COT 6936: Topics in Algorithms

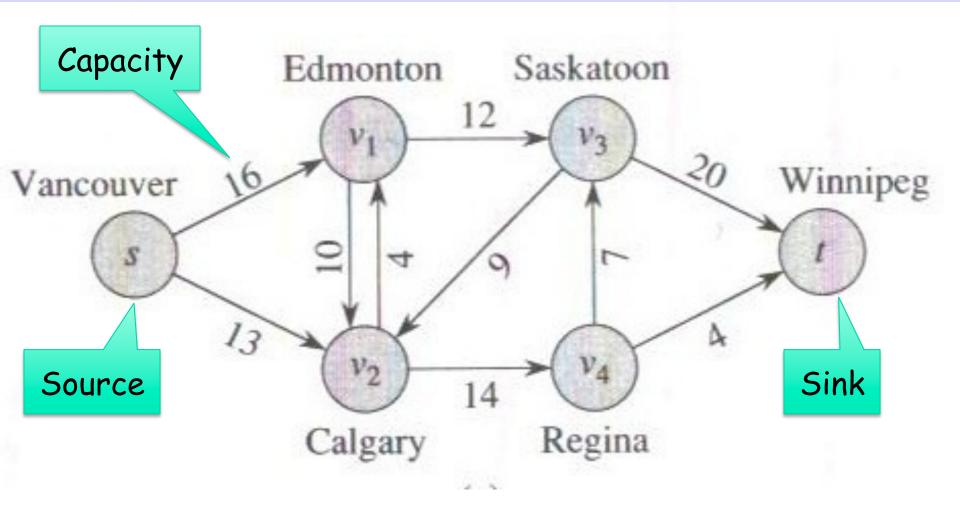
Giri Narasimhan ECS 254A / EC 2443; Phone: x3748 giri@cs.fiu.edu http://www.cs.fiu.edu/~giri/teach/COT6936_S12.html https://moodle.cis.fiu.edu/v2.1/course/view.php?id=174

Types of networks & Types of queries

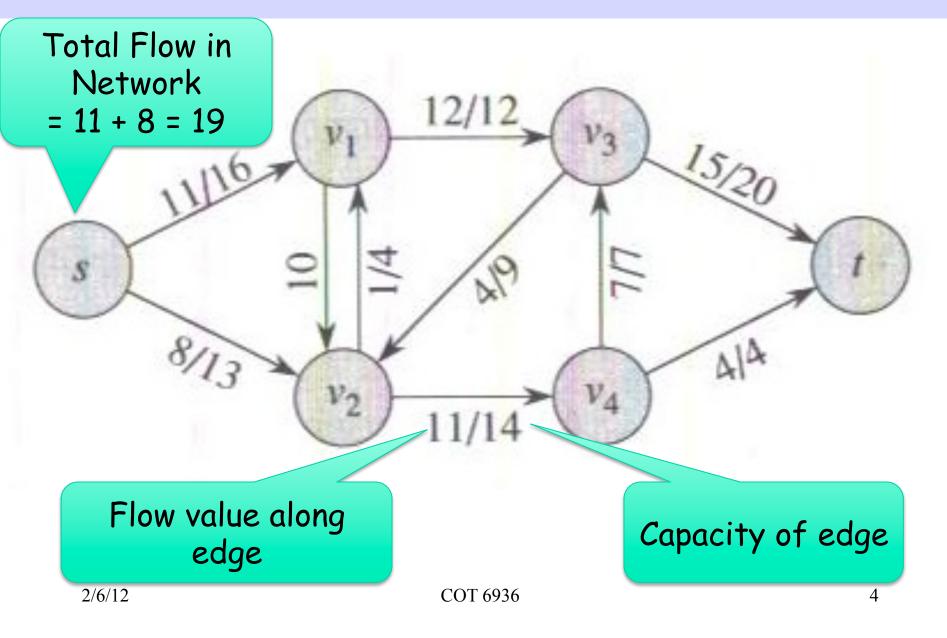
- Road, highway, rail
- Electrical power, water, oil, gas, sewer
- Internet, phone, wireless, sensor

- (1950s) How quickly can Soviet Union get supplies through its rail network to Europe?
- Which links to destroy to reduce flow to under a threshold?

