

# Treewidth

## Algorithms and Networks



# Overview

- Historic introduction: Series parallel graphs
- Dynamic programming on trees
- Dynamic programming on series parallel graphs
- Treewidth
- Dynamic programming on graphs of small treewidth
- Finding tree decompositions

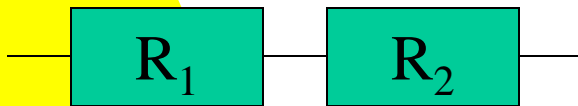


# Computing the Resistance With the Laws of Ohm



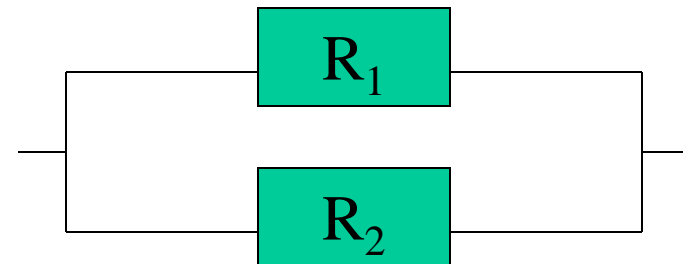
1789-1854

$$R = R_1 + R_2$$



*Two resistors  
in series*

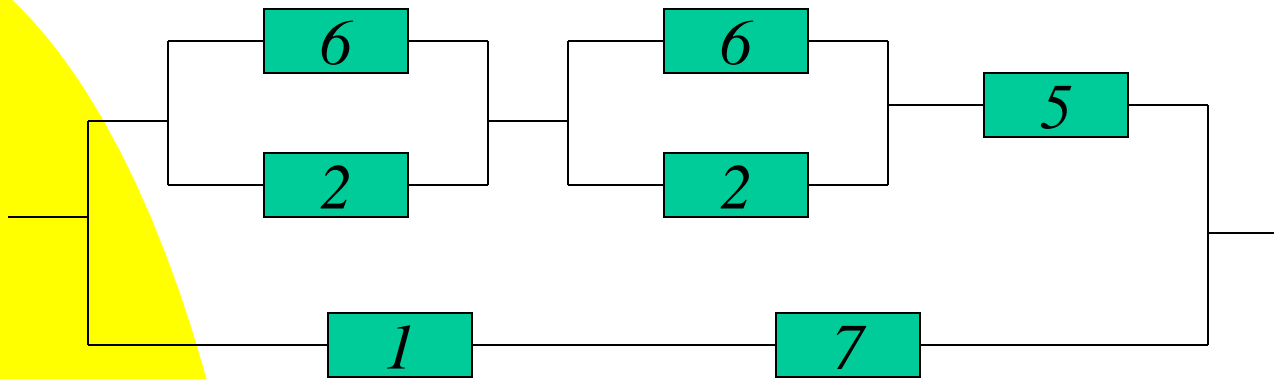
$$\frac{1}{R} = \frac{1}{R_1} + \frac{1}{R_2}$$



*Two resistors  
in parallel*



# Repeated use of the rules



*Has resistance 4*

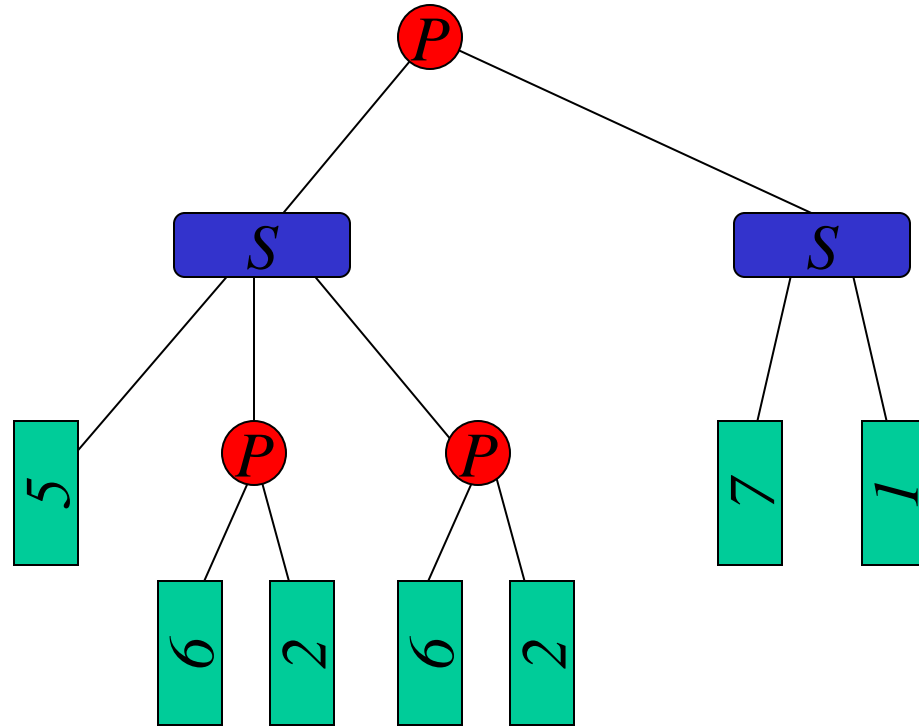
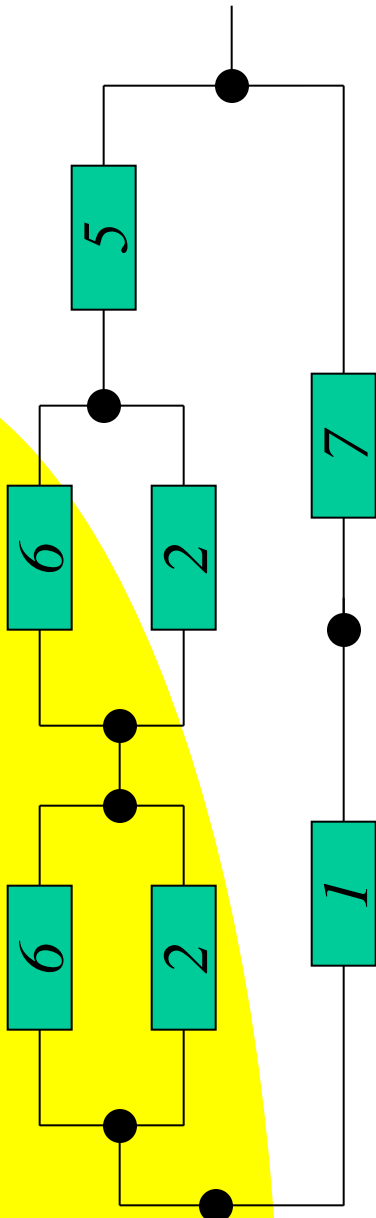
$$1/6 + 1/2 = 1/(1.5)$$

