

Linear Programming

- ▶ brewer's problem
- ▶ simplex algorithm
- ▶ implementation
- ▶ linear programming

References:

The Allocation of Resources by Linear Programming,
Scientific American, by Bob Bland
Algs in Java, Part 5

Overview: introduction to advanced topics

Main topics

- **linear programming**: the ultimate practical problem-solving model
- **reduction**: design algorithms, prove limits, classify problems
- **NP**: the ultimate theoretical problem-solving model
- **combinatorial search**: coping with intractability

Shifting gears

- from linear/quadratic to polynomial/exponential scale
- from individual problems to problem-solving models
- from details of implementation to conceptual framework

Goals


- place algorithms we've studied in a larger context
- introduce you to important and essential ideas
- inspire you to learn more about algorithms!

Linear Programming

What is it? see ORF 307

- Quintessential tool for optimal allocation of scarce resources, among a number of competing activities.
- Powerful and general problem-solving method that encompasses:
shortest path, network flow, MST, matching, assignment...
 $Ax = b$, 2-person zero sum games

Why significant?

- Widely applicable problem-solving model
- Dominates world of industry.  Ex: Delta claims that LP saves \$100 million per year.
- Fast commercial solvers available: CPLEX, OSL.
- Powerful modeling languages available: AMPL, GAMS.
- Ranked among most important scientific advances of 20th century.

Applications

Agriculture. Diet problem.

Computer science. Compiler register allocation, data mining.

Electrical engineering. VLSI design, optimal clocking.

Energy. Blending petroleum products.

Economics. Equilibrium theory, two-person zero-sum games.

Environment. Water quality management.

Finance. Portfolio optimization.

Logistics. Supply-chain management.

Management. Hotel yield management.

Marketing. Direct mail advertising.

Manufacturing. Production line balancing, cutting stock.

Medicine. Radioactive seed placement in cancer treatment.

Operations research. Airline crew assignment, vehicle routing.

Physics. Ground states of 3-D Ising spin glasses.

Plasma physics. Optimal stellarator design.

Telecommunication. Network design, Internet routing.

Sports. Scheduling ACC basketball, handicapping horse races.

- ▶ **brewer's problem**
- ▶ simplex algorithm
- ▶ implementation
- ▶ linear programming

Toy LP example: Brewer's problem

Small brewery produces ale and beer.

- Production limited by scarce resources: corn, hops, barley malt.
- Recipes for ale and beer require different proportions of resources.

	corn (lbs)	hops (oz)	malt (lbs)	profit (\$)
available	480	160	1190	
ale (1 barrel)	5	4	35	13
beer (1 barrel)	15	4	20	23

Brewer's problem: choose product mix to maximize profits.

all ale (34 barrels)	179	136	1190	442
all beer (32 barrels)	480	128	640	736
20 barrels ale 20 barrels beer	400	160	1100	720
12 barrels ale 28 barrels beer	480	160	980	800
more profitable product mix?	?	?	?	>800 ?

34 barrels times 35 lbs malt
per barrel is 1190 lbs
[amount of available malt]

Brewer's problem: mathematical formulation

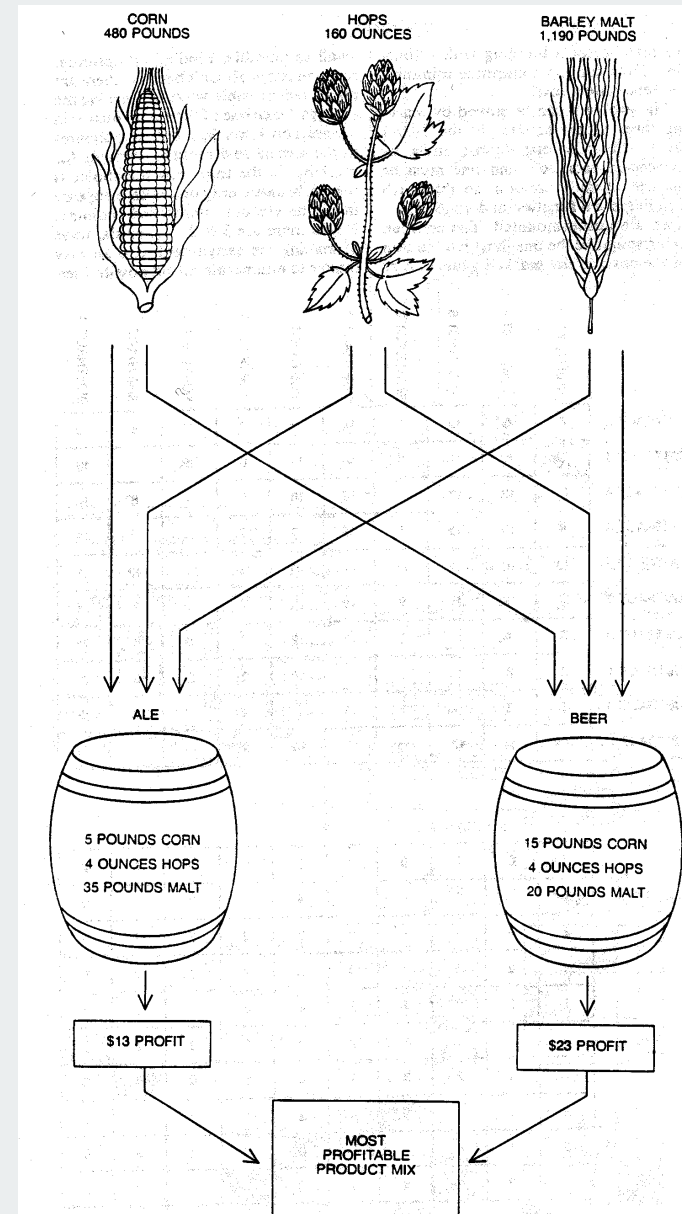
Small brewery produces ale and beer.

- Production limited by scarce resources: corn, hops, barley malt.
- Recipes for ale and beer require different proportions of resources.

