Biologically Inspired Computing: Neural Computation

Lecture 6

Patricia A. Vargas

Lecture 6

I. Lecture 5 – Revision
II. Artificial Neural Networks (Part IV)
    I. Recurrent Artificial Networks
        I. GasNet models
    II. Evolving Artificial Neural Networks
        I. MLPs
        II. GasNet models

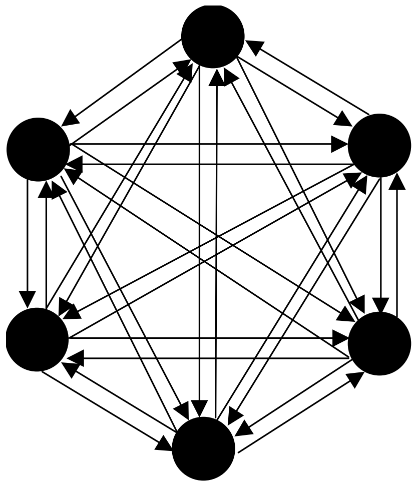
Artificial Neural Networks

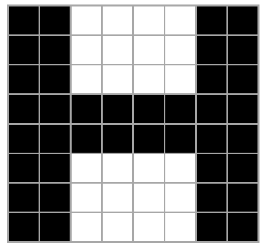
Recurrent Neural Networks

- Hopfield Neural Network

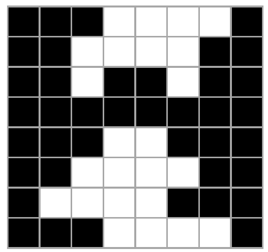
$$w_{ij} = \frac{1}{N} \sum_{k=1}^{n} p_i^k p_j^k$$

$$s_i = sign\left(\sum_{j=1}^{N} w_{ij} s_j \right)$$



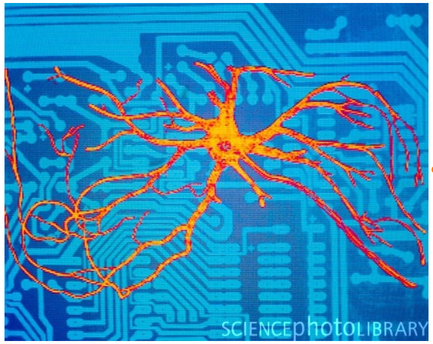


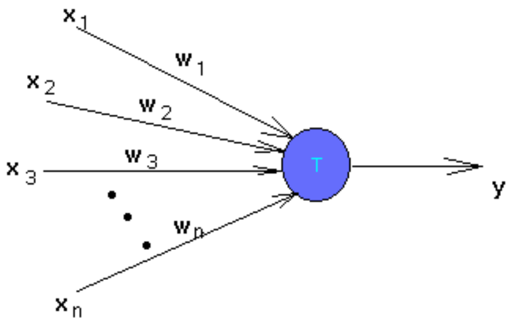
64 pixel image of an "H"

