

Assignment 1

Problem 1: Example 12.3

$$\min f(x) = x_1 + 2x_2$$

s.t.

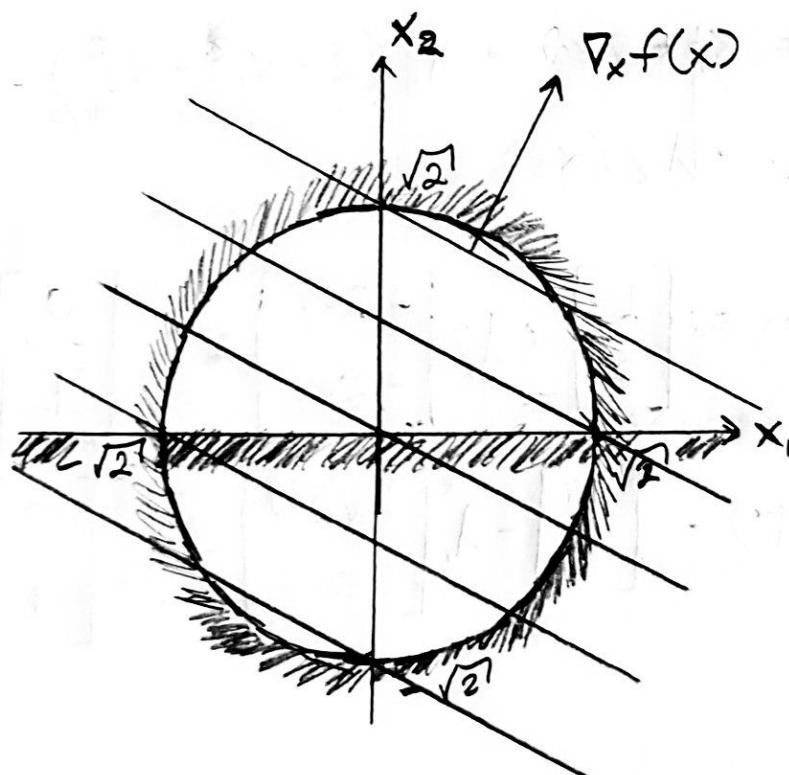
$$C_1(x) = 2 - x_1^2 - x_2^2 \geq 0$$

$$C_2(x) = x_2 \geq 0$$

$$\} \Rightarrow I = \{1, 2\}$$

a)

$$\nabla_x f(x) = \left[\frac{\partial f}{\partial x} \right]^T = \begin{bmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$



By inspection the optimal point is :

$$\underline{x^* = [-\sqrt{2}, 0]^T}$$

b) KKT conditions :

(I) $\nabla_x \mathcal{L}(x^*, \lambda^*) = 0$

(II) $\nabla c_i(x^*) = 0 \quad , \quad i \in E$

(III) $c_i(x^*) \geq 0 \quad , \quad i \in I$

(IV) $\lambda_i^* \geq 0 \quad , \quad i \in I$

(V) $\lambda_i^* c_i(x^*) = 0 \quad , \quad i \in E \cup I$

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

$$= x_1 + 2x_2 - \lambda_1 (2 - x_1^2 - x_2^2) \\ - \lambda_2 (x_2)$$

$$\nabla_x \mathcal{L}(x, \lambda) = \begin{bmatrix} 1 \\ 2 \end{bmatrix} - \lambda_1 \begin{bmatrix} -2x_1 \\ -2x_2 \end{bmatrix} - \lambda_2 \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\nabla_x \mathcal{L}(x^*, \lambda^*) = \begin{bmatrix} 1 \\ 2 \end{bmatrix} - \lambda_1^* \begin{bmatrix} 2\sqrt{2} \\ 0 \end{bmatrix} - \lambda_2^* \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\nabla_x L(x^*, \lambda^*) = 0$$

$$\Rightarrow \begin{bmatrix} 1 \\ 2 \end{bmatrix} - \lambda_1^* \begin{bmatrix} 2\sqrt{2} \\ 0 \end{bmatrix} - \lambda_2^* \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\Rightarrow 1 - \lambda_1^* 2\sqrt{2} = 0$$

