



Constraint satisfaction problems (CSPs)

Unit-III



Outline

- Constraint Satisfaction Problems (CSP)
- Backtracking search for CSPs
- Local search for CSPs



Constraint Satisfaction Problems

- A Constraint Satisfaction Problem (CSP) involves a set of variables, each of which has a domain of possible values, and a set of constraints that define the allowable combinations of values for the variables.
- A constraint satisfaction problem (CSP) is defined by
 - X: A set of variables $\{X_1, X_2, \dots, X_n\}$ and a
 - C: A set of constraints $\{C_1, C_2, \dots, C_m\}$ and
 - D: A set of domains $\{D_1, D_2, \dots, D_n\}$,
- where each variable X_i has a nonempty domain D_i of possible values.
- Each constraint C_i involves some subset of the variables and specifies the allowable combinations of values for that subset.



Constraint Satisfaction Problems

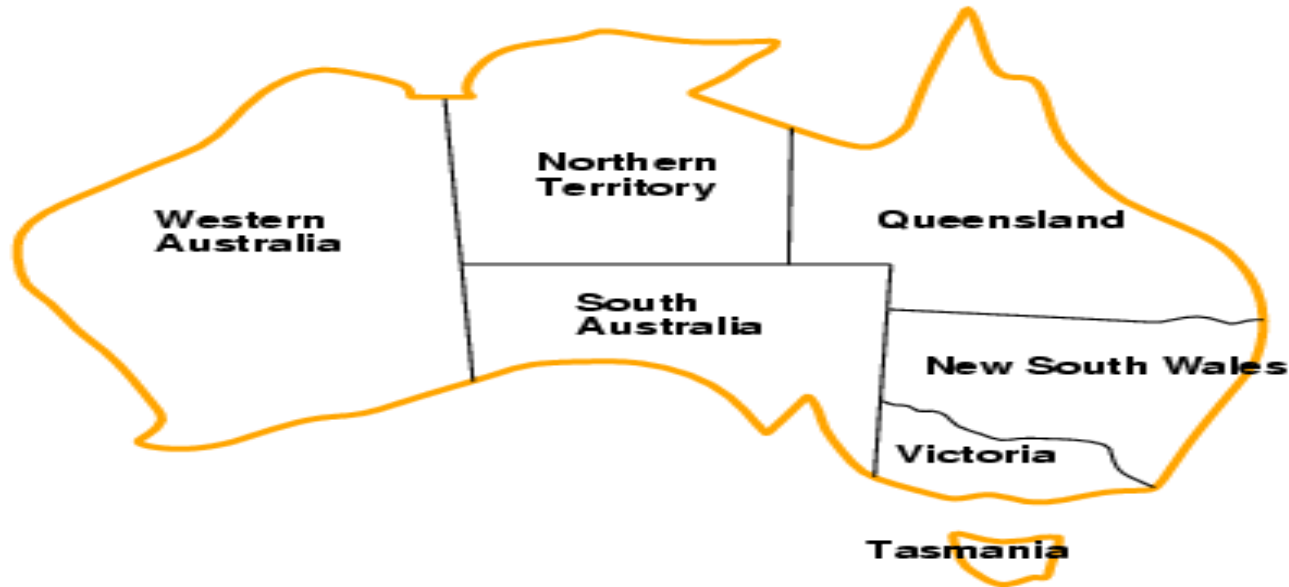
- The goal of a CSP is to find an assignment values to the variables that satisfies all the constraints. This assignment is called a **solution to the CSP**.
- **Standard search problem: State** is a "black box" – any data structure that supports successor function, heuristic function, and goal test.
- **CSP:**
 - **state** is defined by **variables** X_i with **values** from **domain** D_i
 - **goal test** is a set of **constraints** specifying allowable combinations of values for subsets of variables
- Allows useful **general-purpose** algorithms with more power than standard search algorithms



Constraint Satisfaction Problems

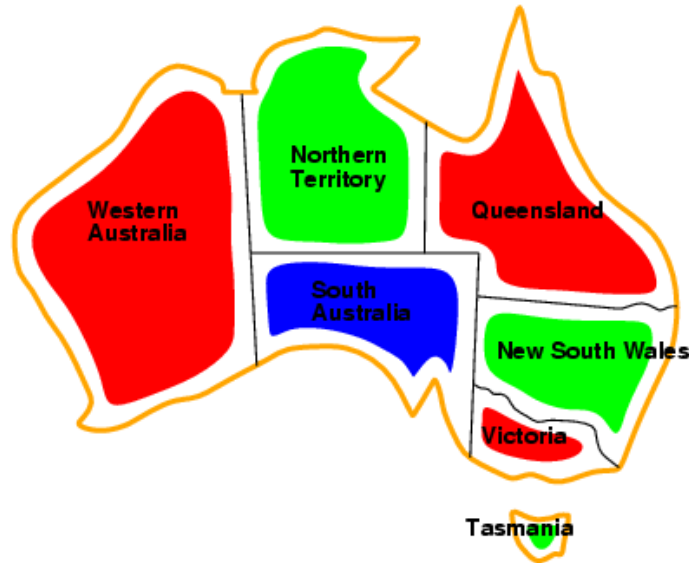
- An assignment of values to some or all of the variables that doesn't violate any constraints is called a **consistent or legal assignment**.
- A **complete assignment** is that in which every variable is mentioned and if it satisfies all the constraints, then it is a **solution**.
- **Partial Assignment:** An assignment which assigns values to some of the variables only such type of assignments are called Partial assignments.

Example: Map-Coloring



- **Variables** WA, NT, Q, NSW, V, SA, T
- **Domains** $D_i = \{\text{red, green, blue}\}$
- **Constraints**: adjacent regions must have different colors
- e.g., $WA \neq NT$, or (WA, NT) in $\{(\text{red, green}), (\text{red, blue}), (\text{green, red}), (\text{green, blue}), (\text{blue, red}), (\text{blue, green})\}$

Example: Map-Coloring

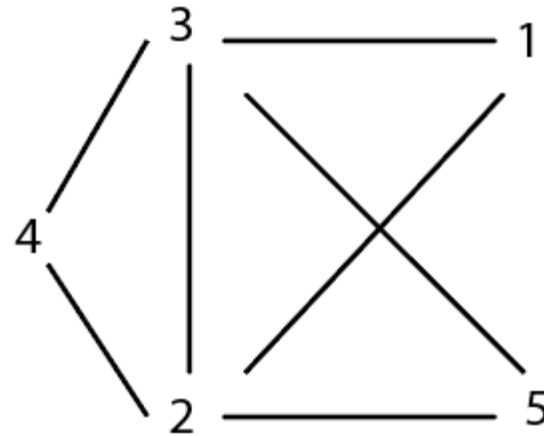
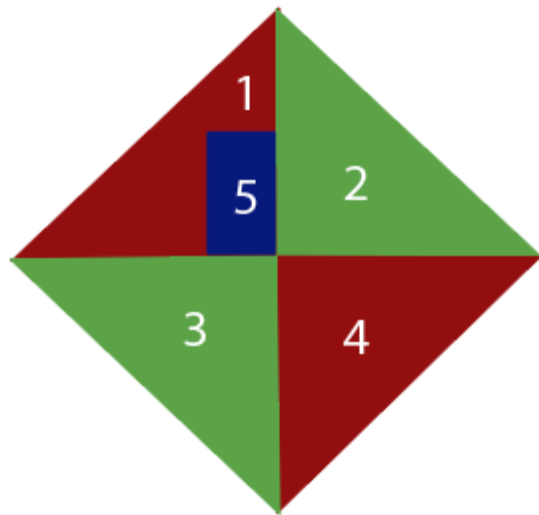


- A search procedure that does not use constraints would have to consider $3^5=243$ assignments for the five neighboring variables;
- With constraints we have only $2^5=32$ assignments to consider, a reduction of 87%.

