Real-Time fMRI

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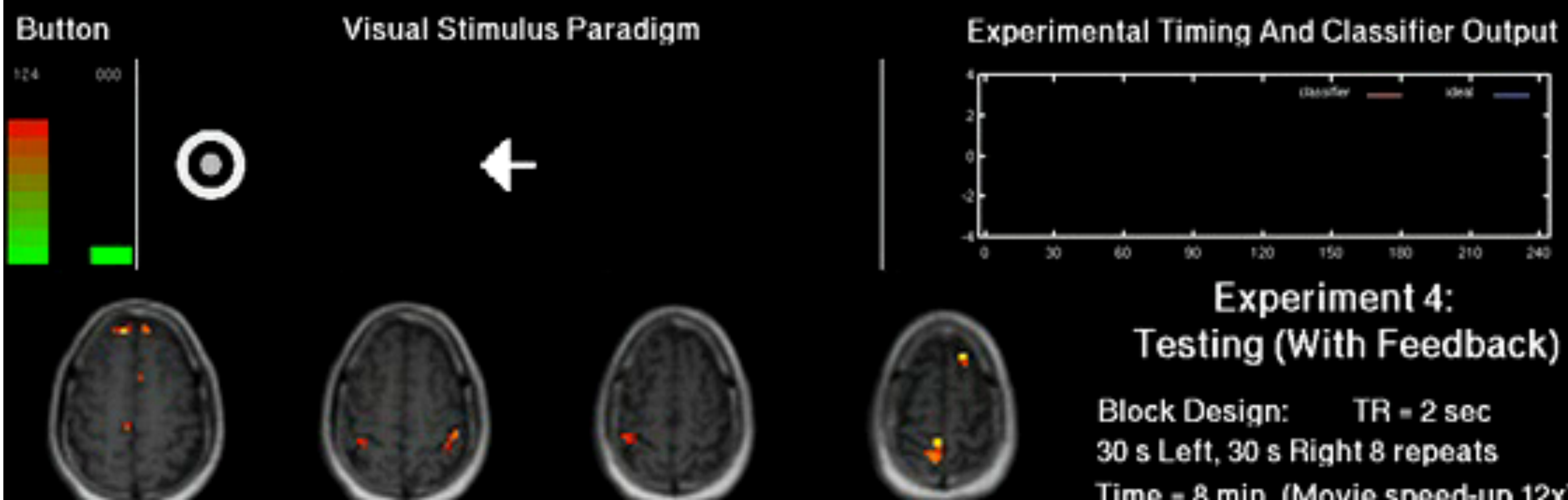
Classification in Real Time

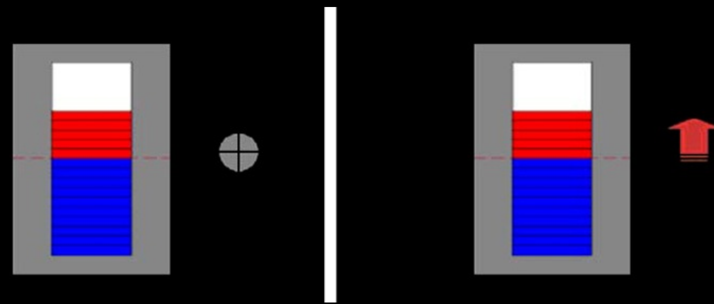


LaConte et al. *Hum Brain Mapp* (2007)

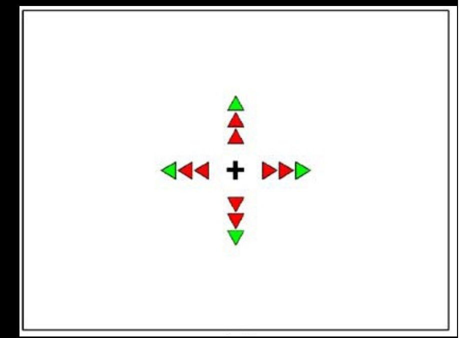
Outline

- Overview of rtfMRI
- Tracking localized brain regions
- Supervised learning-based rtfMRI
- Resources for getting started
- Technical challenges
- Applications

(deCharms et al. 2005)



(Caria et al., 2007)



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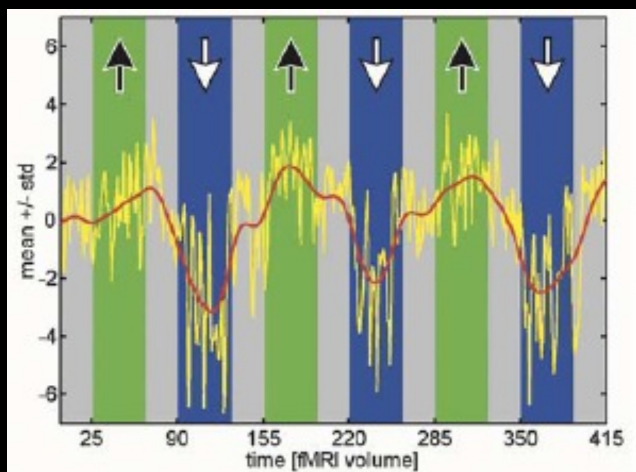
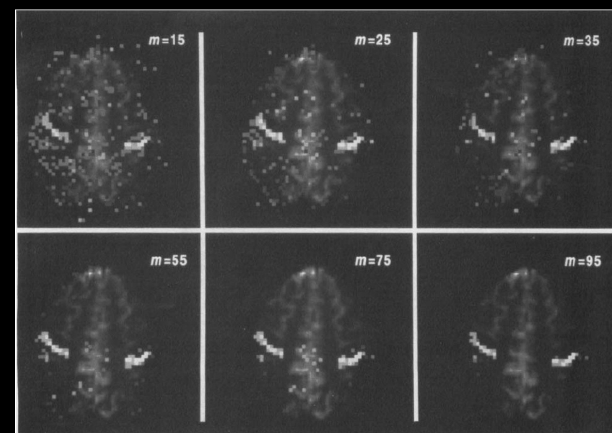


(Weiskopf et al., 2004)



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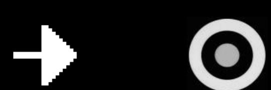

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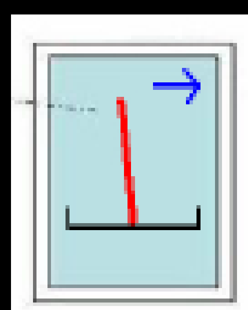

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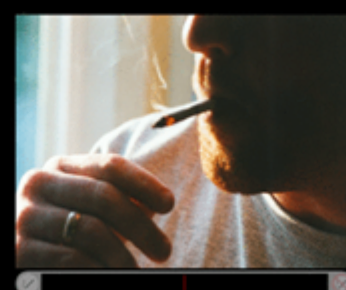
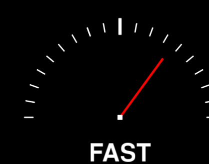
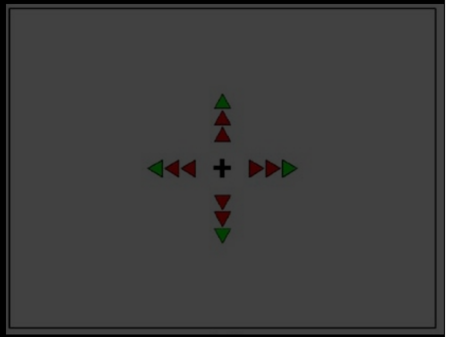




(deCharms et al. 2005)

Chronic Pain:

Continuous display representing percent signal change of rostral anterior cingulate by the size of a virtual fire



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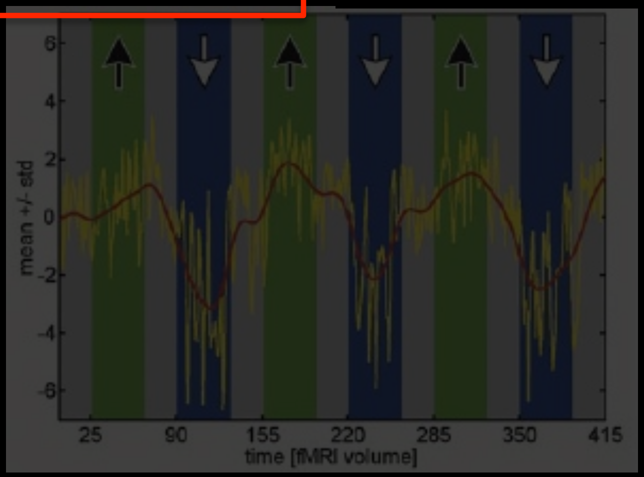

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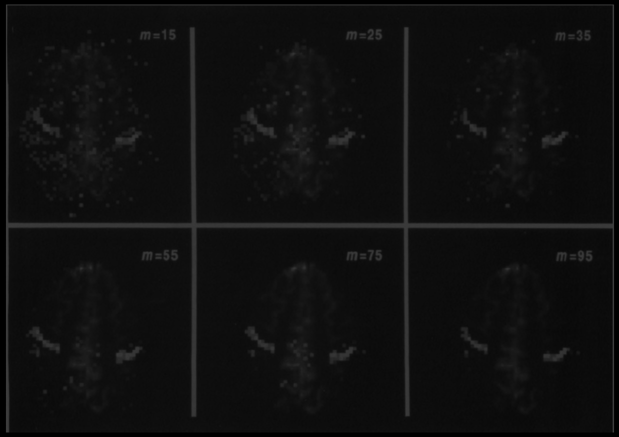

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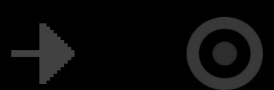

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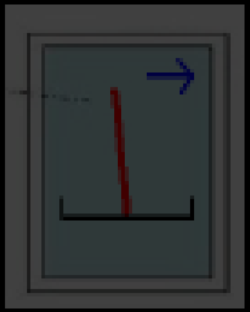

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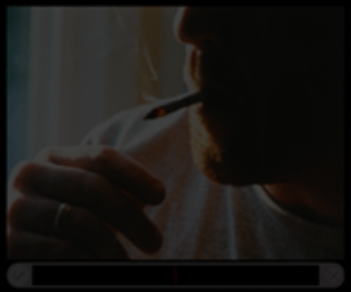

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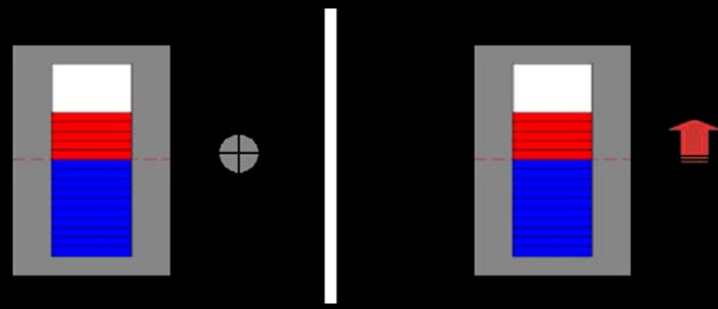

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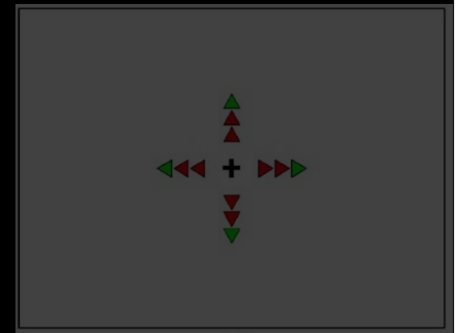

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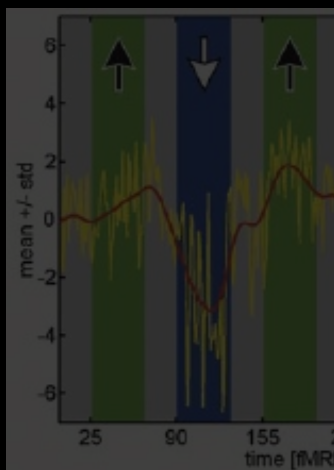
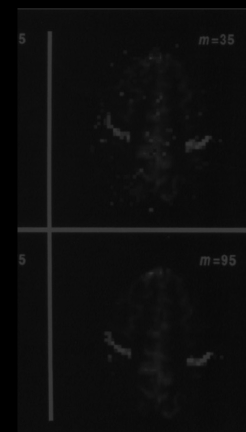


(Weiskopf et al., 2004)

Thermometer display showing signal subtraction between right anterior insula and a large reference ROI

Task cues are to the right of the thermometer



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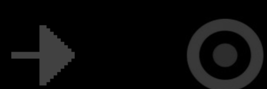

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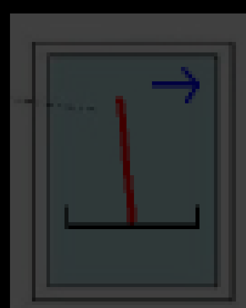

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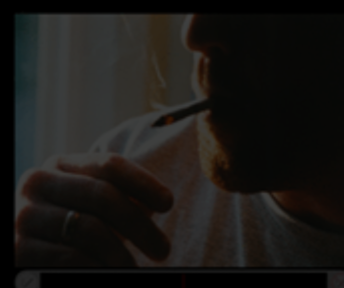
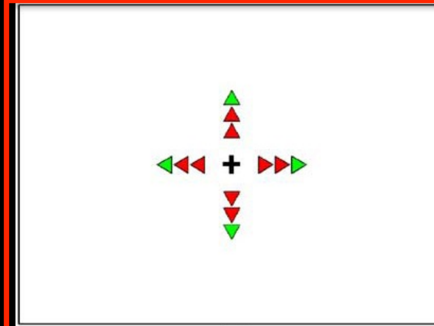


(deCharms et al. 2005

Motion Feedback:

A set of inner, middle, and outer four-way arrows, indicating degree of motion

Task stimuli are presented in the center of the arrows ('+' symbol represents the rest condition)



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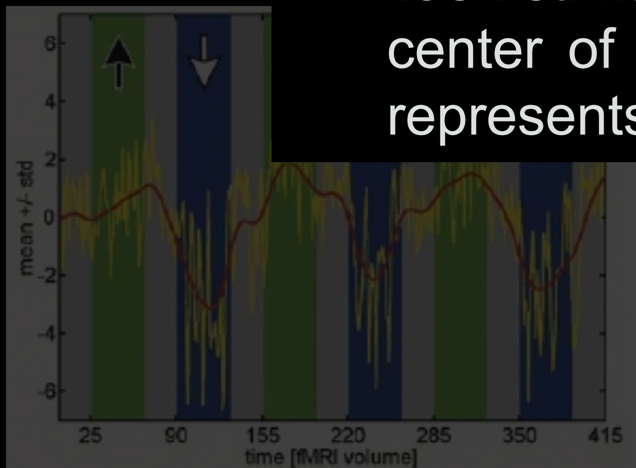

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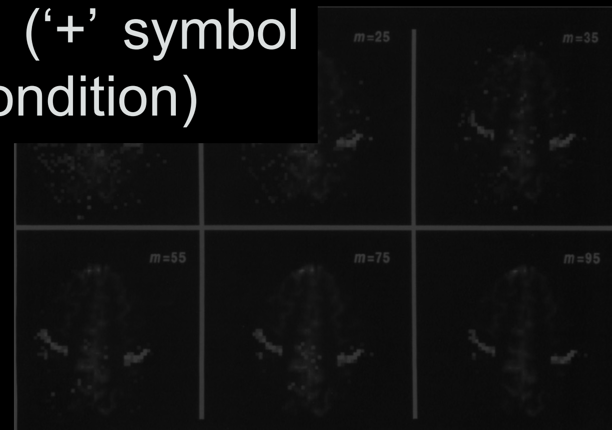

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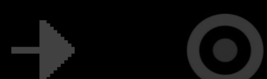

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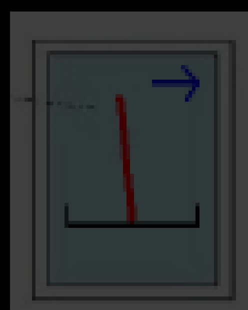

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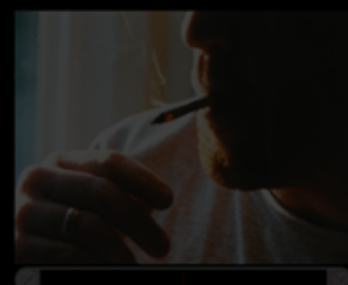

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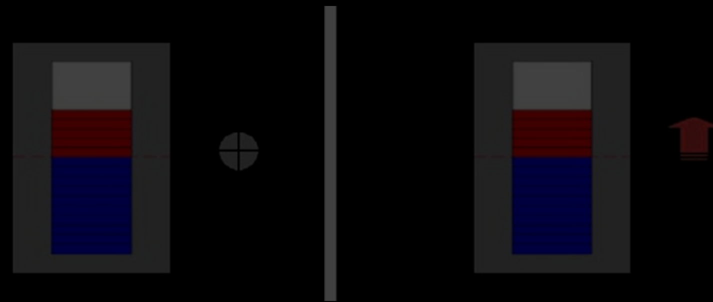

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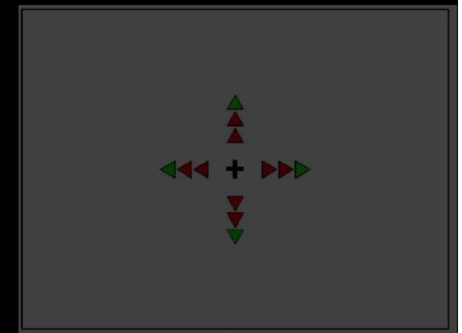

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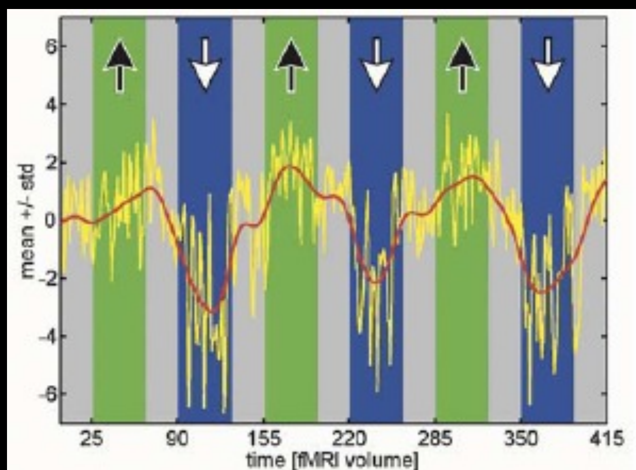

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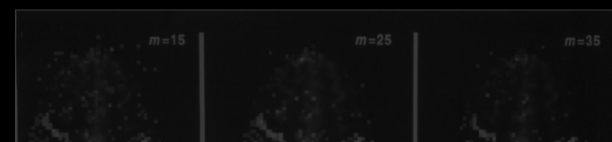
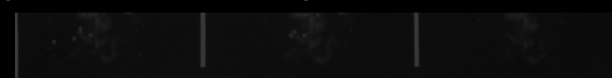


Yellow trace is a running plot of the difference between two brain regions (PPA – SMA)



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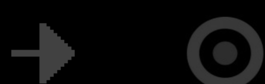

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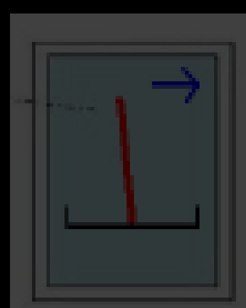

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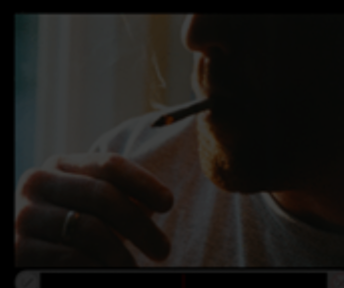

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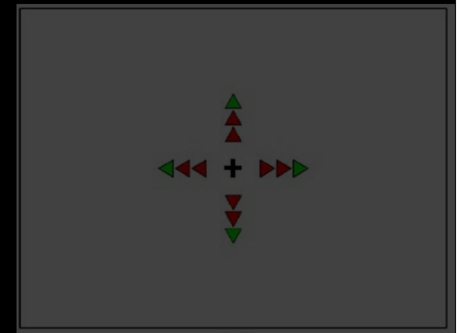


(Yang et al., 2005)

Cox, R.W., Jesmanowicz, A., Hyde, J.S., 1995

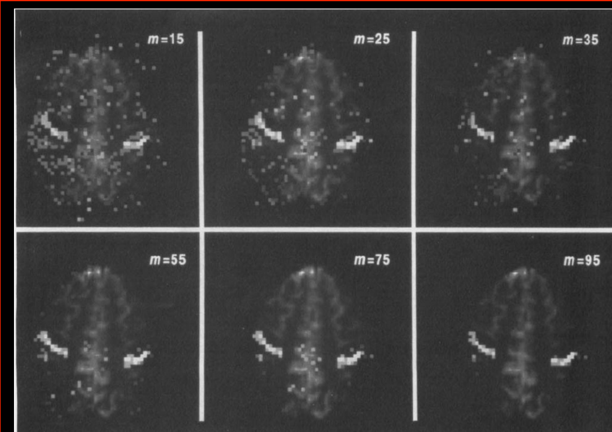
• recursive partial correlation algorithm for fMRI.

• utility of online functional maps

  • monitor data quality

  • evolve experimental protocols more rapidly

  • perform interactive experimental paradigms



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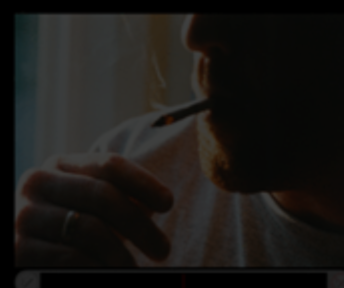

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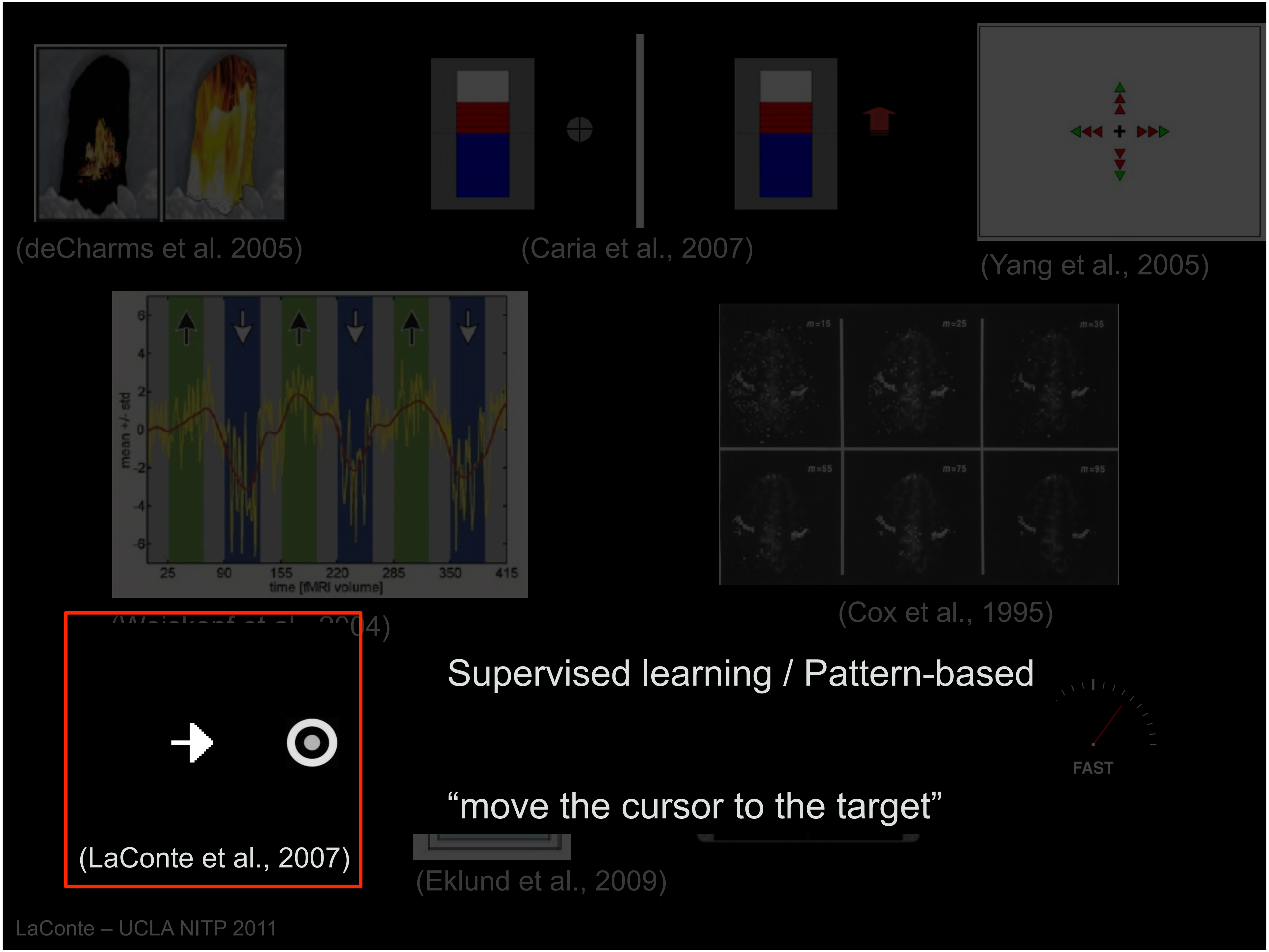
(deCharms et al. 2005)
(Caria et al., 2007)
(Yang et al., 2005)
mean +/- std
time [fMRI volume]
25 90 155 220 285 350 415
m=15 m=25 m=35 m=55 m=75 m=95
(Cox et al., 1995)
Supervised learning / Pattern-based
FAST
“move the cursor to the target”
(LaConte et al., 2007)
(Eklund et al., 2009)
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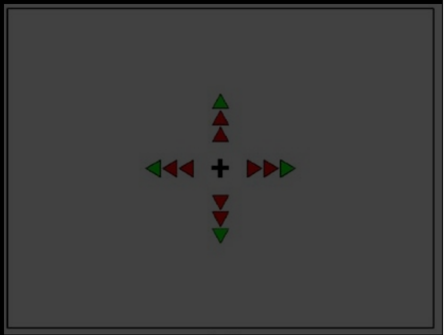
(deCharms et al.



