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Département d'informatique
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Linear regression

Linear regression using the Gradient Descent method

Introduction

What is linear regression?

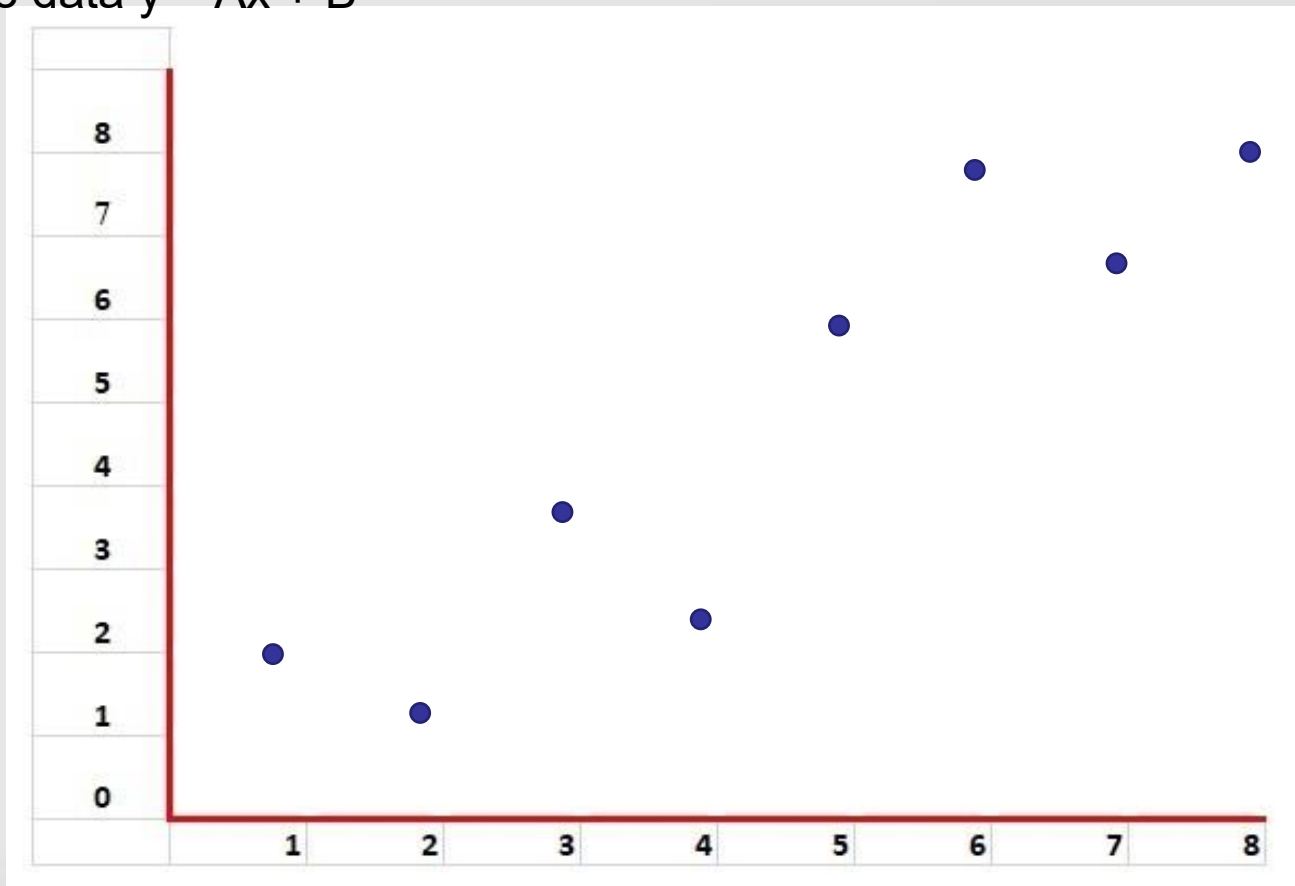
In statistics, a linear regression model is a model that seeks to establish a linear relationship between an independent variable and another dependent variable.