$$1.5 + 1.5 + 5 = 8$$

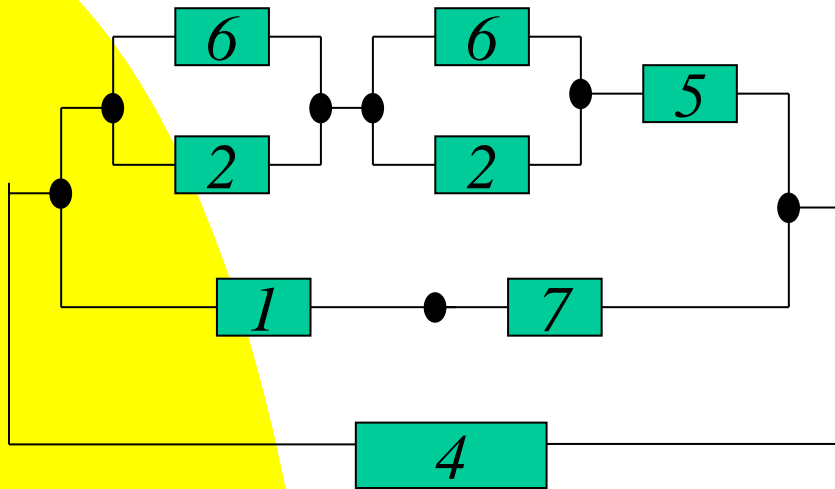
$$1 + 7 = 8$$

$$1/8 + 1/8 = 1/4$$

# A tree structure



# Carry on!



$$\frac{1}{4} + \frac{1}{4} = \frac{1}{2}$$

- Internal structure of graph can be forgotten once we know essential information about it!

# Using tree structures for solving hard problems on graphs 1

- Network is '*series parallel graph*'
- 196\*, 197\*: many problems that are *hard* for general graphs are *easy* for
  - Trees
  - Series parallel graphs
- Many well-known problems

e.g.:  
*NP-complete*

*Linear / polynomial  
time computable*



# Weighted Independent Set

- Independent set: set of vertices that are pairwise non-adjacent.
- **Weighted independent set**
  - **Given:** Graph  $G=(V,E)$ , weight  $w(v)$  for each vertex  $v$ .
  - **Question:** What is the **maximum total weight of an independent set** in  $G$ ?
- NP-complete





# Weighted Independent Set on Trees

- On trees, this problem can be solved in linear time with dynamic programming.
- Choose root  $r$ . For each  $v$ ,  $T(v)$  is subtree with  $v$  as root.
- Write
  - $A(v)$  = maximum weight of independent set  $S$  in  $T(v)$
  - $B(v)$  = maximum weight of independent set  $S$  in  $T(v)$ , such that  $v \notin S$ .



# Recursive formulations

- If  $v$  is a leaf:
  - $A(v) = w(v)$
  - $B(v) = 0$
- If  $v$  has children  $x_1, \dots, x_r$ :
  - $$A(v) = \max \{ w(v) + B(x_1) + \dots + B(x_r), \\ A(x_1) + \dots + A(x_r) \}$$
  - $$B(v) = A(x_1) + \dots + A(x_r)$$



# Linear time algorithm

- Compute  $A(v)$  and  $B(v)$  for each  $v$ , bottom-up.
  - E.g., in [postorder](#)
- Constructing corresponding sets can also be done in linear time.



# Second example:

## Weighted dominating set

- A set of vertices  $S$  is *dominating*, if each vertex in  $G$  belongs to  $S$  or is adjacent to a vertex in  $S$ .
- **Problem:** given a graph  $G$  with vertex weights, what is the **minimum total weight of a dominating set** in  $G$ ?
- Again, NP-complete, but linear time on trees.

# Subproblems

- $C(v)$  = minimum weight of dominating set  $S$  of  $T(v)$
- $D(v)$  = minimum weight of dominating set  $S$  of  $T(v)$  with  $v \in S$ .
- $E(v)$  = minimum weight of a set  $S$  of  $T(v)$  that dominates all vertices, except possibly  $v$ .



# Recursive formulations

- If  $v$  is a leaf, ...
- If  $v$  has children  $x_1, \dots, x_r$ :
  - $C(v)$  = the minimum of:
    - $w(v) + E(x_1) + \dots + E(x_r)$
    - $C(x_1) + \dots + C(x_{i-1}) + D(x_i) + C(x_{i+1}) + \dots + C(x_r)$ ,  
over all  $i, 1 \leq i \leq r$ .
  - $D(v) = w(v) + E(x_1) + \dots + E(x_r)$
  - $E(v) = \min \{ w(v) + E(x_1) + \dots + E(x_r), C(x_1) + \dots + C(x_r) \}$



# Gives again a linear time algorithm

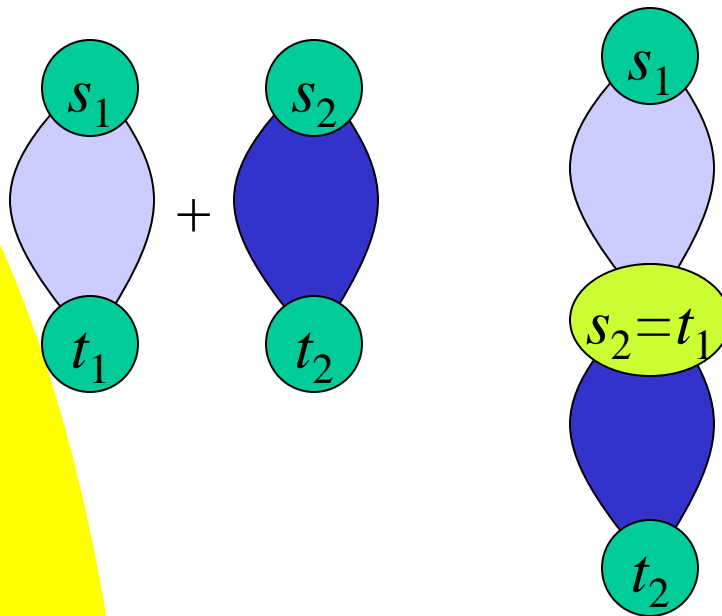
- Compute bottom up (e.g., postorder), and use another type of dynamic programming for the values  $C(v)$ .
- Constructing sets can also be done in linear time

