Event-related fMRI (er-fMRI)

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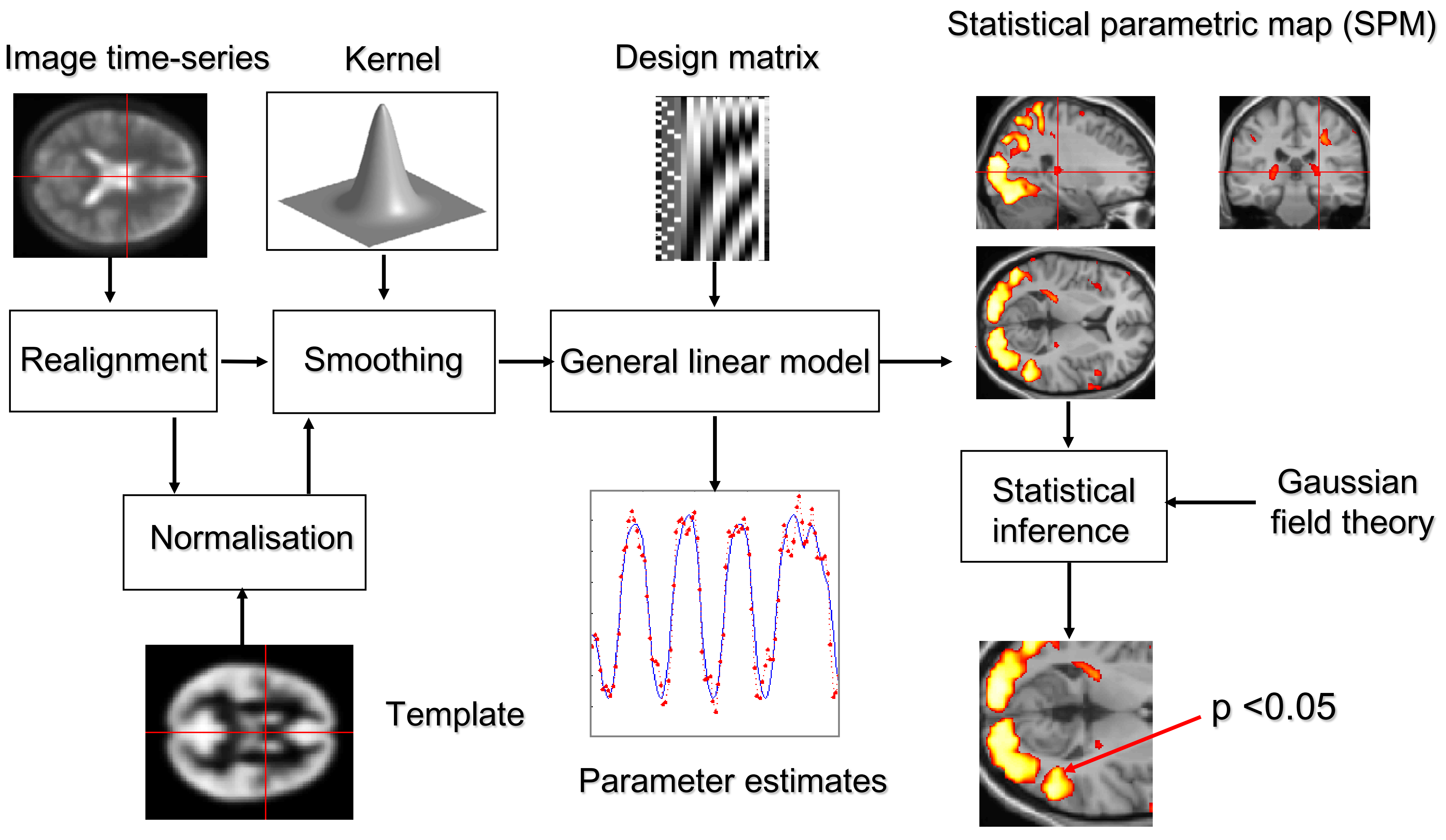
FIL Methods group, particularly Rik Henson and Christian Ruff

Methods & Models for fMRI Data Analysis
06.11.2015

Overview of SPM



Overview

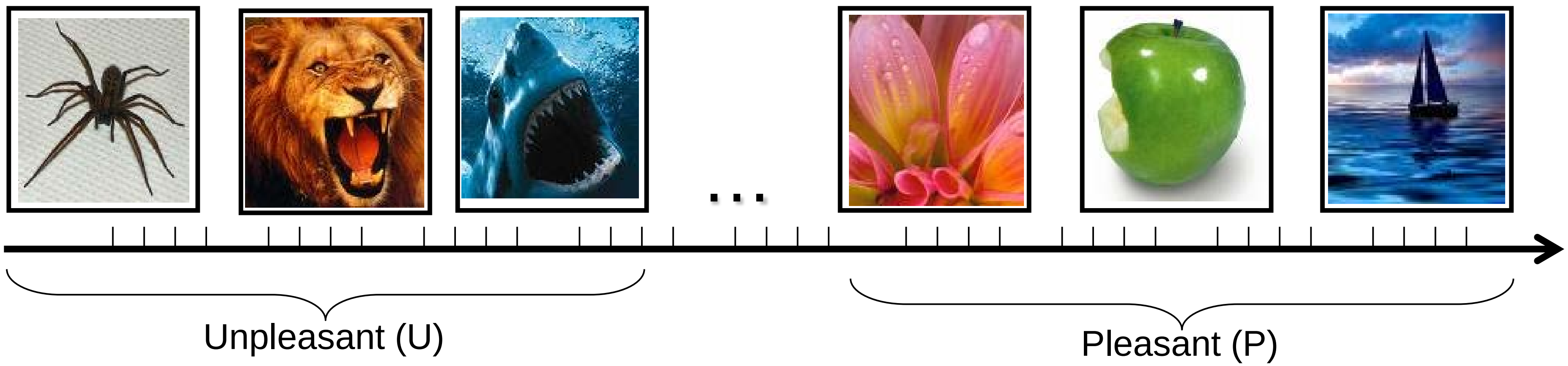
1. Advantages of er-fMRI
2. BOLD impulse response
3. General Linear Model
4. Temporal basis functions
5. Timing issues
6. Design optimisation
7. Nonlinearities at short SOAs

Advantages of er-fMRI

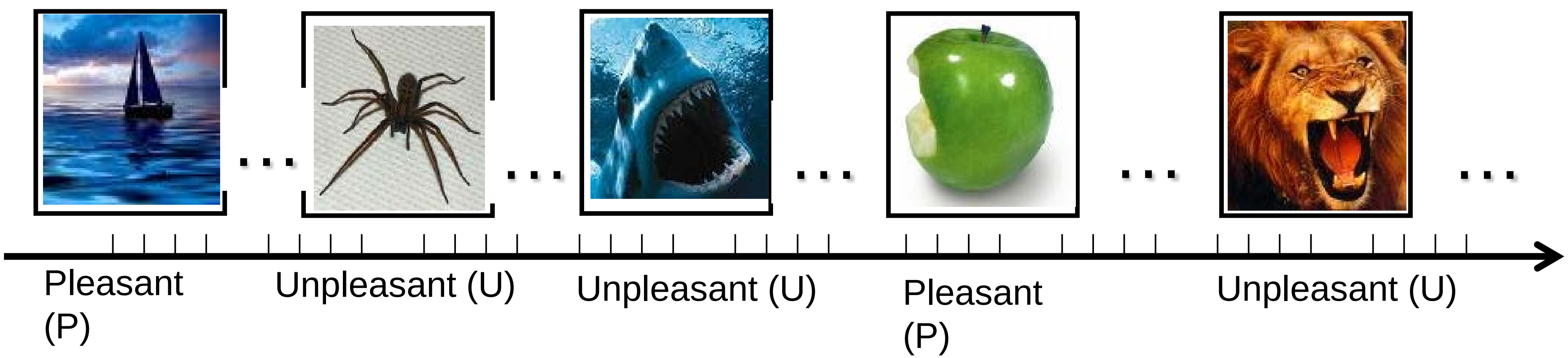
1. Randomised trial order
   c.f. confounds of blocked designs

er-fMRI: Stimulus randomisation

Blocked designs may trigger expectations and cognitive sets



Intermixed designs can minimise this by stimulus randomisation



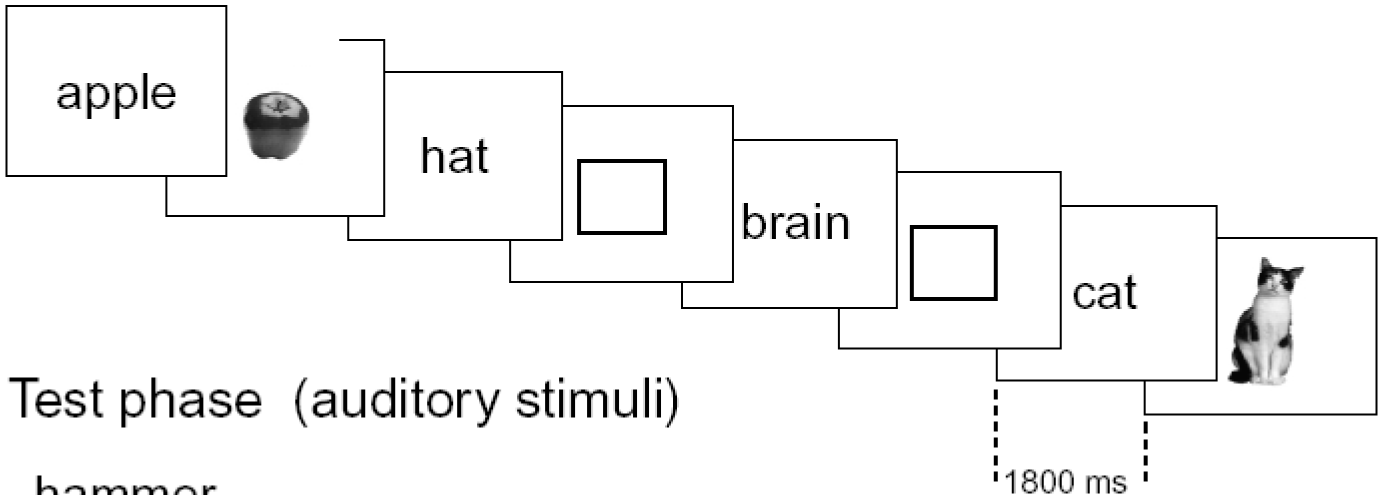
Advantages of er-fMRI

1. Randomised trial order
   c.f. confounds of blocked designs

2. **Post hoc classification of trials**
   e.g. according to performance or subsequent memory

er-fMRI: post-hoc classification of trials

Study phase (visual stimuli)



Participant response:

„was *not* shown as picture“

„was shown as picture“

Test phase (auditory stimuli)

hammer
apple
cat
brain
hat
2500 ms

➔ Items with wrong memory of picture („hat“) were associated with more occipital activity *at encoding* than items with correct rejection („brain“)

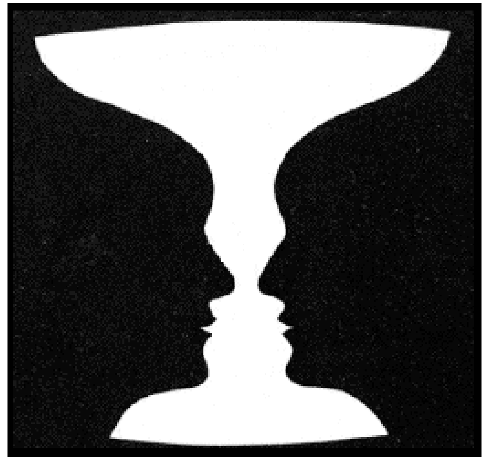
Gonsalves & Paller (2000) *Nature Neuroscience*

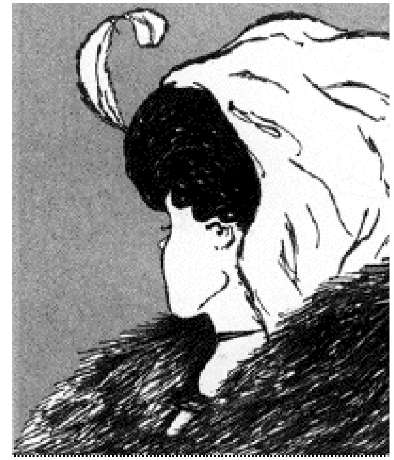
Advantages of er-fMRI

1. Randomised trial order
   c.f. confounds of blocked designs
2. Post hoc classification of trials
   e.g. according to performance or subsequent memory
3. **Some events can only be indicated by the subject**
   e.g. spontaneous perceptual changes

