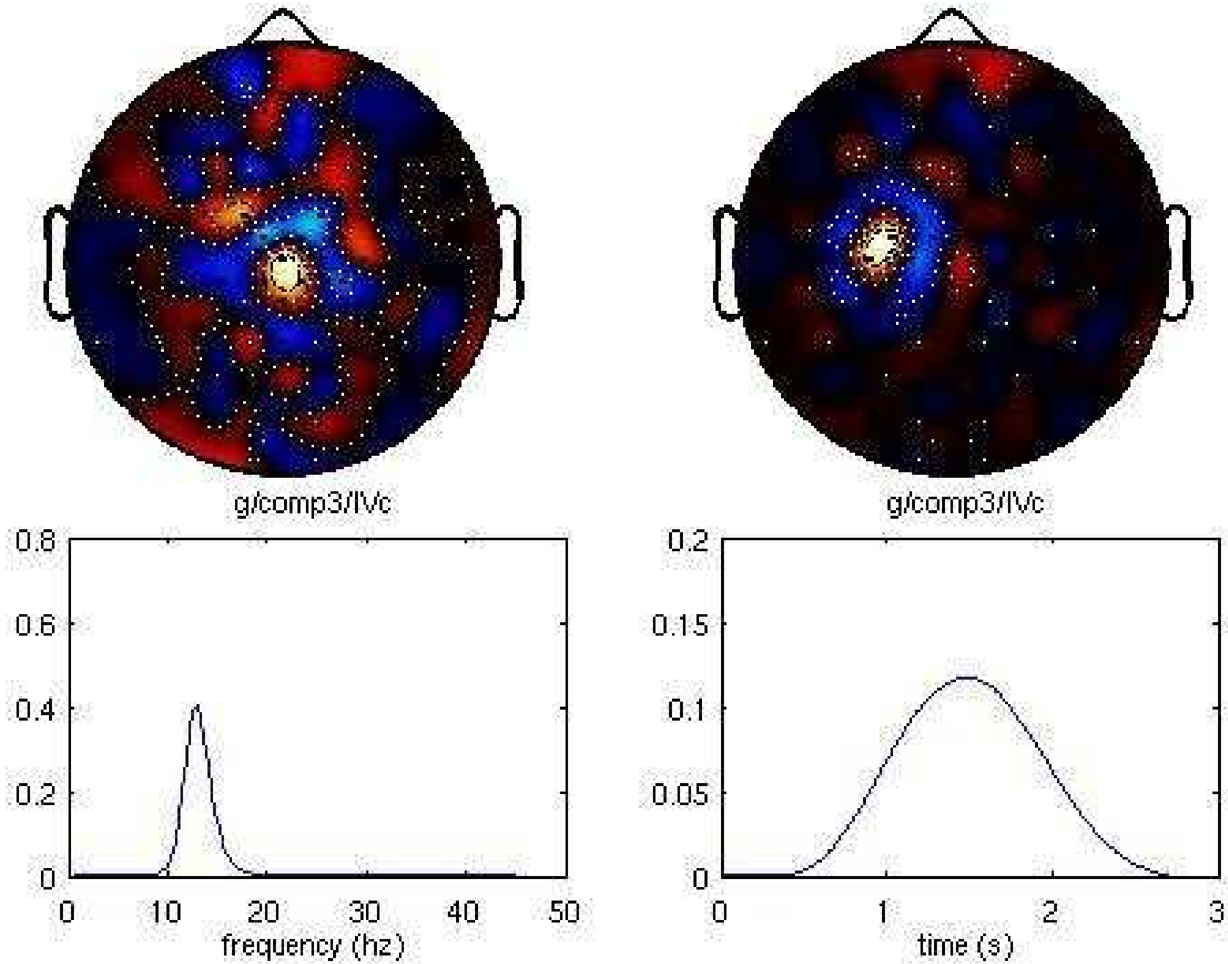
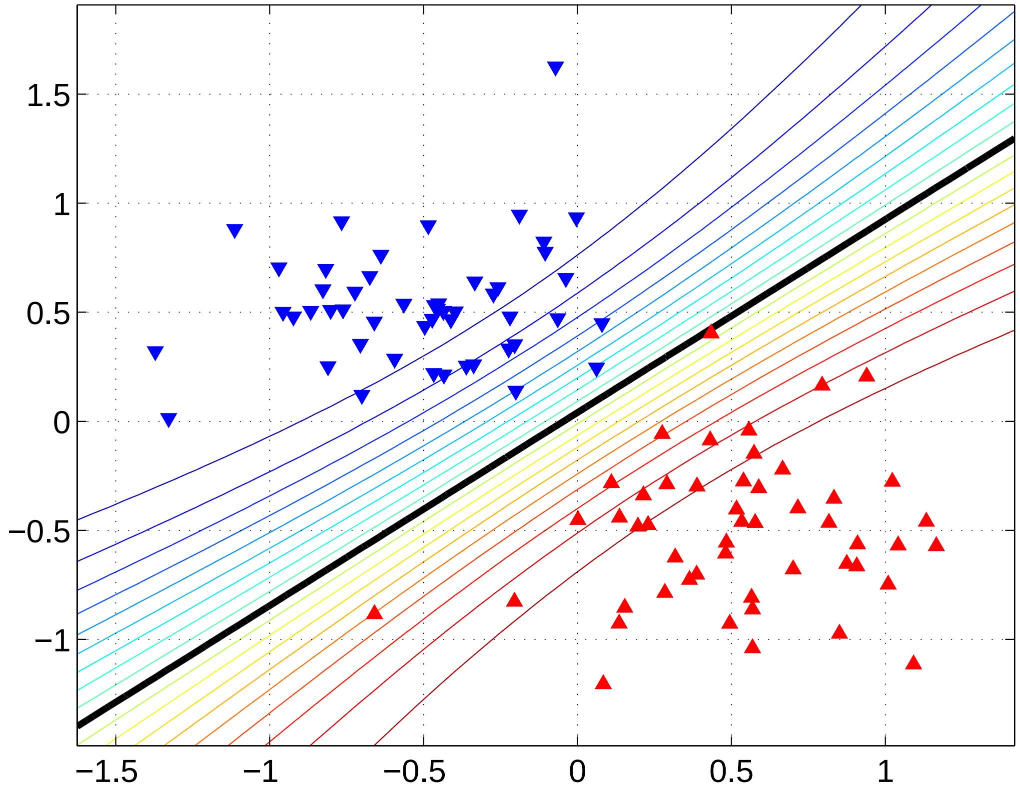
