Lecture 4: Adaptivity and Machine Learning

Introduction to Modern Brain-Computer Interface Design

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Outline

1. Adaptivity in BCIs
2. Machine Learning
3. Concrete Case Study
4. Performance Evaluation


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4.1 Adaptivity in BCIs

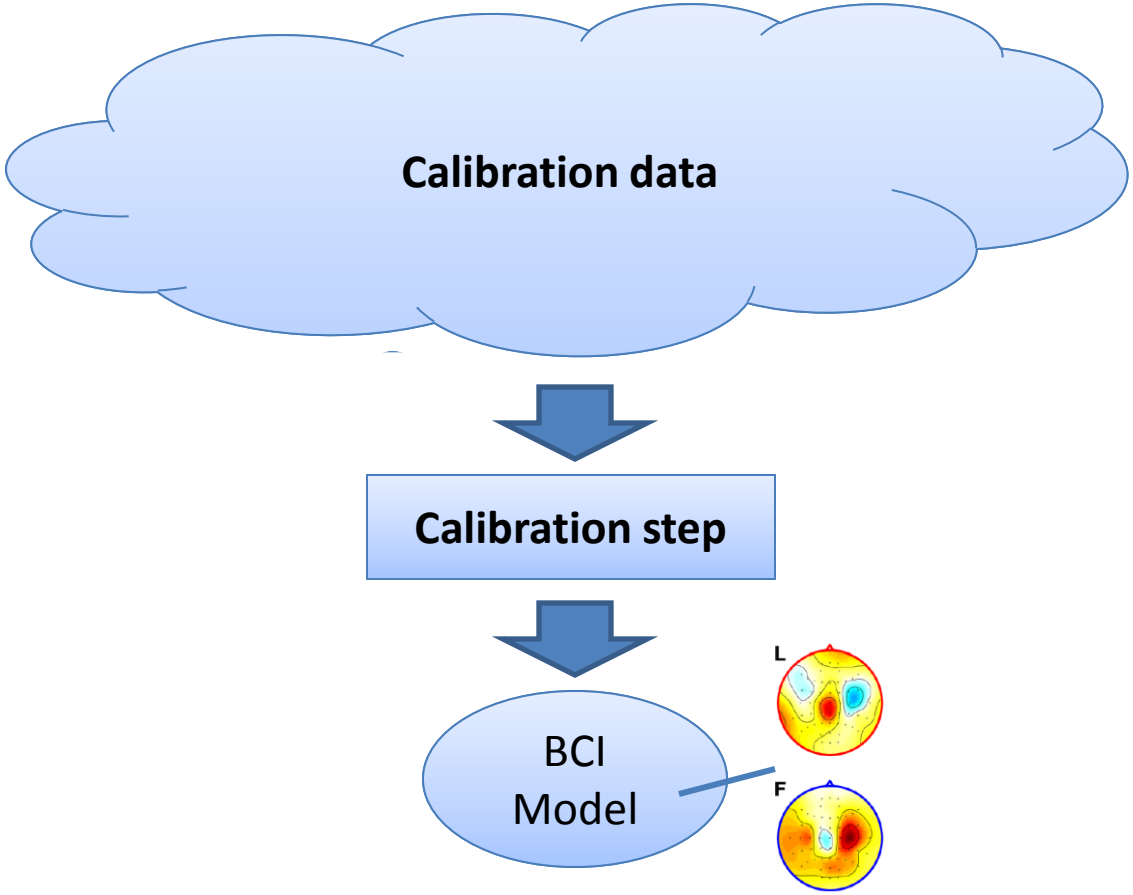
Unknown Parameters

- for most BCI questions and implementations, the parameters leading to best accuracy (**W**,b, …) are *a priori* unknown…
  - Depend on highly variable factors (e.g., sensor placement, subject state)
  - Different for every person, task, montage, etc.
  - Depend on hard-to-measure factors (e.g., brain functional map)
  - Depend on expensive-to-measure factors (e.g., brain folding)

- How to solve this problem?

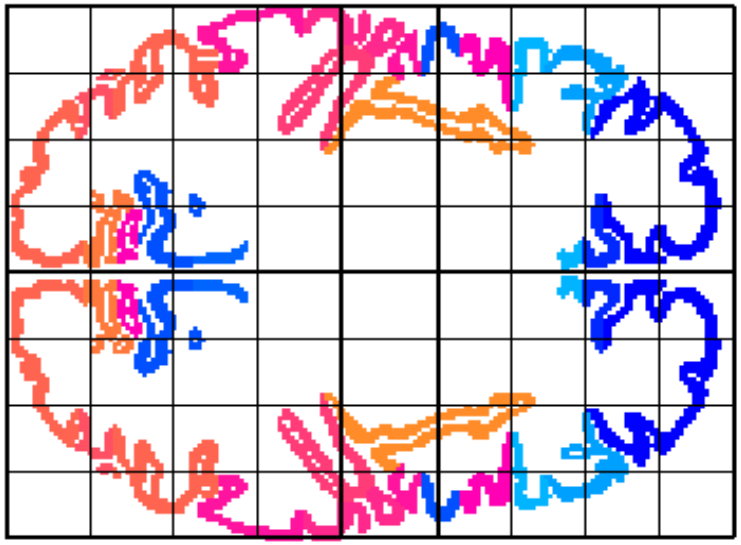
Model Calibration

- Can use *calibration / training data* to estimate parameters from, and a separate *calibration step*



Prior Knowledge

- Prior knowledge is neuroscientific, such as:
  - Anatomical atlases (e.g. Talairach, LONI)
  - Functional atlases (if available)



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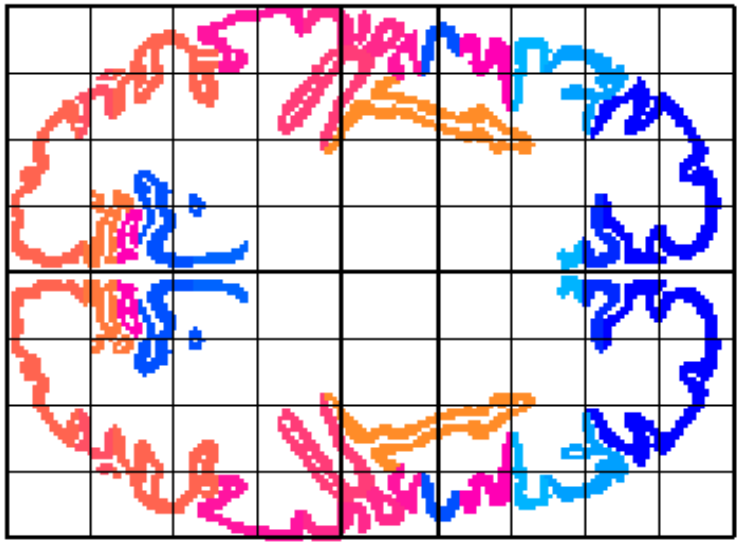

Prior Knowledge

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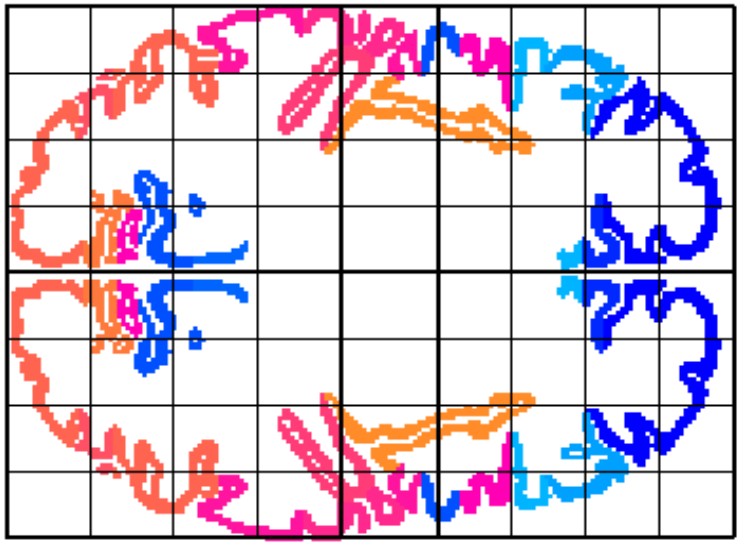
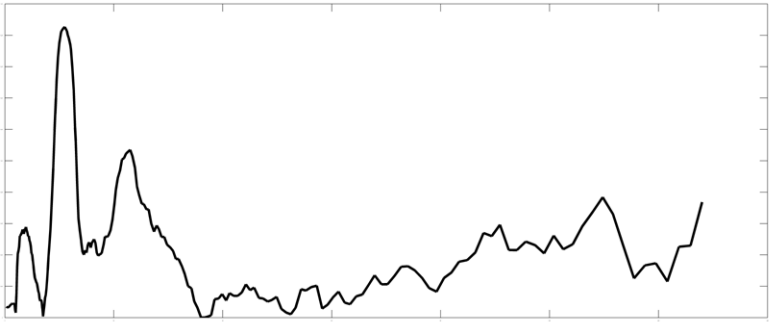
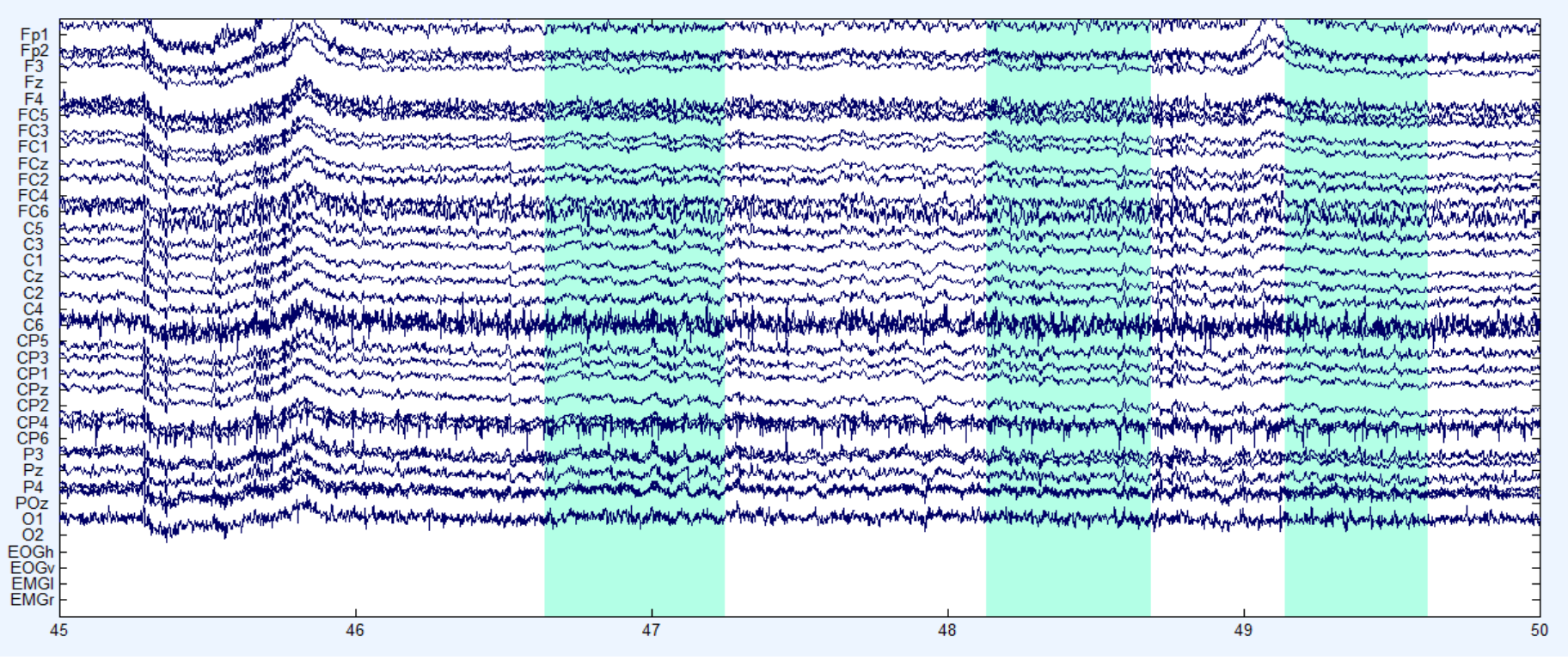
  - Anatomical atlases (e.g. Talairach, LONI)
  - Functional atlases (if available)
  - Timing information (e.g. neural latencies, reaction times)
  - Frequency bands of oscillatory processes (alpha, beta, theta, …)





