

## Assignment 5

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### Problem 1

#### question 1

**Indices:**  $i = 1, 2, \dots, N$  and  $j = 1, 2, \dots, N$  for different products.  $s = 1, 2, \dots, M$  and  $t = 1, 2, \dots, M$  for different inputs.  $k = 1, 2, \dots, q$  for different linear constraints.

**Variables:** The definition of variables is put before the definition of data in order to clarify the definition of data.  $x_i$  is the amount of product  $i$  that is sold.  $y_s$  is the amount of inputs  $s$  that is purchased.

**Data:**

- $A_{i,j}$  and  $b_i$  together form the price of the products  $P_x = b - Ax$ , where the  $i$ th entry of the vector  $(P_x)_i = b_i - \sum_{j=1}^N A_{i,j}x_j$ .
- $C_{s,t}$  and  $d_s$  together form the price of the inputs  $P_y = d + Cy$ , where the  $s$ th entry of the vector  $(P_y)_s = d_s + \sum_{t=1}^M C_{s,t}y_t$ .
- $E_{k,j}$ ,  $F_{k,t}$ , and  $g_k$  together form  $q$  linear constraints  $Ex + Fy \leq g$ , where for the  $k$ th constraint,  $\sum_{j=1}^N E_{k,j}x_j + \sum_{t=1}^M F_{k,t}y_t \leq g_k$ .

**Objective:** maximize  $xP_x - yP_y$ , which equals maximizing  $\sum_{i=1}^N (x_i b_i - \sum_{j=1}^N A_{i,j}x_j x_i) - \sum_{s=1}^M (y_s d_s + \sum_{t=1}^M C_{s,t}y_t y_s)$

**Constraints:**  $\sum_{j=1}^N E_{k,j}x_j + \sum_{t=1}^M F_{k,t}y_t \leq g_k$  for every  $k$ .

**Bounds:**  $x_i$  and  $y_s$  have lower bound 0.

#### question 2

Result as shown in Figure 1.

Iteration	Objective	Constraint 1	Constraint 2	Constraint 3	Constraint 4	Constraint 5	Constraint 6
7	9.63305368e+03	1.60429367e+04	4.84e-14	1.61e-12	1.97e+01	0s	
8	1.11349586e+04	1.28436170e+04	4.80e-14	2.84e-13	5.26e+00	0s	
9	1.16392866e+04	1.19012767e+04	2.31e-14	4.55e-13	8.06e-01	0s	
10	1.17187145e+04	1.17799909e+04	3.15e-13	3.41e-13	1.89e-01	0s	
11	1.17436178e+04	1.17442510e+04	1.57e-13	1.25e-12	1.95e-03	0s	
12	1.17438982e+04	1.17439025e+04	1.46e-11	1.71e-12	1.32e-05	0s	
13	1.17439015e+04	1.17439015e+04	4.88e-10	7.39e-13	1.42e-08	0s	
14	1.17439015e+04	1.17439015e+04	1.63e-09	5.12e-13	1.42e-11	0s	

Barrier solved model in 14 iterations and 0.06 seconds  
Optimal objective 1.17439015e+04

Figure 1

## Problem 2

### question 1

**Indices:**  $i = 1, 2, \dots, m$  for different dimensions in space  $R^m$ .  $j = 1, 2, \dots, n$  for different dimensions in space  $R^n$ .

**Data:**  $A \in R^{m \times n}$  is a matrix with  $A_{i,j}$  as its entry at  $i$ th row and  $j$ th column.  $a_i^T$  is the  $i^{\text{th}}$  row of the matrix  $A$ .  $b \in R^m$  is a vector with  $b_i$  as its  $i$ th entry.

**Variables:**  $x_j$  is the decision variable.  $y_i$  is the auxiliary variable that represent each reciprocals.

**Objective:** minimize  $\sum_{i=1}^m y_i$

**Constraints:**

- $\|(2, a_i^T x - b_i - y_i)\|_2 \leq a_i^T x - b_i + y_i$  for every  $i$ . This is because  $y_i \geq \frac{1}{a_i^T x - b_i}$ . Since  $y_i \geq 0$  and  $a_i^T x - b_i \geq 0$ ,  $y_i \geq \frac{1}{a_i^T x - b_i}$  equals  $\|(2, a_i^T x - b_i - y_i)\|_2 \leq a_i^T x - b_i + y_i$ .
- $a_i^T x - b_i \geq 0$  for every  $i$ , so that  $Ax > b$ .
- $a_i^T x - b_i + y_i \geq 0$  for every  $i$ , this constraint may be redundant but is a must for Gurobi program.

