

LOGISTIC REGRESSION for Image Classification

CREATIVE PROGRAMMING

AND COMPUTING

Course

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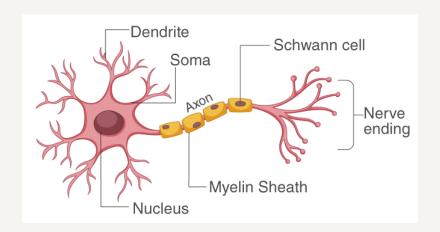
NEURON

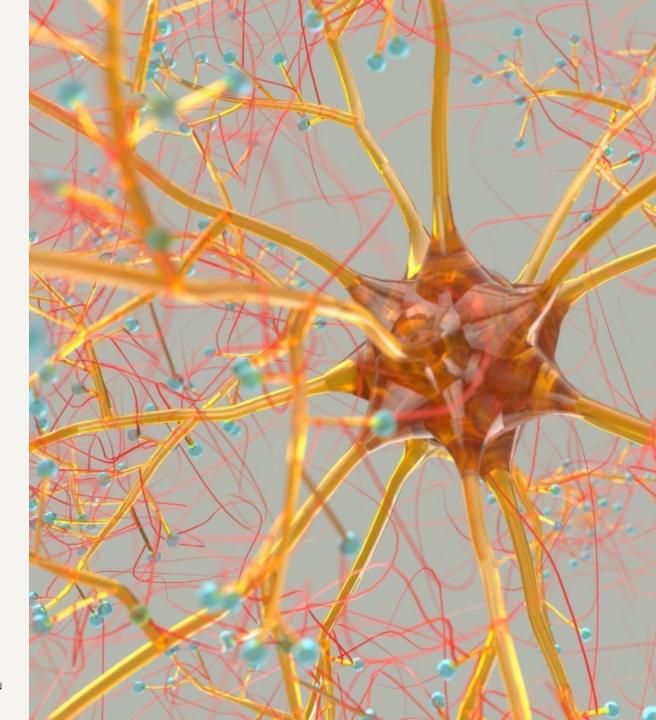
The brain is a network of neurons

Dendrites collect electrical stimuli coming from other neurons and accumulate input charges

Activation Process

The neuron fires an electrical impulse when the total charge exceeds a certain threshold



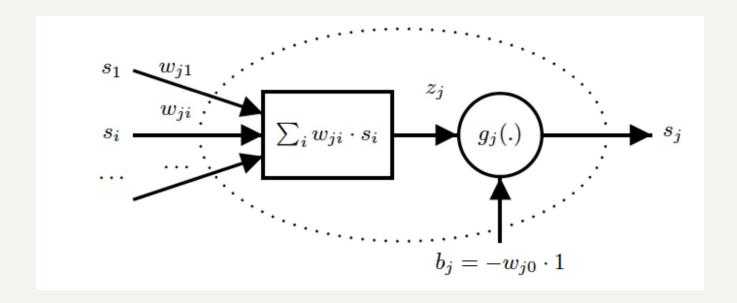




PERCEPTRON

Feed-Forward Model

$$s_j = g_j(z_{ij} - b_j) = g_j\left(\sum_{i=1}^N w_{ij}s_i + w_{j0}s_0\right) \qquad \longrightarrow \qquad s_j = g_j\left(\sum_{i=0}^N w_{ij}s_i\right) \qquad \text{Output}$$