Example

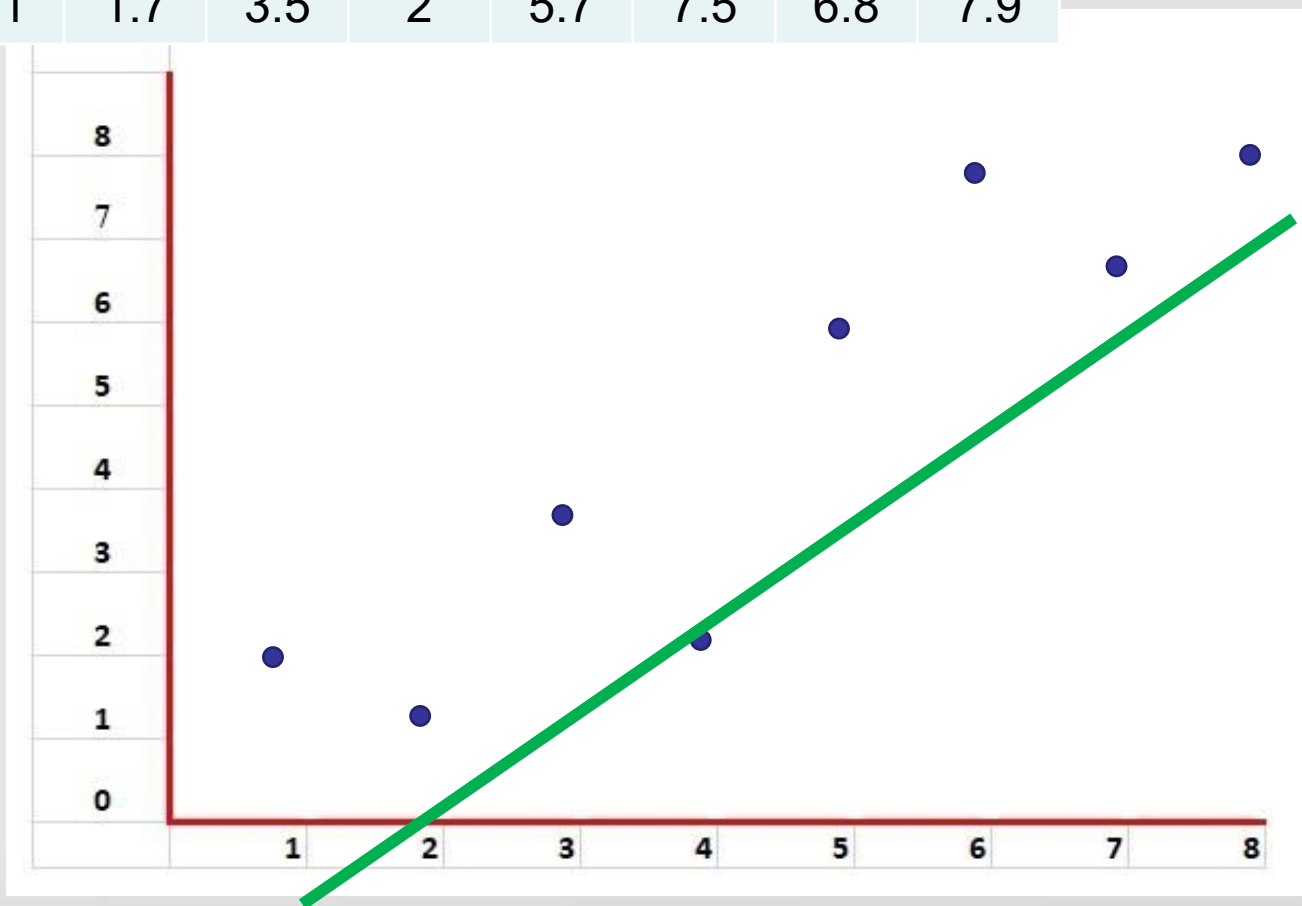
X	1	2	3	4	5	6	7	8
Y	1.9	1.1	3.5	2	5.7	7.5	6.8	7.9

L'objectif?

