fMRI Course, Day 5

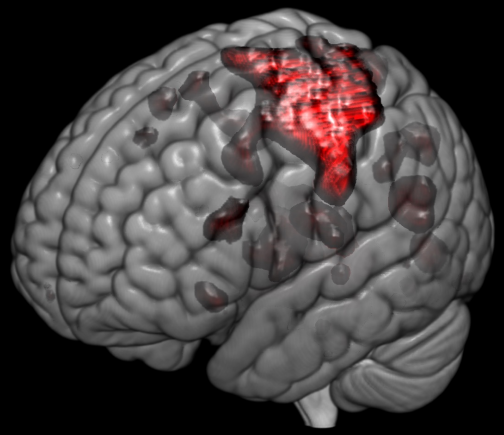
1st-Level Analysis

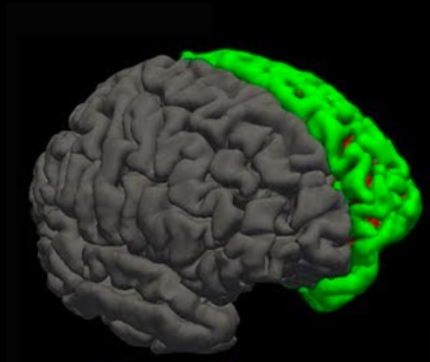
August 4th, 2023

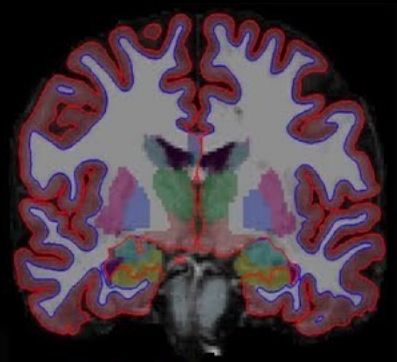
About Me

Neuroimaging Initiative (NII)

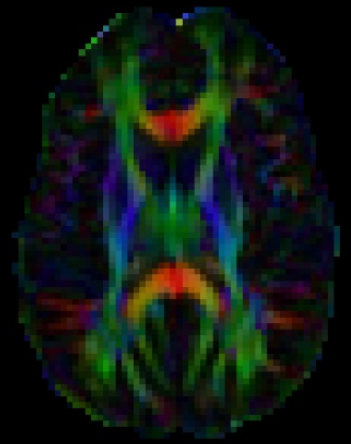
Consulting for anyone who does neuroimaging







Surface Volume



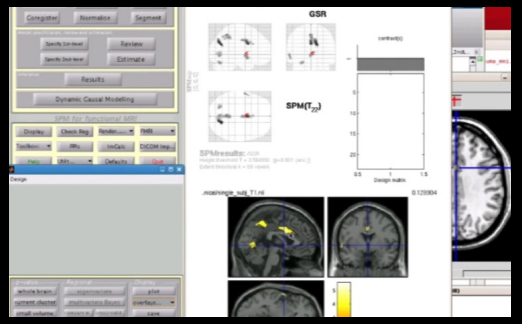
Goals

1. Understand how to do the steps

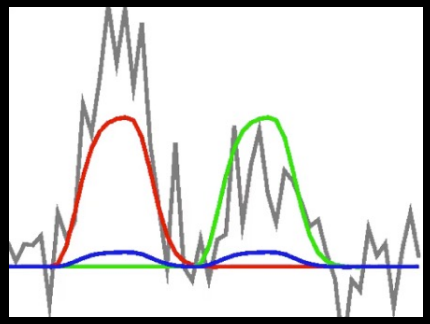
2. Understand why we did the steps

↓

Both Remember Steps and Apply Concepts



+



Problem

How to accommodate dozens of labs spread across three campuses?

How to stay current with the latest methods and tools?

How to make sure the ideas “stick”?

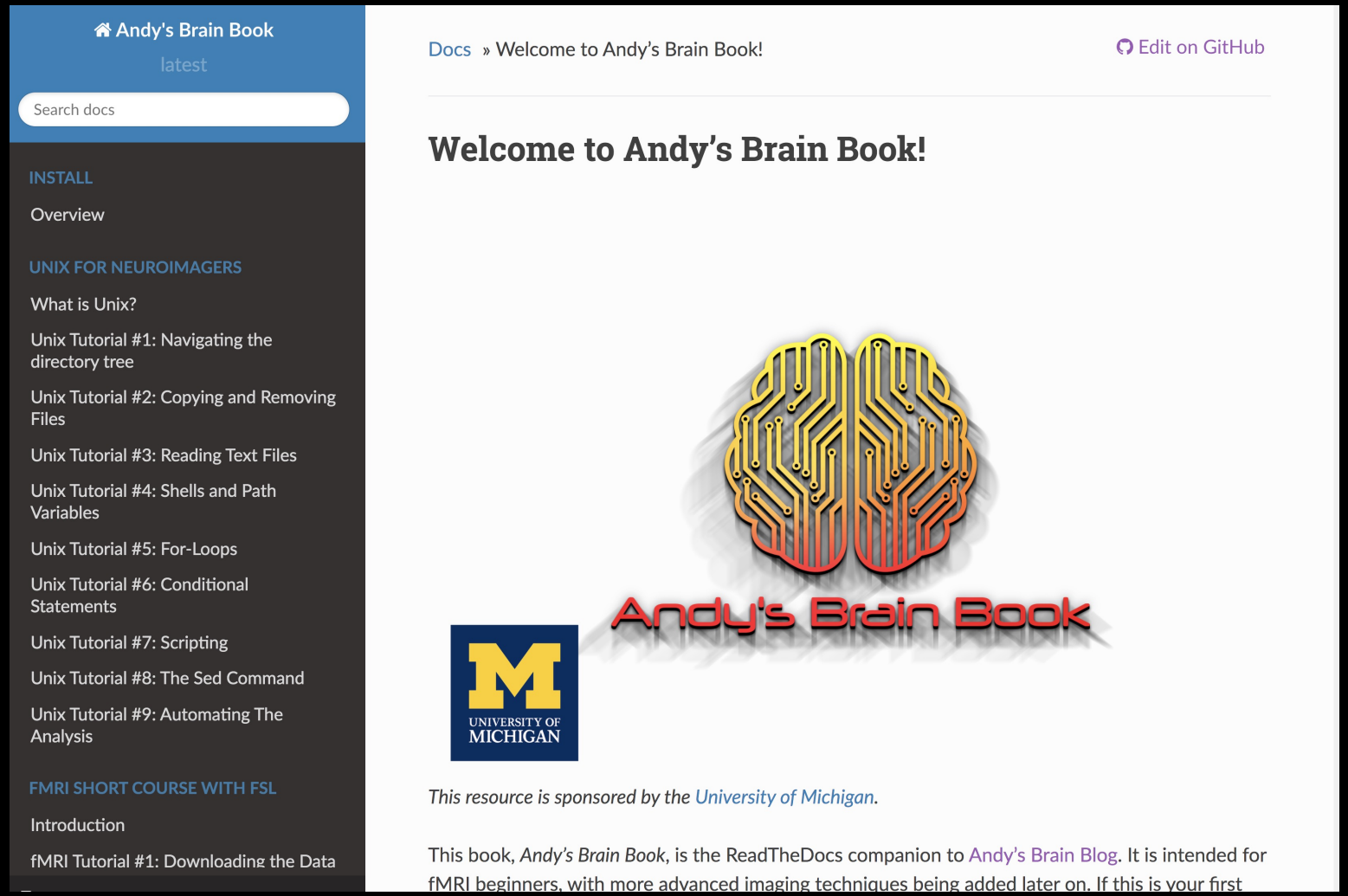
Solutions

Illustrations and demonstrations using data

Goal is for you to analyze your own data

Feedback is highly appreciated!

About Me


Andy's Brain Book
latest
Search docs
INSTALL
Overview
UNIX FOR NEUROIMAGERS
What is Unix?
Unix Tutorial #1: Navigating the directory tree
Unix Tutorial #2: Copying and Removing Files
Unix Tutorial #3: Reading Text Files
Unix Tutorial #4: Shells and Path Variables
Unix Tutorial #5: For-Loops
Unix Tutorial #6: Conditional Statements
Unix Tutorial #7: Scripting
Unix Tutorial #8: The Sed Command
Unix Tutorial #9: Automating The Analysis
FMRI SHORT COURSE WITH FSL
Introduction
fMRI Tutorial #1: Downloading the Data
Docs » Welcome to Andy's Brain Book!
Edit on GitHub
Welcome to Andy's Brain Book!
Andy's Brain Book
UNIVERSITY OF MICHIGAN
This resource is sponsored by the University of Michigan.
This book, Andy's Brain Book, is the ReadTheDocs companion to Andy's Brain Blog. It is intended for fMRI beginners, with more advanced imaging techniques being added later on. If this is your first

Overview of The Schedule

Monday 8/7/2023	8:30 AM – 12:30 PM	Contrasts, Group Analysis & Double Dissociations	Andy Jahn University of Michigan
	4:00 PM- 5:00 PM	Pattern Analysis & Classification via MVPA-virtual but live in 1360 East Hall. MUST be in 1360 for the virtual lecture.	Stephen LaConte Virginia Tech
Tuesday 8/8/2023	8:30 AM - 12:30 PM	Pitfalls in fMRI Research	Andy Jahn University of Michigan
Wednesday 8/9/2023	8:30 AM – 12:30 PM	Network Analysis & Tools	Scott Peltier University of Michigan Alex Iordan University of Michigan
Thursday 8/10/2023	8:30 AM – 12:30 PM	Part 1- Introduction to Open Science Part 2- BIDS, MRIQC & fMRI Prep	Andy Jahn University of Michigan Scott Peltier University of Michigan
Friday 8/11/2023	8:30 AM – 12:30 PM	Reproduciibility	Andy Jahn University of Michigan

Overview of The Schedule

At regular intervals, I will be asking you to download software and data

This is just to help with the demonstrations; don't worry if you are unable to download or install these!

Today's Agenda

1. Overview of fMRI

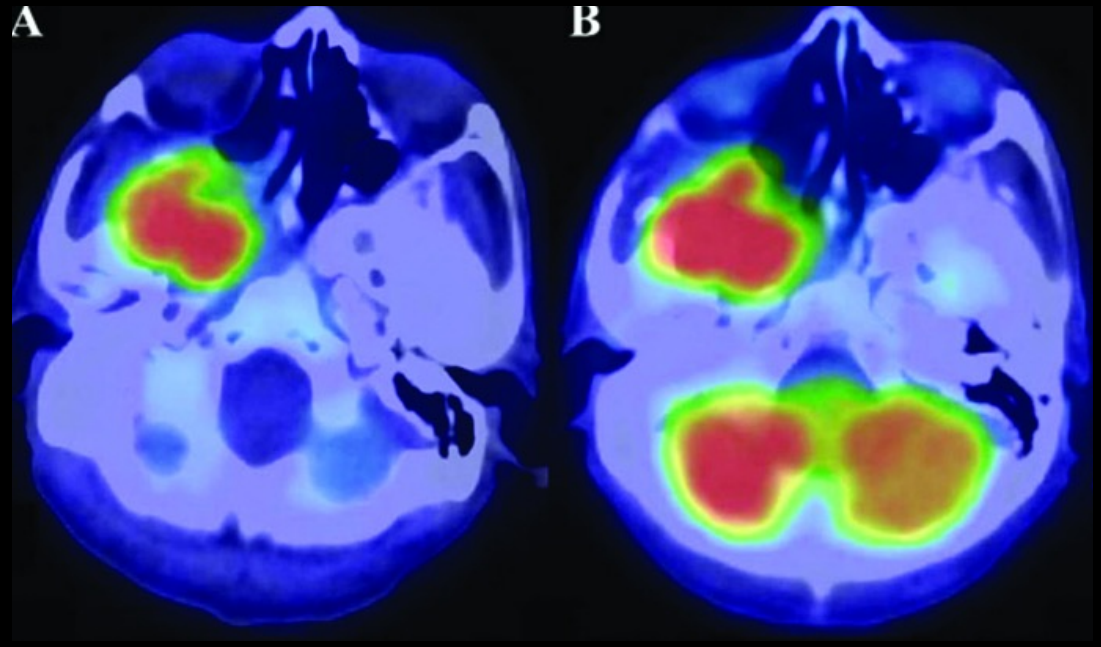
2. The BOLD Response

3. Model Fitting and 1st-Level Analysis

4. Other Modeling Options: Parametric Modulation and Finite Impulse Response

Review of fMRI

Neuroimaging Scene: The Early 1990's



Review of fMRI

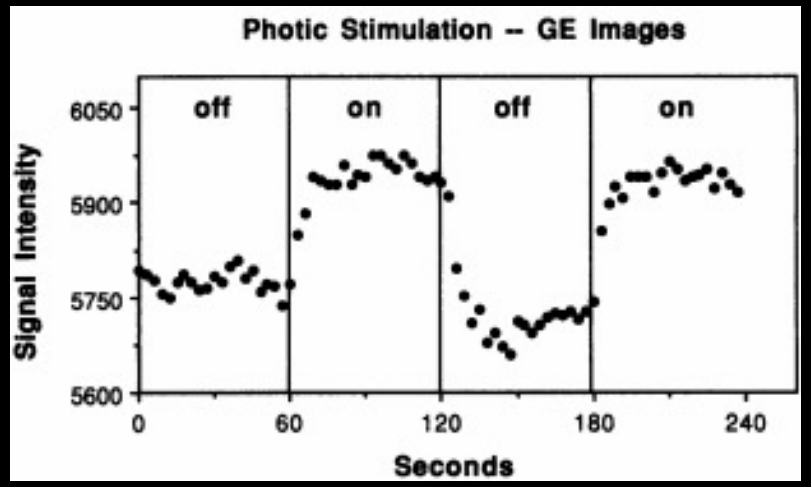
MRIs: More powerful & More widespread

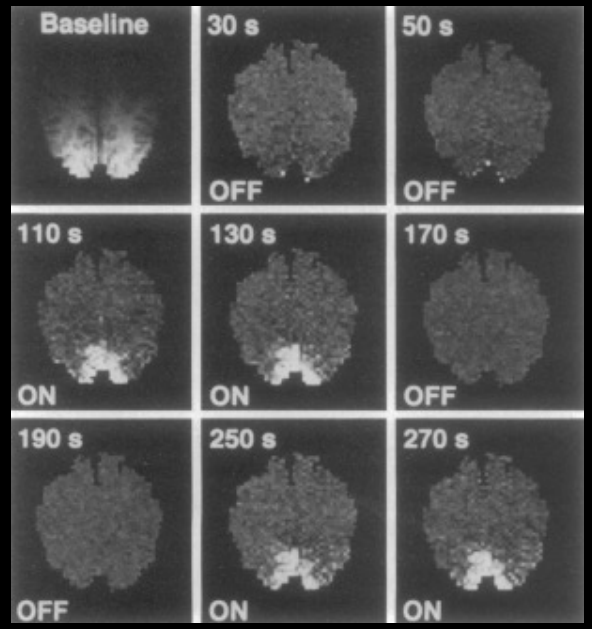
Deoxygenated blood = Lower signal

Oxygenated blood = Higher signal

Blood Oxygenation Level Dependent Signal (BOLD Signal)

Review of fMRI

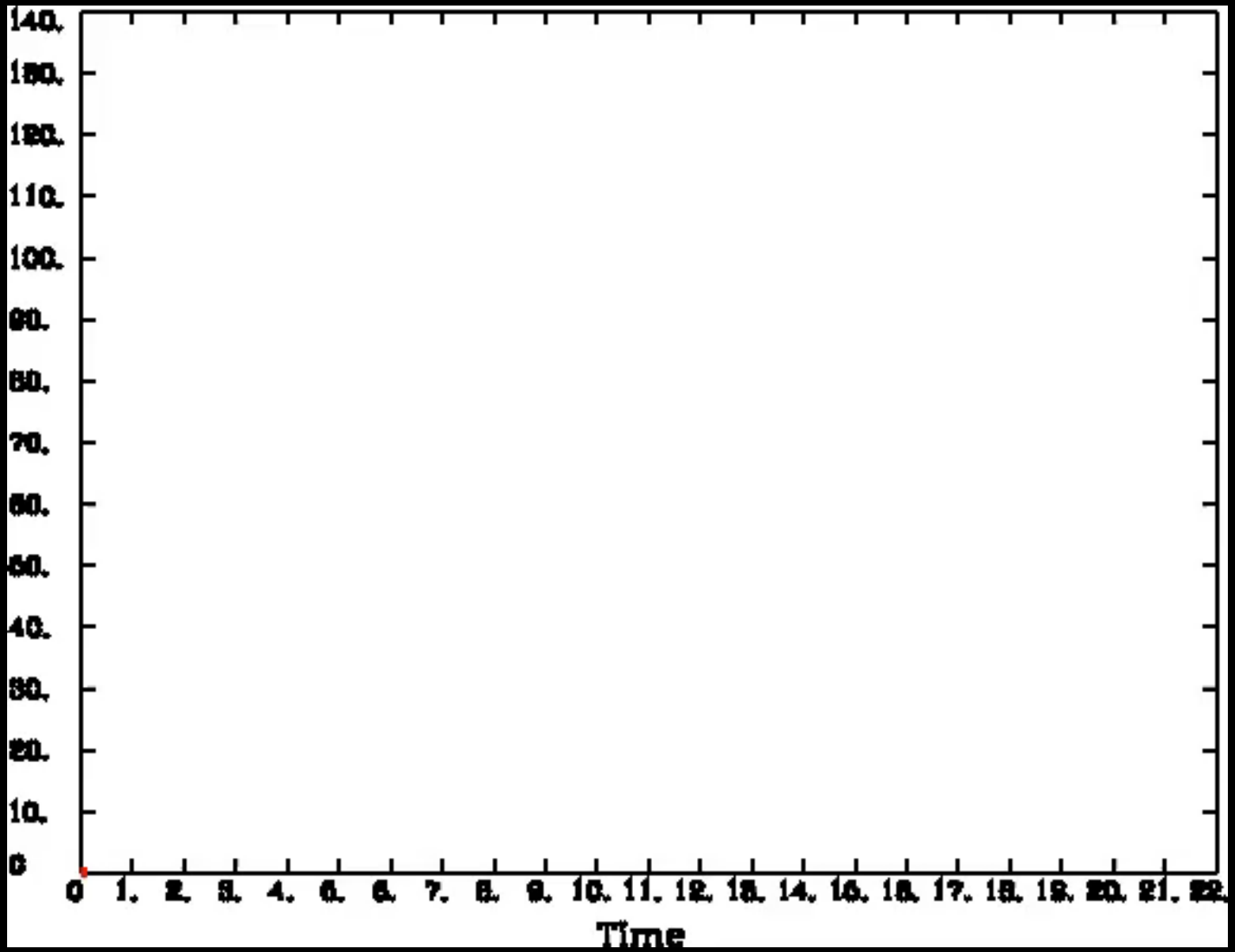




Kwong et al., 1992

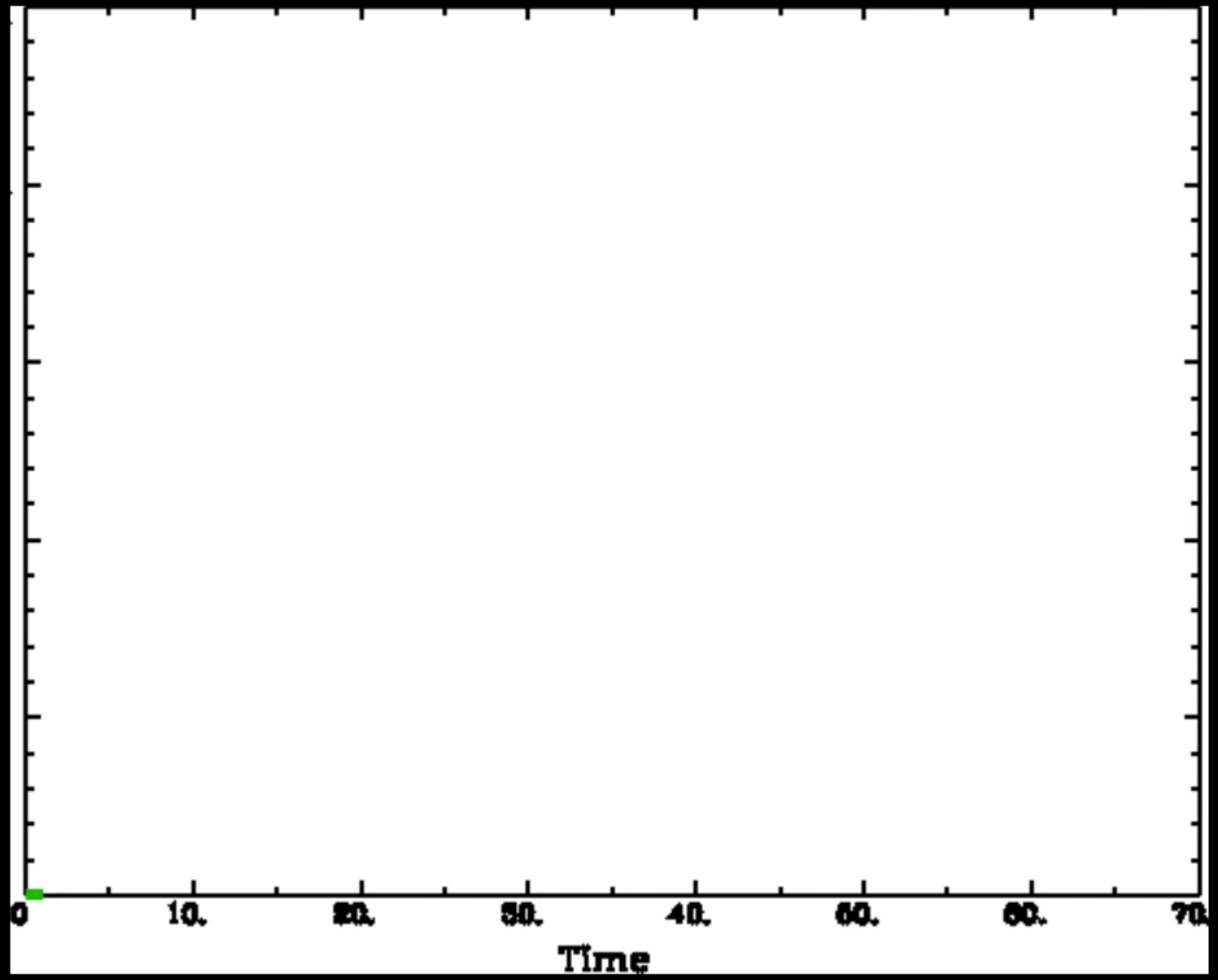
Review of fMRI

The BOLD Response



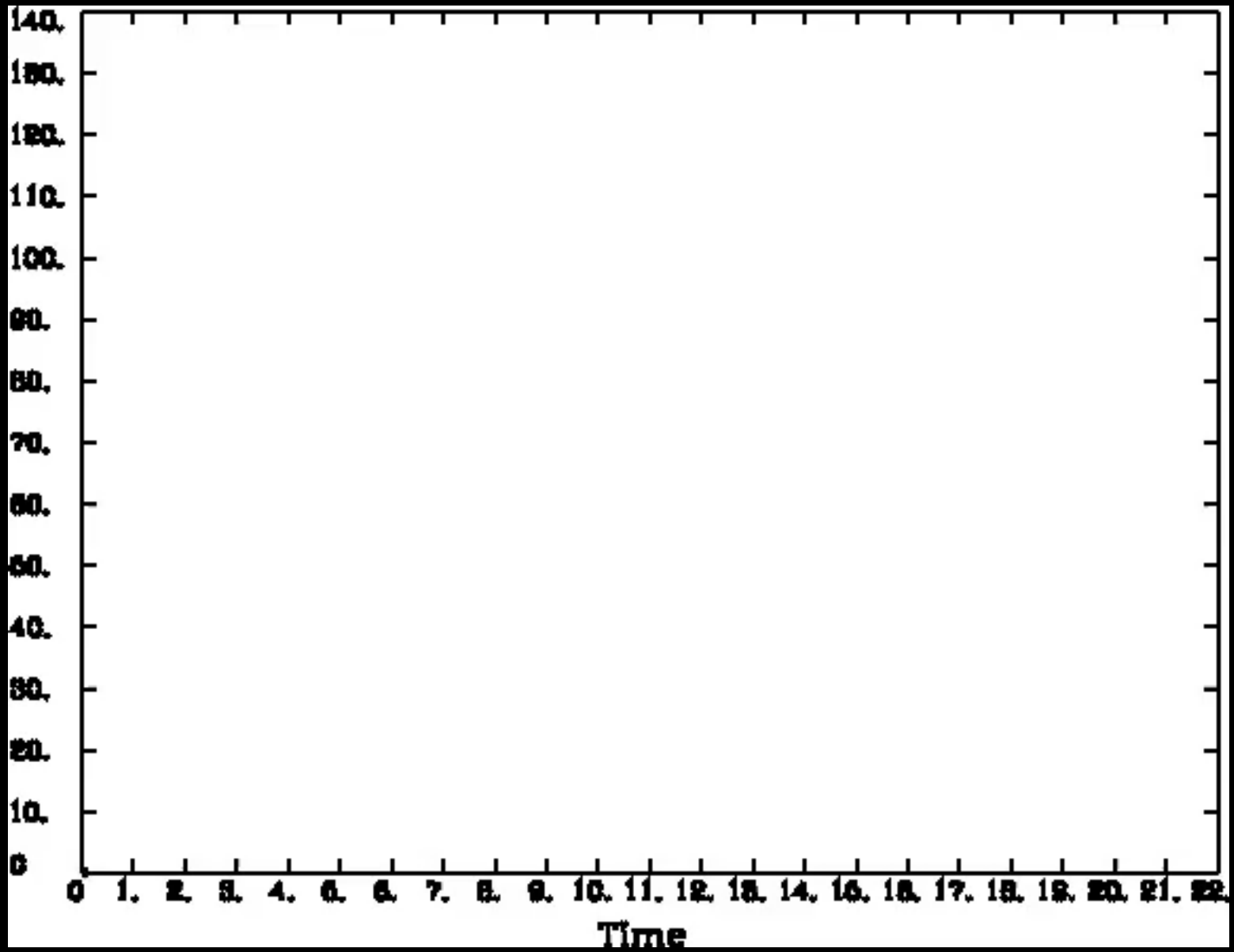
Bob Cox, AFNI

The BOLD Response: Duration



Bob Cox, AFNI

The BOLD Response: Convolution



Bob Cox, AFNI

Applet Demonstration of Convolution

https://phiresky.github.io/convolution-demo/

Interim Summary

1. Stimulus transducted into neural firing

2. More neural firing = more oxygen consumption

3. More oxygen consumption = more blood flow

4. More blood flow = greater measured signal

Observed signal is a few steps removed from actual neural activity

What We've Done So Far…

1. Overview of fMRI

2. Preprocessing the individual subject

3. Experimental Designs

4. Timing Files

5. Creating the general linear model (GLM)

Behavioral vs. fMRI Experiments

Flanker task: Behavioral task adapted for fMRI analysis

Behavioral

* Dependent measure of interest is reaction time
* Can have the same amount of time between trials

fMRI

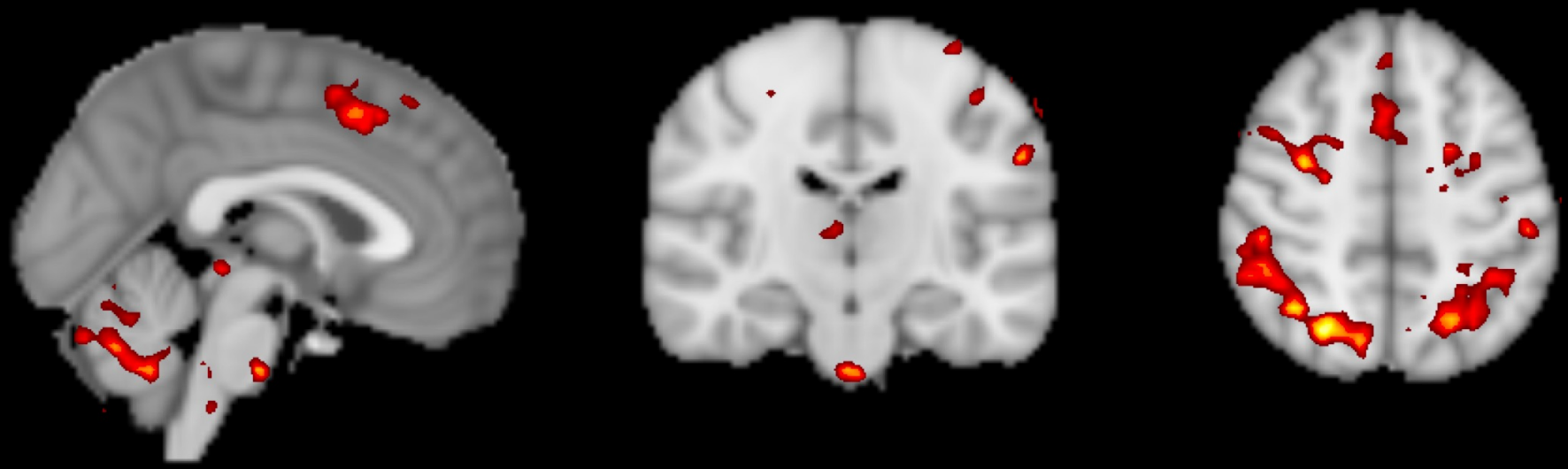
* Two dependent measures: reaction time & the BOLD response
* Will need differing amounts of time between trials

