EEG classification and crossvalidation using the BCILAB toolbox: practicum

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Download the latest toolbox version from:

ftp://sccn.ucsd.edu/pub/bcilab/

System requirements

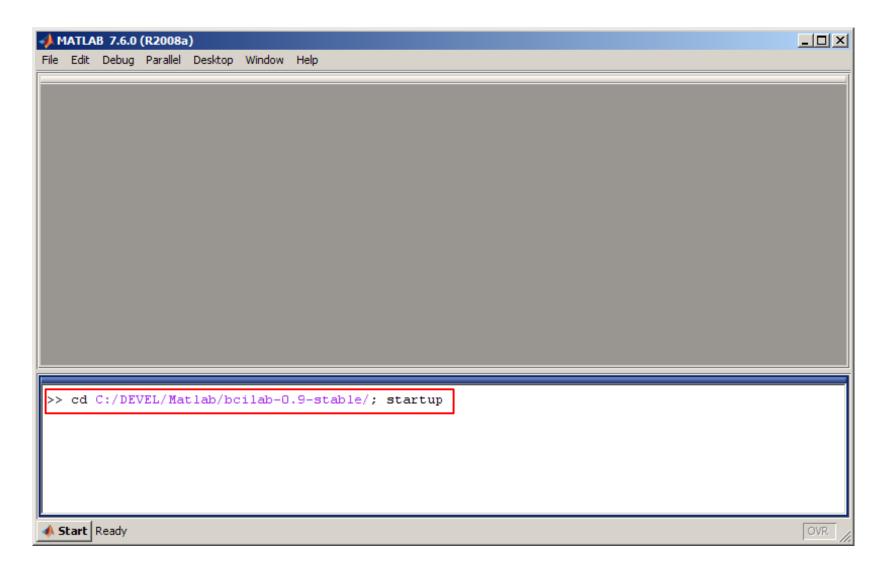
- MATLAB 2008a+ (scripts will run on 7.1+ (2005), but not this version)
- 1GB+ RAM (better: 2GB+)
- Windows, Linux, or Mac
- For smooth workshop: No toolboxes in MATLAB path other than Mathworks toolboxes (or EEGLAB)
- To use certain additional features (not covered today): Signal Processing Toolbox, Statistics Toolbox, Real-time experimentation environment (DataRiver, BCI2000, OpenViBE or your own)
- To use certain advanced features (also not covered today):
 Correct MEX compiler setting (this requires Microsoft Visual C++ Express under Win64)

Installation

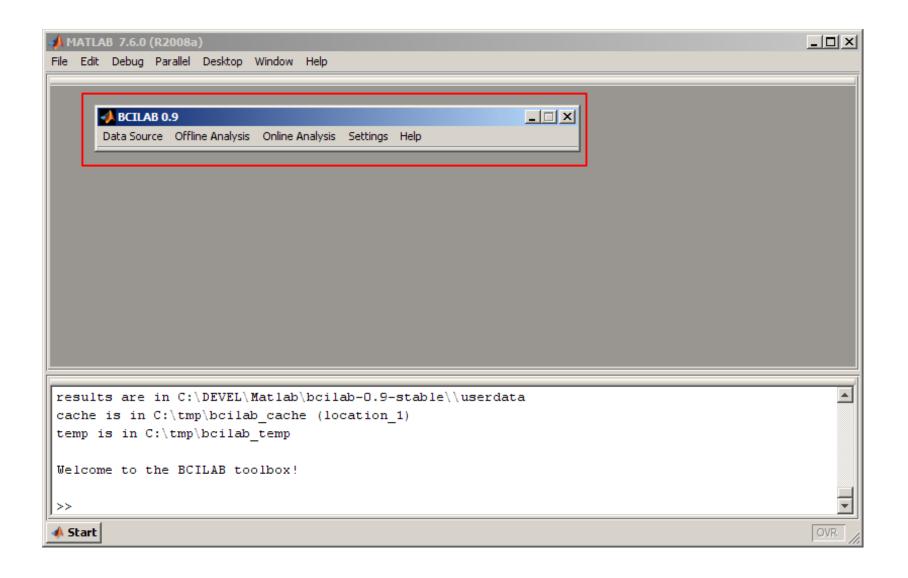
- Extract the .zip file (it contains one folder)
- Open MATLAB, type

```
cd /your/directory/bcilab-0.9-stable startup
```

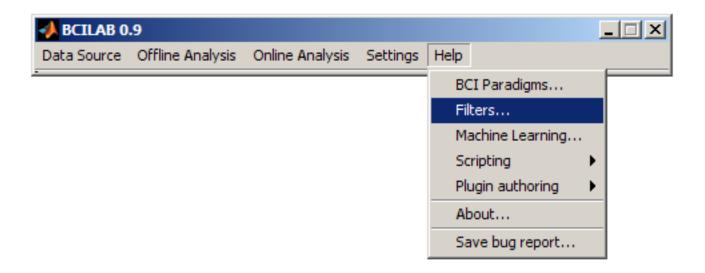
Startup



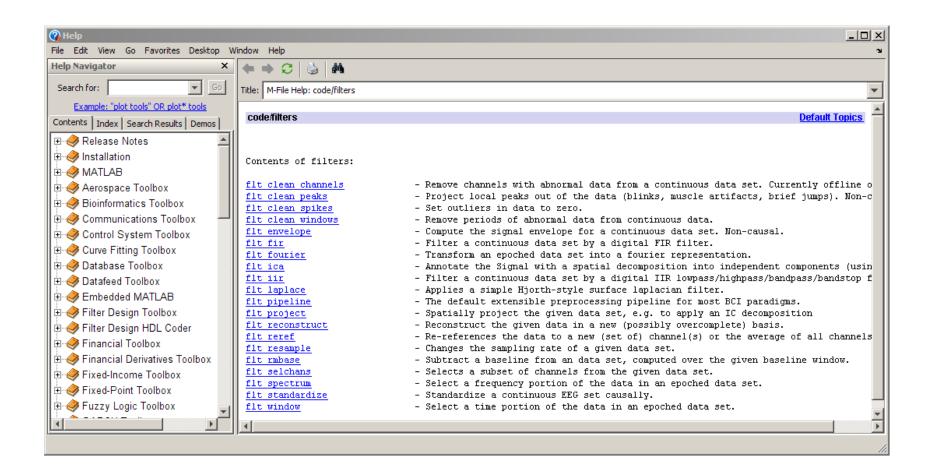
Toolbox GUI



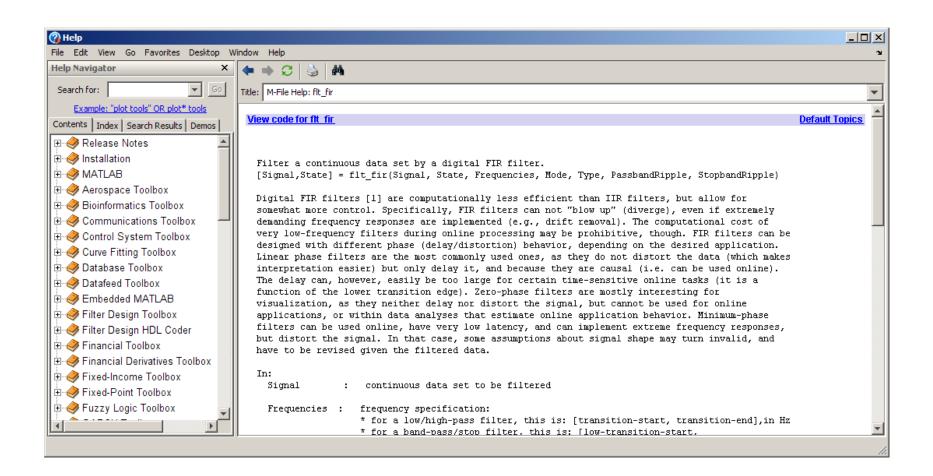
Getting help (if needed)



