

TP1 Optimisation

Part 1.

1.1.

$$\forall x \in \mathbb{R}^2, \quad f(x) = 3x_1^2 + 0,5x_2^2 + 2x_2 + 2$$

$$\nabla f(x) = \begin{pmatrix} \frac{\partial}{\partial x_1} f(x) \\ \frac{\partial}{\partial x_2} f(x) \end{pmatrix} = \begin{pmatrix} 6x_1 \\ x_2 + 2 \end{pmatrix}$$

Among $[1 \ 2]^T, [0 \ 3]^T, [1 \ 0]^T, [0 \ 0]^T$, only $[0 \ 0]^T$ give

$$\forall d \in (\mathbb{R}^+)^2 \text{ faisable direction } d^T \nabla f \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix} \right) \text{ positive}$$

So according to FONC, which is not for any

$$x \in \{[1 \ 2]^T, [0 \ 3]^T, [1 \ 0]^T\},$$

$$\boxed{[0 \ 0]^T \text{ is a local minimum of } f(\cdot)}$$

1.2.

$$\forall x \in \mathbb{R}^2, \nabla f_1(x) = \begin{pmatrix} -x_1 - 1 \\ -4x_2 + 2 \end{pmatrix} \text{ and } \nabla f_2(x) = \begin{pmatrix} 6x_1^2 + x_2^2 + 10x_1 \\ 2x_1x_2 + 2x_2 \end{pmatrix}$$

- $D^2 f_1(x) = \begin{bmatrix} -1 & 0 \\ 0 & -4 \end{bmatrix}$ which is symmetric

So since diagonal values are negatives, $\forall x \in \mathbb{R}^2, D^2 f_1(x) < 0$

and because $\nabla f_1 \left(\begin{pmatrix} -1 \\ \frac{1}{2} \end{pmatrix} \right) = 0$,

then $x^* = \begin{pmatrix} -1 \\ \frac{1}{2} \end{pmatrix}$ is a local minimiser

- $D^2 f_2(x) = \begin{bmatrix} 12x_1 + 10 & 2x_2 \\ 2x_2 & 2x_1 + 2 \end{bmatrix}$ which is symmetric

Since $\{x^* \in \mathbb{R}^2 / \nabla f_2(x^*) = 0\} = \{(-1, -2), (-1, 2), \left(-\frac{10}{6}, 0\right), (0, 0)\}$

We can now find cases for which one solution is a saddle points, a local minimum or a local maximum:

a) For $x^* = (-1, -2)$

$$D^2 f_1(x^*) = \begin{bmatrix} -2 & -4 \\ -4 & 0 \end{bmatrix} \text{ which is symmetric}$$

So since diagonal values are negatives, $D^2 f_2(x^*) < 0$

then $x^* = (-1, -2)$ is a local minimum of $f(\cdot)$

b) For $x^* = (-1, 2)$

$$D^2 f_1(x^*) = \begin{bmatrix} -2 & 4 \\ 4 & 0 \end{bmatrix} \text{ which is symmetric}$$

So since diagonal values are negatives, $D^2 f_2(x^*) < 0$

then $x^* = (-1, 2)$ is a local minimum of $f(\cdot)$

c) For $x^* = \left(-\frac{10}{6}, 0\right)$,

$$D^2 f_1(x^*) = \begin{bmatrix} -10 & 0 \\ 0 & -\frac{4}{3} \end{bmatrix} \text{ which is symmetric}$$

So since diagonal values are negatives, $D^2 f_2(x^*) < 0$

then $x^* = \left(-\frac{10}{6}, 0\right)$ is a local minimum of $f(\cdot)$

d) For $x^* = (0, 0)$,

$$D^2 f_1(x^*) = \begin{bmatrix} 10 & 0 \\ 0 & 2 \end{bmatrix} \text{ which is diagonal}$$

So since diagonal values are positive, $\forall x \in \mathbb{R}^2, D^2 f_1(x) > 0$

then $x^* = (-1, 2)$ is a local maximum of $f(\cdot)$

1.3.

$$\text{for } x_0 = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \text{ for } d = \begin{pmatrix} 2 \\ -1 \end{pmatrix},$$

$$\begin{aligned} \forall \alpha \in \mathbb{R}, f(x_0 + \alpha d) &= (1 + 2\alpha)^2 + (1 + 2\alpha)(1 - \alpha) - 4(-1 + \alpha)^2 + 5 \\ &= 3 + 3\alpha - 2\alpha^2 \end{aligned}$$

$$\text{Since } f(x_0) = 1 + 1 - 4 + 5 = 3$$

$$\text{then } \frac{f(x_0 + \alpha d) - f(x_0)}{\alpha} = -2\alpha + 3$$

$$\text{so } \frac{\partial}{\partial d} f(x_0) = \lim_{\alpha \rightarrow 0} \frac{f(x_0 + \alpha d) - f(x_0)}{\alpha} = 3 > 0$$

We conclude that $d = \begin{pmatrix} 2 \\ -1 \end{pmatrix}$ is an increase direction.

