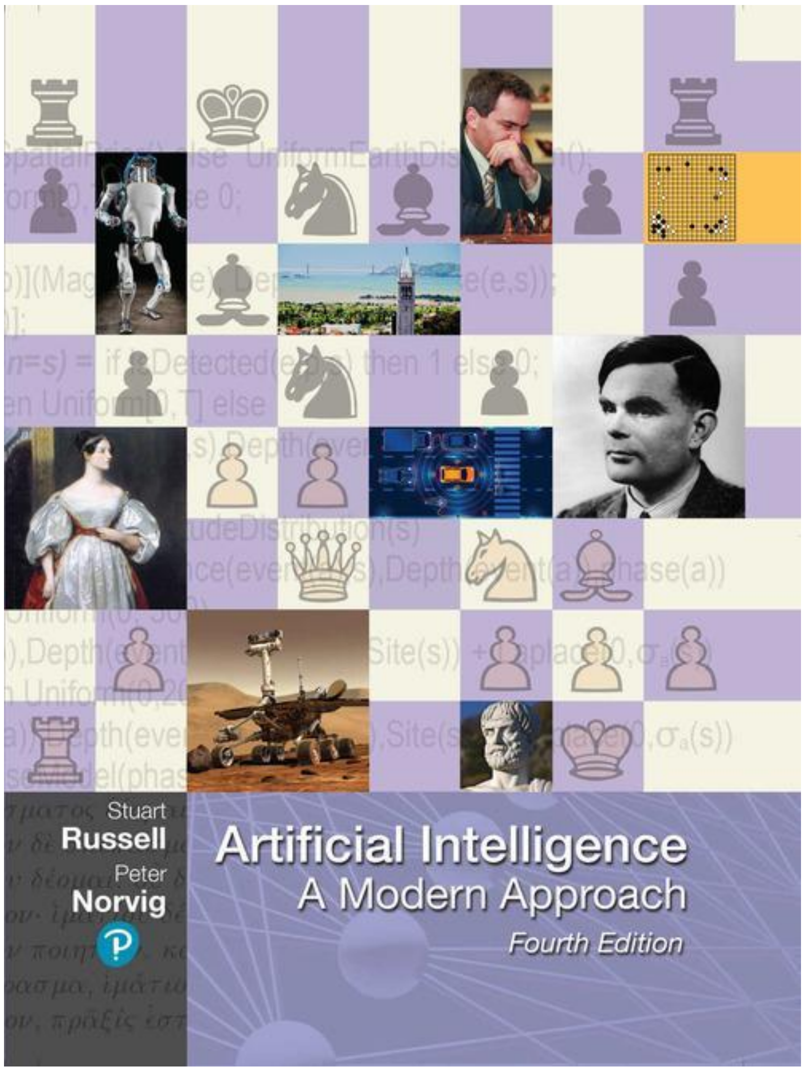
Artificial Intelligence: A Modern Approach

Fourth Edition



Chapter 6

Constraint Satisfaction Problems

Outline

- Defining Constraint Satisfaction Problems (CSP)
- CSP examples
- Backtracking search for CSPs
- Local search for CSPs
- Problem structure and problem decomposition

Defining Constraint Satisfaction Problems

A constraint satisfaction problem (CSP) consists of three components, *X*, *D*, and *C:*

- *X* is a set of variables, $\{X_1 \ldots\ldots X_n\}$.
- *D* is a set of domains, $\{D_1, \ldots, D_n\}$, one for each variable
- *C* is a set of constraints that specify allowable combination of values

CSPs deal with assignments of values to variables.

- A complete assignment is one in which every variable is assigned a value, and a solution to a CSP is a consistent, complete assignment.
- A partial assignment is one that leaves some variables unassigned.
- Partial solution is a partial assignment that is consistent

Constraint satisfaction problems (CSPs)

Standard search problem:

state is a "black box"—any old data structure

that supports goal test, eval, successor

CSP:

state is defined by variables X_i with values from domain D_i

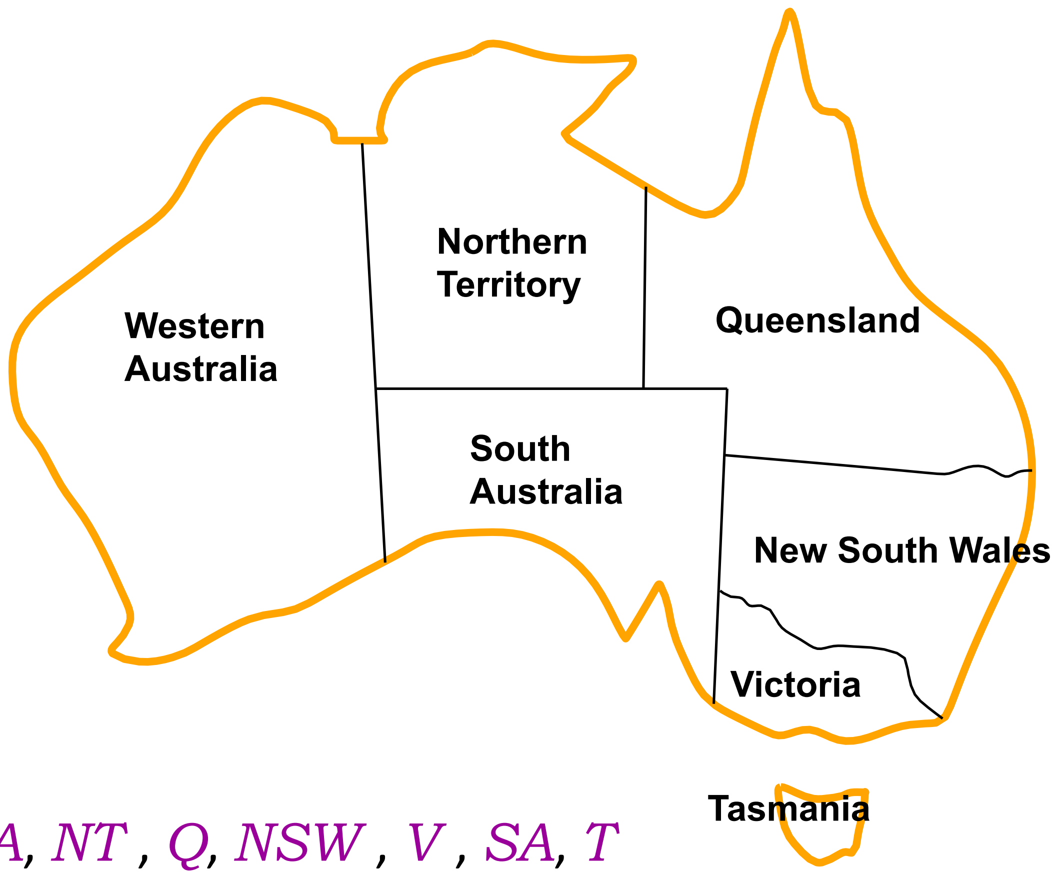
goal test is a set of constraints specifying

allowable combinations of values for subsets of variables

Simple example of a formal representation language

Allows useful general-purpose algorithms with more power than standard search algorithms

