Intelligent Agents

CHAPTER 2

Oliver Schulte

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Outline

- Agents and environments
- Rationality
- PEAS (Performance measure, Environment, Actuators, Sensors)
- Environment types
- Agent types

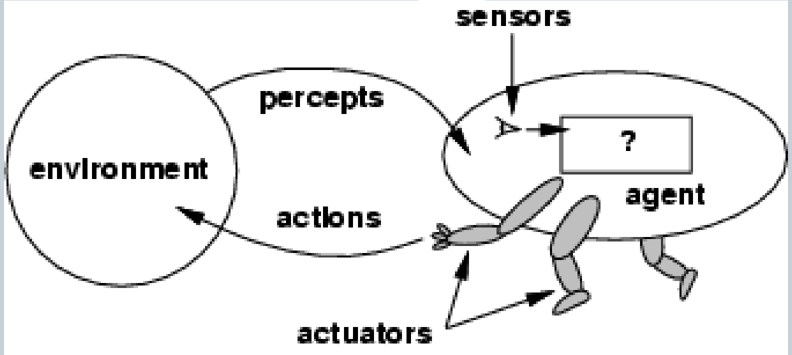
Agents

- An agent is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through actuators

- Human agent:
  - eyes, ears, and other organs for sensors;
  - hands, legs, mouth, and other body parts for actuators

- Robotic agent:
  - cameras and infrared range finders for sensors
  - various motors for actuators

Agents and environments

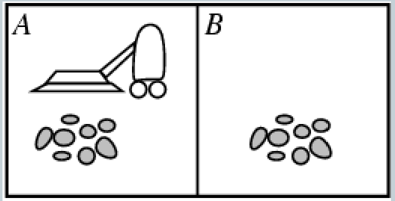


- The agent function maps from percept histories to actions:

$$[f: \mathcal{P}^\star \rightarrow \mathcal{A}]$$

- The agent program runs on the physical architecture to produce *f*
- agent = architecture + program

Vacuum-cleaner world



Demo:
http://www.ai.sri.com/~oreilly/aima3ejava/aima3ejavademos.html

- Percepts: location and contents, e.g., [A,Dirty]
- Actions: *Left*, *Right*, *Suck*, *NoOp*
- *Agent's function → look-up table*
  - *For many agents this is a very large table*

Percept sequence	Action
$[A, Clean]$	$Right$
$[A, Dirty]$	$Suck$
$[B, Clean]$	$Left$
$[B, Dirty]$	$Suck$
$[A, Clean], [A, Clean]$	$Right$
$[A, Clean], [A, Dirty]$	$Suck$
⋮	⋮

Rational agents

- Rationality
  - Performance measuring success
  - Agents prior knowledge of environment
  - Actions that agent can perform
  - Agent’s percept sequence to date

- Rational Agent: 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.

Examples of Rational Choice

- See File: intro-choice.doc

Rationality

- Rational is different from omniscience
  - Percepts may not supply all relevant information
  - E.g., in card game, don’t know cards of others.

- Rational is different from being perfect
  - Rationality maximizes expected outcome while perfection maximizes actual outcome.

Autonomy in Agents

The **autonomy** of an agent is the extent to which its behaviour is determined by its own experience, rather than knowledge of designer.

- Extremes
  - No autonomy – ignores environment/data
  - Complete autonomy – must act randomly/no program
- Example: baby learning to crawl
- Ideal: design agents to have some autonomy
  - Possibly become more autonomous with experience

PEAS

- PEAS: Performance measure, Environment, Actuators, Sensors

- Must first specify the setting for intelligent agent design

- Consider, e.g., the task of designing an automated taxi driver:
  - Performance measure: Safe, fast, legal, comfortable trip, maximize profits
  - Environment: Roads, other traffic, pedestrians, customers
  - Actuators: Steering wheel, accelerator, brake, signal, horn
  - Sensors: Cameras, sonar, speedometer, GPS, odometer, engine sensors, keyboard

