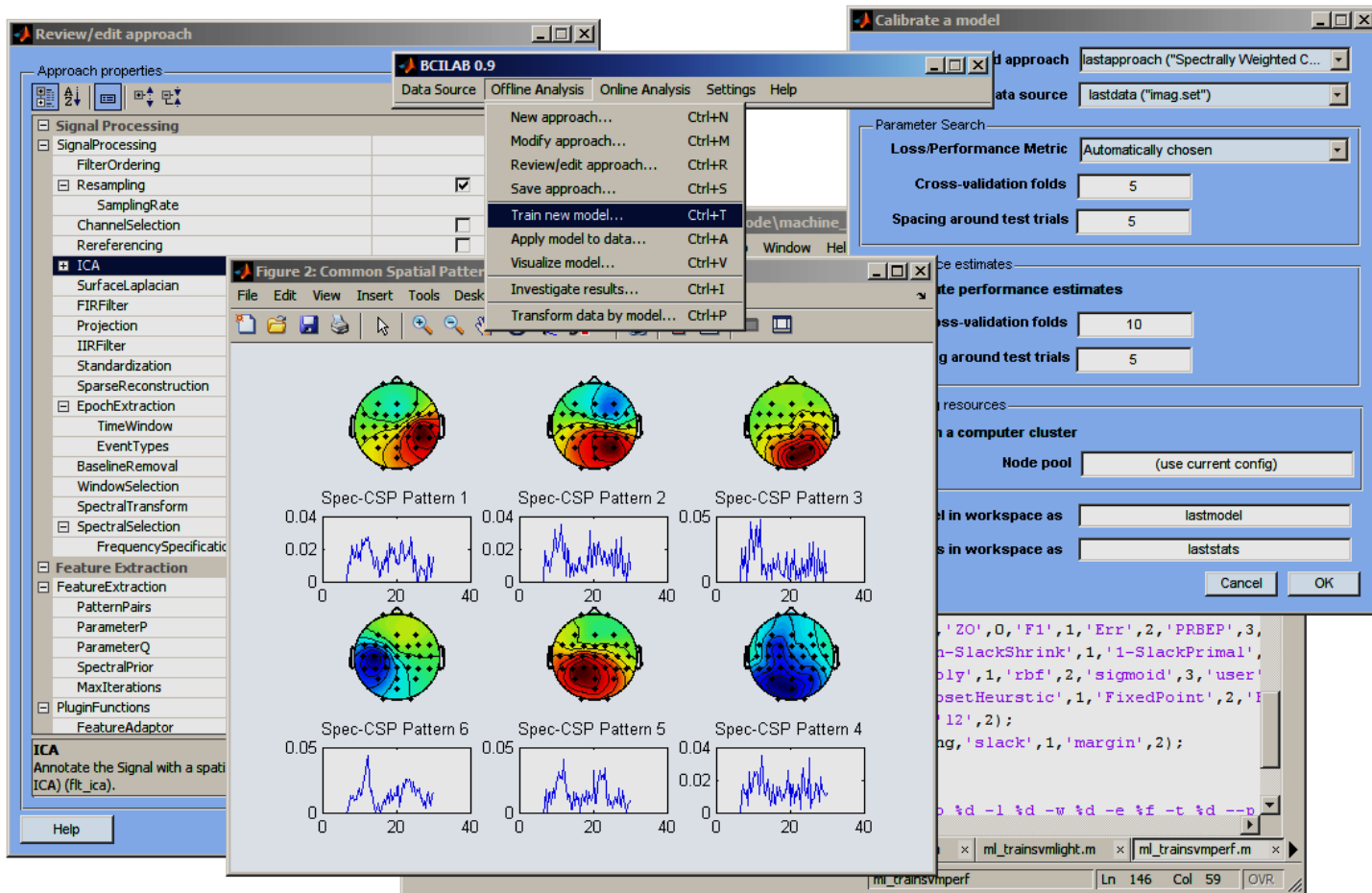


BCILAB

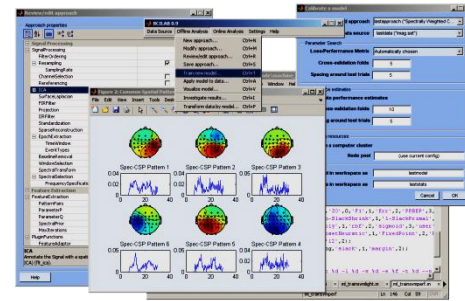


The screenshot displays the BCILAB 0.9 software interface with several windows open:

- Review/edit approach:** Shows approach properties such as Signal Processing, ICA, Feature Extraction, and Feature Adaptor.
- BCILAB 0.9:** The main application window with a menu bar (File, Edit, View, Insert, Tools, Desk) and a toolbar.
- Calibrate a model:** A dialog box for configuring model training, including fields for Loss/Performance Metric, Cross-validation folds (set to 5), and Spacing around test trials (set to 5).
- Figure 2: Common Spatial Patterns:** A window displaying six topographic maps and corresponding time-frequency plots for Spec-CSP Patterns 1 through 6. Each plot shows power over time (0 to 40) for a specific spatial pattern.
- Terminal:** A window at the bottom right showing MATLAB code for training and evaluating a model, including commands like `ml_trainsvm` and `ml_trainsvmperf`.

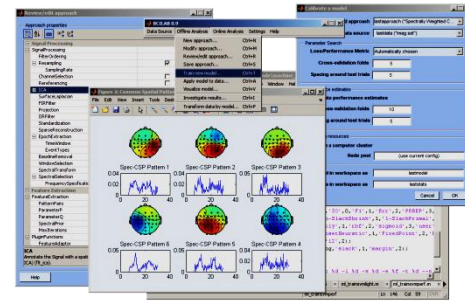


Summary



- Software environment for:
 - Design & rapid prototyping of cognitive monitoring systems
 - Offline testing, performance assessment
 - Simulated online testing
 - Real-time use, prototype deployment

Features



- Largest collection of machine learning and signal processing methods for BCI / CSA publicly available (open source)
- Currently ca. 130 algorithms:
 - conventional BCI components (CSP, LDA, logBP, Spec-CSP, SVMs, ...)
 - state-of-the-art approaches (DSLRL, AMICA, HKL, DPGMM, ...)
 - new approaches (RSSD, OSR, ICSD, SSB, WPI, ...)
 - fast/general backend solvers (DAL, glm-ie, CVX, ...)
- All fully integrated

BCILAB Components

Framework

GUI / Scripting Interfaces

Approach
Definition

Online
Execution

Offline
Evaluation

Visualization

Plugins

Signal Processing

ICA

SSA

FIR

IIR

FFT

...

Machine Learning

LDA

QDA

DAL

GMM

SVM

...

BCI Paradigms

CSP

Spec-CSP

ERP

RSSD

...

Devices

TCP

OSC

BCI2000

...

Infrastructure

GUI
generation

cluster
computing

disk
caching

helper
functions

environment
services

Dependencies

CVX

BNT

EGLAB

GUI utils

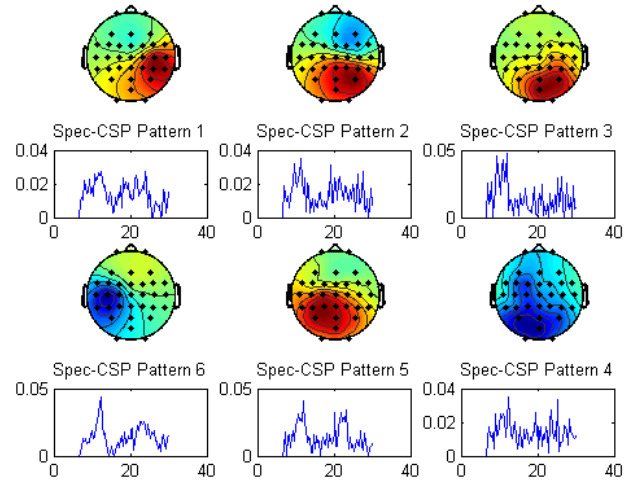
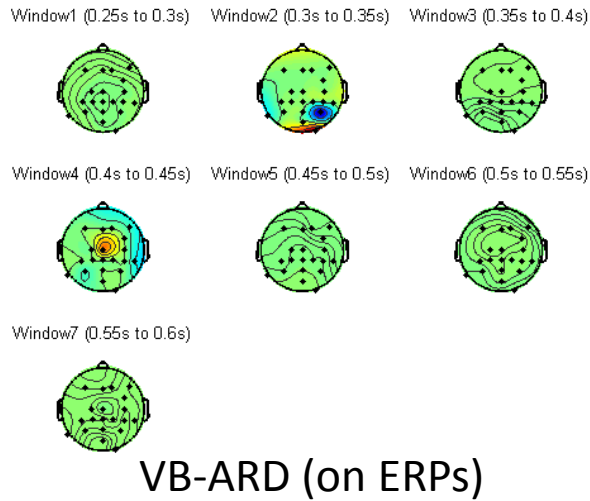
LIBSVM

GLMNET

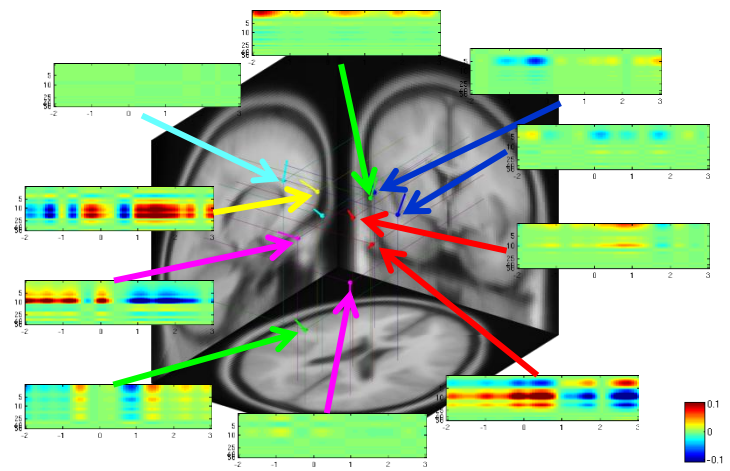
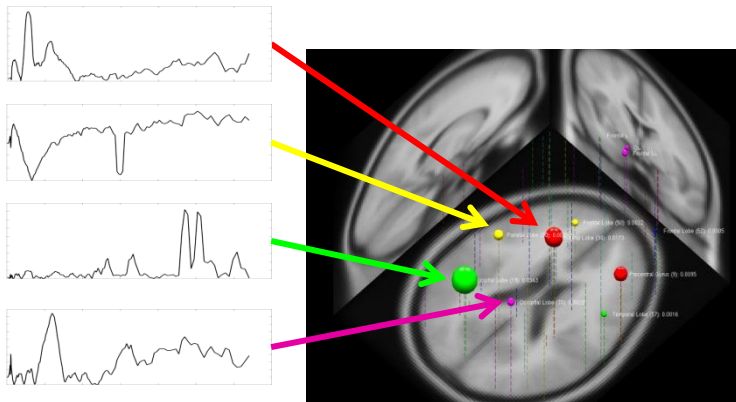
...

