Reinforcement Learning (& Decision-Making) with hBayesDM

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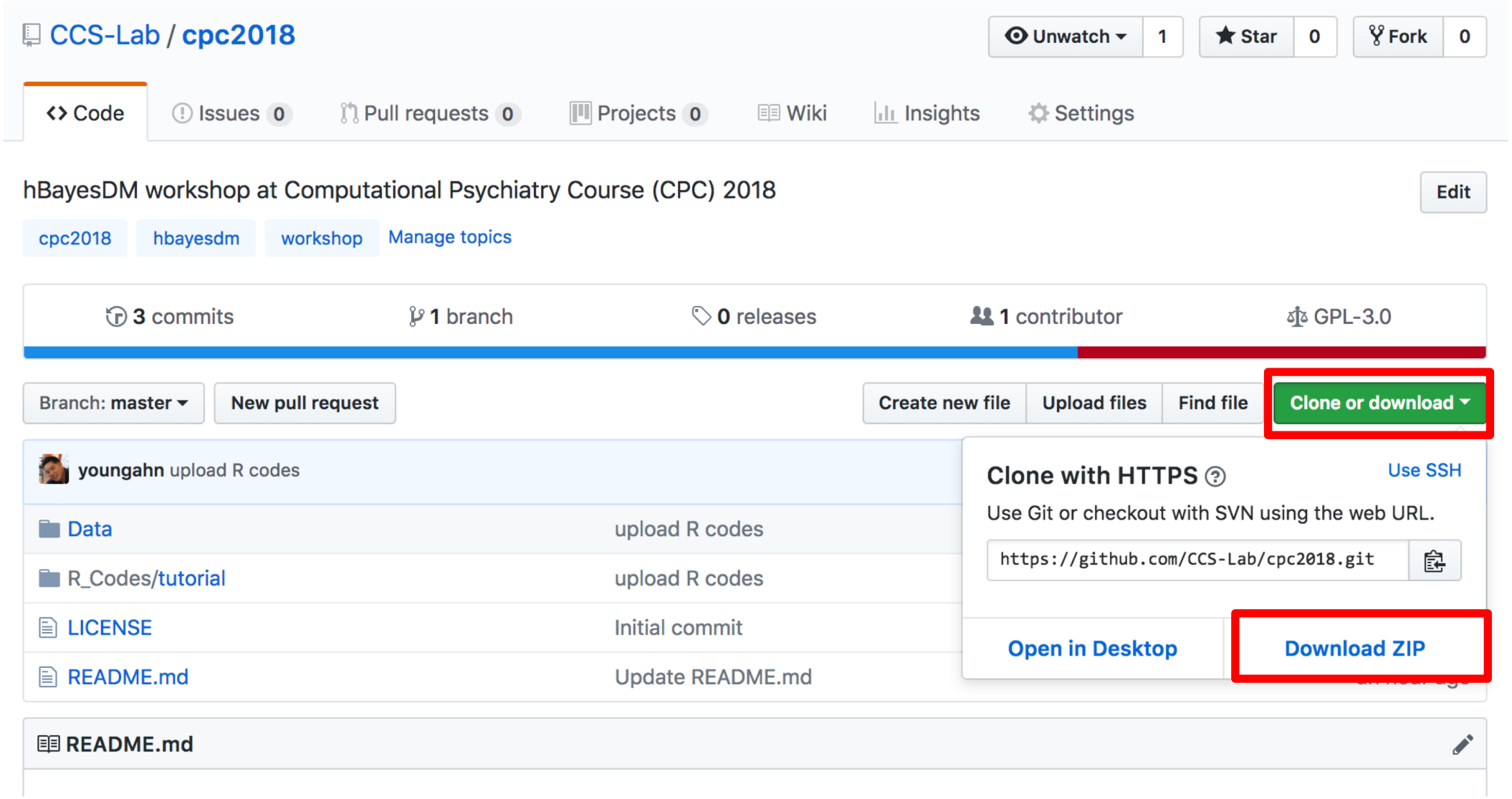
General Outline

*Part I: Introduction to computational modeling and **hBayesDM** (**h**ierarchical **Bayes**ian modeling of **D**ecision-**M**aking tasks)*

Part II: Hands-on tutorials on Bayesian modeling / hBayesDM

Nate Haines

github.com/ccs-lab/cpc2018



git clone https://github.com/CCS-Lab/cpc2018.git

Learning objectives

Participants will…

- *Know popular and cutting-edge methods for fitting computational models*
- *Review the concept of Bayesian data analysis*
- *Evaluate outputs from Bayesian data analysis*
- *Use hBayesDM package to model reinforcement learning and decision-making tasks*

Outline for Part I

- *What is computational modeling (a.k.a. cognitive modeling)?*
- *Why/how do we lower the barrier to computational modeling?*
  - *Brief introduction to hBayesDM*
- *How to fit a computational model?*
  - *Maximum likelihood estimation (MLE)*
  - *Bayesian analysis & MCMC sampling*
  - *Hierarchical Bayesian analysis*
  - *Tools for Bayesian data analysis*
- *Things to know when performing MCMC sampling*

Software installation (1/2)

- *Install the latest R (+3.4): https://cloud.r-project.org/*
- *Install RStudio: https://www.rstudio.com/products/rstudio/download2/*

Windows users

- *Install Rtools: https://cran.r-project.org/bin/windows/Rtools/Rtools34.exe*
- ***"Carefully"** follow the instructions: https://github.com/stan-dev/rstan/wiki/Install-Rtools-for-Windows*

Mac users

- *Install Xcode (https://developer.apple.com/xcode/)*

Software installation (2/2)

hBayesDM tutorial: http://rpubs.com/CCSL/hBayesDM
"How to install hBayesDM" (Google "hBayesDM rpubs")

Windows users

- *Install hBayesDM from CRAN. Takes ~10 seconds.*

```
install.packages("hBayesDM", dependencies=TRUE)
```

Mac/Linux users

- *Install hBayesDM from GitHub. Takes ~5-10 minutes.*

```
# install 'devtools' if required
if (!require(devtools)) install.packages("devtools")
devtools::install_github("CCS-Lab/hBayesDM")
```

Outline

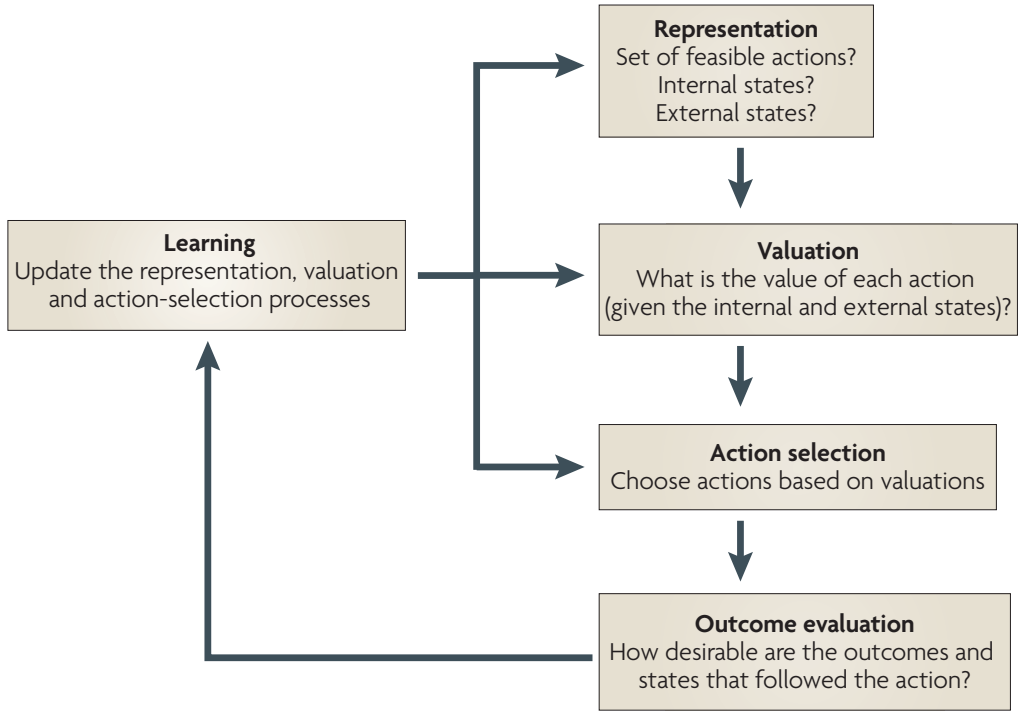
- *Understand the concepts of computational modeling*
- *Know popular and cutting-edge methods for fitting computational models / Understand the concept of Bayesian data analysis*
- *Things to know when performing MCMC sampling*
- *Use hBayesDM package to model several tasks*

Reinforcement learning and Decision-making (RLDM)

A framework for studying the neurobiology of value-based decision making

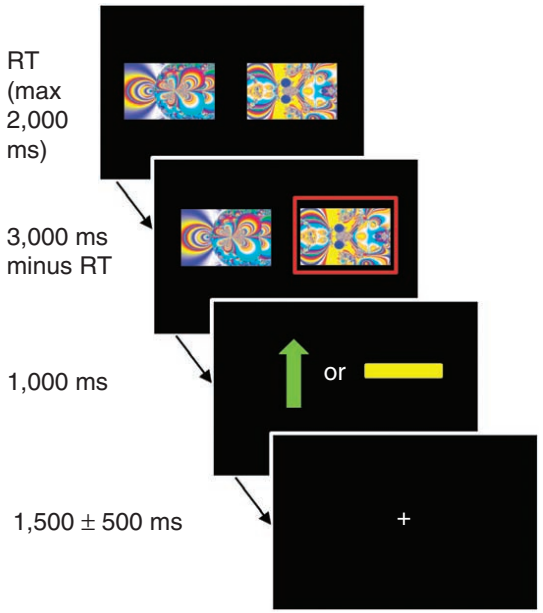
Antonio Rangel, Colin Camerer* and P. Read Montague‡*