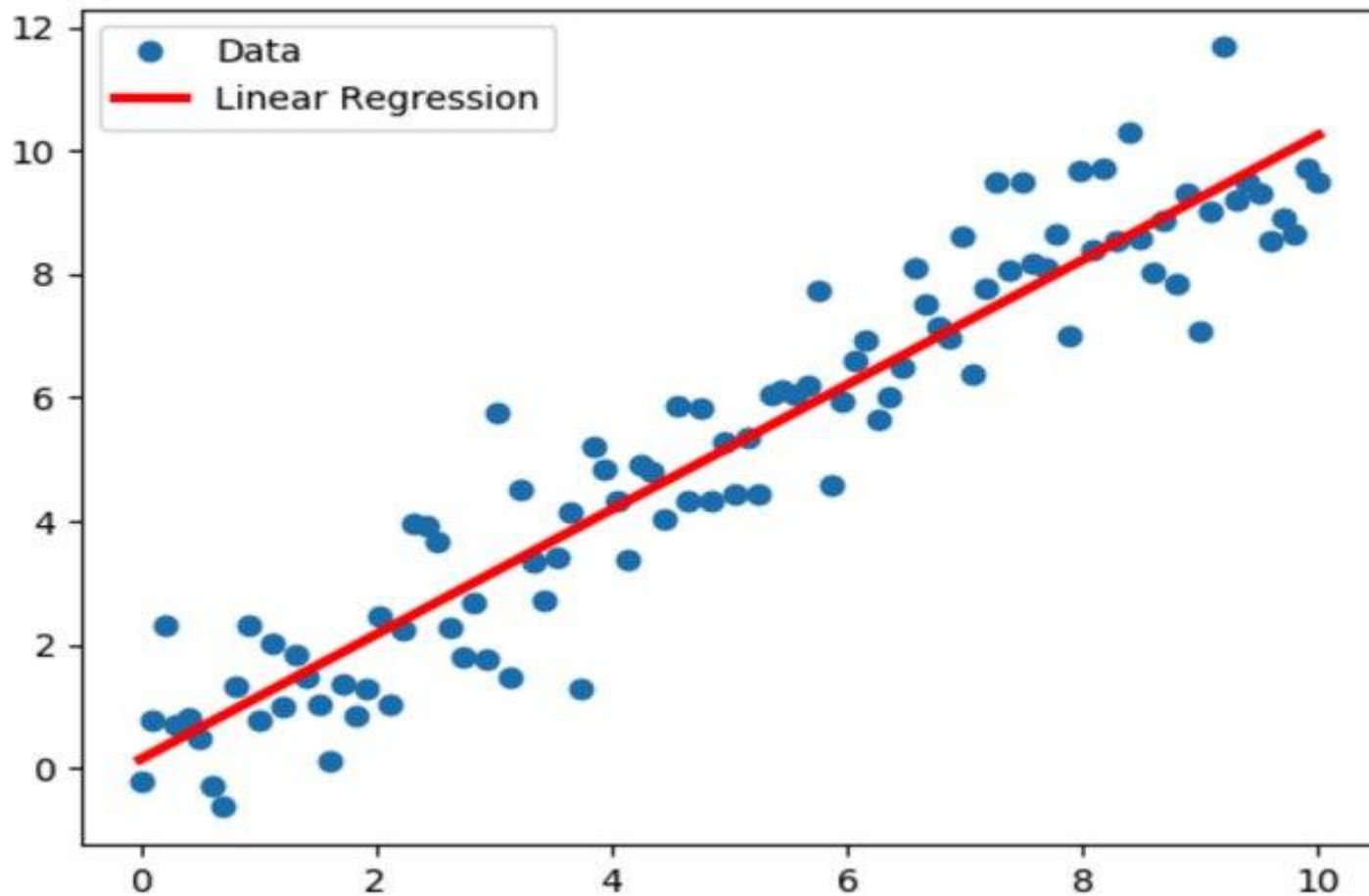
The goal in linear regression is to find the equation of the line that represents the best fit for the data $y = Ax + B$