- Solutions are **complete** and **consistent** assignments, e.g., WA = red, NT = green, Q = red, NSW = green, V = red, SA = blue, T = green

Graph Coloring

- **Graph Coloring:** The problem where the constraint is that no adjacent sides can have the same color.



Graph Coloring

Sudoku

- **Sudoku Playing:** The gameplay where the constraint is that no number from 0-9 can be repeated in the same row or column.

SUDOKU

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

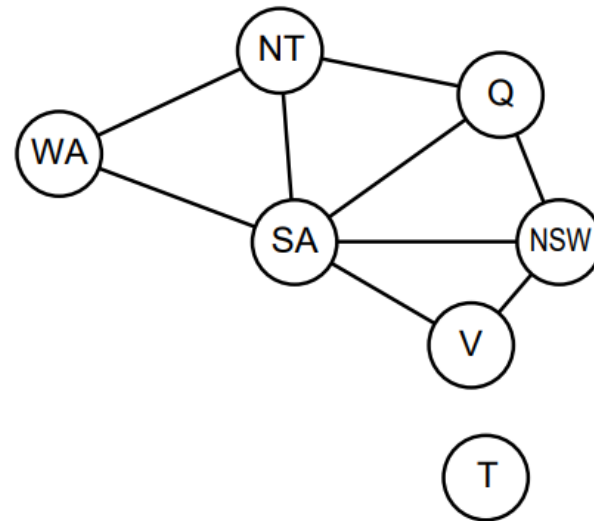
Puzzle

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

Solution

Constraint graph

- **Binary CSP:** each constraint relates two variables
- **Constraint graph:** nodes are variables, arcs are constraints



- A **constraint graph** can be used to visualize binary constraints.
- General-purpose CSP methods use the graph structure to speed up search. e.g., Tasmania is an independent subproblem!



Varieties of CSPs

■ Discrete variable:

■ finite domains:

- n variables, domain size $d \rightarrow O(d^n)$ complete assignments
- e.g., Boolean CSPs, incl. ~Boolean satisfiability (NP-complete)

■ infinite domains:

- integers, strings, etc.
- e.g., job scheduling, variables are start/end days for each job
- need a constraint language, e.g., $StartJob_1 + 5 \leq StartJob_3$
- linear constraints solvable, nonlinear undecidable

➤ Continuous variables

- e.g., start/end times for Hubble Space Telescope observations
 - linear constraints solvable in polynomial time by linear programming



Varieties of constraints

- **Unary constraints** involve a single variable.
 - e.g., $SA \neq \text{green}$
- **Binary constraints** involve pairs of variables.
 - e.g., $SA \neq WA$
- The **ternary constraint** $\text{Between}(X, Y, Z)$, for example, can be defined as $\{(X, Y, Z), X < Y < Z \text{ or } X > Y > Z\}$.
- **Global Constraints/Higher-order** constraints involve 3 or more variables or an arbitrary number of variables.
 - e.g., cryptarithmic column constraints
- The name is traditional but confusing because a global constraint need not involve all the variables in a problem.

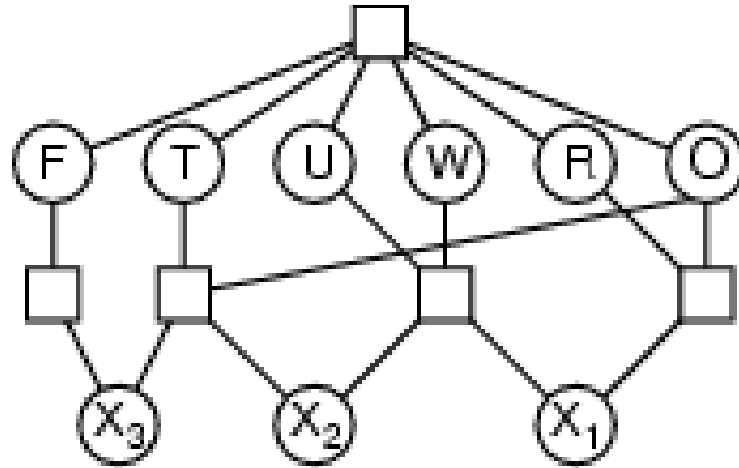


Varieties of constraints

- One of the most common global constraints is **Alldiff**, which says that all of the variables involved in the constraint must have different values.
- In Sudoku problems, all variables in a row, column, or 3X3 box must satisfy an **Alldiff** constraint.
- **Preferences/soft constraints** e.g., red is better than green often representable by a cost for each variable assignment
→ constrained optimization problems

Example: Cryptarithmic

$$\begin{array}{r} \text{T W O} \\ + \text{T W O} \\ \hline \text{F O U R} \end{array}$$



- Variables: $F T U W R O X_1 X_2 X_3$
- Domains: $\{0, 1, 2, 3, 4, 5, 6, 7, 8, 9\}$
- Constraints: $Alldiff(F, T, U, W, R, O)$
- - $O + O = R + 10 \cdot X_1$
 - $X_1 + W + W = U + 10 \cdot X_2$
 - $X_2 + T + T = O + 10 \cdot X_3$
 - $X_3 = F, T \neq 0, F \neq 0$

Example: crypt arithmetic problem

$$\begin{array}{rcccc} & C4 & C3 & C2 & C1 \\ & S & E & N & D \\ + & M & O & R & E \\ \hline M & O & N & E & Y \end{array}$$

1. $D + E = 10 * C1 + Y$
2. $C1 + N + R = 10 * C2 + E$
3. $C2 + E + O = 10 * C3 + N$
4. $C3 + S + M = 10 * C4 + O$
5. $C4 = M = 1$ As M has to be non-zero .

Where $C1, C2, C3$ and $C4$ can be either 0 or 1.

Other alphabets can take unique values from the set $\{ 0,1,2,3,4,5,6,7,9\}$

Example: crypt arithmetic problem

S E N D
+ M O R E

M O N E Y

Initial state

M=1
S=8 OR 9
O=0 OR 1 $\Rightarrow O = 0$
N=E OR E+1 $\Rightarrow N = E + 1$
C2=1
N+R>8
E<>9, E = 2, 3, 4 ends with conflict

D = Y + 5
R = 8

D=7

Y= 2

E=5

N=6
C3= 0 AND S=9
R=9 - C1
5+D=Y OR 5+D=10 + Y

R = 9
Contradiction
as s=9

C1=1

C1=0

SOLUTION: {S=9,E=5,N=6,D=7,M=1,O=0, R=8,Y=2} and { C1 =1, C2 = 1, C3 =0 , C4 = 4 }

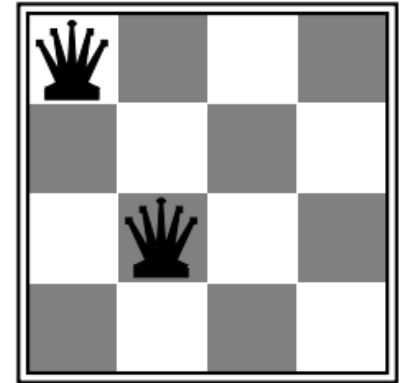
Sudoku as a CSP

- Variables: 81 variables
 - $A1, A2, A3, \dots, I9$
 - Letters index rows, top to bottom
 - Digits index columns, left to right
- Domains: The nine positive digits
 - $A1 \in \{1, 2, 3, 4, 5, 6, 7, 8, 9\}$
 - Etc.
- Constraints: *Alldiff* constraints
 - $Alldiff(A1, A2, A3, A4, A5, A6, A7, A8, A9)$
 - Etc.
- [Why constraint satisfaction?]

