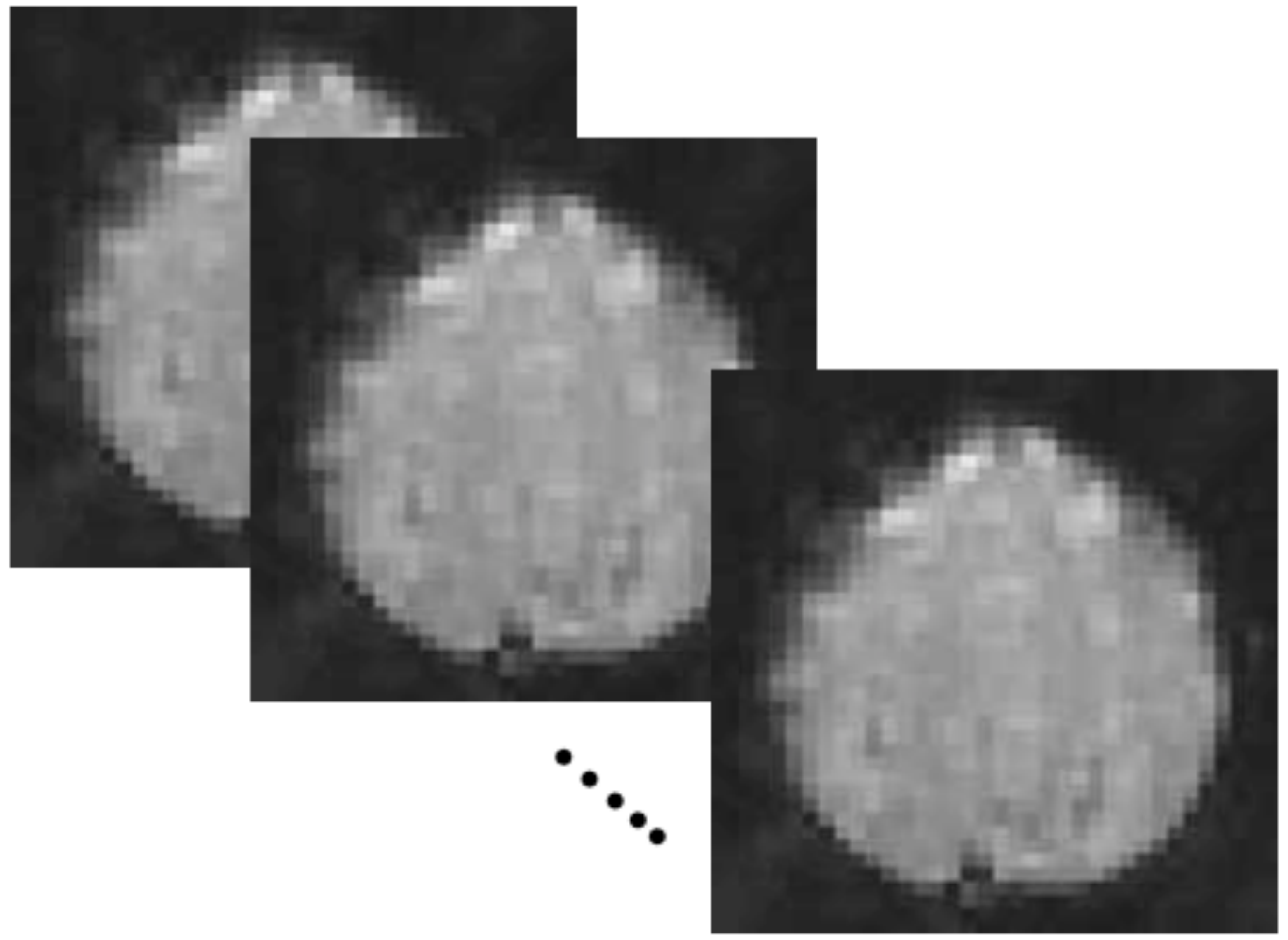
Basic fMRI analysis

Brain Imaging 2022

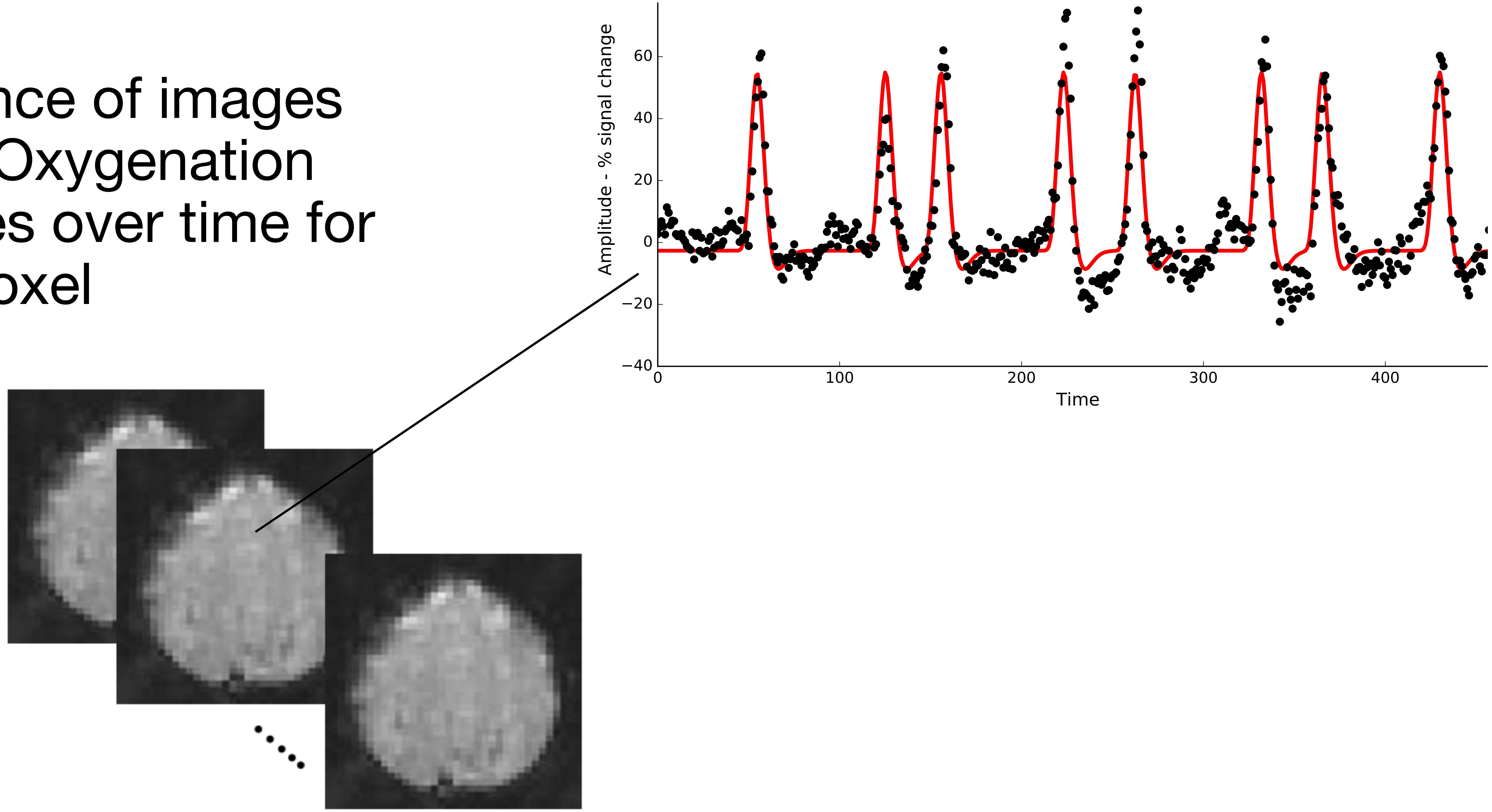
fMRI



- fMRI is used to study brain function
- T2* contrast images
- Lower spatial resolution, Higher temporal resolution
- We relate changes in T2* values to our experimental manipulations