Getting help (if needed)



Getting help (if needed)



Use case 1

- You just recorded pilot data for some new study
- The idea is to try to estimate a certain aspecty of cognitive state
- The question is what method works best, and what accuracies can be achieved

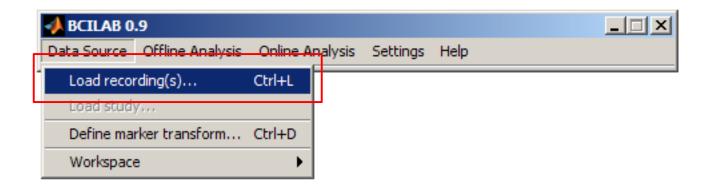
Use case 1

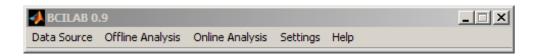
- Scenario: Subject is instructed to imagine a hand movement, either left hand or right hand (standard BCI case)
- Task: Estimate, from raw data, which hand movement was imagined
- Experimental data: EEG, 32 channels, 2 sessions (each ~30 min.), 2 sub-blocks per session with intermittent pause

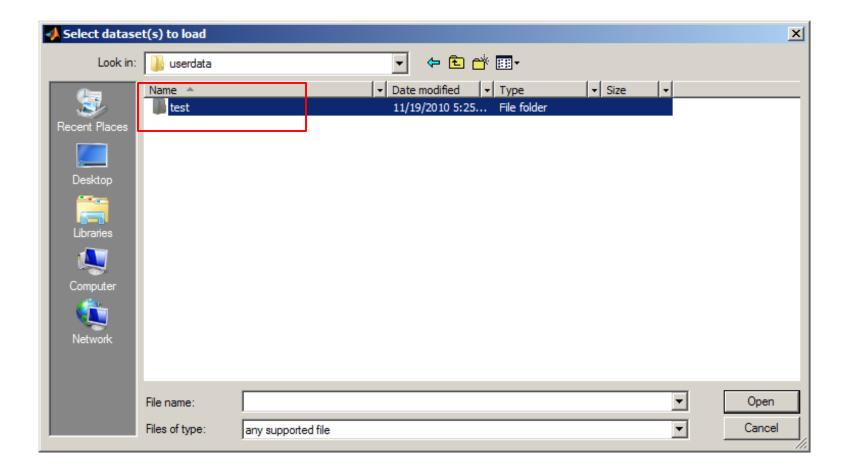
Experimental task

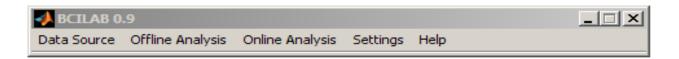
- 160 trials
- Randomized Instruction: L or R
- Displayed for 3s, followed by blank screen for 3.5s
- Sample:

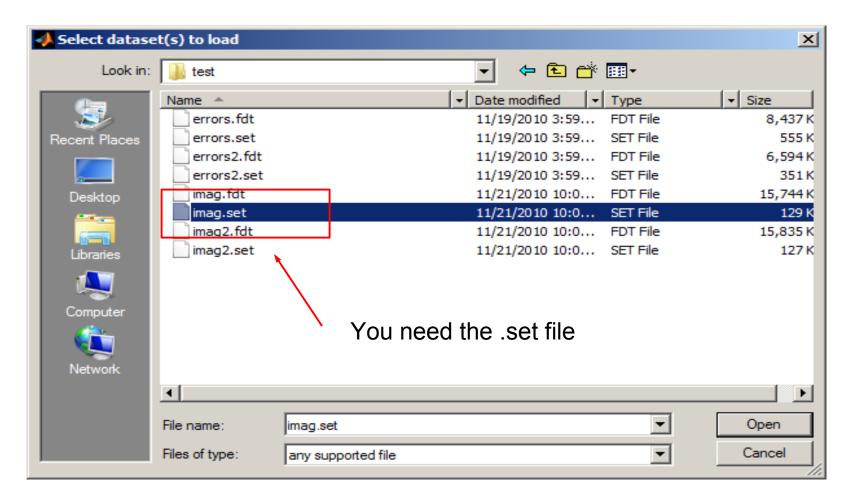








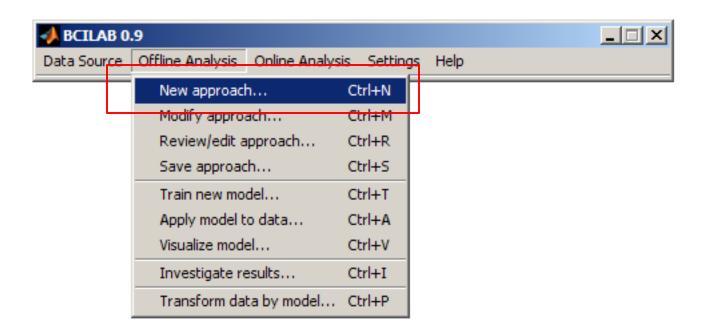




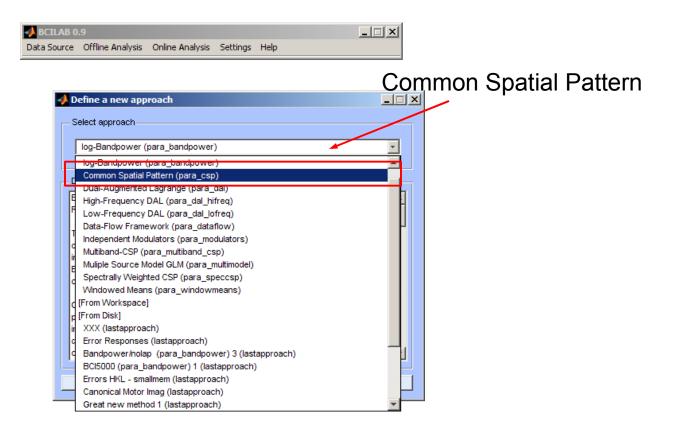
◆ BCILAB 0.	.9				_ X
Data Source	Offline Analysis	Online Analysis	Settings	Help	

Load source data	_ X					
— Optionally load data in reduced form——————						
Channel index subset						
Sample range subset						
Time range subset						
— Optionally add fields, if missing (raw files only)————						
Sampling rate						
Save data in workspace as	lastdata					
Add markers	Cancel OK					

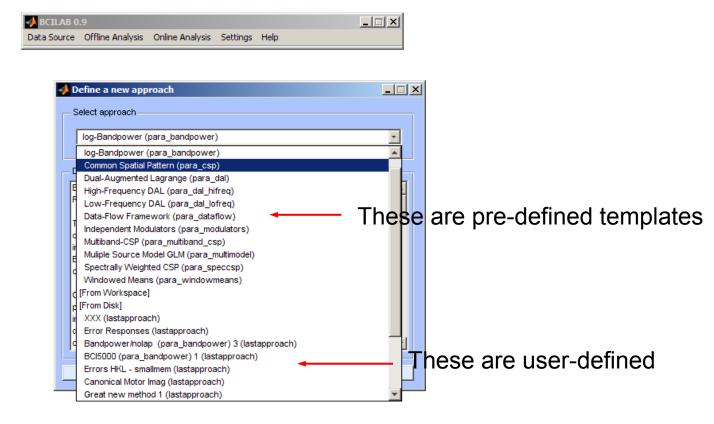
 An approach addresses both parts of the BCI problem:
 Mapping from observed signals to predictions, and learning the unknown parameters