$$\underline{\lambda_1^* = \frac{1}{2\sqrt{2}}}$$

$$\Rightarrow 2 - \lambda_2^* = 0$$

$$\underline{\lambda_2^* = 2}$$

(I) satisfied

(IV) satisfied

(II) satisfied since $\epsilon = \emptyset$

$$C_1(x^*) = 2 - (-\sqrt{2})^2 - (0)^2$$

$$= 2 - 2 - 0 = 0$$

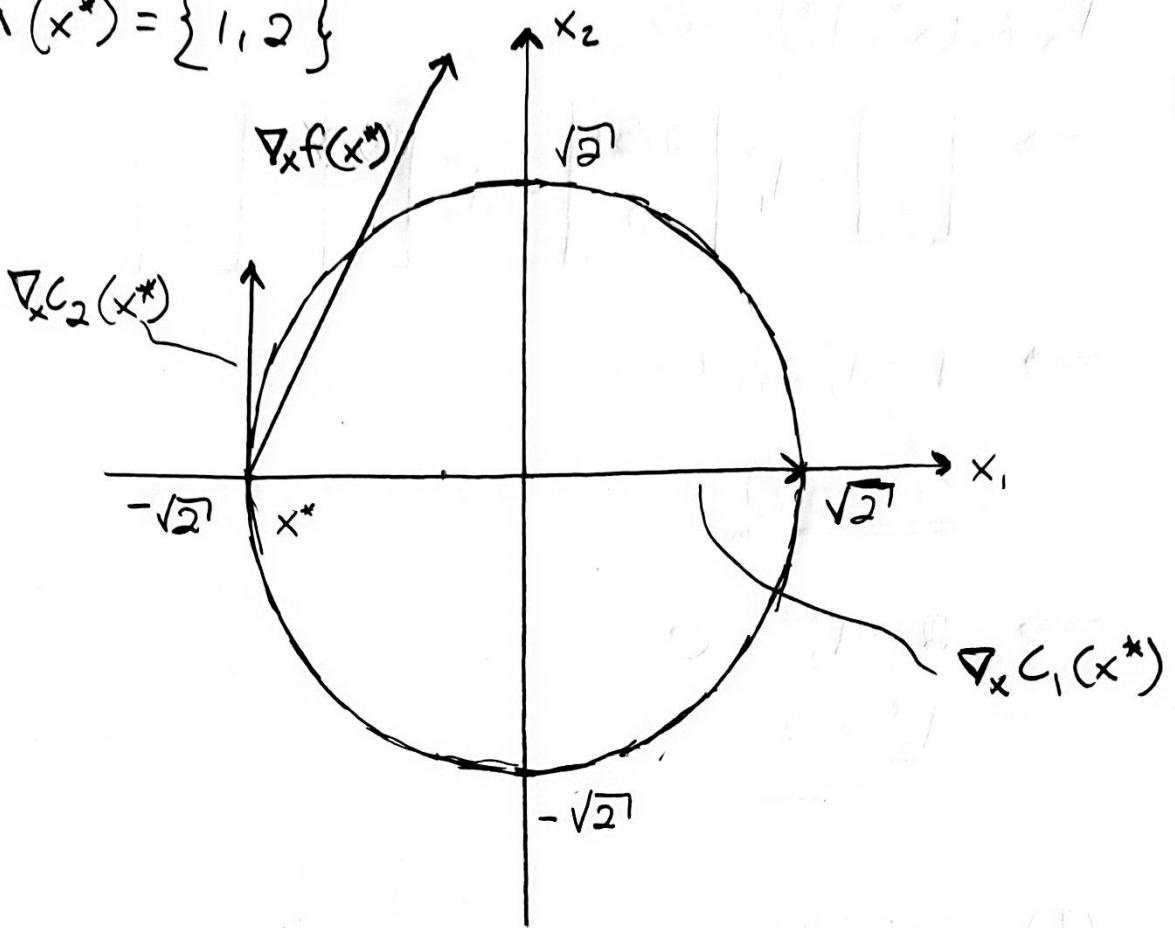
$$C_2(x^*) = 0$$

(III) satisfied

(V) satisfied

All of the KKT conditions are satisfied
at $x^* = [-\sqrt{2}, 0]^T$

c) $A(x^*) = \{1, 2\}$



$$\nabla_x C_1(x^*) = \begin{bmatrix} 2\sqrt{2} \\ 0 \end{bmatrix}$$

$$\nabla_x C_2(x^*) = \begin{bmatrix} 0 \\ 2 \end{bmatrix}$$

$$\nabla_x f(x^*) = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

d) The Lagrangean multipliers are positive because the gradients of the constraints points in a similar direction as that of the gradient of the objective function.

e) Ω is convex since a line can be drawn between any two points $x' \in \Omega$ and $x'' \in \Omega$.