Otherwise, $\forall x \in \mathbb{R}^2, \nabla f(x) = \begin{pmatrix} 2x_1 + x_2 \\ x_1 - 8x_2 \end{pmatrix}$,

$$\text{So } \nabla f(x_0) = \begin{pmatrix} 3 \\ -7 \end{pmatrix}$$

$$\text{Since } \frac{\partial}{\partial d} f(x_0) = \nabla f(x_0)^T d = (3 \quad -7) \begin{pmatrix} 2 \\ -1 \end{pmatrix} = 13 > 0$$

We conclude that d is increase direction too.

1.4.

$$\begin{aligned} \nabla f(x) &= \begin{pmatrix} 6x_1 - 2x_2 - 10 \\ 2x_1 + 6x_2 - 2 \end{pmatrix} \\ \nabla f(x^*) &= 0 \text{ if } \begin{bmatrix} 6 & -2 \\ -2 & 6 \end{bmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} 10 \\ 2 \end{pmatrix} \\ \text{Since } \det \begin{bmatrix} 6 & -2 \\ -2 & 6 \end{bmatrix} &= 32 \end{aligned}$$

So the problem is solvable and it exists one and only one solution:

$$x^* = \begin{pmatrix} 2 \\ 1 \end{pmatrix} \text{ works.}$$

Moreover, $D^2 f(x^*) = \begin{bmatrix} 6 & -2 \\ -2 & 6 \end{bmatrix}$ which is symmetric matrix

According to Sylvester's Criterion, since $\Delta_1 = 6 > 0$ and $\Delta_2 = 32 > 0$

$D^2 f(x^*)$ is positive definite.

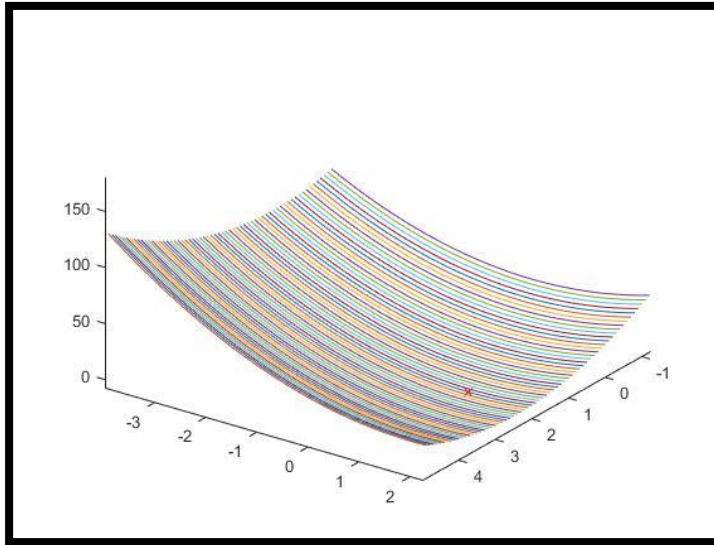
So $x^* = \begin{pmatrix} 2 \\ 1 \end{pmatrix}$ is the minimum for the programming problem

In order to verify my answer, I plot the graph of the cost function in the domain:

$$\begin{aligned} -5 &\leq x_1 \leq 5 \\ -5 &\leq x_2 \leq 5 \end{aligned}$$

And it gives on Matlab script:

```
x1=-5:0.1:5;
x2=x1;
[X,Y]=meshgrid(x1,x2);
Z=(Y+X-3).^2+2*(Y-X+1).^2;
plot3(X,Y,Z)
hold on
plot3(2,1,0,'rx')
```



Visually it gives us the the same solution:

$$x^* = \begin{pmatrix} 2 \\ 1 \end{pmatrix} \text{ works.}$$

And it reaches a minimum $f(x^*) = 0$

Part 2.

2.1.

I want to solve this problem:

$$\begin{aligned} \min_x f(x) &= x^4 + 4x^3 + 9x^2 + 6x + 6 \\ \text{s.t. } x &\in [-2, 2] \end{aligned}$$

So I write 2 Matlab scripts.

The first, [*fgolden.m*](#), defines the cost function:

```
function [y] = fgolden(x)
y = (x^4)+4*(x^3)+9*(x^2)+6*x+6
```

The second, [*Goldensection part2 2 1*](#), use Golden section method with a tolerance $\varepsilon = 10^{-2}$.

```
a0=-2;
b0=2;
ro=(3-sqrt(5))/2;
e=b0-a0;
while e>(10^(-2))
    a1= ro*(b0-a0)+a0;
    b1= ro*(b0-a1)+a1;
    y=fgolden(b1);
    yb=y;
    y=fgolden(a1);
    ya=y;
```

```

if yb>ya
    b0=b1;
else
    a0=a1;
end
e=b0-a0
end
fprintf('a1 = %.2f\n',a1);

```

So it gives me this result:

$$x^* = -0.45 \text{ with a precision of } e = 0.0077$$

2.2.

