

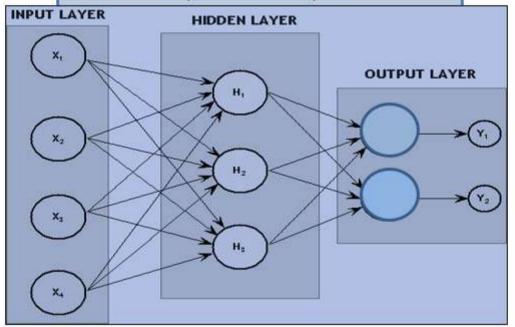


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A 2-layer Feed-Forward Network with 4 Inputs and 2 Outputs





Consider a neural network with $n-input\{x_1,x_2.....x_n\}$, with l neurons in the hidden layer and $m-output\{y_1,y_2.....y_m\}$ layer.

Let u_{ij} be the weight connecting i^{th} input and j^{th} hidden neuron and v_{ik} be the weight connecting j^{th} hidden neuron and the k^{th} output neuron.

The value at the j^{th} hidden layer is given by

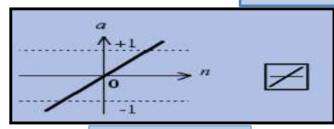
where

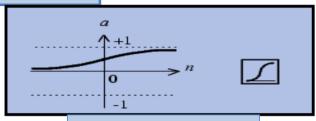
$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

is a sigmoid function which is used here as the transfer function.



The Transfer Functions





Linear transfer function

$$Y^{linear} = X$$

log-sigmoid transfer function

$$Y^{sigmoid} = \frac{1}{1 + e^{-X}}$$

Some other Kinds of sigmoid used in perceptron's

$$f(s) = \frac{s}{|s| + \alpha}$$

$$f(s) = \tanh \frac{s}{\alpha} = \frac{e^{\frac{s}{\alpha}} - e^{-\frac{s}{\alpha}}}{e^{\frac{s}{\alpha}} + e^{-\frac{s}{\alpha}}}$$



The value at the output y_k : k = 1,2, m is given by:

Denoting $X = [x_1 \ x_2 \ \dots \ \dots \ x_n]'$ and $Y = [y_1 \ y_2 \ \dots \ \dots \ y_m]'$

$$U_{n \times l} = \{u_{ij}\}_{\substack{i=1,n \ j=1,l}} \text{ and } V_{l \times m} = \{v_{jk}\}_{\substack{j=1,l \ k=1,m}}$$

Equation (2) can be written as:

$$Y = V'\sigma(U'X) \dots \dots \dots \dots (3)$$



Function Approximation using Neural Network

Let $f: \mathbb{R}^n \to \mathbb{R}^m$ be a continuous function defined on a closed and bounded set $\Omega \subset \mathbb{R}^n$, then there exists weight matrices U and V such that f(X) is approximated using neural network as in equation (3), i.e. ,for any given $\epsilon > 0$, thereexists matrices U and V such that:

$$||f(X) - Y|| < \epsilon$$

where Y is given by Equation (3).

Weight Updating Algorithm

Let *f* be a given function and

$$E(V, U) = ||f(X) - Y||^2$$

be the error in the approximation.

Hence E is a function of U and V: $i = 1,2, \dots, n$, $j = 1,2, \dots, l$, $k = 1,2, \dots, m$

Gradient Descent Iteration and Algorithm

$$U^{\gamma+1} = U^{\gamma} - \alpha. (DU)^{\gamma} : \gamma = 0,1,2,.......(4)$$

where

$$(DU)^{\gamma} = \left\{ \frac{\partial E}{\partial u_{ij}} \right\}_{\substack{i=1,n\\j=1,l}}^{\gamma}$$

and

$$V^{\gamma+1} = V^{\gamma} - \alpha. (DV)^{\gamma} : \gamma = 0,1,2,...$$

where

$$(DV)^{\gamma} = \left\{ \frac{\partial E}{\partial v_{jk}} \right\}_{\substack{j=1,l\\k=1,m}}^{\gamma}$$

Initialize the weights V and W as zero matrices. α is called the learning rate which can be chosen to be a small positive real number less than 1(e.g. say $\alpha = 0.01$)



We have one input x, two neurons in the hidden layer, one output y. Let

$$y = v_1 \sigma(u_1 x) + v_2 \sigma(u_2 x)$$

be the neural network.

Let a be the required constant output.

To approximate a using neural network y, define:

$$E = |a - y|^2$$

be the error.

$$E = [a - v_1 \sigma(u_1 x) - v_2 \sigma(u_2 x)]^2$$

Here the sigmoid function σ is:

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$



$$E = \left[a - \frac{v_1}{1 + e^{-u_1 x}} - \frac{v_2}{1 + e^{-u_2 x}} \right]^2 = N^2$$
$$\frac{\partial E}{\partial V_1} = 2N \left(-\frac{1}{1 + e^{-u_1 x}} \right)$$

$$\frac{\partial E}{\partial w_1} = 2N \left(\frac{v_1}{(1 + e^{-u_1 x})^2} \right) (-x)e^{-u_1 x}$$



One input x, Two hidden neurons, one output y.

