Model-based fMRI

Zurich SPM Course
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To model or not to model

GLM

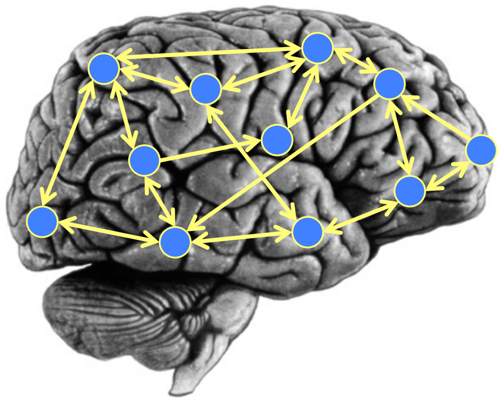
DCM

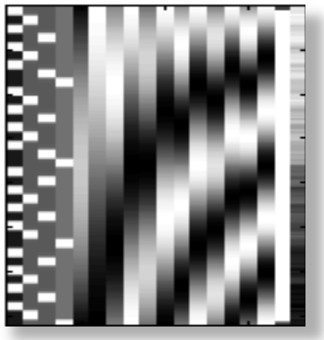
Classification

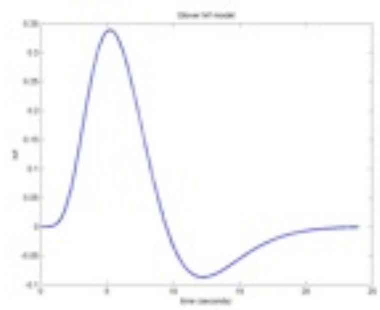
Multivariate Bayes

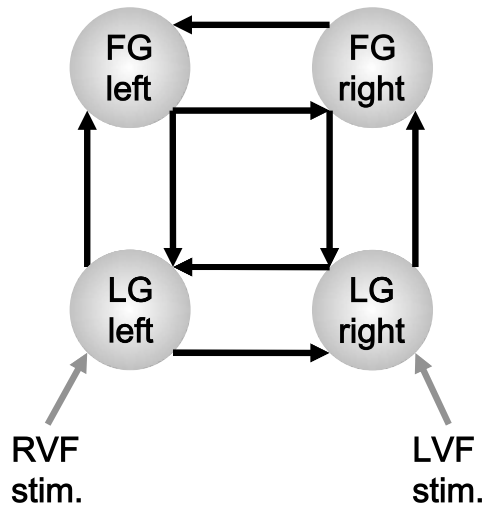
fMRI uses models at different stages

- Hemodynamic response (hrf)
- Activation levels
- Time courses
- Connectivity
- t-tests







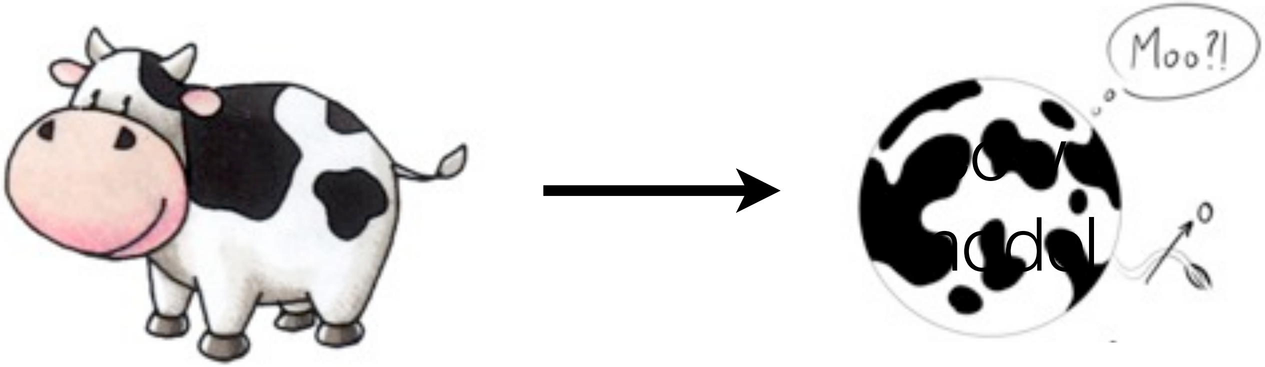


Model-based fMRI

- 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)

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

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

- Tractable
  computationally efficient

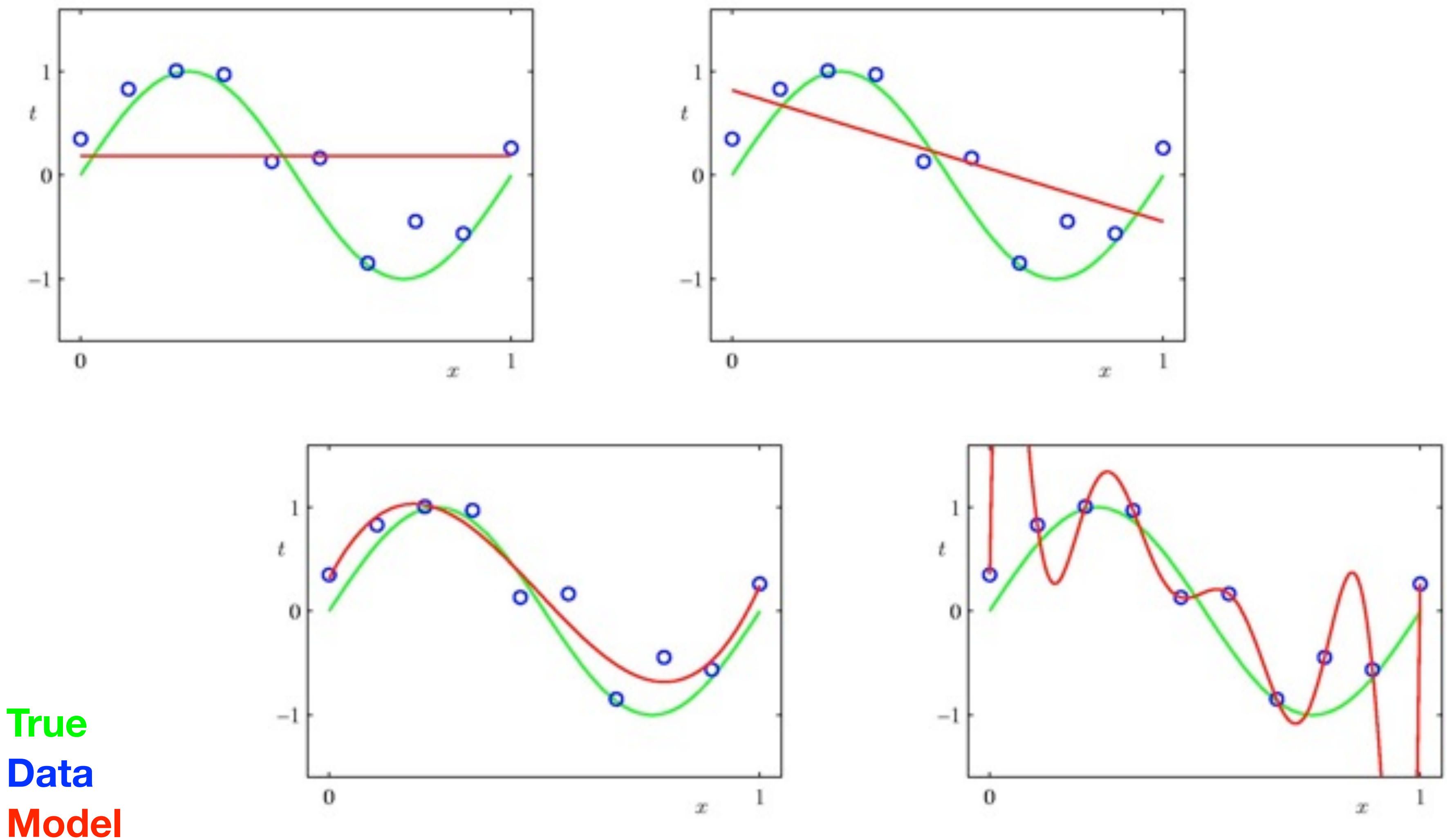
A good model (2)

- Realistic
  hrf better than spherical cow
  e.g., incorporate knowledge about brain anatomy and neuronal responses

- Simple
  spherical cow better than hrf

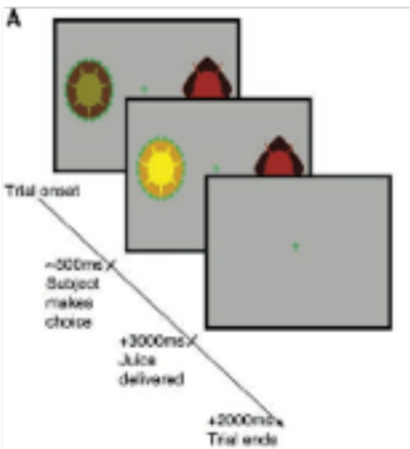
- BUT Occam's razor: as simple as possible, as flexible as needed
  hrf better than spherical cow

As simple as possible, as flexible as needed

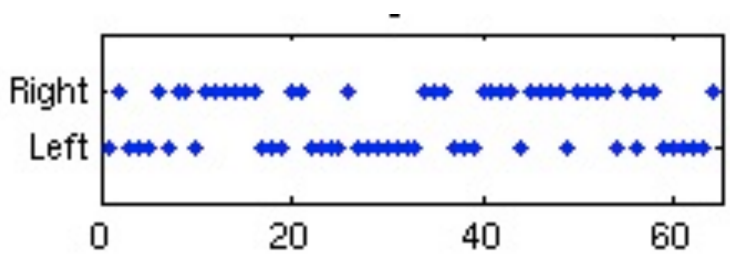


Model-based fMRI

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



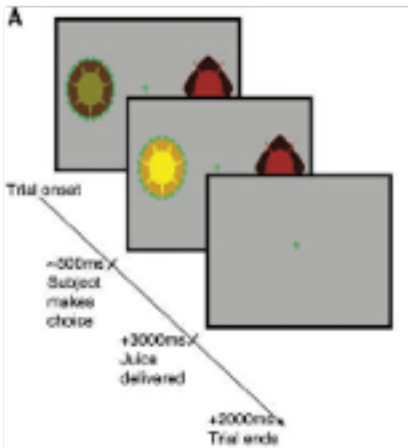
Participant response



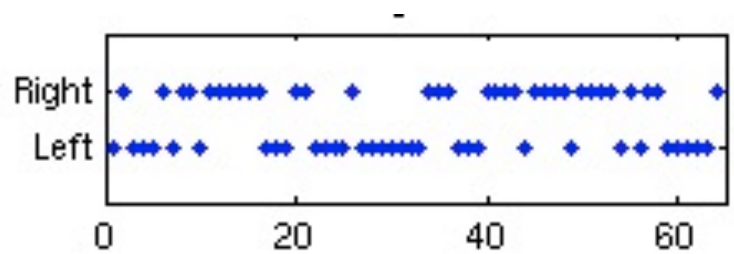
- Goal: uncover hidden variables or processes

