

CO 250 - Introduction to Optimization

Cameron Roopnarine

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1.1 Example (Manufacturing Tables and Chairs)

PROCESS: raw materials \rightarrow machine \rightarrow labour \rightarrow final products

RULES:

- Company has 30 workers and 40 machines available 40hrs/week.
- Manufacturing a table requires 2 machine-hours and 1 labour-hour.
- Manufacturing a chair requires 1 machine-hours and 3 labour-hours.
- Each manufacturer table yields \$10 of profit and each manufacturer chair yields \$15 of profit.

GOAL: The company wants to prepare a weekly production plan which maximizes total profit.

Variables

- x_1 := the number of tables manufactured per week
- x_2 := the number of chairs manufactured per week

Objective function

The total profit per week can be modelled by $10x_1 + 15x_2$, which is what we want to maximize.

Constraints

- Machine-hours used per week \leq machine-hours available per week which can be modelled by $2x_1 + x_2 \leq 40 \times 40 = 1600$
- Labour-hours used per week \leq labour-hours available per week which can be modelled by $x_1 + 3x_2 \leq 30 \times 40 = 1200$

We can then formulate the linear programming (LP) model:

(LP)

$$\max 10x_1 + 15x_2$$

subject to

$$2x_1 + x_2 \leq 1600$$

$$x_1 + 3x_2 \leq 1200$$

$$x_1, x_2 \geq 0$$

An *optimal* solution to the LP using an algorithm later in in this course is $x := (720, 160)^\top$, which means that we want 720 tables, and 160 chairs.

1.2 Example (A General Production Planning Problem)

There are resources $I := \{1, \dots, m\}$ and products $J := \{1, \dots, n\}$. There are b_i units of resource i available per week $\forall i \in I$. One unit of product j yields c_j of profit for $\forall j \in J$. Manufacturing one unit of product j requires a_{ij} units of resource i . We want to maximize the total profit of this manufacturing process. x_j := amount of product j manufactured per week. (LP)

$$\max c_1x_1 + \dots + c_nx_n = \sum_{j=1}^n c_jx_j$$

subject to

$$\begin{aligned} \sum_{j=1}^n a_{ij}x_{ij} &\leq b_i & \forall i \in \{1, \dots, m\} \\ x_j &\geq 0 & \forall j \in \{1, \dots, n\} \end{aligned}$$

If $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$ and $\mathbf{x} \leq \mathbf{y}$, then $x_1 \leq y_1, \dots, x_n \leq y_n$.

$$\mathbf{c} := \begin{bmatrix} c_1 \\ \vdots \\ c_n \end{bmatrix}, \mathbf{x} := \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}, A := \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix}, \mathbf{b} := \begin{bmatrix} b_1 \\ \vdots \\ b_n \end{bmatrix}$$

Given $A, \mathbf{b}, \mathbf{c}$ with $\mathbf{x} \in \mathbb{R}^n$ as the variable vector, we realize that $\mathbf{c}^\top \mathbf{x} = \sum_{j=1}^n c_j x_j$ is exactly the model that we wanted to maximize in 1.2 such that it satisfies $A\mathbf{x} \leq \mathbf{b}$, with $\mathbf{x} \geq \mathbf{0}$.

1.3 Definition (Affine Function)

Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$. f is an *affine function* if $f(\mathbf{x}) = \mathbf{a}^\top \mathbf{x} + \beta$ for some $\mathbf{a} \in \mathbb{R}^n$, and $\beta \in \mathbb{R}$.

1.4 Definition (Linear Function)

Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$. f is a *linear function* if f is an affine function such that $\beta = 0$.

Every linear function is affine, but the converse is not true.

1.5 Definition (Linear Constraint)

A *linear constraint* is one of

$$\begin{aligned} f(\mathbf{x}) &\leq \beta \\ f(\mathbf{x}) &= \beta \\ f(\mathbf{x}) &\geq \beta \end{aligned}$$

where f is a linear function and $\beta \in \mathbb{R}$

1.6 Definition (Linear Program)

A *linear program* (LP) is the problem of minimizing or maximizing an affine function subject to a finite number of linear constraints.

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Recall the family of LP problems:

$$\max\{\mathbf{c}^\top \mathbf{x} : A\mathbf{x} \leq \mathbf{b}, \mathbf{x} \geq \mathbf{0}\}$$

An assignment of values to all variables such that every constraint is satisfied is called a feasible solution. A feasible region is the set of all feasible solutions. An optimal solution is a feasible solution which has the best possible objective value among all feasible solutions. Note that an optimization problem may have many optimal solutions, but it may have one optimal value.

2.1 Example (Refer to 1.1)

Suppose an entrepreneur offers at most 500 machine hours/week (rental) at \$2.5/hour. Can we incorporate this new situation into our mathematical model? Can it still be a LP? Yes. x_3 := the number of machine hours rented from the business person per week.

$$\max 10x_1 + 15x_2 - 2.5x_3$$

subject to

$$2x_1 + x_2 \leq 1600 + x_3$$

$$x_1 + 3x_2 \leq 1200$$

$$x_3 \leq 500$$

$$x_1, x_2, x_3 \geq 0$$

2.2 Example (Constraints on Ratios, Percentages and Proportions)

Suppose we are required to manufacture at least 10 tables and 80 chairs per week. Also

$$\text{\#of tables manufactured/week} / \text{\#of chairs manufactured/week} \geq 6$$

$$\left\{ \begin{array}{l} x_1 \geq 10 \\ x_2 \geq 80 \\ x_2/x_1 \geq 6 \end{array} \right\} \iff \left\{ \begin{array}{l} x_1 \geq 10 \\ x_2 \geq 80 \\ x_2 \geq 6x_1 \end{array} \right\}$$

In general suppose f, g are affine functions

$$b_1 \leq f(\mathbf{x})/g(\mathbf{x}) \leq b_2$$

provided that $g(\mathbf{x}) > 0$ for every feasible solution \mathbf{x} we can equivalently write

$$f(\mathbf{x}) \leq b_2 g(\mathbf{x})$$

$$f(\mathbf{x}) \geq b_1 g(\mathbf{x})$$

2.3 Example (Multi-period, Multi-stage optimization problems)

Consider planning for multiple periods where in each period we want to decide how much to produce, how much to keep in stock (inventory) for the upcoming periods.

Variables

For all $i \in \{1, \dots, T\}$, where T is the last period, we have:

- s_i := the amount of units sold in period i
- p_i := the amount of units purchased/manufactured of period i
- t_i := the amount of units in stock at the end of period i
- t_0 := the amount of units in stock at the beginning of the first period.

Key Constraints

$$\begin{array}{ll} p_i + t_{i-1} = s_i + t_i & \forall i \in \{1, \dots, T\} \\ p_i, s_i, t_i \geq 0 & \forall i \in \{1, \dots, T\} \end{array}$$

Typically we have additional constraints on s_i, p_i, t_i, t_0 .

2.4 Definition (Integer Program)

An *integer program* (IP) is obtained from linear program by requiring a non-empty subset of variables to be integers.

If all variables are restricted to be integers we say that we have a *Pure IP*, and if at least some variables may take real values, we call it a *Mixed IP*.

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Recall, IP problems are obtained from LP problems by requiring a non-empty subset of variables to be integers. So, in IP problems we are allowed to have constraints $x_i \in \mathbb{Z}$, $x \in \mathbb{Z}^n$, $x_i \in \{0, 1\}$, x_i is an integer, $x_i \in \{0, 1\}^n$.

3.1 Example (Assignment Problem)

SPIT has a campus near the North Pole. They have three buildings named A, B, C which need to be renovated to be served as one of a Library, Laboratory, or Gym (sometimes called functions). Each building must be assigned one activity, and each activity must be assigned one building. Renovation costs in millions of dollars are given:

	Library	Laboratory	Gym
A	10	60	20
B	60	70	50
C	20	60	40

Find an assignment of activities to buildings so that the total renovation cost is minimized. Let us generalize to n buildings and n activities.

$$x_{ij} := \begin{cases} 1, & \text{if } i \text{ is assigned to activity } j \\ 0, & \text{otherwise} \end{cases} \quad \forall i, j \in \{1, \dots, n\}$$

$c_{ij} :=$ renovation cost for assigning activity j to building i

(LP)

$$\min \sum_{i=1}^n \sum_{j=1}^n c_{ij} x_{ij}$$

subject to

$$\sum_{i=1}^n x_{ij} = 1 \quad \forall j \in \{1, \dots, n\} \quad (1)$$

$$\sum_{j=1}^n x_{ij} = 1 \quad \forall i \in \{1, \dots, n\} \quad (2)$$

$$x_{ij} \in \{0, 1\} \quad \forall i, j \in \{1, \dots, n\} \quad (3)$$

(1) \implies every activity is assigned exactly one building

(2) \implies every building is assigned exactly one activity

(3) \implies x_{ij} is a *binary* variable that takes values only 1 or 0. If we wanted an IP formulation, we would remove the constraint $x_{ij} \in \{0, 1\}$ and add: $x_{ij} \geq 0$, $x_{ij} \leq 1$ and x_{ij} integer.

Suppose $c_{ij} \in \mathbb{R}$ and consider the inequality version (if we don't assign exactly one item to another):

$$\min \sum_{i=1}^n \sum_{j=1}^n c_{ij} x_{ij}$$

subject to

$$\begin{aligned} \sum_{i=1}^n x_{ij} &\leq 1 & \forall j \in \{1, \dots, n\} \\ \sum_{j=1}^n x_{ij} &\leq 1 & \forall i \in \{1, \dots, n\} \\ x_{ij} &\in \{0, 1\} & \forall i, j \in \{1, \dots, n\} \end{aligned}$$

We can generalize this class optimization problem further.

3.2 Definition (Undirected Graph, Vertices, and Edges)

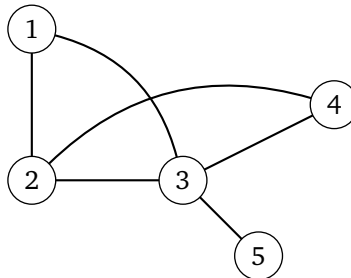
An *undirected graph* is a pair $G = (V, E)$, where V is a finite set of elements called *vertices*, and E is a set of pairs of distinct vertices called *edges*. All edges in an undirected graph are bidirectional.

3.3 Definition (Adjacent, Endpoints, and Incident)

Let $G = (V, E)$ be a graph. Suppose $uv \in E$. u, v are *adjacent* vertices. u, v are the *endpoints* of the edge uv . The edge uv is *incident* to vertices u and v .

3.4 Example (Undirected Graph)

Given $G :=$



we have

$$\begin{aligned} V &= \{1, \dots, 5\} \\ E &= \{12, 13, 23, 24, 35, 34\} \end{aligned}$$

3.5 Definition (Matching)

Given a graph $G = (V, E)$, a *matching* M in G is a subset of edges in G such that no two edges in M share a common vertex.

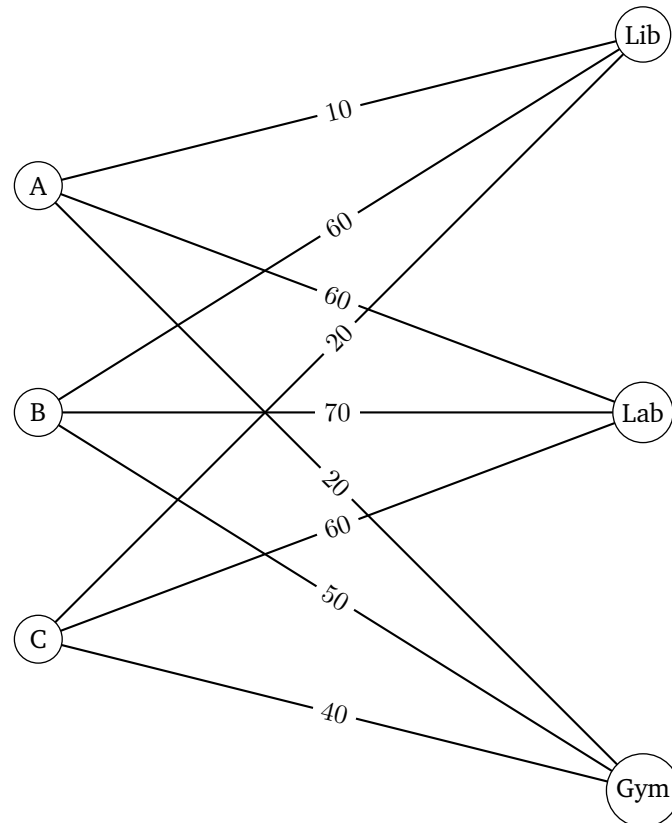
In the above example:

Matching	Not matching
$M := \{12\}$	$M := \{12, 25\}$
$M := \emptyset$	$M := \{67\}$
$M := \{12, 35\}$	

3.6 Definition (Perfect Matching)

Given a graph $G = (V, E)$, if every vertex V in G is an endpoint of an edge in M , we call the matching a *perfect matching*.