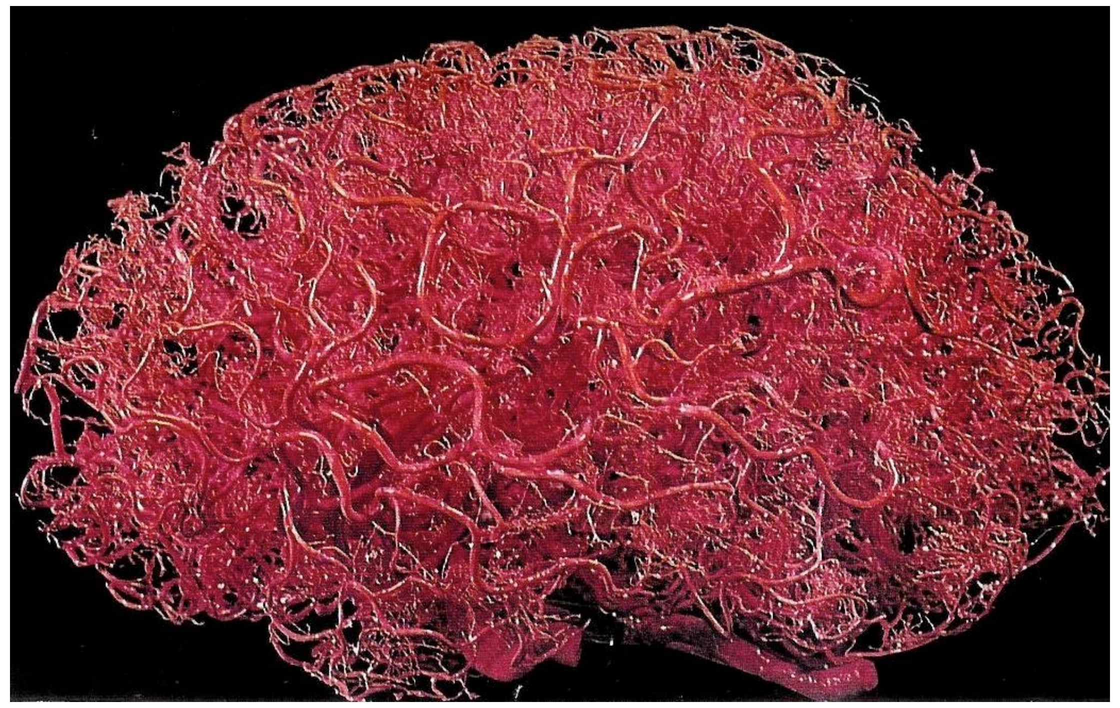
fMRI

- Sequence of images tracks Oxygenation changes over time for each voxel



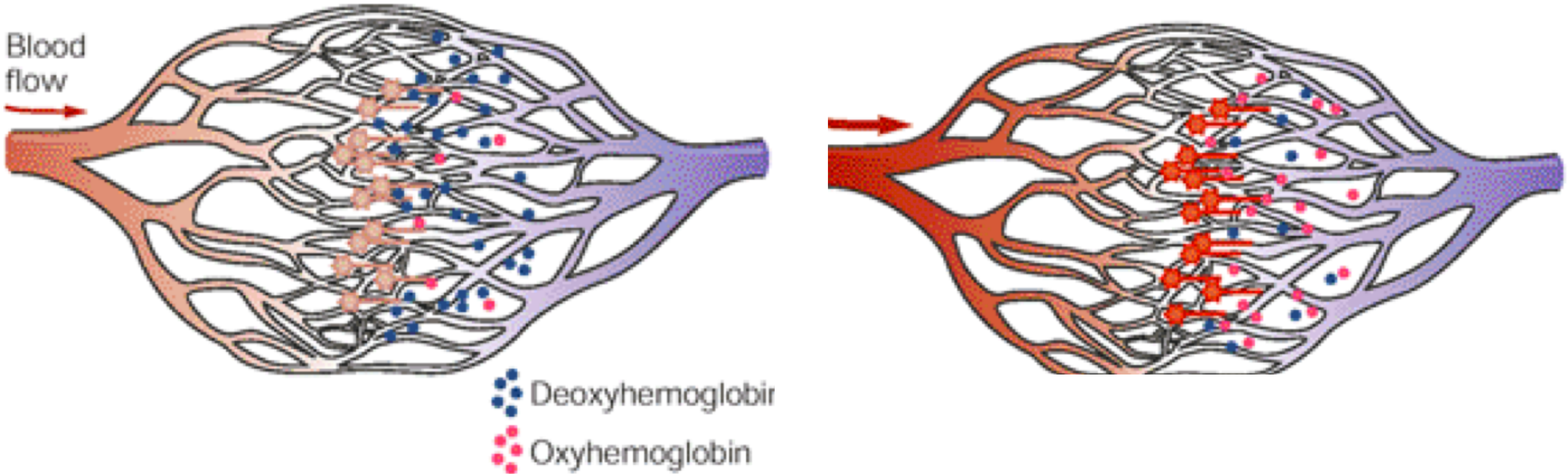
fMRI

- BOLD - Blood Oxygenation Level Dependent
- The ratio of oxygenated vs de-oxygenated haemoglobin in the blood.
- Measures metabolism, and not(!) neuronal activations!
- The link between neuronal firing and BOLD is indirect, and extremely complicated.



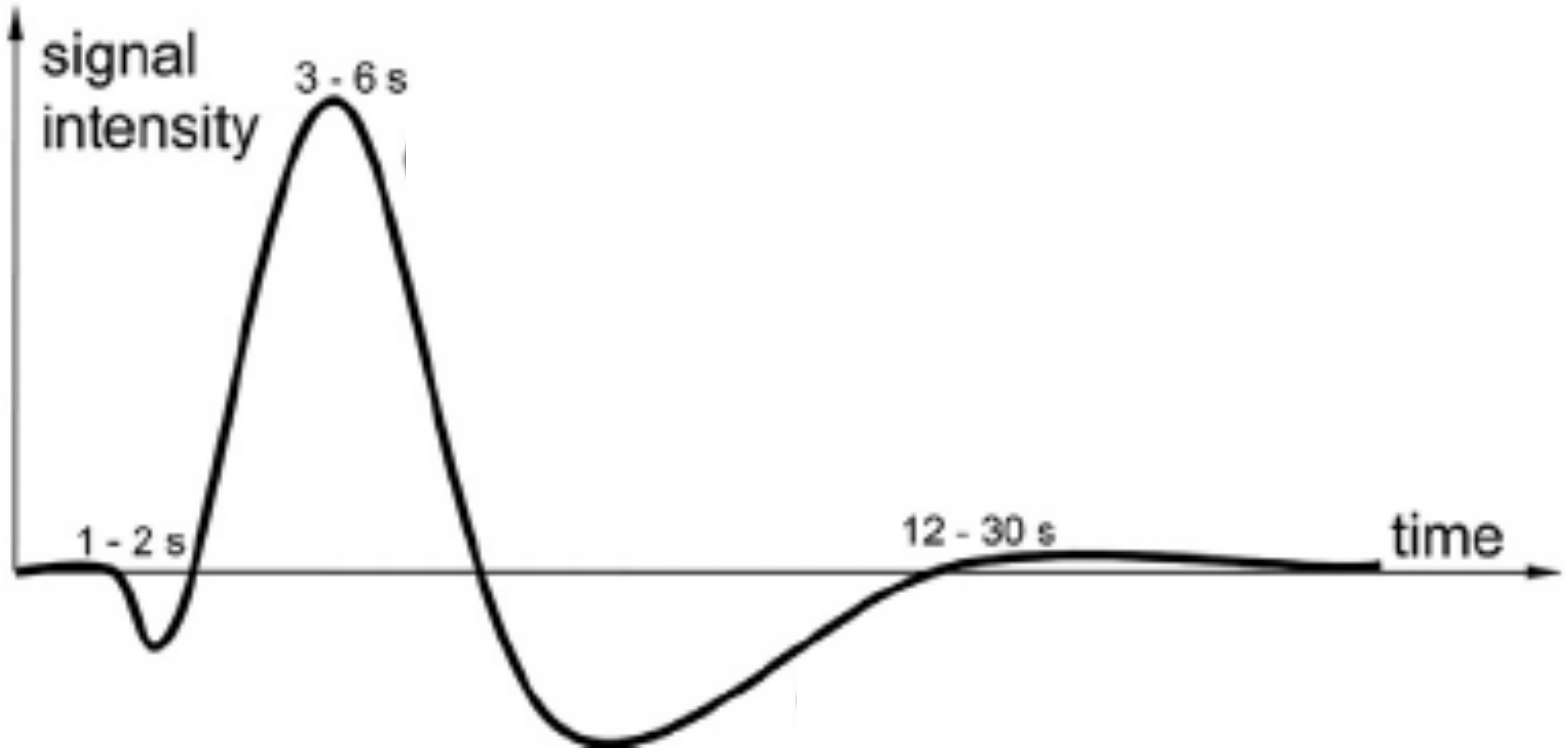
Signals - Haemodynamics

- So, neuronal activity should decrease the T2* values, right?
- The Haemodynamics are more complicated: the vasculature ‘overreacts’ and oversupplies new, oxygenated blood to the tissue.



