

# Model-Based fMRI Analysis

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## ❖ Motivation

- ❖ Models (general)
- ❖ Why you ought to care

## ❖ Model-based fMRI

- ❖ Models (specific)
- ❖ From model to analysis

## ❖ Extended Example

- ❖ Hampton, Bossaerts, & O'Doherty (2006)
-

## ❖ Motivation

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-

You probably already use a model

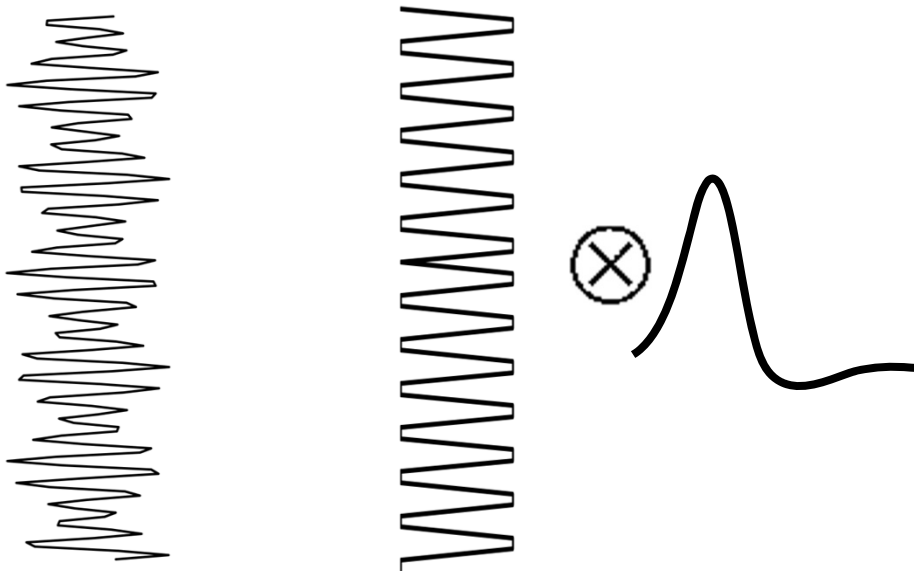
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# Trivial sense

## General Linear Model

$$Y = X \cdot \beta + \epsilon$$

BOLD signal      Design Matrix convolved with HRF      Contribution of X to Y      Error



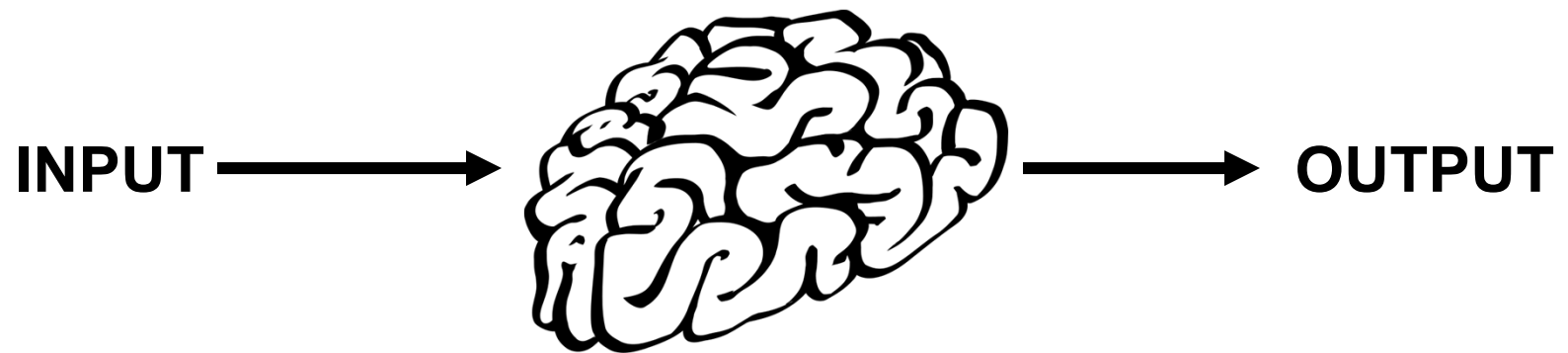
## Design matrix is a model of an experiment

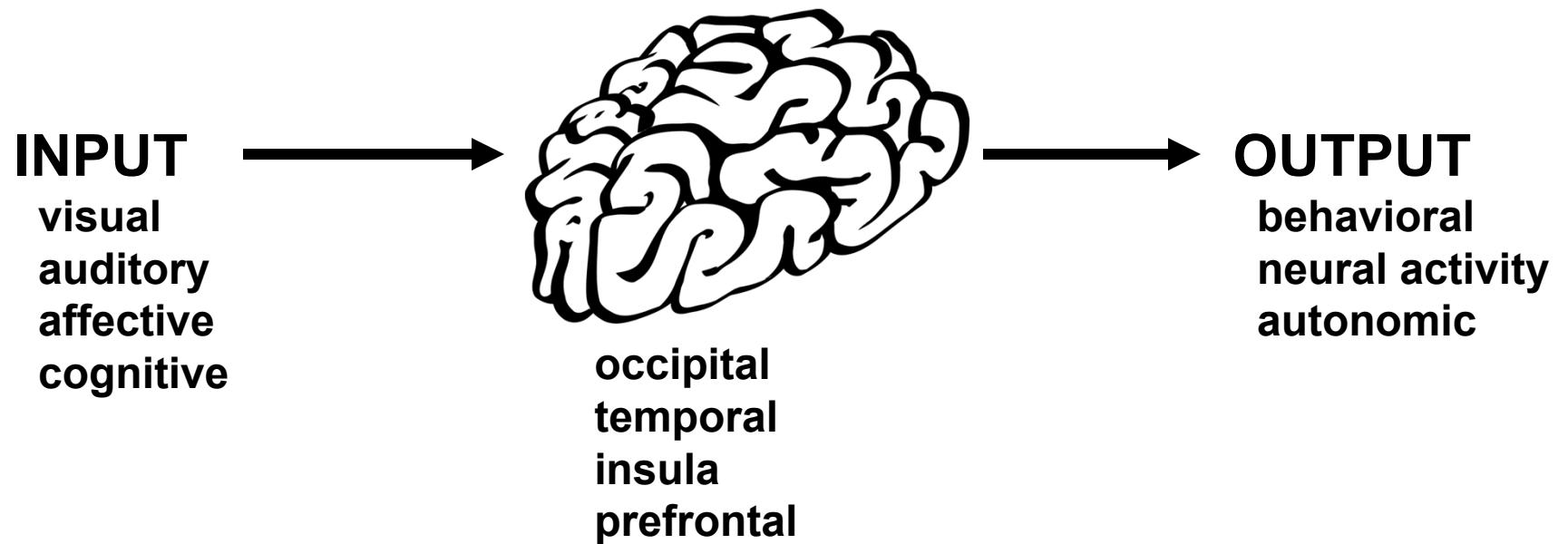
- May not be the best model
- Model-free analyses  
ICA, clustering, etc

## Model of BOLD signal

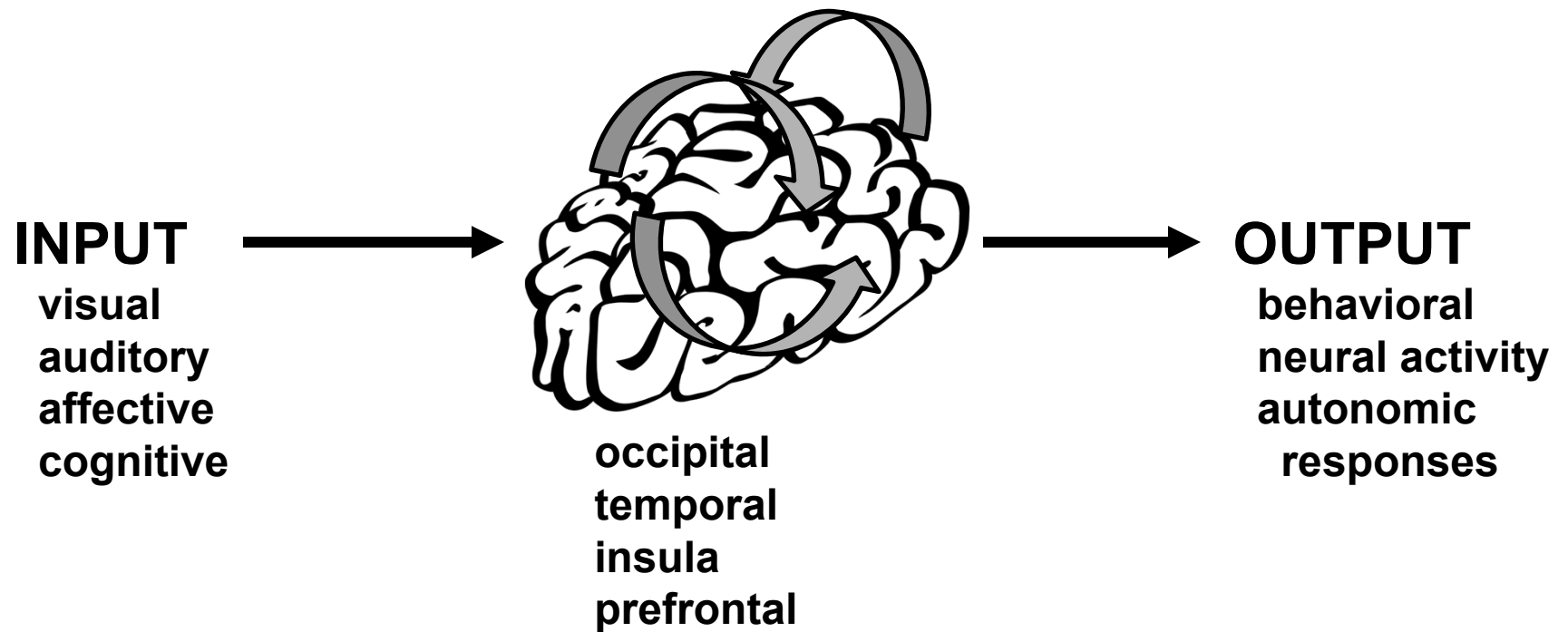
- HRF may vary from trial to trial, or  
from region to region
-

