Model-based fMRI

Zurich SPM Course
February 18, 2011

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To model or not to model

GLM

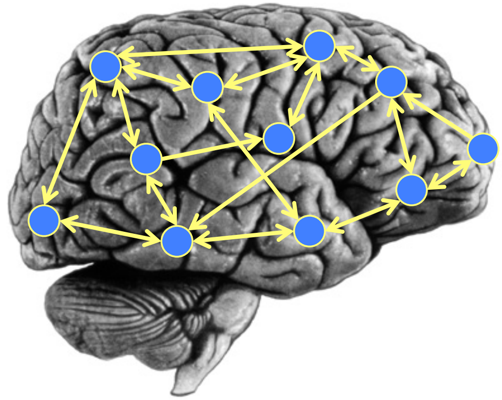
DCM

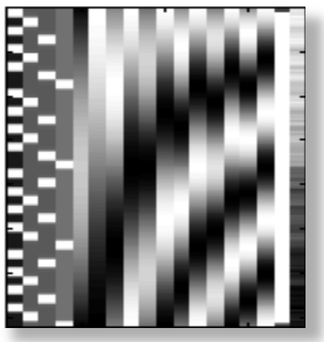
Classification

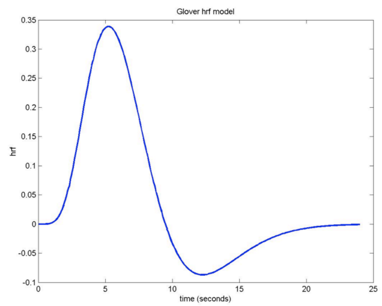
Multivariate Bayes

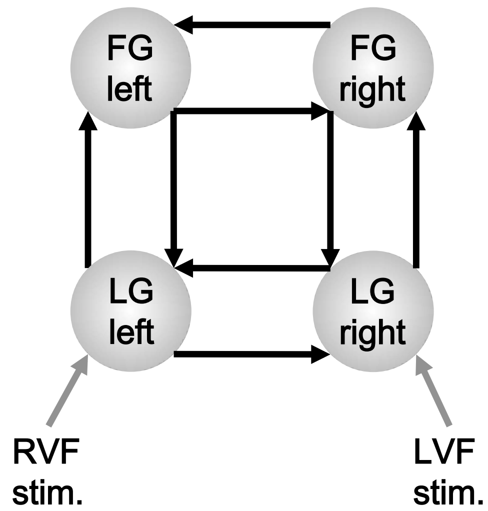
fMRI

- hemodynamic response
- activation levels
- time courses
- connectivity
- t-tests







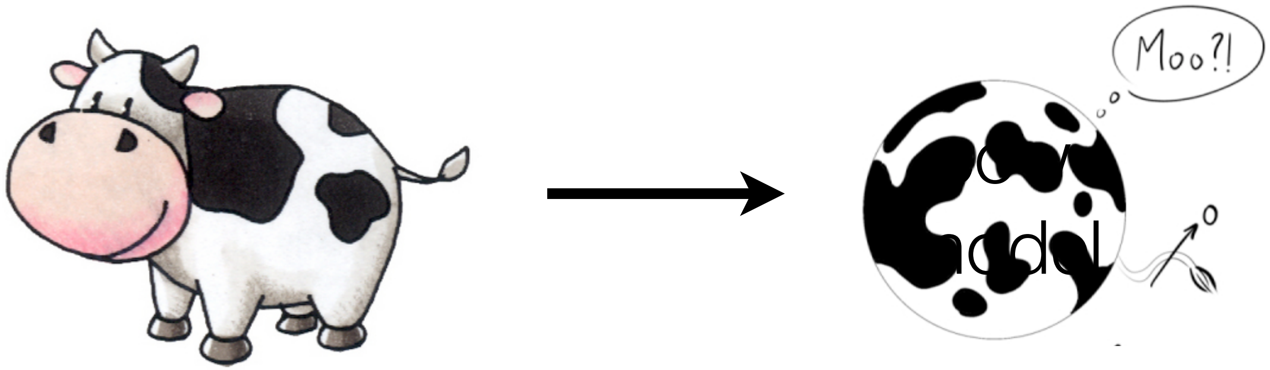


Model-based fMRI

- applying quantitative computational models to generate regressors of interest beyond stimulus inputs and behavioral responses

What is a good model?

The computer engineer, who, when asked to describe how he would write a computer program to recognize a cow, replied, “first, assume a spherical cow.”...



A good model (1)

- clearly specified object of modeling
  cow
  BOLD response
  expected value of a certain action

- clearly specified purpose
  recognize cows
  analyze fMRI data, inferences about neural processes
  model ventromedial frontal projections from the midbrain

- tractable
  computationally efficient

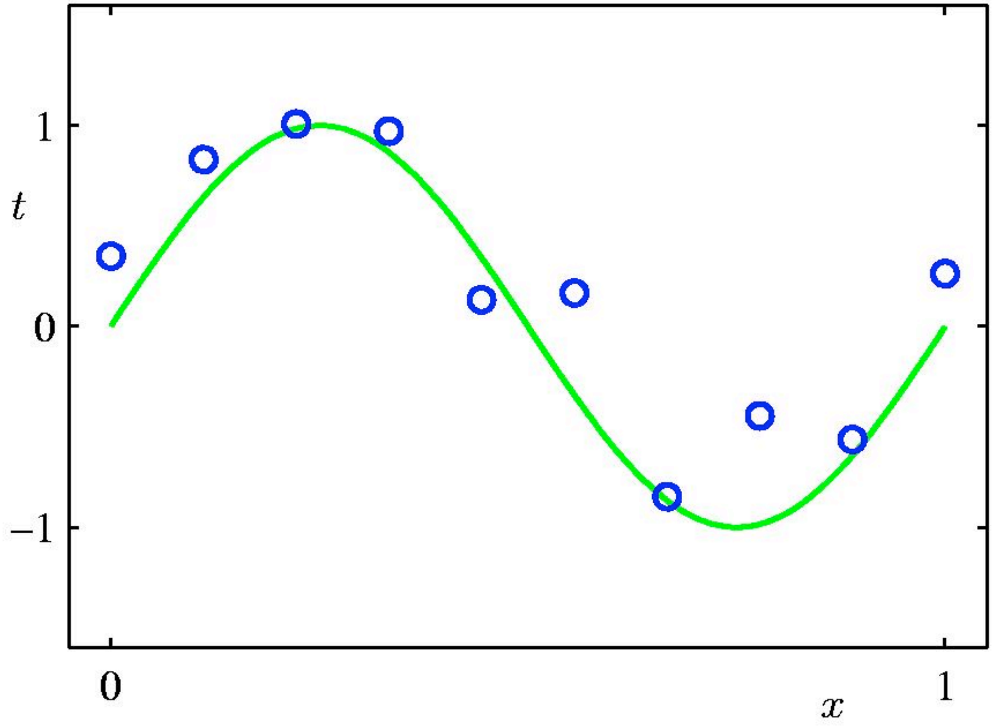
A good model (2)

- realistic
  hrf beats spherical cow
  e.g., incorporate knowledge about brain anatomy and neuronal responses

- simple
  spherical cow beats hrf

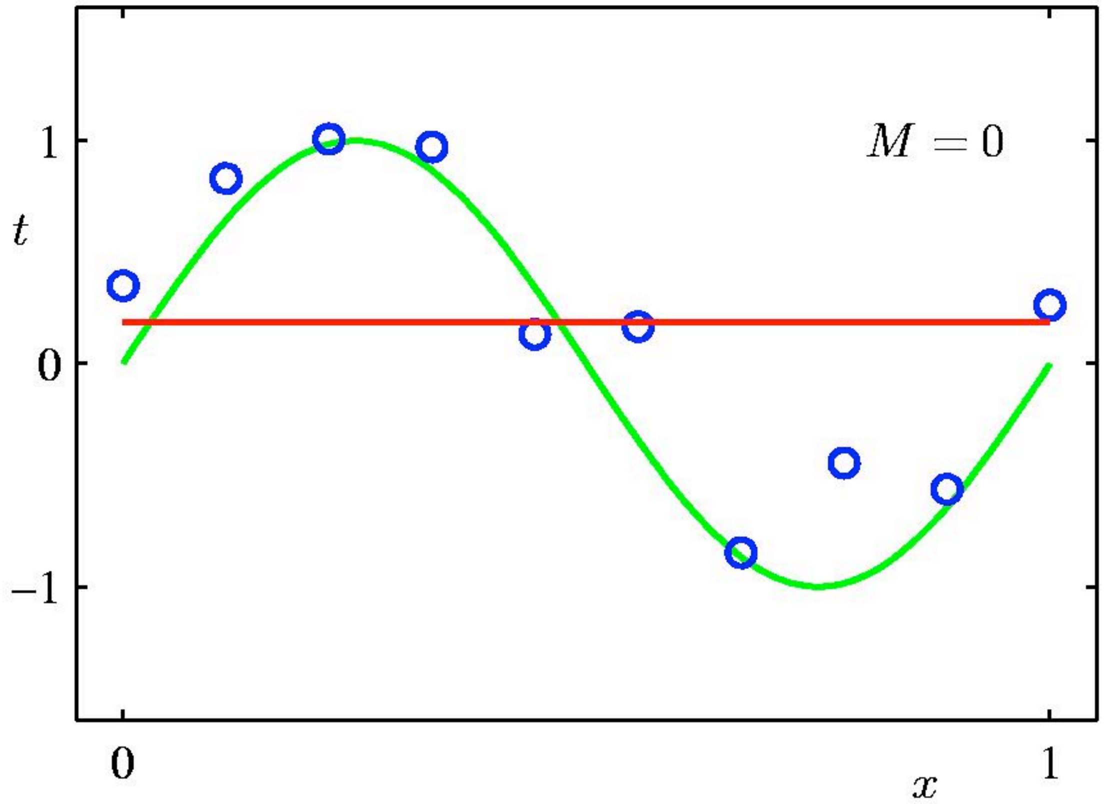
- BUT Occam's razor: as simple as possible, as flexible as needed
  hrf beats spherical cow

Polynomial Curve Fitting

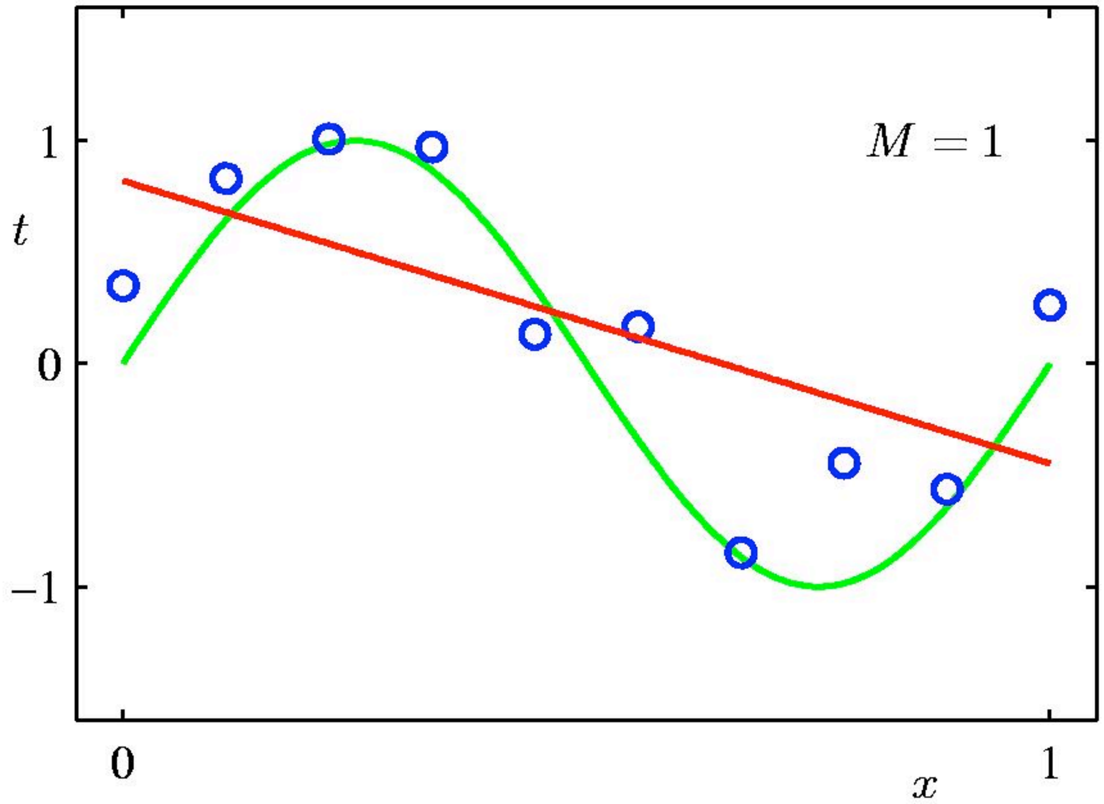


$$y(x, \mathbf{w}) = w_0 + w_1 x + w_2 x^2 + \ldots + w_M x^M = \sum_{j=0}^{M} w_j x^j$$

