Artificial Intelligence

5. Constraint Satisfaction Problems

CSPs as Search Problems, Solving CSPs, Problem Structure

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Constraint Satisfaction Problems

- In search problems, the state does not have a structure (everything is in the data structure). In CSPs, states are explicitly represented as variable assignments.
- A CSP consists of
  - a set of variables \( \{x_1, x_2, \ldots, x_n\} \) to which
  - values \( \{d_1, d_2, \ldots, d_k\} \) can be assigned
  - such that a set of constraints over the variables is respected
- A CSP is solved by a variable assignment that satisfies all given constraints.
- Formal representation language with associated general inference algorithms

Example: Map-Coloring

- Variables: \( \text{WA, NT, SA, Q, NSW, V, T} \)
- Values: \( \{\text{red, green, blue}\} \)
- Constraints: adjacent regions must have different colors, e.g., NSW \( \neq \) V
Australian Capital Territory (ACT) and Canberra (inside NSW)

View of the Australian National University and Telstra Tower

One Solution

Solution assignment:
- \{ \text{WA = red, NT = green, Q = red, NSW = green, V = red, SA = blue, T = green} \}
- Perhaps in addition \text{ACT = blue}

Constraint Graph

- Works for \text{binary CSPs (otherwise hyper-graph)}
- \text{Nodes = variables, arcs = constraints}
- Graph structure can be important (e.g., connected components)

Note: Our problem is 3-colorability for a planar graph

Variations

- \text{Binary, ternary, or even higher arity}
- \text{Finite domains (d values) => d^n possible variable assignments}
- \text{Infinite domains (reals, integers)}
  - \text{linear constraints: solvable (in P if real)}
  - \text{nonlinear constraints: unsolvable}
Applications

- Timetabling (classes, rooms, times)
- Configuration (hardware, cars, ...)
- Spreadsheets
- Scheduling
- Floor planning
- Frequency assignments
- ...

Backtracking Search over Assignments

- Assign values to variables step by step (order does not matter)
- Consider only one variable per search node!
- DFS with single-variable assignments is called backtracking search
- Can solve $n$-queens for $n \approx 25$

Algorithm

```python
function BACKTRACKING-SEARCH(csp) returns solution/failure
    return RECURSIVE-BACKTRACKING([], csp)

function RECURSIVE-BACKTRACKING(assigned, csp) returns solution/failure
    if assigned is complete then return assigned
    var ← SELECT-UNASSIGNED-VARIABLE(VARIABLES[csp], assigned, csp)
    for each value in ORDER-DOMAIN-VALUES(var, assigned, csp) do
        if value is consistent with assigned according to CONSTRAINTS[csp] then
            result ← RECURSIVE-BACKTRACKING([var = value]assigned, csp)
            if result ≠ failure then return result
    end
    return failure
```

Example (1)
Improving Efficiency: CSP Heuristics & Pruning Techniques

- **Variable ordering**: Which one to assign first?
- **Value ordering**: Which value to try first?
- Try to detect failures early on
- Try to exploit problem structure

➢ **Note**: all this is not problem-specific!
**Variable Ordering: Most constrained first**

- Most constrained variable:
  - choose the variable with the **fewest** remaining legal values
  - reduces branching factor!

**Variable Ordering: Most Constraining Variable First**

- Break ties among variables with the same number of remaining legal values:
  - choose variable with the **most constraints on** remaining unassigned variables
  - reduces branching factor in the next steps

**Value Ordering: Least Constraining Value First**

- Given a variable,
  - choose first a value that rules out the **fewest** values in the remaining unassigned variables
  - We want to find an assignment that satisfies the constraints (of course, does not help if unsat.)

