# Today: – Linear Programming

### COSC 581, Algorithms March 27, 2014

Many of these slides are adapted from several online sources

# **Reading Assignments**

- Today's class:
  - Chapter 29.1
- Reading assignment for next Thursday's class:
   Chapter 29.2-3
- Announcement: Exam #2 on Tuesday, April 1

   Will cover greedy algorithms, amortized analysis
   HW 6-9

#### Linear Programming Example: A Political problem

Suppose a politician is trying to win an election

3 types of areas --- urban, suburban, rural

Certain issues --- roads, gun control, farm subsidies, gasoline tax

Politician wants to find out the minimum amount of money he/she needs to win 50,000 urban, 100,000 suburban, 25,000 rural votes.

The effects of policies on votes:

Policy	urban	suburban	rural	
Build roads	-2	5	3	
Gun control	8	2	-5	
Farm subsidies	0	0	10	
Gasoline tax	10	0	-2	

#### How to Solve?

Define 4 variables :

 $x_1$  is the # of thousands of dollars spent on advertising on building roads  $x_2$  is the # of thousands of dollars spent on advertising on gun control  $x_3$  is the # of thousands of dollars spent on advertising on farm subsidies  $x_4$  is the # of thousands of dollars spent on advertising on gasoline tax

We format this problem as a *linear program*:

The solution of this linear program will yield an optimal strategy for the politician.

## **Applications of Linear Programming**

LP is a widely used Mathematical Optimization Model:

- Used frequently in management science (operations research), engineering, technology, industry, commerce, economics.
- Efficient resource allocation technique:
  - Airline transportation
  - Communication networks e.g., optimize transmission routing
  - Factory inventory/production control
  - Fund management, stock portfolio optimization
- Can be used to approximate hard optimization problems
- . . .

## History of LP

 3000-200 BC: Egypt, Babylon, India, China, Greece: [geometry & algebra] Egypt: polyhedra & pyramids. India: <u>Sulabha suutrah (Easy Solution Procedures) [2 equations, 2 unknowns]</u> China: <u>Jiuzhang suanshu (9 Chapters on the Mathematical Art)</u> [Precursor of Gauss-Jordan elimination method on linear equations]
 Greece: <u>Pythagoras, Euclid, Archimedes, ...</u>
 825 AD: Persia: <u>Muhammad ibn-Musa Alkhawrazmi (author of 2 influential books):</u> "Al-Maqhaleh fi Hisab al-jabr w'almoqhabeleh" (An essay on Algebra and equations) "Kitab al-Jam'a wal-Tafreeq bil Hisab al-Hindi" (Book on Hindu Arithmetic).

originated the words algebra & algorithm for solution procedures of algebraic systems.

**Fourier** [1826], Motzkin [1933] [Fourier-Motzkin elimination method on linear inequalities]

 Minkowski [1896], Farkas [1902], De la Vallée Poussin [1910], von Neumann [1930's], Kantorovich [1939], Gale [1960] [LP duality theory & precursor of Simplex]

George Dantzig [1947]: Simplex algorithm. Exponential time in the worst case, but effective in practice.

Leonid Khachiyan [1979]: Ellipsoid algorithm.

The first weakly polynomial-time LP algorithm: poly(n,d,L).

□ **Narendra Karmarkar** [1984]: Interior Point Method.

Also weakly polynomial-time. IPM variations are very well studied.

□ Megiddo-Dyer [1984]: Prune-&-Search method.

O(n) time if the dimension is a fixed constant. Super-exponential on dimension.