Example: Map-Coloring



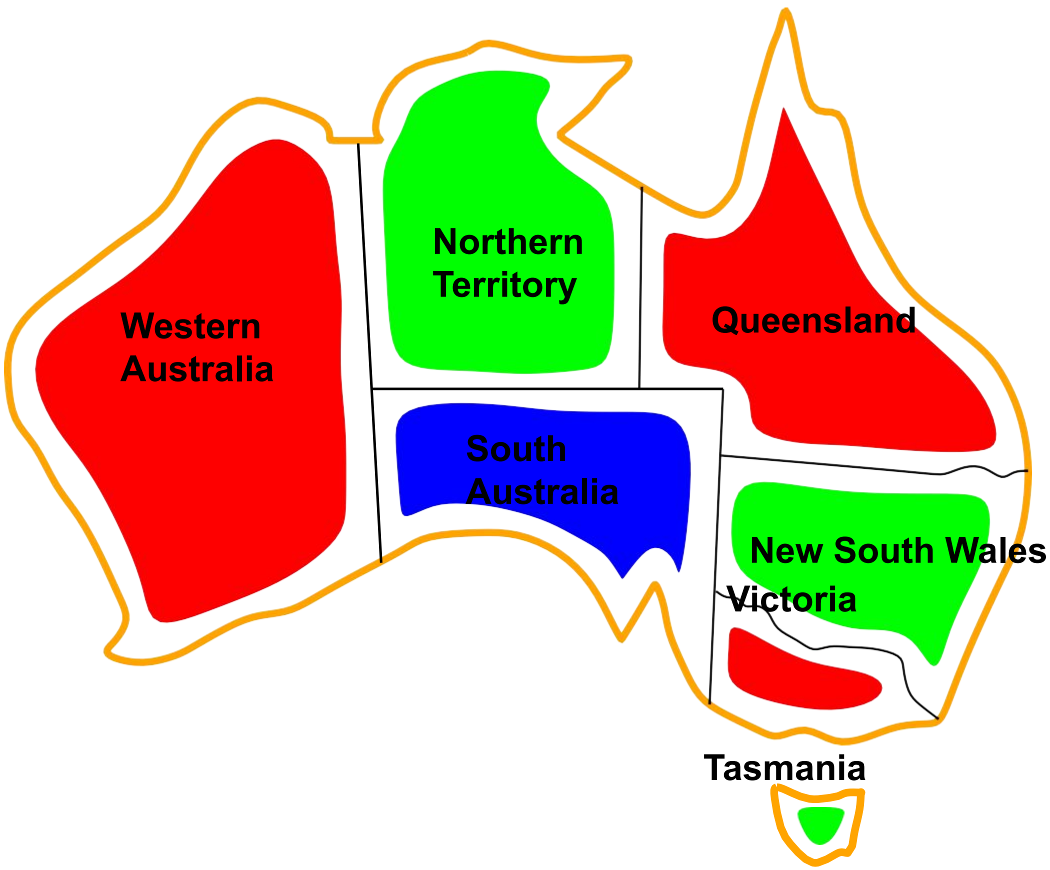
Variables WA, NT, Q, NSW, V, SA, T

Domains $D_i = \{red, green, blue\}$

Constraints: adjacent regions must have different colors e.g., $WA \neq NT$ (if the language allows this), or

$(WA, NT) \in \{(red, green), (red, blue), (green, red), (green, blue), \ldots\}$

Example: Map-Coloring contd.

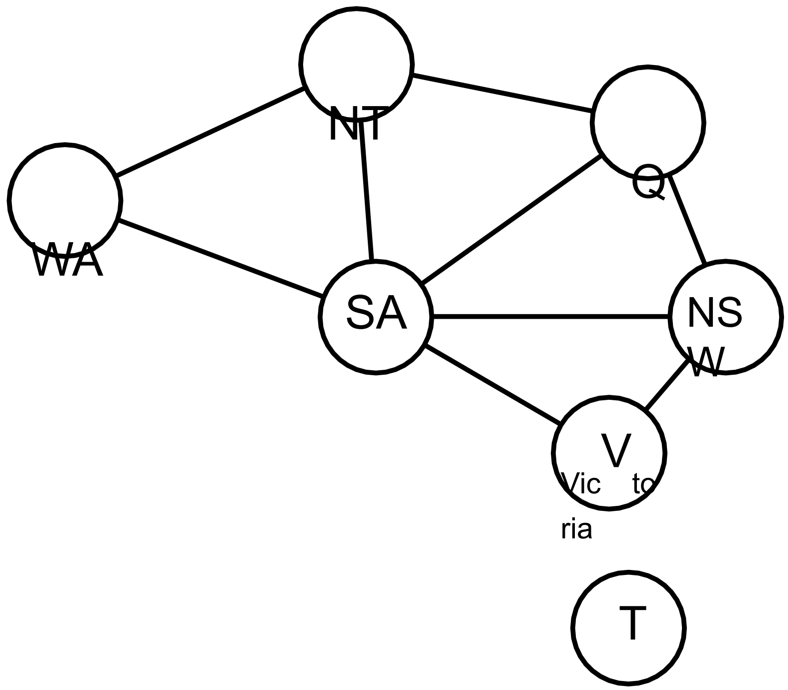


Solutions are assignments satisfying all constraints, e.g.,
{*WA* = *red*, *NT* = *green*, *Q* = *red*, *NSW* = *green*, *V* = *red*, *SA* = *blue*, *T* = *green*}

Constraint graph

Binary CSP: each constraint relates at most two variables

Constraint graph: nodes are variables, arcs show constraints



General-purpose CSP algorithms use the graph structure to speed up search. E.g., Tasmania is an independent subproblem!

Varieties of CSPs

Discrete variables

finite domains; 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 Telescope observations
- linear constraints solvable in poly time by LP methods

Varieties of constraints

Unary constraints involve a single variable, e.g., *SA /= green*

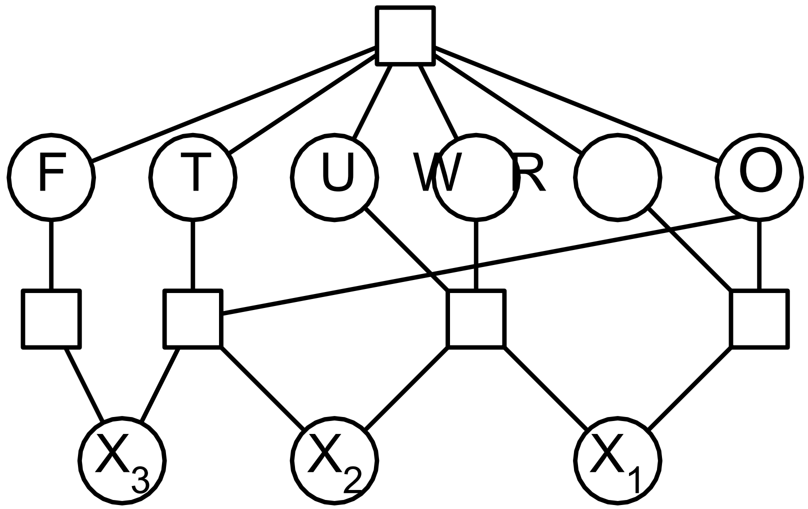
Binary constraints involve pairs of variables, e.g., *SA /= WA*

Higher-order constraints involve 3 or more variables, e.g., cryptarithmetic column constraints

Preferences (soft constraints), e.g., *red* is better than *green*
often representable by a cost for each variable assignment
→ constrained optimization problems

Example: Cryptarithmetic

T W
O
+ T W
O F O
U R



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)

$O + O = R + 10 \cdot X_1$, etc.