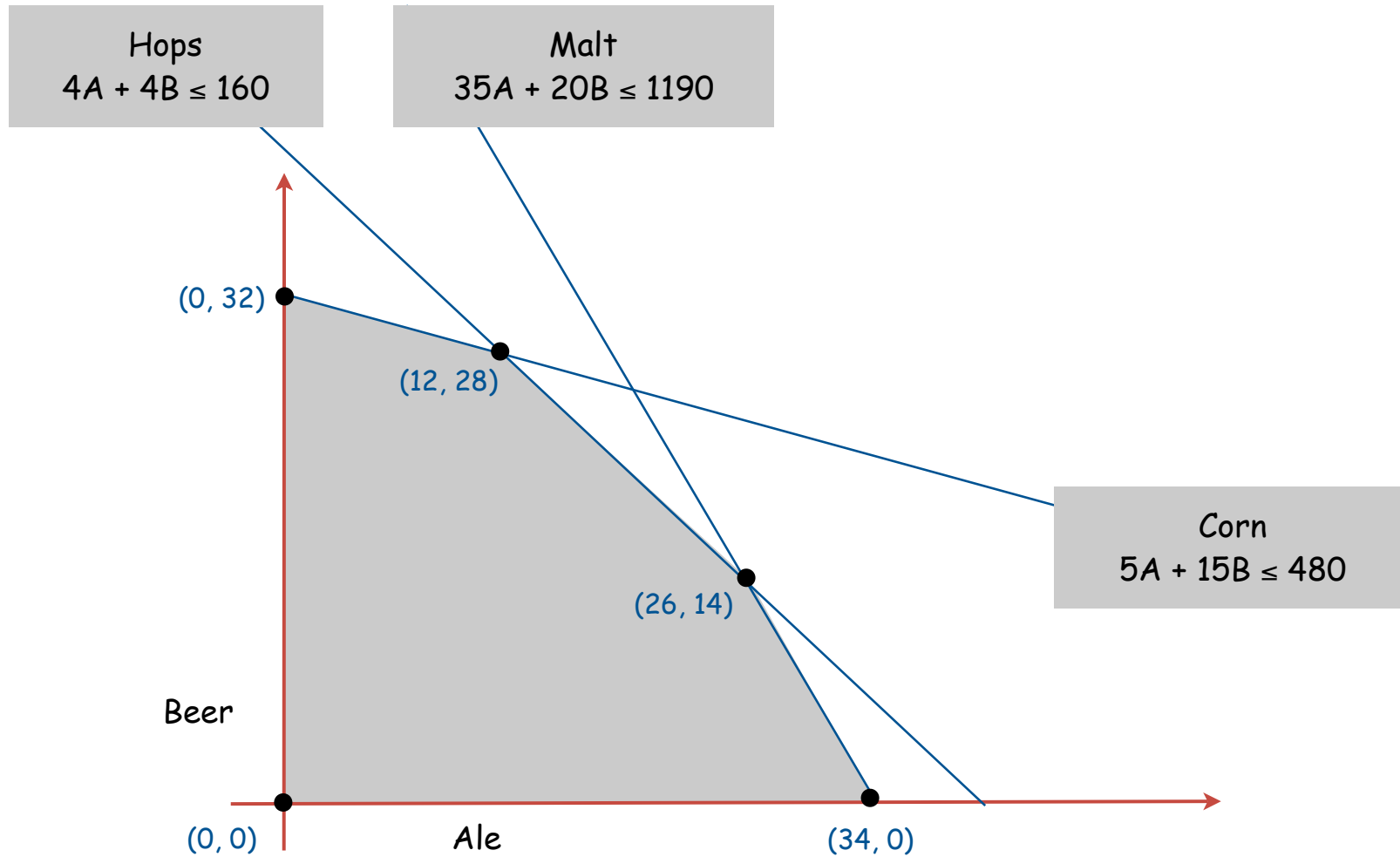
Mathematical formulation

- let A be the number of barrels of beer
- and B be the number of barrels of ale

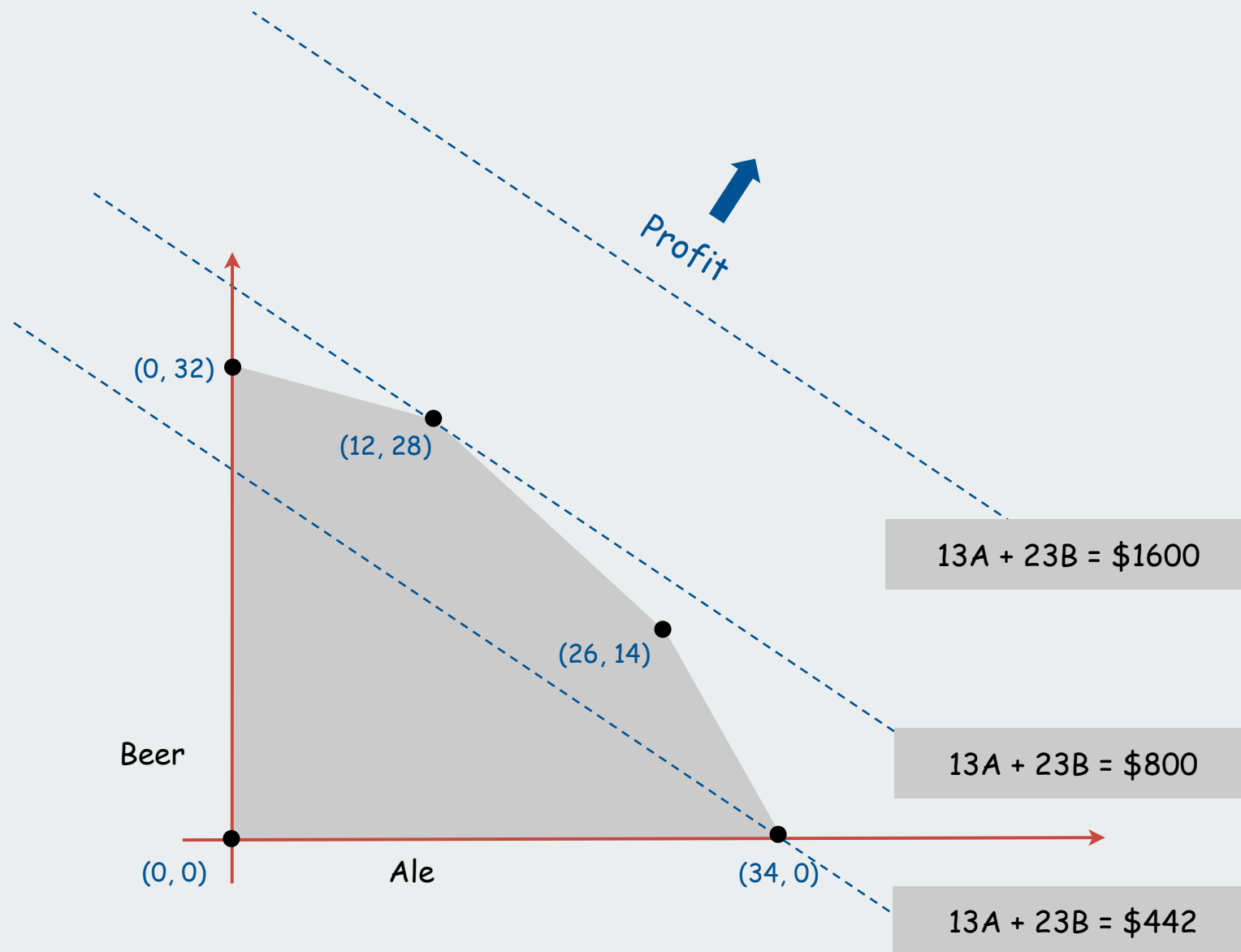
	ale		beer		
maximize	$13A$	+	$23B$		profit
subject	$5A$	+	$15B$	\leq	480 corn
to the	$4A$	+	$4B$	\leq	160 hops
constraints	$35A$	+	$20B$	\leq	1190 malt
			A	\geq	0
			B	\geq	0



Brewer's problem: Feasible region

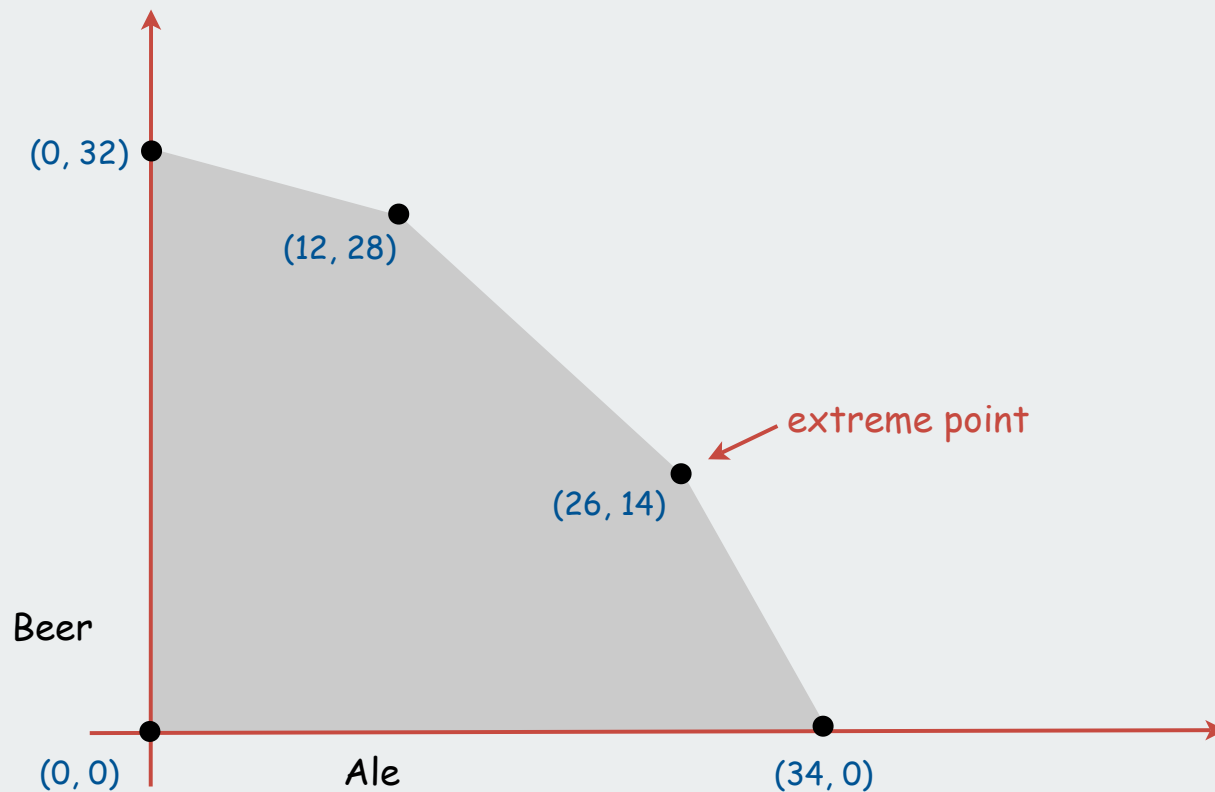


Brewer's problem: Objective function



Brewer's problem: Geometry

Brewer's problem observation. Regardless of objective function coefficients, an optimal solution occurs at an **extreme point**.



Standard form linear program

Input: real numbers a_{ij} , c_j , b_i .

Output: real numbers x_j .

$n = \#$ **nonnegative** variables, $m = \#$ constraints.

Maximize linear objective function subject to linear **equations**.

n variables

maximize

$$c_1 x_1 + c_2 x_2 + \dots + c_n x_n$$

subject to the
constraints

m equations

$$a_{11} x_1 + a_{12} x_2 + \dots + a_{1n} x_n = b_1$$

$$a_{21} x_1 + a_{22} x_2 + \dots + a_{2n} x_n = b_2$$

...

$$a_{m1} x_1 + a_{m2} x_2 + \dots + a_{mn} x_n = b_m$$

$$x_1, x_2, \dots, x_n \geq 0$$

matrix version

maximize

$$c^T x$$

subject to the
constraints

$$A x = b$$

$$x \geq 0$$

"Linear" No x^2 , xy , $\arccos(x)$, etc.

