Optimal Receptive Fields for Natural Tasks: Efficiency, Redundancy and Neural Noise

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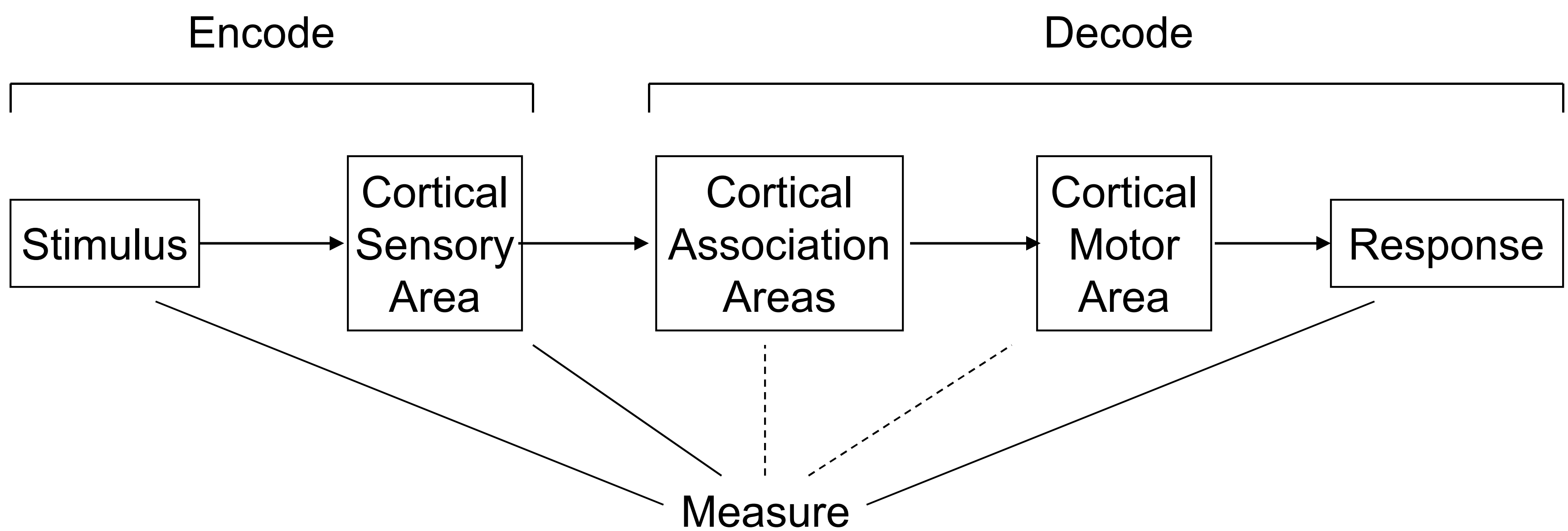
Schematic of processing flow in perceptual-motor tasks



task

stimulus properties

neural noise

task

stimulus properties

encoding

neural noise

Natural Systems Analysis

1. Identify and characterize natural tasks

2. Measure and characterize relevant environmental properties (e.g., measure natural scene statistics) and biological constraints (e.g., neural noise)

3. Determine how to exploit the measured environmental properties to perform natural tasks optimally, given the biological constraints

4. Formulate hypotheses and test them in physiological and behavioral studies that capture the essence of the natural task

Focus of talk

Encoding:

What feature dimensions (RFs) are optimal for specific natural tasks?

How do those optimal RFs depend on neural noise?

Decoding:

How should responses of the optimal RFs be decoded to perform the natural tasks?

What performance can be obtained given the optimal RFs?

Logic of Accuracy Maximization Analysis (AMA)

1. Specify a natural task

2. Specify neural noise and other biological constraints

3. Obtain appropriate training and test sets of natural stimuli

4. Find a set of RFs for the specific set of training stimuli using a Bayes optimal decoder specific to the training stimuli

5. Find a general decoder given the optimal RFs

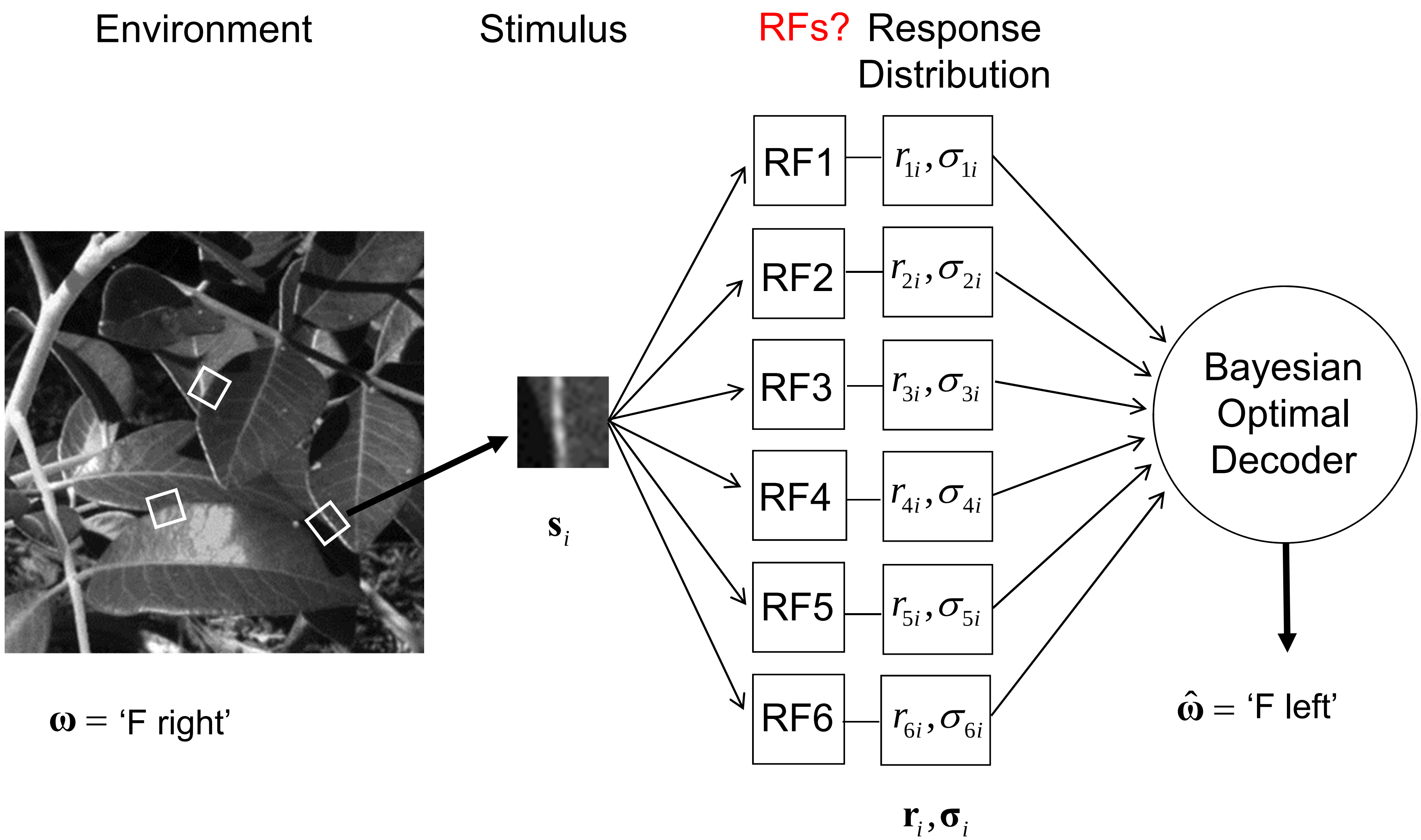
6. Measure general decoder performance and compare with real performance