Real-world CSPs

Assignment problems
e.g., who teaches what class

Timetabling problems
e.g., which class is offered when and where?

Hardware configuration
Spreadsheets

Transportation

scheduling Factory

scheduling

Floorplanning

Notice that many real-world problems involve real-valued variables

Standard search formulation (incremental)

Let’s start with the straightforward, dumb 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.
  ⇒ fail if no legal assignments (not fixable!)
- Goal test: the current assignment is complete

1) This is the same for all CSPs!
2) Every solution appears at depth n with n variables
   ⇒ use depth-first search
3) Path is irrelevant, so can also use complete-state formulation
4) $b = (n - €)d$ at depth €, 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

⇒ $b = d$ and there are d^n leaves

Depth-first search for CSPs with single-variable assignments is called backtracking search

Backtracking search is the basic uninformed algorithm for

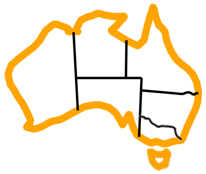
CSPs Can solve n-queens for $n \approx 25$

Backtracking search

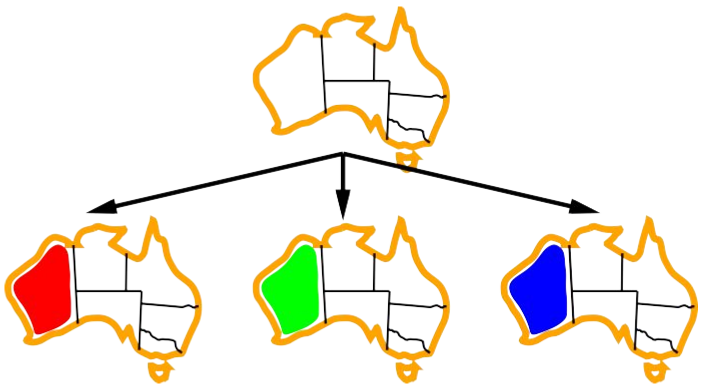
```
function Backtracking-Search(csp) returns solution/failure
   return Recursive-Backtracking({ }, csp)

function Recursive-Backtracking(assignment, csp) returns soln/failure
   if assignment is complete then return assignment
   var ← 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 ← Recursive-Backtracking(assignment, csp)
           if result /= failure then return result
           remove {var = value} from assignment
   return failure
```

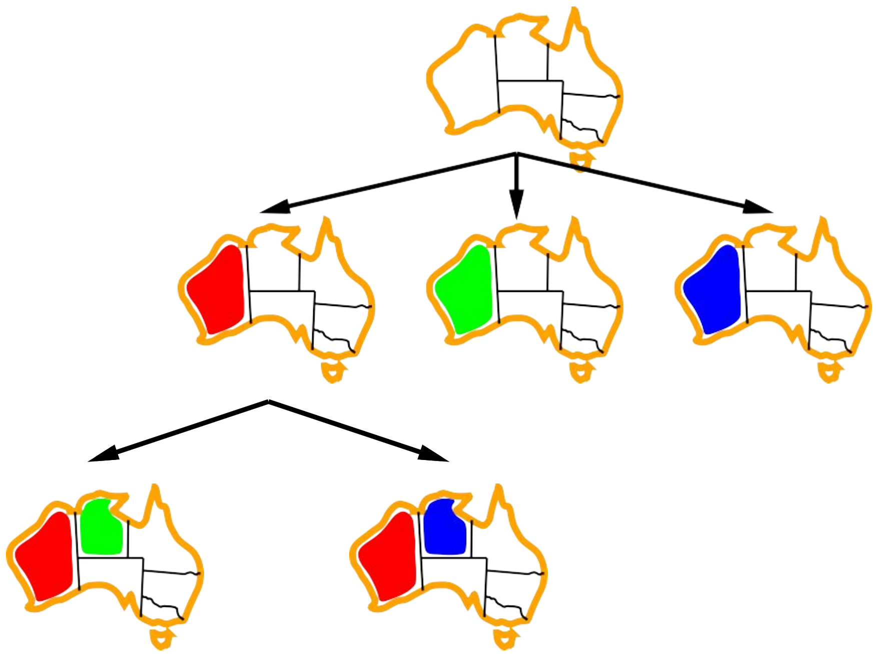
Backtracking example



Backtracking example



Backtracking example



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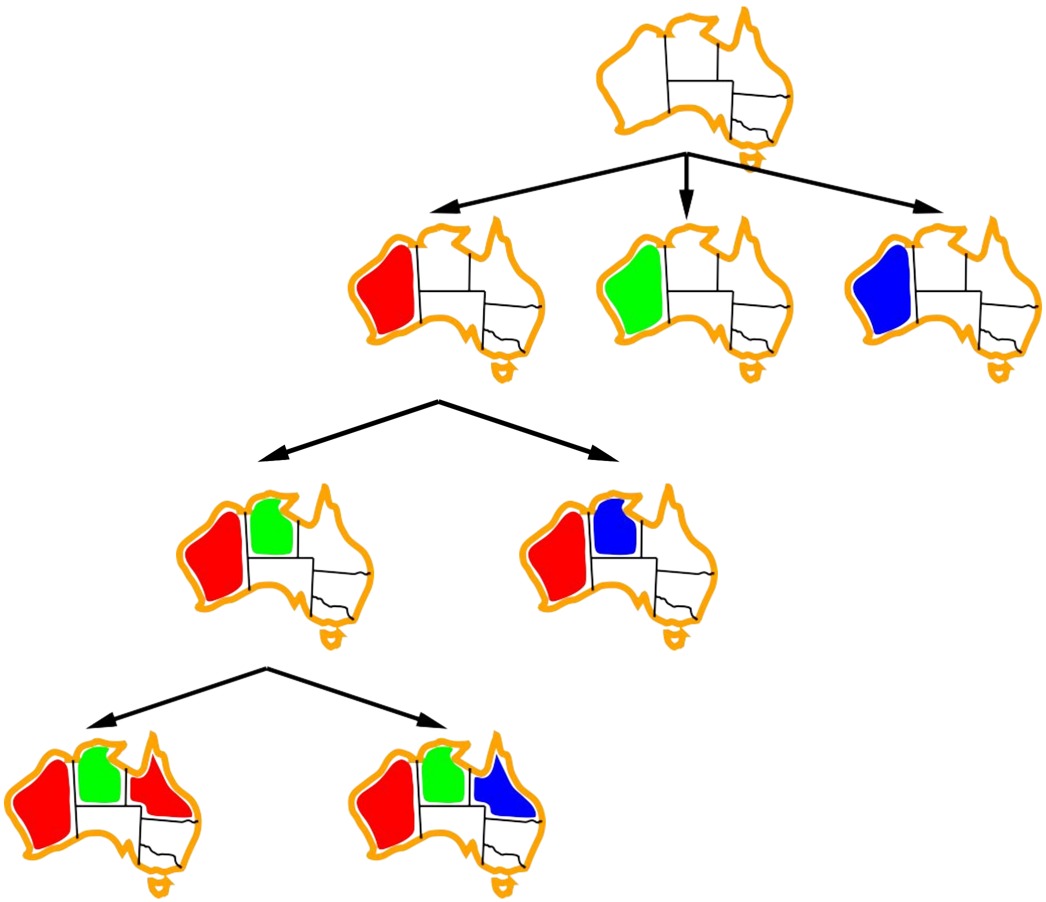