Rangel et al (2008) Nature Rev. Neuro

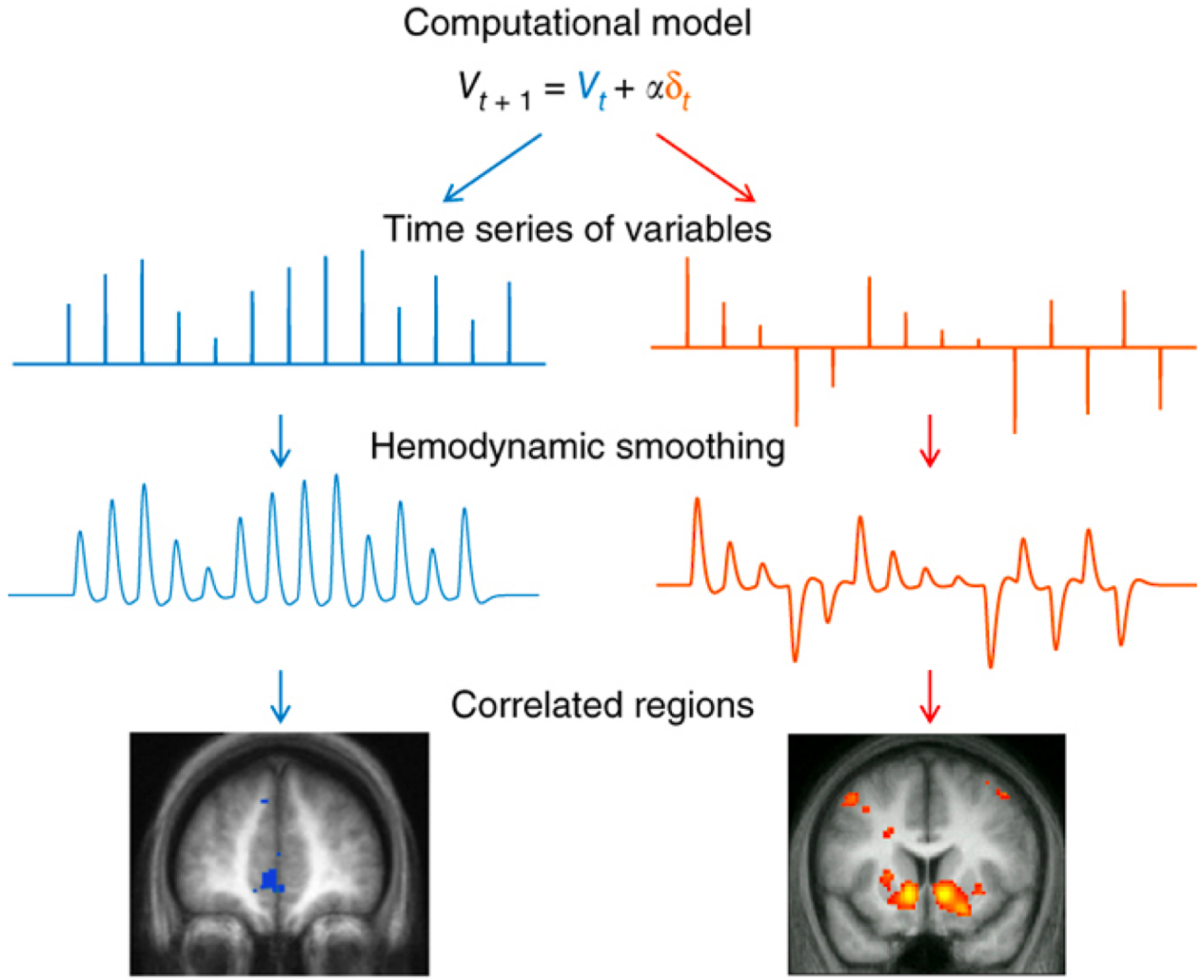


Model-based fMRI/EEG

e.g., Forstmann & Wagenmakers (2015); O'Doherty et al (2007); Cohen et al (2017)



Chowdhury et al (2013) Nature neuro.



Cohen et al (2017) Nature neuro.

Review

Review

Cell PRESS

Special Issue: Cognition in Neuropsychiatric Disorders

Computational psychiatry

P. Read Montague[1,2], Raymond J. Dolan[2], Karl J. Friston[2] and Peter Dayan[3]

CrossMark

Computational psychiatry: the brain as a phantastic organ

Karl J Friston, Klaas Enno Stephan, Read Montague, Raymond J Dolan

Available online at www.sciencedirect.com

ScienceDirect

Current Opinion in Neurobiology

ELSEVIER

Computational approaches to psychiatry

Klaas Enno Stephan[1,2,3] and Christoph Mathys[3]

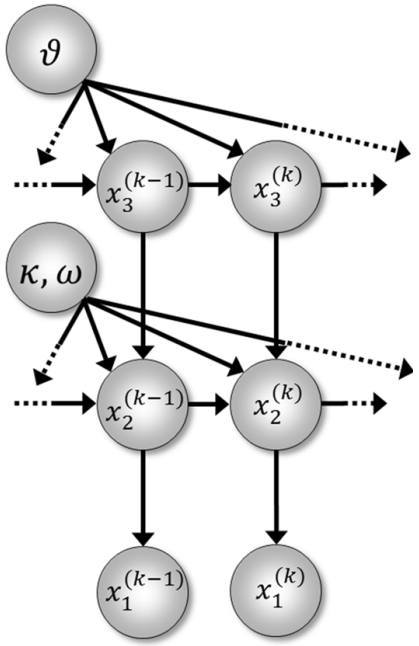
Computational accounts of abnormal cognition & its biological underpinnings

Limitations & Future directions

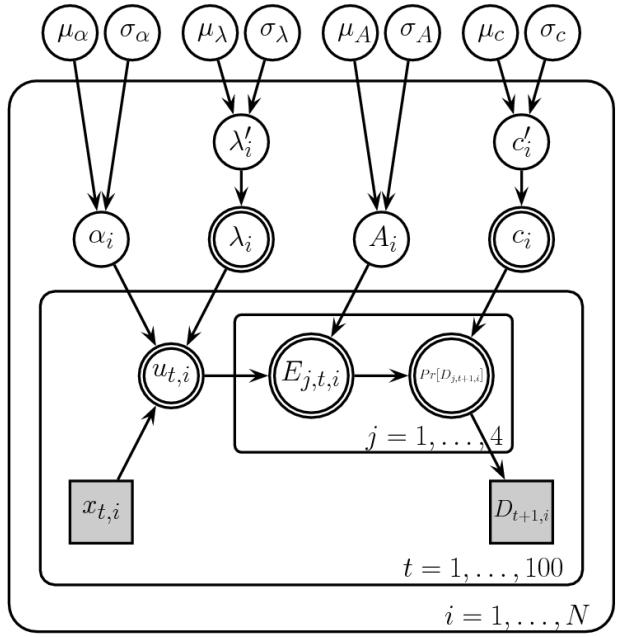
- *Overly simplified "toy" problems*
  - *Violated assumptions (e.g., discrete space/action & Markov..) , (Gershman & Daw, 2016, Annu Rev Psych)*
  - *Predict real-life DM? (Mobb et al., 2018, Nat Rev Neuro)*
- *One-shot learning with sparse data*
  - *Episodic memory (hippocampus) (Gabrieli, 1998; Eichenbaum et al., 1999)*
- *Adaptive Design Optimization (ADO)*
- *Modeling of even toy problems is hard for many people*

I like the idea of modeling

But…



Mathys et al (2011) Frontiers

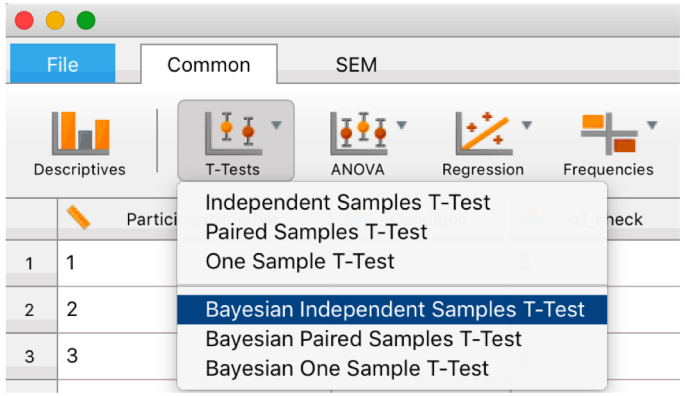


Ahn et al (2011) JNPE

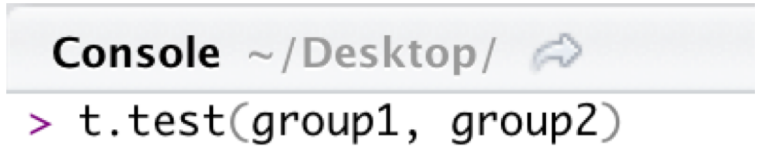
Can we make it easy to do computational modeling?

Q) As easy as doing a T-test?

JASP, SPSS



R



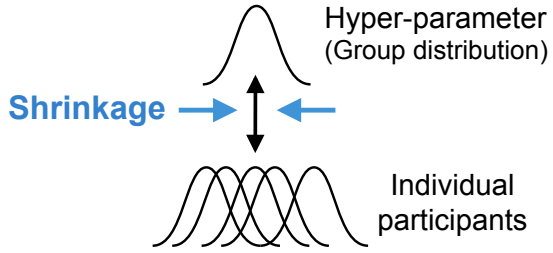
Several packages exist, but …

Matze et al (2013) Frontiers; Wabersich & Vandekerckhove (2014); Wiecki et al (2013) Frontiers; Daunizeau et al (2014) PLoS Comp Biol

hBayesDM *(hierarchical Bayesian modeling of Decision-Making tasks) Package*

- *Models for "many" tasks/paradigms (next slide)*
- *Single-line of coding in R*
  - *Model fitting, visualization, model comparisons*
- *Based on the advanced Bayesian software, Stan (https://mc-stan.org).*
- *Hierarchical Bayesian modeling*
- *All codes are publicly available*

https://github.com/CCS-Lab/hBayesDM



What tasks and models are available?
in CPC2017

Ahn & Busemeyer (2016) Curr Opin Behav Sci

- *Choice reaction time → sequential sampling models*
- *Delay Discounting* *(e.g., Mazur, 1987)*
- *Iowa Gambling* *(Bechara et al, 1994)*
- *(Orthogonalized) Go/Nogo* *(Guitart-Masip et al, 2012)*
- *Two-armed Bandit (Experience-based) including Reversal Learning* *(e.g., Erev et al, 2010)*
- *Four-armed Bandit (Experience-based)* *(e.g., Seymour et al, 2012)*
- *Two-choice Description-based* *(e.g., Sokol-Hessner et al, 2009; Tom et al, 2007)*
- *Ultimatum Game* *(e.g., Xiang et al, 2013)*
- **Two-Step* *(Daw et al, 2011)*

**Version 0.4.1. or later*

What tasks and models are available in CPC2018?

