NeuroImaging Data Processing

aka. Statistical Parametric Mapping short course

Course 5:

Evoked response fMRI &
Design efficiency

LIÈGE université
GIGA
CRC Human Imaging

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fnrs
LA LIBERTÉ DE CHERCHER

Content

- Block/epoch vs. event-related fMRI
- (Dis)Advantages of efMRI
- GLM: Convolution
- BOLD impulse response
- Temporal Basis Functions
- Timing Issues
- Design Optimisation – “Efficiency”

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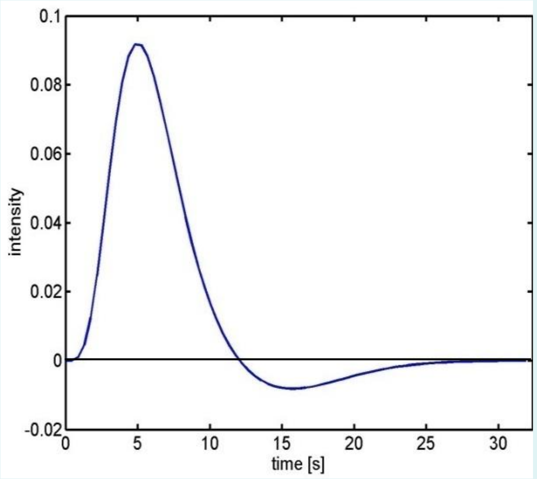
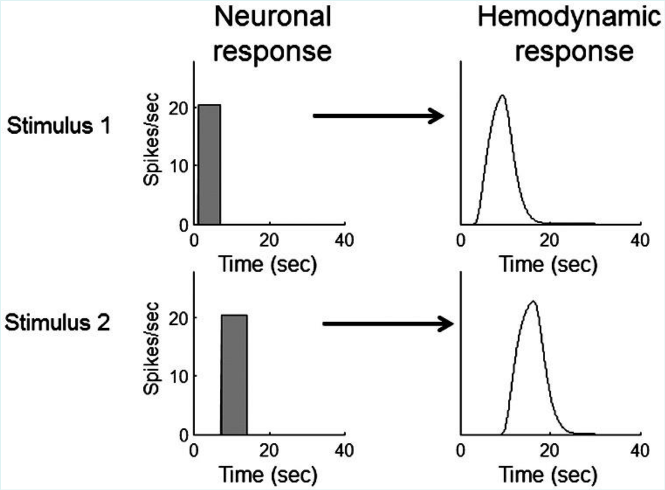
BOLD response

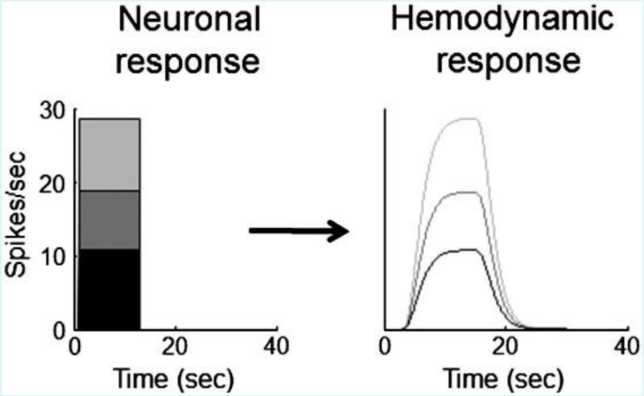
Hemodynamic response function (HRF):



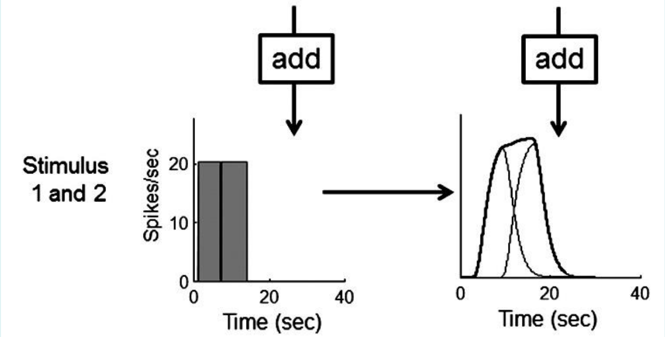
Shift invariance



Scaling



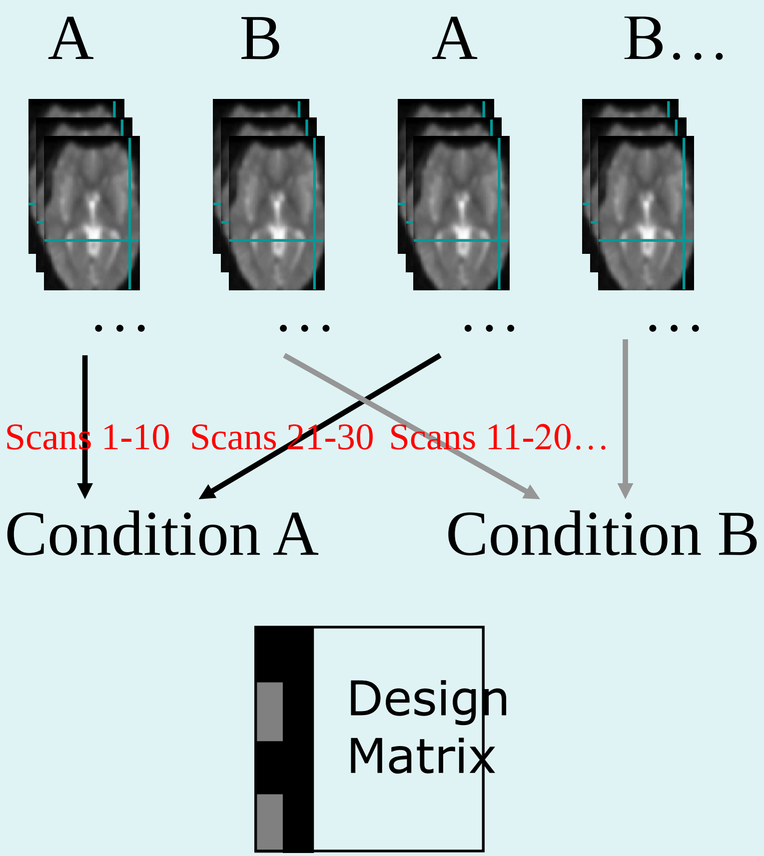
Additivity



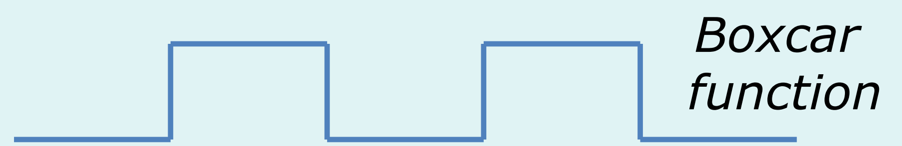
Boynton et al, NeuroImage, 2012.

Epoch vs. event related design

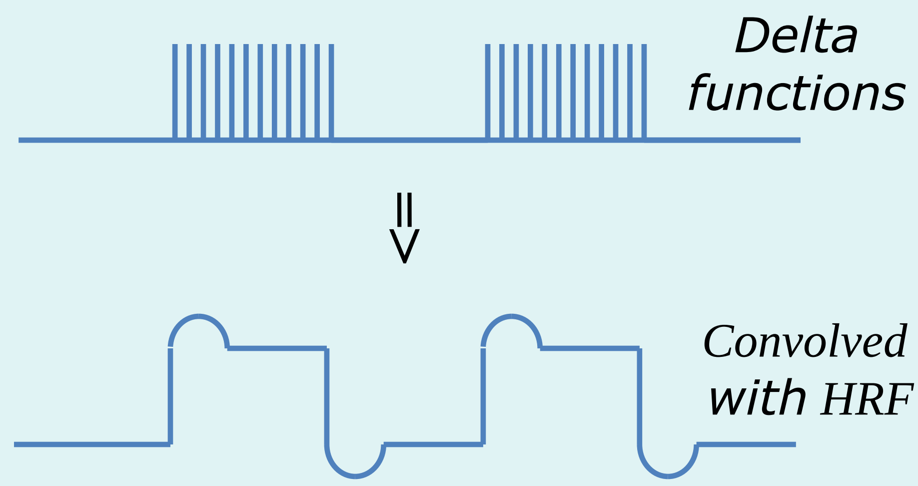
"PET Blocked conception"
(scans assigned to conditions)



"fMRI Epoch conception"
(scans treated as timeseries)



"fMRI Event-related conception"



Advantages of Event-Related design

- Randomised trial order

  c.f. confounds of blocked designs

Blocked designs may trigger expectations and cognitive sets

Intermixed designs can minimise this by stimulus randomisation

Advantages of Event-Related design

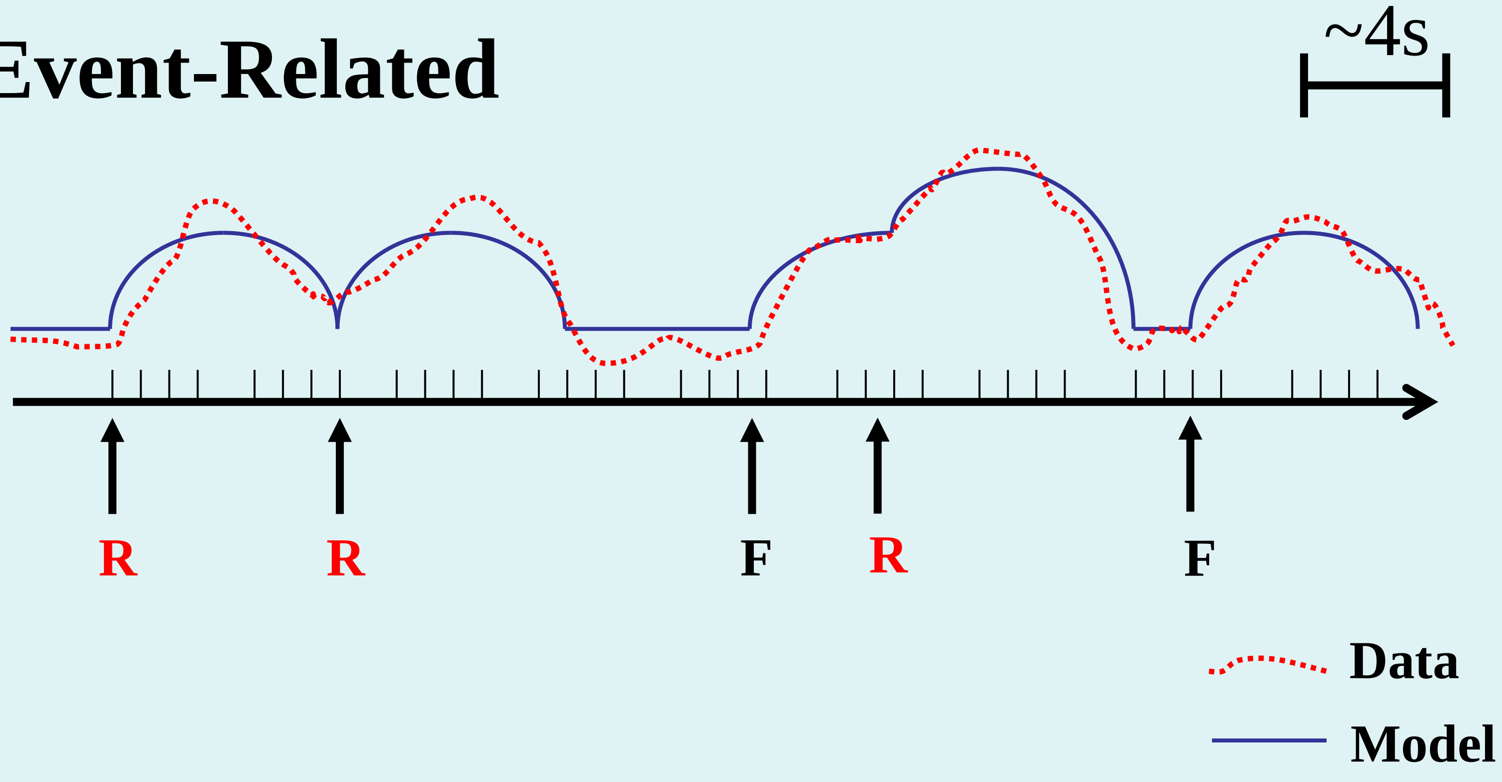
- Randomised trial order
  c.f. confounds of blocked designs

- Post hoc / subjective classification of trials
  e.g, according to subsequent memory