Foreground Identification Task (J. Najemnik & A.D. Ing)

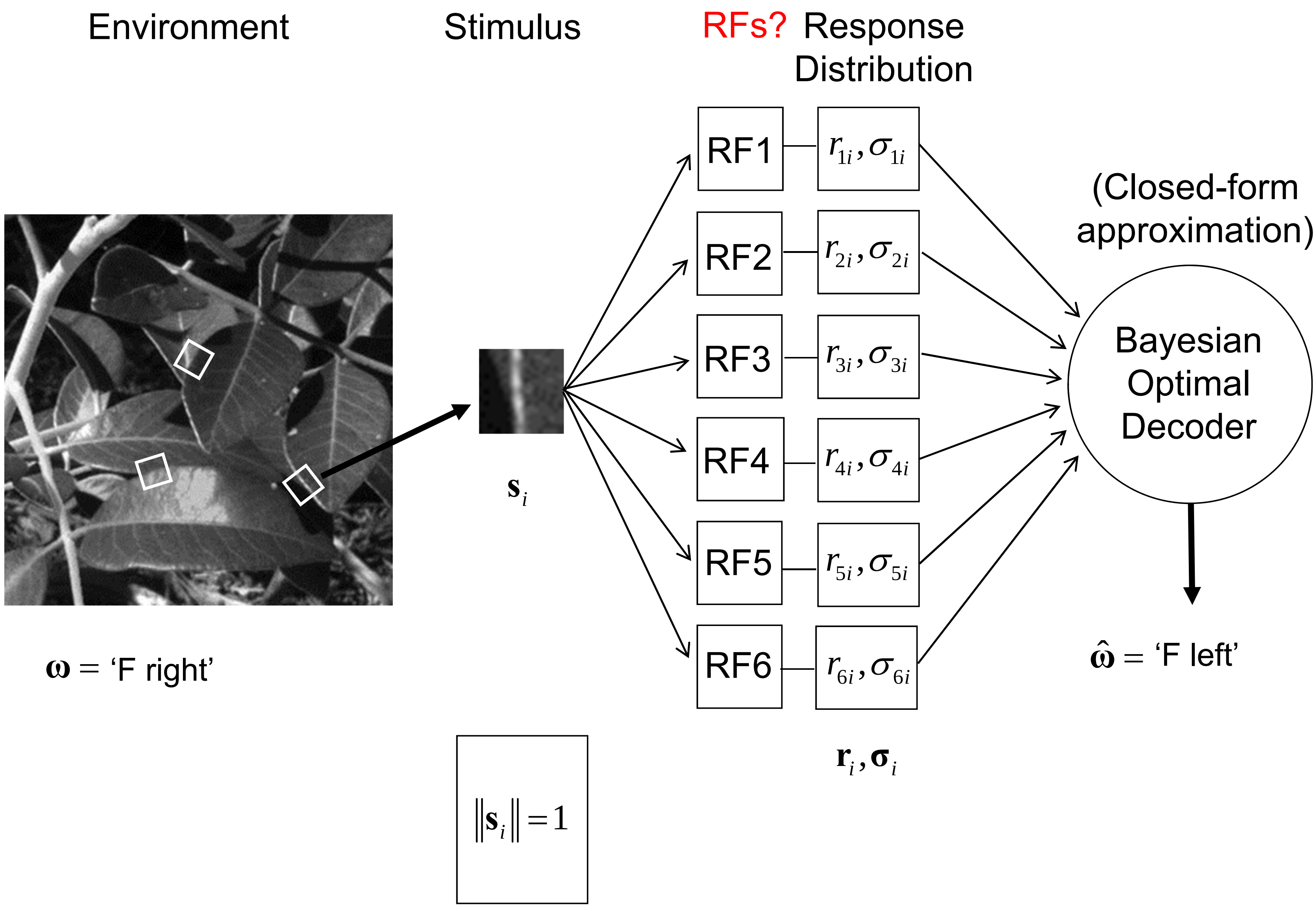
Which side of a surface boundary belongs to the foreground surface?

Sampled from CPS database of segmented close-up foliage images

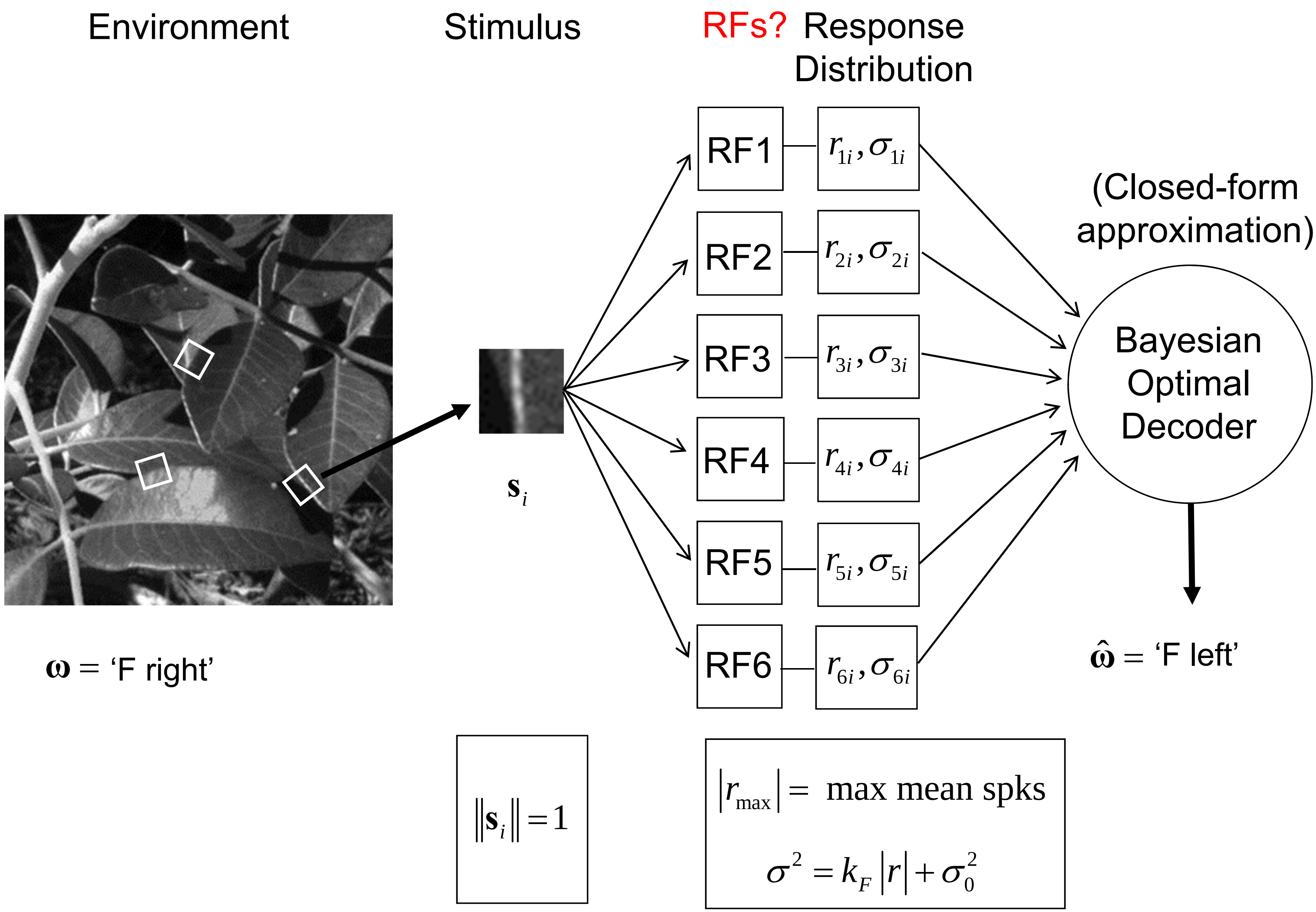
Finding optimal encoders (AMA)



