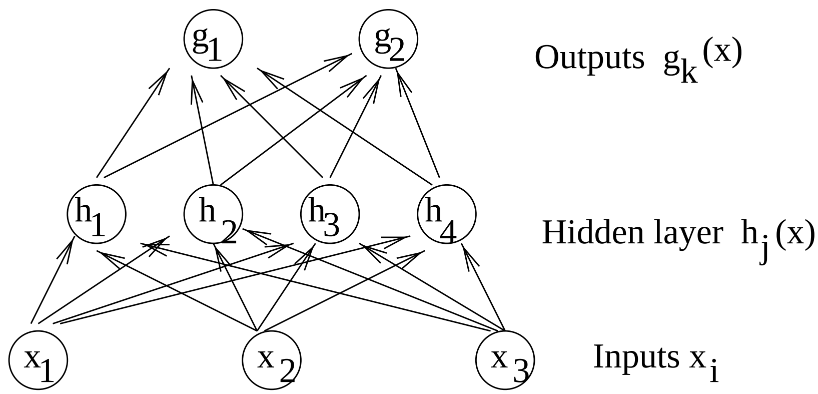

Figure 1: A Feed Forward Network

Abstract

Neural Networks as a way to specify nonparametric regression and classification models.

Feed Forward Neural Nets Models

Feed forward Neural Nets are also known as multilayer perceptrons or back-propagation networks. The figure shows a network with a layer of 4 hidden units.

The outputs are computed from the following formulas,

$$g_k(x) = b_k + \sum_j v_{jk} h_j(x) \tag{1}$$

$$h_j(x) = \tanh(a_j + \sum_i u_{ij} x_i) \tag{2}$$

where $\{a_j\}, \{b_k\}, \{u_{ij}\}, \{v_{jk}\}$ are the parameters of the network. The parameters with one index are known as biases and those with two indeces are known as weights. We assume that $x = (x_1, \ldots, x_d) \in R^d, h(x) = (h_1(x), \ldots, h_l(x)) \in R^l, g(x) = (g_1(x), \ldots, g_p(x)) \in R^p$. The hyperbolic tangent,

$$\tanh(z) = \frac{\sinh(z)}{\cosh(z)} = \frac{e^z - e^{-z}}{e^z + e^{-z}} = \frac{1 - e^{-2z}}{1 + e^{-2z}}$$

is an example of a sigmoid function. A sigmoid is a non-linear function, $s(z)$, that goes through the origin, approaches $+1$ as $z \to \infty$ and approaches -1 as $z \to -\infty$.

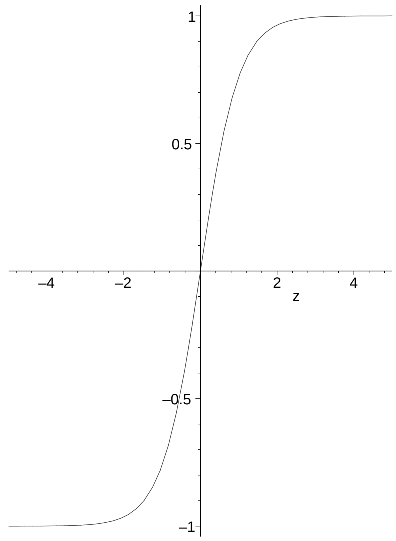

Figure 2: Hyperbolic Tangent

It is known since 1989 (only) that as the number of hidden units increases, any function defined on a compact set can be approximated by linear combinations of sigmoids.