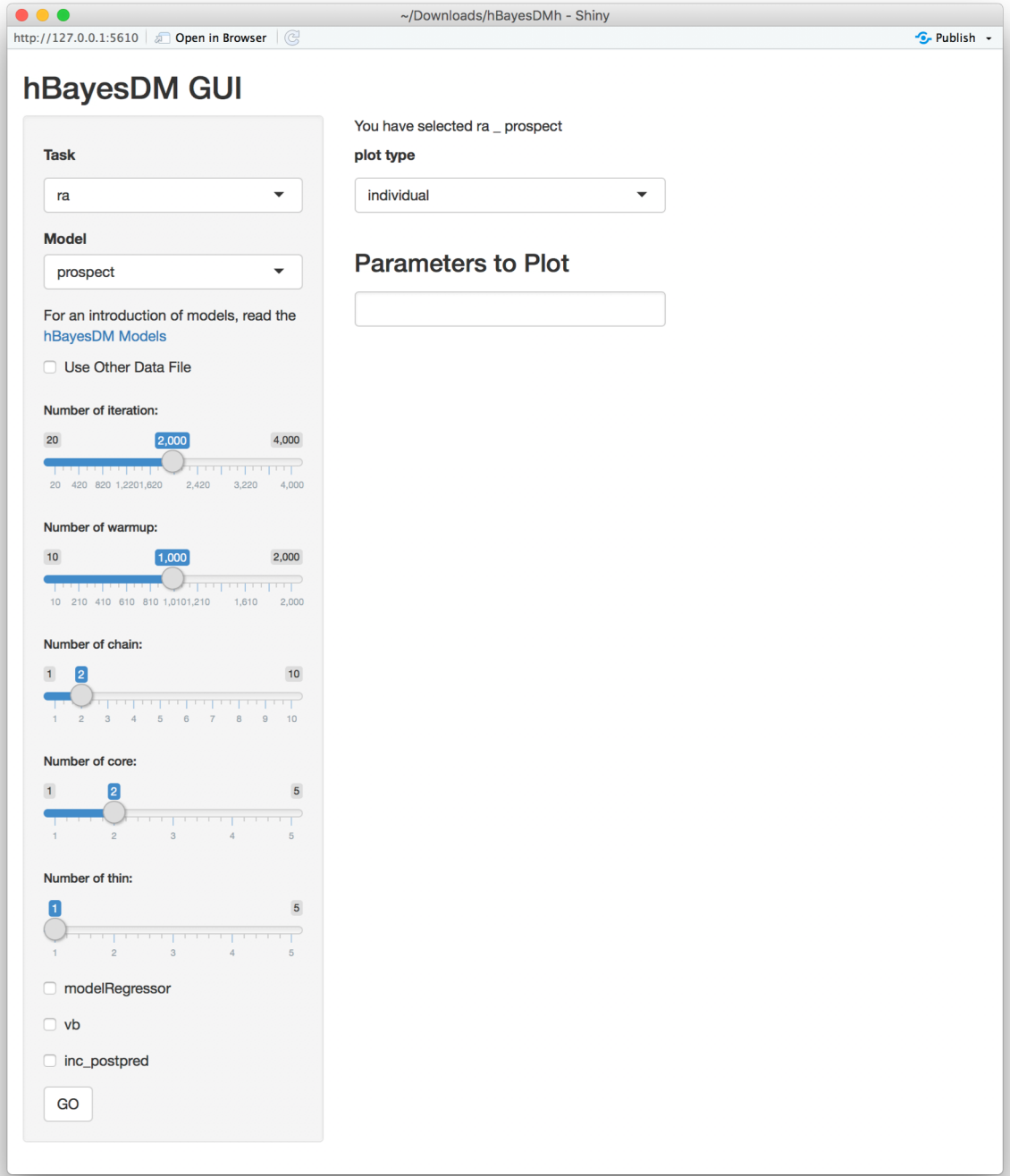
Ahn & Busemeyer (2016) Curr Opin Behav Sci

- Balloon Analogue Risk Task (BART) (Wallsten et al, 2005)
- Choice under Risk and Ambiguity (Levy et al, 2010)
- Choice reaction time → sequential sampling models
- Delay Discounting (e.g., Mazur, 1987)
- Iowa Gambling (Bechara et al, 1994)
- (Orthogonalized) Go/Nogo (Guitart-Masip et al, 2012)
- Peer influence task (Chung et al, 2015)
- Probabilistic Selection task (e.g., Frank et al, 2007)
- Two-armed Bandit (Experience-based) including Reversal Learning (e.g., Erev et al, 2010)
- Four-armed Bandit (Experience-based) (e.g., Seymour et al, 2012)
- Two-choice Description-based (e.g., Sokol-Hessner et al, 2009; Tom et al, 2007)
- Ultimatum Game (e.g., Xiang et al, 2013)
- Two Step task (Daw et al, 2011)
- Wisconsin Card Sorting task (Bishara et al, 2010)

To-do list

- *More tasks*
  - *Kalman-filter (Daw et al., 2006)*
  - *Hierarchical Gaussian Filtering (Mathys et al., 2011)*
  - *More models for the delay discounting task.*
  - *More sequential sampling models (e.g., drift diffusion models with different drift rates for multiple conditions).*
  - *Passive avoidance learning task (Newman & Kosson, 1986; Newman et al., 1985)*
  - *Description-based tasks with a probability weighting function (e.g., Erev et al., 2010; Hertwig et al., 2004; Jessup et al., 2008)*
  - *Stop Signal Task (SST)*
  - *Model-based regressors (O'Doherty et al., 2007) from more tasks.*

- *hBayesDM in Python → easy to use with Python-based neuroimaging packages (e.g., Nipype)*
- *GUI interface (RShiny)*


~/Downloads/hBayesDMh - Shiny
http://127.0.0.1:5610
Open in Browser
Publish
hBayesDM GUI
Task
ra
Model
prospect
For an introduction of models, read the
hBayesDM Models
Use Other Data File
Number of iteration:
20
2,000
4,000
20 420 820 1,220 1,620 2,420 3,220 4,000
Number of warmup:
10
1,000
2,000
10 210 410 610 810 1,010 1,210 1,610 2,000
Number of chain:
1
2
10
1 2 3 4 5 6 7 8 9 10
Number of core:
1
2
5
1 2 3 4 5
Number of thin:
1
5
1 2 3 4 5
modelRegressor
vb
inc_postpred
GO
You have selected ra _ prospect
plot type
individual
Parameters to Plot

How can I use it?

Tutorials available at

http://rpubs.com/CCSL/hBayesDM

(you can find it by Googling 'hBayesDM')

Install it just like other R packages

```
install.packages("hBayesDM", dependencies=TRUE)
```

```
devtools::install_github("CCS-Lab/hBayesDM")
```

Brief step-by-step tutorials

** Part II for detailed tutorials*

1. *Prepare raw (trial-by-trial) data*
2. *Fit candidate models*
3. *Plot (visualize) and inspect model parameters*
4. *Compare models (if there exist competing models)*

The Orthogonalized Go/Nogo task

- `gng_m1`
- `gng_m2`
- `gng_m3`
- `gng_m4`

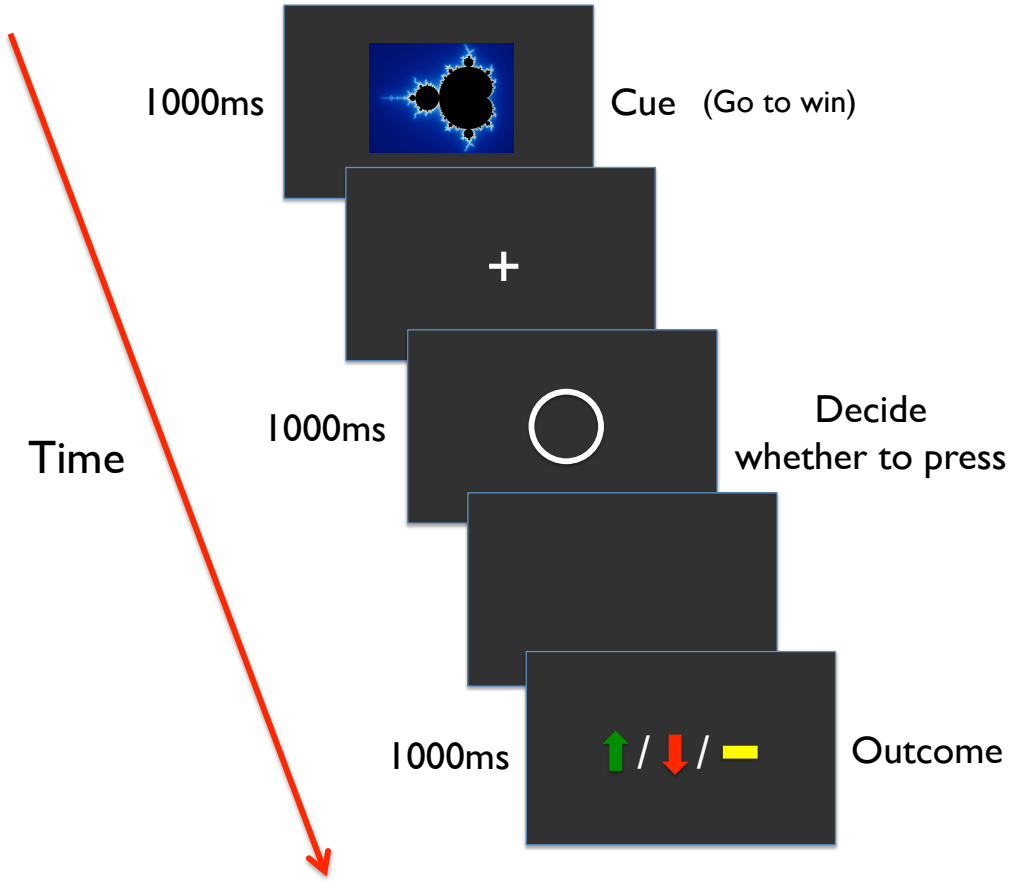
Guitart-Masip et al, 2012 Neuroimage
Cavanagh et al, 2013 J Neuro