Network Flow: Example



Network Flow: Example of a flow



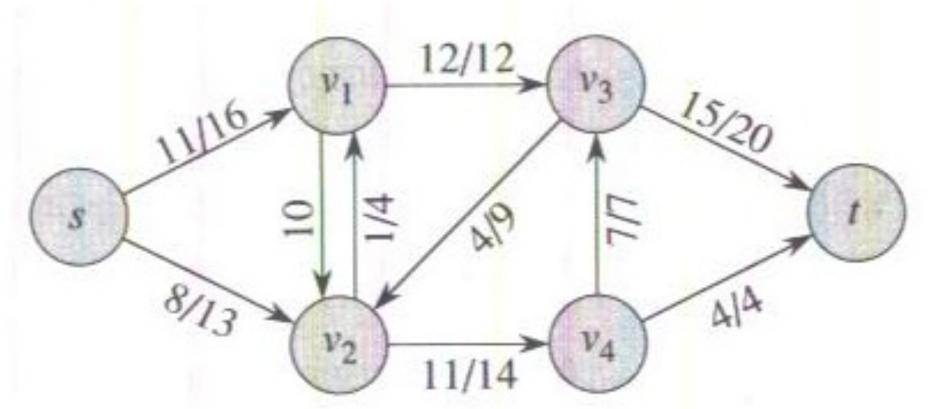
Network Flow

- <u>Directed graph</u> G(V,E) with <u>capacity function</u> on edges given by non-negative function c: E(G) → *R*⁺.
 - Capacity of each edge, e, is given by c(e)
 - Source vertex s
 - Sink vertex t
- Flow function f is a non-negative function of the edges
 - f: E(G) → *R*⁺
 - <u>Capacity constraints</u>: $f(e) \le c(e)$
 - Flow conservation constraints: For all vertices except source and sink, sum of flow values along edges <u>entering</u> a vertex equals sum of flow values along edges <u>leaving</u> that vertex
- <u>Flow value</u>: sum of flow values from <u>source</u> vertex (or sum of flow into <u>sink</u> vertex)

Flow Conservation

- For any legal flow function:
 - Flow out of source = Flow into sink (Why?)

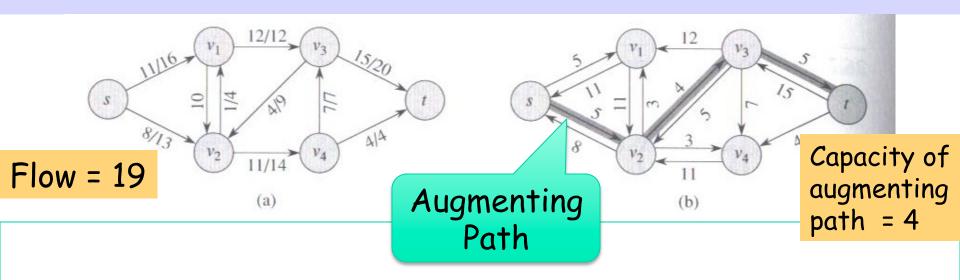
Network Flow: How to increase flow



Find path with <u>residual capacity</u> and increase flow along path.

- Path s to v_1 to v_3 to t has no residual capacity
 - edge v_1 to v_3 is saturated
- Path s to v_2 to v_3 to t has residual capacity

Residual Flows and Augmenting Paths



$$Flow = 23$$

Residual Flow Network: Definition

- Directed Graph G(V,E) with capacity function c and flow function f
- <u>Residual flow network</u> G_f(V,E')
 - For every edge e = (u,v) in E with f(e) < c(e), there are two edges in E': (u,v) and (v,u) with capacities c(e) = f(e) and f(e), respectively
 - For every edge e = (u,v) in E with f(e) = c(e),
 there is one edge in E': (v,u) with capacity f(e)
 - For every edge e = (u,v) in E with f(e) = 0, there is one edge in E': (u,v) with capacity f(e)

Ford Fulkerson Algorithm

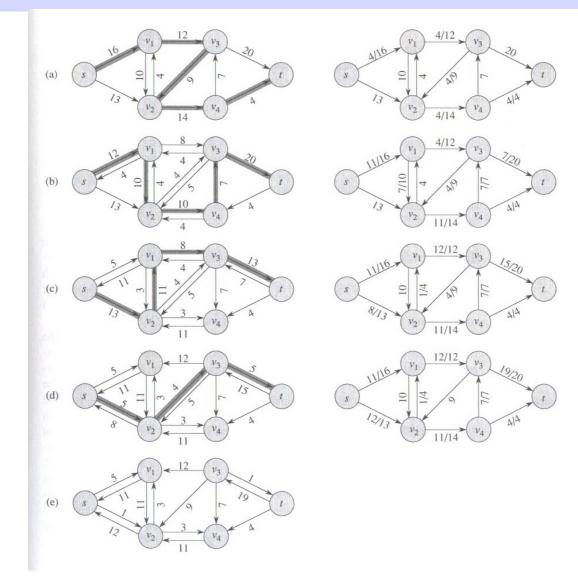
- Initialize flow f to 0.
- While (there exists augmenting path p from s to t) do
 - Augment flow along augmenting path p
- Return flow f as maximum flow from s to t