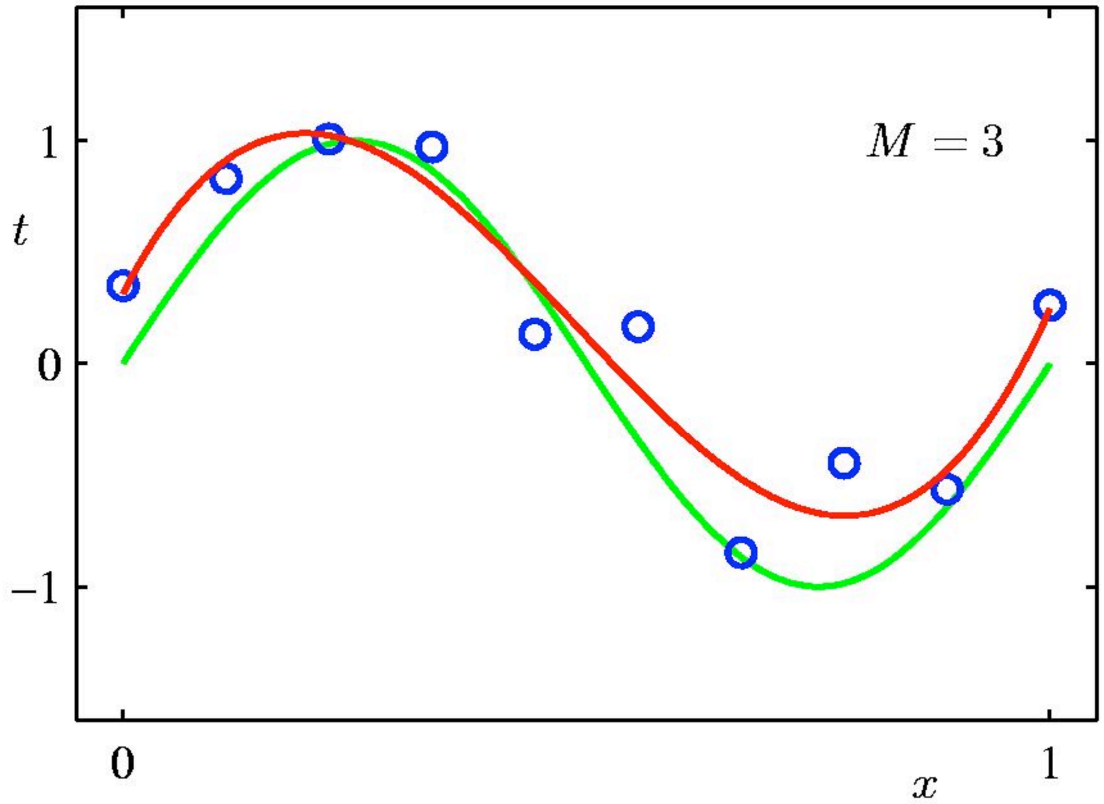
0th Order Polynomial



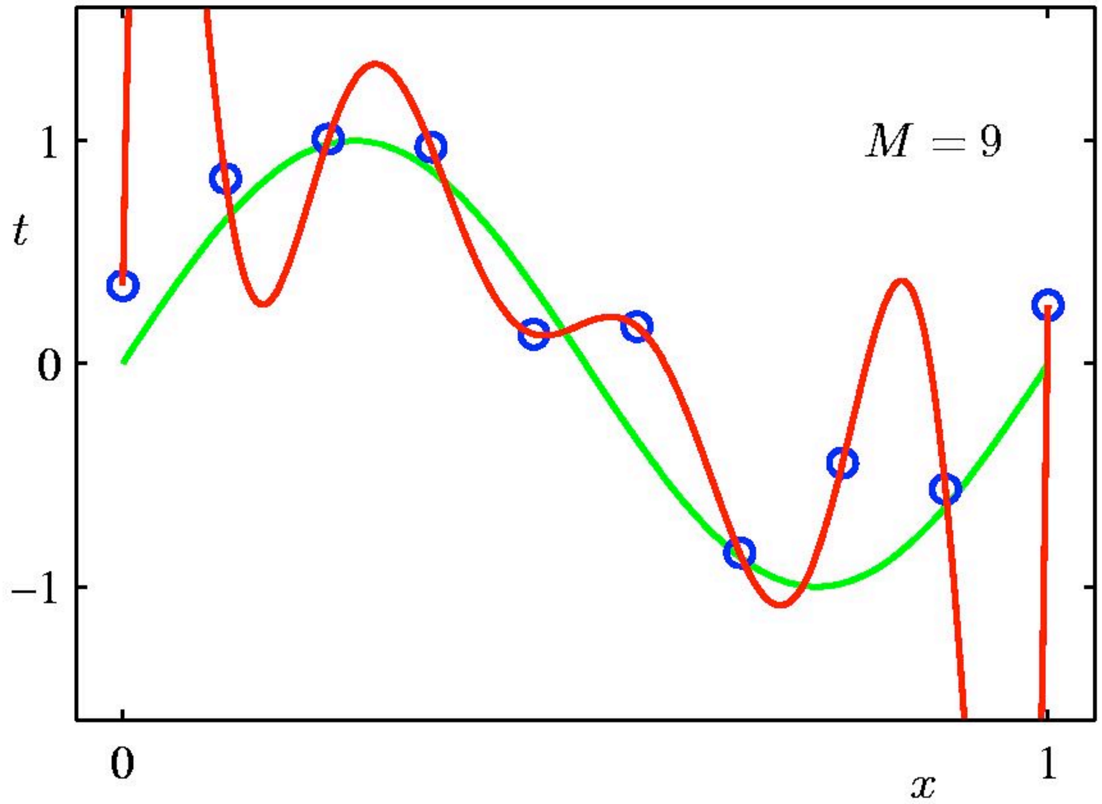
1st Order Polynomial



3rd Order Polynomial



9th Order Polynomial



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  hrf beats spherical cow
  e.g., incorporate knowledge about brain anatomy and neuronal responses

- simple
  spherical cow beats hrf

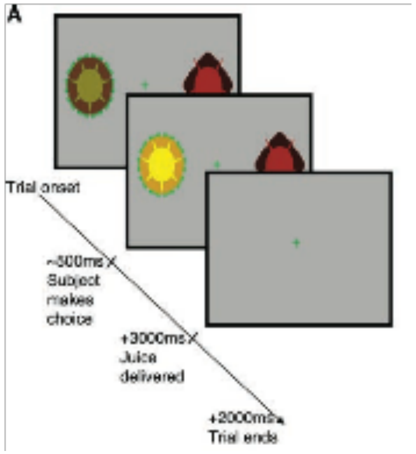
- BUT Occam’s razor: as simple as possible, as flexible as needed
  hrf beats spherical cow

A good model (3)

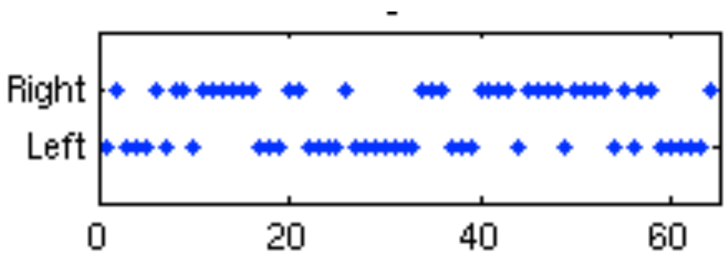
- extensible and reusable
  e.g., reward learning models, Rescorla-Wagner to TD learning to sophisticated versions

Model-based fMRI

- applying quantitative computational models to generate regressors of interest beyond stimulus inputs and behavioral responses



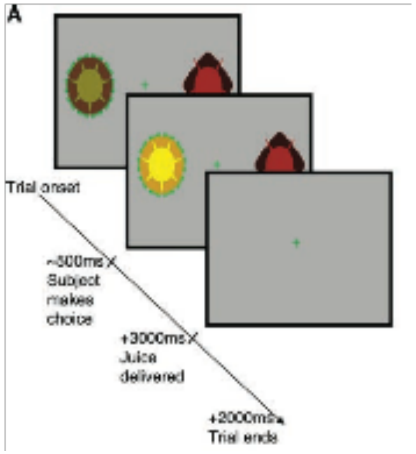
Participant response



- goal: uncover hidden variables and/or processes

Model-based fMRI: questions answered

- How (i.e., by activation of which areas) does the brain implement a particular cognitive process?



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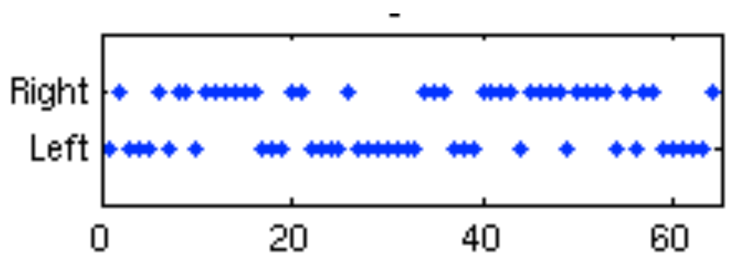


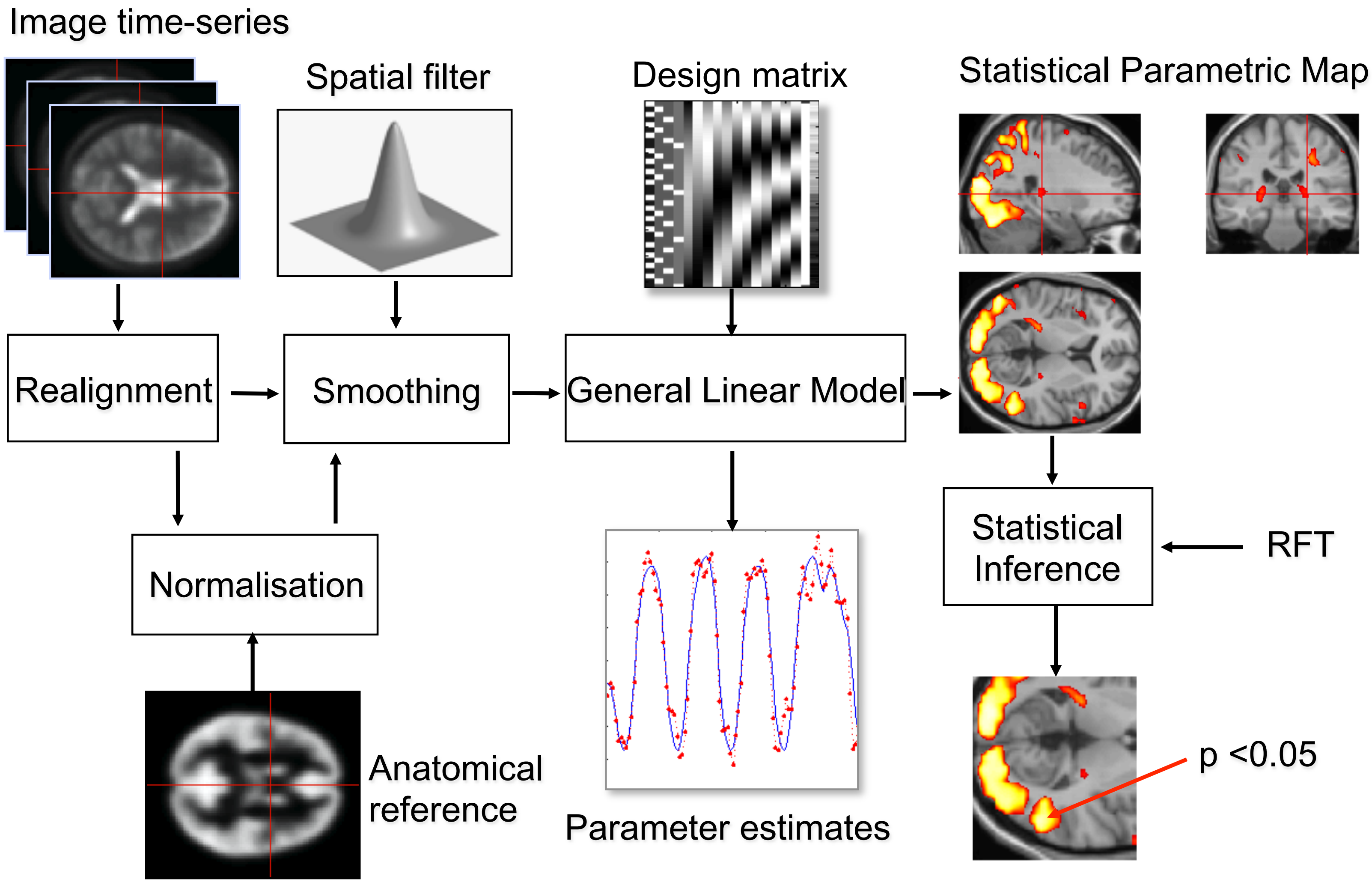


Image time-series
Spatial filter
Design matrix
Statistical Parametric Map
Realignment
Smoothing
General Linear Model
Statistical Inference
RFT
Normalisation
Anatomical reference
Parameter estimates
p <0.05

Classic designs vs. model-based designs

- Classic event and block related designs
  - Conditions are predefined by the experimental design or given by the participant‘s response and are limited to discrete values.
- Parametric designs
  - Continuous spectrum of levels and responses; leaves more degrees of freedom.
- Model-based
  - Access hidden variables and cognitive processes.

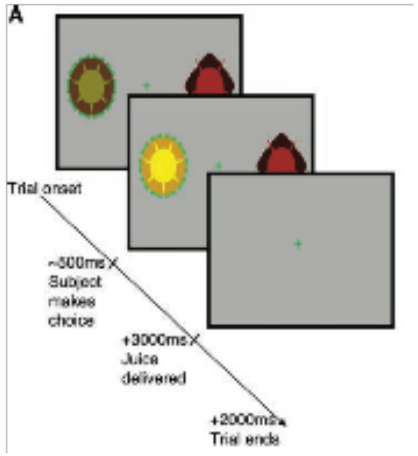
Outline

1. Basic recipe for model-based fMRI
2. Using model-based regressors in the GLM
3. Generating model-based regressors: Examples from the literature

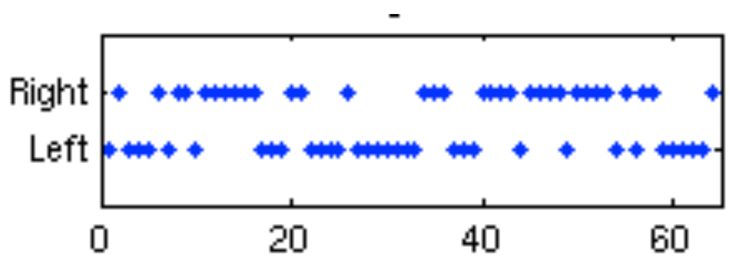
How do we construct regressors that correspond to cognitive processes and use them in SPM?

0. Find someone who knows a model

- Reinforcement learning model
- Hierarchical bayesian model
- Spherical cow model
- Hemodynamic response function
- ...