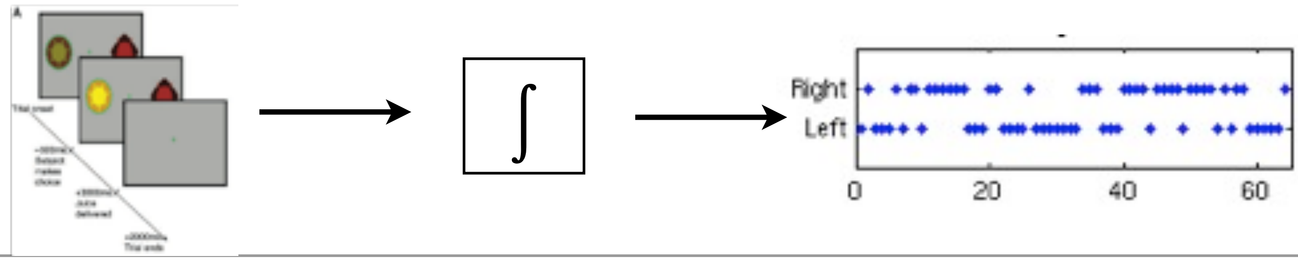
Model-based fMRI: questions answered

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



Participant response




Right
Left
0
20
40
60

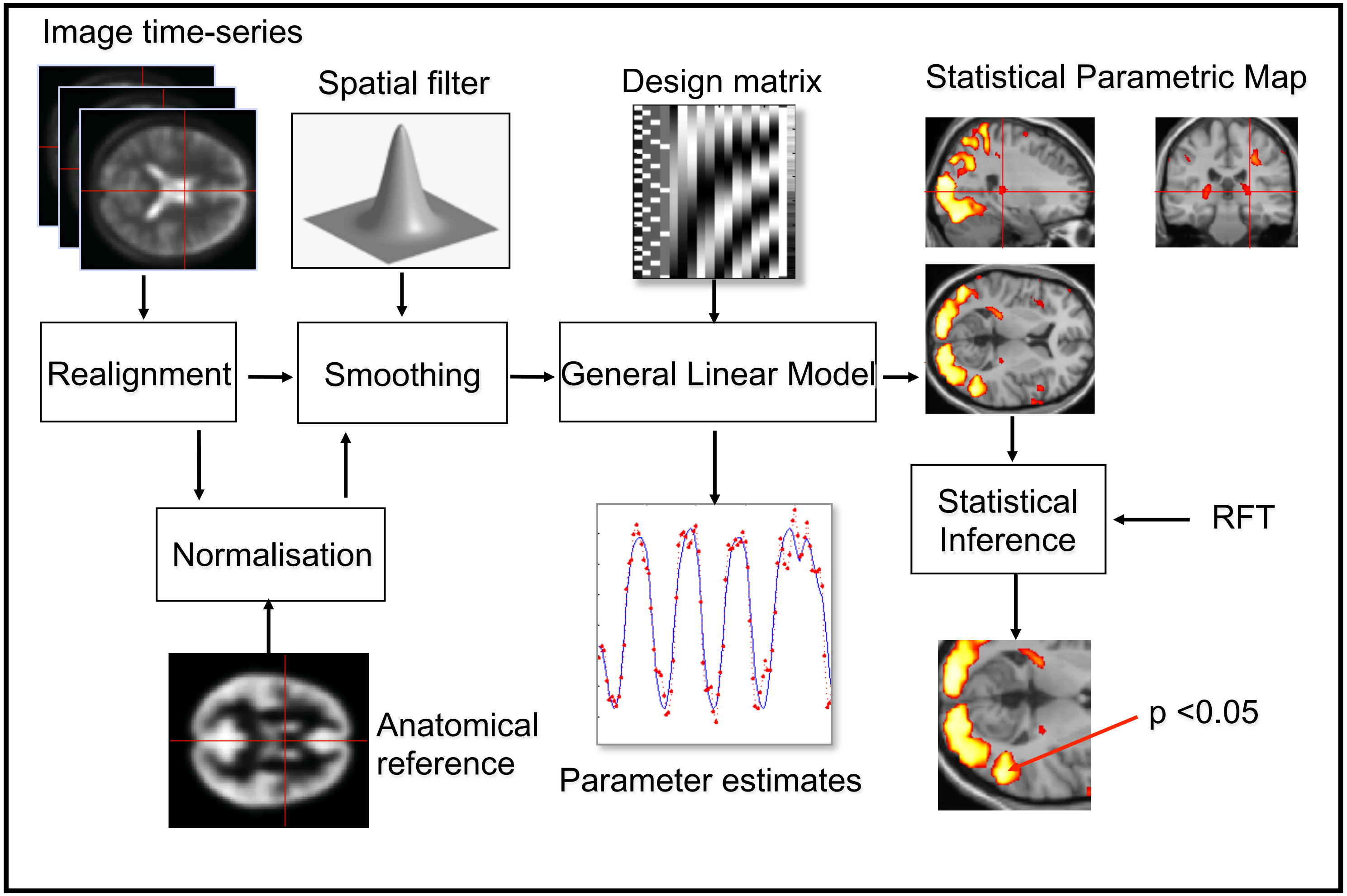


Image time-series
Spatial filter
Design matrix
Statistical Parametric Map
Realignment
Smoothing
General Linear Model
Normalisation
Statistical Inference
RFT
Anatomical reference
Parameter estimates
p <0.05

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

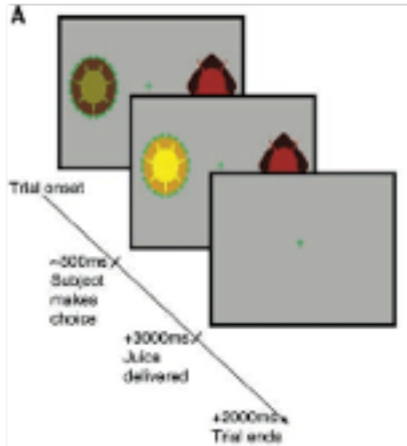
1. Basic recipe for model-based fMRI

2. Using model-based regressors in the GLM

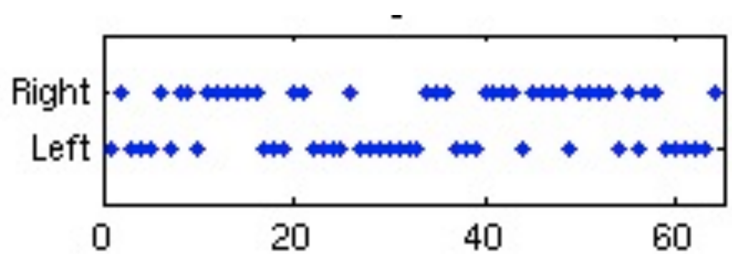
3. Examples

Model-based fMRI

1. Decide on a model
   - This should happen *before* you run the experiment.
   - Start with a research question and choose a model that adequately addresses this question.
   - Design your experiment with this model in mind.
   - E.g., reinforcement learning model, hierarchical bayesian model.



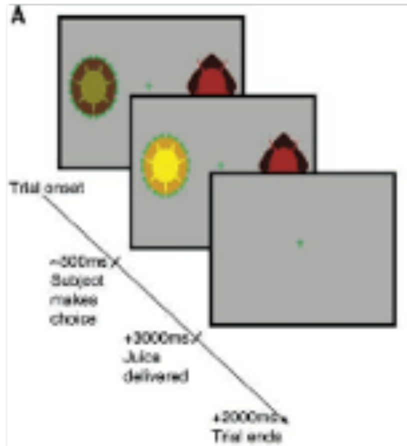
Participant response



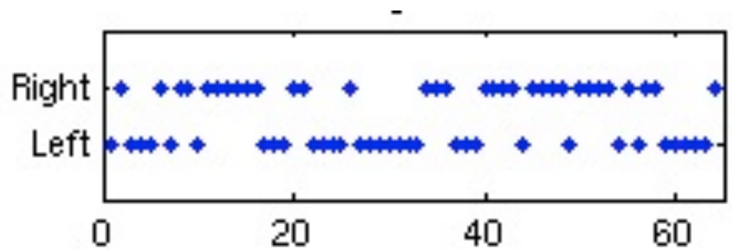
Model-based fMRI

1. Decide on a model

   - Reinforcement learning model

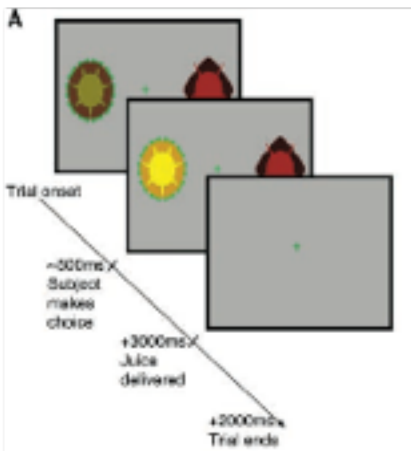


Participant response

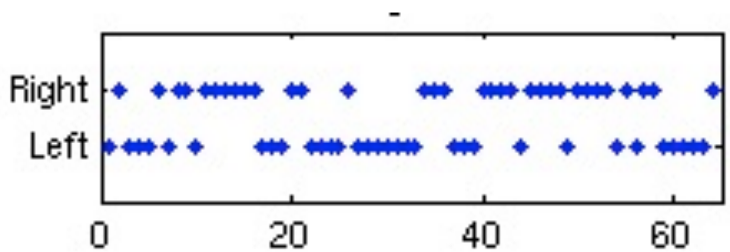


Model-based fMRI

2. Pass individual subject trial history to model



Participant response



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

$$V_{t+1}^A = V_t^A + \alpha\delta$$

Model-based fMRI

3. Find best-fitting parameters of the model (e.g., learning rate) to behavioral data

4. Generate

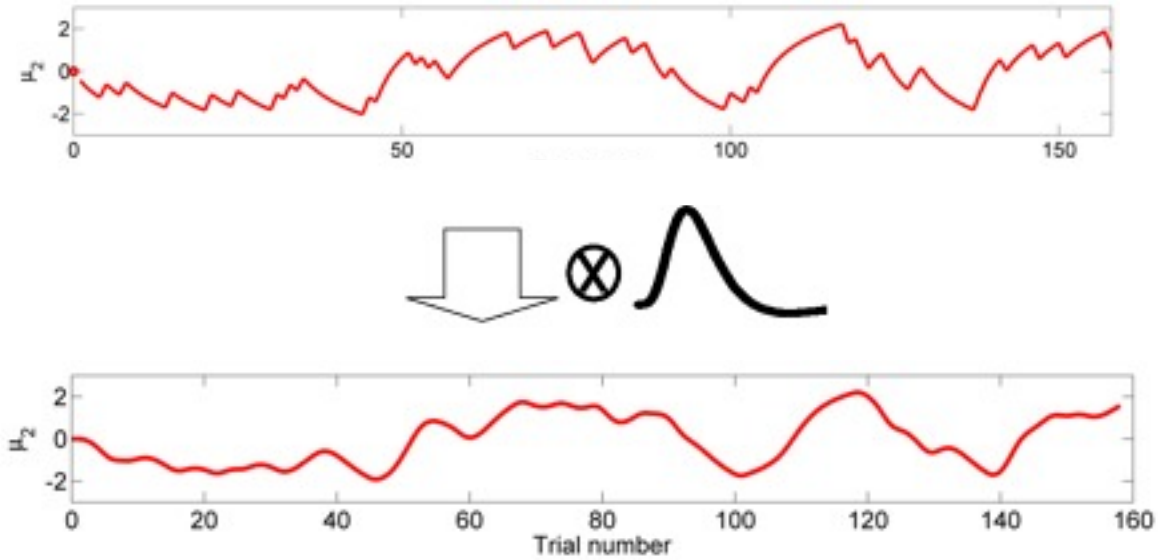
   a. parametric modulators (first level)

   b. model-based time series (first level)

   c. subject-specific parameters (e.g., second level, DCM)

Model-based fMRI

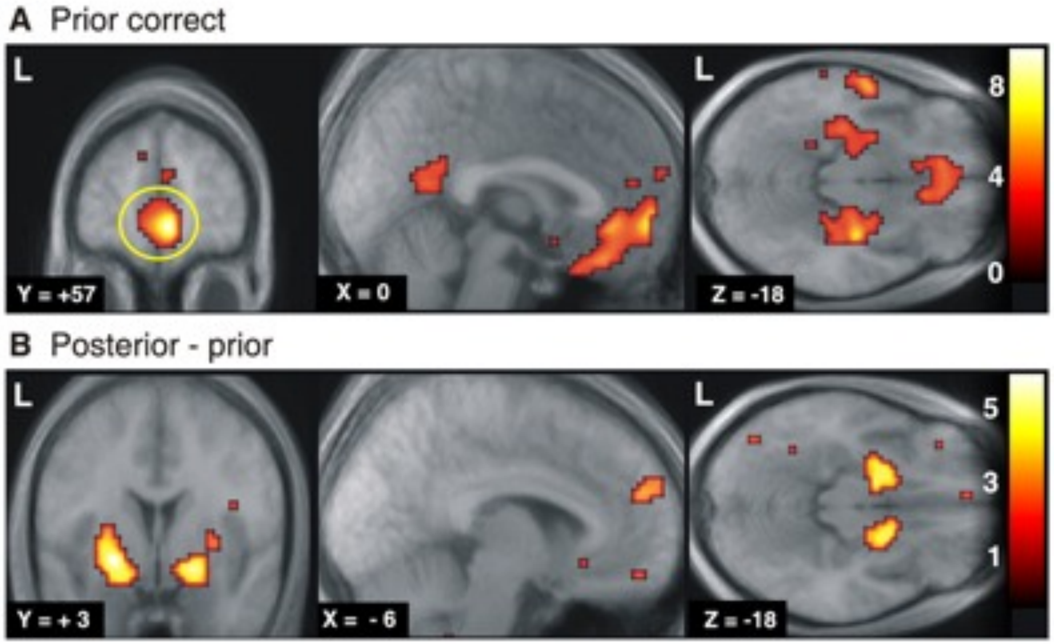
5. Convolve time series with hemodynamic response function



