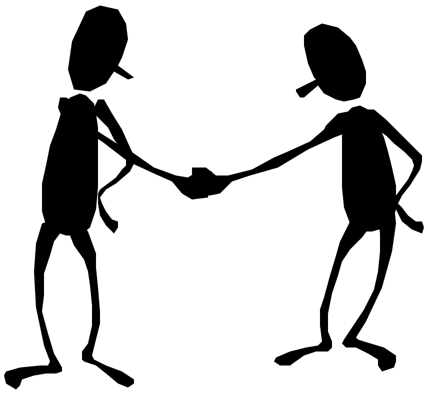
Perceptual Learning in Non-Stationary Contexts: Selective Re-Weighting vs Representation Enhancement

Alexander Petrov
Barbara Dosher
Zhong-Lin Lu

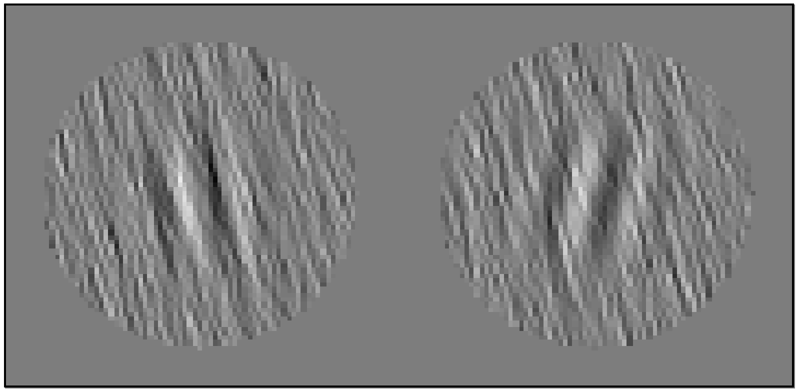
I'm glad to meet you!

- M.S. in computer science
  (1995, Sofia University, Bulgaria)
- Ph.D. in cognitive science
  (1998, New Bulgarian University)
- Interest in biologically grounded computational models and theoretical neuroscience

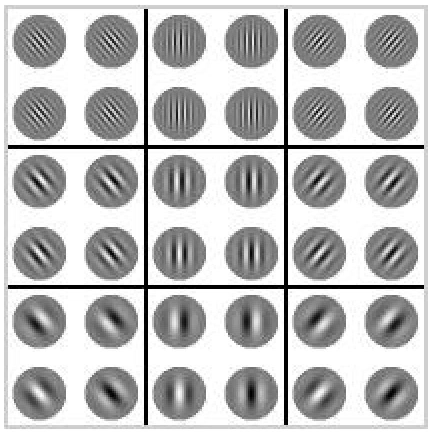


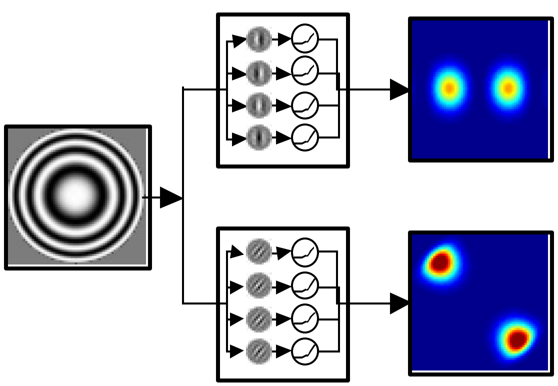
Perceptual Learning

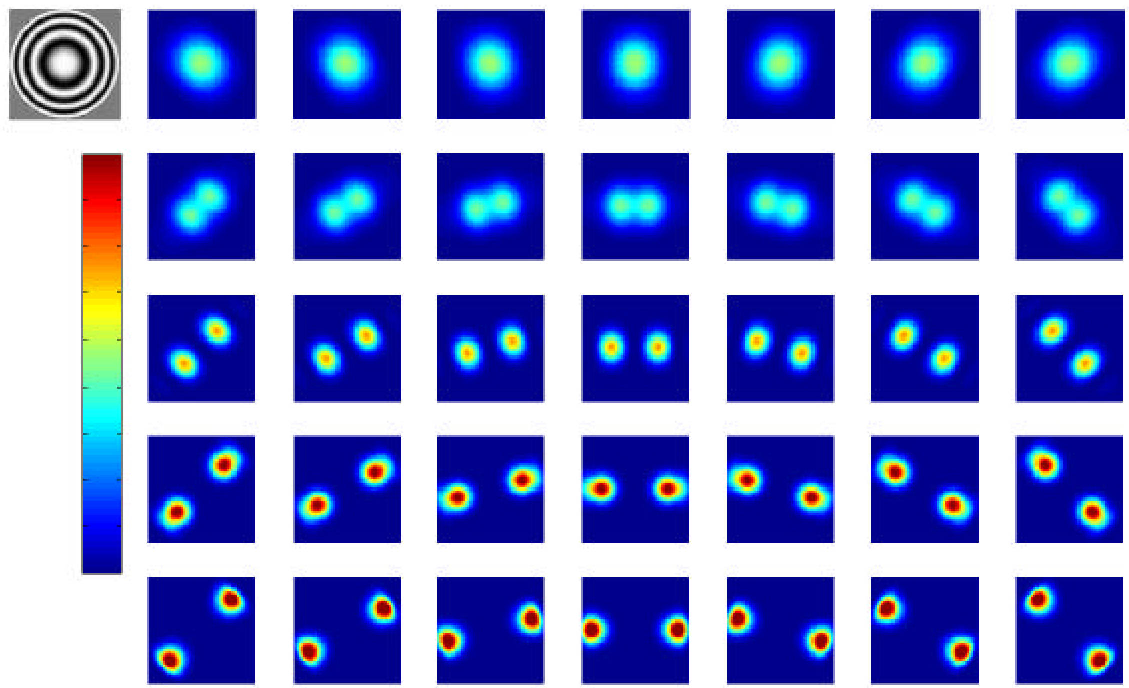
- Performance on perceptual tasks improves with (extensive) practice.
- This improvement tends to be stimulus-specific.