Participant response



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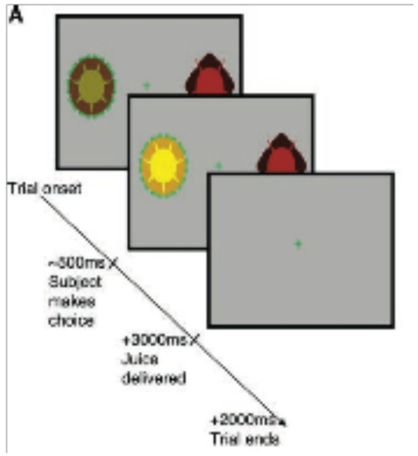
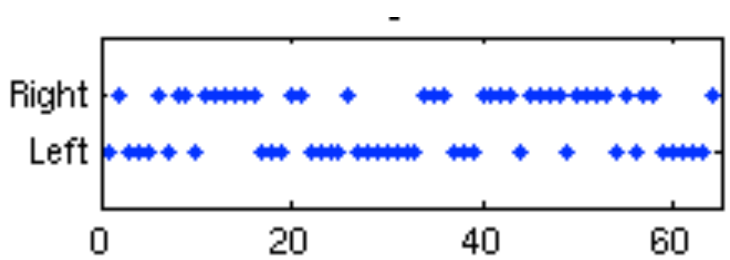
- Reinforcement learning model

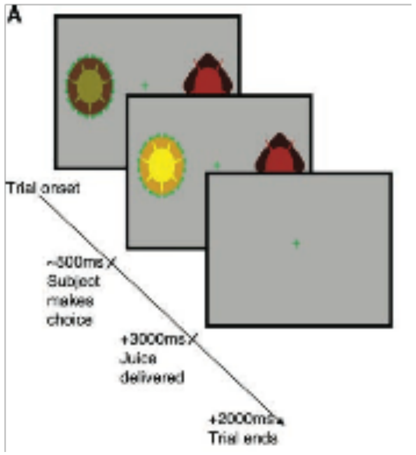


Participant response

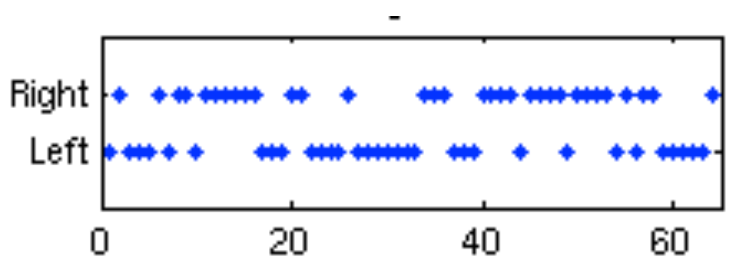


How do we construct regressors that correspond to cognitive processes and use them in SPM?

1. Pass individual subject trial history to model



Participant response



$$\delta = R_{t+1} + \gamma V_{t+1} - V_t$$

$$V^A_{t+1} = V^A_t + \alpha\delta$$

How do we construct regressors that correspond to cognitive processes and use them in SPM?

2. Find best-fitting parameters of model to behavioral data

Model inversion:

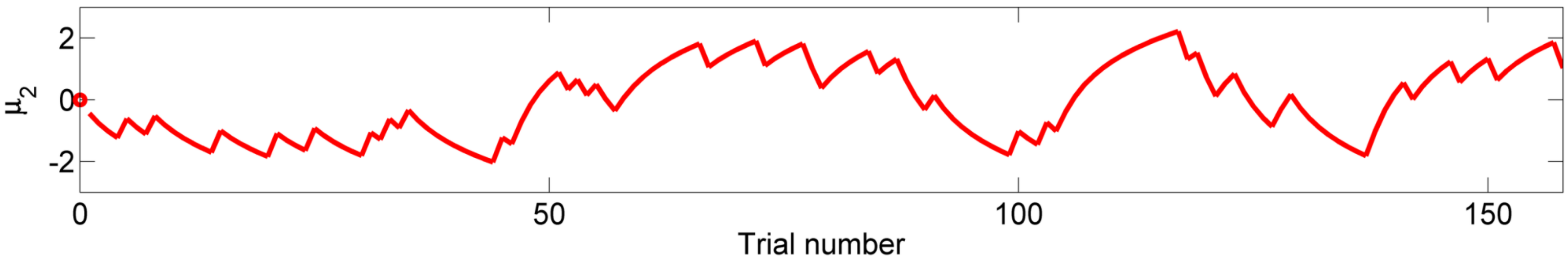
```
>> est = bp_sssr_est(srdata1);

Parameters:
     lamu0: 1.2107e-10
     lasa0: 1.0000
     lanu0: 3.4476e-10
    latau0: 1.0000
        ka: 0.9754
        om: -15.7392
        th: 0.4993
        ze: 0.3319

>>
```

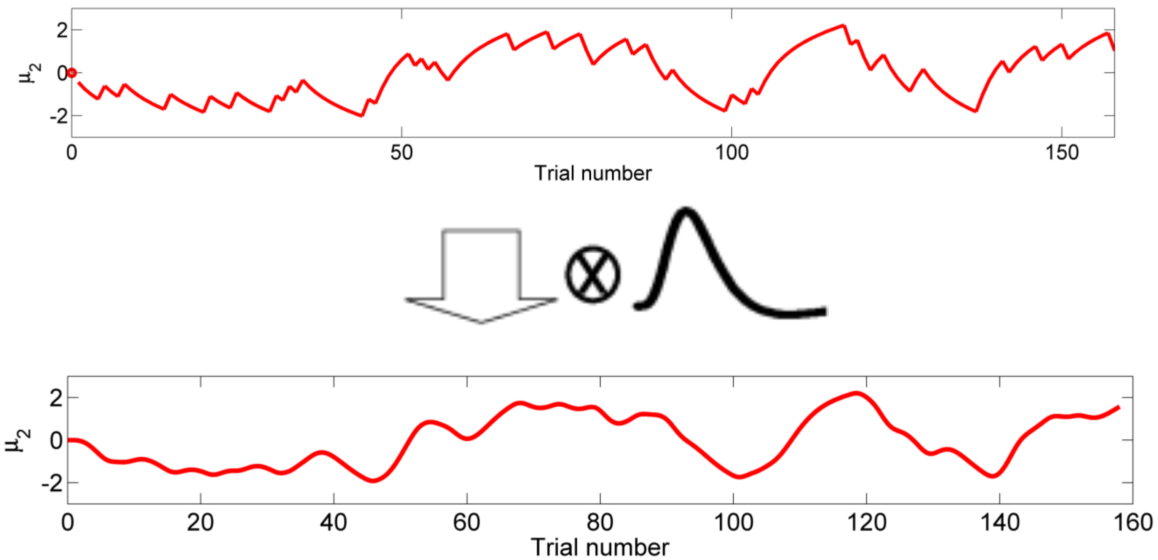
How do we construct regressors that correspond to cognitive processes and use them in SPM?

3. Generate model-based time series



How do we construct regressors that correspond to cognitive processes and use them in SPM?

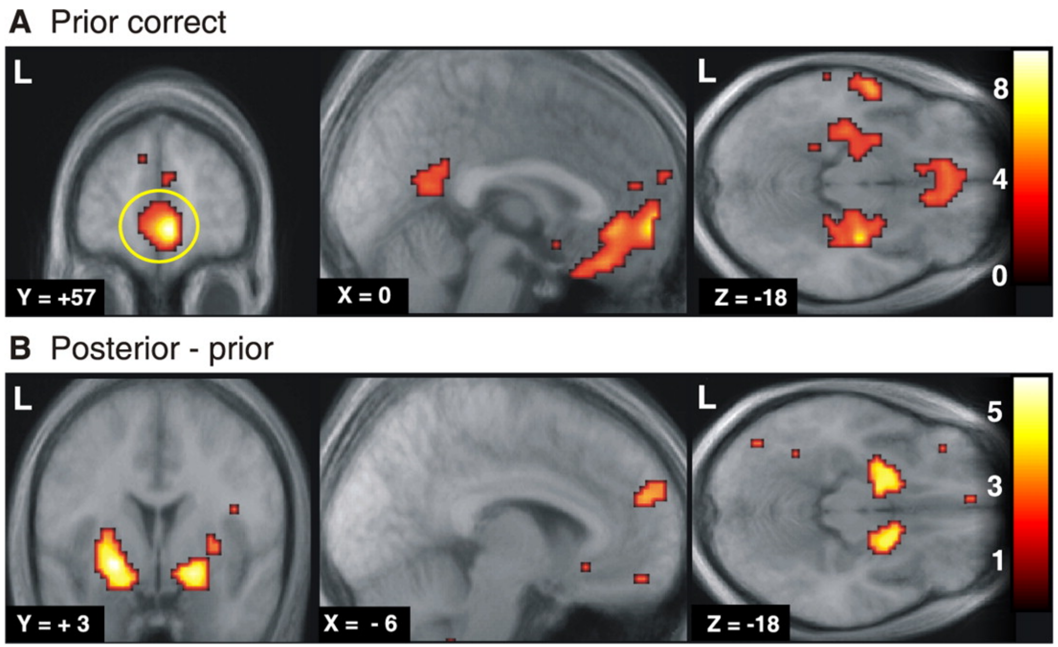
4. Convolve time series with hemodynamic response function



Adapted from O'Doherty et al., (2007)

How do we construct regressors that correspond to cognitive processes and use them in SPM?

5. Regress against fMRI data



Hampton et al., (2006)

Model-based fMRI

1. Pass individual subject trial history to model

2. Find best-fitting parameters of model to behavioral data

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3. Generate model-based time series

