



EE908 Assignment-5 Solution

eMasters in Communication Systems, IITK

EE908: Optimization in SPCOM

Instructor: Prof. Ketan Rajawat

Student Name: Venkateswar Reddy Melachervu

Roll No: 23156022

Q1. Consider the following linear program $\min c^T x$ s.t. $Ax \leq b$ where A is square and full rank

(a) When is the problem infeasible

Solution:

When the set of constraints represented by $Ax \leq b$ cannot be satisfied by any vector x .

Few scenarios this can happen are:

- If there is no x such that $x \leq A^{-1}b$ (A is square and full rank \Rightarrow invertible) – Empty feasible region or b is NOT a combination of columns of A i.e. $b \notin \mathcal{R}(A) \Rightarrow$ The optimal value is ∞
- If A, x, c, b have incompatible dimensions - $x, c \in \mathbb{R}^n, A \in \mathbb{R}^{m \times n}, b \in \mathbb{R}^m$
- When the solution is infeasible, the solution to the problem, is said to have a value of ∞

(b) When is the problem unbounded below

Solution:

- When a feasible solution exists to this problem and the objective function $c^T x < 0$ is such that it decreases indefinitely in the feasible region.
- This condition occurs when $x < 0$ and $c > 0$ or $x > 0$ and $c < 0$ and the constraint is satisfied i.e for any vector x s.t. $Ax \leq b$.
- When the solution is unbounded below, the problem is said to have a solution value of $-\infty$

(c) When does the problem have a finite solution, and what is it?

Solution:

- The LP will have a finite solution when the objective function $c^T x$ has a definitive minimum value achievable/solvable within the feasible and bounded region/solutions for any x s.t. $Ax \leq b$.
- The finite solution for this problem is an optimal value:

$$x^* = \operatorname{argmin} \{c^T x \mid Ax \leq b\} \text{ or } x^* = \min_x c^T x \text{ s.t. } Ax \leq b$$

Q2. Show that any linear programming problem can be expressed as $\min c^T x$ s.t. $Ax = b, x_i \geq 0, i = 1, 2, \dots, n$

Solution:

The general form of optimization is:

$$x^* = \min_x c^T x$$

s.t. $Wx \leq c, i = 1, 2, \dots, m$ – inequality constraint (less than)

$Dx = h$ – equality constraints (x can be +ve or -ve)

To convert above general form to LP form, we need to use two tricks

1. Use **slack variable s** to convert the inequality to equality

$$Wx \leq c \Rightarrow Wx + s = c \text{ s.t. } s \geq 0$$

$$\begin{bmatrix} W & I \end{bmatrix} \begin{bmatrix} x \\ s \end{bmatrix} = c \Rightarrow Ay = c, A = \begin{bmatrix} W & I \end{bmatrix}, y = \begin{bmatrix} x \\ s \end{bmatrix}$$

2. To bring x into the positive domain select $y = \begin{bmatrix} x \\ s \end{bmatrix}, x \geq 0, s > 0,$



$$y = u - v \text{ select } u, v \text{ s.t. } u \geq 0, v \geq 0, u \geq v$$

Hence,

$$\min c^T y$$

$$\text{s.t. } Ay = b, y_i \geq 0, i = 1, 2, \dots, n$$

QED

Q3. Consider the following linear program $\min c^T x \text{ s.t. } Ax = b$

(a) When is the problem infeasible?

Solution:

The solution is infeasible when the given constraint is not met:

- When $\{x \mid Ax \neq b\}$ i.e. there is no vector x that satisfies all constraints $Ax = b$ – Unmet or inconsistent constraints – $b \notin \text{dom } Ax$
- If some of the constraints of $Ax = b$, $A_{12}x_1 = b_1, A_{22}x_2 = b_2$ etc. are met but some are not met $A_{11}x_1 \neq b_1$ – Contradictory constraints
- When the solution is infeasible, the solution to the given minimization problem is said to have a value of ∞

(b) When is the problem unbounded below

Solution:

- When the constraints $Ax = b$ are met (feasible solution exists) and the objective function $c^T x < 0$ is such that it decreases indefinitely in the feasible region.
- This condition occurs when $x < 0$ and $c > 0$ or $x > 0$ and $c < 0$ and the constraint $Ax = b$ is satisfied for any vector x i.e. $\{b \in Ax, b \in \mathbb{R}^m, Ax \in \mathbb{R}^m, A \in \mathbb{R}^{m \times n}, x \in \mathbb{R}^n\}$.
- When the solution is unbounded below, the problem is said to have a solution value of $-\infty$

(c) When does the problem have a finite solution, and what is it?

