

# NeuroImaging Data Processing

aka. Statistical Parametric Mapping short course

## Course 5:

Evoked response fMRI &  
Design efficiency

# Content

---

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

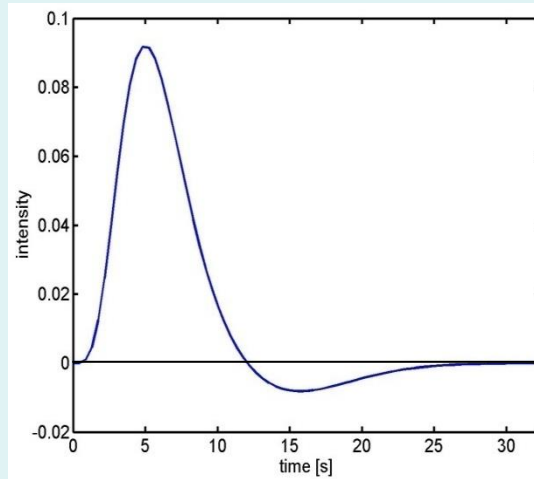
# Content

---

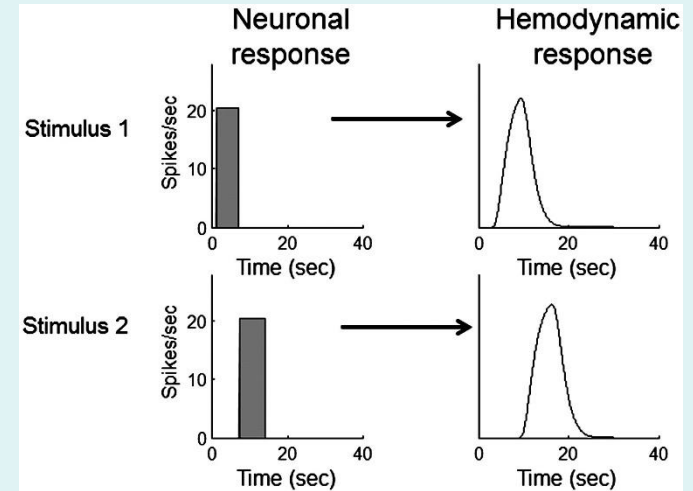
- **Block/epoch vs. event-related fMRI**
- **(Dis)Advantages of efMRI**
- GLM: Convolution
- BOLD impulse response
- Temporal Basis Functions
- Timing Issues
- Design Optimisation – “Efficiency”

# BOLD response

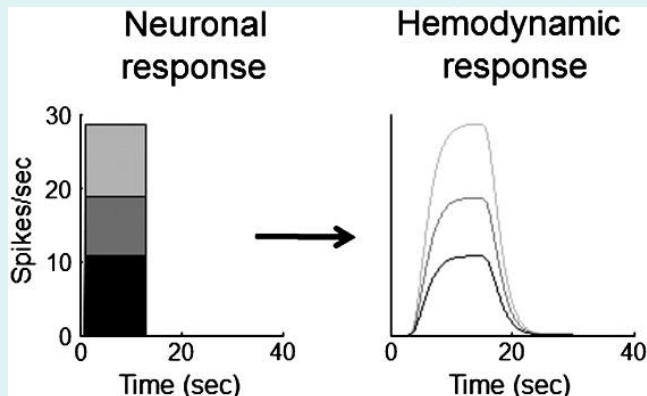
Hemodynamic response function (HRF):



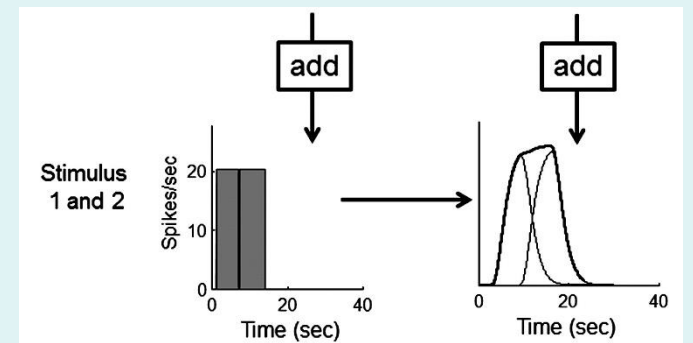
Shift invariance



Scaling

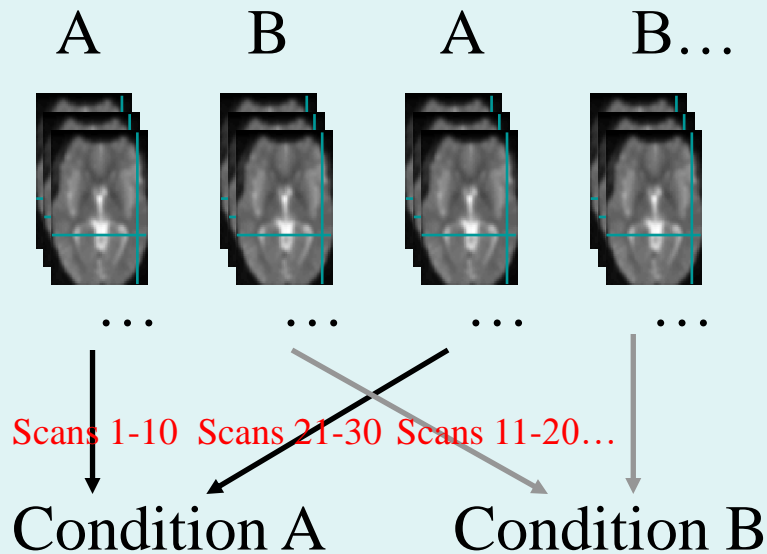


Additivity



# Epoch vs. event related design

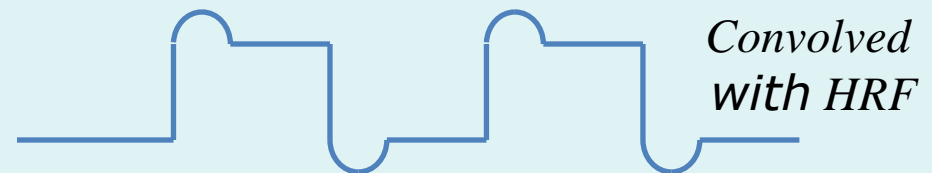
"PET **Blocked** conception"  
(scans assigned to conditions)



"fMRI **Epoch** conception"  
(scans treated as timeseries)



"fMRI **Event-related** conception"



# Advantages of Event-Related design

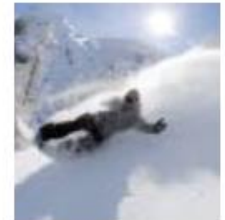
---

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

## Blocked designs may trigger expectations and cognitive sets



...



Unpleasant (U)

Pleasant (P)

## Intermixed designs can minimise this by stimulus randomisation



...



...



...



...



...

Pleasant (P)

Unpleasant (U)

Unpleasant (U)

Pleasant (P)

Unpleasant (U)

# Advantages of Event-Related design

---

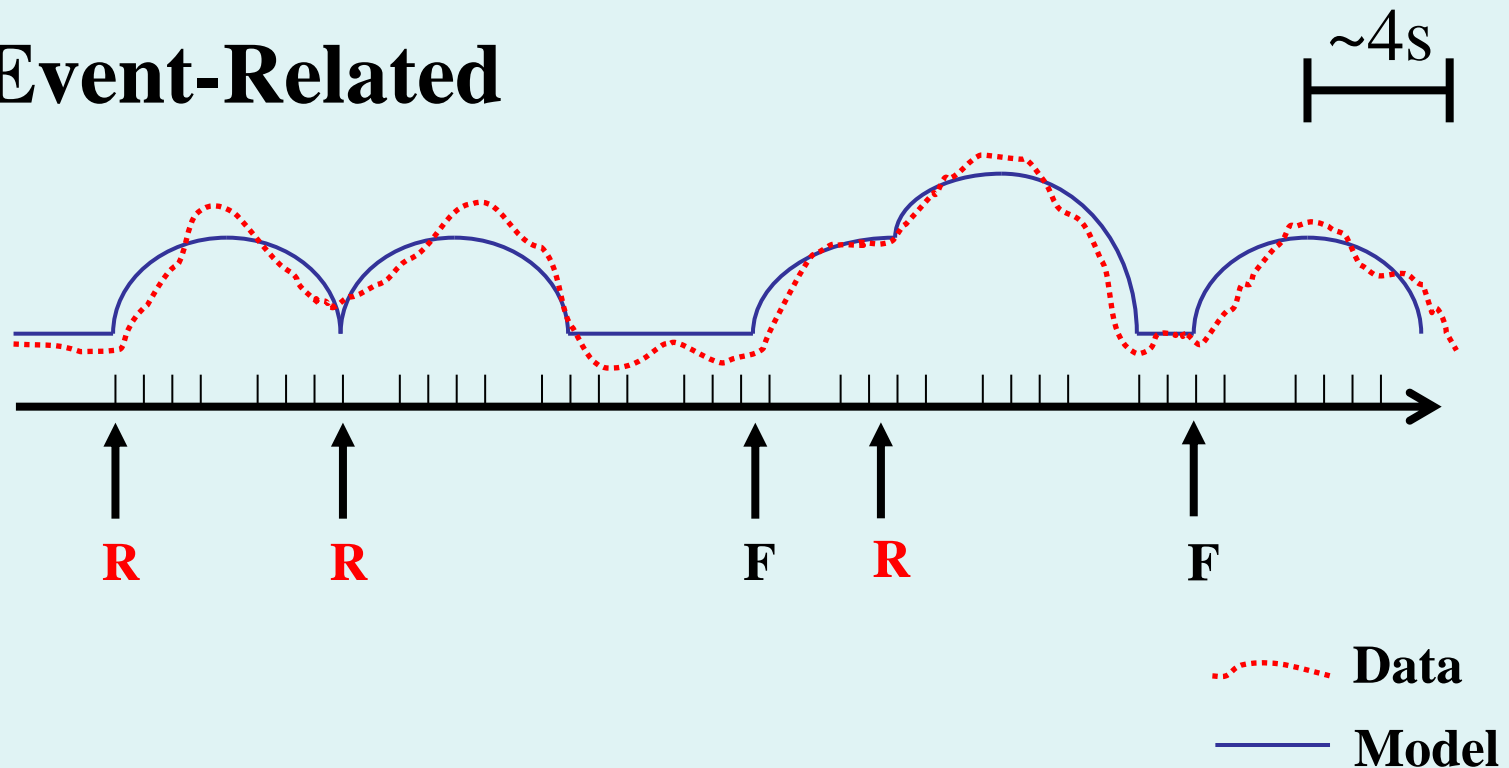
- Randomised trial order  
*c.f. confounds of blocked designs*
- Post hoc / subjective classification of trials  
*e.g, according to subsequent memory*



