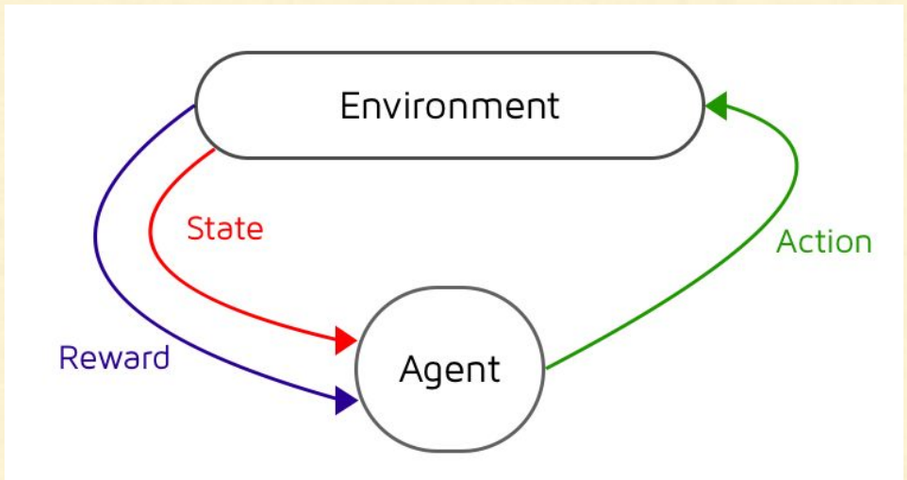


Reinforcement Learning

Reinforcement Learning

- Reinforcement Learning has been around since 1950s and
  - Produced many interesting applications over the years
  - Like TD-Gammon, a Backgammon playing program

Reinforcement Learning

- In 2013, researchers from an English startup **DeepMind**
  - Demonstrated a system that could learn to play
  - Just about any Atari game from scratch and
  - Which outperformed human
  - It used only row pixels as inputs and
  - Without any prior knowledge of the rules of the game
- In March 2016, their system AlphaGo defeated
  - Lee Sedol, the world champion of the game of Go
  - This was possible because of Reinforcement Learning

Reinforcement Learning

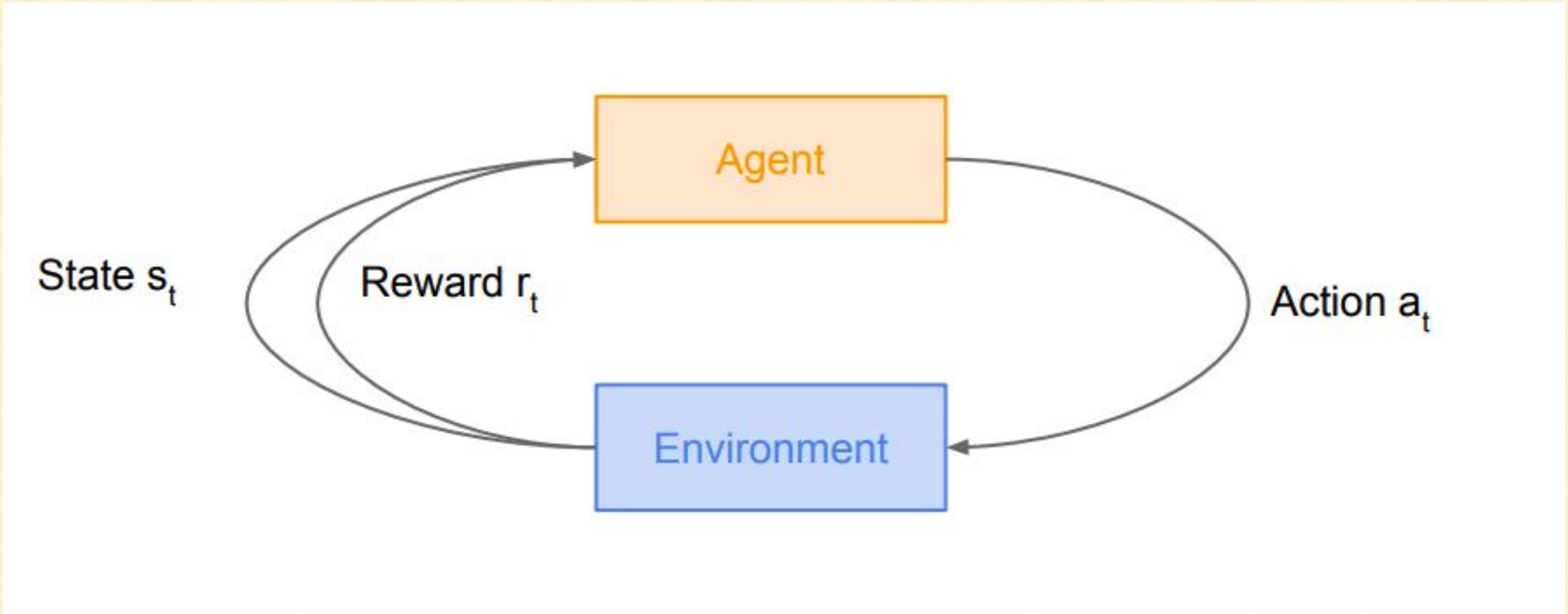
- In this chapter, we will learn about
  - What Reinforcement Learning is and
  - What it is good at