# Generalizing to series parallel graphs

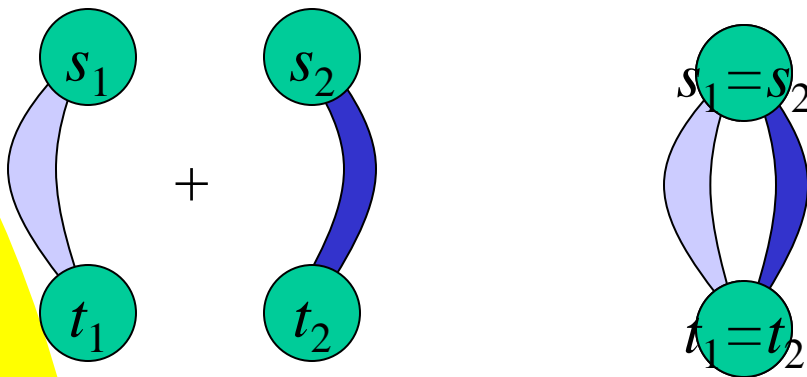
- A 2-terminal graph is a graph  $G=(V,E)$  with two special vertices  $s$  and  $t$ , its *terminals*.
- A 2-terminal (multi)-graph is **series parallel**, when it is:
  - A **single edge**  $(s,t)$ .
  - Obtained by **series composition** of 2 series parallel graphs
  - Obtained by **parallel composition** of 2 series parallel graphs



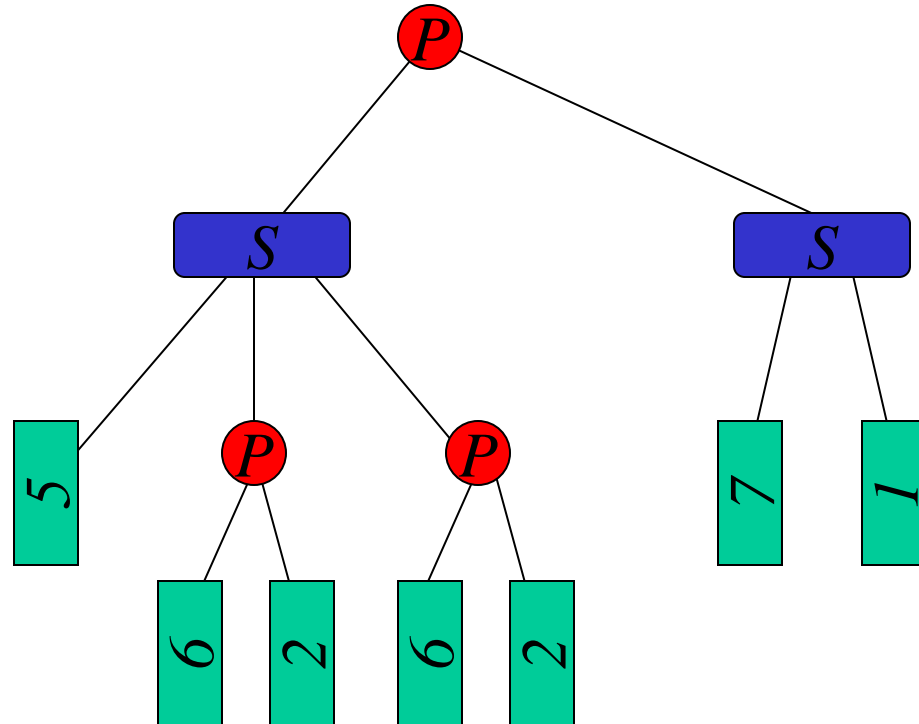
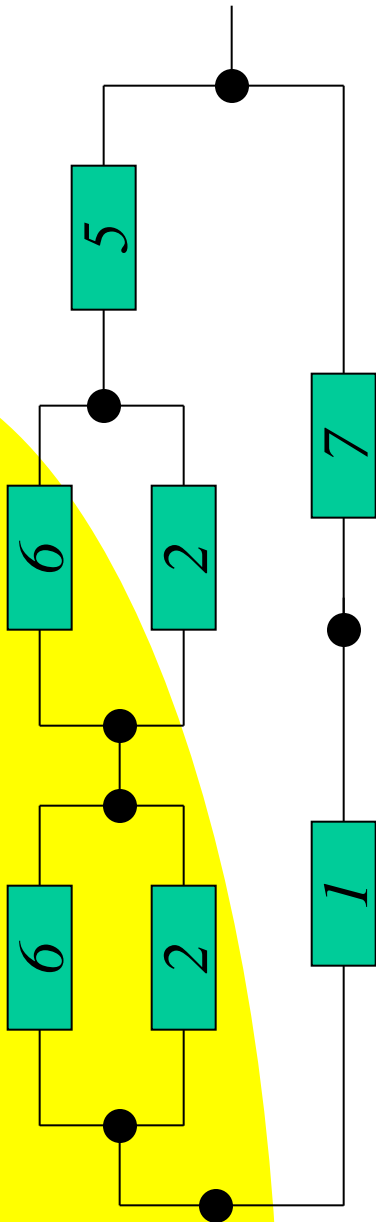
# Series composition



