CSC520 - Artificial Intelligence

Lecture 2

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In The News

LinkedIn Jobs on the Rise 2025: The 25 fastest-growing jobs in the U.S.

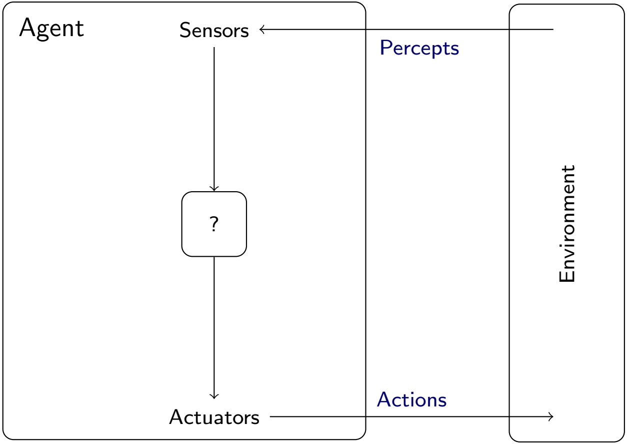
1. **Artificial Intelligence Engineer**
2. **Artificial Intelligence Consultant**
3. Physical Therapist
4. Workforce Development Manager
5. Travel Advisor
6. Event Coordinator
7. Director of Development
8. Outside Sales Representative
9. Sustainability Specialist
10. Security Guard

https://www.linkedin.com/pulse/linkedin-jobs-rise-2025-25-fastest-growing-us-linkedin-news-gryie/

Agenda

- Agents and environments
- Agent function
- Performance measures
- Rational agent
- Task environment

Agent and Environment



Definitions

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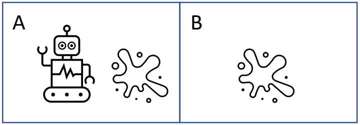
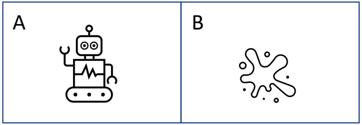
- *Agent program* is a concrete implementation; internal characterization

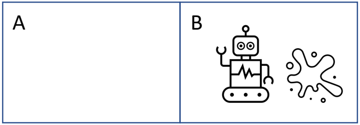
Vacuum Cleaner Example



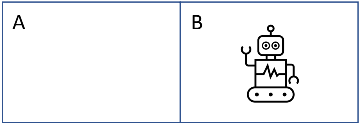
1: $[A, \mathit{dirtyA}] \rightarrow \mathit{vacA}$



2: $[A, \mathit{dirtyA}], [A, \mathit{cleanA}] \rightarrow \mathit{right}$



3: $[A, \mathit{dirtyA}], [A, \mathit{cleanA}], [B, \mathit{dirtyB}] \rightarrow \mathit{vacB}$



4: $[A, \mathit{dirtyA}], [A, \mathit{cleanA}], [B, \mathit{dirtyB}], [B, \mathit{cleanB}] \rightarrow \mathit{left}$

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- What if the performance measure of a vacuum cleaner agent is the amount of dirt cleaned per hour?
  - Rational agent picks up the dirt and drop it back on the floor
    Be careful what you ask for !
- Better performance measure will be amount of clean area per time step

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- Rationality means maximizing *expected* performance

Rationality

Rationality

For each possible *percept sequence*, a rational agent should select an *action* that is expected to maximize its *performance measure*, given the evidence provided by the percept sequence and whatever built-in *knowledge* the agent has.

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Agent Type	Performance Measure	Environment	Actuators	Sensors
Taxi driver	Maximize profits while providing safe, fast, legal trip	Roads, traffic, weather, pedestrians, customers	Steering, accelerator, brake, signal, horn	Cameras, radar, speedometer, GPS, engine sensors

Class Exercise

- Select a task of your choice and give PEAS specification for an AI agent to solve that task

Task Environment Properties

- Fully vs. Partially Observable
- Deterministic vs. Stochastic
- Episodic vs. Sequential
- Static vs. Dynamic
- Discrete vs. Continuous
- Known vs. Unknown
- Single vs. Multi-agent

Observability

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- *Unobservable* task environment, the agent has no sensors

Single-agent vs. Multiagent

- *Single agent* if everything else can be treated as environment
  - E.g. an agent solving cross-word puzzle
- *Multiagent* if multiple agents exist and influence each other's performance measures
  - E.g. two agents playing chess is a *competitive multiagent* environment
  - E.g. multiple taxi drivers minimizing accidents and traffic congestion is *cooperative multiagent* environment

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    - E.g. Vacuum cleaner
- *Stochastic* if we know the probability distribution of the next state given the current state and the action
    - E.g. Taxi driver

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- *Sequential* if agent's current decision can affect the future
    - E.g. Current move in chess can affect the future

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    - E.g. Chess when played with a clock

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  - E.g. Rover sent to a new planet

Class Exercise

- Determine the characteristics of the task environment for the task from the PEAS exercise

Examples

Task Env.	Observable	Agents	Deterministic	Episodic	Static	Discrete
Crossword puzzle						
Medical diagnosis						
Taxi driving						

Agent Function vs. Program vs Architecture

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- *Agent architecture* is the computing device with sensors and actuators

- *Agent* is the combination of architecture and program
  $agent = architecture + program$

Simple Reflex Agent

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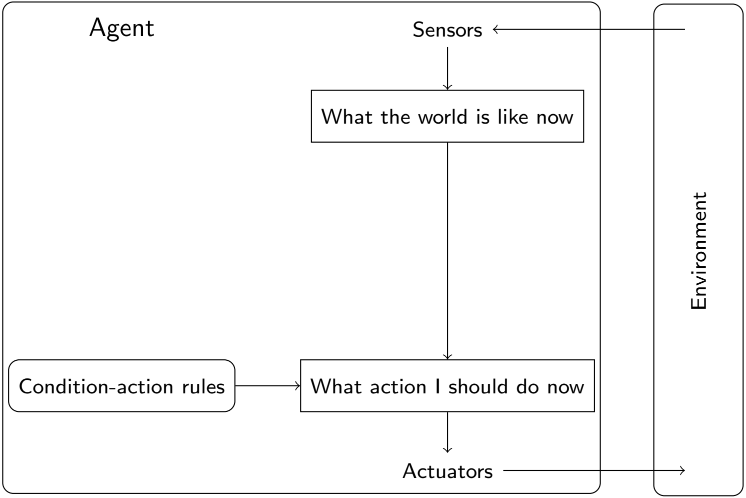
- Does not track history of percepts
- Simple but can fail if the environment is not fully observable
    - Agent cannot figure out if a car infront is braking by observing only a single image frame

Simple Reflex Agent



Simple Reflex Agent

```
function SIMPLE-REFLEX-AGENT(percept) return an action
    persistent: rules, a set of condition-action rules
    state ← INTERPRET-INPUT(percept)
    rule ← RULE-MATCH(state, rules)
    action ← rule.ACTION
    return action
```