

Solutions to exercise set 6

1 Consider a constrained minimisation problem with continuously differentiable objective function and constraints. Which of the following statements are true?

(CQ ... constraint qualification)

- 1.  $x^*$  is a global minimum  $\implies x^*$  is a KKT point.
- 2.  $x^*$  is a local minimum and CQ holds  $\implies x^*$  is a KKT point.
- 3.  $x^*$  is a KKT point and CQ holds  $\implies x^*$  is a local minimum.
- 4.  $x^*$  is a global minimum and the problem is convex  $\implies x^*$  is a KKT point.
- 5.  $x^*$  is a KKT point and the problem is convex  $\implies x^*$  is a global minimum.

## Solution:

- 1. False; one needs CQ.
- 2. True; KKT is necessary for local minima when CQ holds.
- 3. False; consider the minimization of  $-x^2$  subject to  $-1 \le x \le 1$ , then  $x^* = 0$  is a KKT point where CQ holds.
- 4. False; consider the convex problem of minimizing x, subject to  $-x^2 y^2 \ge 0$ .
- 5. True; KKT is sufficient for global minima when the function is convex.
- 2 For the following two examples, sketch the region  $\Omega$  defined by the constraints and compute for each point in  $\Omega$  both the tangent cone and the set of linearized feasible directions. For which points is the LICQ satisfied?

Note that the sets  $\Omega$  considered in this example occur again in problems 5 and 6 on this exercise sheet.

**a)** The region  $\Omega \subset \mathbb{R}^2$  defined by the inequalities

 $y \ge x$  and  $y^4 \le x^3$ .

Solution: We first define constraint functions

 $c_1(x,y) = y - x$  and  $c_2(x,y) = x^3 - y^4$ ,

so that  $\Omega = \{(x, y) \in \mathbb{R}^2 : c_1(x, y) \ge 0 \text{ and } c_2(x, y) \ge 0\}$ , and sketch the region in Figure 1 below.



Figure 1: Region  $\Omega$  in grey, with colors on the boundary specifying the active constraints.

In order to characterise the tangent cone  $T_{\Omega}(x, y)$  and the set of linearised feasible directions  $\mathcal{F}(x, y)$ , we employ Lemma 12.2 in N&W, which states that if the LICQ condition holds at a feasible point (x, y), then  $T_{\Omega}(x, y) = \mathcal{F}(x, y)$ . Note first that the LICQ condition holds vacuously in the interior of  $\Omega$  because all constraints are inactive, and therefore,  $T_{\Omega}(x, y) = \mathcal{F}(x, y) = \mathbb{R}^2$  (why?) at interior points.

Next we consider boundary points with precisely one active constraint. Starting with points for which  $c_1(x, y) = 0$ —and excluding (0, 0) and (1, 1) where also  $c_2$  is active—we find that  $\nabla c_1(x, y) = (-1, 1)$ . Since  $\nabla c_1 \neq 0$ , the LICQ condition holds, and so

$$T_{\Omega}(x,y) = \mathcal{F}(x,y) = \left\{ d \in \mathbb{R}^2 : \nabla c_1(x,y)^{\top} d \ge 0 \right\}$$
$$= \left\{ d \in \mathbb{R}^2 : d_2 \ge d_1 \right\},$$

where d is short for  $(d_1, d_2)$ .

Similarly, if only  $c_2$  is active, we observe that the LICQ condition holds because  $\nabla c_2(x,y) = (3x^2, -4y^3) \neq 0$  away from (0,0). This yields

$$T_{\Omega}(x,y) = \mathcal{F}(x,y) = \left\{ d \in \mathbb{R}^2 : \nabla c_2(x,y)^{\top} d \ge 0 \right\}$$
$$= \left\{ d \in \mathbb{R}^2 : 3x^2 d_1 \ge 4y^3 d_2 \right\}.$$

Constraint gradients at (1, 1) equal  $\nabla c_1 = (-1, 1)$  and  $\nabla c_2 = (3, -4)$ , which are linearly independent. Thus the LICQ condition is true, and

$$T_{\Omega}(1,1) = \mathcal{F}(1,1) = \left\{ d \in \mathbb{R}^2 : \nabla c_1(1,1)^{\top} d \ge 0 \text{ and } \nabla c_2(1,1)^{\top} d \ge 0 \right\}$$
$$= \left\{ d \in \mathbb{R}^2 : 3d_1 \ge 4d_2 \right\}.$$

