



Constraint Satisfaction Problems

Based on Norvig&Russell, Ch. 5



Constraint satisfaction problems (CSPs)

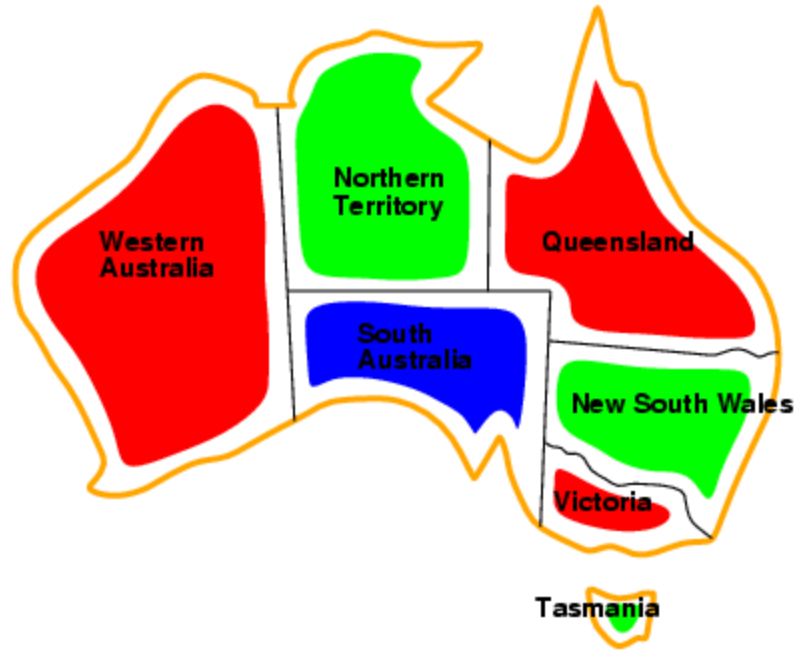
- Standard search problem: **state** is a "black box" – any data structure that supports successor function, heuristic function, and goal test
- Constraint Satisfaction Problems:
 - **state** is defined by **variables** X_i with **values** from **domain** D_i
 - **goal test** is a set of **constraints** specifying allowable combinations of values for subsets of variables
- Simple example of a **formal representation language**
- Supports useful **general-purpose** algorithms with more power than standard search algorithms

Example: Map-Coloring



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

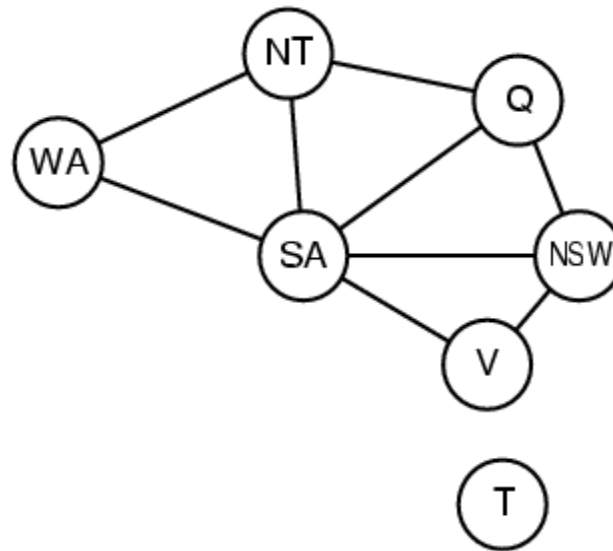
Example: Map-Coloring



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

Constraint graph

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





Varieties of CSPs

Discrete variables

- finite domains:
 - n variables, domain size $d \rightarrow O(d^n)$ complete assignments
 - e.g., Boolean CSPs, incl. \sim 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., $StartJob_1 + 5 \leq StartJob_3$

