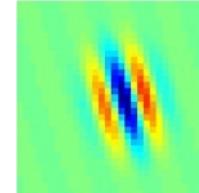


System Identification

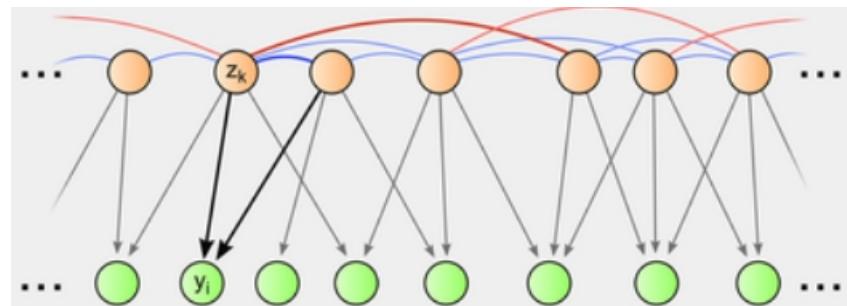
AIL087
Ján Antolík
MFF UK, 2019

Computational modeling taxonomy

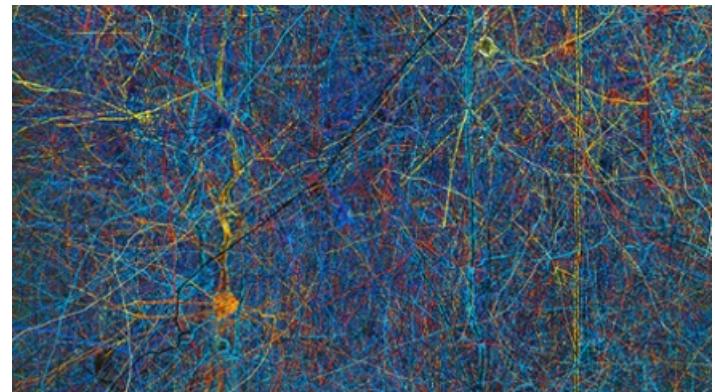
- System identification models



- Normative models
(often Bayesian based)



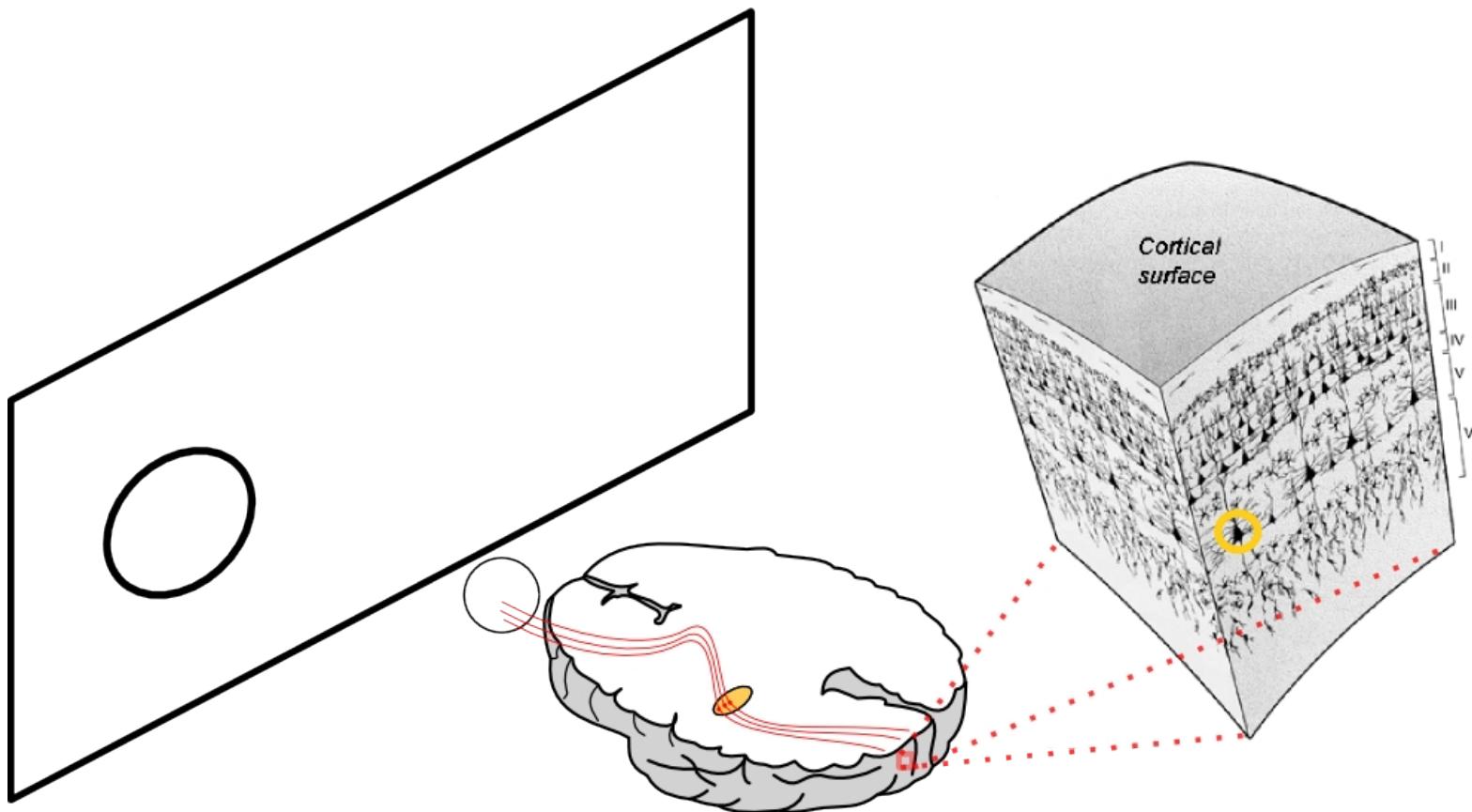
- Full dynamical models
• (aka. simulations)



System identification

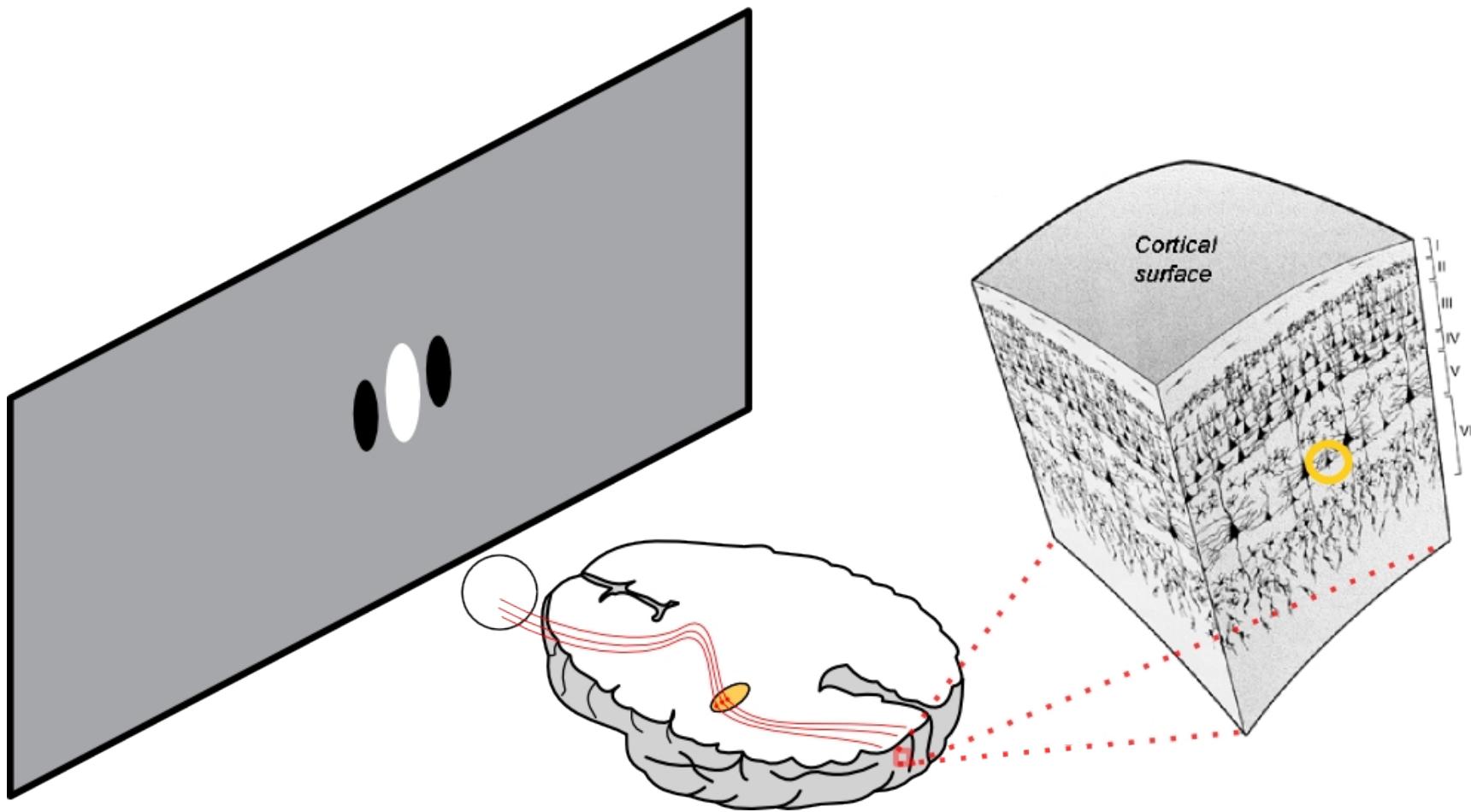
- Most linked to data: we directly fit them
- Compact representation of the function: easy interpretability
- Over-simplified – we can have too many parameters and the fitting has to be mathematically tractable
- No dynamics (mostly) – those are difficult to fit
- Overfitting

RF: position in visual field



Responses can be obtained in a given optic nerve fiber only upon illumination of a certain restricted region of the retina, termed the receptive field of the fiber. Hartline, H K (1938)

RF: map of exc/inh regions

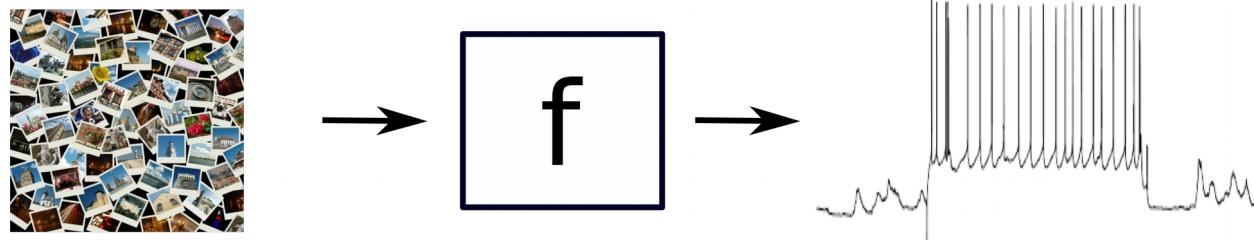


Kuffler (1953); Hubel and Wiesel (1962)

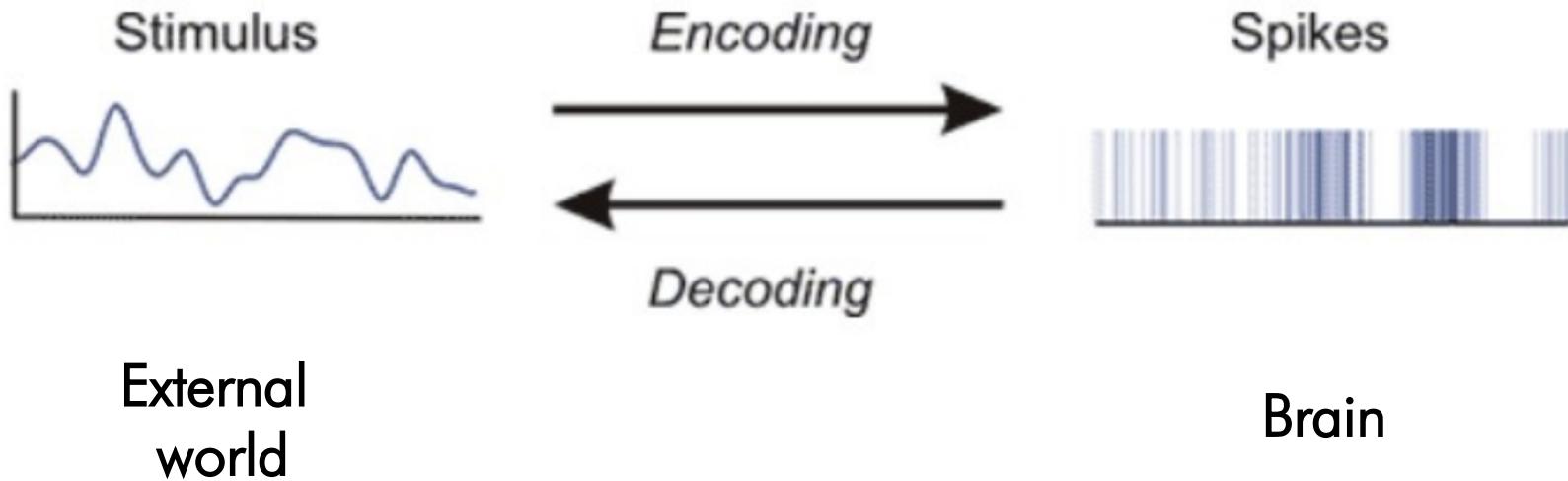
RF as a function



$$f: I^n \rightarrow (0,1)$$



Encoding vs. Decoding



- ENCODING: How is information about stimulus transformed into spikes
- DECODING: How to infer stimulus (**or output variable**) given spikes