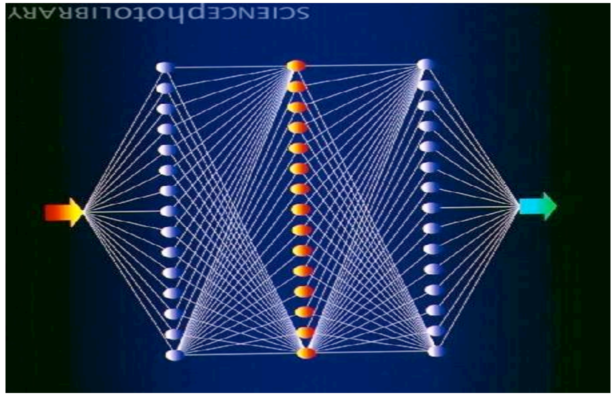


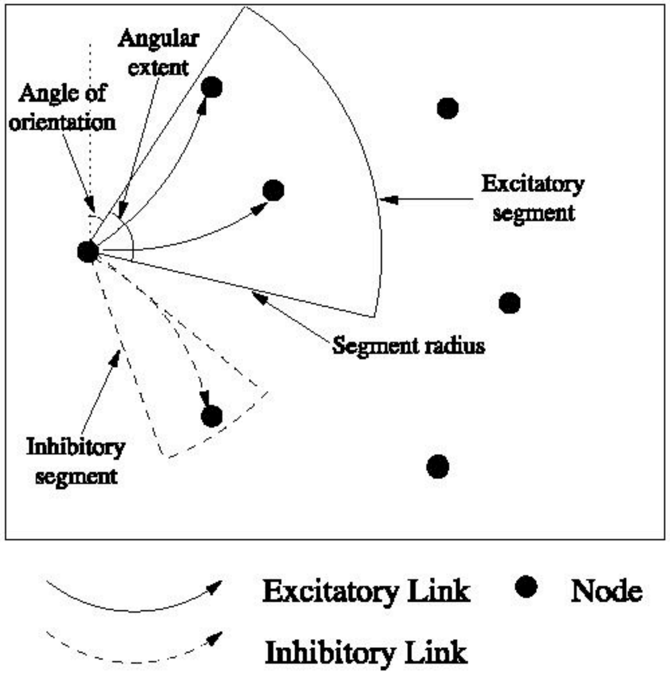
Same image with 10 pixels altered
(I.e. approximately 16% noise added)