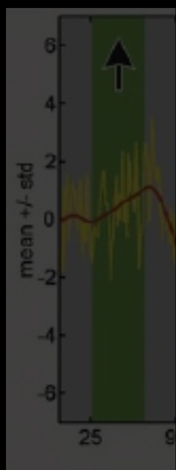
(Yang et al., 2005)

Neural Network:

Using conditions:

- Right hand
- Left hand
- Rest

subjects controlled a simulated inverted pendulum



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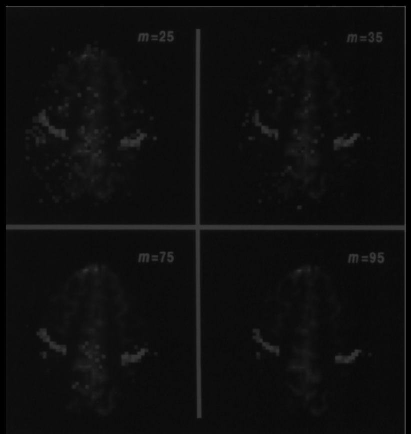
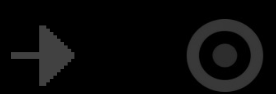


Cox et al., 1995)



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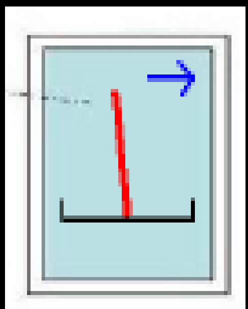

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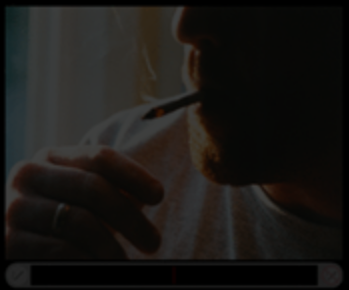

Applications of real-time fMRI

- Monitoring experiments
- Quality assurance
- Surgical planning
- Reading and controlling localized brain function
- Performing adaptive fMRI experiments
- Enabling therapy and rehabilitation

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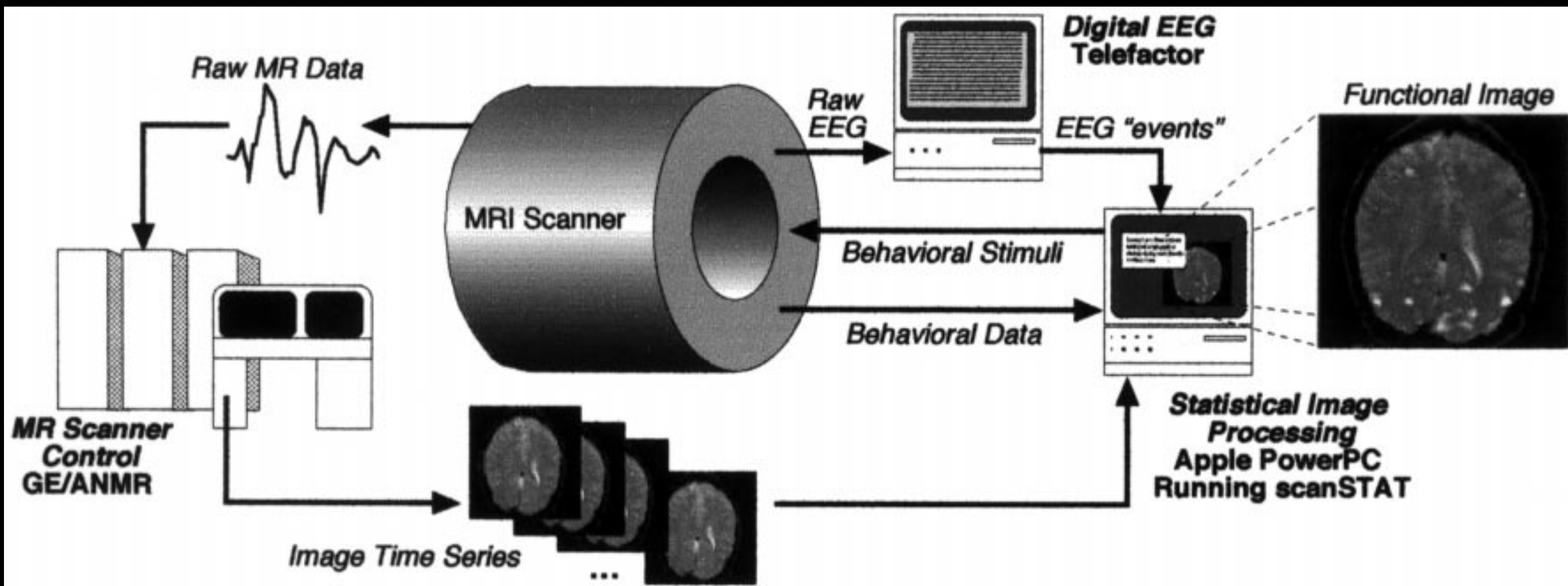
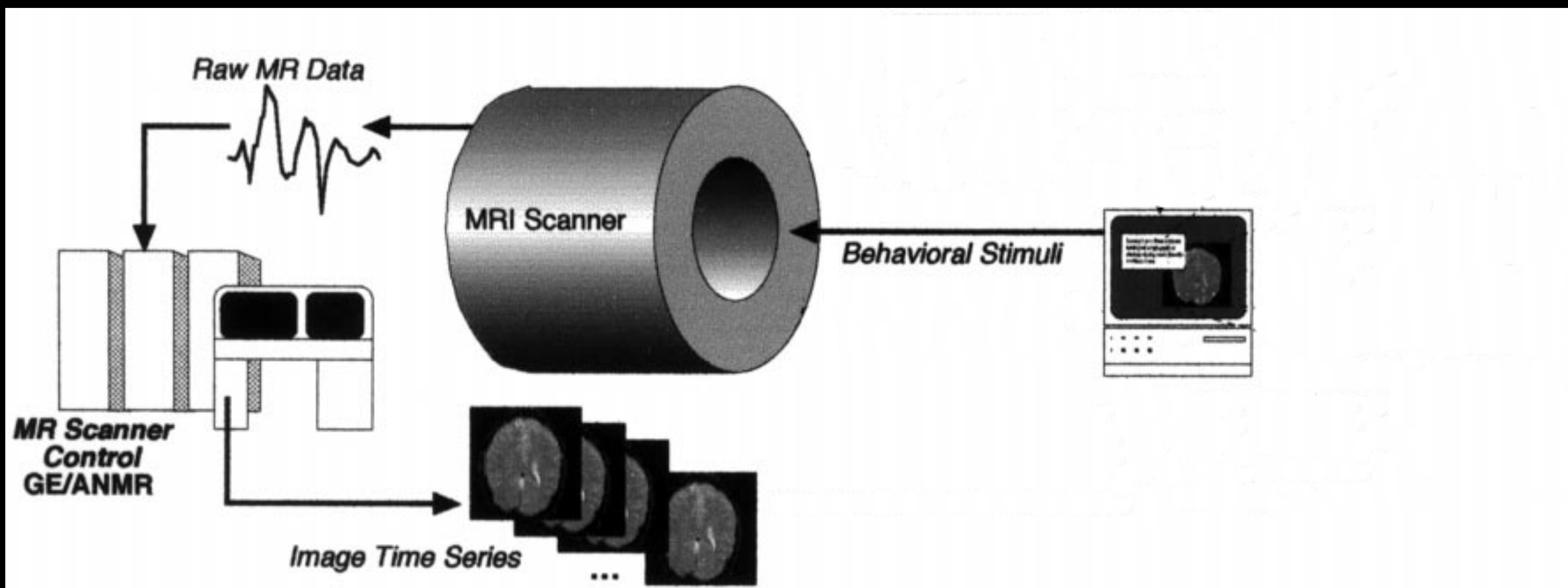

Raw MR Data
Digital EEG
Telefactor
Functional Image
Raw
EEG
EEG "events"
MRI Scanner
Behavioral Stimuli
Behavioral Data
MR Scanner
Control
GE/ANMR
Statistical Image
Processing
Apple PowerPC
Running scanSTAT
Image Time Series
...

Cohen, 2001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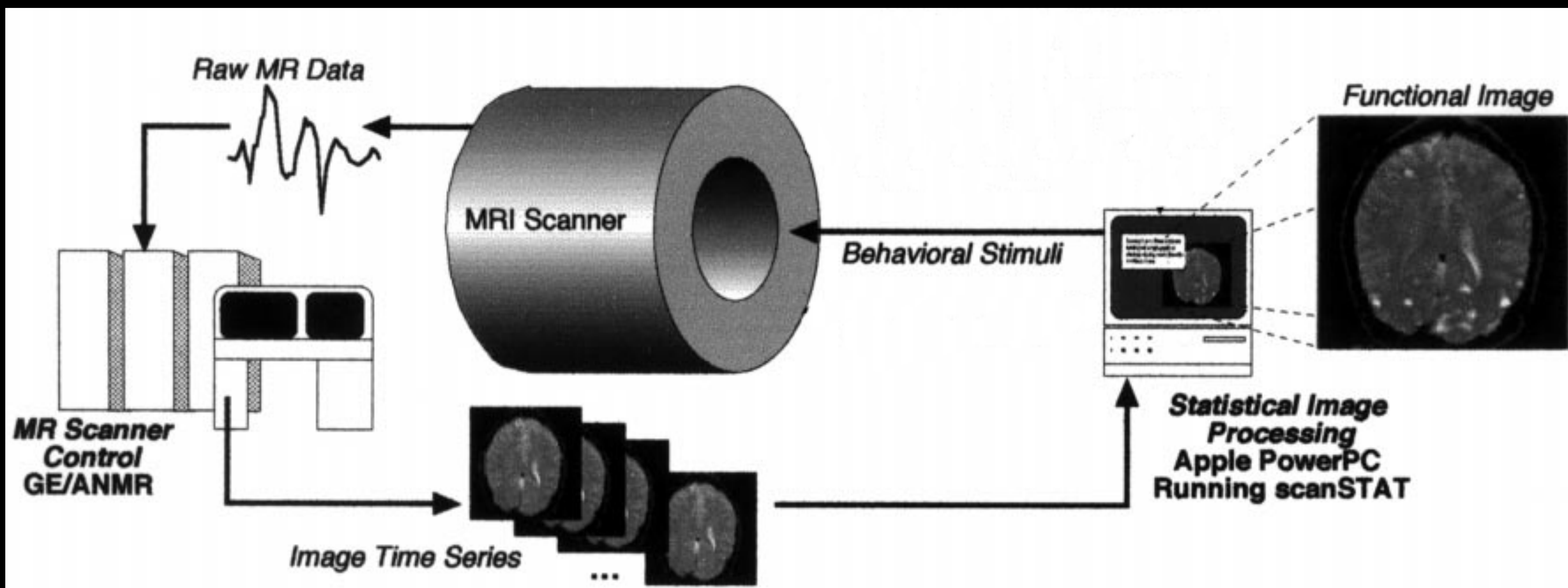
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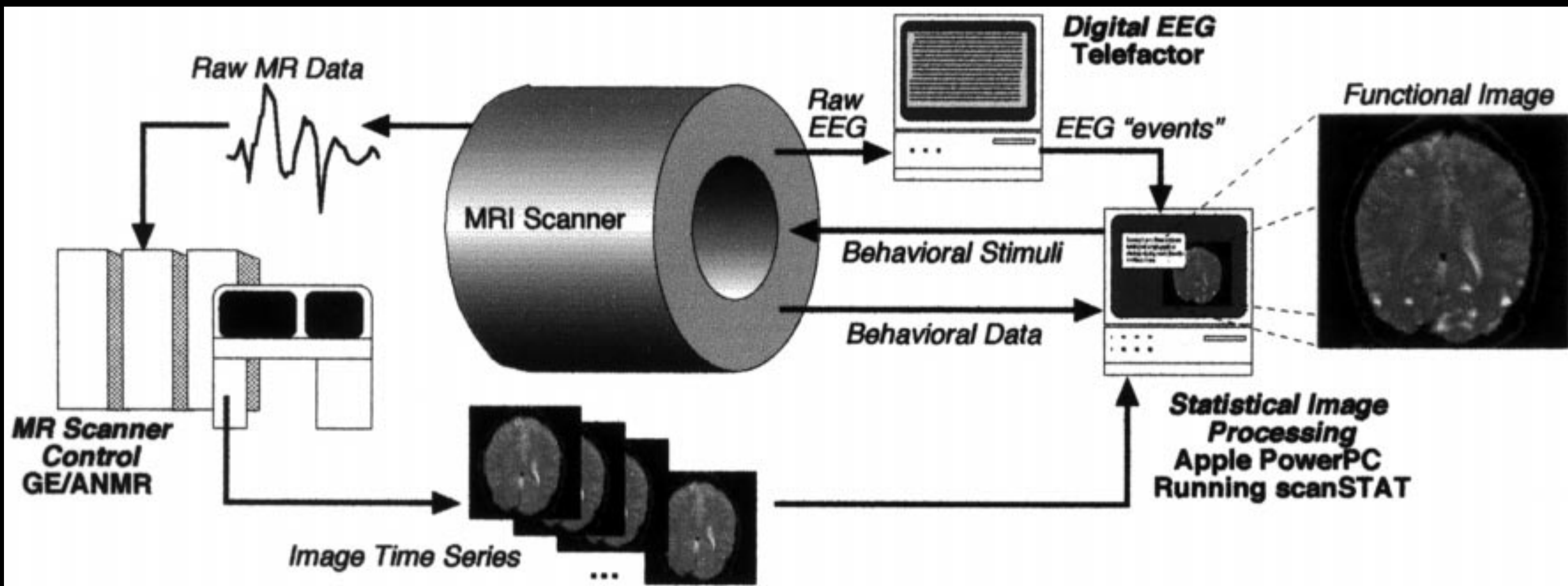
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Cohen, 2001

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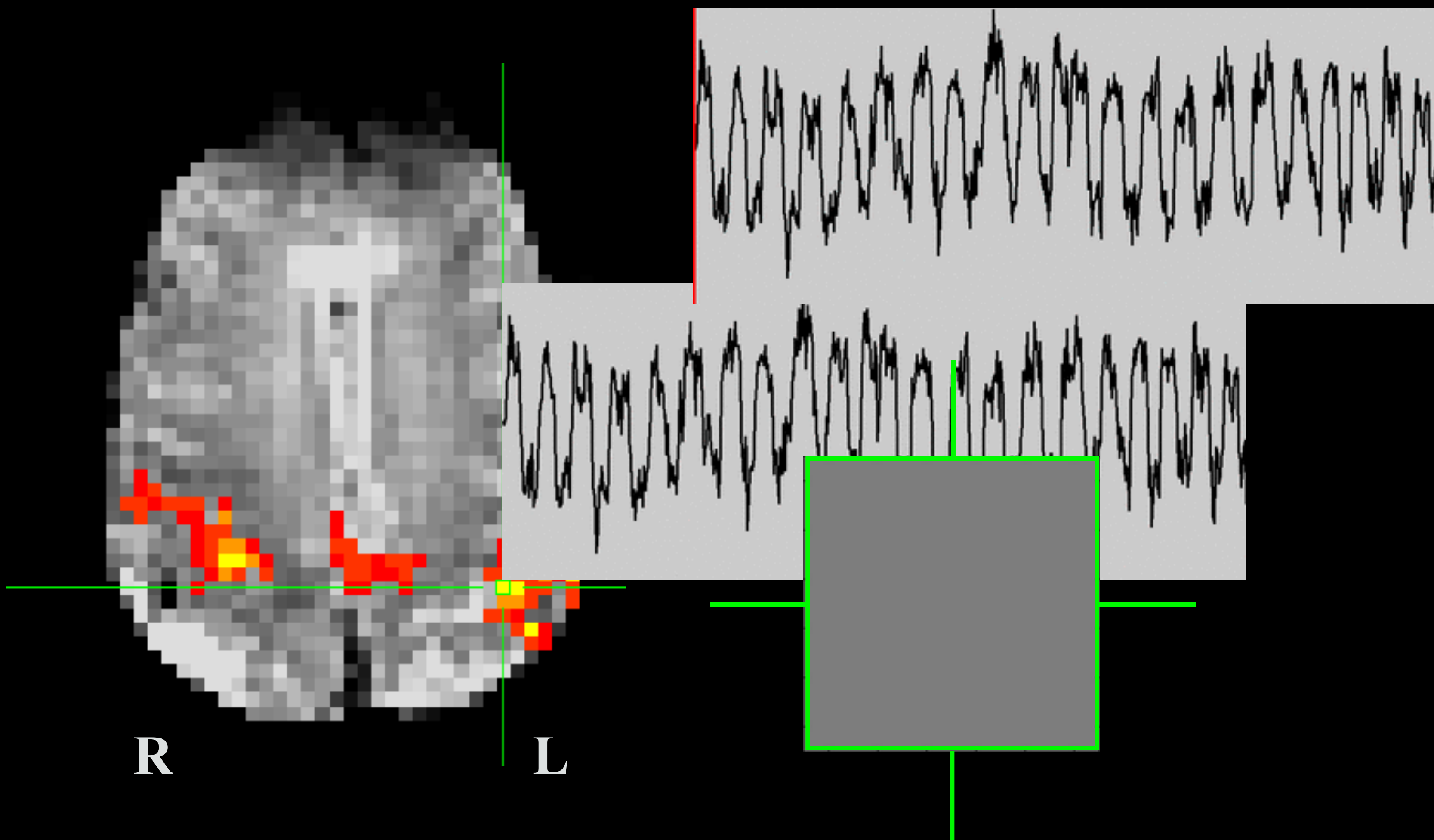
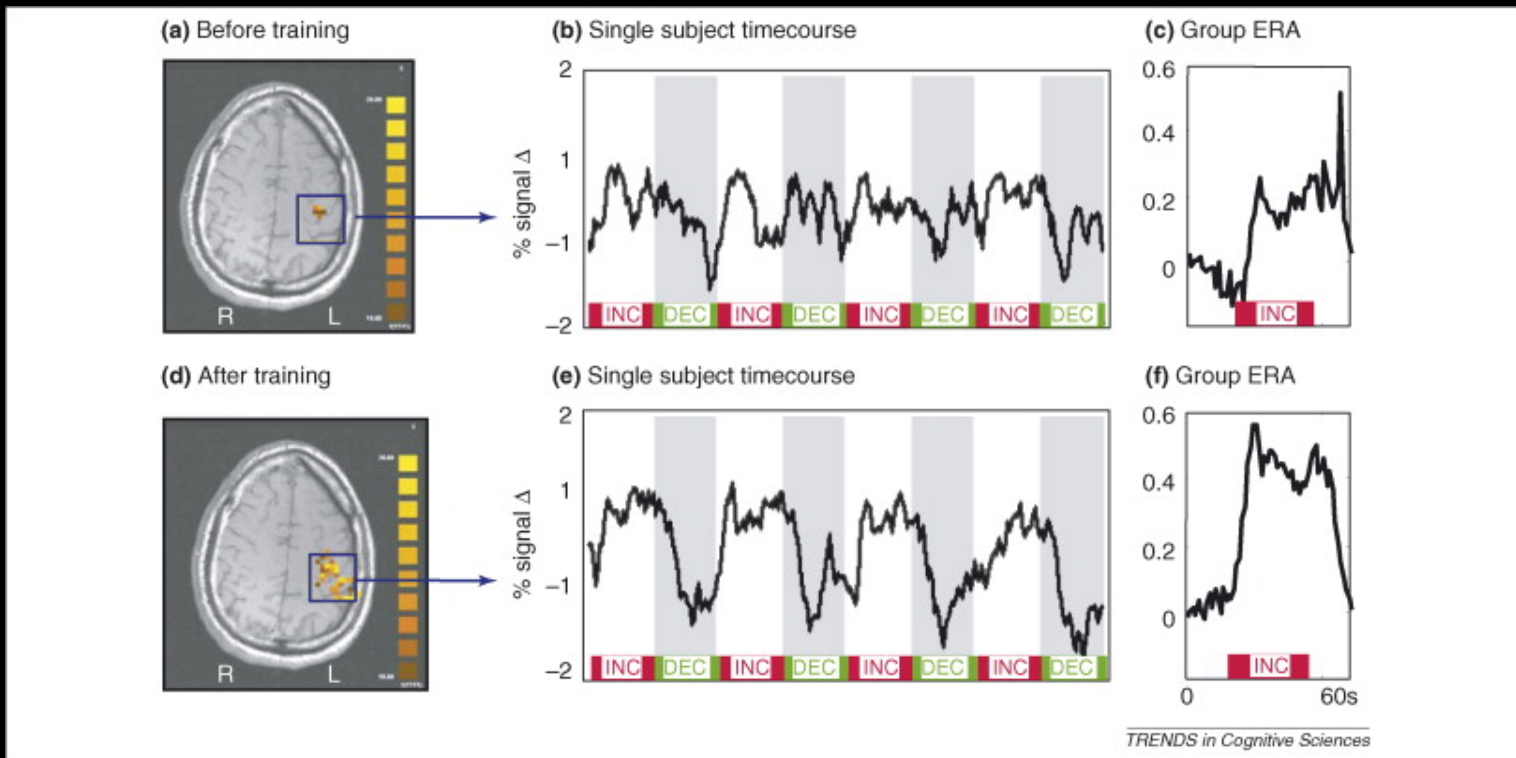
- Supervised learning-based rtfMRI
- Resources for getting started
- Technical challenges
- Applications

Localized fMRI signals



Example:
Increasing volitional control over somatomotor cortex



deCharms, R.C. (2004) NeuroImage, 21, 436-443

deCharms (2007) Trends Cogn. Sci., 11, 473-481

Subjects can learn to control a number of different brain areas

- Somatomotor cortex
  - Posse 2001, Yoo 2002, deCharms 2004, Yoo 2004
- Parahippocampal place area
  - Weiskopf 2004
- Amygdala
  - Posse 2003
- Insular cortex
  - Caria 2007
- Anterior cingulate cortex
  - Weiskopf 2003, Yoo 2004, Birbaumer 2007, deCharms 2005

Localized real-time fMRI

- Localized approaches have demonstrated a high degree of potential
- Activated areas are generally noisy
- Generating a map requires
  - Updating statistics at each pixel
  - Time window considerations
  - Interpretation of brain activation
- Tracking a region of interest requires
  - designation of that region
  - filtering and spatial averaging

