Biologia Quantitativa

Ensino Remoto

Redes Neurais

Departamento de Zoologia – UnB
11 de maio de 2021

Roteiro da Aula

- Definição de Redes Neurais
- Neurônios - Funções de Ativação e pesos de conexão
- Estruturas das Redes Neurais
- Redes Neurais de Propagação Reversa
- Memória de Hopfield
- Redes de Kohonen
- Aplicações

Referências

- David Skapura - Building Neural Networks
- Helge Ritter - Neural Computation and Self Organizing Maps

Características das Redes Neurais

- Camada de Entrada
- Uma ou mais camadas escondidas
- Camada de Saída

- Conexões entre camadas
- Função de ativação do neurônio
- Peso de cada conexão

- Algoritmo de otimização/treinamento

Tipos de Redes Neurais

- Geralmente definidos em função do tipo de algoritmo de treinamento e otimização

- Propagação para diante
- Propagação reversa
- Memória de Hopfield
- Redes de Kohonen

Redes Neurais de Propagação Reversa

- Tipo de rede mais comum
- Conjunto de vetores x e y usado para treinamento
- Define-se um conjunto de pesos iniciais
- Geralmente uma camada oculta apenas
- Funções de ativação escolhidas dependendo do tipo de resposta procurado
- A cada ciclo a intensidade das conexões é recalculada multiplicando a derivada da função de ativação pelo erro observado na soma dos quadrados

CTomada Decisão Rede Neural

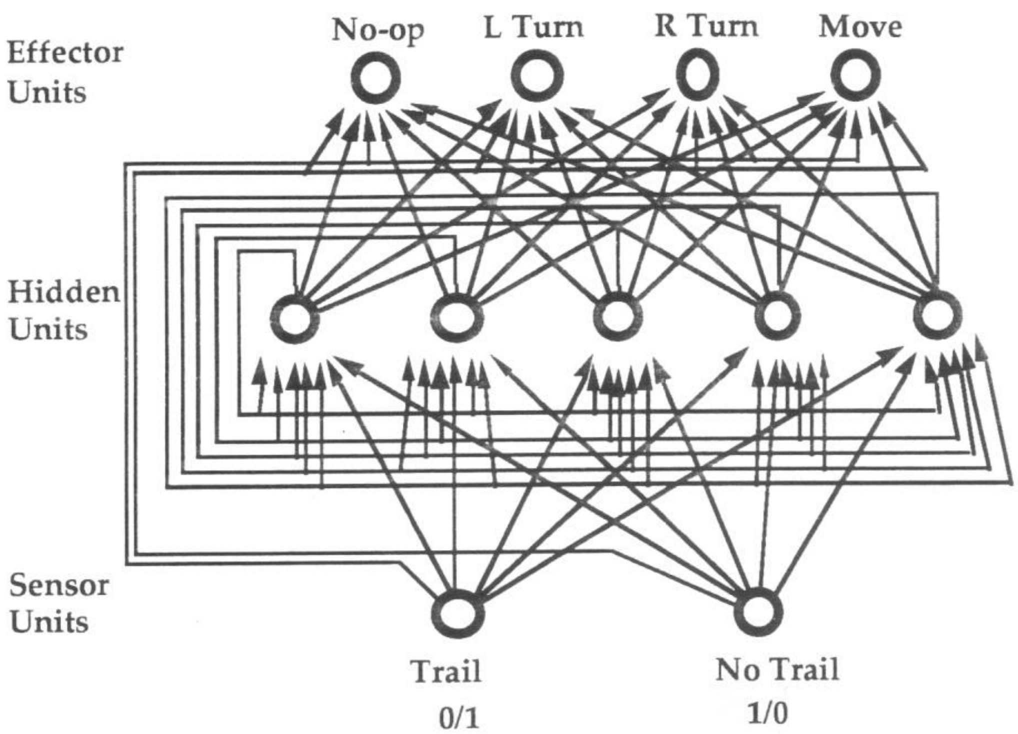


FIGURE 5 Architecture of the recurrent ANN representing an ant.