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

Model-based fMRI

6. Regress against fMRI data



Hampton et al., (2006)

Model-based fMRI

1. Decide on a model

2. Pass individual subject trial history to model

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

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4. Generate parametric modulators & model-based time series

5. Convolve time series with hemodynamic response function

6. Regress against fMRI data

From classic design to model based fMRI

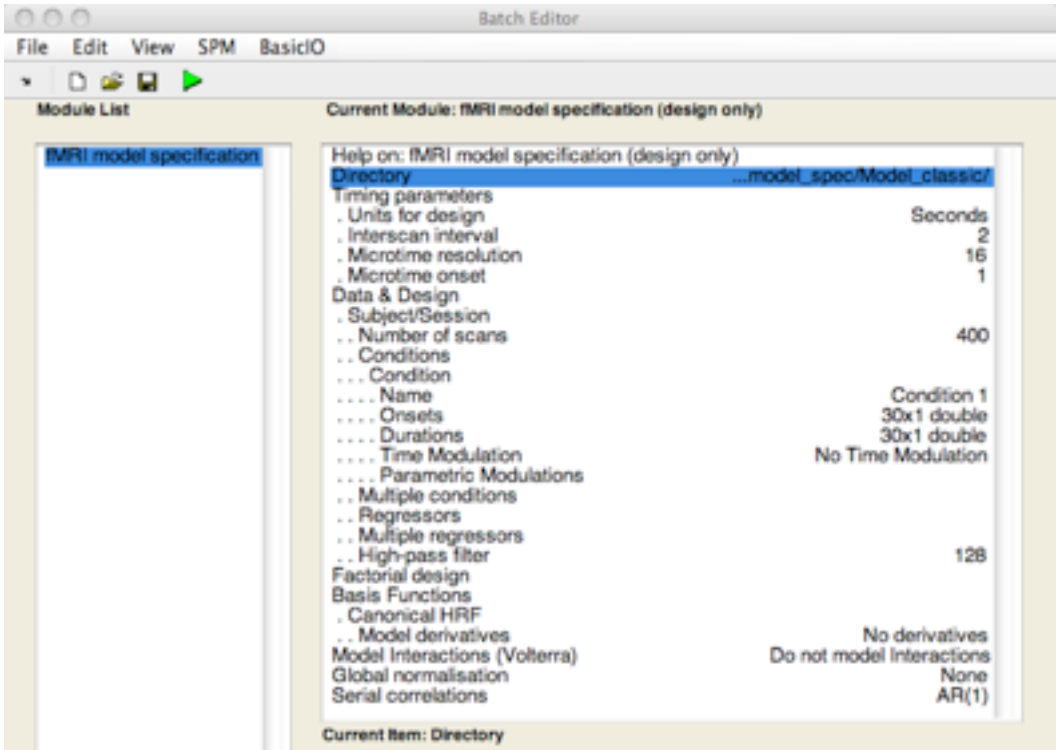
1. Classic event/block design

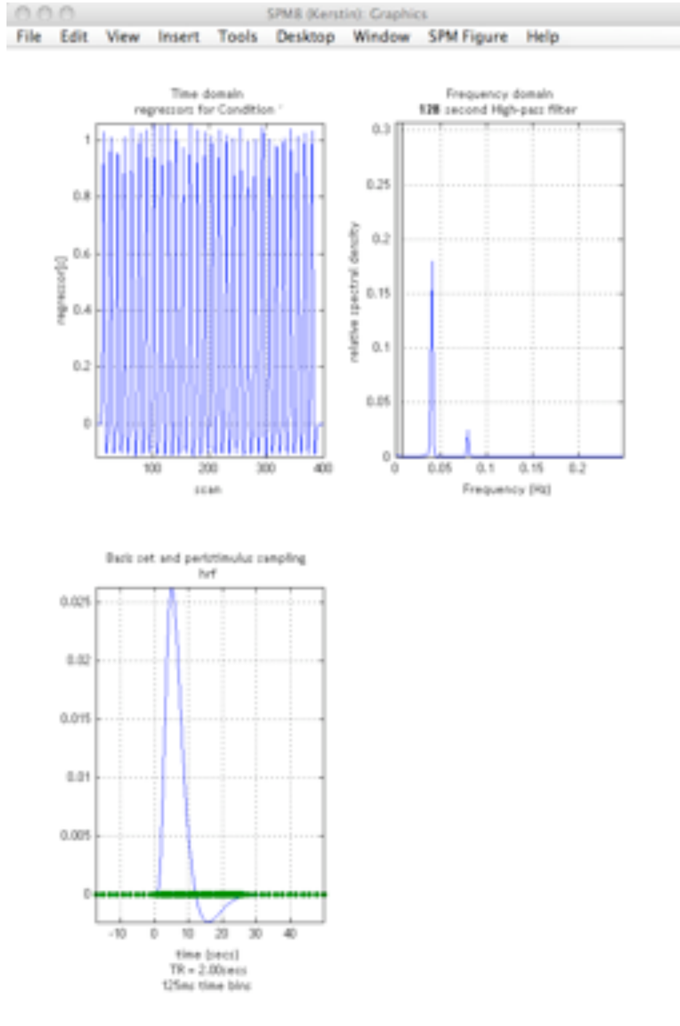
2. Adding parametric regressors

3. Model-based design

Model-based fMRI: comparisons

