



PROBLEM SOLVING AND SEARCH IN ARTIFICIAL INTELLIGENCE

Lecture 2 Constraint Satisfaction Problems

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Agenda

- 1 Introduction
- 2 Constraint Satisfaction Problems (CSP)
- 3 Uninformed Search versus Informed Search (Best First Search, A* Search, Heuristics)
- 4 Local Search, Stochastic Hill Climbing, Simulated Annealing
- 5 Tabu Search
- 6 Answer-set Programming (ASP)
- 7 Evolutionary Algorithms/ Genetic Algorithms
- 8 Structural Decomposition Techniques (Tree/Hypertree Decompositions)

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
- **Main idea**: eliminate large portions of search space all at once by identifying variable/value combinations that violate constraints

Defining CSPs

Constraint Satisfaction Problem (CSP)

A CSP is defined as a tuple $C = \langle X, D, C \rangle$, with

- X a set of variables, $\{X_1, \dots, X_n\}$.
 - D a set of domains, $\{D_1, \dots, D_n\}$, for each variable.
 - C a set of constraints that specify allowable combinations of values.
-
- Each **domain** D_i consists of a set of allowable values, $\{v_1, \dots, v_k\}$ for variable X_i .
 - Each **constraint** C_i consists of a pair $\langle scope, rel \rangle$, where $scope$ is a tuple of variables in the constraint, and rel defines the possible values.
 - A **relation** can be
 - an **explicit list** of all tuples of values satisfying the constraint, or
 - an **abstract** relation.

Defining CSPs ctd.

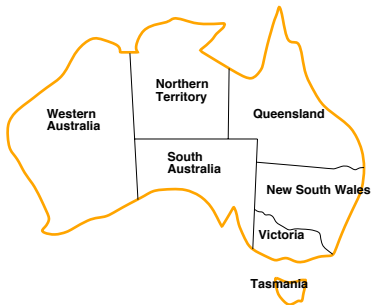
If X_1 and X_2 both have domain $\{A, B\}$, the constraint saying they have different values can be written as:

- $\langle (X_1, X_2), [(A, B), (B, A)] \rangle$, or
- $\langle (X_1, X_2), X_1 \neq X_2 \rangle$.

To solve a CSP, we define a **state space** and the notion of a solution.

- Each state in a CSP is defined by an **assignment** of values to some (or all variables), $\{X_i = v_i, X_j = v_j, \dots\}$.
- An assignment is **consistent** if it does not violate any constraints.
- A **complete assignment** has a value assigned to each variable.
- A **solution** is a consistent, complete assignment.
- A **partial assignment** is one that assigns values to only some of the variables.

Example: Map-Coloring

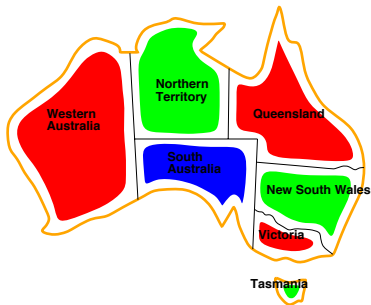


Variables WA, NT, Q, NSW, V, SA, T

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

Constraints: adjacent regions must have different colors e.g., $WA \neq NT$ (if the language allows this), or
 $(WA, NT) \in \{(red, green), (red, blue), (green, red), (green, blue), \dots\}$

Example: Map-Coloring ctd.



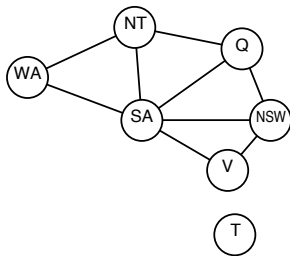
Solutions are assignments satisfying all constraints, e.g.,

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

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 sub-problem!

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., $SA \neq green$

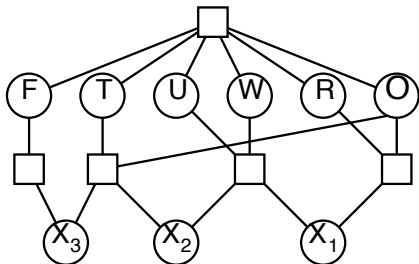
Binary constraints involve pairs of variables,
e.g., $SA \neq WA$

Higher-order constraints involve 3 or more variables,
e.g., cryptarithmic 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: 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 $\text{alldiff}(F, T, U, W, R, O)$, $O + O = R + 10 \cdot X_1$, 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

Constraint Propagation: Inference in CSPs

In regular state-space search, an algorithm can only perform search. In CSPs there is a choice

- an algorithm can search (choose a new variable assignment from several possibilities), or
- do a specific type of **inference** called **constraint propagation**:
 - using the constraints to reduce the number of legal values for a variable
 - this can reduce the legal values for another variable,
 - and so on.

