# Introduction to Artificial Intelligence

Lecture 1: Foundations

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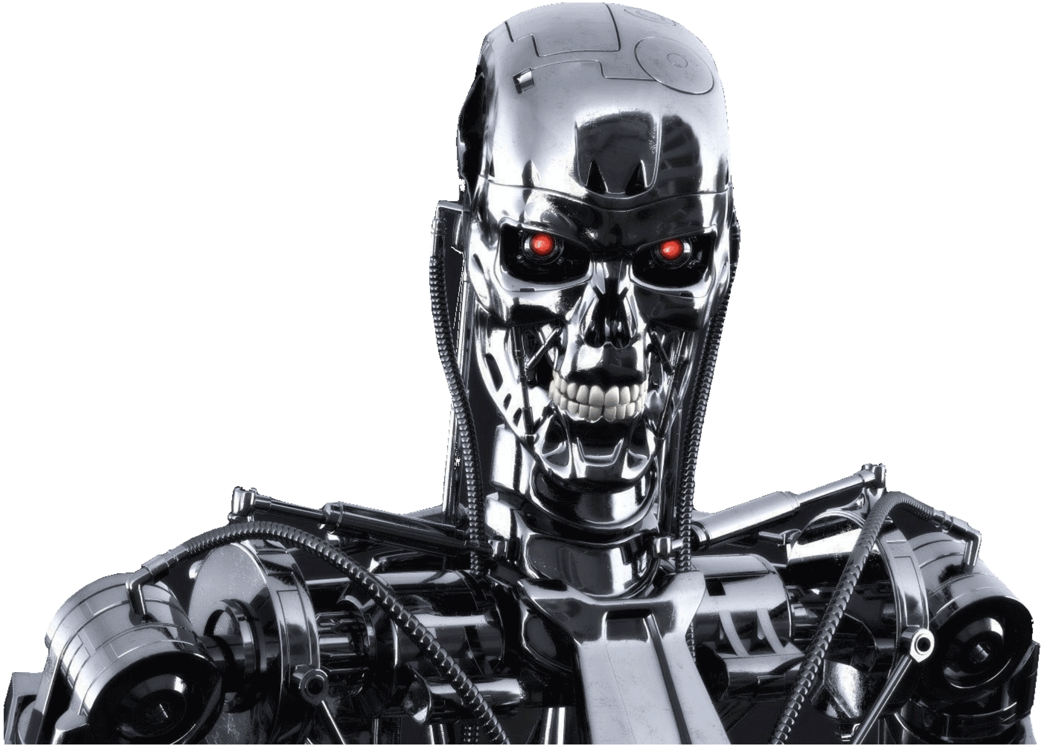
# Introduction



"With artificial intelligence we are summoning the demon" -- Elon Musk

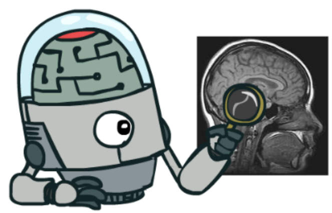
"We're really closer to a smart washing machine than Terminator" -- Fei-Fei Li, Director of Stanford AI Lab.

# What is AI?

# What is AI?

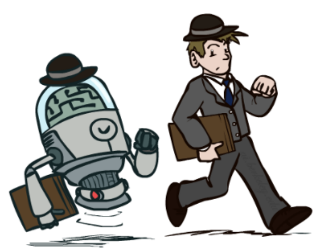
Artificial intelligence is the science of making machines or programs that:

Think like people



Think rationally

Act like people



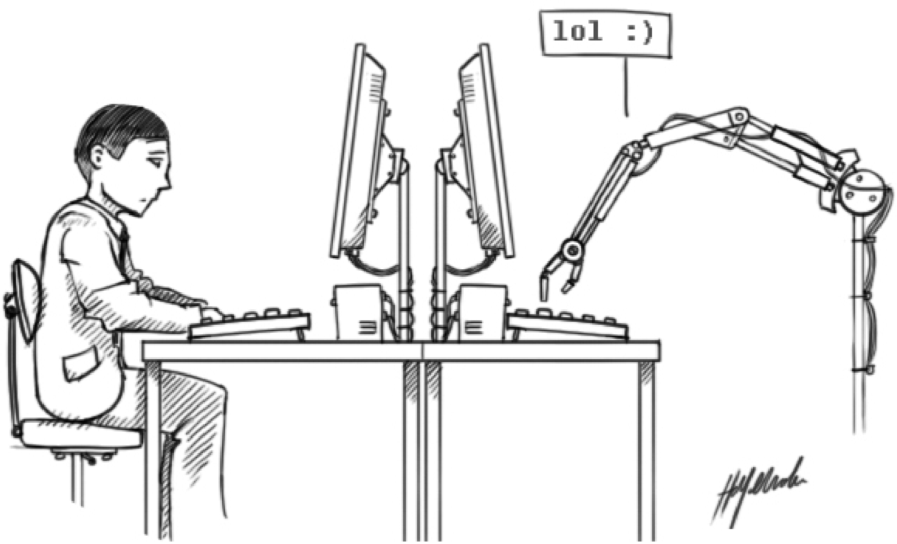
Act rationally

Credits: CS188, UC Berkeley.

# Acting humanly

## The Turing test

A computer passes the Turing test (also known as the Imitation Game) if a human operator, after posing some written questions, cannot tell whether the written responses come from a person or from a computer.




*Can machines think?*
*(Alan Turing, 1950)*

An agent would not pass the Turing test without the following requirements:

- natural language processing
- knowledge representation
- automated reasoning
- machine learning
- computer vision (total Turing test)
- robotics (total Turing test)

Despite being proposed almost 70 years ago, the Turing test is still relevant today.

## Limitations of the Turing test

The Turing test tends to focus on human-like errors, linguistic tricks, etc.

