The Minimum Labeling Spanning Tree Problem: Heuristic and Metaheuristic Approaches

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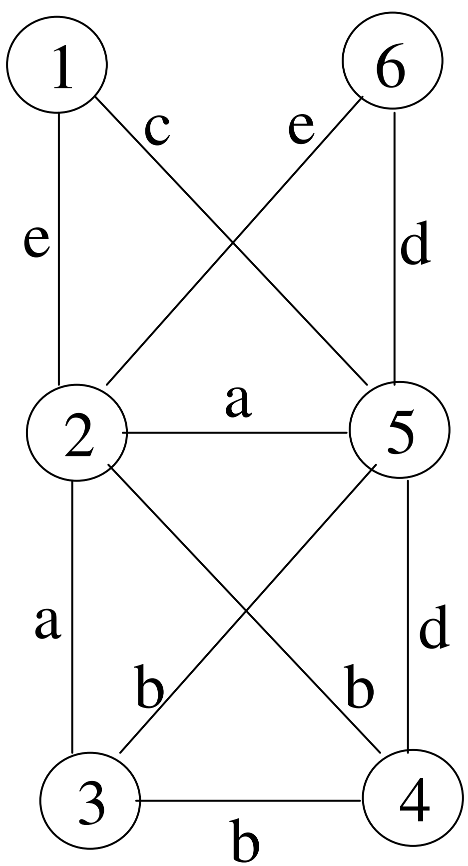
Introduction

- The Minimum Labeling Spanning Tree (MLST) Problem
  - Communications network design
  - Edges may be of different types or media (e.g., fiber optics, cable, microwave, telephone lines, etc.)
  - Each edge type is denoted by a unique letter or color
  - Construct a spanning tree that minimizes the number of colors

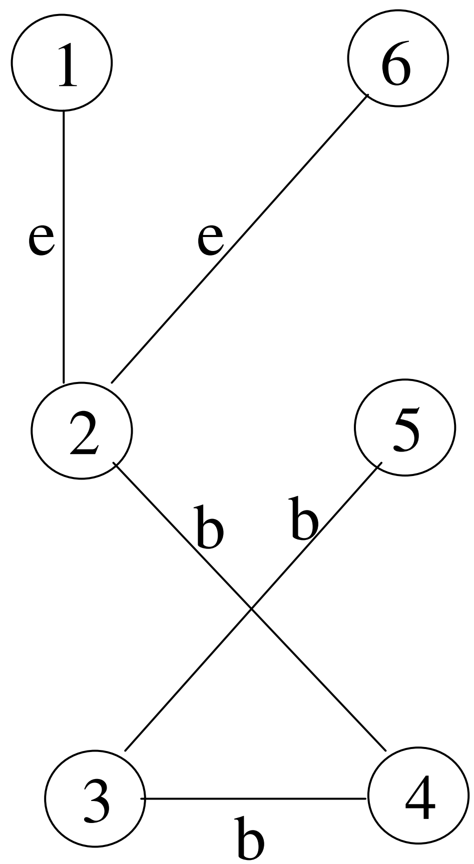
Introduction

- A Small Example

Input



Solution



Literature Review

- Where did we start?

  - The MLST Problem is NP-hard
  - Several heuristics had been proposed
  - One of these, MVCA (version 2), was very fast and effective
  - Worst-case bounds for MVCA had been obtained

Literature Review

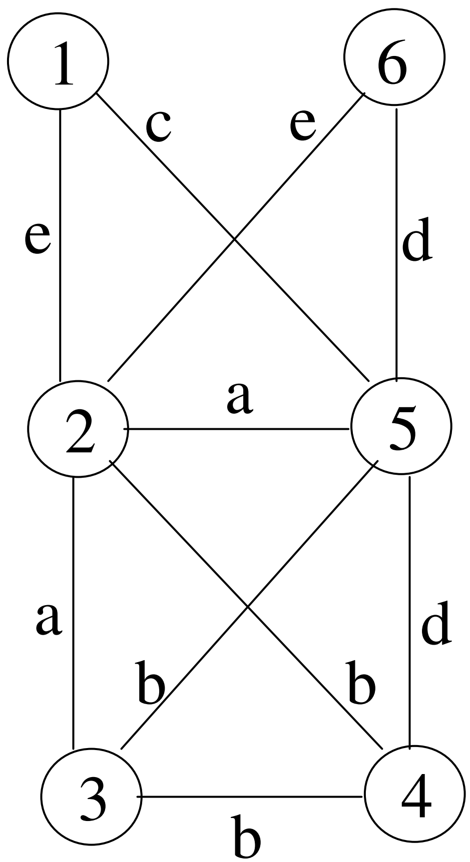
- An optimal algorithm (using backtrack search) had been proposed
- On small problems, MVCA consistently obtained nearly optimal solutions
- See [Chang & Leu, 1997], [Krumke & Wirth, 1998], [Wan, Chen & Xu, 2002], and [Bruggemann, Monnot & Woeginger, 2003]