Closed-form approximation for decoder accuracy



Environment
Stimulus
RFs?
Response Distribution
RF1
RF2
RF3
RF4
RF5
RF6
r_{1i}, σ_{1i}
r_{2i}, σ_{2i}
r_{3i}, σ_{3i}
r_{4i}, σ_{4i}
r_{5i}, σ_{5i}
r_{6i}, σ_{6i}
(Closed-form approximation)
Bayesian Optimal Decoder
$\mathbf{s}_i$
$\boldsymbol{\omega}$ = 'F right'
$\hat{\boldsymbol{\omega}}$ = 'F left'
$\mathbf{r}_i, \boldsymbol{\sigma}_i$
$\|\mathbf{s}_i\| = 1$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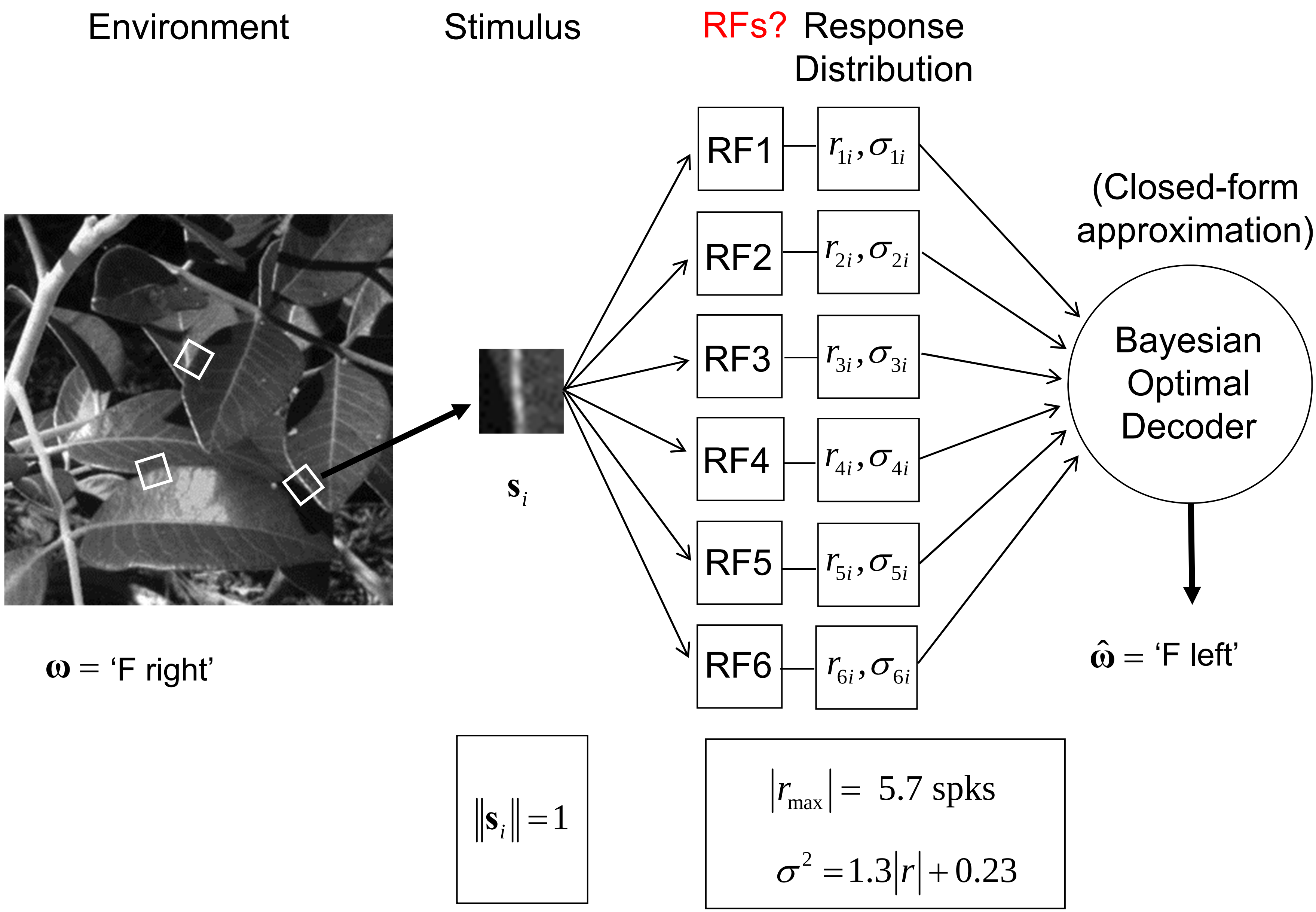
Bayesian Optimal Decoder
$\hat{\boldsymbol{\omega}}$ = 'F left'
$\|\mathbf{s}_i\| = 1$
$|r_{\max}| =$ max mean spks
$\sigma^2 = k_F |r| + \sigma_0^2$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Bayesian Optimal Decoder
$\mathbf{s}_i$
$\boldsymbol{\omega}$ = 'F right'
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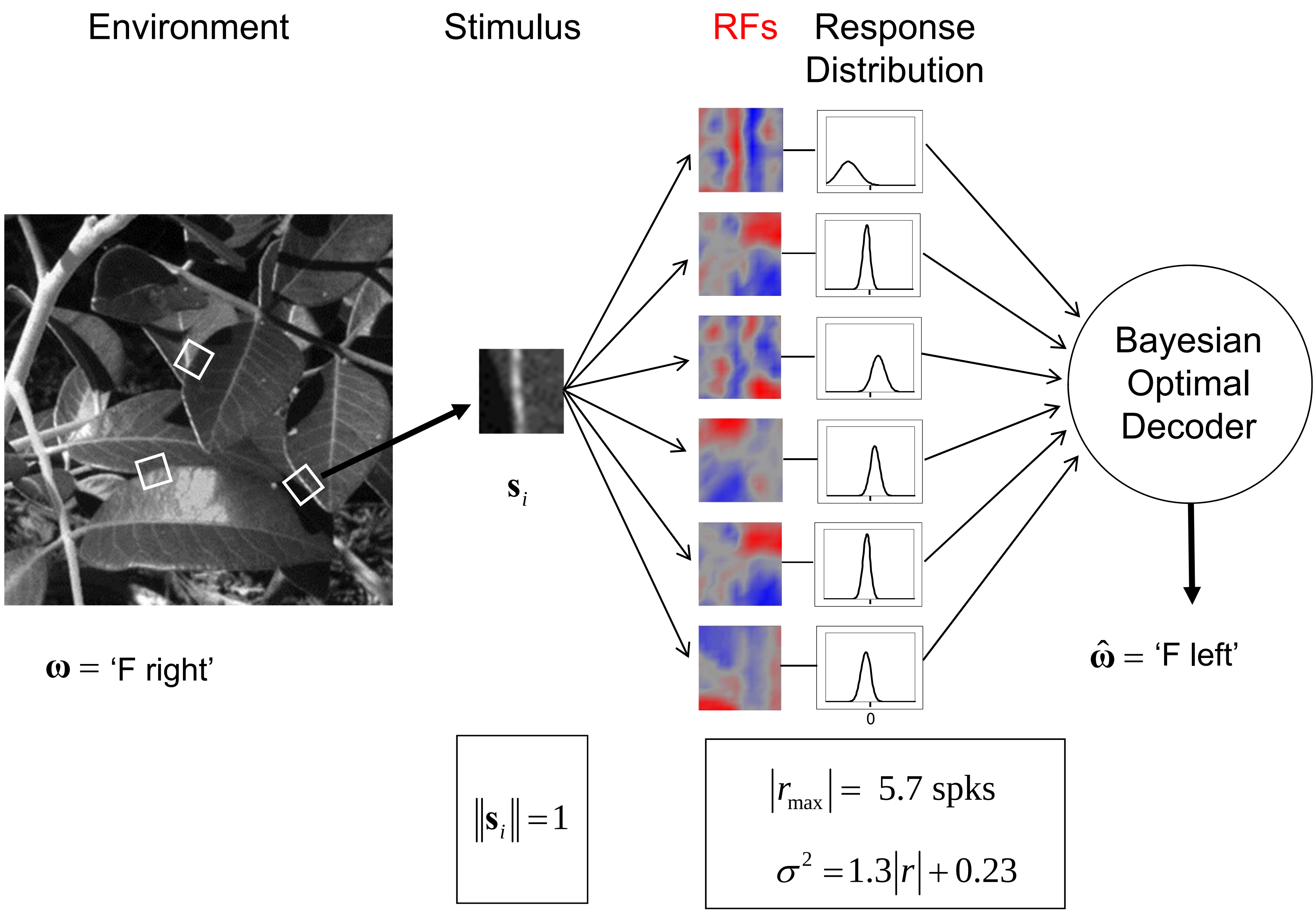
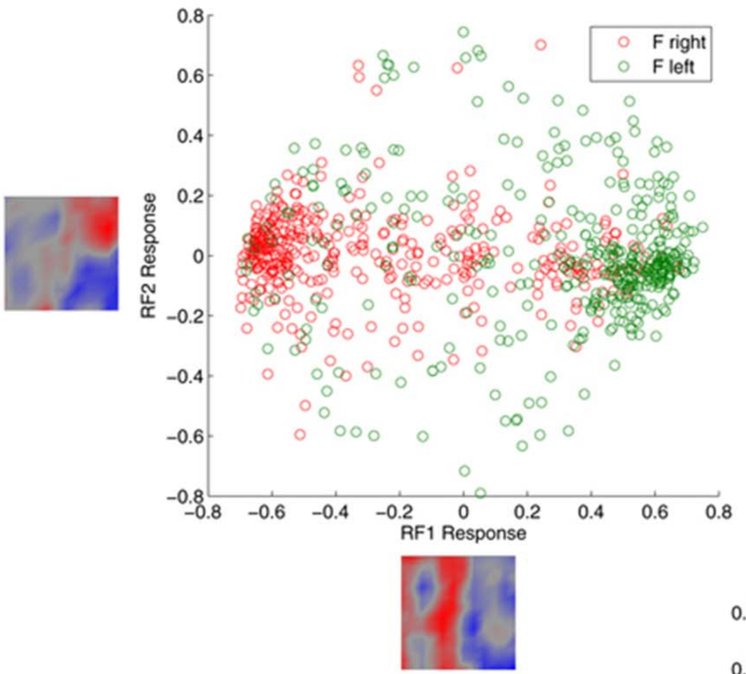
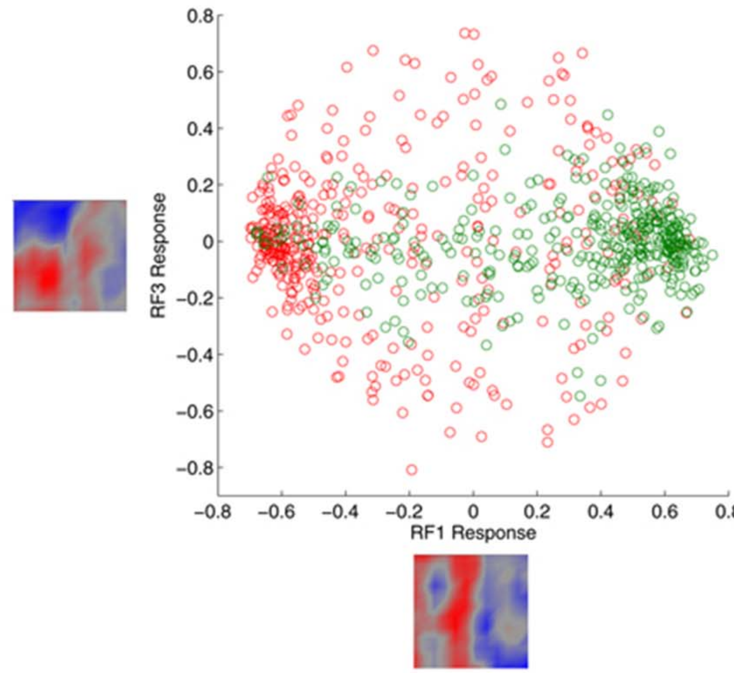
$\|\mathbf{s}_i\| = 1$
$|r_{\max}| = 5.7$ spks
$\sigma^2 = 1.3|r| + 0.23$

