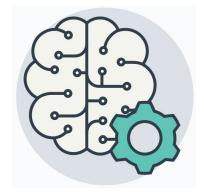
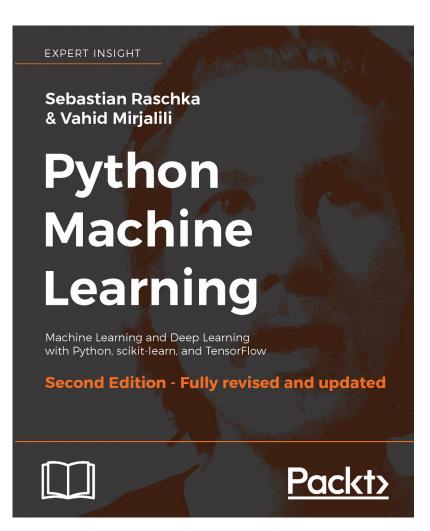
Aprendizado de Máquina

Regressão



Prof. Regis Pires Magalhães regismagalhaes@ufc.br - http://bit.ly/ufcregis

Main Reference



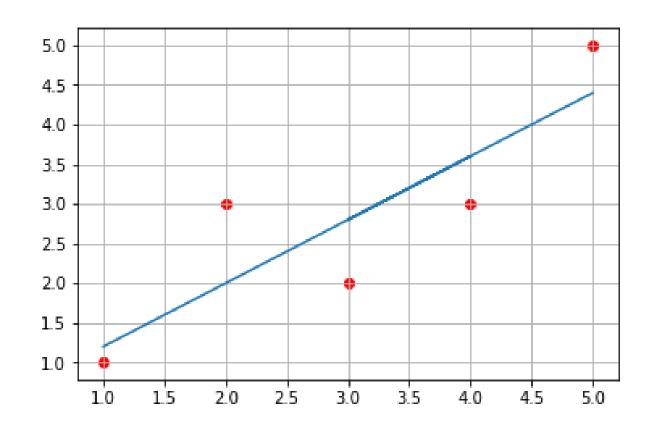
Python Machine Learning

Chapter 10 - Predicting Continuous Target Variables with Regression Analysis

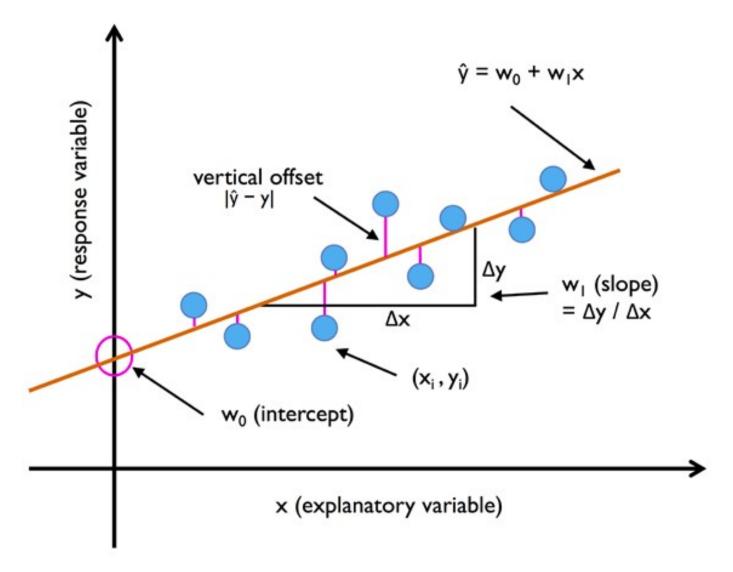
scikit-learn datasets

datasets.load_boston ([return_X_y])	Load and return the boston house-prices dataset (regression).
datasets.load_breast_cancer([return_X_y])	Load and return the breast cancer wisconsin dataset (classification).
datasets.load_diabetes ([return_X_y])	Load and return the diabetes dataset (regression).
datasets.load_digits ([n_class, return_X_y])	Load and return the digits dataset (classification).
datasets.load_files (container_path[,])	Load text files with categories as subfolder names.
datasets.load_iris ([return_X_y])	Load and return the iris dataset (classification).
datasets.load_linnerud ([return_X_y])	Load and return the linnerud dataset (multivariate regression).
datasets.load_mlcomp (name_or_id[, set_,])	DEPRECATED: since the http://mlcomp.org/ website will shut down in March 2017, the load_mlcomp function was deprecated in version 0.19 and will be removed in 0.21.
datasets.load_sample_image (image_name)	Load the numpy array of a single sample image
datasets.load_sample_images()	Load sample images for image manipulation.