Orthogonalized Go/Nogo task

	Loss	Gain
Go	Go to avoid	Go to win
Nogo	Nogo to avoid	Nogo to win

Pavlovian congruent

Pavlovian incongruent

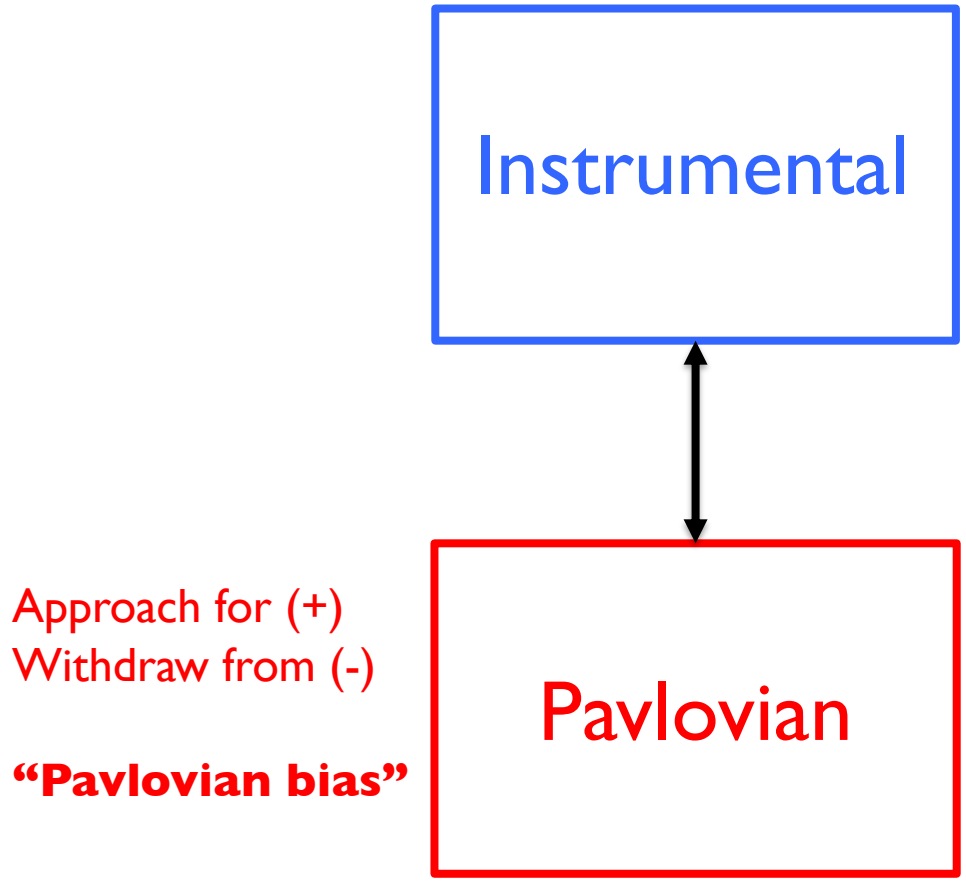


- *4 cues (conditions)*

  2 actions (Go / Nogo) x
  2 valence (Gain / Loss)

Guitart-Masip et al (2012) Neuroimage
Cavanagh et al (2013) J Neuro

Orthogonalized Go/Nogo task
Pavlovian-Instrumental competition



"Learn what's best"

Approach for (+)
Withdraw from (-)

"Pavlovian bias"

Balleine & O'Doherty (2010); Dayan et al (2006); Dayan (2013); Dayan & Niv (2008); Dolan & Dayan (2013); Dayan & Berridge (2014); Rangel et al (2008)

Pavlovian-Instrumental competition

Nogo

Instrumental

response

Young on diet

Go

Pavlovian

response

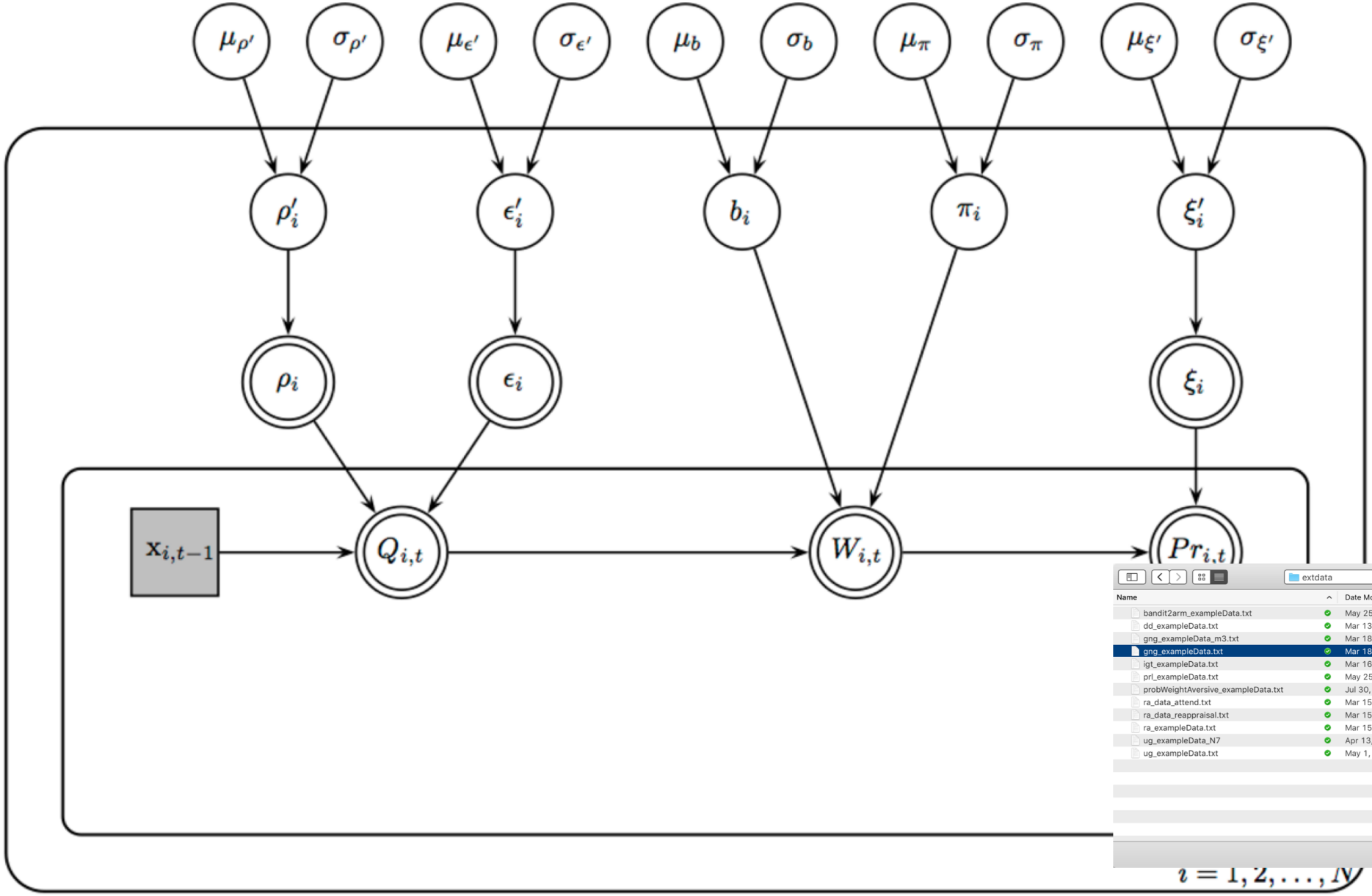
Instrumental goal: To lose weight

1. *Prepare raw (trial-by-trial) data as a single text file*

	A	B	C	D	E	F	G
1	trialNum	cue	keyPressed	success	congruentOutcome	outcome	subjID
2	1	1	1	1	2	0	1
3	2	2	0	1	1	1	1
4	3	4	0	1	1	0	1
5	4	4	1	0	1	-1	1
6	5	4	0	1	1	0	1
7	6	1	1	1	1	1	1
8	7	3	0	0	1	-1	1
9	8	1	1	1	1	1	1
10	9	3	1	1	1	0	1
11	10	3	0	0	1	-1	1
12	11	4	0	1	1	0	1
13	12	4	0	1	1	0	1
14	13	4	0	1	1	0	1

2. Fit candidate models

```
output1 =
```

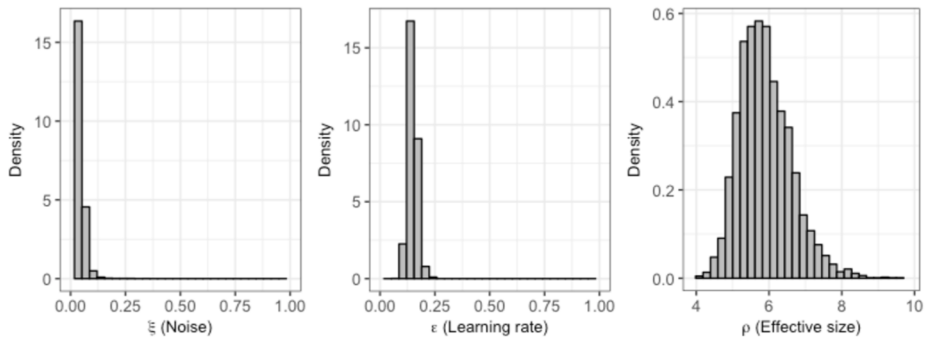


```
Details:
 # of chains                     =  4
 # of cores used                 =  4
 # of MCMC samples (per chain) =  2000
 # of burn-in samples           =  1000
 # of subjects                   =  10
 # of (max) trials per subject =  240

************************************
**  Loading a precompiled model  **
************************************
starting worker pid=75130 on localhost:11950 at 08:25:48.905
starting worker pid=75138 on localhost:11950 at 08:25:49.101

SAMPLING FOR MODEL 'gng_m1' NOW (CHAIN 1).

Chain 1, Iteration:    1 / 2000 [  0%]  (Warmup)
SAMPLING FOR MODEL 'gng_m1' NOW (CHAIN 2).
...
```

