Introduction to computational models

Lab assignment 2. Multilayer perceptron for classification problems

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Module "Introduction to computational models"
4th year of "Grado en Ingeniería Informática"
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Objectives of the lab assignment

- To implement the *off-line* version of the error backpropagation algorithm for the multilayer perceptron.
- To adapt the formulation in classification problems by interpreting the outputs using a probabilistic perspective (*softmax* function).
- To use a probabilistic error function to train the network (cross entropy).
- To check whether these modifications improve the results.

Classification

- Please, read and analyse the theory notes.
- We have studied how to adapt MLP to classification problems:
  - Representation of the class label using a 1-of-J coding.
  - Use of multiple neurons in the output layer and the softmax activation function.
  - During training, use of the cross-entropy cost function as an alternative to MSE.
  - For checking the goodness-of-fit, use of the CCR evaluation function.

Summary of the modifications to be performed

- We must make the program show information about the *CCR*.
- We must incorporate the *softmax* function in the output layer, that is, change the way the inputs are propagated (according to the definition of the *softmax*) and the way error is backpropagated (according to the new expression of δ_j^h).
- We must incorporate the L error function (cross entropy), calculating it in the functions that have to obtain an error and modifying the way in which the error is backpropagated for δ_j^H (only output layer).
- We must incorporate the *off-line* version of the algorithm (previous lab assignment).

Obtaining δ_j^h

- Derivatives for sigmoid neurons:
  - Output layer:
    - *MSE*:
      $\delta_j^H \leftarrow -\left(d_j - out_j^H\right) \cdot out_j^H \cdot \left(1 - out_j^H\right)$
    - Cross-entropy:
      $\delta_j^H \leftarrow -\left(d_j / out_j^H\right) \cdot out_j^H \cdot \left(1 - out_j^H\right)$
  - Hidden layers:
    $\delta_j^h \leftarrow \left(\sum_{i=1}^{n_{h+1}} w_{ij}^{h+1} \delta_i^{h+1}\right) \cdot out_j^h \cdot \left(1 - out_j^h\right)$
- Derivatives for *softmax* functions:
  - Only output layer:
    - *MSE*:
      $\delta_j^H \leftarrow -\sum_{i=1}^{n_H} \left(\left(d_i - out_i^H\right) \cdot out_j^H (I(i = j) - out_i^H)\right)$
    - Cross-entropy:
      $\delta_j^H \leftarrow -\sum_{i=1}^{n_H} \left(\left(d_i / out_i^H\right) \cdot out_j^H (I(i = j) - out_i^H)\right)$

Adjustment of derivatives for *off-line* mode

- When using the *off-line* mode, derivatives are accumulated for all the patterns and their magnitude can be very high.
- As we are using an averaged error, it is a good idea to divide the derivative by the number of patterns (N).

Adjustment of derivatives for *off-line* mode

weightAdjustment()

Start

1. **For** h from 1 to H *// For each layer ($\Rightarrow\Rightarrow$)*
   1. **For** j from 1 to n_h *// For each neuron of layer h*
      1. **For** i from 1 to n_{h-1} *// For each neuron of layer $h-1$*
         $w_{ji}^h \leftarrow w_{ji}^h - \frac{\eta\Delta w_{ji}^h}{N} - \frac{\mu\left(\eta\Delta w_{ji}^h(t-1)\right)}{N}$
         End For
      2. $w_{j0}^h \leftarrow w_{j0}^h - \frac{\eta\Delta w_{j0}^h}{N} - \frac{\mu\left(\eta\Delta w_{j0}^h(t-1)\right)}{N}$ *// Bias*

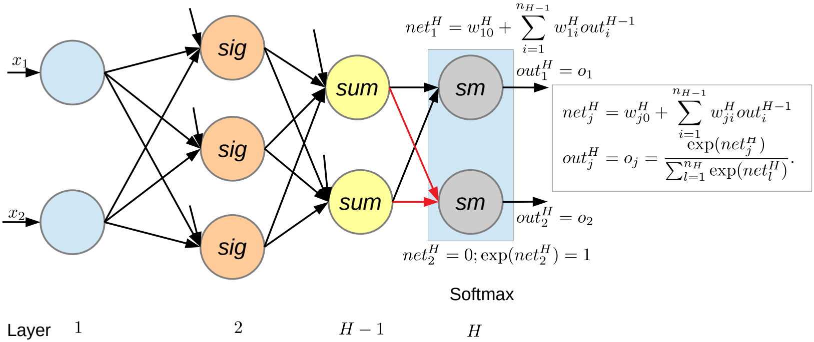
      End For

   End For

End

Optimization

An optimization technique consist of removing the last output neuron of the last layer (softmax) to avoid unnecesary computations associated to that neuron.



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