Reinforcement Learning

Learning to Optimize Rewards

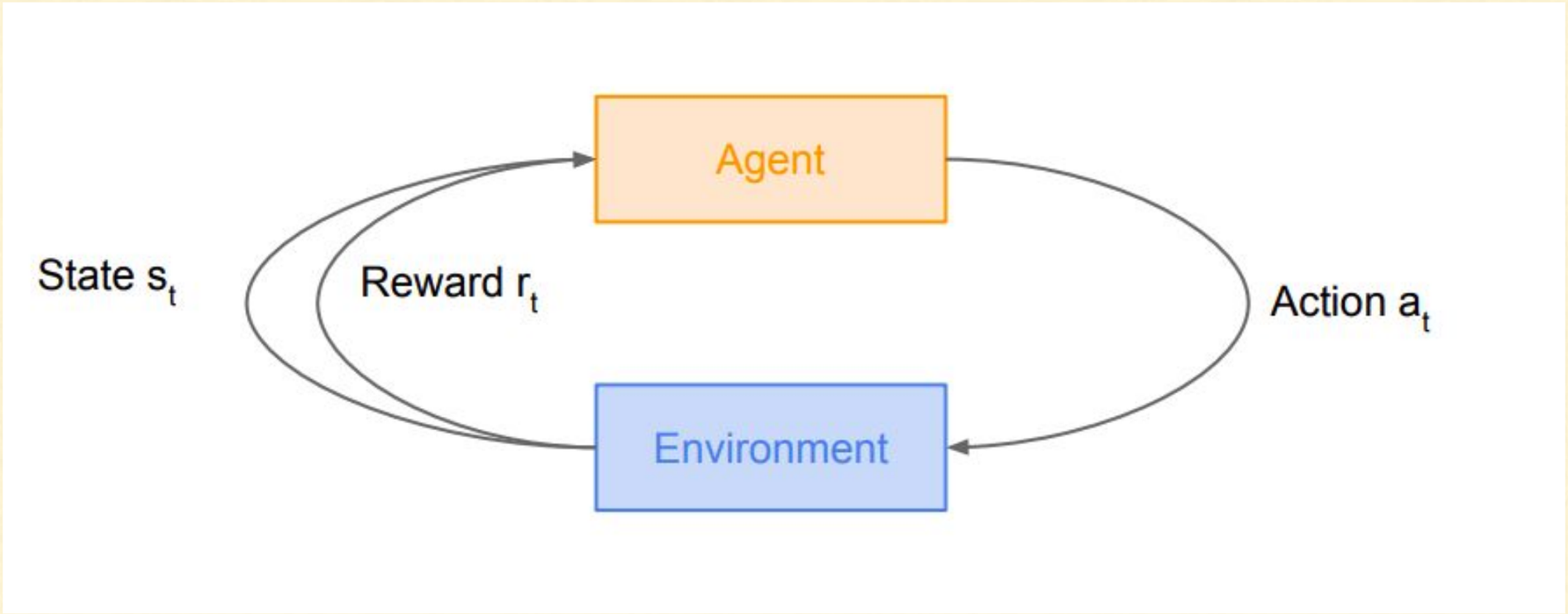
Learning to Optimize Rewards

- In Reinforcement Learning
  - A software **agent** makes **observations** and
  - Takes **actions** within an **environment** and
  - In return it receives rewards



Learning to Optimize Rewards

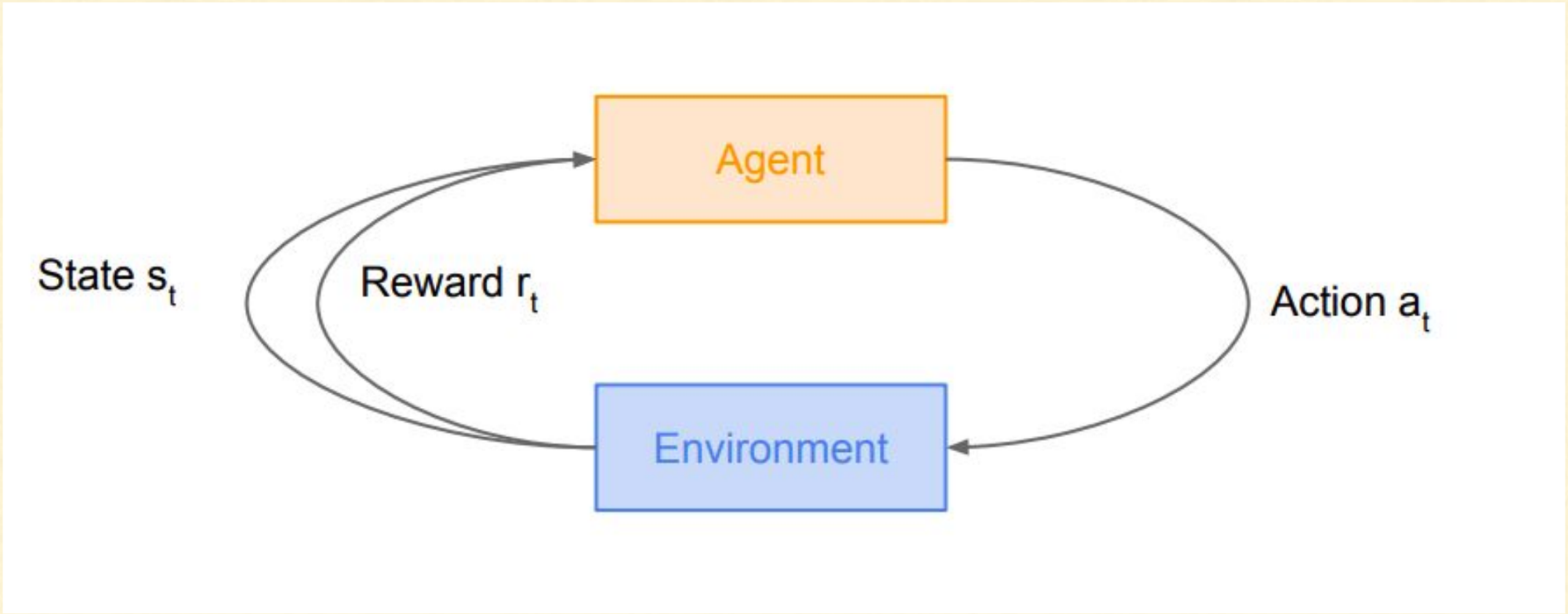
Goal?