## Less trivial sense

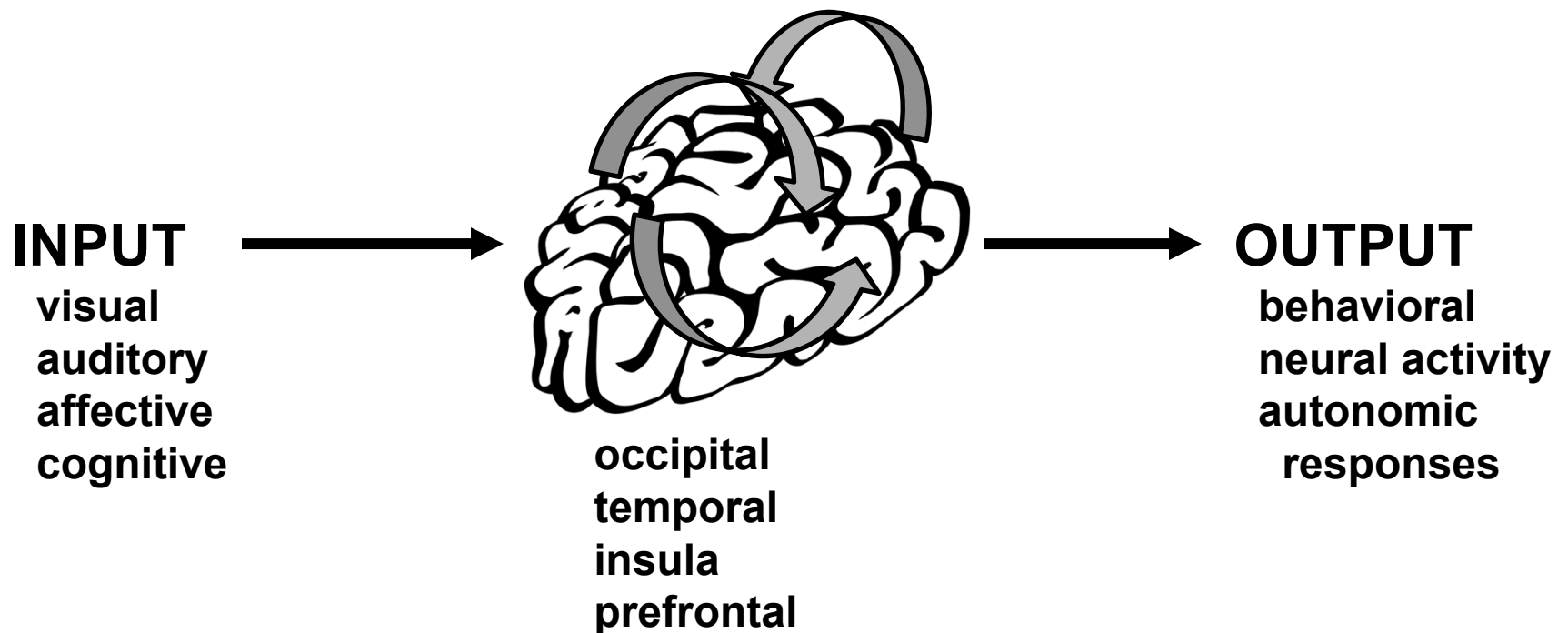








## What do the arrows mean?



# Model-Based fMRI analysis

Computational/mathematical models

Target behavior

Mathematical formalization

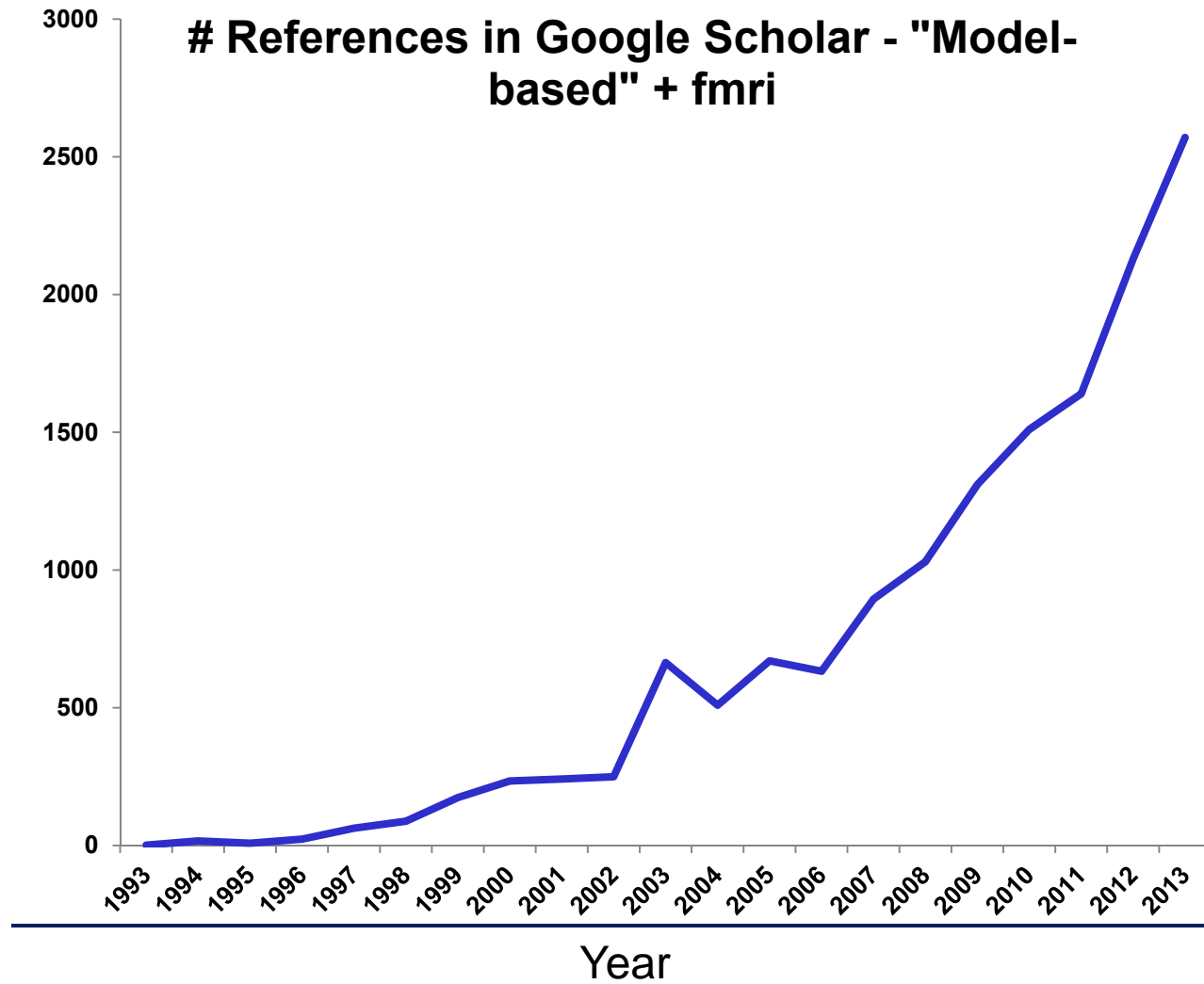
Specify underlying mechanism

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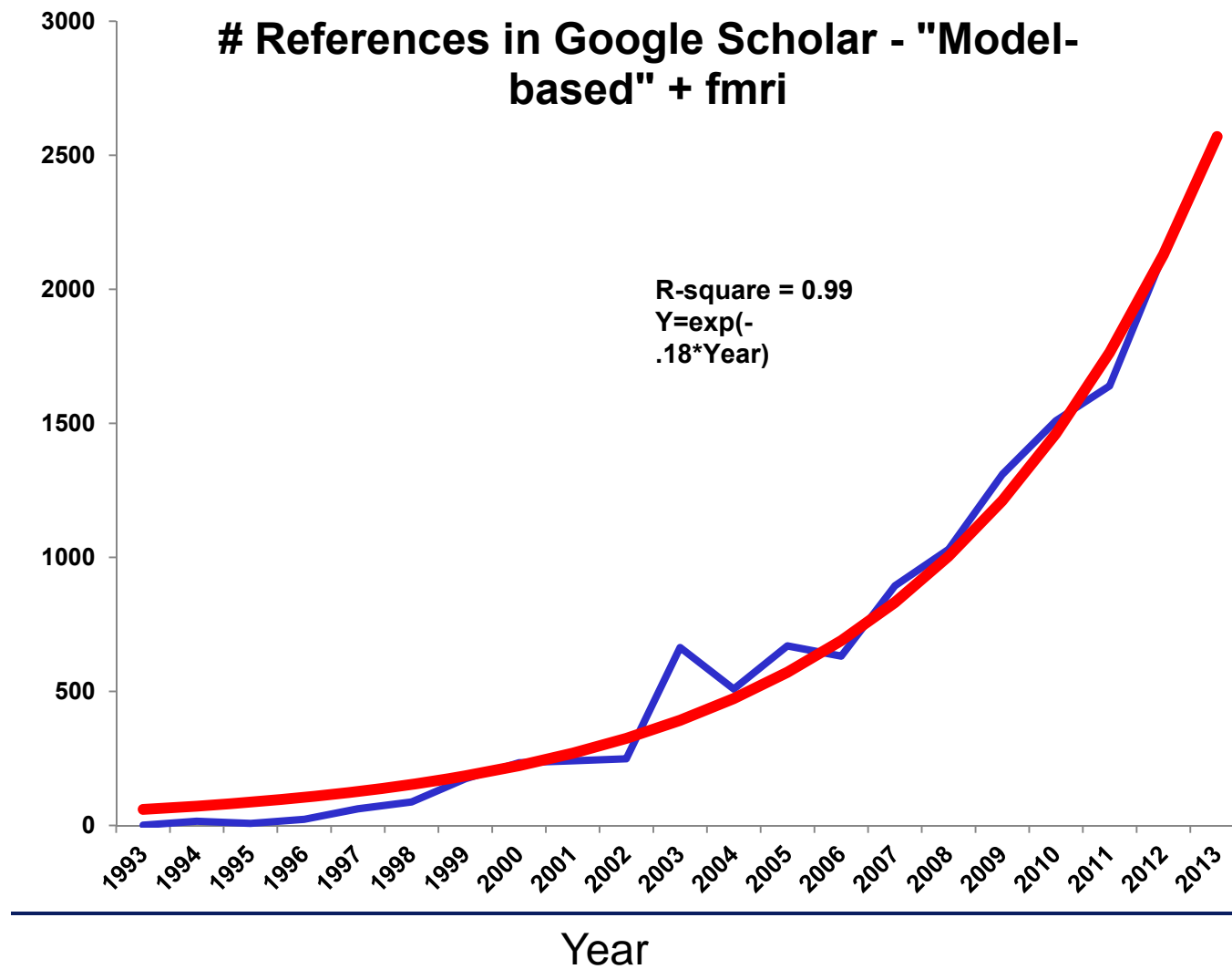
Why should we care?

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# Appeal to Self Interest



# Appeal to Self Interest



# Appeal to Abstract Principles

Scientific progress depends on making and testing predictions

Quantifiable predictions are more amenable to testing

No perfect models, but there are less imperfect models

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# Appeal to Abstract Principles II

Explanation vs. Description

Specification of mechanism

Understanding rather knowing

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## Appeal to Self Interest II

A good model allows you to predict the future.

Saves work

Identify interesting research questions (before everyone else)

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## ❖ Motivation

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## ❖ Model-based fMRI

- ❖ Models (specific)
- ❖ From model to analysis

## ❖ Extended Example

- ❖ Hampton, Bossaerts, & O'Doherty (2006)
-

## Goal of Model-Based fMRI analysis

Identify where/whether/how a particular cognitive mechanism, as specified by a computational/mathematical model, is implemented in the brain.

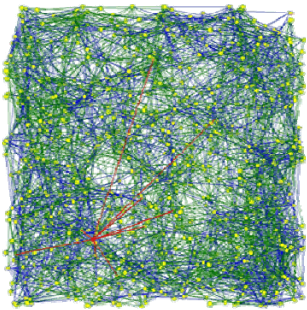
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# Steps in Model-Based Analysis

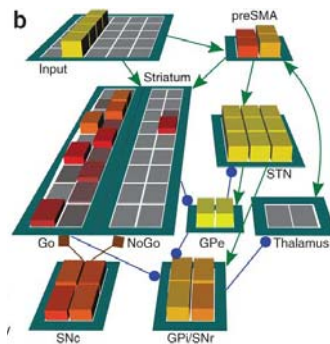
1. Select/create a computational model
  2. Design experimental task in order to test model
  3. Fit model to behavioral data
  4. Generate model predictions of brain activity
  5. Regress model predictions against fMRI data
-

# Types of models

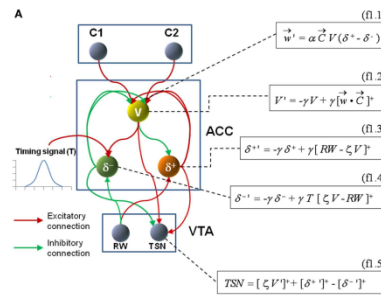
## Spiking Neural Networks



## Dynamical Systems Models



## RL/Connectionist Models



## Mathematical/ Bayesian Models

$$P(s_k = 1 | s_{k-1})$$

$$= \int P(s_k = 1 | r_k) p(r_k | s_{k-1}) dr_k = \int r_k p(r_k | s_{k-1}) dr_k = \langle r_k | s_{k-1} \rangle.$$

$$p(r_k | s_{k-1}) = \alpha p(r_{k-1} | s_{k-1}) + (1 - \alpha) p_0(r_k),$$

$$p(r_k | s_k) \propto P(s_k | r_k) p(r_k | s_{k-1}).$$

Concrete

Abstract

Neurobiologically  
Realistic

Neurobiologically  
Plausible

Related to Brain  
Structure

Passing  
Acquaintance with  
the Brain

Activity of Individual  
Neurons

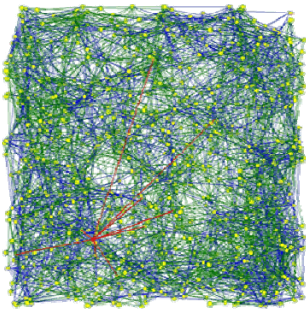
Activity of Groups  
of Neurons

Activity of Brain  
Regions

Networks of Brain  
Regions

# Types of models

## Spiking Neural Networks

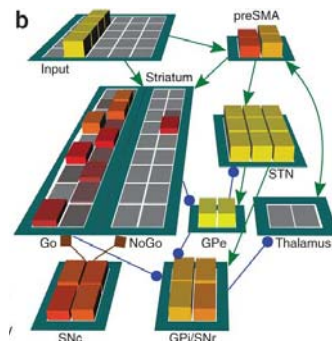


Concrete

Neurobiologically  
Realistic

Activity of Individual  
Neurons

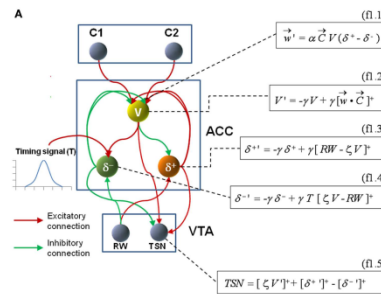
## Dynamical Systems Models



Neurobiologically  
Plausible

Activity of Groups  
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## RL/Connectionist Models



