Logical Agents

Logical agents for the Wumpus World

Three (non-exclusive) agent architectures:

- Reflex agents
  - Have rules that classify situations based on percepts and specify how to react to each possible situation
- Model-based agents
  - Construct an internal model of their world
- Goal-based agents
  - Form goals and try to achieve them

A simple reflex agent

- Rules to map percepts into observations:

  $\forall b,g,u,c,t\ Percept([Stench, b, g, u, c], t) \rightarrow Stench(t)$

  $\forall s,g,u,c,t\ Percept([s, Breeze, g, u, c], t) \rightarrow Breeze(t)$

  $\forall s,b,u,c,t\ Percept([s, b, Glitter, u, c], t) \rightarrow AtGold(t)$

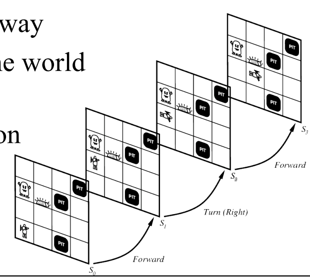
- Rules to select an action given observations:

  $\forall t\ AtGold(t) \rightarrow Action(Grab, t);$

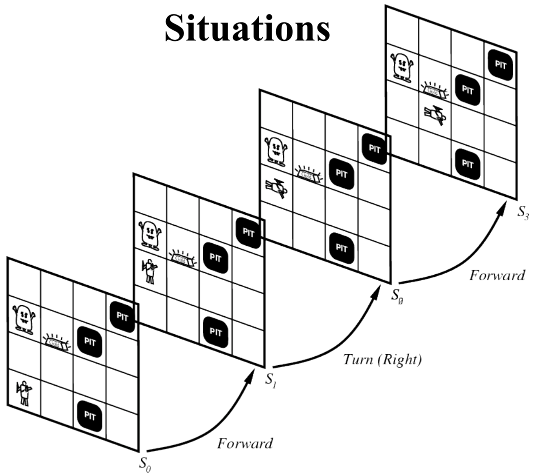
- Some difficulties:
  - Consider Climb: There's no percept that indicates the agent should climb out – position and holding gold are not part of the percept sequence
  - Loops – the percept will be repeated when you return to a square, which should cause the same response (unless we maintain some internal model of the world)

Representing change

- Representing change in the world in logic can be tricky
- One way is just to change the KB
  - Add and delete sentences from the KB to reflect changes
  - How do we remember the past, or reason about changes?
- **Situation calculus** is another way
- A **situation** is a snapshot of the world at some instant in time
- When the agent performs action A in situation S1, the result is a new situation S2.



Situations



Situation calculus

- A **situation** is a snapshot of the world at an interval of time during which nothing changes w.r.t a particular situation
  - Add **situation variables** to every predicate.
  - at(Agent,1,1) becomes at(Agent,1,1,s0): at(Agent,1,1) is true in situation (i.e., state) s0
  - Or, add a special 2nd-order predicate, **holds(f,s),** meaning "f is true in situation s", e.g., holds(at(Agent,1,1),s0)
- Add a new function, **result(a,s),** mapping situation s into a new situation as a result of performing action a. E.g., result(forward, s) is a function returning next situation
- Example: The action agent-walks-to-location-y could be represented by
  - $(\forall x)(\forall y)(\forall s)$ (at(Agent,x,s) $\wedge$ $\neg$onbox(s)) $\rightarrow$ at(Agent,y,result(walk(y),s))

Deducing hidden properties

- From the perceptual information we obtain in situations, we can **infer properties of locations**

  $\forall$l,s at(Agent,l,s) $\wedge$ Breeze(s) $\rightarrow$ Breezy(l)

  $\forall$l,s at(Agent,l,s) $\wedge$ Stench(s) $\rightarrow$ Smelly(l)
- Neither Breezy nor Smelly need situation arguments because pits and Wumpuses do not move around

Deducing hidden properties II

- We need to write rules relating various aspects of a single world state (as opposed to across states)
- There are two main kinds of such rules:
  - **Causal rules** reflect assumed direction of causality in the world:

    ($\forall$l1,l2,s) At(Wumpus,l1,s) $\wedge$ Adjacent(l1,l2) $\rightarrow$ Smelly(l2)

    ($\forall$ l1,l2,s) At(Pit,l1,s) $\wedge$ Adjacent(l1,l2) $\rightarrow$ Breezy(l2)

  Systems that reason with causal rules are model-based reasoning systems
  - **Diagnostic rules** infer presence of hidden properties directly from the percept-derived information, e.g.

    ($\forall$ l,s) At(Agent,l,s) $\wedge$ Breeze(s) $\rightarrow$ Breezy(l)

    ($\forall$ l,s) At(Agent,l,s) $\wedge$ Stench(s) $\rightarrow$ Smelly(l)

Representing change: frame problem

Frame axioms: If property x doesn't change as a result of applying action a in state s, then it stays the same.

