

PLANNING AND SCHEDULING: CSP – CONSTRAINT SATISFACTION PROBLEMS

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Acknowledgements

- These slides refer to Chapter 5 of the textbook:
S. Russell and P. Norvig:
Artificial Intelligence: A Modern Approach
Prentice Hall, 2003, 2nd Edition (or more recent edition)
- These slides are an adaptation of slides by Min-Yen Kan
- The contributions of these authors are gratefully acknowledged.



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Outline

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



Constraint Satisfaction Problems (CSPs)

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



Example: Map-Coloring



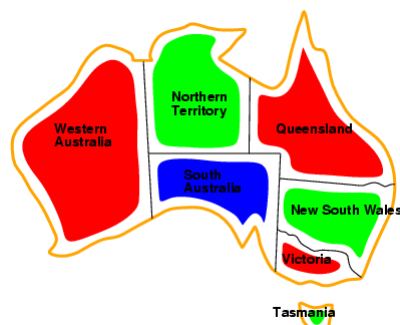
- **Variables** WA, NT, Q, NSW, V, SA, T
- **Domains** $D_i = \{\text{red}, \text{green}, \text{blue}\}$
- **Constraints**: adjacent regions must have different colors
- e.g., $WA \neq NT$, or $(WA, NT) \in \{(\text{red}, \text{green}), (\text{red}, \text{blue}), (\text{green}, \text{red}), (\text{green},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



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Example: Map-Coloring



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

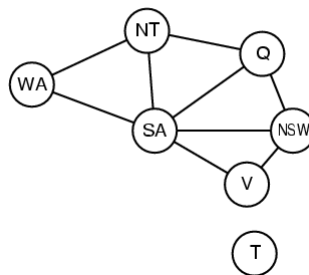


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Constraint Graph

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



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Varieties of CSPs

- Discrete variables
 - 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., $\text{StartJob1} + 5 \leq \text{StartJob3}$
- Continuous variables
 - e.g., start/end times for Hubble Space Telescope observations
 - linear constraints solvable in polynomial time by linear programming



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Varieties of Constraints

- **Unary** constraints involve a single variable,
 - e.g., $SA \neq \text{green}$
- **Binary** constraints involve pairs of variables,
 - e.g., $SA \neq WA$
- **Higher-order** constraints involve 3 or more variables,
 - e.g., crypto-arithmetic column constraints

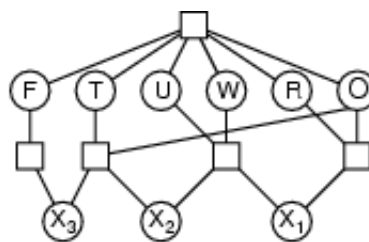


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Example: Cryptarithmic

$$\begin{array}{r} \text{TWO} \\ + \text{TWO} \\ \hline \text{FOUR} \end{array}$$



- 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)
 - $O + O = R + 10 \cdot X_1$
 - $X_1 + W + W = U + 10 \cdot X_2$
 - $X_2 + T + T = O + 10 \cdot X$
 - $X_3 = F, T \neq 0, F \neq 0$



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



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Standard Search Formulation (Incremental)

- 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
 - → fail if no legal assignments
 - **Goal test:** the current assignment is complete
- This is the same for all CSPs
- Every solution appears at depth n with n variables
→ use depth-first search
- Path is irrelevant, so can also use complete-state formulation
- $b = (n - l)d$ at depth l , hence $n! \cdot d^n$ leaves