R = Words Later Remembered

F = Words Later Forgotten

Event-Related



Advantages of Event-Related design

- Randomised trial order
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- Post hoc / subjective classification of trials
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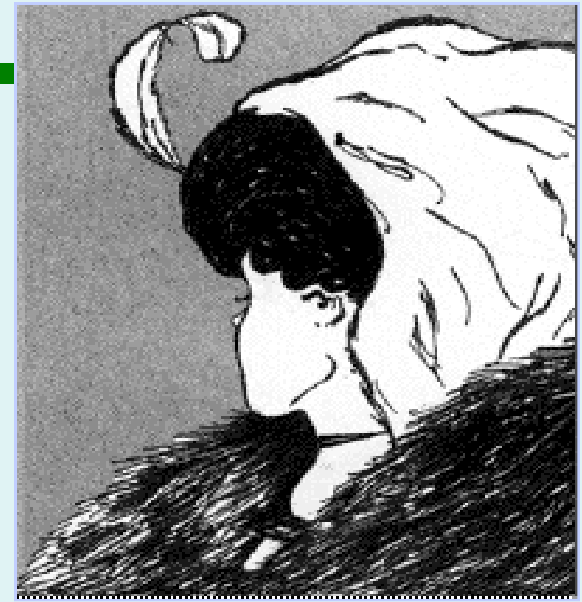
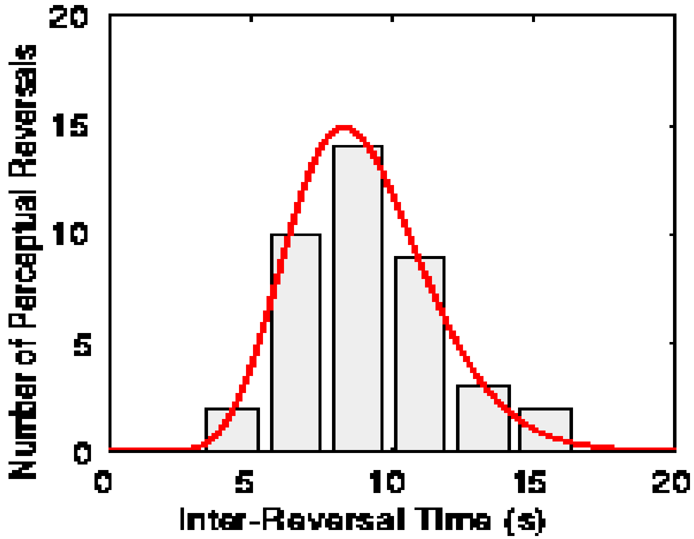
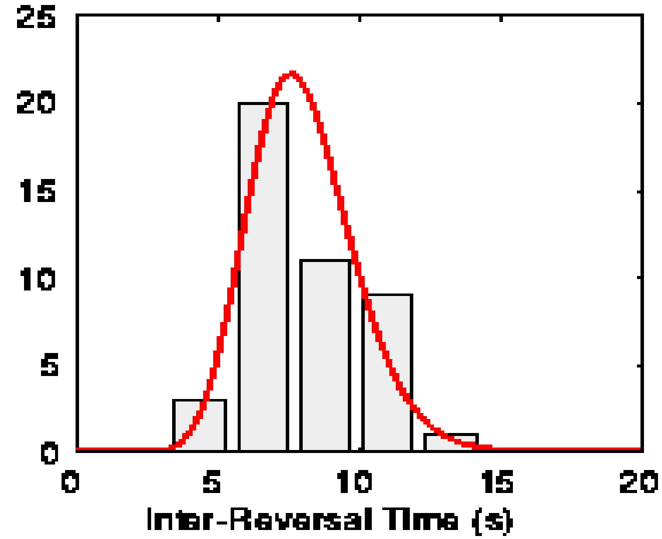
- Some events can only be indicated (in time)
  e.g, spontaneous perceptual changes




20
15
10
5
0
Number of Perceptual Reversals
0
5
10
15
20
Inter-Reversal Time (s)


25
20
15
10
5
0
0
5
10
15
20
Inter-Reversal Time (s)

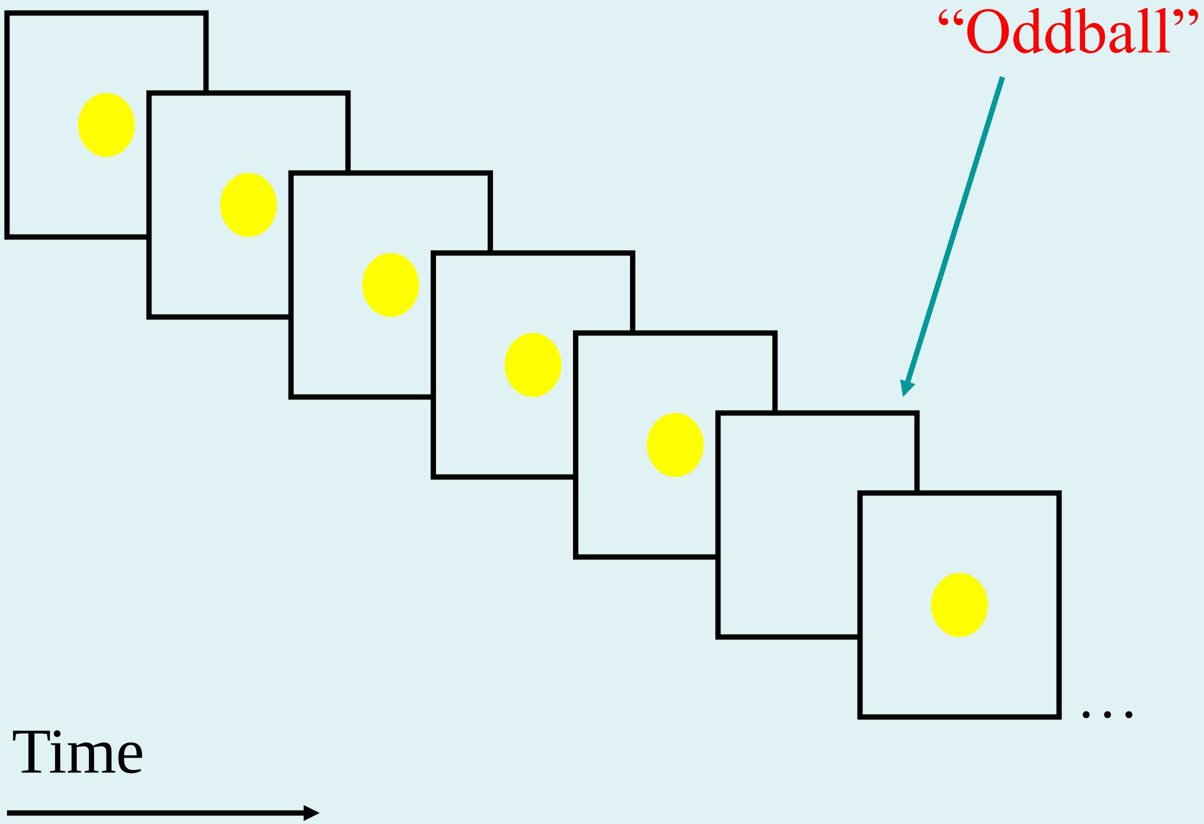
Advantages of Event-Related design

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

- Post hoc / subjective classification of trials
  e.g, according to subsequent memory

- Some events can only be indicated (in time)
  e.g, spontaneous perceptual changes

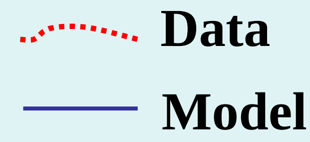
- Some trials cannot be blocked
  e.g, "oddball" designs


"Oddball"
. . .
Time

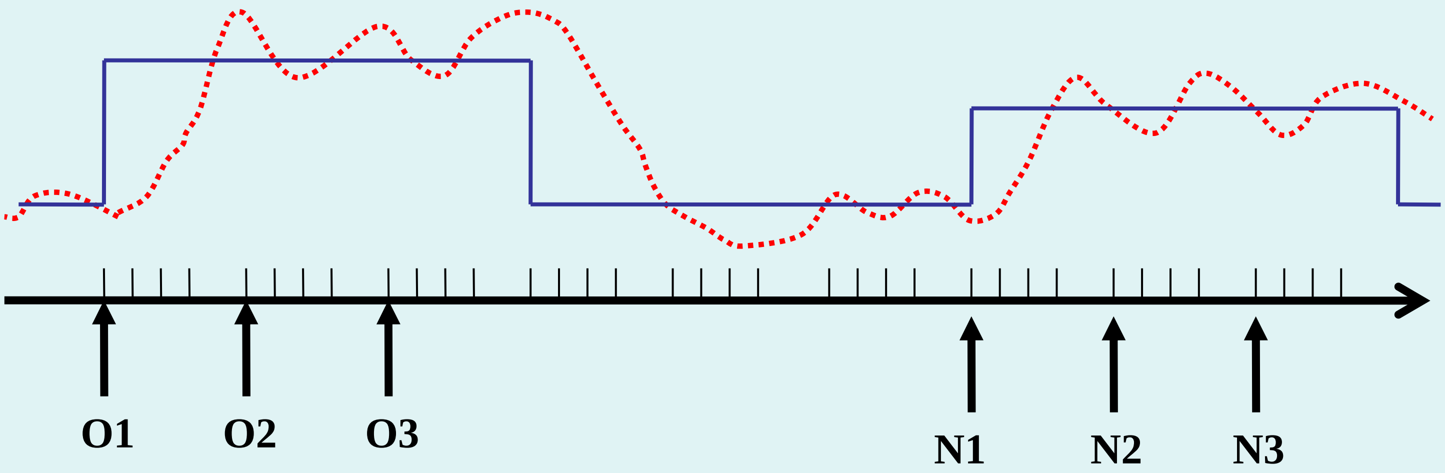
Advantages of Event-Related design

- Randomised trial order
  c.f. confounds of blocked designs
- Post hoc / subjective classification of trials
  e.g, according to subsequent memory
- Some events can only be indicated (in time)
  e.g, spontaneous perceptual changes
- Some trials cannot be blocked
  e.g, "oddball" designs
- More accurate models even for blocked designs?
  e.g, "state-item" interactions

