# Numerical Optimization

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### Homework 3

Exercise 3.1 (a) [3 points] Given  $c_1 \in (0,1)$ , prove that for any smooth function  $f: \mathbb{R}^n \to \mathbb{R}$ , point  $\mathbf{x} \in \mathbb{R}^n$  and a decent direction  $\mathbf{p} \in \mathbb{R}^n$  at that point, there is an interval for  $\alpha > 0$  such that the Armijo(or sufficient decrease) condition

$$f(\mathbf{x} + \alpha \mathbf{p}) \le f(\mathbf{x}) + c_1 \alpha [\nabla f(\mathbf{x})]^{\top} \mathbf{p}$$

holds. (This condition guarantees that f is actually reduced by the doing the step  $\alpha \mathbf{p}$ . It excludes too long steps: Sufficiently small  $\alpha$  would always satisfy this condition.)

## Solution:

Let  $\phi(\alpha) = f(\mathbf{x} + \alpha \mathbf{p})$  and  $l(\alpha) = f(\mathbf{x}) + c_1 \alpha [\nabla f(\mathbf{x})]^{\top} \mathbf{p}$ . Since  $\phi(0) = l(0)$ ,  $\phi'(0) = [\nabla f(\mathbf{x})]^{\top} \mathbf{p} < c_1 [\nabla f(\mathbf{x})]^{\top} \mathbf{p} = l'(0)$ ,  $\phi(\alpha)$  is bounded below and  $l(\alpha)$  is unbounded below, there is a first intersection point  $\alpha_0$  that  $f(\mathbf{x} + \alpha_0 \mathbf{p}) = f(\mathbf{x}) + c_1 \alpha_0 [\nabla f(\mathbf{x})]^{\top} \mathbf{p}$ . When  $0 < \alpha \le \alpha_0$ ,

$$\phi(\alpha) = f(\mathbf{x} + \alpha \mathbf{p}) \le l(\alpha) = f(\mathbf{x}) + c_1 \alpha \left[\nabla f(\mathbf{x})\right]^{\top} \mathbf{p}$$

(b) [1 point] Consider

$$f(x,y) := 5x^2 + 5y^2 - 6xy + 10x + 6y + 5 \rightarrow \min, \quad \mathbf{x} := (x,y) \in \mathbb{R}^2$$

 $\mathbf{x} = (0,0)^{\mathsf{T}}, \mathbf{p} = -\nabla f(\mathbf{x})$  and  $c_1 = 0.01$ . Find largest possible interval where the Armijo condition holds.

Solution:

$$\mathbf{x} = (0,0)^{\top}, \mathbf{p} = -\nabla f(\mathbf{x}) = -\begin{pmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{pmatrix} = -\begin{pmatrix} 10 \\ 6 \end{pmatrix}$$
, Armijo condition is:

$$500\alpha^2 + 180\alpha^2 - 360\alpha^2 - 100\alpha - 36\alpha + 5 \le 5 - 0.01(100 + 36)\alpha$$

So  $0 < \alpha \le 0.42925$ 

**Exercise 3.2** (a) [3 points] Given  $c_2 \in (c_1, 1)$ , prove that for any smooth function  $f : \mathbb{R}^n \to \mathbb{R}$ , point  $\mathbf{x} \in \mathbb{R}^n$  and a decent direction  $\mathbf{p} \in \mathbb{R}^n$  at that point, there is an interval for  $\alpha > 0$  such that the curvature condition

$$[\nabla f(\mathbf{x} + \alpha \mathbf{p})]^{\top} \mathbf{p} \ge c_2 [\nabla f(\mathbf{x})]^{\top} \mathbf{p}$$

holds. (This condition excludes too short steps so that the steps do not deteriorate during the iteration.)

