Constraint Satisfaction Problems

Chapter 6

single state search problem:
initial state, find sequence of actions
that get you to the goal state

Outline

◇ CSP examples

◇ Backtracking search for CSPs

◇ Problem structure and problem decomposition

◇ Local search for CSPs

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 → sets of possible values for Xi

goal test is a set of *constraints* specifying
allowable combinations of values for subsets of variables

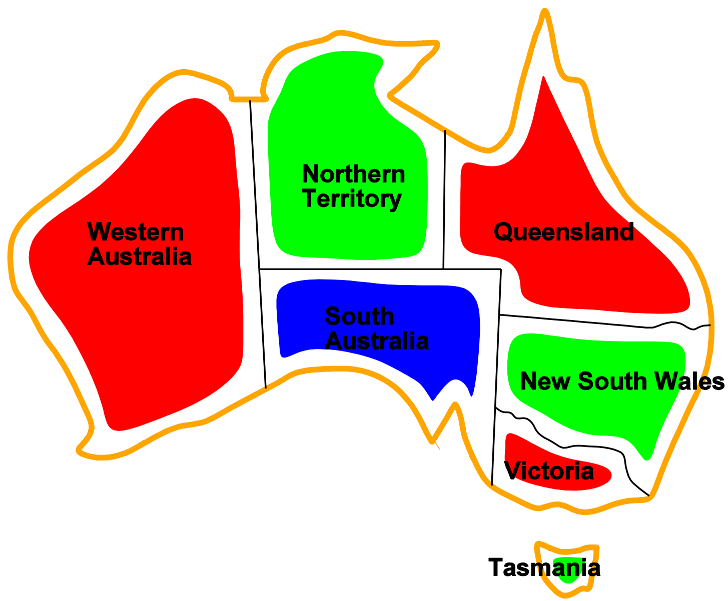
Simple example of a *formal representation language*

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.,
$\{WA = red, NT = green, Q = red, NSW = green,$
$V = red, SA = blue, T = green\}$

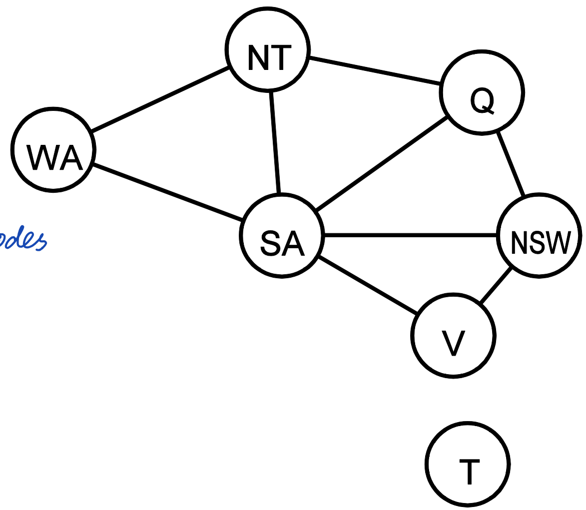
Constraint graph

Binary CSP: each constraint relates at most two variables

Constraint graph: nodes are variables, arcs show constraints

draw the state as nodes

constraint between the nodes



General-purpose CSP algorithms use the graph structure
to speed up search. E.g., Tasmania is an $\boxed{\text{independent subproblem}}$!

Varieties of CSPs

Discrete variables

eg. $d=3$ for 3 colours

finite domains; size $d \Rightarrow O(d^n)$ complete assignments

where n is the number of variables in the CSP

$\{T, F\}$

◇ 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 polynomial time
by linear programming (LP) methods

Varieties of constraints

hard constraint

Unary constraints involve a single variable,
 e.g., $SA \neq green$

constraint satisfaction

Binary constraints involve pairs of variables,
 e.g., $SA \neq WA$

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

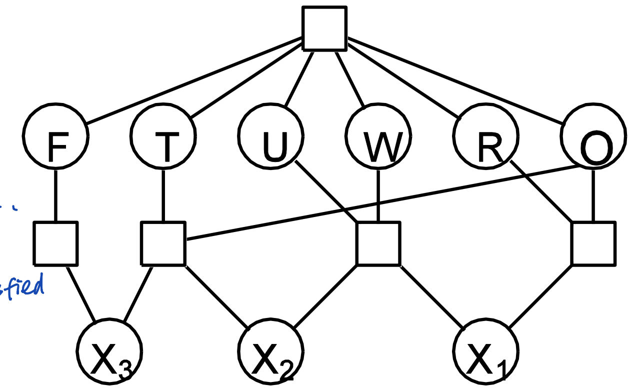
Preferences (soft constraints), e.g., *red* is better than *green*
often representable by a cost for each variable assignment
 → constrained optimization problems