# Parallel composition

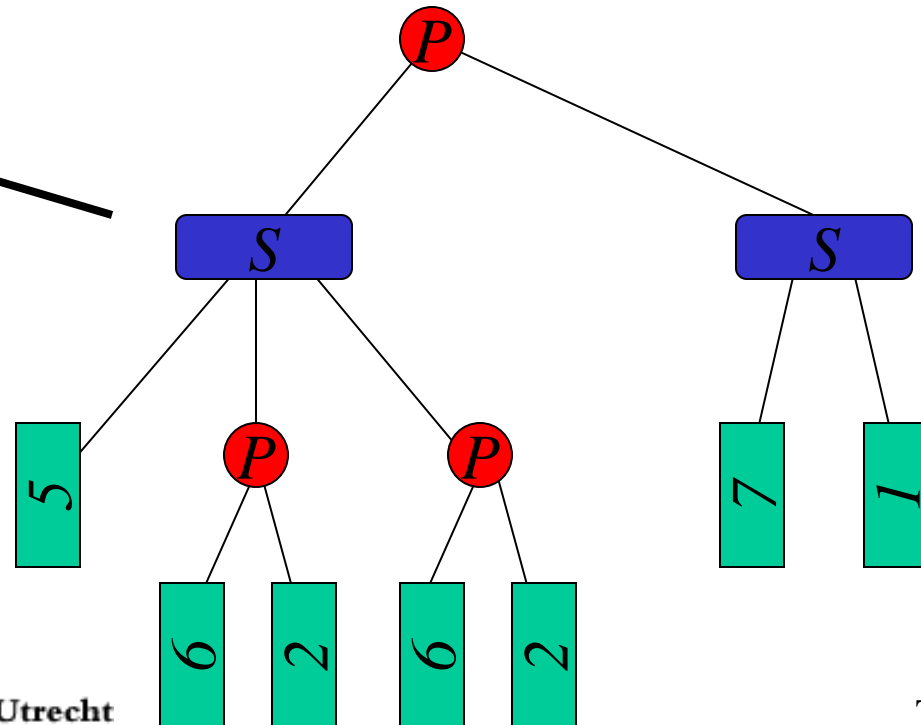
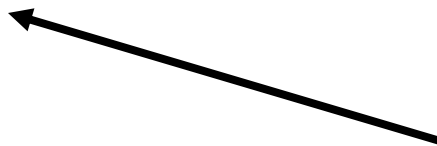
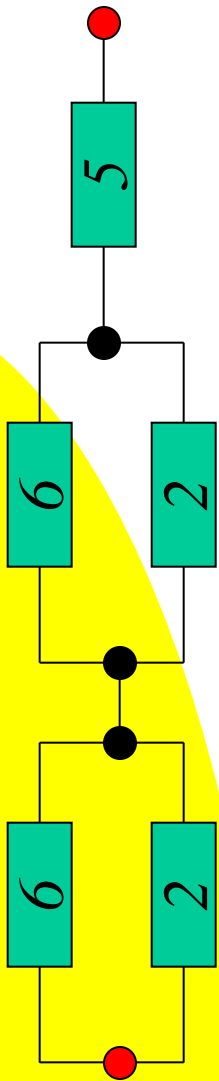


# Series Parallel Graphs have an *SP-tree*



$G(i)$

- Associate to each node  $i$  of SP tree a 2-terminal graph  $G(i)$ .



# Maximum weighted independent set for series parallel graphs

- $G(i)$ , say with terminals  $s$  and  $t$
- $AA(i)$  = maximum weight of independent set  $S$  of  $G(i)$  with  $s \in S, t \in S$
- $BA(i)$  = maximum weight of independent set  $S$  of  $G(i)$  with  $s \notin S, t \in S$
- $AB(i)$  = maximum weight of independent set  $S$  of  $G(i)$  with  $s \in S, t \notin S$
- $BB(i)$  = maximum weight of independent set  $S$  of  $G(i)$  with  $s \notin S, t \notin S$



# Maximum weighted independent set of series parallel graphs 2

- Computing AA, AB, BA, BB for
  - Leaves of SP-tree: trivial
  - Series, parallel composition: case analysis, using values for sub-sp-graphs  $G(i_1)$ ,  $G(i_2)$
  - E.g., series operation,  $s'$  terminal between  $i_1$  and  $i_2$ 
    - $AA(i) = \max \{ AA(i_1) + AA(i_2) - w(s'), AB(i_1) + BA(i_2) \}$
- $O(1)$  time per node of SP-tree:  $O(n)$  total.

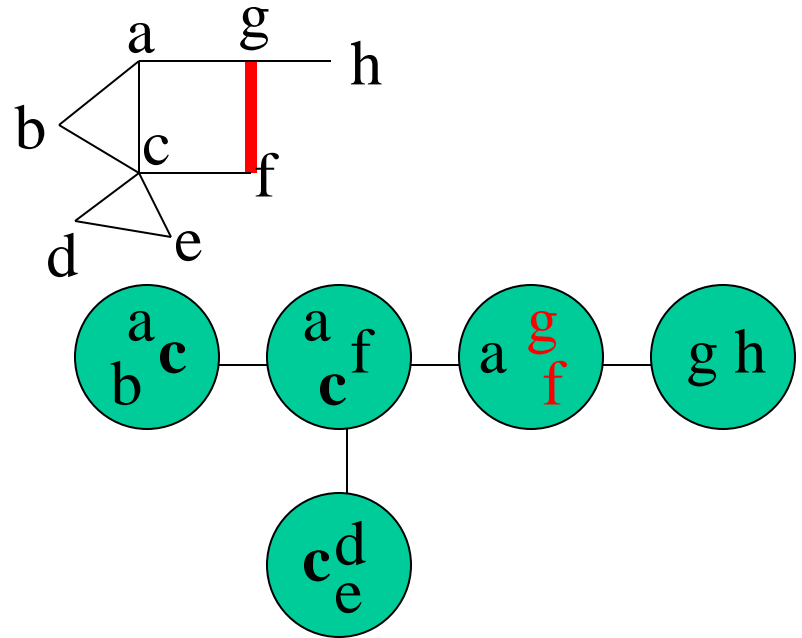
# Many generalizations

- Many other problems
- Other classes of graphs to which we can assign a *tree-structure*, including
  - Graphs of treewidth  $k$ , for small  $k$ .