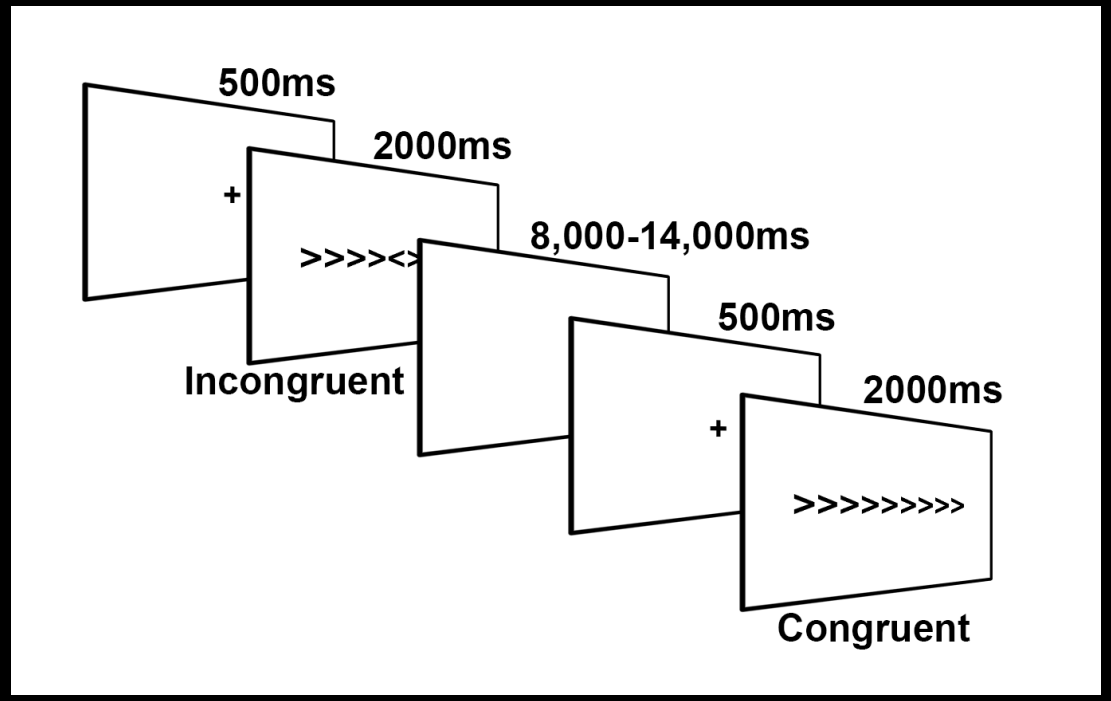
>>>><>>>>

Incongruent

>>>>>>>>>>

Congruent





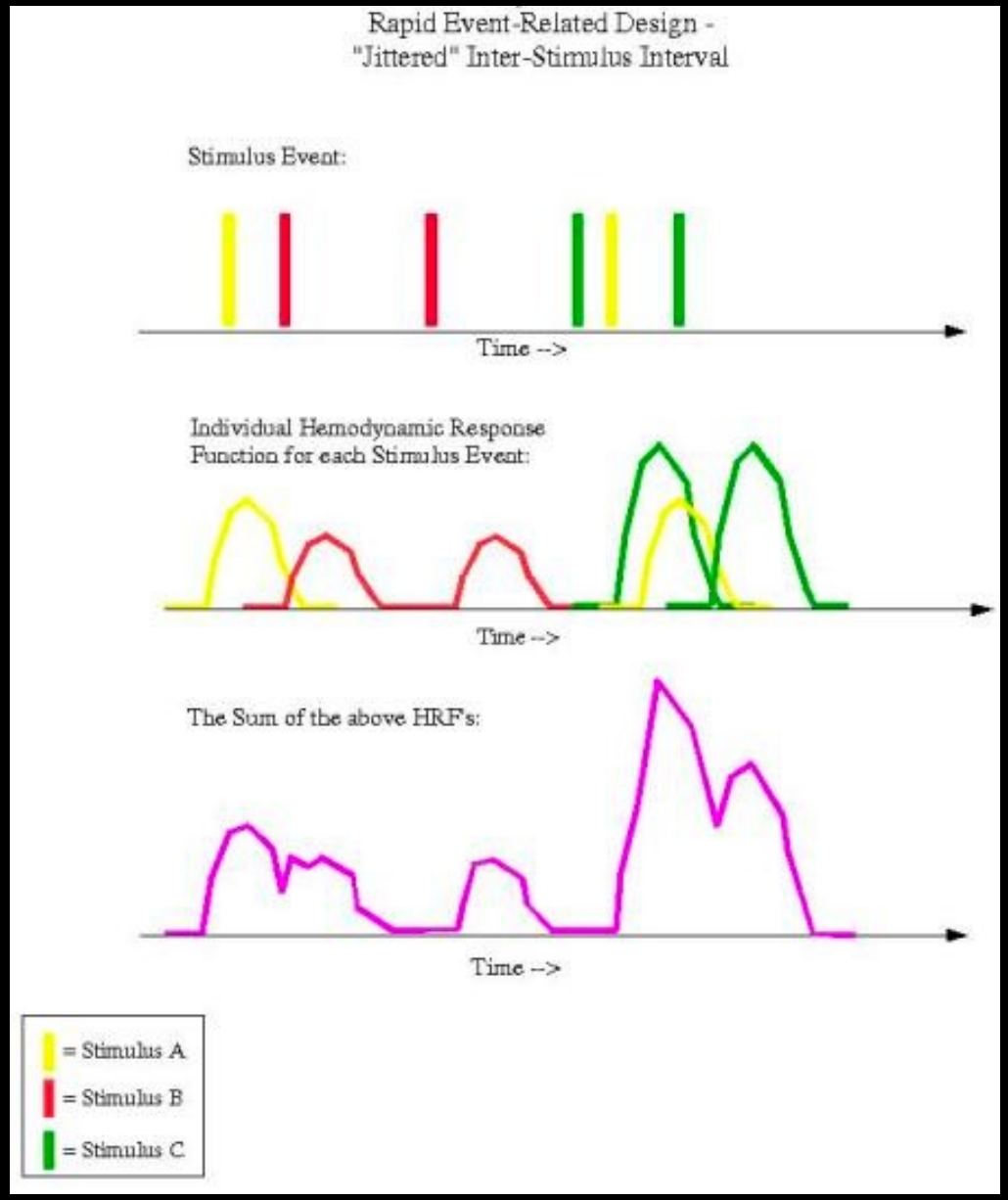
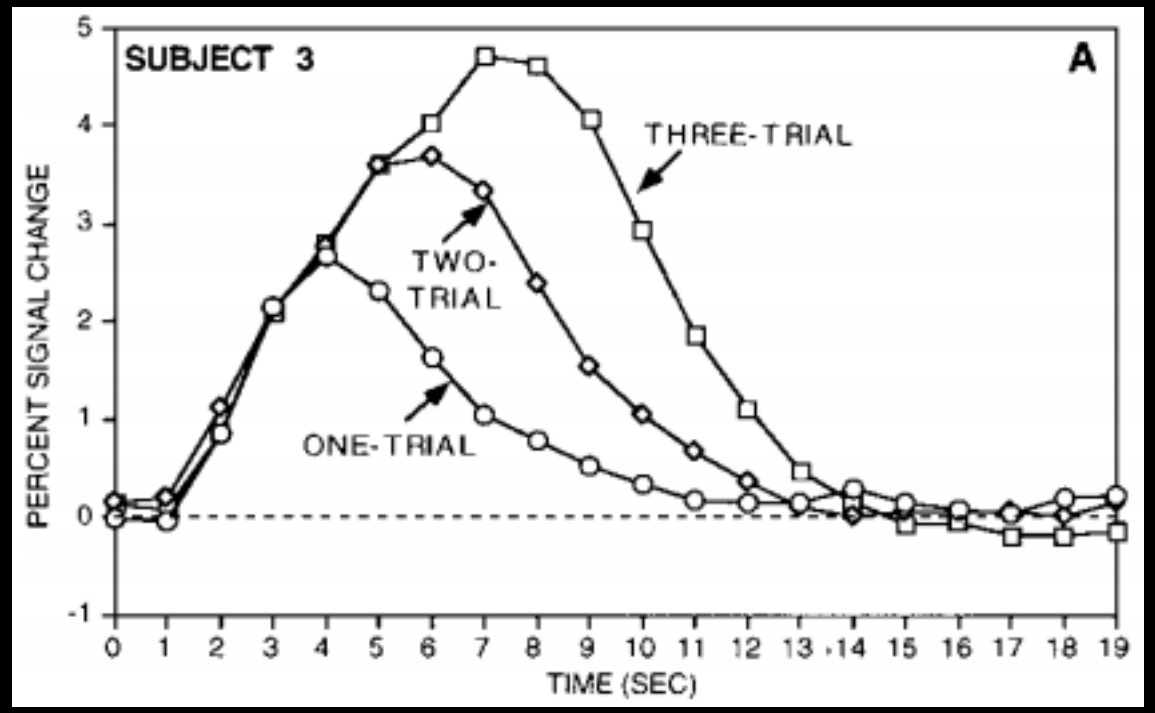
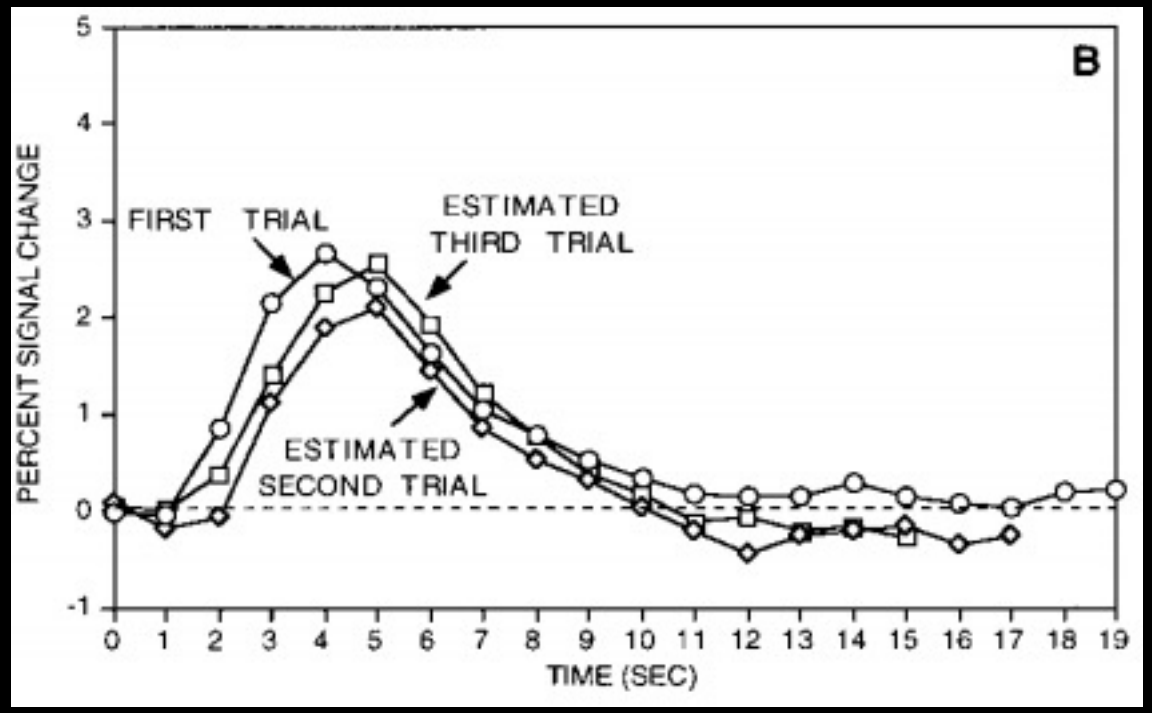


Image from Bob Cox

Experimental Designs

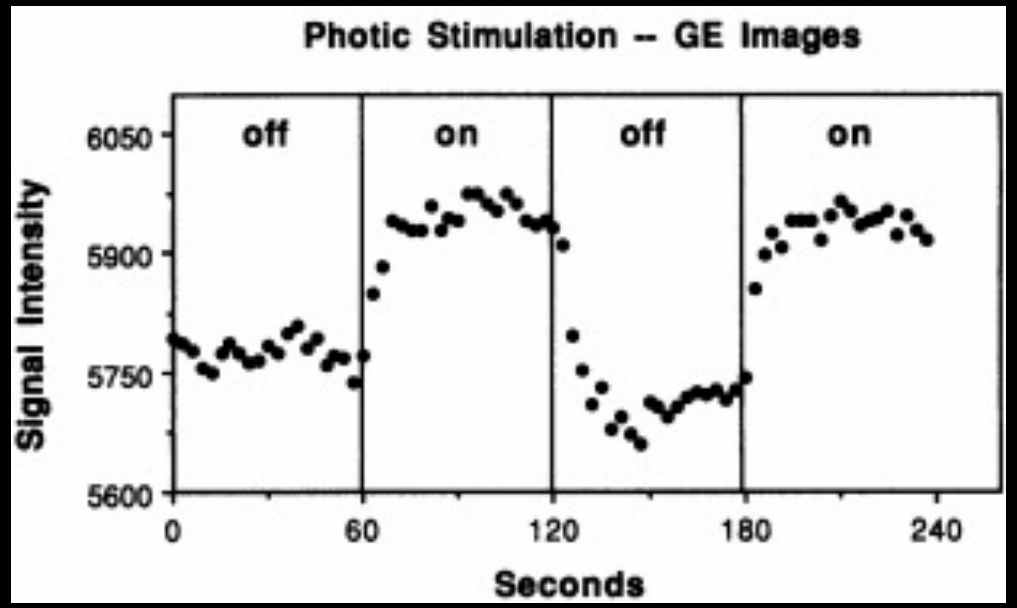
Linearity





Experimental Designs

1. Block design (e.g., Kwong et al., 1992)

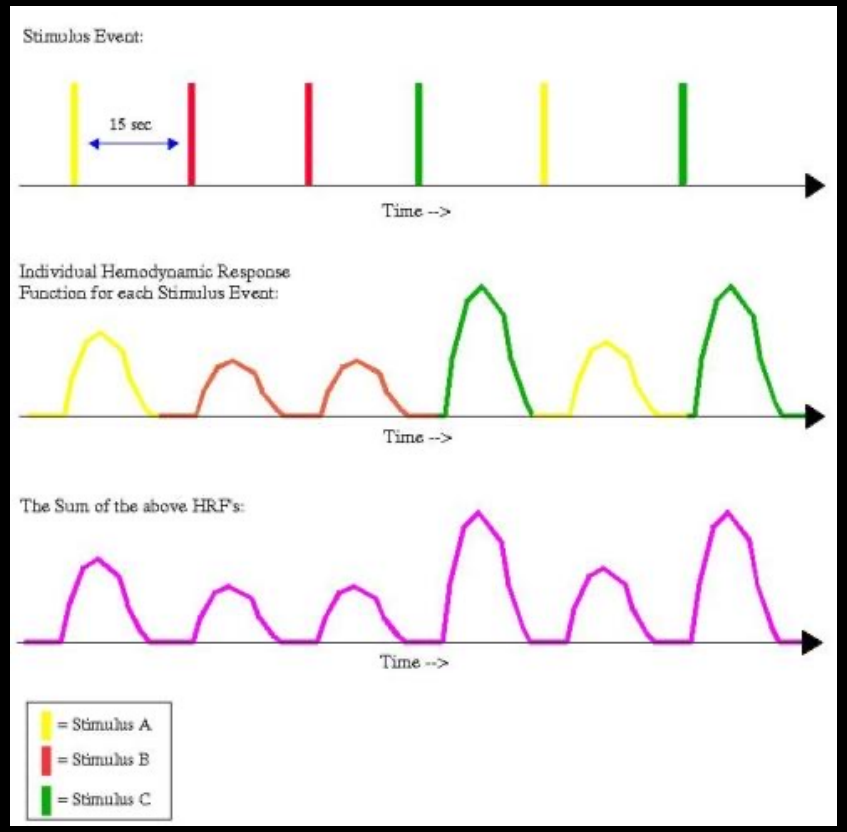


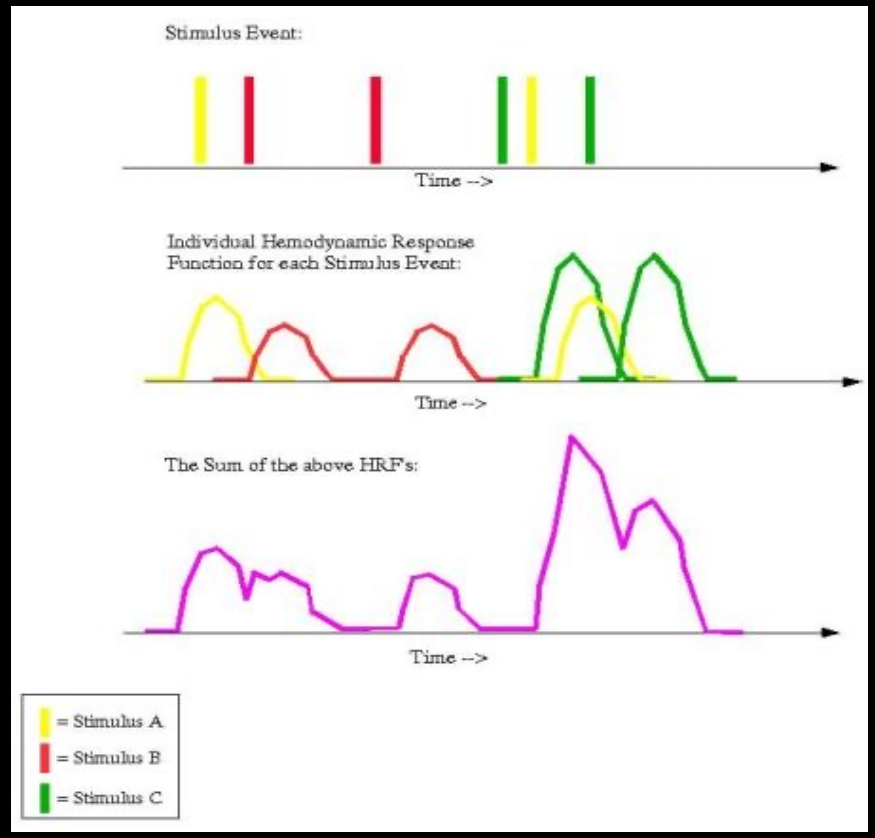
Advantages: Powerful, easy to design

Disadvantages: Boring, predictable, cannot use complex designs

Experimental Designs

2. Event-related designs



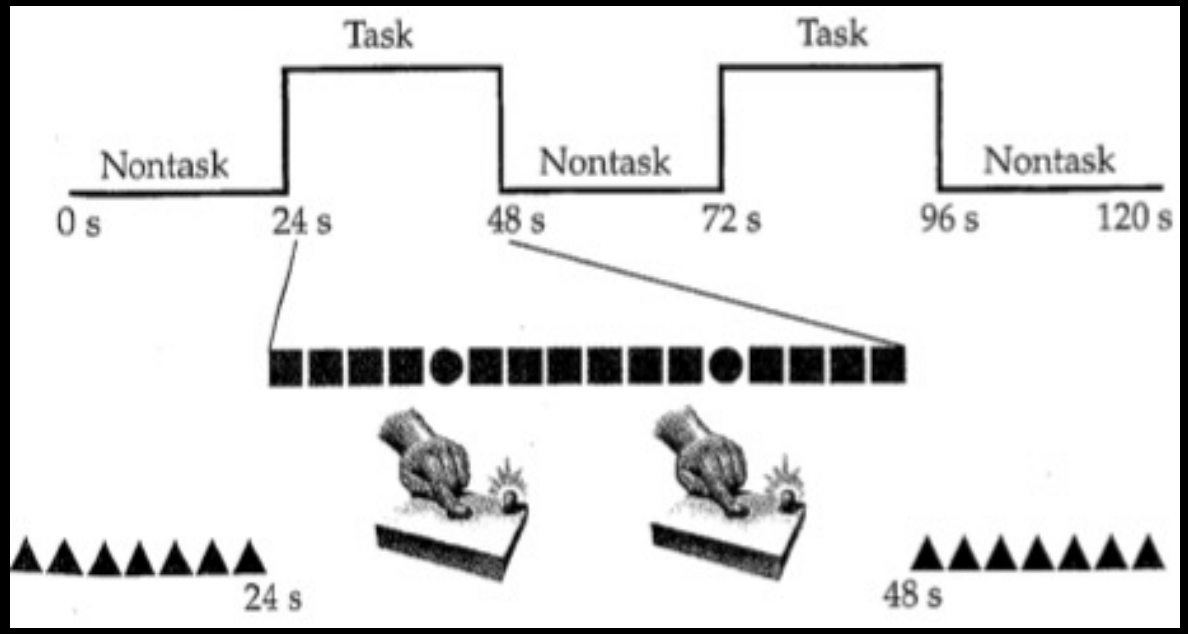


Advantages: More engaging, can use more complex designs

Disadvantages: Less power, susceptible to collinearity

Experimental Designs

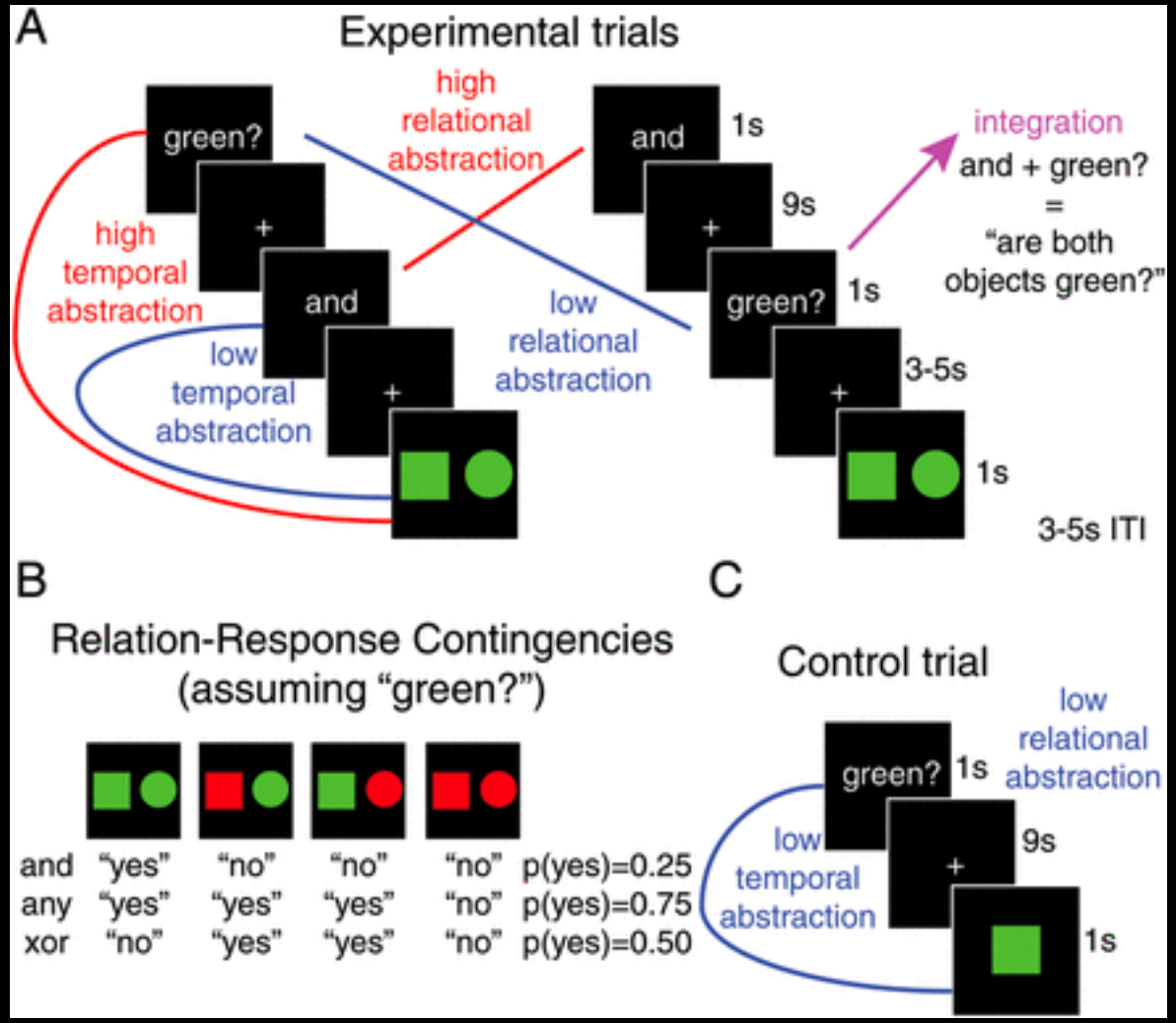
Mixed Designs



Block: State effects; trial: item-related effects

Disadvantages: Very sensitive to errors in HRF modeling

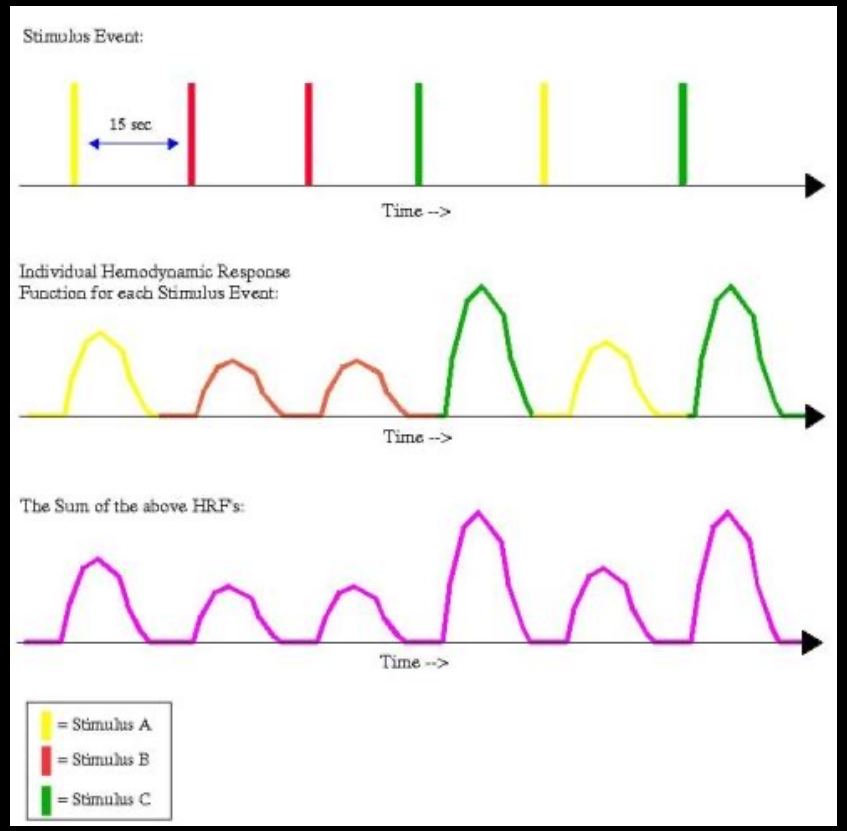
Experimental Designs



Nee et al., 2013

Behavioral vs. fMRI Experiments

Differing amounts of time between trials (i.e., jitter) are needed to avoid collinearity



Behavioral vs. fMRI Experiments

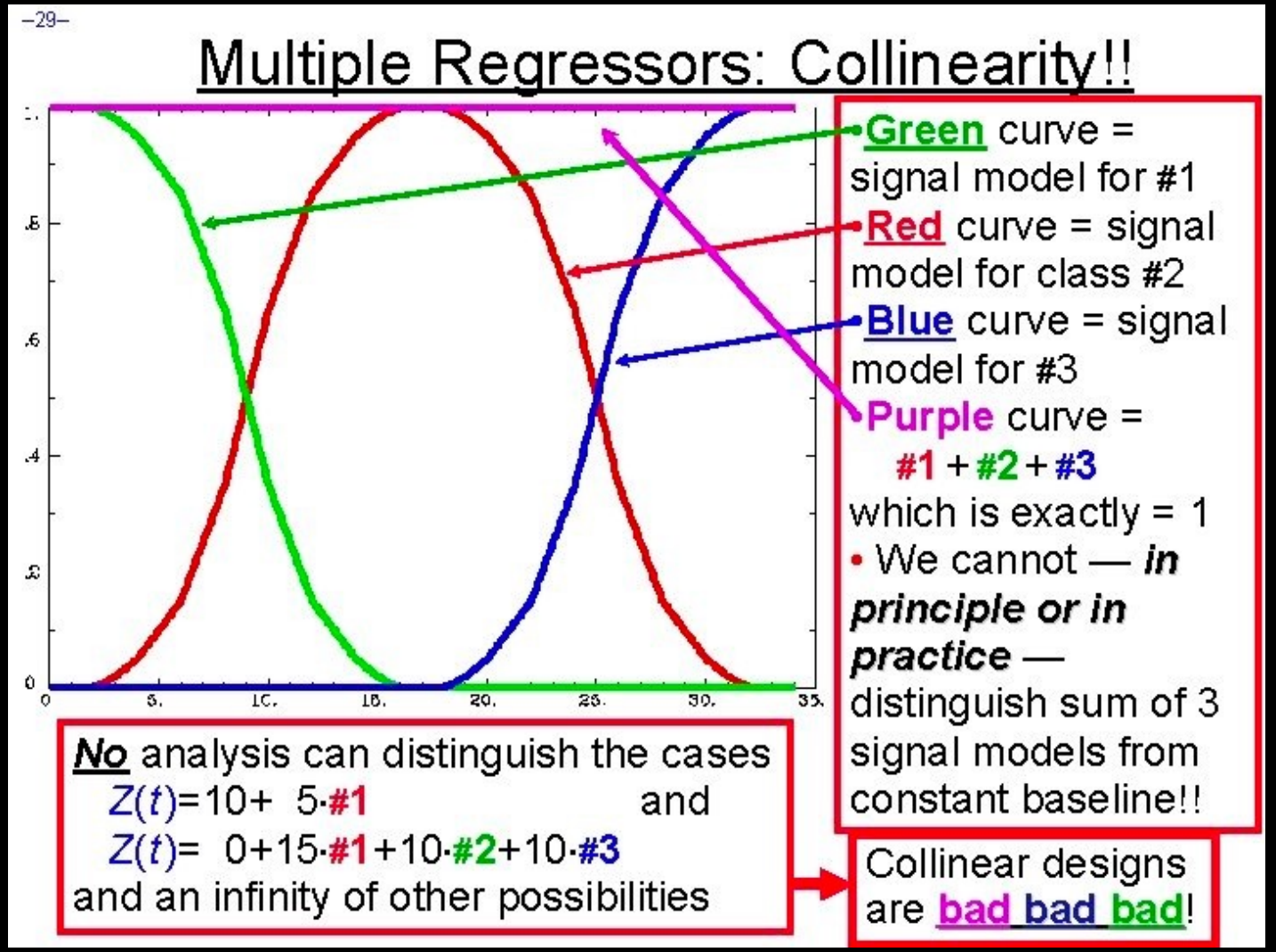
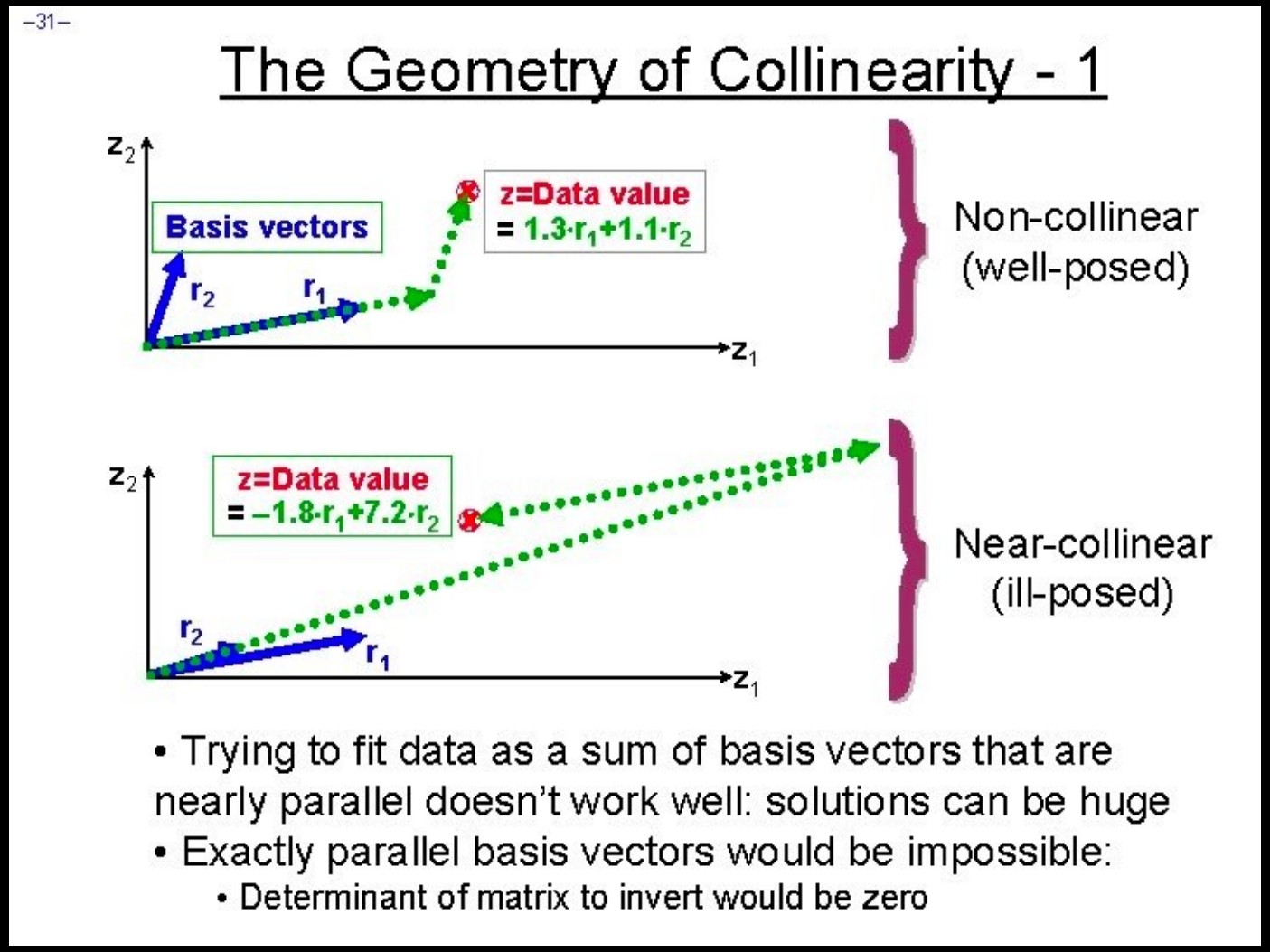


Image from AFNI

Behavioral vs. fMRI Experiments



Questions?

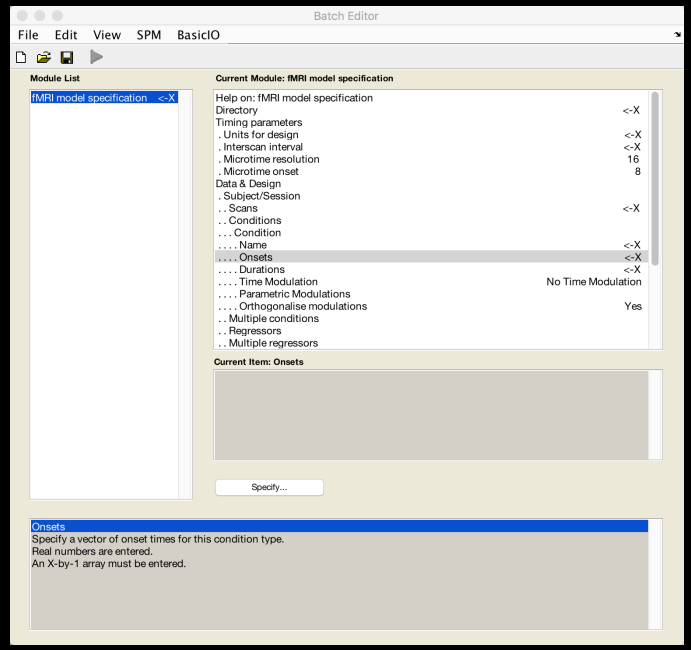
Demonstration of viewing the time-series

Timing Files

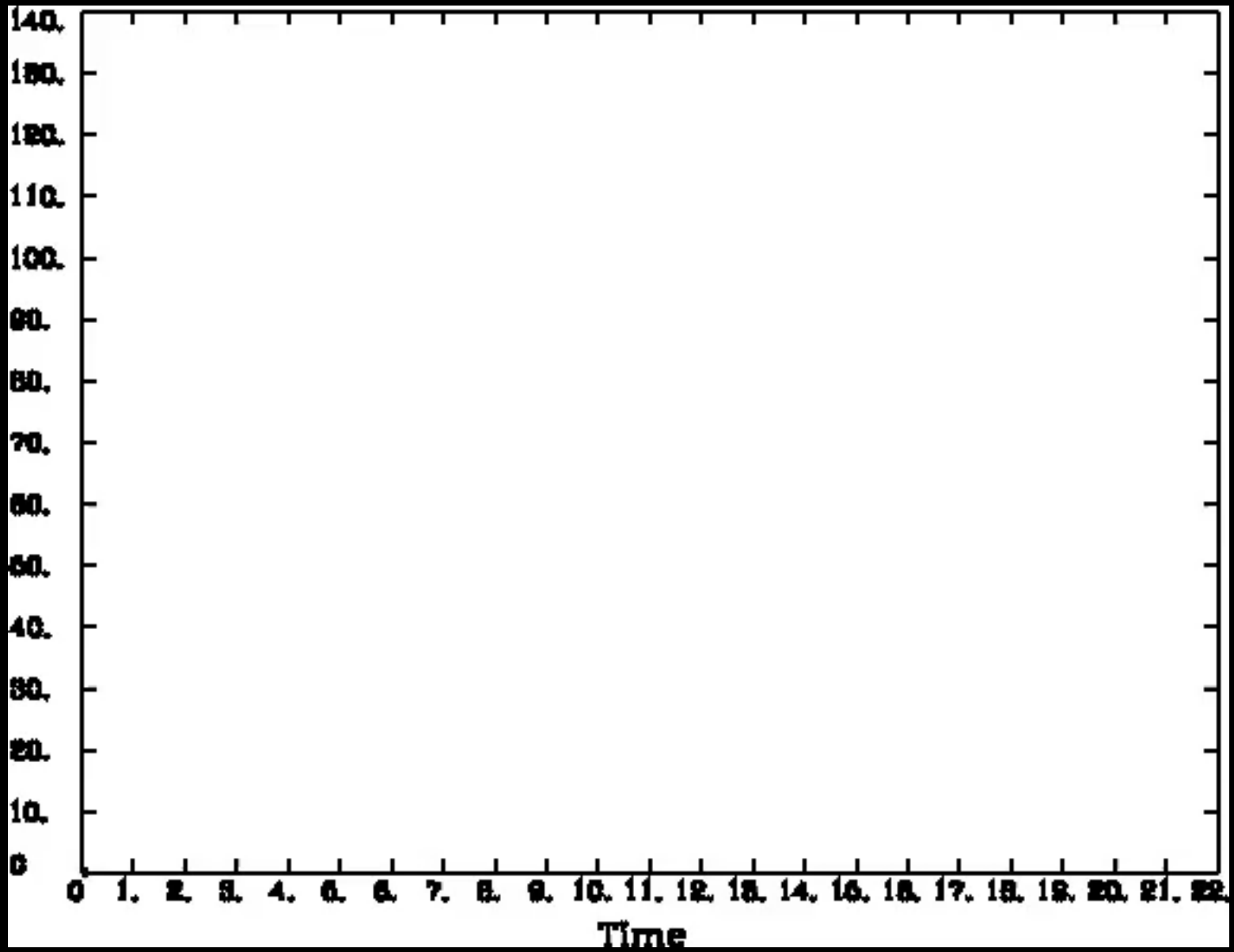
SUB-01_TASK-FLANKER_RUN-1_EVENTS.TSV DOWNLOAD

onset	duration	tri…	res…	co…
0.0	2.0	incongrue…	1.095	correct
10.0	2.0	incongrue…	0.988	correct
20.0	2.0	congruent…	0.591	correct
30.0	2.0	congruent…	0.499	correct
40.0	2.0	incongrue…	0.719	correct
52.0	2.0	congruent…	0.544	correct
64.0	2.0	congruent…	0.436	correct
76.0	2.0	incongrue…	0.47	correct
88.0	2.0	congruent…	0.409	correct

onset	duration	trial_type
0.0	2.0	incongruent_correct
10.0	2.0	incongruent_correct
20.0	2.0	incongruent_correct
32.0	2.0	congruent_correct
42.0	2.0	congruent_correct
52.0	2.0	incongruent_correct
64.0	2.0	congruent_correct
76.0	2.0	congruent_correct
88.0	2.0	incongruent_correct
102.0	2.0	congruent_correct
116.0	2.0	congruent_correct

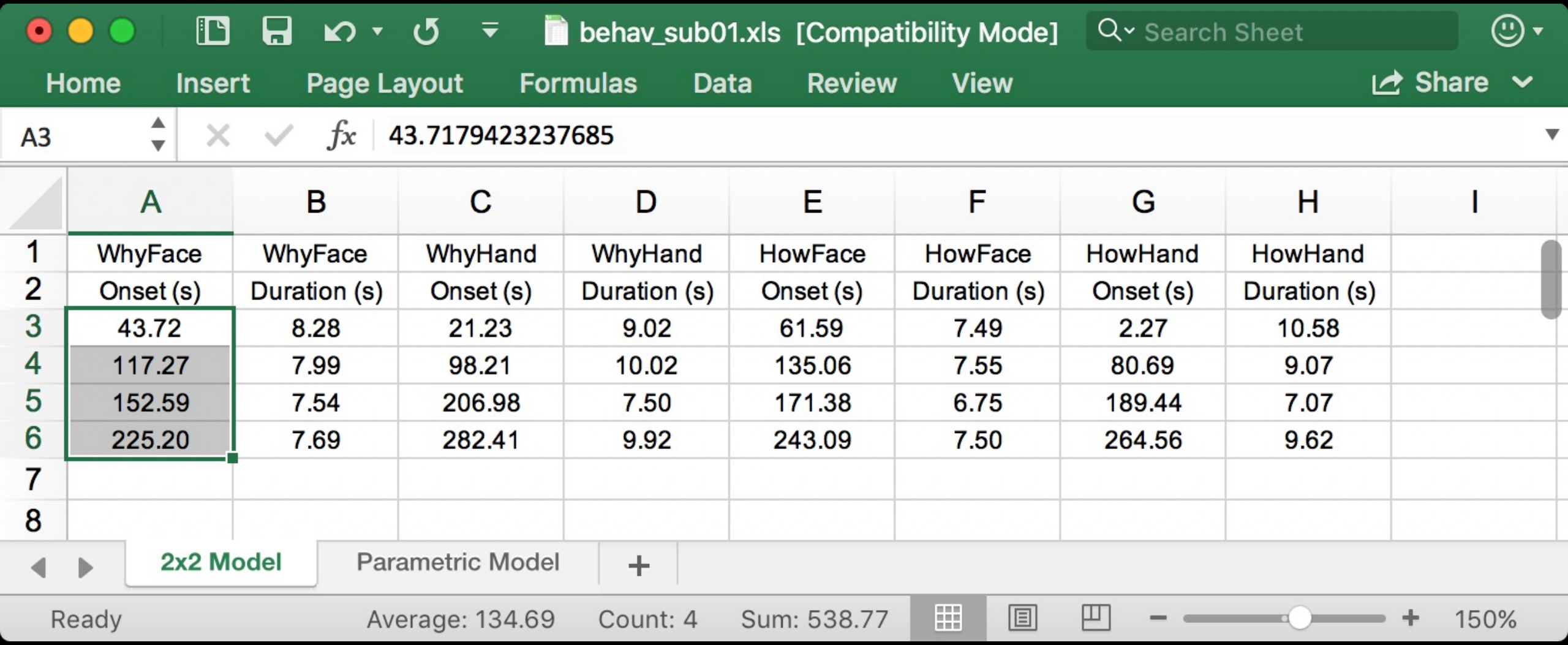


The BOLD Response: Convolution



Bob Cox, AFNI

How to Write out Timings?