The assignment problem is a special case of a *minimum cost perfect matching problem* or weighted graphs (in this case every edge is given a weight/cost c_{ij})



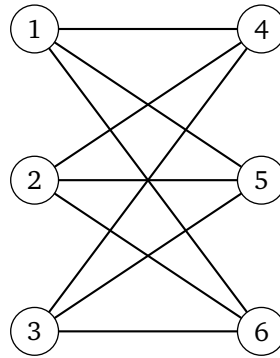
In a perfect matching graph, there are n^2 edges, and $2n$ (an even number of) vertices.

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4.1 Example (Minimum-Cost Perfect Matching Problem)

Given an undirected graph $G = (V, E)$, and $c_e \in \mathbb{R}$, for every $e \in E$, we want to find a perfect matching in G with minimum total cost. The cost of matching M is $\sum_{e \in M} c_e$. For each $v \in V$, $\delta(v) :=$ the set of edges incident

to v . $G :=$



$$\delta(1) = \{14, 15, 16\}$$

$$\delta(5) = \{15, 25, 35\}$$

$$x_e := \begin{cases} 1, & \text{if } e \text{ is chosen in the matching} \\ 0, & \text{otherwise} \end{cases}$$

(IP)

$$\min \sum_{e \in E} c_e x_e$$

subject to

$$\begin{aligned} \sum_{e \in E} x_e &= 1 & \forall v \in V \\ x_e &\in \{0, 1\} & \forall e \in E \end{aligned}$$

4.2 Definition (Bipartite)

A graph $G = (V, E)$ is *bipartite* if there exists a partition V_1, V_2 of V where $V_1 \cup V_2 = V$ and $V_1 \cap V_2 = \emptyset$ such that

$$E \subseteq \{uv \mid u \in V_1, v \in V_2\}$$

Assignment problems are a special case of minimum cost perfect matching problems in bipartite graphs. A graph is *bipartite* \iff it does not contain an odd cycle. Given a situation where we have binary-valued variables

$$x_j := \begin{cases} 1, & \text{option } j \text{ is chosen} \\ 0, & \text{otherwise} \end{cases} \quad \forall j \in \{1, \dots, n\}$$

We solve how to formulate in an IP in the following conditions:

- at most k options are chosen: $\sum_{j=1}^n x_j \leq k$
- at least k options are chosen: $\sum_{j=1}^n x_j \geq k$
- exactly k options are chosen: $\sum_{j=1}^n x_j = k$

We can also formulate many classes of the "OR" type constraint in IP problems.

4.3 Example (Refer to 1.1)

(IP)

$$\max 10x_1 + 15x_2$$

subject to

$$2x_1 + x_2 \leq 1600$$

$$x_1 + 3x_2 \leq 1200$$

$$x_1, x_2 \geq 0$$

Suppose C&O is required to produce at least 10 tables per week or at least 80 chairs per week, or possibly both. $x_1 \geq 10$ or $x_2 \geq 80$ or both. We introduce a new binary-valued variable $z \in \{0, 1\}$.

$$z := \begin{cases} 1, & \text{if } x_1 \geq 10 \\ 0, & \text{if } x_2 \geq 80 \end{cases}$$

$$\{(x_1 \geq 10 \text{ OR } x_2 \geq 80) \text{ AND } (x_1 \geq 0 \text{ OR } x_2 \geq 0)\} \iff \begin{cases} x_1 \geq 10z \\ x_2 \geq 80(1-z) \\ z \in \{0, 1\} \\ x_1, x_2 \geq 0 \end{cases}$$

Possibly both means that you can choose either one of these conditions in the first OR above and it will be correct.

Now, suppose C&O has a new condition every week. We must manufacture either exactly 3 chairs for every table or exactly 8 chairs for every table. Show how to incorporate this in an IP formulation

$$\{x_2 = 3x_1 \text{ OR } x_2 = 8x_1\} \iff \{(x_2 \leq 3x_1 \text{ AND } x_2 \geq 3x_1) \text{ OR } (x_2 \leq 8x_1 \text{ AND } x_2 \geq 8x_1)\}$$

Introduce a new binary-valued variable $z \in \{0, 1\}$.

$$z := \begin{cases} 1, & \text{if } x_2 = 3x_1 \\ 0, & \text{if } x_2 = 8x_1 \end{cases}$$

Existing constraints:

$$\begin{cases} 2x_1 + x_2 \leq 1600 \\ x_1 + 3x_2 \leq 1200 \\ x_1, x_2 \geq 0 \end{cases} \implies \begin{cases} x_1 \in [0, 800] \\ x_2 \in [0, 500] \end{cases}$$

So,

$$x_2 \leq 3x_1 + 400(1-z)$$

$$x_2 \geq 3x_1 - 2400(1-z)$$

$$x_2 \leq 8x_1 + 400z$$

$$x_2 \geq 8x_1 - 6400z$$

$$z \in \{0, 1\}$$

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5.1 Definition (Non-linear Program)

A non-linear program has the form

$$\min f(\mathbf{x})$$

subject to

$$g_1(\mathbf{x}) \leq 0$$

$$g_2(\mathbf{x}) \leq 0$$

$$\vdots$$

$$g_m(\mathbf{x}) \leq 0$$

where $f : \mathbb{R}^n \rightarrow \mathbb{R}$, $g_i : \mathbb{R}^n \rightarrow \mathbb{R}$, $\forall i \in \{1, \dots, m\}$.

Every LP problem is a very special case of a NLP problem. IP problems can also be formulated as NLP problems.

5.2 Example (Formulating LP problems as NLP problems)

$$x_i \in \mathbb{Z} \iff \sin(\pi x_i) = 0$$

$$\iff [\sin(\pi x_i)]^2 \leq 0$$

$$x_i \in \{0, 1\} \iff x_i(1 - x_i) = 0$$

$$\iff x_i^2(1 - x_i)^2 \leq 0$$

NLP problems have huge modelling power, as a result, one must understand the structure of the underlying problem and construct "good" NLP models that are amenable to analysis and solution techniques.

5.3 Example (Portfolio Optimization)

There are n stocks $1, \dots, n$ to invest in. We have a budget of B dollars. We have an expected return (for \$1 investment at the end of our planning horizon) of μ_1, \dots, μ_n . We are also given $V \in \mathbb{R}^{n \times n}$, a variance covariance matrix so that if we invest in x_1, \dots, x_n dollars in n stocks, $1, \dots, n$ respectively, then the expected risk of such an investment is given by $\mathbf{x}^\top V \mathbf{x}$.

$$\sum_{i=1}^n \sum_{j=1}^n V_{ij} x_i x_j$$

$x_j :=$ amount of investment in stock j in dollars.

Suppose we are also given a goal G (a dollar amount we want as the value of our portfolio at the end of the planning horizon).

Data

- Budget (\$) $\rightarrow B$
- Goal (\$) $\rightarrow G$
- Expected return $\rightarrow (\mu_1, \dots, \mu_n)^\top$
- Variance-covariance matrix $\rightarrow V \in \mathbb{R}^{n \times n}$

We want to minimize the risk of our portfolio while satisfying the budget and the goal constraints.

(NLP)

$$\min \mathbf{x}^\top V \mathbf{x}$$

subject to

$$\begin{aligned} \sum_{j=1}^n x_j &\leq B \\ \sum_{j=1}^n \mu_j x_j &\geq G \\ \mathbf{x} &\geq \mathbf{0} \end{aligned}$$

There are many variants of such models and extensions. For example, instead of a goal G , we may given an upper bound on the risk, say $R \in \mathbb{R}_{>0}$.

(NLP)

$$\max \sum_{j=1}^n \mu_j x_j$$

subject to

$$\begin{aligned} \sum_{j=1}^n x_j &\leq B \\ \mathbf{x}^\top V \mathbf{x} &\leq R \\ \mathbf{x} &\geq \mathbf{0} \end{aligned}$$

We can handle many more variants and extensions. Suppose investing in stock j below ℓ_j dollars is not allowed. For diversity of our portfolio, we want to invest in at least 20 stocks, and for the sake of simplicity we want to invest in at most 150 stocks. We introduce a binary-valued variable z_j .

$$z_j := \begin{cases} 1, & \text{if we invest in stock } j \\ 0, & \text{otherwise} \end{cases} \quad \forall j \in \{1, \dots, n\}$$

Add these constraints:

$$\begin{aligned} \ell_j z_j &\leq x_j \leq B z_j & \forall j \in \{1, \dots, n\} \\ 20 &\leq \sum_{j=1}^n z_j \leq 150 & \forall j \in \{1, \dots, n\} \\ z_j &\in \{0, 1\} & \forall j \in \{1, \dots, n\} \end{aligned}$$

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6.1 Feasible and Infeasible Solutions

Consider an LP with variables x_1, \dots, x_n . Then the assignment of values to all variables such that all constraints are satisfied, gives a *feasible solution*.

An optimization problem is called *feasible* if it has at least one feasible solution, otherwise it is called *infeasible*.

6.2 Example (Infeasible LP)

(LP)

$$\max x_1 + 2x_2 + 3x_3 + 4x_4 + 5x_5$$

subject to

$$\begin{array}{c} 1 \\ -2 \end{array} \underbrace{\begin{bmatrix} -3 & 2 & 7 & 1 & -7 \\ -2 & 1 & 2 & 0 & -4 \end{bmatrix}}_A \underbrace{\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix}}_x = \underbrace{\begin{bmatrix} 6 \\ 4 \end{bmatrix}}_b$$

$$x \geq 0$$

Let $y := (1, -2)^\top$ and consider the facts

$$\begin{aligned} Ax &= b \\ \Rightarrow y^\top Ax &= y^\top b \\ \Rightarrow \underbrace{\begin{bmatrix} 1 & 0 & 3 & 1 & 1 \end{bmatrix}}_{\geq 0^\top} \underbrace{x}_{\geq 0} &= \underbrace{6 - 8}_{< 0} = -2 \end{aligned}$$

Therefore, since \nexists any solution to $Ax = b, x \geq 0$ the LP is infeasible.

6.3 Proposition (Infeasibility)

If $\exists y \in \mathbb{R}^m$ such that

(1) $y^\top A \geq 0^\top$

(2) $y^\top b < 0$

then, the LP

$$\max \{c^\top x : Ax = b, x \geq 0\}$$

is infeasible. In particular, we call a vector y a *certificate of infeasibility*.

Proof. Suppose there exists such a y . Suppose for a contradiction that $\exists \bar{x} \in \mathbb{R}^n$ (there is a feasible solution) such that

$$\begin{aligned} A\bar{x} &= b, \bar{x} \geq 0 \\ A\bar{x} = b &\Rightarrow \underbrace{y^\top A}_{\geq 0^\top} \underbrace{\bar{x}}_{\geq 0} = \underbrace{y^\top b}_{< 0} \end{aligned}$$

a contradiction to (2). □

An optimization problem is called unbounded if $\forall M \in \mathbb{R}$, there exists a feasible solution of the optimization problem with the objective value strictly better than M .

6.4 Example (Unbounded LP)

$$\max [-1 \ 3 \ 0 \ 0 \ 1] x$$

subject to

$$\begin{bmatrix} -1 & 3 & -1 & 1 & 0 \\ -2 & 4 & 1 & 0 & 1 \end{bmatrix} x = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

$$x \geq 0$$

Consider

$$\tilde{\mathbf{x}} := \underbrace{\begin{bmatrix} 0 \\ 0 \\ 0 \\ 2 \\ 1 \end{bmatrix}}_{\mathbf{x}} + t \underbrace{\begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \\ 2 \end{bmatrix}}_{\mathbf{d}}, t \geq 0$$

$$A\mathbf{x} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}, \bar{\mathbf{x}} \geq \mathbf{0}. \text{ Therefore } \bar{\mathbf{x}} \text{ is a feasible solution.}$$

$$A\mathbf{d} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \mathbf{d} \geq \mathbf{0}.$$

$$A\tilde{\mathbf{x}} = A(\bar{\mathbf{x}} + t\mathbf{d}) = A\bar{\mathbf{x}} + t(A\mathbf{d}) = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

$$\tilde{\mathbf{x}} = \bar{\mathbf{x}} + t\mathbf{d}$$

Therefore, $\tilde{\mathbf{x}}$ is a feasible solution $\forall t \geq 0$.

Objective function value of $\tilde{\mathbf{x}}$:

$$\begin{bmatrix} -1 & 3 & 0 & 0 & 1 \end{bmatrix} \left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 2 \\ 1 \end{bmatrix} + t \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \\ 2 \end{bmatrix} \right) = 1 + t(-1 + 2) = 1 + t \rightarrow +\infty \text{ as } t \rightarrow +\infty$$

Therefore the LP is unbounded.

6.5 Proposition (Unboundedness)

If $\exists \bar{\mathbf{x}} \in \mathbb{R}^n$ such that

$$A\bar{\mathbf{x}} = \mathbf{b}, \bar{\mathbf{x}} \geq \mathbf{0}.$$

and $\exists \mathbf{d} \in \mathbb{R}^n$ such that

- (1) $A\mathbf{d} = \mathbf{0}$
- (2) $\mathbf{d} \geq \mathbf{0}$
- (3) $\mathbf{c}^\top \mathbf{d} > 0$

then, the LP

$$\max\{\mathbf{c}^\top \mathbf{x} : A\mathbf{x} = \mathbf{b}, \mathbf{x} \geq \mathbf{0}\}$$

is unbounded. In particular, we call a pair of vectors $\bar{\mathbf{x}}, \mathbf{d}$ a *certificate of unboundedness*.