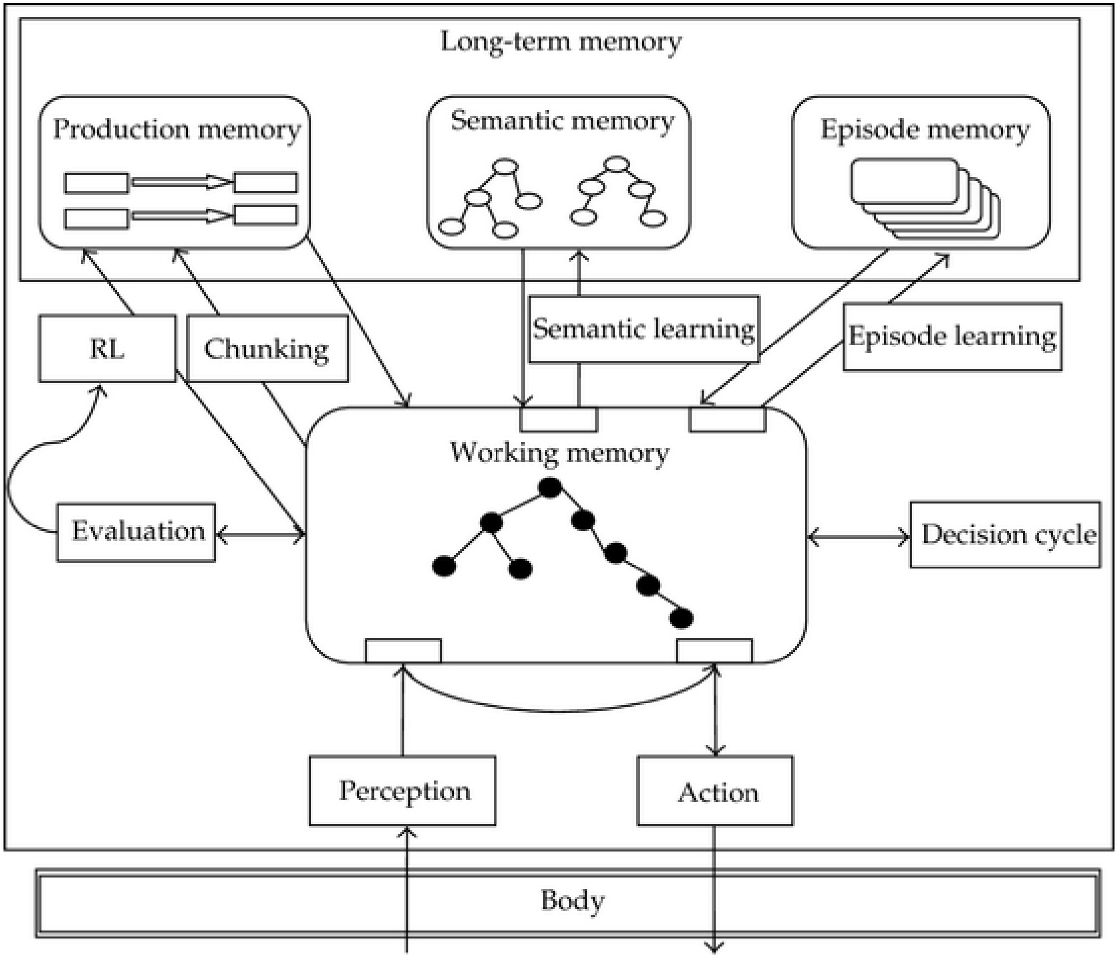
However, it seems more important to study the principles underlying intelligence than to replicate an exemplar.

*Aeronautics is not defined as the field of making machines that fly so exactly like pigeons that they can fool even other pigeons.*

# Thinking humanly

Cognitive science is the study of the human mind and its processes. The goal of cognitive science is to form a theory about the structure of the mind, summarized as a comprehensive computer model.

A cognitive architecture usually follows human-like reasoning and can be used to produce testable predictions (time of delays during problem solving, kinds of mistakes, learning rates, etc).




The modern SOAR cognitive architecture, as a descendant of the Logic Theorist (Alan Newell, Herbert Simon, 1956).

## Limitations of cognition for AI

- In linguistics, the argument of poverty of the stimulus states that children do not receive sufficient input to generalize grammatical rules through linguistic input alone.
    - A baby hears too few sentences to deduce the grammar of English before he speaks correctly.
- (Controversial) Therefore, humans must be biologically pre-wired with innate knowledge for representing language.

*How do we know what we know? (Noam Chomsky, 1980)*

Therefore, it may not be possible to implement a fully functioning computer model of the human mind without background knowledge of some sort. This is a huge technical obstacle, as accessing this knowledge would require reverse-engineering the brain.

# Thinking rationally

## The logical approach

- The rational thinking approach is concerned with the study of irrefutable reasoning processes. It ensures that all actions performed by a computer are formally provable from inputs and prior knowledge.
- The "laws of thought" were supposed to govern the operation of the mind. Their study initiated the field of logic and the logicist tradition of AI (1960-1990).

## The Zebra puzzle

- There are five houses.
- The English man lives in the red house.
- The Swede has a dog.
- The Dane drinks tea.
- The green house is immediately to the left of the white house.
- They drink coffee in the green house.
- The man who smokes Pall Mall has birds.
- In the yellow house they smoke Dunhill.
- In the middle house they drink milk.
- The Norwegian lives in the first house.
- The man who smokes Blend lives in the house next to the house with cats.
- In a house next to the house where they have a horse, they smoke Dunhill.
- The man who smokes Blue Master drinks beer.
- The German smokes Prince.
- The Norwegian lives next to the blue house.
- They drink water in a house next to the house where they smoke Blend.

Who owns the zebra?

```
select([A|As],S):- select(A,S,S1),select(As,S1).
select([],_).

next_to(A,B,C):- left_of(A,B,C) ; left_of(B,A,C).
left_of(A,B,C):- append(_,[A,B|_],C).

zebra(Owns, HS):-  % color,nation,pet,drink,smokes
      HS =    [ h(_,norwegian,_,_,_), _,  h(_,_,_,milk,_), _, _],
      select( [ h(red,englishman,_,_,_),  h(_,swede,dog,_,_),
                h(_,dane,_,tea,_),         h(_,german,_,_,prince) ], HS),
      select( [ h(_,_,birds,_,pallmall),  h(yellow,_,_,_,dunhill),
                h(_,_,_,beer,bluemaster) ],                          HS),
      left_of(  h(green,_,_,coffee,_),    h(white,_,_,_,_),          HS),
      next_to(  h(_,_,_,_,dunhill),       h(_,_,horse,_,_),          HS),
      next_to(  h(_,_,_,_,blend),         h(_,_,cats, _,_),          HS),
      next_to(  h(_,_,_,_,blend),         h(_,_,_,water,_),          HS),
      next_to(  h(_,norwegian,_,_,_),     h(blue,_,_,_,_),           HS),
      member(   h(_,Owns,zebra,_,_), HS).

:- ?- time(( zebra(Who, HS), maplist(writeln,HS), nl, write(Who), nl, nl,
           ; write('No more solutions.') )).
```