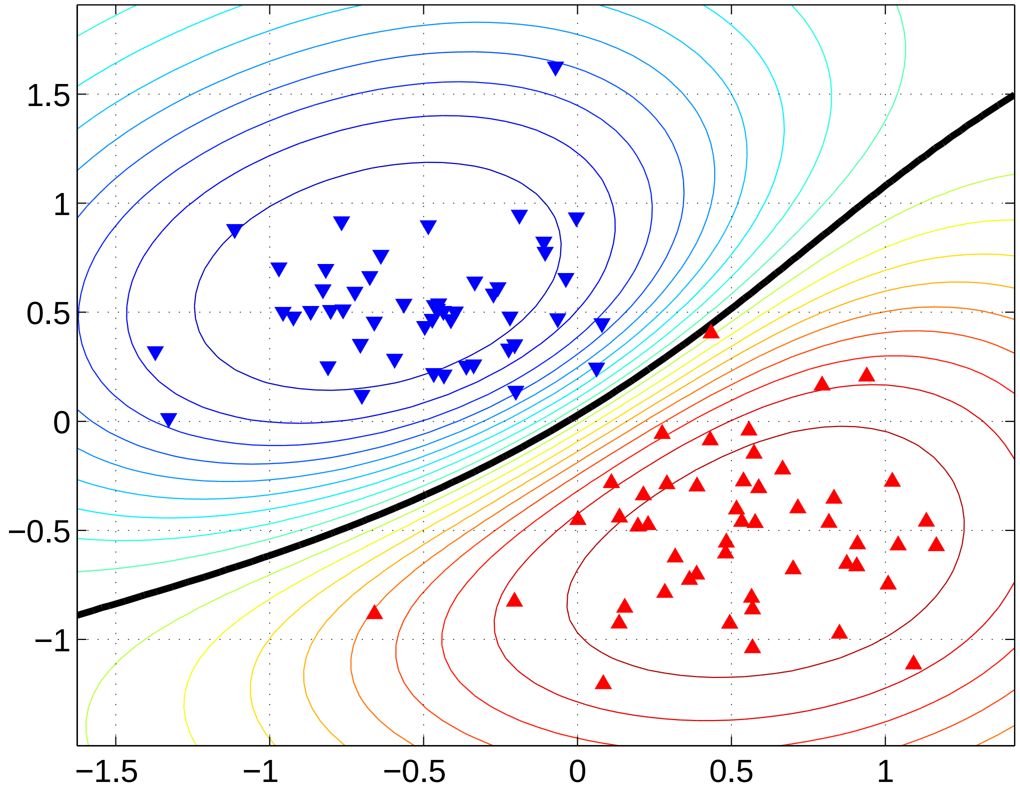


