Hierarchical structural model of primary visual cortex

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EUROPEAN UNION
European Structural and Investment Funds
Operational Programme Research,
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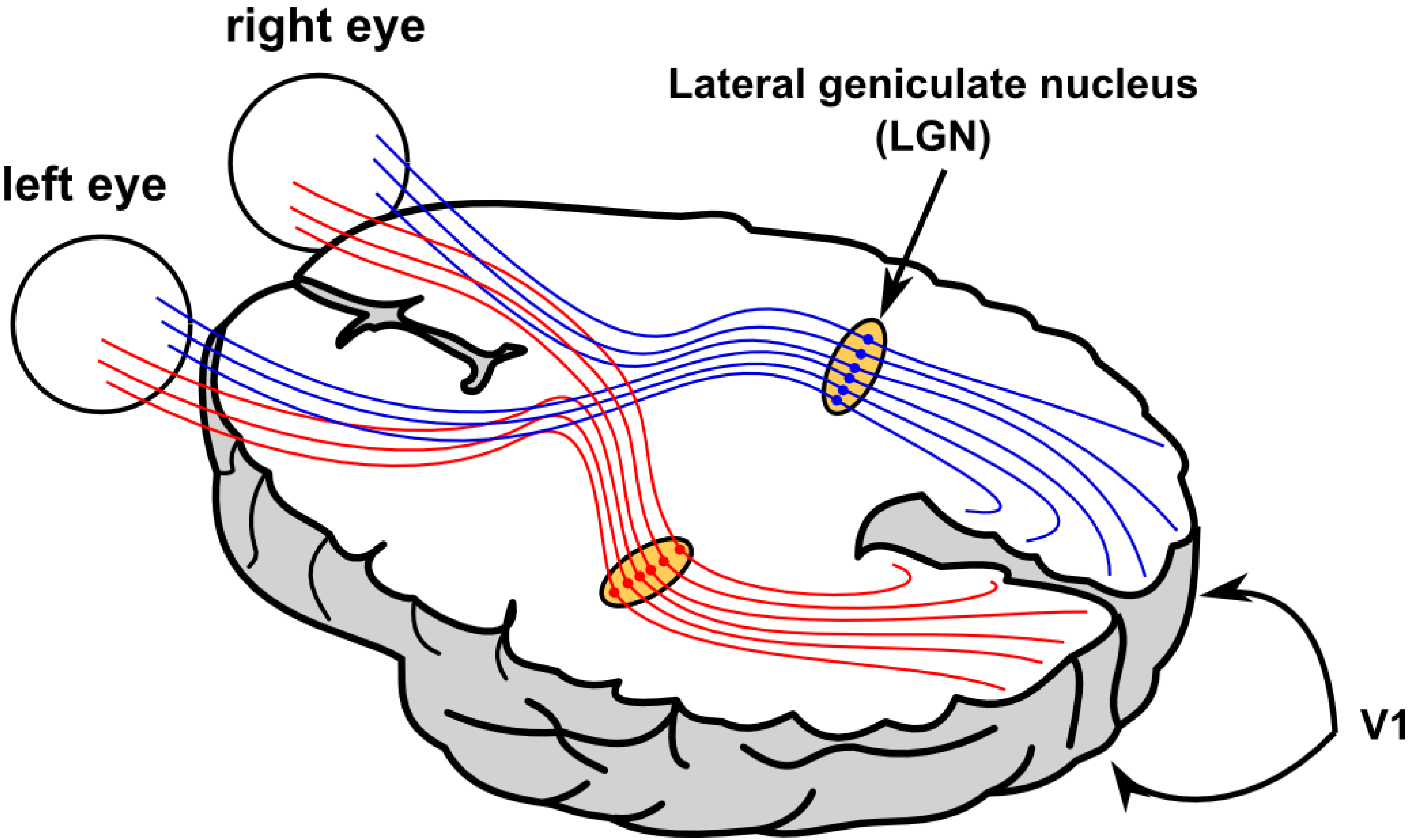
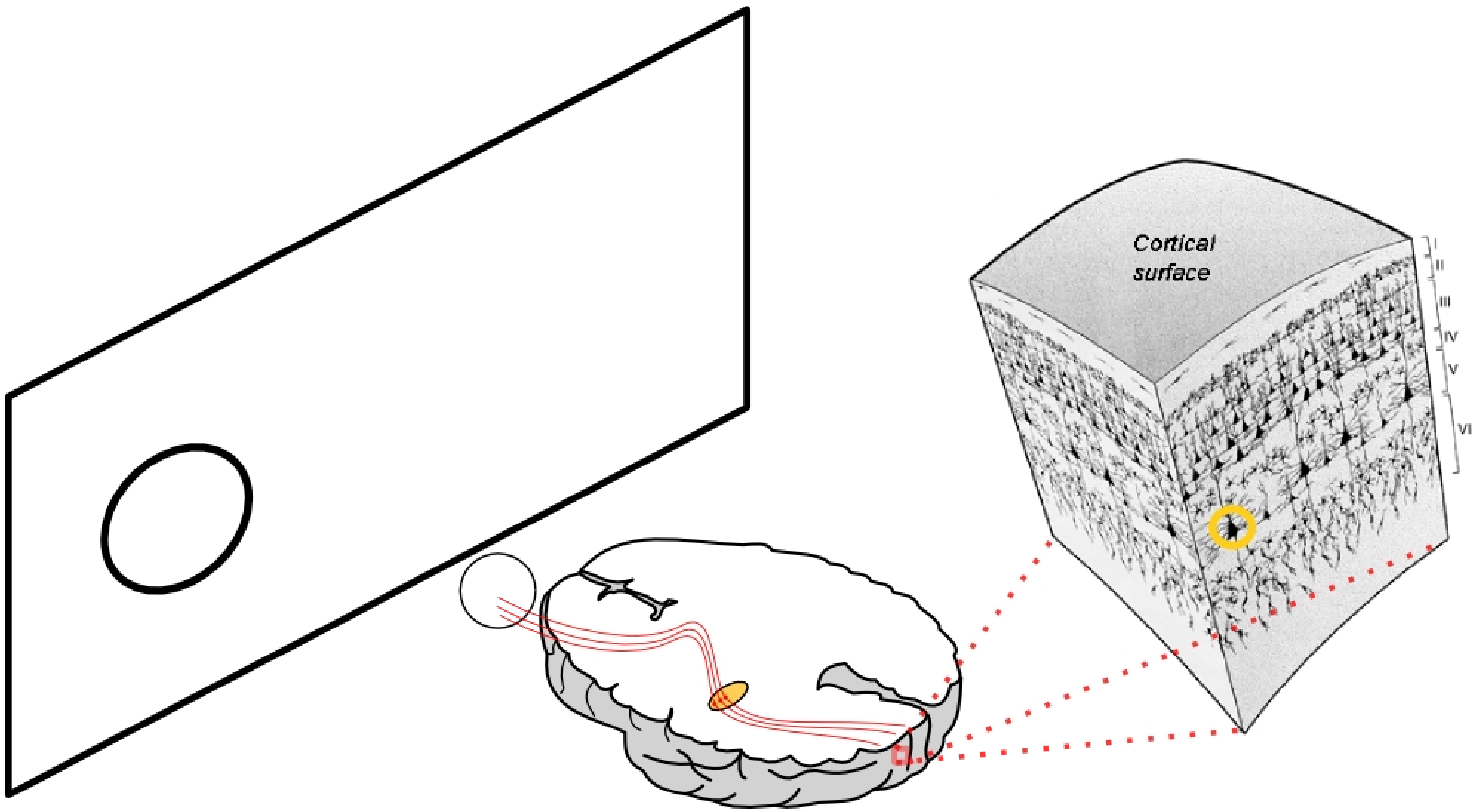
Early visual system



How do neurons in primary visual cortex process visual information?

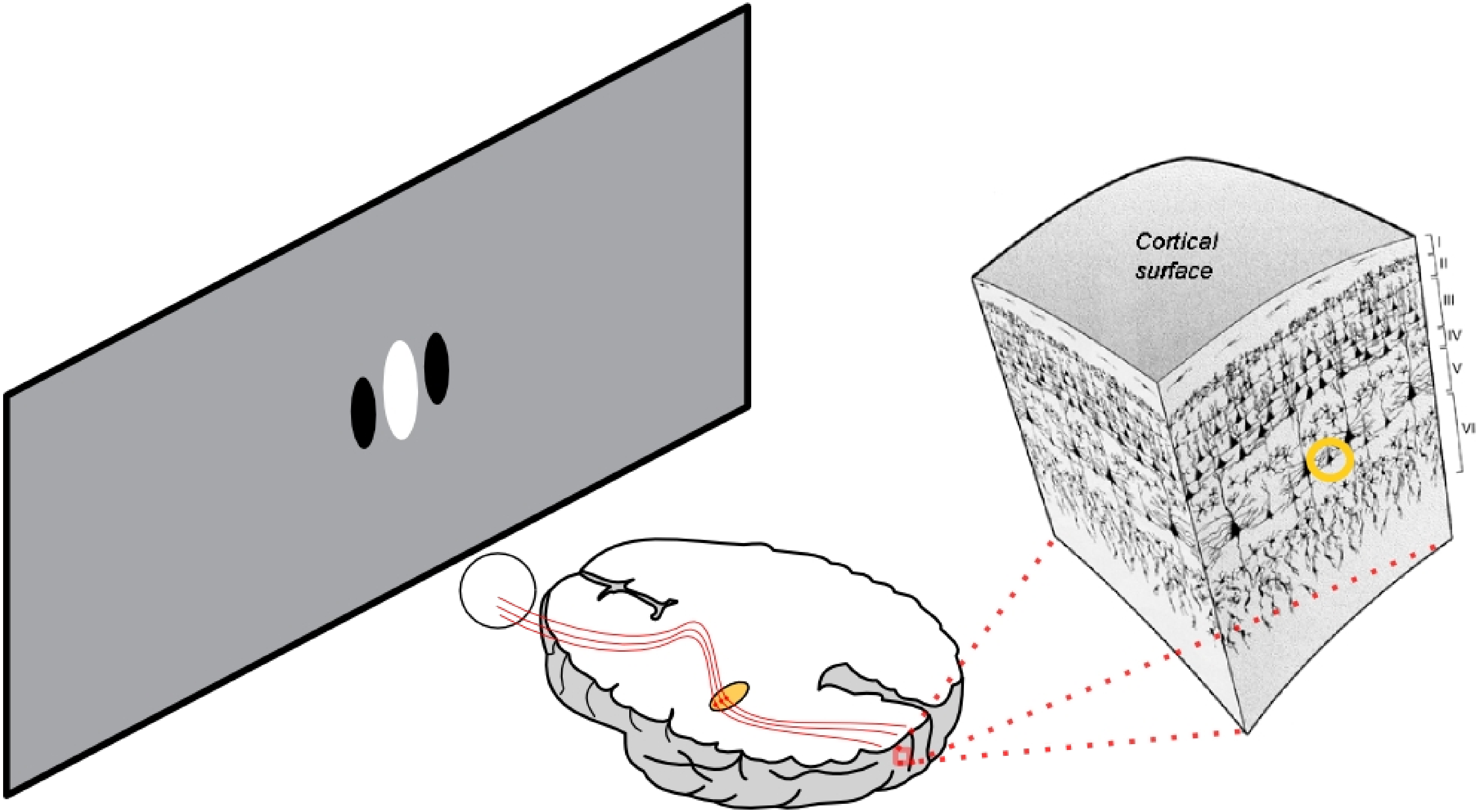
RF: position in visual field



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.

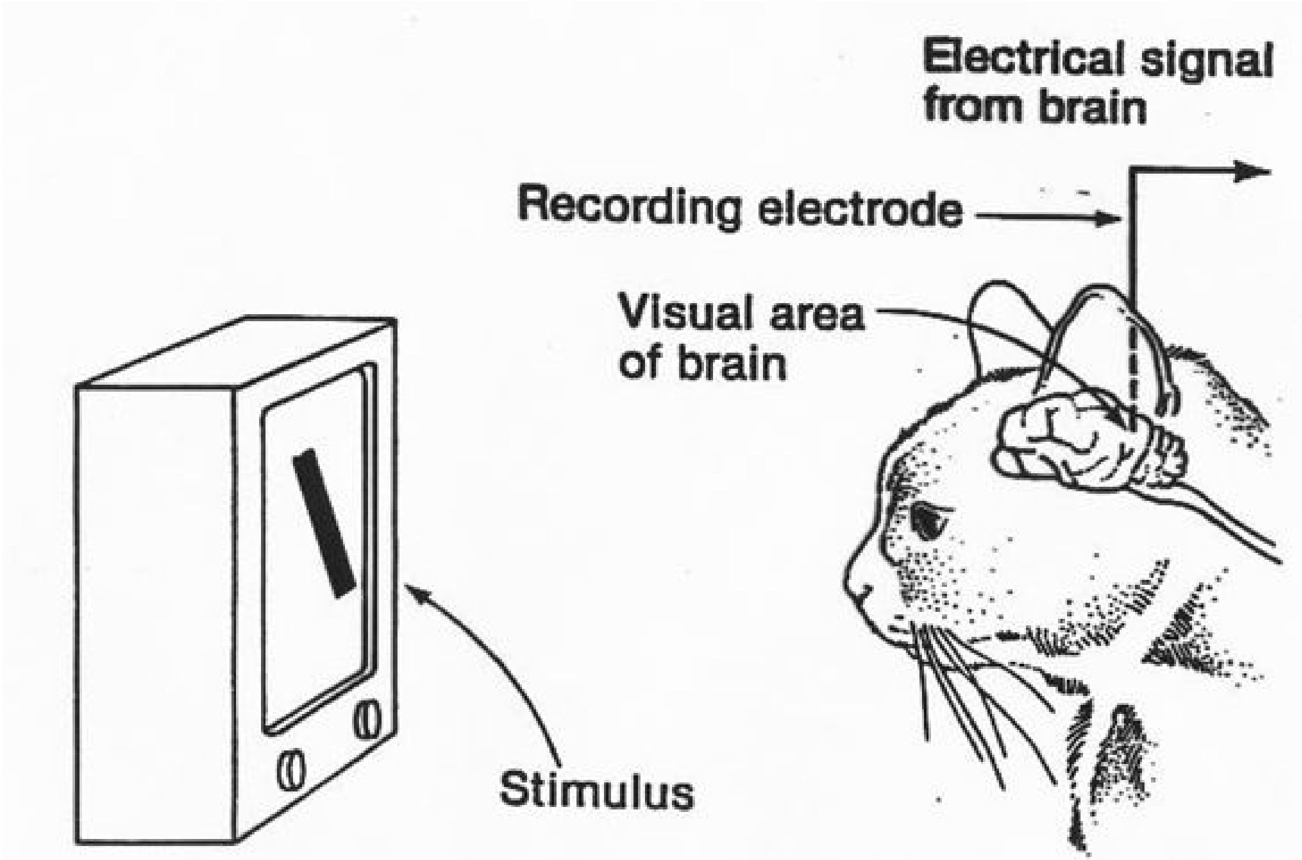
Hartline, H K (1938)