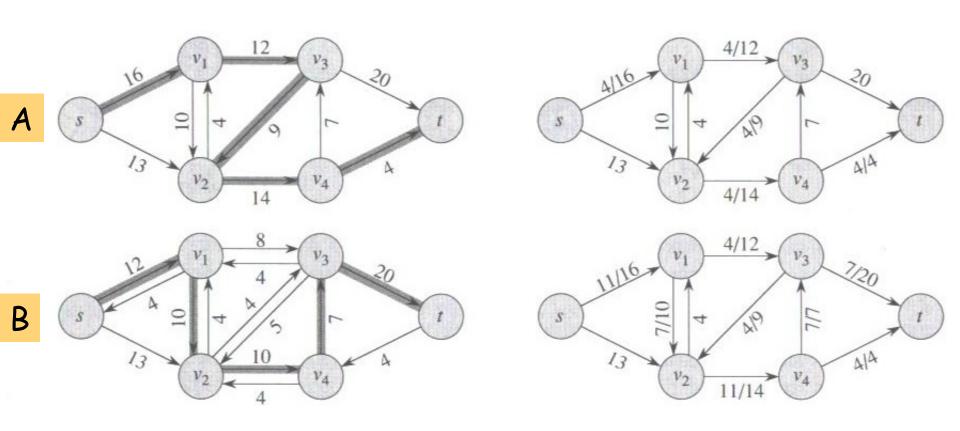
Ford Fulkerson Algorithm

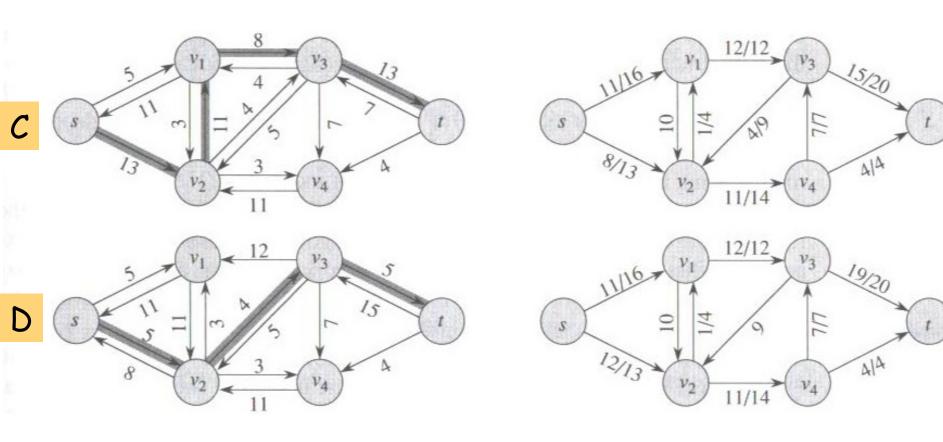
- Initialize flow f to 0.
- While (there exists directed path p from s to t in residual flow network G_f) do

