Principles of fMRI

Part II

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Basis Sets II

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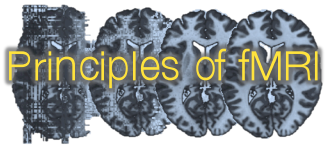
Temporal Basis Functions

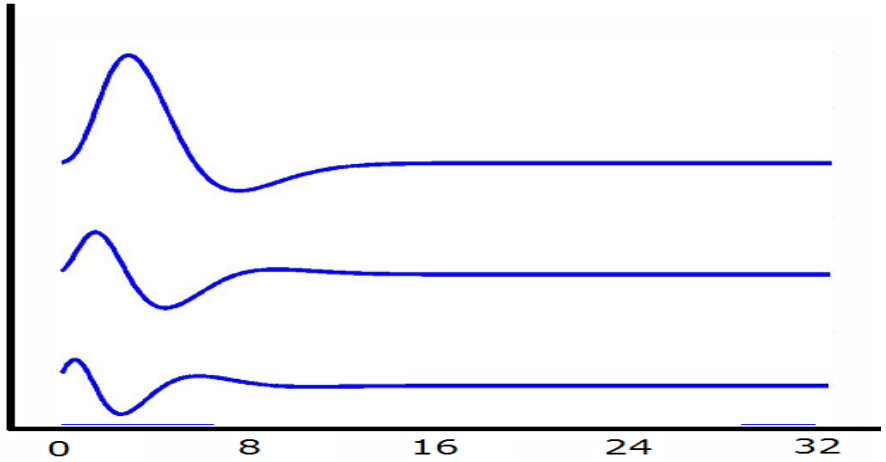


- Recall that when performing the GLM we often use temporal basis functions to allow for different types of HRFs in different brain regions.

- These consist of a linear combination of pre-specified temporal functions:
  - The stimulus function is convolved with each of the basis functions to give a set of predictors.
  - The parameter estimates are weights on the basis functions, so that the weighted average provides a model for the hemodynamic response.
  - Usually fit for each trial type in each voxel for each subject.

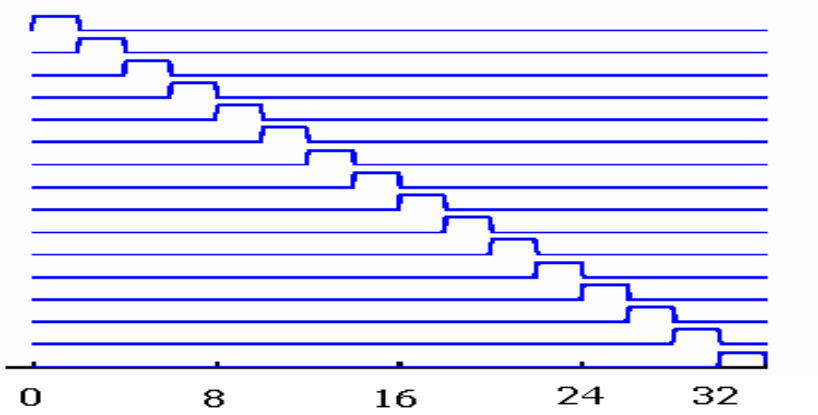
Basis Sets

Canonical HRF + Derivatives



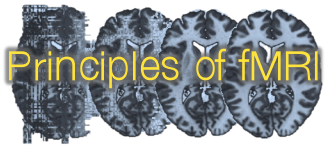
Including the derivatives allows for a shift in delay and dispersion.

Finite Impulse Response



Estimates an HRF of arbitrary shape for each event type in each voxel of the brain