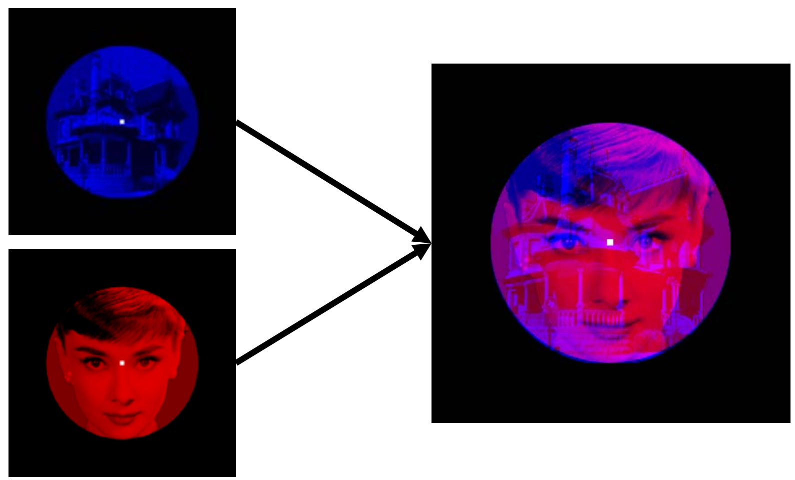
eFMRI: “on-line” event-definition

Bistable percepts





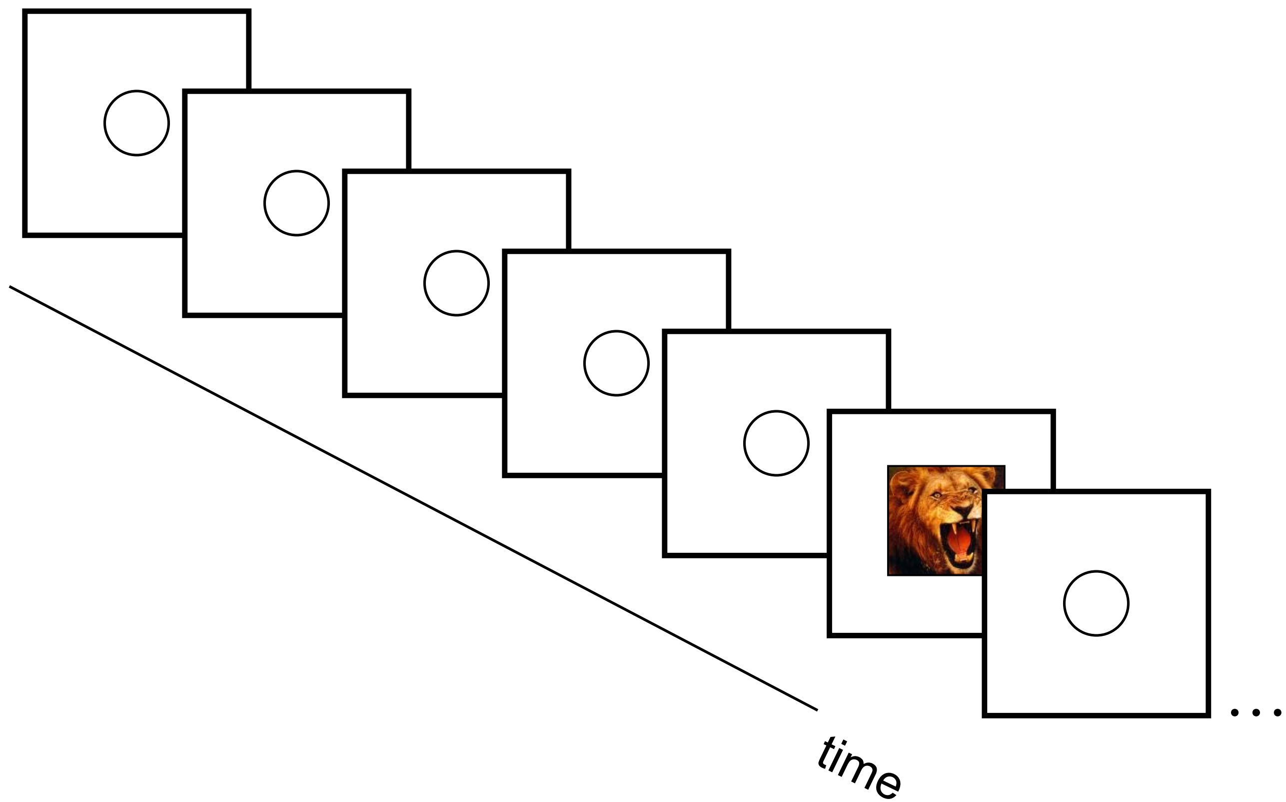
Binocular rivalry



Advantages of er-fMRI

1. Randomised trial order
   c.f. confounds of blocked designs
2. Post hoc classification of trials
   e.g. according to performance or subsequent memory
3. Some events can only be indicated by the subject
   e.g. spontaneous perceptual changes
4. **Some trials cannot be blocked**
   e.g. “oddball” designs

er-fMRI: “oddball” designs



Advantages of er-fMRI

1. Randomised trial order
   c.f. confounds of blocked designs

2. Post hoc classification of trials
   e.g. according to performance or subsequent memory

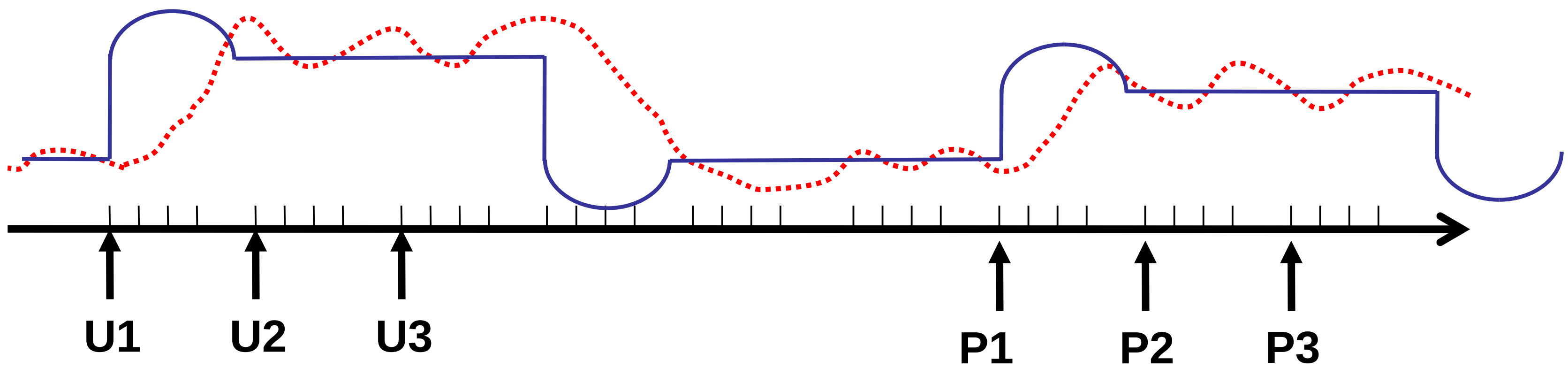
3. Some events can only be indicated by subject
   e.g. spontaneous perceptual changes

4. Some trials cannot be blocked
   e.g. “oddball” designs

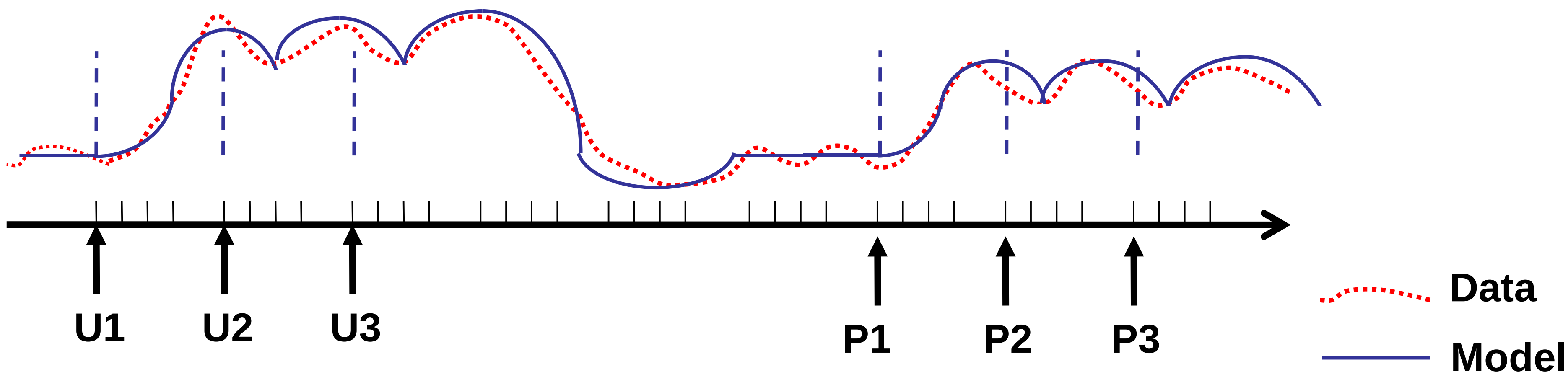
5. **More accurate models even for blocked designs?**
   “state-item” interactions

er-fMRI: “event-based” model of block-designs

“Epoch” model assumes constant neural processes throughout block

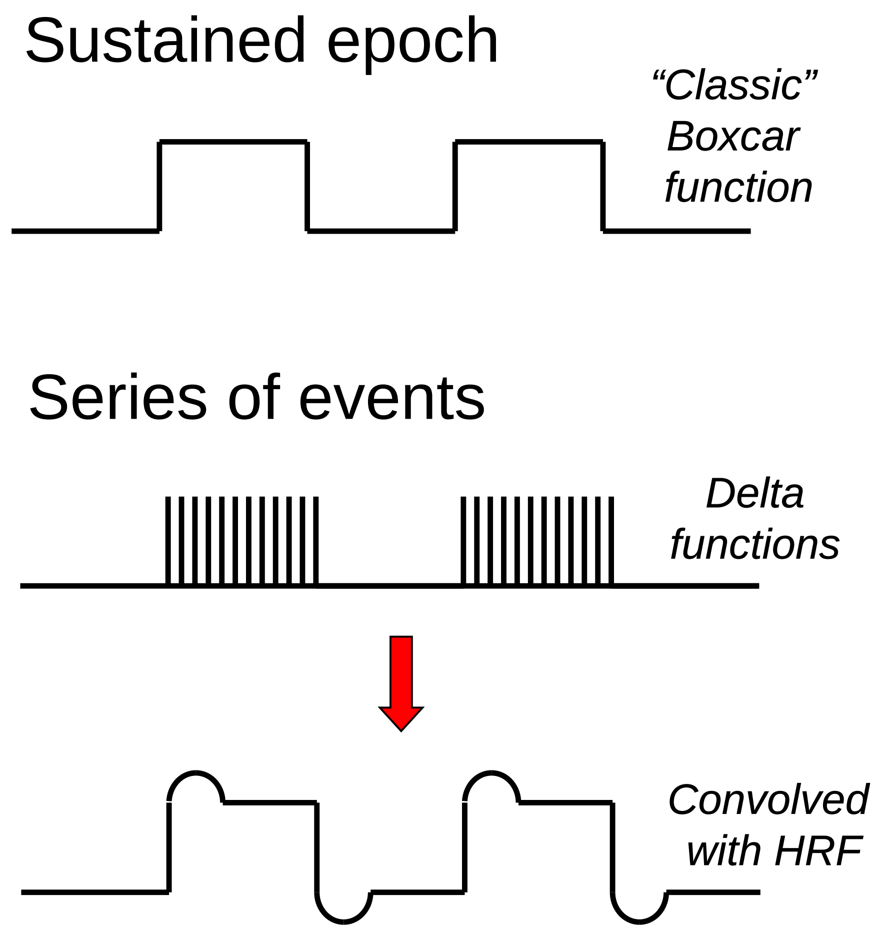


“Event” model may capture state-item interactions



Modeling block designs: epochs vs events

- *Designs* can be blocked or intermixed, BUT *models* for blocked designs can be epoch- or event-related
- Epochs are periods of sustained stimulation (e.g, box-car functions)
- Events are impulses (delta-functions)
- Near-identical regressors can be created by 1) sustained epochs, 2) rapid series of events (SOAs<~3s)
- In SPM, all conditions are specified in terms of their 1) onsets and 2) durations
  … epochs: variable or constant duration
  … events: zero duration