Crash Course in Spatial Vision



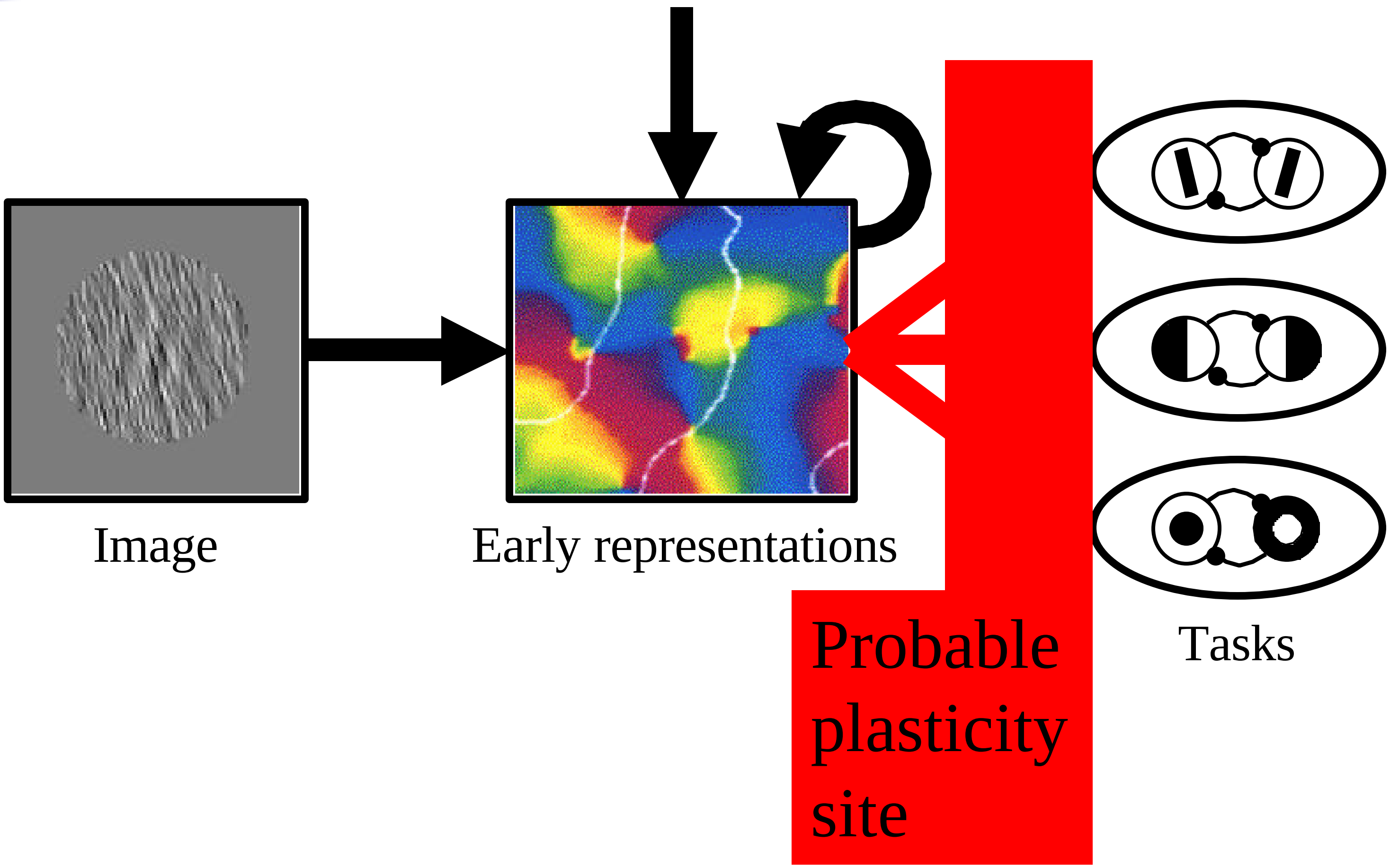




Representation Enhancement

- Perceptual learning may be due to *recruitment* of new units or *sharpening* the existing ones.
- Dominant hypothesis in the neurophysiological literature on cortical plasticity.
- Abundant evidence but...
  - Lesions or invasive manipulations
  - Not in adult brains
  - By analogy with other modalities
- Null results in three visual studies with intact adult monkeys (Crist et al, 2001; Ghose et al, 2002; Schoups et al, 2001).

