

**TMA947/MAN280
APPLIED OPTIMIZATION**

- Date:** 04-08-23
- Time:** House M, morning
- Aids:** Text memory-less calculator
- Number of questions:** 7; passed on one question requires 2 points of 3.
Questions are *not* numbered by difficulty.
To pass requires 10 points and three passed questions.
- Examiner:** Michael Patriksson
- Teacher on duty:** Anton Evgrafov (0740-459022)
- Result announced:** 04-09-06
Short answers are also given at the end of
the exam on the notice board for optimization
in the MD building.

Exam instructions

When you answer the questions

*Use generally valid methods and theory.
State your methodology carefully.*

*Only write on one page of each sheet. Do not use a red pen.
Do not answer more than one question per page.*

At the end of the exam

*Sort your solutions by the order of the questions.
Mark on the cover the questions you have answered.
Count the number of sheets you hand in and fill in the number on the cover.*

Question 1

(linear programming duality)

- (2p) a) Consider the following linear program:

$$\begin{aligned} & \text{maximize} && z = x_1 + 2x_2, \\ & \text{subject to} && -2x_1 + x_2 \leq 2, \\ & && -x_1 + 2x_2 \leq 7, \\ & && x_1 \leq 3, \\ & && x_1, x_2 \geq 0. \end{aligned}$$

This problem has the optimal solution $\mathbf{x}^* = (3, 5)^T$. By using duality and complementarity, determine the optimal dual solution, as well as confirm that the solution \mathbf{x}^* given is indeed optimal in the primal problem.

- (1p) b) Consider the standard LP problem to

$$\begin{aligned} & \text{minimize} && \mathbf{c}^T \mathbf{x}, \\ & \text{subject to} && \mathbf{A}\mathbf{x} \geq \mathbf{b}, \\ & && \mathbf{x} \geq \mathbf{0}^n, \end{aligned}$$

where $\mathbf{A} \in \mathbb{R}^{m \times n}$, $\mathbf{c}, \mathbf{x} \in \mathbb{R}^n$, and $\mathbf{b} \in \mathbb{R}^m$.

Suppose that this problem has a feasible solution. Prove that if it has an unbounded solution, then the corresponding dual problem cannot have any feasible solution.

(3p) Question 2

(convexity)

Show the following result for convex sets, known as the *Separation Theorem*:

Suppose that the set $C \subseteq \mathbb{R}^n$ is closed and convex, and that the point \mathbf{y} does not lie in C . Then there exist a real α and an $n \times 1$ vector $\boldsymbol{\pi} \neq \mathbf{0}^n$ such that $\boldsymbol{\pi}^T \mathbf{y} > \alpha$ and $\boldsymbol{\pi}^T \mathbf{x} \leq \alpha$ for all $\mathbf{x} \in C$.

Illustrate it also geometrically.

When showing this result, you may refer to any other theorems needed without proof, but you *must* state the ones you use *clearly*.

(3p) **Question 3**

(modelling)

An American oil company manufactures three types of gasoline (gas 1, gas 2, gas 3). Each type of gasoline is produced by mixing together three types of crude oil (crude 1, crude 2, crude 3). The sales price per barrel of gasoline and the purchase price per barrel of crude oil is given below.

The company can purchase up to 5,000 barrels of each type of crude oil daily. The three types of gasoline differ in their octane rating and lead content. The crude oil blended to form gas 1 must have an octane rating of at least 10 and contain at most 1% lead. The crude oil blended to form gas 2 must have an octane rating of at least 8 and contain at most 2% lead. The crude oil blended to form gas 3 must have an octane rating of at least 6 and contain at most 1% lead. The octane rating and the lead content of the three types of oil are given in a table below. It costs USD 4 to transform one barrel of oil into one barrel of gasoline. The company's refinery can process up to 14,000 barrels of crude oil daily.

The company's customers require the following amounts each gasoline: gas 1—3,000 barrels per day, gas 2—2,000 barrels per day, gas 3—3,000 barrels per day. The company considers it an obligation to meet these demands. The company also has the option of advertising to stimulate demand for its products. Each dollar spent daily in advertising a particular type of gas increases the daily demand for that type of gas by ten barrels. For example, if the company decides to spend USD 20 daily in advertising gas 2, the daily demand for gas 2 will increase by $20 \times 10 = 200$ barrels.