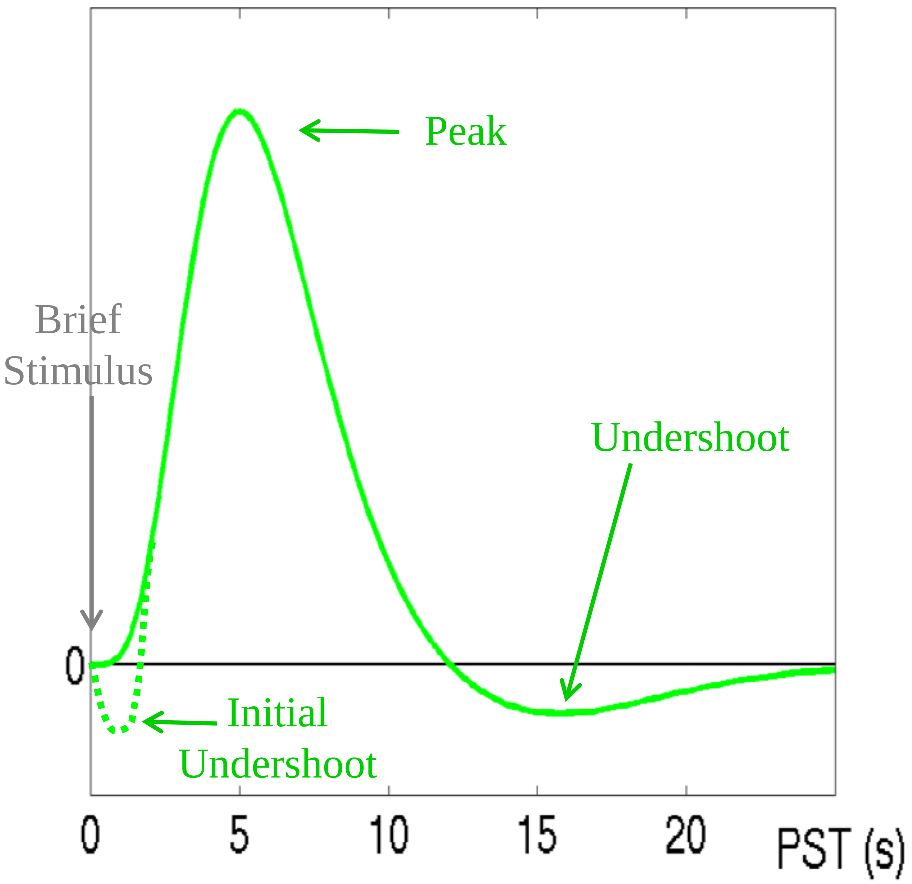
Disadvantages of er-fMRI

1. Less efficient for detecting effects than blocked designs.

2. Some psychological processes may be better blocked (e.g. task-switching, attentional instructions).

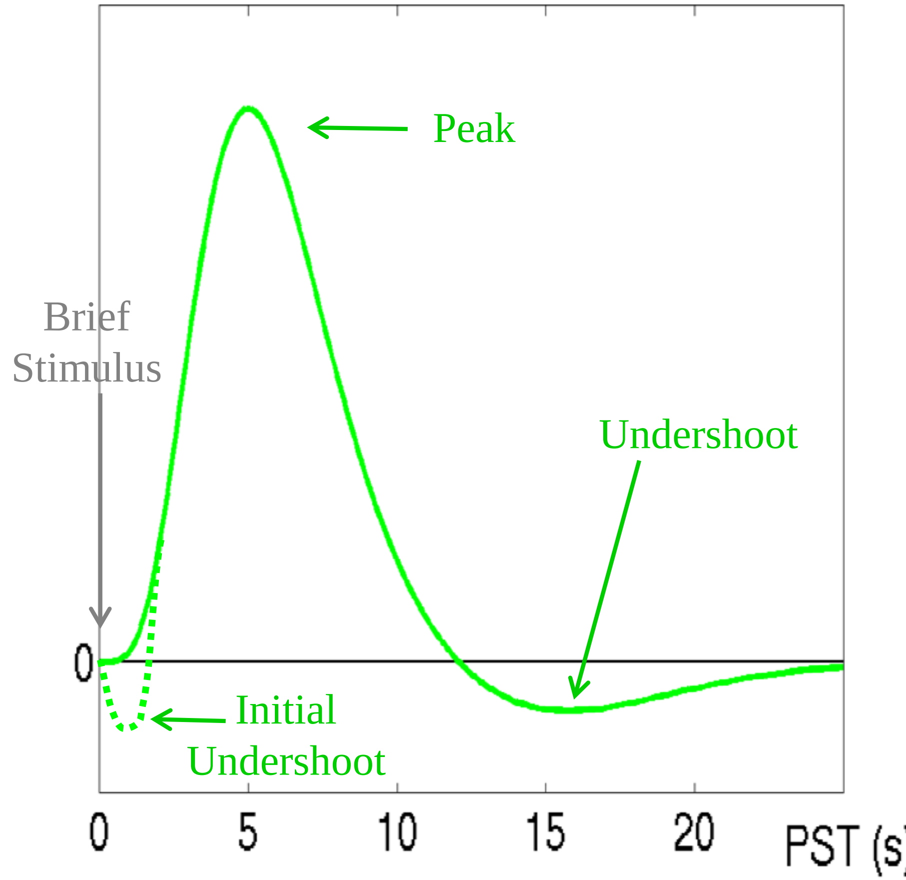
BOLD impulse response

- Function of blood volume and deoxyhemoglobin content (Buxton et al. 1998)
- Peak (max. oxygenation) 4-6s post-stimulus; return to baseline after 20-30s
- initial undershoot sometimes observed (Malonek & Grinvald, 1996)
- Similar across V1, A1, S1…
- … but differences across other regions (Schacter et al. 1997) and individuals (Aguirre et al. 1998)



BOLD impulse response

- Early er-fMRI studies used a long Stimulus Onset Asynchrony (SOA) to allow BOLD response to return to baseline.
- However, if the BOLD response is explicitly modelled, overlap between successive responses at short SOAs can be accommodated…
- … particularly if responses are assumed to superpose linearly.
- Short SOAs can give a more efficient design (see below).

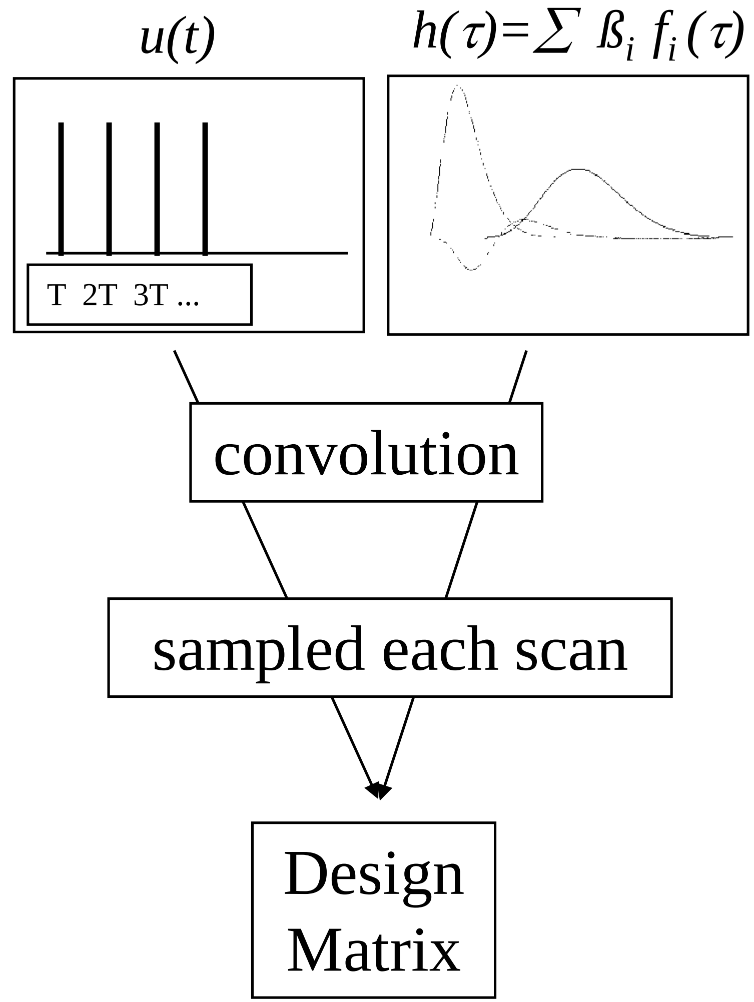


General Linear (Convolution) Model

For block designs, the exact shape of the convolution kernel (i.e. HRF) does not matter much.

For event-related designs this becomes much more important.

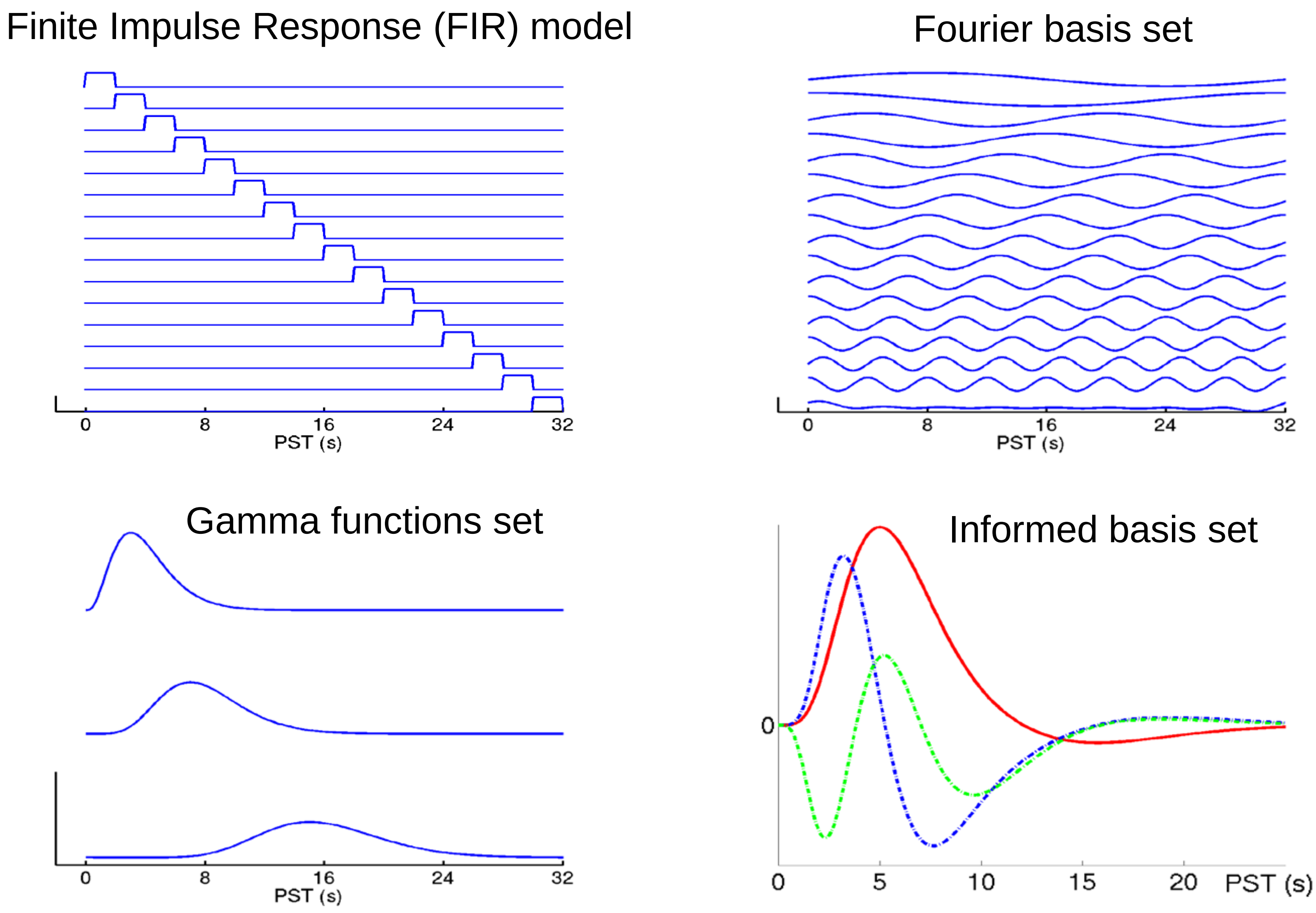
Usually, we use more than a single basis function to model the HRF.



