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Nonlinear Optimization Problems

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1 Sheet 6

1.1 Exercise 35

Let $M \in \mathbb{R}^{n \times n}$ with ||M|| < 1. Show that I - M is regular and

$$\|(I-M)\| \le \frac{1}{1-\|M\|}.$$
 (1)

Suppose I-M is not singular then for $x \in \mathbb{R}^n$ we have that

$$(I - M)x = 0 (2)$$

$$\Leftrightarrow Ix - Mx = 0 \tag{3}$$

$$\Leftrightarrow Mx = x. \tag{4}$$

But since ||M|| < 1 then $\forall x \in \mathbb{R}^n$ we have that ||Mx|| < ||x||. This means that

$$\ker\left(I - M\right) = \emptyset,\tag{5}$$

so I-M is regular. The identity on the other hand is derived by the following observation

$$(I-M)^{-1} - (I-M)^{-1}M = (I-M)(I-M)^{-1} = I,$$
(6)

Then we calculate

$$\|(I-M)^{-1}\| = \|I + (I-M)^{-1}M\|$$
 (7)

$$\leq ||I|| + ||(I - M)^{-1}|||M||, \tag{8}$$

rearranging gives

$$\|(I - M)^{-1}\| - \|(I - M)^{-1}\| \le \|I\| \tag{9}$$

$$\|(I-M)^{-1}\| (1-\|M\|) \le 1 \tag{10}$$

$$\|(I-M)^{-1}\| \le \frac{1}{1-\|M\|}.$$
 (11)

Now let $A, B \in \mathbb{R}^{n \times n}$ with ||I - BA|| < 1. Show that A and B are regular and that

$$||B^{-1}|| \le \frac{||A||}{1 - ||I - BA||} \tag{12}$$

$$||A^{-1}|| \le \frac{||B||}{1 - ||I - BA||} \tag{13}$$

(14)

We know that for $M \in \mathbb{R}^{n \times n}$ with ||M|| < 1 then I - M is regular and the inequality in 1 holds. Set M = I - BA then I - M = AB is regular. Because AB is regular so is A and B. Now note that for all regular matrices we have that $||A^{-1}|| \le ||A||^{-1}$. Furthermore

$$\|(AB)^{-1}\| \le \|B^{-1}\| \|A^{-1}\|. \tag{15}$$

Then for A we have

$$||A^{-1}|| \le \frac{1}{||B^{-1}||} \frac{1}{1 - ||I - BA||} \le \frac{||B||}{1 - ||I - BA||}.$$
 (16)

and for B

$$||B^{-1}|| \le \frac{1}{||A^{-1}||} \frac{1}{1 - ||I - BA||} \le \frac{||A||}{1 - ||I - BA||}.$$
 (17)

1.2 Exercise 36

Let $f: \mathbb{R}^2 \to \mathbb{R}$, $f(x,y) = x^4 + 2x^2y^2 + y^4$. Show that the local Newton algorithm converges to the unique global minimum of f for every $(x^0,y^0) \in \mathbb{R}^2 \setminus \{(0,0)^T\}$. First we determine the minimum x^* . Note that $f(x,y) = (x^2 + y^2)^2 \ge 0$ for all $(x,y)^T \in \mathbb{R}^2$. Since f is strongly convex the only minimum, which is the global minimum is $(x,y)^T = (0,0)^T$. The Hessian of f is

$$\nabla^2 f(x,y) = \begin{pmatrix} 12x^2 + 4y^2 & 8xy \\ 8xy & 12y^2 + 4x^2 \end{pmatrix}. \tag{18}$$

Now note that the Hessian at the minimum $\nabla^2 f(0,0)$ is the zero matrix which is singular. But considering starting vectors $(x,y)^T \neq (0,0)^T$, all we need in the local Newton algorithm is the solution to the equation $\nabla^2 f(x^k) d_k = -\nabla f(x^k)$. Meaning we need to show that $\nabla^2 f(x,y)$ is regular for all $(x,y)^T \neq (0,0)^T$, in this case we look at the determinant of the Hessian

$$\det(\nabla^2 f(x,y)) = 48 * (x^2 + y^2)^2 > 0 \ \forall (x,y)^T \neq (0,0)^T.$$
 (19)

This means that the sequence $(x^k)_{k\geq 0}$ produced by the local newton algorithm converges to the unique global minimum of f given by $(0,0)^T$. Indeed if we calculate the solution of the system $\nabla^2 f(x,y)d = -\nabla f(x,y)$ we get that $d = (\frac{x}{3}, \frac{y}{3})^T$.

