Artificial Intelligence

Chapter 5

Stuart RUSSEL

reorganized by L. Aszalós

April 27, 2016

Outline

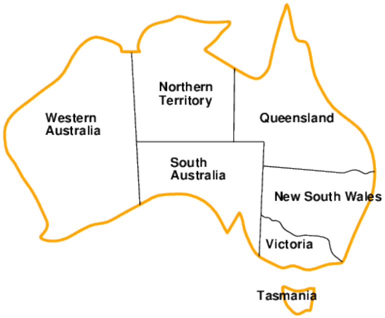
- CSP examples
- Backtracking search for CSPs
- Problem structure and problem decomposition
- Local search for CSPs

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

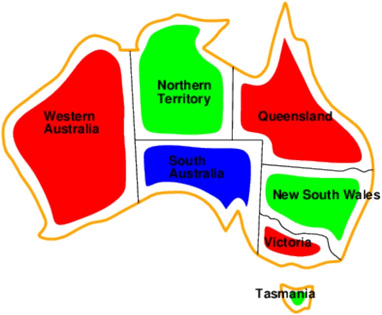
Simple example of a *formal representation language*
Allows useful *general-purpose* algorithms with more power than standard search algorithms

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

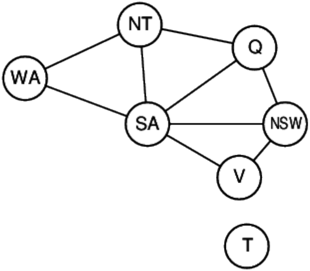
Example: Map-Coloring contd.



- *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!

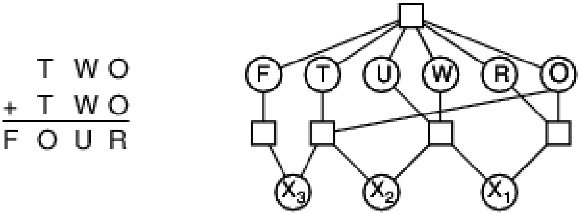
Varieties of CSPs

- Discrete variables
  - finite domains; size $d \implies O(d^n)$ 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., $SA \neq green$
- *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 $\rightarrow$ constrained optimization problems

Example: Cryptarithmetic



- *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*:
  - $\mathit{Alldiff}(F, T, U, W, R, O)$
  - $O + O = R + 10 \cdot X_1$, 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, $\emptyset$
- *Successor function*: assign a value to an unassigned variable that does not conflict with current assignment. $\Longrightarrow$ 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 $\Longrightarrow$ use depth-first search
3. Path is irrelevant, so can also use complete-state formulation
4. $b = (n - \ell)d$ 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
  - $\implies b = d$ 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 $n \approx 25$