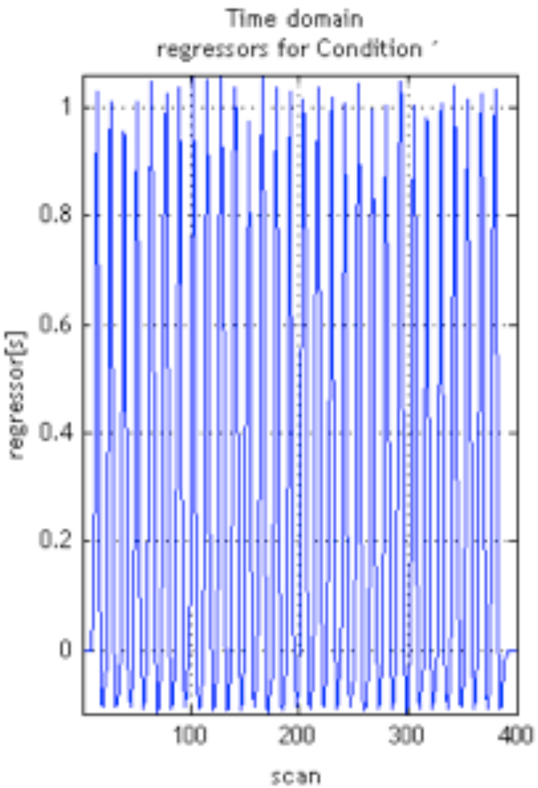
- Classical event/block design

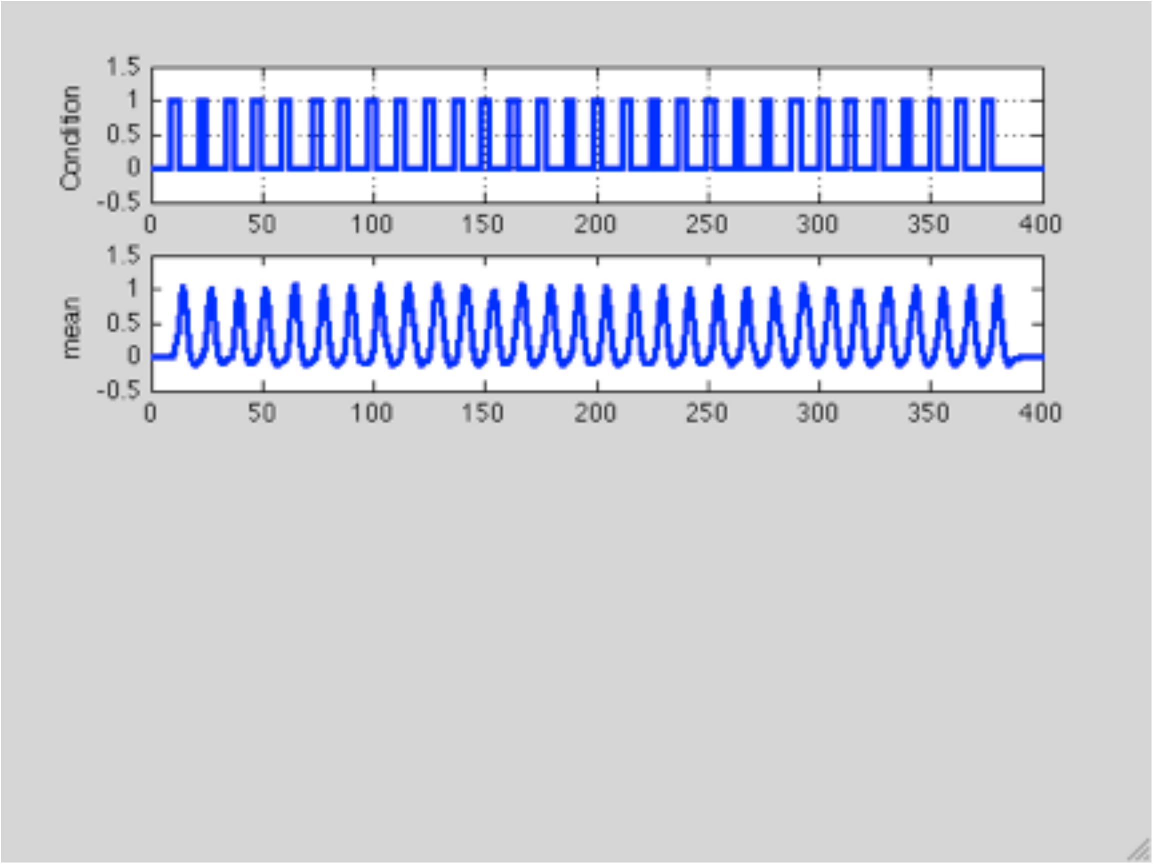




Model-based fMRI: comparisons

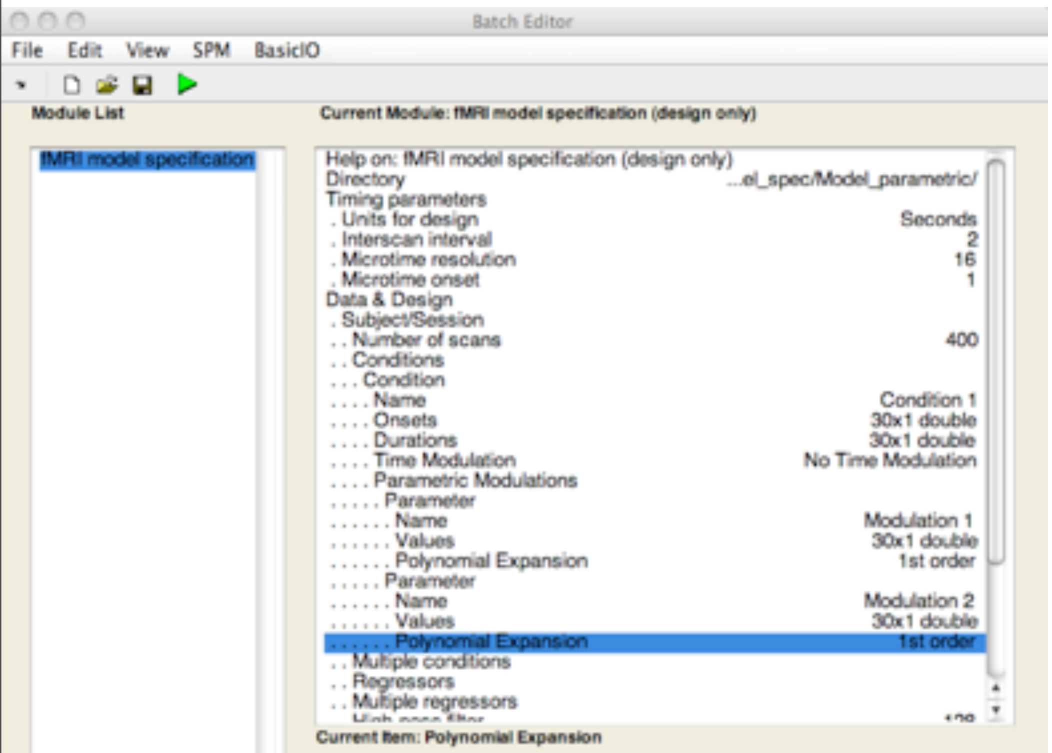
- Classical event/block design

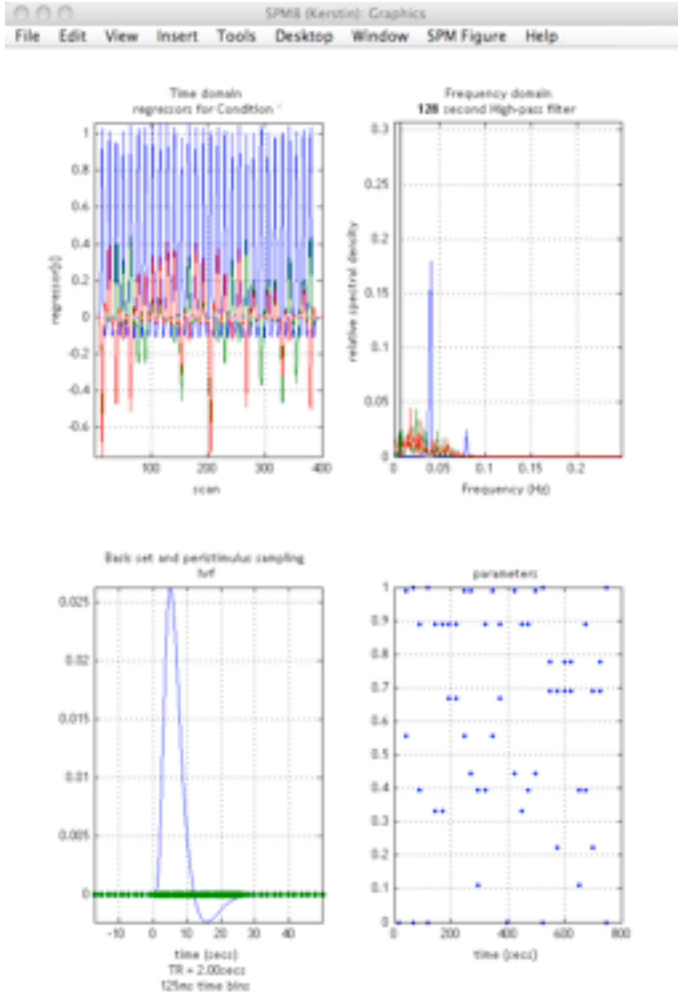




Model-based fMRI: comparisons

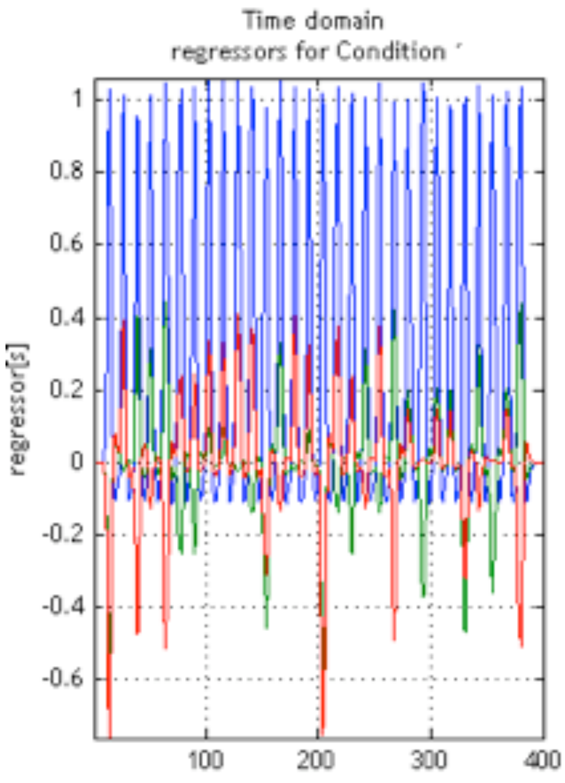
- Parametric regressors

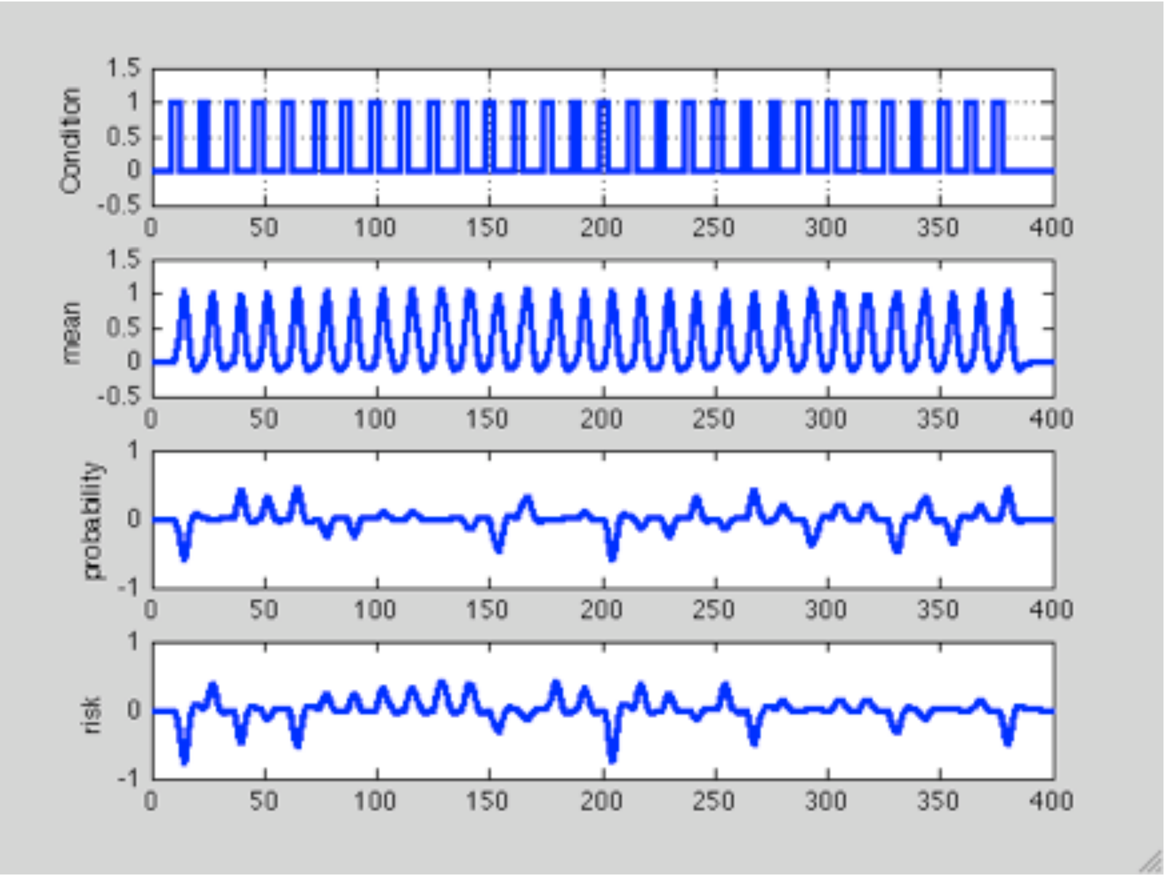




Model-based fMRI: comparisons

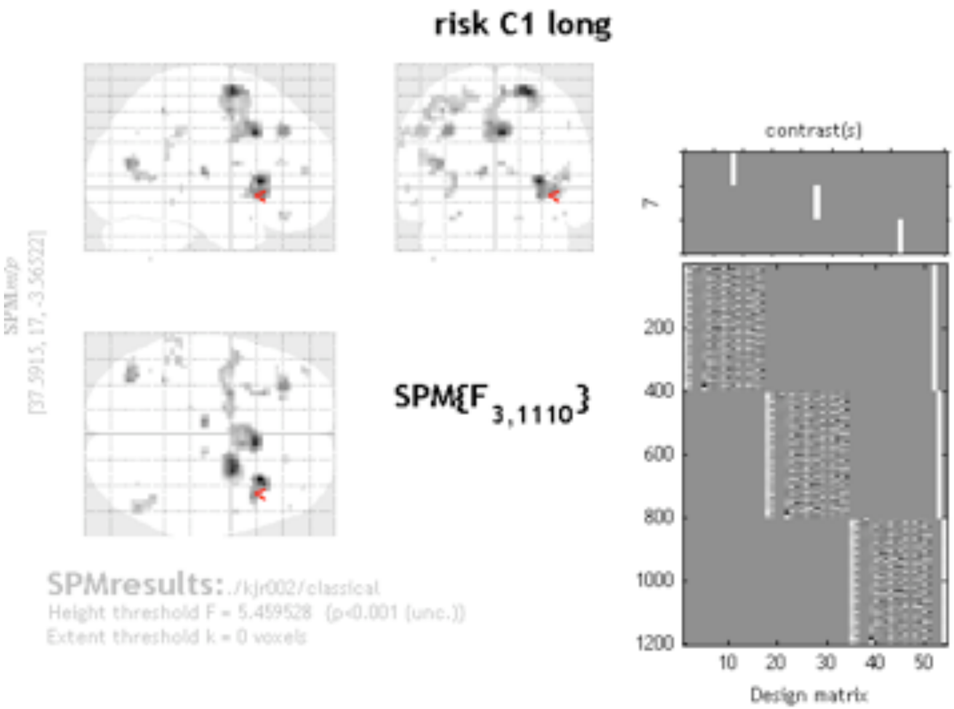
- Parametric regressors

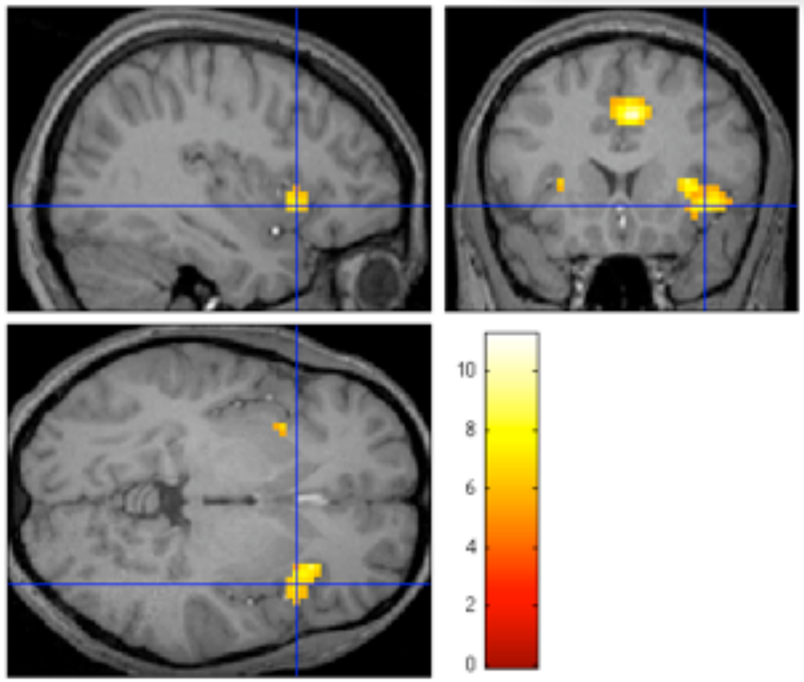




Model-based fMRI: comparisons

- Parametric regressors





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

4. Generate

a. parametric modulators (first level)