Checking if the objective function is convex:

f is convex \Leftrightarrow



$$f(\alpha x + (1-\alpha)y) \leq \alpha f(x) + (1-\alpha)f(y)$$

$$f(x) = x_1 + 2x_2$$

$$\begin{aligned} \rightarrow f(\alpha x + (1-\alpha)y) &= \alpha x_1 + (1-\alpha)y_1 + 2\alpha x_2 \\ &\quad + 2(1-\alpha)y_2 \\ &= \alpha(x_1 + 2x_2) \\ &\quad + (1-\alpha)(y_1 + 2y_2) \\ &= \alpha f(x) + (1-\alpha)f(y) \end{aligned}$$

\Rightarrow $f(x)$ is convex

The problem is a convex problem

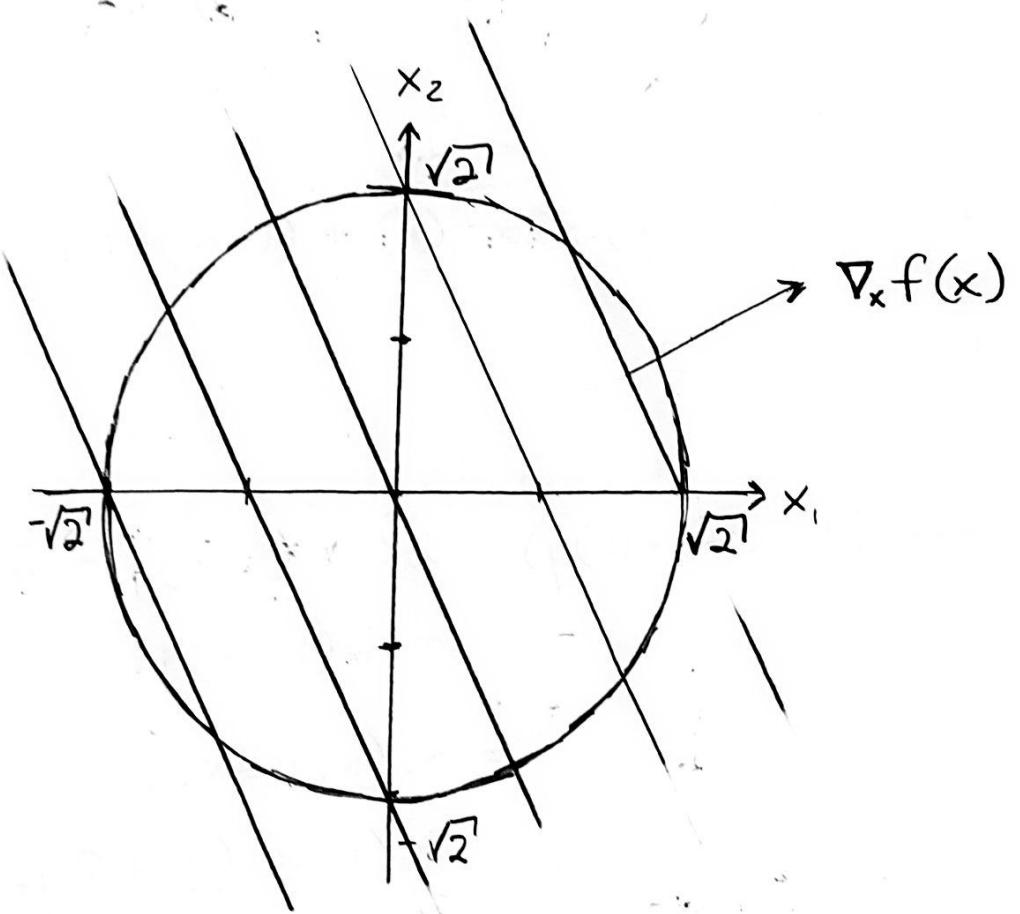
Problem 2: Example 12.1

$$\min f(x) = 2x_1 + x_2$$

s.t.