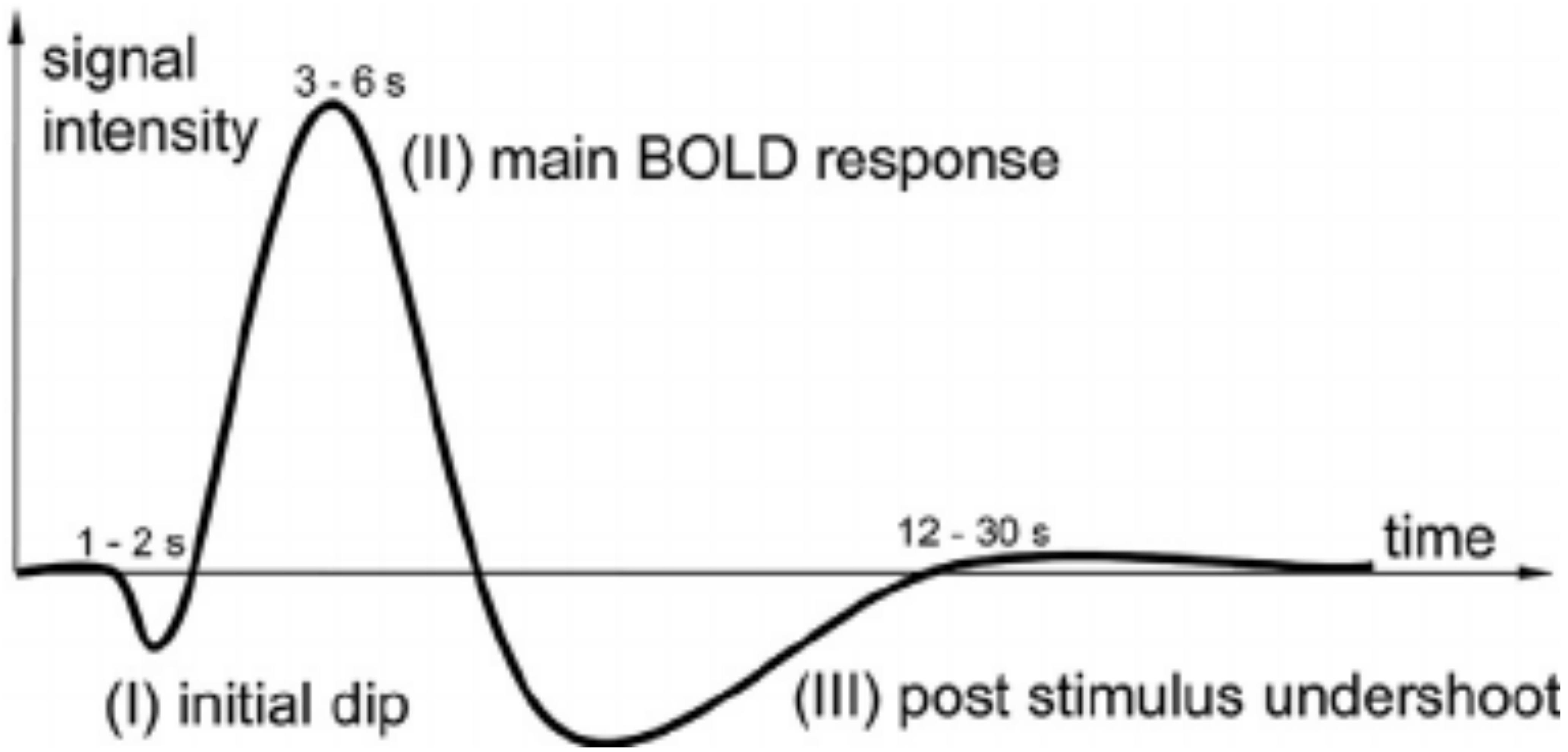
Signals - Haemodynamics

- This complicated sequence of metabolic events causes a stereotypical change in T2* over time
- A short burst of neuronal activity produces a stereotypical BOLD signal, called the Haemodynamic Response Function



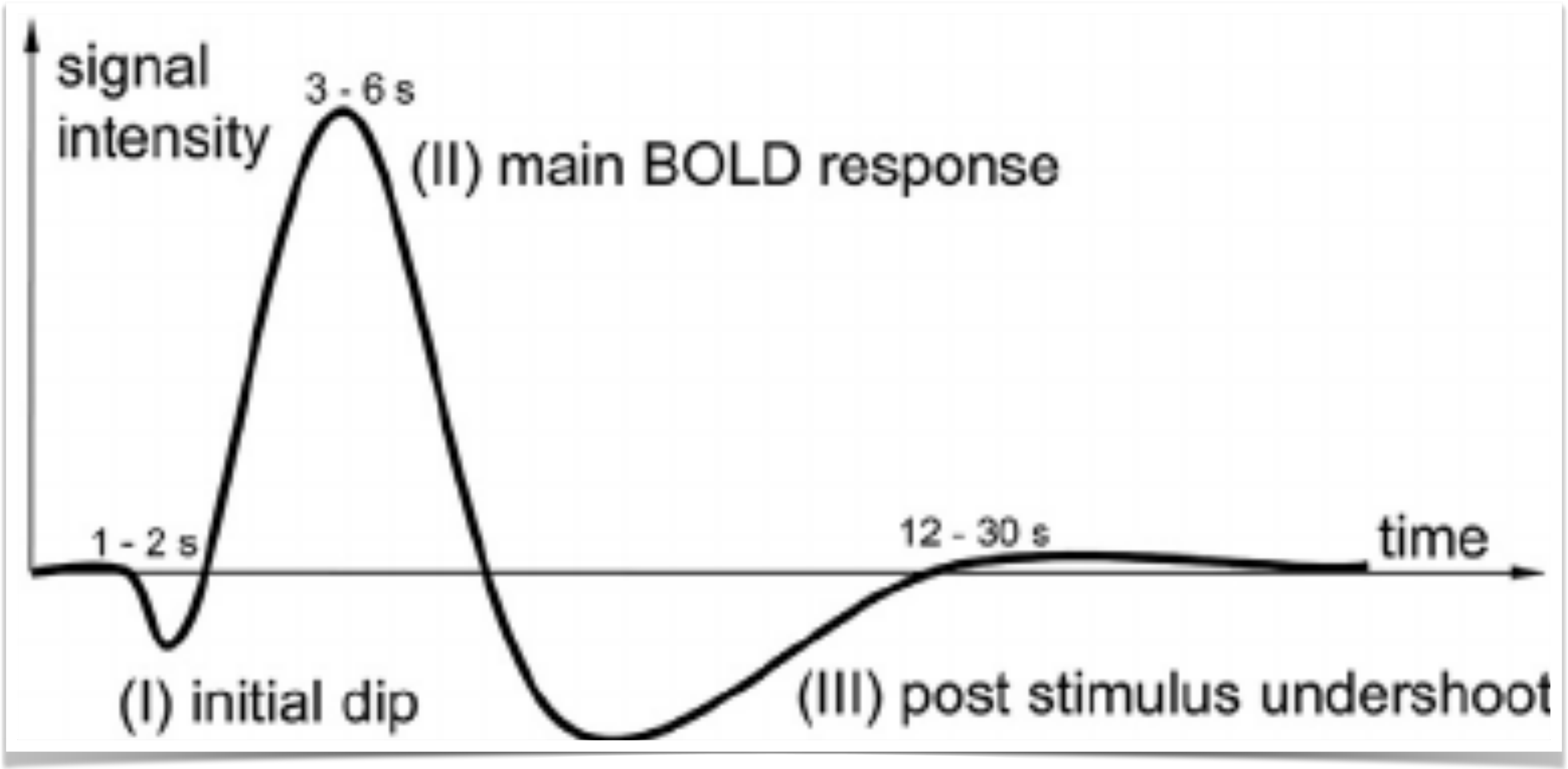
HRF phases

- Initial dip: first use of oxygen (deoxygenation) hits before the vasculature can react (difficult to measure).
- Neural activity is followed by an increase in oxygenated blood, causing peak in T2* signal strength
- Post-stimulus undershoot:
  Reduced blood flow after a while, with increased blood volume