Rede Neural Computação

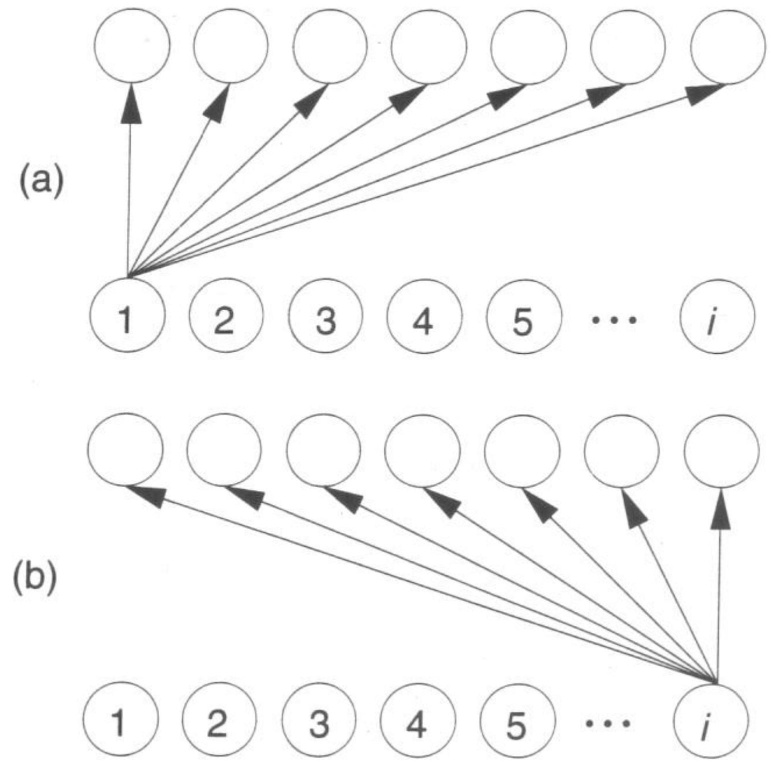


Figure 1.10 The process of accessing memory patterns is shown. (a) Unit 1 wins the competition, and sends its memory pattern to the output layer. (b) When unit *i* wins the competition, the output from the network becomes the memory pattern stored in the connections between unit *i* and the output layer.

Função Ativação Gaussiana

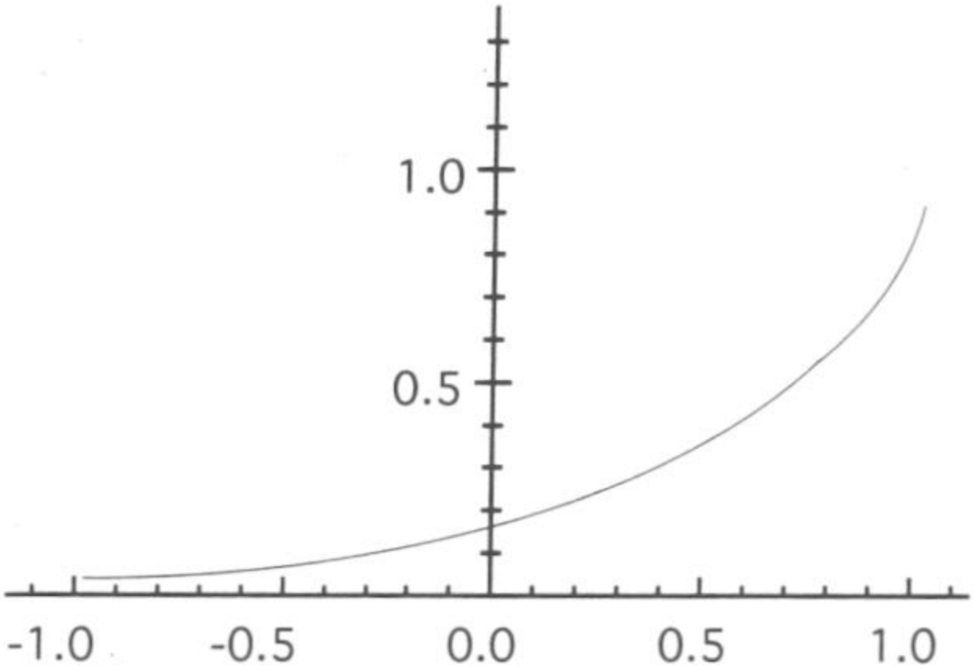


Figure 1.13 This graph shows the form of a Gaussian activation function. Because this is an exponential function, the output is limited only by the value of the input. Units that employ this activation function must therefore be designed to ensure that their input value never exceeds one.