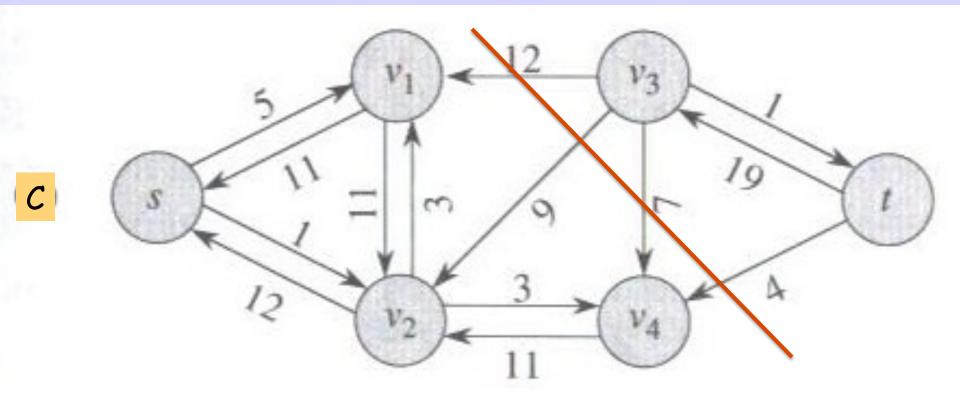
- Augment flow along augmenting path p

Return flow f as maximum flow from s to t





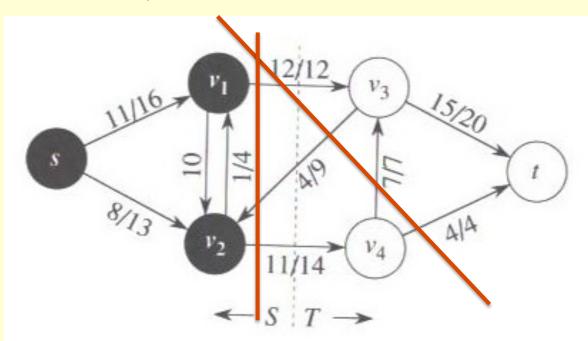




- Max-Flow has been reached. Why?
- Cut with zero capacity has been found. Which Cut?
 - ({ s,v_1,v_2,v_4 },{ v_3,t })

Correctness of Ford-Fulkerson Method

- Augmentation is possible if
 - Every cut-set is NOT saturated



Cut (S,T):

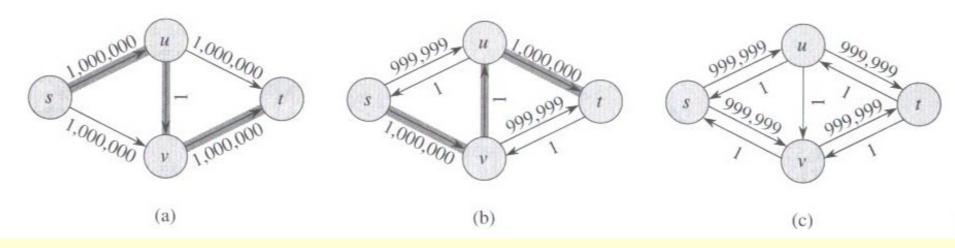
Cut (S',T'):

• Flow across cut = 19

<u>Theorem</u>: Min-Cut = Max-Flow

Time Complexity

• It can be arbitrarily large.



- Solution: When finding augmenting path, find the shortest path
- In that case, # of augmentations = O(mn)

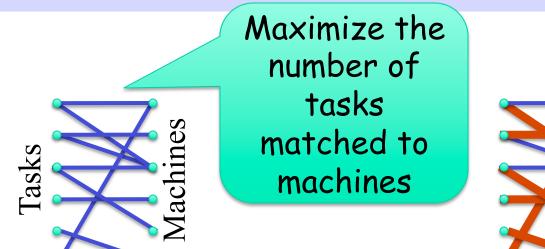
More efficient Network Flow algorithms

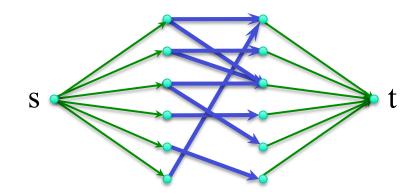
- Push-relabel algorithms [Goldberg, '87]
 - Local algorithm, works on one vertex at a time
 - Avoids maintaining flow conservation rule
 - Excess flow in each node
 - Height function
 - O(mn²) time complexity
 - Can be improved to $O(n^3)$

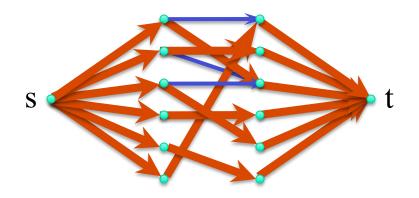
Generalizations

- Multiple sources and sinks.
 - Can be reduced to single source and sink

Bipartite Matching







Network Flow

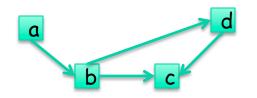
- Input: <u>Directed graph</u> G(V,E) with <u>capacity function</u> on edges given by non-negative function c: E(G) → *R*⁺.
 - Capacity of each edge, e, is given by c(e)
 - Source vertex s
 - Sink vertex t
- Question: Find a <u>flow function</u> f with the maximum flow value

Min-Cost Network Flow

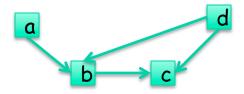
- Input: <u>Directed graph</u> G(V,E) with <u>capacity function</u> on edges given by non-negative function c: E(G) → *R*⁺.
 - Capacity of each edge, e, is given by c(e)
 - Flow cost of each edge, e, is given by a(e)
 - Implies that cost of flow in e is a(e)•f(e)
 - Total cost of flow = Σ a(e)•f(e)
 - Source vertex s
 - Sink vertex t
 - Flow required = F
- Question: Find <u>min-cost</u> flow function f with flow value = F

Minimum Path Cover in DAGs

- Path Cover: set of vertex disjoint paths that cover all vertices
- Minimum Path Cover in directed acyclic graphs can be reduced to network flow (?)
- Examples:



Can be covered with one path: $a \rightarrow b \rightarrow d \rightarrow c$



Cannot be covered with one path; needs at least two paths to cover all vertices

COT 6936: Topics in Algorithms

Linear Programming

Gaussian Elimination

Solving a system of simultaneous equations

\mathbf{x}_1	-2x ₃	= 2
	x ₂ + x ₃	= 3
x ₁ +	x ₂	$-x_4 = 4$
	$x_2 + 3x_3$	$+ x_4 = 5$

 $O(n^3)$ algorithm

\mathbf{x}_1	-2x ₃	= 2
	x ₂ + x ₃	= 3
	$x_2 + 2x_3 -$	$x_4 = 2$
	x ₂ + 3x ₃ +	x ₄ = 5

Linear Programming

- Want more than solving simultaneous equations
- We have an objective function to optimize

Chocolate Shop [DPV book]

- 2 kinds of chocolate
 - milk [Profit: \$1 per box] [Demand: 200]
 - Deluxe [Profit: \$6 per box] [Demand: 300]
- Production capacity: 400 boxes
- Goal: maximize profit
 - Maximize $x_1 + 6x_2$ subject to constraints:
 - x₁ ≤ 200
 - $x_2 \le 300$
 - $x_1 + x_2 \le 400$
 - $x_1, x_2 \ge 0$

Diet Problem

- Food type: F_1, \dots, F_m
- Nutrients: N_1, \dots, N_n
- Min daily requirement of nutrients: c₁,...,c_n

 $b_{1},...,b_{m}$

aii

- Price per unit of food:
- Nutrient N_j in food F_i:
- Problem: Supply daily nutrients at minimum cost
 - Min $\Sigma_i b_i x_i$
 - $\Sigma_i a_{ij} x_i \ge c_j$ for $1 \le j \le n$
 - x_i ≥ 0

Transportation Problem

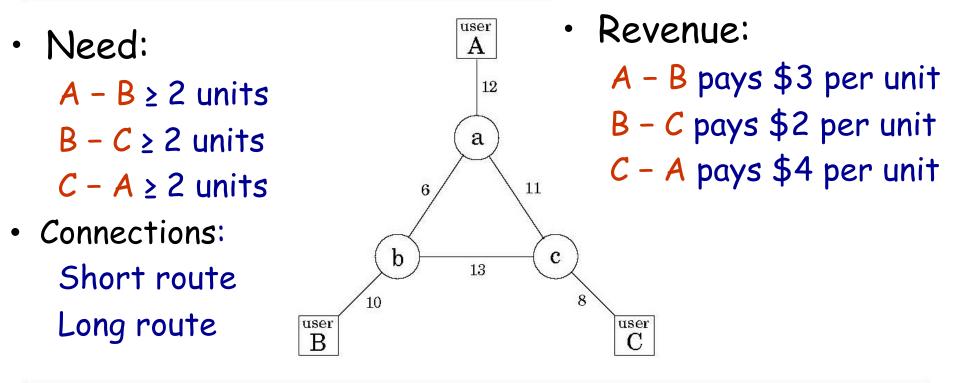
- Ports or Production Units: P₁,...,P_m
- Markets to be shipped to: M_1, \dots, M_n
- Min daily market need: r_1, \dots, r_n
- Port/production capacity: s_1, \dots, s_m
- Cost of transporting to M_j from port P_i : a_{ij}
- Problem: Meet market need at minimum transportation cost

Assignment Problem

- Workers: b₁,...,b_n
- **Jobs**: *g*₁,...,*g*_m
- Value of assigning person b_i to job g_j: a_{ij}
- Problem: Choose job assignment to maximize value

Bandwidth Allocation Problem

Figure 7.3 A communications network between three users A, B, and C. Bandwidths are shown.



Bandwidth Allocation Pr

- Maximize revenue by allocating connections along two routes wi exceeding bandwidth capacities
- Max $3(x_{AB}+x_{AB}') + 2(x_{BC}+x_{BC}') + 4(x_{AC}+x_{AC}')$ s.t. $x_{AB} + x_{AB}' + x_{BC} + x_{BC}' \le 10$ $x_{AB} + x_{AB}' + x_{AC} + x_{AC}' \le 12$ $x_{BC} + x_{BC} + x_{AC} + x_{AC} \leq 8$ $x_{AB} + x_{BC}' + x_{AC}' \le 6; \quad x_{AB} + x_{AB}' \ge 2;$ $x_{BC} + x_{BC}' \ge 2$ $x_{AB}' + x_{BC} + x_{AC}' \le 13;$ $X_{AC} + X_{AC}' \ge 2$ $x_{AB}' + x_{BC}' + x_{AC} \le 11$; & all nonneg constraints