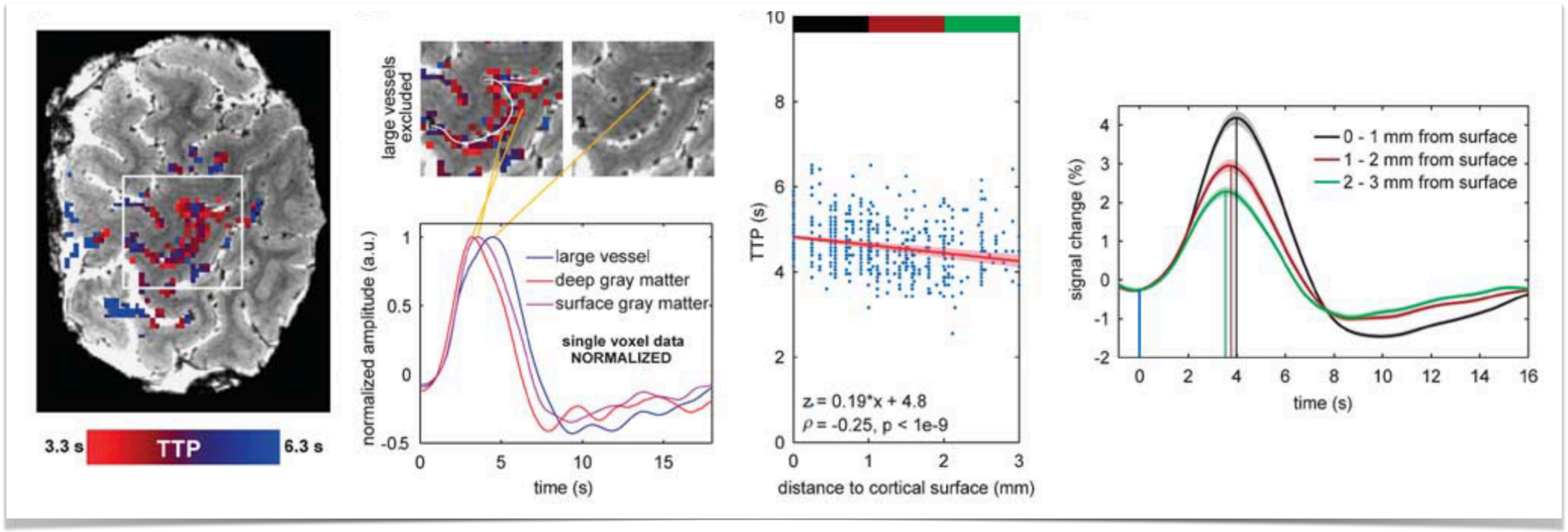


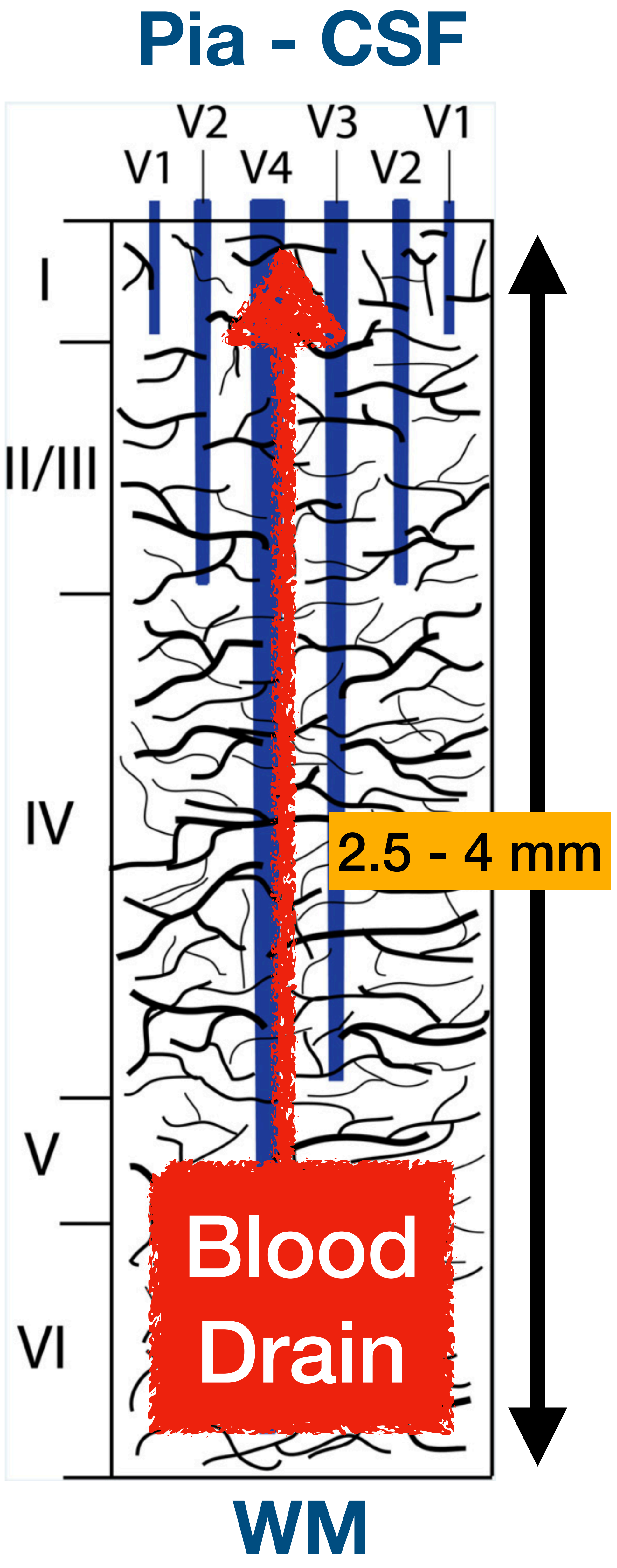
Signals - what does a BOLD signal look like?

- Slow signal, much much slower than EEG/MEG
- (Sort of) Stereotypical course, but varies with:
    - Subject,
    - Age,
    - Brain Region,
    - Attention and the like



And… cortical depth





BOLD is blood:
Vascular structure

Signals - how do we measure BOLD signals?

- TR - repetition time (100 ms - 10 s)
  - The longer, the more signal
- voxel size (250 micron - 5 mm)
  - Smaller means less signal (cf. TR)
- field of view
  - Do you need whole-brain scanning?
- magnetic field strength (1 - 9.4 T)
- standard fMRI method:
  - EPI - echo planar imaging, measure in slices
- A lot of preprocessing!

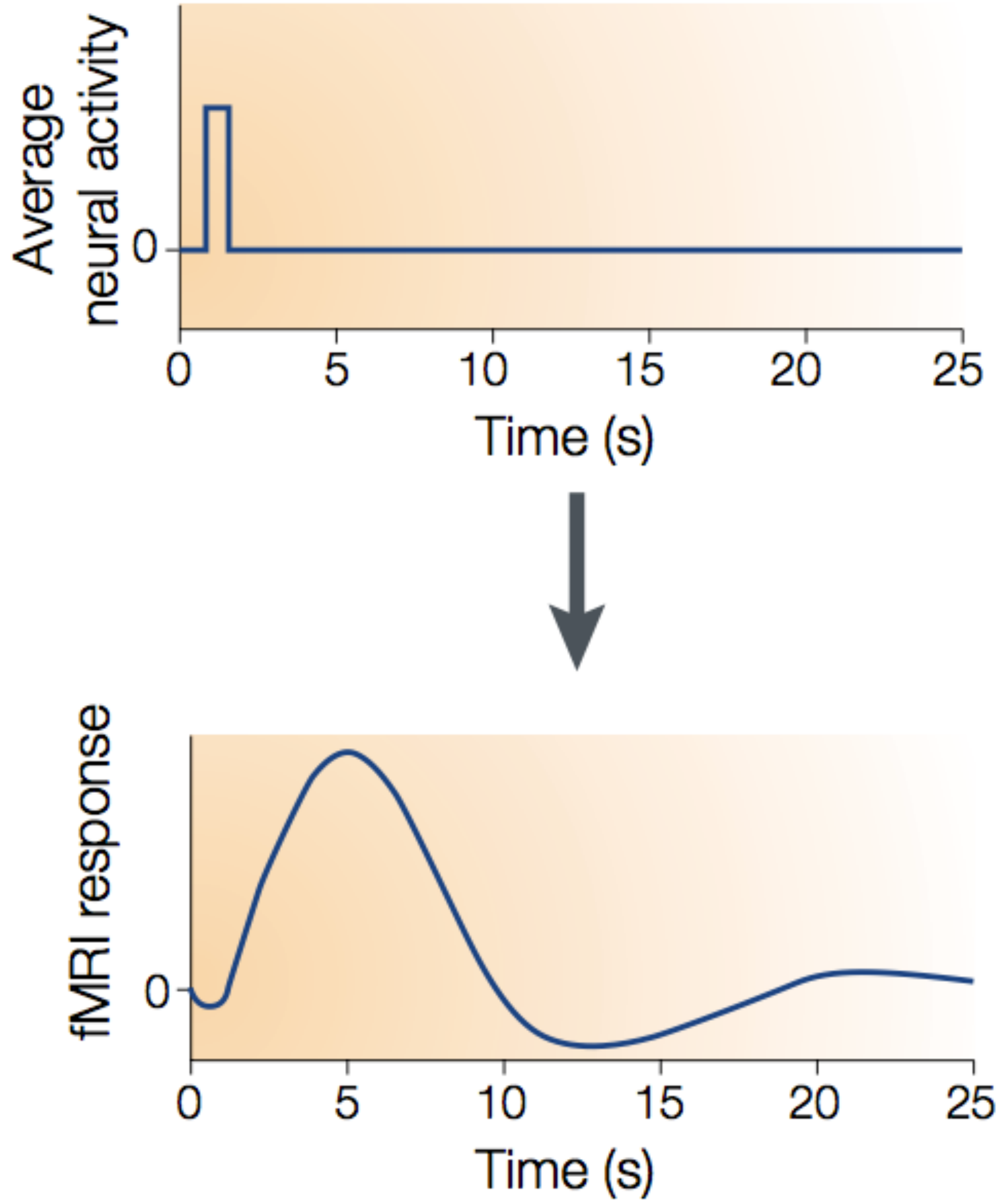
basic fMRI analysis:
The General Linear Model