	1	2	3	4	5	6	7	8	9
A		6		1		4		5	
B			8	3		5	6		
C	2								1
D	8			4		7			6
E			6				3		
F	7			9		1			4
G	5								2
H			7	2		6	9		
I		4		5		8		7	

4-Queens as a CSP

- Assume one queen in each column. Which row does each one go in?



$$Q_1 = 1 \quad Q_2 = 3$$

- Variables $Q_1, Q_2, Q_3,$ and Q_4
- Domains $D_i = \{ 1, 2, 3, 4 \}$
- Constraints $Q_i \neq Q_j$ (cannot be in same row)
- $|Q_i - Q_j| \neq |i - j|$ (cannot be on same diagonal)
- Translate each constraint into set of allowable values for its variables
- E.g., values for (Q_1, Q_2) are $(1, 3) (1, 4) (2, 4) (3, 1) (4, 1) (4, 2)$



Real-world CSPs

- Assignment problems
 - e.g., who teaches what class
- Timetabling problems
 - e.g., which class is offered when and where?
- Transportation scheduling
- Factory scheduling: Job-shop scheduling
- Notice that many real-world problems involve real-valued variables



Standard search formulation (incremental)

- A CSP can easily be expressed as a standard search problem.
- Let's start with the straightforward approach, then fix it
- States are defined by the values assigned so far
 - **Initial state**: the empty assignment $\{ \}$
 - **Successor function**: assign a value to an unassigned variable that does not conflict with current assignment
 - \rightarrow fail if no legal assignments
 - **Goal test**: the current assignment is complete



Standard search formulation (incremental)

■ Note:

1. This is the same for all CSPs:
2. Every solution appears at depth n with n variables \rightarrow use depth-first search.
3. Path is irrelevant, so can also use complete-state formulation.
4. However, with domain of size d , branching factor $b = (n - \ell) d$ at depth ℓ , hence $n!d^n$ leaves!



Backtracking search

- Variable assignments are **commutative**,
- i.e., [WA = red then NT = green] same as [NT = green then WA = red]
- Only need to consider assignments to a single variable at each node.
- Chooses values for one variable at a time and backtracks when a variable has no legal values left to assign.
- *Depth-first search* for CSPs with single-variable assignments is called **backtracking** search
- Backtracking search is the basic uninformed search algorithm for CSPs
- Can solve n -queens for $n \approx 25$

Backtracking search

```
function BACKTRACKING-SEARCH(csp) returns a solution, or failure
  return RECURSIVE-BACKTRACKING({}, csp)

function RECURSIVE-BACKTRACKING(assignment, csp) returns a solution, or
failure
  if assignment is complete then return assignment
  var ← SELECT-UNASSIGNED-VARIABLE(Variables[csp], assignment, csp)
  for each value in ORDER-DOMAIN-VALUES(var, assignment, csp) do
    if value is consistent with assignment according to Constraints[csp] then
      add { var = value } to assignment
      result ← RECURSIVE-BACKTRACKING(assignment, csp)
      if result ≠ failure then return result
      remove { var = value } from assignment
  return failure
```

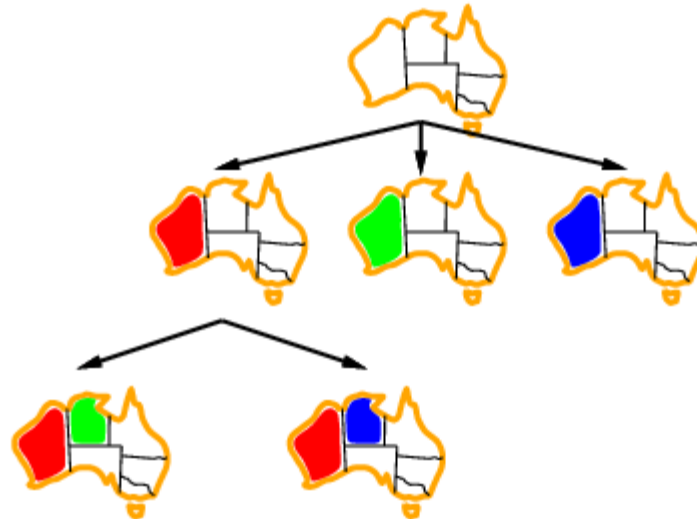
Backtracking example



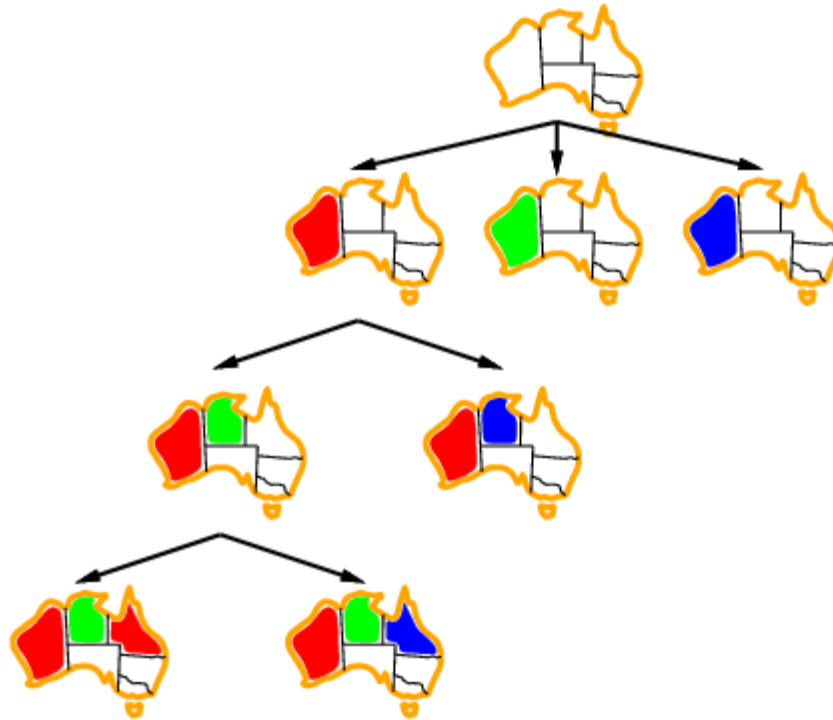
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Backtracking example