Driver
I/O

Some Model Types Visualized



Spec-CSP



OSR

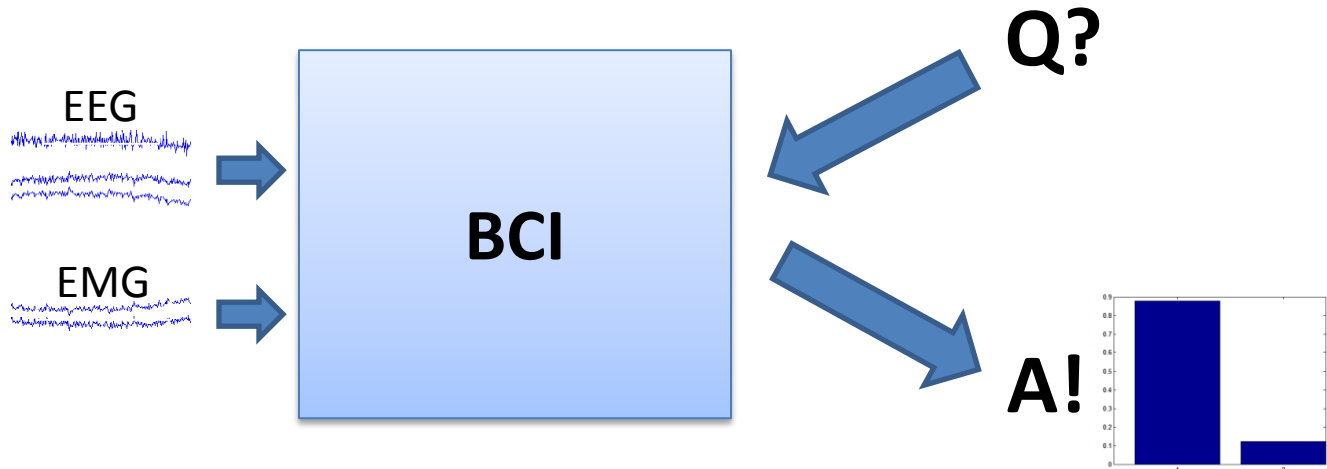
RSSD

Framework

- Fully automated pipeline (artifact rejection, caching, filtering, parallelization, parameter search, cross-validation, cloud deployment)
- Fully probabilistic framework
- Neuroscience-aware features (anatomical constraints, source-level analysis, ...)
- Support for batch processing
- Support for corpus-scale analysis (multiple sessions, persons, etc.)

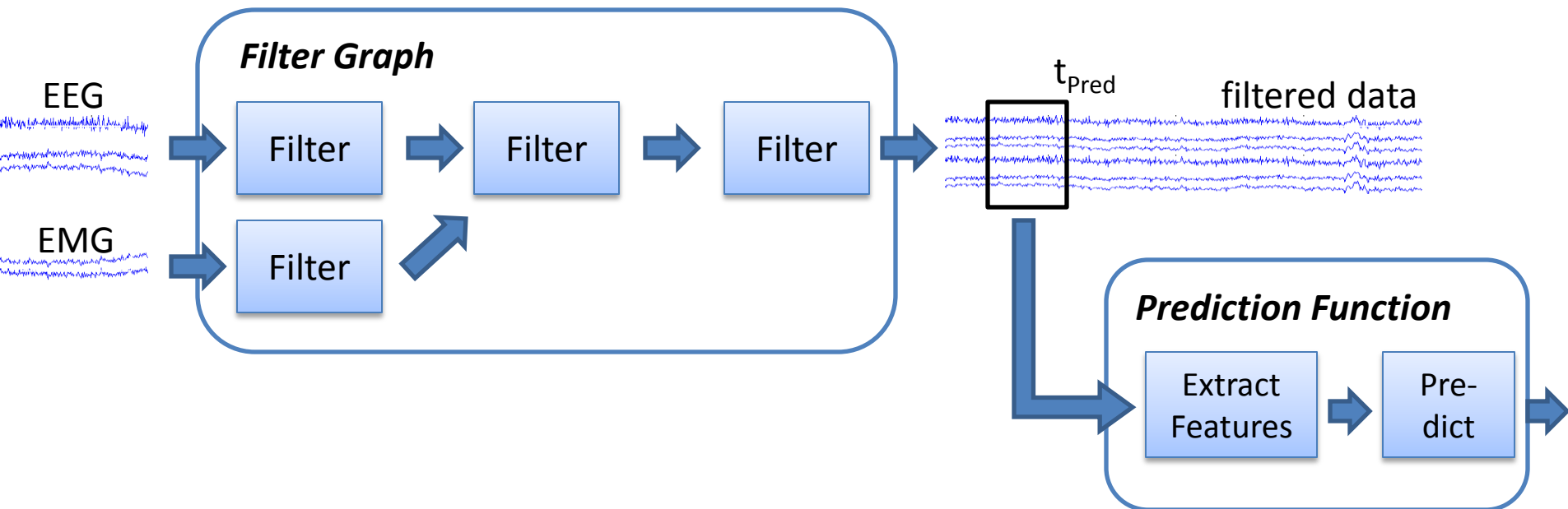
BCI Metaphor

- BCIs in BCILAB are acting as an oracle that consumes one or more biosignals and can respond to (pre-defined) queries about cognitive state



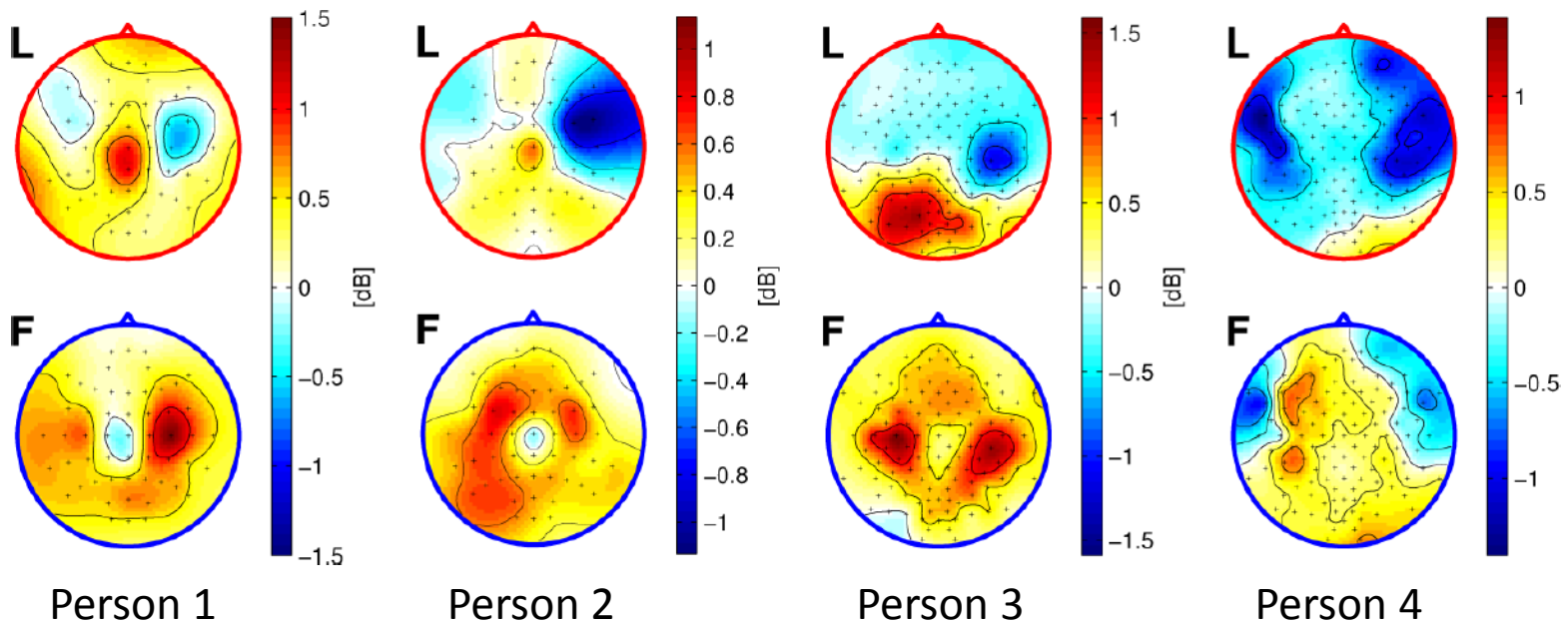
Online Data Flow

- A filter graph receives all input samples and produces pre-filtered data
- The prediction function may be queried on demand on the filter graph's outputs



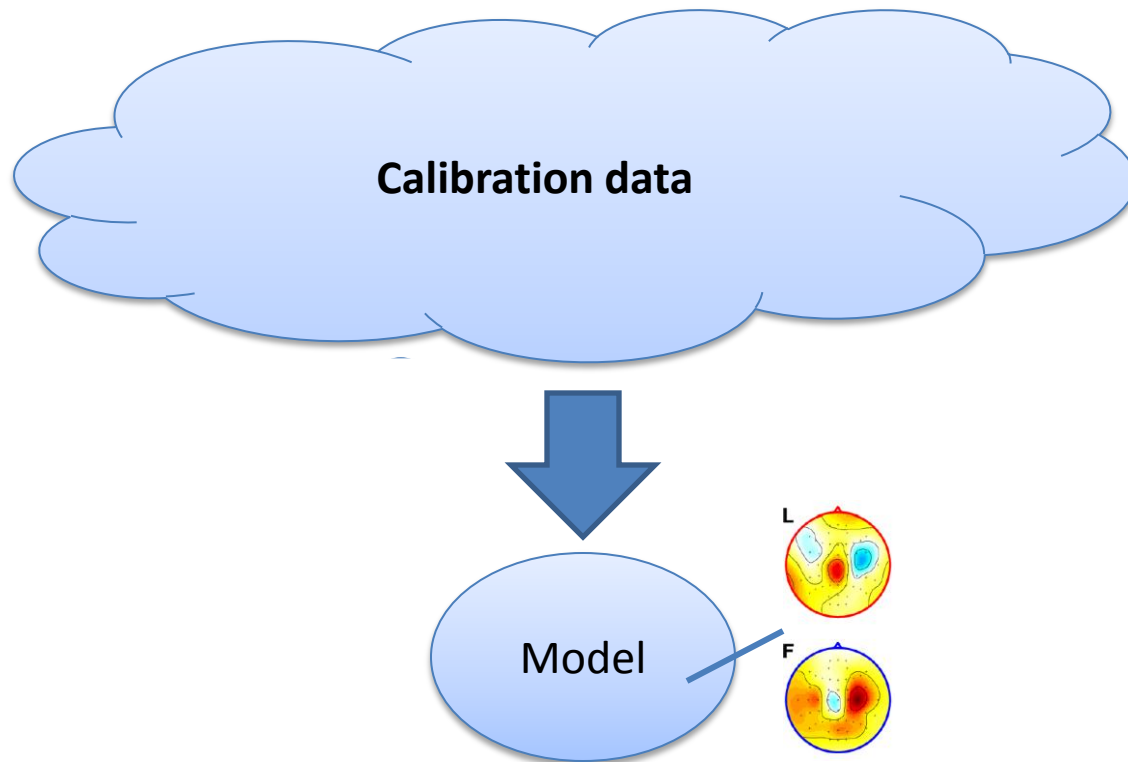
Model Calibration

- Problem:** optimal parameters for a BCI model depend on person, montage, task, etc.