$$c_1(x) = x_1^2 + x_2^2 - 2 = 0 \rightarrow E = \{1\}$$

$$I = \emptyset$$



$$\nabla_x f(x) = \left[\frac{\partial f}{\partial x} \right]^T = \begin{bmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \end{bmatrix} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

$$a) \quad \mathcal{L}(x, \lambda) = f(x) - \sum_{i \in E \cup I} \lambda_i c_i(x) = f(x) - \lambda_1 c_1(x)$$

$$= 2x_1 + x_2 - \lambda_1 (x_1^2 + x_2^2 - 2)$$

$$\nabla_x \mathcal{L}(x, \lambda) = \begin{bmatrix} 2 \\ 1 \end{bmatrix} - \lambda_1 \begin{bmatrix} 2x_1 \\ 2x_2 \end{bmatrix}$$

Finding extreme points by setting

$$\nabla_x \mathcal{L}(x, \lambda) = 0$$

$$\Rightarrow \begin{bmatrix} 2 \\ 1 \end{bmatrix} - \lambda_1 \begin{bmatrix} 2x_1 \\ 2x_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$2 - 2\lambda_1 x_1 = 0 \rightarrow \lambda_1 x_1 = 1$$

$$1 - 2\lambda_1 x_2 = 0 \rightarrow \lambda_1 x_2 = \frac{1}{2}$$

$$\Rightarrow \left. \begin{array}{l} \lambda_1 = \frac{1}{x_1} \\ \lambda_1 = \frac{1}{2x_2} \end{array} \right\} \Rightarrow 2x_2 = x_1$$

$$c_1(x) = x_1^2 + x_2^2 - 2 = 0$$

$$\Rightarrow (2x_2)^2 + x_2^2 - 2 = 0$$

$$5x_2^2 = 2$$

$$x_2^2 = \frac{2}{5}$$

$$x_2 = \pm \sqrt{\frac{2}{5}}$$

Gives me two extremes:

$$x_2 = \sqrt{\frac{2}{5}} \implies x_1 = \frac{2\sqrt{2}}{\sqrt{5}}$$

$$x_2 = -\sqrt{\frac{2}{5}} \implies x_1 = -\frac{2\sqrt{2}}{\sqrt{5}}$$

$$\underline{x'} = \left[\frac{2\sqrt{2}}{\sqrt{5}}, \sqrt{\frac{2}{5}} \right]^T$$

$$\underline{x''} = \left[-\frac{2\sqrt{2}}{\sqrt{5}}, -\sqrt{\frac{2}{5}} \right]^T$$

b) KKT conditions:

$$(I) \nabla_x L(x^*, \lambda^*) = 0$$

$$(II) c_i(x^*) = 0, i \in E$$

$$(III) c_i(x^*) \geq 0, i \in I$$

$$(IV) \lambda_i^* \geq 0, i \in I$$

$$(V) \lambda_i^* c_i(x^*) = 0, i \in E \cup I$$

$I = \emptyset \rightarrow (III)$ and (IV) satisfied at both points

(I) satisfied at both points by explicitly setting $\nabla_x L(x, \lambda) = 0$ when the points were found.

$$\underline{x' = \left[\frac{2\sqrt{2}}{\sqrt{5}}, \sqrt{\frac{2}{5}} \right]^T} \quad \underline{x'' = \left[-\frac{2\sqrt{2}}{\sqrt{5}}, -\sqrt{\frac{2}{5}} \right]^T}$$

$$\begin{aligned} C_1(x') &= \left(\frac{2\sqrt{2}}{\sqrt{5}}\right)^2 + \left(\sqrt{\frac{2}{5}}\right)^2 - 2 \\ &= 4 \cdot \frac{2}{5} + \frac{2}{5} - 2 = 8 \cdot \frac{2}{8} - 2 = 0 \end{aligned}$$

$$\begin{aligned} C_1(x'') &= \left(-\frac{2\sqrt{2}}{\sqrt{5}}\right)^2 + \left(-\sqrt{\frac{2}{5}}\right)^2 - 2 \\ &= 4 \cdot \frac{2}{5} + \frac{2}{5} - 2 = 8 \cdot \frac{2}{8} - 2 = 0 \end{aligned}$$