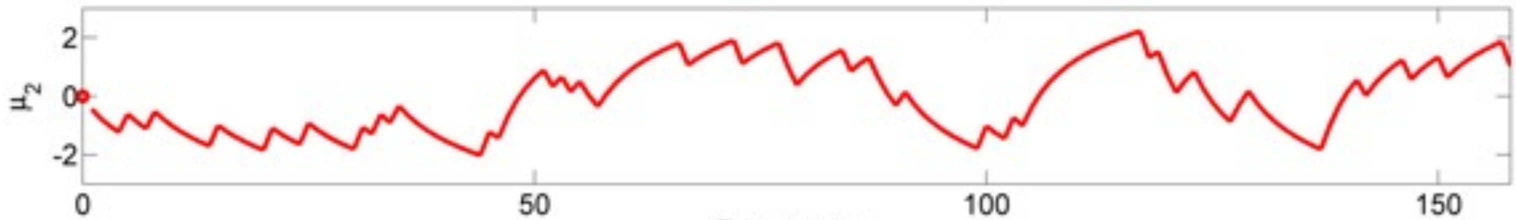
b. model-based time series (first level)

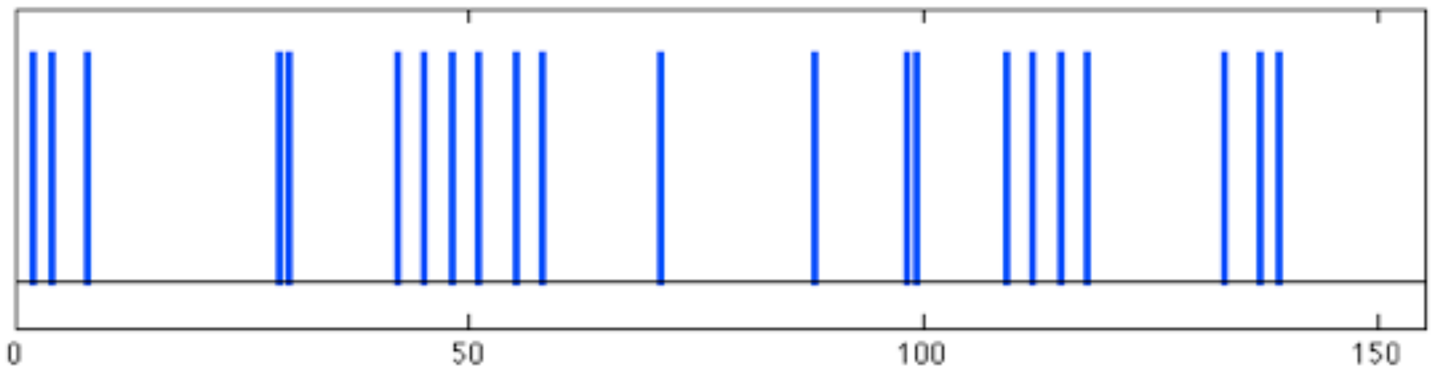
c. subject-specific parameters (e.g., second level, DCM)

How do we construct regressors from a time series and use them in SPM?

Sample time-series at points of interest (e.g., participant response)

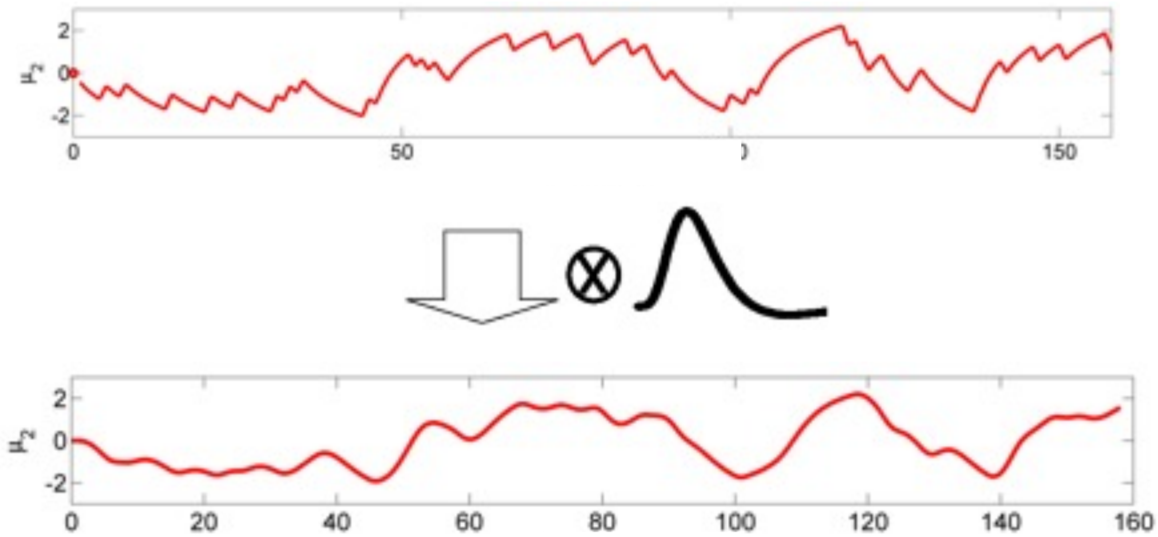
Enter as parametric modulation for condition ‘participant response’





How do we construct regressors from a time series and use them in SPM?

Convolve time series with hemodynamic response function

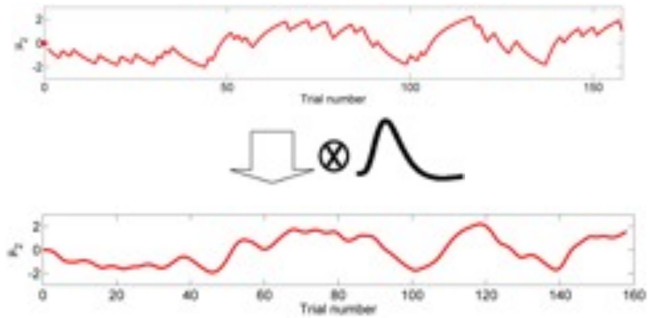


Adapted from O'Doherty et al., (2007)

How do we construct regressors from a time series and use them in SPM?

Convolve time series with hemodynamic response function

- sample time series at the same rate as the basis functions



- convolve with the basis functions `SPM.xBF.bf`

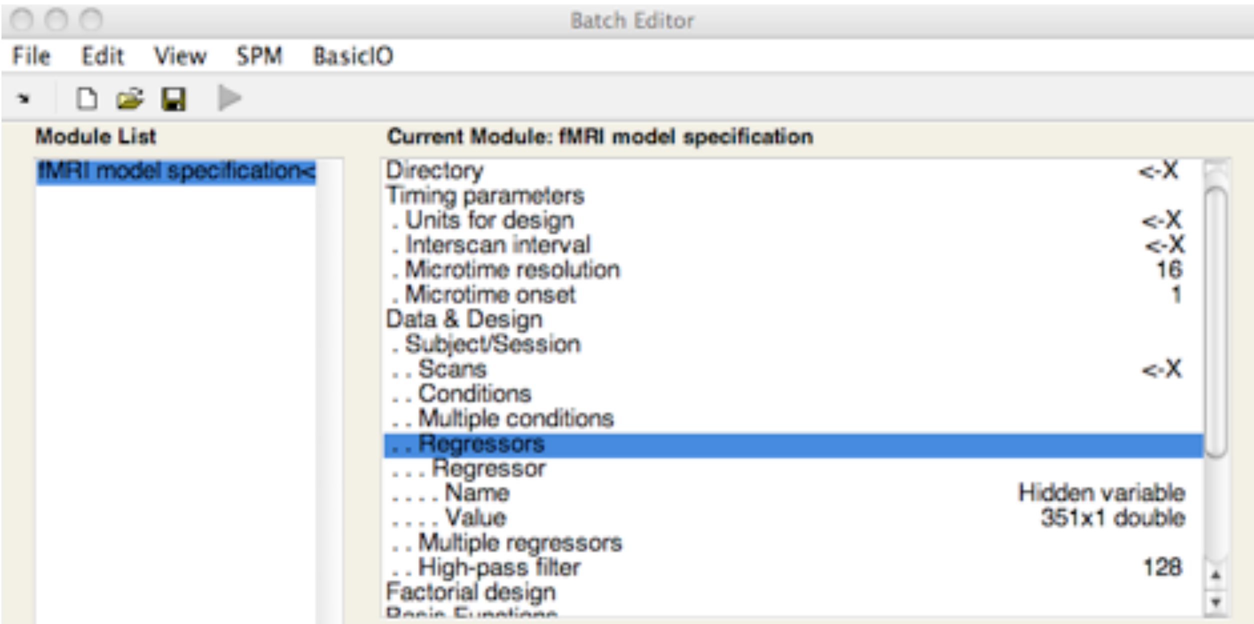
- sample at TR (i.e., one sample per functional volume)

- add to design matrix as (multiple) regressor(s)

How do we construct regressors from a time series and use them in SPM?

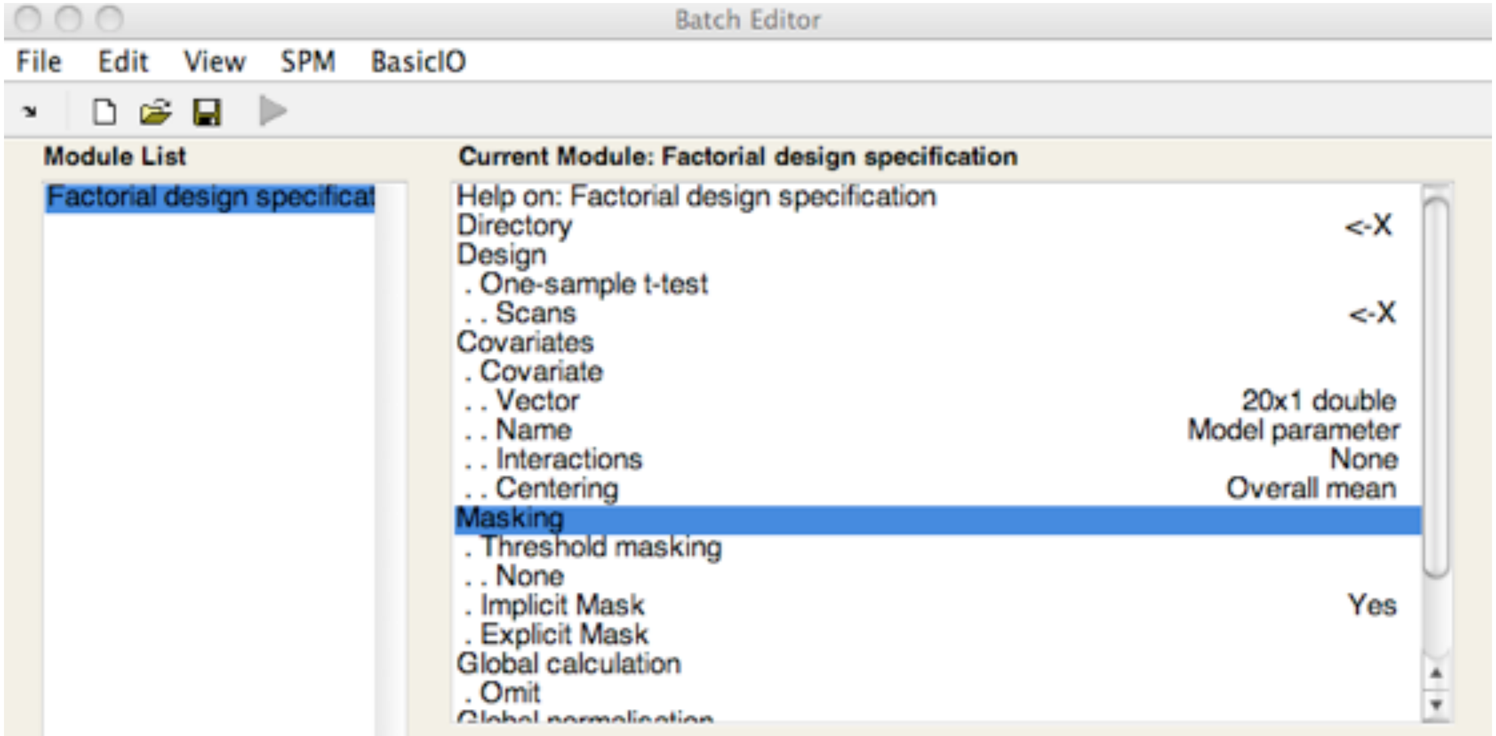
Convolve time series with hemodynamic response function