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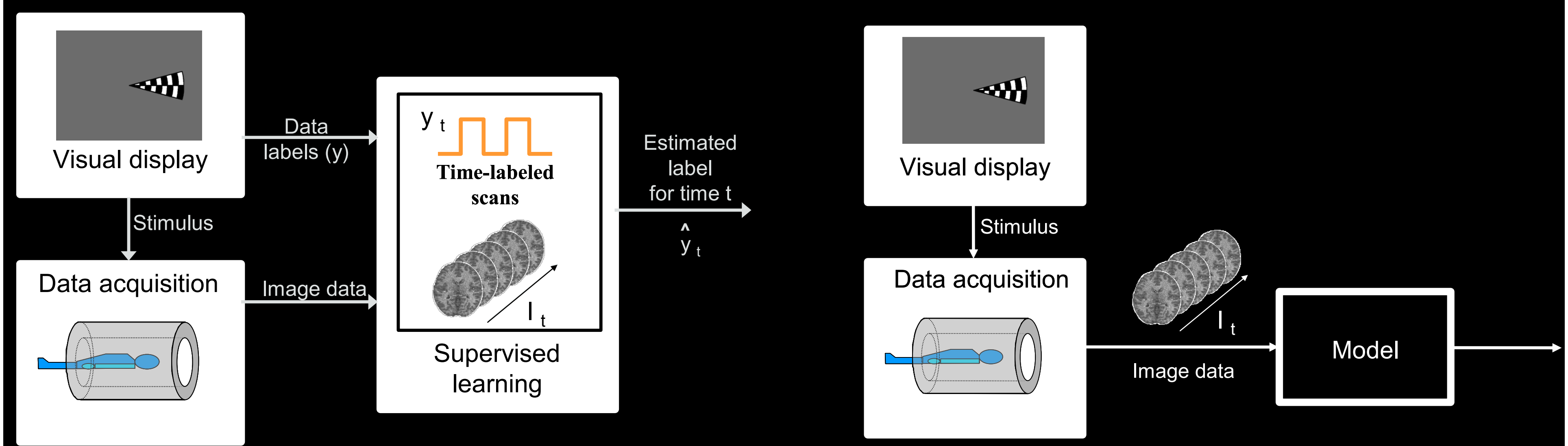
Supervised learning applied to fMRI

Step 1: Train with labeled data

Step 2: Use model to predict/decode



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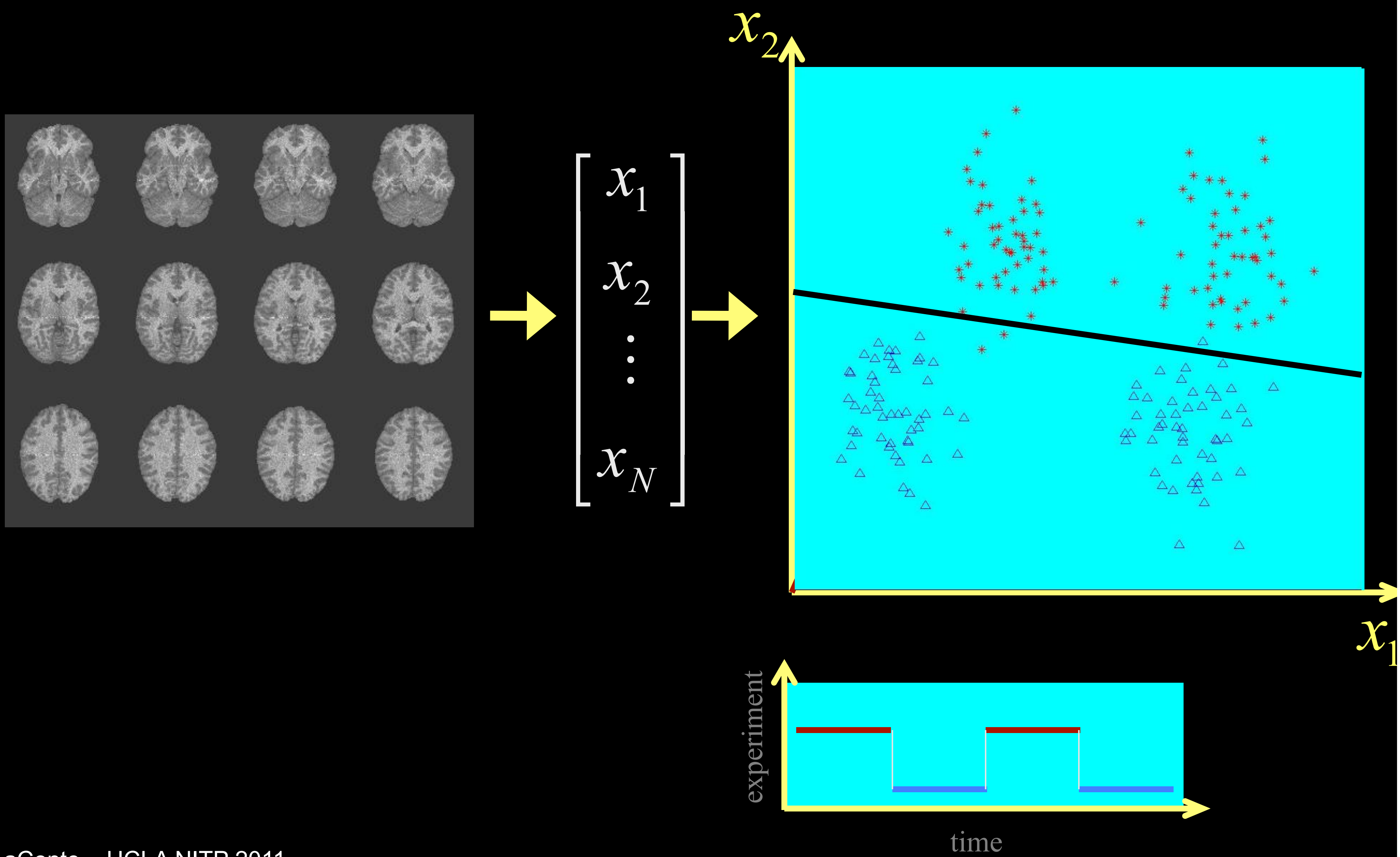
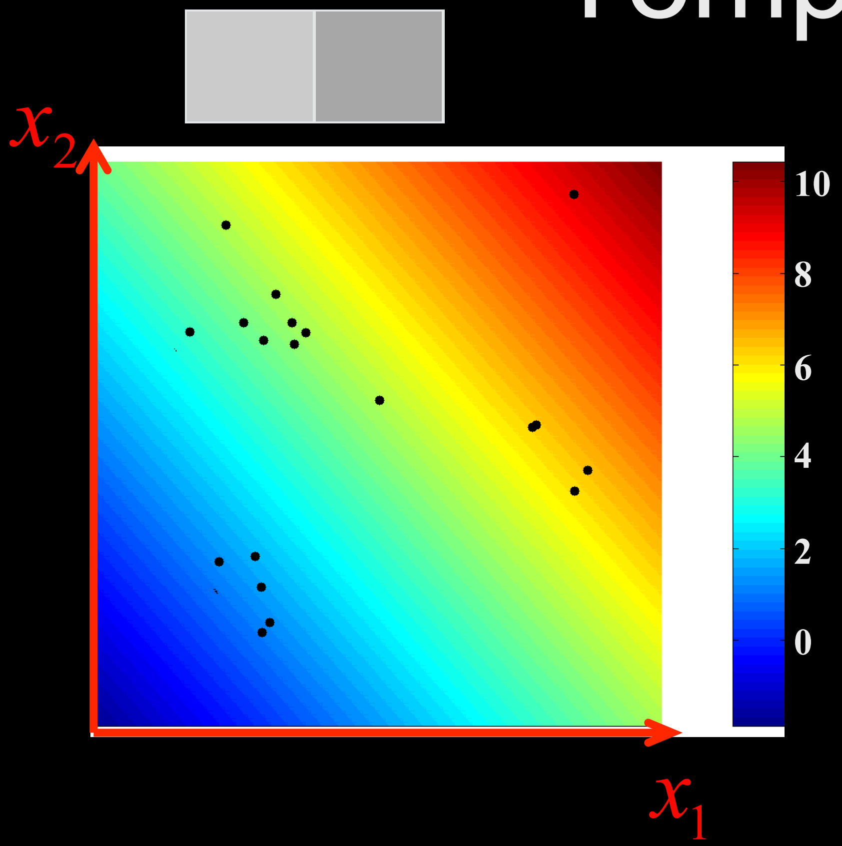
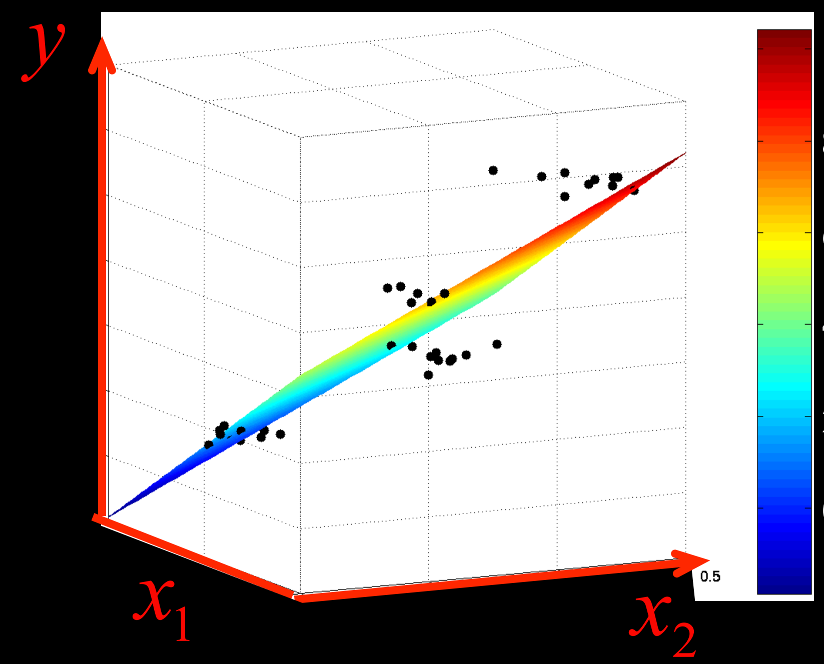
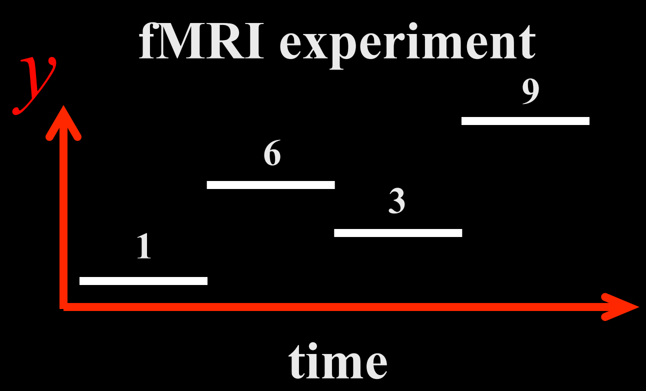
Temporal Brain State Classification



Temporal Regression



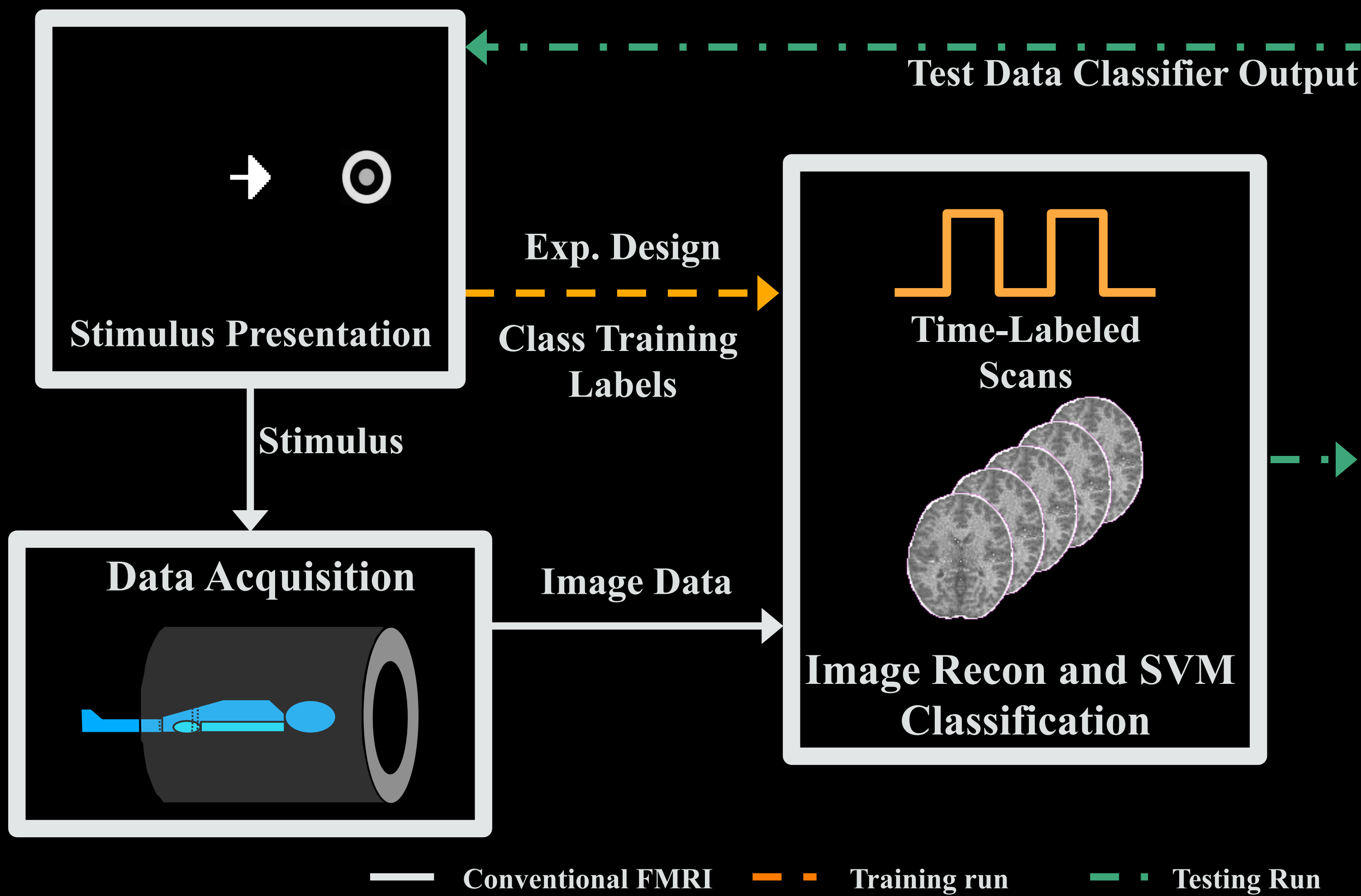




$$f(x) = x^T \beta + \beta_0$$

$$L(y, f(x))$$

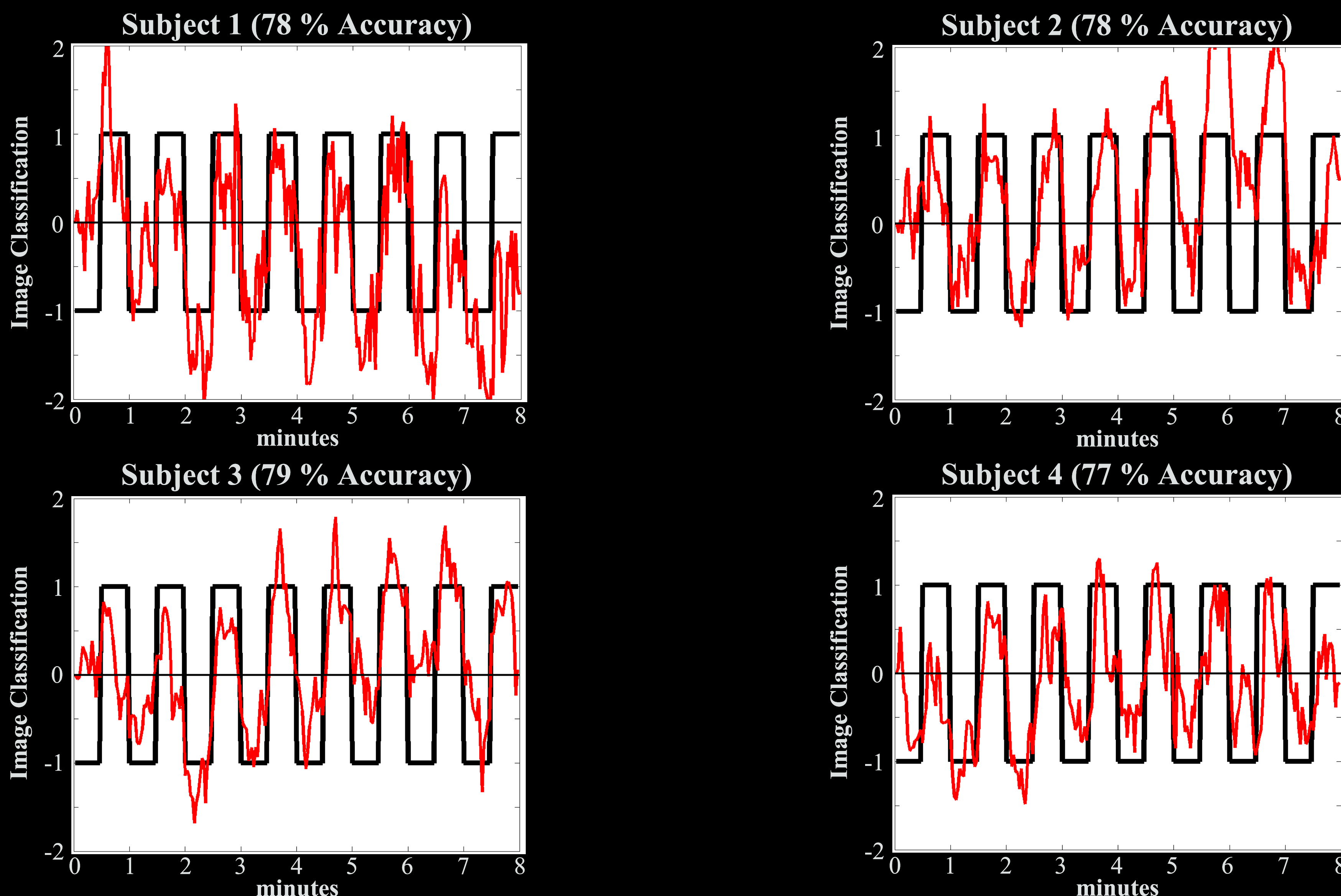
Real-Time Classification



LaConte, et al. (2007) Hum Brain Mapp. 28: 1033-1044

Experimental Timing and Classifier Output

(left finger = -1, right finger = +1)



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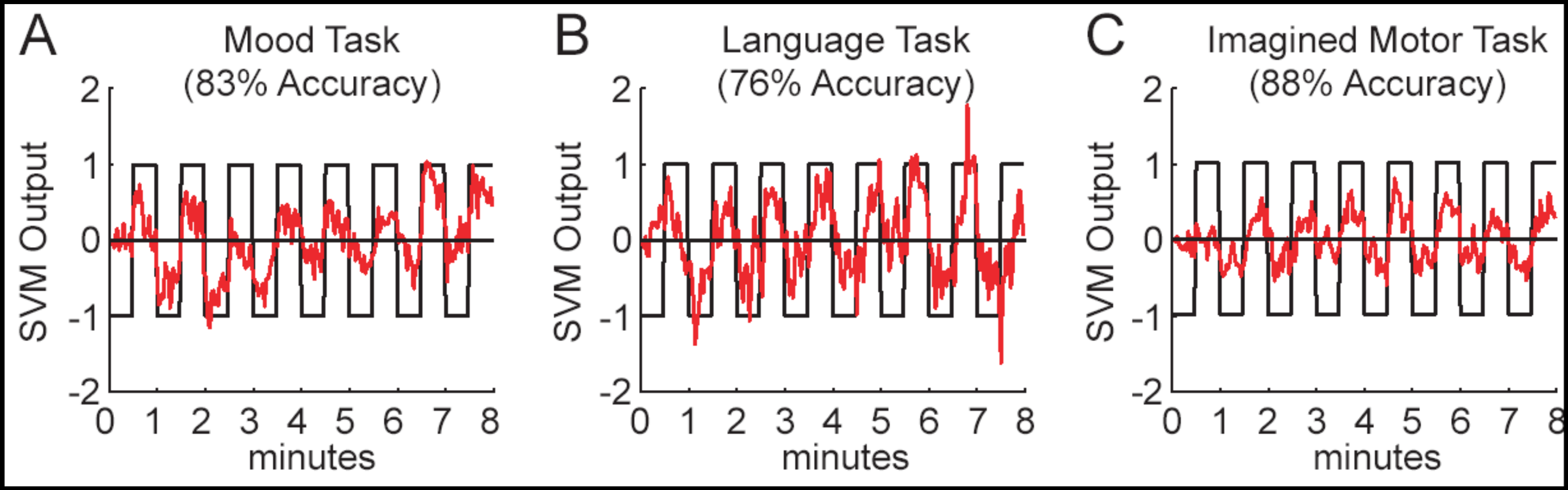
Brain state classification: a variety of cognitive domains.

With the exact same experimental setup (different instructions), subjects can learn to move the arrow



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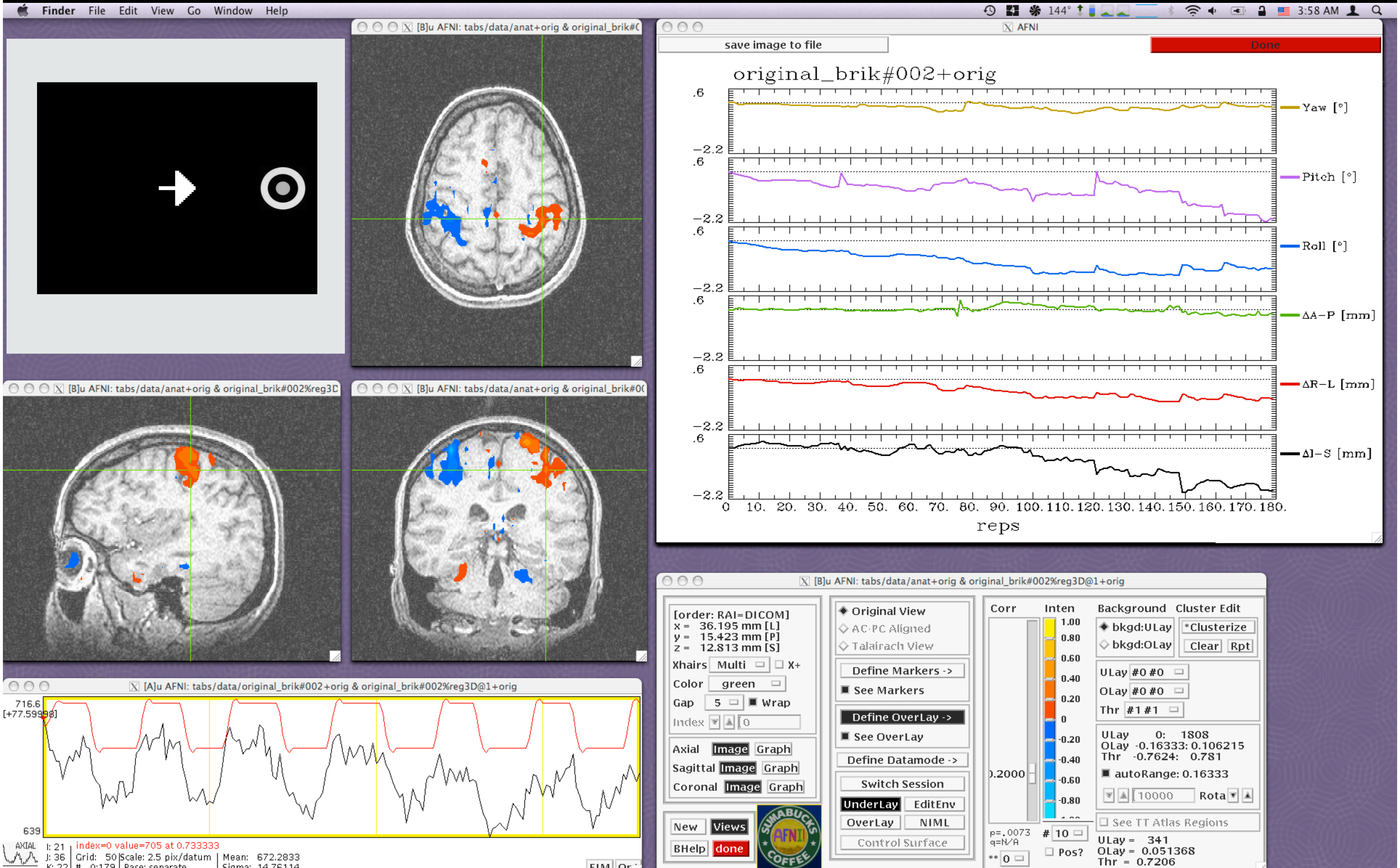
Stimulus seen by volunteer

Updated fMRI results

Motion tracking and correction



Intensity (brightness) of a single pixel, changing during stimulus conditions

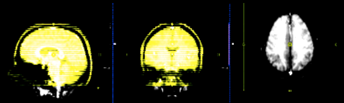
Controller interface for some display parameters

LaConte – UCLA NITP 2011

demonstration experiment

Initial scans

- **Localizer** (9 seconds)
  Acquires images in three planes that enable the operator to locate images during the rest of the session.