Description of MVCA

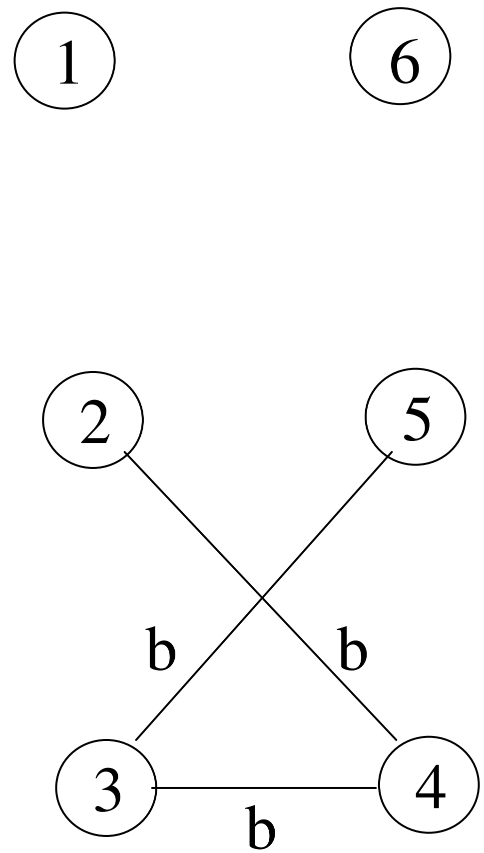
0. Input: $G\ (V, E, L)$.
1. Let $C \leftarrow \{\ \}$ be the set of used labels.
2. repeat
3. Let H be the subgraph of G restricted to V and edges with labels from C.
4. for all $i \in L - C$ do
5. Determine the number of connected components when inserting all edges with label i in H.
6. end for
7. Choose label i with the smallest resulting number of components and do: $C \leftarrow C \cup \{i\}$.
8. Until H is connected.

How MVCA Works

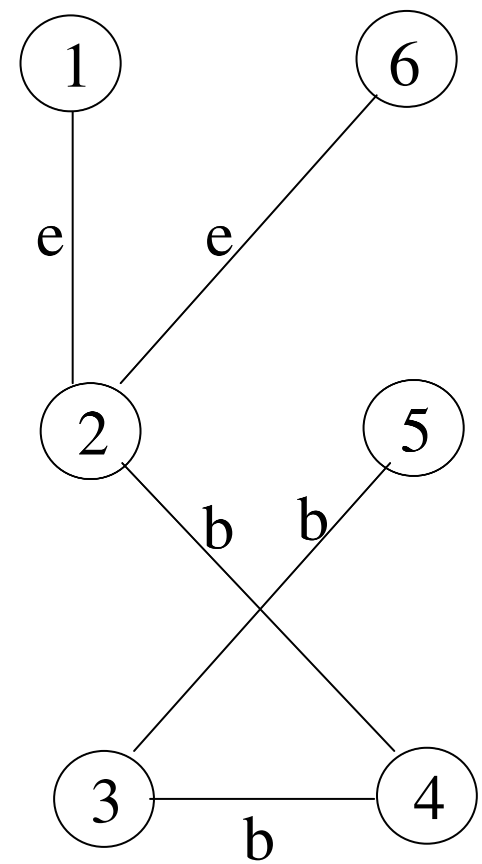
Input



Intermediate Solution



Solution



Worst-Case Results

1. Krumke, Wirth (1998): $$\frac{\text{MVCA}}{\text{OPT}} \leq 1 + 2\ln n$$

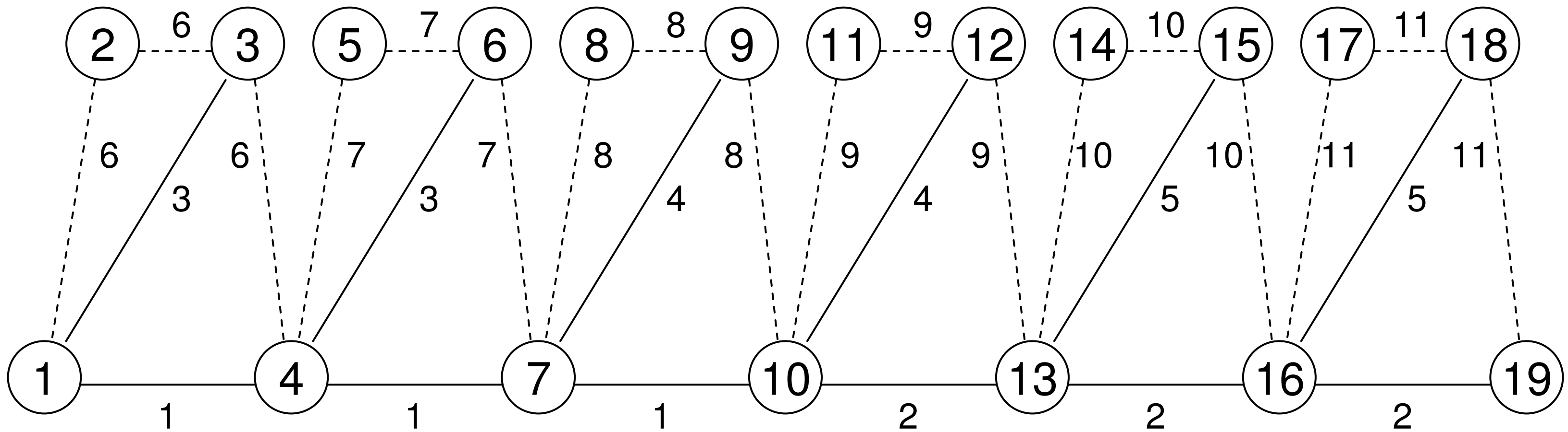
2. Wan, Chen, Xu (2002): $$\frac{\text{MVCA}}{\text{OPT}} \leq 1 + \ln(n-1)$$

