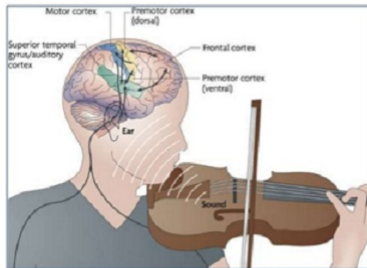


# Sparse Distribution representation

## Sparse Distributed Representations (SDRs)



SDRs are used everywhere in the cortex.

Figure: 1

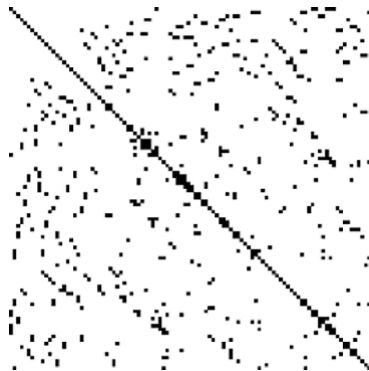


Figure: 2

# Sparsely Connected Autoassociative Lattice Memories

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# Organization of this talk

- 1 Introduction
- 2 Sparsely Connected Autoassociative Lattice Memories
- 3 The Relationship between SCALMs and Gray-Scale AMMs
- 4 Application of SCALMs for the Reconstruction of Color Images

# Some definitions on Morphological Operators

## Erosion and Dilation

let  $\mathbb{L}$  and  $\mathbb{M}$  be complete lattices and  $\epsilon, \delta : \mathbb{L} \rightarrow \mathbb{M}$ :

- ①  $\epsilon$  is called an (*algebraic*) **erosion** if  $\forall J, \forall x_j \in \mathbb{L}$ :

$$\epsilon\left(\bigwedge_{j \in J} x_j\right) = \bigwedge_{j \in J} \epsilon(x_j).$$

- ②  $\delta$  is called an (*algebraic*) **dilation** if  $\forall J, \forall x_j \in \mathbb{L}$ :

$$\delta\left(\bigvee_{j \in J} x_j\right) = \bigvee_{j \in J} \delta(x_j).$$

# Some definitions on Morphological Operators

## Adjunctions

Consider  $\epsilon : \mathbb{L} \rightarrow \mathbb{M}$  and  $\delta : \mathbb{M} \rightarrow \mathbb{L}$  where  $\mathbb{L}$  and  $\mathbb{M}$  are complete lattices.

- 1 The pair  $(\epsilon, \delta)$  is called an **adjunction** (*from  $\mathbb{L}$  to  $\mathbb{M}$* ) iff :

$$\delta(x) \leq y \Leftrightarrow x \leq \epsilon(y) \forall x \in \mathbb{L}, y \in \mathbb{M}.$$

In this case,  $\epsilon$  and  $\delta$  are said to be adjoint.

- 2 If  $\epsilon$  and  $\delta$  are adjoint then  $\epsilon$  is an erosion and  $\delta$  is a dilation.
- 3 Let  $(\epsilon, \delta)$  be an adjunction then the following relation hold;

$$\epsilon(x) = \bigvee \{y \in \mathbb{M} : \delta(y) \leq x\}$$

$$\delta(y) = \bigwedge \{x \in \mathbb{L} : y \leq \epsilon(x)\}$$

# Sparsely Connected Autoassociative Lattice Memories

## Autoassociative Memories

Given a set  $\{x^1 \dots x^k\}$ , an AM is a mapping  $\mathcal{A}$  such that  $\mathcal{A}(x^\xi) = x^\xi$ .  
Furthermore,  $\mathcal{A}(\tilde{x}^\xi) = x^\xi$  for noise or incomplete version  $\tilde{x}^\xi$  of  $x^\xi$ .

## Characteristics

- 1 They exhibit optimal absolute storage capacity.
- 2 They exhibit one step convergence when employed with feedback.