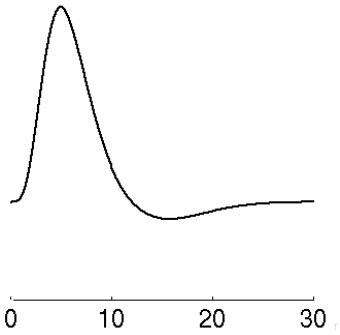
Basis Sets

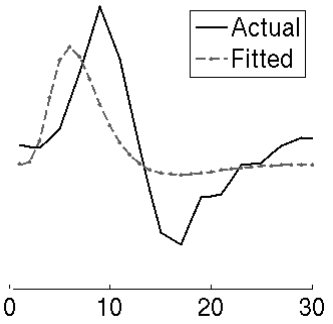


Basis functions

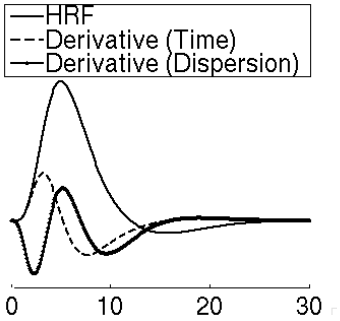
Data & Fitted

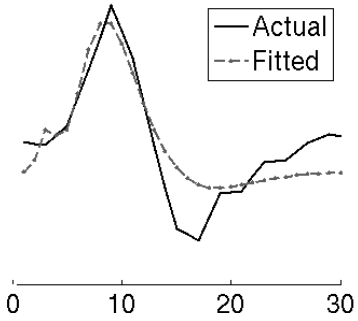
Single HRF



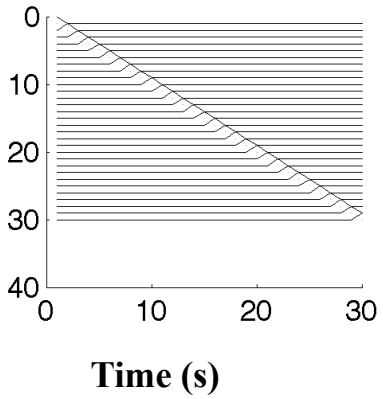


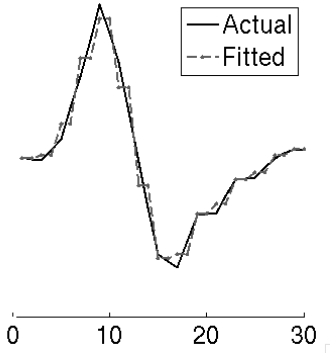
HRF + derivatives





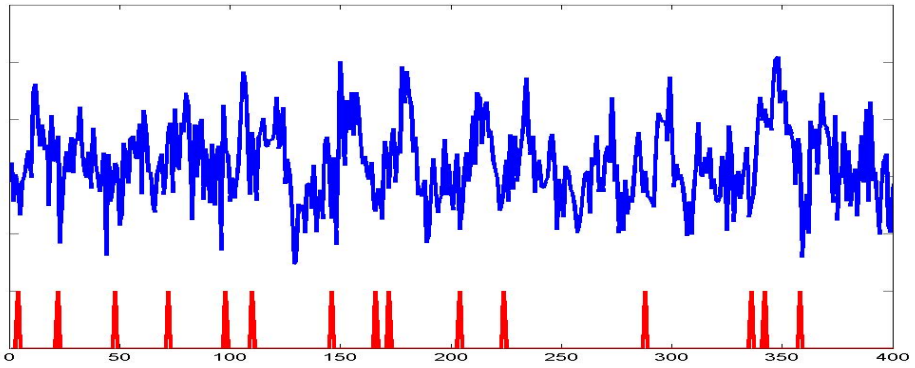
Finite Impulse Response (FIR)

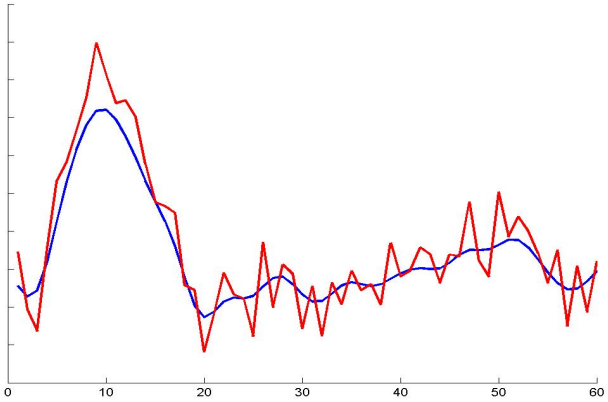




Smooth FIR

- The standard FIR method can give rise to noisy estimates of the HRF.
  - One can impose smoothness constraints by specifying a Gaussian prior on the filter parameters.
  - The maximum a posteriori estimate gives a smoothed version of the FIR fit (Goutte et al., 2000).