Output =

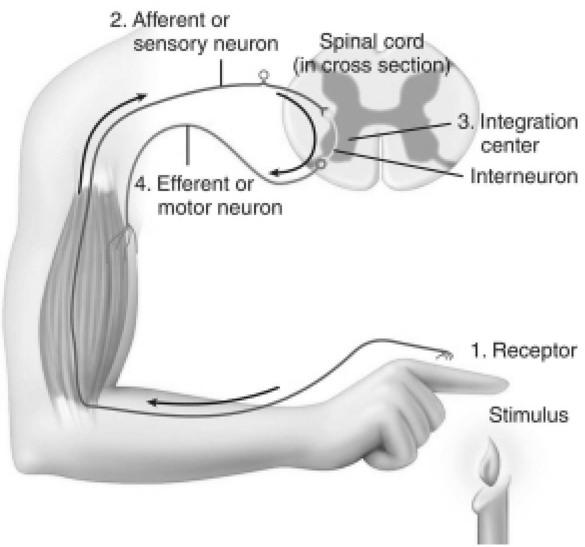
```
h(yellow,norwegian, cats,  water, dunhill)
h(blue,  dane,      horse, tea,   blend)
h(red,   englishman,birds, milk,  pallmall)
h(green, german,    zebra, coffee,prince)
h(white, swede,     dog,   beer,  bluemaster)

german

No more solutions.
% 5,959 inferences, 0.000 CPU in 0.060 seconds (0% CPU, Infinite Lips)
```

## Limitations of logical inference

- Representation of informal knowledge is difficult.
- Hard to define provable plausible reasoning.
- Combinatorial explosion (in time and space).
- Logical inference is part of intelligence. It does not cover everything:
    - e.g., might be no provably correct thing to do, but still something must be done;
    - e.g., reflex actions can be more successful than slower carefully deliberated ones.




*Pain withdrawal reflexes do not involve inference.*

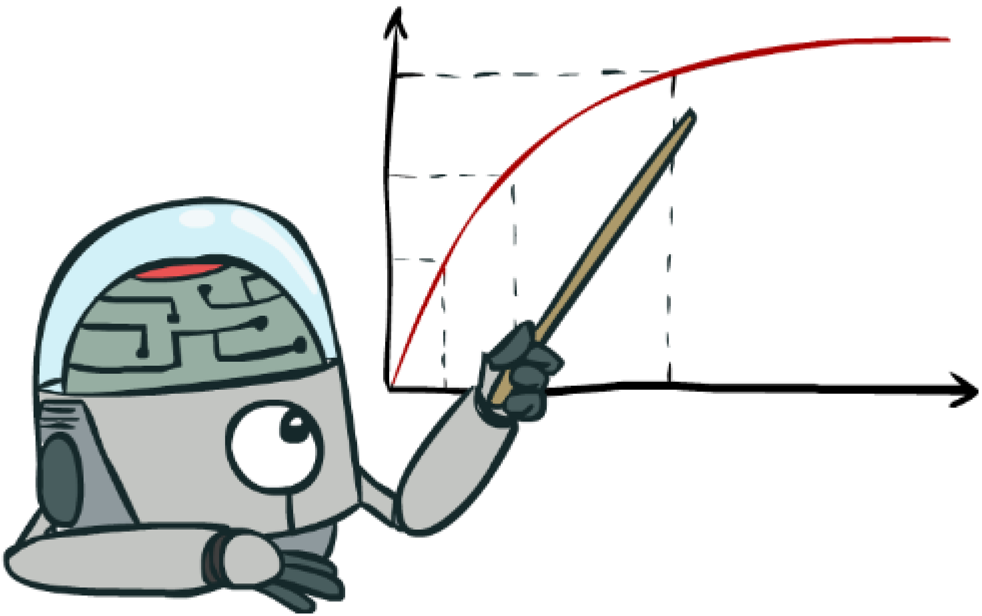
# Acting rationally

A rational agent acts so as to achieve the best (expected) outcome.

- Correct logical inference is just one of several possible mechanisms for achieving this goal.
- Perfect rationality cannot be achieved due to computational limitations! The amount of reasoning is adjusted according to available resources and importance of the result.
- The brain is good at making rational decisions but not perfect either.

Rationality only concerns what decisions are made (not the thought process behind them, human-like or not).

Goals are expressed in terms of the performance or utility of outcomes. Being rational means maximizing its expected performance. The standard of rationality is general and mathematically well defined.



In this course, Artificial intelligence = Maximizing expected performance

# AI prehistory

- Philosophy: logic, methods of reasoning, mind as physical system, foundations of learning, language, rationality.
- Mathematics: formal representation and proof, algorithms, computation, (un)decidability, (in)tractability, probability.
- Psychology: adaptation, phenomena of perception and motor control, psychophysics.
- Economics: formal theory of rational decisions.
- Linguistics: knowledge representation, grammar.
- Neuroscience: plastic physical substrate for mental activity.
- Control theory: homeostatic systems, stability, simple optimal agent designs.

# A short history of AI

### 1940-1950: Early days

- 1943: McCulloch and Pitts: Boolean circuit model of the brain.
- 1950: Turing's "Computing machinery and intelligence:.

### 1950-1970: Excitement and expectations

- 1950s: Early AI programs, including Samuel's checkers program, Newell and Simon's Logic Theorist and Gelernter's Geometry Engine.
- 1956: Dartmouth meeting: "Aritificial Intelligence" adopted.
- 1958: Rosenblatt invents the perceptron.
- 1965: Robinson's complete algorithm for logical reasoning.
- 1966-1974: AI discovers computational complexity.

## 1970-1990: Knowledge-based approaches

- 1969: Neural network research almost disappears after Minsky and Paper's paper.
- 1969-1979: Early development of knowledge-based systems.
- 1980-1988: Expert systems industrial boom.
- 1988-1993: Expert systems industry busts (AI winter).