4. Convolve time series with hemodynamic response function

5. Regress against fMRI data

From classic design to model based fMRI

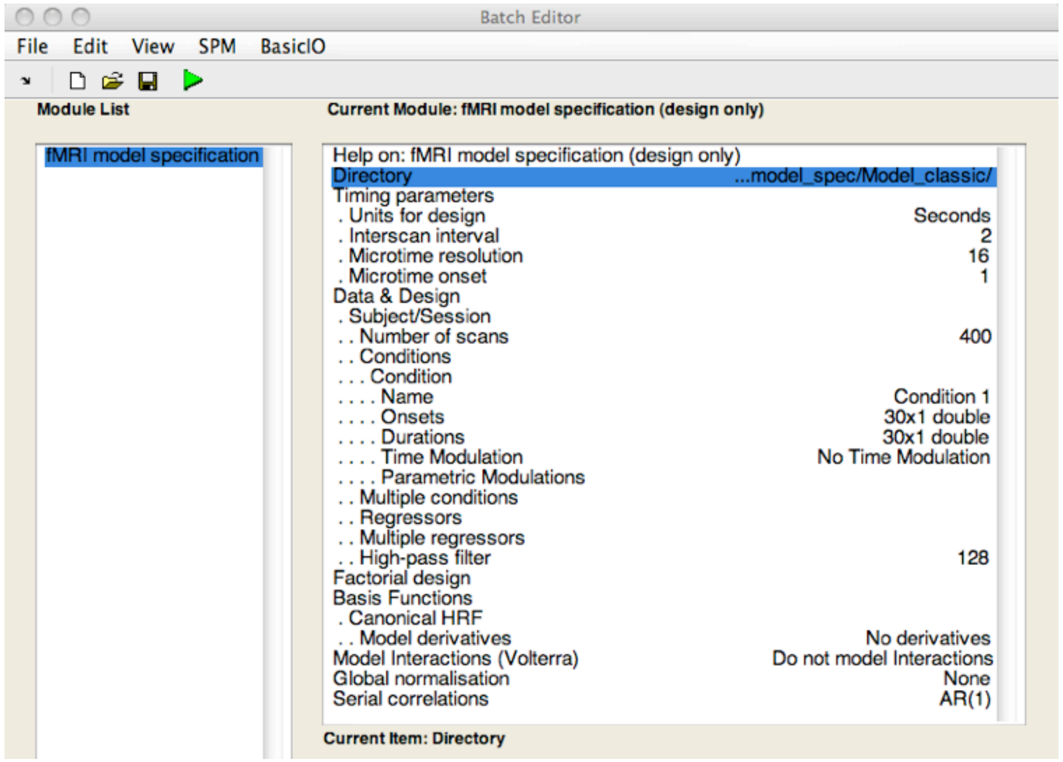
1. Classic event/block design

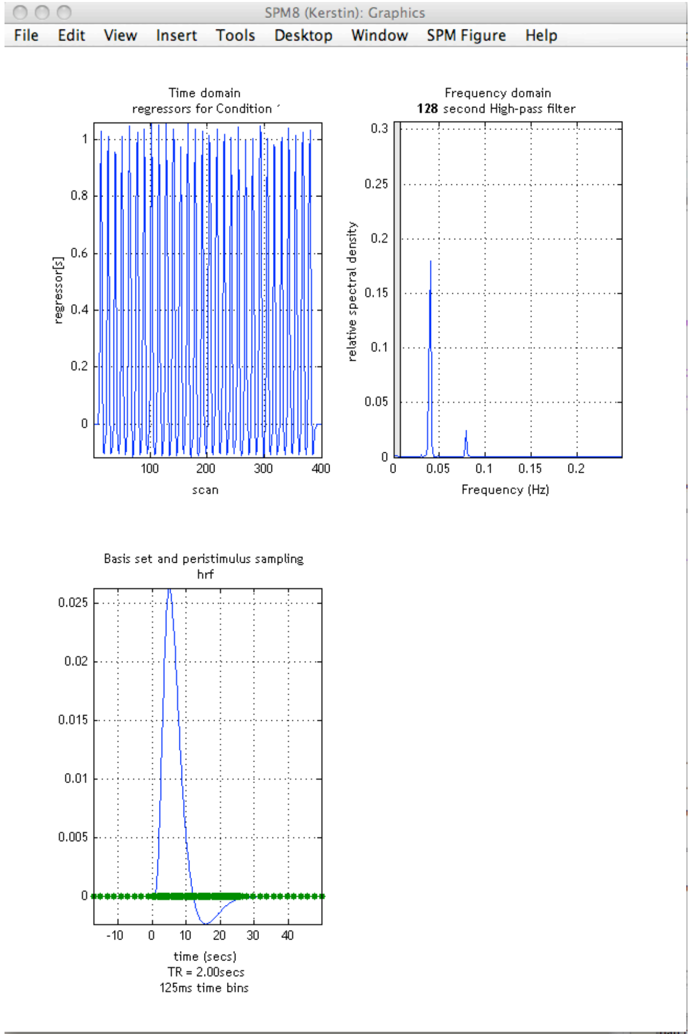
2. Adding parametric regressors

3. Model-based design

Model-based fMRI: comparisons

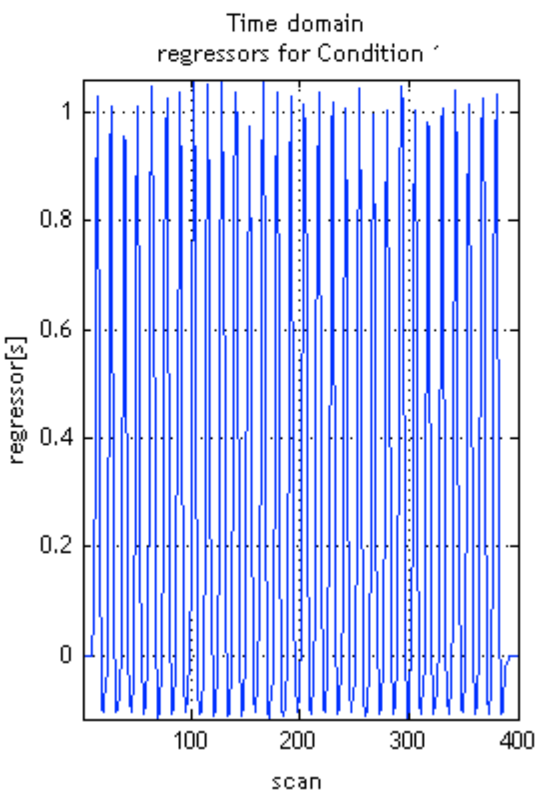
- Classical event/block design

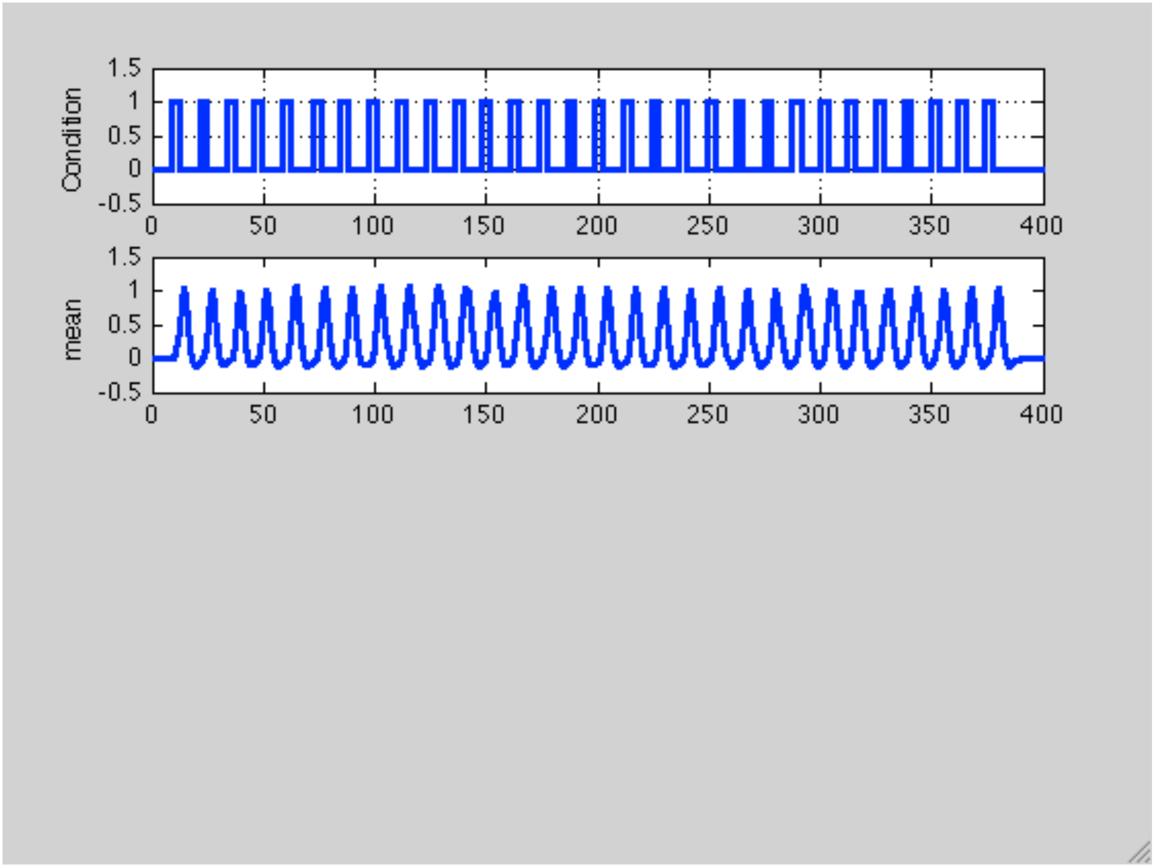




Model-based fMRI: comparisons

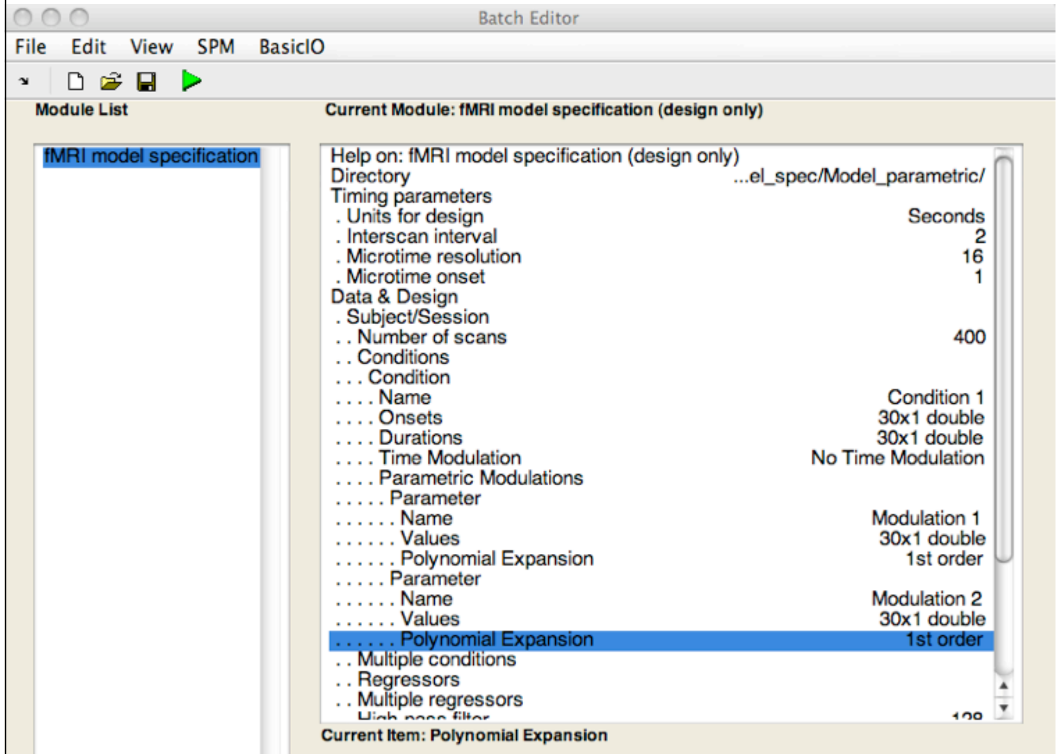
