Universidad del País Vasco
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A Novel Lattice Associative Memory Based on Dendritic Computing

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Introduction

- **Associative memory** seems to be one of the primary functions of the brain

- In classical **pattern recognition**, patterns are viewed as column vectors in Euclidean space.

$$\mathbf{x} = (x_1 \ldots x_n)' \in R^n$$

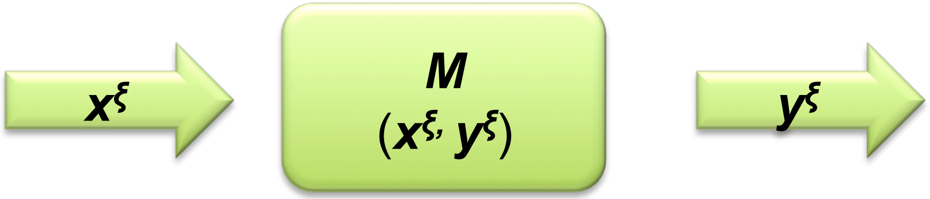
One **goal** in the theory of associative memories is for the memory to **recall** a stored pattern $\mathbf{y} \in R^m$ when presented a pattern $\mathbf{x} \in R^n$

Introduction

Suppose $X = \{x^1, \ldots, x^K\} \subset R^n$ $Y = \{y^1, \ldots, y^K\} \subset R^m$

are **two sets** of pattern vectors with desired **association** given by the diagonal $\{(x^\xi, y^\xi) : \xi = 1, \ldots, K\}$

The **goal** is to **store** these pattern pairs (x^ξ, y^ξ) in some memory ***M*** such that ***M*** recalls y^ξ when presented with the pattern x^ξ.



If ***X=Y*** , then the memory ***M*** is called an **auto-associative** memory, otherwise it is called a **hetero-associative** memory or simply an associative memory.

The Dendritic Lattice Based Model of ANNs

A **lattice based neural network** is an ANN in which the basic neural **computations** are based on the **operations** of a **lattice ordered group**.

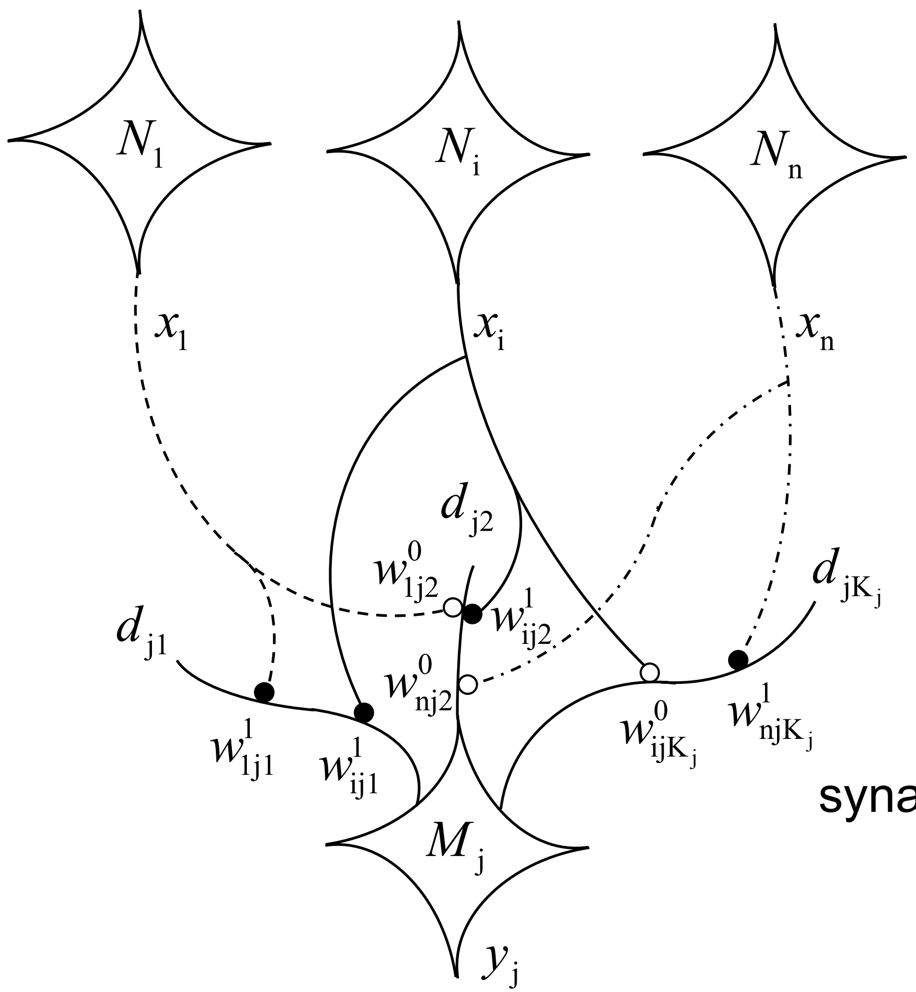
Lattice ordered group: a set ***L*** with an associated algebraic structure

$$(L, \vee, \wedge, +)$$

Where $(L, \vee, \wedge)$ is a lattice and $(L, +)$ is a group with the property that every group translation is isotone:

$$\text{if } x \leq y, \text{ then } a + x + b \leq a + y + b, \ \forall a, b \in L$$