Constraint propagation may be

- intertwined with search, or
- done as a **pre-processing** step (could solve the whole problem; no search is required).

Constraint Propagation

The key idea is **local consistency**.

- Treat each variable as a node in a graph.
- Each binary constraint represents an arc.
- Enforcing local consistency in each part of the graph eliminates inconsistent values throughout the graph.

Different types of local consistency:

- Node consistency
- Arc consistency
- Path consistency

Node Consistency

Node consistency

A variable X is **node-consistent** if all values in the domain of X satisfy the **unary** constraints of X . A CSP is node-consistent if every variable is node consistent.

Example

South Australia dislikes green.

- Variable SA starts with $\{red, green, blue\}$,
- make it node consistent by eliminating $green$,
- reduced domain of SA is $\{red, blue\}$.

Arc Consistency

Arc consistency

A variable is **arc-consistent** if every value in its domain satisfies the variable's binary constraints. X_i is arc-consistent wrt. X_j if for every value in D_i there is some value in D_j that satisfies the binary constraint on the arc (X_i, X_j) . A CSP is arc-consistent if every variable is arc-consistent with every other variable.

Example

Consider the constraint $Y = X^2$, where the domain of both X and Y is the set of digits. We can write the constraint explicitly as

$$\langle (X, Y), \{(0, 0), (1, 1), (2, 4), (3, 9)\} \rangle.$$

To make X arc-consistent wrt. Y , we reduce X 's domain to $\{0, 1, 2, 3\}$. We also reduce Y 's domain to $\{0, 1, 4, 9\}$ and the CSP is arc-consistent.

Path Consistency

- Arc consistency can reduce domains of variables and sometimes find a solution (or failure).
- But for other networks, arc consistency fails to make enough inferences.
- Example of map coloring of Australia with two colors.

Path consistency

A two-variable set $\{X_i, X_j\}$ is **path-consistent** wrt. a third variable X_m if, for every assignment $\{X_i = a, X_j = b\}$ consistent with constraints on $\{X_i, X_j\}$, there is an assignment to X_m that satisfies the constraints on $\{X_i, X_m\}$ and $\{X_m, X_j\}$.

Example: Path Consistency



Consider two-coloring of Australia. We make $\{WA, SA\}$ path consistent wrt. NT .

- Start by enumerating the consistent assignments to the set.
 - $\{WA = red, SA = blue\}$
 - $\{WA = blue, SA = red\}$
- With both assignments NT can be neither *red* nor *blue*.
- Eliminate both assignments.
- Thus, there is no solution to the problem.

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 $b = (n - \ell)d$ 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

