Analysis of Algorithms

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CSCI 570

Lecture 10

University of Southern California

Linear Programming

Reading: chapter 8

HW4, #6

DP Linear Programming

In this lecture we describe linear programming that is used to express a wide variety of different kinds of problems. LP can solve the max-flow problem and the shortest distance, find optimal strategies in games, and many other things.

We will primarily discuss the setting and how to code up various problems as linear programs.

Solving by Reduction

Formally, to reduce a problem Y to a problem X (we write $Y \leq_p X$) we want a function f that maps Y to X such that:

- f is a polynomial time computable
- \forall instance $y \in Y$ is solvable if and only if $f(y) \in X$ is solvable.

A Production Problem

A company wishes to produce two types of souvenirs: type-A will result in a profit of \$1.00, and type-B in a profit of \$1.20.

To manufacture a type-A souvenir requires 2 minutes on machine I and 1 minute on machine II.

A type-B souvenir requires 1 minute on machine I and 3 minutes on machine II.

There are 3 hours available on machine I and 5 hours available on machine II.

How many souvenirs of each type should the company make in order to maximize its profit?

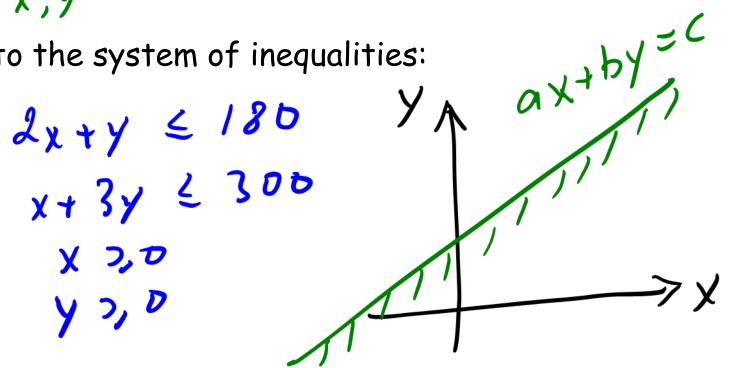
A Production Problem

	Type-A	Type-B	Time Available
Profit/Unit Machine I Machine II	\$1.00 2 min ×	\$1.20 1 min 4 3 min 34	≤ 180 min≤ 300 min

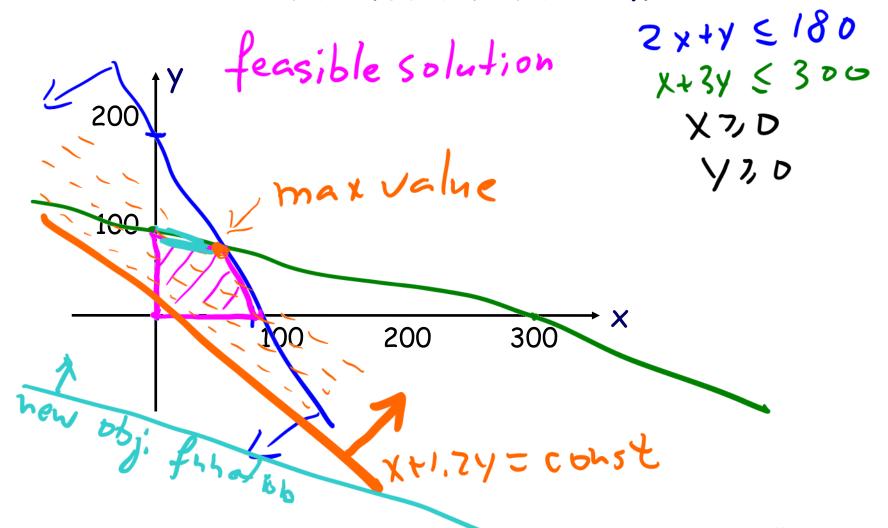
A Linear Program

We want to maximize the objective function

subject to the system of inequalities:



A Production Problem



We need to find the feasible point that is farthest in the "objective" direction X + I. Z

Fundamental Theorem

If a linear programming problem has a solution, then it must occur at a vertex, or corner point, of the feasible set S associated with the problem.