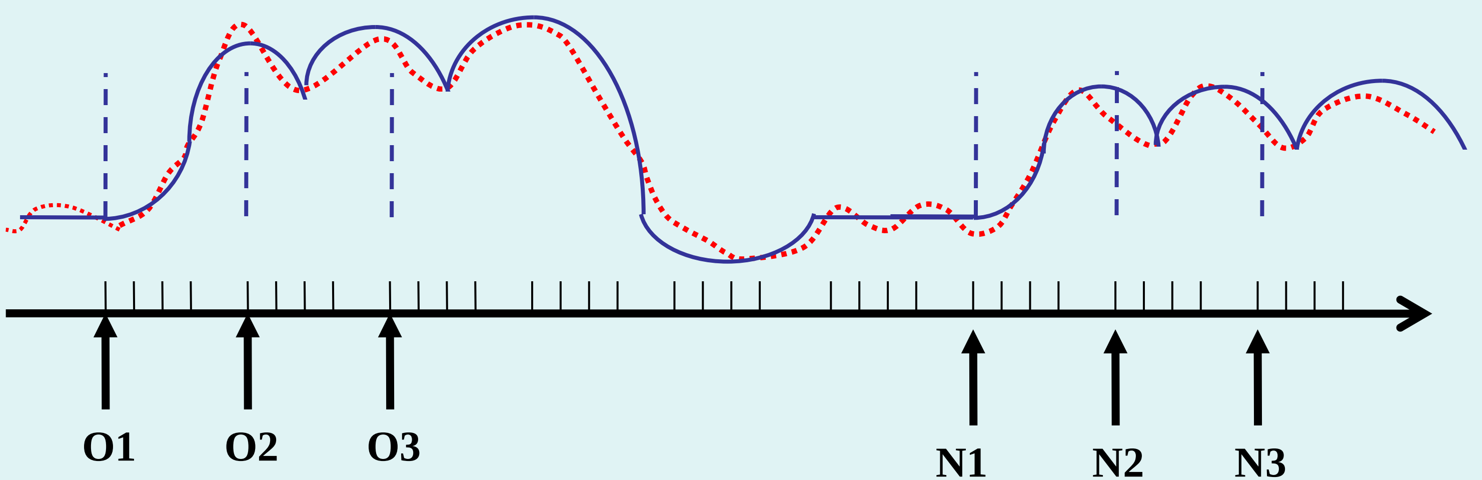
Blocked Design



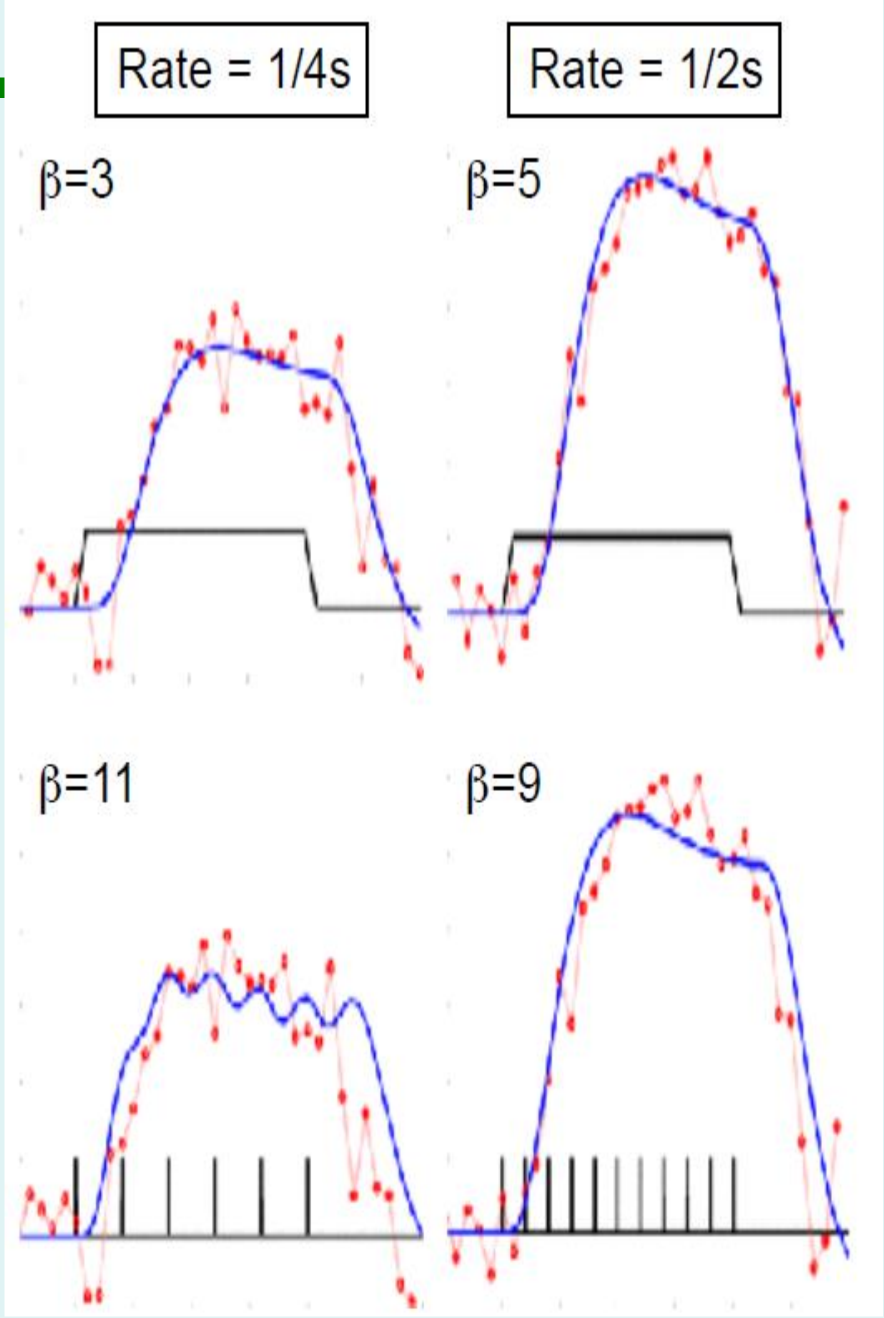
“Epoch” model



“Event” model



- Blocks of trials can be modeled as boxcars or runs of events
- BUT: interpretation of the parameter estimates may differ
- Consider an experiment presenting words at different rates in different blocks:
  - An "epoch" model will estimate parameter **that increases with rate**, because the parameter reflects response per block
  - An "event" model may estimate parameter **that decreases with rate**, because the parameter reflects response per word



Disadvantages of ER designs

- Less efficient for detecting effects than are blocked designs *(see later…)*
- Some psychological processes may be better blocked (e.g. task-switching, attentional instructions)

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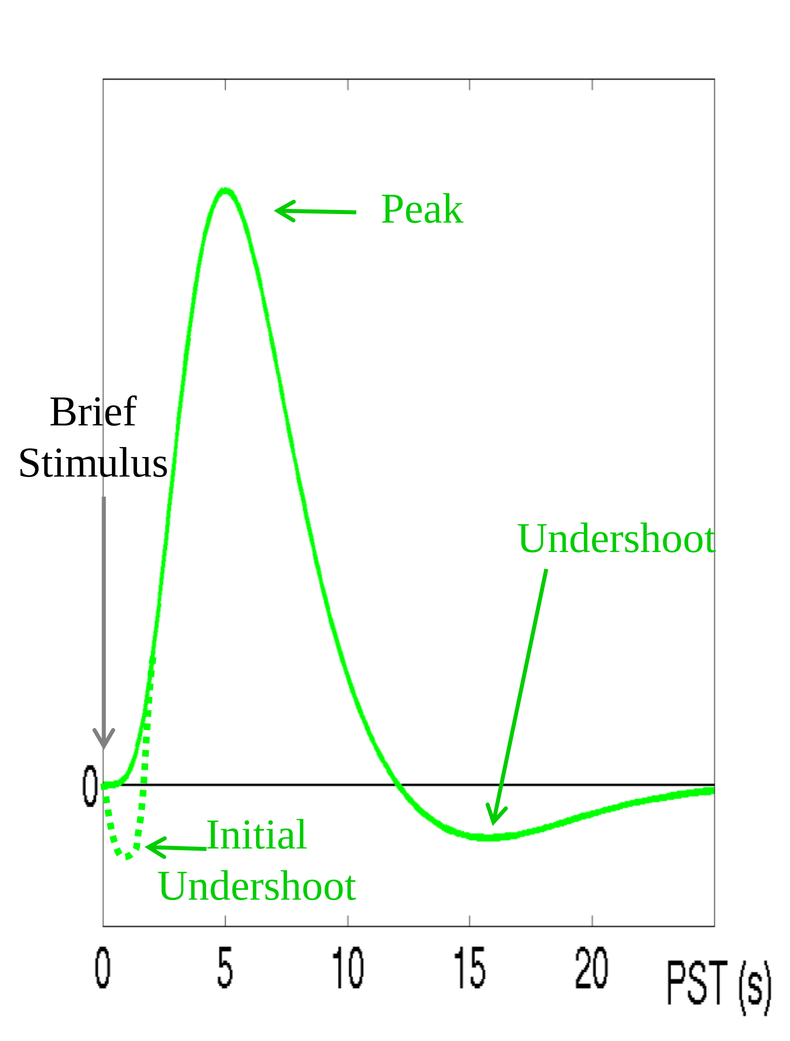
Haemodynamic response function

- Function of blood oxygenation, flow, volume (Buxton et al, 1998)
- Peak (max. oxygenation) 4-6s poststimulus; baseline after 20-30s
- Initial undershoot can be observed (Malonek & Grinvald, 1996)
- Similar across V1, A1, S1…
- … but differences across: other regions (Schacter et al 1997) and individuals (Aguirre et al, 1998)



General Linear (Convolution) Model

GLM for a single voxel:

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

$u(t)$ = neural causes (stimulus train)

$$u(t) = \sum \delta\,(t - nT)$$

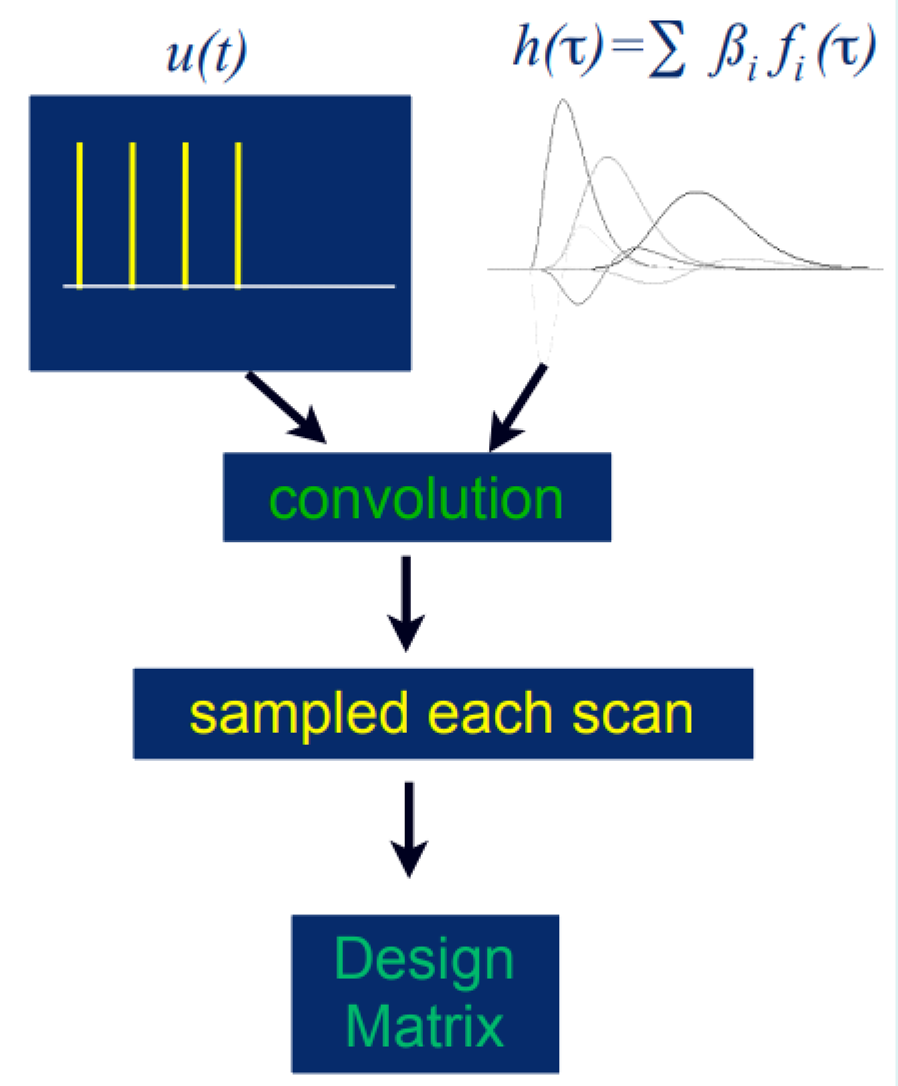
$h(\tau)$ = hemodynamic (BOLD) response

$$h(\tau) = \sum \beta_i\, f_i\,(\tau)$$

$f_i(\tau)$ = temporal basis functions

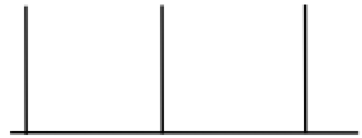
$$y(t) = \sum \sum \beta_i\, f_i\,(t - nT) + \varepsilon(t)$$

$$\mathbf{y} \quad = \quad \mathbf{X}\,\boldsymbol{\beta} \quad + \; \boldsymbol{\varepsilon}$$

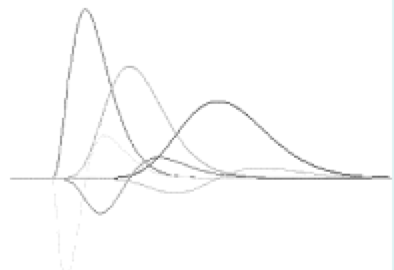


General Linear Model in SPM

Stimulus every 20s



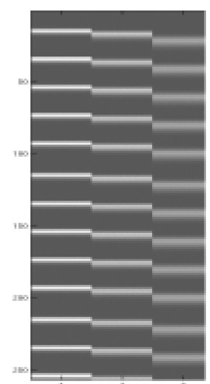
Gamma functions $f_i(\tau)$ of peristimulus time τ (Orthogonalised)



