



Aprendizaje de Máquina

ITAM

Semestre agosto-diciembre 2017

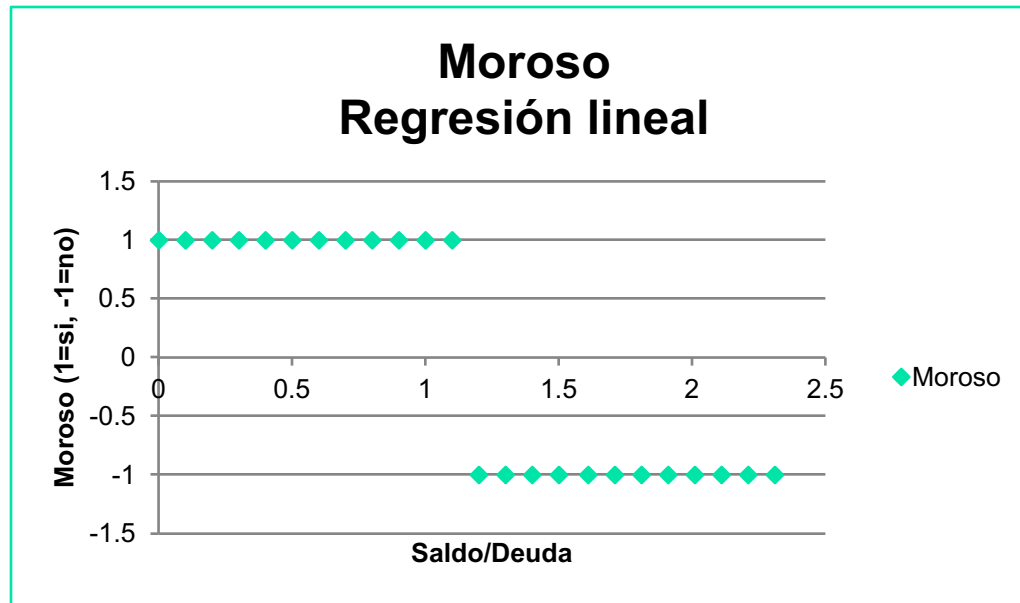


Menu

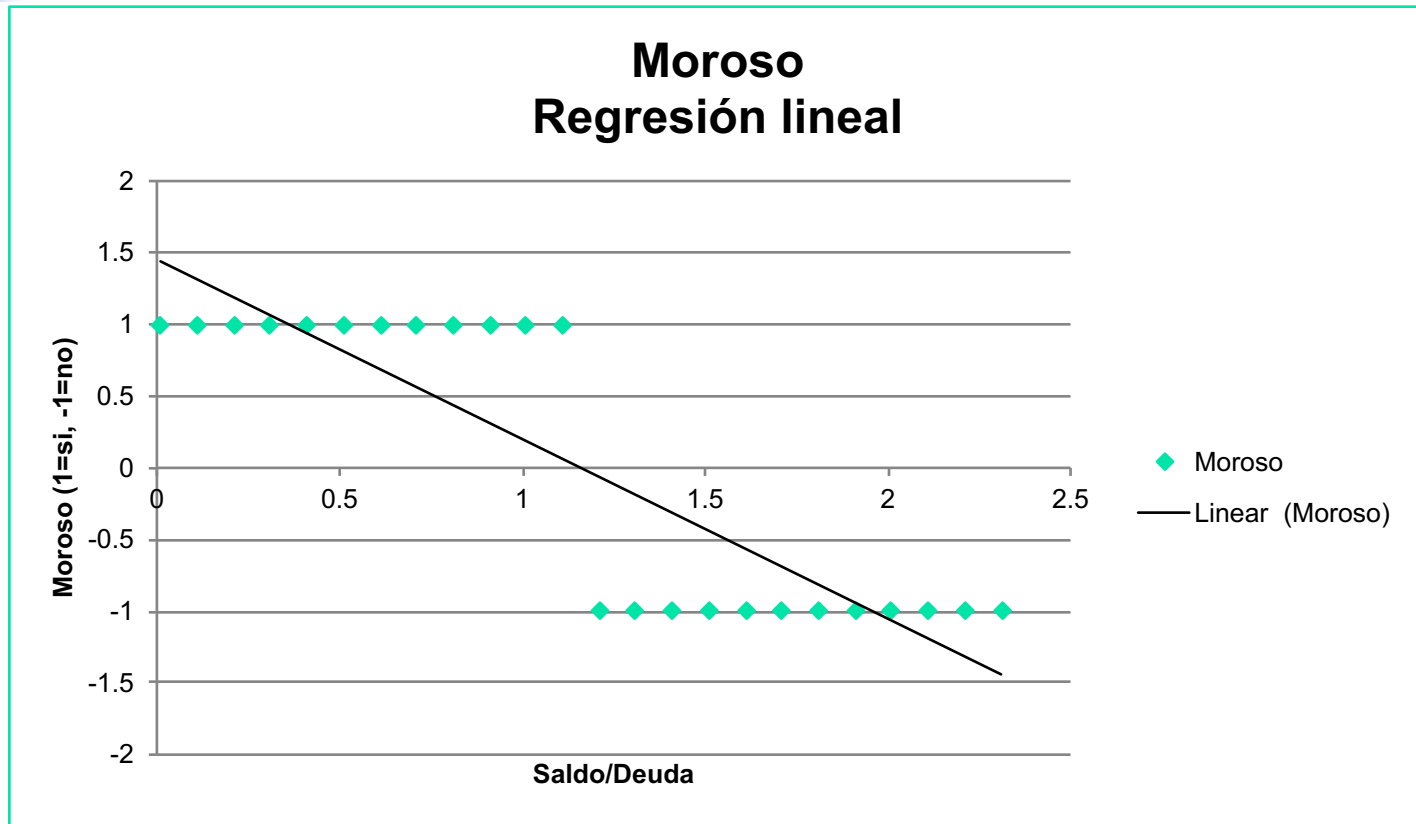
- In this session we will see how to use what we know about doing linear regression to perform classification
 - We are going to see the perceptron model