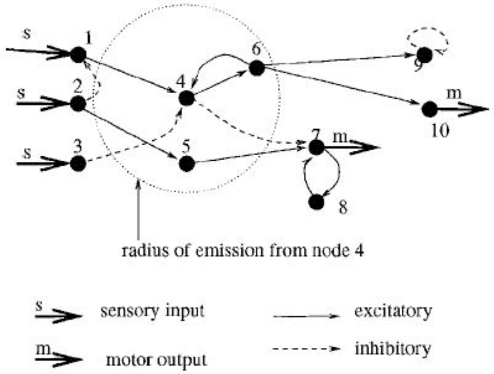
GasNet Models x Classical ANN

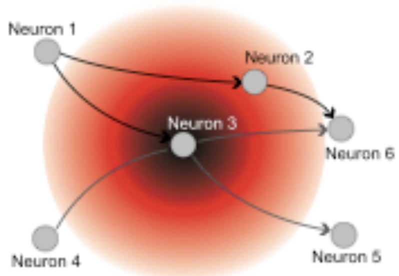












GasNet models

Original

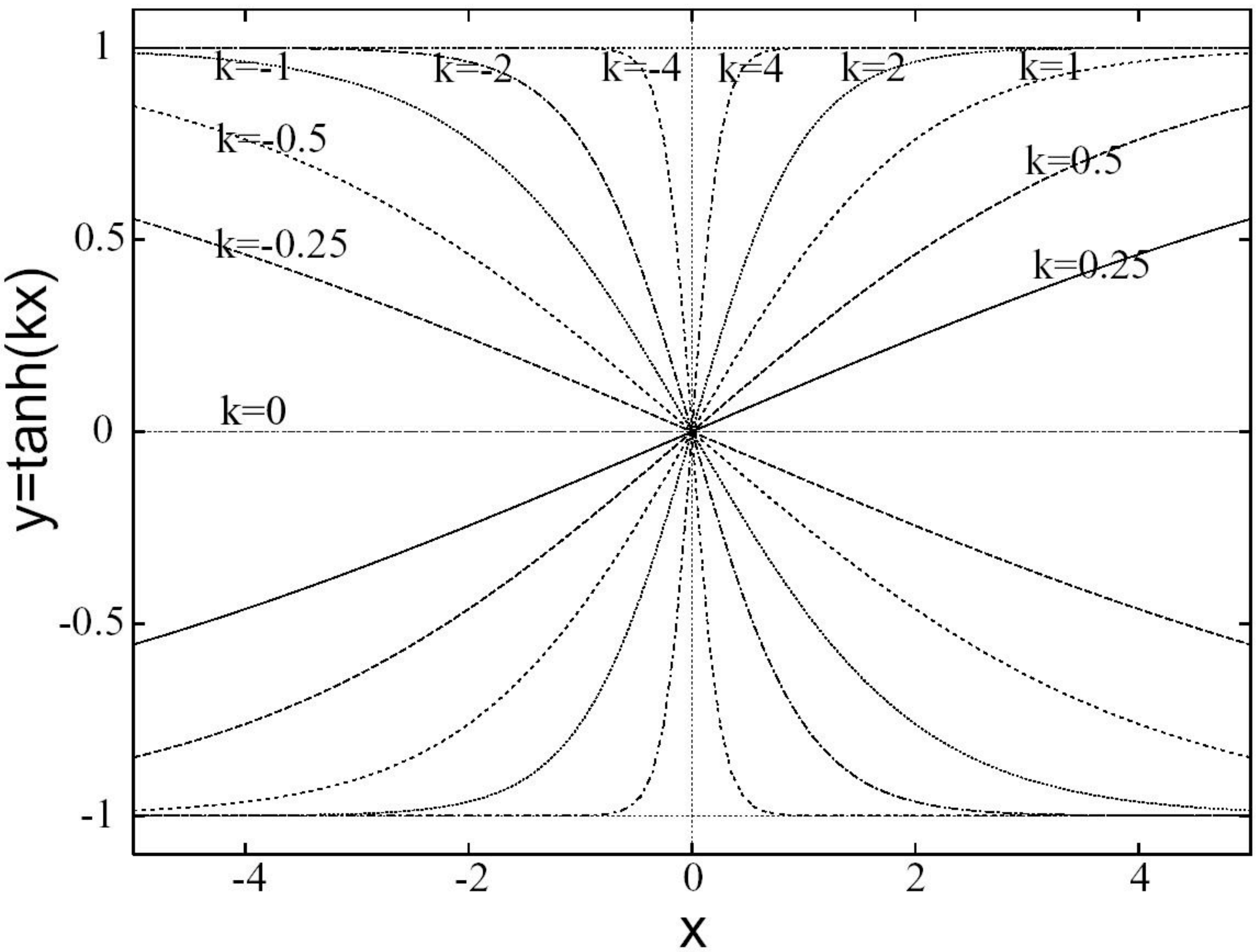
Plexus

Receptor

NSGasNet

Original Model

$$O_i^n = \tanh\left[k_i^n\left(\sum_{j \in C_i} w_{ji} O_j^{n-1} + I_i^n\right) + b_i\right] \qquad k_i^n = k_i^0 + \alpha C_1^n - \beta C_2^n$$



Original Model

$$k_i^n = k_i^0 + \alpha C_1^n - \beta C_2^n$$

$$C(d,t) = \begin{cases} e^{-2d/r} \times T(t), d < r \\ 0, \qquad \text{else} \end{cases}$$

Original Model

$$C(d,t) = \begin{cases} e^{-2d/r} \times T(t), & d < r \\ 0, & \text{else} \end{cases}$$

$$T(t) = \begin{cases} H\left(\frac{t-t_e}{s}\right), & \text{emitting} \\ H\left[H\left(\frac{t_s-t_e}{s}\right) - H\left(\frac{t-t_s}{s}\right)\right], & \text{not emitting} \end{cases}$$

Original Model

$$T(t) = \begin{cases} H\left(\frac{t-t_e}{s}\right), & \text{emitting} \\ H\left[H\left(\frac{t_s-t_e}{s}\right) - H\left(\frac{t-t_s}{s}\right)\right], & \text{not emitting} \end{cases}$$

$$H(x) = \begin{cases} 0, & x \leq 0 \\ x, & 0 < x < 1 \\ 1, & \text{else} \end{cases}$$

Plexus Model

Gas dispersion NOT centred on the node

$$C(d,t) = \begin{cases} e^{-2d/r} \times T(t), d < r \\ 0, & \text{else} \end{cases}$$

