NEURAL EVIDENCE FOR OPTIMAL INFERENCE AND LEARNING IN PRIMARY VISUAL CORTEX

PIETRO BERKES

Volen Center for Complex Systems

Brandeis University

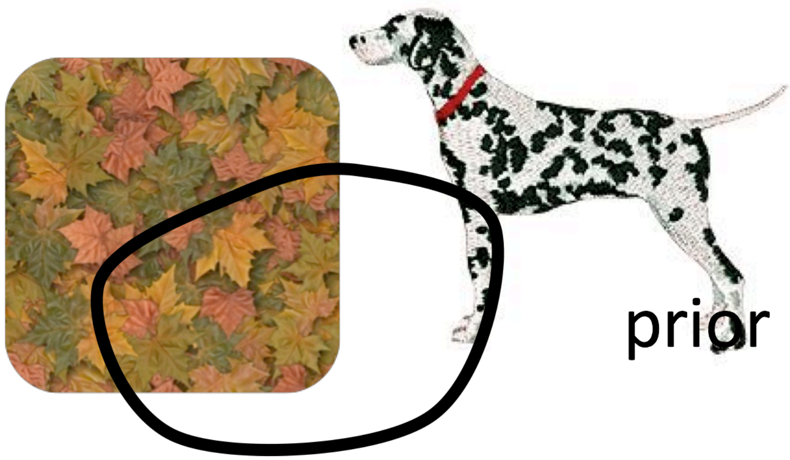
PERCEPTION IS NOT FEED-FORWARD

THE IMPORTANCE OF PRIOR KNOWLEDGE

perception

evidence
from visual input

THE IMPORTANCE OF PRIOR KNOWLEDGE



prior knowledge

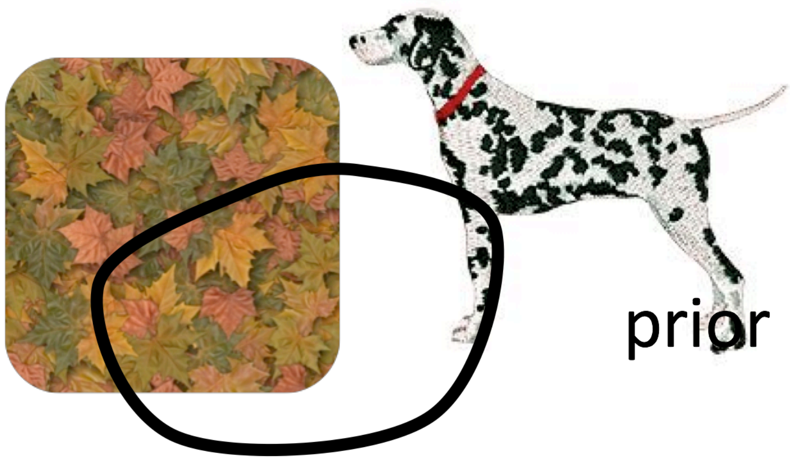
↓

perception

↑

evidence
from visual input

THE IMPORTANCE OF PRIOR KNOWLEDGE



prior knowledge

↓

“Dalmatian dog in a park”

perception

↑

evidence
from visual input

PERCEPTION AS INFERENCE

prior knowledge $P(\mathbf{x})$

“Dalmatian dog in a park”

perception $P(\mathbf{x}|\mathbf{y})$

evidence from visual input $\mathbf{y}$

STATISTICALLY OPTIMAL INFERENCE

prior knowledge

$$P(\mathbf{x})$$

"Dalmatian dog in a park"

perception

optimal inference

$$\boxed{P(\mathbf{x}|\mathbf{y}) = \frac{P(\mathbf{y}|\mathbf{x})P(\mathbf{x})}{P(\mathbf{y})}}$$

Bayes' theorem

evidence
from visual input

$$\mathbf{y}$$

STATISTICALLY OPTIMAL LEARNING

prior knowledge ← learning

↓

perception

↑

evidence
from visual input

"Dalmatian dog
in a park"

STATISTICALLY OPTIMAL LEARNING

optimal learning

$$\boxed{P_\theta(\mathbf{y}) \rightarrow P_{\mathrm{real}}(\mathbf{y})}$$

prior knowledge ← learning

↓

“Dalmatian dog in a park”

perception

↑

evidence from visual input

PROBABILISTIC COMPUTATIONS IN THE BRAIN

Computation

Evidence	Inference	Learning
Behavioral	Atkins *et al.*, 2001 Ernst & Banks, 2002 Körding & Wolpert, 2004 Weiss *et al.*, 2002 Yang & Shadlen, 2007 Kepecs *et al.*, 2008	Dayan *et al.*, 2000 Tenenbaum *et al.*, 2006 Orbán *et al.*, 2008
Neural	? Platt & Glimcher, 1999 Yang & Shadlen, 2007 Kepecs, *et al.*, 2008	?

NEURAL ACTIVITY AS REPRESENTING SAMPLES

(Hyvarinen & Hoyer, 2003; Lee & Mumford, 2003)

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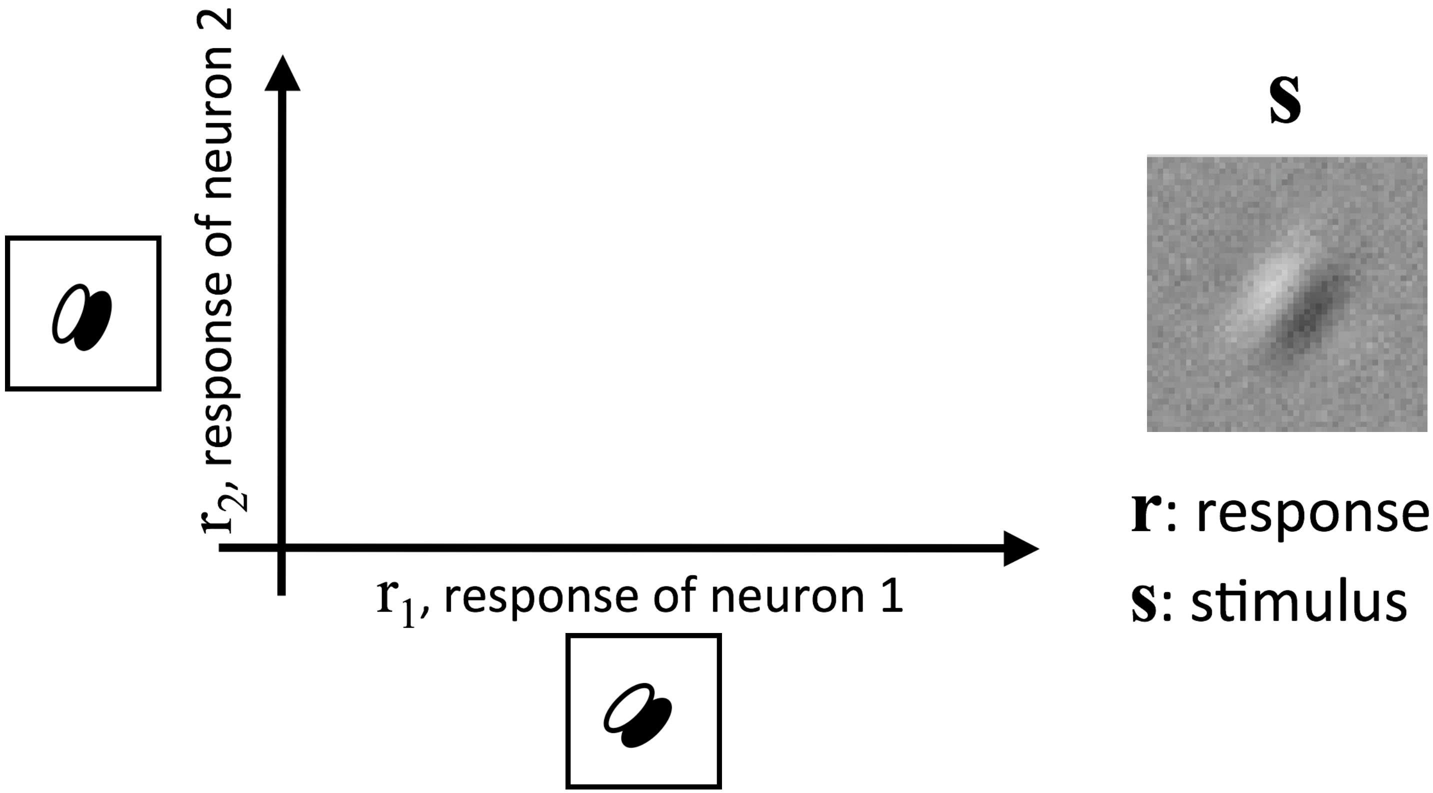

$\mathbf{r}$: response

$\mathbf{s}$: stimulus

(Hyvarinen & Hoyer, 2003; Lee & Mumford, 2003)

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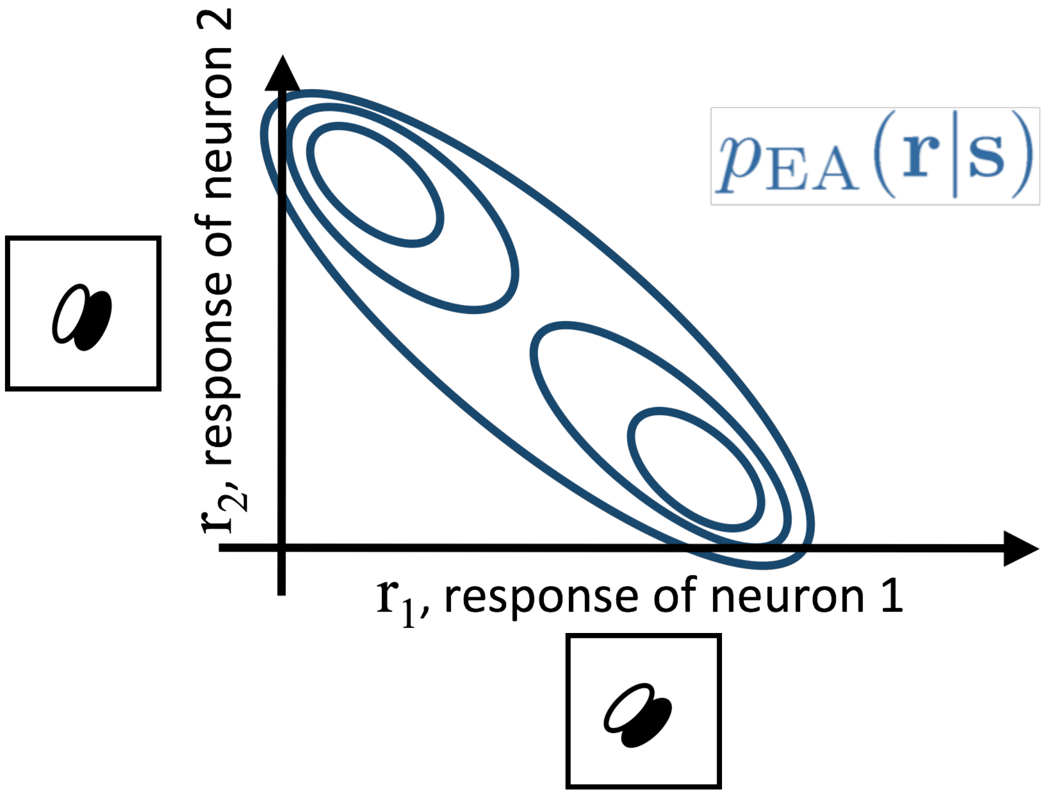
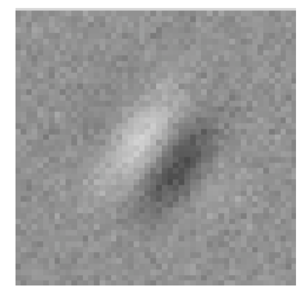