Lastly, since  $\nabla c_1(0,0) = (-1,1)$  and  $\nabla c_2(0,0) = 0$ , the LICQ condition fails at (0,0), and we cannot expect that  $T_{\Omega}(0,0) = \mathcal{F}(0,0)$ . Readily,

$$\mathcal{F}(0,0) = \left\{ d \in \mathbb{R}^2 : \nabla c_1(0,0)^\top d \ge 0 \text{ and } \nabla c_2(0,0)^\top d \ge 0 \right\}$$
$$= \left\{ d \in \mathbb{R}^2 : d_2 \ge d_1 \right\}.$$

In order to find the tangent cone, we first consider limiting directions along the constraint boundaries  $c_1(x, y) = 0$  and  $c_2(x, y) = 0$  as  $(x, y) \to (0, 0)$ . Travelling towards (0, 0) when  $c_1$  is active, we may put, using the notation in N&W,

$$z_k = (1/k, 1/k)$$
 and  $t_k = 1/k$ 

and obtain the limiting direction

$$d = \lim_{k \to \infty} \frac{z_k - (0, 0)}{t_k} = (1, 1).$$

Note: the length of d is irrelevant; we only care about its direction. Similarly, travelling along  $c_2(x, y) = 0$  yields d = (0, 1), using for example, the sequences

$$z_k = (k^{-1/3}, k^{-1/4})$$
 and  $t_k = k^{-1/4}$ .

It can furthermore be seen that approaching (0,0) from the interior of  $\Omega$  gives tangent directions "between" these borderline cases, and so

$$T_{\Omega}(0,0) = \{ d \in \mathbb{R}^2 : d_2 \ge d_1 \ge 0 \}.$$

**b)** The region  $\Omega \subset \mathbb{R}^2$  defined by the inequalities

$$y \ge x^4$$
 and  $y \le x^3$ .

Solution: Defining

$$c_1(x,y) = y - x^4$$
 and  $c_2(x,y) = x^3 - y$ 

gives  $\Omega = \{(x, y) \in \mathbb{R}^2 : c_1(x, y) \ge 0 \text{ and } c_2(x, y) \ge 0\}$ , which is shown in Figure 2.



Figure 2: Region  $\Omega$  in grey, with colors on the boundary specifying the active constraints.

Omitting details—the process is very similar to the previous question—we obtain that the LICQ condition holds at all feasible points except (0,0). Moreover,  $T_{\Omega}(x,y) = \mathcal{F}(x,y)$  if (x,y) lies in the interior of  $\Omega$ ;

$$T_{\Omega}(x,y) = \mathcal{F}(x,y) = \left\{ d \in \mathbb{R}^2 : d_2 \ge 4x^3 d_1 \right\}$$

when only  $c_1$  is active;

$$T_{\Omega}(x,y) = \mathcal{F}(x,y) = \left\{ d \in \mathbb{R}^2 : 3x^2 d_1 \ge d_2 \right\}$$

when only  $c_2$  is active;

$$T_{\Omega}(1,1) = \mathcal{F}(1,1) = \left\{ d \in \mathbb{R}^2 : 3d_1 \ge d_2 \ge 4d_1 \right\};$$

and

$$\mathcal{F}(0,0) = \left\{ d \in \mathbb{R}^2 : d_2 = 0 \right\} \text{ and } T_{\Omega}(0,0) = \left\{ d \in \mathbb{R}^2 : d_2 = 0 \text{ and } d_1 \ge 0 \right\}.$$

3 Assume that one wants to solve the optimisation problem

$$\max_{x} f(x) \qquad \text{such that} \qquad \begin{cases} c_i(x) = 0 & \text{for all } i \in \mathcal{E}, \\ c_i(x) \ge 0 & \text{for all } i \in \mathcal{I}. \end{cases}$$

How do the KKT conditions have to be modified such that one obtains (first order) necessary conditions for this maximisation problem?