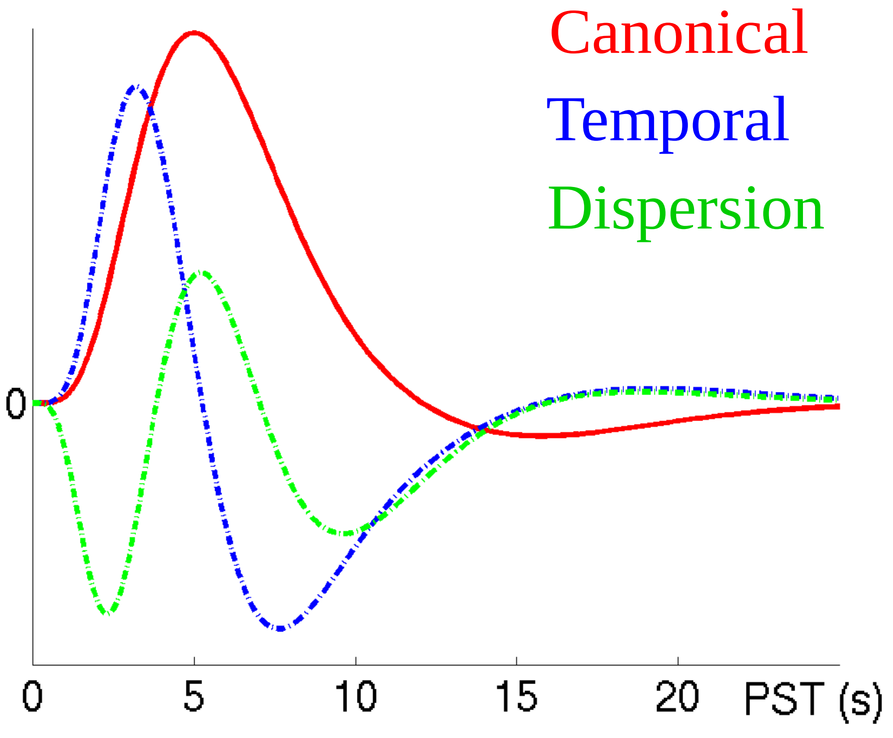
GLM for a single voxel:

$$\mathbf{y(t) = u(t) \otimes h(\tau) + \varepsilon(t)}$$

Temporal basis functions



Informed basis set



- Canonical HRF (2 gamma functions)

  plus Multivariate Taylor expansion in:
  time (*Temporal Derivative*)
  width (*Dispersion Derivative*)

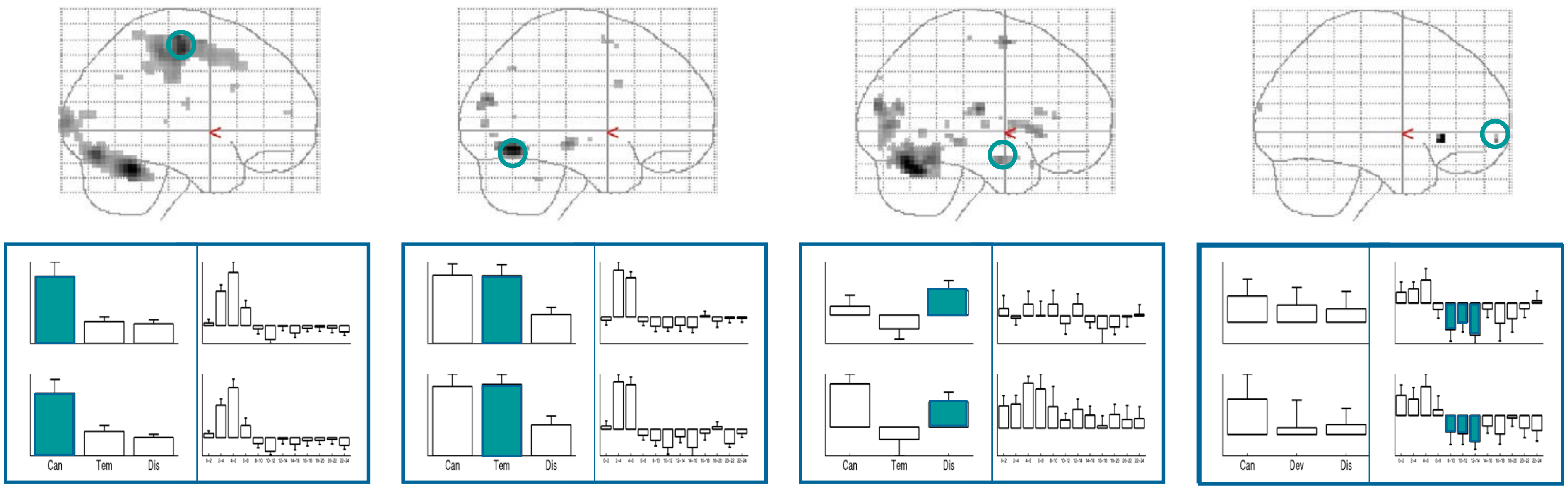
- F-tests allow testing for any responses of any shape.

- T-tests on canonical HRF alone (at 1st level) can be improved by derivatives reducing residual error, and can be interpreted as "amplitude" differences, assuming canonical HRF is a reasonable fit.

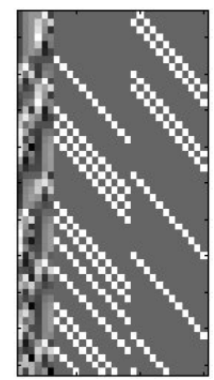
Friston et al. 1998, *NeuroImage*

Temporal basis sets: Which one?

In this example (rapid motor response to faces, *Henson et al, 2001*)…



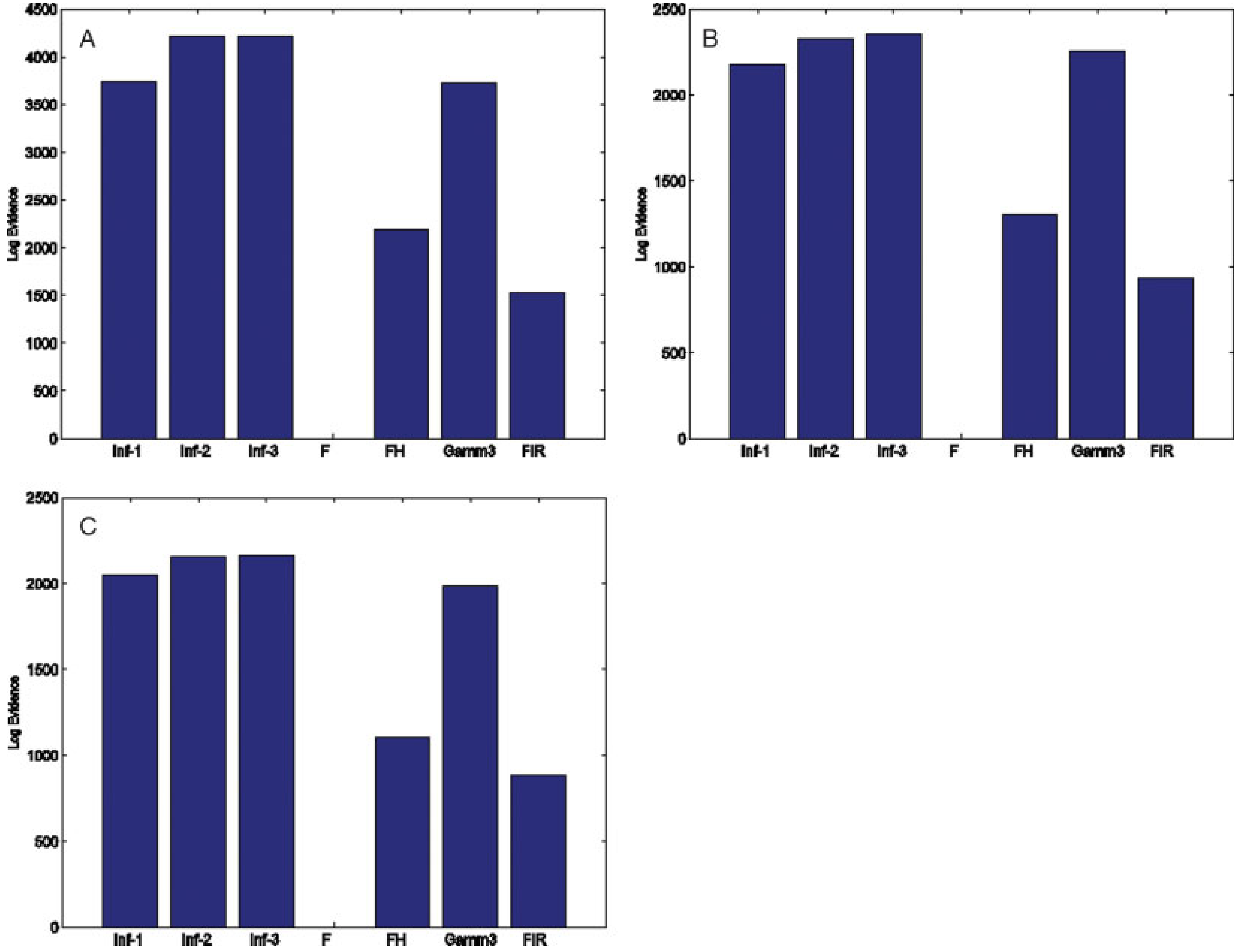
Canonical **+ Temporal** **+ Dispersion** **+ FIR**



- canonical + temporal + dispersion derivatives appear sufficient
- may not be for more complex trials (e.g. stimulus-delay-response)
- but then such trials better modelled with separate neural components (i.e. activity no longer delta function) (Zarahn, 1999)

left occipital cortex

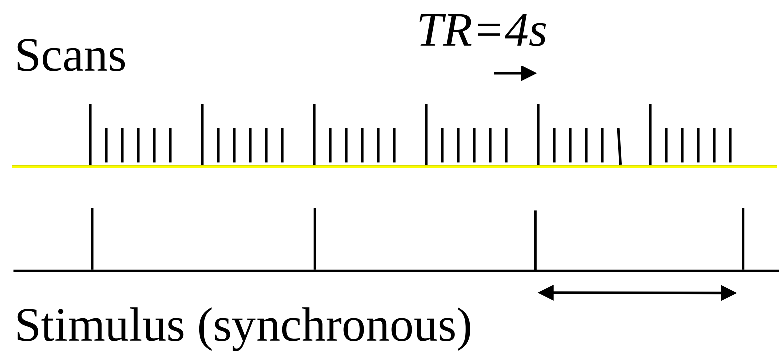
right occipital cortex

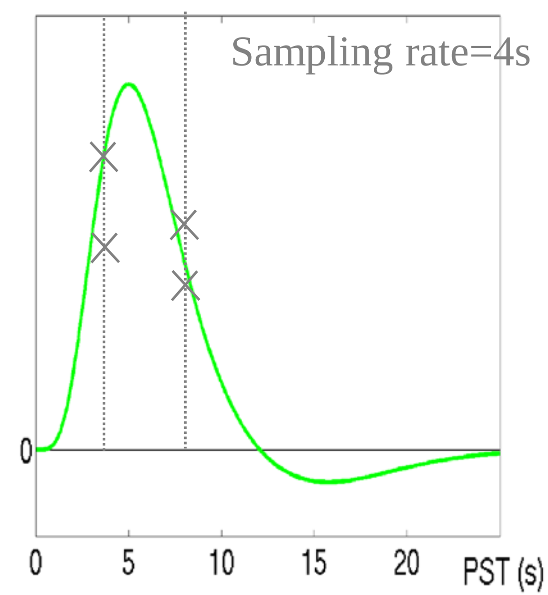


Penny et al. 2007, *Hum. Brain Mapp.*

Timing Issues : Practical

- Assume TR is 4s
- Sampling at [0,4,8,12…] post- stimulus may miss peak signal

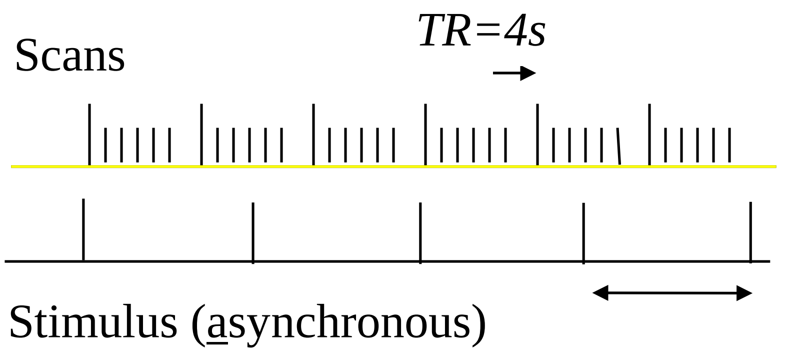


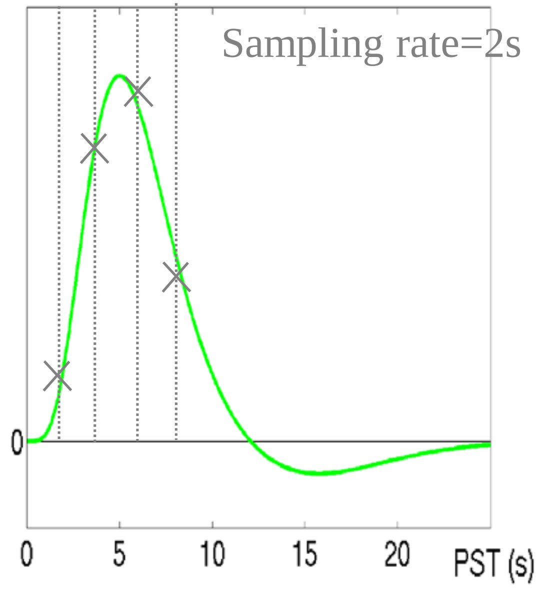


SOA = Stimulus onset asynchrony
(= time between onsets of two subsequent stimuli)

Timing Issues : Practical

- Assume TR is 4s
- Sampling at [0,4,8,12…] post- stimulus may miss peak signal
- Higher effective sampling by:
  - 1. Asynchrony, *e.g. SOA* = 1.5×TR