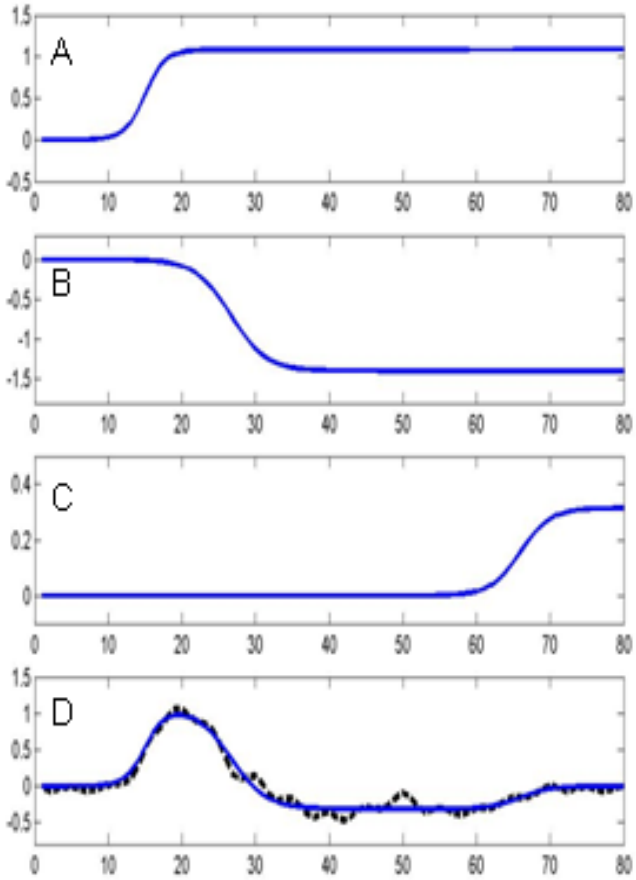


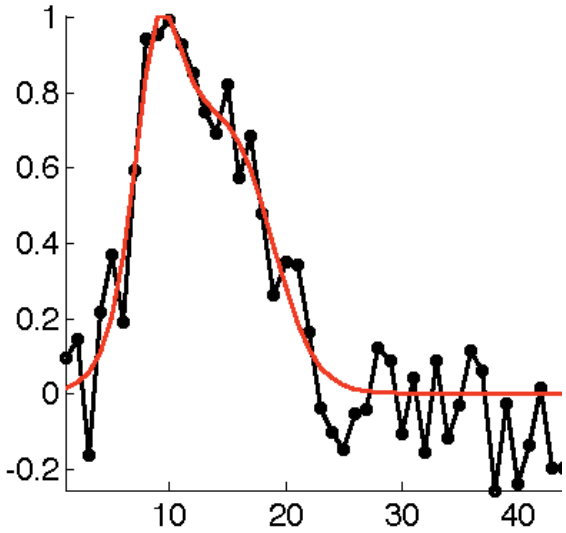


Red – FIR
Blue – Smooth FIR

Inverse Logit Model

- Alternatively one can use a superposition of three inverse logit (sigmoid) functions.

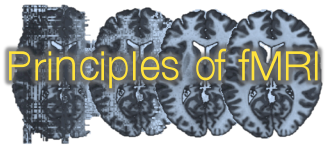




Black – Data
Red – Fitted response

Lindquist & Wager (2007; 2008)