Signals - GLM analysis

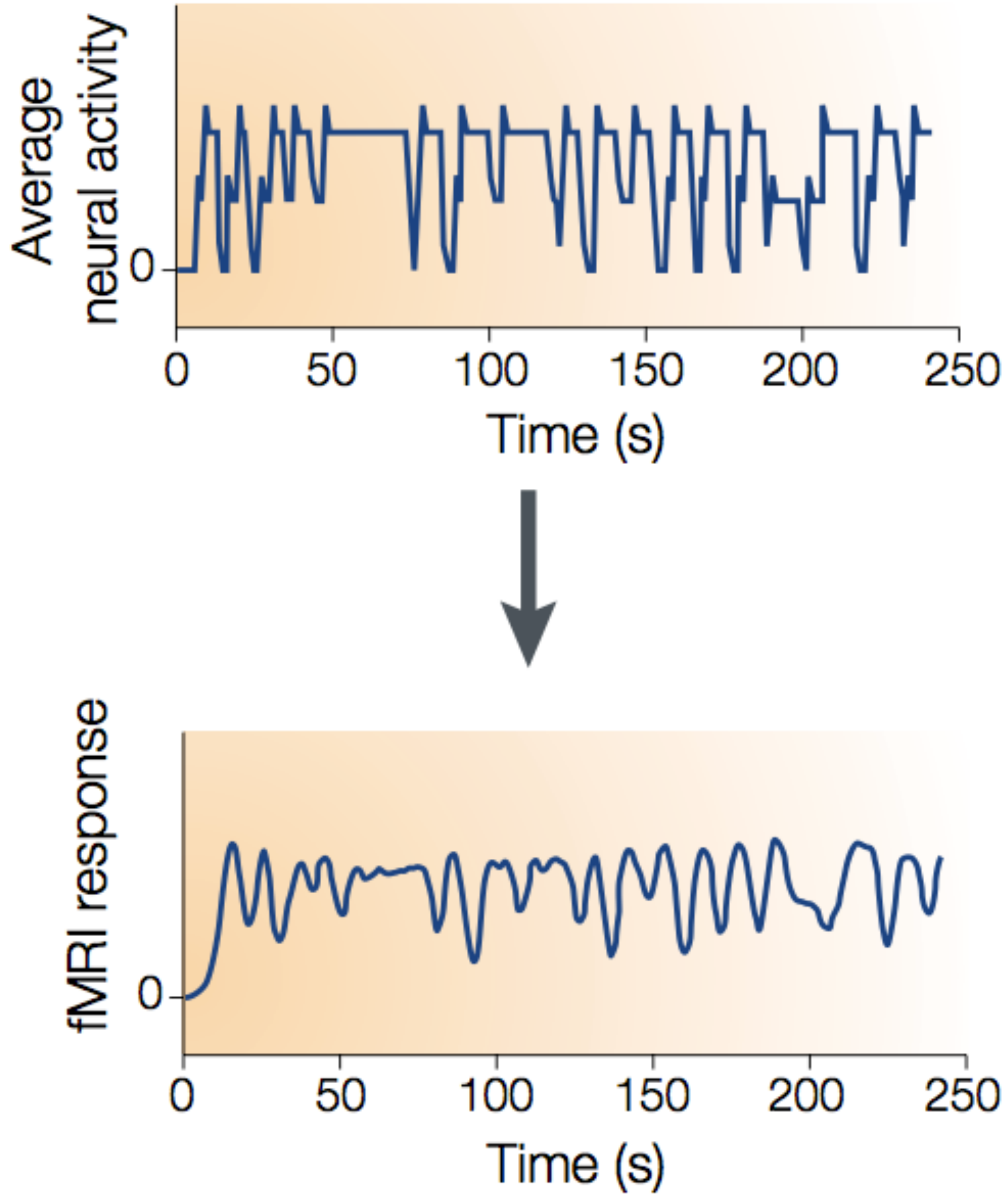
- GLM - general linear model approach to fMRI analysis.
- Relate measured BOLD responses to expectations of what responses should look like, using HRF.
- Create models of certain types of responses using assumptions.
- How do we create our expectations?

