



# **COL333/671: Introduction to AI**

## Semester I, 2024-25

## Constraint Satisfaction

**Rohan Paul**

# Outline

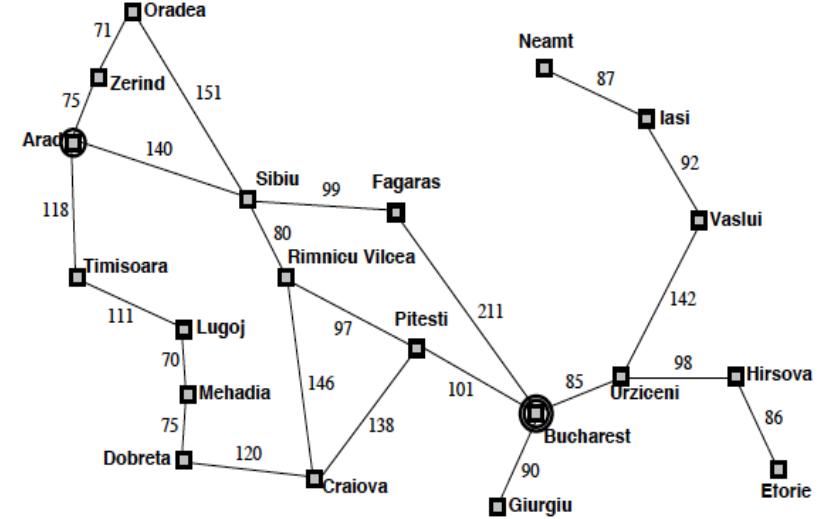
- Last Class
  - Local Search Algorithms
- This Class
  - Constraint Satisfaction Problems
- Reference Material
  - AIMA Ch. 6

# Acknowledgement

**These slides are intended for teaching purposes only. Some material has been used/adapted from web sources and from slides by Doina Precup, Dorsa Sadigh, Percy Liang, Mausam, Dan Klein, Nicholas Roy and others.**

# Standard Search Problems

- A path from the start to the goal state is the solution.
- Paths have costs (or depths).
- Heuristics provide **problem-specific** guidance.
- State is a “**black box**”, arbitrary data structure
- Goal test can be **any** function over states.



Route finding problem solved as a search problem

# Constraint Satisfaction Problems (CSPs)

- CSP
  - A set of **variables**  $\{X_1, X_2, \dots, X_n\}$  to which **values**  $(d_1, d_2, \dots, d_n)$  from a domain  $D$  can be assigned.
- Solution
  - A **complete** variable assignment that is **consistent** (satisfies all the given constraints).
- States
  - Explicitly represented as **variable assignments**
- Goal test:
  - The **set of constraints** specifying allowable combination of values for subset of variables.

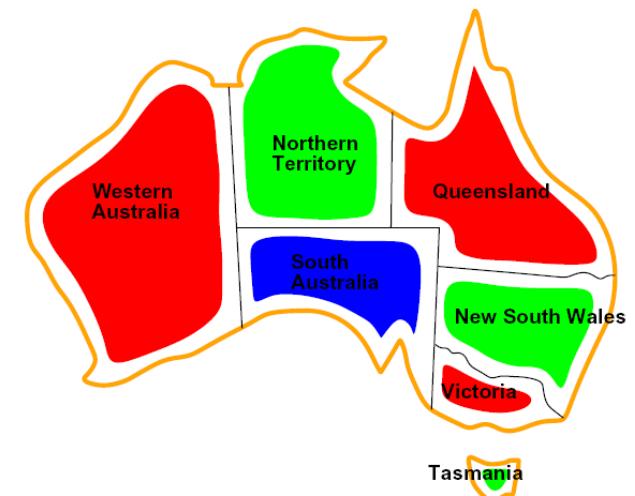
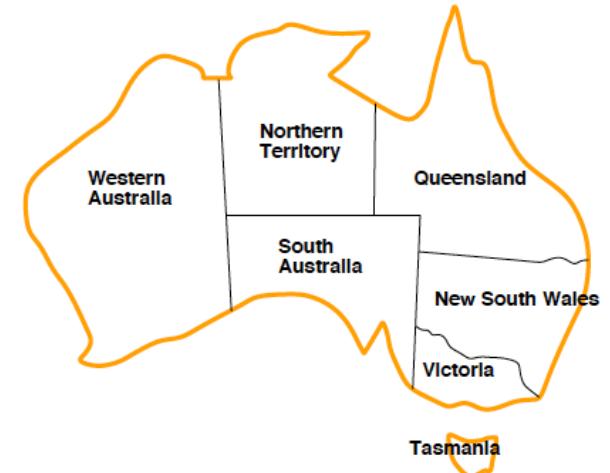
# Example: Map Coloring

- Variables: WA, NT, Q, NSW, V, SA, T
- Domains:  $D = \{\text{red, green, blue}\}$
- Constraints: adjacent regions must have different colors

Implicit:  $\text{WA} \neq \text{NT}$

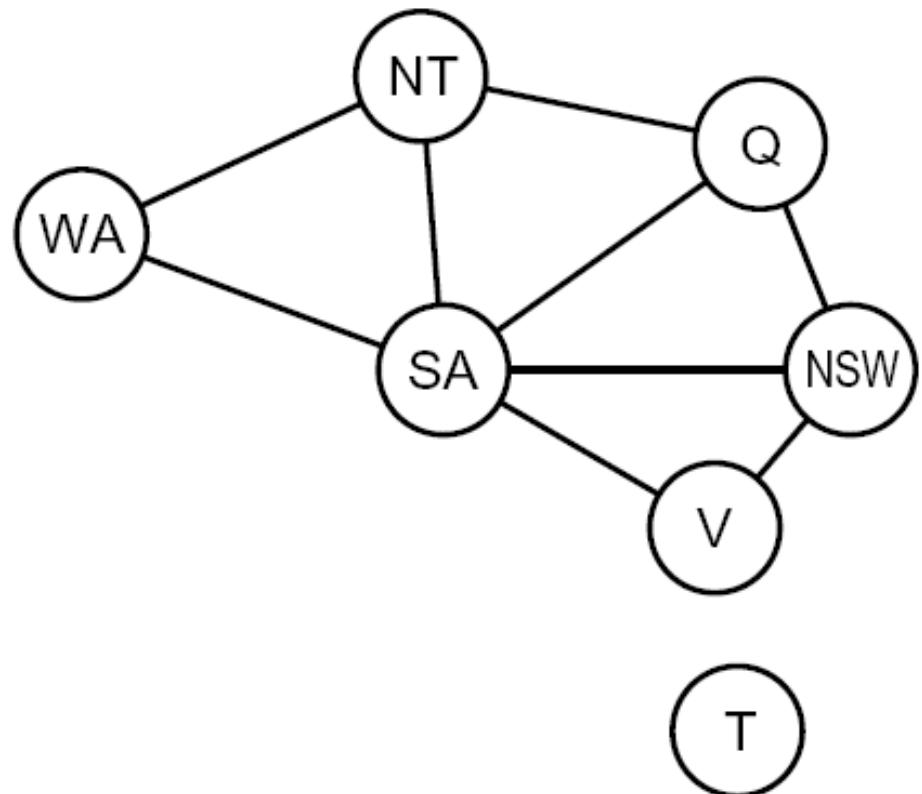
Explicit:  $(\text{WA}, \text{NT}) \in \{(\text{red, green}), (\text{red, blue}), \dots\}$