How to convert a regressor into a classifier

- Suppose we have the following data



How to convert a regressor into a classifier





How to convert a regressor into a classifier

- It doesn't make much sense to allow our model to take values higher than 1 and lower than -1. There is no data with such values
- Solution: Limit the possible to this range via a transfer function---a function that takes the output of the regressor and transforms it into something else

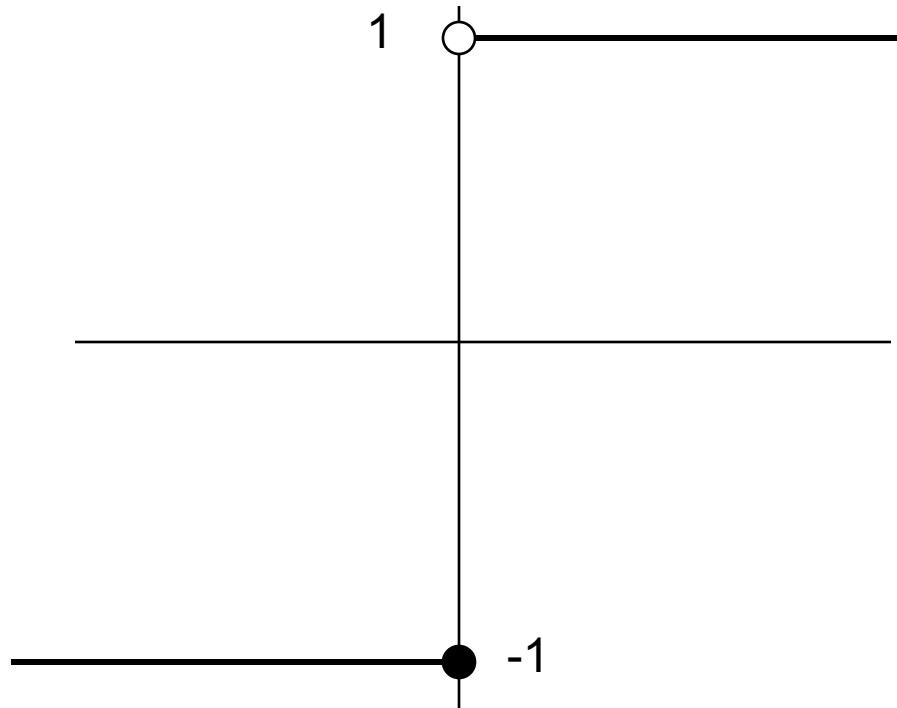


The perceptron: a model neuron

- The function that represents the activation of the perceptron is
 - $$g(x_1, x_2, \dots, x_n) = \begin{cases} 1 & \text{si } w_0 + \sum_{i=1, n} w_i x_i \geq 0 \\ -1 & \text{otherwise} \end{cases}$$
 - We can think of w_0 as a threshold value since it does not depend on an input variable.
 - We could say that the perceptron fires if there is enough stimulus in the input, if the weighed sum of the inputs is greater than $-w_0$.