"Programming" "Planning" (term predates computer programming).

Converting the brewer's problem to the standard form

Original formulation

$$\begin{array}{llllll} \text{maximize} & 13A & + & 23B & & \\ \text{subject} & 5A & + & 15B & \leq & 480 \\ \text{to the} & 4A & + & 4B & \leq & 160 \\ \text{constraints} & 35A & + & 20B & \leq & 1190 \\ & & & A, B & \geq & 0 \end{array}$$

Standard form

- add variable Z and equation corresponding to objective function
- add **slack** variable to convert each **inequality** to an **equality**.
- now a 5-dimensional problem.

$$\begin{array}{llllllll} \text{maximize} & Z & & & & & & \\ \text{subject} & 13A & + & 23B & & & - Z & = & 0 \\ \text{to the} & 5A & + & 15B & + & S_C & & = & 480 \\ \text{constraints} & 4A & + & 4B & & + & S_H & = & 160 \\ & 35A & + & 20B & & & + & S_M & = & 1190 \\ & & & A, B, S_C, S_H, S_M & & & & \geq & 0 \end{array}$$

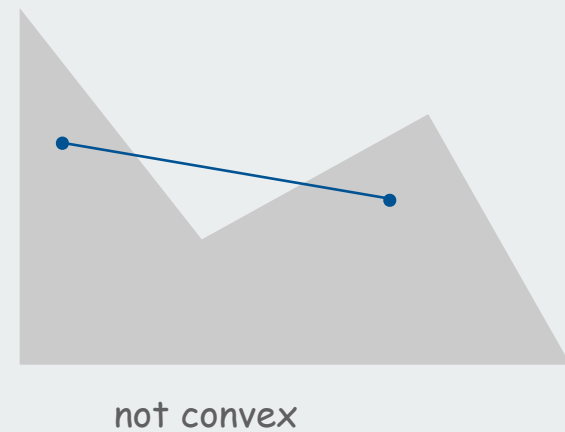
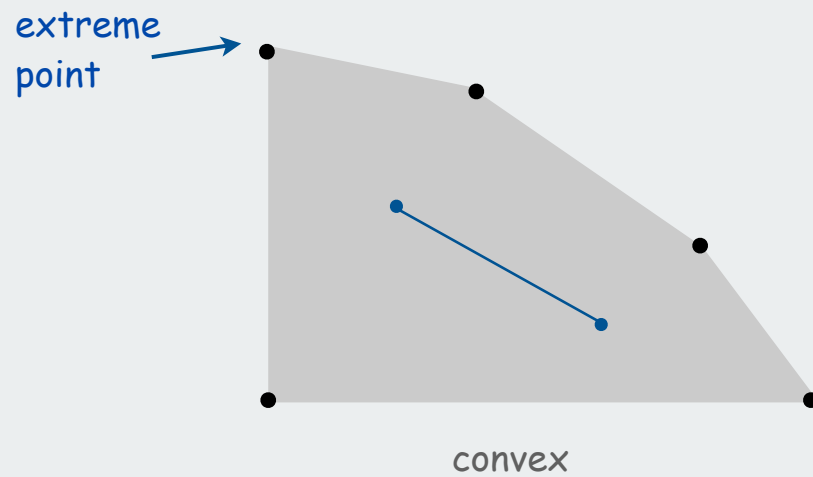
Geometry

A few principles from geometry:

- inequality: halfplane (2D), hyperplane (kD).
- bounded feasible region: convex polygon (2D), convex polytope (kD).

Convex set. If two points a and b are in the set, then so is $\frac{1}{2}(a + b)$.

Extreme point. A point in the set that can't be written as $\frac{1}{2}(a + b)$, where a and b are two distinct points in the set.



Geometry (continued)

Extreme point property. If there exists an optimal solution to (P), then there exists one that is an extreme point.

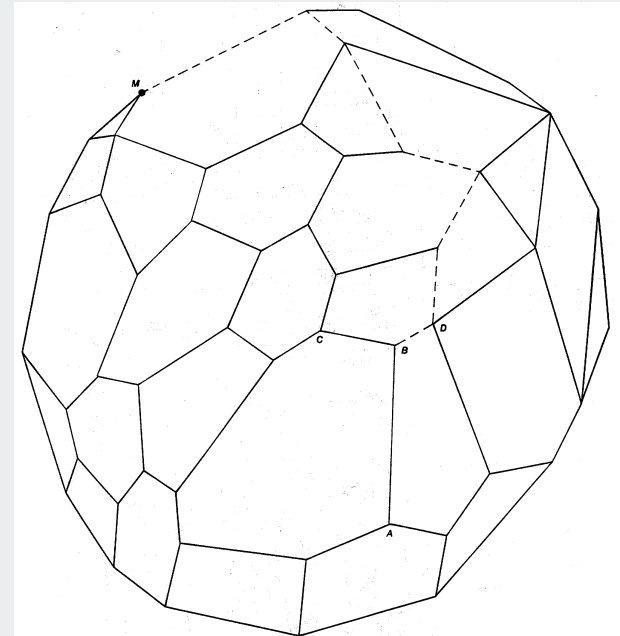
Good news. Only need to consider **finitely** many possible solutions.

Bad news. Number of extreme points can be **exponential** !

Ex: n-dimensional hypercube

Greedy property. Extreme point is optimal iff no neighboring extreme point is better.

↑
local optima are global optima



- ▶ brewer's problem
- ▶ **simplex algorithm**
- ▶ implementation
- ▶ linear programming

Simplex Algorithm

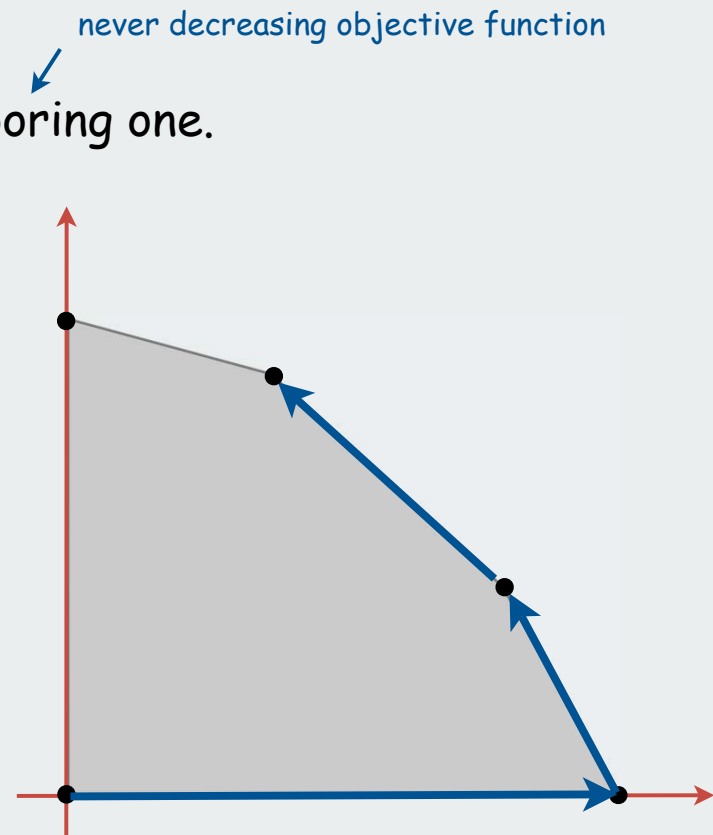
Simplex algorithm. [George Dantzig, 1947]

- Developed shortly after WWII in response to logistical problems, including Berlin airlift.
- One of greatest and most successful algorithms of all time.

Generic algorithm.

- Start at some extreme point.
- **Pivot** from one extreme point to a neighboring one.
- Repeat until optimal.

How to implement? Linear algebra.



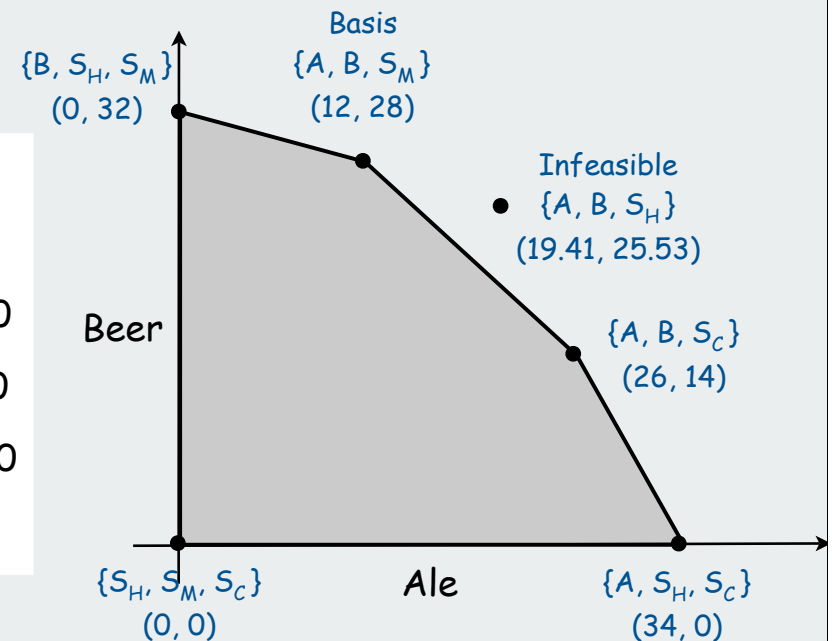
Simplex Algorithm: Basis

Basis. Subset of m of the n variables.