PEAS

- Agent: Part-picking robot
- Performance measure: Percentage of parts in correct bins
- Environment: Conveyor belt with parts, bins
- Actuators: Jointed arm and hand
- Sensors: Camera, joint angle sensors

PEAS

- Agent: Interactive English tutor
- Performance measure: Maximize student's score on test
- Environment: Set of students
- Actuators: Screen display (exercises, suggestions, corrections)
- Sensors: Keyboard

Environment types

- Fully observable (vs. partially observable)
- Deterministic (vs. stochastic)
- Episodic (vs. sequential)
- Static (vs. dynamic)
- Discrete (vs. continuous)
- Single agent (vs. multiagent):

Fully observable (vs. partially observable)

- Is everything an agent requires to choose its actions available to it via its sensors? Perfect or Full information.
  - If so, the environment is fully accessible
- If not, parts of the environment are inaccessible
  - Agent must make informed guesses about world.
- In decision theory: perfect information vs. imperfect information.

Cross Word	Poker	Backgammon	Taxi driver	Part picking robot	Image analysis
Fully	Partially	Partially	Partially	Fully	Fully

Deterministic (vs. stochastic)

- Does the change in world state
  - Depend only on current state and agent's action?
- Non-deterministic environments
  - Have aspects beyond the control of the agent
  - Utility functions have to guess at changes in world

Cross Word	Poker	Backgammon	Taxi driver	Part picking robot	Image analysis
Deterministic	Stochastic	Stochastic	Stochastic	Stochastic	Deterministic

Episodic (vs. sequential):

- Is the choice of current action
  - Dependent on previous actions?
  - If not, then the environment is episodic
- In non-episodic environments:
  - Agent has to plan ahead:
    - Current choice will affect future actions

Cross Word	Poker	Backgammon	Taxi driver	Part picking robot	Image analysis
Sequential	Sequential	Sequential	Sequential	Episodic	Episodic

Static (vs. dynamic):

- Static environments don't change
  - While the agent is deliberating over what to do
- Dynamic environments do change
  - So agent should/could consult the world when choosing actions
  - Alternatively: anticipate the change during deliberation OR make decision very fast
- Semidynamic: If the environment itself does not change with the passage of time but the agent's performance score does.

Cross Word	Poker	Backgammon	Taxi driver	Part picking robot	Image analysis
Static	Static	Static	Dynamic	Dynamic	Semi

Another example: off-line route planning vs. on-board navigation system

Discrete (vs. continuous)

- A limited number of distinct, clearly defined percepts and actions vs. a range of values (continuous)

Cross Word	Poker	Backgammon	Taxi driver	Part picking robot	Image analysis
Discrete	Discrete	Discrete	Conti	Conti	Conti

Single agent (vs. multiagent):

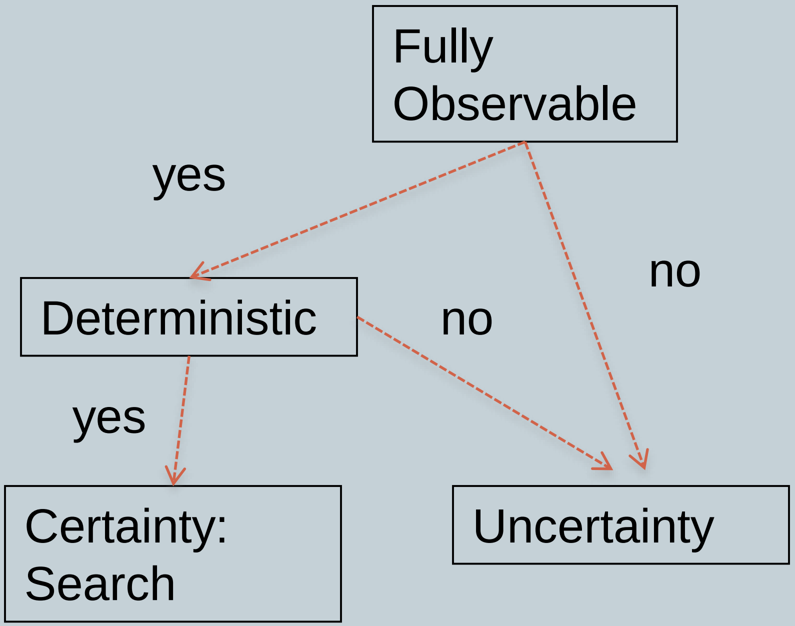
- An agent operating by itself in an environment or there are many agents working together