$\mathbf{s}$



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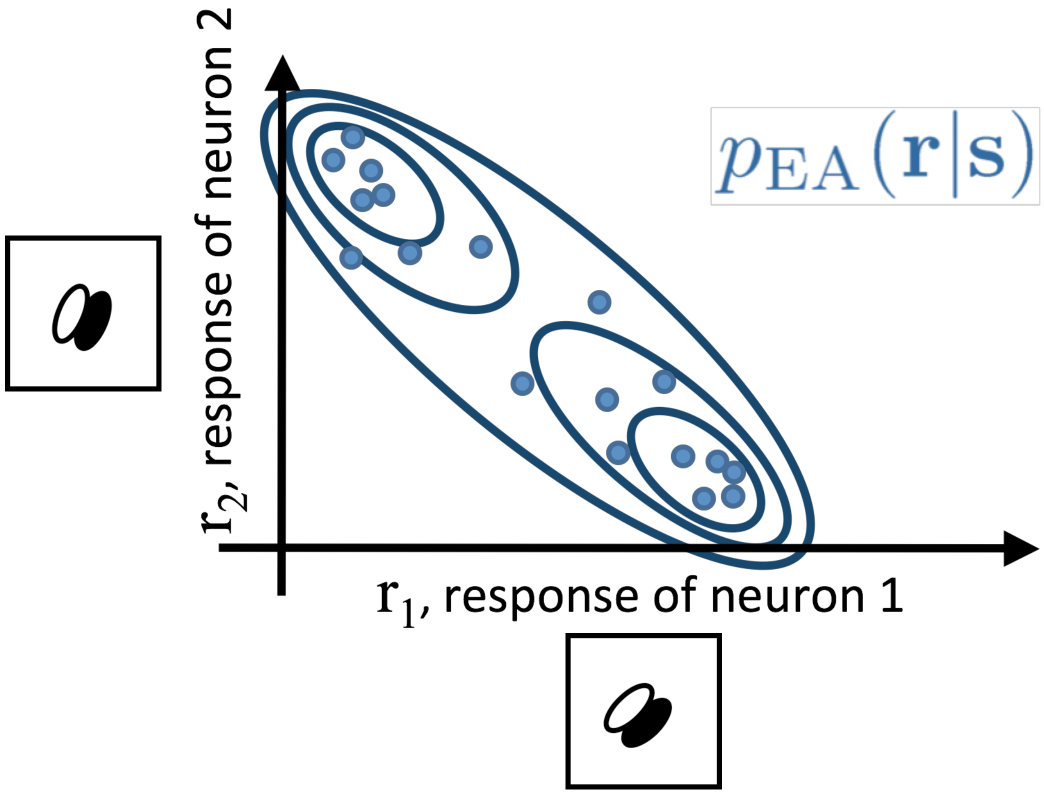

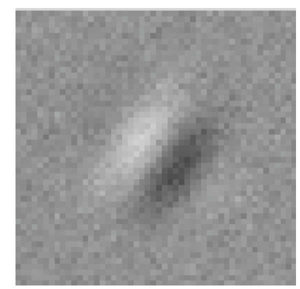

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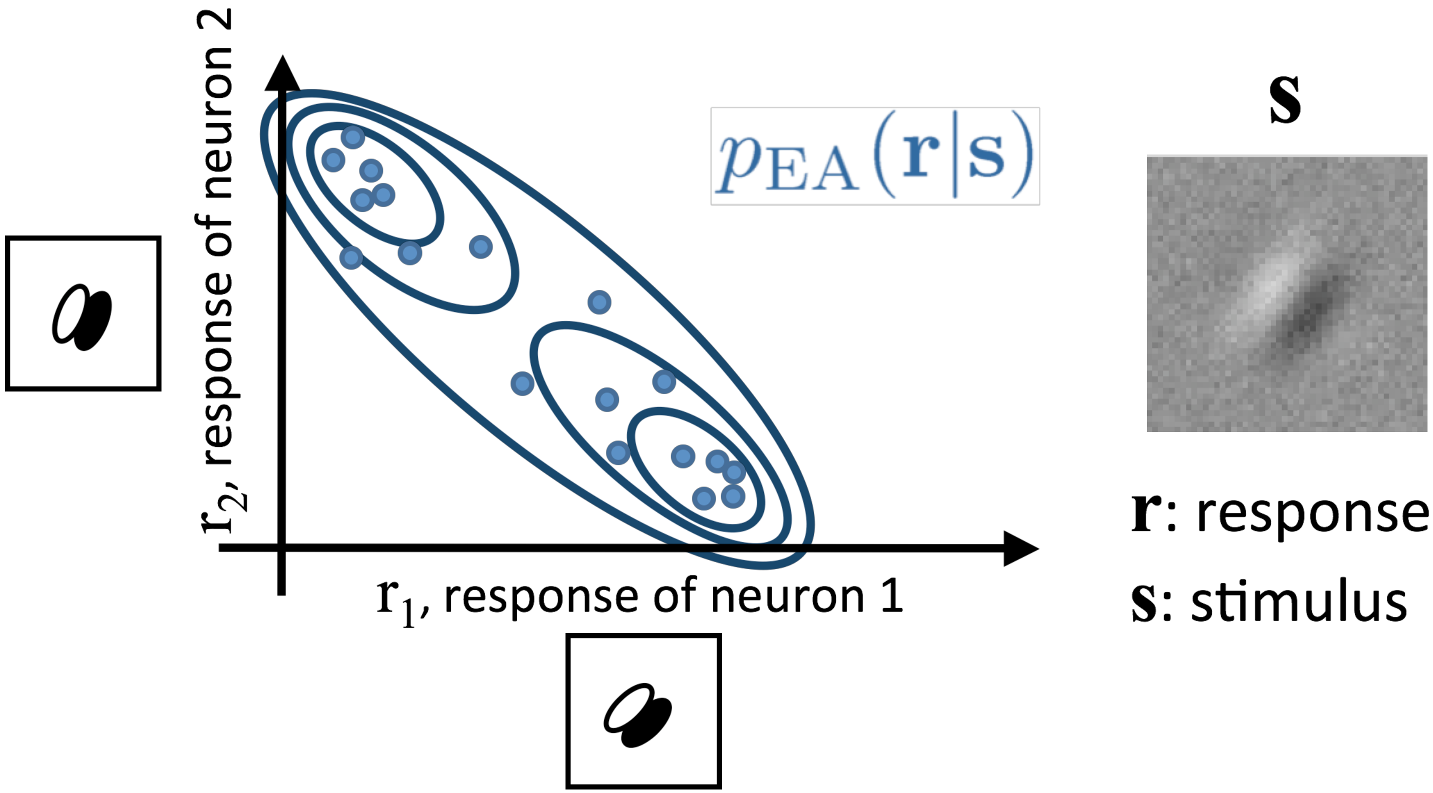


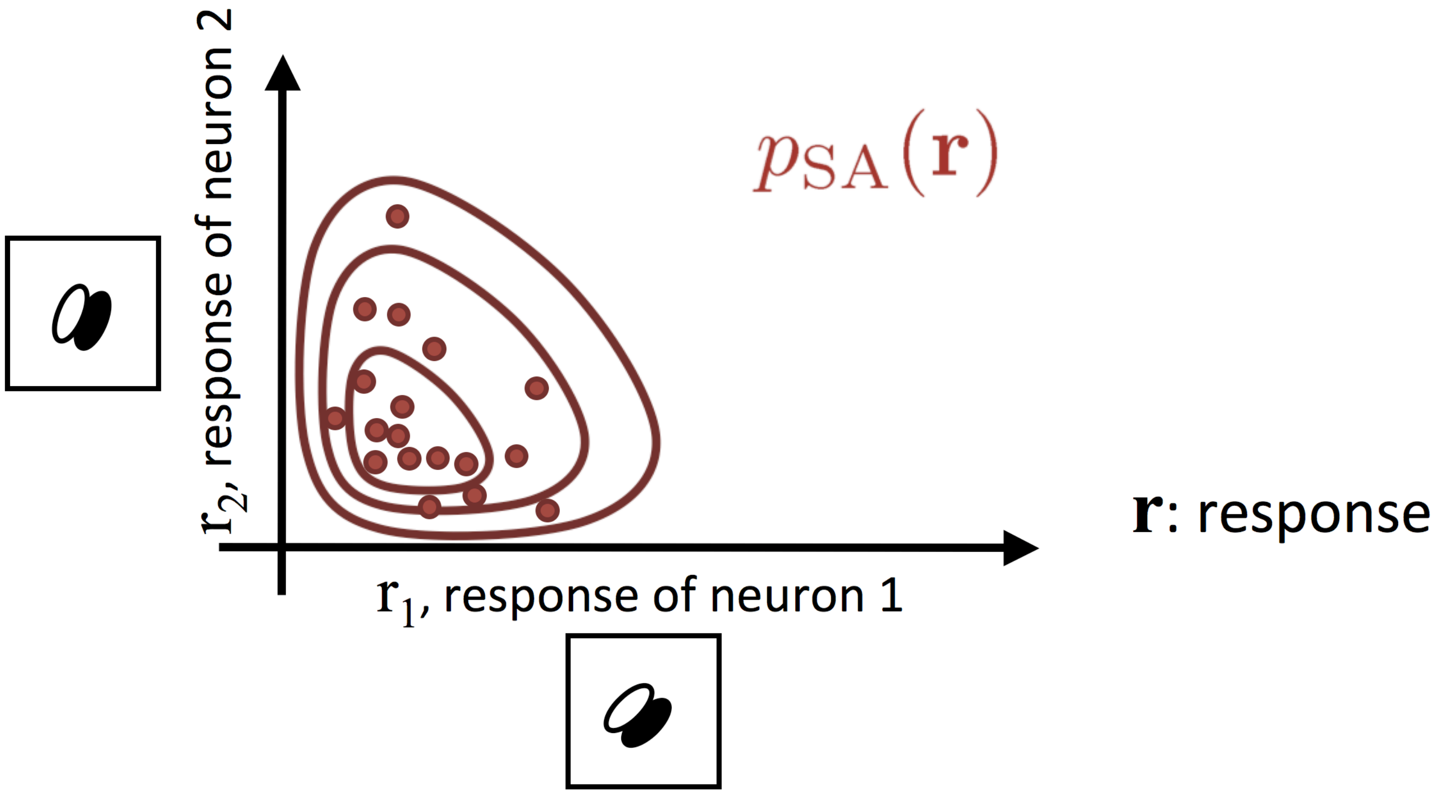
Natural explanation for neural variability, bistable perception, neural response to illusory contours, …

(Hyvarinen & Hoyer, 2003; Lee & Mumford, 2003; Sundareswara & Schrater, 2008)

