

# TP 5 : DESCENT METHODS

# Introduction to descent methods and to their role in machine learning

## Problem description

**Machine learning requires to calibrate a pre-established function in order to match as best as possible with a training set (inputs  $(x, \dots)$  & outputs  $v$ )**

Ex : let  $F_p$  be the function to calibrate, with a set of parameters  $p$  to determine, and  $(x, \dots, v)$  the training set.

## Questions

1. Pose this problem as an optimization problem
2. Is it constrained or unconstrained ? Why ?

Consider now a linear regression ( $F(x) = ax + b$ , where  $p=(a,b)$ ) and let  $G(a,b)$  be the function to minimize

1. Is it differentiable or not ? Why ?
2. Write  $DG_a$  and  $DG_b$  (gradient of  $G$  in  $a$  and  $b$  respectively) formulas & implement them in python
3. Implement a gradient algorithm for this problem, on the training set given in the Excel file (trainingSet1.xlsx)
4. Compare your results with Excel linear regression

## Gradient descent algorithms

- 1 Start from  $x_0$
- 2 At Step  $k$ ,
  - choose  $h^k$  such that  $\nabla\varphi(x^k) \cdot h^k$  (HOW?)
  - choose small Step length  $t^k > 0$  (HOW?), and update:  
$$x_{k+1} = x_k + t^k h^k$$
- 3 Compute  $\nabla\varphi(x^{k+1})$ 
  - if  $\sim 0$ , STOP
  - Otherwise, go back to 2

$x = [x_1, \dots, x_N]$

$t$  : fixed (very small)

$h_i = -$  gradient  $f$  in  $x_i$

Stop when  $f(x^{k+1}) - f(x^k) < \text{tolerance}$

Main example of descent direction:

- $h^k = -\nabla\varphi(x^k)$ :  $\nabla\varphi(x^k) \cdot h^k \leq \nabla\varphi(x^k) \cdot h$  provided  $|h| = |\nabla\varphi(x^k)|$
- Newton's method  $h^k = -(\nabla^2\varphi(x^k))^{-1}\nabla\varphi(x^k)$
- or  $h^k = -Q^k\nabla\varphi(x^k)$ , for some positive symmetric matrix  $Q^k$