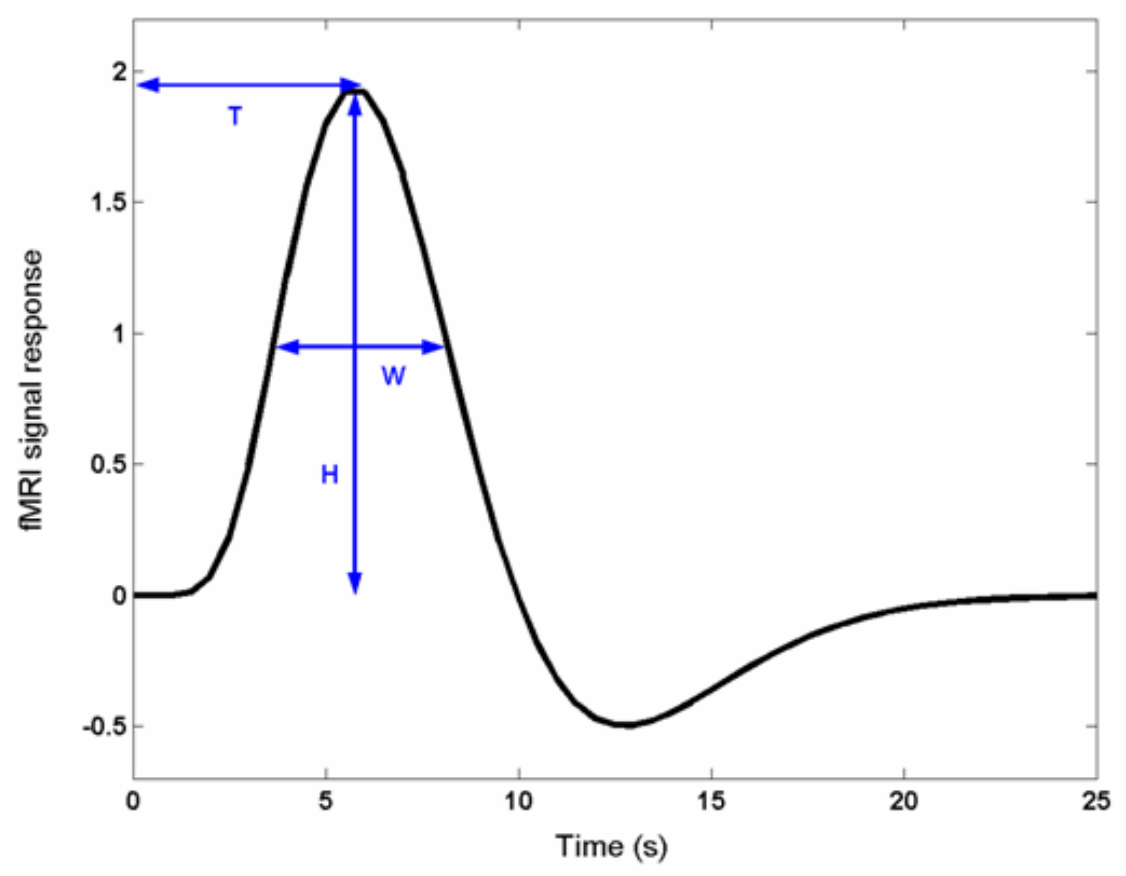
Summarizing the HRF



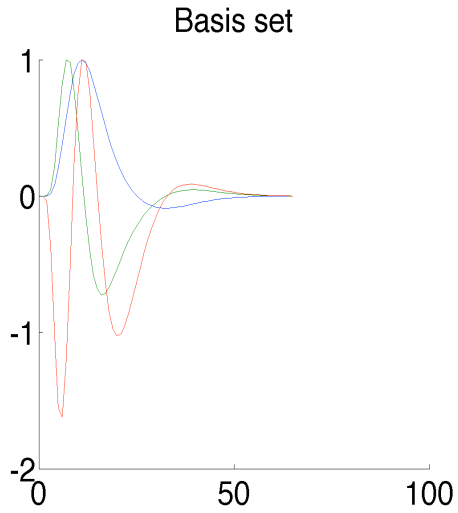
- One problem with using basis sets is that it is difficult to summarize the response magnitude using a single number.
  - Problematic for second-level analysis.

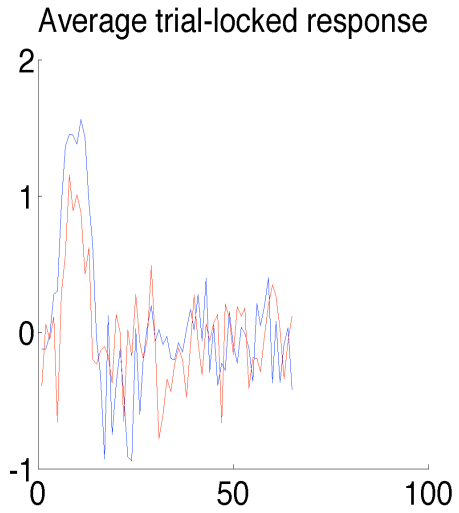
- One can get around this by using
  - the "main" basis function,
  - all basis functions, or
  - re-parameterized fitted responses (Calhoun et al. (2004); Lindquist et al. (2009)).
    - Recreate the HRF and estimate the magnitude.
    - Use this information at the second level.