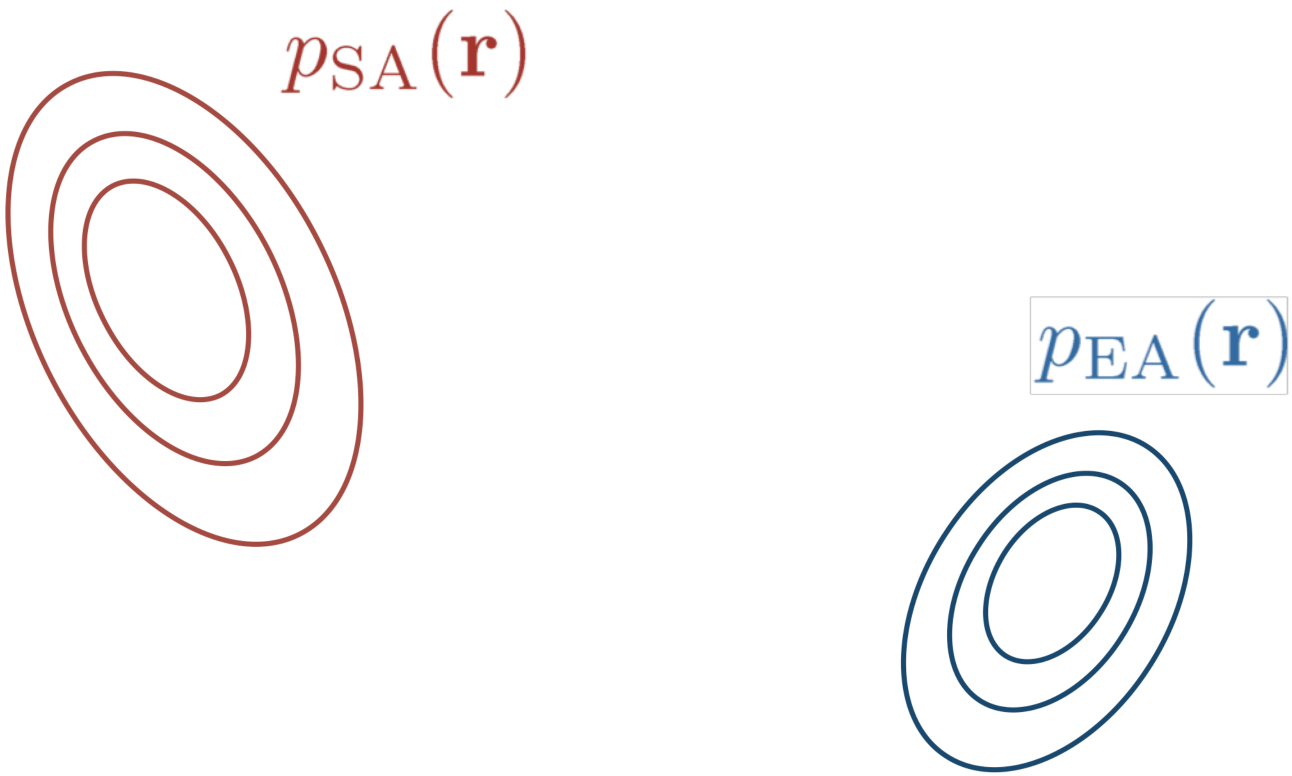
SPONTANEOUS ACTIVITY AS PRIOR PROBABILITY

Electrophysiological data: SA is high, related to EA

(Kenet *et al.*, 2003; Fiser *et al.*, 2004; Yao *et al.*, 2007; Jermakowicz *et al.*, 2009)



LEARNING AND SPONTANEOUS ACTIVITY



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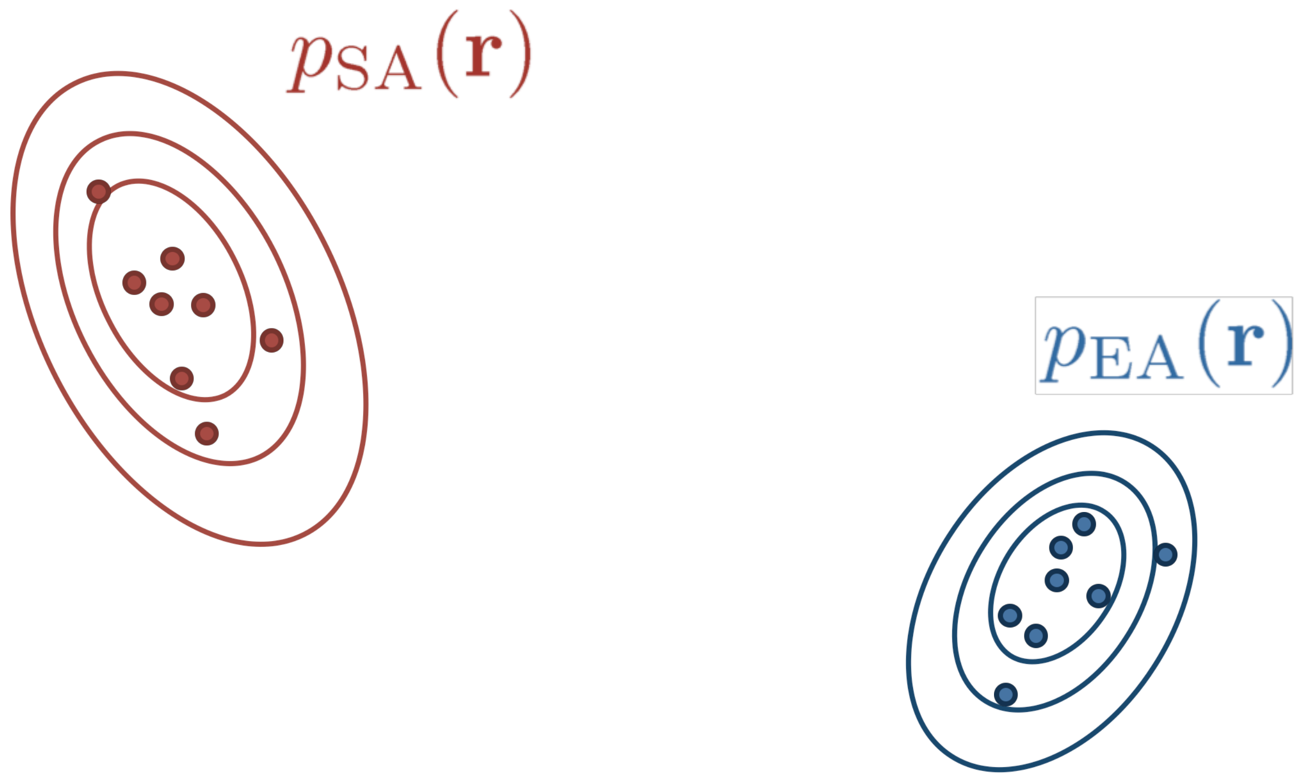

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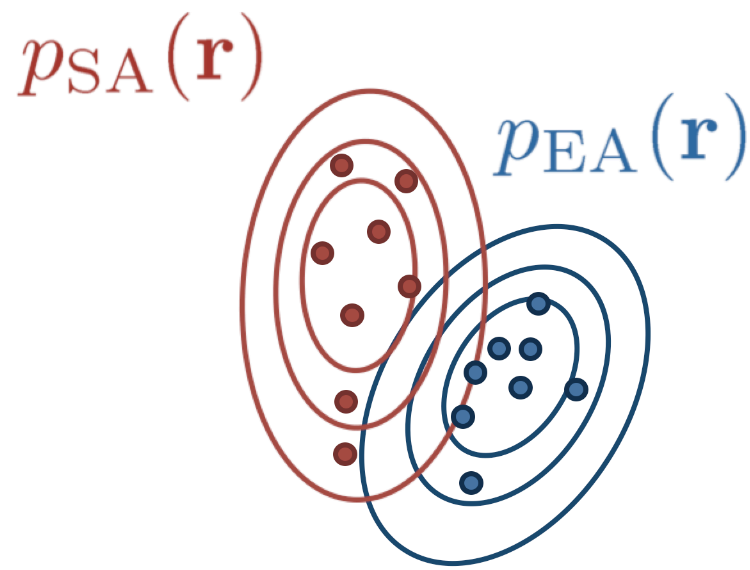
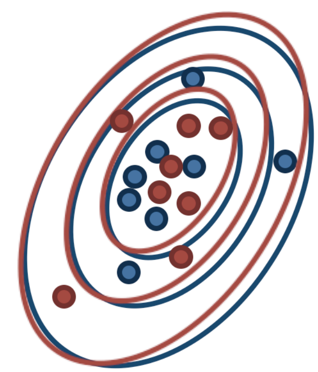


LEARNING AND SPONTANEOUS ACTIVITY

$$p_{\mathrm{SA}}(\mathbf{r}) = p_{\mathrm{EA}}(\mathbf{r})$$



HALLMARKS OF OPTIMAL LEARNING

$p_\theta(\mathbf{s}) \to p_{\mathrm{real}}(\mathbf{s})$ optimal learning

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$$\boxed{p_{\mathrm{SA}}(\mathbf{r})} \longrightarrow \boxed{\langle p_{\mathrm{EA}}(\mathbf{r}|\mathbf{s})\rangle_{p_{\mathrm{real}}(\mathbf{s})}}$$

spontaneous activity **evoked activity** **natural images**

HALLMARKS OF OPTIMAL LEARNING

Predictions

1)The distribution of spontaneous activity and that of evoked activity will become more and more similar with visual experience

2)The match will only hold for natural stimuli

$$p_{\mathrm{SA}}(\mathbf{r}) \longrightarrow \langle p_{\mathrm{EA}}(\mathbf{r}|\mathbf{s})\rangle_{p_{\mathrm{real}}(\mathbf{s})}$$

spontaneous activity **evoked activity** **natural images**

NEURAL RECORDINGS

awake ferrets
aged P29 (eye opening) – P151 (mature visual system)
multi-unit recordings from layers 2-3 in V1
16 electrodes, with 200 μm spacing

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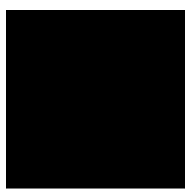
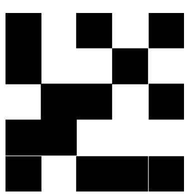
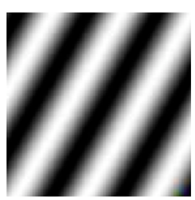
Movie evoked activity



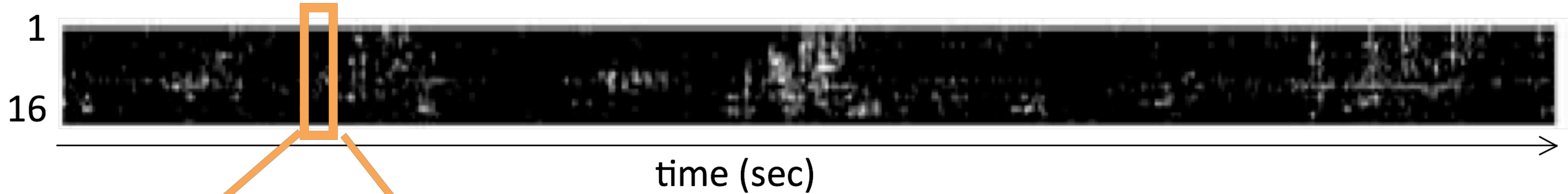
Spontaneous activity in darkness





Control stimuli:
- **dynamic block noise**
- **drifting gratings**

DATA ANALYSIS



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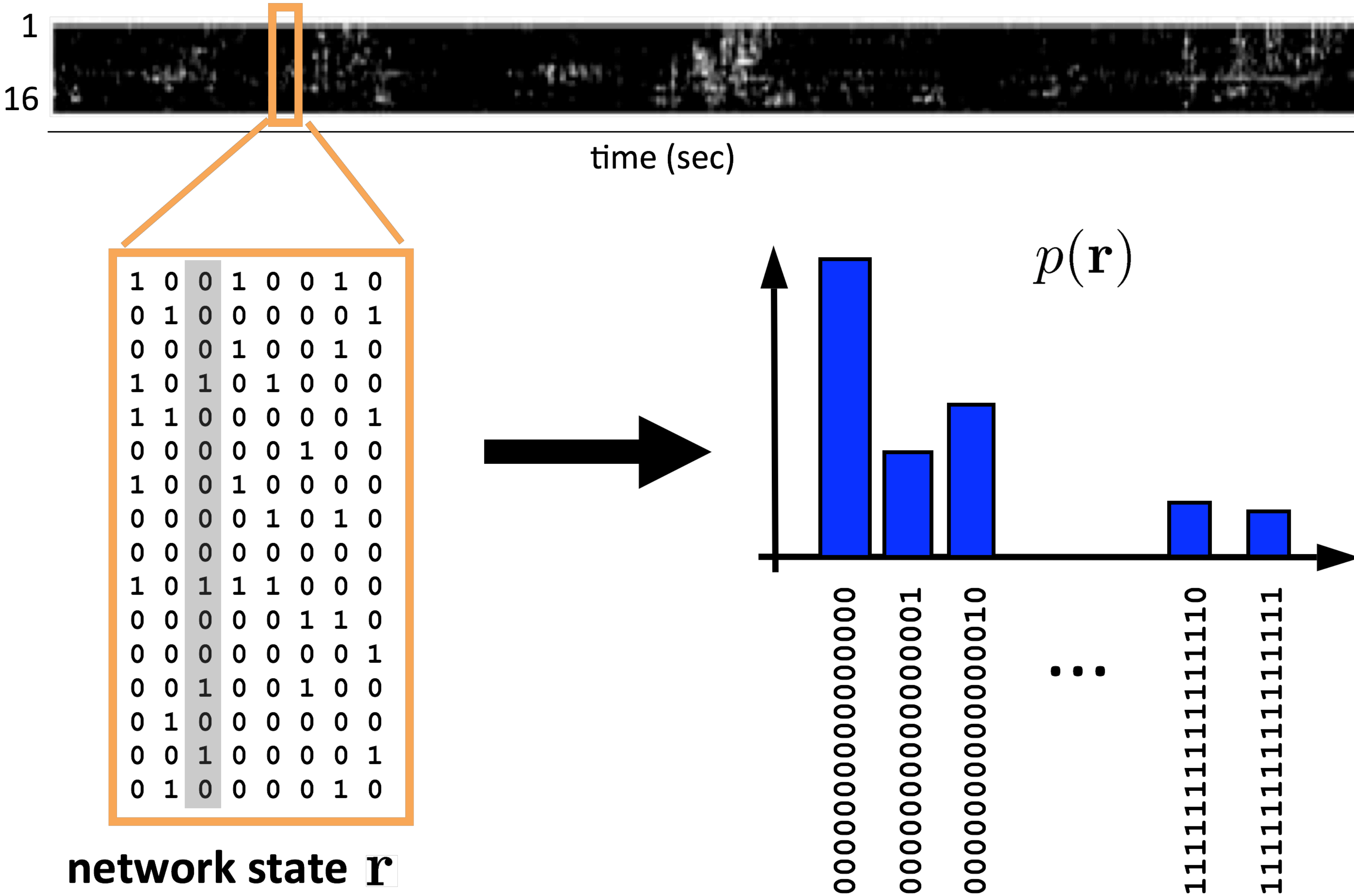
1	1	0	0	0	0	0	1
0	0	0	0	0	1	0	0
1	0	0	1	0	0	0	0
0	0	0	0	1	0	1	0
0	0	0	0	0	0	0	0
1	0	1	1	1	0	0	0
0	0	0	0	0	1	1	0
0	0	0	0	0	0	0	1
0	0	1	0	0	1	0	0
0	1	0	0	0	0	0	0
0	0	1	0	0	0	0	1
0	1	0	0	0	0	1	0