## 1990-Present: Statistical approaches

- 1985-1995: The return of neural networks.
- 1988-: Resurgence of probability, focus on uncertainty, general increase in technical depth.
- 1995-2010: New fade of neural networks.
- 1995-: Complete intelligent agents and learning systems.
- 2000-: Availability of very large datasets.
- 2010-: Availability of fast commodity hardware (GPUs).
- 2012-: Resurgence of neural networks with deep learning approaches.

# What can AI do at present?

- Translate spoken Chinese to spoken English, live?
- Answer multi choice questions, as good as an 8th grader?
- Converse with a person for an hour?
- Play decently at Chess? Go? Poker? Soccer?
- Buy groceries on the web? in a supermarket?
- Prove mathematical theorems?
- Drive a car safely on a parking lot? in New York?
- Perform a surgery?
- Identify skin cancer better than a dermatologist?
- Write a funny story?
- Paint like Vangogh? Compose music?
- Show common sense?

Playing Atari games

Beat the best human Go players

Beat teams of human players at real-time strategy games (Dota 2)

Speech translation and synthesis

Semantic segmentation

Generating image descriptions

Detecting skin cancer

Learning to walk

Folding laundry

Playing soccer

Driving a car

Learning to sort waste (Norman Marlier, ULiège, 2018)

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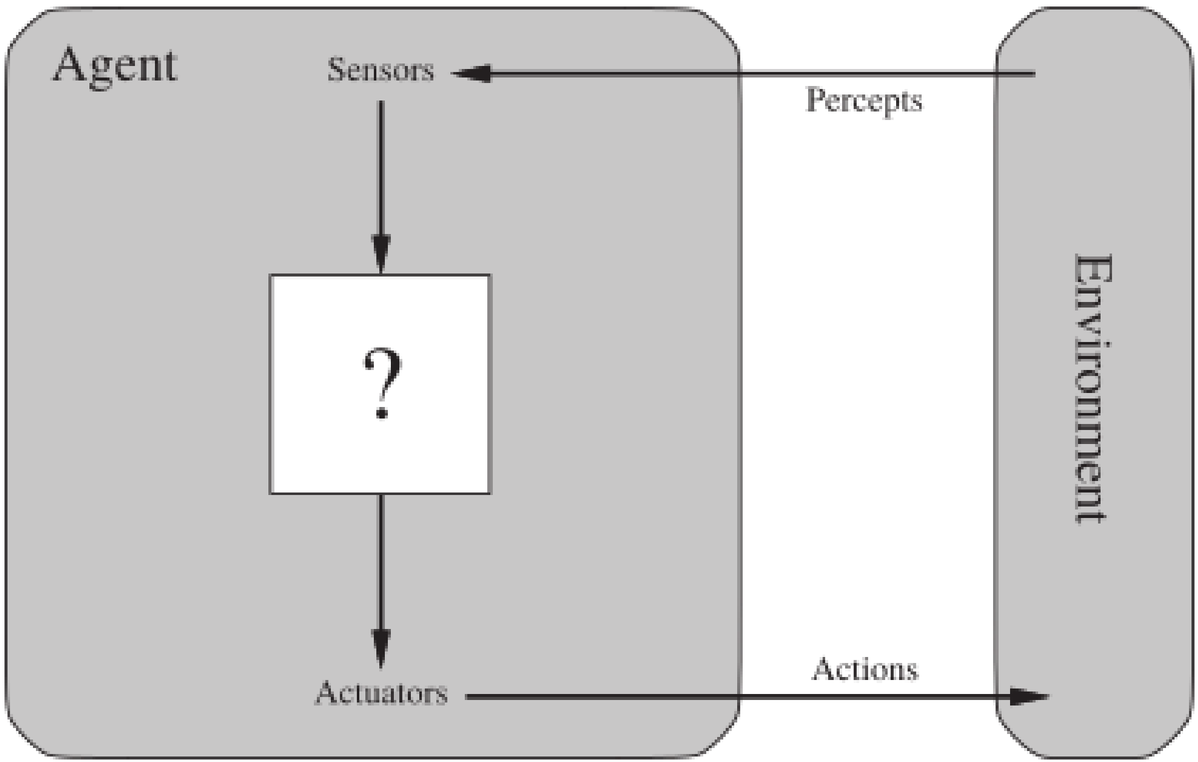
# Intelligent agents

# Agents and environments



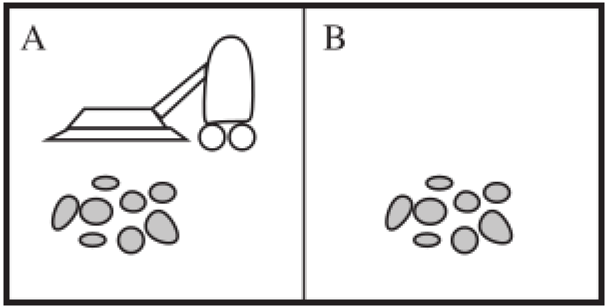
## Agents

- An agent is an entity that perceives its environment through sensors and take actions through actuators.
- The agent behavior is described by the agent function, or policy, that maps percept histories to actions:

$$f : \mathcal{P}^* \rightarrow \mathcal{A}$$

- The agent program runs on the physical architecture to produce $f$.

## Vacuum-cleaner world




- Percepts: location and content, e.g. $[A, Dirty]$
- Actions: $Left, Right, Suck, NoOp$

## A vacuum-cleaner agent

Partial tabulation of a simple vacuum-cleaner agent function:

| Percept sequence | Action |
|---|---|
| $[A, Clean]$ | $Right$ |
| $[A, Dirty]$ | $Suck$ |
| $[B, Clean]$ | $Left$ |
| $[A, Dirty]$ | $Suck$ |
| $[A, Clean], [A, Clean]$ | $Right$ |
| $[A, Clean], [A, Dirty]$ | $Suck$ |
| (...) | (...) |

## The optimal vacuum-cleaner?

What is the right agent function?