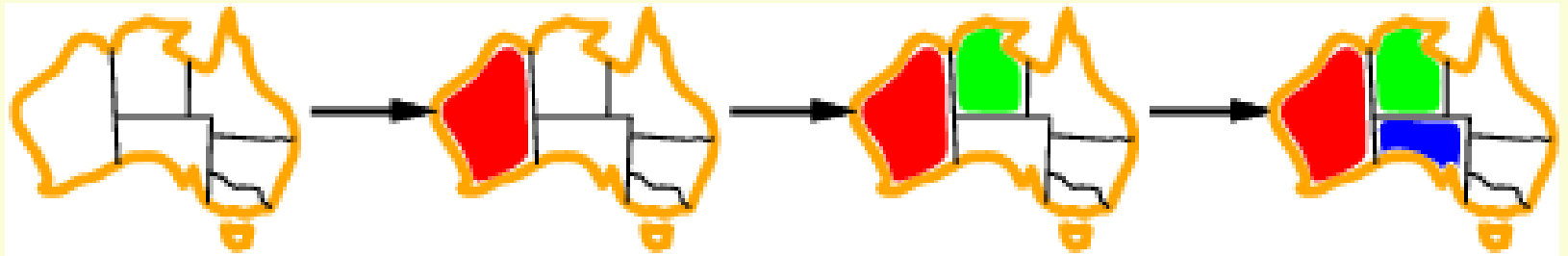


Improving backtracking efficiency

- **General-purpose** methods can give huge gains in speed:
 - Which variable should be assigned next?
 - In what order should its values be tried?
 - Can we detect inevitable failure early?

Most constrained variable

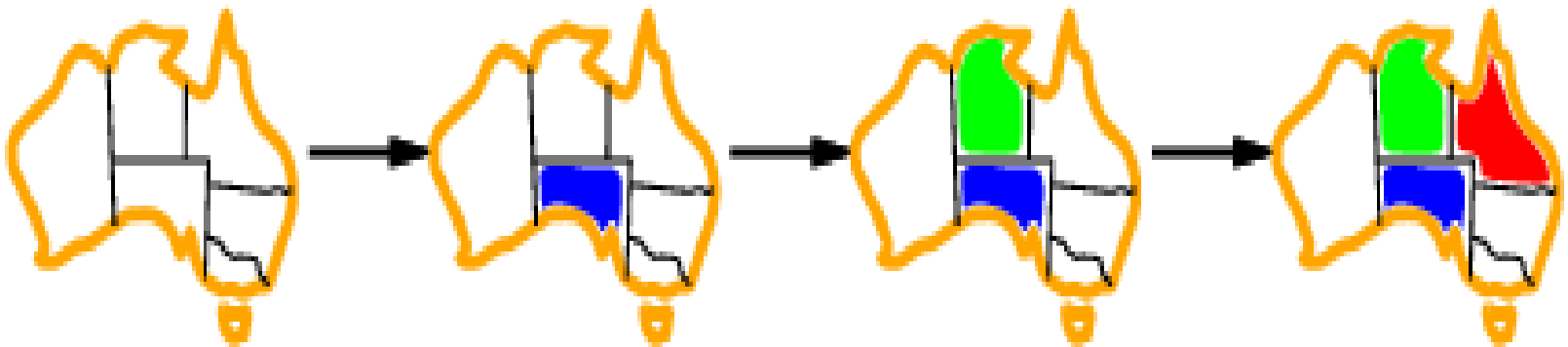
- Most constrained variable:
Choose the variable with the fewest legal values



- Minimum remaining values (MRV) heuristic

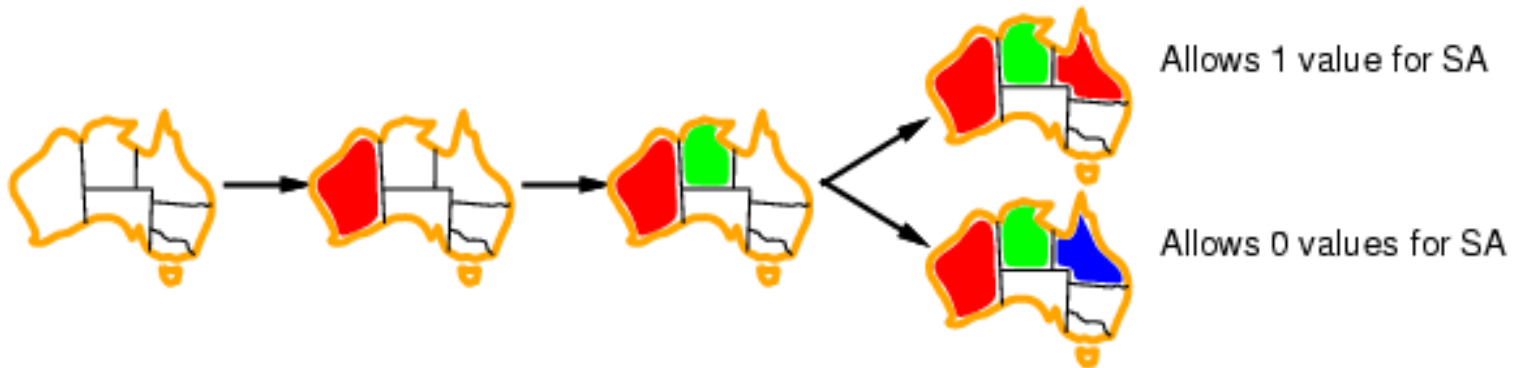
Most constraining variable

- Tie-breaker among **most constrained variables**
- Most constraining variable:
- Choose the variable with the most constraints on remaining variables.



Least constraining value

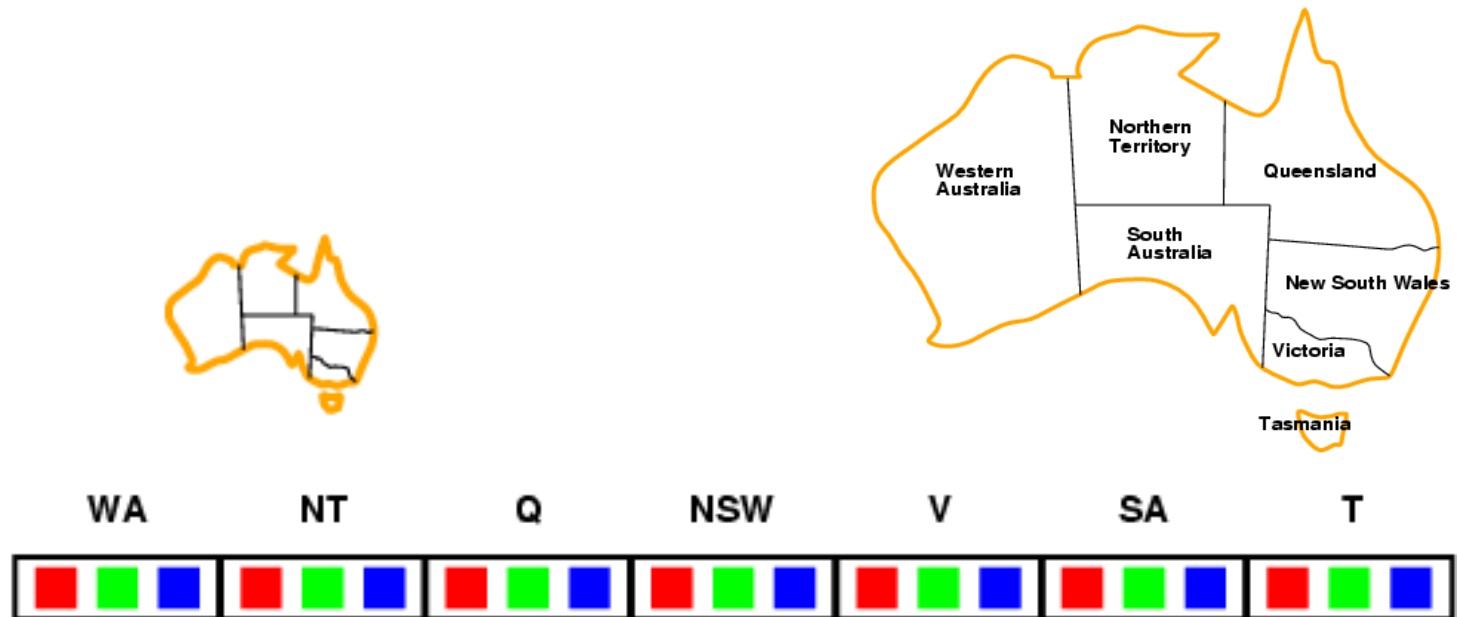
- Given a variable, choose the least constraining value:
- The one that rules out the fewest values in the remaining variables