Proof. Suppose there exists such \mathbf{d} . Consider

$$\tilde{\mathbf{x}} = \bar{\mathbf{x}} + t\mathbf{d}, t \geq 0$$

Then,

$$A\tilde{\mathbf{x}} = \underbrace{A\bar{\mathbf{x}}}_{\mathbf{b}} + t \underbrace{(A\mathbf{d})}_{\mathbf{0}} = \mathbf{b}$$

Therefore $\tilde{\mathbf{x}}$ is a feasible solution of the LP, $t \geq 0$. The objective value of the function is

$$\mathbf{c}^\top \tilde{\mathbf{x}} = \mathbf{c}^\top \bar{\mathbf{x}} + t \underbrace{(\mathbf{c}^\top \mathbf{d})}_{>0} \rightarrow +\infty \text{ as } t \rightarrow +\infty$$

Therefore, the LP is unbounded. □

If the LP is min, then flip the equality for (3).

6.6 Example (Optimal LP)

$$\max 10x_1 + 15x_2$$

subject to

$$2x_1 + x_2 + x_3 = 1600$$

$$x_1 + 3x_2 + x_4 = 1200$$

$$\mathbf{x} \geq \mathbf{0}$$

Consider $\bar{\mathbf{x}} := (720, 160, 0, 0)^\top$ and $\mathbf{y} := (3, 4)^\top$.

Note that $A\bar{\mathbf{x}} = \mathbf{b}$, with $\bar{\mathbf{x}} \geq \mathbf{0}$, so $\bar{\mathbf{x}}$ is a feasible solution.

Also, $\mathbf{c}^\top \bar{\mathbf{x}} = 7200 + 2400 = 9600$. Every feasible solution satisfies

$$A\mathbf{x} = \mathbf{b}$$

$$\implies \mathbf{y}^\top A\mathbf{x} = \mathbf{y}^\top \mathbf{b}$$

$$\mathbf{y}^\top A = [10 \quad 15 \quad 3 \quad 4] \geq [10 \quad 15 \quad 0 \quad 0] = \mathbf{c}^\top$$

$$\mathbf{y}^\top \mathbf{b} = 3 \times 1600 + 4 \times 1200 = 9600 = \mathbf{c}^\top \bar{\mathbf{x}}$$

Therefore $\bar{\mathbf{x}}$ is an optimal solution.

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7.1 Summary of outcomes

(P)

$$\max\{\mathbf{c}^\top \mathbf{x} : A\mathbf{x} = \mathbf{b}, \mathbf{x} \geq \mathbf{0}\}$$

- If there exists a vector \mathbf{y} such that
 - (1) $\mathbf{y}^\top A \geq \mathbf{0}^\top$
 - (2) $\mathbf{y}^\top \mathbf{b} < 0$
 then (P) is infeasible. We call \mathbf{y} a certificate of infeasibility.
- If there exists a feasible solution $\bar{\mathbf{x}}$ and a vector \mathbf{d} such that:
 - (1) $A\mathbf{d} = \mathbf{0}$
 - (2) $\mathbf{d} \geq \mathbf{0}$
 - (3) $\mathbf{c}^\top \mathbf{d} > 0$
 then (P) is unbounded. We call a pair of vectors $\bar{\mathbf{x}}, \mathbf{d}$ a certificate of unboundedness.
- If there exists a feasible solution $\bar{\mathbf{x}}$ and a vector $\bar{\mathbf{y}}$ such that:
 - (1) $A^\top \bar{\mathbf{y}} \geq \mathbf{c}$
 - (2) $\mathbf{c}^\top \bar{\mathbf{x}} = \bar{\mathbf{y}}^\top \mathbf{b}$
 then $\bar{\mathbf{x}}$ is an optimal solution of (P). We call $\bar{\mathbf{y}}$ a certificate of optimality.

7.2 Definition (Standard Equality Form)

An LP is said to be in *Standard Equality Form* (SEF) if it has the Form

$$\max\{\mathbf{c}^\top \mathbf{x} + \bar{z} : A\mathbf{x} = \mathbf{b}, \mathbf{x} \geq \mathbf{0}\}$$

where \bar{z} is a constant. In other words, it satisfies all of the conditions:

- (1) It is a maximization problem
- (2) All constraints are equations (other than non-negativity constraints)
- (3) Every variable has a non-negativity constraint

Every LP can be converted to SEF. A pair of LP problems LP1 and LP2 are equivalent if they both have the same status (infeasible, unbounded, or optimal) and certificate of such a status for one problem can easily be converted into a certificate of the same type for the other LP.

Given an arbitrary LP problem,

- if the objective function is a minimization problem, then $\min c^\top x \rightarrow -(\max -c^\top x)$ We often omit one negative sign from a TA on Piazza: "It's more just a convention of not putting $-$ before max when doing this and it's understood that the optimal value of one is the negative of the optimal value of the other"
- if there are constraints $\alpha x \leq \alpha$, introduce a new non-negative *slack variable* x_{n+1} , $x_{n+1} \geq 0$.
- if some x_j has no constraint on it, such variables are called *free variables* and we represent that free variable as a difference of two non-negative variables, $x_j = x_j^+ - x_j^-$, $x_j^+ \geq 0$, $x_j^- \geq 0$.
- if some $x_j < 0$ flip all signs correlating to x_j

7.3 Example (Converting an LP to SEF)

(P)

$$\max 100x_1 + 200x_2$$

subject to

$$\begin{aligned} x_1 + 2x_2 &\leq 20 \\ 3x_1 + 4x_2 &\geq 10 \\ x_1 &\geq 0 \end{aligned}$$

Converting into SEF we get (P'):

$$\max 100x_1 + 200(x_2^+ - x_2^-)$$

subject to

$$\begin{aligned} x_1 + 2(x_2^+ - x_2^-) + x_3 &= 20 \\ 3x_1 + 4(x_2^+ - x_2^-) - x_4 &= 10 \\ x_1, x_2^+, x_2^-, x_3, x_4 &\geq 0 \end{aligned}$$

(P) and (P') are equivalent.

Let $(\bar{x}_1, \bar{x}_2^+, \bar{x}_2^-, \bar{x}_3, \bar{x}_4)^\top$ be a feasible solution of (P').

If

$$\begin{aligned} \hat{x}_1 &:= \bar{x}_1 \\ \hat{x}_2 &:= \bar{x}_2^+ - \bar{x}_2^- \end{aligned}$$

Then $(\hat{x}_1, \hat{x}_2)^\top$ is a feasible solution of (P).

Let $(\bar{x}_1, \bar{x}_2)^\top$ be a feasible solution of (P).

If

$$\begin{aligned} \bar{x}_3 &:= 20 - \bar{x}_1 - 2\bar{x}_2 \\ \bar{x}_4 &:= 3\bar{x}_1 + 4\bar{x}_2 - 10 \end{aligned}$$

and if $\bar{x}_2 \geq 0$

$$\begin{aligned} \bar{x}_2^+ &:= \bar{x}_2 \\ \bar{x}_2^- &:= 0 \end{aligned}$$

or $\bar{x}_2 < 0$

$$\bar{x}_2^+ := 0$$

$$\bar{x}_2^- := -\bar{x}_2$$

then $(\bar{x}_1, \bar{x}_2^+, \bar{x}_2^-, \bar{x}_3, \bar{x}_4)^\top$ is a feasible solution of (P').

7.4 Definition (Basis)

Let $A \in \mathbb{R}^{m \times n}$, $B \subseteq \{1, \dots, n\}$ such that $|B| = m$. If

$$A_B := [a_i \mid i \in B] \in \mathbb{R}^{m \times m}$$

where A_B is non-singular (i.e. IMT holds), then B is a *basis* of A . If B is a basis of A , then A_B is a basis for \mathbb{R}^m . We denote N as the set that does not have the elements of B .

7.5 Definition (Basic Solution)

A vector \bar{x} is a *basic solution* of $Ax = b$ for a basis B of A if:

$$(1) A\bar{x} = b$$

$$(2) \bar{x}_N = 0$$

where \bar{x}_N is the vector formed by the non-basic variables. That is, $N := \{1, \dots, n\} \setminus B$.

7.6 Definition (Basic Feasible Solution)

A vector \bar{x} is a *basic feasible solution* of $\{Ax = b, x \geq 0\}$ if it is a basic solution of $Ax = b$ determined by a basis B of A that also satisfies $\bar{x} \geq 0$. Thus \bar{x} satisfies $A\bar{x} = b$, $\bar{x}_N = 0$, and $\bar{x} \geq 0$.

7.7 Example (Bases of A)

$$A := \begin{bmatrix} 1 & 0 & 2 & -1 & 1 \\ 0 & 1 & 2 & -1 & 2 \end{bmatrix}, b := \begin{bmatrix} 2 \\ 5 \end{bmatrix}$$

Bases of A: $\{1, 2\}$, $\{2, 3\}$, $\{1, 4\}$.

Not a bases of A: \emptyset , $\{1\}$, $\{1, 2, 3\}$, $\{3, 4\}$.

To find the basic solution determined by $B := \{1, 4\}$, solve

$$\begin{bmatrix} 1 & -1 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_4 \end{bmatrix} = \begin{bmatrix} 2 \\ 5 \end{bmatrix}$$

and we get $\bar{x} = (-3, 0, 0, -5, 0)^\top$.

8 2019-10-01

Let $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^m$, $c \in \mathbb{R}^n$. Consider (P)

$$\max c^\top x$$

subject to

$$Ax = b$$

$$x \geq 0$$

Suppose we are given $\bar{x} \in \mathbb{R}^n$ such that, $A\bar{x} = b$, $\bar{x} \geq 0$ and $y \in \mathbb{R}^m$ such that $A^\top y \geq c$, $y^\top b = c^\top \bar{x}$ with objective function value $= c^\top \bar{x}$.

Computing $\mathbf{c}^\top \bar{\mathbf{x}}$ we get

$$\begin{aligned}\mathbf{c}^\top \bar{\mathbf{x}} &= \mathbf{y}^\top \mathbf{b} \\ &= \mathbf{y}^\top (A\tilde{\mathbf{x}}) \\ &= \underbrace{(\mathbf{y}^\top A)}_{\geq \mathbf{c}^\top} \underbrace{\tilde{\mathbf{x}}}_{\geq \mathbf{0}} \\ &\geq \mathbf{c}^\top \tilde{\mathbf{x}}\end{aligned}$$

Since $\bar{\mathbf{x}}$ achieves the objective value of $\mathbf{c}^\top \bar{\mathbf{x}}$ and for every feasible solution the objective value is at most $\mathbf{c}^\top \bar{\mathbf{x}}$, $\bar{\mathbf{x}}$ is an optimal solution of (P).

8.1 Definition (Canonical form)

Consider the following LP in SEF:

(P)

$$\max \mathbf{c}^\top \mathbf{x} + \bar{z}$$

subject to

$$A\mathbf{x} = \mathbf{b}$$

$$\mathbf{x} \geq \mathbf{0}$$

We say (P) is in *canonical form* for a basis B of A if

(C1) A_B is an identity matrix

(C2) $\mathbf{c}_B = \mathbf{0}$

Now,

$$\begin{aligned}A\mathbf{x} &= \sum_{j=1}^n \mathbf{a}_j x_j \\ &= \sum_{j \in B} \mathbf{a}_j x_j + \sum_{j \in N} \mathbf{a}_j x_j \\ &= A_B \mathbf{x}_B + A_N \mathbf{x}_N\end{aligned}$$

Since B is a basis of A , A_B is non-singular,

$$\begin{aligned}A\mathbf{x} &= \mathbf{b} \\ \iff A_B^{-1} A\mathbf{x} &= A_B^{-1} \mathbf{b} \\ \iff A_B^{-1} (A_B \mathbf{x}_B + A_N \mathbf{x}_N) &= A_B^{-1} \mathbf{b} \\ \iff \underbrace{(A_B^{-1} A_B)}_I \mathbf{x}_B + (A_B^{-1} A_N \mathbf{x}_N) &= A_B^{-1} \mathbf{b} \\ \iff \mathbf{x}_B &= A_B^{-1} \mathbf{b} - (A_B^{-1} A_N \mathbf{x}_N)\end{aligned}$$

Consider (C2). For any $\mathbf{y} := (y_1, \dots, y_m)^\top$ the equation

$$\mathbf{y}^\top A\mathbf{x} = \mathbf{y}^\top \mathbf{b}$$

can be written as

$$0 = \mathbf{y}^\top \mathbf{b} - \mathbf{y}^\top A\mathbf{x}$$

Since this equation holds for every feasible solution, we can add this constraint to the objective function which is now:

$$\max \mathbf{c}^\top \mathbf{x} + \bar{z} + \mathbf{y}^\top \mathbf{b} - \mathbf{y}^\top A\mathbf{x} \implies \max (\mathbf{c}^\top - \mathbf{y}^\top A)\mathbf{x} + \mathbf{y}^\top \mathbf{b} + \bar{z}$$

Let $\bar{c}^\top := c^\top - y^\top A$. For (C2) to be satisfied we need $\bar{c}_B = 0$, so we need to choose y accordingly, such as

$$\bar{c}_B^\top = c_B^\top - y^\top A_B = 0^\top$$

equivalently,

$$y^\top A_B = c_B^\top \implies y^\top = c_B^\top A_B^{-1}$$

We have shown the following:

8.2 Proposition (Canonical Form)

Suppose an LP

$$\max\{c^\top x + \bar{z} : Ax = b, x \geq 0\}$$

and a basis B of A are given. Then

$$\max(c^\top - y^\top A)x + y^\top b + \bar{z}$$

subject to

$$A_B^{-1}Ax = A_B^{-1}b$$

$$x \geq 0$$

where $y^\top = c_B^\top A_B^{-1}$, is an equivalent LP in canonical form for the basis B of A .