If the objective function P is optimized at two adjacent vertices of S, then it is optimized at every point on the line segment joining these vertices, in which case there are infinitely many solutions to the problem.

Existence of Solution

Suppose we are given a LP problem with a feasible set S and an objective function P. There are 3 cases to consider

(1) Siscompoly, LPhas Nosolution XE-1 X70

max(x)

max/x)

x 60

XZD

SoloD

- 2) S is unbounded LP may or may not have a solution
- 3) Sis bounded LP has a solution (5)

Standard LP form

We say that a maximization linear program with (n) variables is in standard form if for every variable x_k we have the inequality $x_k \ge 0$ and all other mlinear inequalities. A LP in standard form is written as

Inequalities. A LP in standard form is written as
$$\begin{array}{c}
h_{j,h} \\
max(c_1x_1 + ... + c_nx_n) \\
subject to
\end{array}$$

$$\begin{array}{c}
x_1 \\
x_2 \\
x_n
\end{array}$$

$$\begin{array}{c}
x_1 \\
x_n
\end{array}$$

$$x_{20} \{x_{1} \ge 0, ..., x_{n} \ge 0\} \le 2$$

Standard LP in Matrix Form

The vector c is the column vector (c_1, \ldots, c_n) . The vector x is the column vector (x_1, \ldots, x_n) . The matrix A is the n × m matrix of coefficients of the left-hand sides of the inequalities, and $b = (b_1, \ldots, b_m)$ is the vector of right-hand sides of the inequalities.

max (
$$c^T x$$
)
subject to
$$A \times \leq b$$

$$x \geq 0$$

Exercise: Convert to Matrix Form

$$\max(x_1 + 1.2 x_2)$$

 $2x_1 + x_2 \le 180$
 $x_1 + 3x_2 \le 300$
 $x_1 \ge 0$
 $x_2 \ge 0$

$$X = \begin{pmatrix} X_{1} \\ X_{2} \end{pmatrix}, C = \begin{pmatrix} 1 \\ 1.2 \end{pmatrix}$$

$$A = \begin{pmatrix} 180 \\ 300 \end{pmatrix}$$

$$A = \begin{pmatrix} 2 & 1 \\ 1 & 3 \end{pmatrix}$$

Algorithms for LP

The standard algorithm for solving LPs is the Simplex Algorithm, due to Dantzig, 1947

This algorithm starts by finding a vertex of the polytope, and then moving to a neighbor with increased cost as long as this is possible. By linearity and convexity, once it gets stuck it has found the optimal solution.

Unfortunately simplex does not run in polynomial time it does well in practice, but poorly in theory.

Algorithms for LP

In 1974 Khachian has shown that LP could be done in polynomial time by something called the Ellipsoid Algorithm (but it tends to be fairly slow in practice).

In 1984 Karmarkal discovered a faster polynomial-time algorithm called "interior-point". While simplex only moves along the outer faces of the polytope, "interior-point" algorithm moves inside the polytope.

MATLAB

https://www.mathworks.com/help/optim/ug/linprog.html

linprog

Linear programming solver

Finds the minimum of a problem specified by

$$\min_{x} f^{T}x \text{ such that } \begin{cases} A \cdot x \leq b, \\ Aeq \cdot x = beq, \\ lb \leq x \leq ub. \end{cases}$$

f, x, b, beq, lb, and ub are vectors, and A and Aeq are matrices.

Description

x = linprog(f,A,b) solves min f'*x such that $A*x \le b$.

x = linprog(f,A,b,Aeq,beq) includes equality constraints Aeq*x = beq. Set A = [] and b = [] if no inequalities exist.

x = linprog(f,A,b,Aeq,beq,lb,ub) defines a set of lower and upper bounds on the design variables, x, so that the solution is always in the range $lb \le x \le ub$. Set Aeq = [] and beq = [] if no equalities exist.