Calibration Data

- Example/calibration data is used to calculate optimal parameters of a BCI, and is *extremely important*



The Ideal Calibration Data

- Collected with the same/similar measurement apparatus as used for online runs
  - otherwise extra transformations and uncertainty incurred
- Comprises *multiple independent realizations / repetitions / trials* (to quantify variability)
  - one-shot learning (one exemplar) is *much* harder

The Ideal Calibration Data

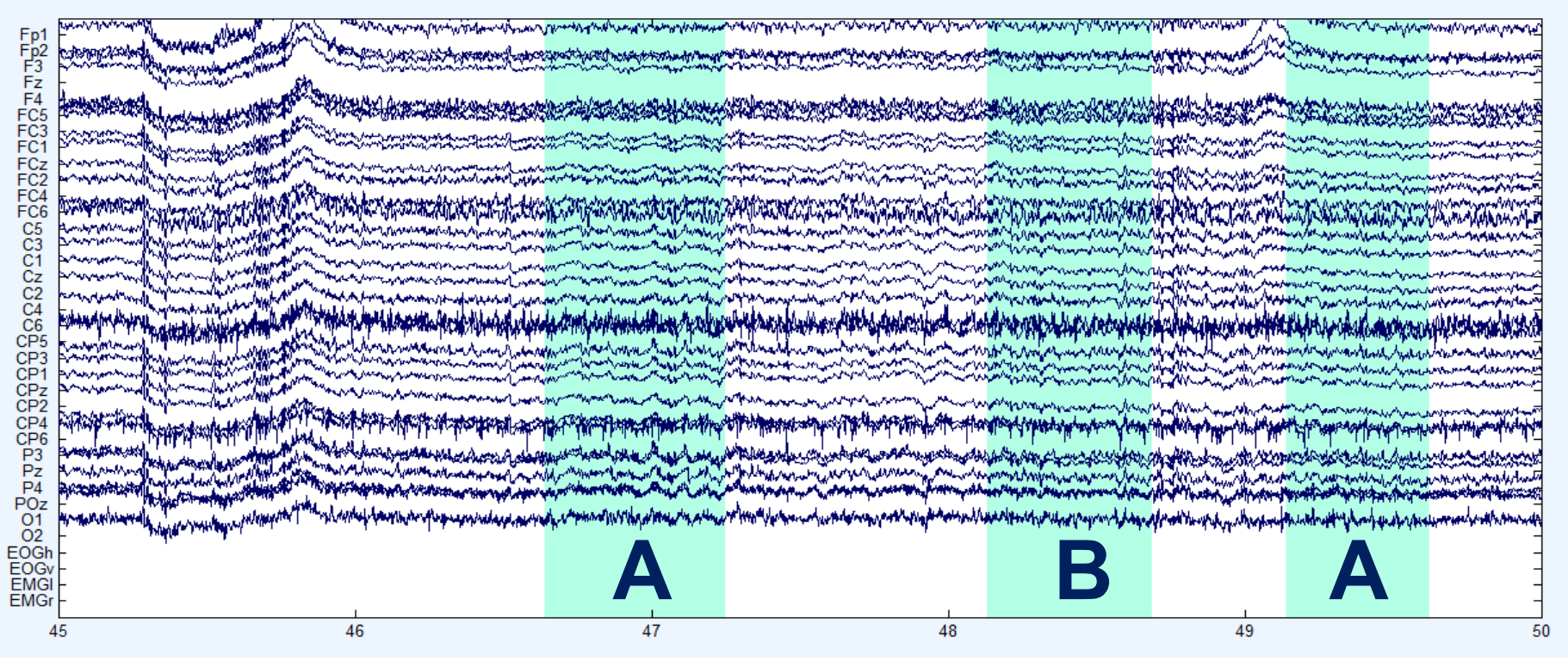
- Collected under conditions that are as close to those of the online runs as possible (i.e., drawn from the same statistical distribution)
  - Same person is preferable
  - Same sensor arrangement is preferable
  - Same session is preferable
  - Task parameters (stress level, …) should be similar
- Obviously a cost/benefit tradeoff:
  - Would trade off some performance for being able to reuse one recording for multiple sessions and persons

The Ideal Calibration Data

- If there is a bias (e.g., different session), data should cover multiple realizations (e.g., multiple sessions) to capture variability
- A plain EEG recording is “unlabeled” (no knowledge about the association between raw observed signal and the cognitive state variable of interest)
- Labeled data (person is “surprised” / “not surprised”) is *far* more useful than unlabeled

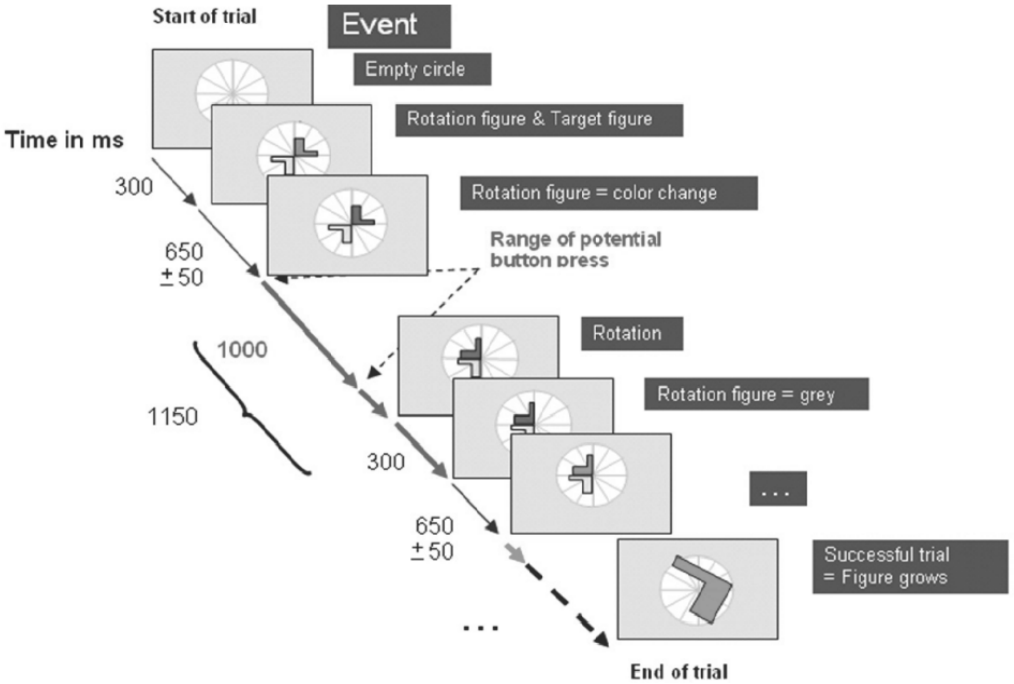
The Ideal Calibration Data

- Labels are assigned per realization (e.g., per trial) and *index the output that the BCI shall produce for this class of data*



Summary

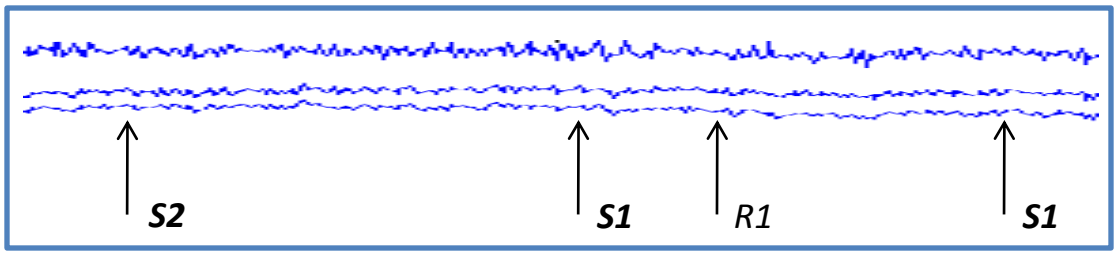
- The required data to calibrate a BCI resembles data produced by *controlled psychological experiments*