<pre>datasets.load_svmlight_file (f[, n_features,])</pre>	Load datasets in the symlight / libsym format into sparse CSR matrix
datasets.load_svmlight_files (files[,])	Load dataset from multiple files in SVMlight format
datasets.load_wine ([return_X_y])	Load and return the wine dataset (classification).

Regressão Linear



$$y = w_0 + w_1 x$$



$$\cdot$$
 y = B0 + B1 × x

$$B1 = \frac{\sum_{i=1}^{n} (x_i - mean(x)) \times (y_i - mean(y))}{\sum_{i=1}^{n} (x_i - mean(x))^2}$$

$$B1 = \frac{covariance(x, y)}{variance(x)}$$

$$B0 = mean(y) - B1 \times mean(x)$$

$$mean(x) = 3$$

 $mean(y) = 2.8$

$$B1 = \frac{8}{10}$$
$$B1 = 0.8$$

$$B0 = mean(y) - B1 \times mean(x)$$

$$B0 = 2.8 - 0.8 \times 3$$

$$B0 = 0.4$$

$$y = B0 + B1 \times x$$
$$y = 0.4 + 0.8 \times x$$

$$RMSE = 0.692820323$$

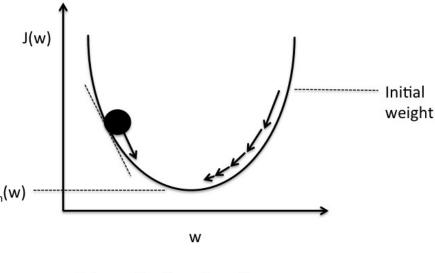
Atalho

$$B1 = corr(x,y) \times \frac{stdev(y)}{stdev(x)}$$

$$B1 = 0.852802865 \times \frac{1.483239697}{1.58113883}$$

 $B1 = 0.8$

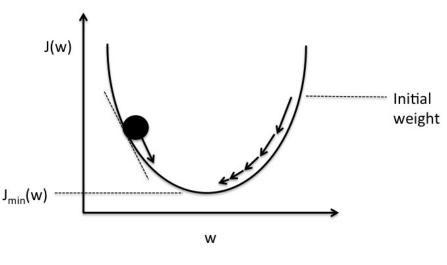
 Imagine uma bola rolando ao longo do gráfico de uma função de custo.



Schematic of gradient descent.

- A medida que a bola rola, ela segue a rota mais íngreme, eventualmente chegando ao fundo.
- Em resumo, é isso que ocorre com o gradiente descendente.

• Escolha um ponto no gráfico, encontre a direção que tem a inclinação mais íngrer

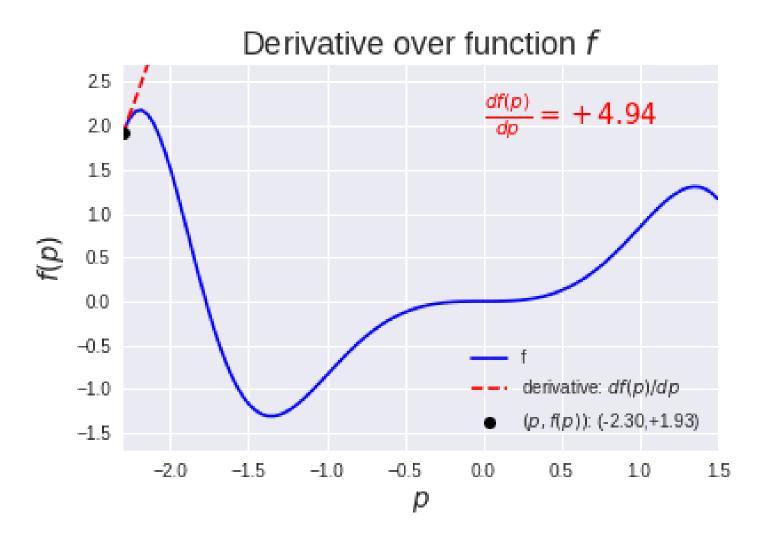


Schematic of gradient descent.