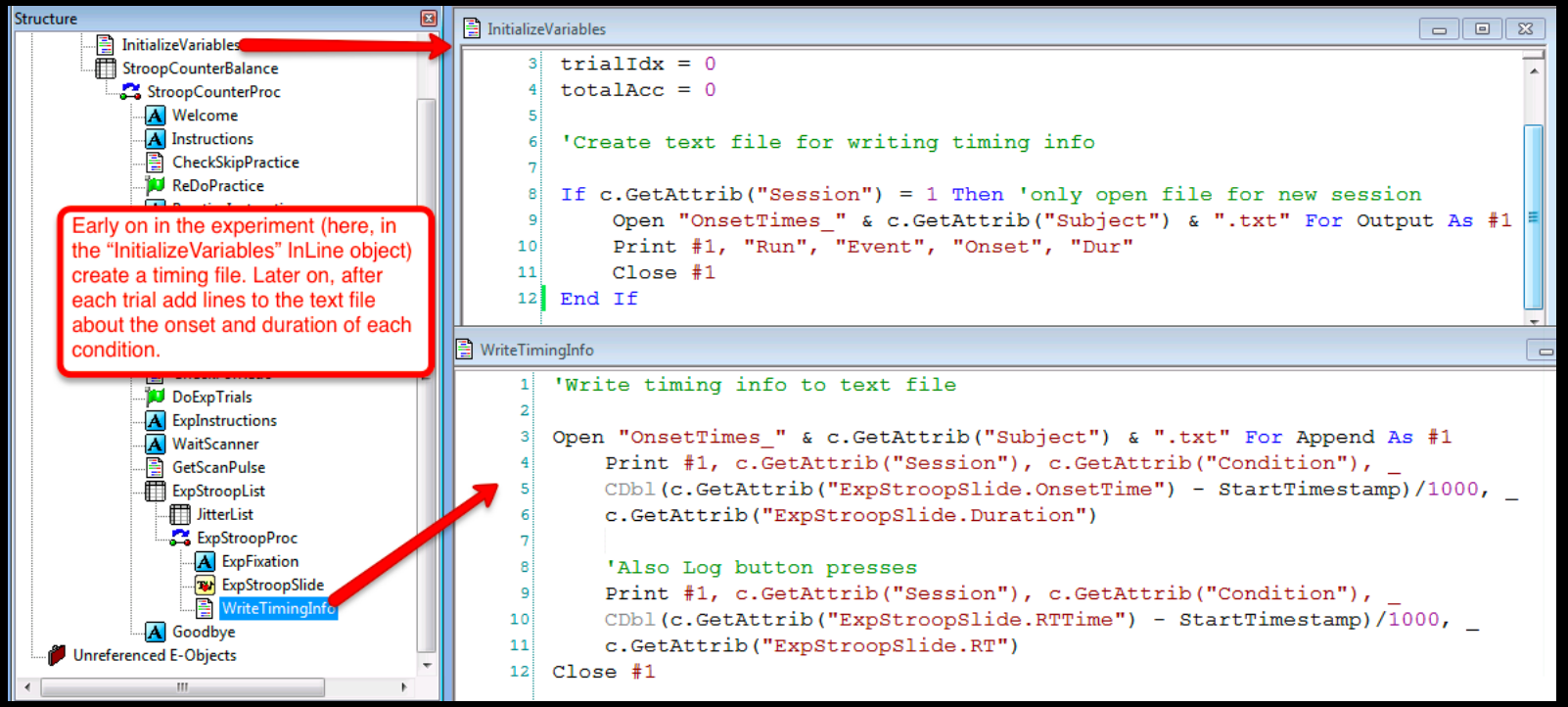
	A	B	C	D	E	F	G	H	I
1	WhyFace	WhyFace	WhyHand	WhyHand	HowFace	HowFace	HowHand	HowHand	
2	Onset (s)	Duration (s)	Onset (s)	Duration (s)	Onset (s)	Duration (s)	Onset (s)	Duration (s)	
3	43.72	8.28	21.23	9.02	61.59	7.49	2.27	10.58	
4	117.27	7.99	98.21	10.02	135.06	7.55	80.69	9.07	
5	152.59	7.54	206.98	7.50	171.38	6.75	189.44	7.07	
6	225.20	7.69	282.41	9.92	243.09	7.50	264.56	9.62	
7									
8									

How to Write out Timings?

Depends on what stimulus presentation software you use

My advice: Write the timings in BIDS format (Onset, Duration, Trial Type, etc)

These can be easily edited and imported into any of the major packages



How to Write out Timings?

DS000102 - SUB-01 - FUNC - SUB-01_TASK-FLANKER_RUN-1_EVENTS.TSV

DOWNLOAD

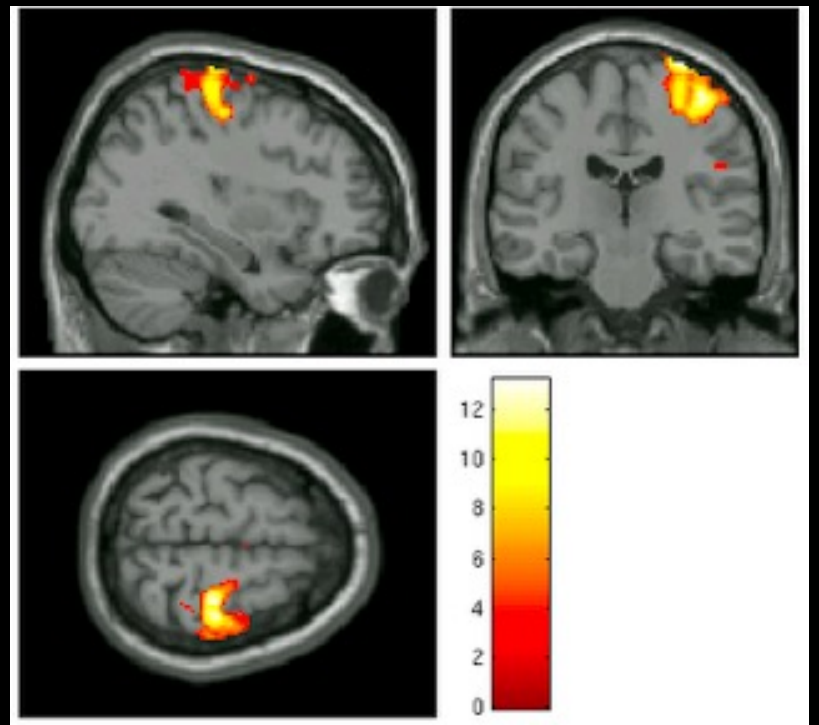
ONSET	DURATION	TRIAL_TYPE	RESPONSE_T…	CORRECTNESS	STIMVAR	RSPONSE	STIMULUS	COND
0.0	2.0	incongruen…	1.095	correct	2	1	incongruent	cond003
10.0	2.0	incongruen…	0.988	correct	2	1	incongruent	cond003
20.0	2.0	congruent_…	0.591	correct	1	1	congruent	cond001
30.0	2.0	congruent_…	0.499	correct	1	1	congruent	cond001
40.0	2.0	incongruen…	0.719	correct	2	1	incongruent	cond003
52.0	2.0	congruent_…	0.544	correct	1	1	congruent	cond001
64.0	2.0	congruent_…	0.436	correct	1	1	congruent	cond001
76.0	2.0	incongruen…	0.47	correct	2	1	incongruent	cond003
88.0	2.0	congruent_…	0.409	correct	1	1	congruent	cond001
102.0	2.0	incongruen…	0.563	correct	2	1	incongruent	cond003
116.0	2.0	congruent_…	0.493	correct	1	1	congruent	cond001
130.0	2.0	congruent_…	0.398	correct	1	1	congruent	cond001
140.0	2.0	congruent_…	0.466	correct	1	1	congruent	cond001
150.0	2.0	incongruen…	0.518	correct	2	1	incongruent	cond003
164.0	2.0	incongruen…	0.56	correct	2	1	incongruent	cond003
174.0	2.0	incongruen…	0.533	correct	2	1	incongruent	cond003
184.0	2.0	congruent_…	0.439	correct	1	1	congruent	cond001

Onset Times Recommendations

No matter how you choose to write them out, you need to verify them

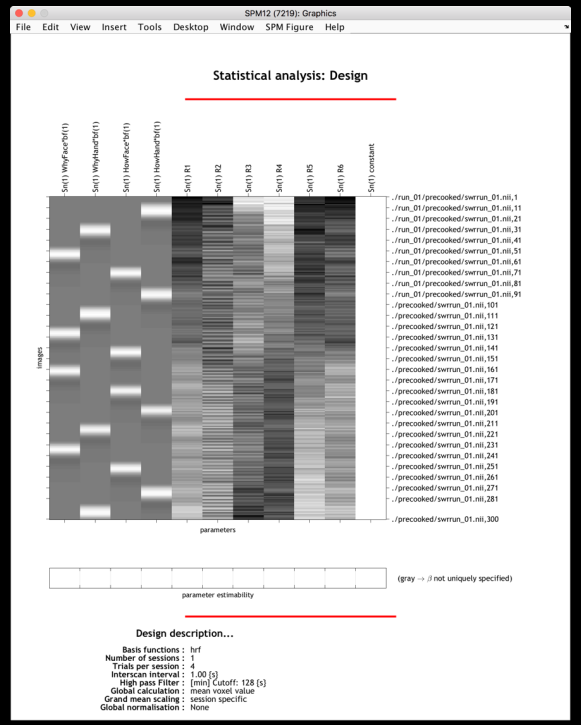
Some scanners acquire a few “dummy scans” at the beginning

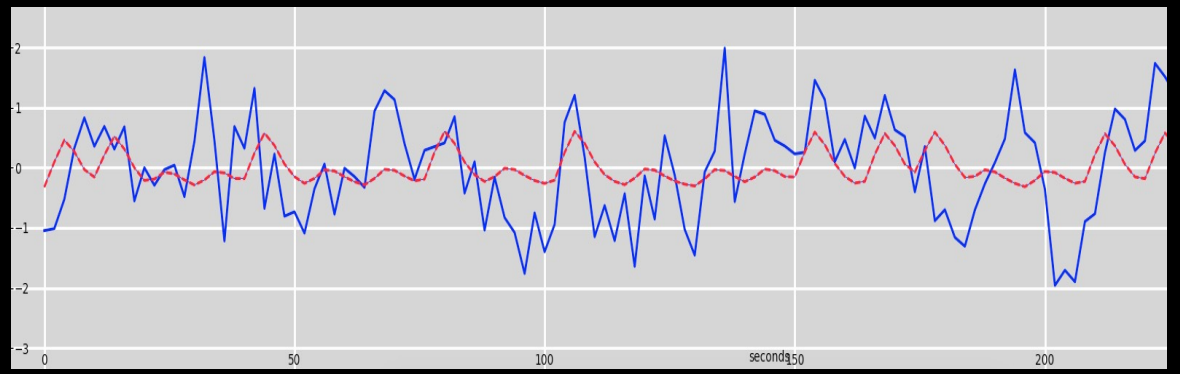
If the experiment has a motor response, check that contrast first

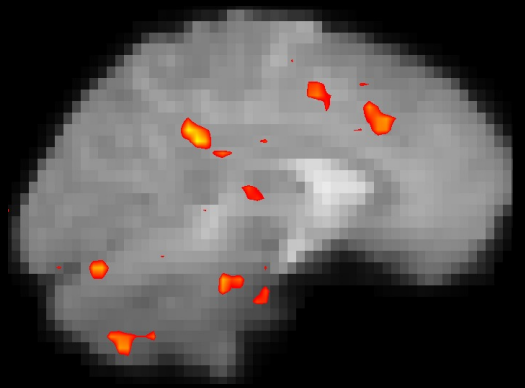


Overview of model fitting

Fit the Model at each voxel (“mass univariate”)







The General Linear Model (GLM)

Uses one or more regressors (independent variables)
to predict an outcome measure (dependent variable)

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon$$

Y= Outcome variable

β = Beta Weights (parameter estimates)

X= Regressor

ε = Residual

The General Linear Model (GLM)

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon$$

Assume that:

Y = GPA, X_1 = IQ, X_2 = Drinks per week, X_3 = Height

$$GPA = (\beta_1 * IQ) + (\beta_2 * Drinks) + (\beta_3 * Height) + \varepsilon$$

$$\beta_1 = 0.05^{*}, \beta_2 = -0.07^{*}, \beta_3 = 0.01\ (not\ significant)$$

IQ and drinks per week contribute to GPA; height doesn't

The General Linear Model (GLM)

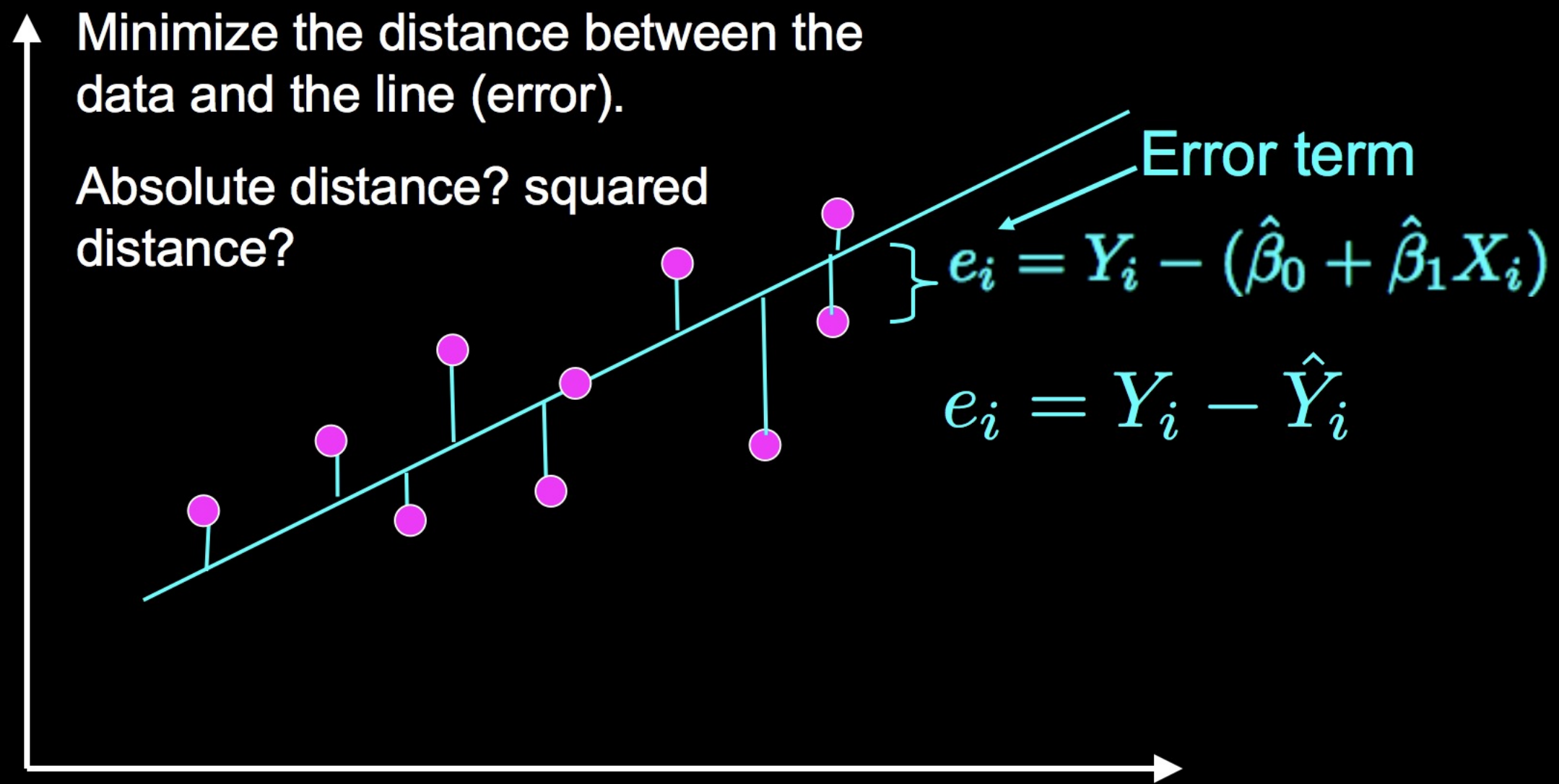


Figure from Jeanette Mumford

The General Linear Model (GLM)

We can use these numbers to calculate the variance

$$SSE = \sum \left(Y_i - \hat{Y}_i \right)^2 = \sum e_i^2$$

$$\sigma^2 = \frac{\Sigma e_i^2}{N - 1}$$

The General Linear Model (GLM)

Test statistic

$$t = (\bar{x} - \mu_0) / (s / \sqrt{n})$$

where:

- $\bar{x}$ = the sample mean
- μ_0 = the hypothesized population mean
- s = the sample standard deviation
- n = the sample size

The General Linear Model (GLM)

Deriving a beta weight (β) can be calculated by using linear algebra:

$$Y = X\hat{\beta}$$

$$X'Y = (X'X)\hat{\beta}$$

$$(X'X)^{-1}X'Y = \hat{\beta}$$

$$\widehat{\mathrm{Var}}[\hat{\beta}] = \hat{\sigma}^2(X'X)^{-1}$$

The General Linear Model (GLM)

t-statistics in fMRI are conceptually similar, but computed slightly differently:

$$t = \frac{c(X'X)^{-1}X'Y}{\sqrt{\hat{\sigma}^2 c(X'X)^{-1}c'}}$$

$$\hat{\sigma}^2 = \frac{e'e}{N-p}$$

where $e = Y - X\hat{\beta} = Y - \hat{Y}$

N = Number of time-points
p = Number of regressors

The General Linear Model (GLM)

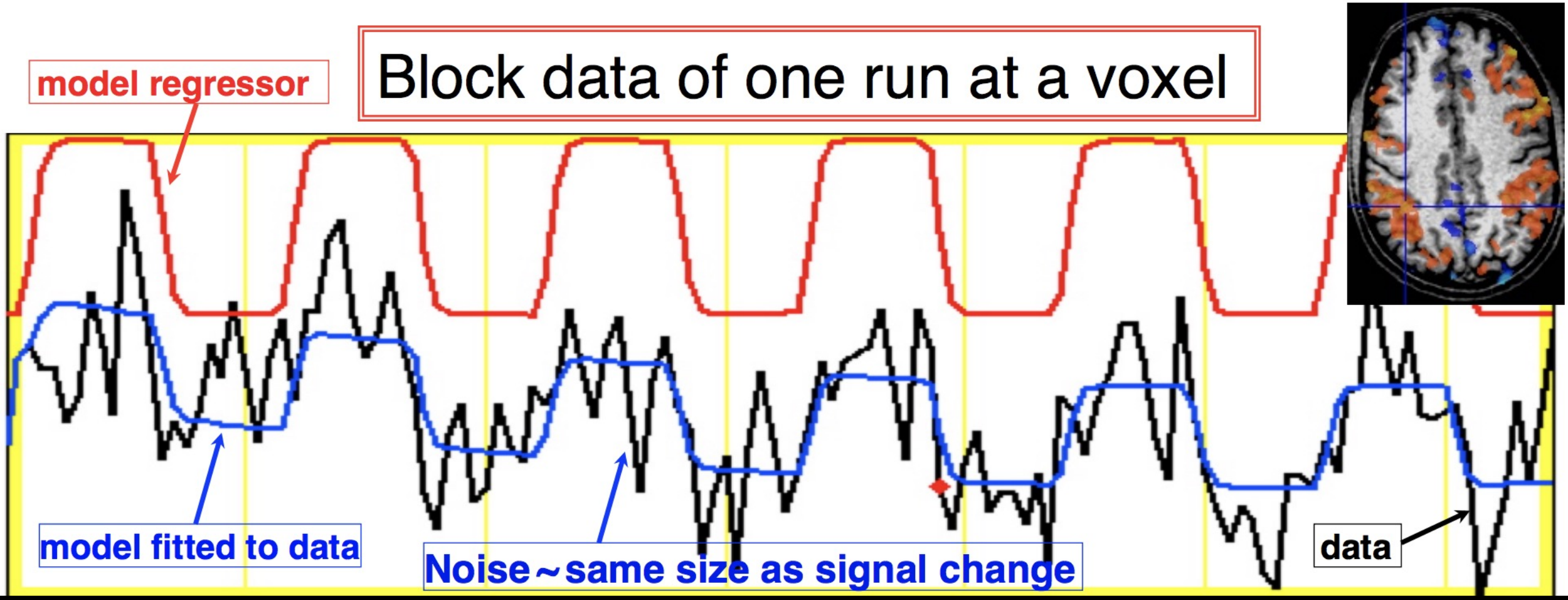
Note: t-statistics are calculated at the 1st-level, but usually aren't carried into the 2nd-level analysis