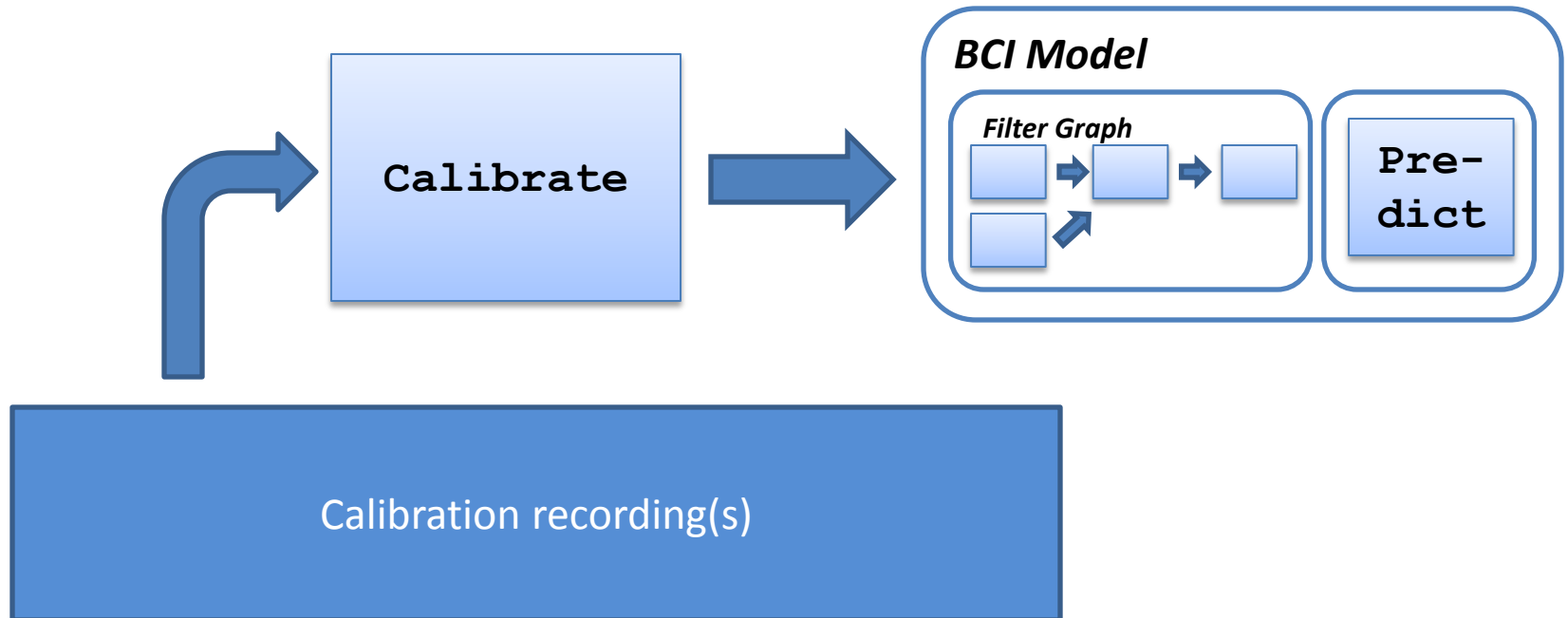
Model Calibration

- Therefore infer model parameters from calibration / training data



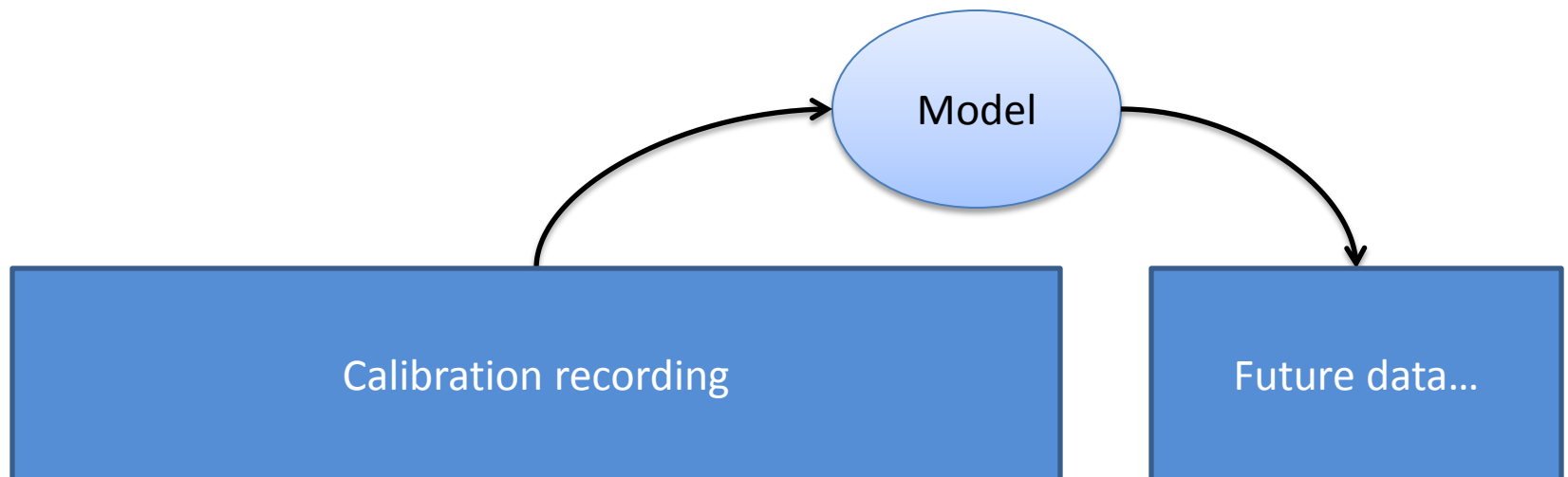
Calibration: BCI Paradigms

- BCI paradigms are the coarsest plugin type in BCILAB and tie all parts of a BCI approach together
- They are seeds for new BCI designs and cornerstones of BCILAB usage



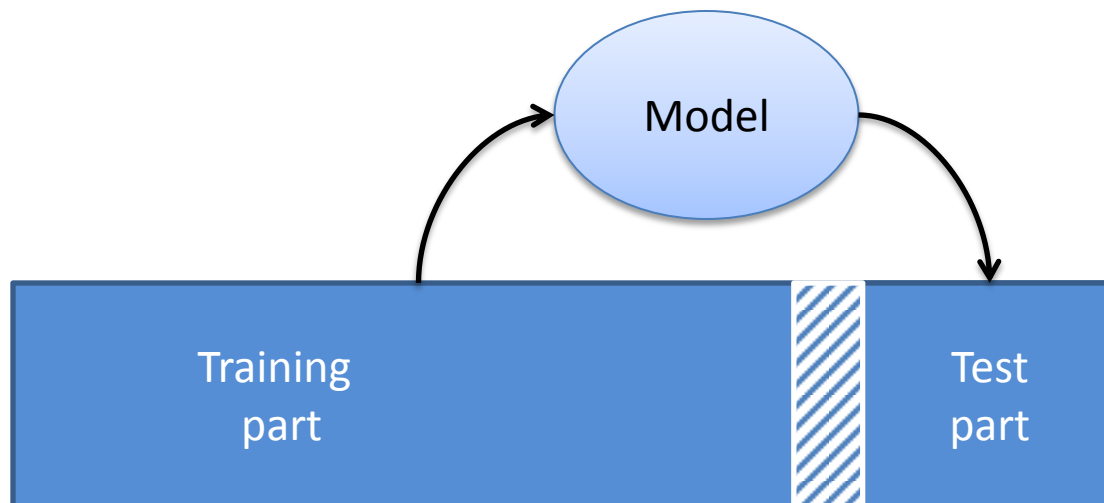
Evaluation: Offline

- Given calibration data
- Estimate model parameters (spatial filters, statistics)
- Apply the model to new data (online / single-trial)



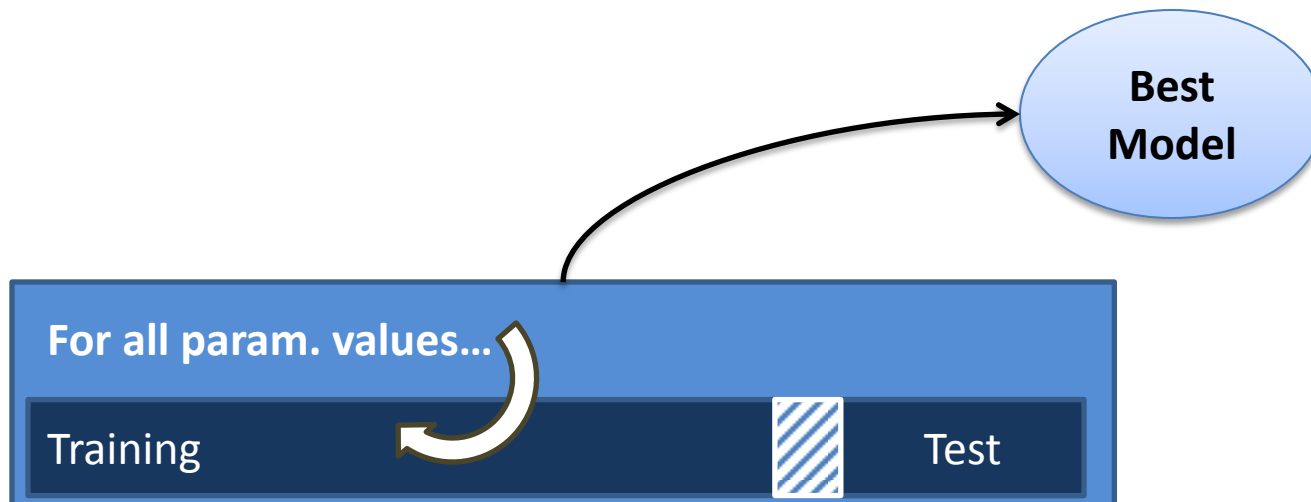
Evaluation: Offline

- Evaluation of computational approaches on a single data set?
- can split data set repeatedly into training/test blocks systematically, a.k.a. *cross-validation*