Learning to Optimize Rewards

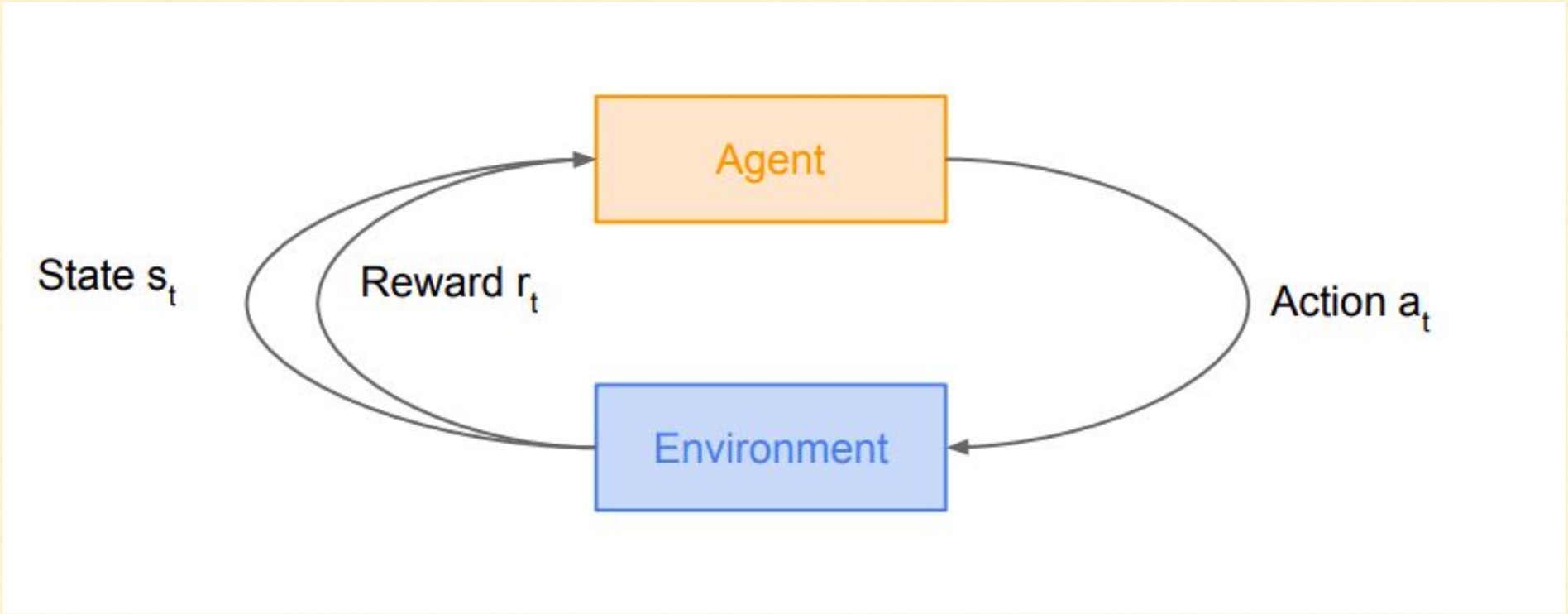
Goal

Learn how to take actions in order to maximize reward



Learning to Optimize Rewards

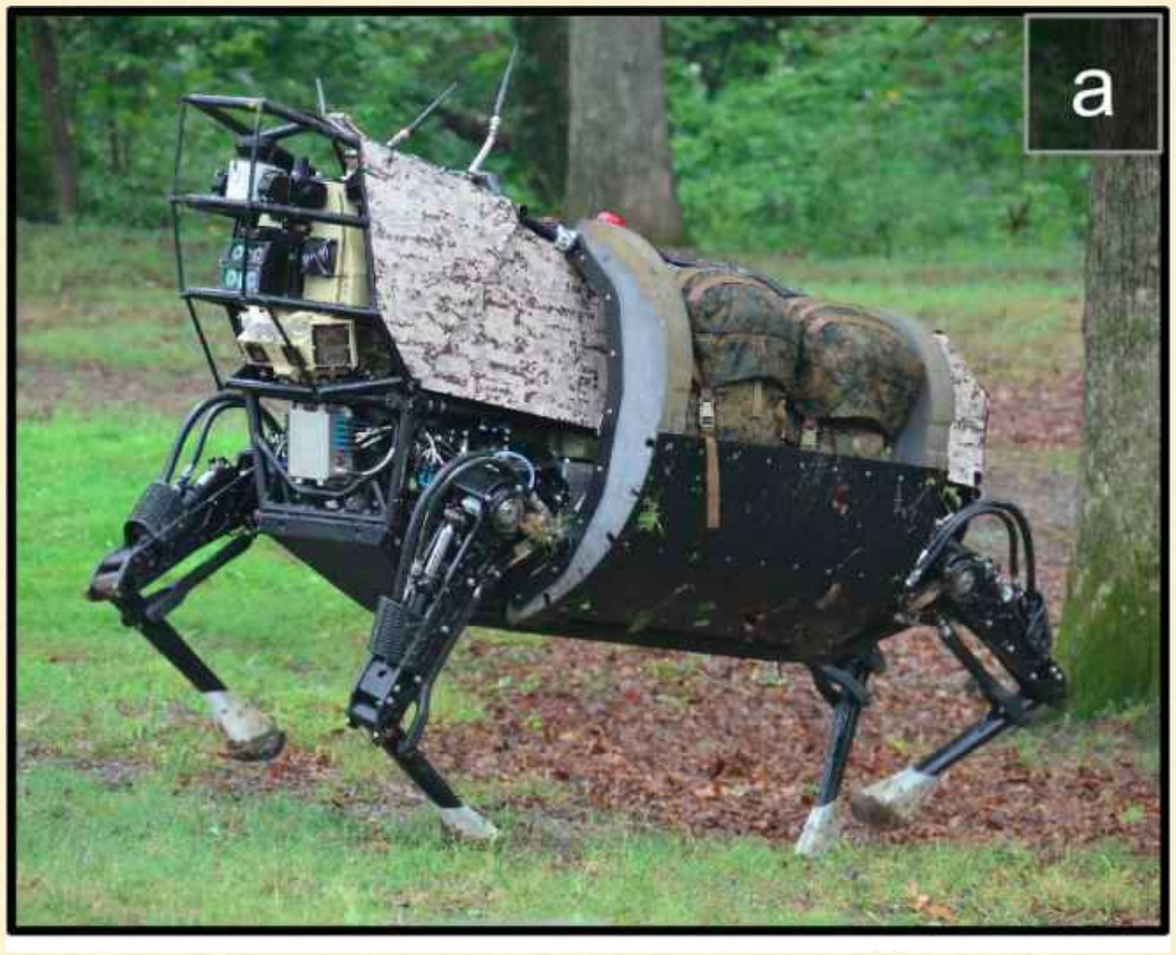
- In short, the agent acts in the environment and
  - Learns by trial and error to
  - Maximize its reward



Learning to Optimize Rewards

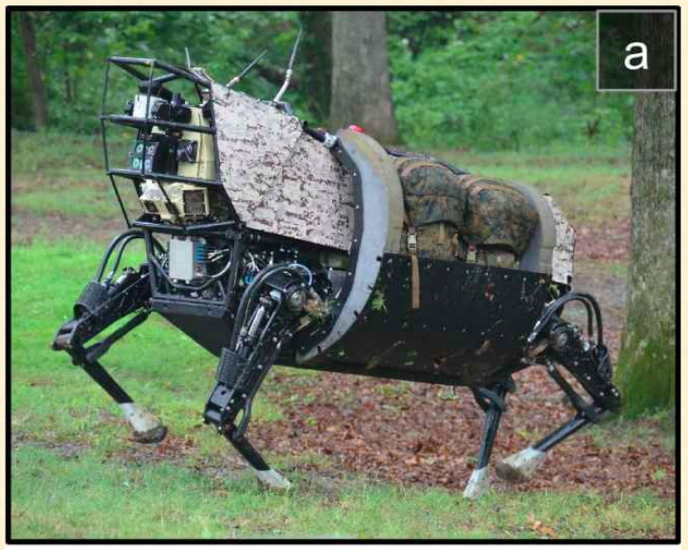
So how can we apply this in real-life applications?