- add to design matrix as (multiple) regressor(s)



How do we include individual model parameters?

e.g., enter as covariates at the second level



Model-based fMRI recipe

1. Decide on a model (*before* finishing your experimental design)
2. Pass individual subject trial history to model
3. Find best-fitting parameters of model to behavioral data

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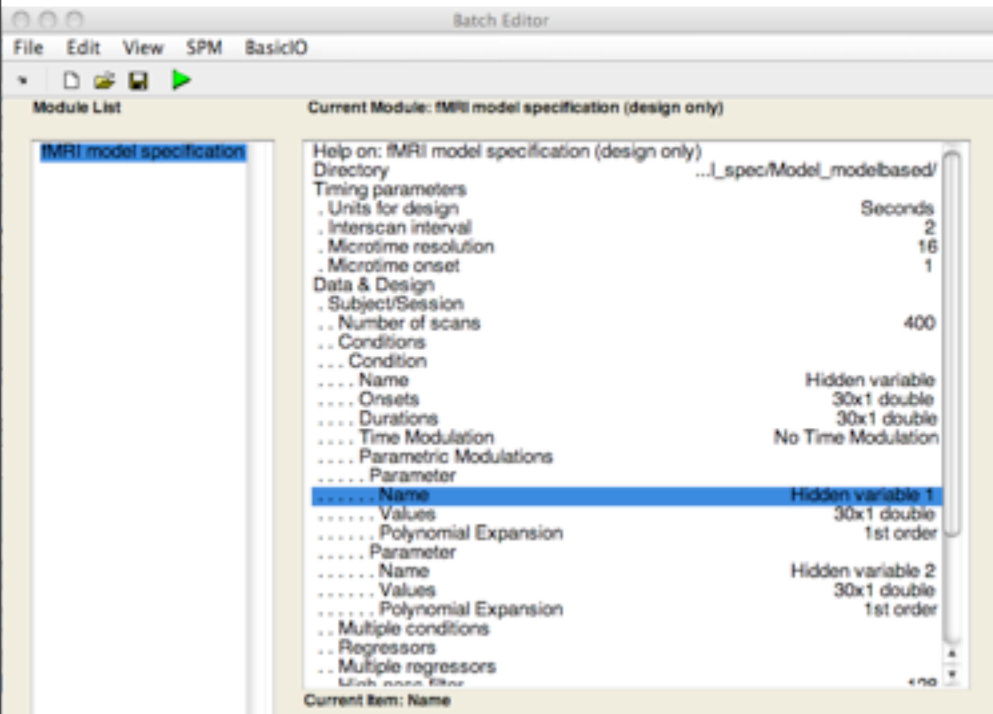
4. Generate parametric modulators & model-based time series
5. Convolve time series with hemodynamic response function
6. Regress against fMRI data

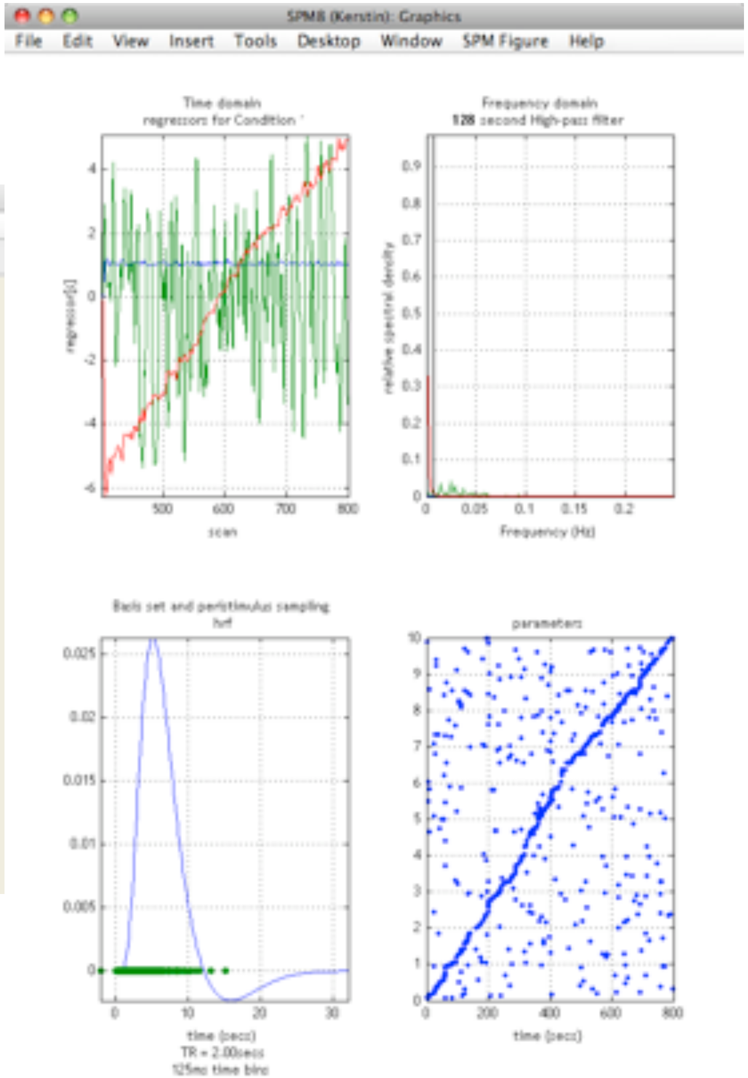
Design efficiency

- Regressors and design matrix not fully specified before data collection.
- To estimate design efficiency:
  - Simulate behavioral data, conduct behavioral pilot study
  - Obtain simulated/pilot time course from the model
  - Optimize design efficiency

Model-based fMRI: design efficiency

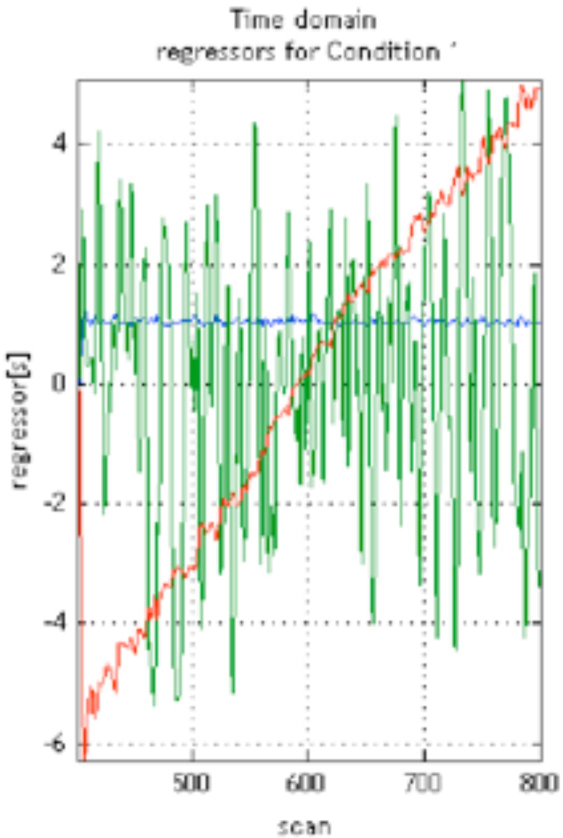
- Model based fMRI

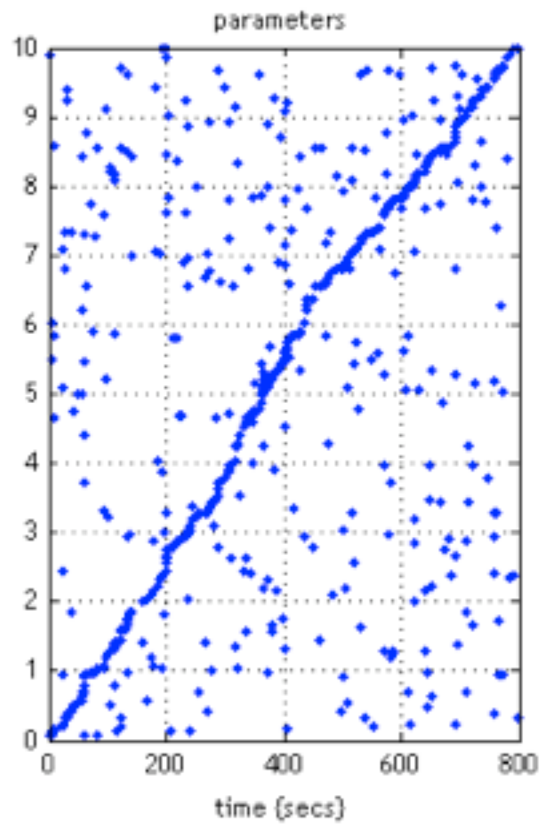




Model-based fMRI: comparisons

- Model based fMRI





Model-based fMRI recipe

1. Decide on a model

2. Pass individual subject trial history to model

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

---

4. Generate model-based time series

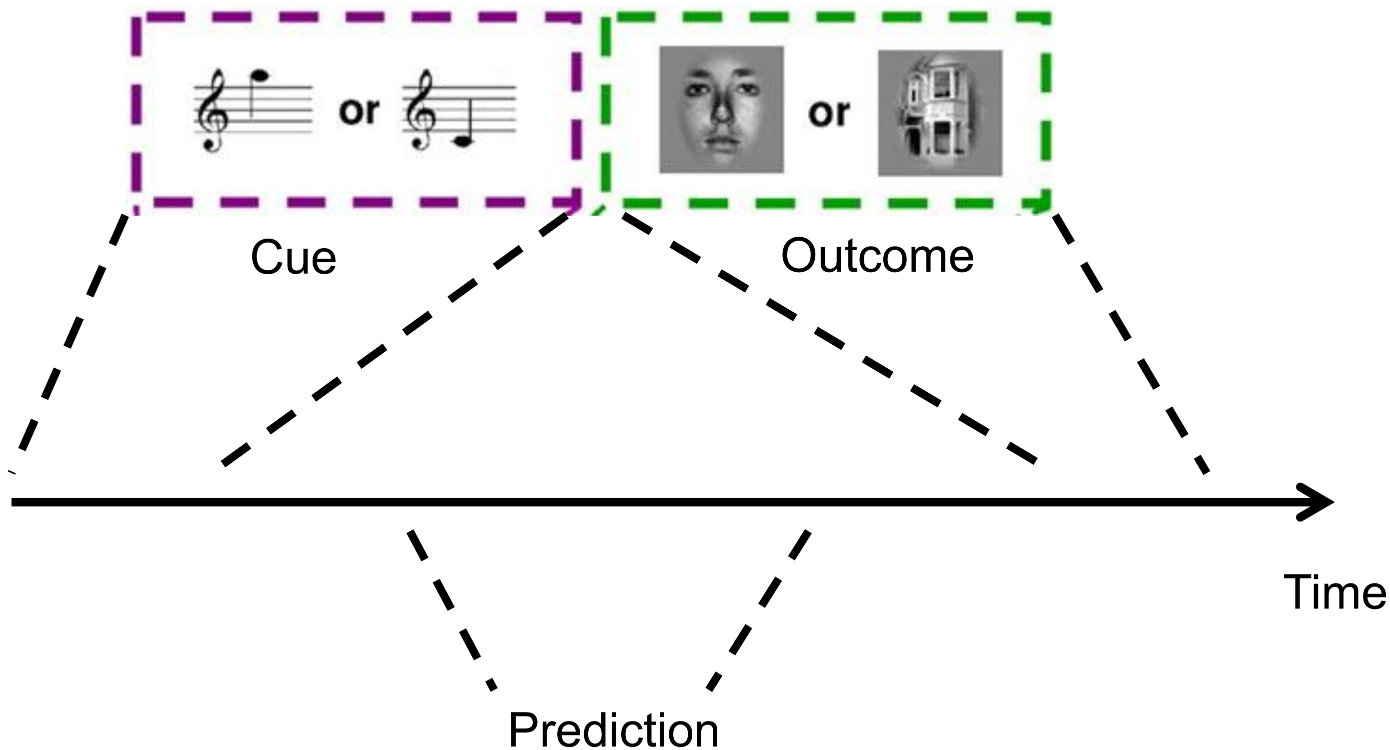
5. Convolve time series with hemodynamic response function