Linear or non-linear?



$$k(\mathrm{X}_i, \mathrm{X}_j) = v \left[1 + \sum_{k=1}^{m} \sigma_k^{-2} \log\left(\mathbf{f}_k^\top \mathrm{X}_i \mathrm{X}_i^\top \mathbf{f}_k\right) \; \log\left(\mathbf{f}_k^\top \mathrm{X}_j \mathrm{X}_j^\top \mathbf{f}_k\right) \right]$$

Linear or non-linear?



$$k(\mathrm{X}_i, \mathrm{X}_j) = v \exp\left(-\frac{1}{2}\sum_{k=1}^{m} \sigma_k^{-2} d_k^2\right)$$

where

$$d_k = \log\left(\mathbf{f}_k^\top \mathrm{X}_i \mathrm{X}_i^\top \mathbf{f}_k\right) - \log\left(\mathbf{f}_k^\top \mathrm{X}_j \mathrm{X}_j^\top \mathbf{f}_k\right)$$

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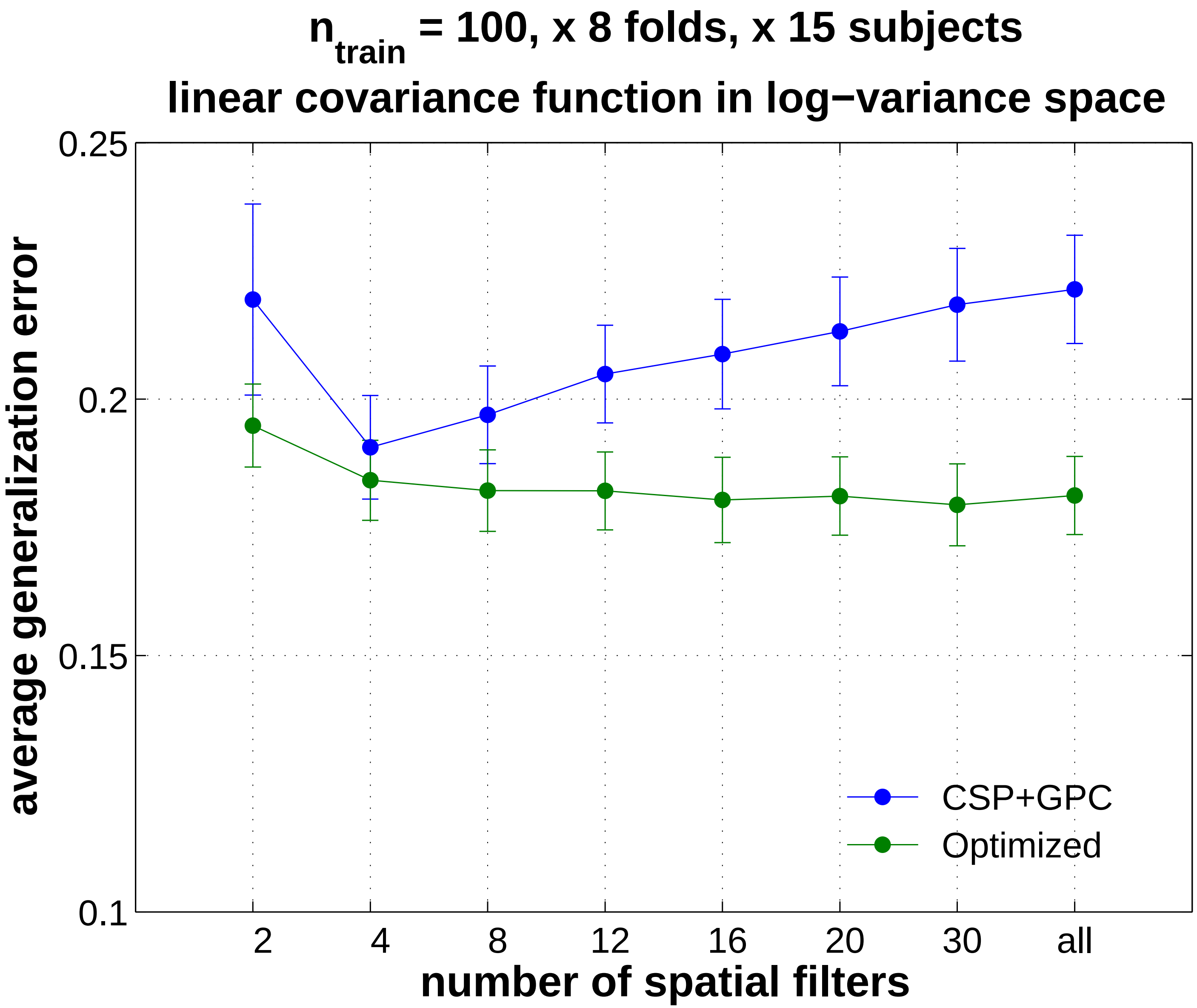