- Classical event/block design

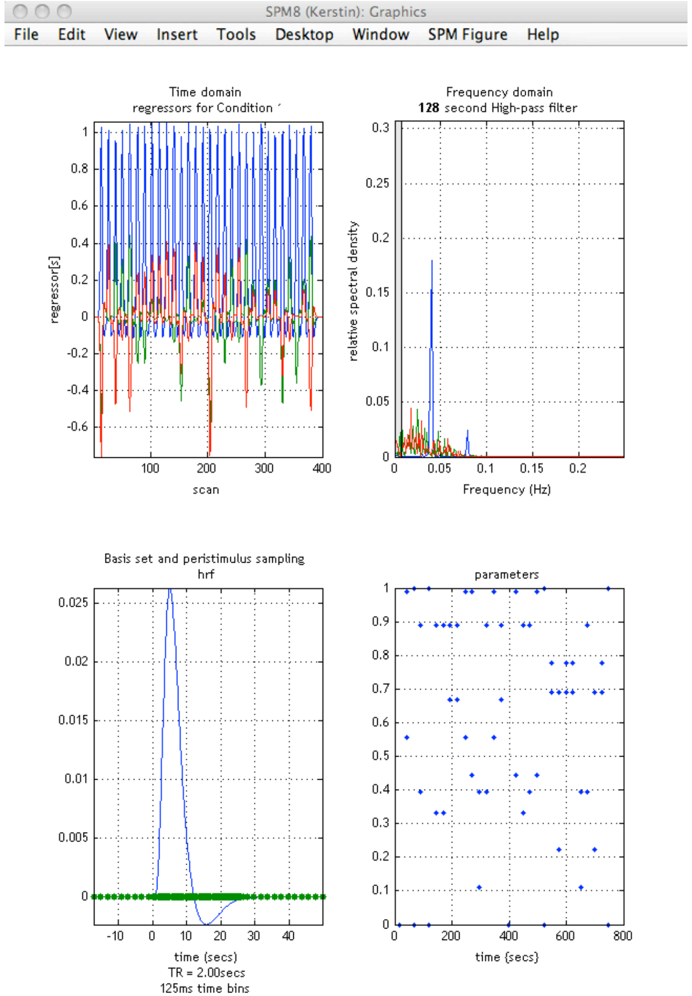




Model-based fMRI: comparisons

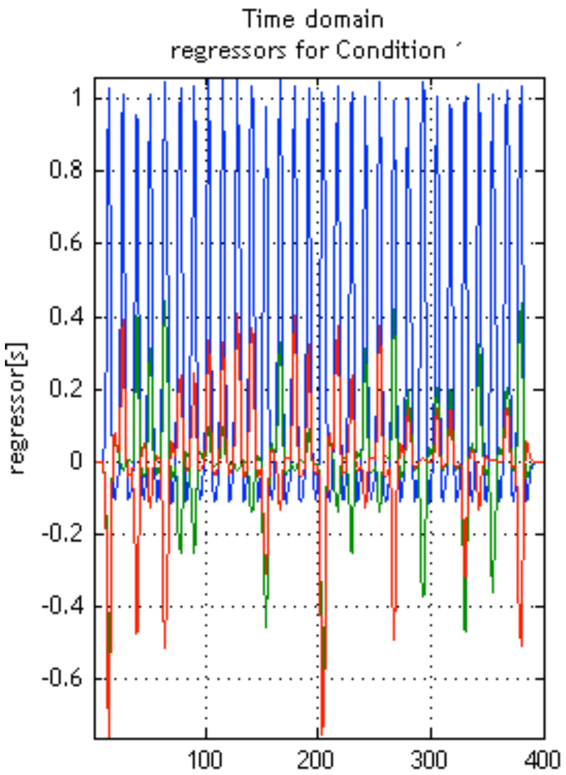
- Parametric regressors

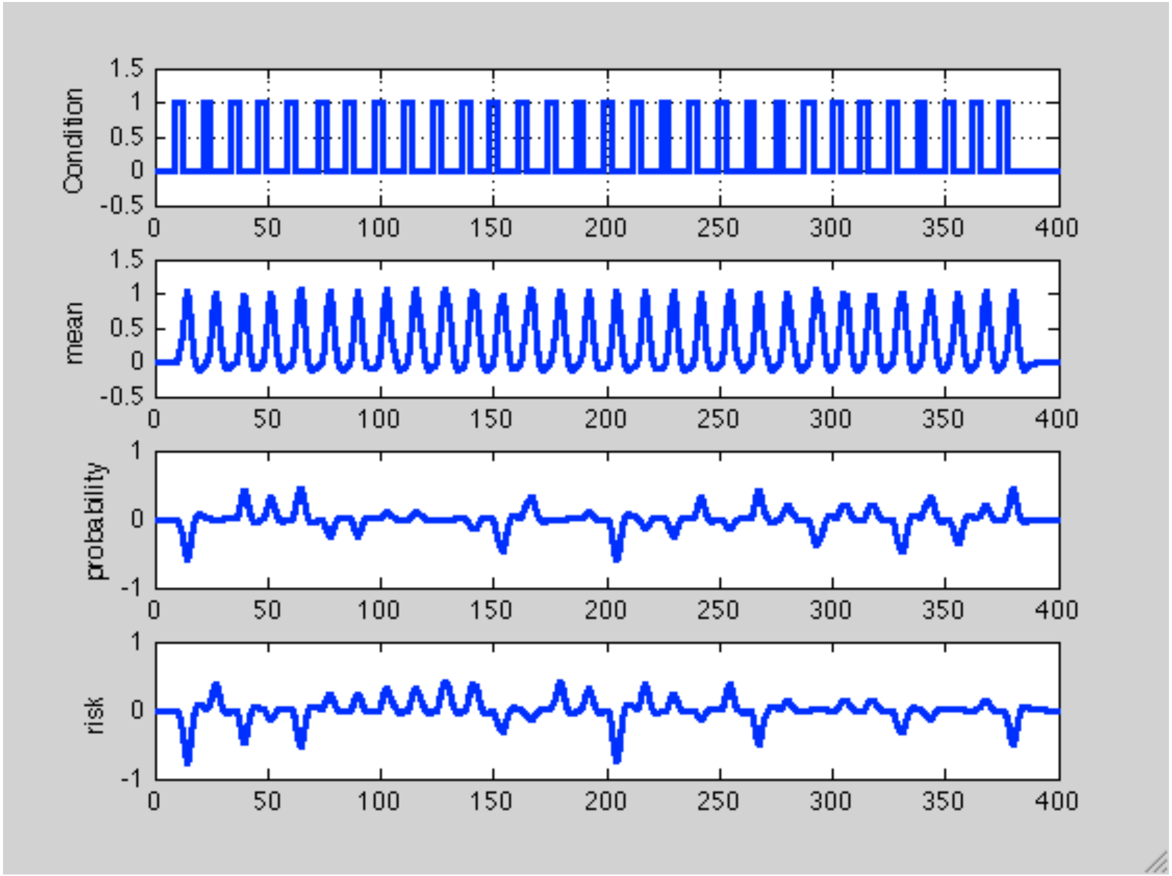




Model-based fMRI: comparisons

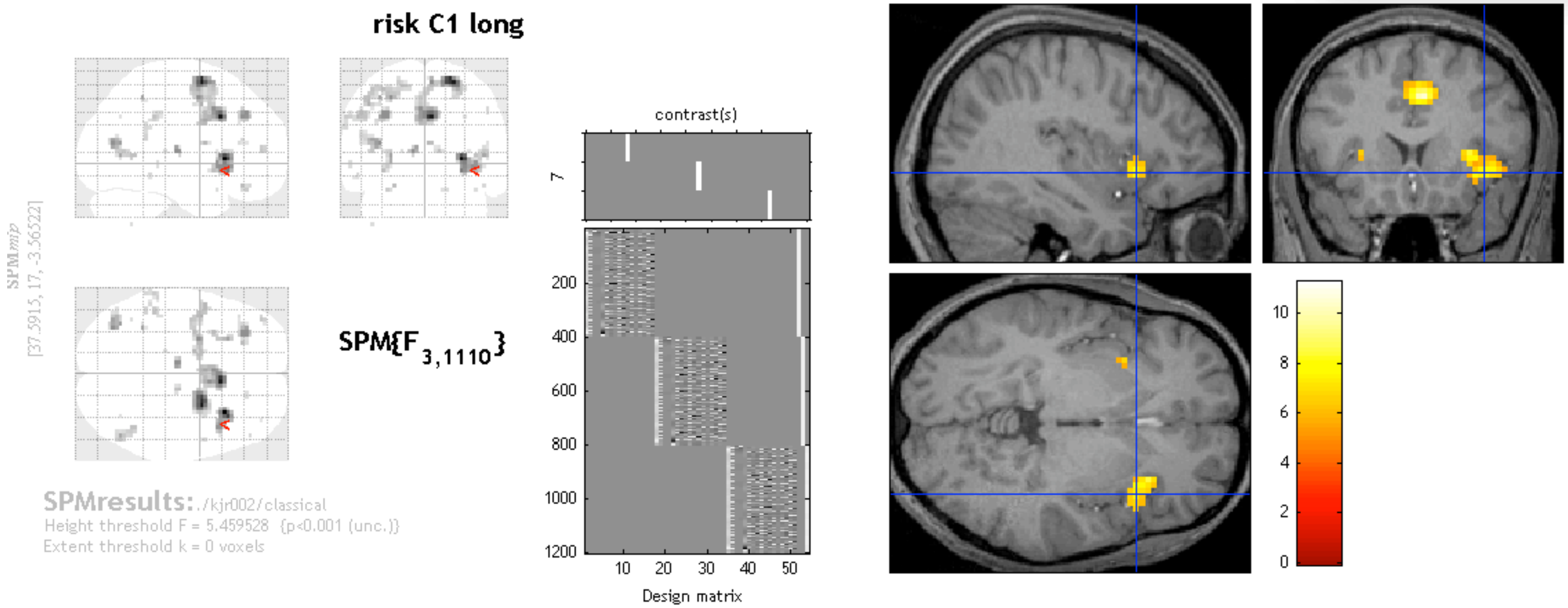
- Parametric regressors





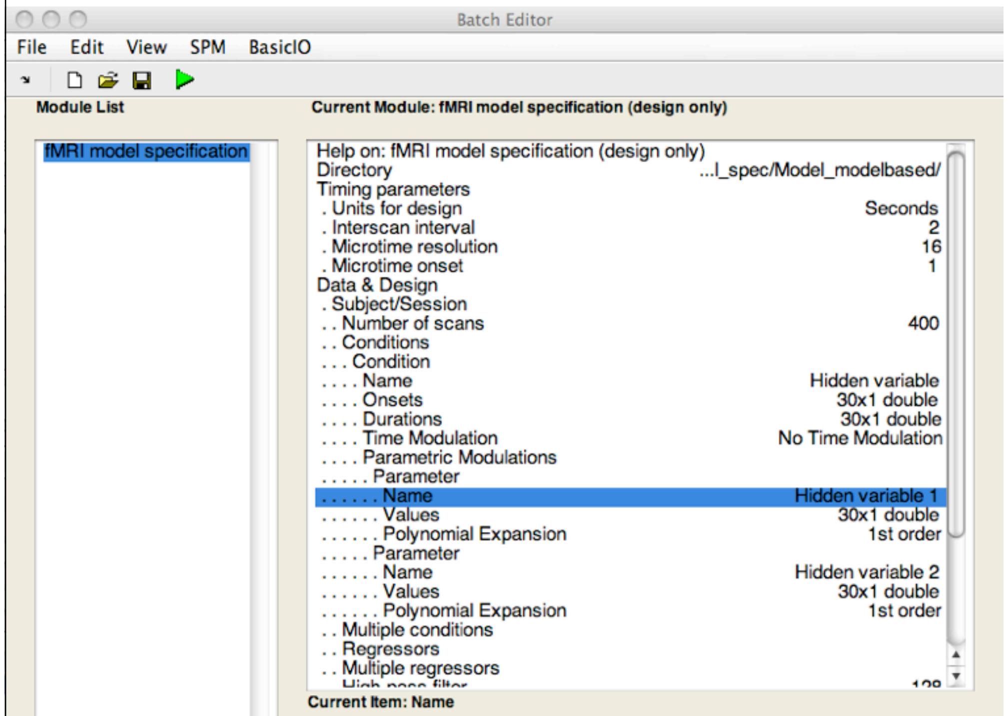
Model-based fMRI: comparisons

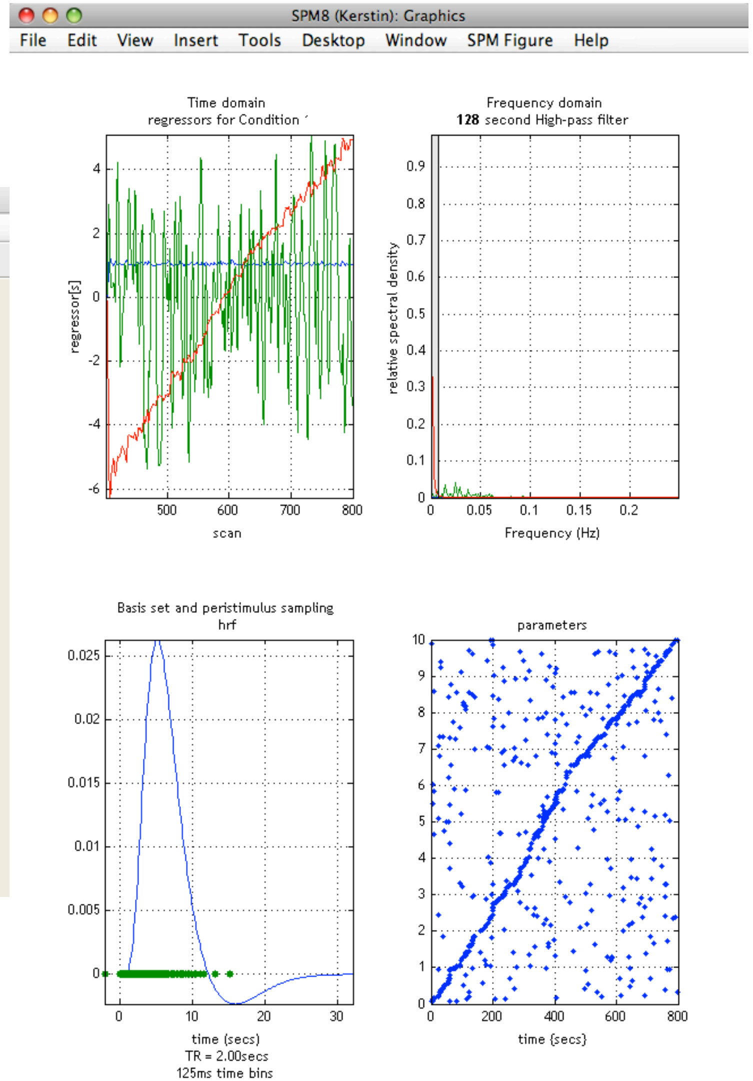
- Parametric regressors



Model-based fMRI: comparisons

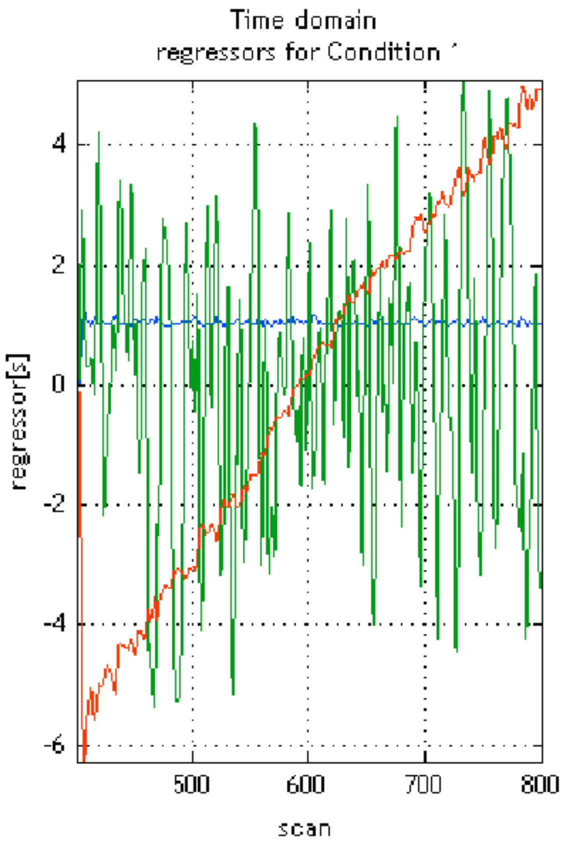