– $On(x, z, s) \wedge Clear(x, s) \rightarrow$
  $On(x, table, Result(Move(x, table), s)) \wedge$
  $\neg On(x, z, Result(Move(x, table), s))$

– $On(y, z, s) \wedge y \neq x \rightarrow On(y, z, Result(Move(x, table), s))$

– The proliferation of frame axioms becomes very cumbersome in complex domains

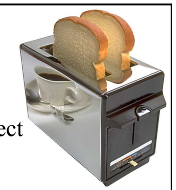
The frame problem II

- **Successor-state axiom**: General statement that characterizes every way in which a particular predicate can become true:
  - Either it can be **made true**, or it can **already be true and not be changed**:
  - $On(x, table, Result(a,s)) \leftrightarrow$
    $[On(x, z, s) \wedge Clear(x, s) \wedge a = Move(x, table)] \vee$
    $[On(x, table, s) \wedge a \neq Move(x, z)]$
- In complex worlds, where you want to reason about longer chains of action, even these types of axioms are too cumbersome
  - Planning systems use special-purpose inference methods to reason about the expected state of the world at any point in time during a multi-step plan

Qualification problem

- How can you characterize every effect of an action, or every exception that might occur?
- When I put my bread into the toaster, and push the button, it will become toasted after two minutes, unless…
  - The toaster is broken, or…
  - The power is out, or…
  - I blow a fuse, or…
  - A neutron bomb explodes nearby and fries all electrical components, or…
  - A meteor strikes the earth, and the world we know it ceases to exist, or…

Ramification problem



It's nearly impossible to characterize every side effect of every action, at every possible level of detail

When I put my bread into the toaster, and push the button, the bread will become toasted after two minutes, and…

- The crumbs that fall off the bread onto the bottom of the toaster over tray will also become toasted, and…
- Some of the those crumbs will become burnt, and…
- The outside molecules of the bread will become "toasted," and…
- The inside molecules of the bread will remain more "breadlike," and…
- The toasting process will release a small amount of humidity into the air because of evaporation, and…
- The heating elements will become a tiny fraction more likely to burn out the next time I use the toaster, and…
- The electricity meter in the house will move up slightly, and…

Knowledge engineering!

- Modeling the *right* conditions and the *right* effects at the *right* level of abstraction is very difficult
- Knowledge engineering (creating and maintaining KBs for intelligent reasoning) is an entire field of investigation
- Many hope that automated knowledge acquisition and machine learning tools can fill the gap:
  - Our intelligent systems should be able to **learn** about the conditions and effects, just like we do!
  - Our intelligent systems should be able to learn when to pay attention to, or reason about, certain aspects of processes, depending on the context!

Preferences among actions

- A problem with the Wumpus world KB described so far is that it's difficult to decide which action is best among a number of possibilities
- For example, to decide between a forward and a grab, axioms describing when it is OK to move to a square would have to mention glitter
- This is not modular!
- We can solve this problem by separating **facts about actions** from **facts about goals**
- This way our agent can be reprogrammed just by asking it to achieve different goals

Preferences among actions

- The first step is to describe the desirability of actions independent of each other.
- In doing this we will use a simple scale: actions can be Great, Good, Medium, Risky, or Deadly
- Obviously, the agent should always do the best action it can find:

$(\forall a,s)\ Great(a,s) \rightarrow Action(a,s)$

$(\forall a,s)\ Good(a,s) \wedge \neg(\exists b)\ Great(b,s) \rightarrow Action(a,s)$

$(\forall a,s)\ Medium(a,s) \wedge (\neg(\exists b)\ Great(b,s) \vee Good(b,s)) \rightarrow Action(a,s)$

...

Preferences among actions

- Use this action quality scale in the following way
- Until it finds the gold, basic agent strategy is:
  - Great actions include picking up the gold when found and climbing out of the cave with the gold
  - Good actions include moving to a square that's OK and hasn't been visited yet
  - Medium actions include moving to a square that is OK and has already been visited
  - Risky actions include moving to a square that is not known to be deadly or OK
  - Deadly actions are moving into a square that is known to have a pit or a Wumpus

Goal-based agents

- Once the gold is found, we must change strategies. So now we need a new set of action values.
- We could encode this as a rule:
  - $(\forall s)$ Holding(Gold,s) $\rightarrow$ GoalLocation([1,1]),s)
- We must now decide how the agent will work out a sequence of actions to accomplish the goal
- Three possible approaches are:
  - **Inference**: good versus wasteful solutions
  - **Search**: make a problem with operators and set of states
  - **Planning**: to be discussed later

Coming up next

- Logical inference
- Knowledge representation
- Planning