# Tree decomposition

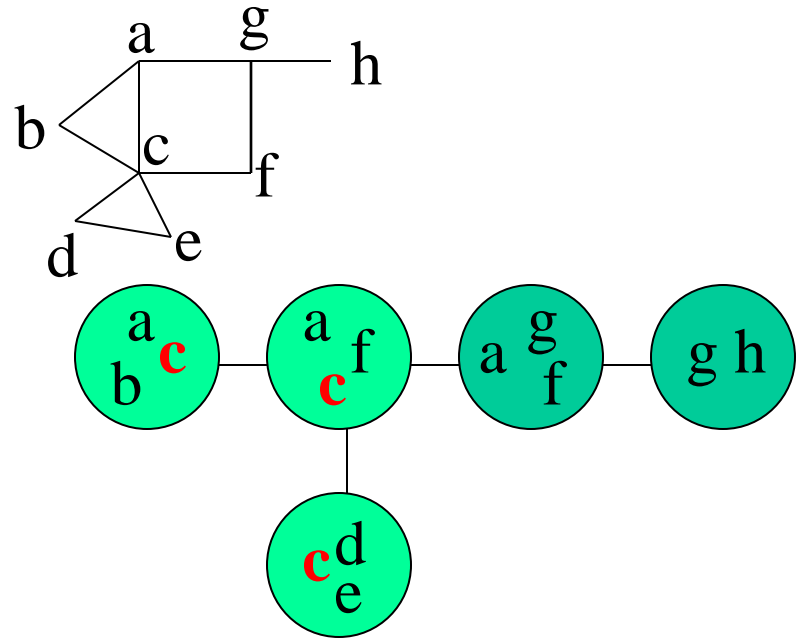
- A **tree decomposition**:
  - Tree with a vertex set associated to every node.
  - For all edges  $\{v,w\}$ : there is a set containing both  $v$  and  $w$ .
  - For every  $v$ : the nodes that contain  $v$  form a connected subtree.





# Tree decomposition

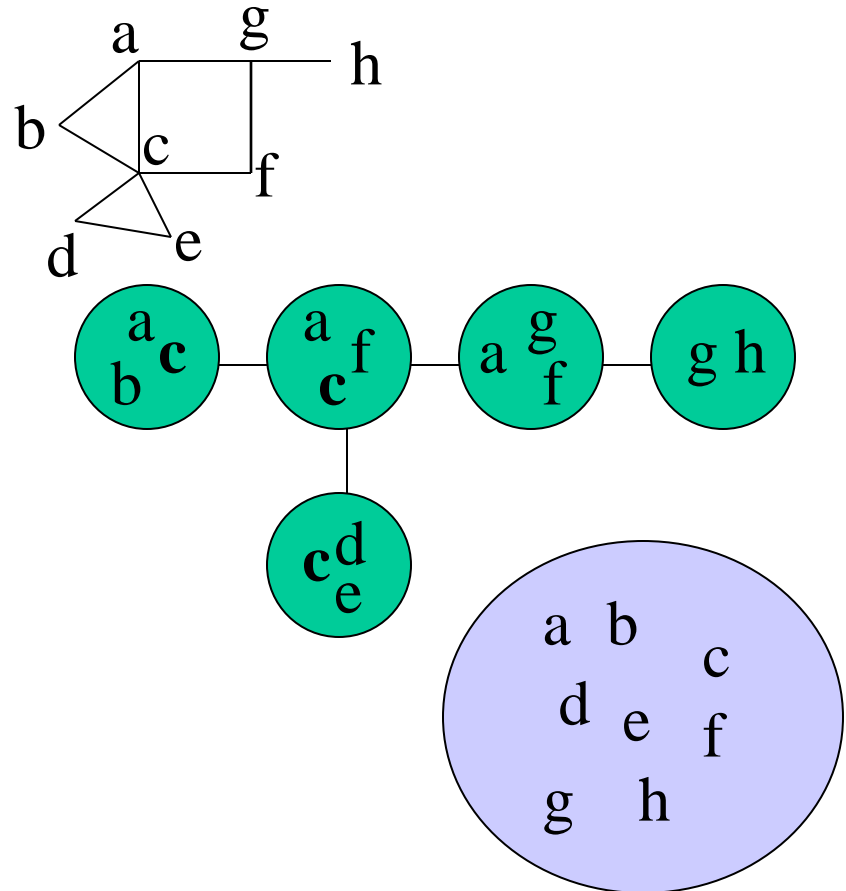
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# Treewidth (definition)

- **Width** of tree decomposition:  

$$\max_{i \in I} |X_i| - 1$$
- **Treewidth** of graph  $G$ :  
 $\text{tw}(G) = \text{minimum width over all tree decompositions of } G.$



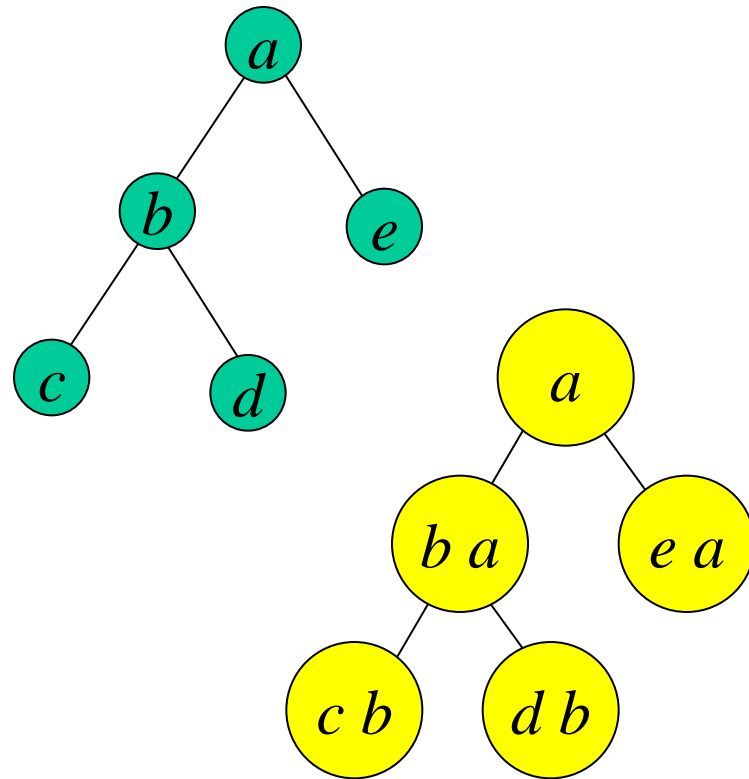
# Some graphs have small treewidth

- Appearing in some applications (e.g., probabilistic networks)
- Trees have treewidth 1
- Series Parallel graphs have treewidth 2.
- ...



# Trees have treewidth one

- Choose a root  $r$
- Take  $X_r = \{r\}$ , and for each other node  $i$ :  
 $X_i = \{i, \text{parent}(i)\}$
- $T$  with these bags gives a tree decomposition of width 2



# Algorithms using tree decompositions

- **Step 1: Find a tree decomposition** of width bounded by some small  $k$ .
  - Heuristics.
  - $O(f(k)n)$  in theory.
  - Fast  $O(n)$  algorithms for  $k=2, k=3$ .
  - By construction, e.g., for trees, sp-graphs.
- **Step 2. Use dynamic programming**, bottom-up on the tree.