Cross Word	Poker	Backgammon	Taxi driver	Part picking robot	Image analysis
Single	Multi	Multi	Multi	Single	Single

Summary.

	Observable	Deterministic	Episodic	Static	Discrete	Agents
Cross Word	Fully	Deterministic	Sequential	Static	Discrete	Single
Poker	Fully	Stochastic	Sequential	Static	Discrete	Multi
Backgammon	Partially	Stochastic	Sequential	Static	Discrete	Multi
Taxi driver	Partially	Stochastic	Sequential	Dynamic	Conti	Multi
Part picking robot	Partially	Stochastic	Episodic	Dynamic	Conti	Single
Image analysis	Fully	Deterministic	Episodic	Semi	Conti	Single

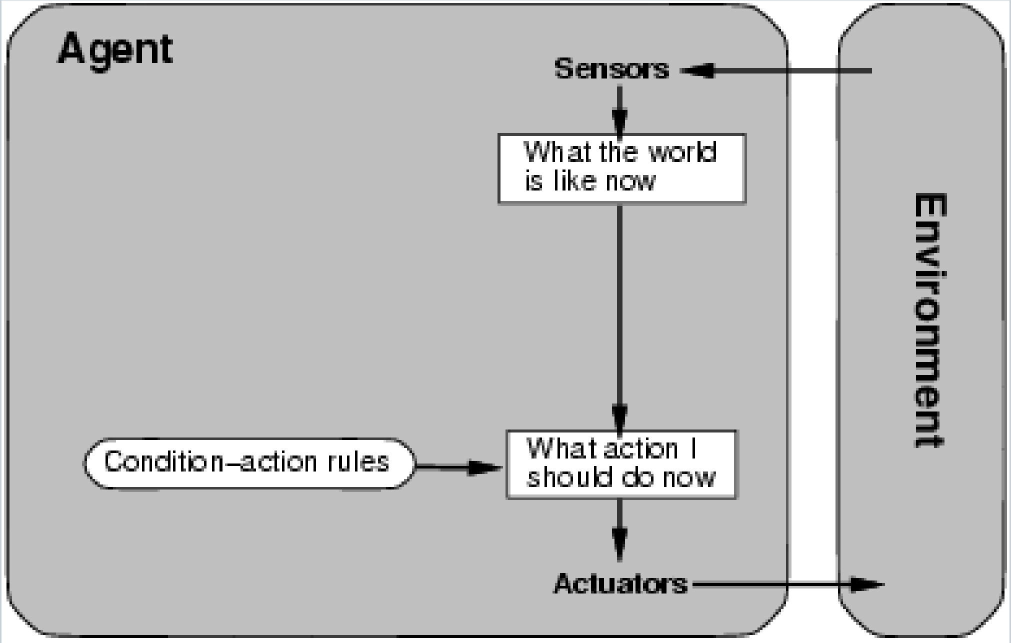
Choice under (Un)certainty



Agent types

- Four basic types in order of increasing generality:
  - Simple reflex agents
  - Reflex agents with state/model
  - Goal-based agents
  - Utility-based agents
  - All these can be turned into learning agents
  - http://www.ai.sri.com/~oreilly/aima3ejava/aima3ejavademos.html