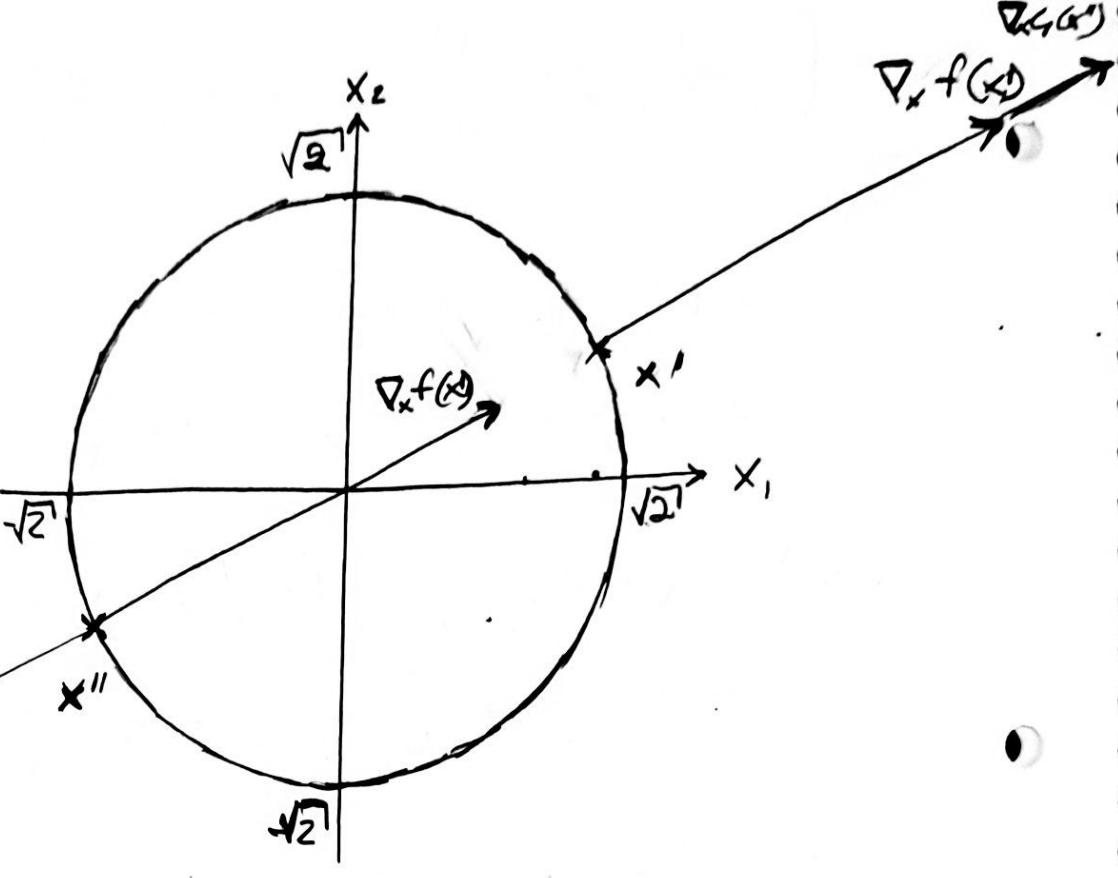
(II) and (IV) satisfied at both points.

\Rightarrow Both x' and x'' satisfies the KKT conditions.

$$C) \nabla_x C_1(x) = \begin{bmatrix} 2x_1 \\ 2x_2 \end{bmatrix}$$

$$\nabla_x C_1(x') = \begin{bmatrix} 2 \cdot \frac{2\sqrt{2}}{\sqrt{5}} \\ 2 \cdot \sqrt{\frac{2}{5}} \end{bmatrix} = \begin{bmatrix} \frac{4\sqrt{2}}{\sqrt{5}} \\ \frac{2\sqrt{2}}{\sqrt{5}} \end{bmatrix}$$

$$\nabla_x C_1(x'') = \begin{bmatrix} 2 \cdot \left(-\frac{2\sqrt{2}}{\sqrt{5}}\right) \\ 2 \cdot \left(-\sqrt{\frac{2}{5}}\right) \end{bmatrix} = \begin{bmatrix} -\frac{4\sqrt{2}}{\sqrt{5}} \\ -\frac{2\sqrt{2}}{\sqrt{5}} \end{bmatrix}$$



