CONVEX OPTIMISATION ASSIGNMENT

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Question 1

(a)

Problem (2), (3) and (4) are always convex but Problem (3) are not always convex because hessian of objective for problem (1) is,

$$\mathbf{H} = \mathbf{A}^T\mathbf{A} + \alpha\mathbf{I}$$

Positive definitness of hessian is dependent on the value α.

(b)

$$\Delta Objective = \left(\partial\frac{\overline{x}^T(\mathbf{A}^T\mathbf{A} + \alpha\mathbf{I})\overline{x} - \overline{y}^T\mathbf{A}\overline{x} + \overline{y}^T\overline{y}}{\partial\overline{x}}\right)^T$$
$$\implies \Delta Objective = 2(\mathbf{A}^T\mathbf{A} + \alpha\mathbf{I})\overline{x} - \overline{y}^T\mathbf{A}$$

(c)

$$\Delta Objective = 0$$
$$\implies \overline{x}^* = 0.5(\mathbf{A}^T\mathbf{A} + \alpha\mathbf{I})^{-1}\mathbf{A}^T\overline{y}$$

(d)

(e)

Question 2

Question 3

(a)

To prove that the objective function is quasi-convex we ned to show that all α level subsets are convex.

$$\frac{\overline{\mu}^T\overline{x}}{||\mathbf{V}\overline{x}||_2} \leq \alpha \implies \frac{\overline{x}^T\overline{\mu}\overline{\mu}^T\overline{x}}{\overline{x}^T\mathbf{V}^T\mathbf{V}\overline{x}} \leq \alpha^2$$
$$\implies \overline{x}^T\left(\alpha^2\mathbf{V}^T\mathbf{V} + \overline{\mu}\overline{\mu}^T\right)\overline{x} \geq 0$$

Given that $\mathbf{V}$ is symmentric which means $\mathbf{V}^T\mathbf{V}$ and outer product of matrices is positive defnite matrix. Therefore sum of positive semidefnite matrices is positive semidefnite. Thus the given objective function is quasi-convex.

(b)

$$\overline{z} = \frac{\overline{x}}{\overline{\mu}^T\overline{x}}$$

$$\implies \frac{\overline{z}}{\overline{1}^T\overline{z}} = \frac{\frac{\overline{x}}{\overline{\mu}^T\overline{x}}}{\frac{\overline{1}^T\overline{x}}{\overline{\mu}^T\overline{x}}}$$

$$\implies \boxed{\overline{x} = \frac{\overline{z}}{\overline{1}^T\overline{z}}}$$

$$\frac{\overline{\mu}^T\overline{x}}{||\mathbf{V}\overline{x}||_2} = \frac{\overline{\mu}^T\frac{\overline{z}}{\overline{1}^T\overline{z}}}{||\mathbf{V}\frac{\overline{z}}{\overline{1}^T\overline{z}}||_2} = \frac{sgn\left(\overline{1}^T\overline{z}\right)}{||\mathbf{V}\overline{z}||_2}$$

Given $\overline{\mu}^T\overline{x} \geq 0$ and $\overline{1}^T\overline{x} = 1$ which means $\overline{1}^T\overline{z} = \frac{1}{\overline{\mu}^T\overline{x}} > 0$.

$$\implies \boxed{\frac{\overline{\mu}^T\overline{x}}{||\mathbf{V}\overline{x}||_2} = \frac{1}{||\mathbf{V}\overline{z}||_2}}$$

$$||\overline{x}||_1 \leq L \implies ||\frac{\overline{z}}{\overline{1}^T\overline{z}}||_1 \leq L$$

$$||\overline{z}||_1 \leq L\overline{1}^T\overline{z}$$

Now transformed problem is,

$$\begin{aligned} \min \quad & ||\mathbf{V}\overline{z}||_2 \\ \text{s.t} \quad & ||\overline{z}||_1 \leq L\overline{1}^T\overline{z} \end{aligned}$$

The above transformed problem has both convex objective and constraints thus it is convex optimisation problem.

Question 4

Question 5

Question 6

Primal is

$$\overline{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$\begin{aligned} \min \quad & \overline{x}^T \begin{bmatrix} 1 & -0.5 \\ -0.5 & 2 \end{bmatrix} \overline{x} + \begin{bmatrix} -1 & 0 \end{bmatrix} \overline{x} \\ \text{s.t} \quad & \begin{bmatrix} 1 & -2 \\ 1 & 4 \\ 5 & -76 \end{bmatrix} \overline{x} \leq \begin{bmatrix} u_1 \\ u_2 \\ 1 \end{bmatrix} \end{aligned}$$

Dual is

(a)

The above objective is in quadratic form and eigen decomposition of the hessian is

$$\begin{bmatrix} 1 & -0.5 \\ -0.5 & 2 \end{bmatrix} = \begin{bmatrix} -0.92387953 & 0.38268343 \\ -0.38268343 & -0.92387953 \end{bmatrix} \begin{bmatrix} 0.79289322 & 0 \\ 0 & 2.20710678 \end{bmatrix} \begin{bmatrix} -0.92387953 & -0.38268343 \\ 0.38268343 & -0.92387953 \end{bmatrix}$$

Here both eigen values are positive, which implies that hessian is positive semidefnite. With linear constraints, The problem is convex and is a QP.