6. Regress against fMRI data

Model-based fMRI – an example

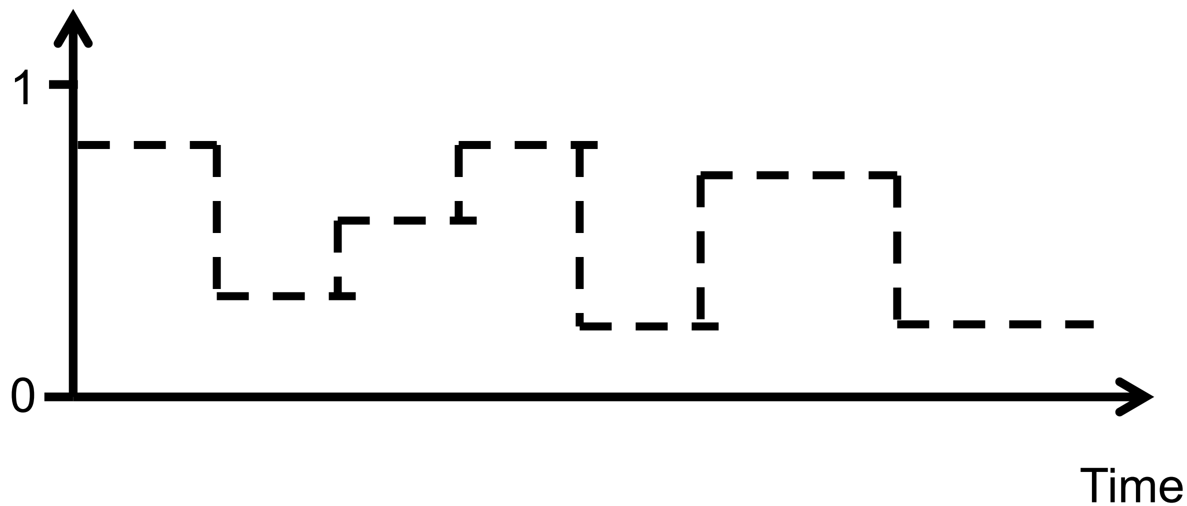
- The task
- The decision model
- The learning model
- Combined inversion
- fMRI results

The task – single trial



The task – probabilistic structure

Probability of Face,
given high tone
=
Probability of House,
given low tone

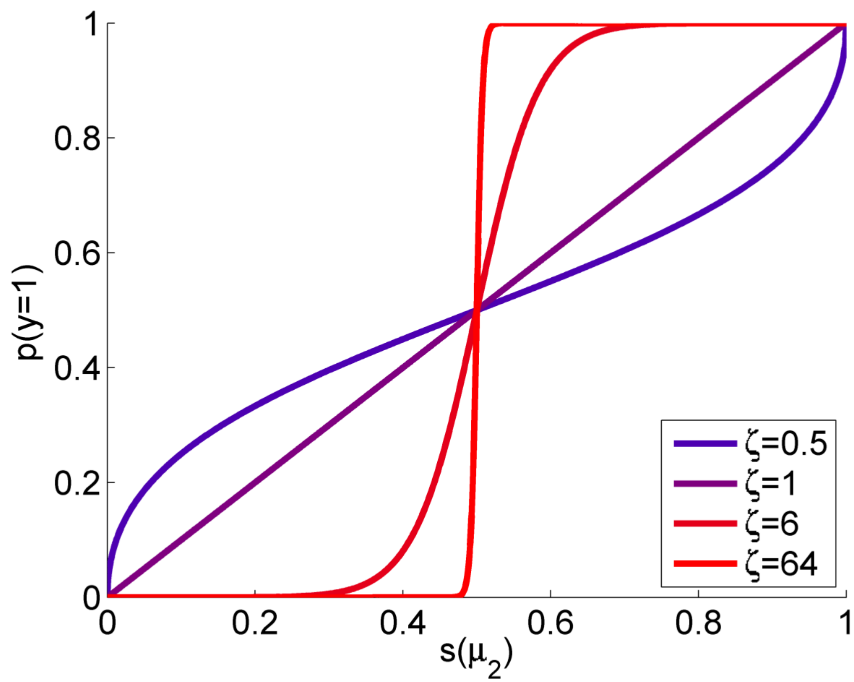


The decision model

- Softmax decision rule
- Curve shape is determined by the parameter ζ
- Translates beliefs into decision probabilities

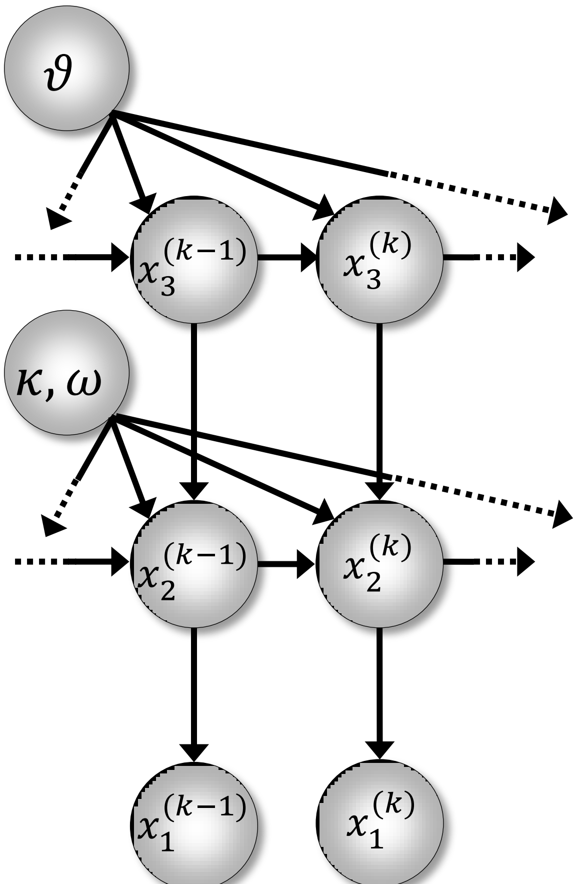
Probability of decision "1",

(i.e., of betting on "1")

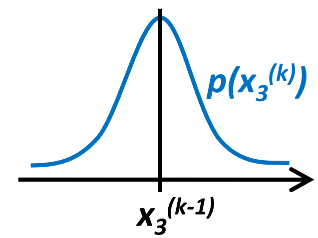
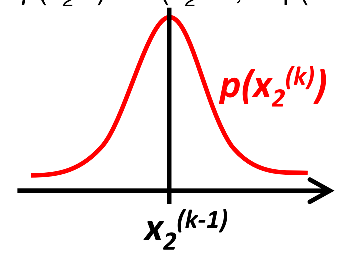
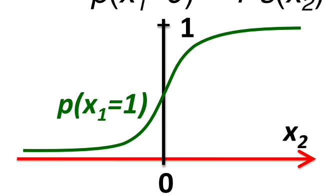


Prediction ("certainty") that next stimulus is "1"

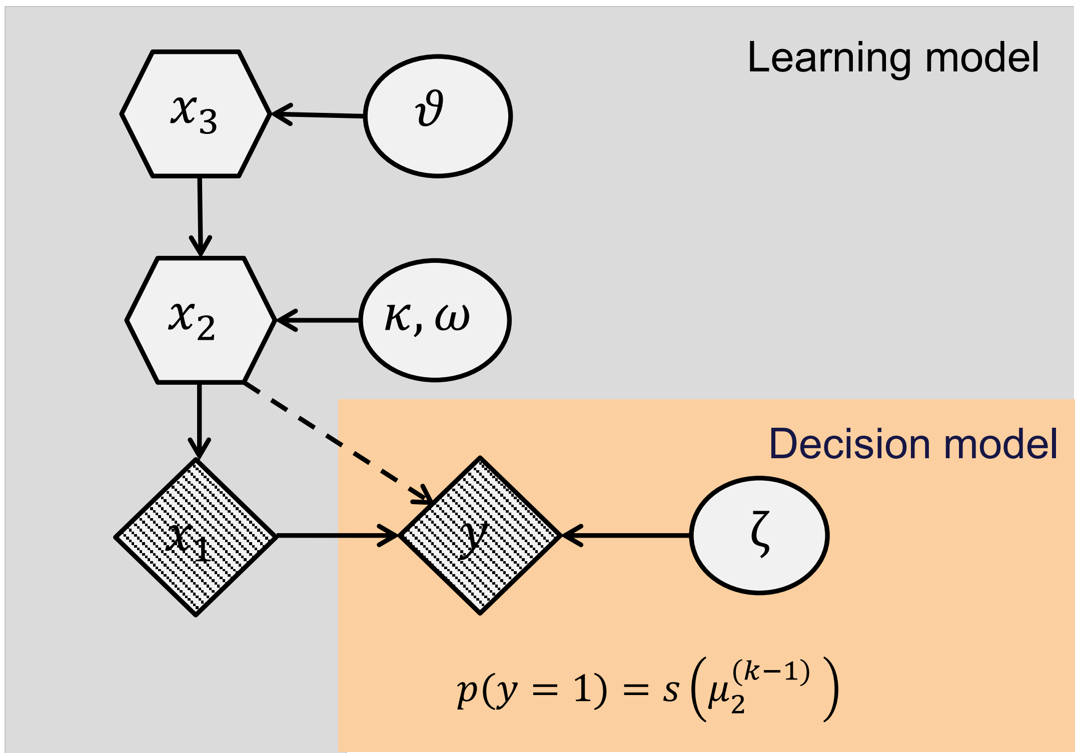
The learning model



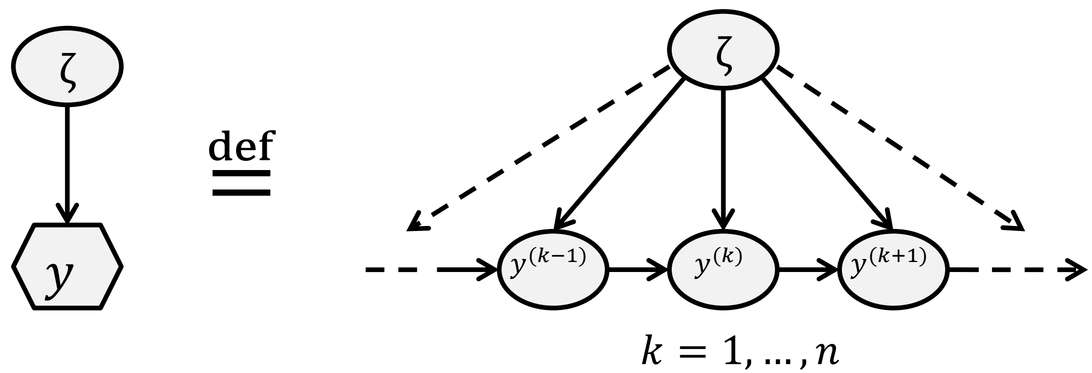
Mathys et al. (2011)