2.2.1.

I want to solve this problem with 2 different methods:

$$\min_x f(x) = 2x^4 - 5x^3 + 100x^2 + 30x - 75$$

$$\text{s.t. } x \in \mathbb{R}$$

So I write 5 Matlab scripts.

The 3 first ([fnewtsec.m](#), [derivfnewtsec.m](#), [derive2fnewtsec.m](#)) define the cost function and its first derivative and its second derivative:

```

function [y] = fnewtsec(x)
y = 2*(x^4)-5*(x^3)+100*(x^2)+30*x-75
function [y] = derivfnewtsec(x)
y = 8*(x^3)-15*(x^2)+200*x+30
function [y] = derive2fnewtsec(x)
y = 24*(x^2)-30*x+200

```

And the newton methods is then used in this routine [Newton part2 2 1.m](#):

```

x0=2;
y=derivfnewtsec(x0);
e=y;
while e>(10^(-4))
    y=derivfnewtsec(x0);
    df=y;
    y=derive2fnewtsec(x0);
    df2=y;
    xk=x0-df/df2;
    y=derivfnewtsec(xk);
    e=y;
    x0=xk;
end
fprintf('xk = %.2f\n',xk);
y=fnewtsec(xk);

```

Which give me this result:

$$x^* = -0.15$$

$$\text{for } f(x^*) = -77.2279$$

2.2.2

Secondly, the secant method is written in this routine:

```
x0=2;
xm1=2.1;
y=derivefnewtsec(x0);
e=y;
while e>(10^(-4))
    y=derivefnewtsec(x0);
    df=y;
    y=derivefnewtsec(xm1);
    dfm1=y;
    xk=x0-(x0-xm1)/(df-dfm1)*df;
    y=derivefnewtsec(xk);
    e=y;
    xm1=x0;
    x0=xk;
end
fprintf('xk = %.2f\n',xk);
y=fnewtsec(xk);
```

Which give me this result:

$$x^* = -0.15$$

$$\text{for } f(x^*) = -77.2324$$

Remarks: With a difference of 0.01 on the minimum value, we can say that the secant method is good alternative if the function f is not twice differentiable.

Part 3.

3.1.

$$\min_x f(x) = 1 + 2x_1 e^{-x_1^2 - x_2^2}$$

$$\text{s. t. } x \in \mathbb{R}^2$$

$$\nabla f = \begin{pmatrix} 2\exp(-x_1^2 - x_2^2)[1 - 2x_1^2] \\ -4x_2x_1\exp(-x_1^2 - x_2^2) \end{pmatrix}$$

The MATLAB routine to solve this problem is:

```
x1 = x0-alpha(x0(1), x0(2))*[df1(x0(1), x0(2)) df2(x0(1), x0(2))];
ex = abs(df1(x1(1), x1(2))^2 + df2(x1(1), x1(2))^2);
while (ex>=tol)
    x0 = x1 ;
    x1 = x0-alpha(x0(1), x0(2))*[df1(x0(1), x0(2)) df2(x0(1), x0(2))];
    ex = abs(df1(x1(1), x1(2))^2 + df2(x1(1), x1(2))^2);
end
disp(x1);
```

3.2.

We check that the vector given is a global minimizer of the function.

$$\nabla f = \begin{pmatrix} 202x_1 - 200x_2 - 2 \\ 200x_2^2 - 200x_1 \end{pmatrix}$$

$$\nabla f \begin{pmatrix} 1 \\ 1 \end{pmatrix} = 0$$

$$D^2 f(x) = \begin{pmatrix} 202 & -200 \\ -200 & 400x_2 \end{pmatrix}$$

$$D^2 f \begin{pmatrix} 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 202 & -200 \\ -200 & 400 \end{pmatrix}$$

The eigenvalues are $x_1 \approx 524$ $x_2 \approx 77$

which are both >0 .

The SOSC are satisfied, so it is a global minimizer.

Is it the only one ?

Let $a, b \in \mathbb{R}$, if (a, b) is a minimizer, we have to solve :

$$202a - 200b - 2 = 0 \text{ and } 200b^2 - 200a = 0$$

so $b = 1$ and $a = 1$ OR $b = -\frac{1}{101}$ and $a = b^2$

but $f \begin{pmatrix} a \\ b \end{pmatrix} \approx 1 > 0$

So, $\begin{pmatrix} 1 \\ 1 \end{pmatrix}$ is the only global minimizer of the function f .

3.3.

We calculate the conditions numbers of the different Q given. The smaller this number is, the faster the algorithm converges.

We found that $Q = \lambda I$ is the case that converges faster (the condition number is equal to 1).

Then, the case $Q = \begin{pmatrix} 2 & 0 \\ 0 & 1 \end{pmatrix}$ (the condition number is equal to 2).

Finally, the case $Q = \begin{pmatrix} 10 & 0 \\ 0 & 1 \end{pmatrix}$ is the slowest (the condition number is equal to 10).