# **15.093 Optimization Methods**

Lecture 11: Network Optimization The Network Simplex Algorithm

# Network Optimization

### Why do we care?

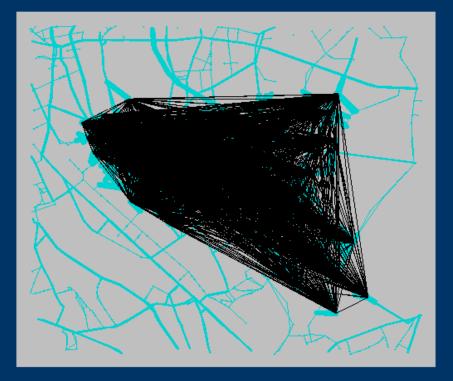
- Networks and associated optimization problems constitute reoccurring structures in many real-world applications.
- The network structure often leads to additional insight and improved understanding.
- Given integer data, the standard models have integer optimal solutions.
- The network structure also enables us to design more efficient algorithms.

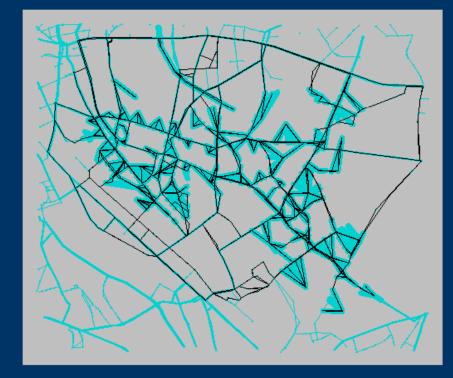
# Network Optimization

### A Comparison

Sample Instance...

#### 1,772 nodes and 2,880 arcs





# Network Optimization

### A Comparison

**Running Times** 

Algorithm	Running Time (sec)	# Iterations
Standard Simplex	334.59	42759
Network Simplex	7.37	23306
Ratio	2.2 %	54 %

Average over 5 random instances with 10,000 nodes and 25,000 arcs each.

# Outline

### **Today's Lecture**

- The Simplex Algorithm: A Reminder
   The Network Simplex: A Combineterial
- The Network Simplex: A Combinatorial View
- The Network Simplex: An Animated View
- The Network Simplex: An Algebraic View

# The Simplex Algorithm

### **A Reminder**

The Problem...

 $\begin{array}{ll} \min \ c'x\\ \mathrm{s.t.} \ Ax = b\\ x \geq 0 \end{array}$ 

SMA-HPC ©2000 MIT

# The Simplex Algorithm

### **A Reminder**

**The Algorithm** 

- 1. Start with basis  $B = [A_{B(1)}, \ldots, A_{B(m)}]$  and BFS x.
- 2. Compute  $\overline{c}_j = c_j c'_B B^{-1} A_j$ .
  - If  $\overline{c}_j \geq 0$ ; *x* optimal; stop.
  - Select j such that  $\overline{c}_j < 0$ .

3. Compute  $u = B^{-1}A_j$ .  $\theta^* = \min_{1 \le i \le m, u_i > 0} \frac{x_{B(i)}}{u_i} = \frac{x_{B(\ell)}}{u_\ell}$ .

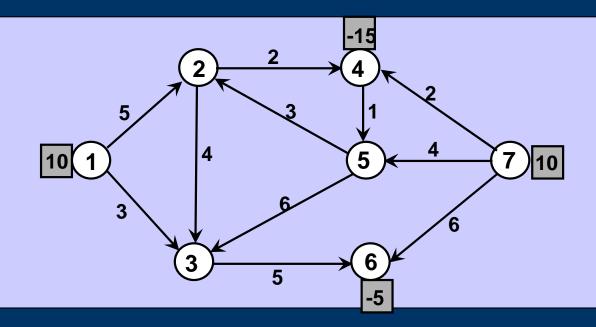
4. Form a new basis by replacing  $A_{B(\ell)}$  with  $A_j$ .

5. 
$$y_j = \theta^*$$
;  $y_{B(i)} = x_{B(i)} - \theta^* u_i$ .

#### **The Problem**

#### **Combinatorially...**

Determine a least cost shipment of a commodity through a network in order to satisfy demands at certain nodes from available supplies at other nodes. Arcs have costs associated with them.



- Network G = (N, A).
- Arc costs  $c: A \to \mathbb{Z}$ .
- Node balances  $b: N \to \mathbb{Z}$ .

#### **The Problem**

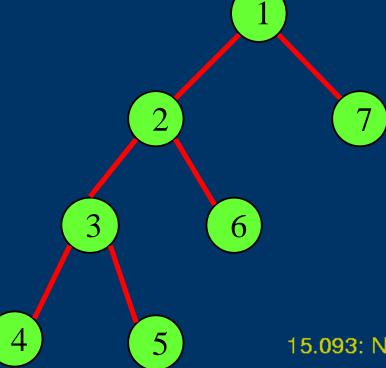
#### Algebraically...