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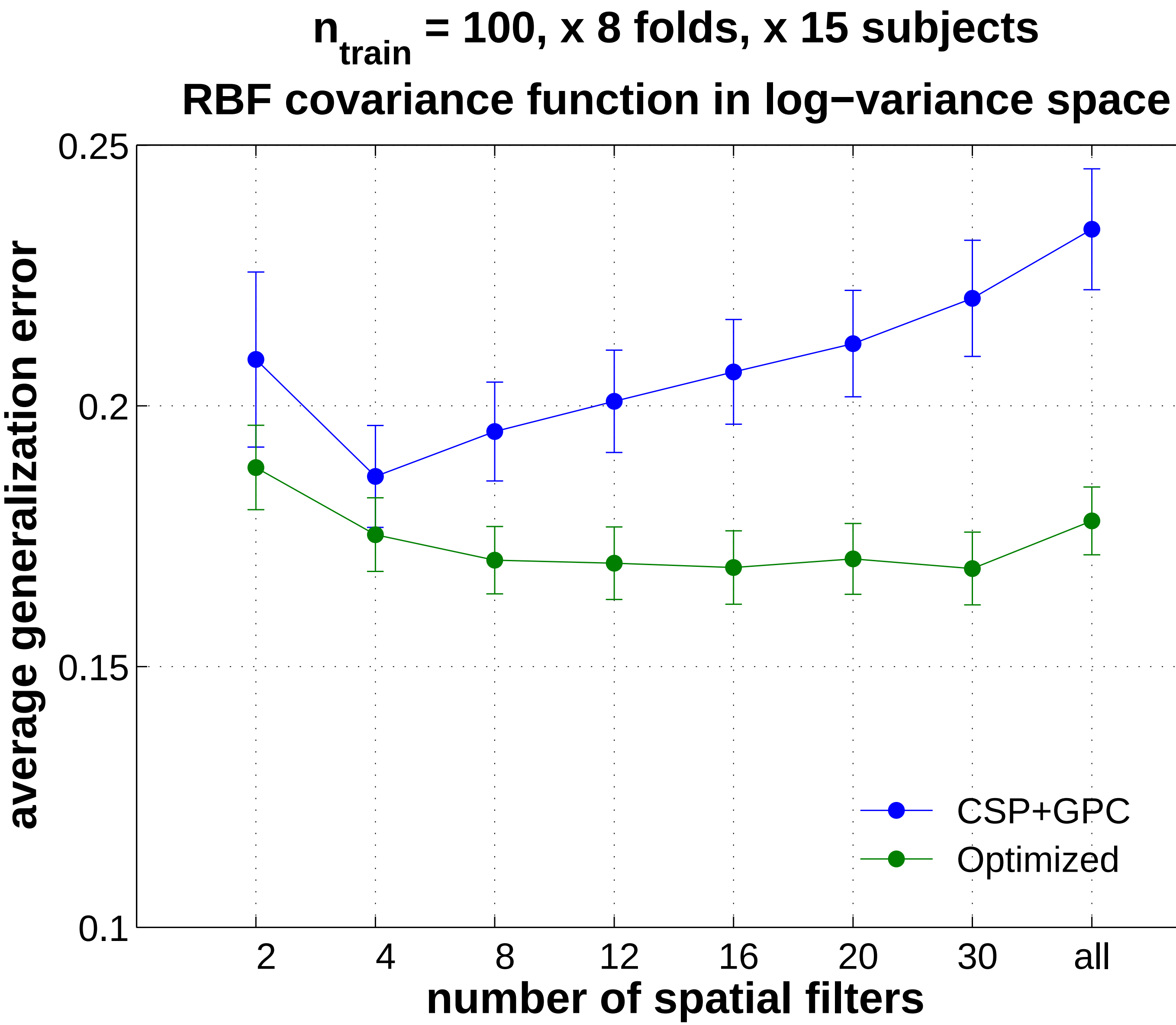


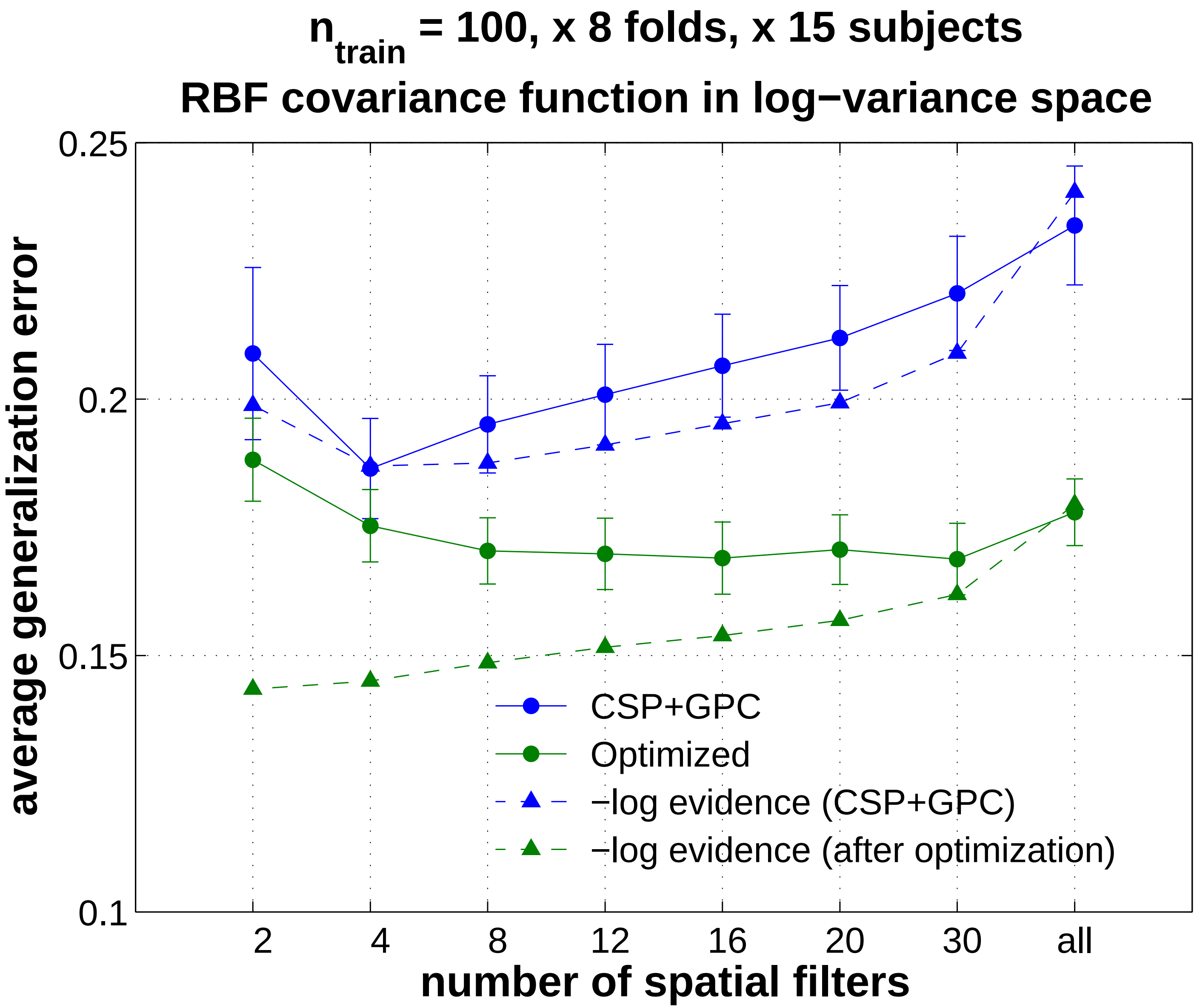
Linear or non-linear?

