



Figure 7.3 MAXNET for \$p\$ classes: (a) network architecture and (b) neuron's activation function

\$W\_M\$ of size \$p \times p\$ is thus of the form (Pao 1989)

$$W_M = \begin{bmatrix} 1 & -\epsilon & -\epsilon & \dots & -\epsilon \\ -\epsilon & 1 & -\epsilon & \dots & -\epsilon \\ -\epsilon & & & \ddots & \\ \vdots & & & & \vdots \\ -\epsilon & -\epsilon & & -\epsilon & 1 \end{bmatrix} \quad (7.4)$$

where \$\epsilon\$ must be bounded \$0 < \epsilon < 1/p\$. The quantity \$\epsilon\$ can be called the *lateral interaction coefficient*. With the activation function as shown in Figure 7.3(b) and the initializing inputs fulfilling conditions

$$0 \leq y_i^0 \leq 1, \quad \text{for } i = 1, 2, \dots, p$$

the MAXNET network gradually suppresses all but the largest initial network excitation. When initialized with the input vector \$y^0\$, the network starts processing it by adding positive self-feedback and negative cross-feedback. As a result of a number of recurrences, the only unsuppressed node will be the one with the largest initializing entry \$y\_m^0\$. This means that the only nonzero output response node is the node closest to the input vector argument in HD sense. The recurrent processing by MAXNET leading to this response is

$$y^{k+1} = \Gamma[W_M y^k] \quad (7.5a)$$