Coursework 2

IMPERIAL COLLEGE LONDON

DEPARTMENT OF COMPUTING

477 - Computational Optimisation

Coursework 2

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1 Part 1

1.1 Q.1

a) To show that Δx_k is descent direction at x_k , we need to show that:

$$\nabla f(x_k)^{\top} \Delta x_k < 0 \tag{1}$$

(2)

Since:

$$\nabla^2 f(x_k) \Delta x_k = -\nabla f(x_k) \tag{3}$$

(4)

We can get:

$$\nabla f(x_k)^{\top} \Delta x_k = -\nabla f(x_k)^{\top} \frac{\nabla f(x_k)}{\nabla^2 f(x_k)}$$
(5)

$$= -\frac{\nabla f(x_k)^{\top} \nabla f(x_k)}{\nabla^2 f(x_k)}$$
 (6)

We can see that this is less than zero since the numerator is positive definite and the same for denominator:

$$\nabla^2 f(x_k) \ge mI \tag{7}$$

b) We can set tolerane to e^{-08} and say that:

$$|f(x_{k+1}) - f(x_k)| < tor \tag{8}$$

$$\|\nabla f(x_k)\|_2 < tor \tag{9}$$

$$||x_{k+1} - x_k||_2 < tor (10)$$

This is to check that the First Order Necessary Condition is satisfied.

- c) Yes, since the function is strongly convex, but the condition is that the initial point x_0 has to be close enough to the optimal point.
- d) First say that:

$$x_{k+1} = x_k + t_k \Delta x_k \tag{11}$$

Then

$$f(x_{k+1}) = f(x_k + t_k \Delta x_k) \tag{12}$$

Now use Taylor expansion to expand the above function into second order:

$$f(x_k + t_k \Delta x_k) \approx f(x_k) + t_k \langle \nabla f(x_k), \Delta x_k \rangle + \frac{1}{2} \nabla^2 f(x_k) ||t_k||_2^2 ||\Delta x_k||_2^2$$
 (13)

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$$\Delta x_k = -\frac{\nabla f(x_k)}{\nabla^2 f(x_k)} \tag{14}$$

$$\langle \nabla f(x_k), \Delta x_k \rangle = -\frac{\|\nabla f(x_k)\|_2^2}{\nabla^2 f(x_k)}$$
 (15)

We need to show that:

$$f(x_k) + t_k \langle \nabla f(x_k), \Delta x_k \rangle + \frac{1}{2} \nabla^2 f(x_k) ||t_k||_2^2 ||\Delta x_k||_2^2 \le f(x_k) + \alpha t_k \langle \nabla f(x_k), \Delta x_k \rangle \rangle \quad (16)$$

$$t_k \langle \nabla f(x_k), \Delta x_k \rangle + \frac{1}{2} \nabla^2 f(x_k) ||t_k||_2^2 ||\Delta x_k||_2^2 \le \alpha t_k \langle \nabla f(x_k), \Delta x_k \rangle \rangle \quad (17)$$

Now let's look at first term fisrt:

$$t_k \langle \nabla f(x_k), \Delta x_k \rangle \rangle \tag{18}$$

Since we have the condition on t_k :

$$t \le -\frac{\langle \nabla f(x_k), \Delta x_k \rangle}{M \|\nabla x_k\|_2^2} \tag{19}$$

$$0 > \langle \nabla f(x_k), \Delta x_k \rangle \rangle t_k > -\langle \nabla f(x_k), \Delta x_k \rangle \rangle^{\top} \frac{\langle \nabla f(x_k), \Delta x_k \rangle}{M \|\nabla x_k\|_2^2}$$
 (20)

$$0 > \langle \nabla f(x_k), \Delta x_k \rangle t_k > -\frac{\|\nabla f(x_k)\|^2 \|\Delta x_k\|^2}{M \|\nabla x_k\|_2^2}$$
 (21)

$$0 > \langle \nabla f(x_k), \Delta x_k \rangle t_k > -\frac{\|\nabla f(x_k)\|^2}{M}$$
 (22)

Now let's take a look at second term:

$$\frac{1}{2}\nabla^2 f(x_k) ||t_k||_2^2 ||\Delta x_k||_2^2$$
 (23)

Again substitute in condition for t:

$$t \le -\frac{\langle \nabla f(x_k), \Delta x_k \rangle}{M \|\nabla x_k\|_2^2}$$
 (24)

$$||t||_{2}^{2} \leq \frac{||\nabla f(x_{k})||^{2}||\Delta x_{k})||^{2}}{M^{\top}M||\nabla x_{k}||_{2}^{4}}$$
(25)

$$||t||_{2}^{2} \le \frac{||\nabla f(x_{k})||^{2}}{\mathbf{M}^{\top} \mathbf{M} ||\nabla x_{k}||_{2}^{2}}$$
(26)

$$||t||_{2}^{2}||\Delta x_{k}||_{2}^{2} \leq \frac{||\nabla f(x_{k})||^{2}}{M^{T}M}$$
(27)

(28)