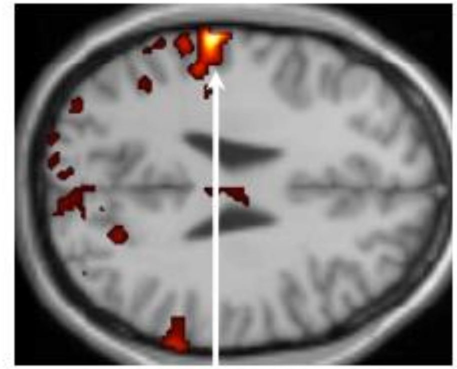
Sampled every TR = 1.7s

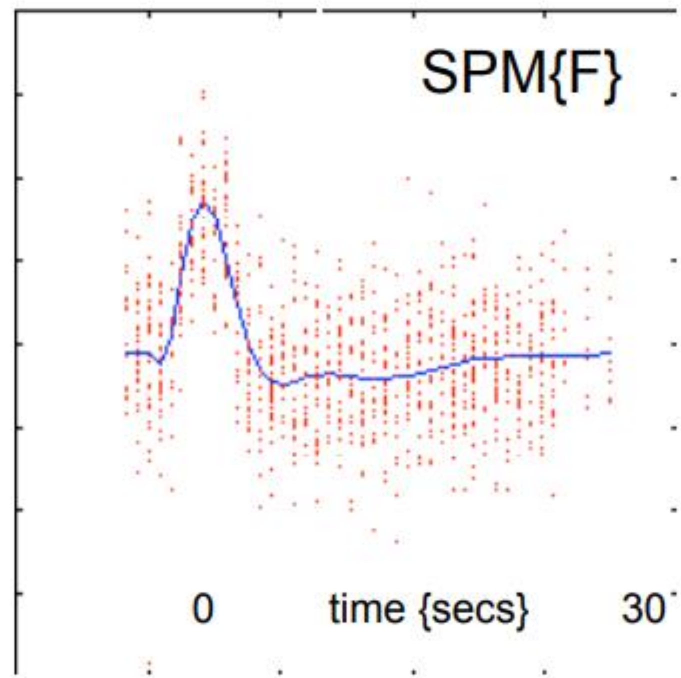
Design matrix, $\mathbf{X}$

$[x(t)\otimes f_1(\tau) \mid x(t)\otimes f_2(\tau) \mid \ldots]$



…





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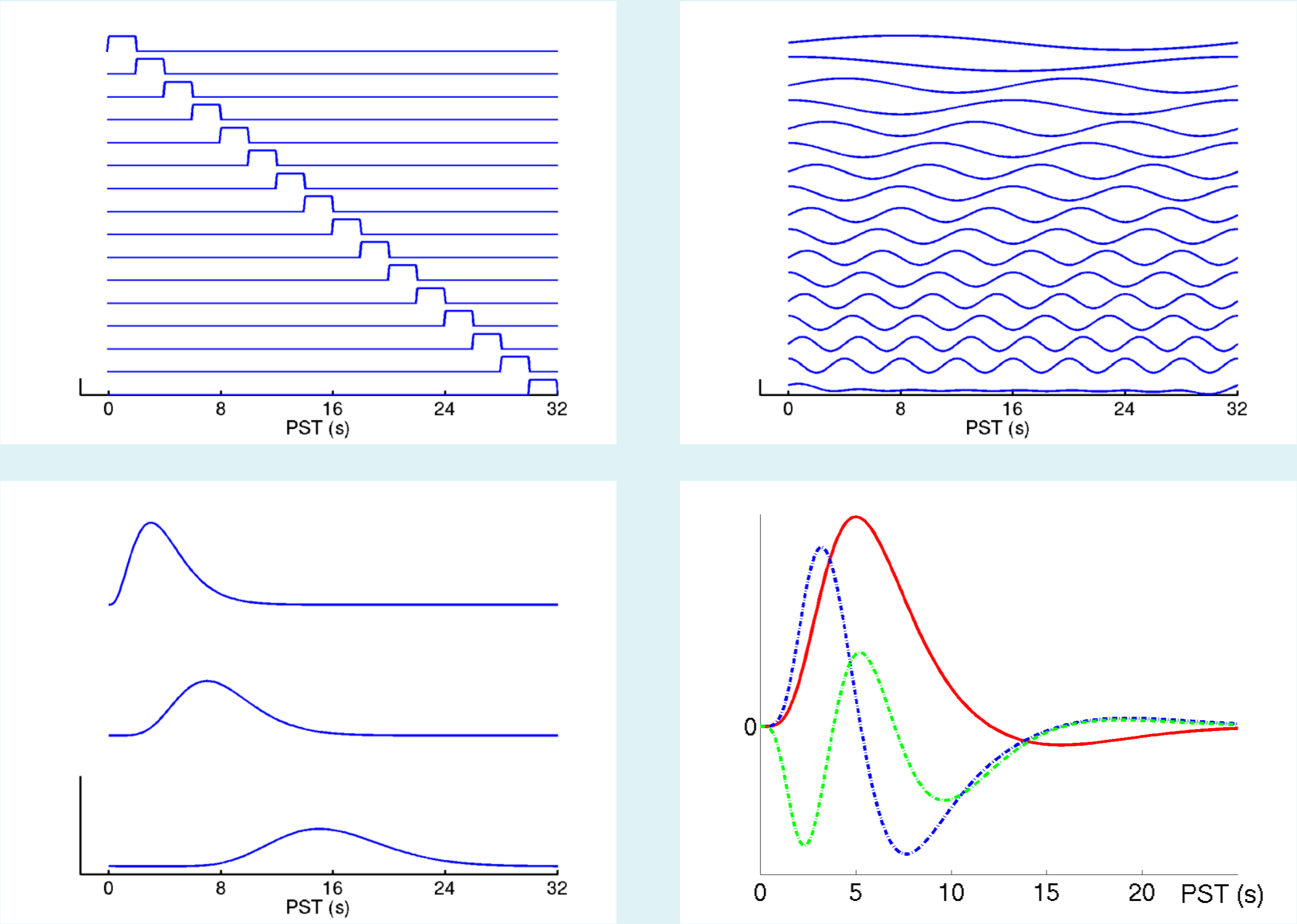
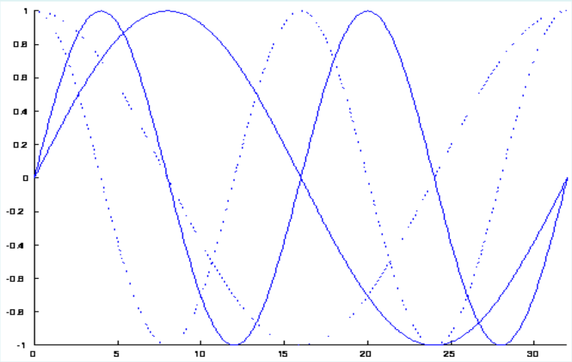
Temporal Basis Functions



Temporal Basis Functions

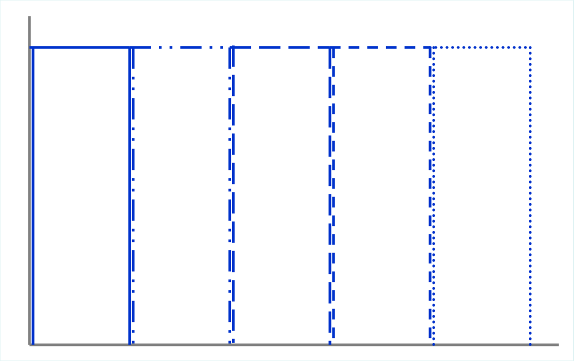
- Fourier Set

  Windowed sines & cosines
  Any shape (up to frequency limit)
  Inference via F-test



- Finite Impulse Response (FIR)

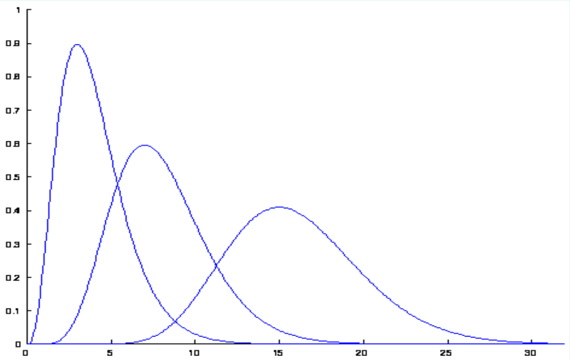
  Mini timebins (selective averaging)
  Any shape (up to bin-width)
  Inference via F-test



Temporal Basis Functions

- Gamma Functions

  Bounded, asymmetrical (like BOLD)
  Set of different lags
  Inference via F-test



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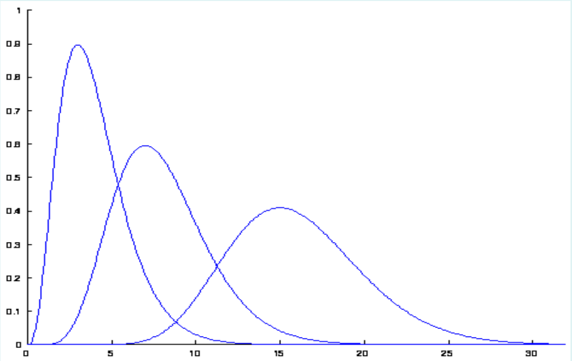
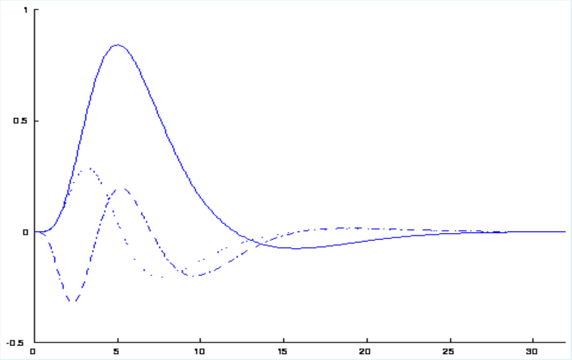
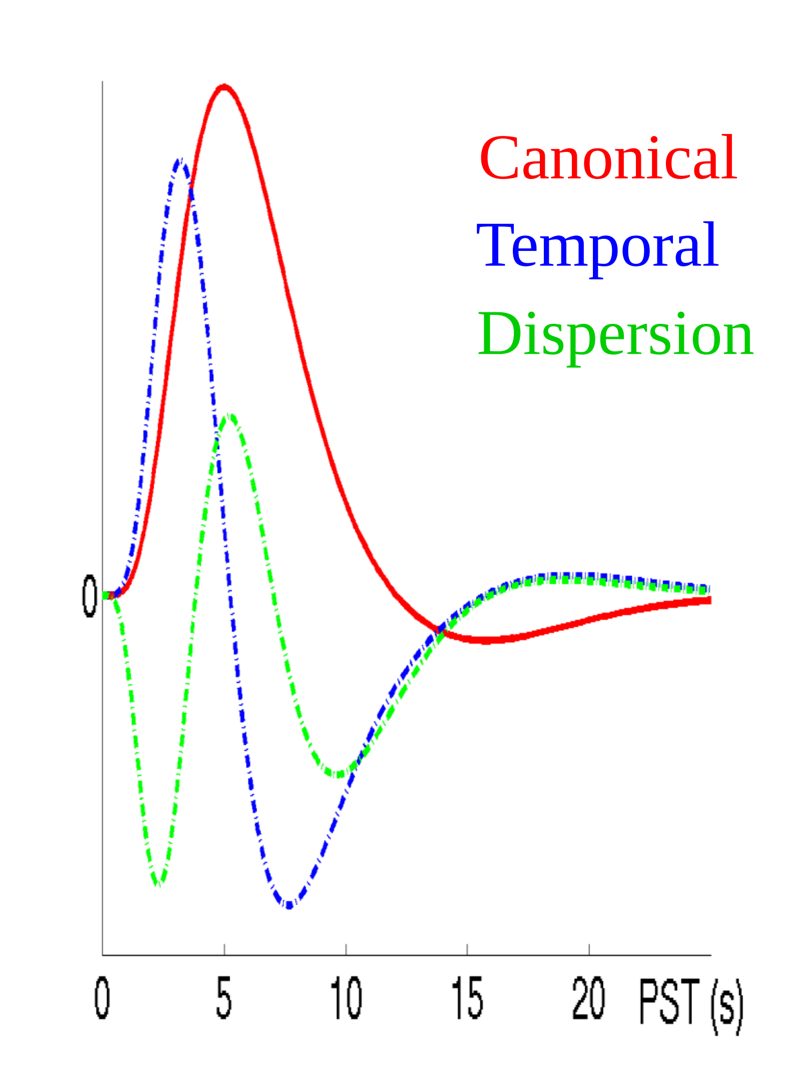


- Informed Basis Set

  Best guess of canonical BOLD response
  Variability captured by Taylor expansion
  “Magnitude” inferences via
  t-test…?