The neural pathways from the presynaptic neurons to the postsynaptic neuron



N_i - presynaptic neurons

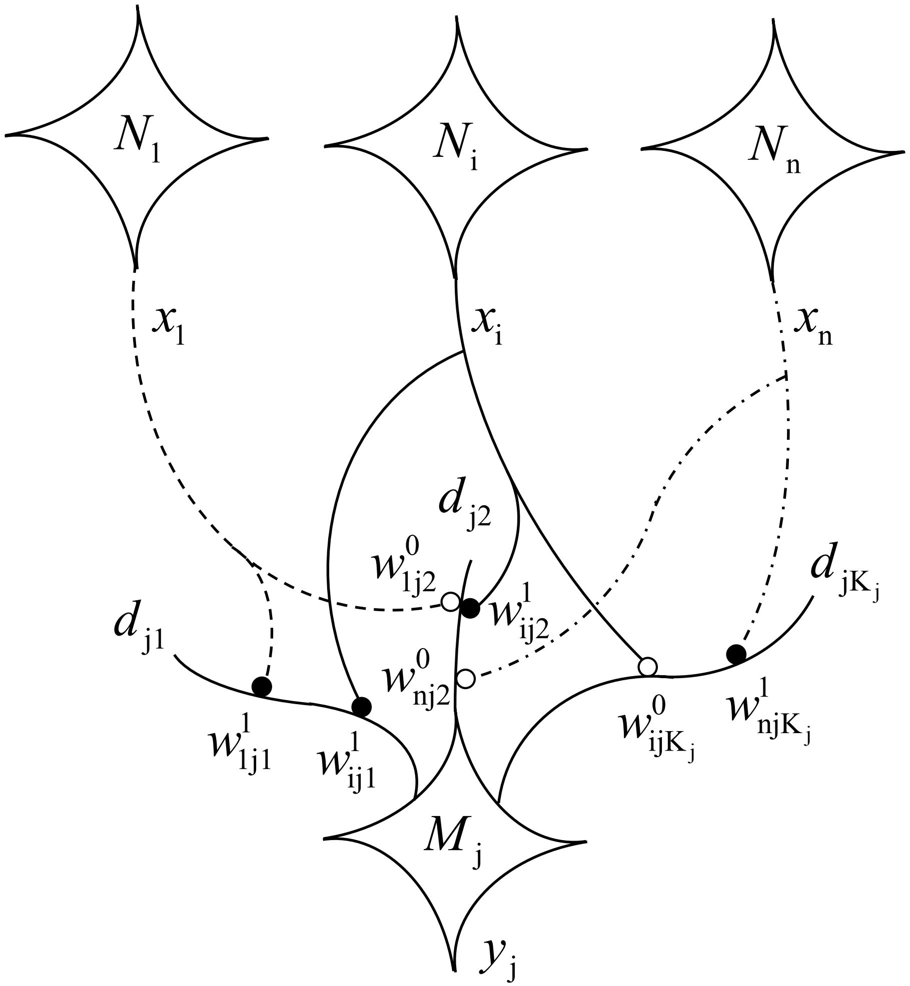
axon

dendritic tree: K-dendritic branches

synaptic weight: inhibitory or excitatory

M_j - Postsynaptic neurons

The Dendritic Lattice Based Model of ANNs



The total **response** (or output) of **dendritic branch** to the received input at its synaptic sites is given by