Activation Value
$$z_{ij} = \sum_{i=1}^{N} w_{ij} s_i$$

Activation Function $g_j(\cdot)$

Activation Threshold
$$b_j = -w_{j0}s_0 = -w_{j0}$$

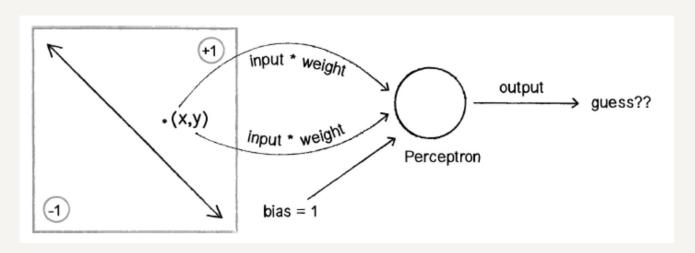


Linear separation

Decision boundary is described as a line

$$x_1w_1 + x_2w_2 + w_0 = 0$$

$$x_2 = -\frac{w_1}{w_2}x_1 - \frac{w_0}{w_2}$$



BINARY CLASSIFICATION

The learning process consists into learning the weights giving the best linear decision boundary

The perceptron keeps learning by mistakes and updates the weights to find the best ones

The **output** is a **class** in the classification problem



BINARY CLASSIFICATION

Learning Process

- Start with a random guess for the weights
- The perceptron guesses an answer

$$s_j = g_j \left(\sum_{i=0}^N w_{ij} s_i - b_j \right) = g_j \left(\sum_{i=0}^N w_{ij} s_i \right)$$

Compute the error function

$$\epsilon = \widehat{s_j} - s_j$$

where $\widehat{s_i}$ is the estimated output and s_i is the desired output

Adjust the weights

$$w_i^{n+1} = w_i^n + \Delta w_i$$

$$w_i^{n+1} = w_i^n + \Delta w_i \qquad \Delta w_i = \eta \cdot \widehat{s_j} \cdot s_i$$

Repeat the process until stop condition

 η is the **learning rate**

The **number of iterations** is denoted as the **number of epochs**



for Binary Classification

Logistic Regression is a process of modelling the probability of a discrete outcome given an input variable.

The most common logistic regression models a binary outcome: TRUE/FALSE, YES/NO, -1/1, 0/1

Given a feature vector x, logistic regression aims to find





Learning Process

Learning the weights w and the bias b giving the best estimate \hat{y} for the probability P(y=1|x)

$$\widehat{\mathbf{y}} = \mathbf{g}(\mathbf{w}^T \mathbf{x} + \mathbf{b})$$



for Binary Classification

Activation function $g(\cdot)$ is applied

$$\hat{y} = g(w^T x + b)$$

We need a function mapping input data into a probability,

i.e. within the range [0,1]



$$g(z_j) = \frac{1}{1 + e^{Kz_j}}K < 0$$





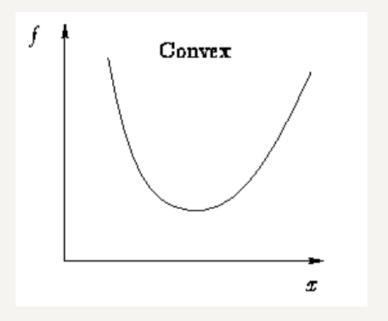
for Binary Classification

Loss Function

In order to learn the best weights w and the bias b we need a loss function $L(\hat{y}, y)$ to be minimized

$$L(\hat{y}, y) = -\log(y \log \hat{y} + (1 - y) \log(1 - \hat{y}))$$

for a single feature vector





for Binary Classification

Cost Function

For the whole dataset (multiple feature vectors)

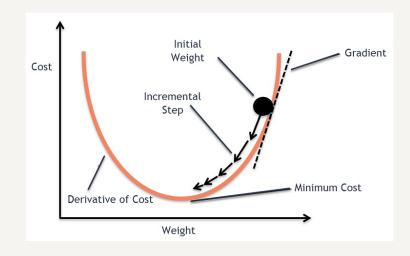
$$J(w,b) = \frac{1}{m} \sum_{I=1}^{m} L(\hat{y}^{(i)}, y^{(i)}) = -\frac{1}{m} \sum_{I=1}^{m} (y^{(i)} \log \hat{y}^{(i)} + (1 - y^{(i)}) \log (1 - \hat{y}^{(i)}))$$