Discussion Problem 1

A cargo plane can carry a maximum weight of 100 tons and a maximum volume of 60 cubic meters. There are three materials to be transported, and the cargo company may choose to carry any amount of each, up to the maximum available limits given below.

	Density	Volume	Price
Material 1	2 tons/m³	•	
Material 2	1 tons/m³	30 m ³	\$2,000 per m ³
Material 3	3 tons/m³	20 m ³	$$12,000 per m^3$

Write a linear program that optimizes revenue within the constraints.

let X1, X2, X3 be the volumes ... objective function: max (1000 X, +2000 X+12000 X3) subject to: 2:X1 +1:X2+3:X3 5100 0 5 x 1 5 40 0 5 k 5 30; 0 5 x 5 5 20 $X = \begin{pmatrix} X_1 \\ X_2 \\ X_3 \end{pmatrix}, C = \begin{pmatrix} 12000 \\ 12000 \\ 1000 \end{pmatrix}$ $A = \begin{pmatrix} 2 & 1 & 3 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$ $A = \begin{pmatrix} 2 & 1 & 3 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}$ $A = \begin{pmatrix} 2 & 1 & 3 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}$ $A = \begin{pmatrix} 2 & 1 & 3 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}$

$$0 \le X_{1} \le 40 \implies \begin{cases} X_{1} \ge 40 \\ X_{1} \le 40 \end{cases}$$

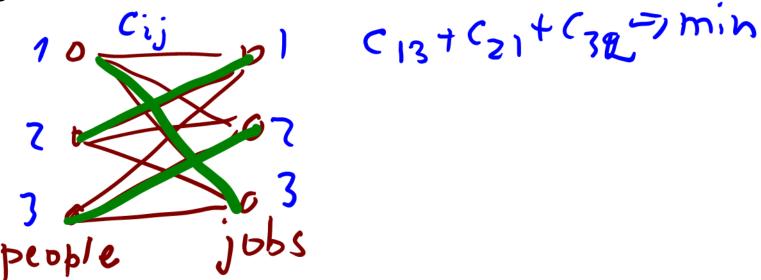
$$X_{1} = Y_{0} + Y_{1} + D \cdot X_{2} + D \cdot X_{3} \le 40$$

$$X_{2} = Y_{2} + D \cdot X_{3} + D \cdot X_{3} \le 30$$

$$X_{3} = Y_{3} = Y_{3} + D \cdot X_{4} + D \cdot X_{5} \le 30$$

Discussion Problem 2

There are n people and n jobs. You are given a cost matrix, C, where c_{ij} represents the cost of assigning person i to do job j. You need to assign all the jobs to people and also only one job to a person. You also need to minimize the total cost of your assignment. Write a linear program that minimizes the total cost of your assignment.



1) Define variables. Let Xij be an assignment between i+h person and j-th job. @ Objedive fination. min \(\int \text{Xij'Cij'} ション 3) Constraints.

pick a person i = 1,7,...,n

pick a person i = 1, 7, ..., t XiI + Xi2 + ... + Xin = 1 YiI + Xi2 + ... + Xin = 1 YiI + Xi2 + ... + Xin = 1 Yij + Xij + ... + Xin = 1

(1) Constraints oh Xij

Xij t {1,0} Integer LP, vars EN we do not know how to solve ILP in polyhomial time.

BREAK-!

Discussion Problem 3

Convert the following LP to standard form

$$\max (5x_{1} - 2x_{2} + 9x_{3}) \quad 3x_{1} + x_{2} + 4x_{3} = 8$$

$$2x_{1} + 7x_{2} - 6x_{3} \le 4$$

$$x_{1} \le 0 \quad x_{3} \ge 1 \quad x_{2} = 7$$

$$x_{2} = 7 \quad x_{3} =$$

Discussion Problem 4

Explain why LP <u>cannot</u> contain constrains in the form of <u>strong</u> inequalities.