Temporal Basis Functions



- Informed Basis Set

  (Friston et al. 1998)

- Canonical HRF (2 gamma functions)

  plus Multivariate Taylor expansion in:

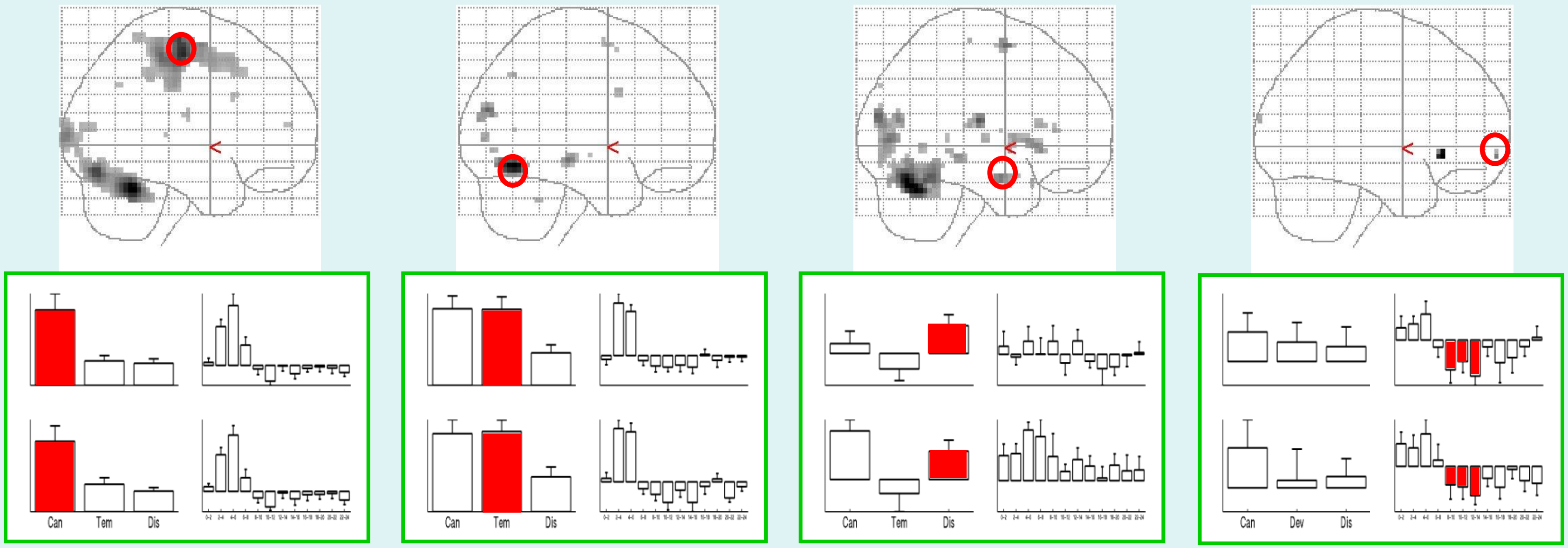
  time (*Temporal Derivative*)

  width *(Dispersion Derivative)*

- "Magnitude" inferences via t-test on canonical parameters (providing canonical is a good fit…more later)
- "Latency" inferences via tests on *ratio* of derivative : canonical parameters (more later…)

Temporal Basis Functions, which one(s)?

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 (eg stimulus-delay-response)

…but then such trials better modelled with separate neural components (ie activity no longer delta function) + constrained HRF (Zarahn, 1999)

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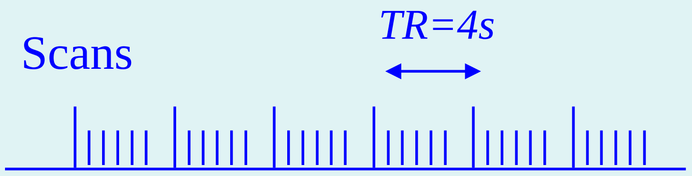
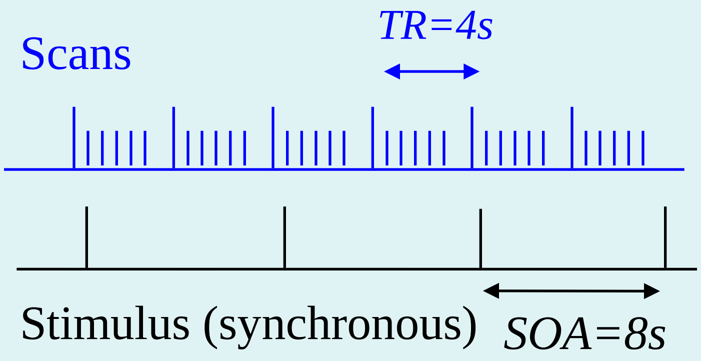
Timing Issues

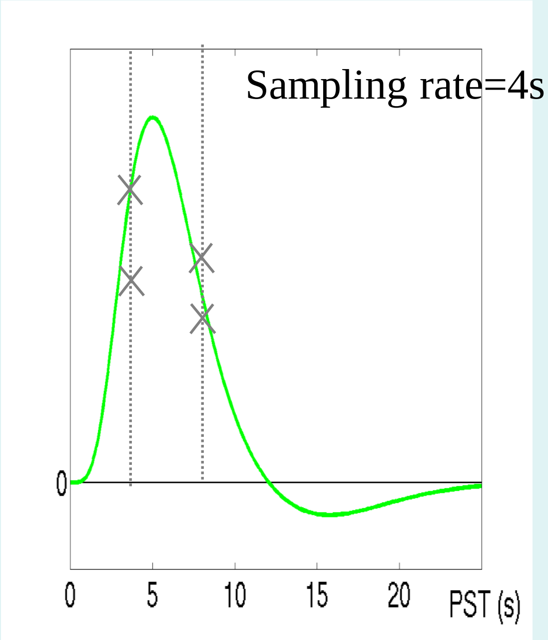
- Typical TR for 48 slice EPI at 3mm spacing is ~ 4s



Timing Issues

- Typical TR for 48 slice EPI at 3mm spacing is ~ 4s
- Sampling at [0,4,8,12…] post- stimulus may miss peak signal





Timing Issues

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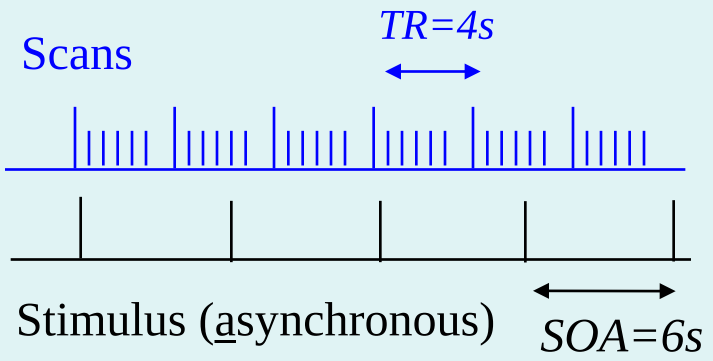
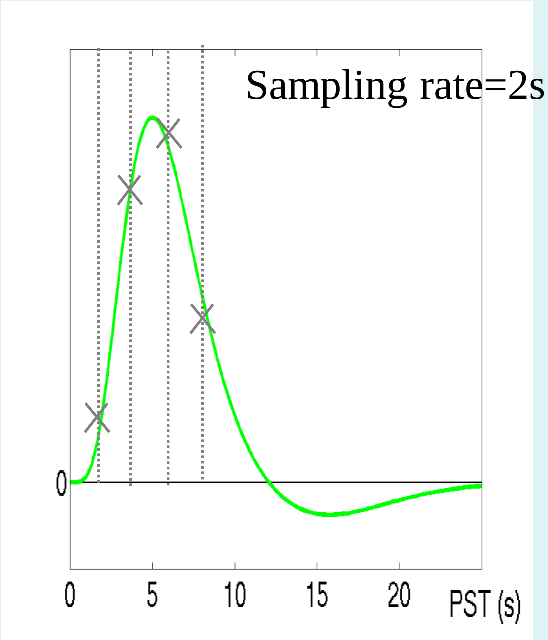
- Higher effective sampling by:
  1. Asynchrony, *e.g. SOA=1.5TR*

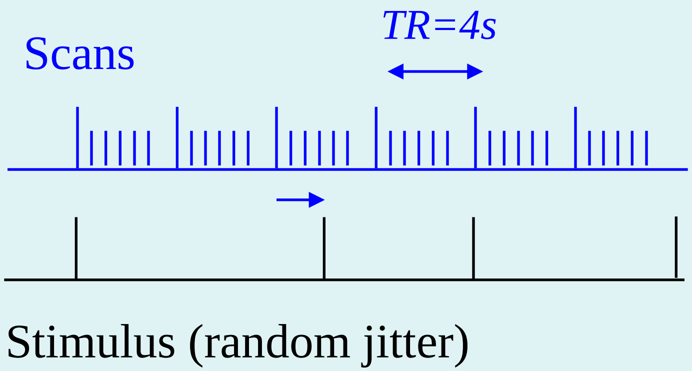


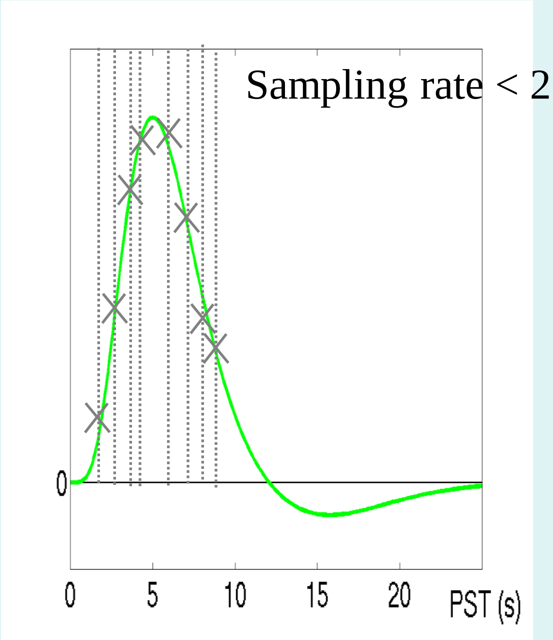


Timing Issues

- Typical TR for 48 slice EPI at 3mm spacing is ~ 4s
- Sampling at [0,4,8,12…] post- stimulus may miss peak signal
- Higher effective sampling by:

  1. Asynchrony, *e.g.* *SOA=1.5TR*
  2. Random Jitter, e.g. *SOA=(2±0.5)TR*





BOLD Response Latency (Linear)

- Assume the real response, $r(t)$, is a scaled (by α) version of the canonical, $f(t)$, but delayed by a small amount dt:

$$r(t) = \alpha f(t+dt) \sim \alpha f(t) + \alpha f\,'(t)\, dt \qquad \text{1}^{st}\text{-order Taylor}$$

- If the fitted response, $R(t)$, is modelled by the canonical + temporal derivative:

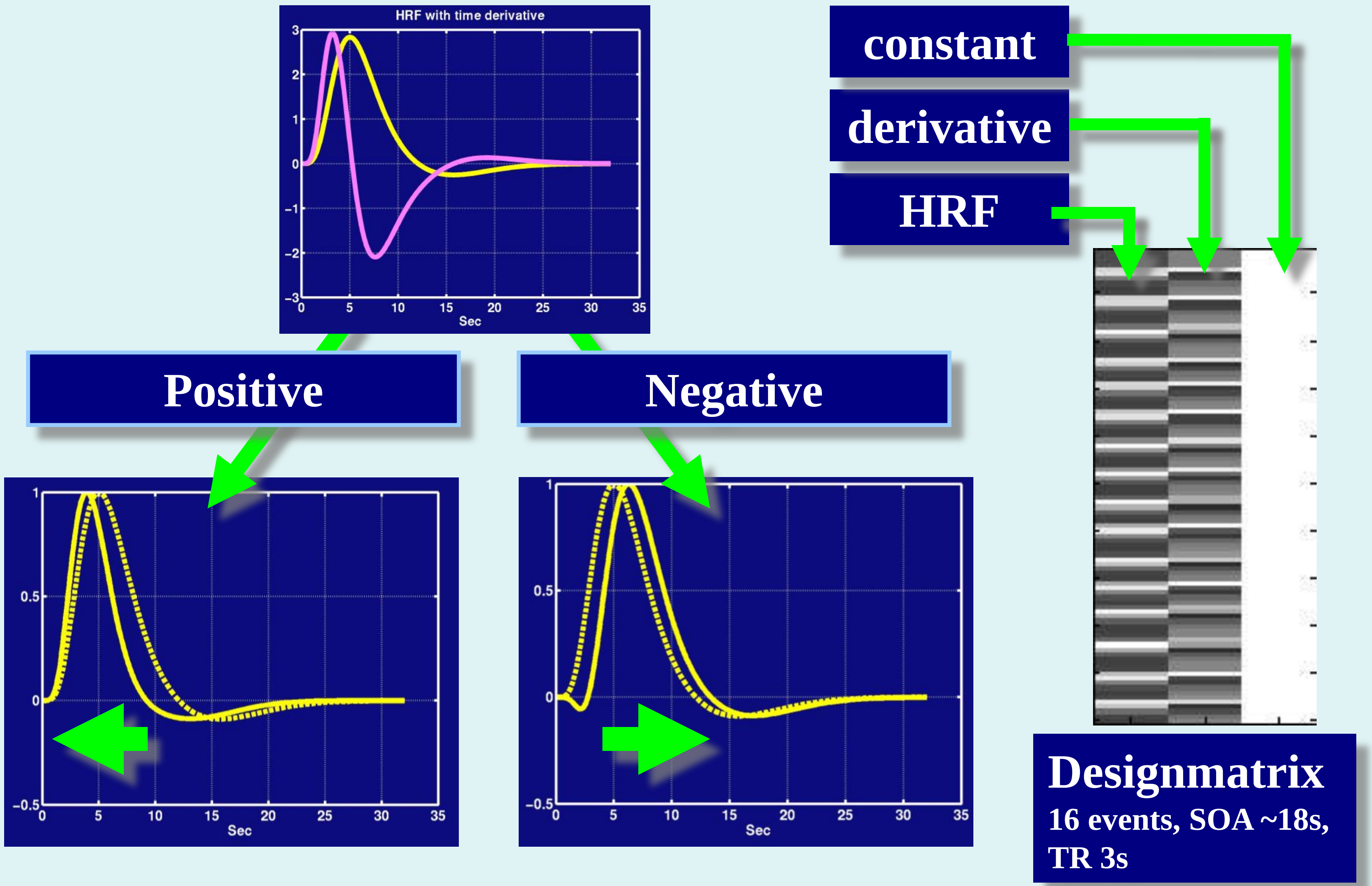
$$R(t) = ß_1\, f(t) + ß_2\, f\,'(t) \qquad \text{GLM fit}$$