## Solution: Let

$$\mathcal{L}(x,\lambda) = f(x) - \sum_{i \in \mathcal{E} \cup \mathcal{I}} \lambda_i c_i(x)$$

be the Lagrangian associated with the maximisation problem. Since solving  $\max_x f(x)$  is equivalent to solving  $\min_x -f(x)$ , we can state the KKT conditions for the minimisation problem. To this end, let

$$\widehat{\mathcal{L}}(x,\mu) = -f(x) - \sum_{i \in \mathcal{E} \cup \mathcal{I}} \mu_i c_i(x)$$

be the Lagrangian for the minimisation problem, so that the KKT conditions become

$$\begin{aligned} -\nabla f(x) - \sum_{i \in \mathcal{E} \cup \mathcal{I}} \mu_i \nabla c_i(x) &= \nabla_x \widehat{\mathcal{L}}(x, \mu) = 0, \\ c_i(x) &= 0 \quad \text{for all } i \in \mathcal{E}, \\ c_i(x) &\geq 0 \quad \text{for all } i \in \mathcal{I}, \\ \mu_i &\geq 0 \quad \text{for all } i \in \mathcal{I}, \\ \mu_i c_i(x) &= 0 \quad \text{for all } i \in \mathcal{E} \cup \mathcal{I}. \end{aligned}$$

Since

$$\mathcal{L}(x,-\mu) = -\widehat{\mathcal{L}}(x,\mu) \text{ and } \nabla_x \mathcal{L}(x,-\mu) = -\nabla_x \widehat{\mathcal{L}}(x,\mu),$$

we see that changing the signs of the Lagrange multipliers, that is, putting  $\lambda = -\mu$ , is the only modification in the KKT conditions for the maximisation problem.

4 Consider the constrained optimization problem

$$x^2+y^2 \to \min \qquad \text{such that} \qquad \begin{cases} x+y \geq 1, \\ y \leq 2, \\ y^2 \geq x. \end{cases}$$

a) Formulate the KKT-conditions for this optimization problem.

**Solution:** We begin by stating the problem in standard form, writing  $\mathbf{x} = [x, y]^T$ :

$$\min_{\mathbf{x}\in\mathbb{R}^2} f(\mathbf{x}) \quad \text{s.t.} \quad c_i(\mathbf{x}) \ge 0, \quad i = 1, 2, 3,$$

where

$$f(\mathbf{x}) = x^{2} + y^{2},$$
  

$$c_{1}(\mathbf{x}) = x + y - 1,$$
  

$$c_{2}(\mathbf{x}) = 2 - y,$$
  

$$c_{3}(\mathbf{x}) = y^{2} - x.$$

The KKT conditions can now be stated as follows:

$$2x^* - \lambda_1^* + \lambda_3^* = 0 \tag{1a}$$

$$2y^* - \lambda_1^* + \lambda_2^* - 2y^* \lambda_3^* = 0 \tag{1b}$$

$$x^* + y^* - 1 \ge 0 \tag{1c}$$

$$2 - y^* \ge 0 \tag{1d}$$

$$y^{*2} - x^* \ge 0$$
 (1e)

$$\lambda_i^* \ge 0, \quad i = 1, 2, 3 \tag{1f}$$

$$\lambda_1^*(x^* + y^* - 1) = 0 \tag{1g}$$

$$\lambda_2^*(2 - y^*) = 0 \tag{1h}$$

$$\lambda_3^*(y^{*2} - x^*) = 0. \tag{1i}$$

b) Find all KKT points for this optimization problem.

Solution: The feasible set is sketched in Figure 3.





We will find all KKT points by systematically considering all possible active sets of constraints. Remember that a constraint  $c_i$  is active at a point  $\mathbf{x}$  if  $c_i(\mathbf{x}) = 0$ .

Also, the LICQ conditions are satisfied at every point we consider here; with one active constraint, the LICQ conditions hold trivially, and in the cases with two constraints it is not hard to check that the LICQ conditions do hold.

Observe that if  $\mathbf{x}^* = [x^*, y^*]^T$  is a KKT point, then from (1a) and (1b) we have:

$$x^* = \frac{\lambda_1^* - \lambda_3^*}{2}, \quad y^* = \frac{\lambda_1^* - \lambda_2^*}{2(1 - \lambda_3^*)}$$

From here on, we will drop the asterisk in the notation and write x for  $x^*$ , etc.

First, suppose that the active set is empty, i.e. neither of (1c)-(1e) are equalities. This corresponds to the interior of the domain. Then, by (1g)-(1i), we have  $\lambda_1 = \lambda_2 = \lambda_3 = 0$ , and so x = y = 0. But this point is not feasible, since it violates condition (1c). Thus, with the active set empty, there are no KKT points.