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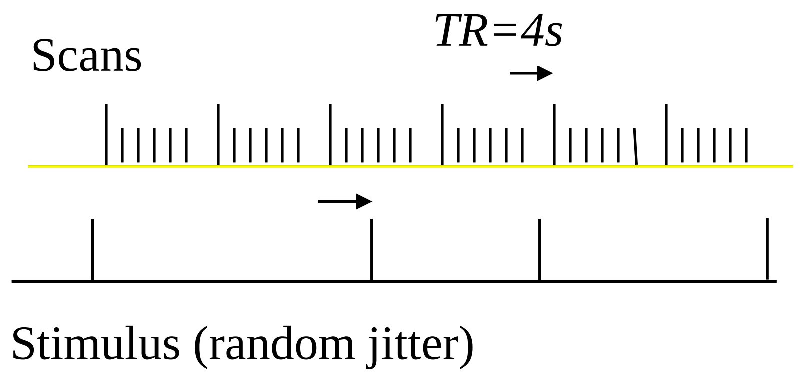
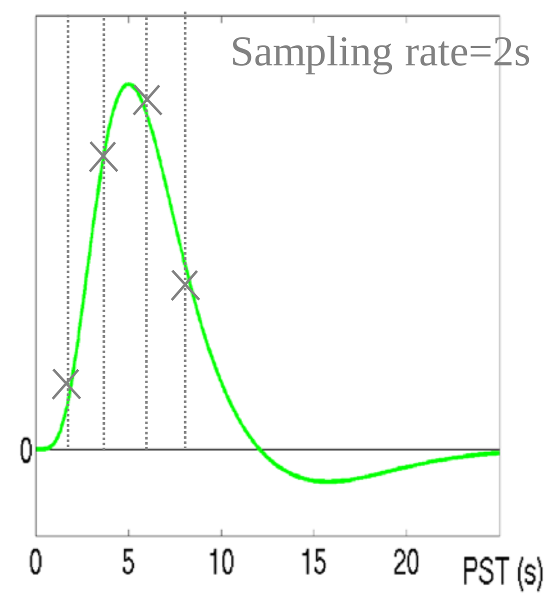
Timing Issues : Practical

- Assume TR is 4s
- Sampling at [0,4,8,12…] post- stimulus may miss peak signal
- Higher effective sampling by:
  - 1. Asynchrony, *e.g. SOA* = 1.5×TR
  - 2. Random jitter, e.g. SOA = (2 ± 0.5)×TR
- Better response characterisation (Miezin et al, 2000)





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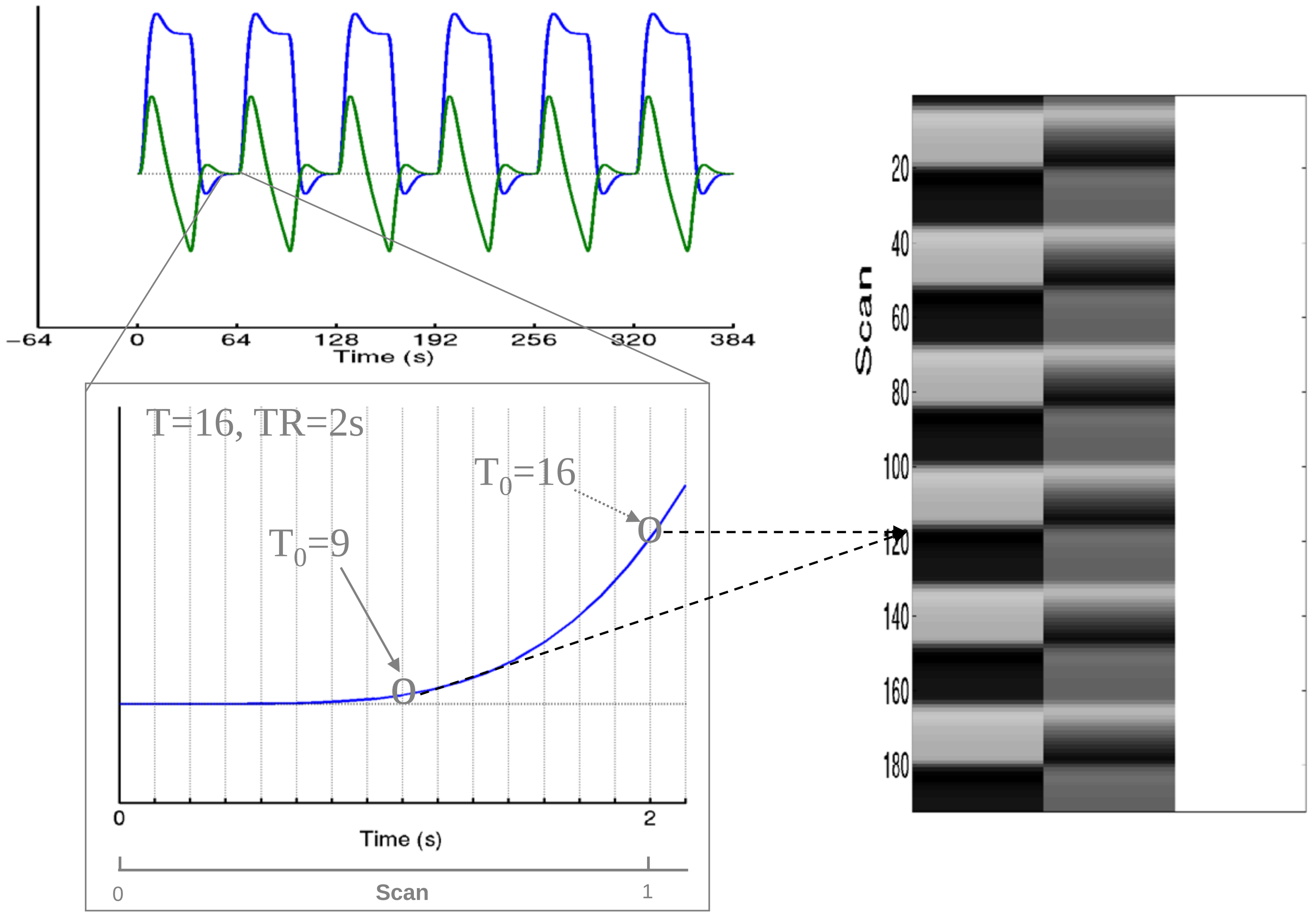
(= time between onsets of two subsequent stimuli)

Slice-timing



Slice-timing

- Slices acquired at different times, yet model is the same for all slices

  => *different results (using canonical HRF) for different reference slices*

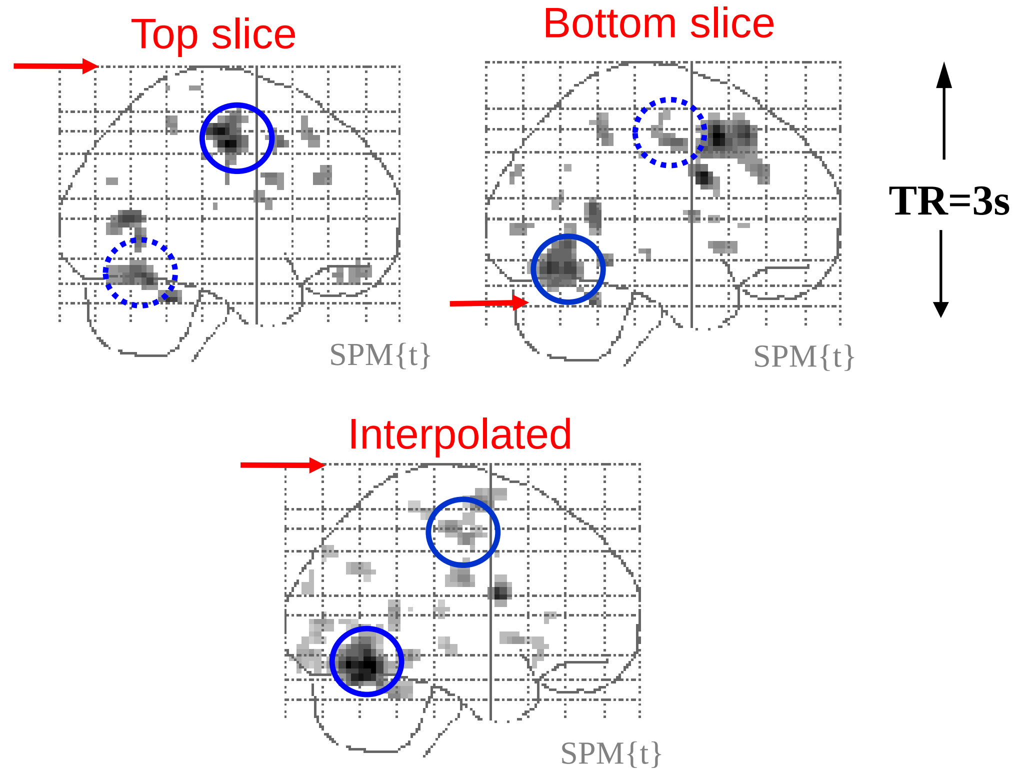
- Solutions:

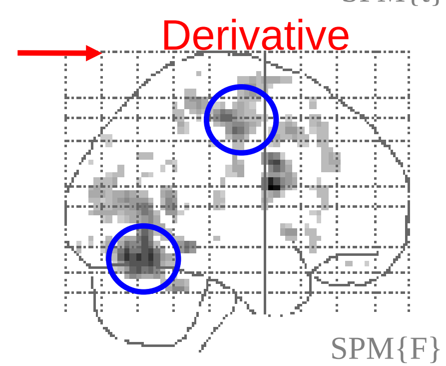
1. Temporal interpolation of data

   … but less good for longer TRs

2. More general basis set (e.g. with temporal derivatives)

   … but more complicated design matrix





Henson et al. 1999

Design efficiency

- The aim is to minimize the standard error of a *t*-contrast (i.e. the denominator of a t-statistic).

$$\mathrm{var}(c^T\hat{\beta}) = \hat{\sigma}^2 c^T (X^T X)^{-1} c$$

$$T = \frac{c^T\hat{\beta}}{\sqrt{\mathrm{var}(c^T\hat{\beta})}}$$

- This is equivalent to maximizing the efficiency ε:

$$\varepsilon(\hat{\sigma}^2, c, X) = (\hat{\sigma}^2 c^T (X^T X)^{-1} c)^{-1}$$

Noise variance ($\hat{\sigma}^2$)   Design variance ($X^T X$)

- If we assume that the noise variance is independent of the specific design:

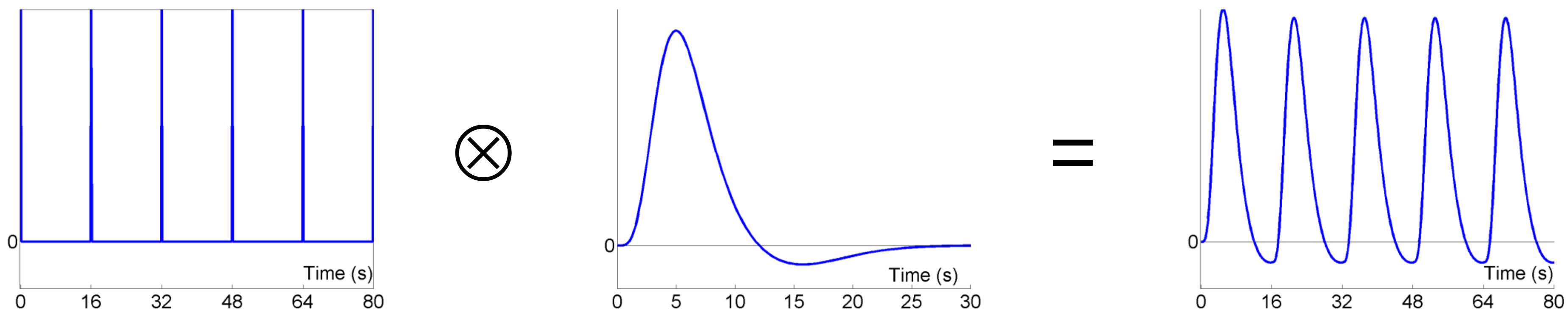
$$\varepsilon(c, X) = (c^T (X^T X)^{-1} c)^{-1}$$

NB: efficiency depends on design matrix and the chosen contrast !

- This is a relative measure: all we can say is that one design is more efficient than another (for a given contrast).