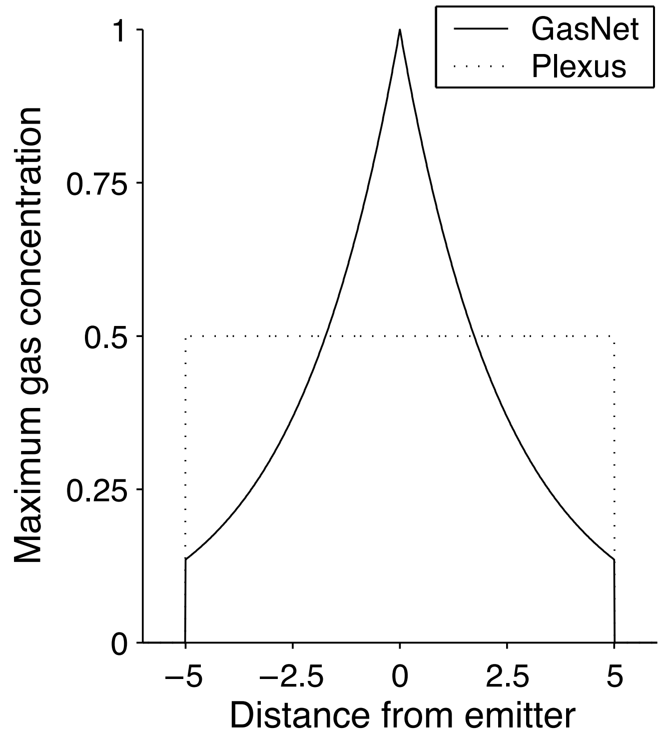
$$C(d,t) = \begin{cases} 0.5 \times T(t), d < r \\ 0, & \text{else} \end{cases}$$

Original X Plexus

Gas Concentration around emitter

$$C(d,t) = \begin{cases} e^{-2d/r} \times T(t), d < r \\ 0, & \text{else} \end{cases}$$

$$C(d,t) = \begin{cases} 0.5 \times T(t), d < r \\ 0, & \text{else} \end{cases}$$



Receptor Model

$$C(d,t) = \begin{cases} e^{-2d/r} \times T(t), d < r \\ 0, \qquad\qquad\qquad \text{else} \end{cases}$$

$$\Delta M_j^n = \rho_i C_i^n \mathrm{R}_j$$

New GasNet model

NSGasNet Model

Nodes do NOT have a spatial relation

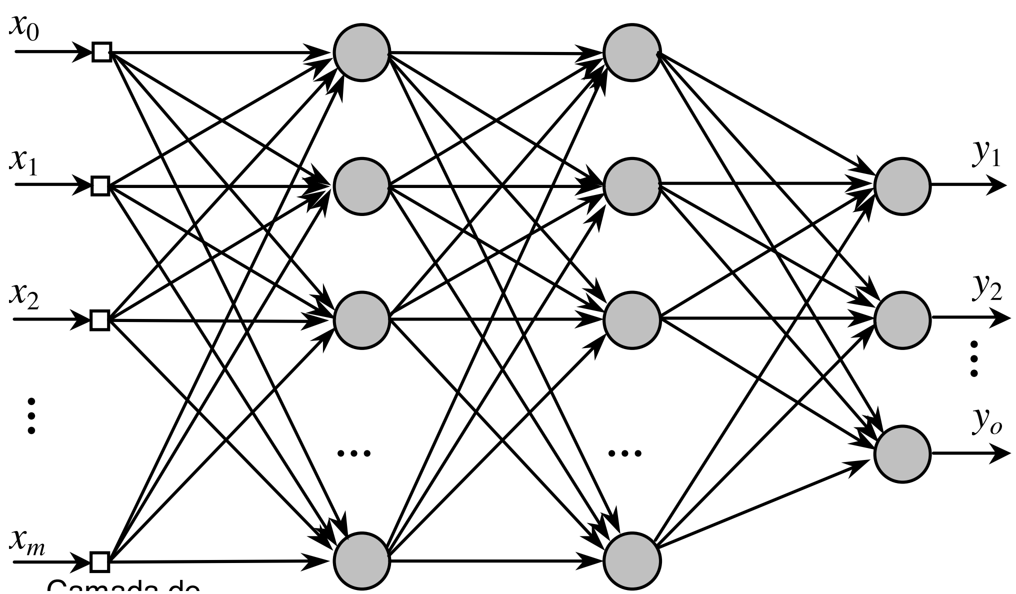
$$C(d,t) = \begin{cases} e^{-2d/r} \times T(t), d < r \\ 0, \qquad \text{else} \end{cases}$$

?