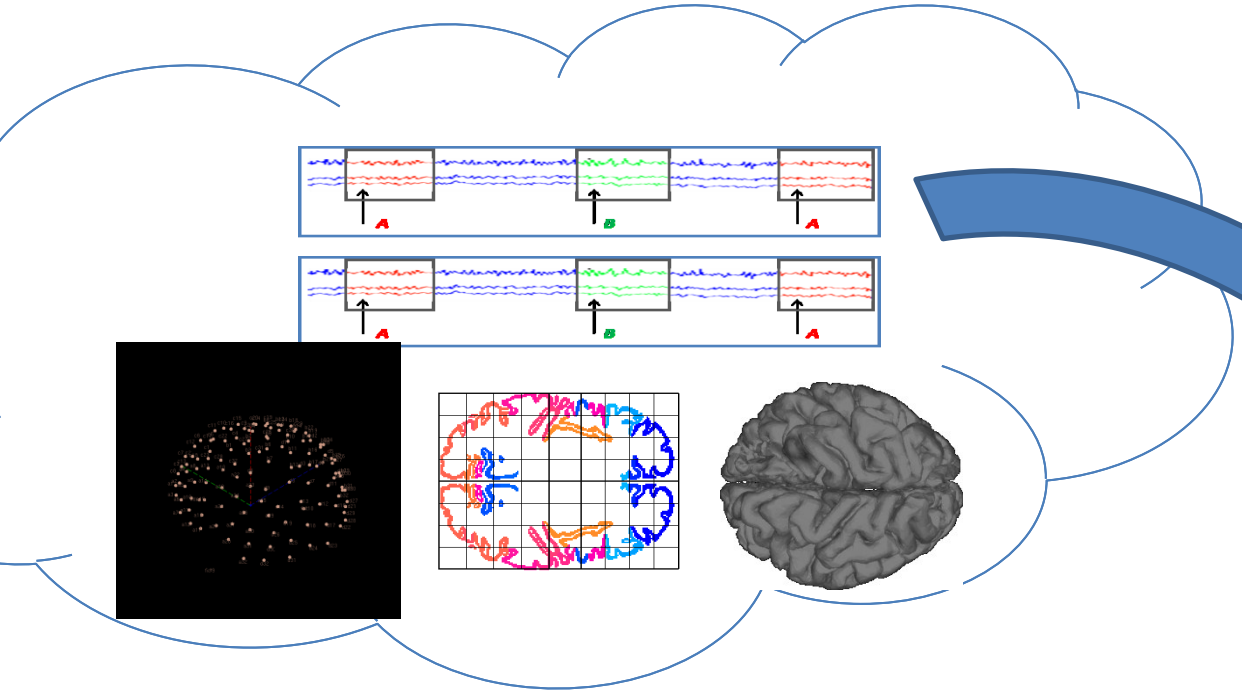
Zander et al., 2010

Summary

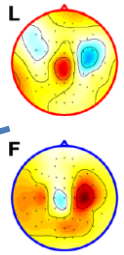
- Features
  - continuous EEG (or other)
  - multiple trials/blocks (capturing variation)
  - randomized (eliminating confounds)
  - event markers to encode cognitive state conditions of interest, e.g., stimuli/responses (called "*target markers*" in BCILAB)
- Can also be used for offline performance tests

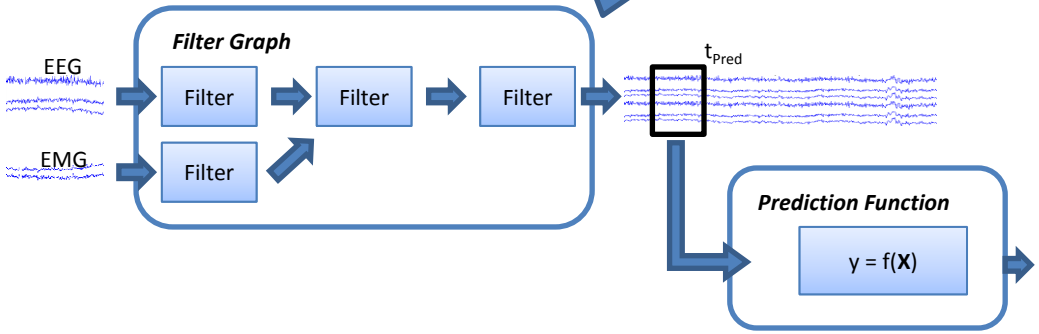


Big Picture



Learning Function



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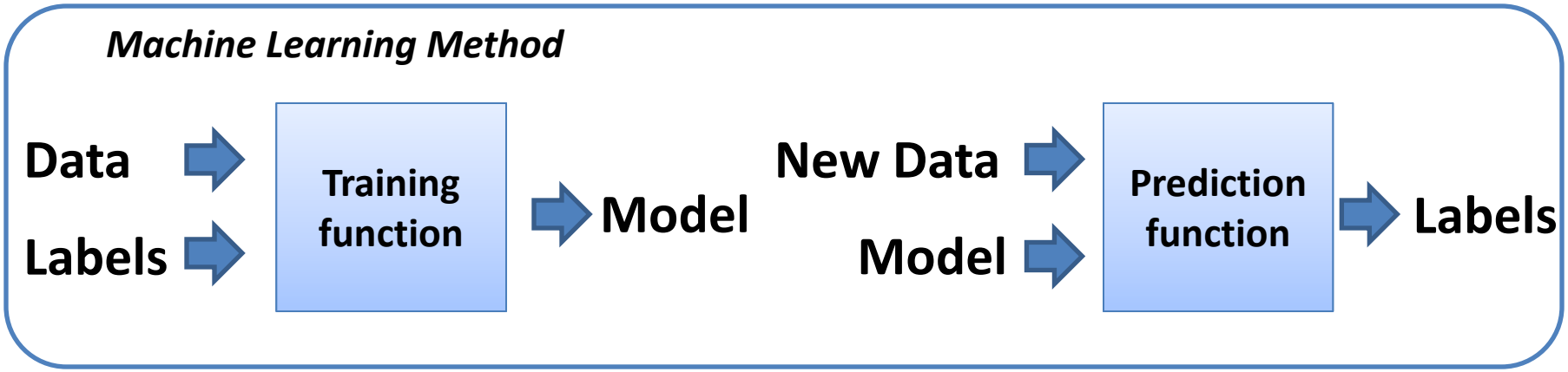
4.2 Machine Learning

Machine Learning

- Large field with 100s of algorithms
- Most methods conform to a common framework of a *training function* and a *prediction function*



- Intermediate model parameters $\boldsymbol{\theta}$ capture the learned relationship
- Data $\boldsymbol{X} \in \mathbb{R}^{N \times F}$ and Labels / target values $\boldsymbol{y} \in \mathbb{R}^{N \times D}$
  N = #trials, F = #features, D = #output dims.

Machine Learning

- The Machine Learning Framework is largely *trial-based* (learning from exemplars)
- Most methods come in form of two functions: *learning function* and *prediction function*
- Learning function is often *far* more complex than the prediction function

Sub-Types In ML

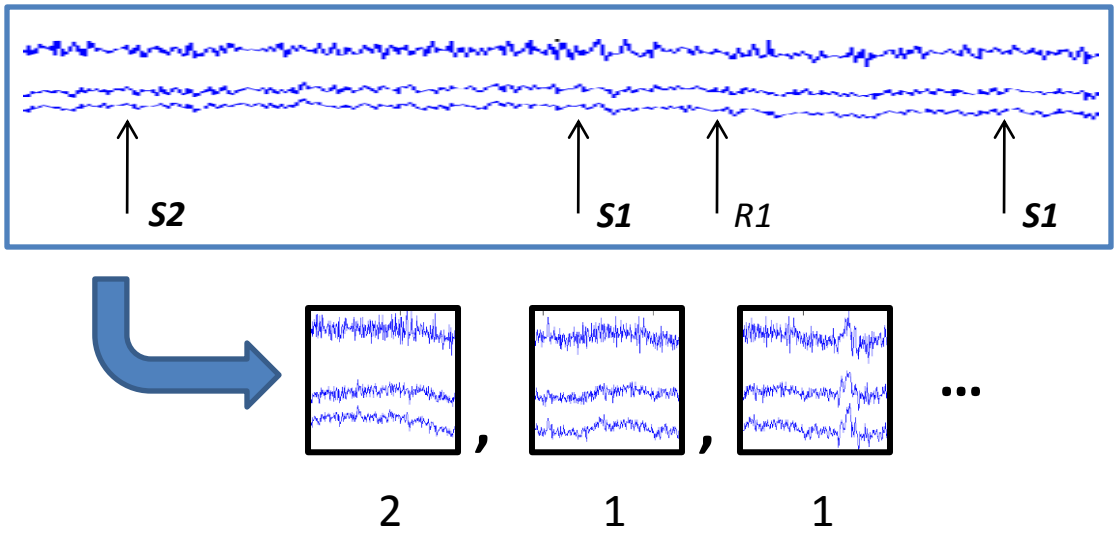
- **Supervised Learning:** given a set of (input,output) pairs as training data, learn a parametric (or "non-parametric") model M that encodes the mapping from input to output
- **Unsupervised Learning:** given a set of training examples, learn the structure in the input space (e.g. clusters, manifolds, probability density)
- **Semi-Supervised Learning:** Some training examples have labels, others do not
- **Others:** e.g., Active Learning, Online Learning, …

Related Areas

- Probability Theory
- Statistics
- Optimization
- Neural Networks
- Artificial Intelligence, …