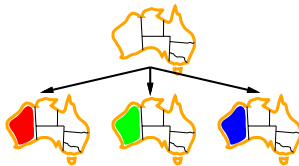
```
function Backtracking-Search(csp) returns solution/failure
  return Recursive-Backtracking({ }, csp)

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

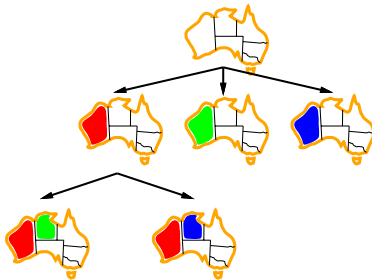
Backtracking example



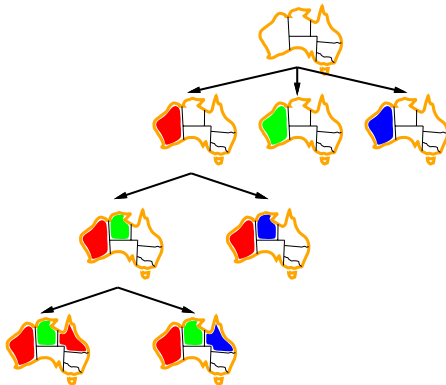
Backtracking example



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

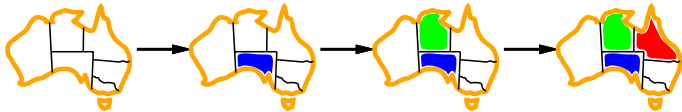


Degree heuristic

Tie-breaker among MRV variables

Degree heuristic:

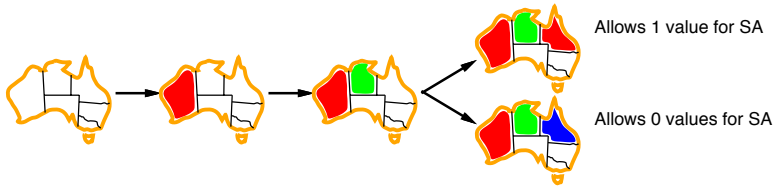
- choose the variable with the most constraints on remaining variables



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:

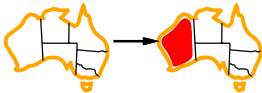
- Keep track of remaining legal values for unassigned variables
- Terminate search when any variable has no legal values



Forward checking

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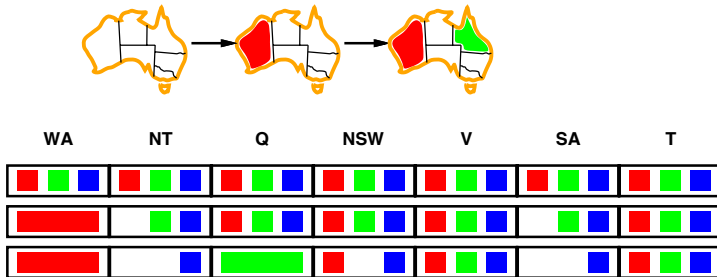
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Forward checking

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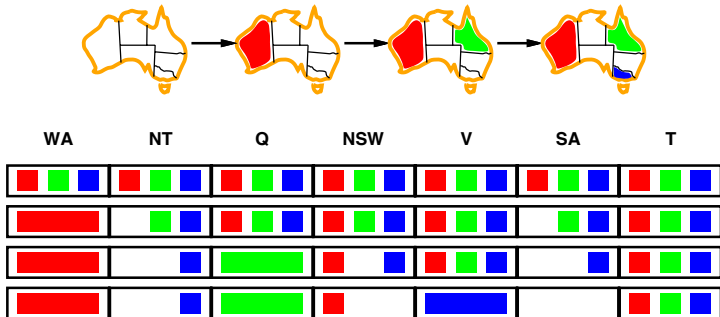
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Forward checking

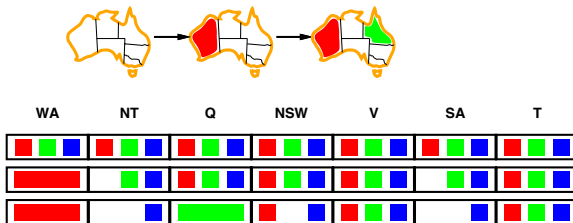
Idea:

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



Constraint propagation

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



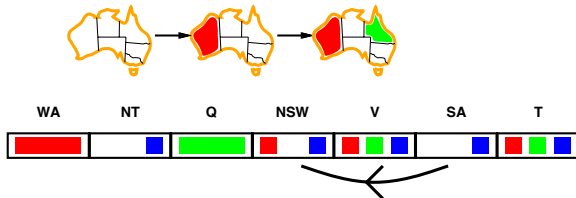
- *NT* and *SA* cannot both be blue!
- **Constraint propagation** repeatedly enforces constraints locally

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

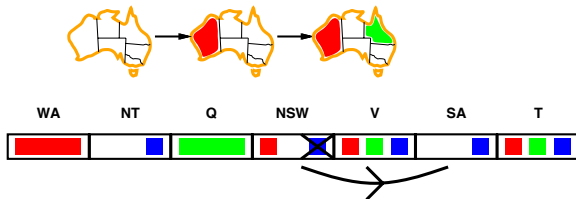


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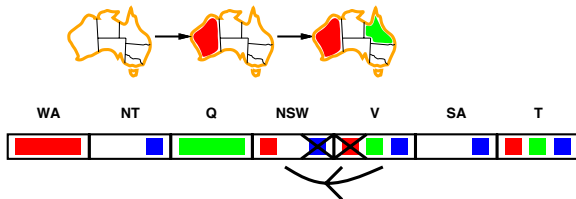


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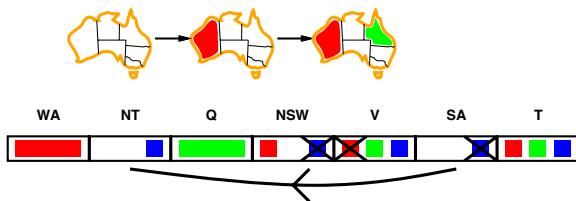
- If X loses a value, neighbors of X need to be rechecked

