Neural Network basics and its Application

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Soft Computing

- What is Soft Computing?
- Hard Computing Vs. Soft Computing
- Soft Computing Methods
  - Neural Network
  - Support Vector Machine
  - Genetic Algorithm
  - Fuzzy Logic
  - Probabilistic reasoning
- How to integrate / use for specific Application?
- Any other technique to be used with Soft Computing technique?

Soft Computing Techniques

- How to select soft computing technique?
- Neural networks –
  - learning, classification, optimization
- Fuzzy logic –
  - forming imprecision and reasoning on a semantic or linguistic level
- Genetic algorithm –
  - exploring set of all possible solutions
- Probabilistic reasoning
  - deals with uncertainty
- substantial areas of overlapping among different techniques
- they are complementary rather than competitive

Outline

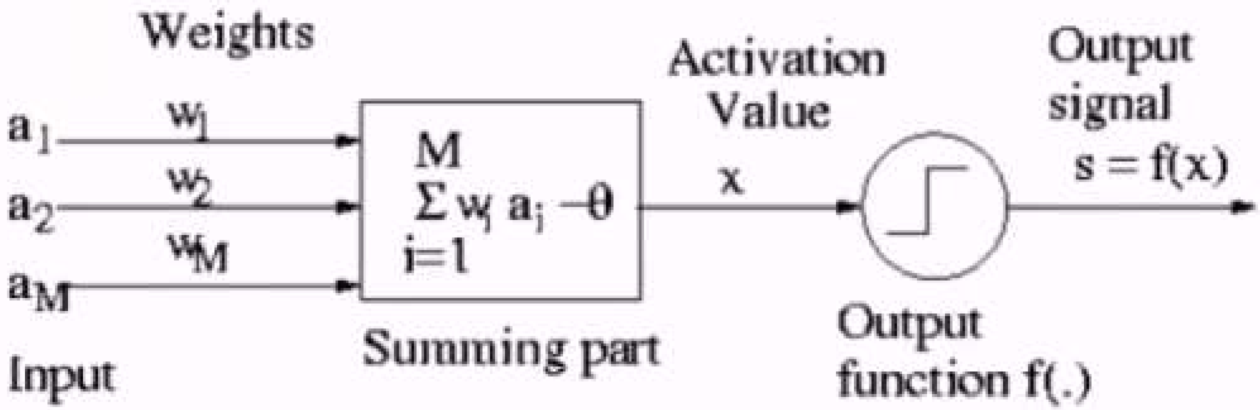
- Why Optimization?
- Problem Statement
- Neural Network
- Tracking using Neural Network
  - Problem Formulation
  - Proposed Algorithm
- Tracking using Genetic Algorithm
  - Problem Formulation
  - Proposed Algorithm
- Discussion

Why optimization?

- To achieve the goal with
  - Minimum computations
  - Minimum search
  - Efficient and Fast enough (for real time application)
  - At par with ideal goal (optimal solution)
- Optimization Techniques
  - Neural Network
  - Genetic Algorithm