In other words: Magnitude is carried to the group-level, not variance

This can be done in other programs, e.g. AFNI's 3dMEMA

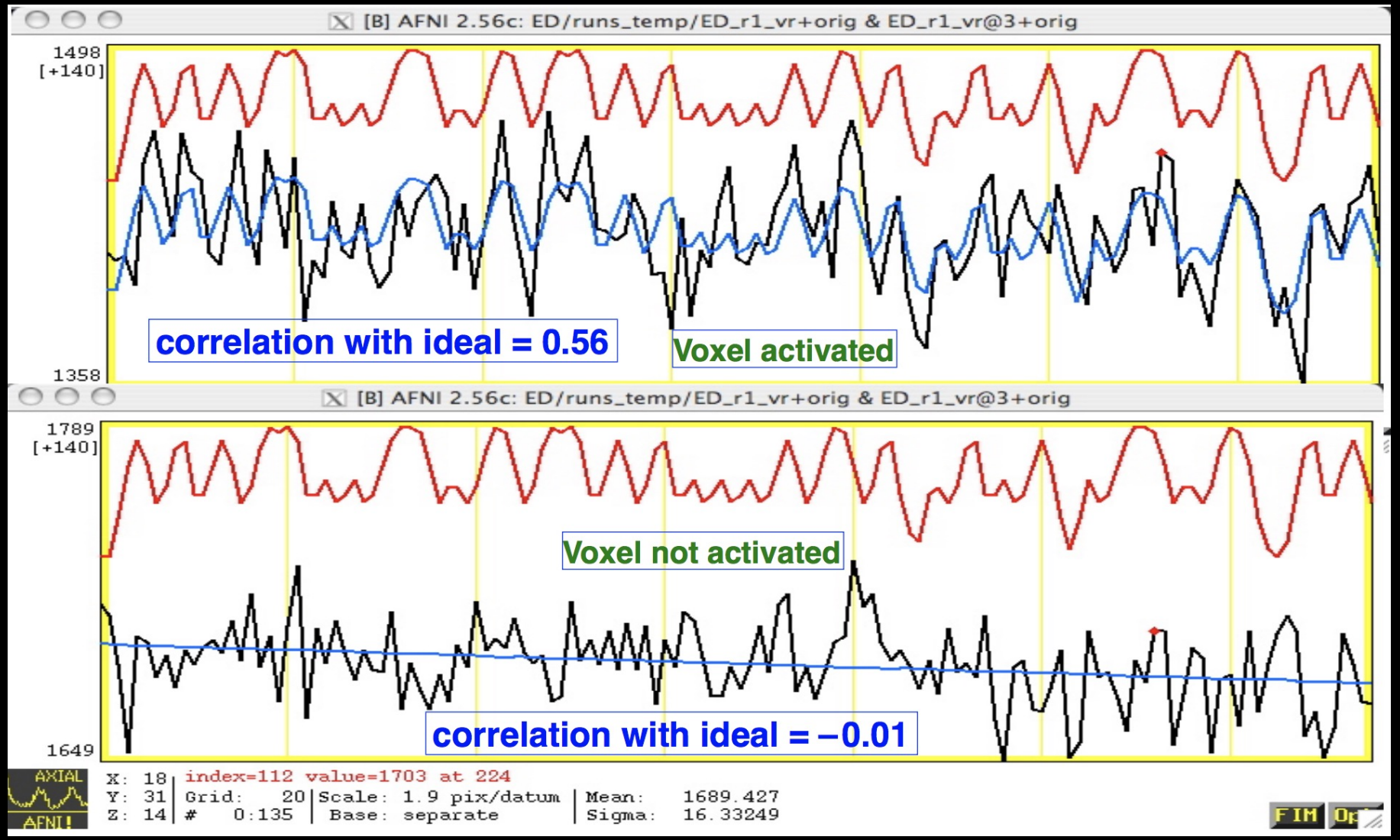
Applying the GLM to fMRI Data

Applying the GLM to fMRI Data



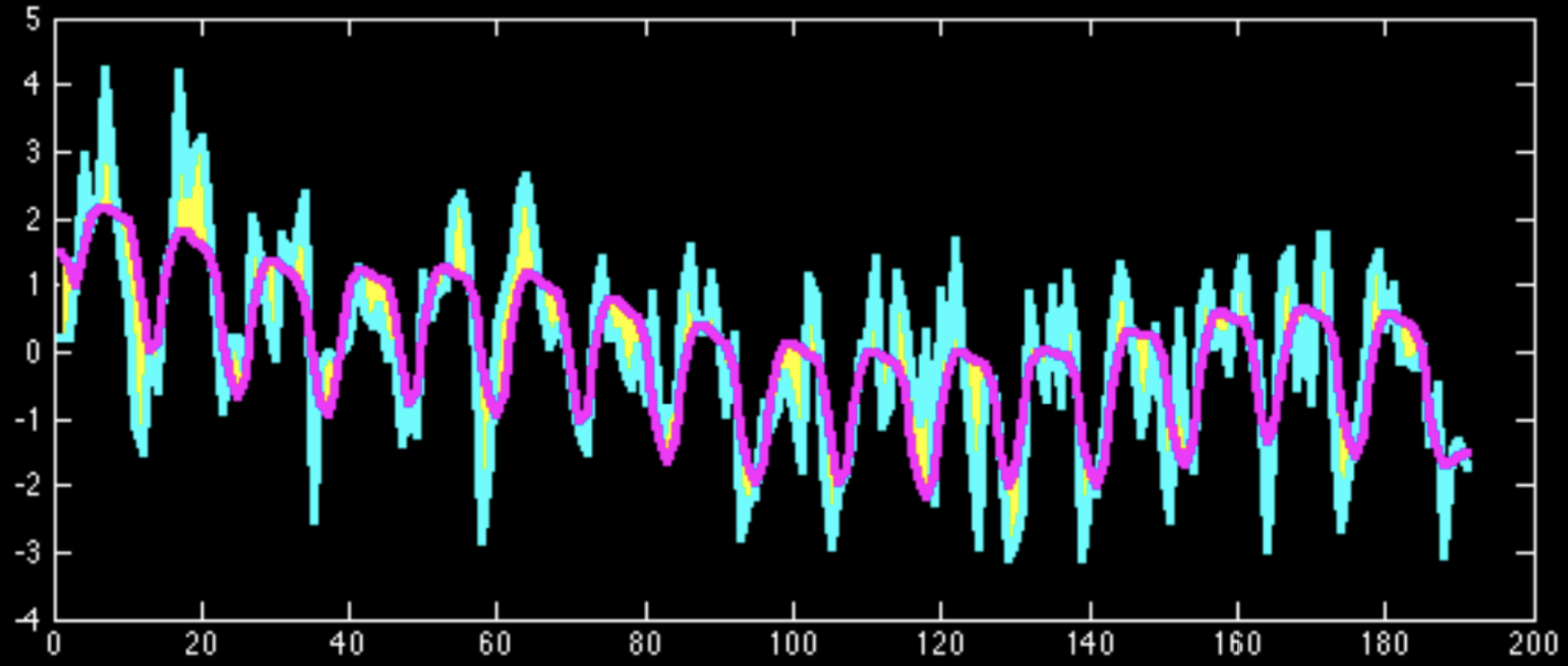
Source: AFNI

Applying the GLM to fMRI Data



Source: AFNI

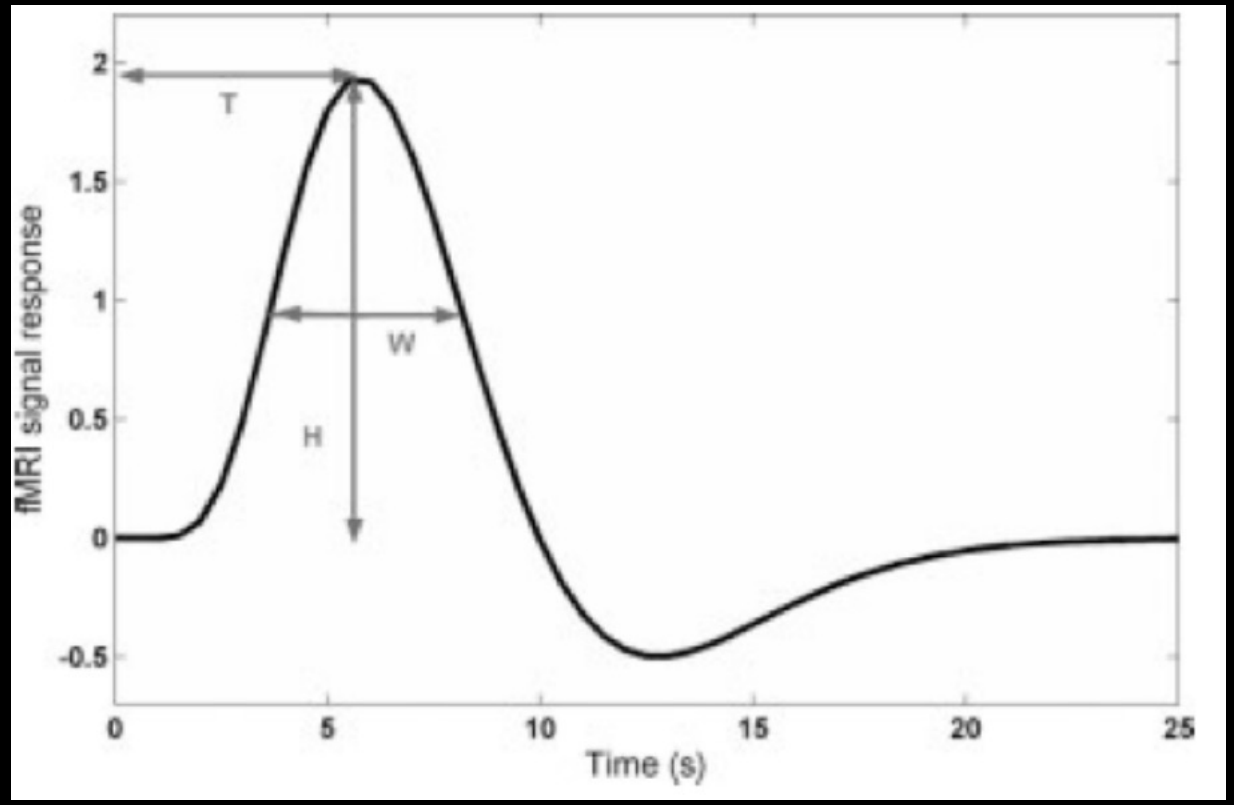
Applying the GLM to fMRI Data



Source: Jeanette Mumford

Applying the GLM to fMRI Data

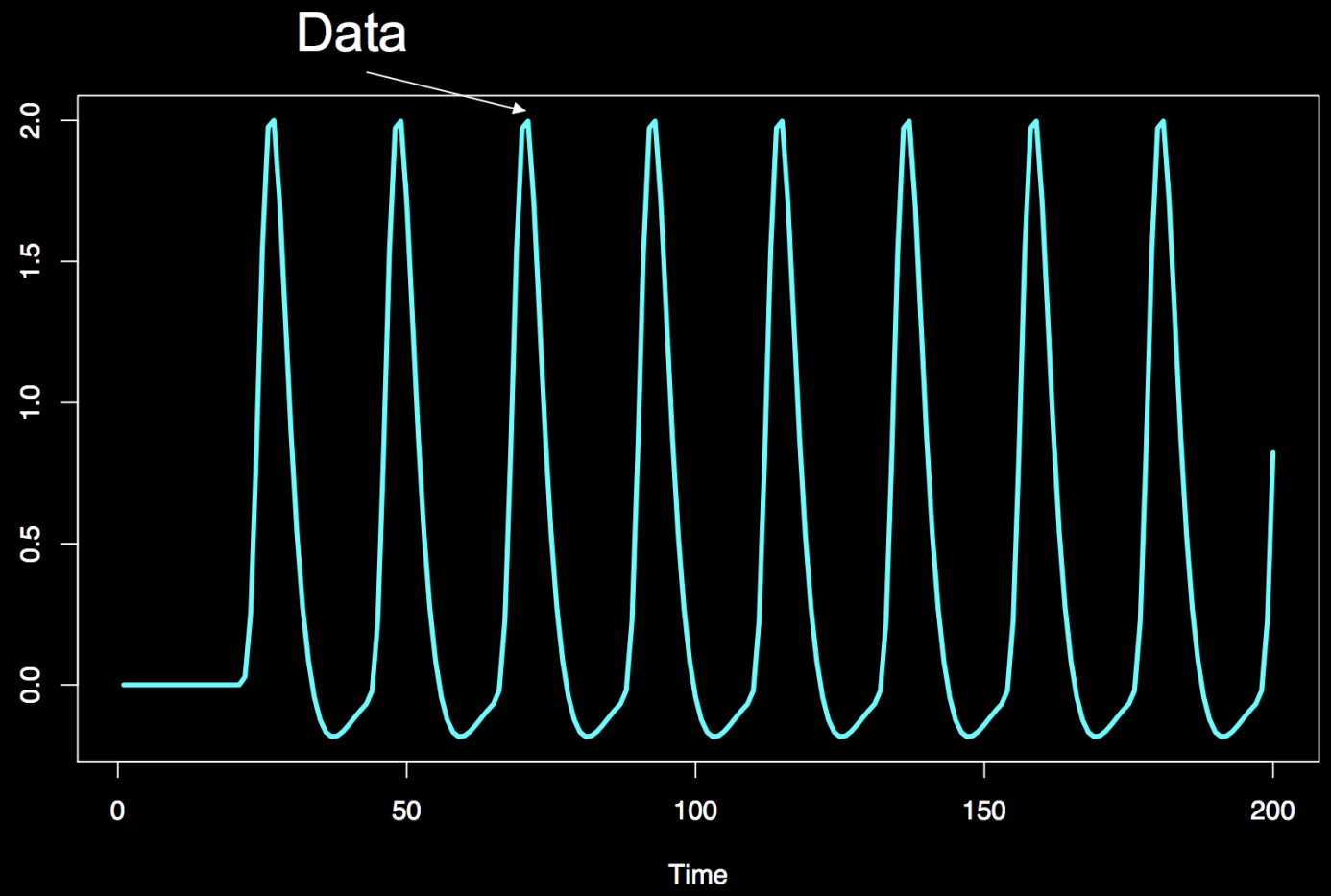
Revisiting the HRF



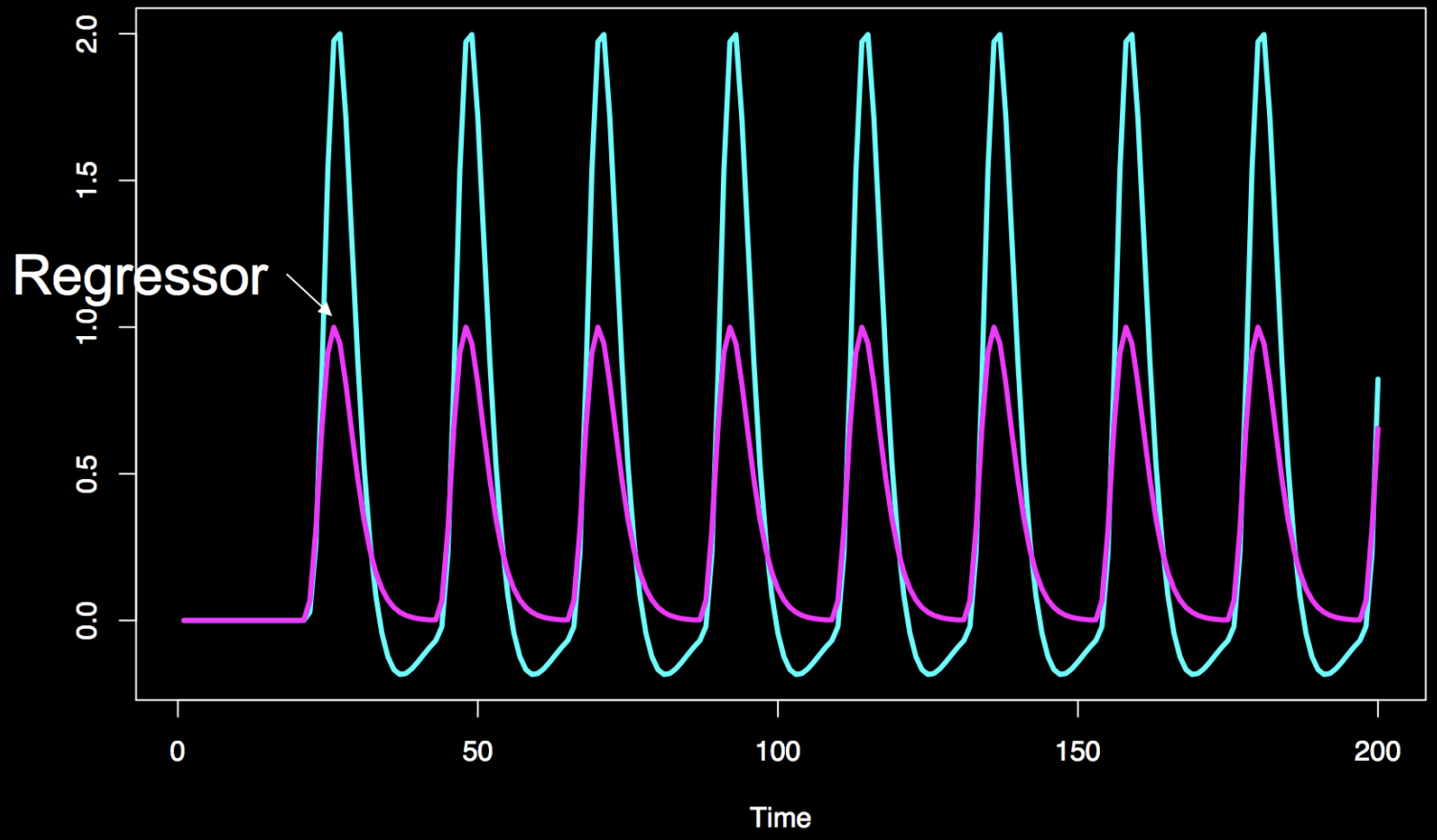
Canonical HRF: Width and delay are fixed, height is estimated as a beta

Applying the GLM to fMRI Data

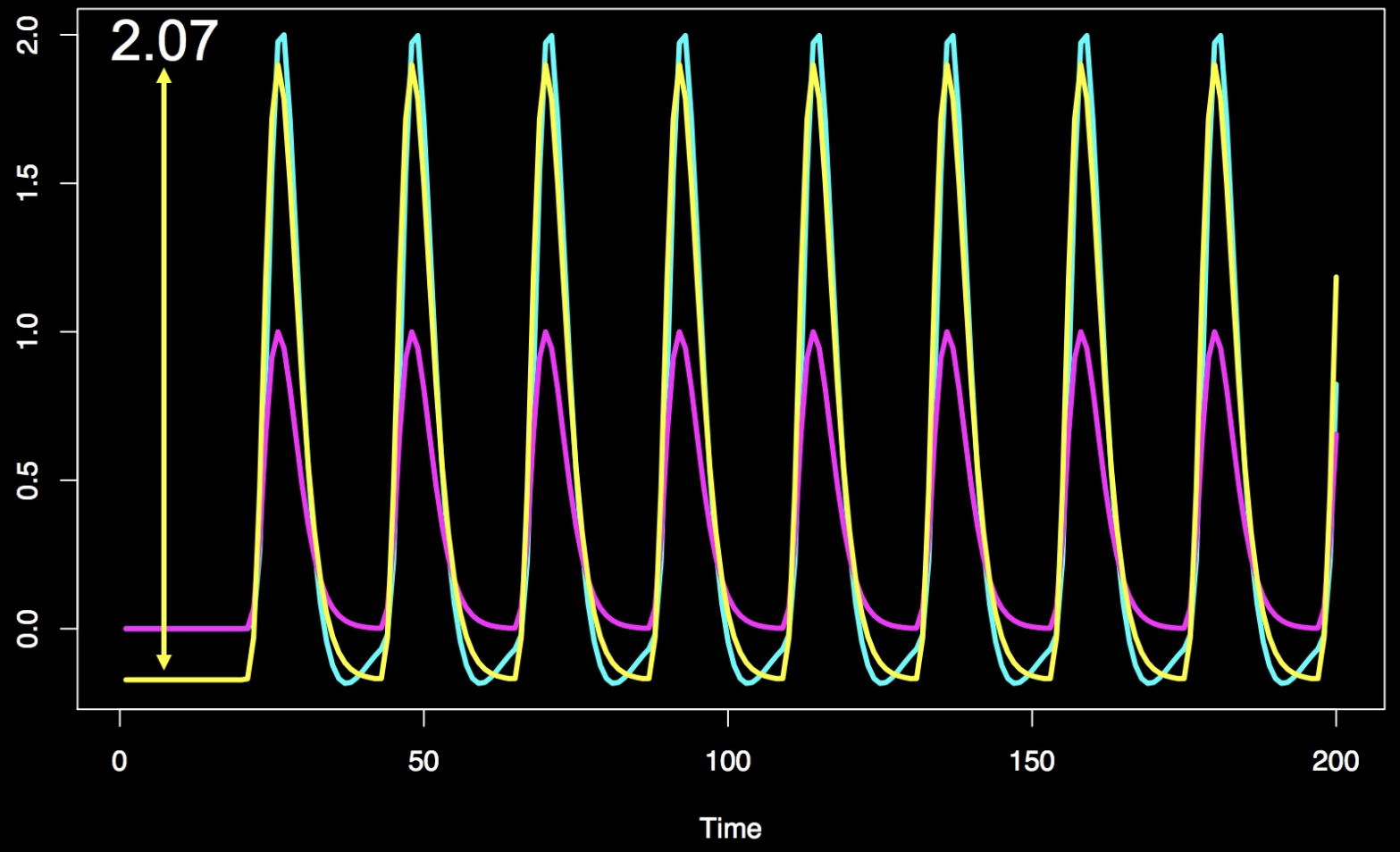
Why use a double-gamma (e.g., model the undershoot?)



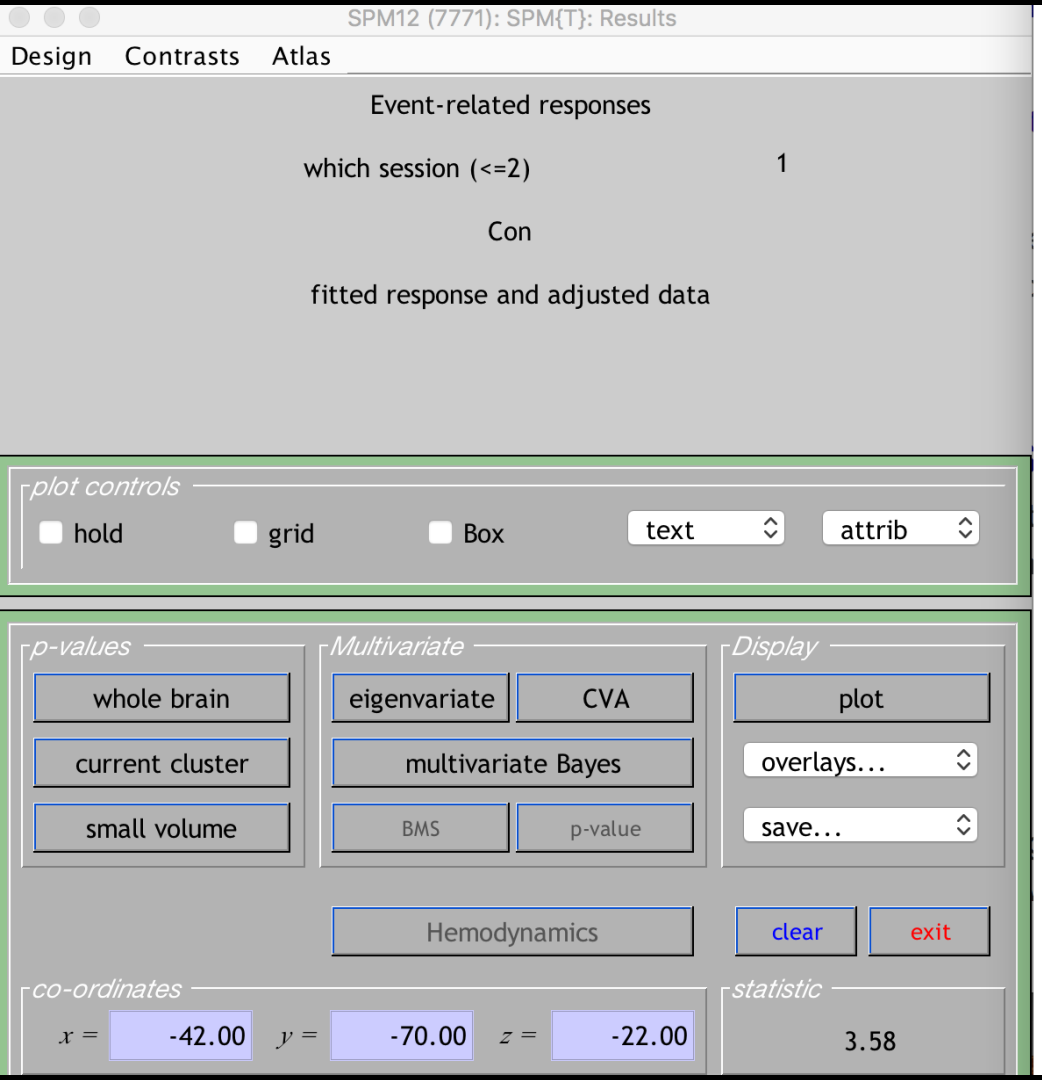
Applying the GLM to fMRI Data

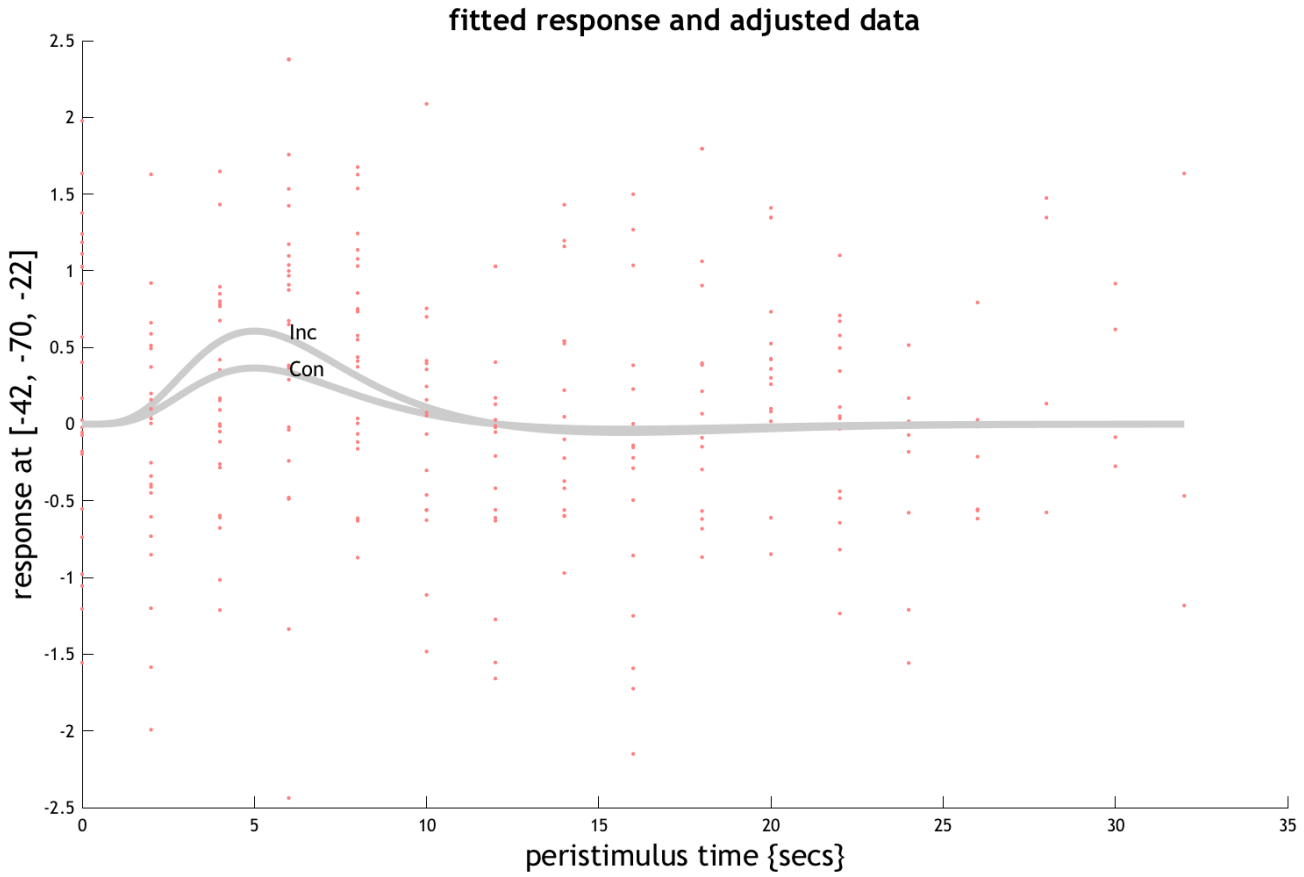


Applying the GLM to fMRI Data



Applying the GLM to fMRI Data





Applying the GLM to fMRI Data

SPM12 (7771): SPM{T}: Results

Design Contrasts Atlas

Fitted responses

Inc-Con - All Sessions

predicted or adjusted response? adjusted

scan or time

plot controls

hold grid Box text attrib

p-values

whole brain

current cluster

small volume

Multivariate

eigenvariate CVA

multivariate Bayes

BMS p-value

Display

plot

overlays...

save...

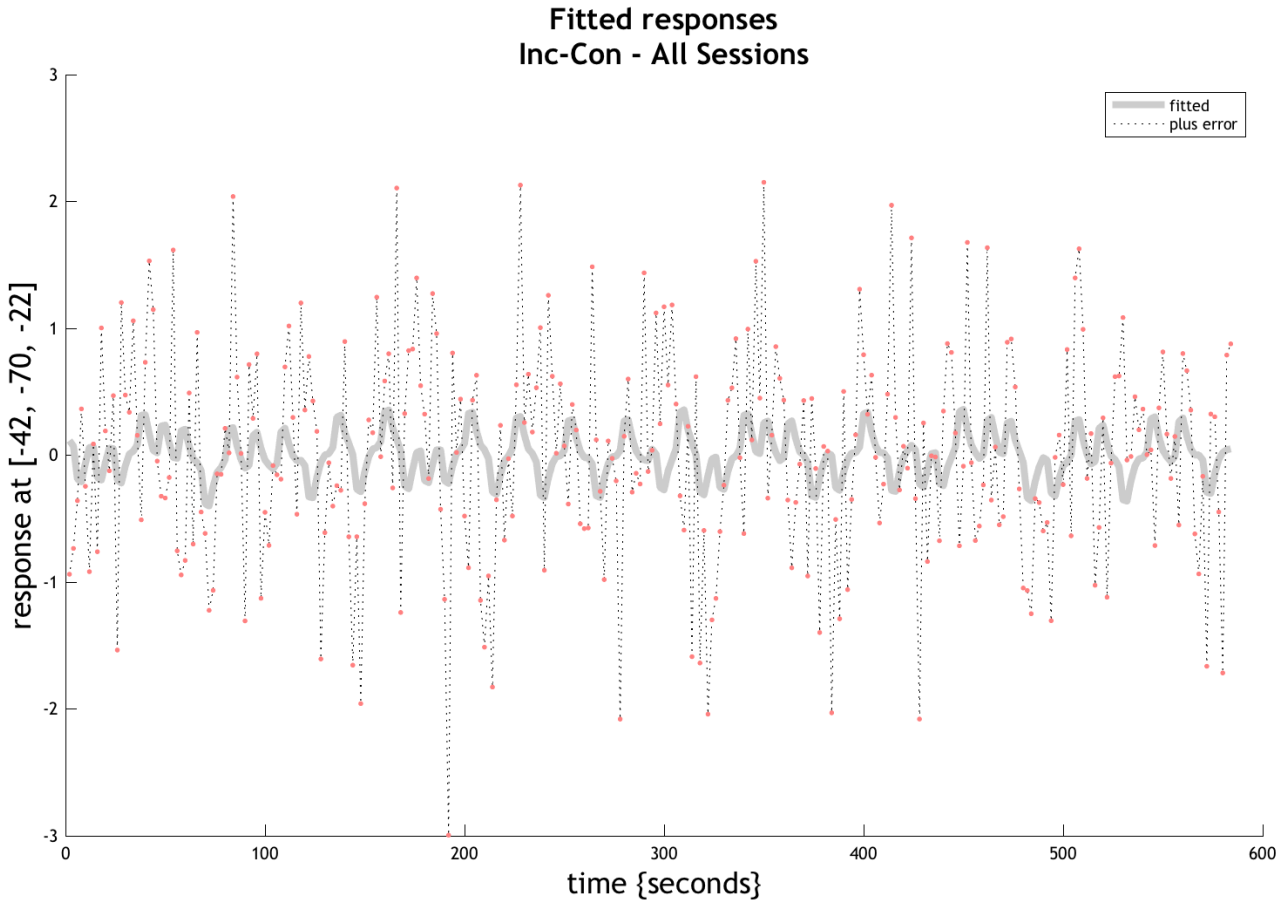
Hemodynamics clear exit

co-ordinates

x = -42.00 y = -70.00 z = -22.00

statistic

3.58



Applying the GLM to fMRI Data

SPM12 (7771): SPM{T}: Results

Design Contrasts Atlas

Fitted responses

Inc-Con - All Sessions

predicted or adjusted response? adjusted

scan or time

plot controls

hold grid Box text attrib

p-values

whole brain

current cluster

small volume

Multivariate

eigenvariate CVA

multivariate Bayes

BMS p-value

Display

plot

overlays...

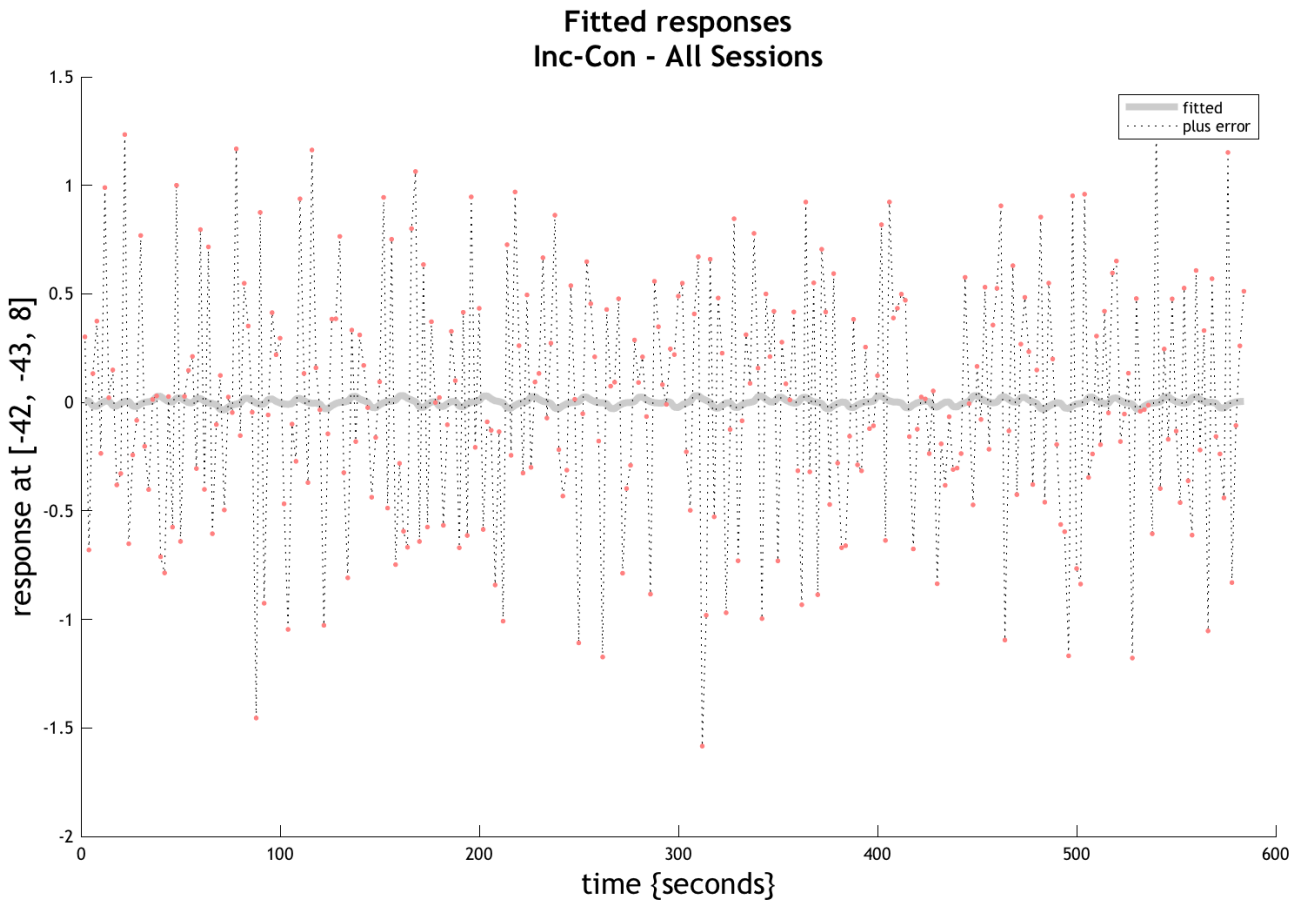
save...

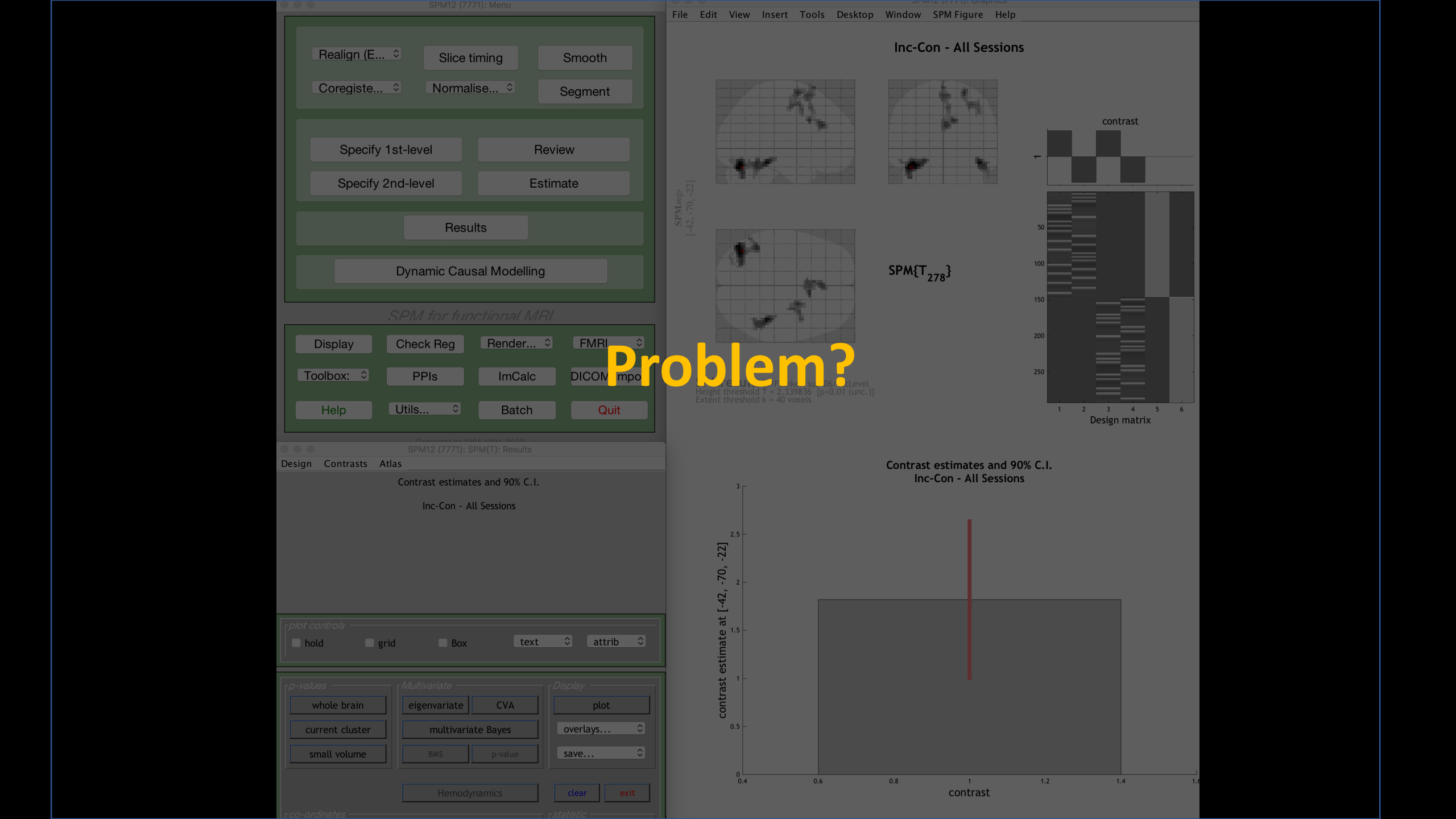
Hemodynamics clear exit

co-ordinates

x = -42.00 y = -43.00 z = 8.00

statistic




SPM12 (7771): Menu
Realign (E...
Slice timing
Smooth
Coregiste...
Normalise...
Segment
Specify 1st-level
Review
Specify 2nd-level
Estimate
Results
Dynamic Causal Modelling
SPM for functional MRI
Display
Check Reg
Render...
FMRI
Toolbox:
PPIs
ImCalc
Help
Utils...
Batch
Quit
SPM12 (7771): SPM{T}: Results
Design
Contrasts
Atlas
Contrast estimates and 90% C.I.
Inc-Con - All Sessions
plot controls
hold
grid
Box
text
attrib
p-values
whole brain
current cluster
small volume
Multivariate
eigenvariate
CVA
multivariate Bayes
BMS
p-value
Display
plot
overlays...
save...
Hemodynamics
clear
exit
File
Edit
View
Insert
Tools
Desktop
Window
SPM Figure
Help
Inc-Con - All Sessions
SPM{T278}
Problem?
contrast
Design matrix
Contrast estimates and 90% C.I.
Inc-Con - All Sessions
contrast estimate at [-42, -70, -22]
contrast

Applying the GLM to fMRI Data

Other options

Grand mean scaling: Removes intersession variance, allows for combining data across subjects

Intensity normalization: Forces each volume to have the same mean (not recommended)

$$g_s = \frac{\sum_{n=1}^{N} g_{ns}}{N}$$

Session-specific grand mean scaling: Multiplies each volume in session s by $100/g_s$