 $egin{array}{lll} \min & \displaystyle{\sum_{(i,j)\in A}c_{ij}x_{ij}} \ {
m s.t.} & \displaystyle{\sum_{j:(i,j)\in A}x_{ij}-\sum_{j:(j,i)\in A}x_{ji}=b_i} \ {
m for all } i\in N \ {
m } x_{ij}\geq 0 \ {
m for all } (i,j)\in A \end{array}$ 

### **Tree Solutions**

#### Definition...

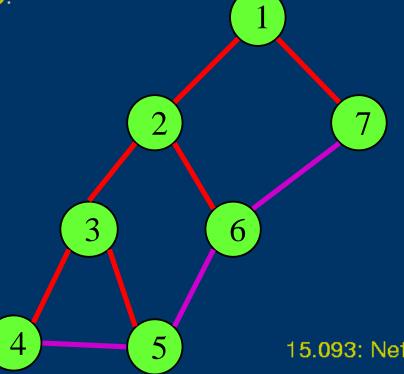
- A tree is a graph that is connected and has no cycles.
- A spanning tree of a graph G is a subgraph that is a tree and contains all nodes of G.
- A flow *a* forms a *tree solution* with a spanning tree of the network if every non-tree arc has flow 0.



### **Tree Solutions**

#### **Definition...**

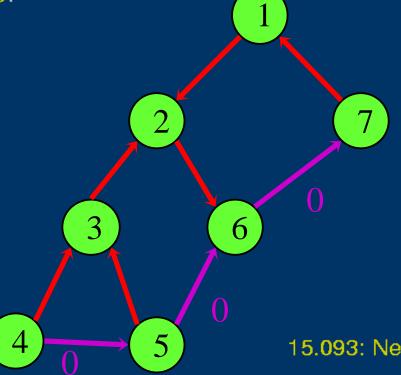
- A tree is a graph that is connected and has no cycles.
- A spanning tree of a graph G is a subgraph that is a tree and contains all nodes of G.
- A flow *a* forms a *tree solution* with a spanning tree of the network if every non-tree arc has flow 0.



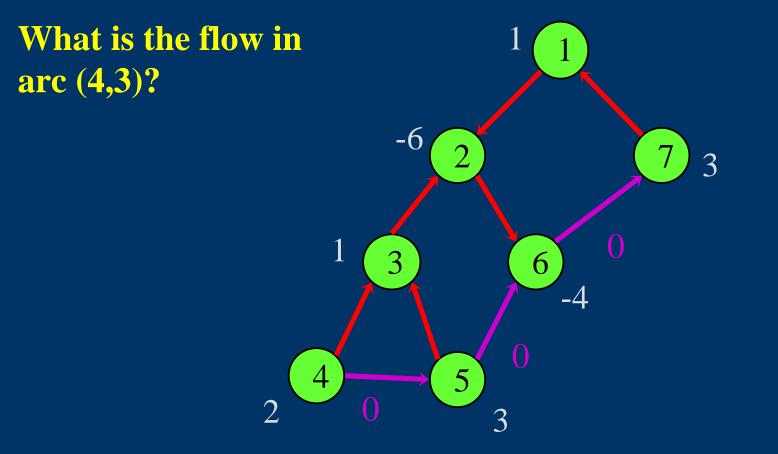
### **Tree Solutions**

#### Definition...

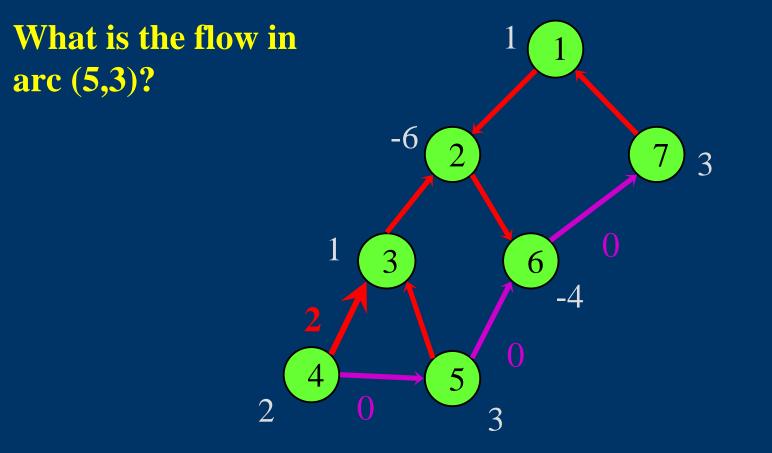
- A tree is a graph that is connected and has no cycles.
- A spanning tree of a graph G is a subgraph that is a tree and contains all nodes of G.
- A flow *a* forms a *tree solution* with a spanning tree of the network if every non-tree arc has flow **0**.