Related to Brain  
Structure

Activity of Brain  
Regions

## Mathematical/ Bayesian Models

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Abstract

Passing  
Acquaintance with  
the Brain

Networks of Brain  
Regions



# Example Models

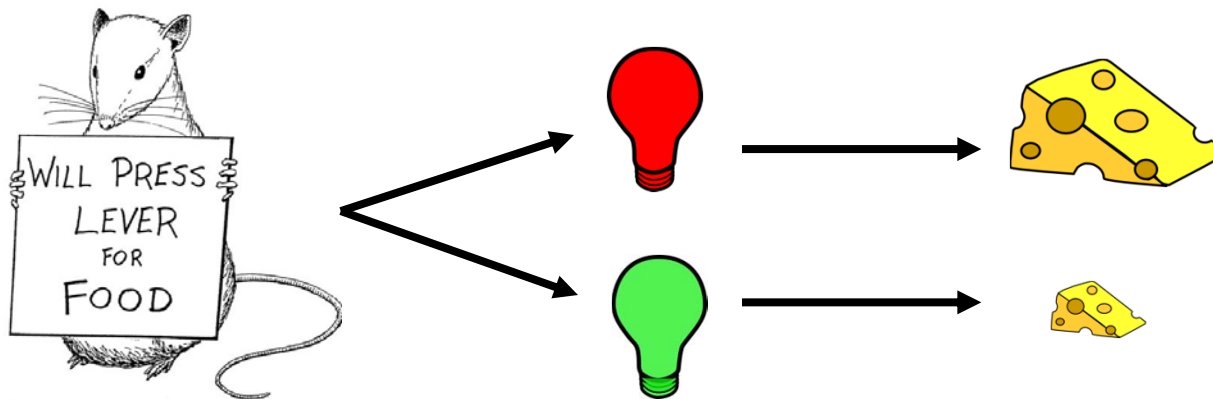
## Reinforcement Learning

e.g., Rescorla & Wagner  
(1972)

-Behavioral output  
Choice

-Cognitive Mechanisms  
Value Prediction

Prediction Error



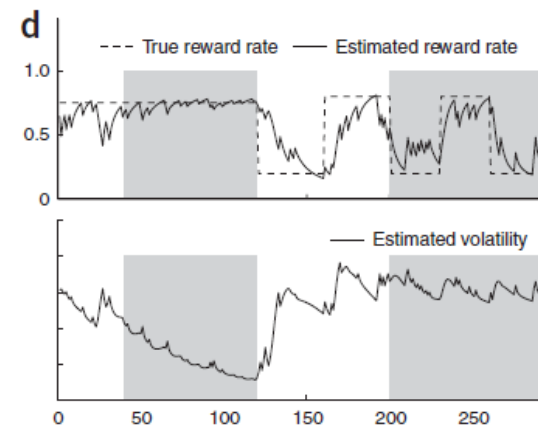
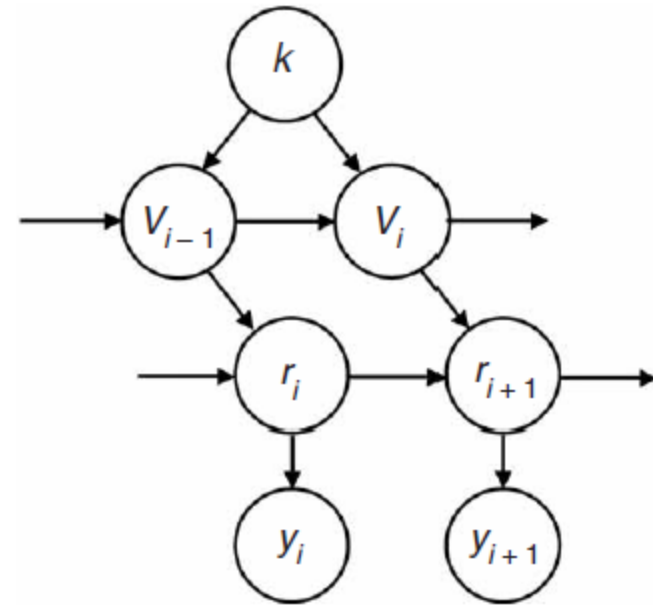
# Example Models

## Bayesian Prediction & Evaluation

Behrens et al., 2007

-Behavioral Output  
Choice

-Cognitive Mechanisms  
Reward Probability  
Environmental  
Volatility





# Example Models

## Drift Diffusion model

Ratcliff(1985)

-Behavioral output

Choice

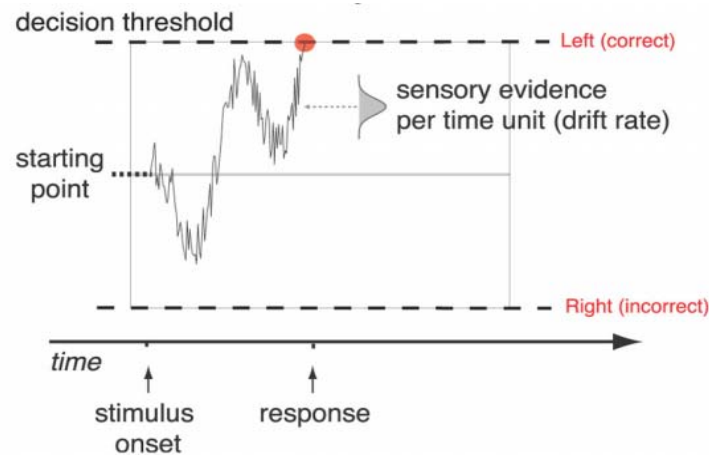
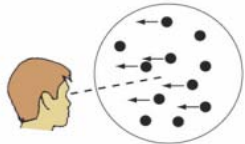
Reaction Time

-Cognitive Mechanisms

Information  
accumulation

Processing bias

“Are the dots moving to  
the right or to the left?”



# Example Models

## Conflict Model

Yeung et al. (2004)

-Behavioral output

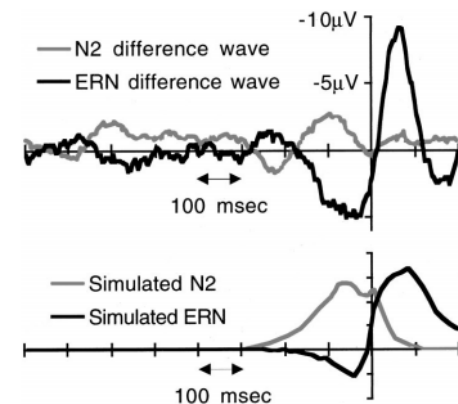
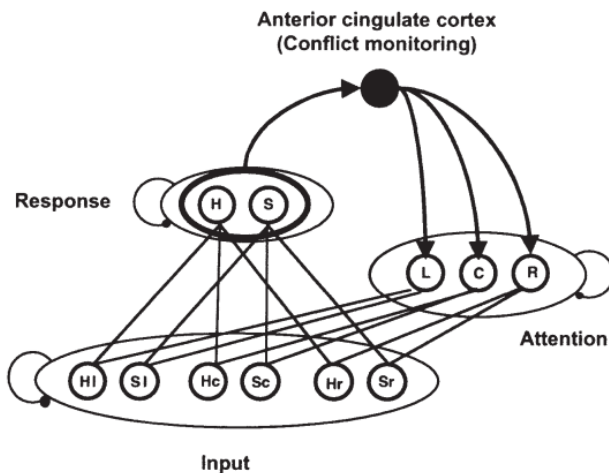
Error Rate

Reaction Time

-Cognitive Mechanisms

Behavioral Conflict

Attention



## Example – Simple Reinforcement Learning

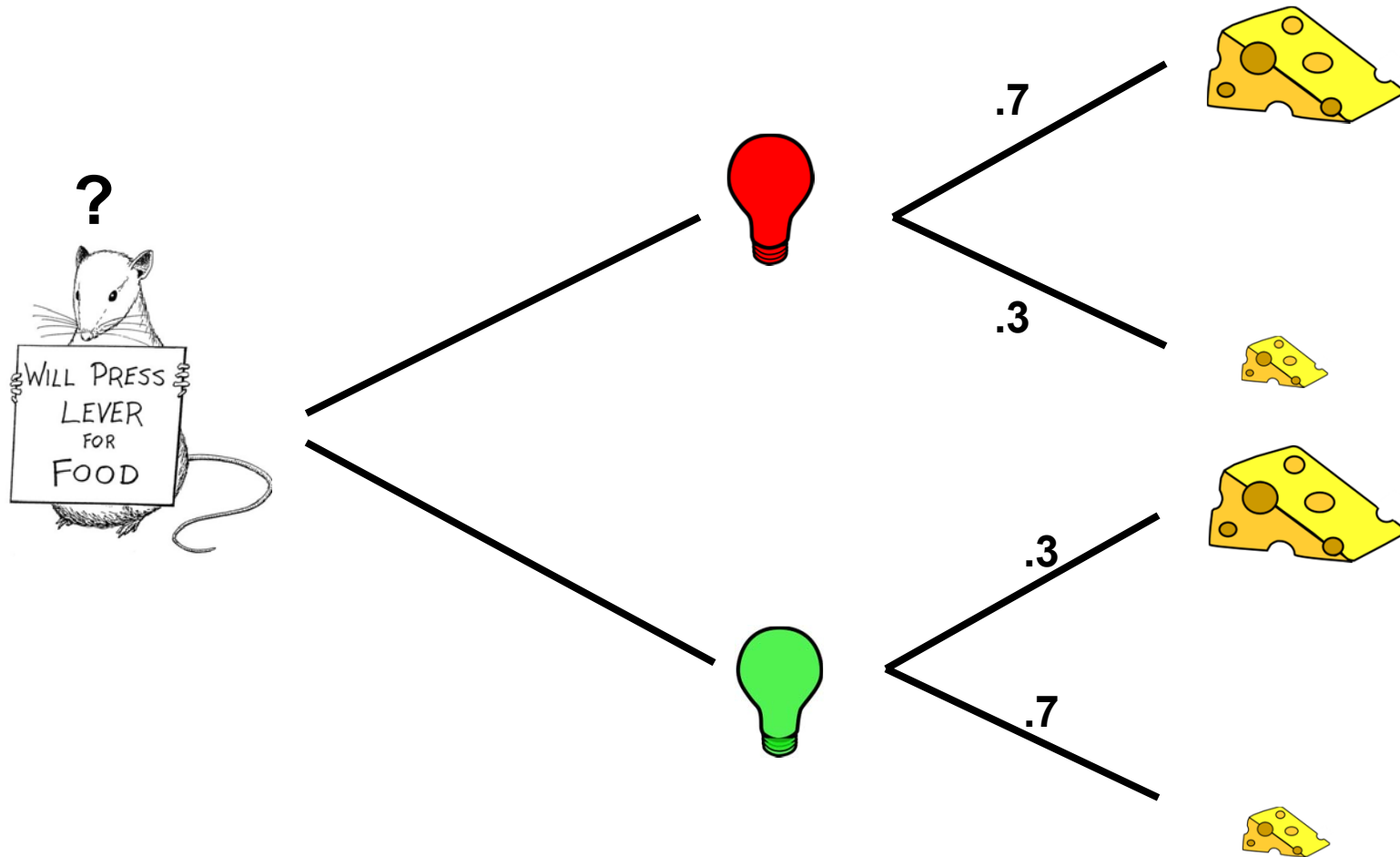
### ***General Algorithm***

- **Value Prediction** – Expected value of each option
  - **Select Action** – Probabilistic choice of option with highest value
  - **Comparison** – predicted outcome vs. actual outcome (prediction error)
  - **Learning** – Update value predictions in proportion to discrepancy
-