Selective Re-Weighting



Evidence for Re-Weighting

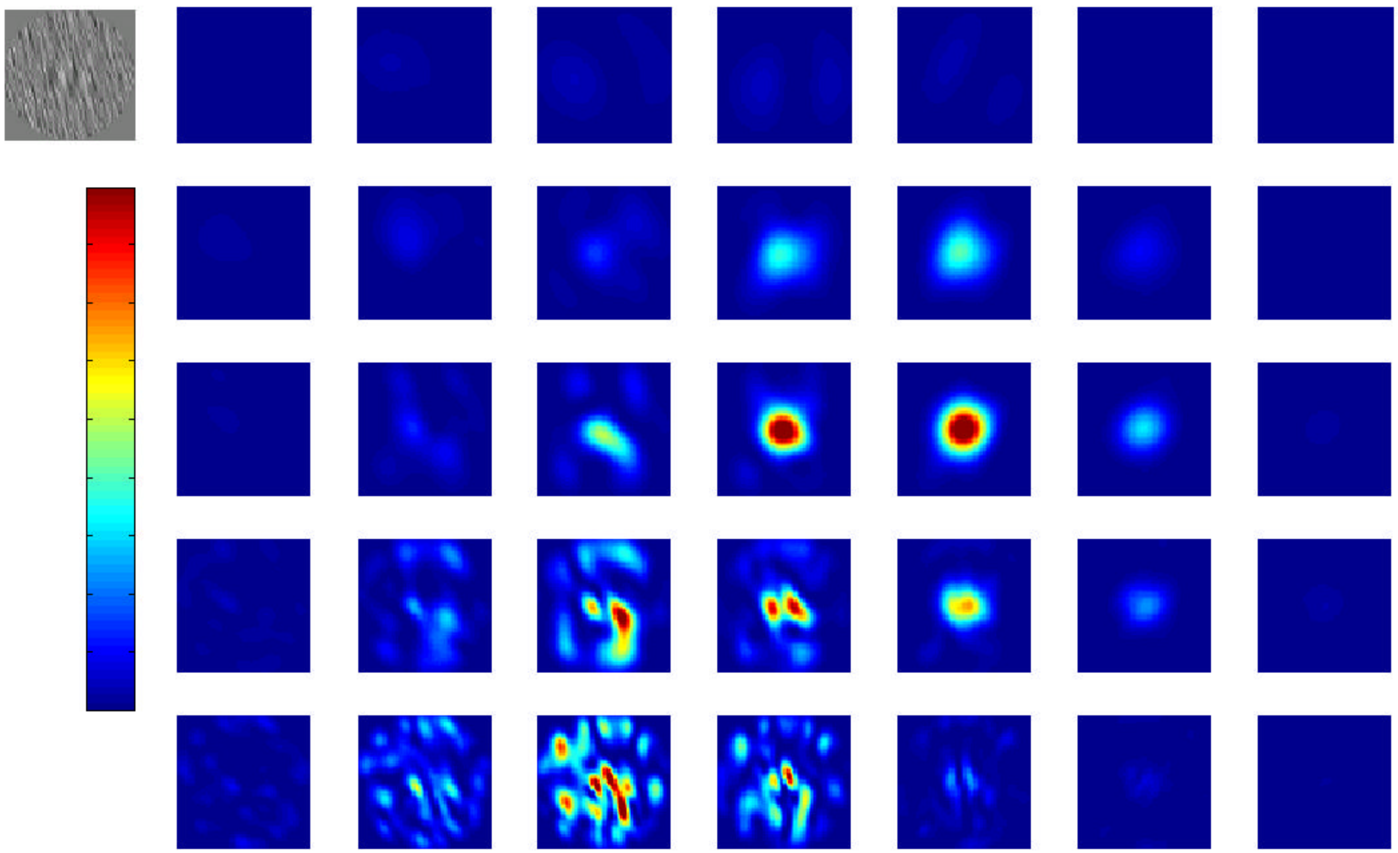
- *Task specificity* of perceptual learning.
- Functional analysis: V1 is important, don’t mess with it unless really needed.
- *Associative* learning is the preeminent mechanism in so many other domains.
- Psychophysical evidence (Dosher & Lu, 1998).
- Hard to imagine re-representation without re-weighting.