Resposta Sigmóide

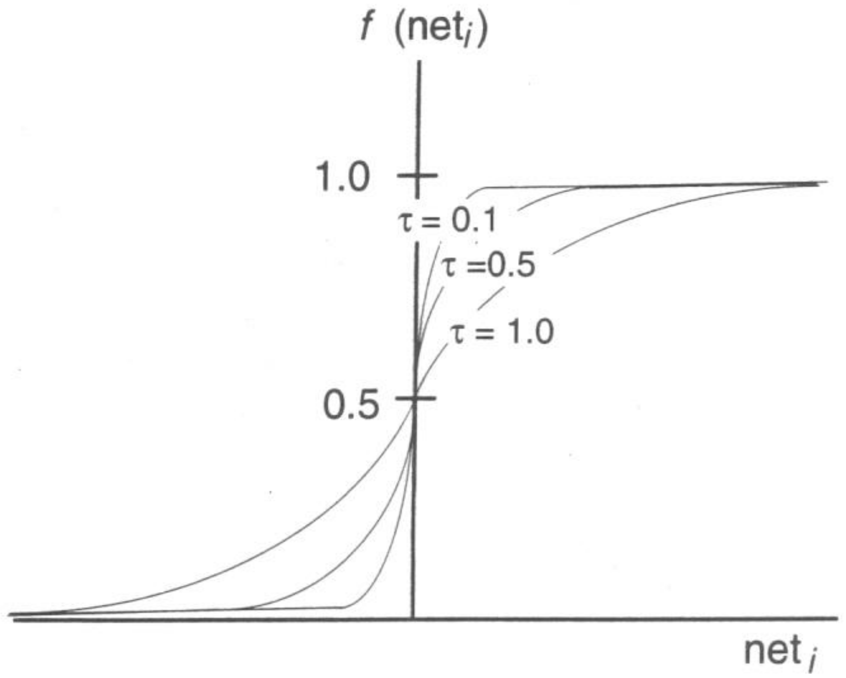


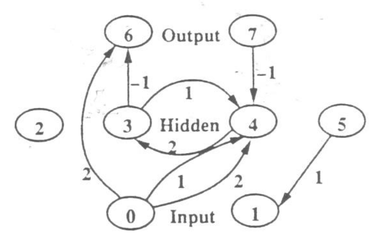
Figure 1.9 The graph of the sigmoid function for different values of τ is shown. Notice that as τ approaches zero, the sigmoid becomes deterministic, because there is no stochastic element to the function value.

Rede Neural e Alg Genétic

TABLE 1 A comparison of AntFarm to Genesys/Tracker. The AntFarm simulation is larger and more complex in many dimensions.

Dimension	AntFarm	Genesys/Tracker
Population	16,384 colonies 2,097,152 ants	65,536 ants
Info/Environment Location	32 bits	1 bit
Level of Selection	Colony	Individual
Sensory Input/Time Step	~ 200 bits	1 bit
Effector Outputs/Time Step	13 bits	2 bits
Internal Memory (max)	21 bits	5 bits
Genome Size	25,590 bits	450 bits

From	To	Weight
5	1	1
3	4	1
0	6	2
7	4	-1
0	4	2
4	3	2
3	6	-1
0	4	1



Genotype

101001001011100001000110010111100111000100010100011010011110111000100001

FIGURE 4 The connection descriptors (left), the network (right) and the genotype (bottom) of an ANN encoded with connection descriptors. Each descriptor specifies the pair of units that it connects (*From* and *To* columns), and the strength (*Weight*) of the connection (each of these three fields is 3 bits wide in this example). Note that some units have no connections associated with them, some have no out-going connections, some pairs of units are connected by multiple connections, and recurrent connections are allowed.