#### Solution:

From Exercise 3.1, we got  $\alpha_0$  such that

$$f(\mathbf{x} + \alpha_0 \mathbf{p}) = f(\mathbf{x}) + c_1 \alpha_0 \left[ \nabla f(\mathbf{x}) \right]^{\top} \mathbf{p}$$

By the mean value theorem, there exists  $\alpha_1 \in (0, \alpha_0)$  such that

$$f(\mathbf{x} + \alpha_0 \mathbf{p}) - f(\mathbf{x}) = \alpha_0 \left[ \nabla f(\mathbf{x} + \alpha_1 \mathbf{p}) \right]^{\mathsf{T}} \mathbf{p}$$

By combining these two equations, we have

$$\left[\nabla f\left(\mathbf{x} + \alpha_{1}\mathbf{p}\right)\right]^{\top}\mathbf{p} = c_{1}\left[\nabla f\left(\mathbf{x}\right)\right]^{\top}\mathbf{p} > c_{2}\left[\nabla f\left(\mathbf{x}\right)\right]^{\top}\mathbf{p}$$

Since the continuity of  $\nabla f(\mathbf{x})$  there exist a  $\delta$ , when  $\alpha \in U(\alpha_1, \delta)$ ,

$$\left[\nabla f\left(\mathbf{x} + \alpha \mathbf{p}\right)\right]^{\top} \mathbf{p} \ge c_2 \left[\nabla f\left(\mathbf{x}\right)\right]^{\top} \mathbf{p}$$

(b) [1 point] Consider f(x, y) from Exercise 3.1(b),  $\mathbf{x} = (0, 0)^{\top}$ ,  $\mathbf{p} = -\nabla f(\mathbf{x})$  and  $c_2 = 0.9$ . Find largest possible interval where the curvature condition holds.

Solution:

From the curvature condition:

$$\left[\nabla f\left(\mathbf{x} + \alpha \mathbf{p}\right)\right]^{\top} \mathbf{p} \ge c_2 \left[\nabla f\left(\mathbf{x}\right)\right]^{\top} \mathbf{p}$$

We have:

$$-\begin{pmatrix} -64\alpha + 10 \\ 6 \end{pmatrix}^{\top} \begin{pmatrix} 10 \\ 6 \end{pmatrix} \ge -0.9 \begin{pmatrix} 10 \\ 6 \end{pmatrix}^{\top} \begin{pmatrix} 10 \\ 6 \end{pmatrix}$$

So  $\alpha \ge 0.02125$ 

**Exercise 3.3** (a) [4 points] Reimplement your code from Exercise 2.3(b) (the gradient method) for the same quadratic function f(x, y) with the following backtracking linesearch strategy: In the k-th iteration, having  $\mathbf{x}_{k}$  and  $\mathbf{p}_{k}$  compute successively

$$\mathbf{x}_{k+1}^{(i)} = \mathbf{x}_k + s_k^{(i)} \mathbf{p}_k, \quad i = 0, \dots, n_{ls}$$

with  $s_k^{(i)} = 2^{-i}$  (i.e.  $s_k^{(0)} = 1, s_k^{(i+1)} = \frac{1}{2}s_k^{(i)}$  - backtracking). Choose the smallest  $i =: i^*$  for which the sufficient descent is achieved:

 $f\left(\mathbf{x}_{k} + s_{k}^{(i)}\mathbf{p}_{k}\right) \leq f\left(\mathbf{x}_{k}\right) + \sigma s_{k}^{(i)}\left[\nabla f\left(\mathbf{x}_{k}\right)\right]^{\top}\mathbf{p}_{k}.$ 

(If this condition does not hold for any  $i=0,\ldots,n_{\rm ls}$ , take  $i^*=n_{\rm ls}$ .) Then set  $\mathbf{x}_{k+1}=\mathbf{x}_k+s_k^{(i^*)}\mathbf{p}_k$ . Use the parameters  $n_{\rm ls}=8$  and  $\sigma=10^{-3}$ . Start with  $\mathbf{x}_0=(1,0.2)^{\top}$  and compute  $\mathbf{x}_1,\ldots,\mathbf{x}_5$ . After every iteration k as well as for the initial guess (k=0), print  $\mathbf{x}_k, f(\mathbf{x}_k), \|\nabla f(\mathbf{x}_k)\|_2$  as well as  $\|\mathbf{e}_k\|_2$  for  $\mathbf{e}_k:=\mathbf{x}_k-\mathbf{x}_*$ . For  $k\geq 1$ , print also  $\rho_k:=\|\mathbf{e}_k\|_2/\|\mathbf{e}_{k-1}\|_2$ .