Improving backtracking efficiency

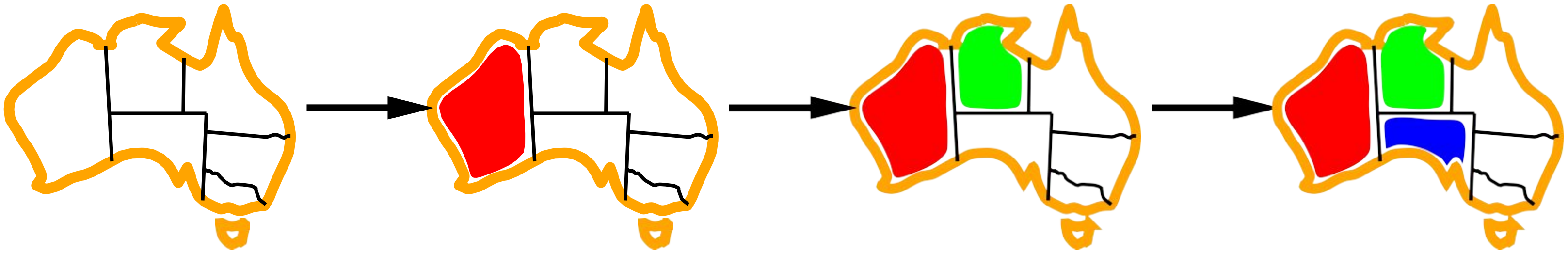
General-purpose methods can give huge gains in speed:

1. Which variable should be assigned next?
2. In what order should its values be tried?
3. Can we detect inevitable failure early?
4. Can we take advantage of problem structure?

Minimum remaining values

Minimum remaining values (MRV):

choose the variable with the fewest legal values

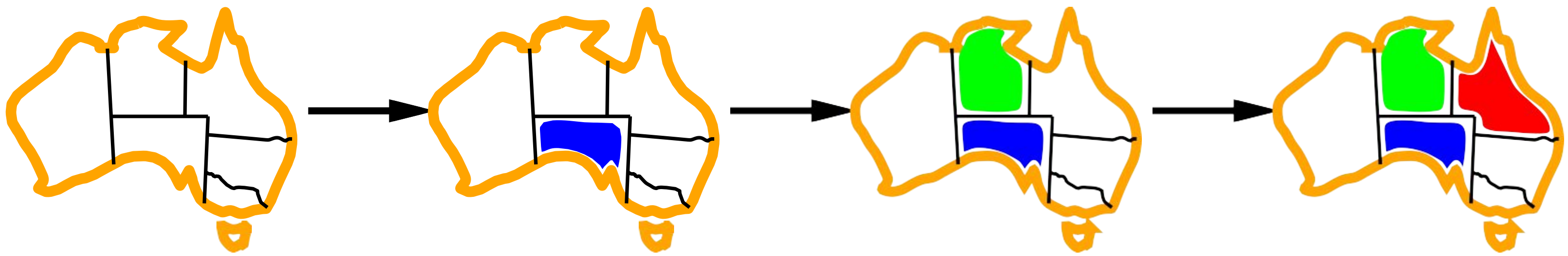


Degree heuristic

Tie-breaker among MRV variables

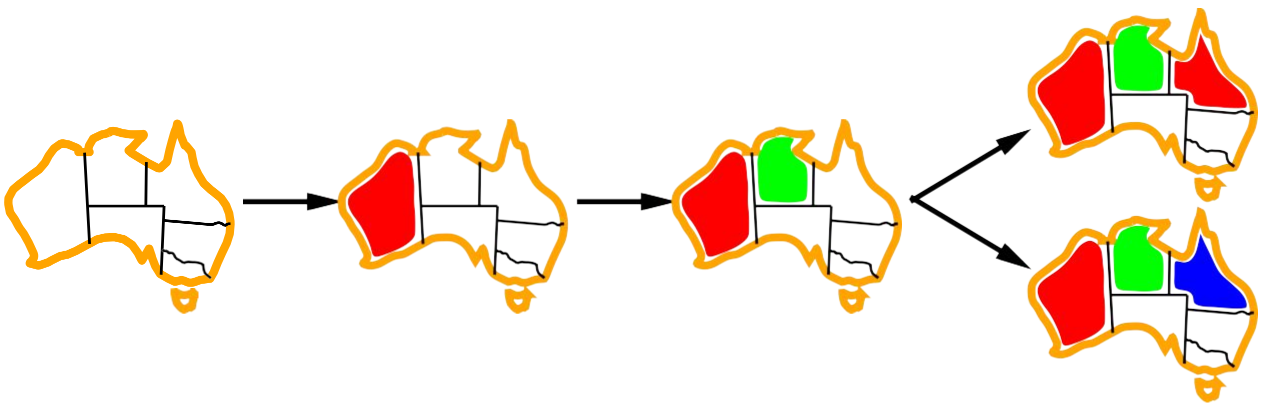
Degree heuristic:

choose the variable with the most constraints on remaining variables



Least constraining value

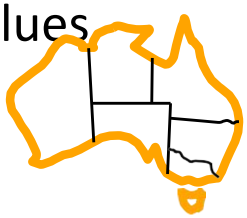
Given a variable, choose the least constraining value:
the one that rules out the fewest values in the remaining variables



Combining these heuristics makes 1000 queens feasible

Forward checking

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



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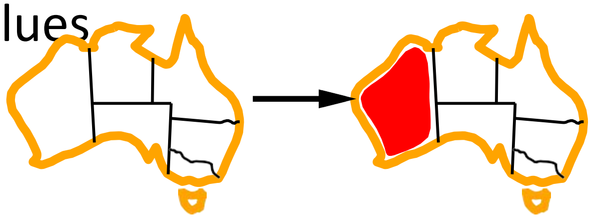