- Solutions are assignments satisfying all constraints, e.g.:  
 $\{\text{WA=red, NT=green, Q=red, NSW=green, V=red, SA=blue, T=green}\}$

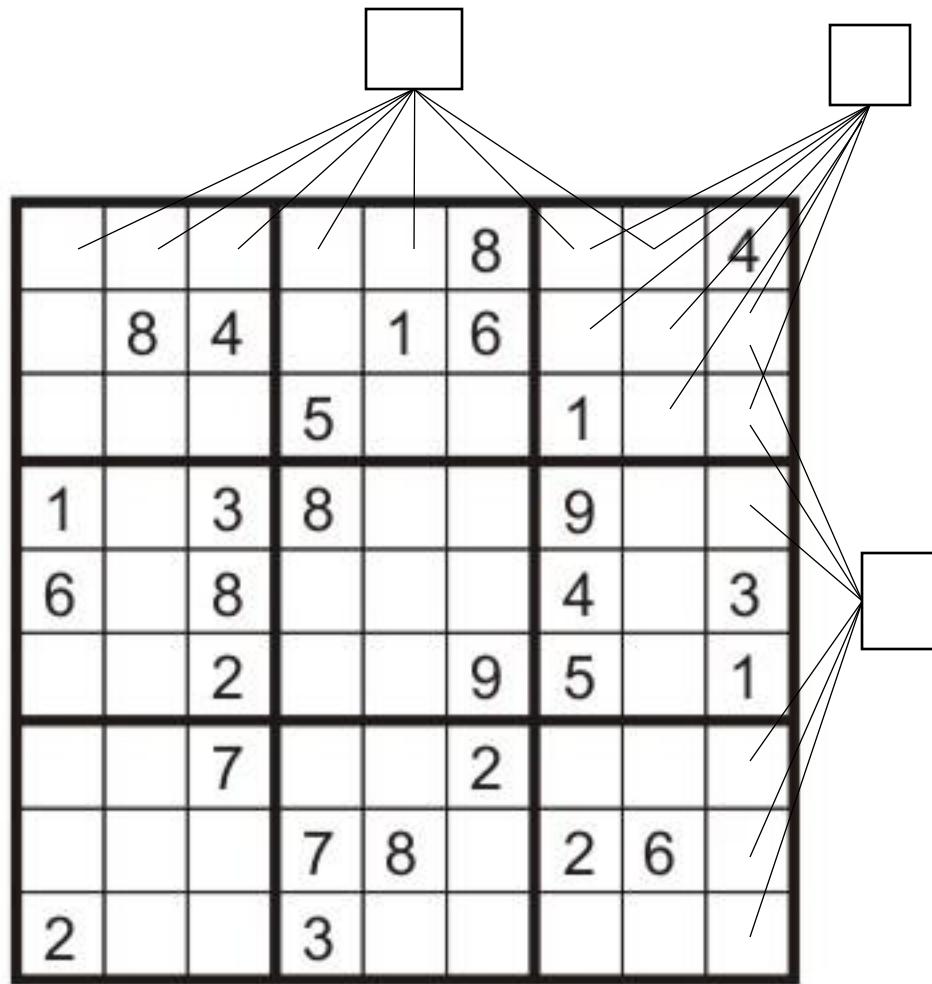


# Constraint Graph

- Binary constraint satisfaction problem
  - Each constraint relates (at most) two variables
- Binary constraint graph
  - Nodes are variables
  - Arcs show constraints
- General-purpose CSP solvers make use of the graph structure to speed up search.
  - E.g., Tasmania is an independent subproblem.



# Example: Sudoku



Variables: Each (open) square

Domains: {1, 2, ..., 9}

Constraints:

9-way alldiff for each column

9-way alldiff for each row

9-way alldiff for each region

# Example: Scheduling

NAME OF STAFF	DUTY ROSTER FOR THE MONTH OF C3 L.R / MAT. OT . OCTOBER 81																														Remarks
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
1. Ms MARY ANTHONY	A	D	D	O	D	A	A	A	A	B	D	A	A	A	D	D	O	C	D	D	O	A	D	A	N	D	D	R	9		
2. Ms PUSHPA DALAL	A	S	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	9	
3. Ms PUNAM SINHA	S	D	B	N	D	O	A	A	D	O	A	A	A	D	O	A	D	A	D	A	N	D	D	O	A	D	A	N	D	9	
4. Ms KUNDALIKA RANI	A	D	A	A	D	O	A	A	D	O	A	A	D	O	A	B	A	A	D	O	A	D	A	N	D	D	O	A	N	9	
5. Ms KHOLNENI L HAI	S	N	D	O	D	A	A	A	D	O	B	E	C	D	A	N	A	D	N	A	N	D	D	R	9						
6. Ms ARCHANA SINHAI SHIV	S	N	D	O	D	A	A	A	D	O	B	D	A	A	A	D	N	D	O	A	A	D	N	D	R	9					
7. Ms MAYA VINESH	S	N	N	D	O	B	B	D	A	A	A	D	N	D	N	D	B	A	D	N	A	A	D	A	N	D	R	9			
8. Ms JESTY JOY	N	E	D	D	N	N	D	O	A	A	D	N	A	A	D	N	D	O	C	D	N	A	D	A	N	D	R	9			
9. Ms TIAKA MARY THOMAS	N	E	D	D	N	N	D	B	D	O	A	A	D	N	D	B	M	S	A	A	A	D	N	N	D	R	9				
10. Ms PRONITA CHOWDHURY	A	D	A	A	D	O	A	A	D	O	B	D	N	D	B	B	D	N	A	A	D	N	N	D	R	9					
11. Ms SHEENA M TAJAB	N	N	N	D	O	E	B	A	D	O	A	A	D	N	D	B	B	D	N	A	A	D	N	N	D	R	9				
12. Ms MADHU SOLANKI	N	E	D	D	N	N	D	O	A	A	D	N	D	N	D	B	A	A	D	N	N	D	R	9							
13. Ms PARVATHY DAS	N	E	D	A	A	A	D	O	A	A	D	N	N	D	B	A	A	A	D	N	N	D	R	9							
14. Ms TINTA THOMAS	N	E	D	D	N	N	D	B	B	D	O	A	A	D	N	D	B	C	D	N	A	D	N	R	R	R	9				
15. Ms SHASI	N	E	D	A	D	B	D	N	D	B	D	N	D	B	B	D	A	D	N	N	D	B	B	B	R	R	R	9			
16. Ms RENU CHAUHAN	N	E	D	B	B	A	D	N	D	S	C	B	I	A	D	D	A	A	D	N	N	D	B	B	B	R	R	9			

An example of a manually prepared roster of persons assigned to shifts/rooms.