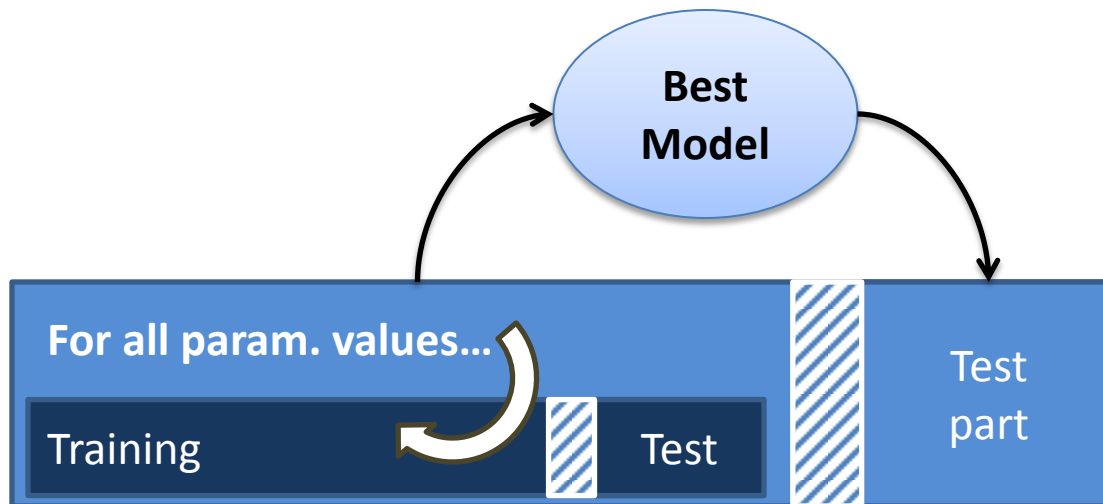
Finding Best Parameters

- Can be done using cross-validation in a grid search (try all values of free parameters)
- Quite general (e.g. can search for best method)



Finding Best Parameters

- Can be done using cross-validation in a grid search (try all values of free parameters)
- Evaluation: Can be nested *within* an outer cross-validation (“nested cross-validation”)



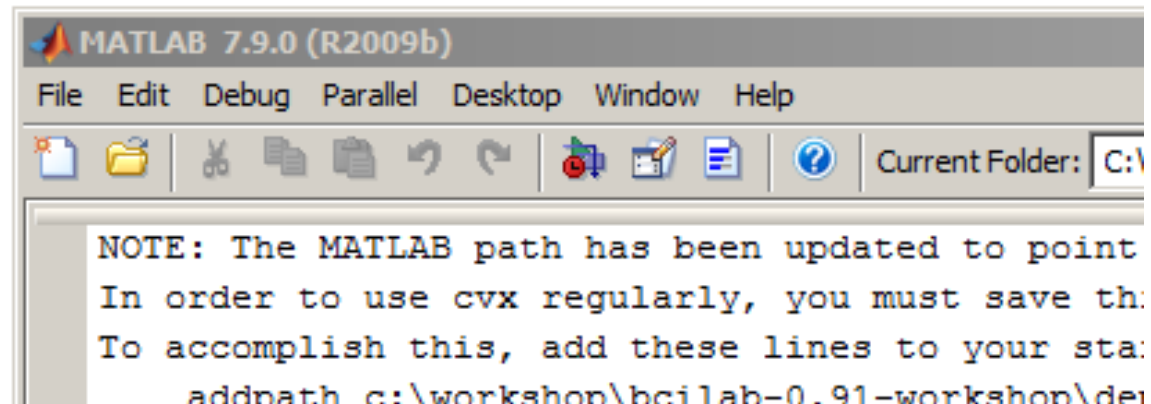
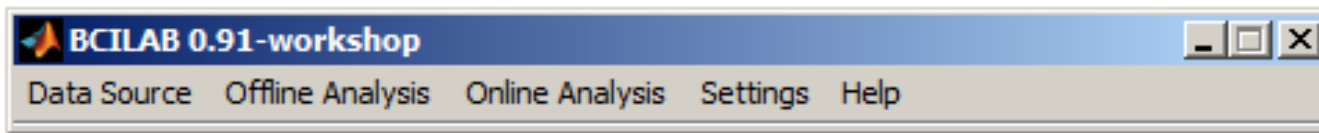


Neat Feature

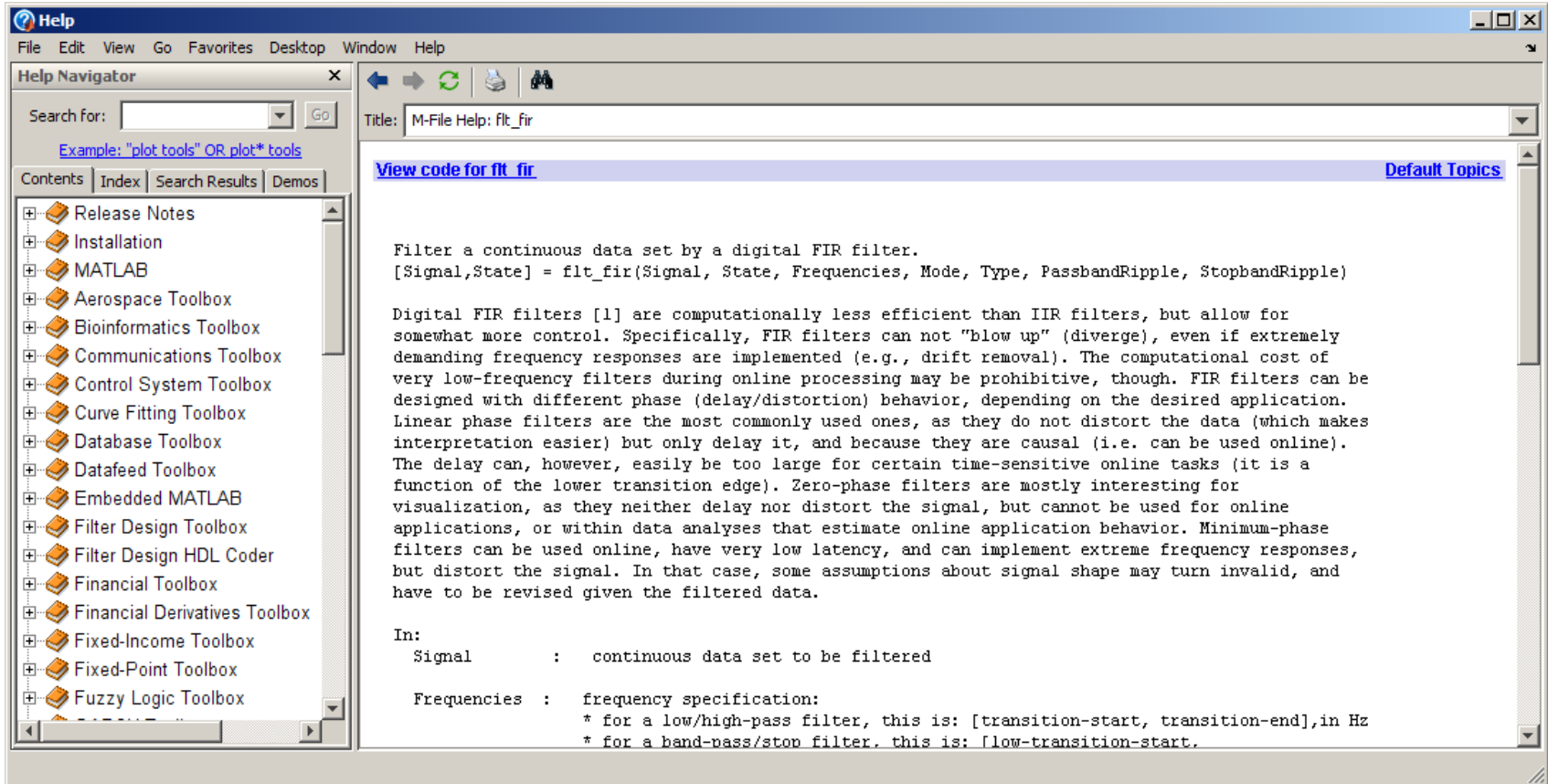
- All offline analysis can be executed in parallel on a cluster (or the cloud)
- Batch analysis, cross-validation, parameter search, methods comparisons

GUI Tour

- Alternative to scripting, for experimenters, psychologists, quick-and-dirty analysis



Integrated Help

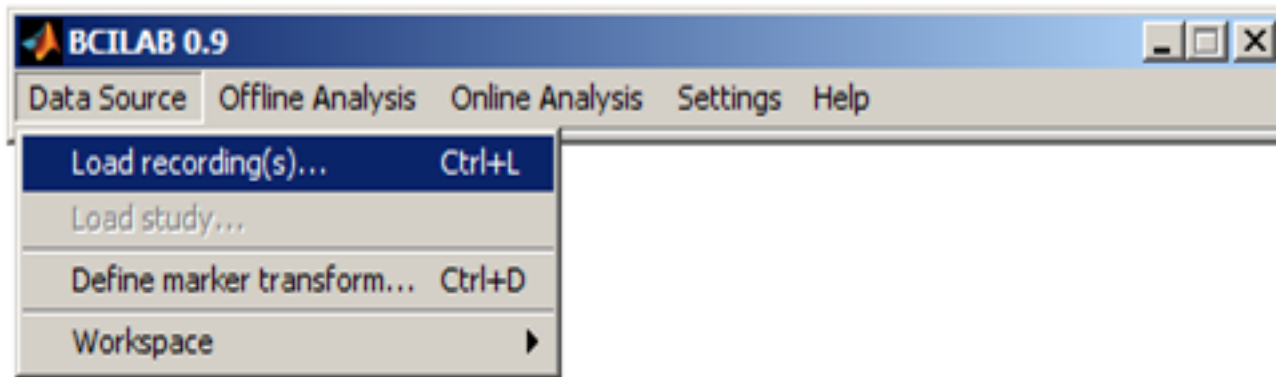


Help Wiki

The screenshot shows a web browser window at sccn.ucsd.edu/wiki/BCILAB. The page features a header with navigation tabs: 'page', 'discussion', 'view source', and 'history'. The main content area displays the title 'BCILAB' and the subtitle 'Open Source Matlab Toolbox for Brain-Computer Interface research.' To the left, there is a sidebar with a logo for the 'Swartz Center for Computational Neuroscience' and two sections of links: 'home' (including SCCN web site, EEGLAB Wiki, DataSuite Wiki, MoBI Lab Wiki, and SCCN Wiki Home) and 'eeglab wiki pages' (including EEGLAB web page, EEGLAB Wiki, EEGLAB Tutorial, Online EEGLAB Workshop, Download EEGLAB, and Revision history). The main content area also contains an embedded image of a 'Review/edit approach' window for 'BCILAB 0.9'. This window shows a tree view of properties: 'Signal Processing' (expanded), 'SignalProcessing' (expanded), 'FilterOrdering', 'Resampling' (expanded, with 'SamplingRate' checked), 'ChannelSelection', 'Rereferencing', 'ICA' (expanded, with 'SurfaceLaplacian', 'FIRFilter', 'Projection', and 'IIRFilter' listed), and 'Figure 2: Common Spatial Patter'. The window also includes a menu bar (File, Edit, View, Insert, Tools, Desk) and a toolbar with various icons.