X	1	2	3	4	5	6	7	8
Y	1.1	1.7	3.5	2	5.7	7.5	6.8	7.9



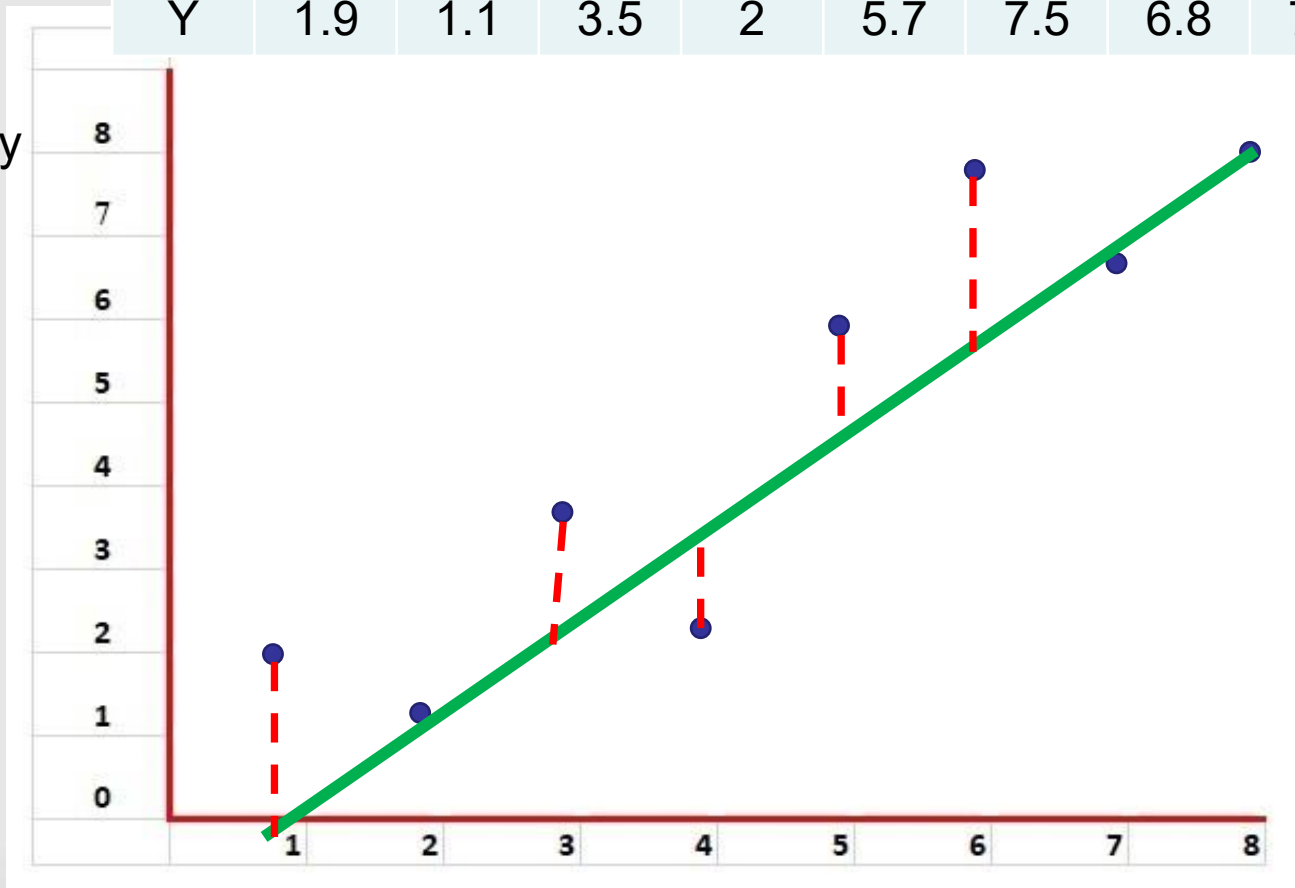
Example



$$h(x) = y$$

$$h'(x) = Ax + B = y$$

X	1	2	3	4	5	6	7	8
Y	1.9	1.1	3.5	2	5.7	7.5	6.8	7.9



The cost function

The cost function

$$\text{Loss} = \sum_{i=1}^n (y_i - h(x_i))$$

So our objective is :

$$\text{minimiser } \sum_{i=1}^n (y_i - h(x_i))$$

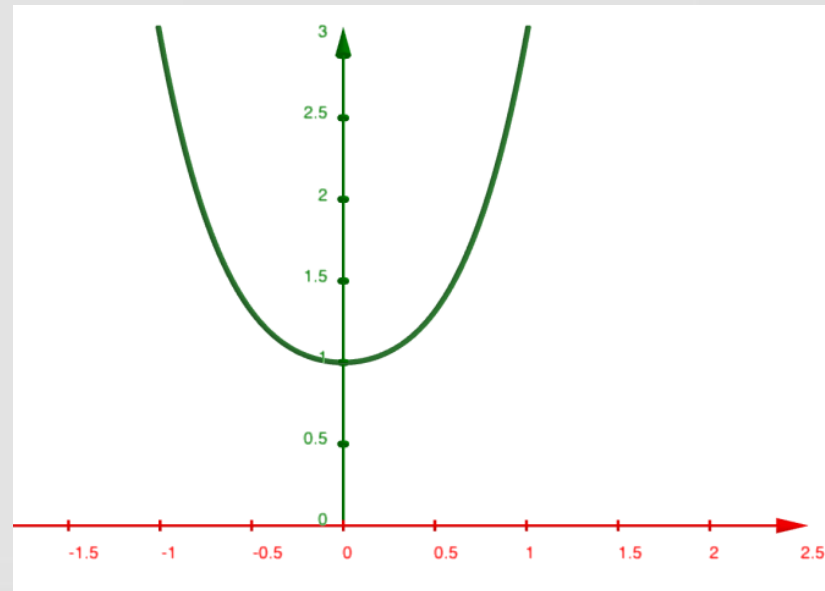
Sum of Squared Errors (SSE)

But because of a problem in this function, we use

$$\text{minimiser } \sum_{i=1}^n (y_i - h(x_i))^2 \quad 1/2$$

So our objective is :

$$\text{minimiser } \sum_{i=1}^n (x)^2$$



Descente de la gradient

$$\text{loss} = \sum_{i=1}^n (y_i - h(x_i))^2$$

$$\text{loss} = \sum_{i=1}^n (y_i - (Ax_i + B))^2$$

The derivative with respect to A:

$$\begin{aligned} \frac{d \text{loss}}{d A} &= \frac{d}{d A} \left(\sum_{i=1}^n (y_i - (Ax_i + B))^2 \right) \\ &= \sum_{i=1}^n -2x_i (y_i - (Ax_i + B)) \end{aligned}$$

Descente de la gradient

$$\text{loss} = \sum_{i=1}^n (y_i - h(x_i))^2$$

$$\text{loss} = \sum_{i=1}^n (y_i - (Ax_i + B))^2$$

The derivative with respect to B:

$$\begin{aligned} \frac{d \text{loss}}{d B} &= \frac{d}{d B} \left(\sum_{i=1}^n (y_i - (Ax_i + B))^2 \right) \\ &= \sum_{i=1}^n -2 (y_i - (Ax_i + B)) \end{aligned}$$

We will start from initial and random values of A and B, denoted respectively A_0 and B_0 and we calculate: :

$$slope_A = \frac{d \text{ loss } (A_0, B_0)}{d A}$$

$$slope_B = \frac{d \text{ loss } (A_0, B_0)}{d B}$$

$Step_A$ and $Step_B$ are two variables used to update the two values A and B. And they also define the learning rate.

$$Step_A = Slope_A * Learning \text{ rate}$$

$$Step_B = Slope_B * Learning \text{ rate}$$

The new values of A and B are calculated as follows:

$$\begin{aligned} new_A &= old_A - Step_A \\ new_B &= old_B - Step_B \end{aligned}$$

We repeat this process until we obtain very small values for steps, or we reach the limit of the number of iterations.