- Then canonical and derivative parameter estimates, $ß_1$ and $ß_2$, are such that:

$$\alpha = ß_1\,, \quad dt = ß_2 / ß_1$$

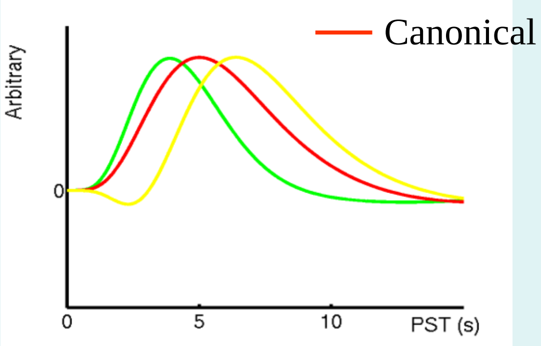
- *i.e. latency can be approximated by the ratio of derivative-to-canonical parameter estimates (within limits of first-order approximation, +/- 1s)*

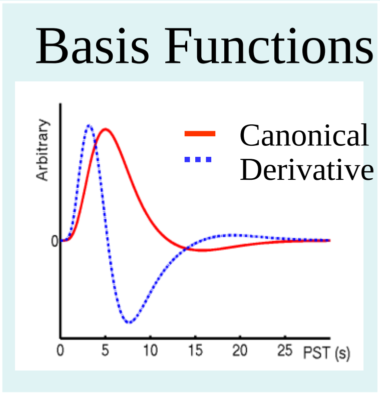
BOLD Response Latency: example

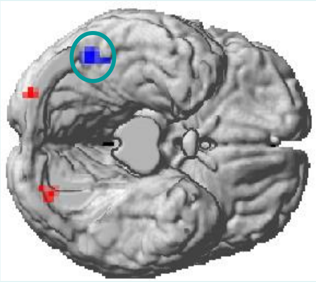


BOLD Response Latency (Linear)

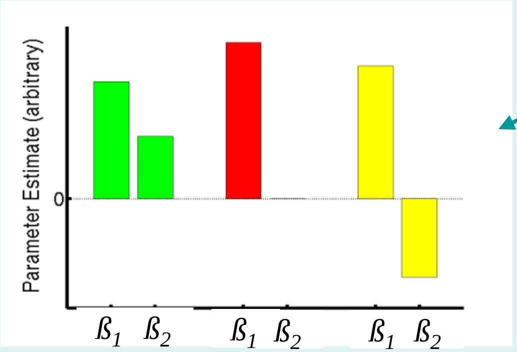
Delayed Responses (green/yellow)

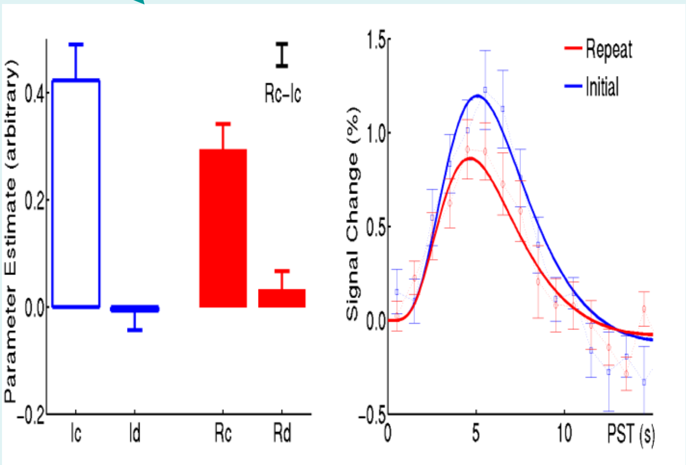




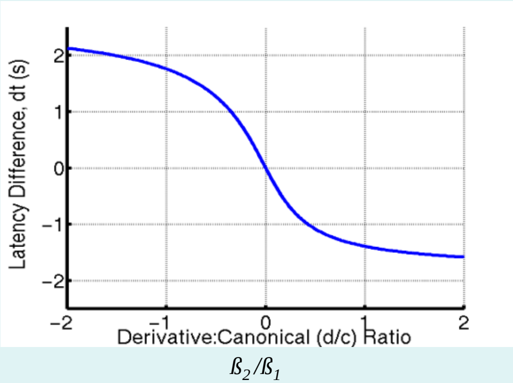


Parameter Estimates





Actual latency, *dt*, vs. β_2 / β_1



Face repetition reduces latency as well as magnitude of fusiform response

Neural Response Latency

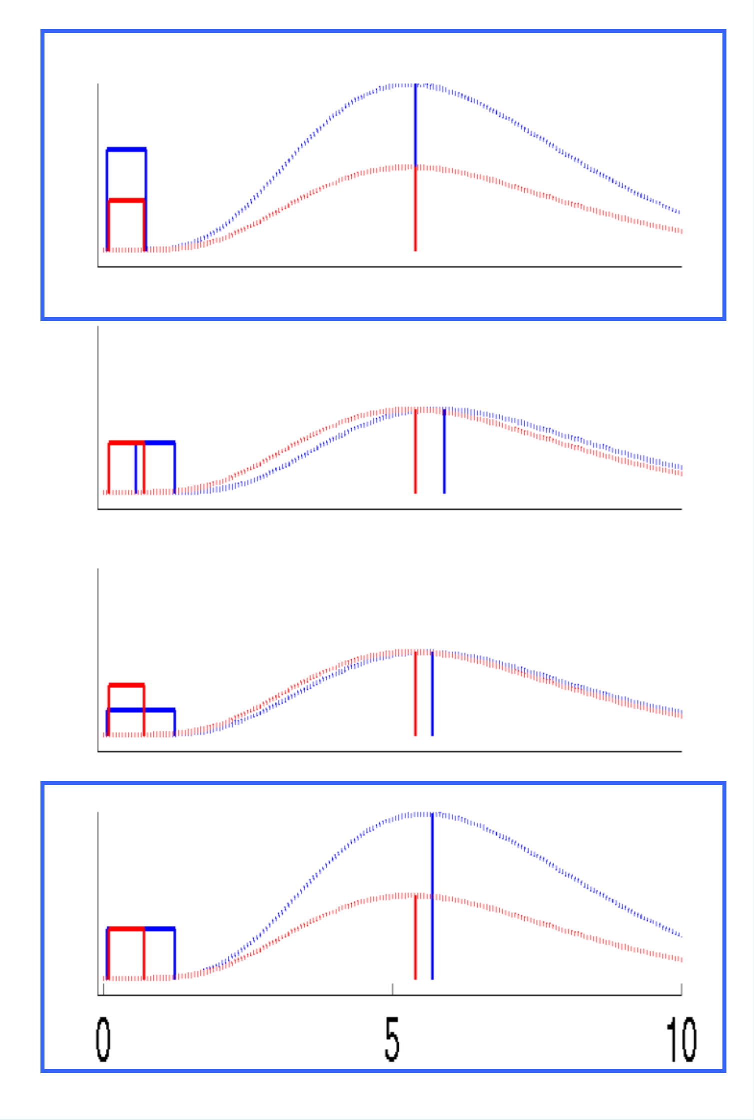
Neural

A. Decreased

B. Advanced

C. Shortened (same integrated)

D. Shortened (same maximum)



BOLD

A. Smaller Peak

B. Earlier Onset

C. Earlier Peak

D. Smaller Peak *and earlier Peak*

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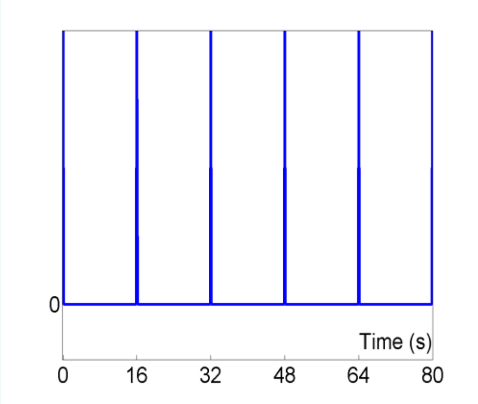
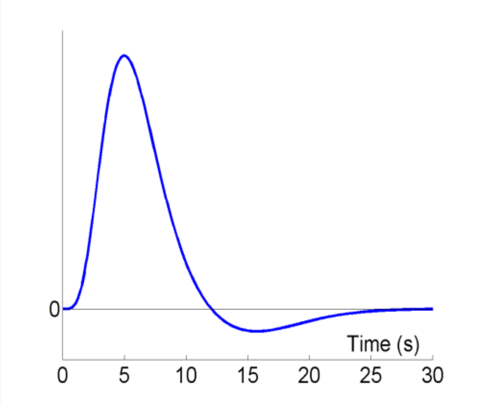
Fixed SOA = 16s

Stimulus ("Neural")



$\otimes$

HRF



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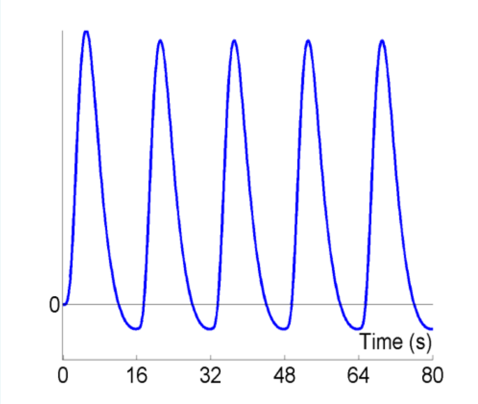
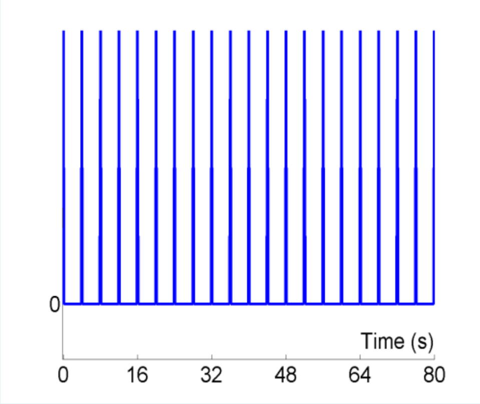
Predicted Data



Not particularly efficient…

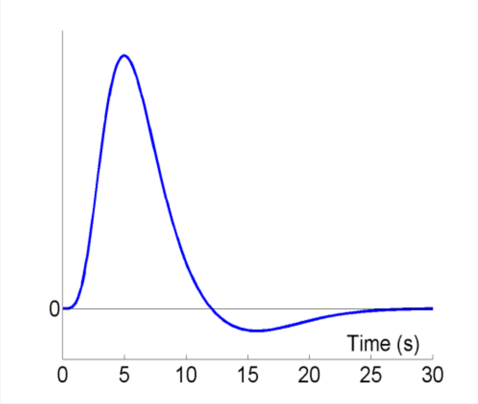
Fixed SOA = 4s

Stimulus ("Neural")



$\otimes$

HRF



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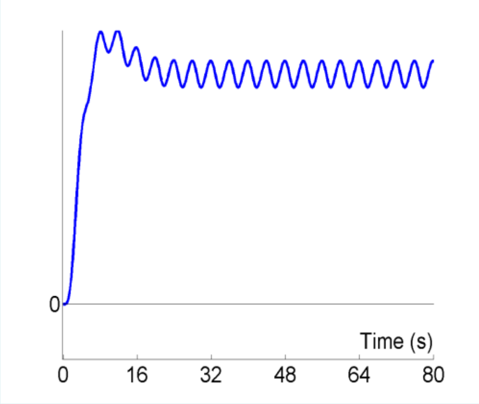
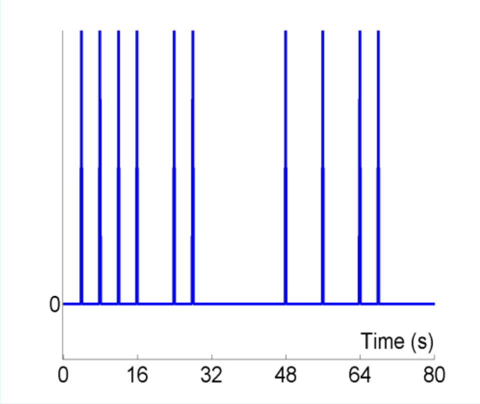
Predicted Data