Redes Neurais de Hopfield

- Também chamadas de redes de memória de Hopfield.
- Uma matriz pré-determinada que armazena as informações do vetor original.
- Se multiplicar o vetor de memória pela matriz de memória recupera-se o vetor original.
- Parece trivial mas tem aplicações importantes
- É possível armazenar várias memórias em uma matriz, desde que esparsa
- A memória pode ser recuperada a partir de estímulos incompletos ou com erros

Reconhecimento Padrões
Rede de Hopfield

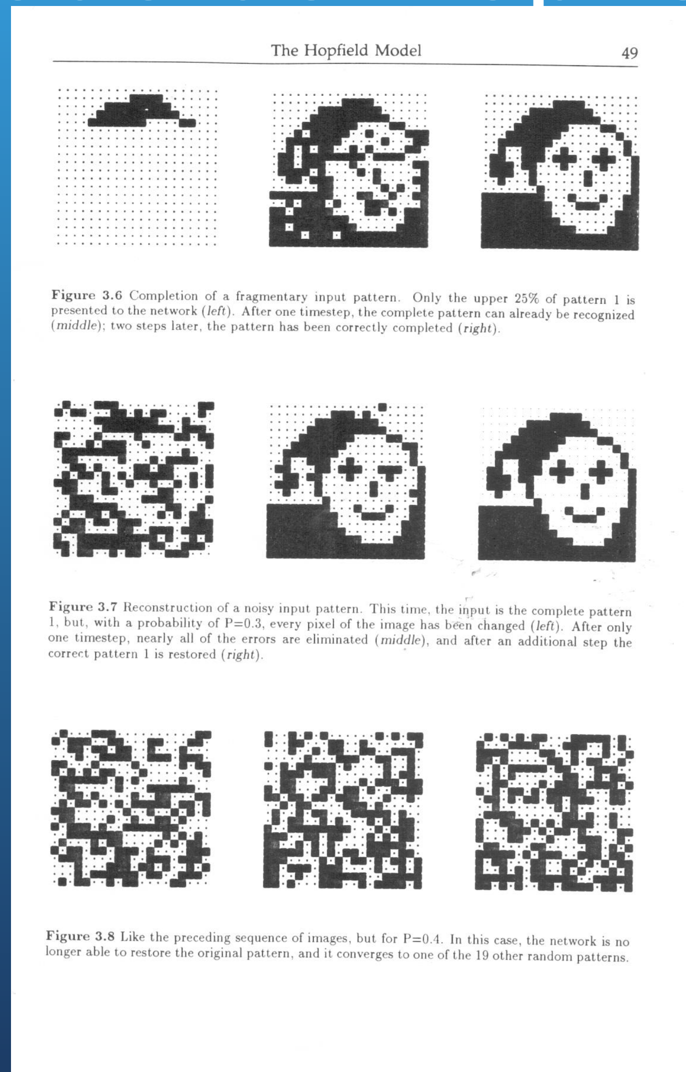


Figure 3.6 Completion of a fragmentary input pattern. Only the upper 25% of pattern 1 is presented to the network (*left*). After one timestep, the complete pattern can already be recognized (*middle*); two steps later, the pattern has been correctly completed (*right*).

Figure 3.7 Reconstruction of a noisy input pattern. This time, the input is the complete pattern 1, but, with a probability of P=0.3, every pixel of the image has been changed (*left*). After only one timestep, nearly all of the errors are eliminated (*middle*), and after an additional step the correct pattern 1 is restored (*right*).

Figure 3.8 Like the preceding sequence of images, but for P=0.4. In this case, the network is no longer able to restore the original pattern, and it converges to one of the 19 other random patterns.