network state $\mathbf{r}$

DATA ANALYSIS



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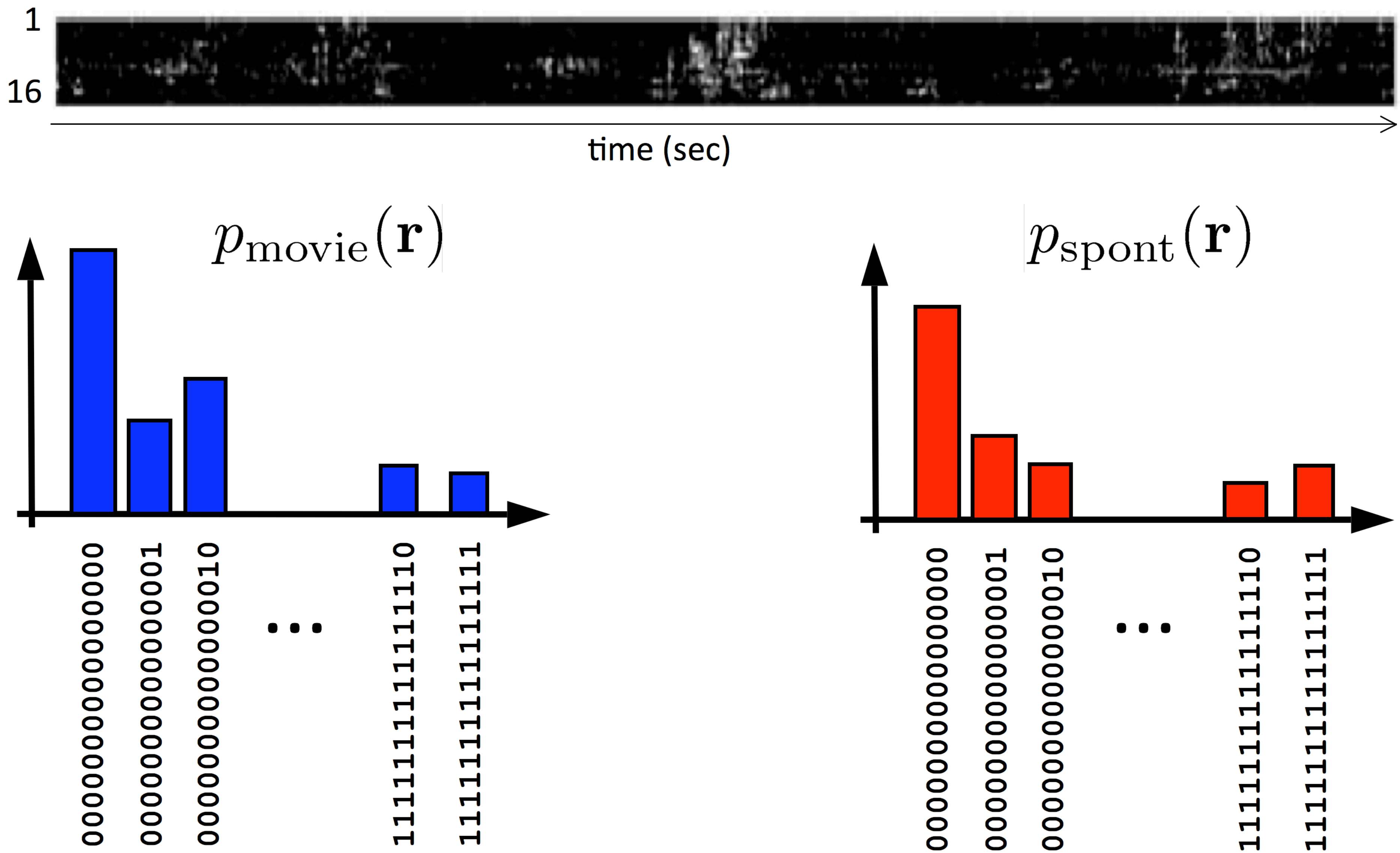

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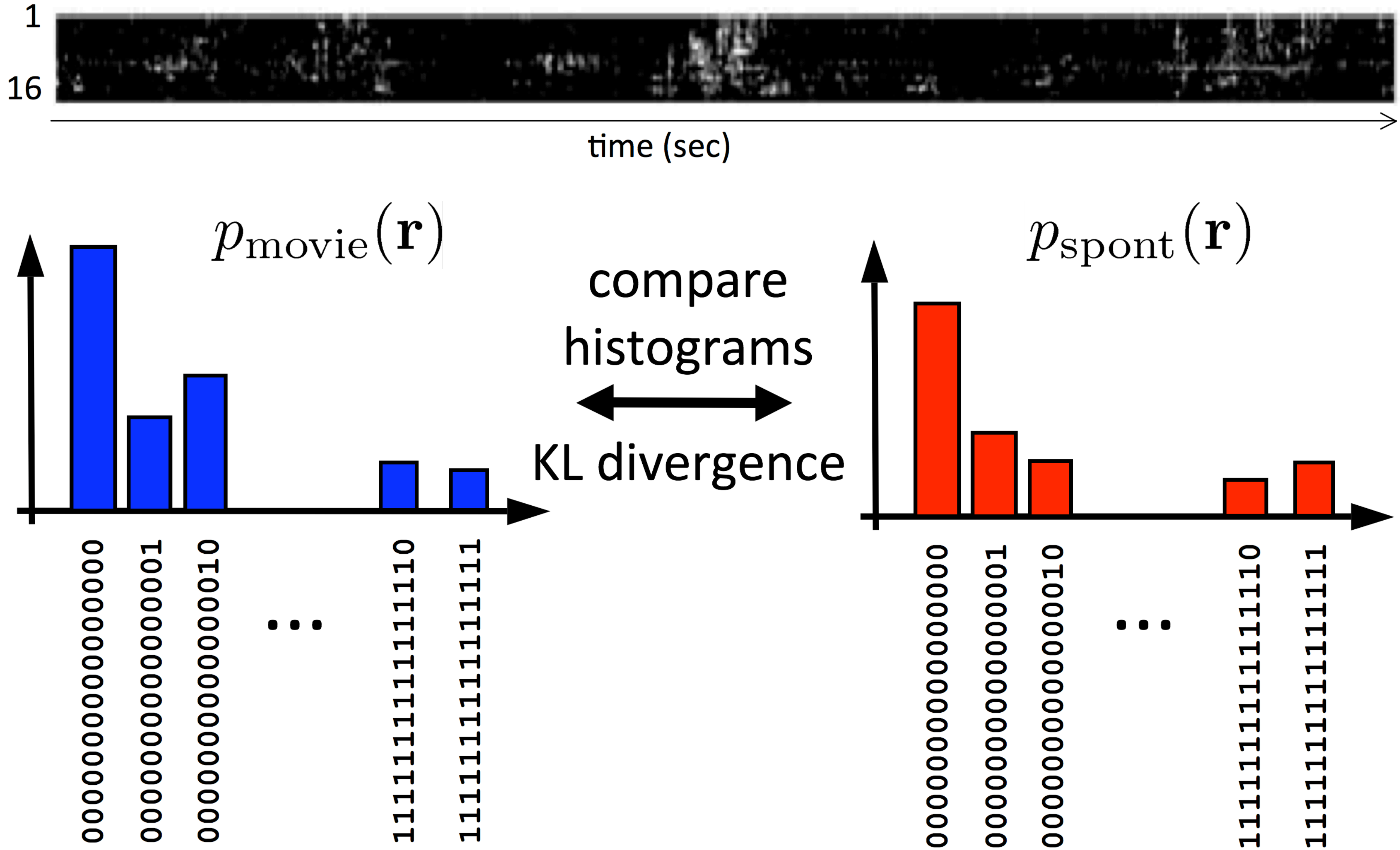
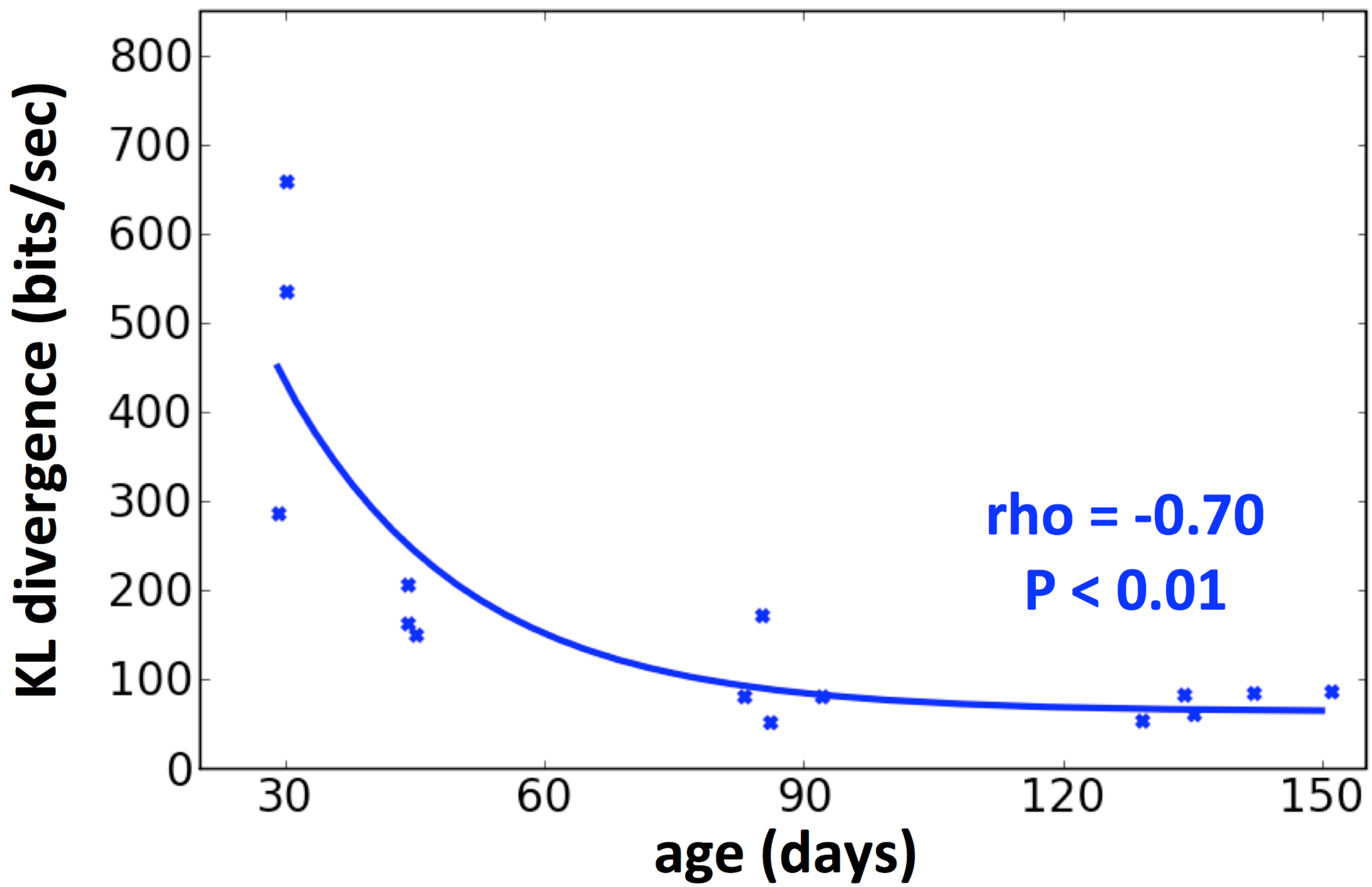