**Bounds:**  $y_i \geq 0$ .

**Note:** Assume  $x_0$  is the optimal solution,  $\frac{1}{x_0}$  is the optimal solution for the original question.

### question 2

Result as shown in Figure 2.

**Note:** Assume  $x_0$  is the optimal solution,  $\frac{1}{x_0}$  is the optimal solution for the original question.

		solve_socp()			
tun: reciprocal					
11	9.83733627e+01	9.83190072e+01	1.70e-04	5.07e-13	
12	9.83439162e+01	9.83196342e+01	7.55e-05	2.57e-12	
13	9.83323244e+01	9.83200640e+01	3.82e-05	4.46e-12	
14	9.83265566e+01	9.83202234e+01	1.96e-05	6.35e-12	
15	9.83241166e+01	9.83203516e+01	1.18e-05	1.34e-11	
16	9.83216470e+01	9.83204408e+01	3.80e-06	4.56e-11	
Barrier solved model in 16 iterations and 0.04 seconds					
Optimal objective 9.83216470e+01					
Process finished with exit code 0					

Figure 2

### Problem 3

#### question 1

**Indices:**  $i = 1, 2, \dots, m$  for different dimensions in space  $R^m$ , and  $j = 1, 2, \dots, n$  for different dimensions in space  $R^n$ .

**Data:**  $M \in R^{m \times n}$  is a matrix with  $M_{i,j}$  as its entry at  $i$ th row and  $j$ th column.  $b \in R^m$  is a vector with  $b_i$  as its  $i$ th entry.

**Variables:**  $z_j$  is the decision variable.  $x_i$  is the auxiliary variable that represent the square of the  $i$ th entry of  $Mz - b$ .

**Objective:** minimize  $\sum_{i=1}^m x_i x_i$

**Constraints:**  $x_i \geq (\sum_{j=1}^n M_{i,j} z_j - b_i)(\sum_{j=1}^n M_{i,j} z_j - b_i)$  for every  $i$ .

**Bounds:**  $x_i \geq 0$ .

**Note:** Assume  $x_0$  is the optimal solution,  $x_0^{1/4}$  is the optimal solution for the original question.

#### question 2

Result as shown in Figure 3.

**Note:** Assume  $x_0$  is the optimal solution,  $x_0^{1/4}$  is the optimal solution for the original question.

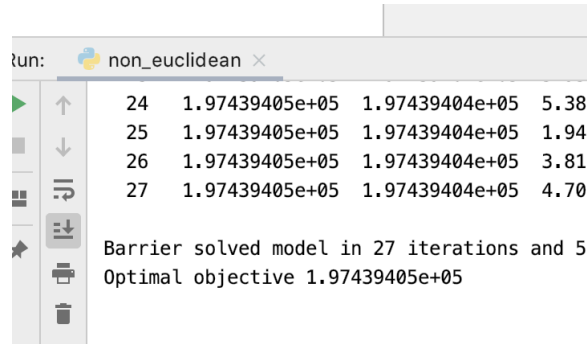


Figure 3

### Problem 4

#### question 1

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The KKT conditions for  $Q$

- $\vec{c} - E^T \vec{\mu} + A^T \vec{\lambda} = 0$
- $\vec{d} - E \vec{x} \leq 0$
- $A \vec{x} - \vec{b} = 0$

- $\vec{\mu} \geq \vec{0}$
- $\vec{\mu}^T(\vec{d} - E\vec{x}) = 0$

**The KKT conditions for  $Q_\rho$**

- $\vec{c} + \rho A^T(A\vec{x} - \vec{b}) - E^T\vec{\mu} = 0$
- $\vec{d} - E\vec{x} \leq 0$
- $\vec{\mu} \geq \vec{0}$
- $\vec{\mu}^T(\vec{d} - E\vec{x}) = 0$

**The conditions that a  $Q_\rho$  KKT point can be used to generate a  $Q$  KKT point**

Combine the KKT conditions of  $Q$ , we can get the KKT point would satisfy the equation  $\vec{x}^T\vec{c} - \vec{d}^T\vec{\mu} + \vec{b}^T\vec{\lambda} = 0$ . Similarly, the KKT conditions of  $Q_\rho$  can be combined, and we can get the KKT point of  $Q_\rho$  would satisfy the equation  $\vec{x}^T\vec{c} + \rho\vec{x}^T A^T(A\vec{x} - \vec{b}) - \vec{d}^T\vec{\mu} = 0$ .

