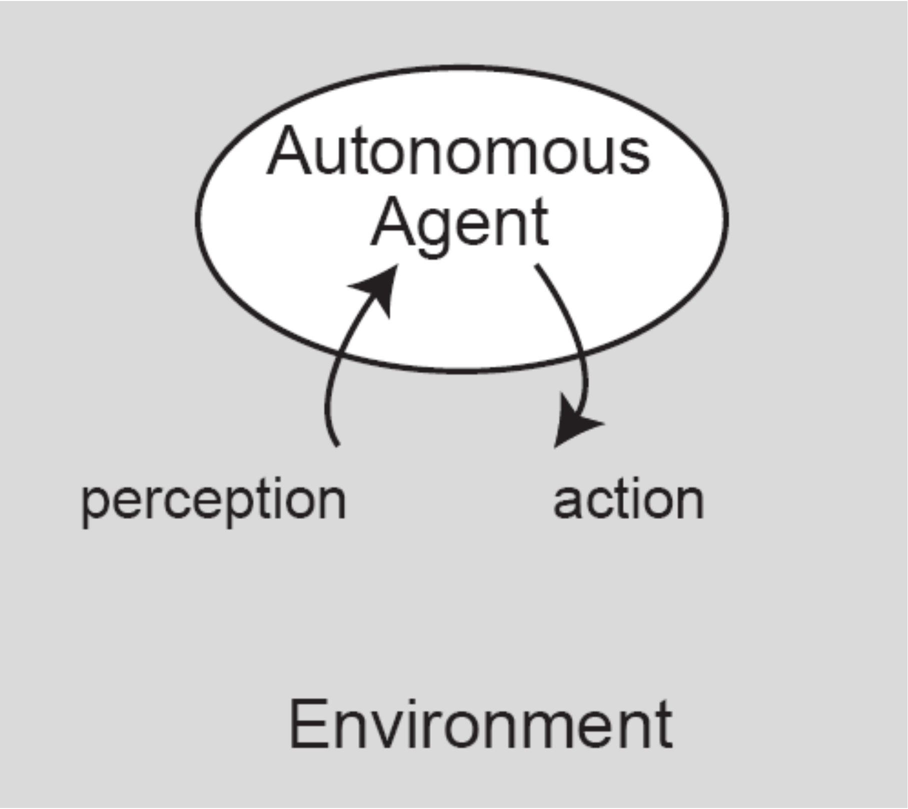
The PDP with Reactive Agents

Intelligent Agents

Fall 2019

Reactive Agents

- Simple behaviours that react to stimuli from the environment
- Robot-like:
  - « Stimuli » from sensor « information »



Our Reactive Agent Architecture

- Vehicles as reactive agents
- Percepts from the environment (state):
  - Route?
  - City?
  - Task?
- Actions the agent can take :
  - Move in a direction according to the topology
  - Pickup a task
  - Deliver a task

Three Steps

1. Learn off-line the actions to take (strategy) in order to optimally search and deliver tasks (MAIN PART)

2. Using the learned strategy, travel through the network

3. When a task has been picked up, deliver it on the shortest path (given)

Assumptions (1)

- The vehicle starts from its home city
- When the vehicle arrives in a city, it finds out whether a task is available or not in that city. The vehicle sees at most one task!
- If task, agent can decide to:
  - Deliver it
  - Give it up and continue to a neighbour city

Assumptions (2)

- There exists a probability distribution of the tasks

- A vehicle can transport only one task
- Must deliver it, and on the shortest path (given)

Applying reinforcement learning (Markov Decision Processes - MDP)

- Goal:
  - learn optimal strategy to move in the network and deliver tasks
  - i.e. react optimally on the basis of a probability distribution of the tasks in the network
- MDP Solver: offline, before agent travels!

Existing two tables

- P(i,j):
  - probabilities pij that in city i, there is a task for city j
- R(i,j):
  - average reward rij for a task to be transported from city i to city j

- Beforehand, tasks tij have been created with the probablity pij and a variation reward around rij

Reinforcement Learning

- Define MDP on paper (and in report!):
  - A **state** representation of the world,
  - the **actions** for the transitions between those states,
  - with the corresponding **rewards**,
  - and the **probability** of the transition.

Algorithm

- Compute V(S) by value iteration:

```
initialize V(S) arbitrarily
loop until good enough
    loop for s ∈ S
        loop for a ∈ A
            Q(s,a) ← R(s,a) + γ Σ_{s'∈S} T(s,a,s')V(s')
        V(s) ← max_a Q(s,a)
```

$$Q(s,a) \leftarrow R(s,a) + \gamma \sum_{s' \in S} T(s,a,s')V(s')$$

$$V(s) \leftarrow max_a Q(s,a)$$

Data Structures (1)

- $V(s)$:
  - vector indicating the discounted sum of the rewards to be earned (on expectation) by following that solution from state s
- $R(s,a)$:
  - table that indicates the rewards for taking action a being in state s
- $T(s,a,s')$
  - $= p(s'|s,a)$, i.e. probability to arrive in state s' given that you are in state s and that you take action a
- Discount Factor γ: between 0 and 1

Data Structures (2)

Q(s,a)	**State s1**	**State s2**	**...**
Action a1	Q(s1,a1)	Q(s1, a1)	...
Action a2	Q(s1, a2)	Q(s2, a2)	...
...	...	...	...

To Do

- Implement a simple reactive agent
- Define:
  - state representation s
  - possible actions a,
  - reward table R(s,a)
  - probability transition table T(s,a,s')
- Implement the offline reinforcement learning algorithm
- Run simulations, analyze the performance of your agent and test limit cases