Simple reflex agents



function REFLEX-VACUUM-AGENT([*location*,*status*]) **returns** an action

  if *status* = *Dirty* **then return** *Suck*
  else if *location* = *A* **then return** *Right*
  else if *location* = *B* **then return** *Left*

Simple reflex agents

- Simple but very limited intelligence.
- **Action does not depend on percept history, only on current percept.**
- Therefore no memory requirements.
- Infinite loops
  - Suppose vacuum cleaner does not observe location. What do you do given location = clean? Left of A or right on B -> infinite loop.
  - Fly buzzing around window or light.
  - Possible Solution: Randomize action.
  - Thermostat.
- Chess – openings, endings
  - Lookup table (not a good idea in general)
    - 35^{100} entries required for the entire game

States: Beyond Reflexes

- Recall the agent function that maps from percept histories to actions:

  $[f\colon \mathcal{P}^{*} \rightarrow \mathcal{A}]$

  - An agent program can implement an agent function by maintaining an **internal state**.
  - The internal state can contain information about the state of the external environment.
  - The state depends on the history of percepts and on the history of actions taken:

  $[f\colon \mathcal{P}^{*}, \mathcal{A}^{*} \rightarrow \mathcal{S} \rightarrow \mathcal{A}]$ where $\mathcal{S}$ is the set of states.

  - If each internal state includes all information relevant to information making, the state space is **Markovian**.

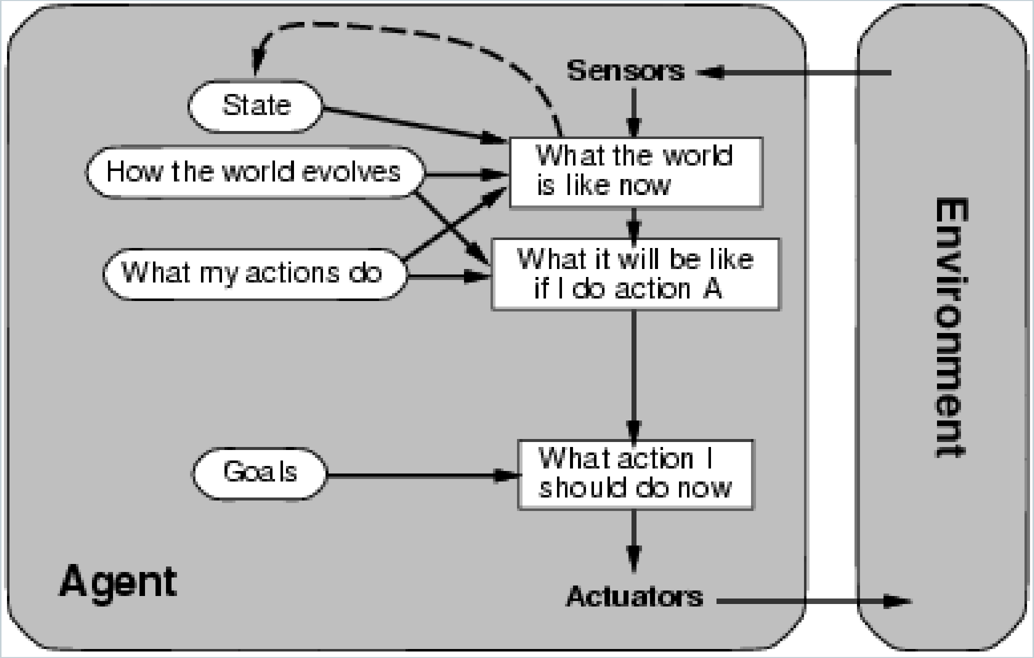
States and Memory: Game Theory

- If each state includes the information about the percepts and actions that led to it, the state space has **perfect recall**.
- **Perfect Information** = Perfect Recall + Full Observability.