## Nurse Scheduling Problem

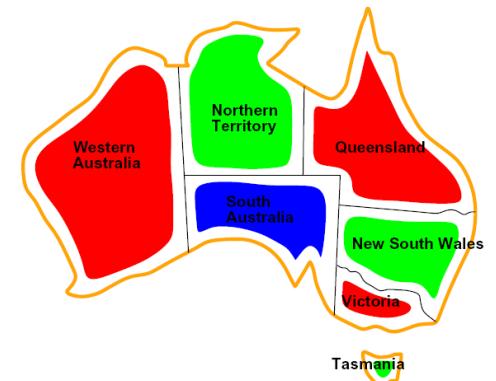
- $I$  set of nurses
- $T$  discrete time horizon
- $A$  set of activities
- cover constraints  $C_t$  / day  $t$
- working rules  $R_i$  / nurse  $i$

$N$  night,  $M$  morning,  $E$  evening,  $R$  rest  
 $28$  days  
between 2 and 3 nurses at night  
at least 2 mornings a week

employees		time						
		N	N	E	$X_3^0$	M	M	R
$R_2$	$X_0^2$	$X_1^2$	$X_2^2$	$X_3^2$	$X_4^2$	$X_5^2$	$X_6^2$	
	E	N	N	$X_3^3$	R	R	M	
	N	R	R	$X_3^4$	E	N	N	
	R	R	M	$X_3^5$	N	N	N	

# Types of Constraints

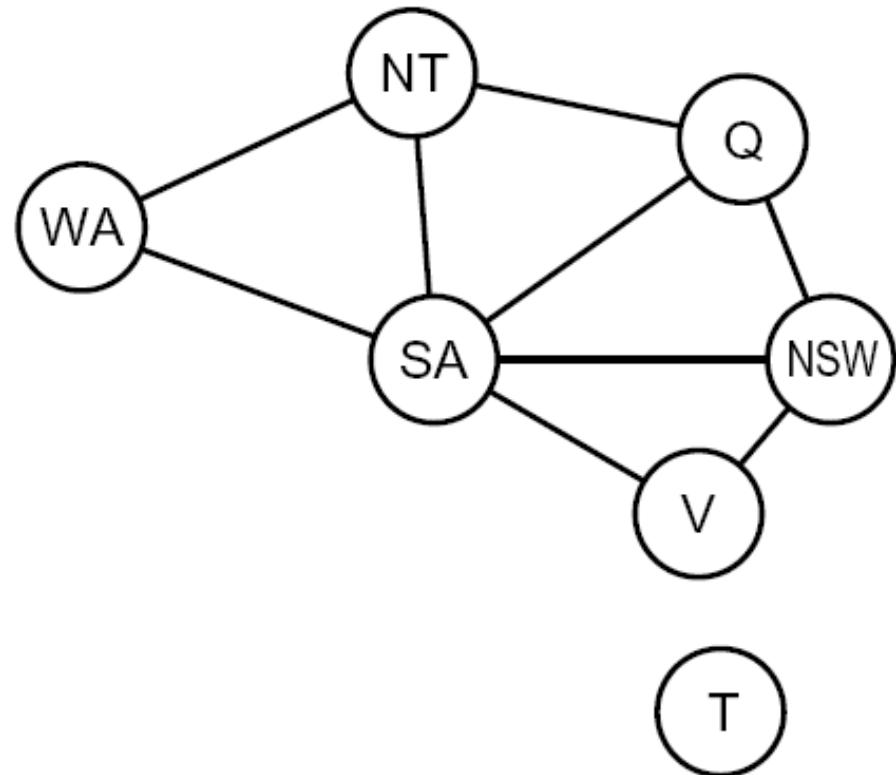
- Varieties of Constraints
  - Unary constraints involve a single variable (equivalent to reducing domains),  
e.g.:  
 $SA \neq \text{green}$
  - Binary constraints involve pairs of variables, e.g.:  
 $SA \neq WA$
  - Higher-order constraints involve 3 or more variables:  
e.g., sudoku constraints
- Preferences (soft constraints):
  - E.g., red is better than green
  - Often representable by a cost for each variable assignment
  - Gives constrained optimization problems



			8	4
	8	4	1	6
			5	1
1	3	8		9
6	8		4	3
	2		9	5
	7		2	
		7	8	2
2		3		6

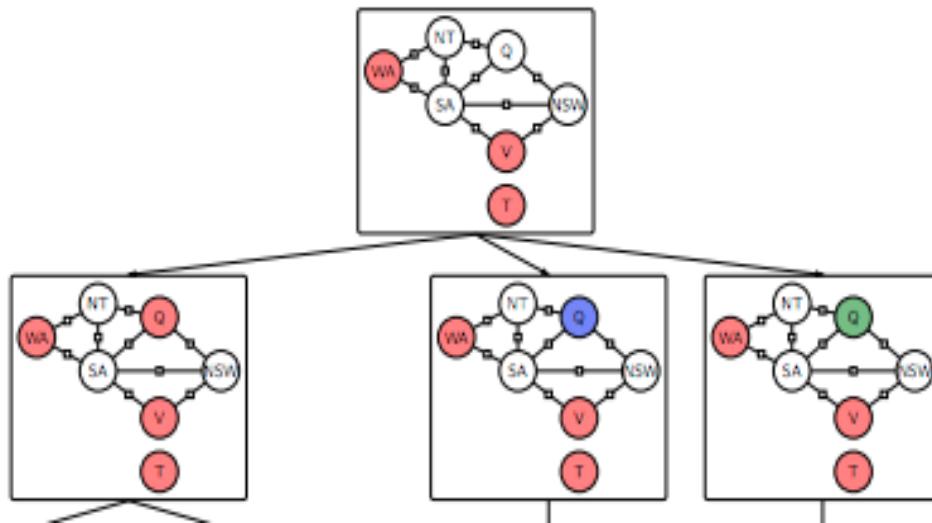
# Solving CSPs

- Standard search formulation of CSPs
- States: values assigned so far (partial assignments)
  - Initial state: the empty assignment, {}
  - Successor function: assign a value to an unassigned variable
  - Goal test: the current assignment is complete and satisfies all constraints

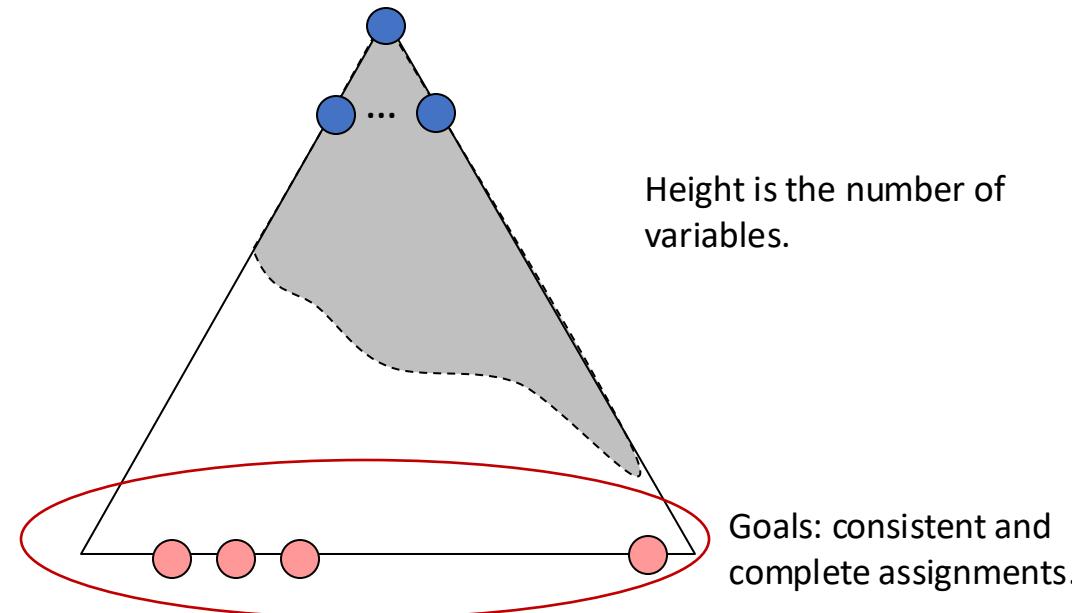


# Standard Search

One stage of successor generation. Select variable Q and try Red, Blue or Green values.