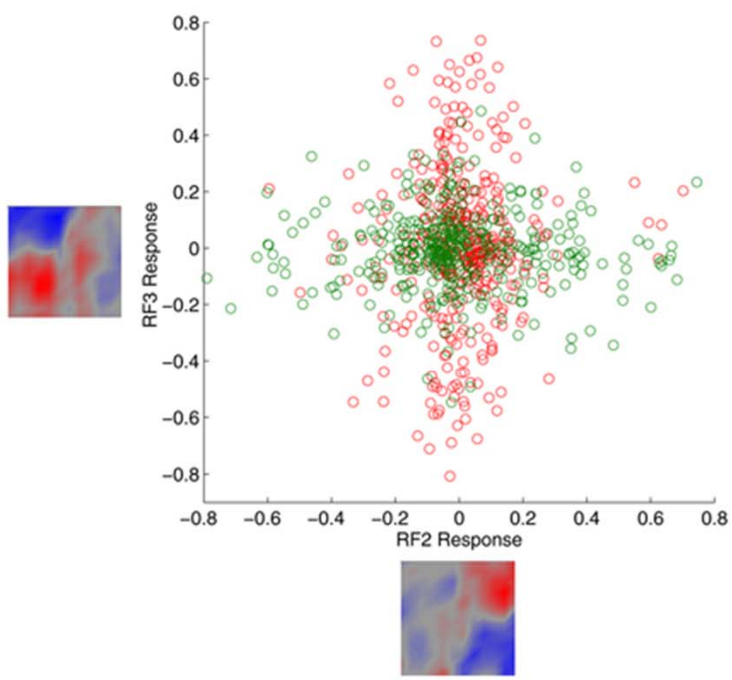


Environment
Stimulus
RFs
Response Distribution
Bayesian Optimal Decoder
$\mathbf{s}_i$
0
$\boldsymbol{\omega}$ = 'F right'
$\hat{\boldsymbol{\omega}}$ = 'F left'
$\|\mathbf{s}_i\| = 1$
$|r_{\max}| = 5.7$ spks
$\sigma^2 = 1.3|r| + 0.23$

RF responses to natural image patches (no neural noise)





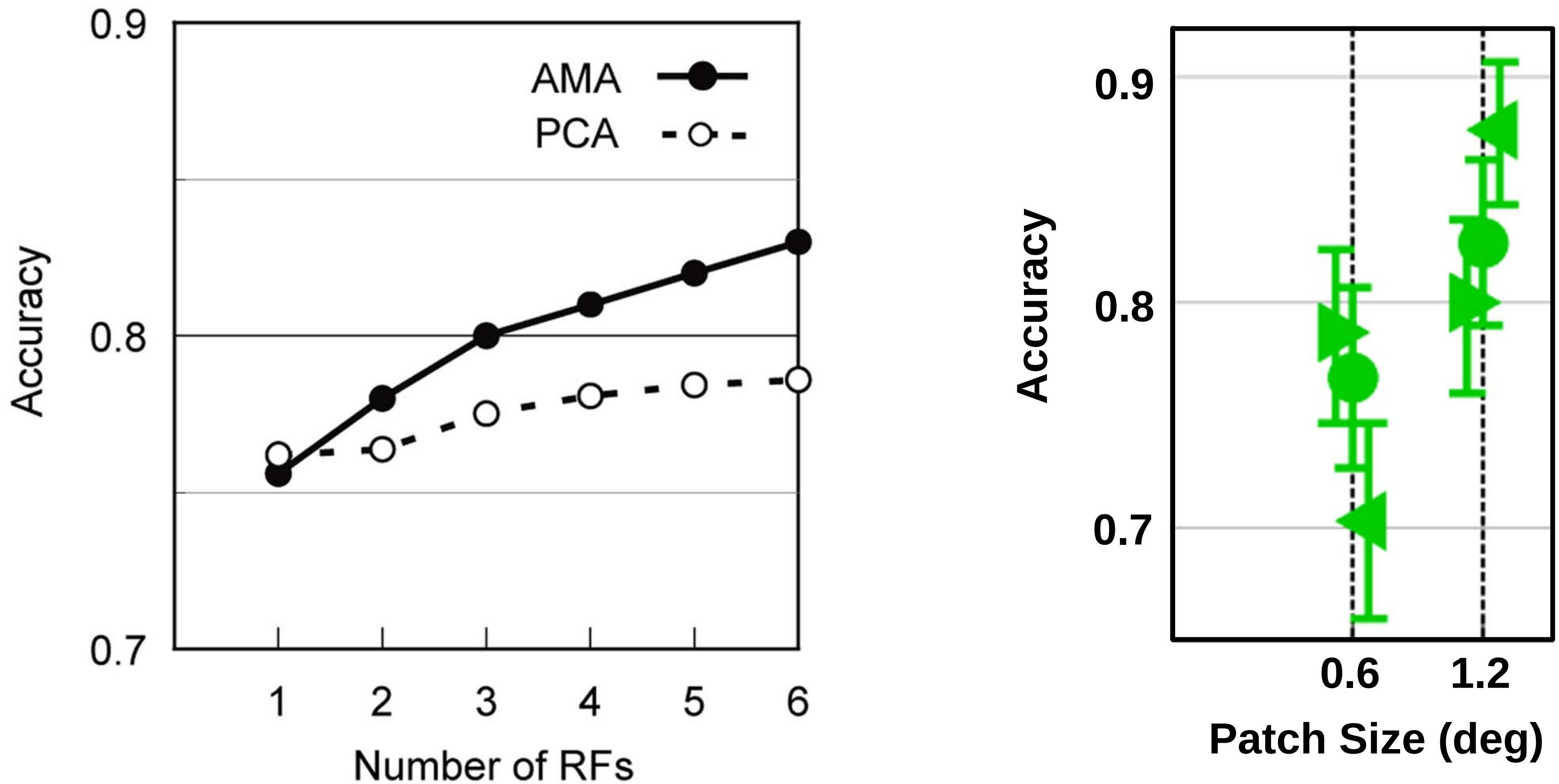


measure likelihoods

$$p\left(\mathbf{R}\middle|F\ left\right)$$

$$p\left(\mathbf{R}\middle|F\ right\right)$$

Identification accuracy



response

$$\text{'}\mathit{left}\text{'} \text{ if } p\left(F\ \mathit{left} \middle| \mathbf{R}\right) > p\left(F\ \mathit{right} \middle| \mathbf{R}\right) \text{ else '}\mathit{right}\text{'}$$

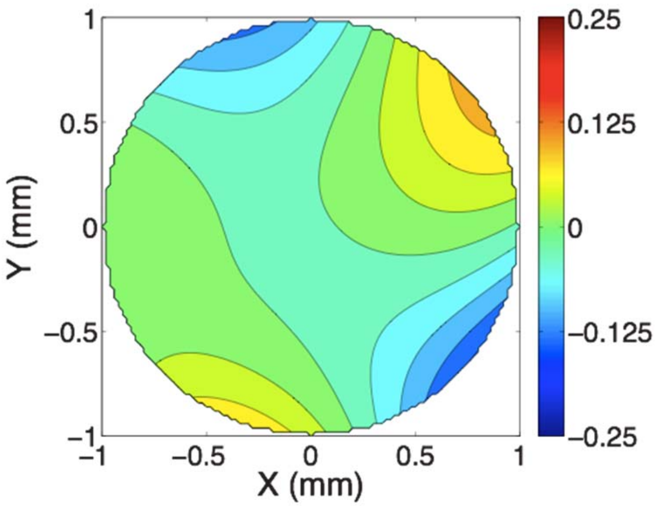
Defocus estimation (J. Burge)