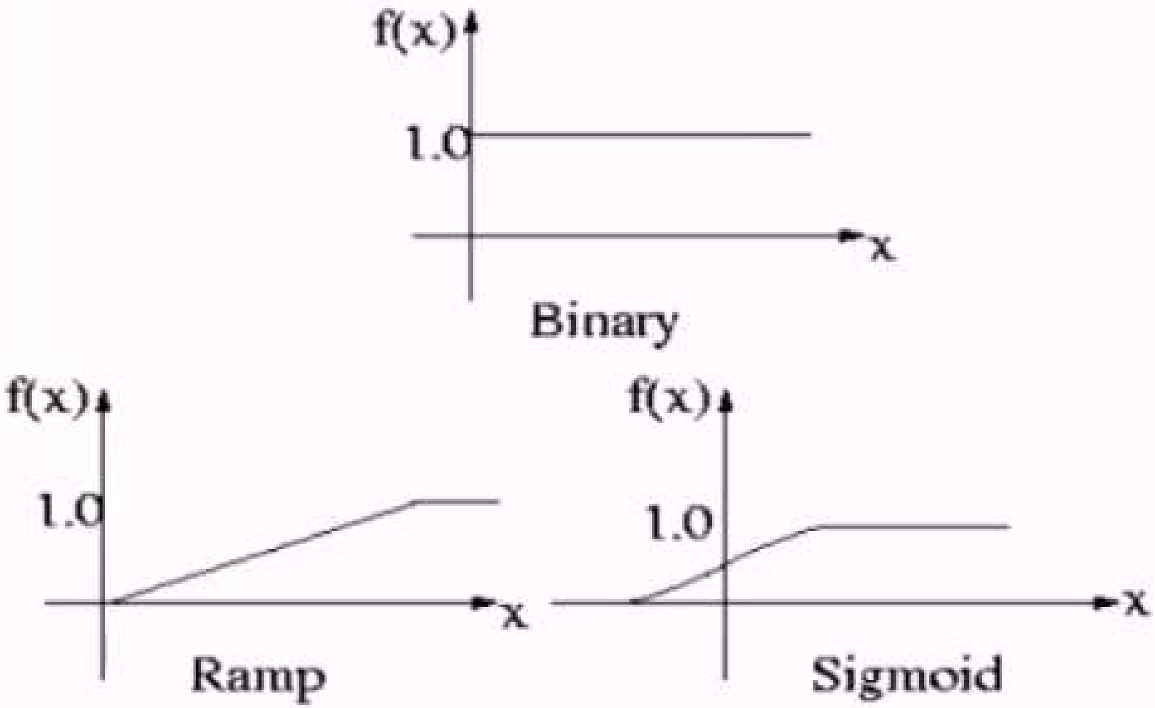
Introduction to Neural Network

Neuron Model



(Figure Src: ANN book)

Output Function



Output function (1) Logistic (2) Hyperbolic tangent

$$f(x) = \frac{1}{1 + \exp(-2\beta x)} \quad 0 \le f(x) \le 1$$

$$f(x) = \tanh(x) \quad -1 \le f(x) \le 1$$

(Figure Src: ANN book)

Classical Neuron Models

- McCulloch-Pitts model
  - Fixed weights, not capable of learning
- Rosenblatt's Perceptron model
  - Adjustment of weights

$$
\begin{array}{ll}
\text{Activation:} & x = \sum_{i=1}^{M} w_i a_i - \theta \\
\text{Output signal:} & s = f(x) \\
\text{Error:} & \delta = b - s \\
\text{Weight change:} & \Delta w_i = \eta \delta a_i
\end{array}
$$

Activation Dynamics

- Activation state: set of activation values at given instant
- Activation state space, Short term memory
- Activation dynamics leads to solution state
  - First order time derivative of activation state
- Stability: Equilibrium behavior of activation state
- Synchronous, asynchronous update

Activation models

Additive activation model

Dynamics equation: $\dot{x}_i(t) = -A_i x_i(t)$	Solution: $x_i(t) = x_i(0) \exp^{-A_i t}$
with nonzero resting potential	$\dot{x}_i(t) = -A_i x_i(t) + P_i$
Solution:	$x_i(t) = x_i(0) \exp^{-A_i t} + \frac{P_i}{A_i}(1 - \exp^{-A_i t})$
with constant external excitatory input	$\dot{x}_i(t) = -A_i x_i(t) + B_i I_i$
Solution:	$x_i(t) = x_i(0) \exp^{-A_i t} + \frac{B_i I_i}{A_i}(1 - \exp^{-A_i t})$

with external input and input from the output of the units:

(additive autoassociative model) $\quad \dot{x}_i(t) = -A_i x_i(t) + \sum_{j=1}^{N} f_j(x_j(t)) w_{ij} + B_i I_i$

Synaptic Dynamics

- Weight space, Long term memory
- Search for optimal weights for equilibrium state
  - Criteria: mean squared error, gradient descent, maximum likelihood, relative entropy
- Synaptic dynamics: trajectory of weight states
  - First order time derivative of weight state
- Learning algorithm
  - Supervised and unsupervised
- Convergence: Adjustment behavior of weights during learning

Learning Methods

Learning Function

$$\dot{\mathbf{w}}_i(t) = \eta g(\mathbf{w}_i(t), \mathbf{a}(t), b_i(t))\mathbf{a}(t)$$