**R** = Words Later Remembered

**F** = Words Later Forgotten

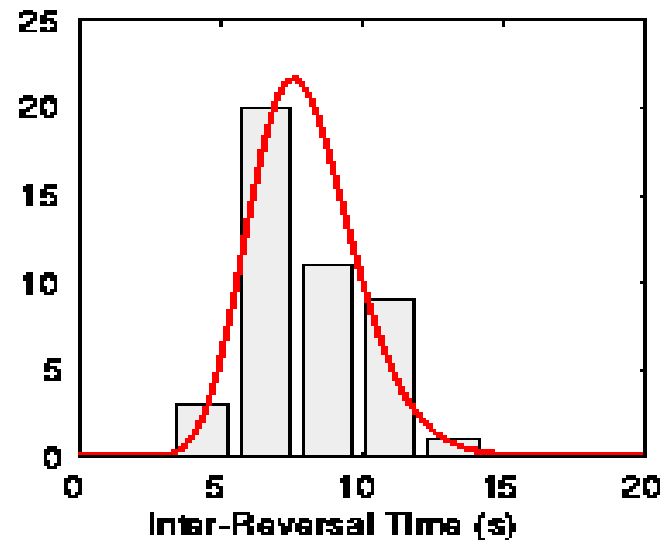
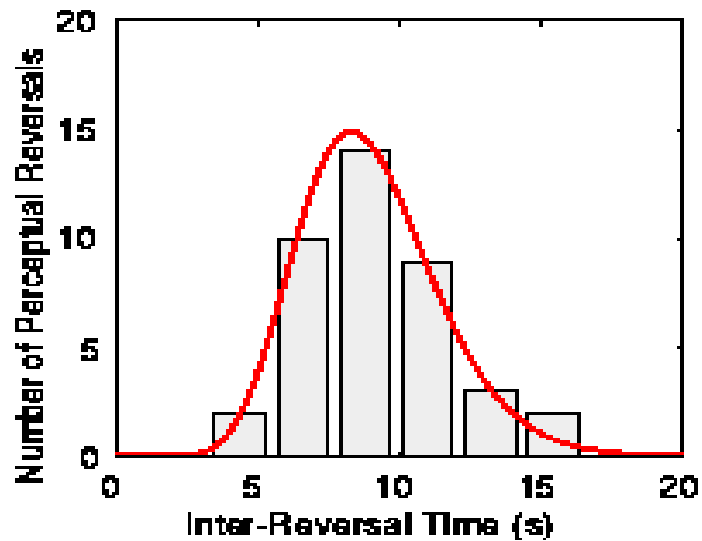
## Event-Related



# Advantages of Event-Related design

---

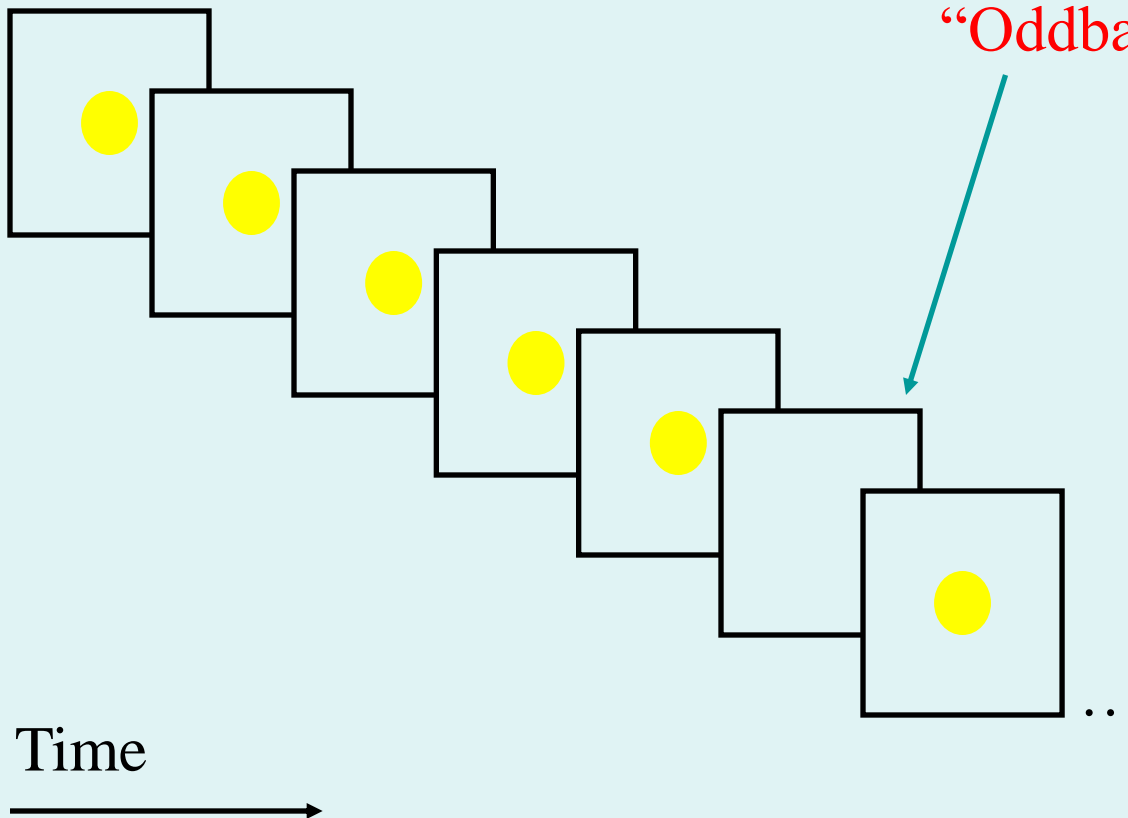
- Randomised trial order  
*c.f. confounds of blocked designs*
- Post hoc / subjective classification of trials  
*e.g, according to subsequent memory*
- Some events can only be indicated (in time)  
*e.g, spontaneous perceptual changes*