Fixed SOA = 16s

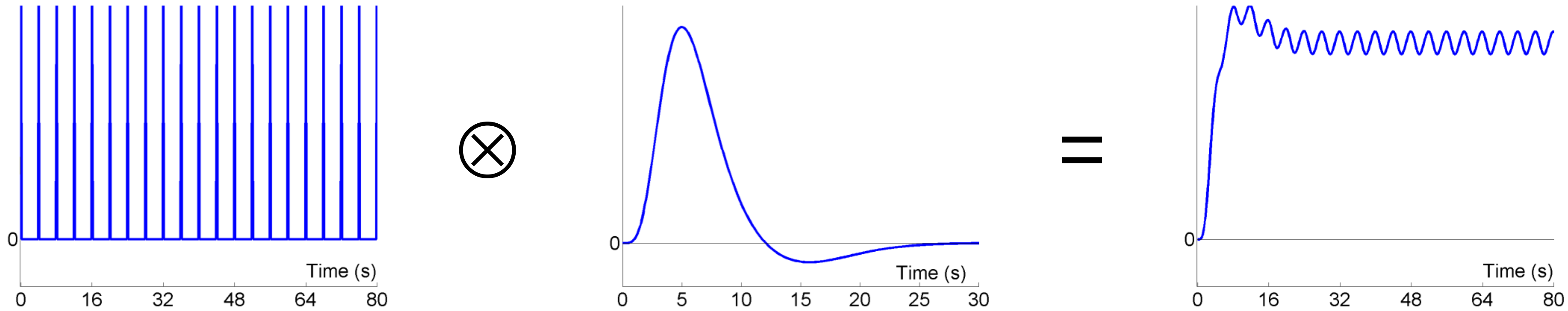
Stimulus (“Neural”)　　HRF　　Predicted Data



Not particularly efficient…

Fixed SOA = 4s

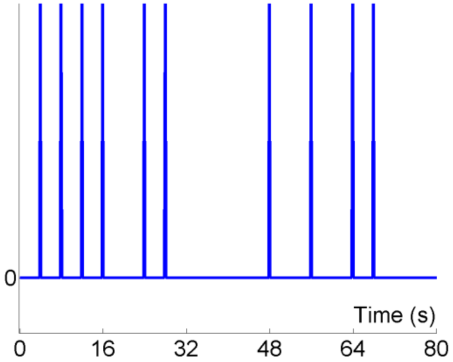
Stimulus (“Neural”) HRF Predicted Data



Very inefficient…

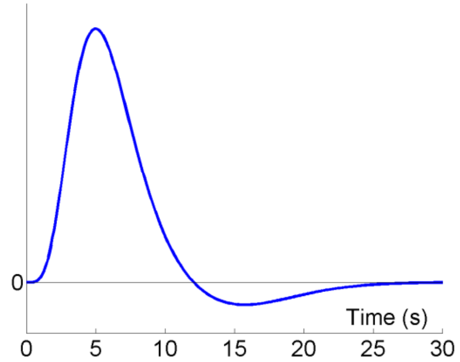
Randomised, SOA_{min} = 4s

Stimulus (“Neural”)



$\otimes$

HRF



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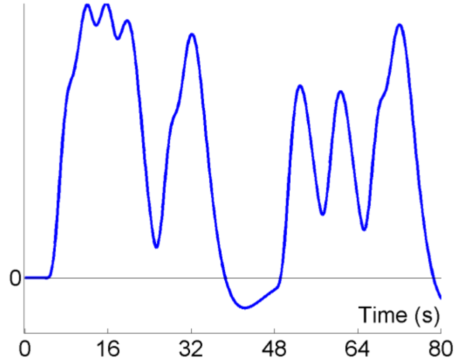
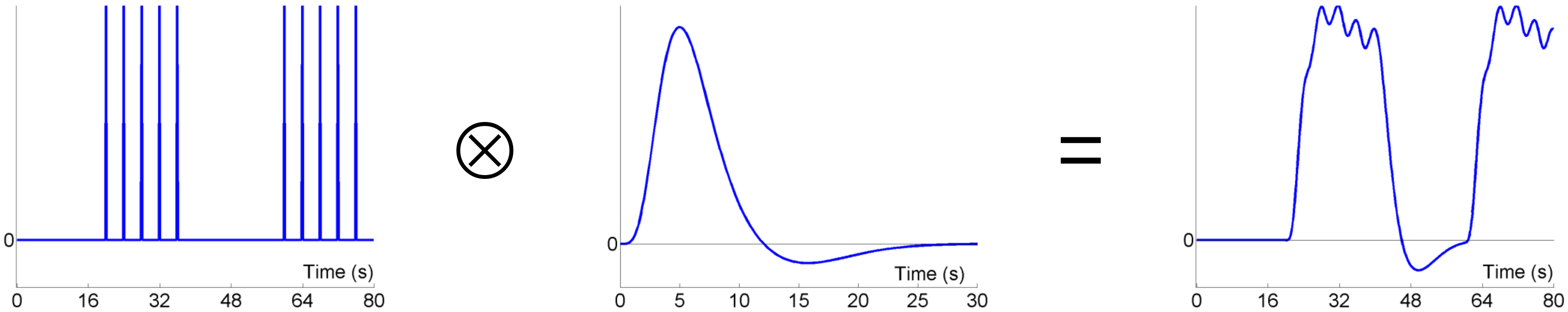
Predicted Data



More efficient …

Blocked, SOA_{min} = 4s

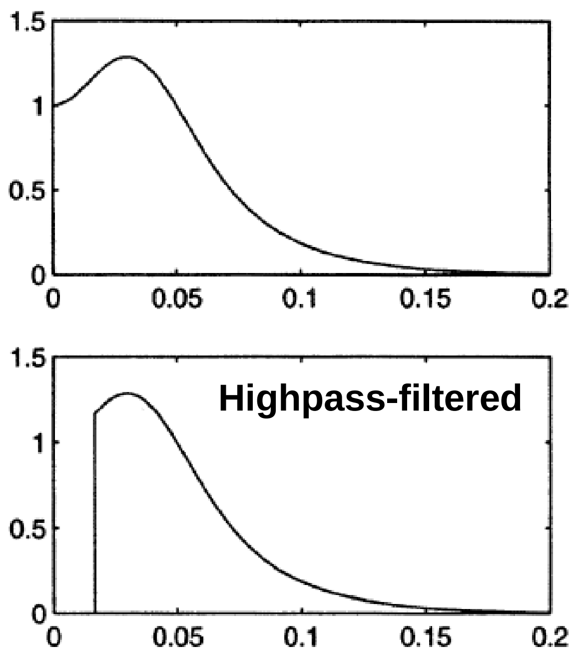
Stimulus (“Neural”) HRF Predicted Data

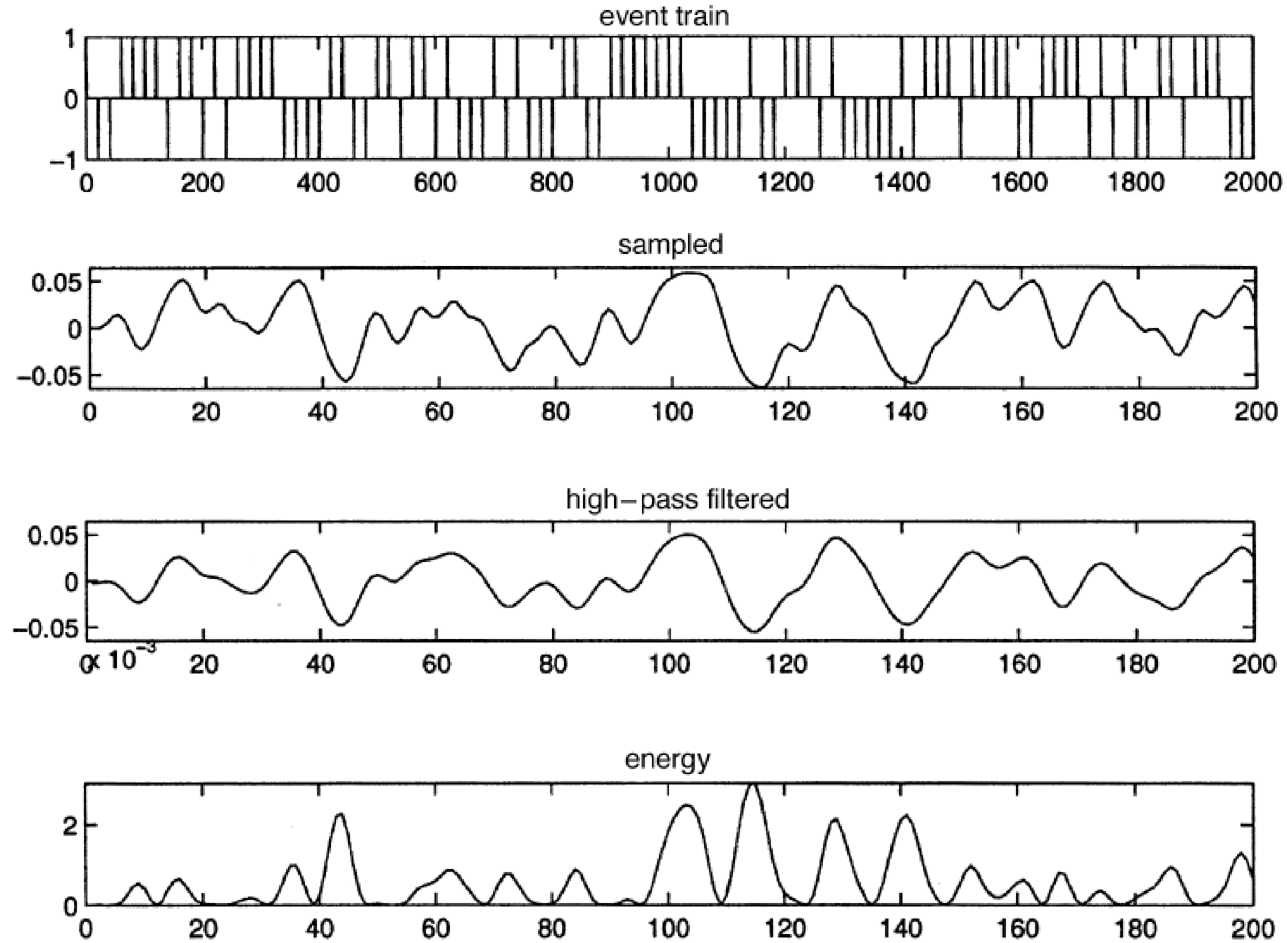


Even more efficient…

Another perspective on efficiency

Hemodynamic transfer function
(based on canonical HRF)**:**
neural activity (Hz) → BOLD