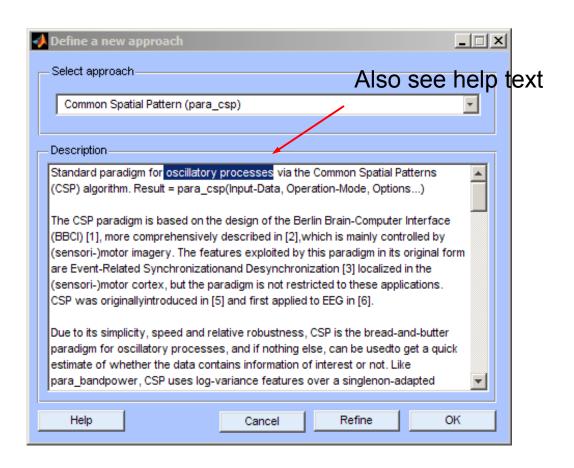
 You never start completely from scratch, but on the basis of what is known to work

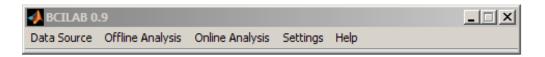


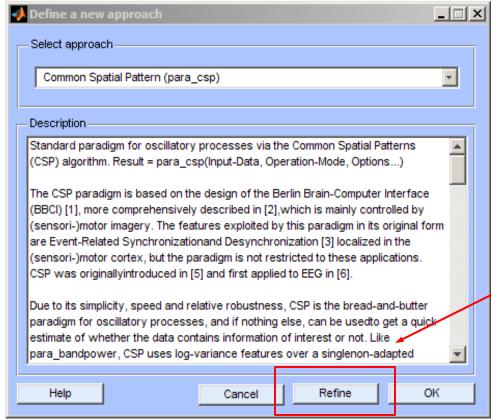
 Some of these work best for oscillatory processes, others for ERP-like features, etc.





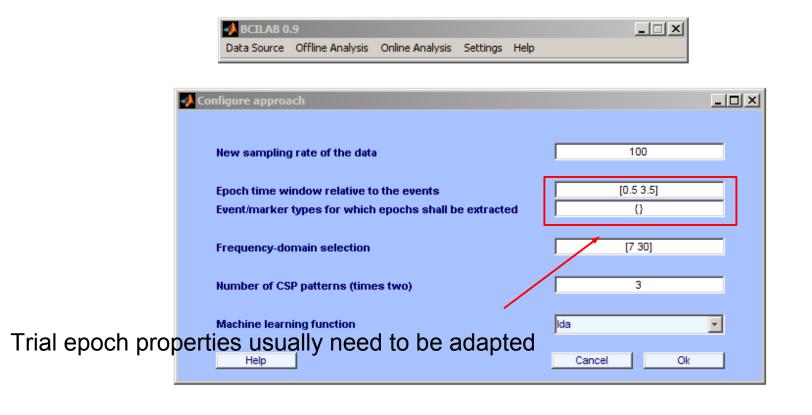


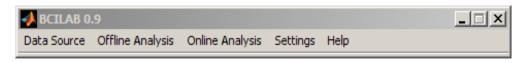


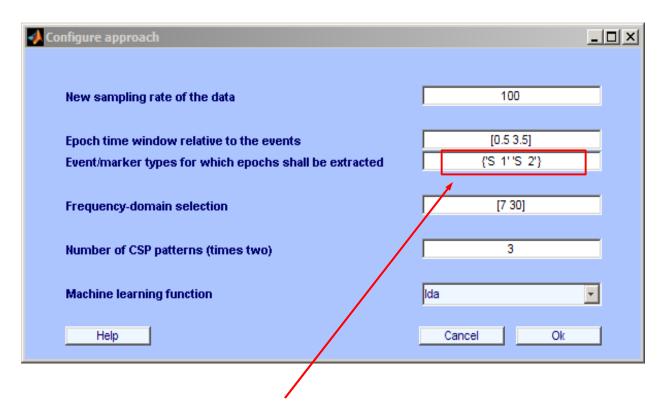


Adapt the template to your experiment

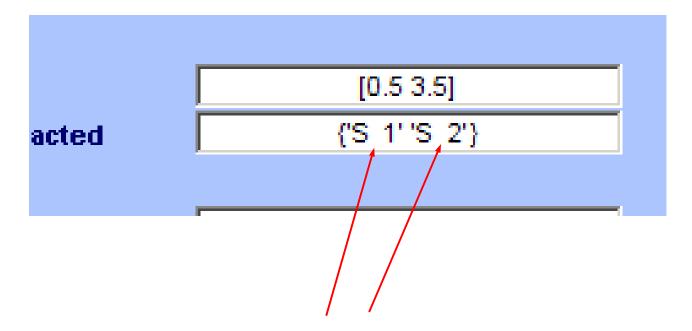
Key properties can be configured in this dialog



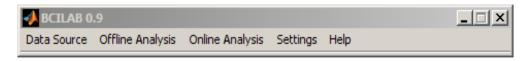




Fill in the 2 event types for this dataset; Stimulus 1 & 2, called 'S 1' and 'S 2' (Brain Products names)



Note the **two** spaces between the S and the number!



◆ Configure approach	_ D X
New sampling rate of the data	100
Epoch time window relative to the events	[0.5 3.5]
Event/marker types for which epochs shall be extracted	{'S 1' 'S 2'}
Frequency-domain selection	[7 30]
Number of CSP patterns (times two)	3
Machine learning function	lda
Help	Cancel Ok

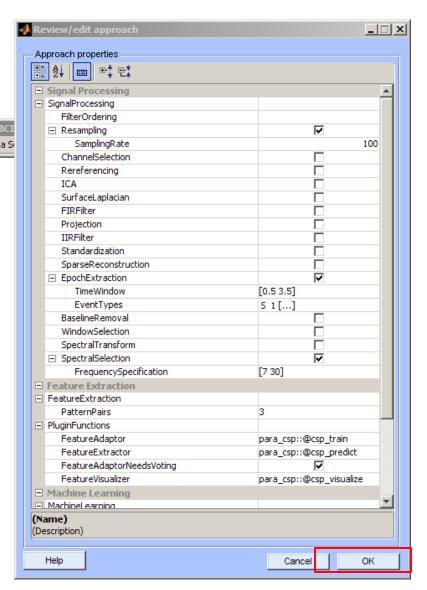
(Takes a while after clicking OK)

Review/edit approach

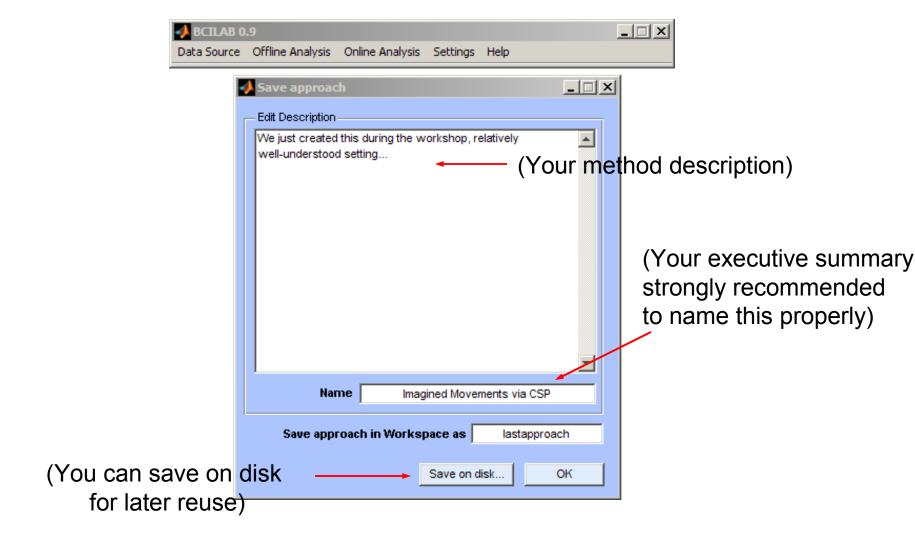
 The next panel allows to edit all properties of the approach.