Encoding vs. Decoding

S – Stimulus

R – Response

Encoding

$$P(R | S)$$

vs

Decoding

$$P(S | R)$$

Encoding vs. Decoding

S – Stimulus

R – Response

Encoding

$$P(R|S)$$

vs

Decoding

$$P(S|R)$$

Encoding and decoding are related by **Bayes theorem**:

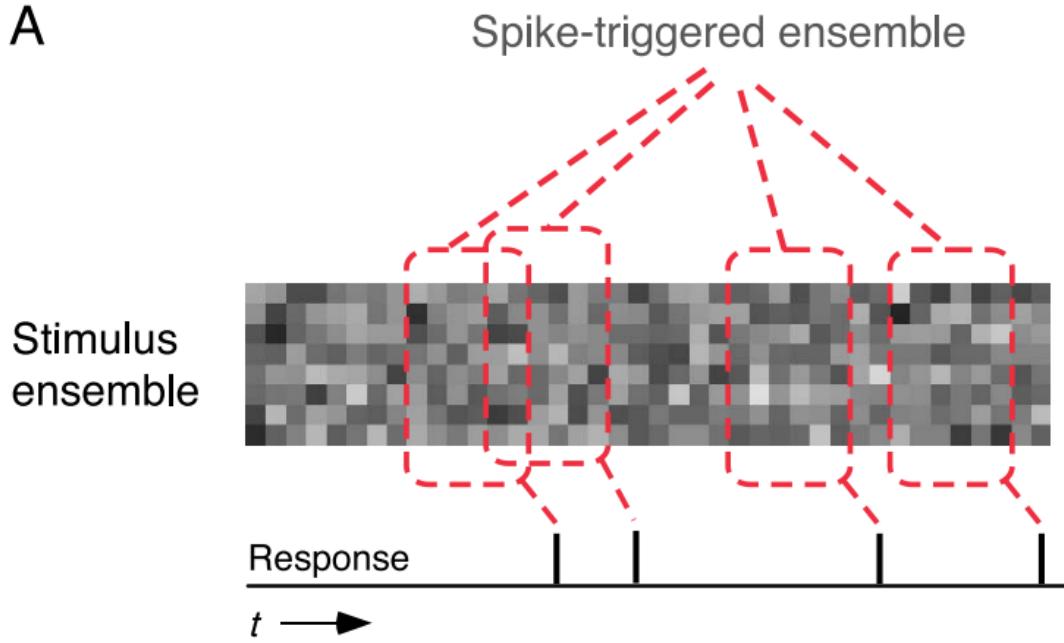
$$P(R,S) = P(R|S)P(S) = P(S|R)P(R)$$

$$P(S|R) = \frac{P(R|S)P(S)}{P(R)}$$

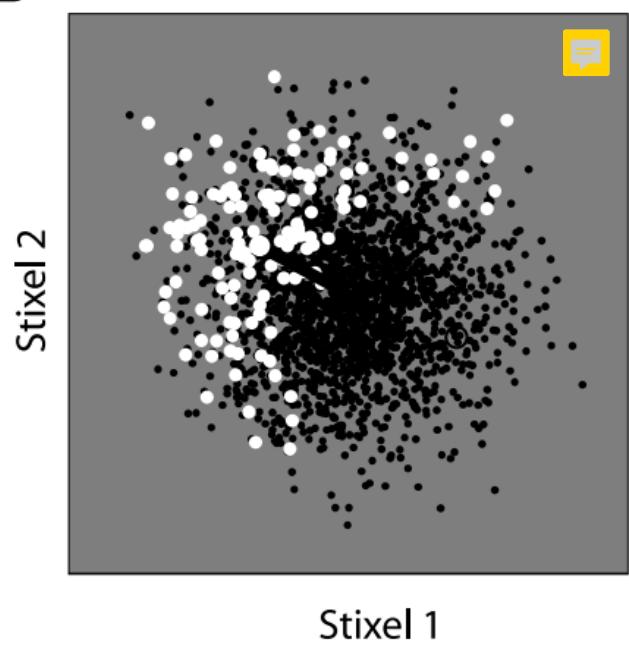
Spike Triggered Formalism

Spike-triggered ensemble

A



B



Poisson firing

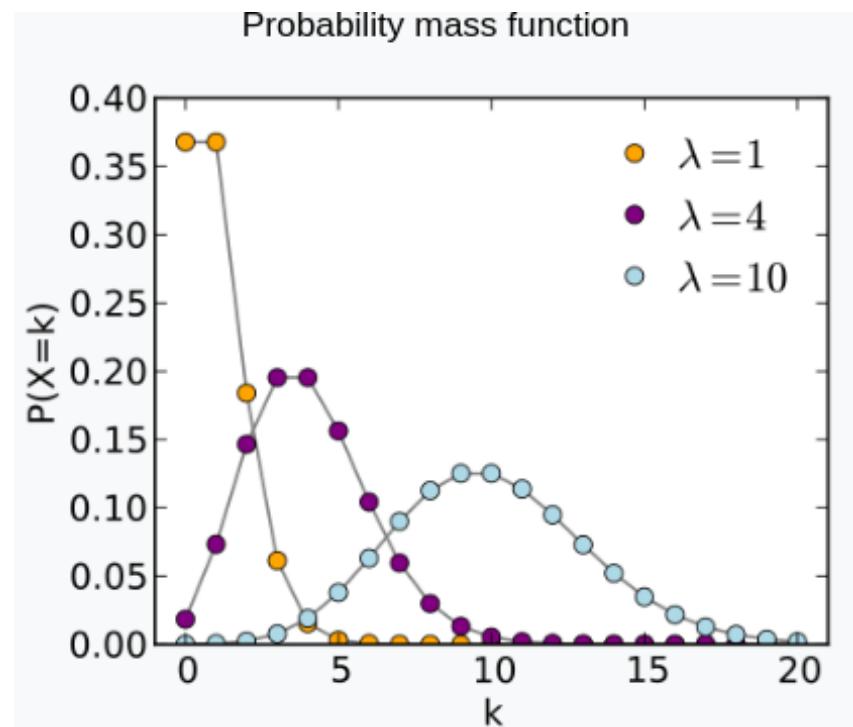
$$y \sim \text{Poiss}(\lambda)$$

$$P(y) = \frac{1}{y!} \lambda^y e^{-\lambda}$$

y – spike count

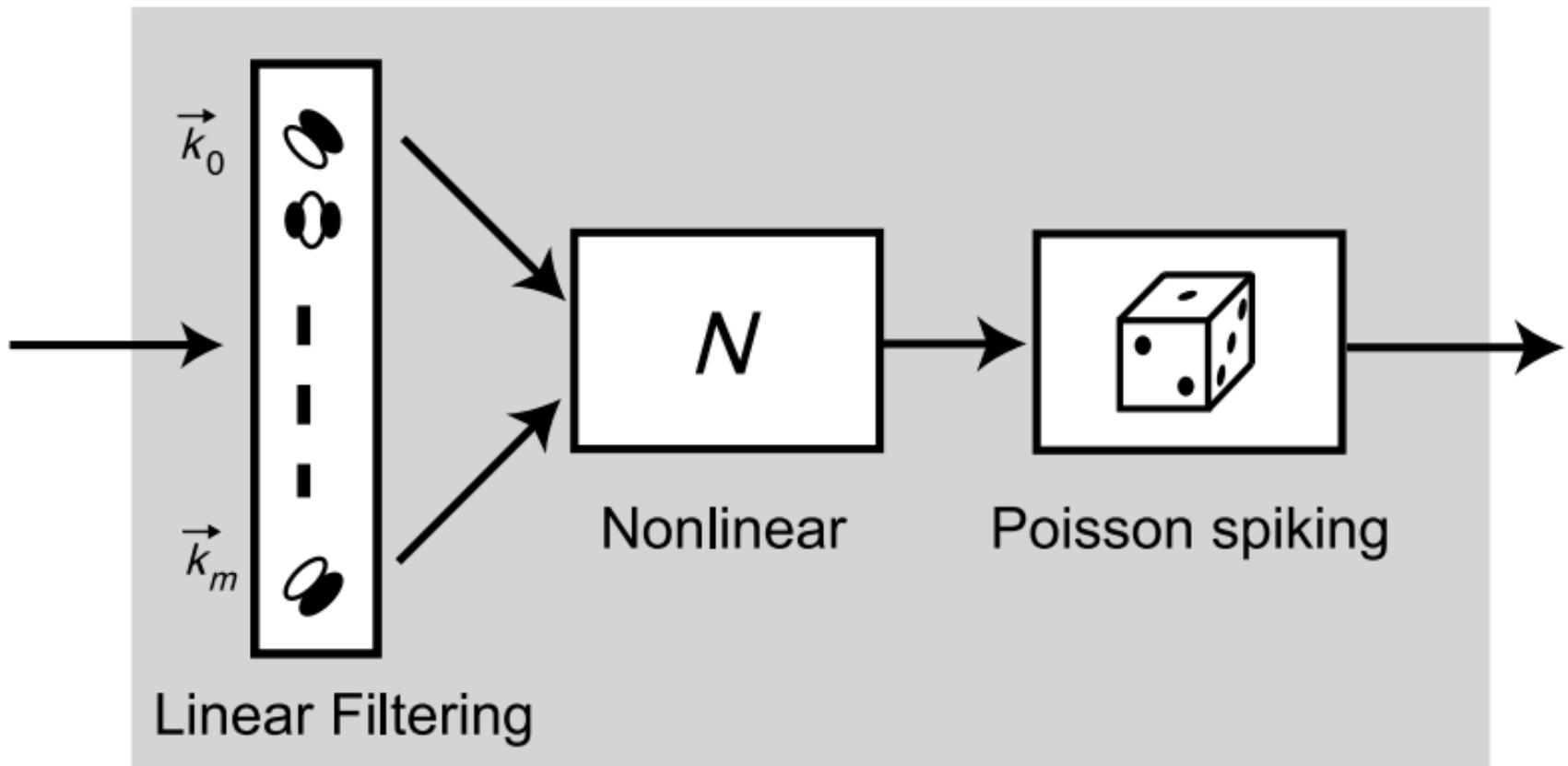
λ – spike rate

x – stimulus



$P(y|x)$: how many spikes occur within unit interval of time given assumed rate

Linear non–linear Poisson (LNP) model

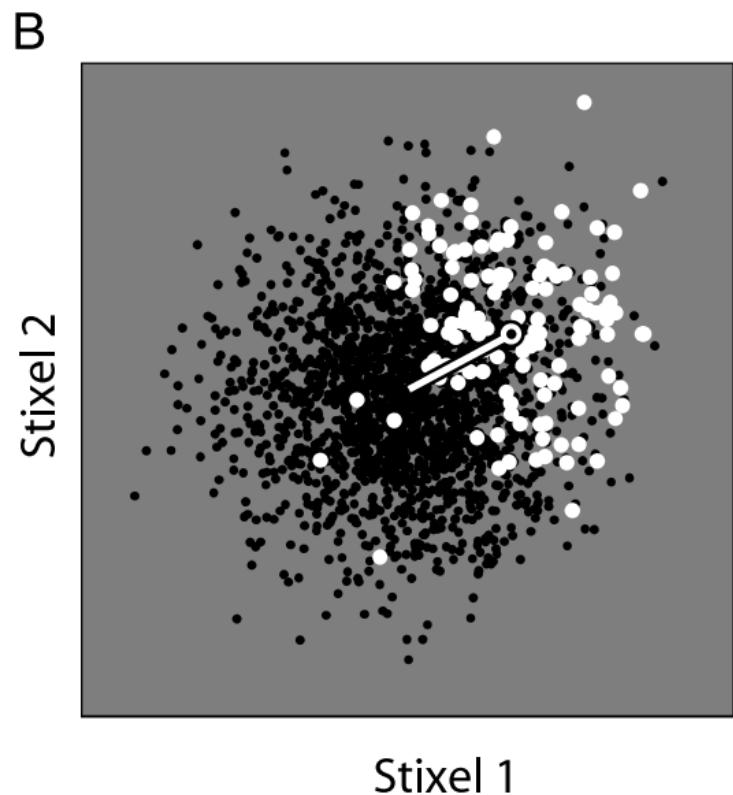
