System Identification Using Machine Learning Methods

Felix A. Wichmann

Eberhard Karls Universität Tübingen

Faculty of Science
Computer Science Department
Neural Information Processing Group

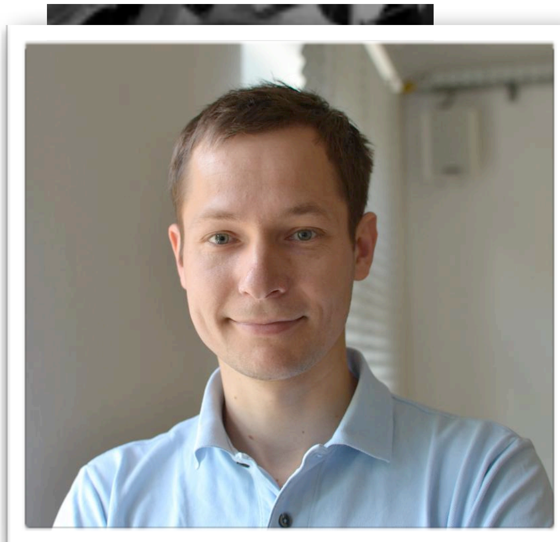
Bernstein Center for
Computational Neuroscience
Tübingen

Max-Planck-Gesellschaft

Max Planck Institute for Intelligent Systems
Empirical Inference Department

Werner Reichardt
Centre for Integrative
Neuroscience

Former lab @ TU Berlin:
Simon Barthelmé, Marianne Maertens, Ingo Fründ, Hannah Dold & Vinzenz Schönfelder



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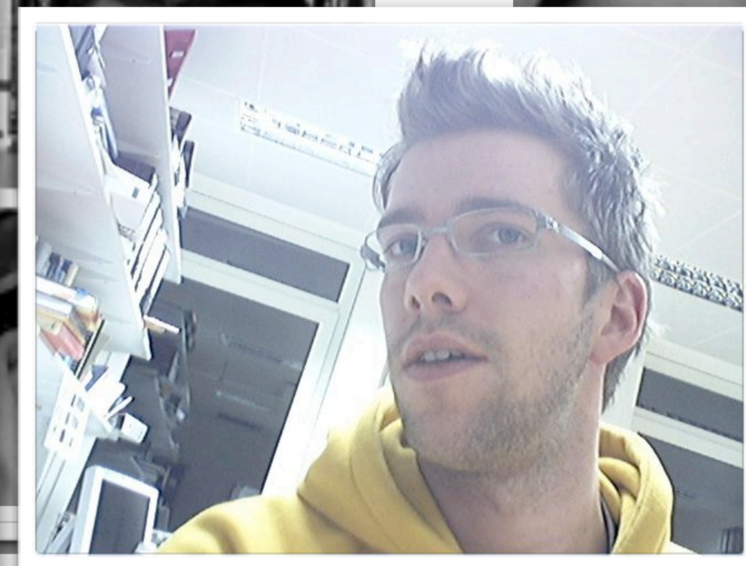
Tübingen



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Microsoft (Seattle)

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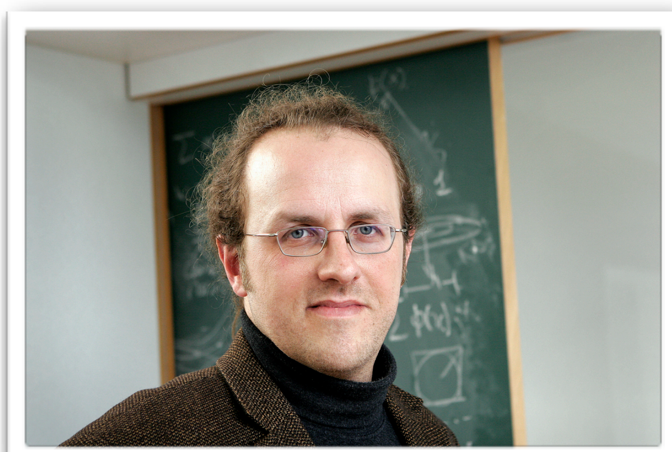

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How many animals?

Animal detection in natural scenes: Critical features revisited

Felix A. Wichmann
Modelling of Cognitive Processes, Berlin Institute of Technology & Bernstein Center for Computational Neuroscience Berlin, Berlin, Germany

Jan Drewes
Abteilung Allgemeine Psychologie, Universität Giessen, Giessen, Germany

Pedro Rosas
Centro de Neurociencias Integradas, Facultad de Medicina, Universidad de Chile, Santiago, Chile

Karl R. Gegenfurtner
Abteilung Allgemeine Psychologie, Universität Giessen, Giessen, Germany

S. J. Thorpe, D. Fize, and C. Marlot (1996) showed how rapidly observers can detect animals in images of natural scenes, but it is still unclear which image features support this rapid detection. A. B. Torralba and A. Oliva (2003) suggested that a simple image statistic based on the power spectrum allows the absence or presence of objects in natural scenes to be predicted. We tested whether human observers make use of power spectral differences between image categories when detecting animals in natural scenes. In Experiments 1 and 2 we found performance to be essentially independent of the power spectrum. Computational analysis revealed that the ease of classification correlates with the proposed spectral cue without being caused by it. This result is consistent with the hypothesis that in commercial stock photo databases a majority of animal images are pre-segmented from the background by the photographers and this pre-segmentation causes the power spectral differences between image categories and may, furthermore, help rapid animal detection. Data from a third experiment are consistent with this hypothesis. Together, our results make it exceedingly unlikely that human observers make use of power spectral differences between animal- and no-animal images during rapid animal detection. In addition, our results point to potential confounds in the commercially available “natural image” databases whose statistics may be less natural than commonly presumed.

Keywords: rapid animal detection, natural scenes, power spectrum, amplitude spectrum, scene gist, local features, natural image statistics

Citation: Wichmann, F. A., Drewes, J., Rosas, P., & Gegenfurtner, K. R. (2010). Animal detection in natural scenes: Critical features revisited. *Journal of Vision, 10*(4):6, 1–27, http://journalofvision.org/10/4/6/, doi:10.1167/10.4.6.

Introduction

The classification of objects in complex, natural scenes is considered a difficult task—certainly from a computational point of view as no computer vision algorithm as yet exists that is able to reliably signal the presence or absence of arbitrary object classes in images of natural scenes. Work by Thorpe, Fize, and Marlot (1996) demonstrated, however, that humans are capable of detecting animals within novel natural scenes with remarkable speed and accuracy: In a go/no-go animal categorization task images were only briefly presented (20 msec) and already 150 msec after stimulus onset the no-go trials showed a distinct frontal negativity in the event related potentials (ERPs). Median reaction times (RTs) showed a speed-accuracy trade-off but for RTs as short as 390 msec observers were already approx. 92% correct (increasing to 97% correct for 570 msec).

This basic result—ultra rapid and accurate animal detection in natural scenes—has been replicated reliably many times: in non-human primates (Fabre-Thorpe, Richard, & Thorpe, 1998; Vogels, 1999a, 1999b), using gray-scale instead of color images (Delorme, Richard, & Fabre-Thorpe, 2000), using different response paradigms and modalities (yes-no or go-no-go versus forced-choice; eye movements versus button presses; e.g. Kirchner & Thorpe, 2006), and while measuring neurophysiological correlates (ERPs; Rousselet, Fabre-Thorpe, & Thorpe, 2002; Thorpe et al., 1996; MEG, Rieger, Braun, Bülthoff, & Gegenfurtner, 2005). Ultra rapid animal detection is even robust to inversion (180 deg rotation) and nearly orientation invariant (Kirchner & Thorpe, 2006; Rieger, Köchy, Schalk, Grüschow, & Heinze, 2008; Rousselet, Macé, & Fabre-Thorpe; 2003; but note that Rieger et al., 2008 found a slight performance decrement for intermediate rotation angles but none for 180 deg inversions). Finally, there are suggestions that rapid animal detection

doi: 10.1167/10.4.6 Received July 30, 2008; published April 15, 2010 ISSN 1534-7362 © ARVO

Critical Features: System Identification

“Determining the features of natural stimuli that are most useful for specific natural tasks is critical for understanding perceptual systems” (Geisler, Najemnik & Ing, *Journal of Vision*, 2009, 9(13)17: 1-16.

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Third: Show the importance of sparse regularization in a human auditory task.

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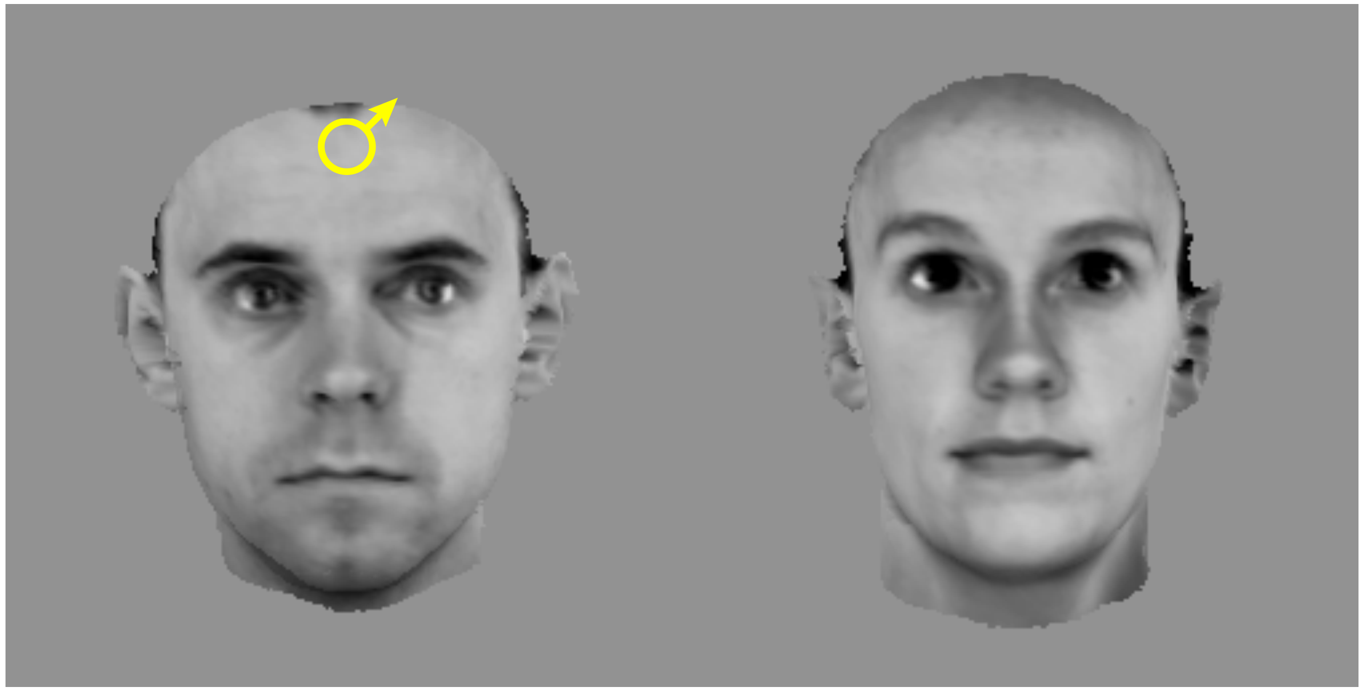
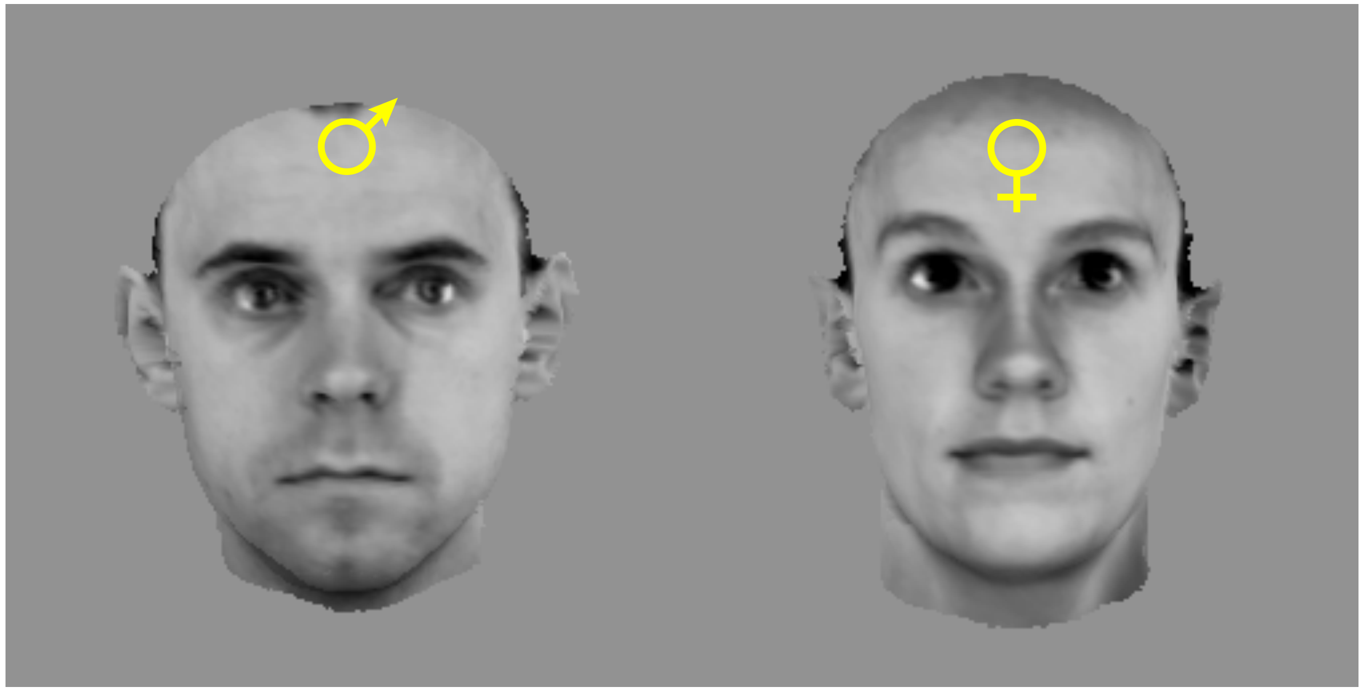
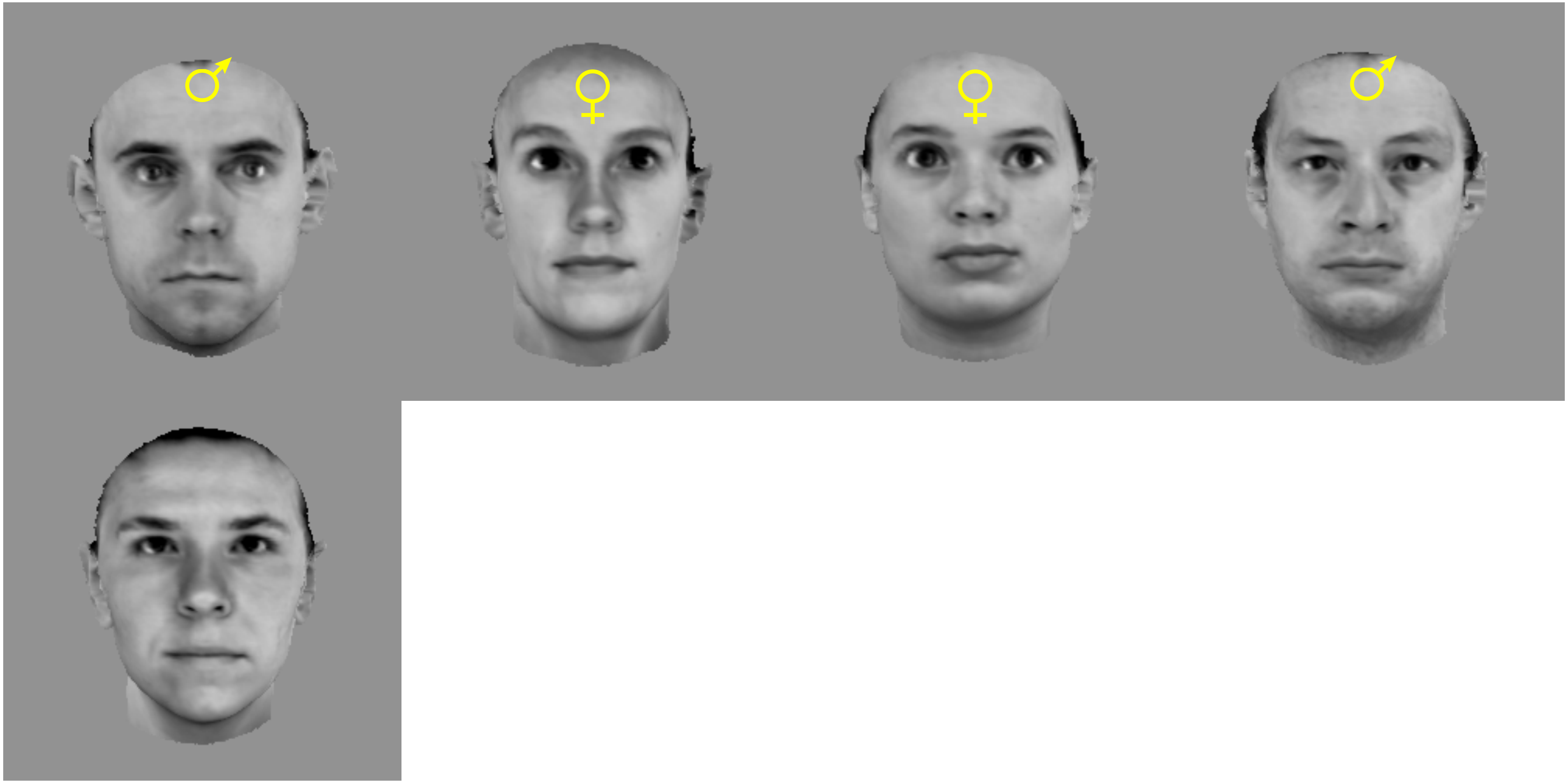
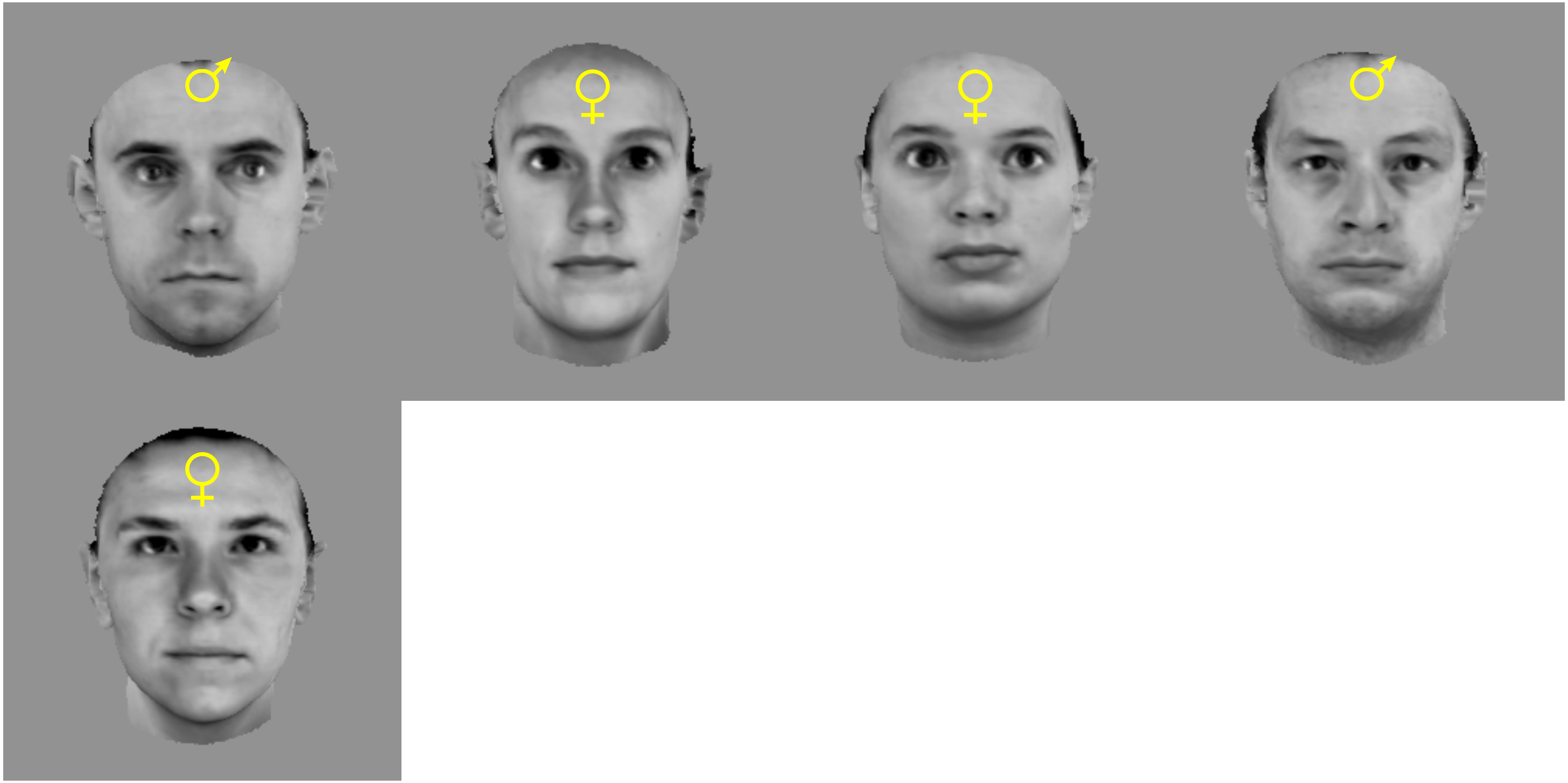
Psychophysics—really the Cognitive Neurosciences in general—seem a good application!