Forward checking

■ Idea:

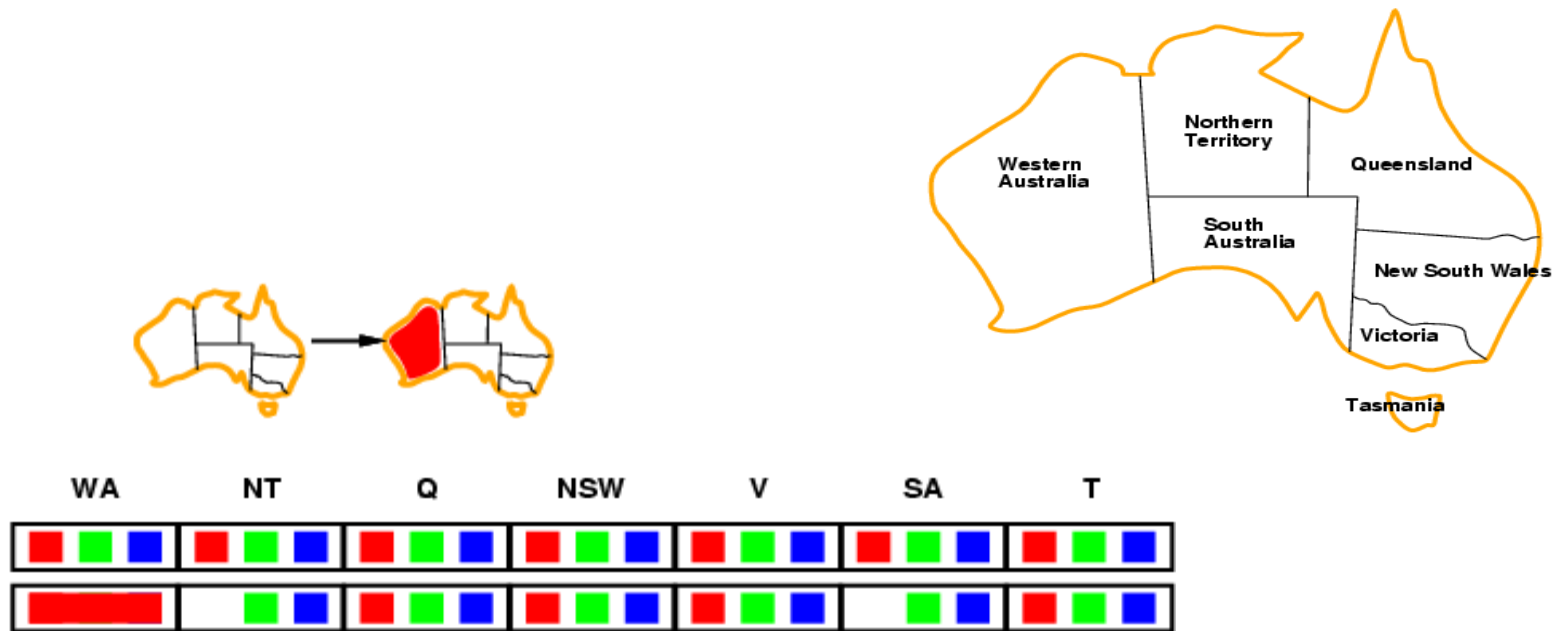
- Keep track of remaining legal values for unassigned variables
- Terminate search when any variable has no legal values



Forward checking

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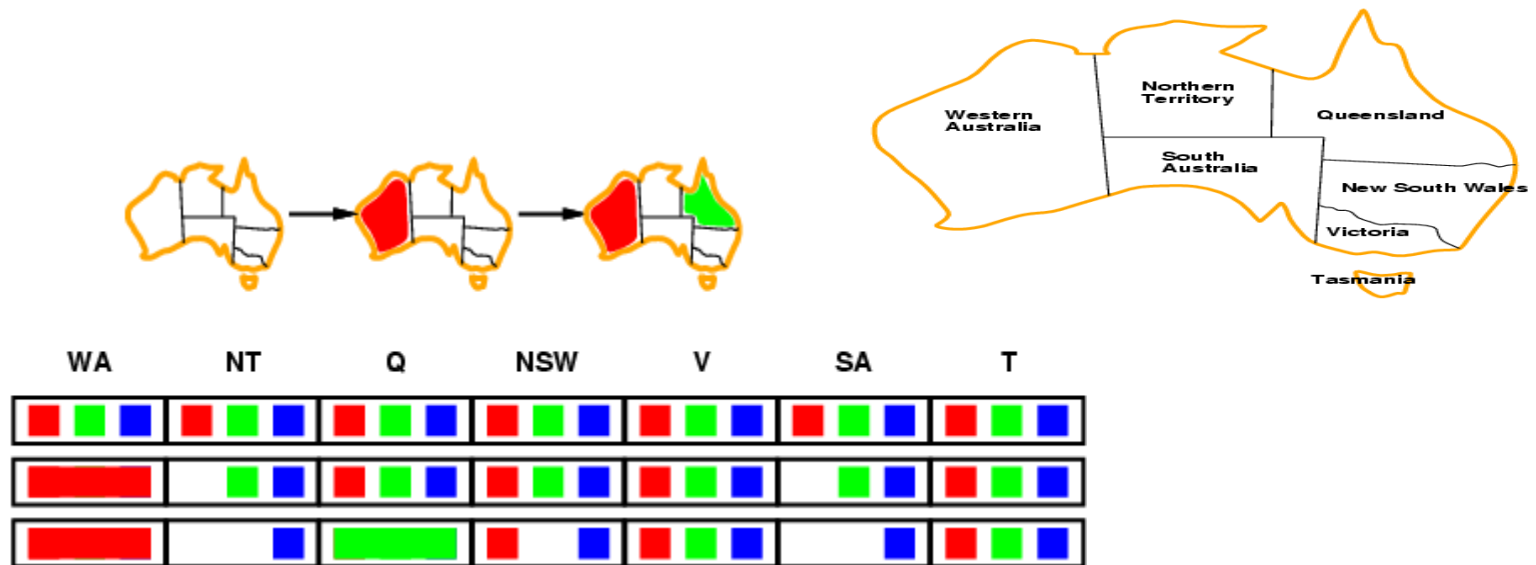
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Forward checking