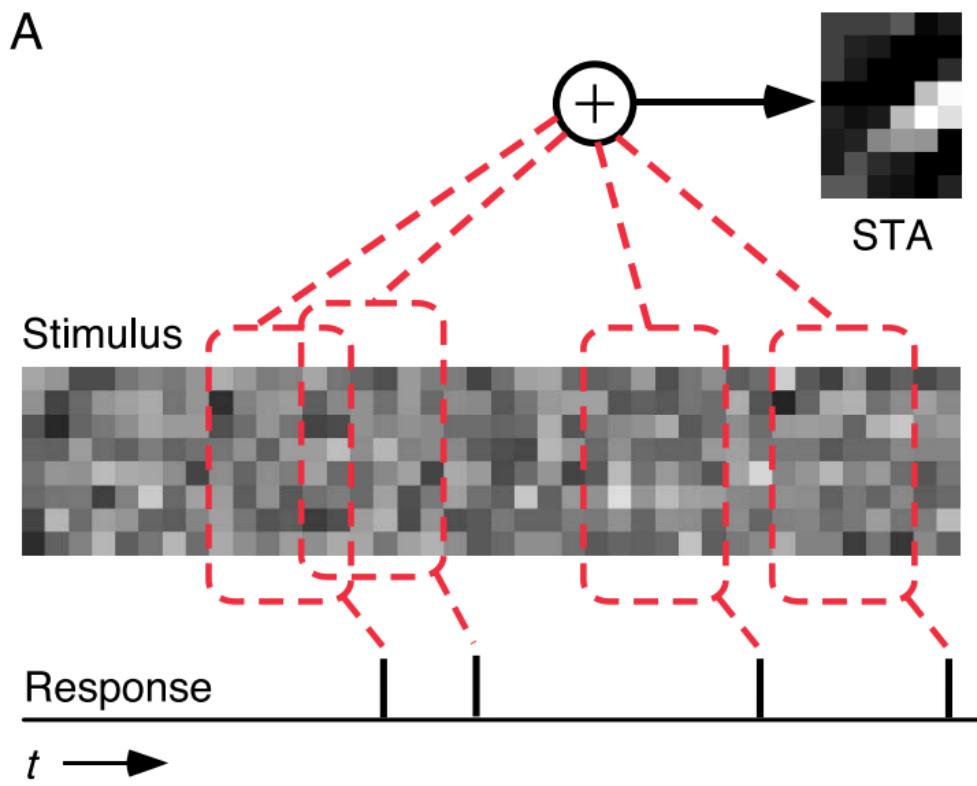


How to estimate linear filters?

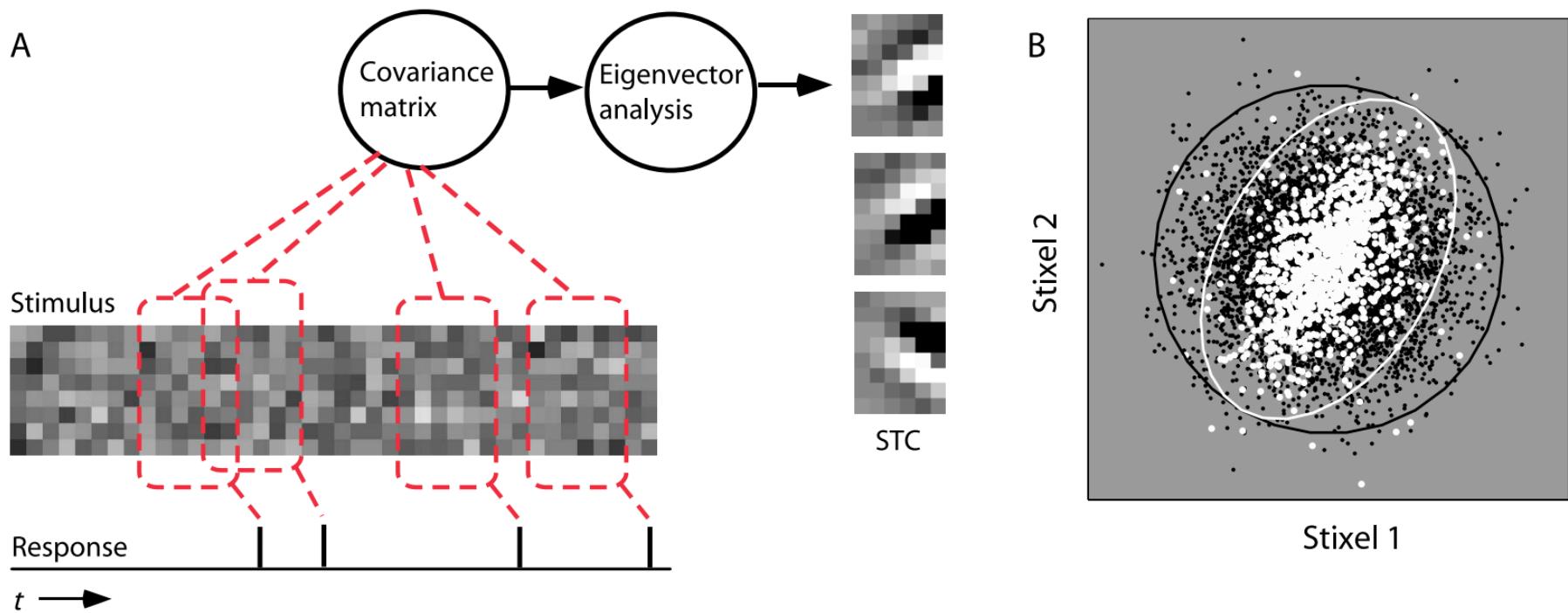
- Look for deviations between raw and spike triggered stimulus.
- For LNP model, assuming
 - raw stimulus spherically symmetric
 - non-linearity leads to shift of the mean of the spike-triggered ensemble relative to raw stim.
- Spike-triggered averaging.

$$\hat{A} = \frac{1}{N} \sum_{n=1}^N \vec{s}(t_n),$$

Spike-triggered averaging



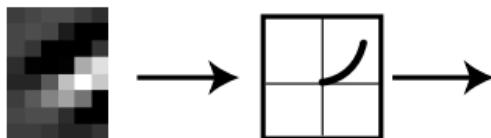
Spike-triggered covariance



$$\hat{C} = \frac{1}{N-1} \sum_{n=1}^N [\vec{s}(t_n) - \hat{A}] [\vec{s}(t_n) - \hat{A}]^T,$$

STC: fitting linear model

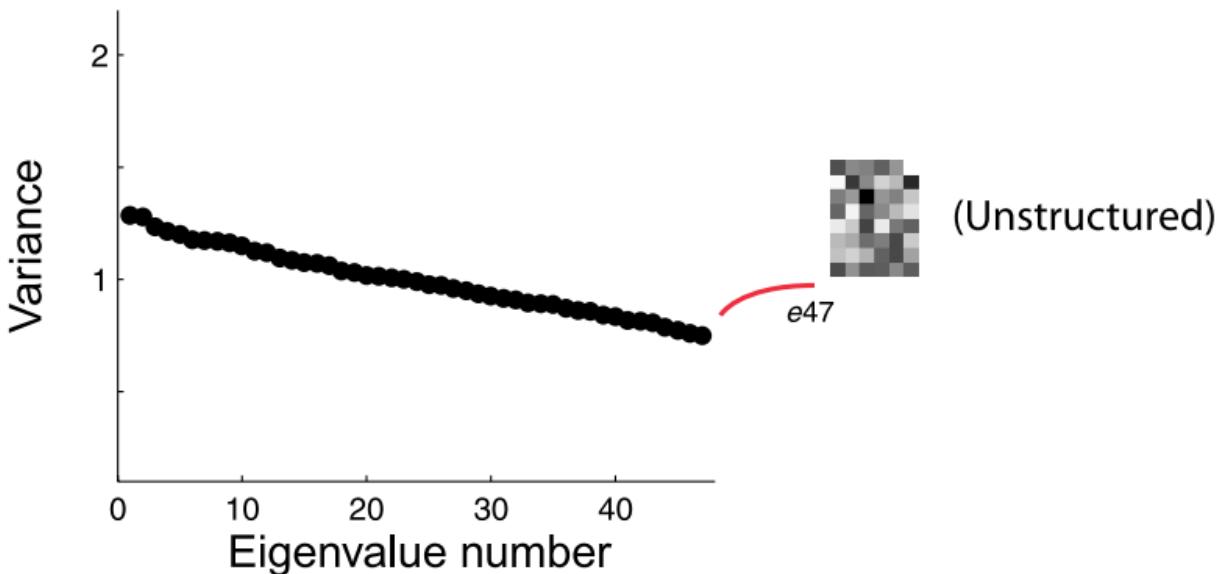
Model neuron:



STA analysis:

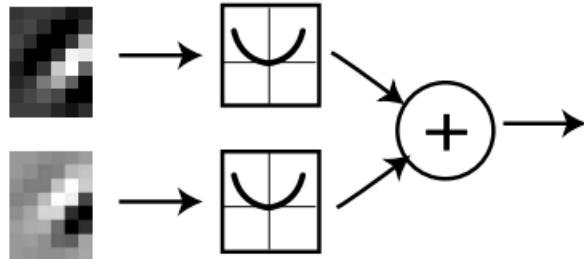


STC analysis:

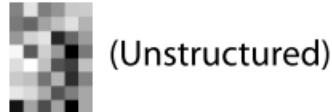


STC: fitting non-linear model

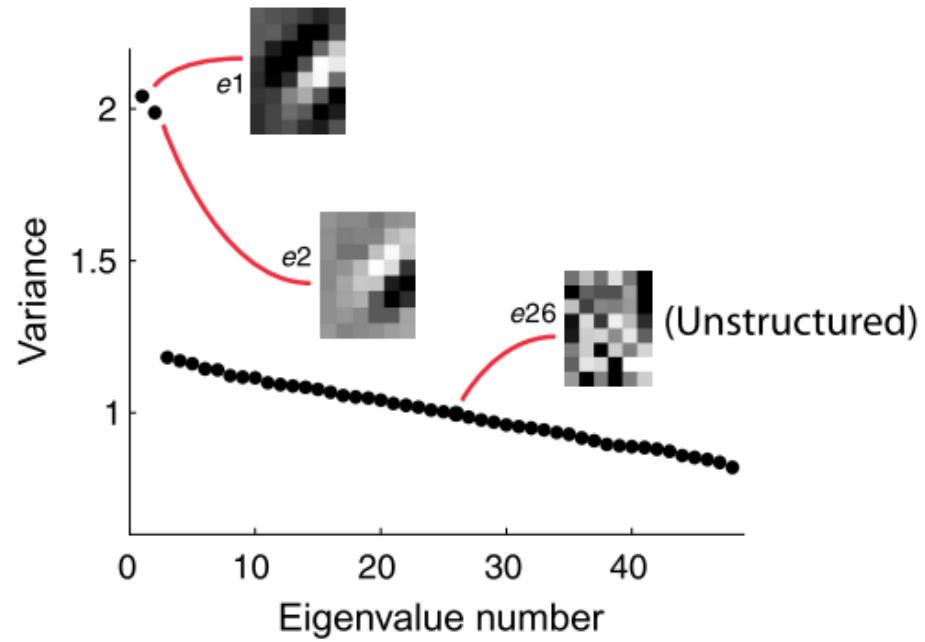
Model neuron:



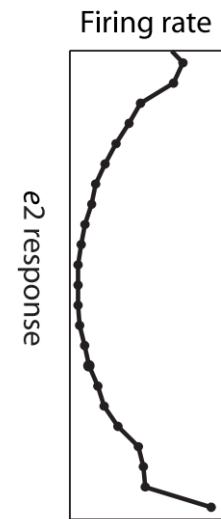
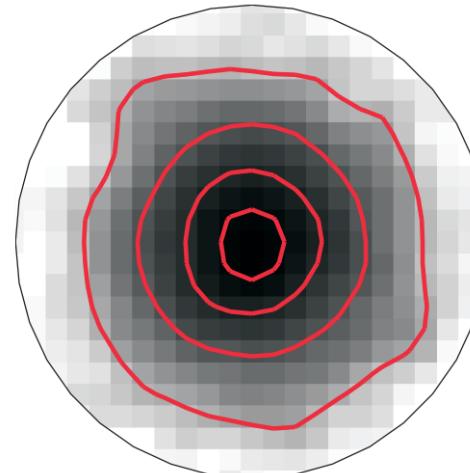
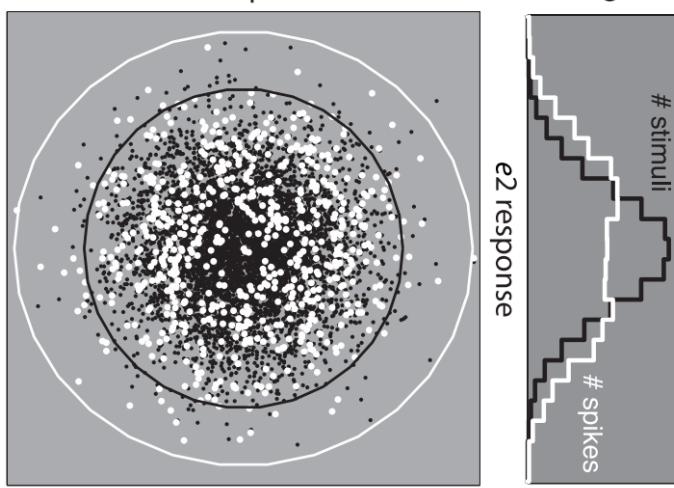
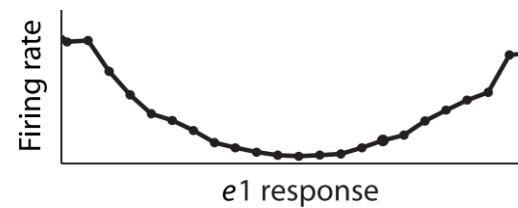
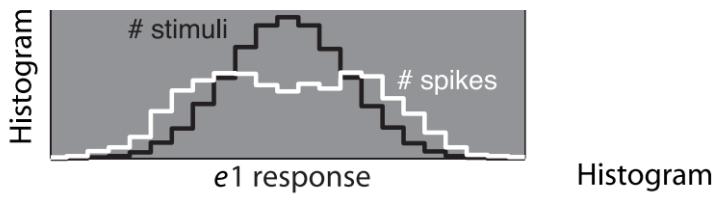
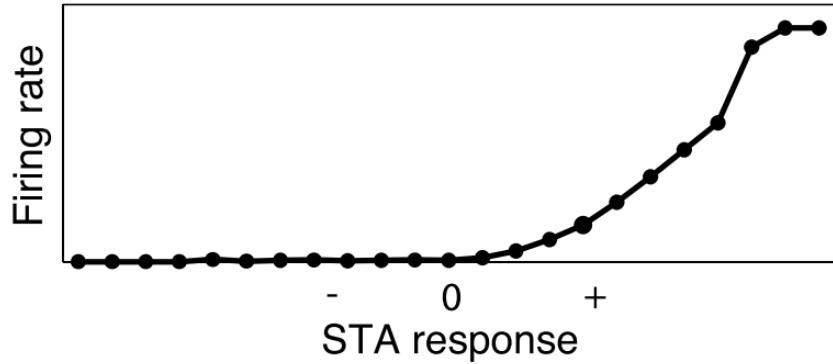
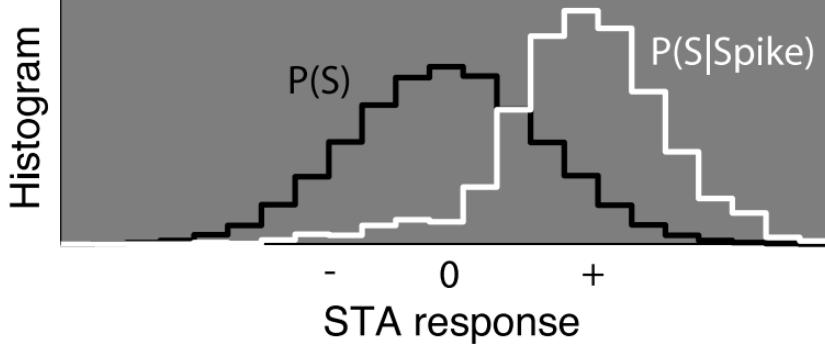
STA analysis:



STC analysis:

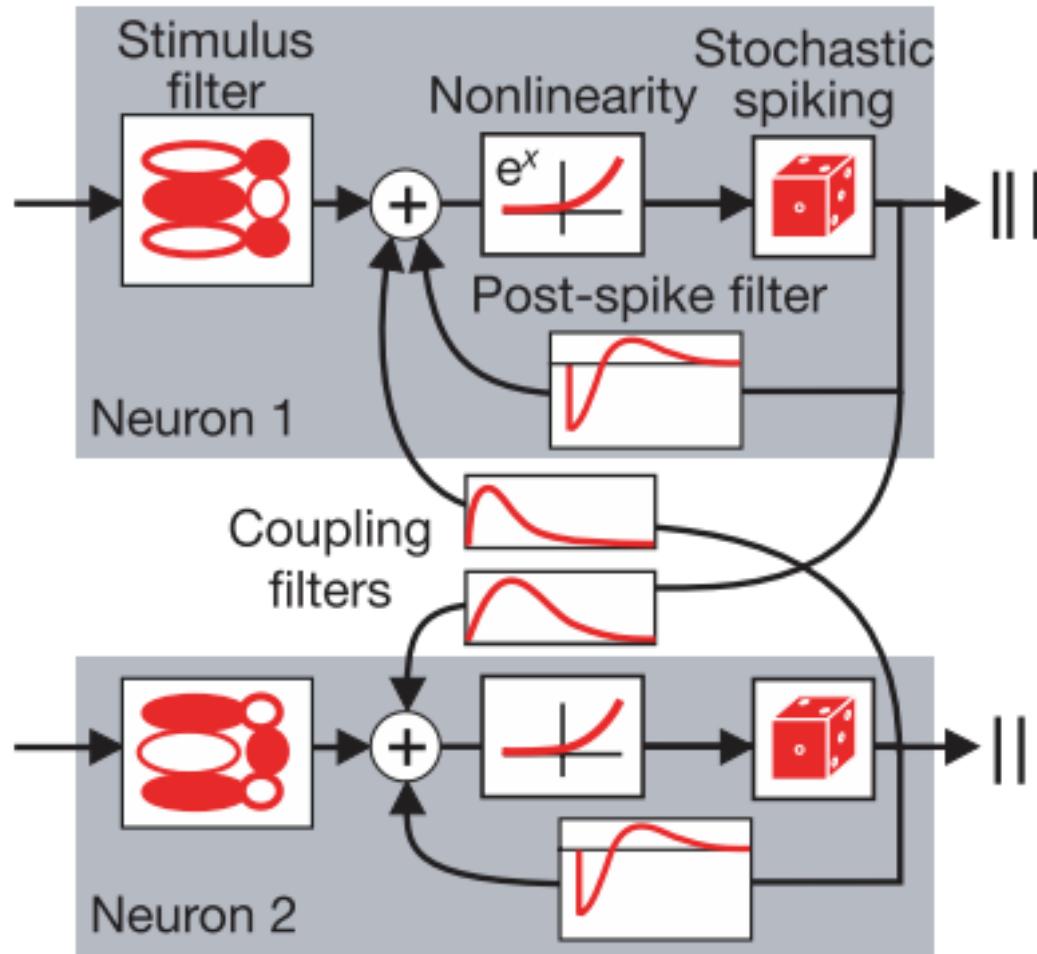


STC: estimating non-linearity



Coupling in GLMs

a Coupled spiking model

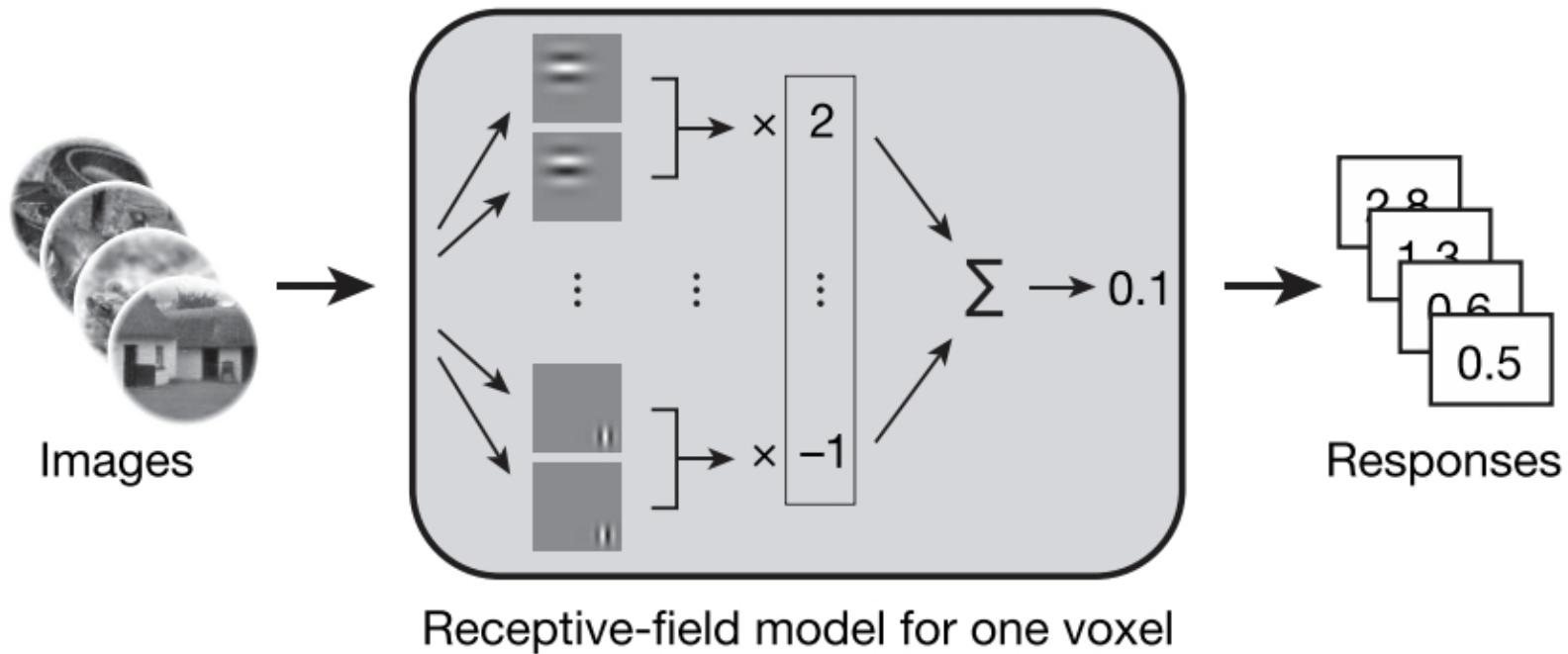


Beyond Linear Models

Barkley Wavelet Transform

Stage 1: model estimation

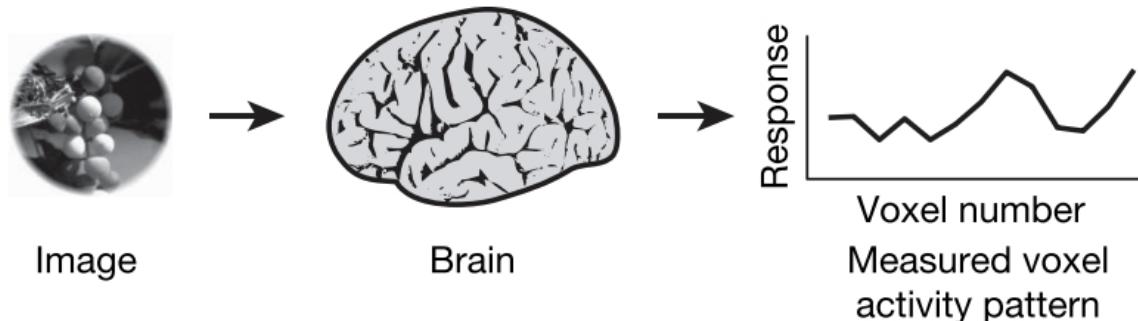
Estimate a receptive-field model for each voxel