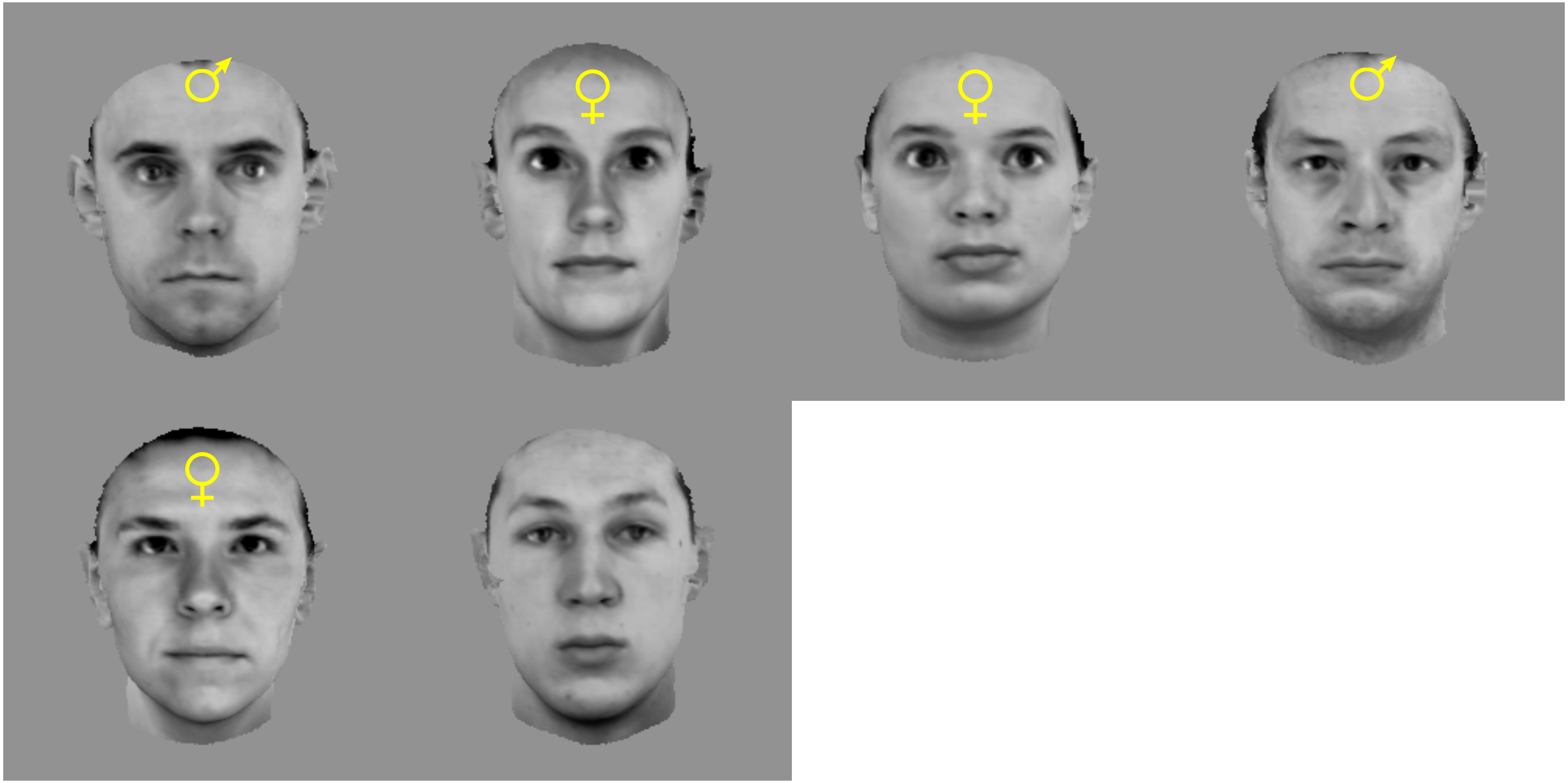
1

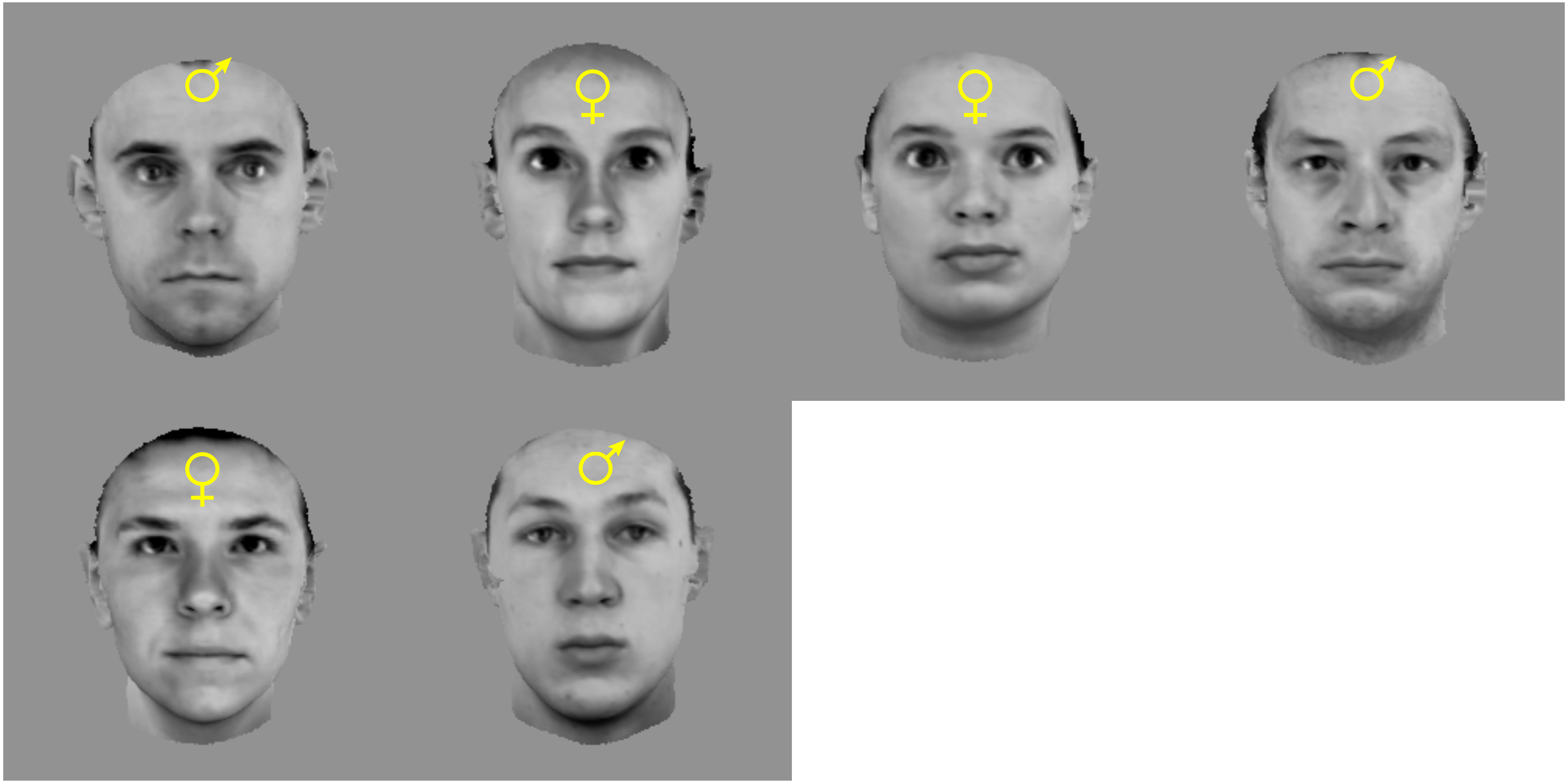


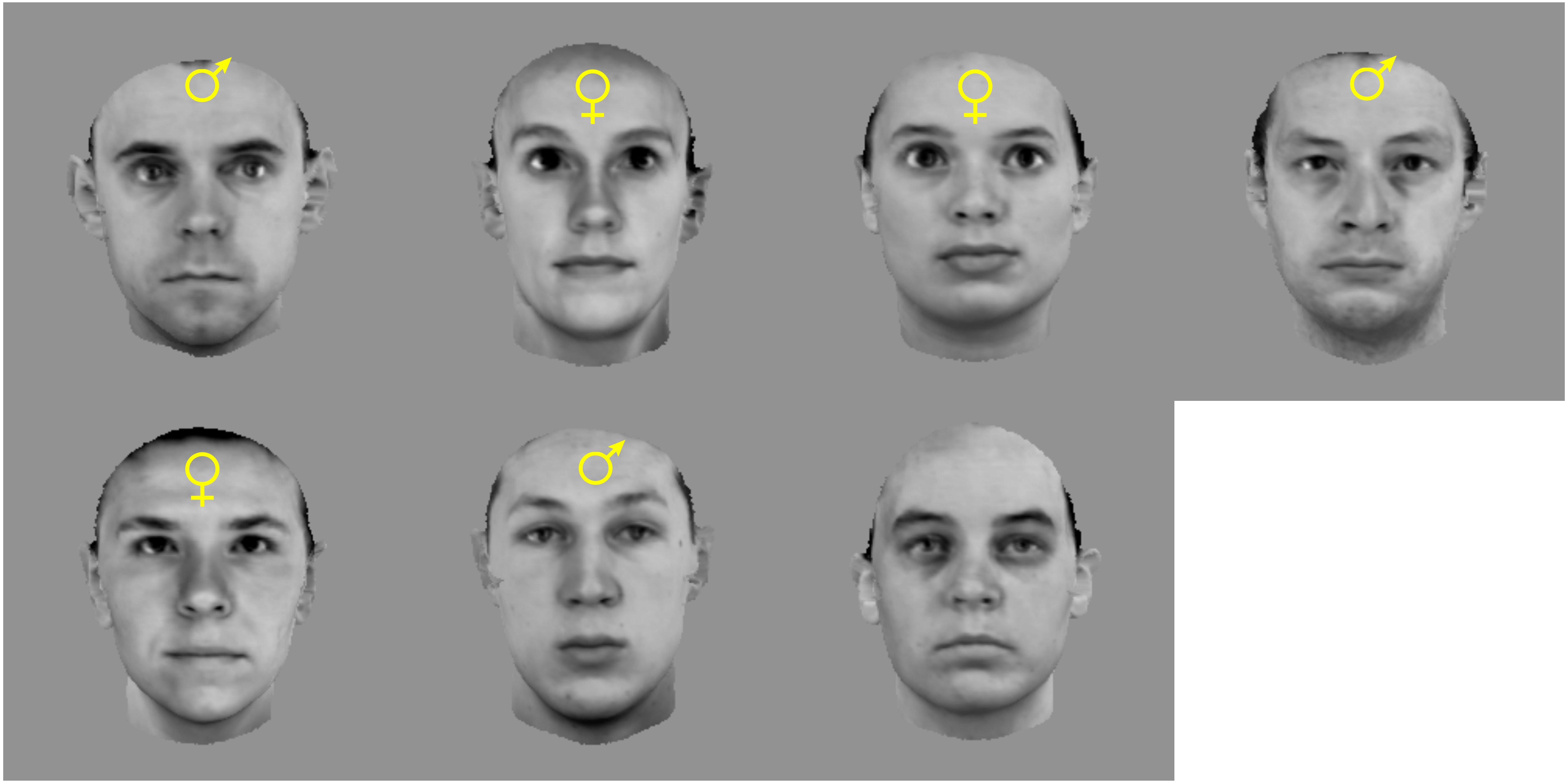


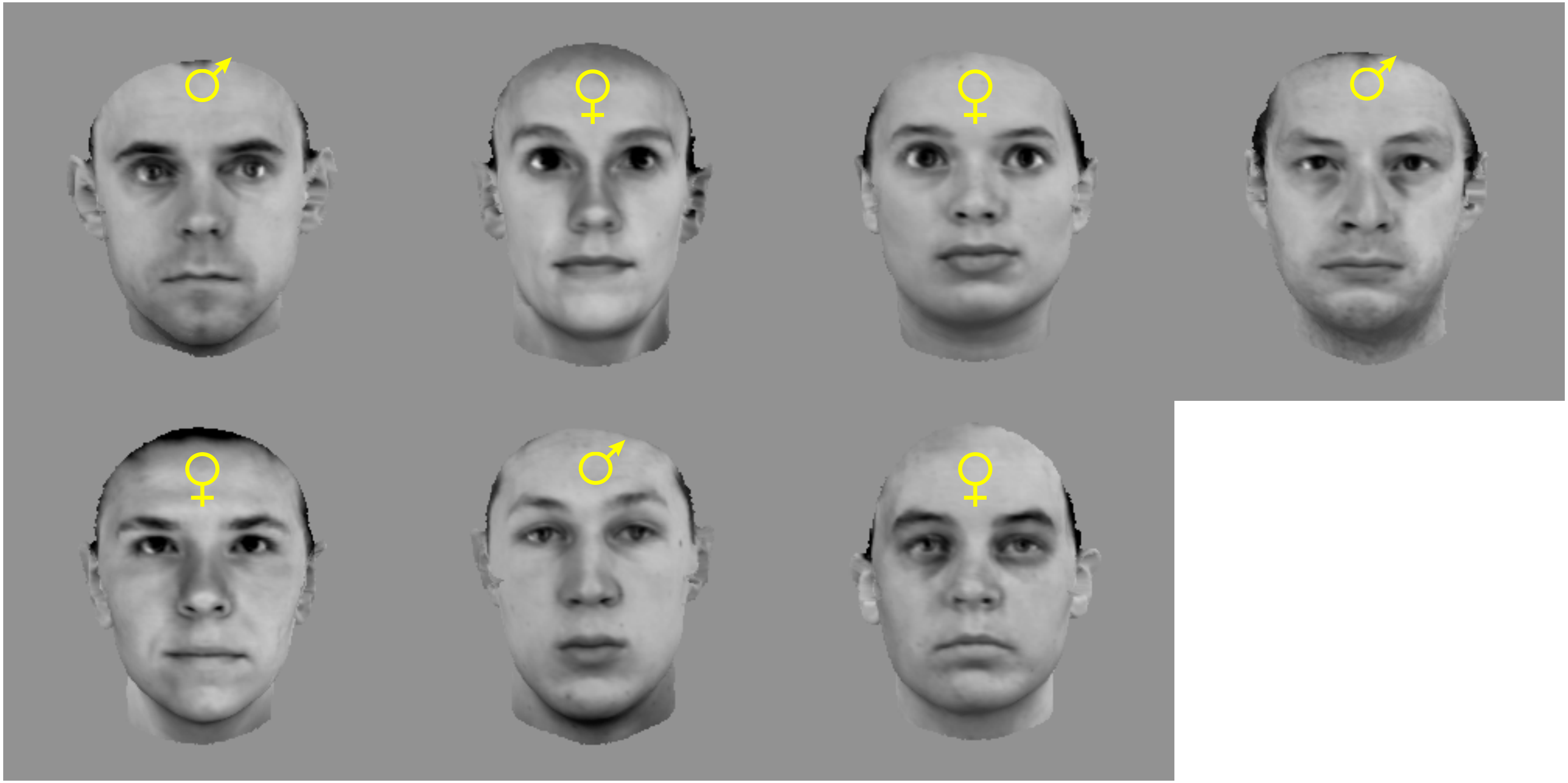


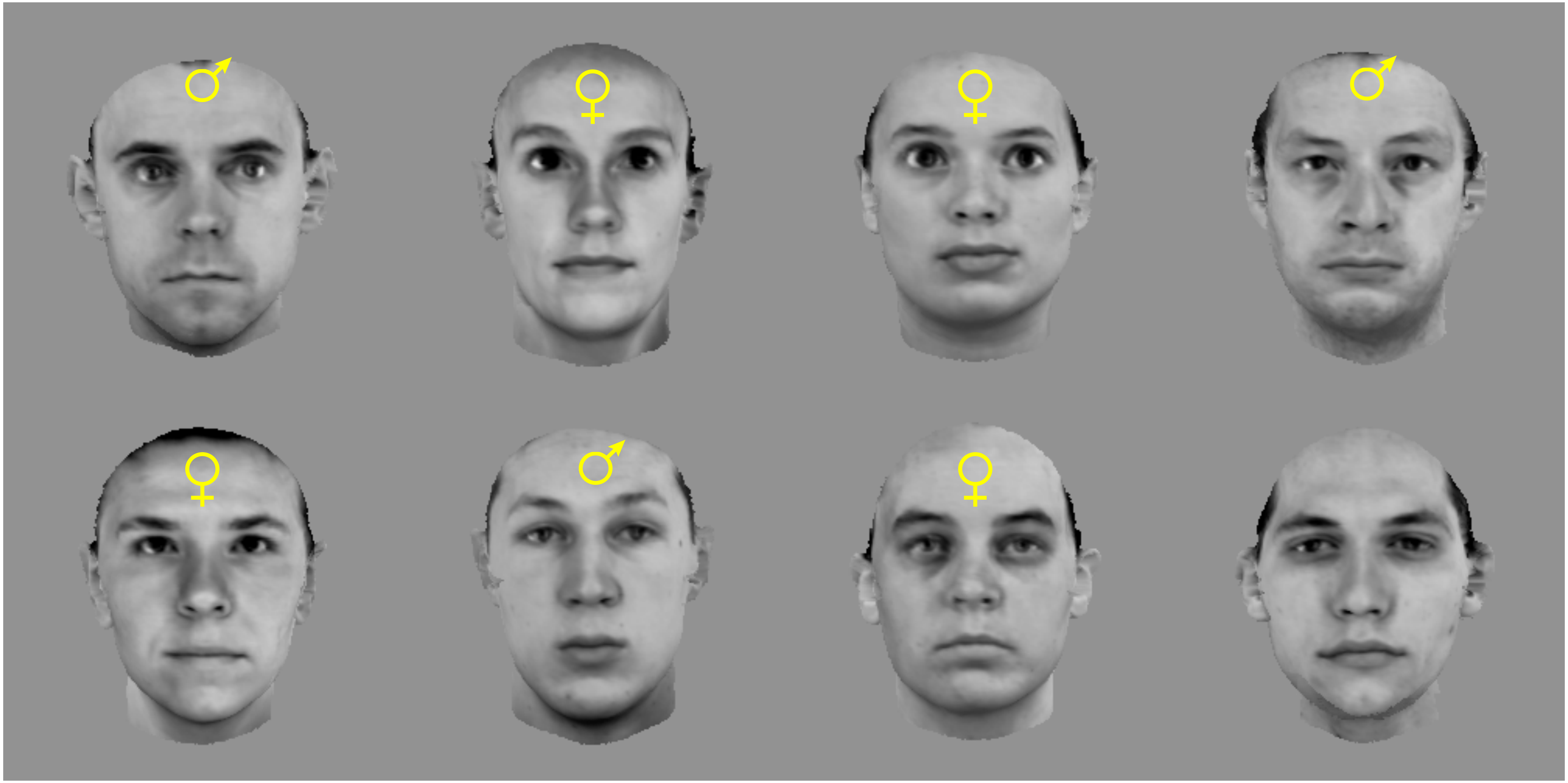


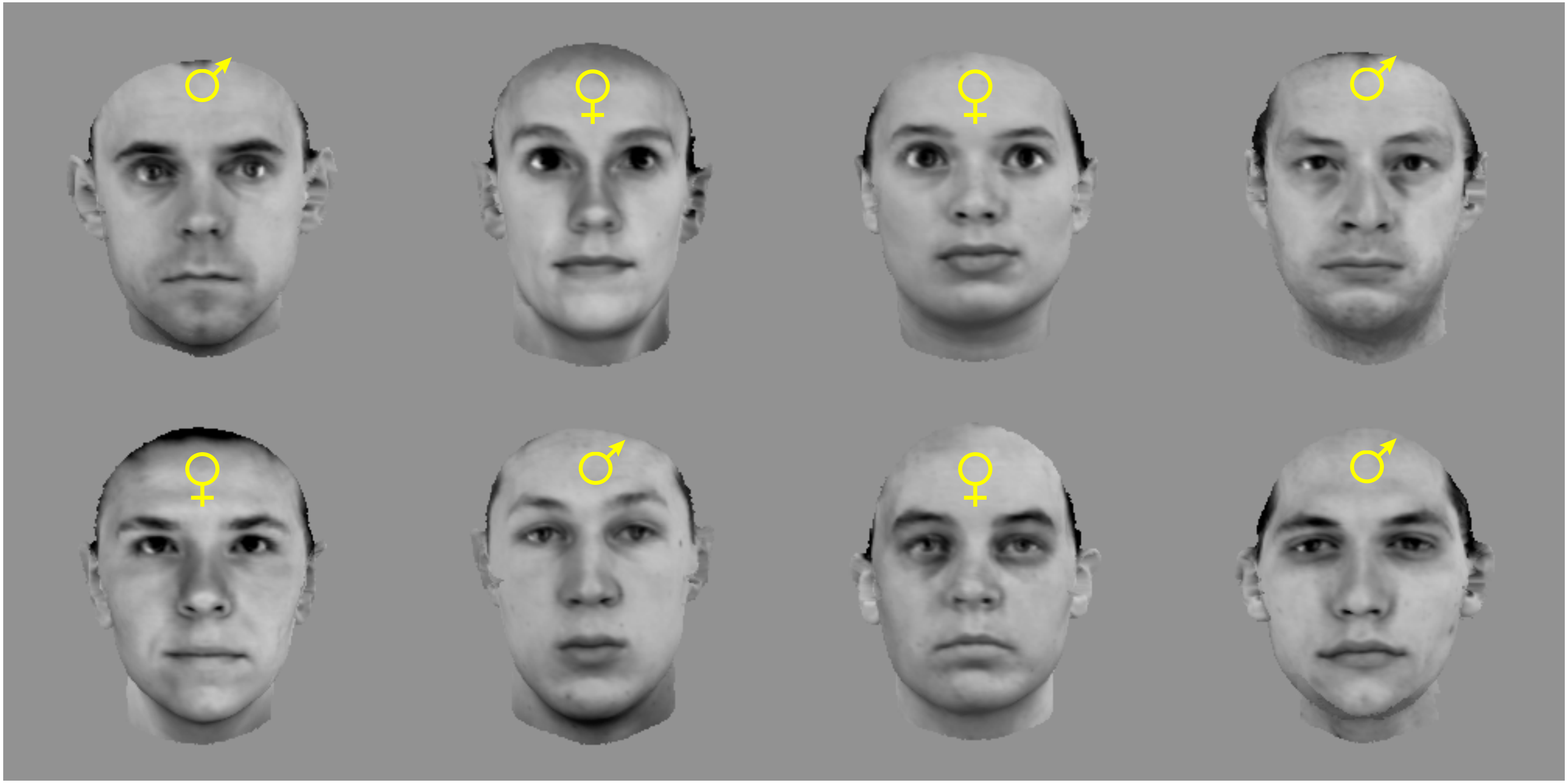




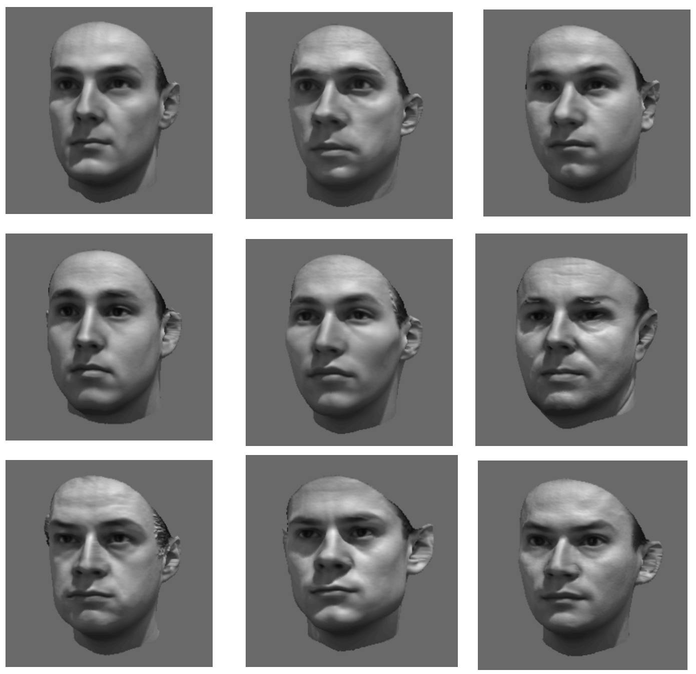


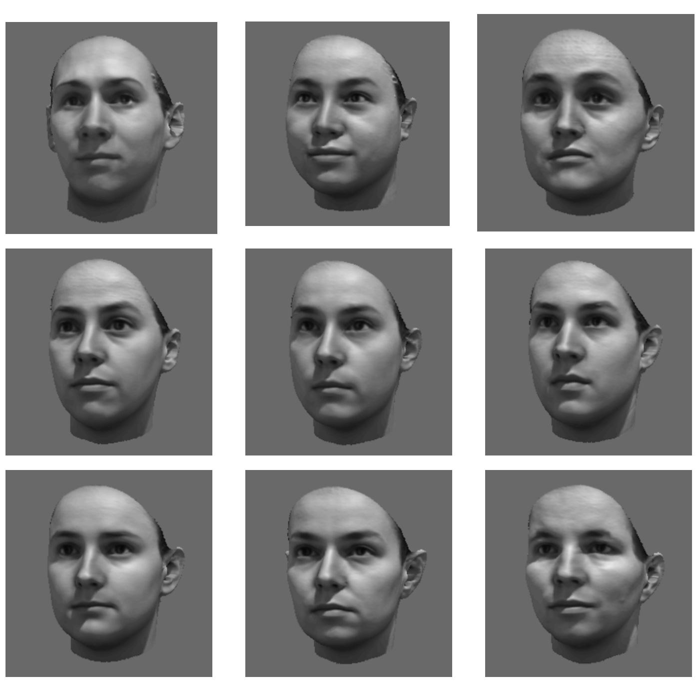






Gender Categorization of Human Faces





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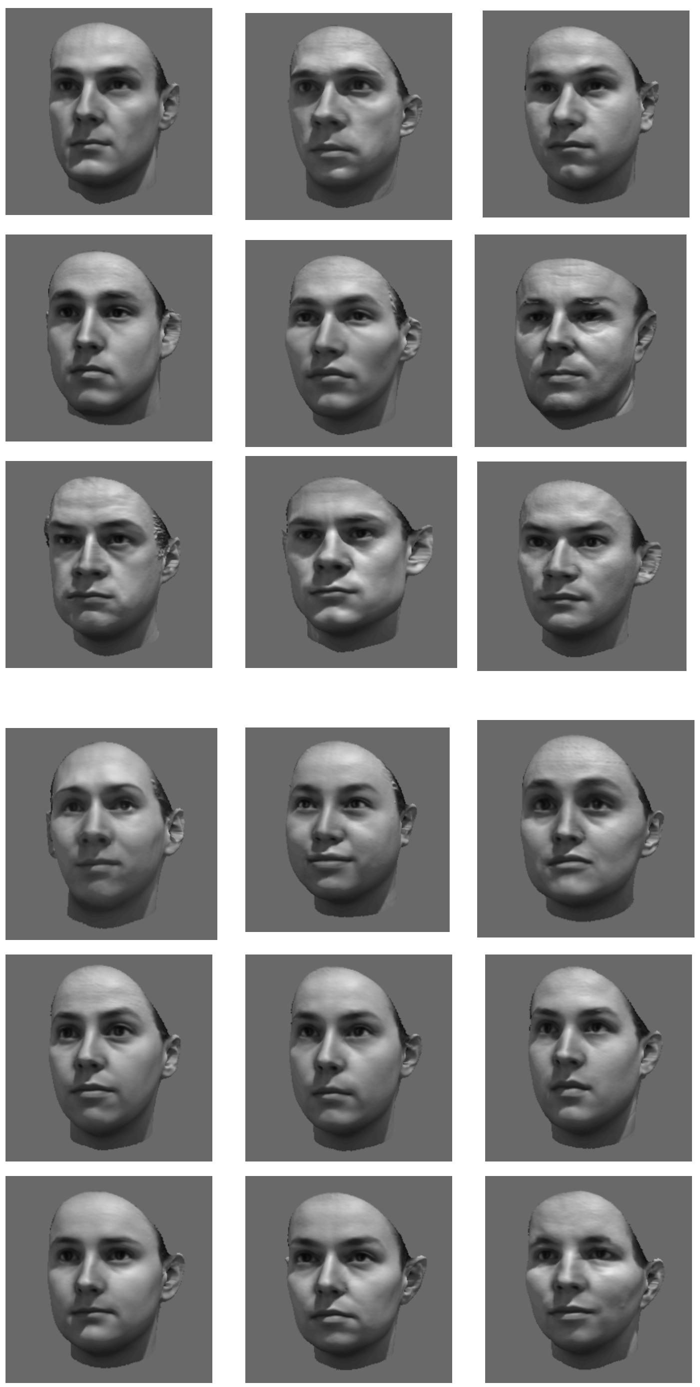

- We eliminated "obvious" cues such as
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  texture (i.e. facial hair)

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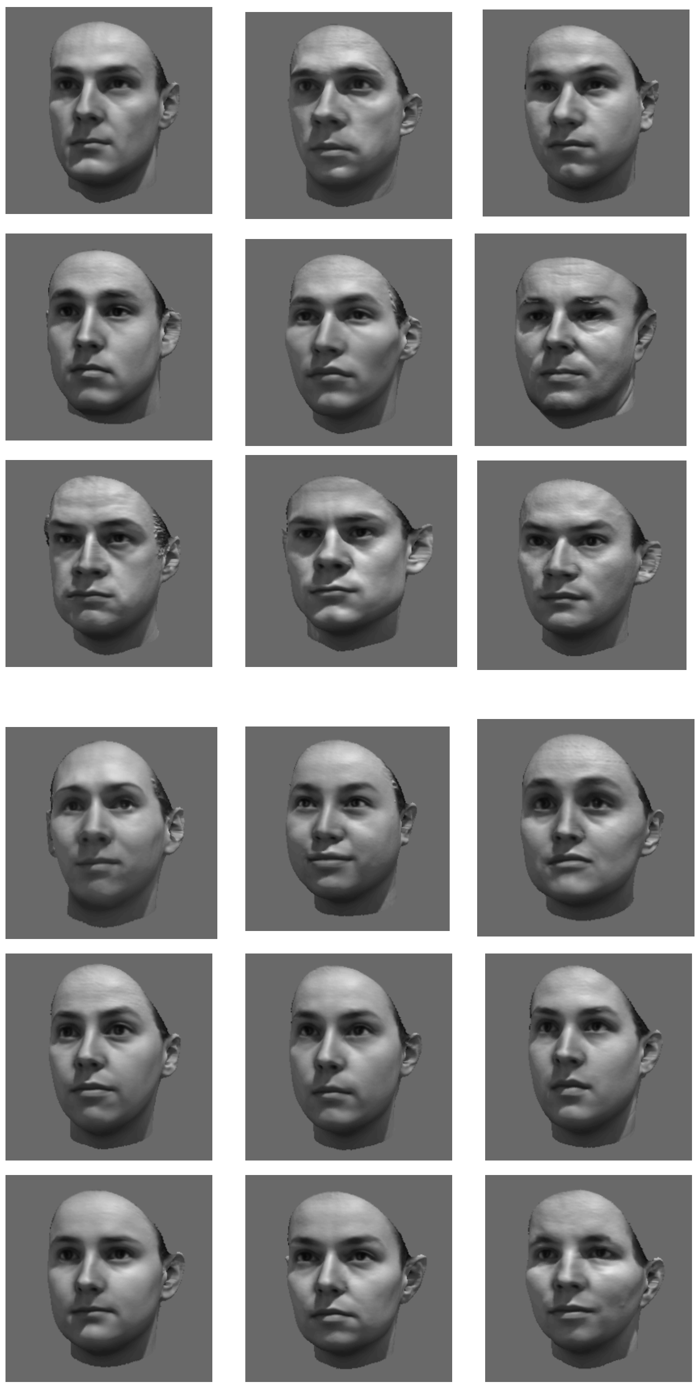

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- In what ways are (perceived) "female" faces different to "male" faces?

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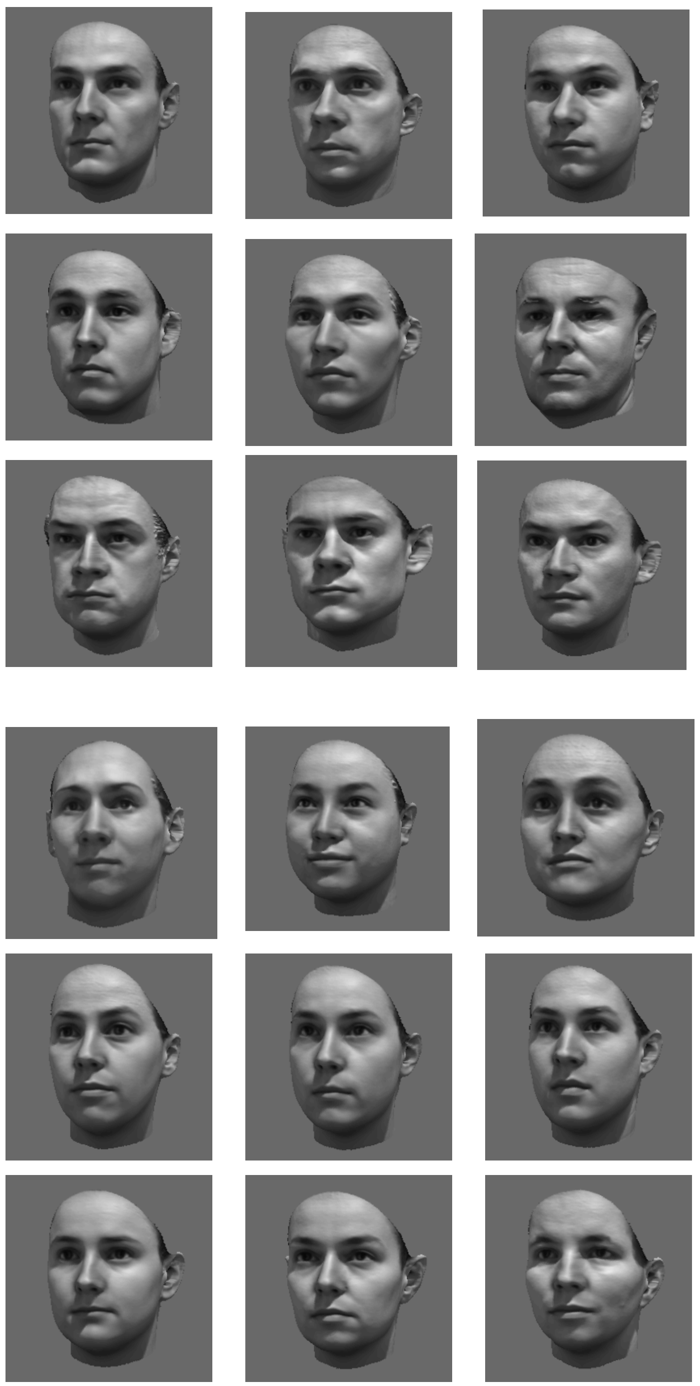

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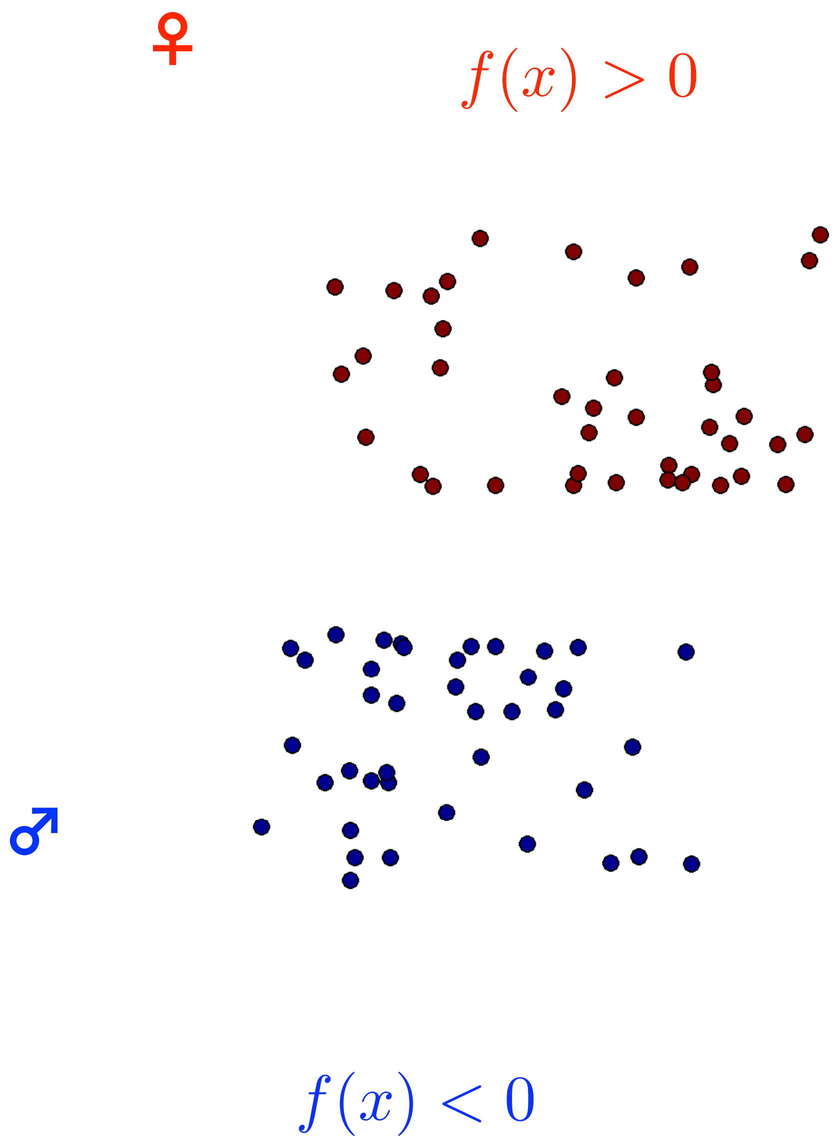
- In what ways are (perceived) "female" faces different to "male" faces?