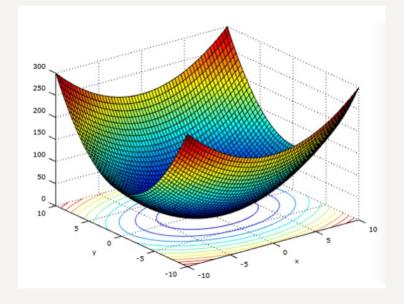
Therefore, weights w and b keep being adjusted minimizing J(w,b) until the local minimum (global optimum) has been reached

$$w = w - \alpha \frac{dJ(w)}{dw}$$
 $b = b - \alpha \frac{dJ(b)}{db}$

 α is the **learning rate**

The adjustment procedure is called **Back-Propagation** and the algorithm employed for optimization process is called **Gradient Descent**







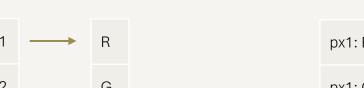
for Image Classification

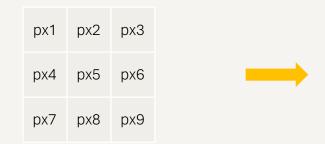






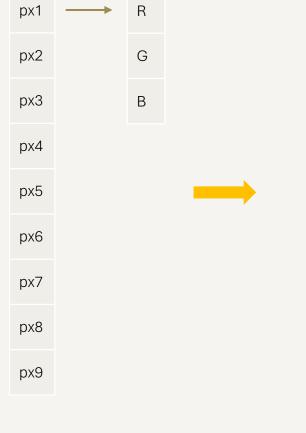
Flattening Process





Dimensions: (width, height, channels)

(R, G, B) color



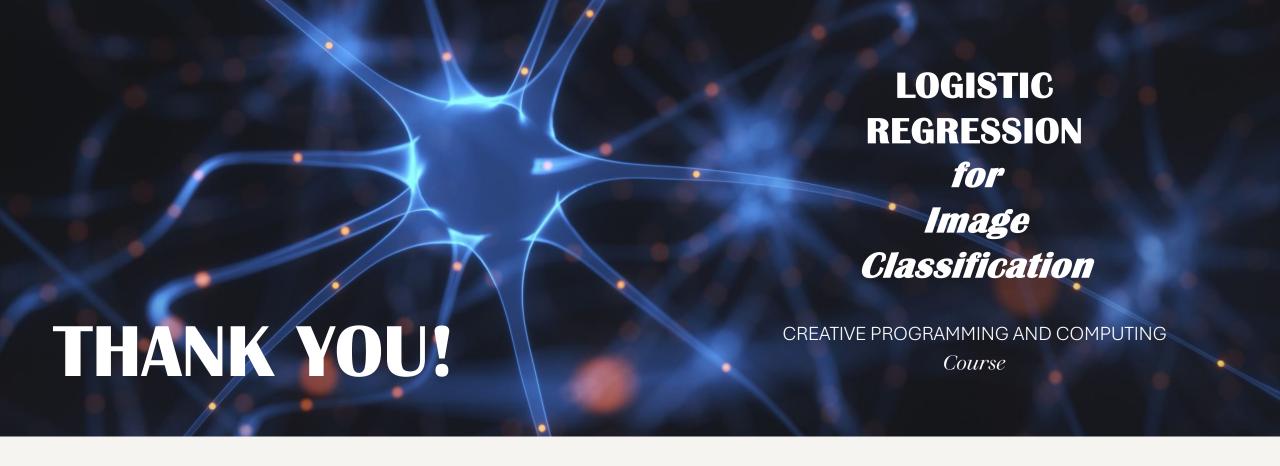
px1:R px1: G px1: B px2: R px2: G px2: B px3: R рх3: G рх3: В

Feature Vector





Let's jump to the code!



References

- Lecture Slides by Prof. Massimiliano Zanoni
- Edgar, T.W. & Manz, D.O.. (2017). Research Methods for Cyber Security. Chapter 4.





Prof. Massimiliano Zanoni

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