RF: map of exc/inh regions



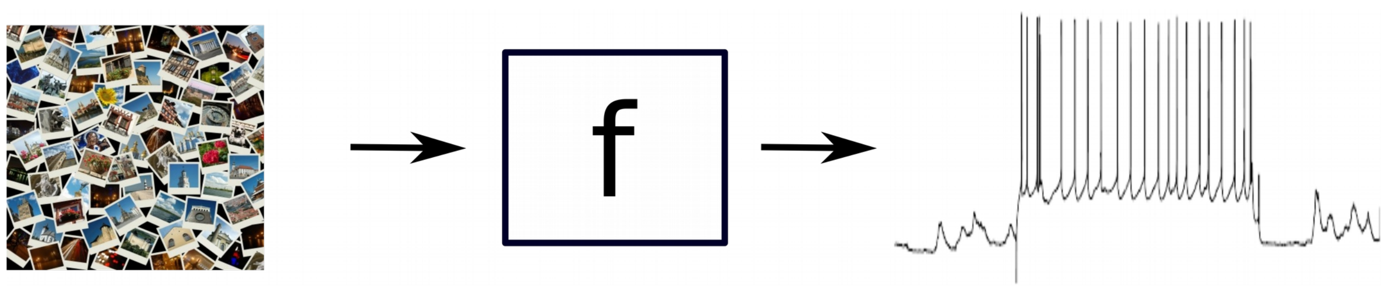
Kuffler (1953); Hubel and Wiesel (1962)

Receptive Field Estimation

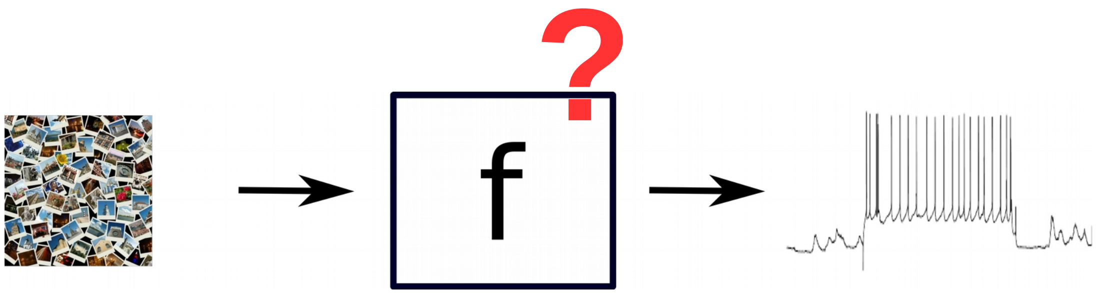


RF as a function

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



RF estimation



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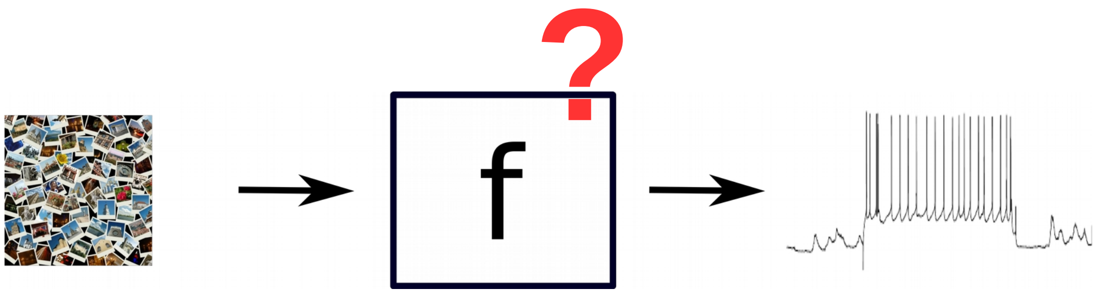
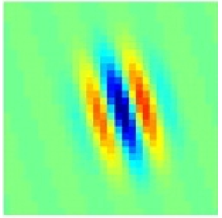
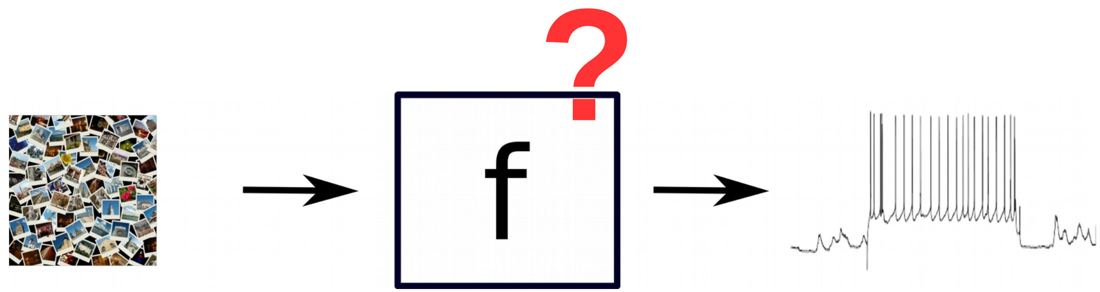


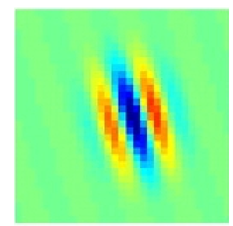
Spike triggered averaging :



RF estimation

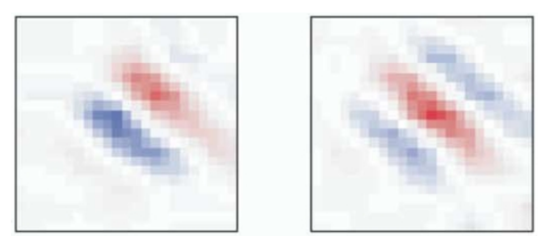


Spike triggered averaging :



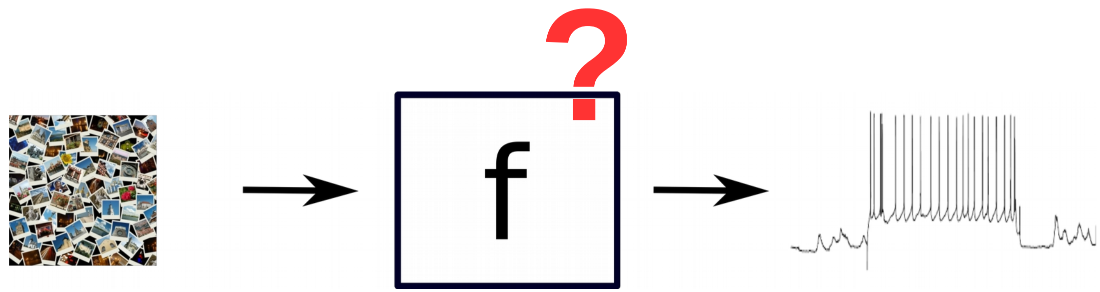
1st eig. vec. 2nd eig. vec.

Spike triggered covariance :

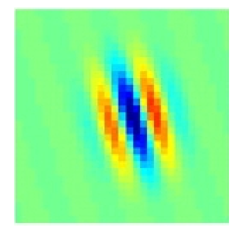


...

RF estimation



Spike triggered averaging :



Spike triggered covariance :

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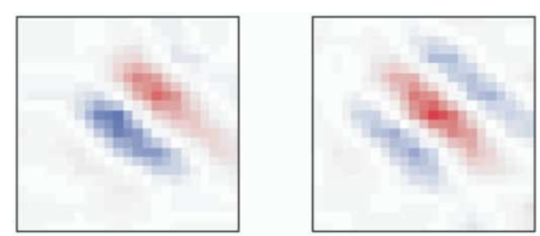

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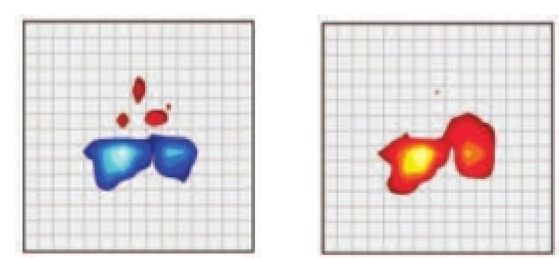
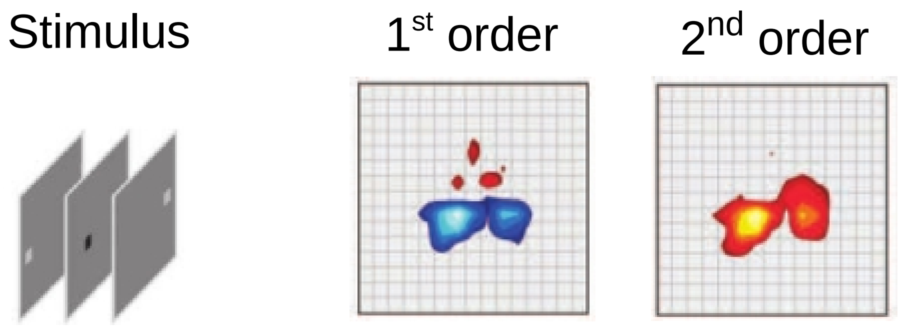
Volterra kernel estimation :

1st order   2nd order



Is RF real ?

Volterra kernel estimation :



(Fournier et al, 2011)

(David et al, 2004)

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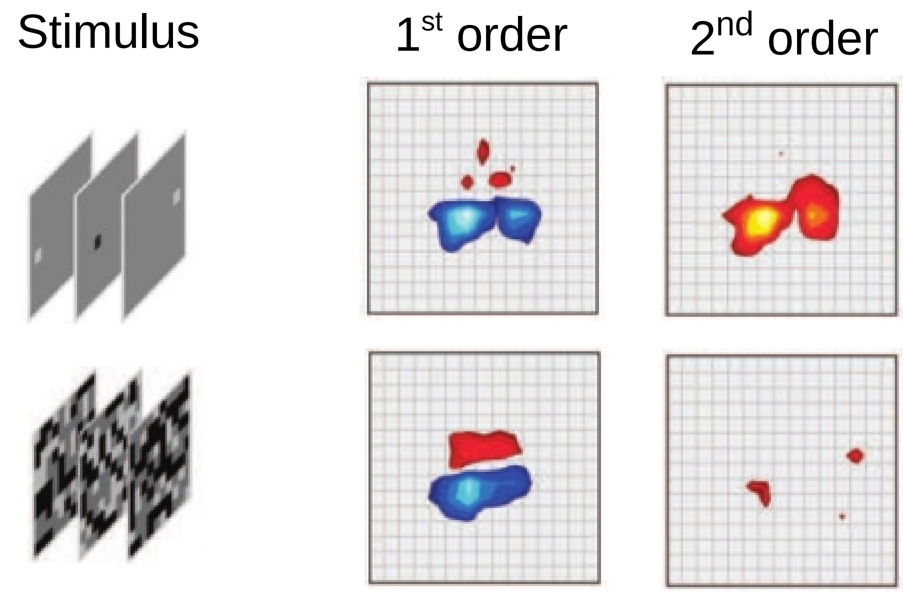

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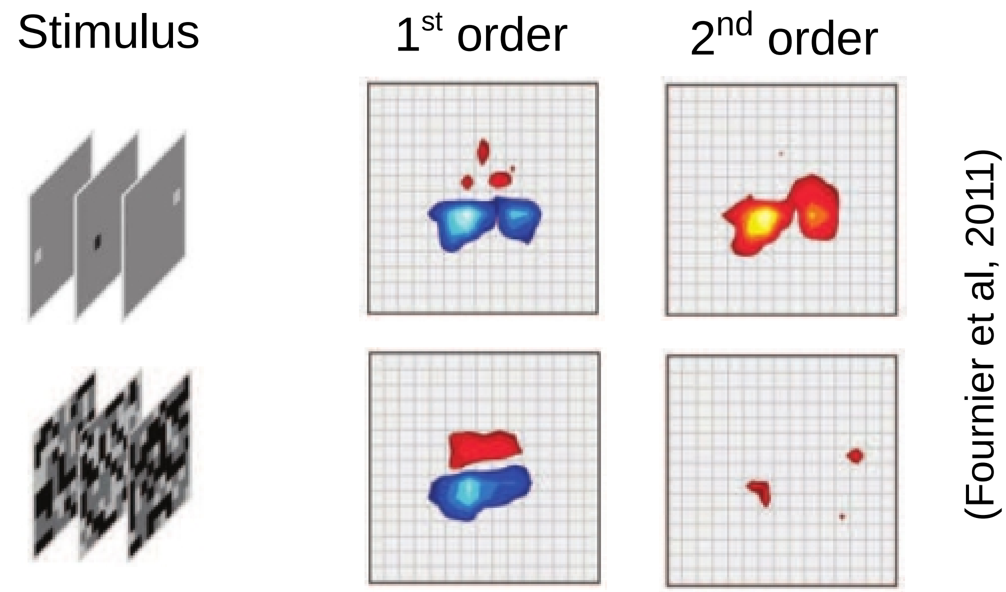