 Filter stages can be added and configured

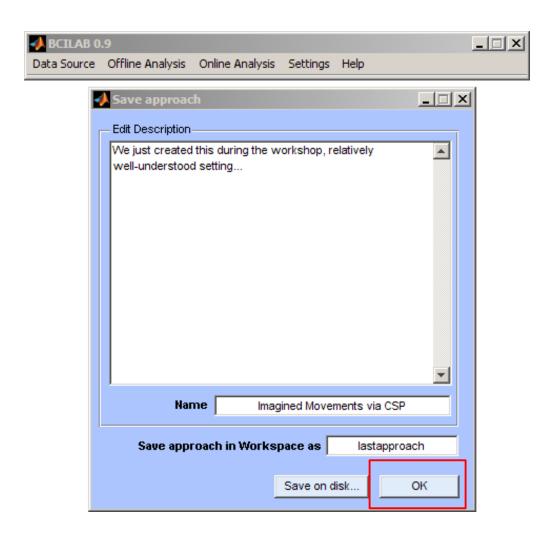
- Feature extraction can be configured
- Machine learning components can be selected and configured
- For now, nothing to do



Save approach

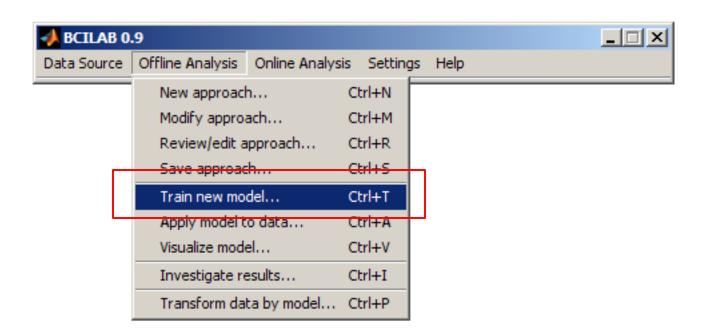


Save approach

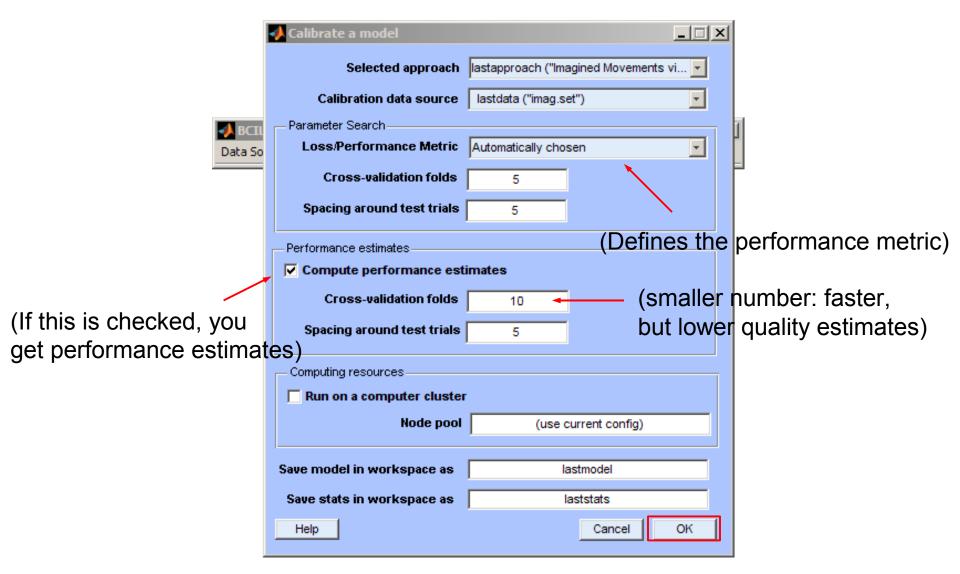


Learn a predictive model

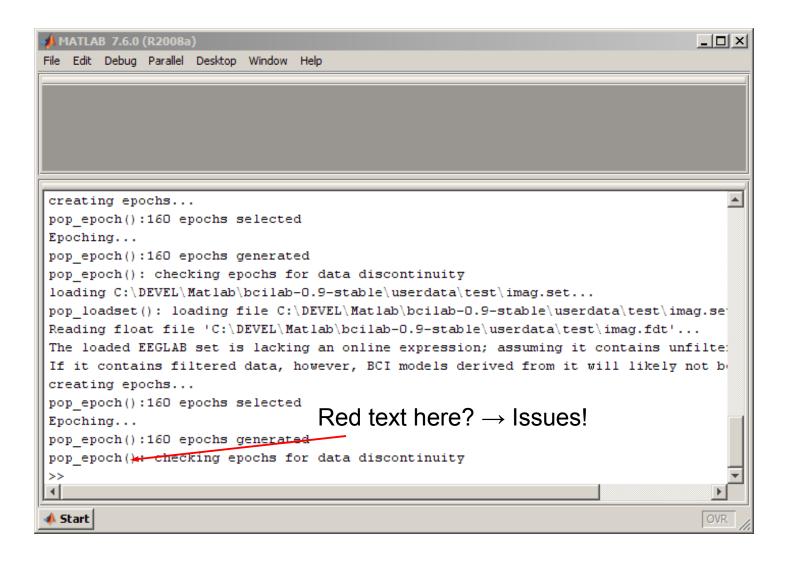
Put the method to the test...