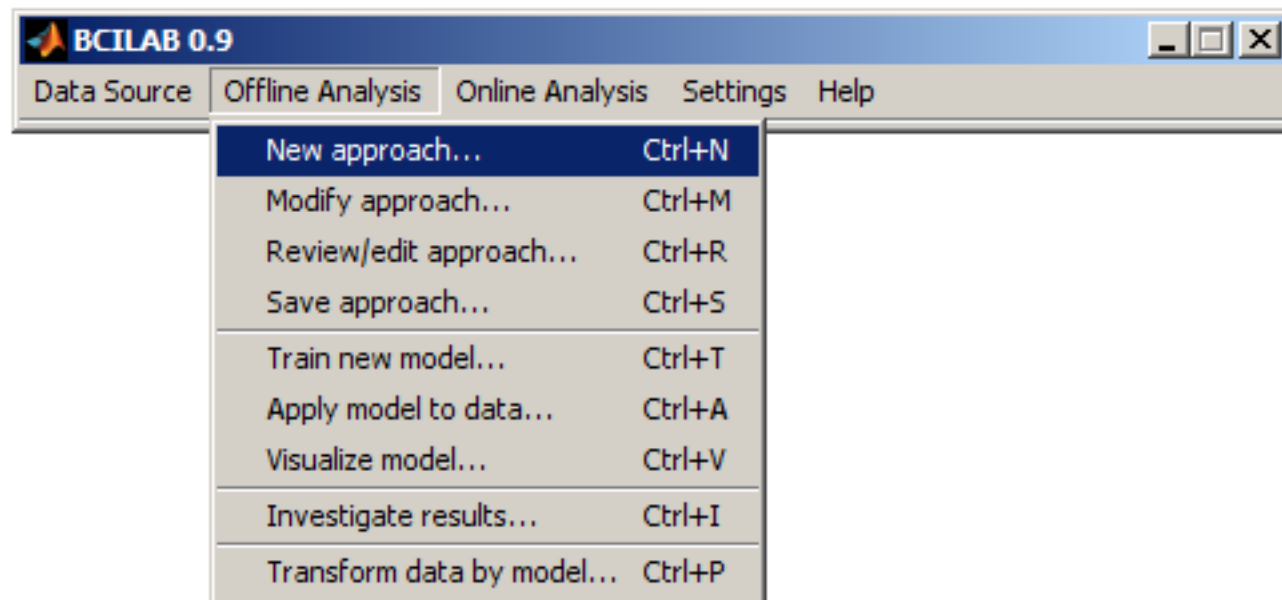
<http://sccn.ucsd.edu/wiki/BCILAB>

Loading data



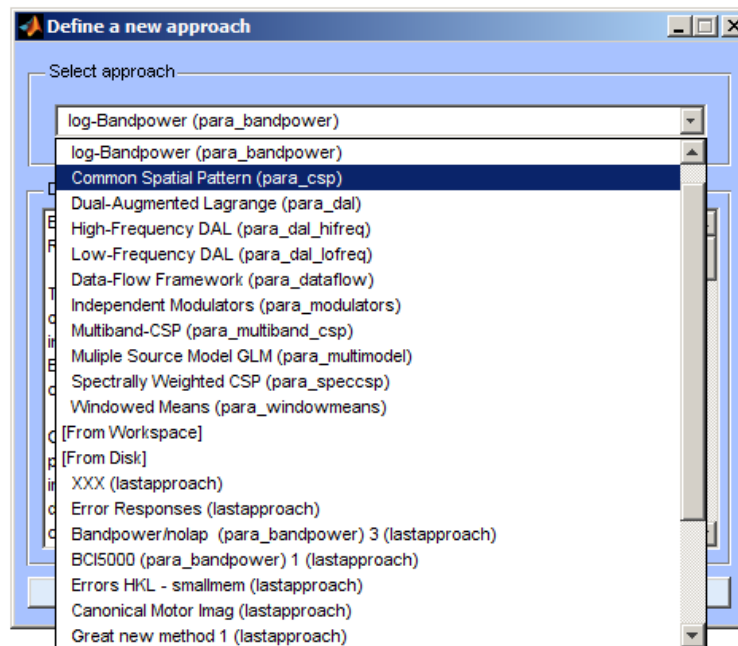
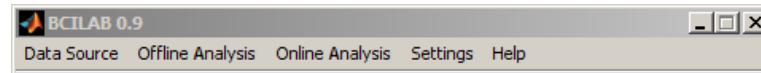
- Supports >20 common file formats

Offline Analysis

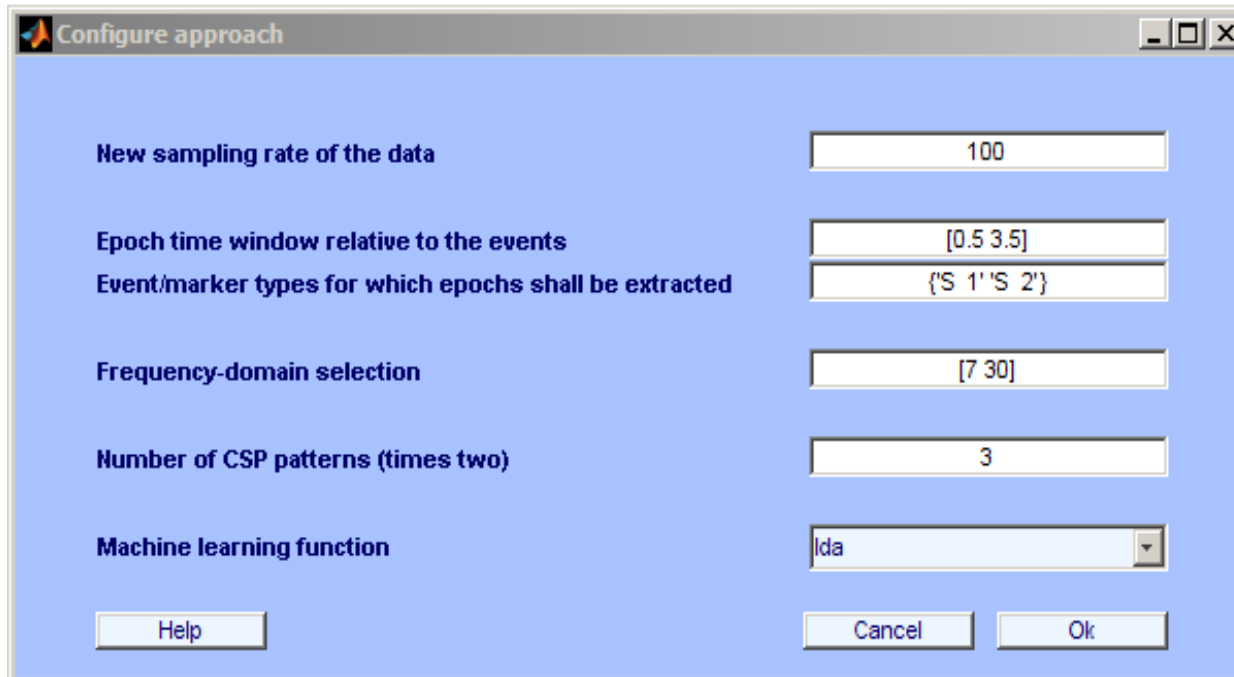
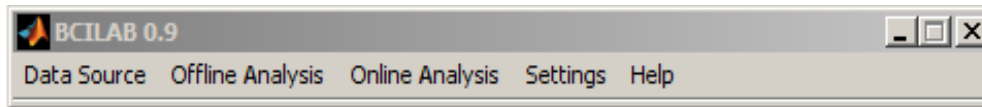


Defining an Approach

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

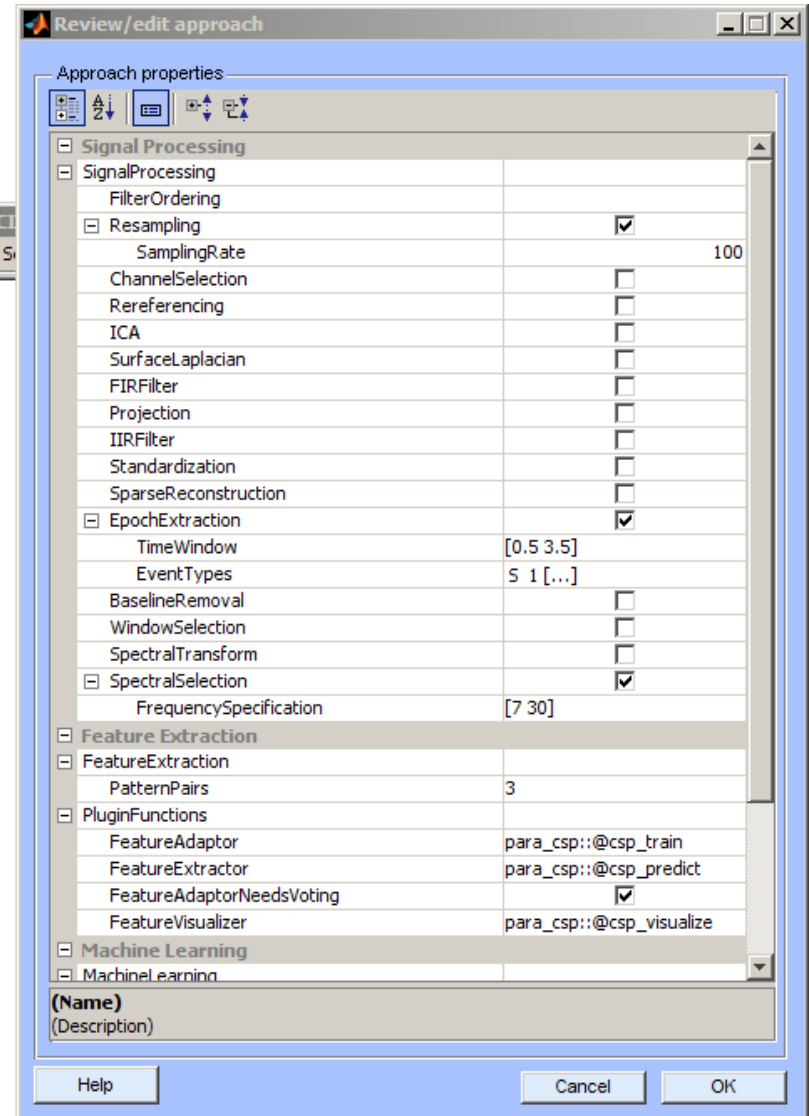


Quick Setup



Or Detailed Configuration

- Allows to edit all properties of the chosen approach
- Filter stages can be added and configured
- Feature extraction can be configured
- Machine learning components can be selected and configured
- ...