Basic feasible solution (BFS).

- Set $n - m$ nonbasic variables to 0, solve for remaining m variables.
- Solve m equations in m unknowns.
- If unique and feasible solution \Rightarrow BFS.
- BFS \Leftrightarrow extreme point.

maximize	Z				
subject	$13A + 23B$		$-Z = 0$		
to the	$5A + 15B + S_C$		$= 480$		
constraints	$4A + 4B + S_H$		$= 160$		
	$35A + 20B + S_M$		$= 1190$		
	A, B, S_C, S_H, S_M		≥ 0		



Simplex Algorithm: Initialization

Start with slack variables as the basis.

Initial basic feasible solution (BFS).

- set non-basis variables $A = 0$, $B = 0$ (and $Z = 0$).
- 3 equations in 3 unknowns give $S_c = 480$, $S_c = 160$, $S_c = 1190$ (immediate).
- extreme point on simplex: origin

maximize	Z					
subject to the constraints	13A	+	23B			- Z = 0
	5A	+	15B	+ S _C		= 480
	4A	+	4B		+ S _H	= 160
	35A	+	20B		+ S _M	= 1190
			A, B, S _C , S _H , S _M			≥ 0

$$\text{basis} = \{S_C, S_H, S_M\}$$

$$A = B = 0$$

$$Z = 0$$

$$S_c = 480$$

$$S_H = 160$$

$$S_M = 1190$$

Simplex Algorithm: Pivot 1

maximize	Z					
subject	13A	+	23B			- Z = 0
to the	5A	+	15B	+	S _C	= 480
constraints	4A	+	4B		+ S _H	= 160
	35A	+	20B		+ S _M	= 1190
	A, B, S _C , S _H , S _M					≥ 0

$$\begin{aligned} \text{basis} &= \{S_C, S_H, S_M\} \\ A &= B = 0 \\ Z &= 0 \\ S_C &= 480 \\ S_H &= 160 \\ S_M &= 1190 \end{aligned}$$

Substitution $B = (1/15)(480 - 5A - S_C)$ puts **B** into the basis
 (rewrite 2nd equation, eliminate B in 1st, 3rd, and 4th equations)

← which variable
does it replace?

maximize	Z					
subject	(16/3)A		- (23/15) S _C			- Z = -736
to the	(1/3) A	+	B	+	(1/15) S _C	= 32
constraints	(8/3) A		- (4/15) S _C	+	S _H	= 32
	(85/3) A		- (4/3) S _C		+ S _M	= 550
	A, B, S _C , S _H , S _M					≥ 0

$$\begin{aligned} \text{basis} &= \{B, S_H, S_M\} \\ A &= S_C = 0 \\ Z &= 736 \\ B &= 32 \\ S_H &= 32 \\ S_M &= 550 \end{aligned}$$

Simplex Algorithm: Pivot 1

maximize	Z						
subject	13A	+	23B			- Z	= 0
to the	5A	+	15B	+	S_C		= 480
constraints	4A	+	4B		+	S_H	= 160
	35A	+	20B			+	S_M
							= 1190
							≥ 0
							A, B, S_C , S_H , S_M

$$\text{basis} = \{S_C, S_H, S_M\}$$

$$A = B = 0$$

$$Z = 0$$

$$S_C = 480$$

$$S_H = 160$$

$$S_M = 1190$$

Why pivot on B?

- Its objective function coefficient is **positive**
(each unit increase in B from 0 increases objective value by \$23)
- Pivoting on column 1 also OK.

Why pivot on row 2?

- Preserves feasibility by ensuring $RHS \geq 0$.
- Minimum ratio rule: $\min \{ 480/15, 160/4, 1190/20 \}$.

Simplex Algorithm: Pivot 2

$$\begin{array}{llllllll}
 \text{maximize} & Z & & & & & & \\
 \text{subject} & (16/3)A & & - (23/15) S_C & & - Z & = & -736 \\
 \text{to the} & (1/3) A & + & B & + & (1/15) S_C & = & 32 \\
 \text{constraints} & (8/3) A & & - (4/15) S_C & + & S_H & = & 32 \\
 & (85/3) A & & - (4/3) S_C & & + S_M & = & 550 \\
 & & & A, B, S_C, S_H, S_M & & & \geq & 0
 \end{array}$$

$$\begin{aligned}
 \text{basis} &= \{B, S_H, S_M\} \\
 A &= S_C = 0 \\
 Z &= 736 \\
 B &= 32 \\
 S_H &= 32 \\
 S_M &= 550
 \end{aligned}$$

Substitution $A = (3/8)(32 + (4/15) S_C - S_H)$ puts A into the basis
 (rewrite 3rd equation, eliminate A in 1st, 2nd, and 4th equations)

$$\begin{array}{llllllll}
 \text{maximize} & Z & & & & & & \\
 \text{subject} & & - & S_C & - & 2S_H & - Z & = -800 \\
 \text{to the} & & B & + & (1/10) S_C & + & (1/8) S_H & = 28 \\
 \text{constraints} & A & - & (1/10) S_C & + & (3/8) S_H & = 12 \\
 & & - & (25/6) S_C & - & (85/8) S_H & + S_M & = 110 \\
 & & & A, B, S_C, S_H, S_M & & & \geq & 0
 \end{array}$$

$$\begin{aligned}
 \text{basis} &= \{A, B, S_M\} \\
 S_C &= S_H = 0 \\
 Z &= 800 \\
 B &= 28 \\
 A &= 12 \\
 S_M &= 110
 \end{aligned}$$

Simplex algorithm: Optimality

Q. When to stop pivoting?

A. When all coefficients in top row are non-positive.

Q. Why is resulting solution optimal?

A. Any feasible solution satisfies system of equations in tableaux.

- In particular: $Z = 800 - S_C - 2 S_H$
- Thus, optimal objective value $Z^* \leq 800$ since $S_C, S_H \geq 0$.
- Current BFS has value 800 \Rightarrow optimal.

maximize	Z					
subject		-	S_C	-	$2S_H$	- Z = -800
to the						
constraints	B	+	$(1/10) S_C$	+	$(1/8) S_H$	= 28
	A	-	$(1/10) S_C$	+	$(3/8) S_H$	= 12
		-	$(25/6) S_C$	-	$(85/8) S_H$	+ S_M = 110
			A, B, S_C, S_H, S_M			≥ 0

basis = {A, B, S_M }

$S_C = S_H = 0$

Z = 800

B = 28

A = 12

$S_M = 110$

- ▶ brewer's problem
- ▶ simplex algorithm
- ▶ **implementation**
- ▶ linear programming

Simplex tableau

Encode standard form LP in a single Java 2D array

$$\begin{array}{llllllll}
 \text{maximize} & Z & & & & & & \\
 \text{subject} & 13A & + & 23B & & & -Z & = & 0 \\
 \text{to the} & & & & & & & & \\
 \text{constraints} & 5A & + & 15B & + & S_C & & = & 480 \\
 & 4A & + & 4B & & + & S_H & = & 160 \\
 & 35A & + & 20B & & & + & S_M & = & 1190 \\
 & & & & & & & & & A, B, S_C, S_H, S_M \geq 0
 \end{array}$$

5	15	1	0	0	480
4	4	0	1	0	160
35	20	0	0	1	1190
13	23	0	0	0	0

m	A					I					b
	c					0					0
1											
	n					m					1

Simplex tableau

Encode standard form LP in a single Java 2D array (solution)

$$\begin{array}{ll}
 \text{maximize} & Z \\
 \text{subject to the constraints} &
 \end{array}
 \begin{array}{rcl}
 - S_C - 2S_H - Z & = & -800 \\
 B + (1/10) S_C + (1/8) S_H & = & 28 \\
 A - (1/10) S_C + (3/8) S_H & = & 12 \\
 - (25/6) S_C - (85/8) S_H + S_M & = & 110 \\
 A, B, S_C, S_H, S_M & \geq & 0
 \end{array}$$

0	1	1/10	1/8	0	28
1	0	1/10	3/8	0	12
0	0	25/6	85/8	1	110
0	0	-1	-2	0	-800

m	A	I	b
1	c	0	0
	n	m	1

Simplex **algorithm** transforms initial array into solution

Simplex algorithm: Bare-bones implementation

Construct the simplex tableau.