Phase-separated Fourier model:

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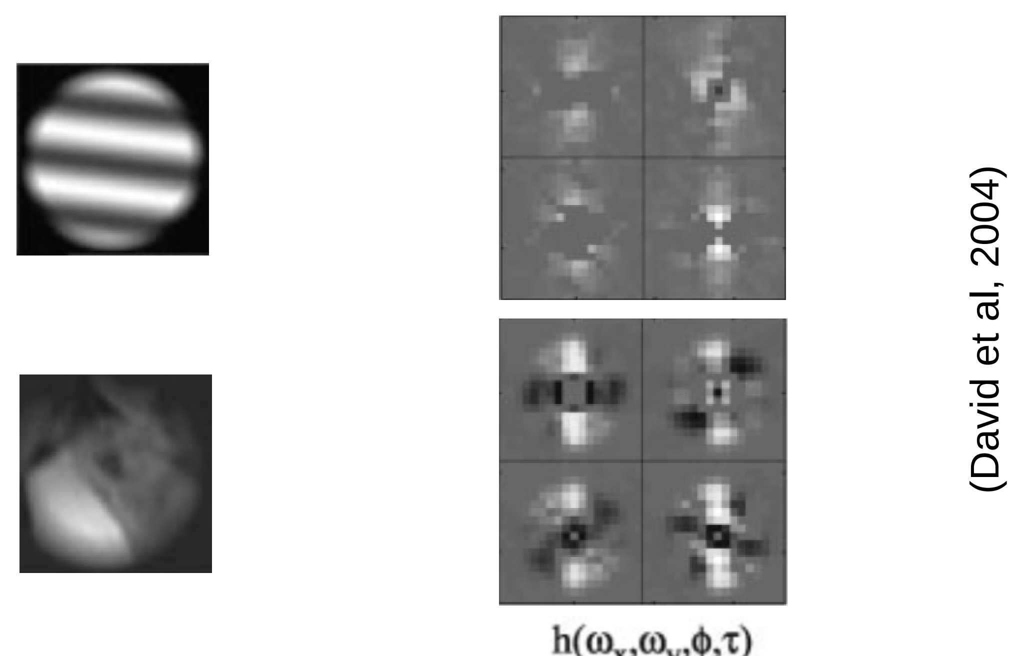

RF estimation limitations

- Limited expressiveness of the fitted models
- Fitting to narrow stimulus statistics

↓

- Limited prediction power
- Non unique estimation of the RF
- Poor interpretability in terms of underlying biological substrate

What can we do about it?

1. Introduce domain knowledge:

   more priors = better and less biased fit

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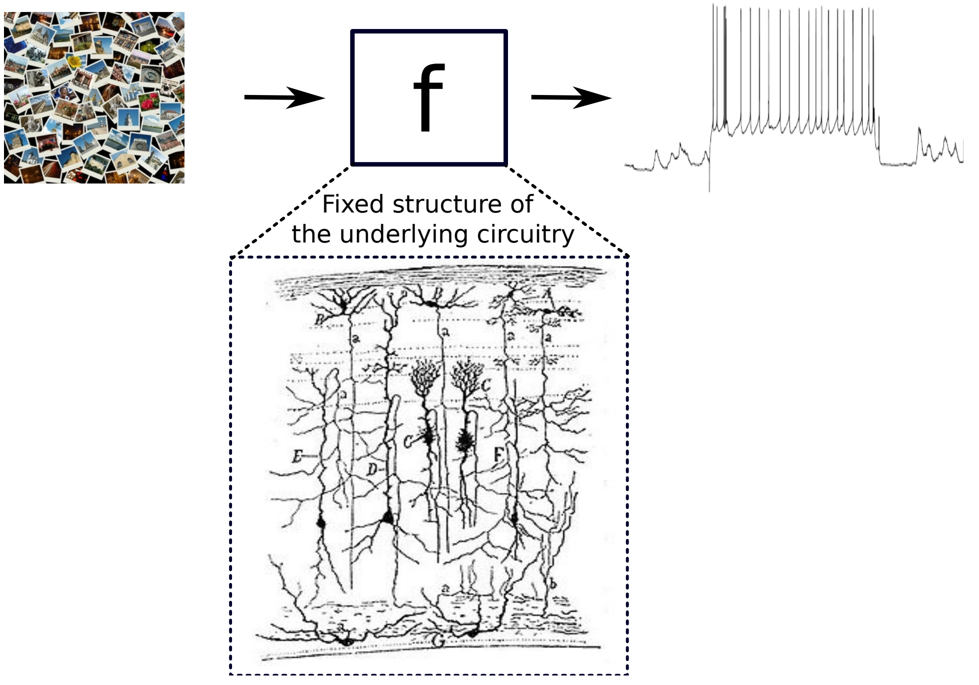

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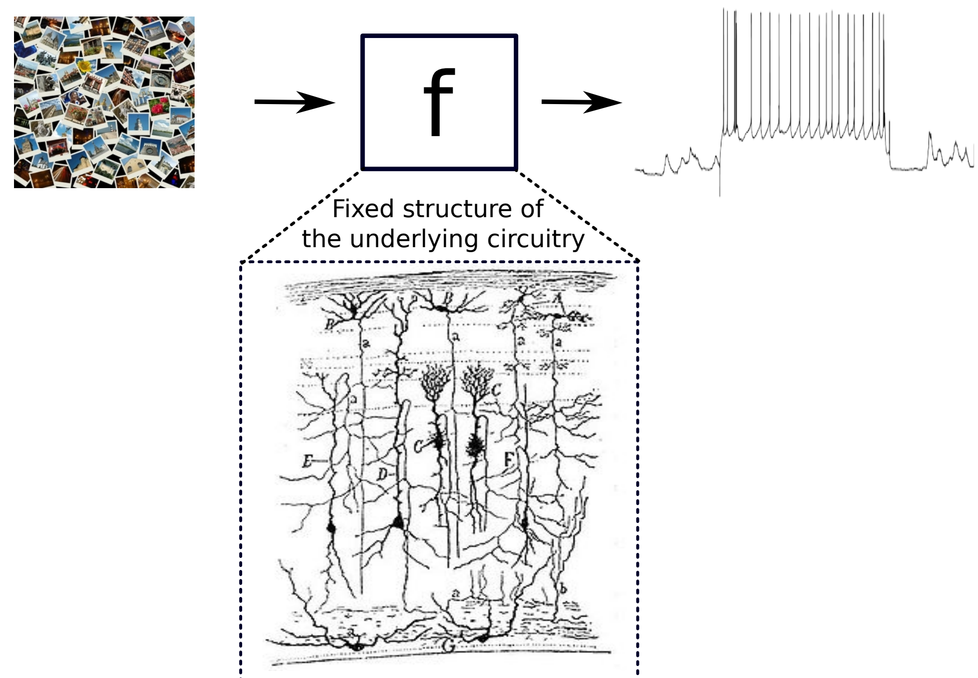
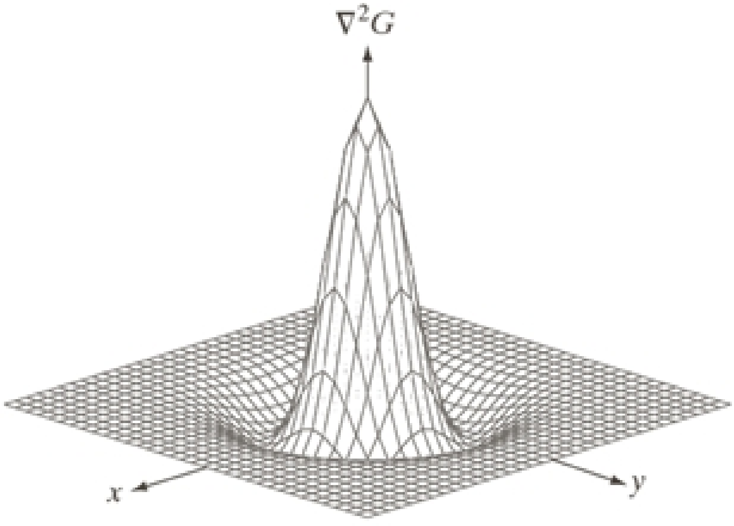


1+2 : Use knowledge about the architecture of the underlying neural circuitry as prior for your model.

Hierarchical structural model (HSM)

The structural priors

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



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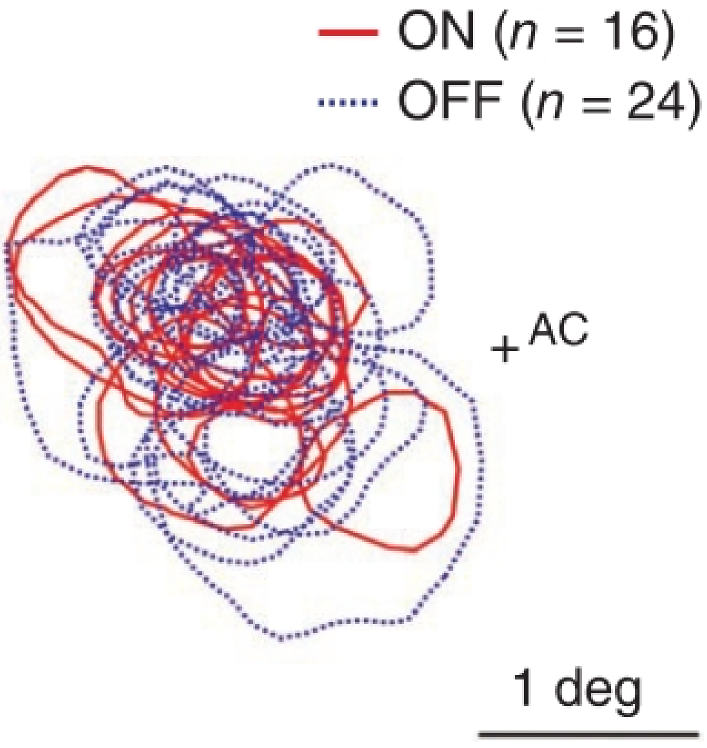
- Local population of V1 neurons receives common input from limited number of LGN cells



(Jin et al, 2011)

The structural priors

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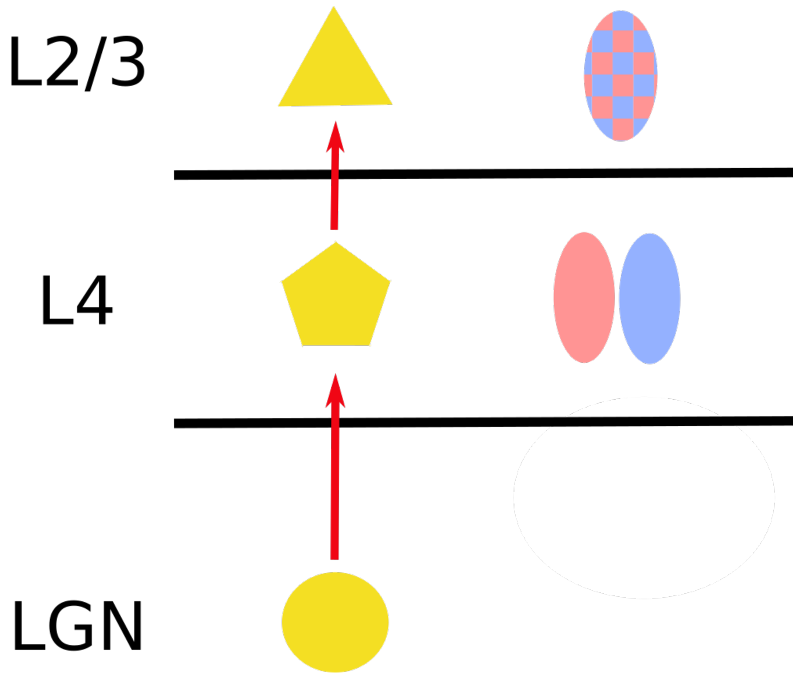
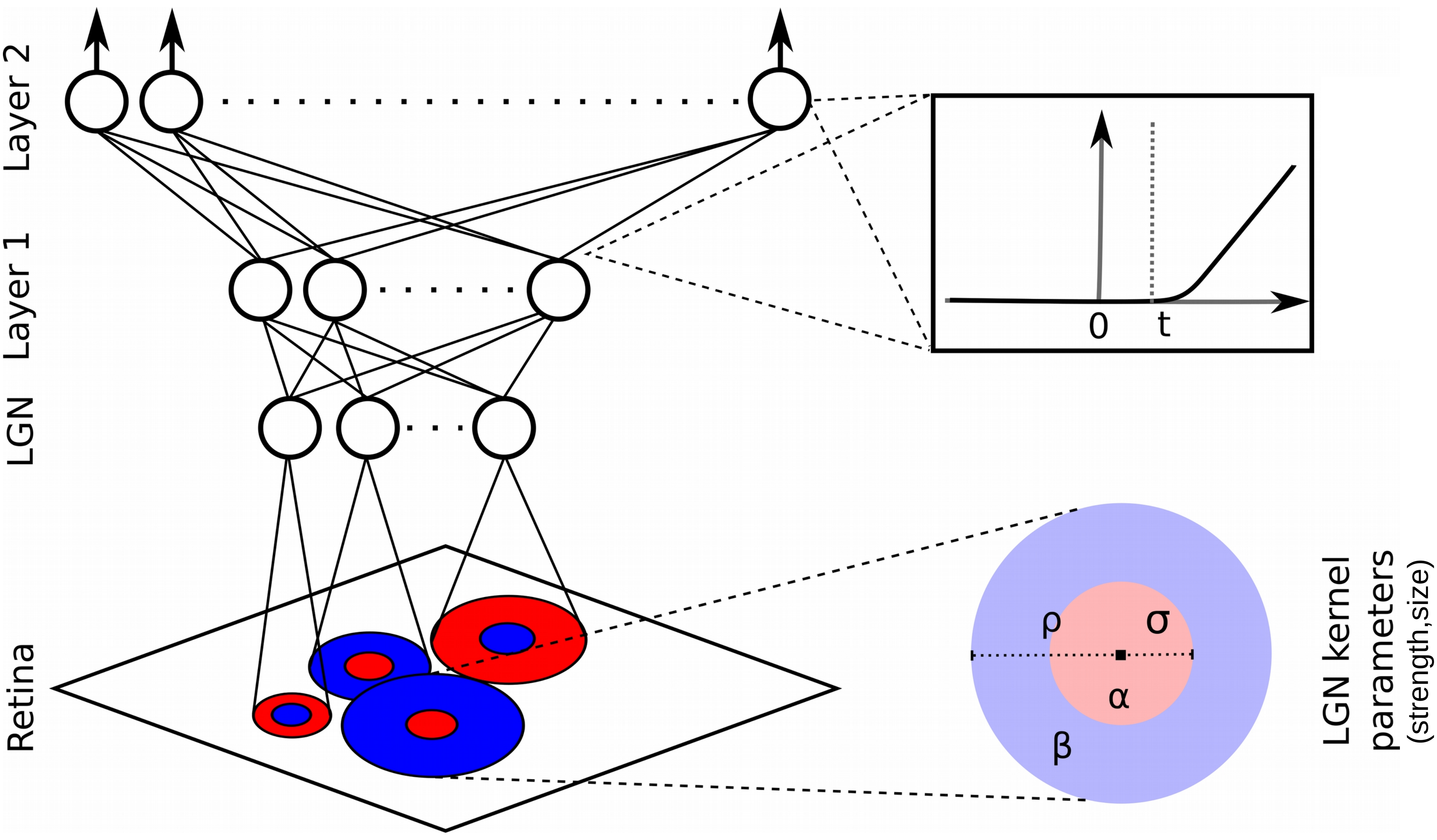
- Hierarchical organization