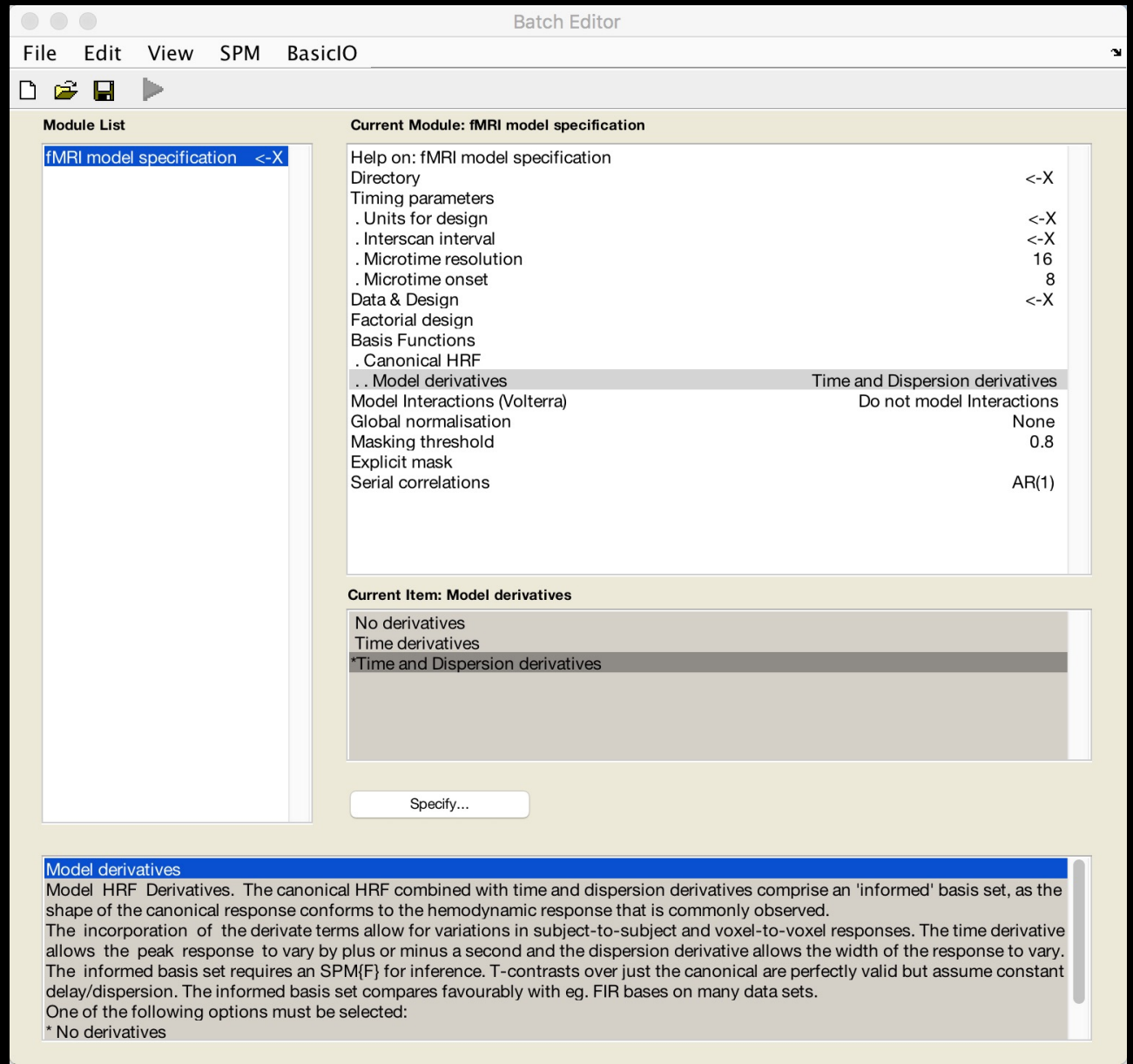
Percent Signal Change

Some recommend reporting percent signal change instead of beta weights

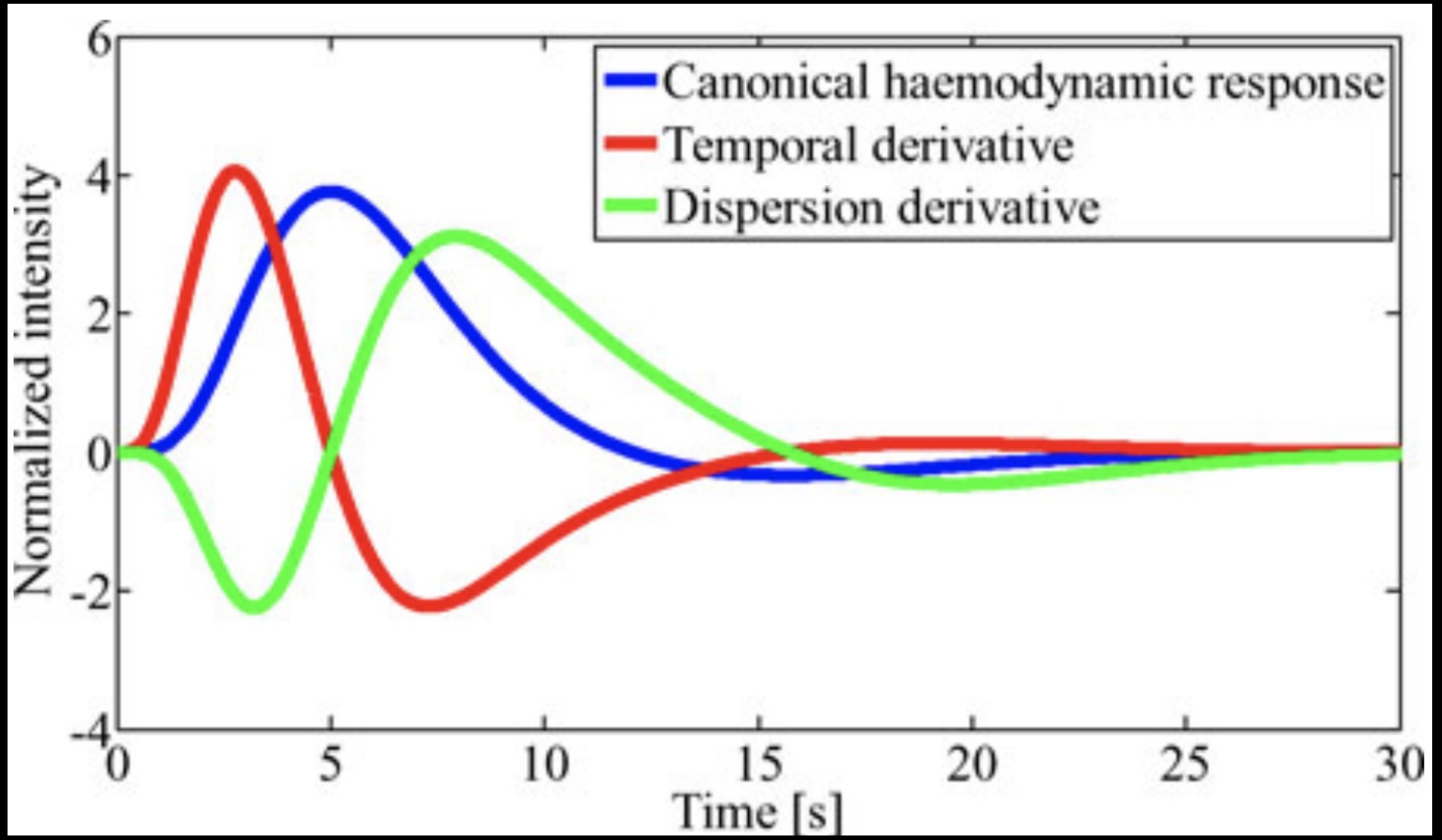
More accurate reflection of effect size, more comparable between studies

ROI tool like Marsbar will scale by the overall mean of the voxels in the region

Applying the GLM to fMRI Data



Applying the GLM to fMRI Data



Applying the GLM to fMRI Data

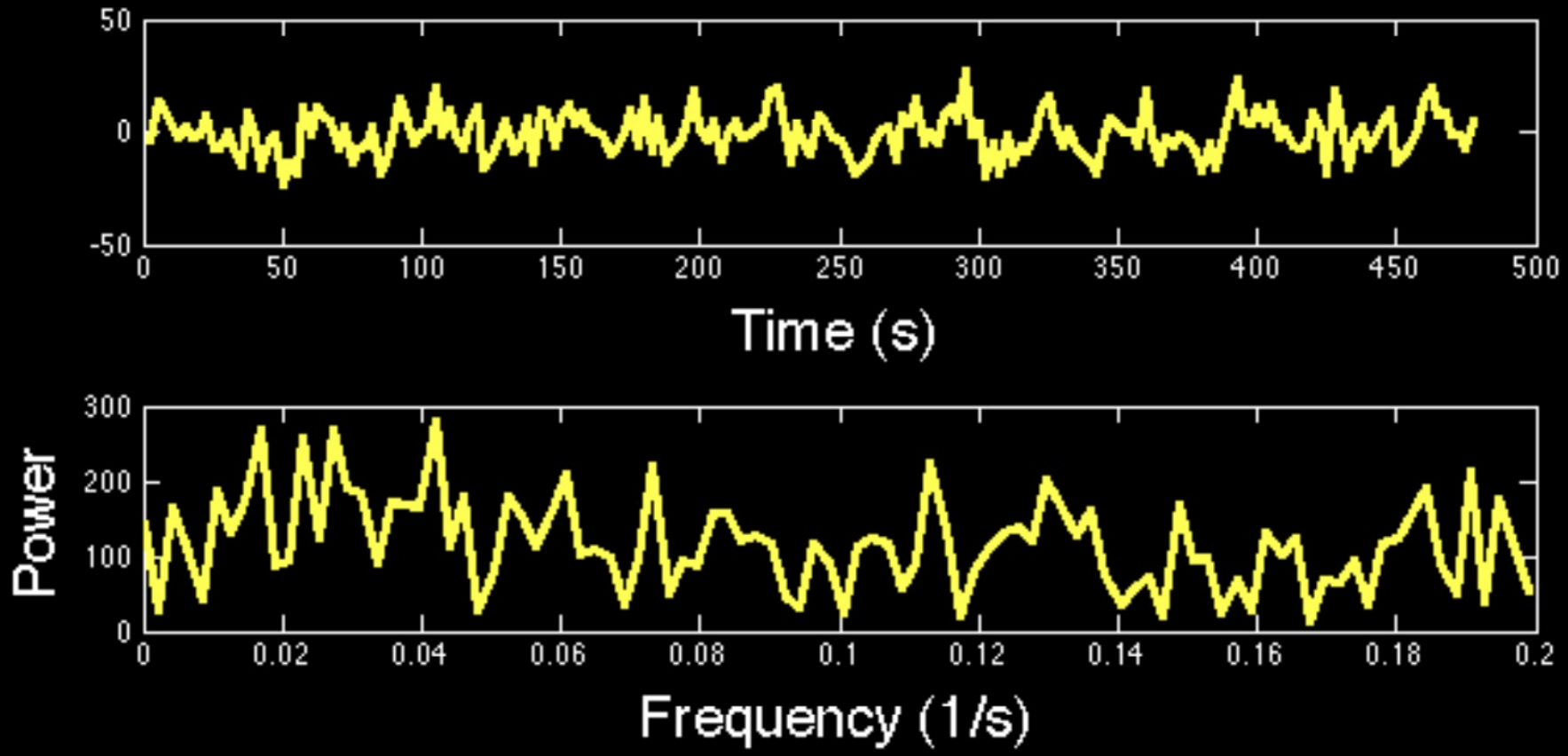
Benefits of time derivative

No interpolation of raw data, may capture variability in BOLD response

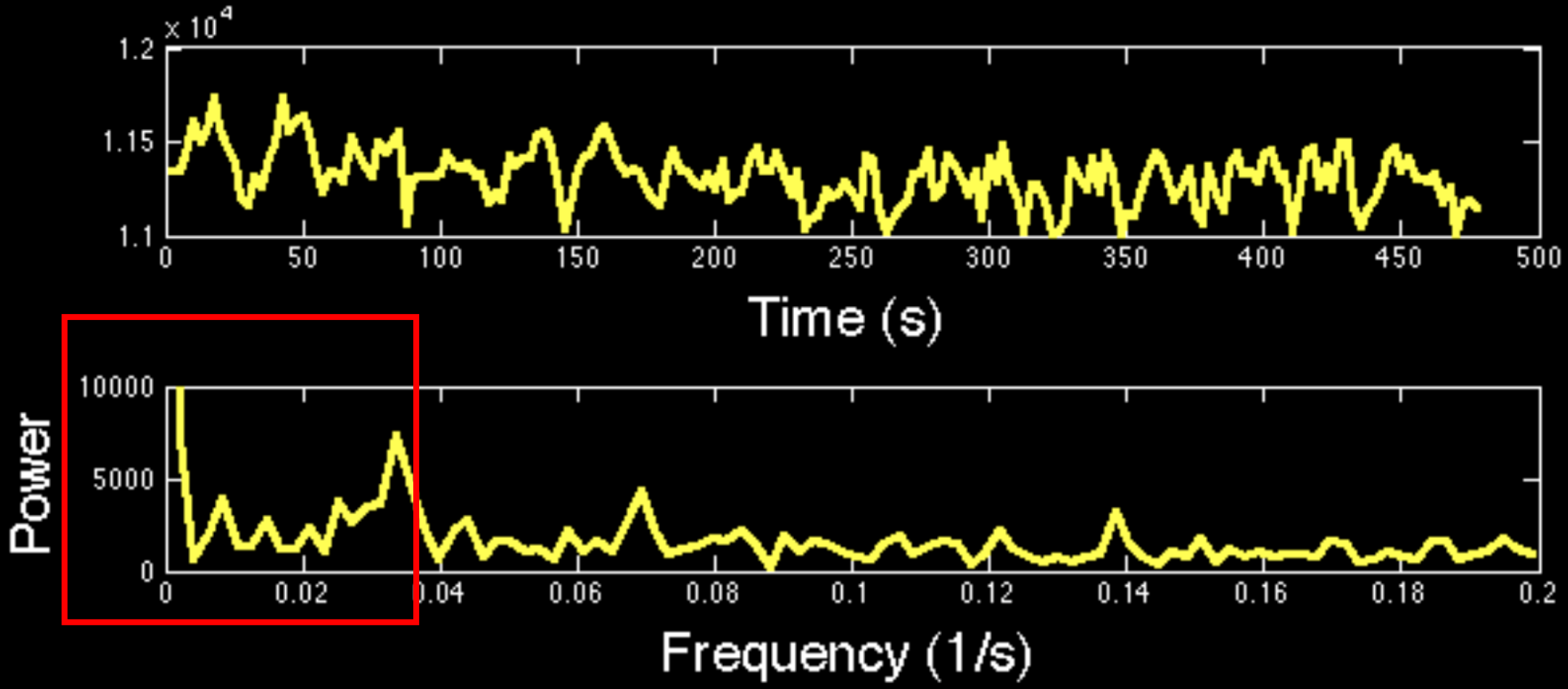
Cons: Requires an additional regressor in the model per condition

Applying the GLM to fMRI Data

Other options: Highpass filtering and prewhitening

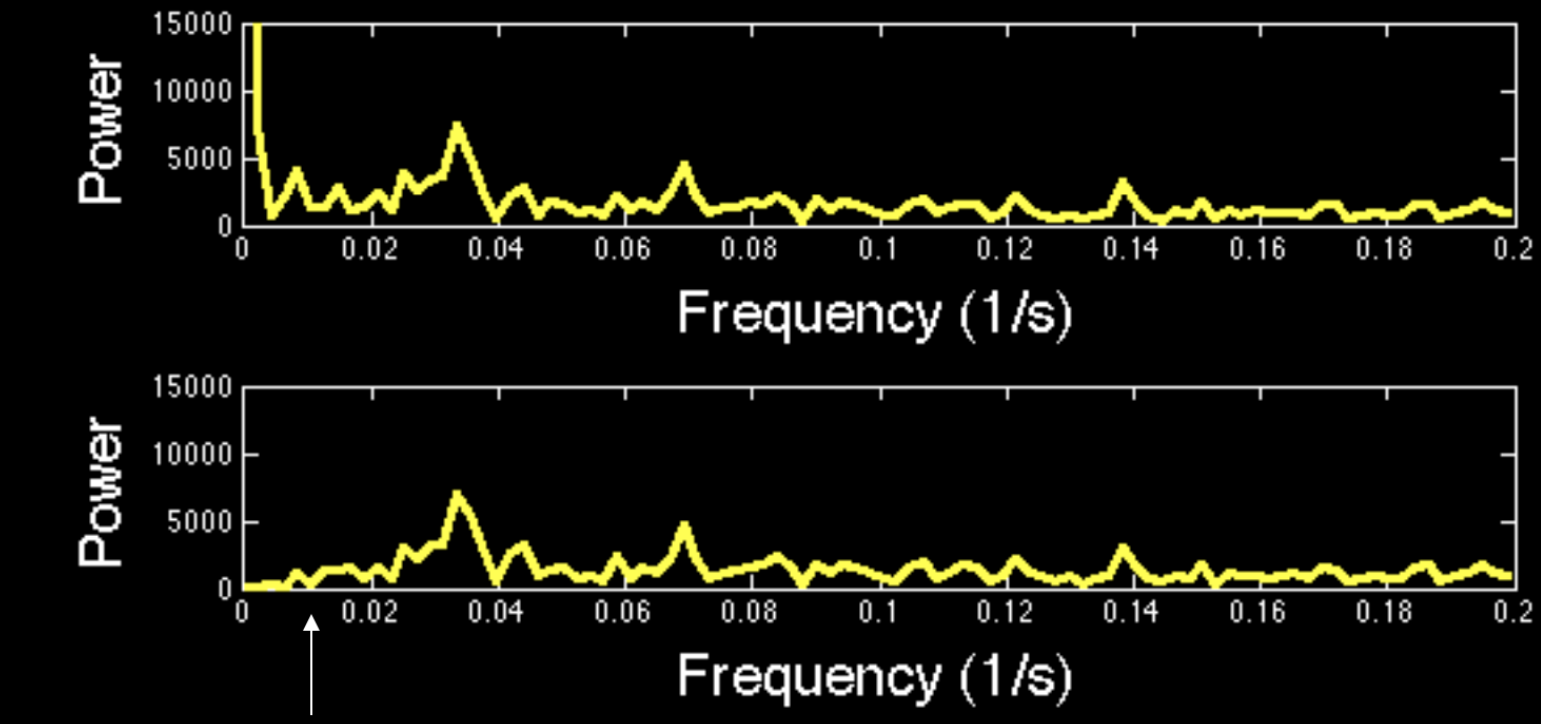


Applying the GLM to fMRI Data



Applying the GLM to fMRI Data

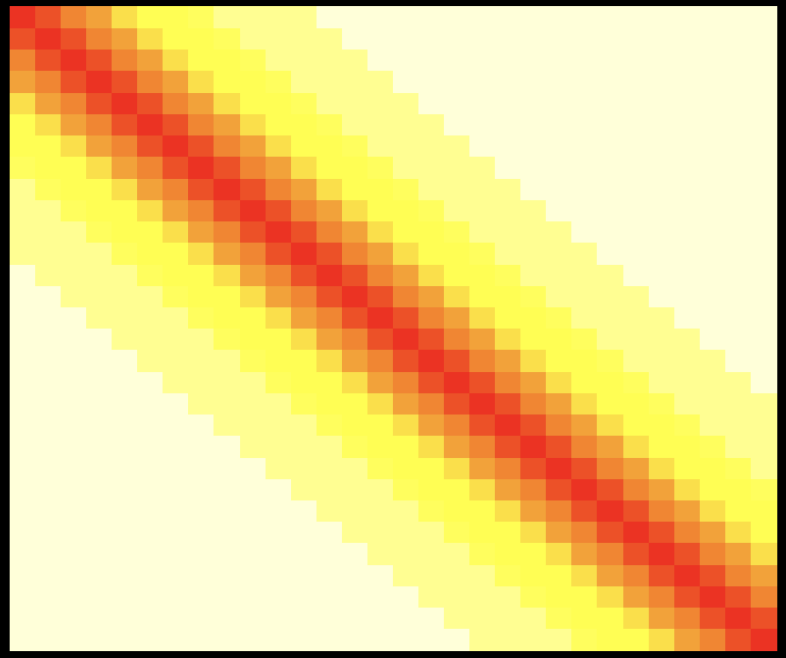
Highpass filter removes frequencies <u>below</u> a certain threshold



Applying the GLM to fMRI Data

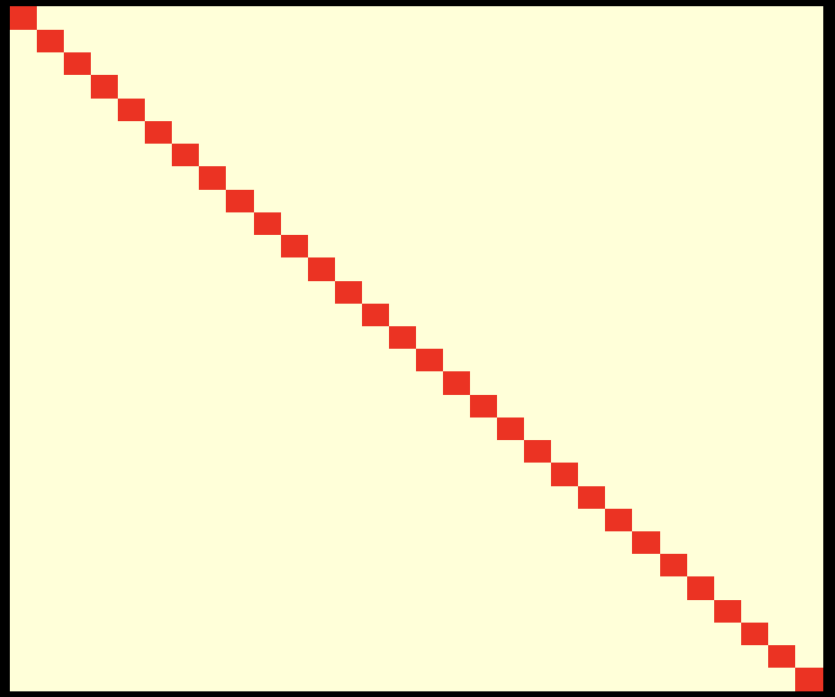
$$Y = X\beta + \epsilon$$

$$\mathrm{Cov}(\epsilon) =$$



Applying the GLM to fMRI Data

$$\mathrm{Cov}(K\epsilon) =$$



$$KY = KX\beta + K\epsilon$$

Applying the GLM to fMRI Data

Prewhitening

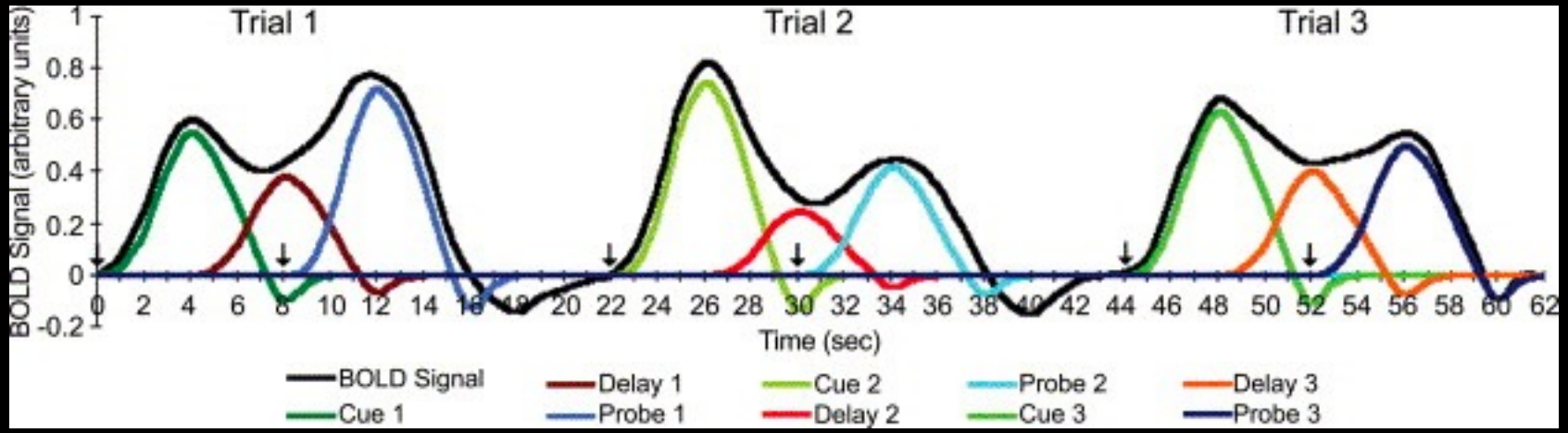
Gauss-Markov assumptions: Normally distributed errors, constant variance, and no temporal autocorrelation

Are fMRI data temporally autocorrelated?

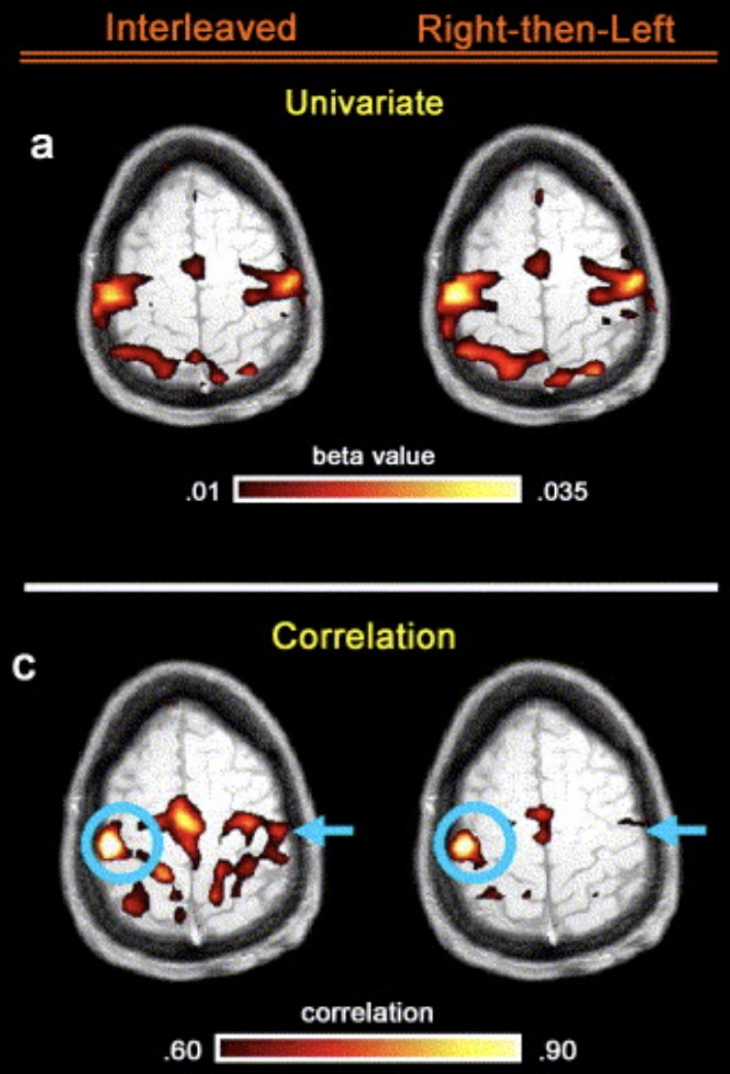
Applying the GLM to fMRI Data

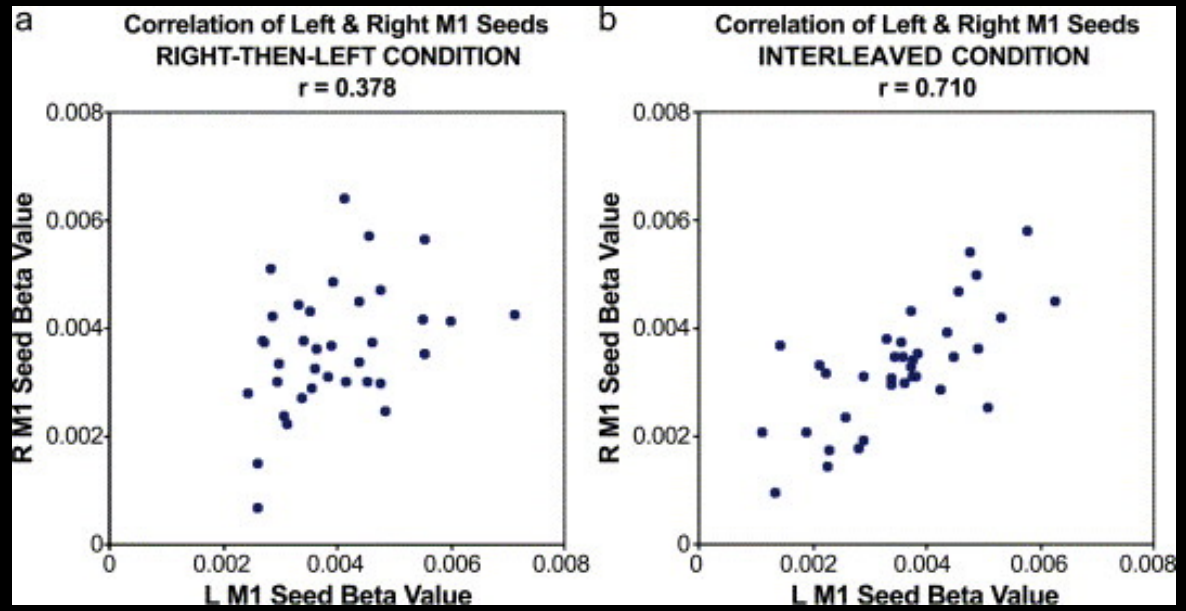
Other options: Individual Modulation

Useful for beta-series correlation, MVPA classification

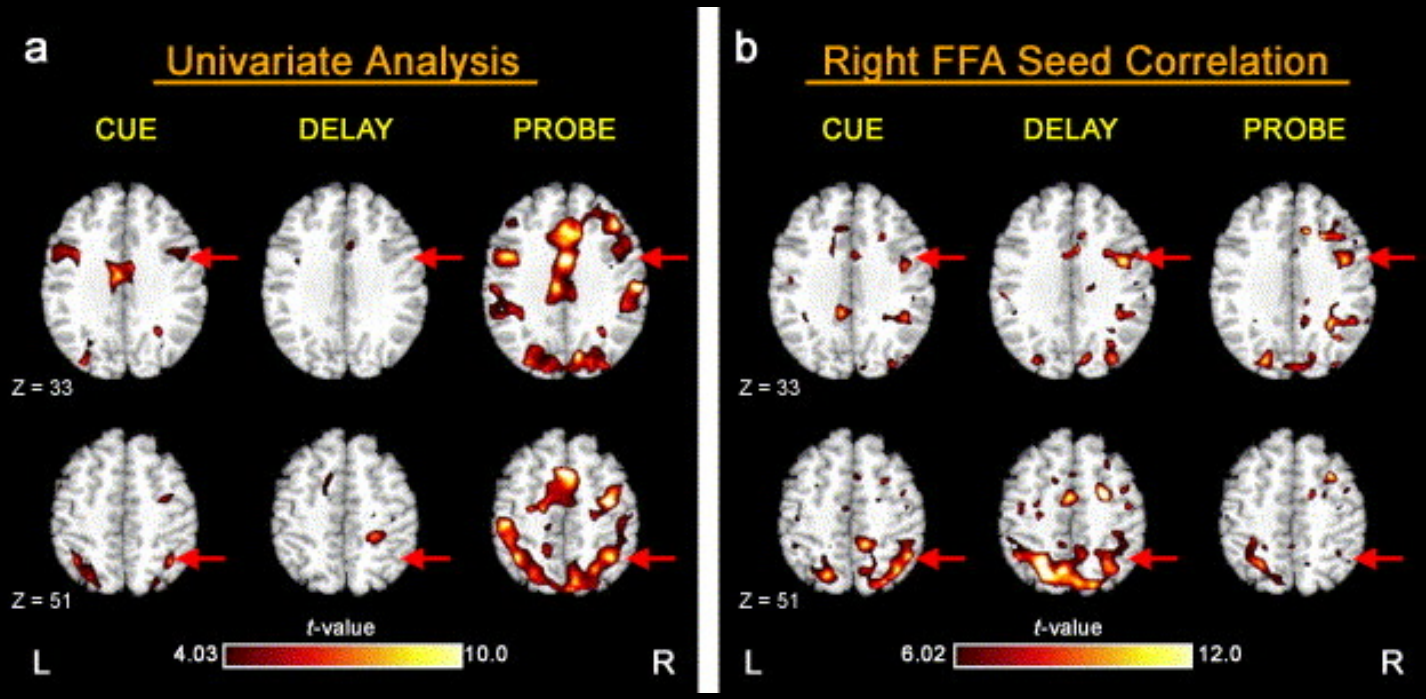


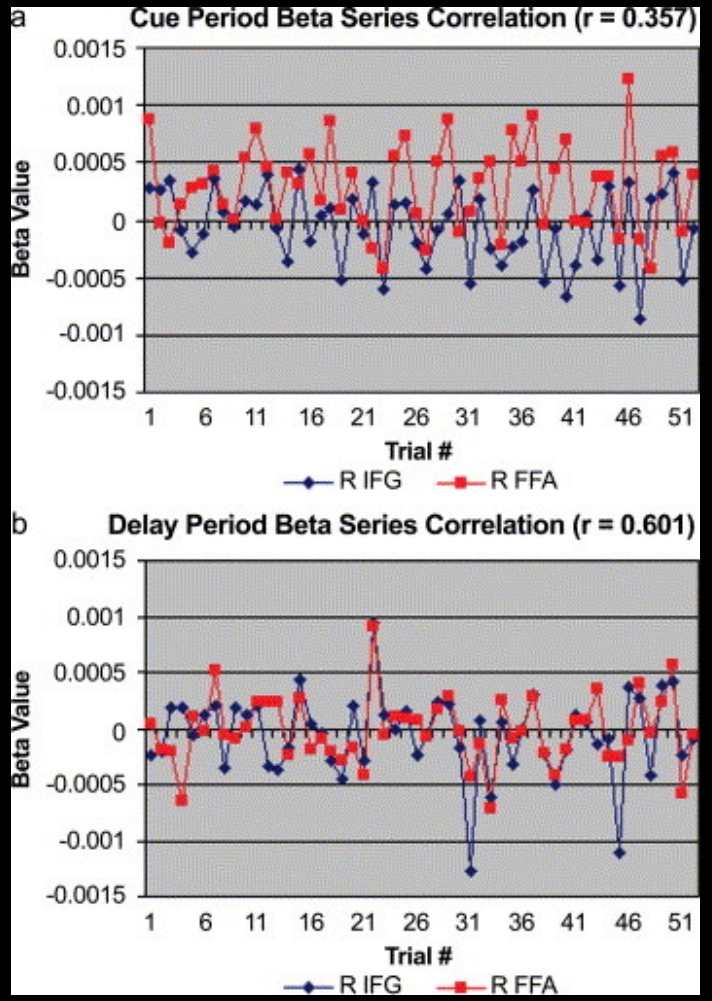
Applying the GLM to fMRI Data





Applying the GLM to fMRI Data





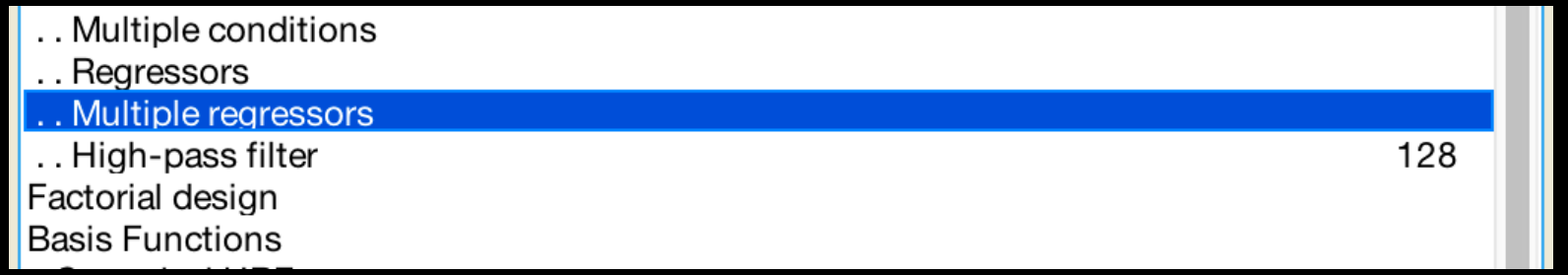
Applying the GLM to fMRI Data

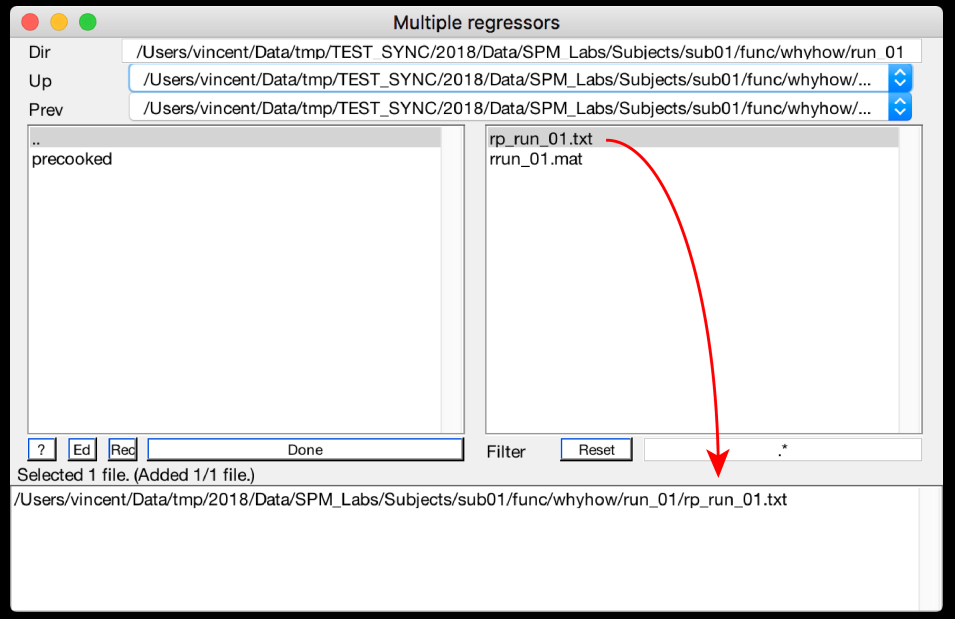
Drawback: Very tedious to implement without scripting!