Use of the classifier's criterion to optimize preprocessing parameters means

- projection into higher-dimensional feature spaces via a non-linear kernel can help;
- not just "any classifier will do."

See also: Tomioka et al. (NIPS 2006) - logistic regression on (non-logged) variance features.

Model selection: how many filters?



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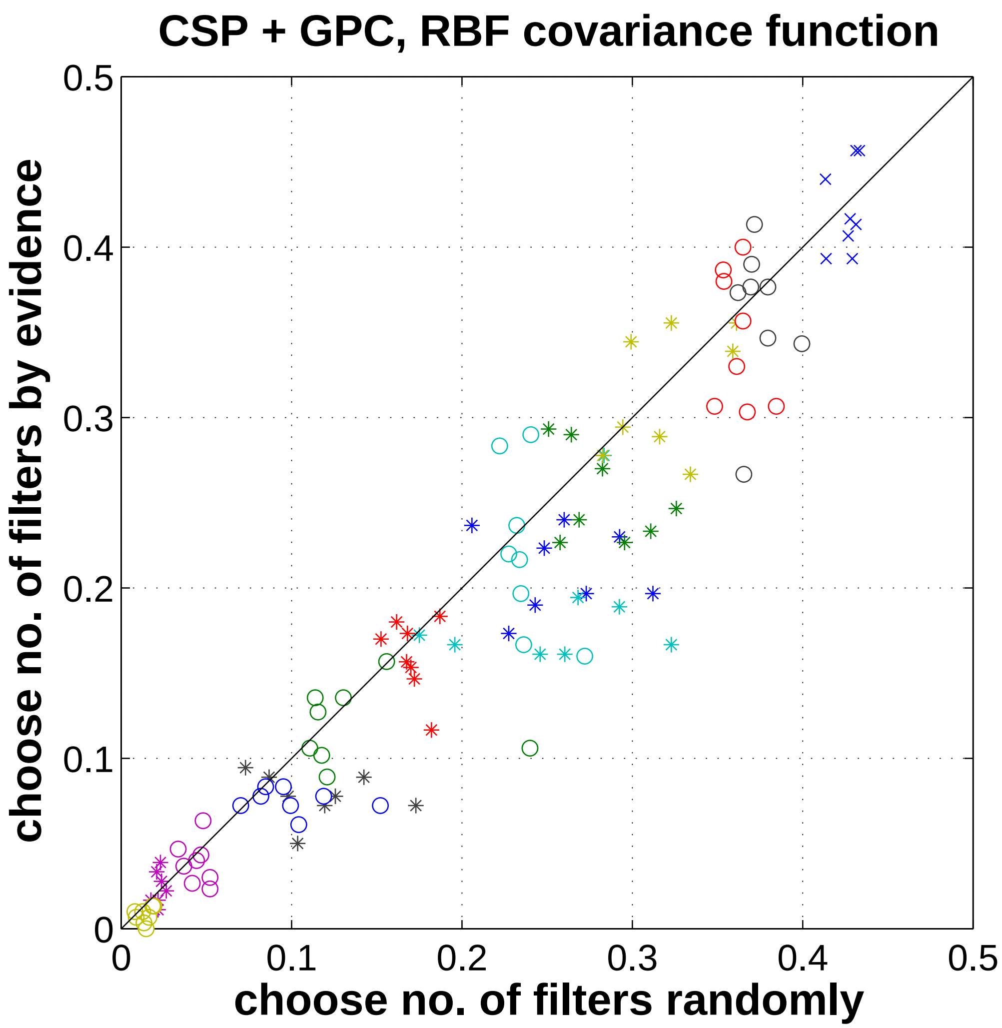