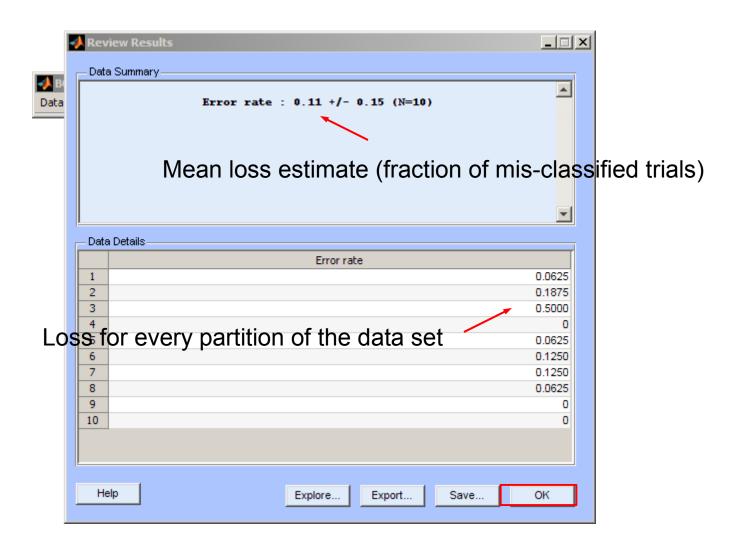
Learn a predictive model



Wait for results



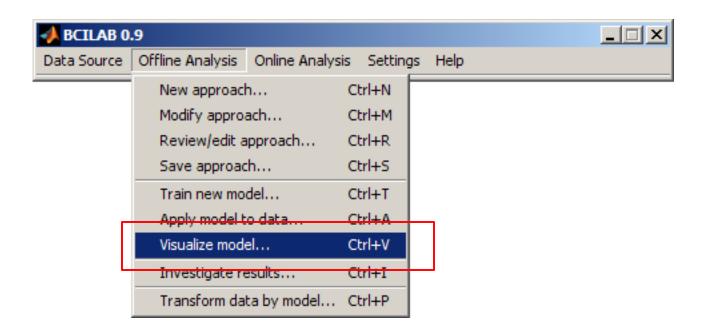
Review results



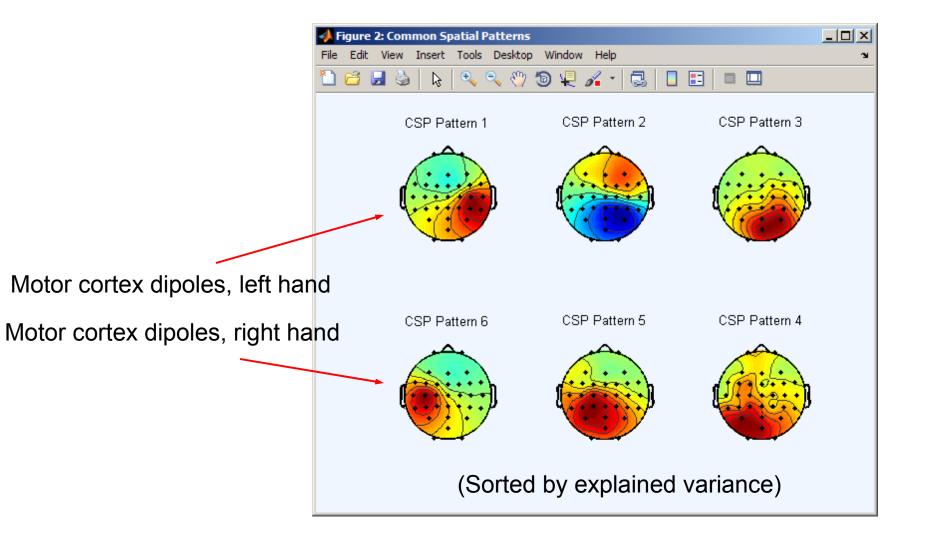
Review results

- 11% error rate is quite good for imagined movements; mean across studies & methods is probably closer to 25%
- chance level is here 50% (keep that in mind when evaluating)
- You may get multiple outputs (e.g., false positives, true positives, which show up in the table), depending on loss measure

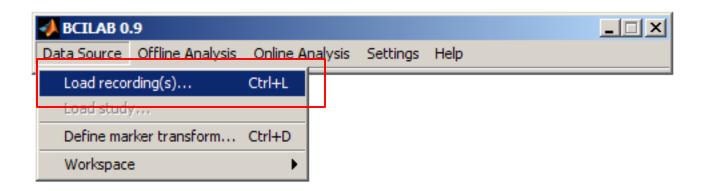
Visualize model properties



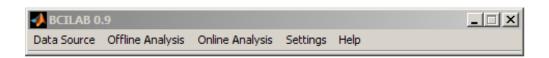
Visualize model properties

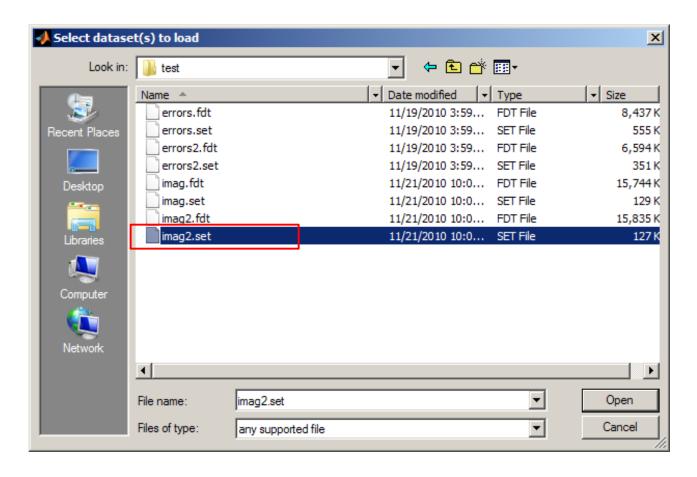


Apply model to 2nd session

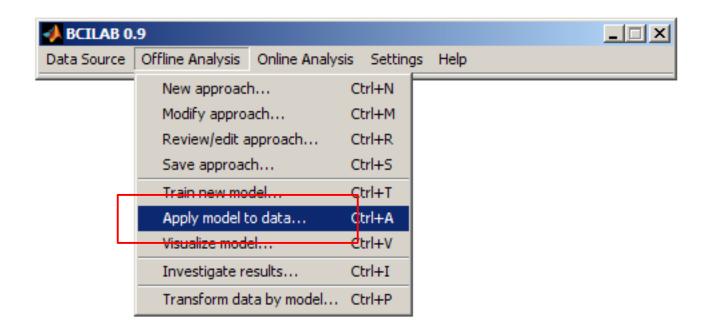


Apply model to 2nd session

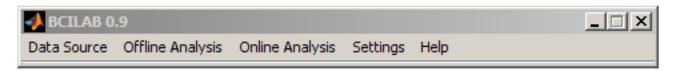


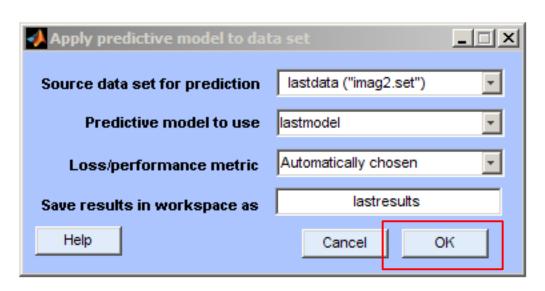


Apply model to 2nd session

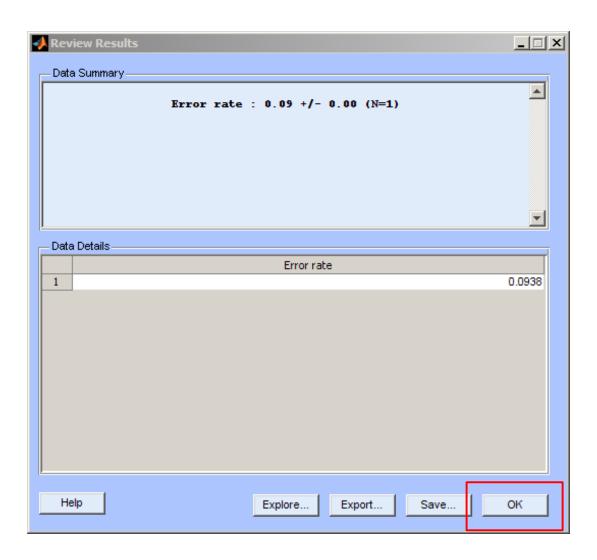


Apply model to 2nd session



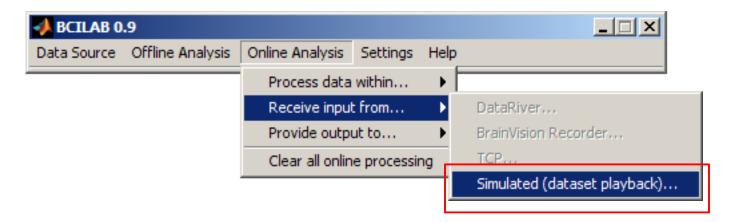


Review results



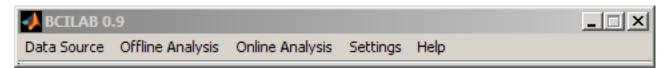
OR: Apply model online

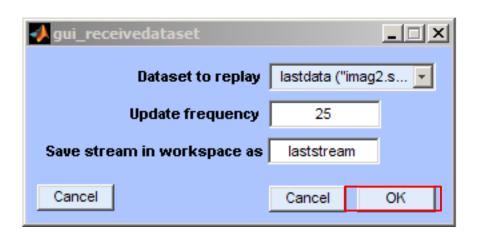
- (if you have a subject sitting next to you)
- Today: use a simulated data source (playing back the 2nd session)