# 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*



# Advantages of Event-Related design

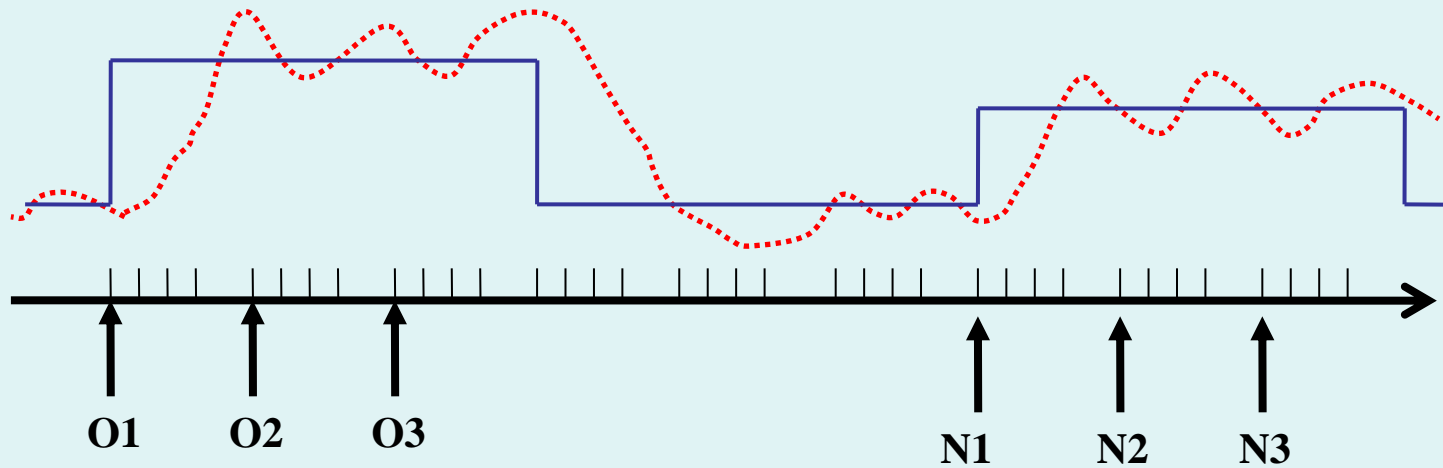
---

- 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*

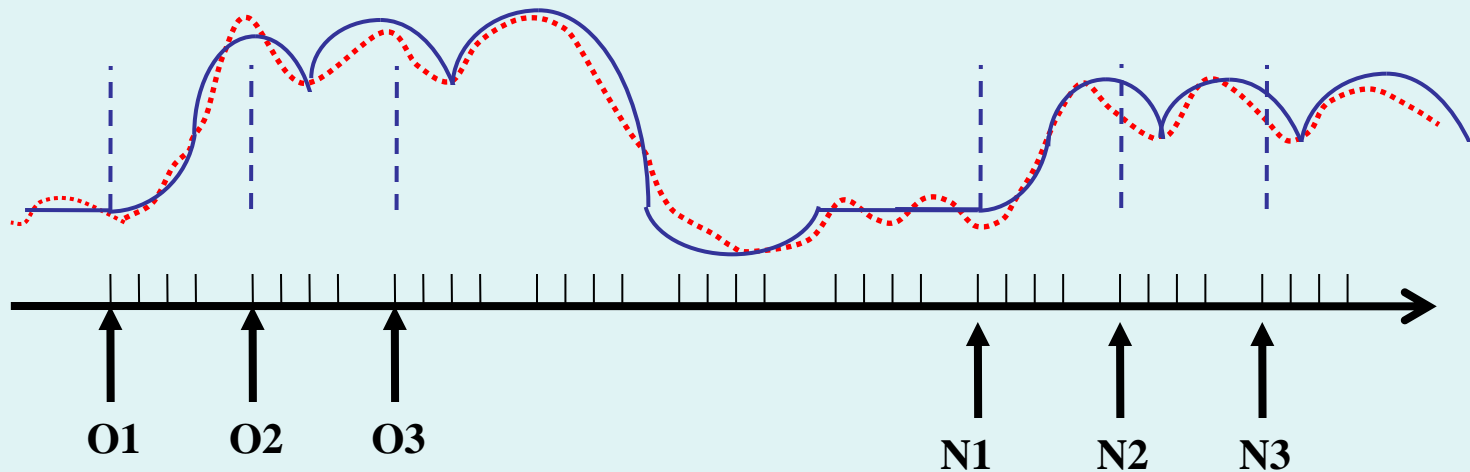
# Blocked Design

..... Data  
——— Model

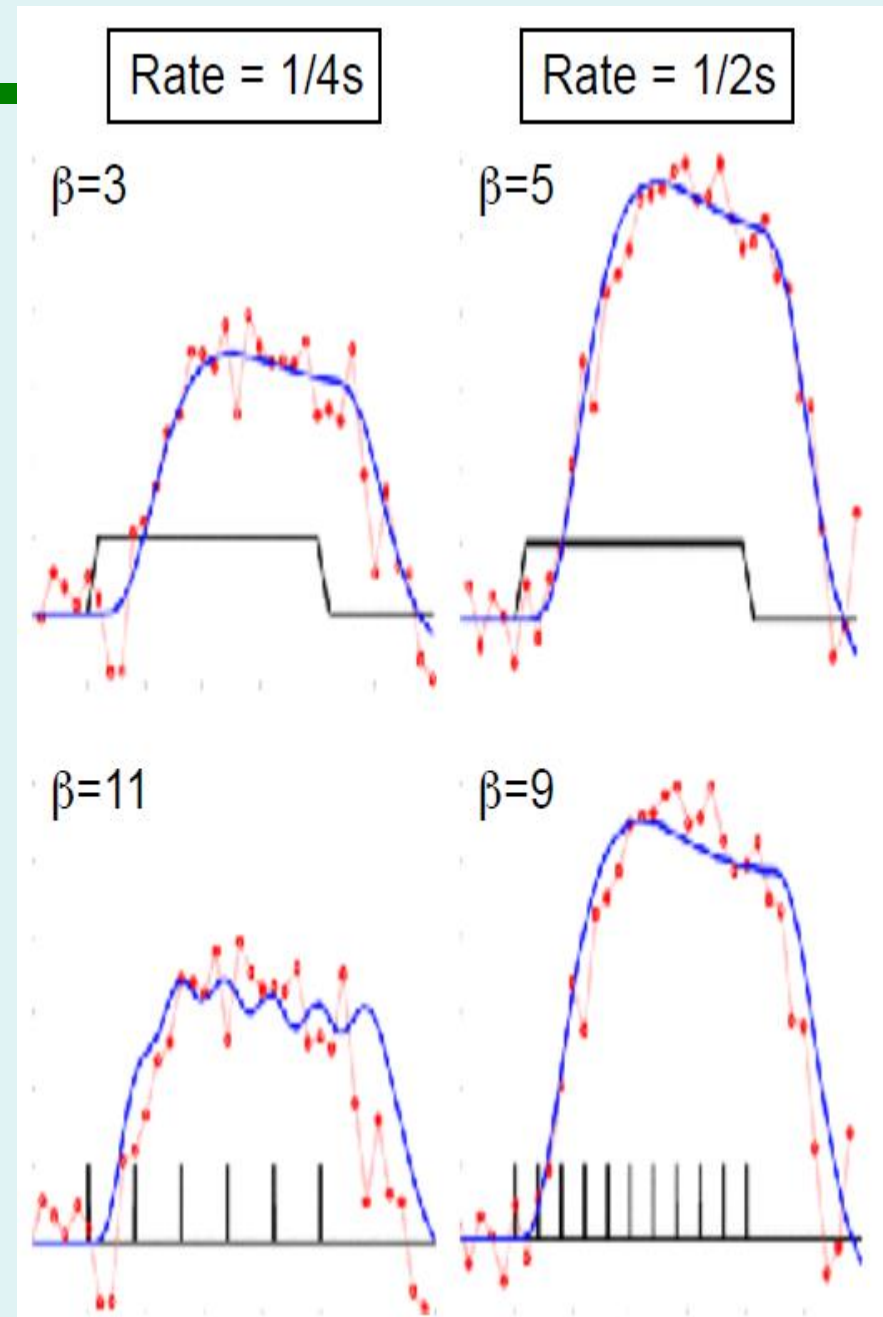
## “Epoch” model



## “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)

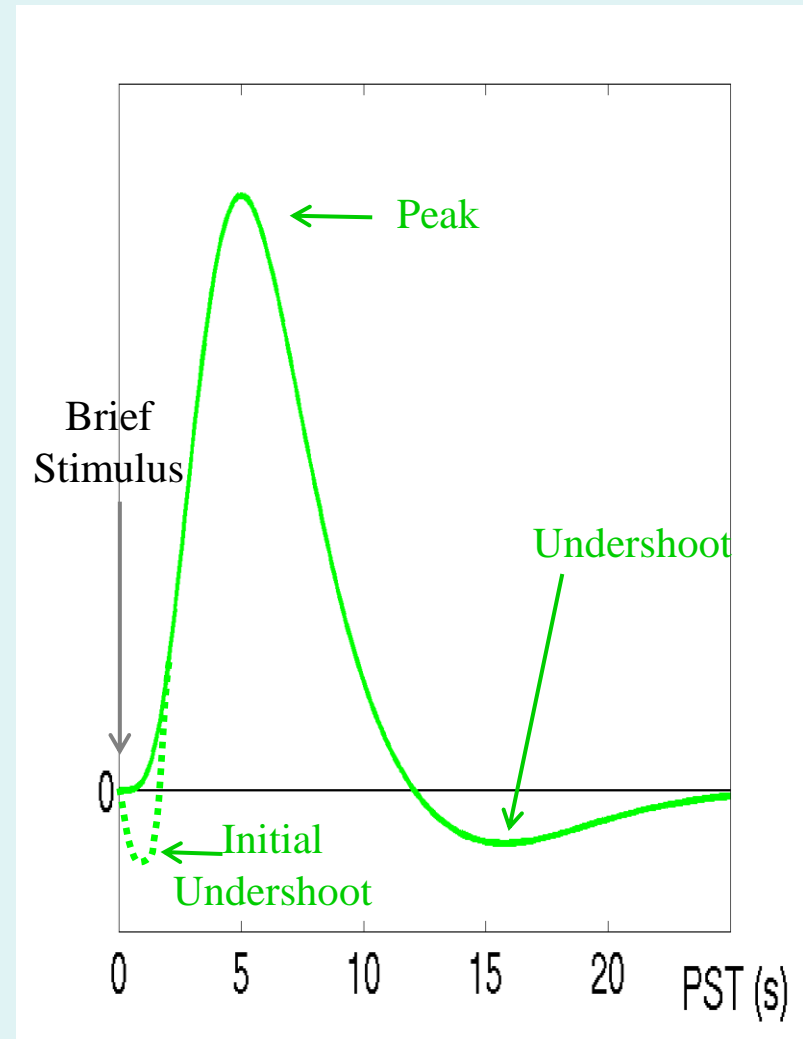
# Content

---

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

# 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)

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

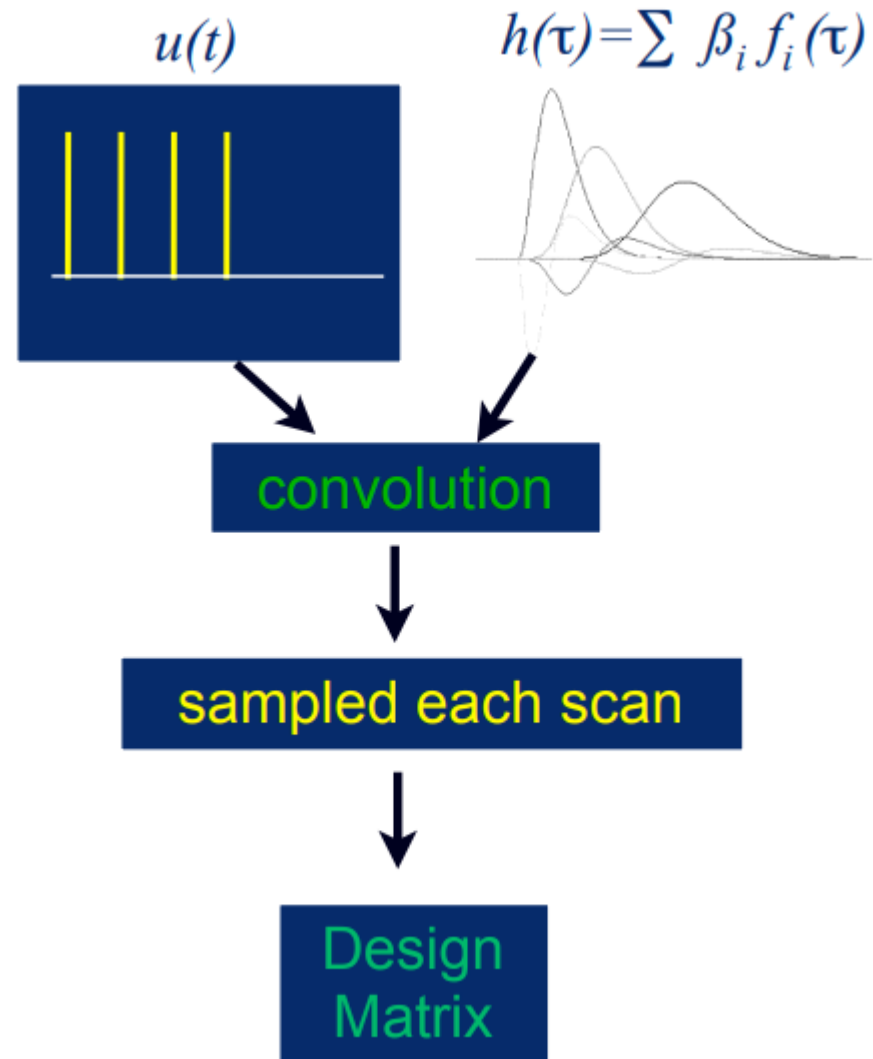
$h(\tau)$  = hemodynamic (BOLD) response

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

$f_i(\tau)$  = temporal basis functions

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

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

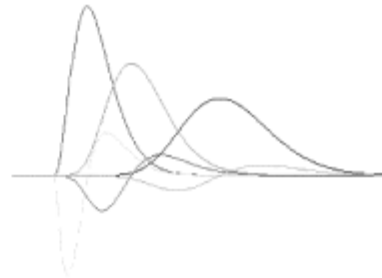


# General Linear Model in SPM

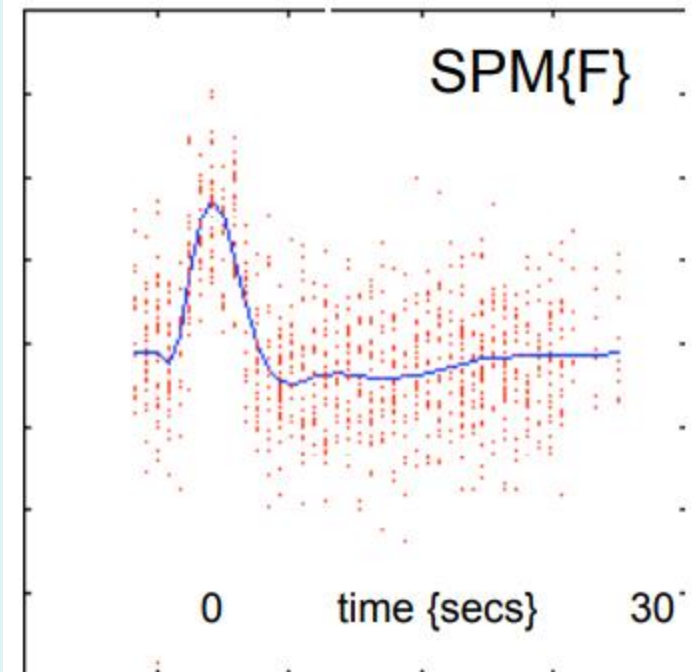
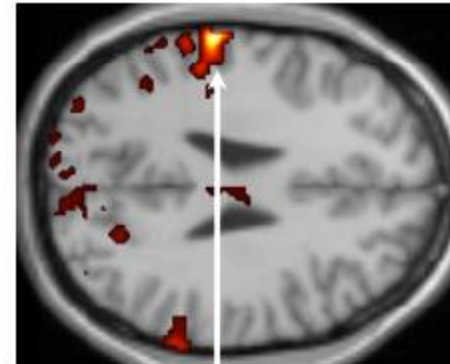
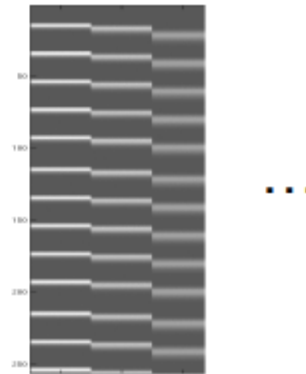
Stimulus  
every 20s



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



Sampled every TR = 1.7s  
Design matrix,  $\mathbf{X}$   
 $[x(t) \otimes f_1(\tau) \mid x(t) \otimes f_2(\tau) \mid \dots]$