$$d) \quad \lambda_1 = \frac{1}{x_1}$$

$$\lambda'_1 = \frac{1}{x'_1} = \frac{1}{\frac{2\sqrt{2}}{\sqrt{5}}} = \underline{\underline{\frac{\sqrt{5}}{2\sqrt{2}}}}$$

$$\lambda''_1 = \frac{1}{x''_1} = \frac{1}{-\frac{2\sqrt{2}}{\sqrt{5}}} = -\underline{\underline{\frac{\sqrt{5}}{2\sqrt{2}}}}$$

The Lagrangean multipliers are consistent with the KKT conditions since they belong to an equality constraint and thus have no requirement in terms of sign.

e) Second order condition:

$z^T \nabla_{xx}^2 \mathcal{L}(x^*, \lambda^*) z$ is positive definite

$$\nabla_x \mathcal{L}(x^*, \lambda^*) = \begin{bmatrix} 2 \\ 1 \end{bmatrix} - \lambda_1^* \begin{bmatrix} 2x_1^* \\ 2x_2^* \end{bmatrix} = \begin{bmatrix} 2 - 2\lambda_1^* x_1^* \\ 1 - 2\lambda_1^* x_2^* \end{bmatrix}$$

$$\nabla_{xx}^2 \mathcal{L}(x^*, \lambda^*) = \begin{bmatrix} -2\lambda_1^* & 0 \\ 0 & -2\lambda_1^* \end{bmatrix}$$

$$\nabla_{xx}^2 \mathcal{L}(x^*, \lambda_1^*) = \begin{bmatrix} -2 \cdot \frac{\sqrt{5}}{2\sqrt{2}} & 0 \\ 0 & -2 \cdot \frac{\sqrt{5}}{2\sqrt{2}} \end{bmatrix}$$

$$= \begin{bmatrix} -\sqrt{\frac{5}{2}} & 0 \\ 0 & -\sqrt{\frac{5}{2}} \end{bmatrix}$$

→ $z^T \nabla_{xx}^2 \mathcal{L}(x^*, \lambda^*) z$ is negative definite.

$$\nabla_{xx}^2 \mathcal{L}(x'', \lambda_1'') = \begin{bmatrix} -2 \cdot \left(-\frac{\sqrt{5}}{2\sqrt{2}}\right) & 0 \\ 0 & +2 \cdot \left(-\frac{\sqrt{5}}{2\sqrt{2}}\right) \end{bmatrix}$$

$$= \begin{bmatrix} \sqrt{\frac{5}{2}} & 0 \\ 0 & \sqrt{\frac{5}{2}} \end{bmatrix}$$

$\Rightarrow z^T \nabla_{xx}^2 L(x'', \lambda'') z$ is positive definite.

This means that x' maximizes $f(x)$,
while x'' minimizes $f(x)$.

f) Ω is convex since any line s between the two points $x' \in \Omega$ and $x'' \in \Omega$ is also in Ω .

$$f(x) = 2x_1 + x_2$$

$$f(\alpha x + (1-\alpha)y) \leq \alpha f(x) + (1-\alpha)f(y)$$

$$\begin{aligned} f(\alpha x + (1-\alpha)y) &= 2(\alpha x_1 + (1-\alpha)y_1) \\ &\quad + (\alpha x_2 + (1-\alpha)y_2) \\ &= 2\alpha x_1 + 2(1-\alpha)y_1 \\ &\quad + \alpha x_2 + (1-\alpha)y_2 \\ &= \alpha(2x_1 + x_2) + (1-\alpha)(2y_1 + y_2) \\ &= \alpha f(x) + (1-\alpha)f(y) \end{aligned}$$

$\Rightarrow f(x)$ is convex

\Rightarrow The problem is a convex problem

Problem 3 : Exercise 2.19

$$\min f(x) = -2x_1 + x_2$$

s.t.