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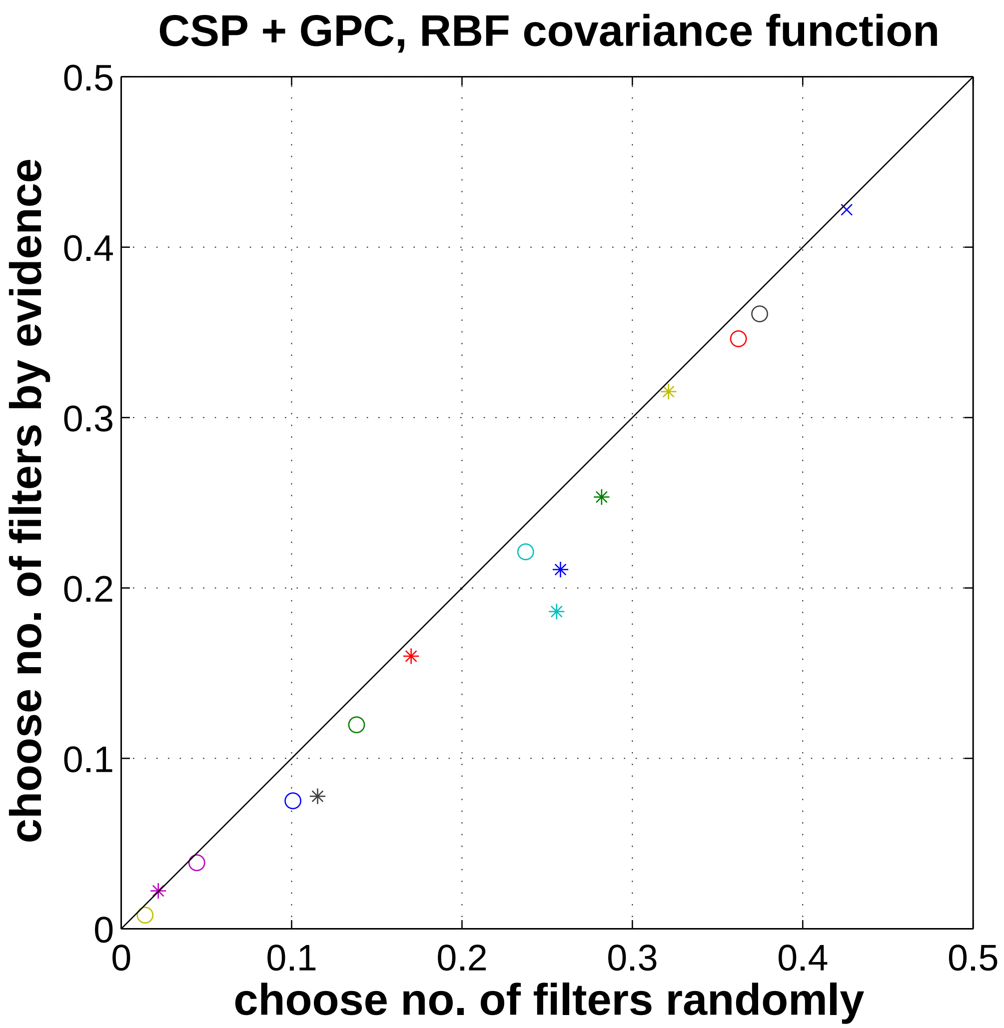

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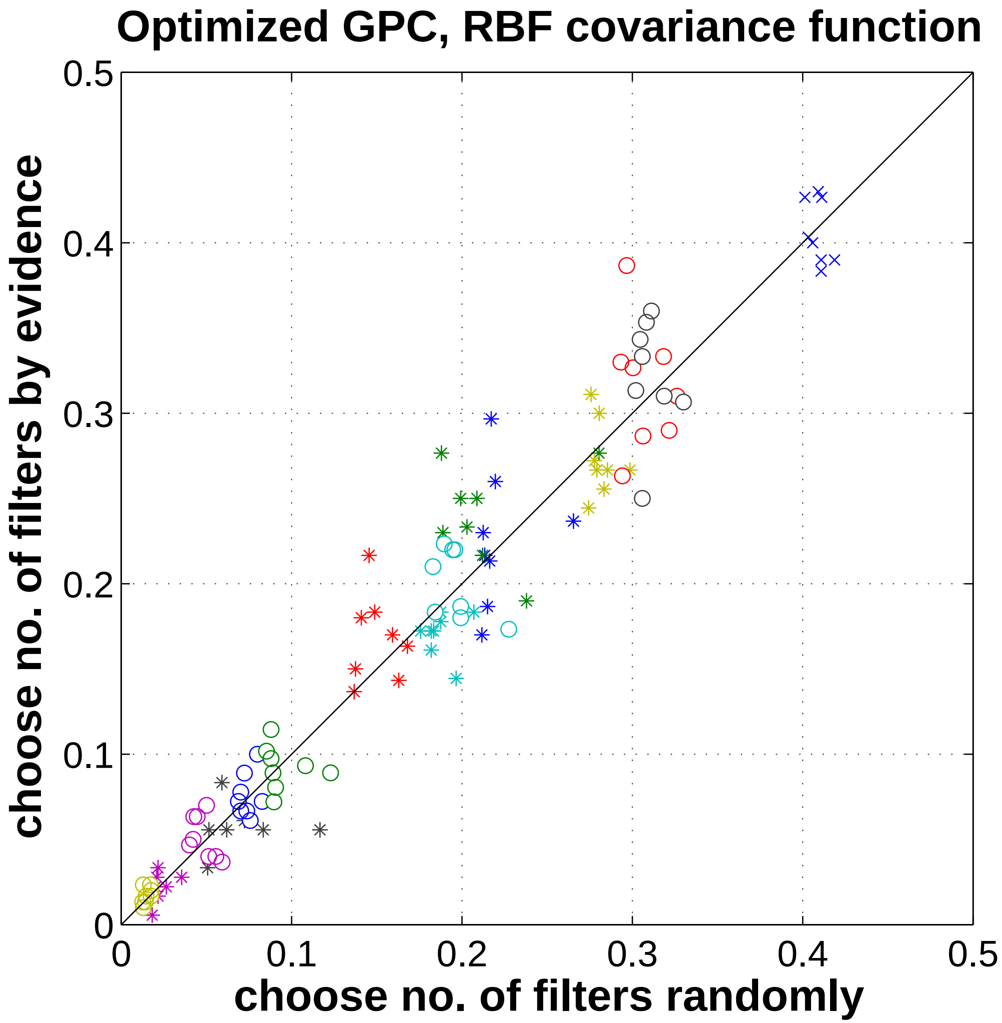

