

Solutions to Exercise Set 11

Problem 1**Steepest descent method with a step obtained by exact minimization**

- (a) The steepest descent direction of f in (x_0, y_0) is given by:

$$\mathbf{d} = - \begin{pmatrix} 6x_0 \\ 6y_0 \end{pmatrix} = \begin{pmatrix} -6 \\ -6 \end{pmatrix}$$

Computation of the step α_{min} :

$$\alpha_{min} = \underset{\alpha \geq 0}{\operatorname{argmin}} g(\alpha) = \underset{\alpha \geq 0}{\operatorname{argmin}} f((x_0 \ y_0)^T + \alpha \mathbf{d})$$

We get that $g(\alpha) = f((1 - 6\alpha \ 1 - 6\alpha)^T) = 6(1 - 6\alpha)^2$. Moreover, as the function is strictly convex, the step is obtained by setting $g'(\alpha) = 0$:

$$1 - 6\alpha = 0 \Rightarrow \alpha_{min} = \frac{1}{6}$$

The new iterate is:

$$(x_1 \ y_1)^T = (x_0 \ y_0)^T + \alpha_{min} \mathbf{d} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

We find the minimum of f in one iteration.

- (b) From a theoretical point of view, there is no result that gives the number of iterations necessary to converge in the general case for this method.

Newton's Method

- (a) The Newton's direction is given by:

$$\mathbf{d} = - \begin{pmatrix} 6 & 0 \\ 0 & 6 \end{pmatrix}^{-1} \begin{pmatrix} 6 \\ 6 \end{pmatrix} = \begin{pmatrix} -1 \\ -1 \end{pmatrix}$$

The new iterate is:

$$(x_1 \ y_1)^T = (x_0 \ y_0)^T + \mathbf{d} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

We find the minimum in one iteration.

- (b) Newton's method converges in one iteration for strictly convex quadratic problems. Newton's direction is obtained by minimizing a quadratic function explaining why it converges in one iteration.

Conjuguate gradient method

(a) \mathbf{Q} is a symmetric positive definite matrix given by:

$$\begin{pmatrix} 6 & 0 \\ 0 & 6 \end{pmatrix},$$

$\mathbf{b} = (0 \ 0)^T$ and $c = 0$. Let's set $\mathbf{x} = (x_0 \ y_0)^T$.

The direction is given by:

$$\mathbf{d} = -\mathbf{Q}\mathbf{x} - \mathbf{b} = \begin{pmatrix} -6 \\ -6 \end{pmatrix}$$

The step is:

$$\alpha = -\frac{\mathbf{d}^T(\mathbf{Q}\mathbf{x} + \mathbf{b})}{\mathbf{d}^T\mathbf{Q}\mathbf{d}} = \frac{1}{6}$$

The new iterate:

$$(x_1 \ y_1)^T = \mathbf{x} + \alpha\mathbf{d} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

We find the minimum in one iteration.

(b) The maximal number of iterations for this method is given by the dimension of the problem, i.e. 2 in this example.

Problem 2

a) The gradient and the hessian of f are:

$$\nabla f(\mathbf{x}) = \begin{pmatrix} 4(x-2)^3 + 2(x-2)y^2 \\ 2(x-2)^2y + 2(y+1) \end{pmatrix} \quad \forall \mathbf{x} \in \mathbb{R}^2$$

$$\nabla^2 f(\mathbf{x}) = \begin{pmatrix} 12(x-2)^2 + 2y^2 & 4(x-2)y \\ 4(x-2)y & 2(x-2)^2 + 2 \end{pmatrix} \quad \forall \mathbf{x} \in \mathbb{R}^2$$

b) The new iterate \mathbf{x}_{k+1} is given by

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \mathbf{s}_k$$

The step \mathbf{s}_k is given by solving the following linear system at each iteration :

$$\nabla^2 f(\mathbf{x}_k)\mathbf{s}_k = -\nabla f(\mathbf{x}_k)$$

We get the following values:

k	\mathbf{x}_k	\mathbf{s}_k	$f(\mathbf{x}_k)$
0	$\begin{pmatrix} 1 & 1 \end{pmatrix}^T$	$\begin{pmatrix} 0 & -1.5 \end{pmatrix}^T$	6
1	$\begin{pmatrix} 1.0 & -0.5 \end{pmatrix}^T$	$\begin{pmatrix} 0.3913 & -0.1956 \end{pmatrix}^T$	1.5
2	$\begin{pmatrix} 1.3913 & -0.6956 \end{pmatrix}^T$	$\begin{pmatrix} 0.3546 & -0.2532 \end{pmatrix}^T$	$4.092 \cdot 10^{-1}$
3	$\begin{pmatrix} 1.7459 & -0.9491 \end{pmatrix}^T$	$\begin{pmatrix} 0.2403 & -0.0991 \end{pmatrix}^T$	$6.49 \cdot 10^{-2}$
4	$\begin{pmatrix} 1.9862 & -1.0482 \end{pmatrix}^T$	—	$2.5 \cdot 10^{-3}$

Problem 3

We compute the gradient:

$$\nabla f(\mathbf{x}) = \begin{pmatrix} 2x_1 + 2x_2 \\ 2x_1 + 4x_2 \end{pmatrix},$$

the hessian:

$$H(\mathbf{x}) = \begin{pmatrix} 2 & 2 \\ 2 & 4 \end{pmatrix}$$

and its inverse:

$$H^{-1}(\mathbf{x}) = \begin{pmatrix} 1 & -1/2 \\ -1/2 & 1/2 \end{pmatrix}.$$

We note that

$$H^{-1}(\mathbf{x})\nabla f(\mathbf{x}) = \begin{pmatrix} 1 & -1/2 \\ -1/2 & 1/2 \end{pmatrix} \begin{pmatrix} 2x_1 + 2x_2 \\ 2x_1 + 4x_2 \end{pmatrix} = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \mathbf{x}$$

For any $\mathbf{x}^{(0)} \in \mathbb{R}^2$, we have that:

$$\mathbf{x}^{(1)} = \mathbf{x}^{(0)} - H^{-1}(\mathbf{x}^{(0)})\nabla f(\mathbf{x}^{(0)}) = \mathbf{x}^{(0)} - \mathbf{x}^{(0)} = 0$$

Consequently, the Newton's method converges in one iteration independently from the starting point. This result is true for any positive definite quadratic function.

Problem 4

$$1. \nabla f(x,y) = \begin{pmatrix} 4x^3 - 4x \\ 3y^2 - 3 \end{pmatrix}.$$

$$\nabla f^2(x,y) = \begin{pmatrix} 12x^2 - 4 & 0 \\ 0 & 6y \end{pmatrix}.$$

$$(2,2) \text{ is not minimum since } \nabla f(2,2) = \begin{pmatrix} 24 \\ 9 \end{pmatrix}.$$

$$(-1,1) \text{ is a minimum since } \nabla f(-1,1) = \begin{pmatrix} 0 \\ 0 \end{pmatrix} \text{ and } \nabla f^2(-1,1) = \begin{pmatrix} 8 & 0 \\ 0 & 6 \end{pmatrix} \text{ is positive definite.}$$

$$(0,-1) \text{ is a maximum since } \nabla f(0,-1) = \begin{pmatrix} 0 \\ 0 \end{pmatrix} \text{ and } \nabla f^2(0,-1) = \begin{pmatrix} -4 & 0 \\ 0 & -6 \end{pmatrix} \text{ is negative definite.}$$

$$2. x_0 = \begin{pmatrix} 2 \\ 2 \end{pmatrix}$$

$$x_1 = x_0 - (\nabla^2 f(2,2))^{-1}\nabla f(2,2) = \begin{pmatrix} 2 \\ 2 \end{pmatrix} - \begin{pmatrix} \frac{1}{44} & 0 \\ 0 & \frac{1}{12} \end{pmatrix} \begin{pmatrix} 24 \\ 9 \end{pmatrix} = \begin{pmatrix} \frac{16}{11} \\ \frac{5}{4} \end{pmatrix}.$$

The method is not applicable to the other points since $\nabla f(x,y)$ is null at these points.

$$3. \text{ The Armijo rule: } f\left(\frac{16}{11}, \frac{5}{4}\right) \simeq -1.552 \leq f\left(\frac{2}{2}, \frac{2}{2}\right) - 0.1(24 \ 9) \begin{pmatrix} \frac{1}{44} & 0 \\ 0 & \frac{1}{12} \end{pmatrix} \begin{pmatrix} 24 \\ 9 \end{pmatrix} \simeq 8.016$$

is satisfied.