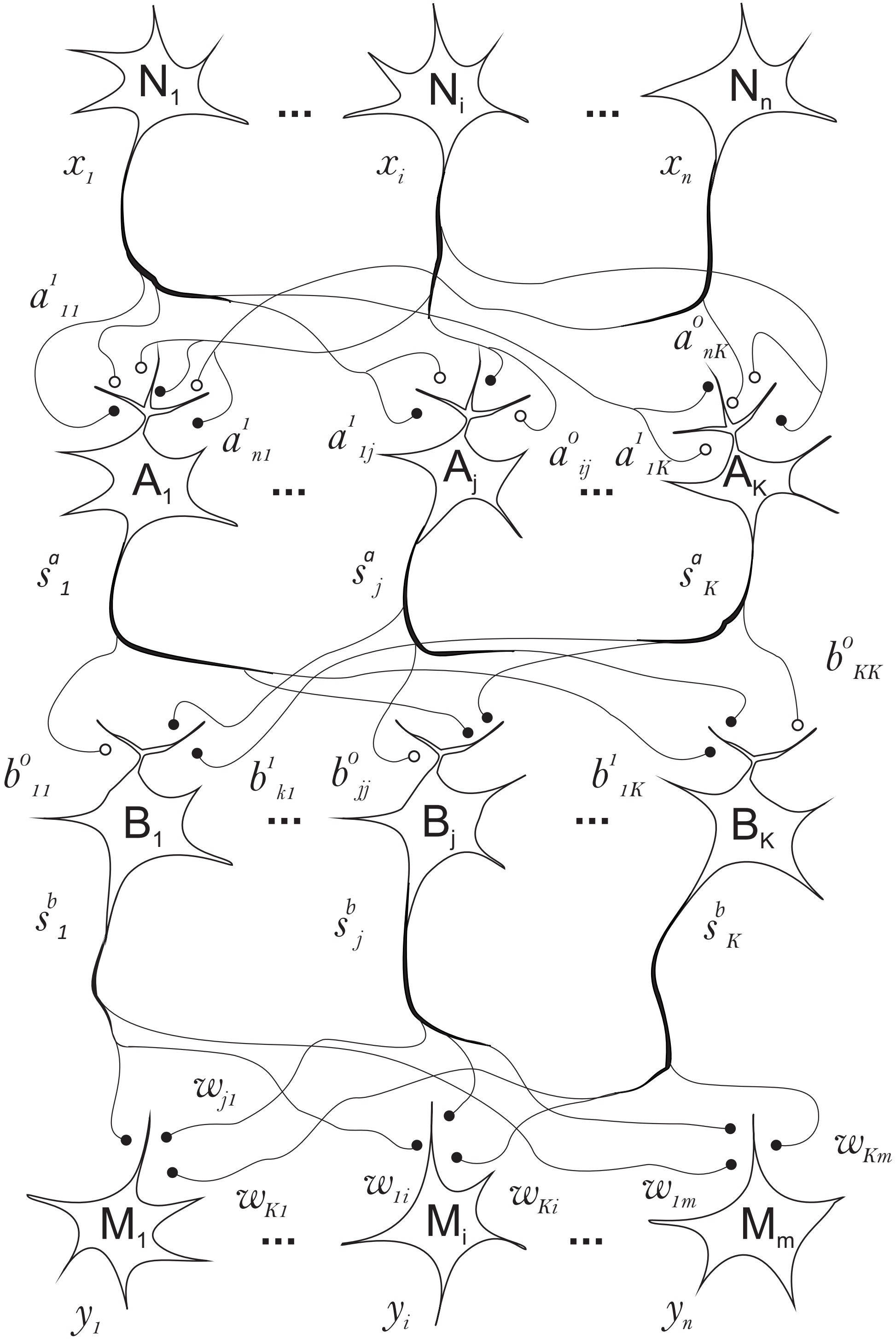
$$\boldsymbol{\tau}_k^{\,j}(\mathbf{x}) = p_{jk} \bigvee_{i\in I(k)} \bigwedge_{l\in L(i)} (-1)^{1-l}(x_i + \omega_{ijk}^{l})$$

The state of postsynaptic neurons M_j

$$\boldsymbol{\tau}^{j}(\mathbf{x}) = p_j \sum_{k=1}^{K_j} \boldsymbol{\tau}_k^{\,j}(\mathbf{x})$$