$\mathbf{w}_i$	$(w_{i1}, w_{i2}, \ldots, w_{iM})^T$	weight vector for the ith unit
$\mathbf{a}$	$(a_1, a_2, \ldots, a_M)^T$	input vector
$\mathbf{b}$	$(b_1, b_2, \ldots, b_N)^T$	output vector
	for small increment	$\Delta\mathbf{w}_i(t) = \eta g(\mathbf{w}_i(t), \mathbf{a}(t), b_i(t))\mathbf{a}(t)$
		$\mathbf{w}_i(t+1) = \mathbf{w}_i(t) + \Delta\mathbf{w}_i(t)$

Learning Methods

Learning Method	Synaptic dynamics equation
Hebbian	$\dot{w}_{ij}(t) = -w_{ij}(t) + s_i s_j$
Differential Hebbian	$\dot{w}_{ij}(t) = -w_{ij}(t) + s_i s_j + \dot{s}_i \dot{s}_j$
Competitive	$\dot{w}_{ij}(t) = -s_i w_{ij}(t) + s_i s_j$
Differential Competitive	$\dot{w}_{ij}(t) = \dot{s}_i [s_j - w_{ij}(t)]$
Error Correction	
Rosenblatt's perceptron	$\dot{w}_{ij}(t) = \eta(b_i - s_i)a_j \quad s_i = \mathrm{sgn}(\sum_j w_{ij} a_j)$
Continuous perceptron	$\dot{w}_{ij}(t) = \eta(b_i - s_i)\dot{f}_i(x_i)a_j$
(Delta learning)	$s_i = f_i(x_i)$ and $x_i = \sum_{j=1}^{M} w_{ij} a_j$

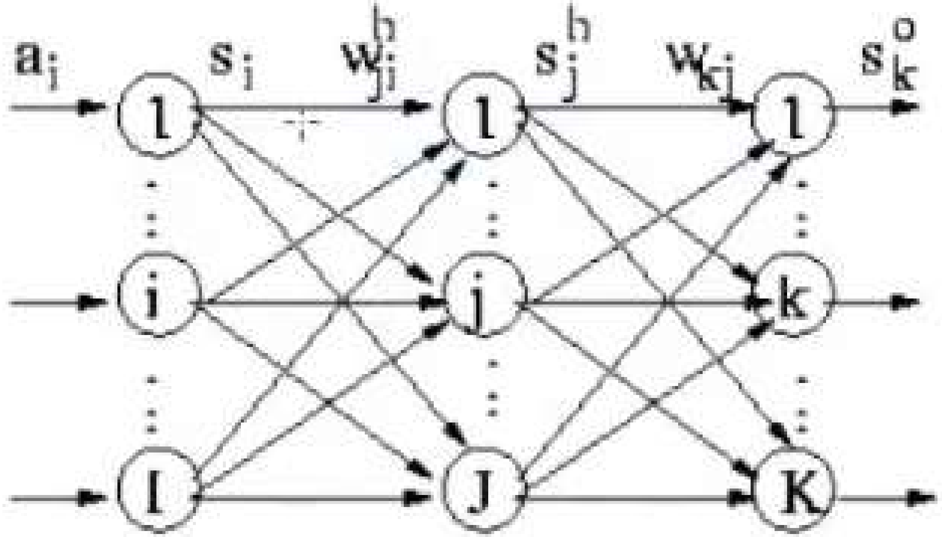
Learning Methods

Learning law	Weight adjustment	Initial weights	Learning
Hebbian	$\Delta w_{ij} = \eta f(\mathbf{w}_i^T \mathbf{a}) a_j = \eta s_i a_j$ for $j = 1, 2, \ldots, j$	0	Unsupervised
Perceptron	$\Delta w_{ij} = \eta [b_i - \operatorname{sgn}(\mathbf{w}_i^T \mathbf{a})] a_j = \eta (b_i - s_i) a_j$ for $j = 1, 2, \ldots, M$	Random	Supervised
Delta	$\Delta w_{ij} = \eta [b_i - f(\mathbf{w}_i^T \mathbf{a})] \dot{f}(\mathbf{w}_i^T \mathbf{a}) a_j = \eta [b_i - \mathbf{s}_i] \dot{f}(x_i) a_j$ for $j = 1, 2, \ldots, M$	Random	Supervised
Widrow-Hoff	$\Delta w_{ij} = \eta [b_i - \mathbf{w}_i^T \mathbf{a}] a_j$ for $j = 1, 2, \ldots, j$	Random	Supervised