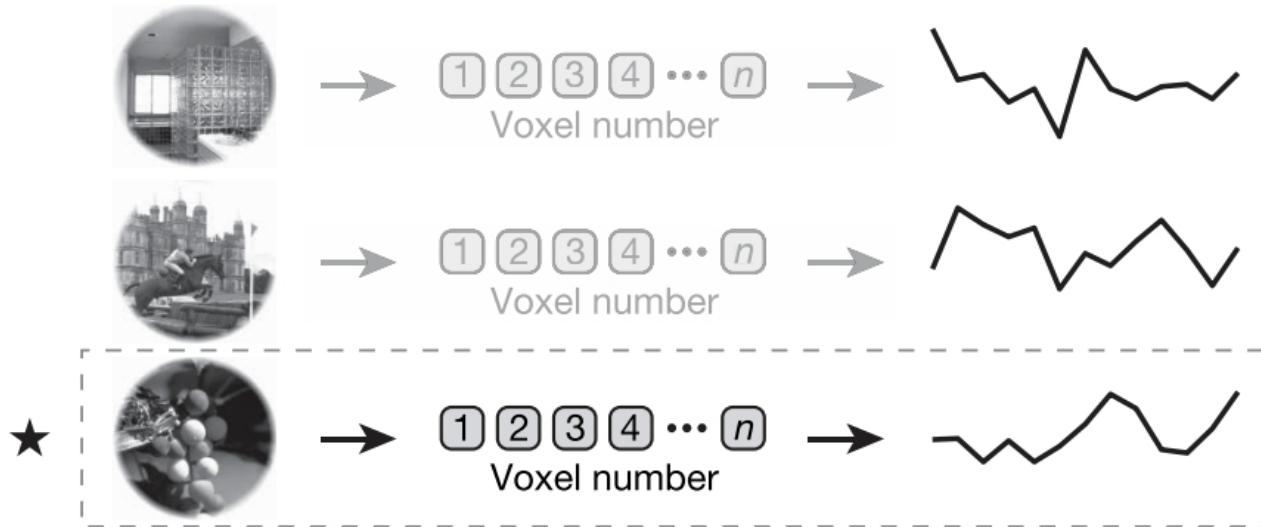
Barkley Wavelet Transform

Stage 2: image identification

(1) Measure brain activity for an image



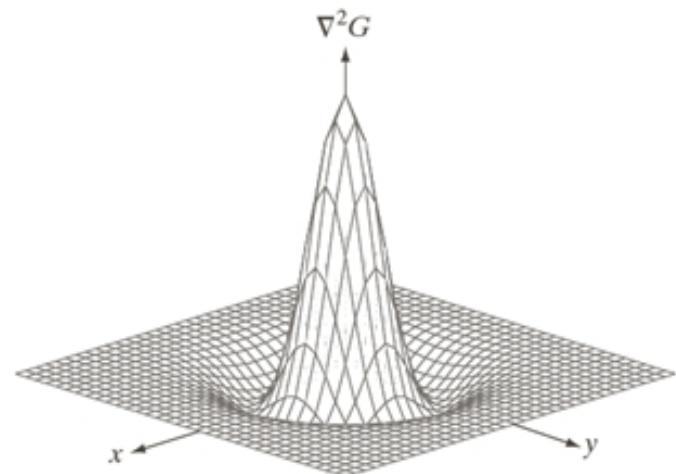
(2) Predict brain activity for a set of images using receptive-field models



Hierarchical structural model (HSM)

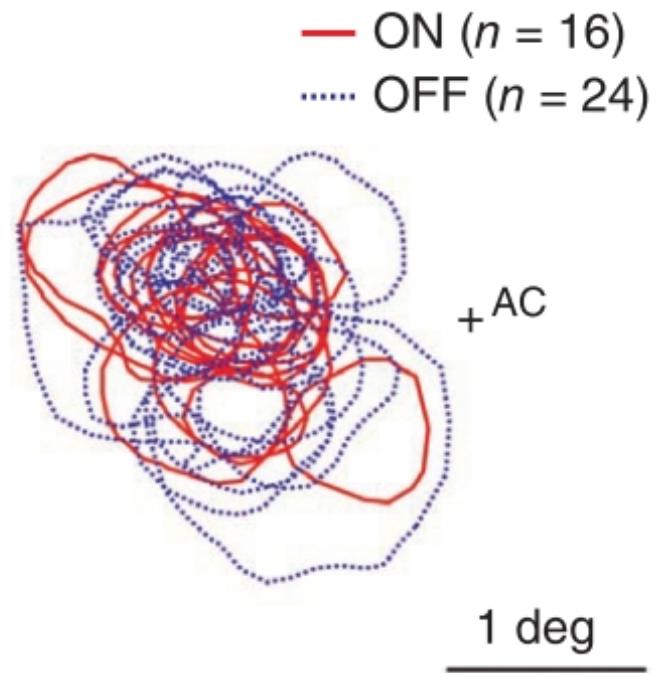
The structural priors

- Receptive fields of LGN units can be well approximated by difference-of-Gaussian function



The structural priors

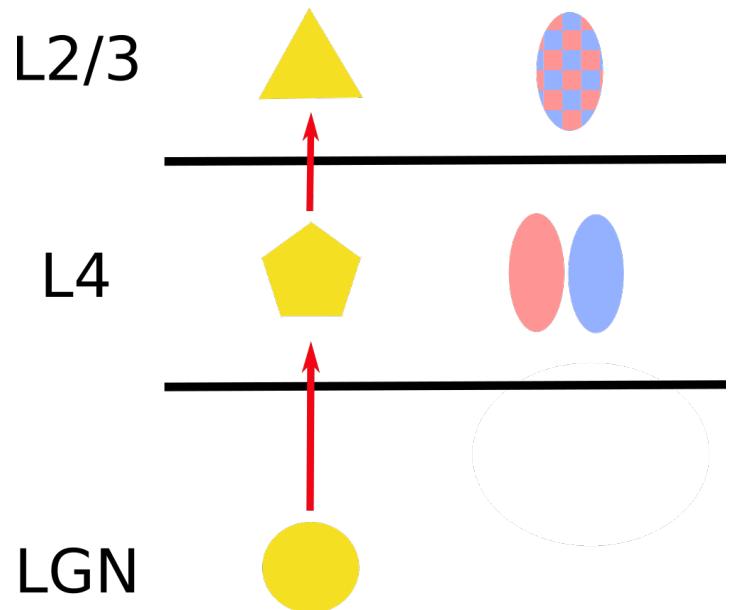
- Receptive fields of LGN units can be well approximated by difference-of-Gaussian function
- Local population of V1 neurons receives common input from limited number of LGN cells



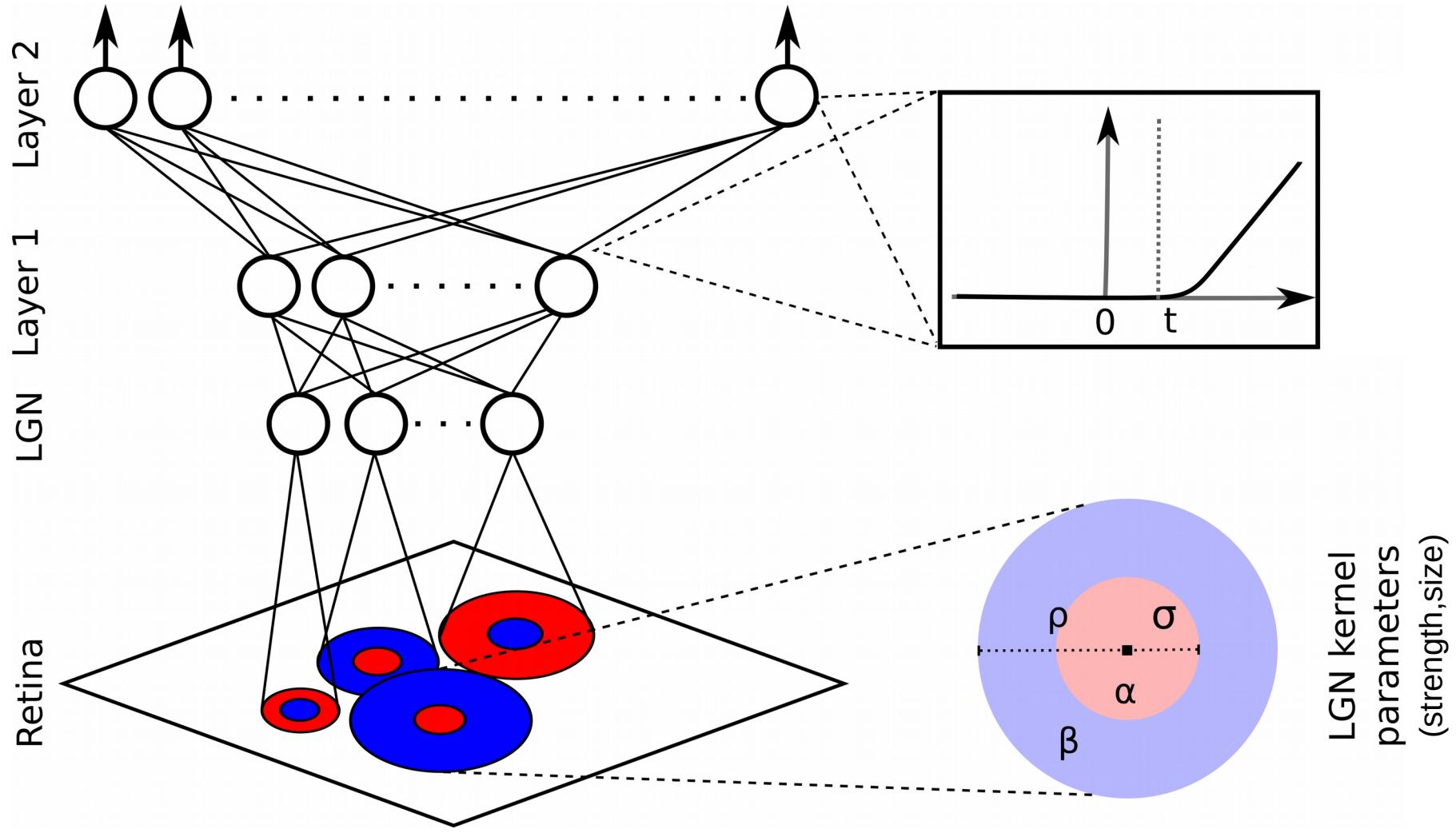
(Jin et al, 2011)

The structural priors

- Receptive fields of LGN units can be well approximated by difference-of-Gaussian function
- Local population of V1 neurons receives common input from limited number of LGN cells
- Hierarchical organization



The HSM structure



The model

LGN units:

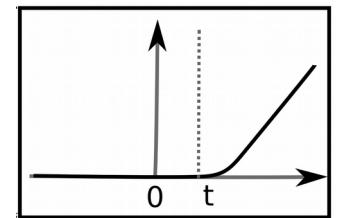
$$\psi_{i1} = \sum_{k,l} I_{kl} \left(\frac{\alpha_i}{\sigma_i^2} e^{-\frac{(k-\mu_i^x)^2 + (l-\mu_i^y)^2}{2\sigma_i^2}} - \frac{\beta_i}{\rho_i^2} e^{-\frac{(k-\mu_i^x)^2 + (l-\mu_i^y)^2}{2\rho_i^2}} \right)$$

Cortical units:

$$\psi_{il} = f \left(\sum_j w_{ij} \psi_{j(l-1)} \right)$$

Transfer function:

$$f(x) = \log(1 + \exp(x - t_i))$$



Log-likelihood:

$$\log p(y|x, \phi) = \sum_i y_i \log M(\phi, x_i) - \sum_i M(\phi, x_i)$$

Model optimization

- Optimized with Constrained Truncated Newton Conjugate method
- Non-convex model
 - 100 restarts with different seeds of initial random parameter initialization
 - pick the best fit to **training** data
- Meta-parameters:
 - Number of LGN units (9)
 - Number of hidden units (20%)
 - Determined based on prior 1D searches based on **training** data performance