Problem 5

(a) the hessian of f is given by \mathbf{Q} for all $\mathbf{x} \in \mathbb{R}^3$. \mathbf{Q} is positive definite and f is strictly convex over \mathbb{R}^3 .

The unique minimum of f over \mathbb{R}^3 is given by the unique solution of the system of equations $\mathbf{Q}\mathbf{x} = -\mathbf{b}$ that can be rewritten as:

$$\begin{cases} x_1 = -1 \\ 5x_2 = -1 \\ 25x_3 = -1 \end{cases}$$

The solution is given by:

$$\begin{cases} x_1^* = -1 \\ x_2^* = -\frac{1}{5} \\ x_3^* = -\frac{1}{25} \end{cases}$$

This is the unique minimum.

(b) The gradient of f is given by:

$$\nabla f(\mathbf{x}) = \begin{pmatrix} x_1 + 1 \\ 5x_2 + 1 \\ 25x_3 + 1 \end{pmatrix} \quad \forall x \in \mathbb{R}^3$$

The steepest descent direction for f at \mathbf{x}^0 is:

$$\mathbf{d}^0 = -\nabla f(\mathbf{x}^0) = \begin{pmatrix} -1 \\ -1 \\ -1 \end{pmatrix}$$

Problem 6

(a) The gradient of f is given by:

$$\nabla f(x, y) = \begin{pmatrix} 2x^3 - 2xy + x - 1 \\ -x^2 + y \end{pmatrix} \quad \forall (x, y) \in \mathbb{R}^2$$

Candidates to be a local minimum are given by the solutions of the system $\nabla f(x, y) = 0$:

$$\begin{cases} 2x^3 - 2xy + x - 1 = 0 \\ -x^2 + y = 0 \end{cases}$$

We get $x^2 = y$ from the second equation and if we replace y by x^2 in the first equation, we immediately obtain that $x = 1$. So the solution is given by:

$$\begin{cases} x = 1 \\ y = 1 \end{cases}$$

Let's have a look at the hessian matrix at $(1, 1)$:

$$\nabla^2 f(x, y) = \begin{pmatrix} 6x^2 - 2y + 1 & -2x \\ -2x & 1 \end{pmatrix}$$

and we get:

$$\nabla^2 f(1, 1) = \begin{pmatrix} 5 & -2 \\ -2 & 1 \end{pmatrix}.$$

This matrix is positive definite. Indeed $(x \ y) \nabla^2 f(1, 1) (x \ y)^T = 5x^2 - 4xy + y^2 = (2x - y)^2 + x^2 \geq 0$ with equality only when $x = y = 0$. So we conclude that this is the unique minimizer of f over \mathbb{R}^2 .

(b) At $(x^0, y^0) = (2, 2)$, we have that:

$$\nabla f(x^0, y^0) = \begin{pmatrix} 9 \\ -2 \end{pmatrix} \text{ and } \nabla^2 f(x^0, y^0) = \begin{pmatrix} 21 & -4 \\ -4 & 1 \end{pmatrix}$$

Newton's direction at (x^0, y^0) is:

$$\mathbf{d}^0 = -[\nabla^2 f(x^0, y^0)]^{-1} \nabla f(x^0, y^0) = -\begin{pmatrix} 0.2 & 0.8 \\ 0.8 & 4.2 \end{pmatrix} \begin{pmatrix} 9 \\ -2 \end{pmatrix} = \begin{pmatrix} -0.2 \\ 1.2 \end{pmatrix}$$

Consequently:

$$\begin{pmatrix} x^1 \\ y^1 \end{pmatrix} = \begin{pmatrix} x^0 \\ y^0 \end{pmatrix} + \mathbf{d}^0 = \begin{pmatrix} 1.8 \\ 3.2 \end{pmatrix}$$

The new iterate is not closer to the optimal value but the objective function has decreased in value of approximately 2.18. So the new iterate is a better point even though it is not closer to the optimal solution!

Newton's method needs 5 iterations to converge to (1,1). The different iterates are given below:

x^k	y^k
2	2
1.8	3.2
1.0593	0.5733
1.0310	1.0622
1	0.9991
1	1