SPONTANEOUS ACTIVITY → EVOKED ACTIVITY



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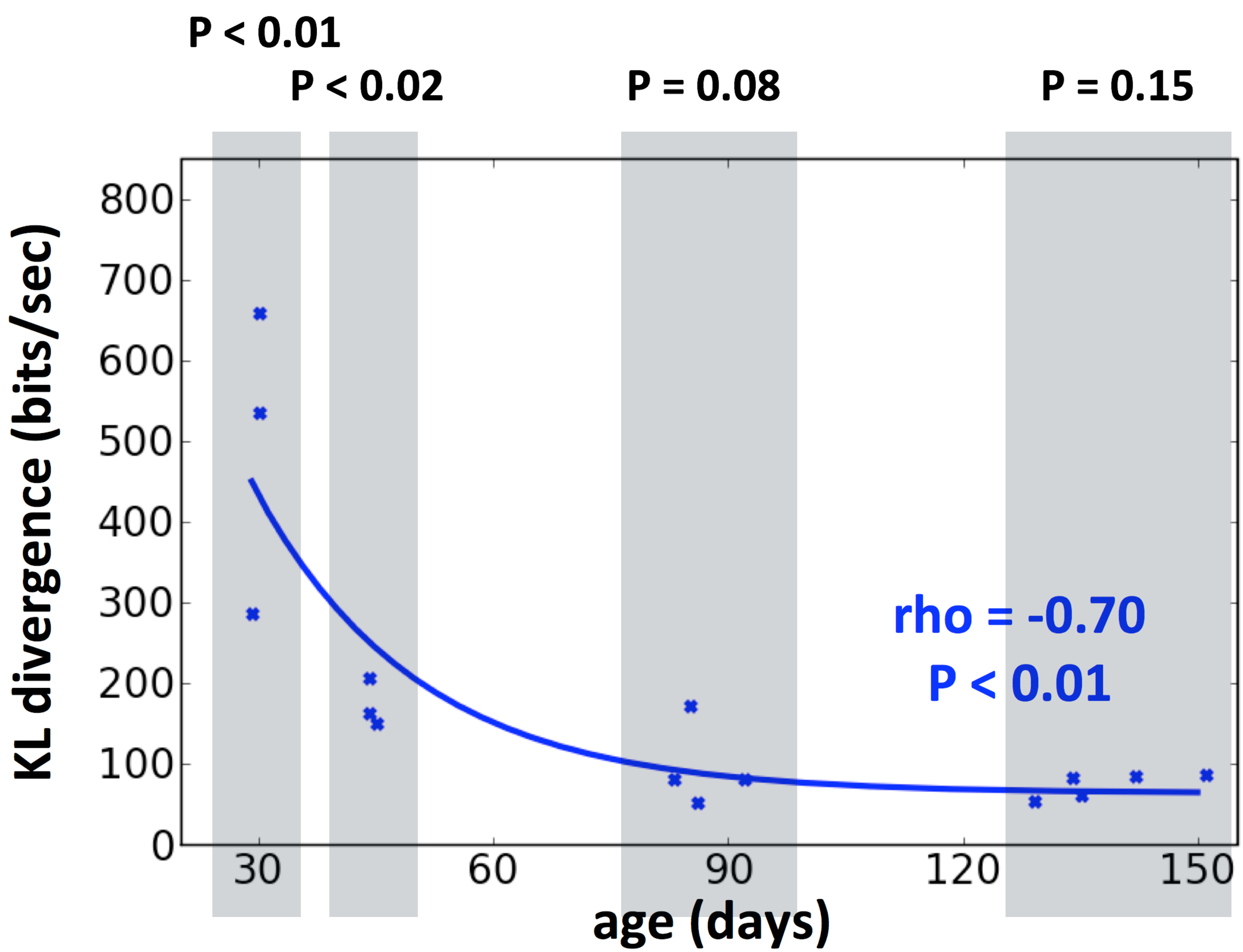
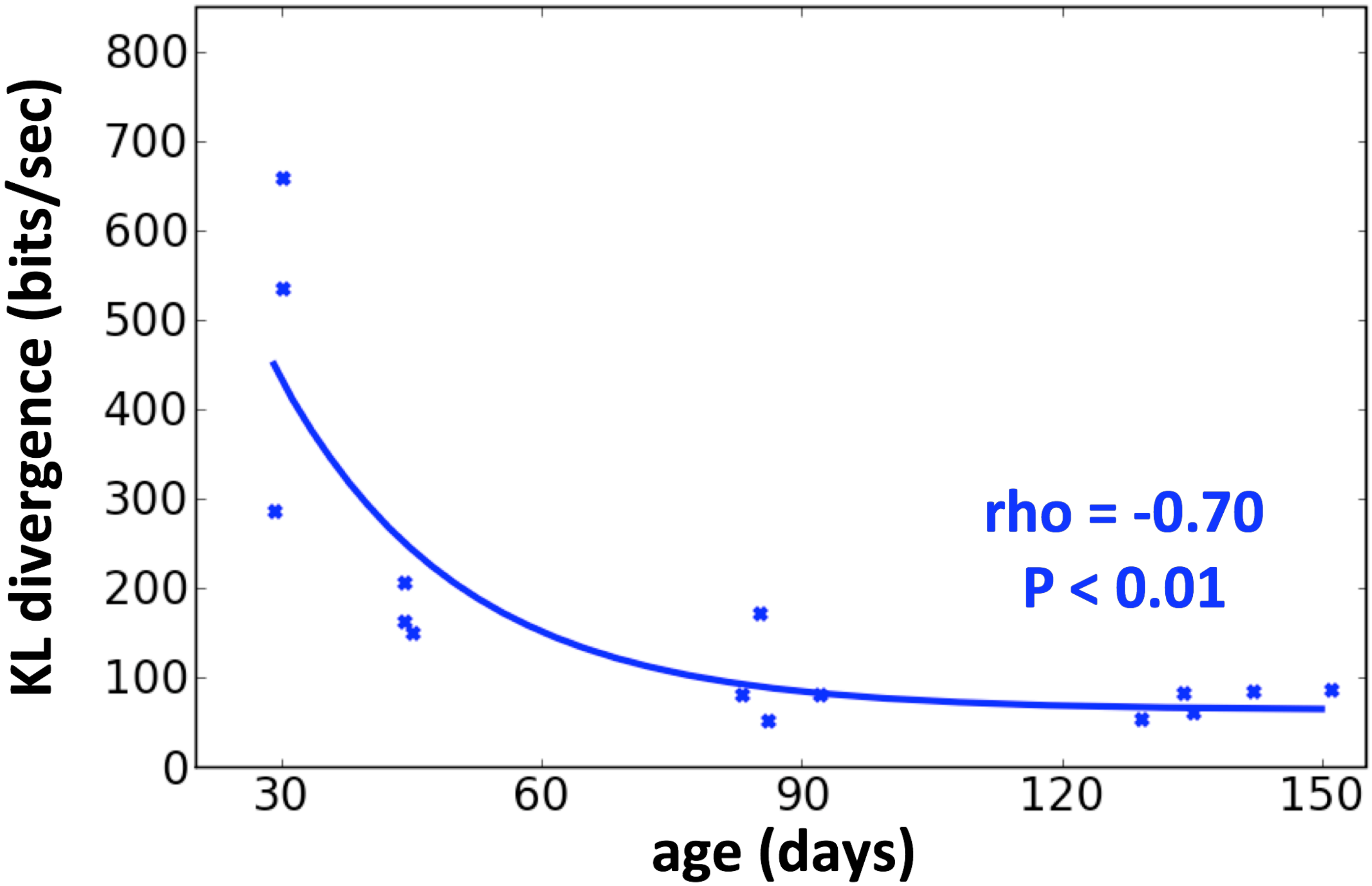


SPATIAL DEPENDENCIES MATTER

$$\tilde{p}(r_1, \ldots, r_{16}) = p(r_1) \cdot \ldots \cdot p(r_{16})$$



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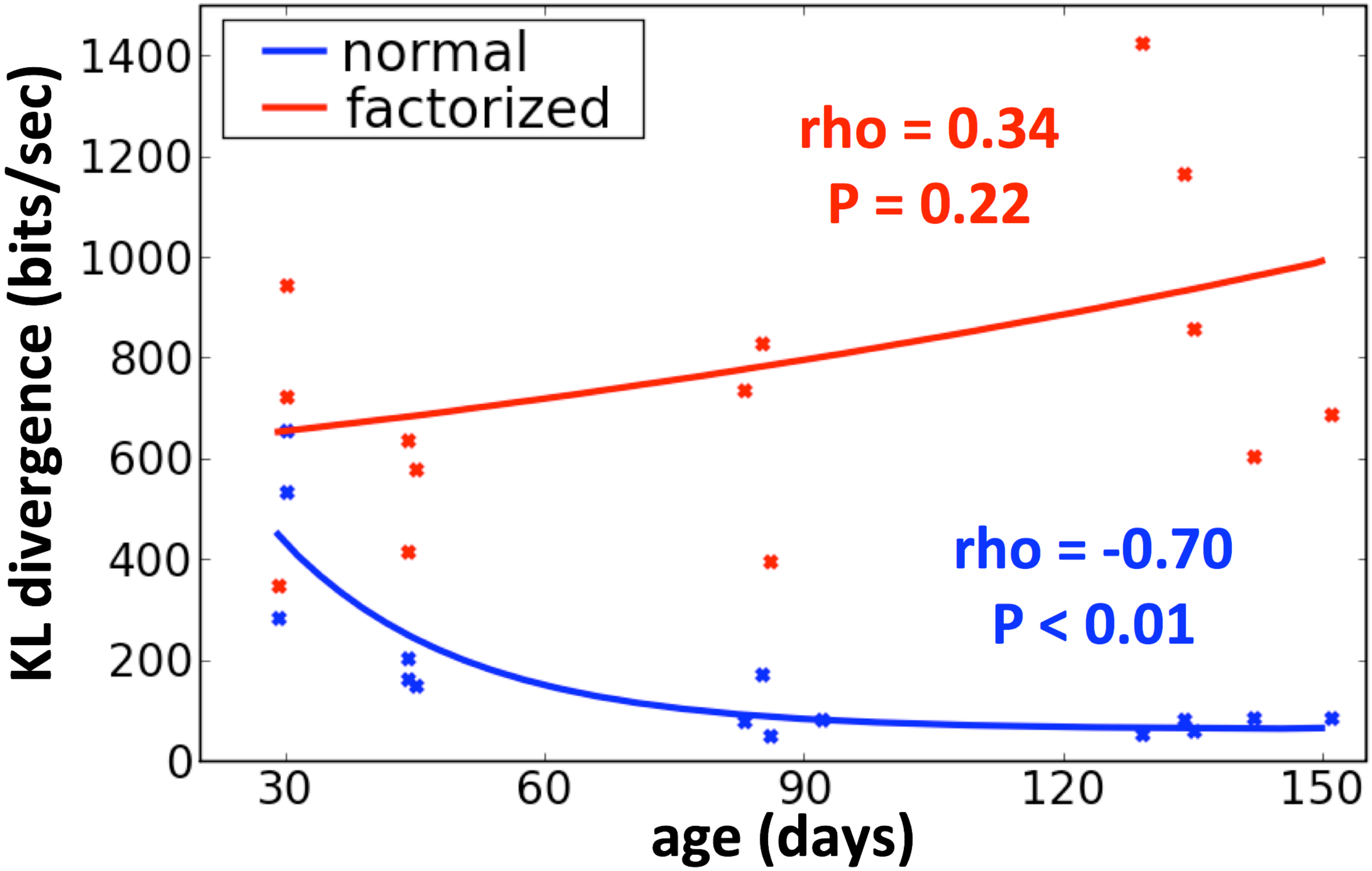
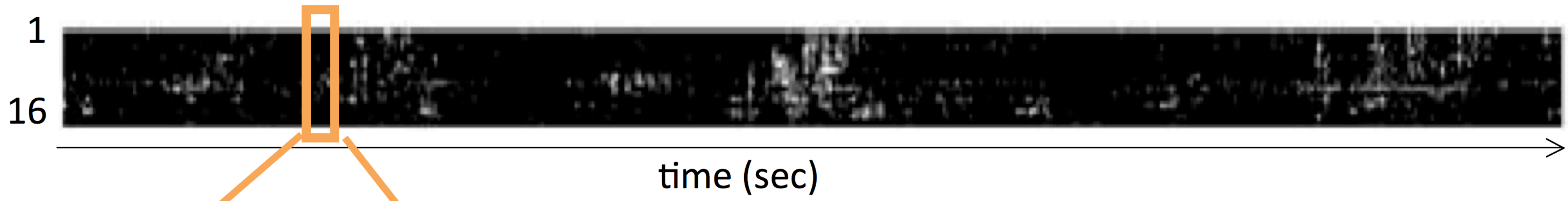