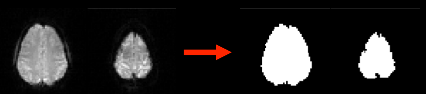


- **Anatomical scan** (4.5 minutes)
  High resolution (1 mm^3)

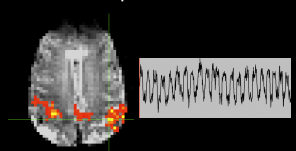
fMRI runs: low resolution 3D movies

- **Masking run** (10 seconds)
  A few frames are used that match the resolution of the fMRI runs.

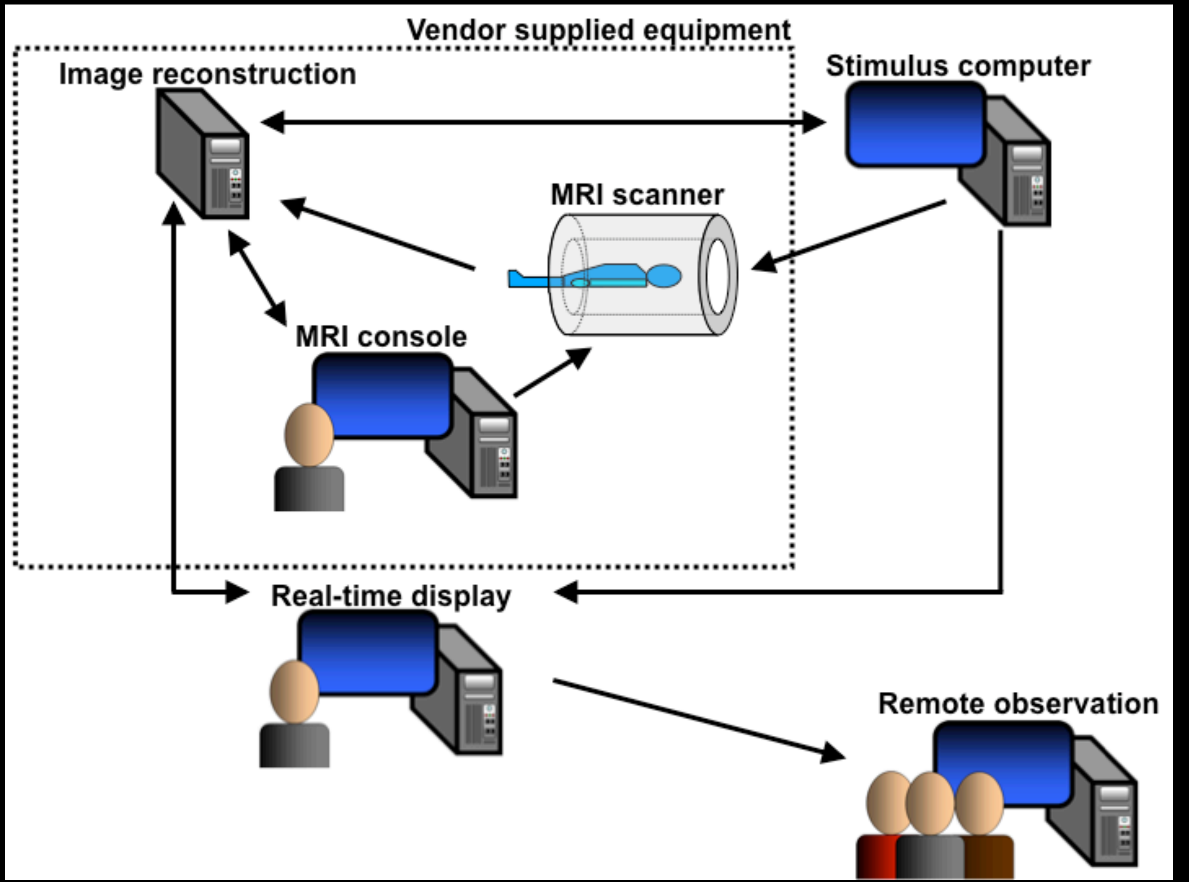
  Image processing is performed to detect ("mask out") brain regions from regions outside the brain. This point in the experiment could also be used to focus the rest of the experiment on a specific anatomical site.



- **Training run** (6 minutes)
  As fMRI brain volumes are being acquired, machine learning algorithms are processing the images and the stimuli/behavior to create a predictive model.



- **Feedback run** (6 minutes)
  Uses the training run model. Specifically, the model is applied to each image as it is acquired, allowing prediction of psychological state. In other words, the model is used to decode the stimulus/behavioral conditions that are associated with the current image. The output of the model is converted into a control signal that can modify the stimulus being presented to the volunteer.

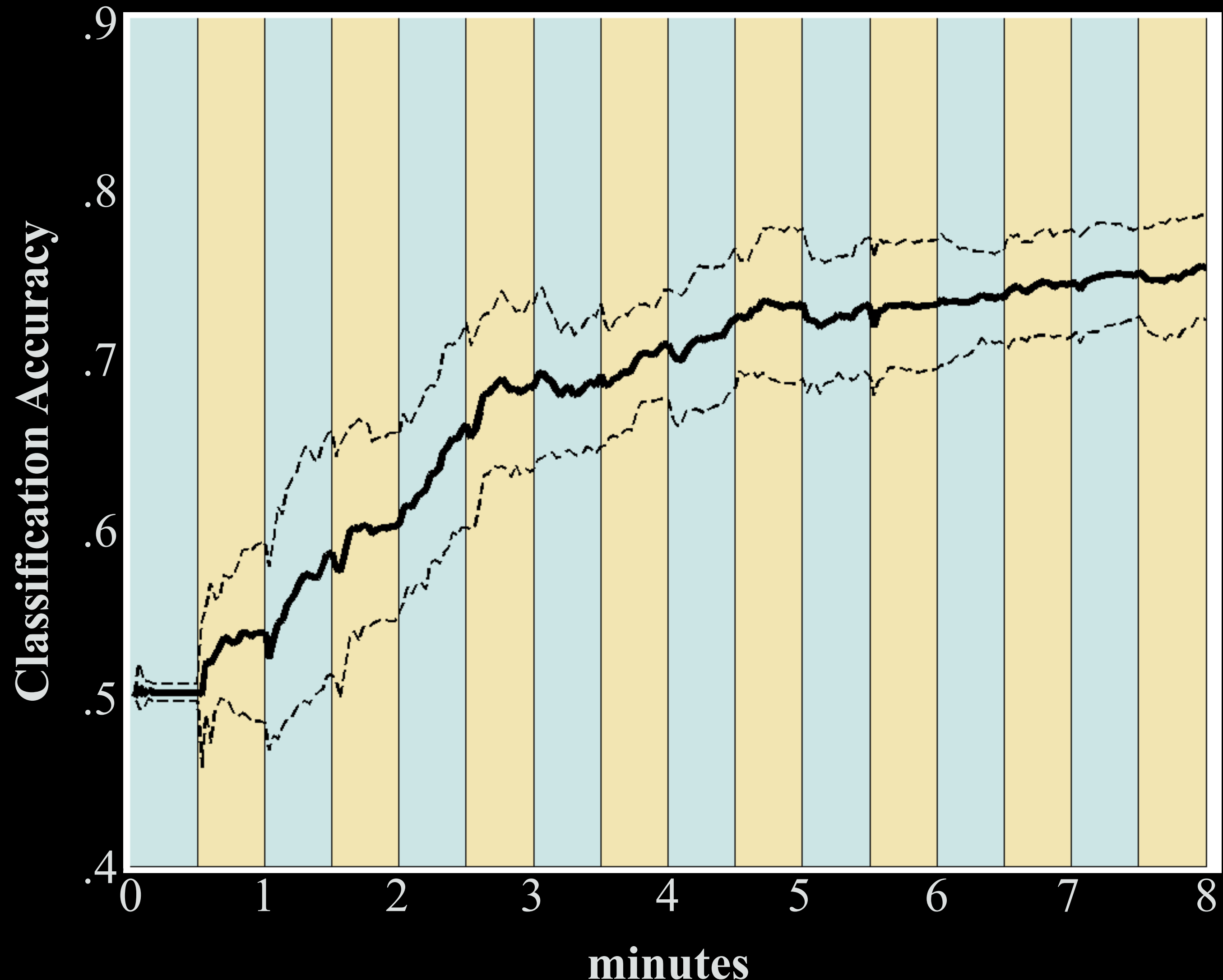


LaConte, *NeuroImage* (2011)

Basic Benchmarks

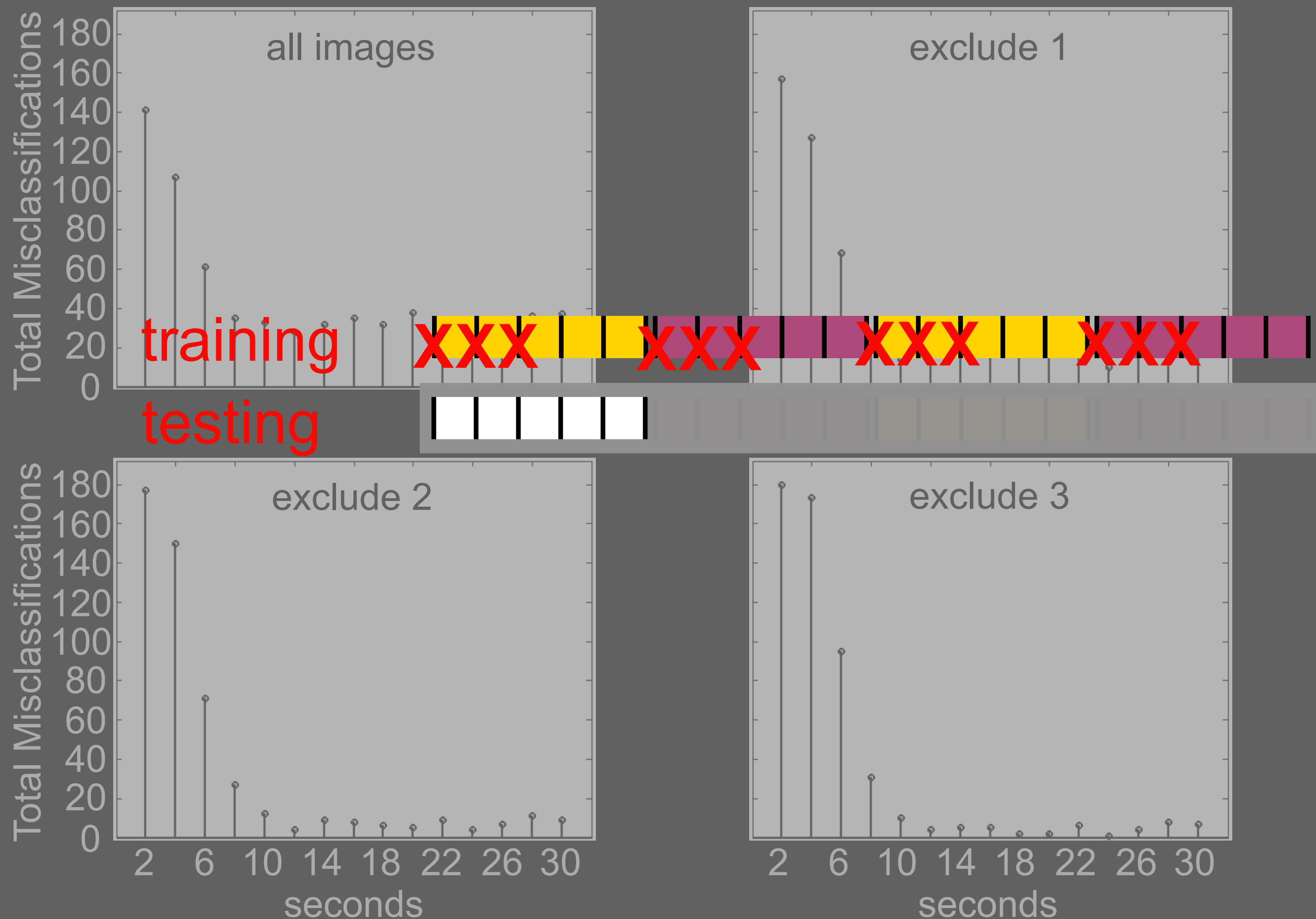
- Classifier safety factor > 20,000x.
  - Approximately 1μsec / dot product.
- Network/AFNI Transfers > 20x volumes
  - Approximately 100 μsec / slice to transfer

Average Learning Curve (+/- Standard Deviation) Subject 1



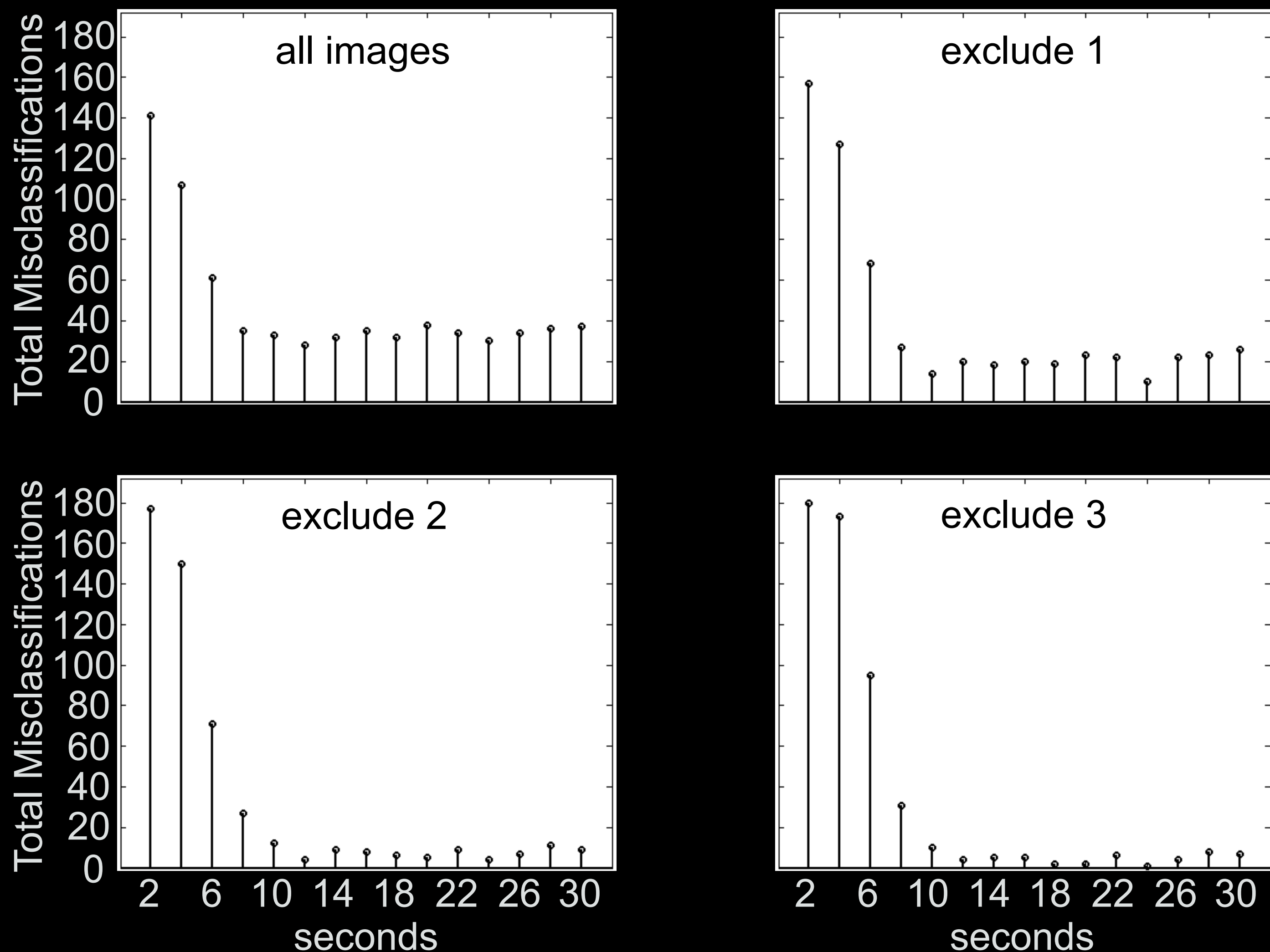
LaConte, et al. (2007) Hum Brain Mapp. 28: 1033-1044

Effect of training with task transition images



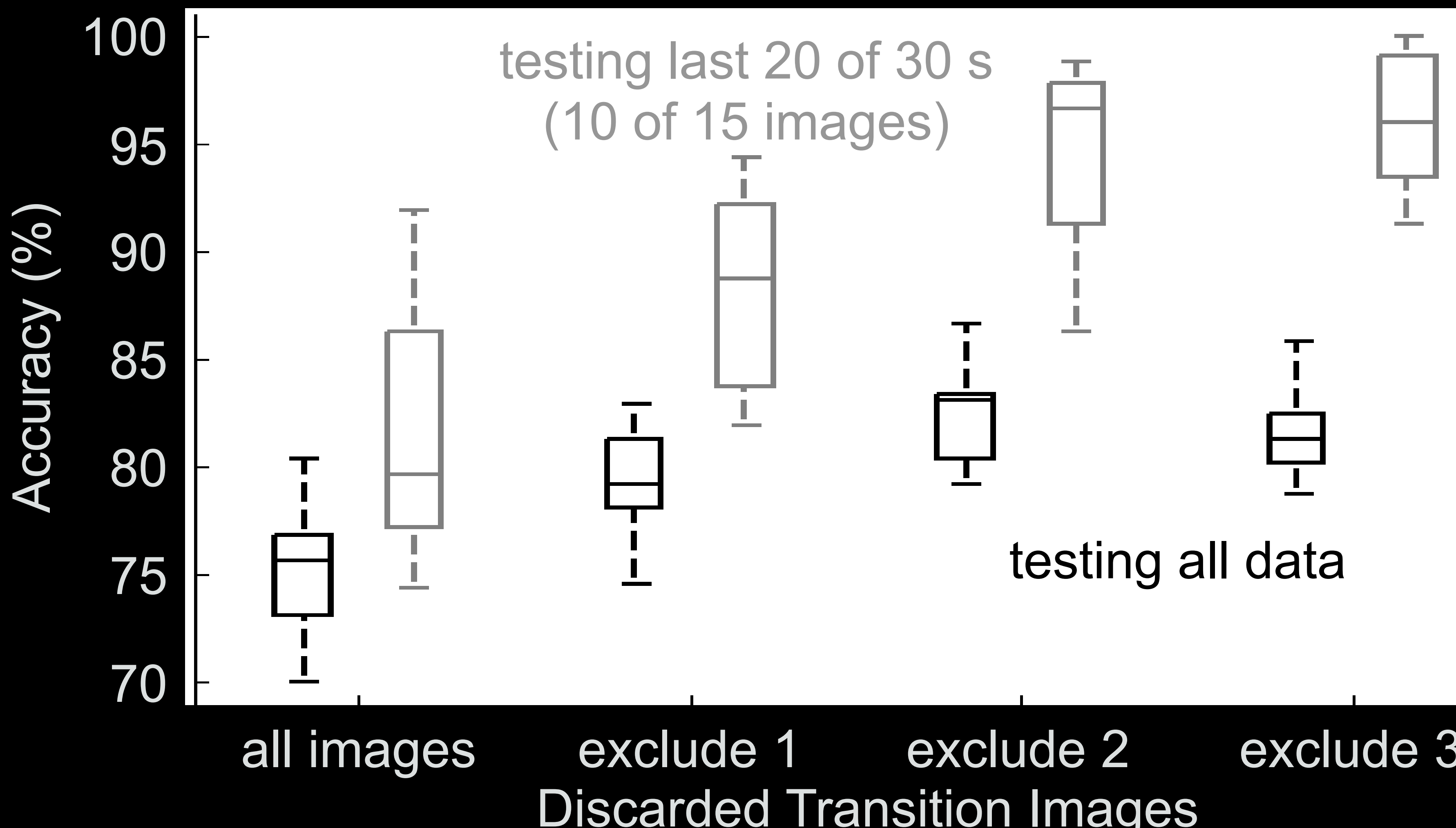
LaConte, et al. (2007) Hum Brain Mapp. 28: 1033-1044

Effect of training with task transition images



LaConte, et al. (2007) Hum Brain Mapp. 28: 1033-1044

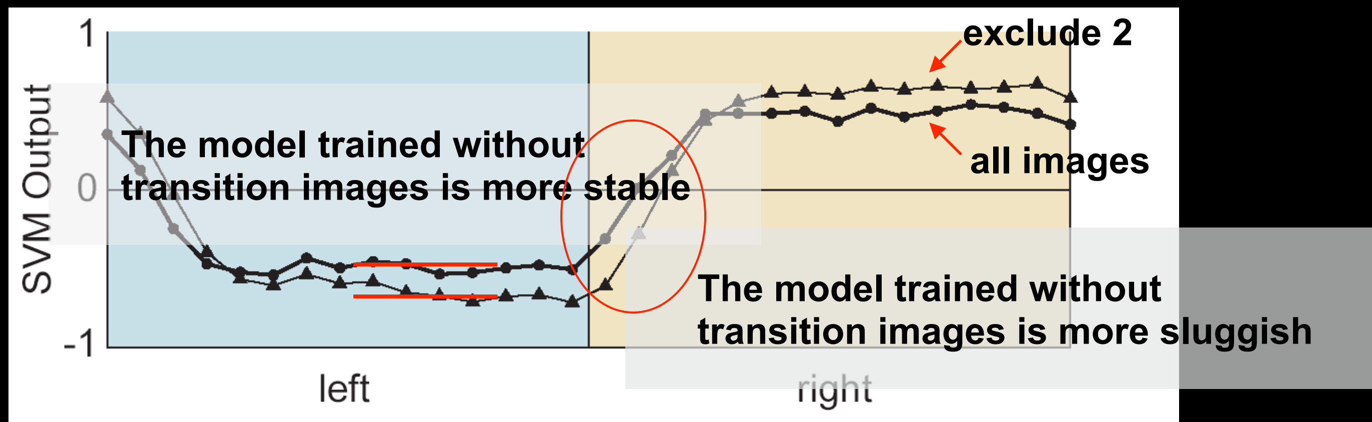
Effect of training with task transition images



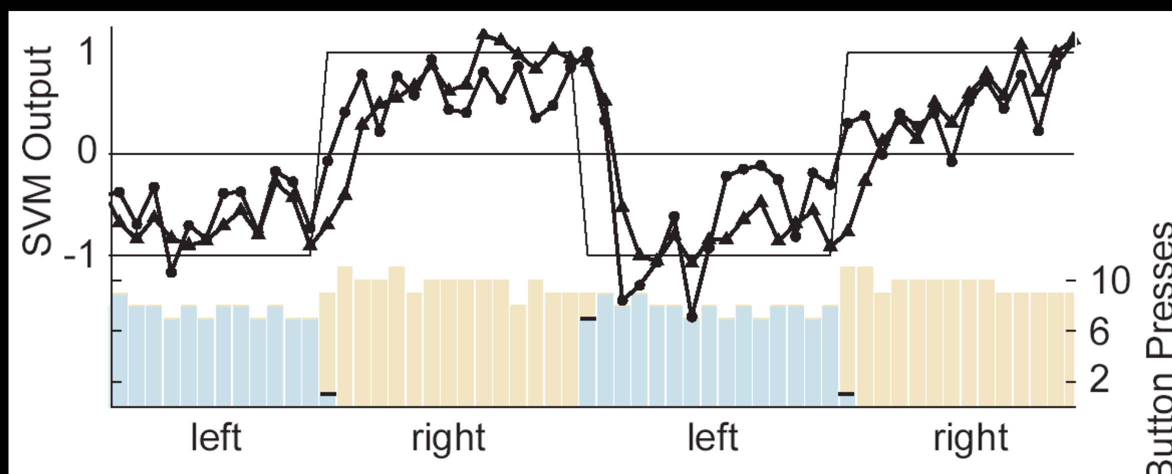
LaConte, et al. (2007) Hum Brain Mapp. 28: 1033-1044