$$c_1(x) = (1-x_1)^3 - x_2 \geq 0$$

$$c_2(x) = x_2 + 0.25x_1^2 - 1 \geq 0$$

$$x^* = (0, 1)^T$$

$$A(x^*) = \{1, 2\}$$

a) $\nabla_x c_1(x) = \begin{bmatrix} -3(1-x_1)^2 \\ 1 \end{bmatrix}$

$$\nabla_x c_2(x) = \begin{bmatrix} 0.5x_1 \\ 1 \end{bmatrix}$$

$$\nabla_x c_1(x^*) = \begin{bmatrix} -3(1-0)^2 \\ 1 \end{bmatrix} = \begin{bmatrix} -3 \\ 1 \end{bmatrix}$$

$$\nabla_x c_2(x^*) = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\nabla_x c_1(x^*) \text{ and } \nabla_x c_2(x^*) \text{ linearly independent}$$

→ $\nabla_x c_1(x^*)$ and $\nabla_x c_2(x^*)$ are linearly independent.

→ LQ holds for x^*

b)

$$\mathcal{L}(x, \lambda) = f(x) - \lambda_1 c_1(x) - \lambda_2 c_2(x)$$
$$= -2x_1 + x_2$$

$$= -\lambda_1((1-x_1)^3 - x_2)$$
$$-\lambda_2(x_2 + 0,25x_1^2 - 1)$$

$$\nabla_x \mathcal{L}(x, \lambda) = \begin{bmatrix} -2 \\ 1 \end{bmatrix} - \lambda_1 \begin{bmatrix} -3(1-x_1)^2 \\ -1 \end{bmatrix} - \lambda_2 \begin{bmatrix} 0,5x_1 \\ 1 \end{bmatrix}$$

$$\nabla_x \mathcal{L}(x^*, \lambda^*) = 0$$

$$\Rightarrow \begin{bmatrix} -2 \\ 1 \end{bmatrix} - \lambda_1^* \begin{bmatrix} -3 \\ -1 \end{bmatrix} - \lambda_2^* \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\Rightarrow -2 + 3\lambda_1^* = 0$$

$$\underline{\lambda_1^* = \frac{2}{3}}$$

$$\rightarrow 1 + \lambda_1^* - \lambda_2^* = 0$$

$$\lambda_2^* = \lambda_1^* + 1 = \frac{2}{3} + 1 = \underline{\frac{5}{3}}$$

KKT conditions :

$$(I) \nabla_x L(x^*, \lambda^*) = 0$$

$$(II) c_i(x^*) = 0 \quad , \quad i \in E$$

$$(III) c_i(x^*) \geq 0 \quad , \quad i \in I$$

$$(IV) \lambda_i^* \geq 0 \quad , \quad i \in I$$

$$(V) \lambda_i^* c_i(x^*) = 0 \quad , \quad i \in E \cup I$$

$$c_1(x^*) = (1-\sigma)^3 - 1 = 1 - 1 = 0$$

$$c_2(x^*) = 1 + \sigma - 1 = 0$$

\Rightarrow The KKT conditions are satisfied

$$\text{at } x^* = [0, 1]^T$$

d) Second-order necessary conditions:

x^* is a local solution

KKT holds

$$w^T \nabla_{xx}^2 L(x^*, \lambda^*) w \geq 0, \quad w \in C(x^*, \lambda^*)$$

$$\nabla c_1(x^*) = \begin{bmatrix} -3 \\ -1 \end{bmatrix}$$

$$\nabla c_2(x^*) = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$F(x^*) = \left\{ d \mid \begin{array}{l} d^T \nabla c_i(x^*) = 0, \quad i \in E \\ d^T \nabla c_i(x^*) \geq 0, \quad i \in A(x^*) \cap I \end{array} \right\}$$

$$E = \emptyset, \quad I = \{1, 2\}, \quad A(x^*) = \{1, 2\}$$

$$\Rightarrow F(x^*) = \left\{ d \mid \begin{array}{l} d^T \nabla c_1(x^*) \geq 0 \\ d^T \nabla c_2(x^*) \geq 0 \end{array} \right\}$$

$$d^T \nabla c_2(x^*) = [d_1 \ d_2] \begin{bmatrix} 0 \\ 1 \end{bmatrix} = d_2 \geq 0$$

$$d^T \nabla c_1(x^*) = [d_1 \ d_2] \begin{bmatrix} -3 \\ -1 \end{bmatrix} = -3d_1 - d_2 \geq 0$$