The HSM structure



The model

LGN units:

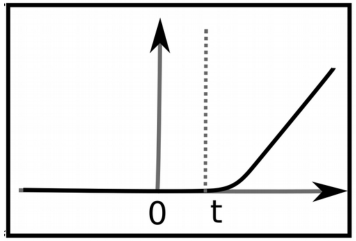
$$\psi_{i1} = \sum_{k,l} I_{kl} \left(\frac{\alpha_i}{\sigma_i^2} e^{-\frac{\left(k-\mu_i^x\right)^2 + \left(l-\mu_i^y\right)^2}{2\sigma_i^2}} - \frac{\beta_i}{\rho_i^2} e^{-\frac{\left(k-\mu_i^x\right)^2 + \left(l-\mu_i^y\right)^2}{2\rho_i^2}} \right)$$

Cortical units:

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

Transfer function:

$$\mathrm{f}(\mathrm{x}) = \log\left(1 + \exp\left(\mathrm{x} - \mathrm{t}_\mathrm{i}\right)\right)$$



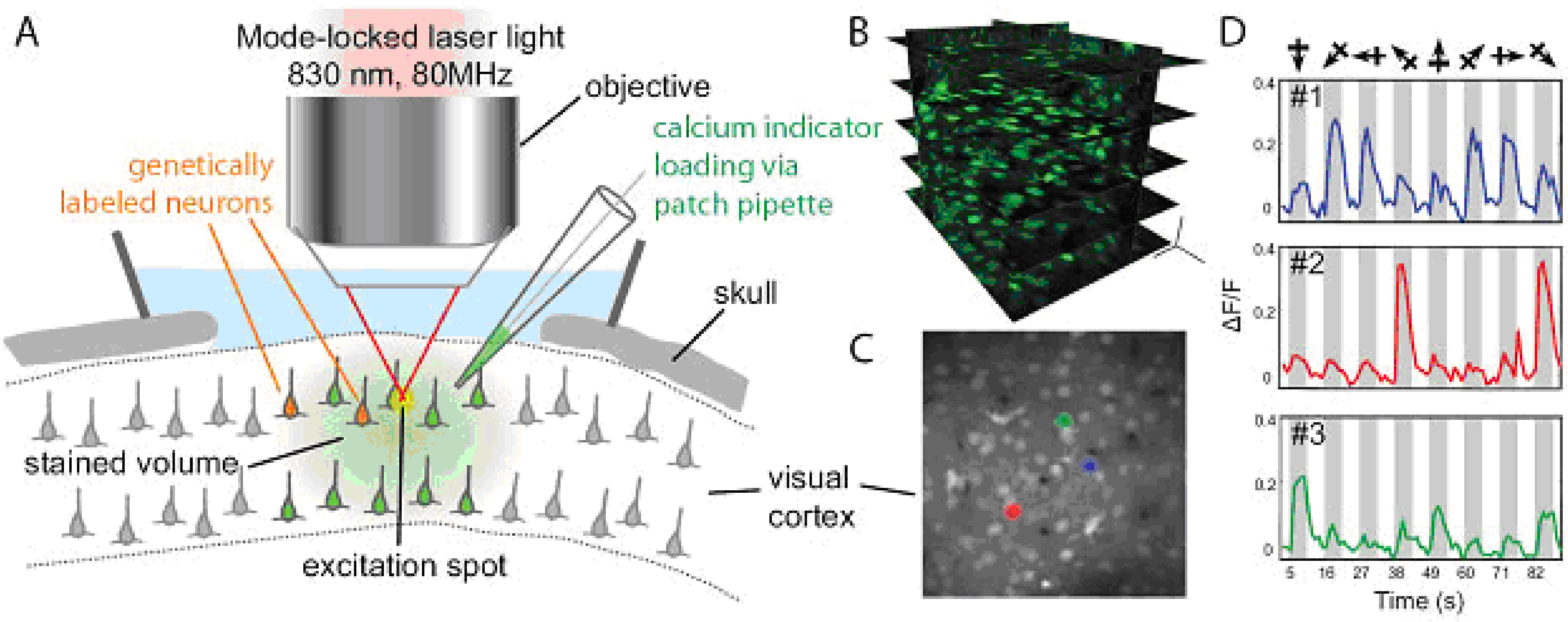
Log-likelyhood:

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

Model optimization

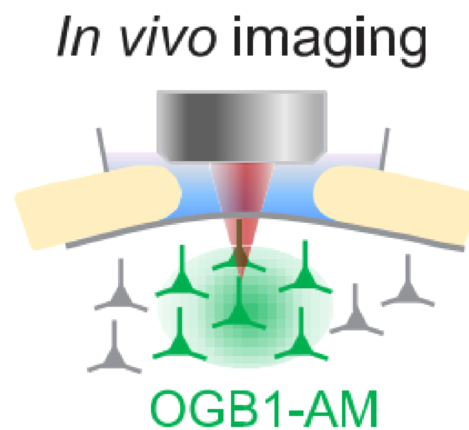
- Optimized with Constrained Truncated Newton Conjugate method
- Non-convex model
  - 100 restarts with different seeds of initial random parameter initialization
  - pick the best fit to **training** data
- Meta-parameters:
  - Number of LGN units (9)
  - Number of hidden units (20%)
  - Determined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

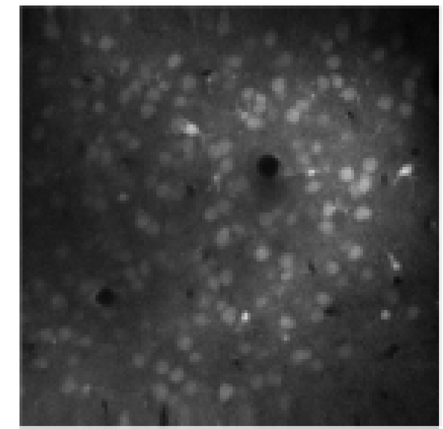
2-photon imaging of neural populations

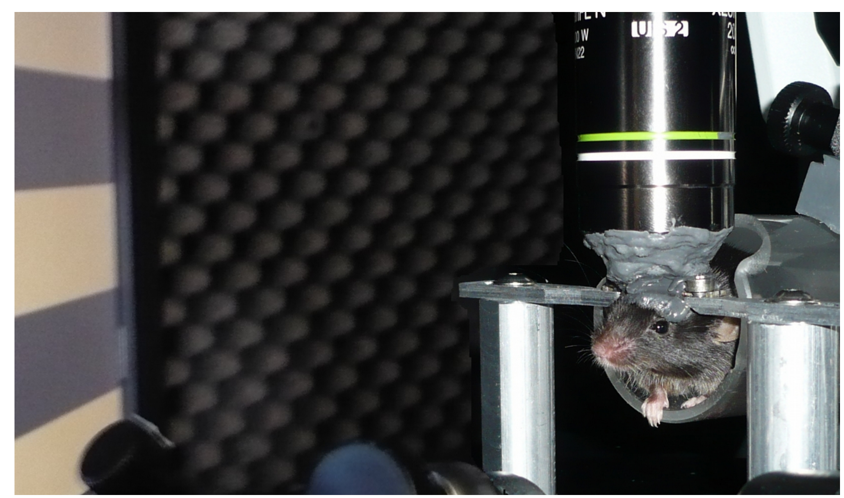


Calcium imaging of local population of neurons in mouse V1

- 2 mice, 30-40 postnatal day
- Anesthesized: isoflurane
- 3 imaged regions
- OGB1-AM calcium indicator