Calcium imaging of local population of neurons in mouse V1

2 mice, 30–40 postnatal day

**Anesthetized:
isoflurane**

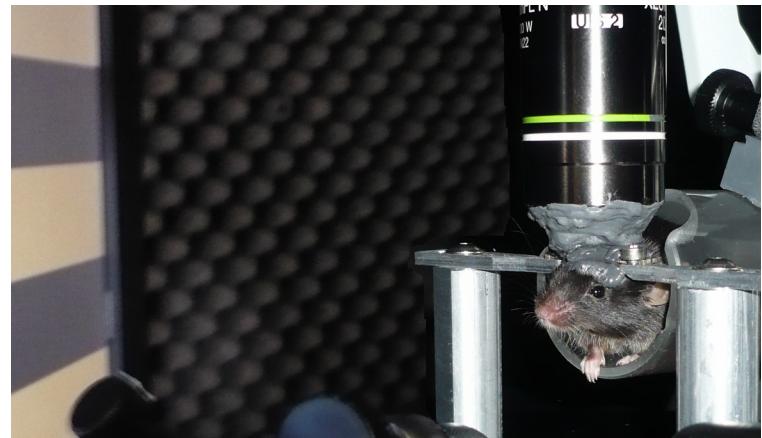
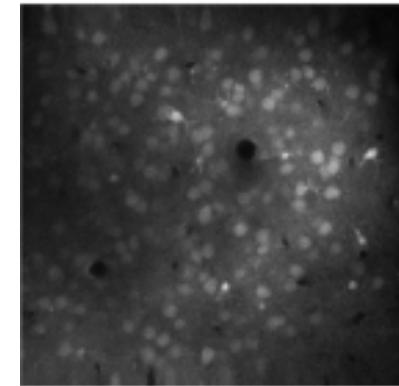
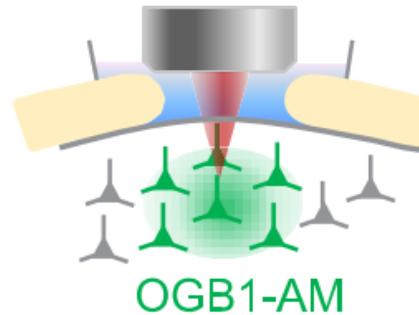
**3 imaged regions
OGB1 – AM calcium indicator**

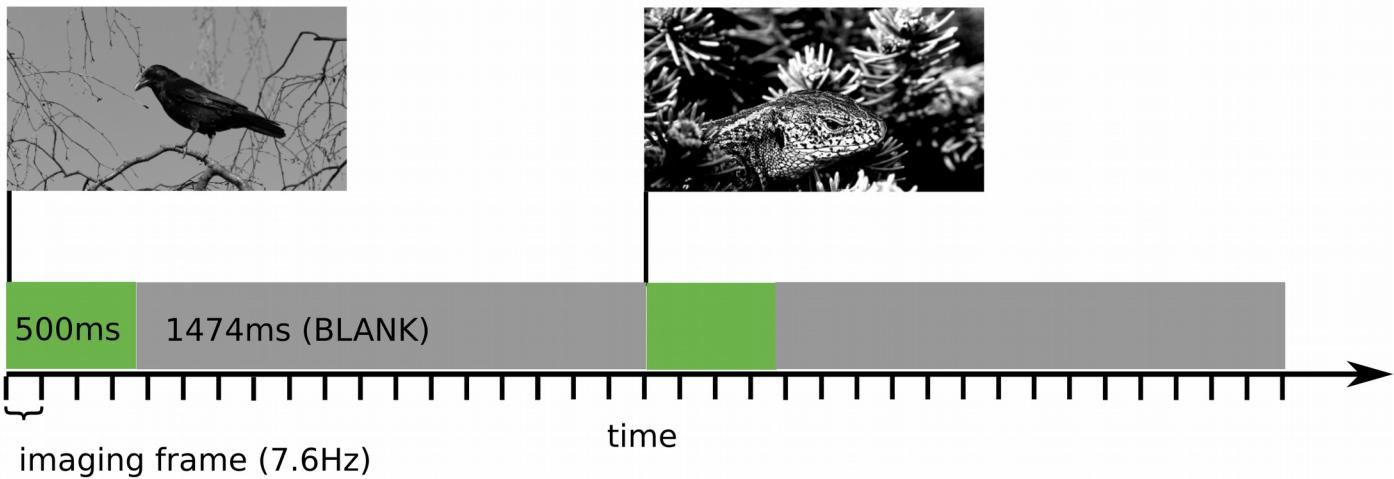
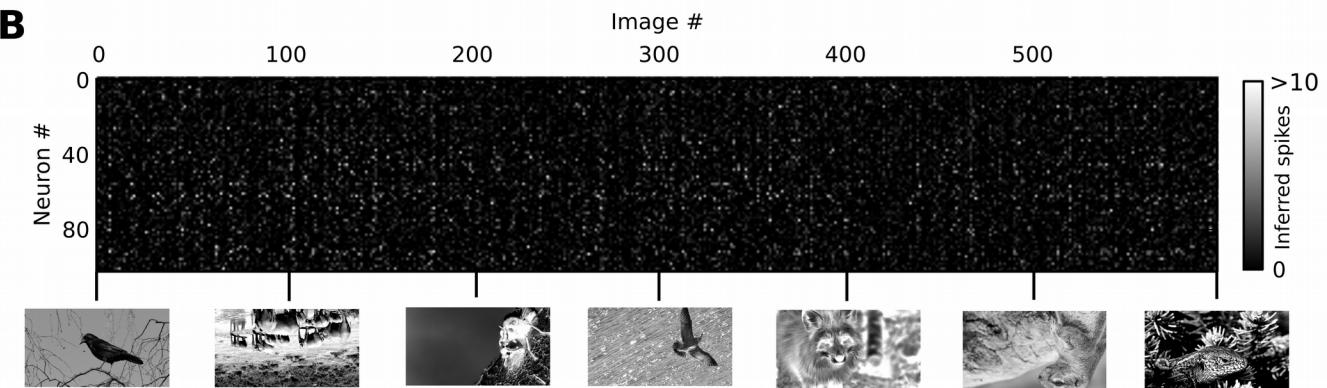
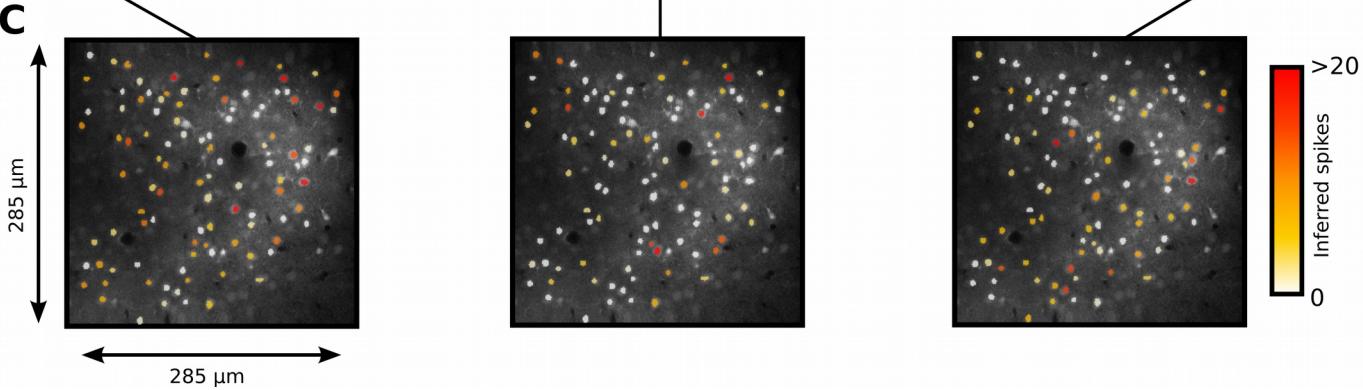
Sonja Hofer