Example: Cryptarithmetic

```
   T W O
+  T W O
 -------
 F O U R
```

(a)

eg
560
+560
1120 X.
not satisfied



← constraint

(b)

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

$alldiff(F,T,U,W,R,O)$ no pair of variables should have the same values

① $O+O=R+10\cdot X_1$, etc.

carry over value

② $W+W+X_1=U+10\cdot X_2$

③ $T+T+X_2=O+10\cdot X_3$

④ $X_3=F$

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, $\emptyset$

◇ *Successor function:* assign a value to an unassigned variable that does not conflict with current assignment.
$\Rightarrow$ fail if no legal assignments (not fixable!)

◇ *Goal test:* the current assignment is complete

level 0 n variables
nd leaves

level 1 (n-1) variable
(n-1)d leaves

1) This is the same for all CSPs!
2) Every solution appears at depth n with n variables
$\Rightarrow$ use depth-first search

at depth l, we already assigned l variables so far
remaining n-l variables

3) $b = (n - \ell)d$ at depth ℓ, hence $n!d^n$ leaves!!!!

0 1 ... n-1
$nd \times (n-1)d \times \dots \times 1d = n!d^n$

4) Path is irrelevant, so can also use complete-state formulation

order doesn't matter $\Rightarrow d^n$

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

$\Rightarrow$ $b = d$ 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

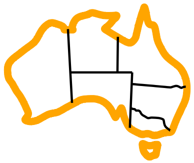
Can solve n-queens for $n \approx 25$

Backtracking search

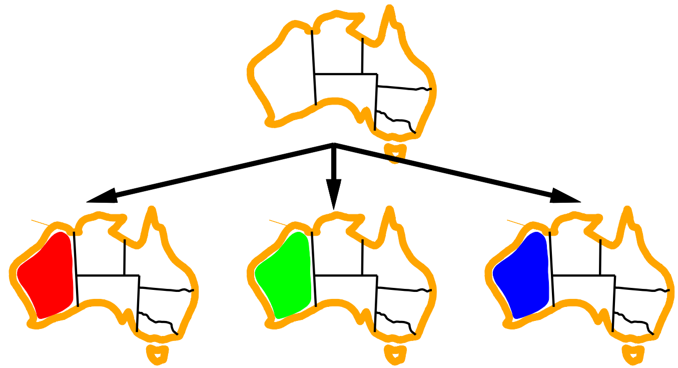
```
function Backtracking-Search(csp) returns solution/failure
    return Recursive-Backtracking({ }, csp)

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)
cannot      if result ≠ failure then return result
find a      remove {var = value} from assignment
solution
    return failure
```

