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## Solutions to exercise set 4

11 As seen in the previous exercise sheet, a strongly-convex twice-differentiable function satisfies

$$
p^{T} \nabla^{2} f(x) p \geq \sigma\|p\|^{2} \quad \forall p \in \mathbb{R}^{n} .
$$

We have that by Taylor's theorem

$$
\nabla f\left(x_{k+1}\right)=\nabla f\left(x_{k}\right)+\int_{0}^{1}\left[\nabla^{2} f\left(x_{k}+t \alpha_{k} p_{k}\right) \alpha_{k} p_{k}\right] d t .
$$

This implies that

$$
\begin{aligned}
\alpha_{k} p_{k}^{T} y_{k} & =\alpha_{k} p_{k}^{T}\left[\nabla f_{k+1}-\nabla f_{k}\right] \\
& =\alpha_{k}^{2} \int_{0}^{1}\left[p_{k}^{T} \nabla^{2} f\left(x_{k}+t \alpha_{k} p_{k}\right) p_{k}\right] d t \geq \\
\geq \sigma \alpha_{k}^{2}\left\|p_{k}\right\|^{2}>0 . &
\end{aligned}
$$

We can hence conclude noticing that $\alpha_{k} p_{k}=s_{k}$ and hence $s_{k}^{T} y_{k}>0$.

2 The second strong Wolfe condition implies that

$$
\left.\nabla f\left(x_{k}+\alpha_{k} p_{k}\right)^{T} p_{k} \geq-c_{2} \mid \nabla f\left(x_{k}\right)^{T} p_{k}\right) \mid=c_{2} \nabla f\left(x_{k}\right)^{T} p_{k}
$$

if we recall that $p_{k}$ is a descent direction. Thus

$$
\begin{aligned}
s_{k}^{T} y_{k} & =\alpha_{k} p_{k}^{T}\left(\nabla f_{k+1}-\nabla f_{k}\right)=\alpha_{k} p_{k}^{T}\left(\nabla f\left(x_{k}+\alpha_{k} p_{k}\right)-\nabla f\left(x_{k}\right)\right) \geq \\
& \geq \alpha_{k} p_{k}^{T}\left(c_{2} \nabla f\left(x_{k}\right)-\nabla f\left(x_{k}\right)\right)=\alpha_{k}\left(c_{2}-1\right) p_{k}^{T} \nabla f\left(x_{k}\right)>0
\end{aligned}
$$

since $c_{2}-1<0$ and so is $p_{k}^{T} \nabla f\left(x_{k}\right)$. This means that the curvature condition holds.

3 When dealing with one-dimensional functions, all gradients and hessians become just scalar function. Recall that we always set $\alpha_{k}=1$ in this exercise. The iteration of BFGS and of DFP method hence write

$$
\begin{gathered}
x_{k+1}=x_{k}-H_{k}^{B F G S} f^{\prime}\left(x_{k}\right), \\
x_{k+1}=x_{k}-H_{k}^{D F P} f^{\prime}\left(x_{k}\right) .
\end{gathered}
$$

For BFGS method we have that called $\rho_{k}=1 /\left(s_{k} y_{k}\right)$,

$$
H_{k+1}^{B F G S}=\left(1-\rho_{k} s_{k} y_{k}\right) H_{k}^{B F G S}\left(1-\rho_{k} y_{k} s_{k}\right)+\rho_{k} s_{k}^{2}=\frac{s_{k}}{y_{k}}=\frac{x_{k+1}-x_{k}}{f^{\prime}\left(x_{k+1}\right)-f^{\prime}\left(x_{k}\right)}
$$

since $1-\rho_{k} s_{k} y_{k}=0$. This gives exactly the update rule of the secant method. For DFP method we have (see equation 6.15 Nocedal and Wright)

$$
H_{k+1}^{D F P}=H_{k}^{D F P}-\frac{H_{k}^{D F P} y_{k} y_{k} H_{k}^{D F P}}{y_{k} H_{k}^{D F P} y_{k}}+\frac{s_{k}^{2}}{s_{k} y_{k}}=\frac{s_{k}}{y_{k}}=\frac{x_{k+1}-x_{k}}{f^{\prime}\left(x_{k+1}\right)-f^{\prime}\left(x_{k}\right)}
$$

that gives the same expression of the secant method.

4 You can find an implementation to solve this exercise here https://github.com/ davidemurari/TMA4180_2022/tree/main/ExSheet4