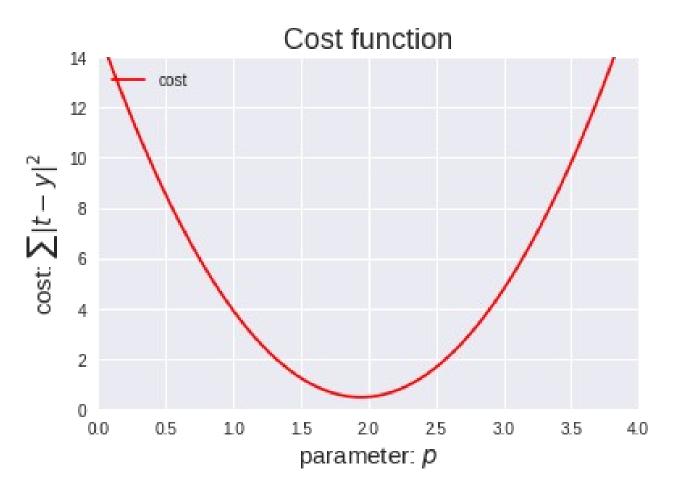
naquela direção, e repita o processo.

- Eventualmente, encontraremos um mínimo da função de custo.
- E porque aquele ponto é o mínimo, ele possui os parâmetros necessários para desenhar nossa linha.

Derivada de uma função f



Função de custo objetivo: minimizar o erro quadrado



Função de Erro

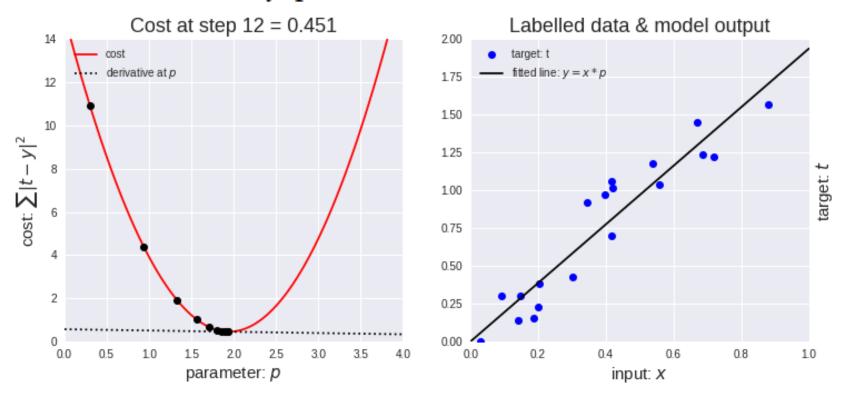
$$y = b_1x + b_0$$

 b_1 é a inclinação
 b_0 é onde y é interceptado.

$$Error_{\beta_0,\beta_1} = \frac{1}{N} \sum_{i=1}^{N} (y_i - (\beta_1 x_i + \beta_0))^2$$

Minimizando a função de custo

$$Error_{\beta_0,\beta_1} = \frac{1}{N} \sum_{i=1}^{N} (y_i - (\beta_1 x_i + \beta_0))^2$$



Minimizando a função de custo

$$Error_{\beta_0,\beta_1} = \frac{1}{N} \sum_{i=1}^{N} (y_i - (\beta_1 x_i + \beta_0))^2$$

É necessário calcular a derivada parcial para b0 e b1:

$$\frac{\partial}{\partial \beta_1} = \frac{2}{N} \sum_{i=1}^{N} -x_i (y_i - (\beta_1 x_i + \beta_0))$$

$$\frac{\partial}{\partial \beta_0} = \frac{2}{N} \sum_{i=1}^{N} -(y_i - (\beta_1 x_i + \beta_0))$$