Responsiveness to stimulus changes

Average classifier output

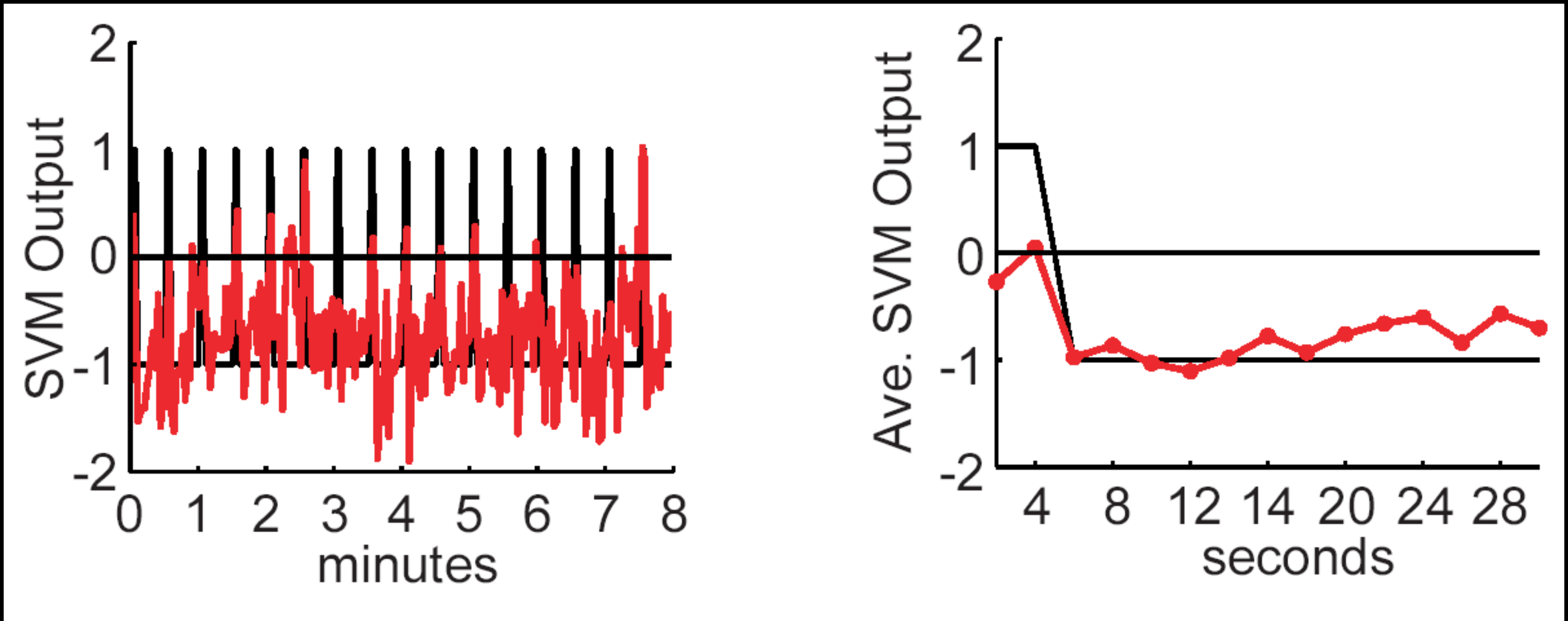


Individual classifier output with behavioral data



LaConte, et al. (2007) Hum Brain Mapp. 28: 1033-1044

Classification of "transition" images



LaConte, et al. (2007) Hum Brain Mapp. 28: 1033-1044

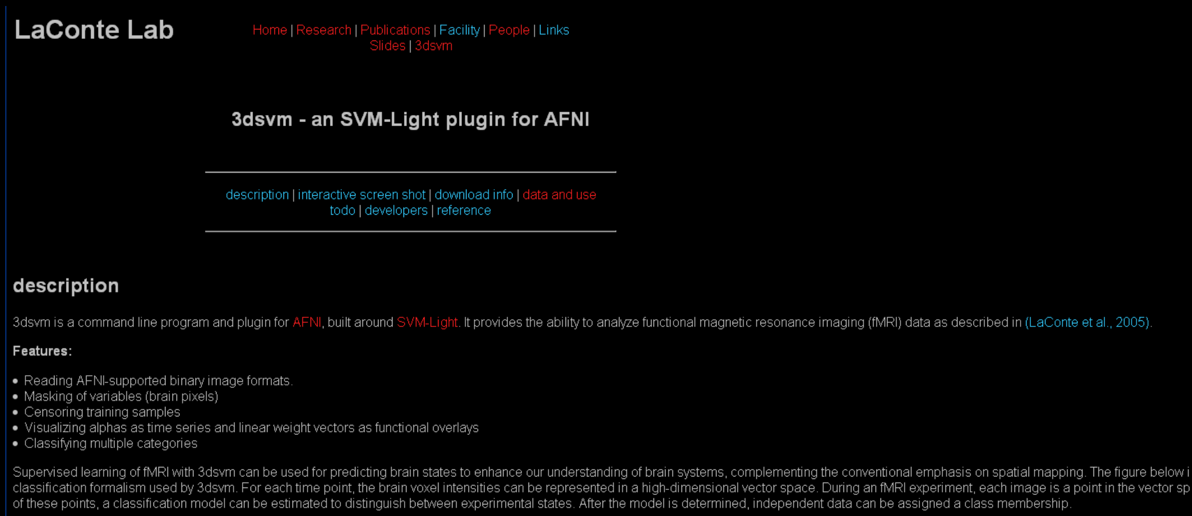
Outline

- Overview of rtfMRI
- Tracking localized brain regions
- Supervised learning-based rtfMRI
- Resources for getting started
- Technical challenges
- Applications

Resources

- Review Articles
  - LaConte, *NeuroImage* (2011)
  - deCharms, *Trends Cogn Sci* (2007)
  - deCharms, *Nat Rev Neurosci* (2008)
  - Weiskopf, *IEEE Trans Biomed Eng* (2004)
  - Weiskopf, *Magn Resn Imaging* (2007)
- Software
  - TurboFire (Gebris et al. 2000)
  - Turbo-Brain Voyager (Goebel, 2001)
  - AFNI (Cox, 1996)

3dsvm


LaConte Lab

Home | Research | Publications | Facility | People | Links
Slides | 3dsvm

3dsvm - an SVM-Light plugin for AFNI

description | interactive screen shot | download info | data and use
todo | developers | reference

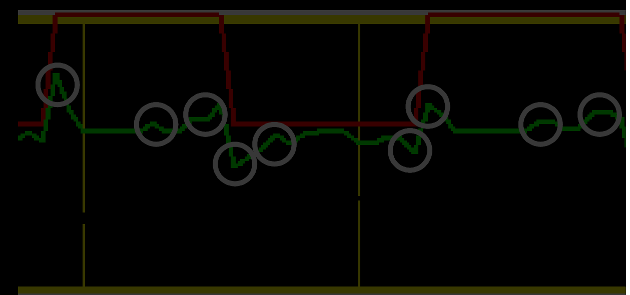
description

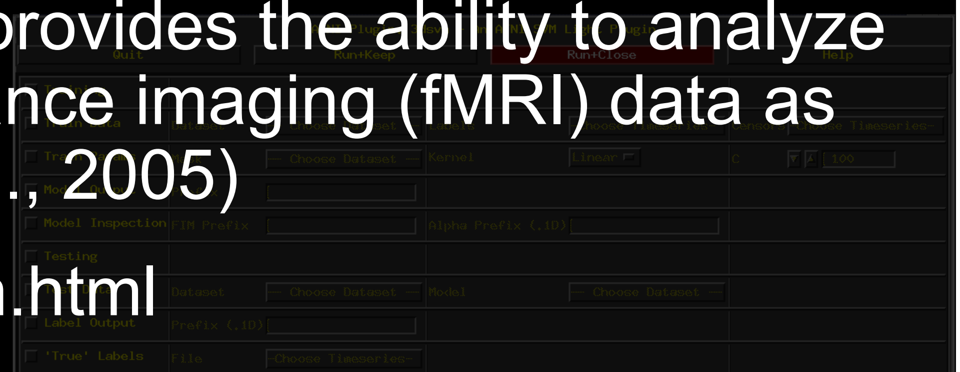
3dsvm is a command line program and plugin for AFNI, built around SVM-Light. It provides the ability to analyze functional magnetic resonance imaging (fMRI) data as described in (LaConte et al., 2005).

Features:

- Reading AFNI-supported binary image formats.
- Masking of variables (brain pixels)
- Censoring training samples
- Visualizing alphas as time series and linear weight vectors as functional overlays
- Classifying multiple categories

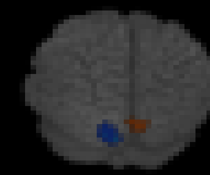
Supervised learning of fMRI with 3dsvm can be used for predicting brain states to enhance our understanding of brain systems, complementing the conventional emphasis on spatial mapping. The figure below i classification formalism used by 3dsvm. For each time point, the brain voxel intensities can be represented in a high-dimensional vector space. During an fMRI experiment, each image is a point in the vector sp of these points, a classification model can be estimated to distinguish between experimental states. After the model is determined, independent data can be assigned a class membership.



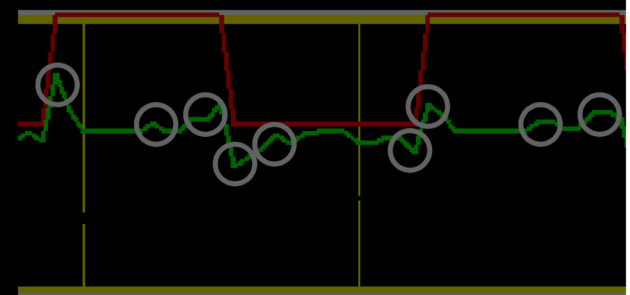


- 3dsvm is a command line program and plugin for AFNI, built around SVM-Light. It provides the ability to analyze functional magnetic resonance imaging (fMRI) data as described in (LaConte et al., 2005)
- http://lacontelab.org/3dsvm.html

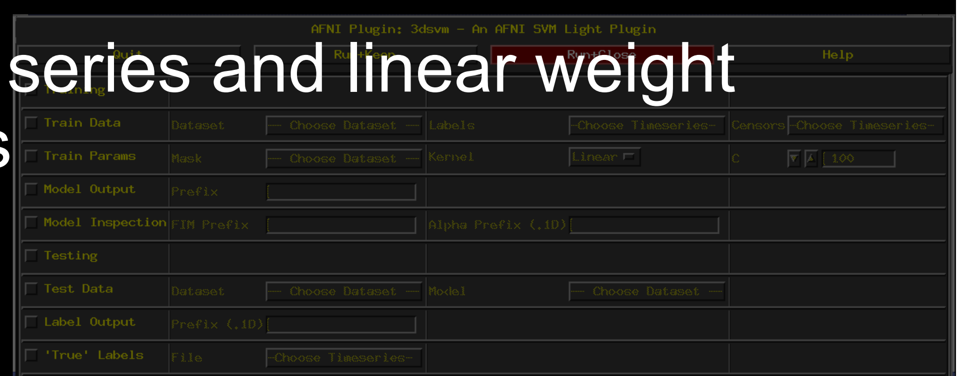
3dsvm features



- Distributed with AFNI
- Reading AFNI-supported formats (including NIfTI)
  - Thus all preprocessing and data manipulation of the major software packages



- Classification and regression
- Masking of variables (brain pixels)
- Censoring training samples



- Visualizing alphas as time series and linear weight vectors as functional maps
- Multi-class classification
- Non-linear kernels
- Real-time fMRI

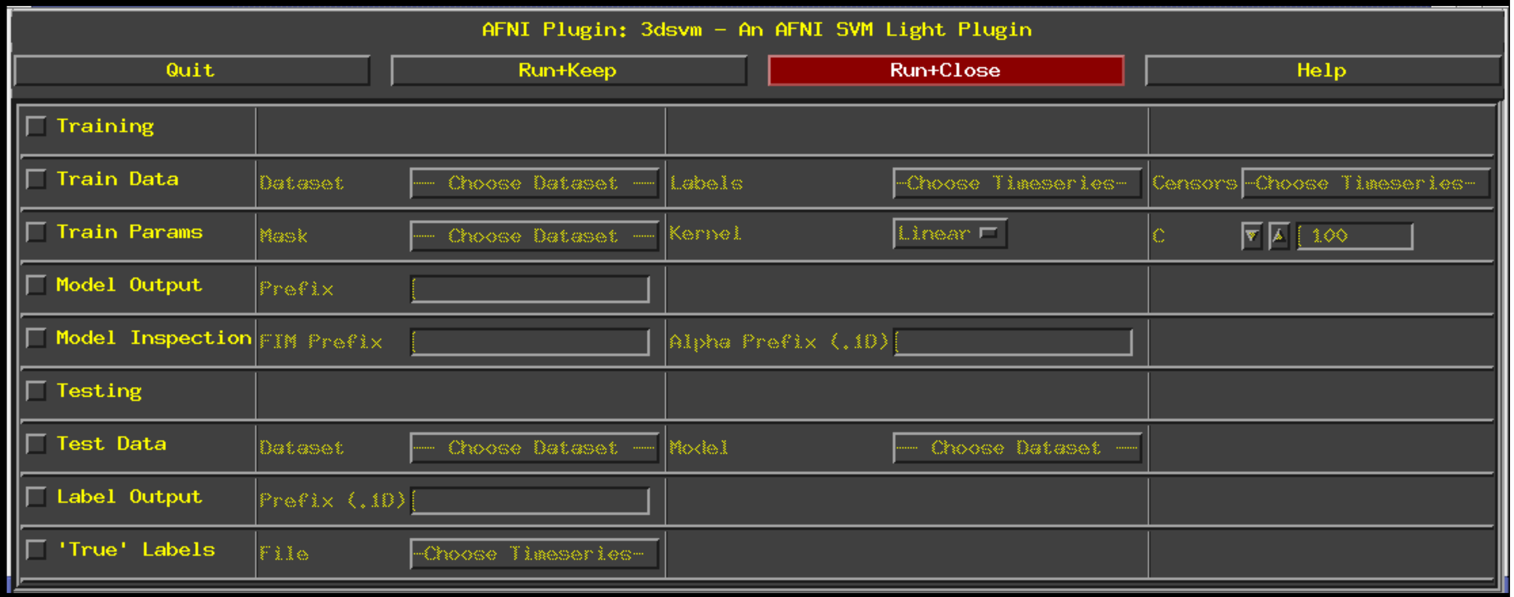
3dsvm tour: basic steps

- Prepare training and test data sets
  - fMRI (3D+t)
  - Labels (1D) – labels for test data are optional (needed to to calculate accuracy)
  - Mask for training data (3D) – 3dsvm considers mask to be part of the model it generates
- 3dsvm training
  - Creates a model that can be tested with independent data
  - For convenience, inspecting the model
    - Model alphas (1D)
    - Weight vector map (3D)
- 3dsvm testing
  - Calculates class and/or distance measure for each new timepoint
  - Prediction accuracy (if test set labels are available)

3dsvm tour: plugin snapshot

training

testing



3dsvm tour: command line

```
Training -  3dsvm  -trainvol run1+orig \
                   -trainlabels run1_categories.1D \
                   -mask mask+orig \
                   -model model_run1
```

```
Testing -   3dsvm  -testvol run2+orig \
                   -model model_run1+orig \
                   -predictions pred2_model1
```

```
#!/bin/csh
# example by Prashant Prasad

3dsvm -trainvol volreg_run1_PPA+orig \
          -trainlabels LABEL_PPA_1.1D \
          -mask automask_run1_PPA+orig \
          -bucket bucket_run1_PPA \
          -model model_run1_PPA

3dsvm -classout \
           -testvol volreg_run2_PPA+orig \
           -testlabels LABEL_PPA_2.1D \
           -model model_run1_PPA+orig \
           -predictions pred_run2_frmRun1_classout

3dsvm -testvol volreg_run2_PPA+orig \
          -testlabels LABEL_PPA_2.1D \
          -model model_run1_PPA+orig \
          -predictions pred_run2_frmRun1

# optional, move bucket files to Tailarach
# @auto_tlrc -base TT_N27+tlrc -input anatomical_PPA+orig
# @auto_tlrc -apar anatomical_PPA_at+tlrc –input bucket_run1_PPA_0_1+orig -dxyz 4
# @auto_tlrc -apar anatomical_PPA_at+tlrc -input bucket_run1_PPA_0_2+orig -dxyz 4
# @auto_tlrc -apar anatomical_PPA_at+tlrc -input bucket_run1_PPA_1_2+orig -dxyz 4
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        -model model_run1_PPA

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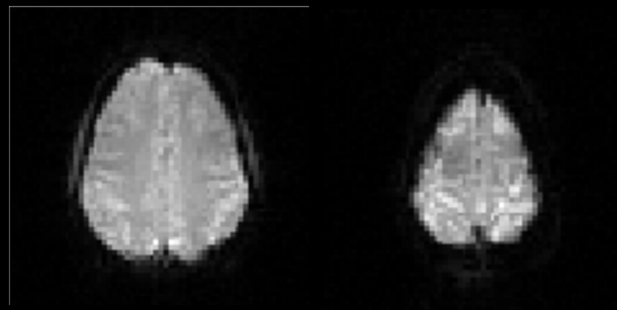

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         -testlabels LABEL_PPA_2.1D \
         -model model_run1_PPA+orig \
         -predictions pred_run2_frmRun1_classout

3dsvm -testvol volreg_run2_PPA+orig \
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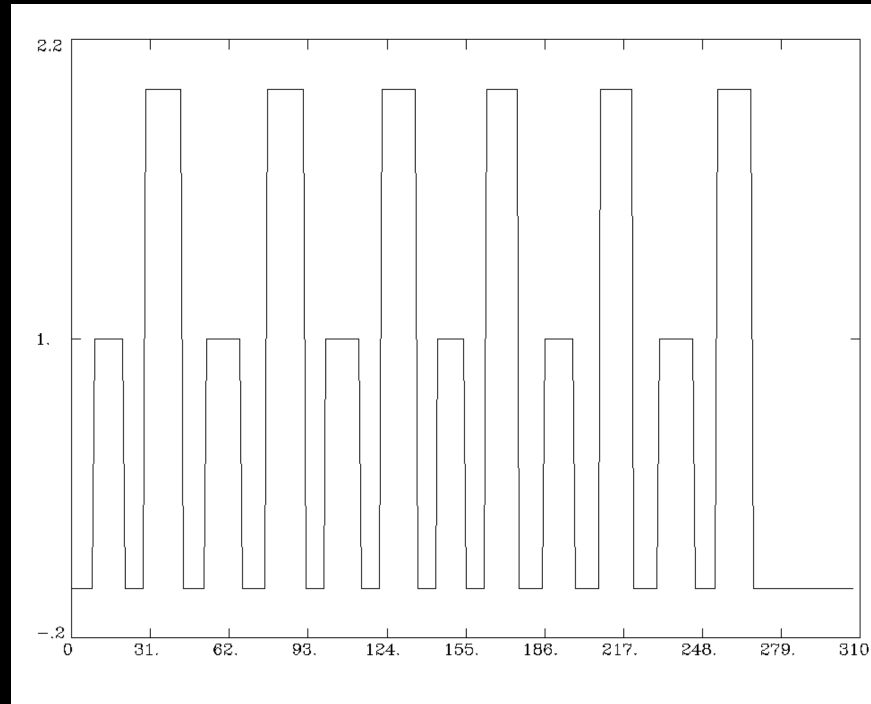


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        -bucket bucket_run1_PPA \
        -model model_run1_PPA

3dsvm -classout \
         -testvol volreg_run2_PPA+orig \
         -testlabels LABEL_PPA_2.1D \
         -model model_run1_PPA+orig \
         -predictions pred_run2_frmRun1_classout

3dsvm -testvol volreg_run2_PPA+orig \
        -testlabels LABEL_PPA_2.1D \
        -model model_run1_PPA+orig \
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3dsvm -testvol volreg_run2_PPA+orig \
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# @auto_tlrc -apar anatomical_PPA_at+tlrc -input bucket_run1_PPA_0_2+orig -dxyz 4
# @auto_tlrc -apar anatomical_PPA_at+tlrc -input bucket_run1_PPA_1_2+orig -dxyz 4
```

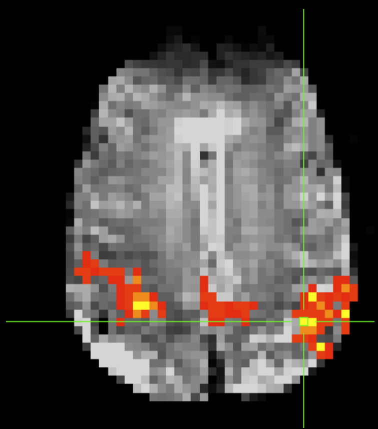

```
#!/bin/csh
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        -trainlabels LABEL_PPA_1.1D \
        -mask automask_run1_PPA+orig \
        -bucket bucket_run1_PPA \
        -model model_run1_PPA

3
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[slaconte@awesomo.hnl.bcm.edu: Fri Jul 17 04:36:16 2009] 3dsvm -trainvol volreg_run1_PPA+orig -trainlabels LABEL_PPA_1.1D -mask automask_run1_PPA+orig -bucket bucket_run1_PPA -model model_run1_PPA~

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# @auto_tlrc -apar anatomical_PPA_at+tlrc –input bucket_run1_PPA_0_1+orig -dxyz 4
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# @auto_tlrc -apar anatomical_PPA_at+tlrc -input bucket_run1_PPA_1_2+orig -dxyz 4
```
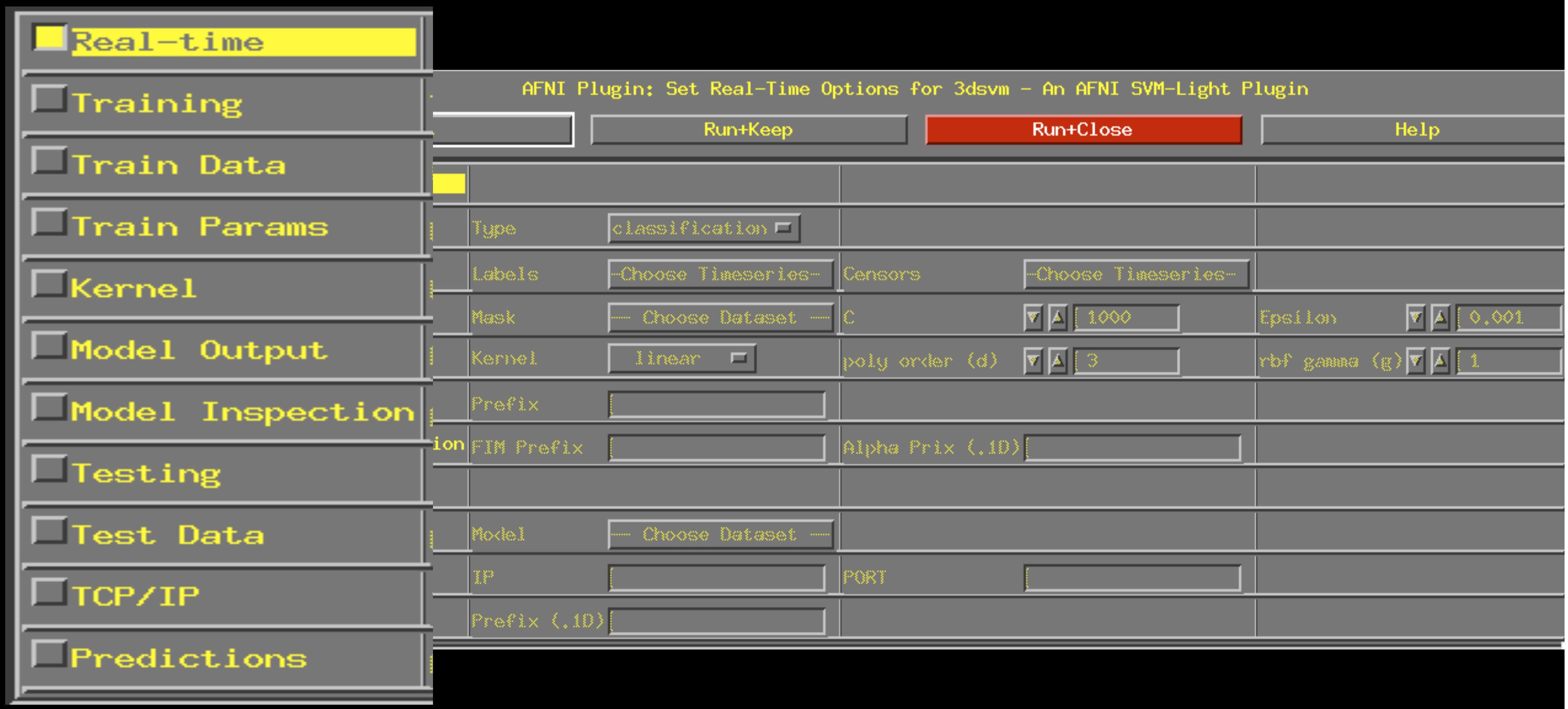