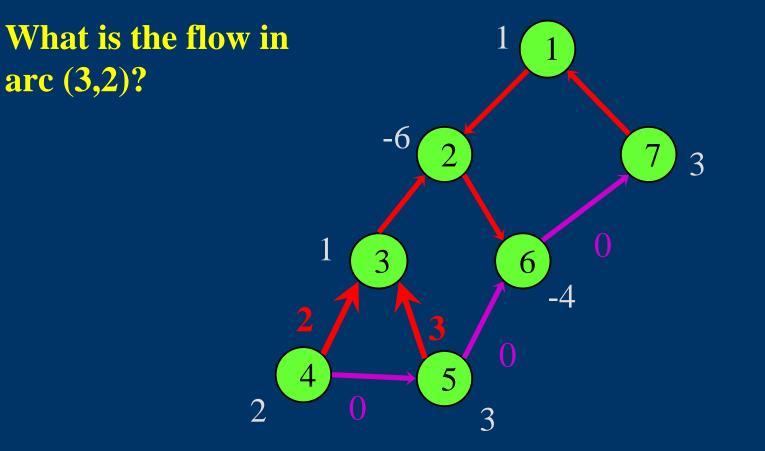
### **Tree Solutions**



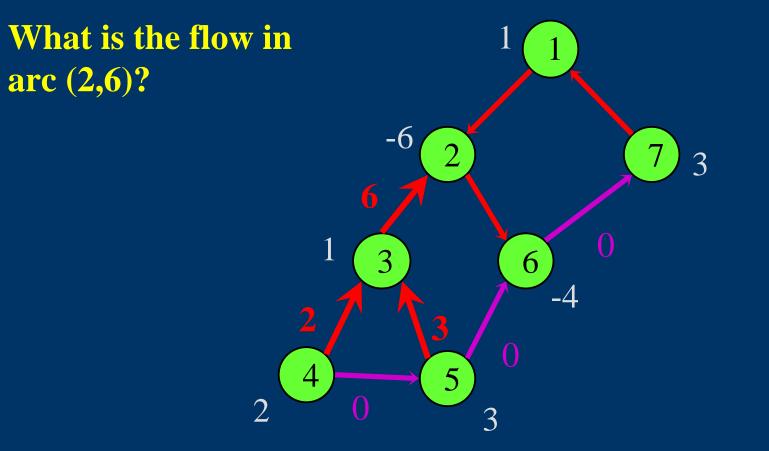
### **Tree Solutions**



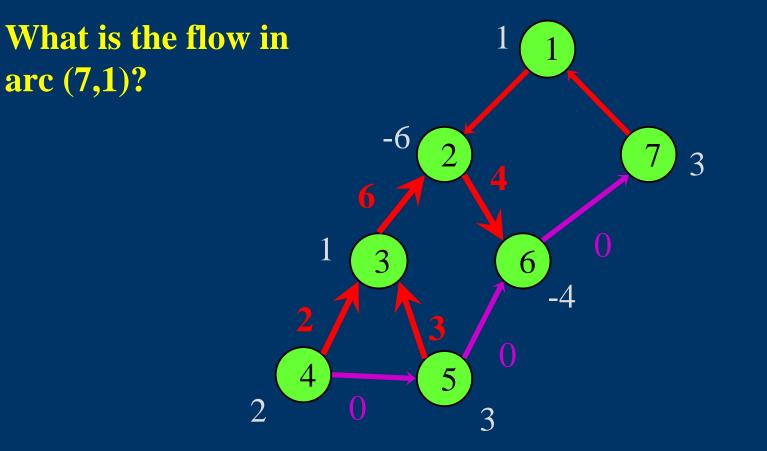
### **Tree Solutions**



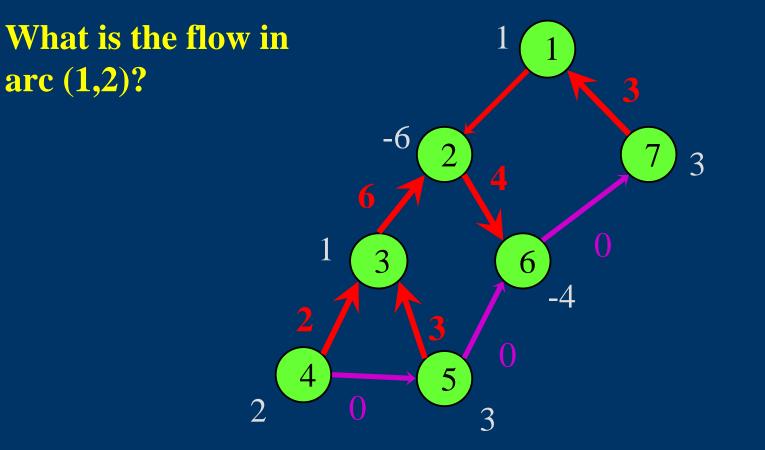
### **Tree Solutions**



### **Tree Solutions**



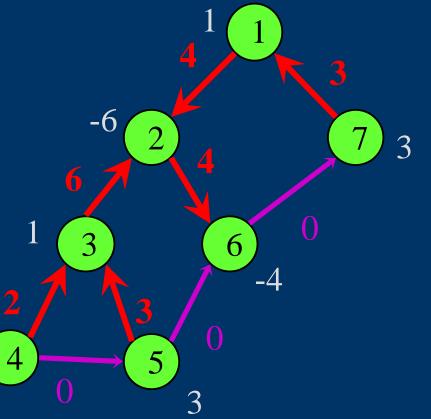
### **Tree Solutions**



### **Tree Solutions**

#### **Computing the Flow...**

**Note:** there are two different ways of calculating the flow on (1,2), and both ways give a flow of 4. Is this a coincidence?



2

### **Tree Solutions**

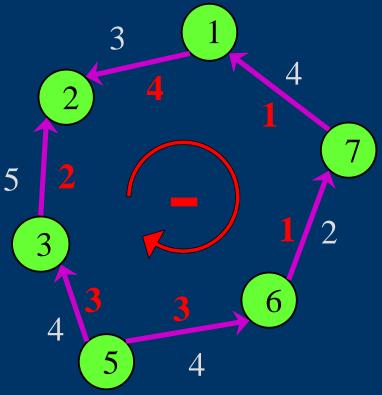
Trees vs. Tree Flows...

- Every tree flow has a corresponding tree (and perhaps more than one).
- Given a tree, we obtain a unique tree flow associated with it.

### **Tree Solutions**

**BFS Property...** 

**Theorem 1** If the objective function is bounded from below, a min-cost flow problem always has an optimal tree solution.

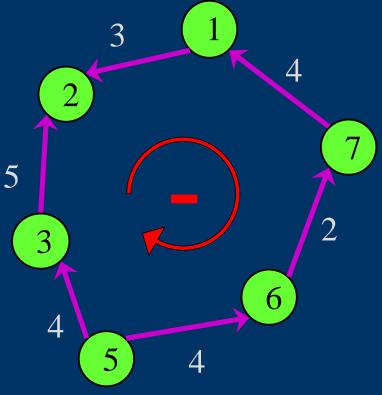