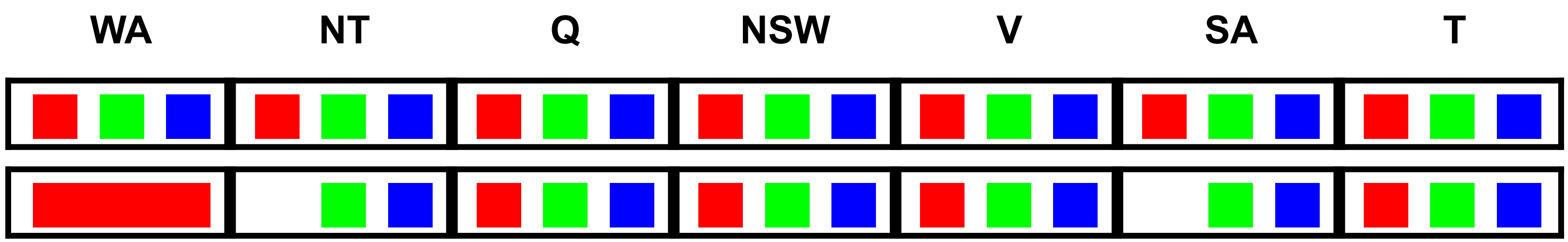

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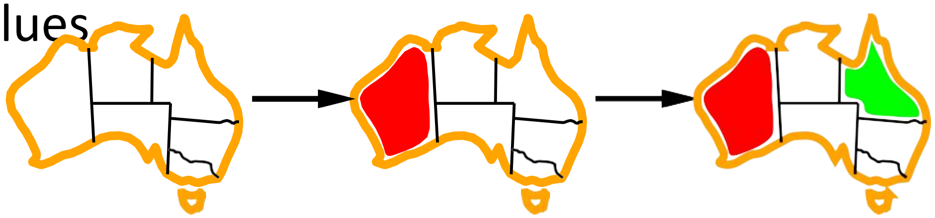

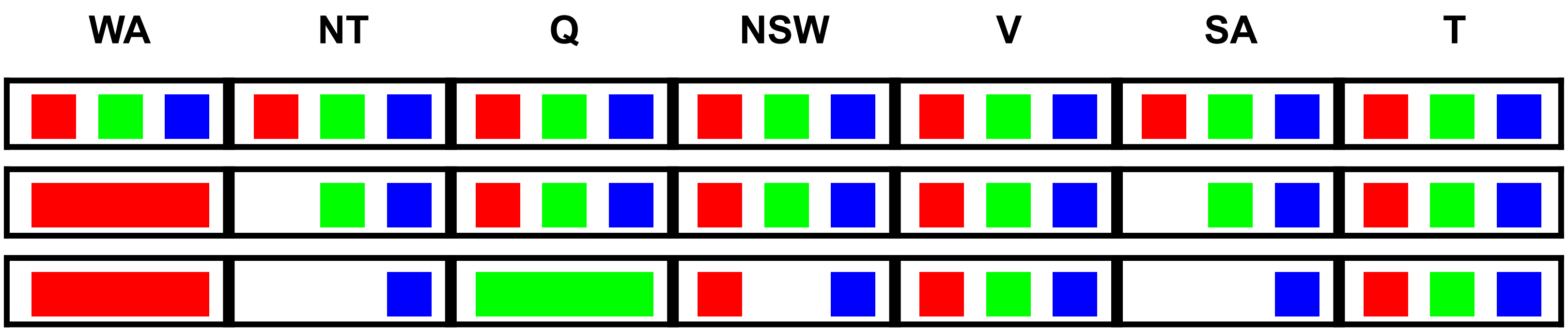

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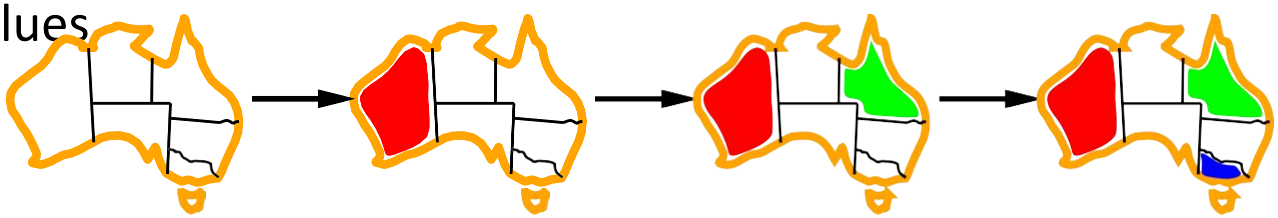
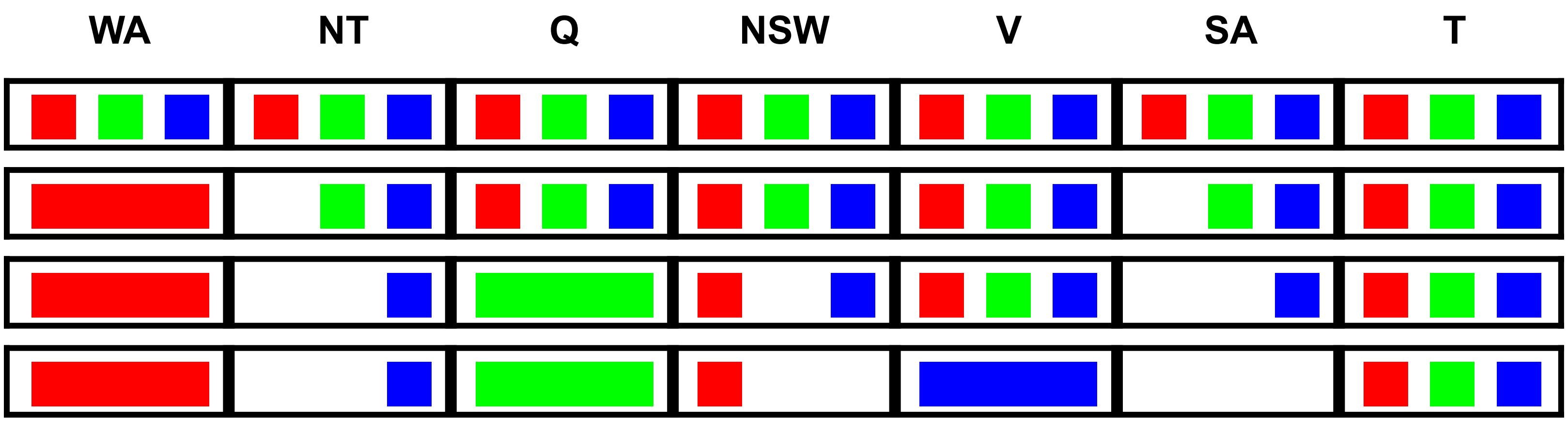
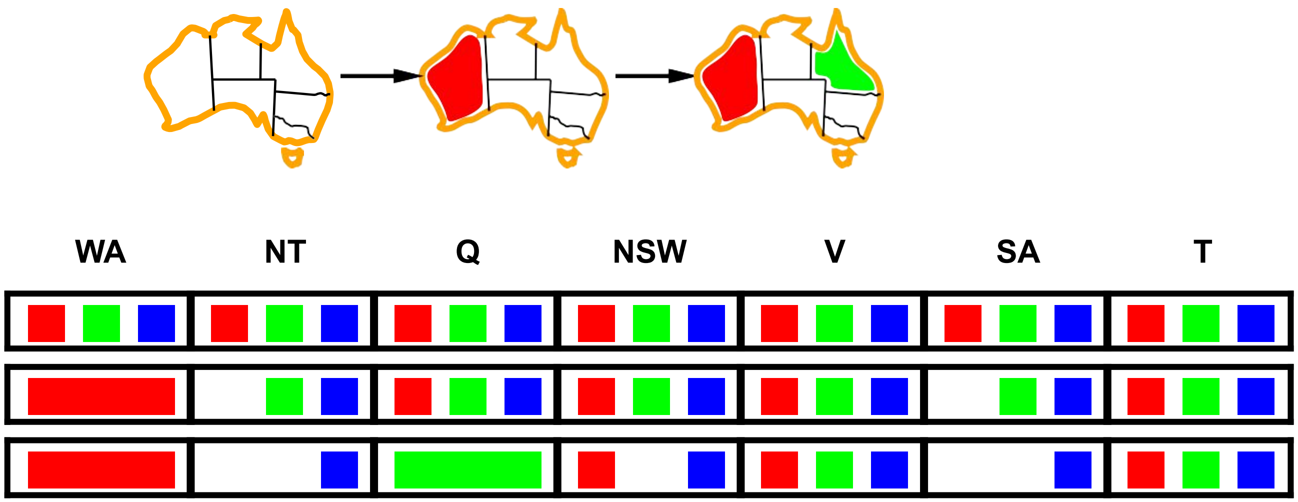