Learning to Optimize Rewards - Walking Robot



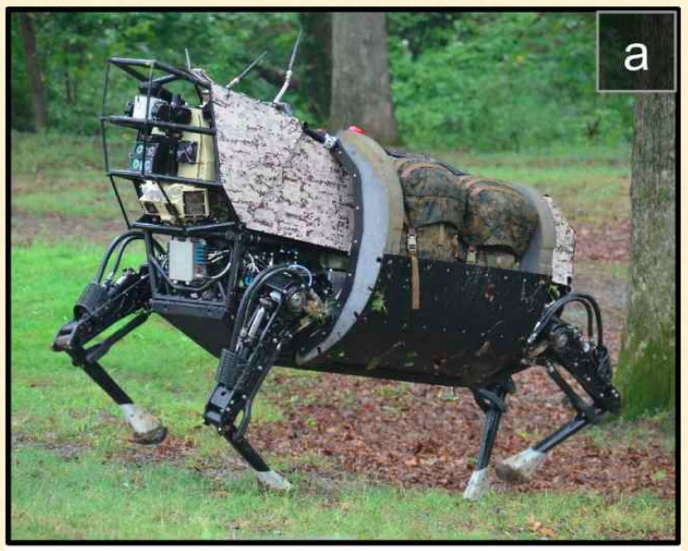
Learning to Optimize Rewards - Walking Robot

- Agent - Program controlling a walking robot
- Environment - Real world
- The agent observes the environment through a set of sensors such as
    - Cameras and touch sensors
- Actions - Sending signals to activate motors

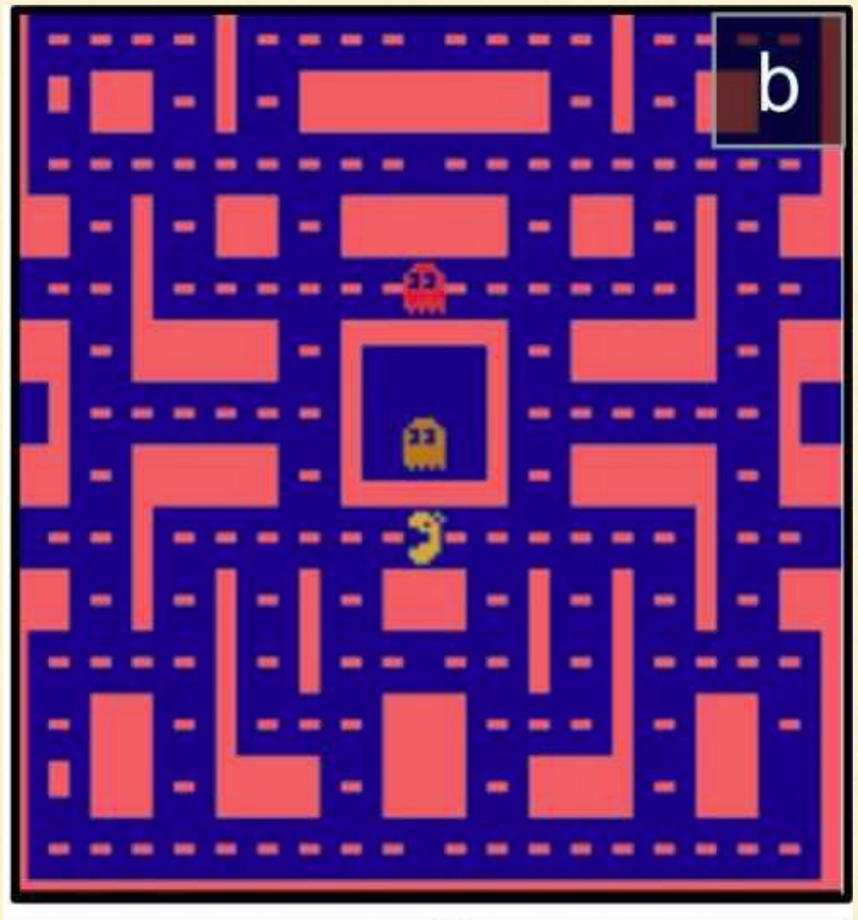


Learning to Optimize Rewards - Walking Robot

- It may be programmed to get
  - Positive rewards whenever it approaches the target destination and
  - Negative rewards whenever it
    - Wastes time
    - Goes in the wrong direction or
    - Falls down

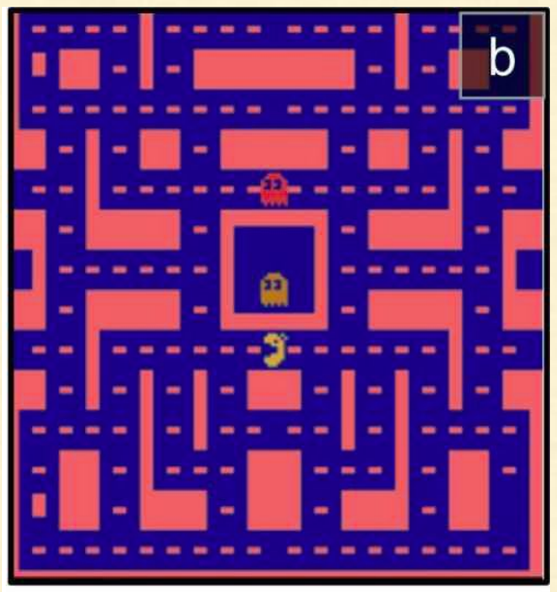


Learning to Optimize Rewards - Ms. Pac-Man



Learning to Optimize Rewards - Ms. Pac-Man

- Agent - Program controlling Ms. Pac-Man
- Environment - Simulation of the Atari game
- Actions - Nine possible joystick positions
- Observations - Screenshots
- Rewards - Game points



Learning to Optimize Rewards - Thermostat

Learning to Optimize Rewards - Thermostat

- Agent - Thermostat
  - Please note, the agent does not have to control a
  - Physically (or virtually) moving thing
- Rewards -
  - Positive rewards whenever agent is close to the target temperature
  - Negative rewards when humans need to tweak the temperature
- Important - Agent must learn to anticipate human needs

Learning to Optimize Rewards - Auto Trader

Learning to Optimize Rewards - Auto Trader

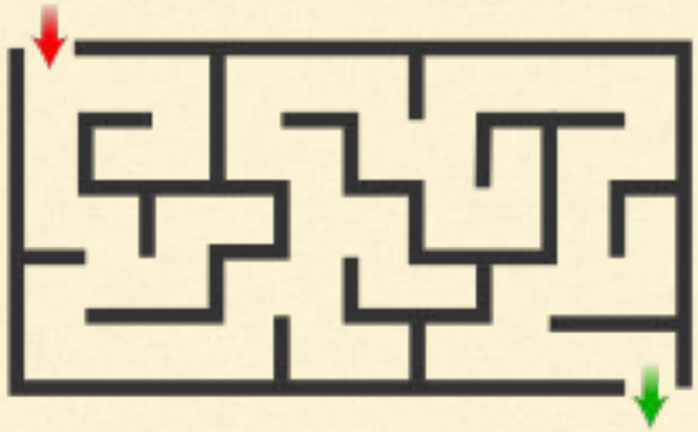
- Agent -
  - Observes stock market prices and
  - Decide how much to buy or sell every second
- Rewards - The monetary gains and losses