Behavioral Experiment

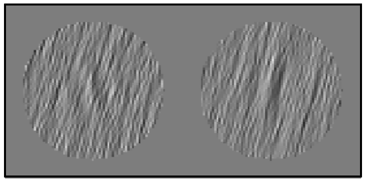
- Fixed task: orientation discrimination
- Massively overlapping representations
- Filtered-noise background “contexts”
- Non-stationary presentation schedule

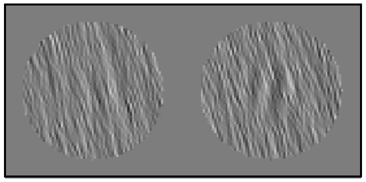
- 13 human observers
- 9600 trials over 8 sessions

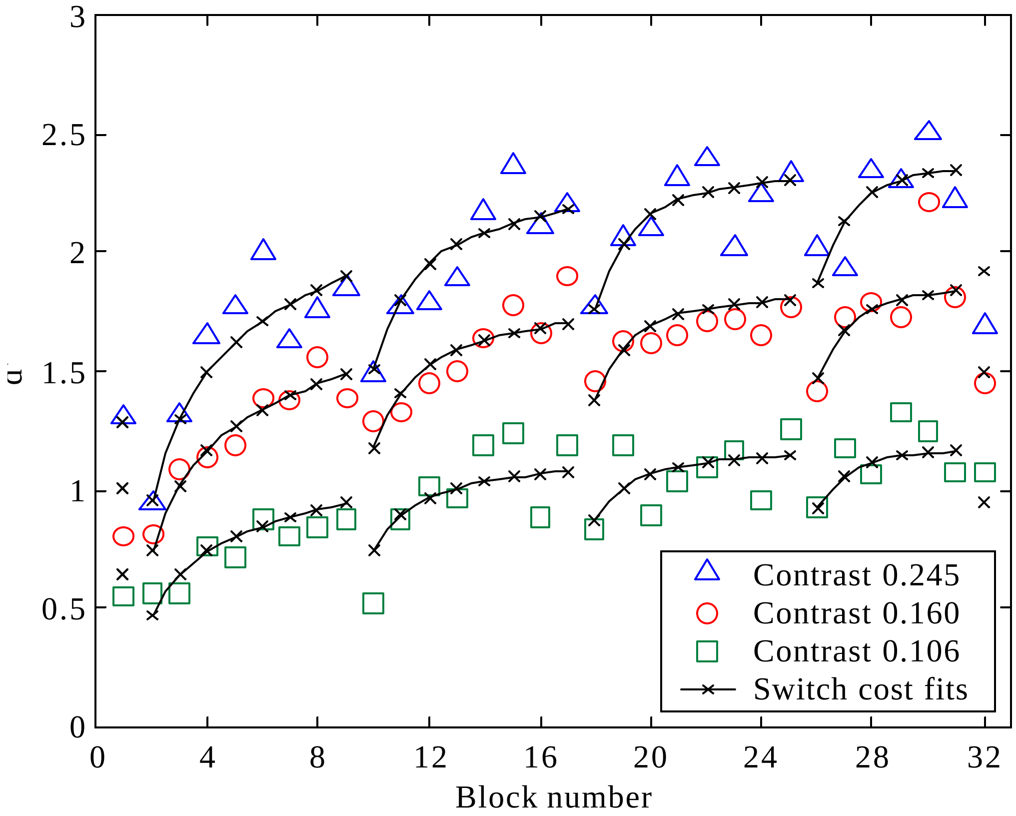
Overlapping Representations



Results: Switch Costs







Main Principles

- Orientation- and frequency-tuned repres.
- Normalization (contrast gain control)
- Weighted decision units
- **Incremental associative re-weighting**
- Intrinsic variability

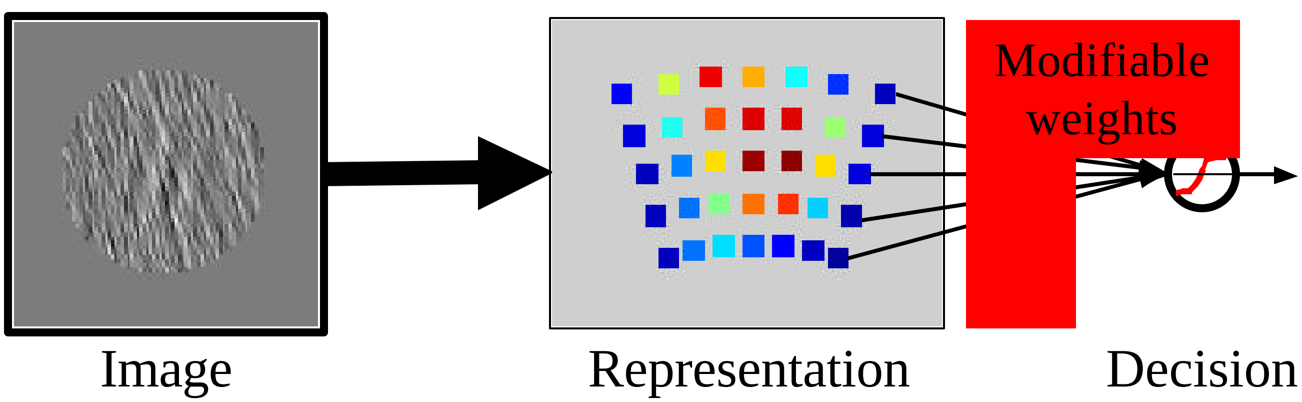
Computational Model

- Instantiates the same principles
- Fully functional
- Neurobiologically plausible
- Parsimonious

