

REDWOOD CENTER
for Theoretical Neuroscience

Evidence for sparse coding

Mushroom body, locust (Laurent)

HVC, zebra finch (Fee)

Auditory cortex, mouse (DeWeese & Zador)

Hippocampus, rat/primate (Thompson & Best; Skaggs)

Motor cortex, rabbit (Swadlow)

Barrel cortex, rat (Brecht)

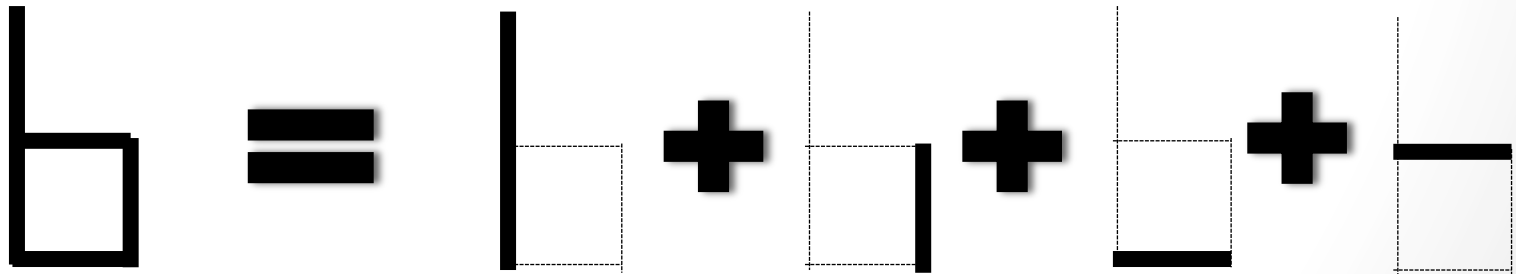
Visual cortex, monkey/cat (Vinje & Gallant)

Visual cortex, cat (Gray; McCormick)

Inferotemporal cortex, human (Fried & Koch)

Olshausen BA, Field DJ (2004) Sparse coding of sensory inputs. *Current Opinion in Neurobiology*, 14, 481-487.

Evidence Slide from B. Olshausen



Sparse Coding

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08/25/15

Olshausen Lab

Redwood Center for Theoretical Neuroscience

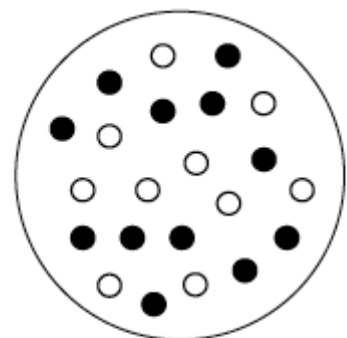
Outline

- Sparse Coding is both an organizing principle for understanding the brain and a useful machine learning tool
1. What is a sparse code?
 2. Mathematical Model?
 3. Sparse coding in V1?

WHAT IS A SPARSE CODE?

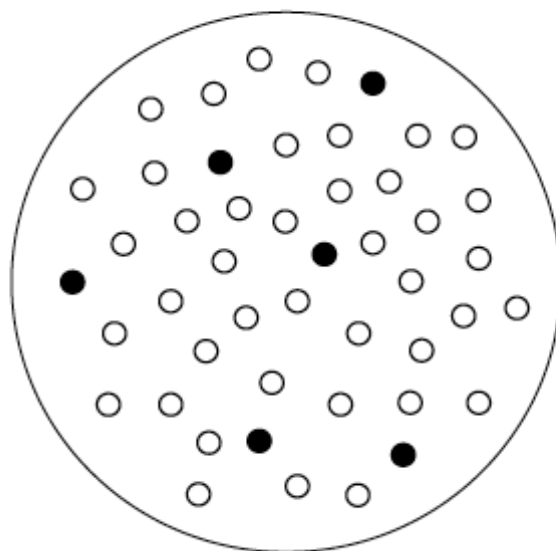
Dense codes

(e.g., ascii)