Signals - GLM analysis after preprocessing

Very short neural activity causes a ‘canonical’ response

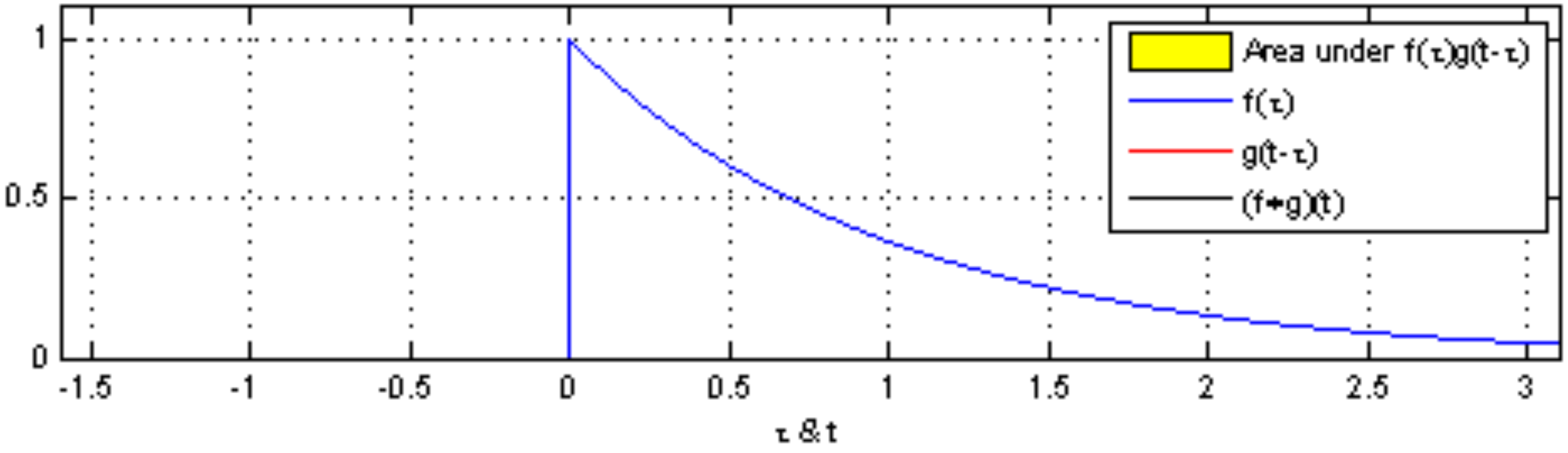


Take your experiment’s neural activity, and convolve with canonical response

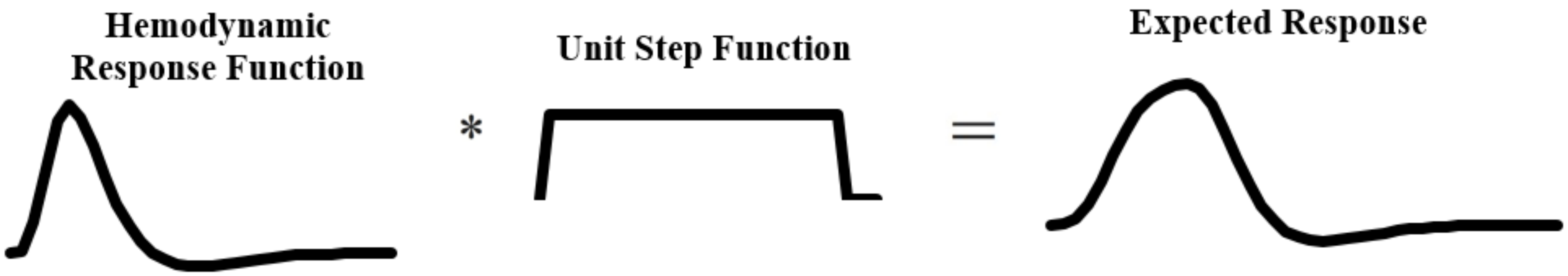


Expected fMRI time-course

Convolution



for fMRI:
Convolve (*) input with HRF

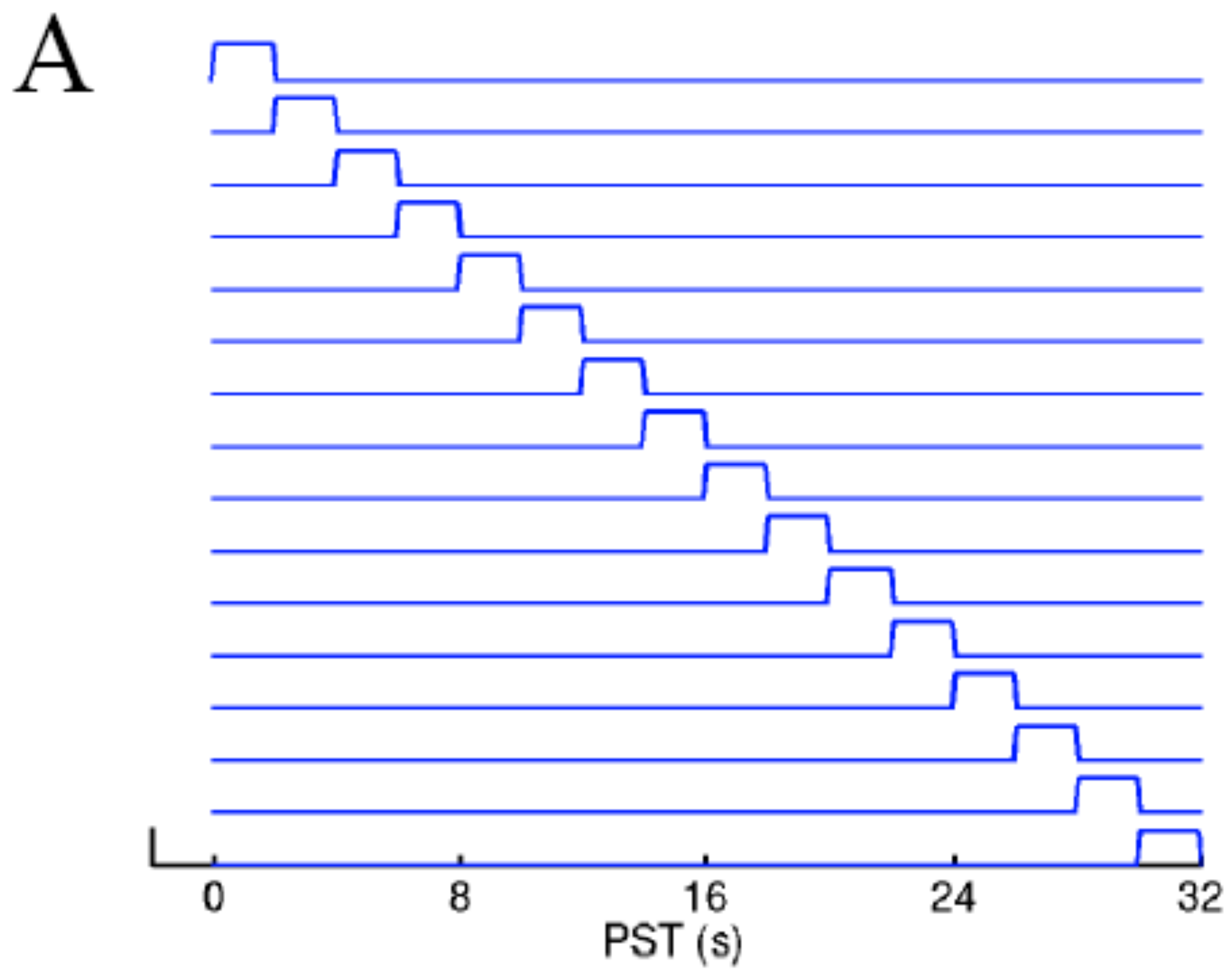


Basis functions

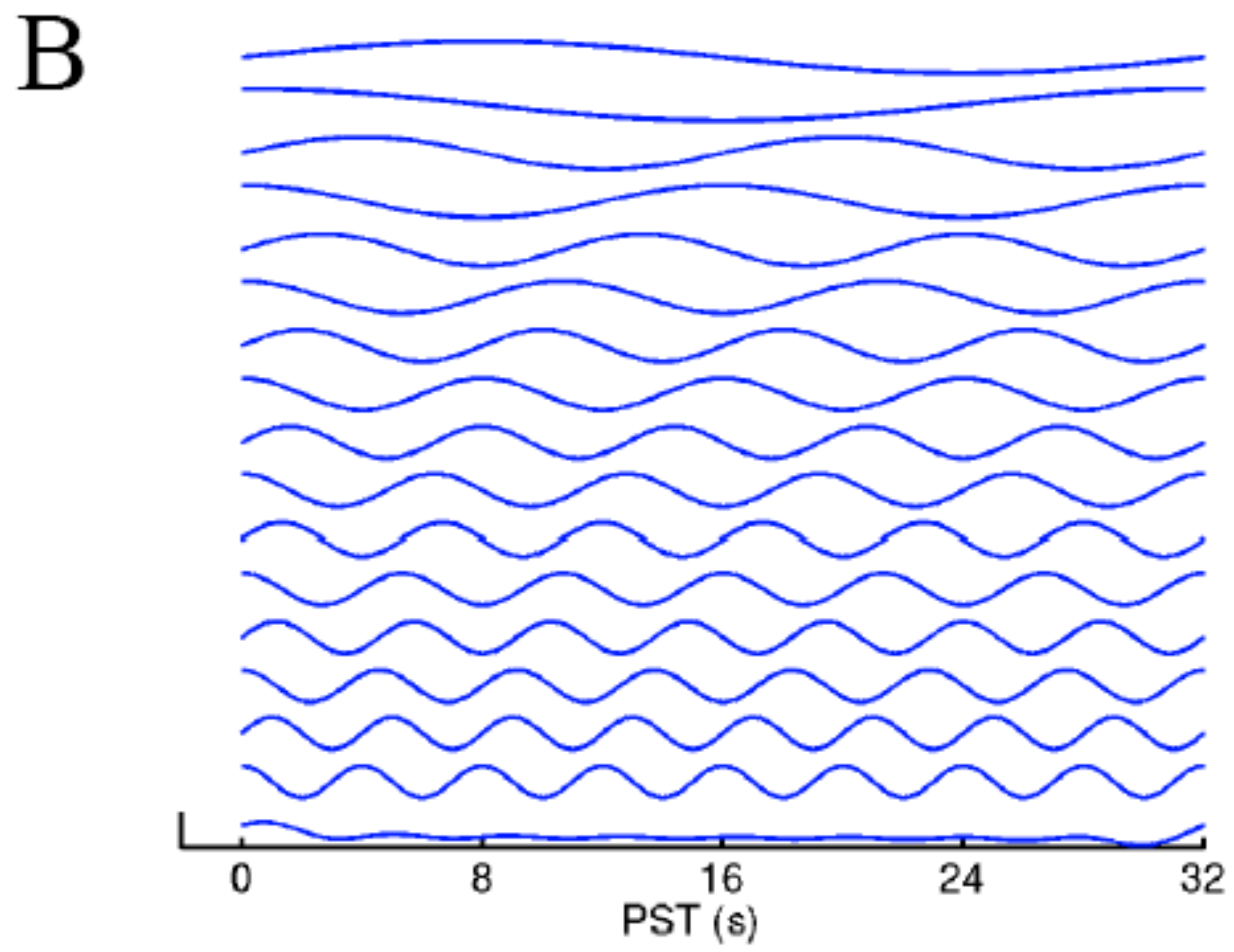
- We’ve now represented the HRF with a fixed shape.
  - but, sometimes we want to be more flexible, and fit the shape too.
  - So, we have to describe the shape, which takes more regressors.
  - What should these new regressors look like?

Different basis functions

- There are different ways of describing functions of time



By ones:
each timepoint is a regressor
Finite Impulse Response

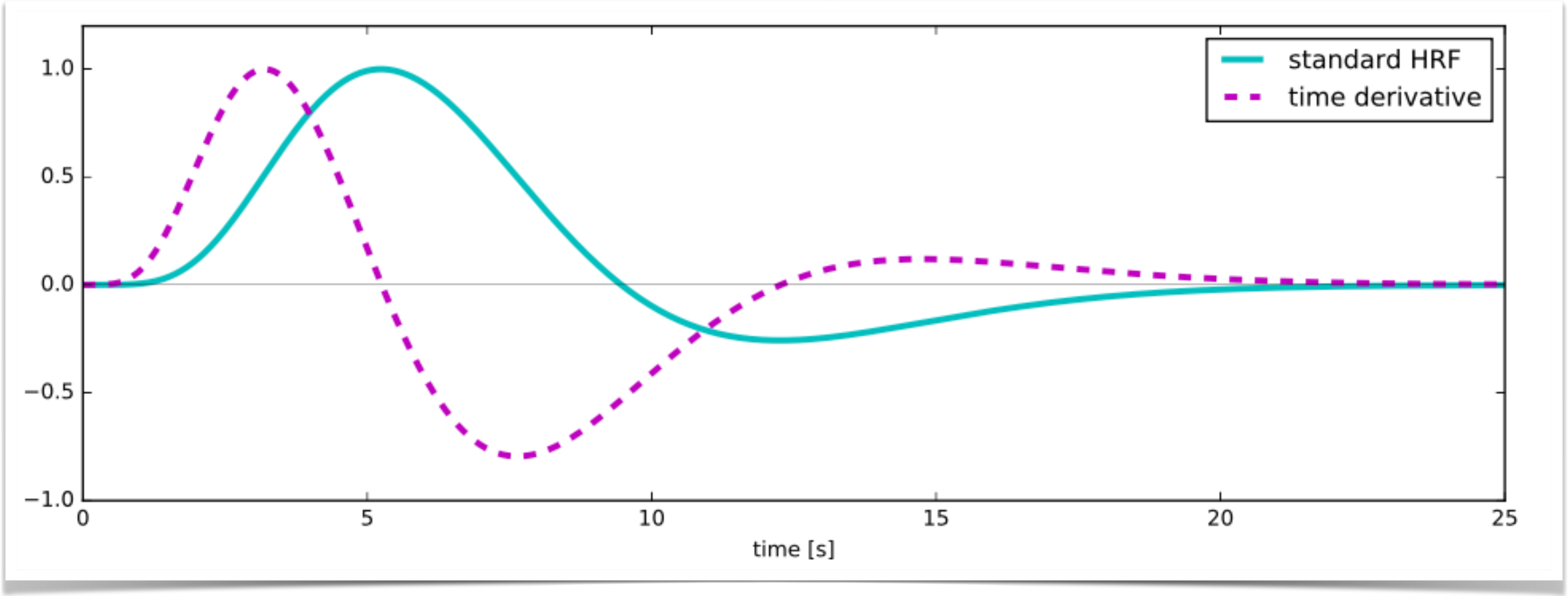


By frequencies:
each frequency is a regressor:
Fourier Decomposition

Many different regressors: very good estimate of HRF shape!