m	A	I	b
1	c	0	0
	n	m	1

```
public class Simplex
{
    private double[][] a;    // simplex tableaux
    private int M, N;

    public Simplex(double[][] A, double[] b, double[] c)
    {
        M = b.length;
        N = c.length;
        a = new double[M+1][M+N+1];
        for (int i = 0; i < M; i++)
            for (int j = 0; j < N; j++)
                a[i][j] = A[i][j];
        for (int j = N; j < M + N; j++) a[j-N][j] = 1.0;
        for (int j = 0; j < N; j++) a[M][j] = c[j];
        for (int i = 0; i < M; i++) a[i][M+N] = b[i];
    }
}
```

constructor

← put A[] into tableau

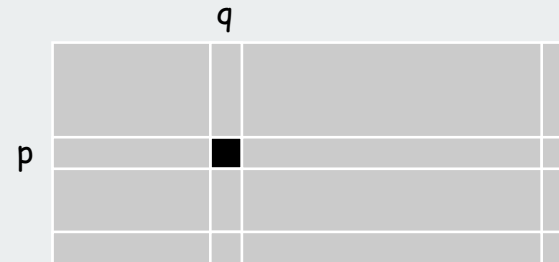
← put I[] into tableau

← put c[] into tableau

← put b[] into tableau

Simplex algorithm: Bare-bones Implementation

Pivot on element (p, q).



```
public void pivot(int p, int q)
{
    for (int i = 0; i <= M; i++)
        for (int j = 0; j <= M + N; j++)
            if (i != p && j != q)
                a[i][j] -= a[p][j] * a[i][q] / a[p][q];

    for (int i = 0; i <= M; i++)
        if (i != p) a[i][q] = 0.0;

    for (int j = 0; j <= M + N; j++)
        if (j != q) a[p][j] /= a[p][q];
    a[p][q] = 1.0;
}
```

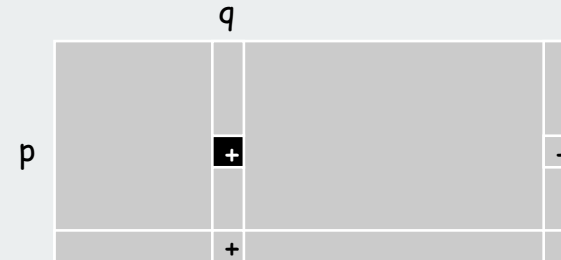
← scale all elements but
row p and column q

← zero out column q

← scale row p

Simplex Algorithm: Bare Bones Implementation

Simplex algorithm.



```
public void solve()
{
    while (true)
    {
        int p, q;
        for (q = 0; q < M + N; q++)
            if (a[M][q] > 0) break;
        if (q >= M + N) break;

        for (p = 0; p < M; p++)
            if (a[p][q] > 0) break;
        for (int i = p+1; i < M; i++)
            if (a[i][q] > 0)
                if (a[i][M+N] / a[i][q]
                    < a[p][M+N] / a[p][q])
                    p = i;

        pivot(p, q);
    }
}
```

find entering variable q
(positive objective function coefficient)

find row p according
to min ratio rule

min ratio test

Simplex Algorithm: Running Time

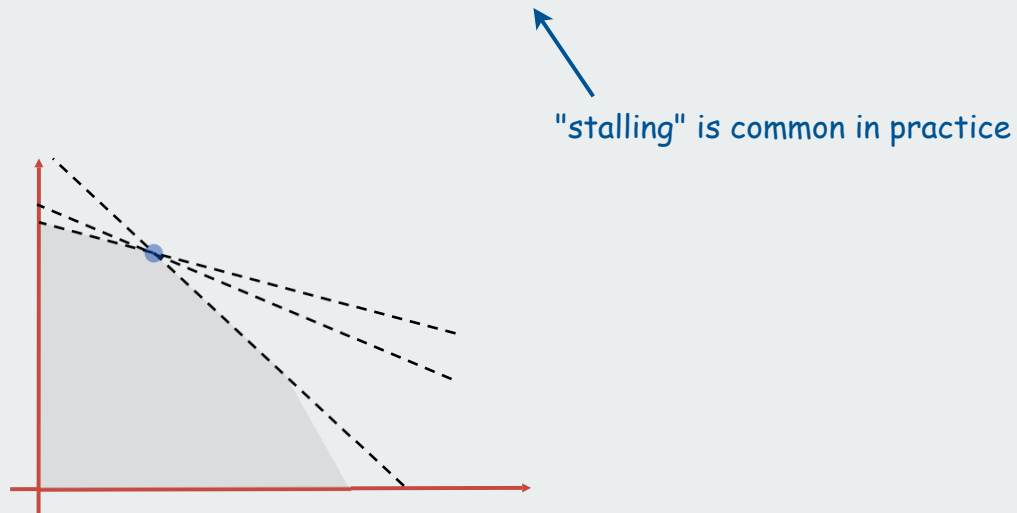
Remarkable property. In practice, simplex algorithm typically terminates after at most $2(m+n)$ pivots.

- No pivot rule that is guaranteed to be polynomial is known.
- Most pivot rules known to be exponential (or worse) in worst-case.

Pivoting rules. Carefully balance the cost of finding an entering variable with the number of pivots needed.

Simplex algorithm: Degeneracy

Degeneracy. New basis, same extreme point.




Cycling. Get stuck by cycling through different bases that all correspond to same extreme point.

- Doesn't occur in the wild.
- Bland's least index rule guarantees finite # of pivots.

Simplex Algorithm: Implementation Issues

To improve the bare-bones implementation

- Avoid stalling.
- Choose the pivot wisely.
- Watch for numerical stability.
- Maintain **sparsity**.  requires fancy data structures
- Detect infeasibility
- Detect unboundedness.
- Preprocess to reduce problem size.

Basic implementations available in many programming environments.

Commercial solvers routinely solve LPs with **millions** of variables.

LP solvers: basic implementations

Ex. 1: OR-Objects Java library

```
import drasys.or.mp.*;
import drasys.or.mp.lp.*;

public class LPDemo
{
    public static void main(String[] args) throws Exception
    {
        Problem prob = new Problem(3, 2);
        prob.getMetadata().put("lp.isMaximize", "true");
        prob.newVariable("x1").setObjectiveCoefficient(13.0);
        prob.newVariable("x2").setObjectiveCoefficient(23.0);
        prob.newConstraint("corn").setRightHandSide( 480.0);
        prob.newConstraint("hops").setRightHandSide( 160.0);
        prob.newConstraint("malt").setRightHandSide(1190.0);

        prob.setCoefficientAt("corn", "x1", 5.0);
        prob.setCoefficientAt("corn", "x2", 15.0);
        prob.setCoefficientAt("hops", "x1", 4.0);
        prob.setCoefficientAt("hops", "x2", 4.0);
        prob.setCoefficientAt("malt", "x1", 35.0);
        prob.setCoefficientAt("malt", "x2", 20.0);

        DenseSimplex lp = new DenseSimplex(prob);
        System.out.println(lp.solve());
        System.out.println(lp.getSolution());
    }
}
```

Ex. 2: MS Excel (!)

LP solvers: commercial strength

AMPL. [Fourer, Gay, Kernighan] An algebraic modeling language.

CPLEX solver. Industrial strength solver.

	ale		beer			
maximize	13A	+	23B			profit
subject	5A	+	15B	≤	480	corn
to the	4A	+	4B	≤	160	hops
constraints	35A	+	20B	≤	1190	malt
			A	≥	0	
			B	≥	0	

```
set INGR;
set PROD;
param profit {PROD};
param supply {INGR};
param amt {INGR, PROD};
var x {PROD} >= 0;

maximize total_profit:
    sum {j in PROD} x[j] * profit[j];

subject to constraints {i in INGR}:
    sum {j in PROD} amt[i,j] * x[j] <= supply[i];
```

beer.mod

```
[cos226:tucson] ~> ampl
AMPL Version 20010215 (SunOS 5.7)
ampl: model beer.mod;
ampl: data beer.dat;
ampl: solve;
CPLEX 7.1.0: optimal solution; objective 800
ampl: display x;
x [*] := ale 12 beer 28;
```

separate data from model

```
set PROD := beer ale;
set INGR := corn hops malt;

param: profit :=
ale 13
beer 23;

param: supply :=
corn 480
hops 160
malt 1190;

param amt: ale beer :=
corn      5 15
hops      4 4
malt     35 20;
```

beer.dat

History

1939. Production, planning. [Kantorovich]

1947. Simplex algorithm. [Dantzig]

1950. Applications in many fields.

1979. Ellipsoid algorithm. [Khachian]

1984. Projective scaling algorithm. [Karmarkar]

1990. Interior point methods.

- Interior point faster when polyhedron smooth like disco ball.
- Simplex faster when polyhedron spiky like quartz crystal.