Summary

- 1- Calculate the derivative of the **Loss** function for each parameter (A and B).
- 2- Give random initial values for A and B
- 3- Calculate **slope_A** and **slope_B**
- 4- Calculate **step_A** and **step_B** such as **$step = slope * learning\ rate$**
- 5- Calculate **new_A** and **new_B** such as **$new_A = old_A - step_A$**
- 6- Repeat from 3 down to a very small number of steps or a maximum number of iterations.

Example

x	0.5	2.3	3.2
y	1.4	1.9	2.9

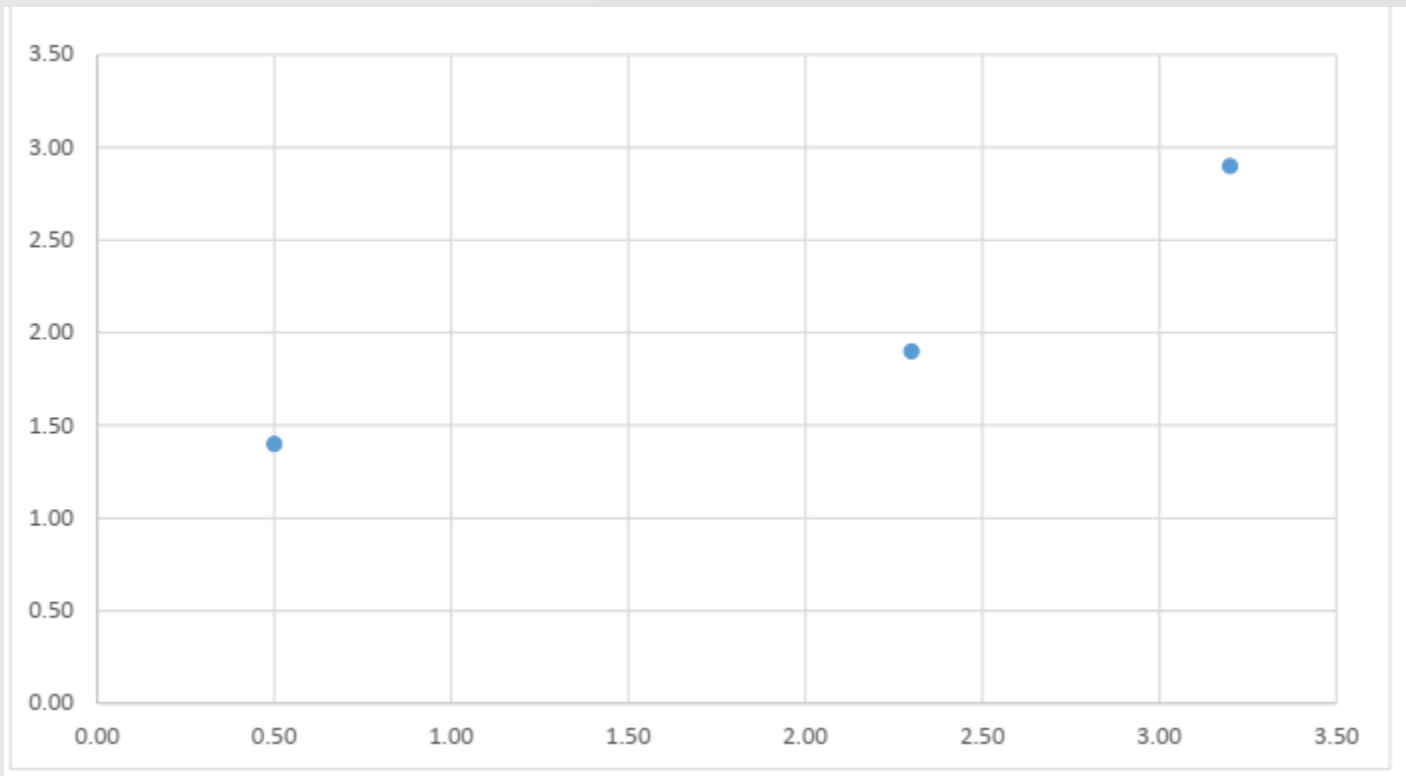
A = 0

B = 0

$$slope_A = \frac{d \text{ loss } (A_0, B_0)}{d A} = \sum_{i=1}^n -2x_i(y_i - (Ax_i + B))$$

$$slope_B = \frac{d \text{ loss } (A_0, B_0)}{d B} = \sum_{i=1}^n -2(y_i - (Ax_i + B))$$