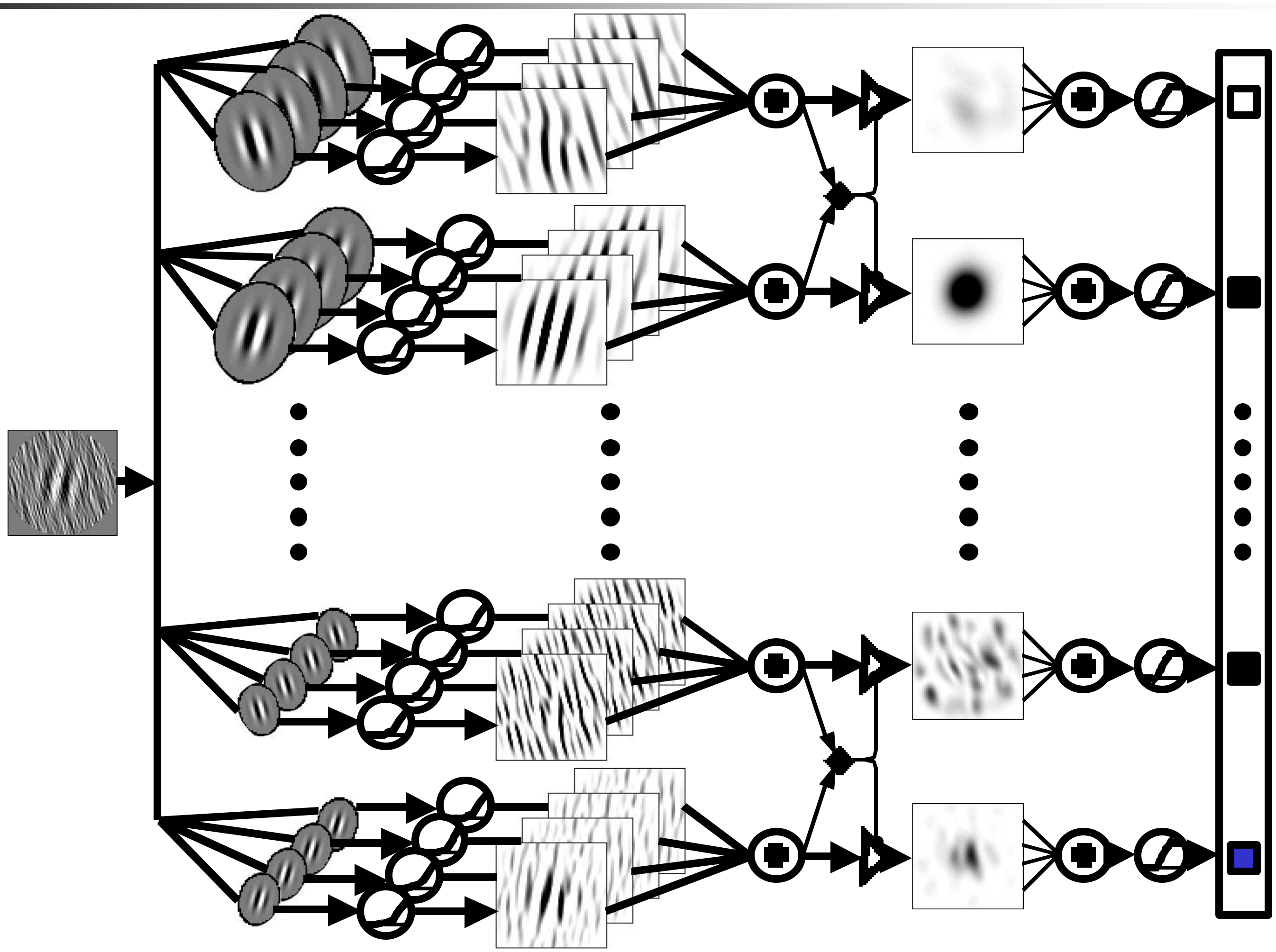
- Existence proof that the selective re-weighting hypothesis is sufficient to account for the data.