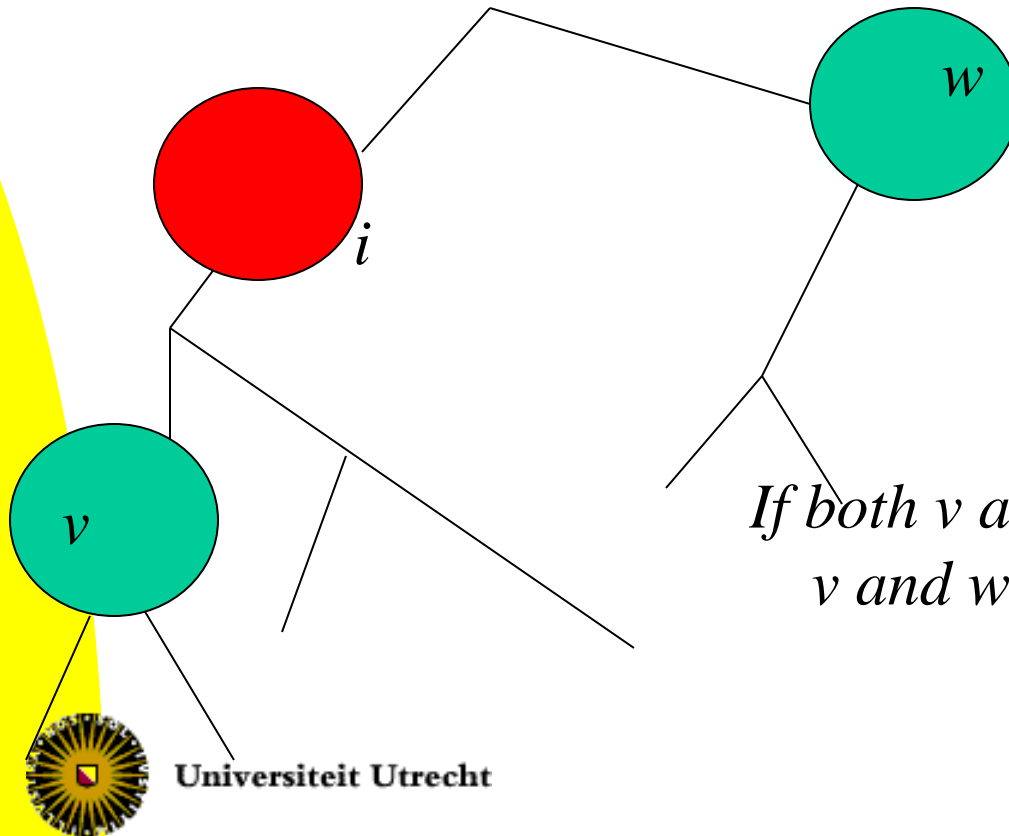


# Determining treewidth

- **Treewidth** problem (decision version):
  - **Given:** Graph  $G$ , integer  $k$
  - **Question:** Is the treewidth of  $G$  at most  $k$
- **Treewidth** problem (construction version):
  - **Given:** Graph  $G$
  - **Question:** construct a tree decomposition of  $G$  with minimum width
- NP-complete (Arnborg, Proskurowski)
- $\Theta(n)$  time algorithm for fixed  $k$  (B.)
- Practical  $O(n)$  algorithms for  $k= 1, 2, 3$  (Arnborg, Corneil, Proskurowski)
- Practical  $O^*(2^n)$  algorithm for small graphs (B. et al.)
- Many (often good) heuristics



# Separator property



# Nice tree decompositions

- Rooted tree, and four types of nodes  $i$ :
  - *Leaf*: leaf of tree with  $|X_i| = 1$ .
  - *Join*: node with two children  $j, j'$  with  $X_i = X_j = X_{j'}$ .
  - *Introduce*: node with one child  $j$  with  $X_i = X_j \cup \{v\}$  for some vertex  $v$
  - *Forget*: node with one child  $j$  with  $X_i = X_j - \{v\}$  for some vertex  $v$
- There is always a nice tree decomposition with the same width.



# Define $G(i)$

- Nice tree decomposition.
- For each node  $i$ ,  $G(i)$  subgraph of  $G$ , formed by all nodes in sets  $X_j$ , with  $j=i$  or  $j$  a descendant of  $i$  in tree.
  - Notate:  $G(i) = ( V(i), E(i) )$ .

# Maximum weighted independent set on graphs with treewidth $k$

- For node  $i$  in tree decomposition,  $S \subseteq X_i$   
write
  - $R(i, S) =$  maximum weight of independent set  $W$  of  $G(i)$  with  $W \cap X_i = S$ ,
    - $-\infty$  if such  $W$  does not exist

# Leaf nodes

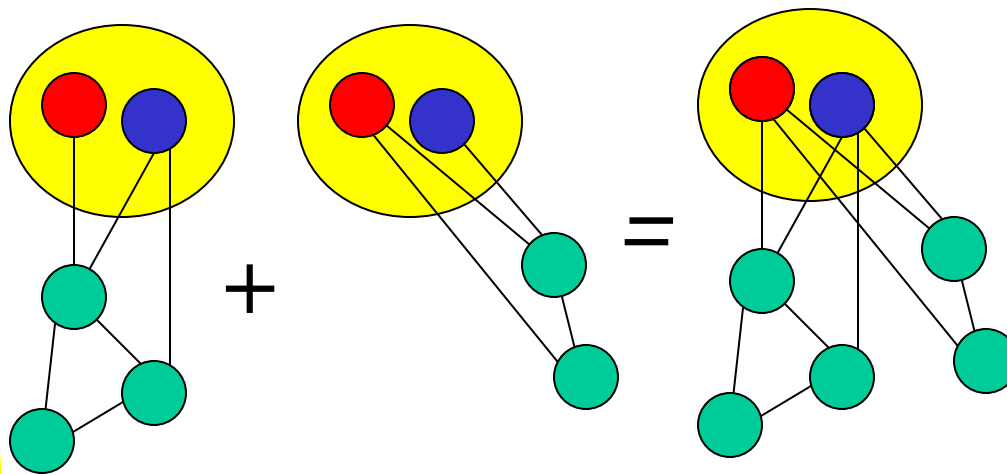
- Let  $i$  be a leaf node. Say  $X_i = \{v\}$ .
- $R(i, \{v\}) = w(v)$
- $R(i, \emptyset) = 0$