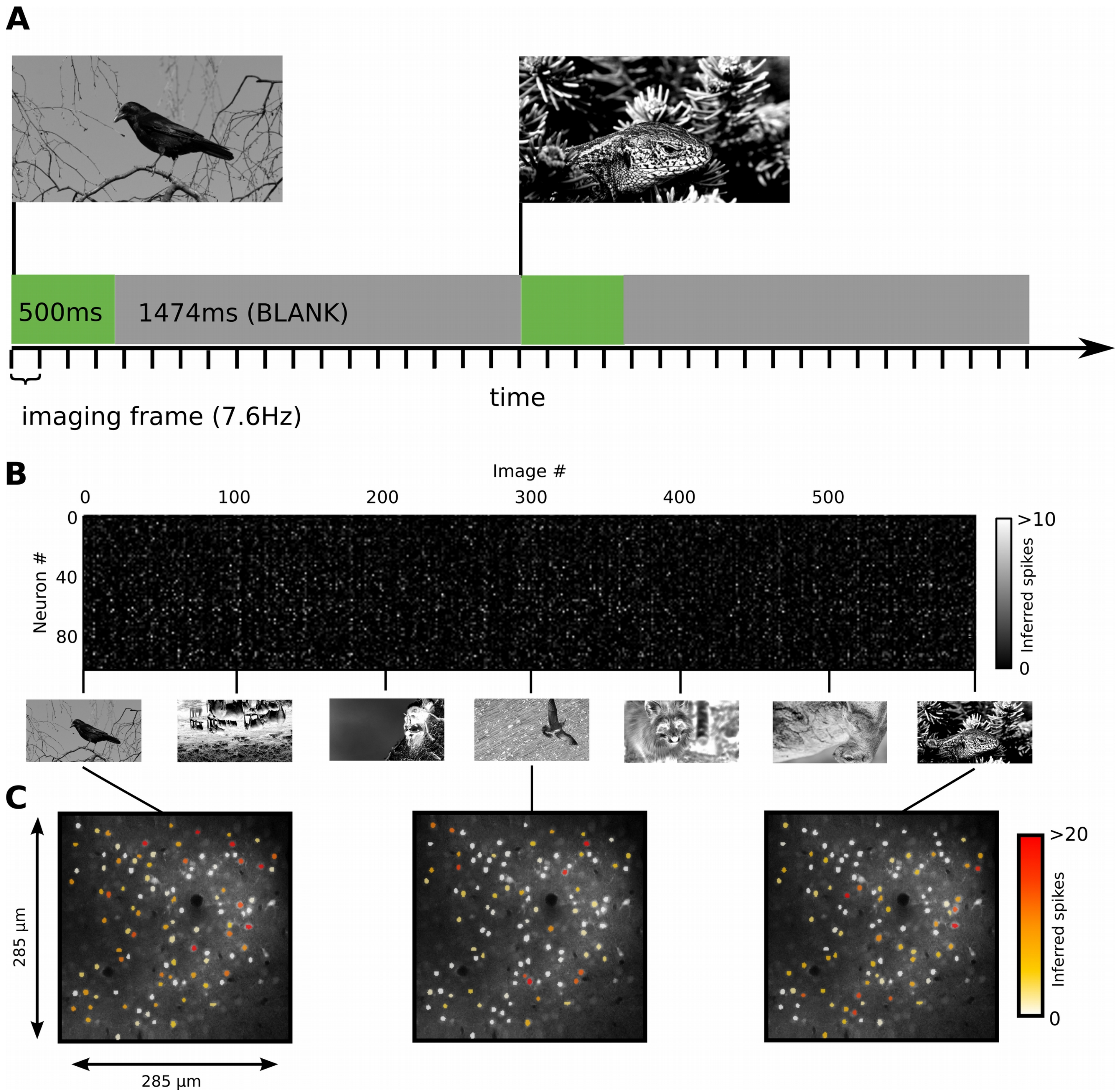






Sonja Hofer

Thomas Mrsic-Flogel

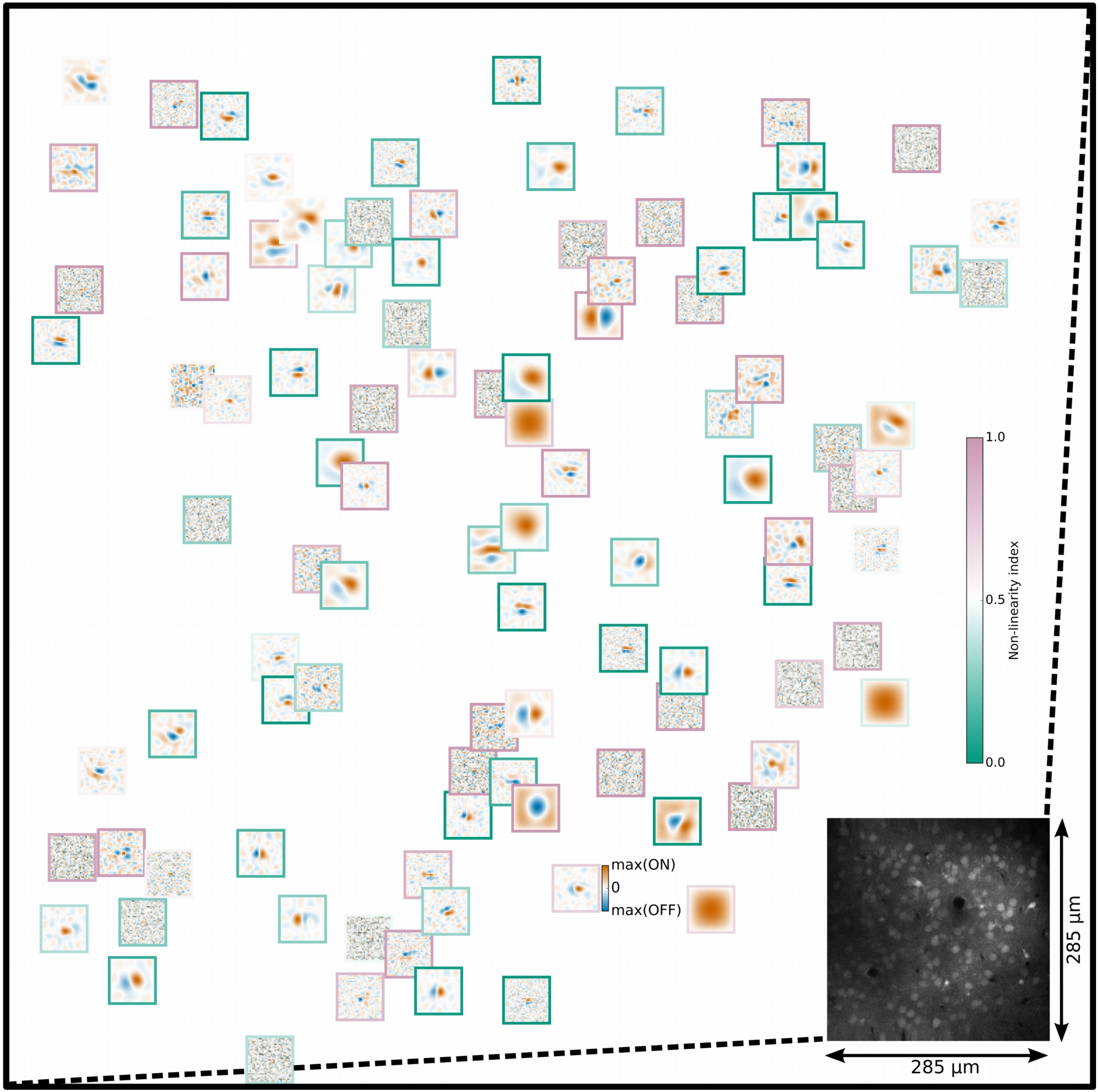


A
500ms
1474ms (BLANK)
time
imaging frame (7.6Hz)
B
Image #
0
100
200
300
400
500
Neuron #
0
40
80
>10
Inferred spikes
0
C
285 µm
285 µm
>20
Inferred spikes
0

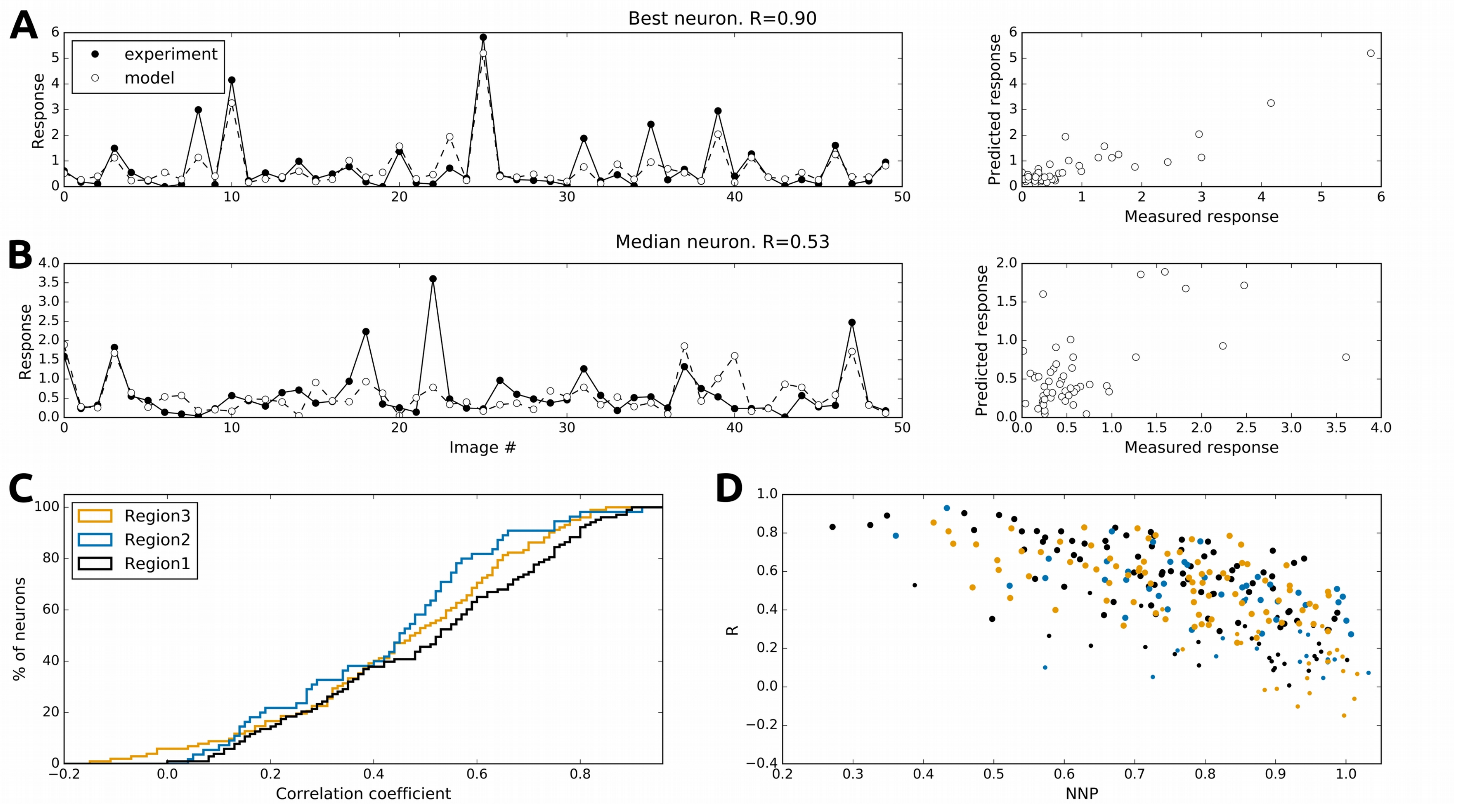
The recordings

- 3 imaged regions in 2 mice
- 257 neurons in total
- Training set: 1260-1800 images 1 trial
- Validation set: 50 images 8-12 trials

Results


1.0
0.5
0.0
Non-linearity index
max(ON)
0
max(OFF)
285 µm
285 µm

The model performance



Comparison: reference models

STA with laplacian regularization
(Smyth et. al, Journal of Neuroscince, 2003)

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

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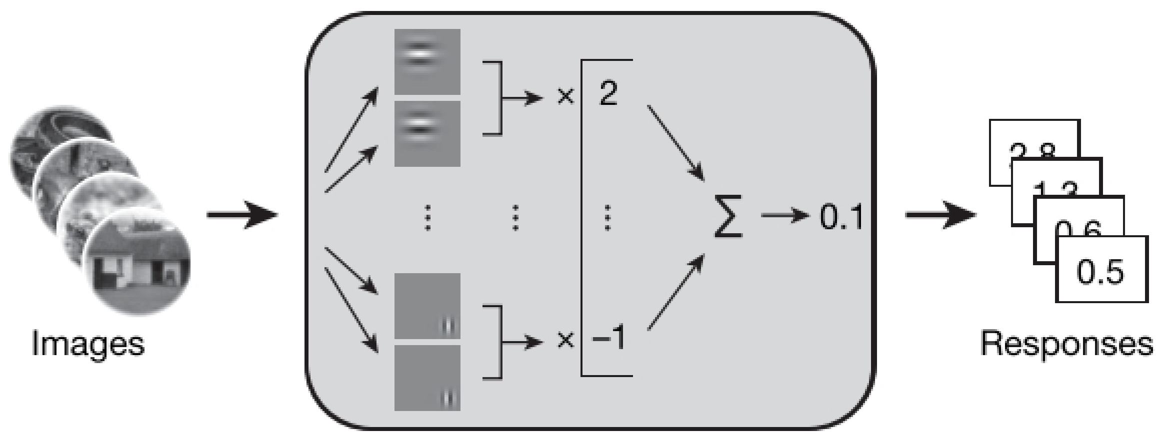
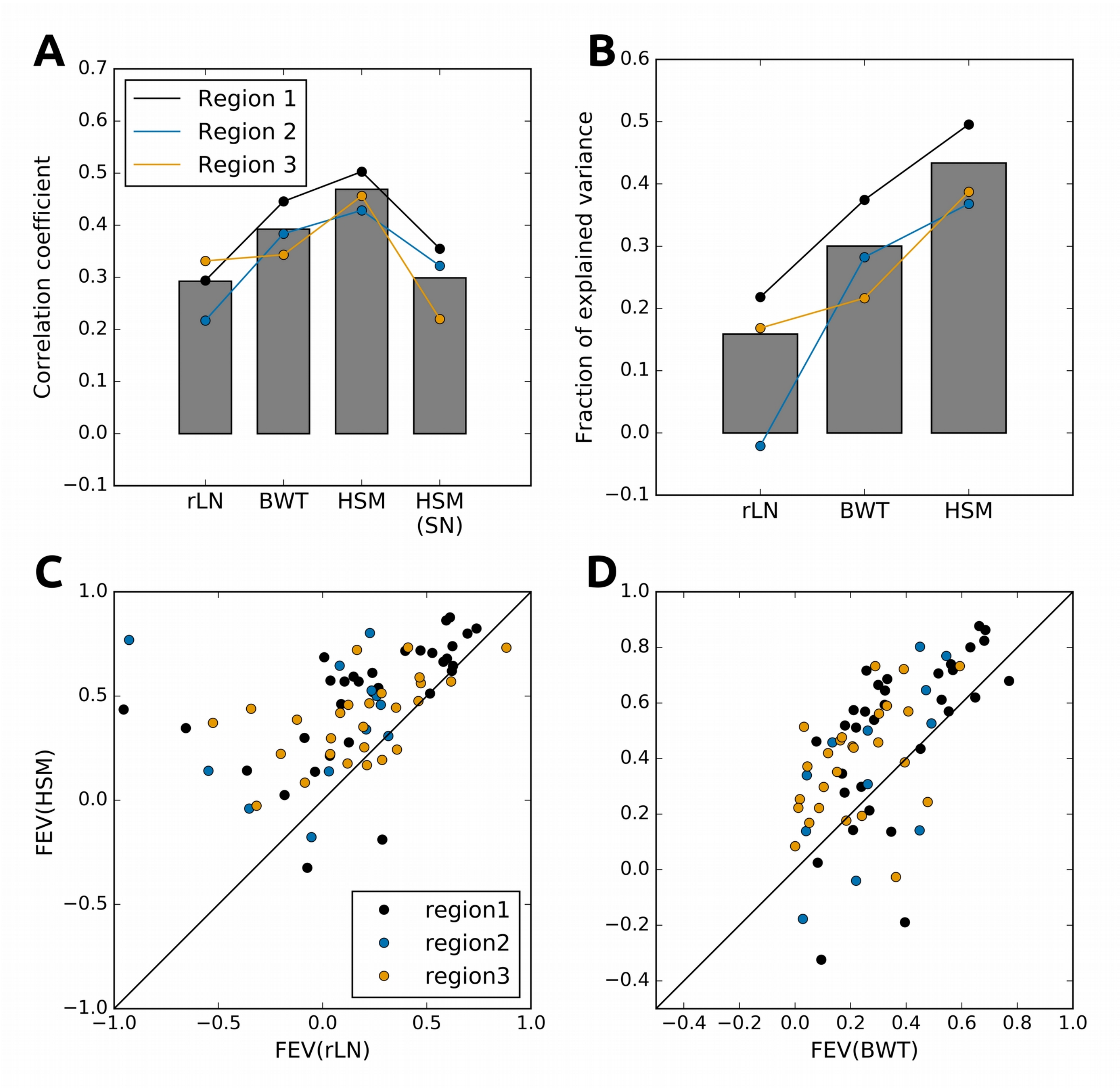
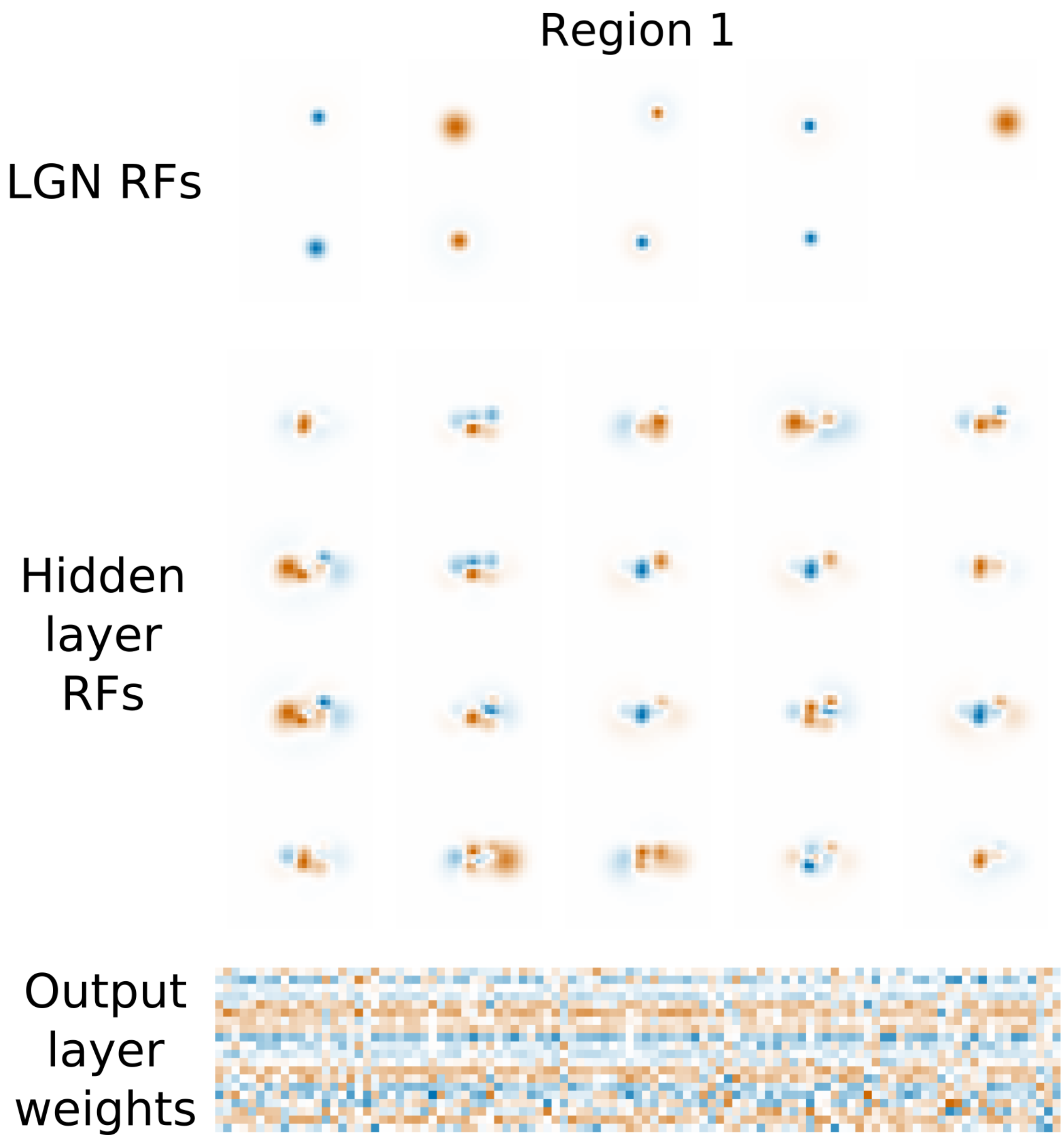
Barkely-wavelet transform based linear model
(Kay et. al, Nature, 2008)