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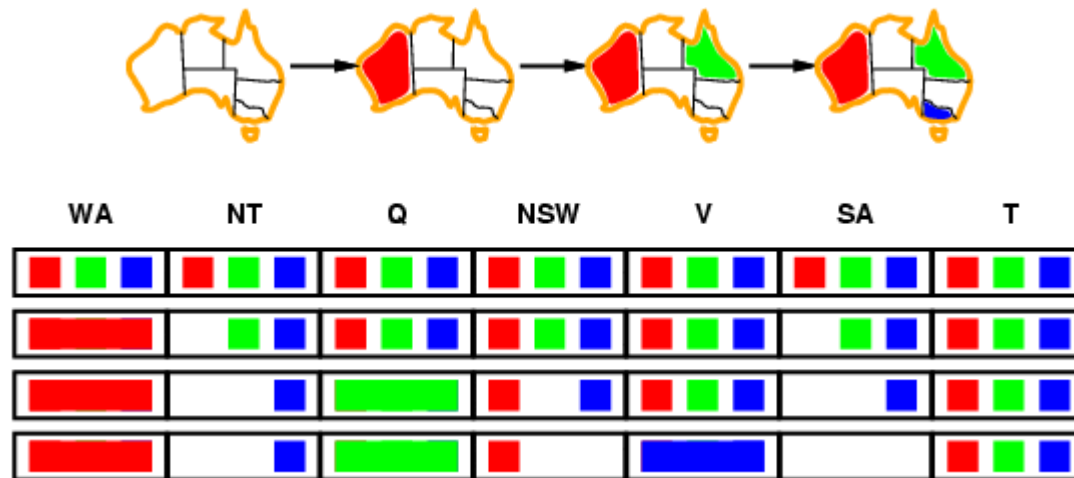
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Forward checking

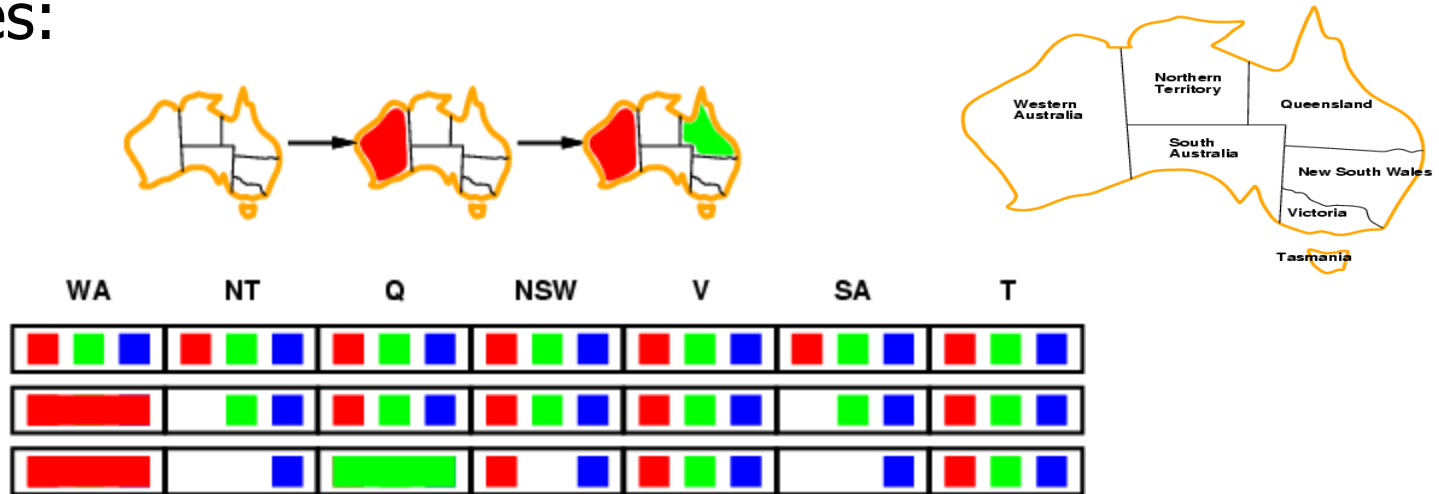
Idea:

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- Terminate search when any variable has no legal values



Constraint propagation

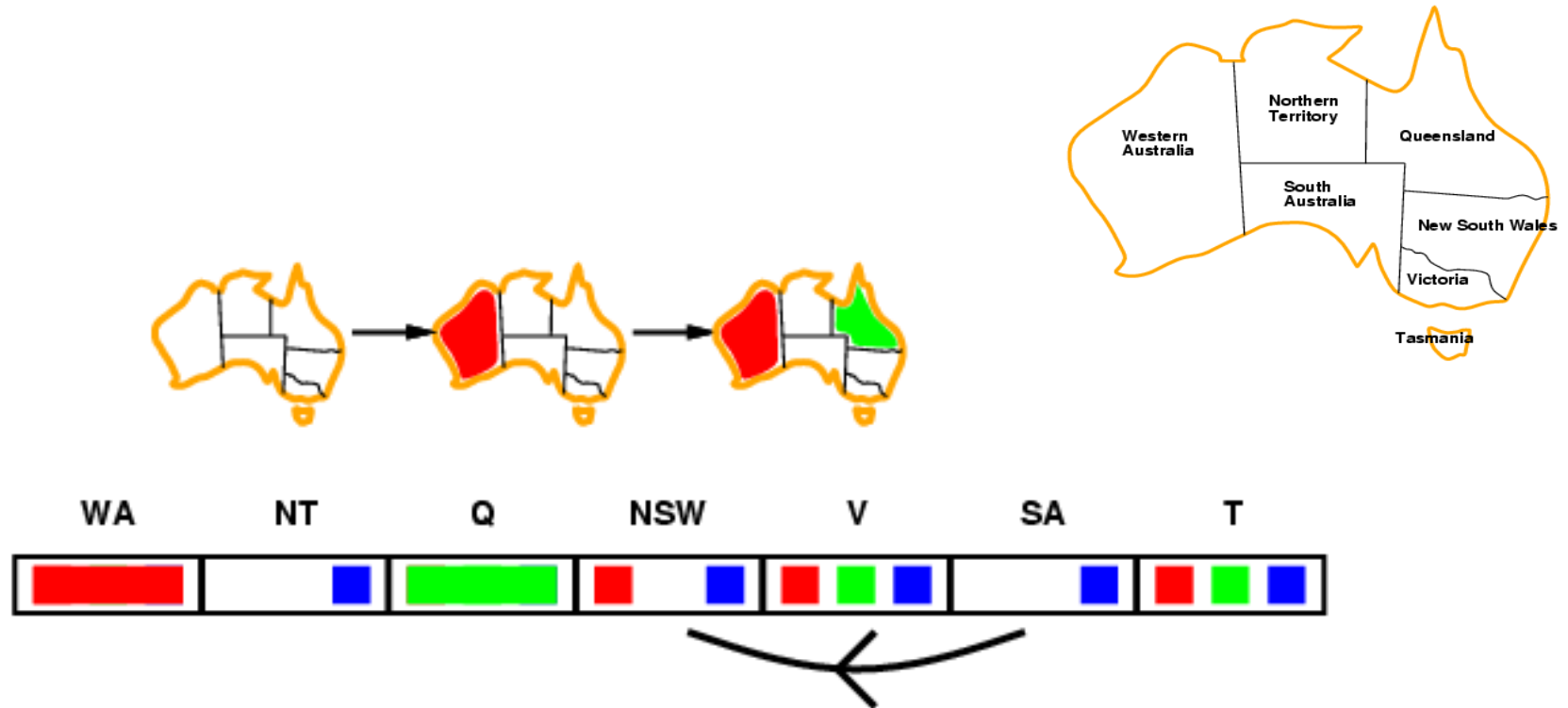
- Forward checking propagates information from assigned to unassigned variables, but doesn't provide early detection for all failures:



- NT and SA cannot have both blue!
- Constraint propagation repeatedly enforces constraints locally.

