Previously

- Formulating problems as search
- Blind search algorithms
  - Depth first
  - Breadth first (uniform cost)
  - Iterative deepening
- Heuristic Search
  - Best first
    - Beam (Hill climbing)
    - A*
    - IDA*
- Heuristic generation
  - Exact soln to a relaxed problem
  - Pattern databases
- Local Search
  - Hill climbing, random moves, random restarts, simulated annealing
What is Search For?

Planning: sequences of actions
- The *path to the goal* is the important thing
- Paths have various costs, depths
- Assume little about problem structure

Identification: assignments to variables
- The *goal itself* is important, *not the path*
- All paths at the same depth (for some formulations)
Constraint Satisfaction Problems

Ps are *structured* (factored) identification problems
Constraint Satisfaction Problems

Standard search problems:
- State is a “black box”: arbitrary data structure
- Goal test can be any function over states
- Successor function can also be anything

Constraint satisfaction problems (CSPs):
- A special subset of search problems
- State is defined by variables \( X_i \) with values from a domain \( D \) (sometimes \( D \) depends on \( i \))
- Goal test is a set of constraints specifying allowable combinations of values for subsets of variables

Making use of CSP formulation allows for optimized algorithms
- Typical example of trading generality for utility (in this case, speed)
Constraint Satisfaction Problems

- “Factoring” the state space
- Representing the state space in a knowledge representation

Constraint satisfaction problems (CSPs):
- A special subset of search problems
- State is defined by variables $X_i$ with values from a domain $D$ (sometimes $D$ depends on $i$)
- Goal test is a set of constraints specifying allowable combinations of values for subsets of variables
CSP Example: N-Queens

Formulation 1:
- Variables: \( X_{ij} \)
- Domains: \{0, 1\}
- Constraints

\[
\begin{align*}
\forall i, j, k \ (X_{ij}, X_{ik}) \in \{(0, 0), (0, 1), (1, 0)\} \\
\forall i, j, k \ (X_{ij}, X_{kj}) \in \{(0, 0), (0, 1), (1, 0)\} \\
\forall i, j, k \ (X_{ij}, X_{i+k,j+k}) \in \{(0, 0), (0, 1), (1, 0)\} \\
\forall i, j, k \ (X_{ij}, X_{i+k,j-k}) \in \{(0, 0), (0, 1), (1, 0)\} \\
\sum_{i,j} X_{ij} = N
\end{align*}
\]
CSP Example: N-Queens

Formulation 2:

Variables: $Q_k$

Domains: $\{1, 2, 3, \ldots, N\}$

Constraints:

Implicit: $\forall i, j$ non-threatening($Q_i, Q_j$)

Explicit: $(Q_1, Q_2) \in \{(1, 3), (1, 4), \ldots\}$

\ldots
CSP Example: Sudoku

- Variables:
  - Each (open) square
- Domains:
  - \{1,2,\ldots,9\}
- Constraints:

  9-way alldiff for each column
  9-way alldiff for each row
  9-way alldiff for each region
  (or can have a bunch of pairwise inequality constraints)
Propositional Logic

\[ (((p \leftrightarrow q) \land r) \lor (p \land q \land \sim r)) \]

Variables: propositional variables
Domains: \{T, F\}
Constraints: logical formula
CSP Example: Map Coloring

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

Domains: D = {red, green, blue}

Constraints: adjacent regions must have different colors

Implicit: WA ≠ NT

Explicit: (WA, NT) ∈ {(red, green), (red, blue), …}

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

{WA=red, NT=green, Q=red, NSW=green, V=red, SA=blue, T=green}
Constraint Graphs
Constraint Graphs

Binary CSP: each constraint relates (at most) two variables

Binary 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 subproblem!
Example: Cryptarithmetic

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:
\[ \text{alldiff}(F, T, U, W, R, O) \]
\[ O + O = R + 10 \cdot X_1 \]
\[ \ldots \]
Chinese Constraint Network

- Soup: Must be Hot&Sour
- Chicken Dish: No Peanuts
- Vegetable: No Peanuts
- Rice: Not Chow Mein
- Pork Dish
- Seafood
- Appetizer

Total Cost < $40
Real-World CSPs

Assignment problems: e.g., who teaches what class
Timetabling problems: e.g., which class is offered when and where?
Hardware configuration
Gate assignment in airports
Space Shuttle Repair
Transportation scheduling
Factory scheduling
Lots more!
Example: The Waltz Algorithm

The Waltz algorithm is for interpreting line drawings of solid polyhedra as 3D objects. An early example of an AI computation posed as a CSP.
Waltz on Simple Scenes

Assume all objects:

- Have no shadows or cracks
- Three-faced vertices
- “General position”: no junctions change with small movements of the eye.

Then each line on image is one of the following:

- Boundary line (edge of an object) (> ) with right hand of arrow denoting “solid” and left hand denoting “space”
- Interior convex edge (+)
- Interior concave edge (-)
Only certain junctions are physically possible
How can we formulate a CSP to label an image?

**Variables:** edges

**Domains:** >, <, +, -

**Constraints:** legal junction types
Slight Problem: Local vs Global Consistency
Varieties of CSPs
Varieties of CSP Variables

**Discrete Variables**

- Finite domains
  - Size $d$ means $O(d^n)$ complete assignments
  - E.g., Boolean CSPs, including Boolean satisfiability (NP-complete)

- Infinite domains (integers, strings, etc.)
  - E.g., job scheduling, variables are start/end times for each job
  - Linear constraints solvable, nonlinear undecidable

**Continuous variables**

E.g., start/end times for Hubble Telescope observations

Linear constraints solvable in polynomial time by linear program methods (see CSE 521 for a bit of LP theory)
Varieties of CSP Constraints

Varieties of Constraints
- Unary constraints involve a single variable (equivalent to reducing domains), 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., cryptarithmetic column constraints

Preferences (soft constraints):
- E.g., red is better than green
- Often representable by a cost for each variable assignment
- Gives constrained optimization problems
  (We’ll ignore these until we get to Bayes’ nets)
Solving CSPs
CSP as Search
Standard Depth First Search
Standard Search Formulation

Standard search formulation of CSPs

States defined by the values assigned so far (partial assignments)
- Initial state: the empty assignment, {};
- Successor function: assign a value to an unassigned variable;
- Goal test: the current assignment is complete and satisfies all constraints.

We’ll start with the straightforward, naïve approach, then improve it.
Backtracking Search

Backtracking search is the basic uninformed algorithm for solving CSPs

Idea 1: One variable at a time
- Variable assignments are commutative, so fix ordering
- 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 step

Idea 2: Check constraints as you go
- I.e. consider only values which do not conflict previous assignments
- Might have to do some computation to check the constraints
- “Incremental goal test”

Depth-first search with these two improvements called backtracking search

Can solve n-queens for n \approx 25
Backtracking Example
Backtracking Search

```plaintext
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 ≠ failure then return result
            remove {var = value} from assignment
        end if
    end for
    return failure
```

- What are the choice points?
Backtracking Search

Kind of depth first search
Is it complete?
Improving Backtracking

General-purpose ideas give huge gains in speed

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

Filtering: Can we detect inevitable failure early?

Structure: Can we exploit the problem structure?
Next: Constraint Satisfaction Problems - Part 2