- Model based fMRI

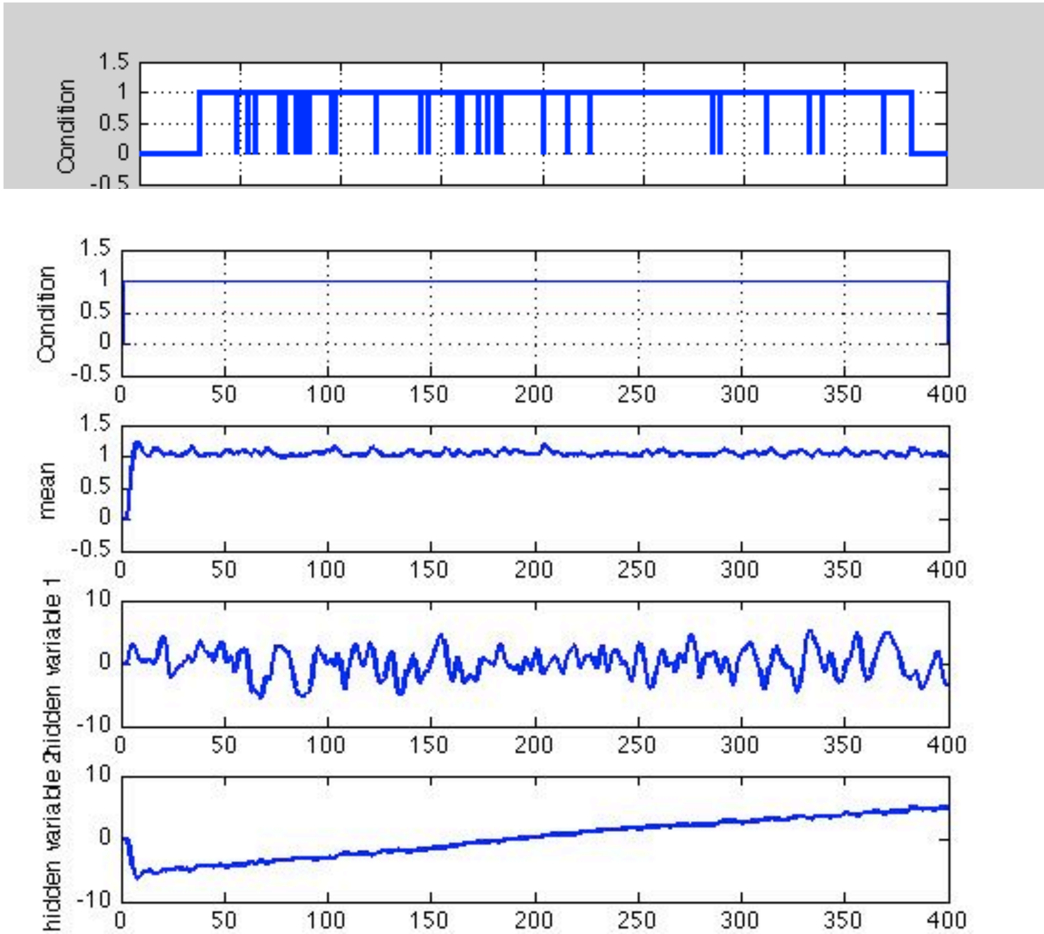




Model-based fMRI: comparisons

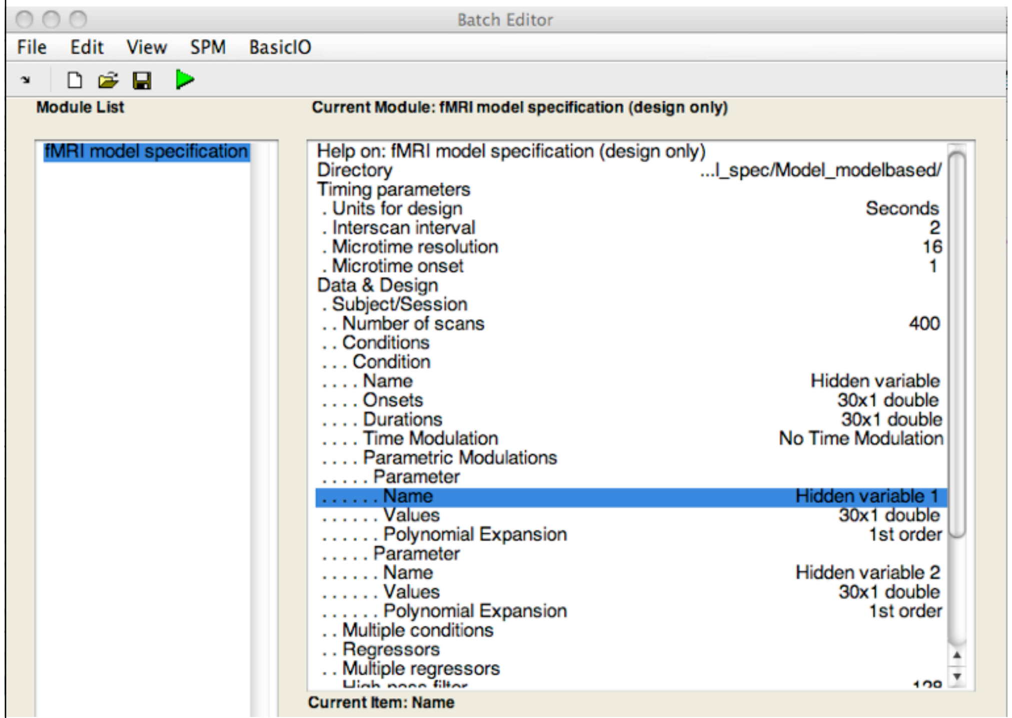
- Model based fMRI

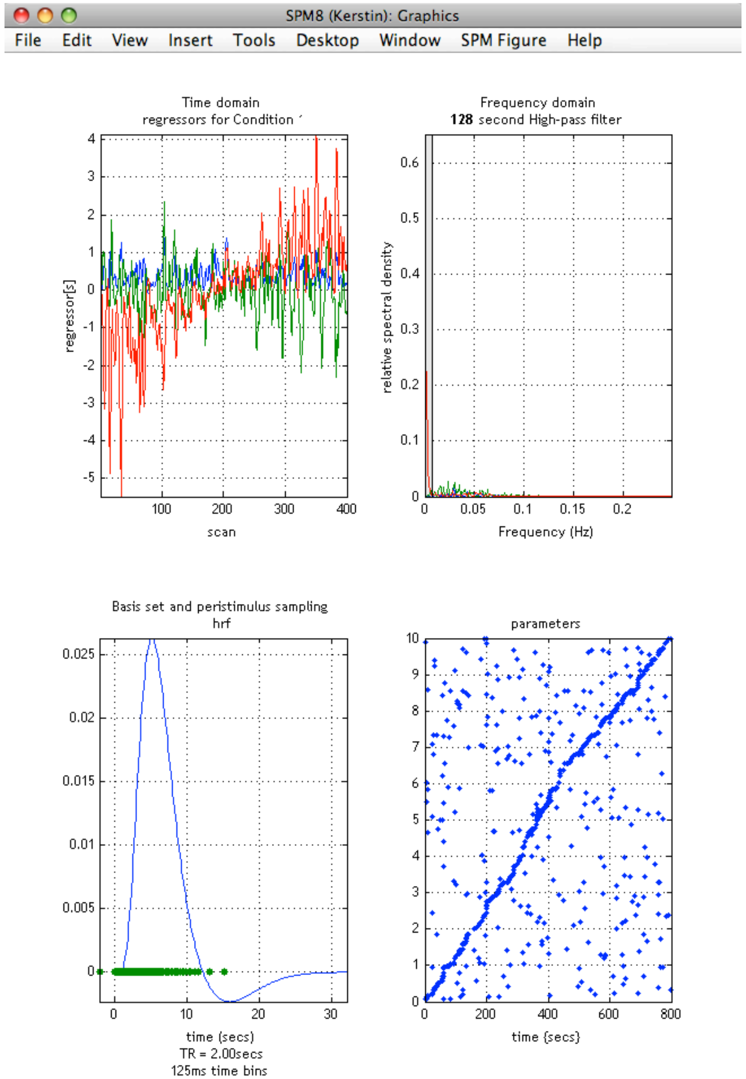




Model-based fMRI: comparisons

- Model based fMRI





Model-based fMRI: comparisons

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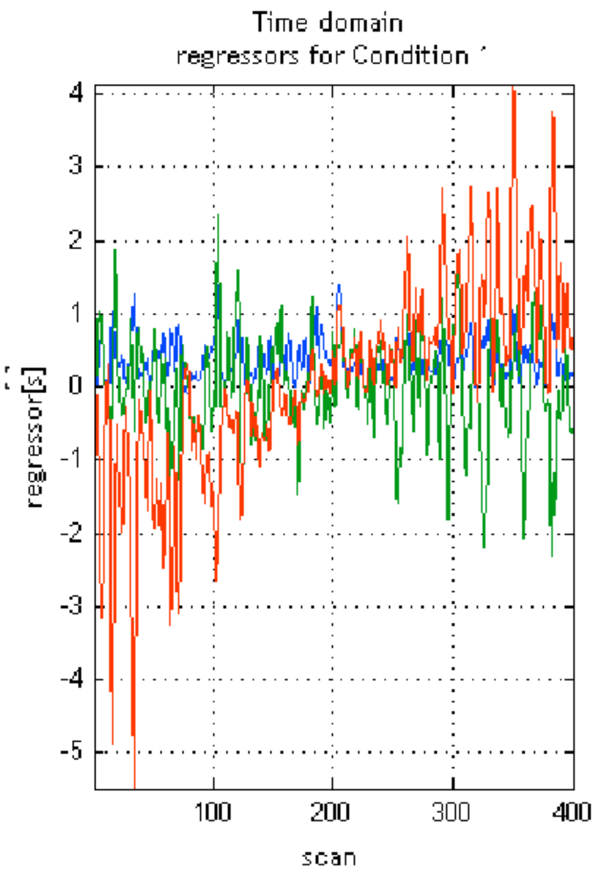
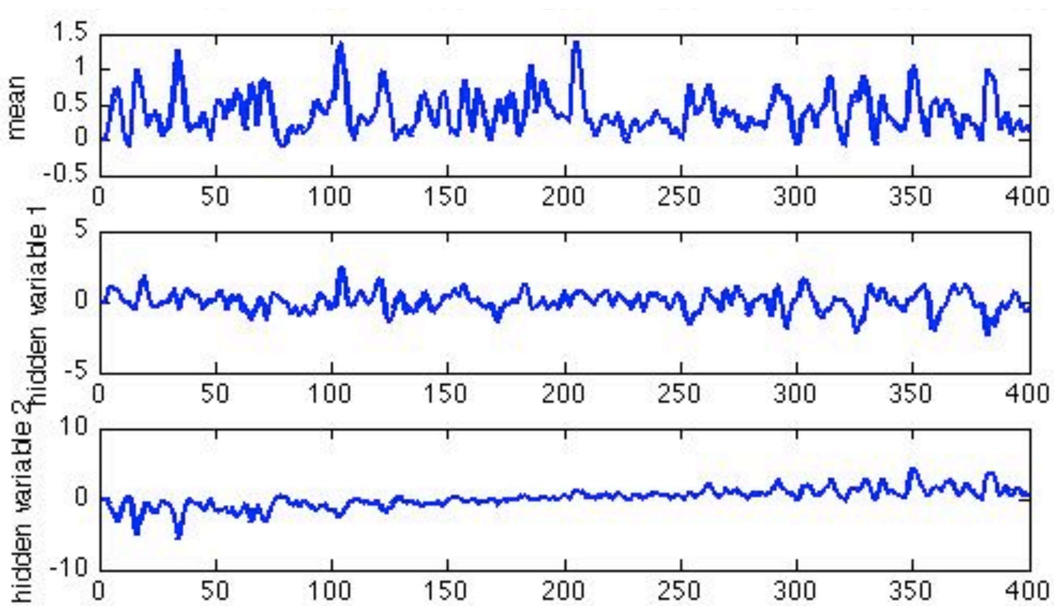
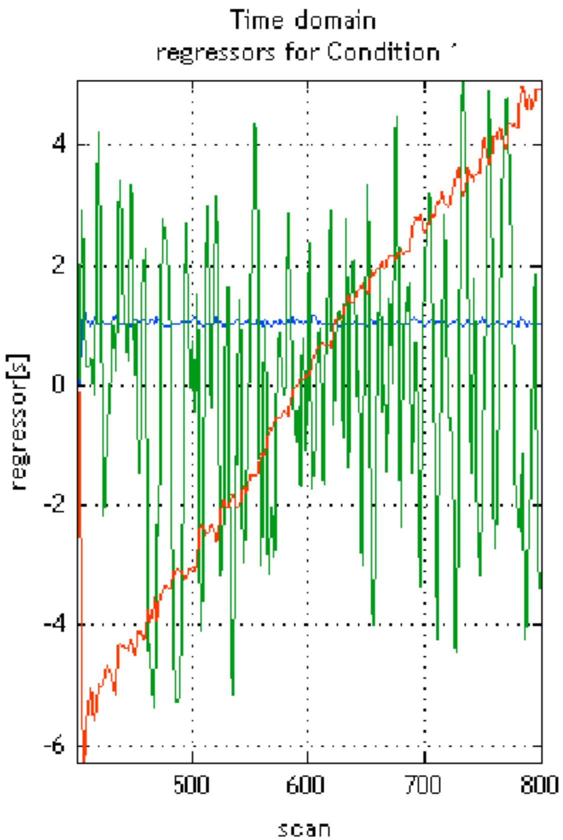
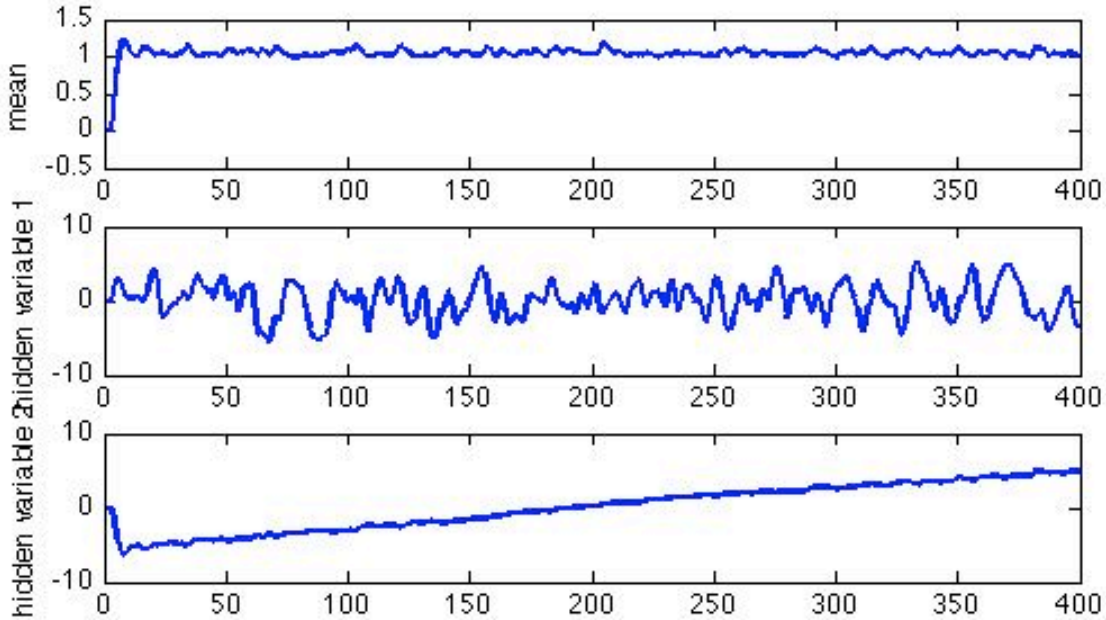