Comparison: performance



Fitted HSM weights



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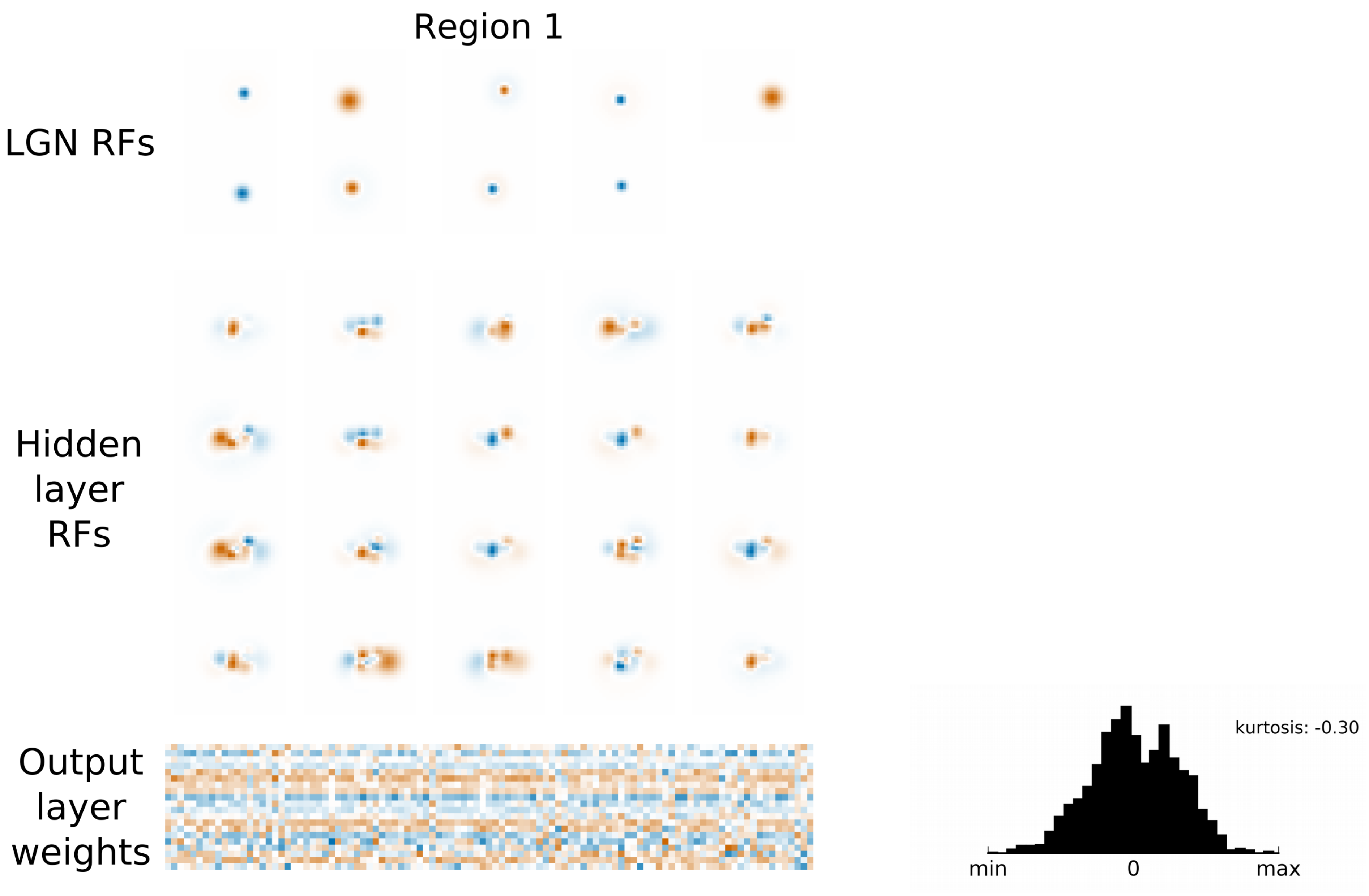

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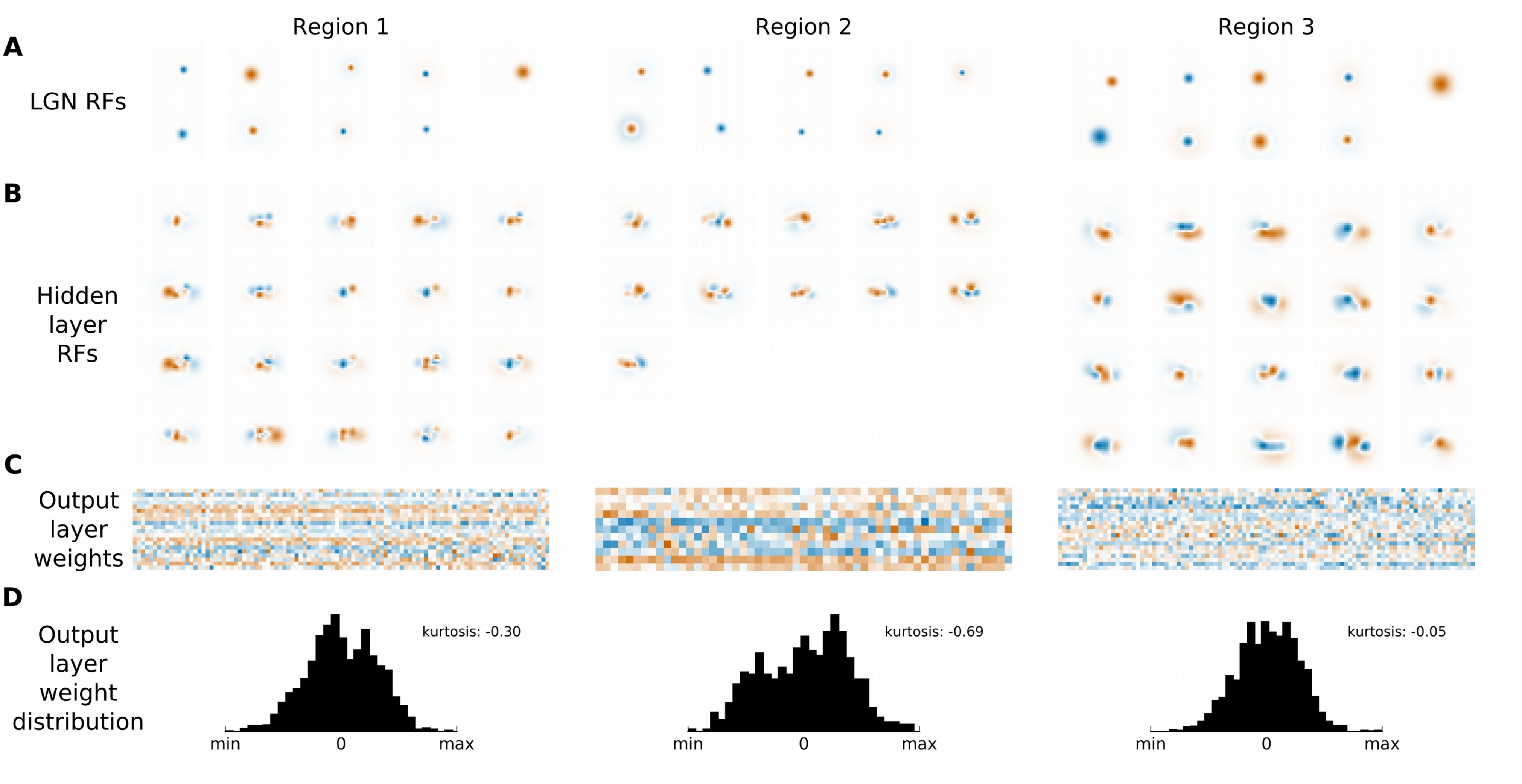
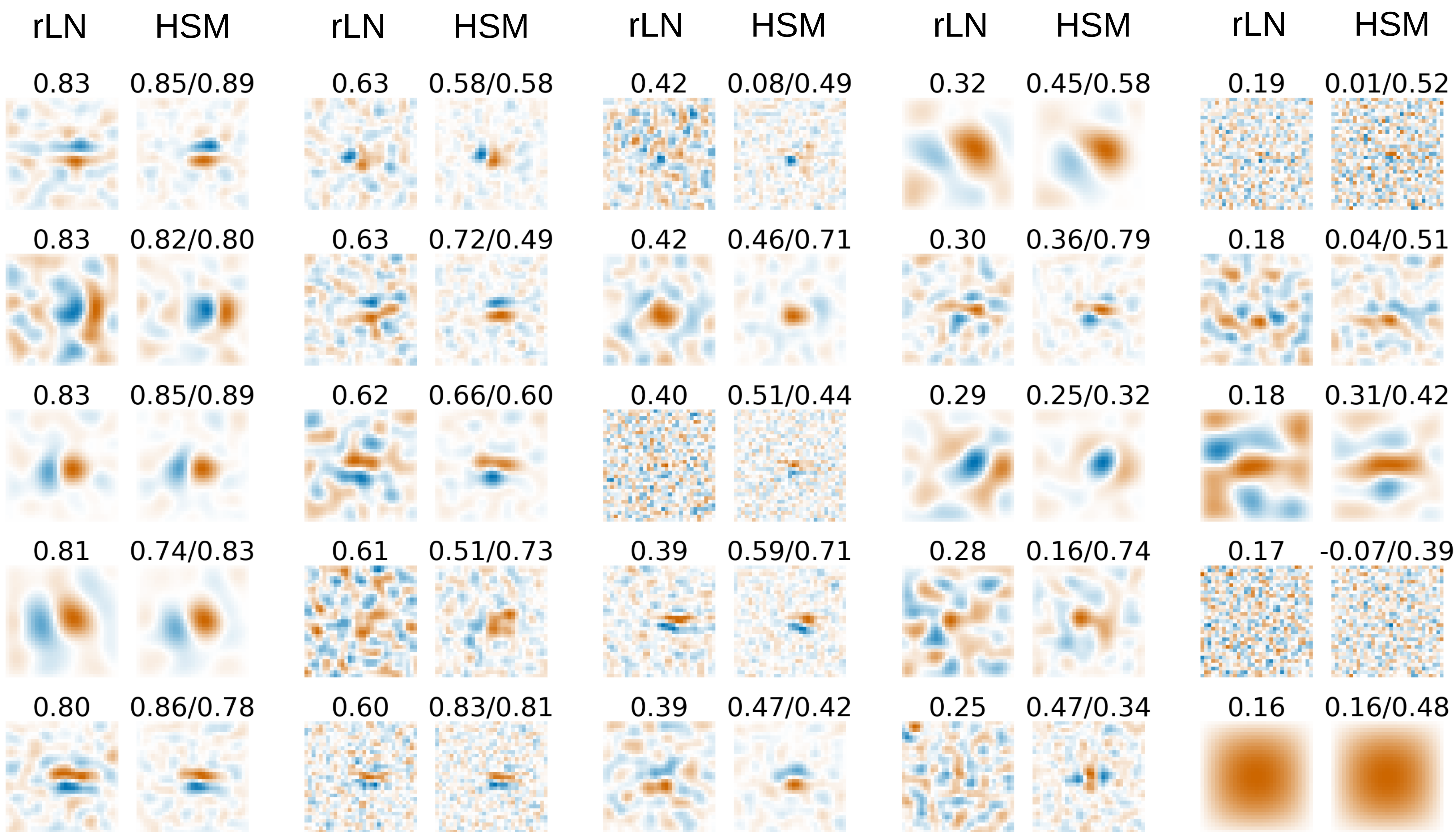
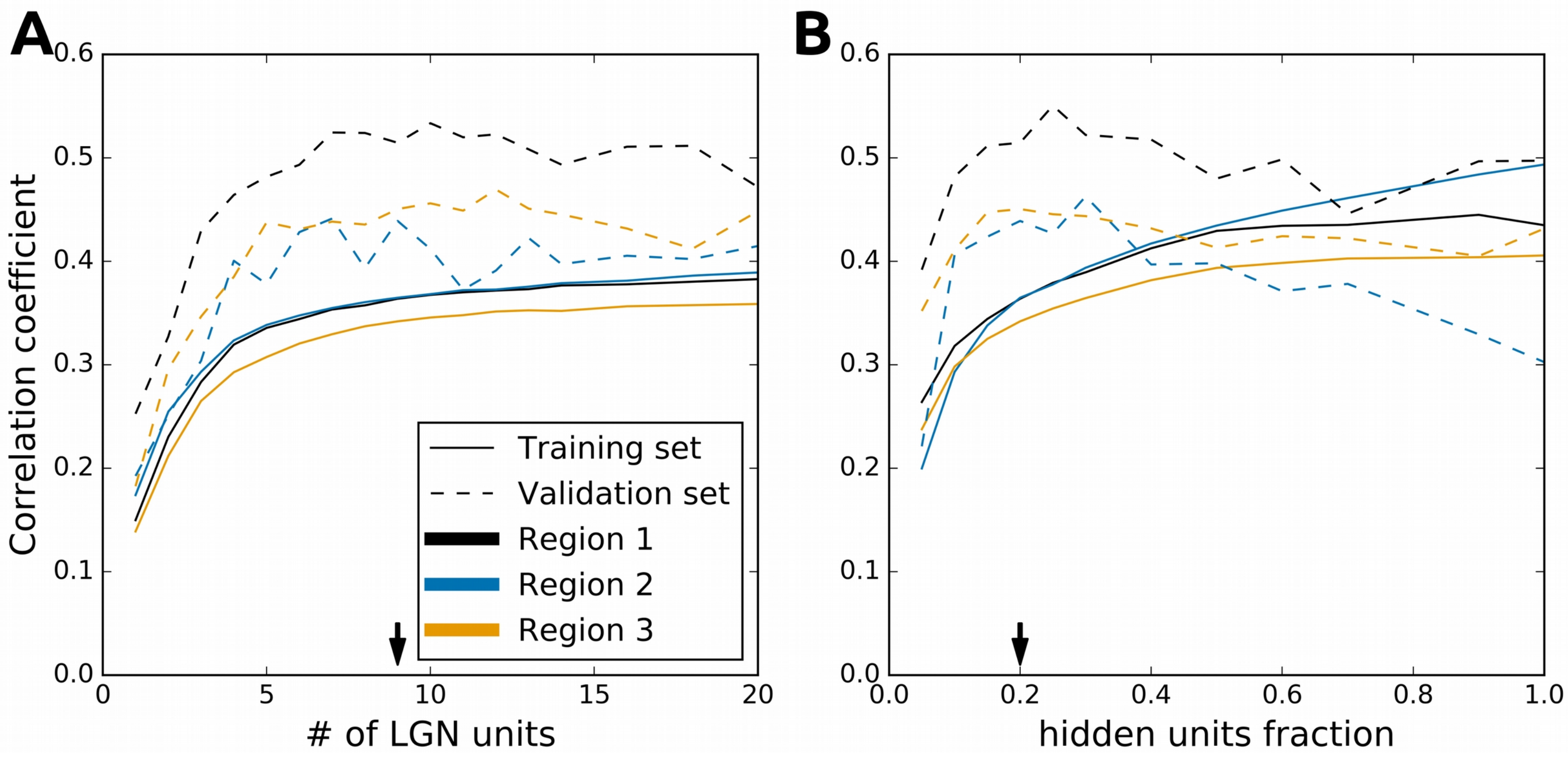