# Sparsely Connected Autoassociative Lattice Memories

## Definition

Given a fundamental memory set  $\{x^1, \dots, x^p\} \subseteq \mathbb{V}^n$ , the partial order define on  $\mathbb{V}$  is used in the set  $S \subseteq N \times N$  where  $N = \{1, 2, \dots, n\}$ .

$$S = \{(i, j) : x_i^\xi \leq x_j^\xi, \forall \xi = 1, 2, \dots, p\} \quad (1)$$

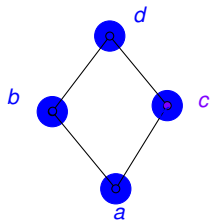
## Supremum and infimum operations on SCALM

Let  $\mathcal{M}$  and  $\mathcal{W}$  be the mapping on  $\chi = \mathbb{V}^n$  defined as follows: for  $x \in \chi$

$$[\mathcal{M}(x)]_i = \bigwedge \{x_j : (i, j) \in S\} \forall i \in N \quad (2)$$

$$[\mathcal{W}(x)]_i = \bigvee \{x_j : (j, i) \in S\} \forall i \in N \quad (3)$$

# Example of the SCALM



## Hasse diagram

$\mathbb{V} = \{a, b, c, d\}$   
 represent complete  
 lattice with  $b \vee c = d$   
 and  $b \wedge c = a$ .

## Example

Fundamental memory

$$x^1 = [d, b, c, c], x^2 = [d, c, a, b] \text{ and}$$

$$x^3 = [b, a, c, d] \in \mathbb{V}^4$$

$S =$

$$\{(1, 1), (2, 1), (2, 2), (3, 3), (3, 4), (4, 4)\}.$$

Input pattern  $x = [c, b, c, a]$ .

Output patterns :

$$\mathcal{M}(x) = [x_1, x_1 \wedge x_2, x_3 \wedge x_4, x_4] = [c, a, a, a]$$

$$\mathcal{W}(x) = [x_1 \vee x_2, x_2, x_3, x_3 \vee x_4] = [d, b, c, c].$$



# Properties of the SCALM

- 1 SCALMs exhibit optimal absolute storage capacity.
- 2 They exhibit one step convergence when employed with feedback.
- 3 They correspond to single layer feedforward neural network.
- 4 Computational point view, the number of synaptic junctions of  $\mathcal{M}$  and  $\mathcal{W}$  usually decreases (considerably) as the number of fundamental memories increase.
- 5 The pattern recalled by  $\mathcal{W}$  represents the smallest fixed point of the model that is greater than or equal to the input pattern.
- 6 They require less computational efforts.
- 7 They have large number of spurious memories.

# Erosion, Dilation and Adjunction on SCALMs

## Erosion and Dilation

Given a fundamental memory set  $\{x^1, \dots, x^p\}$ , the SCALMs  $\mathcal{M}$  and  $\mathcal{W}$  given by (1), (2) and (3) respectively.

- ① An erosion is defined by for all subset  $X \subseteq \chi^n$ :

$$\mathcal{M}(\bigwedge X) = \bigwedge_{x \in X} \mathcal{M}(x).$$

- ② A dilation is given by for all subset  $X \subseteq \chi^n$ :

$$\mathcal{W}(\bigvee X) = \bigvee_{x \in X} \mathcal{W}(x).$$

# Adjunction on SCALMs

## Adjunction

Consider the pair  $(\mathcal{M}, \mathcal{W})$  is an **adjunction** on  $\mathcal{X}$ , i.e the following relation hold for all  $x, y \in \mathcal{X}$ .

$$\mathcal{W}(y) \leq_x x \Leftrightarrow y \leq_x \mathcal{M}(x).$$

- The relation between  $\mathcal{M}$  and  $\mathcal{W}$  as follows for every input pattern  $x \in \mathcal{X}$ .

$$\mathcal{M}(x) = \bigvee \{y \in \mathcal{X} : \mathcal{W}(y) \leq_x x\},$$

$$\mathcal{W}(x) = \bigwedge \{y \in \mathcal{X} : x \leq_x \mathcal{M}(y)\},$$

# The Opening and Closing on SCALMs

The SCALMs  $\mathcal{M}$  and  $\mathcal{W}$  constitute an opening and closing respectively.

## Opening $\mathcal{M}$

- $\mathcal{M}$  is increasing i.e  $(x \leq_x y \Rightarrow \mathcal{M}(x) \leq_x \mathcal{M}(y))$ .
- $\mathcal{M}$  is idempotent i.e  $\mathcal{M}^2 = \mathcal{M}$ .
- $\mathcal{M}$  is anti-extensive i.e  $(\mathcal{M}(x) \leq_x x \forall x \in \mathcal{X})$ .