The canonical form is useful because it:

- allows us to simply read a basic solution
- gives us easy ways to move in the feasible region to improve the current basic feasible solution
- gives us a way to obtain optimality certificates if $c^\top - y^\top A \leq 0^\top$

8.3 Example (Canonical Form)

(P)

$$\max [0 \ 0 \ -4 \ 1 \ 0] x$$

subject to

$$\begin{bmatrix} 1 & 0 & -1 & 1 & 0 \\ 0 & 1 & 2 & -1 & 0 \\ 0 & 0 & -3 & 2 & 1 \end{bmatrix} x = \begin{bmatrix} 4 \\ 2 \\ 6 \end{bmatrix}$$

$$x \geq 0$$

$B := \{1, 2, 5\}$ is a basis of A . Thus, the basic solution corresponding to the basis is

$$\bar{x} := (4, 2, 0, 0, 6)^\top$$

$c_3 = -4$, increasing the value of x_3 from 0 will decrease the objective value by -4 units
 $c_4 = 1$, we want to increase the value of x_4 , so

$$\begin{bmatrix} x_1 \\ x_2 \\ x_5 \end{bmatrix} = \begin{bmatrix} 4 \\ 2 \\ 6 \end{bmatrix} - x_4 \begin{bmatrix} 1 \\ -1 \\ 2 \end{bmatrix} \geq 0$$

Let t denote the maximum value we can assign to x_4 and stay feasible.

So, $t = \min\{4/1, 6/2\} = 3$

9 2019-10-03

9.1 Example (Continuation of 8.3)

So, the new basic feasible solution is $\bar{x} := (1, 5, 0, 3, 0)^\top$ determined by the basis $B := \{1, 2, 5\} \cup \{4\} \setminus \{5\} = \{1, 2, 4\}$. Note that we exclude $\{5\}$ since the index of which t achieved the minimum was at $6/2$, i.e. index 5 (row x_5). The canonical form determined by the new basis is

$$\max [0 \quad 0 \quad -5/2 \quad 0 \quad -1/2] \mathbf{x} + 3$$

subject to

$$\begin{bmatrix} 1 & 0 & 1/2 & 0 & -1/2 \\ 0 & 1 & 1/2 & 0 & 1/2 \\ 0 & 0 & -3/2 & 1 & 1/2 \end{bmatrix} \mathbf{x} = \begin{bmatrix} 1 \\ 5 \\ 3 \end{bmatrix}$$

\bar{x} is the optimal solution with optimal value 3. How did we arrive to this LP? Using the formulae in Proposition 8.2. If you didn't want to calculate A_B^{-1} , then follow the below instructions.

9.2 Example (Canonical form without computing the inverse)

The following was not taught in class or the textbook. This method can be confusing and not intuitive.

Write

$$A := \left[\begin{array}{ccccc|c} 1 & 0 & -1 & 1 & 0 & 4 \\ 0 & 1 & 2 & -1 & 0 & 2 \\ 0 & 0 & -3 & 2 & 1 & 6 \end{array} \right] \rightarrow \left[\begin{array}{ccccc|c} 1 & 0 & 1/2 & 0 & -1/2 & 1 \\ 0 & 1 & 1/2 & 0 & 1/2 & 5 \\ 0 & 0 & -3/2 & 1 & 1/2 & 3 \end{array} \right] \begin{array}{l} -x_1 \\ -x_2 \\ -x_4 \end{array}$$

and row reduce A to make fourth column get a leading one as seen above. The row-reduced matrix and the augment are your new constraints.

The objective function is tricky, we want a 0 in the fourth column of our c^\top . Also, we denote x_1, x_2, x_4 as the rows of the matrix respectively as seen above. Using x_4 (which is our row-reduced A), we get

$$(-1) ([0 \quad 0 \quad -3/2 \quad 1 \quad 1/2] \mathbf{x} - 3) + ([0 \quad 0 \quad -4 \quad 1 \quad 0] \mathbf{x})$$

The -3 right after the first matrix was the row of \mathbf{b} . General form:

$$c([\text{Row}_i(A)]\mathbf{x} - \mathbf{b}_i) + \text{original objective function}$$

where c is a constant.

9.3 Algorithm (Simplex Algorithm)

Algorithm 1: Simplex Algorithm

Input : $A \in \mathbb{R}^{m \times n}$, $\mathbf{b} \in \mathbb{R}^m$, $\mathbf{c} \in \mathbb{R}^n$ such that we have linear program (P):

$$\max \{ \mathbf{c}^\top \mathbf{x}, A\mathbf{x} = \mathbf{b}, \mathbf{x} \geq \mathbf{0} \}, \text{ and a feasible basis } B.$$

Output: An optimal solution \bar{x} of (P) or a certificate proving that the (P) is unbounded.

- 1 Compute the canonical form for the basis B . Let \bar{x} be the basic feasible solution for B .
- 2 If $c_N \leq 0$, then stop (\bar{x} is optimal).
- 3 Choose $k \in N$ such that $c_k > 0$.
- 4 If $a_k \leq 0$, then stop (the LP is unbounded).
- 5 Let r be any index i where the following minimum is attained:

$$t = \min \left\{ \frac{b_i}{a_{ik}} : a_{ik} > 0 \right\}$$

- 6 Let ℓ be the r^{th} basis element.
 - 7 Set $B := B \cup \{k\} \setminus \{\ell\}$.
 - 8 Go to step 1.
-

9.4 Bland's Rule

Throughout the Simplex iterations with $t = 0$, in Step 3, among all $j \in N$, with $c_j > 0$, choose $k := \min \{j \in N : c_j > 0\}$; also in Step 5, define t as before and choose the smallest $r \in B$ with $a_{rk} > 0$, and $b_r/a_{rk} = t$.

9.5 Example (Simplex Algorithm with Bland's Rule)

Solve (P)

$$\max [0 \ 3 \ 1 \ 0] \mathbf{x}$$

subject to

$$\begin{bmatrix} 1 & 2 & -2 & 0 \\ 0 & 1 & 3 & 1 \end{bmatrix} \mathbf{x} = \begin{bmatrix} 2 \\ 5 \end{bmatrix}$$

$$\mathbf{x} \geq \mathbf{0}$$

using the Simplex Algorithm with Bland's Rule. Give a certificate of optimality or unboundedness for the problem, and verify it.

Solution.

Iteration 1

Useful values computed:

$$A_B = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \Rightarrow A_B^{-1} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$\mathbf{y}^\top = \mathbf{c}_B^\top A_B^{-1} = [0 \ 0] \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

1. The LP is already in canonical form determined by $B = \{1, 4\}$. Let $\bar{\mathbf{x}} := (2, 0, 0, 5)^\top$ be the basic feasible solution for B .

2. $c_{\{2,3\}} \not\leq \mathbf{0}$, so $\bar{\mathbf{x}}$ is not optimal.

3. Using Bland's Rule we choose $k = 2 \in N$ which enters the basis as $c_2 \geq 0$.

4. $a_2 = \begin{bmatrix} 2 \\ 1 \end{bmatrix} \not\leq \mathbf{0}$, so the LP is not unbounded.

5. $\begin{bmatrix} x_1 \\ x_4 \end{bmatrix} = \begin{bmatrix} 2 \\ 5 \end{bmatrix} - t \begin{bmatrix} 2 \\ 1 \end{bmatrix} \geq \mathbf{0}$ so

$$t = \min \left\{ \frac{2}{2}, \frac{5}{1} \right\}$$

Minimum is attained at index 1 (x_1). Let $r = 1$ be the index which attains the smallest value of t .

6. Let 1 be the 1st basis element.

7. Set $B := \{1, 4\} \cup \{2\} \setminus \{1\} = \{2, 4\}$

Iteration 2

Useful values computed:

$$A_B = \begin{bmatrix} 2 & 0 \\ 1 & 1 \end{bmatrix} \Rightarrow A_B^{-1} = \begin{bmatrix} 1/2 & 0 \\ -1/2 & 1 \end{bmatrix}$$

$$\mathbf{y}^\top = \mathbf{c}_B^\top A_B^{-1} = [3 \ 0] \begin{bmatrix} 1/2 & 0 \\ -1/2 & 1 \end{bmatrix} = \begin{bmatrix} 3/2 \\ 0 \end{bmatrix}$$

1. Canonical form determined by $B = \{2, 4\}$ is

$$\max [-3/2 \quad 0 \quad 4 \quad 0] + 3$$

subject to

$$\begin{bmatrix} 1/2 & 1 & -1 & 0 \\ -1/2 & 0 & 4 & 1 \end{bmatrix} \mathbf{x} = \begin{bmatrix} 1 \\ 4 \end{bmatrix}$$

$$\mathbf{x} \geq \mathbf{0}$$

Let $\bar{\mathbf{x}} := (0, 1, 0, 4)^\top$ be the basic feasible solution.

2. $c_{\{1,3\}} \not\leq \mathbf{0}$, so $\bar{\mathbf{x}}$ is not optimal.

3. Using Bland's Rule we choose $k = 3 \in N$ which enters the basis as $c_3 \geq 0$.

4. $a_3 = \begin{bmatrix} -1 \\ 4 \end{bmatrix} \not\leq \mathbf{0}$, so the LP is not unbounded.

5. $\begin{bmatrix} x_2 \\ x_4 \end{bmatrix} = \begin{bmatrix} 1 \\ 4 \end{bmatrix} - t \begin{bmatrix} -1 \\ 4 \end{bmatrix} \geq \mathbf{0}$ so

$$t = \min \left\{ -, \frac{4}{4} \right\}$$

Minimum is attained at index 2 (x_4). Let $r = 2$ be the index which attains the smallest value of t .

6. Let 4 be the 2nd basis element.

7. Set $B := \{1, 4\} \cup \{3\} \setminus \{4\} = \{2, 3\}$

Iteration 3

Useful values computed:

$$A_B = \begin{bmatrix} 2 & -2 \\ 1 & 3 \end{bmatrix} \Rightarrow A_B^{-1} = \begin{bmatrix} 3/8 & 1/4 \\ -1/8 & 1/4 \end{bmatrix}$$

$$\mathbf{y}^\top = \mathbf{c}_B^\top A_B^{-1} = [3 \quad 1] \begin{bmatrix} 3/8 & 1/4 \\ -1/8 & 1/4 \end{bmatrix} = [1 \quad 1]$$

1. Canonical form determined by $B = \{2, 3\}$ is

$$\max [-1 \quad 0 \quad 0 \quad -1] + 7$$

subject to

$$\begin{bmatrix} 3/8 & 1 & 0 & 1/4 \\ -1/8 & 0 & 1 & 1/4 \end{bmatrix} \mathbf{x} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

$$\mathbf{x} \geq \mathbf{0}$$

Let $\bar{\mathbf{x}} := (0, 2, 1, 0)^\top$ be the basic feasible solution.

2. $c_{\{1,4\}} \leq \mathbf{0}$, stop $\bar{\mathbf{x}}$ is optimal.

The certificate of optimality is $\bar{\mathbf{y}} = (1, 1)^\top$.

To verify that $\bar{\mathbf{y}} = (1, 1)^\top$ is the certificate of optimality. We compute

$$A^\top \bar{\mathbf{y}} = \begin{bmatrix} 1 \\ 3 \\ 1 \\ 1 \end{bmatrix} \geq \begin{bmatrix} 0 \\ 3 \\ 1 \\ 0 \end{bmatrix} = \mathbf{c}$$

and

$$\mathbf{c}^\top \bar{\mathbf{x}} = \begin{bmatrix} 0 & 3 & 1 & 0 \end{bmatrix} \begin{bmatrix} 0 \\ 2 \\ 1 \\ 0 \end{bmatrix} = 7 = \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 5 \end{bmatrix} = \bar{\mathbf{y}}^\top \mathbf{b}$$

This was obviously not done in class (in fact it's a textbook question!). It can be verified that $\bar{\mathbf{y}}$ is indeed the certificate of optimality by using the summary of outcomes as seen above.