flow cost

### **Tree Solutions**

**BFS Property...** 

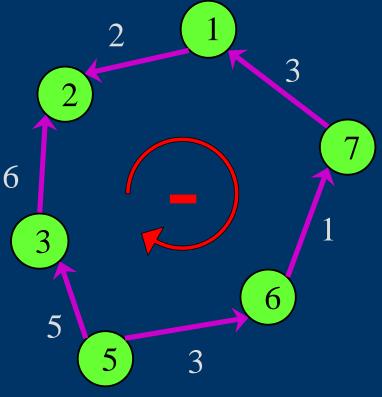
**Theorem 1** If the objective function is bounded from below, a min-cost flow problem always has an optimal tree solution.



### **Tree Solutions**

**BFS Property...** 

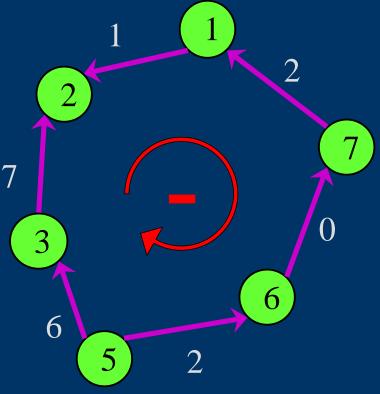
**Theorem 1** If the objective function is bounded from below, a min-cost flow problem always has an optimal tree solution.



### **Tree Solutions**

**BFS Property...** 

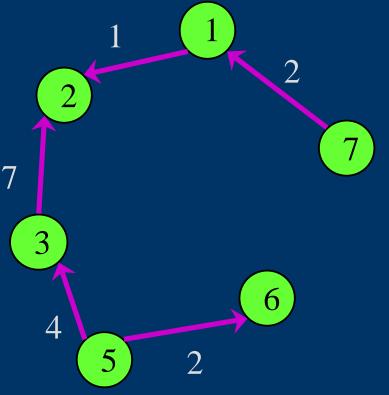
**Theorem 1** If the objective function is bounded from below, a min-cost flow problem always has an optimal tree solution.



### **Tree Solutions**

**BFS Property...** 

**Theorem 1** If the objective function is bounded from below, a min-cost flow problem always has an optimal tree solution.