Next, we consider the case when the active set contains one index, i.e. exactly one of (1c)-(1e) is an equality. This corresponds to the boundaries of the domain, excepting the corner points. If (1c) is active, then  $\lambda_2 = \lambda_3 = 0$  while  $\lambda_1 \ge 0$ . We get

$$x = \frac{\lambda_1}{2}, \quad y = \frac{\lambda_1}{2},$$

and inserting this into (1c) (which is now an equality), we get the condition

$$\frac{\lambda_1}{2} + \frac{\lambda_1}{2} - 1 = 0 \Rightarrow \lambda_1 = 1,$$

giving us the point  $(x, y) = (\frac{1}{2}, \frac{1}{2})$ . But this point violates condition (1e), so  $(\frac{1}{2}, \frac{1}{2})$  is not a KKT point.

If (1d) is active, then  $\lambda_1 = \lambda_3 = 0$  while  $\lambda_2 \ge 0$ , so

$$x = 0, \quad y = -\frac{\lambda_2}{2}.$$

Inserting this into the equality (1d), we get

$$2 + \frac{\lambda_2}{2} = 0 \Rightarrow \lambda_2 = -4.$$

Since the Lagrange multiplier is negative, KKT conditions are not satisfied at this point.

If (1e) is active, then  $\lambda_1 = \lambda_2 = 0$  while  $\lambda_3 \ge 0$ , so

$$x = -\frac{\lambda_3}{2}, \quad y = 0.$$

Inserting this into the equality (1e), we get

$$\frac{\lambda_3}{2} = 0 \Rightarrow \lambda_3 = 0.$$

This gives the candidate point (0,0), which is not feasible since it violates (1c), and thereby is not a KKT point.

Having considered all possible active sets of one index, we now turn to the cases with two indices, i.e. exactly two of (1c)-(1e) are equalities. This corresponds to the corner points of the domain. First, if (1c) and (1d) are both active, then  $\lambda_3 = 0$  while  $\lambda_1, \lambda_2 \ge 0$ . This gives us

$$x = \frac{\lambda_1}{2}, \quad y = \frac{\lambda_1 - \lambda_2}{2}.$$

Plugging this into equalities (1c) and (1d) yields:

$$\frac{\lambda_1}{2} + \frac{\lambda_1 - \lambda_2}{2} - 1 = 0$$
$$2 - \frac{\lambda_1 - \lambda_2}{2} = 0,$$

with solutions  $\lambda_1 = -2$  and  $\lambda_2 = -6$ . Since the multipliers are negative, this is not a KKT point.

Next, if (1c) and (1e) are both active, then  $\lambda_2 = 0$  while  $\lambda_1, \lambda_3 \ge 0$ , which means

$$x = \frac{\lambda_1 - \lambda_3}{2}, \quad y = \frac{\lambda_1}{2(1 - \lambda_3)}.$$

Plugging this into equalities (1c) and (1e) yields:

$$\frac{\lambda_1 - \lambda_3}{2} + \frac{\lambda_1}{2(1 - \lambda_3)} - 1 = 0$$
$$\frac{\lambda_1^2}{4(1 - \lambda_3)^2} - \frac{\lambda_1 - \lambda_3}{2} = 0.$$

Solving this set of equations yields  $\lambda_1 = 5 \pm \frac{9}{\sqrt{5}}$  and  $\lambda_3 = 2 \pm \frac{4}{\sqrt{5}}$ , thereby giving the candidate points  $(x, y) = (\frac{1}{2}(3 \pm \sqrt{5}), \frac{1}{2}(-1 \mp \sqrt{5}))$  which both satisfy the KKT conditions. Since  $\lambda_1, \lambda_3 \ge 0$ , these points are minimizer candidates. Note: This result can be arrived upon by the easier approach of first finding the points (x, y) where  $c_1$  and  $c_3$  are both active, then working out what  $\lambda_1$  and  $\lambda_3$  are.

Finally, we check the case where (1d) and (1e) are both active, i.e.  $\lambda_1 = 0$  while  $\lambda_2, \lambda_3 \ge 0$ . This gives us

$$x = -\frac{\lambda_3}{2}, \quad y = -\frac{\lambda_2}{2(1-\lambda_3)}.$$

Plugging this into equalities (1d) and (1e) yields:

$$2 + \frac{\lambda_2}{2(1 - \lambda_3)} = 0$$
$$\frac{\lambda_2^2}{4(1 - \lambda_3)^2} + \frac{\lambda_3}{2} = 0,$$

which can be solved to find  $\lambda_2 = -28$  and  $\lambda_3 = -8$ . Since the multipliers are negative, this is not a KKT point.