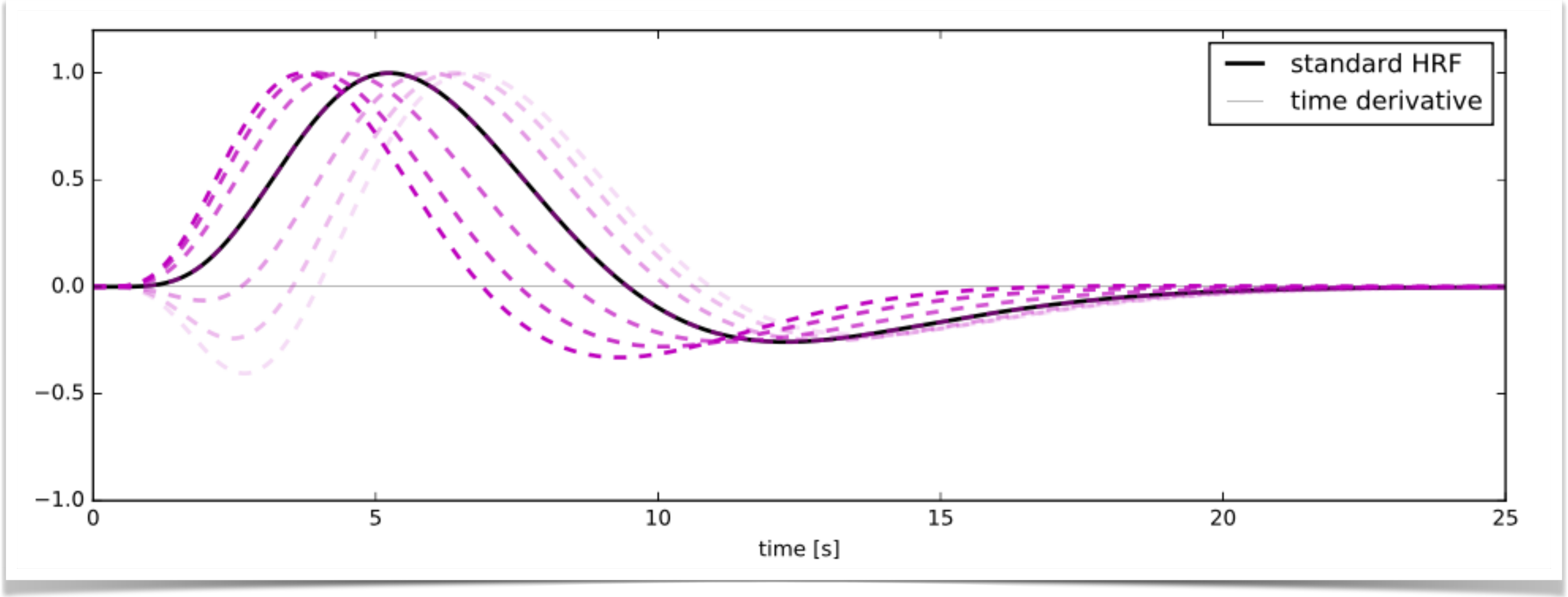
Gamma basis functions

- But these very precise descriptions take a lot of regressors, so we'd need a lot of data to estimate them!
- We sort of know what the HRF looks like, so we can use this knowledge.
- Use the gamma shape as a backbone, add a regressor of neural activity convolved with the HRF's time derivative



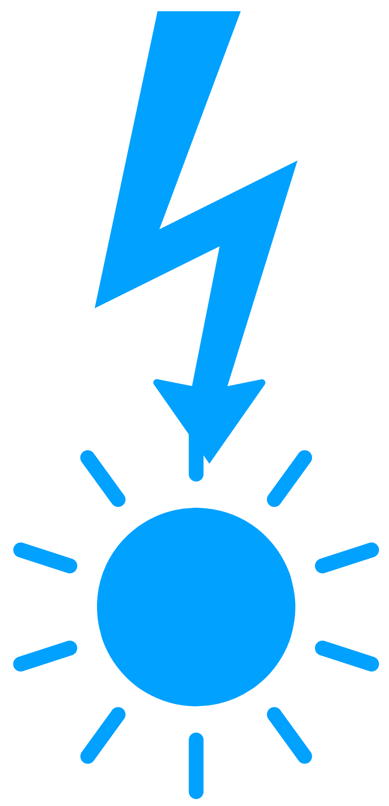
Gamma basis functions

- What does adding a regressor convolved with the time derivative of the standard HRF do?
-



- It allows us to change the timing of the HRF, so that we better capture the subject's HRF shape: flexibility, but not too many extra regressors
- Extra regressor still: Dispersion Derivative - changes the shape of the HRF more than its timing.

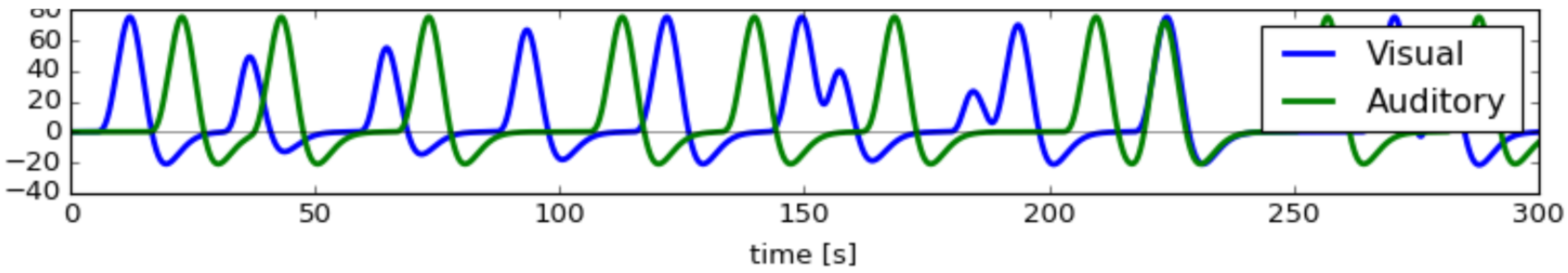
Signals - GLM analysis after preprocessing



But, your experiment will not contain just one type of event.

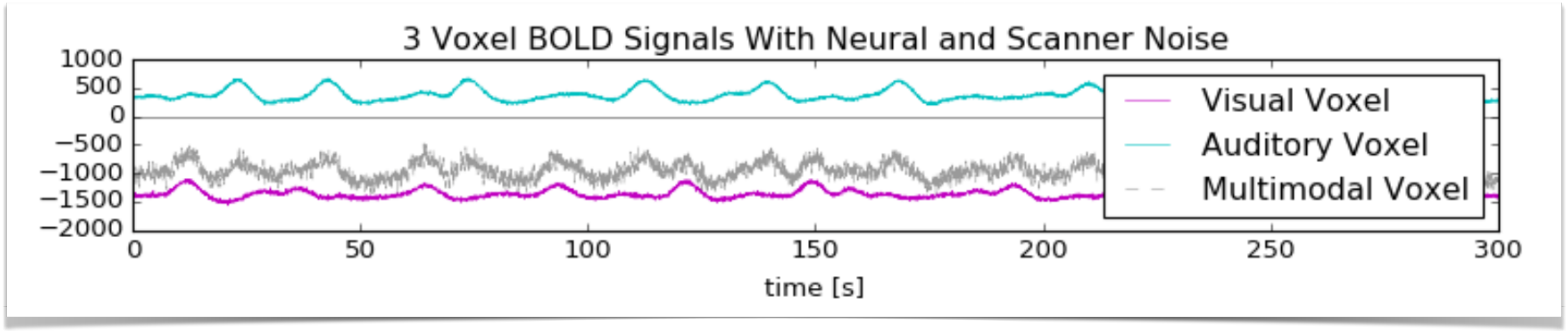
There will be multiple types of events, and you’ll be interested in differential responses to these events:
-does this voxel respond more strongly to vision or audition?

different expectations for different conditions, events, etc.
These are called
Explanatory Variables, Predictors, or Regressors



Signals - GLM analysis after preprocessing

Our goal with this analysis is to try to explain the measured BOLD signal as a combination of our Explanatory Variables



For example, with 2 EVs:

$$y = a \cdot x1 + b \cdot x2 + c + N(\mu, \sigma)$$

Where y is the data, $x1$ and $x2$ are Visual and Auditory EVs, and we want to find a, b, and c, our parameters of interest.

These are scaling factors that determine whether a voxel is visual, auditory or multimodal.

Signals - GLM analysis after preprocessing

We have to do regression, to distribute the to-be-explained variance to different explanatory variables

General linear model: GLM

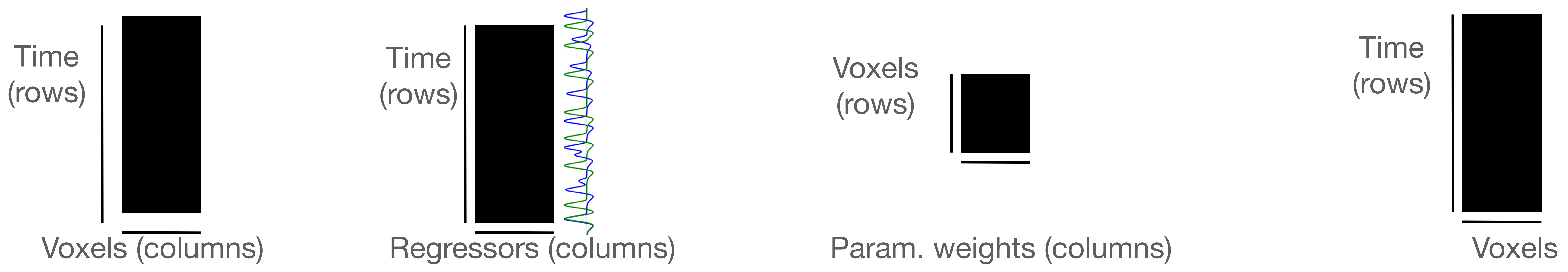
$$Y = X \cdot \beta + \epsilon$$

Y: Matrix of BOLD at various time points in a single voxel (What you collect)

X: Design matrix (This is your model specification)

