## Parallel fully connected implementations

Let N = the number of input features,

M = the number of hidden neurons (in our case it is always 40),

C = the number of output neurons/ number of classes

 $x_i$  be the i\_th\_ input feature,

 $h_i^{\circ}$  be the i\_th\_ hidden neuron, also used to denote it's output value before binarization,

 $s_i$  be the i\_th\_ hidden neuron's output after binarization, so  $s_i = h_i > 0$ ,

 $y_i^{\, \cdot}$  be the i\_th output neuron, also used to denote it's output value, W1 = the weight matrix of the first layer,

W2 = the weight matrix of the second layer,

rows represent neurons and columns represent input activations, so  $W1_{i,j}$  is the weight of the first layer that corresponds to the connection between the input feature  $x_i$  and the neuron  $h_i$ .

## Positive-Negative Sum

For each neuron in the first layer two sums are calculated.  $\Sigma_i^+$  is the sum of the input features for which the connection with the i\_th\_hidden neuron has a positive weight , whereas  $\Sigma_i^-$  the sum of those that have a negative weight associated. The two sums are then compared and if the positive sum is greater than or equal to the negative the output of the neuron is 1, otherwise 0.

$$\Sigma_i^+ = \sum_{i=0}^{N-1} x_j [W1_{i,j} > 0]$$

$$\Sigma_i^- = \sum_{i=0}^{N-1} x_j [W1_{i,j} < 0]$$

$$h_i = \Sigma_i^+ \geq \Sigma_i^-$$

Sample code snippet:

For each neuron of the output layer it's value is calculated by summing the output of hidden neurons. The binary output of the hidden neuron  $s_j$  is added as-is to the sum of the output neuron  $y_i$  in the case that the weight of their connection  $W2_{i,j}$  is positive and it's binary inverse is added to the sum if  $W2_{i,j}$  is negative. This is equivalent to the sum of the xnor between the output vector of the hidden layer and the weight vector of the output neuron.

$$y_i = \sum_{j=0}^{N-1} \begin{cases} s_j, & \text{if } W2_{i,j} > 0 \\ \neg s_j, & \text{if } W2_{i,j} < 0 \end{cases}$$