- Can we find statistical quantities that differentiate one class of images from the other class?

$$
\begin{aligned}
f : \text{all images} &\quad\rightarrow\quad \mathbb{R} \\
f(\text{image}) &\quad>\quad 0 \text{ if female} \\
f(\text{image}) &\quad<\quad 0 \text{ if male}
\end{aligned}
$$

Linear Decision Rules



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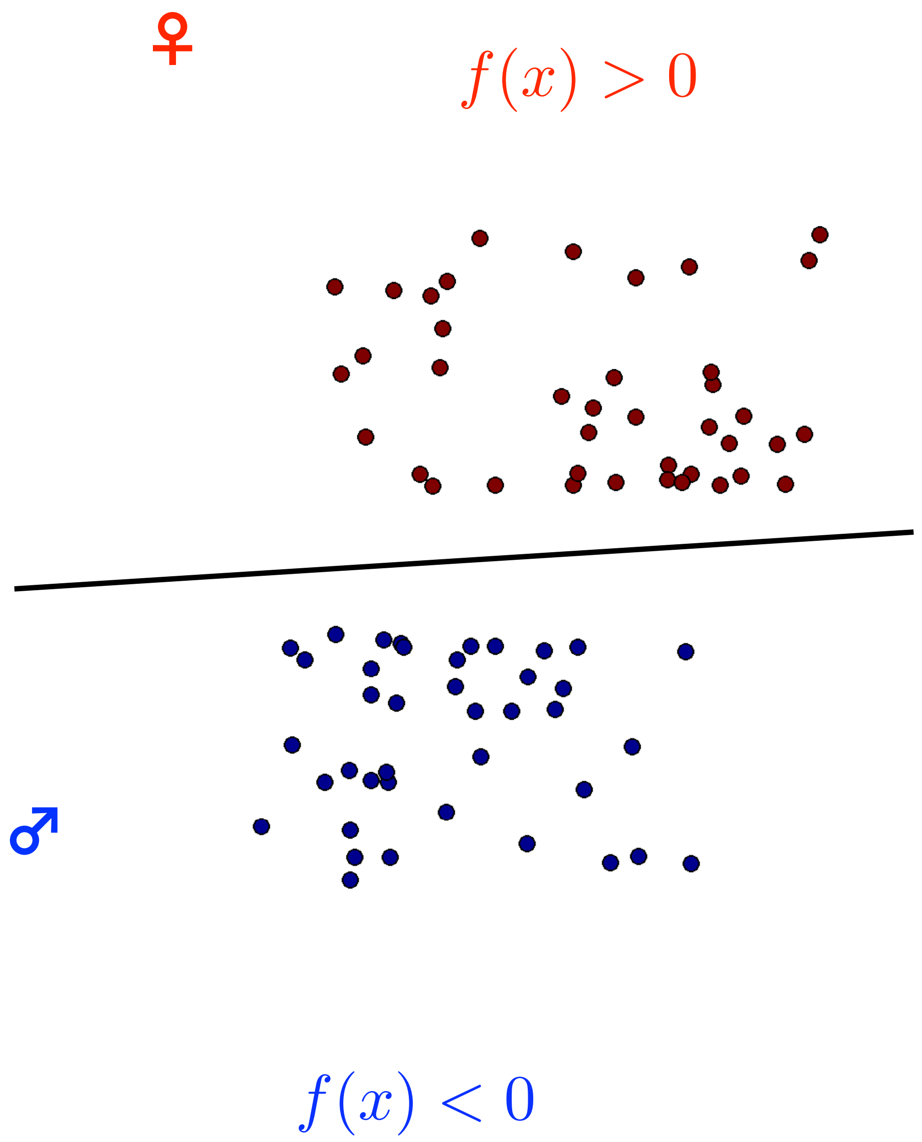

- We restrict ourselves to linear functions:

$$f(x) = \omega^\top x + b$$

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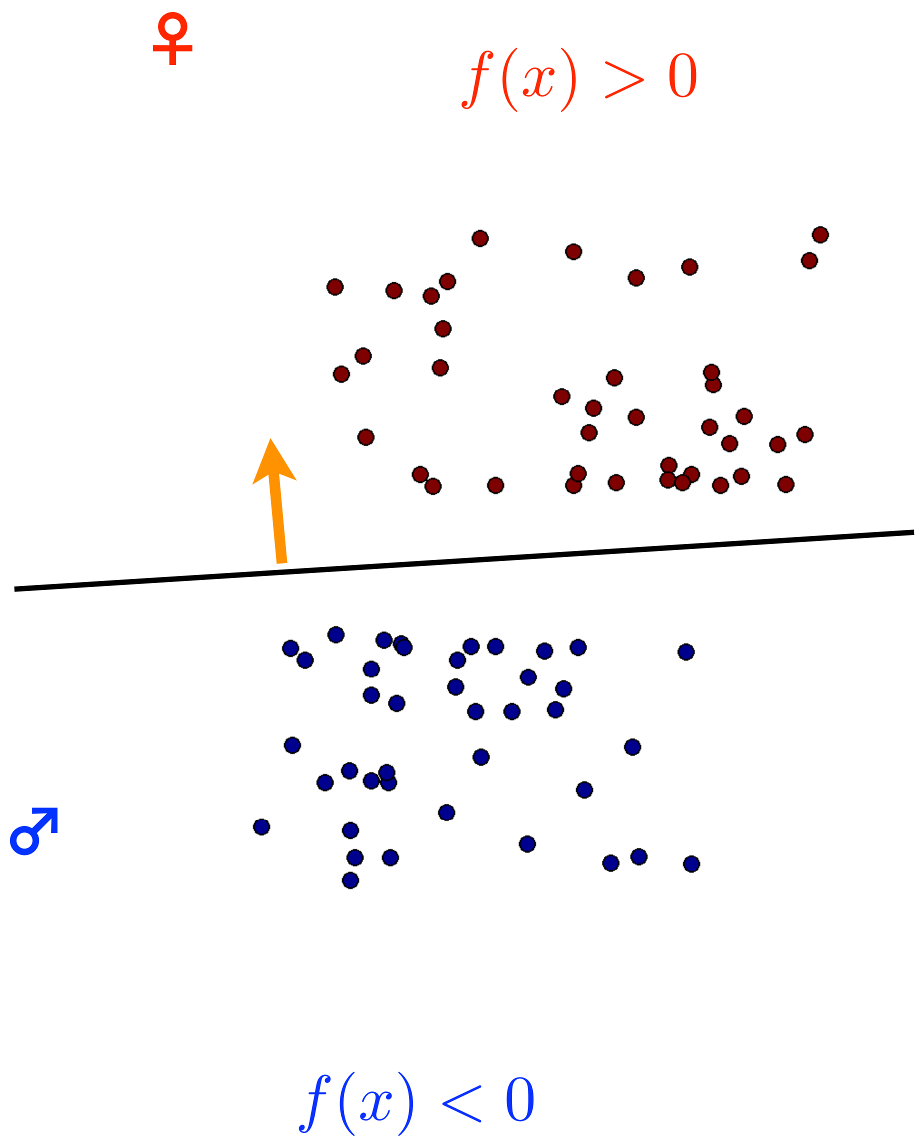

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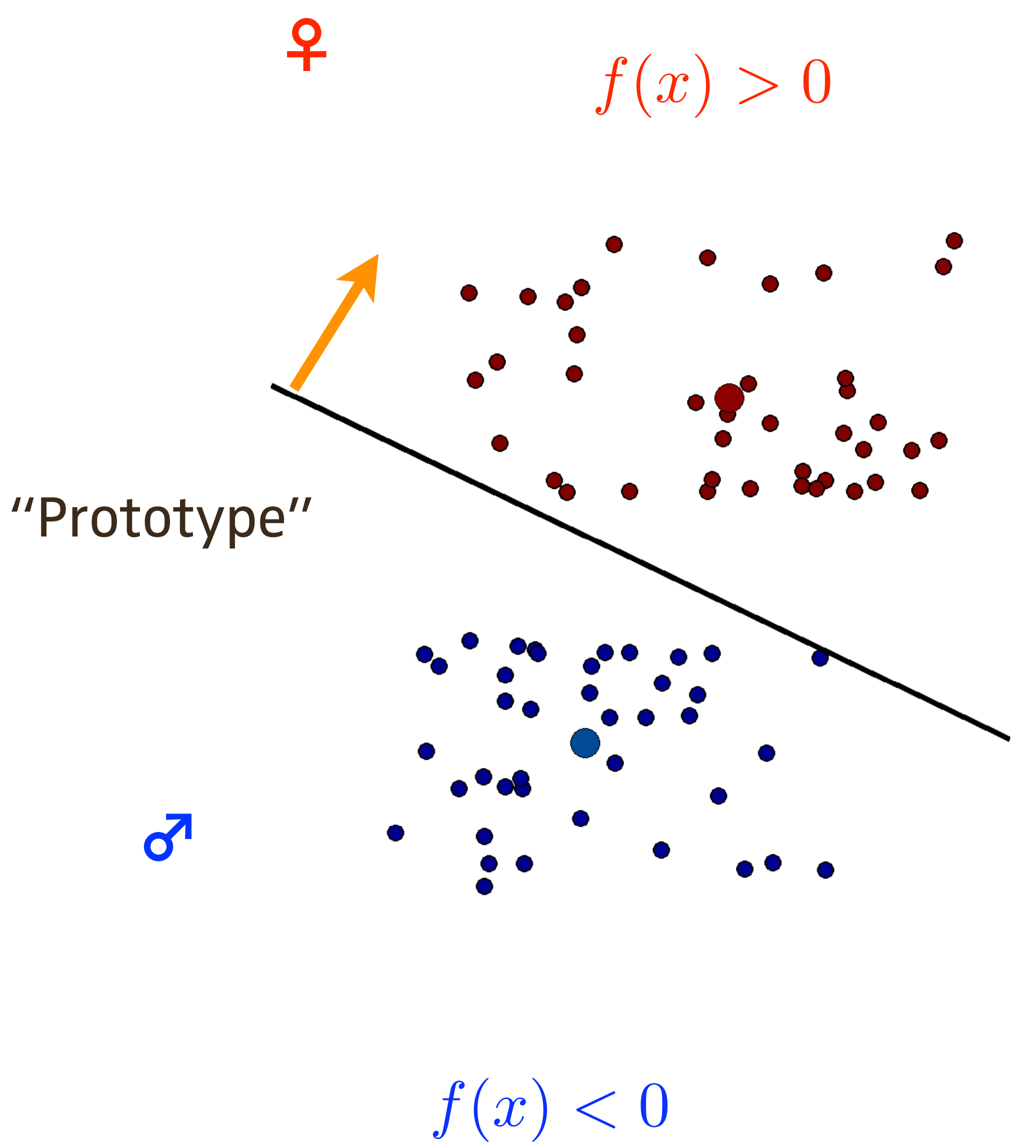

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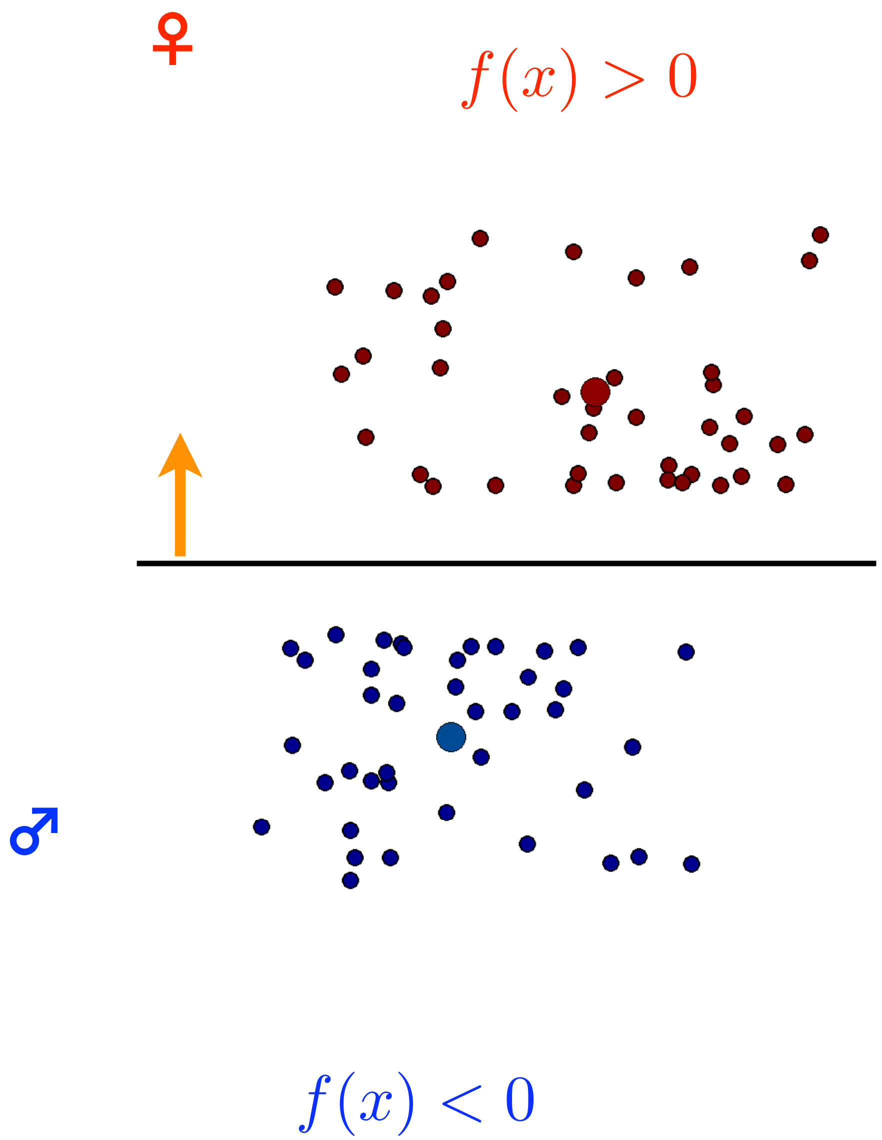

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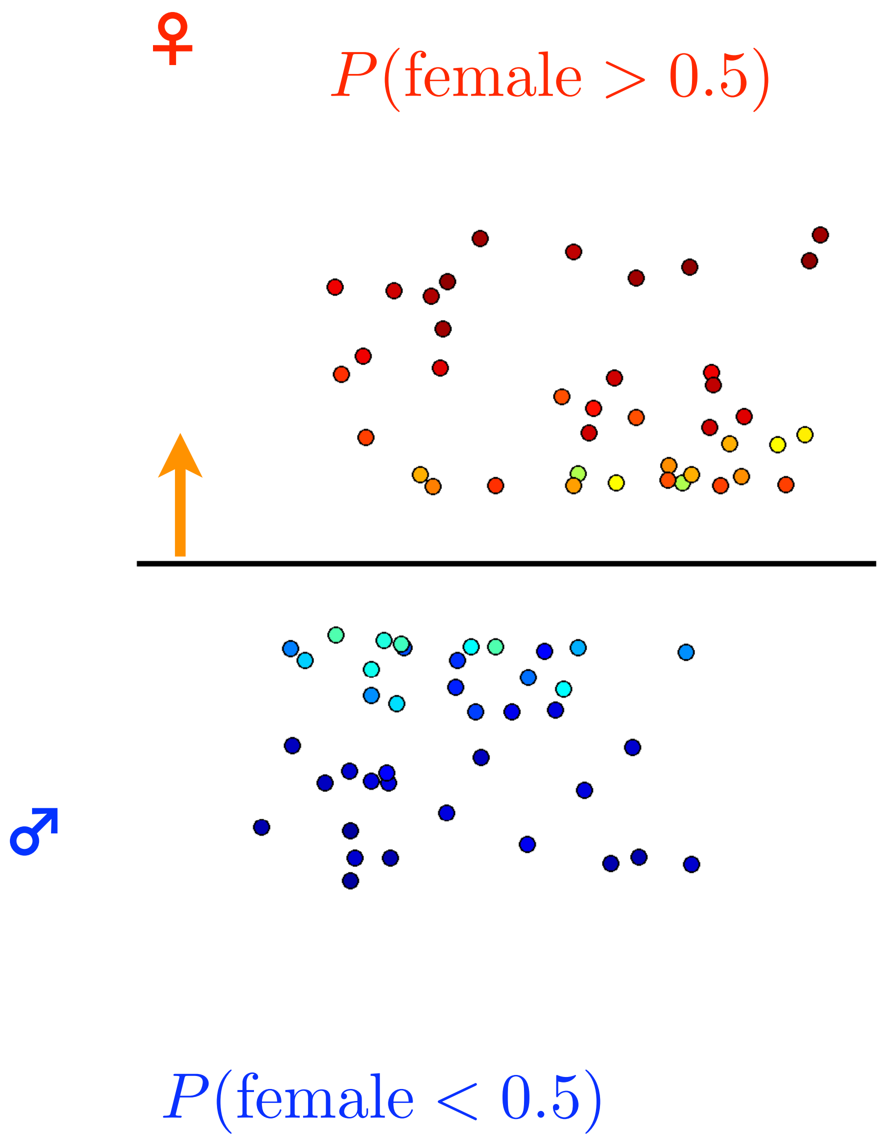

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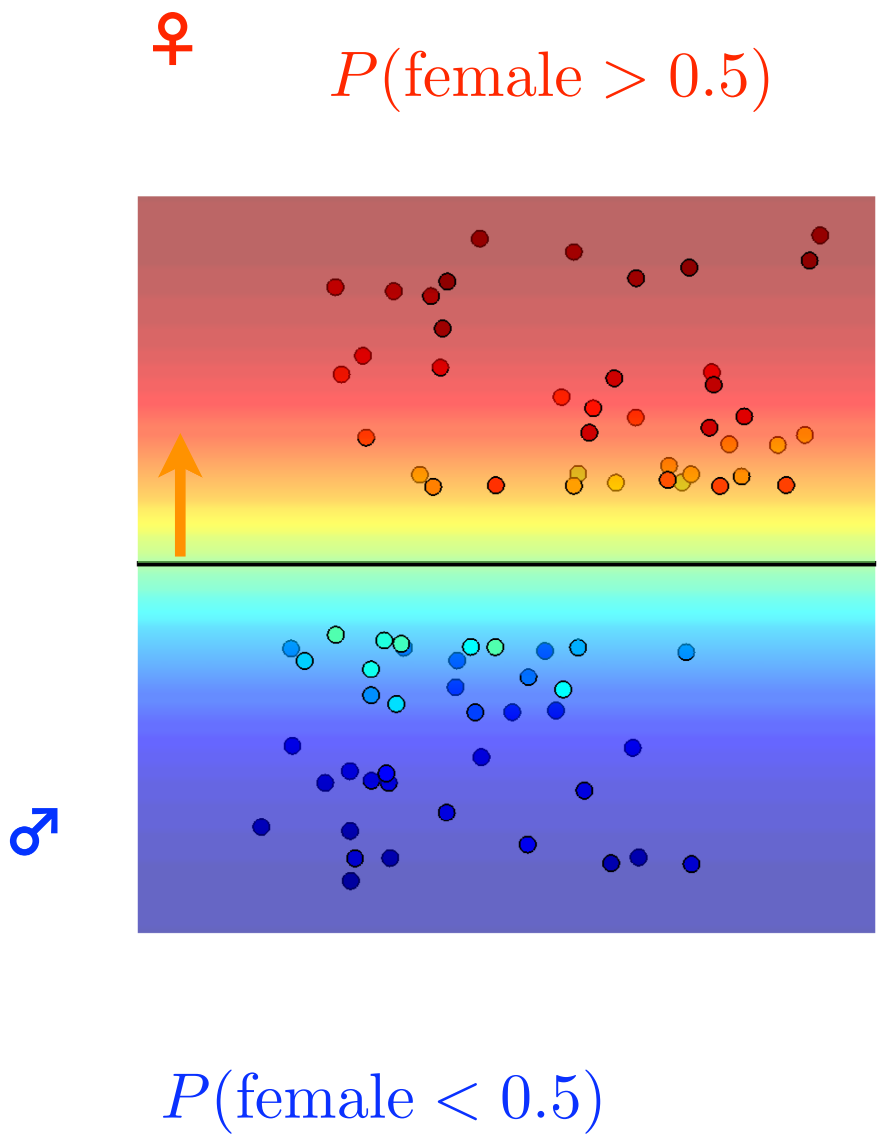

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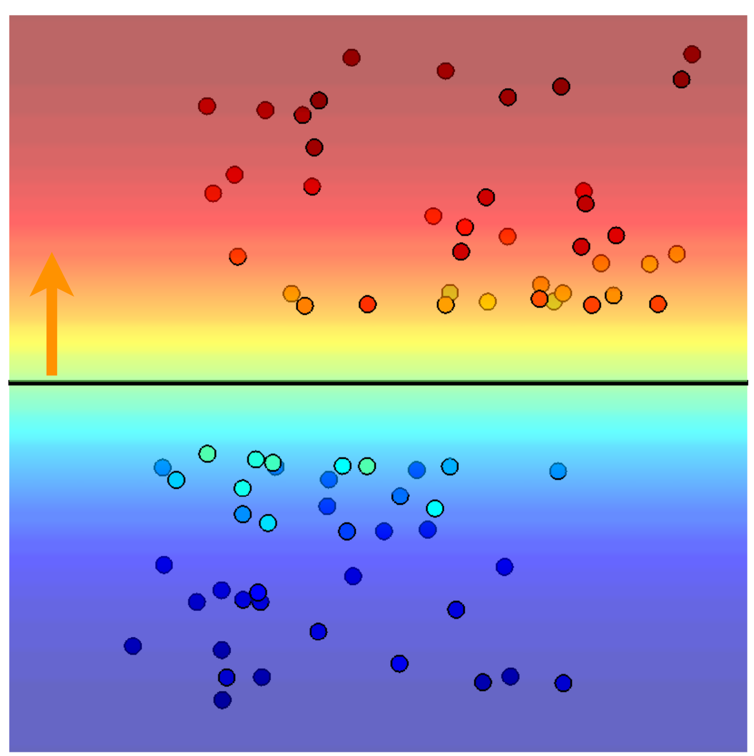
- By modelling decision probabilities, we get additional information about the location of the boundary:

$$P(\text{female}|x) = g(f(x))$$

Linear Decision Rules

♀ $P(\text{female} > 0.5)$



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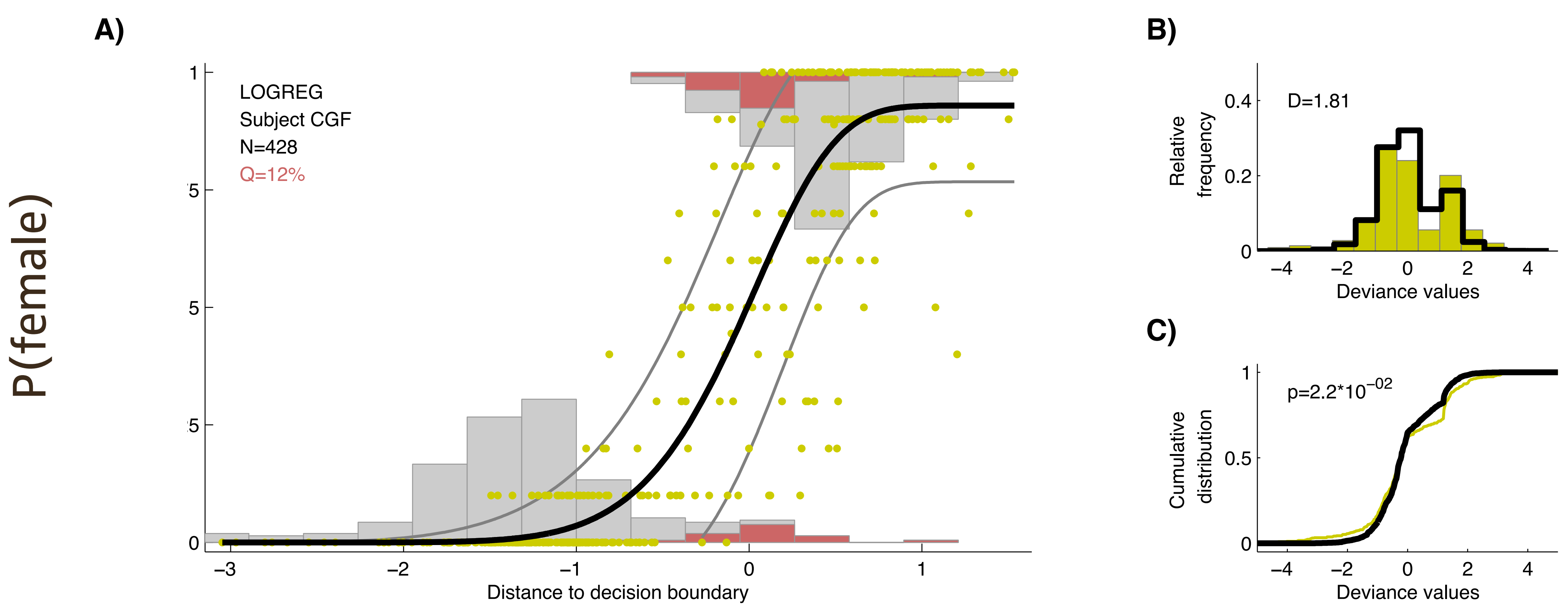
- ω is found by likelihood optimization: regularized logistic regression

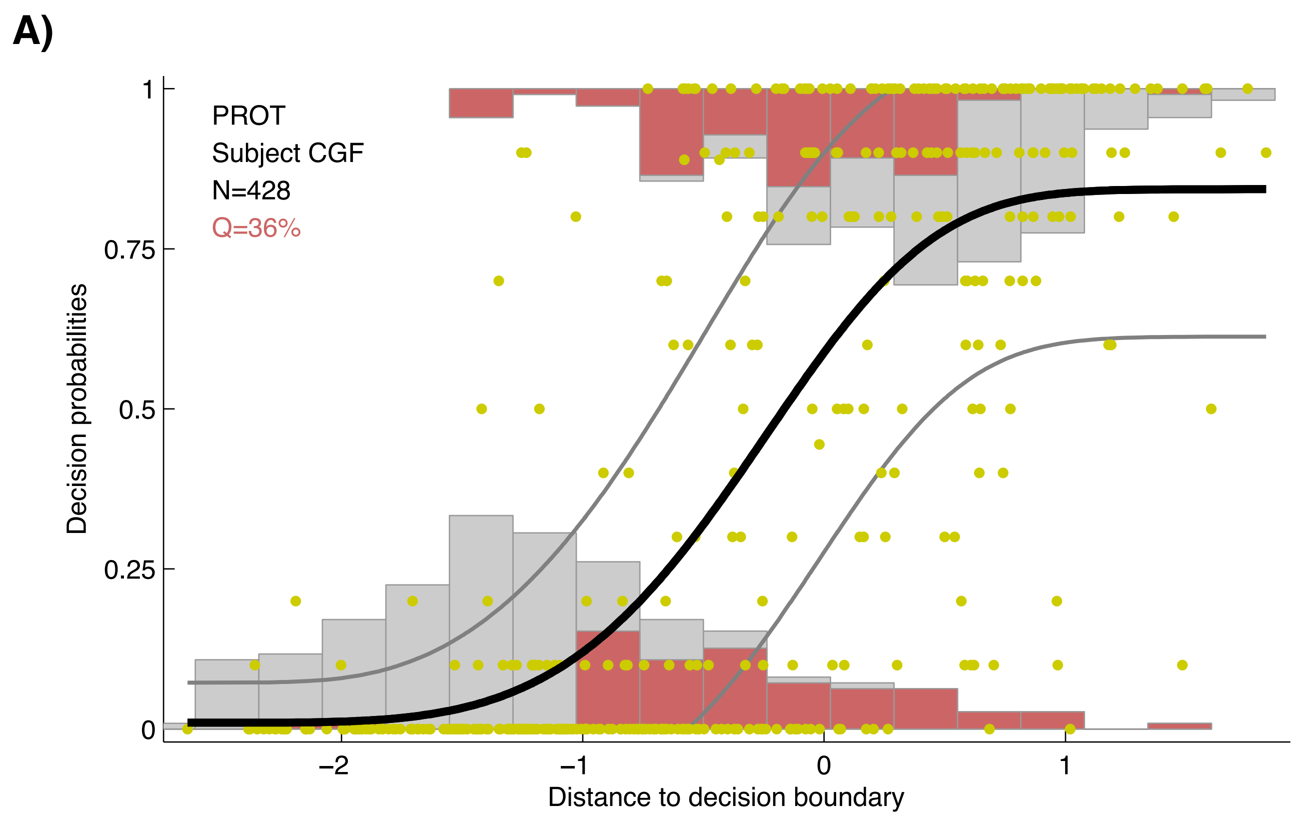
Psychometric Function along Logisitc Regression-ω

Distribution of residuals



Distance to boundary

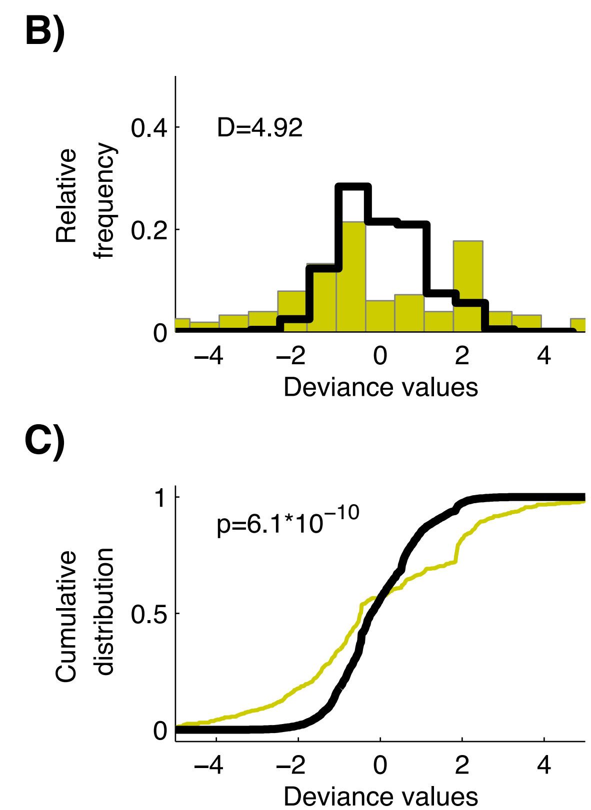
Psychometric Function along Prototype-ω



P(female)

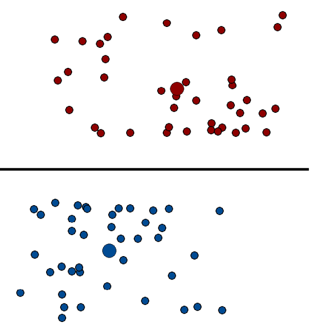
Distance to boundary

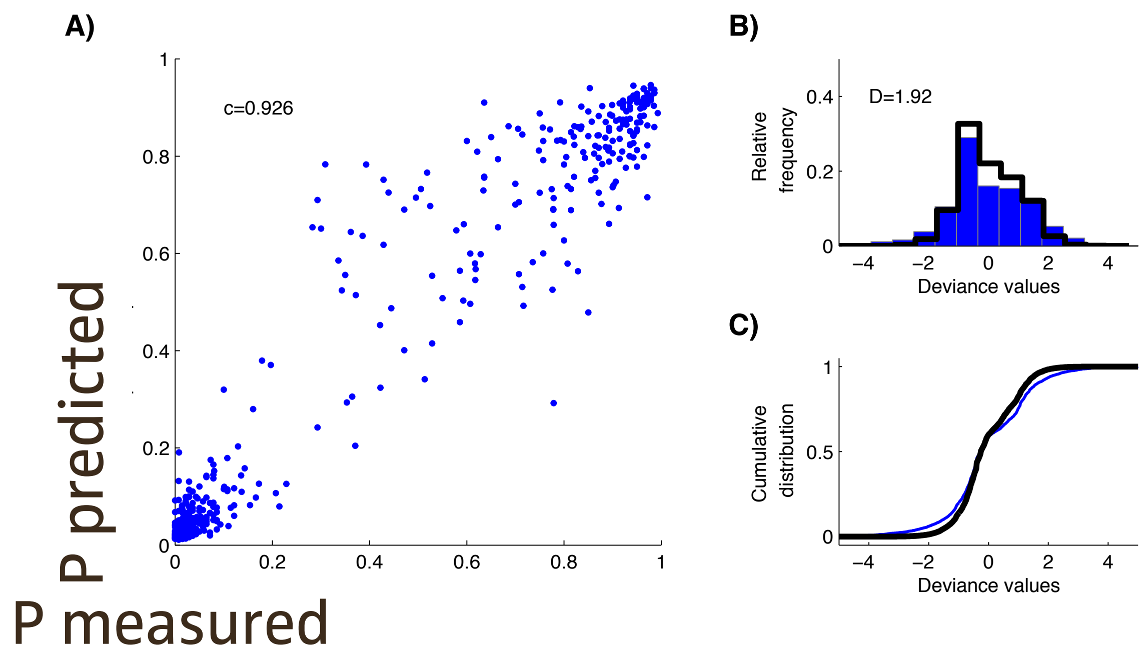
Distribution of residuals



Summary Statistics across Observers

Logistic regression





Prototype

Summary Statistics across Observers

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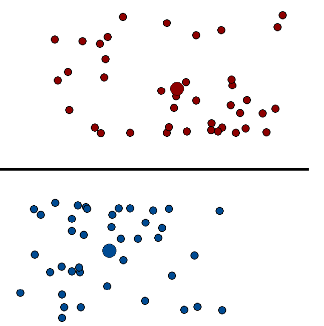