$$\max(7x_1 - x_2 + 5x_3)$$

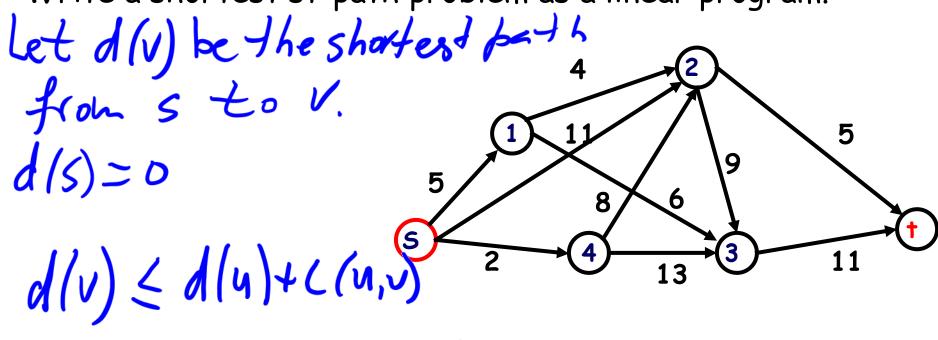
 $x_1 + x_2 + 4x_3 < 8$
 $3x_1 - x_2 + 2x_3 > 3$
 $2x_1 + 5x_2 - x_3 \le -7$
 $x_1, x_2, x_3 \ge 0$

Exercise: Max-Flow as LP

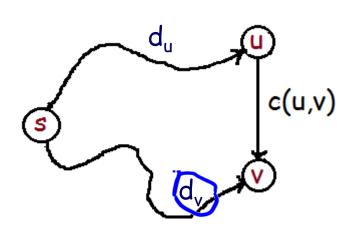
Write a max-flow problem as a linear program. fur-flow on edge (u,v), 401 te EE Objective function: max(fot+ de) max (fratfer) Constraints 0 < 755 < 4 1 < 5+4 c 5= + 6c+4 ha 05 fac 53 LortveV\{s,t} for tetE

Exercise: Shortest Path as LP

 $SP \leq LP$ Write a shortest st-path problem as a linear program.



we use it for withing constraints



d(1) < d(s)+5 ENAMPLE d(4) \(\) d(5)+2 A(2) 3 A(1)+4 1(2) 5 1 (4) + 8 Objective Innetion: dri) Ed (5) 741 min d(t) tor te E E max d(1) Example: t=1 LP: bin d(1) d(1) & d(s)+5=5 0/1/70 Max d(1)=5

min /1/1 = 0

Discussion Problem 5

Write a 0-1 Knapsack Problem as a linear program.

Given n items with weights w_1 , w_2 , ..., w_n and values v_1 , v_2 , ..., v_n . Put these items in a knapsack of capacity W to get the maximum total value in the knapsack.

Given
$$\sum_{k=1}^{m} w_k \leq W$$
optimize $\sum_{k=1}^{m} v_k \rightarrow \max$

$$K napsack \leq p$$

Variables $X_i = \int_{D}^{1} item i$ is selected. Obj. Junction: max/ Xi. Vi) 5 Xi·wi ZW Constraints: $x \in \{1, 0\}$ Knapsacu Ep ILP

Dual LP



To every linear program there is a dual linear program

If (ap(A,B)

2. max-160 = nin-ont

Duality

Definition. The dual of the standard (primal) maximum problem

$$\begin{array}{c}
\text{max c} \\
\text{N} \\
\text{Ax \leq b and x \geq 0}
\end{array}$$

is defined to be the standard minimum problem

$$\begin{array}{cc}
 & \text{min } b \overline{\Diamond} \\
 & A^{T}y \ge c \text{ and } y \ge 0
\end{array}$$