## Closing $\mathcal{W}$

- $\mathcal{W}$  are increasing and idempotent.
- $\mathcal{W}$  is extensive i.e  $x \leq_x \mathcal{W}(x) \forall x \in \mathcal{X}$ .

# Invariance Domain of $\mathcal{M}$ and $\mathcal{W}$

## Invariance Domain

Invariance domain is the collection of all fixed points of  $\psi$ , i.e

$$\text{Inv}(\psi) = \{x \in \mathcal{X} : \psi(x) = x\}.$$

$\text{Inv}(\mathcal{M})$  is sup-closed.

Mathematically as, for every pattern  $x \in \mathcal{X}$ .

$$\mathcal{M}(x) = \bigvee \{y \in \text{Inv}(\mathcal{M}) : y \leq_x x\}$$

$\text{Inv}(\mathcal{W})$  is inf-closed.

Mathematically as,

$$\mathcal{W}(x) = \bigwedge \{y \in \text{Inv}(\mathcal{W}) : x \leq_x y\}$$

# Lattice based operations from Minimax algebra

## Max product, Min product

Let  $\mathbb{V}$  be a complete  $\mathbb{L}$ -group extension. Let  $A \in \mathbb{V}^{m \times p}$  and  $B \in \mathbb{V}^{p \times n}$ .

- 1 The max-product of  $A$  and  $B$  is given by

$$C = A \boxtimes B \iff c_{ij} = \bigvee_{\xi=1}^p (a_{i\xi} + b_{\xi j}).$$

- 2 The min-product of  $A$  and  $B$  is given by

$$C = A \boxdot B \iff c_{ij} = \bigwedge_{\xi=1}^p (a_{i\xi} + b_{\xi j}).$$

In this case we assume that  $\mathbb{V} = \mathbb{R} \cup \{-\infty, +\infty\}$

# Gray-scale AMMs

Definitions of  $W_{XX}$  and  $M_{XX} \in \mathbb{V}^{n \times n}$

For  $X = [\mathbf{x}^1, \dots, \mathbf{x}^p] \in \mathbb{V}^{n \times p}$

$$[W_{XX}]_{ij} = \bigwedge_{\xi=1}^p \left( x_i^\xi + (x_j^\xi)^* \right). \quad (4)$$

$$[M_{XX}]_{ij} = \bigvee_{\xi=1}^p \left( x_i^\xi + (x_j^\xi)^* \right). \quad (5)$$

Gray-scale AMMs  $\mathcal{M}_{XX}$  and  $\mathcal{W}_{XX}$

Given  $x \in \mathcal{X}$ , the outputs of  $\mathcal{M}_{XX}$  and  $\mathcal{W}_{XX}$  are resp. calculated in terms of a **dilation** and an **erosion**:

$$\mathcal{M}_{XX}(x) = M_{XX} \boxtimes x, \quad \mathcal{W}_{XX}(x) = W_{XX} \boxdot x.$$

# Relationship between the gray-scal AMMs and the SCALMs

## Theorem

Given a set  $\{x^1, \dots, x^p\}$ , the SCALMs  $\mathcal{M}$  and  $\mathcal{W}$  given by (1), (2) and (3). So there exist unique synaptic weight matrices  $M$  and  $W \in \mathbb{V}^{n \times n}$  such that

$$\mathcal{M}(x) = M \boxtimes x, \quad \mathcal{W}(x) = W \boxtimes x.$$

for any input pattern  $x \in \chi$ .