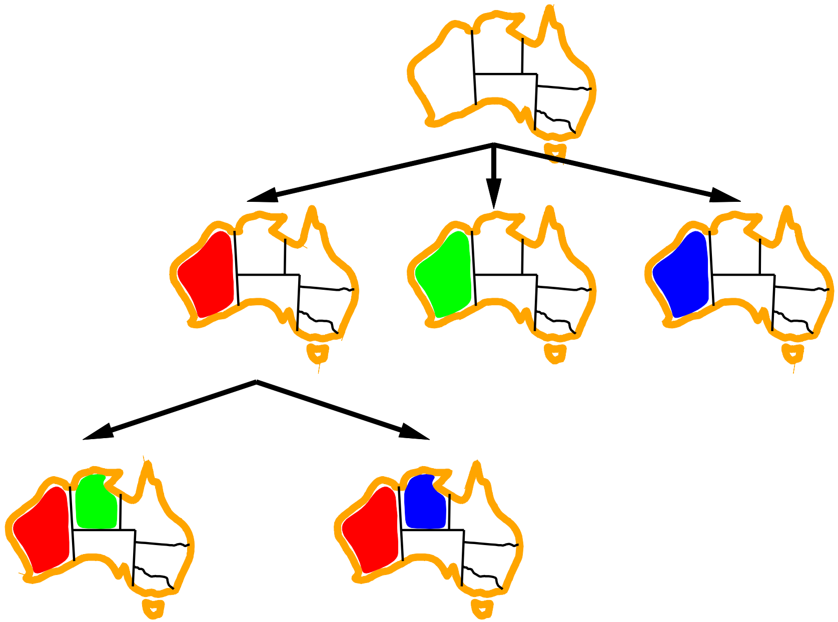
Backtracking example



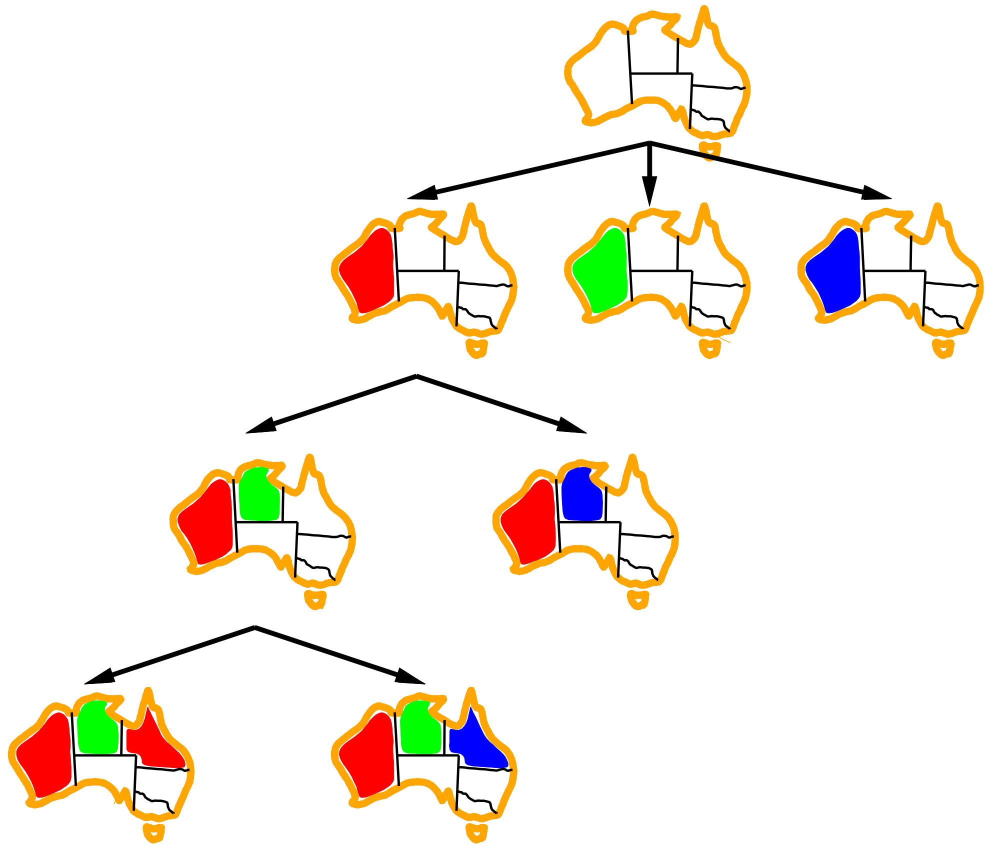
Backtracking example



Backtracking example



Backtracking example



Improving backtracking efficiency

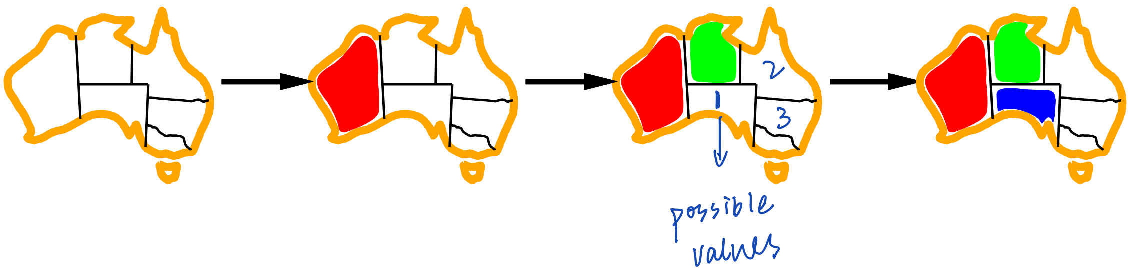
General-purpose methods can give huge gains in speed:

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

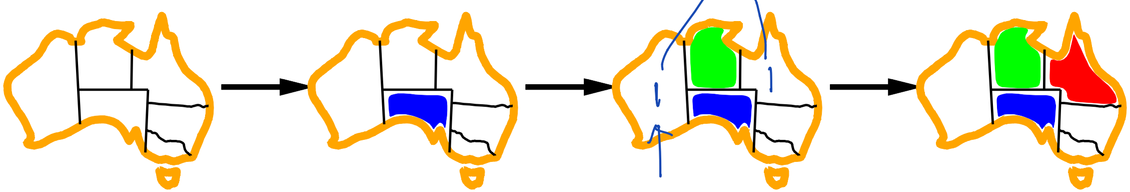


Degree heuristic

Tie-breaker among MRV variables

Degree heuristic:
choose the variable with the most constraints on remaining variables

both has 1 remaining value
⇒ a tie



but
doesn't
have many
constraint

对比: variable selection ⇒ failure first ⇒ detect failure early, useful to prune

value selection ⇒ failure last ⇒ choose the most possible value.

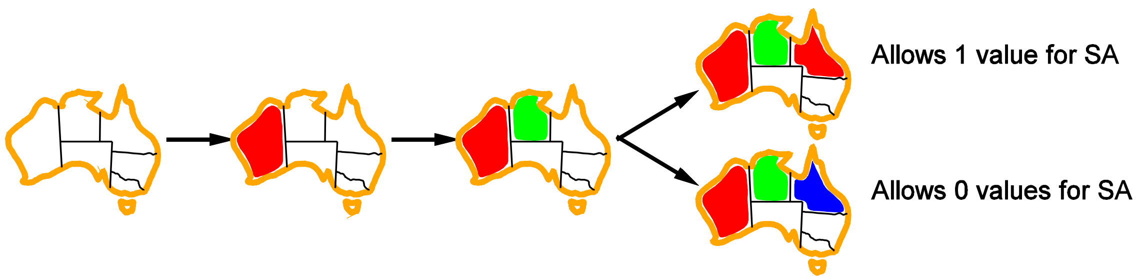
Least constraining value

Given a variable, choose the least constraining value:

the one that rules out the fewest values in the remaining variables

?

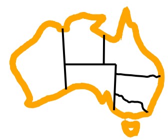
⇒ give more choice to neighbour

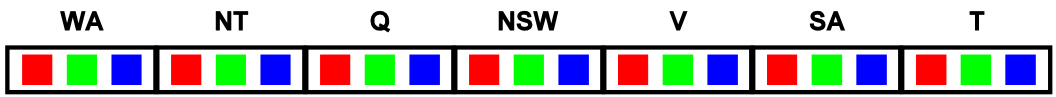


Combining these heuristics makes 1000 queens feasible

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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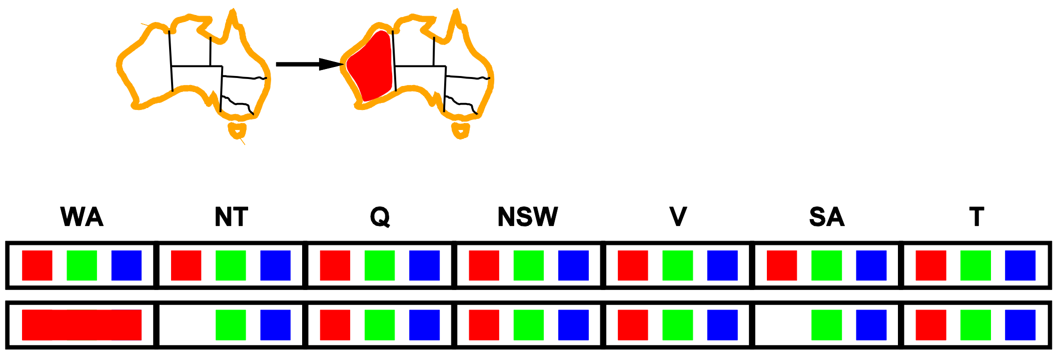