Concerning the case with all constraints active, we may conclude that no KKT point exists; all three constraint functions cannot be active at the same point. The investigation is summarized in the table below.

Point	$\lambda_1$	$\lambda_2$	$\lambda_3$	KKT?
(0,2)	0	-4	0	No
$(\frac{1}{2}(3+\sqrt{5}),\frac{1}{2}(-1-\sqrt{5}))$	$5 + \frac{9}{\sqrt{5}}$	0	$2 + \frac{4}{\sqrt{5}}$	Yes
$(\frac{1}{2}(3-\sqrt{5}),\frac{1}{2}(-1+\sqrt{5}))$	$5 - \frac{9}{\sqrt{5}}$	0	$2 - \frac{4}{\sqrt{5}}$	Yes
(-1,2)	-2	-6	0	No
(4,2)	0	-28	-8	No

c) Find all local and global minima for this optimization problem.

**Solution:** To determine whether the KKT points that are minimizer candidates are in fact local minimizers, we check the second order sufficient conditions from Theorem 12.6 in N&W, i.e. whether

$$w^T \nabla_{xx}^2 \mathcal{L}(x,\lambda) w > 0 \ \forall w \in \mathcal{C}(x,\lambda), w \neq 0,$$
(2)

where,  $C(x, \lambda)$  is the critical cone at x, given by (12.53) in N&W.

For both candidates, i.e.  $(\frac{1}{2}(3 \pm \sqrt{5}), \frac{1}{2}(-1 \mp \sqrt{5}))$ , we have that the critical cone is simply given as  $C(x, \lambda) = \{0\}$ . This is because any  $w \in C(x, \lambda)$  must be orthogonal to the  $\nabla c_i(x)$  for which  $\lambda_i > 0$ , of which there are two for each point. Since the LICQ conditions hold at both points, these two vectors are linearily independent and thus span  $\mathbb{R}^2$ . The only vector orthogonal to  $\mathbb{R}^2$  is the zero vector. Thereby, the only vector in  $C(x, \lambda)$  is the zero vector for these points, and thus condition (2) holds. We can conclude that  $(\frac{1}{2}(3 \pm \sqrt{5}), \frac{1}{2}(-1 \mp \sqrt{5}))$  are strict local minimizers.

We note that  $f(\frac{1}{2}(3-\sqrt{5}),\frac{1}{2}(-1+\sqrt{5})) < f(\frac{1}{2}(3+\sqrt{5}),\frac{1}{2}(-1-\sqrt{5}))$  and  $f(\mathbf{x}) \to \infty$  in the unbounded region of the feasible domain. This means that  $(\frac{1}{2}(3-\sqrt{5}),\frac{1}{2}(-1+\sqrt{5}))$  is a global minimizer and  $(\frac{1}{2}(3+\sqrt{5}),\frac{1}{2}(-1-\sqrt{5}))$  is a local minimizer.

5 Consider the constrained optimization problem

$$x \to \min$$
 such that  $\begin{cases} y \ge x^4, \\ y \le x^3, \end{cases}$ 

Find all KKT points and local minima for this optimization problem.

**Solution:** We begin by stating the problem in standard form, writing  $\mathbf{x} = [x, y]^T$ :

$$\min_{\mathbf{x} \in \mathbb{R}^2} f(\mathbf{x}) \quad \text{s.t.} \quad c_i(\mathbf{x}) \ge 0, \quad i = 1, 2$$

where

 $f(\mathbf{x}) = x,$   $c_1(\mathbf{x}) = y - x^4$  $c_2(\mathbf{x}) = x^3 - y$  The KKT conditions for this problem can be stated as follows:

$$1 + 4x^3\lambda_1 - 3x^2\lambda_2 = 0 \tag{3a}$$

$$-\lambda_1 + \lambda_2 = 0 \tag{3b}$$

$$y - x^{4} \ge 0 \tag{3c}$$
$$x^{3} - y \ge 0 \tag{3d}$$

$$y^3 - y \ge 0$$
 (3d)

$$\lambda_i \ge 0, \quad i = 1, 2$$
 (3e)  
 $\lambda_1(y - x^4) = 0$  (3f)

$$\lambda_1(y^3 - y) = 0.$$
 (3g)

Now, we can take a shortcut; from (3b), we see that  $\lambda_1 = \lambda_2$ , and from (3a) we see that there cannot exist any KKT point for which  $\lambda_1 = \lambda_2 = 0$ . Therefore, the cases with no active constraints ( $\lambda_1 = \lambda_2 = 0$ ) and one active constraint ( $\lambda_1 = 0$  or  $\lambda_2 = 0$ ) cannot produce KKT points. We are left with considering the case where both constraints are active, i.e. the corner points (0,0) and (1,1).