Model Calibration

Calibrate a model

Selected approach lastapproach ("Imagined Movements vi...")

Calibration data source lastdata ("imag.set")

Parameter Search

Loss/Performance Metric Automatically chosen

Cross-validation folds 5

Spacing around test trials 5

Performance estimates

Compute performance estimates

Cross-validation folds 10

Spacing around test trials 5

Computing resources

Run on a computer cluster

Node pool (use current config)

Save model in workspace as lastmodel

Save stats in workspace as laststats

Help Cancel OK

Reviewing Results

Review Results

Data Summary

```

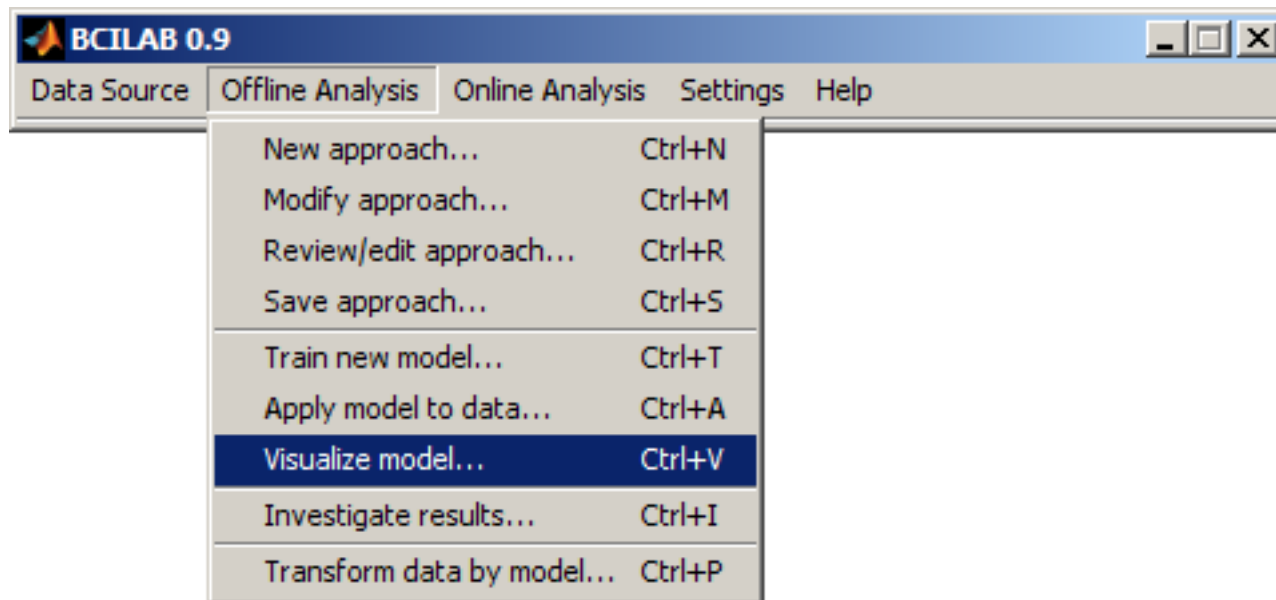
True positive rate : 0.90 +/- 0.14 (N=10)
False positive rate : 0.10 +/- 0.14 (N=10)
True negative rate : 0.84 +/- 0.17 (N=10)
False negative rate : 0.16 +/- 0.17 (N=10)
Error rate : 0.14 +/- 0.14 (N=10)
  
```

Data Details

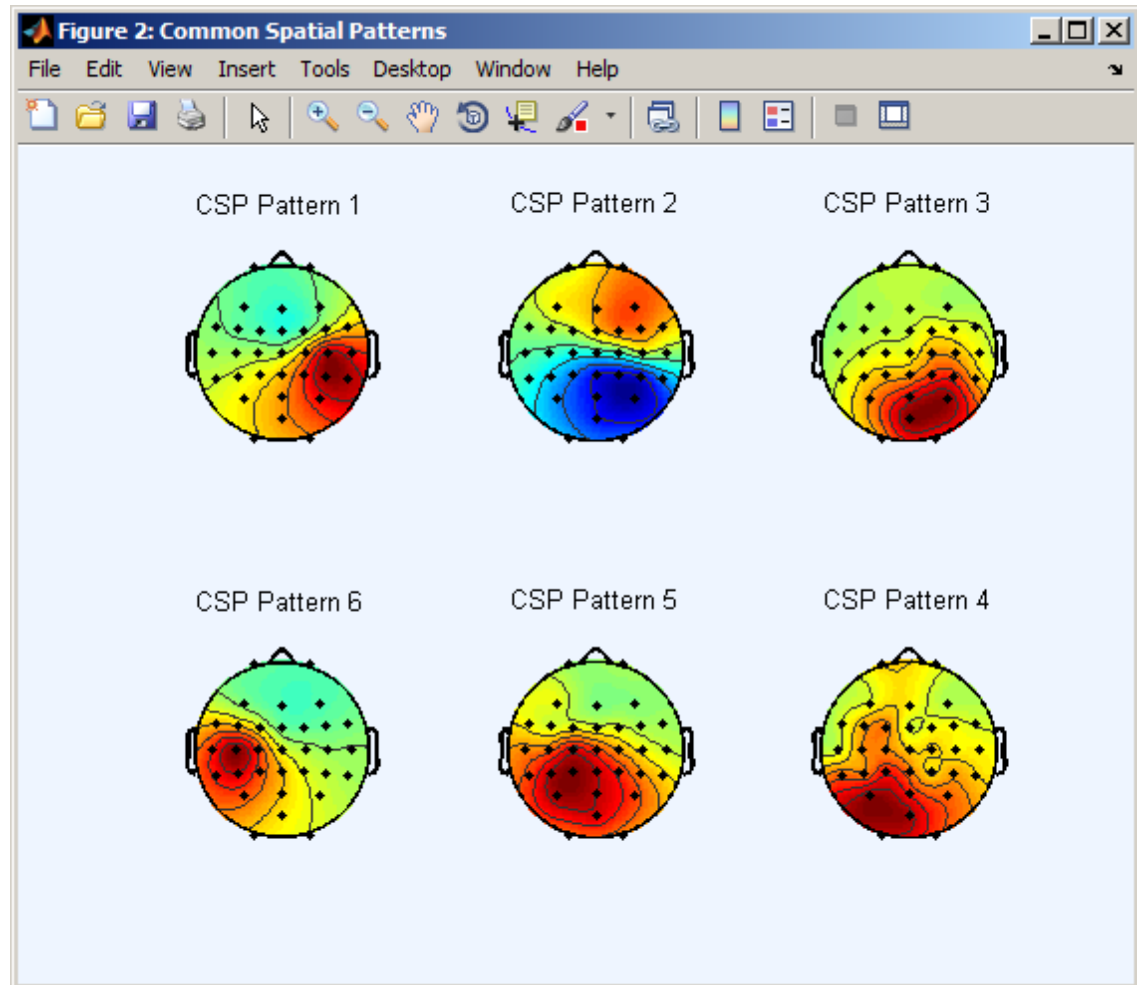
	True positive rate	False positive rate	True negative r...	False negative r...	Error rate
1	0.8333	0.1667	0.8750	0.1250	0.1429
2	0.5714	0.4286	0.7143	0.2857	0.3571
3	1	0	0.7500	0.2500	0.1333
4	1	0	1	0	0
5	1	0	0.8571	0.1429	0.0667
6	0.8750	0.1250	1	0	0.0714
7	0.8000	0.2000	0.4444	0.5556	0.4286
8	0.9000	0.1000	1	0	0.0667
9	1	0	0.8333	0.1667	0.0714
10	1	0	0.9000	0.1000	0.0667