Formulate the linear program that will enable the company to maximize daily profits (profits = revenues – costs). To simplify matters, assume the company cannot store any extra gasoline. This implies that the daily amount of gas produced should equal the daily demand for each gas type.

Data:

Sales price per barrel (in USD): Gas 1: 70; Gas 2: 60; Gas 3: 50.

Purchase price per barrel (in USD): Crude 1: 45; Crude 2: 35; Crude 3: 25.

Octane rating: Crude 1: 12; Crude 2: 6; Crude 3: 8.

Lead content (in %): Crude 1: 0.5; Crude 2: 2.0; Crude 3: 3.0.

Question 4

(on the Armijo step length rule in unconstrained optimization)

Consider the unconstrained optimization problem to

$$\begin{aligned} & \text{minimize } f(\mathbf{x}), \\ & \text{subject to } \mathbf{x} \in \mathbb{R}^n, \end{aligned} \tag{1a}$$

where $f : \mathbb{R}^n \mapsto \mathbb{R}$ is continuously differentiable and weakly coercive, hence lower bounded, on \mathbb{R}^n . Suppose that to this problem we apply the steepest descent algorithm with the Armijo step length rule, starting at some $\mathbf{x}_0 \in \mathbb{R}^n$. In the Armijo rule, we replace the exact line search, in which we

$$\underset{\alpha \geq 0}{\text{minimize}} \varphi(\alpha) := f(\mathbf{x}_k + \alpha \mathbf{p}_k),$$

by the following rule:

Let $\mu \in (0, 1)$. The step lengths accepted by the Armijo step length rule are the positive values α which satisfy the inequality

$$\varphi(\alpha) - \varphi(0) \leq \mu \alpha \varphi'(0), \tag{2a}$$

that is,

$$f(\mathbf{x}_k + \alpha \mathbf{p}_k) - f(\mathbf{x}_k) \leq \mu \alpha \nabla f(\mathbf{x}_k)^T \mathbf{p}_k. \tag{2b}$$

Usually, the value of the step length α is taken to be of the form $\alpha := \alpha_0 \cdot \beta^i$, where $\alpha_0 > 0$ is the initial step taken, $\beta \in (0, 1)$ is a factor by which we multiply the initial step if it is not successful (usually, we set $\beta = 1/2$ so that the step length is halved repeatedly), and i is an integer which we first give the value 0, and then increase by one until $\alpha := \alpha_0 \cdot \beta^i$ is small enough to satisfy (2).

The purpose of this exercise is to point out that the Armijo rule is not always a good rule, because the initial step length α_0 may be hard to choose appropriately. (Especially, the initial step might be *too small* to provide fast convergence; since the Armijo rule is based on decreasing the trial step length and never to increase it, fast convergence can in such cases not occur.)

Recall the following on the issue of convergence rates: Suppose that $\{\mathbf{x}_k\} \rightarrow \mathbf{x}^*$. We say that the speed of convergence is *linear* if the quotients

$$q_k := \frac{\|\mathbf{x}_{k+1} - \mathbf{x}^*\|}{\|\mathbf{x}_k - \mathbf{x}^*\|}$$

satisfy that

$$\limsup_{k \rightarrow \infty} q_k < 1.$$

Suppose now that

$$f(x) := x^4/4, \quad x \in \mathbb{R}. \quad (3)$$

- (2p) a) Describe the iteration of the steepest descent method for the problem (1) when f is given by (3), that is, give the formula that provides x_{k+1} from x_k when the step length chosen is α_k .

Further, show that no matter how small or large (but finite and positive) the value of α_0 is chosen, linear convergence cannot be obtained for the steepest descent method using the Armijo step length rule, when applied to the given problem. Explain why!

- (1p) b) Suppose we instead apply Newton's method with line searches. Show that linear convergence is guaranteed for any choice of $\alpha_0 > 0$ small enough, or for $\alpha_k = 1$ for all k and any value of $\mu > 0$ small enough.

