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Tutorial: No tutorial on February 14. If you have questions, contact Markus directly.

1 a) Find the global minima (in $\mathbb{R}^{2}$ ) of the function

$$
\begin{equation*}
f(x, y)=2 x^{2}+y^{2}-2 x y-2 x^{3}+x^{4} . \tag{1}
\end{equation*}
$$

List the general results you are using.

## Solution:

We compute $\nabla f$ and $\nabla^{2} f$ :

$$
\begin{aligned}
\nabla f(x, y) & =\left[\begin{array}{c}
4 x-2 y-6 x^{2}+4 x^{3} \\
2 y-2 x
\end{array}\right], \\
\nabla^{2} f(x, y) & =\left[\begin{array}{cr}
4-12 x+12 x^{2} & -2 \\
-2 & 2
\end{array}\right] .
\end{aligned}
$$

The candidate points will be solutions of

$$
y=x, \quad 4 x-6 x^{2}+4 x^{3}=2 y
$$

which are easily seen to be

$$
\begin{aligned}
& x_{(1)}=(0,0)^{\mathrm{T}}, \\
& x_{(2)}=\left(\frac{1}{2}, \frac{1}{2}\right)^{\mathrm{T}}, \\
& x_{(3)}=(1,1)^{\mathrm{T}} .
\end{aligned}
$$

Now,

$$
\begin{aligned}
\nabla^{2} f(0,0) & =\left[\begin{array}{rr}
4 & -2 \\
-2 & 2
\end{array}\right]>0 \\
\nabla^{2} f\left(\frac{1}{2}, \frac{1}{2}\right) & =\left[\begin{array}{rr}
1 & -2 \\
-2 & 2
\end{array}\right], \text { indefinite, } \\
\nabla^{2} f(1,1) & =\left[\begin{array}{rr}
4 & -2 \\
-2 & 2
\end{array}\right]>0
\end{aligned}
$$

Thus, only $(0,0)^{\mathrm{T}}$ and $(1,1)^{\mathrm{T}}$ are minima, and both are strict since the Hessian is positive definite. The point in the middle is a saddle point. The function values in both minima are equal to 0 , so they are both global.

The problem may also be solved by the following trick:

$$
f(x, y)=2 x^{2}+y^{2}-2 x y-2 x^{3}+x^{4}=(x-y)^{2}+\left(x-x^{2}\right)^{2}
$$

Thus, the global minimum is 0 , which is obtained for $x=x^{2}, y=x$, i.e. $(0,0)^{\mathrm{T}}$ and $(1,1)^{\mathrm{T}}$.
b) Estimate the drop in the error per iteration (expressed in terms of the appropriate norm) of the steepest descent method near the global minima in a).

Solution: If we denote the Hessian near the global minima by $A$, the error estimate is given by

$$
\frac{\left\|x_{k+1}-x^{*}\right\|_{A}}{\left\|x_{k}-x^{*}\right\|_{A}} \leq \frac{\kappa(A)-1}{\kappa(A)+1}
$$

The Hessians at $(0,0)^{\mathrm{T}}$ and $(1,1)^{\mathrm{T}}$ are the same,

$$
A=\left[\begin{array}{rr}
4 & -2 \\
-2 & 2
\end{array}\right]
$$

with eigenvalues $\lambda_{1}=3+\sqrt{5}$ and $\lambda_{2}=3-\sqrt{5}$. Hence $\kappa(A)=(3+\sqrt{5}) /(3-$ $\sqrt{5}) \approx 6.8541$, and

$$
\frac{\left\|x_{k+1}-x^{*}\right\|_{A}}{\left\|x_{k}-x^{*}\right\|_{A}} \leq \frac{\kappa(A)-1}{\kappa(A)+1} \approx 0.745
$$

that is, about a 25\% decrease per iteration.

2 When it is easy to compute first and second derivatives of a one-dimensional function (that is, $x \in \mathbb{R}$ and $f(x) \in \mathbb{R}$ ), it is possible to combine a trust region algorithm with Newton's method for finding the minimum. Outline an algorithm for this.
Hint: First derive a quadratic approximation to the function. Show that minimizing this function corresponds to the Newton step, plus an investigation involving the endpoints of the domain.
Solution: We start at a point $x_{k}$ and have now an interval on the real line as the trust region,

$$
D_{k}=\left[x_{k}-\Delta_{k}, x_{k}+\Delta_{k}\right] .
$$

The quadratic approximation is the simple parabola

$$
m_{k}(x)=f\left(x_{k}\right)+f^{\prime}\left(x_{k}\right)\left(x-x_{k}\right)+\frac{1}{2} f^{\prime \prime}\left(x_{k}\right)\left(x-x_{k}\right)^{2}
$$

and solving

$$
x_{k+1}=\underset{x \in D_{k}}{\arg \min } m_{k}(x)
$$

means finding the minimum of the parabola within the interval $D_{k}$. Clearly, the global minimum of $m_{k}(x)$ is given by

$$
f^{\prime}\left(x_{k}\right)+f^{\prime \prime}\left(x_{k}\right)\left(x_{g}-x_{k}\right)=0
$$

corresponding to the Newton step,

$$
x_{g}=x_{k}-\frac{1}{f^{\prime \prime}\left(x_{k}\right)} f^{\prime}\left(x_{k}\right)
$$

Thus, $x_{k+1}$ may be equal to $x_{g}$ or being one of the endpoints.
The rest of the algorithm is as before, starting by considering the actual vs. the predicted decrease

$$
\rho=\frac{f\left(x_{k}\right)-f\left(x_{k+1}\right)}{f\left(x_{k}\right)-m_{k}\left(x_{k+1}\right)} .
$$

We increase $\Delta$ if $\rho>\beta$ and shrink $\Delta$ if $\rho<\alpha, 0<\alpha<\beta<1$. It may be reasonable to let $x_{k+1}=x_{k}$ when $\rho$ is very small, at least when $\rho<0$.

3 Solve the following problems by use of the trust region method, using the file trustdemo.m which can be found on the lecture plan.
Try using the Cauchy point, the dogleg method as well as the exact solution of the TR problem.

$$
\begin{align*}
& f(x)=x_{1}^{2}-5 x_{1} x_{2}+x_{2}^{4}-25 x_{1}-8 x_{2}  \tag{2}\\
& f(x)=100\left(x_{2}-x_{1}^{2}\right)^{2}+\left(1-x_{1}\right)^{2}  \tag{3}\\
& f(x)=e^{x_{1}}\left(4 x_{1}^{2}+2 x_{2}^{2}+4 x_{1} x_{2}+2 x_{2}+1\right) \tag{4}
\end{align*}
$$

Compare these methods with the ones you tried in Exercise 2.

Solution: You just have to modify the file. I think this is self-explanatory.