- O erro diminui a cada interação.
- A direção do movimento em cada interação é calculada a partir das 2 derivadas parciais.

```
def compute_error_for_line_given_points(b0, b1, x, y):
               N = len(y)
                totalError = 1/N * np.sum((y - (b1 * x + b0)) ** 2)
                return totalError
def step_gradient(b0_current, b1_current, x, y, learning_rate):
               N = len(y)
                b0 gradient = 2/N * np.sum(-(y - ((b1 current * x) +
b0 current)))
                bl gradient = 2/N * np.sum(-x * (y - ((bl current * x) +
b0 current)))
                new b0 = b0 current - (learning_rate * b0_gradient)
                new b1 = b1 current - (learning rate * b1 gradient)
                return new b0, new b1
def gradient_descent_runner(x, y, b0, b1, learning_rate,
num iterations):
                for in range(num iterations):
b0, b1 \(\frac{\phi}{2}\) gradiented este electrodia entrum hebitx, \(\times\), \(\times\)
initedurbibo, learning rate, num iterations)
```

Após 100000 iterações, obtemos

```
\Box b0 = 4.247984440219184
```

$$\Box b1 = 1.3959992655297515$$

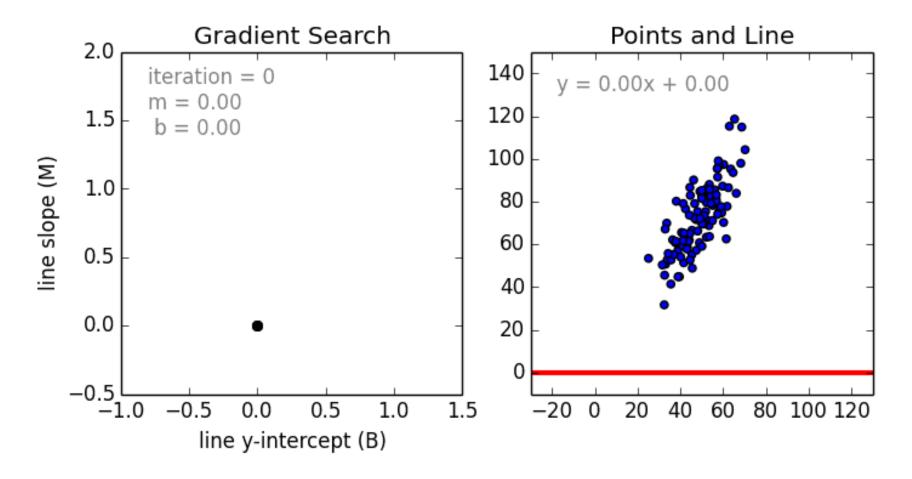
 \Box error = 110.78631929745077

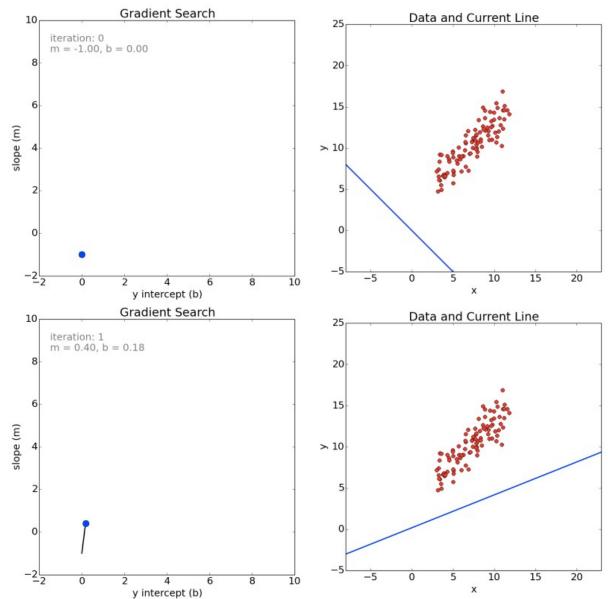
Linear Regression do Scikit Learn