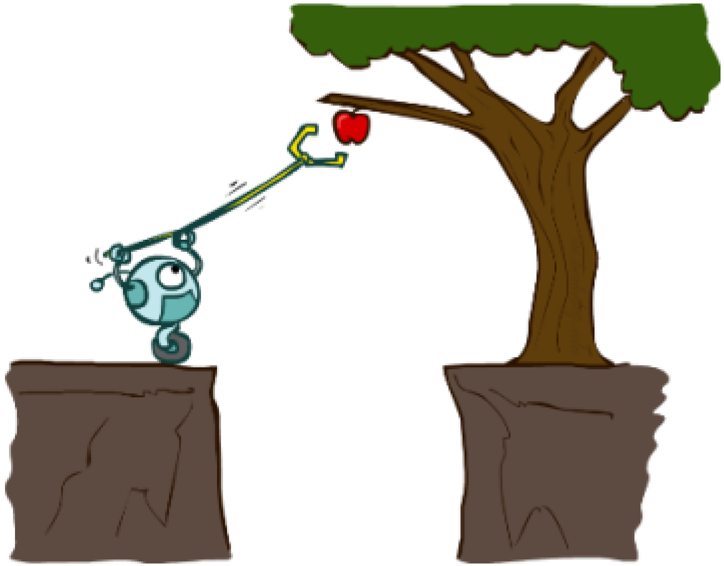
How to formulate the goal of the vacuum-cleaner agent?

- 1 point per square cleaned up at time $t$?
- 1 point per clean square per time step, minus one per move?
- penalize for $> k$ dirty squares?

Can it be implemented in a small agent program?

# Rational agents

- Informally, a rational agent is an agent that does the "right thing".
- A performance measure evaluates a sequence of environment states caused by the agent's behavior.
- A rational agent is an agent that chooses whichever action that maximizes the expected value of the performance measure, given the percept sequence to date.



- Rationality $\neq$ omniscience
  - percepts may not supply all relevant information.
- Rationality $\neq$ clairvoyance
  - action outcomes may not be as expected.
- Hence, rational $\neq$ successful.
- However, rationality leads to exploration, learning and autonomy.

# Performance, environment, actuators, sensors

The characteristics of the performance measure, environment, action space and percepts dictate techniques for selecting rational actions.

These characteristics are summarized as the task environment.

**Example 1: an autonomous car**

- performance measure: safety, destination, legality, comfort, ...
- environment: streets, highways, traffic, pedestrians, weather, ...
- actuators: steering, accelerator, brake, horn, speaker, display, ...
- sensors: video, accelerometers, gauges, engine sensors, GPS, ...

## Example 2: an Internet shopping agent

- performance measure: price, quality, appropriateness, efficiency
- environment: current and future WWW sites, vendors, shippers
- actuators: display to user, follow URL, fill in form, ...
- sensors: web pages (text, graphics, scripts)

# Environment types

- Fully observable vs. partially observable
  - Whether the agent sensors give access to the complete state of the environment, at each point in time.
- Deterministic vs. stochastic
  - Whether the next state of the environment is completely determined by the current state and the action executed by the agent.
- Episodic vs. sequential
  - Whether the agent's experience is divided into atomic independent episodes.
- Static vs. dynamic
  - Whether the environment can change, or the performance measure can change with time.
- Discrete vs. continuous
  - Whether the state of the environment, the time, the percepts or the actions are continuous.
- Single agent vs. multi-agent
  - Whether the environment include several agents that may interact which each other.
- Known vs unknown
  - Reflects the agent's state of knowledge of the "law of physics" of the environment.

Are the following task environments fully observable? deterministic? episodic? static? discrete? single agents? Known?

- Crossword puzzle
- Chess, with a clock
- Poker
- Backgammon
- Taxi driving
- Medical diagnosis
- Image analysis
- Part-picking robot
- Refinery controller
- The real world

# Agent programs

The job of AI is to design an agent program that implements the agent function. This program will run on an architecture, that is a computing device with physical sensors and actuators.

$$agent = program + architecture$$

## Implementation

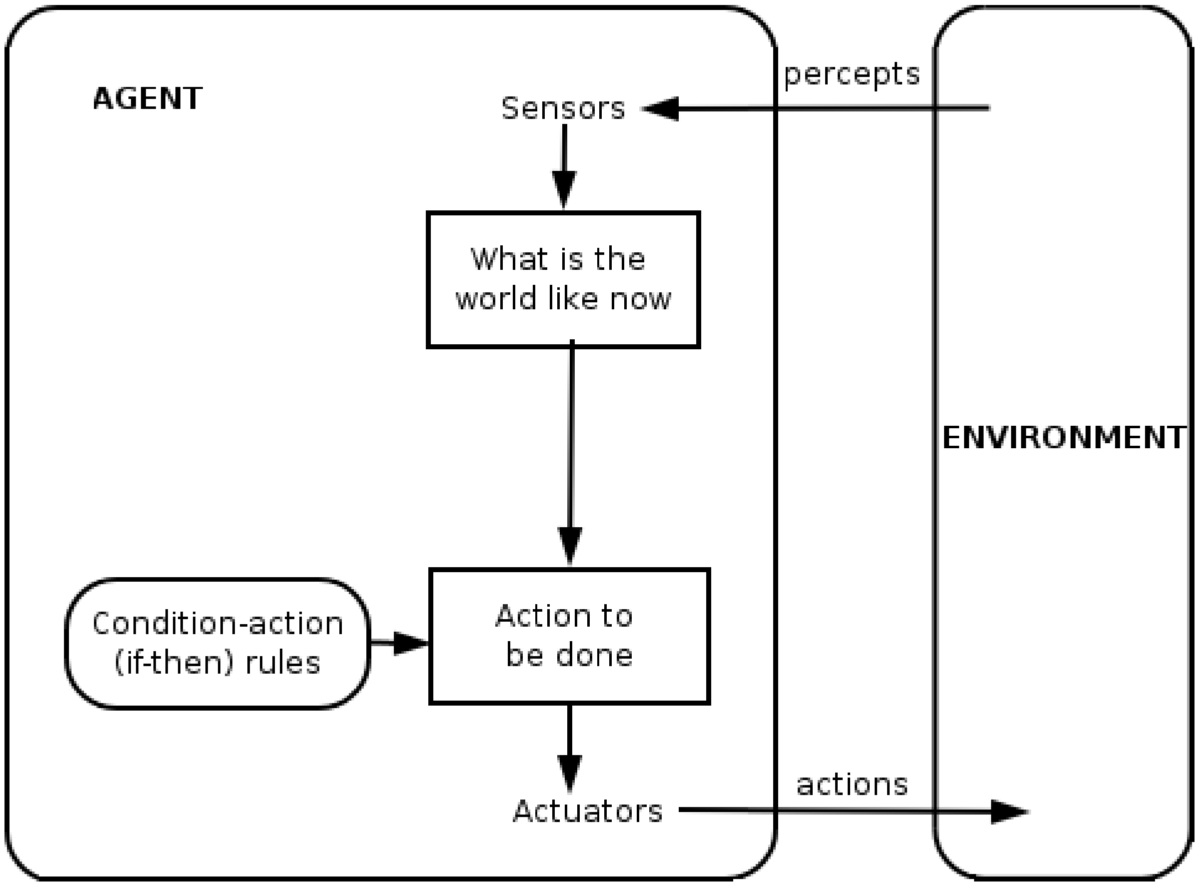
Agent programs can be designed and implemented in many ways:

- with tables
- with rules
- with search algorithms
- with learning algorithms

# Table-driven agents

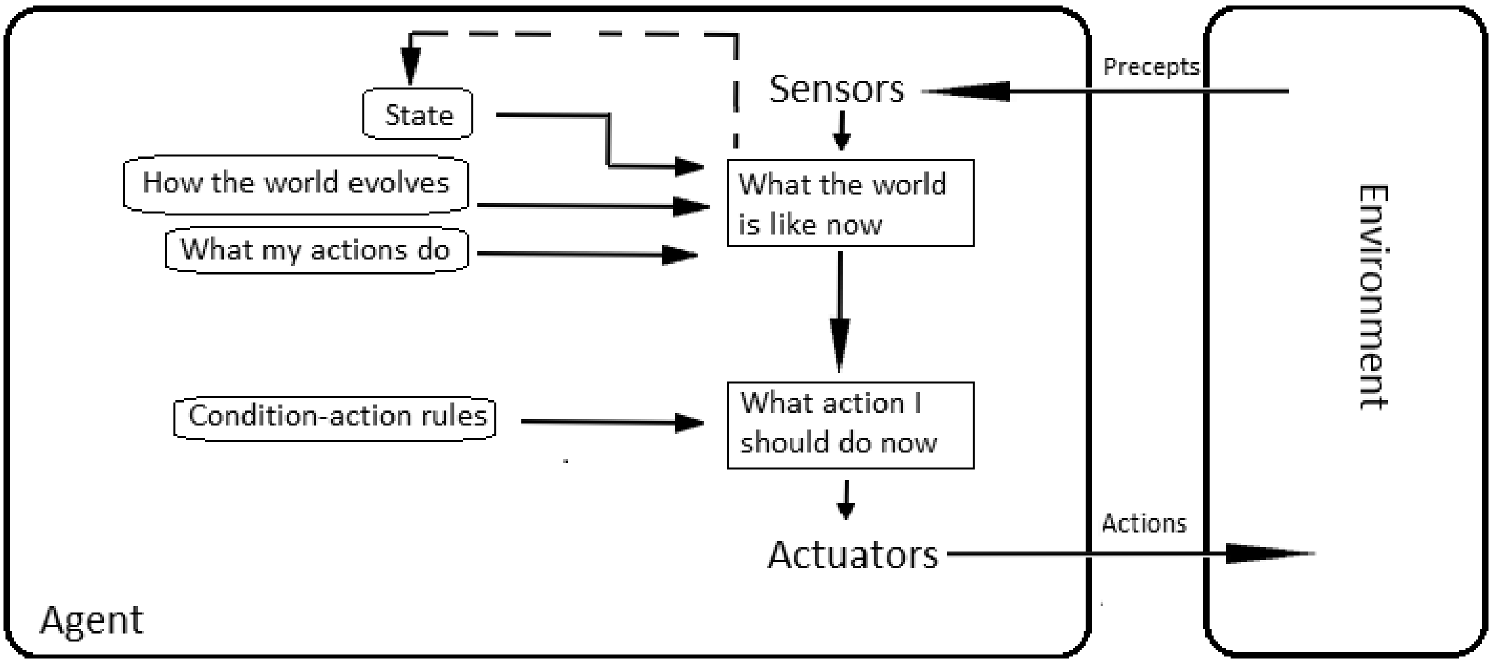
- A table-driven agent determines its next action with a table that contains the appropriate action for every possible percept sequence.
- Design issue: one needs to anticipate all sequence of percepts and how the agent should respond.
- Technical issue: the lookup table will contain $\sum_{t=1}^{T} |\mathcal{P}|^t$ entries.
    - Example (autonomous car): using a 30fps 640x480 RBG camera as sensor, this results in a table with over $10^{250000000000}$ entries for an hour of driving.