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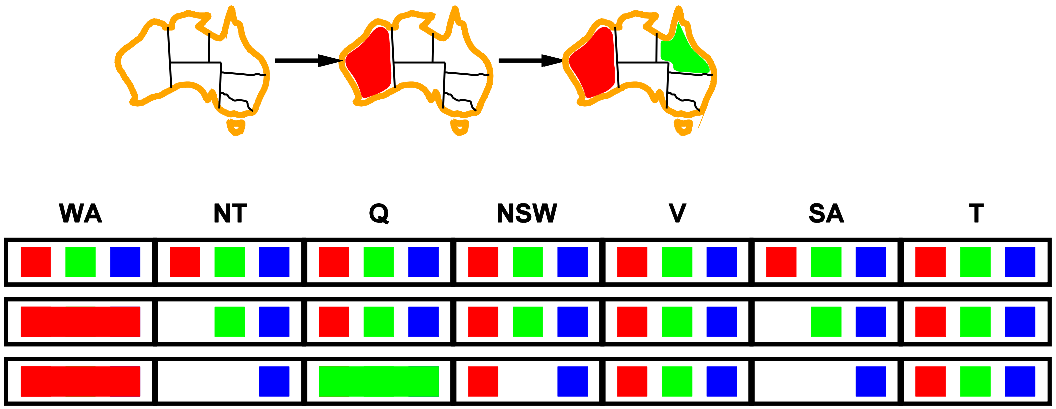

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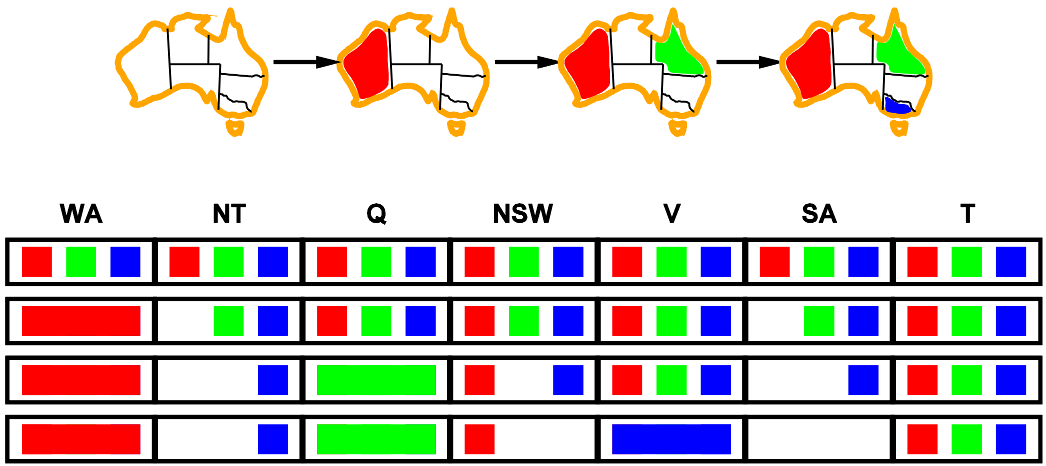
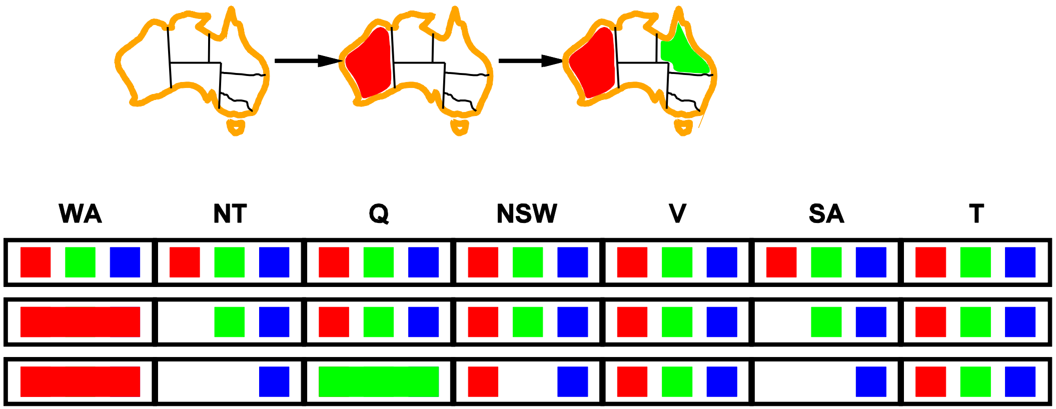


Constraint propagation

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



NT and SA cannot both be blue!