3dsvm Plugin Screenshot
Support Vector Machine Analysis



3dsvm real-time

plugout_drive –com “3DSVM –rt_train -trainlabels run1_categories.1D -mask mask+orig -model model_run1

plugout_drive -com "3DSVM -rt_test -rt_ip 10.10.10.2 -rt_port 5000 –model model_run1+orig -predictions pred_run2"

Outline

- Overview of rtfMRI
- Tracking localized brain regions
- Supervised learning-based rtfMRI
- Resources for getting started
- Technical challenges
- Applications

Future Challenges

(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
- Model updates during real-time feedback
- Detecting and correcting temporal non-stationarity
- Feedback and feedback interfaces

Future Challenges

(LaConte, NeuroImage, 2011)

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Spatial transformation of support vector machine models for multi-session and group real-time fMRI

- capability of multi-session and group-based SVM models
  - handling movement between runs within a session
  - progressive training and testing across sessions
  - using group models to affect rehabilitation/therapy

Future Challenges

(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
- Model updates during real-time feedback
- Detecting and correcting temporal non-stationarity
- Feedback and feedback interfaces

Spatial transformation of support vector machine models for multi-session and group real-time fMRI

- requires that the SVM model and the test data be spatially aligned
- investigate alignment strategies
  - classification accuracy
  - computational demands

Future Challenges

(LaConte, NeuroImage, 2011)

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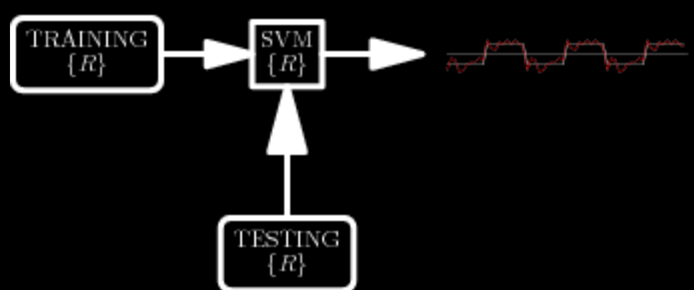
Spatial transformation of support vector machine models for multi-session and group real-time fMRI



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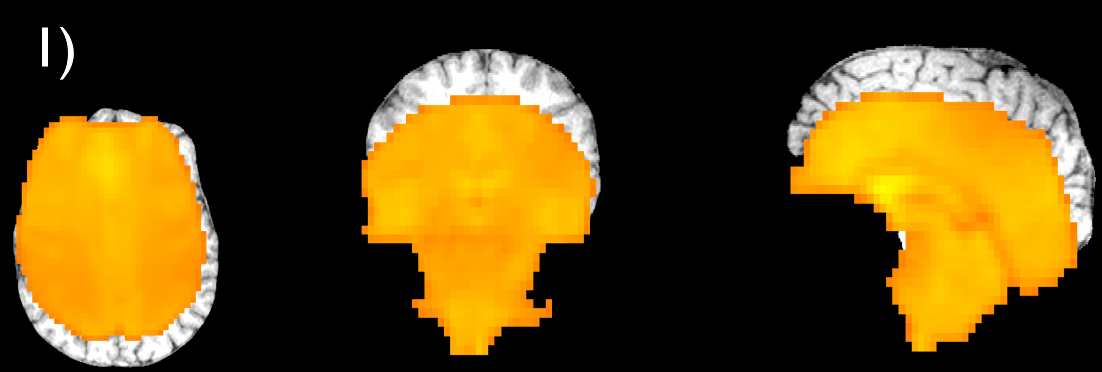
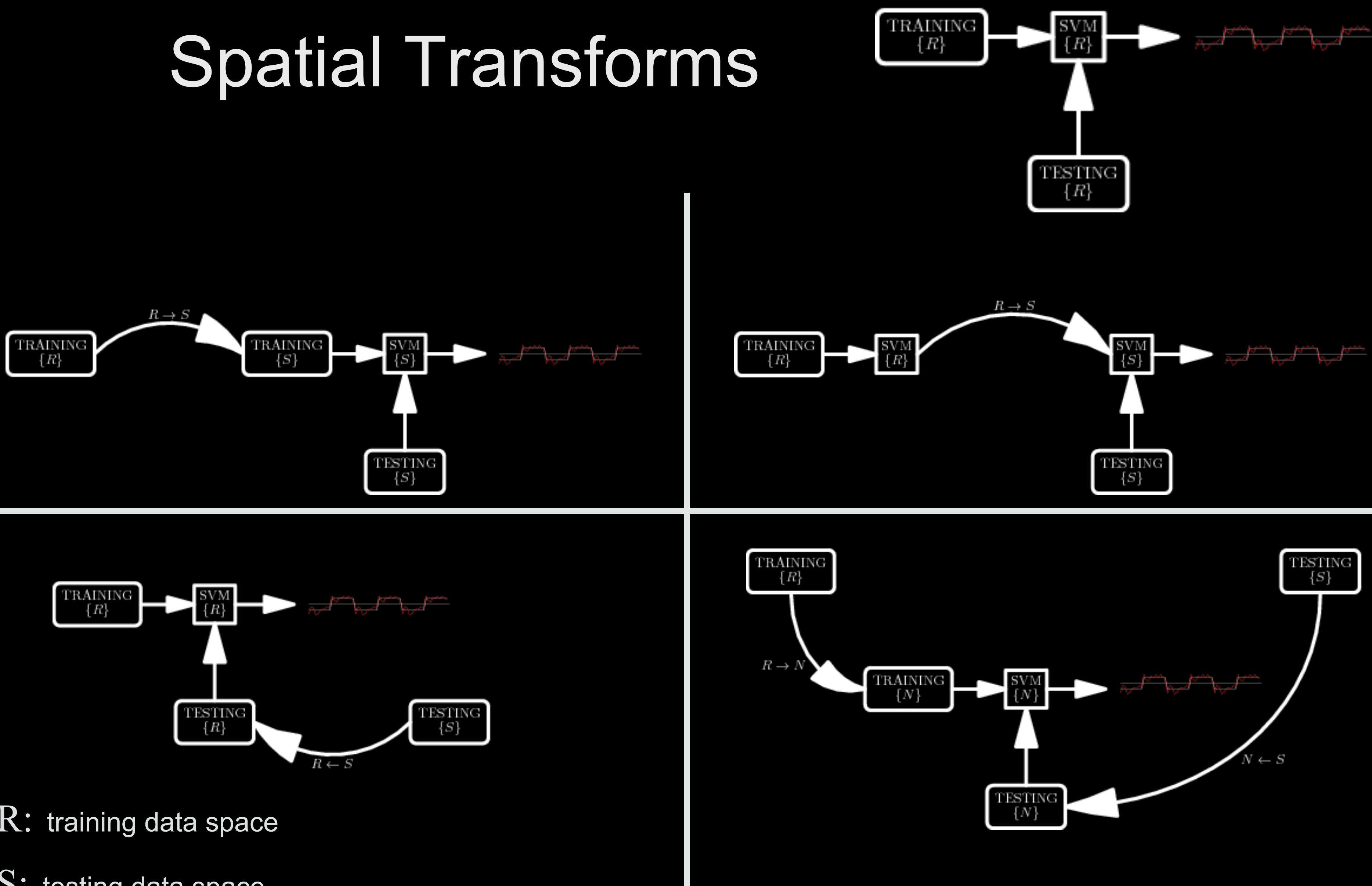
Spatial transformation of support vector machine models for multi-session and group real-time fMRI



Spatial Transforms



R: training data space

S: testing data space

N: "normalized" brain space

Future Challenges

(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
- Model updates during real-time feedback
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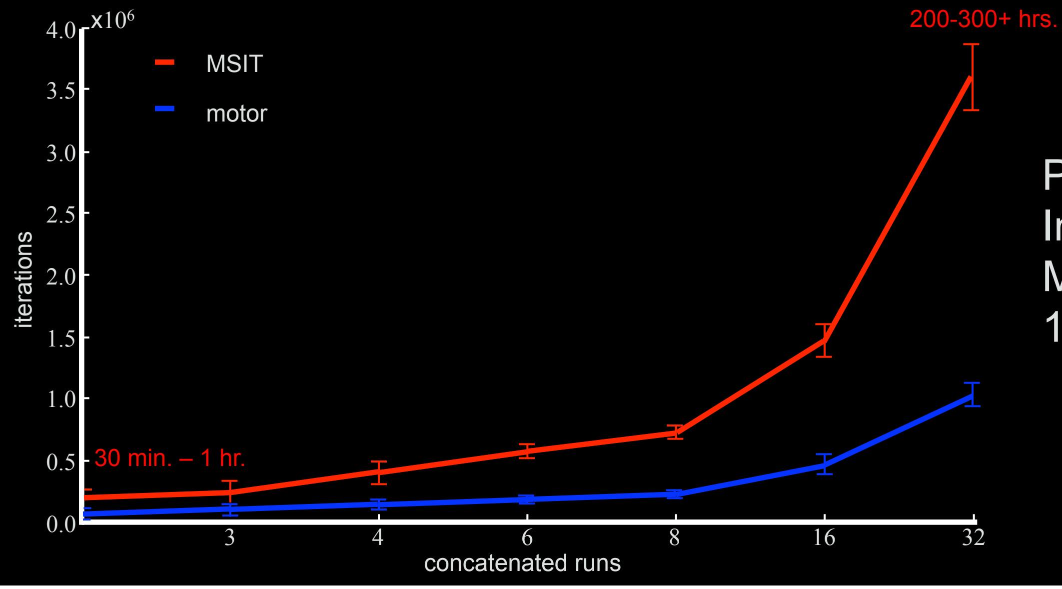
- Feedback and feedback interfaces

Spatial transformation of support vector machine models for multi-session and group real-time fMRI



Processor:
Intel Xeon Quad Core E5462 (2.80 GHz)
Memory:
16GB DDR2 SDRAM @ 800 MHz

Future Challenges

(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
- Model updates during real-time feedback
- Detecting and correcting temporal non-stationarity
- Feedback and feedback interfaces

Spatial transformation of support vector machine models for multi-session and group real-time fMRI

	Percent prediction accuracies									
	Align training data to test space and retrain		Align model to test data space		Align model to test data (replaced alphas)		Talairach		Control (intra run)	
training data	Tapping	MSIT	Tapping	MSIT	Tapping	MSIT	Tapping	MSIT	Tapping	MSIT
single run	90.83±7.23	69.44±9.05	90.71±7.61	69.48±9.11	90.79±7.39	69.46±9.00	91.12±7.17	69.26±8.93	93.33±7.40	72.01±8.37
2 runs combined	93.96±5.84	73.21±8.54	93.98±6.10	73.59±8.28	94.01±5.67	73.31±8.62				

Future Challenges

(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
- Model updates during real-time feedback
- Detecting and correcting temporal non-stationarity
- Feedback and feedback interfaces

Spatial transformation of support vector machine models for multi-session and group real-time fMRI

- alignment across scanning sessions is comparable to alignment within a scanning session
- no deleterious interpolation error effects
- model-to-scan alignment is feasible for real-time fMRI
- group SVM models can be used in real-time experiments

Future Challenges

(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
- Model updates during real-time feedback
- Detecting and correcting temporal non-stationarity
- Feedback and feedback interfaces

Brain state feedback requires a training data and a model

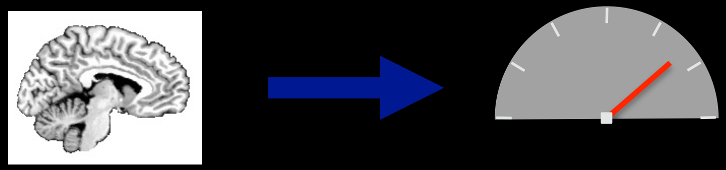
- There are likely important differences between feedback and no-feedback variations of a task
- Given a start-up model, it might be possible to proceed to continuous training and feedback, leading to progressively more accurate feedback

Future Challenges

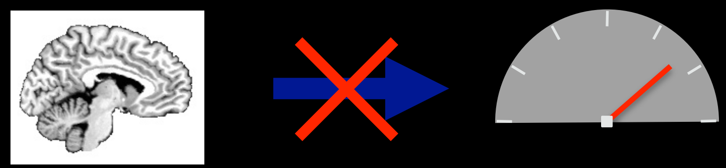
(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
- Model updates during real-time feedback
- Detecting and correcting temporal non-stationarity
- Feedback and feedback interfaces

Feedback runs differ from no-feedback runs



Feedback (FB): Brain Controls Needle



No Feedback (noFB): Computer Controls Needle

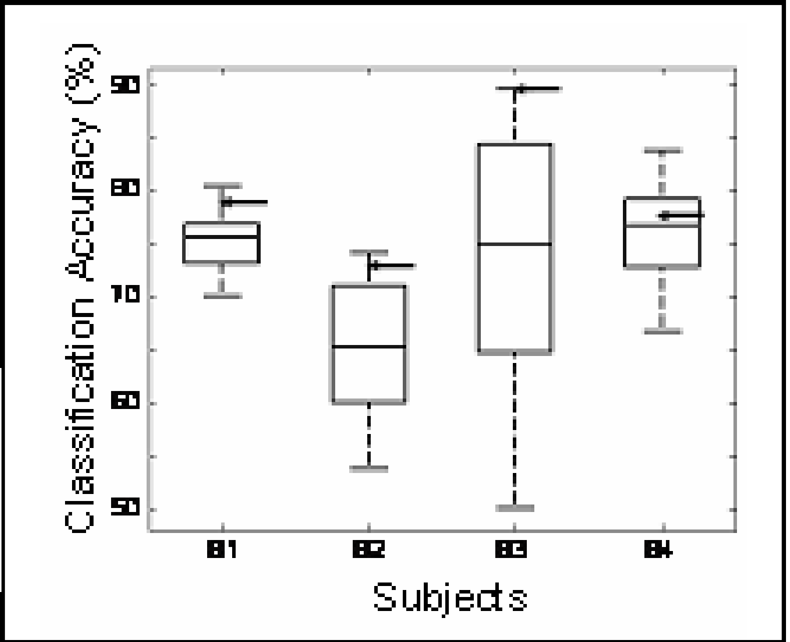
Future Challenges

(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
- Model updates during real-time feedback
- Detecting and correcting temporal non-stationarity
- Feedback and feedback interfaces

Feedback runs differ from no-feedback runs

[1]We have initial data suggesting that these permutations may not be completely identical. Specifically we see a slight tendency for higher prediction accuracy in Run 4 (regardless of training run) compared to Runs 1–3 (across all training run permutations). If this is the case,



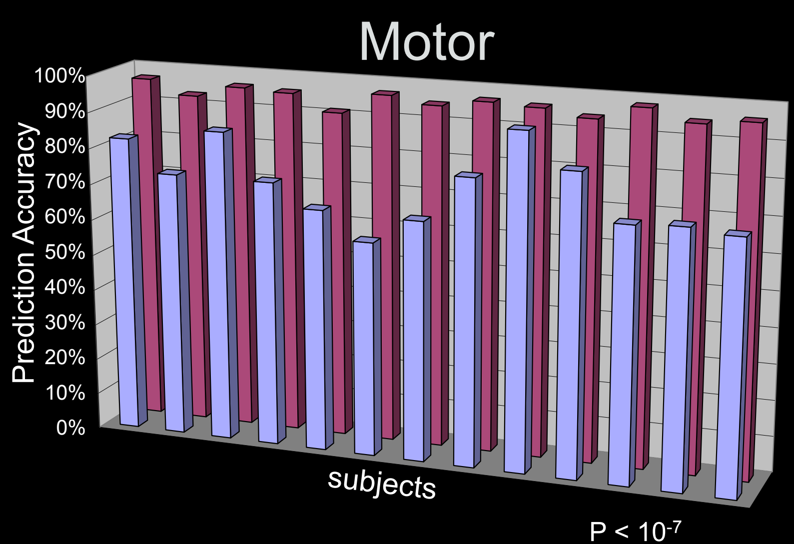
(LaConte, et al. HBM, 2007)

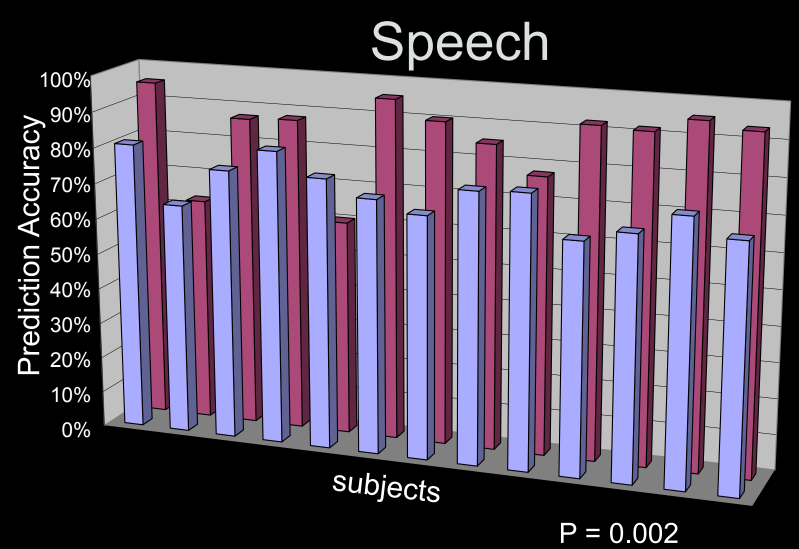
Future Challenges

(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
- Model updates during real-time feedback
- Detecting and correcting temporal non-stationarity
- Feedback and feedback interfaces

Feedback runs differ from no-feedback runs





(Papageorgiou, et al. 2009)

Future Challenges

(LaConte, NeuroImage, 2011)

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- Model updates during real-time feedback
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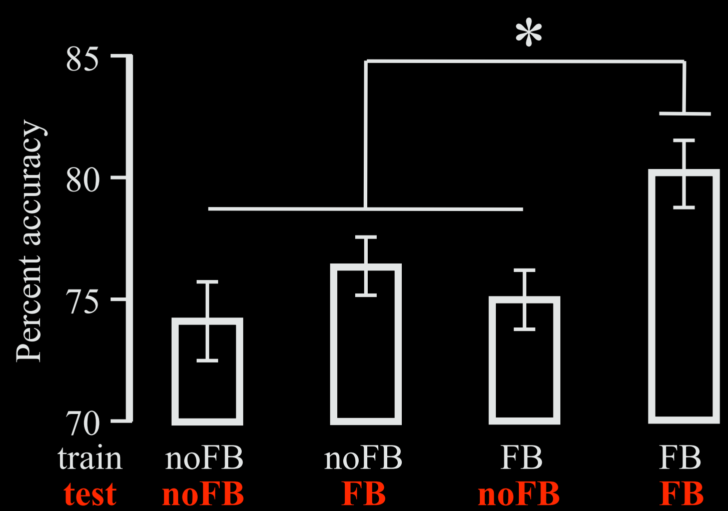
Feedback runs differ from no-feedback runs

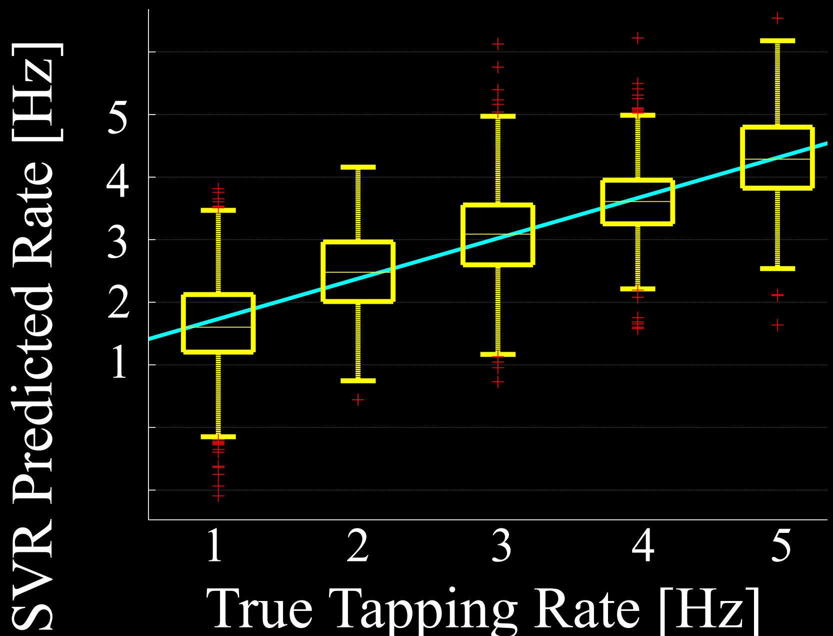


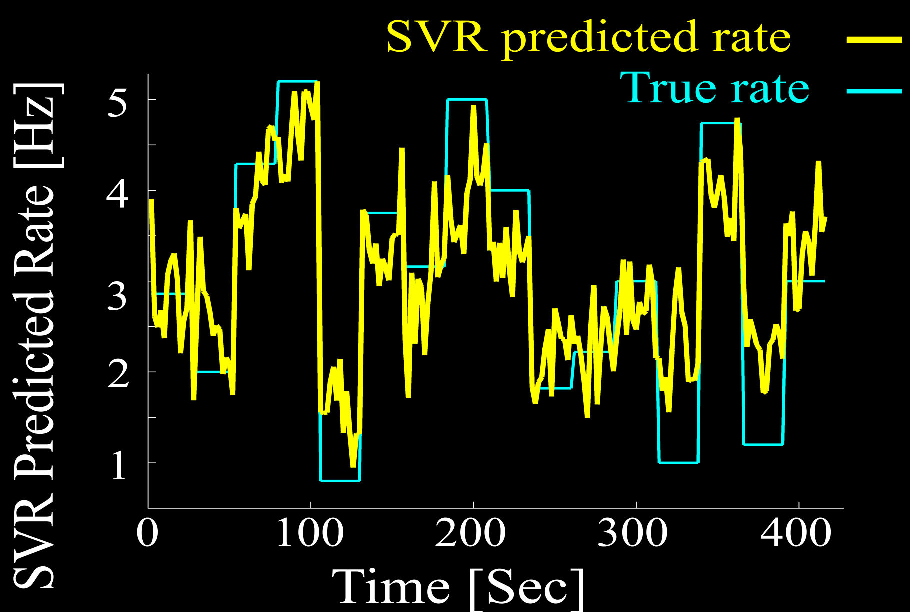
Future Challenges

(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
- Model updates during real-time feedback
- Detecting and correcting temporal non-stationarity
- Feedback and feedback interfaces

Humans Out-Learning the Machine





Future Challenges

(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
- Model updates during real-time feedback
- Detecting and correcting temporal non-stationarity
- Feedback and feedback interfaces

Humans Out-Learning the Machine

- Complex Motor:
  - Finger Sequence
    - short-term motor learning
  - Regression: button press rate
    - Regression error correlation with mean button press rate
    - (0.75, 0.94, 0.94, 0.80, 0.91, 0.99, 0.99).