- Enumerate all assignments to variables. Create the entire tree.
- Check all the constraints at the end. Goal can be checked at the bottom of the tree.
- Can use a search method like DFS.



## Problem with a direct DFS search?

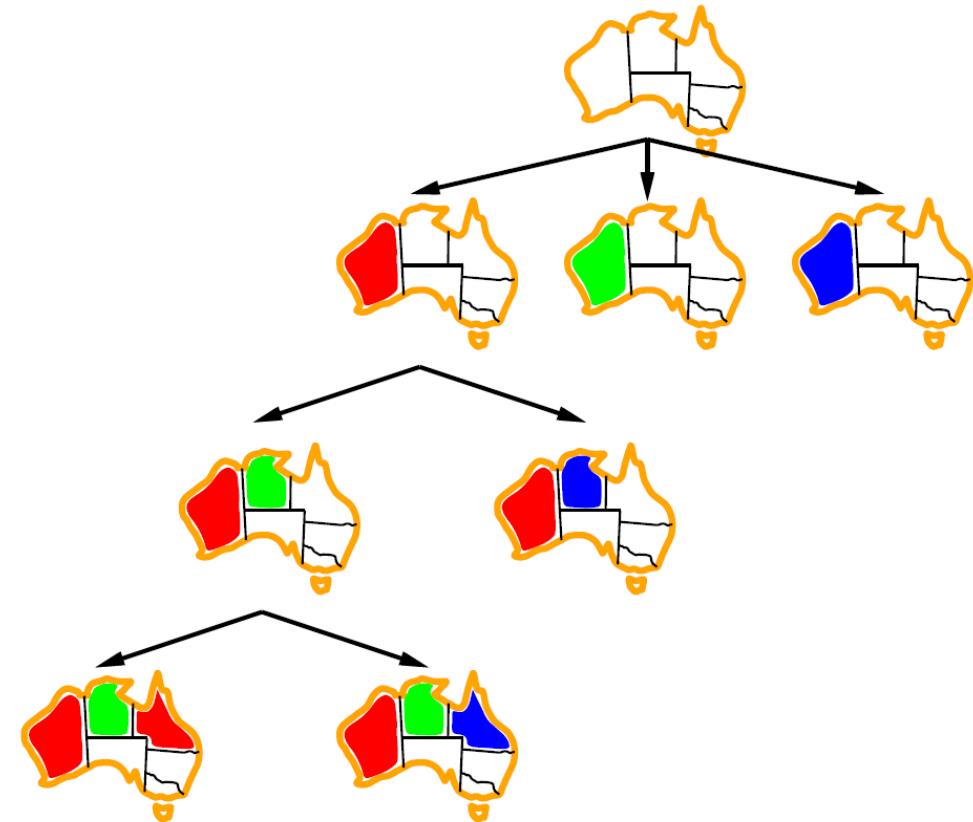
- Testing the constraints at the end, only then we know that the goal has been attained.
- *Do we need to wait till all variables assigned if we already know that the assignment is failing.*
- *Can we test incrementally and detect failures earlier than the complete assignment?*

# Backtracking Search over Assignments

- **Search component**
  - At each step, consider assignments to a single variable
  - Variable assignments are commutative (we can pick the order)
  - I.e., [WA = red then NT = green] same as [NT = green then WA = red]
- **Inference or Constraint Checking**
  - **Can we check constraints incrementally instead of all at the end?**
    - Incremental "goal test". Check constraints as the variable is assigned.
    - I.e. only assign values to variables which do not conflict previous assignments.
    - Some computation is involved in checking constraints.
- **Backtracking Search**
  - Depth-first search with *incremental variable assignment* and *constraint checking on the go*.
  - **Back track as soon as a failure is detected.**

# Backtracking Search

- Informally,
  - Pick a variable to assign.
  - Pick an assignment for the variable.
  - Check if all the constraints are satisfied.
  - If the constraints are not satisfied, then try a different assignment.
  - If no assignments left, need to back track.
  - If the assignment is complete, then we have a solution.
  - .....



Generate successors by selecting variables and values. Incrementally check the violation of constraints (backtrack when necessary).

# Backtracking Search: Pseudocode

```
function BACKTRACKING-SEARCH(csp) returns solution/failure
    return RECURSIVE-BACKTRACKING({ }, csp)
function RECURSIVE-BACKTRACKING(assignment, csp) returns soln/failure
    if assignment is complete then return assignment
    var  $\leftarrow$  SELECT-UNASSIGNED-VARIABLE(VARIABLES[csp], assignment, csp)
    for each value in ORDER-DOMAIN-VALUES(var, assignment, csp) do
        if value is consistent with assignment given CONSTRAINTS[csp] then
            add {var = value} to assignment
            result  $\leftarrow$  RECURSIVE-BACKTRACKING(assignment, csp)
            if result  $\neq$  failure then return result
            remove {var = value} from assignment
    return failure
```

Backtracking = DFS + variable-ordering + fail-on-violation

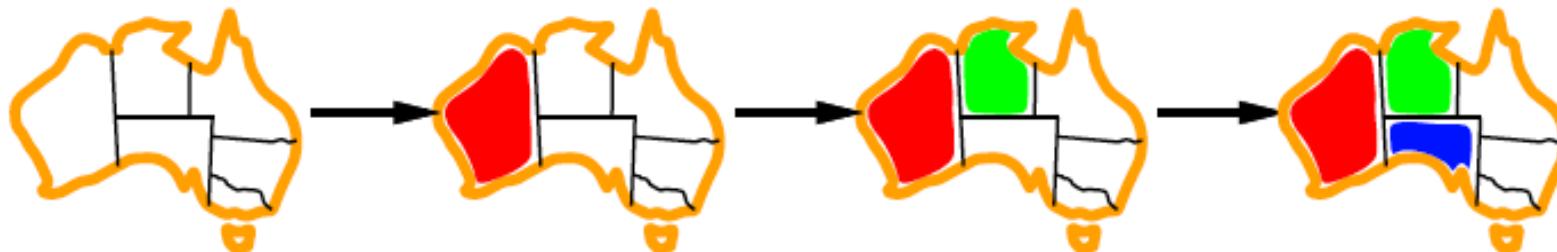
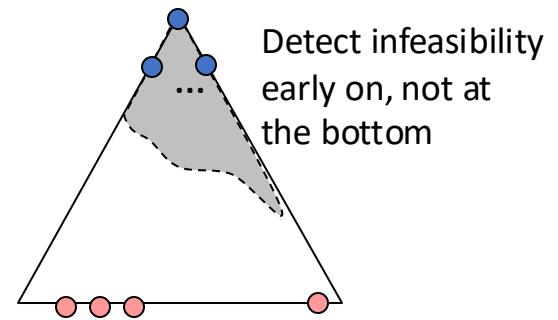
# Backtracking Search

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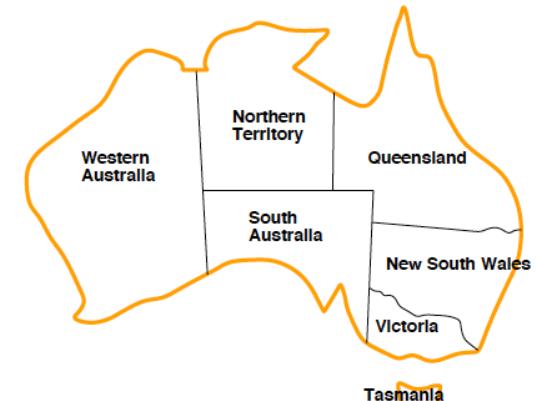
How to order the variables during backtracking search?