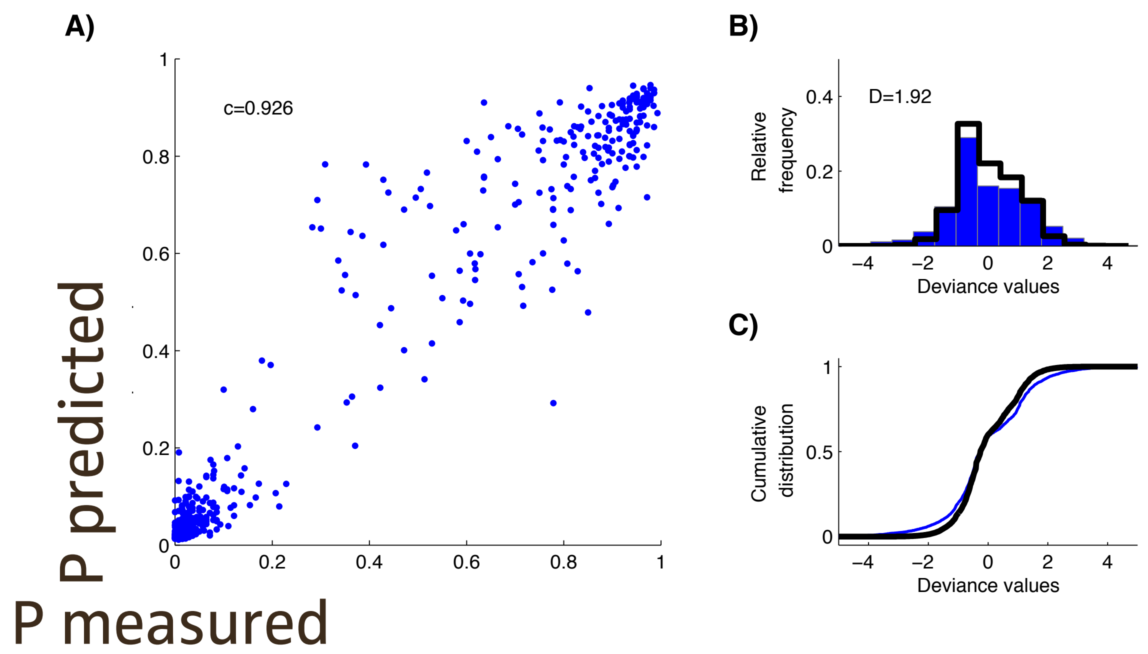

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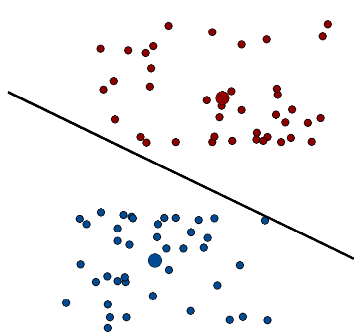
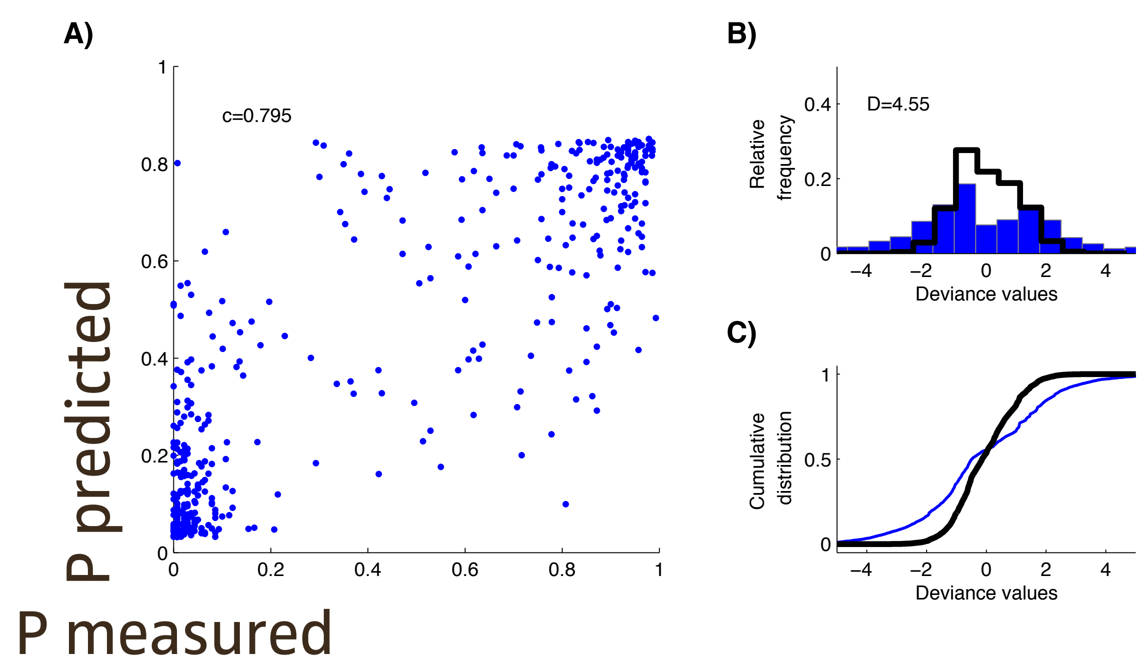
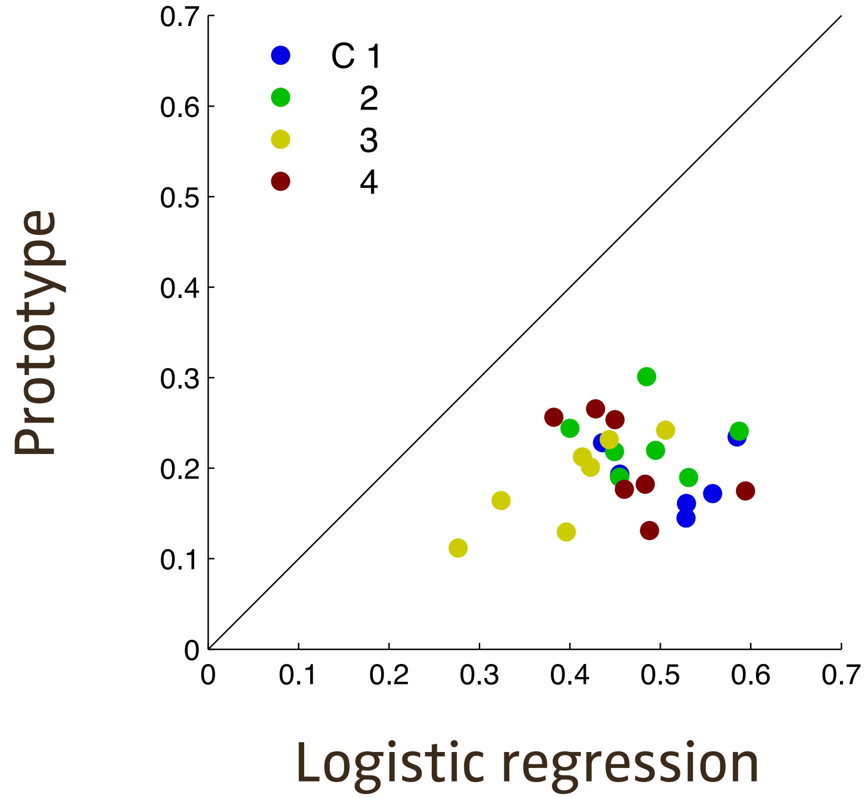


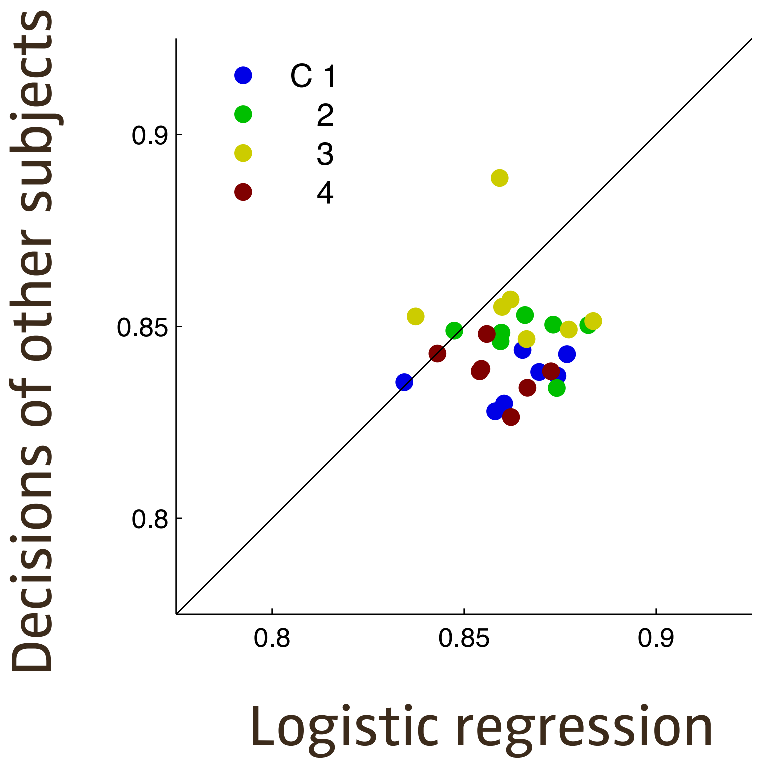


How Good is the Prediction?

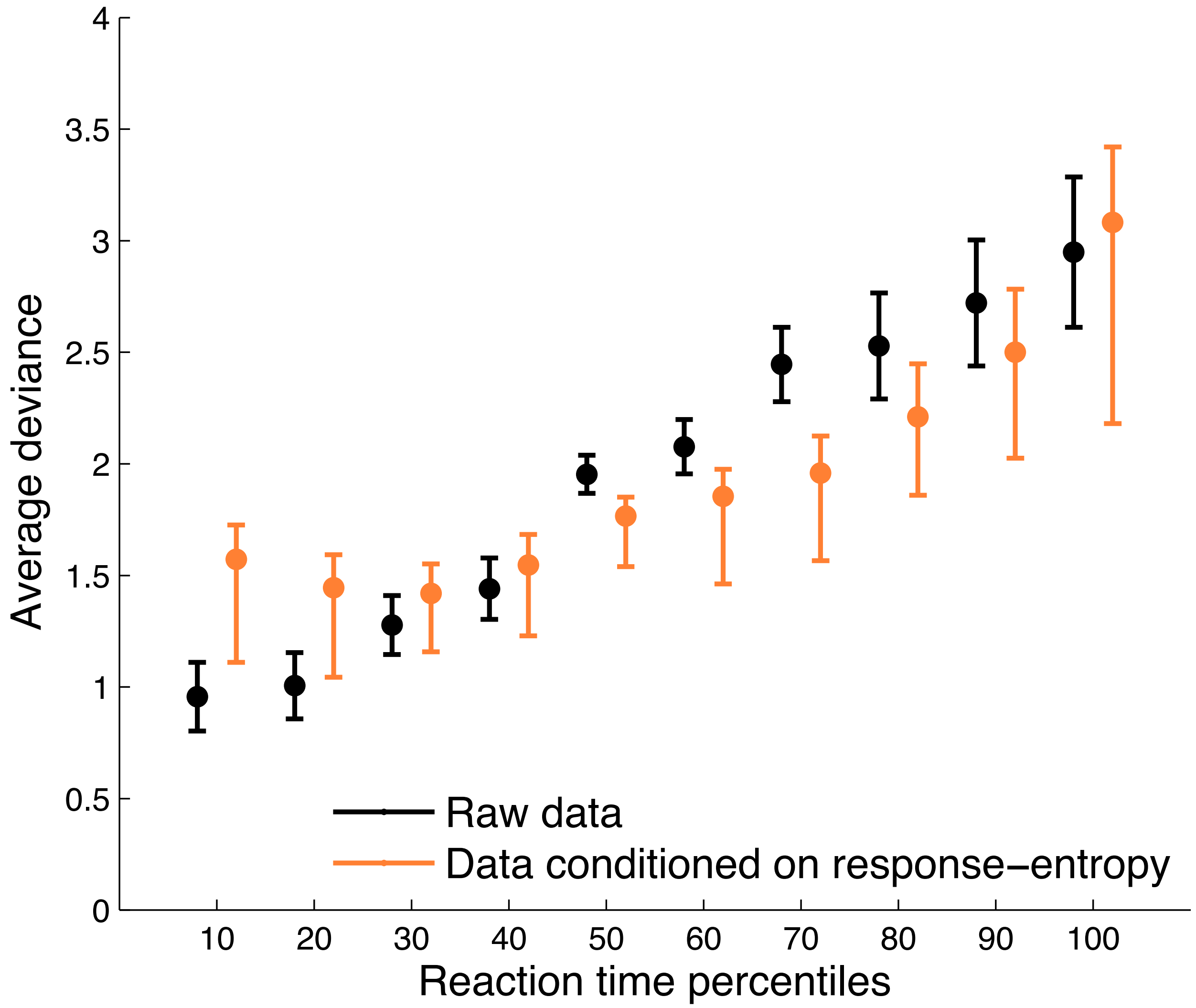
How good are predictions conditioned on real gender?



Are the algorithms sensitive to inter-observer differences?

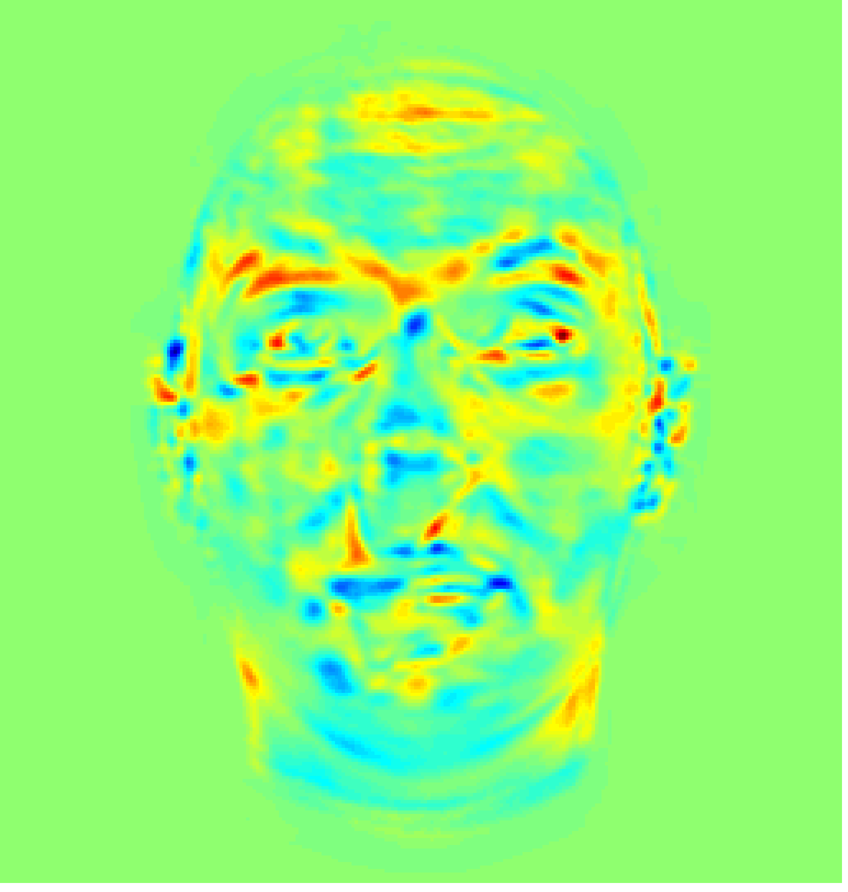


Predictability and Reaction Times

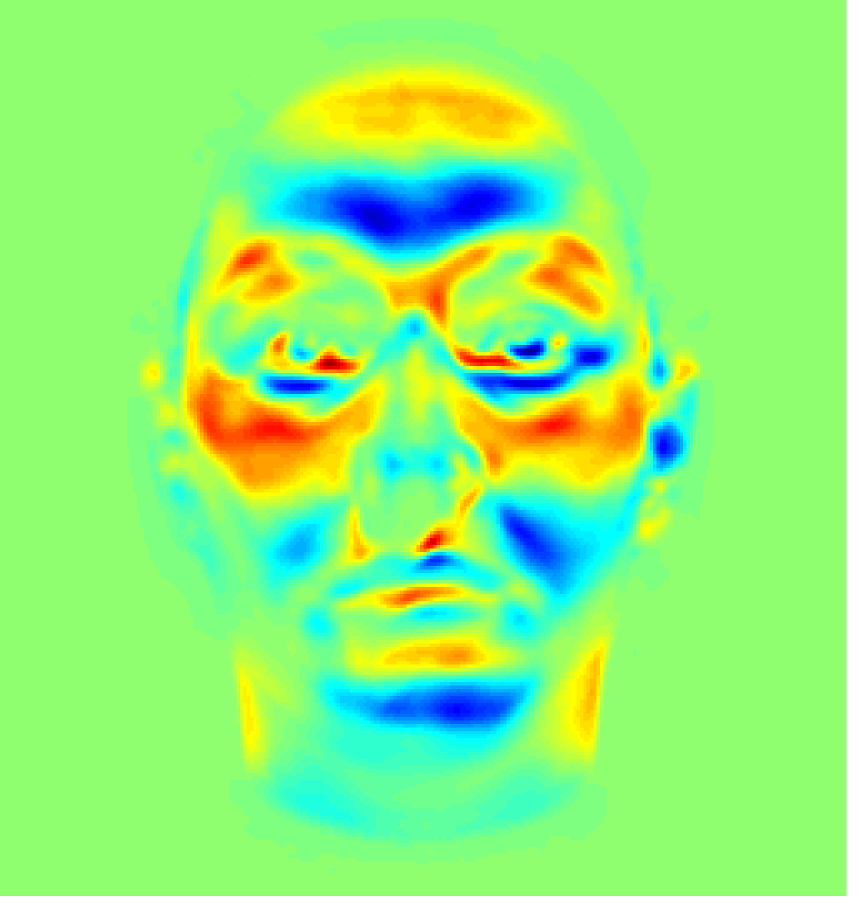


The Decision Images ω

Logistic regression

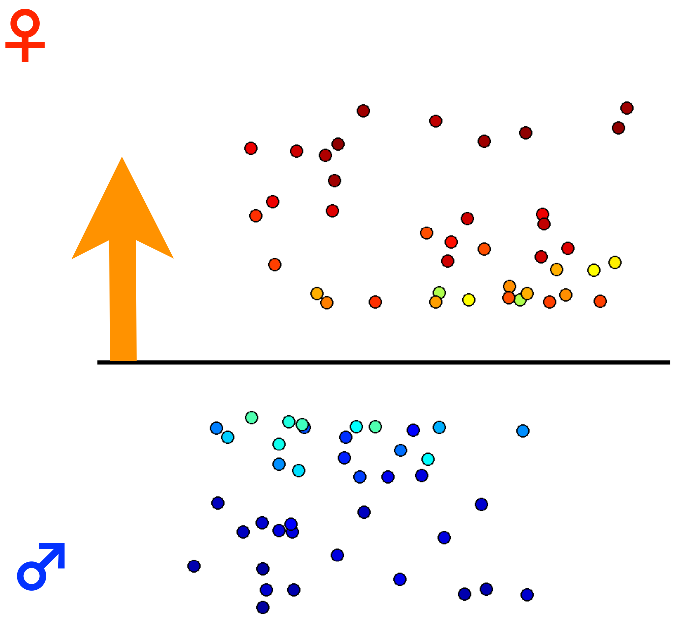


Prototype classifier



Evaluating Decision Images with Optimized Stimuli

Decision probabilities



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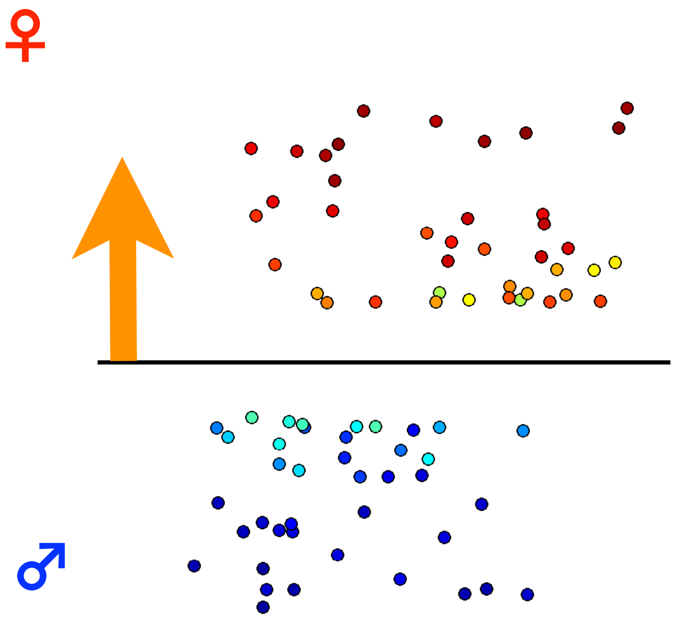

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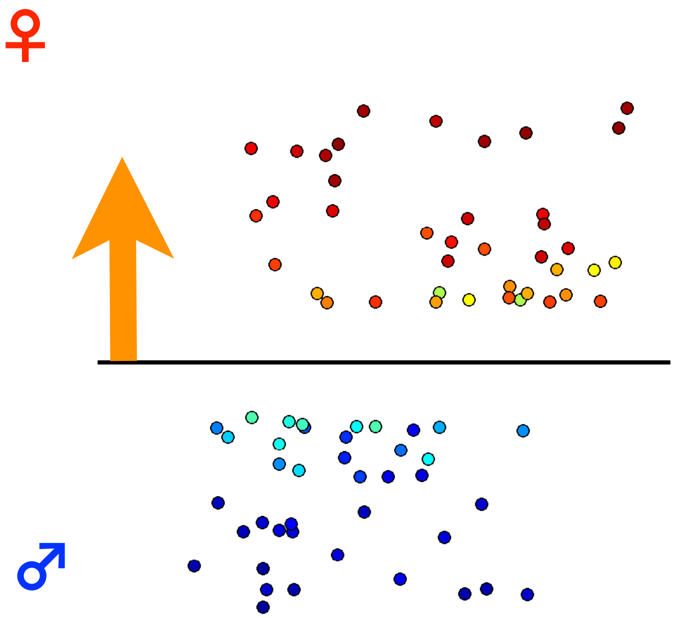
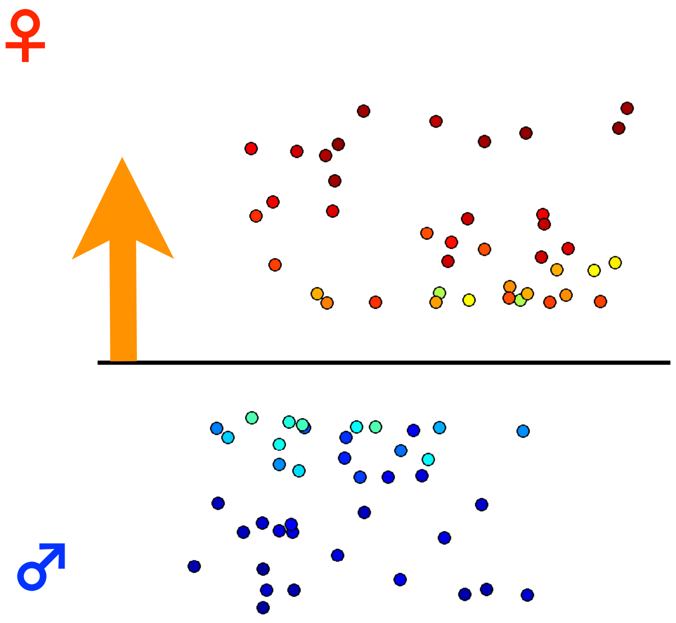


Decision probabilities

i. change quickly **orthogonal** to boundary.

Evaluating Decision Images with Optimized Stimuli

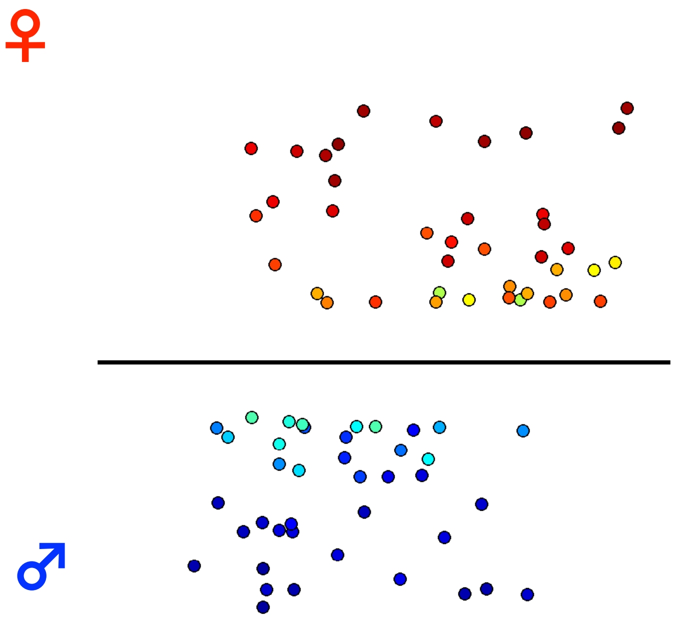


Decision probabilities

i. change quickly **orthogonal** to boundary.

ii. do not change **within** boundary.

Evaluating Decision Images with Optimized Stimuli



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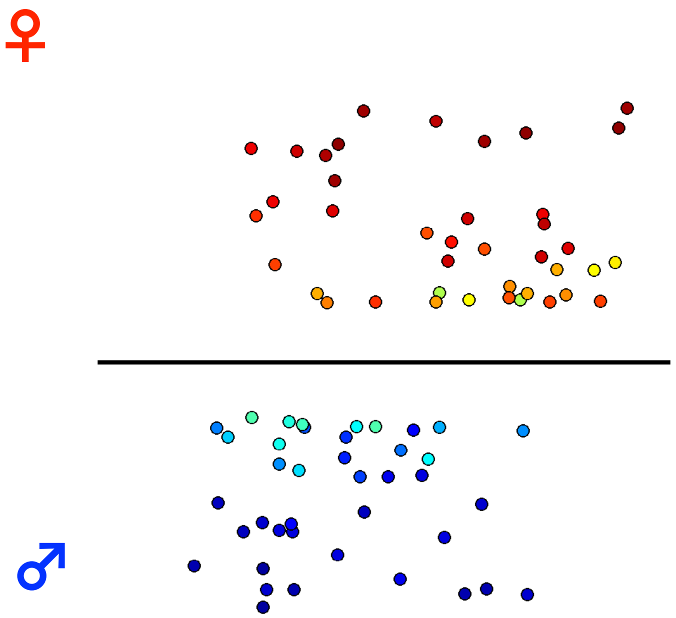

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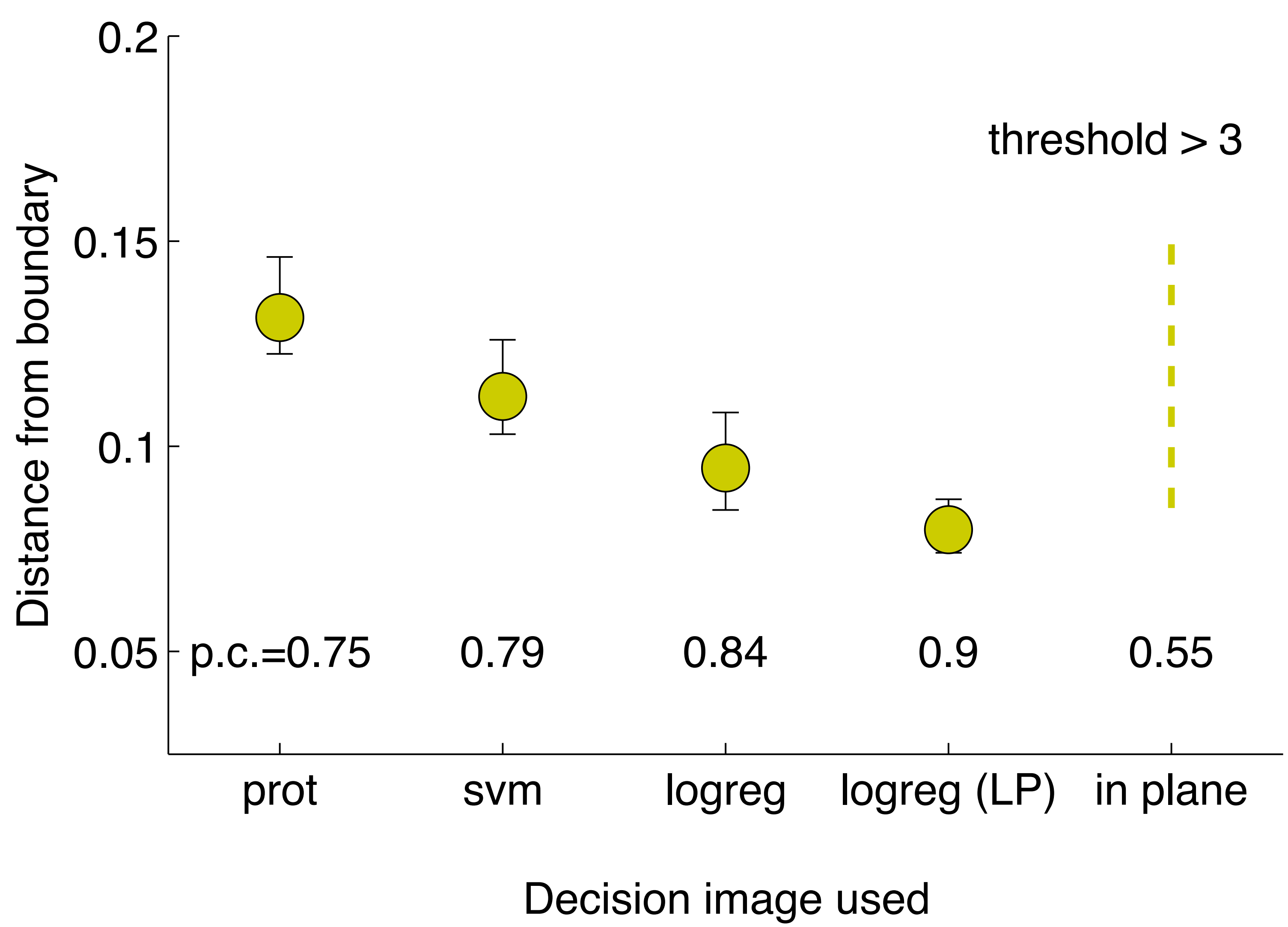

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While the methods used here were linear, the approach can be extended to nonlinear decision images using kernels.

②

Scientific Question

What is special about the local image structure at fixation points?

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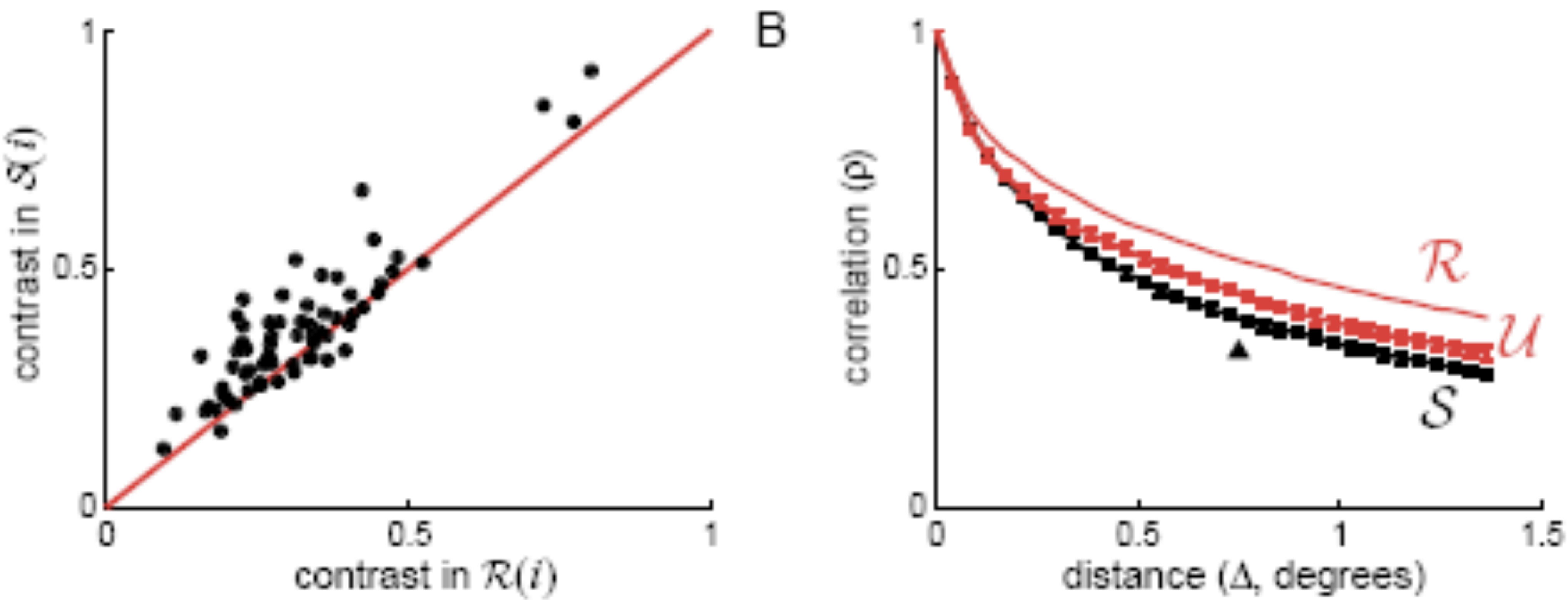
What is special about the local image structure at fixation points?