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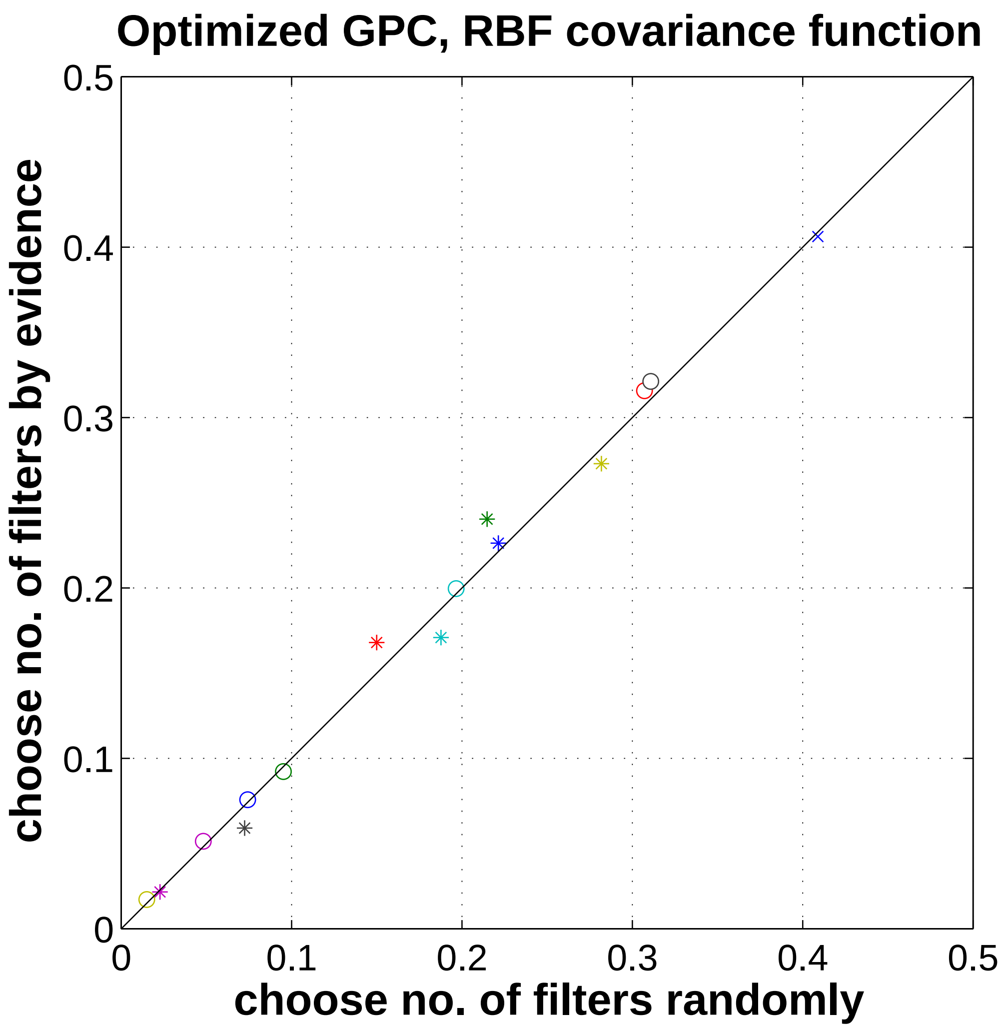

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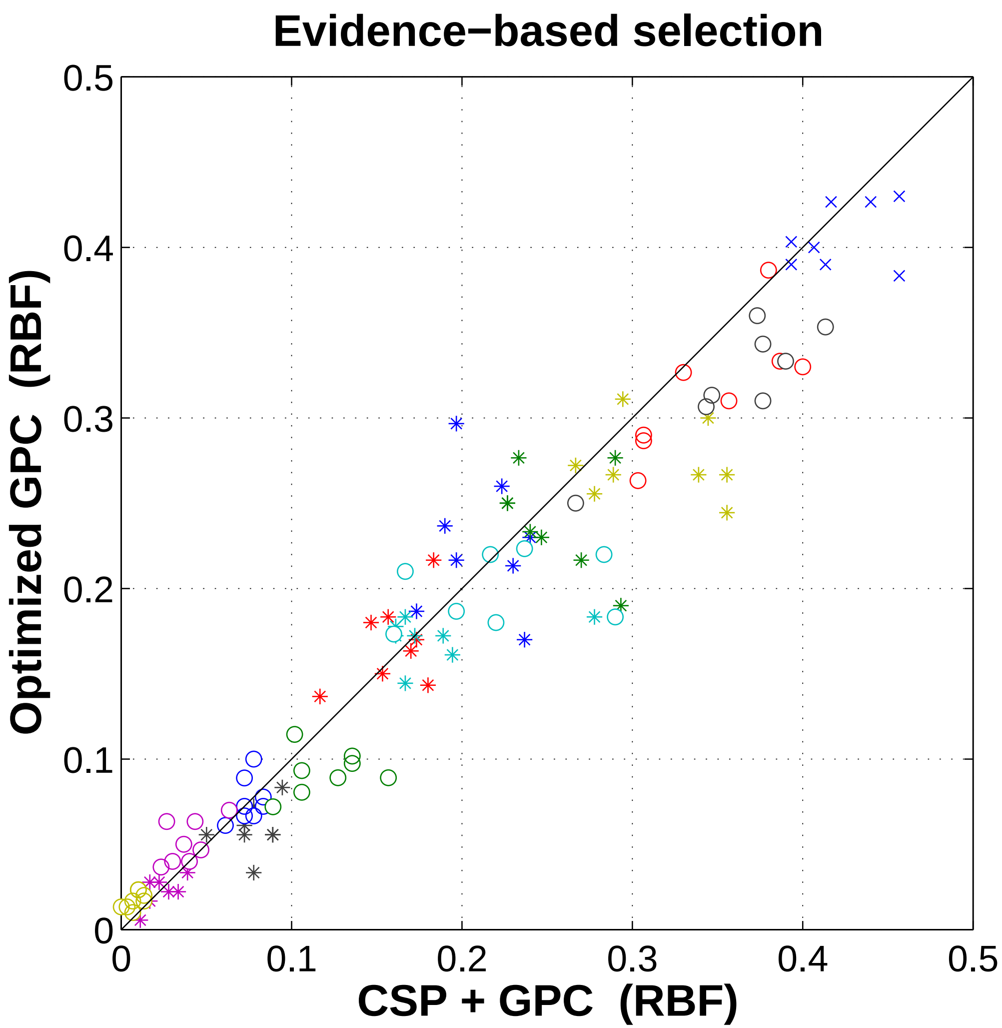