For AFNI users: Can use ‘IM’ basis function in 3dDeconvolve

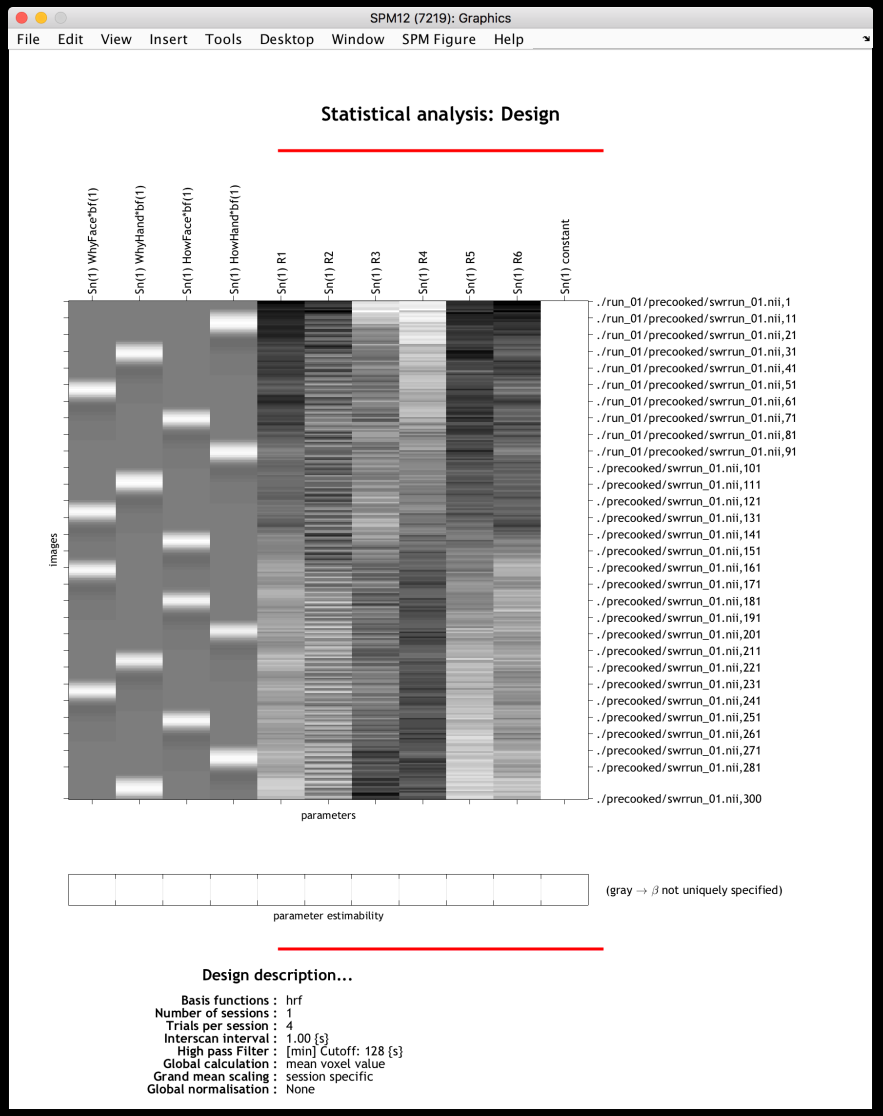
Applying the GLM to fMRI Data

What about nuisance regressors, such as motion?

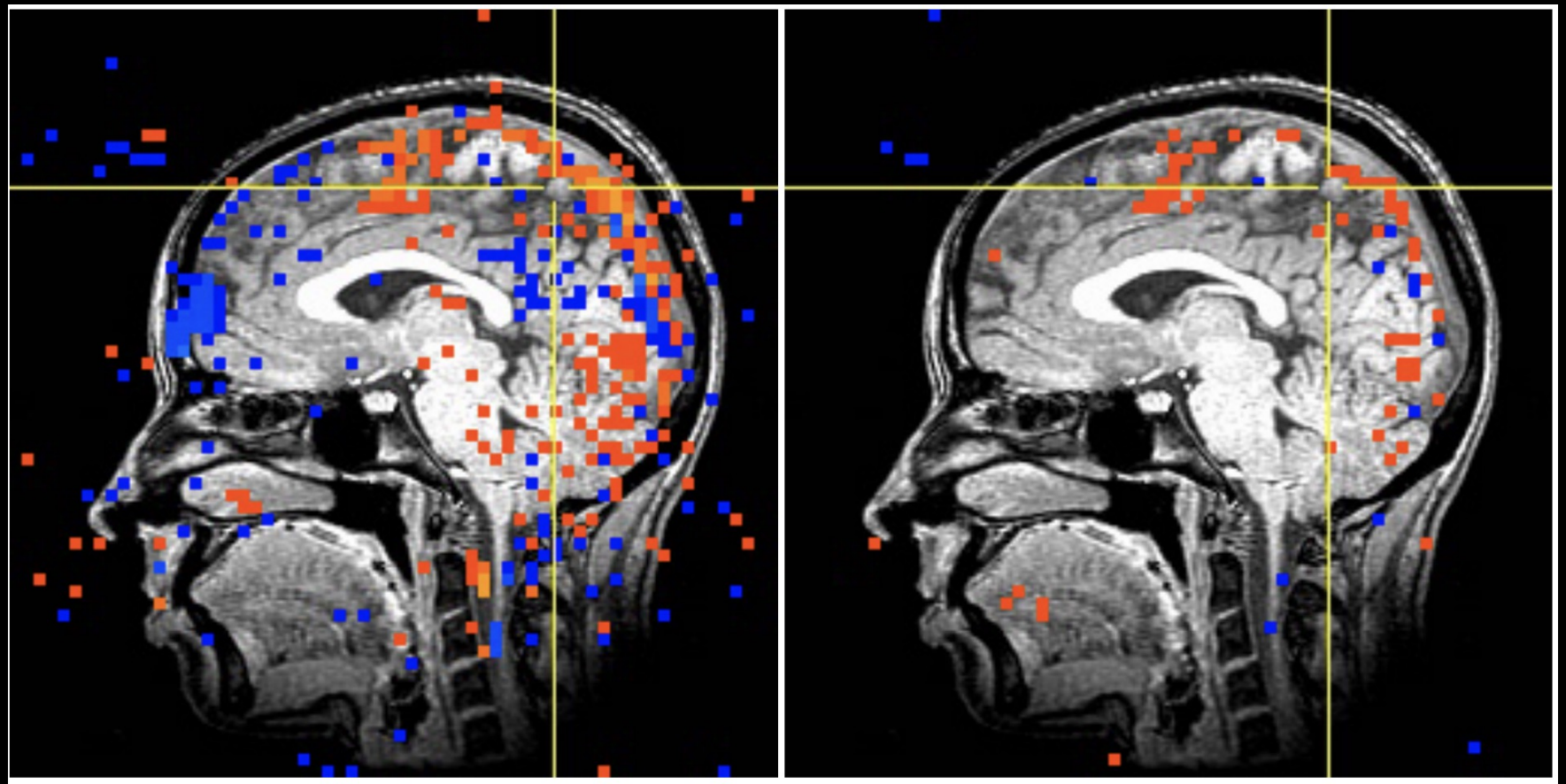




Applying the GLM to fMRI Data



Applying the GLM to fMRI Data

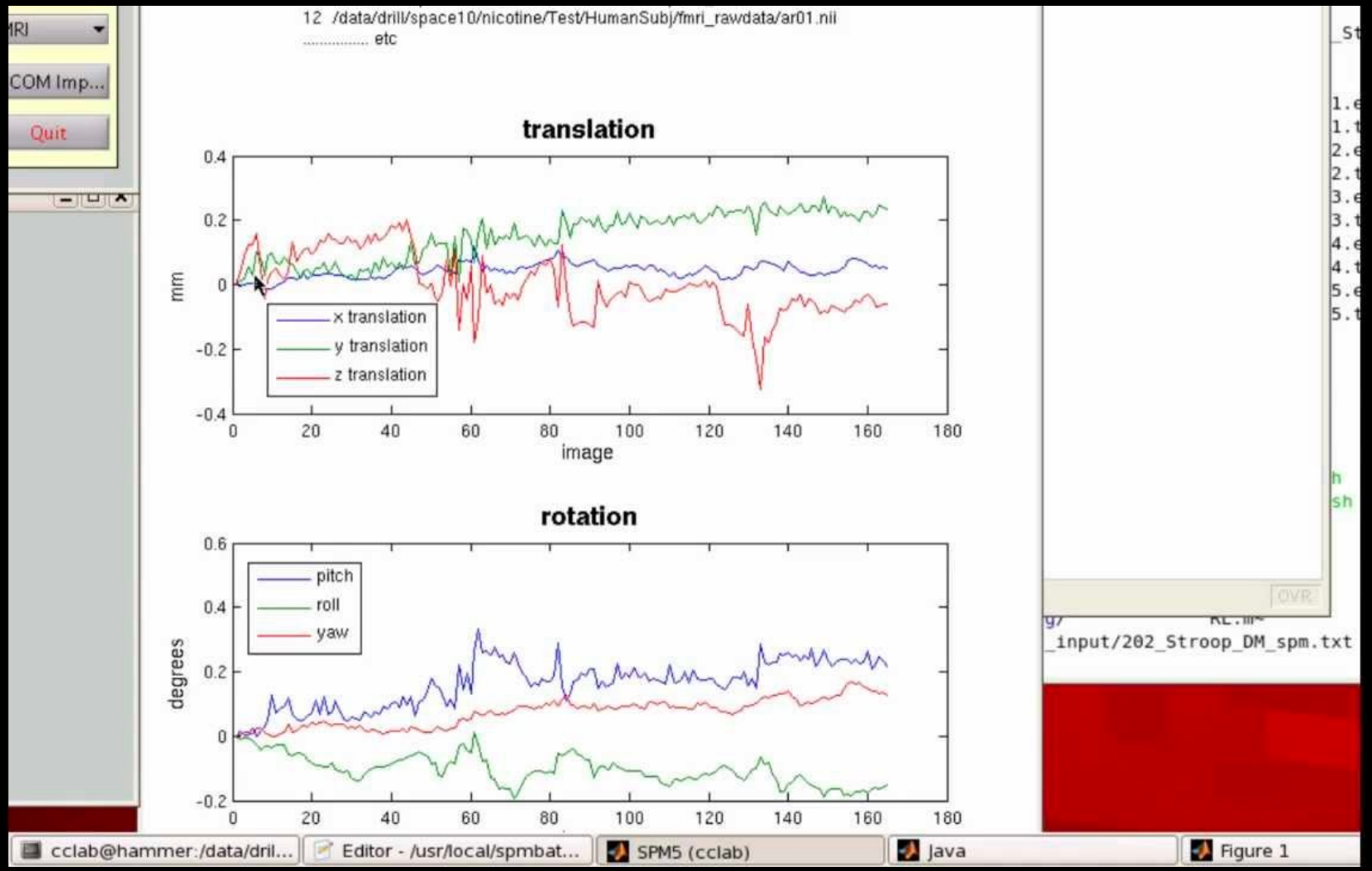


Activation map with image registration but *without* using movement estimates as regressors

Activation map when also using movement estimates as regressors

Source: AFNI

Applying the GLM to fMRI Data



Applying the GLM to fMRI Data

Perennial Question: How much is too much?

Guideline from days of yore: >1 voxel over entire run, >0.5 voxel between volumes

More important: Does motion correlate with your task?

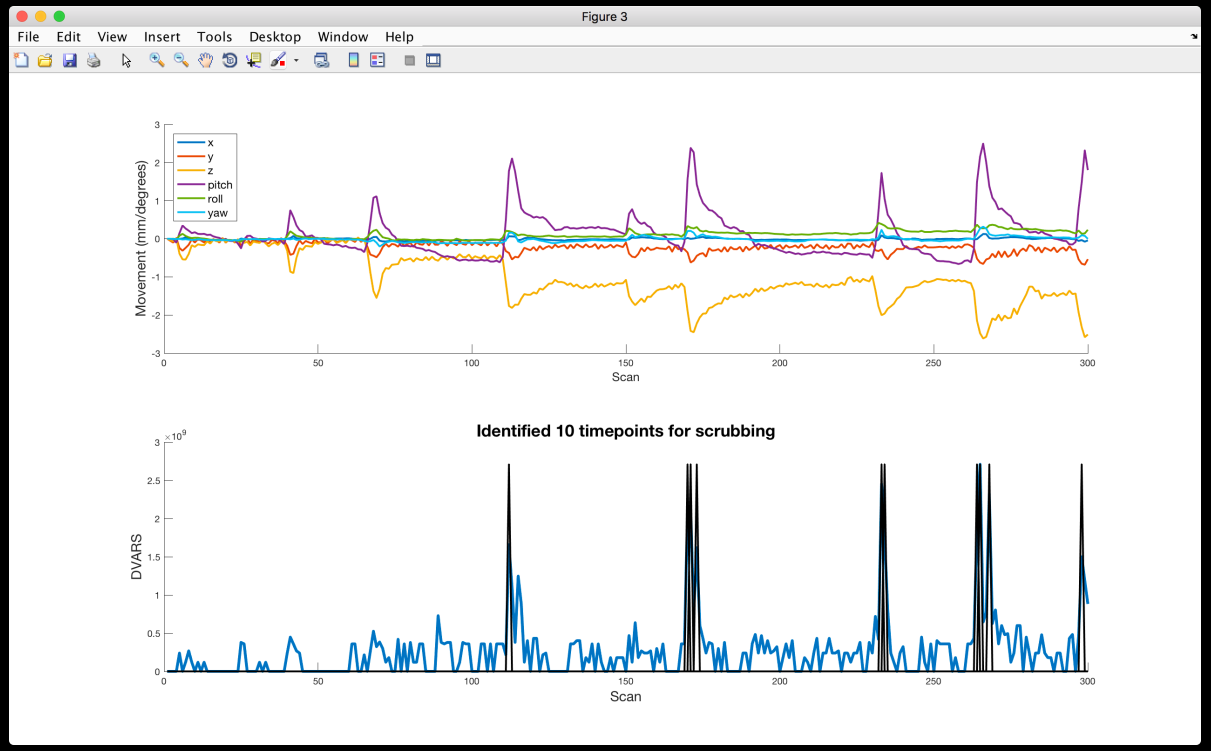
Applying the GLM to fMRI Data

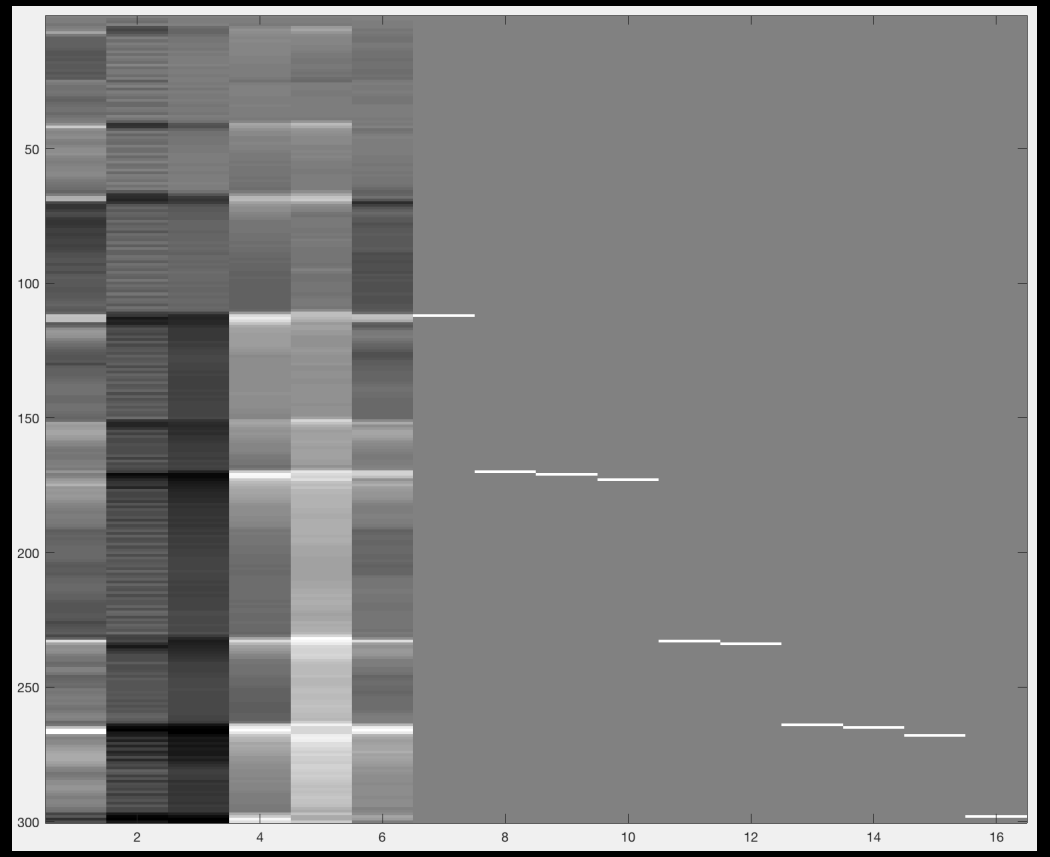
Other nuisance regressors: DVARS, Framewise Displacement (FD)

Derivative Variance (DVARS) measures abrupt global signal changes from volume to volume (Power et al., 2011)

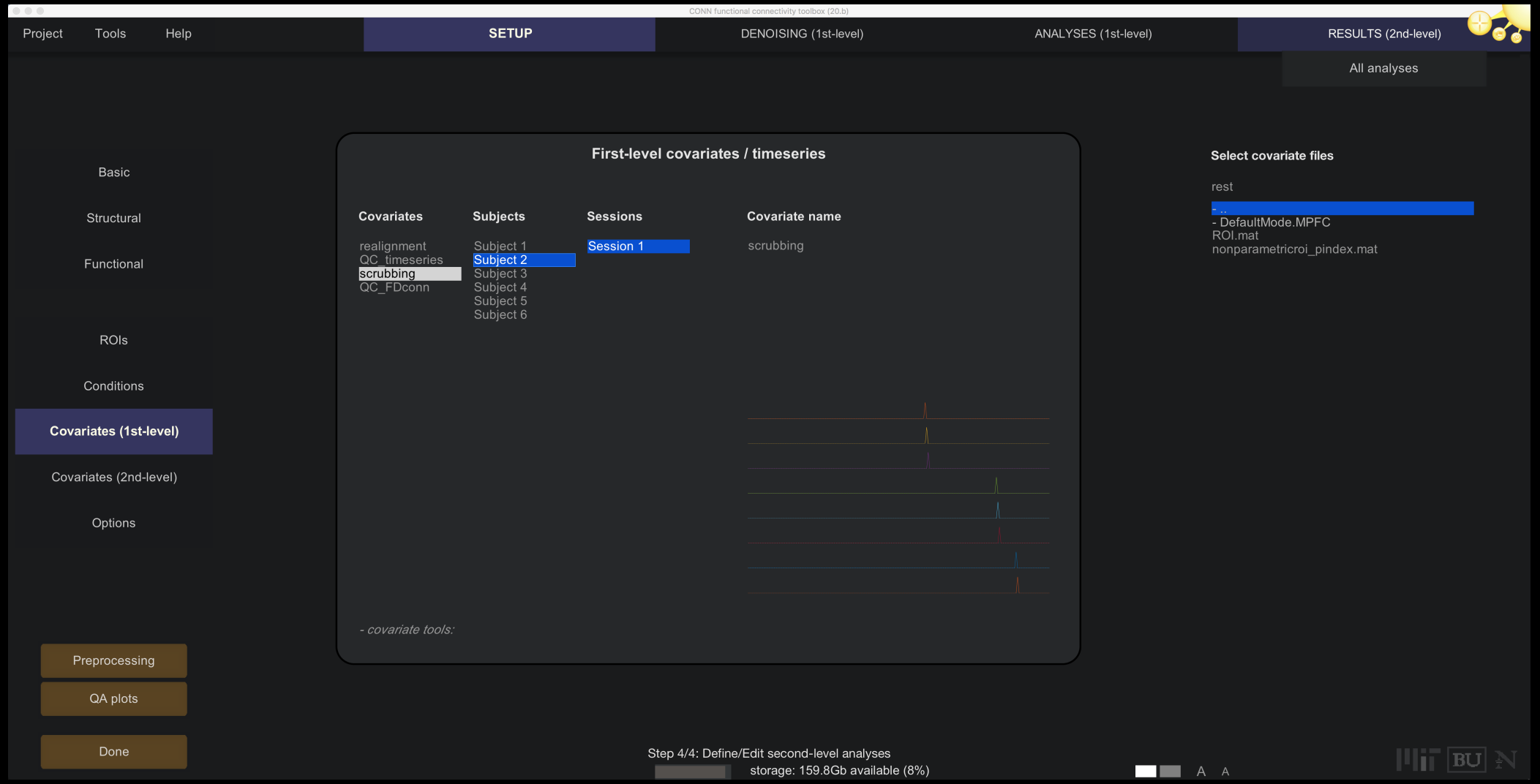
Volumes that exceed a specified threshold are flagged for scrubbing: Inserting that volume as a regressor into the GLM

Applying the GLM to fMRI Data





Applying the GLM to fMRI Data



Before we begin the Demo: SPM Terms for Analysis

1st-Level Analysis: Individual subject (all runs within the subject)

2nd-Level Analysis: Group-Level Analysis (all subjects within the experiment)

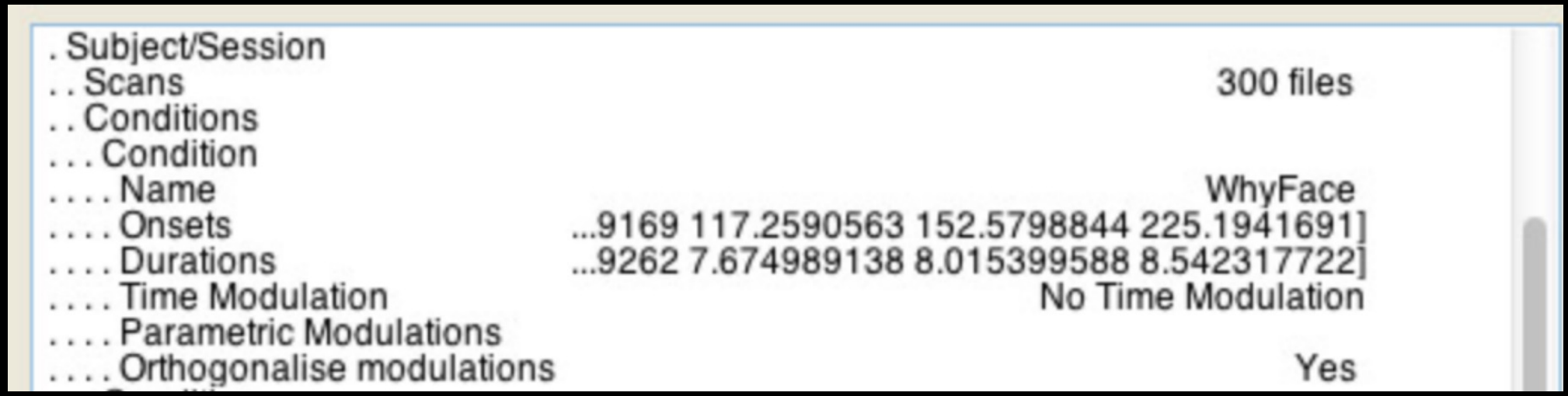
Also Before we begin: Contrasts and Contrast Weights

A contrast is simply one condition's beta weight subtracted from another

e.g., A-B

General recommendations: Model everything that is related to the task, and don't model any baseline events (e.g., implicit baseline)

Also Before we begin: Contrasts and Contrast Weights



Also Before we begin: Contrasts and Contrast Weights

Example: Pos/Neg/Neu images

Onset time (s)	Duration (s)	Description
11	4	Negative
17	.5	Face
27.5	4	Neutral
33.5	.5	Face

Also Before we begin: Contrasts and Contrast Weights

Example: Where is Pos activation greater than Neg activation?

Contrast weights for each side should sum to +1 and -1

	Pos IAPS	Neg IAPS	Neu IAPS	Face after Pos	Face after Neg	Face after Neu
PosIAPS > NegIAPS	1	-1	0	0	0	0

Also Before we begin: Contrasts and Contrast Weights

Where is Pos activation greater than Neu activation?

	Pos IAPS	Neg IAPS	Neu IAPS	Face after Pos	Face after Neg	Face after Neu
PosIAPS > NegIAPS	1	-1	0	0	0	0

Also Before we begin: Contrasts and Contrast Weights

Where is both Pos and Neg activation greater than Neu activation?

	Pos IAPS	Neg IAPS	Neu IAPS	Face after Pos	Face after Neg	Face after Neu
PosIAPS > NegIAPS	1	-1	0	0	0	0

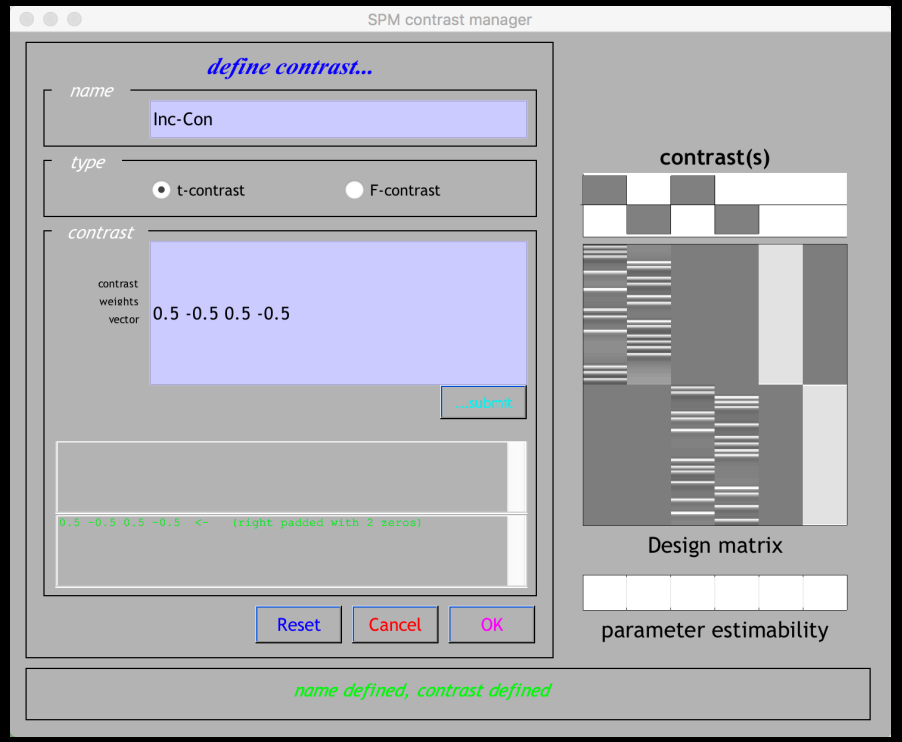
Also Before we begin: Contrasts and Contrast Weights

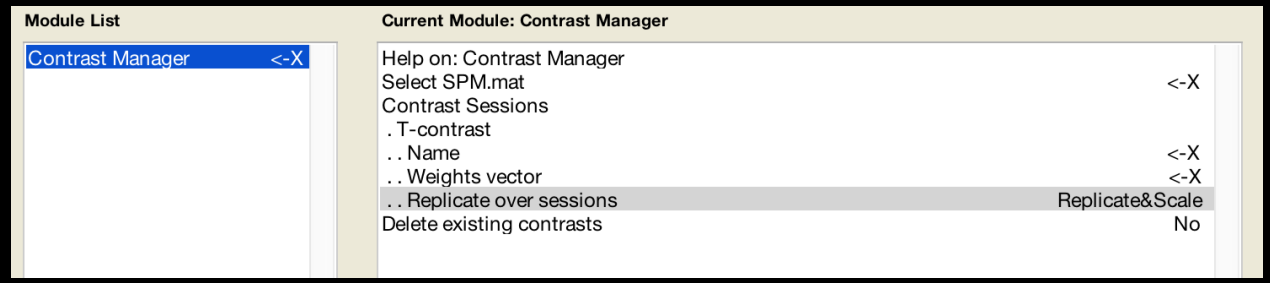
Where is average face activation greater than baseline?

	Pos IAPS	Neg IAPS	Neu IAPS	Face after Pos	Face after Neg	Face after Neu
PosIAPS > NegIAPS	1	-1	0	0	0	0

Also Before we begin: Contrasts and Contrast Weights

Contrast weights need to be weighted for number of runs as well





Also Before we begin: Contrasts and Contrast Weights

Module List

Named File Selector	
Realign: Estimate & Reslice	DEP
Slice Timing	DEP
Coregister: Estimate & Reslice	DEP
Segment	DEP
Normalise: Write	DEP
Smooth	DEP
File Set Split	DEP
fMRI model specification	DEP
Model estimation	DEP
Contrast Manager	DEP

Current Module: Contrast Manager

Help on: Contrast Manager	
Select SPM.mat	DEP Model estimation: SPM.mat File
Contrast Sessions	
. T-contrast	
. . Name	Inc-Con
. . Weights vector	[1 -1]
. . Replicate over sessions	Replicate&Scale
. T-contrast	
. . Name	Con-Inc
. . Weights vector	[-1 1]
. . Replicate over sessions	Replicate&Scale
. T-contrast	
. . Name	Inc
. . Weights vector	[1 0]
. . Replicate over sessions	Replicate&Scale
. T-contrast	
. . Name	Con
. . Weights vector	[0 1]
. . Replicate over sessions	Replicate&Scale
Delete existing contrasts	No

1st-level setup: Demonstration

Other Experimental Modeling Options

Parametric Modulation

Finite Impulse Response (FIR)

Why do these types of analyses?

Parametric Modulation

Uses Auxiliary Behavioral Information (ABI)

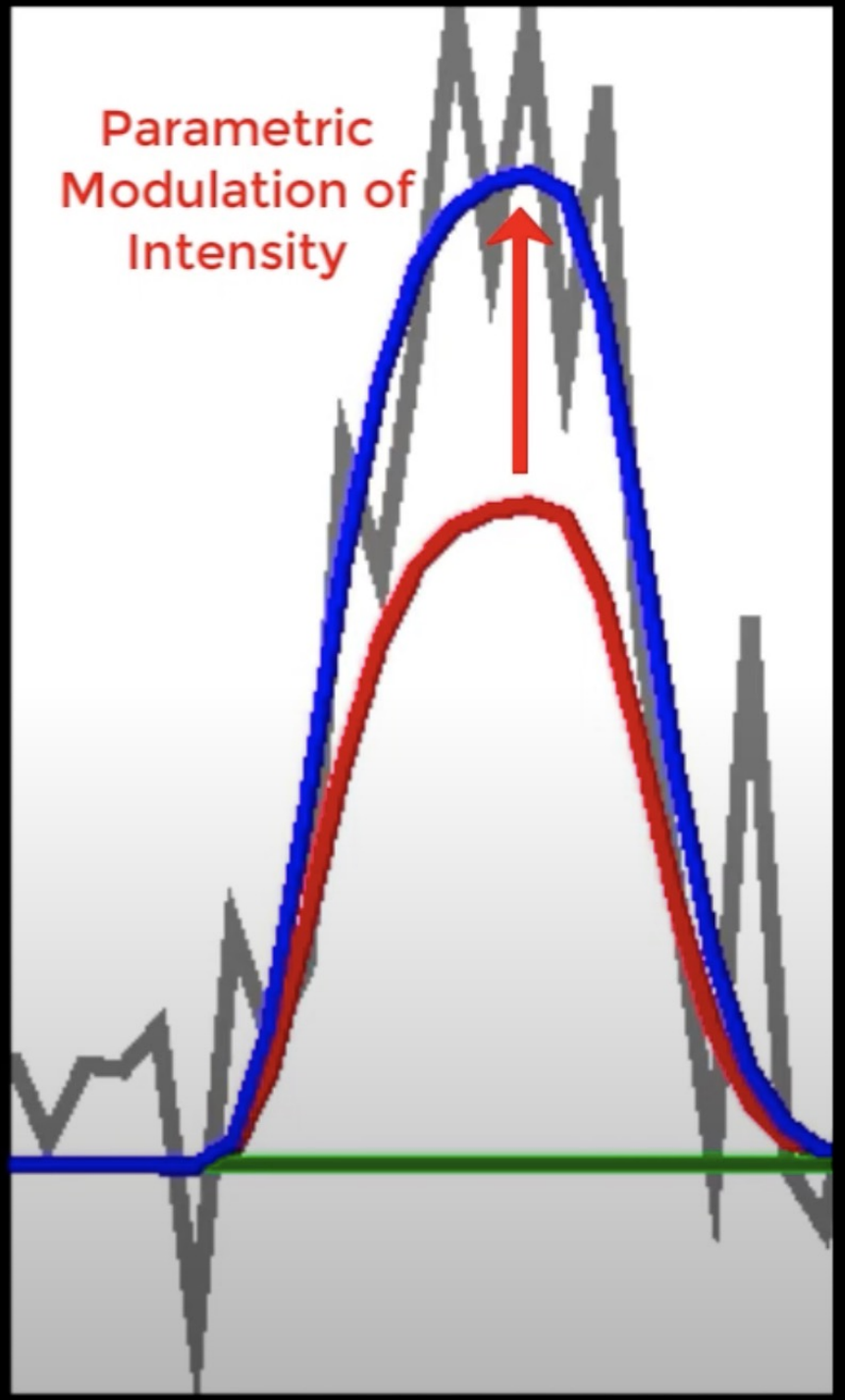
Continuous (or several finely graded) ABI levels