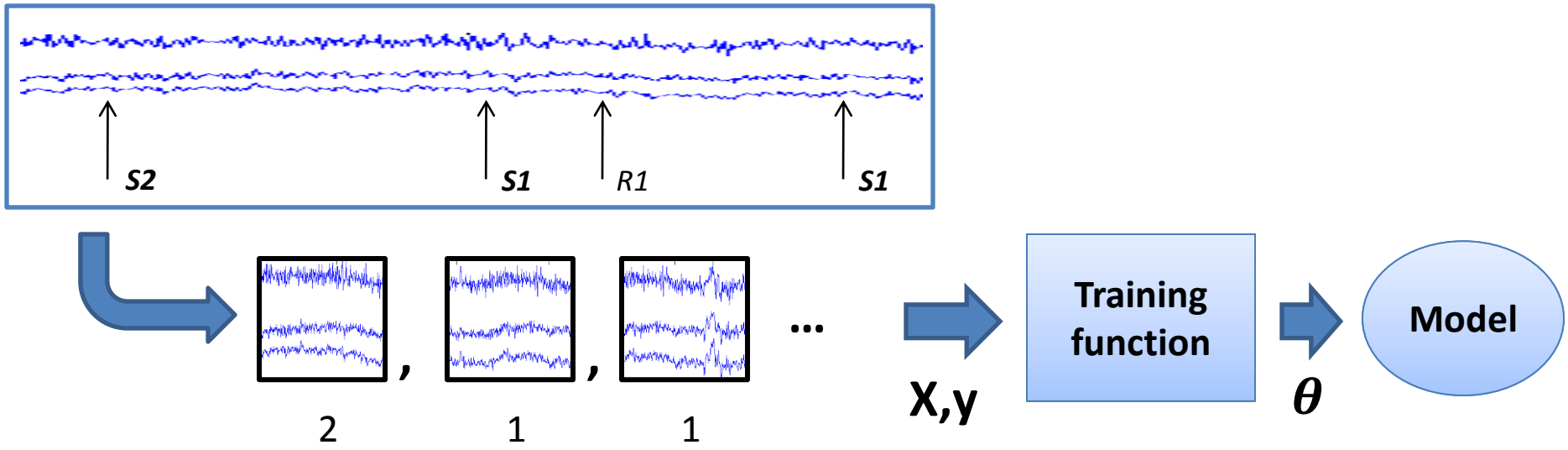
Using Machine Learning

- Often, one trial segment (sample) is extracted for every target marker in the calibration recording and is used as *training exemplar* $\boldsymbol{X}_k$
- Its associated label y_k can be deduced from the target marker



Using Machine Learning

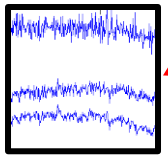
- The training function computes a parameter (here $\boldsymbol{\theta}$) of the prediction function *such that the performance on the given example data is optimal*
- What is considered optimal depends on *extra assumptions* (a.k.a. *priors*)



Detour: Feature Extraction

- **Caveat:** Off-the-shelf machine learning methods often do not work very well when applied to raw signal segments of the calibration recording
  - too high-dimensional (too many parameters to fit)
  - too complex structure to be captured (too much modeling freedom)

1000s of degrees of freedom!



Detour: Feature Extraction

- **Solution**: Introduce additional mapping (called *"feature extraction")* from raw signal segments onto feature vectors
  - output is often of lower dimensionality
  - hopefully statistically "better" distributed (easier to handle for machine learning)

Examples of Feature Extraction

- Depends on the process of interest (e.g. oscillation, ERP peak, complex phenomenon)
- For oscillations, e.g.:
  - log-Variance (logarithm yields more convenient data distributions)
  - Part of the Fourier spectrum
- For ERPs, e.g.:
  - Peak latency, height, width (artificial example)
  - Mean in one or more time ranges relative to an event
  - Subset of Wavelet coefficients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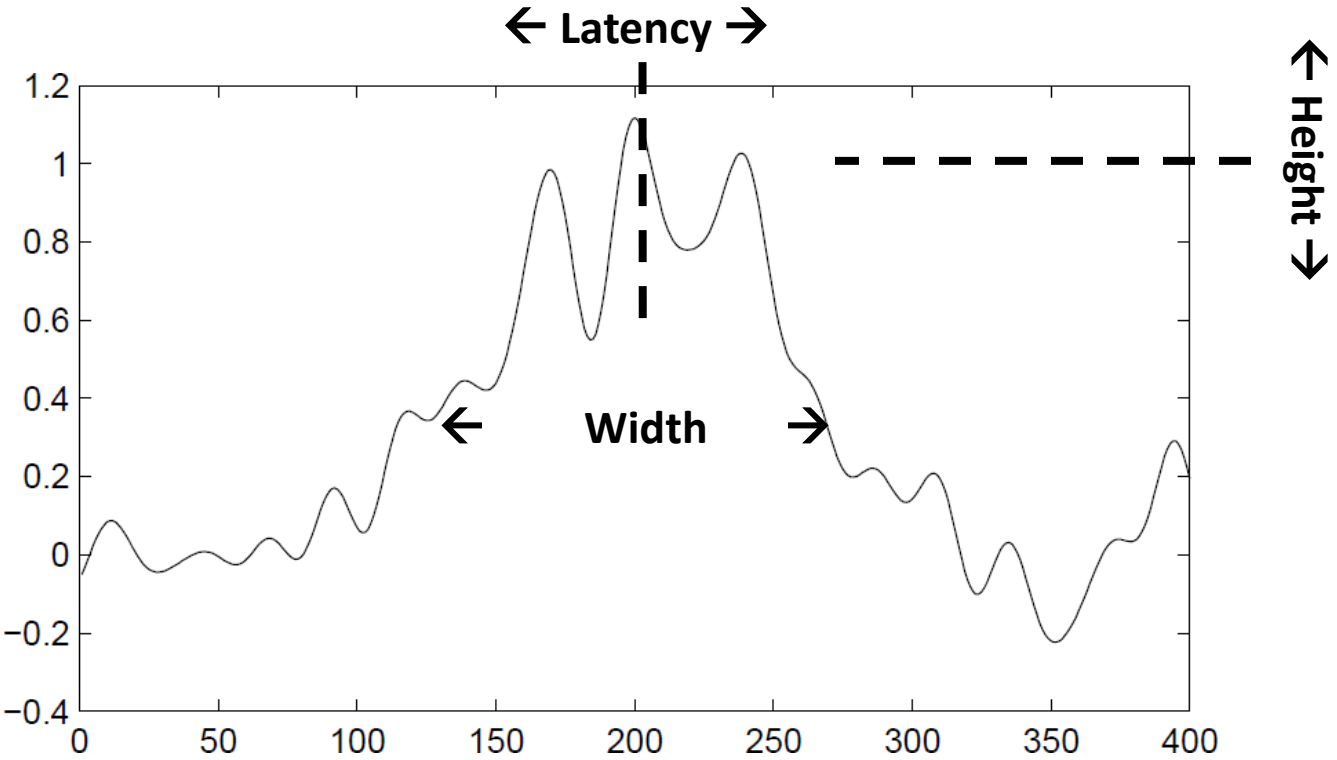
4.3 Concrete Case Study

Example Calibration Problem

- **Task:** A person is presented with a sequence of 300 images (one ever 2 seconds). Half of the images are exciting, the other half are not. One channel of EEG (at Cz location) is recorded.
- **Question:** How to design a BCI that can determine whether a person is shown an exciting or a non-exciting image?
- **Approach:** For each trial k, cut out an epoch $\mathbf{X}_k$ of 1s length, extract a short vector of features $\mathbf{f}_k$, and assign a label y_k in {E,NE}. Use machine learning to find an optimal statistical mapping from $\mathbf{f}_k$ onto y_k.

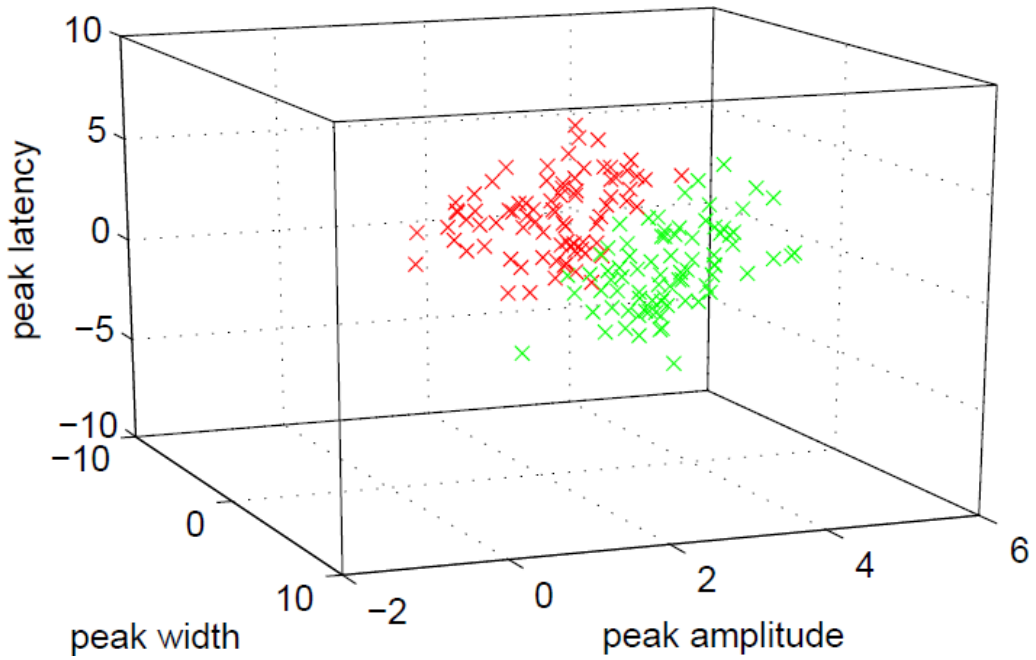
Extracting Features of a Peak

- A supposed characteristic peak in a time window (relative to an event) could be characterized by three parameters:



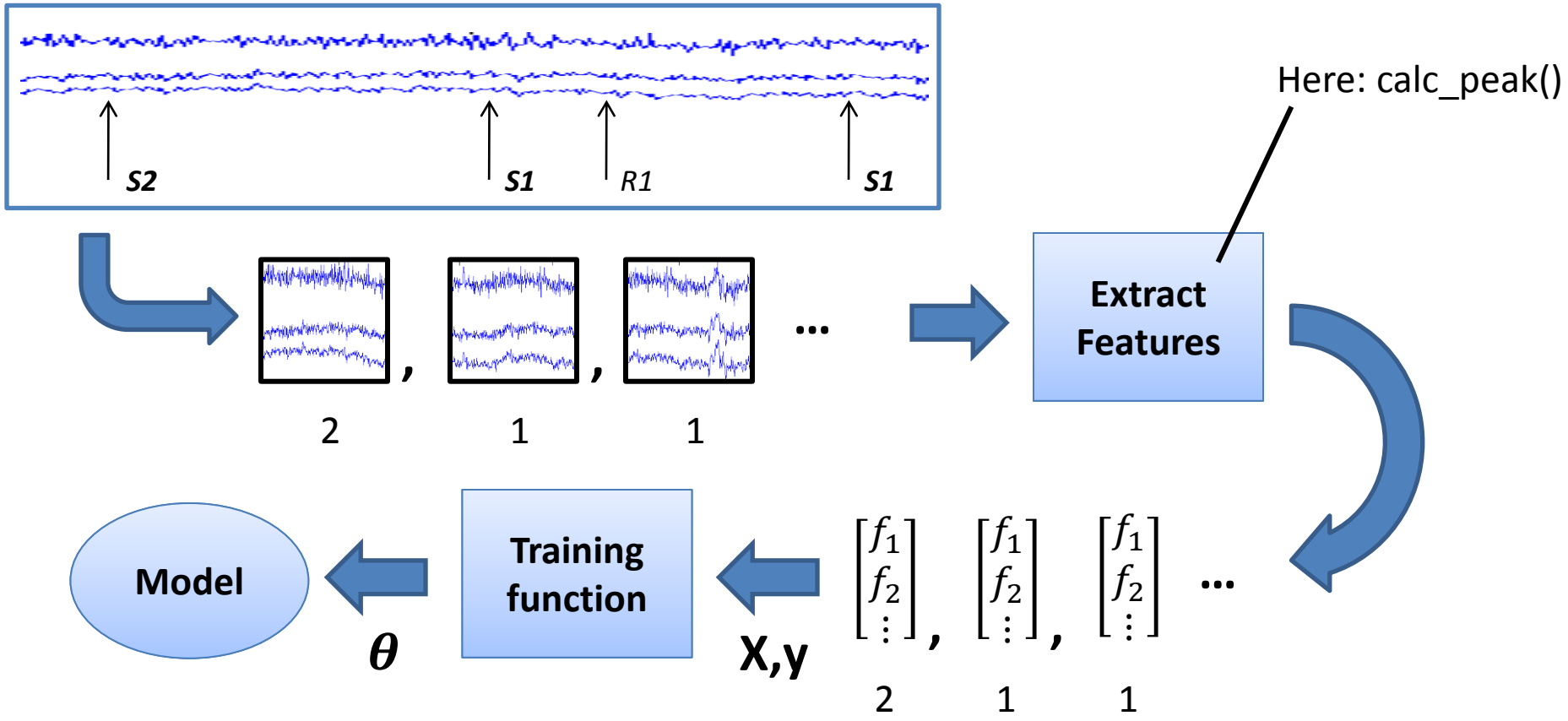
Resulting Feature Space

- Plotting the 3-element feature vectors for all exciting trials in red, and non-exciting trials in green, we obtain two distributions in a 3d space:



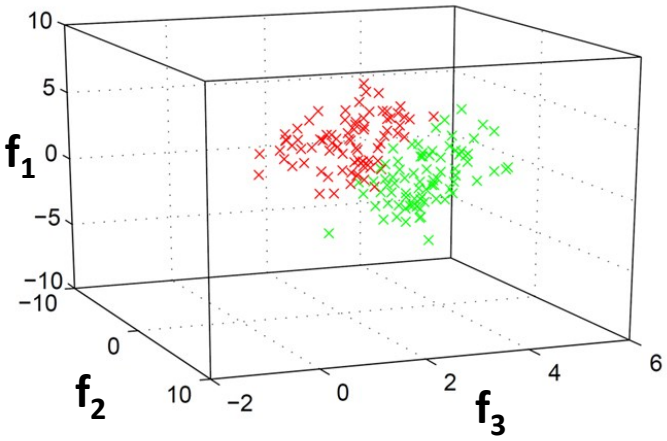
ML with Feature Extraction

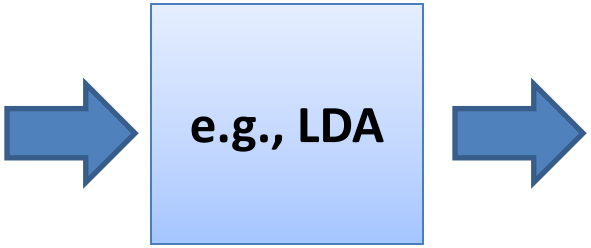
- Including the feature extraction, the analysis process is as follows:

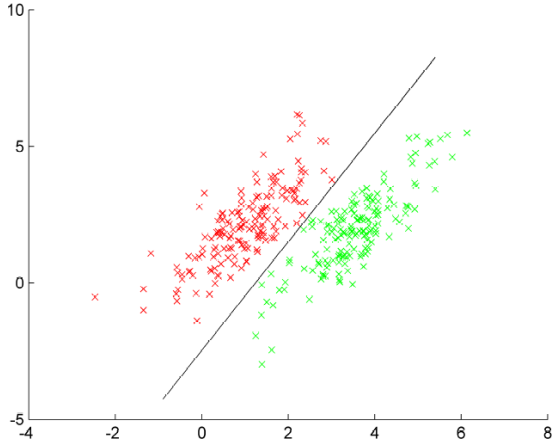


Using Machine Learning

- The feature vectors are passed on to a machine learning function (e.g., Linear Discriminant Analysis)

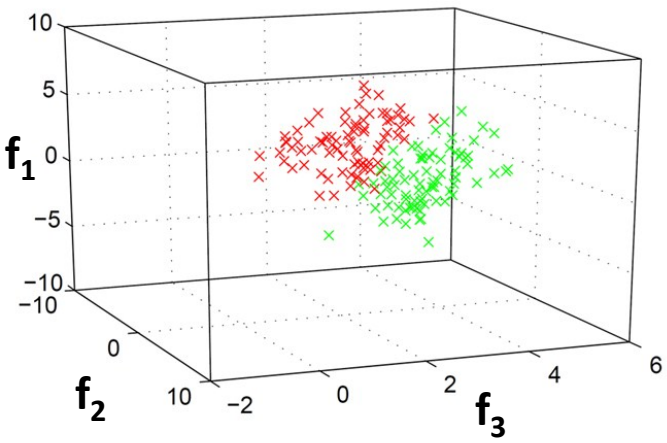


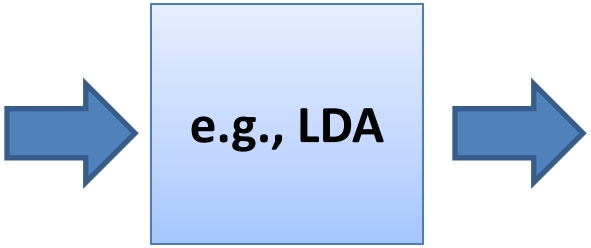


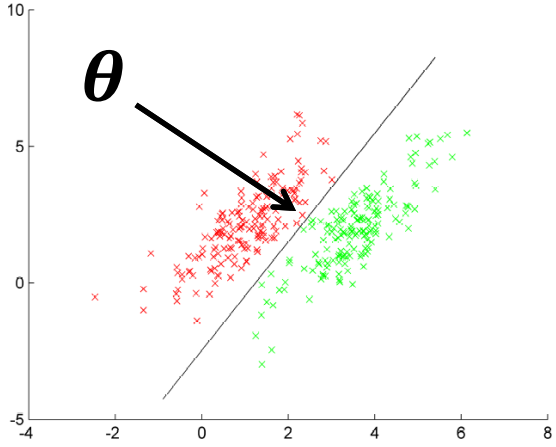


Using Machine Learning

- The feature vectors are passed on to a machine learning function (e.g., Linear Discriminant Analysis)
- … which determines a parametric predictive mapping





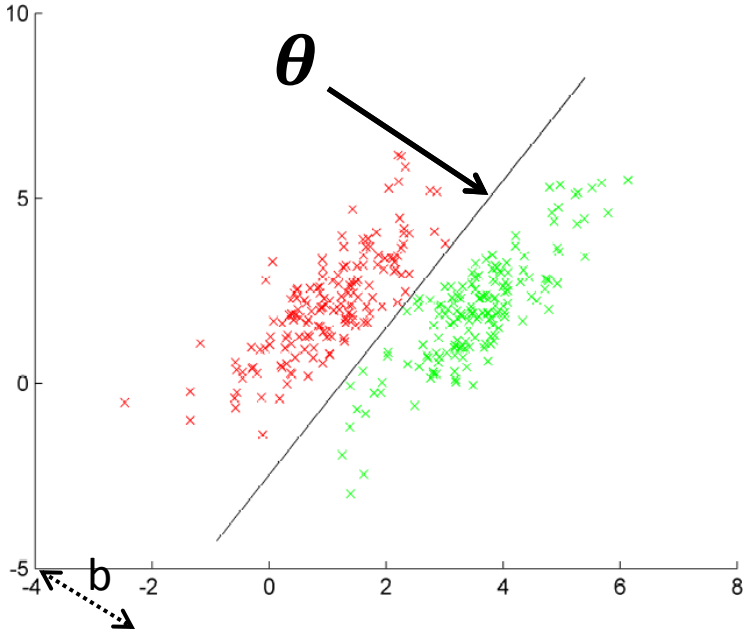


LDA In a Nutshell

- Given trial segments $\boldsymbol{x}_k$ (in vector form) in $\mathcal{C}_1$ and $\mathcal{C}_2$,

$$\boldsymbol{\mu}_i = \frac{1}{|\mathcal{C}_i|}\sum_{k\in\mathcal{C}_i}\boldsymbol{x}_k\,, \qquad \Sigma_i = \sum_{k\in\mathcal{C}_i}(\boldsymbol{x}_k-\boldsymbol{\mu}_i)(\boldsymbol{x}_k-\boldsymbol{\mu}_i)^{\mathsf{T}}$$

$$\boldsymbol{\theta} = (\Sigma_1+\Sigma_2)^{-1}(\boldsymbol{\mu}_2-\boldsymbol{\mu}_1), \qquad \mathrm{b} = -\boldsymbol{\theta}^{\mathsf{T}}(\boldsymbol{\mu}_1+\boldsymbol{\mu}_2)/2$$