Redes Neurais de Kohonen

- Não usam algoritmo externo de treinamento
- São auto-organizadas criando conexões de acordo com o tipo de estímulo externo e a intensidade de repetição
- Criam um modelo interno do mundo externo

Aprendizado Rede Kohonen

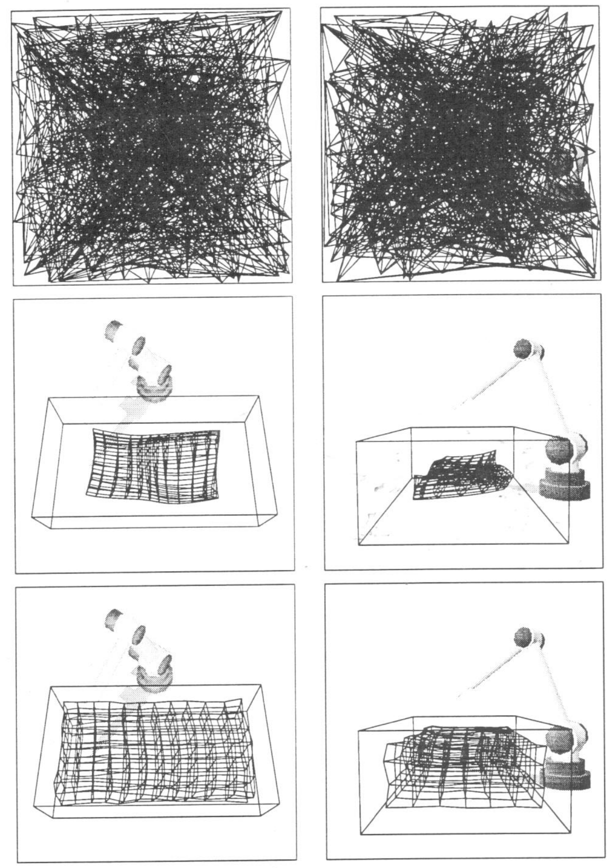


Figure 11.4 Configuration of the neural lattice initially (top), after 2000 (middle), and after 6000 learning steps (bottom). The left column presents the image plane of camera 1, showing $\mathbf{w}_{\mathbf{r}1}$ for all lattice nodes; the right column shows the image plane of camera 2, showing $\mathbf{w}_{\mathbf{r}2}$