**Rule out Failures early on: Forward Checking**

- Whenever a value is assigned to a variable, values that are now **illegal** for other variables are **removed**
- **Implements** what the ordering heuristics implicitly compute
- WA = *red*, then NT cannot become *red*
- If all values are removed for one variable, we can **stop!**
Forward Checking (1)

- Keep track of remaining values
- Stop if all have been removed

Forward Checking (2)

- Keep track of remaining values
- Stop if all have been removed

Forward Checking (3)

- Keep track of remaining values
- Stop if all have been removed

Forward Checking (4)

- Keep track of remaining values
- Stop if all have been removed
Forward Checking: Sometimes it Misses Something

- Forward Checking propagates information from assigned to unassigned variables
- However, there is no propagation between unassigned variables

Arc Consistency

- A directed arc $X \rightarrow Y$ is “consistent” iff
  - for every value $x$ of $X$, there exists a value $y$ of $Y$, such that $(x, y)$ satisfies the constraint between $X$ and $Y$
- Remove values from the domain of $X$ to enforce arc-consistency
- Arc consistency detects failures earlier
- Can be used as preprocessing technique or as a propagation step during backtracking

Arc Consistency Example

AC3 Algorithm

```python
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)
  if REMOVE-INCONSISTENT-VALUES$(X_i, X_j)$ then
    for each $X_k$ in NEIGHBORS$(X_i)$ do
      add $(X_k, X_j)$ to queue

function REMOVE-INCONSISTENT-VALUES$(X_i, X_j)$ returns true iff we remove a value
  removed = false
  for each $x$ in DOMAIN$(X_i)$ do
    if no value $y$ in DOMAIN$(X_j)$ allows $(x, y)$ to satisfy the constraint between $X_i$ and $X_j$
    then delete $x$ from DOMAIN$(X_i)$; removed = true
  return removed
```
Properties of AC3

- AC3 runs in $O(d^3n^2)$ time, with $n$ being the number of nodes and $d$ being the maximal number of elements in a domain.
- Of course, AC3 does not detect all inconsistencies (which is an NP-hard problem).

Problem Structure (1)

- CSP has two independent components.
- Identifiable as connected components of constraint graph.
- Can reduce the search space dramatically.

Problem Structure (2): Tree-structured CSPs

- If the CSP graph is a tree, then it can be solved in $O(nd^2)$.
  - General CSPs need in the worst case $O(d^n)$.
- Idea: Pick root, order nodes, apply arc consistency from leaves to root, and assign values starting at root.
- Algorithm linear in $n$.
Problem Structure (3): Almost Tree-structured

- **Conditioning**: Instantiate a variable and prune values in neighboring variables

- **Cutset conditioning**: Instantiate (in all ways) a set of variables in order to reduce the graph to a tree (note: finding minimal cutset is NP-hard)

Another Method: Tree Decomposition (1)

- Decompose problem into a set of connected sub-problems, where two sub-problems are connected when they share a constraint
- Solve sub-problems independently and combine solutions

Another Method: Tree Decomposition (2)

- A tree decomposition must satisfy the following conditions:
  - Every variable of the original problem appears in at least one sub-problem
  - Every constraint appears in at least one sub-problem
  - If a variable appears in two sub-problems, it must appear in all sub-problems on the path between the two sub-problems
  - The connections form a tree

Another Method: Tree Decomposition (3)

- Consider sub-problems as new mega-nodes, which have values defined by the solutions to the sub-problems
- Use technique for tree-structured CSP to find an overall solution (constraint is to have identical values for the same variable)
**Tree Width**

- **Tree width of a tree decomposition** = size of largest sub-problem minus 1
- **Tree width of a graph** is minimal tree width over all possible tree decompositions
- If a graph has tree width \( w \) and we know a tree decomposition with that width, we can solve the problem in \( O(nd^{w+1}) \)
- Finding a tree decomposition with minimal tree width is NP-hard

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**Summary & Outlook**

- **CSPs** are a special kind of search problem:
  - states are value assignments
  - goal test is defined by constraints
- **Backtracking** = DFS with one variable assigned per node. Other intelligent backtracking techniques possible
- **Variable/value ordering** heuristics can help dramatically
- **Constraint propagation** prunes the search space
- **Path-consistency** is a constraint propagation technique for triples of variables
- **Tree structure** of CSP graph simplifies problem significantly
- **Cutset conditioning** and **tree decomposition** are two ways to transform part of the problem into a tree
- CSPs can also be solved using **local search**