# A Feedback-Based Modified Perceptron Trained with the Pseudo-Linear Regression Algorithm

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## Objective

Artificial Neural Networks (ANNs) are mathematical models designed to perform certain computations and to mimic the main features of the human brain [1]. One of the ANN basic elements is the *artificial neuron*, in which we highlight the model known as *perceptron* [1]. The perceptron can be viewed as a linear combiner – similar to a *Finite Impulse Response* filter (FIR) [1] – followed by a non-linearity (hard limiter). This model is able to classify data into two linearly separable patterns. However, for discrete time signals with statistical temporal dependence, e.g. in time series [1], the perceptron exhibits a considerably limited memory, which does not allow a suitable representation of certain known neural physiological behaviours. Therefore, the main objective of this work is to propose a modified version of the classical perceptron, so that its memory can be increased. This can be accomplished, for instance, by substituting the linear combiner for an *Infinite Impulse Response* (IIR) system. This modification would allow us to retrieve a signal previously distorted by another nonlinear system with memory.

## Materials and Methods

The output $y(n)$ of the proposed perceptron can be expressed as follows:

$$y(n) = f\left(\sum_{i=1}^{N} a_i y(n-i) + \sum_{j=0}^{M} b_j x(n-j)\right) \quad (1)$$

where $x(n)$ is the input signal, $a_i$ and $b_j$ are the adjustable weights of the perceptron and $f(\cdot)$ is its activation function. In order to train this model, the *Pseudo-Linear Regression* (PLR-LMS) algorithm was used, which is an approximated gradient-based approach [2].

## Results

For simulations, we assumed that the distorting system is a Hammerstein system [1] composed of a nonlinear $atgh(\cdot)$ function followed by a linear combiner with impulse response $H(z) = 1 + 0{,}6z^{-1} + 0{,}5z^{-10}$. The Hammerstein system input $s(n)$ is an i.i.d. signal uniformly distributed from -0.9 to 0.9, and its output is the signal $x(n)$. In order to test the memory capability of the modified perceptron, it is desired to retrieve $s(n)$ by only using the samples of $x(n)$, i.e. the perceptron must be able to compensate the Hammerstein system. The performance of the classical perceptron was also analysed and both of them were implemented in *Python,* using $tgh(\cdot)$ as the activation function. We assumed $N = M = 3$ and 10000 samples. The parameters were initialised at the origin and a *learning rate* of 0.02 was used in both models. The Mean Square Error (MSE) of the output signals $y(n)$ obtained through the classical and the modified perceptron were 1.2670 e 0.0693, respectively.

## Conclusions

The proposed modified perceptron showed an improved MSE performance in comparison with the classical model, indicating that the proposition is able to use its memory in a promising and efficient manner. For future works, we intend to propose an ANN based on this modified perceptron.

## References

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