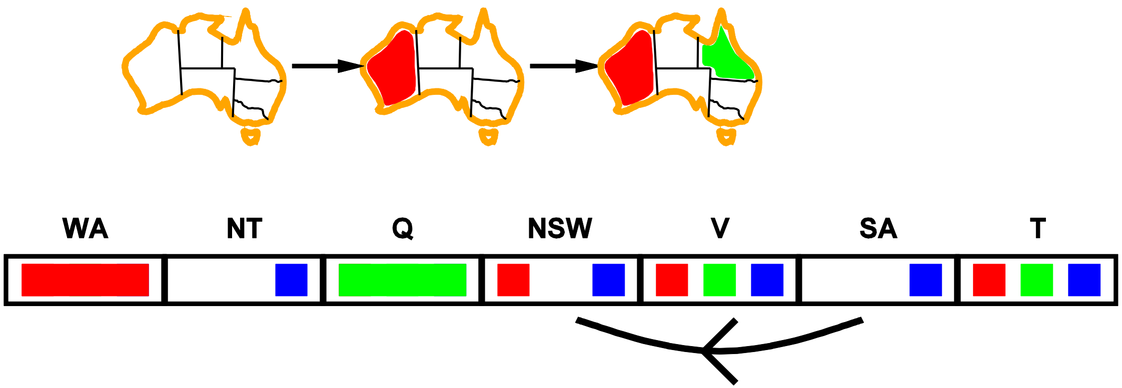
$Constraint\ propagation$ repeatedly enforces constraints locally

Arc consistency

Simplest form of propagation makes each arc *consistent*

$X \rightarrow Y$ is arc consistent iff

for *every* value x of X there is *at least one value* y of Y
that satisfies the constraint between X and Y



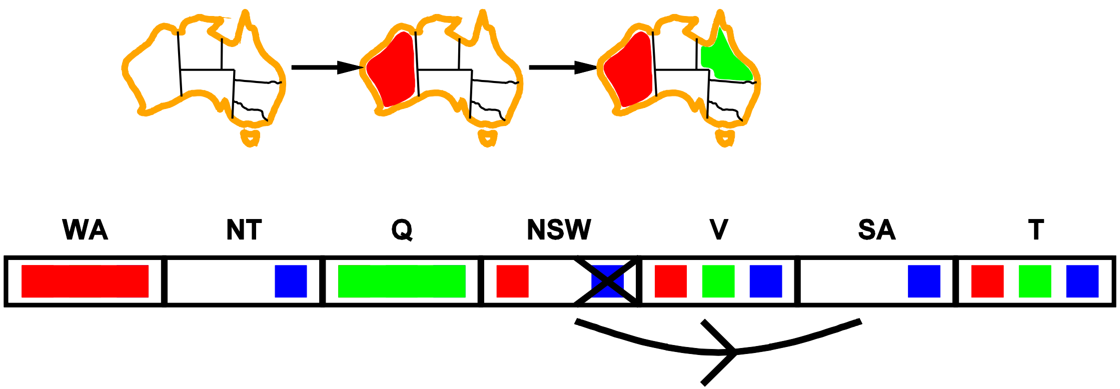
Arc consistency

Simplest form of propagation makes each arc *consistent*

X is arc consistent with respect to Y

$X \to Y$ is consistent iff

for *every* value x of X there is *some* allowed y



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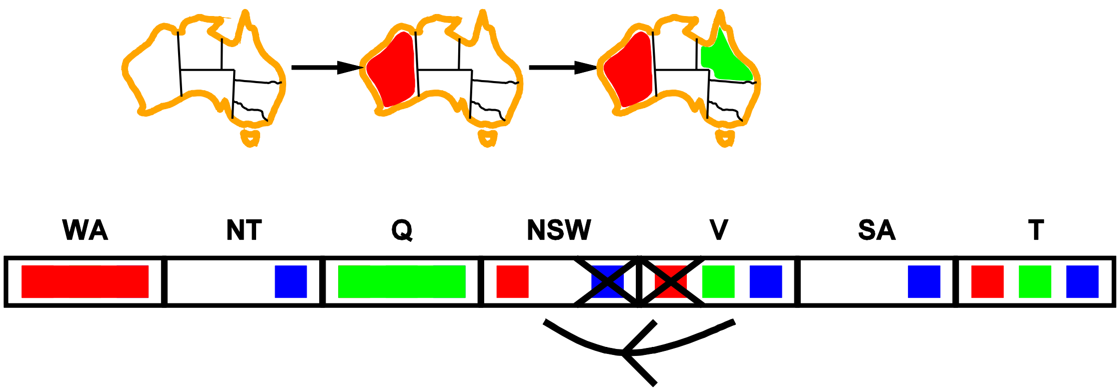