Does p(fixation) depend on local image statistics? (Bottom-up visual saliency)

Previous Work (1)

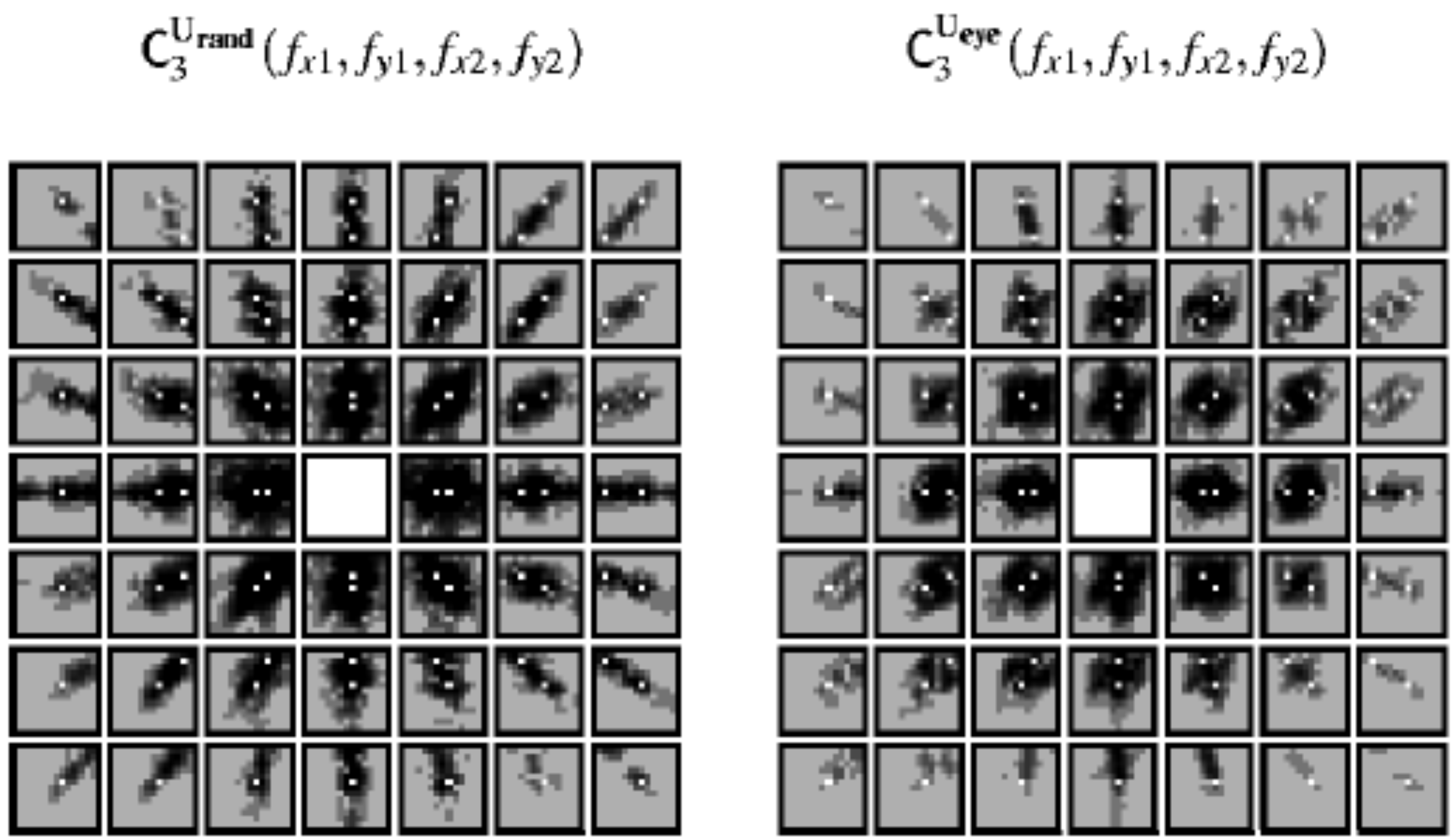
Correlation coefficient of RMS and model output: 0.69



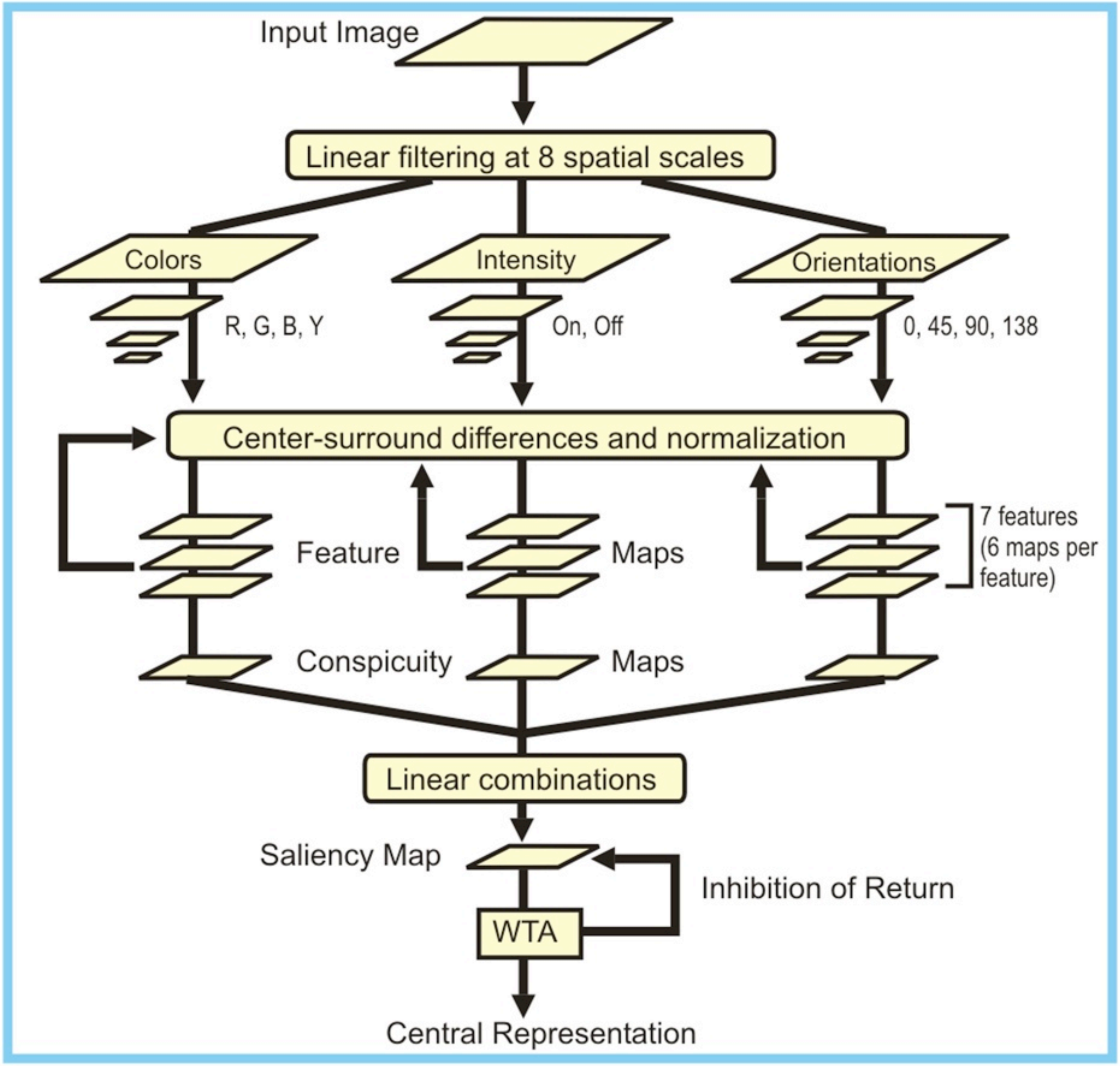
Center pixel "more different" to surrounding pixels in fixation patches (Reinagel & Zador, 1998)

Previous Work (2)

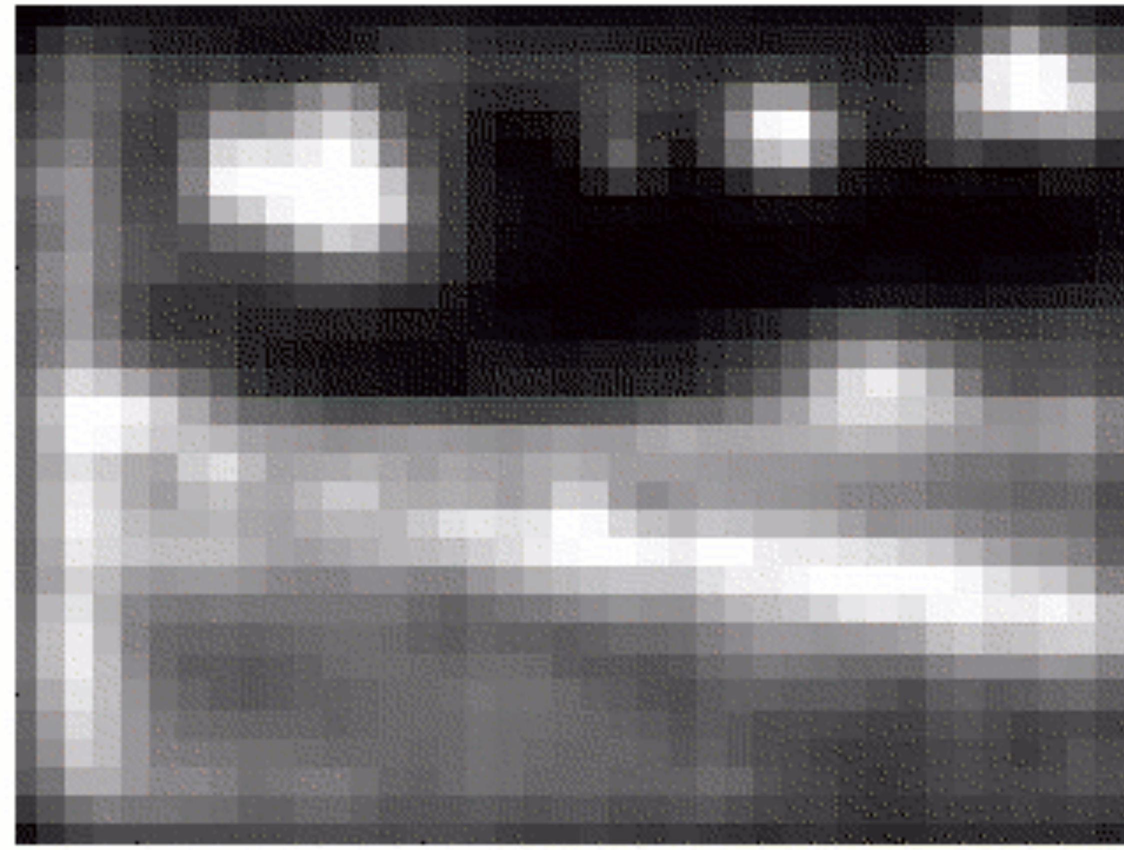
"The saccadic selection system avoids image regions which are dominated by a single oriented structure. Instead, it selects regions containing different orientations, like occlusions, corners, etc." (Krieger et al., 2001)
Third order statistics, "energy distribution is more circular":



Previous Work (3)



Saliency Maps



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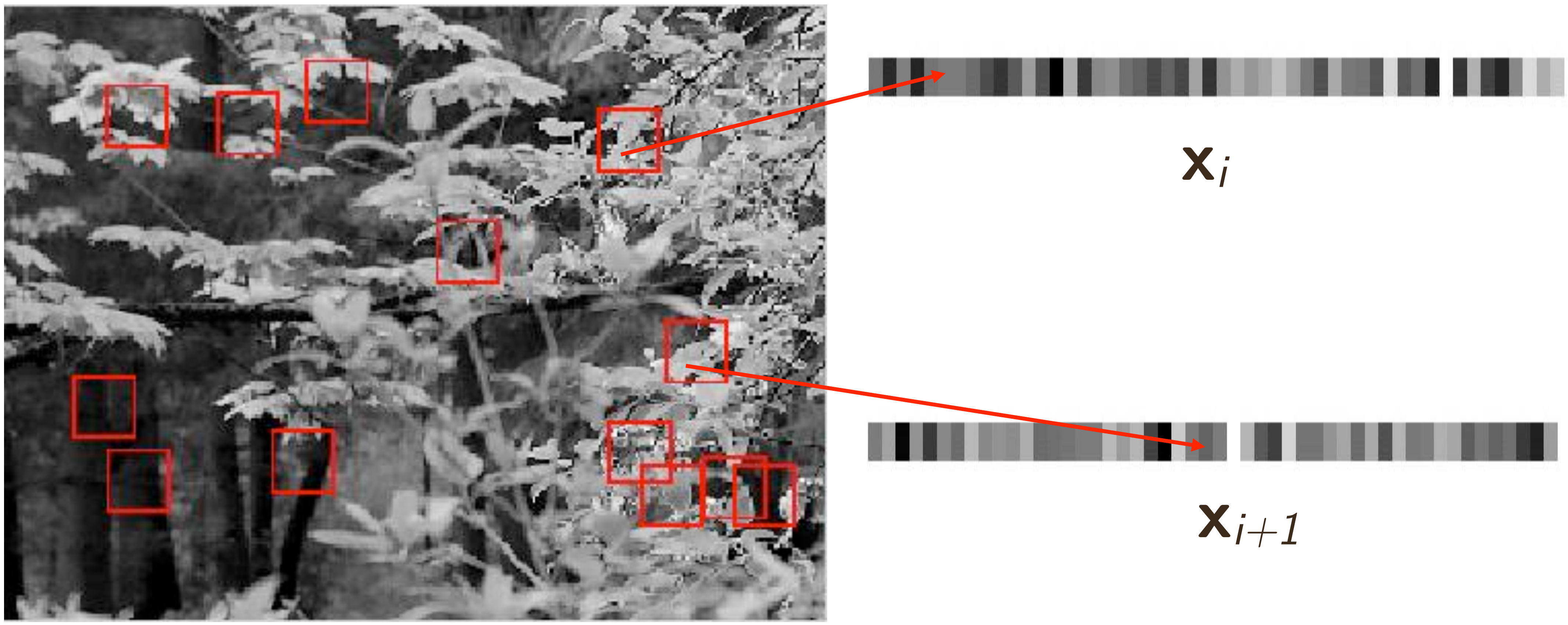
Machine Learning approach: construct a model from the data, i.e. ...

i. Use a very general model class that does not "know" about the problem, but can adapt very well to a large class of problems.

ii. Numerically optimize (= learn) its parameters such that data is explained best.

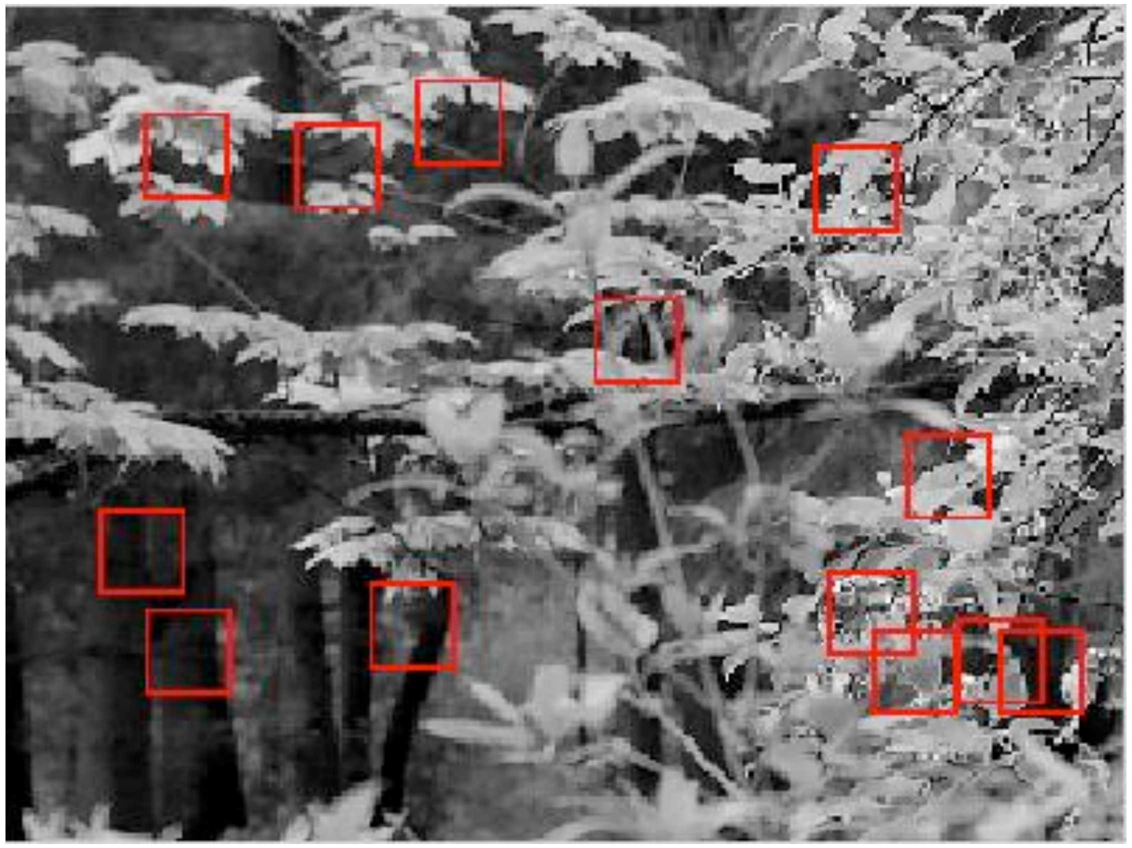
Data Representation

For each data point (i = 1…36,000), store local pixel values in a feature vector $\mathbf{x}_i$ and associate a label $\mathbf{y}_i$ = 1/-1 (fixation/background)

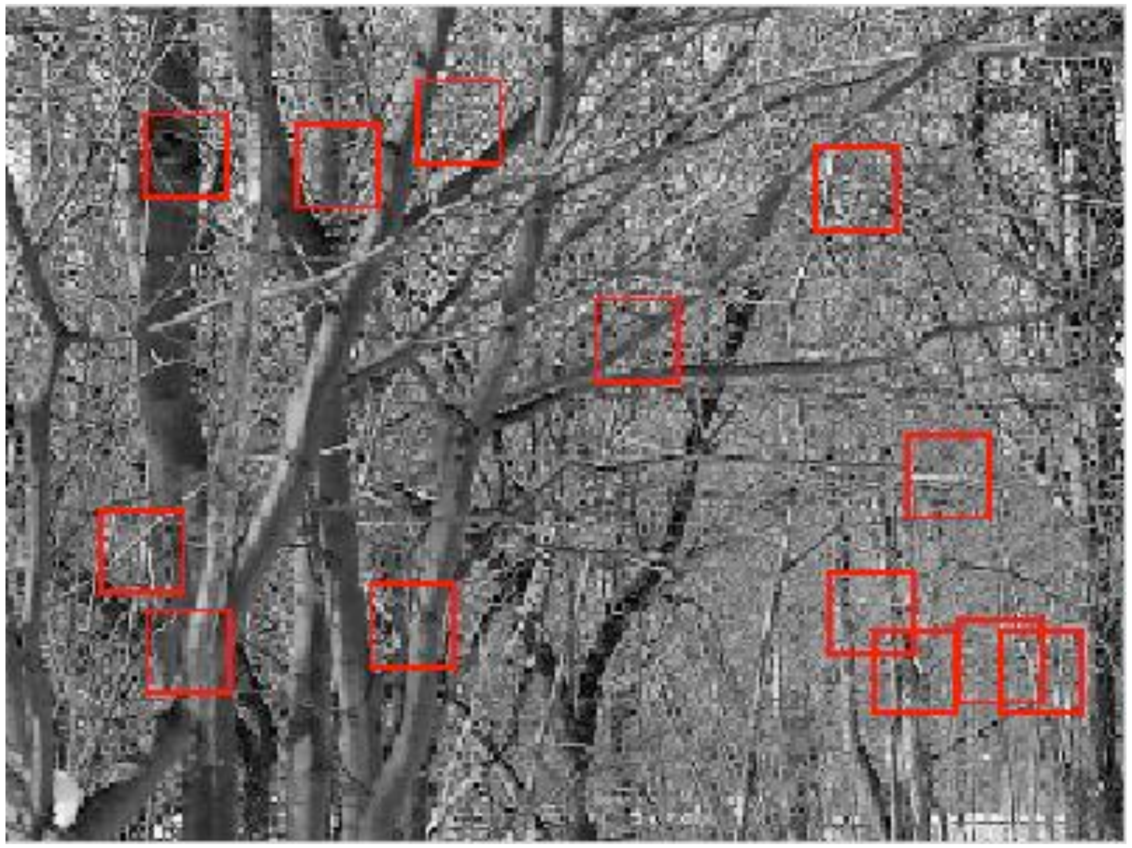


Background Examples

Generate background examples with same spatial distribution as fixations (Reinagel & Zador 1998).



Fixations



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Overall strategy: make the model class as general as possible

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The model is a radial basis function (RBF) network with one basis function centered on each training example. (''Nonparametric'' as its complexity grows with the number of data points.)

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Overall strategy: make the model class as general as possible

The model is a radial basis function (RBF) network with one basis function centered on each training example. ("Nonparametric" as its complexity grows with the number of data points.)

General? Universal approximation property, no preference for any image structure, no knowledge about shape or size of receptive fields.

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We compute the weights (α_i) using hinge loss + L2-regularizer (= SVM)—finding α_i is convex, i.e. efficient and guaranteed to find the global optimum.

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We find the *design parameters* λ, γ, and patch size d via exhaustive grid-search, using cross-validation estimates of accuracy—feasible, as problem only 3D (and we had access to Bernhard Schölkopf's MPI Compute Cluster in Tübingen!).

Radial-Basis-Function Support Vector Machine (RBF-SVM)

Kernel bandwidth

$$f(\mathbf{x}) = \sum_{i=1}^{m} \alpha_i \exp\left(-\gamma \|\mathbf{x} - \mathbf{x}_i\|^2\right)$$

Patch size: d

Weights

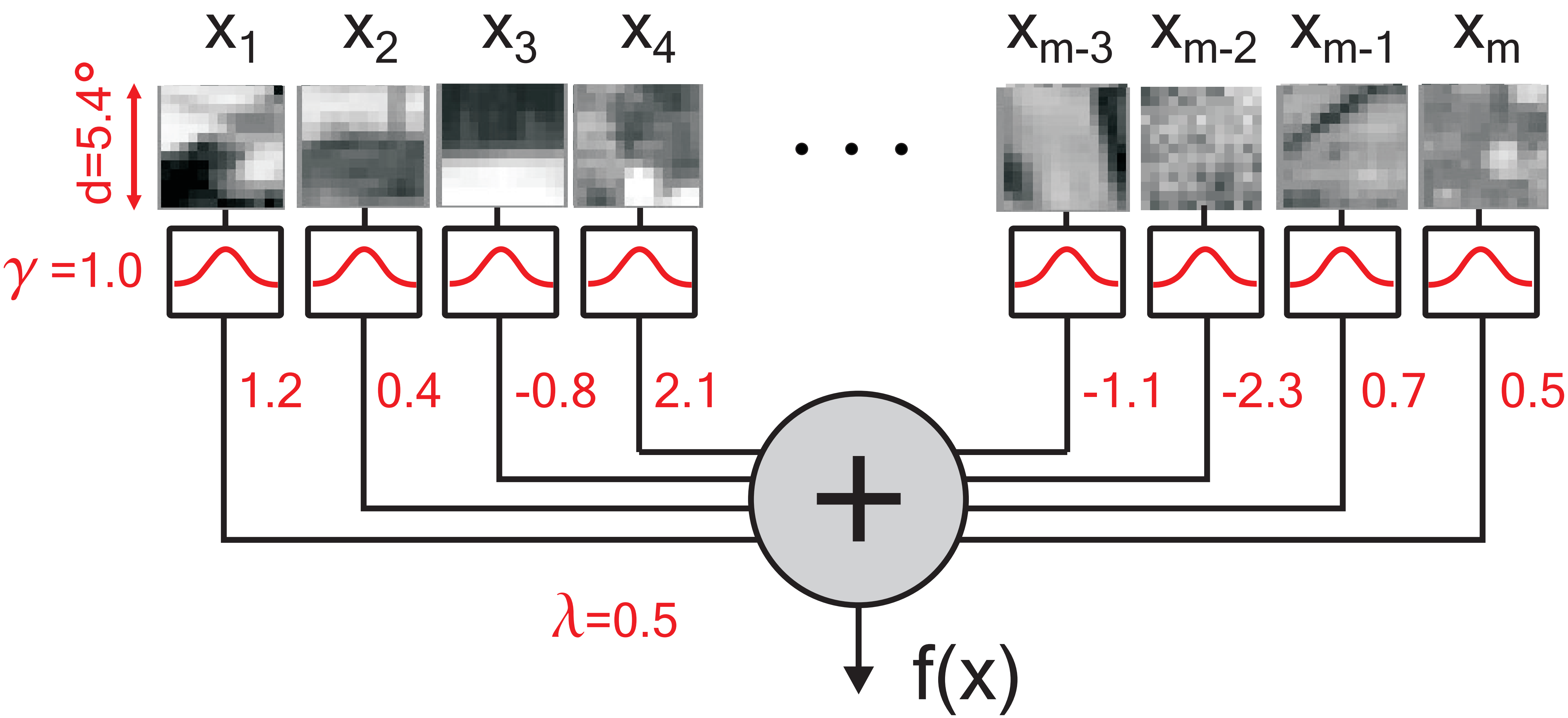
$$\lambda \|f\|^2 + \sum_{i=1}^{m} \max(0, 1 - y_i f(\mathbf{x}_i))$$

Smoothness

$>$24,000 weights

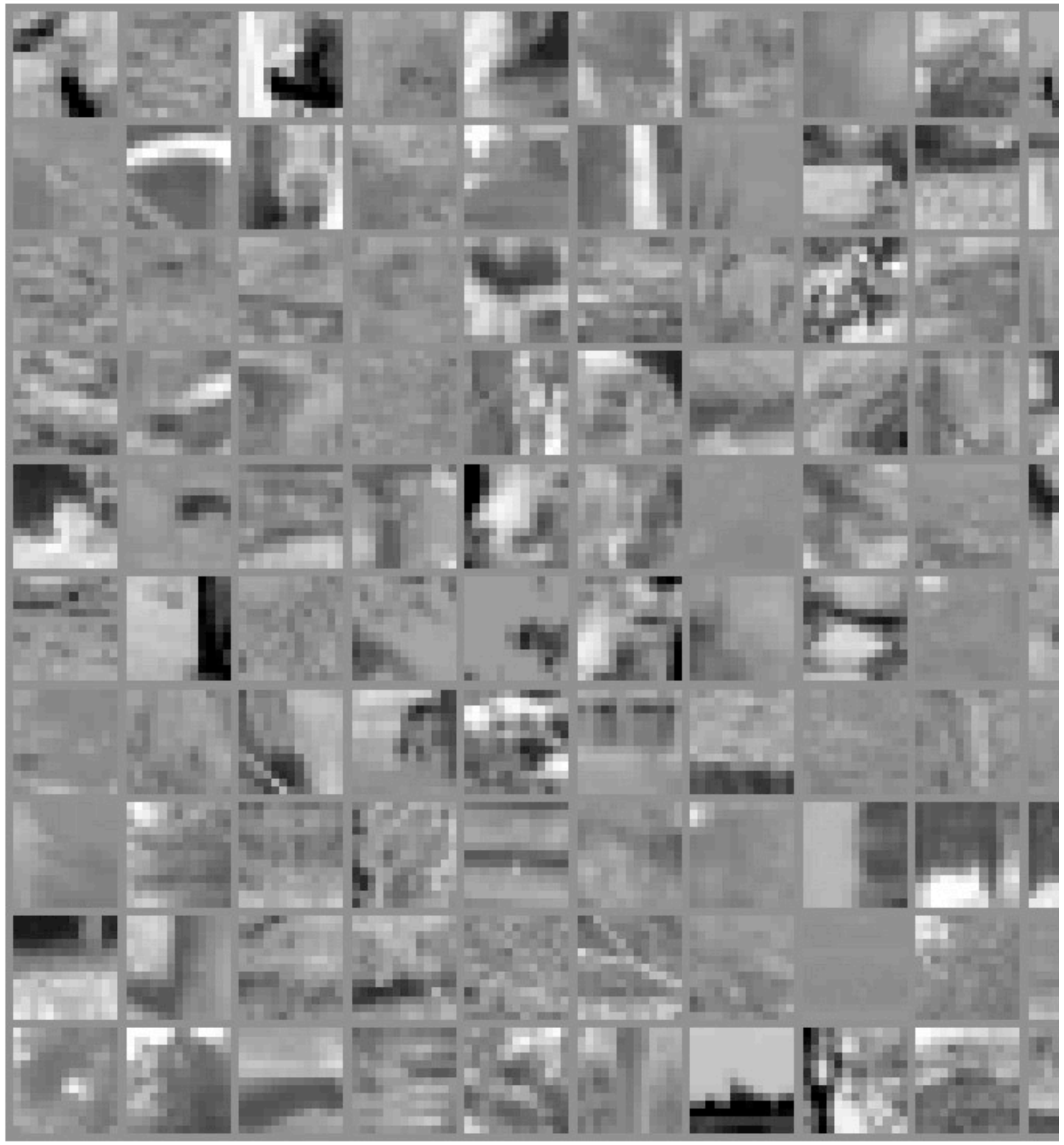
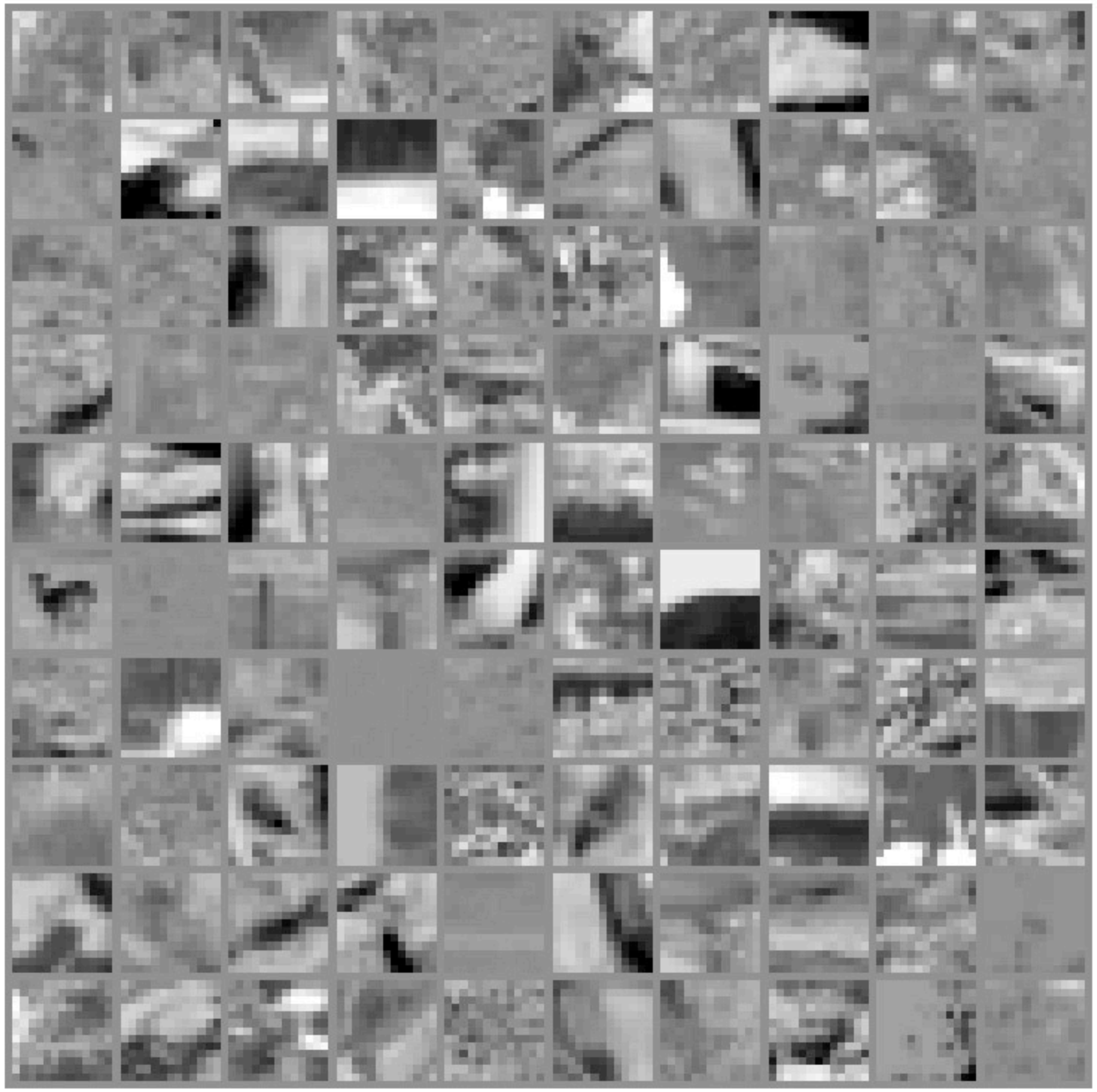
3 design parameters

RBF-SVM after Optimization ("Learning")

