

## Homework nr. 8

Consider  $F : \mathbb{R} \times \mathbb{R} \longrightarrow \mathbb{R}$  a real function. Approximate a (local or global) minimum point of function  $F$  using the gradient descent method. Test different methods to calculate the learning rate. Compute the gradient of the function  $F$  using the analytic formula and the approximation formula. Compare the solutions obtained by using the two computing methods of the function's  $F$  gradient, in terms of number of iterations used by the two methods (for the same precision  $\epsilon > 0$ ).

### Functions' Minimization

Let  $F : \mathbb{R} \times \mathbb{R} \longrightarrow \mathbb{R}$  be a real function, twice differentiable,  $F \in C^2(\mathbb{R} \times \mathbb{R})$ , for which we want to approximate the solution  $x^*$  of the minimization problem:

$$\min\{F(x, y); (x, y) \in V\} \quad \longleftrightarrow \quad F(x^*, y^*) \leq F(x, y) \quad \forall (x, y) \in V \quad (1)$$

where  $V$  is either  $V = \mathbb{R} \times \mathbb{R}$  (where  $(x^*, y^*)$  is a global minimum point) or  $V = S((\bar{x}, \bar{y}), r)$ , is a sphere with the center  $(\bar{x}, \bar{y})$  and the radius  $r$  (which is a local minimum point).

A point  $(\tilde{x}, \tilde{y})$  is a *critical point* for function  $F$ , if it is the solution of the next system of equations:

$$\nabla F(\tilde{x}, \tilde{y}) = 0 \quad , \quad \nabla F(x, y) = \begin{pmatrix} \frac{\partial F}{\partial x}(x, y) \\ \frac{\partial F}{\partial y}(x, y) \end{pmatrix}. \quad (2)$$

It is known that, for twice differentiable functions, the minimum points of function  $F$  are among the critical points. A critical point is a minimum point if the Hessian matrix is positively semi-definable:

$$H(x, y) = \begin{pmatrix} \frac{\partial^2 F}{\partial x^2} & \frac{\partial^2 F}{\partial x \partial y} \\ \frac{\partial^2 F}{\partial y \partial x} & \frac{\partial^2 F}{\partial y^2} \end{pmatrix} \quad , \quad (H(\tilde{x}, \tilde{y})z, z)_{\mathbb{R}^2} \geq 0 \quad \forall z \in \mathbb{R}^2$$

## Gradient Descendent Method

The minimum point of a function  $F$  is approximated by constructing the string  $\{(x_k, y_k)\}$  which, under certain conditions, converges to the minimum point  $(x^*, y^*)$ . The convergence of this string depends on the choice of the first element of the string, i.e.,  $(x_0, y_0)$ .

The  $k + 1$ -element of the string  $(x_{k+1}, y_{k+1})$ , is constructed from the previous one,  $(x_k, y_k)$ , as follows:

$$\begin{pmatrix} x_{k+1} \\ y_{k+1} \end{pmatrix} = \begin{pmatrix} x_k \\ y_k \end{pmatrix} - \eta_k \nabla F(x_k, y_k), \quad k = 0, 1, \dots, \quad (3)$$

where  $\begin{pmatrix} x_0 \\ y_0 \end{pmatrix}$  – is randomly chosen.

The element  $\eta_k$  is called the learning rate, or the iteration step.

### *Strategies for choosing the learning rate*

1.  $\eta_k = \eta$ ,  $\forall k$  ( $\eta = 10^{-3}, 10^{-4}, \dots$ ). A constant learning rate with a too big value makes the minimum point hard to be found, while a too small value for the learning rate has the disadvantage of a too costing computation.
2. A possibility to solve problems with a constant learning rate is to consider a variable value, depending on the local context. The method described below is called *backtracking* adjustment of the step length/learning rate (or *backtracking line search*). This method works for convex functions.

Consider  $\beta \in (0, 1)$  a constant value (usually we take  $\beta = 0.8$ ). At each step the learning rate is computed as follows:

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 $\eta = 1;$ 
 $p = 1;$ 
while  $F((x_k, y_k) - \nabla F(x_k, y_k)) > F(x_k, y_k) - \frac{\eta}{2} \|\nabla F(x_k, y_k)\|^2$  &&  $p < 8$ 
     $\eta = \eta \beta;$ 
     $p++$  ;

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**Important remark:** The way in which the initial element,  $(x_0, y_0)$  is chosen may cause the convergence or divergence of the string  $(x_k, y_k)$  to

$(x^*, y^*)$ . Usually, a choice of the initial data in the proximity of  $(x^*, y^*)$  assures the convergence  $(x_k, y_k) \longrightarrow (x^*, y^*)$  for  $k \rightarrow \infty$ .