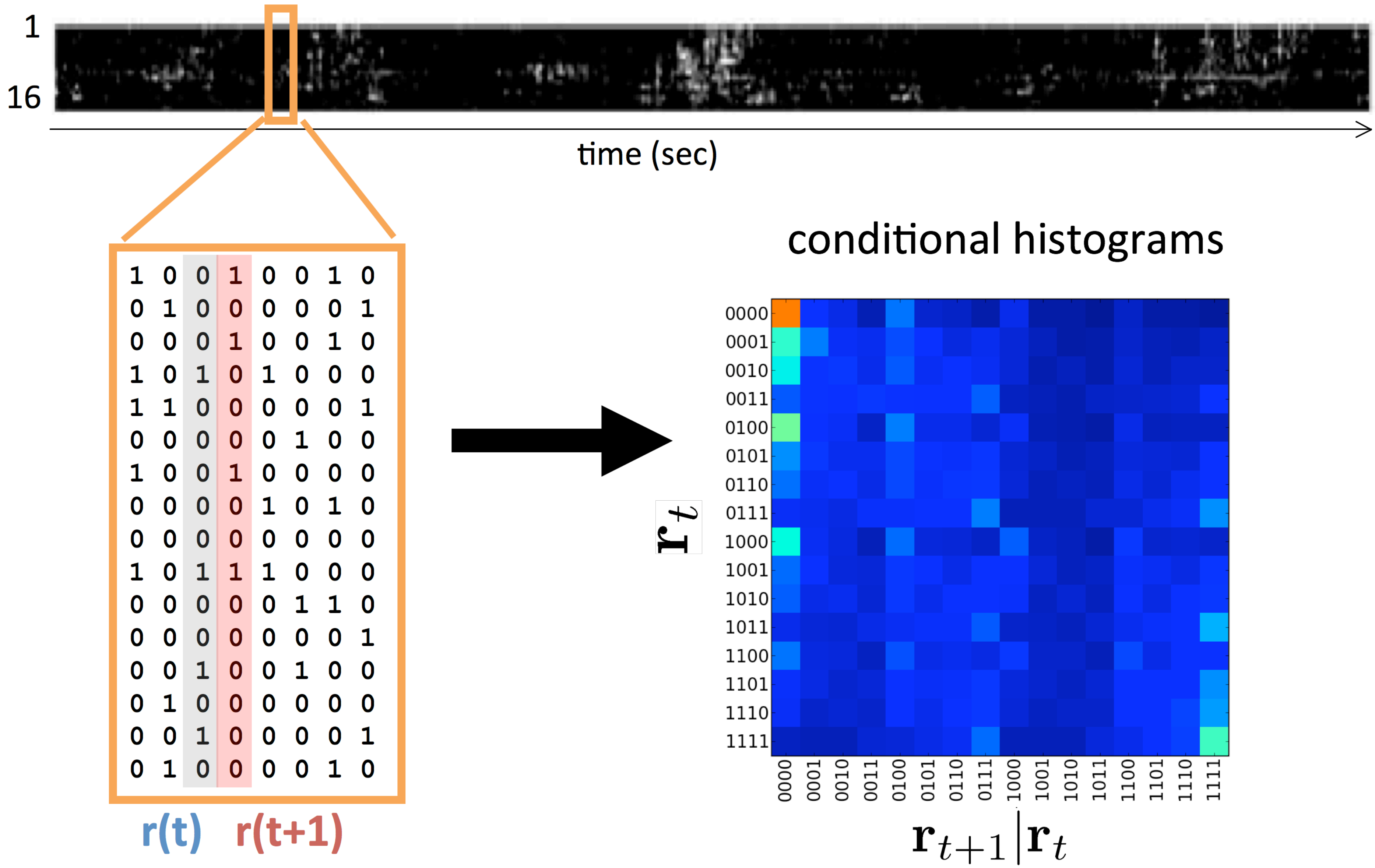
NETWORK DYNAMICS



1	0	0	1	0	0	1	0
0	1	0	0	0	0	0	1
0	0	0	1	0	0	1	0
1	0	1	0	1	0	0	0
1	1	0	0	0	0	0	1
0	0	0	0	0	1	0	0
1	0	0	1	0	0	0	0
0	0	0	0	1	0	1	0
0	0	0	0	0	0	0	0
1	0	1	1	1	0	0	0
0	0	0	0	0	1	1	0
0	0	0	0	0	0	0	1
0	0	1	0	0	1	0	0
0	1	0	0	0	0	0	0
0	0	1	0	0	0	0	1
0	1	0	0	0	0	1	0

r(t) **r(t+1)**

NETWORK DYNAMICS



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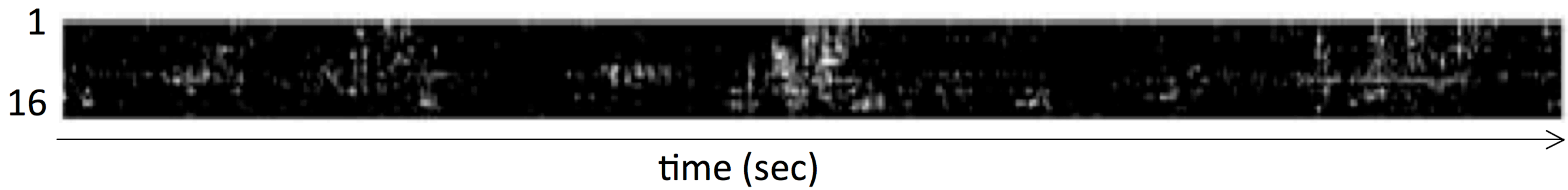
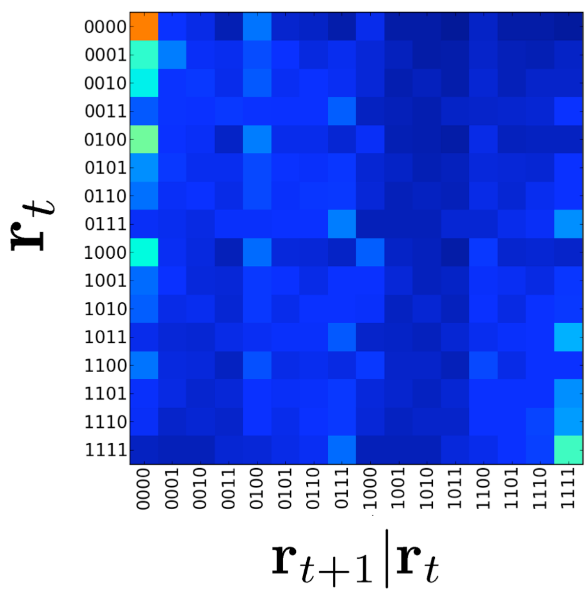


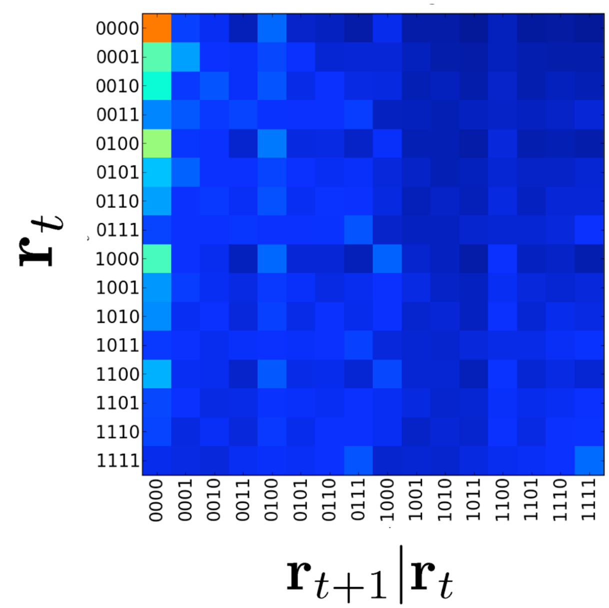
$p_{\text{movie}}(\mathbf{r}_{t+1}|\mathbf{r}_t)$