Constraint propagation

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



NT and *SA* cannot both be blue!

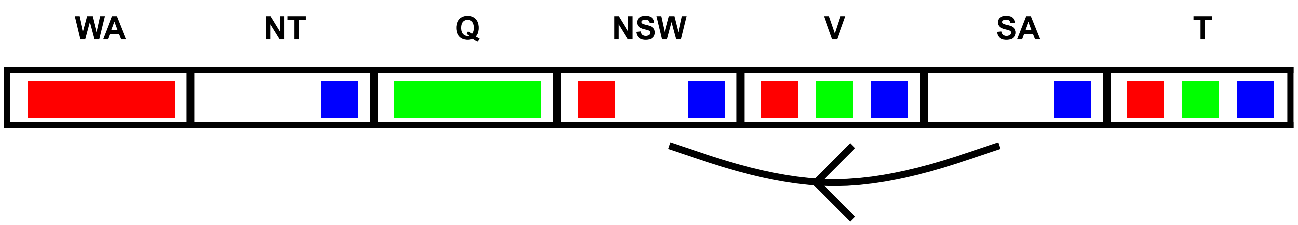
Constraint propagation repeatedly enforces constraints locally

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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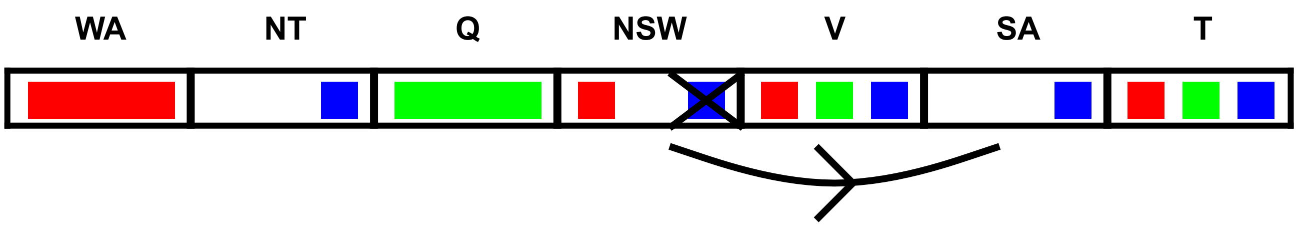

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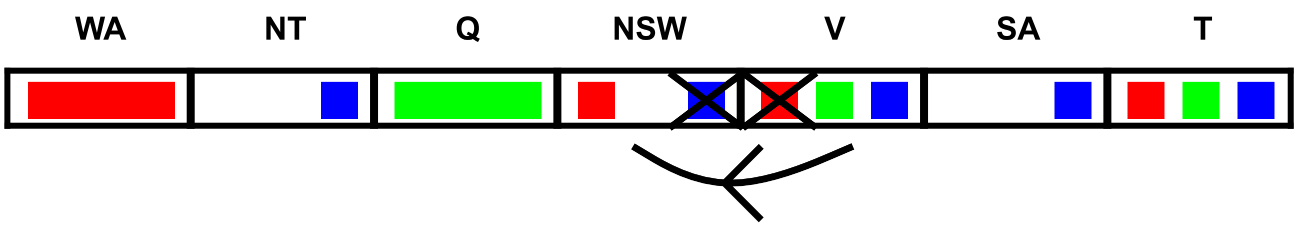

If X loses a value, neighbors of X need to be rechecked

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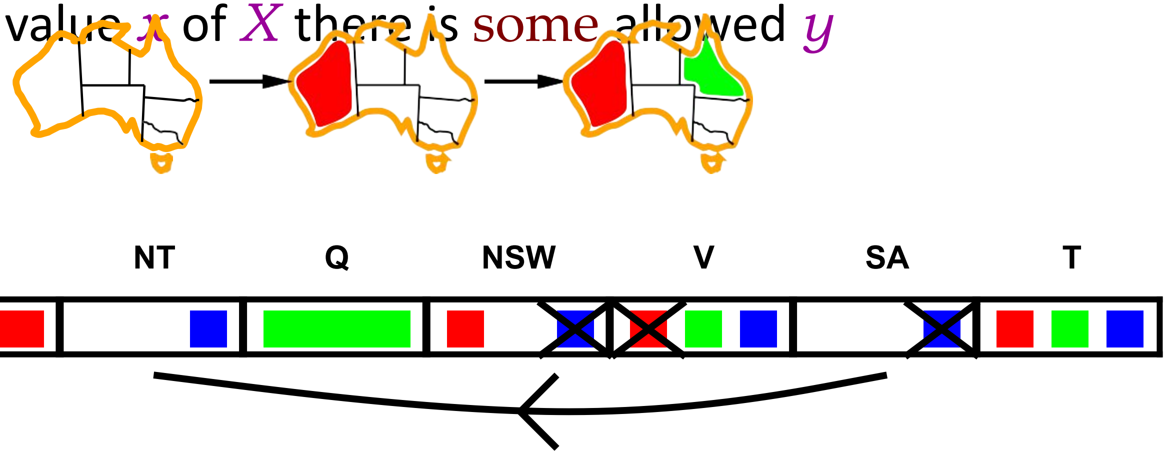


If X loses a value, neighbors of X need to be rechecked

Arc consistency detects failure earlier than forward

checking Can be run as a preprocessor or after each

assignment

Arc consistency algorithm

```
function AC-3( csp) returns the CSP, possibly with reduced domains
    inputs: csp, a binary CSP with variables {X_1, X_2, . . . , 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) ← Remove-First(queue)
        if Remove-Inconsistent-Values(X_i, X_j) then for
            each X_k in Neighbors[X_i] do
                add (X_k, X_i) to queue
```

```
function Remove-Inconsistent-Values( X_i, X_j) returns true iff succeeds
    removed ← false
    for each x in Domain[X_i] do
        if no value y in Domain[X_j] allows (x,y) to satisfy the constraint X_i ↔ X_j
            then delete x from Domain[X_i];    removed ← true
    return removed
```

$O(n^2d^3)$, can be reduced to $O(n^2d^2)$ (but detecting all is NP-hard)

Local Search for CSPs

Local search algorithms can be very effective in solving many CSPs.