# Steps in Model-Based Analysis

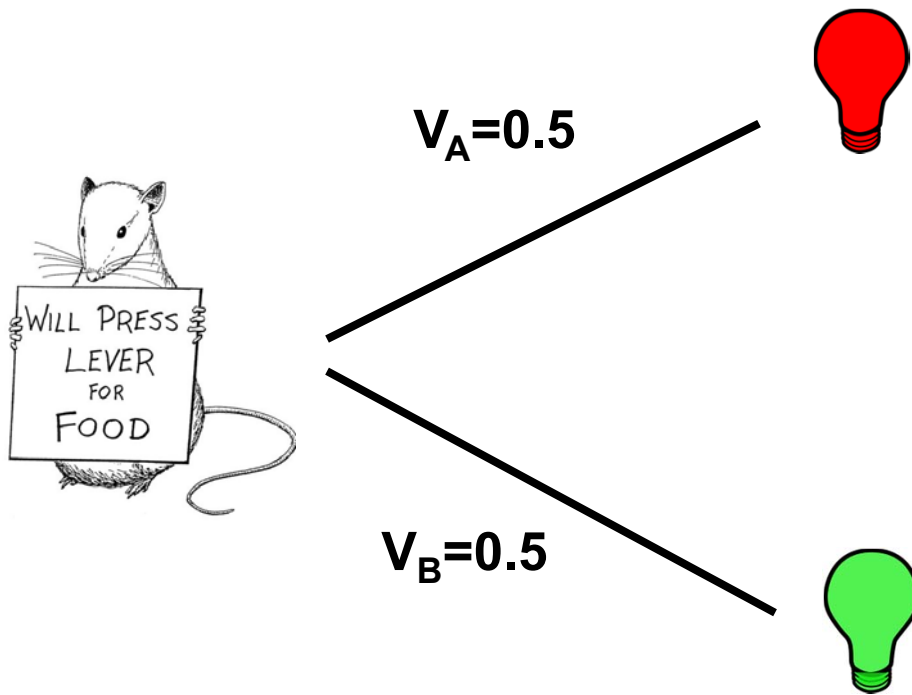
1. Select/create a computational model
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# Example – Simple Reinforcement Learning



# Example – Simple Reinforcement Learning

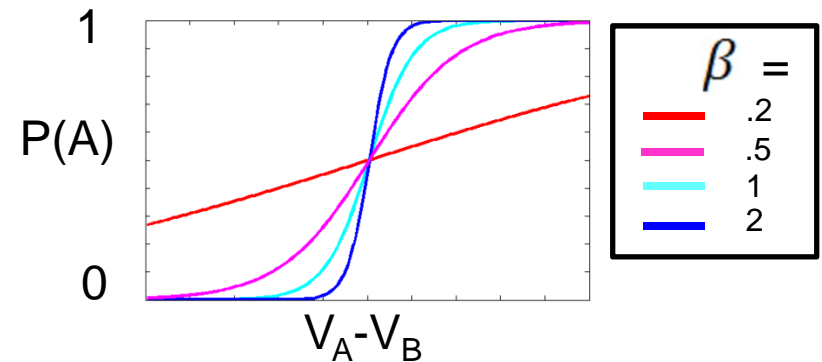
## Value Prediction



## Action Selection – Softmax:

$$P(A) = \frac{\exp(\beta * V_A)}{\exp(\beta * V_A) + \exp(\beta * V_B)}$$

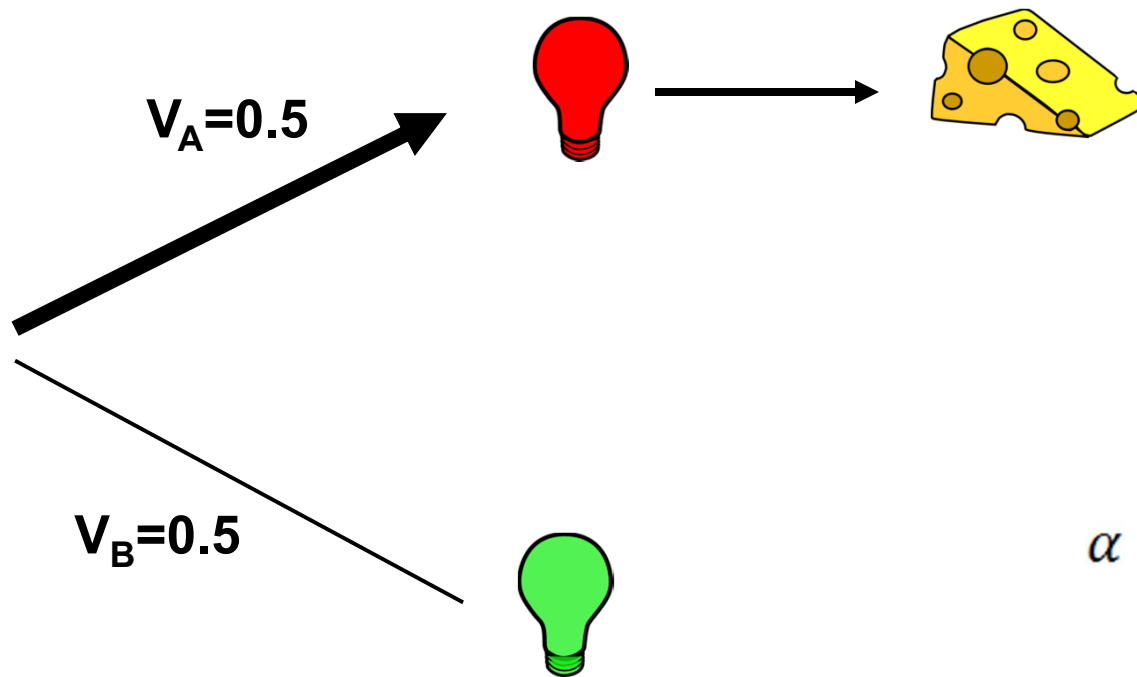
$$P(B) = 1 - P(A)$$



$\beta$  = inverse temperature parameter  
"decisiveness"

## Example – Simple Reinforcement Learning

**Comparison :**  
**Outcome – Prediction**



$$\delta = \text{reward} - V_A$$

**Learning:**

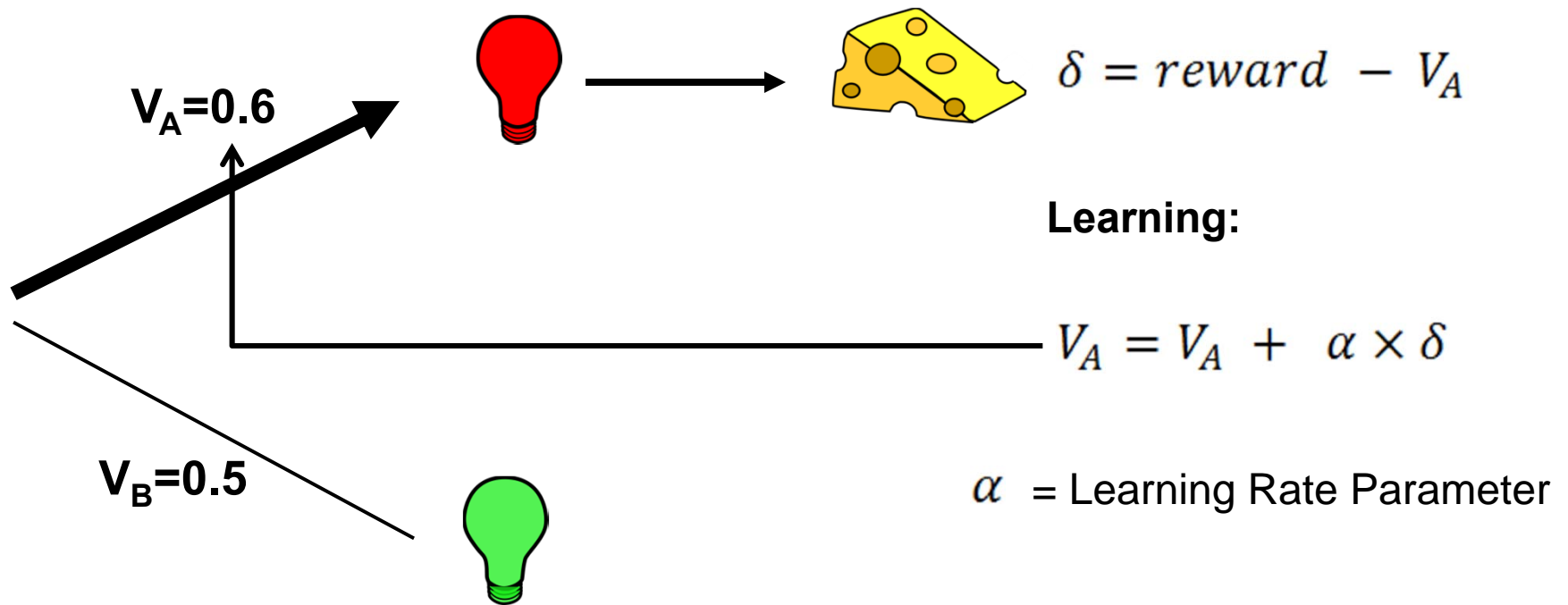
$$V_A = V_A + \alpha \times \delta$$

$\alpha$  = Learning Rate Parameter

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## Example – Simple Reinforcement Learning

**Comparison :**  
**Outcome – Prediction**





# Model Predictions

## Simple RL Model

-Behavioral output

Choice

-Cognitive Mechanisms

Value Prediction

Prediction Error

***Governed by model parameters:  $\alpha$ ,  $\beta$***

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# Steps in Model-Based Analysis

1. Select/create a computational model
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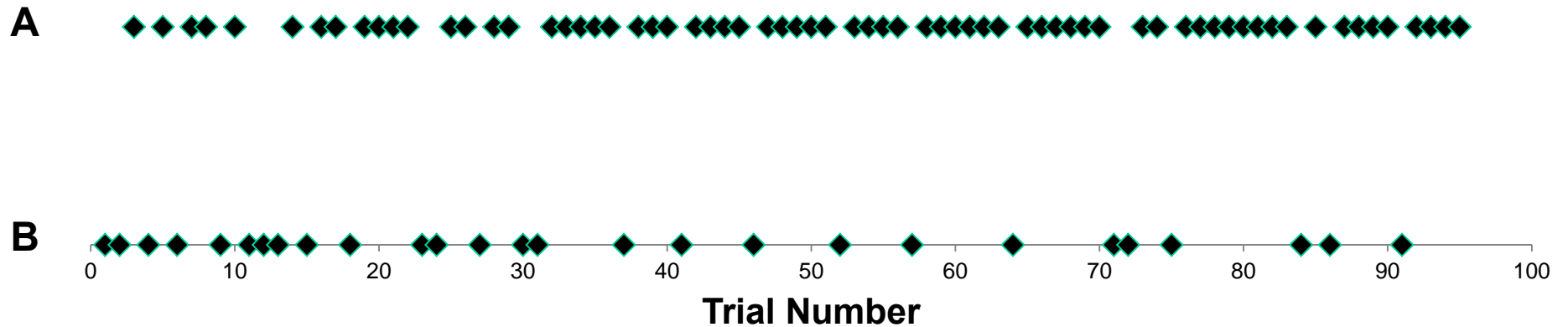
## Fitting the model to data

Given our observed data and a model,  
what model parameters best explain the  
data?