Let
$$x = 2, y = 5$$

Then

$$y = v_1 \sigma(u_1 x) + v_2 \sigma(u_2 x)$$

$$5 = \frac{v_1}{1 + e^{-2u_1}} - \frac{v_2}{1 + e^{-2u_2}}$$

$$\begin{pmatrix} v_1 \\ v_2 \\ u_1 \\ u_2 \end{pmatrix}^1 = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}^0 - (0.1).2(5-0) \begin{pmatrix} -1 \\ -1 \\ 0 \\ 0 \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 0 \end{pmatrix}$$

$$\begin{pmatrix} v_1 \\ v_2 \\ u_1 \\ u_2 \end{pmatrix}^1 = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 0 \end{pmatrix}$$

$$\begin{pmatrix} v_1 \\ v_2 \\ u_1 \\ u_2 \end{pmatrix}^2 = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 0 \end{pmatrix} - (0.1) \cdot 2 \cdot (5 - \frac{1}{2} - \frac{1}{2}) \begin{pmatrix} -1 \\ -1 \\ -2 \\ -2 \end{pmatrix}$$

$$(w)^2 = \begin{pmatrix} v_1 \\ v_2 \\ u_1 \\ u_2 \end{pmatrix}^2 = \begin{pmatrix} 1.8 \\ 1.8 \\ 1.6 \\ 1.6 \end{pmatrix} \Rightarrow \frac{1.8}{1 + e^{-(1.6) \cdot 2}} + \frac{1.8}{1 + e^{-3 \cdot 2}} \approx 3$$

Proceeding as above, we can see that the weights are converging.

Let $f(x) = x^2$: $x \in [0,1]$ be a given (one variable) function. To approximate it using Neural Network; Consider a partition $[0.1,0.2, \dots \dots 0.9,1]$

and the corresponding values $[0.01,0.04, \dots \dots 0.8,1]$

Let
$$x_k = (0.1)k$$
; $k = 1, 2, \dots \dots 10$

$$a_k = (0.1)^2 k^2$$
; $k = 1, 2, \dots \dots 10$

Consider a hidden layer with 5 neurons.

Let

$$y(x) = \sum_{j=1}^{5} v_j \ \sigma\left(\sum_{i=1}^{5} u_i \cdot x\right)$$

be the Neural Network as a function of x. Let

$$y_k = \sum_{j=1}^5 v_j \ \sigma\left(\sum_{i=1}^5 u_i.x_k\right)$$



Define

$$E = \sum_{k=1}^{10} (a_k - y_k)^2$$

By minimizing E using the gradient method, we can get u_i and v_j and the approximation of f(x) as a Neural Network.

Solving Inverse Kinematics using Neural Network

Consider the kinematics of a 2-link manipulator as

$$x_1 = l_1 \cos \theta_1 + l_2 \cos(\theta_1 + \theta_2)$$

 $x_2 = l_1 \sin \theta_1 + l_2 \sin(\theta_1 + \theta_2)$

Let (x_1, x_2) be the input and

$$\theta_k^N = \sum_{j=1}^l v_{jk} \ \sigma\left(\sum_{i=1}^2 u_{ij} x_i\right) k$$
; $k = 1,2$

be the Neural Network for θ_k . Let

$$x_1^N = l_1 \cos \theta_1^N + l_2 \cos(\theta_1^N + \theta_2^N) x_2^N = l_1 \sin \theta_1^N + l_2 \sin(\theta_1^N + \theta_2^N)$$

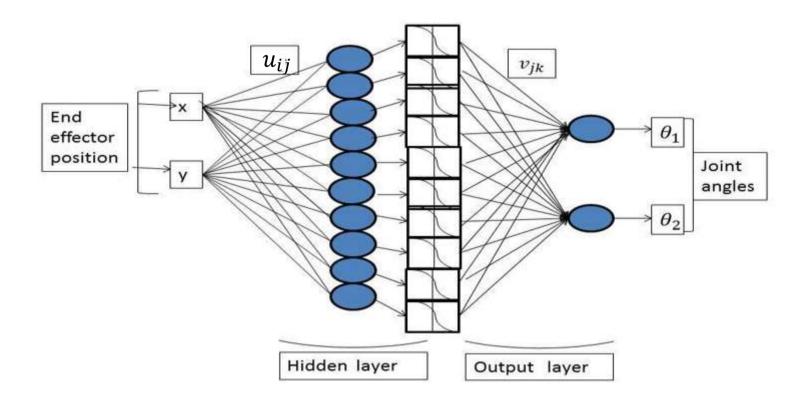
Be the Neural Network for x_1 and x_2

To find the weights v_{jk} and u_{ij} , we define the error E which is minimized using the learning algorithm as given by steepest descent iterative formula (4).

Define the error E as

$$E = \sum_{i=1}^{2} (x_i - x_i^N)^2$$









Neural Network Trajectory Generation

For 4 constrains:

$$x_A(t) = \left(\frac{t - t_0}{t_f - t_0}\right)^2 N_1(t, U_1, V_1) + \left(\frac{t_f - t_0}{t_f - t_0}\right)^2 N_2(t, U_2, V_2)$$

For 6constrains:

$$x_{A}(t) = \begin{pmatrix} \left(\frac{t_{2} - t}{t_{2}}\right) \left(\left(\frac{t - t_{0}}{t_{f} - t_{0}}\right)^{2} N_{1}(t, U_{1}, V_{1}) + \left(\frac{t_{f} - t}{t_{f} - t_{0}}\right)^{2} N_{2}(t, U_{2}, V_{2})\right) \\ + \left(\frac{(t_{f} - t)t}{t_{2}(t_{f} - t_{2})}\right)^{2} N_{3}(t, U_{3}, V_{3}) \end{pmatrix}$$



Thanks!