[SRC: Zurada, 1992]

Feed forward and Feedback Neural Network

- Multilayer Perceptron Network
  - Generalized delta rule
- Hopfield Network
  - Bounded function and Symmetric weights



(Figure Src: ANN book)

Backpropagation Algorithm

A set of input-output patterns $(\mathbf{a}_l, \mathbf{b}_l)$, $l = 1, 2, \ldots, L$
lth input vector $\mathbf{a}_l = (a_{l1}, a_{l2}, \ldots, a_{lI})^T$
lth output vector $\mathbf{b}_l = (b_{l1}, b_{l2}, \ldots, b_{lK})^T$
Let $\mathbf{a} = \mathbf{a}(m) = \mathbf{a}_l$ and $\mathbf{b} = \mathbf{b}(m) = \mathbf{b}_l$

Activation of unit i in the input layer	$x_i = a_i(m)$
Activation of unit j in the hidden layer	$x_j^h = \sum_{i=1}^{I} w_{ji}^h x_i$
Output signal from jth unit in the hidden layer	$s_j^h = f_j^h(x_j^h)$
Activation of unit k in the output layer	$x_k^o = \sum_{j=1}^{J} w_{kj} s_j^h$
Output signal from unit k in the output layer	$s_k^o = f_k^o(x_k^o)$
Error term for the kth output unit	$\delta_k^o = (b_k - s_k^o)\dot{f}_k^o$
Update weights on output layer	$w_{kj}(m+1) = w_{kj}(m) + \eta\delta_k^o s_j^h$
Error term for the jth hidden unit	$\delta_j^h = \dot{f}_j^h \sum_{k=1}^{K} \delta_k^o w_{kj}$
Update the weights on the hidden layer	$w_{ji}^h(m+1) = w_{ji}^h(m) + \eta\delta_j^h a_i$
Calculate the error for the lth pattern	$E_l = \frac{1}{2}\sum_{k=1}^{K}(b_{lk} - s_k^o)^2$
Total error for all patterns	$E = \sum_{l=1}^{L} E_l$

Apply the given patterns one by one, several times in random order
Update the weights until the total error reduces to an acceptable value

Radial Basis Function Network

- Feed forward Network with one hidden layer
- Hidden layer unit has a receptive field
- Training: Deciding centre and sharpness of Gaussian
- Advantage: Extra units with centres near parts of input which are difficult to classify
  - Many sensory neurons respond only to some small subspace of input space and are silent in response to other inputs

$$f(x) = \sum_{i=1}^{r} w_i \phi_i(\|\mathbf{X} - \mu_i\|, \theta_i)$$

$\mathbf{X}$ input vector ϕ_i Basis function

w_i weights

$\mu_i = (\mu_{i1}, \mu_{i2}, \ldots, \mu_{in})^T$ center vector

$\theta_i = (\theta_{i1}, \theta_{i2}, \ldots, \theta_{in})^T$ bandwidth vector of ith node

if ϕ_i is Gaussian

$$\phi_i(\|\mathbf{X} - \mu_i\|, \theta_i) = \exp\{[-\|\mathbf{X} - \mu_i\|/(\theta_{i1}, \theta_{i2}, \ldots, \theta_{in})]^2\}$$

Support Vector Machine

- Pattern analysis, classification
- Linear separable, nonlinear separable problems
- When to use SVM?
  - Unknown and nonlinear dependency
  - High dimensional data Learning Methods
  - No information about underlying joint probability function
- Features
  - Perform distribution free learning
  - Nonparametric: parameters not predefined and their number depends on training data
  - Structural Risk Minimization (SRM)

Applications

- Investment analysis
- Signature analysis
- Process control and Monitoring
- Marketing
- Character recognition
- Information retrieval
- Travelling salesman problem
- Image pattern recognition, segmentation
- Vector quantization
- Texture classification and segmentation

Advanced Soft Computing Techniques (Incomplete List)

- Advanced Neural Network
  - Probabilistic Neural Network
  - Deep Belief Neural Network
  - Recurrent Neural Network
  - Convolution Neural Network
- Advanced Fuzzy based Techniques
  - Type II Fuzzy logic
  - Rough Set Theory
- Biological / Nature inspired Techniques
  - Ant Colony
  - Particle Swarm Optimization