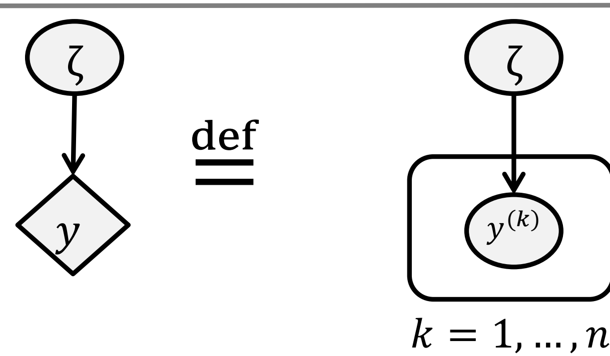
State of the world	**Model**	
Log-volatility $\boldsymbol{x_3}$ of tendency	Gaussian random walk with constant step size ϑ	$p(x_3^{(k)}) \sim N(x_3^{(k-1)}, \vartheta)$ 
Tendency $\boldsymbol{x_2}$ towards category "1"	Gaussian random walk with step size $\exp(\kappa x_3+\omega)$	$p(x_2^{(k)}) \sim N(x_2^{(k-1)}, \exp(\kappa x_3+\omega))$ 
Stimulus category $\boldsymbol{x_1}$ ("0" or "1")	Sigmoid trans-formation of x_2	$p(x_1=1) = s(x_2)$ $p(x_1=0) = 1-s(x_2)$ 

Learning and decision models combined



Notation


ζ
y
def
$y^{(k-1)}$
$y^{(k)}$
$y^{(k+1)}$
$k = 1, \ldots, n$


ζ
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$y^{(k)}$
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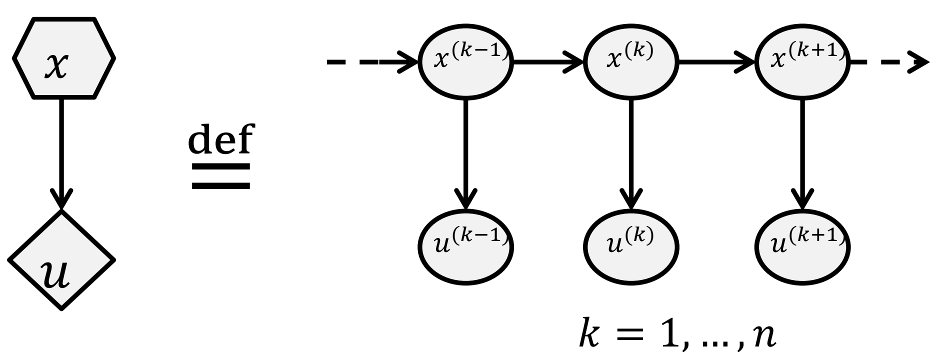
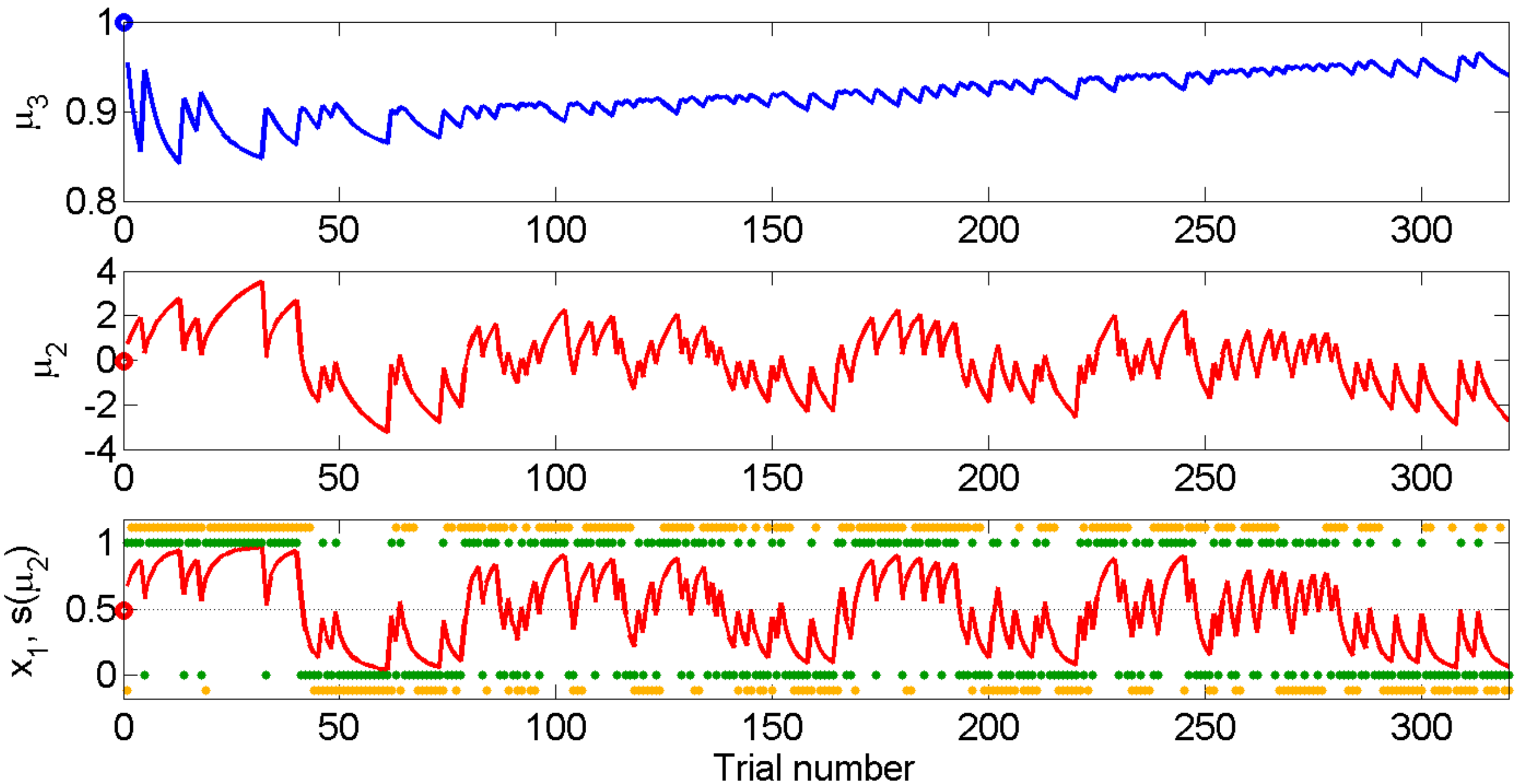
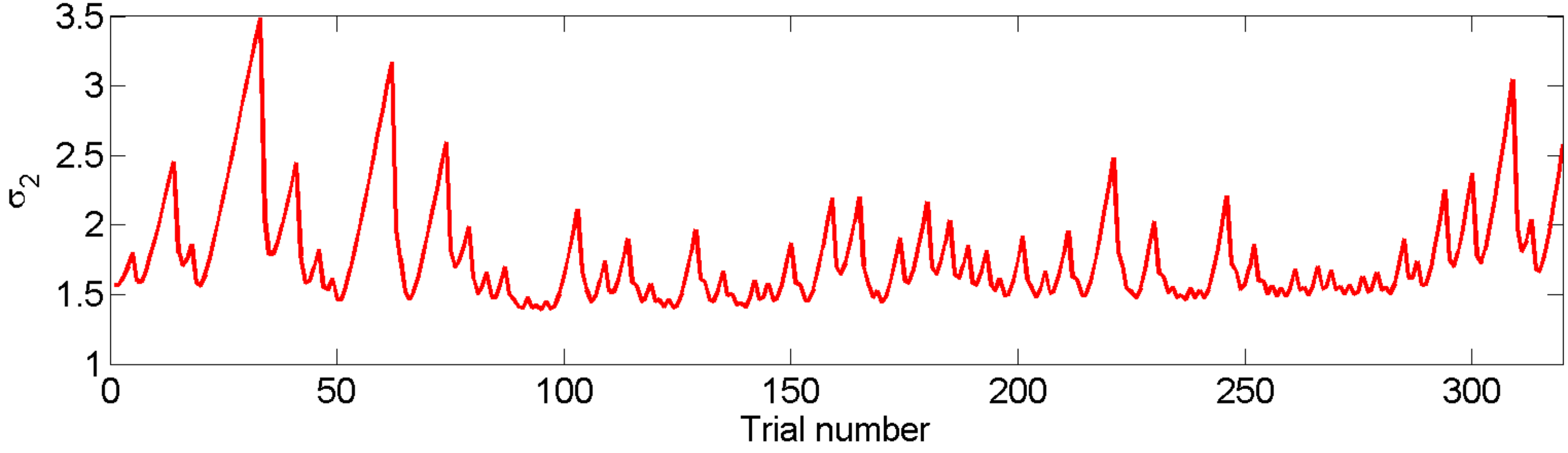

x
u
def
$x^{(k-1)}$
$x^{(k)}$
$x^{(k+1)}$
$u^{(k-1)}$
$u^{(k)}$
$u^{(k+1)}$
$k = 1, \ldots, n$

Model inversion



Regressor: Uncertainty

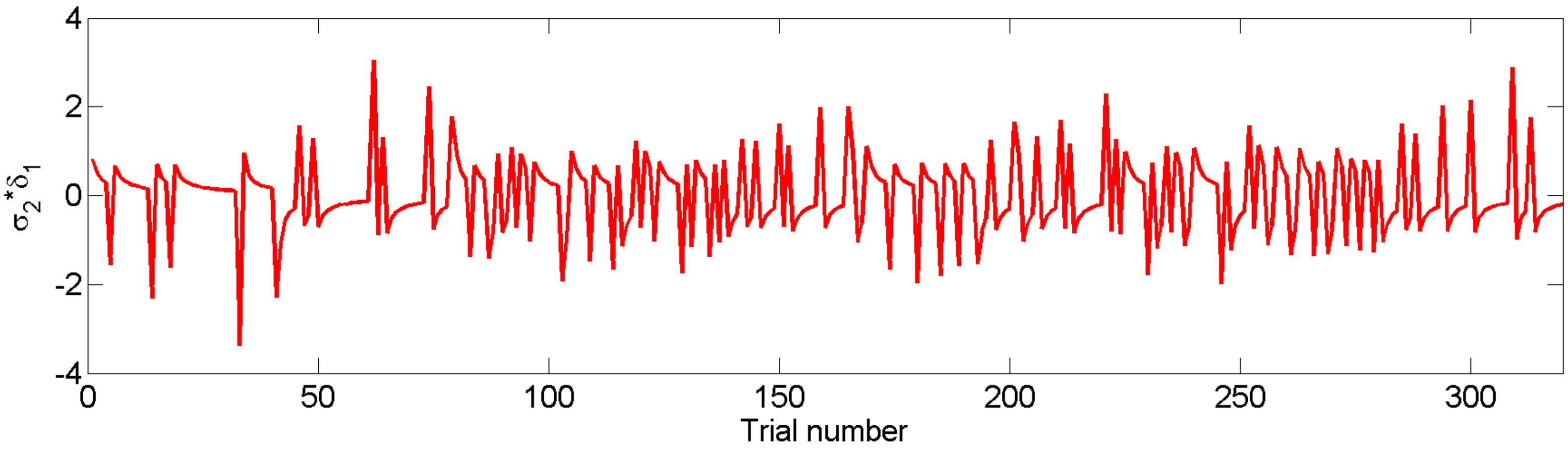


The update equations

Level 3	$\Delta\mu_3 = \sigma_3 \cdot \frac{\kappa}{2} \cdot w_2 \cdot \delta_2$ with	$\Delta\mu_3 = \mu_3^{(k)} - \mu_3^{(k-1)}$ $\sigma_3 = \sigma_3^{(k)}$ $w_2 = \frac{e^{\kappa\mu_3^{(k-1)}+\omega}}{\sigma_2^{(k-1)} + e^{\kappa\mu_3^{(k-1)}+\omega}}$ $\delta_2 = \frac{\sigma_2^{(k)} + \left(\mu_2^{(k)} - \mu_2^{(k-1)}\right)^2}{\sigma_2^{(k-1)} + e^{\kappa\mu_3^{(k-1)}+\omega}} - 1$
Level 2	$\Delta\mu_2 = \sigma_2 \cdot \delta_1$ with	$\Delta\mu_2 = \mu_2^{(k)} - \mu_2^{(k-1)}$ $\sigma_2 = \sigma_2^{(k)}$ $\delta_1 = \mu_1^{(k)} - s\left(\mu_2^{(k-1)}\right)$

Expectation update
(Unweighted) learning rate
Weighting factor
Prediction error

Regressor: Uncertainty-weighted prediction error



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