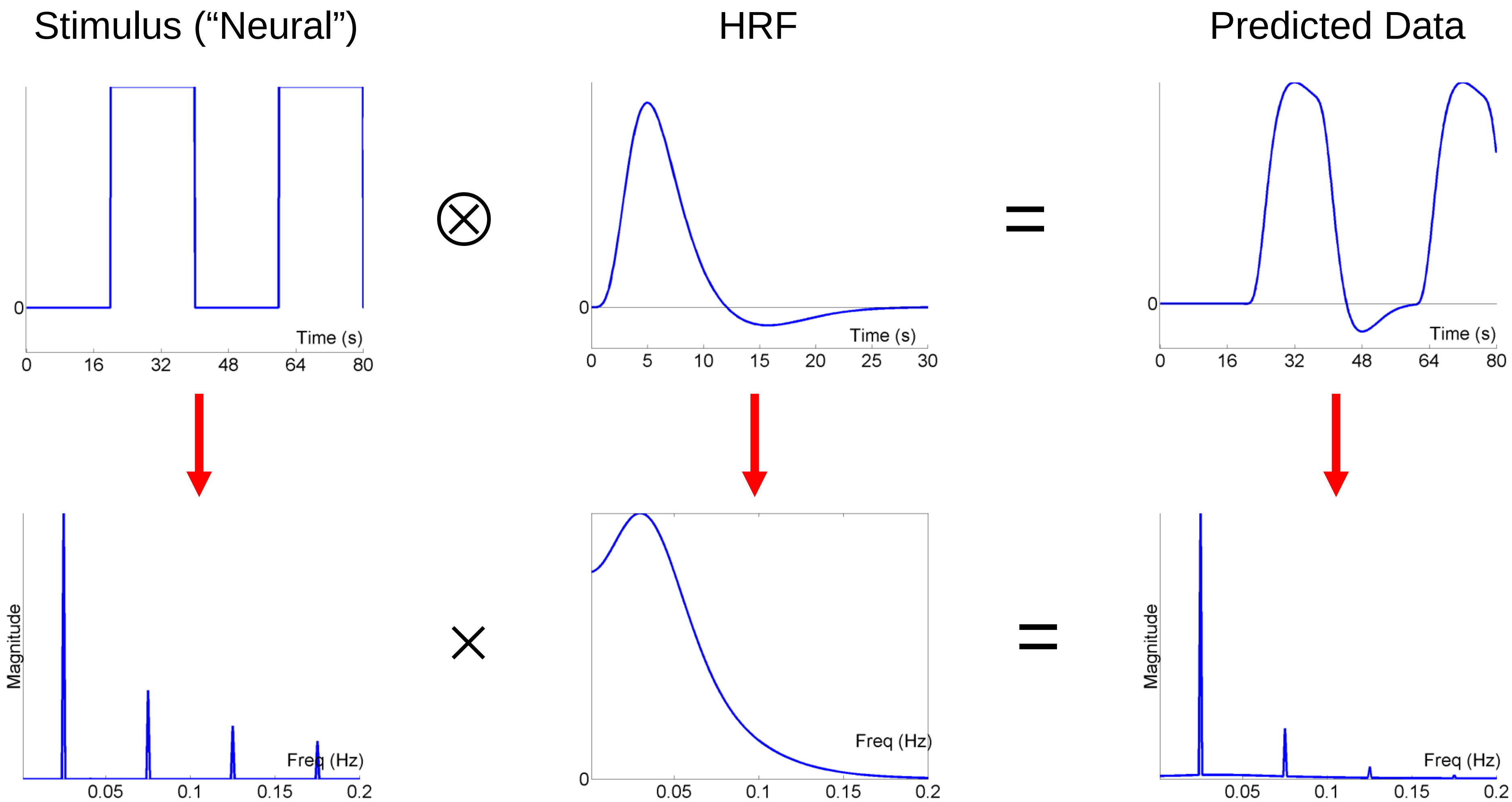




efficiency = bandpassed signal energy

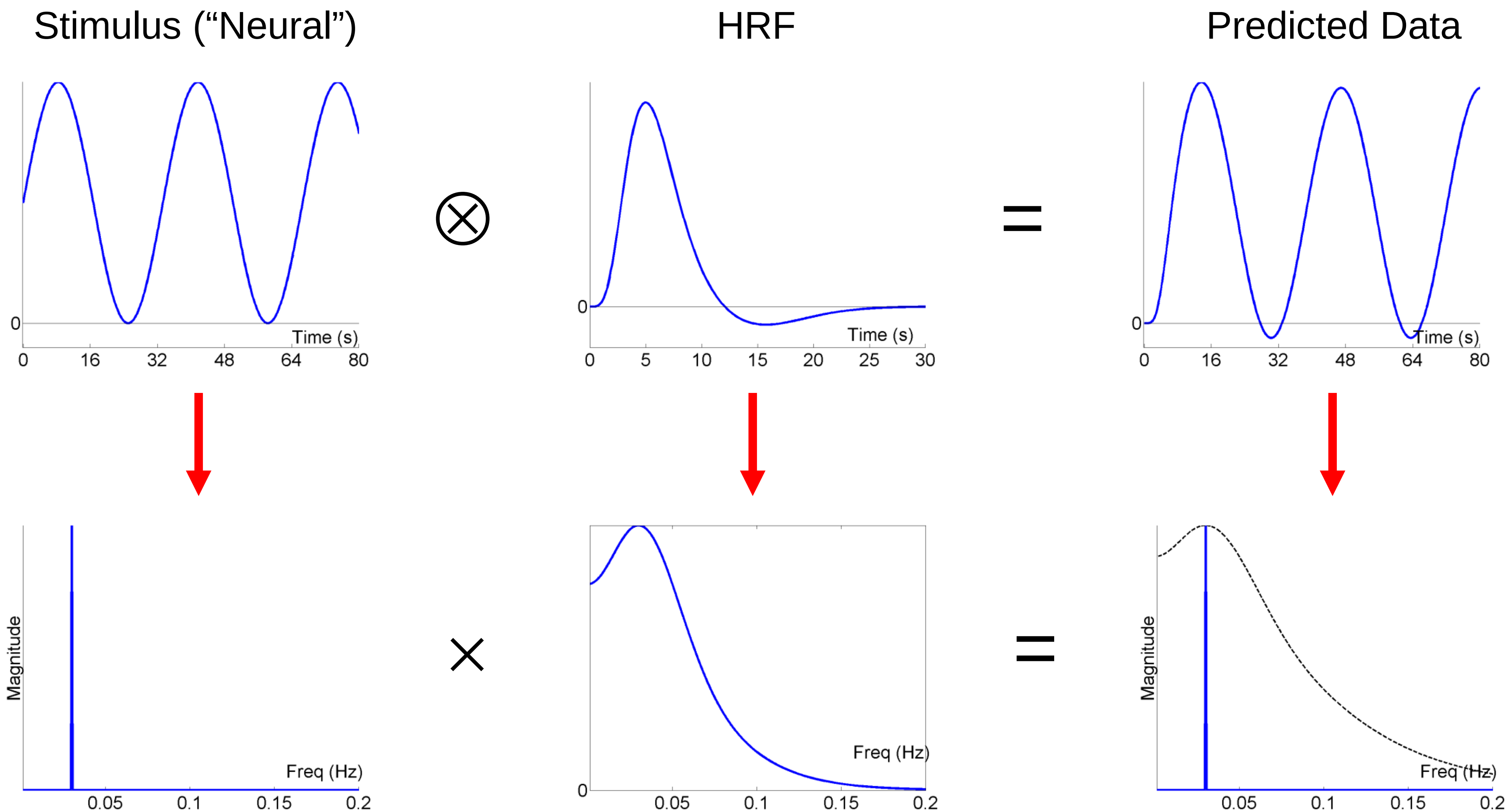
Josephs & Henson 1999, *Phil Trans B*

Blocked, epoch = 20s



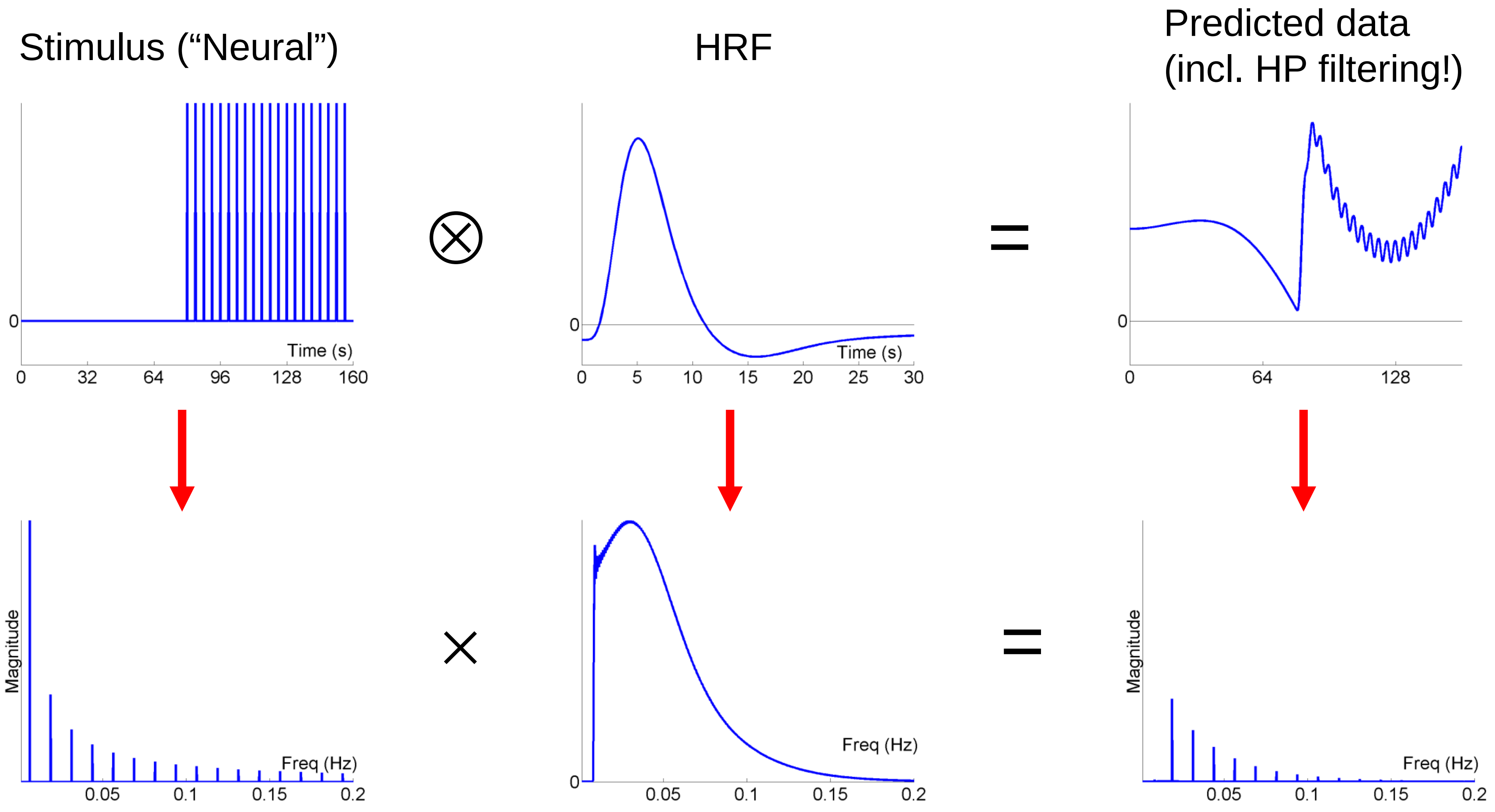
Blocked-epoch (with short SOA)

Sinusoidal modulation, f = 1/33s



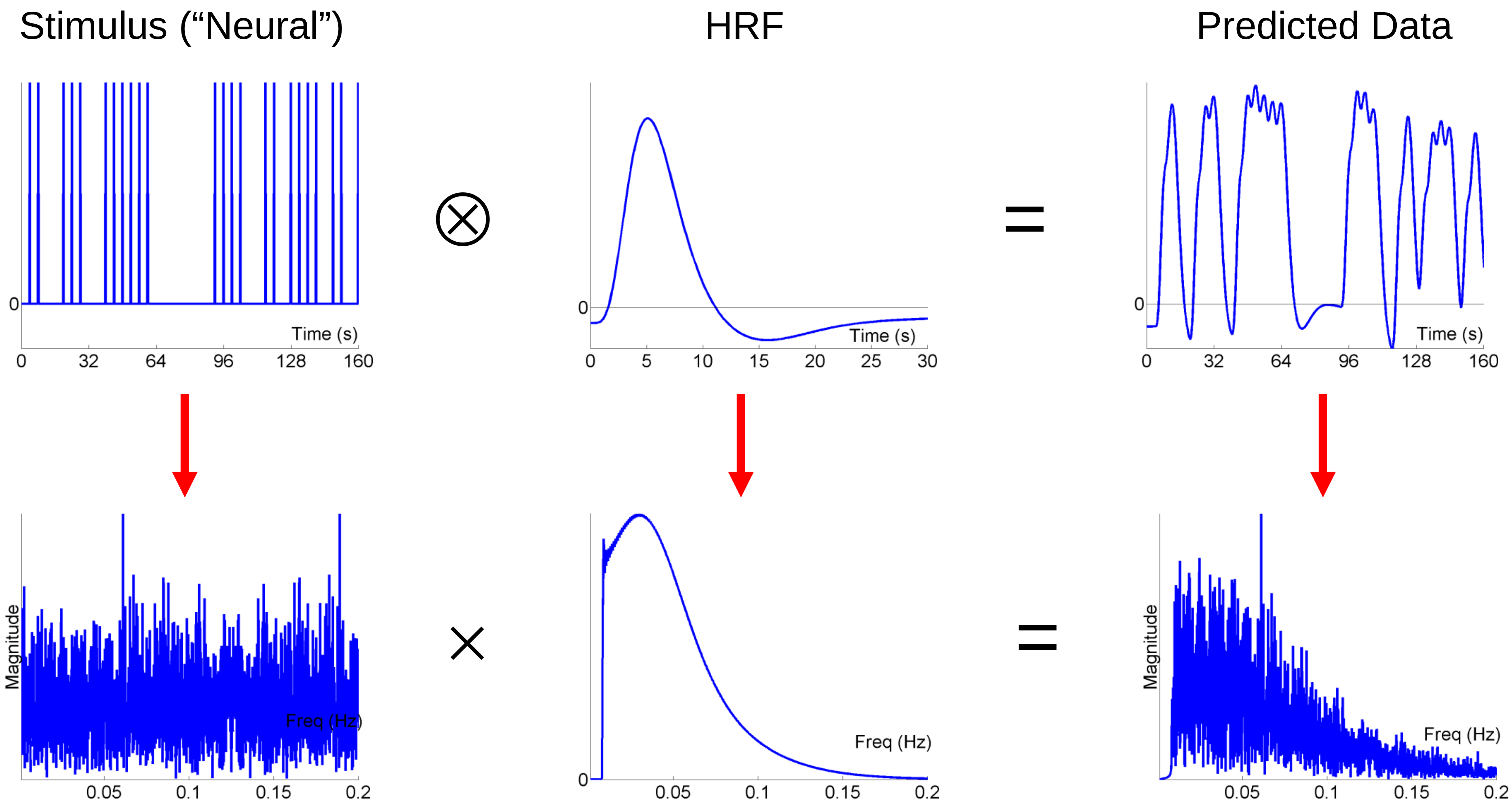
The most efficient design of all!

Blocked (80s), SOA_{min}=4s, highpass filter = 1/120s



Don't use long (>60s) blocks!

Randomised, SOA_{min}=4s, highpass filter = 1/120s



Randomised design spreads power over frequencies.