Α

a

13

10

12

11

С

user C

Standard LP

- Maximize $\sum c_j x_j$ [Objective Function] Subject to $\sum a_{ij} x_j \le b_j$ [Constraints] and $x_j \ge 0$ [Nonnegativity Constraints]
- Matrix formulation of LP Maximize $c^{T}x$ Subject to $Ax \le b$ and $x \ge 0$

Converting to standard form

- Min $-2x_1 + 3x_2$ Subject to $x_1 + x_2 = 7$ $x_1 - 2x_2 \le 4$ $x_1 \ge 0$ • Max $2x_1 - 3x_2$ Subject to $x_1 + x_2 \le 7$
 - $-x_1 x_2 \le -7$ $x_1 - 2x_2 \le 4$ $x_1 \ge 0$

Converting to standard form

- Max $2x_1 3x_2$ Subject to $x_1 + x_2 \le 7$ $-x_1 - x_2 \le -7$ $x_1 - 2x_2 \le 4$ $x_1 \ge 0$ • Max $2x_1 - 3x_2$ Subject to x_2 is not constrained to be non-negative
- Max $2x_1 3(x_3 x_4)$ Subject to $x_1 + x_3 - x_4 \le 7$ $-x_1 - (x_3 - x_4) \le -7$ $x_1 - 2(x_3 - x_4) \le 4$ $x_{1,} x_3, x_4 \ge 0$

Converting to Standard form

• Max
$$2x_1 - 3x_2 + 3x_3$$
 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

• Max $2x_1 - 3x_2 + 3x_3$ Subject to $x_1 + x_2 - x_3 \le 7$ $-X_1 - X_2 + X_3 \le -7$ $x_1 - 2x_2 - 2x_3 \le 4$ $x_1 x_2, x_3 \ge 0$ • Max $2x_1 - 3x_2 + 3x_3$ Subject to $x_1 + x_2 - x_3 + x_4 = 7$ $-X_1 - X_2 + X_3 + X_5 = -7$ $x_1 - 2x_2 - 2x_3 + x_6 = 4$ $x_1, x_2, x_3, x_4, x_5, x_6 \ge 0$

Duality

- Max $c^T x$ Subject to $Ax \le b$ and $x \ge 0$
- Min y^Tb Subject to $y^TA \ge c^T$ and $y \ge 0$

[Primal]



Understanding Duality

Maximize x₁ + 6x₂ subject to constraints:

(1)

- ×₁ ≤ 200
- x₂ ≤ 300 (2)
- $x_1 + x_2 \le 400$ (3)
- $x_1, x_2 \ge 0$

How were mutipliers determined?

- (100,300) is feasible; v...ae = 1900. Optimum?
- Adding 1 times (1) + 6 times (2) gives us

• $x_1 + 6x_2 \le 2000$

- Adding 1 times (3) + 5 times (2) gives us
 - $x_1 + 6x_2 \le 1900$

• "Certificate of Optimality" for solution (100,300)

Understanding Duality

- Maximize $x_1 + 6x_2$ subject to:
 - $x_1 \le 200$ (y₁) • $x_2 \le 300$ (y₂) [(100,300)] • $x_1 + x_2 \le 400$ (y₃) • $x_1, x_2 \ge 0$
- Different choice of multipliers gives us different bounds. We want smallest bound.
- Minimize $200y_1 + 300y_2 + 400y_3$ subject to:
 - $\begin{array}{cccc} \cdot y_1 & + y_3 \ge 1 & (x_1) \\ \cdot & y_2 + y_3 \ge 6 & (x_2) & [(0,5,1)] \end{array}$
 - y₁, y₂ ≥ 0

Duality Principle

- Primal feasible values < dual feasible values
- Max primal value = min dual value
- Duality Theorem: If a linear program has a bounded optimal value then so does its dual and the two optimal values are equal.