Question 5

(nonlinear programming optimality)

Consider the optimization problem to

$$\underset{\mathbf{x}}{\text{minimize}} \quad f(\mathbf{x}), \quad (1a)$$

$$\text{subject to} \quad g_i(\mathbf{x}) \leq 0, \quad i = 1, \dots, m, \quad (1b)$$

$$h_j(\mathbf{x}) = 0, \quad j = 1, \dots, \ell, \quad (1c)$$

where the functions f , g_i ($i = 1, \dots, m$), and h_j ($j = 1, \dots, \ell$) are continuously differentiable on \mathbb{R}^n .

- (1p) a) Suppose that $\bar{\mathbf{x}}$ is feasible in the problem (1). Prove the following statement by using linear programming duality: $\bar{\mathbf{x}}$ satisfies the Karush–Kuhn–Tucker (KKT) conditions if and only if the following LP problem has the optimal value zero:

$$\underset{\mathbf{p}}{\text{minimize}} \quad \nabla f(\bar{\mathbf{x}})^T \mathbf{p},$$

$$\begin{aligned} \text{subject to } \quad & g_i(\bar{\mathbf{x}}) + \nabla g_i(\bar{\mathbf{x}})^T \mathbf{p} \leq 0, & i = 1, \dots, m, \\ & h_j(\bar{\mathbf{x}}) + \nabla h_j(\bar{\mathbf{x}})^T \mathbf{p} = 0, & j = 1, \dots, \ell. \end{aligned}$$

Describe briefly how this LP problem could be used to devise an iterative method for the problem (1).

- (2p) b) Prove that if the problem (1) is convex then each one of its KKT points is globally optimal.

(3p) Question 6

(linear programming geometry)

Consider the non-empty polyhedron $X = \{\mathbf{x} \in \mathbb{R}^n \mid \mathbf{A}\mathbf{x} \leq \mathbf{b}; \mathbf{x} \geq \mathbf{0}^n\}$, where $\mathbf{A} \in \mathbb{R}^{m \times n}$ and $\mathbf{b} \in \mathbb{R}^m$. We say that a linear inequality of the form $\mathbf{d}^T \mathbf{x} \leq d_0$ is *redundant relative to the set X* if $X \cap \{\mathbf{x} \in \mathbb{R}^n \mid \mathbf{d}^T \mathbf{x} \leq d_0\} = X$.

Show the following:

$$\begin{aligned} \mathbf{d}^T \mathbf{x} \leq d_0 \text{ is redundant relative to the set } X \\ \iff \\ \exists \boldsymbol{\mu} \geq \mathbf{0}^m \text{ with } \mathbf{A}^T \boldsymbol{\mu} \geq \mathbf{d} \text{ and } \mathbf{b}^T \boldsymbol{\mu} \leq d_0. \end{aligned}$$

Hint: Use LP duality in one of the directions.

[This result implies a natural procedure for detecting unnecessary constraints in LP problems.]

Question 7

(Lagrangian duality)

Consider the following optimization (linear) problem:

$$\begin{aligned} \text{minimize } & f(x, y) = x - 0.5y, \\ \text{subject to } & -x + y \leq -1, \\ & -2x + y \leq -2, \\ & (x, y) \in \mathbb{R}_+^2. \end{aligned} \tag{1}$$

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- (2p) a) Show that the problem satisfies Slater's constraint qualification. Derive the Lagrangian dual problem corresponding to the Lagrangian relaxation of the two linear inequality constraints, and show that its set of optimal solutions is convex and bounded.
- (1p) b) Calculate the set of subgradients of the Lagrangian dual function at the dual points $(1/4, 1/3)^T$ and $(1, 0)^T$.
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Good luck!

Chalmers/GU
Mathematics

EXAM SOLUTION

**TMA947/MAN280
APPLIED OPTIMIZATION**

Date: 04-08-23

Examiner: Michael Patriksson

Question 1

(linear programming duality)

a) The LP dual is to

$$\begin{aligned} & \text{minimize} && w = 2y_1 + 7y_2 + 3y_3, \\ & \text{subject to} && -2y_1 - y_2 + y_3 \geq 1, \\ & && y_1 + 2y_2 \geq 2, \\ & && y_1, y_2, y_3 \geq 0. \end{aligned}$$

The complementarity conditions are next investigated. First, we check the conditions of the type

$$y_i^* \cdot \left(\sum_{j=1}^n a_{ij} x_j^* - b_i \right) = 0, \quad i = 1, \dots, m.$$