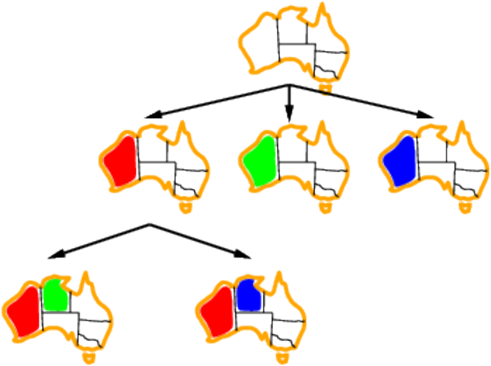
Backtracking search

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

function Recursive-Backtracking(assignment,csp): 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
```

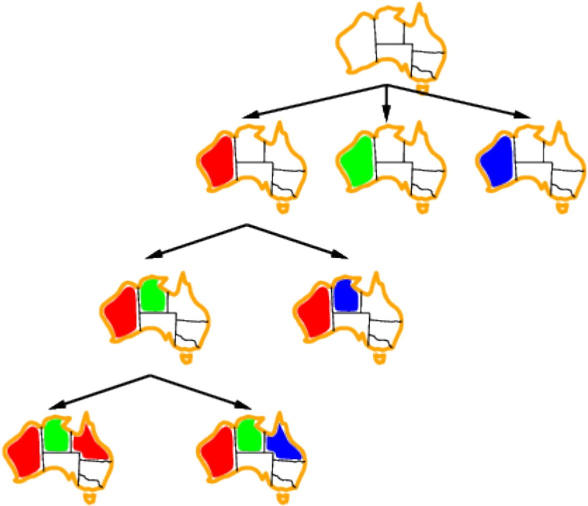
Backtracking example

Backtracking example

Backtracking example



Backtracking example



Improving backtracking efficiency

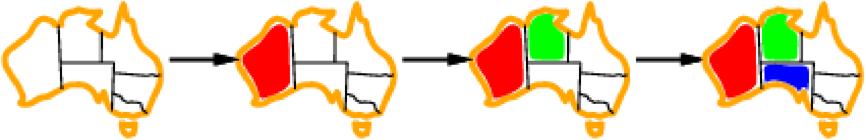
General-purpose methods can give huge gains in speed:

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

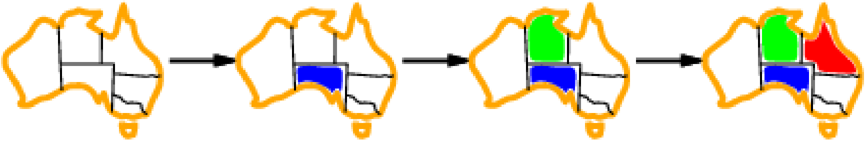


Degree heuristic

Tie-breaker among MRV variables

Degree heuristic:

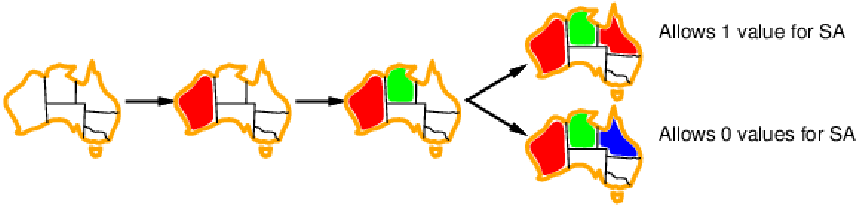
- choose the variable with the most constraints on remaining variables



Least constraining value

Given a variable, choose the **least constraining value**:

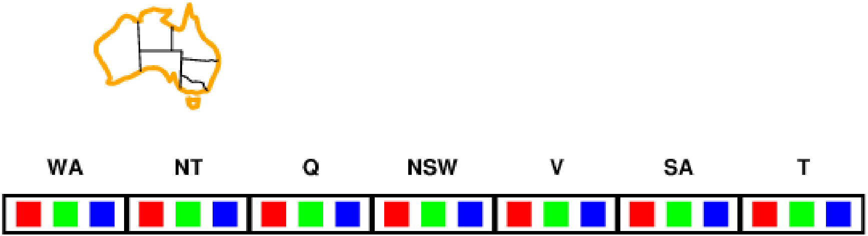
- the one that rules out the fewest values in the remaining variables



Combining these heuristics makes 1000 queens feasible

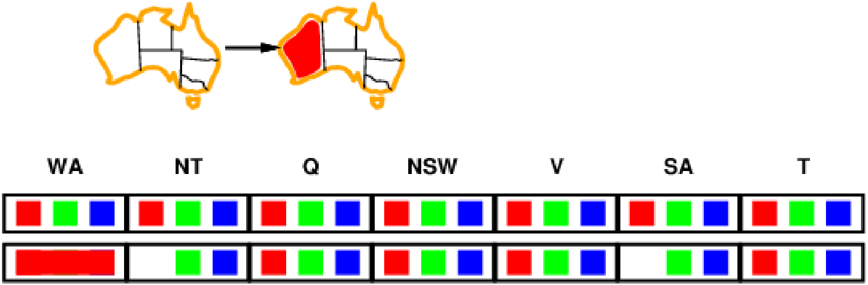
Forward checking

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



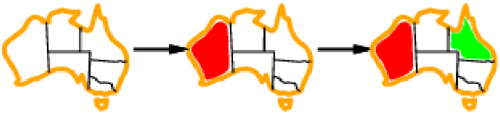
Forward checking

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



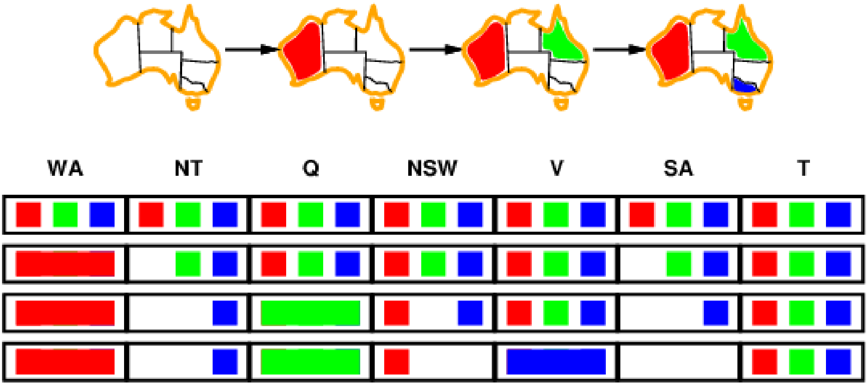
Forward checking

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