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# Hypothetical Data

## Subject Choice



## RL model Parameters

$\alpha$  Learning Rate

$\beta$  Decision Temperature

---

# Determining Parameter Values

Previously published parameter values

- may not apply to your data/task

“Reasonable” Parameters

- biologically/psychologically plausible
- open to interpretation

Optimization over a cost function

- comparison of the behavior of a model with subject behavior
-

# Cost Functions

## Ordinary Least Squares

- minimize sum of squared errors

$$\sum (Observed\ Behavior - Model\ Prediction)^2$$

## Maximum Likelihood Estimation

$$\ln \mathcal{L}(\theta | x_1, \dots, x_n) = \sum_{i=1}^n \ln f(x_i | \theta),$$

Others . . .

---

# Cost function minimization

## Gradient descent on cost function

- Parameter values
- Calculate local gradient
- Adjust parameters
- Repeat until minimum reached

## Existing tools

- e.g, MatLab fmincon/fminsearch
- Others...

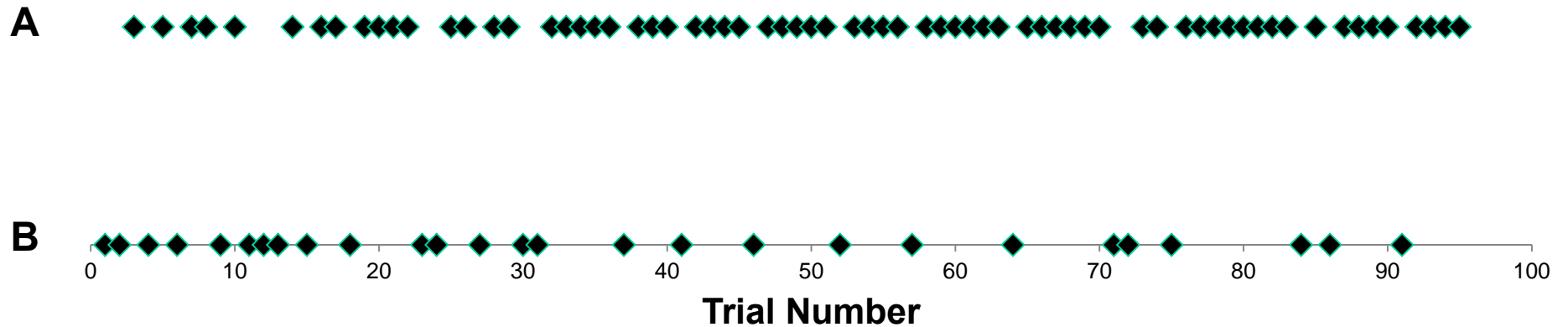
## Caveats

- Local minima vs. Global minimum
- Correlated parameters → unreliable estimates

---

# Hypothetical Data

## Subject Choice



## RL model Parameters

- $\alpha$  Learning Rate
- $\beta$  Decision Temperature

## Cost Function

$$\sum_t (\underbrace{Choice_t}_{\text{Subject Behavior}} - \underbrace{P(V_t^{choice})}_{\text{Model Action Selection}})^2$$



# Steps in Model-Based Analysis

1. Select/create a computational model
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-

# Internal Model Variables

## Simple RL model:

Estimated value of free parameters determines

How model learns/acts

Development of internal model variables

Value Predictions

Prediction Errors

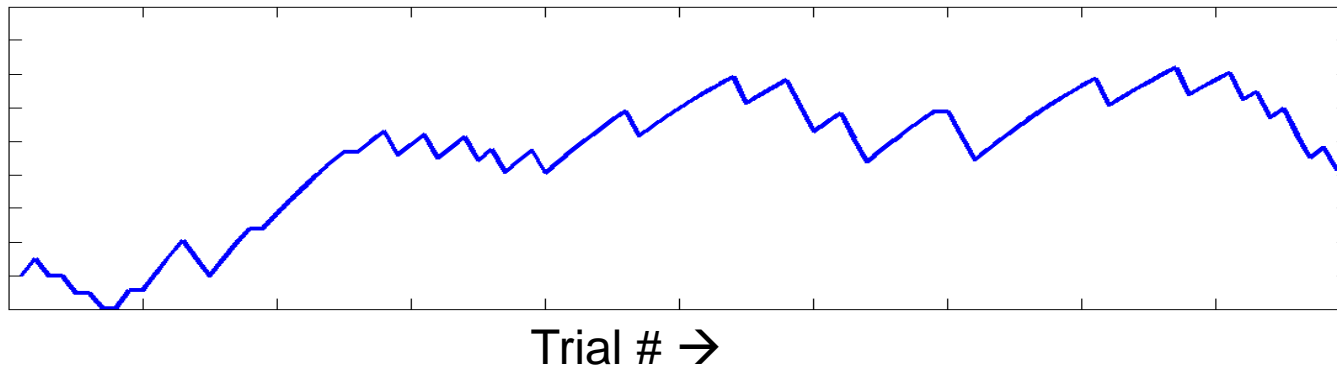
Internal model variables may be related to cognitive mechanism implemented by the brain

Model Variables → Brain Activity?

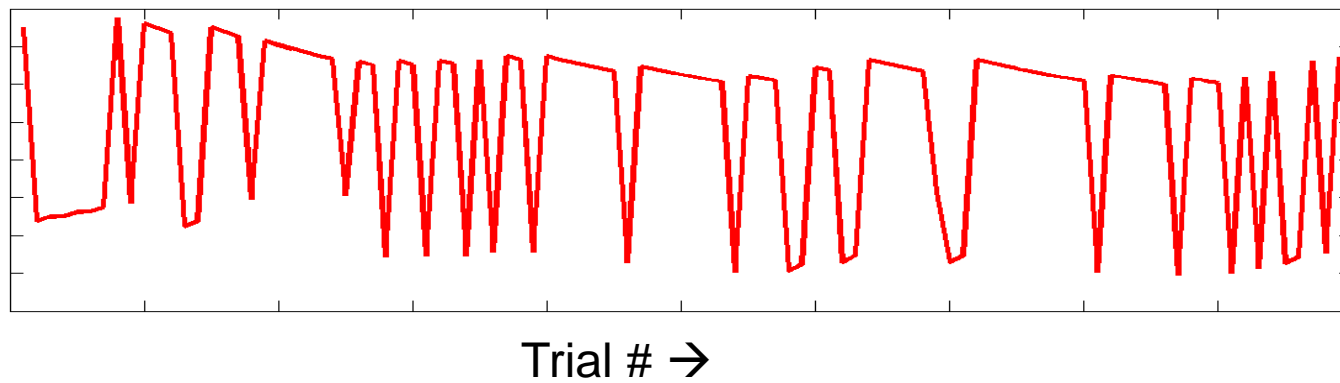
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# Internal Model Variables

## Value Prediction

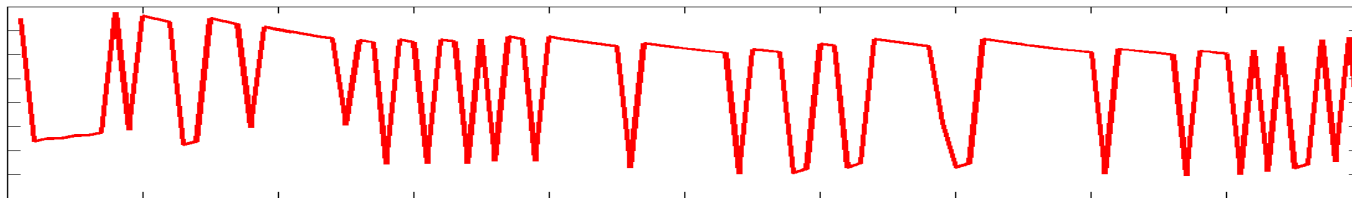


## Prediction Error

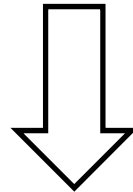


# Internal Model Variables

## Prediction Error



Trial # →



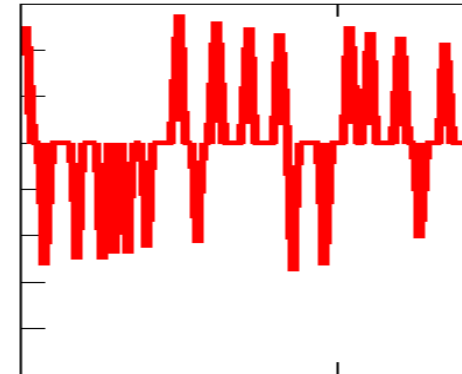
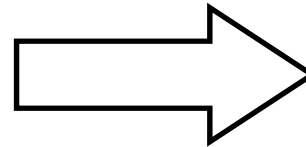
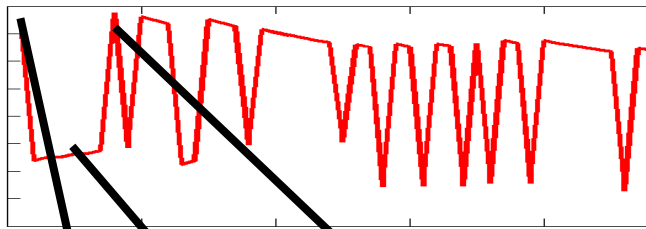
## BOLD time course



# Model Variables to fMRI analysis

Resample model activity to match fMRI time course

**Prediction Error**



**BOLD signal**

Outcome Trial 1:  
Frame 10

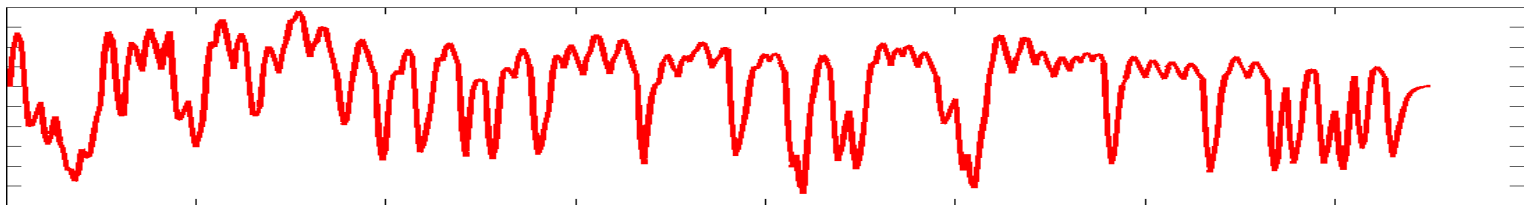
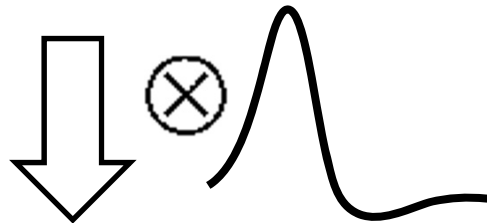
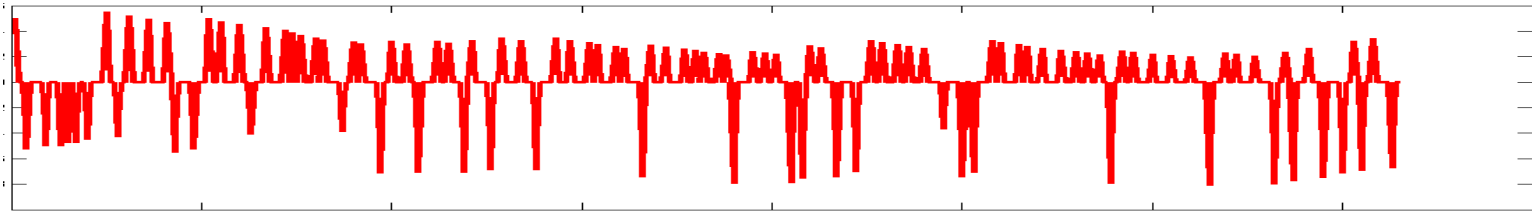
Outcome Trial 2:  
Frame 22

Outcome Trial 3:  
Frame 34



# Model Variables to fMRI analysis

Generate regressor from model variable:

