

# A Non Linear Gated Perceptron

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## Abstract

In this article, we propose a new type of perceptron characterized by the addition of an (AND) gate for the input data. We explain that this type of logic AND gate perceptron allows the processing of data nonlinearity and presents superiority in terms of performance. A theoretical comparison between the new and old perceptron is carried out and the learning algorithm is presented.

**Keywords:** Perceptron, Gate AND, Non linearity, Classification.

## 1. Introduction

The first artificial neuron was introduced by Warren McCulloch in 1943 [1]. As described, without training, the weighted sum of inputs is compared to a threshold to determine the output of the neuron.

In the 1950s, Franks Rosenblatt proposed a learning rule for training the neural network (the neuron called perceptron) [2].

The limitations of the perceptrons was published by Marvin Minsky and Seymour Papert [3]. They shown that the non linearity can't be taken into account.

Later, the proposition of composition of perceptrons and the algorithms of training (back propagation) allowed to process non linear problems.

In this paper, we propose a new kind of perceptron, able to deal with non linearity of data. Figure 1 shows a gated perceptron with two inputs and one output. We will see that the new added gate (AND) allows to get a third input and allows to the perceptron to the non linearity of data.

## 2. The Gated Perceptron

The new idea behind the gated perceptron is to deal with the non linearity of data. If we consider the perceptron with two inputs  $X_1, X_2$ , then a third input is generated as the product (AND) of the two inputs as illustrated by figure 1.

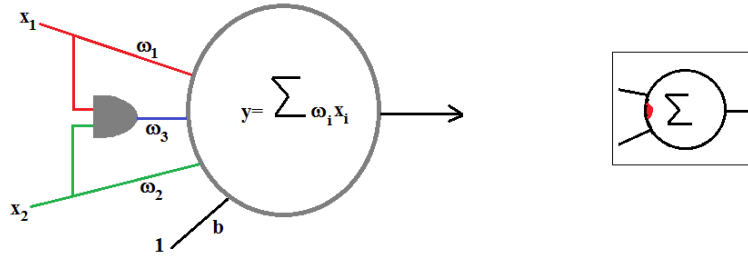


Figure 1: (Left) A gated perceptron, (Right) the used symbol of gated perceptron for the next figures.

As the case of the conventional perceptron, each input is weighted and the sum is calculated as follow:

$$y = \omega_1 X_1 + \omega_2 X_2 + \omega_3 X_1 X_2 + b$$

In order to study the function of the output  $y$ , we write  $y = 0$  and we draw the allure of the following equation.

$$X_2(\omega_2 + \omega_3 X_1) + \omega_1 X_1 + b = 0$$

$$X_2 = -\frac{\omega_1 X_1 + b}{\omega_3 X_1 + \omega_2} \quad (1)$$

Figure 2 show in red the pairs  $(X_1, X_2)$  satisfying  $y = 0$ . Three distinct areas are defined with positive or negative value of  $y$ , depending of the expression of equation 1. We can see that if the data to be classified is in different areas of the 2D space (case of two inputs), the use of the gated perceptron allows the classification of the data.

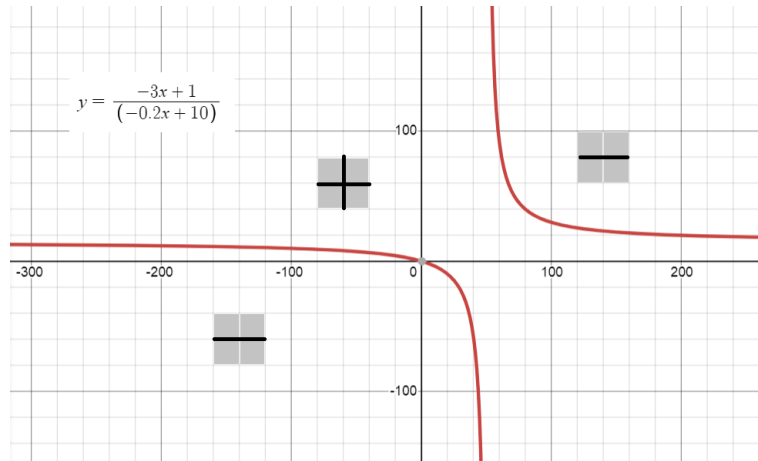
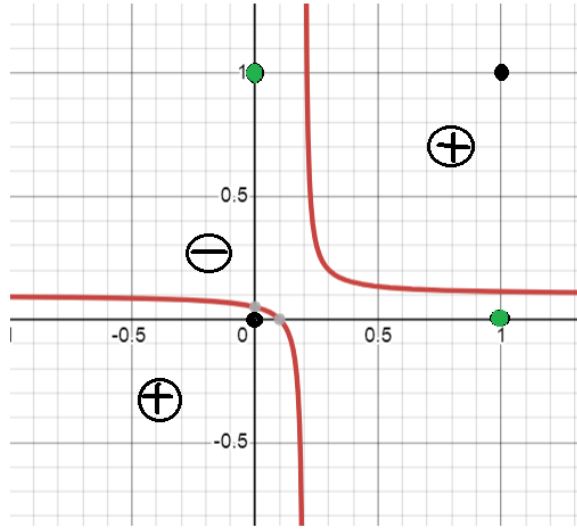