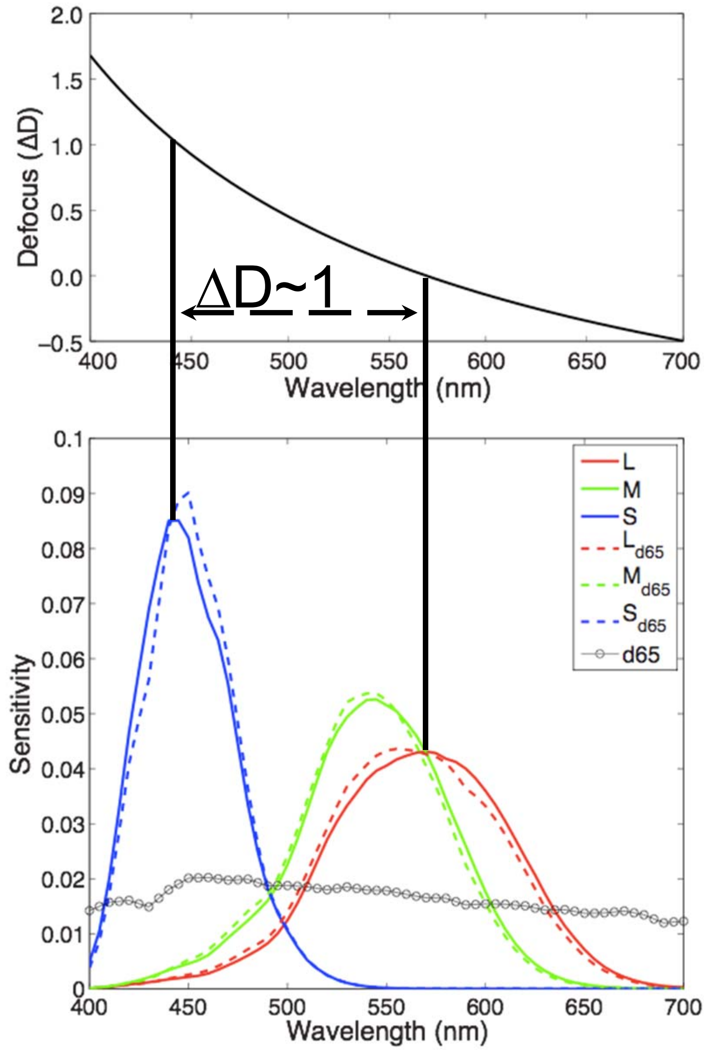
What is the level of defocus at each image location?