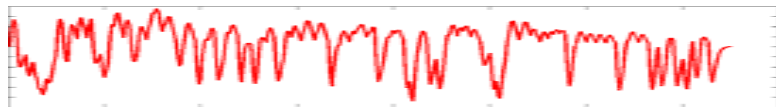
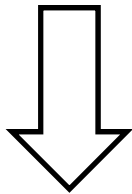
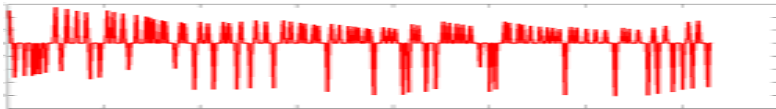


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1. Select/create a computational model
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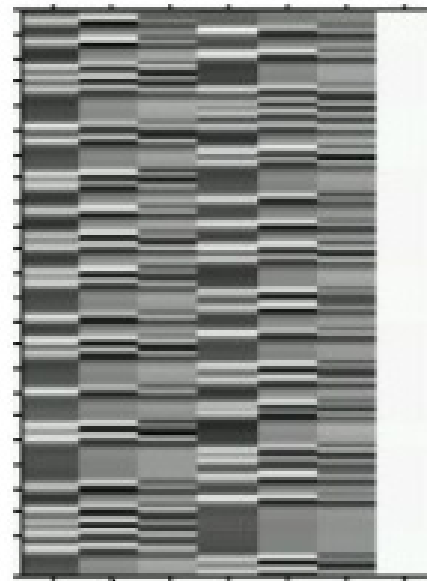
# Add regressor to 1<sup>st</sup> level design matrix as parametric modulator

Model Activity

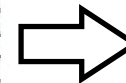


Parametric  
Modulator

Design Matrix



Onset  
Regressor



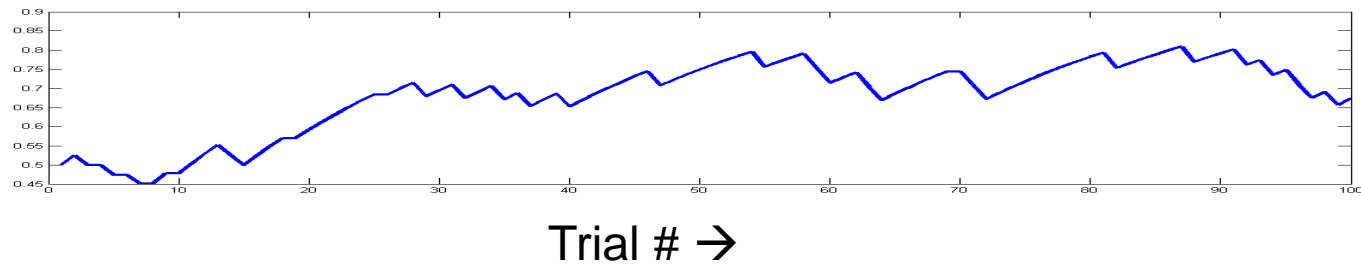
SPM for  
regressor



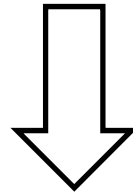


# Internal Model Variables

## Value Prediction



Trial # →



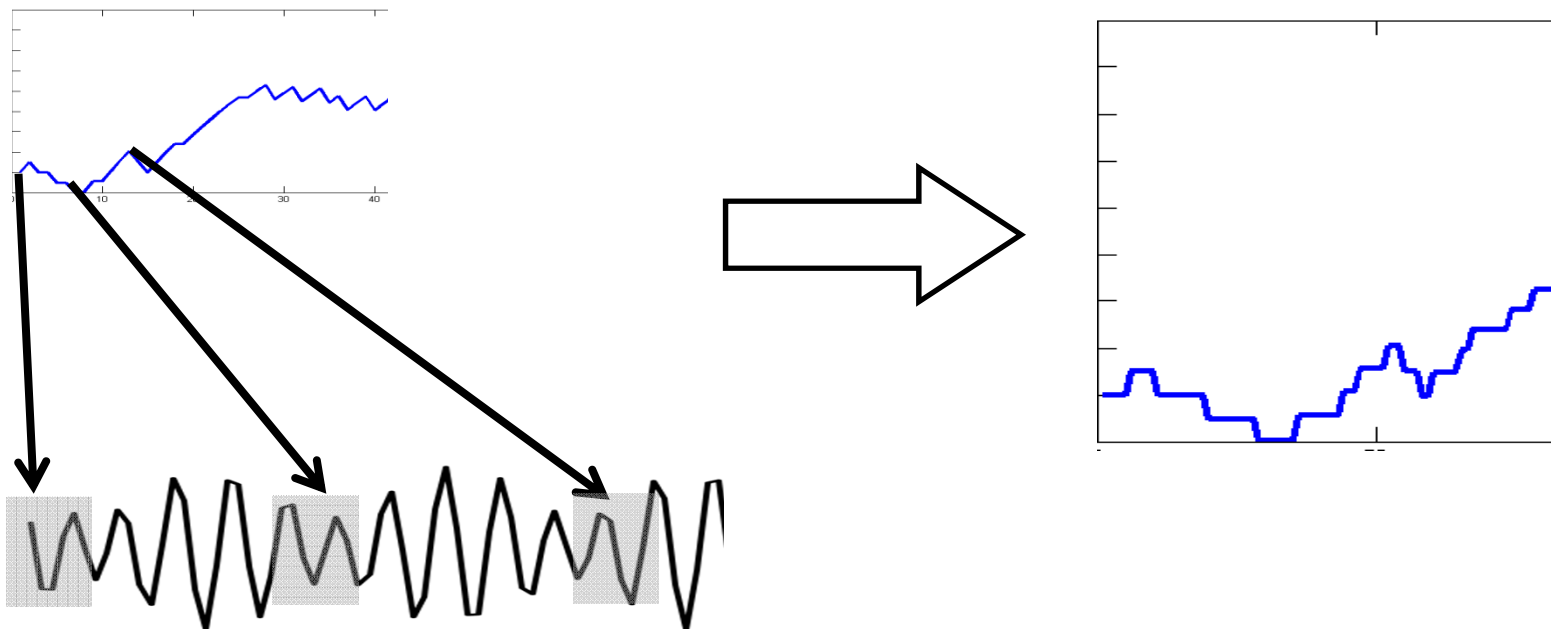
## BOLD time course



# Model Variables to fMRI analysis

Resample model activity to match fMRI time course

## Value Prediction



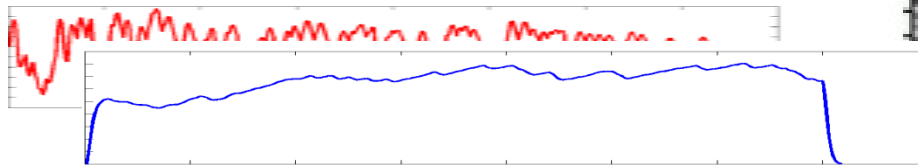
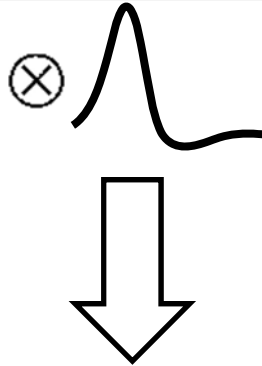
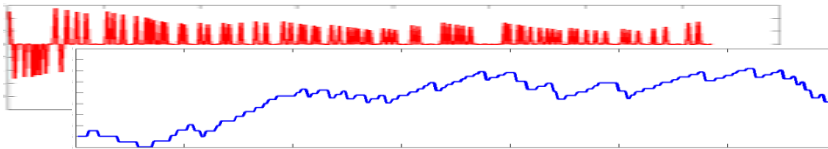
Prediction Trial 1: Frame 6-9      Prediction Trial 2: Frame 18-21      Prediction Trial 3: Frame 30-33