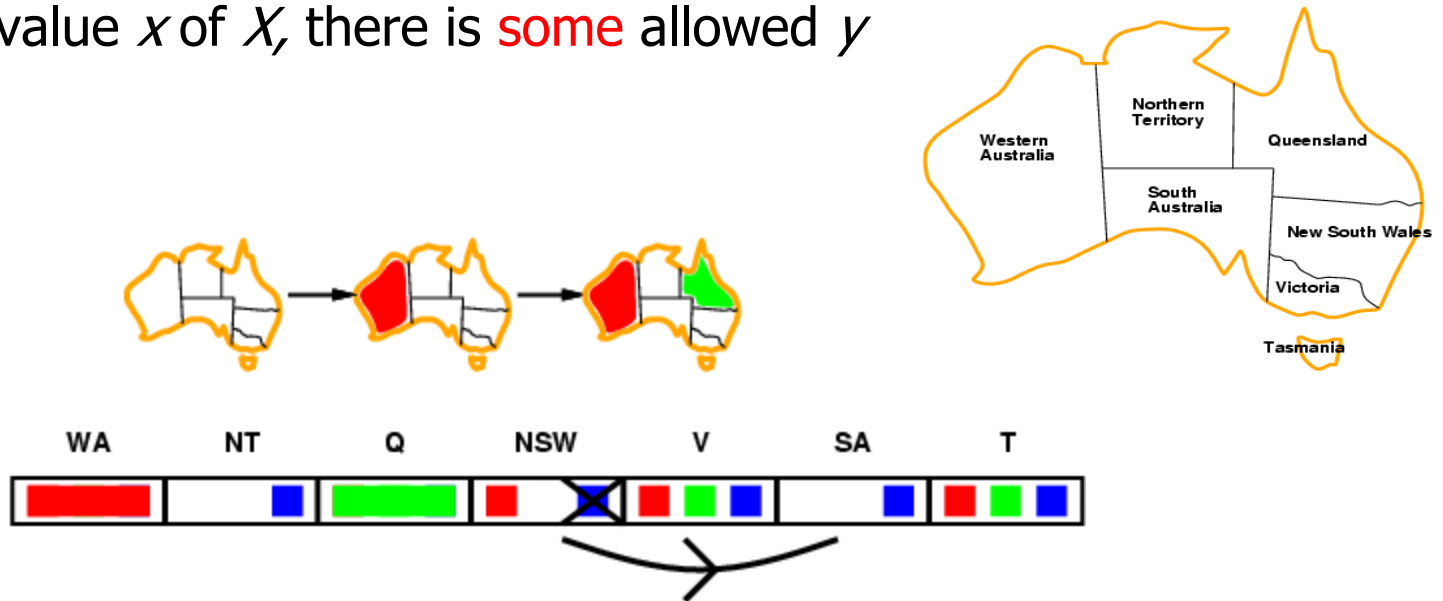
Arc consistency

- Simplest form of propagation makes each arc **consistent**
- $X \rightarrow Y$ is consistent iff for **every** value x of X , there is **some** allowed y



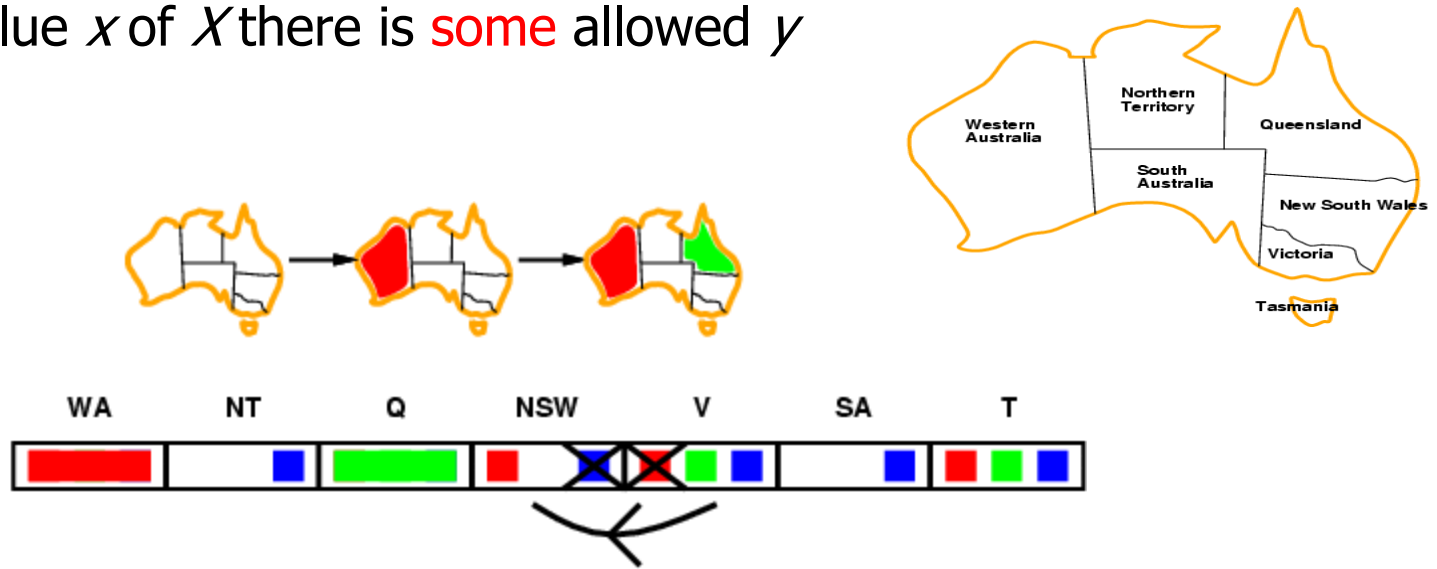
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Arc consistency