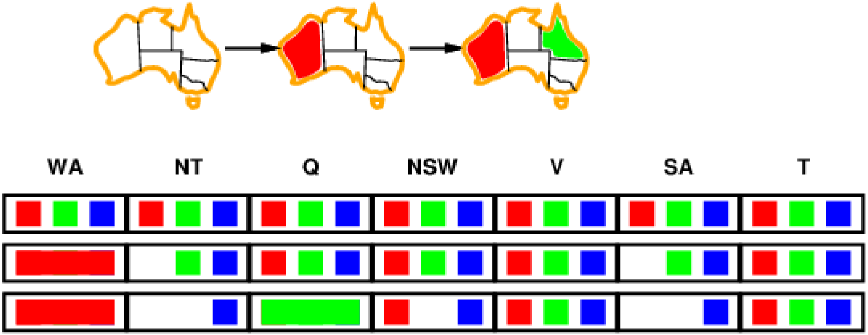
Forward checking

- *Idea*: Keep track of remaining legal values for unassigned variables
  - 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:

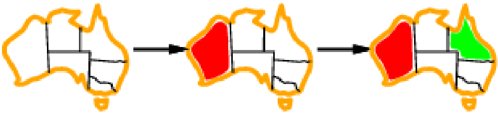


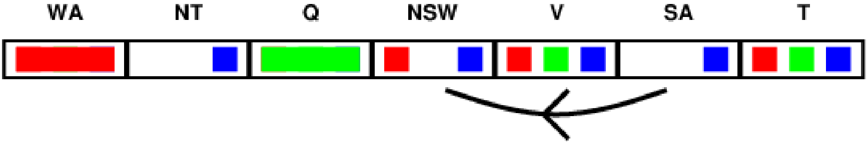
NT and *SA* cannot both be blue!
Constraint propagation repeatedly enforces constraints locally

Arc consistency

Simplest form of propagation makes each arc *consistent*

$X \to Y$ is consistent iff for **every** value x of X there is **some** allowed y

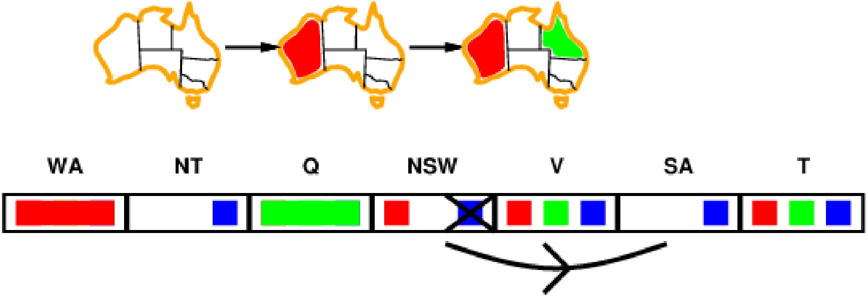




Arc consistency

Simplest form of propagation makes each arc *consistent*

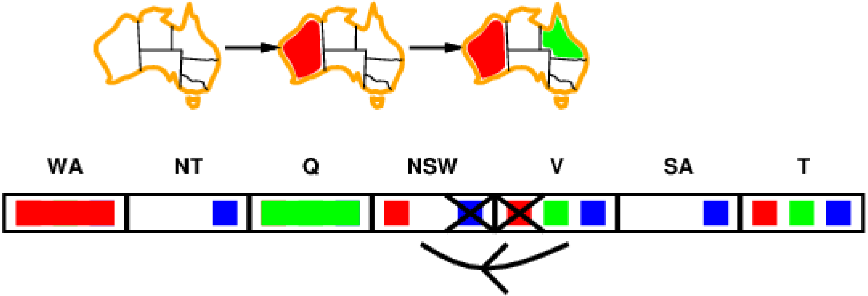
$X \rightarrow Y$ is consistent iff for **every** value x of X there is **some** allowed y



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

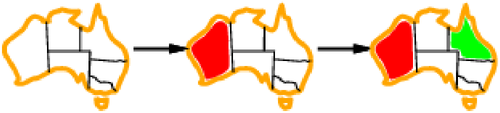


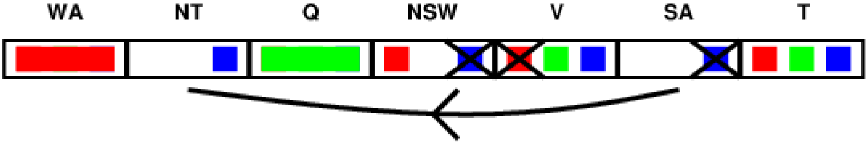
- If X loses a value, neighbors of X need to be rechecked

Arc consistency

Simplest form of propagation makes each arc *consistent*

$X \to Y$ 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

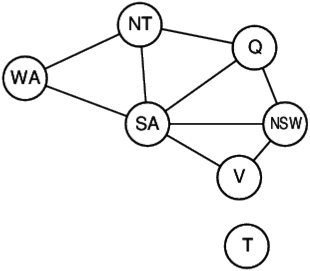
```
function AC-3(csp): the CSP, possibly with reduced domains
    inputs: csp, a binary CSP with variables {X1,X2,...,Xn}
    local var.: queue, a queue of arcs,
                initially all the arcs in csp