$$2^N$$

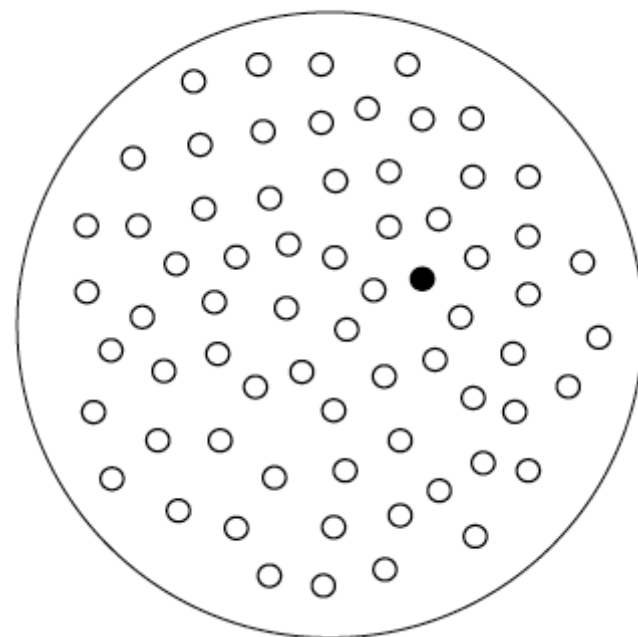
Sparse, distributed codes



$$\binom{N}{K}$$

Local codes

(e.g., grandmother cells)



$$N$$



Barlow (1972)

Perception, 1972, volume 1, pages 371-394

Single units and sensation: A neuron doctrine for perceptual psychology?

H B Barlow

Department of Physiology-Anatomy, University of California, Berkeley, California 94720

Received 6 December 1972

Abstract. The problem discussed is the relationship between the firing of single neurons in sensory pathways and subjectively experienced sensations. The conclusions are formulated as the following five dogmas:

1. To understand nervous function one needs to look at interactions at a cellular level, rather than either a more macroscopic or microscopic level, because behaviour depends upon the organized

2. The sensory system is organized to achieve as complete a representation of the sensory stimulus as possible with the minimum number of active neurons.

neurons, each of which corresponds to a pattern of external events of the order of complexity of the events symbolized by a word.

5. High impulse frequency in such neurons corresponds to high certainty that the trigger feature is present.

The development of the concepts leading up to these speculative dogmas, their experimental basis, and some of their limitations are discussed.

MATHEMATICAL MODEL

Model in Pictures

Neuron Receptive Field /
Dictionary Elements, D

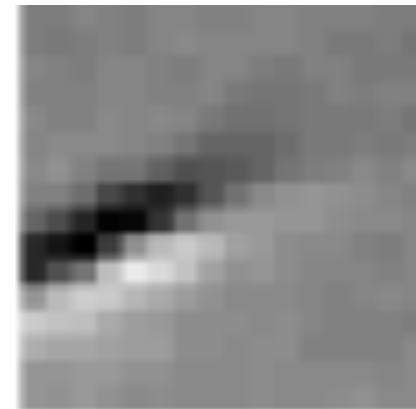


$$= -0.5 \times$$



Image, I

$$+ 0.5 \times$$



Neuron Activity /
Sparse Coefficient, a

$$+$$



Sparse Coefficients,
different for each image

Image n

The diagram illustrates the components of the equation $I_n = D_1 * A_1(I_n) + D_2 * A_2(I_n) + \dots$. An arrow from 'Image n' points to I_n . An arrow from 'Sparse Coefficients, different for each image' points to the $A_1(I_n)$ and $A_2(I_n)$ terms. An arrow from 'Dictionary elements, one set for all images' points to the D_1 and D_2 terms.