Efficiency: Multiple event types

- Design parametrised by:

  SOA$_{min}$ Minimum SOA

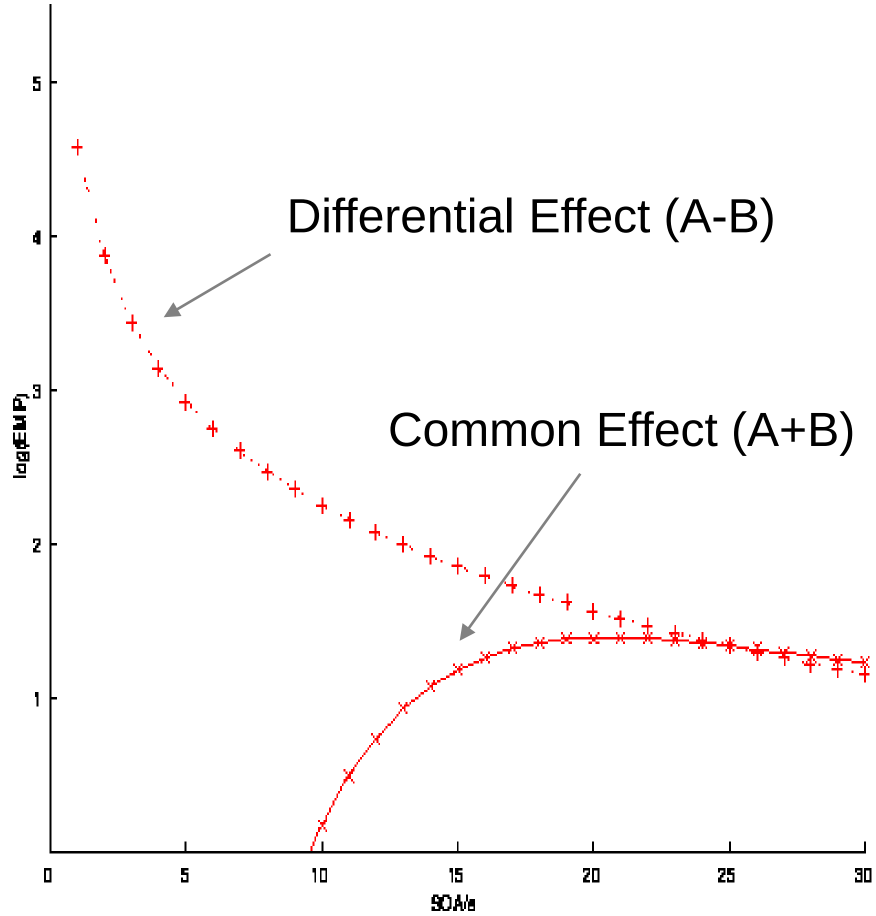
  $p_i(\boldsymbol{h})$ Probability of event-type *i* given history ***h*** of last *m* events

- With *n* event-types $p_i(\boldsymbol{h})$ is a $n^m \times n$ *Transition Matrix*

- Example: Randomised AB

	A	B
A	0.5	0.5
B	0.5	0.5

=> **ABBBABAABABAAA...**



4s smoothing; 1/60s highpass filtering

Efficiency: Multiple event types

- Example: Alternating AB

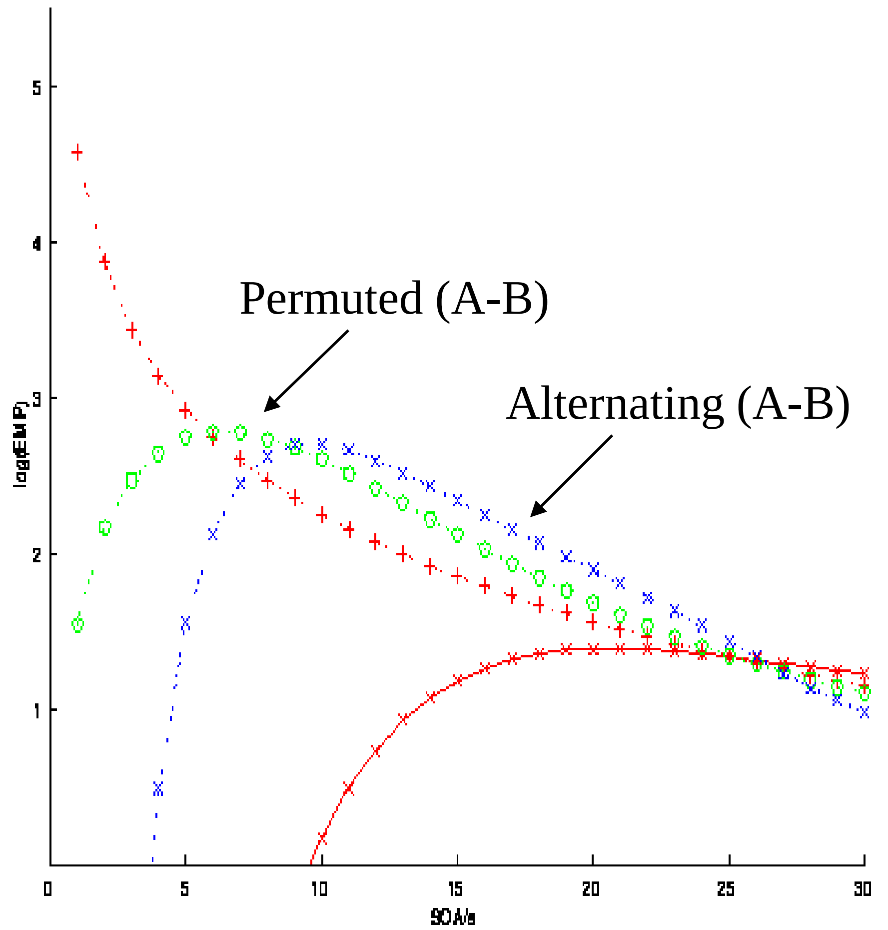
	A	**B**
A	0	1
B	1	0

=> **ABABABABABAB...**

- Example: Permuted AB

	A	**B**
AA	0	1
AB	0.5	0.5
BA	0.5	0.5
BB	1	0

=> **ABBAABABABBA...**



4s smoothing; 1/60s highpass filtering

Efficiency: Multiple event types

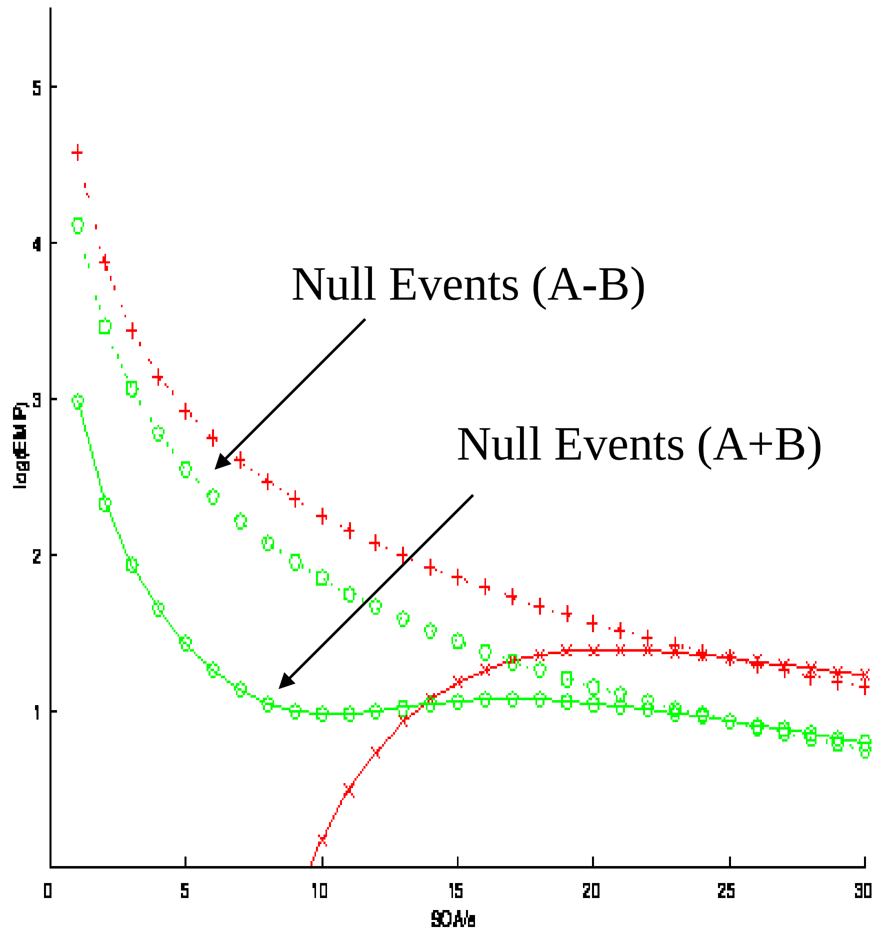
- Example: Null events

	A	**B**
A	0.33	0.33
B	0.33	0.33

=> **AB-BAA--B---ABB...**

- Efficient for differential ***and*** main effects at short SOA

- Equivalent to stochastic SOA (null event corresponds to a third unmodelled event-type)

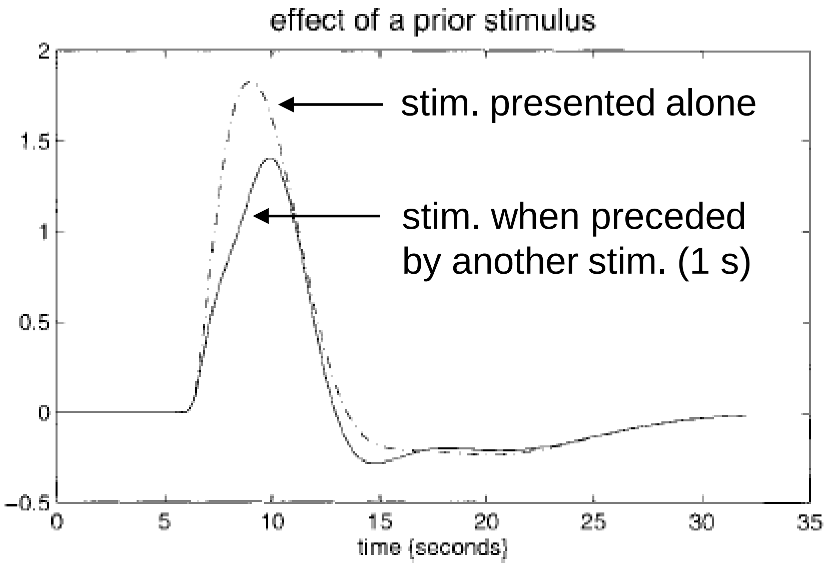


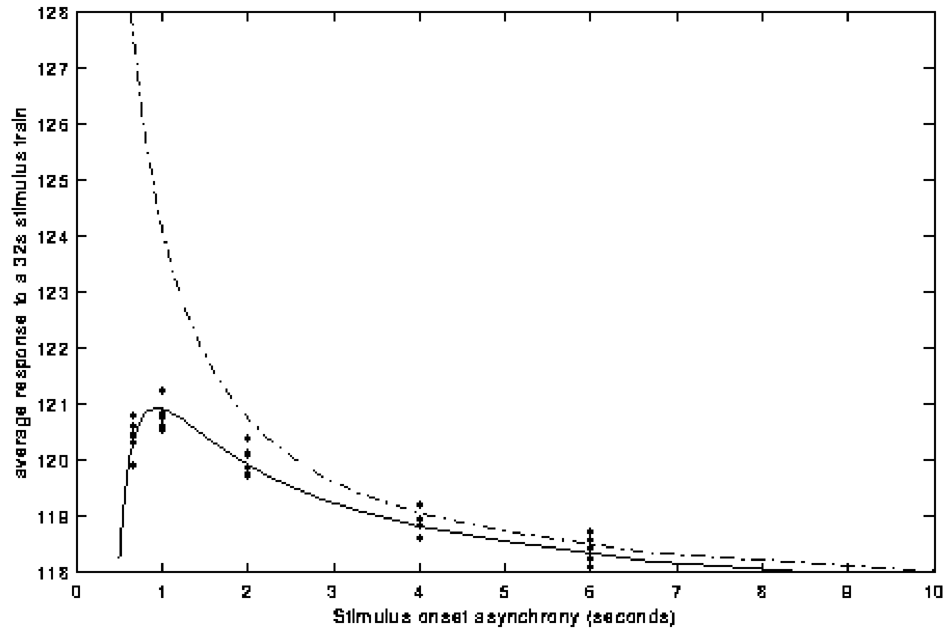
4s smoothing; 1/60s highpass filtering

Design efficiency: Conclusions

- Optimal design for one contrast may not be optimal for another
- Blocked designs generally most efficient (with short SOAs, given optimal block length is not exceeded)
- However, psychological efficiency often dictates intermixed designs, and often also sets limits on SOAs
- With randomised designs, optimal SOA for differential effect (A-B) is minimal SOA (>2 seconds, and assuming no saturation), whereas optimal SOA for main effect (A+B) is 16-20s
- Inclusion of null events improves efficiency for main effect at short SOAs (at cost of efficiency for differential effects)
- If order constrained, intermediate SOAs (5-20s) can be optimal
- If SOA constrained, pseudorandomised designs can be optimal (but may introduce context-sensitivity)

But beware: Nonlinearities at short SOAs





Friston et al. 2000, *NeuroImage*

Friston et al. 1998, *Magn. Res. Med.*

Thank you