10 2019-10-08

10.1 Convergence of Simplex Algorithm

In each iteration, we choose $k \in N$ such that $c_k > 0$. Then, we compute $t = \min\{b_i/A_{ik} \mid A_{ik} > 0\}$. Then, throughout the rest of the Simplex iterations, we never see the same basis again. There are at most $\binom{n}{m}$ bases of A . Therefore, if $t > 0$ in each iteration, the Simplex Algorithm will terminate in at most $\binom{n}{m}$ iterations. The only way the algorithm will not terminate is when $t = 0$ for all iterations (after some # of iterations). If our choices for k and l are deterministic and consistent in this case if we repeat a basis we call it a *cycle*.

10.2 Theorem

The Simplex Algorithm starting from a basic feasible solution with Bland's Rule terminates.

10.3 Implementation of the Simplex Algorithm in "Big Data"

In a given iteration of the Simplex Algorithm, what information do we need to execute the algorithm?

We have the original data $(A, \mathbf{b}, \mathbf{c})$ and we have the current $B, \bar{\mathbf{x}}, \bar{\mathbf{v}}$.

Pick any $k \in N$ such that $\bar{c}_k \geq 0$. $\bar{c}_k = c_k - \bar{\mathbf{y}}^\top A_{\mathbf{k}}$ (where $\bar{\mathbf{y}}^\top = \mathbf{c}_B A_B^{-1}$).

Then to compute t , we need $t = \min\{b_i/A_{ik} \mid A_{ik} > 0\}$.

So, we need \bar{A}_k : $\bar{A}_k = A_B^{-1} A_k$ and note that $\bar{\mathbf{x}}_N = \mathbf{0}$, $\bar{\mathbf{x}}_B = \bar{\mathbf{b}}$

We solve linear systems $A_B^\top \mathbf{y} = \mathbf{c}_B$ and $A_B \mathbf{d}_B = A_k$.

In implementations, we typically express A_B or A_B^{-1} as a product of elementary matrices.

In practice, good implementations of the Simplex Algorithm terminates after $2m$ to $n/2$ iterations. Each iteration is very fast.

It is an open problem whether there exists a variant of Simplex Algorithm which is guaranteed to terminate in at most pn^q iterations for LP problems in SEF with n variables, where p, q are constants.

2019-10-10

Midterm 1 was written on this day, as a result no classes were held.

11 2019-10-22

Given any LP problem, we know how to convert it into an equivalent LP problem in SEF:

(P)

$$\max z := \mathbf{c}^\top \mathbf{x}$$

subject to

$$\begin{aligned} Ax &= b \\ x &\geq 0 \end{aligned}$$

where $A \in \mathbb{R}^{m \times n}$ has $\text{rank}(A) = m$.

Given an LP in SEF, with a given basic feasible solution, we know how to solve it.

11.1 Finding a Feasible Solution To LPs (Two Phase Method)

Given an LP in SEF with $\text{rank}(A) = m$, how do we find a feasible solution or prove that none exists.

We will construct an *auxiliary LP problem*.

We can always make sure $b \geq 0$. (If any $b_i < 0$, multiply both sides of that equation by (-1)) Introduce artificial variables x_{n+1}, \dots, x_{n+m}

11.2 Definition (Auxiliary Linear Program, Auxiliary Variables)

Given (P): $\max \{c^\top x, Ax = b, x \geq 0\}$, we define the *auxiliary linear program* of (P) as: (P_{aux})

$$\min w := x_{n+1} + \dots + x_{n+m}$$

subject to

$$\begin{bmatrix} A & | & I \end{bmatrix} \underbrace{\begin{bmatrix} x_1 \\ \vdots \\ x_n \\ x_{n+1} \\ \vdots \\ x_{n+m} \end{bmatrix}}_x = b$$

$$x \geq 0$$

where $b \geq 0$, and I is the $m \times m$ identity matrix.

We call the variables x_{n+1}, \dots, x_{n+m} *auxiliary variables*.

For every feasible solution of (P_{aux}) , $w \geq 0$.

Therefore, (P_{aux}) is not unbounded.

If the optimal value of (P_{aux}) is zero, let $(\hat{x}_1, \dots, \hat{x}_{n+m})^\top$ be the basic feasible solution of (P_{aux}) . Then, $(\hat{x}_1, \dots, \hat{x}_n)^\top$ is a basic feasible solution of (P).

It is basic since $\{A_j : \hat{x}_j > 0\}$ is linearly independent where J is the column indices j of A for which $\hat{x}_j \neq 0$.

If $|\{j : \hat{x}_j > 0\}| = m$, this index set is a basis of A which determines $(\hat{x}_1, \dots, \hat{x}_n)^\top$.

If $|\{j : \hat{x}_j > 0\}| \leq m - 1$, we can extend this index set to be a basis of A , since $\text{rank}(A) = m$.

If the optimal value of (P_{aux}) is positive, then (P) is infeasible. We state this as a theorem.

11.3 Theorem

Let $\bar{x} = (\bar{x}_1, \dots, \bar{x}_{n+m})^\top$ be an optimal solution to (P_{aux}) .

(1) if $w = 0$, then $(\bar{x}_1, \dots, \bar{x}_n)^\top$ is a solution to (P).

(2) if $w > 0$, then (P) is infeasible.

Proof. Let $\bar{x} = (\bar{x}_1, \dots, \bar{x}_{n+m})^\top$ be an optimal solution to (P_{aux}) .

(1) Assume $w = 0$, then $\bar{x}_{n+1} = \dots = \bar{x}_{n+m} = 0$. Thus $(\bar{x}_1, \dots, \bar{x}_n)^\top$ is a feasible solution of (P).

(2) Assume $w > 0$. Suppose for a contradiction that there exists a feasible solution $(\bar{x}_1, \dots, \bar{x}_n)^\top$ to (P). Then, $(\bar{x}_1, \dots, \bar{x}_n, \underbrace{0, \dots, 0}_{m \text{ terms}})$ is a feasible solution to (P_{aux}) with optimal objective value 0 which is a contradiction to the fact that \bar{x} is optimal. \square

11.4 Algorithm (Two Phase Method)

Algorithm 2: Two Phase Method

Input : A, b, c data for LP in SEF such that full row rank and $b \geq 0$.

- 1 Construct (P_{aux}) put into SEF, $B := \{n+1, n+2, \dots, n+m\}$
- 2 Put (P_{aux}) into the canonical form determined by B .
- 3 Solve (P_{aux}) starting with basis B by Simplex Method.
- 4 If the optimal value of (P_{aux}) is zero, then we have a basic feasible solution of (P). Solve (P) using Simplex Method. This is known as Phase II.
- 5 If the optimal objective value of (P_{aux}) is not zero, then (P) is infeasible (a certificate of infeasibility is given by the last \bar{y} computed).

As seen above, the original LP can either have an optimal solution or be infeasible when performing the Two Phase Method.

11.5 Example (Two Phase Method - Optimal)

(P)

$$\max z := [1 \quad 2 \quad -1] x$$

subject to

$$\begin{bmatrix} 1 & -2 & -3 \\ -1 & 1 & 1 \end{bmatrix} x = \begin{bmatrix} -3 \\ 1 \end{bmatrix}$$

$$x \geq 0$$

Since $b_1 < 0$ we write

$$\begin{bmatrix} -1 & 2 & 3 \\ -1 & 1 & 1 \end{bmatrix} x = \begin{bmatrix} 3 \\ 1 \end{bmatrix}$$

we do this because we will not have a feasible solution if $b < 0$.

Introduce artificial variables: x_4, x_5

Phase I

(P_{aux})

$$\max -w := [0 \quad 0 \quad 0 \quad -1 \quad -1] x$$

subject to

$$\begin{bmatrix} -1 & 2 & 3 & 1 & 0 \\ -1 & 1 & 1 & 0 & 1 \end{bmatrix} x = \begin{bmatrix} 3 \\ 1 \end{bmatrix}$$

$$x := (x_1, x_2, x_3, x_4, x_5)^\top \geq 0$$

Turn (P_{aux}) into canonical form for $B := \{4, 5\}$

$$\max -w := [-2 \quad 3 \quad 4 \quad 0 \quad 0] x$$

subject to

$$\begin{bmatrix} -1 & 2 & 3 & 1 & 0 \\ -1 & 1 & 1 & 0 & 1 \end{bmatrix} \mathbf{x} = \begin{bmatrix} 3 \\ 1 \end{bmatrix}$$

$$\mathbf{x} \geq \mathbf{0}$$

We solve the LP via Simplex Algorithm and obtain the following LP corresponding to the optimal basis of $B = \{1, 2\}$

$$\max -w := [0 \quad 0 \quad 0 \quad -1 \quad -1] \mathbf{x}$$

subject to

$$\begin{bmatrix} 1 & 0 & 1 & 1 & -2 \\ 0 & 1 & 2 & 1 & -1 \end{bmatrix} \mathbf{x} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$$\mathbf{x} \geq \mathbf{0}$$

End of Phase I.

Phase II

We rewrite the original LP in canonical form corresponding to basis $B = \{1, 2\}$ to obtain

$$\max z := [0 \quad 0 \quad -6] \mathbf{x} + 5$$

subject to

$$\begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 2 \end{bmatrix} \mathbf{x} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$$\mathbf{x} := (x_1, x_2, x_3)^\top \geq \mathbf{0}$$

We obtain the optimal basic feasible solution of (P_{aux}) via the Simplex Algorithm

$$(\hat{x}_1, \hat{x}_2, \hat{x}_3, \hat{x}_4, \hat{x}_5) := (1, 2, 0, 0, 0)^\top$$

Thus, the corresponding basic feasible solution of (P) is

$$(\hat{x}_1, \hat{x}_2, \hat{x}_3) = (1, 2, 0)^\top$$

with an optimal objective value of $z := 5$.

11.6 Example (Two Phase Method - Infeasible)

(P)

$$\max z := [3 \quad 2 \quad 4] \mathbf{x}$$

subject to

$$\underbrace{\begin{bmatrix} 5 & 1 & 1 \\ -1 & 1 & 2 \end{bmatrix}}_A \mathbf{x} = \begin{bmatrix} 1 \\ 5 \end{bmatrix}$$

$$\mathbf{x} \geq \mathbf{0}$$

(P_{aux})

$$\max -w := \underbrace{[0 \quad 0 \quad 0 \quad -1 \quad -1]}_{\tilde{c}_B} \mathbf{x}$$

subject to

$$\underbrace{\begin{bmatrix} 5 & 1 & 1 & 1 & 0 \\ -1 & 1 & 2 & 0 & 1 \end{bmatrix}}_{\tilde{A}} \mathbf{x} = \begin{bmatrix} 1 \\ 5 \end{bmatrix}$$

$$\mathbf{x} := (x_1, x_2, x_3, x_4, x_5)^\top \geq \mathbf{0}$$

Turn (P_{aux}) into canonical form for $B := \{4, 5\}$ (by adding the constraints up to the original objective function).

$$\max -w := \begin{bmatrix} 4 & 2 & 3 & 0 & 0 \end{bmatrix} \mathbf{x} - 4$$

subject to

$$\begin{bmatrix} 5 & 1 & 1 & 1 & 0 \\ -1 & 1 & 2 & 0 & 1 \end{bmatrix} \mathbf{x} = \begin{bmatrix} 1 \\ 5 \end{bmatrix}$$

$$\mathbf{x} \geq \mathbf{0}$$

Starting with the basis $B = \{4, 5\}$, solve (P_{aux}) with the Simplex Algorithm to get:

$$\max -w = \begin{bmatrix} -11 & -1 & 0 & -3 & 0 \end{bmatrix} \mathbf{x} - 3$$

subject to

$$\begin{bmatrix} 5 & 1 & 1 & 1 & 0 \\ -11 & -1 & 0 & -2 & 1 \end{bmatrix} \mathbf{x} = \begin{bmatrix} 1 \\ 3 \end{bmatrix}$$

$$\mathbf{x} \geq \mathbf{0}$$

The optimal value of (P_{aux}) is not zero. Therefore, (P) is infeasible. The basis in the last iteration was $B = \{3, 5\}$.

$$\mathbf{y}^\top = \tilde{\mathbf{c}}_B^\top \tilde{A}_B^{-1} \iff \mathbf{y}^\top = \underbrace{\begin{bmatrix} 0 & -1 \end{bmatrix}}_{\text{SEF of } (P_{aux})} \begin{bmatrix} 1 & 0 \\ 2 & 1 \end{bmatrix}^{-1}$$

$\bar{\mathbf{y}} = (2, -1)^\top$ is a certificate of infeasibility of (P).

Compute $\bar{\mathbf{y}}^\top A = \begin{bmatrix} 11 & 1 & 0 \end{bmatrix} \geq \mathbf{0}^\top$ and $\bar{\mathbf{y}}^\top \mathbf{b} = -3 = \mathbf{c}^\top \mathbf{x}$ where $\bar{\mathbf{x}} = (0, 0, 0, 1, 3)^\top$.

Thus, $\bar{\mathbf{y}}$ is a certificate of optimality for (P_{aux}) .

11.7 Theorem (Fundamental Theorem of LP (SEF))

Let (P) be an LP problem in SEF, where $A \in \mathbb{R}^{m \times n}$ has $\text{rank}(A) = m$.

- (1) if (P) does not have an optimal solution, then (P) is either infeasible or unbounded.
- (2) if (P) has a feasible solution, then (P) has a basic feasible solution.
- (3) if (P) has an optimal solution, then (P) has an optimal basic feasible solution.