dendritic tree: *K*-dendritic branches

M_j - Postsynaptic neurons



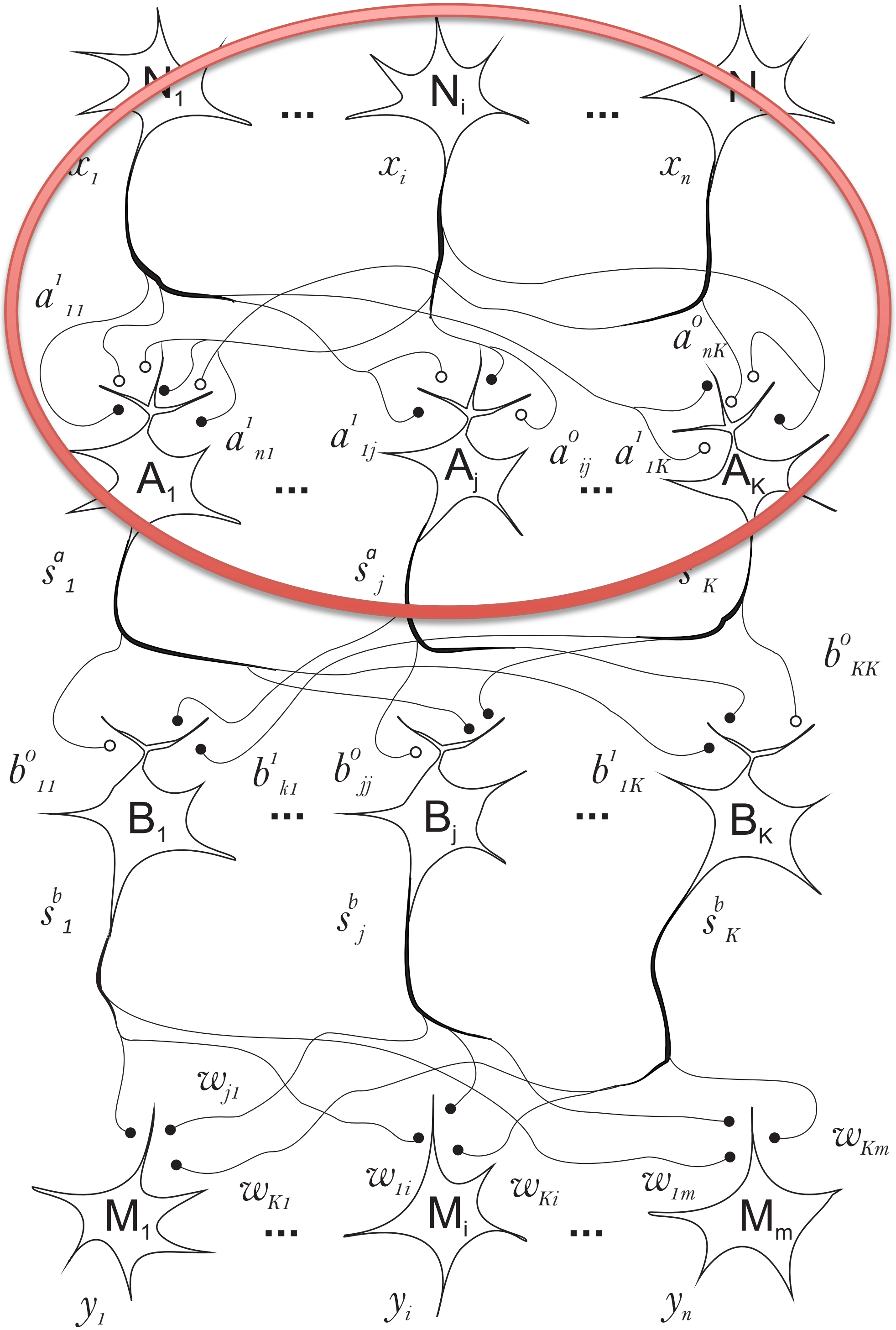
A dendritic network

1. N_i - an input layer

2. A_j - the first hidden layer

3. B_j - the second hidden layer

4. M_i - an output layer



2. A_j - the first hidden layer

The synaptic weights: $a_{ij}^{l} = -x_i$

$$\tau_i^{\ j}(\mathbf{x}) = -\bigwedge_{l=0}^{1}(-1)^{1-l}(x_i + a_{ij}^{l}) =$$

$$= (x_i - x_i^{j}) \vee (x_i^{j} - x_i)$$

The state of neuron A_j:

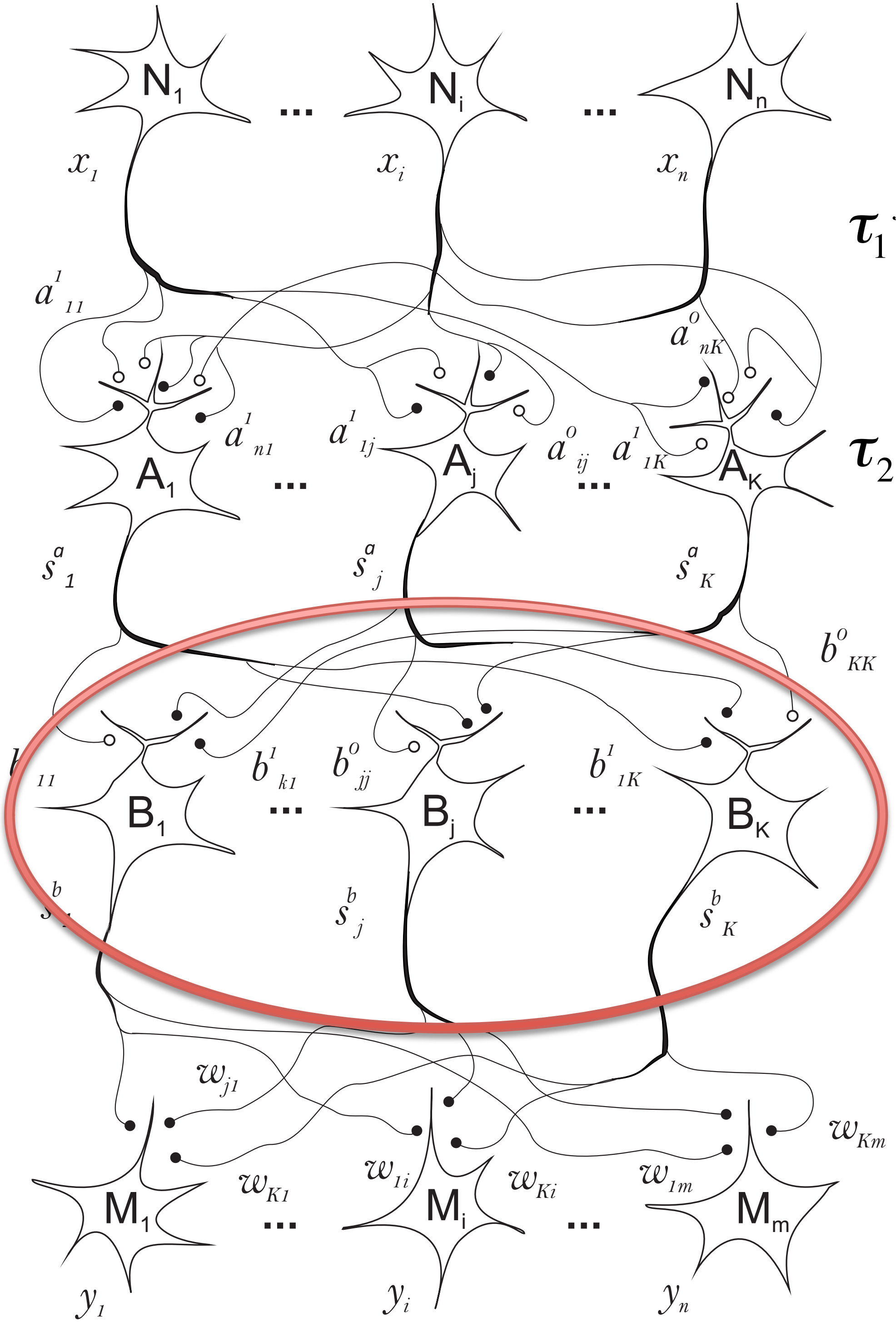
$$\tau_A^{j}(\mathbf{x}) = \sum_{i=1}^{n}(x_i - x_i^{j}) \vee (x_i^{j} - x_i) =$$