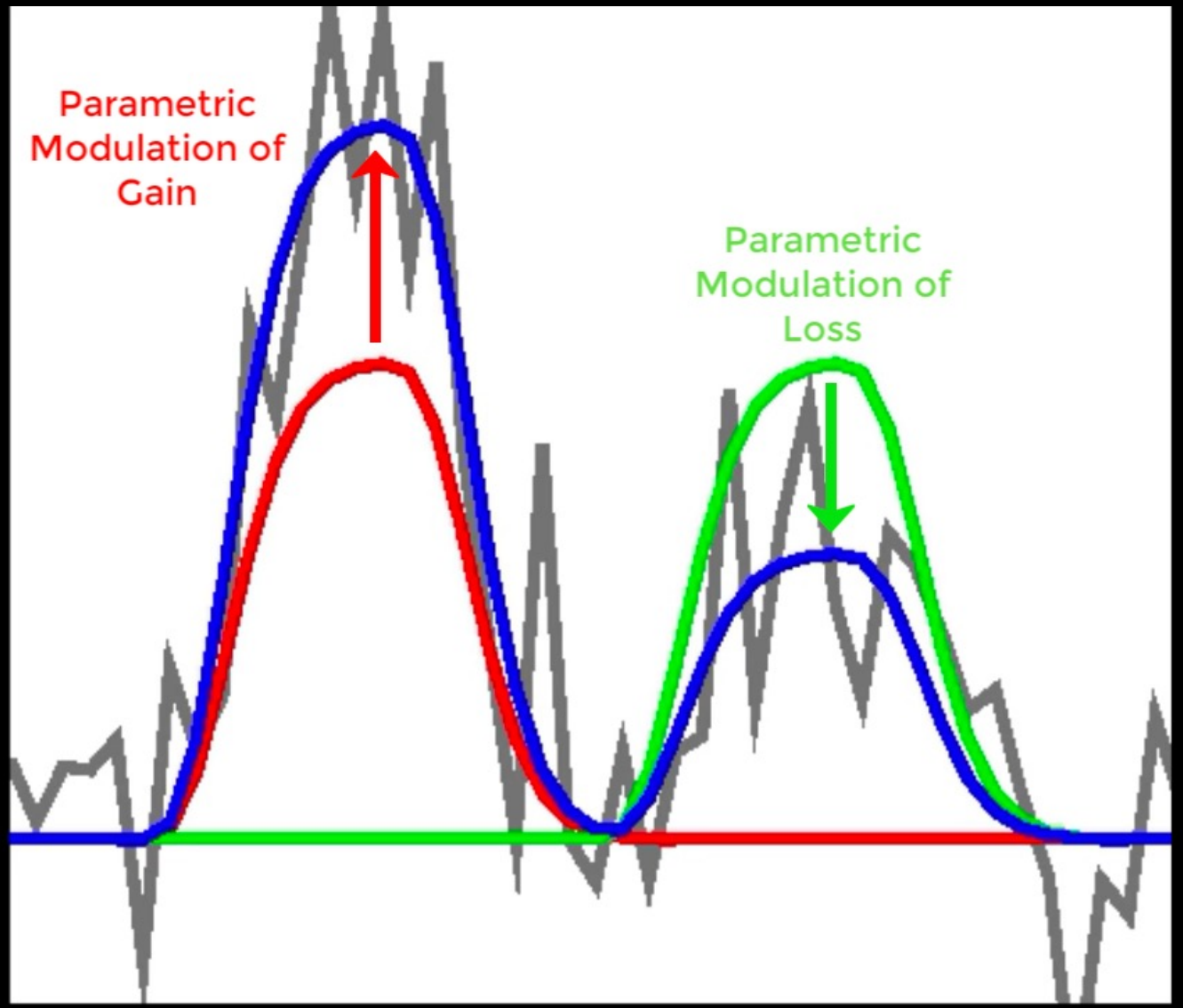
Parametric modulators are estimated in addition to the regressor they modulate

Parametric Modulation

Example: Light intensity

Regressor for a “Light” trial, and also a regressor for the intensity of the light


Parametric
Modulation of
Intensity


Parametric
Modulation of
Gain
Parametric
Modulation of
Loss

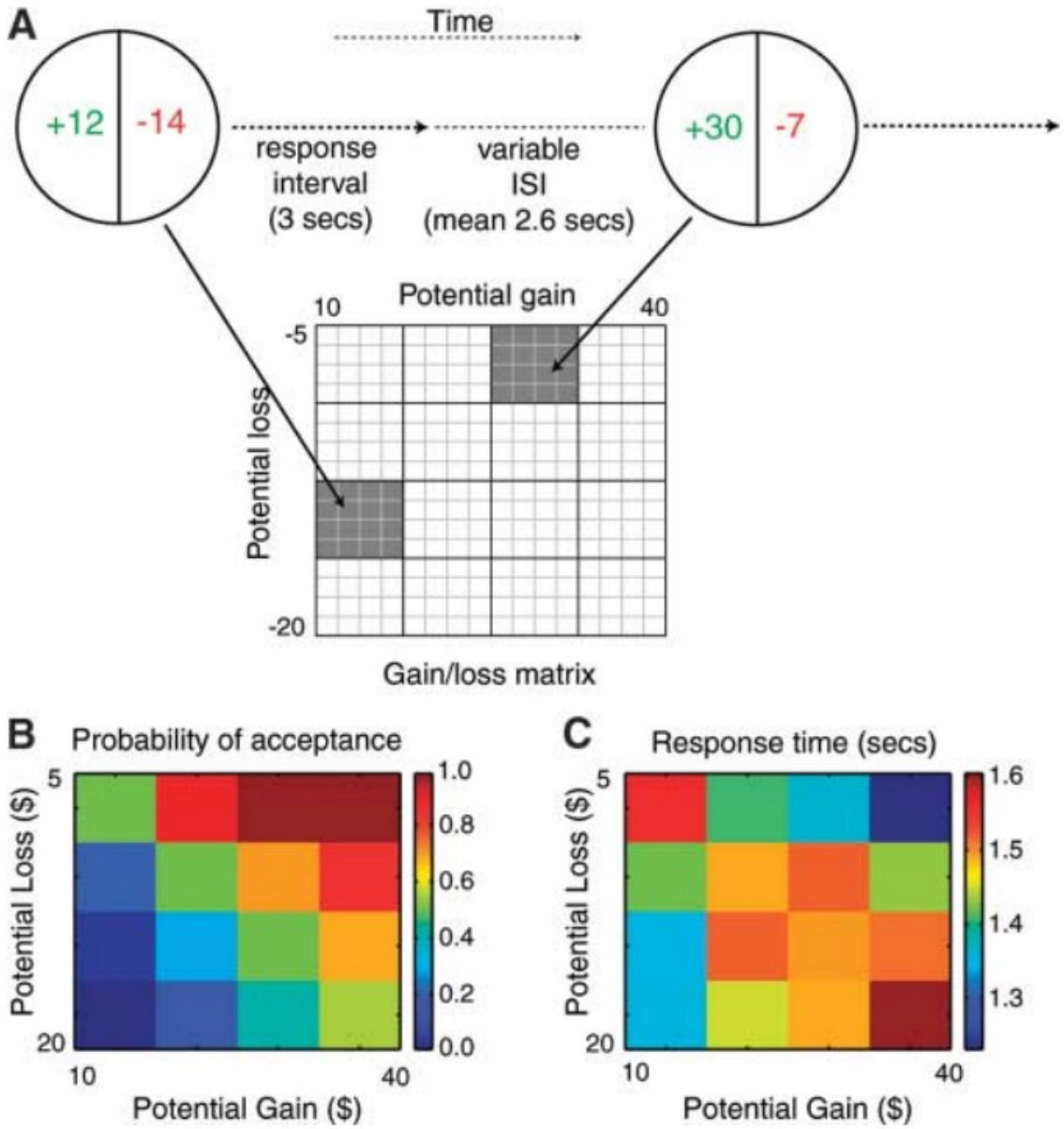


Fig. 1. (**A**) An illustration of the event-related task design. During each trial, the participant was presented for 3 s with a display showing the size of the potential gain (in green) and loss (in red). After the accept or reject response, a variable interval was presented to allow for optimal deconvolution of fMRI responses to each trial (*27*). Gambles were not resolved during scanning. The values of gain and loss for each trial were sampled from the gain/loss matrix, as shown here for two example gambles; a gamble from each cell in this 16 × 16 matrix was presented during scanning, but the data were collapsed into a 4 × 4 matrix for analysis. All combinations of gains and losses were presented. ISI, interstimulus interval. (**B**) Color-coded heatmap of probability of gamble acceptance at each level of gain/loss (red indicates high willingness to accept the gamble, and blue indicates low willingness to accept the gamble). (**C**) Color-coded heatmap of response times (red indicates slower response times, and blue indicates faster response times).

tion (*22*).

Examination of regions of interest in the striatum and VMPFC from the gain/loss conjunction analysis (Fig. 3) revealed that these

sitivity to losses versus gains) is highly correlated across risky and riskless contexts (*23*). Therefore, we surmise that a similar mechanism may contribute to other manifestations of loss aversion.

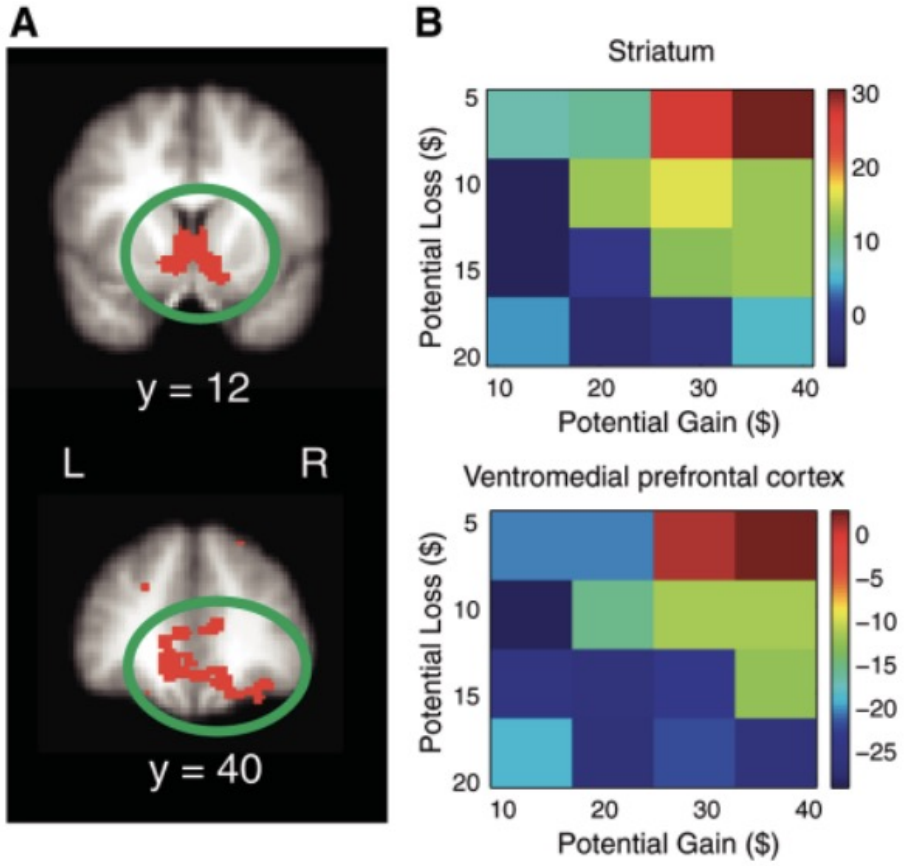


Fig. 3. Conjunction analysis results. (**A**) Map showing regions with conjointly significant positive gain response and negative loss response ($P < 0.05$, whole-brain corrected, in each individual map) (see also table S1). Red pixels indicate regions showing significant conjunction; green circles highlight clusters included in the respective heatmaps to the right. L, left; R, right. (**B**) Heatmaps were created by averaging parameter estimates versus baseline within each cluster in the conjunction map for each of the 16 cells (of 16 gambles each) in the gain/loss matrix; color coding reflects strength of neural response for each condition, such that dark red represents the strongest activation and dark blue represents the strongest deactivation.

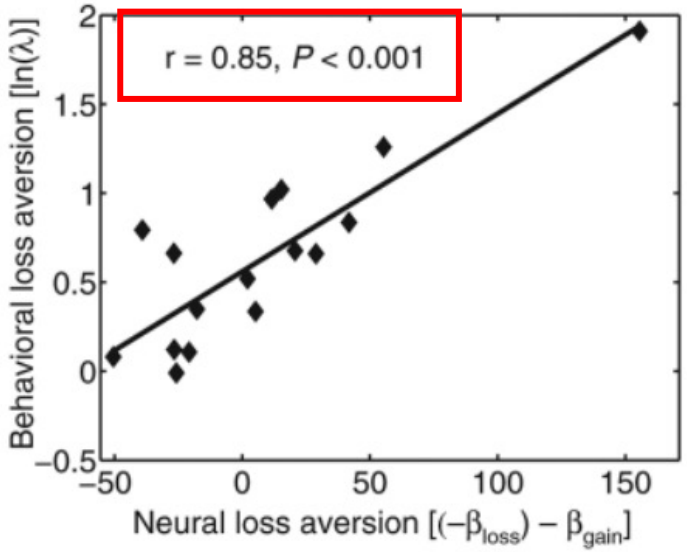
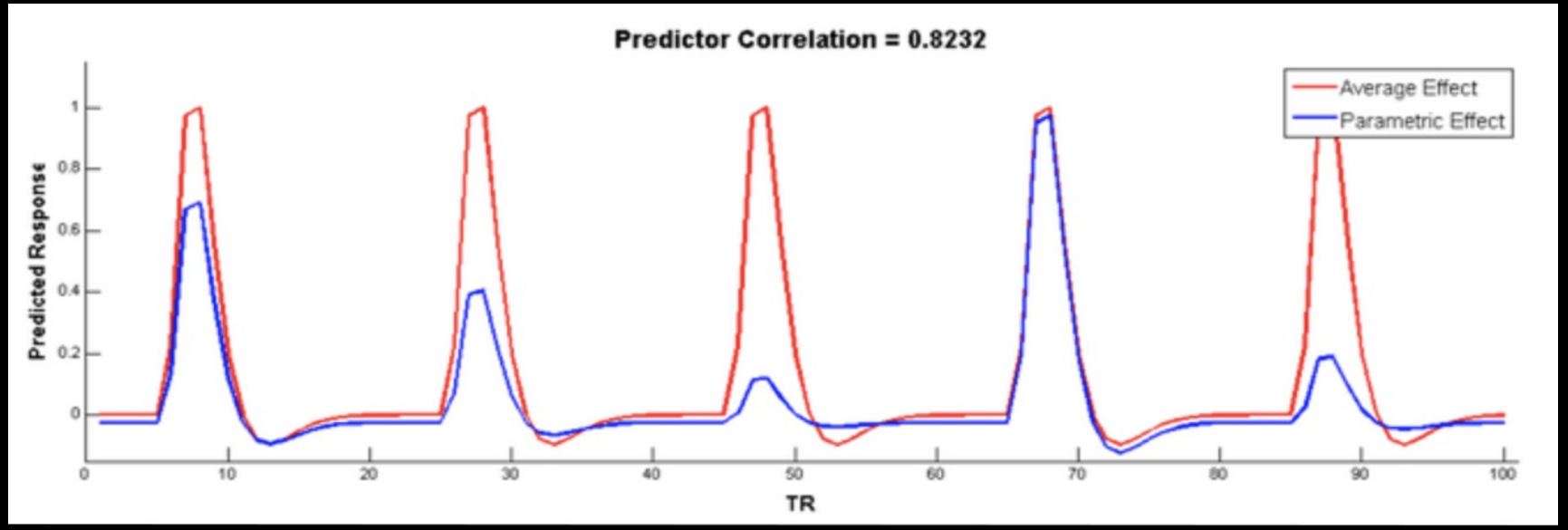
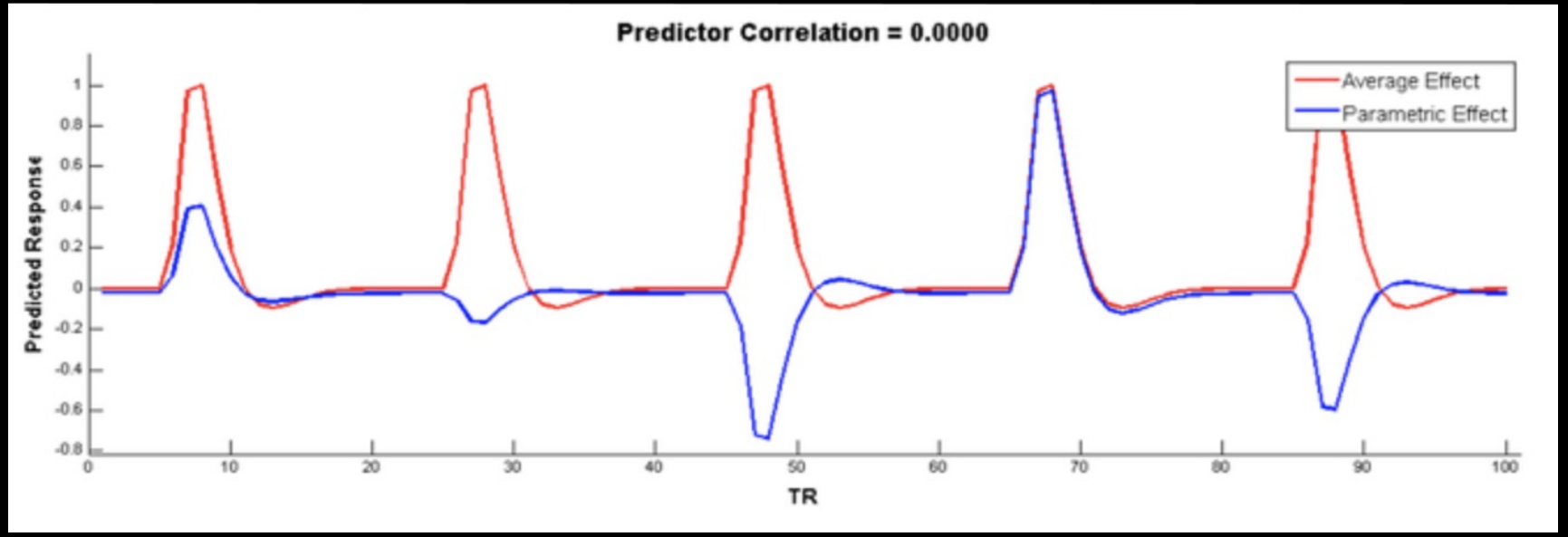


Fig. 4. Scatterplot of correspondence between neural loss aversion and behavioral loss aversion in ventral striatum [Montreal Neurological Institute coordinates (*x*, *y*, *z*): 3.6, 6.3, 3.9; center of gravity in millimeters]. Regression line and *P* value were computed with the use of robust regression by iteratively reweighted least squares to prevent the influence of outliers; however, this regression also remained highly significant ($P = 0.004$) when the extreme data point (top right-hand corner) was removed from the analysis. β_{loss} and β_{gain} are the unstandardized regression coefficients for the loss and gain variables, respectively.

Parametric Modulation: Mean Centering



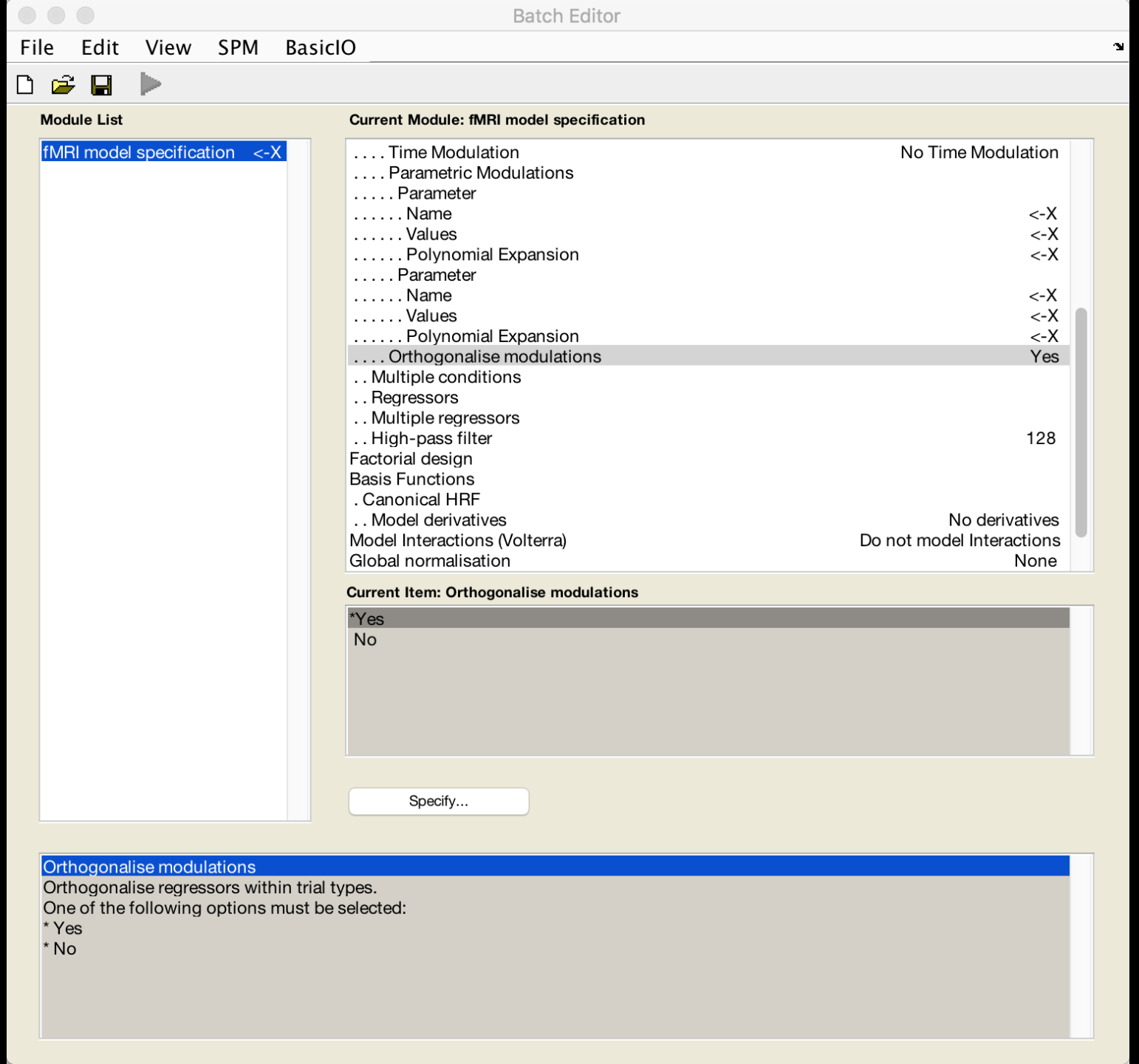


Courtesy of
Bob Spunt

Parametric Modulation: Other Considerations

Orthogonalizing the regressors as part of the design

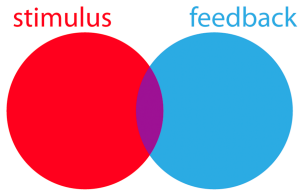
Orthogonalizing as part of the GLM

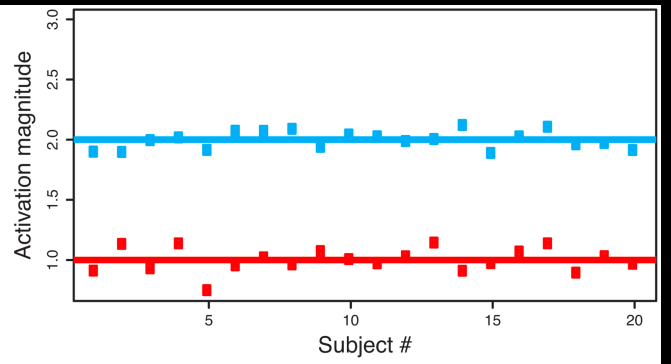


Should be set to “No”

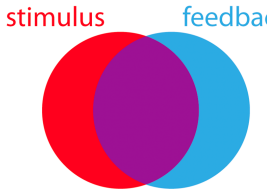
Why?

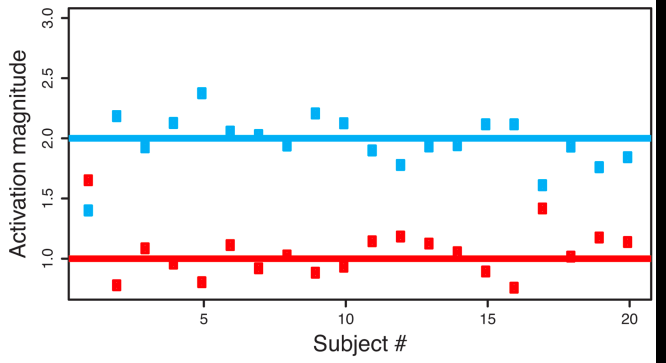
Low collinearity
ISI=3s



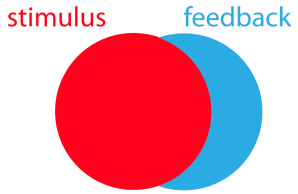


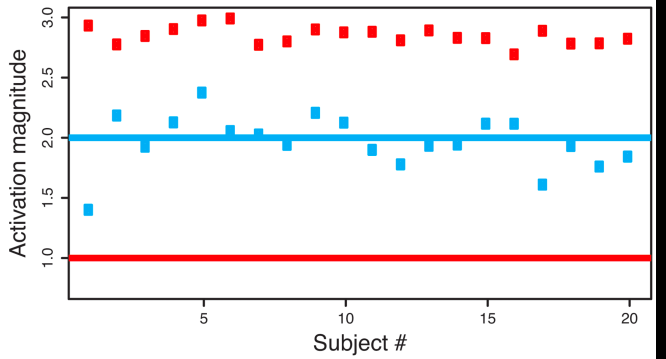
High collinearity
ISI=1s





Feedback orthogonalized with respect to Stimulus

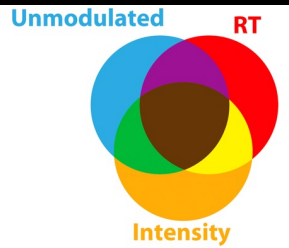




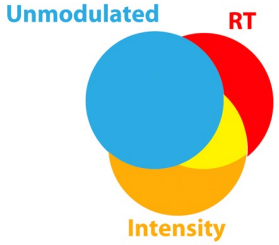
Mumford et al., 2015

Why?

Regressors without orthogonalization

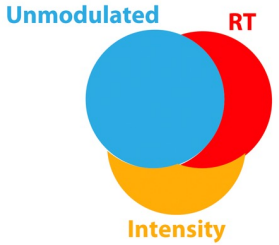


Correct orthogonalization for interpretable Unmodulated



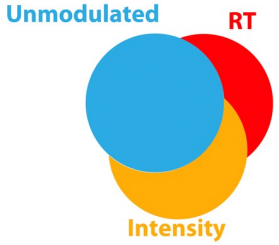
RT wrt Unmod
Intensity wrt Unmod

SPM
RT first
Intensity second



RT wrt Unmod
Intensity wrt Unmod and RT

SPM
Intensity first
RT second



RT wrt Unmod and Intensity
Intensity wrt Unmod

Demonstration of Parametric Modeling Setup

Other Experimental Modeling Options

Parametric Modulation

Finite Impulse Response (FIR)

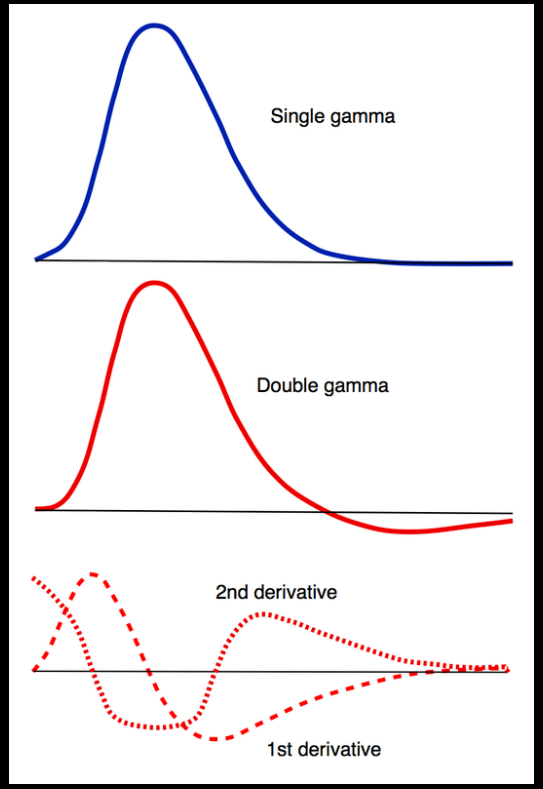
Other Experimental Modeling Options

Parametric Modulation

Finite Impulse Response (FIR)

Finite Impulse Response (FIR)

Basis functions such as the HRF assume a stereotypical shape



Source: mri-q.com

Finite Impulse Response (FIR)

But what if we don't want to assume a shape?

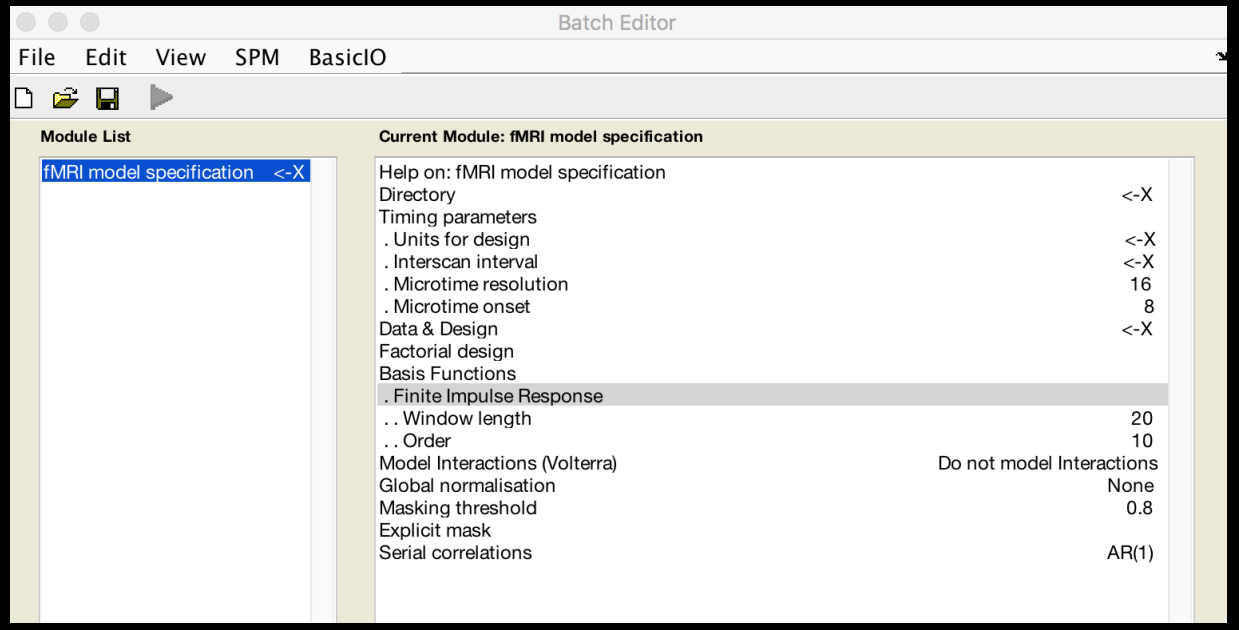
Example: You want to see whether the peak for condition A is later than the peak for condition B

Another example: You think the overall shape of the BOLD response is different between patients and controls, even though the amplitude is the same

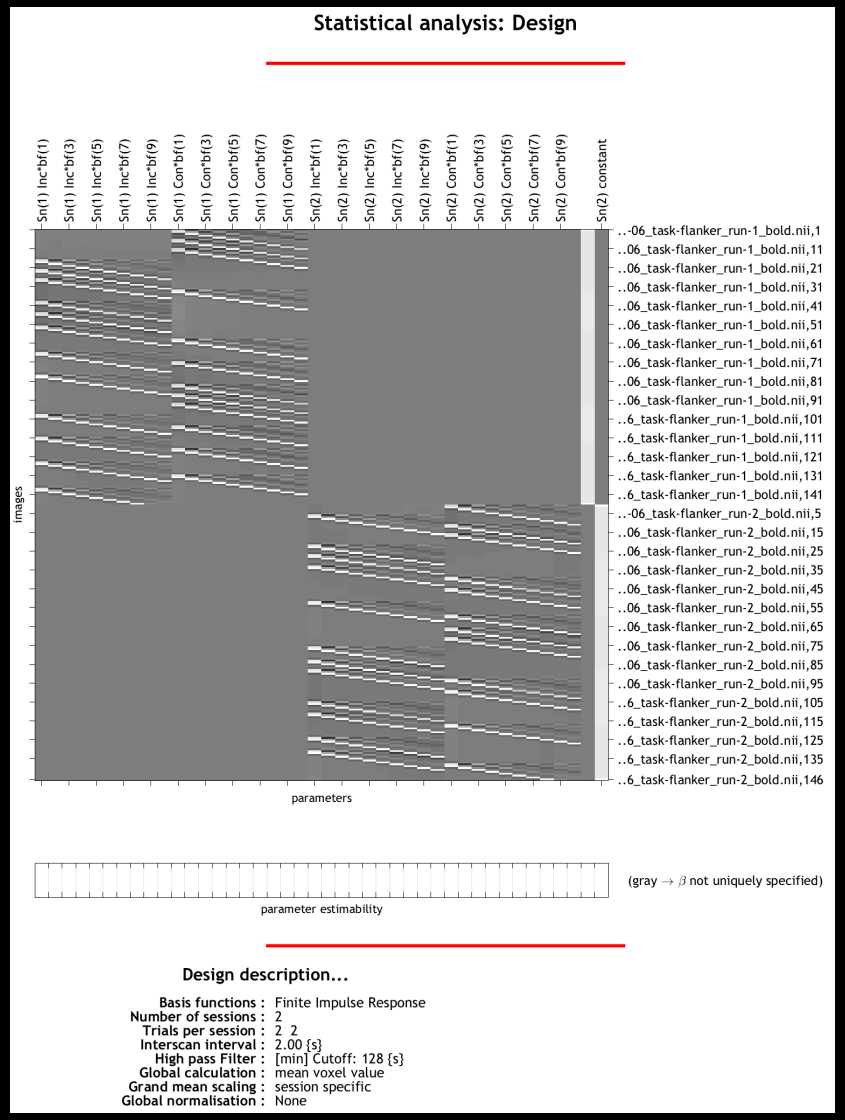
Finite Impulse Response (FIR)

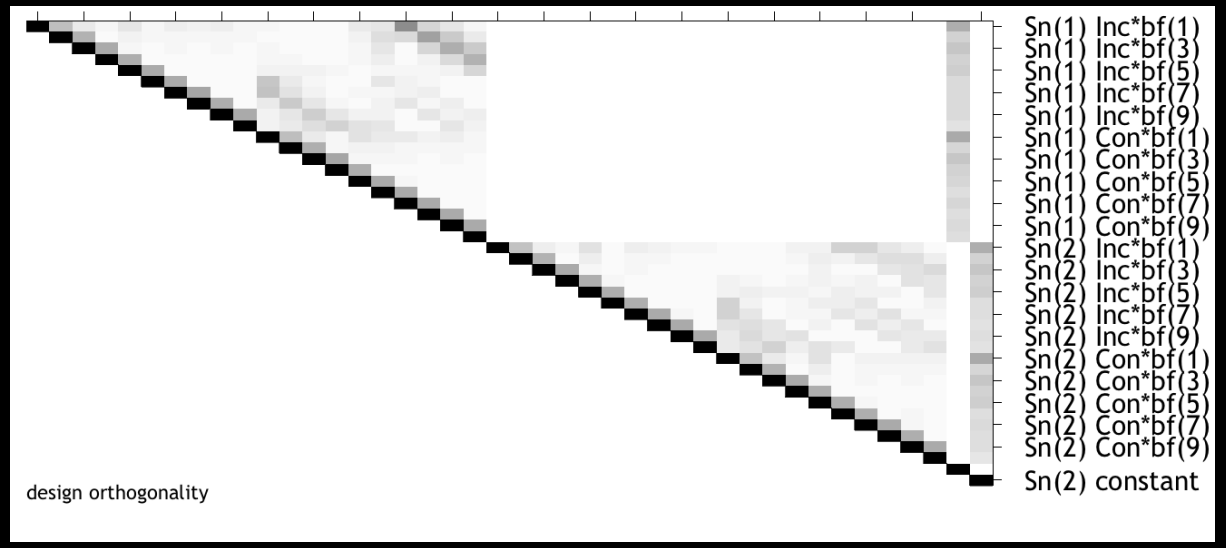
You specify the window length and number of timepoints

e.g.: 20s window, 10 timepoints



Finite Impulse Response (FIR)





Finite Impulse Response (FIR)