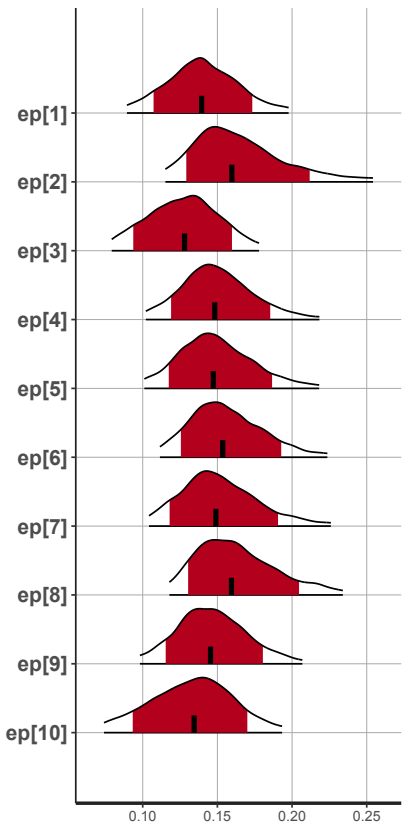
```
************************************
**** Model fitting is complete! ****
************************************
```

3. Plot (visualize) and inspect model parameters

```
plot(output1)
```




```
plotInd(output1, "ep")
```




```
> output1$allIndPars
           xi        ep      rho subjID
1  0.03688558 0.1397615 5.902901      1
2  0.02934812 0.1653435 6.066120      2
3  0.04467025 0.1268796 5.898099      3
4  0.02103926 0.1499842 6.185020      4
5  0.02620808 0.1498962 6.081908      5
...
```

4. Bayesian model comparisons

Vehtari et al. (2016)

Leave-One-Out Information Criterion (LOOIC) - default

Widely Applicable Information Criterion (WAIC)

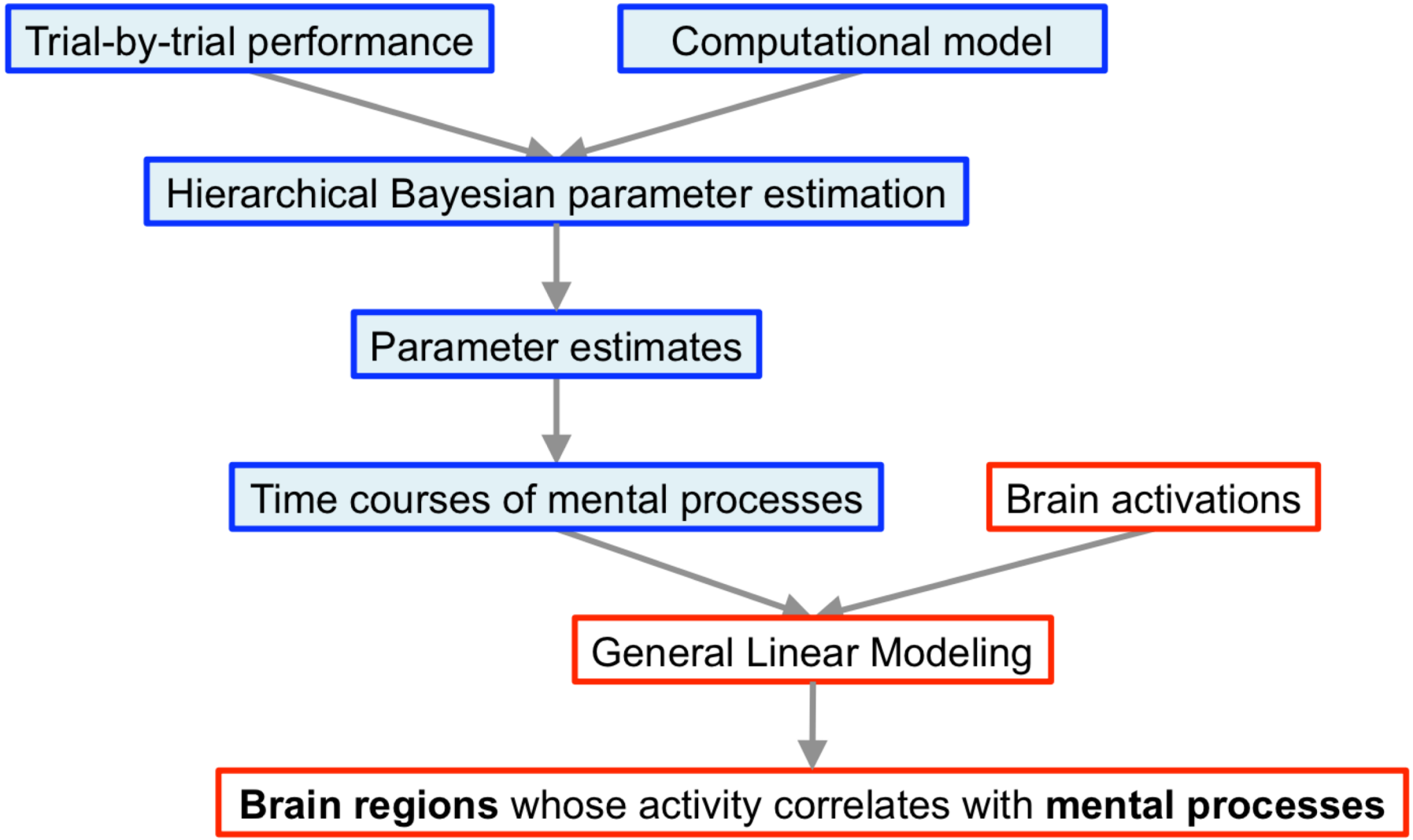
```
> printFit(output1, output2, output3, output4)
```

Model #4 is the best model
(in terms of LOOIC)

5. Group comparisons

```
data_group1 = "~/Project_folder/gng_data_group1.txt"  # data file for group1
data_group2 = "~/Project_folder/gng_data_group2.txt"  # data file for group2

output_group1 = gng_m4(data_group1)  # fit group1 data with the gng_m4 model
output_group2 = gng_m4(data_group2)  # fit group2 data with the gng_m4 model

# After model fitting is complete for both groups,
# evaluate the group difference (e.g., on the 'pi' parameter) by examining the posterior distribution of
 group mean differences.

diffDist = output_group1$parVals$mu_pi - output_group2$parVals$mu_pi  # group1 - group2
HDIofMCMC( diffDist )  # Compute the 95% Highest Density Interval (HDI).
plotHDI( diffDist )    # plot the group mean differences
```

6. Model-based fMRI/EEG



Model-based fMRI/EEG

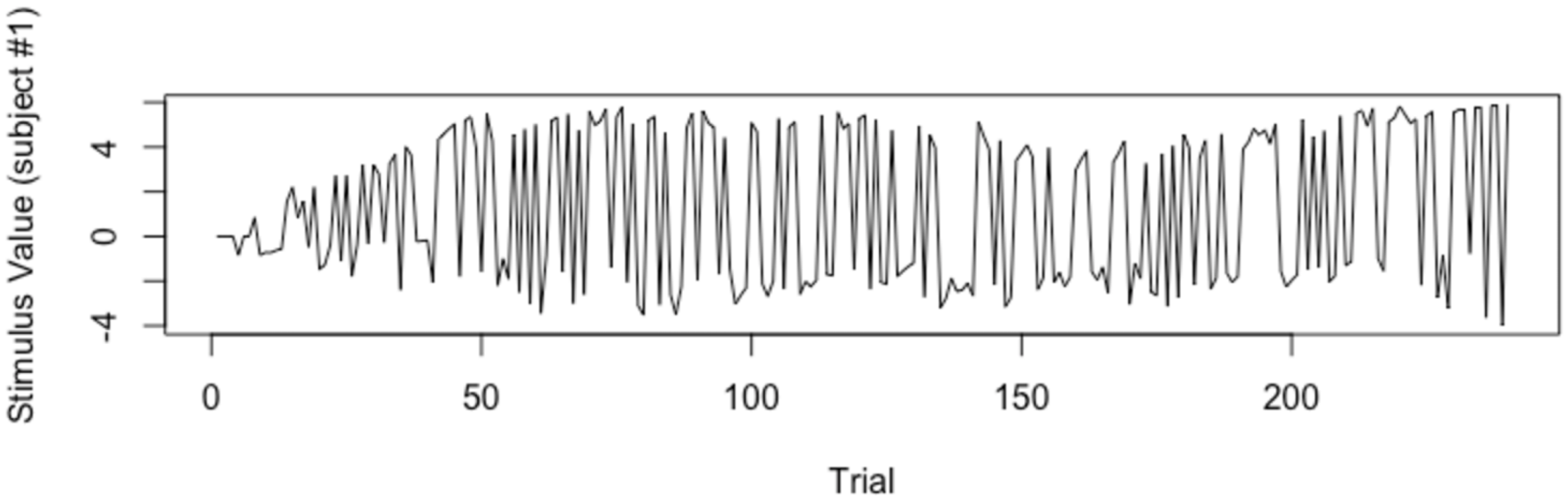
- *Trial-by-trial regressors are readily available*

```
# fit example data with the gng_m3 model
output = gng_m3(data="example", niter=3000, nwarmup=1000, nchain=3, ncore=3, modelRegressor=TRUE)
```

```r
# store all subjects' stimulus value (SV) in 'sv_all'
sv_all = output$modelRegressor$SV

dim(output$modelRegressor$SV)  # number of rows=# of subjects (=10), number of columns=# of trials (=240)
```