(b)

After solving the problem with $CVXPY$ we get,

$$x_1^* = -3; x_2^* = 0$$
$$\lambda_1^* = 5.167; \lambda_2^* = 1.834; \lambda_3^* = 0$$

(c)

KKT Conditions

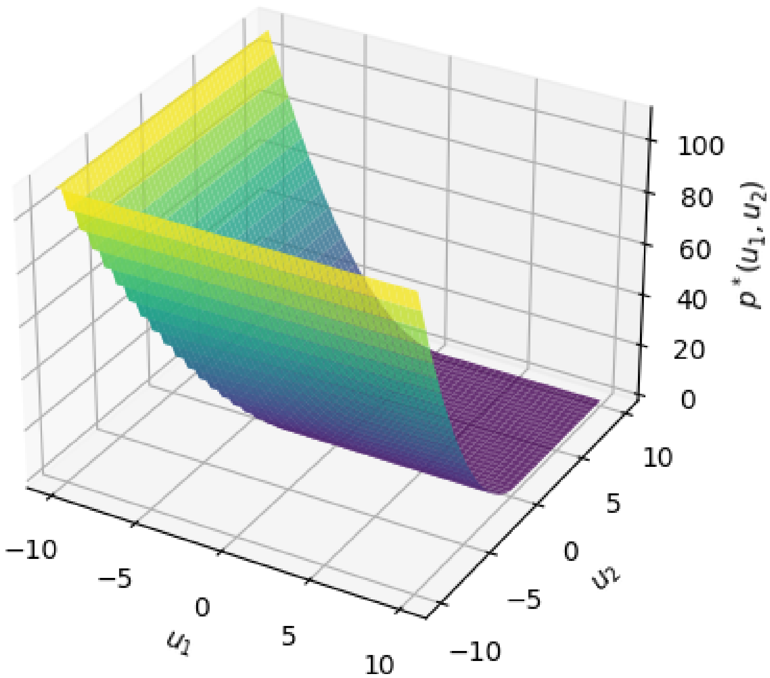
1. $f_i(x^*) \leq 0$, Satisfied.

$$\begin{bmatrix} 1 & -2 \\ 1 & 4 \\ 5 & -76 \end{bmatrix} \begin{bmatrix} -3 \\ 0 \end{bmatrix} \leq \begin{bmatrix} -2 \\ -3 \\ 1 \end{bmatrix} \implies \begin{bmatrix} -3 \\ -3 \\ -15 \end{bmatrix} \leq \begin{bmatrix} -2 \\ -3 \\ 1 \end{bmatrix}$$

2. $\lambda_i^* \geq 0$, Satisfied.
3. $\lambda_i^* f_i(x^*) = 0$, Satisfied.

$$\begin{bmatrix} 5.167 & 1.834 & 0 \end{bmatrix} \left(\begin{bmatrix} -3 \\ -3 \\ -15 \end{bmatrix} - \begin{bmatrix} -2 \\ -3 \\ 1 \end{bmatrix} \right) = 0$$

(d)

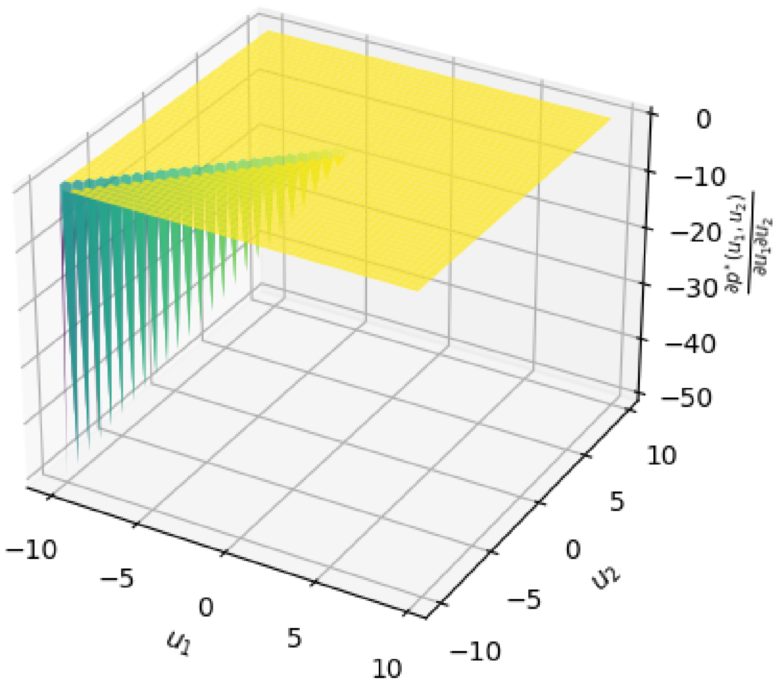


(e)

From above graph it seems like $p^*(u_1, u_2)$ is a convex function.

(f)

Numerically derivated at the given point is 0.


0
−10
−20
−30
−40
−50
$\frac{\partial \phi^*(u_1,u_2)}{\partial u_1 \partial u_2}$
−10
−5
0
5
10
u_1
−10
−5
0
5
10
u_2