When a  $Q_\rho$  KKT point can be used to generate a  $Q$  KKT point, the KKT point  $\vec{x}_\rho$  that satisfy the equation  $\vec{x}_\rho^T\vec{c} + \rho\vec{x}_\rho^T A^T(A\vec{x}_\rho - \vec{b}) = \vec{d}^T\vec{\mu}$  would also satisfy  $\vec{x}_\rho^T\vec{c} + \vec{b}^T\vec{\lambda} = \vec{d}^T\vec{\mu}$ . From the KKT conditions, we can see that  $A\vec{x}_\rho - \vec{b} = 0$  must be satisfied to be a  $Q$  KKT point candidate. Thus,  $\vec{b}^T\vec{\lambda} = 0$  and thus  $\vec{\lambda} = 0$ .

Conclusion: when  $A\vec{x}_\rho - \vec{b} = 0$ , a  $Q_\rho$  KKT point can be used to generate a  $Q$  KKT point and at that time,  $\vec{\lambda} = 0$  should be satisfied for that  $Q$  KKT point.

## question 2

Result as shown in Figure 4.

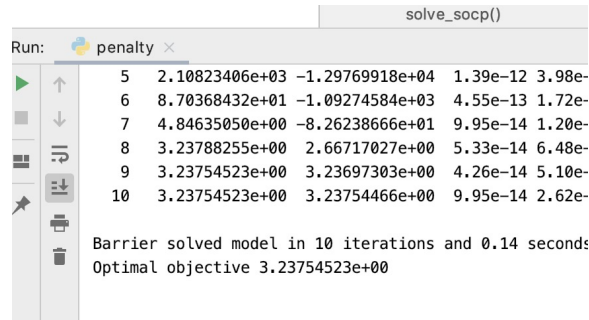


Figure 4

## question 3

Result as shown in Figure 5 and 6.

Observation: when the value of  $\rho$  increases, the distance/difference between  $z$  and  $z_\rho$  decreases to zero as well as the value of the norm of  $Az_\rho - \vec{b}$  decreases to zero. This result supports the conclusion in question (a), where the conclusion says that when  $Az_\rho - \vec{b} = 0$ ,

$z_\rho$  is a KKT point of  $Q$  as well. It also indicates that in Gurobi (or any other computer programs), the optimal solution is not exactly the theoretical solution but a reasonable approximation. When  $\rho$  is comparably small, the product of  $\rho$  and  $Az_\rho - b$  would be comparably small and close to zero so that there still remains a noticeable  $Az_\rho - b$  value. However, when  $\rho$  is comparably big,  $Az_\rho - b$  would need to be closer to zero so that the product of  $\rho$  and  $Az_\rho - b$  could be comparably small. Hence, the raw value of  $Az_\rho - b$  would be close to zero.

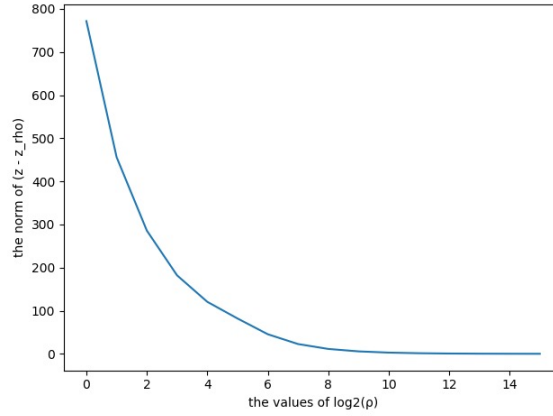


Figure 5

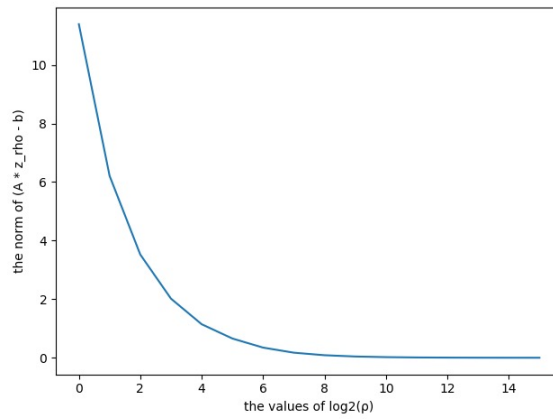


Figure 6