Goal-based agents

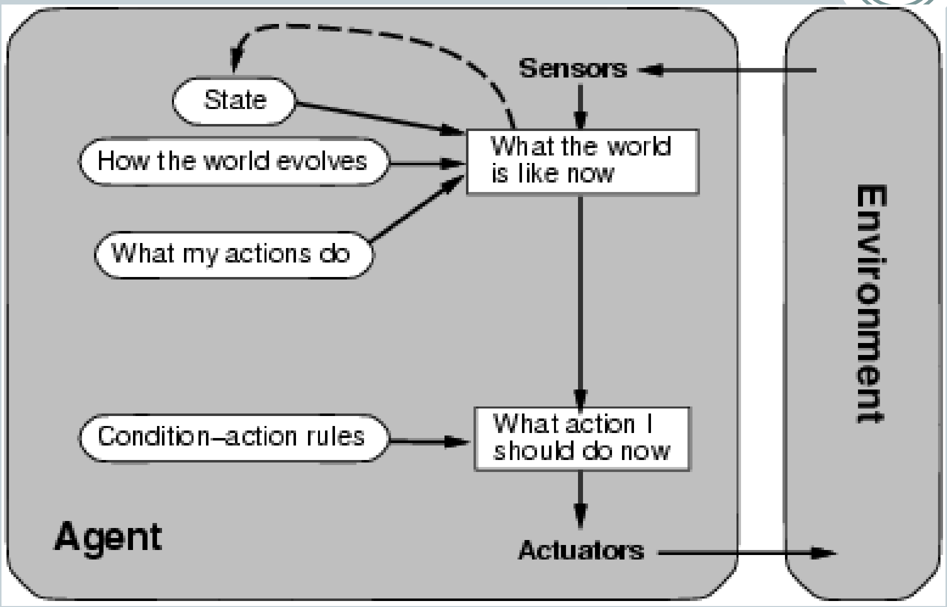
- knowing state and environment? Enough?
  - Taxi can go left, right, straight
- Have a goal
  - A destination to get to
- Uses knowledge about a goal to guide its actions
  - E.g., Search, planning

Goal-based agents



- Reflex agent breaks when it sees brake lights. Goal based agent reasons
  - Brake light -> car in front is stopping -> I should stop -> I should use brake

Model-based reflex agents



- Know how world evolves
  - Overtaking car gets closer from behind
- How agents actions affect the world
  - Wheel turned clockwise takes you right
- Model base agents update their state