In the point (1,1), we find (by (3a) and (3b)) that  $\lambda_1 = \lambda_2 = -1$ , and therefore this is not a KKT point.

The last point is (0,0), for which we cannot write the gradient of f at (0,0) (which is  $[1,0]^T$ ) as a non-negative linear combination of the gradients of the constraints, and which therefore is not a KKT point. This does not, however, mean that it is not a minimizer. Applying common sense, it is clearly a local minimum, as no other points with x = 0 are feasible, and x = 0 is the lowest possible value of the objective function.

6 In this task, we fill in the details of Theorem 17.4 (p. 509) in Nocedal & Wright. We consider the constrained optimisation problem

$$\min_{x \in \mathcal{I}} f(x) \quad \text{subject to} \quad c_i(x) = 0, \quad i \in \mathcal{E}, \quad c_i(x) \ge 0, \quad i \in \mathcal{I}$$

and the associated  $\ell_1$  penalty function

$$\phi_1(x; \mu) = f(x) + \mu \sum_{i \in \mathcal{E}} |c_i(\hat{x})| + \mu \sum_{i \in \mathcal{I}} [c_i(\hat{x})]^-$$

with  $[y]^- = \max\{-y, 0\}.$ 

Suppose that  $\hat{x}$  is a stationary point of the penalty function  $\phi_1(x; \mu)$  for all  $\mu$  greater than a certain threshold  $\hat{\mu} > 0$ .

a) Suppose that  $\hat{x}$  is feasible for the constrained optimisation problem. Prove that

$$D(\phi_1(\hat{x};\mu);p) = \nabla f(\hat{x})^T p + \mu \sum_{i \in \mathcal{E}} \left| \nabla c_i(\hat{x})^T p \right| + \mu \sum_{i \in \mathcal{I} \cap \mathcal{A}(\hat{x})} \left[ \nabla c_i(\hat{x})^T p \right]^-.$$

As usual,  $\mathcal{A}(x)$  denotes the active set, i.e. the set of active constraints.

Solution: We start by noting that

$$D(|x|; a) = \begin{cases} a, & x > 0, \\ -a, & x < 0, \\ |a|, & x = 0. \end{cases}$$

Accordingly, using the chain rule, we have that

$$D(|c_i(x)|; p) = \begin{cases} \nabla c_i(x)^T p, & c_i(x) > 0, \\ -\nabla c_i(x)^T p, & c_i(x) < 0, \\ |\nabla c_i(x)^T p|, & c_i(x) = 0. \end{cases}$$

Since  $\hat{x}$  is feasible, we must have that  $c_i(\hat{x}) = 0$ , meaning that  $D(|c_i(x)|; p) = |\nabla c_i(x)^T p|$  for all  $i \in \mathcal{E}$ . For a similar argument, we have that

$$D([c_i(x)]^-; p) = \begin{cases} 0, & c_i(x) > 0, \\ -\nabla c_i(x)^T p, & c_i(x) < 0, \\ [\nabla c_i(x)^T p]^-, & c_i(x) = 0. \end{cases}$$

This holds for all  $i \in \mathcal{I}$ . For the non-active constraints, this evaluates to zero. Thus, we conclude that

$$D(\phi_1(\hat{x};\mu);p) = D(f(\hat{x});p) + \mu \sum_{i \in \mathcal{E}} D(|c_i(\hat{x})|;p) + \mu \sum_{i \in \mathcal{I} \cap \mathcal{A}(\hat{x})} D([c_i(\hat{x})]^-;p)$$
  
=  $\nabla f(\hat{x})^T p + \mu \sum_{i \in \mathcal{E}} |\nabla c_i(\hat{x})^T p| + \mu \sum_{i \in \mathcal{I} \cap \mathcal{A}(\hat{x})} [\nabla c_i(\hat{x})^T p]^-.$ 

It is then possible to prove that  $\hat{x}$  satisfies the KKT conditions.

b) Suppose that  $\hat{x}$  is infeasible, i.e. that it does not satisfy the KKT conditions. Prove that  $\hat{x}$  is an infeasible stationary point of the penalty function  $\phi_1$ .