with $d_1, d_2 > 0$

$$\implies d_1 \leq -\frac{1}{3}d_2$$

$$F(x^*) = \left\{ d \in \mathbb{R}^2 \mid d_1 \leq -\frac{1}{3}d_2 ; d_2 \geq 0 \right\}$$

$$C(x^*, \lambda^*) = \left\{ w \in F(x^*) \mid \nabla c_i(x^*)^T w = 0, \text{ for all } i \in A(x^*) \cap I \text{ with } \lambda_i^* > 0 \right\}$$

$$\lambda_1^* > 0, \lambda_2^* > 0$$

$$\implies C(x^*, \lambda^*) = \left\{ w \in F(x^*) \mid \nabla c_i(x^*)^T w = 0, \text{ for } i \in \{1, 2\} \right\}$$

$$\nabla c_2(x^*)^T w = 0 \implies w_2 = 0$$

$$\nabla c_1(x^*)^T w = 0 \implies w_1 = 0$$

$$\implies C(x^*, \lambda^*) = \left\{ w = 0 \right\}$$

$$\implies \underline{w^T \nabla_{xx}^2 f(x^*, \lambda^*) w = 0, w \in C(x^*, \lambda^*)}$$

Hence the second-order necessary conditions are satisfied.

Second-order sufficient conditions:

KKT holds

$$w^T \nabla_{xx}^2 L(x^*, \lambda^*) w > 0$$

Since $w^T \nabla_{xx}^2 L(x^*, \lambda^*) w = 0$ the
second-order sufficient conditions are
not satisfied

Problem 4: Exercise 12.21

10) $\max f(x) = x_1 x_2$

s.t.

$$c_1(x) = 1 - x_1^2 - x_2^2 \geq 0$$



$$\min f(x) = -x_1 x_2$$

s.t.

$$c_1(x) = 1 - x_1^2 - x_2^2 \geq 0$$

$$\mathcal{L}(x, \lambda) = -x_1 x_2 - \lambda_1 (1 - x_1^2 - x_2^2)$$

$$\nabla_x \mathcal{L}(x, \lambda) = -\begin{bmatrix} x_2 \\ x_1 \end{bmatrix} - \lambda_1 \begin{bmatrix} -2x_1 \\ -2x_2 \end{bmatrix}$$

$$\nabla_x \mathcal{L}(x^*, \lambda^*) = 0$$

$$\Rightarrow -x_2^* + 2\lambda_1^* x_1^* = 0 \rightarrow x_2^* = 2\lambda_1^* x_1^*$$

$$\Rightarrow -x_1^* + 2\lambda_1^* x_2^* = 0$$

$$-x_1^* + 2\lambda_1^* (2\lambda_1^* x_1^*) = 0$$

$$-x_1^* + 4\lambda_1^{*2} x_1^* = 0$$

$$x_1^* (4\lambda_1^{*2} - 1) = 0$$

$$4\lambda_1^{*2} - 1 = 0$$

$$\lambda_1^{*2} = \frac{1}{4}$$

$$\lambda_1^* = \pm \frac{1}{2}$$

From the KKT conditions we have $\lambda_i^* > 0, i \in I$.

$$\Rightarrow \underline{\lambda_1^* = \frac{1}{2}}$$

$$\Rightarrow x_2^* = 2\lambda_1^* x_1^* = 2 \cdot \frac{1}{2} x_1^* = x_1^*$$

$$x_2^* = x_1^*$$

This yields two points on the boundary

$$x^* = \left[-\frac{1}{\sqrt{2}}, -\frac{1}{\sqrt{2}} \right]^T$$

$$x^{**} = \left[\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}} \right]^T$$

$$\nabla C_1(x) = \begin{bmatrix} -2x_1 \\ -2x_2 \end{bmatrix}$$

$$\nabla f(x) = \begin{bmatrix} -x_2 \\ -x_1 \end{bmatrix}$$

$$\nabla C_1(x^*) = \left[\sqrt{2}, \sqrt{2} \right]^T$$

$$\nabla f(x^*) = \left[\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}} \right]^T$$

$$\nabla C_1(x^{**}) = \left[-\sqrt{2}, -\sqrt{2} \right]^T$$

$$\nabla f(x^{**}) = \left[-\frac{1}{\sqrt{2}}, -\frac{1}{\sqrt{2}} \right]^T$$