1.3 Exercise 37

Show that the local Newton Algorithm is invariant to affine-linear transformation, for a regular matrix $A \in \mathbb{R}^{n \times n}$ and $c \in \mathbb{R}^n$, $(x^k)_{k \geq 0}$ the sequence generated by the local Newton algorithm for minimizing f with starting vector x^0 . Then let $(y^k)_{k \geq 0}$ the sequence generated by the local Newton algorithm for the function g(y) := f(Ay + c) with starting vector y^0 , then

$$x^{0} = Ay^{0} + c \implies x^{k} = Ay^{k} + c \quad \forall k \ge 0.$$
 (20)

First of all we calculate the gradient and the hessian for g

$$\nabla g(y) = \nabla f(Ay + c) = A^T \nabla f(Ay + c) \tag{21}$$

$$\nabla^2 g(y) = \nabla^2 f(Ay + c) = A^T \nabla^2 f(Ay + c) A \tag{22}$$

(23)

Now we need to prove that $x^{k+1} = Ay^{k+1} + c$

$$x^{k+1}q = x^k + d_k = x^k - (\nabla^2 f(x^k))^{-1} \nabla f(x_k)$$
(24)

$$= Ay^{k} + c - (\nabla^{2}(f(Ay^{k} + c))^{-1} \nabla f(Ay^{k} + c)$$
(25)

$$= Ay^{k} + c - AA^{-1} \left(\nabla^{2} (f(Ay^{k} + c))^{-1} \nabla f(Ay^{k} + c) \right)$$
 (26)

$$= Ay^{k} + c - AA^{-1}A^{T}A^{-T} \left(\nabla^{2}(f(Ay^{k} + c))^{-1} \nabla f(Ay^{k} + c)\right)$$
(27)

$$= A\left(y^k - \left(A^T \nabla^2 f(Ay^k + c)A\right)^{-1} A^T \nabla f(Ay^k + c)\right) + c \tag{28}$$

$$=Ay^{k+1}+c. (29)$$

by that the induction is finished.

1.4 Exercise 38

Let $M \in \mathbb{R}^{n \times n}$ be a regular matrix and $\{M\}_{k \geq 0} \in \mathbb{R}^{n \times n}$ a sequence of matrices which converge to M as $k \to \infty$. Sow that there exists a $k_0 \geq 0$ such that M_k is regular for all $k \geq k_0$ and the sequence $\{M_k^{-1}\}_{k \geq 0}$ converges to M^{-1} .

The map $M \to M^{-1}$ is a continuous invertible meaning it is monotone. $M^{-1} = \frac{\operatorname{adj}(M)}{\det(M)}$. Then convergence means that there is a $k \geq k_0$ such that for all $M_k \in B_{\frac{1}{k}}(M)$ we have that $\|M_k - M\| < \frac{1}{k}$ then M_k is sufficiently close to M and so regular. Since $\{M_k\}_{k \geq k_0} \cup M$ is a compact set of invertible matrices so is $\{M_k^{-1}\}_{k \geq k_0} \cup M^{-1}$, meaning it is bounded. This means that $\{M_k^{-1}\}_{k \geq k_0}$ converges to M^{-1} .