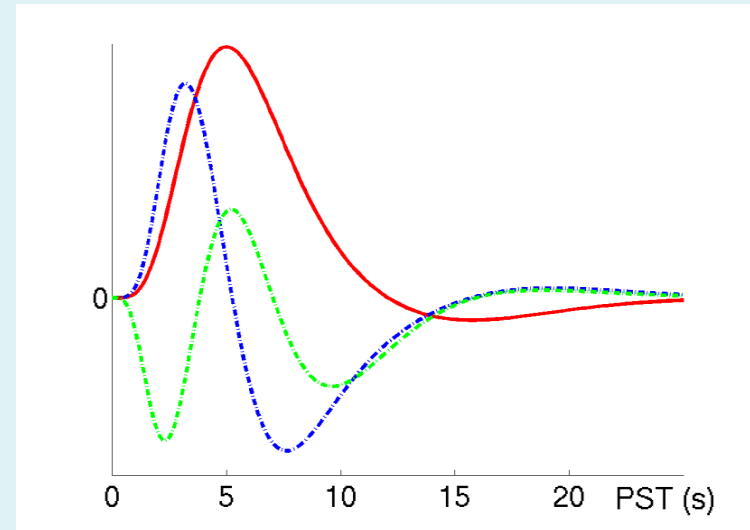
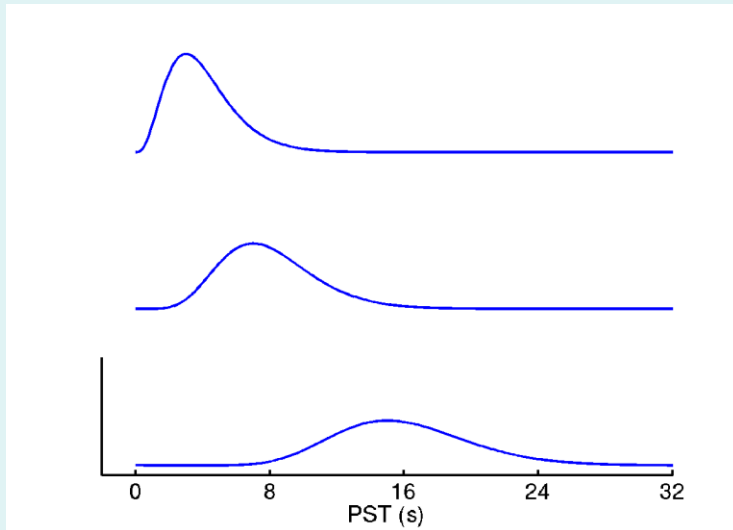
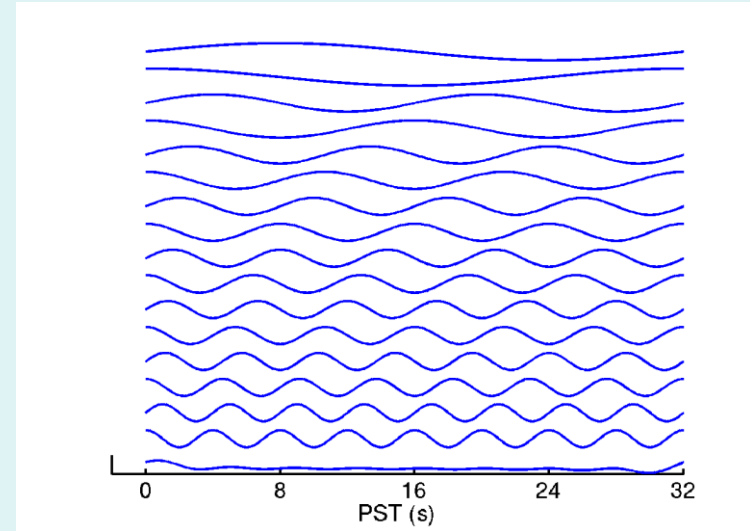
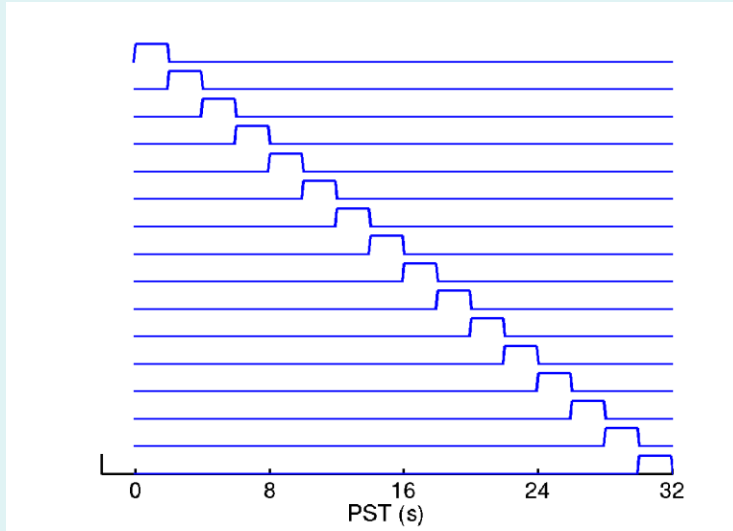


# Content

---

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

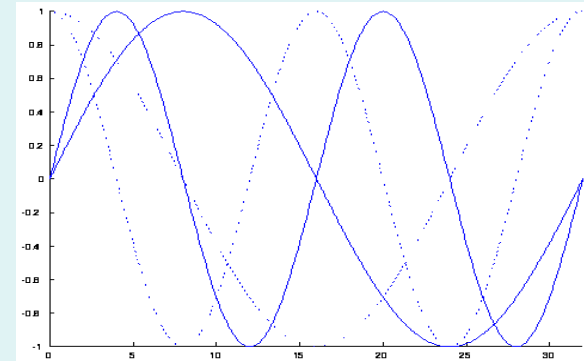
# Temporal Basis Functions



# Temporal Basis Functions

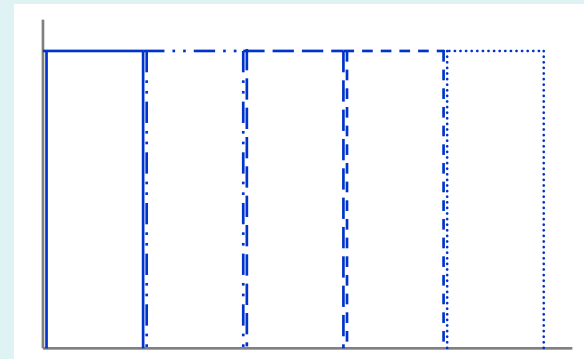
- **Fourier Set**

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

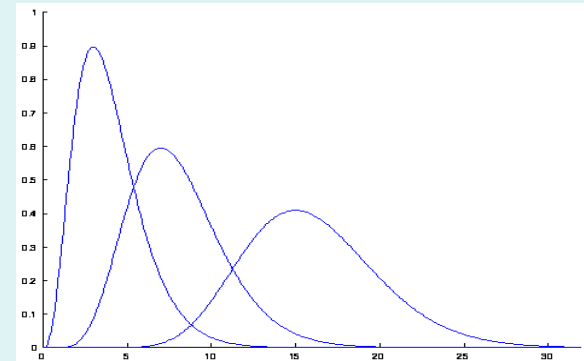
---

- **Gamma Functions**

Bounded, asymmetrical (like BOLD)

Set of different lags

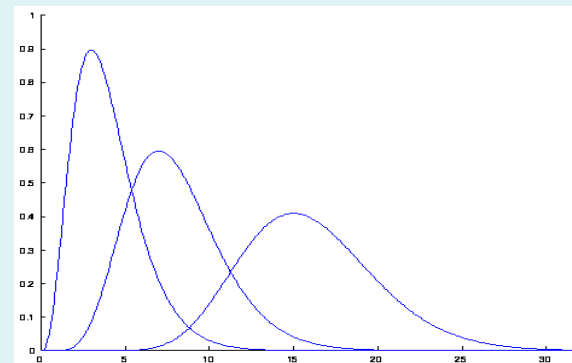
Inference via F-test



# Temporal Basis Functions

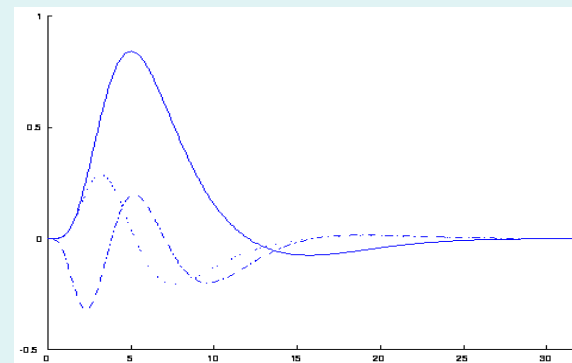
- **Gamma Functions**

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



- **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)

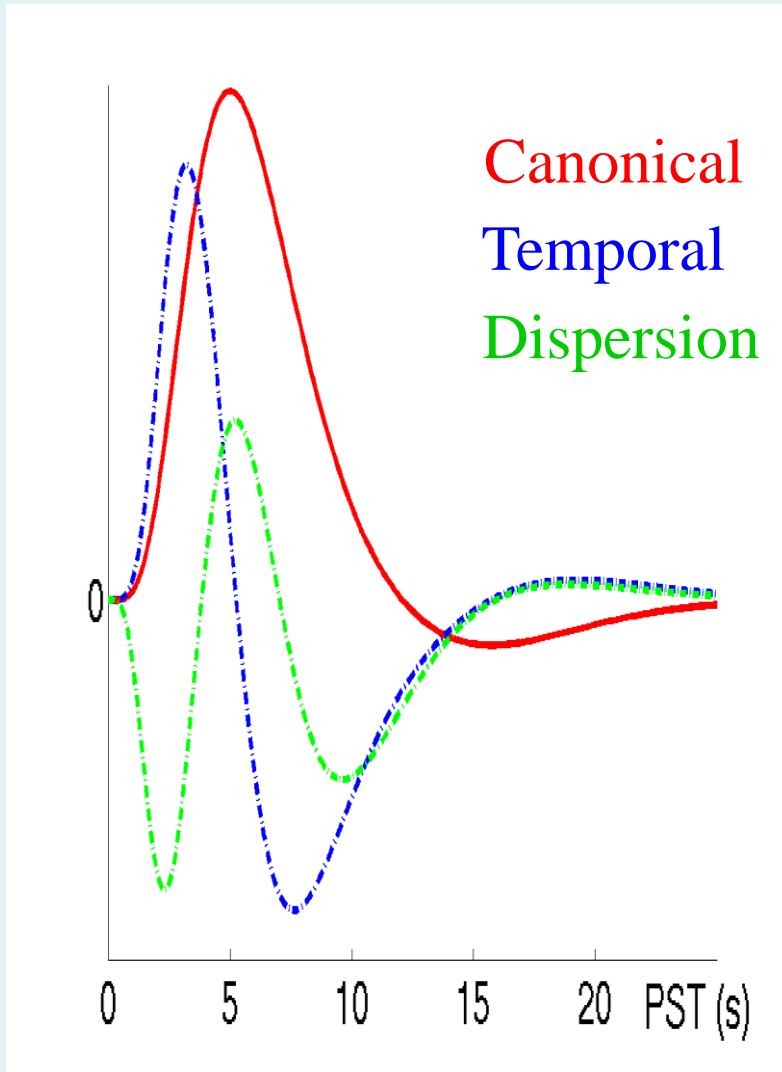
- Canonical HRF (2 gamma functions)

*plus* Multivariate Taylor expansion in:

time (*Temporal Derivative*)

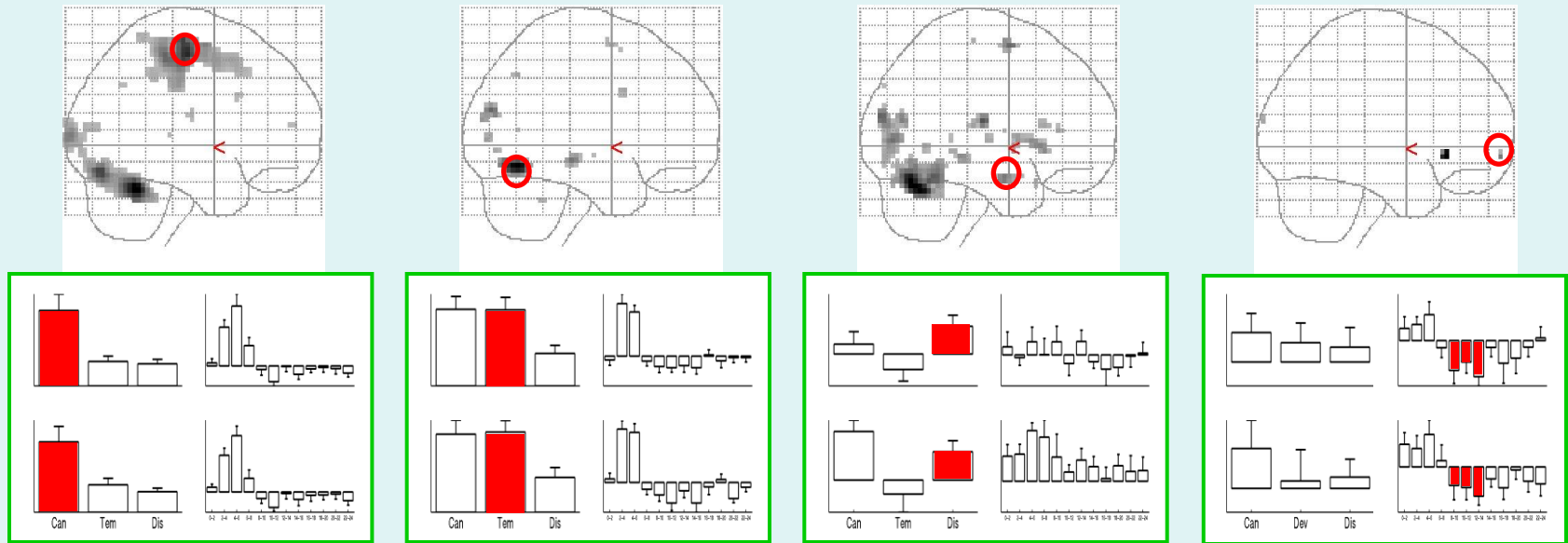
width (*Dispersion Derivative*)

- “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)