Model-based fMRI: comparisons

- Model based fMRI

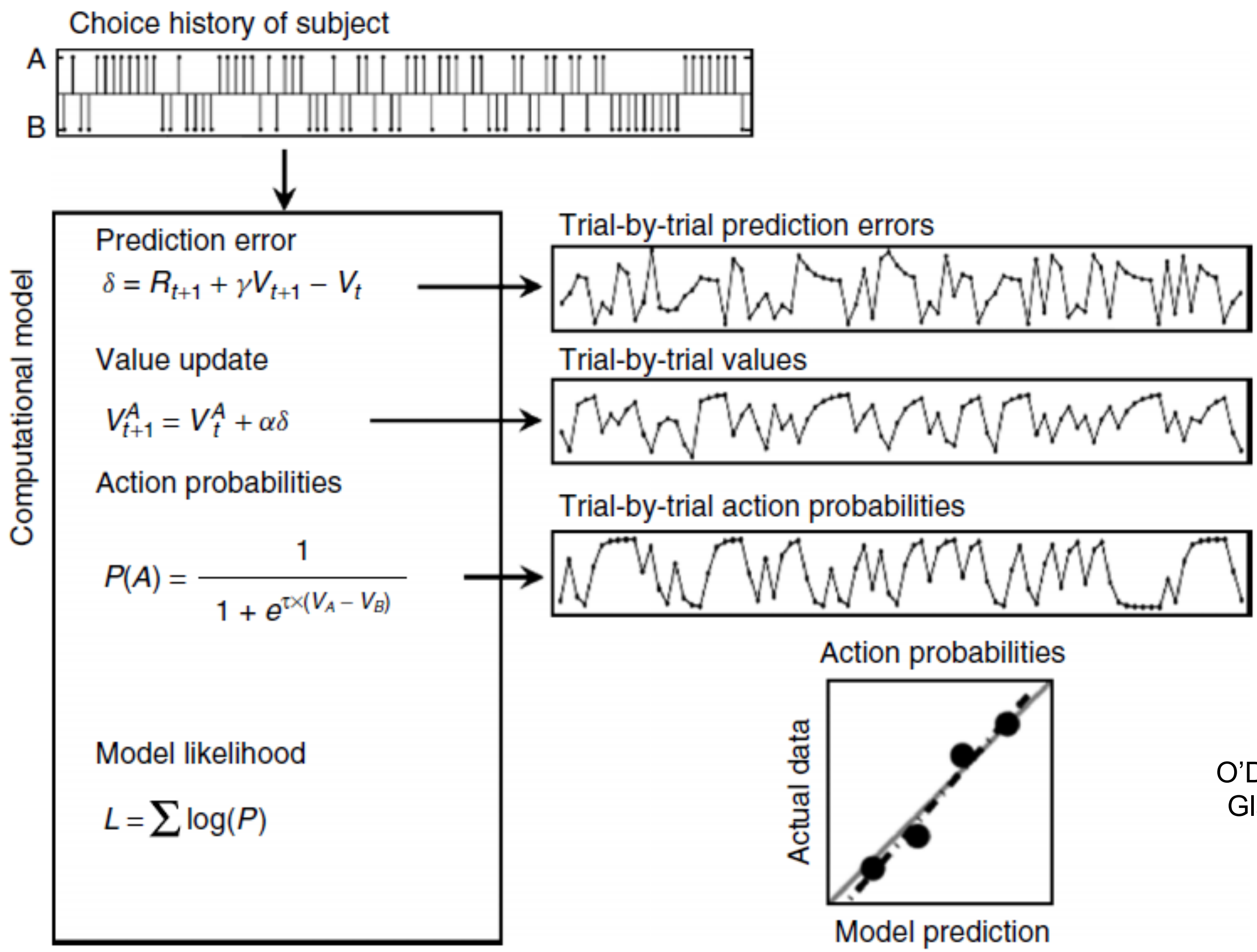




Model-based fMRI - Applications

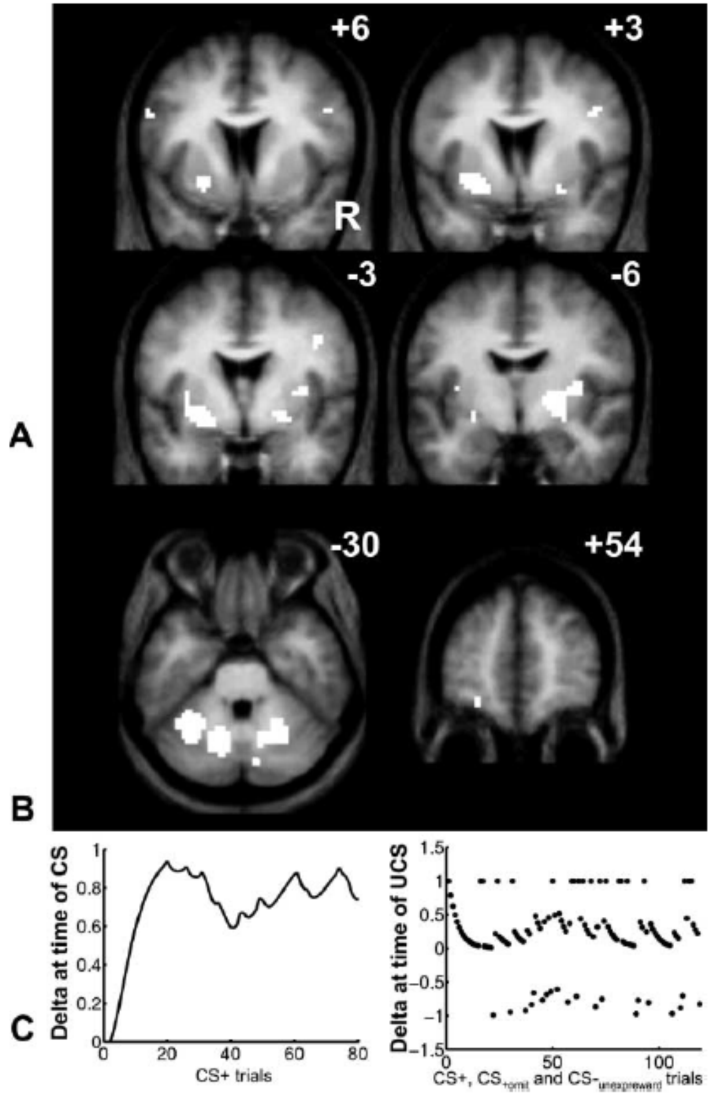
1. Simple learning model
    - O'Doherty et al
      Task, Model, Regressor, Result
2. Advanced Models
    - Behrens et al
      Task, Model, Regressor, Result
    - den Ouden et al
      Task, Model, Regressor, Result
    - Mathys et al
      Task, Model, Regressor, Result

Model-based fMRI – Simple learning model



O'Doherty et al. (2003),
Gläscher et al. (2010)

Model-based fMRI – Simple learning model

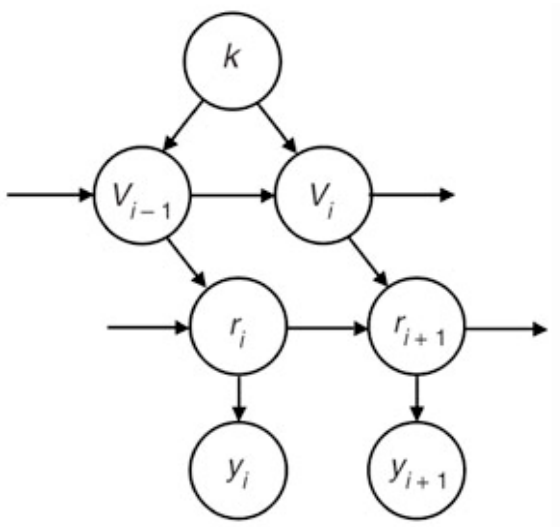


Significant effects of prediction error with fixed learning rate

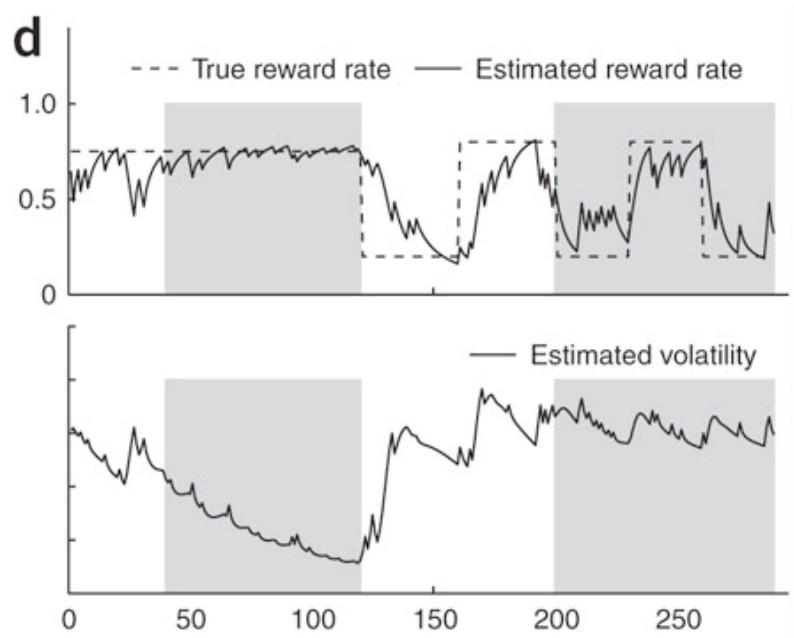
O'Doherty et al. (2003)

Model-based fMRI - Applications

Hierarchical Bayesian generative model



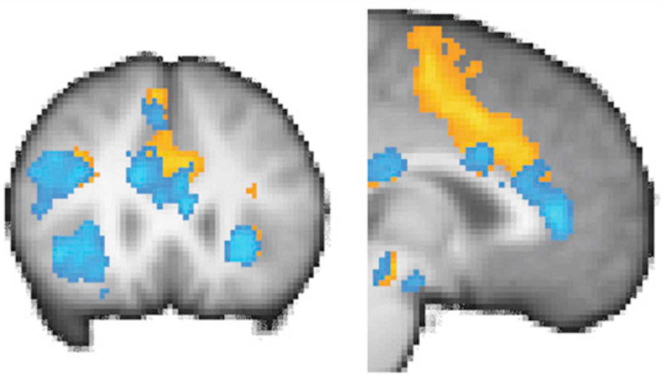
Rewarded decision task



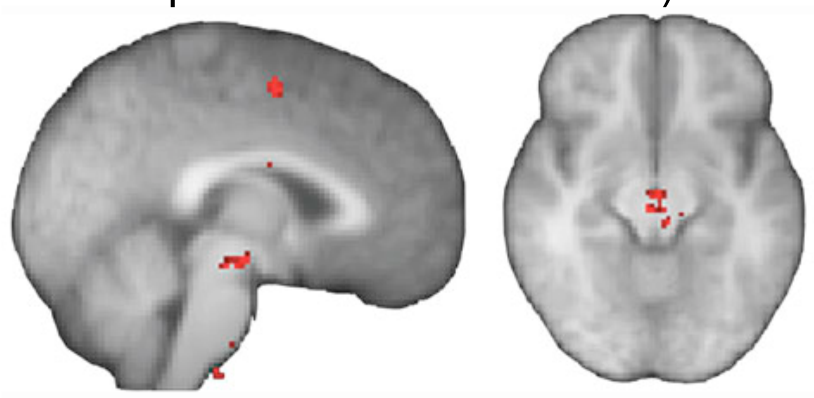
Behrens et al. (2007)

Model-based fMRI - Applications

Correlation with volatility
Orange: decide
Blue: monitor



Correlation with reward probability
(Does not survive multiple comparison correction)



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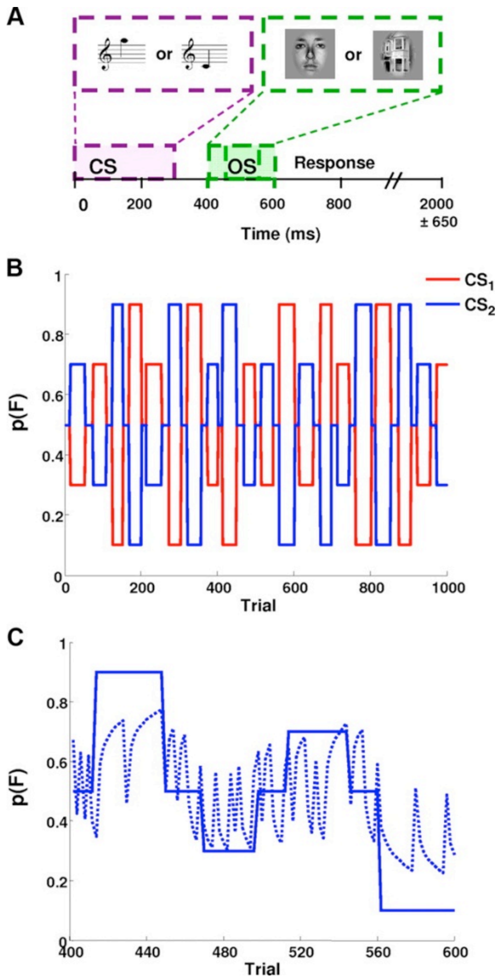
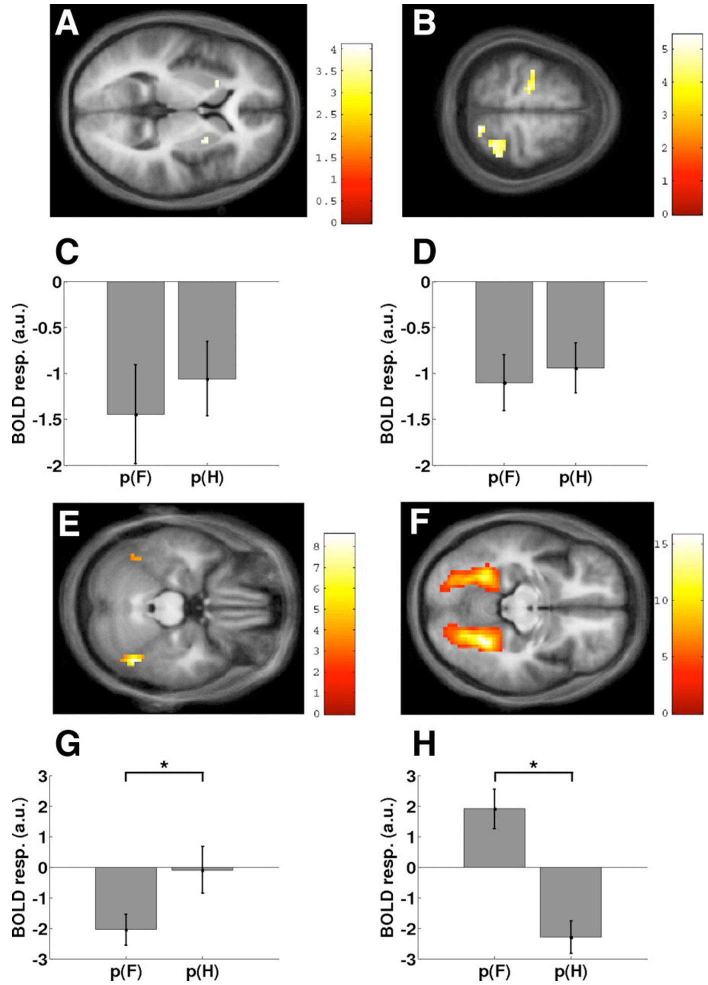
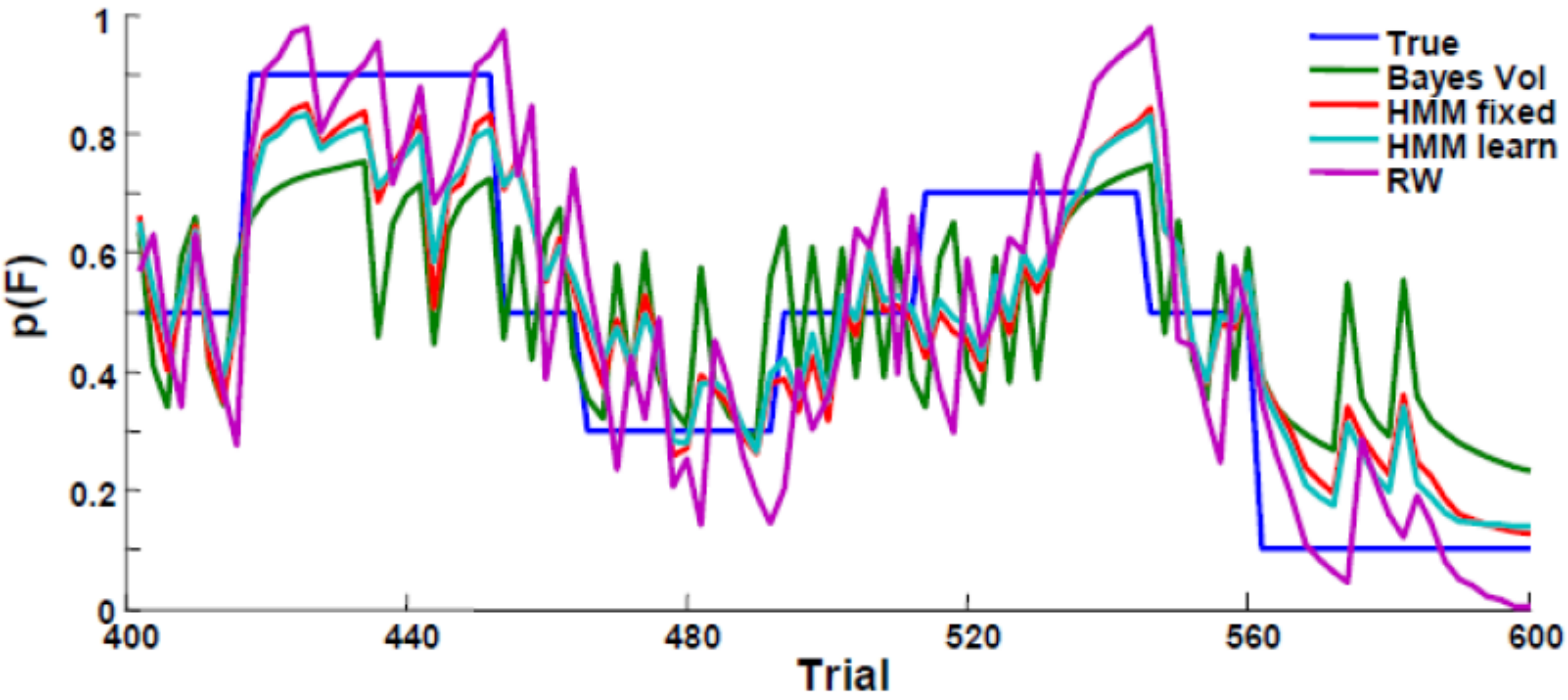
Model-based fMRI - Applications





den Ouden et al. (2010)