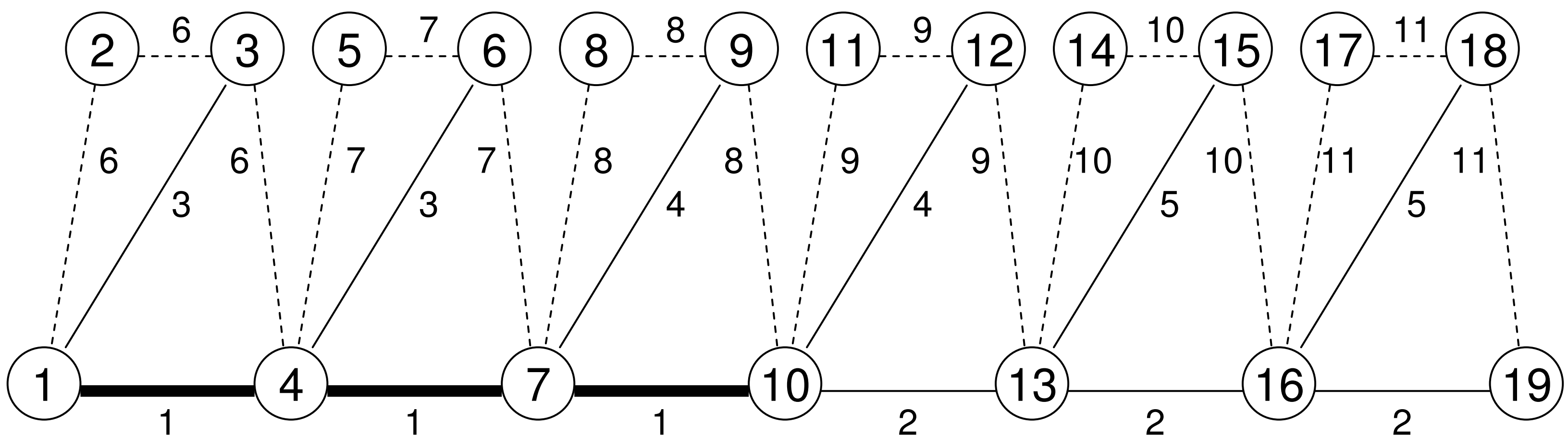
3. Xiong, Golden, Wasil (2005): $$\frac{\text{MVCA}}{\text{OPT}} \leq H_b = \sum_{i=1}^{b} \frac{1}{i} < 1 + \ln b$$