# Content

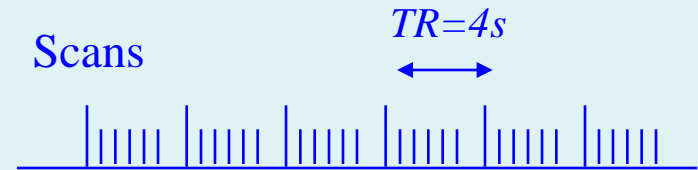
---

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

# Timing Issues

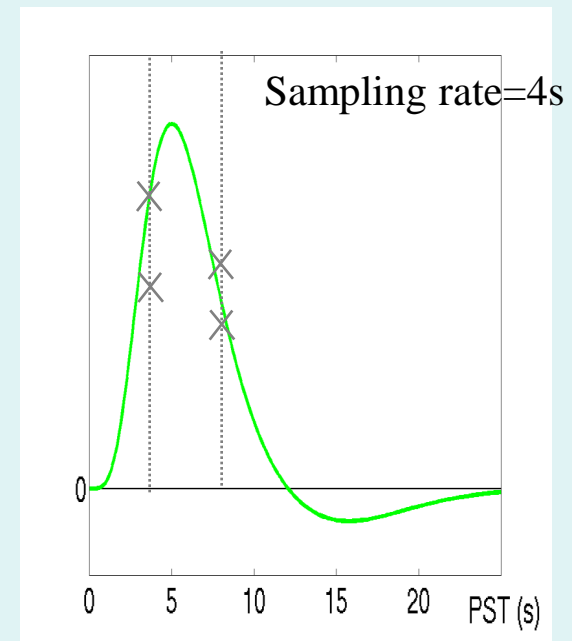
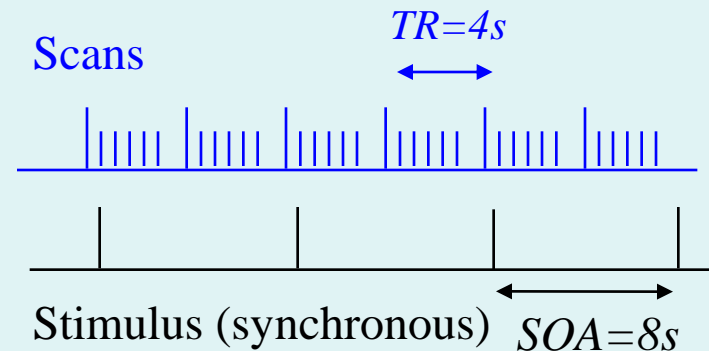
---

- Typical TR for 48 slice EPI at 3mm spacing is  $\sim 4s$



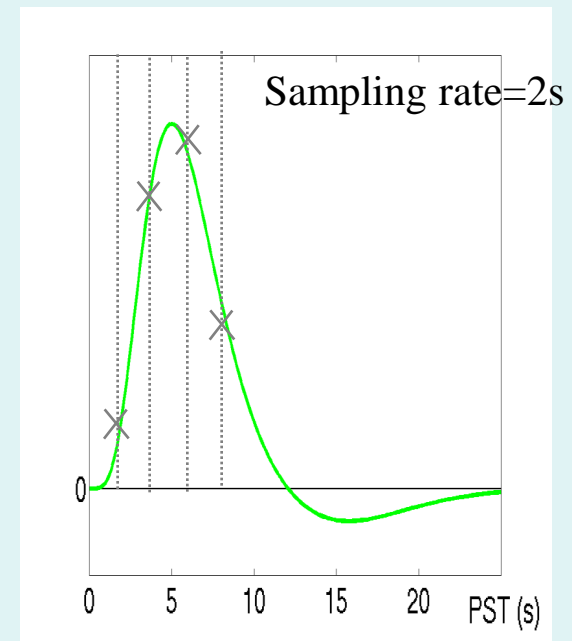
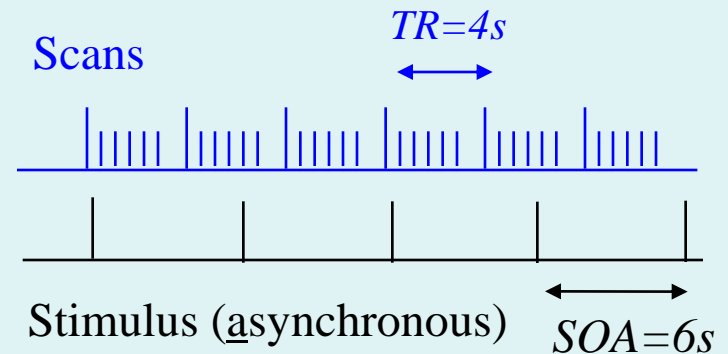
# Timing Issues

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



# Timing Issues

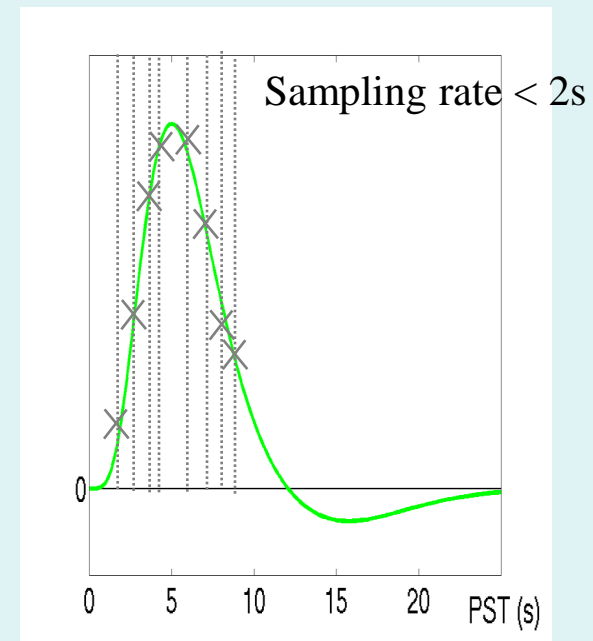
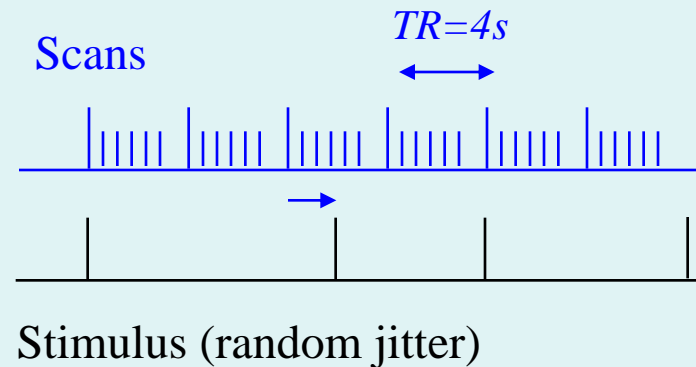
- Typical TR for 48 slice EPI at 3mm spacing is  $\sim 4s$
- Sampling at  $[0,4,8,12\dots]$  post-stimulus may miss peak signal
- Higher effective sampling by:
  1. Asynchrony, e.g.  $SOA=1.5TR$





# Timing Issues

- Typical TR for 48 slice EPI at 3mm spacing is  $\sim 4s$
- Sampling at  $[0, 4, 8, 12\dots]$  post-stimulus may miss peak signal
- Higher effective sampling by:
  1. Asynchrony, e.g.  
 $SOA = 1.5TR$
  2. Random Jitter, e.g.  
 $SOA = (2 \pm 0.5)TR$



# BOLD Response Latency (Linear)

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

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

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

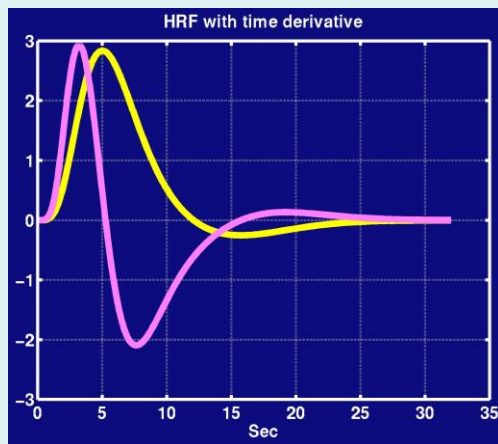
$$R(t) = \beta_1 f(t) + \beta_2 f'(t) \quad \text{GLM fit}$$

- Then canonical and derivative parameter estimates,  $\beta_1$  and  $\beta_2$ , are such that:

$$\alpha = \beta_1, \quad dt = \beta_2 / \beta_1$$

- *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



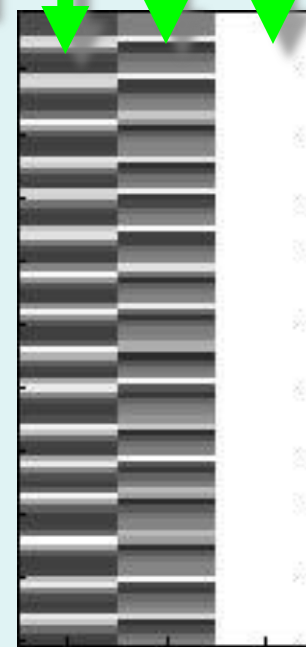
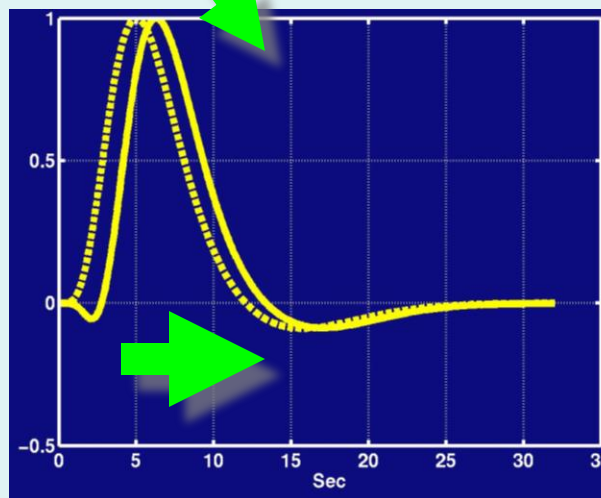
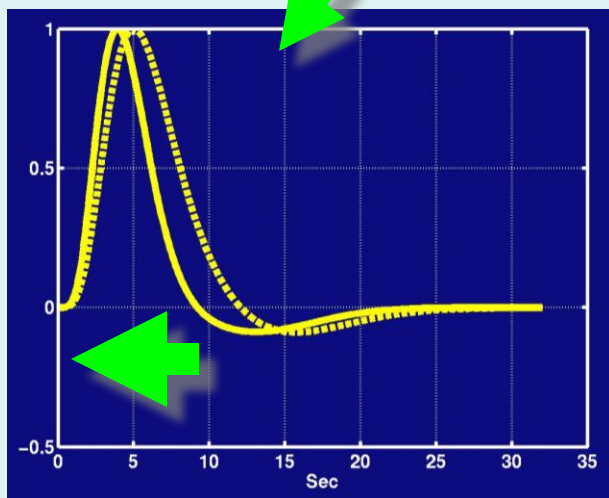
constant

derivative

HRF

Positive

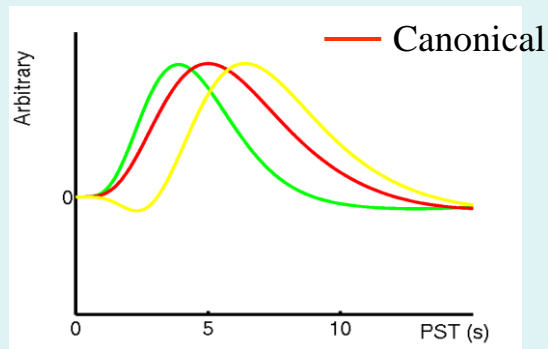
Negative



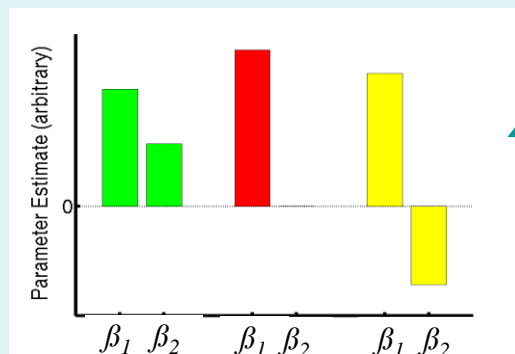
**Designmatrix**  
16 events, SOA ~18s,  
TR 3s