Two Subsystems

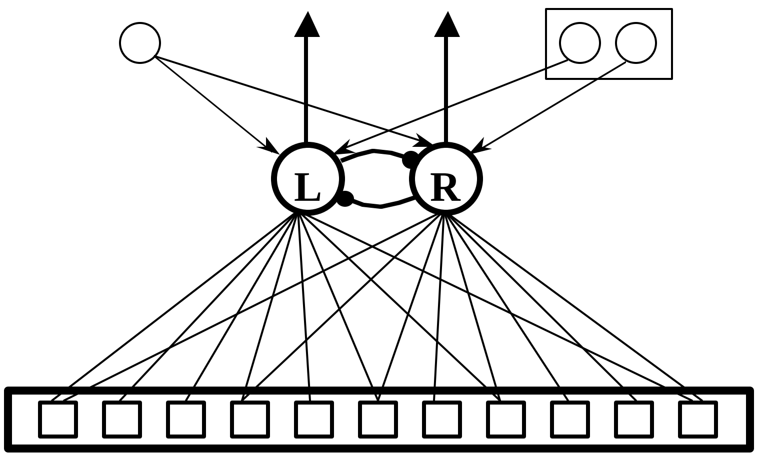
- Representation subsystem
- Task-specific subsystem
  (=implicit categorization system?)
- Hebbian learning over fixed representations