$$I_n = D_1 * A_1(I_n) + D_2 * A_2(I_n) + \dots$$

Dictionary elements,
one set for all images

Image, fixed and given

Sparse Coefficients, Chosen to reconstruct image and be sparse

Dictionary, to be learned from data

$$E = \|I - \sum_i A_i * D_i\|^2 + \sum_i \text{abs}(A_i)$$

$|D_i|^2 = 1$

Cost function

Reconstruction Error

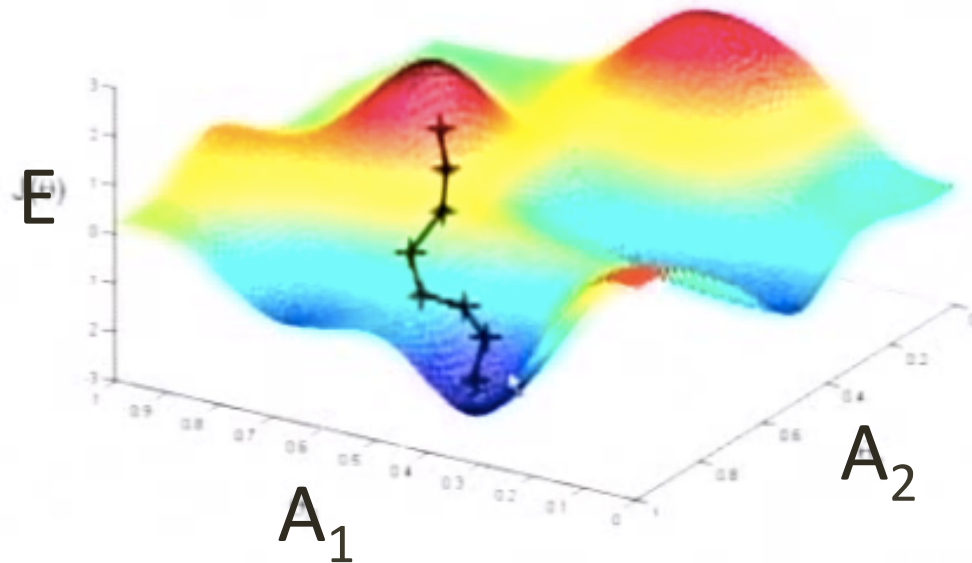
Sparsity

Normed dictionary prevents trivial solution

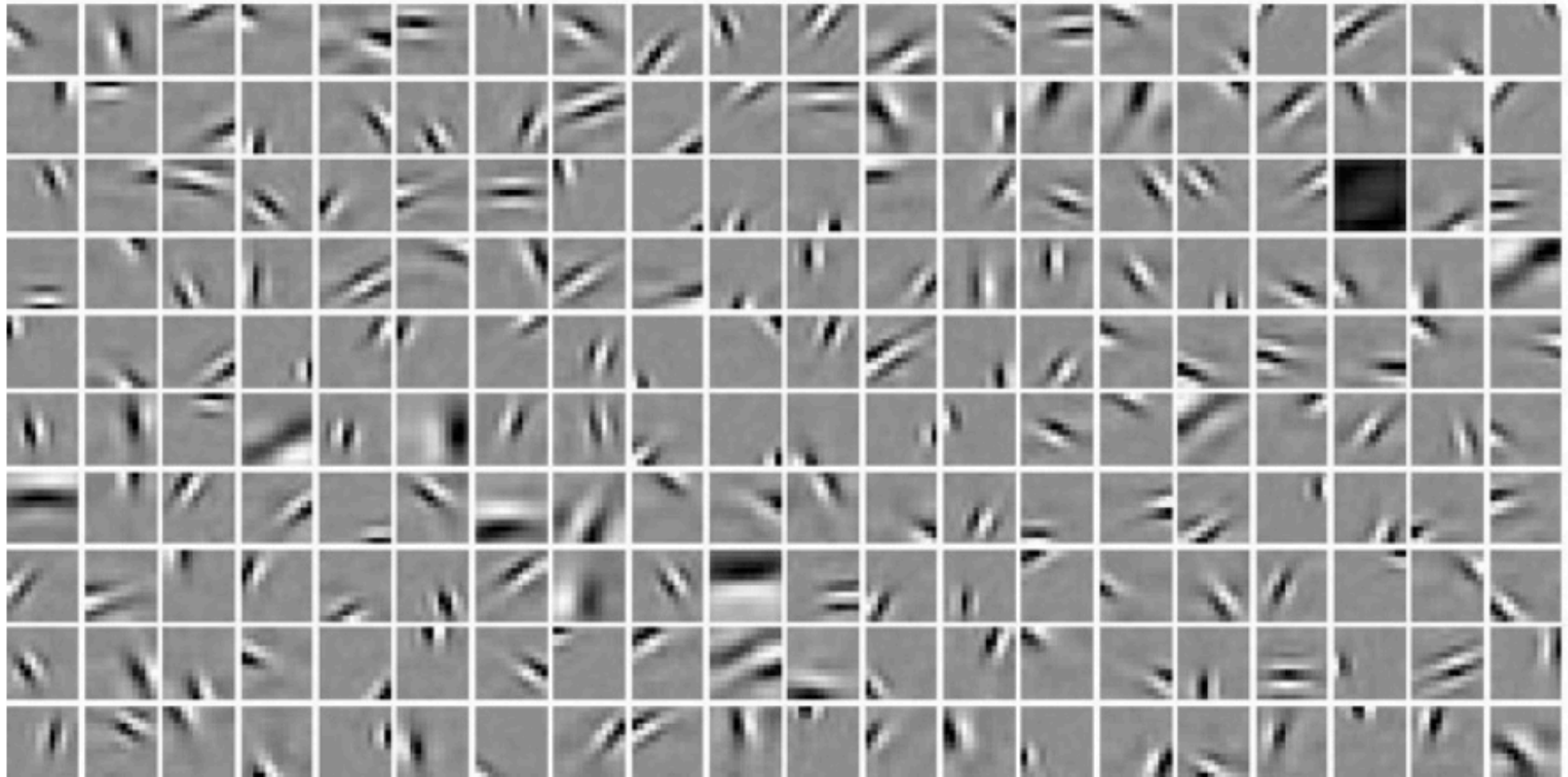
Inference and Learning

- Given the dictionary D , find the sparse coefficients, A , by minimizing the cost function with respect to A .
- Given the sparse coefficients, take one gradient step with respect to the dictionary (and normalize the dictionary).