# BOLD Response Latency (Linear)

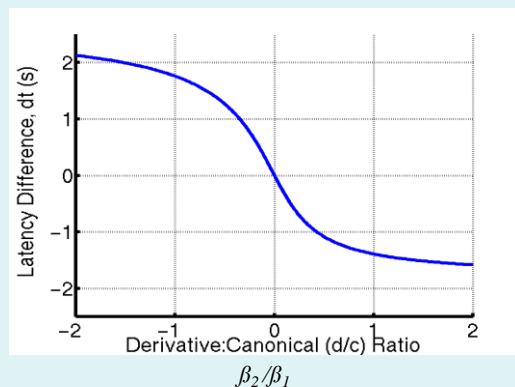
Delayed Responses  
(green/yellow)



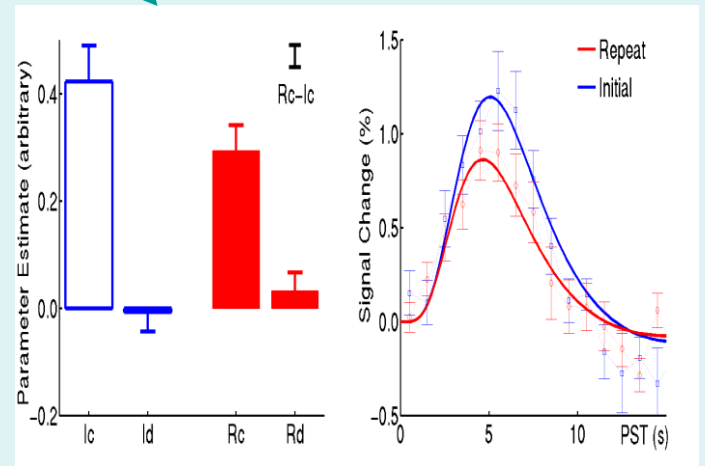
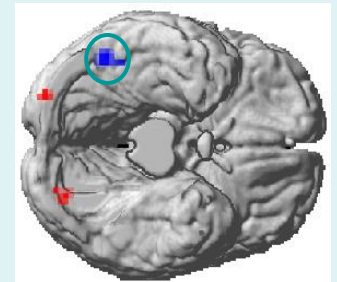
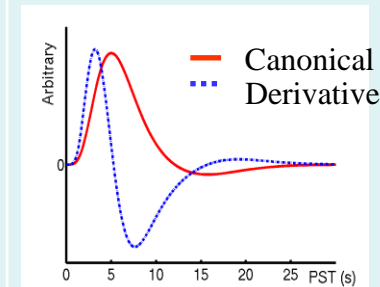
Parameter Estimates



Actual latency,  $dt$ , vs.  $\beta_2/\beta_1$



## Basis Functions



*Face repetition reduces latency as well as magnitude of fusiform response*

# Neural Response Latency

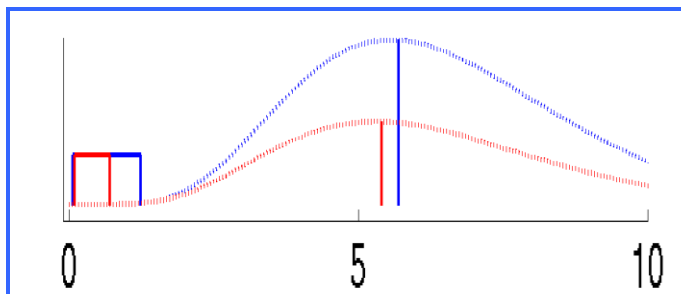
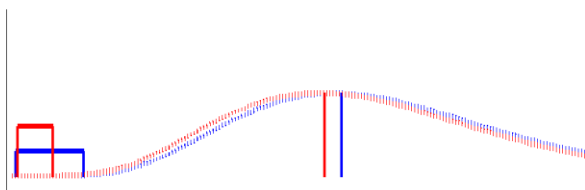
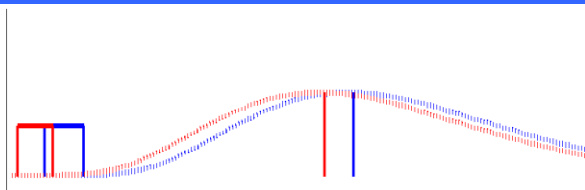
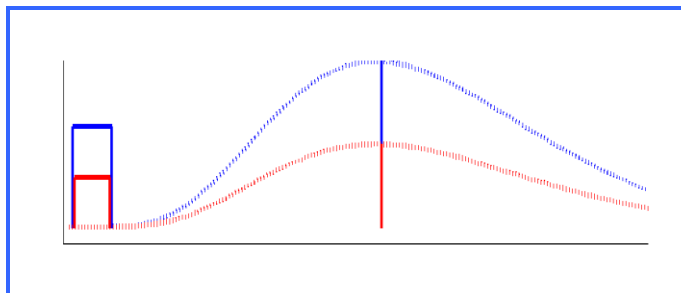
*Neural*

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

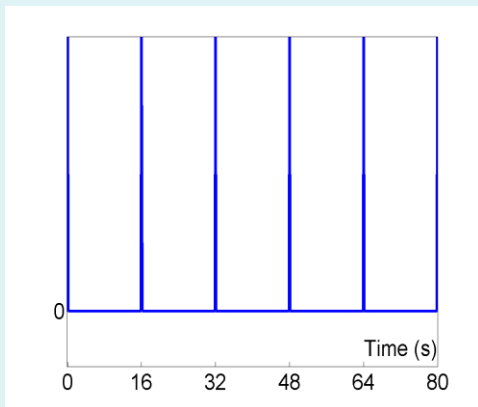
# Content

---

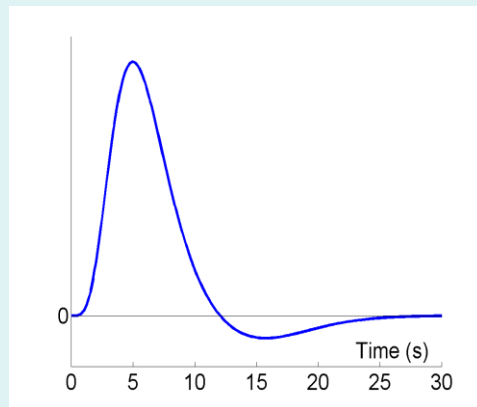
- Block/epoch vs. event-related fMRI
- (Dis)Advantages of efMRI
- GLM: Convolution
- BOLD impulse response
- Temporal Basis Functions
- Timing Issues
- **Design Optimisation – “Efficiency”**

# Fixed SOA = 16s

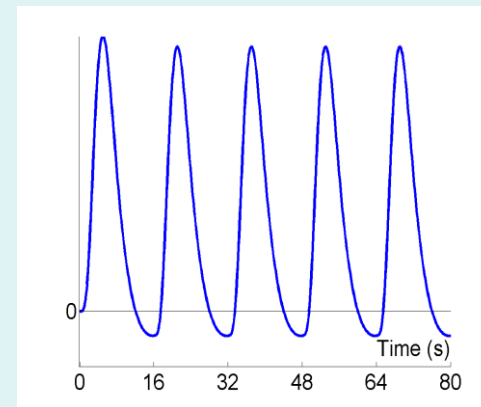
Stimulus (“Neural”)



HRF



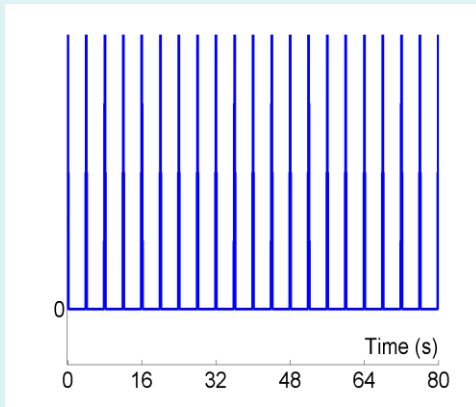
Predicted Data



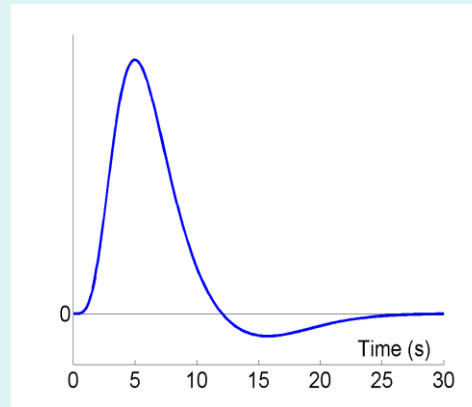
*Not particularly efficient...*

# Fixed SOA = 4s

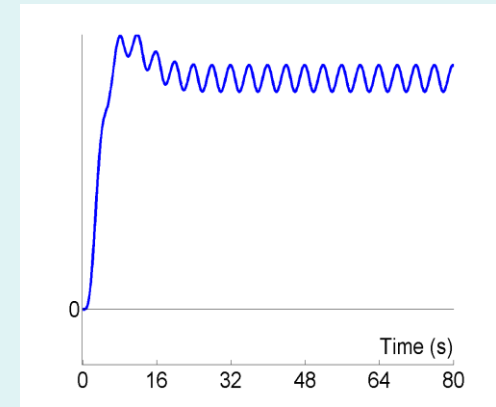
Stimulus (“Neural”)



HRF



Predicted Data

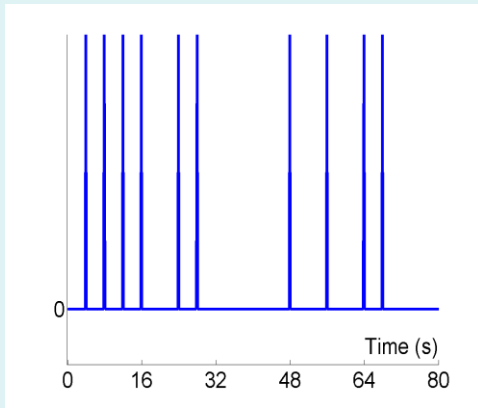


*Very Inefficient...*



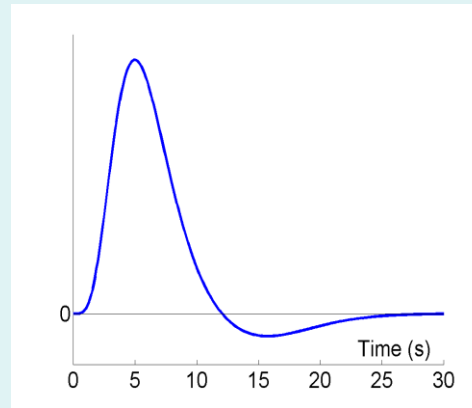
# Randomised, $SOA_{\min} = 4s$

Stimulus (“Neural”)