Continuous variables

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

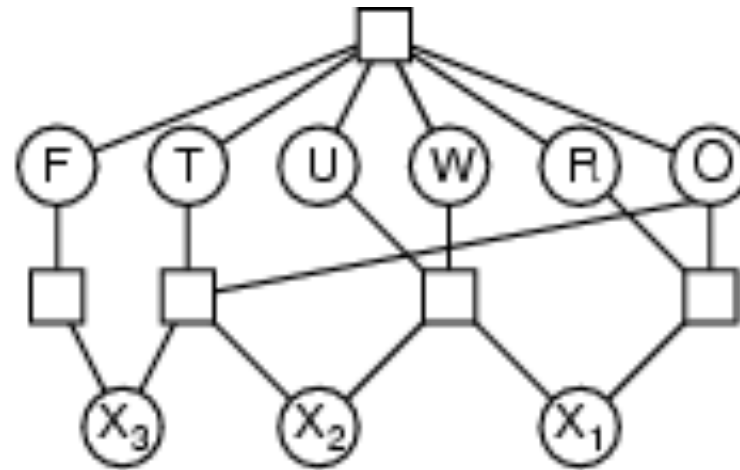


Varieties of constraints

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

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: $Alldiff(F, T, U, W, R, O)$

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



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

Many real-world problems involve real-valued variables



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
 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 we can also use complete-state formulation
 4. $b = (n - \ell)d$ at depth ℓ , hence $n! \cdot d^n$ leaves