These two matrices can be obtained from synaptic weight matrices  $M_{XX}$  and  $W_{XX}$  given by 5 and 4 as for all  $i, j \in \mathbb{N}$ :

$$m_{ij} = \mathcal{T}_+ ([M_{XX}]_{ij}) \quad w_{ij} = \mathcal{T}_- ([W_{XX}]_{ij}).$$



# Relationship between the gray-scal AMMs and the SCALMs

where  $\mathcal{T}_+ : \mathbb{V} \rightarrow \mathbb{V}$  and  $\mathcal{T}_- : \mathbb{V} \rightarrow \mathbb{V}$  are threshold operators given by

$$\mathcal{T}_+(x) = \begin{cases} 0 & \text{if } x \leq 0 \\ +\infty & \text{otherwise} \end{cases}$$

$$\mathcal{T}_-(x) = \begin{cases} 0 & \text{if } x \geq 0 \\ -\infty & \text{otherwise} \end{cases}$$

Its means that SCALMs  $\mathcal{M}$  and  $\mathcal{W}$  can be obtained from the gray-scale AMMs  $\mathcal{M}_{XX}$  and  $\mathcal{W}_{XX}$  by thresholding their synaptic weight matrices.

## Consequences of the previous Theorem

1  $\mathcal{M}_{XX}(x) \leq \mathcal{M}(x)$  and  $\mathcal{W}(x) \leq \mathcal{W}_{XX}(x)$ .

2  $\text{Inv}(\mathcal{M}_{XX}) \subseteq \mathcal{I}$  and  $\text{Inv}(\mathcal{W}_{XX}) \subseteq \mathcal{I}$ .

3 Invariance domains  $\mathcal{I}_{XX} \subseteq \mathcal{I}$ .

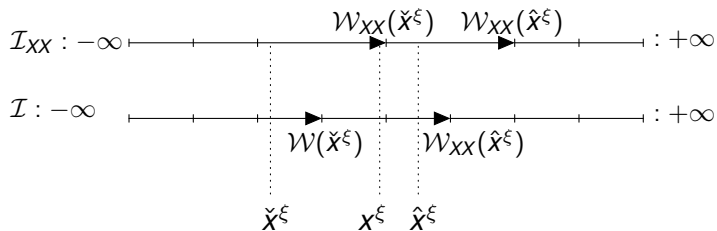
The Invariance domain  $\mathcal{I}$  of the SCALMs include all the fixed points of the gray-scale AMMs  $\mathcal{M}_{XX}$  and  $\mathcal{W}_{XX}$ .

### Advantage of SCALMs

- 1 Less Computational effort and consumed much less memory space.

# Noise tolerance of grayScale MAMs and SCALMs

## Geometrically



# Original Color Images

Consider the following images of size  $384 \times 256$ .



# SCALMs defined on the RGB color models

## Ordering schemes

- Marginal RGB Ordering. ( $\leq_{RGB}^M$ )

$$u \leq_{RGB}^M \mu \Leftrightarrow \begin{cases} u_r \leq \mu_r, \\ u_g \leq \mu_g, \\ u_b \leq \mu_b, \end{cases} \text{ and } .$$

- Lexicographical RGB Ordering. ( $\leq_{RGB}^L$ )

$$u \leq_{RGB}^L \mu \Leftrightarrow \begin{cases} u_r < \mu_r, & \text{or} \\ u_r = \mu_r, & \text{and } u_g < \mu_g, \text{ or} \\ u_r = \mu_r, & u_g = \mu_g, \text{ and } u_b \leq \mu_b. \end{cases}$$

# SCALMs defined on the RGB color models

- Reduce the excessive dependence of the first component by creating equivalence groups.

## Ordering schemes

- $\alpha$ - modulus lexicographical RGB ordering. ( $\leq_{RGB}^\alpha$ )

$$u \leq_{RGB}^\alpha \mu \Leftrightarrow \begin{cases} \lfloor \frac{u_r}{\alpha} \rfloor < \lfloor \frac{\mu_r}{\alpha} \rfloor, & \text{or} \\ \lfloor \frac{u_r}{\alpha} \rfloor = \lfloor \frac{\mu_r}{\alpha} \rfloor, & \text{and } u_g < \mu_g, \text{ or} \\ \lfloor \frac{u_r}{\alpha} \rfloor = \lfloor \frac{\mu_r}{\alpha} \rfloor, & u_g = \mu_g, \text{ and } u_b < \mu_b \text{ or} \\ \lfloor \frac{u_r}{\alpha} \rfloor = \lfloor \frac{\mu_r}{\alpha} \rfloor, & u_g = \mu_g, u_b = \mu_b, \text{ and } u_r \leq \mu_r. \end{cases}$$

Note:  $\alpha \in (0, 1]$  and  $u = (u_r, u_g, u_b), \mu = (\mu_r, \mu_g, \mu_b) \in \mathbb{V}_{RGB}$ .