Resulting Predictive Map

- LDA generates parameters of a linear mapping

$$\mathrm{y} = \boldsymbol{\theta}\boldsymbol{x} + b$$

- For classification, the mapping is actually *non-linear*:

$$\mathrm{y} = \mathrm{sign}(\boldsymbol{\theta}\boldsymbol{x} + b)$$

More on LDA

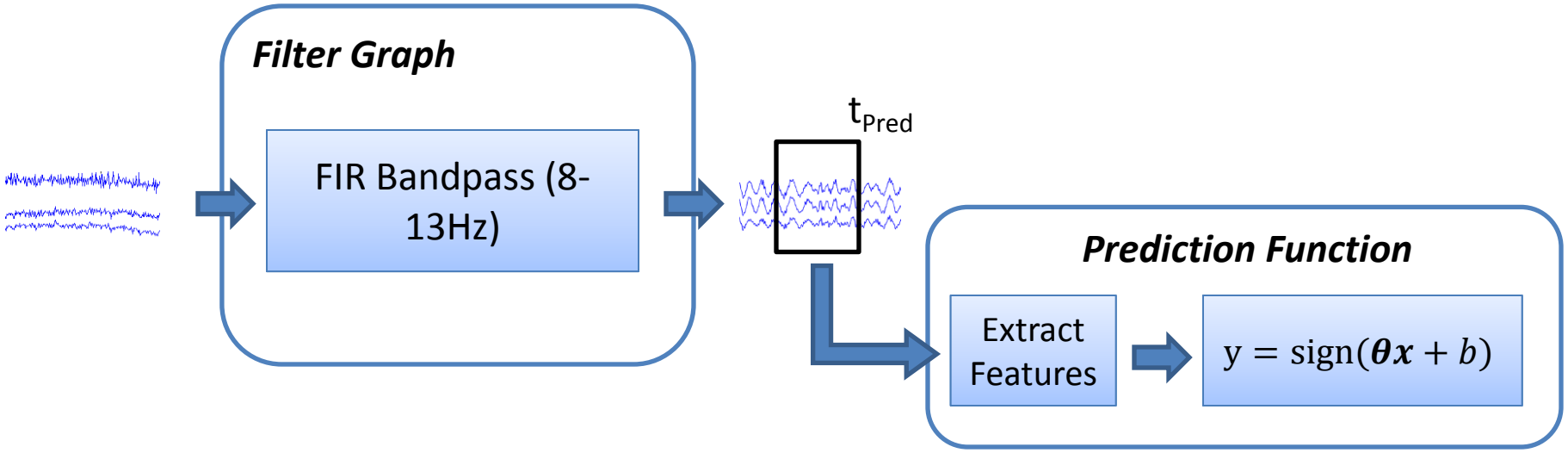
- **Assumptions:**
  - Data in each class is distributed according to a Gaussian distribution
  - Shape of the distribution is identical for all classes
- **Benefits:**
  - Simple, fast and optimal in the large-sample limit if assumptions are true
- **Problems:**
  - Very sensitive to outliers (non-Gaussian)
  - Covariance matrix estimates become unreliable / unusable for too few trials and too many dimensions

Putting it Together

1. Apply band-pass filter to calib. recording
2. Extract epochs relative to target markers
3. Extract features for each epoch (here: peaks)
4. Submit all feature vectors & target labels to LDA to calculate $\boldsymbol{\theta}$ and b of the predictive mapping

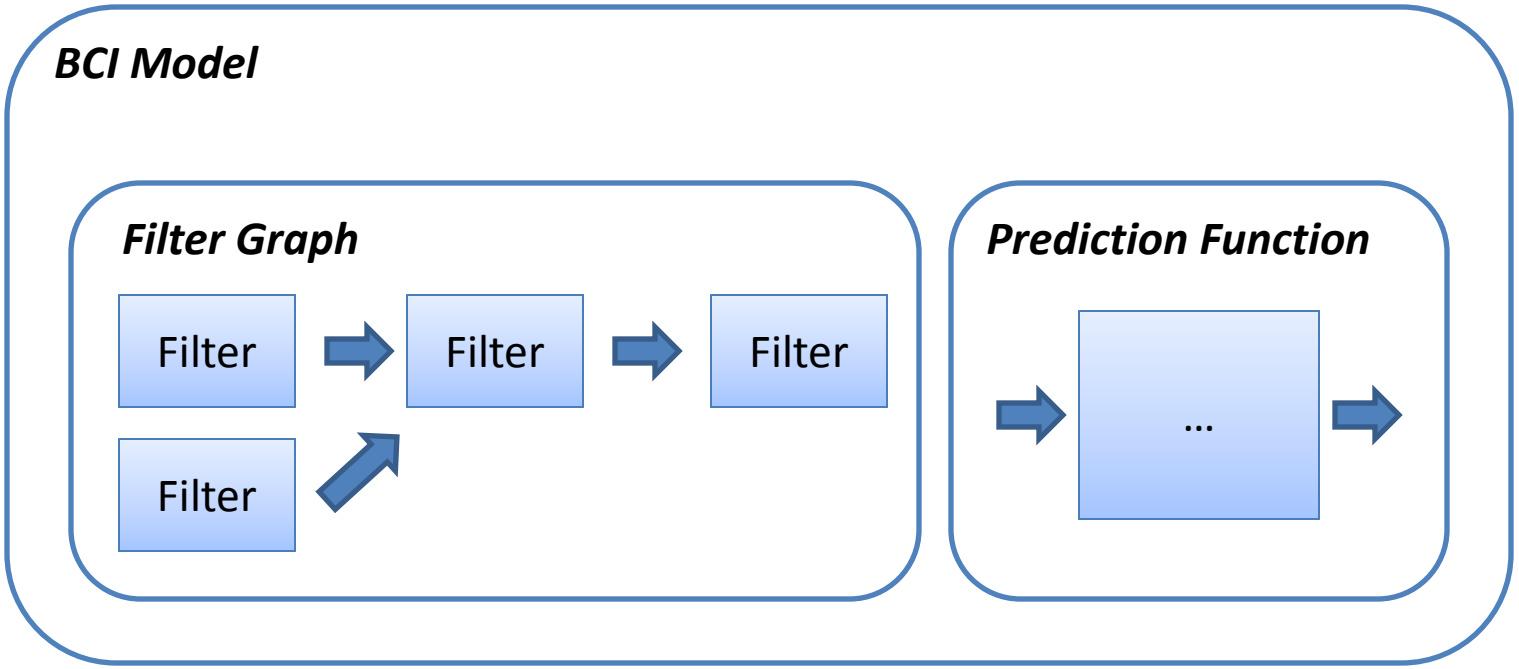
Putting it Together

- For online operation, the overall prediction function consists of the feature extraction followed by the predictive map
- This yield a primitive “excitement detector”



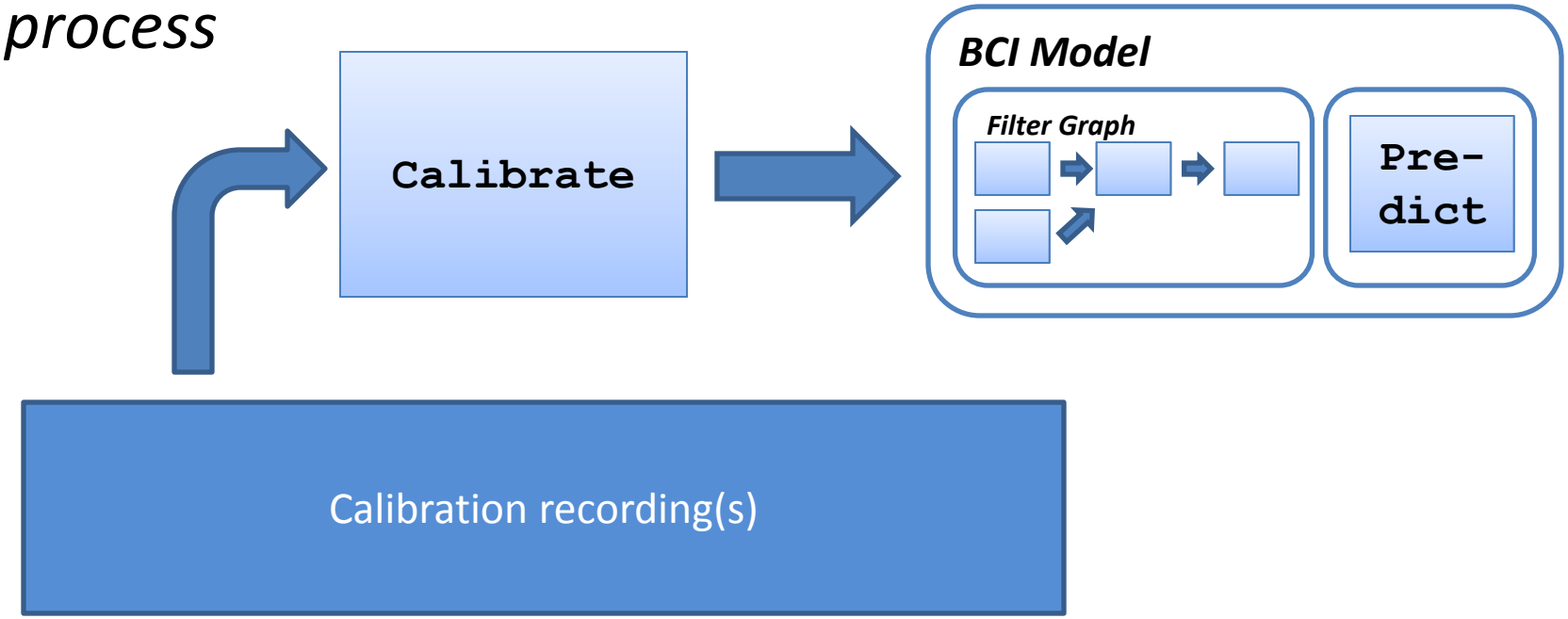
BCI Models

- BCIs are described by "BCI models" that specify both the *filter graph* and the *prediction function* (incl. its parameters)
- These models are the result of the calibration step



“BCI Paradigms”