Multilayer perceptrons are often used as flexible models for nonparametric regression and classification. Given data,

$$(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \ldots, (x^{(n)}, y^{(n)})$$

with,

$$y^{(k)} = g(x^{(k)}, \theta) + \epsilon^{(k)}$$

where

$$\epsilon^{(1)}, \epsilon^{(2)}, \ldots, \epsilon^{(n)} \text{ are iid with } E\epsilon^{(k)} = 0$$

Hence, the g is the regression of y on x, i.e.,

$$E(y|x, \theta) = g(x, \theta) \text{ with } \theta \in \Theta$$

The multilayer perceptrons provide a practical way to define the functions g with high dimensional parameter spaces Θ. We take $\theta = \{\{a_j\}, \{b_k\}, \{u_{ij}\}, \{v_{jk}\}\}$. The objective is to find the predictive distribution of a new target vector y, given the examples $D = ((x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \ldots, (x^{(n)}, y^{(n)}))$ and the new vector of inputs x, i.e.,

$$f(y|x, D) = \int f(y|x, \theta)\pi(\theta|D)d\theta$$

Under the assumption of quadratic loss, the best guess for y will be its mean,

$$\hat{y} = E(y|x, D) = \int g(x, \theta)\pi(\theta|D)d\theta$$

These estimates can be approximated by MCMC by sampling $\theta^{(1)}, \ldots, \theta^{(N)}$ from the posterior and then computing empirical averages,

$$\hat{y}_N = \frac{1}{N} \sum_{j=1}^{N} g(x, \theta^{(j)})$$

Useful Priors on Feed Forward Networks

In the absence of specific information, the following assumptions about the prior $\pi(\theta)$ are reasonable,

1. The components of θ are independent and symmetric about 0.
2. Parameters of the same kind have the same a priori distributions, i.e.,

$$\begin{array}{l} a_1, a_2, \ldots \text{ iid} \\ b_1, b_2, \ldots \text{ iid} \\ u_{1j}, u_{2j}, \ldots \text{ iid for all } \; j \\ v_{1k}, v_{2k}, \ldots \text{ iid for all } \; k \end{array}$$

With these assumptions if $\mathrm{var}_\pi(v_{jk}) = l^{-1}\sigma_v^2 < \infty$ then by the Central Limit Theorem, as $l \to \infty$ the prior on the output units converges to a Gaussian process. Gaussian processess are characterized by their covariance functions and they are often considered innadequate for modeling complex inter-dependence of the outputs. To avoid the Gaussian trap, it is convenient to use a priori distributions for the components of θ that have infinite variance.

A practical choice (used by Neal) is to take,

$$v_{jk} \text{ as t-distribution } \propto \left(1 + \frac{v_{jk}^2}{\alpha\sigma_v^2}\right)^{-(\alpha+1)/2} \quad \text{with } 0 < \alpha < 2$$

Furthermore, if the we take $\sigma_v = w_v l^{-1/\alpha}$ then the resulting prior will converge as $l \to \infty$ to a symmetric stable process of index α.

Recall that $Z_1, Z_2, \ldots, Z_n$ iid with distribution symmetric about 0 are said to be stable of index α if

$$\frac{Z_1 + \ldots + Z_n}{n^{1/\alpha}} \text{ has the same law as } \; Z_1$$

A distribution is said to be in the domain of attraction of a stable law if properly normalized sums of independent observations from this distribution, converge in law to a stable distribution. Hence, distributions with finite variance are in the domain of attraction of the Gaussians. It is also well known that distributions with tails going to zero as $|x|^{-(\alpha+1)}$ as $|x| \to \infty$ are in the domain of attraction of stable laws of index α which justifies the choice of t-dist above.

Postulating an Energy for the Net

An alternative approach without priors (apparently...) is to postulate directly and Energy function for the network, e. g,

$$E(\theta, \gamma) = \frac{1}{n} \sum_{k=1}^{n} L(y^{(k)}, g(x^{(k)}, \theta)) + \gamma ||\theta||^2$$

where $L(y, z)$ is the assumed loss when we estimate y with z. Typical choices are $L(y, z) = R(||y - z||)$ for some nondecreasing function R and some norm $|| \cdot ||$. Then choose θ to minimize this Energy function. Often, the smoothness parameter $\gamma > 0$ is chosen by Cross-Validation or by plain trial and error.

For complicated multi modal energy functions, a combination of simulated annealing with a classical gradient method (such as conjugate gradients) have been the most successful.