cis32-ai — lecture # 4 — wed-8-feb-2006

today's topics:

- behavior-based AI (finish up from last time)
- problem solving agents

production systems, continued from last class

- Another kind of production system will have an overall goal.
- Imagine that we want the robot to follow the boundary until it finds a north-east corner (like the top-left corner in the example) and then stop there.
- We can define another item in the feature vector:

$$x_5 = s_1 s_2 s_3 \overline{s_4 s_5 s_6} s_7 s_8$$

  and then write the production system:

$$\begin{aligned} x_5 &\rightarrow \text{nil} \\ 1 &\rightarrow \text{boundaryfollowing} \end{aligned}$$

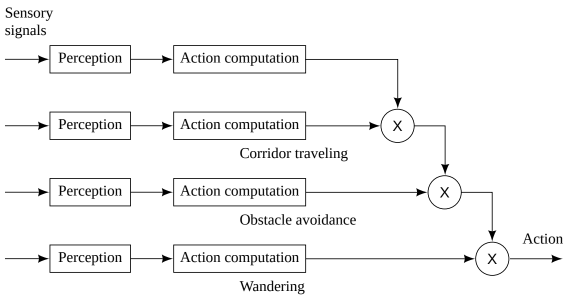
  where nil is an action which does nothing, and boundary_following is a call to the previous production system.

- There are three points to make about this.
- First, in goal-achieving production systems, the topmost rule identifies the situation we are aiming for.
- Once this is acheived, we need do nothing more.
- Second, conditions and actions further down in the production system lead towards the achievement of the topmost condition.
- Indeed, action a_i is intended to bring about c_j where $j < i$.
- Third, we can build up a hierarchy of production systems, where systems lower in the hierarchy move the robot towards meeting the conditions of productions in systems higher up.
- This gives us a means of procedural abstraction.

- Systems of rules like this are called *teleo-reactive* (T-R) programs.
- Every action in a T-R program works towards the achievement of a condition higher in the program.
- It is typically easy to write such programs.
- T-R programs are also very robust.
- Even in the face of faulty sensor readings, carefully constructed T-R programs will get back on track.

Subsumption Architecture

- Another approach to combining simple sensory-driven behavior:



- Each module receives sensory information directly from the world.
- If the sensory inputs match the preconditions of a module, it executes.
- Modules can *subsume* each other (in the picture upper modules can subsume lower ones).
- When module i subsumes j, then if i's precondition is met, the program of i replaces that of j.
- So in the example:
  - The robot wanders until it has to avoid an obstacle;
  - Avoids an obstacle until it is travelling in a corridor.

- Subsumption architecture started with Brooks.
- Idea is that:
  - Build basic behavior;
  - When that is refined, add a subsuming behavior;
  - When that is refined, add another;
  - ...
- So far as I know, the maximum "stack height" is not *that* high.
- However, there are other ways of making the approach more sophisticated.

- We can make the approach more flexible:
  - Rather than having a fixed set of behaviors, construct a task specific set.
  - (Plan, but in terms of behaviors not actions.)
- We can improve on subsumption.
  - Rather than having one behavior replace another, merge behaviors.
  - (Imagine being able to do a weighted sum of actions.)
- Both these features are available in Saffiotti's THINKING CAP.

- How could we program this?
- As follows:

```
if <some condition>
   then <some action>
   else if <another condition>
          then <another action>
          else ...
```

- Here actions higher up in the compound if statement take precedence.

Problem Solving Agents

- earlier, we introduced *rational agents*.
- Now consider agents as *problem solvers*:
  Systems which set themselves *goals* and find *sequences of actions* that achieve these goals.
- What is a problem?
  A *goal* and a *means* for achieving the goal.
- The goal specifies the state of affairs we want to bring about.
- The means specifies the operations we can perform in an attempt to bring about the goal.
- The difficulty is deciding what *order* to carry out the operations.

- Operation of problem solving agent:

```
/* s is sequence of actions */
repeat {
    percept = observeWorld();
    state = updateState(state, p);
    if s is empty then {
         goal = formulateGoal(state);
         prob = formulateProblem(state,p);
         s = search(prob);
    }
    action = recommendation(s);
    s = remainder(s, state);
}
until false; /* i.e., forever */
```


- Key difficulties:
  - `formulateGoal(...)`
  - `formulateProblem(...)`
  - `search(...)`
- It isn't easy to see how to tackle any of these.
- Here we will concentrate mainly on search.

Goal Formulation

- Where do an agent's goals come from?
  - Agent is a *program* with a *specification*.
  - Specification is to maximise performance measure.
  - Should *adopt goal* if achievement of that goal will maximise this measure.
- Goals provide a *focus* and *filter* for decision-making:
  - *focus*: need to consider how to achieve them;
  - *filter*: need not consider actions that are incompatible with goals.

Problem Formulation

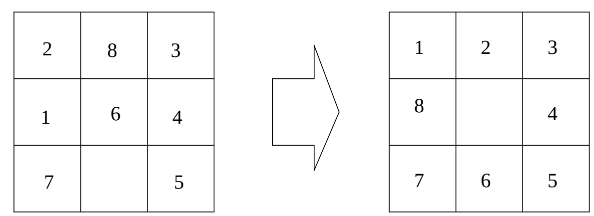
- Once goal is determined, formulate the problem to be solved.
- First determine set of possible states S of the problem.
- Then problem has:
  - *initial state* — the starting point, s_0;
  - *operations* — the actions that can be performed, $\{a_1, \ldots, a_n\}$.
  - *goal* — what you are aiming at — subset of S.