Checking the primal constraints reveals that the first constraint is fulfilled strictly while the remaining two have no slack. This implies that $y_1^* = 0$ must hold. Next, we investigate the second type of complementarity conditions:

$$x_j^* \cdot \left(\sum_{i=1}^m a_{ij} y_i^* - c_j \right) = 0, \quad j = 1, \dots, n.$$

Since $\mathbf{x} = (3, 5)^T$ is strictly positive, both dual constraints are active. Together with the fact that $y_1^* = 0$ leaves the following system of linear equations:

$$\begin{aligned} -y_2^* + y_3^* &= 1; \\ 2y_2^* &= 2; \end{aligned}$$

its unique solution is that $y_2^* = 1$; $y_3^* = 2$.

It remains to check that all dual constraints are satisfied, that is, to also check the sign conditions. Non-negativity is clearly satisfied, so $\mathbf{y}^* = (0, 1, 2)^T$ is the unique dual optimal solution. We therefore know from the complementarity theorem that \mathbf{x}^* and \mathbf{y}^* are optimal in their respective problem. But we check nevertheless that strong duality is fulfilled: $\mathbf{c}^T \mathbf{x}^* = 13 = \mathbf{b}^T \mathbf{y}^*$.

b) The proof is by contradiction. Suppose that (D) has a feasible solution. Since (P) has a feasible solution we can apply the Strong Duality Theorem and conclude that both (P) and (D) have finite optimal solutions which moreover have the same objective value. But this contradicts the fact that (P) has an unbounded solution. Therefore, the claim that (D) has a feasible solution is false. We are done.

Question 2

(convexity)

A proof is found in the course notes (Theorem 3.26).

Question 3

(modeling)

Variable declaration:

- c_i = number of barrels of crude oil of type i bought ($i = 1, 2, 3$);
- b_{ij} = number of barrels of crude oil of type i used to produce gas of type j ($i = 1, 2, 3, j = 1, 2, 3$);
- a_j = number of dollars spent on advertising for gas type i ($i = 1, 2, 3$);
- g_i = number of barrels of gas of type j produced ($j = 1, 2, 3$).

Objective function: maximize the difference between the income of selling oil and the cost of producing it (the latter including buying crude oil, transforming crude oil to gas, and advertizing), that is:

$$\text{maximize } (70 - 4)g_1 + (60 - 4)g_2 + (50 - 4)g_3 - (45c_1 + 35c_2 + 25c_3 + a_1 + a_2 + a_3).$$

Constraints:

- For each type of oil:
 - definition of product;
 - minimum octane rating; and
 - maximum lead content;
- All crude oil bought is used;
- Maximum purchase of crude oil;
- Maximum capacity of production;

- Demand of products;
- Physical constraints.

In the same order:

$$\begin{aligned}
 b_{11} + b_{21} + b_{31} &= g_1, \\
 12b_{11} + 6b_{21} + 8b_{31} &\geq 10g_1, \\
 0.5b_{11} + 2b_{21} + 3b_{31} &\leq g_1, \\
 b_{12} + b_{22} + b_{32} &= g_2, \\
 12b_{12} + 6b_{22} + 8b_{32} &\geq g_2, \\
 0.5b_{12} + 2b_{22} + 3b_{32} &\leq 2g_2, \\
 b_{13} + b_{23} + b_{33} &= g_3, \\
 12b_{13} + 6b_{23} + 8b_{33} &\geq 6g_3, \\
 0.5b_{13} + 2b_{23} + 3b_{33} &\leq g_3, \\
 b_{11} + b_{12} + b_{13} &= c_1, \\
 b_{21} + b_{22} + b_{23} &= c_2, \\
 b_{31} + b_{32} + b_{33} &= c_3, \\
 c_j &\leq 5,000, \quad j = 1, 2, 3, \\
 c_1 + c_2 + c_3 &\leq 14,000, \\
 g_1 &\geq 3,000 + 10a_1, \\
 g_2 &\geq 2,000 + 10a_1, \\
 g_3 &\geq 3,000 + 10a_1, \\
 c_i, b_{ij}, a_j, g_j &\geq 0, \quad i = 1, 2, 3; j = 1, 2, 3.
 \end{aligned}$$

Question 4

(on the Armijo step length rule in unconstrained optimization)

a) We have that $x_{k+1} = x_k(1 - \alpha_k x_k^2)$.