Redes de Kohonen

The Positioning Action 173

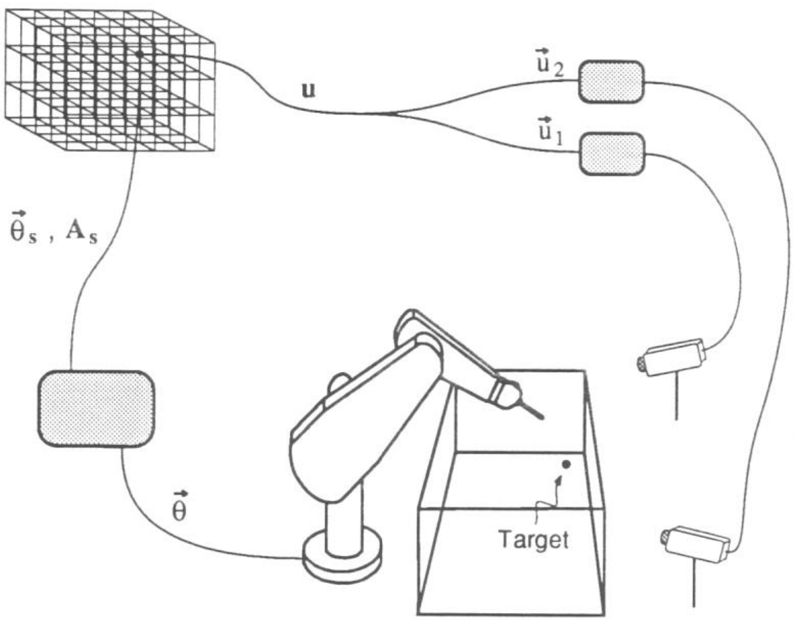
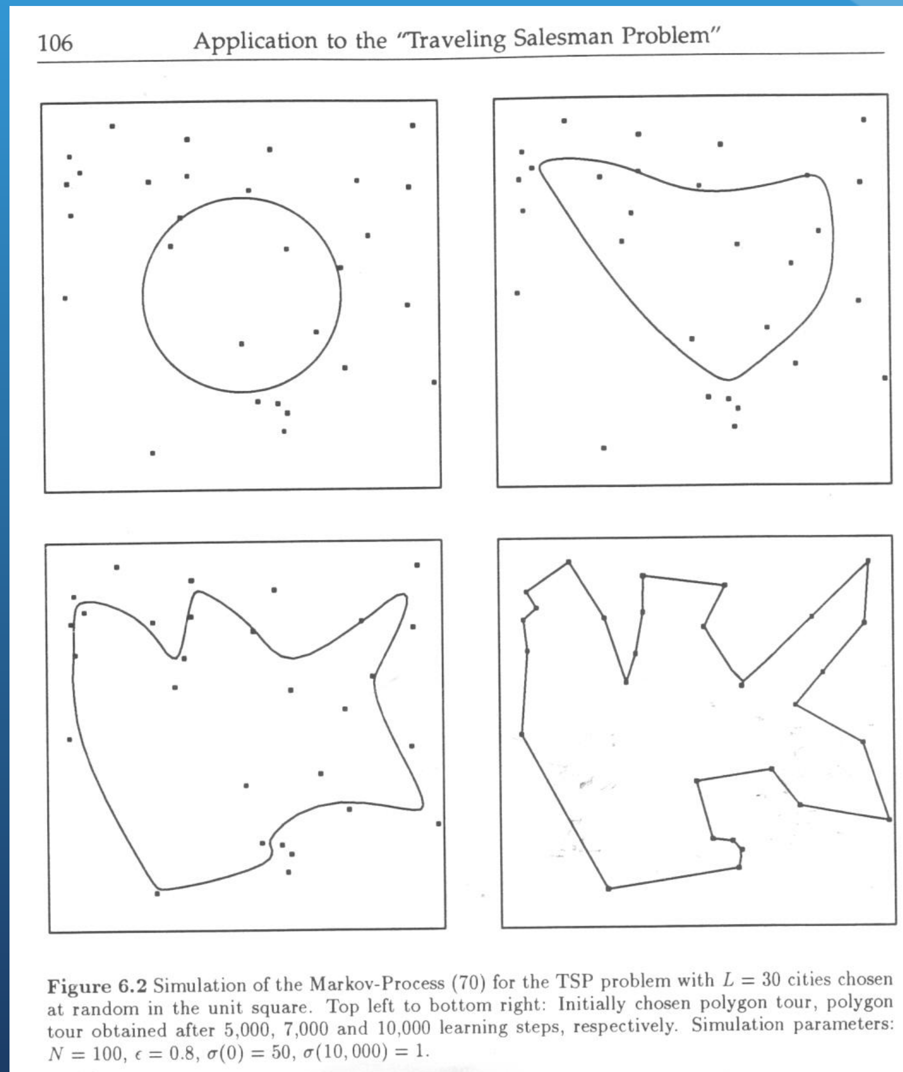


Figure 11.2 Schematic diagram of the positioning action. The two-dimensional coordinates $\vec{u}_1$ and $\vec{u}_2$ of the target in the image planes of cameras 1 and 2 are combined to a four-dimensional vector $\mathbf{u} = (\vec{u}_1, \vec{u}_2)$ and then transmitted to the three-dimensional Kohonen net. The neural unit $\mathbf{s}$ which is responsible for the region in which the target is momentarily located is activated and makes available its two output elements, the expansion terms of 0-th and first order, $\vec{\theta}_\mathbf{s}$ and $\mathbf{A_s}$. These terms determine the joint angles needed for the movement towards the target.

Usos de Redes Neurais

- Reconhecimento e extrações automáticas de padrões, como imagens e sons
- Robótica e automação de processos e procedimentos.
- Otimização e solução de problemas sem algoritmos determinísticos

Problema Caixeiro Viajante



106 Application to the "Traveling Salesman Problem"

Figure 6.2 Simulation of the Markov-Process (70) for the TSP problem with $L = 30$ cities chosen at random in the unit square. Top left to bottom right: Initially chosen polygon tour, polygon tour obtained after 5,000, 7,000 and 10,000 learning steps, respectively. Simulation parameters: $N = 100$, $\epsilon = 0.8$, $\sigma(0) = 50$, $\sigma(10,000) = 1$.