# Lexicographical Ordering on the Karhunen-Loeve Color System

## Karhunen-Loeve Transform (KLT)

let  $u_1, \dots, u_m$  denote the color values of RGB images.

- column vector mean  $m \in \mathbb{R}^3$  and covariance matrix  $C \in \mathbb{R}^{3 \times 3}$ .

$$m = \frac{1}{n} \sum_{i=1}^n u_i \text{ and } C = \frac{1}{n} \left( \sum_{i=1}^n u_i u_i^T \right) - mm^T.$$

- Given a  $u \in \mathbb{V}_{RGB}$ , the corresponding element  $v \in \mathbb{V}_{KLT}$  is given by

$$v = Q(u - m) \iff u = Q^T v + m \text{ by inverse transform.}$$

where  $Q = [q_1, q_2, q_3]^T$  denotes orthogonal matrix.

# Lexicographical Ordering on the Karhunen-Loeve Color System

## Lexicographical order on KLT system

Given two points  $u$  and  $\mu \in \mathbb{V}_{RGB}$  and the corresponding points  $v = (v_1, v_2, v_3)$  and  $\nu = (\nu_1, \nu_2, \nu_3)$  on the KLT system.

- Define  $u \leq_{KLT}^L \mu \Leftrightarrow v \leq_{KLT}^L \nu$  in the lexicographical ordering i.e

$$u \leq_{KLT}^L \mu \Leftrightarrow \begin{cases} v_1 < \nu_1, & \text{or} \\ v_1 = \nu_1, & \text{and } v_2 < \nu_2, \text{ or} \\ v_1 = \nu_1, & v_2 = \nu_2, \text{ and } v_3 \leq \nu_3. \end{cases}$$



# Noisy Images

We introduced the following types of noise:

- 1 Impulsive noise with probabilities  $p_n = 0.1$ ,  $p_r = p_g = p_b = 0.25$ .
- 2 Gaussian noise (mean 0 and variance 0.01).



**Figure:** Images 'parrots' and 'caps' corrupted by impulsive and Gaussian noise

# Experiment of SCALMs for the reconstruction of color images

Image recalled by the SCALMs  $\mathcal{W}_{RGB}^M$  (first row) and  $\mathcal{M}_{RGB}^M$  (Second row).



Figure: 3.  $\mathcal{W}_{RGB}^M$  and  $\mathcal{M}_{RGB}^M$  polluted with white and black colors.

Image recalled by the SCALMs  $\mathcal{W}_{RGB}^L$  (first row) and  $\mathcal{M}_{RGB}^L$  Second row.



Figure: 4.  $\mathcal{W}_{RGB}^L$  and  $\mathcal{M}_{RGB}^L$  have been contaminated with white and black, and caps has polluted with red and cyan.

Image recalled by the SCALMs  $\mathcal{W}_{RGB}^\alpha$  (first row) and  $\mathcal{M}_{RGB}^\alpha$  Second row.



Figure: 5. Very similar Lexicographical order. Here  $\alpha = 20/255$

Image recalled by the SCALMs  $\mathcal{W}_{KLT}^L$  (first row) and  $\mathcal{M}_{KLT}^L$  Second row.

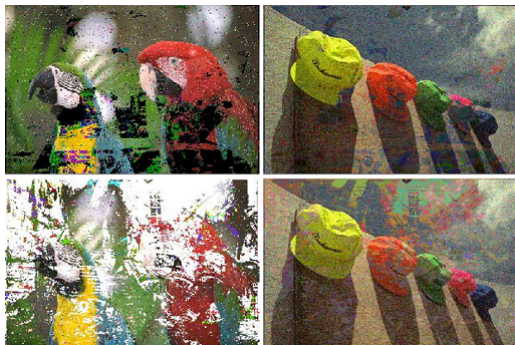


Figure: 6.  $\mathcal{W}_{KLT}^L$  and  $\mathcal{M}_{KLT}^L$  have been contaminated with black and white color.