12 2019-10-24

12.1 Theorem (Fundamental Theorem of LP)

Let (P) be an LP problem. Then exactly one of the following holds:

- (P) is infeasible
- (P) is unbounded
- (P) has an optimal solution

Fundamental Theorem of LP and Fundamental Theorem of LP (SEF) are not the same, they are two completely different theorems!

12.2 Definition (Hyperplane, Half-space)

Let $\mathbf{a} \in \mathbb{R}^n \setminus \mathbf{0}$, $\beta \in \mathbb{R}$.

$H := \{\mathbf{x} \in \mathbb{R}^n : \mathbf{a}^\top \mathbf{x} = \beta\}$ is a *hyperplane*.

$F := \{\mathbf{x} \in \mathbb{R}^n : \mathbf{a}^\top \mathbf{x} \leq \beta\}$ is a *half-space*.

Solution sets of linear equations are intersections of hyperplanes.

12.3 Definition (Polyhedron)

Let $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^m$. $P := \{x \in \mathbb{R}^n : Ax \leq b\}$ is a *polyhedron*.

The set of solutions to any one of the inequalities of $Ax \leq b$ is a half-space.

12.4 Proposition

The feasible region of an LP is a polyhedron or equivalently the intersection of a finite number of half-spaces.

Proof. Let $a \in \mathbb{R}^n$, $x \in \mathbb{R}^n$, $\beta \in \mathbb{R}$.

Given an inequality of the form $a^\top x \geq \beta$, we can rewrite it as $-a^\top x \leq -\beta$.

Given an equation of the form $a^\top x = \beta$ we can rewrite it as $a^\top x \geq \beta$ and $-a^\top x \leq -\beta$.

Thus, any set of linear constraints can be rewritten as $Ax \leq b$ for some $A \in \mathbb{R}^{m \times n}$ and $b \in \mathbb{R}^m$, where a^\top can correspond to each row of A , and β can correspond to each row of the column vector b . \square

Solutions sets of $Ax = b$ are either \emptyset , a single point, a line, or in general, an intersection of a hyperplane.

Note that already in \mathbb{R}^2 there are already equivalent polyhedra. The mathematical modelling power of LPs are significantly more than that of linear systems of equations.

12.5 Definition (Line segment)

The *line segment* joining two points, $x^{(1)}$ and $x^{(2)}$ is

$$\{\lambda x^{(1)} + (1 - \lambda)x^{(2)} : \lambda \in [0, 1]\}$$

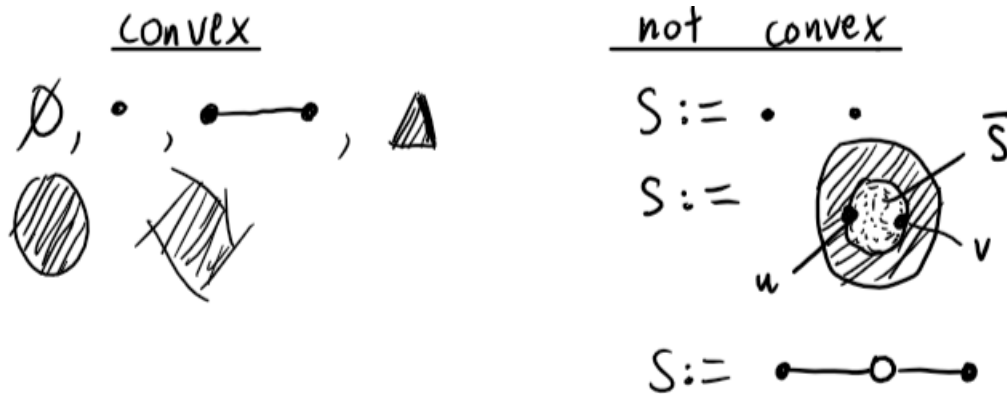
Graphically, the line segment can be seen as:



12.6 Definition (Convex)

A subset $S \subseteq \mathbb{R}^n$ is *convex* if for every pair of points $x^{(1)}, x^{(2)} \in S$, the line segment with ends $x^{(1)}$ and $x^{(2)}$ is included in S . That is,

$$\{\lambda x^{(1)} + (1 - \lambda)x^{(2)} : \lambda \in [0, 1]\} \subseteq S$$



12.7 Proposition

Half-spaces are convex.

Proof. Let $H \subseteq \mathbb{R}^n$ be a half-space. Then $\mathbf{a} \in \mathbb{R}^n \setminus \mathbf{0}$ and $\beta \in \mathbb{R}$ such that

$$H = \{\mathbf{x} \in \mathbb{R}^n : \mathbf{a}^\top \mathbf{x} \leq \beta\}$$

Let $\bar{x} = \lambda x^{(1)} + (1 - \lambda)x^{(2)}$ where $\lambda \in [0, 1]$.

$$\mathbf{a}^\top \bar{x} = \mathbf{a}^\top [\lambda x^{(1)} + (1 - \lambda)x^{(2)}] = \underbrace{\lambda}_{\geq 0} \underbrace{\mathbf{a}^\top x^{(1)}}_{\leq \beta} + \underbrace{(1 - \lambda)}_{\geq 0} \underbrace{\mathbf{a}^\top x^{(2)}}_{\leq \beta} \leq \lambda\beta + (1 - \lambda)\beta = \beta$$

Thus, H is convex since $\bar{x} \in H$. □

12.8 Proposition

The intersection of any collection of convex sets is convex. That is, a convex set C_j for all $j \in J$, the intersection

$$C := \bigcap_{j \in J} C_j$$

is convex.

Proof. Let u, v be two points in C . Let w lie on the line segment between u and v . Then, $w \in C_j$ since C_j is convex for each $j \in J$. Thus, $w \in C$. □

J can be infinite. That is, the intersection of infinitely many convex sets is convex, which can be formally proved by strong induction.

12.9 Proposition

Polyhedra are convex.

12.10 Definition (Properly Contained)

We say that a point x is *properly contained* in a line segment if it is in the line segment and not an endpoint.

12.11 Definition (Extreme Point)

Let $S \subseteq \mathbb{R}^n$ be a convex set. Let $\bar{x} \in \mathbb{R}^n$. \bar{x} is an *extreme point* of S , if $\bar{x} \in S$ and no line segment that properly contains \bar{x} is included in S .

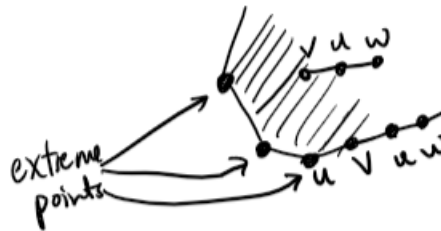
Equivalently, \bar{x} is an *extreme point* of S , if $\bar{x} \in S$ and no two distinct $x^{(1)}, x^{(2)} \in S$ exist satisfying

$$\bar{x} = \lambda x^{(1)} + (1 - \lambda)x^{(2)}$$

for some $\lambda \in (0, 1)$.

Equivalently, \bar{x} is an *extreme point* of S , if $\bar{x} \in S$ and no two distinct $x^{(1)}, x^{(2)} \in S$ exist satisfying

$$\bar{x} = \frac{1}{2}x^{(1)} + \frac{1}{2}x^{(2)}$$



13 2019-10-30

Recall the notions: hyperplane, half-space, polyhedron, feasible regions of LPs, convex sets, extreme points of convex sets.

13.1 Proposition

Let $S \subseteq \mathbb{R}^n$ be a convex set and $\bar{x} \in S$. \bar{x} is an extreme point of S if and only if $S \setminus \{\bar{x}\}$ is convex.

Proof. Assume $S \subseteq \mathbb{R}^n$ is convex and $\bar{x} \in S$.

\Rightarrow Suppose \bar{x} is an extreme point of S . Pick two points $x^{(1)}, x^{(2)} \in S \setminus \{\bar{x}\}$ and $\lambda \in [0, 1]$ and set $\bar{x} = \lambda x^{(1)} + (1 - \lambda)x^{(2)}$. To show that $S \setminus \{\bar{x}\}$ is convex, we have to verify that $x \in S \setminus \{\bar{x}\}$. Now the set S is convex, so $x \in S$. It remains to show that $x \neq \bar{x}$.

Case 1: $\lambda = 0$. Then $x = x^{(1)} \neq \bar{x}$.

Case 2: $\lambda = 1$. Then $x = x^{(2)} \neq \bar{x}$.

Case 3: $\lambda \in (0, 1)$. We know x must be different from \bar{x} , otherwise we would contradict the fact that \bar{x} is an extreme point of S .

\Leftarrow We prove the contrapositive. Assume that \bar{x} is not an extreme point of S . Then there exists two points $x^{(1)}, x^{(2)} \in S$ with $x^{(1)} \neq x^{(2)}$ and some $\lambda \in (0, 1)$ such that $\bar{x} = \lambda x^{(1)} + (1 - \lambda)x^{(2)}$. Note that $x^{(1)}, x^{(2)} \in S \setminus \{\bar{x}\}$ since $x^{(1)} \neq x^{(2)}$. Thus $S \setminus \{\bar{x}\}$ is not convex. \square

13.2 Definition (Tight Constraints)

Let $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^m$. Consider the polyhedron $P \subseteq \mathbb{R}^n$ $P := \{x \in \mathbb{R}^n : Ax \leq b\}$. We say that a constraint $\alpha^\top x \leq \beta$ of $Ax \leq b$ is *tight* for \bar{x} if $\alpha^\top \bar{x} = \beta$. We denote the set of all inequalities of $Ax \leq b$ that are tight at \bar{x} by $A^\top \bar{x} = b^\top$.

13.3 Theorem

Let $P = \{x \in \mathbb{R}^n : Ax \leq b\}$ be a polyhedron and let $\bar{x} \in P$. Let $A^\top x = b^\top$ be the set of tight constraints for \bar{x} . Then $\text{rank}(A^\top) = n$ if and only if \bar{x} is an extreme point of P .

Proof. $\implies [\text{rank}(A^\top) = n \implies \bar{x} \text{ is an extreme point of } P]$

Suppose $\text{rank}(A^\top) = n$. Suppose for a contradiction that \bar{x} is not an extreme point. Then there exists $x^{(1)}, x^{(2)} \in P$, where $x^{(1)} \neq x^{(2)}$ and $\lambda \in (0, 1)$ such that

$$\bar{x} = \lambda x^{(1)} + (1 - \lambda)x^{(2)}$$

Thus,

$$\begin{aligned} b^\top &= A^\top \bar{x} \\ &= A^\top [\lambda x^{(1)} + (1 - \lambda)x^{(2)}] \\ &= \underbrace{\lambda}_{>0} \underbrace{A^\top x^{(1)}}_{\leq b^\top} + \underbrace{(1 - \lambda)}_{>0} \underbrace{A^\top x^{(2)}}_{\leq b^\top} \\ &\leq \lambda b^\top + (1 - \lambda)b^\top \\ &= b^\top \end{aligned}$$

Thus, we must have that everything in the inequality chain starting and ending with b^\top is equal. Thus, $A^\top x^{(1)} = A^\top x^{(2)} = b^\top$. $\text{rank}(A^\top) = n$ implies there is a unique solution to $A^\top \bar{x} = b^\top$, so we have $\bar{x} = x^{(1)} = x^{(2)}$, a contradiction that \bar{x} is an extreme point.

$\Leftarrow [\text{rank}(A^\top) = n \Leftarrow \bar{x} \text{ is an extreme point of } P]$

We will prove the contrapositive of this. That is, we will prove $\text{rank}(A^\top) \neq n \implies \bar{x}$ is not an extreme point of P .

Suppose that $\text{rank}(A^\top) \neq n$, that is $\text{rank}(A^\top) < n$, which means that the columns of A^\top are linearly dependent. Thus, $\exists d$ such that $A^\top d = 0$. Let $\varepsilon > 0$ be arbitrarily small and define

$$x^{(1)} := \bar{x} + \varepsilon d$$

$$x^{(2)} := \bar{x} - \varepsilon d$$

Hence, $\bar{x} = \frac{1}{2}x^{(1)} + \frac{1}{2}x^{(2)}$, where $x^{(1)}$ and $x^{(2)}$ are distinct. Thus, \bar{x} is in the line segment between $x^{(1)}$ and $x^{(2)}$.