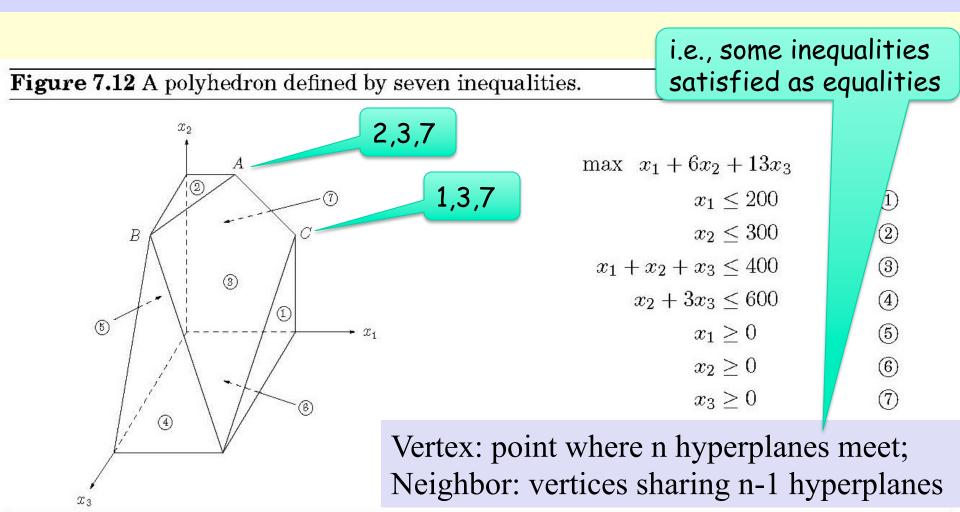
Visualizing Duality

- Shortest Path Problem
 - Build a physical model and between each pair of vertices attach a string of appropriate length
 - To find shortest path from s to t, hold the two vertices and pull them apart as much as possible without breaking the strings
 - This is exactly what a dual LP solves!
 - Max x_s-x_t
 - subject to $|x_u x_v| \le w_{uv}$ for every edge (u.v)
 - The taut strings correspond to the shortest path, i.e., they have no slack

Simplex Algorithm

- Start at v, any vertex of feasible region
- while (there is neighbor v' of v with better objective value) do
 set v = v'
- Report v as optimal point and its value as optimal value
- What is a
 - Vertex?, neighbor?
- Start vertex? How to pick next neighbor?

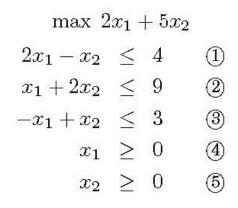
Simplex Algorithm: Example



Steps of Simplex Algorithm

 In order to find next neighbor from arbitrary vertex, we do a change of origin (pivot)

Initial LP:



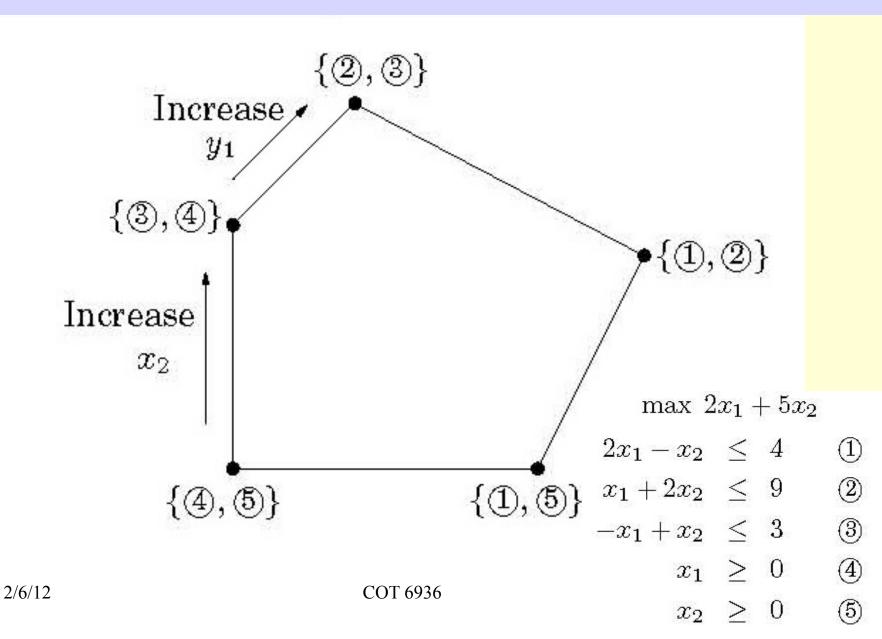
Current vertex: {(4), (5)} (origin). Objective value: 0.

Move: increase x_2 . (5) is released, (3) becomes tight. Stop at $x_2 = 3$.