Since we have the upper bound for $\nabla^2 f(x_k)$:

$$\nabla^2 f(x_k) \le MI \tag{29}$$

$$||t||_{2}^{2}||\Delta x_{k}||_{2}^{2}\nabla^{2}f(x_{k}) \leq \frac{\nabla^{2}f(x_{k})||\nabla f(x_{k})||^{2}}{\mathbf{M}^{\top}\mathbf{M}}$$
(30)

(31)

e)

2 Part 2

2.1 Q.2

a) KKT conditions:

$$min \quad z_1^2 + (x_2 + 1)^2 \tag{32}$$

$$g(x^*) = exp(x_1^*) - x_2^* \le 0$$
(33)

$$\mu^* \ge 0 \tag{34}$$

$$2x_1^* + \mu^* exp(x_1^*) = 0 (35)$$

$$2(x_2^* + 1) + \mu^* * (-1) = 0 (36)$$

$$\mu^*(exp(x_1^*) - x_2^*) = 0 (37)$$

if $\mu^* = 0$:

$$2x_1^* = 0 (38)$$

$$x_1^* = 0 (39)$$

$$2(x_2^* + 1) = 0 (40)$$

$$x_2^* = -1 (41)$$

$$g(x^*) = exp(0) - (-1) = 2 > 0$$
 (42)

(43)

This is contradicting our condition, so $\mu^* > 0$:

$$exp(x_1^*) - x_2^* = 0 (44)$$

$$exp(x_1^*) = x_2^*$$
 (45)

$$2(x_2^* + 1) + \mu^*(-1) = 0 (46)$$

$$2(exp(x_1^*) + 1) = \mu^* \tag{47}$$

$$2x_1^* + \mu^* * exp(x_1^*) = 0 (48)$$

$$2x_1^* + 2(exp(x_1^*) + 1) * exp(x_1^*) = 0$$
(49)

Since $exp(x_1^*) > 0$:

$$2(exp(x_1^*) + 1) * exp(x_1^*) > 0$$
(50)

(51)

combine with

$$2x_1^* + 2(exp(x_1^*) + 1) * exp(x_1^*) = 0$$
 (52)

we got

$$2x_1^* < 0 (53)$$

$$x_1^* < 0$$
 (54)

$$0 < exp(x_1^*) < 1 \tag{55}$$

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$$1 < exp(x_1^*) + 1 < 2 \tag{56}$$

$$0 < (exp(x_1^*) + 1) * exp(x_1^*) < 2$$
(57)

(58)

combine with the above equation agian:

$$x_1^* + (exp(x_1^*) + 1) * exp(x_1^*) = 0$$
(59)

$$-1 < x_1^* < 0 \tag{60}$$

b) KKT condition:

$$min \quad c^{\top}x + 8 \tag{61}$$

$$g(x^*) = \frac{1}{2}||x^*||^2 - 1 \le 0$$
(62)

$$\mu^* \ge 0 \tag{63}$$

$$c + \mu^* x^* = 0 \tag{64}$$

$$\mu^* \ge 0$$

$$c + \mu^* x^* = 0$$

$$\mu^* (\frac{1}{2} ||x^*||^2 - 1) = 0$$
(63)
(64)

We can see that if $\mu^* = 0$, c = 0 as well, which contradicts our given condition $c \neq 0$, so we get $\mu^* > 0$

$$\frac{1}{2}||x^*||^2 - 1 = 0 ag{66}$$

$$||x^*||^2 = 2 \tag{67}$$

$$||a\mathbf{1}||^2 = 2 \tag{68}$$

$$n|a|^2 = 2 \tag{69}$$

$$a = \pm \sqrt{\frac{2}{n}} \tag{70}$$

$$c^{\mathsf{T}}x + 8 = 4 \tag{71}$$

$$c^{\top}x = -4 \tag{72}$$

$$n(ca) = -4 \tag{73}$$

$$c = \frac{-4}{an} \tag{74}$$

$$c = \frac{-4}{an}$$

$$c = \mp \frac{4}{\sqrt{2n}}$$
(74)

Please noted that here c and a have inverse signs.

c) KKT Condition For original problem:

$$min \quad f(x) \tag{76}$$

$$h(x^*) = 0 \tag{77}$$

$$\nabla f(x^*) + \lambda^* \nabla h(x^*) = 0 \tag{78}$$

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KKT Condition For In-Eq problem:

$$g(x^*) = \frac{1}{2} ||h(x^*)||^2 \le 0$$
 (79)

$$\mu^* \ge 0 \tag{80}$$

$$\mu^* \ge 0$$

$$\nabla f(x^*) + \mu^* h(x^*) = 0$$
(80)
(81)

$$\frac{1}{2}\mu^* ||h(x^*)||^2 = 0 (82)$$

If $\mu^* = 0$:

$$\nabla f(x^*) = 0h(x^*) may not be 0 \tag{83}$$

So $\mu^* > 0$:

$$||h(x^*)||^2 = 0\nabla g(x^*) = ||h(x^*)|| = 0h(x^*) = 0$$
(84)

So $h(x^*)$ is not linearly independent, and x^* is not a regular point, so KKT theorem can not be applied on In-Eq problem.