200x. Approximation algorithms, large scale optimization.

- ▶ brewer's problem
- ▶ simplex algorithm
- ▶ implementation
- ▶ **linear programming**

Linear programming

Linear “programming”

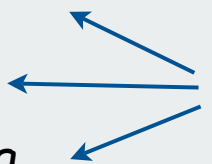
- process of formulating an LP model for a problem
- solution to LP for a specific problem gives solution to the problem

1. Identify **variables**
2. Define **constraints** (inequalities and equations)
3. Define **objective function**

easy part [omitted]:
convert to standard form



Examples:

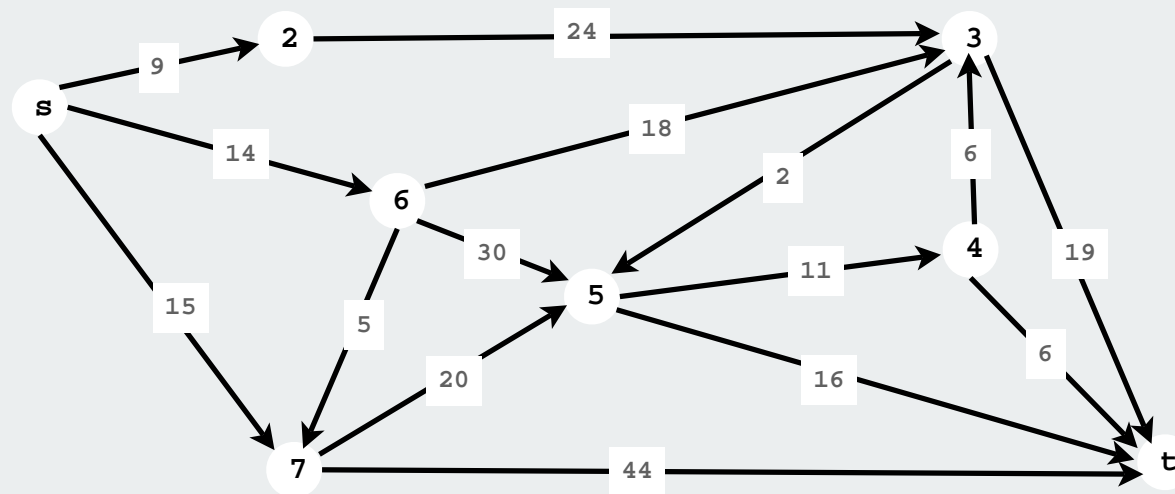
- shortest paths
 - maxflow
 - bipartite matching
 - .
 - .
 - .
 - [a very long list]
- stay tuned [this lecture]
- 

Single-source shortest-paths problem (revisited)

Given. Weighted digraph, single source s .

Distance from s to v : length of the shortest path from s to v .

Goal. Find distance (and shortest path) from s to **every** other vertex.

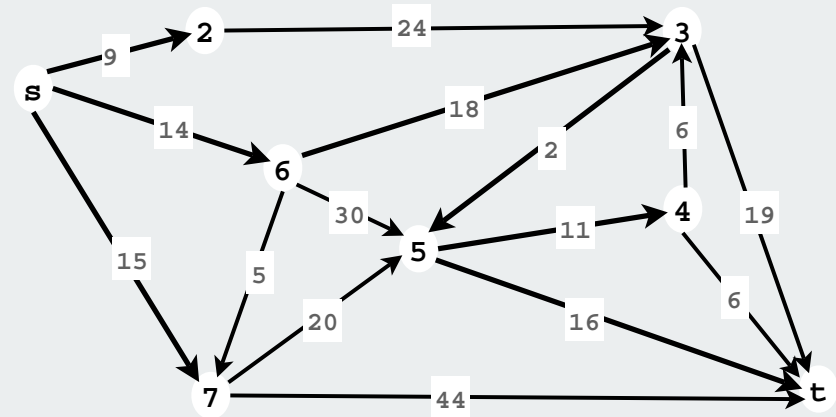


LP formulation of single-source shortest-paths problem

One variable per vertex, one inequality per edge.

minimize	x_t
subject	$x_s + 9 \leq x_2$
to the	$x_s + 14 \leq x_6$
constraints	$x_s + 15 \leq x_7$
	$x_2 + 24 \leq x_3$
	$x_3 + 2 \leq x_5$
	$x_3 + 19 \leq x_t$
	$x_4 + 6 \leq x_3$
	$x_4 + 6 \leq x_t$
	$x_5 + 11 \leq x_4$
	$x_5 + 16 \leq x_t$
	$x_6 + 18 \leq x_3$
	$x_6 + 30 \leq x_5$
	$x_6 + 5 \leq x_7$
	$x_7 + 20 \leq x_5$
	$x_7 + 44 \leq x_t$
	$x_s = 0$
	$x_2, \dots, x_t \geq 0$

interpretation:
 x_i = length of
shortest path from
source to i

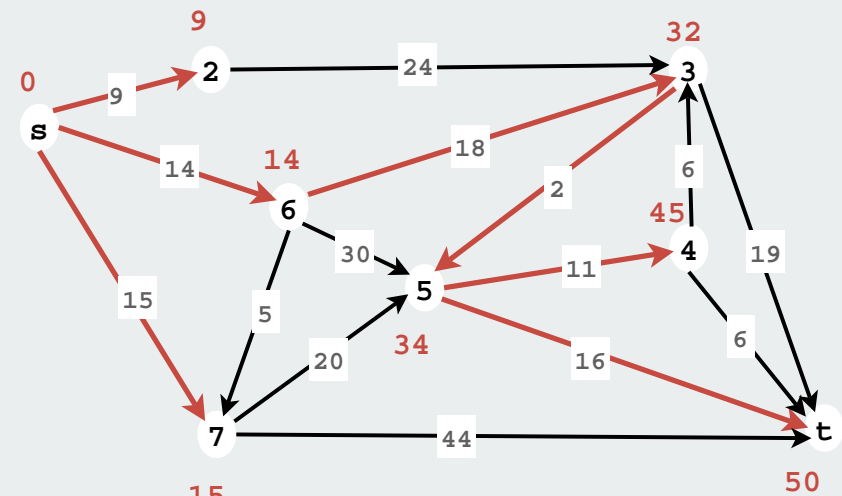


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	$x_4 + 6 \leq x_t$
	$x_5 + 11 \leq x_4$
	$x_5 + 16 \leq x_t$
	$x_6 + 18 \leq x_3$
	$x_6 + 30 \leq x_5$
	$x_6 + 5 \leq x_7$
	$x_7 + 20 \leq x_5$
	$x_7 + 44 \leq x_t$
	$x_s = 0$
	$x_2, \dots, x_t \geq 0$

interpretation:
 x_i = length of
 shortest path from
 source to i



solution

$x_s = 0$
$x_2 = 9$
$x_3 = 32$
$x_4 = 45$
$x_5 = 34$
$x_6 = 14$
$x_7 = 15$
$x_t = 50$

Maxflow problem

Given: Weighted digraph, source s , destination t .

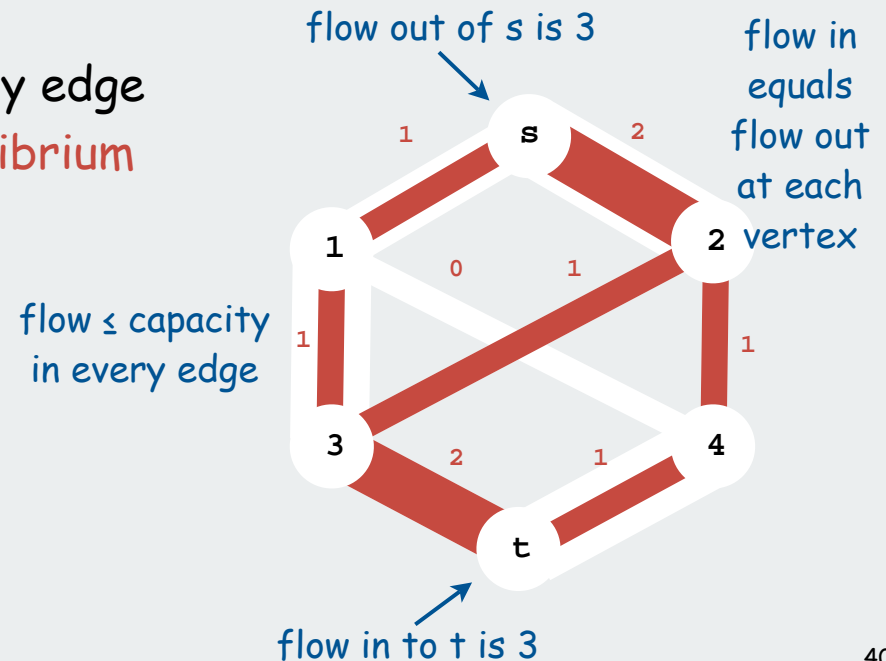
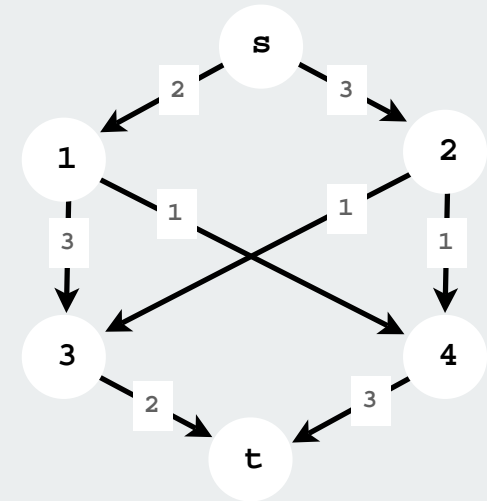
Interpret edge weights as **capacities**

- Models material flowing through network
- Ex: oil flowing through pipes
- Ex: goods in trucks on roads
- [many other examples]

Flow: A different set of edge weights

- flow does not exceed capacity in any edge
- flow at every vertex satisfies **equilibrium**
[flow in equals flow out]

Goal: Find **maximum flow** from s to t



LP formulation of maxflow problem

One variable per edge.