Example



Example

x	0.5	2.3	2.9
y	1.4	1.9	3.2

A = 0

B = 0

$$\begin{aligned} slope_A &= -2 * 0.5(1.4 - (0 * 0.5 + 0)) \\ &\quad -2 * 2.3(1.9 - (0 * 2.3 + 0)) \\ &\quad -2 * 3.2(2.9 - (0 * 3.2 + 0)) = -4.78 \end{aligned}$$

$$\begin{aligned} slope_B &= -2(1.4 - (0 * 0.5 + 0)) \\ &\quad -2(1.9 - (0 * 2.3 + 0)) \\ &\quad -2(2.9 - (0 * 3.2 + 0)) = -2.066 \end{aligned}$$

Example

$$Step_A = Slope_A * Learning\ rate$$

$$Step_B = Slope_B * Learning\ rate$$

$$Step_A = -4.78 * 0.01 = -0.0478$$

$$Step_B = -2.06 * 0.01 = -0.0206$$

$$new_A = 0 - (-0.0478) = 0.0478$$

$$new_B = 0 - (-0.0206) = 0.0206$$

$$A = 0$$

$$B = 0$$

$$A = 0.0478$$

$$B = -0.0206$$

Example

x	0.5	2.3	3.2
y	1.4	1.9	2.9

$$A = 0.0478$$
$$B = -0.0206$$

$$\begin{aligned} slope_A &= -2 * 0.5(1.4 - (0.0478 * 0.5 + 0.0206)) \\ &\quad -2 * 2.3(1.9 - (0.0478 * 2.3 + 0.0206)) \\ &\quad -2 * 3.2(2.9 - (0.0478 * 3.2 + 0.0206)) = -4.490 \end{aligned}$$

$$\begin{aligned} slope_B &= -2(1.4 - (0.0478 * 0.5 + 0.0206)) \\ &\quad -2(1.9 - (0.0478 * 2.3 + 0.0206)) \\ &\quad -2(2.9 - (0.0478 * 3.2 + 0.0206)) = -1.950 \end{aligned}$$

Example

$$Step_A = Slope_A * Learning\ rate$$

$$Step_B = Slope_B * Learning\ rate$$

$$A = 0$$

$$B = 0$$

$$Step_A = -4.490 * 0.01 = -0.0490$$

$$A = 0.0478$$

$$B = -0.0206$$

$$Step_B = -1.950 * 0.01 = -0.0195$$

$$new_A = 0.0478 - (-0.0490) = 0.092$$

$$new_B = 0.0206 - (-0.01958) = 0.04018$$

A	0	0.0478	0.092	0.134	0.174		0.51587
B	0	0.0206	0.092	0.058	0.075		1.03492

$Step_A$	-0.287	-0.1815	-0.11439		7.379491e-05
$Step_B$	-0.1239	-0.08212	-0.05540		-0.000186

Example

x	y	A	B	Ax+B
0.5	1.4	0.51587	1.03492	1.292855
2.3	1.9			2.221421
3.2	2.9			2.685704

If $x = 4.1$ then the prediction is $y = 3.149987$

Méthode de calcul numérique

$$\frac{d \text{ loss}}{d B} = \sum_{i=1}^n -2 (y_i - (Ax_i + B)) = 0$$

$$= \sum_{i=1}^n (y_i - (Ax_i + B)) = 0 \quad \text{Because -2 does not equal 0}$$

$$\sum_{i=1}^n (y_i - (Ax_i + B)) = 0$$

$$\sum y_i - \sum Ax_i - \sum B = 0$$

$$\sum y_i - A \sum x_i - nB = 0$$

$$\sum y_i - A \sum x_i = nB$$

$$B = \frac{\sum y_i}{n} - \frac{A \sum x_i}{n}$$

$$\mathbf{B} = \bar{y} - A \bar{x}$$

$$\frac{d \text{ loss}}{d A} = \sum_{i=1}^n -2x_i(y_i - (Ax_i + B)) = 0 \quad \mathbf{B} = \bar{\mathbf{y}} - \mathbf{A} \bar{\mathbf{x}}$$

$$-2 \sum_{i=1}^n x_i(y_i - (Ax_i + B)) = 0$$

$$\sum_{i=1}^n x_i(y_i - (Ax_i + \bar{\mathbf{y}} - \mathbf{A} \bar{\mathbf{x}})) = 0$$

$$\sum_{i=1}^n x_i(y_i - \bar{\mathbf{y}} - (Ax_i - \mathbf{A} \bar{\mathbf{x}})) = 0$$

$$\sum_{i=1}^n x_i (y_i - \bar{y} - (Ax_i - A\bar{x})) = 0$$

$$\sum_{i=1}^n x_i \left((y_i - \bar{y}) - A(x_i - \bar{x}) \right) = 0$$

$$\sum x_i (y_i - \bar{y}) - A \sum x_i (x_i - \bar{x}) \quad \sum x_i (y_i - \bar{y}) = A \sum x_i (x_i - \bar{x})$$