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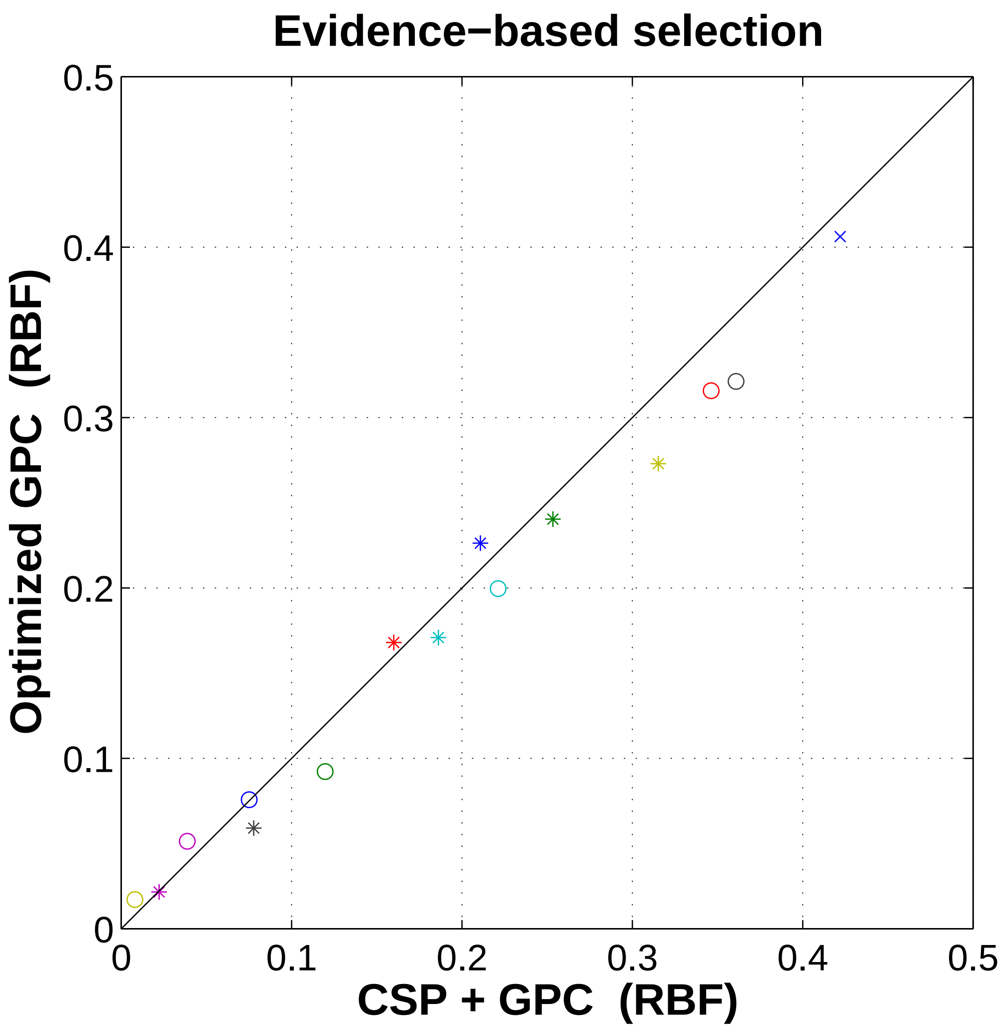

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- Application of the same approach to features in the time domain (and automatic combination of time-domain & band-power features).

Conclusion

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Conclusion

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- Benefits are greatest in the difficult cases: high noise and/or small amounts of data.
- Simultaneous optimization of filters and classifier weights eliminates the need to select filters by hand.
- Early indications are that interpretable, optimal weightings across space, time and frequency can be obtained
  - simultaneously;
  - without being very sensitive to prior assumptions.

Thank you for your attention.