Learning to Optimize Rewards

- There are many other examples such as
  - Self-driving cars
  - Placing ads on a web page or
  - Controlling where an image classification system
    - Should focus its attention

Learning to Optimize Rewards

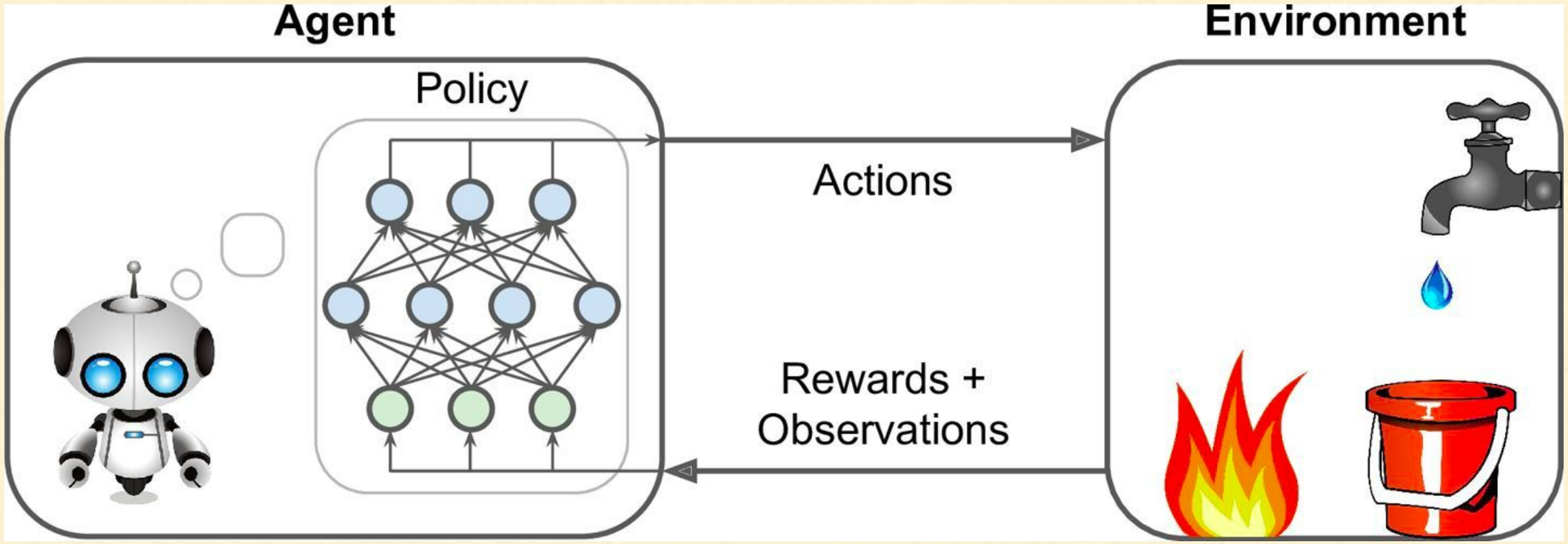
- Note that there may not be any positive rewards at all
- For example
  - The agent may move around in a maze
  - Getting a negative reward at every time step
  - So it better find the exit as quickly as possible



Policy Search

Policy Search

- The algorithm used by the software agent to
  - Determine its actions is called its **policy**
- For example, the policy could be a neural network
  - Taking observations as inputs and
  - Outputting the action to take



Policy Search

- The policy can be any algorithm we can think of
  - And it does not even have to be deterministic
- For example, consider a robotic vacuum cleaner
  - Its reward is the amount of dust it picks up in 30 minutes
- Its policy could be to
  - Move forward with some probability p every second or
  - Randomly rotate left or right with probability 1 – p
  - The rotation angle would be a random angle between –r and +r
- Since this policy involves some randomness
  - It is called a **stochastic policy**

Policy Search

- The robot will have an erratic trajectory, which guarantees that
  - It can get to any place it can reach and
  - Pick up all the dust
- The question is: how much dust will it pick up in 30 minutes?

Policy Search

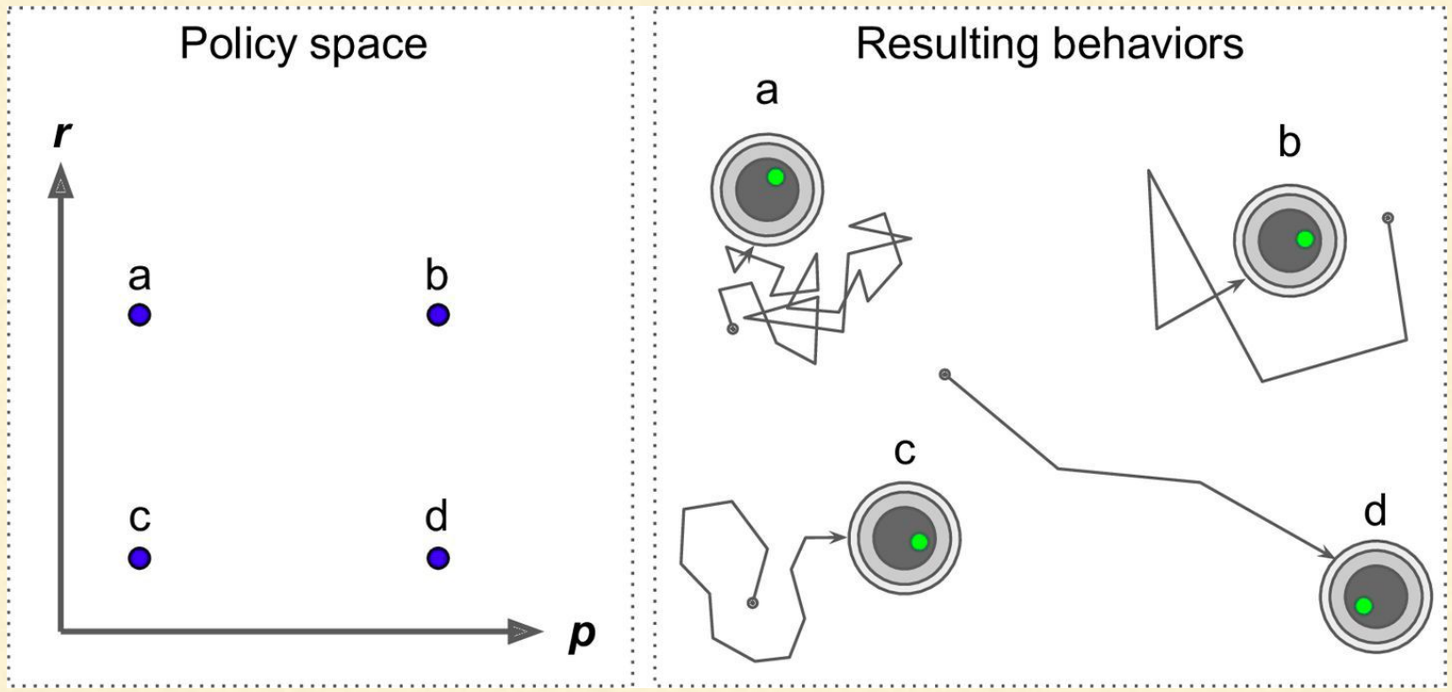
How would we train such a robot?