Future Challenges

(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
- Model updates during real-time feedback
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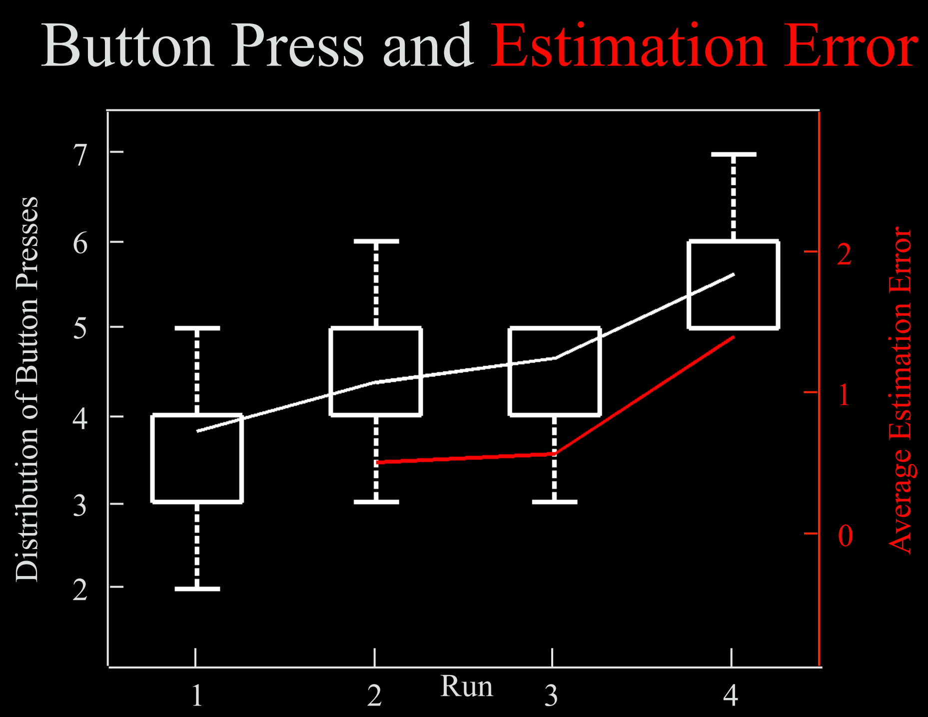
Humans Out-Learning the Machine



Future Challenges

(LaConte, NeuroImage, 2011)

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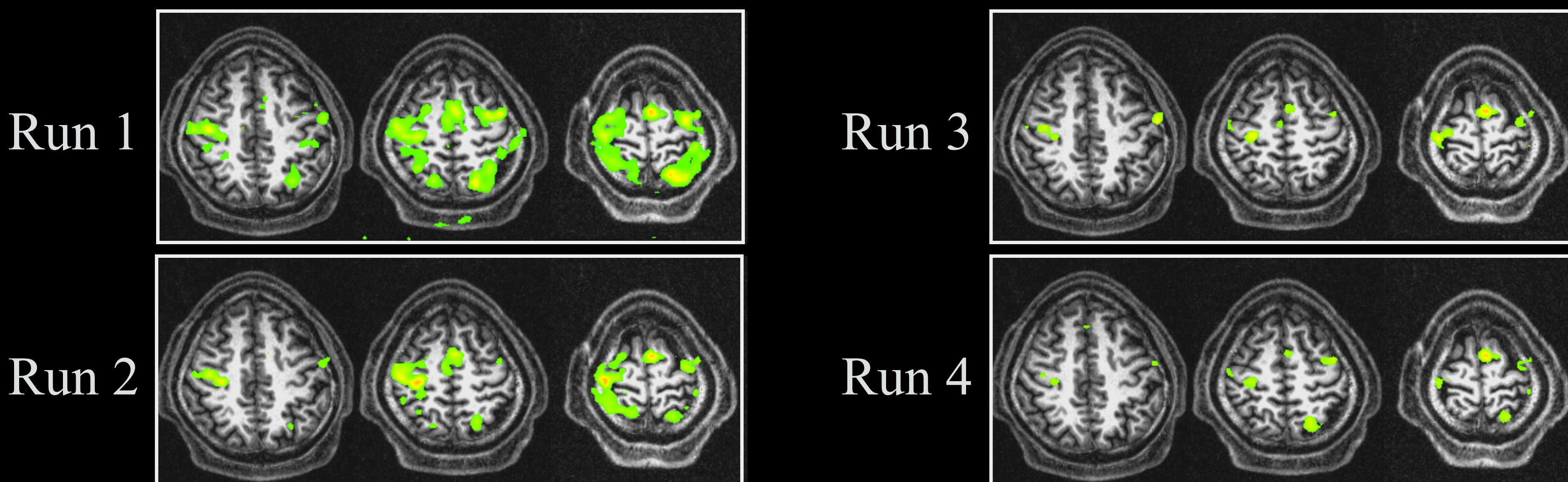


Future Challenges

(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
- Model updates during real-time feedback
- Detecting and correcting temporal non-stationarity
- Feedback and feedback interfaces

Humans Out-Learning the Machine

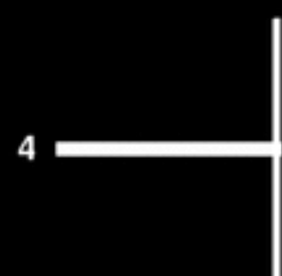
- Human learning makes training data less relevant.
- Performance measures corresponded to observed "learning" in activation patterns.
- A control experiment: paced motor task

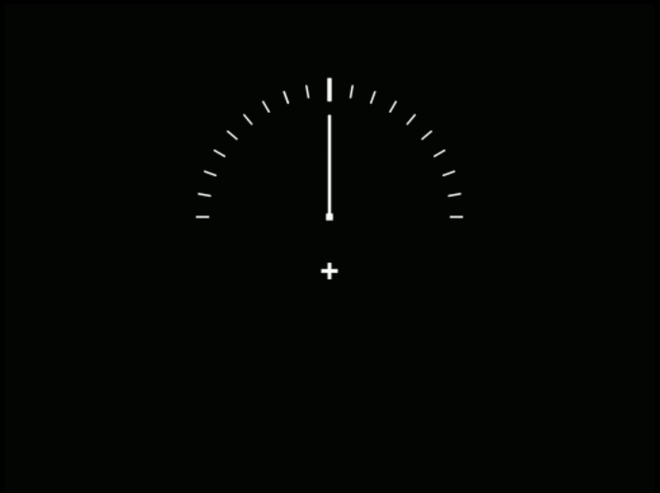
Future Challenges

(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
- Model updates during real-time feedback
- Detecting and correcting temporal non-stationarity
- Feedback and feedback interfaces

Can interfaces be optimized by studying reward processing to promote learning/plasticity?

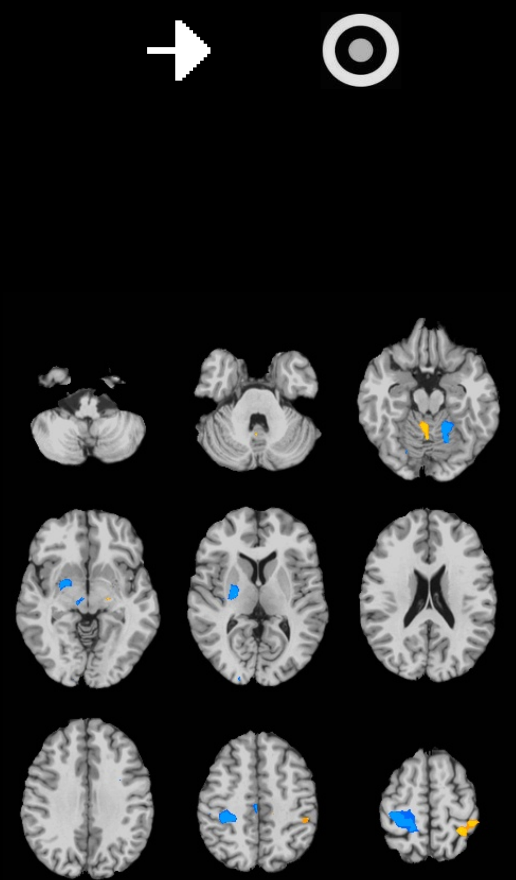




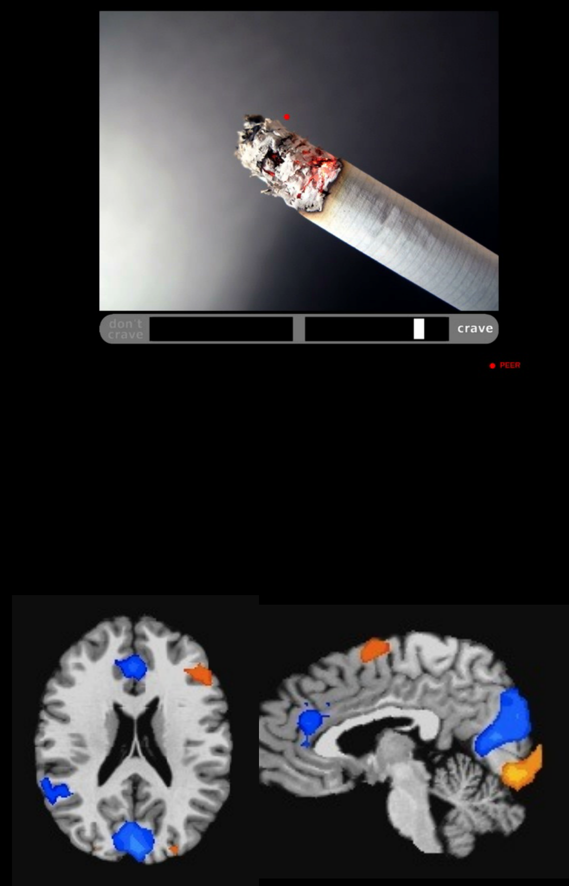
Outline

- Overview of rtfMRI
- Tracking localized brain regions
- Supervised learning-based rtfMRI
- Resources for getting started
- Technical challenges
- Applications

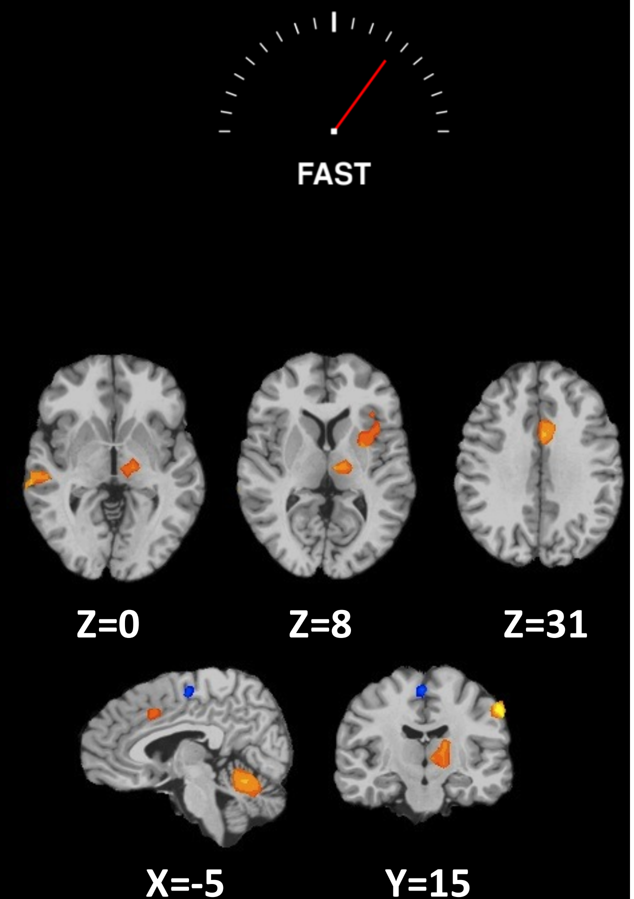
Support Vector Machine Maps of Real-Time Tasks



Right vs. Left Tapping



Crave vs. Don't Crave



Fast vs. Slow Counting

Pathophysiology and treatment of substance dependence

(With Pearl Chiu)

- Substance dependent individuals are characterized in part by susceptibility to drug cue-induced craving

Smoking images presented during "Don't Crave" and "Crave"

Slider gives feedback during "Don't Crave" and "Crave"

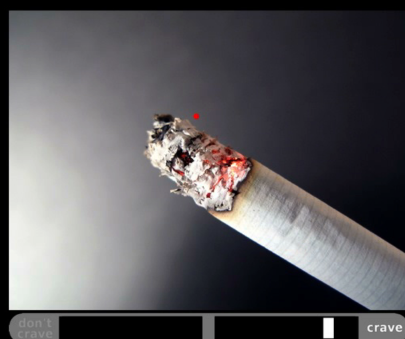
Pathophysiology and treatment of substance dependence

(With Pearl Chiu)

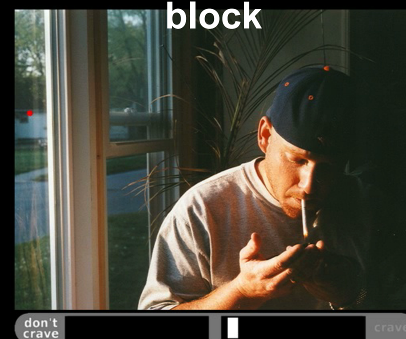
Pathophysiology and treatment of substance dependence

(With Pearl Chiu)

Successful "Crave" block



Non-successful "Don't Crave" block



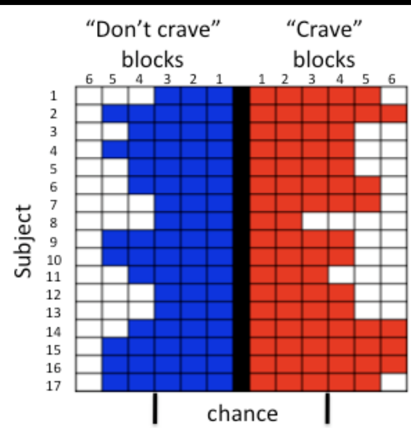


Figure 1: Number of successful blocks per subject for "Don't crave" and "Crave" conditions

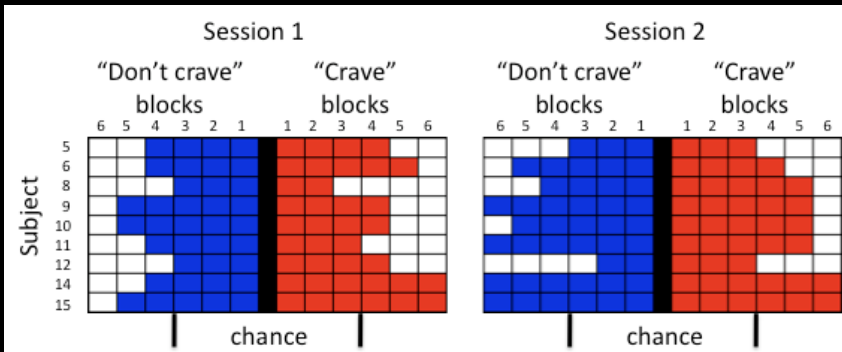
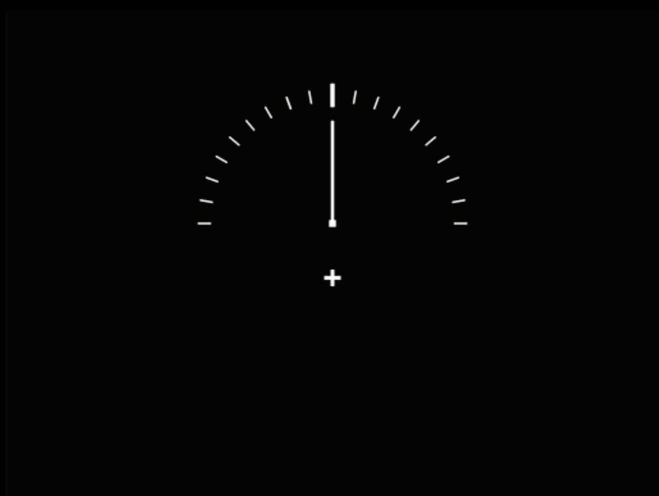
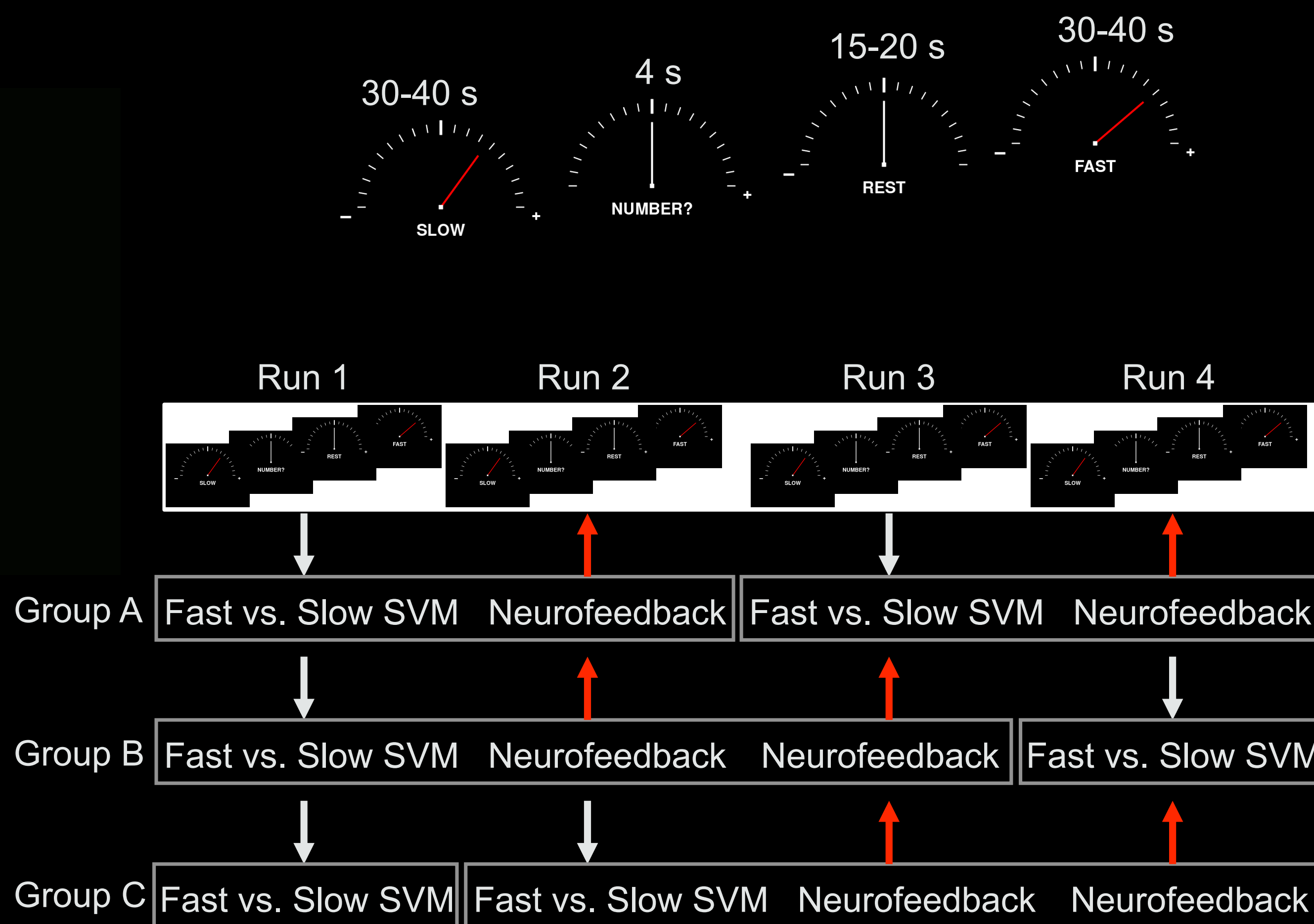


Figure 2: Side-by-side comparison of session 1 and session 2 for subjects who have returned for the second time point.

Speech: Covert counting

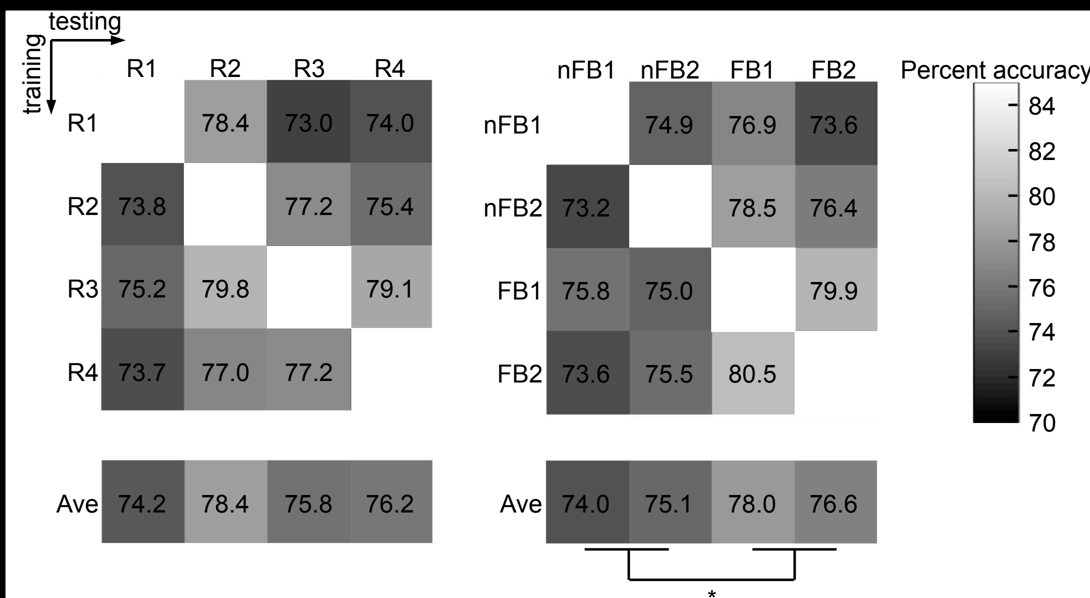
(Papageorgiou, Lisinski, McHenry, White)

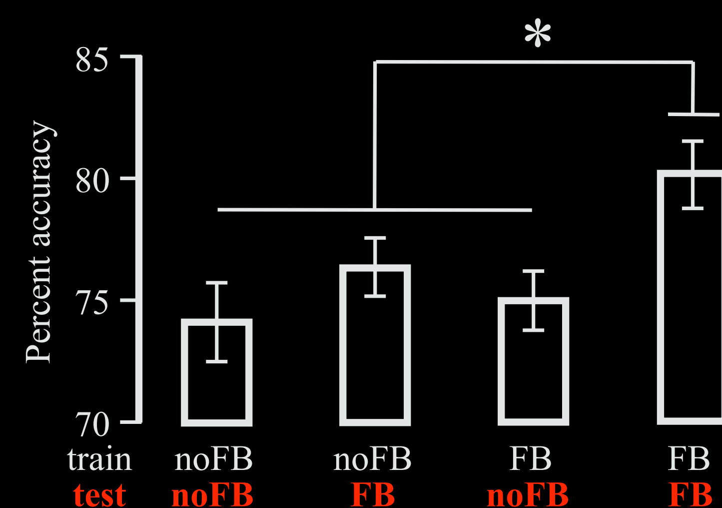




Speech: Covert counting

(Papageorgiou, Lisinski, McHenry, White)

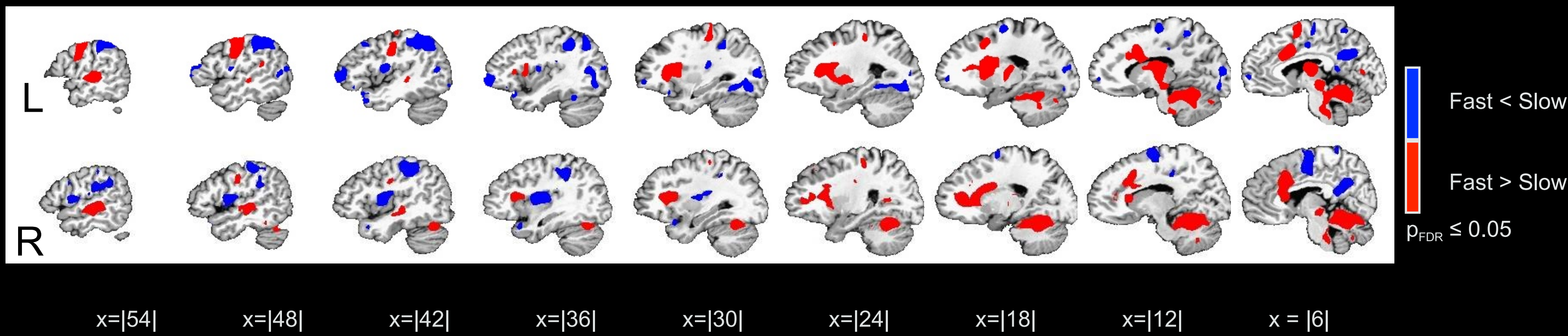




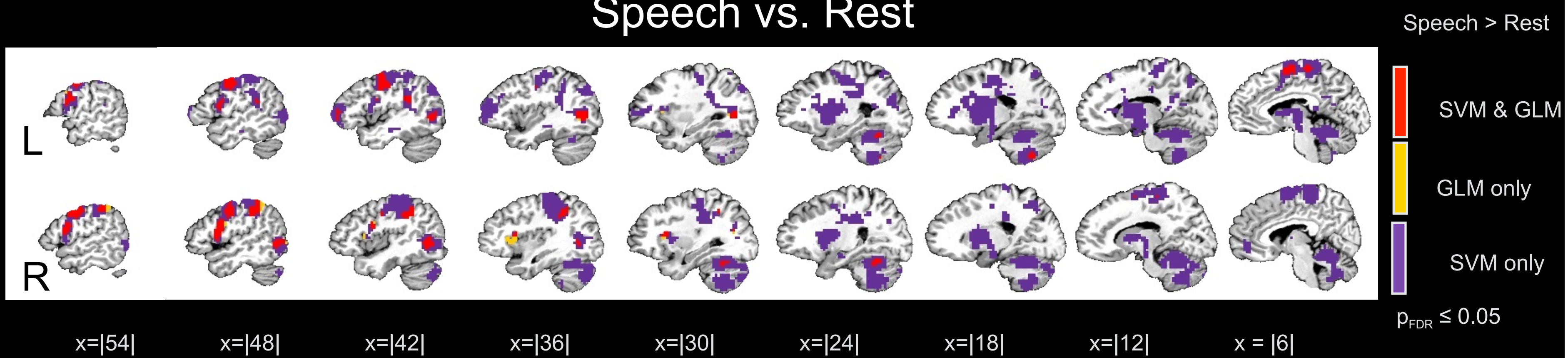
Speech: Covert counting

(Papageorgiou, Lisinski, McHenry, White)