### **Tree Solutions**

**Optimality Condition...** 

**Theorem 2** A (feasible) tree T is optimal if, for some choice of node potentials  $p_i$ ,

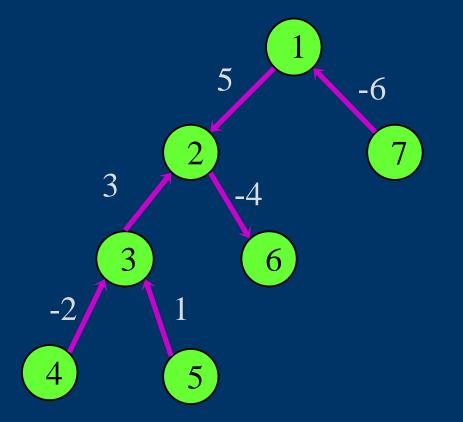
(a)  $\overline{c}_{ij} = c_{ij} - p_i + p_j = 0$  for all  $(i, j) \in T$ , (b)  $\overline{c}_{ij} = c_{ij} - p_i + p_j \ge 0$  for all  $(i, j) \in A \setminus T$ .

Proof:

- $\min \sum_{(i,j)\in A} c_{ij} x_{ij}$  is equivalent to  $\min \sum_{(i,j)\in A} \overline{c}_{ij} x_{ij}$ .
- $\min \sum_{(i,j) \in A} \overline{c}_{ij} x_{ij}$  is equivalent to  $\min \sum_{(i,j) \in A \setminus T} \overline{c}_{ij} x_{ij}$ .
- For any solution  $oldsymbol{x}, oldsymbol{x_{ij}} \geq oldsymbol{x^*_{ij}}$  for all  $(i,j) \in A \setminus T$ .

### **Tree Solutions**

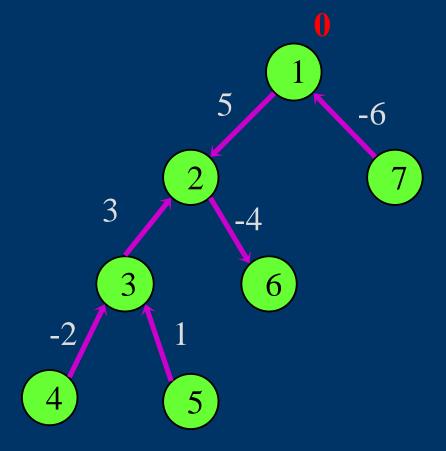
**Computing Node Potentials...** 



Here is a spanning tree with arc costs. How can one choose node potentials so that reduced costs of tree arcs are 0?

### **Tree Solutions**

**Computing Node Potentials...** 



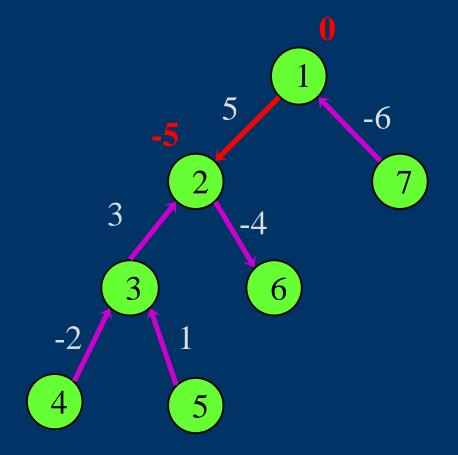
There is a redundant constraint in the minimum cost flow problem.

One can set  $p_1$  arbitrarily. We will let  $p_1 = 0$ .

What is the node potential for 2?