$$= \sum_{i=1}^{n}\left|x_i - x_i^{j}\right|$$ **L_1-distance**

The identity function for A-layer neurons

$$f_A(z) = \begin{cases} z \text{ if } z \leq T \\ \infty \text{ if } z > T \end{cases}$$

The output $s_A^{j} = f_A(\tau_A^{j}(\mathbf{x}))$



3. B_j - the second hidden layer

The synaptic weights: $b^l_{jj} = 0$

$$\tau_1{}^j(s_A) = \bigwedge_{i \in I(k)} \bigwedge_{l \in L(i)} (-1)^{1-l}(s_A^j + b^l_{jj}) = -s_A^j$$

$$b^l_{rj} = 0$$

$$\tau_2{}^j(s_A) = \bigwedge_{i \in I(k)} \bigwedge_{l \in L(i)} (-1)^{1-l}(s_A^r + b^l_{rj}) = -s_A^j$$

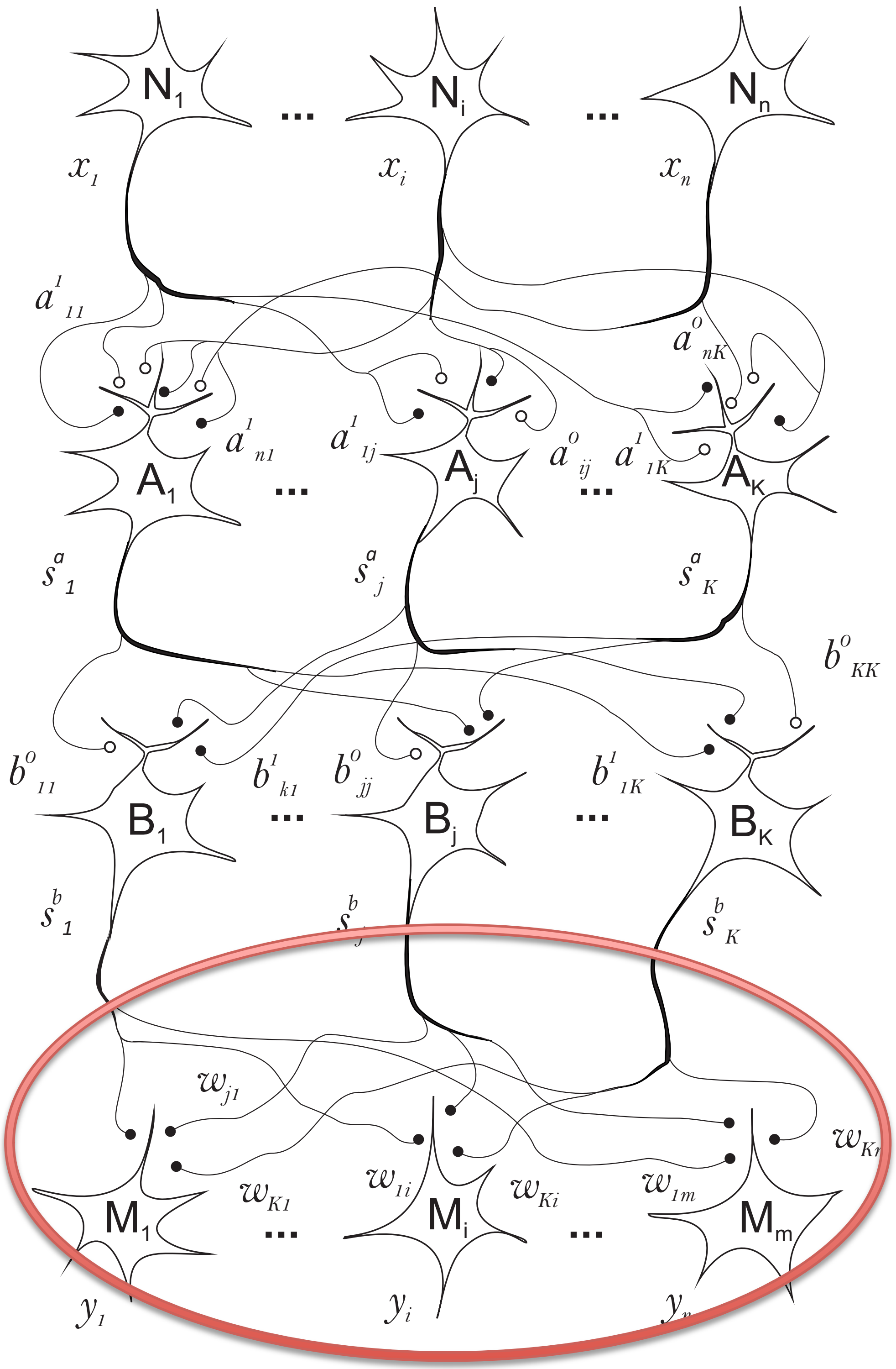
The state of neuron B_j:

$$\tau_B^j(\mathbf{x}) = \sum_{k=1}^{2} \tau_k{}^j(s_A) = \bigwedge_{r \neq j} s_A^r - s_A^j$$

The identity function for B-layer neurons

$$f_B(z) = \begin{cases} 0 \text{ if } z > 0 \\ -\infty \text{ if } z \leq 0 \end{cases}$$

The output $s_B^j = f_B(\tau_B^j(\mathbf{x}))$



4. M_i - an output layer

The synaptic weights: $w^l_{ji} = y^j_i$

The state of neuron M_j:

$$\tau_1^{\ j}(s_B) = \bigvee_{i=1}^{K}(s_B^j + w_{rj}^1) = \bigvee_{i=1}^{K}(s_B^j + y_i^j)$$

The identity function for A-layer neurons

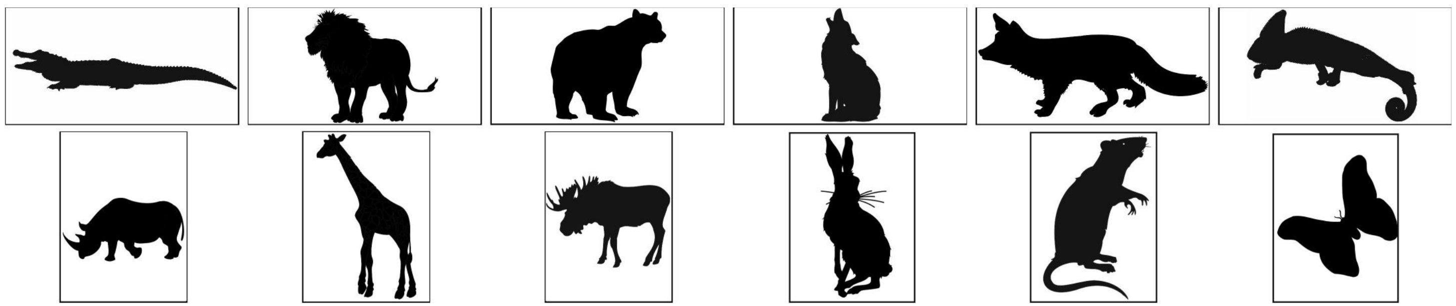
$$f_M(z) = z$$

The output $y_i = \tau^i(s_B)$

Experiments with Noisy and Corrupted Inputs

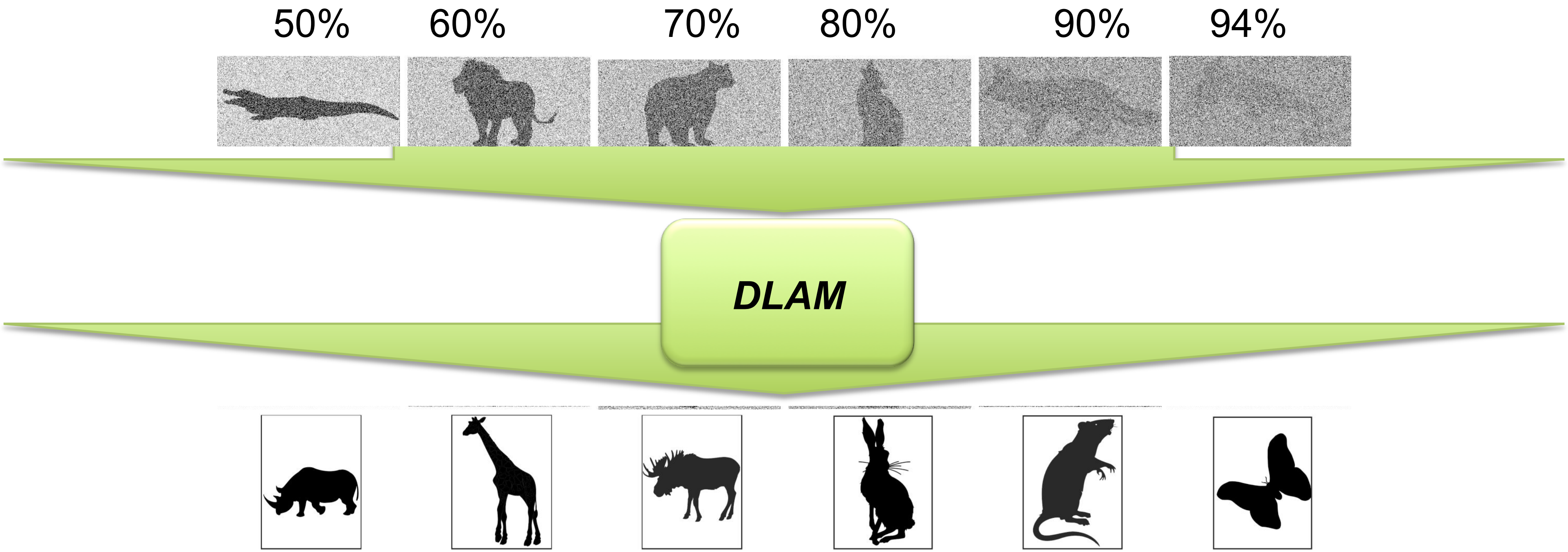
- <u>Experiment 1</u>

  In this experiment, each of the sets X and Y consists of six **Boolean** exemplar patterns. The set X is derived from the set of six **700 × 350** with the set of **associated** output patterns is derived from the six **380 × 500**



Experiment 1

Every pattern image was corrupted adding “salt and pepper” **noise**. Each noisy pixel of corrupted image is rounded to either 0 or 1 to preserve the **Boolean** character of the images.