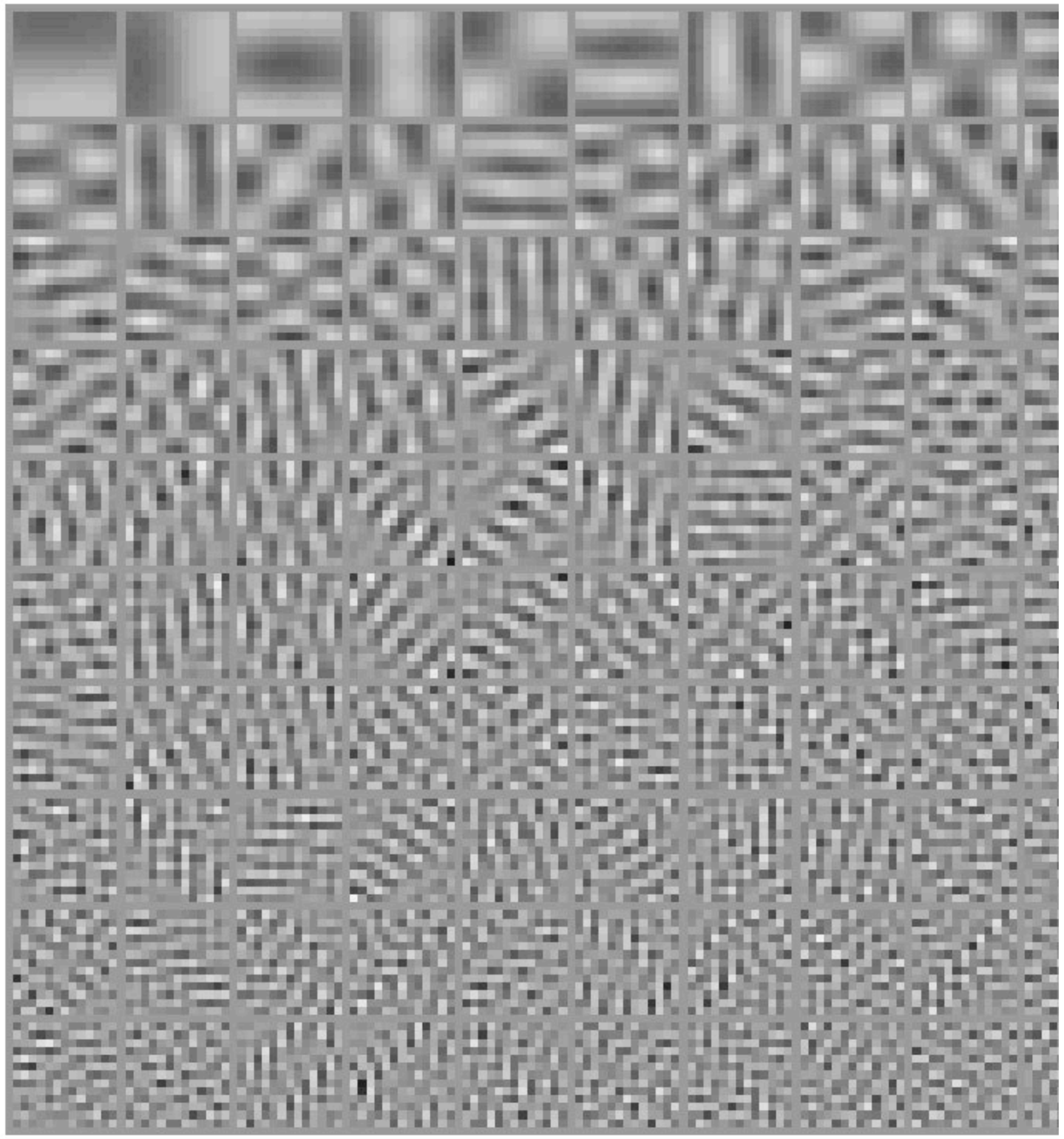


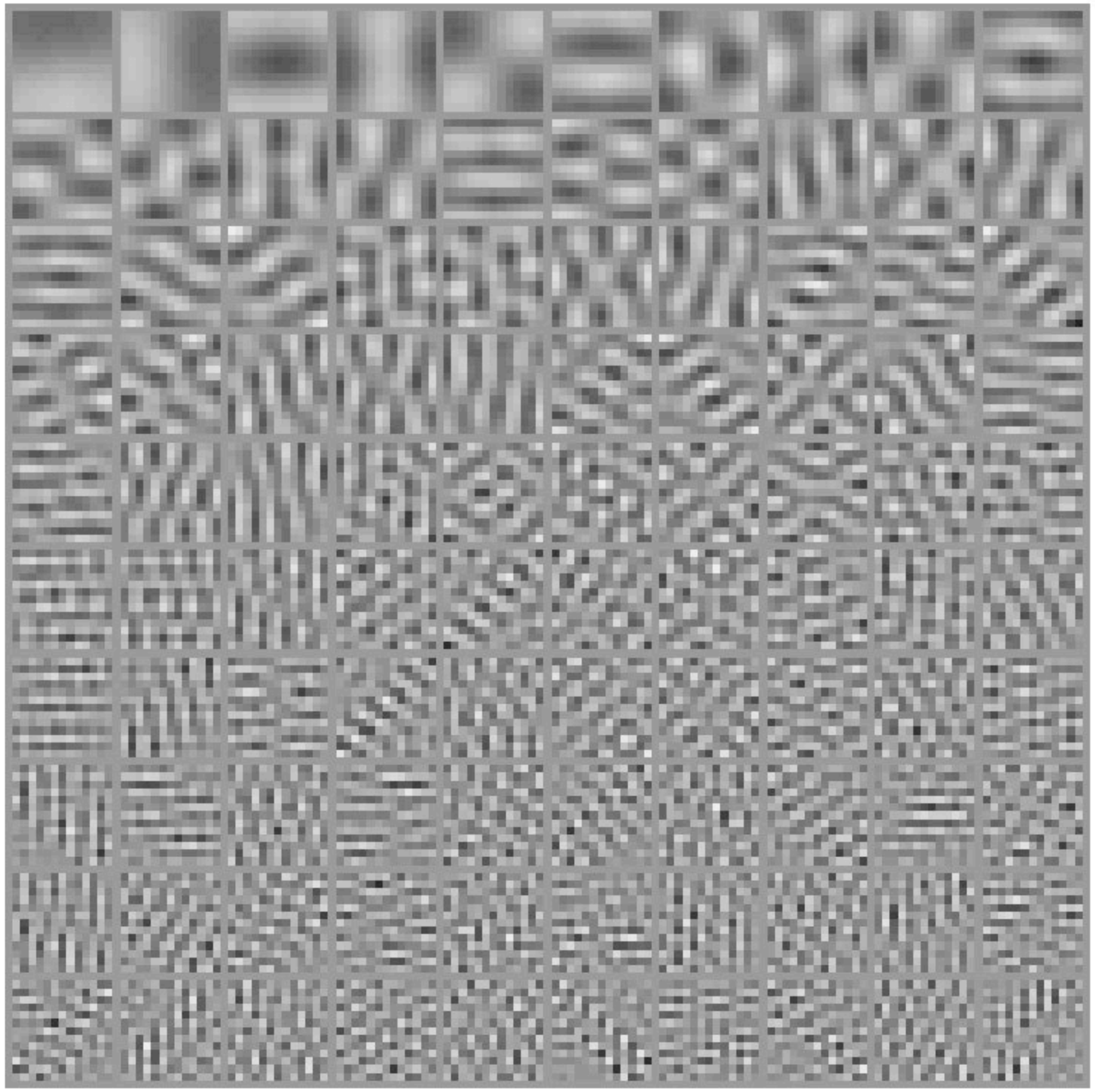
Predicitivity (area under ROC): 0.64±0.010

Randomly Selected vs. Fixated Image Patches

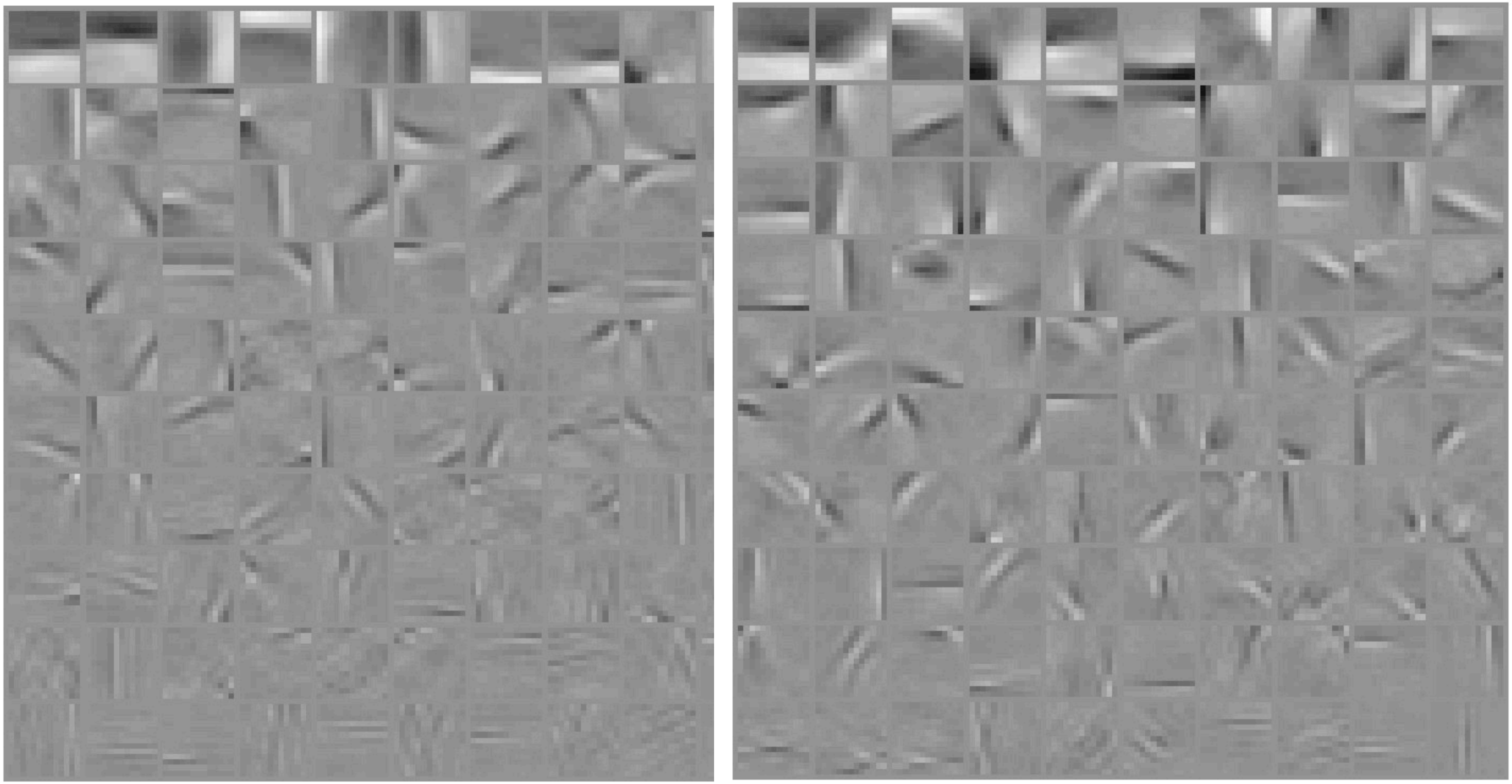



Randomly Selected vs. Fixated Patches: PCA Basis

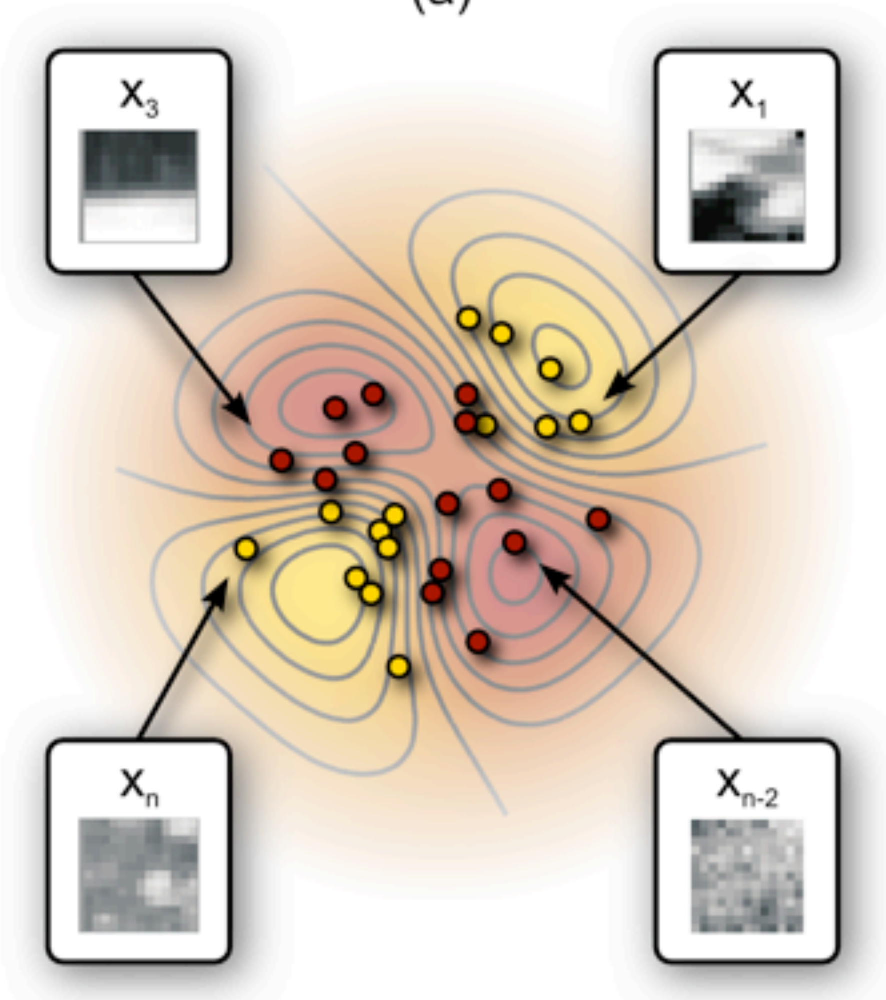


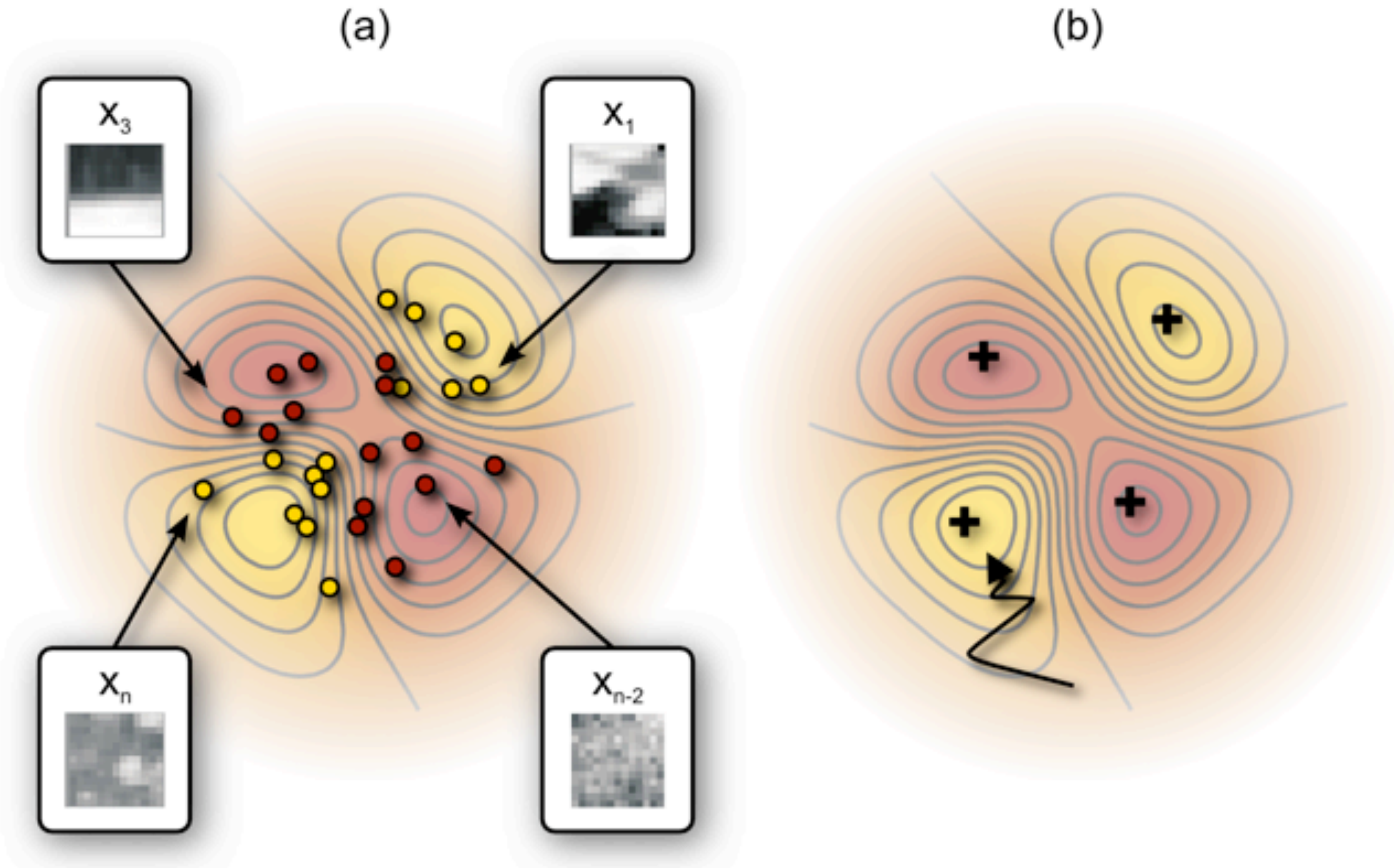


Randomly Selected vs. Fixated Patches: ICA Basis

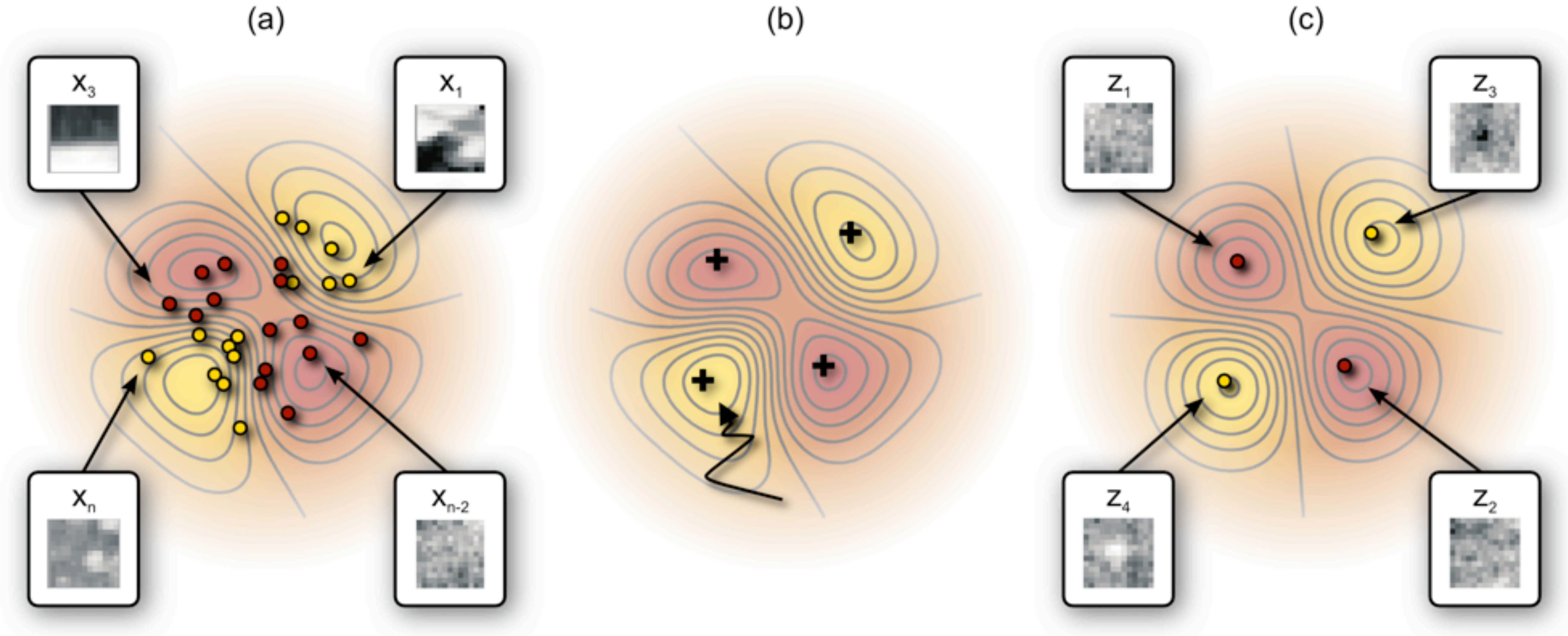


(a)

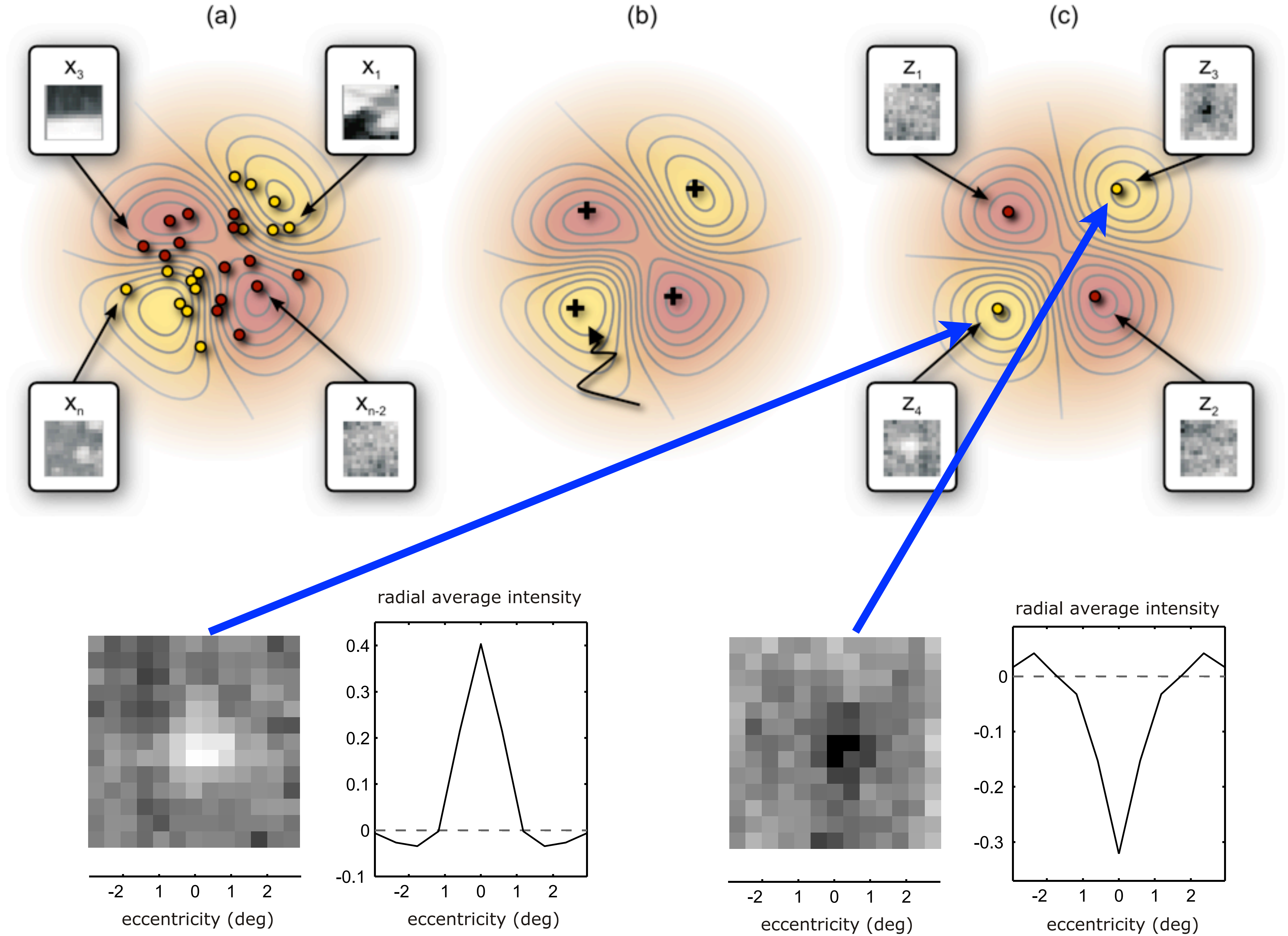




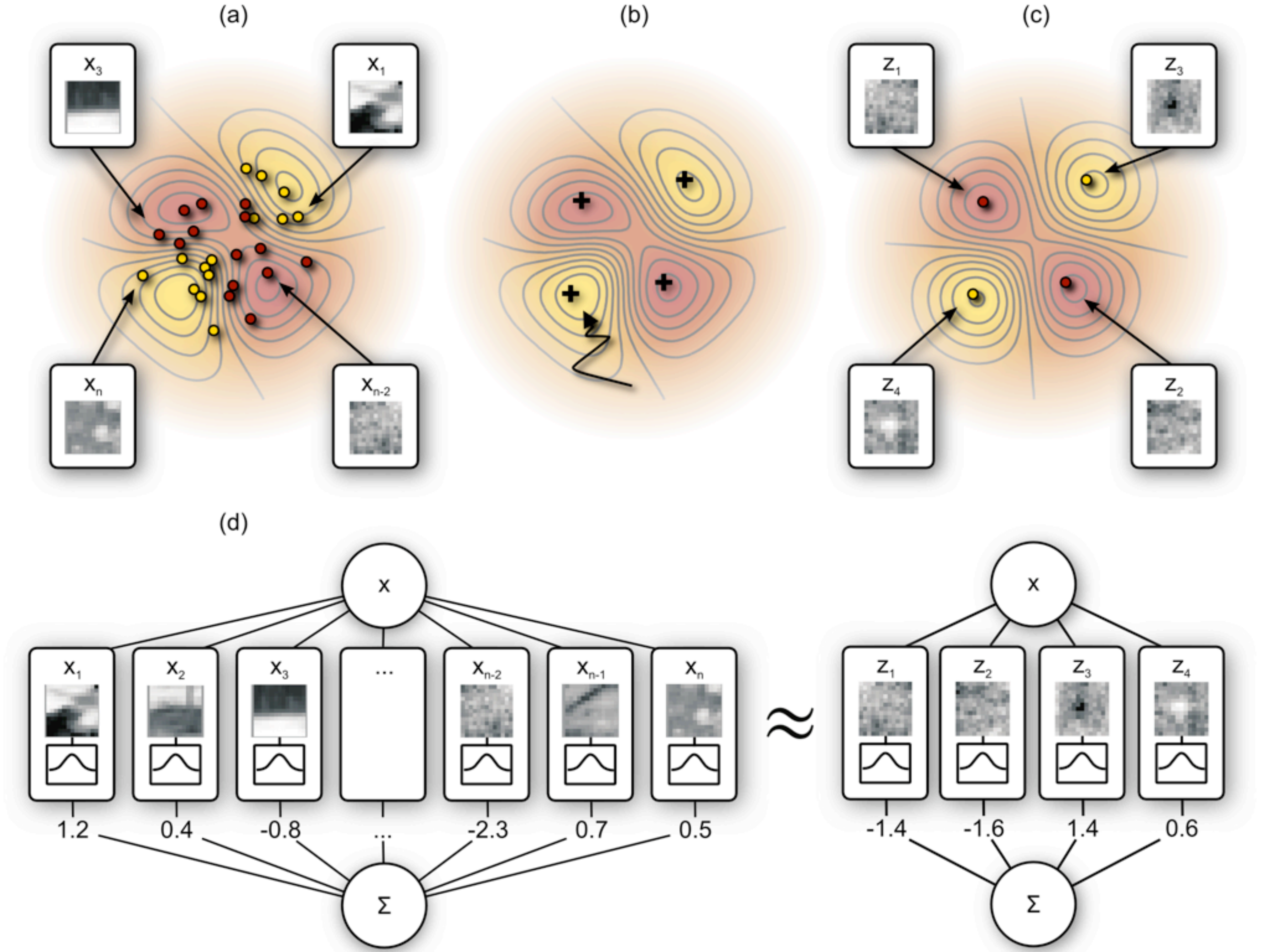
(a)
(b)
X3
X1
Xn
Xn-2



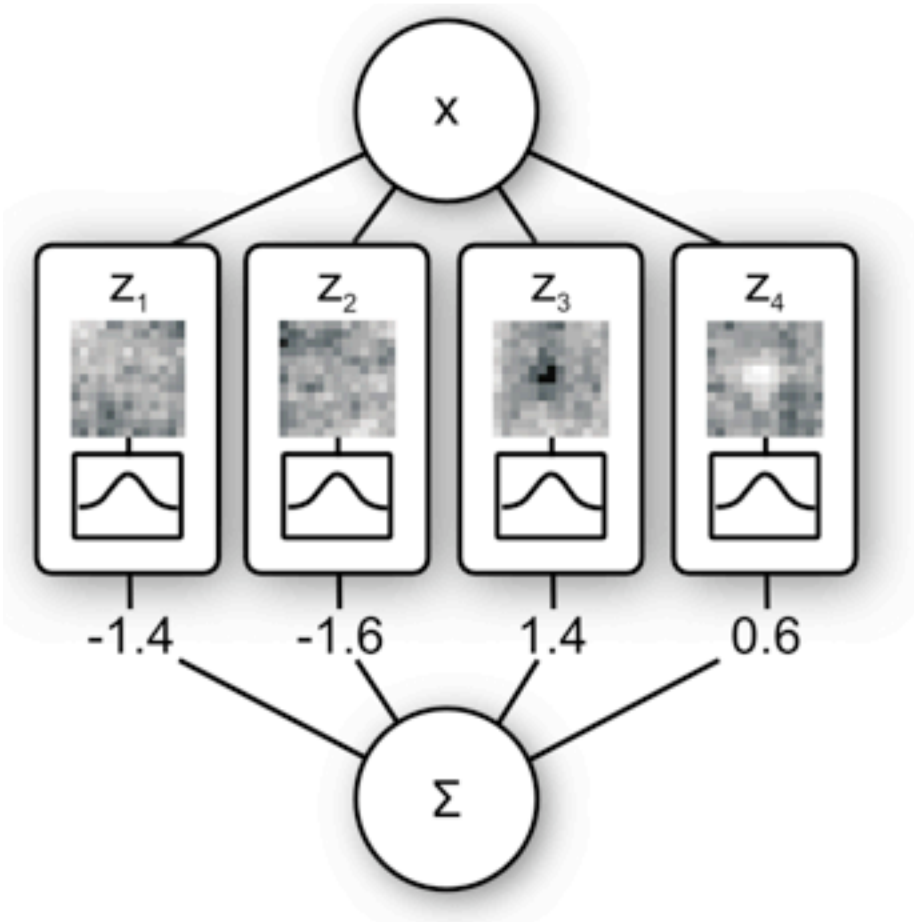
(a)
(b)
(c)
x_3
x_1
x_n
x_{n-2}
z_1
z_3
z_4
z_2