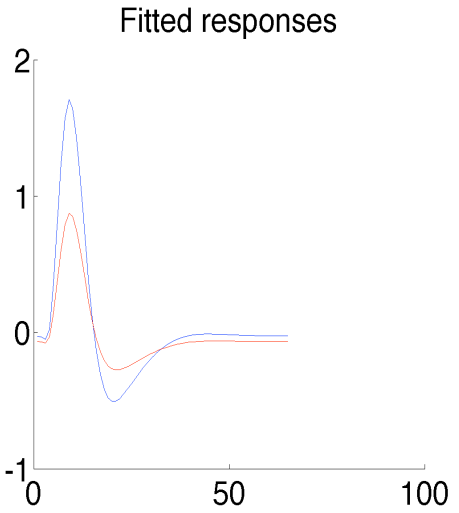
Summarizing the HRF



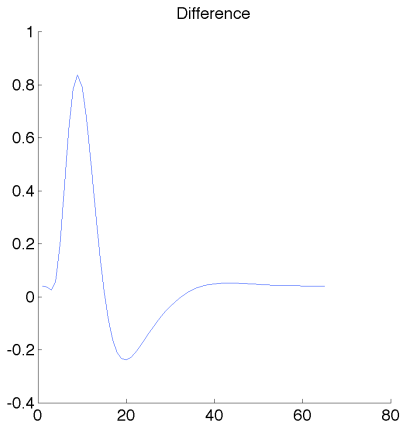
Problems



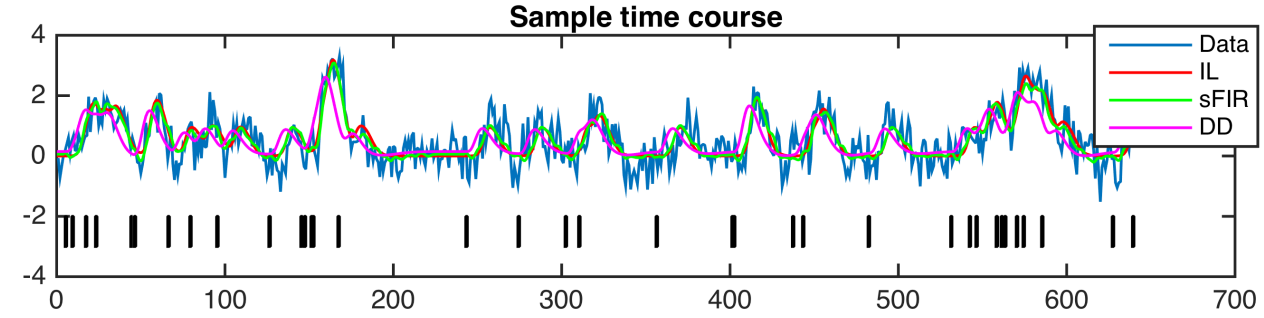


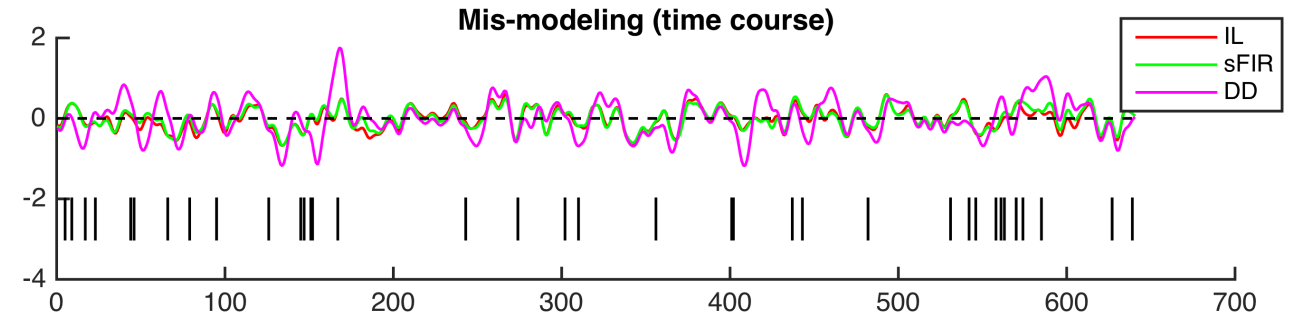


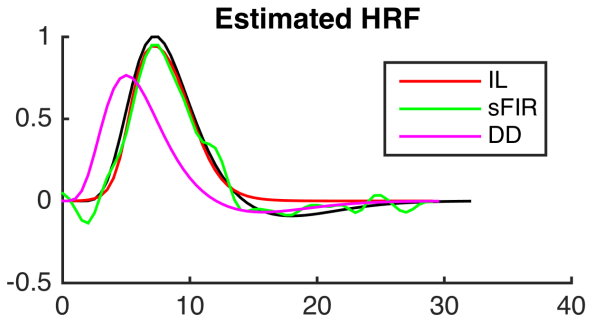
- All three parameters contribute to response magnitude!
  - Difference between amplitudes of fitted responses: 0.84
  - Difference between canonical HRF betas: 0.43
  - Amplitude of the difference does NOT equal difference between 'canonical' parameter estimates.