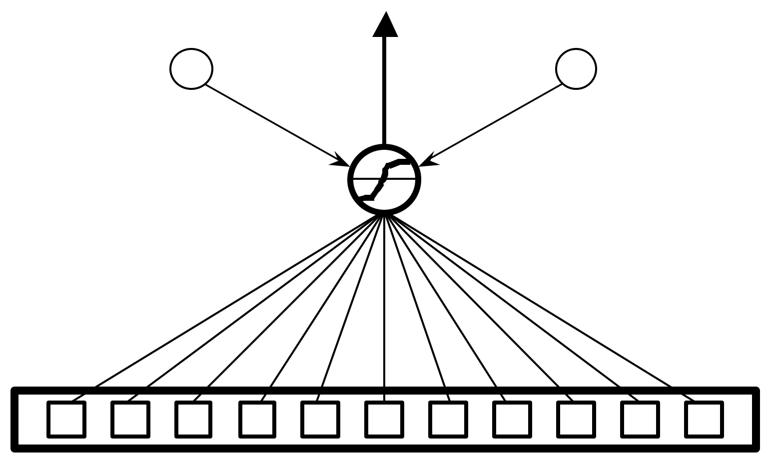


Representation Subsystem

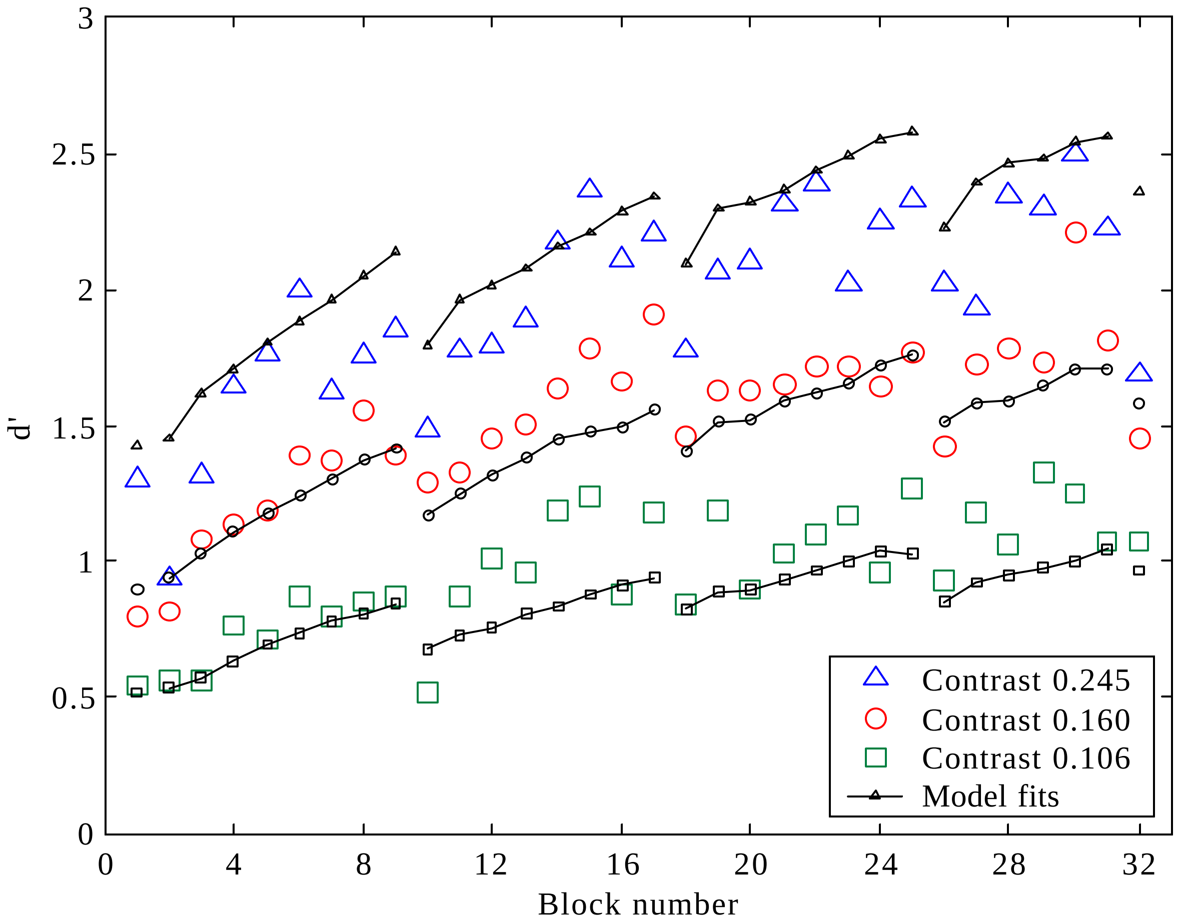


Task-Specific Subsystem



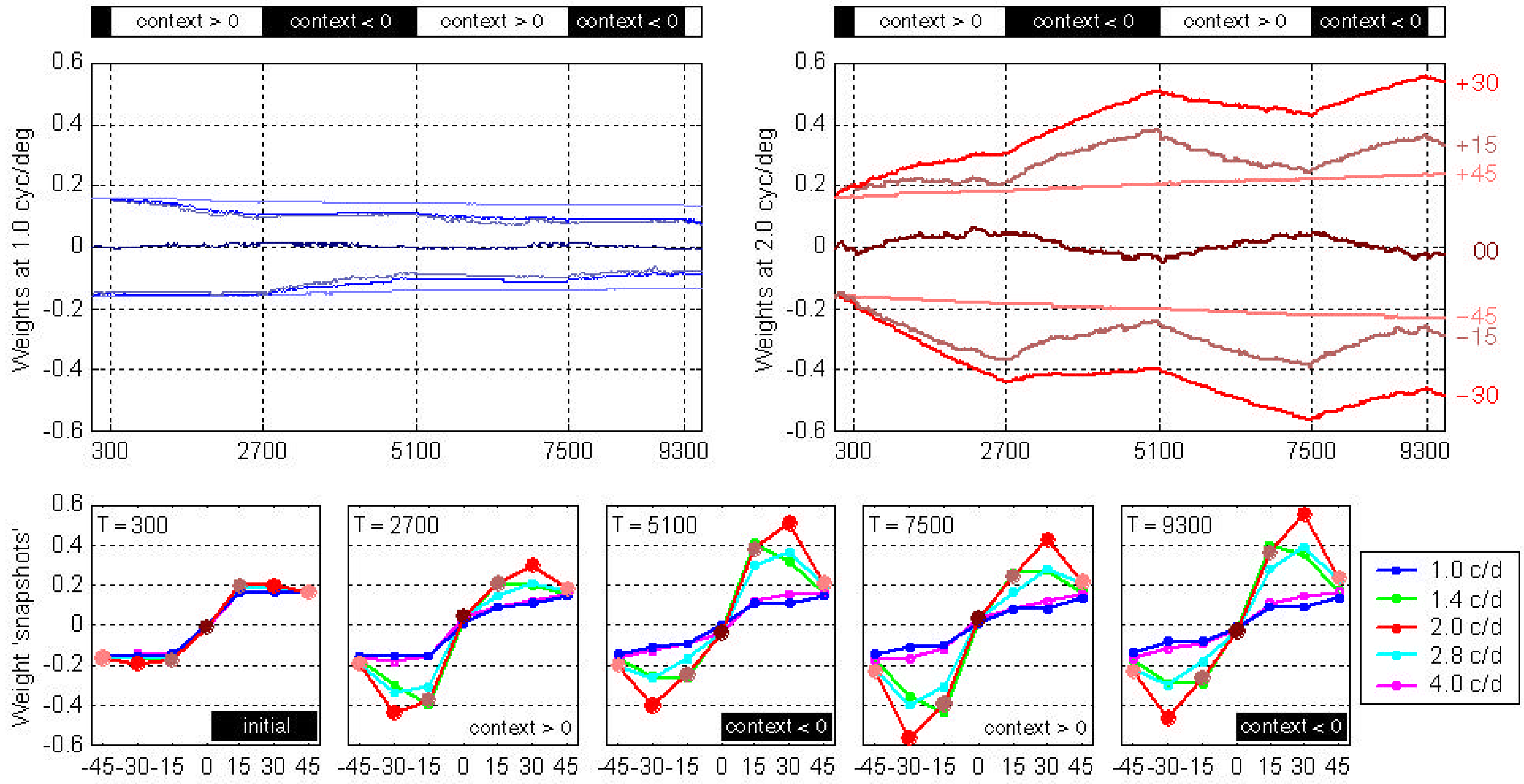


Model Fits



3
2.5
2
1.5
1
0.5
0
d'
0
4
8
12
16
20
24
28
32
Block number
Contrast 0.245
Contrast 0.160
Contrast 0.106
Model fits

Weight Dynamics



Selective Re-Weighting

- Outcome-correlated units develop stronger weights.
- Irrelevant units are “tuned out”.
- This improves the signal-to-noise ratio of the inputs to the decision unit(s).
- Learning is associative, hence both stimulus- and task specific.
- Incremental (and slow).
- Identifies and exploits statistical regularities in the stimulus environment.