Perceptron

Transfer function: Step function



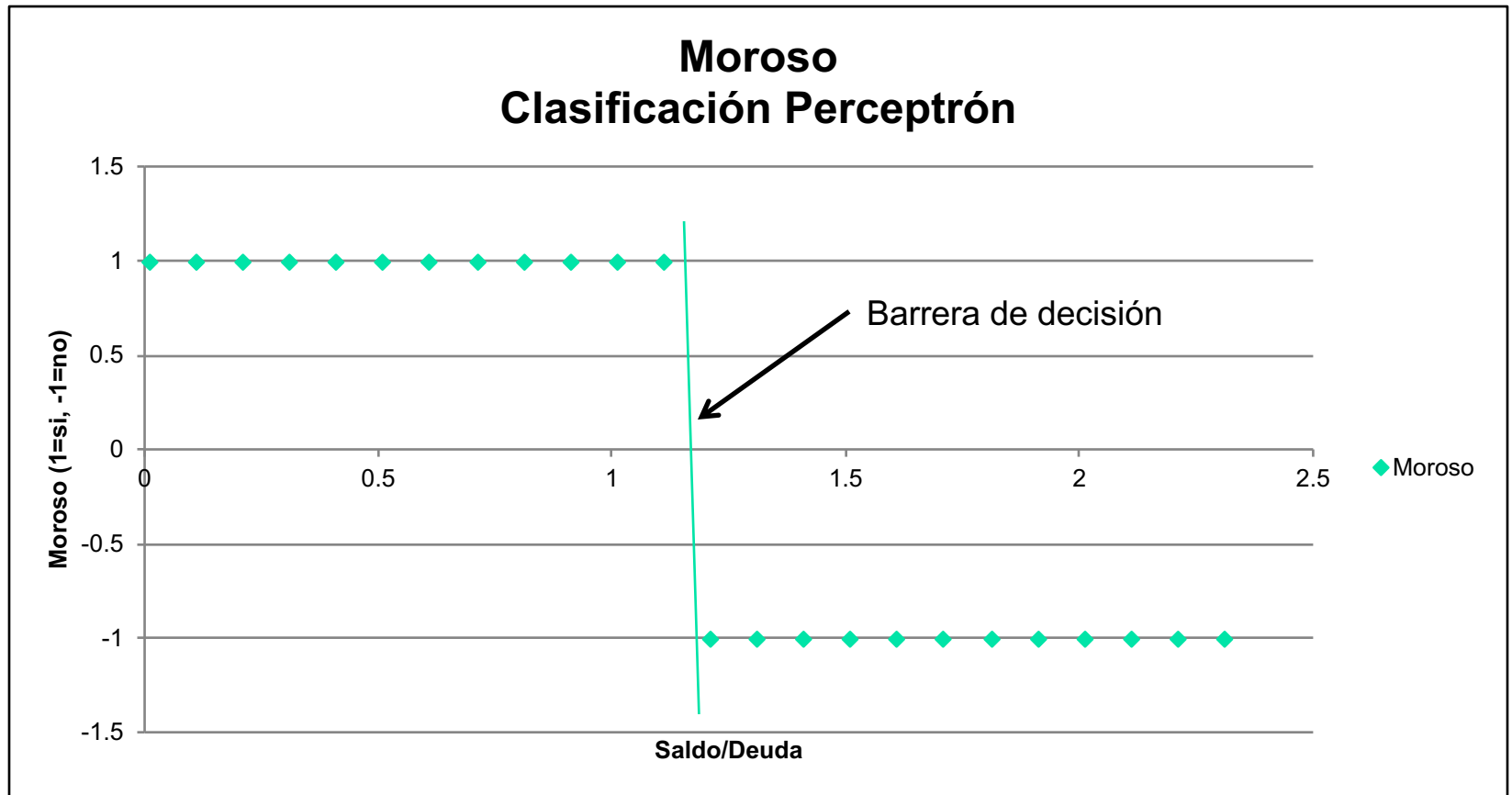


Representational ability

Perceptron

- To illustrate the representation power of the perceptron we can plot the equation
$$\sum_{i=0,n} w_i x_i = 0$$
- Since when $\sum_{i=0,n} w_i x_i$ is greater than or equal to zero it classifies an input as 1 and -1 otherwise
 - $\sum_{i=0,n} w_i x_i = 0$ represents a decision barrier