where b = max label frequency, and

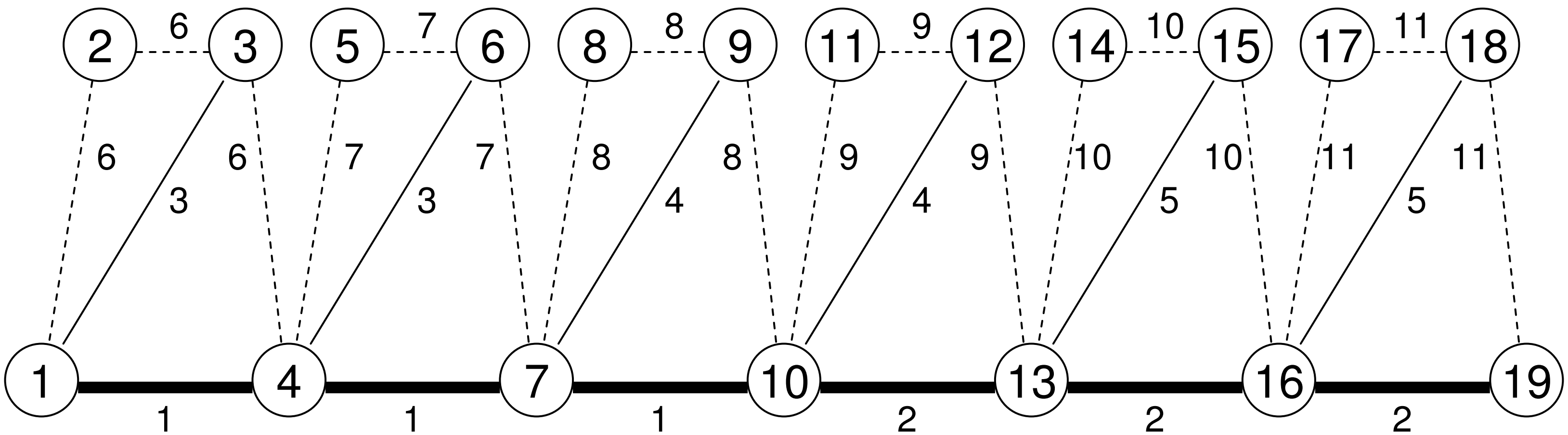
H_b= b^{th} harmonic number

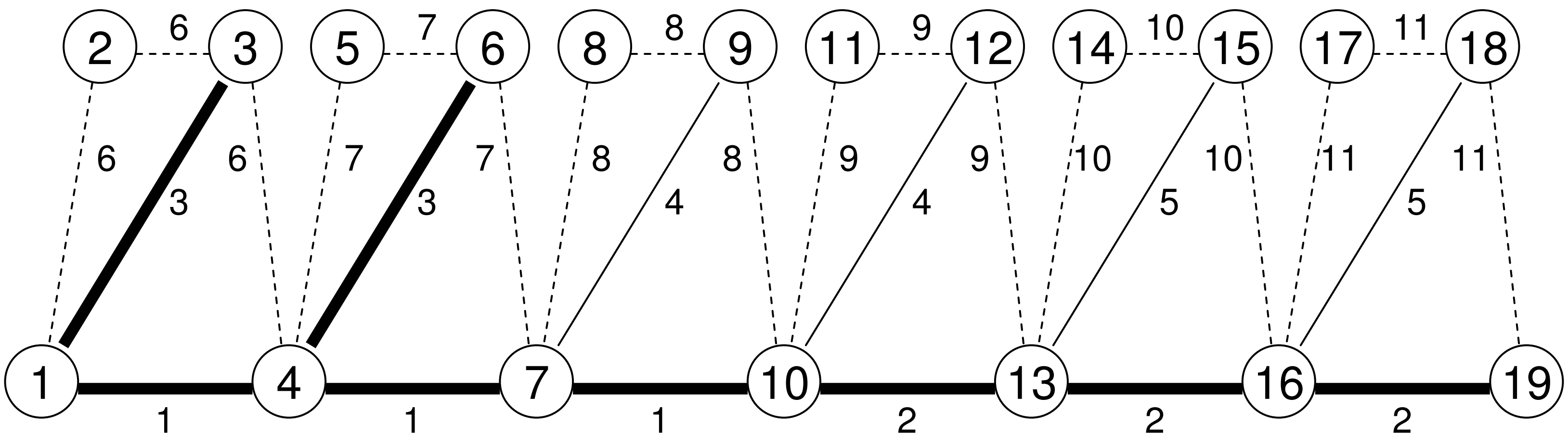
A Worst-Case Example



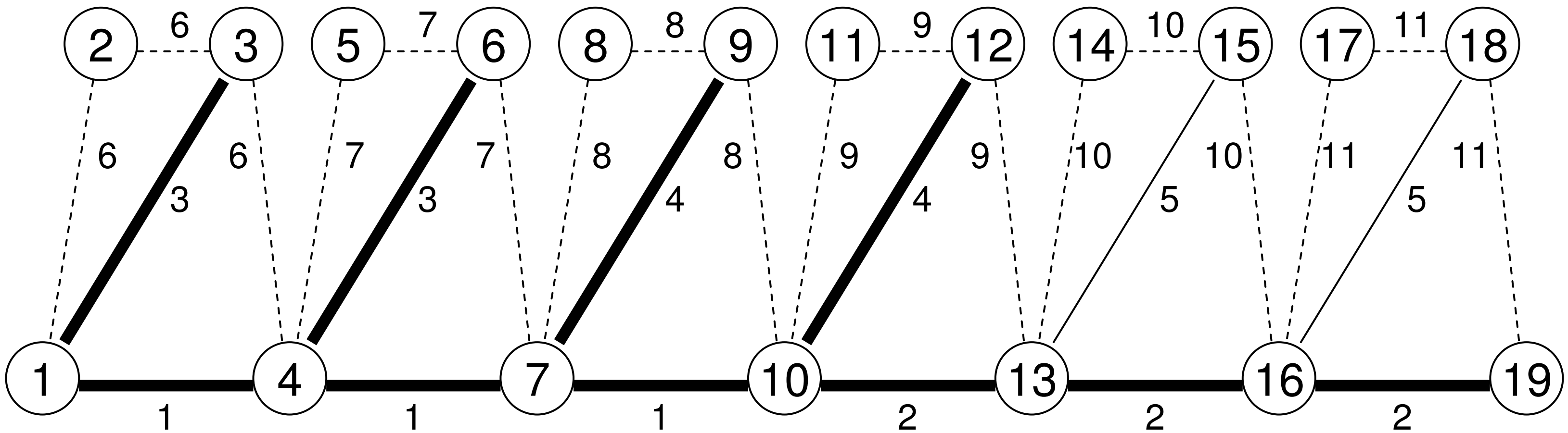


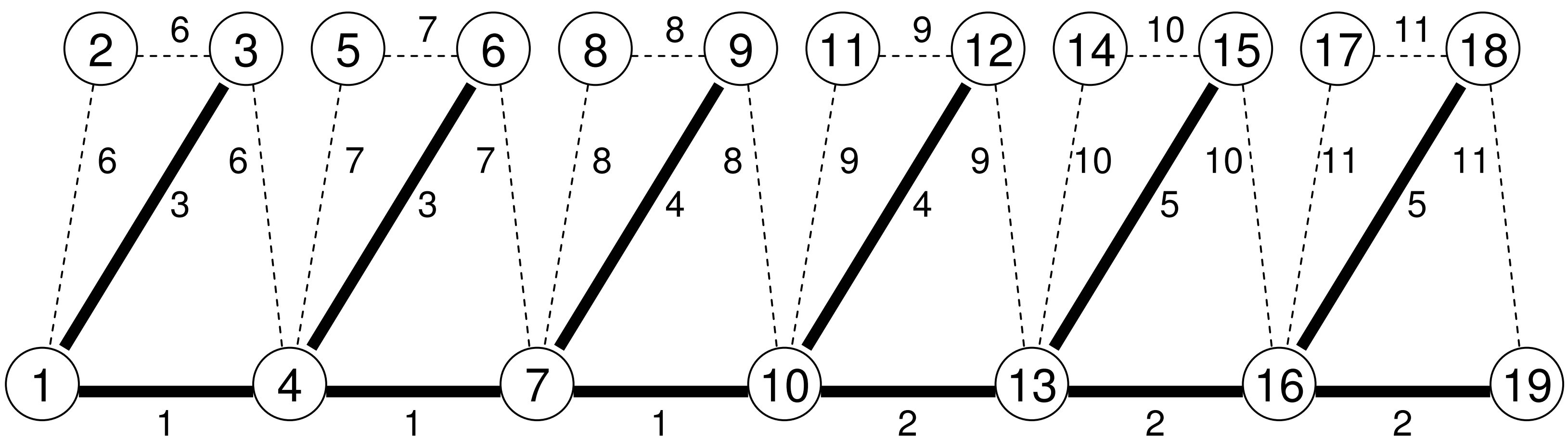
A Worst-Case Example - continued





A Worst-Case Example - continued





Some Observations

- The Xiong, Golden, Wasil worst-case bound is tight
- For the worst-case example with $b = 3$ and $n = 19$,

$$\frac{\text{MVCA}}{\text{OPT}} = \frac{11}{6} = 1 + \frac{1}{2} + \frac{1}{3} = H_3$$

- Unlike the MST, where we focus on the edges, here it makes sense to focus on the labels or colors
- Next, we present a genetic algorithm (GA) for the MLST problem

Genetic Algorithm: Overview

- Randomly choose p solutions to serve as the initial population
- Suppose s [0], s [1], … , s [p – 1] are the individuals (solutions) in generation 0
- Build generation k from generation k – 1 as below

For each j between 0 and p – 1, do:

t [j] = crossover { s [j], s [(j + k) mod p] }

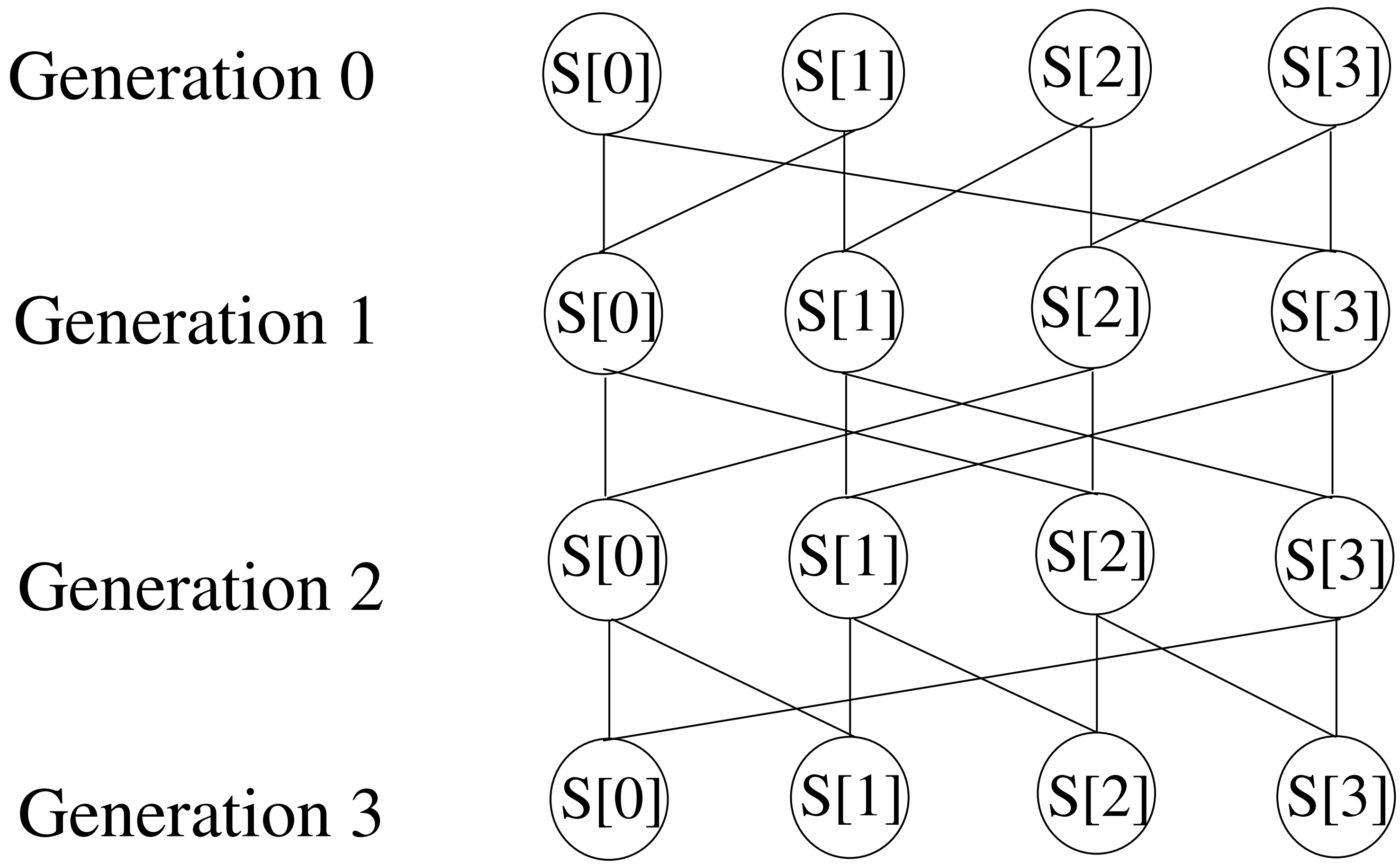
t [j] = mutation { t [j] }

s [j] = the better solution of s [j] and t [j]

End For

- Run until generation p – 1 and output the best solution from the final generation

Crossover Schematic (p = 4)



Crossover

- Given two solutions s [1] and s [2], find the child T = crossover { s [1], s [2] }
- Define each solution by its labels or colors
- Description of Crossover

  a. Let S = s [1] $\cup$ s [2] and T be the empty set

  b. Sort S in decreasing order of the frequency of labels in G

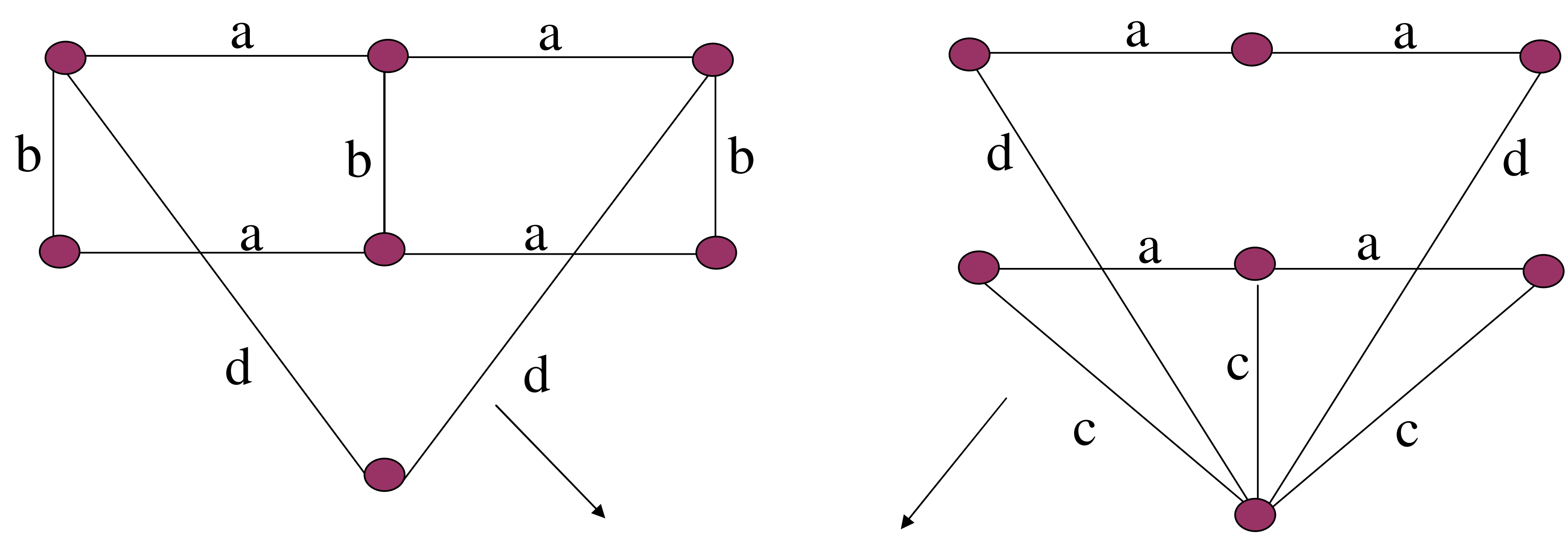
  c. Add labels of S, from the first to the last, to T until T represents a feasible solution