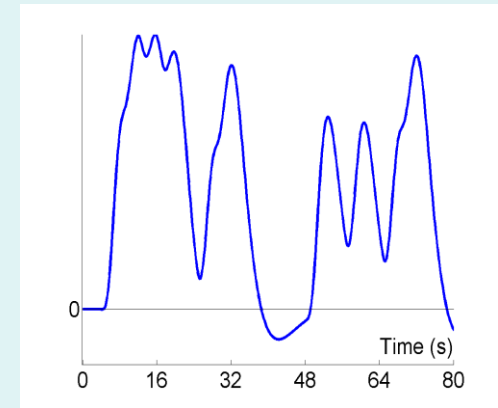
⊗

HRF



=

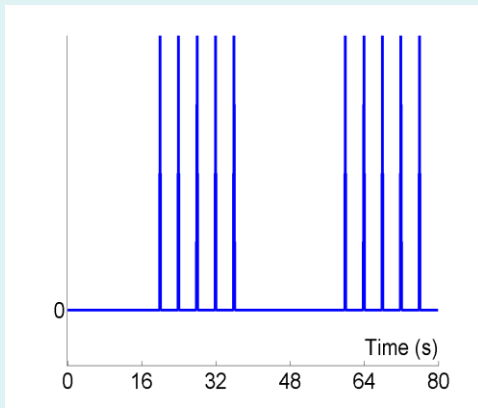
Predicted Data



*More Efficient...*

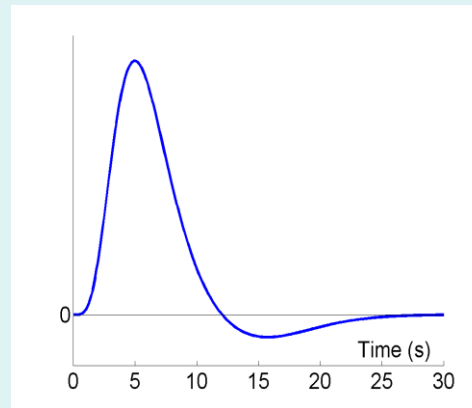
# Blocked, $SOA_{\min} = 4s$

Stimulus (“Neural”)



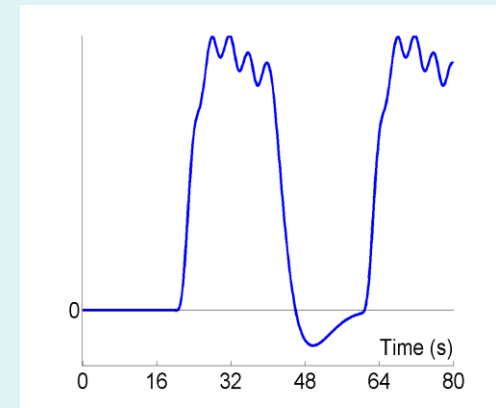
⊗

HRF



=

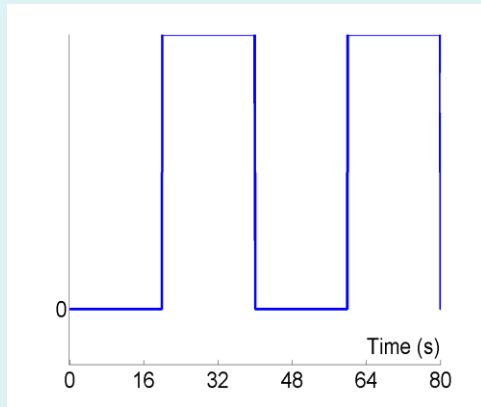
Predicted Data



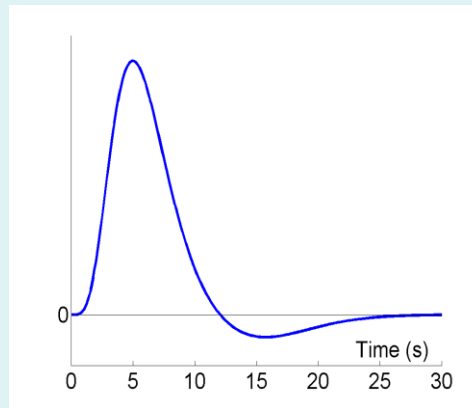
*Even more Efficient...*

# Blocked, epoch = 20s

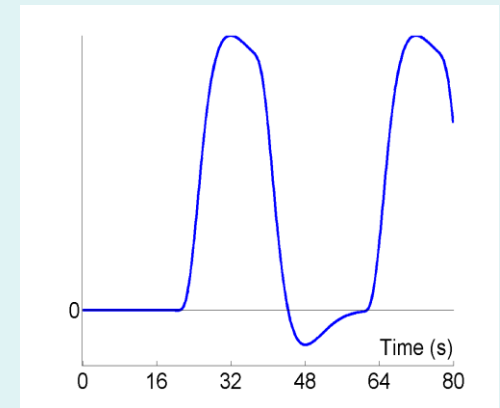
Stimulus (“Neural”)



HRF

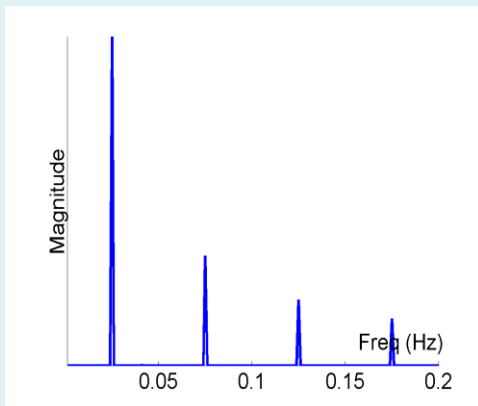


Predicted Data

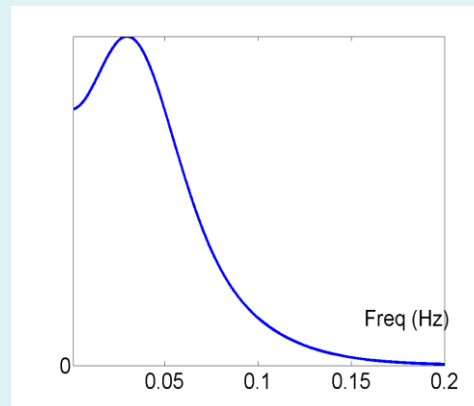


$\otimes$

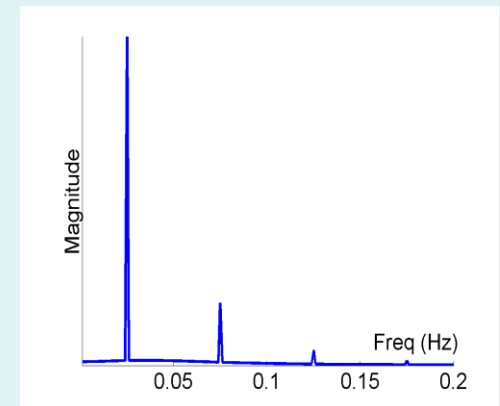
$=$



$\times$



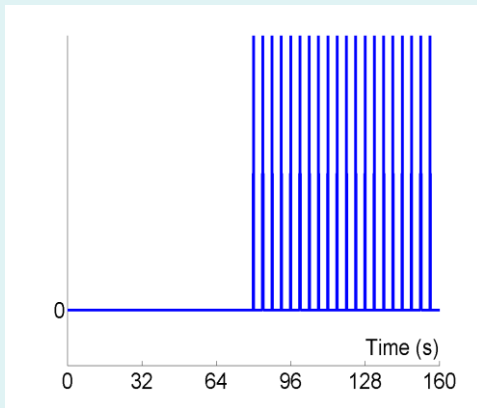
$=$



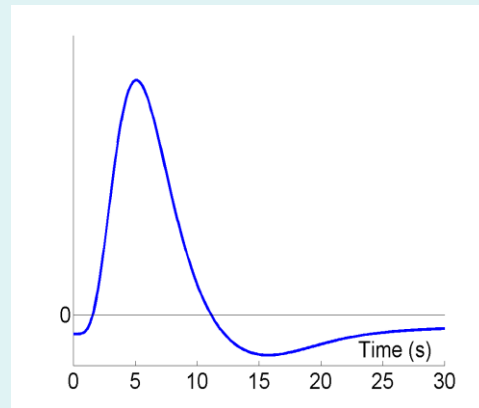
*Blocked-epoch (with small SOA) and Time-Freq equivalences*

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

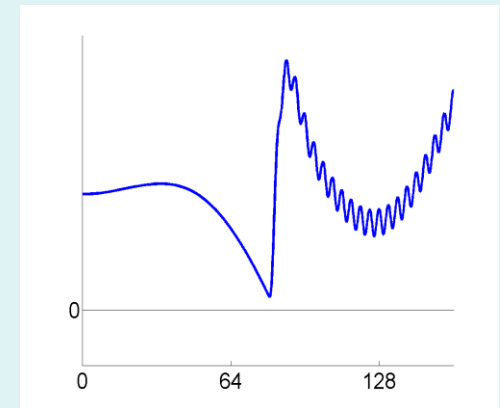
Stimulus (“Neural”)



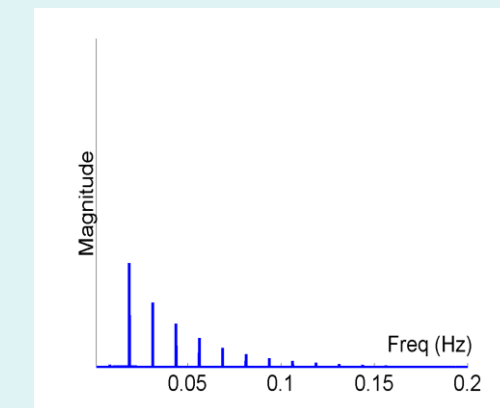
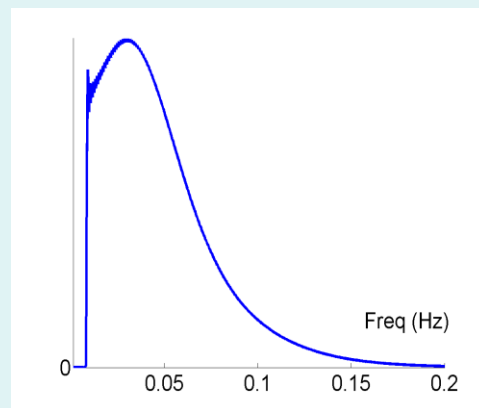
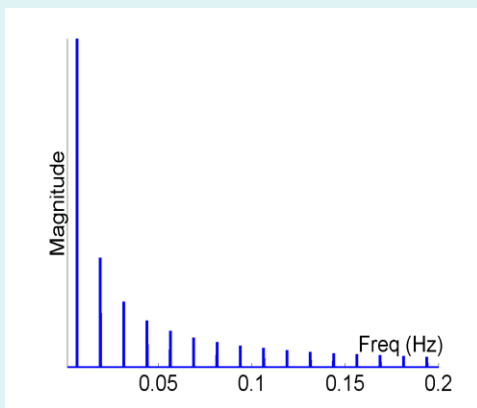
HRF



Predicted Data



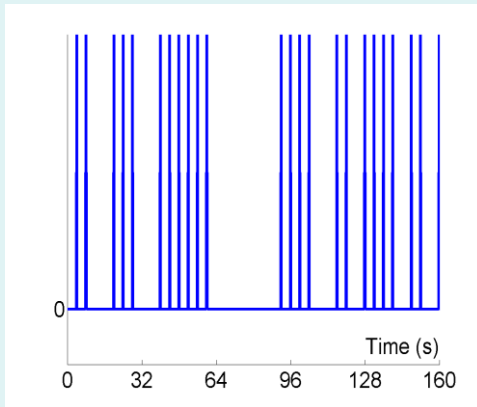
“Effective HRF” (after highpass filtering)  
(Josephs & Henson, 1999)



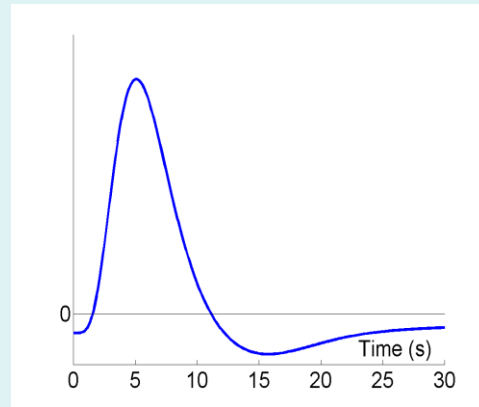
*Don't have long (>60s) blocks!*

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

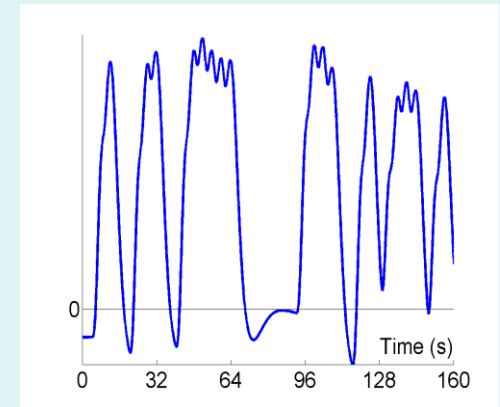
Stimulus (“Neural”)