Backtracking search

- Variable assignments are **commutative**}
So [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 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
```



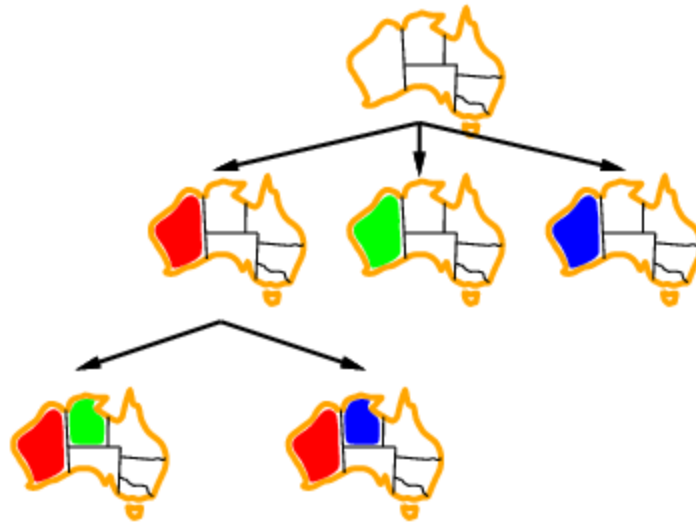
Backtracking example



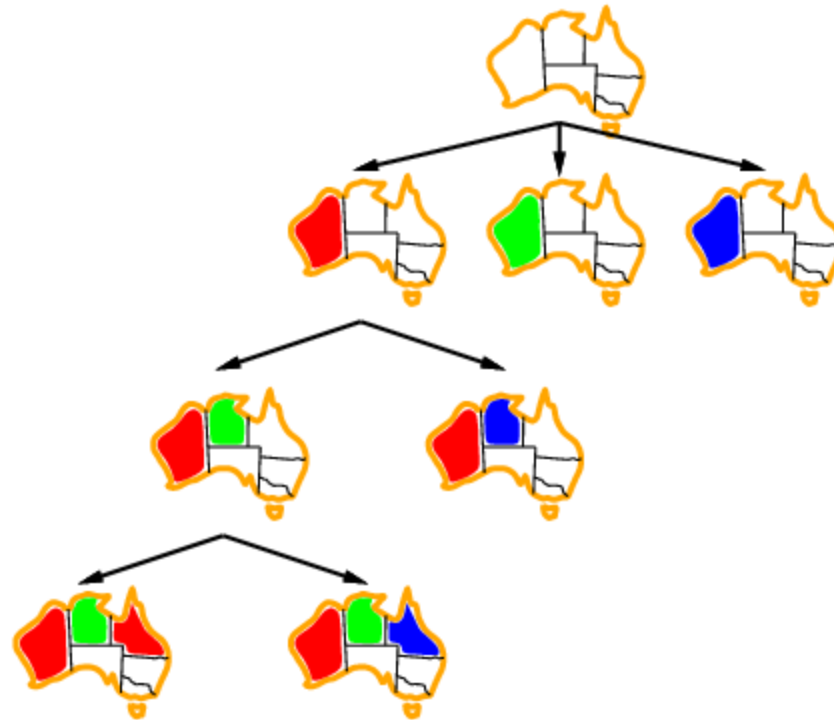
Backtracking example



Backtracking example



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



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

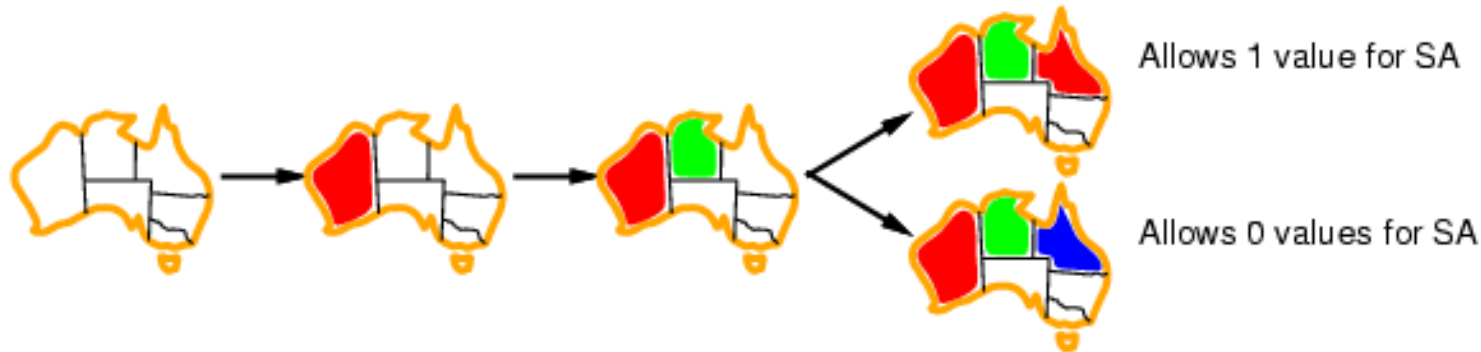
Most constraining variable

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



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:

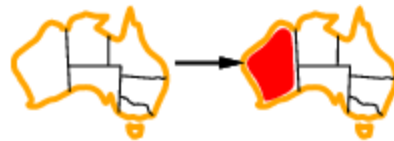
- Keep track of remaining legal values for unassigned variables
- Terminate search when any variable has no legal values



Forward checking

Idea:

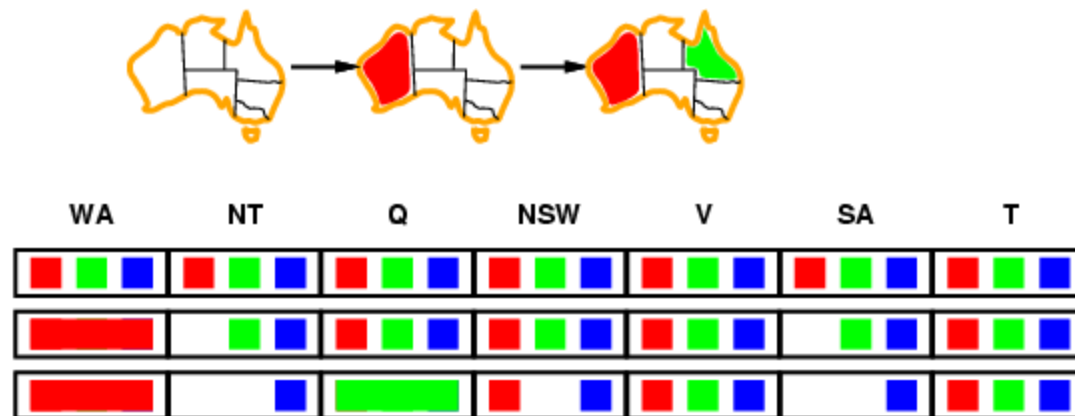
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Forward checking

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Forward checking

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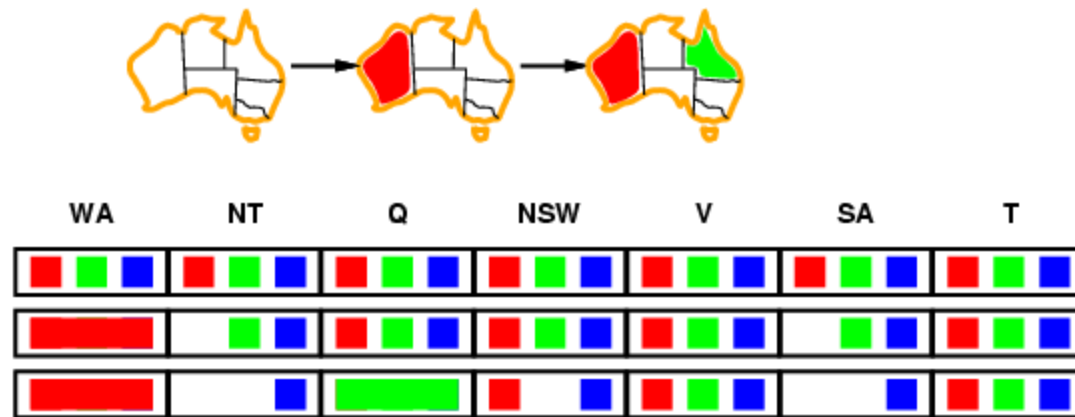
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WA	NT	Q	NSW	V	SA	T