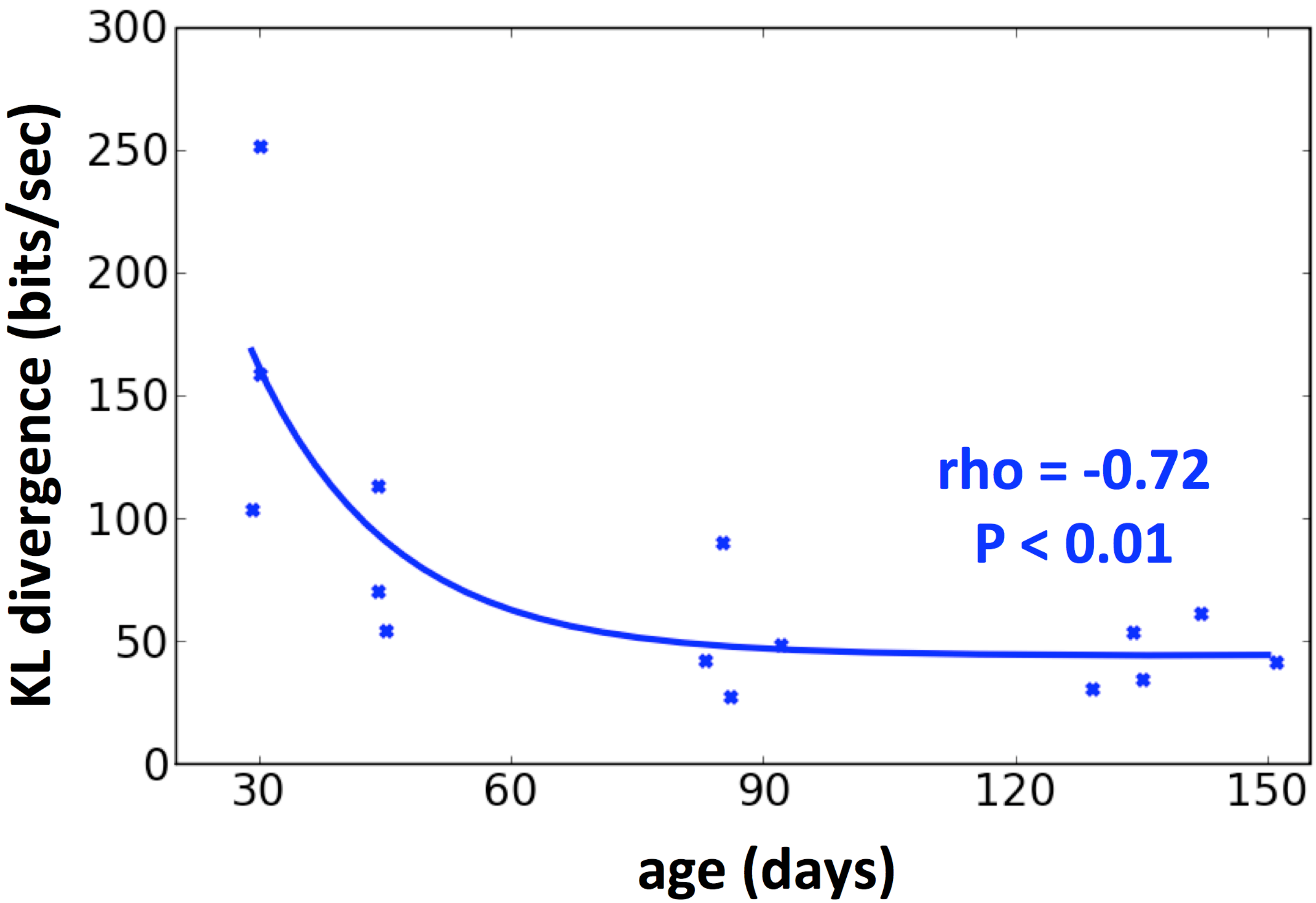
compare histograms

KL divergence

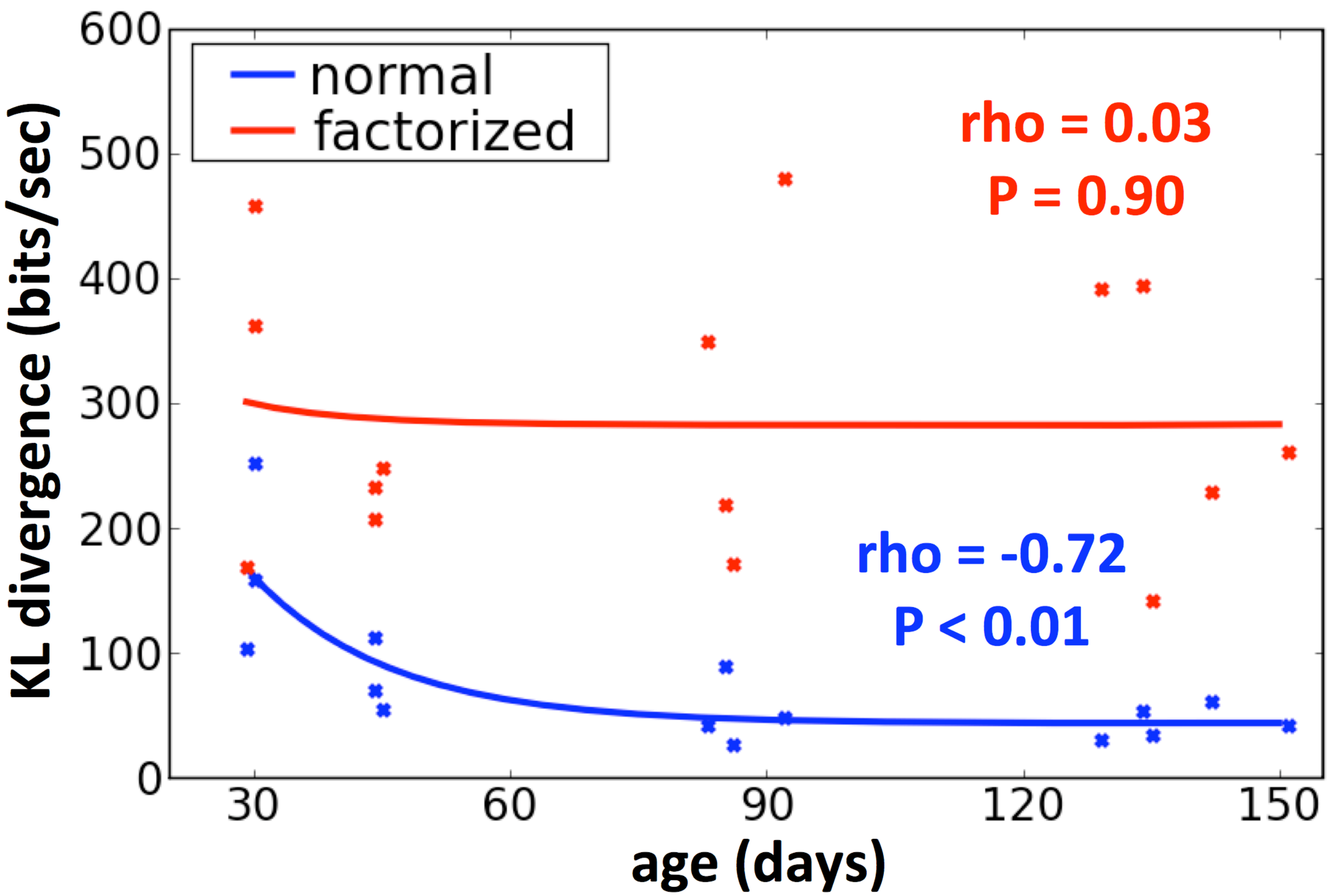
$p_{\text{spont}}(\mathbf{r}_{t+1}|\mathbf{r}_t)$