    while queue is not empty do
        (Xi, Xj) := Remove-First(queue)
        if Remove-Inconsistent-Values(Xi, Xj) then
            for each Xk in Neighbors[Xi] do
                add (Xk, Xi) to queue
```

Arc consistency algorithm

```
function Remove-Inconsistent-Values(Xi, Xj):
                            return true iff succeeds
    removed := false
    for each x in Domain[Xi] do
        if no value y in Domain[Xj] allows
                (x, y) to satisfy the constraint Xi <-> Xj
            then delete x from Domain[Xi];  removed := true
    return removed
```

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

Problem structure

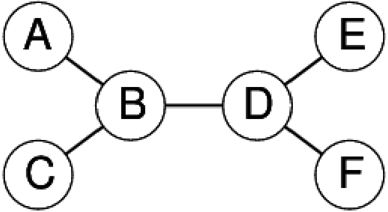


- Tasmania and mainland are *independent subproblems*
- Identifiable as *connected components* of constraint graph

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

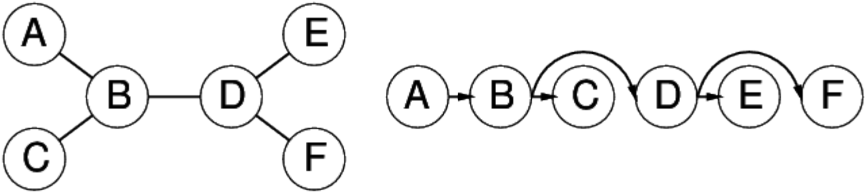


Theorem: if the constraint graph has no loops, the CSP can be solved in $O(n\,d^2)$ time

- 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

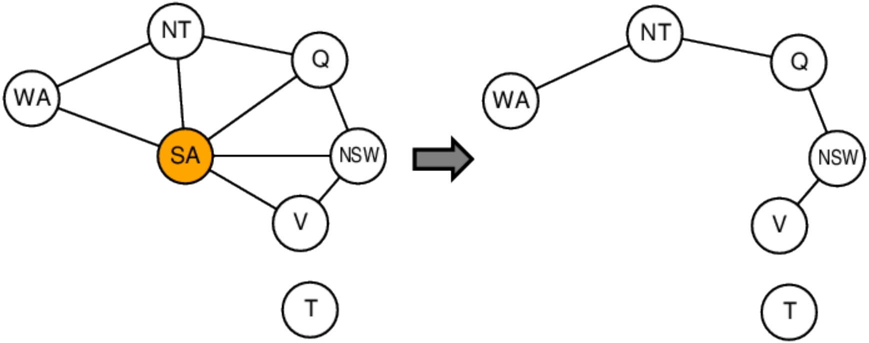
1. Choose a variable as root, order variables from root to leaves such that every node's parent precedes it in the ordering



2. For j from n down to 2, apply 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

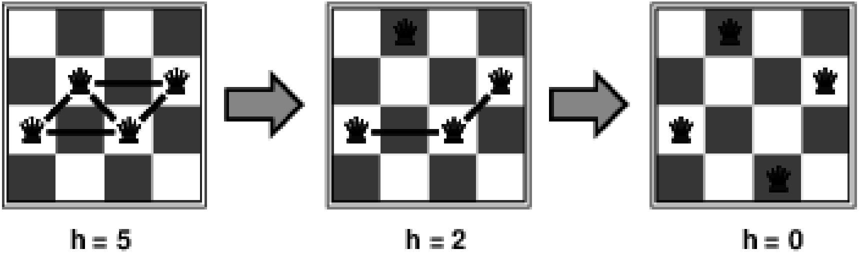
Cutset size $c \implies$ runtime $O(d^c \cdot (n-c)d^2)$, very fast for small c

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

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

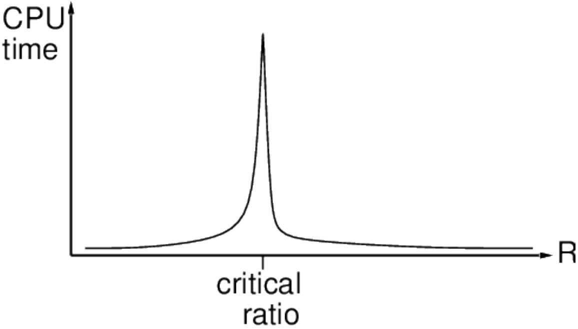


Performance of min-conflicts

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

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



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