### The General LP Problem

maximize  $c_1 x_1 + c_2 x_2 + \dots + c_d x_d$  subject to:  $a_{11} x_1 + a_{12} x_2 + \dots + a_{1d} x_d \le b_1$   $a_{21} x_1 + a_{22} x_2 + \dots + a_{2d} x_d \le b_2$   $\vdots$  $a_{n1} x_1 + a_{n2} x_2 + \dots + a_{nd} x_d \le b_n$ 

# Some terminology

- Objective function: value measure used to rank alternatives; either minimize or maximize this objective
- Decision variables: the quantities you can control to improve your objective function; should completely describe the set of decisions to be made
- Constraints: limitations on the values of the decision variables
- Linear program: a mathematical program in which the objective function is a linear function and the constraints are linear equalities or inequalities
- Objective value: value of objective function at a particular point
- Feasible solution: satisfies all the constraints
- Infeasible solution: doesn't satisfy the constraints
- Optimal solution: best feasible solution
- Unbounded solution: solution to LP does not have finite objective value

## General Idea of LP – via another example

LP Idea: Minimize or maximize a linear objective, Subject to linear equalities and inequalities

*Example:* Bubba is in a pie eating contest that lasts 1 hour. Each torte that he eats takes 2 minutes. Each apple pie that he eats takes 3 minutes. He receives 4 points for each torte and 5 points for each pie. What should Bubba eat so as to get the most points?

**Step 1**: Determine the decision variables:

Let x be the number of tortes eaten by Bubba Let y be the number of pies eaten by Bubba

# General Idea of LP – (con't)

**Step 2**: *Determine the objective function:* 

Maximize z = 4x + 5y

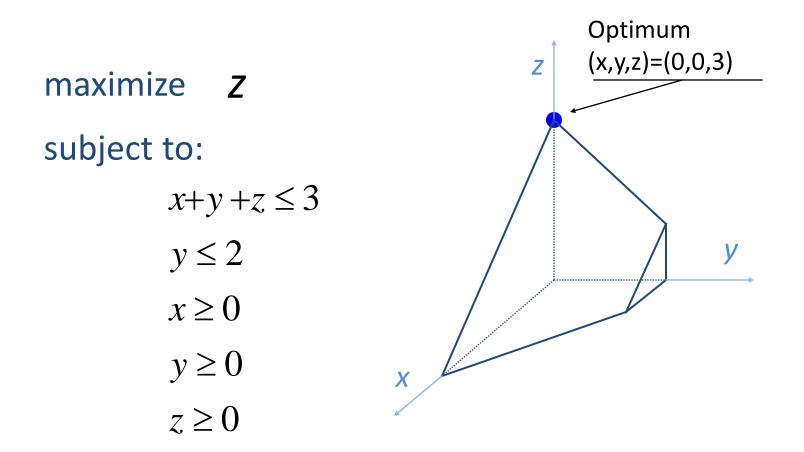
Step 3: Determine the constraints:

### Visualizing LP -- Example in 2D

 $|x_1 = 46/7$  $x_2 = 59/7$ **X**<sub>2</sub>  $x_1 + 8x_2$ max optimal x<sub>1</sub> + 8x<sub>2</sub> subject to: = 74 (3) (5) (1)**X**<sub>1</sub>  $\geq$  3  $x_2 \geq 2$ (2) **Feasible** (3)  $-3x_1 + 4x_2 \leq 14$ (1)Region (4)  $(4) \quad 4x_1 - 3x_2 \leq 25$ (5)  $x_1 + x_2 \leq 15$ (2)**X**<sub>1</sub>

Each constraint is represented by a line and a direction. Intersection of constraints is **feasible region**.

## Visualizing LP -- Example in 3D

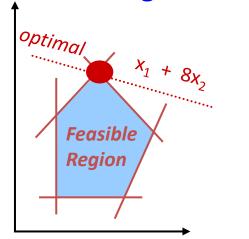


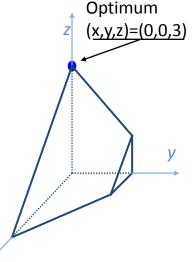
## Multi-dimensional cases (beyond 3D)

- Can't visualize beyond 3D, but same idea holds
- Each constraint defines *half-space* in n-dimensional space
- The objective function is a hyperplane
- Feasible region is area formed by intersection of half-spaces
- This region is called a *simplex*