Very Inefficient…

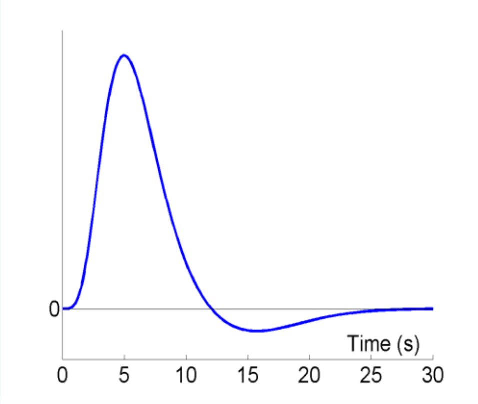
Randomised, SOA_{min}= 4s

Stimulus ("Neural")



$\otimes$

HRF



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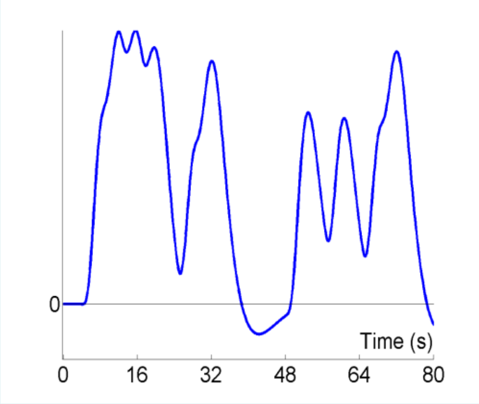
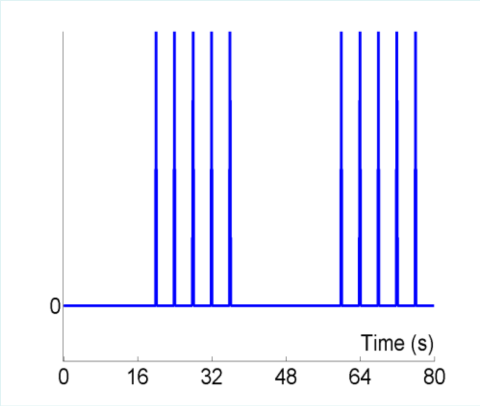
Predicted Data



More Efficient…

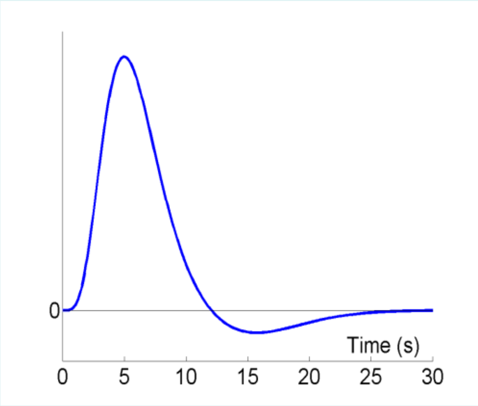
Blocked, $SOA_{min} = 4s$

Stimulus ("Neural")



$\otimes$

HRF



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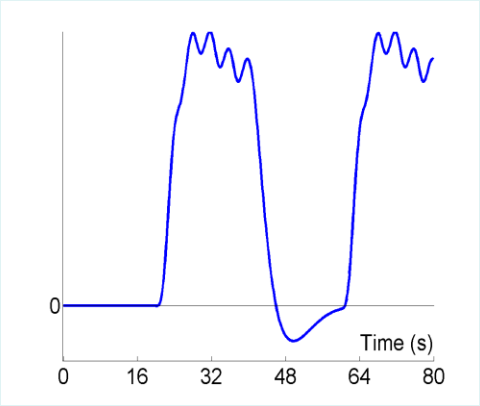
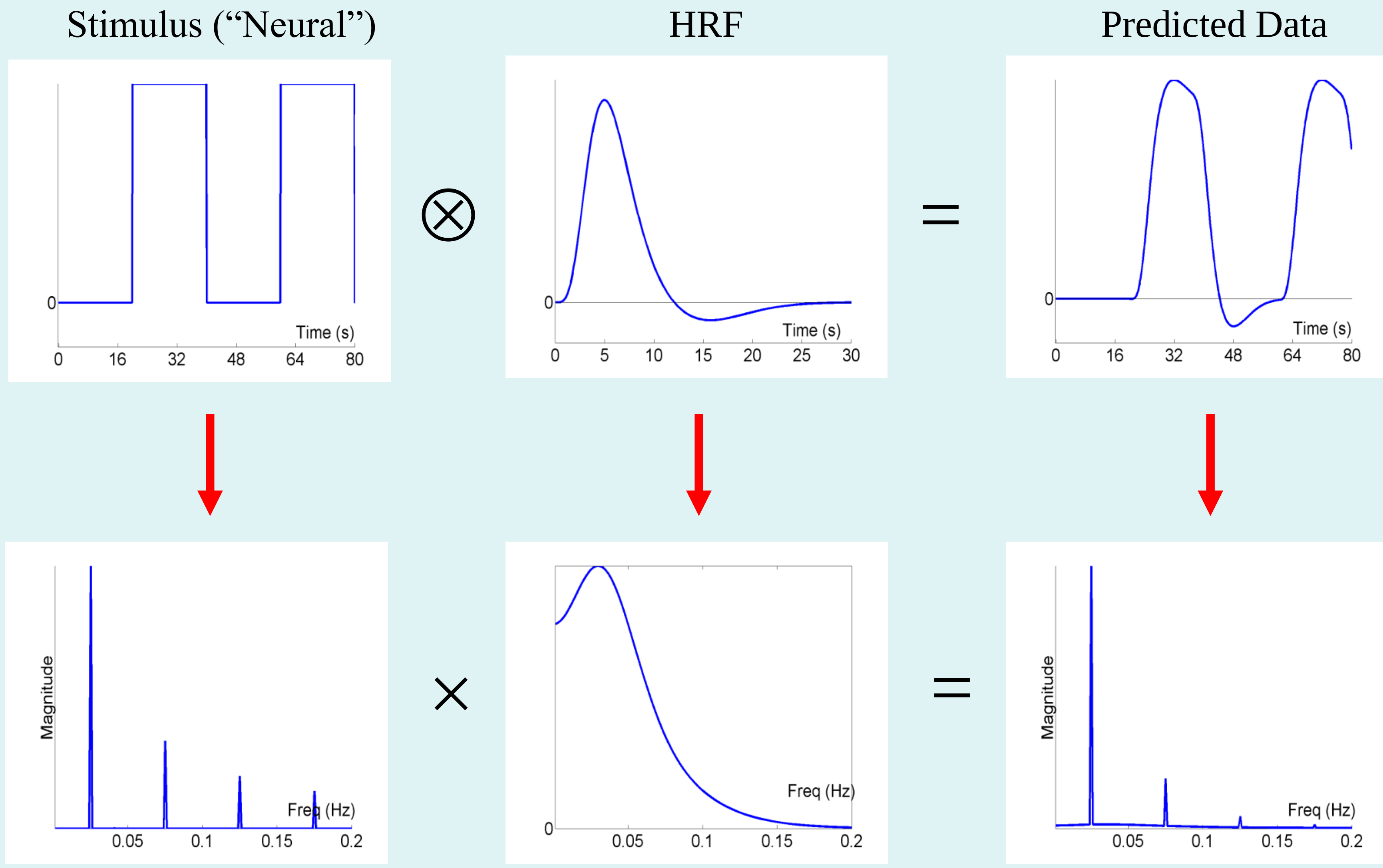
Predicted Data



Even more Efficient…

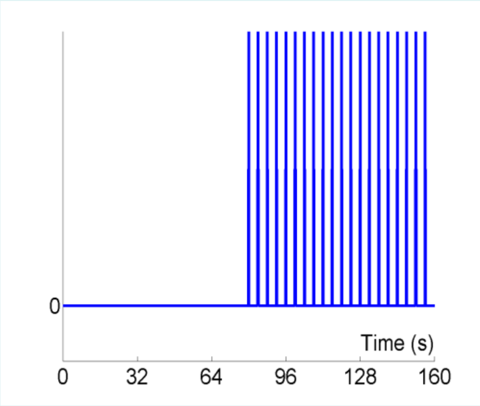
Blocked, epoch = 20s



Blocked-epoch (with small SOA) and Time-Freq equivalences

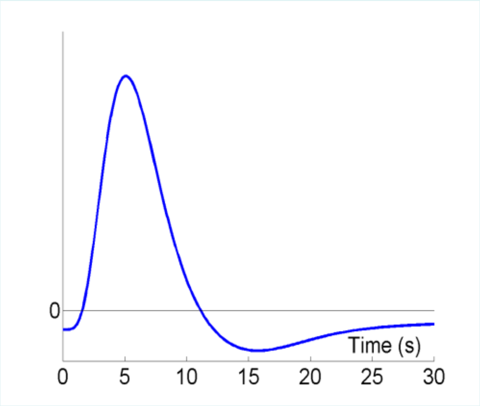
Blocked (80s), SOA_{min}=4s, highpass filter = 1/120s

Stimulus (“Neural”)



$\otimes$

HRF



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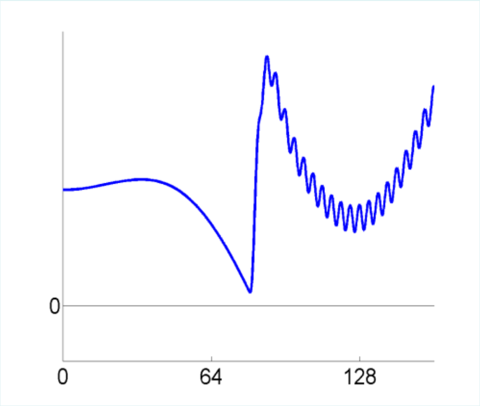
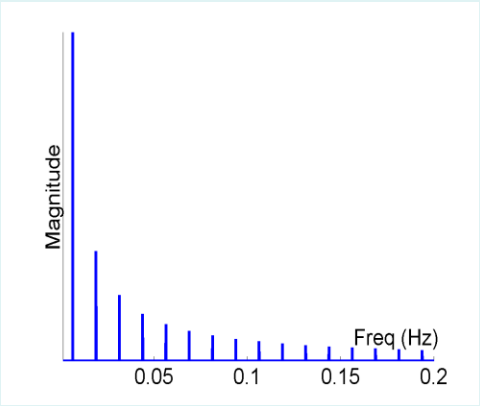
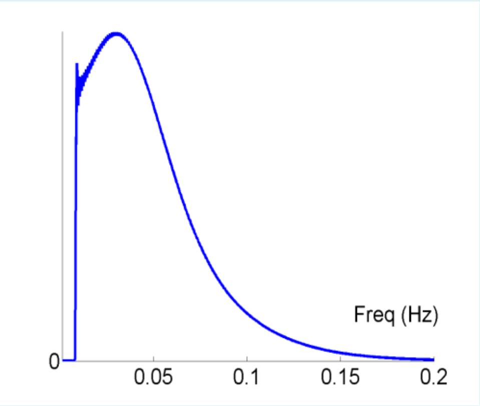
Predicted Data



“Effective HRF” (after highpass filtering)
(Josephs & Henson, 1999)



