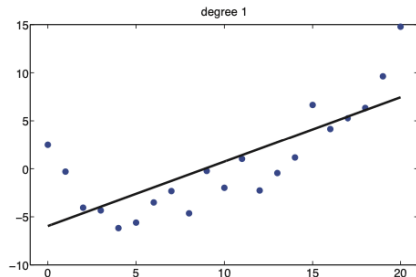


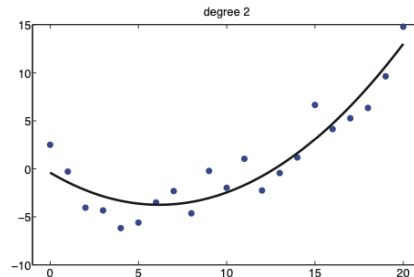
## RESESSIONE LINEARE

venerdì 11 ottobre 2024 16:49

LA REGRESSIONE E' PROPRIO COME LA CLASSIFICAZIONE SOLO CHE NELLA REGRESSIONE E' CONTINUA



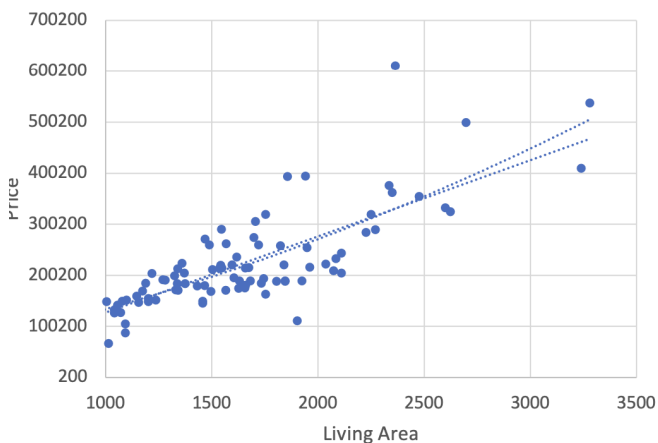
Regressione lineare<sup>(a)</sup>



Regressione Polinomiale

DATO UN GRAFICO VOGLIAMO  
PREVEDERE UN VALORE

→  $x \in \mathbb{R}$



$x$	Living area (feet <sup>2</sup> )	Price (1000\$)
	1656	215
	896	105
	1329	172
	2110	244
	...	...

L'ESEMPIO E' IL SEGUENTE

$(x, y)$  = COPPIA DI VALORI

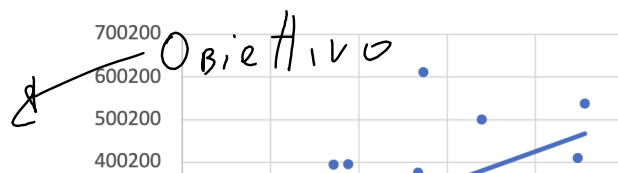
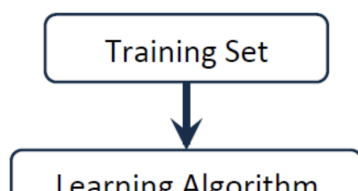
$M$  = NUMERI DI ESEMPI DI FORMAZIONE

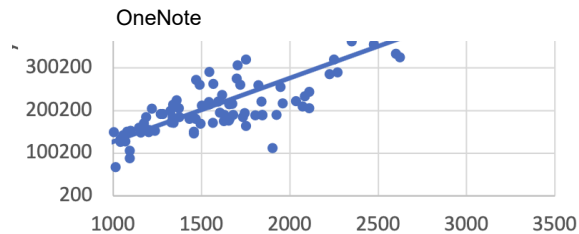
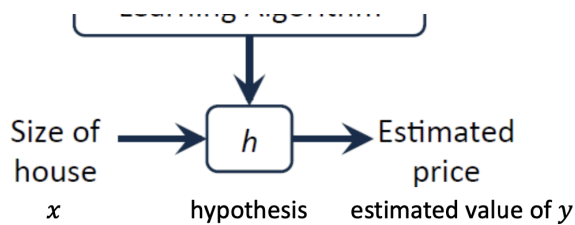
$X$  = INPUT O FEATURE