One inequality per edge, one equality per vertex.

maximize

x_{ts}

subject
to the
constraints

$$x_{s1} \leq 2$$

$$x_{s2} \leq 3$$

$$x_{13} \leq 3$$

$$x_{14} \leq 1$$

$$x_{23} \leq 1$$

$$x_{24} \leq 1$$

$$x_{3t} \leq 2$$

$$x_{4t} \leq 3$$

capacity
constraints

interpretation:
 x_{ij} = flow in edge i-j

equilibrium
constraints

$$x_{ts} = x_{s1} + x_{s2}$$

$$x_{s1} = x_{13} + x_{14}$$

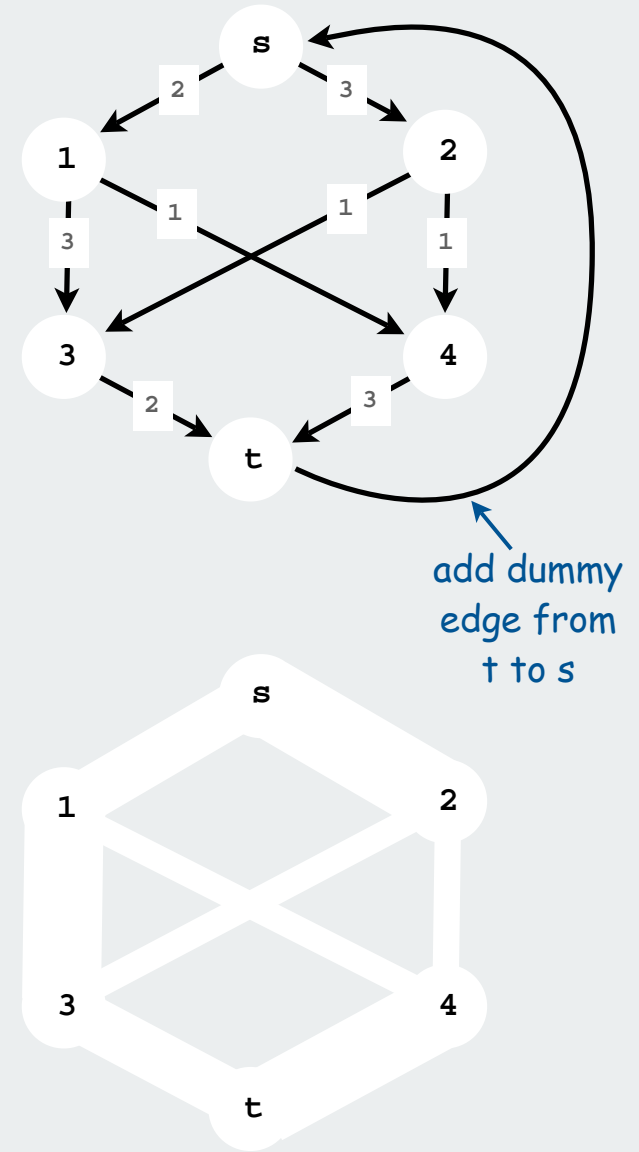
$$x_{s2} = x_{23} + x_{24}$$

$$x_{13} + x_{23} = x_{3t}$$

$$x_{14} + x_{24} = x_{4t}$$

$$x_{3t} + x_{4t} = x_{ts}$$

$$\text{all } x_{ij} \geq 0$$



LP formulation of maxflow problem

One variable per edge.

One inequality per edge, one equality per vertex.

maximize

x_{ts}

subject
to the
constraints

$$x_{s1} \leq 2$$

$$x_{s2} \leq 3$$

$$x_{13} \leq 3$$

$$x_{14} \leq 1$$

$$x_{23} \leq 1$$

$$x_{24} \leq 1$$

$$x_{3t} \leq 2$$

$$x_{4t} \leq 3$$

capacity
constraints

interpretation:
 x_{ij} = flow in edge i-j

equilibrium
constraints

$$x_{ts} = x_{s1} + x_{s2}$$

$$x_{s1} = x_{13} + x_{14}$$

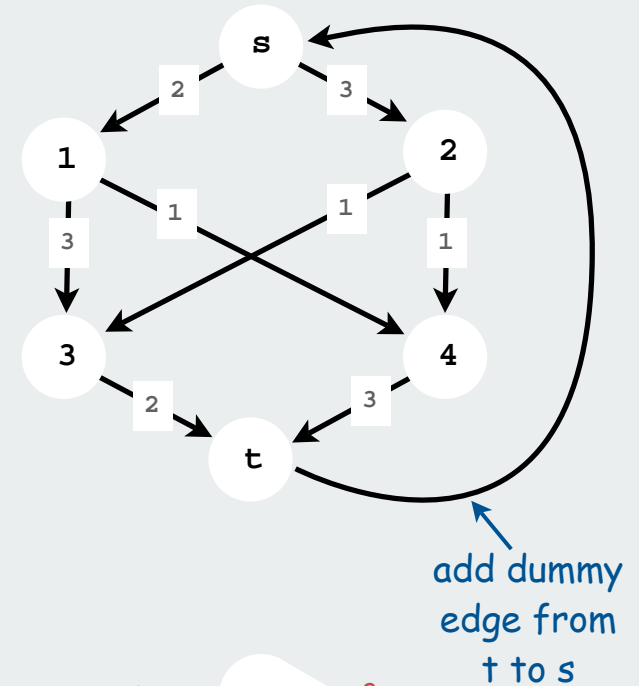
$$x_{s2} = x_{23} + x_{24}$$

$$x_{13} + x_{23} = x_{3t}$$

$$x_{14} + x_{24} = x_{4t}$$

$$x_{3t} + x_{4t} = x_{ts}$$

$$\text{all } x_{ij} \geq 0$$



solution

$$x_{s1} = 2$$

$$x_{s2} = 2$$

$$x_{13} = 1$$

$$x_{14} = 1$$

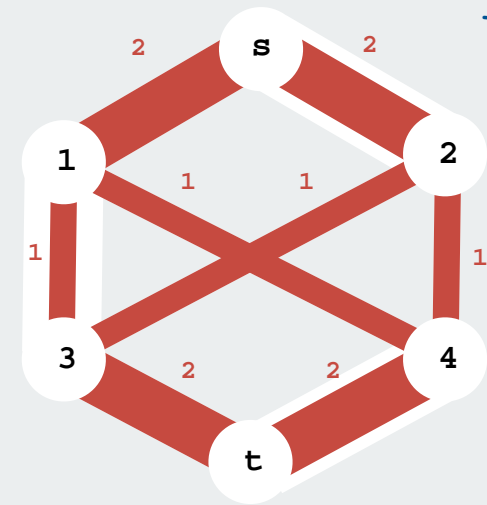
$$x_{23} = 1$$

$$x_{24} = 1$$

$$x_{3t} = 2$$

$$x_{4t} = 2$$

$$x_{ts} = 4$$



Maximum cardinality bipartite matching problem

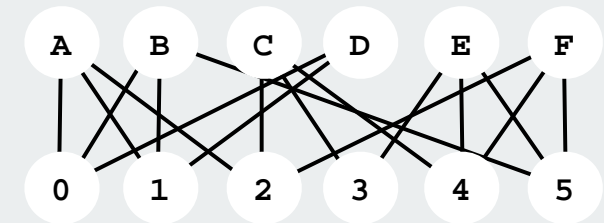
Given: Two sets of vertices, set of edges
(each connecting one vertex in each set)

Matching: set of edges
with no vertex appearing twice

Interpretation: **mutual** preference constraints

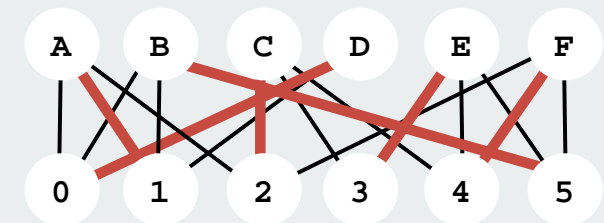
- Ex: people to jobs
- Ex: medical students to residence positions
- Ex: students to writing seminars
- [many other examples]