The range of the noise levels varied from 1% to 99% and was tested on all the images. **The DLAM shows perfect recall.**



Experiment 2

In this example we use a database of **grayscale** images. Both **predator** and **prey** images are of size **265×265**.

Experiment 2

- We **simulate noise** pattern acquisition and **tested** image corruption changes: camera motion, Gaussian noise, the application of a circular averaging filter, a morphological erosion with a line as structuring elements and a morphological dilation with elipsoid as structuring elements.

The DLAMs perfect recall

Experiments with Noisy and Corrupted Inputs

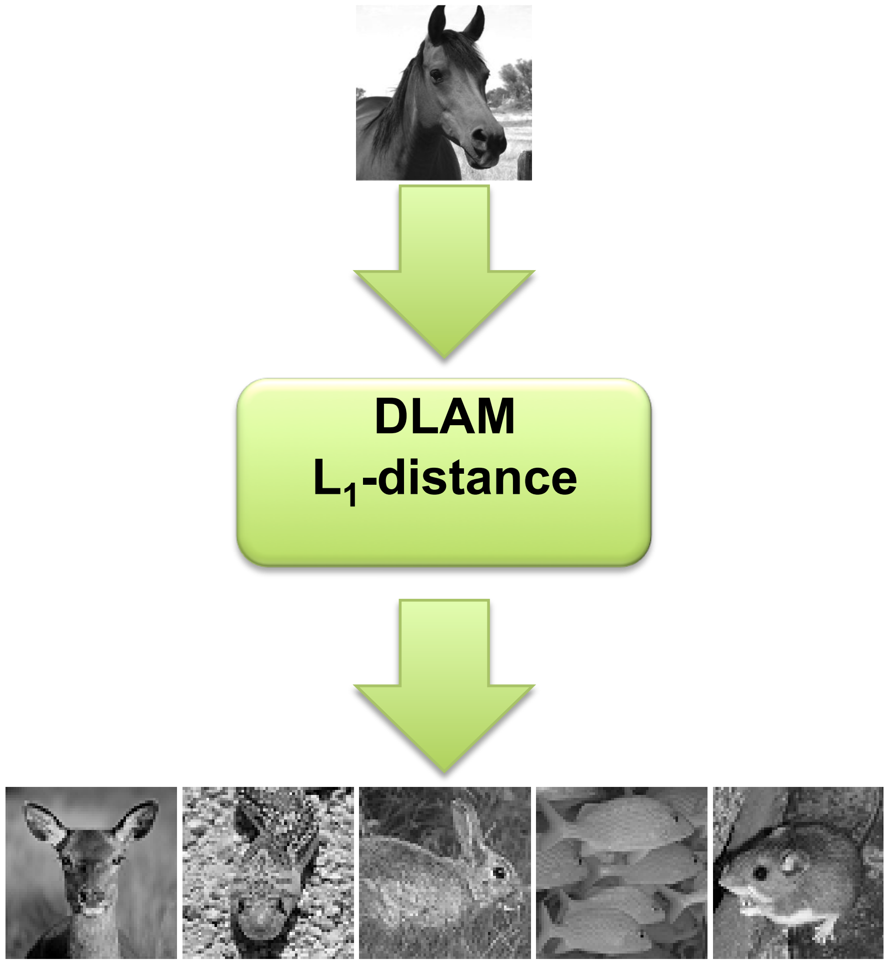
In the Experiment 1 and 2, the threshold **T** for the activation function given by

$$f_A(z) = \begin{cases} z \text{ if } z \le T \\ \infty \text{ if } z > T \end{cases}$$

was set to $T = \infty$

With this threshold, the **DLAM** performance is very **impressive** in that associations can be recalled even at **99% random noise** levels of the input data.
However, images with such high and even lower noise levels of corruption **can not be identified by a human** observer when not first shown the original pattern images.