If X loses a value, neighbors of X need to be rechecked

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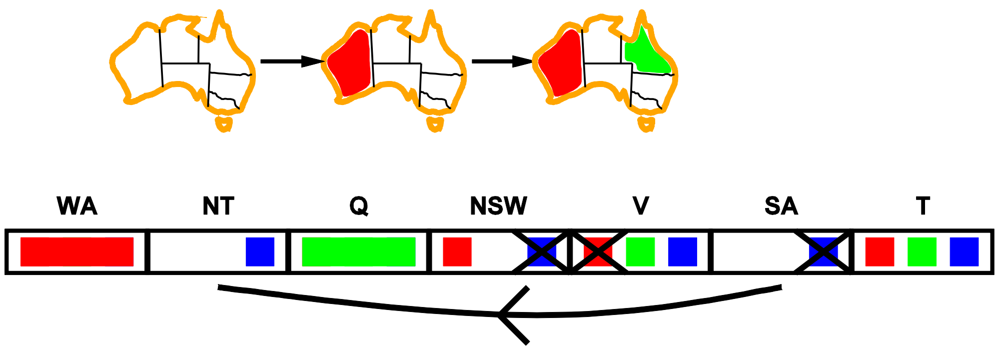


If X loses a value, neighbors of X need to be rechecked

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 $\{X_1,\ X_2,\ \ldots,\ X_n\}$
  local variables: *queue*, a queue of arcs, initially all the arcs in *csp*

  while *queue* is not empty **do**
    $(X_i,\ X_j) \leftarrow$ REMOVE-FIRST(*queue*) → pick next pair of nodes
    if REMOVE-INCONSISTENT-VALUES$(X_i,\ X_j)$ **then** → if updates happen on Xi
      for each X_k **in** NEIGHBORS$[X_i]$ **do**
        add $(X_k,\ X_i)$ to *queue*

check Xi with respect to Xj

O(d²)

function REMOVE-INCONSISTENT-VALUES($X_i,\ X_j$) **returns** true iff succeeds
  removed ← *false*
  for each x **in** DOMAIN$[X_i]$ **do** d
    if no value y in DOMAIN$[X_j]$ allows (x,y) to satisfy the constraint $X_i \leftrightarrow X_j$ d. O(d²).
      then delete x from DOMAIN$[X_i]$; *removed* ← *true*
  return *removed*

每条弧最多只能插入队列d次，因为Xi至多有d个值可删除

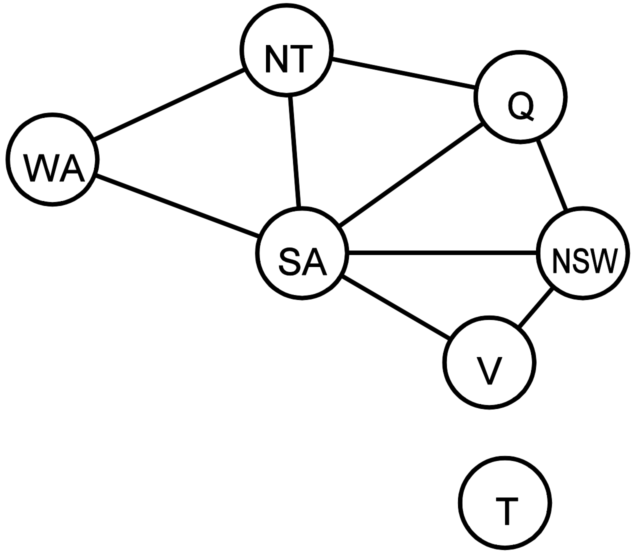
n # of variable (every pairs)
worst case n² arcs → d: size of domains

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

O(n²·d·d²) = O(n²d³)

Alternative approach: exploit structure of the constraint graph
  to find independent subproblems . . .