Model-based fMRI - Applications



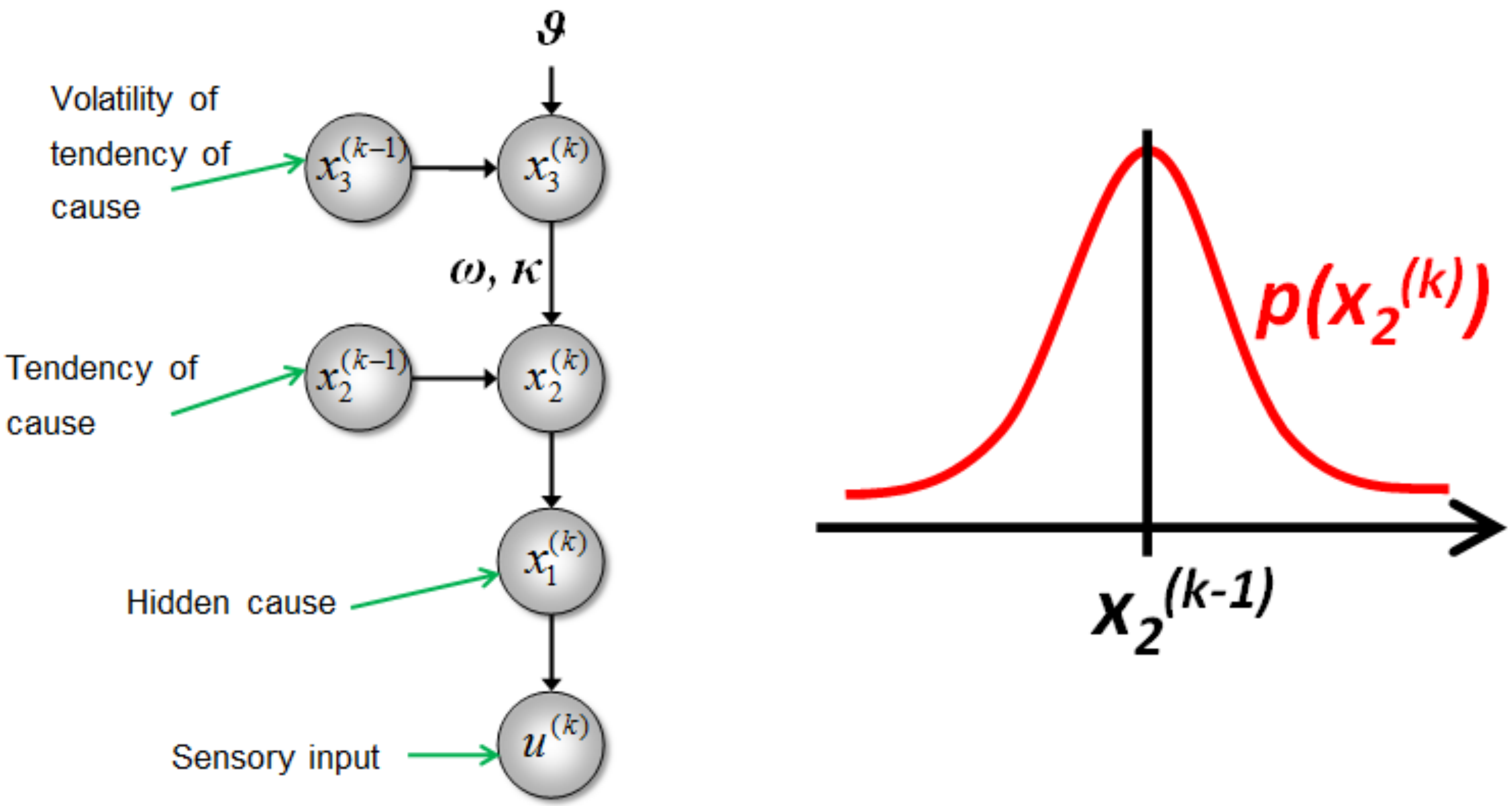
den Ouden et al. (2010)

Model-based fMRI - Applications

- Behavioral task

- 160 trials
- Changing stochastic association of cue with monetary reward
- Stochastic association varies over time
- Subjects: prodromal schizophrenics and healthy controls

Model-based fMRI - Applications: A hierarchy of Gaussian random walks



Model-based fMRI - Applications

- Loss Function

y \ x_1	0	1
0	$-r_A$	0
1	0	$-r_B$

y: Decision (0=A, 1=B)

x_1: Outcome (0=A, 1=B)

r_A, r_B: Rewards associated with A and B

- Expected Loss

$$Q(y;\lambda) = \begin{cases} -r_B\,\mu_1 & \text{for } y = 1 \\ -r_A(1-\mu_1) & \text{for } y = 0 \end{cases}$$

$$\mu_1 = p(x_1 = 1)$$

Model-based fMRI - Applications

- Decision model

$$p\left(y^{(k)}=1 \middle| \lambda^{(k)}, \chi, u\right)=\frac{1}{1+\exp\left(-\zeta\left(\mu_1^{(k)} r_B^{(k)}-\left(1-\mu_1^{(k)}\right) r_A^{(k)}\right)\right)}$$

- Logistic sigmoid of difference in expected loss between options A and B

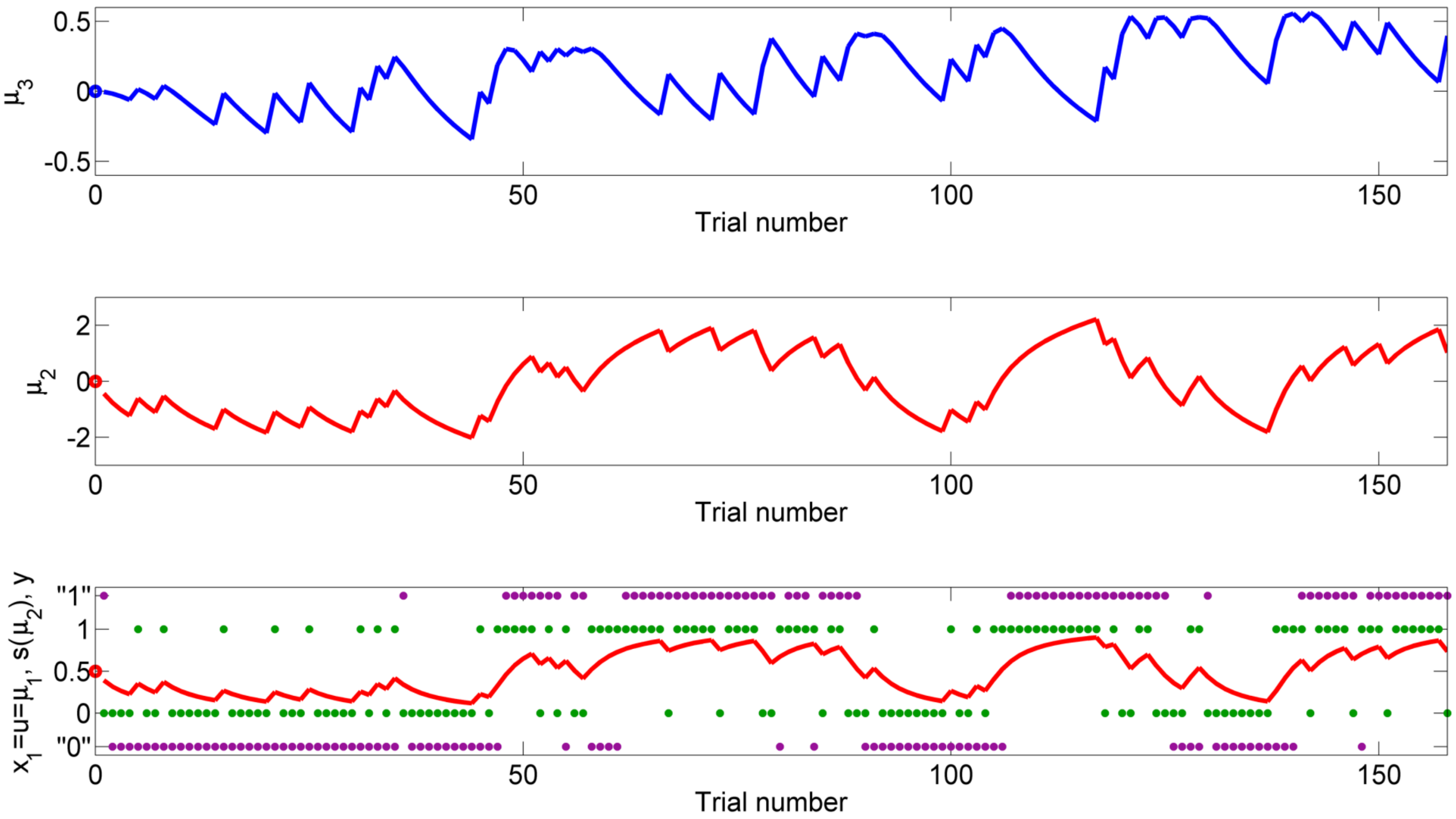
- Parameter ζ determines shape of sigmoid

  (exploration <-> exploitation)

- Inversion leads to estimates for parameters ϑ, ω, κ, and ζ

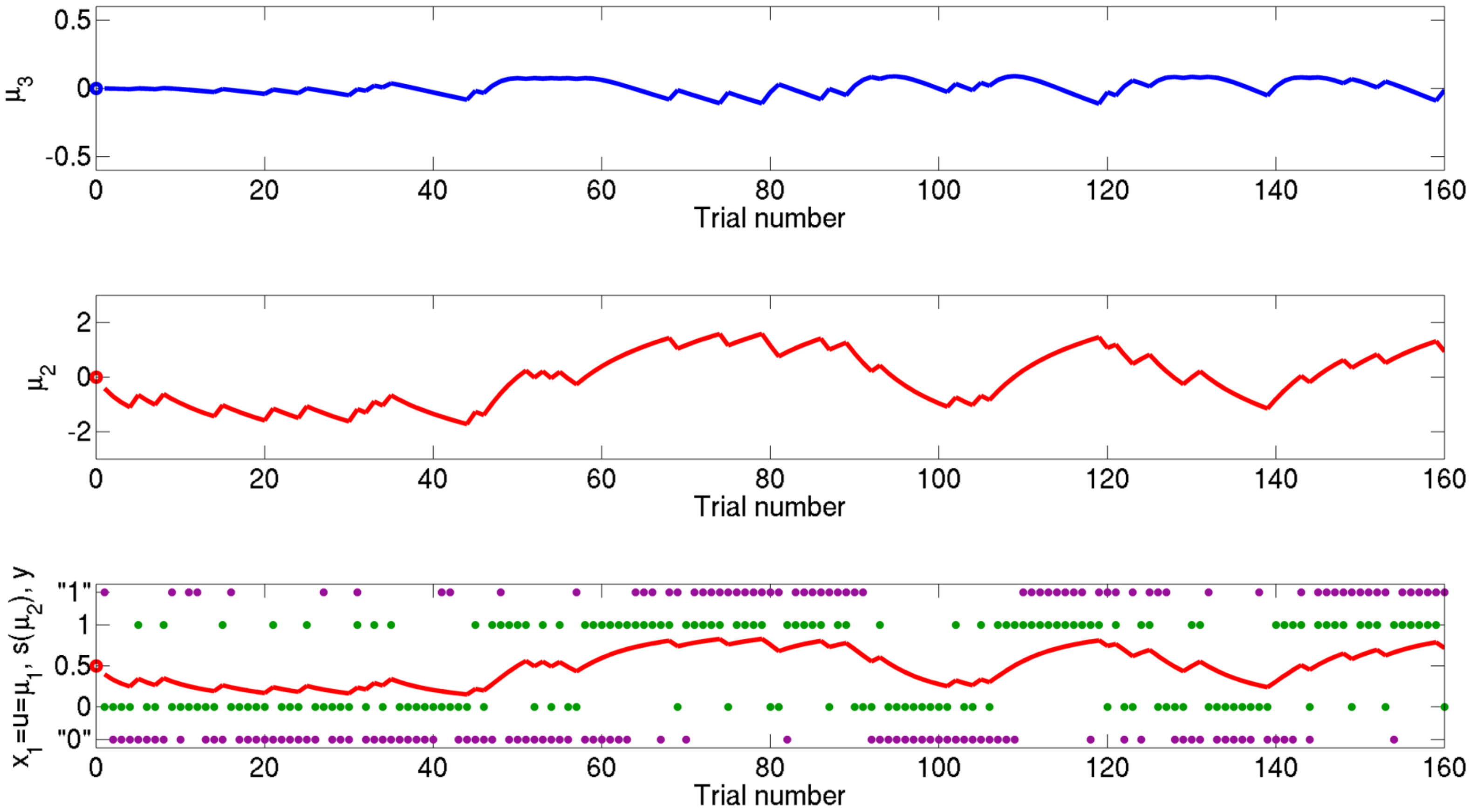
Model-based fMRI - Applications

- Healthy control subject:



Model-based fMRI - Applications

- Prodromal schizophrenic:



Summary

- Model-based fMRI:
  - Application of quantitative computational models to generate regressors of interest beyond stimulus inputs and behavioral responses.
  - Serves to uncover hidden variables and cognitive processes
- A model may be realistic but it is never correct.
- In most cases, hrf beats