- BCI paradigms are a notion that was first developed in the BCILAB framework
- A BCI paradigm is the *full description and codification of a particular type of calibration and prediction process*

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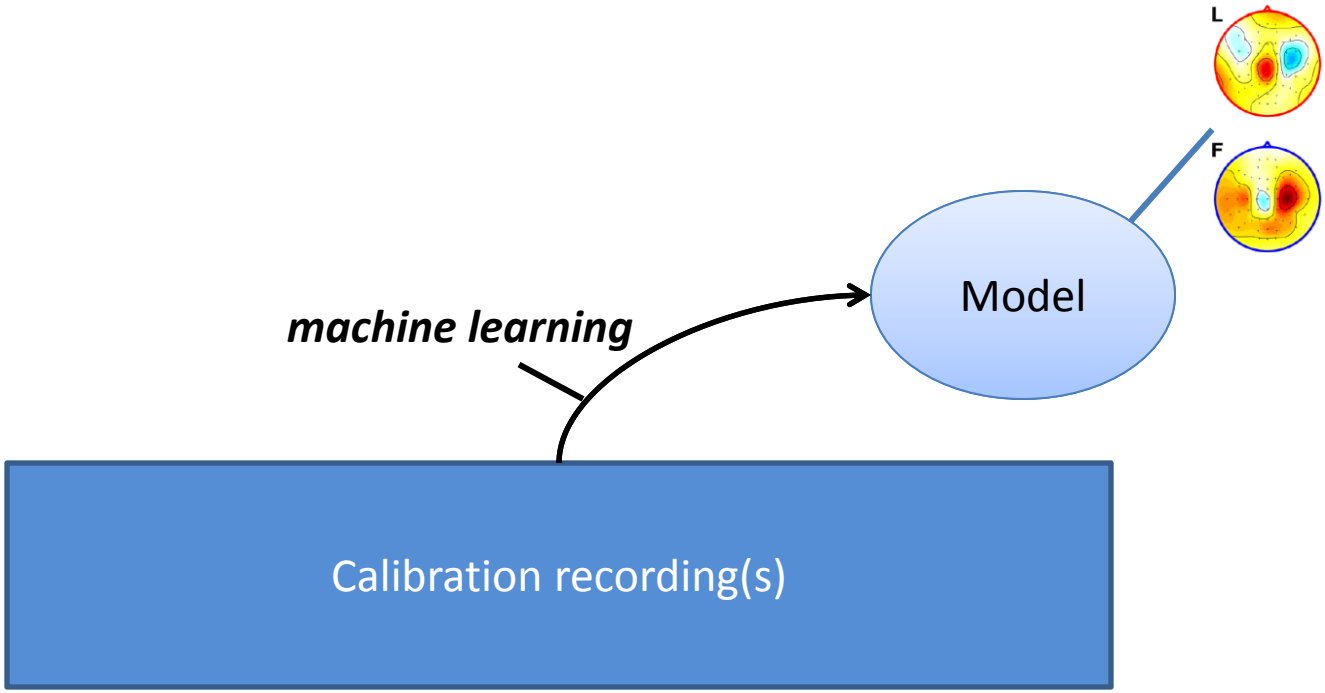
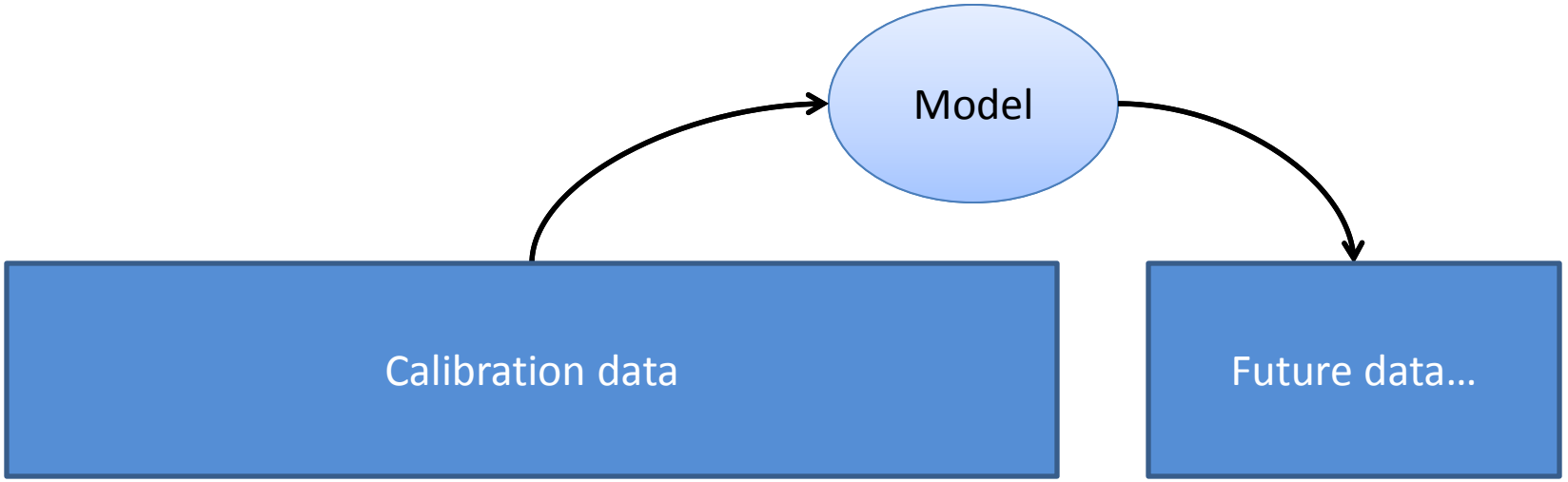
4.4 Performance Evaluation

How to Evaluate a Model?



Overall Evaluation Strategies

- **When given calibration data and test data…**
- Estimate model parameters (spatial filters, statistics)
- Apply the model to new data (online / single-trial)
- Measure prediction performance or loss



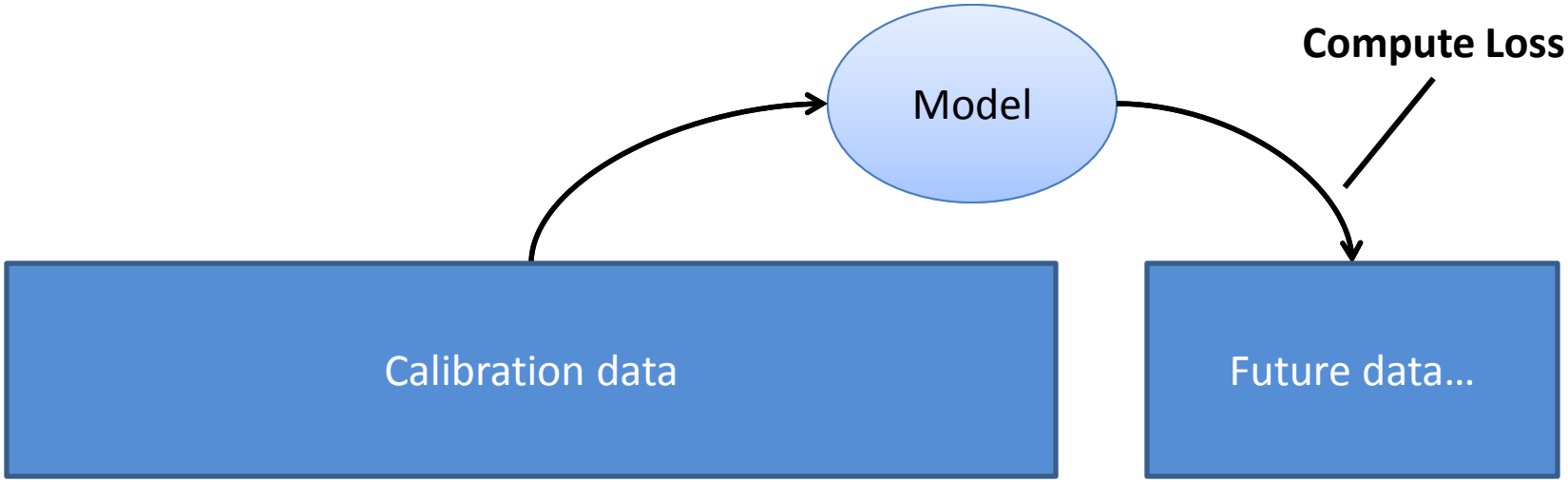
Overall Evaluation Strategies

- Note: Overall *loss estimate* between a vector of predictions $\boldsymbol{p}$ and a vector of targets $\boldsymbol{t}$ is a summary statistic

- **Mean-Square Error:**
  - $L_{MSE}(\boldsymbol{p}, \boldsymbol{t}) = \frac{1}{N}\sum_k (\boldsymbol{p}_k - \boldsymbol{t}_k)^2$
- **Mis-Classification Rate:**
  - $L_{MCR}(\boldsymbol{p}, \boldsymbol{t}) = \frac{1}{N}\sum_k \begin{cases} 1, \boldsymbol{p}_k \neq \boldsymbol{t}_k \\ 0, \boldsymbol{p}_k = \boldsymbol{t}_k \end{cases}$