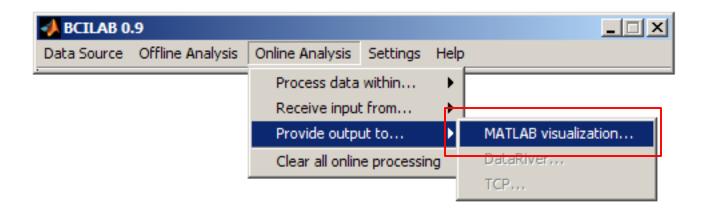
Apply model online

This adds a data feed process in the background



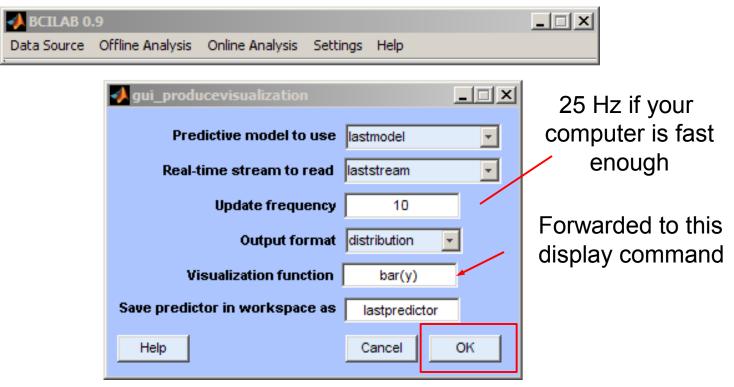


Apply model online

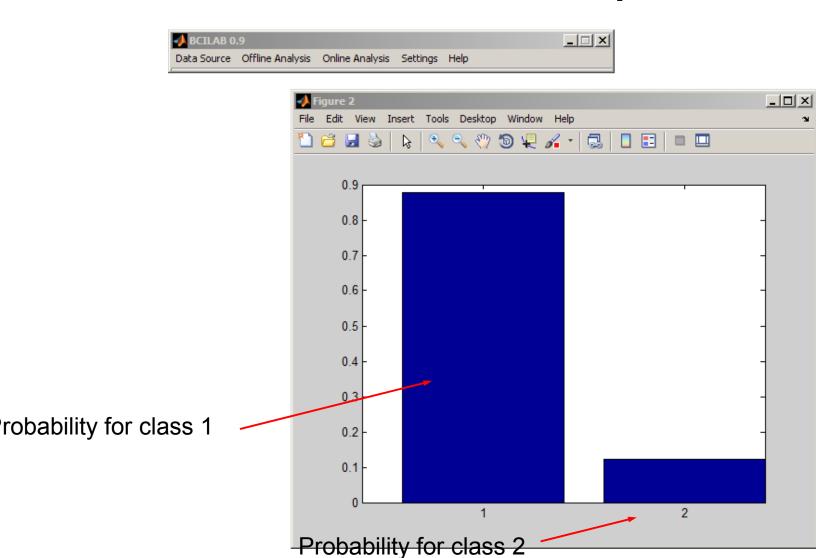


Apply model online

 This adds a real-time inference process in the background



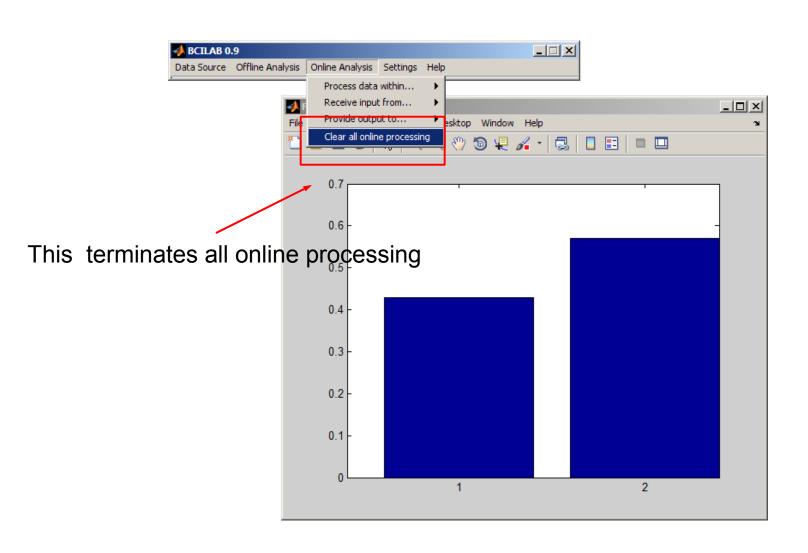
Real-time output



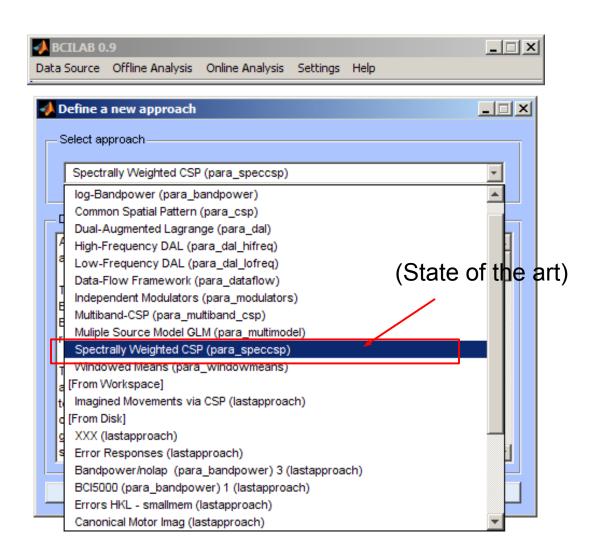
Real-time output

- If you have more classes, you get more bars
- You can also remap to other parameters (e.g. expected value)
- Note: the simple graphics command always renders into the current window

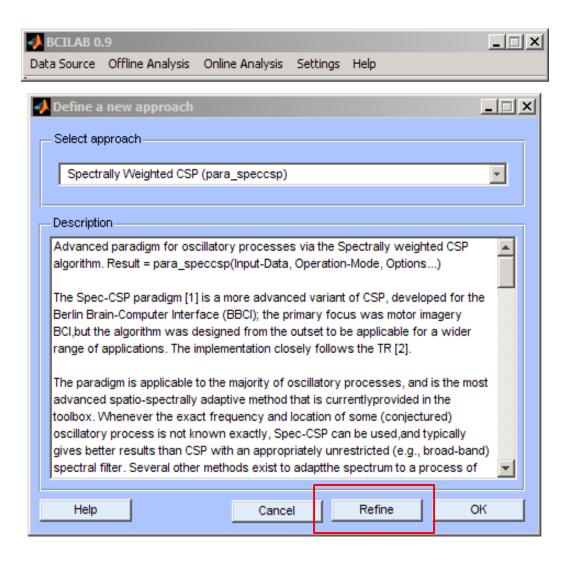
Real-time output



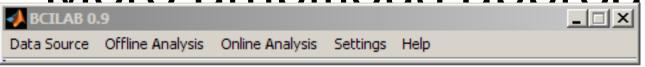
More ambitious approach?