*$G(i)$  is a graph with one vertex*

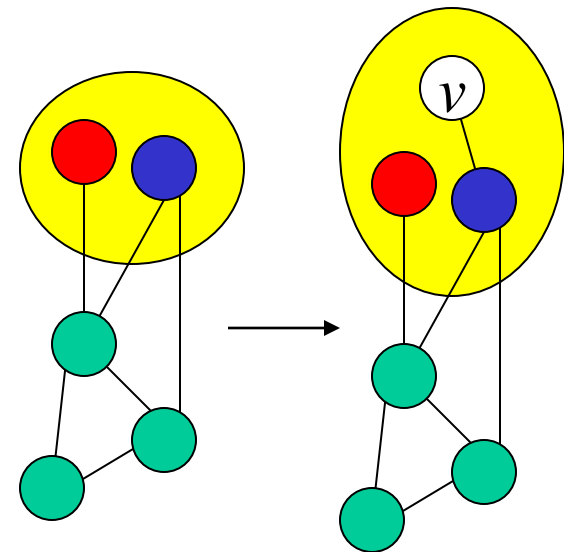
# Join nodes

- Let  $i$  be a join node with children  $j_1, j_2$ .
- $R(i, S) = R(j_1, S) + R(j_2, S) - w(S)$ .



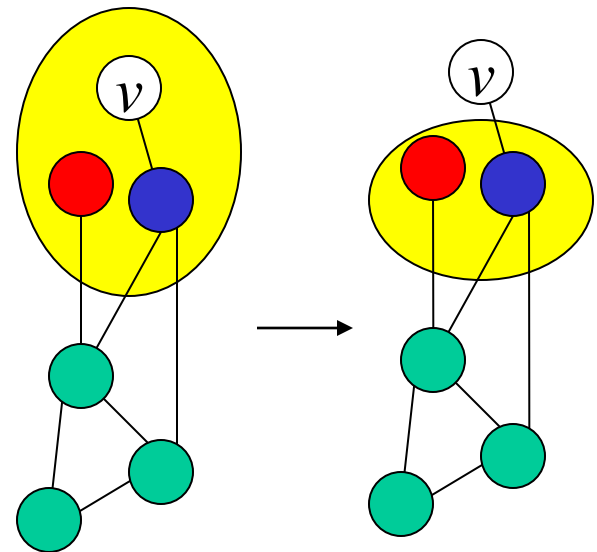
# Introduce nodes

- Let  $i$  be a node with child  $j$ , with  $X_i = X_j \cup \{v\}$ .
- Let  $S \subseteq X_j$ .
- $R(i, S) = R(j, S)$ .
- If  $v$  not adjacent to vertex in  $S$ :  
 $R(i, S \cup \{v\}) = R(j, S) + w(v)$
- If  $v$  adjacent to vertex in  $S$ :  
 $R(i, S \cup \{v\}) = -\infty$ .



# Forget nodes

- Let  $i$  be a node with child  $j$ , with  $X_i = X_j - \{v\}$ .
- Let  $S \subseteq X_i$ .
- $R(i, S) = \max (R(j, S), R(j, S \cup \{v\}))$



# Maximum weighted independent set on graphs with treewidth $k$

- For node  $i$  in tree decomposition,  $S \subseteq X_i$  write
  - $R(i, S) =$  maximum weight of independent set  $W$  of  $G(i)$  with  $W \cap X_i = S$ ,  $-\infty$  if such  $W$  does not exist
- Compute for each node  $i$ , a table with all values  $R(i, \dots)$ .
- Each such table can be computed in  $O(2^k)$  time when treewidth at most  $k$ .
- Gives  $O(n)$  algorithm when treewidth is (small) constant.

# Frequency assignment problem

- **Given:**
  - *Graph*  $G=(V,E)$
  - *Frequency set*  $F(v) \subseteq \mathbf{N}$  for all  $v \in V$
  - *Cost function*
    - $c(e,r,s)$ ,  $e = \{v,w\}$ ,  $r$  a frequency of  $v$ ,  $s$  a frequency of  $w$
- **Question**
  - Find a function  $g$  with
    - For all  $v \in V$ :  $g(v) \in F(v)$
    - The total sum over all edges  $e=\{v,w\}$  of  $c(e,g(v),g(w))$  is as small as possible





# Frequency assignment when treewidth is small

- Suppose sets  $F(v)$  are *small*
- Suppose  $G$  has small treewidth
- Algorithm exploits tree decomposition
  - What tables are we computing?
    - Leaf: trivial
    - Introduce: ...
    - Forget: projection
    - Join: sum but subtract double terms



# General method

- Compute a tree decomposition
  - E.g., with minimum degree heuristic
  - Make it nice
  - Use dynamic programming
- Works for many problems
  - Courcelle: those that can be formulated in **monadic second order logic**
  - Practical: TSP, frequency assignment, problems on planar graphs like dominating set, probabilistic inference



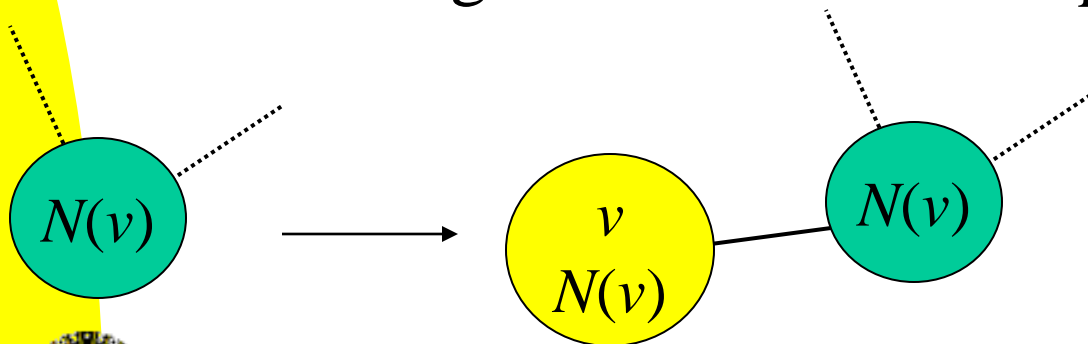
# A lemma

- Let  $(\{X_i \mid i \in I\}, T)$  be a tree decomposition of  $G$ . Let  $Z$  be a **clique** in  $G$ . Then **there is a  $j \in I$  with  $Z \subseteq X_j$** .
  - **Proof:** Take arbitrary root of  $T$ . For each  $v \in Z$ , look at highest node containing  $v$ . Look at such **highpoint of maximum depth**.