From the above example





Learning Algorithm

Perceptron

- For each training example(\mathbf{X}, y)
 - Calculate g with the current w 's
 - For each w_i ,
 - $w_i \leftarrow w_i + \eta(y - g(\mathbf{X})) x_i$
- Where η is a small constant lower than 1 (learning constant)
- The rule is applied iteratively a fixed number of times or until the error reaches a desired value or if no further decrease in the error is detected
- Note again that the difference with the iterative regression is the function g

$$g(x_1, x_2, \dots, x_n) = \begin{cases} 1 & \text{si } \sum_{i=0, n} w_i x_i > 0 \\ -1 & \text{de otra forma} \end{cases}$$



Example

	X0	X1	X2	X3	X4	X5	X6
$x's$	1	1	1	0	2	0	1
$w's$	-1	-0.5	1	0.5	0	1	1
$x_i w_i$	-1	-0.5	1	0	0	0	1

Before without g: $y=-1$, $V^{\wedge}(X)=0.5$, $Error=-1-0.5=-1.5$, $\eta =0.1$

Now: $y=-1$, $V^{\wedge}(X)=g(X)=1$, $Error=-1-1=-2.0$, $\eta =0.1$

$$w0 = -1 + 0.1(-2.0)1 = -1.2 \quad w4 = 0 + 0.1(-2.0)2 = -0.4$$

$$w1 = -0.5 + 0.1(-2.0)1 = -0.7 \quad w6 = 1 + 0.1(-2.0)1 = 0.8$$

$$w2 = 1 + 0.1(-2.0)1 = 0.8$$



Exercise

- Modify the iterative regression algorithm to include the step function as a transfer function
- Generate data for the logical and function

X1	X2	X1 and X2
0	0	0
0	1	0
1	0	0
1	1	1

- Train the perceptron this data set
 - Visualize the data
 - Plot the decision boundary
 - Calculate the classification error
 - Number of misses over number of examples



Exercise

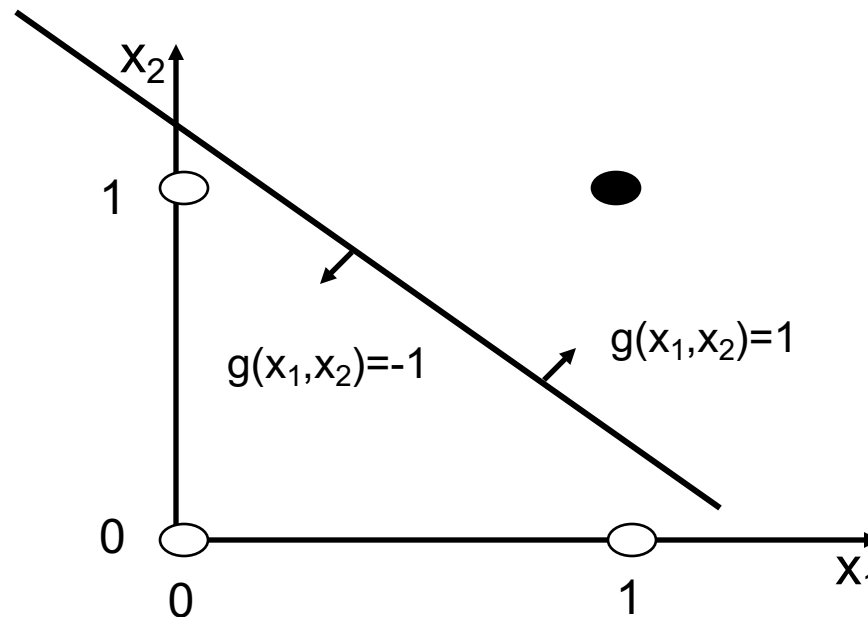
- Repeat for the XOR function

X1	X2	X1 xor X2
0	0	0
0	1	1
1	0	1
1	1	0

- For those that finish early
 - Repeat the exercise
 - How much does the separating hyperplane change from run to run?
 - Using or not using regularization (0.001)

Representation Power

Perceptrón



- White and black circles belong to different categories