Help Explore... Export... Save... OK

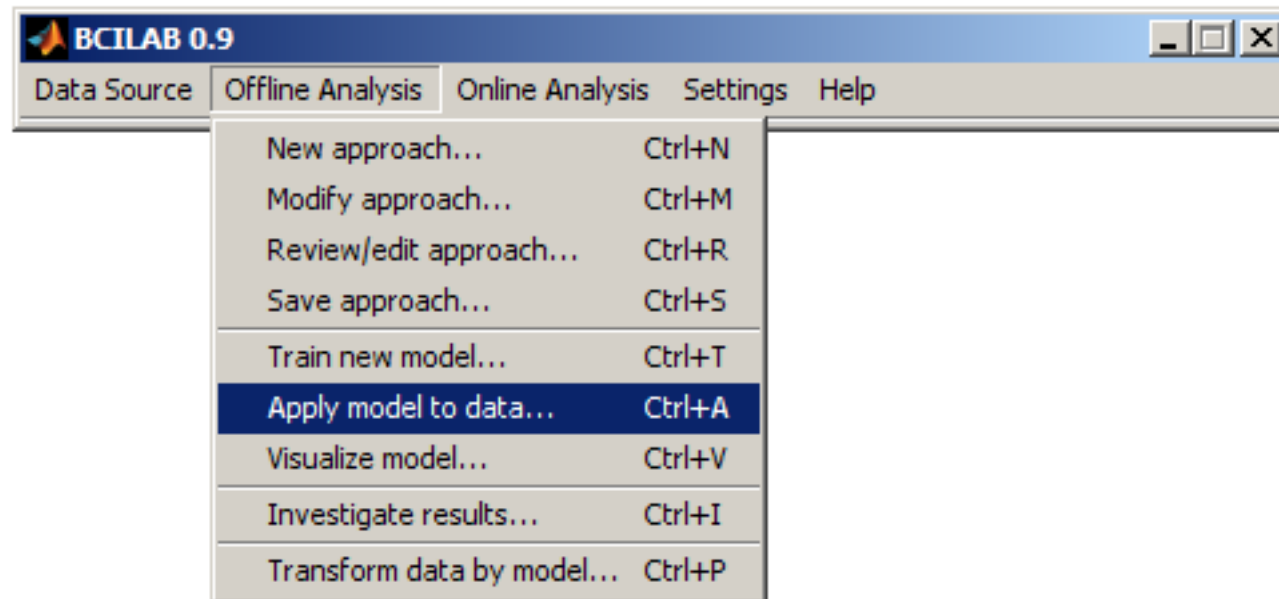
Visualizing model properties



Visualizing model properties

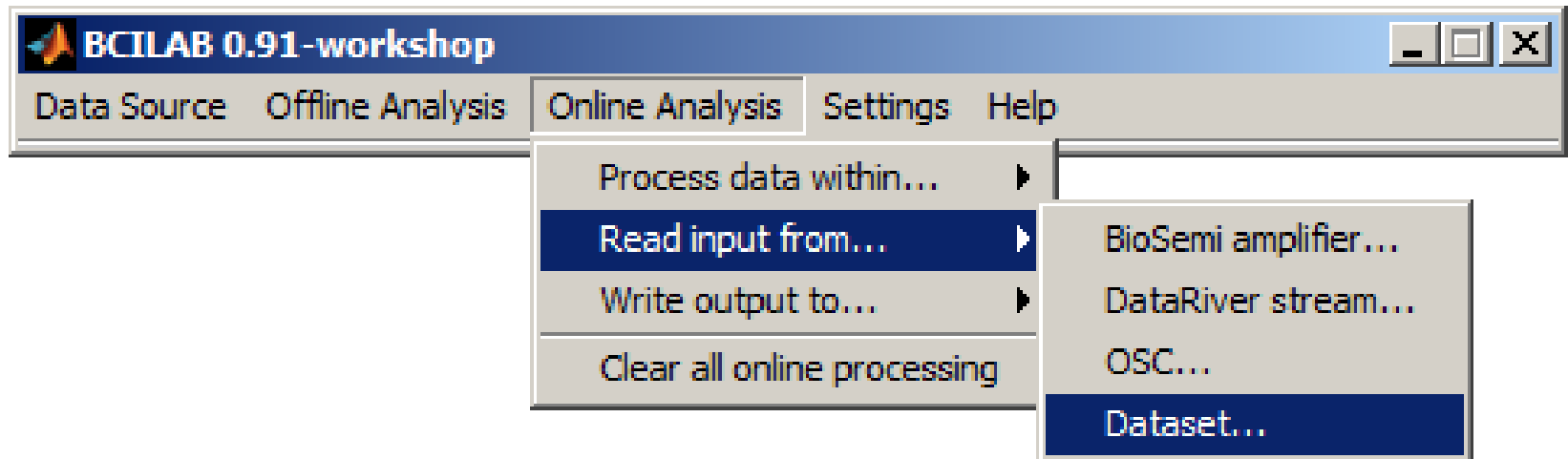


Applying Models Offline



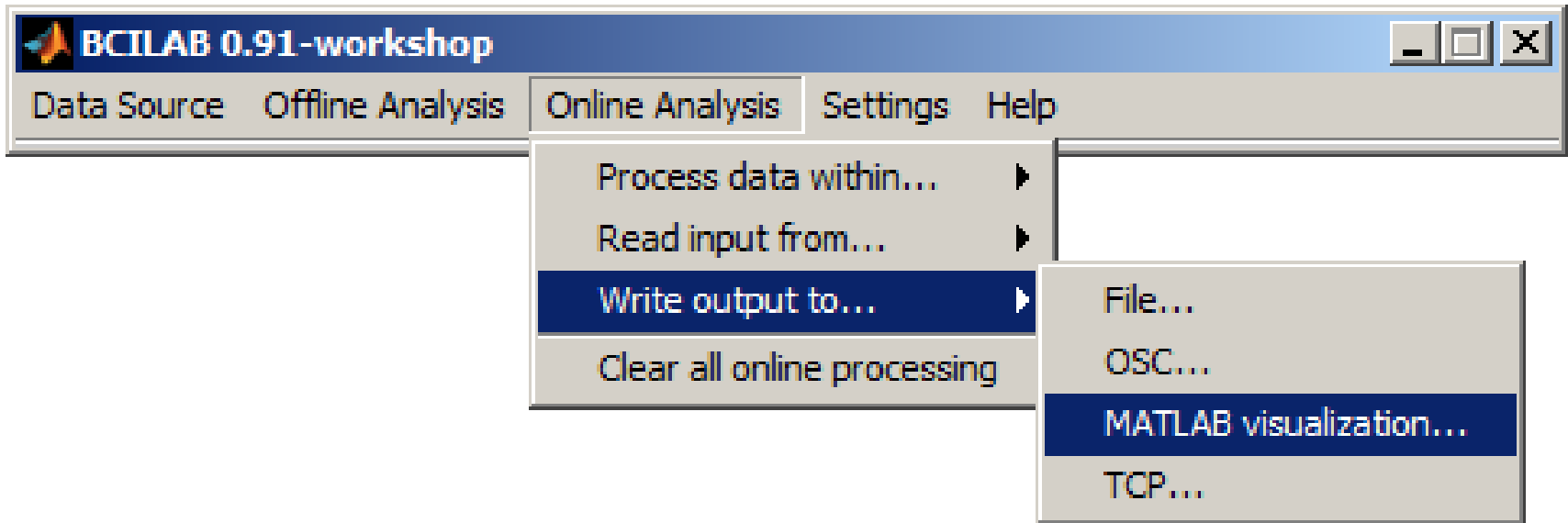
Online Processing

- Select data source

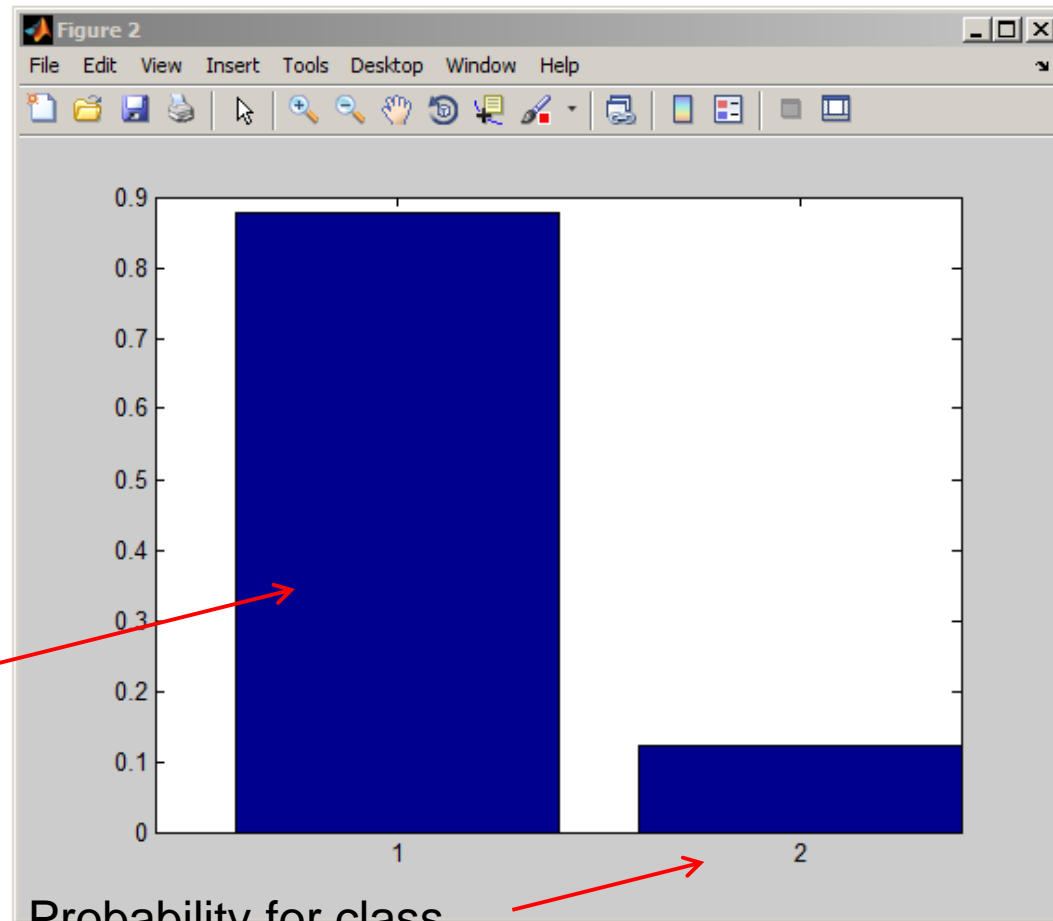
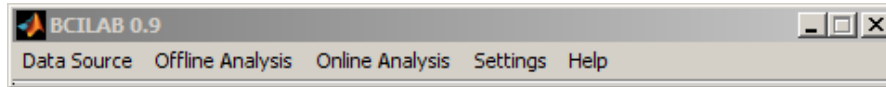


Online Processing

- Select output destination



Sample real-time output



Probability for class

Probability for class

2

Scripting Examples

- Doing a parameter search and nested cross-validation

```
%% --- train an alternative model with parameter search ---
% (over possible values for the number of pattern pairs, using CSP; note: this takes quite some time!)
% (the number of pattern pairs found optimal should be 3 in this case)

% load the data set (BCI2000 format)
traindata = io_loadset('data:/tutorial/imag_movements1/calib/DanielS001R01.dat');

% define approach
myapproach = {'CSP' ...
    'SignalProcessing',{'EpochExtraction',{'TimeWindow',[0 3.5]}, ...
        'EventTypes',{'StimulusCode_2','StimulusCode_3'}}}, ...
    'FeatureExtraction',{'PatternPairs',search(1,2,3)}};

% learn model; here, using only a 5x outer cross-validation as it is otherwise too slow
[trainloss,lastmodel,laststats] = bci_train({'data',traindata,'approach',myapproach, ...
    'eval_scheme',{'chron',5,5}});

% visualize results
bci_visualize(lastmodel);
```

Search over different alternatives

Also: Custom cross-validation scheme



Scripting Examples

- Running the model online

```
% load feedback session
testdata = io_loadset('data:/tutorial/imag_movements1/feedback/DanielS001R01.dat');

% play it back in real time
run_readdataset('Dataset',testdata);

% process data in real time using lastmodel, and visualize outputs
run_writevisualization('Model',lastmodel, 'VisFunction','bar(y)');
```



Scripting Examples

- Running an advanced ERP analysis (with sparse classifier):

```
% define markers; here, two groups of markers are being defined; the first group represents class 1
% (correct responses), and the second group represents class 2 (incorrect responses).
mrks = {'S101', 'S102'}, {'S201', 'S202'};

% define ERP windows of interest; here, 7 consecutive windows of 50ms length each are being
% specified, starting from 250ms after the subject response
wnds = [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];

% define load training data (BrainVision format)
traindata = io_loadset('data:/tutorial/flanker_task/12-08-001_ERN.vhdr');

% define approach
myapproach = {'Windowmeans' ...
    'SignalProcessing', {'EpochExtraction', {'TimeWindow', [0 0.8], 'EventTypes', mrks}, 'SpectralSelection', [0.1 15]}, ...
    'FeatureExtraction', {'TimeWindows', wnds}, ...
    'MachineLearning', {'Learner', {'logreg', [], 'Variant', 'vb-ard'}}};

%learn model
[trainloss, lastmodel, laststats] = bci_train({'data', traindata, 'approach', myapproach});

% visualize results
bci_visualize(lastmodel)
```