Switch Costs Explained

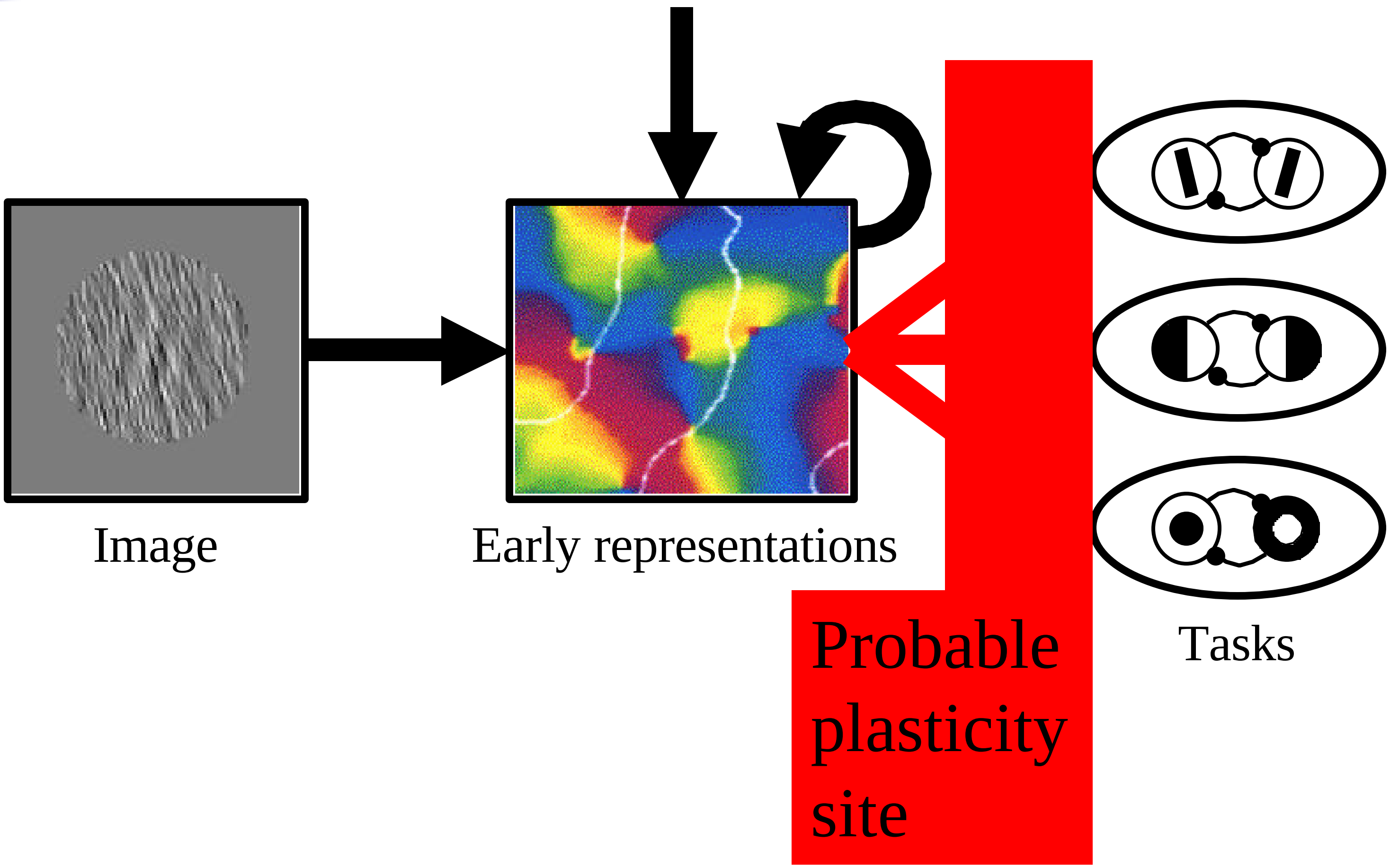
- The statistics of the two contexts are slightly different.
- The optimal weights differ accordingly.
- Emphasize the noise-free "channel."
- Learning is statistically driven and slow.
- After each switch, the system lags behind with suboptimal weights, then re-adjusts again.

There Is Much More to It...

- This talk only scratched the surface
- See the accompanying poster
- 150-page manuscript available for the really interested (and resilient) souls

- Critical feedback always appreciated

Take-Home Message



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