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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 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
```



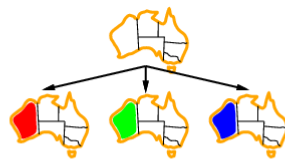
Backtracking Example



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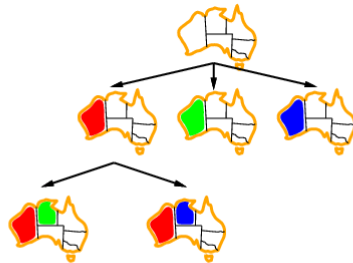
Backtracking Example



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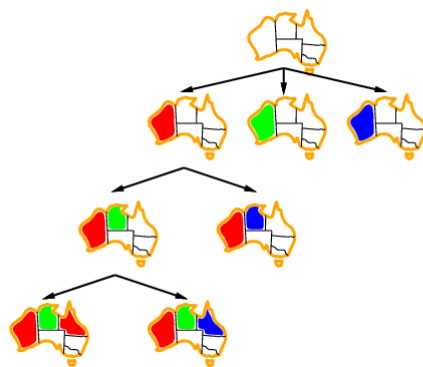
Backtracking Example



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Backtracking Example



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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?

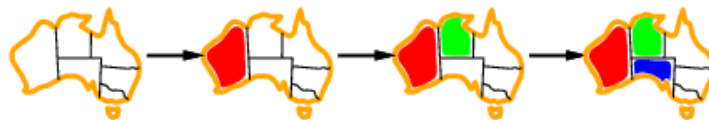


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Most Constrained Variable

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



- a.k.a. minimum remaining values (MRV) heuristic

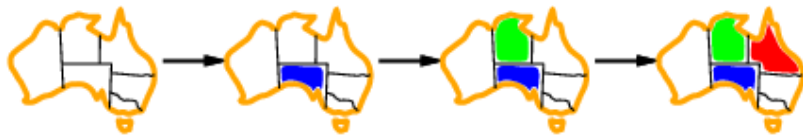


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Most Constraining Variable

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

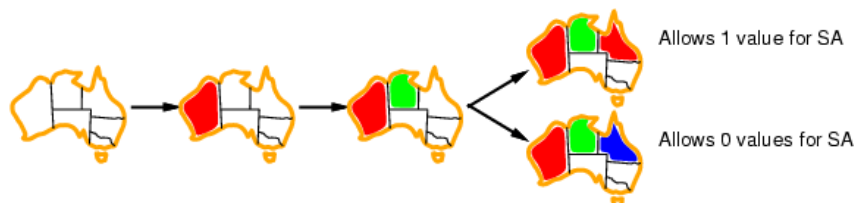


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Least Constraining Value

- 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

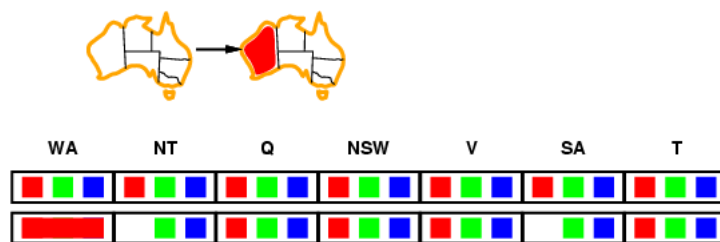


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Forward Checking

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

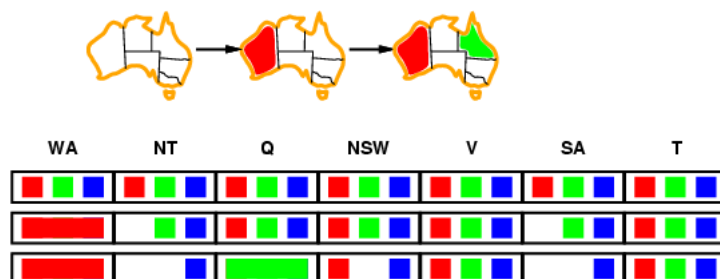


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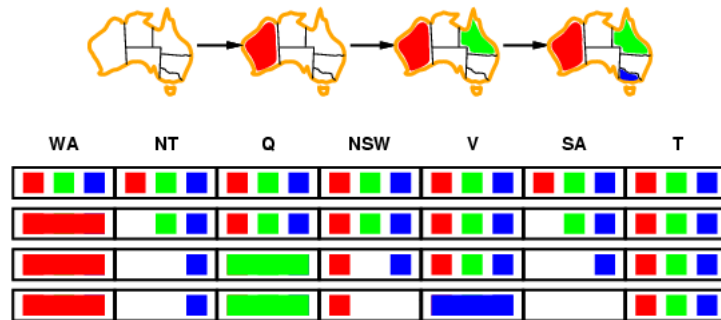


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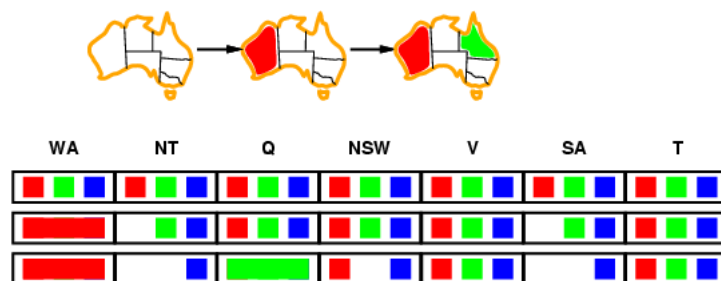


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Constraint Propagation