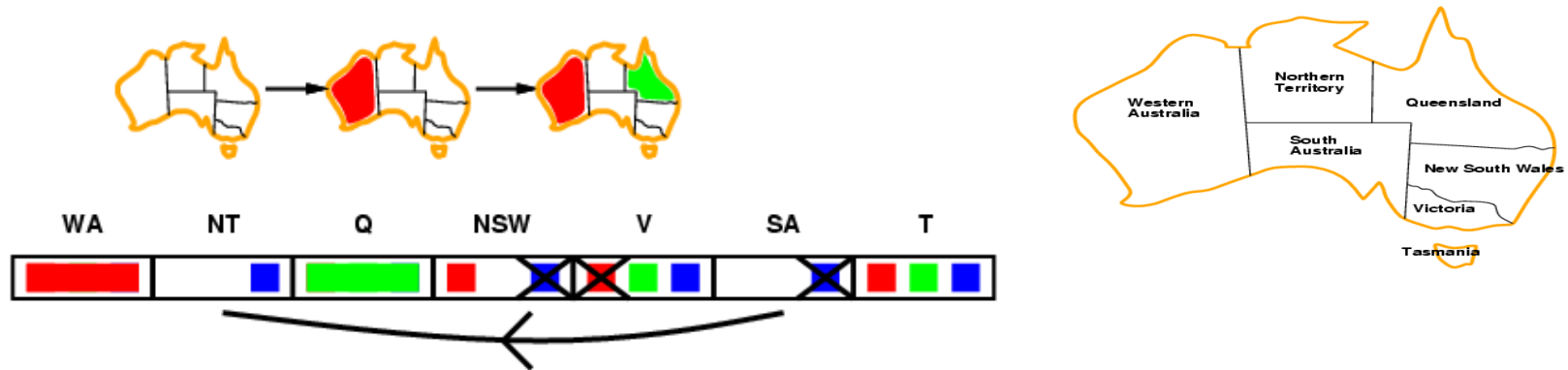
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- If X loses a value, neighbors of X need to be rechecked

Arc consistency

- Simplest form of propagation makes each arc **consistent**
- $X \rightarrow Y$ is consistent iff
- for **every** value x of X there is **some** allowed y



- If X loses a value, neighbors of X need to be rechecked
- Arc consistency detects failure earlier than forward checking
- Can be run as a preprocessor or after each assignment

Arc consistency algorithm AC-3

function AC-3(*csp*) **returns** the CSP, possibly with reduced domains

inputs: *csp*, a binary CSP with variables $\{X_1, X_2, \dots, X_n\}$

local variables: *queue*, a queue of arcs, initially all the arcs in *csp*

while *queue* is not empty **do**

$(X_i, X_j) \leftarrow \text{REMOVE-FIRST}(\textit{queue})$

if RM-INCONSISTENT-VALUES(X_i, X_j) **then**

for each X_k **in** NEIGHBORS[X_i] **do**

 add (X_k, X_i) to *queue*

function RM-INCONSISTENT-VALUES(X_i, X_j) **returns** true iff remove a value

removed \leftarrow false

for each x **in** DOMAIN[X_i] **do**

if no value y in DOMAIN[X_j] allows (x, y) to satisfy constraint(X_i, X_j)

then delete x from DOMAIN[X_i]; *removed* \leftarrow true

return *removed*



Solving CSPs by Searching

- A finite CSP could be solved by exhaustively searching the total assignments where, a **total assignment** assigns a value to every variable..
- The **generate-and-test algorithm** to find one solution is as follows: check each total assignment in turn; if an assignment is found that satisfies all of the constraints, return that assignment.
- A **generate-and-test algorithm** to find all solutions is the same except, instead of returning the first solution found, it enumerates the solutions.
- If there are n variables, each with domain size d , there are d^n total assignments. If there are e constraints, the total number of constraints tested is $O(ed^n)$.
- As n becomes large, this becomes intractable very quickly.



Solving CSPs by Searching

- Suppose the delivery robot must carry out a number of delivery activities, **a**, **b**, **c**, **d**, and **e**.
- Suppose that each activity happens at any of times 1, 2, 3, or 4. Let A be the variable representing the time that activity **a** will occur, and similarly for the other activities.
- The variable domains, which represent possible times for each of the deliveries, are

$$\text{dom}(A) = \{1, 2, 3, 4\}, \quad \text{dom}(B) = \{1, 2, 3, 4\}, \quad \text{dom}(C) = \{1, 2, 3, 4\},$$

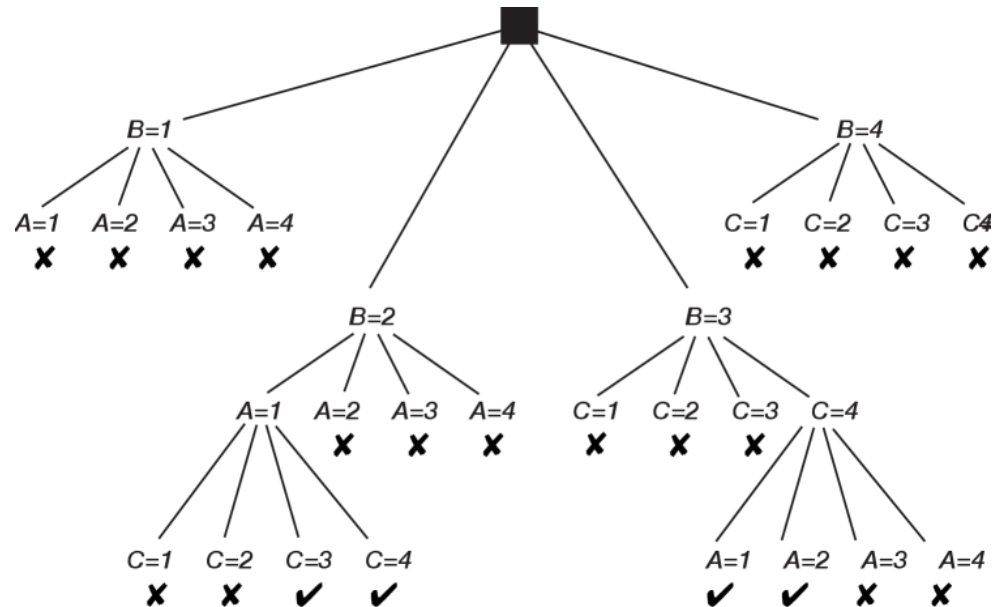
$$\text{dom}(D) = \{1, 2, 3, 4\}, \quad \text{dom}(E) = \{1, 2, 3, 4\}.$$

Suppose the following constraints must be satisfied:

$$\{ \quad (B \neq 3), (C \neq 2), (A \neq B), (B \neq C), (C < D), (A = D), \\ (E < A), (E < B), (E < C), (E < D), (B \neq D). \}$$

Solving CSPs by Searching

- **Example.** Consider a CSP with variables A, B, and C, each with domain {1,2,3,4}, and constraints $A < B$ and $B < C$. A possible search tree is shown in Figure.



- In this figure, a node corresponds to all of the assignments from the root to that node. The potential nodes that are pruned because they violate constraints are labeled **X**.
- The leftmost **X** corresponds to the assignment $\{A=1, B=1\}$. This violates the $A < B$ constraint, and so it is pruned.



Solving CSPs by Searching

- This CSP has four solutions. The leftmost one is $\{A=1, B=2, C=3\}$. The size of the search tree, and thus the efficiency of the algorithm, depends on which variable is selected at each time.
- A static ordering, such as always splitting on A then B then C, is usually less efficient than the dynamic ordering used here,
- But it might be more difficult to find the best dynamic ordering than to find the best static ordering.
- The set of answers is the same regardless of the variable ordering.
- There would be $4^3=64$ total assignments tested in a generate-and-test algorithm.
- For the search method, there are 8 total assignments generated, and 16 other partial assignments that were tested as to whether they satisfy some of the constraints.



Summary

- CSPs are a special kind of problem:
 - states defined by values of a fixed set of variables
 - goal test defined by constraints on variable values
- Backtracking = depth-first search with one variable assigned per node
- Variable ordering and value selection heuristics help significantly
- Forward checking prevents assignments that guarantee later failure
- Constraint propagation (e.g., arc consistency) does additional work to constrain values and detect inconsistencies