Characterize Optics and Receptor Sampling

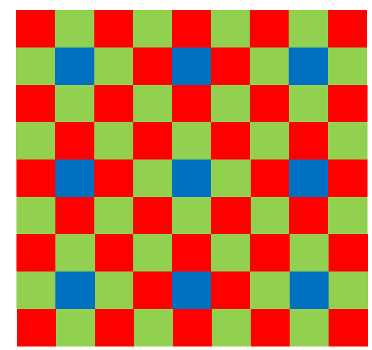
chromatic aberrations

diffraction +
monochromatic
aberrations



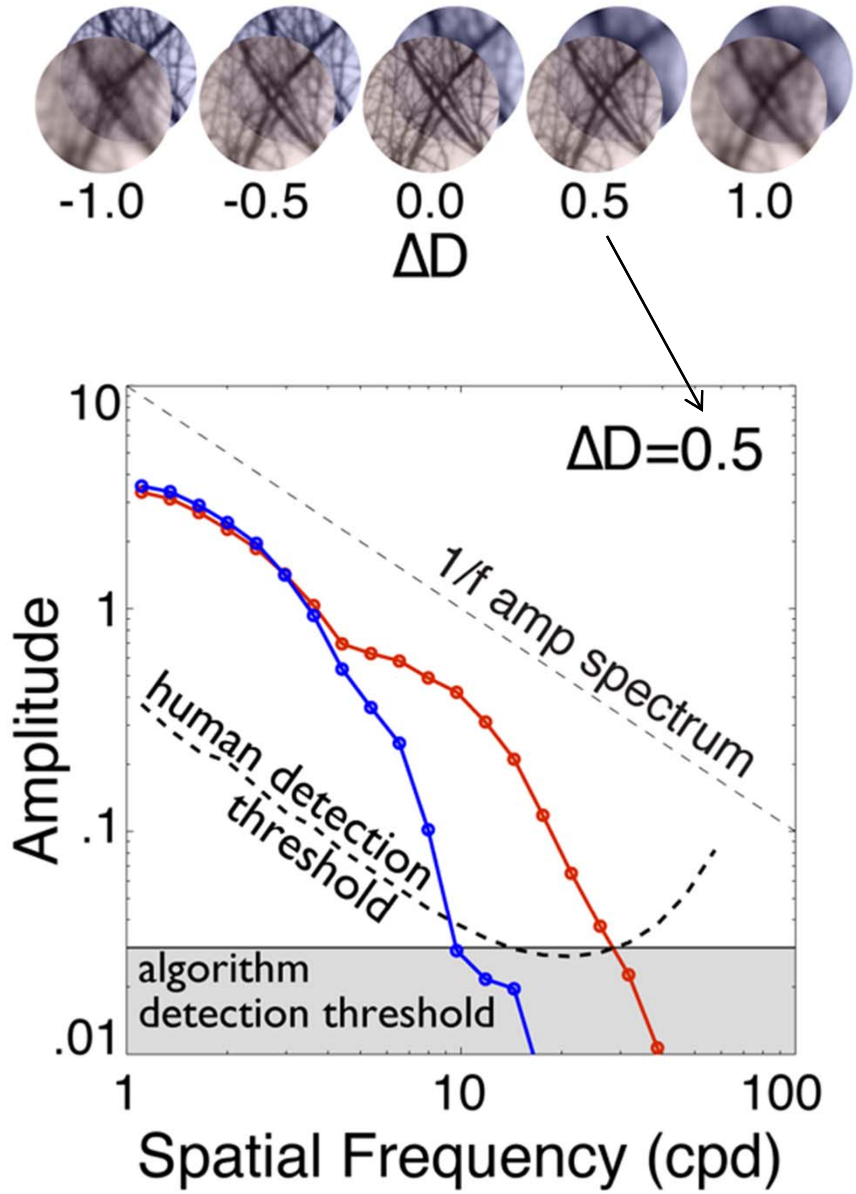


photoreceptor
sampling



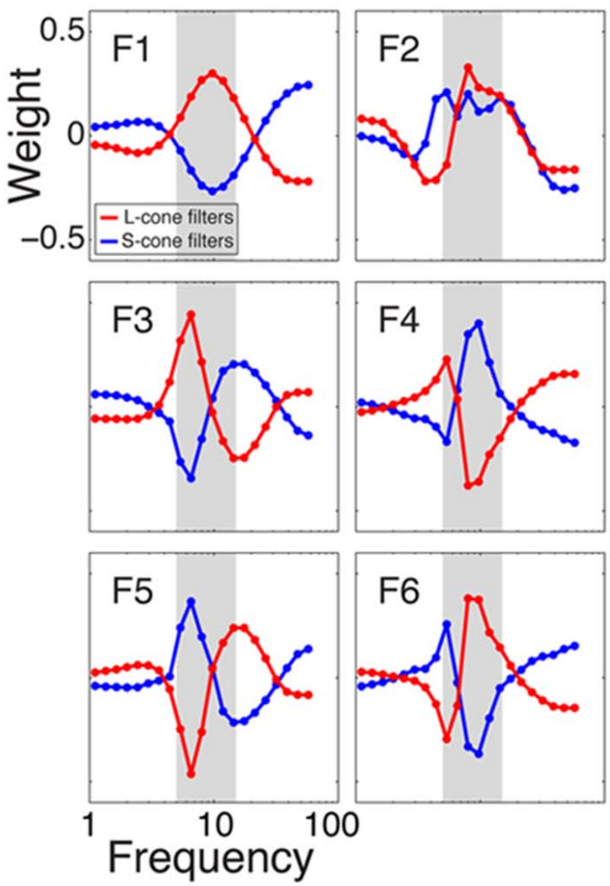
Amplitude spectra of cone responses to image patches