Important Observation: Optimal Solutions are at a Vertex or Line Segment

 Intersection of objective function and feasible region is either vertex or line segment





- Feasible region is *convex* makes optimization much easier!
- Simplex algorithm finds LP solution by:
  - Starting at some vertex
  - Moving along edge of simplex to neighbor vertex whose value is at least as large
  - Terminates when it finds local maximum
- Convexity ensures this local maximum is globally optimal

## Recall – History of LP

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## In-Class exercise

Consider the following linear programming problem:

Maximize: x + y

Subject to:

 $-x + y \le 2$  $2x + y \le 6$  $x + 2y \le 6$  $x, y \ge 0$ 

What does the feasible region look like?

What is the optimal solution?

# Two Canonical Forms for LP: Standard and Slack

 An LP is in <u>standard form</u> if it is the maximization of a linear function subject to linear inequalities

• An LP is in <u>slack form</u> if it is the maximization of a linear function subject to linear equalities

## Standard Form

#### • We're given:

*n* real numbers  $c_1, c_2, \dots c_n$ *m* real numbers  $b_1, b_2, \dots b_m$ *mn* real numbers  $a_{ij}$ , for  $i = 1, 2, \dots, m$  and  $j = 1, 2, \dots n$ 

#### • We want to find:

*n* real numbers  $x_1, x_2, \dots x_n$  that:

Maximize:  $\sum_{j=1}^{n} c_j x_j$ Subject to:

$$\sum_{j=1}^{n} a_{ij} x_j \le b_i \quad \text{for } i = 1, 2, ..., m$$
$$x_j \ge 0 \quad \text{for } j = 1, 2, ..., n$$

## **Compact Version of Standard Form**

• Let: 
$$A = (a_{ij})$$
 be  $m \times n$  matrix  
 $b = (b_i)$  be an  $m$ -vector  
 $c = (c_j)$  be an  $n$ -vector  
 $x = (x_j)$  be an  $n$ -vector

• Rewrite LP as:

Maximize:  $c^T x$ Subject to:  $Ax \le b$  $x \ge 0$ 

• Now, we can concisely specify LP in standard form as (A, b, c)

# **Converting LP to Standard Form**

4 reasons an LP might not be in standard form:

- 1) Objective function might be a minimization instead of maximization
- 2) There might be variables w/o non-negativity constraints
- 3) There might be equality constraints
- 4) There might be inequality constraints that are "≥" instead of "≤"

We can convert any LP into an equivalent standard form

# Step 1: Change min LP to max LP

 To convert a *minimization* linear program *L* into an equivalent *maximization* linear program *L'*, we simply *negate the coefficients in the objective function*.

> Example: minimize  $-2x_1 + 3x_2$ subject to  $x_1 + x_2 = 7$  $x_1 - 2x_2 \le 4$  $x_1 \ge 0$ ,

> > and we negate the coefficients of the objective function, we obtain

minimize 2	$2x_1 - 3x_2$	2
subject to		
	$x_1 + x_2$	$_{2} = 7$
	$x_1 - 2x_2$	$2 \le 4$
	$x_1$	$\geq$ 0.

# Step 2: Dealing with missing non-negativity constraints

- Suppose that some variable x<sub>j</sub> does not have a nonnegativity constraint.
- Then:

- We replace each occurrence of  $x_i$  by  $x'_i - x$ 

# Step 3: Converting equality constraints into inequality constraints

- Suppose that a linear program has an equality constraint f (x1, x2, ..., xn) = b.
- Since x = y if and only if both  $x \ge y$  and  $x \le y$ , we can replace  $f(x_1, x_2, ..., x_n) = b$  by:  $f(x_1, x_2, ..., x_n) \le b$  and  $f(x_1, x_2, ..., x_n) \ge b$ .