# Ordering Variables

- Most Constrained Variable (Minimum Remaining Values)
  - When you have multiple variables to assign, then choose the variable with the *fewest* remaining legal values in its domain
    - A CSP solution must have an assignment for all variables.
    - Try the variables likely to fail early rather than late. Fail fast.

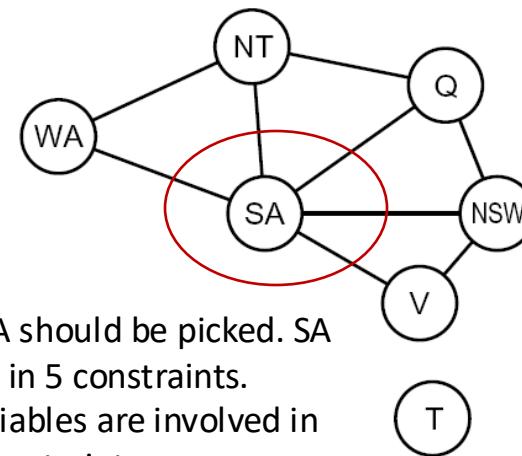
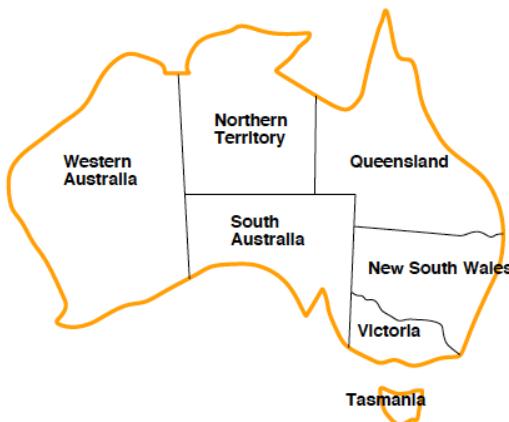


After assigning  $WA = R$ , the variables NT and SA have two legal values whereas Q, NSW, V and T have three legal values. Prefer selecting NT or SA over the other remaining variables.



# Degree Heuristic

- Take the case of picking the first variable to assign.
  - Minimum Remaining Values Heuristic does not help in the first variable. All have the same number of legal values in the domain.
  - In general, how to break ties among MRV variables?
- Degree Heuristic
  - Select the variable involved in the **largest number of constraints** on other unassigned variables.
  - Why?
    - This value reduces possible values for others. In effect, reduces branching factor.



Variable SA should be picked. SA is involved in 5 constraints. Others variables are involved in 3, 2 or 0 constraints.

# Backtracking Search

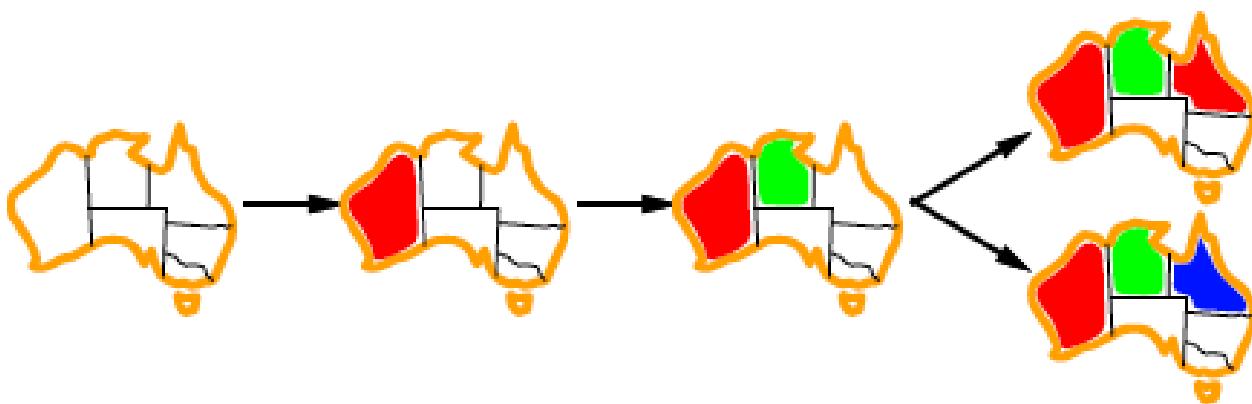
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            if result  $\neq$  failure then return result
            remove  $\{var = value\}$  from assignment
    return failure
```

# Ordering Values

- Least Constrained Value

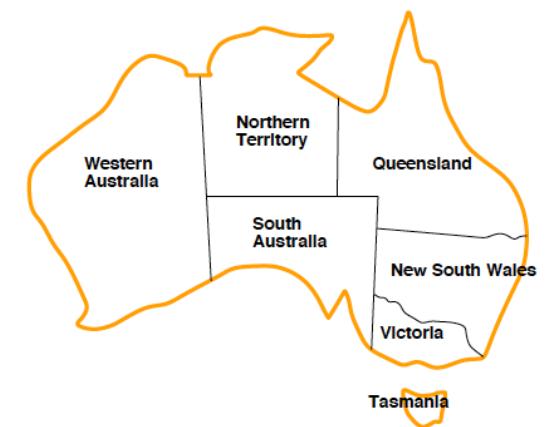
Given a variable choose a value that rules out the fewest values in the remaining unassigned variables.

- Leave maximum flexibility for subsequent assignments.
- We only need one value (assigned to a variable) so that the constraints are satisfied.  
Look for most likely solutions first. Fail last.



If **Q = Red** then, there is one possible assignment for **SA = B**

If **Q = Blue** then, there is no legal value left for **SA**.



Consider the case where:  $WA = R$  and  $NT = G$ .

Next, we pick  $Q$  for an assignment. Options are  $Q=R$  or  $Q=B$ .

Examine effect on  $SA$  ( $Q=Red$  is a better option) as it leaves a possible assignment instead of  $Q=Blue$ .

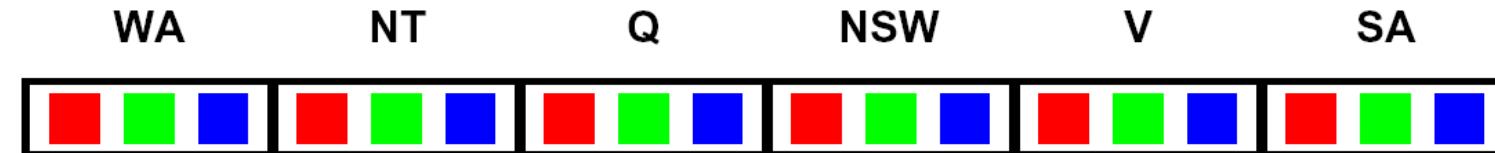
# Solving CSPs: Improving Efficiency

- Which variable should be assigned next?
- In what order should its values be tried?
- Can we detect inevitable failures early?
- Can we take advantage of the problem structure?