### **Tree Solutions**

**Computing Node Potentials...** 

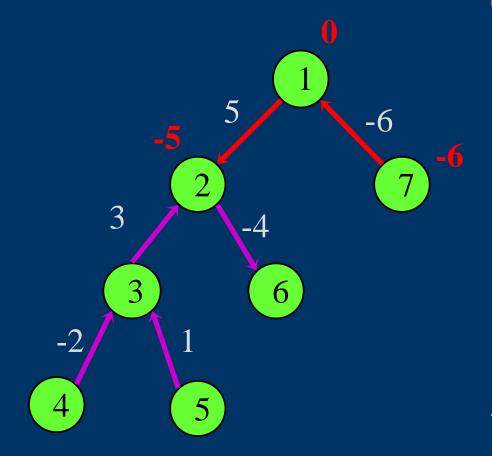


#### What is the node potential for 7?

#### SMA-HPC ©2000 MIT

### **Tree Solutions**

#### **Computing Node Potentials...**

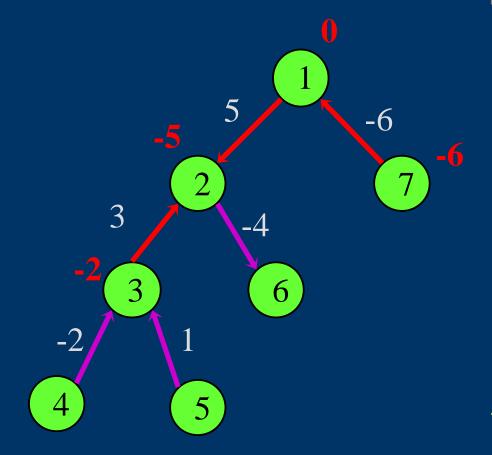


#### What is the potential for node 3?



### **Tree Solutions**

#### **Computing Node Potentials...**

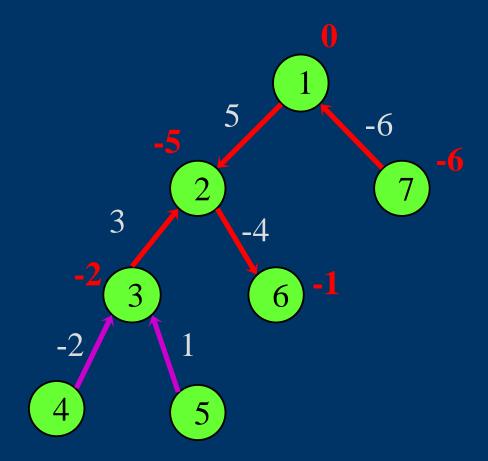


#### What is the potential for node 6?

SMA-HPC ©2000 MIT

### **Tree Solutions**

#### **Computing Node Potentials...**

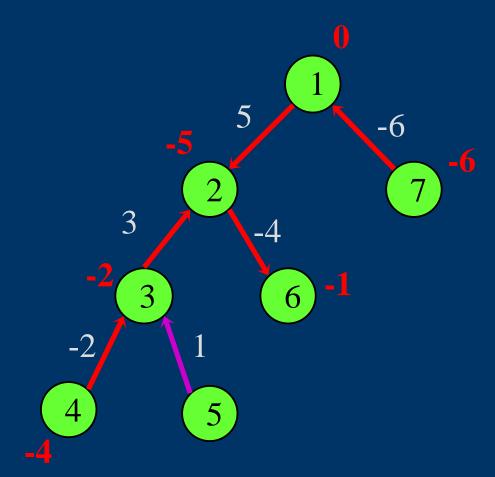


#### What is the potential for node 4?

#### SMA-HPC ©2000 MIT

### **Tree Solutions**

#### **Computing Node Potentials...**



#### What is the potential for node 5?

SMA-HPC ©2000 MIT

5

6

-6

### **Tree Solutions**

**Computing Node Potentials...** 

These are the node potentials associated with this tree. They do not depend on arc flows, nor on costs of non-tree arcs.