Goal: find a maximum cardinality matching



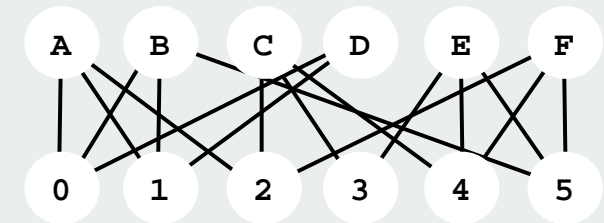
Alice	Adobe
Adobe, Apple, Google	Alice, Bob, Dave
Bob	Apple
Adobe, Apple, Yahoo	Alice, Bob, Dave
Carol	Google
Google, IBM, Sun	Alice, Carol, Frank
Dave	IBM
Adobe, Apple	Carol, Eliza
Eliza	Sun
IBM, Sun, Yahoo	Carol, Eliza, Frank
Frank	Yahoo
Google, Sun, Yahoo	Bob, Eliza, Frank

Example: Job offers



LP formulation of maximum cardinality bipartite matching problem

One variable per edge, one equality per vertex.



maximize

$$\begin{aligned} & x_{A0} + x_{A1} + x_{A2} + x_{B0} + x_{B1} + x_{B5} \\ & + x_{C2} + x_{C3} + x_{C4} + x_{D0} + x_{D1} \\ & + x_{E3} + x_{E4} + x_{E5} + x_{F2} + x_{F4} + x_{F5} \end{aligned}$$

subject
to the
constraints

$$\begin{aligned} x_{A0} + x_{A1} + x_{A2} &= 1 \\ x_{B0} + x_{B1} + x_{B5} &= 1 \\ x_{C2} + x_{C3} + x_{C4} &= 1 \\ x_{D0} + x_{D1} &= 1 \end{aligned}$$

constraints on
top vertices

$$\begin{aligned} x_{E3} + x_{E4} + x_{E5} &= 1 \\ x_{F2} + x_{F4} + x_{F5} &= 1 \end{aligned}$$

$$\begin{aligned} x_{A0} + x_{B0} + x_{D0} &= 1 \\ x_{A1} + x_{B1} + x_{D1} &= 1 \\ x_{A2} + x_{C2} + x_{F2} &= 1 \\ x_{C3} + x_{E3} &= 1 \end{aligned}$$

constraints on
bottom vertices

$$\begin{aligned} x_{C4} + x_{E4} + x_{F4} &= 1 \\ x_{B5} + x_{E5} + x_{F5} &= 1 \end{aligned}$$

$$\text{all } x_{ij} \geq 0$$

interpretation:
An edge is in the
matching iff $x_{ij} = 1$

Crucial point:
not always so lucky!

Theorem. [Birkhoff 1946, von Neumann 1953]

All extreme points of the above polyhedron have **integer** (0 or 1) coordinates

Corollary. Can solve bipartite matching problem by solving LP

LP formulation of maximum cardinality bipartite matching problem

One variable per edge, one equality per vertex.

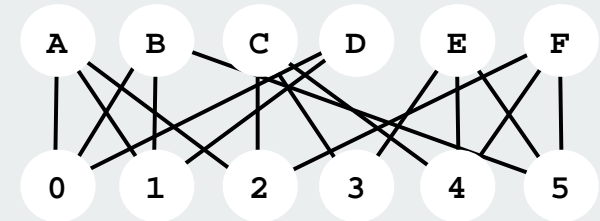
maximize

$$\begin{aligned} & x_{A0} + x_{A1} + x_{A2} + x_{B0} + x_{B1} + x_{B5} \\ & + x_{C2} + x_{C3} + x_{C4} + x_{D0} + x_{D1} \\ & + x_{E3} + x_{E4} + x_{E5} + x_{F2} + x_{F4} + x_{F5} \end{aligned}$$

subject
to the
constraints

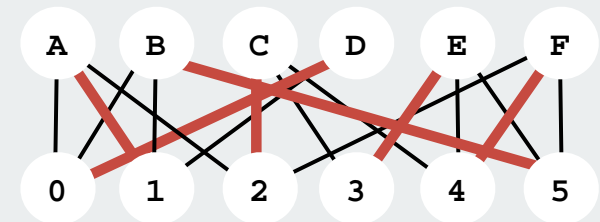
$$\begin{aligned} & x_{A0} + x_{A1} + x_{A2} = 1 \\ & x_{B0} + x_{B1} + x_{B5} = 1 \\ & x_{C2} + x_{C3} + x_{C4} = 1 \\ & x_{D0} + x_{D1} = 1 \\ & x_{E3} + x_{E4} + x_{E5} = 1 \\ & x_{F2} + x_{F4} + x_{F5} = 1 \\ & x_{A0} + x_{B0} + x_{D0} = 1 \\ & x_{A1} + x_{B1} + x_{D1} = 1 \\ & x_{A2} + x_{C2} + x_{F2} = 1 \\ & x_{C3} + x_{E3} = 1 \\ & x_{C4} + x_{E4} + x_{F4} = 1 \\ & x_{B5} + x_{E5} + x_{F5} = 1 \\ & \text{all } x_{ij} \geq 0 \end{aligned}$$

interpretation:
An edge is in the
matching iff $x_{ij} = 1$



solution

$$\begin{aligned} & x_{A1} = 1 \\ & x_{B5} = 1 \\ & x_{C2} = 1 \\ & x_{D0} = 1 \\ & x_{E3} = 1 \\ & x_{F4} = 1 \\ & \text{all other } x_{ij} = 0 \end{aligned}$$



Linear programming perspective

Got an optimization problem?

ex: shortest paths, maxflow, matching, . . . [many, many, more]

Approach 1: Use a specialized algorithm to solve it

- Algs in Java
- vast literature on complexity
- performance on real problems not always well-understood

Approach 2: Use linear programming

- a **direct mathematical representation** of the problem often works
- **immediate solution** to the problem at hand is often available
- might miss specialized solution, but might not care

Got an LP solver? Learn to use it!

```
[cos226:tucson] ~> ampl
AMPL Version 20010215 (SunOS 5.7)
ampl: model maxflow.mod;
ampl: data maxflow.dat;
ampl: solve;
CPLEX 7.1.0: optimal solution;
objective 4;
```

LP: the ultimate problem-solving model (in practice)

Fact 1: Many practical problems are easily formulated as LPs

Fact 2: Commercial solvers can solve those LPs quickly

More constraints on the problem?

- specialized algorithm may be hard to fix
- can just add more inequalities to LP

← Ex. Mincost maxflow and other generalized versions

New problem?

- may not be difficult to formulate LP
- may be very difficult to develop specialized algorithm

Today's problem?

- similar to yesterday's
- edit tableau, run solver

← Ex. Airline scheduling

[similar to vast number of other business processes]

Too slow?

- could happen
- doesn't happen

Want to learn more?
ORFE 307

Ultimate problem-solving model (in theory)

Is there an ultimate problem-solving model?

- Shortest paths
- Maximum flow
- Bipartite matching
- ...
- Linear programming

tractable

- .
- .
- .
- NP-complete problems
- .
- .
- .

intractable ?

[see next lecture]

Does $P = NP$? No universal problem-solving model exists unless $P = NP$.

Want to learn more?
COS 423

LP perspective

LP is near the deep waters of intractability.

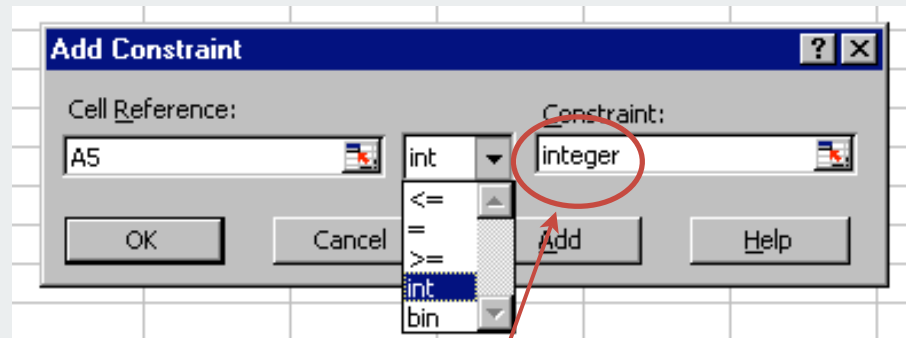
Good news:

- LP has been widely used for large practical problems for 50+ years
- Existence of guaranteed poly-time algorithm known for 25+ years.

Bad news:

- Integer linear programming is NP-complete
- (existence of guaranteed poly-time algorithm is highly unlikely).
- [stay tuned]

constrain variables to have integer values



An unsuspecting MBA student transitions to the world of intractability with a single mouse click.