```
function BACKTRACKING-SEARCH(csp) returns a solution, or failure
  return BACKTRACK({ }, csp)
  
function BACKTRACK(assignment, csp) returns a solution, or failure
  if assignment is complete then return assignment
  var  $\leftarrow$  SELECT-UNASSIGNED-VARIABLE(csp)
  for each value in ORDER-DOMAIN-VALUES(var, assignment, csp) do
    if value is consistent with assignment then
      add {var = value} to assignment
      inferences  $\leftarrow$  INFERENCE(csp, var, value)
      if inferences  $\neq$  failure then
        add inferences to assignment
        result  $\leftarrow$  BACKTRACK(assignment, csp)
        if result  $\neq$  failure then
          return result
        remove {var = value} and inferences from assignment
  return failure
```

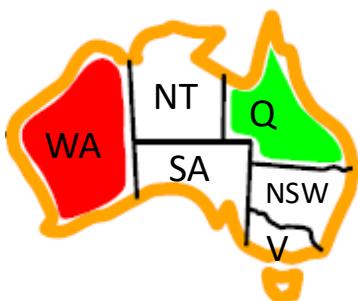
# Inference/Filtering: Forward Checking

- Basic Idea: Track domains for unassigned variables and eliminate values that violate constraints with existing assignments. Propagate information from assigned to unassigned variables linked with a constraint.
- Forward Checking: When a variable X is assigned, check the unassigned variable Y connected to X by a constraint. Delete from Y any value that is inconsistent with the value assigned for X.



# Problem with Forward Checking

- Forward Checking propagates information from assigned to unassigned variables. No propagation between unassigned variables.
- Only 1-step look ahead, does not examine all future implications of the current assignment.



WA	NT	Q	NSW	V	SA
Red	Green	Blue	Red	Green	Blue
Red	Green	Blue	Red	Green	Blue
Red	White	Blue	Red	Green	Blue



NT and SA cannot be blue. This partial assignment could be extended. Still, we went ahead. No information propagated between two unassigned variables.

# Arc Consistency

*How to propagate information further?  
First, we need a formal notion of arc consistency.*

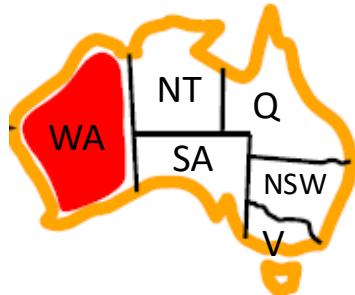
- A directed arc  $X \rightarrow Y$  is “consistent” iff
  - for every value  $x$  of  $X$ , there exists a value  $y$  of  $Y$ , such that  $(x, y)$  satisfies the constraint between  $X$  and  $Y$
- Remove values from the domain of  $X$  to enforce arc-consistency

## Takeaway

- If the domain values at the head ( $Y$ ) change when assigned, then we need to check if the values in the tail ( $X$ ) are still consistent with the assignment to  $Y$ . If not, then remove the values for  $X$  that are inconsistent, thereby making the arc  $X \rightarrow Y$  “arc consistent”.

# Enforcing Consistency of a Single Arc

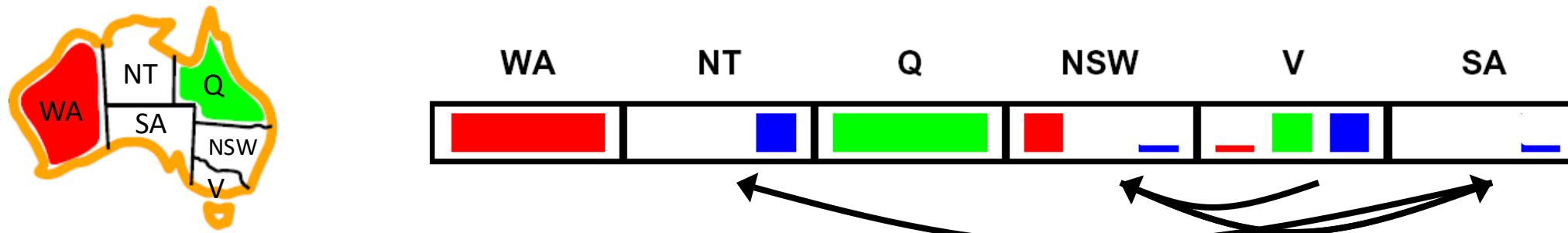
- An arc  $X \rightarrow Y$  is **consistent** iff for *every value for x* (the “tail” of the arc) there is *some value y* (the “head” of the arc) which could be assigned without violating a constraint.



Remember: Always delete the domain value from the “tail” of the arc.

# Enforcing Arc Consistency for the Entire CSP

- Ensure that **all** arcs in the constraint graph are consistent:



- **Take away**
  - If  $X$  loses a value in its domain, the neighbors of  $X$  (arcs coming in) need to be **re-examined** for consistency.
  - Arc consistency detects failure **earlier** than forward checking.
  - Forward checking was 1-step look ahead. Arc consistency further examines **implications**.
  - If no values left in the domain of a variable, then do not continue and backtrack as the CSP does not have a solution

# AC-3: Enforcing Arc Consistency in a CSP

Mackworth, 1977

Maintain a queue of arcs

```
function AC-3(csp) returns false if an inconsistency is found and true otherwise
  inputs: csp, a binary CSP with components (X, D, C)
  local variables: queue, a queue of arcs, initially all the arcs in csp
```

Obtain an arc

```
while queue is not empty do
  (Xi, Xj) ← REMOVE-FIRST(queue)
  if REVISE(csp, Xi, Xj) then
    if size of Di = 0 then return false
    for each Xk in Xi.NEIGHBORS - {Xj} do
      add (Xk, Xi) to queue
  return true
```

If the domain of *X<sub>i</sub>* (tail) changes due to *X<sub>j</sub>* (head) then, add all the edges coming into *X<sub>i</sub>* from the *X<sub>k</sub>*. (Done by inserting *X<sub>k</sub>, X<sub>i</sub>*)