$$A = \frac{\sum x_i (y_i - \bar{y})}{\sum x_i (x_i - \bar{x})} \quad A = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$$

$$B = \bar{y} - A \bar{x}$$

$$A = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$$

Example

x	y
0.5	1.4
2.3	1.9
3.2	2.9

$$B = \bar{y} - A \bar{x}$$

$$A = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$$

Example

x	y
0.5	1.4
2.3	1.9
3.2	2.9
$\bar{x} = 2$	$\bar{y} = 2.066$

$$B = \bar{y} - A \bar{x}$$

$$A = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$$

Example

x	y	$x_i - \bar{x}$
0.5	1.4	-1.5
2.3	1.9	0.3
3.2	2.9	1.2
$\bar{x} = 2$	$\bar{y} = 2.066$	

$$A = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$$

$$B = \bar{y} - A \bar{x}$$

Example

x	y	$x_i - \bar{x}$	$y_i - \bar{y}$
0.5	1.4	-1.5	-0.666
2.3	1.9	0.3	-0.166
3.2	2.9	1.2	0.8333
$\bar{x} = 2$	$\bar{y} = 2.066$		

$$A = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$$

$$B = \bar{y} - A \bar{x}$$

Example

x	y	$x_i - \bar{x}$	$y_i - \bar{y}$	$(x_i - \bar{x}) * (y_i - \bar{y})$
0.5	1.4	-1.5	-0.666	0.999
2.3	1.9	0.3	-0.166	-0.0498
3.2	2.9	1.2	0.8333	1
$\bar{x} = 2$	$\bar{y} = 2.066$			$\sum = 1.9492$

$$A = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$$

$$B = \bar{y} - A \bar{x}$$

Example

x	y	$x_i - \bar{x}$	$y_i - \bar{y}$	$(x_i - \bar{x}) * (y_i - \bar{y})$	$(x_i - \bar{x})^2$
0.5	1.4	-1.5	-0.666	0.999	2.25
2.3	1.9	0.3	-0.166	-0.0498	0.09
3.2	2.9	1.2	0.8333	1	1.44
$\bar{x} = 2$	$\bar{y} = 2.066$			$\sum = 1.9492$	$\sum = 3.78$

$$A = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2} = \frac{1.9492}{3.78} = \mathbf{0.5157}$$

$$B = \bar{y} - A \bar{x} = 2.066 - 0.5157 * 2 = 1.064$$

Example

$$A = 0.5157, B = 1.064$$

x	y	$Ax + B$
0.5	1.4	1.32
2.3	1.9	2.25
3.2	2.9	2.71

Regression Loss Functions

Mean Squared Error (MSE)

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

Regression Loss Functions

Sum of Squared Errors (SSE)