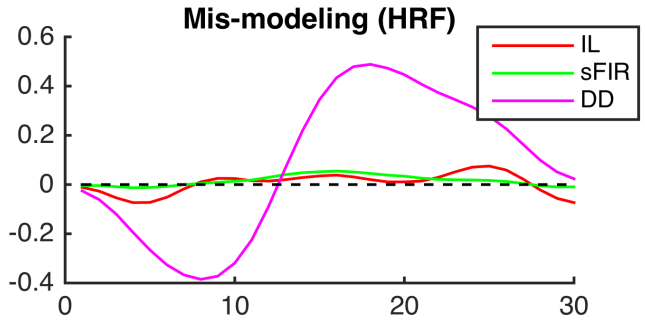


Comparing Hemodynamic Models









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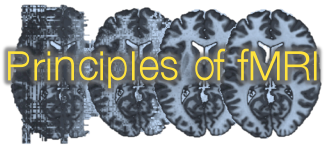
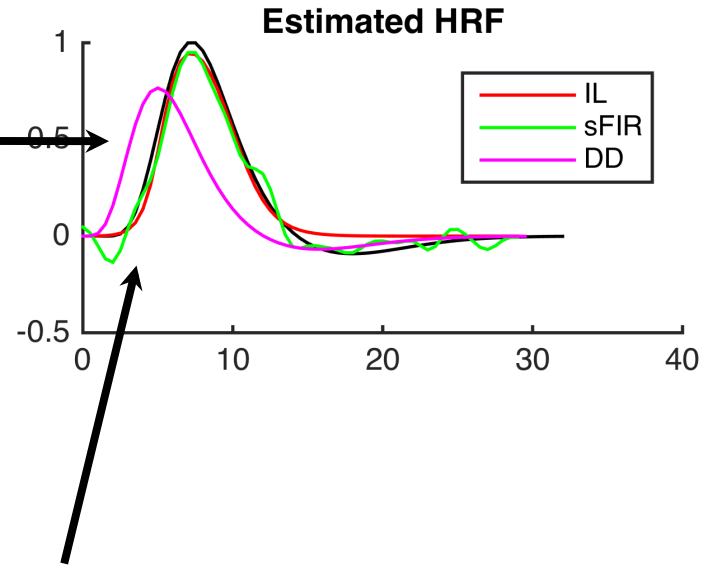
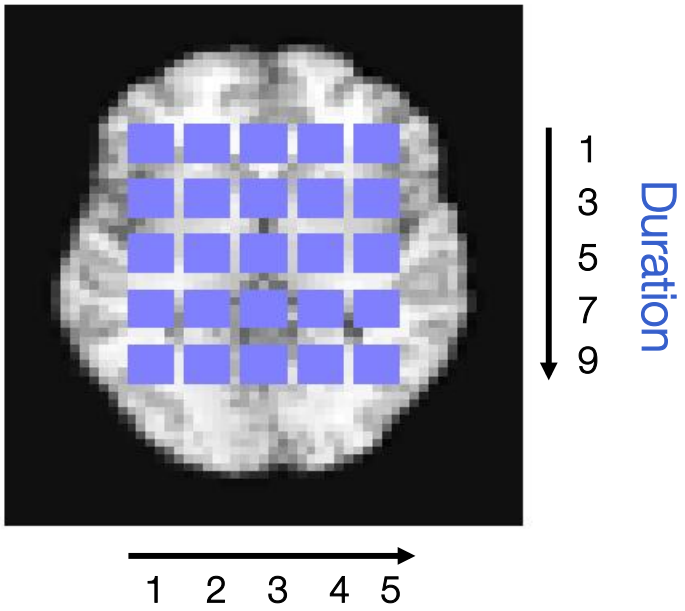


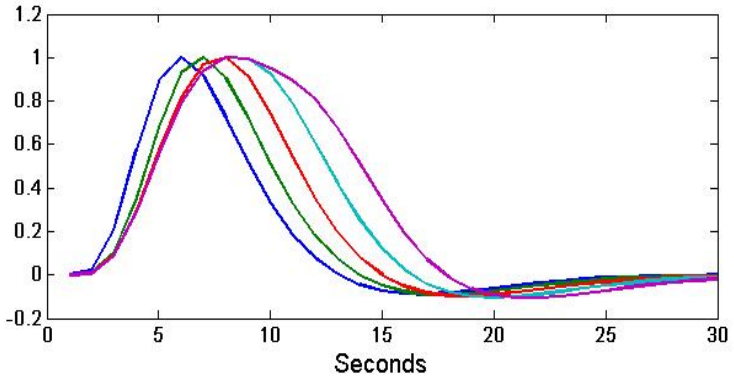
‘Traditional’ derivative model:
Robust to noise, reliable
...but not robust to hemodynamic variability



Flexible models:
Robust to hemodynamic variability
Less robust to noise (but still pretty good)