Exercise: duality

Consider the LP:

$$\max(7x_1 - x_2 + 5x_3)$$

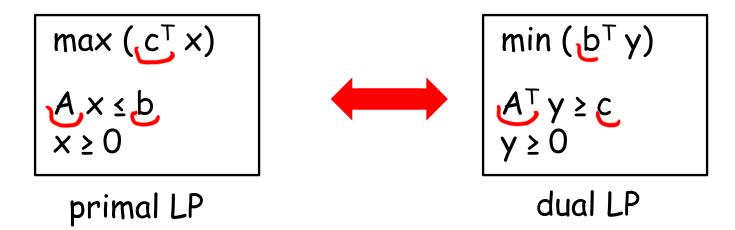
$$x_1 + x_2 + 4x_3 \le 8$$

$$3x_1 - x_2 + 2x_3 \le 3$$

$$2x_1 + 5x_2 - x_3 \le -7$$

$$x_1, x_2, x_3 \ge 0$$

Write the dual problem.



$$x = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}, c = \begin{pmatrix} 7 \\ -1 \\ 5 \end{pmatrix}, b = \begin{pmatrix} 8 \\ 3 \\ -7 \end{pmatrix}, y = \begin{pmatrix} y_1 \\ y_3 \end{pmatrix}$$
 $A = \begin{pmatrix} 1 & 1 & 4 \\ 3 & -1 & 2 \\ 2 & 5 & -1 \end{pmatrix}, A = \begin{pmatrix} 1 & 3 & 2 \\ 1 & -1 & 5 \\ 4 & 2 & -1 \end{pmatrix}$

dual:

 $A = \begin{pmatrix} 1 & 1 & 4 \\ 3 & -1 & 2 \\ 2 & 5 & -1 \end{pmatrix}, A = \begin{pmatrix} 1 & 3 & 2 \\ 1 & -1 & 5 \\ 4 & 2 & -1 \end{pmatrix}$
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 $A = \begin{pmatrix} 1 & 3 & 2 \\ 1 & 2 & -1$

From Primal to Dual

Consider the max LP constrains

- 1) Multiply each equation by a new variable $(y_k \ge 0)$
- 2) Add up those m equations.
- \rightarrow 3) Collect terms wrt to x_k .
 - 4) Choose y_k in a way such that $A^T y \ge c$.

X1 (X1 a11+ ... + Xm am) + ... + Xh (X1 a1 + ... + Xm am) < b1 x1 + ... + bm xm New constraints Y, G, H, tym Gm, J, C)
Y, G, h + m tym Gm h J, Cm)
Objective Innediozi x,·C, t...+xn·Cn & b, Y, + in+bnyn max Primal dual > min



$$\max (c^T x)$$

 $A x \le b$

x ≥ 0

primal linear program



$$min (b^T y)$$

min
$$(b^T y)$$

$$A^T y \ge c$$

$$y \ge 0$$

dual linear program

Weak Duality. The optimum of the dual is an upper bound to the optimum of the primal.

opt(primal) >pt(dual)

Weak Duality

$$\max (c^{T} x)$$

$$A \times \leq b$$

$$x \geq 0$$

$$(4x)^T = \chi^T \cdot A^T$$



$$min(b^Ty)$$

Theorem (The weak duality).

Let P and D be primal and dual Ly correspondingly.

If x is a feasible solution for P and y is a feasible solution

for D, then $c^Tx \leq b^Ty$.

$$C^TX = X^TCY = (A^TY) = (A^TY) = (A^TY)$$

Weak Duality: opt(primal) ≤ opt(dual)

Corollary 1. If a standard problem and its dual are both feasible, then both are feasible bounded.

then the dual of that problem is infeasible.

Strong Duality

$$\max (c^T x)$$

$$A \times \leq b$$

$$x \geq 0$$

$$min (b^T y)$$

$$A^T y \geq c$$

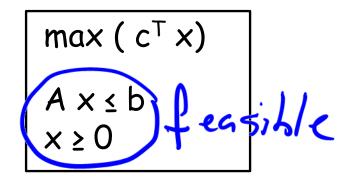
$$y \geq 0$$

Theorem (The strong duality). Let P and D be primal and dual LP correspondingly. If P and D are feasible, then $c^Tx = b^Ty$.

The proof of this theorem is beyond the scope of this course.