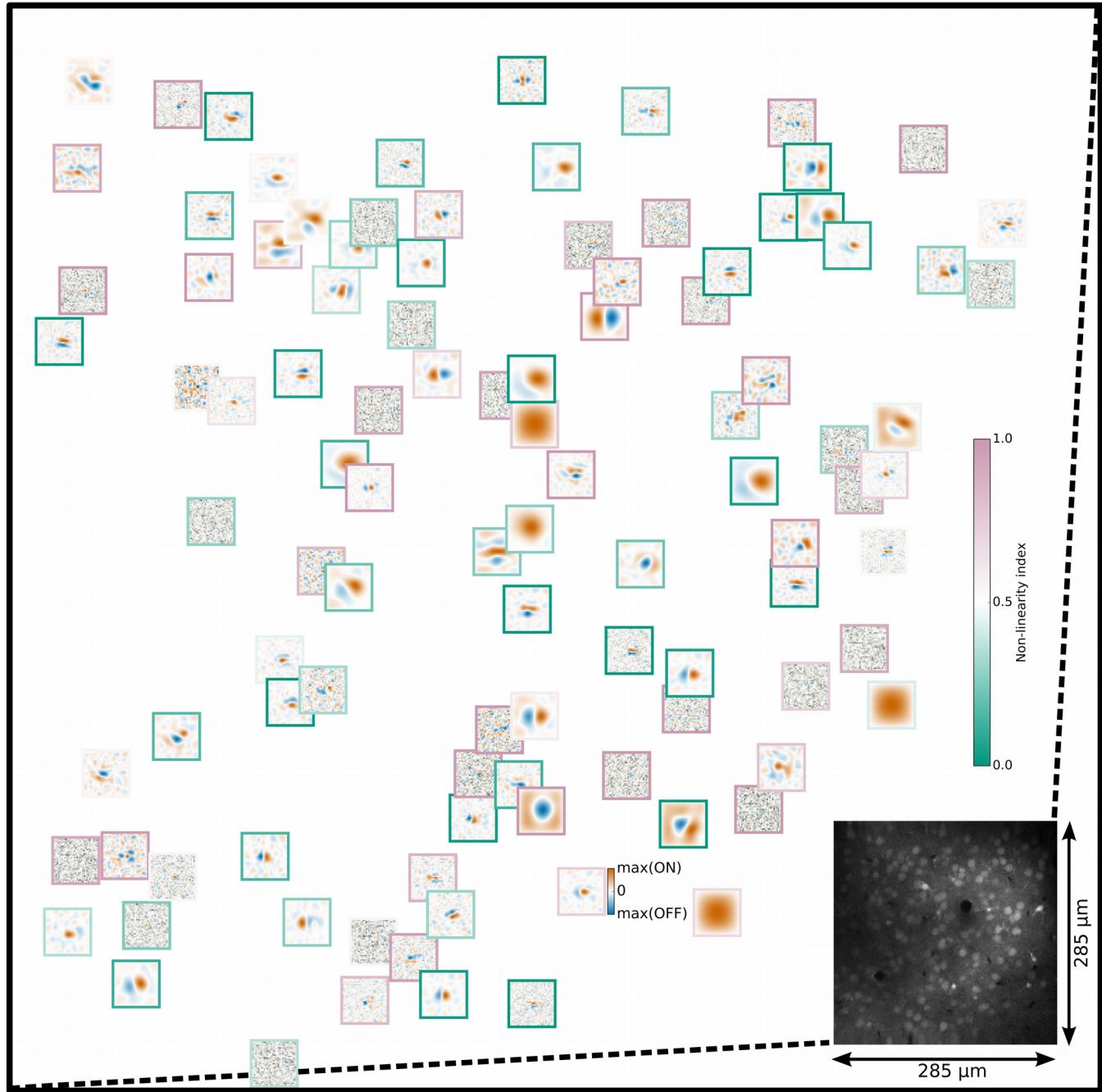


Thomas
Mrsic-Flogel

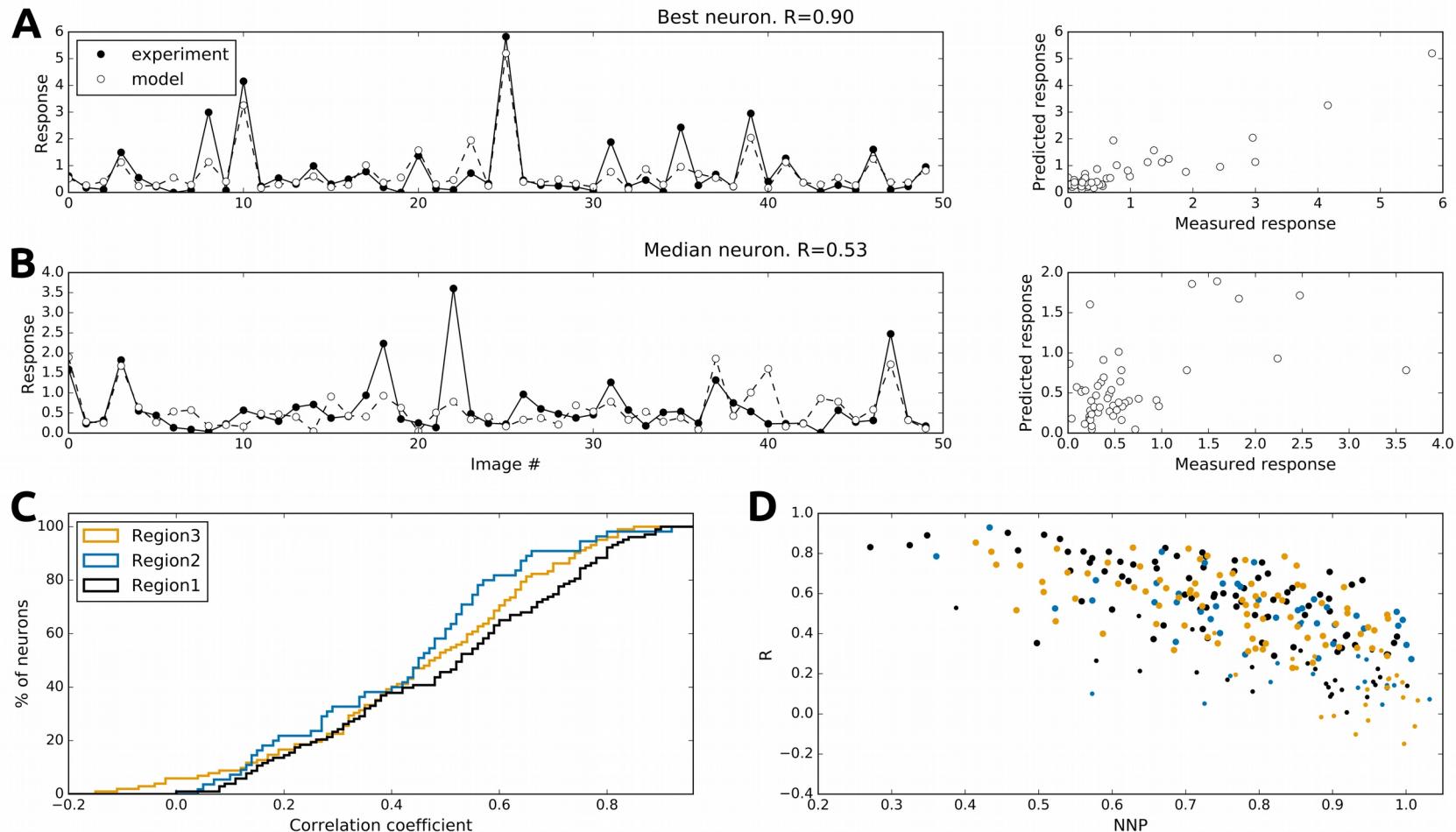
In vivo imaging



A**B****C**



The model performance



Comparison: reference models

STA with laplacian regularization

(Smyth et. al, Journal of Neuroscince, 2003)

$$\mathbf{L}_s = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}. \quad \begin{bmatrix} \mathbf{s} \\ \lambda \mathbf{L} \end{bmatrix} \mathbf{f} = \begin{bmatrix} r \\ 0 \\ \vdots \\ 0 \end{bmatrix},$$

Comparison: reference models

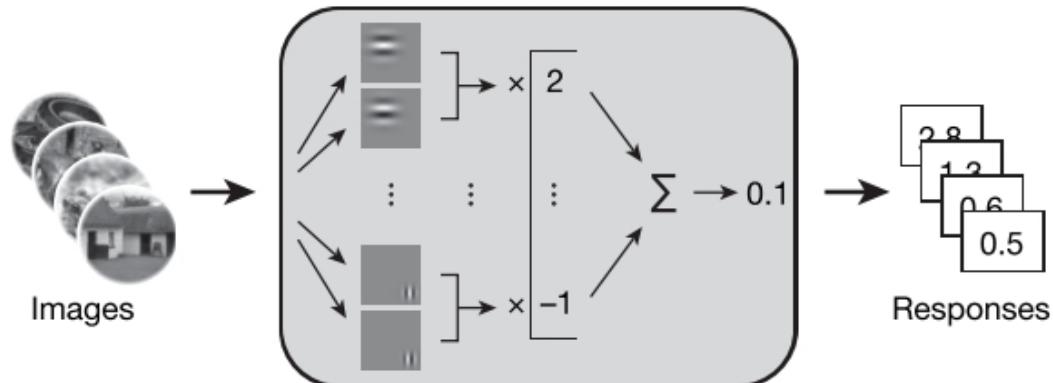
STA with laplacian regularization

(Smyth et. al, Journal of Neuroscince, 2003)

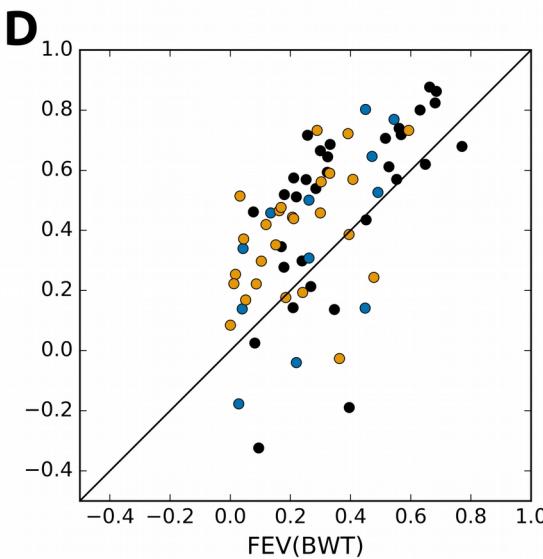
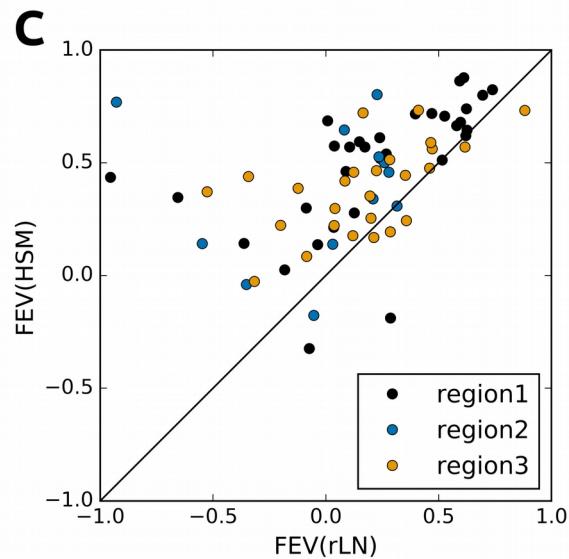
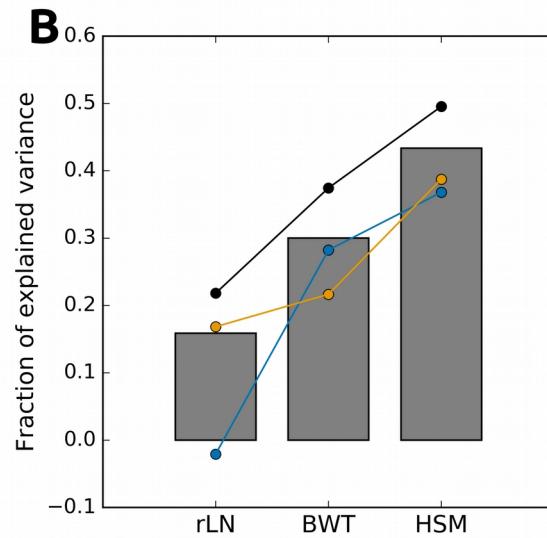
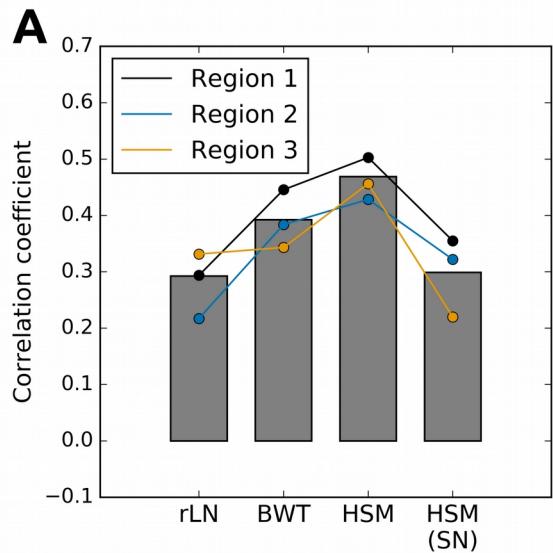
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Barkely-wavelet transform based linear model

(Kay et. al, Nature, 2008)