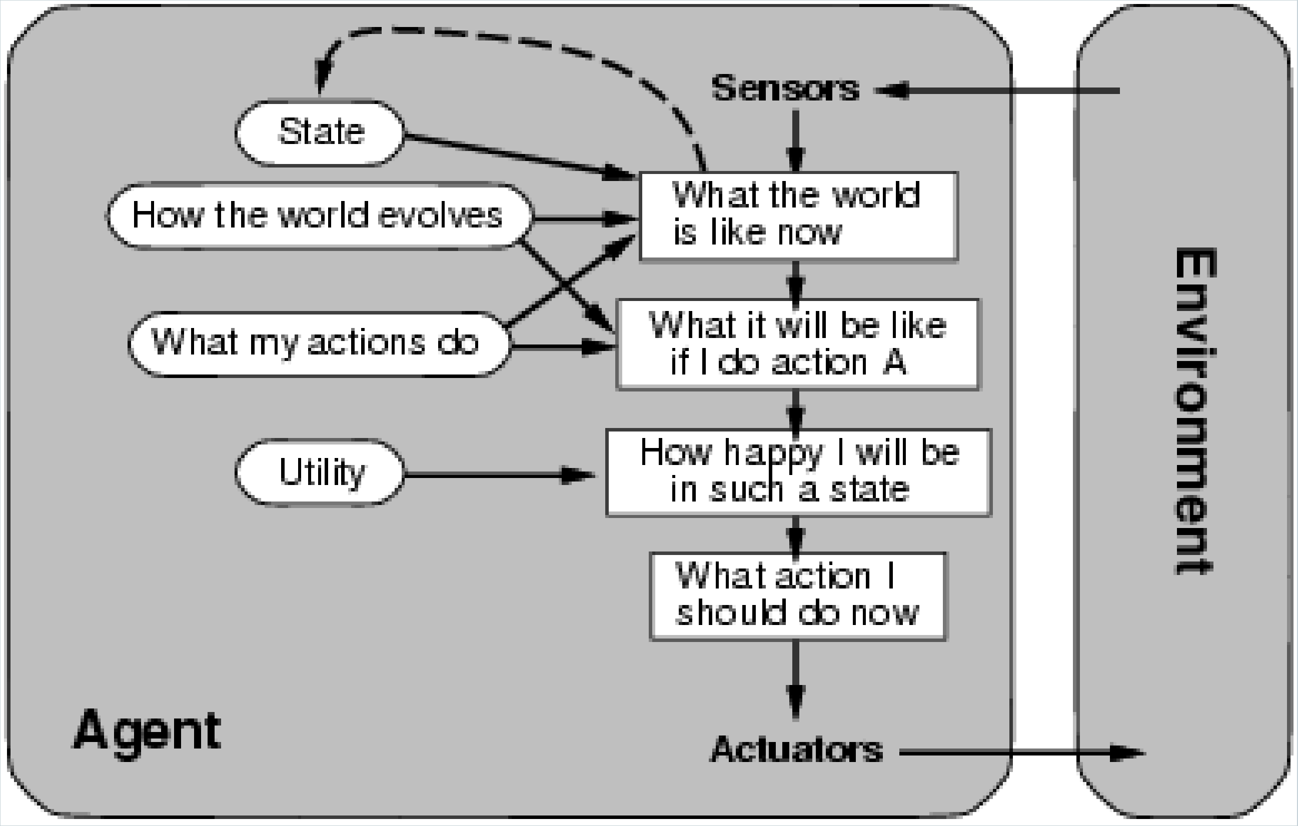
```
function REFLEX-AGENT-WITH-STATE(percept) returns action
   static: state, a description of the current world state
           rules, a set of condition-action rules

   state ← UPDATE-STATE(state, percept)
   rule ← RULE-MATCH(state, rules)
   action ← RULE-ACTION[rule]
   state ← UPDATE-STATE(state, action)
   return action
```