RF comparison across models



Metaparameters



Conclusions

- Introduction of cortical architecture into model leads to more accurate prediction of population responses to natural images
- Significant reduction of free parameters compared to many competing models
- Diverse set of receptive fields in local population of mouse V1 neurons can be constructed from surprisingly few LGN-like units
- Can systematic introduction of prior knowledge about the thalamo-cortical circuitry lead to better correspondence between fitted models and underlying neural substrate, and thus save the RF?

Future work: better calcium imaging systems

- Widefield objective = more simultaneously recorded cells
- Chronic preparation = more image presentations
- Deeper recordings = more available priors
- New dyes = less noise, single spike resolution
- Faster scanning frequency
- Recordings combined with neuronal markers

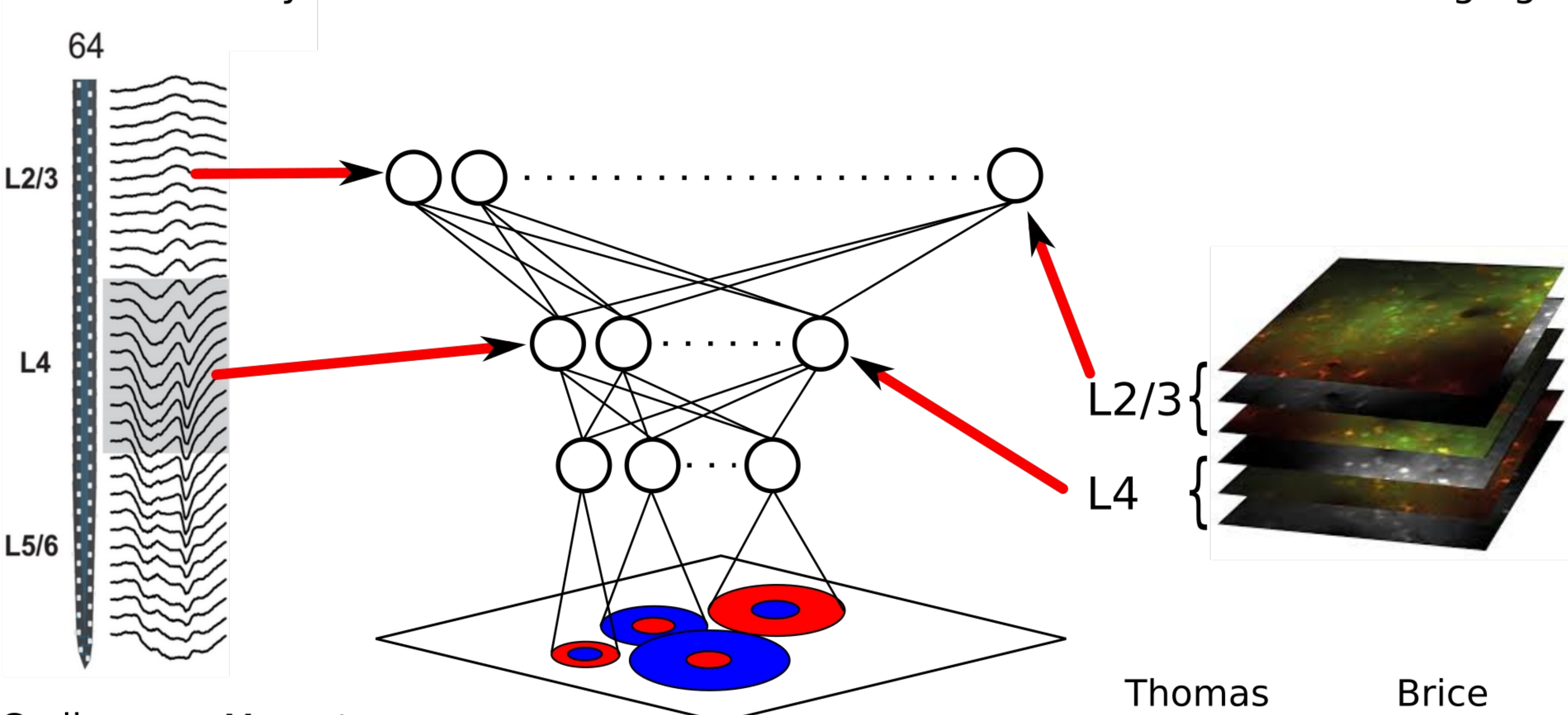
Future work: model extensions

- Temporal receptive fields to fit natural scenes animations
- Stimulus dependent surround contributions, with explicit priors about structure of lateral connectivity
- Coupling filters between cortical neurons (a.k.a. GLM)
- Adaptative mechanisms
- Sepparete excitatory and inhibitory neurons
- Explicit handling of ongoing-state
- Trans-laminar model fitting