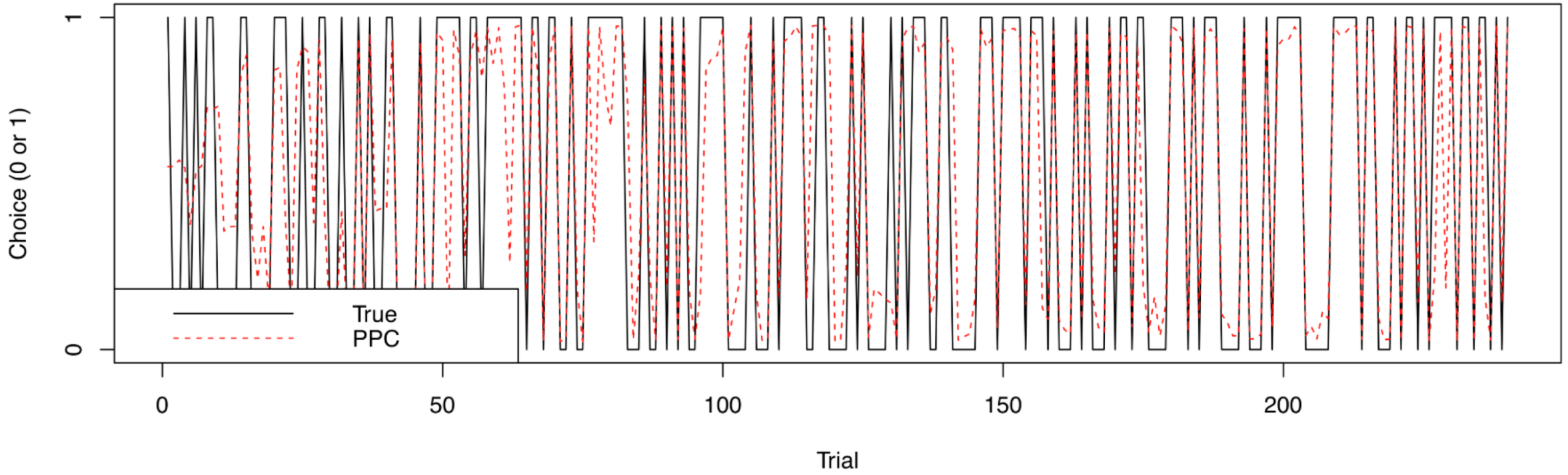
```
## [1]  10 240
```

```r
# visualize SV (Subject #1)
plot(sv_all[1, ], type="l", xlab="Trial", ylab="Stimulus Value (subject #1)")
```



Posterior predictive checks

```
# fit example data with the gng_m3 model and run posterior predictive checks
x = gng_m3(data="example", niter=2000, nwarmup=1000, nchain=4, ncore=4, inc_postpred = TRUE)
```



Outline

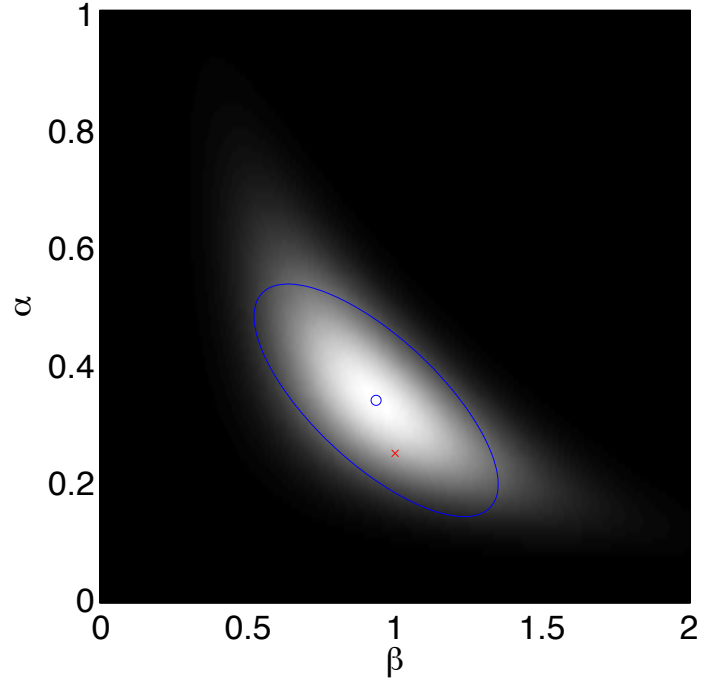
- *Understand the concepts of computational modeling*
- *Know popular and cutting-edge methods for fitting computational models / Understand the concept of Bayesian data analysis*
- *Things to know when performing MCMC sampling*
- *Use hBayesDM package to model several tasks*

Popular methods for model fitting

- *Maximum likelihood estimation (MLE)*
- *Bayesian parameter estimation (or Bayesian data analysis)*
- *Hierarchical Bayesian analysis*

Maximum likelihood estimation

- *Ronald A. Fisher (1920s): finds the value of a parameter that makes the observed data "most likely".*
- *Likelihood function*
  - *L(data | θ): likelihood of getting data given θ*
- *Analytical solutions often don't exist*
- *Nonlinear optimization*
  - *gradient decent*
  - *`fminsearch` (Matlab), `optim` (R), etc.*
- *MLE estimates = point estimates*



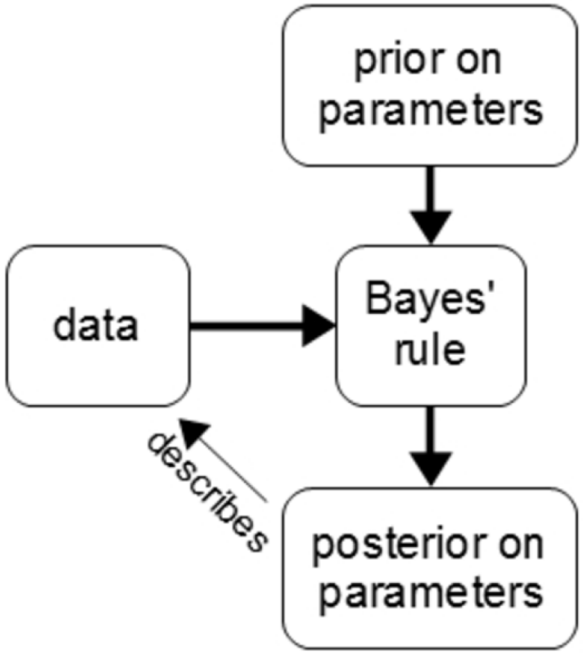
"Likelihood surface" from Daw (2011)