New vertex $\{(4), (3)\}$ has local coordinates (y_1, y_2) :

$$y_1 = x_1, \ \ y_2 = 3 + x_1 - x_2$$

Simplex Algorithm Example



Simplex Algorithm Example

Initial LP: $ \begin{array}{rrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrr$	Current vertex: $\{4, 5\}$ (origin). Objective value: 0. Move: increase x_2 . 5 is released, 3 becomes tight. Stop at $x_2 = 3$. New vertex $\{4, 3\}$ has local coordinates (y_1, y_2) : $y_1 = x_1, y_2 = 3 + x_1 - x_2$
Rewritten LP: $max \ 15 + 7y_1 - 5y_2$ $y_1 + y_2 \le 7$ ① $3y_1 - 2y_2 \le 3$ ② $y_2 \ge 0$ ③ $y_1 \ge 0$ ④ $-y_1 + y_2 \le 3$ ⑤	Current vertex: $\{(4), (3)\}$. Objective value: 15. Move: increase y_1 . (4) is released, (2) becomes tight. Stop at $y_1 = 1$. New vertex $\{(2), (3)\}$ has local coordinates (z_1, z_2) : $z_1 = 3 - 3y_1 + 2y_2, z_2 = y_2$

Simplex Algorithm Example

Rewritten LP:

max $15 + 7y_1 - 5y_2$	0 Geome e
$egin{array}{rcl} y_1+y_2 &\leq & 7 & \ y_1-2y_2 &\leq & 3 & \ \end{array} \ (1)$	Move: incr ④ is releas
$egin{array}{rcl} y_2 &\geq & 0 & @ \ y_1 &\geq & 0 & @ \ -y_1+y_2 &\leq & 3 & @ \end{array} \ \end{array}$	New verte
Rewritten LP: max $22 - \frac{7}{3}z_1 - \frac{1}{3}z_2$	Current ve Objective v
$\begin{array}{rrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrr$	Optimal: a Solve $(2), (x_1, x_2) = ($

Current vertex: $\{4, 3\}$. Objective value: 15.

rease y_1 . used, (2) becomes tight. Stop at $y_1 = 1$. ex $\{(2), (3)\}$ has local coordinates (z_1, z_2) :

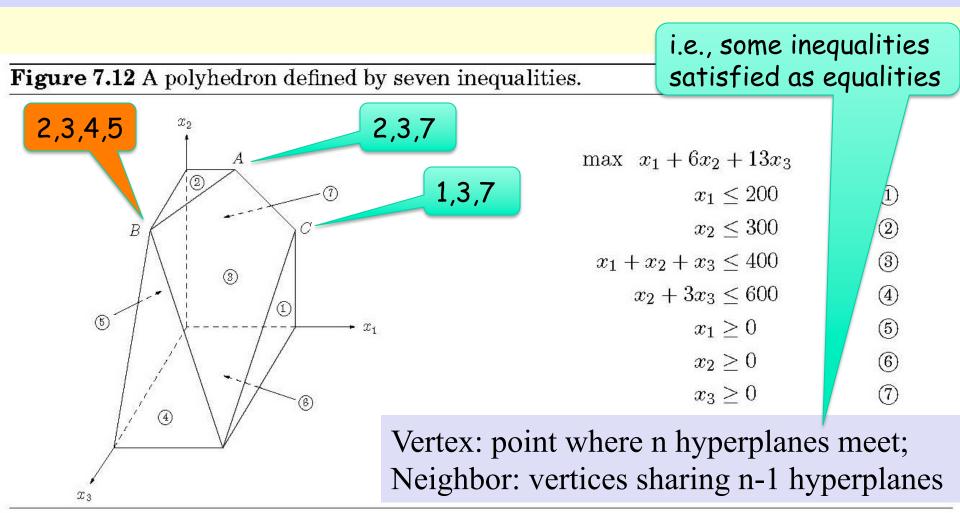
 $z_1 = 3 - 3y_1 + 2y_2, \quad z_2 = y_2$

 $ertex: \{(2), (3)\}.$ value: 22.

all $c_i < 0$.

③ (in original LP) to get optimal solution (1, 4).

Simplex Algorithm: Degenerate vertices



Polynomial-time algorithms for LP

- Simplex is not poly-time in the worst-case
- Khachiyan's ellipsoid algorithm: LP is in *P*
- Karmarkar's interior-point algorithm
- Good implementations for LP exist
 - Works very well in practice
 - More competitive than the poly-time methods for LP

Integer Linear Programming

- LP with integral solutions
- NP-hard
- If A is a totally unimodular matrix, then the LP solution is always integral.
 - A TUM is a matrix for which every nonsingular submatrix has determinant 0, +1 or -1.
 - A TUM is a matrix for which every nonsingular submatrix has integral inverse.

Vertex Cover as an LP?

- For vertex v, create variable x_v
- For edge (u,v), create constraint $x_u + x_v \ge 1$
- Objective function: Σx_v
- Additional constraints: $x_v \le 1$
- Doesn't work because x_v needs to be from $\{0,1\}$