  d. Output T

An Example of Crossover

s [1] = { a, b, d }

s [2] = { a, c, d }



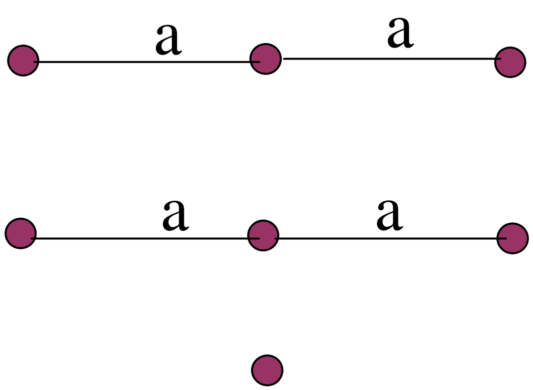
T = { }

S = { a, b, c, d }

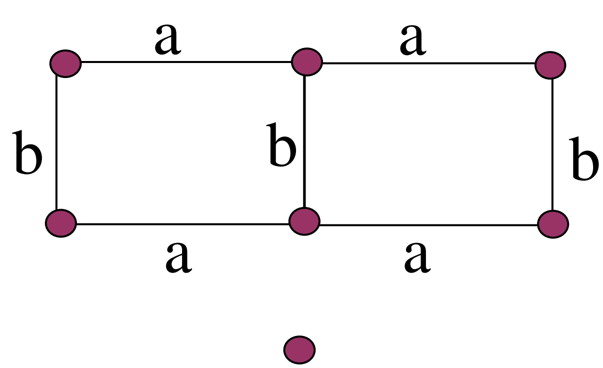
Ordering: a, b, c, d

An Example of Crossover

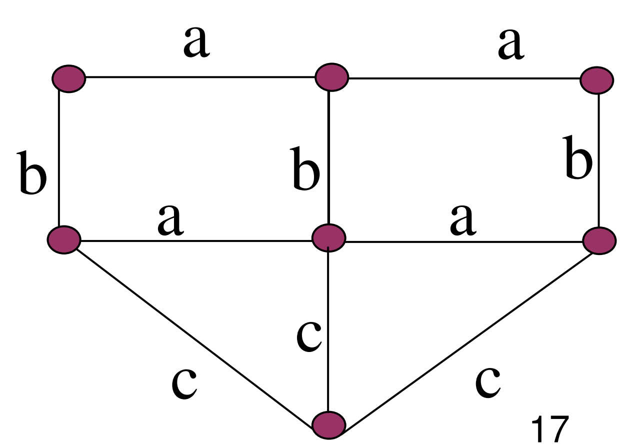
T = { a }



T = { a, b }



T = { a, b, c }



Mutation

- Given a solution S, find a mutation T
- Description of Mutation

  a. Randomly select c not in S and let $T = S \cup c$

  b. Sort T in decreasing order of the frequency of the labels in G

  c. From the last label on the above list to the first, try to remove one label from T and keep T as a feasible solution

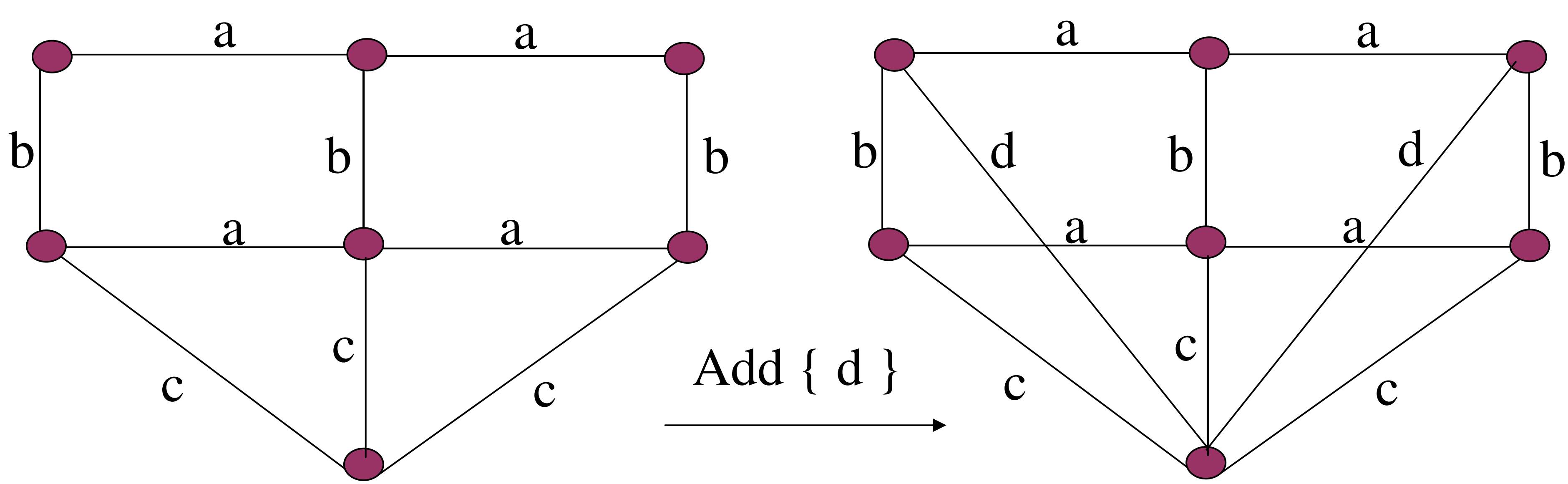
  d. Repeat the above step until no labels can be removed