We need to show that $x^{(1)}, x^{(2)} \in P$ for $\varepsilon > 0$ arbitrarily small. We have

$$\begin{aligned} A^\top x^{(1)} &= A^\top (\bar{x} + \varepsilon d) \\ &= A^\top \underbrace{\bar{x}}_{=b^\top} + \varepsilon \underbrace{A^\top d}_{=0} \\ &= b^\top \end{aligned}$$

Similarly, $A^\top x^{(2)} = b^\top$. Let $a^\top x \leq \beta$ be any of the inequalities of $Ax \leq b$ that is not in $A^\top x \leq b^\top$. It follows for $\varepsilon > 0$ arbitrarily small that:

$$\begin{aligned} a^\top x^{(1)} &= a^\top (\bar{x} + \varepsilon d) \\ &= \underbrace{a^\top \bar{x}}_{\leq \beta} + \varepsilon a^\top d \\ &\leq \beta \end{aligned}$$

hence $x^{(1)} \in P$. Similarly, $x^{(2)} \in P$. Thus, \bar{x} is properly contained in P and hence is not an extreme point. \square

Example

$$F := \left\{ \mathbf{x} \in \mathbb{R}^2 : \begin{bmatrix} 1 & 1 \\ 1 & 0 \\ -1 & 0 \\ 0 & -1 \end{bmatrix} \mathbf{x} \leq \begin{bmatrix} 4 \\ 2 \\ 0 \\ 0 \end{bmatrix}, \mathbf{x} \geq \mathbf{0} \right\}$$

(i) $\mathbf{x}^{(1)} := \begin{bmatrix} 2 \\ 0 \end{bmatrix}$, $A^= = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$

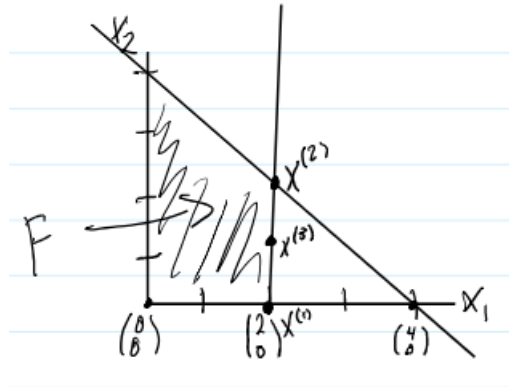
$\text{rank}(A^=) = 2 = n$, therefore $\mathbf{x}^{(1)}$ is an extreme point of F .

(ii) $\mathbf{x}^{(2)} := \begin{bmatrix} 2 \\ 2 \end{bmatrix}$, $A^= = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}$

$\text{rank}(A^=) = 2 = n$, therefore $\mathbf{x}^{(2)}$ is an extreme point of F .

(iii) $\mathbf{x}^{(3)} := \begin{bmatrix} 2 \\ 1 \end{bmatrix}$, $A^= = \begin{bmatrix} 1 & 0 \end{bmatrix}$

$\text{rank}(A^=) = 1 < 2 = n$, therefore $\mathbf{x}^{(3)}$ is not an extreme point of F .

**13.4 Theorem**

Let $A \in \mathbb{R}^{m \times n}$ with $\text{rank}(A) = m$. Let $P = \{\mathbf{x} \in \mathbb{R}^n : A\mathbf{x} = \mathbf{b}, \mathbf{x} \geq \mathbf{0}\}$, and let $\bar{\mathbf{x}} \in P$. $\bar{\mathbf{x}}$ is an extreme point of P if and only if $\bar{\mathbf{x}}$ is a basic feasible solution of $A\mathbf{x} = \mathbf{b}$.

$$F := \left\{ \mathbf{x} \in \mathbb{R}^2 : \begin{bmatrix} 1 & 1 \\ 1 & 0 \\ -1 & 0 \\ 0 & -1 \end{bmatrix} \mathbf{x} \leq \begin{bmatrix} 4 \\ 2 \\ 0 \\ 0 \end{bmatrix}, \mathbf{x} \geq \mathbf{0} \right\}$$

$$P := \left\{ \mathbf{x} \in \mathbb{R}^4 : \begin{bmatrix} 1 & 1 & -1 & 0 \\ 1 & 0 & 0 & -1 \end{bmatrix} \mathbf{x} = \begin{bmatrix} 4 \\ 2 \end{bmatrix}, \mathbf{x} \geq \mathbf{0} \right\}$$

Note that for every feasible solution $\begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix} \in F$, $\begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \\ 4 - \bar{x}_1 - \bar{x}_3 \\ 2 - \bar{x}_1 \end{bmatrix} \in P$.

Conversely, for every $\begin{bmatrix} \hat{x}_1 \\ \hat{x}_2 \\ \hat{x}_3 \\ \hat{x}_4 \end{bmatrix} \in P$, $\begin{bmatrix} \hat{x}_1 \\ \hat{x}_2 \end{bmatrix} \in F$

Consider the basis $B := \{3, 4\}$ of A . The corresponding basic feasible solution is $\bar{x} = (0, 0, 4, 2)^\top$. Thus, \bar{x} is an extreme point of P .

13.5 Geometric Interpretation of Simplex Method

(P)

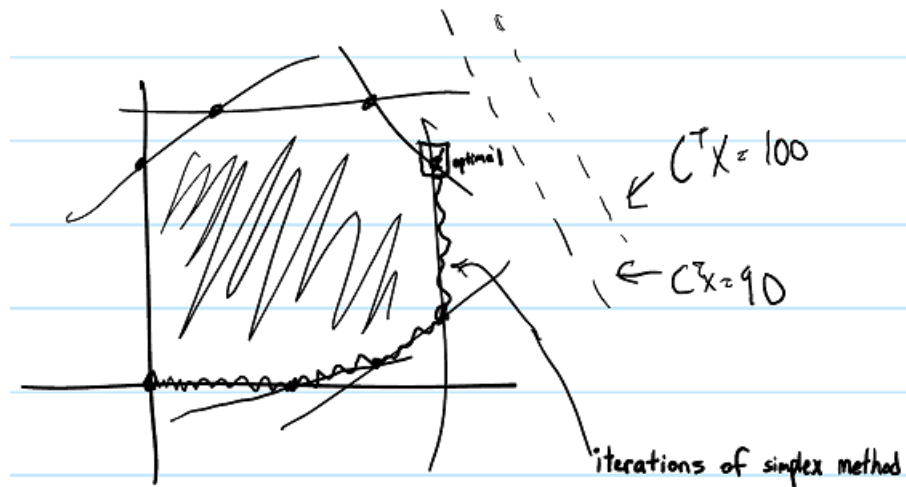
$$\max z := c^\top x$$

subject to

$$Ax \leq b$$

$$x \geq 0$$

Suppose $n = 1$ and $m = 6$ with $b \geq 0$.



13.6 Duality Theory

(P)

$$\max\{c^\top x : Ax = b, x \geq 0\}$$

Recall the notation of optimality certificate $\bar{y} \in \mathbb{R}^m$ such that $A^\top \bar{y} \geq c$. We noted that for every feasible x in (P), $Ax = b \implies \bar{y}^\top Ax = \bar{y}^\top b$

Since $A^\top \bar{y} \geq c$ and $x \geq 0$, we have $c^\top x \leq \bar{y}^\top Ax = \bar{y}^\top b$. So as long as $y \in \mathbb{R}^m$ with $A^\top y \geq c$, we can get an upper bound of $b^\top y$ on the optimal objective value of (P).

We want to minimize $b^\top y$ subject to $A^\top y \geq c$

13.7 Definition (Dual)

Given (P)

$$\max\{c^\top x : Ax = b, x \geq 0\}$$

we define (D)

$$\min\{b^\top y : A^\top y \geq c, y \geq 0\}$$

to be the *dual* of (P).

13.8 Example (Dual)

Find the dual of (P_1) : $\max\{\mathbf{c}^\top \mathbf{x} : A\mathbf{x} \leq \mathbf{b}, \mathbf{x} \geq \mathbf{0}\}$.

Solution.

Convert to SEF by introducing slack variables: $\mathbf{s} = (s_1, \dots, s_n)^\top$.

(P_2)

$$\max \mathbf{c}^\top \begin{bmatrix} \mathbf{x} \\ \mathbf{s} \end{bmatrix}$$

subject to

$$\begin{bmatrix} A & I \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ \mathbf{s} \end{bmatrix} = \mathbf{b}$$

$$(\mathbf{x}, \mathbf{s})^\top \geq \mathbf{0}$$

(D_2)

$$\min \mathbf{b}^\top \mathbf{y}$$

$$\begin{bmatrix} A^\top \\ I \end{bmatrix} \mathbf{y} \geq \begin{bmatrix} \mathbf{c} \\ \mathbf{0} \end{bmatrix}$$

$$\mathbf{y} \geq \mathbf{0}$$

Thus, the dual of (P_1) is (D_2) : $\min\{\mathbf{b}^\top \mathbf{y} : A^\top \mathbf{y} \geq \mathbf{c}, \mathbf{y} \geq \mathbf{0}\}$.

14 2019-10-31

Last lecture, we defined the dual of LPs in SIF and found the dual of (P_1) .

$$(P_1) : \max\{\mathbf{c}^\top \mathbf{x} : A\mathbf{x} \leq \mathbf{b}, \mathbf{x} \geq \mathbf{0}\}$$

$$(D_1) : \min\{\mathbf{b}^\top \mathbf{y} : A^\top \mathbf{y} \geq \mathbf{c}, \mathbf{y} \geq \mathbf{0}\}$$

14.1 How we do directly write down the dual of an LP?

Suppose $A \in \mathbb{R}^{3 \times 4}$.

(P)

$$\max 10x_1 + 20x_2 + 30x_3 + 40x_4$$

subject to

$$\begin{bmatrix} \mathbf{a}_1^\top \\ \mathbf{a}_2^\top \\ \mathbf{a}_3^\top \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \begin{matrix} \leq \\ = \\ \geq \end{matrix} \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$$

$$x_1 \geq 0, x_2 \geq 0, x_3 \leq 0, x_4 \text{ free}$$

where $\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3 \in \mathbb{R}^4$.

(D)

$$\min \begin{bmatrix} 1 & 2 & 3 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}$$

subject to

$$\begin{bmatrix} \mathbf{a}_1 & \mathbf{a}_2 & \mathbf{a}_3 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} \begin{matrix} \geq \\ \geq \\ \leq \\ = \end{matrix} \begin{bmatrix} 10 \\ 20 \\ 30 \\ 40 \end{bmatrix}$$

$$y_1 \geq 0, y_2 \text{ free}, y_3 \leq 0$$

Dual of the dual is the original problem, the primal.

Since:

1. constraint 1 in (P) is \leq , then $y_1 \geq 0$
2. constraint 2 in (P) is $=$, then y_2 free
3. constraint 3 in (P) is \geq , then $y_3 \leq 0$
4. $x_1, x_2 \geq 0$, then constraint 1, 2 in (D) is \geq
5. $x_3 \leq 0$, then constraint 3 in (D) is \leq
6. x_4 free, then constraint 4 in (D) is $=$

14.2 Theorem (Weak Duality - Special Form)

Consider (P)

$$\max\{\mathbf{c}^\top \mathbf{x} : A\mathbf{x} \leq \mathbf{b}, \mathbf{x} \geq \mathbf{0}\}$$

and (P)'s dual (D)

$$\min\{\mathbf{b}^\top \mathbf{y} : A^\top \mathbf{y} \geq \mathbf{c}, \mathbf{y} \geq \mathbf{0}\}$$

Let $\bar{\mathbf{x}}$ be a feasible solution for (P) and $\bar{\mathbf{y}}$ be a feasible solution for (D). Then

- (1) $\mathbf{c}^\top \bar{\mathbf{x}} \leq \mathbf{b}^\top \bar{\mathbf{y}}$
- (2) if $\mathbf{c}^\top \bar{\mathbf{x}} = \mathbf{b}^\top \bar{\mathbf{y}}$, then $\bar{\mathbf{x}}$ is an optimal solution for (P).

Proof. Let $\bar{\mathbf{x}}$ be a feasible solution of (P) and let $\bar{\mathbf{y}}$ be a feasible solution of (D). Then

$$\begin{aligned} \mathbf{c}^\top \bar{\mathbf{x}} &\leq (\bar{\mathbf{y}}^\top A) \bar{\mathbf{x}} \\ &= \bar{\mathbf{y}}^\top (A \bar{\mathbf{x}}) \\ &\leq \bar{\mathbf{y}}^\top \mathbf{b} \end{aligned}$$

If $\mathbf{c}^\top \bar{\mathbf{x}} = \mathbf{b}^\top \bar{\mathbf{y}}$ it follows that $\bar{\mathbf{x}}$ is optimal for (P). □

14.3 Corollary

Let (P) and (D) be a pair of primal-dual LPs. Then

- (1) if (P) is unbounded, then (D) is infeasible
- (2) if (D) is unbounded, then (P) is infeasible
- (3) if (P) and (D) are both feasible, then they both have optimal solutions

Proof. (1) We prove the contrapositive, that is we prove: [(D) feasible \implies (P) not unbounded]

Suppose that (D) is feasible. By Weak Duality theorem, we know that $\mathbf{b}^\top \mathbf{y}$ is an upper bound on (P). Thus, (P) is not unbounded.

(2) We prove the contrapositive, that is we prove: [(P) feasible \implies (D) not unbounded]

Suppose that (P) is feasible. By Weak Duality theorem, we know that $c^\top x$ is a lower bound on (D). Thus, (D) is not unbounded.