Solution:

- The linear program $\min c^T x$ has a finite solution when a feasible solution exists and bounded (not un-bounded below) i.e. $\exists x \text{ s.t. } Ax = b$ and the objective function $c^T x$ has a lower bound within the feasible region - cannot decrease indefinitely without violating the given constraint
- The finite solution exists when $x > 0$ and $c > 0$, the constraint $Ax = b$ is satisfied for any vector $x \{b \in Ax, b \in \mathbb{R}^m, Ax \in \mathbb{R}^m, A \in \mathbb{R}^{m \times n}, x \in \mathbb{R}^n\}$ and the minimum value of the objective function for this condition is **0**.

Q4. Consider the following linear program $\min c^T x \text{ s.t. } a^T x \leq b$

(a) When is the problem infeasible?

Solution:

The solution is infeasible when the given constraint is not met:

- When $\{x \mid a^T x > b\}$ i.e. there are no vectors x and a that satisfy the constraint $a^T x \leq b$ – Unmet constraint
- When the solution is infeasible, the solution to the given minimization problem is said to have a value of ∞

(b) When is the problem unbounded below

Solution:

- When the constraints $a^T x \leq b$ is met (feasible solution exists) and the objective function $c^T x < 0$ is such that it decreases indefinitely in the feasible region.



- This condition occurs when $x < 0$ and $c > 0$ or $x > 0$ and $c < 0$ and the constraint $a^T x \leq b$ is satisfied.
- When the solution is unbounded below, the problem is said to have a solution value of $-\infty$

(c) When does the problem have a finite solution, and what is it?

Solution:

- The linear program $\min c^T x$ has a finite solution when a feasible solution exists and bounded (not un-bounded below) i.e. $\exists x$ s.t. $a^T x \leq b$ and the objective function $c^T x$ has a lower bound within the feasible region - cannot decrease indefinitely without violating the given constraint
- The finite solution exists when $x > 0$ and $c > 0$, the constraint $a^T x \leq b$ is satisfied for any vector x and the minimum value of the objective function for this condition is **0**.

Q5. Solve the following optimization problem for $A \succ 0$, $\min x^T A x$ s.t. $\|x\|_2^2 = 1$

Hint: Given that the eigenvalue decomposition $A = U \Sigma U^T$, use the change of variable $y = U^T x$

Solution:

- The minimization objective program is a quadratic program
- However, the equality constraint $\|x\|_2^2$ - level-2 norm - is a non-linear constraint and let's use change of variable as suggested in the hint

Say $y = U^T x \Rightarrow x = U y$

The objective function $x^T A x = x^T U \Sigma U^T x = (U^T x)^T \Sigma (U^T x) = y^T \Sigma y$

Constraint $\|x\| = x^T x = (U y)^T (U y) = y^T U^T U y = y^T y = \|y\|$ (U is Orthogonal $\Rightarrow U^T U = I$)

$\Rightarrow \|x\|_2^2 = \|y\|_2^2$

Now the optimization problem becomes - $\min_y y^T \Sigma y$ s.t. $\|y\|_2^2 = 1$

Since Σ is a diagonal matrix has positive eigenvalues ($A \succ 0$) in its diagonal, the minimum of $y^T \Sigma y$ occurs when y corresponds to the eigenvector associated with the smallest eigenvalue of Σ .

Let $\lambda_{\min}(A)$ be the smallest eigenvalue of Σ and u_{\min} be the corresponding eigenvector.

Then the solution to minimization problem is $y = u_{\min}$

$x = U y$ and $y = u_{\min}$, the solution is $x = U u_{\min}$

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