SMA-HPC ©2000 MIT

5

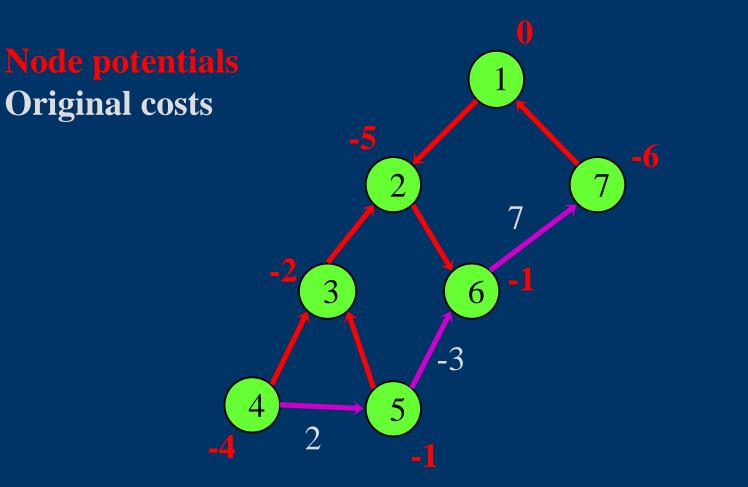
3

-2

3

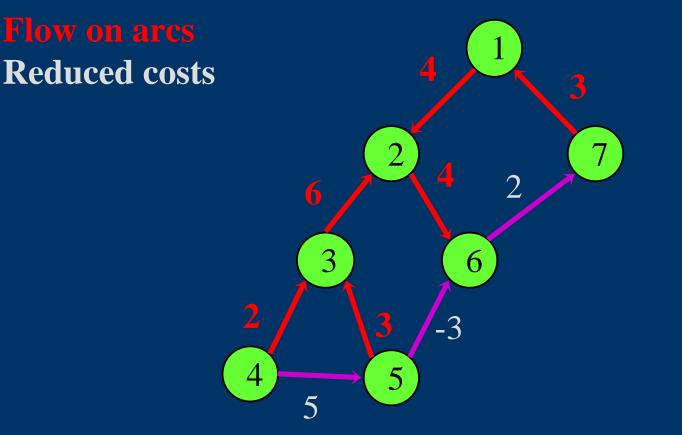
### **Tree Solutions**

**Updating the Tree...** 



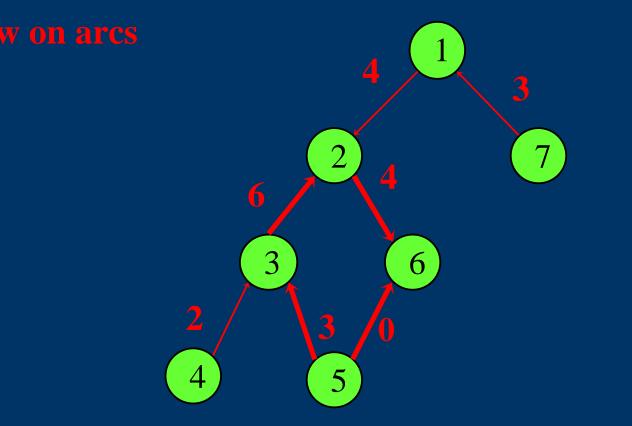
### **Tree Solutions**

**Updating the Tree...** 



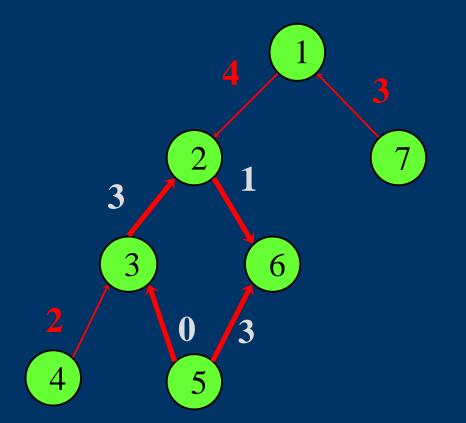
### **Tree Solutions**

**Updating the Tree...** 



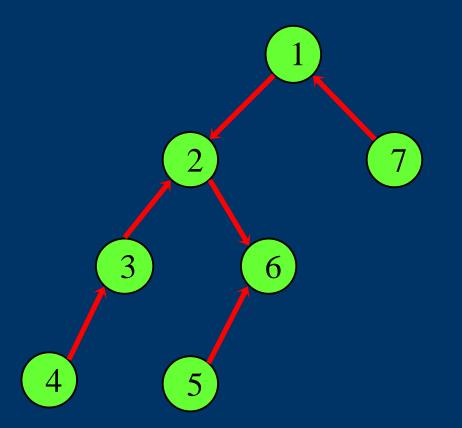
### **Tree Solutions**

**Updating the Tree...** 



### **Tree Solutions**

**Updating the Tree...** 



## **Overview of the Algorithm**

- Determine an initial feasible tree T. Compute flow *a* and node potentials *p* associated with T.
- 2. Calculate  $\overline{c}_{ij} = c_{ij} p_i + p_j$  for  $(i, j) \notin T$ .
  - If  $\overline{c} \geq 0$ , *x* optimal; stop.
  - Select (i, j) with  $\overline{c}_{ij} < 0$ .
- 3. Add (i, j) to T creating a unique cycle C. Send a maximum flow around C while maintaining feasibility. Suppose the exiting arc is  $(k, \ell)$ .
- $4. T := (T \setminus (k, \ell)) \cup (i, j).$

# **Min-Cost Flow**

Our reasoning has two important and far-reaching implications:

Integrality

- There always exists an integer optimal flow (if node balances b<sub>i</sub> are integer).
- There always exist optimal integer node potentials (if arc costs c<sub>ij</sub> are integer).

#### **An Animation**

SMA-HPC ©2000 MIT

**The Algebraic View** 

- Bases and trees.
- Dual variables and node potentials.
- Changing bases and updating trees.
- Optimality testing.

### **The Algebraic View**

Bases vs. Trees...

The constraint matrix A of the min-cost flow problem is the node-arc incidence matrix of the underlying network.

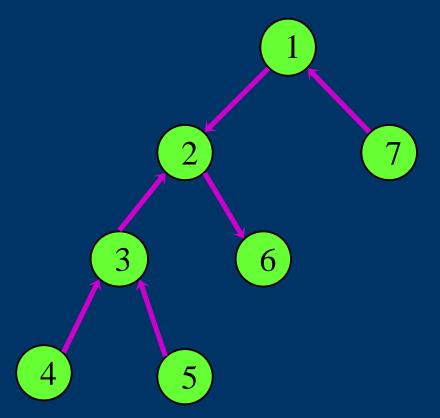
	(1, 2)	(2, 6)	(3, 2)	(4, 3)	(4, 5)	(5,3)	(5, 6)	(6,7)	(7, 1)
1	+1	0	0	0	0	0	0	0	-1
2	-1	+1	-1	0	0	0	0	0	0
3	0	0	+1	-1	0	-1	0	0	0
4	0	0	0	+1	+1	0	0	0	0
<b>5</b>	0	0	0	0	-1	+1	+1	0	0
6	0	-1	0	0	0	0	-1	+1	0
7	0	0	0	0	0	0	0	-1	+1

The rows of *A* are linearly dependent.

## **The Algebraic View**

....Bases vs. Trees...

