

Introduction to computational models

Lab assignment 2. Multilayer perceptron for classification problems

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Module “Introduction to computational models”
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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:

- $$\delta_j^H \leftarrow - (d_j - out_j^H) \cdot out_j^H \cdot (1 - out_j^H)$$

- Cross-entropy:

- $$\delta_j^H \leftarrow - (d_j / out_j^H) \cdot out_j^H \cdot (1 - out_j^H)$$

- Hidden layers:

- $$\delta_j^h \leftarrow \left(\sum_{i=1}^{n_{h+1}} w_{ij}^{h+1} \delta_i^{h+1} \right) \cdot out_j^h \cdot (1 - out_j^h)$$

- Derivatives for *softmax* functions:

- Only output layer:

- MSE:

- $$\delta_j^H \leftarrow - \sum_{i=1}^{n_H} ((d_i - out_i^H) \cdot out_j^H (I(i=j) - out_i^H))$$

- Cross-entropy:

- $$\delta_j^H \leftarrow - \sum_{i=1}^{n_H} ((d_i / out_i^H) \cdot out_j^H (I(i=j) - out_i^H))$$



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

```

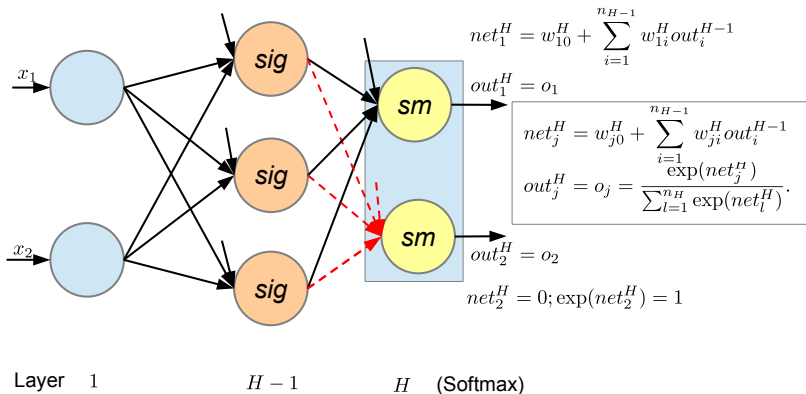
1 For h from 1 to H // For each layer (⇒⇒)
  1 For j from 1 to nh // For each neuron of layer h
    1 For i from 1 to nh-1 // For each neuron of layer h - 1
      
$$w_{ji}^h \leftarrow w_{ji}^h - \frac{\eta \Delta w_{ji}^h}{N} - \frac{\mu (\eta \Delta w_{ji}^h (t-1))}{N}$$

      End For
    2 
$$w_{j0}^h \leftarrow w_{j0}^h - \frac{\eta \Delta w_{j0}^h}{N} - \frac{\mu (\eta \Delta w_{j0}^h (t-1))}{N}$$
 // Bias
    End For
  End For
End
```



Optimization

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



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