Trans-laminar model fitting

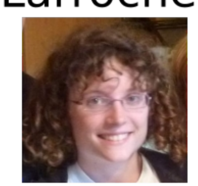
Trans laminar electrode array

Two-photon calcium imaging



Cyril Monier

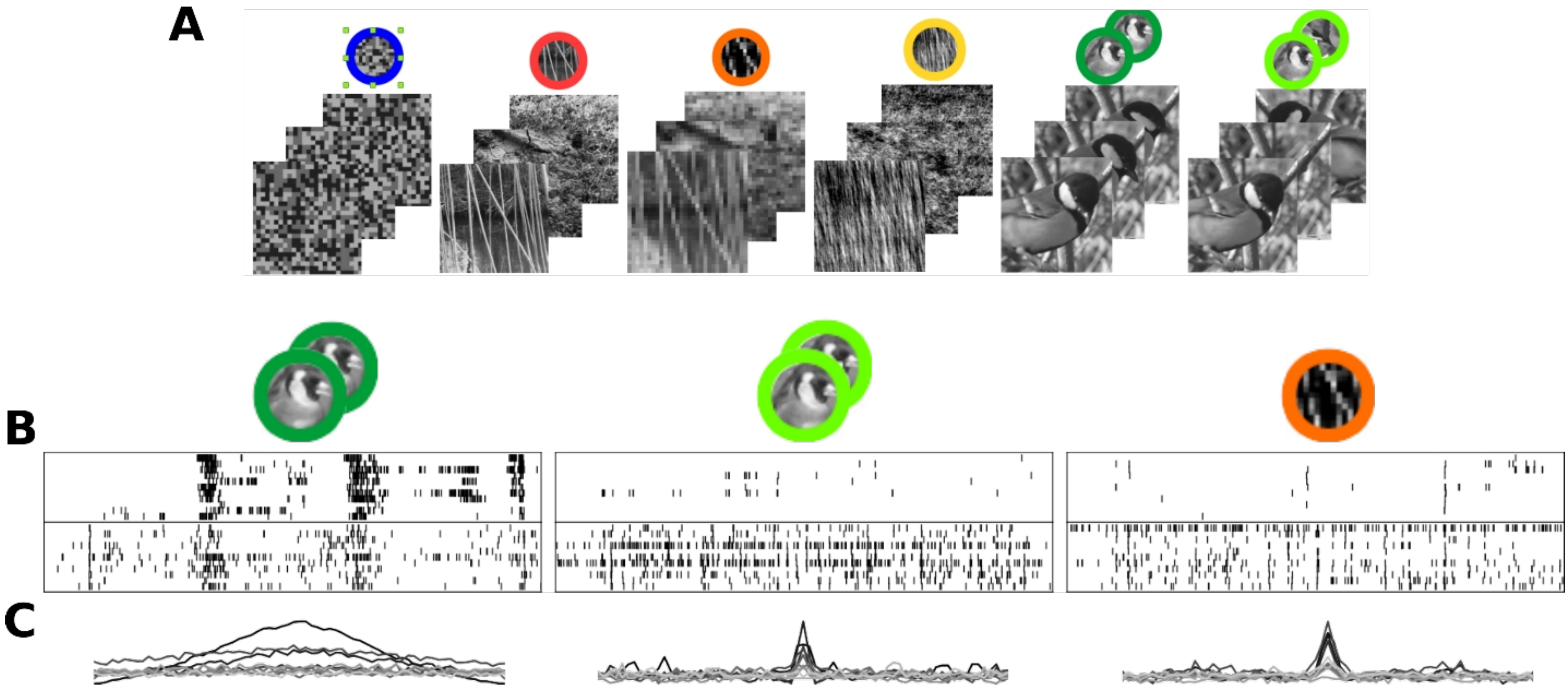
Margot Larroche



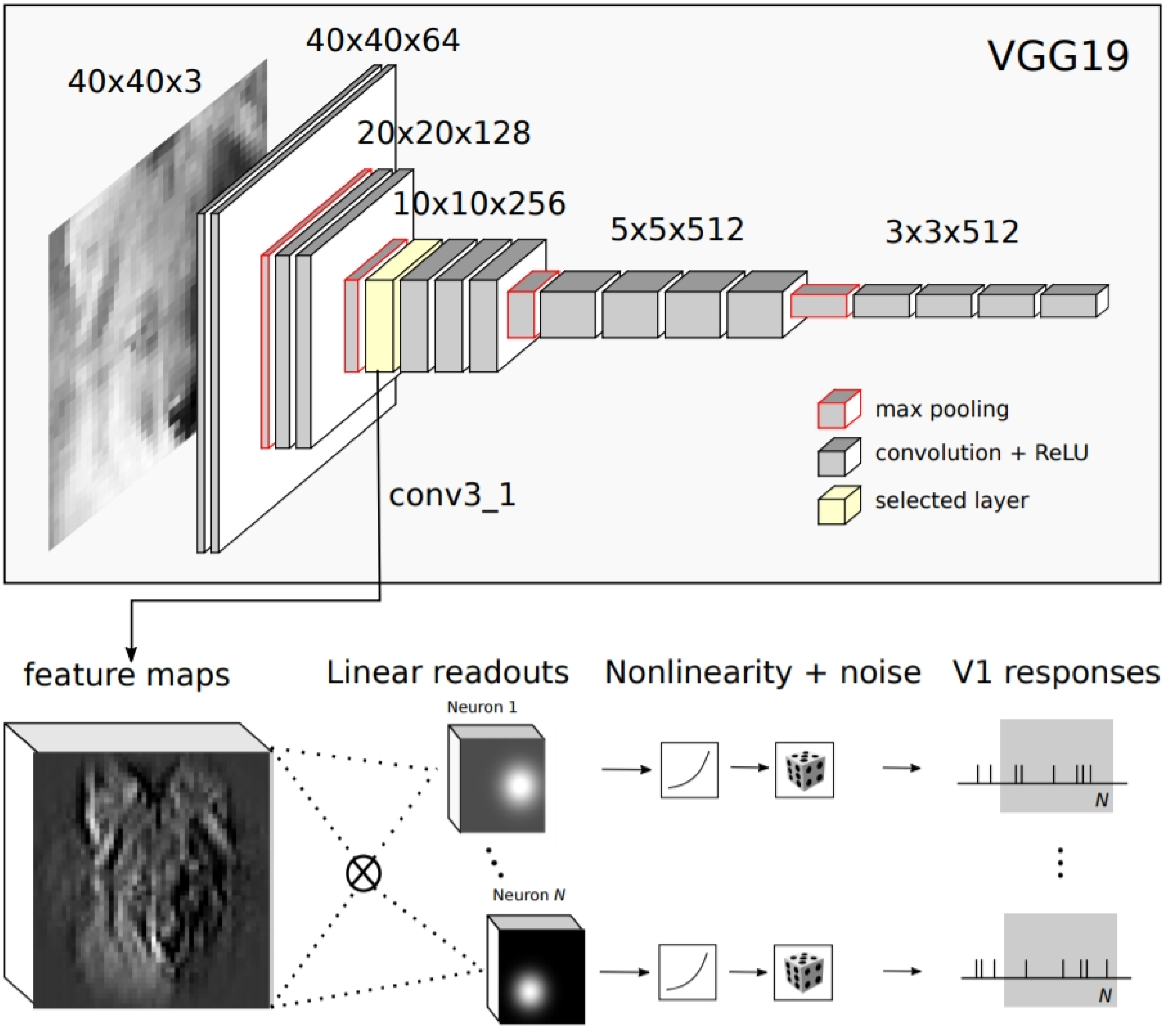
Thomas Deneux

Brice Bathellier

Exploration of different image statistics (adaptation?)

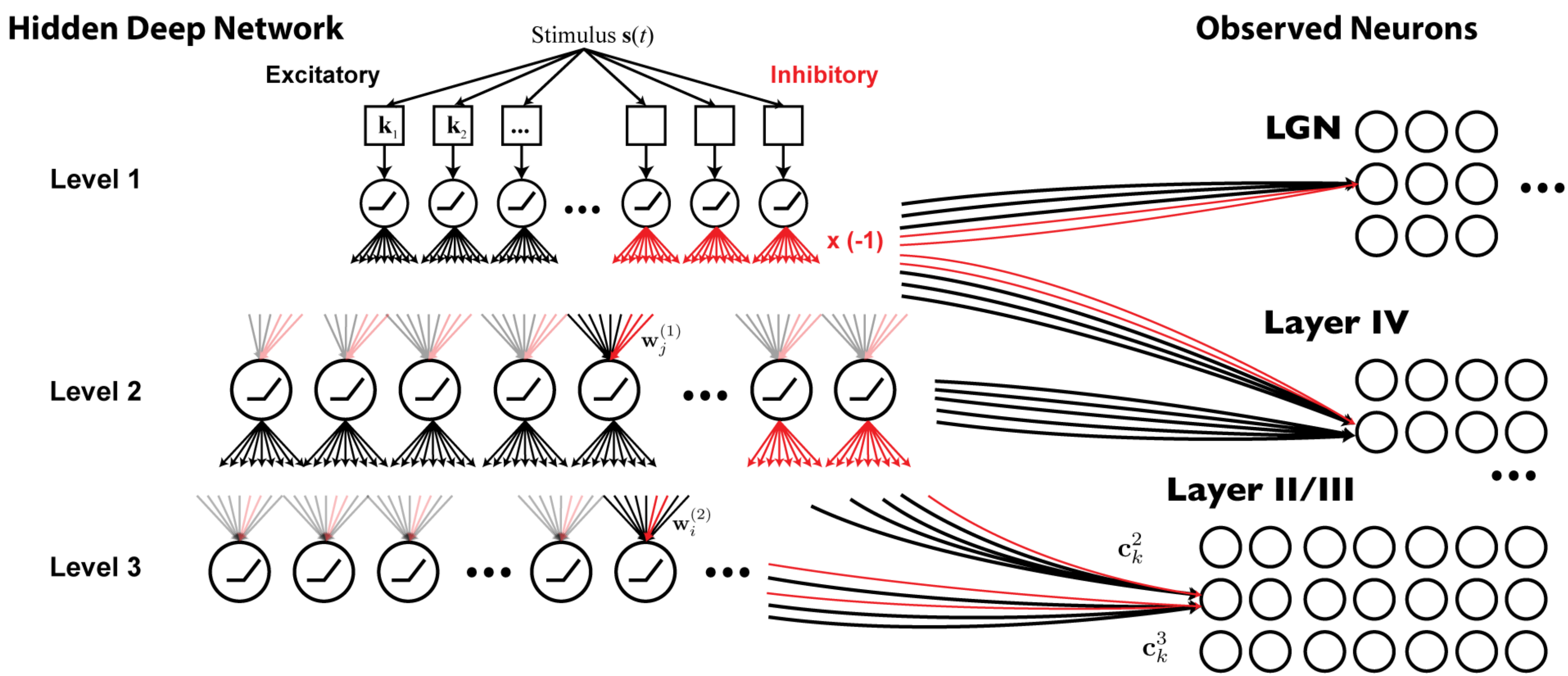


Recent entry of CNNs into neuroscience



Cadena et al. 2018

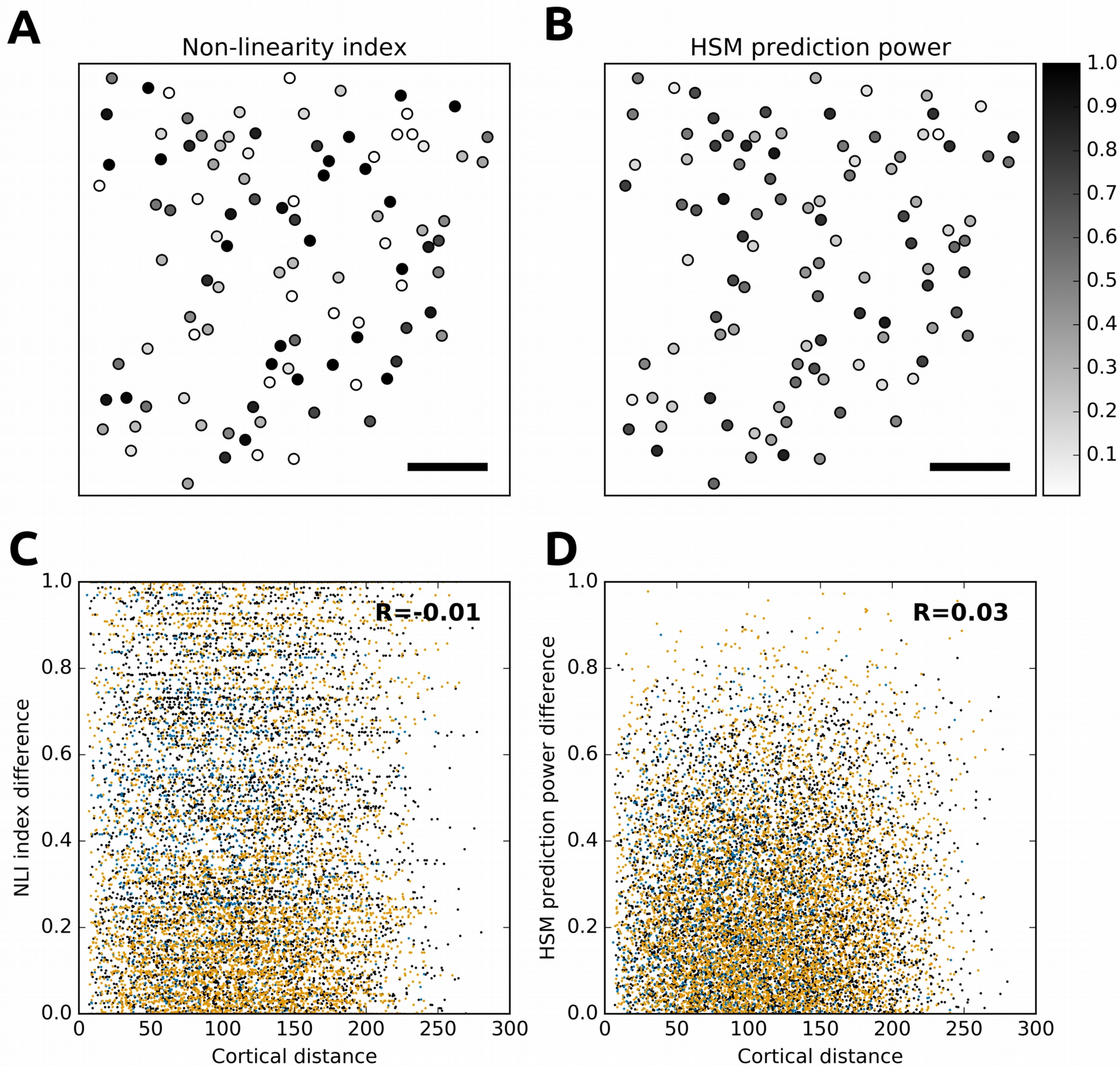
New Deep Architectures



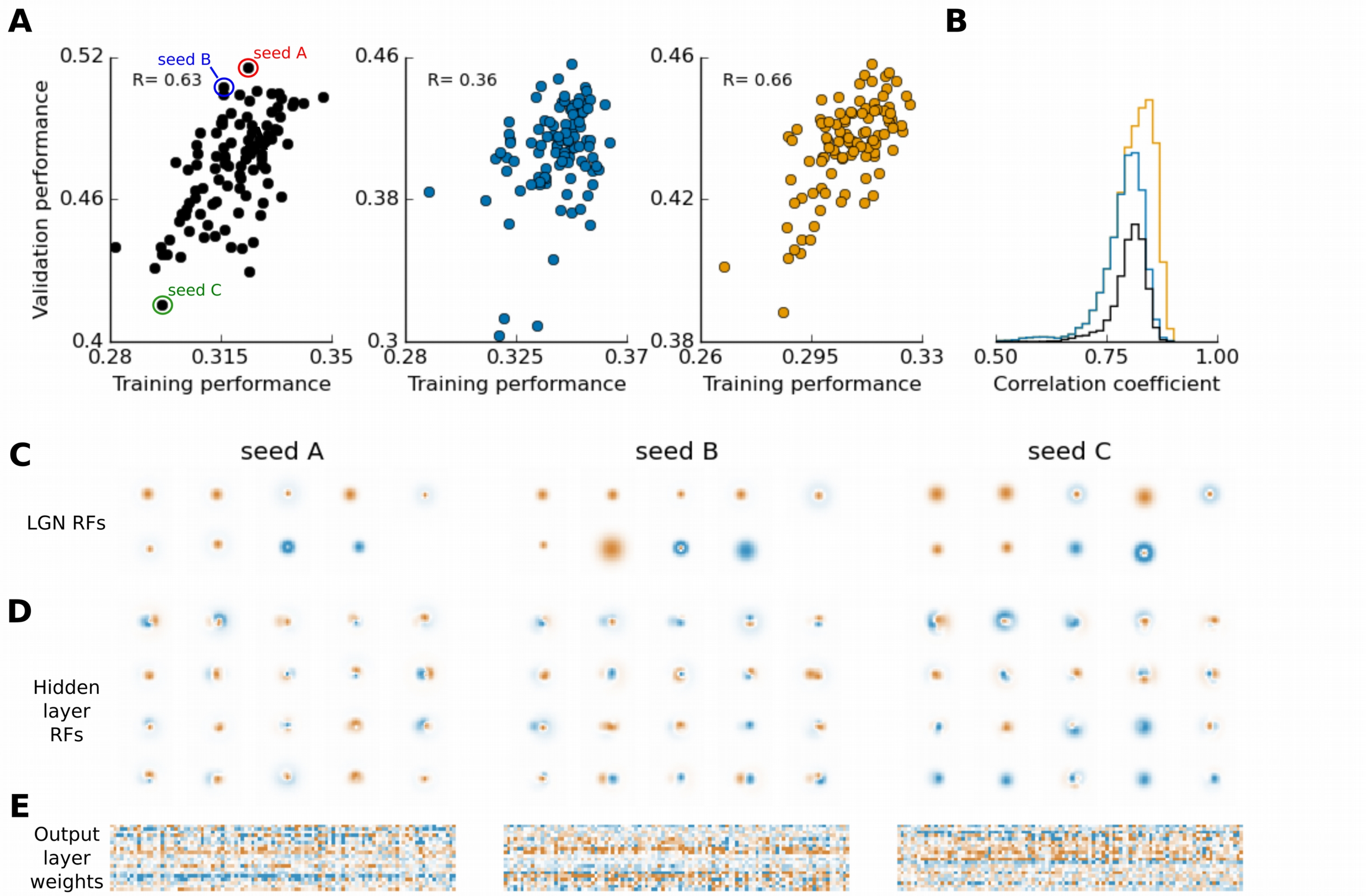
Dan Butts, Univ. of Maryland

THE END

WE ARE ALWAYS LOOKING FOR TALENTED STUDENTS


A
Non-linearity index
B
HSM prediction power
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
C
1.0
0.8
0.6
0.4
0.2
0.0
R=-0.01
NLI index difference
0
50
100
150
200
250
300
Cortical distance
D
1.0
0.8
0.6
0.4
0.2
0.0
R=0.03
HSM prediction power difference
0
50
100
150
200
250
300
Cortical distance

Dependence on initialization seed



Dependence on data resampling