# Simple reflex agents



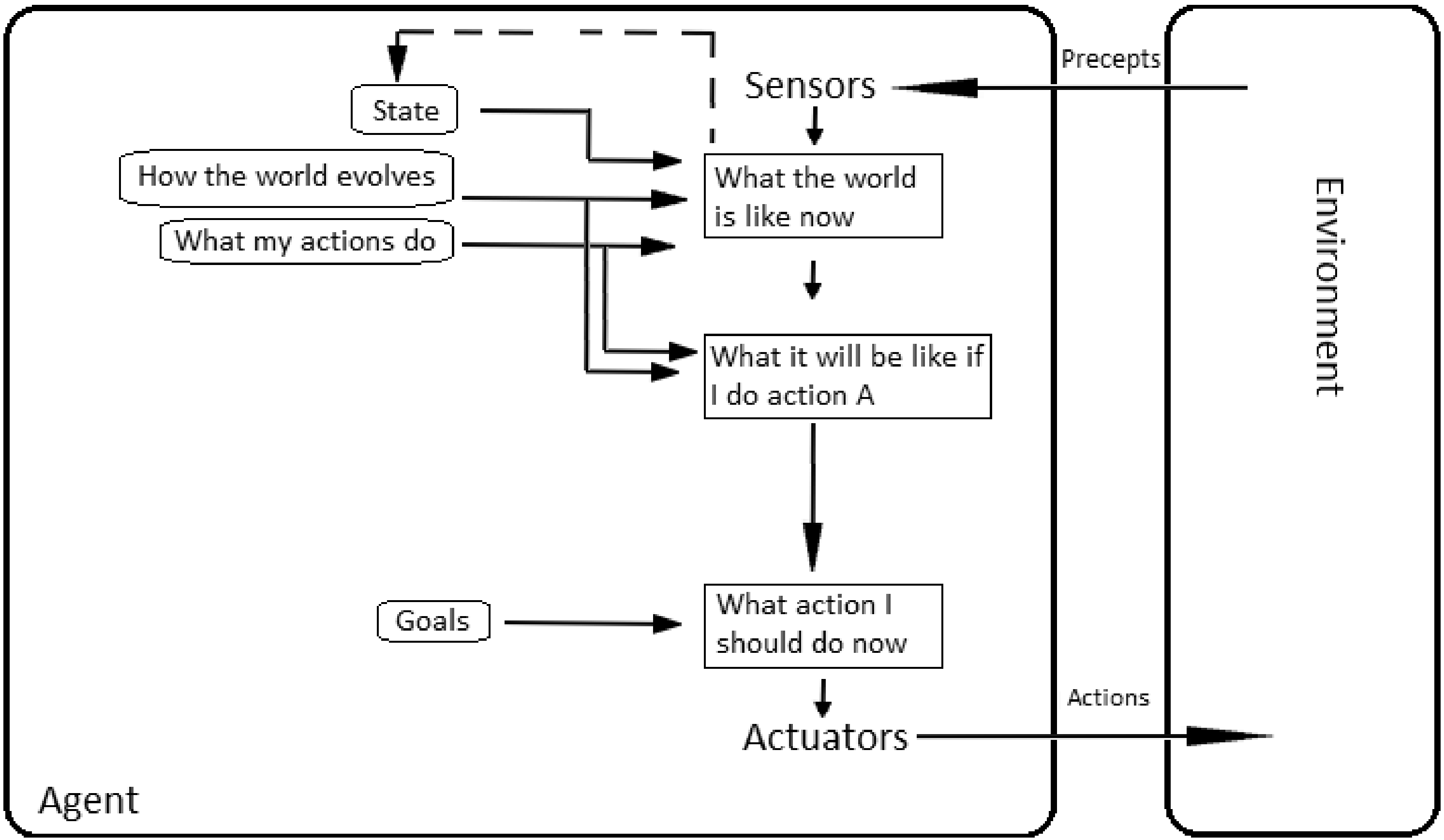
- Simple reflex agents select actions on the basis of the current percept, ignoring the rest of the percept history.
- They implement condition-action rules that match the current percept to an action.
- Rules provide a way to compress the function table.
    - Example (autonomous car): If a car in front of you slow down, you should break. The color and model of the car, the music on the radio or the weather are all irrelevant.
- Simple reflex agents are simple but they turn out to have limited intelligence.
- They can only work in a Markovian environment, that is if the correct decision can be made on the basis of only the current percept. In other words, if the environment is fully observable.

# Model-based reflex agents



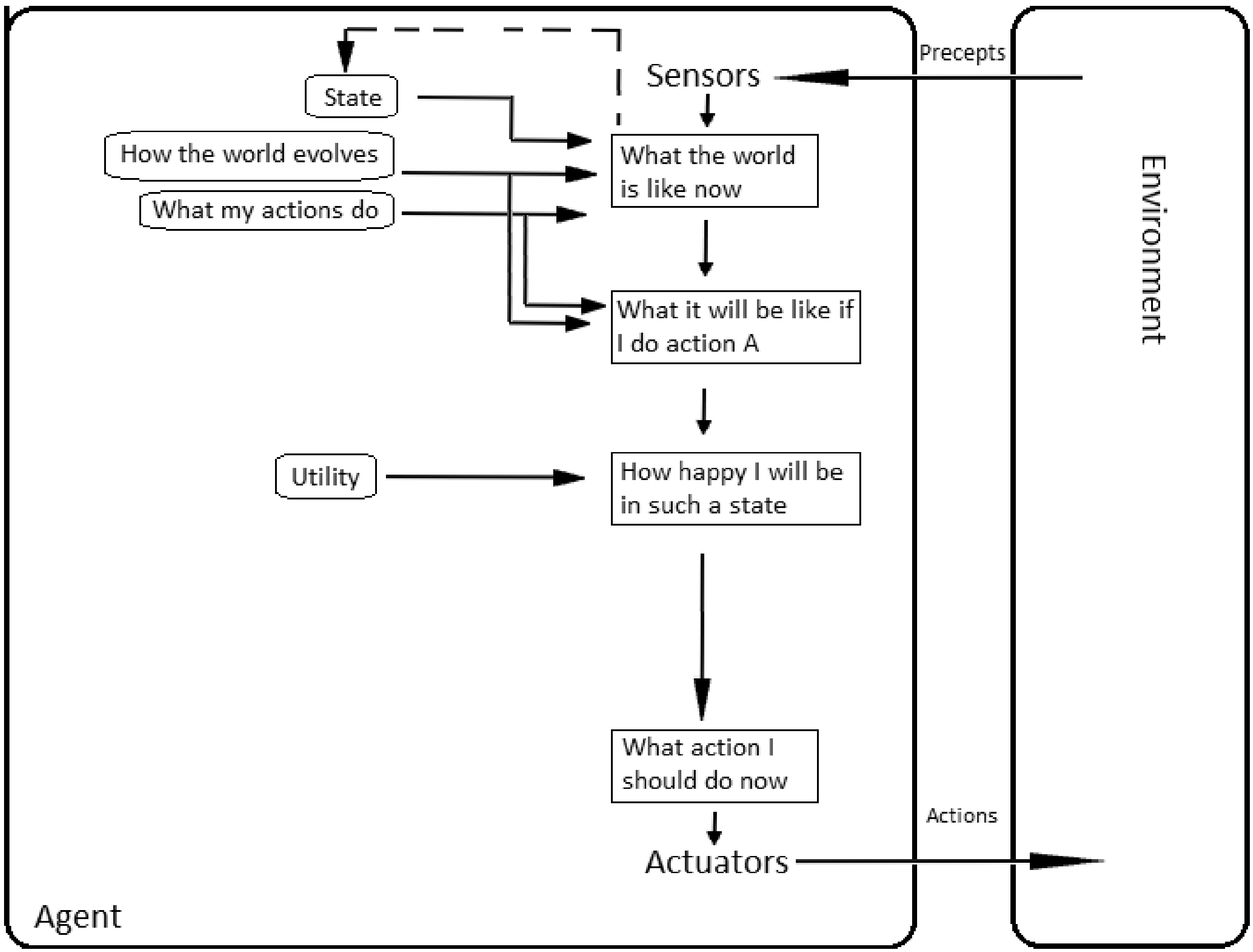
- Model-based agents handle partial observability of the environment by keeping track of the part of the world they cannot see now.
- The internal state of model-based agents is updated on the basis of a model which determines:
    - how the environment evolves independently of the agent;
    - how the agent actions affect the world.