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

\# of subproblem

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

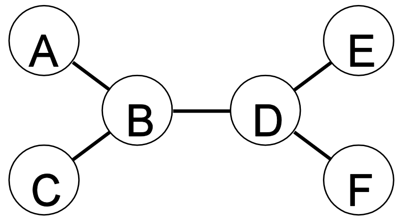
Unfortunately, completely independent subproblems are rare in practice

However, there are other graph strucures that are easy to solve

e.g. when the constraint graph is a tree

Tree-structured CSPs

tree structure
n nodes
n-1 arcs



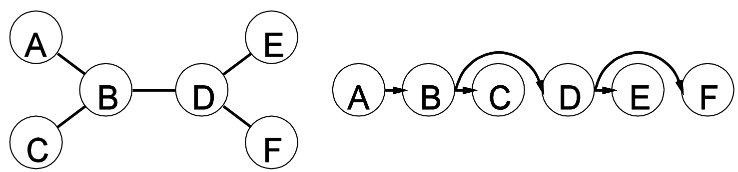
Theorem: if the constraint graph has no loops, the CSP can be solved in $O(n\,d^2)$ time

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



check consistent

$O(n \cdot d^2)$.

parent & child arc consistent

from F to A

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

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

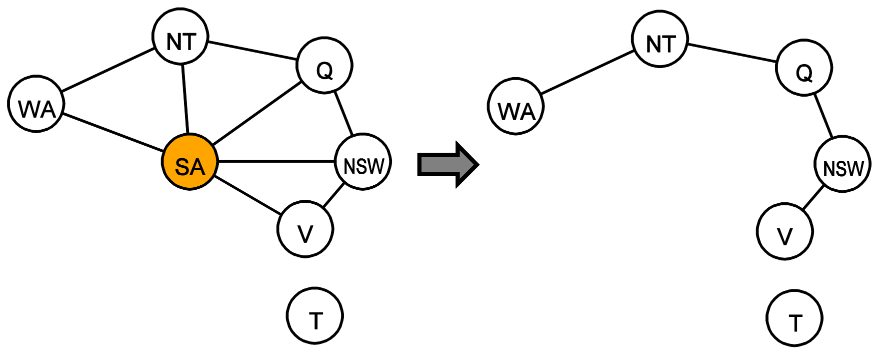
from A to F

every node will have at least one value remaining that is consistent with its children

then during assignment, no matter what value the parent choose, children will always have value to choose

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: set of variables that can be deleted so constraint graph forms a tree

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

→ complexity for tree structure

the possible value cutset can take d^c

want to remaining tree size be bigger

Iterative algorithms for CSPs - Local search

Recall hill-climbing search from Week 3

Hill-climbing typically works with
"complete" states, i.e., all variables assigned

Local search then tries to change one variable assignment at a time

To apply to CSPs:
- allow states with unsatisfied constraints(*variable selection*)
- operators *reassign* variable values (*value selection*)

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

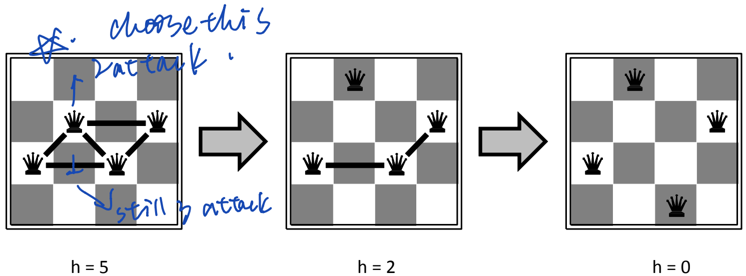
Example: 4-Queens

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



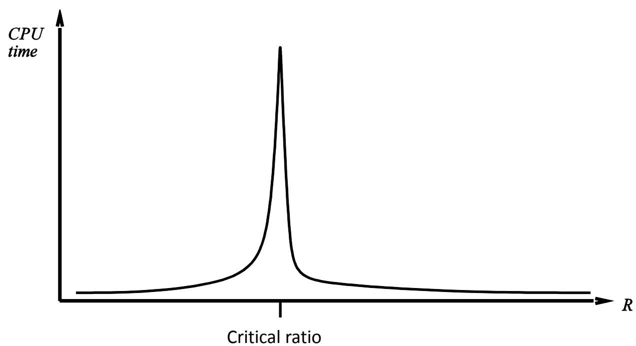
5 attack

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

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



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

The CSP representation allows analysis of problem structure

Tree-structured CSPs can be solved in linear time

Iterative min-conflicts is usually effective in practice

Summary

Examples of skills expected:

♢ Model a given problem as a CSP

♢ Demonstrate operation of CSP search algorithms

♢ Discuss and evaluate the properties of different constraint satisfaction techniques