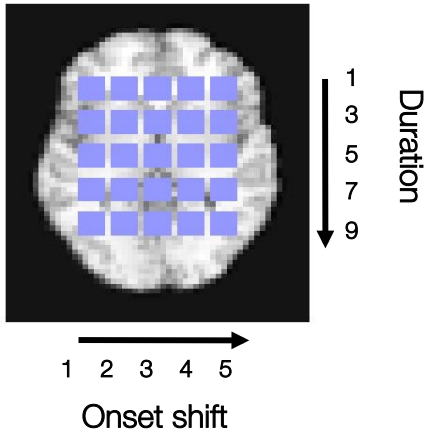
Simulation



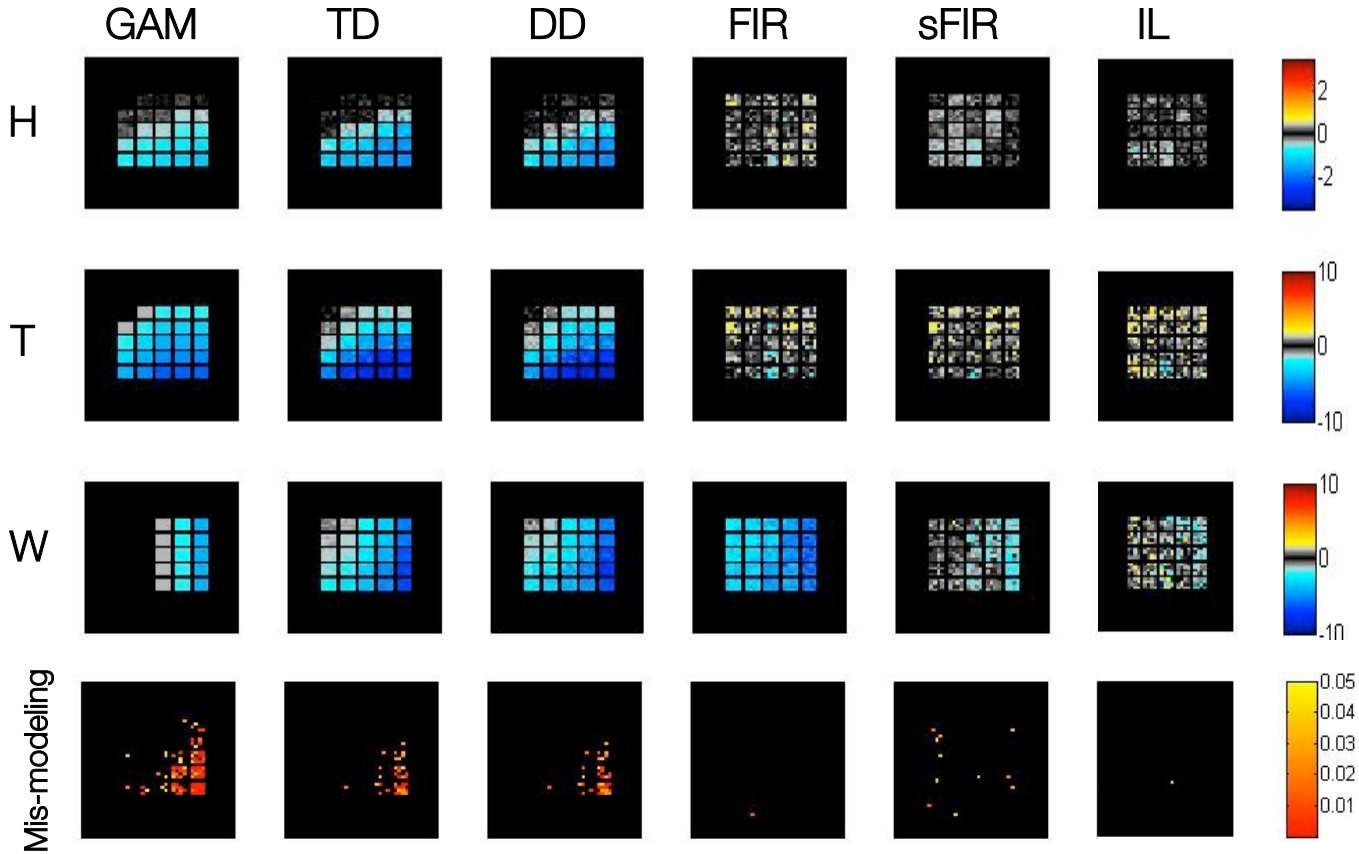


25 unique activations

- TR=1, ISI = 30, 10 epochs, 15 “subjects”, Cohen’s d = 0.5
- Estimates of amplitude were obtained and averaged across the 15 subjects.



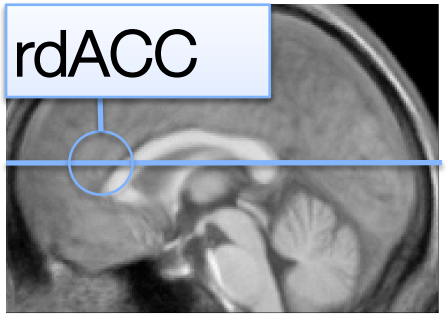
Negative Bias | No Significant Bias | Positive Bias