(3) Assume (P) and (D) are both feasible. By (1) and (2) we know that (P) and (D) are both not unbounded. By Fundamental Theorem of Linear Programming, we know that exactly one of the following holds from (I)-(III):

- (I) (P) and (D) are infeasible
- (II) (P) and (D) are unbounded
- (III) (P) and (D) both have optimal solutions

Clearly, we know that (I) and (II) both do not hold in this part of the proof, thus (P) and (D) both have optimal solutions. \square

14.4 Theorem (Strong Duality Theorem)

Let (P) and (D) be a pair of primal-dual LPs. Then

- (1) If there exists an optimal solution \bar{x} of (P), then there exists an optimal solution \bar{y} of (D).
- (2) The value of \bar{x} in (P) equals the value of \bar{y} in (D).

14.5 Complementary Slackness

Recall our proof of Weak Duality. Then for LPs in SEF: \bar{x}, \bar{y} are feasible in (P) and (D) respectively. \bar{x} is optimal in (P), \bar{y} is optimal in (D) if and only if

$$c^\top \bar{x} = (A^\top \bar{y})^\top \bar{x} = \bar{y}^\top (A\bar{x}) = \bar{y}^\top b$$

The first equality came from $(A^\top \bar{y})^\top = c^\top$, and the last equality came from $A\bar{x} = b$ (check Weak Duality Theorem - Special Form). That is, if and only if

$$\bar{x}^\top (A^\top \bar{y} - c) = 0$$

and

$$\bar{y}^\top (b - A\bar{x}) = 0$$

That is, if and only if $\forall j \in \{1, \dots, n\}$ either $x_j = 0$ or $(A^\top \bar{y} - c)_j = 0$ possibly both, and $\forall i \in \{1, \dots, m\}$ either $y_i = 0$ or $(b - A\bar{x})_i = 0$ possibly both. We call these the Complementary Slackness Conditions (CS).

14.6 Theorem (Complementary Slackness Theorem)

Let (P) and (D) be an arbitrary primal-dual pair. Let \bar{x} be a feasible solution to (P) and let \bar{y} be a feasible solution to (D). Then, \bar{x} is an optimal solution to (P) and \bar{y} is an optimal solution to (D) if and only if the complementary slackness conditions hold.

14.7 Example (Complementary Slackness)

(P)

$$\max [-2 \quad -1 \quad 0] x$$

subject to

$$\begin{bmatrix} 1 & 3 & 2 \\ -1 & 4 & 2 \end{bmatrix} x \begin{matrix} \geq \\ \leq \end{matrix} \begin{bmatrix} 5 \\ 7 \end{bmatrix}$$

$$x_1 \leq 0, x_2 \geq 0, x_3 \text{ free}$$

- (1) Write the dual (D) of (P)

- (2) Write the complementary slackness (CS) conditions for (P) and (D)
 (3) Use weak duality to prove that \bar{x} is optimal for (P) and \bar{y} is optimal for (D)
 (4) Use CS to prove that \bar{x} is optimal for (P) and \bar{y} is optimal for (D)

and

$$\bar{x} = (-1, 0, 3)^\top \quad \bar{y} = (-1, 1)^\top$$

Solution.

(1)

(D)

$$\min [5 \quad 7]$$

subject to

$$\begin{bmatrix} 1 & -1 \\ 3 & 4 \\ 2 & 2 \end{bmatrix} \mathbf{y} \leq \begin{bmatrix} -2 \\ -1 \\ 0 \end{bmatrix}$$

$y_1 \leq 0, y_2 \geq 0, y_3 \text{ free}$

(2)

- $x_1 = 0$ OR $y_1 - y_2 = -2$
- $x_2 = 0$ OR $3y_1 + 4y_2 = -1$
- $y_1 = 0$ OR $x_1 + 3x_2 + 2x_3 = 5$
- $y_2 = 0$ OR $-x_1 + 4x_2 + 2x_3 = 7$

(3) Verify that \bar{x} and \bar{y} are feasible for (P) and (D), and check $\mathbf{c}^\top \bar{x} = \mathbf{b}^\top \bar{y}$.

(4) By Complementary Slackness Theorem, this is trivially true as seen boxed above.

14.8 Geometric Interpretation of CS

(P)

$$\max 2x_1 + x_2$$

subject to

$$\begin{bmatrix} 1 & 1 \\ -1 & 0 \\ 0 & -1 \end{bmatrix} \mathbf{x} \leq \begin{bmatrix} 4 \\ 0 \\ 0 \end{bmatrix}$$

(D)

$$\min 4y_1$$

subject to

$$\begin{bmatrix} 1 & -1 & 0 \\ 1 & 0 & -1 \end{bmatrix} \mathbf{y} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

$y_1, y_2, y_3 \geq 0$

Let \bar{x} be a feasible solution of (P) and $J(\bar{x})$ denote the indices of the tight constraints at \bar{x} .

Then, \bar{x} is optimal in (P) if and only if c is a non-negative linear combination of tight rows ($A^=$).

Suppose $\bar{x} = (4, 0)^\top$. Then $A^= = \begin{bmatrix} 1 & 1 \\ 0 & -1 \end{bmatrix}$. That is, \bar{x} is tight at $\text{row}_1(A)$ and $\text{row}_3(A)$.

$J(\bar{x}) := \{1, 3\}$, so \bar{x} is optimal if and only if $\exists \bar{y}_1, \bar{y}_2$ such that

$$\mathbf{c}^\top = \bar{y}_1 [\text{row}_1(A)] + \bar{y}_2 [\text{row}_3(A)]$$

15 2019-11-05

15.1 Definition (Cone)

Let $a^{(1)}, \dots, a^{(k)} \in \mathbb{R}^n$. We define the *cone* generated by $a^{(1)}, \dots, a^{(k)}$ to be the set

$$C = \text{cone} \left\{ a^{(1)}, \dots, a^{(k)} \in \mathbb{R}^n \right\} = \left\{ \sum_{i=1}^k \lambda_i a^{(i)} : \lambda_i \geq 0, \forall i \in \{1, \dots, k\} \right\}$$

We define the cone generated by an empty set to be $\{0\}$.

15.2 Definition (Cone of tight constraints)

Let $P := \{x : Ax \leq b\}$ and let $\bar{x} \in P$. Let $J(\bar{x})$ be the row indices of A corresponding to the tight constraints of $Ax \leq b$, that is, $i \in J(\bar{x})$ if and only if $\text{row}_i(A)\bar{x} = b_i$. We define the *cone of tight constraints* for \bar{x} to be the cone C generated by the rows of A corresponding to the tight constraints, that is

$$C = \text{cone} \left\{ \text{row}_i(A)^\top : i \in J(\bar{x}) \right\}$$

15.3 Theorem

Let \bar{x} be a feasible solution to $\max \{c^\top x : Ax \leq b\}$. Then \bar{x} is optimal if and only if c is in the cone of tight constraints for \bar{x} .

16 2019-11-12

16.1 Combinatorial Optimization Utilizing Duality

16.2 Shortest-Path Problem

Given a graph $G = (V, E)$, two distinct distinguished nodes $s, t \in V$, $c_e \geq 0 \forall e \in E$, we want to find a shortest path from s to t

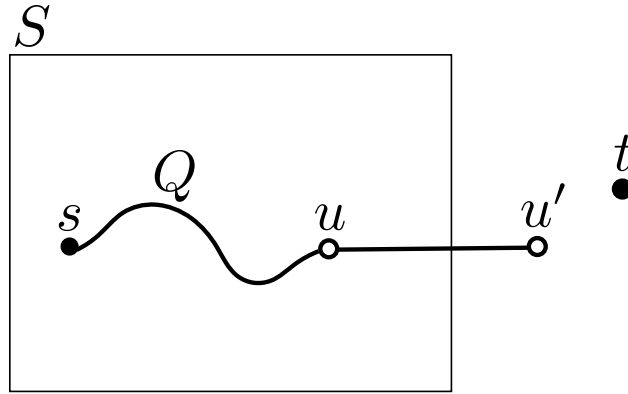
16.3 Notation

Let $G = (V, E)$ be a graph, and let $U \subseteq V$. We let $\delta(U)$ denote the set of edges that have exactly one endpoint in U . That is,

$$\delta(U) = \{uv \in E : u \in U, v \notin U\}$$

16.4 Definition (s-t cut)

Let $G = (V, E)$ be a graph, and let $U \subseteq V$. Suppose G has a distinct pair of vertices s and t . An *s-t cut* is the set of edges of the form $\delta(U)$ where $s \in U, t \notin U$.



16.5 Definition (s-t path)

Let $G = (V, E)$ be a graph. Suppose G has a distinct pair of vertices s and t . An s - t path \mathcal{P} in G is the following sequence of edges of G

$$\{v_1, \dots, v_k\}$$

where $v_1 = s$, $v_k = t$, and $v_i \neq v_j$ for $i \neq j$ (as s and t are distinct).

16.6 Theorem

An s - t path \mathcal{P} intersects every s - t cut.

Proof. Let $G = (V, E)$ be a graph with a distinct pair of vertices s and t , let \mathcal{P} be an s - t path of G , let $U \subseteq V$, and let $\delta(U)$ be an arbitrary s - t cut of G . Follow the path \mathcal{P} starting from s to u where u is the last vertex of \mathcal{P} in U , and denote u' the vertex that follows u in \mathcal{P} . Note that u exists since $s \in U$, $t \notin U$. Then by definition uu' is an edge that is in $\delta(U)$. \square

16.7 Theorem

Let $S \subseteq E$ be a set of edges that contains at least one edge from every s - t cut. Then there exists an s - t path \mathcal{P} that is contained in the edges of S .

Proof. Let $S \subseteq E$ be a set of edges that contains at least one edge from every s - t cut. Let U be the set of vertices that contain s as well as all vertices u for which there exists a path from s to u only using edges in S . We need to show that there exists an s - t path that is contained in the set of edges of S , i.e. $t \in U$. Suppose for a contradiction that $t \notin U$. We know $\delta(U)$ is an s - t cut by definition. By our hypothesis, there exists an edge $uu' \in S$, where $u \in U$, $u' \notin U$. By construction, there exists an s - u path Q that is contained in S . Then the path obtained from Q by adding an edge uu' is an s - u' path contained in S . By definition of U , we have that $u' \in U$, contradiction. \square

Suppose G contains an s - t path. Let $S \subseteq E$ be a set of edges that contains at least one edge from every s - t cut. Then such S contains an s - t path.

$$x_e := \begin{cases} 1, & \text{if edge } e \text{ is in the shortest } s\text{-}t \text{ path} \\ 0, & \text{otherwise} \end{cases}$$

(IP)

$$\min \sum_{e \in E} c_e x_e$$

subject to

$$\begin{aligned} \sum_{e \in \delta(U)} x_e &\geq 1 & (U \subseteq V, s \in U, t \notin U) \\ x_e &\geq 0 & (e \in E) \\ x_e &\in \mathbb{Z} & (e \in E) \end{aligned}$$

If $c_e > 0$ ($e \in E$) then optimal solutions of this IP correspond to shortest s - t paths. If some $c_e = 0$ ($e \in E$), then some optimal solutions will correspond to sets like set S above which contains a shortest s - t path.

Let (P) denote the LP relaxation of (IP) (replace $x_e \in \{0, 1\}$ with $0 \leq x_e \leq 1$ ($e \in E$)). Write down the dual of (P): (D)

$$\max \sum (y_U : \delta(U) \text{ is an } s\text{-}t \text{ cut})$$

subject to

$$\begin{aligned} \sum (y_U : \delta(U) \text{ is an } s\text{-}t \text{ cut containing } e) &\leq c_e & (e \in E) \\ y_U &\geq 0 & (U \subseteq V, s \in U, t \notin U) \end{aligned}$$

A consequence of Complementary Slackness for a shortest path problem is: Let \mathcal{P} be an s - t path (as set of edges) and let \bar{y} be a feasible solution of (D). Suppose

- every edge in \mathcal{P} corresponds to an equality edge $\sum (\bar{y}_U : \delta(U) \text{ is an } s\text{-}t \text{ cut containing } e) = c_e$
- for every active cut (i.e. s - t cut $\delta(U)$ such that $\bar{y}_U > 0$, \mathcal{P} must contain at least one edge from that s - t cut.

Then \mathcal{P} is a shortest s - t path.

$\bar{y}_U := 0$ for all s - t cuts $\delta(U)$ gives a feasible solution of (D)

16.8 A Dual Algorithm for the shortest path problem

Given y , $\text{slack}_y(e)$ is

$$c_e - \sum (y_U : \delta(U) \text{ is a } s\text{-}t \text{ cut containing } e)$$

That is, $\text{slack}_y(e)$ is the length of e minus the total width of all s - t cuts using e .

16.9 Algorithm (Shortest Path)

Algorithm 3: Shortest path

Input : Graph $G = (V, E)$, costs $c_e \geq 0$ for all $e \in E$, $s, t \in V$, where $s \neq t$.

Output: A shortest s - t path \mathcal{P} .

- 1 $y_w := 0$ for all s - t cuts $\delta(W)$. Set $U := \{s\}$
 - 2 **while** $t \notin U$ **do**
 - 3 Let ab be an edge in $\delta(U)$ of smallest slack for y where $a \in U$, $b \notin U$
 - 4 $y_U := \text{slack}_y(ab)$
 - 5 $U := U \cup \{b\}$
 - 6 change edge ab into an arc \vec{ab}
 - 7 **end**
 - 8 **return** A directed s - t path \mathcal{P} .
-