  e. Output T

An Example of Mutation

S = { a, b, c }

S = { a, b, c, d }



Ordering: a, b, c, d

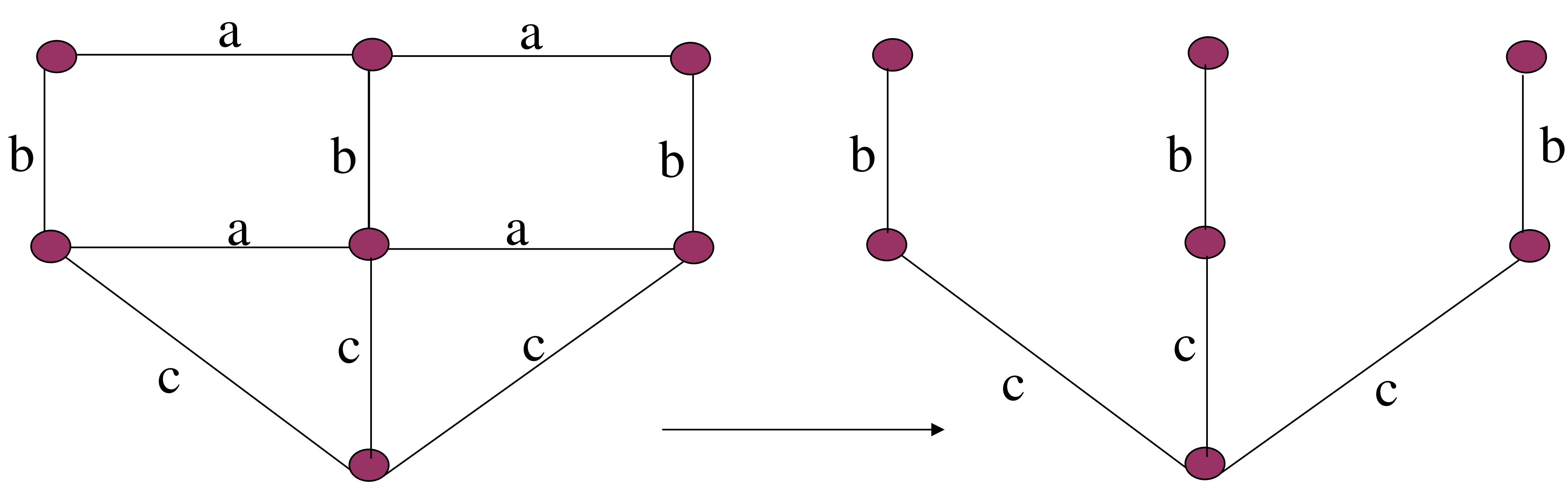
An Example of Mutation

Remove { d }

S = { a, b, c }

Remove { a }

S = { b, c }



T = { b, c }

Computational Results

- 78 combinations: n = 20 to 200 / l = 12 to 250 / density = .2, .5, .8 / p = 30 if n > 100; otherwise p = 20
- 20 sample graphs for each combination
- The average number of labels is compared
- GA beats MVCA in 58 of 78 cases (17 ties, 3 worse)
- The optimal solution was obtained using backtrack search in 740 instances

Computational Results - continued

- The GA obtains optimal solutions in 701 or 94.73% of these instances
- GA is slightly slower than MVCA
- GA required at most 2 seconds CPU time per instance on a Pentium 4 PC with 1.80 GHz and 256 MB RAM
- Backtrack search was run for at most 20 minutes per instance

Conclusions & Future Work

- The GA is fast, conceptually simple, and powerful
- It contains a single parameter
- We think GAs can be applied successfully to a host of other NP – hard problems
- Future work
  - Add edge costs
  - Examine other variants