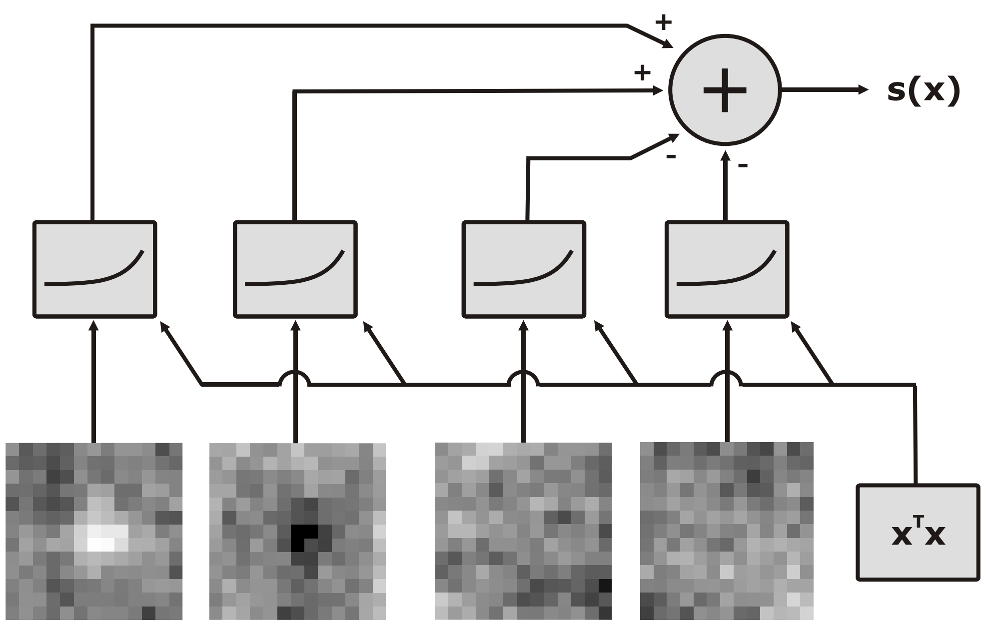


(a)
(b)
(c)
X_3
X_1
X_n
X_{n-2}
Z_1
Z_3
Z_4
Z_2
radial average intensity
0.4
0.3
0.2
0.1
0
-0.1
-2
1
0
1
2
eccentricity (deg)
radial average intensity
0
-0.1
-0.2
-0.3
eccentricity (deg)


(a)
(b)
(c)
(d)
x
Σ

Non-linear Decision-Image Network for Visual Saliency





Critical Controls

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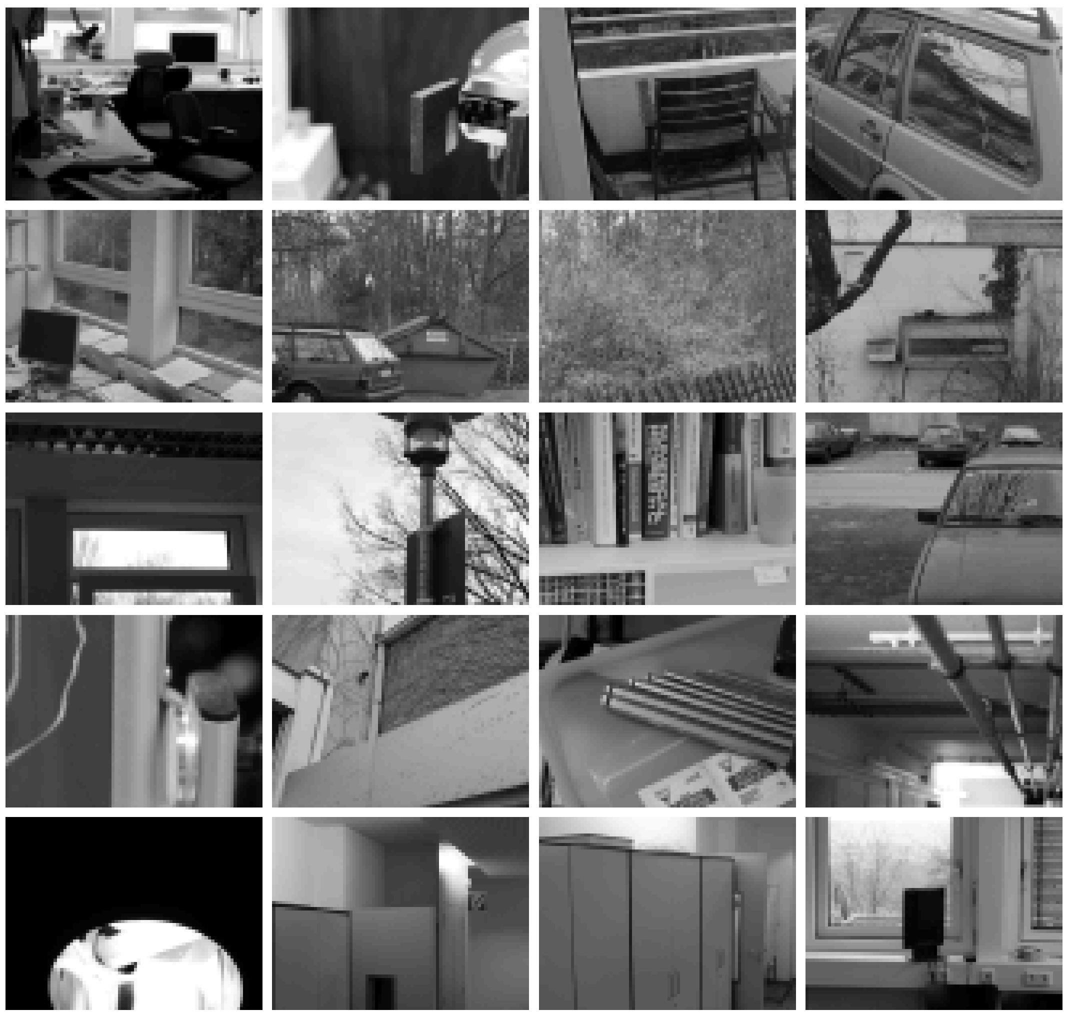

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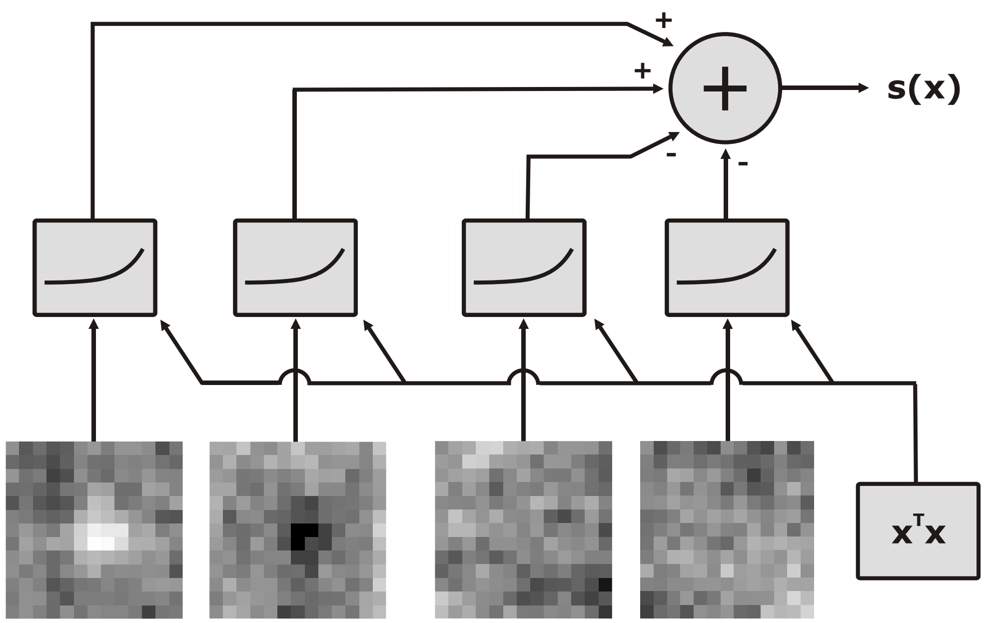
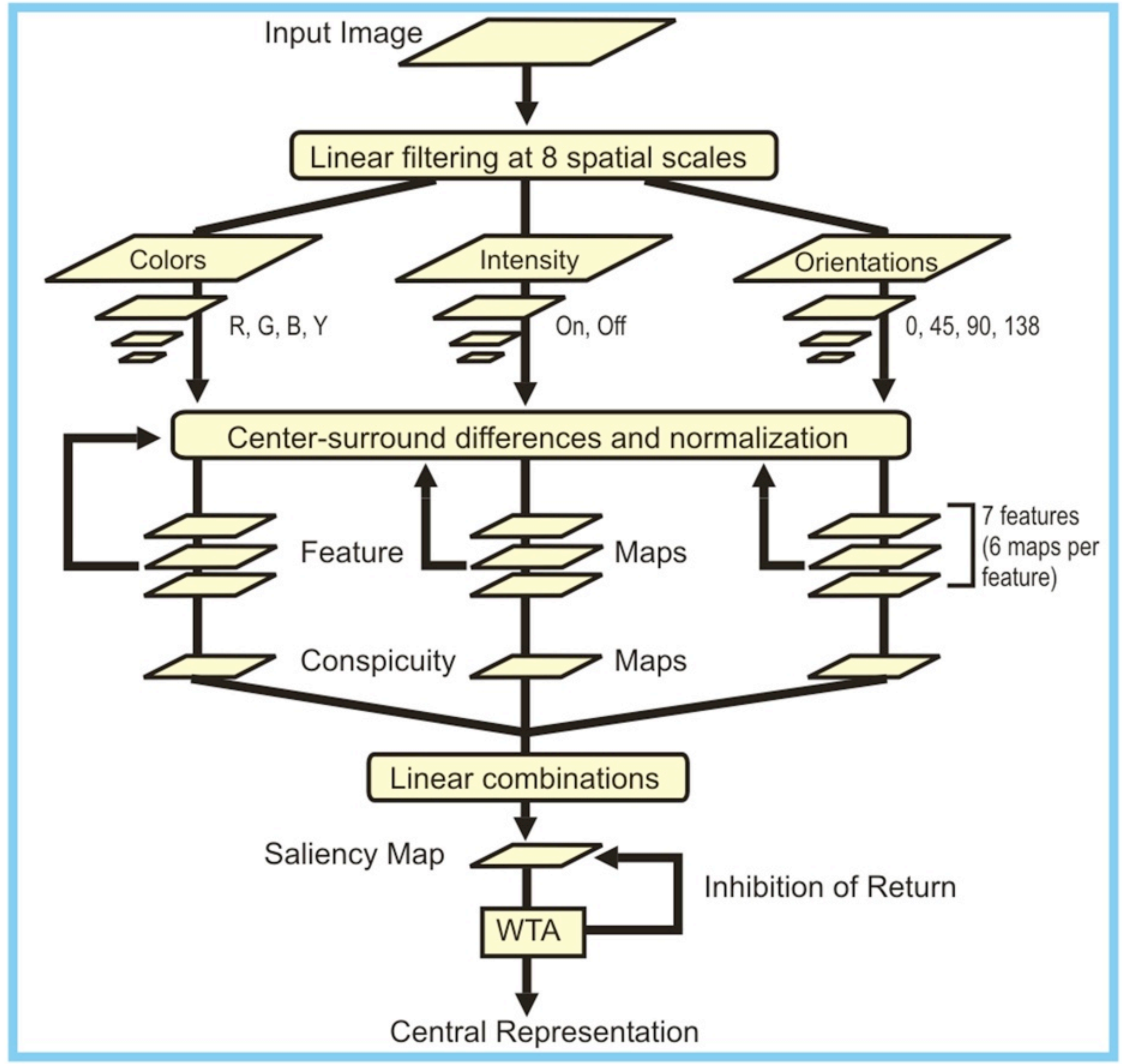
Occam's Razor?





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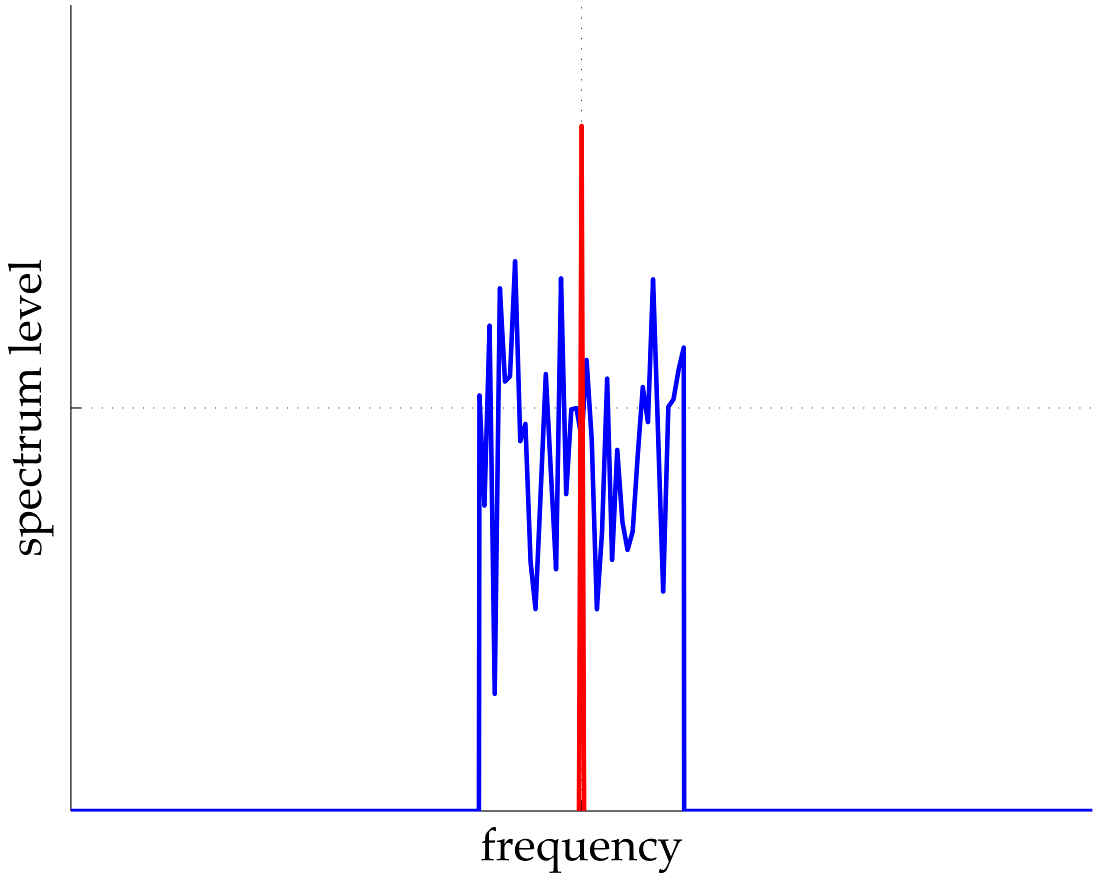
This analysis can be seen as an extended psychophysical receptive or perceptive field analysis, recovering perceptive field networks.

Unlike classification images or the bubbles technique this method can be used under natural viewing conditions, i.e. no image distortion is needed (noise, "bubbles").

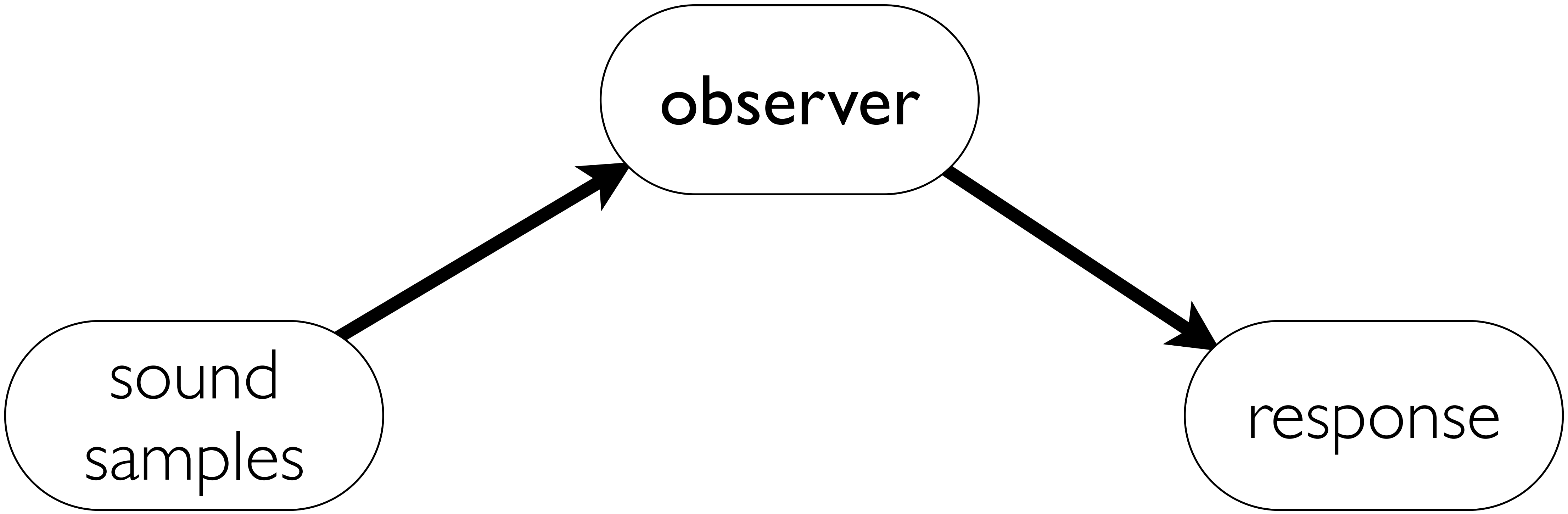
3

Tone-in-Noise Detection



Harvey Fletcher (left) at Bell Telephone Labs in NYC

System Identification Re-Visited



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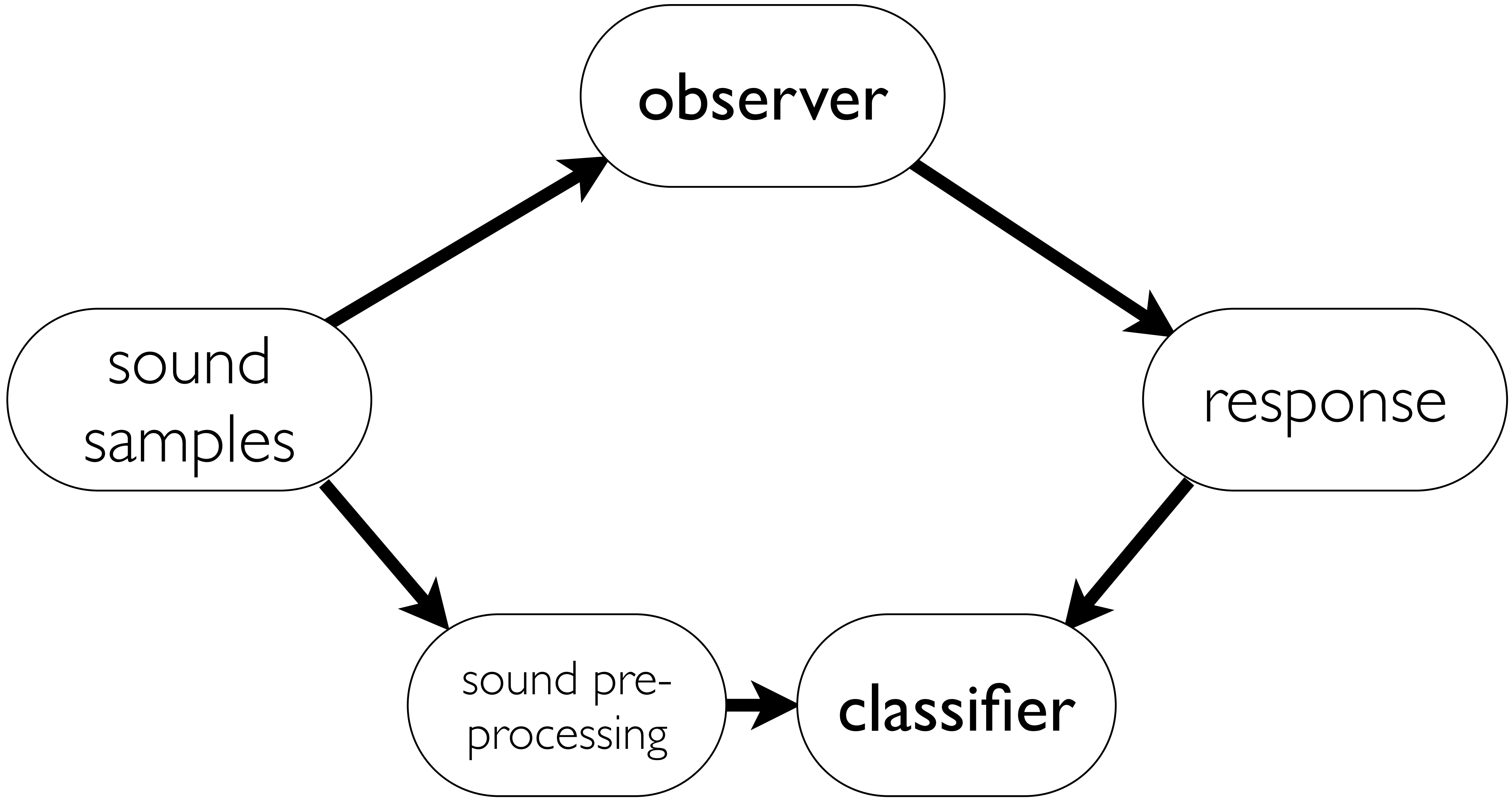

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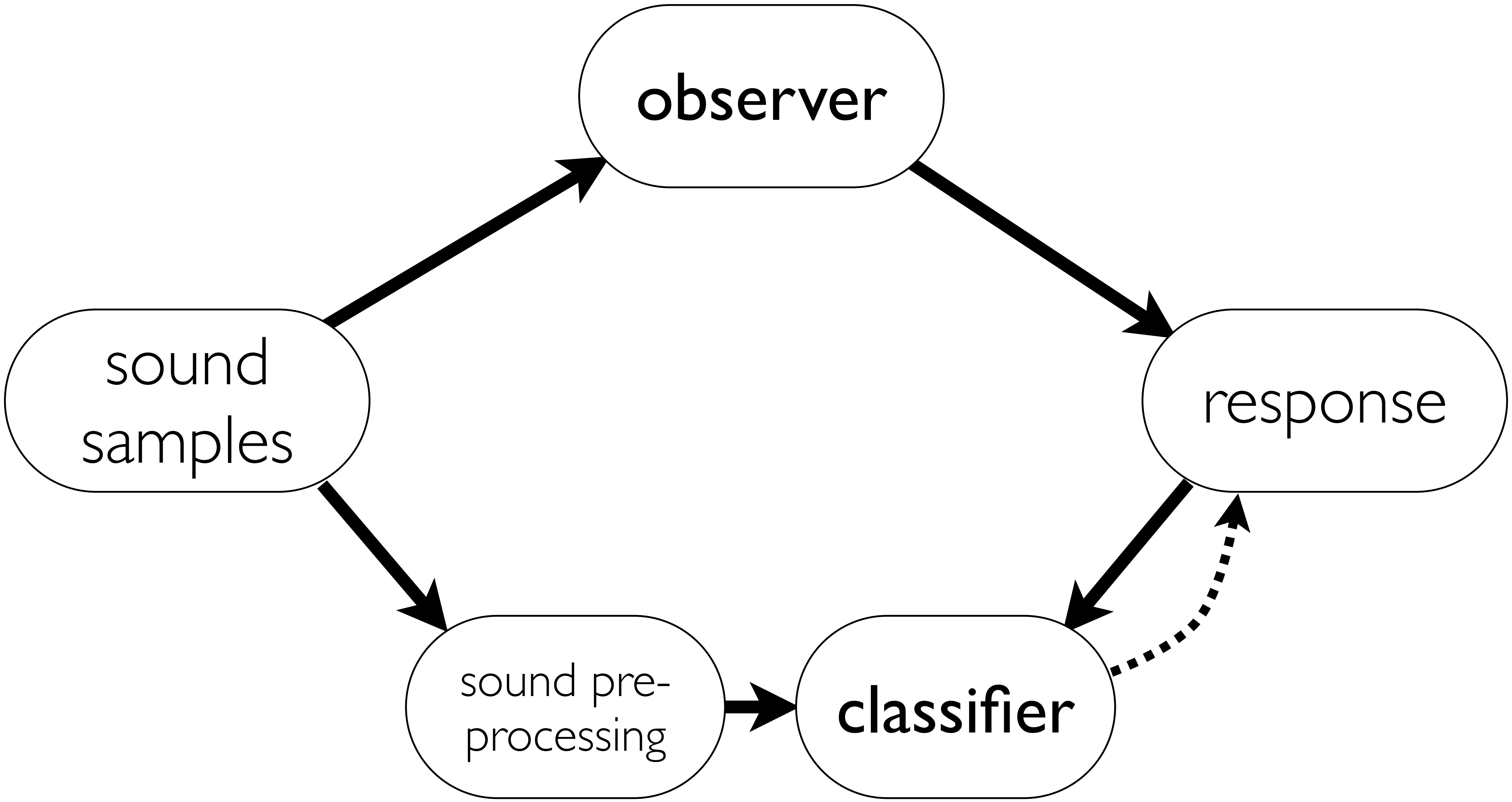

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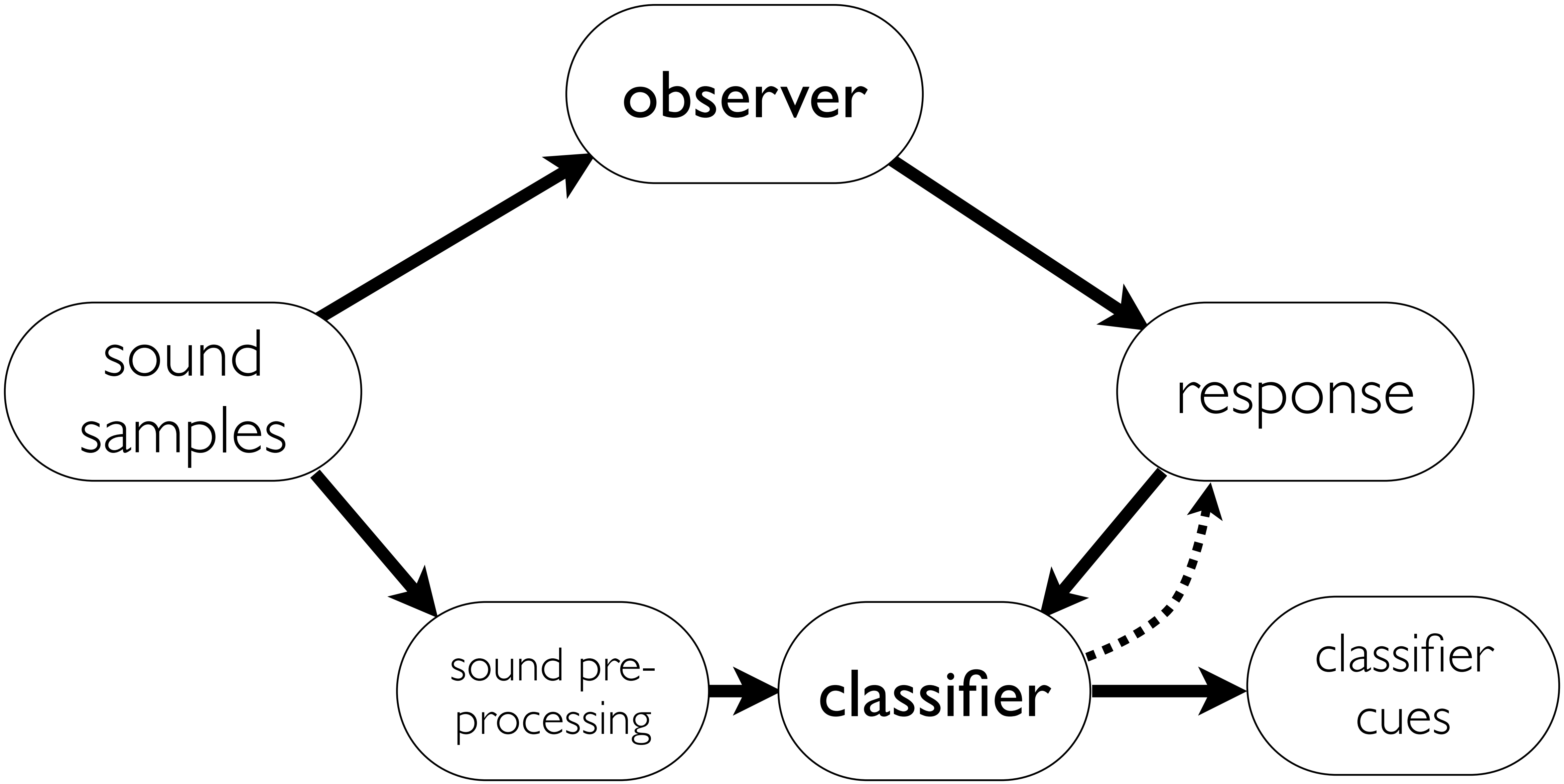

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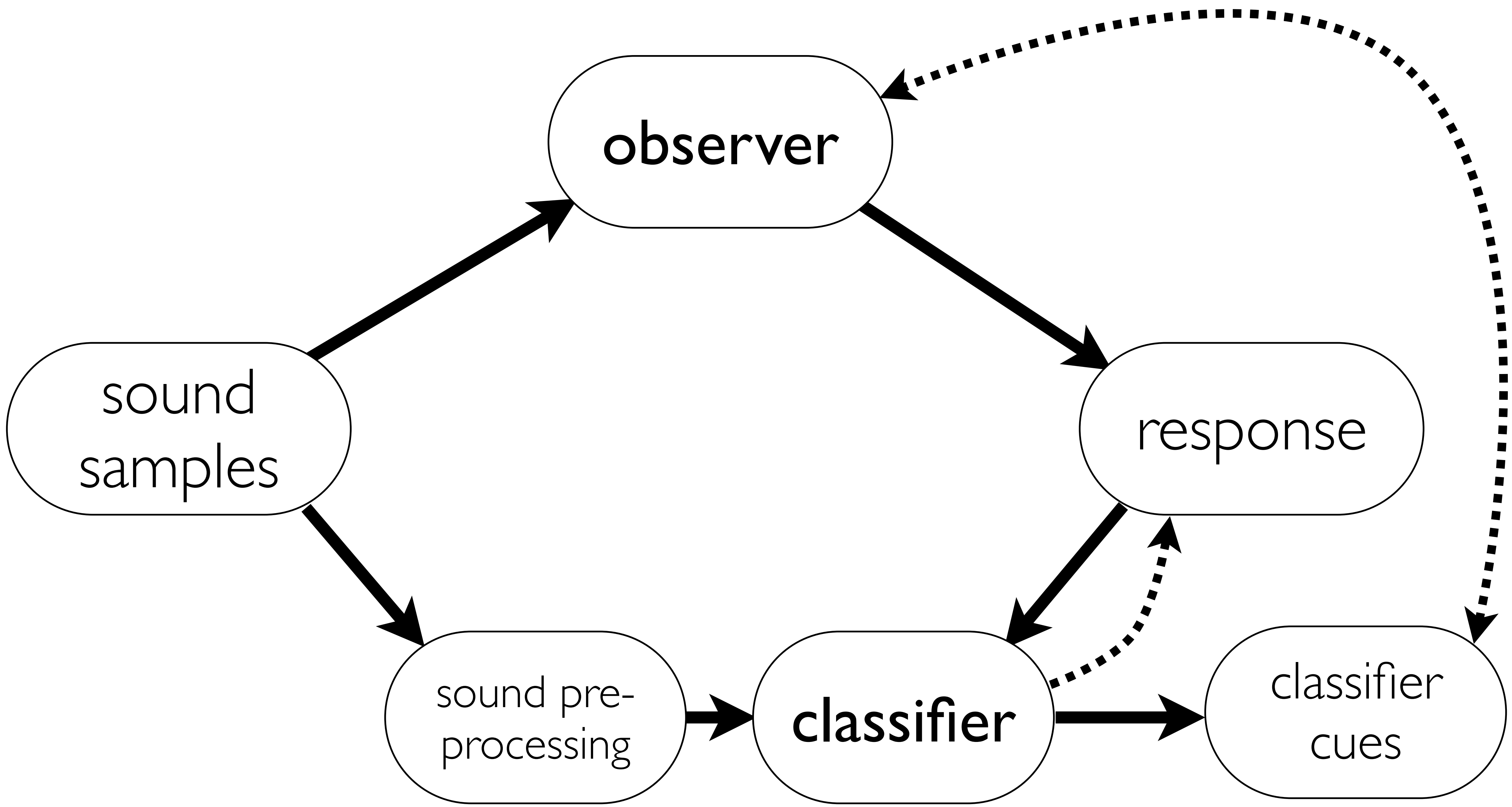
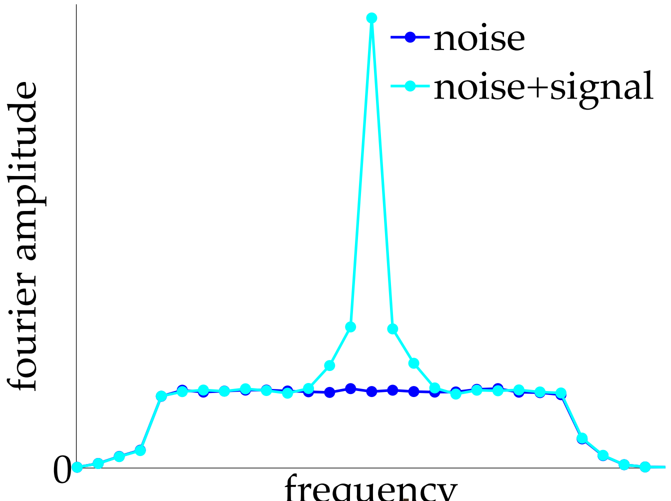
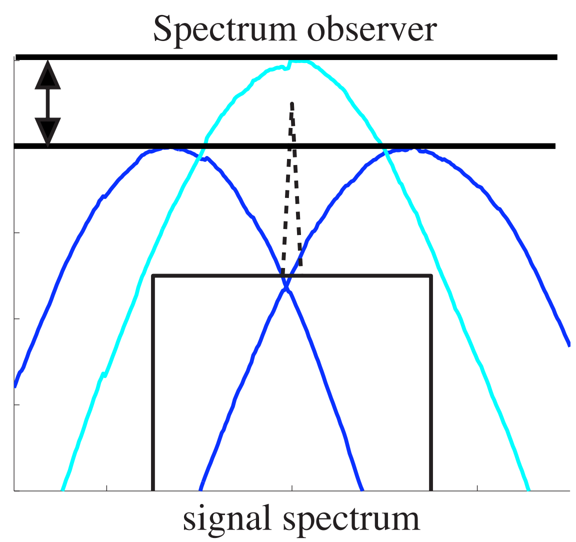
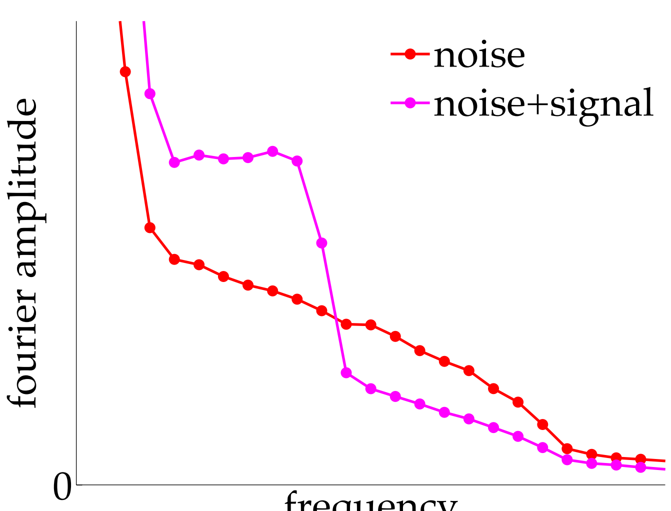