Policy Search

- There are just two policy parameters which we can tweak
  - The probability **p** and
  - The angle range **r**

Policy Search - Brute Force Approach

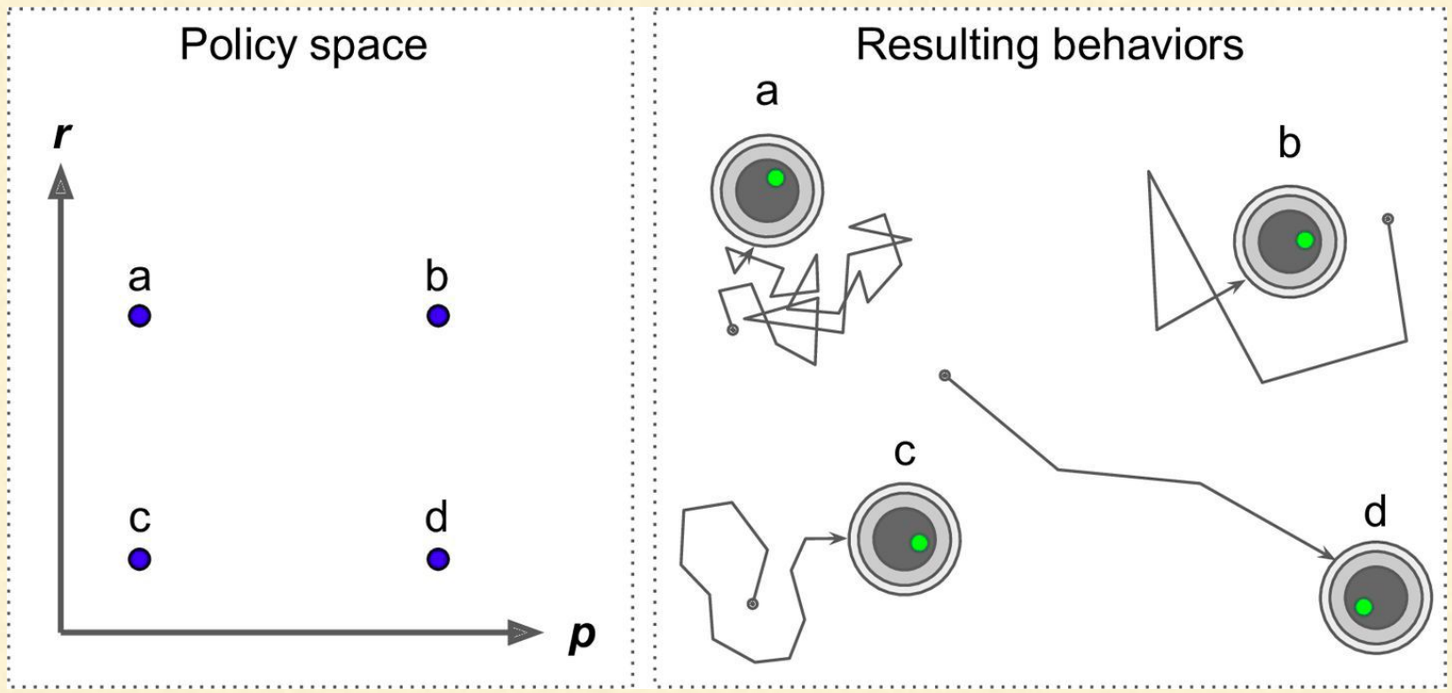
- One possible learning algorithm could be to
  - Try out many different values for these parameters, and
  - Pick the combination that performs best
- This is the example of policy search using a brute force approach



Four points in policy space and the agent's corresponding behavior

Policy Search - Brute Force Approach

- When the policy space is too large then
  - Finding a good set of parameters this way is like
  - Searching for a needle in a gigantic haystack



Four points in policy space and the agent's corresponding behavior

Policy Search - Genetic Algorithms

- Another way to explore the policy space is to
  - Use **genetic algorithms**
- For example
  - Randomly create a first generation of 100 policies and
  - Try them out, then “kill” the 80 worst policies and
  - Make the 20 survivors produce 4 offspring each
- An offspring is just a copy of its parent
  - Plus some random variation

Policy Search - Genetic Algorithms

- The surviving policies plus their offspring together
  - Constitute the second generation
- Continue to iterate through generations this way
  - Until a good policy is found

Policy Search - Optimization Techniques

- Another approach is to use
  - Optimization Techniques
- Evaluate the gradients of the rewards
  - With regards to the policy parameters
  - Then tweaking these parameters by following the
  - Gradient toward higher rewards (gradient ascent)
- This approach is called **policy gradients**

Policy Search - Optimization Techniques

- Let's understand this with an example
- Going back to the vacuum cleaner robot example, we can
  - Slightly increase p and evaluate
  - Whether this increases the amount of dust
  - Picked up by the robot in 30 minutes
  - If it does, then increase p some more, or
  - Else reduce p