Figure 2: Graphical illustration of the output of the gated perceptron.

As example, the XOR gate can be solved using the corresponding weights. Figure 3 shows the classification into two regions (negative including the values (0,1) and (1,0), positive including the values (1,1) and (0,0)).



$$y = \frac{(0.1x - 0.01)}{(x - 0.2)}$$

Figure 3: Graphical illustration of the output of the gated perceptron in case of the XOR problem.

### 3. A Shallow Neural Network with Gated Perceptrons 41

Let be a shallow neural network, the hidden layer is composed by two gated perceptrons, 42  
 their outputs are the inputs of a conventional perceptron as indicated by figure 4. The two 43  
 outputs of the gated perceptrons are weighted and added giving the geometric illustration 44  
 of the output of this shallow neural network as illustrated by figure 5. Seven areas are 45  
 then defined using the two gated perceptrons. 46

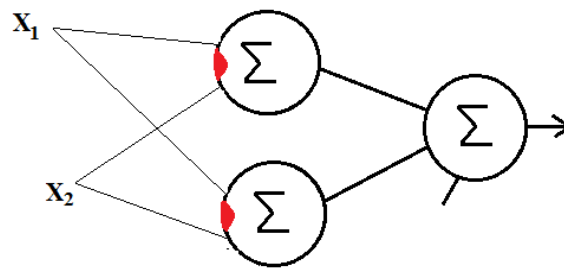


Figure 4: Shallow Neural Network with two gated perceptrons, the last perceptron is a conventional one.

Compared to traditional perceptrons, the graphical illustration corresponding to the 47  
 use of a shallow neural network with two inputs and two perceptrons consists of four 48  
 regions (see figure 6) as explained in [4]. 49

If we add a third traditional perceptron, we obtain seven regions as shown in figures 50  
 7. However, in case of the gated perceptron, adding a third gated perceptron will allow 51  
 the generation of 13 areas as shown in figure 8. 52

Two advantages of the gated perceptron are: 53

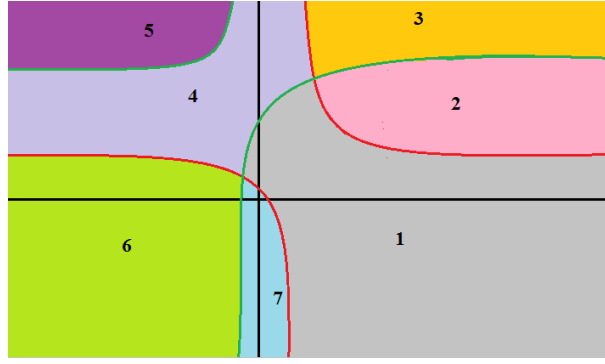


Figure 5: Graphical illustration of the output of the Sallow Neural Network of figure 4.

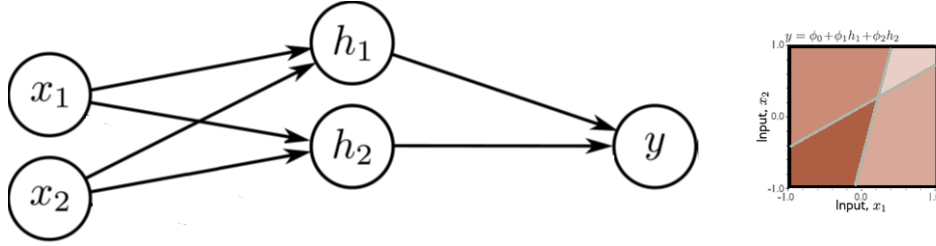


Figure 6: The four regions generated in case of two traditional perceptrons.