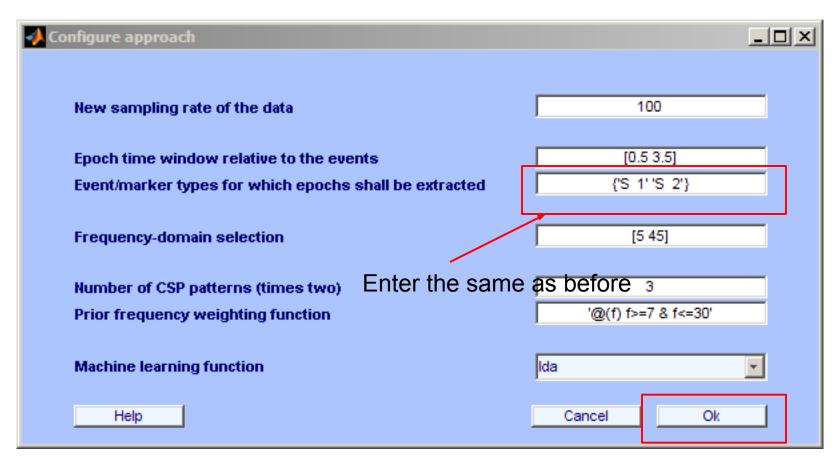


More ambitious approach?



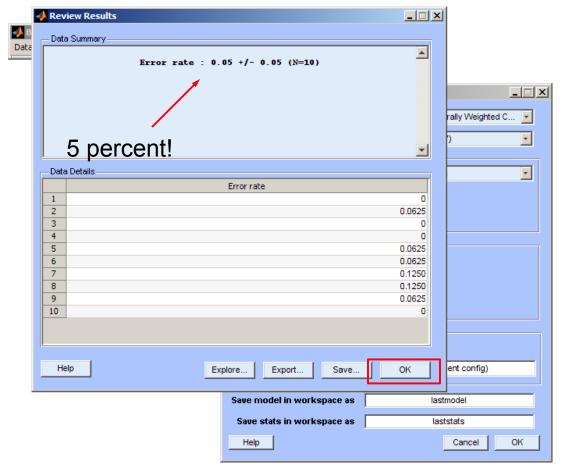
More ambitious approach





Train model, review results

 Note that the model calibration takes longer for Spec-CSP.



Next steps

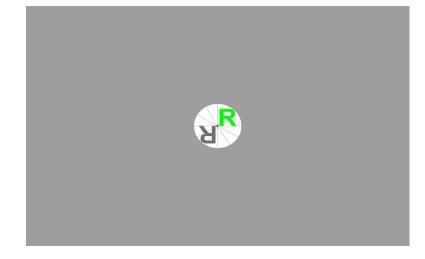
 Run online, apply to dataset, edit parameters, try to improve results, ...

Use case 2

- Question: Can we predict whether the user perceives an event as being an error?
- Experimental data: EEG, 32 channels, 2 sessions

Experimental task

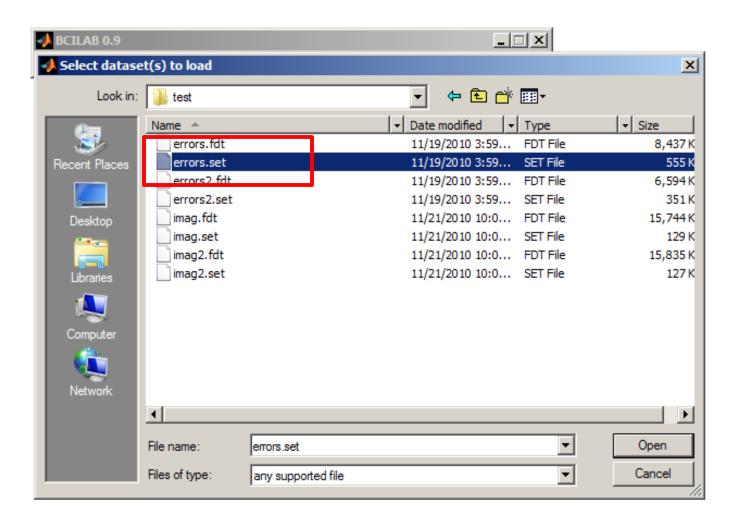
- Experimental task: ~100 randomized trials,
 3 types of stimuli:
 - expected/correct event: type 'S 11'
 - unexpected event A: type 'S 12'
 - unexpected event B: type 'S 13'
- Sample:



Experimental task

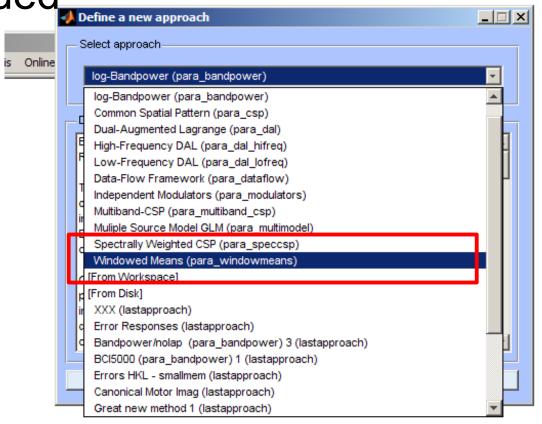
 The colored letter either rotates as expected (in response to a user key command), or differently