Brief Introduction to Bayesian data analysis

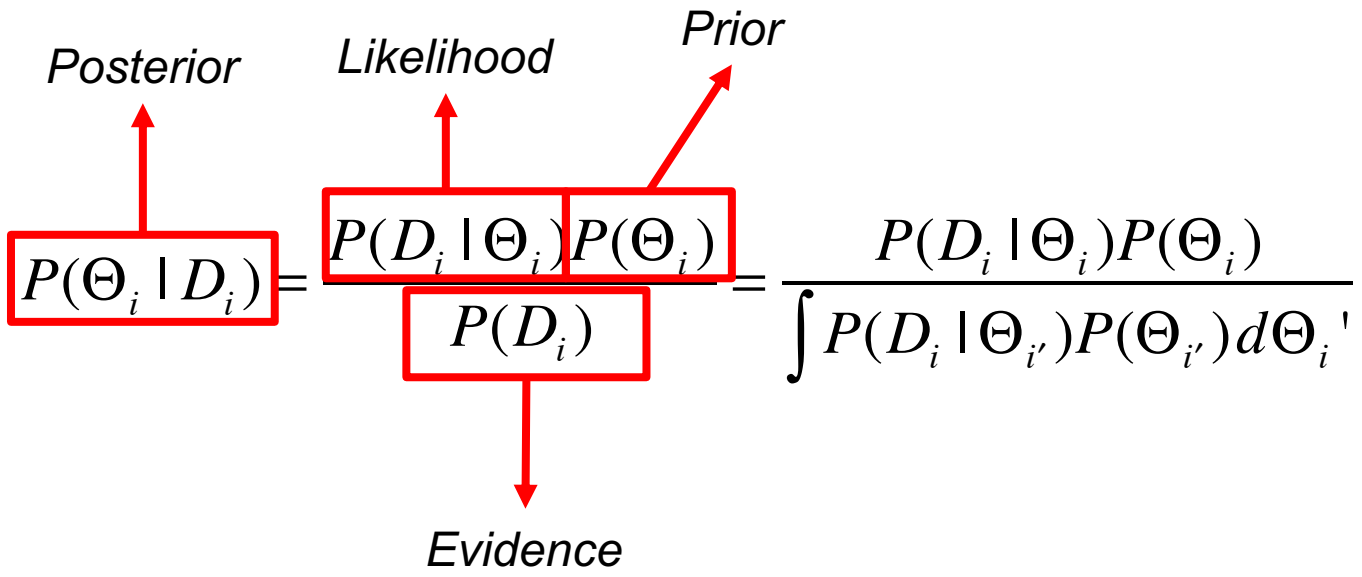
Bayesian data analysis

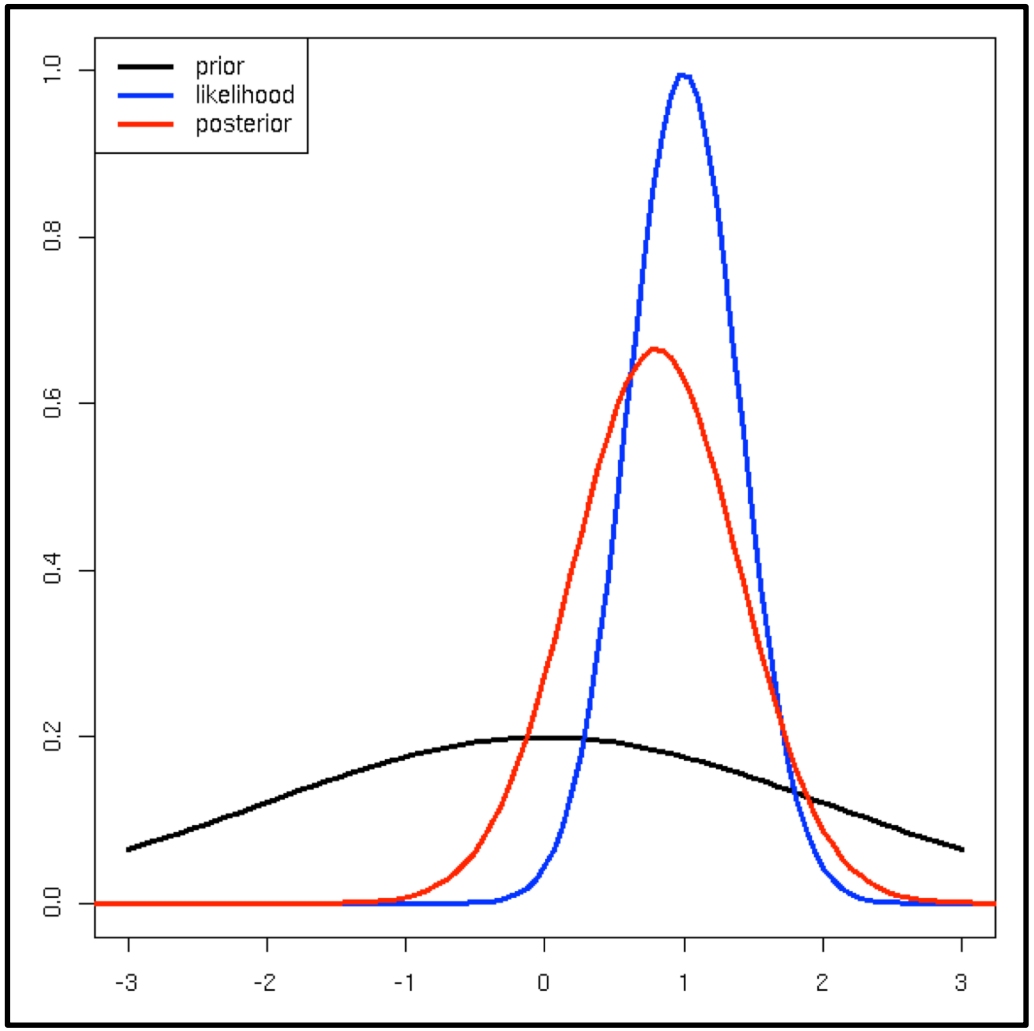
Bayesian data analysis vs. *Bayesian model of mind*

http://doingbayesiandataanalysis.blogspot.hk/2011/10/bayesian-models-of-mind-psychometric.html



Θ: Model parameters (e.g., discounting rate, learning rate, etc.)





http://zoonek.free.fr/blosxom/R/2006-06-22_useR2006.html

Bayesian data analysis

Update prior distributions for model parameters into posterior distributions given the data (e.g., trial-by-trial choices and outcomes) using Bayes' rule

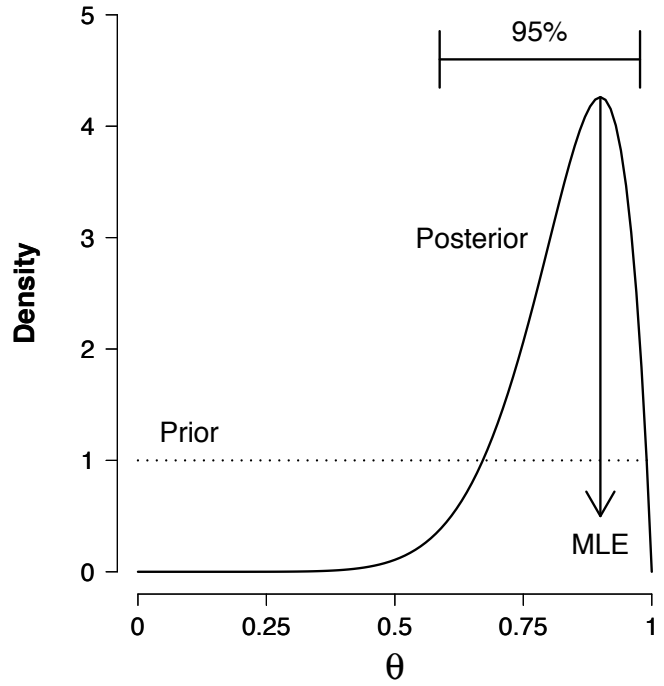
Relationship between MLE and Bayesian data analysis

An example from Lee & Wagenmakers (2012)

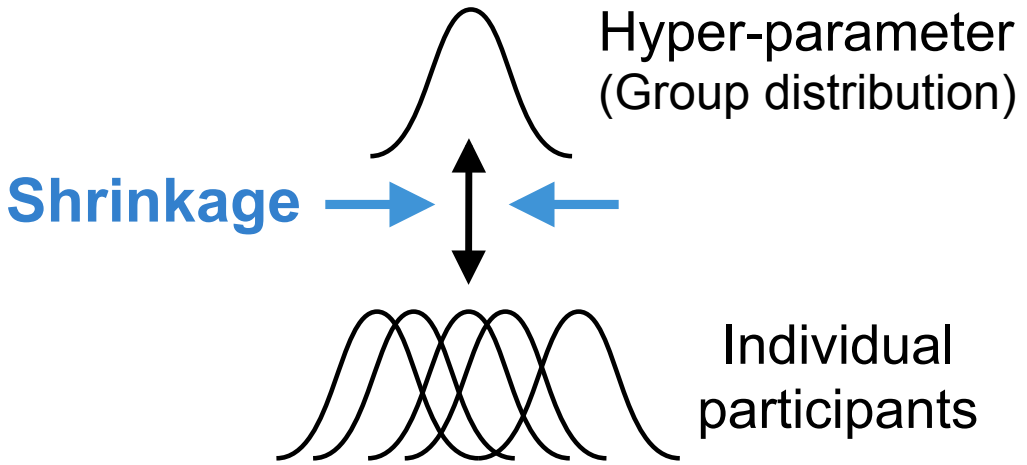
- *A test with 10 questions*
- *Parameter of interest: your ability* ($0 < \theta < 1$)
- *Data: 9 correct answers out of 10 (k=9, n=10)*
- *Likelihood function: Bernoulli*

Bayesian $\boxed{p(\theta \mid D)} = \dfrac{p(D \mid \theta)\, p(\theta)}{p(D)}$

MLE $\boxed{\hat{\theta}} = k/n = 0.9$



Hierarchical Bayesian analysis



Θ: Individual model parameters
Φ: Group model parameters

$$\Theta_i = \{\alpha_i, \beta_i, \gamma_i, \cdots\}$$

$$\Phi = \{\mu_\alpha, \mu_\beta, \mu_\gamma, \sigma_\alpha, \sigma_\beta, \sigma_\gamma, \cdots\}$$

- *Similarities & differences across participants*
- *Small amount of data from each subject*

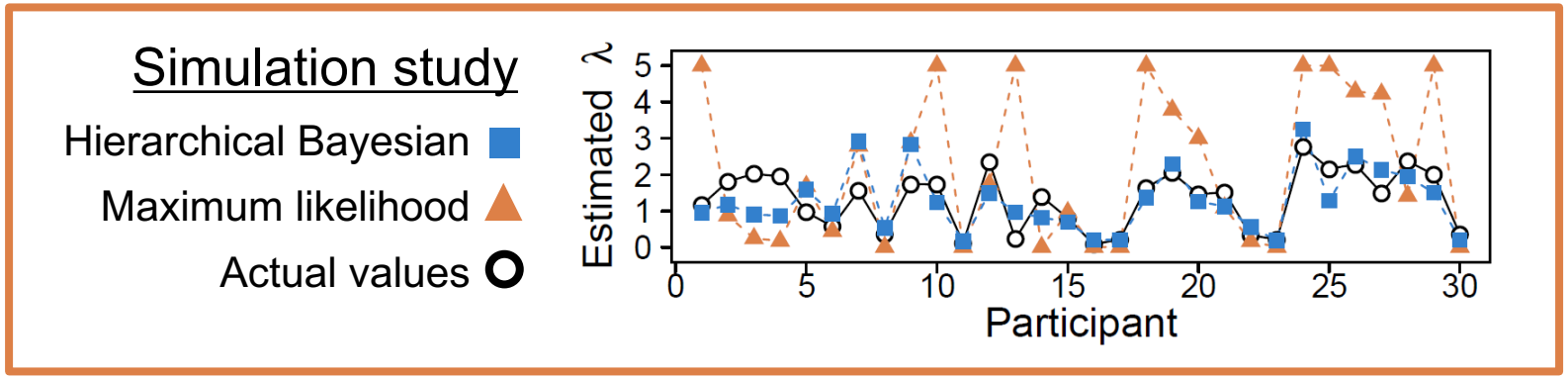
Likelihood Prior

$$P(\Theta,\Phi \mid D) = \frac{P(D \mid \Theta,\Phi)P(\Theta,\Phi)}{P(D)} \propto P(D \mid \Theta)P(\Theta \mid \Phi)P(\Phi)$$

Posterior Evidence

Hierarchical Bayesian data analysis

leads to more accurate parameter estimates



Ahn et al. (2011, JNPE)

Limitations

- *Assumption of a single hyper-group*
- *Shrinkage → regression toward the group mean*

Ahn, W.-Y., Krawitz, A., Kim, W., Busemeyer, J. R., & Brown, J. W. (2011). A Model-Based fMRI Analysis with Hierarchical Bayesian Parameter Estimation. *Journal of Neuroscience, Psychology, and Economics*, *4*(2), 95-110.

Okay sounds good… but how can we actually do Bayesian updating?