Local search algorithms use a complete-state formulation where each state assigns a value to every variable, and the search changes the value of one variable at a time.

Min-conflicts heuristic: value that results in the **minimum number** of **conflicts** with other variables that **brings us closer to a solution.**

- Usually has a series of **plateaus**

Plateau search: allowing sideways moves to another state with the same score.

- can help local search find its way off the plateau.

Constraint weighting aims to concentrate the search on the important constraints

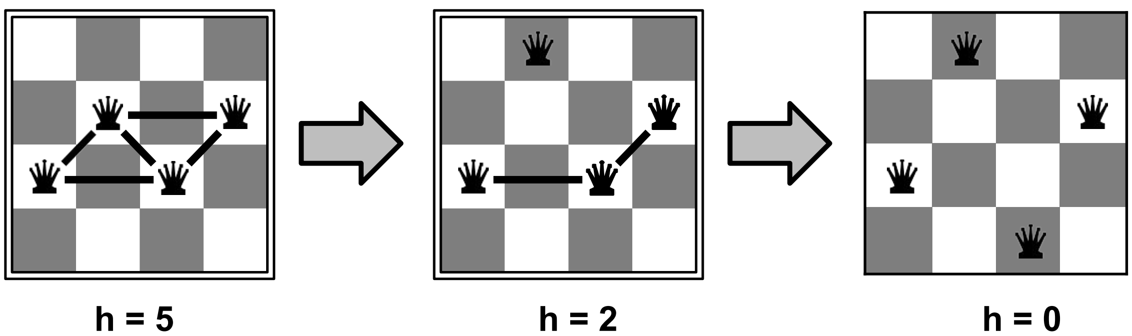
- Each constraint is given a numeric weight, initially all 1.
- weights adjusted by incrementing when it is violated by the current assignment

Example: 4-Queens

States: 4 queens in 4 columns ($4^4 = 256$ states)
Operators: move queen in

column Goal test: no attacks

Evaluation: $h(n)$ = number of attacks

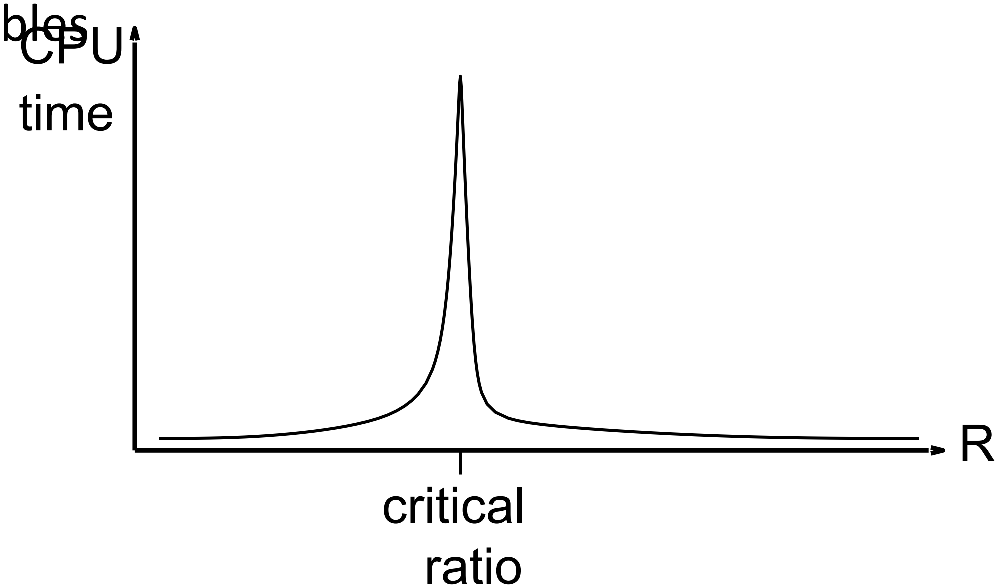


Performance of min-conflicts

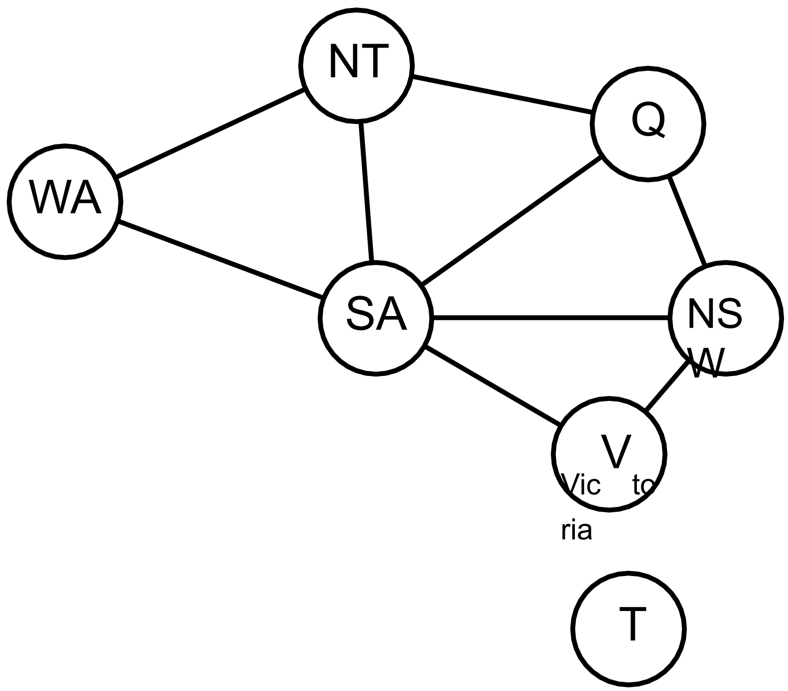
Given random initial state, can solve n-queens in almost constant time for arbitrary n with high probability (e.g., n = 10,000,000)