Scripting Examples

- Running a batch analysis for 3 modern approaches and 136 data sets (latest version only):

```
% define markers; here, two groups of markers are being defined; the first group represents class 1
% (correct responses), and the second group represents class 2 (incorrect responses).
mrks = {'S101', 'S102'}, {'S201', 'S202'};
wnds = [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];

% define approaches
approaches.wmeans_lda = {'Windowmeans' 'flt', {'events', mrks, 'epoch', [0 0.8], 'spectrum', [0.1 15]}, 'fex', {'wnds', wnds}};
approaches.wavelet_lars = {'Dataflow' 'flt', {'events', mrks, 'epoch', [0 0.8], 'spectrum', [0.1 15], 'wavelet', 'on'}, ...
    'ml', {'learner', {'logreg', [], 'variant', 'lars'}}};
approaches.dal = {'DAL_Lofreq', 'SignalProcessing', {'Resampling', 60, 'IIRFilter', 'off', 'FIRFilter', [0.1 0.5 18 21], ...
    'EpochExtraction', {'EventTypes', mrks, 'TimeWindow', [-0.2 0.65]}}, 'MachineLearning', {'Learner', {'dal', 2.^(-0.125:1)}}};

% run a batch analysis...
results = bci_batchtrain('Datasets', '/data/projects/grainne/ERN/*.vhdr', 'Approaches', approaches, 'RetainExistingResults', true);
```



Plugin Authoring: FFT Filter

```
function signal = flt_fft(varargin)
% Apply an FFT to each epoch of an epoched signal (Example).
% Signal = flt_fft(Signal, LogPower)
%
% This is example code to transform a signal into the power domain, or log-power domain. A
% fully-featured version of this is flt_fourier.
%
% In:
%   Signal :   Epoched data set to be processed
%
%   LogPower : whether to take the logarithm of the power (instead of the raw power) (default: false)
%
% Out:
%   Signal :   processed data set
%
%                               Christian Kothe, Swartz Center for Computational Neuroscience, UCSD
%                               2011-01-19
%
if ~exp_beginfun('filter') return; end

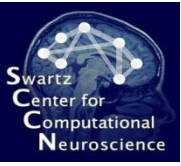
% requires epoched data, works best on spatially filtered data
declare_properties('name','EpochedFFT', 'depends','set_makepos', 'follows',{'flt_project','flt_window'}, 'independent_channels',true);

% declare arguments
arg_define(varargin,...
    arg_norep({'signal','Signal'}), ...
    arg({'do_logpower','LogPower'}, false, [], 'Compute log-power. Taking the logarithm of the power in each frequency band is easier to

% apply FFT and cut mirror half of the resulting samples
tmp = fft(signal.data, [], 2);
tmp = tmp(:, 1:signal.pnts/2, :);

% take signal power or log(power)
if do_logpower
    signal.data = log(abs(tmp));
else
    signal.data = abs(tmp);
end

exp_endfun;
```



Kernel SVMs (via SVMperf)

```
arg_define([0 3],varargin, ...
  arg_norep('trials'), ...
  arg_norep('targets'), ...
  arg({'cost','Cost'}, search(2.^(-5:2:15)), [], 'Regularization parameter. Reasonable range: 2.^(-5:2:15), greater is stronger. By default, it is average
  arg({'ptype','Type'}, 'classification', {'classification','regression','ranking'}, 'Type of problem to solve.','cat','Core Parameters'), ...
  arg({'kernel','Kernel'}, 'rbf', {'linear','rbf','poly','sigmoid','user'}, 'Kernel type. Linear, or Non-linear kernel types: Radial Basis Functions (gene
  arg({'g','RBFScale','gamma'}, search(2.^(-16:2:4)), [], 'Scaling parameter of the RBF kernel. Should match the size of structures in the data; A reasona
  arg({'d','PolyDegree'}, uint32(3), [], 'Degree for the polynomial kernel.','cat','Core Parameters'), ...
  arg({'etube','EpsilonTube','tube'}, 0.1, [], 'Epsilon tube width for regression.','cat','Core Parameters'), ...
  arg({'rbalance','CostBalance','balance'}, 1, [], 'Relative cost of per-class errors. The factor by which training errors on positive examples outweigh
  ...
  arg({'s','SigmoidPolyScale'}, 1, [], 'Scale of sigmoid/polynomial kernel.','cat','Miscellaneous'), ...
  arg({'r','SigmoidPolyBias'}, 1, [], 'Bias of sigmoid/polynomial kernel.','cat','Miscellaneous'), ...
  arg({'u','UserParameter'}, '1', [], 'User-defined kernel parameter.','cat','Miscellaneous','type','char','shape','row'), ...
  arg({'bias','Bias'}, false, [], 'Include a bias term. Only implemented for linear kernel.','cat','Miscellaneous'), ...
  arg({'scaling','Scaling'}, 'std', {'none','center','std','minmax','whiten'}, 'Pre-scaling of the data. For the regularization to work best, the features :
  arg({'clean','CleanUp'}, false, [], 'Remove inconsistent training examples.','cat','Miscellaneous'), ...
  arg({'epsi','Epsilon','eps'}, 0.1, [], 'Tolerated solution accuracy.','cat','Miscellaneous'), ...
  arg({'verbose','Verbose'}, false, [], 'Show diagnostic output.','cat','Miscellaneous'));

if is_search(cost)
  cost = 1; end
if is_search(g)
  g = 0.3; end

% find the class labels
classes = unique(targets);
if length(classes) > 2
  % in this case we use the voter
  model = ml_trainvote(trials,targets,'1v1',@ml_trainsvmlight,@ml_predictsvmlight,varargin{:});
else
  % scale the data
  sc_info = hlp_findscaling(trials,scaling);
  trials = hlp_applyscaling(trials,sc_info);

  % remap target labels to -1,+1
  targets(targets==classes(1)) = -1;
  targets(targets==classes(2)) = +1;

  % rewrite sme string args to numbers
  ptype = hlp_rewrite(ptype,'classification','c','regression','r','ranking','p'); %#ok<*NDEF>
  kernel = hlp_rewrite(kernel,'linear',0,'poly',1,'rbf',2,'sigmoid',3,'user',4);

  % build the arguments
  args = sprintf('-z %s -c %f -v %d -w %f -j %f, -b %d -i %d -e %f -t %d -d %d -g %f -s %f -r %f -u %s', ...
    ptype,cost,verbose,etube,rbalance,bias,clean,epsi,kernel,d,g,s,r,u);

  % run the command
  model = svmllearn(trials,targets,args);
  model.sc_info = sc_info;
  model.classes = classes;
end
```



Complete CSP Paradigm

```
classdef ParadigmCSP < ParadigmDataflowSimplified
    methods

        function defaults = preprocessing_defaults(self)
            defaults = {'FIRFilter',{'Frequencies',[6 8 28 32],'Type','minimum-phase'}, 'EpochExtraction',[0.5 3.5], 'Resampling',10}
        end

        function [model,needsvoting] = feature_adapt(self,varargin)
            arg_define(varargin, ...
                arg_norep('signal'), ...
                arg({'patterns','PatternPairs'},3,[],'Number of CSP patterns (times two).','cat','Feature Extraction','type','express:

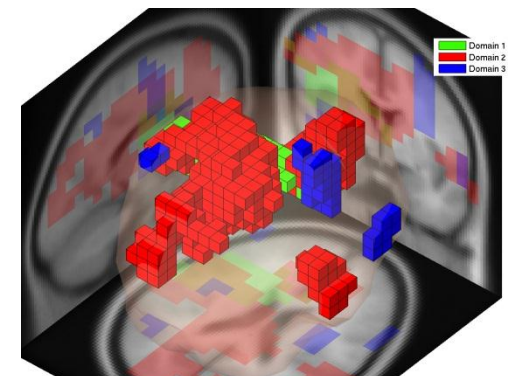
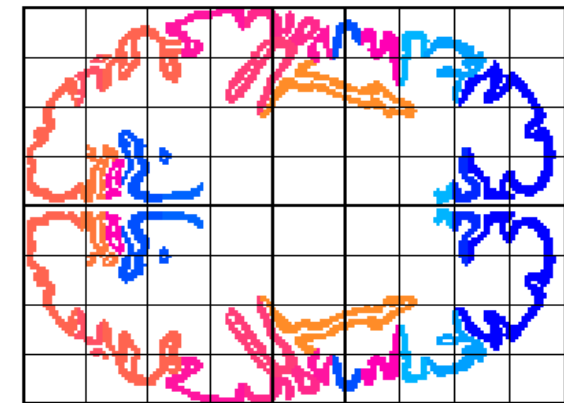
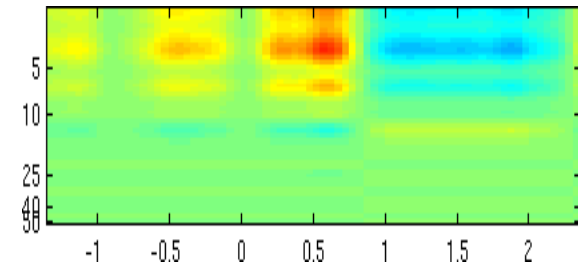
            if signal.nbchan < patterns
                error('CSP requires at least as many channels as you request output patterns. Please reduce the number of pattern pa
            for k=1:2
                trials{k} = exp_eval(set_picktrials(signal,'rank',k),1);
                covar{k} = cov(reshape(trials{k}.data,size(trials{k}.data,1),[]));
                covar{k}(~isfinite(covar{k})) = 0;
            end
            [V,D] = eig(covar{1},covar{1}+covar{2});
            model.filters = V(:,[1:patterns end-patterns+1:end]);
            P = inv(V);
            model.patterns = P([1:patterns end-patterns+1:end],:);
            model.chanlocs = signal.chanlocs;
            needsvoting = true;
        end

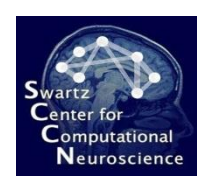
        function features = feature_extract(self,signal,featuremodel)
            features = zeros(size(signal.data,3),size(featuremodel.filters,2));
            for t=1:size(signal.data,3)
                features(t,:) = log(var(signal.data(:, :,t)*featuremodel.filters)); end
        end

        function layout = dialog_layout_defaults(self)
            layout = {'flt.srate','flt.epoch','flt.fir.fspect','flt.fir.ftype',[],'pred.fad.patterns',[],'pred.ml.learner'};
        end
    end
end
```

Ongoing: Source-Space Modeling

- Structural prior knowledge
 - can be introduced as side assumptions in the model (e.g. smoothness, sparsity, group sparsity, low rank, ...)
- Quantitative prior knowledge
 - Structure atlases (Talairach, LONI, ...) can supply information about the *a priori* relevance of a brain process
 - Can adapt the per-parameter penalty
- Empirical data
 - Data collected from other subjects can be co-registered/aligned and yield empirical prior distributions





Upcoming

- Next big toolbox release
- Online motion capture etc. processing via MOBILAB
- Effective connectivity integration via SIFT
- New methods in the pipeline (wave propagation imaging, alignment learning)



Thanks!

Questions?