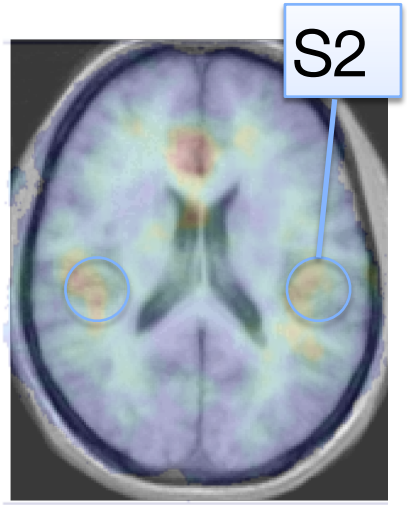


Lindquist & Wager, 2008; Loh, Lindquist, & Wager 2008

Example

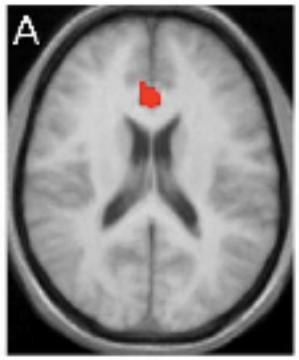
Pain study
Regions of interest

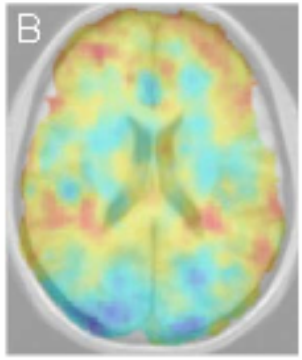




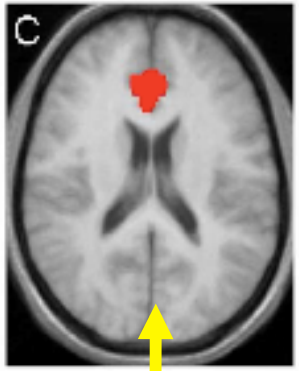
SPM HRF+ Derivatives

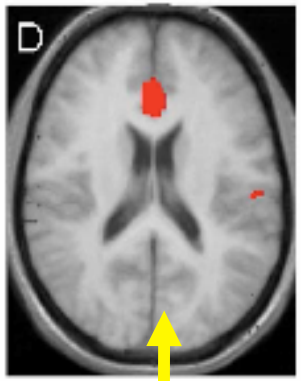
Mis-modeling Map





Loh, Lindqust, & Wager 2008 (yellow/red = mis-modeled)



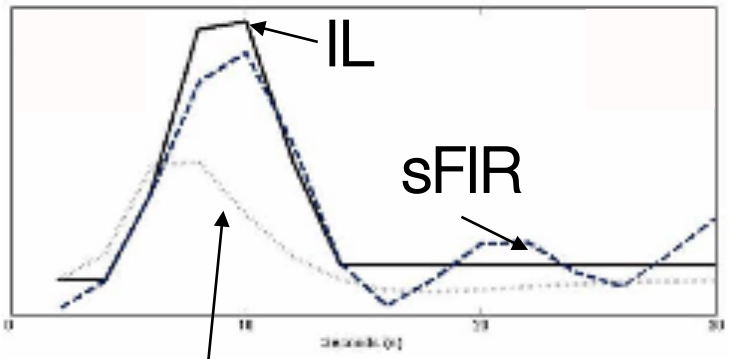


Smooth FIR
Goutte et al.

Inverse Logit
Lindqust, & Wager 2007

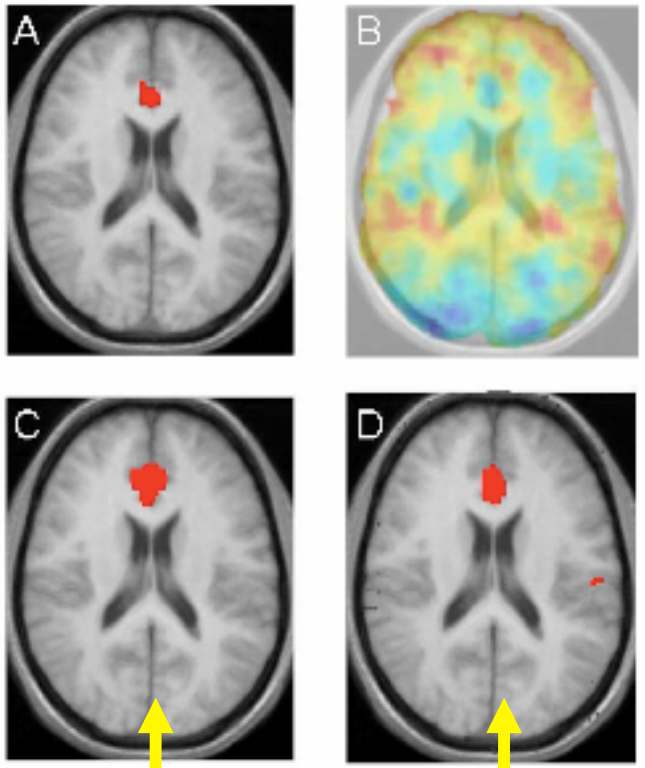
Example

Evoked HRF estimates



SPM HRF+ Derivatives

Mis-modeling Map



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End of Module

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