Gradient Descent

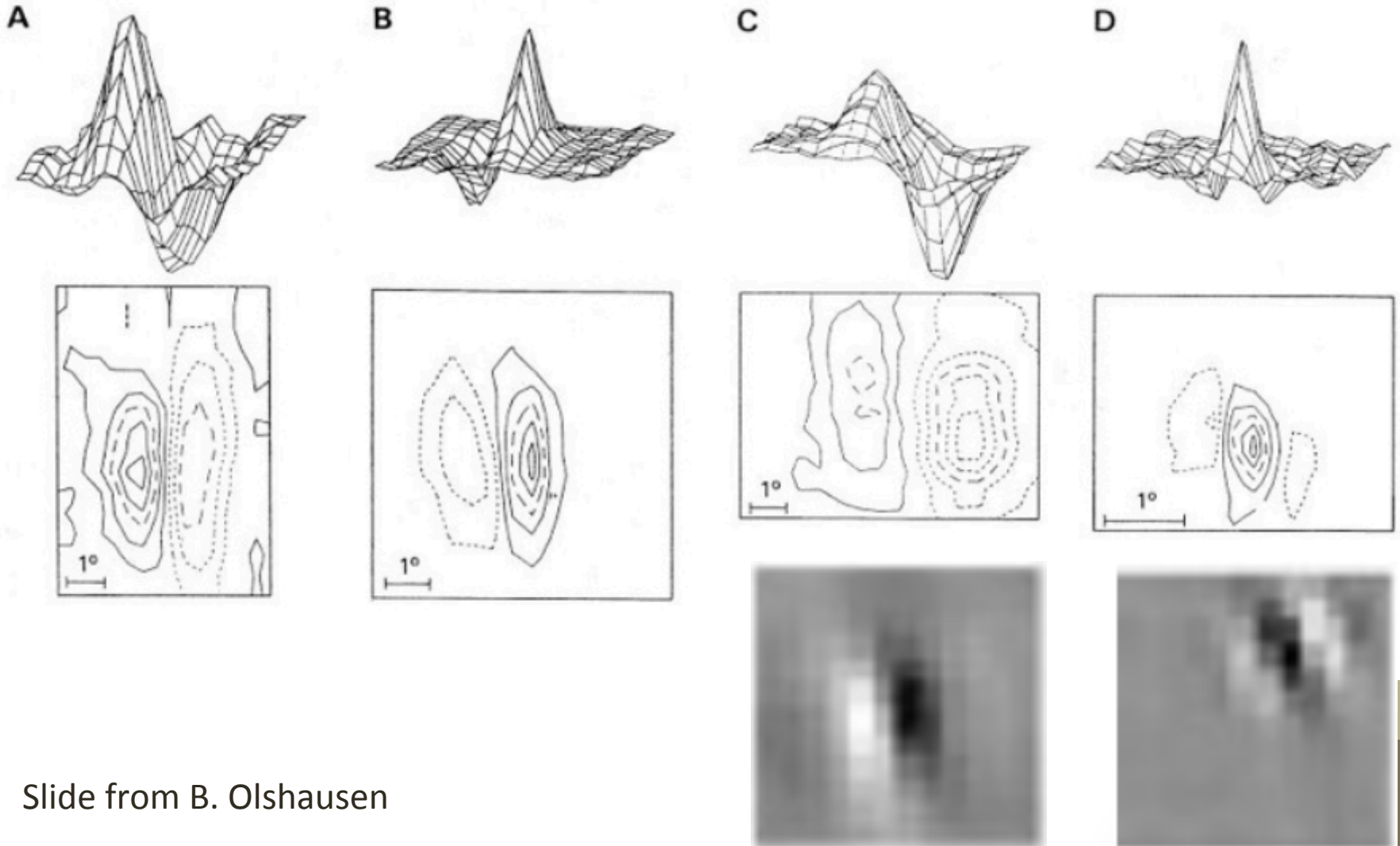


Features learned from natural images (200, 12x12 pixels)



SPARSE CODING IN V1?

V1 Receptive Fields – Edge Detectors (+more)



Key point!

- Images from a camera + sparse coding
- ~
- V1 simple cell RFs
- Brain is adapted to the incoming data

Onto the tutorial!