# Step 4: Convert "≥" constraints to "≤" constraints

- We can convert the "≥" constraints to "≤" constraints by multiplying these constraints through by -1.
- That is, any inequality of the form:

is

$$\sum_{j=1}^{n} a_{ij} x_j \ge b_i$$
  
equivalent to:  
$$\sum_{j=1}^{n} -a_{ij} x_j \le -b_i$$

# Slack Form – Useful for Simplex

• In slack form, the only inequality constraints are the nonnegativity constraints

All other constraints are equality constraints

• Let:

 $\sum_{j=1}^{n} a_{ij} x_j \le b_i$ 

be an inequality constraint

• Introduce new variable *s*, and rewrite as:

$$s = b_i - \sum_{j=1}^n a_{ij} x_j$$
$$s \ge 0$$

• *s* is a slack variable; it represents difference between left-hand and right-hand sides

# Slack Form (con't.)

- In general, we'll use  $x_{n+i}$  (instead of *s*) to denote the slack variable associated with the *i*th inequality.
- The *i*th constraint is therefore:

$$x_{n+i} = b_i - \sum_{j=1}^n a_{ij} x_i$$

along with the non-negativity constraint  $x_{n+i} \ge 0$ 

# Example

#### Standard form:

Maximize 
$$2x_1 - 3x_2 + 3x_3$$
  
subject to:  
 $x_1 + x_2 - x_3 \le 7$   
 $-x_1 - x_2 + x_3 \le -7$   
 $x_1 - 2x_2 + 2x_3 \le 4$   
 $x_1, x_2, x_3 \ge 0$ 

Slack form: Maximize  $2x_1 - 3x_2 + 3x_3$ subject to:  $x_4 = 7 - x_1 - x_2 + x_3$   $x_5 = -7 + x_1 + x_2 - x_3$   $x_6 = 4 - x_1 + 2x_2 - 2x_3$  $x_1, x_2, x_3, x_4, x_5, x_6 \ge 0$ 

## About Slack Form...

#### Slack form:

Maximize 
$$2x_1 - 3x_2 + 3x_3$$
  
subject to:  
 $x_4 = 7 - x_1 - x_2 + x_3$   
 $x_5 = -7 + x_1 + x_2 - x_3$   
 $x_6 = 4 - x_1 + 2x_2 - 2x_3$   
 $x_1, x_2, x_3, x_4, x_5, x_6 = 0$   
Mon-basic variables – variables on right-hand side  
on left-hand side

## **Concise Representation of Slack Form**

- Can eliminate "maximize", "subject to", and non-negativity constraints (all are implicit)
- And, introduce *z* as value of objective function:

$$z = 2x_1 - 3x_2 + 3x_3$$
  

$$x_4 = 7 - x_1 - x_2 + x_3$$
  

$$x_5 = -7 + x_1 + x_2 - x_3$$
  

$$x_6 = 4 - x_1 + 2x_2 - 2x_3$$

- Then, define slack form of LP as tuple (N, B, A, b, c, v) where N = indices of nonbasic variables B = indices of basic variables
- We can rewrite LP as:

$$z = v + \sum_{j \in N} c_j x_j$$
$$x_i = b_i - \sum_{j \in N} a_{ij} x_j \text{ for } i \in B$$

## **In-Class Exercise**

A bank is open Monday-Friday from 9am to 5pm. From past experience, the bank knows that it needs (at least) the following number of tellers:

Time	9:00-	10:00-	11:00-	12:00-	1:00-	2:00-	3:00-	4:00-
period:	10:00	11:00	12:00	1:00	2:00	3:00	4:00	5:00
Tellers required:	4	3	4	6	5	6	8	8

The bank hires two types of tellers. Full time tellers work 9-5 every day, except for 1 hour off for lunch. (The bank determines when a full time teller takes lunch hour, but it must be either 12-1 or 1-2.) Full time employees are paid \$8 per hour (this includes payment for the lunch hour).

The bank can also hire part time tellers. Each part time teller must work exactly 3 consecutive hours each day, and gets paid \$5 per hour. To maintain quality of service, at most 5 part time tellers can be hired.

Formulate a LP to minimize the cost of the bank to meet teller requirements.

# **Reading Assignments**

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 – Chapter 29.2-3

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