## BOLD signal

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# Multiple Model Regressors

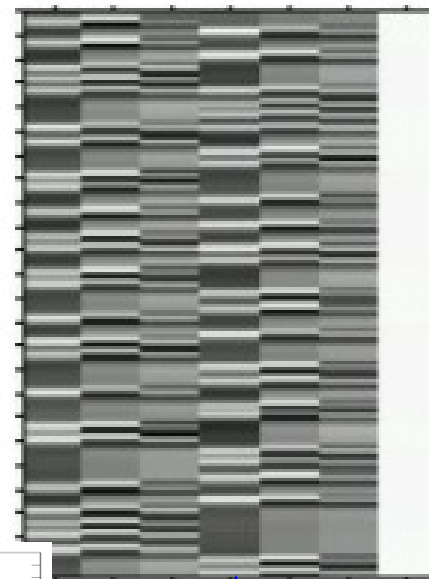
Model Activity



Parametric  
Modulator



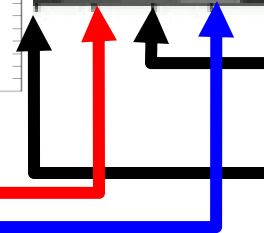
Design Matrix



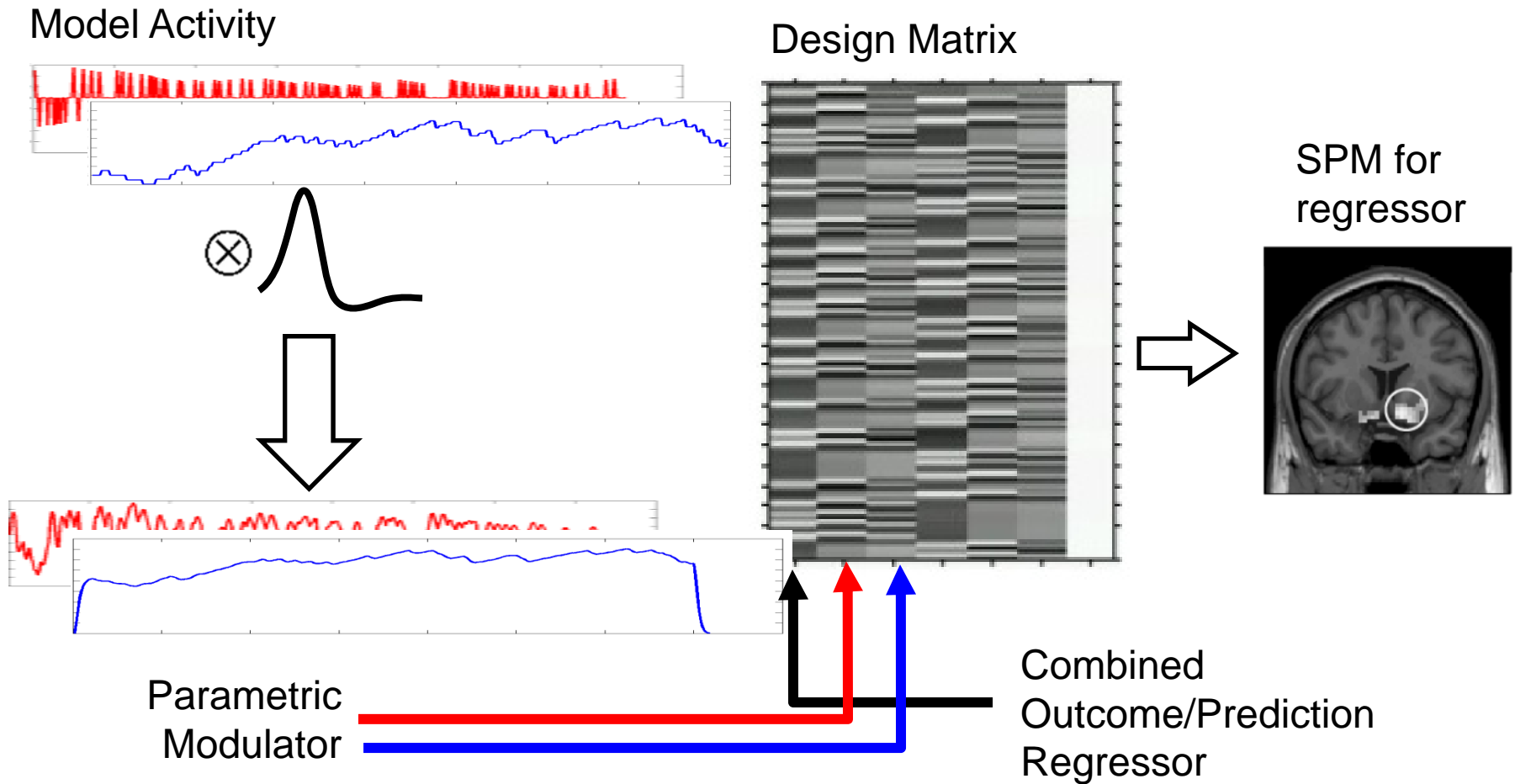
SPM for  
regressor



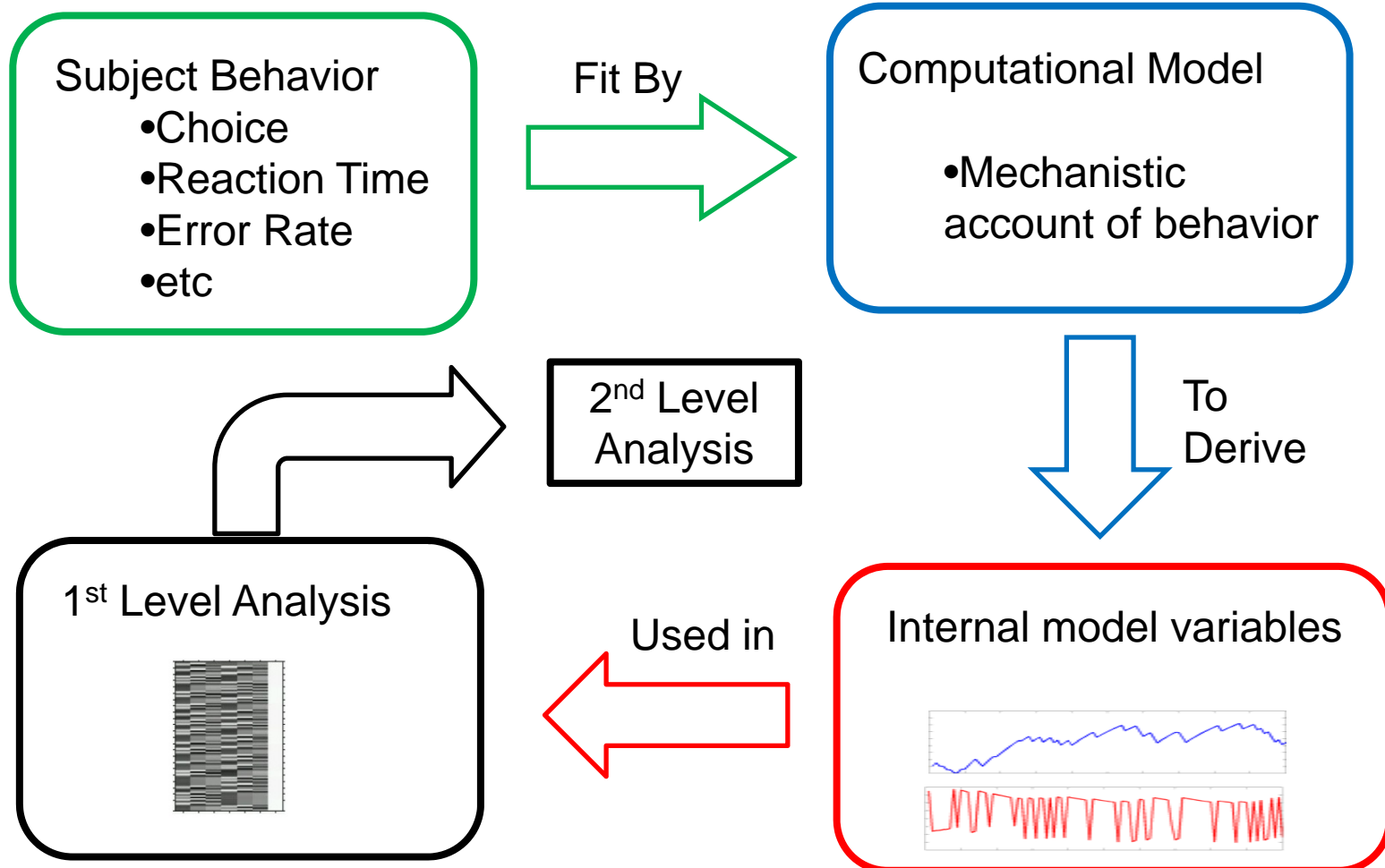
Prediction  
Regressor  
Outcome  
Regressor



# Multiple parametric modulators



## Model-Based fMRI analysis – Summary



# Summary

You already use a model

Model-based fMRI analysis tries to determine how specific cognitive mechanisms may be implemented in the brain

Analysis is straightforward – most of the work is in the modeling

Many, many models to choose from

---

## ❖ Motivation

- ❖ Models (general)
- ❖ Why you ought to care

## ❖ Model-based fMRI

- ❖ Models (specific)
- ❖ From model to analysis

## ❖ Extended Example

- ❖ Hampton, Bossaerts, & O'Doherty (2006)
-

Behavioral/Systems/Cognitive

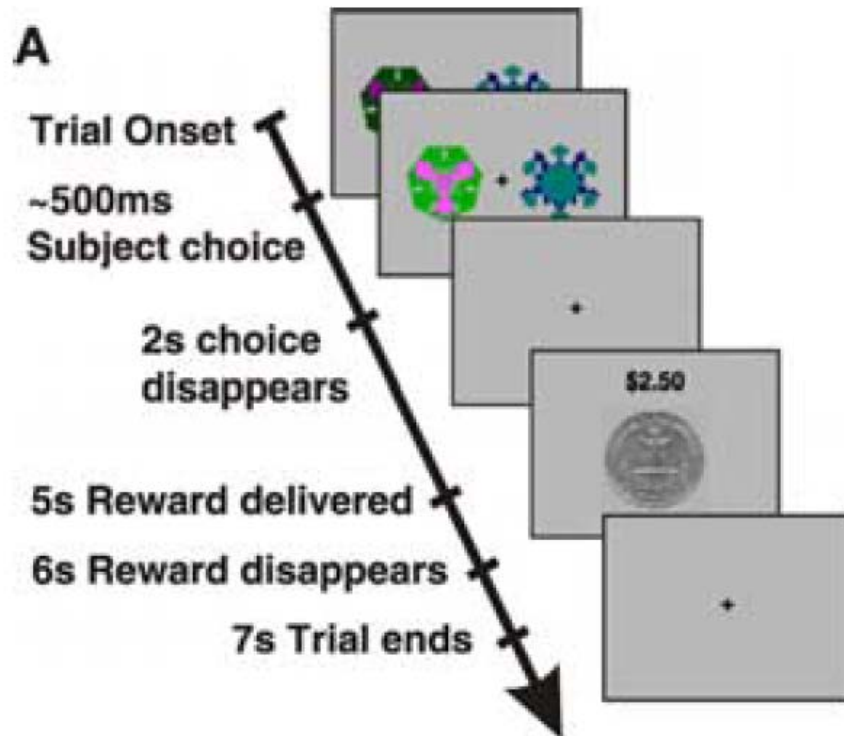
# The Role of the Ventromedial Prefrontal Cortex in Abstract State-Based Inference during Decision Making in Humans

Alan N. Hampton,<sup>1</sup> Peter Bossaerts,<sup>1,2</sup> and John P. O'Doherty<sup>1,2</sup>

<sup>1</sup>Computation and Neural Systems Program and <sup>2</sup>Division of Humanities and Social Sciences, California Institute of Technology, Pasadena, California 91125

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Reward 70% of the time for  
correct choice, punished 30%  
-Net Gain

Reward 40% for incorrect choice,  
punished 60%  
-Net Loss

After choosing correct option 4  
times consecutively, contingencies  
switched with probability .25

## Model 1 Simple RL

Predictions:

$$V_a \quad V_b$$

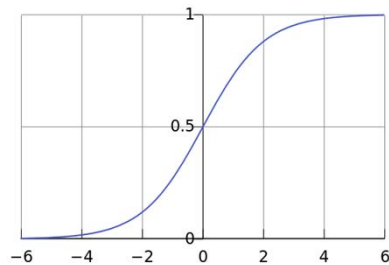
Learning:

$$V_a(t + 1) = V_a(t) + \eta \delta(t),$$

$$\delta(t) = r(t) - V_a(t).$$

Choice:

$$P(A) = \sigma(\beta\{(V_a - V_b) - \alpha\})$$



## Model 2 Hidden State Markov Model

Abstract Hidden State:

$X_t \rightarrow$  Correct/Incorrect choice

Infer probability of hidden state based on previous history, current choice:

$$P(X_t/X_{t-1}, S_t = \text{stay}) = \begin{pmatrix} 1 - \delta & \delta \\ \delta & 1 - \delta \end{pmatrix},$$

$$P(X_t/X_{t-1}, S_t = \text{switch}) = \begin{pmatrix} \delta & 1 - \delta \\ 1 - \delta & \delta \end{pmatrix}$$

Update estimates based on current trial:

$$\text{Posterior}(X_t = \text{correct}) = \frac{P(Y_t/X_t = \text{correct})\text{Prior}(X_t = \text{correct})}{\sum_{X_t \text{ states}} P(Y_t/X_t)\text{Prior}(X_t)}$$

Probability of switch:

$$P(\text{switch}) = \sigma(\beta\{P_{\text{incorrect}} - \alpha\}).$$

# Model Fitting

## Model 1 Simple RL

$$P(A) = \sigma(\beta\{(V_a - V_b) - \alpha\})$$

## Model 2 Hidden State Markov Model

$$P(\text{switch}) = \sigma(\beta\{P_{\text{incorrect}} - \alpha\}).$$

$$\log L = \frac{\sum B_{\text{switch}} \log P_{\text{switch}}}{N_{\text{switch}}} + \frac{\sum B_{\text{stay}} \log P_{\text{stay}}}{N_{\text{stay}}}$$

Behavioral Data

---

# Model Parameters

## Model 1 Simple RL

$$P(A) = \sigma(\beta\{(V_a - V_b) - \alpha\})$$

$$P(\text{switch}) = \sigma(\beta\{P_{\text{incorrect}} - \alpha\}).$$

Temperature –  
exploration/exploitation

Indifference point

## Model 2 Hidden State Markov Model

$$V_a(t + 1) = V_a(t) + \eta \delta(t),$$

Learning Rate

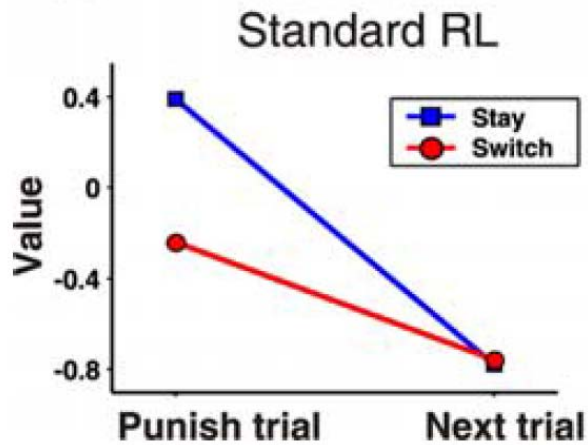
$$P(X_t/X_{t-1}, S_t = \text{stay}) = \begin{pmatrix} 1 - \delta & \delta \\ \delta & 1 - \delta \end{pmatrix},$$

$$P(X_t/X_{t-1}, S_t = \text{switch}) = \begin{pmatrix} \delta & 1 - \delta \\ 1 - \delta & \delta \end{pmatrix}.$$