[0,1] is called the *Mbias* or Modulator Bias

Artificial Neural Networks

I. Evolving Artificial Neural Networks
   I. MLPs
      I. Topology and weights
      II. Example: Evolving (training) MLPs to learn some functions



Artificial Neural Networks

I. Evolving Artificial Neural Networks
   I. GasNet models
      I. Topology + all network parameters + task dependent parameters

$$< genotype >:: (< genes >)$$
$$< gene >=< node >$$

I. Evolving GasNets models - Original

Node variables	Description	[Range]DiscreteValues	Gene locus	Description
Coordinates	Node coordinates on the Euclidean plane ($100x100$)	$[0,99]$ $[0,99]$	$< x >$ $< y >$	$< x\ value >$ $< y\ value >$
Electrical connectivity	Defines the parameters of the two segments of circle centred on the node that will determine the excitatory and inhibitory links	$[0,50]$ $[0,2\pi]$	$< r_p >$ $< r_p >$ $< \theta_e >$ $< \theta_e >$ $< \theta_p >$ $< \theta_p >$	$< radius >$ $< angular\ extent >$ $< orientation >$
Recurrence status	Determines whether the node has an inhibitory, none or excitatory recurrent connection	{-1,0,1}	$< rec >$	$< recurrent\ status >$
Emitting status	Determines the circumstances under which the node will emit gas {none, electrical, gas}	{0,1,2}	$< E_s >$	$< emitting\ status >$
Type of gas	Determines which gas the node will emit	$\{1,2\}$	$< G_t >$	$< gas\ type >$
Rate of build up/ decay	Determines the rate of gas build up and decay	$[1,11]$	$< s >$	$< build\ up/$ $decay\ rate >$
Radius of emission	Maximum radius of gas emission	[10%,60%]* * of plane dimension $100x100$	$< G_r >$	$< gas\ radius >$
Transfer function parameter default value K_i^0	Used in (2) to determine the transfer parameter value K_i^n	$[1,11]$	$< K^0 >$	$< transfer\ function$ $default\ value >$
Bias	The b_i term ? on 1	$[-1.0,1.0]$	$< b >$	$< bias\ value >$
Task parameters	Parameters which depend on the task, e.g. a robot vision sensors input area ([1])	?	$<? >$	?

I. Evolving GasNets models - NSGasNet

Node variables	Description	[Range] DiscreteValues	Gene locus	Description
Recurrence status	Determines whether the node has an inhibitory, none or excitatory recurrent connection	{-1,0,1}	$< rec >$	$< recurrent\ status >$
Emitting status	Determines the circumstances under which the node will emit gas {none, electrical, gas}	{0,1,2}	$< E_s >$	$< emitting\ status >$
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Transfer function parameter default value K_i^0	Used in (2) to determine the transfer parameter value K_i^n	$[1, 11]$	$< K^0 >$	$< transfer\ function\ default\ value >$
Bias	The term b_i on 1	$[-1.0, 1.0]$	$< b >$	$< bias\ value >$
Task parameters	Parameters which depend on the task, e.g. a robot vision sensors input area ([1])	?	$<? >$	?
Modulator Bias $(Mbias_n)$	Parameter which depend on the number of nodes, i.e. there will be as many $Mbias$ as the number of network nodes	$[0, 1]$	$< Mbias_n >$	$< Modulator\ bias\ for\ node\ n >$

Lecture 6

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Lecture 6

I. Artificial Neural Networks (Part IV)
   I. Recurrent Neural Networks
      I. GasNet Models
   II. Evolving ANN
      I. MLP
      II. GasNet models