β: Parameters matrix (These need to be estimated)

ϵ: Error matrix (residual error for each voxel)



Methods

Standard GLM analysis for fMRI:

- Minimizing squared error: $$\|y - X\beta\|^2$$

$$y = X\beta + e, \qquad e \sim N_n(0, \sigma^2\ I)$$

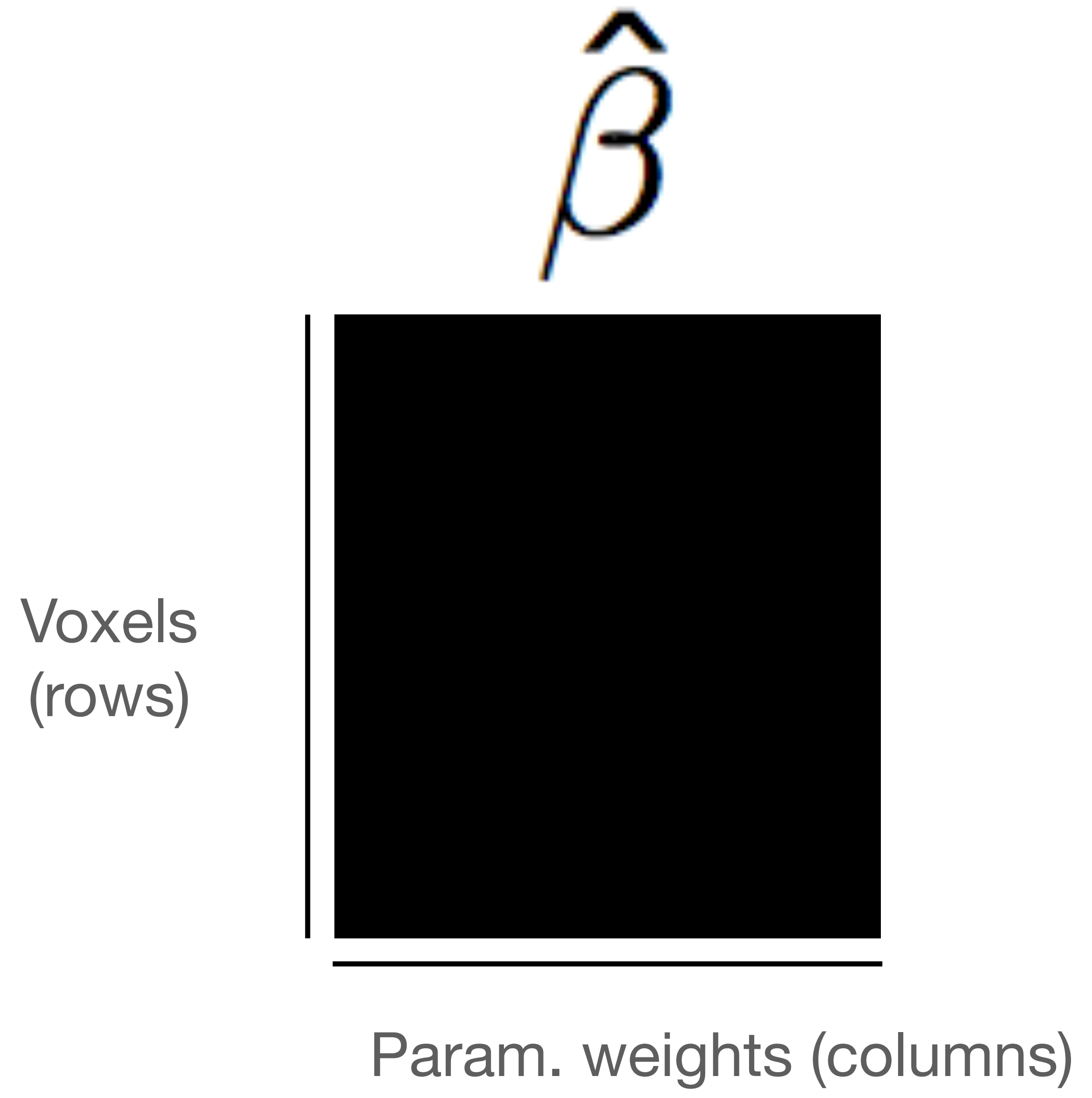
Equation for ordinary least squares estimate:

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

Matrix Equations Are Not Part Of The Exam!
Logic is!

Towards an “End” result of GLM

- The first result of this analysis is beta weights, parameters that together with your design matrix best describe the BOLD responses
- Beta values are the values you need to multiply your EVs with (scaling factors), in order to best explain the data
- The beta weights are what allow you to say whether a voxel is a ‘visual’ or an ‘auditory’ voxel
- The beta weights are the start of all the further statistics that deliver the nice-looking red-and-yellow blobs



Statistics

- The better the model fits, the smaller the error
- Basis for all statistics involving fitting!
- Statistics: t-statistic,

$$t = \frac{\beta}{\hat{\sigma}}$$

- Where the standard error of the model

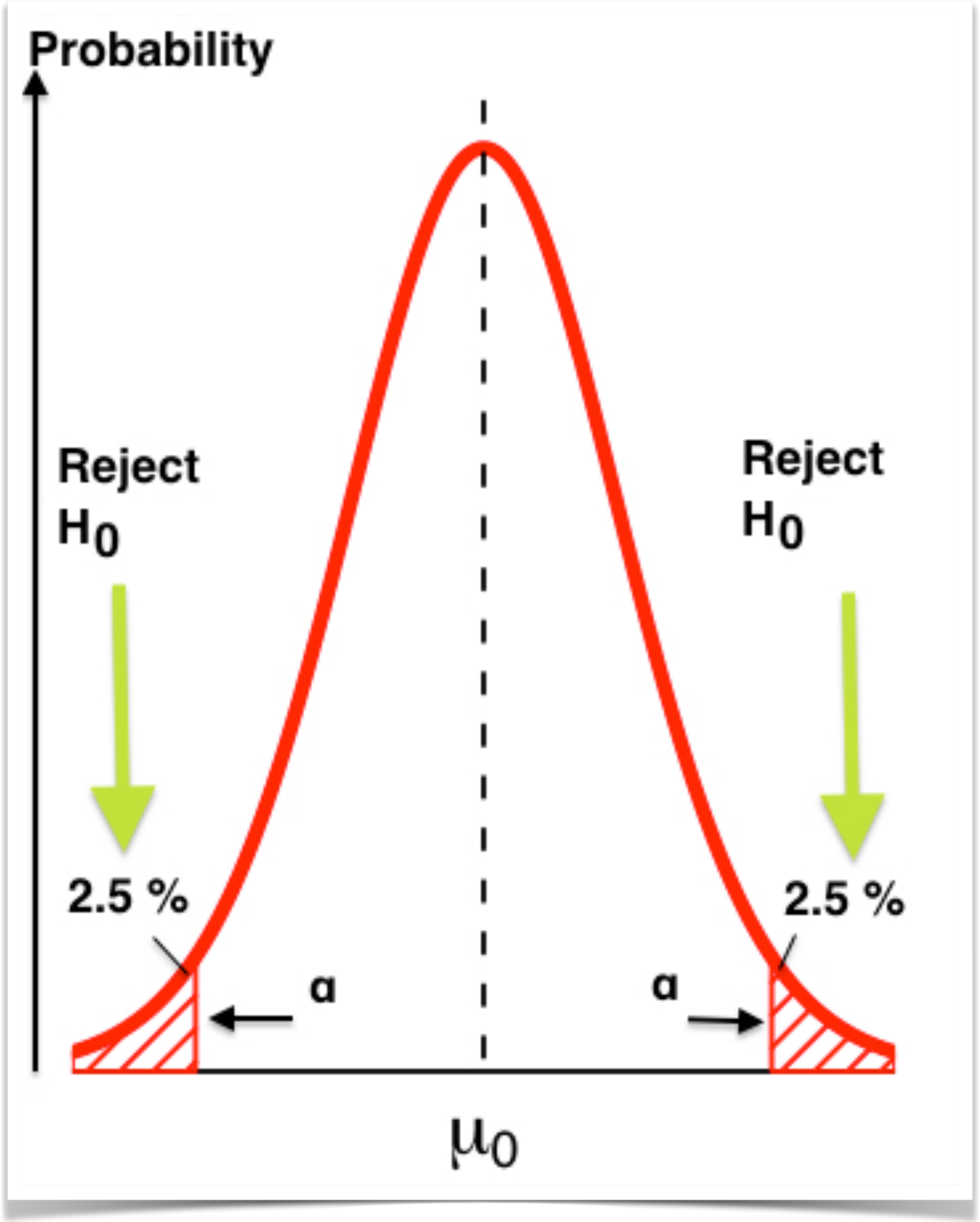
$$\hat{\sigma} = \sqrt{\frac{\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}{df}}$$

- and the degrees of freedom of our fit are

$$df = N - P$$

Statistics

- But then, how do we get to the all-important p-value?
- The t-distribution with df degrees of freedom returns the chance of a given t-value
- Thus, a given t-value corresponds to a certain p-value:
- As df goes to ∞, the t-distribution becomes more and more like a Normal distribution:
  t-values are often converted to Z-score



Beautiful images

- fMRI studies don't show 'activation', but they show a statistic
- "Lies, Damn Lies, and Statistics"
- Easy to fool people!