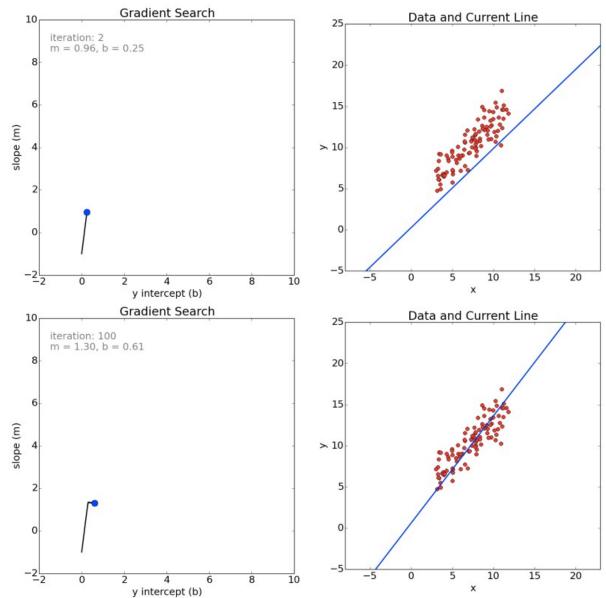
```
\Box b0 = 7.991020982270399
```

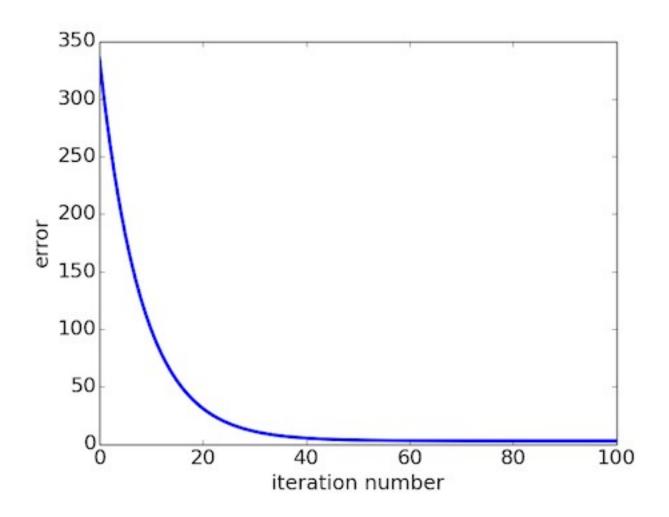
```
\Box b1 = 1.32243102
```

 \Box error = 110.25738346621316









Multivariate Linear Regression

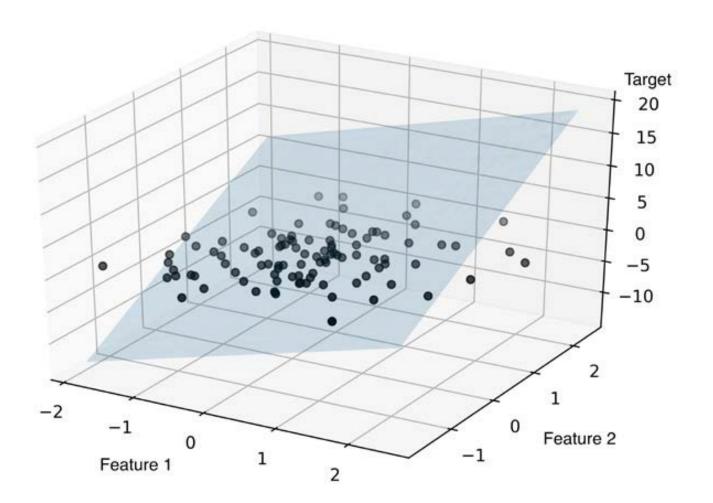
ou Multiple linear regression

$$y = w_0 x_0 + w_1 x_1 + \dots + w_m x_m = \sum_{i=0}^m w_i x_i = w^T x$$

Onde, w_0 é a interseção do eixo y com x_0 =1.

Multivariate Linear Regression

ou Multiple linear regression



Stochastic Gradient Descent

- Gradient Descent is the process of minimizing a function following the slope or gradient of that function.
- Stochastic gradient descent evaluates and updates the coefficients every iteration to minimize the error of a model on our training data.

 $b = b - \text{learning rate} \times \text{error} \times x$

Stochastic Gradient Descent

Parâmetros

- Learning Rate
 - Used to limit the amount that each coefficient is corrected each time it is updated.
- Epochs
 - The number of times to run through the training data while updating the

$$b_1(t) = fib_1(t) + fib_1(t) +$$

$$b_0(t + 1) = b_0(t) - learning rate \times error(t)$$

Referências

• https://www.kdnuggets.com/2017/04/simple-understand-gradient-descent-

algorithm.html