HRF

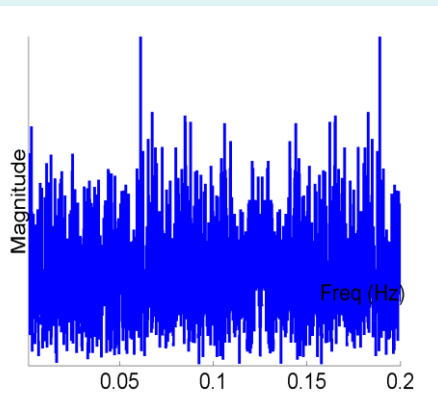


Predicted Data

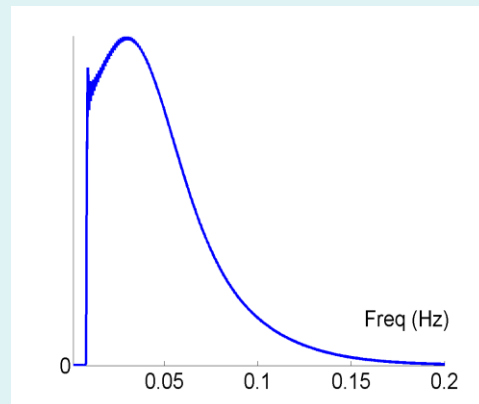


$\otimes$

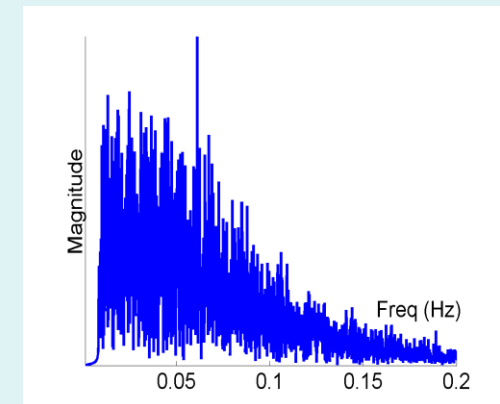
=



$\times$



=



*(Randomised design spreads power over frequencies)*

# Design Efficiency

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

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

X: design matrix  
c: contrast vector  
 $\beta$ : beta vector

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

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

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

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

Formal definition of **design efficiency**  $e \gg$  minimises variance:

$$e \gg \frac{1}{\sqrt{c^T (X^T X)^{-1} c}}$$

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

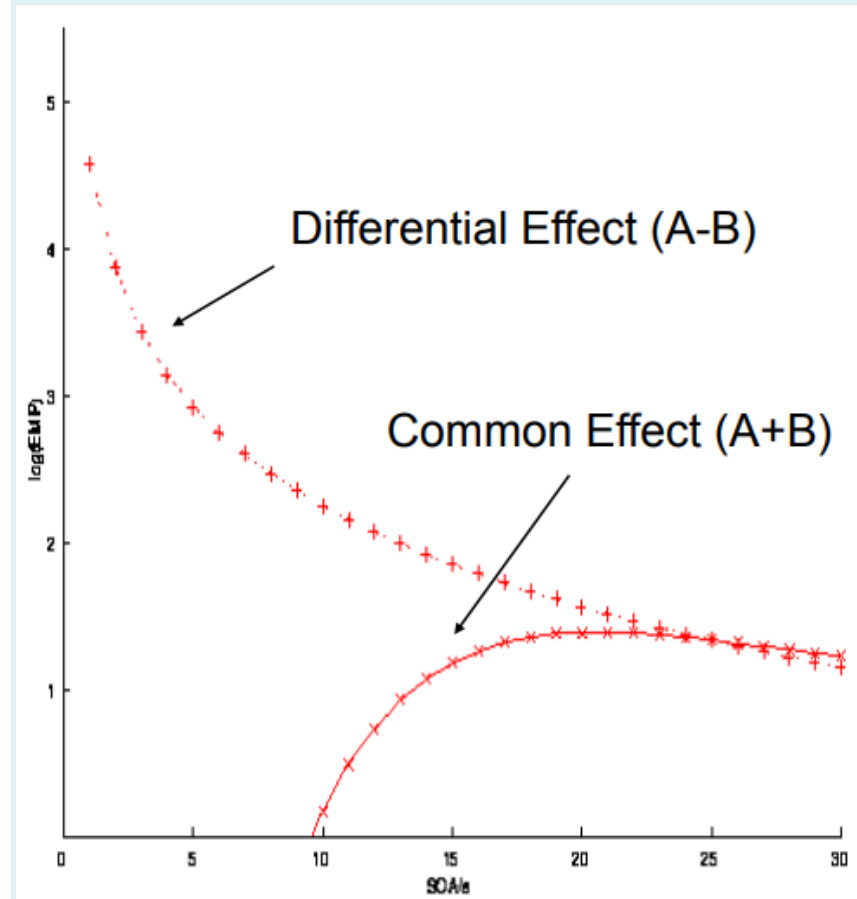
**Efficiency can be estimated before using the design**

# 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

|          |          |          |
|----------|----------|----------|
|          | <b>A</b> | <b>B</b> |
| <b>A</b> | 0.5      | 0.5      |
| <b>B</b> | 0.5      | 0.5      |

=> **ABBBABAABABAAA...**



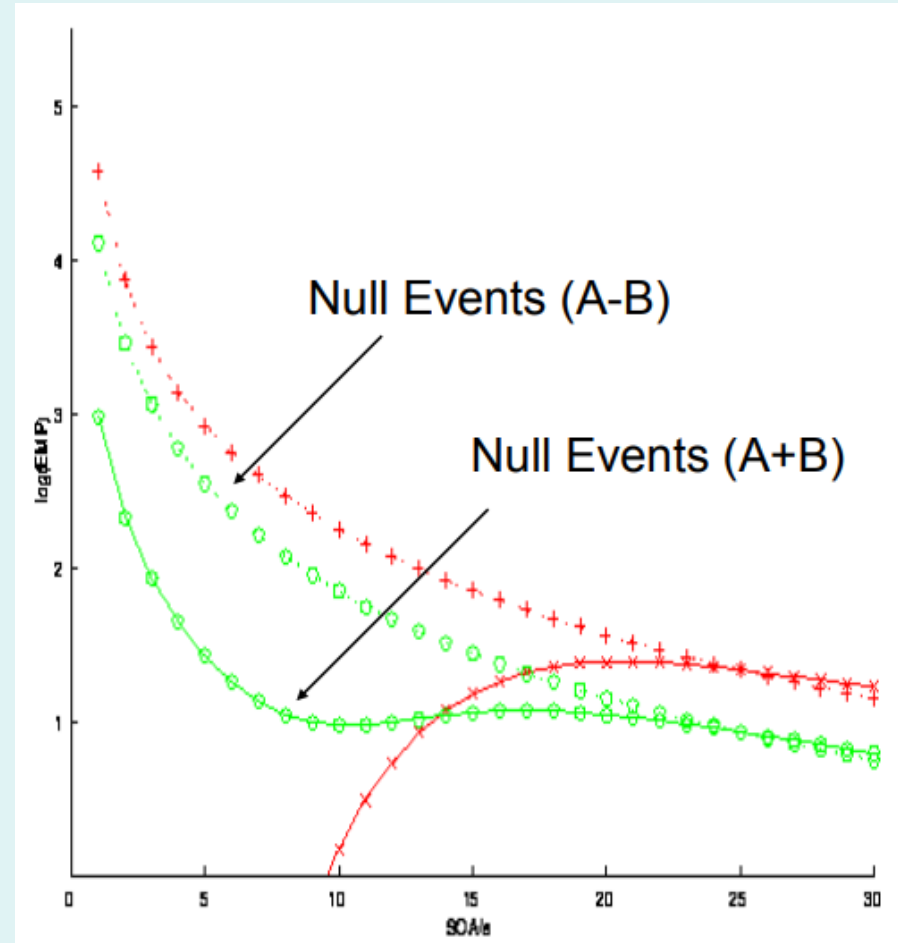
# Design efficiency: Trial sequencing

- Example: Null events

|          | <b>A</b> | <b>B</b> |
|----------|----------|----------|
| <b>A</b> | 0.33     | 0.33     |
| <b>B</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

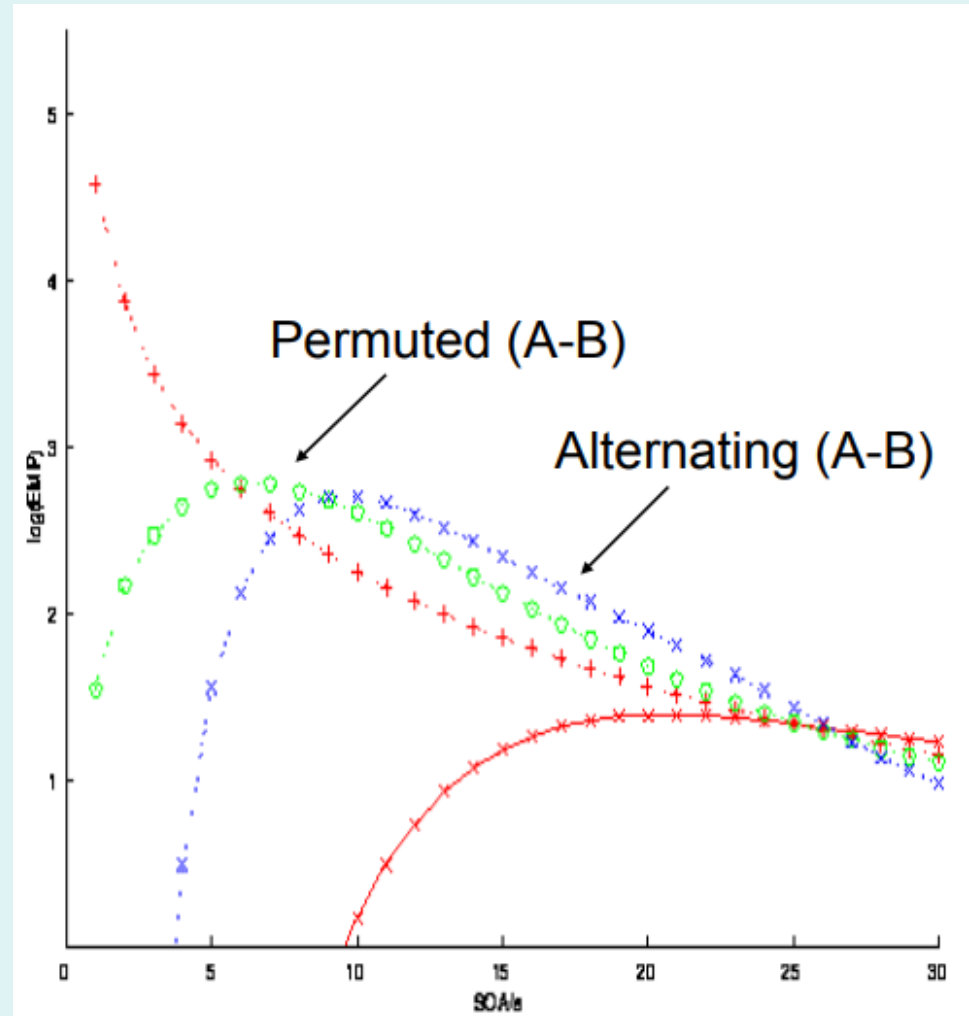
|          |          |          |
|----------|----------|----------|
|          | <b>A</b> | <b>B</b> |
| <b>A</b> | 0        | 1        |
| <b>B</b> | 1        | 0        |

=> **ABABABABABAB...**

- Example: Permuted AB

|           |          |          |
|-----------|----------|----------|
|           | <b>A</b> | <b>B</b> |
| <b>AA</b> | 0        | 1        |
| <b>AB</b> | 0.5      | 0.5      |
| <b>BA</b> | 0.5      | 0.5      |
| <b>BB</b> | 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, pseudorandomised designs can be optimal (but may introduce context-sensitivity)