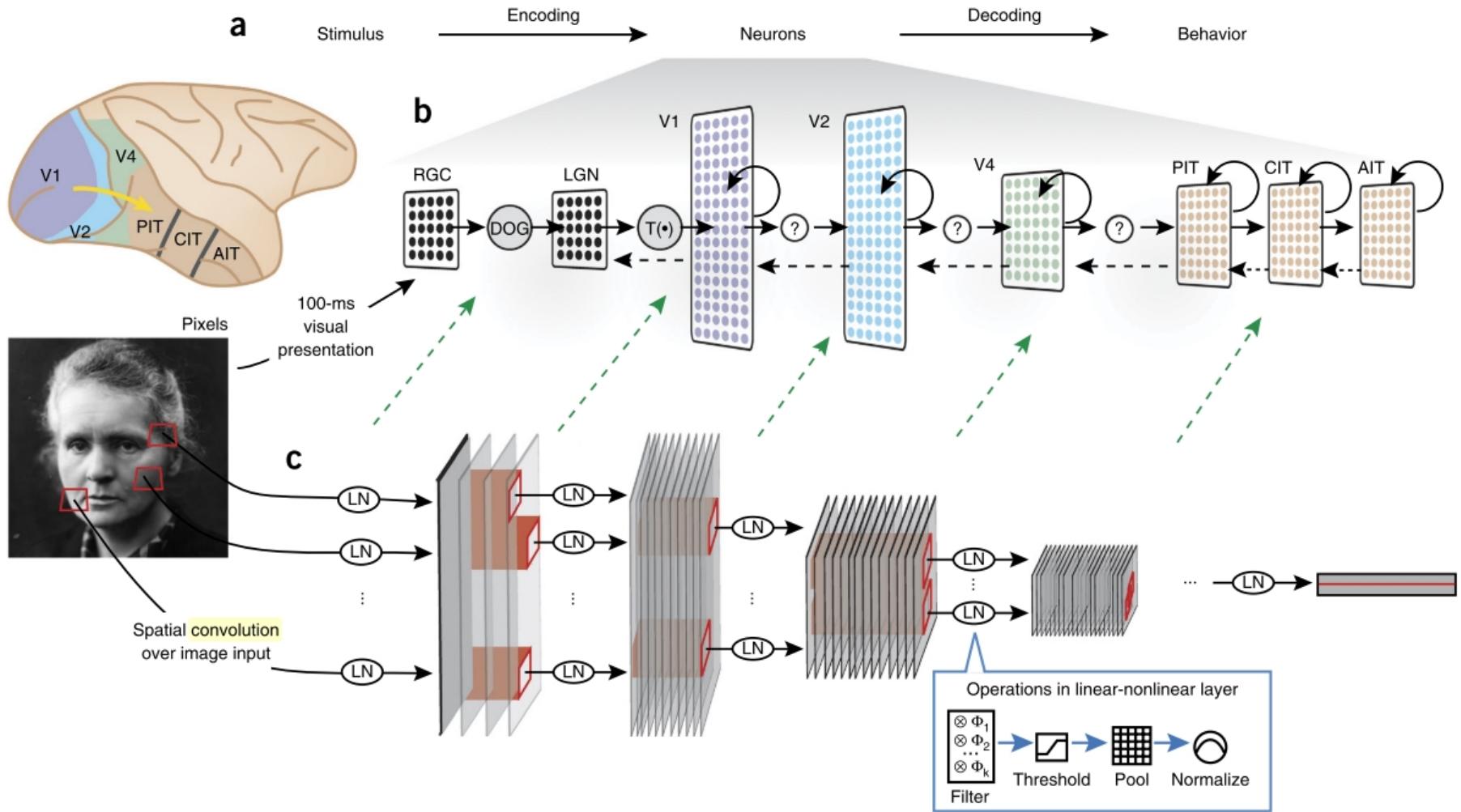


Comparison: performance

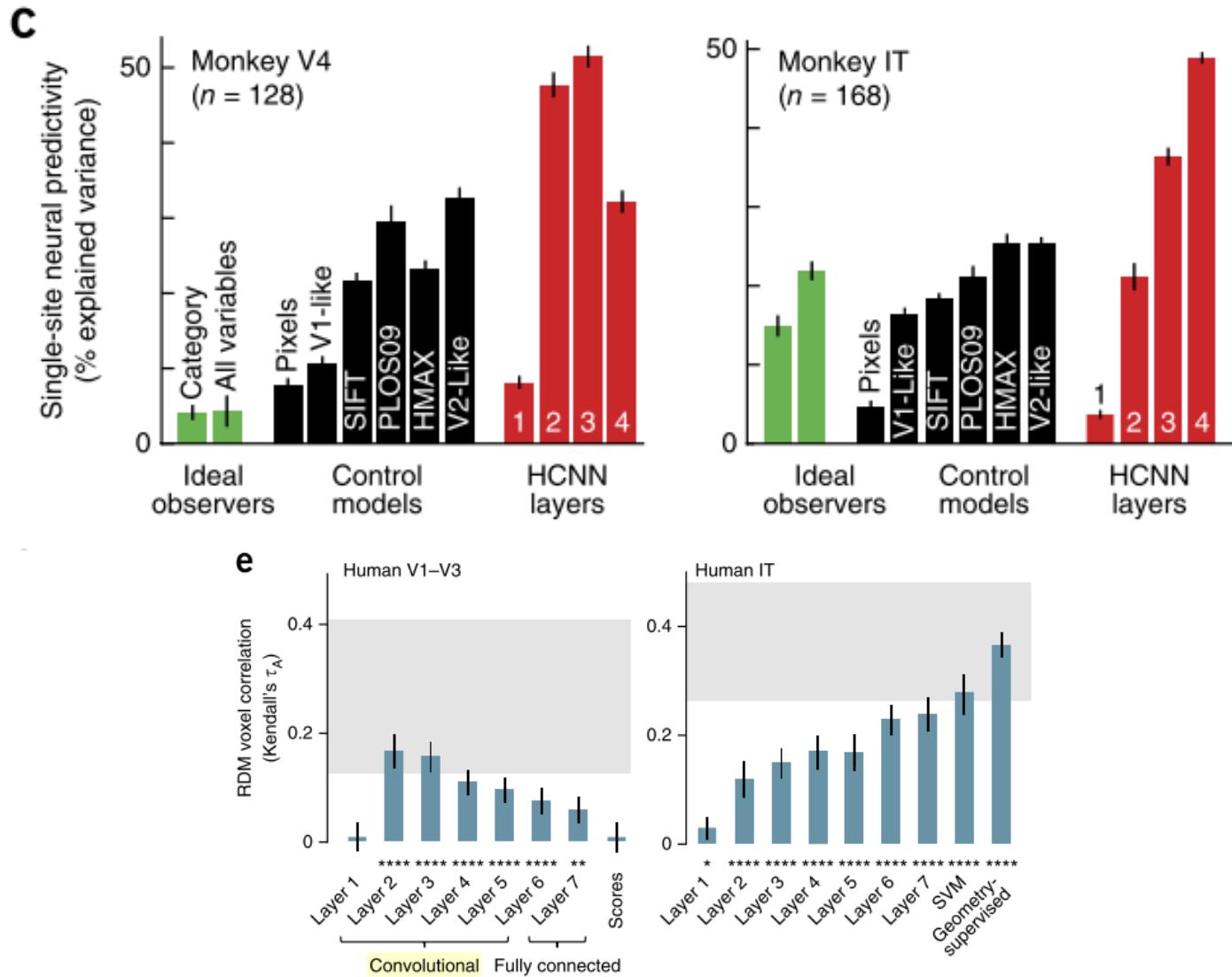


Deep Neural Networks In Neuroscience

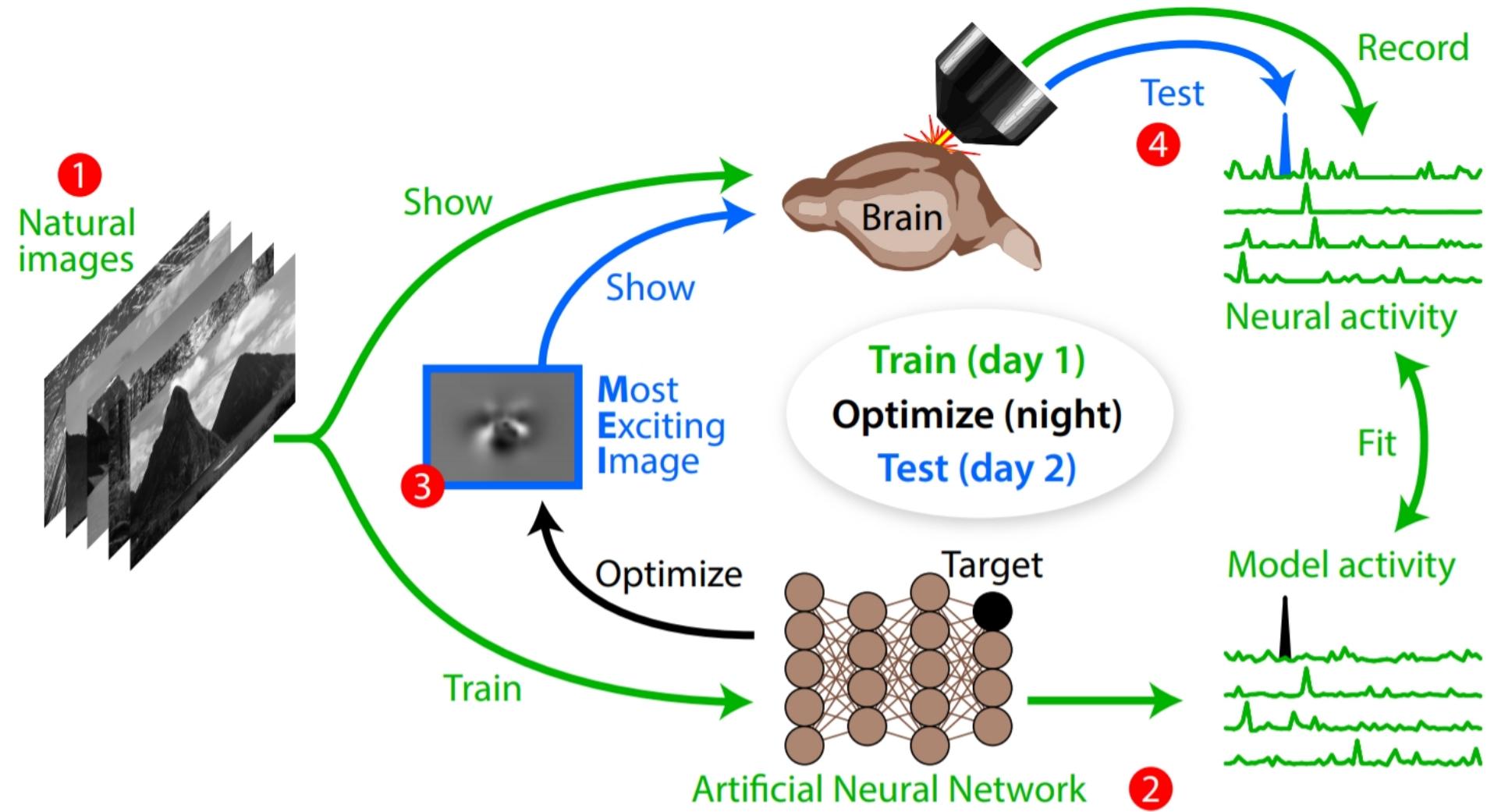
Using goal–driven deep learning models to understand sensory cortex



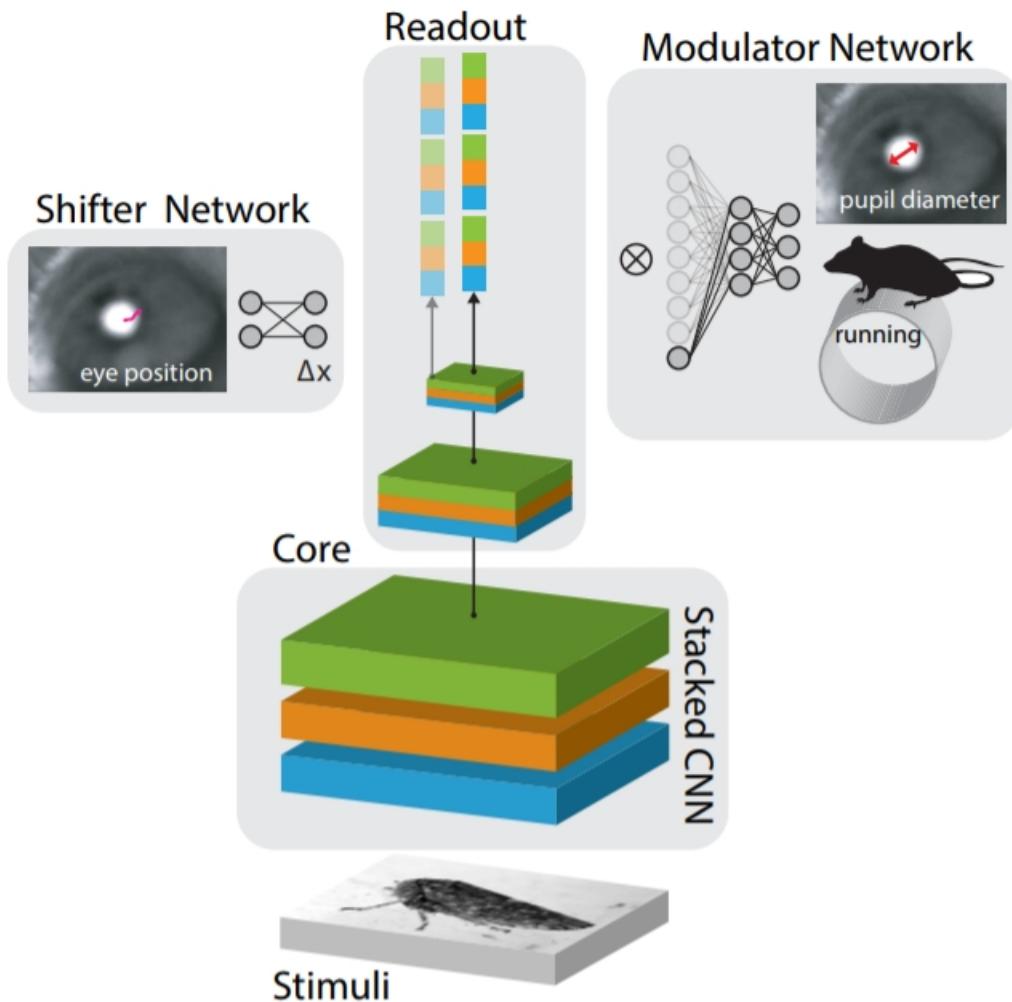
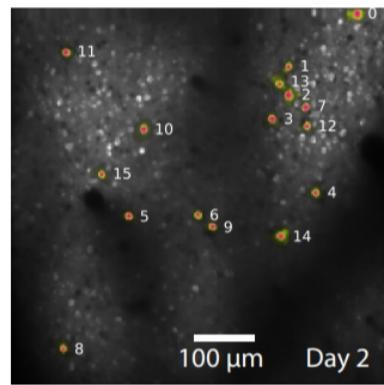
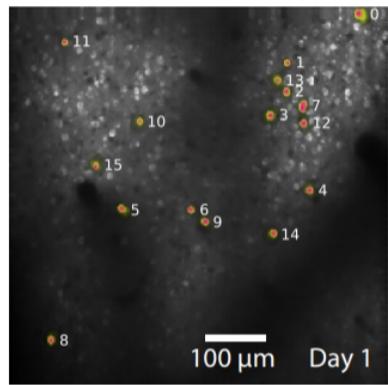
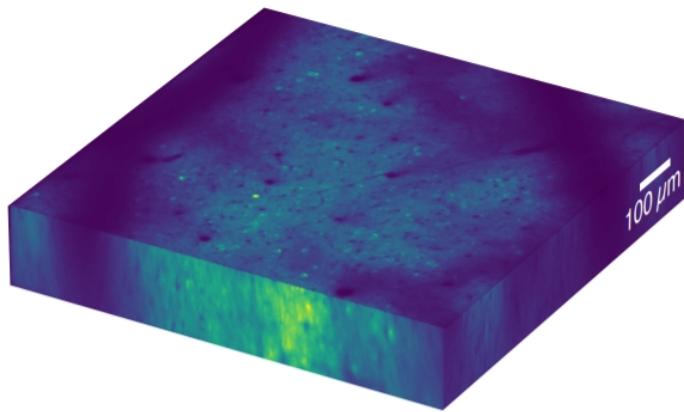
Using goal–driven deep learning models to understand sensory cortex



Inception in visual cortex: in vivo–silico loops reveal most exciting images



Inception in visual cortex: in vivo–silico loops reveal most exciting images



Inception in visual cortex: in vivo–silico loops reveal most exciting images