Experiment 3



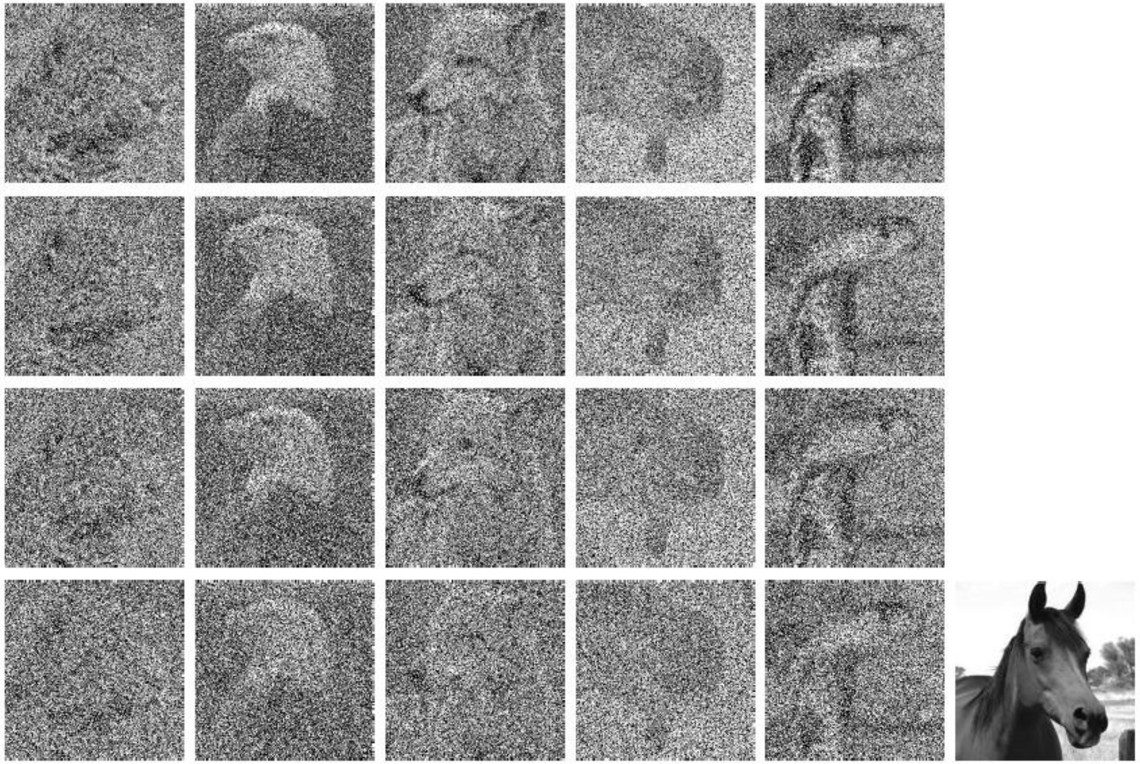
To **avoid misclassification** of intruders, a threshold ***T*** is determined as $T < \infty$

Experiment 3

Noise	0%	50%	60%	63%	65%	70%	80%	90%	100%	Horse
Leopard	0	4470	5374	5634	5813	6297	7158	8066	8932	**5667**
Eagle	0	4492	5348	5626	5844	6252	7154	8080	8947	6293
Wolf	0	4484	5396	5663	5832	6265	7177	8051	8965	6367
Dolphin	0	4452	5385	5640	5816	6281	7162	8059	8952	6713
Cobra	0	4487	5277	5621	5801	6292	7147	8052	8946	6189
Avarage	0	4477	5276	**5637**	5821	6277	7160	8062	8948	6246

The **nearest** predator is the **leopard.**
Thus, the **deer** will be associated with the horse when the **horse** is used as **input** to the DLAM.

Experiment 3



Computing $T_j = d_1(x^j, \overline{x}^j)$ for each j and each noise level as well as $d_1(x^1, x) = 5667$, where $x^1 = leopard$ and $x = horse$, and $T = \frac{1}{5}\sum_{j=1}^{5} T^j = 5637$ when $\overline{x}^j$ represents as 63% corruption of x^j

Thus, *T* eliminates *x* as an intruder.

Conclusions

- We present a new **hetero**-associative **lattice** memory based on **dendritic computing.**
- We report experimental results showing that this memory exhibits extreme **robustness** in the presence of various types of **noise**.

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