The requirements of linear convergence imply that $1 - \alpha_k x_k^2$ must be bounded away from 1, that is, that $\alpha_k x_k^2$ must be bounded away from zero. But since $x^* = 0$ this requires that α_k tends to infinity faster than x_k^2 tends to zero; there is obviously no finite value of α_0 that can produce such step lengths.

b) We have that $x_{k+1} = x_k(1 - \alpha_k/3)$.

According to the Newton formula above, if we can ensure that $\alpha_k = 1$ is always going to be accepted by the Armijo rule, then we have linear convergence with rate $q := 2/3$. In this case, we then have that $x_{k+1} = (2/3)x_k$. With $\alpha_k = 1$ the Armijo rule requires that $1 - (2/3)^4 \geq (4/3)\mu$ which clearly is satisfied as long as the value of μ is small enough. ($\mu \leq 0.6$ will do.)

Question 5

(nonlinear programming optimality)

a) Let us first rewrite the LP problem into the following equivalent form, and note that $h_j(\bar{\mathbf{x}}) = 0$ for all j , since $\bar{\mathbf{x}}$ is feasible:

$$\begin{aligned} & \underset{\mathbf{p}}{\text{minimize}} && \nabla f(\bar{\mathbf{x}})^T \mathbf{p}, \\ & \text{subject to} && -\nabla g_i(\bar{\mathbf{x}})^T \mathbf{p} \geq g_i(\bar{\mathbf{x}}), \quad i = 1, \dots, m, \\ & && -\nabla h_j(\bar{\mathbf{x}})^T \mathbf{p} = 0, \quad j = 1, \dots, \ell. \end{aligned}$$

Letting $\boldsymbol{\mu} \geq \mathbf{0}^m$ and $\boldsymbol{\lambda} \in \mathbb{R}^\ell$ be the dual variable vector for the inequality and equality constraints, respectively, we obtain the following dual program:

$$\begin{aligned} & \underset{(\boldsymbol{\mu}, \boldsymbol{\lambda})}{\text{maximize}} && \sum_{i=1}^m \mu_i g_i(\bar{\mathbf{x}}), \\ & \text{subject to} && -\sum_{i=1}^m \mu_i \nabla g_i(\bar{\mathbf{x}}) - \sum_{j=1}^{\ell} \lambda_j \nabla h_j(\bar{\mathbf{x}}) = \nabla f(\bar{\mathbf{x}}), \\ & && \mu_i \geq 0, \quad i = 1, \dots, m. \end{aligned}$$

LP duality now establishes the result sought: First, suppose that the optimal value of the above primal problem over \mathbf{p} is zero. Then, the same is true for the dual problem. Hence, by the sign conditions $\mu_i \geq 0$ and $g_i(\bar{\mathbf{x}}) \leq 0$, each term in the sum must be zero. Hence, we established that *complementarity* holds. Next, the two constraints in the dual problem are precisely the *dual feasibility* conditions, which hence are fulfilled. Finally, *primal feasibility* of $\bar{\mathbf{x}}$ was assumed. It follows that this vector indeed is a KKT point.

Conversely, if $\bar{\mathbf{x}}$ is a KKT point, then the dual problem above has a feasible solution given by any KKT multiplier vector $(\boldsymbol{\mu}, \boldsymbol{\lambda})$. The dual objective is

upper bounded by zero, since each term in the sum is non-positive. On the other hand, there is a feasible solution with the objective value 0, namely any KKT point! So, each KKT point must constitute an optimal solution to this dual LP problem! It then follows by duality theory that the dual of this problem, which is precisely the primal problem in \mathbf{p} above, has a finite optimal solution, whose optimal value must then be zero. We are done.

The LP problem given in the exam is essentially the subproblem in the *Sequential Linear Programming* (SLP) algorithm. By the above analysis, the optimal value must be negative if $\bar{\mathbf{x}}$ is not a KKT point, and it must therefore also be negative (since a zero value is given by setting $\mathbf{p} = \mathbf{0}^n$). The optimal value of \mathbf{p} , if one exists, is therefore a descent direction with respect to f at $\bar{\mathbf{x}}$. A convergent SLP method introduces additional box constraints on \mathbf{p} in the LP subproblem to make sure that the solution is finite, and the update is made according to a line search with respect to some penalty function.