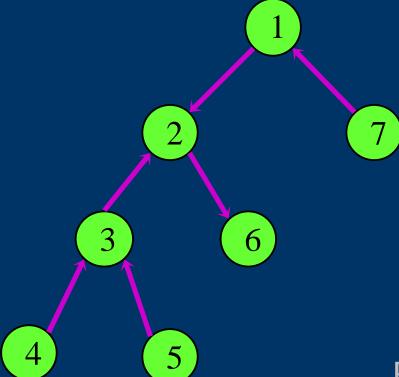
Let **B** be the submatrix corresponding to the tree



## **The Algebraic View**

...Bases vs. Trees...

Let **B** be the submatrix corresponding to the tree



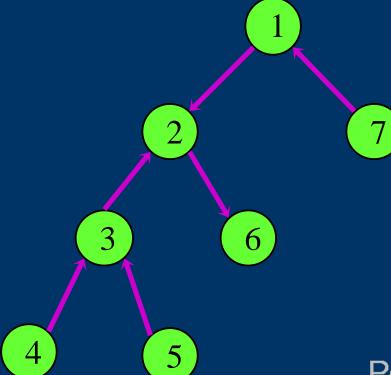
	(1, 2)	(2, 6)	(3, 2)	(4, 3)	(5,3)	(7,1)
4	0	0	0	+1	0	0
<b>5</b>	0	0	0	0	+1	0
6	0	-1	0	0	0	0
7	0	0	0	0	0	+1
3	0	0	+1	-1	-1	0
<b>2</b>	-1	+1	-1	0	0	0
1	+1	0	0	0	0	1

Permuting Rows

## **The Algebraic View**

...Bases vs. Trees...

Let **B** be the submatrix corresponding to the tree



	(4, 3)	(5, 3)	(2, 6)	(7,1)	(3, 2)	(1, 2)
4	+1	0	0	0	0	0
<b>5</b>	0	+1	0	0	0	0
6	0	0	-1	0	0	0
7	0	0	0	+1	0	0
3	-1	-1	0	0	+1	0
2	0	0	+1	0	-1	- <b>1</b>
1	0	0	0	-1	0	+1

**Permuting Columns** 

SMA-HPC ©2000 MIT

## **The Algebraic View**

...Bases vs. Trees...

### **Corollary 1**

# (a) The matrix *A* has rank *n* - 1. (b) Every tree solution is a basic solution.

## **The Algebraic View**

...Bases vs. Trees...

**Theorem 3** Every tree defines a basis and, conversely, every basis definies a tree.

Suppose the graph defined by a basis contains a cycle 1 - 2 - 3 - 4 - 5 - 6:

#### The Algebraic View

Dual Variables vs. Node Potentials...

Remember, the simplex algorithm computes the dual variables p as the solution to  $p' B = c'_B$ .

	(+1)	0	0	0	0	0
	0					
), m, m, m,	0	0	- <b>1</b>	0	0	0
$(p_6, p_7, p_3, p_2)$	0	0	0	+1	0	0
					+1	· · · · · · · · · · · · · · · · · · ·
	0	0	+1	0	-1	-1

 $(p_4, p_5, p$ 

 $(c_{43}, c_{53}, c_{26}, c_{71}, c_{32}, c_{12})$ 

Hence,  $p_2 = -c_{12}, p_3 = c_{32} + p_2, p_7 = c_{71}, \dots$ 

SMA-HPC ©2000 MIT

\_

## **The Algebraic View**

**Optimality Testing...** 

Remember, the simplex algorithm computes the reduced costs  $\overline{c}$  as  $\overline{c}_{ij} = c_{ij} - p'A_{ij}$ .

	(1, 2)	(2, 6)	(3, 2)	(4, 3)	(4, 5)	(5, 3)	(5, 6)	(6,7)	(7, 1)
1	+1	0	0	0	0	0	0	0	-1
<b>2</b>	-1	+1	-1	0	0	0	0	0	0
3	0	0	+1	-1	0	-1	0	0	0
4	0	0	0	+1	+1	0	0	0	0
<b>5</b>	0	0	0	0	-1	+1	+1	0	0
6	0	-1	0	0	0	0	-1	+1	0
7	0	0	0	0	0	0	0	-1	+1

Therefore,  $\overline{c}_{ij} = c_{ij} - p_i + p_j$ .

## Summary

- The network simplex algorithm is extremely fast in practice.
- Relying on network data structures, rather than matrix algebra, causes the speedups. It leads to simple rules for selecting the entering and exiting variables.
- Running time per pivot:
  - arcs scanned to identify an entering arc,
  - arcs scanned of the basic cycle,
  - nodes of the subtree.
- A good pivot rule can dramatically reduce running time in practice.

MIT OpenCourseWare http://ocw.mit.edu

15.093J / 6.255J Optimization Methods Fall 2009

For information about citing these materials or our Terms of Use, visit: http://ocw.mit.edu/terms.