Load data

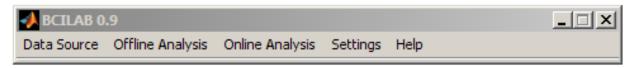


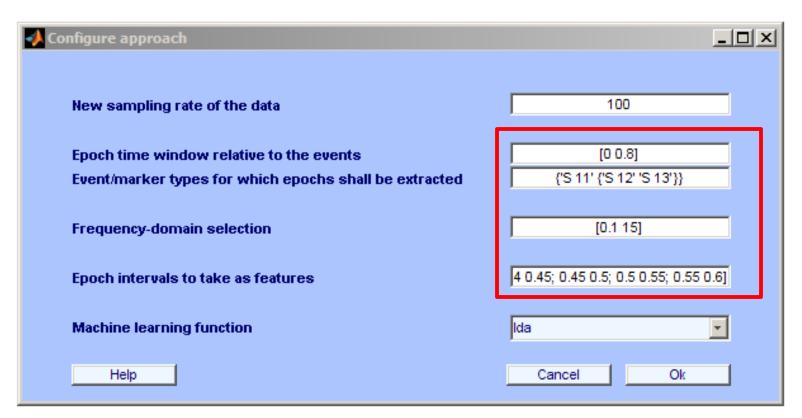
Define approach

This time, an ERP-specific approach is needed_____



Major customizations

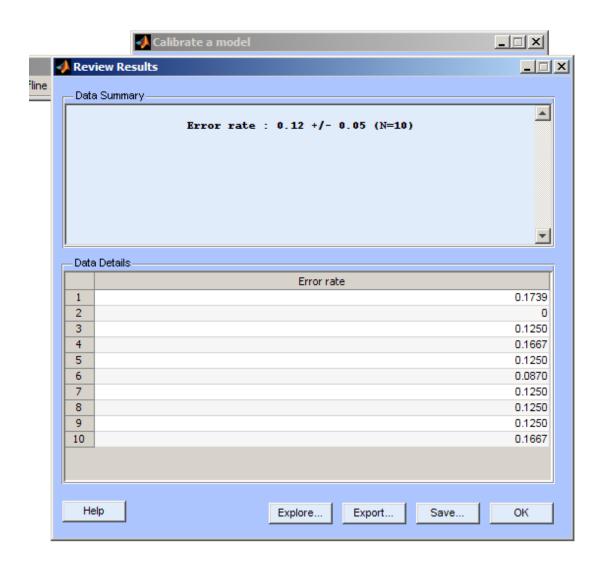




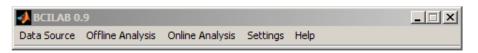
Event markers: {'S 11' {'S 12' 'S 13'}}

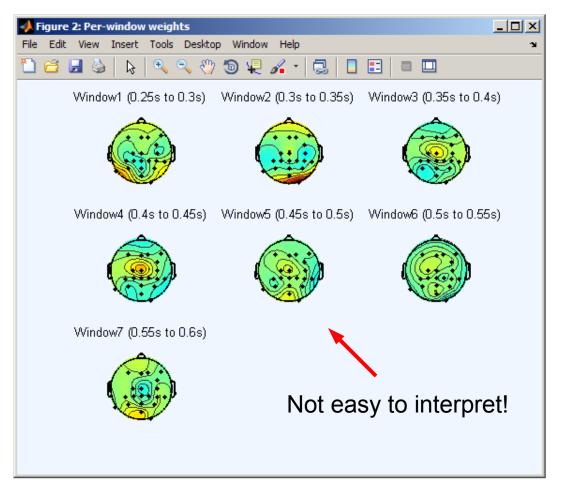
Epoch intervals: [0.25 0.3; 0.3 0.35; 0.35 0.4; 0.4 0.45; 0.45 0.5; 0.5 0.55; 0.55 0.6]

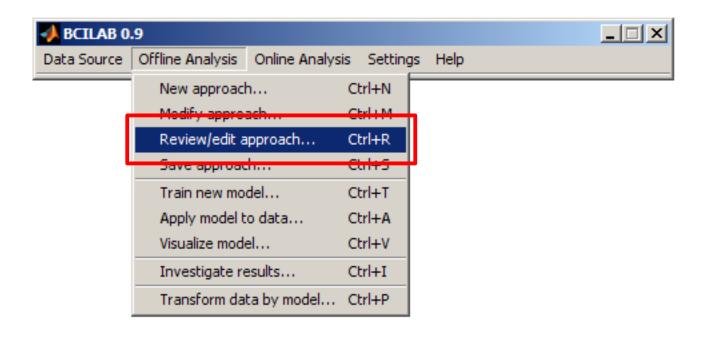
Train model, visualize



Train model, visualize

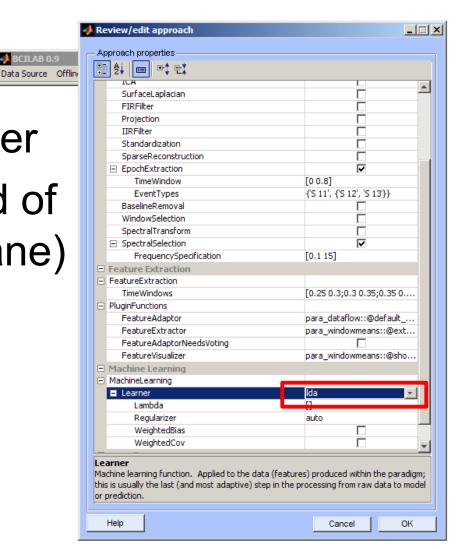




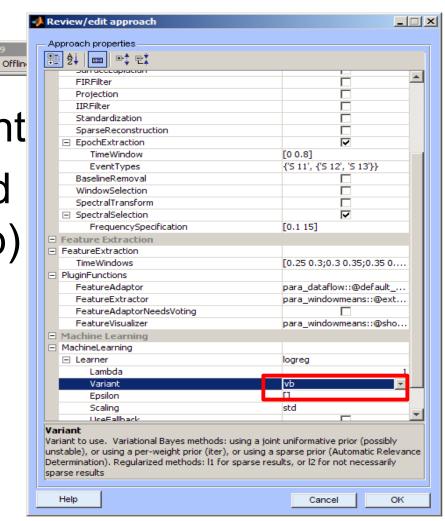


BCILAB 0.9

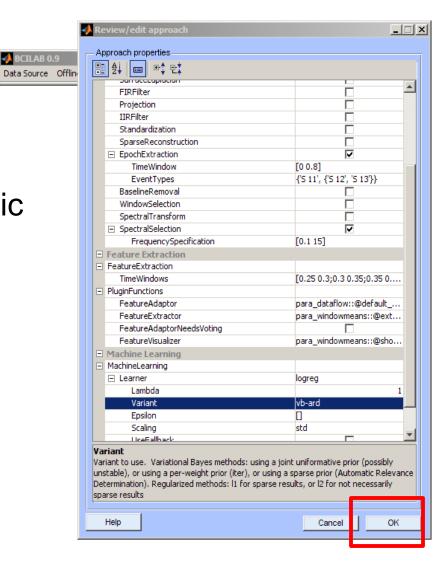
- Scroll down to Learner
- Select logreg instead of Ida (also see help pane)
- do not close yet!



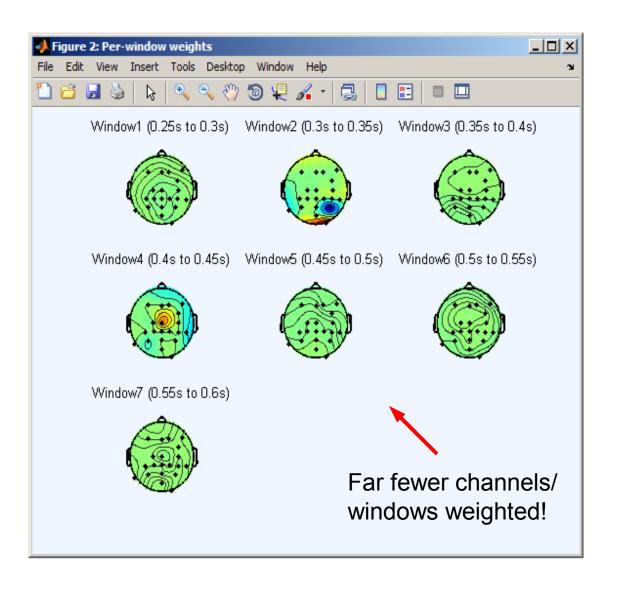
- Scroll down to Variant
- Select vb-ard instead of vb (again see help)



- Done!
- You selected:
 "Variational Bayesian Logistic
 Regression with Automatic
 Relevance Determination"
 as classifier



Train model, visualize



Train model, visualize

 Sparse classifiers can give you more robust models (fewer channels / sources of errors used), and more interpretable models (only the most relevant features retained)

Scripting

- For analogous scripts, see userscripts/workshop_script.m
 - Also contains a 3-class case at the end

 For plugins, see code/filters/* code/machine_learning/* code/paradigms/* code/online_plugins/*

Thanks!

Questions?