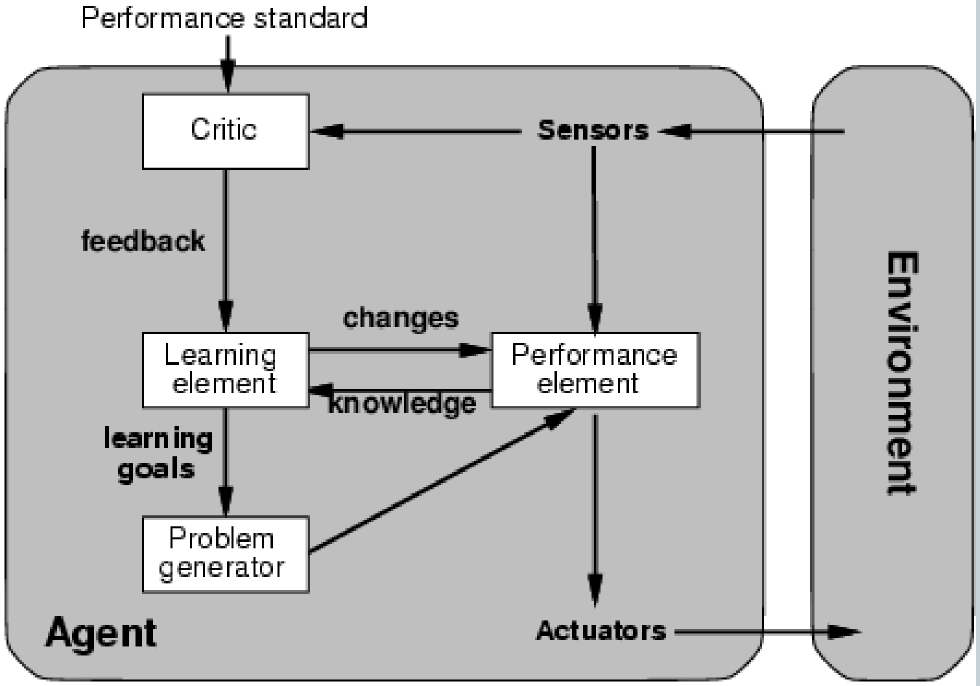
Utility-based agents

- Goals are not always enough
  - Many action sequences get taxi to destination
  - Consider other things. How fast, how safe.....
- A utility function maps a state onto a real number which describes the associated degree of “happiness”, “goodness”, “success”.
- Where does the utility measure come from?
  - Economics: money.
  - Biology: number of offspring.
  - Your life?

Utility-based agents

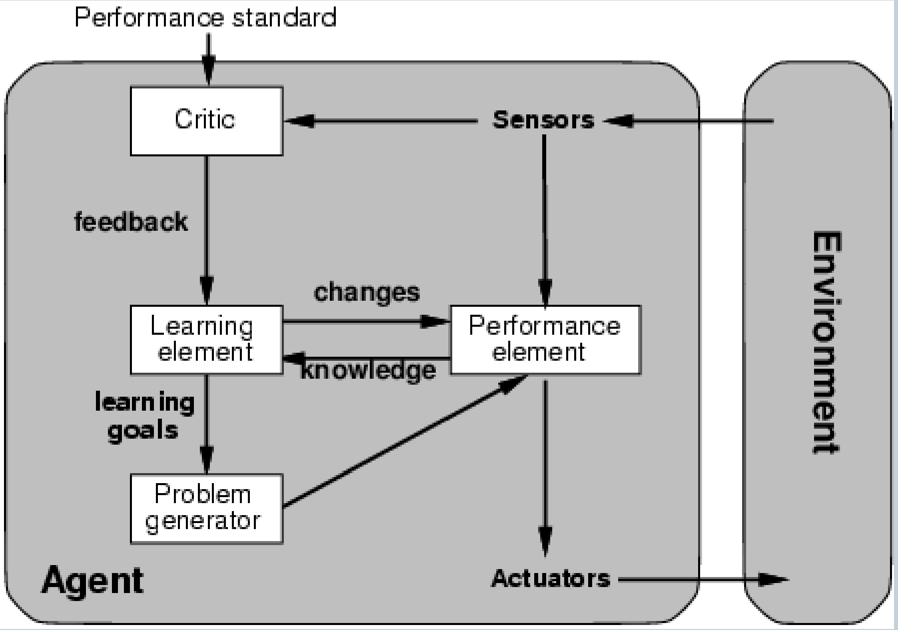


Learning agents



- Performance element is what was previously the whole agent
  - Input sensor
  - Output action
- Learning element
  - Modifies performance element.

Learning agents



- Critic: how the agent is doing
  - Input: checkmate?
  - Fixed
- Problem generator
  - Tries to solve the problem differently instead of optimizing.
  - Suggests **exploring** new actions -> new problems.

Learning agents(Taxi driver)

- Performance element
  - How it currently drives
- Taxi driver Makes quick left turn across 3 lanes
  - Critics observe shocking language by passenger and other drivers and informs bad action
  - Learning element tries to modify performance elements for future
  - Problem generator suggests experiment out something called Brakes on different Road conditions
- Exploration vs. Exploitation
  - Learning experience can be costly in the short run
  - shocking language from other drivers
  - Less tip
  - Fewer passengers