Solution:

The output of the program is shown in Figure 1 and 2.

(b) [2 points] Extend the method implemented in Exercise 3.3(a) with the following termination criterion: Compute  $\mathbf{x}_1, \dots, \mathbf{x}_K$  until  $\|\nabla f(\mathbf{x}_k)\|_2 \le \epsilon = 10^{-8}$  but stop after at most  $K_{\text{max}} = 50$  iterations.

Solution:

The output of the program is shown in Figure 3.

Exercise 3.4 [2 points] Characterize the type of the convergence of the coordinate and gradient methods in Exercise 2.3: Is it linear, superlinear or quadratic? Explain why. Solution:

$$f(x,y) = \left(\begin{array}{cc} x \\ y \end{array}\right)^\top \left(\begin{array}{cc} 5 & -3 \\ -3 & 5 \end{array}\right) \left(\begin{array}{c} x \\ y \end{array}\right) + \left(\begin{array}{c} 10 \\ 6 \end{array}\right)^\top \left(\begin{array}{c} x \\ y \end{array}\right) + 5$$

 $Q = \begin{pmatrix} 5 & -3 \\ -3 & 5 \end{pmatrix}$ , the eigenvalues of Q are 8 and 2. For exact line search, we have

$$\|x_{k+1} - x^*\|_Q^2 \le \left(\frac{\lambda_n - \lambda_1}{\lambda_n + \lambda_1}\right)^2 \|x_k - x^*\|_Q^2 = 0.36 \|x_k - x^*\|_Q^2$$

So it's linear.

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Microsoft Visual Studio Debug Console
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                              _ 🗆 🗆 X
Initial guess x0=1
y0=0.2
x(0]= 1 0.2
f(0]= 20.2
df2[0]=18.9061
e2[0]=3.75117
x(1]= -1.35 -0.05
f[1]= -0.08
df2[1]=1.98274
rho[1]= 0.528566
x(2]= -0.95 -1.75
f[2]= -5.15
df2[2]=12.4354
e2[2]=1.18163
rho[2]= 0.595959
x(3]= -2.325 -1.025
f[3]= -6.4175
df2[3]=12.0208
e2[3]=0.873212
rho[3]= 0.79899
x(4]= -1.4375 -2.2375
f[4]= -6.73437
df2[4]=0.772215
rho[4]= 0.89064
x(5]= -2.56875 -1.26875
df3[5]= -6.81359
df2[5]=0.751301
rho[5]= 0.96658
x(6]= -1.55938 -2.35938
f[6]= -6.8334
df2[6]=11.8816
e2[6]=0.744682
rho[6]= 0.99119
x(7]= -2.09453 -1.84453
f[7]= -11.2463
df2[7]=0.172357
e2[7]=0.0430893
rho[7]= 0.0578627
x[8]= -2.125 -1.875
f[8]= -1.25
df2[8]=0
e2[8]=6.28037e-16
rho[8]= 1.45752e-14
x(9]= -2.125 -1.875
f[9]= -11.25
df2[9]=0
e2[9]=6.28037e-16
rho[9]=1
x[10]= -2.125 -1.875
f[10]= -11.25
df2[11]=0
e2[11]=6.28037e-16
rho[10]=1
x[11]= -2.125 -1.875
f[11]= -11.25
df2[11]=0
e2[11]=6.28037e-16
rho[10]=1
x[11]= -2.125 -1.875
f[11]= -11.25
df2[11]=0
e2[11]=6.28037e-16
rho[10]=1
x[11]= -2.125 -1.875
f[11]= -11.25
df2[11]=0
e2[11]=6.28037e-16
rho[10]=1
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Figure 1: The output of backtracking linesearch(step 1 to 11)

Figure 2: The output of backtracking linesearch(step 11 to 20)

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Initial guess
x0-1
y0-0.2
x[0]= 1 0.2
x[0]= 20.2
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Figure 3: The output of backtracking linesearch(step 1 to 8)