Introduction to OpenAI Gym

Introduction to OpenAI Gym

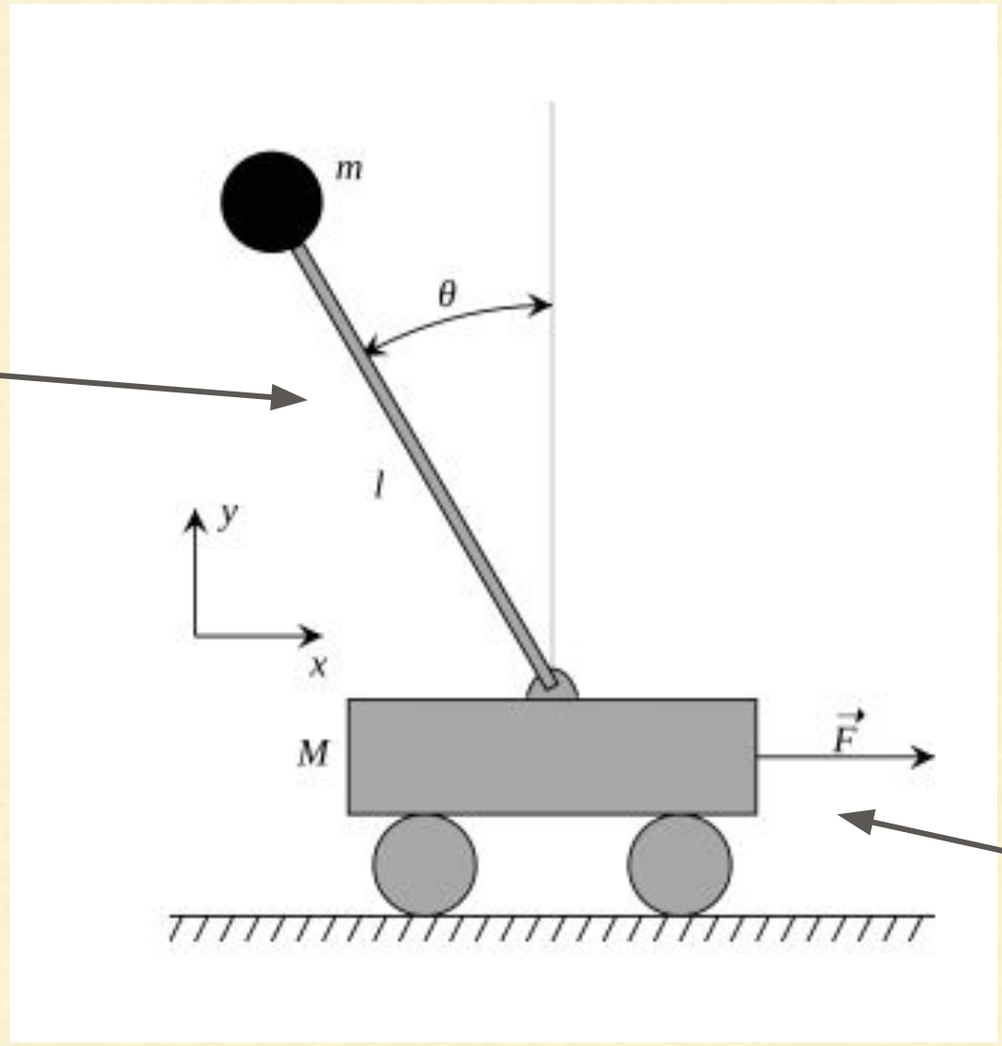
- To train an agent in Reinforcement Learning
  - We need a working environment
- For example, if we want agent to run how to play Atari game,
  - We will need a Atari game simulator
- OpenAI gym is a toolkit that provides wide variety of simulations like
  - Atari games
  - Board games
  - 2D and 3D physical simulations and so on

Policy Search - Optimization Techniques

Let’s do a hands-on

Policy Search - Optimization Techniques

Goal - Balance a pole on top of a movable cart. Pole should be upright

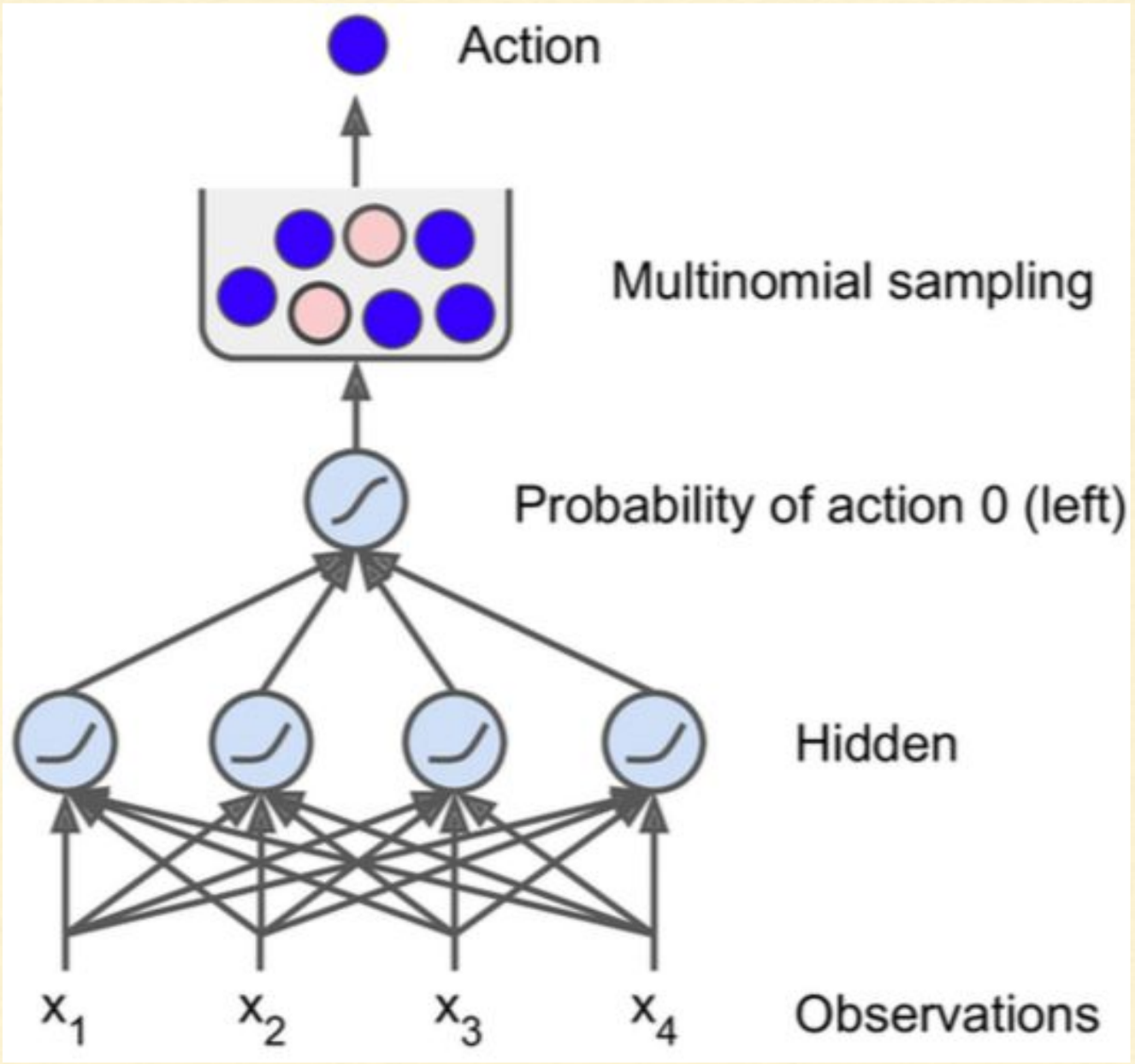


Pole

Cart

Neural Network Policies

Let's create a neural network policy.



- Take an observation as input
- Output the action to be executed
- Estimate probability for each action
- Select an action **randomly according to the estimated probabilities**

Example, In cart pole:

- If it outputs 0.7, then we will pick action 0 with 70% probability, and action 1 with 30% probability.

Neural Network Policies

Q: Why we are picking a random action based on the probability given by the neural network, rather than just picking the action with the highest score.

Neural Network Policies

Q: Why we are picking a random action based on the probability given by the neural network, rather than just picking the action with the highest score.