The same appears to be true for any randomly-generated CSP except in a narrow range of the ratio

$$R = \frac{\text{number of constraints}}{\text{number of variables}}$$



Problem structure



Tasmania and mainland are independent subproblems

Identifiable as connected components of constraint

graph

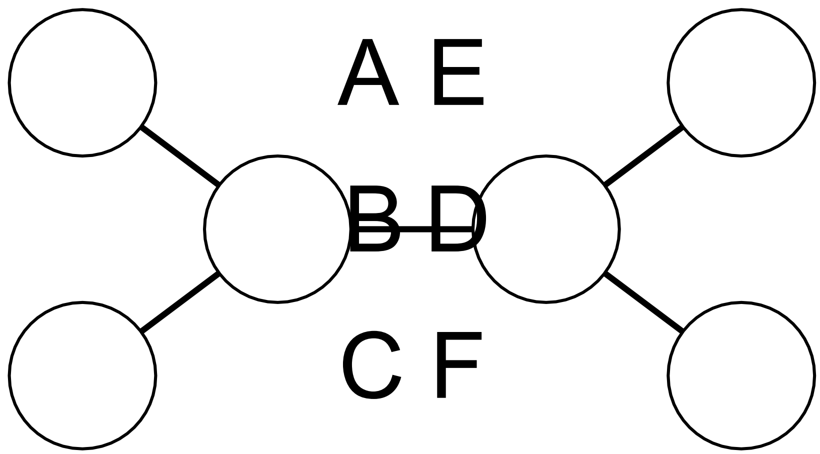
Problem structure contd.

Suppose each subproblem has c variables out of n total

Worst-case solution cost is $n/c \cdot d^c$, linear in n

E.g., $n = 80$, $d = 2$, $c = 20$
2^{80} = 4 billion years at 10 million nodes/sec
$4 \cdot 2^{20}$ = 0.4 seconds at 10 million nodes/sec

Tree-structured CSPs



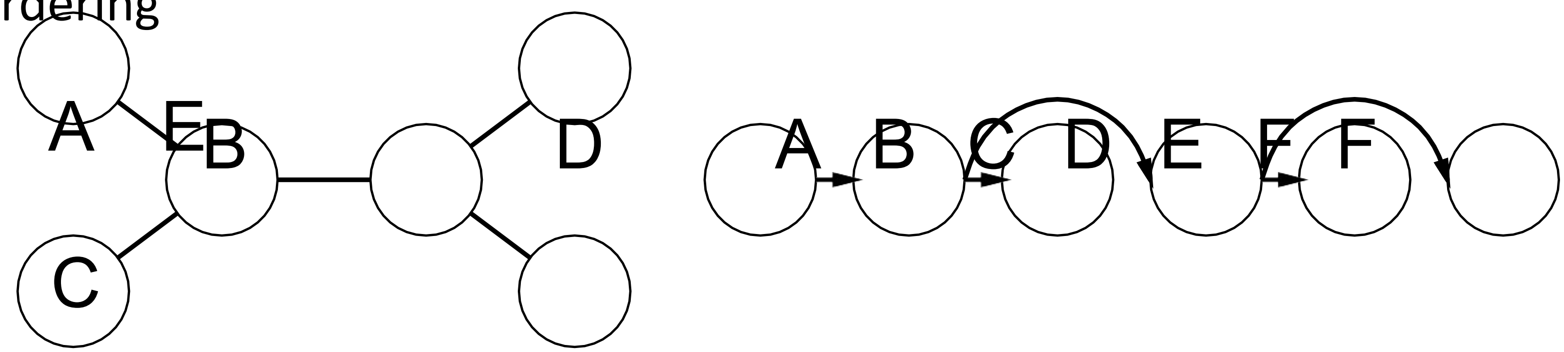
Theorem: if the constraint graph has no loops, the CSP can be solved in $O(n\, d^2)$ time

Compare to general CSPs, where worst-case time is $O(d^n)$

This property also applies to logical and probabilistic reasoning: an important example of the relation between syntactic restrictions and the complexity of reasoning.

Algorithm for tree-structured CSPs

1. Choose a variable as root, order variables from root to leaves such that every node's parent precedes it in the ordering

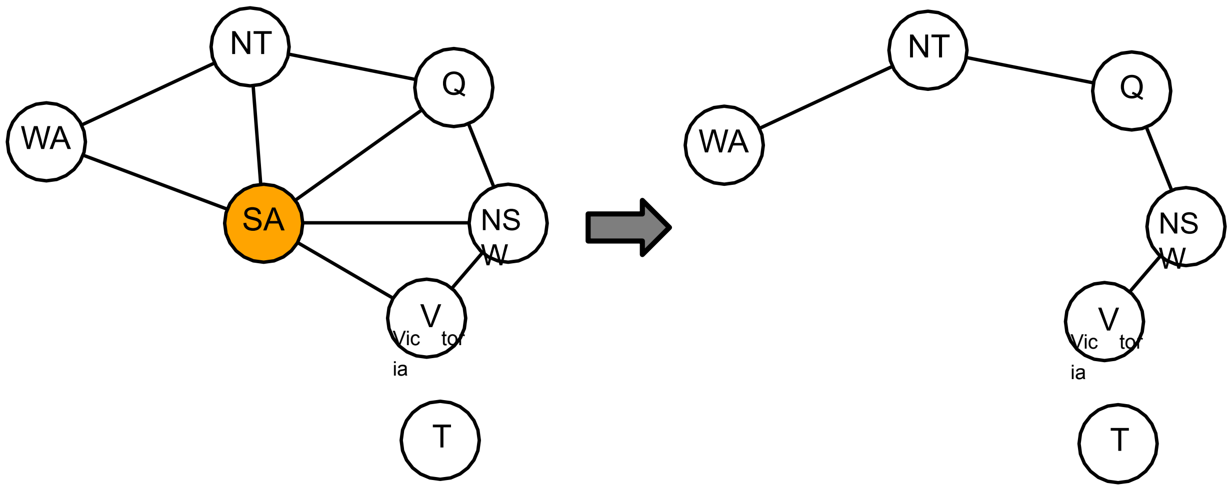


2. For j from n down to 2, apply $\text{RemoveInconsistent}(Parent(X_j), X_j)$

3. For j from 1 to n, assign X_j consistently with $Parent(X_j)$

Nearly tree-structured CSPs

Conditioning: instantiate a variable, prune its neighbors' domains



Cutset conditioning: instantiate (in all ways) a set of variables such that the remaining constraint graph is a tree

Cutset size $c \Rightarrow$ runtime $O(d^c \cdot (n-c)d^2)$, very fast for small c

Iterative algorithms for CSPs

Hill-climbing, simulated annealing typically work
with "complete" states, i.e., all variables assigned

To apply to CSPs:
allow states with unsatisfied
constraints operators reassign
variable values
Variable selection: randomly select any conflicted

variable Value selection by min-conflicts heuristic:

choose value that violates the fewest constraints
i.e., hillclimb with $h(n)$ = total number of violated 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

Local search using the min-conflicts heuristic has also been applied
to constraint satisfaction problems with great success
The CSP representation allows analysis of problem

structure Tree-structured CSPs can be solved in linear