Red, Green, Blue	Red, Green, Blue	Red, Green, Blue	Red, Green, Blue	Red, Green, Blue	Red, Green, Blue	Red, Green, Blue
Red, Red, Red	Green, Blue	Red, Green, Blue	Red, Green, Blue	Red, Green, Blue	Green, Blue	Red, Green, Blue
Red, Red, Red	Blue	Green, Green, Green	Red, Blue	Red, Green, Blue	Blue	Red, Green, Blue
Red, Red, Red	Blue	Green, Green, Green	Red	Blue, Blue, Blue		Red, Green, Blue

Constraint propagation

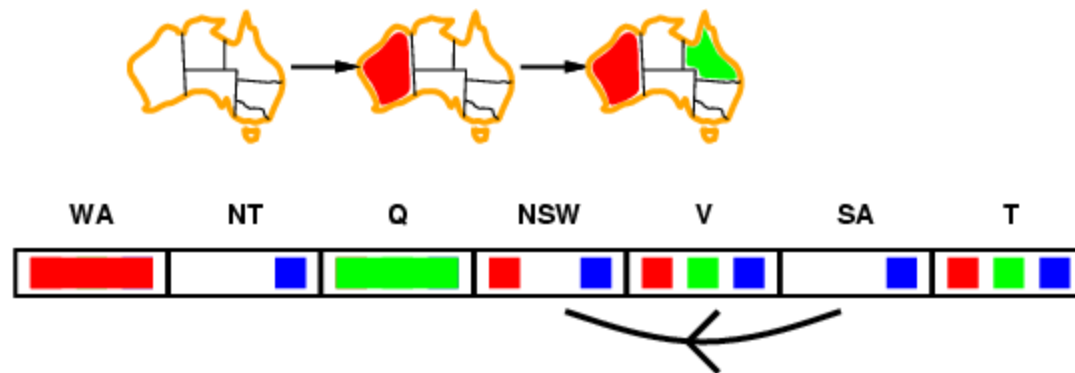
- Forward checking propagates information from assigned to unassigned variables, but doesn't provide early detection for all failures:



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

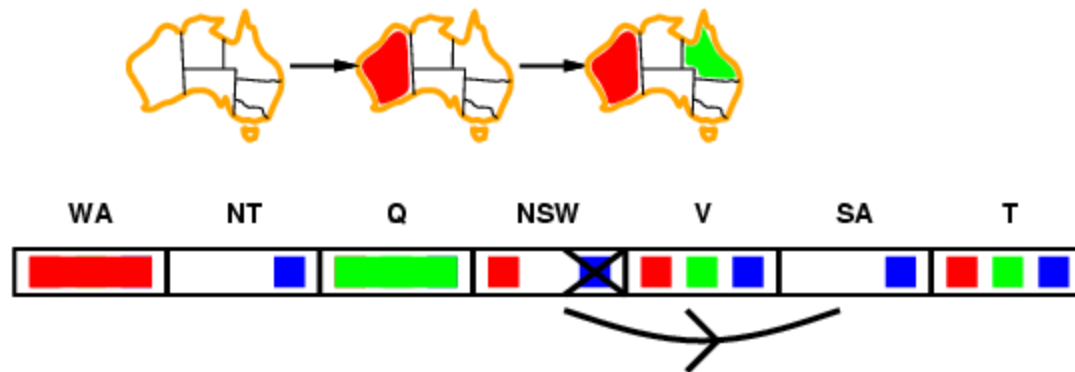
Arc consistency

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



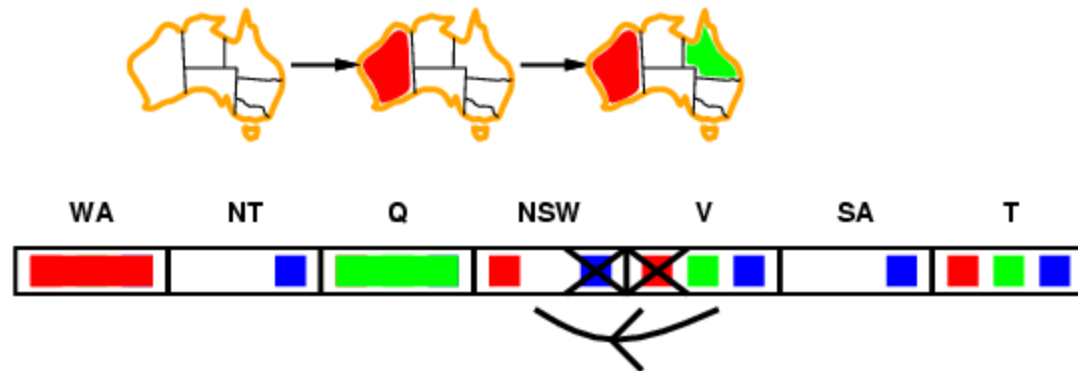
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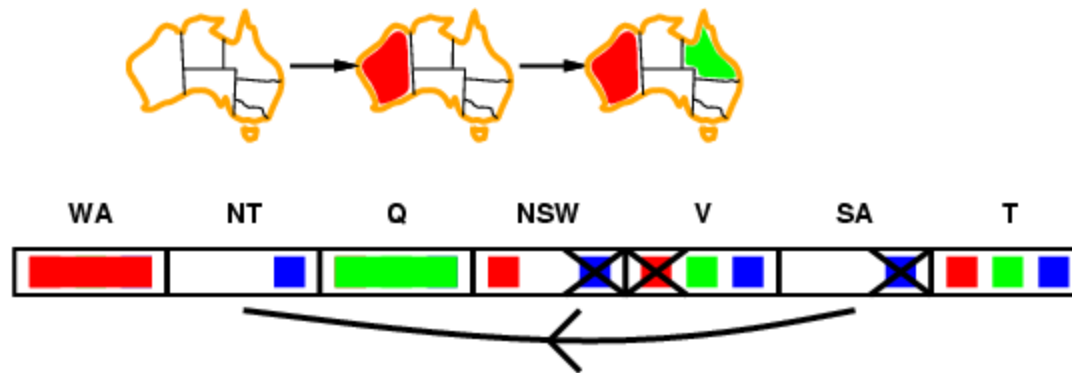
- Simplest form of propagation makes each arc **consistent** for **every** value x of X there is **some** allowed y



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

Arc consistency

Arc consistency detects failure earlier than forward checking and 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
```