- The initial state together with operations determines *state space* of problem.
- Operations cause *changes* in state.
- Solution is a sequence of actions such that when applied to initial state s_0, we have goal state.
- Pictorially:

Examples of Toy Problems

- *Example 1*: The 8 puzzle.

  Do the following transformation, moving tile from occupied space to filled space.



- Initial state as shown above.
- Goal state as shown below.
- Operations:
  - a_1: move any tile to left of empty square to right;
  - a_2:
  - a_3:
  - a_4:

- This defines the following state space:

- Example 2: The n queens problem from chess.
- Place n queens on chess board so that no queen can be taken by another.
- Initial state: empty chess board.
- Goal state: n queens on chess board, one occupying each space, so that none can take others.
- Operations: place queen in empty square.

Solution Cost

- For most problems, some solutions are better than others:
  - in 8 puzzle, number of moves to get to solution;
  - number of moves to checkmate;
  - length of distance to travel.
- Mechanism for determining *cost* of solution is *path cost function*.
- This is the length of the path through the state-space from the initial state to the goal state.

- As an example, consider the following state in the 8-puzzle:

2	8	3
1	6	4
7		5

- How many moves are there to the solution?

- There are four moves:
  1.
  2.
  3.
  4.
- And the path through the solution space looks like:

Problem Solving as Search

- In the state space view of the world, finding a solution is finding a path through the state space.
- When we solve a problem like the 8-puzzle, we have some idea of what constitutes the next best move.
- It is hard to program this kind of approach.
- Instead we start by programming the kind of repetitive task that computers are good at.
- A *brute force* approach to problem solving involves *exhaustively searching* through the space of *all possible* action sequences to find one that achieves goal.

- Systematically generate a *search tree*
- For the 8-puzzle setup as:

2	8	3
1	6	4
7		5

- The search tree is:

- The tree is built by taking the initial state and identifying some states that can be obtained by applying a single operator.
- These new states become the *children* of the initial state in the tree.
- These new states are then examined to see if they are the goal state.
- If not, the process is repeated on the new states.
- We can formalise this description by giving an algorithm for it.

- General algorithm for search:

```
agenda = initial state;
while agenda not empty do{
   pick node from agenda;
   new nodes = apply operations to state;
   if goal state in new nodes
   then {
                return solution;
      }
   add new nodes to agenda;
}
```

- Question: How to pick states for expansion?
- Two obvious solutions:
  - depth first search;
  - breadth first search.

Breadth First Search

- Start by *expanding* initial state — gives tree of depth 1.
- Then expand *all* nodes that resulted from previous step — gives tree of depth 2.
- Then expand *all* nodes that resulted from previous step, and so on.
- Expand nodes at depth n before level $n + 1$.

```
/* Breadth first search */

agenda = initial state;

while agenda not empty do
{
    pick node from front of agenda;
    new nodes = apply operations to state;
    if goal state in new nodes then
    {
         return solution;
    }

    APPEND new nodes to END of agenda;
 }
```


- Advantage: *guaranteed* to reach a solution if one exists.
- If all solutions occur at depth n, then this is good approach.
- Disadvantage: time taken to reach solution!
- Let b be *branching factor* — average number of operations that may be performed from any level.
- If solution occurs at depth d, then we will look at

$$1 + b + b^2 + \cdots + b^d$$

nodes before reaching solution — *exponential*.

- Time for breadth first search (circa 1995 hardware):

Depth	Nodes	Time
0	1	1 msec
1	11	.01 sec
2	111	.1 sec
4	11,111	11 secs
6	10^6	18 mins
8	10^8	31 hours
10	10^{10}	128 days
12	10^{12}	35 years
14	10^{14}	2500 years
20	10^{20}	3^{15} years

- *Combinatorial explosion!*

Importance of ABSTRACTION

- When formulating a problem, it is crucial to pick the right level of *abstraction*.
- Example: Given the task of driving from New York to Boston.
- Some possible actions. . .
  - depress clutch;
  - turn steering wheel right 10 degrees;

. . . inappropriate level of *abstraction*.

Too much *irrelevant detail*.

- Better level of abstraction:
  - Take the Henry Hudson Parkway north
  - Take the Cross County turnoff

  . . . and so on.
- Getting abstraction level right lets you focus on the specifics of problem and is one way to combat the combinatorial explosion.
- (Tell that to Mapquest).

Depth First Search

- Start by expanding initial state.
- Pick one of nodes resulting from 1st step, and expand it.
- Pick one of nodes resulting from 1nd step, and expand it, and so on.
- Always expand *deepest* node.
- Follow one "branch" of search tree.


```
/* Depth first search */

agenda = initial state;

while agenda not empty do
{
    pick node from front of agenda;
    new nodes = apply operations to state;
    if goal state in new nodes then
    {
         return solution;
    }

put new nodes on FRONT of agenda;
}
```


- Depth first search is *not* guaranteed to find a solution if one exists.
- However, if it *does* find one, amount of time taken is much less than breadth first search.
- *Memory requirement* is much less than breadth first search.
- Solution found is *not* guaranteed to be the best.

Performance Measures for Search

- *Completeness*:
  Is the search technique *guaranteed* to find a solution if one exists?
- *Time complexity*:
  How many computations are required to find solution?
- *Space complexity*:
  How much memory space is required?
- *Optimality*:
  How good is a solution going to be w.r.t. the path cost function.

Summary

- This lecture finished simple behavior-based systems from last time.
  - *subsumption architecture*
- This lecture also introduced the basics of problem solving.
  - *problem solving*
  - *goal formulation*
  - *state space search*
  - *abstraction*
  - *undirected search*
    * breadth 1st search
    * depth 1st search
  - performance measures for search
- *state space* models
  - search for the goal through the state space
  - solution is a/the (best, shortest, cheapest, ...) path through the state space