```
function REVISE(csp, Xi, Xj) returns true iff we revise the domain of Xi
  revised ← false
  for each x in Di do
    if no value y in Dj allows (x,y) to satisfy the constraint between Xi and Xj then
      delete x from Di
      revised ← true
  return revised
```

Enforce arc consistency between *X<sub>i</sub>* (tail) → *X<sub>j</sub>* (head). Checking if due to assignment for *X<sub>j</sub>* is adjustment needed for *X<sub>i</sub>*?

Runtime:  $O(n^2d^3)$  [ $n^2$  edges  $\times d^2$  time in consistency  $\times d$  arc insertions (only domain reduction triggers insertion of an edge in the queue)]

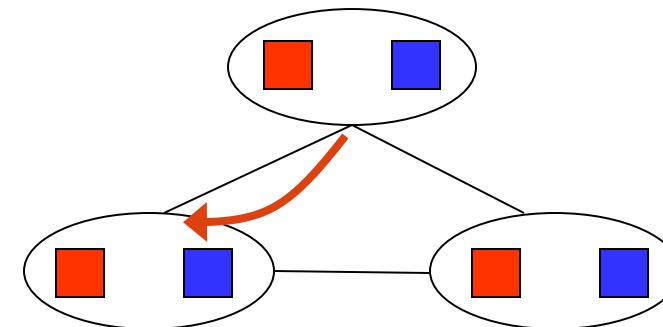
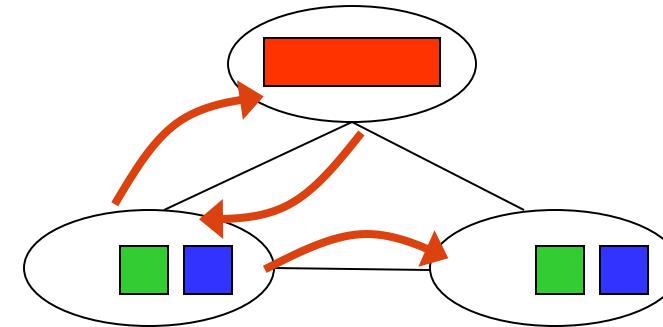
# Backtracking Search (with Inference)

- Run Forward Checking or Arc Consistency.
- Also called interleaving search and inference.
- Polynomial time
- We will still back track at times as AC-3 cannot detect all the inconsistencies (detecting all inconsistencies is NP-hard).

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            inferences  $\leftarrow$  INFERENCE(csp, var, value)
            if inferences  $\neq$  failure then
                add inferences to assignment
                result  $\leftarrow$  BACKTRACK(assignment, csp)
                if result  $\neq$  failure then
                    return result
                remove {var = value} and inferences from assignment
            return failure
```

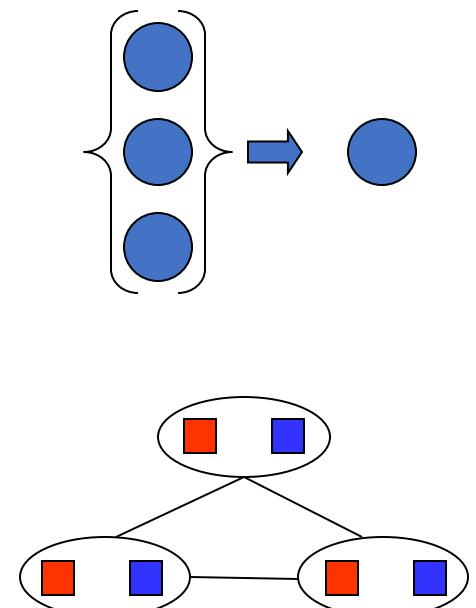
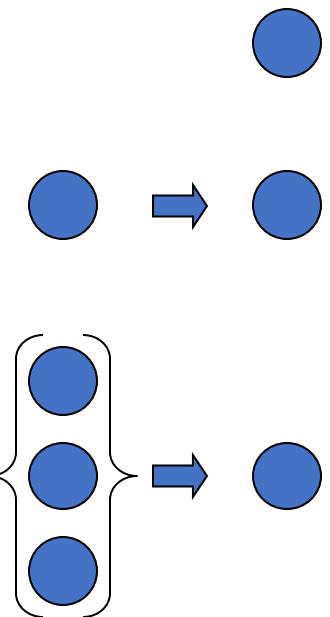
# Arc Consistency: Limitation

- After enforcing arc consistency:
  - Can have one solution left
  - Can have multiple solutions left
  - Can have no solutions left (and not know it)
- Example:
  - This CSP has a consistent assignment (see top figure).
  - Consider the second assignment, arc consistency is established but there is no overall solution in this case (see below figure).



# K-Consistency

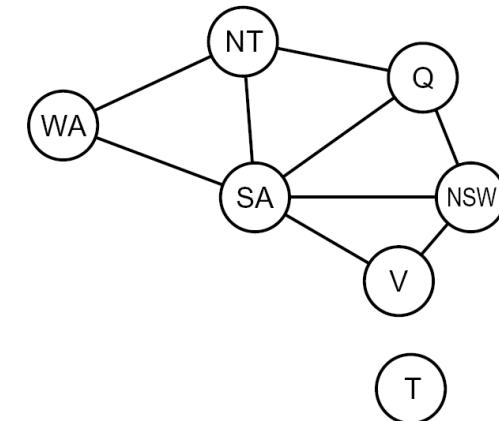
- Increasing degrees of consistency
  - 1-Consistency (Node Consistency): Each single node's domain has a value which meets that node's unary constraints
  - 2-Consistency (Arc Consistency): For each pair of nodes, any consistent assignment to one can be extended to the other
  - K-Consistency: For each k nodes, any consistent assignment to k-1 can be extended to the k<sup>th</sup> node.
  - Higher k more expensive to compute.
- k=2 case is arc consistency.
  - In our example, arc consistency was enforced (K=2) but path consistency (K=3) was not. The overall inconsistency could not be detected with K=2.



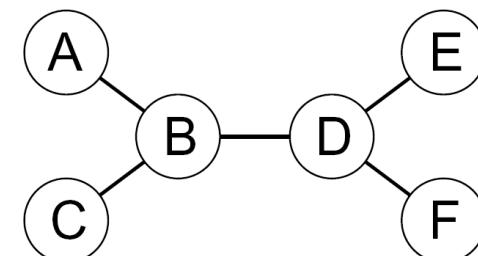
# Exploiting Problem Structure

**General idea:** Some CSP structures are easy to solve. Either find and exploit that structure or perform reductions to simplify the problem.

- **Independent subproblems** are identifiable as connected components of constraint graph
  - Example: Tasmania and mainland do not interact
  - Decomposing a graph of  $n$  variables into subproblems of only  $c$  variables simplifies the problem.

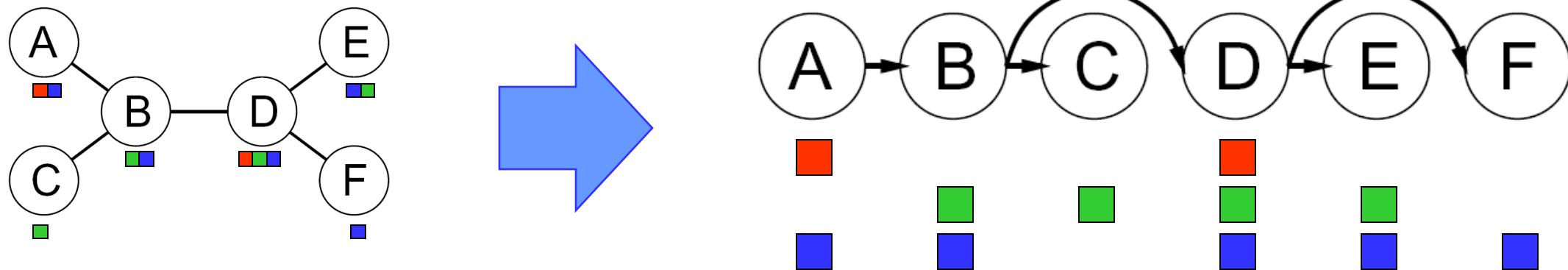


- **Tree-structured CSPs**
  - Some CSP structures are easier to solve
  - Theorem: if the constraint graph has no loops, the CSP can be solved in  $O(n d^2)$  time
  - Compare to general CSPs, where worst-case time is  $O(d^n)$