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 detects failure earlier than forward checking
- Can be run as a pre-processor 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 $\{X_1, X_2, \dots, X_n\}$

local variables: *queue*, a queue of arcs, initially all the arcs in *csp*

while *queue* is not empty **do**

 (X_i, X_j) \leftarrow 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 \leftarrow false

for each *x* **in** Domain[X_i] **do**

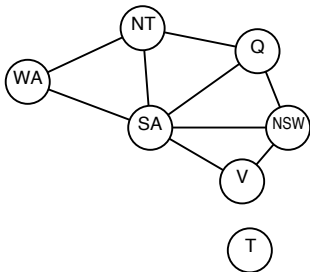
if no value *y* in Domain[X_j] allows (*x*,*y*) to satisfy the constraint $X_i \leftrightarrow X_j$

then delete *x* from Domain[X_i]; *removed* \leftarrow 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

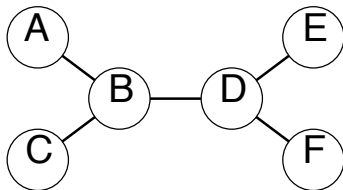


- Tasmania and mainland are **independent sub-problems**
- Identifiable as **connected components** of constraint graph

Problem structure ctd.

- 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



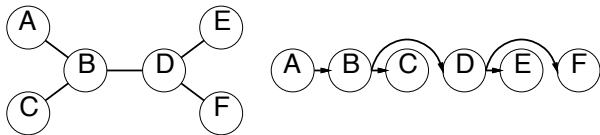
Theorem

If the constraint graph has no loops, the CSP can be solved in $O(nd^2)$ 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

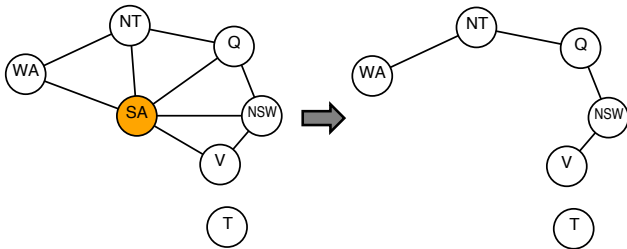
- 1 Choose a variable as root, order variables from root to leaves such that every node's parent precedes it in the ordering



- 2 For j from n down to 2, apply $\text{RemoveInconsistent}(\text{Parent}(X_j), X_j)$
- 3 For j from 1 to n , assign X_j consistently with $\text{Parent}(X_j)$

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

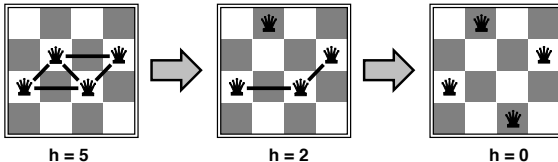
Example: 4-Queens

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

Operators: move queen in column

Goal test: no attacks

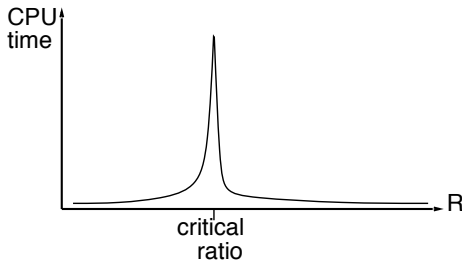
Evaluation: $h(n)$ = number of attacks



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

References



Stuart J. Russell and Peter Norvig.

Artificial Intelligence - A Modern Approach (3. edition). Pearson Education, 2010.