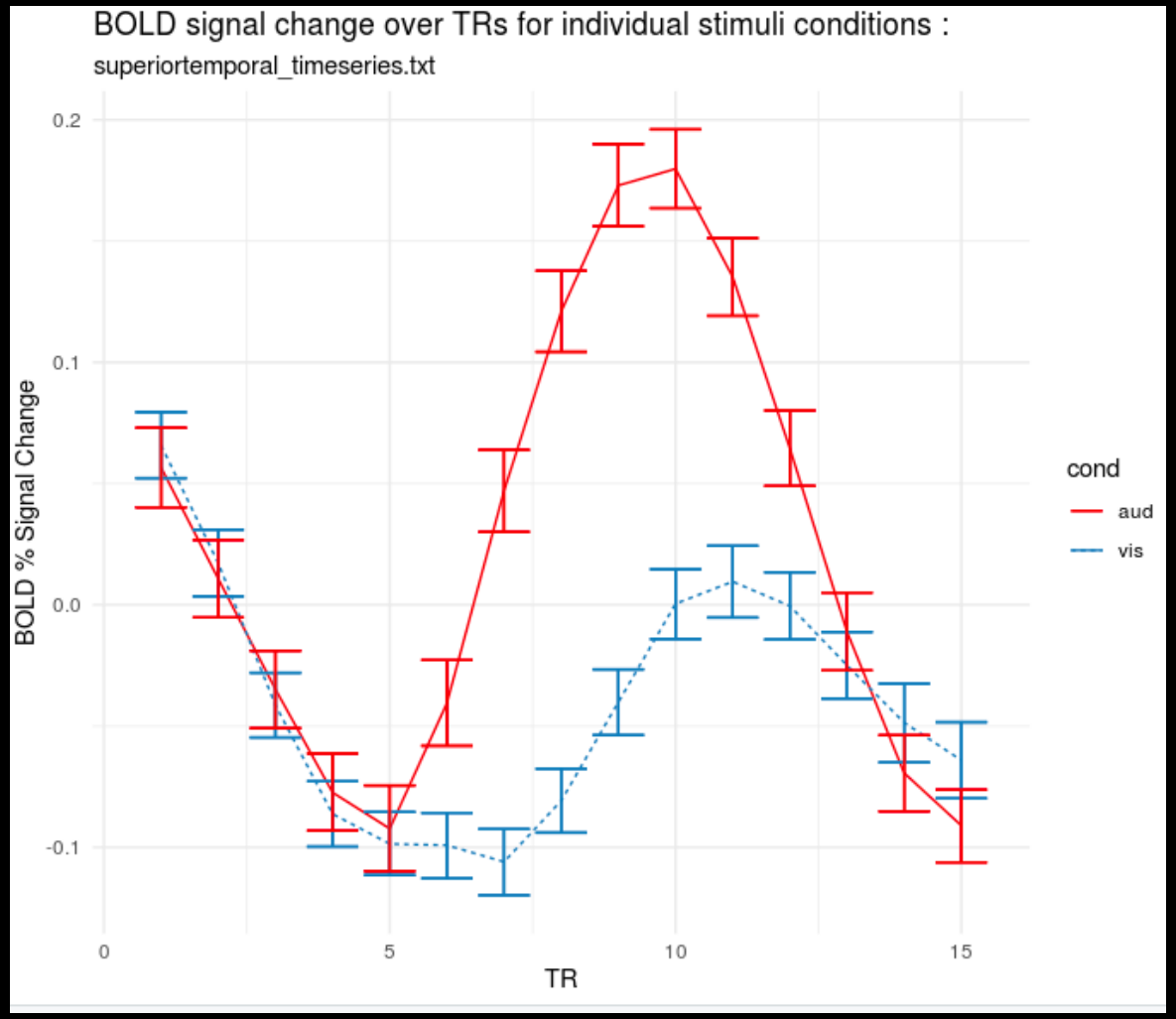
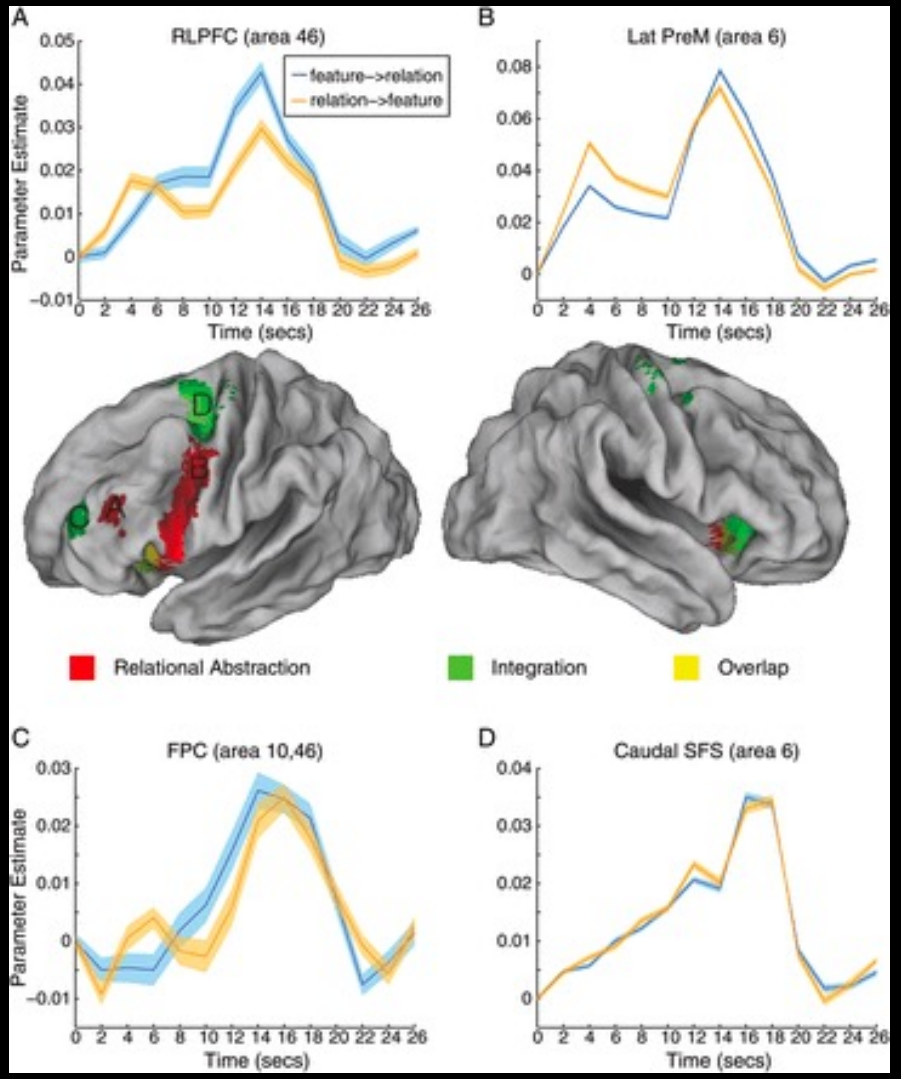


Image by Karthik Ganesan

Finite Impulse Response (FIR)



Nee et al., 2013

Demonstration of FIR Modeling Setup

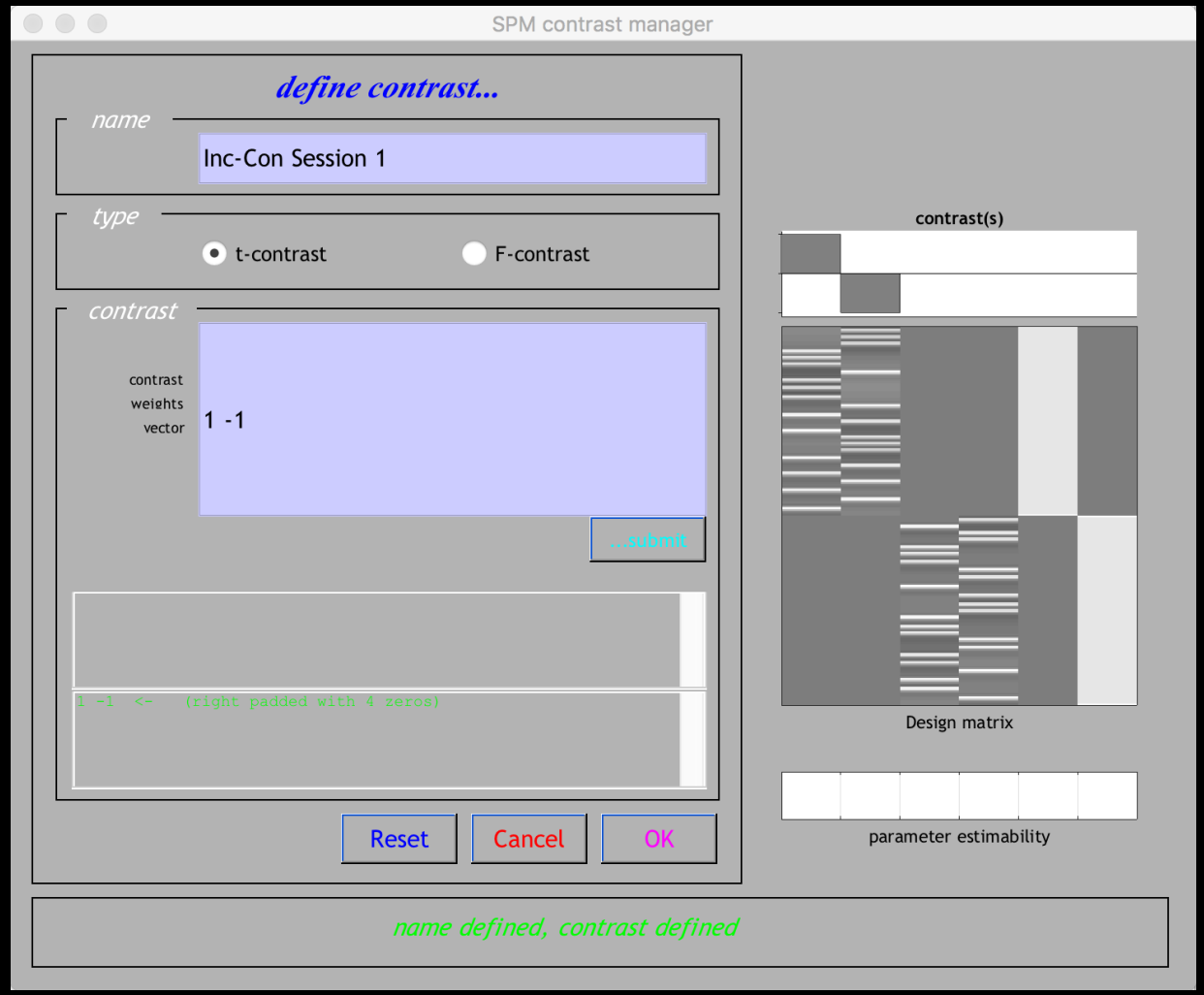
ImCalc: The Image Calculator

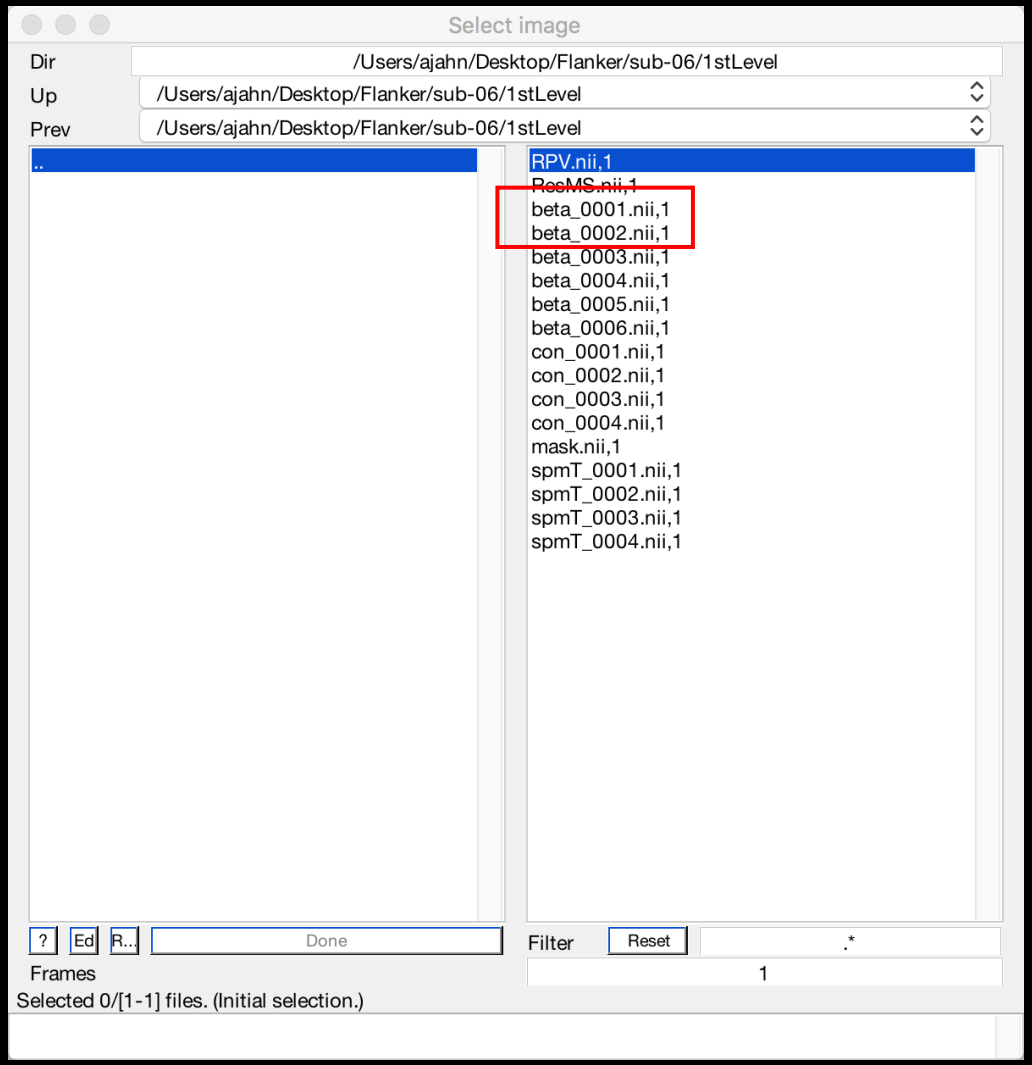
One of the most versatile tools is the image calculator

Every package has one (AFNI, FSL, MRtrix, etc.)

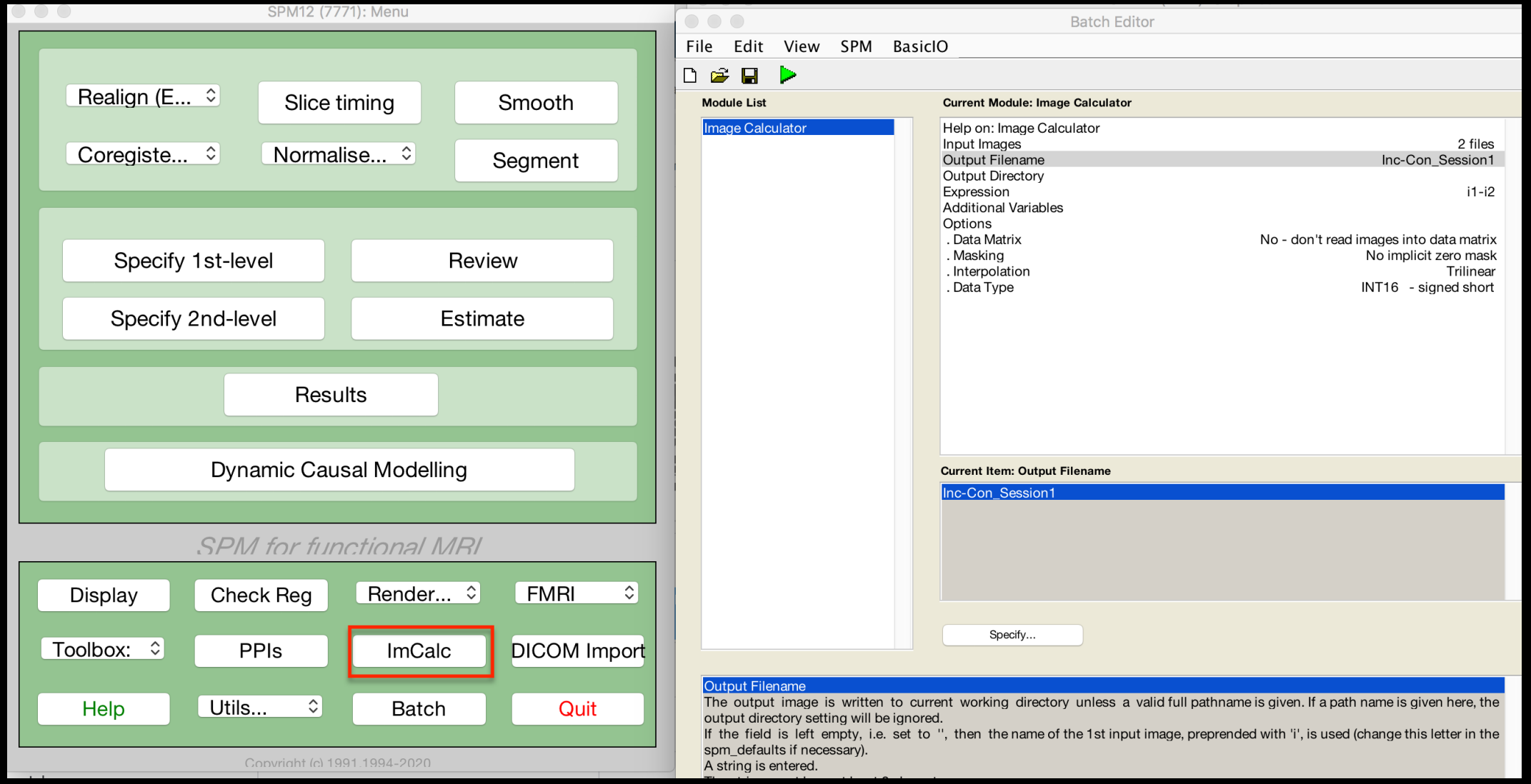
Simple to do basic arithmetic on a 3D image

ImCalc: The Image Calculator

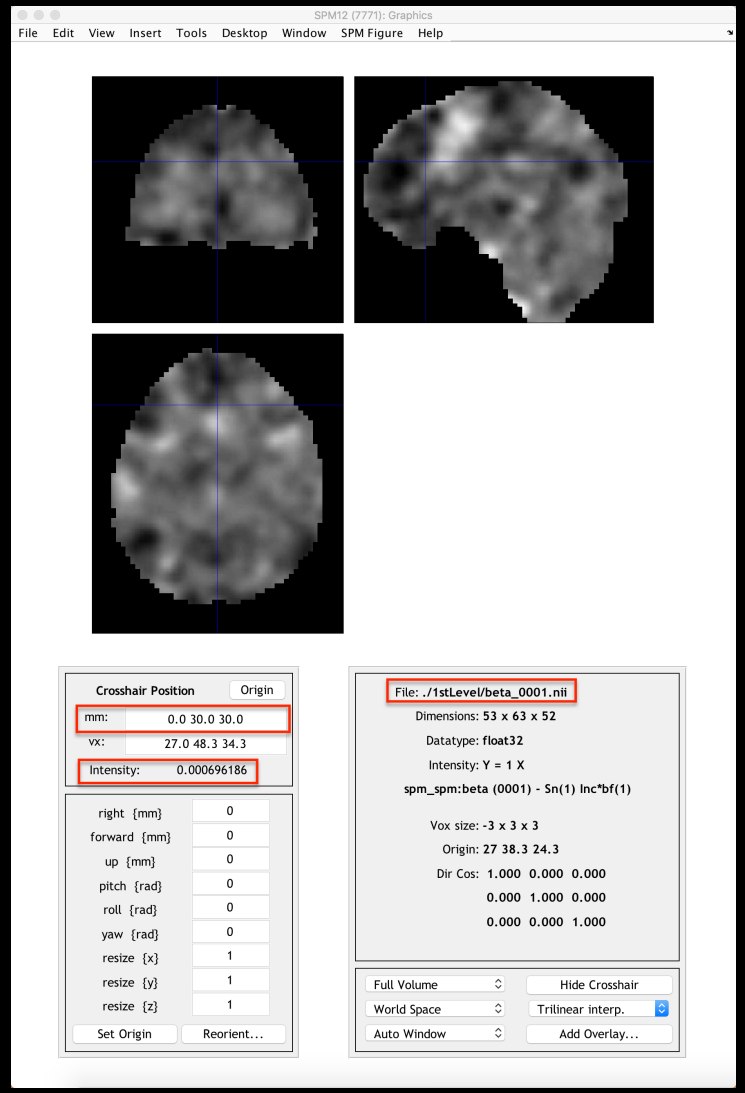


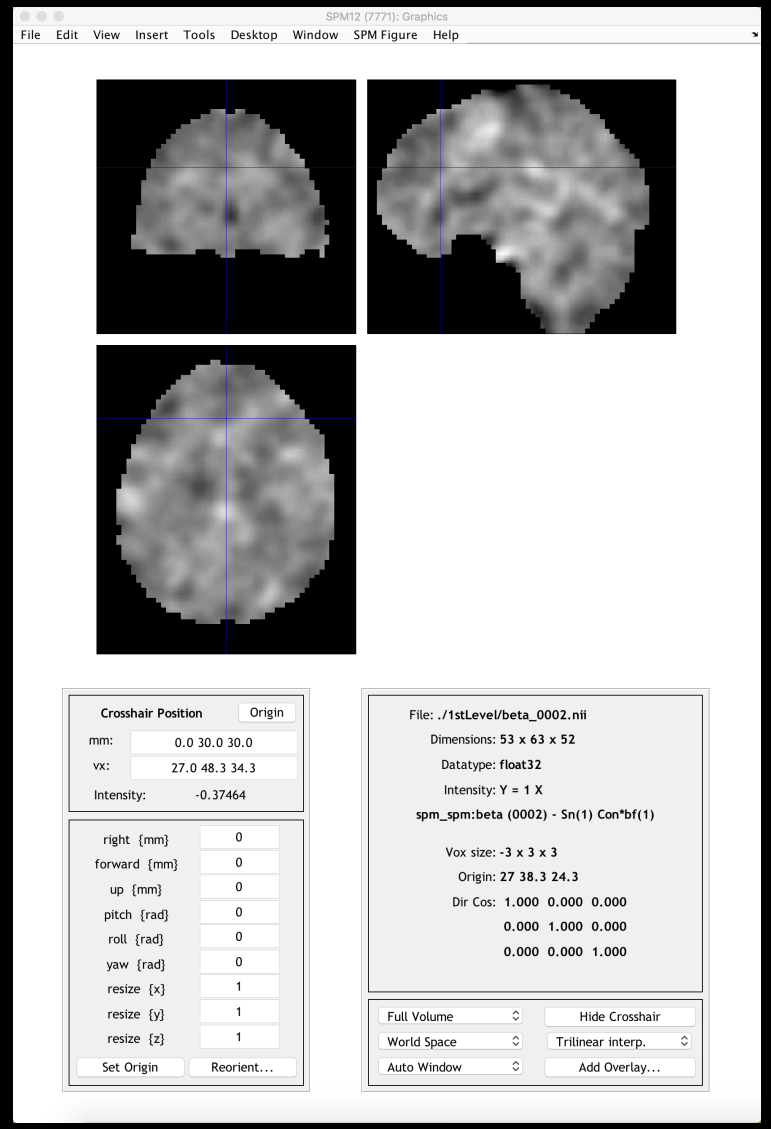


ImCalc: The Image Calculator

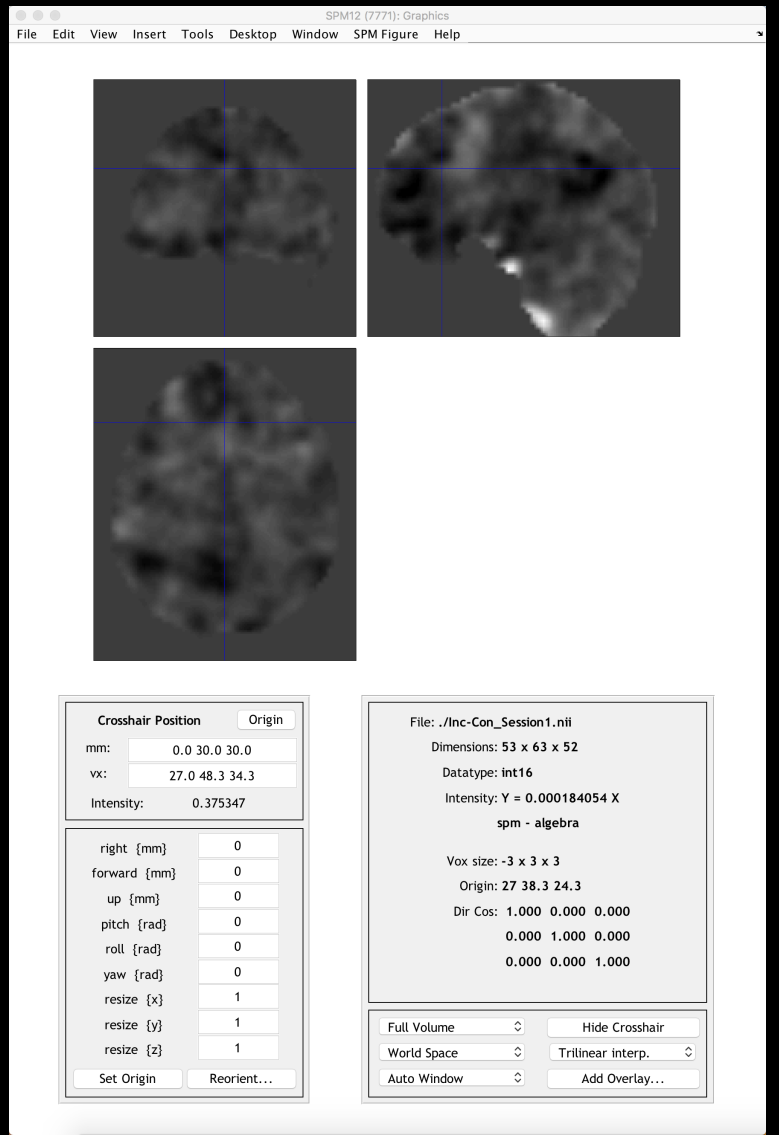


ImCalc: The Image Calculator





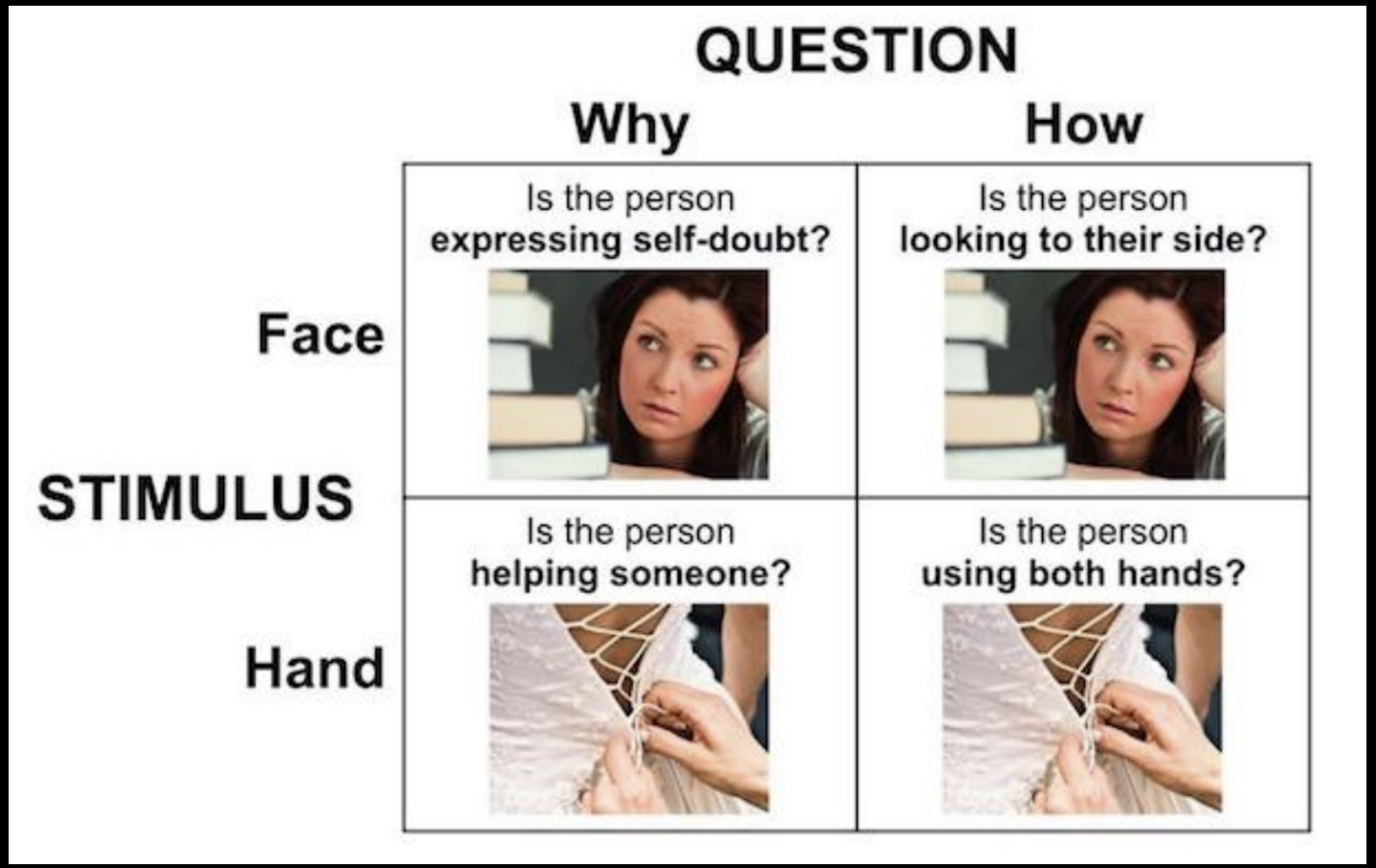
ImCalc: The Image Calculator



Demonstration

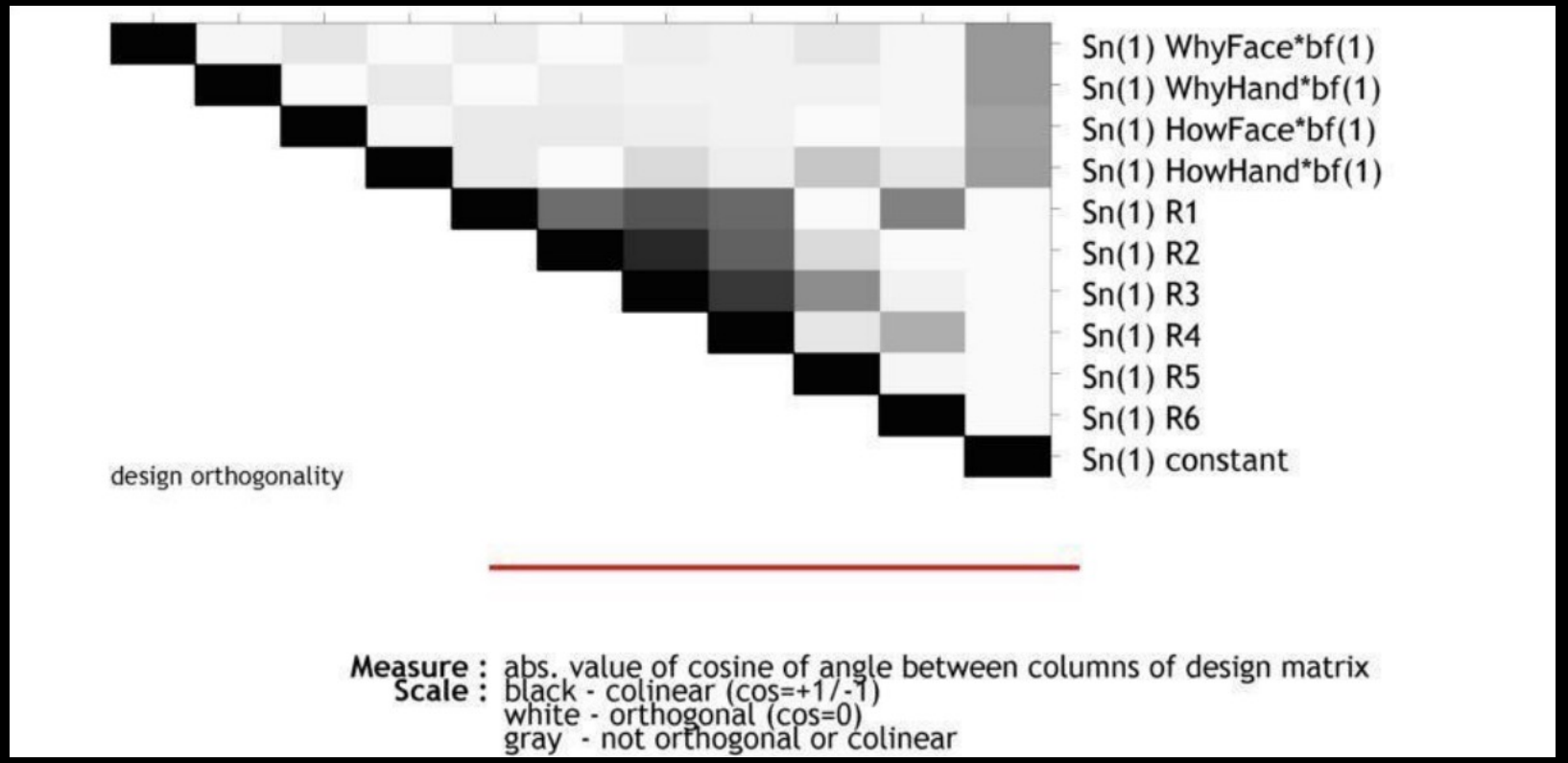
Preview of Today's Lab

Dataset collected by Emily Falk; 2x2 factorial design



Preview of Today's Lab

Block design



Preview of Today's Lab

. . . . Name	HowFace
. . . . Onsets	...284 135.0593544 171.3800147 243.0883199]
. . . . Durations	...4532 10.7859291 8.894711134 9.210554915]
. . . . Time Modulation	No Time Modulation
. . . . Parametric Modulations	
. . . . Orthogonalise modulations	Yes
. . . Condition	
. . . . Name	HowHand
. . . . Onsets	...6296 80.6916593 189.4403629 264.5608179]
. . . . Durations	...313 10.45648544 9.137848595 10.19211621]
. . . . Time Modulation	No Time Modulation
. . . . Parametric Modulations	
. . . . Orthogonalise modulations	Yes
. . Multiple conditions	
. . Regressors	
. . Multiple regressors	...eLab/sub05/func/whyhow/run_01/rp_run_01.txt
. . High-pass filter	128
Factorial design	
Basis Functions	
. Canonical HRF	
. . Model derivatives	No derivatives
Model Interactions (Volterra)	Do not model Interactions
Global normalisation	None
Masking threshold	0.8
Explicit mask	
Serial correlations	AR(1)

Current Item: Directory

Questions?