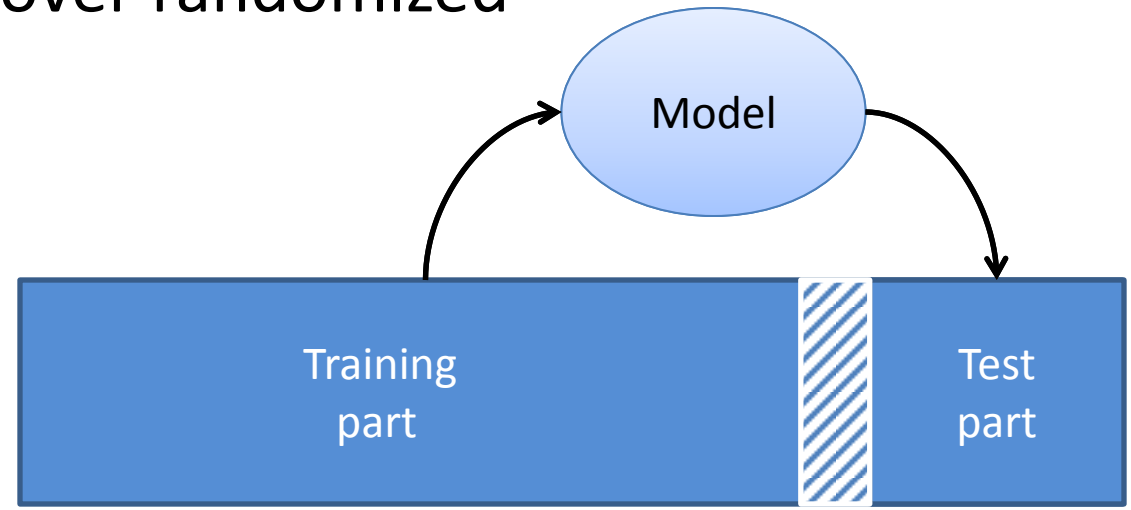
Overall Evaluation Strategies

- **What if there is no second data set?**



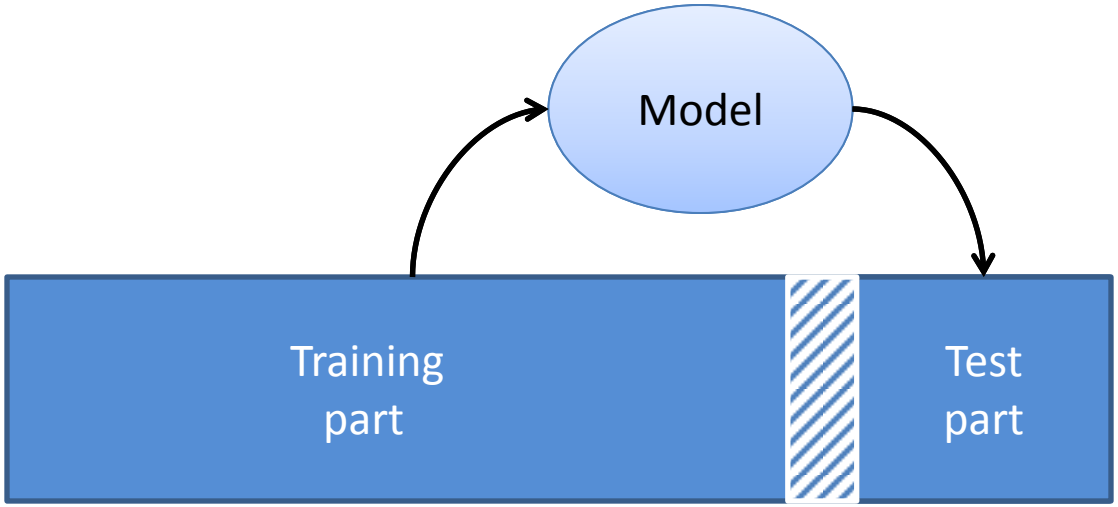
Overall Evaluation Strategies

- **Alternative:** split *one data set* repeatedly into training/test blocks systematically, a.k.a. *cross-validation*
- Each trial is used for testing once
- Time series data: Prefer block-wise cross-validation over randomized



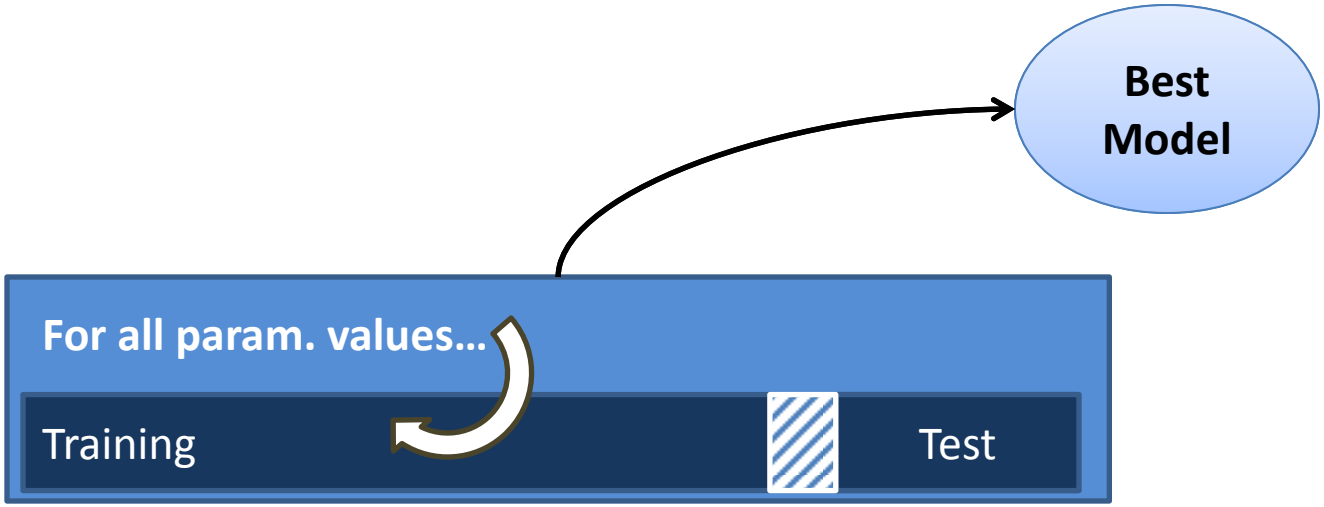
Overall Evaluation Strategies

- **Consideration:** Since neighboring trials are more closely related than training and future online data, *leave a margin of several trials/seconds between training and test*
- Standard splitting schemes: 5x, 10x



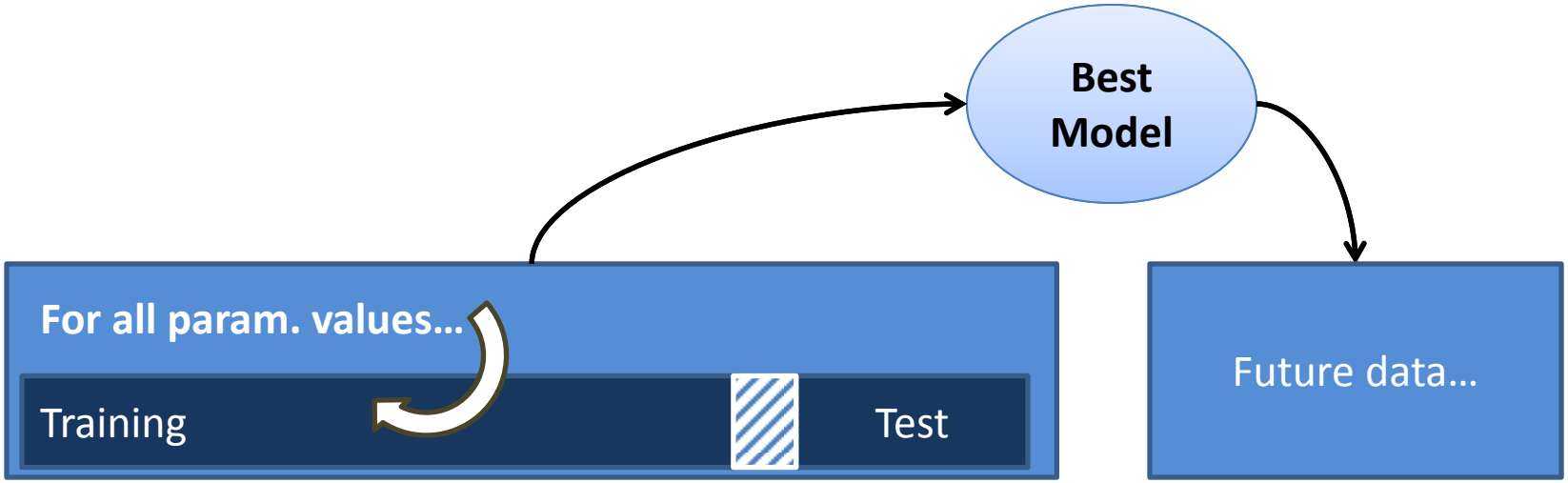
Overall Evaluation Strategies

- **Parameter search** 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)



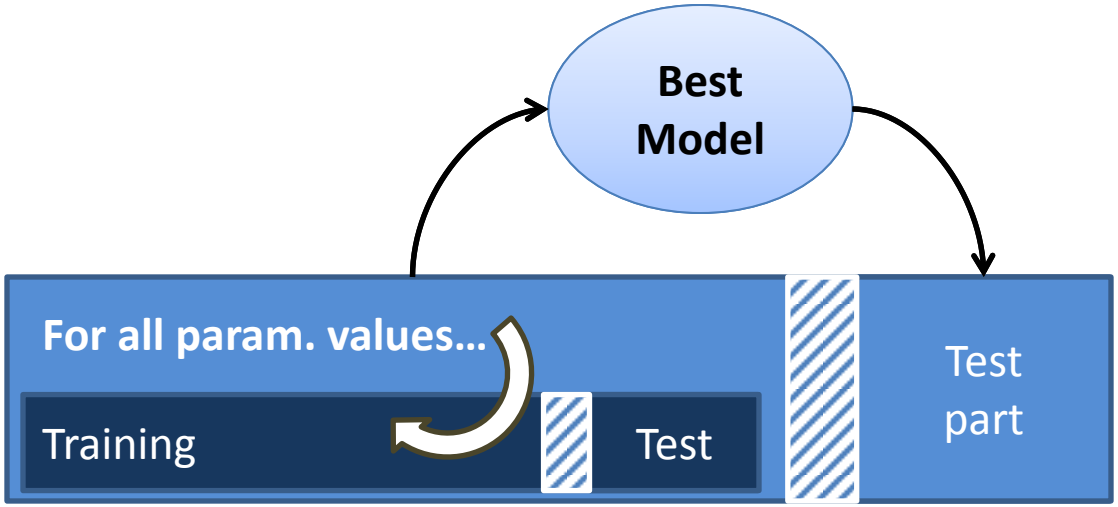
Overall Evaluation Strategies

- **Parameter search** 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)
- **However:** Cannot directly report "best performance" estimates (=cherry-picked), except on future data



Overall Evaluation Strategies

- **Parameter search** can be done using cross-validation in a grid search (try all values of free parameters)
- **Alternatively:** Parameter search can be nested *within* an outer cross-validation ("nested cross-validation")

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L4 Questions?