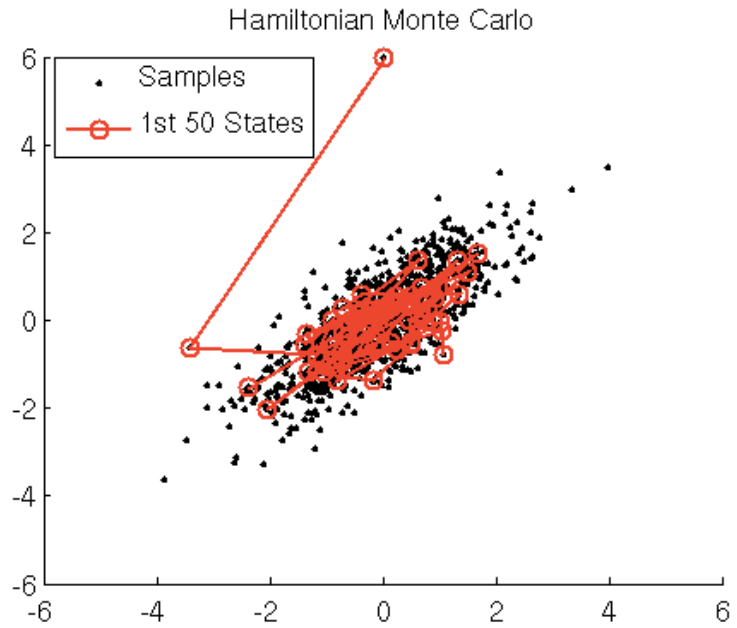
$$P(\Theta_i \mid D_i) = \frac{P(D_i \mid \Theta_i)P(\Theta_i)}{P(D_i)} = \frac{P(D_i \mid \Theta_i)P(\Theta_i)}{\int P(D_i \mid \Theta_{i'})P(\Theta_{i'})d\Theta_i'}$$

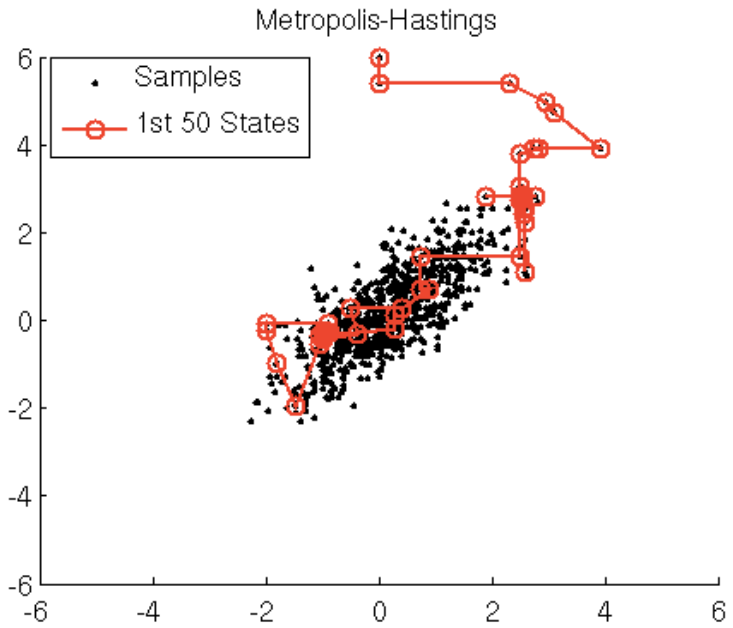
1. *Analytical solutions (often don't exist)*
2. *Grid approximation*
3. *Variational Bayes*
4. *Markov Chain Monte Carlo (MCMC)*

Markov Chain Monte Carlo (MCMC)

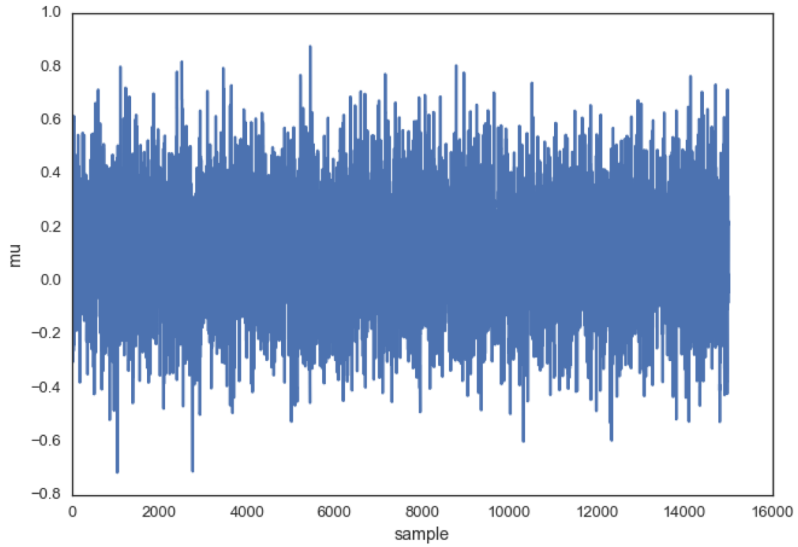
Approximate posterior distributions by drawing samples from the posterior distributions (after reaching an equilibrium).

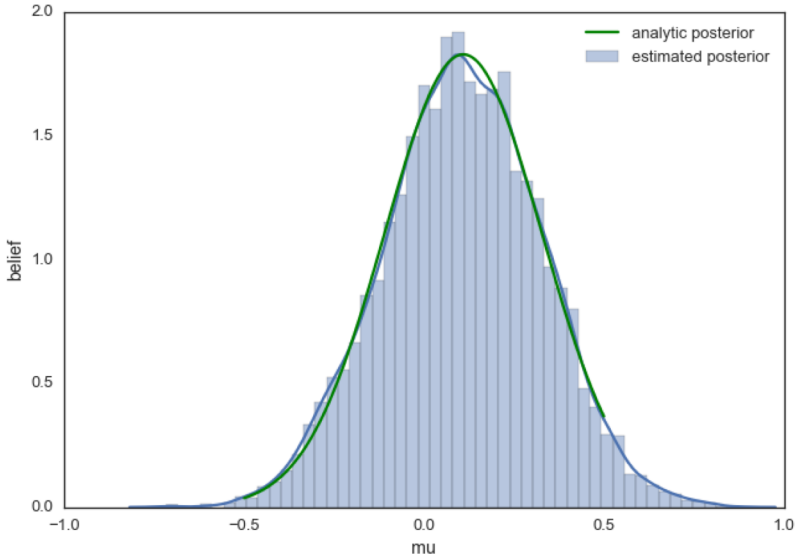
Some samplers are more efficient than others!





https://theclevermachine.wordpress.com/2012/11/18/





http://twiecki.github.io/blog/2015/11/10/mcmc-sampling/

Tools for MCMC sampling

1. *Program your own!?*
2. *User-friendly packages*
   - *WinBUGS/OpenBUGS*
   - *JAGS*
   - *PyMC3 (in Python)*
   - *Stan*

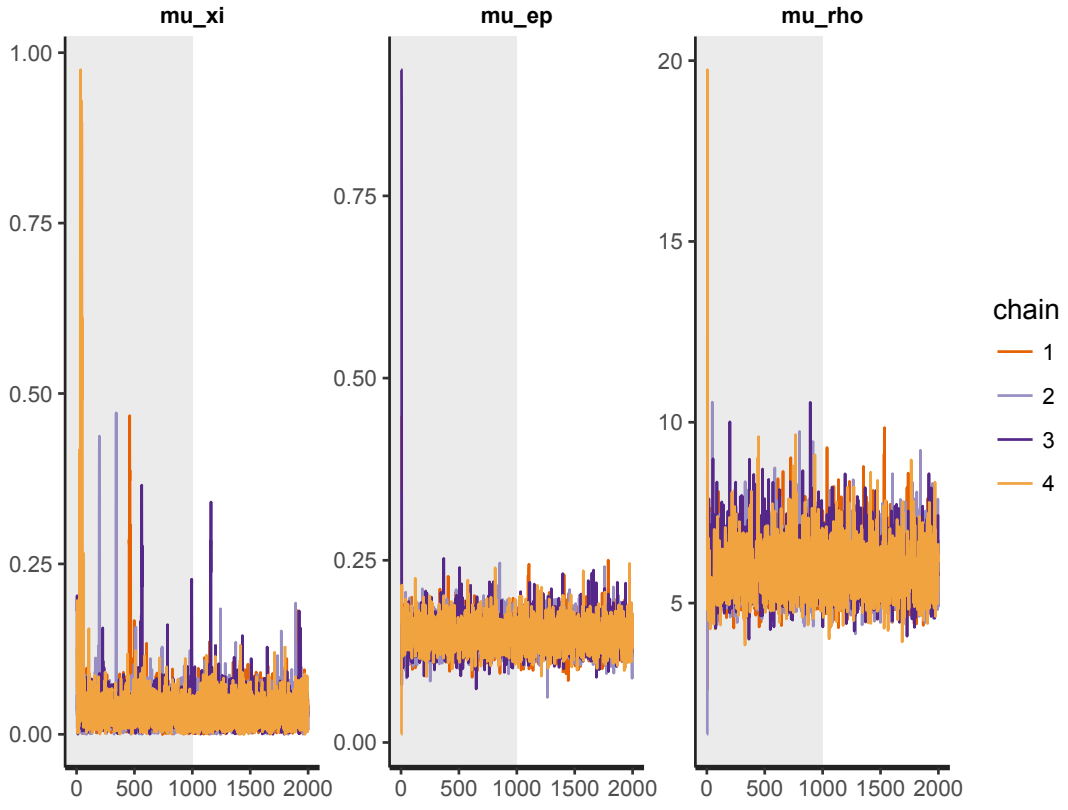
3. *hBayesDM utilizes Stan (http://mc-stan.org/), which is well-maintained by a team led by Andrew Gelman.*
4. *Stan & hBayesDM support VB as well!*

Outline

- *Understand the concepts of computational modeling*
- *Know popular and cutting-edge methods for fitting computational models / Understand the concept of Bayesian data analysis*
- *Things to know when performing MCMC sampling*
- *Use hBayesDM package to model several tasks*

Things to know when performing MCMC sampling

"Beware: hBayesDM can be dangerous!"




```
plot(output1, type="trace", inc_warmup=T)
```

Check the convergence!

- *Number of chains → at least 4*
- *Burn-in (warm-up) samples*
- *Convergence index (e.g., $\hat{R}$)*
  → Close to 1.00
  At least less than ~1.10

Outline

- *Understand the concepts of computational modeling*
- *Know popular and cutting-edge methods for fitting computational models*
- *Understand the concept of Bayesian data analysis*
- *Evaluate outputs from Bayesian data analysis*
- *Use hBayesDM package to model several tasks (Part II)*
  - *If you learn how to model one task, you know how to model all!*