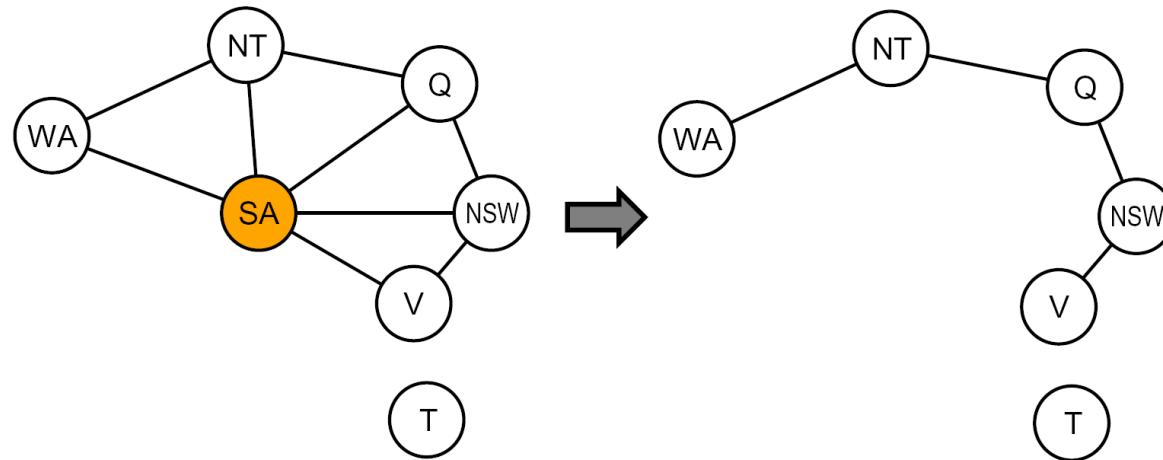
# Tree-Structured CSPs

- Algorithm for tree-structured CSPs
  - Topological sort: Choose a root variable, order variables so that parents precede children



- Remove backward: For  $i = n : 2$ , apply Make-Arc-Consistent ( $\text{Parent}(X_i), X_i$ )
- Assign forward: For  $i = 1 : n$ , assign  $X_i$  consistently with  $\text{Parent}(X_i)$  by picking any consistent value from the domain.

# Improving Structure



- Overall idea
    - If we can handle the instantiation of certain variables, then the remaining problem can be simplified.
    - Conditioning: instantiate a variable, prune its neighbors' domains and solve the residual graph
    - The residual graph is easier to solve as it is tree structured.
  - Cutset conditioning
    - Find a subset of variables  $S$ , such that the remaining constraint graph becomes a tree after the removal of  $S$  ( $S$  is a cycle cut set).
    - Instantiate (in all ways) a set of variables such that the remaining constraint graph is a tree.
    - Remove from the domains of the remaining variables any values that are inconsistent with the assignment for  $S$

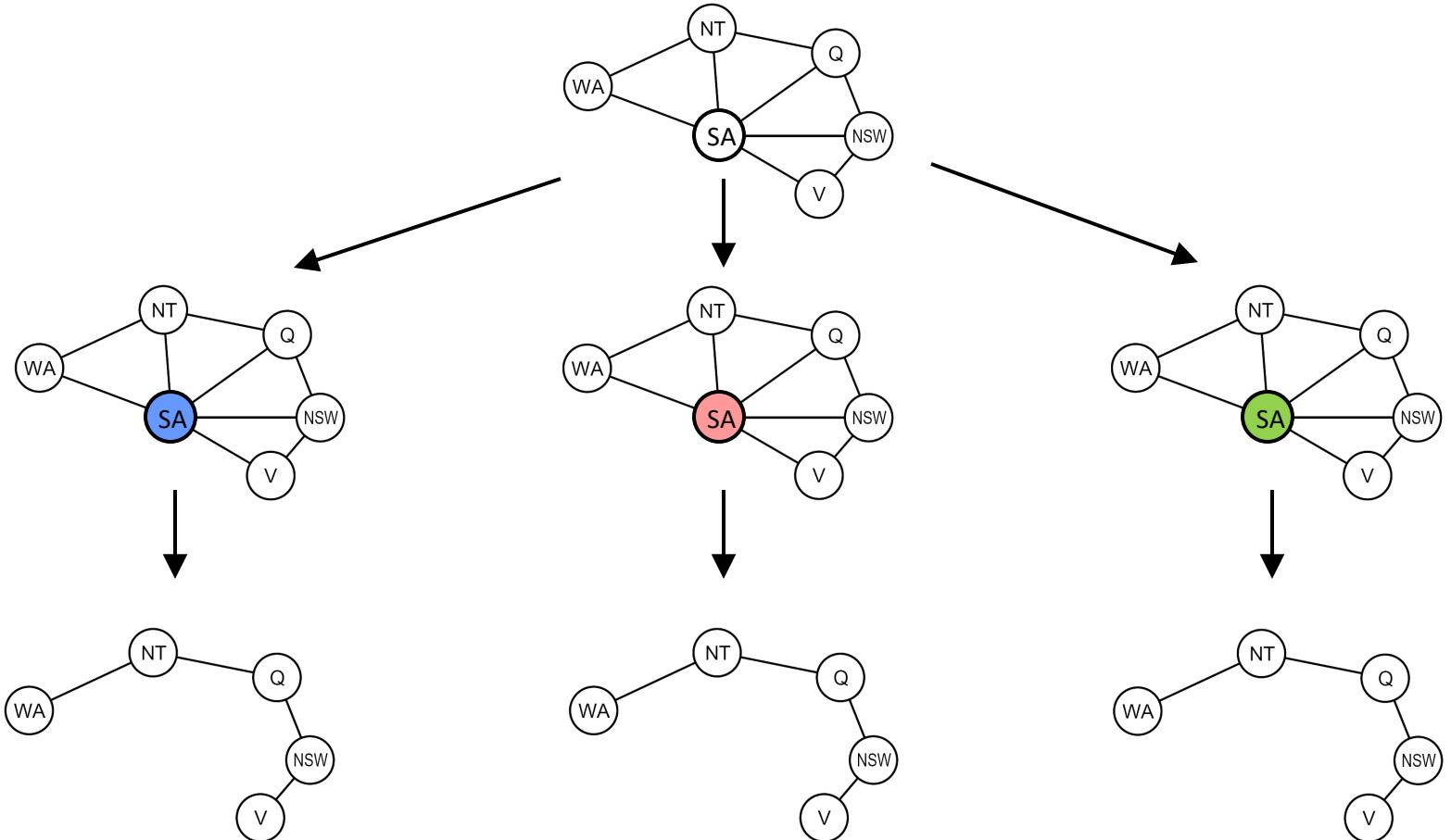
# Cutset Conditioning

Choose a cutset

Instantiate the cutset  
(all possible ways)

Compute residual CSP  
for each assignment

Solve the residual CSPs  
(tree structured)



Note: branching on the number of ways to instantiate the cut set variables.

Finding the “optimal” cutset is not easy (in general NP-hard). Easier if we know about the problem structure.

# Applications of CSPs

- Assignment problems
  - e.g., who teaches what class
- Timetable problems
  - e.g., which class is offered when and where?
- Scheduling problems
- VLSI or PCB layout problems
- Boolean satisfiability
- N-Queens
- Graph coloring
- Games: Minesweeper, Magic Squares, Sudoku, Crosswords
- Line-drawing labeling