# Goal-based agents



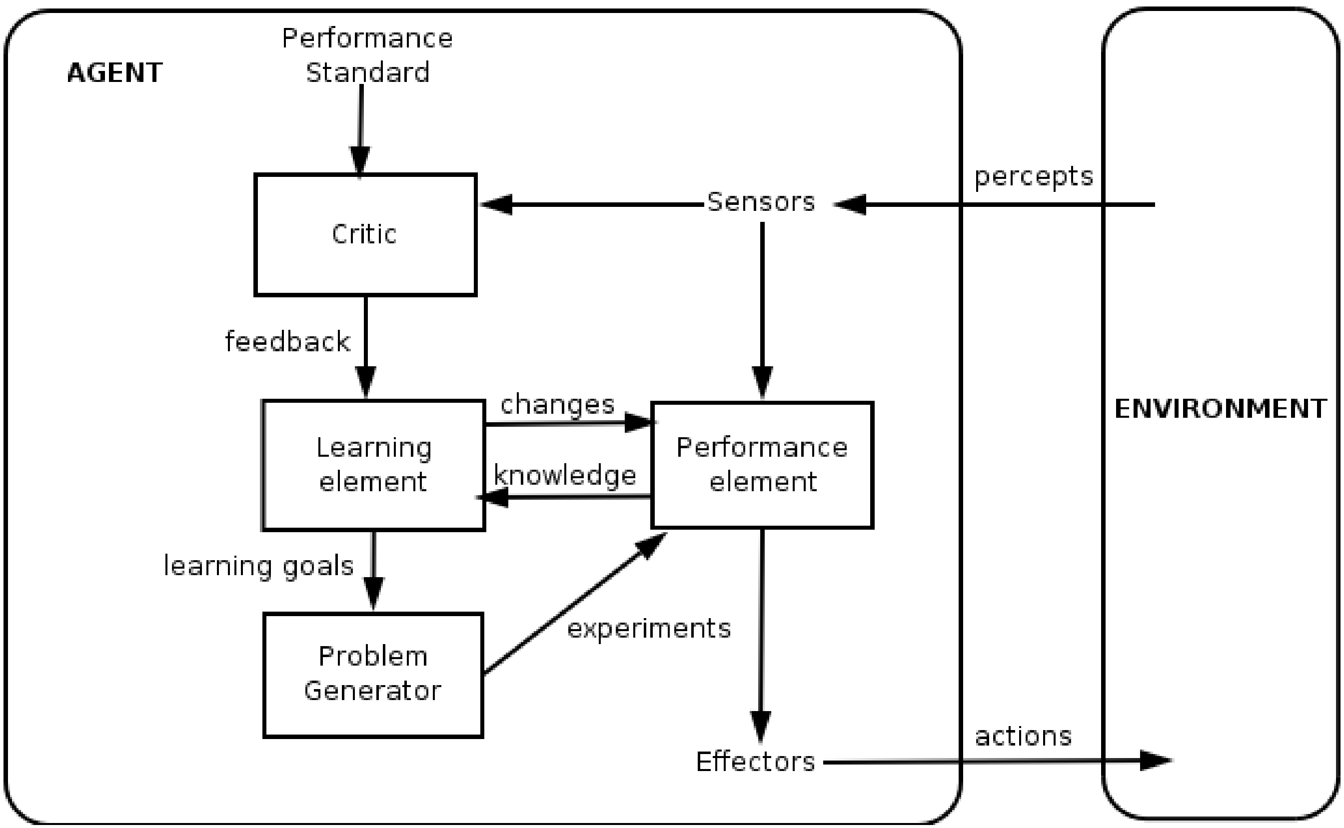
- Principle: i) generate possible sequences of actions, ii) predict the resulting states and iii) assess goals in each.
    - Example (autonomous car): Has the car arrived to destination?
- A goal-based agent chooses an action that will achieve the goal.
    - More general than rules. Goals are rarely explicit in condition-action rules.
    - Finding action sequences that achieve goals is difficult. Search and planning are two strategies.

# Utility-based agents



- Goals are often not enough to generate high-quality behavior.
  - Example (autonomous car): There are many ways to arrive to destination, but some are quicker or more reliable.
  - Goals only provide binary assessment of performance.
- A utility function scores any given sequence of environment states.
  - The utility function is an internalization of the performance measure.
- A rational utility-based agent chooses an action that maximizes the expected utility of its outcomes.

# Learning agents



- Learning agents are capable of self-improvement. They can become more competent than their initial knowledge alone might allow.
- They can make changes to any of the knowledge components by:
  - learning how the world evolves;
  - learning what are the consequences of actions;
  - learning the utility of actions through rewards.

## A learning autonomous car

- Performance element:
  - The current system for selecting actions and driving.
- The critic observes the world and passes information to the learning element.
  - E.g., the car makes a quick left turn across three lanes of traffic. The critic observes shocking language from the other drivers and informs bad action.
  - The learning element tries to modifies the performance element to avoid reproducing this situation in the future.
- The problem generator identifies certain areas of behavior in need of improvement and suggest experiments.
  - E.g., trying out the brakes on different surfaces in different weather conditions.

# Summary

- An agent is an entity that perceives and acts in an environment.
- The performance measure evaluates the agent's behavior. Rational agents act so as to maximize the expected value of the performance measure.
- Task environments includes performance measure, environment, actuators and sensors. They can vary along several significant dimensions.
- The agent program effectively implements the agent function. Their designs are dictated by the task environment.
- Simple reflex agents respond directly to percepts, whereas model-based reflex agents maintain internal state to track the world. Goal-based agents act to achieve goals while utility-based agents try to maximize their expected performance.
- All agents can improve their performance through learning.

The end.

# References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