Fast vs. Slow

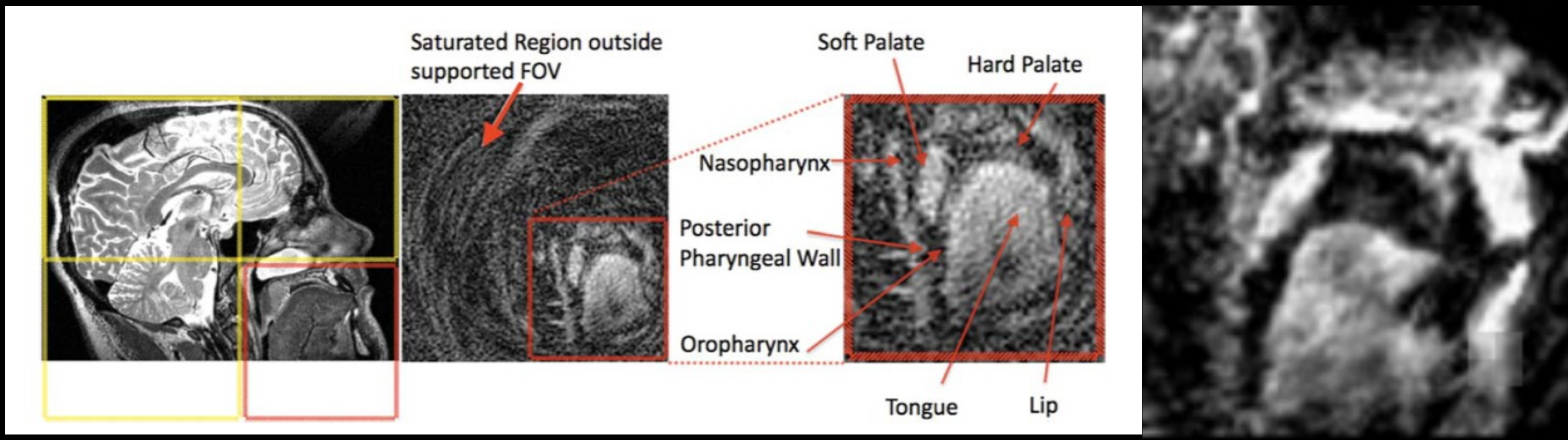


Speech vs. Rest



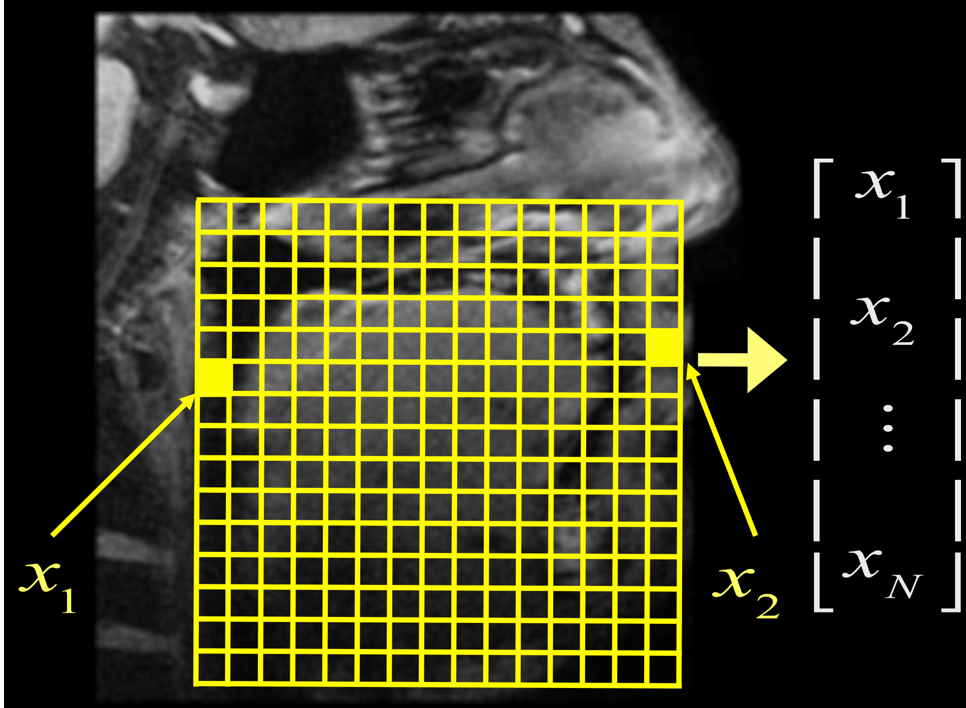
Dynamic Field Corrected Imaging of Speech

(With Brad Sutton)



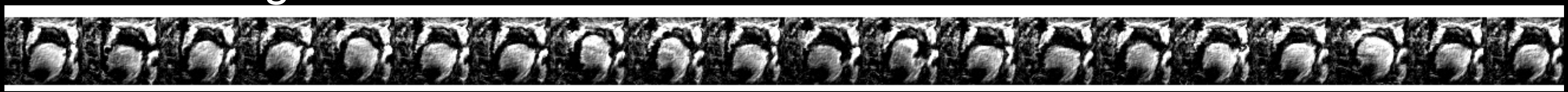
Sutton et al. *JMRI*, 2010.

Temporal Classification
(With Brad Sutton)

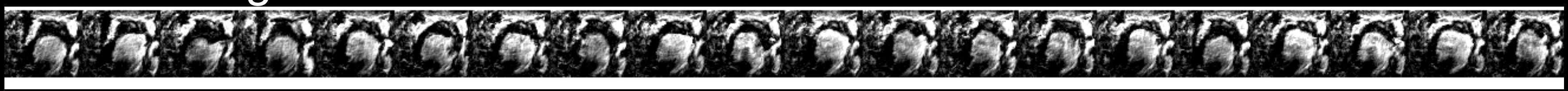


Decoding speech from structural movies
(With Brad Sutton)

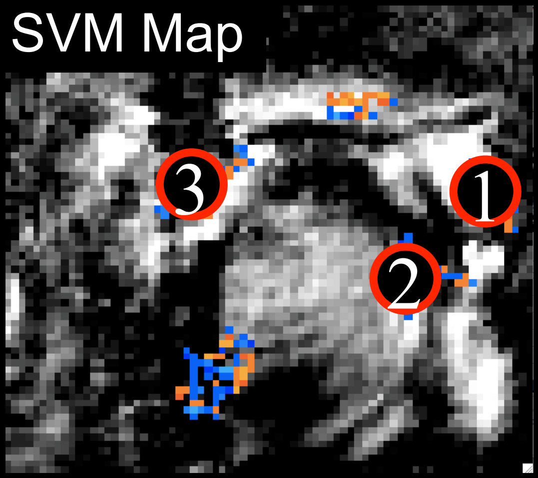
slow counting



fast counting



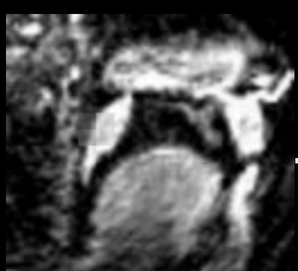
Cross-validated accuracy 88% out of 1896 frames
Chance = 50%

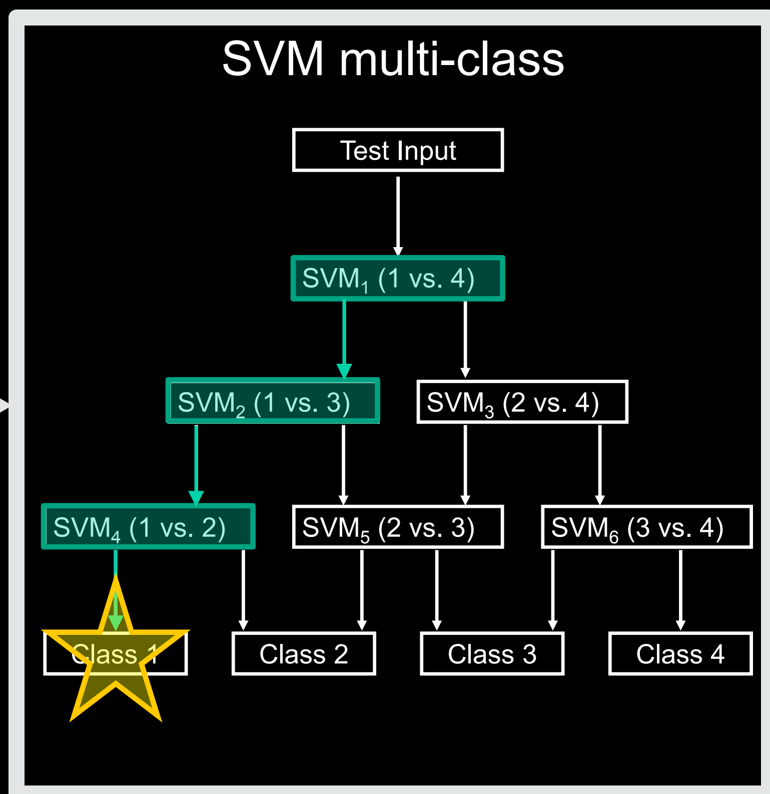


Can we decode the words?
“Mouth-reading” the mid-sagittal slice

(With Brad Sutton)

cross-validated accuracy 96% out of 48 spoken numbers (chance = 25%)





1

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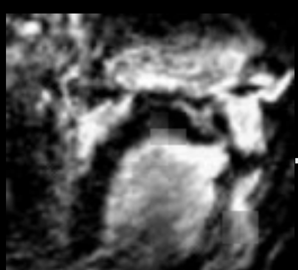

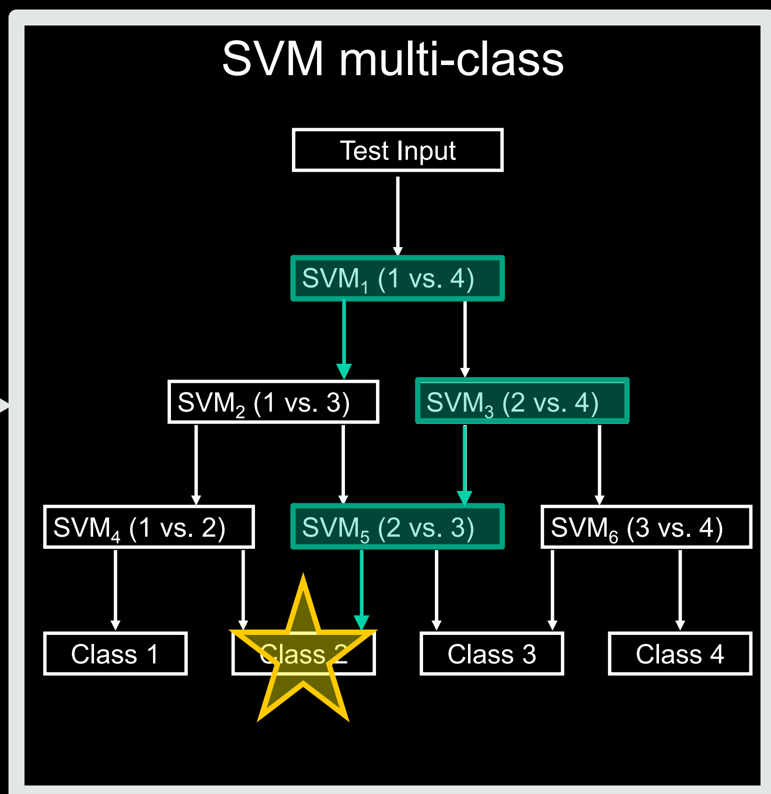

2

Can we decode the words?
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(With Brad Sutton)

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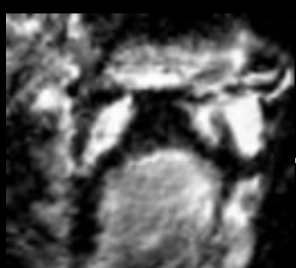
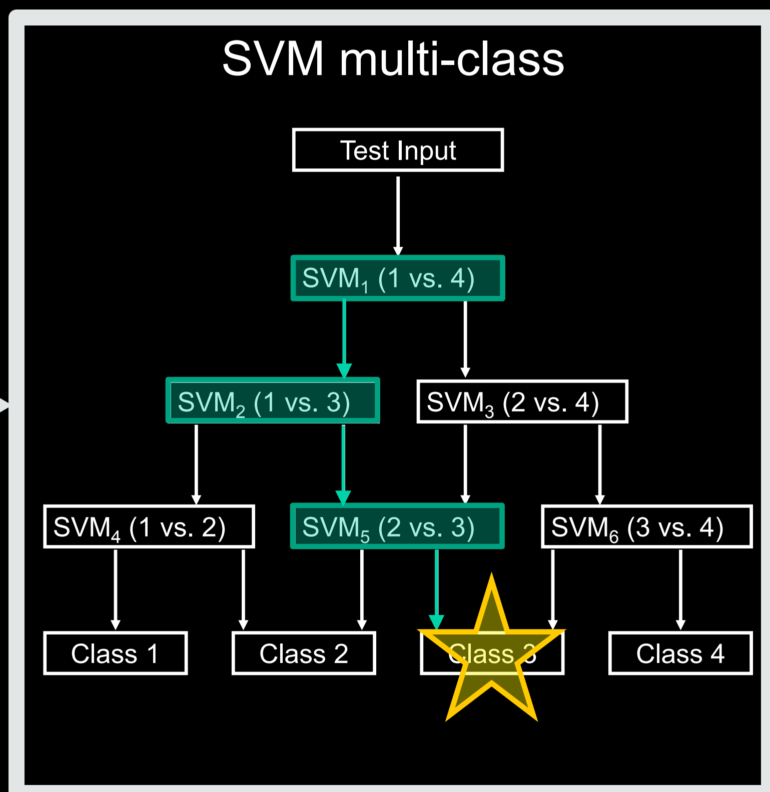


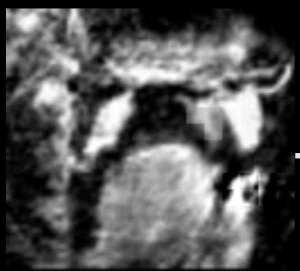


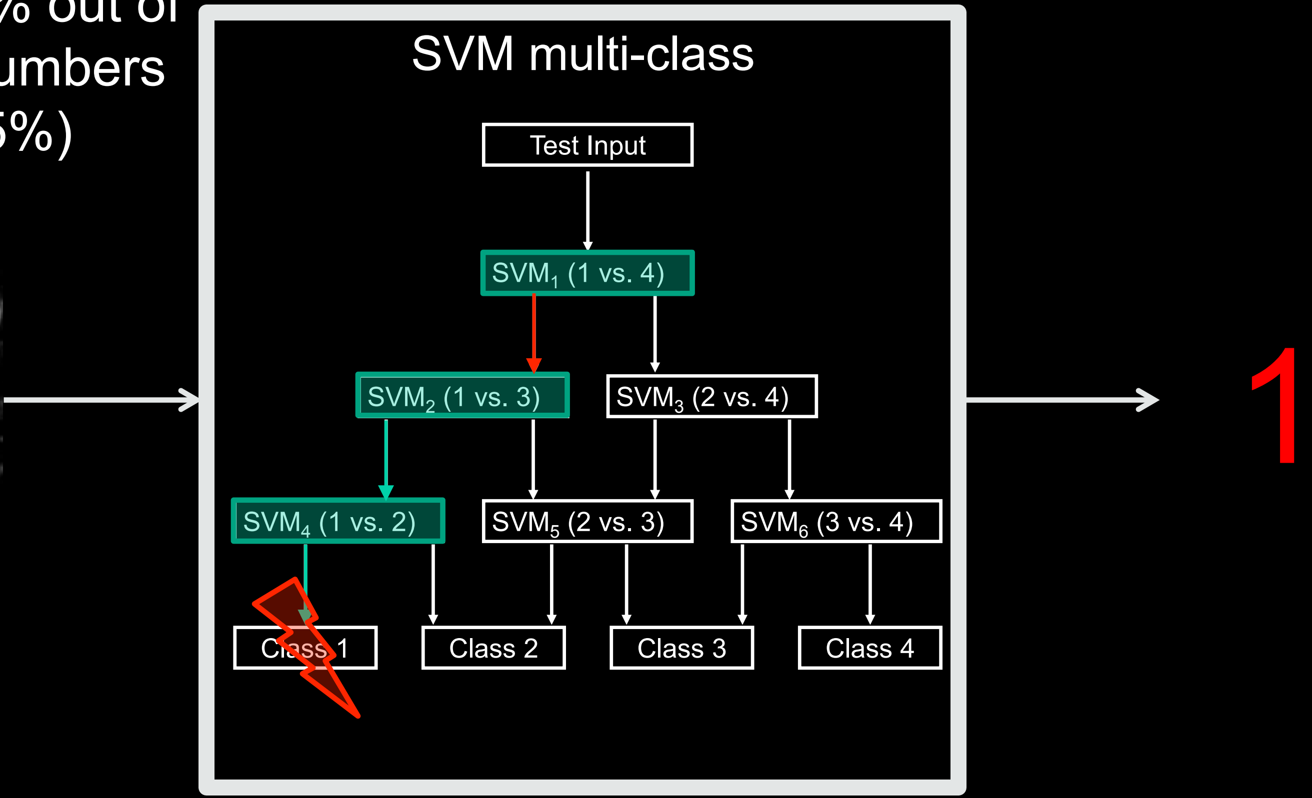
3

Can we decode the words?
"Mouth-reading" the mid-sagittal slice

(With Brad Sutton)

cross-validated accuracy 96% out of 48 spoken numbers (chance = 25%)





Can we decode the words?
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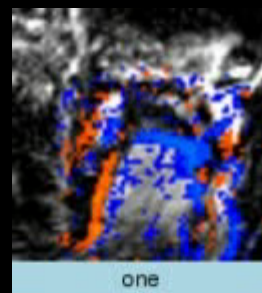
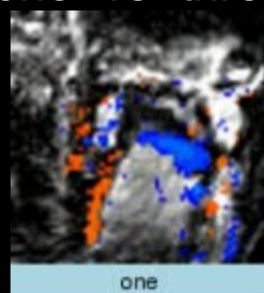
accuracy 96% out of
48 spoken numbers
(chance = 25%)

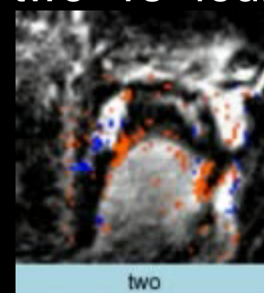
"one" vs "four"



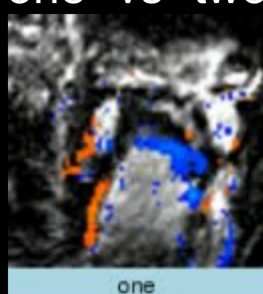
"one" vs "three"



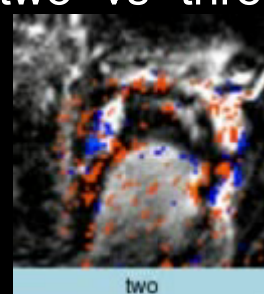
"two" vs "four"



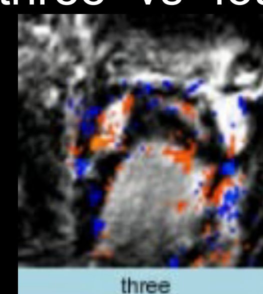
"one" vs "two"



"two" vs "three"

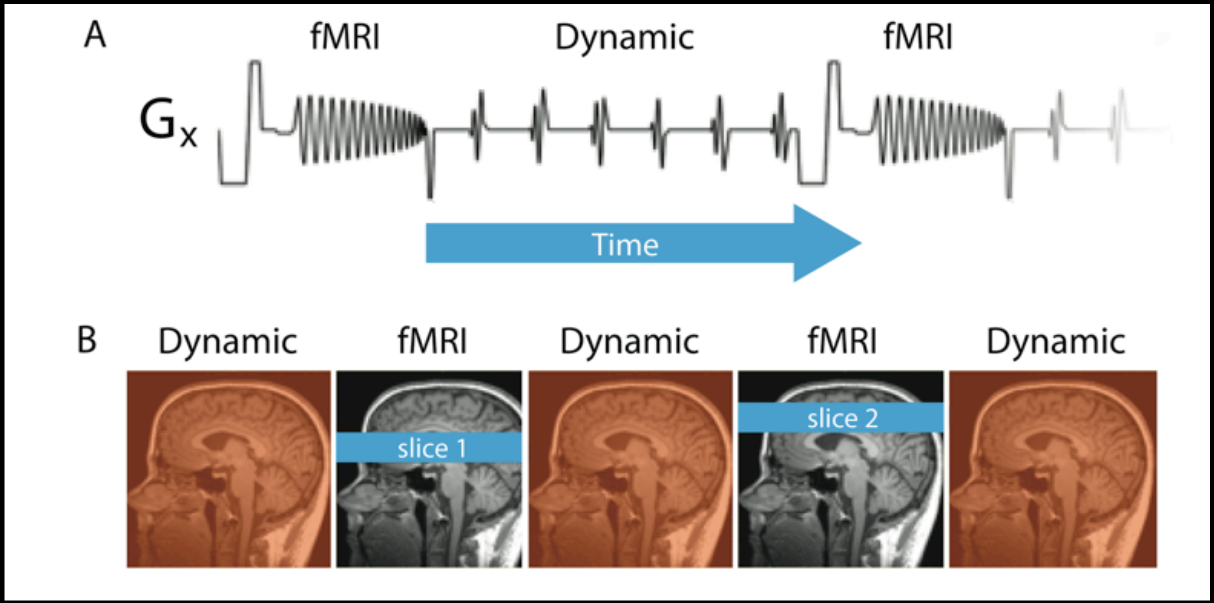


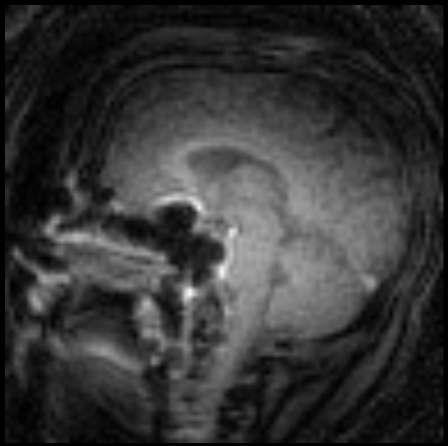
"three" vs "four"



Brad Sutton's SIMULSCAN

Acquisition of dynamic anatomical for every functional slice.

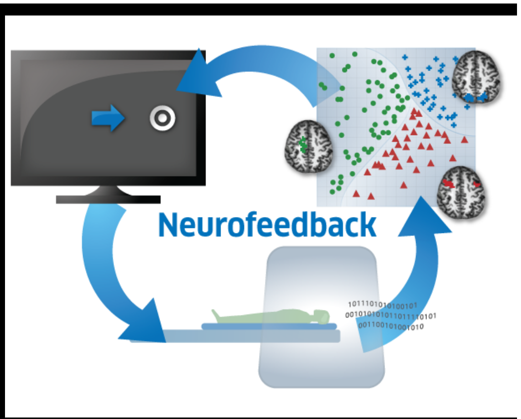




Paine, et al.
Mag. Res Med. 2011.

	Anatomical	Functional
Sequence	6-shot spiral out	Single-shot Spiral-in
Matrix Size	96 x 96	64 x 64
FOV	240 mm	240 mm
TR per shot	6.5 ms	25.7 ms
TE	1.1 ms	25 ms

Real-Time fMRI



- Adaptive feedback based on classified brain state
  - goes beyond linear systems input-output relationships
  - adaptive fMRI and other RT techniques may provide insights unattainable through traditional stimulus-response experiments
- Applications
  - flexible fMRI experiments, biofeedback rehabilitation, …

Acknowledgments

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Chas Conway

Vladimir Cherkassky
Stephen Strother
Xiaoping Hu
Scott Peltier
Keith Heberlein
Jihong Chen
Will Curtis
Jeffrey Prescott
Yang Zhi
Zhihao Li

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