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

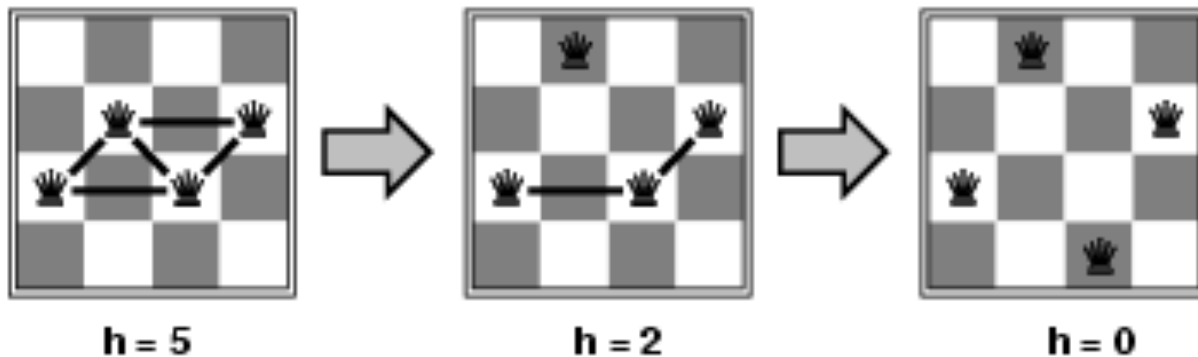


Local search for CSPs

- *Hill-climbing* and *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., $n = 10,000,000$)



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