ML 567: 5VM

Possibilities for the Feasibility



$min (b^T y)$	
$A^{T}y \geq c$	
y ≥ 0	

P\D	F.B.	F.U.	I.
F.B.	ves cor. 1)/b	ND
F.U.	N b	ND	485
I.	ν ₀ ς, <u>ζ</u>	755	cor.2

feasible bounded - F.B. feasible unbounded - F.U. infeasible - I.

example

min (-4/, +2/z) x-Y, +Y272 1, - 42 7, 1 41-423-2 intensible

Discussion Problem 6

Consider the LP:

$$min(3x_1 + 8x_2 + x_3)$$

$$x_{1} + 4x_{2} - 2x_{3} \le 20$$

$$x_{1} + x_{2} + x_{3} \ge 7$$

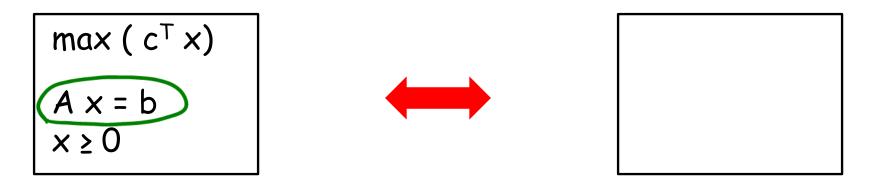
$$x_{2} + x_{3} = 3$$

$$x_{1}, x_{2}, x_{3} \ge 0$$



Write the dual problem.

Finding the Dual in Equality Form



Very often linear programs are encountered in equality form $A \times = b$. A problem can be transformed into inequality form by replacing each equation by two inequalities.

The dual can then be found by applying the definition of the dual to this problem. Let y^+ and y^- be the dual variables associated with each of the above inequality.

Finding the Dual in Equality Form

$$max (cT x)$$

$$A x = b$$

$$x \ge 0$$

 $max (c^T x)$

$$A \times \leq b$$

$$-A \times \leq -b$$

$$\times \geq 0$$

$$A = y^{4} - y^{4}$$

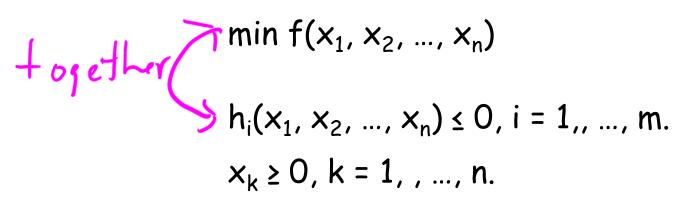
min
$$(b^{T}y^{+} - b^{T}y^{-})$$

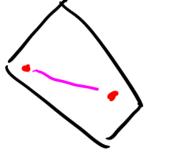
 $A^{T}y^{+} - A^{T}y^{-} \ge c$
 $y^{+} \ge 0, y^{-} \ge 0$

min
$$(b^{T}(y^{+} - y^{-}))$$

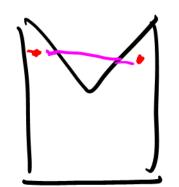
 $A^{T}(y^{+} - y^{-}) \ge c$
 $y^{+} \ge 0, y^{-} \ge 0$

CONVEX Nonlinear Optimization









Here f and/or h are nonlinear functions.

The problem is solved using Lagrange multipliers λ_k .

Lagrange Duality (KKT-1951)

Primal in x:

Dual in
$$\lambda := / / \ldots / /)$$

min
$$f(x)$$
subject to
 $h_k(x) \le 0$

$$\max_{subject\ to} g(\lambda)$$

$$\lambda_k \ge 0$$

The Lagrangian:
$$(L(x,\lambda) = f(x) + \sum_{k} \lambda_{k} h_{k}(x))$$

The dual:

$$g(\lambda) = \min_{x} L(x, \lambda)$$

Weak Duality:

Let P and D be the optimum of primal and dual problems respectively. Then $opt(P) \le opt(D)$.

Equality (strong duality) holds for convex functions under some conditions.