$y$  = OUTPUT O TARGET

GENERALIZZANDO LA COPPIA

→  $(x^i, y^i) = i^{th}$





$$h_{\theta}(x) = \theta_0 + \theta_1 x \triangleq h(x)$$

FUNZIONE IPOTESI

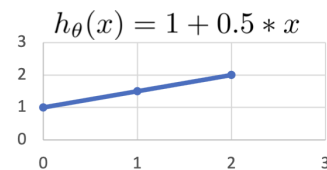
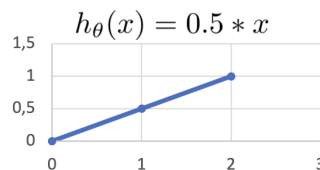
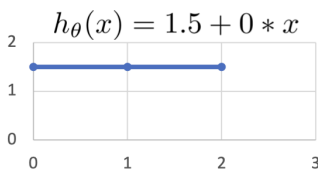
LA DOMANDA E' LA SEGUENTE COME FACCIAMO A CAPIRE

CHE ?

$$\theta_i = \text{Weights} / \text{peso}$$

Se  $h(x) = \theta_0 + \theta_1 x$  SOSTITUIAMO:

$\theta_1$  COEFFICIENTE ANGOLARE RETTA



COST FUNCTION: INTUITION

FUNZIONE DI COSTO QUADRATICO

$$J(\theta_0, \theta_1) = \frac{1}{2n} \sum_{i=1}^M \left( h_{\theta}(x^{(i)}) - y^{(i)} \right)^2$$

funzione predittiva

m numero degli esempio di allenamento.

Y = valore associato di x ( VALORE DELLA CASA)

IL NOSTRO OBIETTIVO

è trovare i valori di  $\theta_1$  e  $\theta_2$  che minimizzano la funzione di costo:

$$\theta_{\min} = \arg\min_{\theta} J(\theta)$$

TALE FUNZIONE DI COSTO SOMIGLIA MOLTO A QUELLA DELLA MSE EQUAZIONE DI ERRORE QUADRATICO MEDIO

$$MSE = \frac{1}{m} \sum_{i=1}^m (y_1 - y_2)^2$$

IN DEFINITIVA

$$\underset{\theta_0, \theta_1}{\operatorname{argmin}} \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(\mathbf{x}^{(i)}) - y^{(i)})^2$$

$\downarrow$  #training examples       $\downarrow$  Squared error function  
 $h_{\theta}(\mathbf{x}^{(i)}) = \theta_0 + \theta_1 x^{(i)}$

$$J(\theta_0, \theta_1) = J(\theta) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(\mathbf{x}^{(i)}) - y^{(i)})^2$$

(Cost Function)

$$\theta_{min} = \operatorname{argmin}_{\theta} (J(\theta_0, \theta_1)) = \operatorname{argmin}_{\theta} (J(\theta)).$$

### 1.5.1 LR Cost function and some considerations

Defining a cost function is important because we need to estimate how much accurate are our prediction  $h_{\theta}(x) = \theta_0 + \theta_1 x$  compared to the real value  $y$ .

#### Coefficients $\theta$ randomly choosed

The easiest approach consist of choosing random coefficients  $\theta$  hoping to find a good approximation.

#### Intuition of LR

We search for the minimum parameters such that the average prediction  $h_{\theta}(x^{(i)})$  is as much close to the real values  $y^{(i)}$ . The problem is defined as it follows:

$$\theta^* = \underset{\theta_0, \theta_1}{\operatorname{argmin}} \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2 = \underset{\theta_0, \theta_1}{\operatorname{argmin}} J(\theta_0, \theta_1) = \underset{\theta}{\operatorname{argmin}} J(\theta)$$

Where every prediction is defined as  $h_{\theta}(x^{(i)}) = \theta_0 + \theta_1 x^{(i)}$ .

The cost function is defined as:

$$J(\theta) = J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

**Note:** this form of error is called Mean Square Error (MSE)