$$\text{SSE} = \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

Regression Loss Functions

Root Mean Squared Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

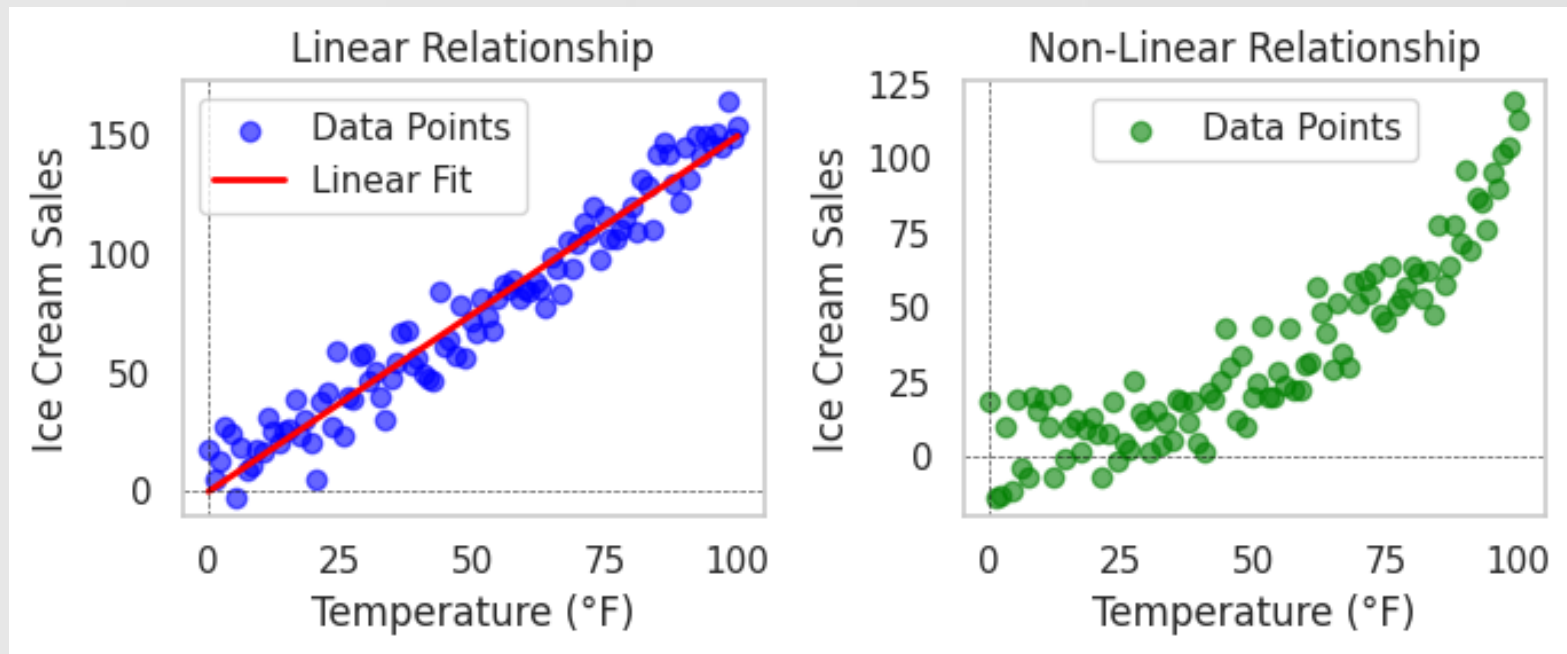
Regression Loss Functions

Mean Absolute Error (MAE)

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

The main problems of linear regression

Linearity Assumption (Biggest Problem)

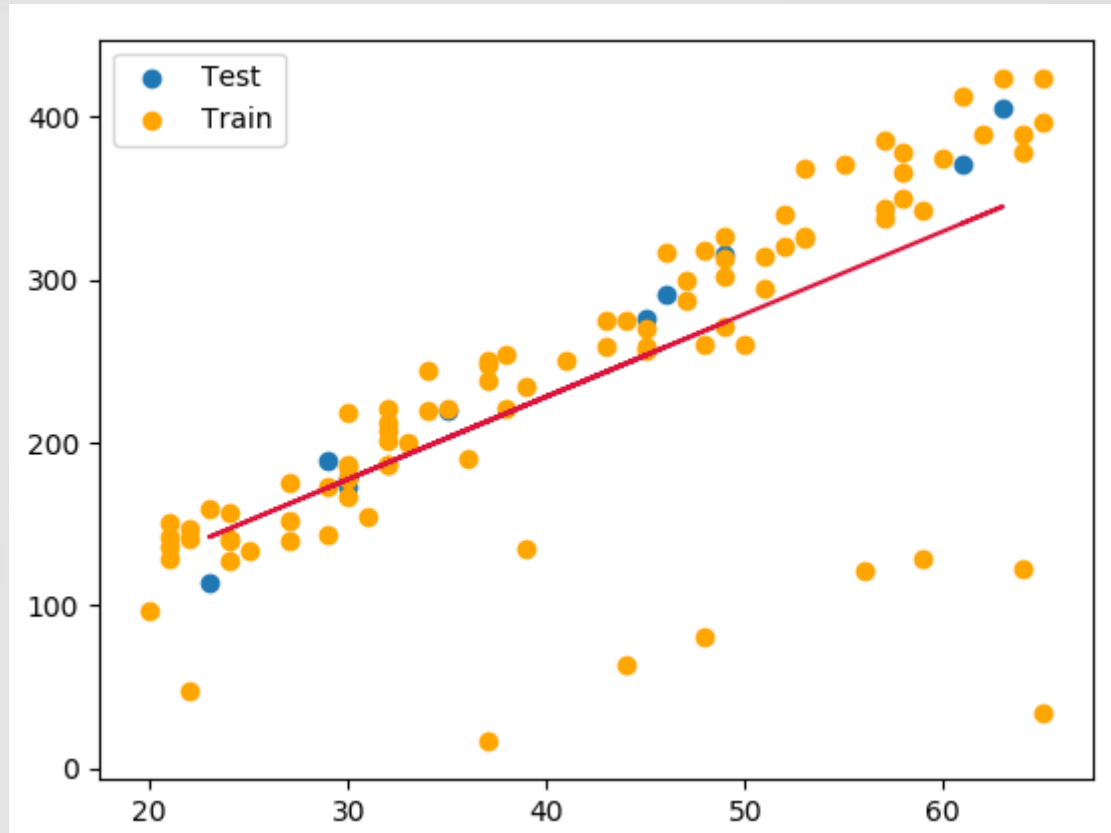


The main problems of linear regression

Sensitive to Outliers

Because MSE squares the error, a single extreme point can damage the model badly.

Example:
1 wrong measurement = huge squared error = model is distorted.



x	y
2.4	1.5
9.8	2.7
5.4	2.1
7.8	1.8
8.9	2.4
4.1	1.5

Find a linear fit for these data using the two methods seen in class.