It is not necessary to memorize all elements of the string  $\{(x_k, y_k)\}$ , but only the 'last' computed element  $(x_{k_0}, y_{k_0})$ . We say that an element  $(x_{k_0}, y_{k_0})$  approximates a minimum point,  $(x^*, y^*)$ , denoted by  $(x_{k_0}, y_{k_0}) \approx (x^*, y^*)$  (where  $(x_{k_0}, y_{k_0})$  is the last element of the string that we want to compute), if the difference between two successive elements of the string is small enough, i.e.,

$$\left\| \begin{pmatrix} x_{k_0} \\ y_{k_0} \end{pmatrix} - \begin{pmatrix} x_{k_0-1} \\ y_{k_0-1} \end{pmatrix} \right\| \leq \epsilon \quad (4)$$

where  $\epsilon$  is the precision with which we want to approximate the solution  $(x^*, y^*)$ .

Therefore, a possible approximation scheme of the solution  $(x^*, y^*)$ , is the following one:

### Computing Scheme

randomly choose the initial values of the string,  $x, y$  ;  
 $k = 0$  ;  
do  
  {  
    - compute  $\nabla F(x, y)$  ;  
    - compute the learning rate  $\eta$  using  
      one of the two methods;  
    -  $x = x - \eta \frac{\partial F}{\partial x}(x, y)$  ;  
    -  $y = y - \eta \frac{\partial F}{\partial y}(x, y)$  ;  
    -  $k = k + 1$ ;  
  }  
while (  $\eta \|\nabla F(x, y)\| \geq \epsilon$  and  $k \leq k_{\max}$  and  
       $\eta \|\nabla F(x, y)\| \leq 10^{10}$  )  
if (  $\eta \|\nabla F(x, y)\| \leq \epsilon$  )  $(x, y) \approx (x^*, y^*)$  ;  
else "*divergence*" ; //(try to change the initial data)

A possible value for  $k_{\max}$  is 30000 and  $\epsilon > 10^{-5}$ .

To compute the value of function's  $F$  gradient in a certain point, the analytical gradient formula must be used (where the function is declared in the program). Also use the following approximation formula:

$$\nabla F(x, y) \approx \begin{pmatrix} G_1(x, y, h) \\ G_2(x, y, h) \end{pmatrix}$$

where

$$\frac{\partial F}{\partial x}(x, y) \approx G_1(x, y, h) = \frac{3F(x, y) - 4F(x - h, y) + F(x - 2h, y)}{2h}$$

$$\frac{\partial F}{\partial y}(x, y) \approx G_2(x, y, h) = \frac{3F(x, y) - 4F(x, y - h) + F(x, y - 2h)}{2h}$$

with  $h = 10^{-5}$  or  $10^{-6}$  (may be considered as an input parameter).

### Examples

$$F(x, y) = x^2 + y^2 - 2x - 4y - 1, \quad \nabla F(x, y) = \begin{pmatrix} 2x - 2 \\ 2y - 4 \end{pmatrix}, \quad x^* = 1, y^* = 2$$

$$F(x, y) = 3x^2 - 12x + 2y^2 + 16y - 10, \quad \nabla F(x, y) = \begin{pmatrix} 6x - 12 \\ 4y + 16 \end{pmatrix}, \quad x^* = 2, y^* = -4$$

$$F(x, y) = x^2 - 4xy + 5y^2 - 4y + 3, \quad \nabla F(x, y) = \begin{pmatrix} 2x - 4y \\ -4x + 10y - 4 \end{pmatrix}, \quad x^* = 4, y^* = 2$$

$$F(x, y) = x^2y - 2xy^2 + 3xy + 4, \quad \nabla F(x, y) = \begin{pmatrix} 2xy - 2y^2 + 3y \\ x^2 - 4xy + 3x \end{pmatrix}, \quad x^* = -1, y^* = 0.5$$