Reminder: CSPs

- **CSPs:**
  - Variables
  - Domains
  - Constraints
    - Implicit (provide code to compute)
    - Explicit (provide a list of the legal tuples)
    - Unary / Binary / N-ary

- **Goals:**
  - Here: find any solution
  - Also: find all, find best, etc.

Backtracking Search

```python
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 ← 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 is not failure then return result
            remove {var = value} from assignment
    return failure
```
Improving Backtracking

- General-purpose ideas give huge gains in speed
  - ... but it’s all still NP-hard

- Filtering: Can we detect inevitable failure early?

- Ordering:
  - Which variable should be assigned next? (MRV)
  - In what order should its values be tried? (LCV)

- Structure: Can we exploit the problem structure?

Arc Consistency and Beyond

Arc Consistency of an Entire CSP

- A simple form of propagation makes sure all arcs are simultaneously consistent:

- Arc consistency detects failure earlier than forward checking
- Important: If X loses a value, neighbors of X need to be rechecked!
- Must rerun after each assignment!

<table>
<thead>
<tr>
<th>WA</th>
<th>NT</th>
<th>Q</th>
<th>NSW</th>
<th>V</th>
<th>SA</th>
</tr>
</thead>
<tbody>
<tr>
<td>**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Limitations of Arc Consistency

- After enforcing arc consistency:
  - Can have one solution left
  - Can have multiple solutions left
  - Can have no solutions left (and not know it)

- Arc consistency still runs inside a backtracking search!
K-Consistency

- Increasing degrees of consistency
  - 1-Consistency (Node Consistency): Each single node’s domain has a value which meets that node’s unary constraints
  - 2-Consistency (Arc Consistency): For each pair of nodes, any consistent assignment to one can be extended to the other
  - K-Consistency: For each k nodes, any consistent assignment to k-1 can be extended to the kth node.
  - Higher k more expensive to compute
  - (You need to know the k=2 case: arc consistency)

Strong K-Consistency

- Strong k-consistency: also k-1, k-2, ... 1 consistent
- Claim: strong n-consistency means we can solve without backtracking!
- Why?
  - Choose any assignment to any variable
  - Choose a new variable
  - By 2-consistency, there is a choice consistent with the first
  - Choose a new variable
  - By 3-consistency, there is a choice consistent with the first 2
  - ...
- Lots of middle ground between arc consistency and n-consistency! (e.g. k=3, called path consistency)
Problem Structure

- Extreme case: independent subproblems
  - Example: Tasmania and mainland do not interact
- Independent subproblems are identifiable as connected components of constraint graph
- Suppose a graph of \( n \) variables can be broken into subproblems of only \( c \) variables:
  - Worst-case solution cost is \( O\left(\left(\frac{n}{c}\right)(d^c)\right) \), linear in \( n \)
  - E.g., \( n = 80, d = 2, c = 20 \)
  - \( 2^{20} = 4 \text{ billion years at 10 million nodes/sec} \)
  - \( 4(2^{20}) = 0.4 \text{ seconds at 10 million nodes/sec} \)

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 probabilistic reasoning (later): an example of the relation between syntactic restrictions and the complexity of reasoning

Tree-Structured CSPs

- Algorithm for tree-structured CSPs:
  - Order: Choose a root variable, order variables so that parents precede children
  - Remove backward: For \( i = n : 2 \), apply RemoveInconsistent(Parent(\( X_i \)), \( X_i \))
  - Assign forward: For \( i = 1 : n \), assign \( X_i \) consistently with Parent(\( X_i \))
  - Runtime: \( O(n d^2) \) (why?)
Improving Structure

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 $c$ gives runtime $O((d^c)(n-c)d^2)$, very fast for small $c$

Cutset Conditioning

- Choose a cutset
- Instantiate the cutset (all possible ways)
- Compute residual CSP for each assignment
- Solve the residual CSPs (tree structured)

Cutset Quiz

- Find the smallest cutset for the graph below.
Tree Decomposition

- Idea: create a tree-structured graph of mega-variables
- Each mega-variable encodes part of the original CSP
- Subproblems overlap to ensure consistent solutions

Iterative Improvement

Iterative Algorithms for CSPs

- Local search methods typically work with “complete” states, i.e., all variables assigned
- To apply to CSPs:
  - Take an assignment with unsatisfied constraints
  - Operators reassign variable values
  - No fringe! Live on the edge.
- Algorithm: While not solved,
  - Variable selection: randomly select any conflicted variable
  - Value selection: min-conflicts heuristic:
    - Choose a 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)
- Operators: move queen in column
- Goal test: no attacks
- Evaluation: \( c(n) = \) number of attacks

[Demo: n-queens – iterative improvement (L5D1)]
[Demo: coloring – iterative improvement]
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

- CSPs are a special kind of search problem:
  - States are partial assignments
  - Goal test defined by constraints
- Basic solution: backtracking search
- Speed-ups:
  - Ordering
  - Filtering
  - Structure
- Iterative min-conflicts is often effective in practice
Local Search

- Tree search keeps unexplored alternatives on the fringe (ensures completeness)
- Local search: improve a single option until you can’t make it better (no fringe!)
- New successor function: local changes
- Generally much faster and more memory efficient (but incomplete and suboptimal)

Hill Climbing

- Simple, general idea:
  - Start wherever
  - Repeat: move to the best neighboring state
  - If no neighbors better than current, quit
- What’s bad about this approach?
  - Complete?
  - Optimal?
- What’s good about it?

Hill Climbing Diagram
Hill Climbing Quiz

- Starting from X, where do you end up?
- Starting from Y, where do you end up?
- Starting from Z, where do you end up?

Simulated Annealing

- **Idea:** Escape local maxima by allowing downhill moves
  - But make them rarer as time goes on

  ```
  function SIMULATED-ANNEALING(problem, schedule) returns a solution state
  inputs: problem, a problem
          schedule, a mapping from time to "temperature"
  local variables: current, a node
                   next, a node
                   T, a "temperature" controlling prob. of downward steps
  current ← MAKE-NODE(INITIAL-STATE(problem))
  for t ← 1 to ∞ do
      T ← schedule(t)
      if T = 0 then return current
      next ← a randomly selected successor of current
      ΔE ← VALUE(next) − VALUE(current)
      if ΔE > 0 then current ← next
      else current ← next only with probability e^(-ΔE/T)
  ```

- **Theoretical guarantee:**
  - Stationary distribution: \( p(x) \propto e^{-E(x)/T} \)
  - If T decreased slowly enough, will converge to optimal state!

- **Is this an interesting guarantee?**

- **Sounds like magic, but reality is reality:**
  - The more downhill steps you need to escape a local optimum, the less likely you are to ever make them all in a row
  - People think hard about *ridge operators* which let you jump around the space in better ways

Genetic Algorithms

- **Genetic algorithms use a natural selection metaphor**
  - Keep best N hypotheses at each step (selection) based on a fitness function
  - Also have pairwise crossover operators, with optional mutation to give variety

- **Possibly the most misunderstood, misapplied (and even maligned) technique around**
Example: N-Queens

- Why does crossover make sense here?
- When wouldn’t it make sense?
- What would mutation be?
- What would a good fitness function be?

Next Time: Adversarial Search!