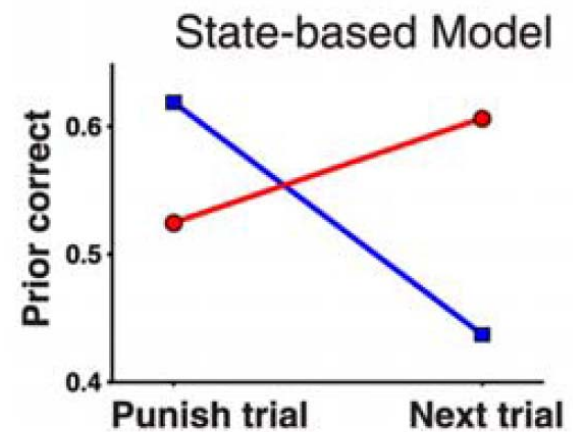
Probability of reversal

# Model Predictions

## Model 1 Simple RL



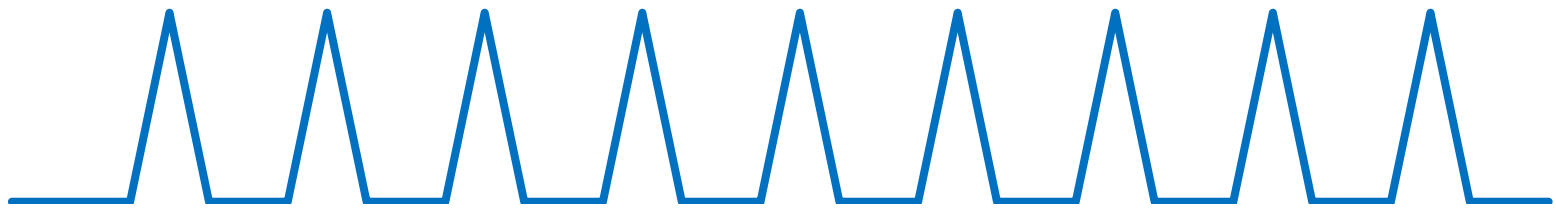
## Model 2 Hidden State Markov Model



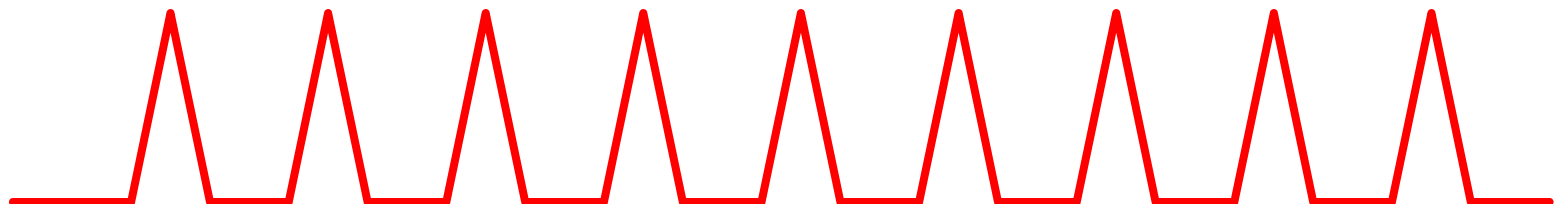
# fMRI Analysis

**Regressors:**

**Delta function at choice**



**and outcome**



# fMRI Analysis

## Parametric Modulation of Choice

### Delta function at Choice



RL Model - Value Prediction

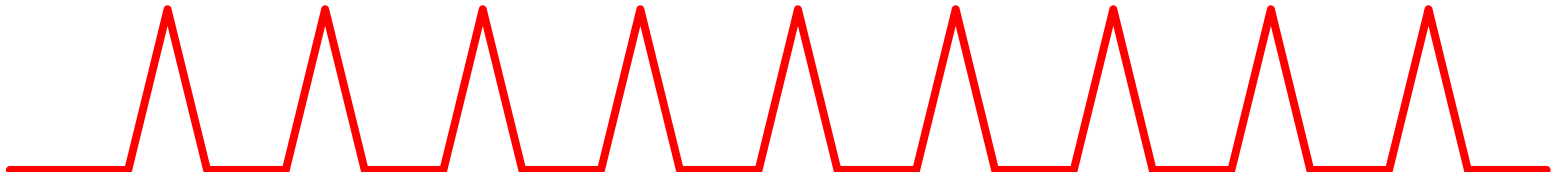
HMM -  $P(X=\text{correct})$



# fMRI Analysis

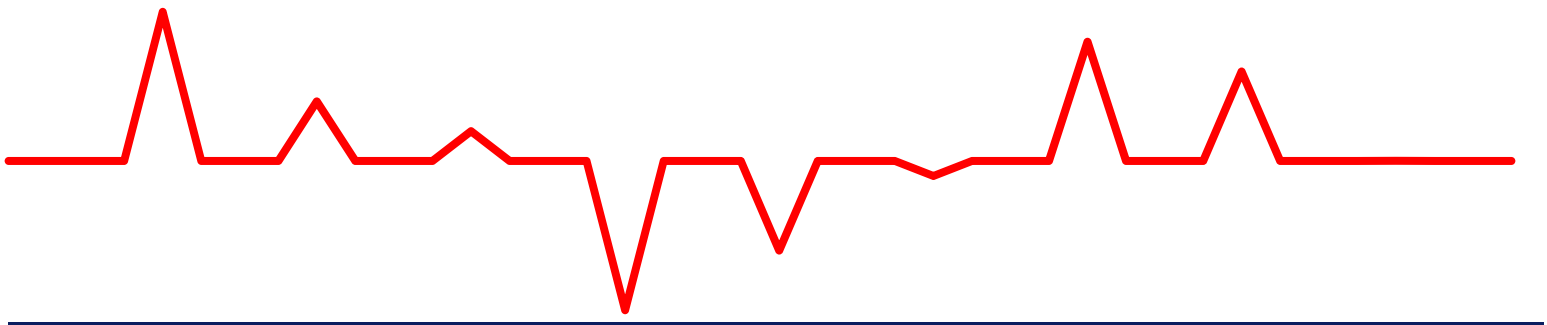
## Parametric Modulation of Outcome

### Delta function at Outcome



RL Model – Prediction Error

HMM – (Posterior Probability – Prior Probability)

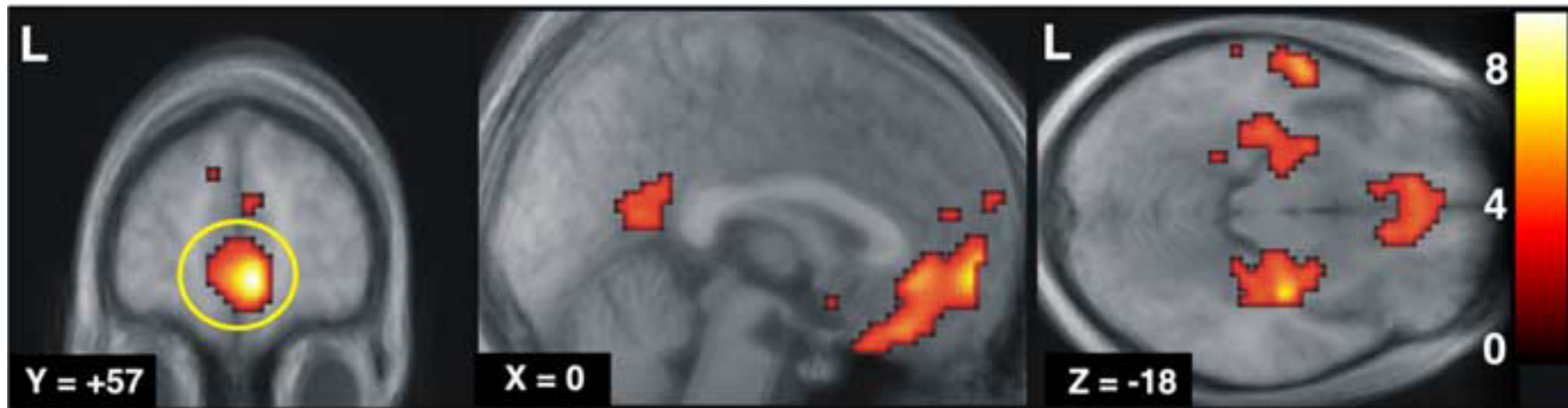




## fMRI Results

### HMM Model (Choice): $P(X=\text{correct})$

A Prior correct

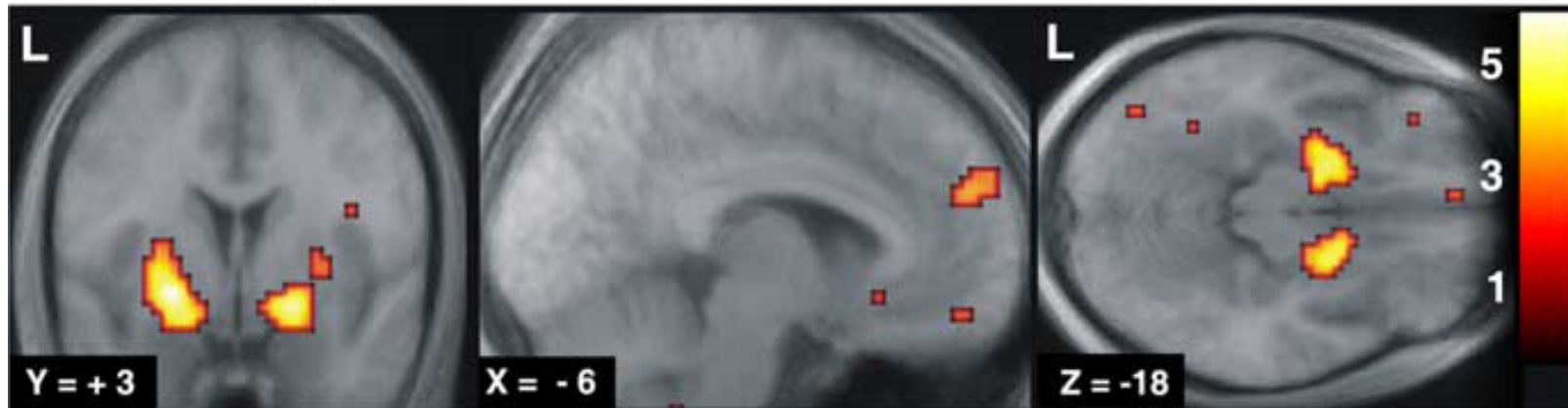


Time locked to time of choice

## fMRI Results

### HMM Model (Outcome): Posterior – Prior

**B** Posterior - prior

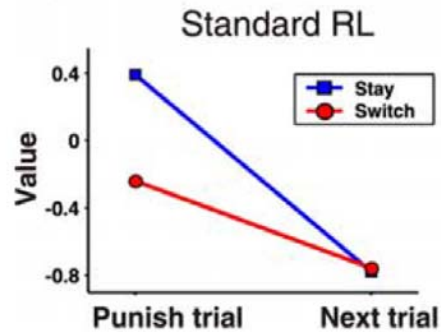


# fMRI Results

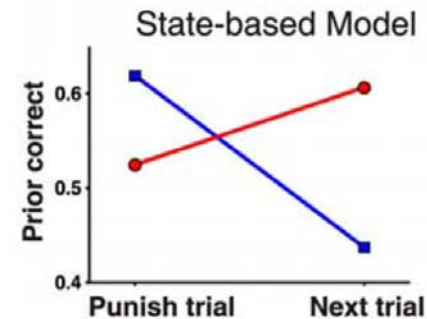
## Comparison of Model Predictions

### Model 1 Simple RL

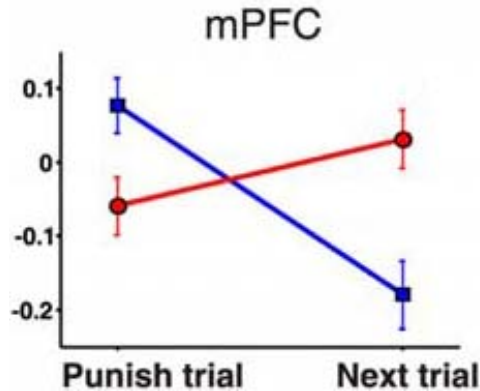
Predictions



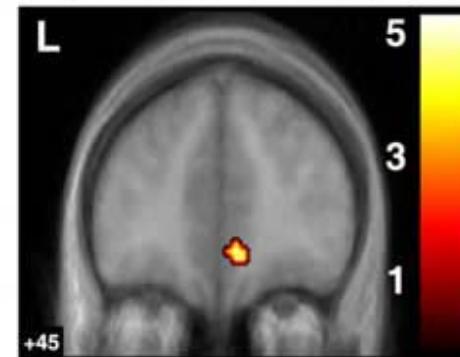
### Model 2 Hidden State Markov Model



Results



### B State-based > standard RL





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