- 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

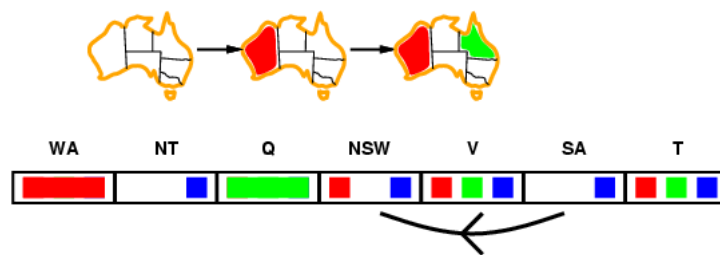


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Arc Consistency

- 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

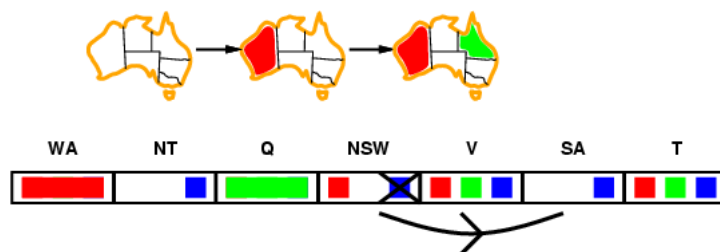


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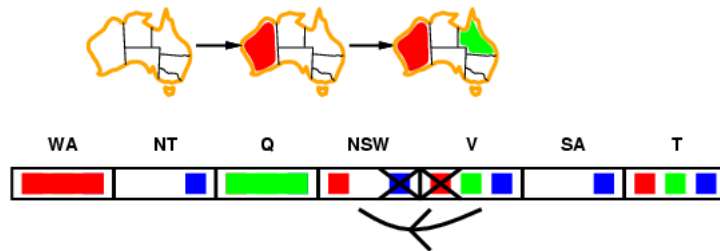


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Arc Consistency

- Simplest form of propagation makes each arc consistent
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- If X loses a value, neighbors of X need to be rechecked

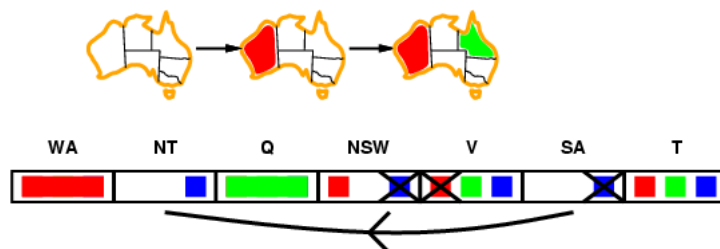


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Arc Consistency

- Simplest form of propagation makes each arc consistent
- $X \rightarrow Y$ is consistent iff
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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



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

- Time complexity: $O(n^2d^3)$



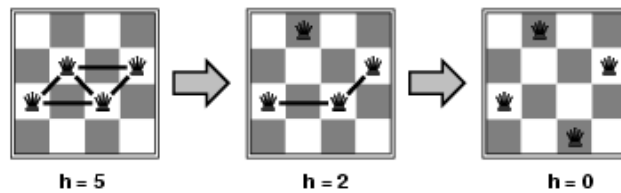
Local Search for CSPs

- 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., hill-climb with $h(n)$ = total number of violated constraints



Example: 4-Queens

- States: 4 queens in 4 columns ($4^4 = 256$ states)
- Actions: move queen in column
- Goal test: no attacks
- Evaluation: $h(n)$ = number of attacks



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



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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
- Iterative min-conflicts is usually effective in practice



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