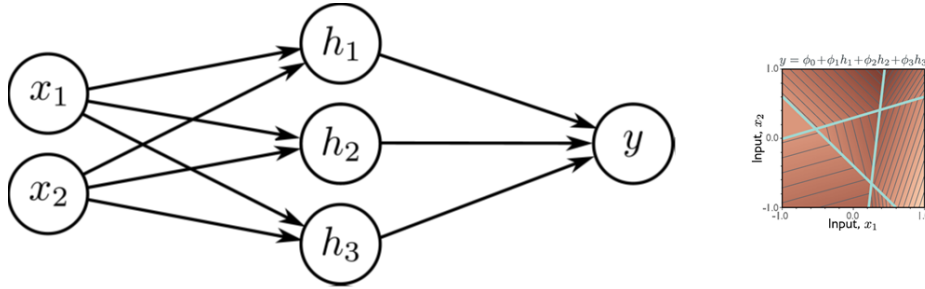


Figure 7: Regions generated using a shallow neural network with 3 conventional perceptrons.

- In terms of regions, the number of areas generated by the gated perceptrons is greater than the number of areas generated by the conventional perceptrons. 54
- In terms of boundary of regions, with the gated perceptron, an asymptotic replace the line (case of conventional perceptron), this will allow to get more power in the adjustment of region's boundaries in the classification problems. 55

## 4. Learning Algorithm 59

In this case of gated perceptron, the unique difference in the expression is in the computation of the derivative of the loss function with respect to the weights. 60

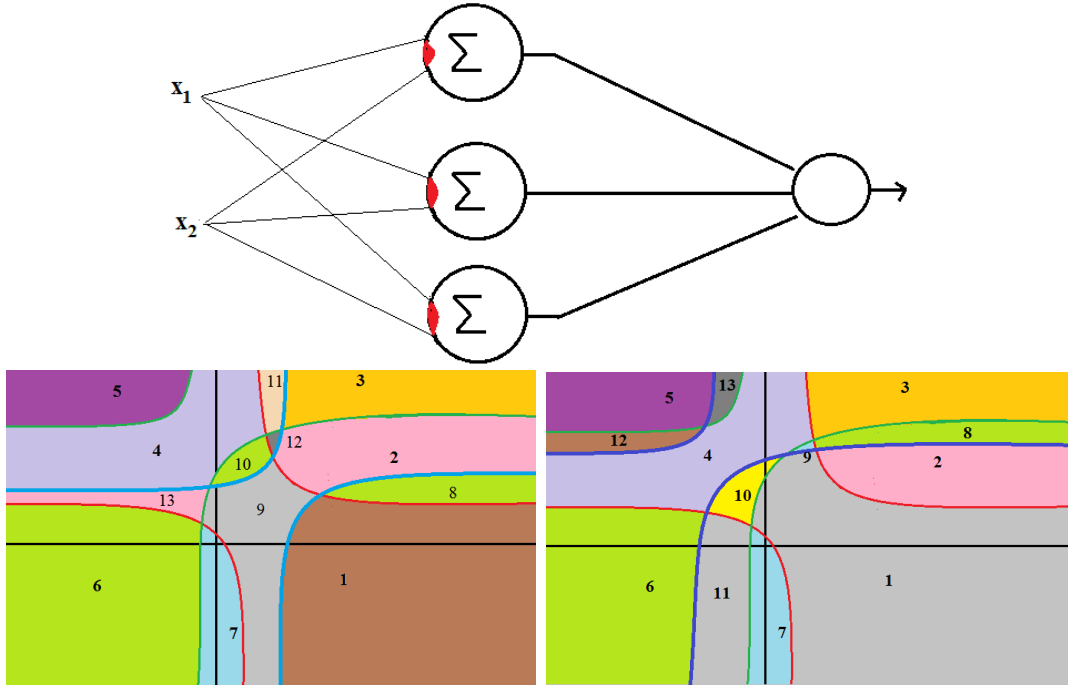


Figure 8: (Top) The shallow neural network, (Bottom) left and right: the 13 Regions generated using a shallow neural network with 3 gated perceptrons, depending on randomly chosen parameters.

## 5. Conclusion

In this short paper we presented a new perceptron called gated perceptron which, can enhance the area of deep learning with the improvements that it presents with respect to the traditional perceptron.

## References

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