Synthetic Observers (i.e. Simulated Features)

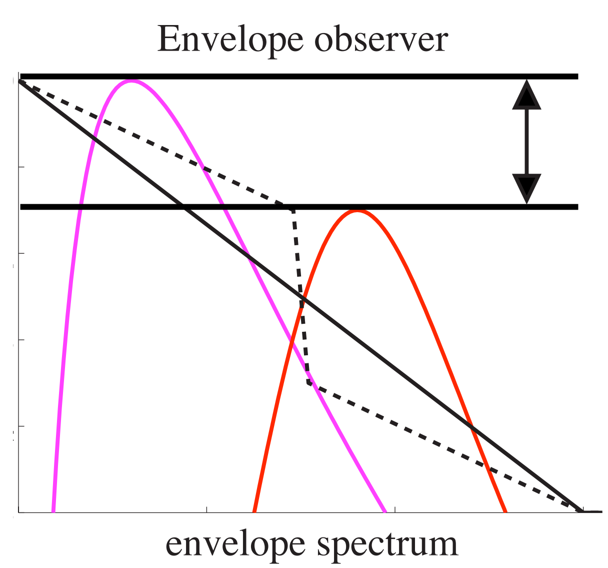


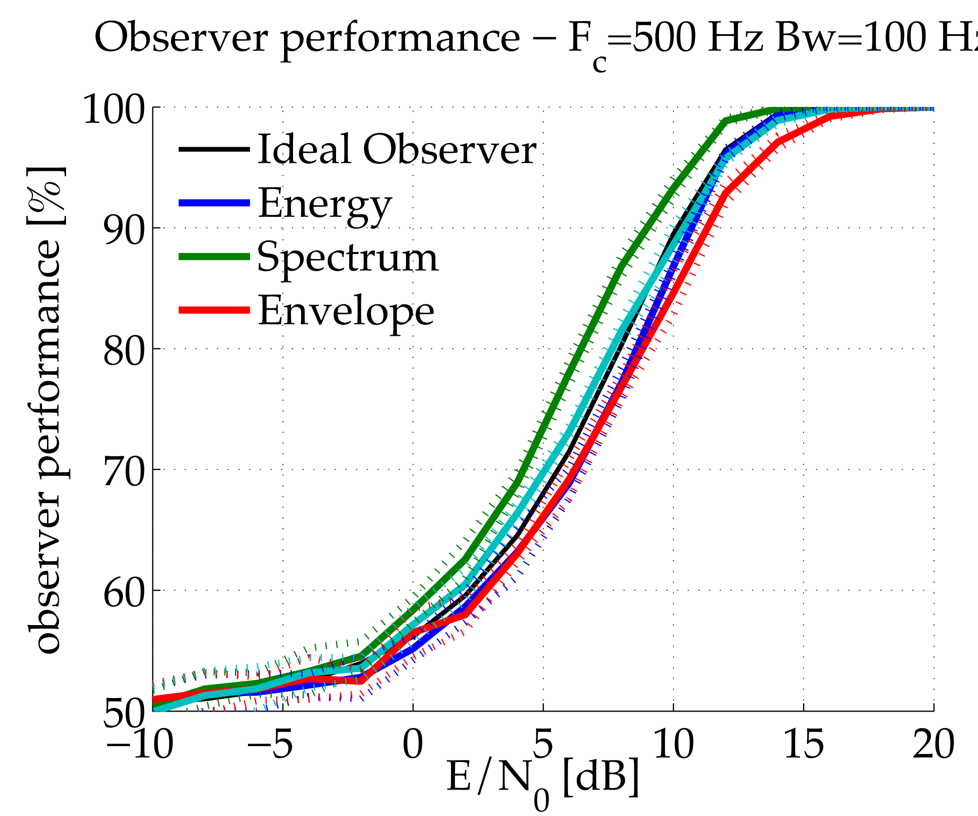
sound spectrum



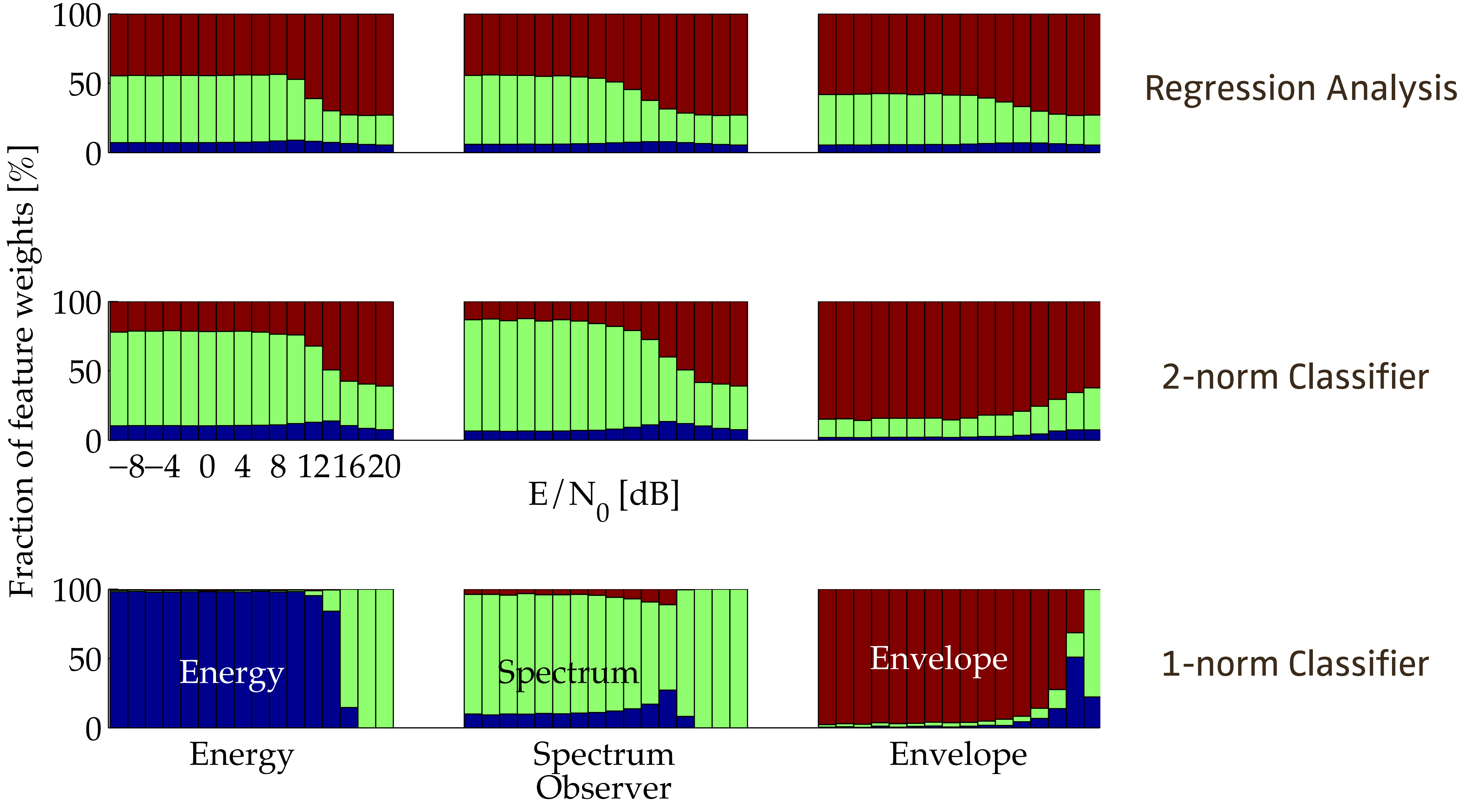


envelope spectrum

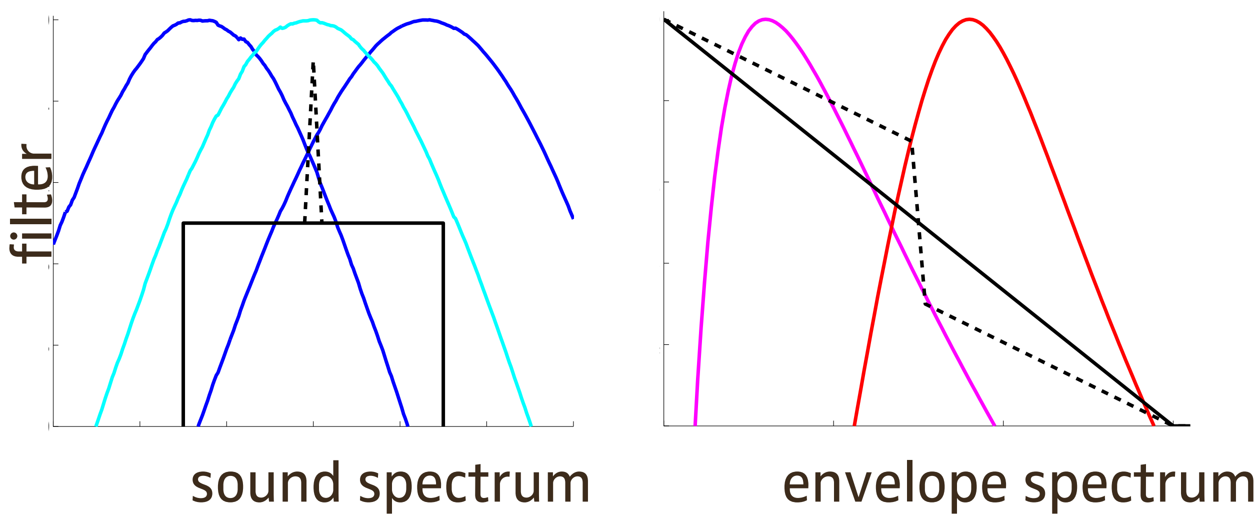




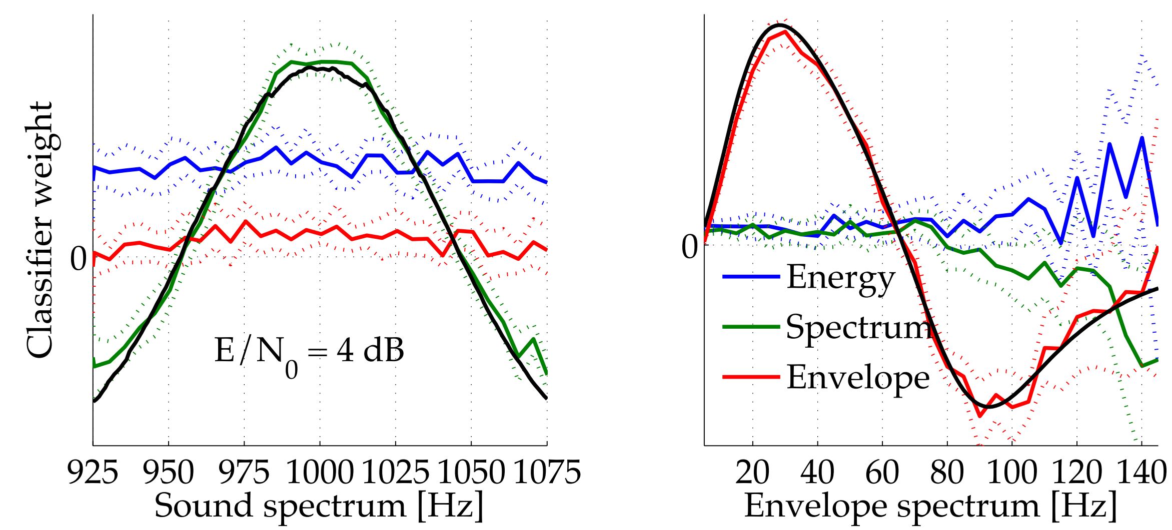
Observer Reconstruction—Feature Weights



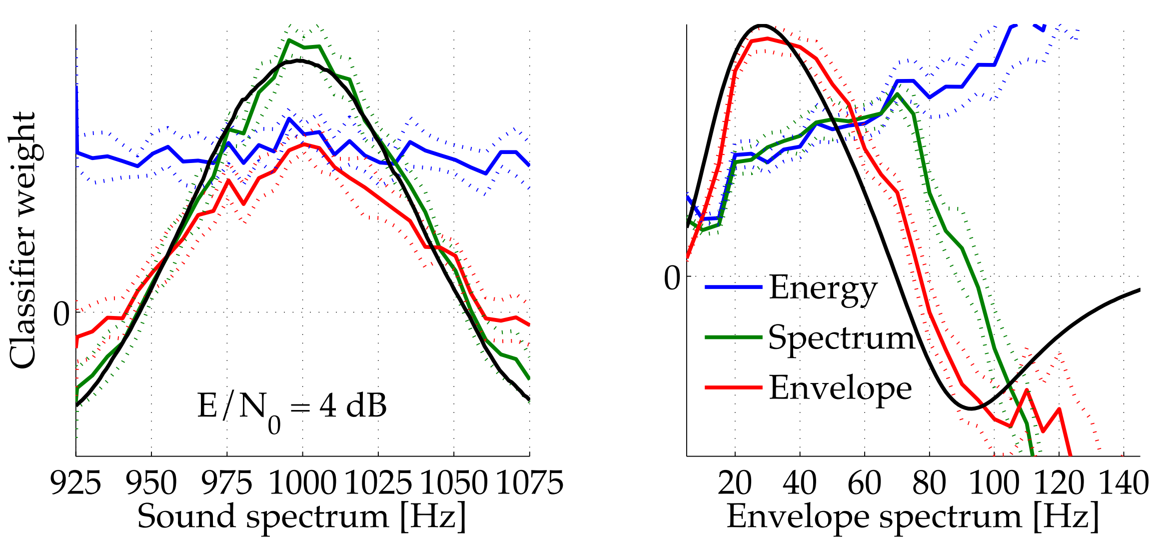
Observer Reconstruction—Inferred Filter Shapes



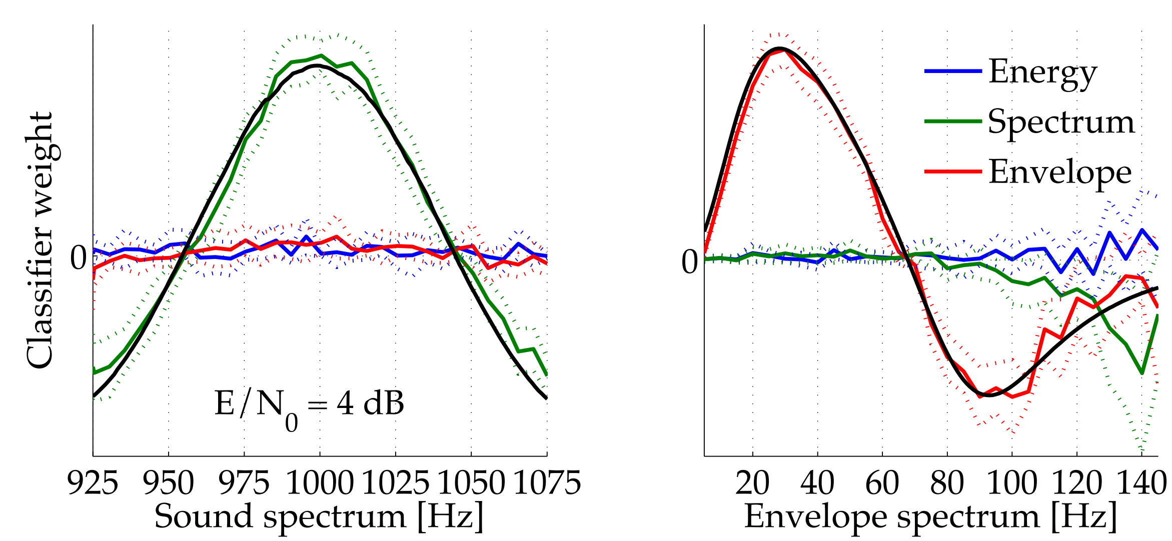
Ground Truth



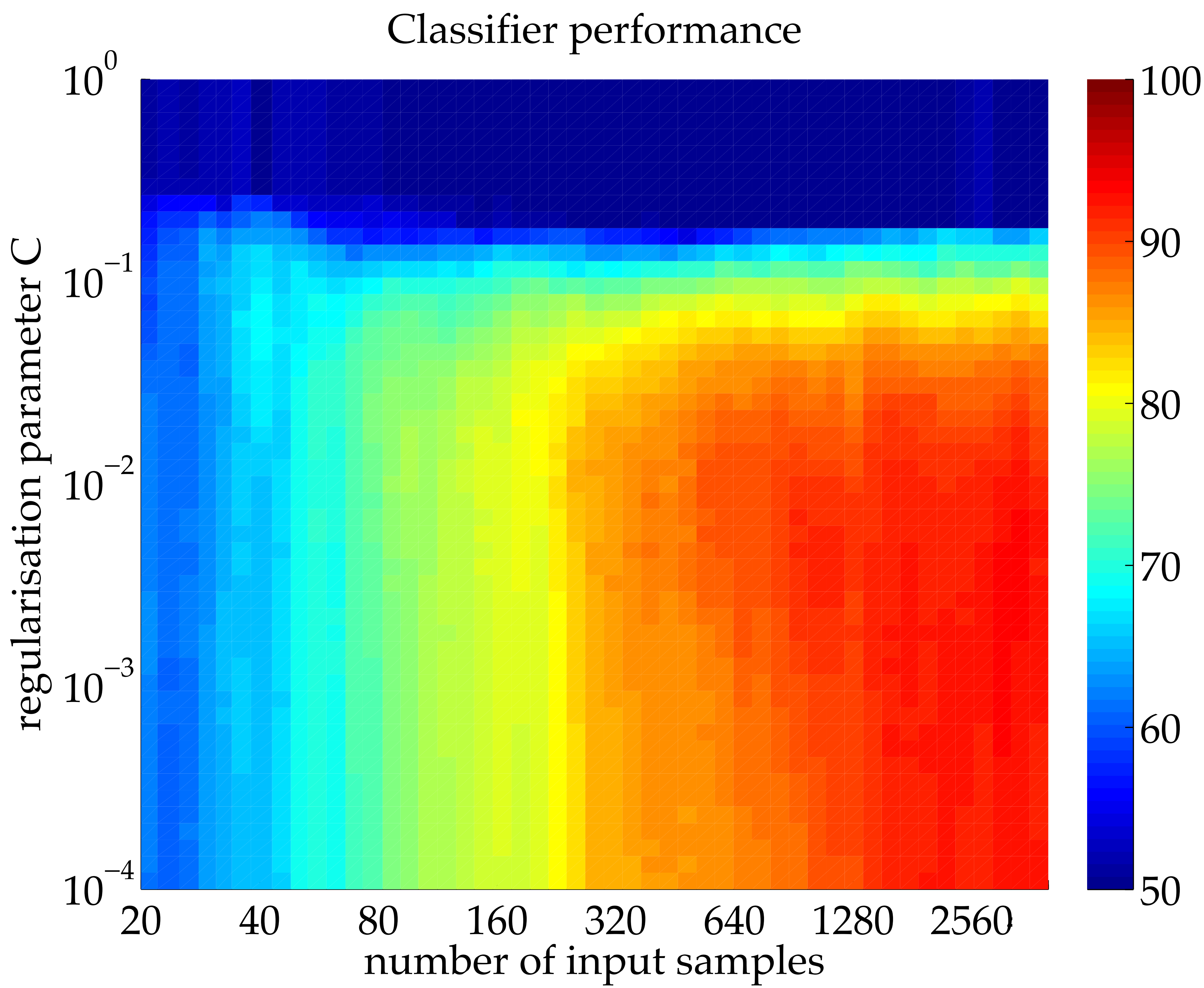
2-norm Classifier

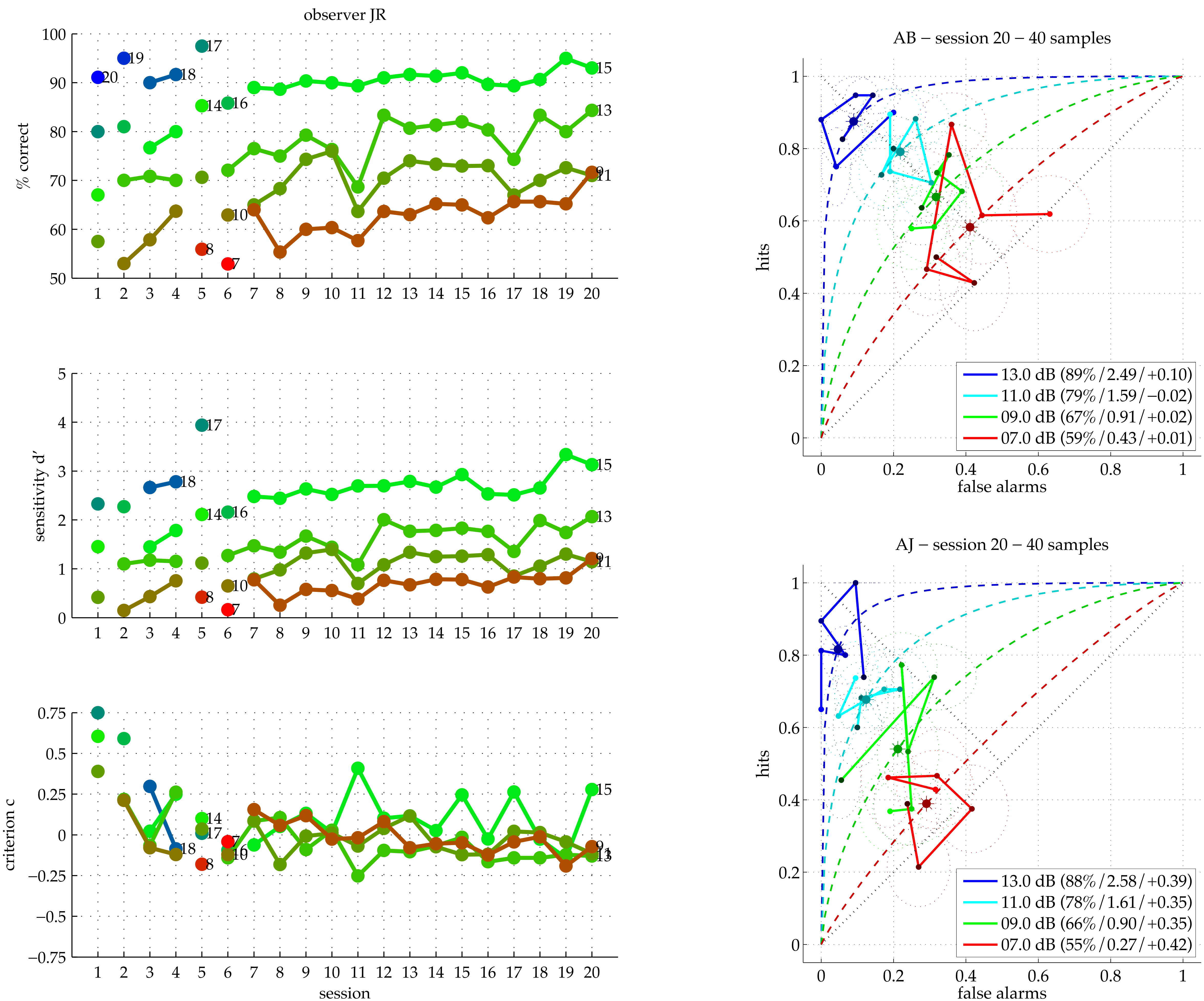


Regression Analysis



1-norm Classifier


Classifier performance
regularisation parameter C
10^0
10^{-1}
10^{-2}
10^{-3}
10^{-4}
20
40
80
160
320
640
1280
2560
number of input samples
100
90
80
70
60
50


observer JR
% correct
sensitivity d′
criterion c
session
AB – session 20 – 40 samples
hits
false alarms
13.0 dB (89% / 2.49 / +0.10)
11.0 dB (79% / 1.59 / −0.02)
09.0 dB (67% / 0.91 / +0.02)
07.0 dB (59% / 0.43 / +0.01)
AJ – session 20 – 40 samples
hits
false alarms
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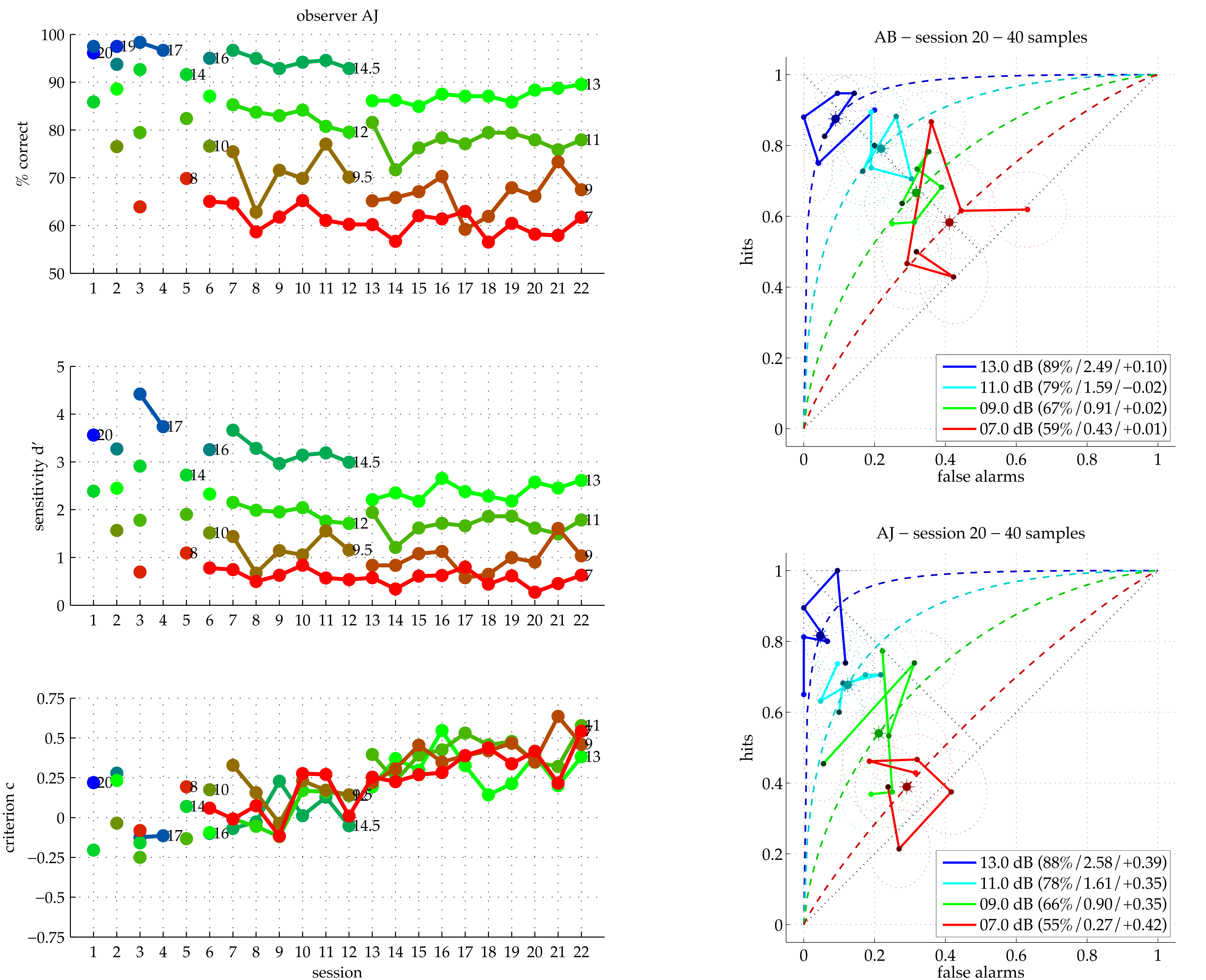
09.0 dB (66% / 0.90 / +0.35)
07.0 dB (55% / 0.27 / +0.42)


observer AJ
% correct
sensitivity d′
criterion c
session
AB – session 20 – 40 samples
hits
false alarms
13.0 dB (89% / 2.49 / +0.10)
11.0 dB (79% / 1.59 / −0.02)
09.0 dB (67% / 0.91 / +0.02)
07.0 dB (59% / 0.43 / +0.01)
AJ – session 20 – 40 samples
hits
false alarms
13.0 dB (88% / 2.58 / +0.39)
11.0 dB (78% / 1.61 / +0.35)
09.0 dB (66% / 0.90 / +0.35)
07.0 dB (55% / 0.27 / +0.42)

Literature (Heavily Biased Sample)

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Thank you very much!

Felix A. Wichmann

EBERHARD KARLS UNIVERSITÄT TÜBINGEN

Faculty of Science
Computer Science Department
Neural Information Processing Group

Bernstein Center for Computational Neuroscience Tübingen

MAX-PLANCK-GESELLSCHAFT

Max Planck Institute for Intelligent Systems
Empirical Inference Department

Werner Reichardt Centre for Integrative Neuroscience