# The minimum degree heuristic

*A heuristic for treewidth  
Works often well*

- Repeat:
  - Take vertex  $v$  of minimum degree
  - Make neighbors of  $v$  a clique
  - Remove  $v$ , and repeat on rest of  $G$
  - Add  $v$  with neighbors to tree decomposition



# Other heuristics

- Minimum fill-in heuristic
  - Similar to minimum degree heuristic, but takes vertex with smallest *fill-in*:
    - Number of edges that must be added when the neighbours of  $v$  are made a clique
- Other choices of vertices, refining, using separators, ...



# Representation as permutation

- A correspondence between tree decompositions and permutations of the vertices
  - Repeat: remove superfluous leaf bag, or take vertex that appears in 1 leaf bag and no other bag
  - Make neighbours of  $v = \pi(1)$  into a clique; recursively make tree decomposition of graph  $- v$ ; add bag with  $v$  and neighbours
- Used in heuristics, and local search methods (e.g., taboo search, simulated annealing) and genetic algorithms



# Connection to Gauss eliminating

- Consider Gauss elimination on a symmetric matrix
- For  $n$  by  $n$  matrix  $M$ , let  $G_M$  be the graph with  $n$  vertices, and edge  $(i,j)$  if  $M_{ij} \neq 0$
- If we eliminate a row and corresponding column, effect on  $G$  is:
  - Make neighbors of  $v$  a clique
  - Remove  $v$

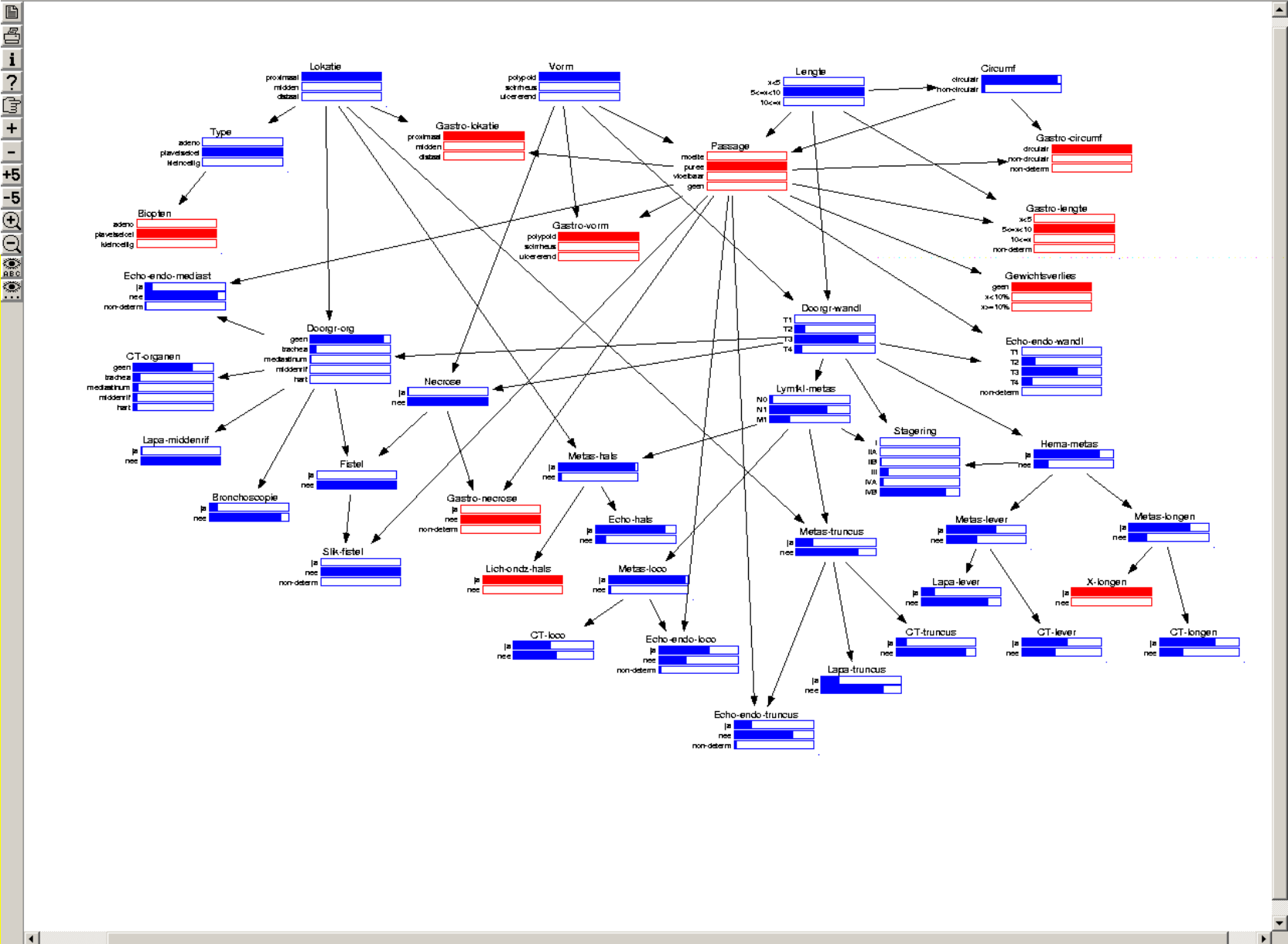


# Application: Probabilistic networks

- Lauritzen-Spiegelhalter algorithm for **inference on probabilistic networks** (belief networks) uses a tree decomposition of the *moralized* form of the network
- Underlying several modern decision support networks







# Designing a DP algorithm

- Methodology:
  1. What are “partial certificates”?
  2. What characterizes a partial certificate (essential for extending to full certificate)? Gives set of subproblems
  3. Give recurrences for subproblems
  4. Find order in which recurrences are evaluated; or use memorization
  5. Give algorithm; possibly save memory or make construction version



# Conclusions

- Dynamic programming for graphs with tree-like structure
- Works for a large collection of problems, as long as there is (and we can find) such a structure...