- b) The problem is convex if f and the functions g_i ($i = 1, \dots, m$) are convex, and the functions h_j ($j = 1, \dots, \ell$) are affine. A proof that every KKT point is globally optimal is found in the course notes (Theorem 6.45).

Question 6

(linear programming geometry)

We prove first the result in the direction “ \Leftarrow ”. So we assume that such a vector $\boldsymbol{\mu}$ exists. Let $\mathbf{x} \in X$. Then,

$$\mathbf{d}^T \mathbf{x} \leq \boldsymbol{\mu}^T \mathbf{A} \mathbf{x} \leq \boldsymbol{\mu}^T \mathbf{b} \leq d_0$$

holds, which establishes that the inequality is redundant: it is always fulfilled on X .

We next prove the result in the direction “ \Rightarrow ”. So we assume that the inequality is redundant. An implication of that is that the following LP problem must have an optimal value which is less than or equal to d_0 , because otherwise we would reach a contradiction:

$$\begin{aligned} & \text{maximize } \mathbf{d}^T \mathbf{x}, \\ & \text{subject to } \mathbf{A} \mathbf{x} \leq \mathbf{b}, \\ & \mathbf{x} \geq \mathbf{0}^n. \end{aligned}$$

Since the primal problem has a finite optimal solution, so does the dual problem to

$$\begin{aligned} & \text{minimize } \mathbf{b}^T \boldsymbol{\mu}, \\ & \text{subject to } \mathbf{A}^T \boldsymbol{\mu} \geq \mathbf{d}, \\ & \boldsymbol{\mu} \geq \mathbf{0}^m. \end{aligned}$$

This solution is in particular feasible, and its optimal value must also be less than or equal to d_0 . We are done.

Question 7

(Lagrangian duality)

- (2p) a) The Slater's CQ is clearly verified since the problem is convex (even linear), and there is a strictly feasible point [e.g., $(x, y)^T = (3, 1)^T$].

Introducing Lagrange multipliers μ_1 and μ_2 we calculate the Lagrangian dual function q :

$$\begin{aligned} q(\mu_1, \mu_2) &= \min_{(\mu_1, \mu_2) \in \mathbb{R}_+^2} \{x - 0.5y + \mu_1(-x + y + 1) + \mu_2(-2x + y + 2)\} \\ &= \mu_1 + 2\mu_2 + \min_{x \geq 0} (1 - \mu_1 - 2\mu_2)x + \min_{y \geq 0} (-0.5 + \mu_1 + \mu_2)y \\ &= \begin{cases} \mu_1 + 2\mu_2, & \text{if } \mu_1 + 2\mu_2 \leq 1 \text{ and } \mu_1 + \mu_2 \geq 0.5, \\ -\infty, & \text{otherwise.} \end{cases} \end{aligned}$$

Thus the set of optimal Lagrange multipliers is $\{(\mu_1, \mu_2) \mid \mu_1 \geq 0, \mu_2 \geq 0, \mu_1 + 2\mu_2 = 1\}$, which is clearly convex and bounded (e.g., you may illustrate this graphically) as it should be in the presence of Slater's CQ.

- (1p) b) Subgradients of the Lagrangian dual function are calculated as follows:
1. At $(\mu_1, \mu_2)^T = (1, 0)^T$ the set of optimal solutions to the Lagrangian relaxed problem is the singleton $\{(0, 0)^T\}$. Hence, the Lagrangian function is differentiable at this point and its gradient equals the value of the vector of constraint functions evaluated at the optimal solution to the relaxed problem, i.e., $(-0 + 0 + 1, -2 \cdot 0 + 0 + 2)^T = (1, 2)^T$. Alternatively, we may directly differentiate q at a given point to obtain the same result.
 2. At $(\mu_1, \mu_2)^T = (1/4, 1/3)^T$ the set of optimal solutions to the Lagrangian relaxed problem is not a singleton: it equals $\{(x, 0)^T \mid x \geq$

0 }. Hence, the dual function is not differentiable, and the set of subgradients is obtained by evaluating the constraint functions at the optimal solutions to the relaxed problem, i.e., $\partial q(1/4, 1/3) = \{(-x + 1, -2x + 2)^T \mid x \geq 0\}$.