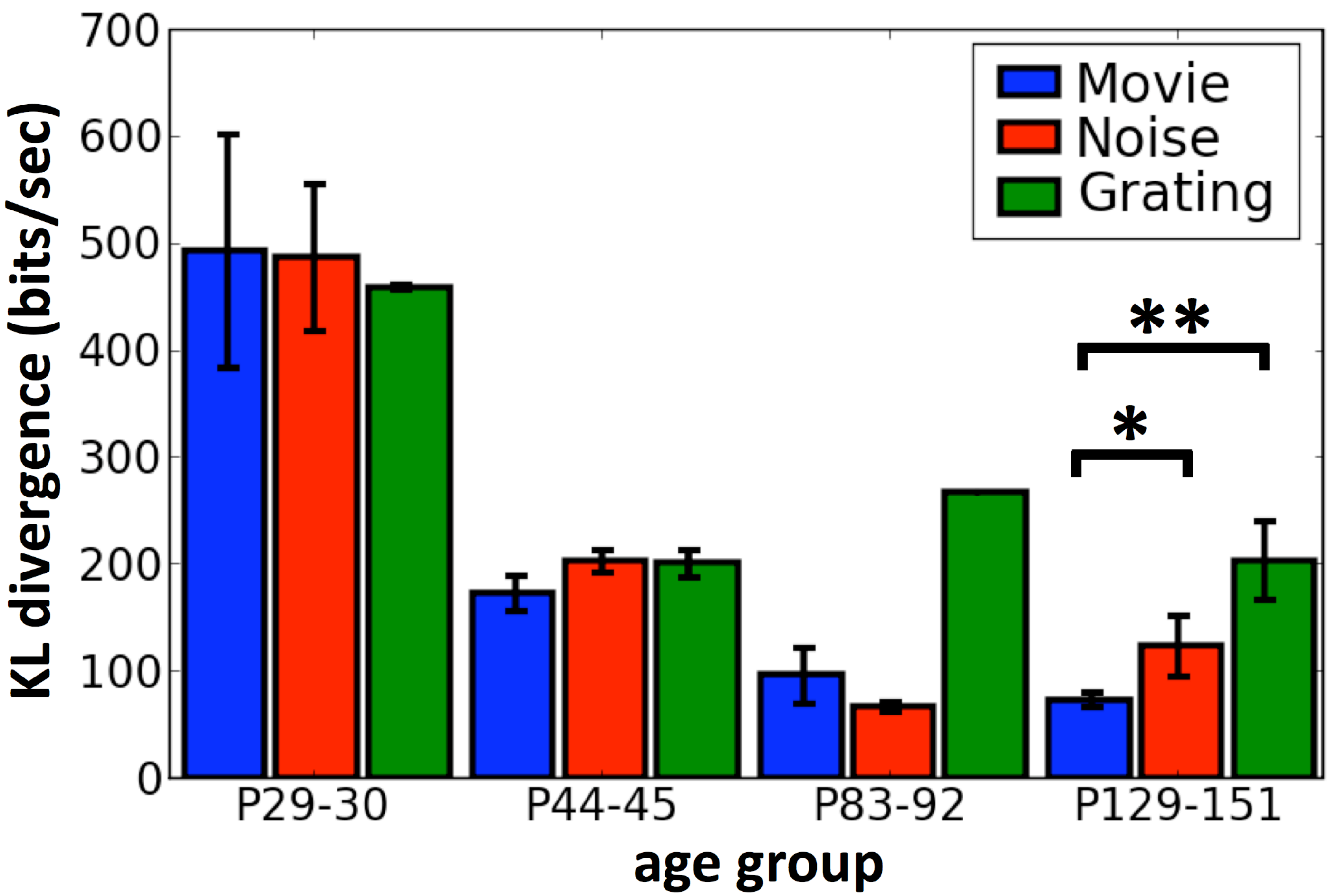
MATCHING TEMPORAL TRANSITIONS



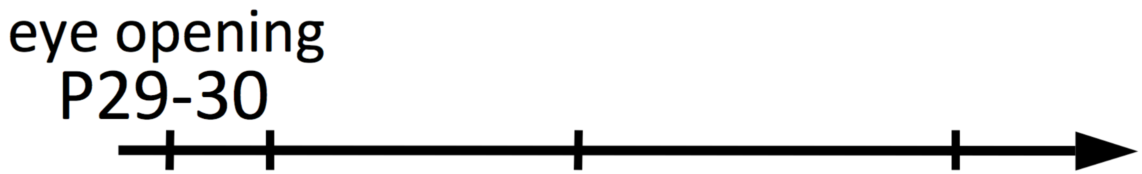
TEMPORAL DEPENDENCIES ALSO MATTER

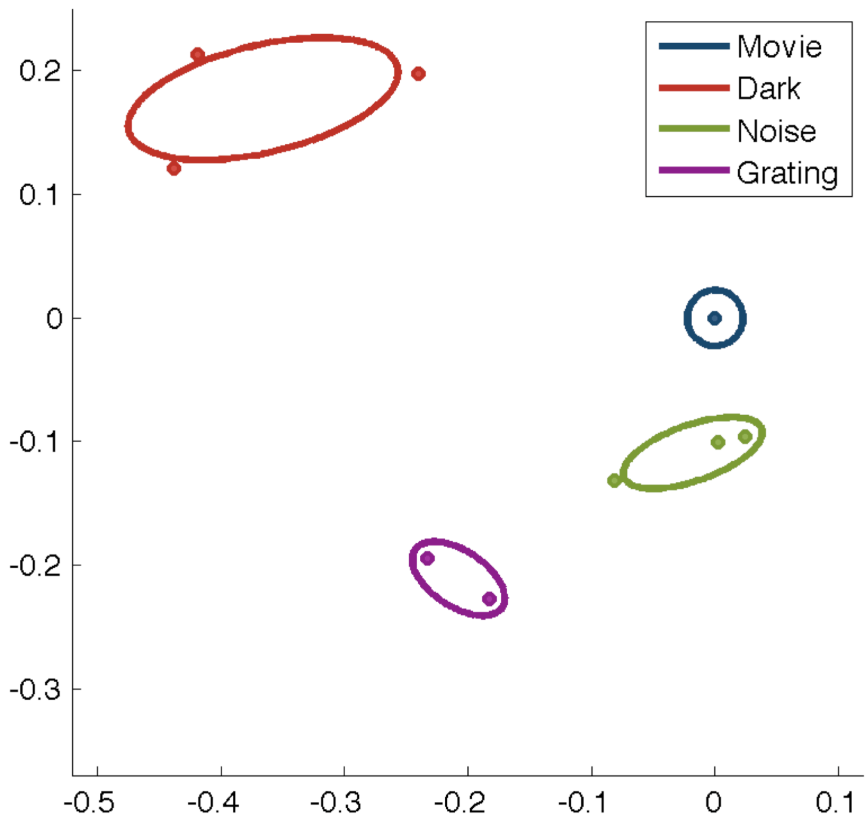


MATCH IS SPECIFIC TO NATURAL STIMULI



SUMMARY OF LEARNING





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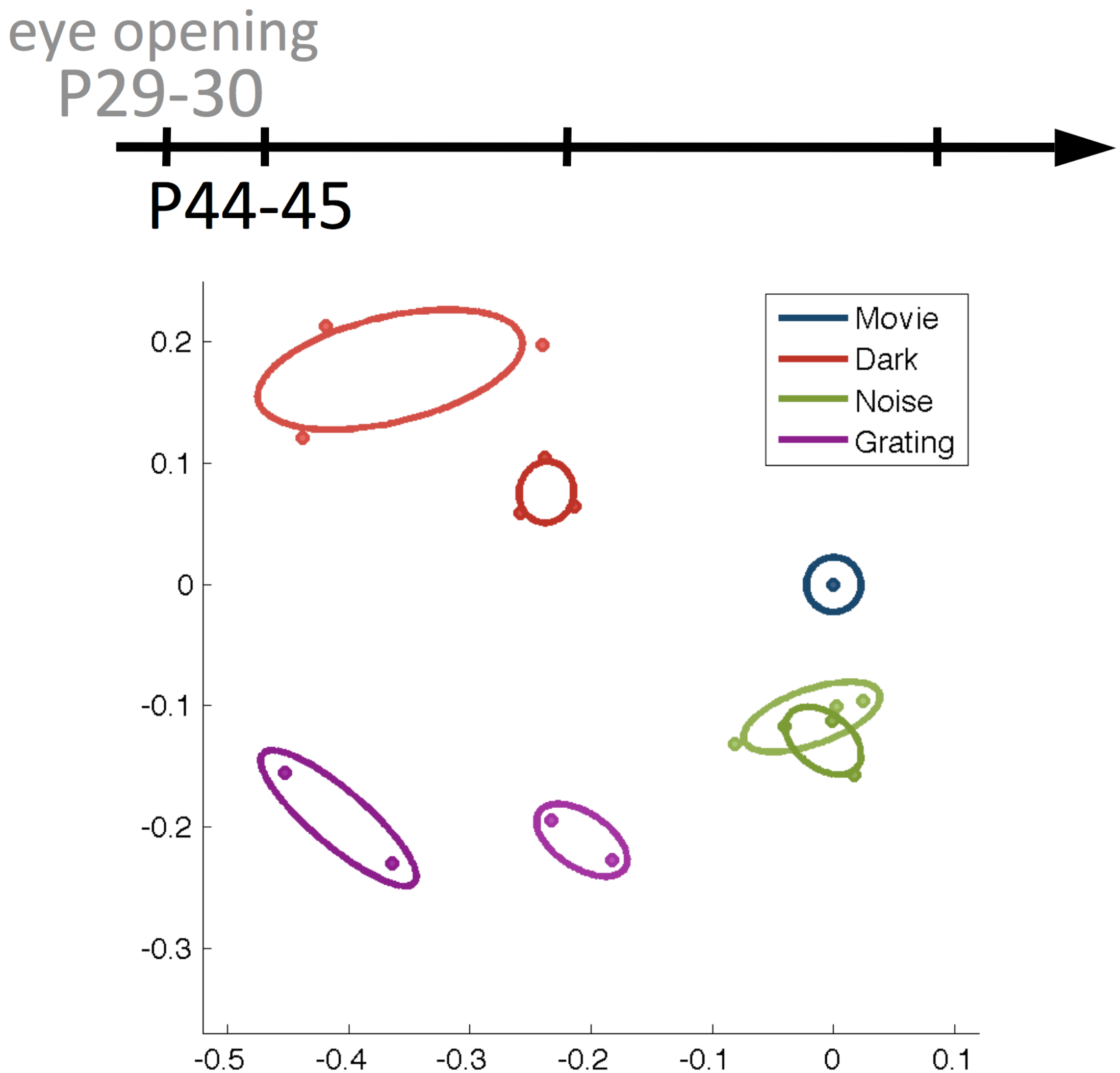

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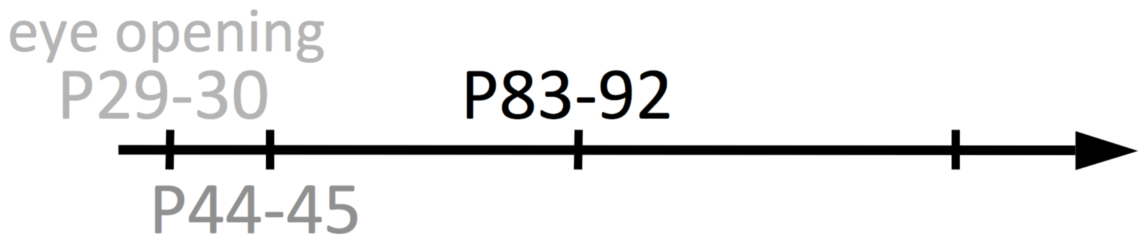

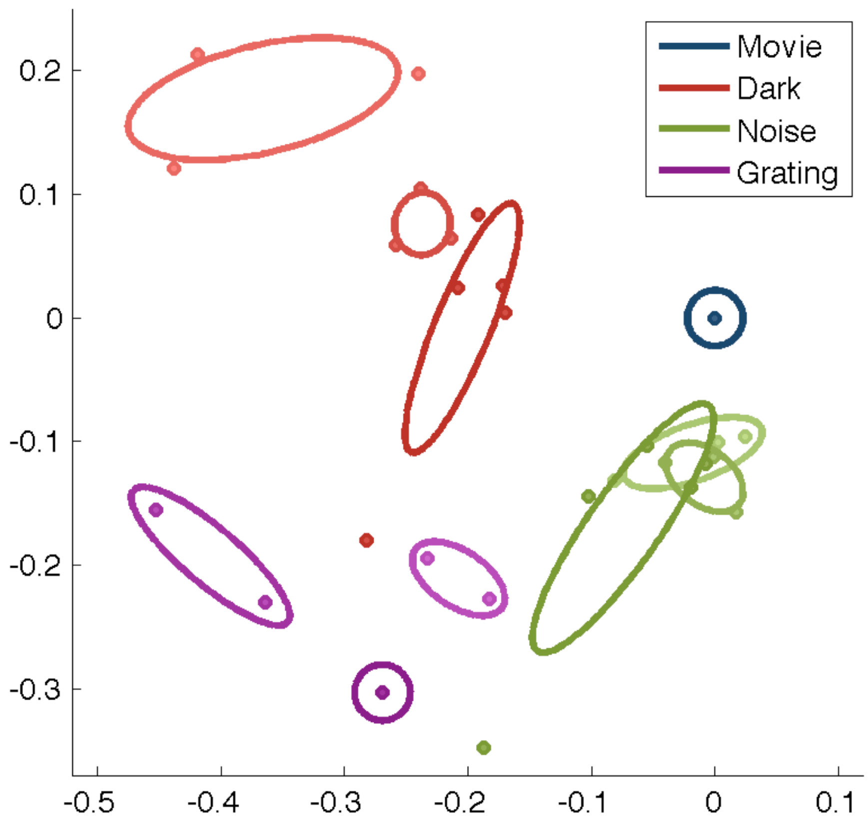

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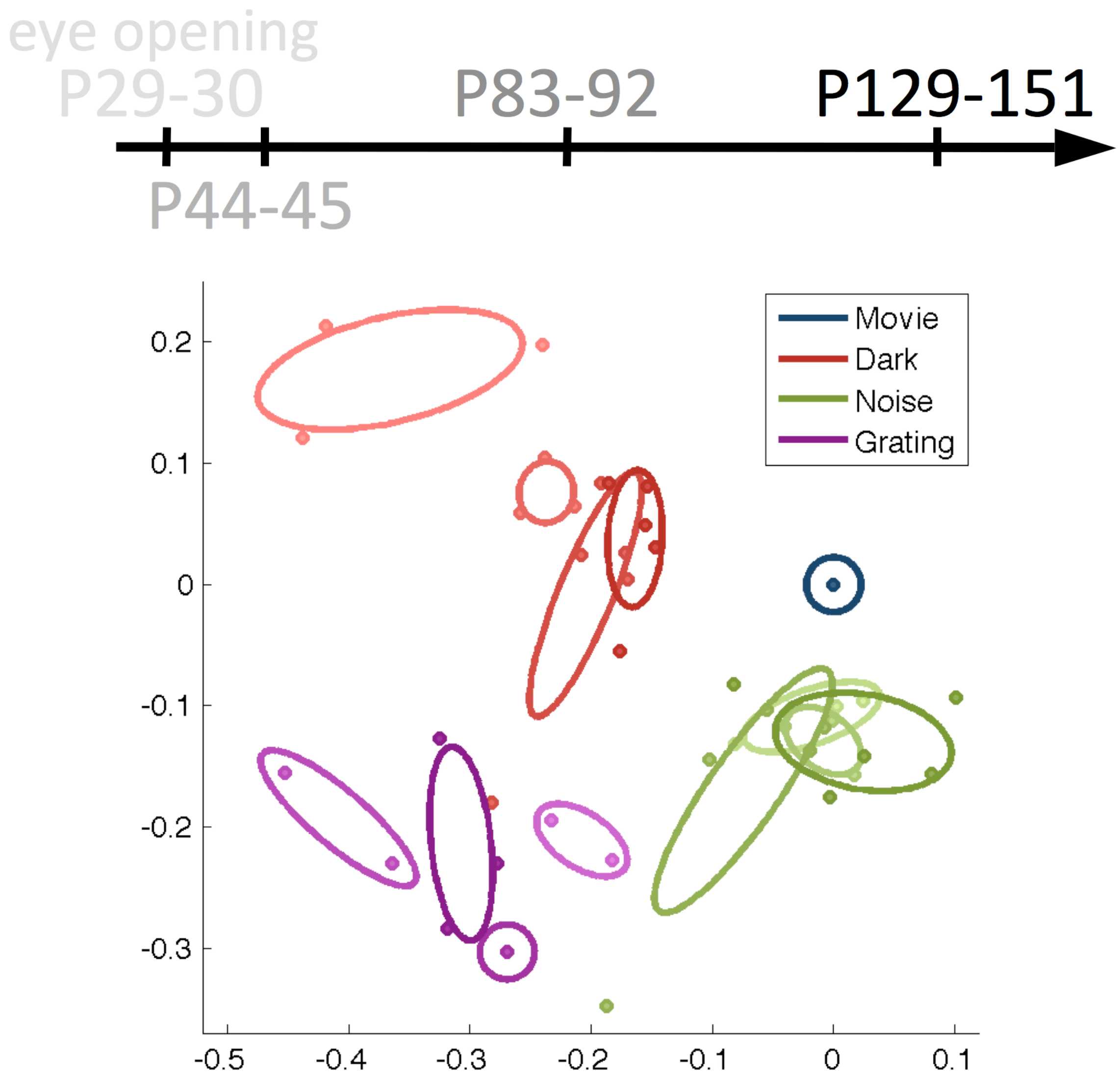

SUMMARY

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- These results confirm our predictions, and are thus supporting evidence for optimal inference and learning in the primary visual cortex

ACKNOWLEDGMENTS

Brandeis University
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