1.5 Exercise 39

Let $H \in \mathbb{R}^{n \times n}$ be regular $u, v \in \mathbb{R}^n$ arbitrary. Show that $H + uv^T$ regular $\Leftrightarrow 1 + v^T H^{-1} u \neq 0$, then the Sherman-Morrison formula holds

$$(H + uv^{T})^{-1} = \left(I - \frac{1}{1 - v^{T}H^{-1}u}H^{-1}uv^{T}\right)H^{-1}$$
(30)

Let $1 + v^T H^{-1} u = 0$ then

$$\det(H + uv^T) = (1 + v^T H^{-1}u)\det(H) = 0.$$
(31)

This means that H is not invertible. Now we need to check if the inverse really holds which is done by simply multiplying

$$(H + uv^{T})\left(H^{-1} - \frac{H^{-1}uv^{T}H^{-1}}{1 + v^{T}H^{-1}u}\right) =$$
(32)

$$= HH^{-1} + uv^{T}H^{-1} - H\frac{H^{-1}uv^{T}H^{-1}}{1 + v^{T}H^{-1}u}uv^{T}\frac{H^{-1}uv^{T}H^{-1}}{1 + v^{T}H^{-1}u}$$

$$(33)$$

$$= I + uv^{T}H^{-1} - \frac{uv^{T}H^{-1} + uv^{T}H^{-1}uv^{T}H^{-1}}{1 + v^{T}H^{-1}u}$$
(34)

$$= I + uv^{T}H^{-1} - \frac{u\left(1 + v^{T}H^{-1}u\right)v^{T}H^{-1}}{1 + v^{T}H^{-1}u}$$
(35)

$$= I + uv^T H^{-1} - uv^T H^{-1} (36)$$

$$=I\tag{37}$$

Since these are square matrices AB = I is the same as BA = I.

1.6 Exercise 40

Consider the quadratic optimization problem

min
$$f(x) := \gamma + c^T x + \frac{1}{2} x^T Q x,$$
 (38)
s.t $h(x) := b^T x = 0,$

with $Q \in \mathbb{R}^{n \times n}$ SPD, $b, c \in \mathbb{R}^n$, $b \neq 0$ and $\gamma \in \mathbb{R}$. For a given $\alpha > 0$ find the minimum $x^*(\alpha)$ of the penalty function

$$P(x;\alpha) := f(x) + \frac{\alpha}{2} \left(h(x) \right)^2 \tag{39}$$

determine $x^* := \lim_{\alpha \to \infty} x^*(\alpha)$ and prove that x^* is a unique optimal solution of the optimization problem in 38. We start with calculating the minimum of $P(x(\alpha))$

$$\nabla P(x(\alpha)) = \nabla f(x) + \frac{\alpha}{2} \nabla h(x)^2$$
(40)

$$= c + Qx + \frac{\alpha}{2} 2h(x)\nabla h(x) \tag{41}$$

$$= c + Qx + \alpha b^T x b = 0 (42)$$

$$Qx + \alpha bb^T x = -c \tag{43}$$

$$(Q + \alpha bb^T) x = -c. (44)$$

Using the Sherman-Morrison formula in 30 for $H=Q, u=\alpha b$ and v=b we get

$$x^*(\alpha) = \left(\frac{\alpha}{1 + \alpha b^T Q^{-1} b} Q^{-1} b b^T - I\right) Q^{-1} c \tag{45}$$

The limit is then (the standard limit $\frac{x}{1+kx} \to \frac{1}{k}$ as x goes to infinity)

$$x^* = \lim_{\alpha \to \infty} x^*(\alpha) \tag{46}$$

$$= \left(\frac{Q^{-1}bb^T}{b^TQ^{-1}b} - I\right)Q^{-1}c. \tag{47}$$

To show that x^* is a unique solution of the optimization problem 38 we need to show that it satisfies the optimality condition and that it is unique. Now it is unique because Q is SPD meaning it is regular and invertible and $\nabla^2 f = Q > 0$. Further more (x^*, α) is a KKT point of $P(x, \alpha)$ then x^* is a minumum of the optimization problem. Now we show that $b^T x^* = 0$:

$$b^{T}x^{*} = \left(\frac{b^{T}Q^{-1}bb^{T}Q^{-1}}{b^{T}Q^{-1}b} - b^{T}Q^{-1}\right)c \tag{48}$$

$$= \left(b^T Q - b^T Q\right) c \tag{49}$$

$$=0. (50)$$