sample of the 400 training patches

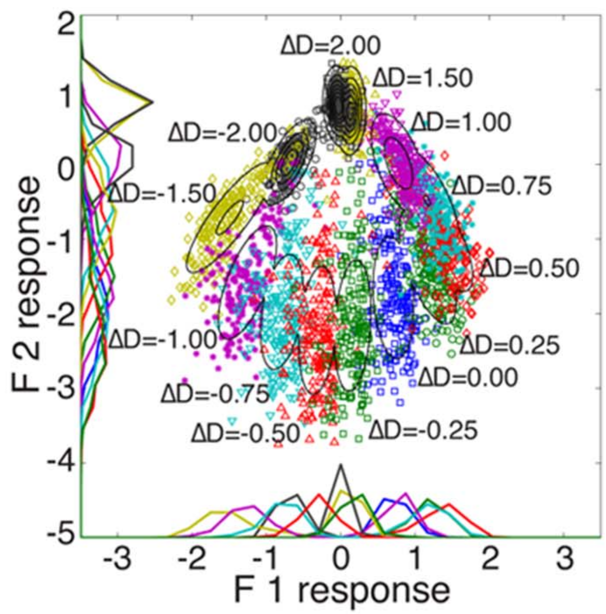


Find optimal RFs and determine performance

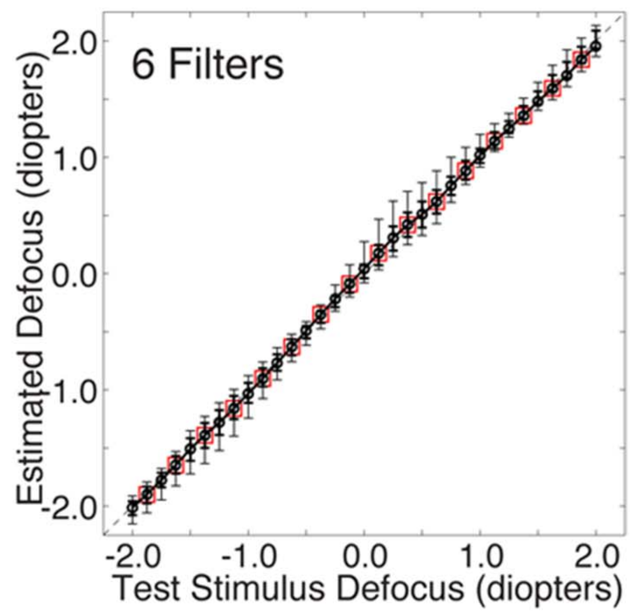
optimal RFs



responses to natural patches



estimation performance



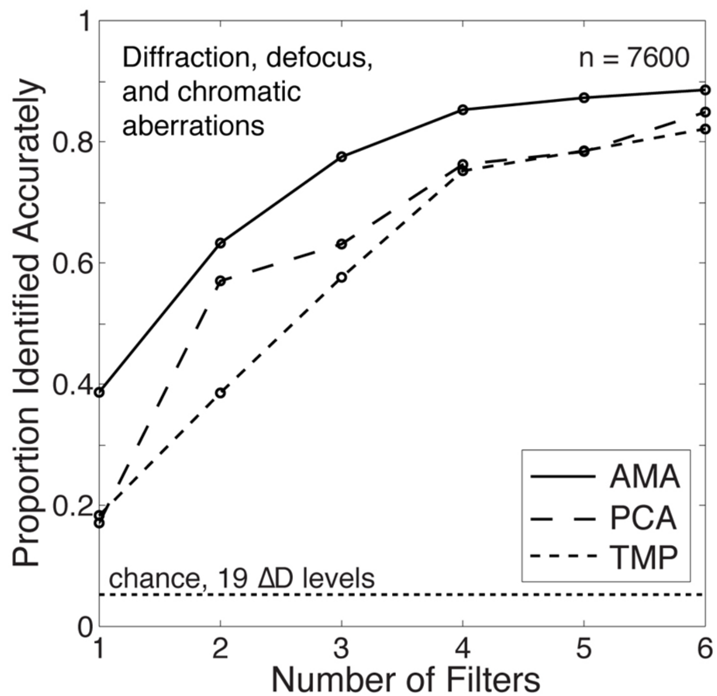
measure likelihoods

$$p\left(\mathbf{R} \middle| \Delta D\right)$$

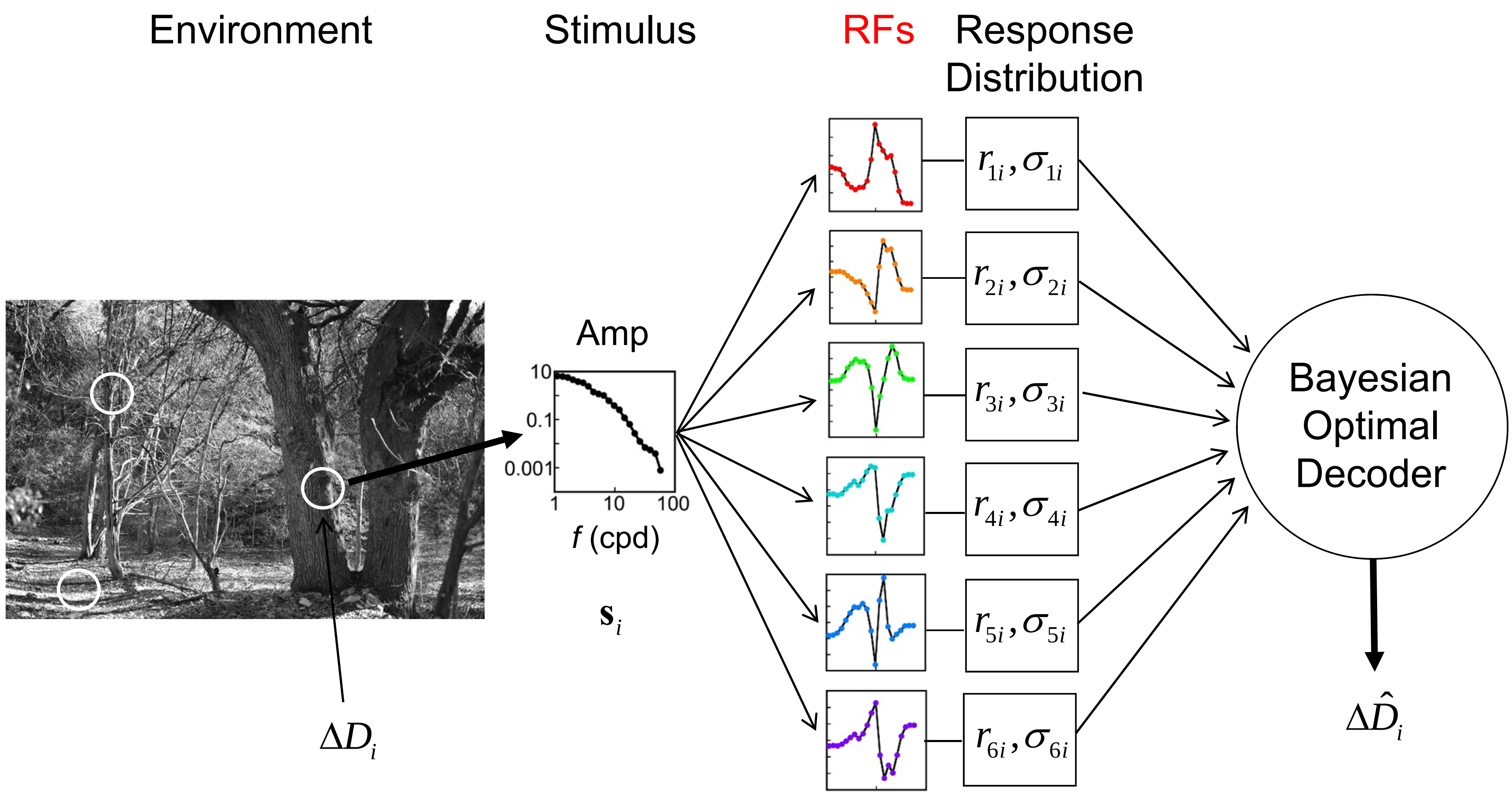
MMSE estimate

$$\Delta\hat{D} = \sum_{i=1}^{n} \Delta D_i \, p\left(\Delta D_i \middle| \mathbf{R}\right)$$

Performance comparisons



Finding optimal encoders (AMA)



$$|r_{\max}| = \text{max mean spks}$$

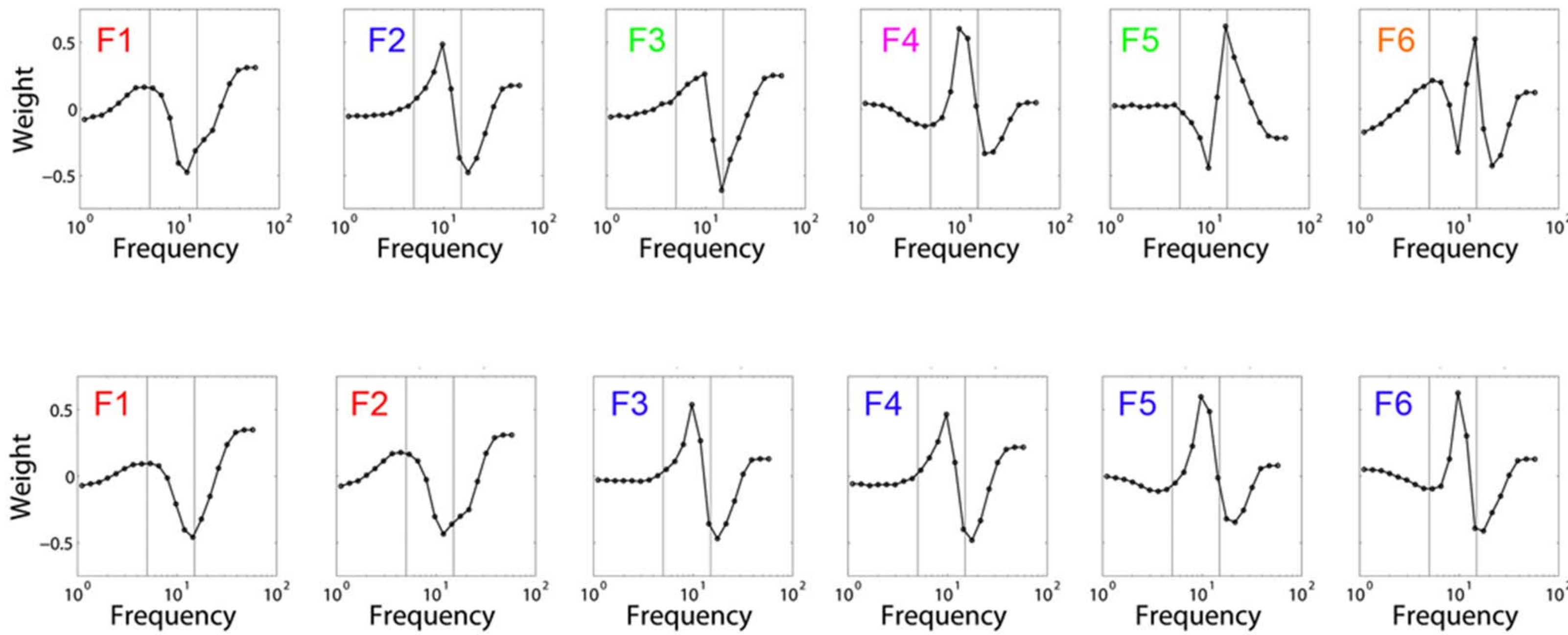
$$\sigma^2 = k_F |r| + \sigma_0^2$$

Effect of varying the Fano factor

Fano Factor k_F

0.01

1.0



$$r_{\max} = 5.7$$

$$\sigma_0^2 = 0.23$$

Summary and conclusions

1. Propose AMA to find optimal RFs for specific natural tasks
2. Method depends on explicitly representing neural noise
3. RFs for foreground identification task extract edge and T-junction-like structure
4. RFs for defocus estimation task consist of smooth spatio-chromatic filters in 5-15 cpd range, similar to those reported early visual cortex
5. Performance of RFs on natural stimuli is excellent using Gaussian likelihood distributions
6. As neural noise increases the correlation between optimal RFs increases (redundancy increases)
7. The optimal RF shapes are robust to variation in neural noise
8. Provides principled hypotheses for encoding and decoding in natural tasks given natural scene statistics and biological constraints

Collaborators

Optimal encoding & foreground identification

Jiri Najemnik

David Ing

Geisler et al. (2009) *Journal of Vision* 9(13):17, 1-16.

Defocus estimation

Johannes Burge