$\times$



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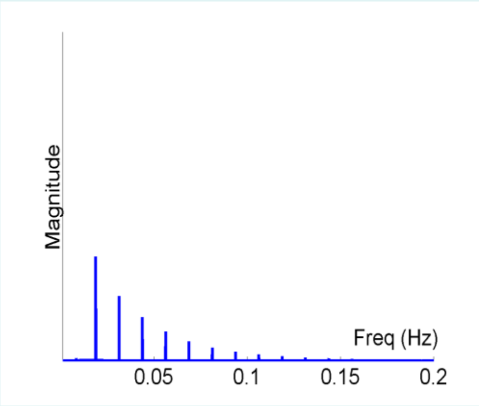
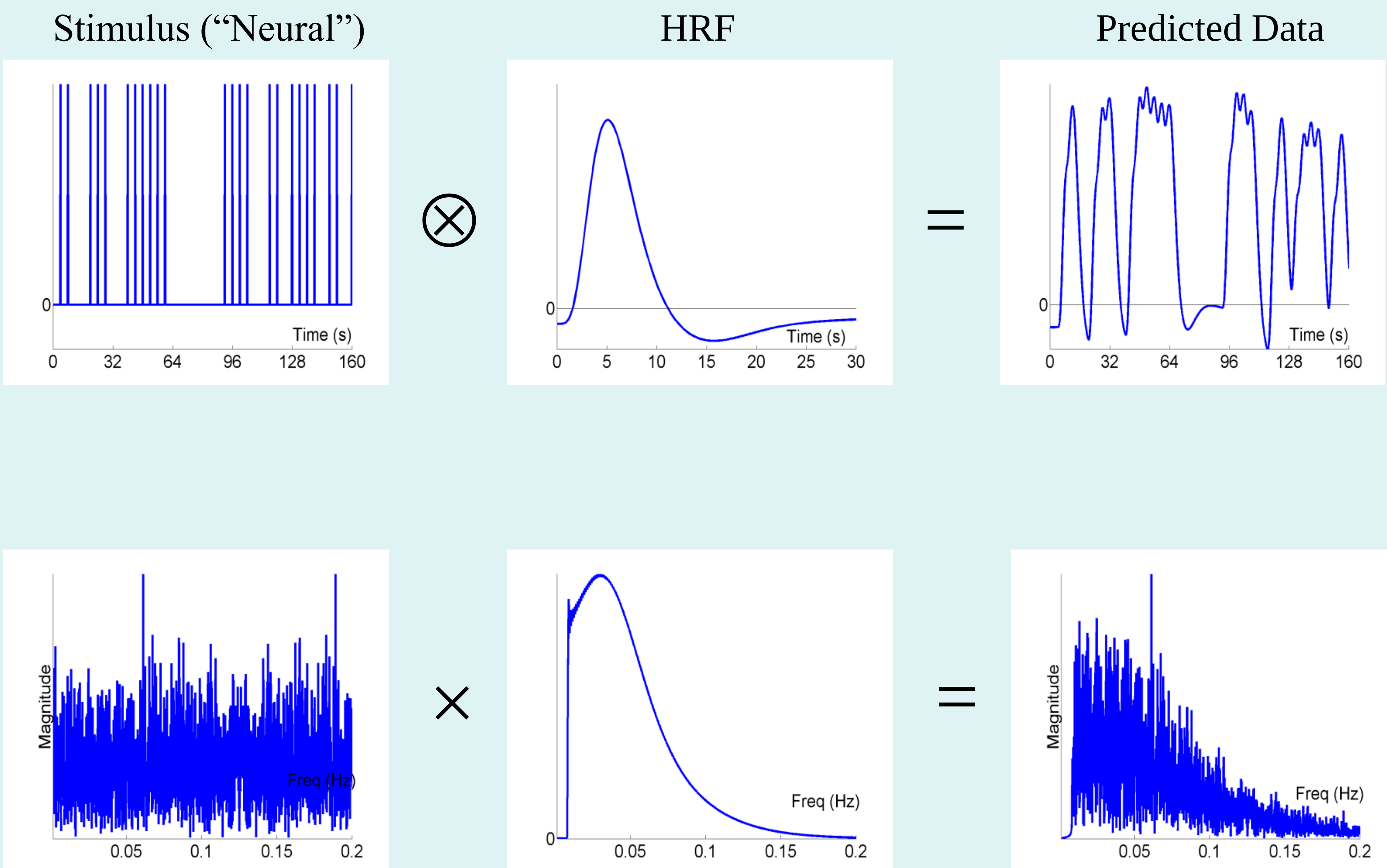


Don’t have long (>60s) blocks!

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



(Randomised design spreads power over frequencies)

Design Efficiency

Maximise efficiency by maximising t, by minimising the squared variance:

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

X: design matrix
c: contrast vector
β: beta vector

Assuming that the error in our model is ‘iid’, each observation is drawn independently from a Gaussian distribution:

$$b \sim N(b, s^2 (X^T X)^{-1})$$

$$\mathrm{var}(c^T b) = s^2 c^T (X^T X)^{-1} c$$

Assuming σ is independent of our design, taking a fixed contrast we can only alter our design matrix to improve efficiency.

Formal definition of **design efficiency** minimises variance:

$$e \,\text{»}\, \frac{1}{\sqrt{c^T (X^T X)^{-1} c}}$$

Given the contrast of interest, **minimise covariance in the design matrix**

Efficiency can be estimated before using the design

Design efficiency: Trial sequencing

- Design parametrised by:

  SOA_{min} Minimum SOA

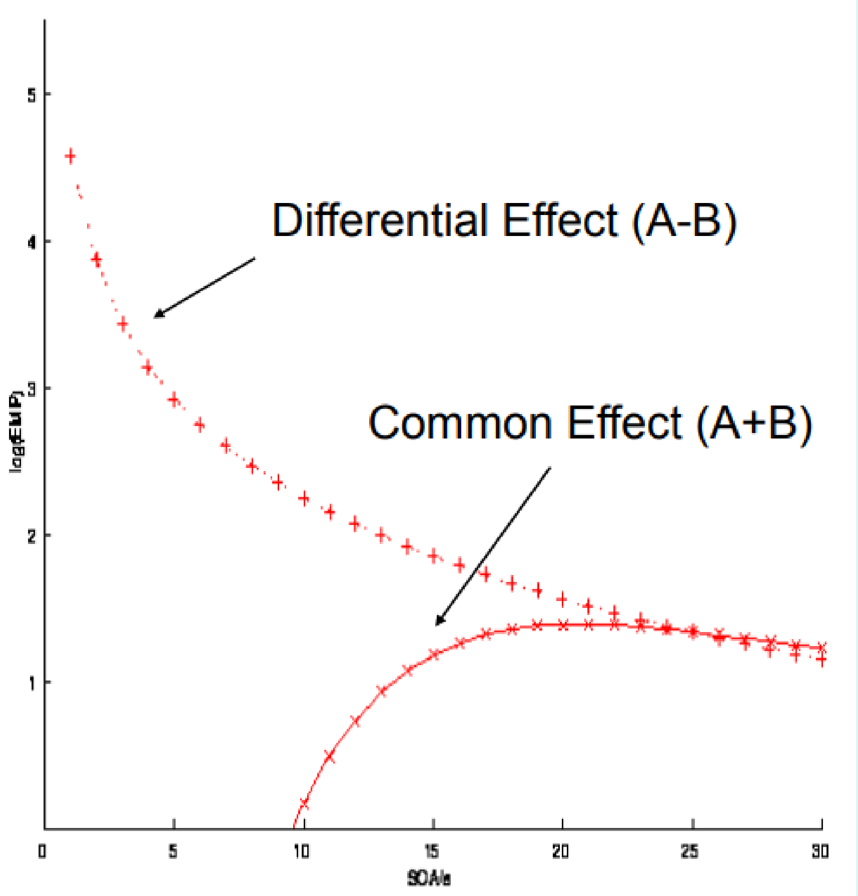
  $p_i(\mathbf{h})$ Probability of event-type i given history $\mathbf{h}$ of last m events

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

- Example: Randomised AB

	A	B
A	0.5	0.5
B	0.5	0.5

=> ABBBABAABABAAA...



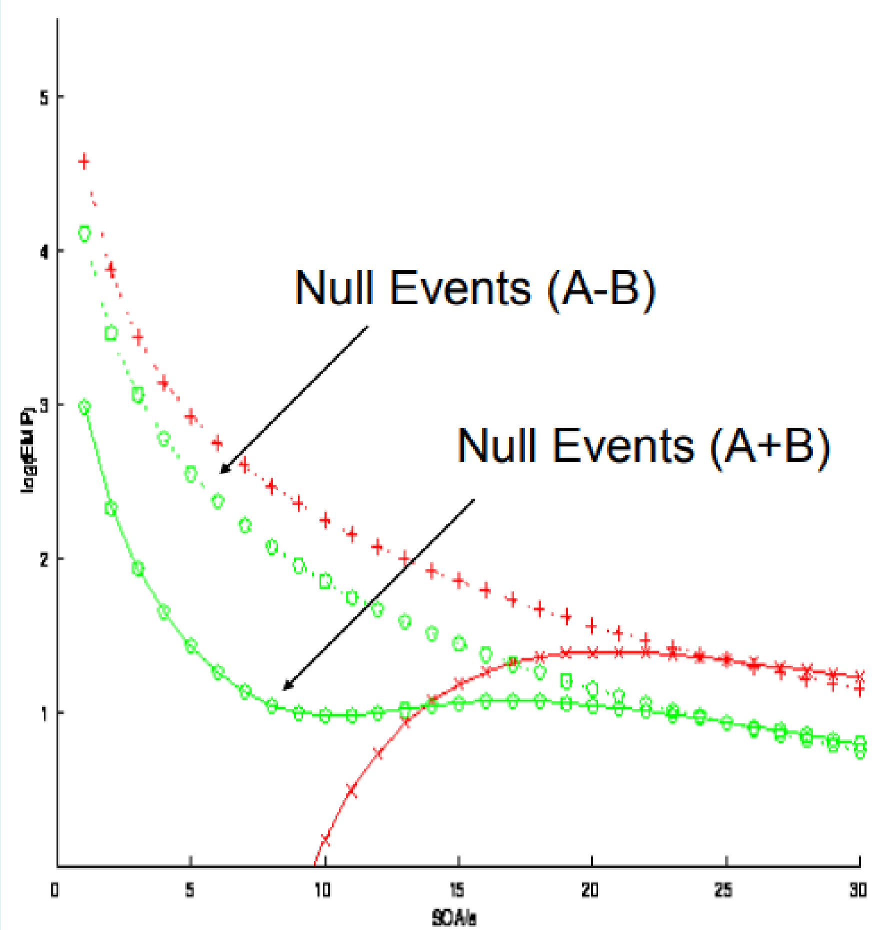
Design efficiency: Trial sequencing

- 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 like third unmodelled event-type)



Design efficiency: Trial sequencing

- Example: Alternating AB

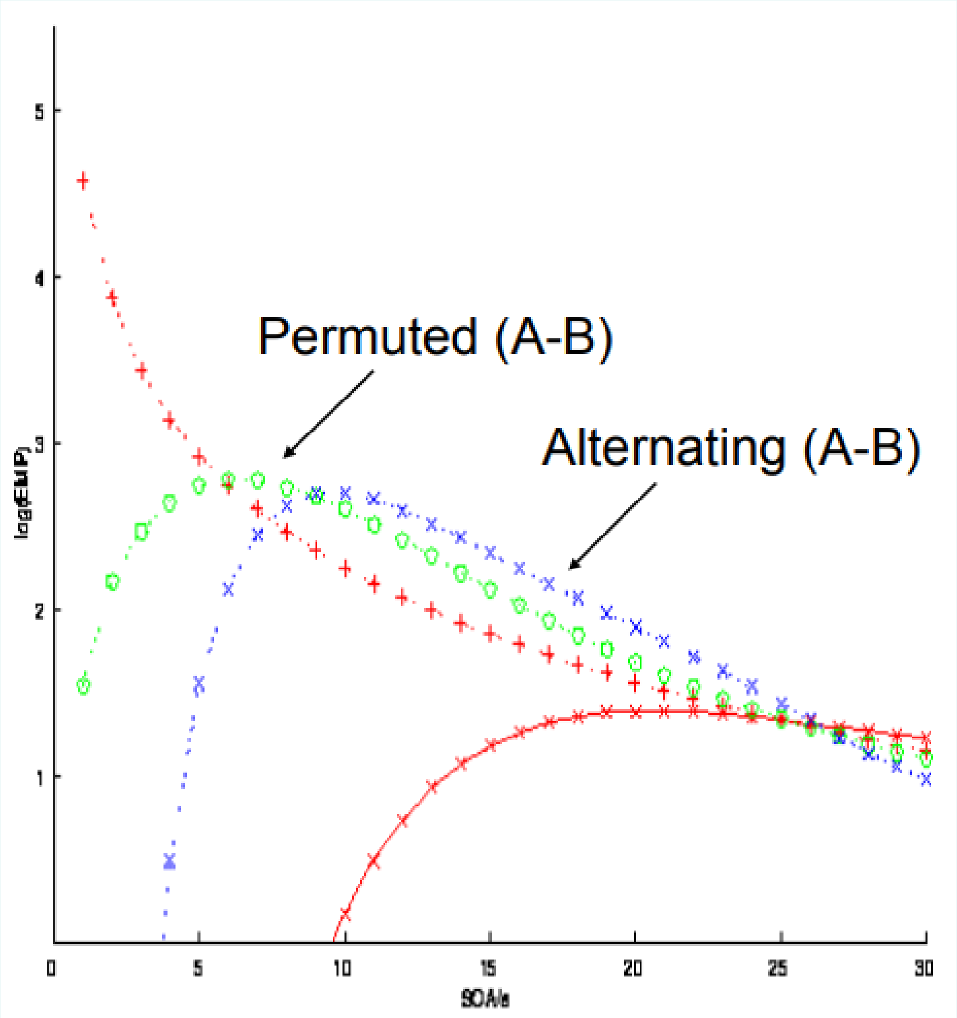
	A	B
A	0	1
B	1	0

=> ABABABABAB...

- Example: Permuted AB

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

=> ABBAABABABBA...



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

Design efficiency: Conclusions

- 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, pseudo-randomised designs can be optimal (but may introduce context-sensitivity)