This approach lets the agent find the **right balance between exploring new actions** and **exploiting the actions that are known to work** well.

Neural Network Policies

Q: Why we are picking a random action based on the probability given by the neural network, rather than just picking the action with the highest score.

This approach lets the agent find the **right balance between exploring new actions** and **exploiting the actions that are known to work** well.

We will never discover a new dish at restaurent if we don't try anything new. Give serendipity a chance.

Neural Network Policies

Check the complete code in Jupyter notebook

Evaluating Actions: The Credit Assignment Problem

If we knew what the best action was at each step,

- we could train the neural network as usual,
- by minimizing the cross entropy
- between the estimated probability and the target probability.

It would just be regular supervised learning.

Evaluating Actions: The Credit Assignment Problem

If we knew what the best action was at each step,

- we could train the neural network as usual,
- by minimizing the cross entropy
- between the estimated probability and the target probability.

It would just be regular supervised learning.

However, in Reinforcement Learning

- the only guidance the agent gets is through rewards,
- and rewards are typically **sparse and delayed.**

Evaluating Actions: The Credit Assignment Problem

For example,
If the agent manages to balance the pole for 100 steps, how can it know which of the 100 actions it took were good, and which of them were bad?

All it knows is that the pole fell after the last action, but surely this last action is not entirely responsible.

Evaluating Actions: The Credit Assignment Problem

This is called the credit assignment problem

- When the agent gets a reward, it is hard for it to know which actions should get credited (or blamed) for it.

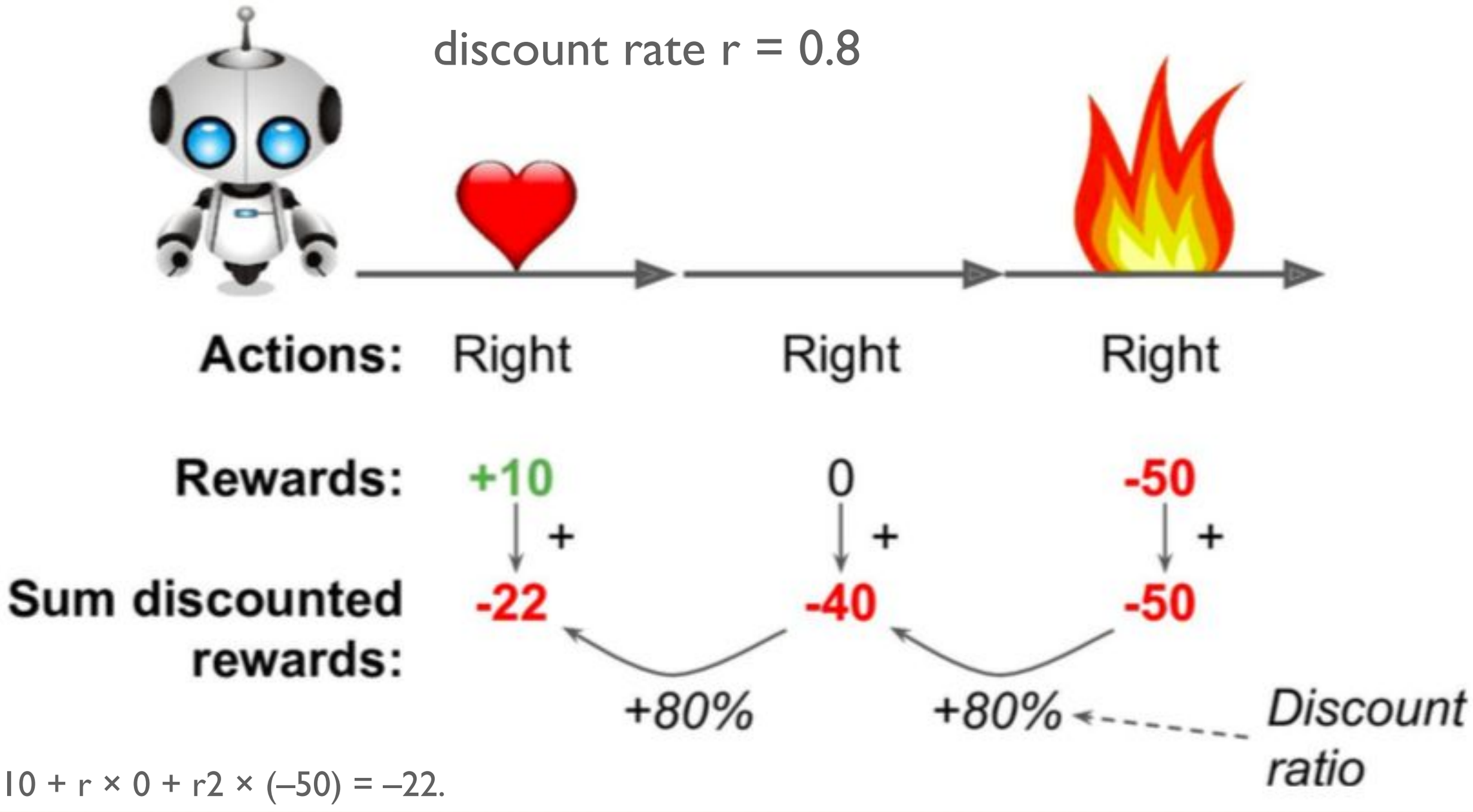
- Think of a dog that gets rewarded hours after it behaved well; will it understand what it is rewarded for?

Evaluating Actions: The Credit Assignment Problem

To tackle this problem,

- A common strategy is to evaluate an action based on the sum of all the rewards that come after it
- usually applying a discount rate r at each step.
- Typical discount rates are 0.95 or 0.99.

Evaluating Actions: The Credit Assignment Problem



10 + r × 0 + r2 × (–50) = –22.

Policy Gradients

PG algorithms

- Optimize the parameters of a policy
- by following the gradients toward higher rewards.

One popular class of PG algorithms, called REINFORCE algorithms:

- was introduced back in 19929 by Ronald Williams. Here is one common variant:

Policy Gradients

Here is one common variant of REINFORCE:

1. Let the neural network policy play the game several times
    a. Compute the gradients that would make the chosen action even more likely,
    b. but don't apply these gradients yet.

Policy Gradients

Here is one common variant of REINFORCE:

1. Let the neural network policy play the game several times
   a. Compute the gradients that would make the chosen action even more likely,
   b. but don't apply these gradients yet.
2. Once you have run several episodes, compute each action's score (using the method described earlier).

Policy Gradients

Here is one common variant of REINFORCE:

3.

    If an **action's score is positive**, it means that the action was good and you want to **apply the gradients** computed earlier to make the action even more likely to be chosen in the future.

    However, if the **score is negative**, it means the action was bad and you want to **apply the opposite gradients** to make this action slightly less likely in the future. The solution is simply to multiply each gradient vector by the corresponding action's score.

Policy Gradients

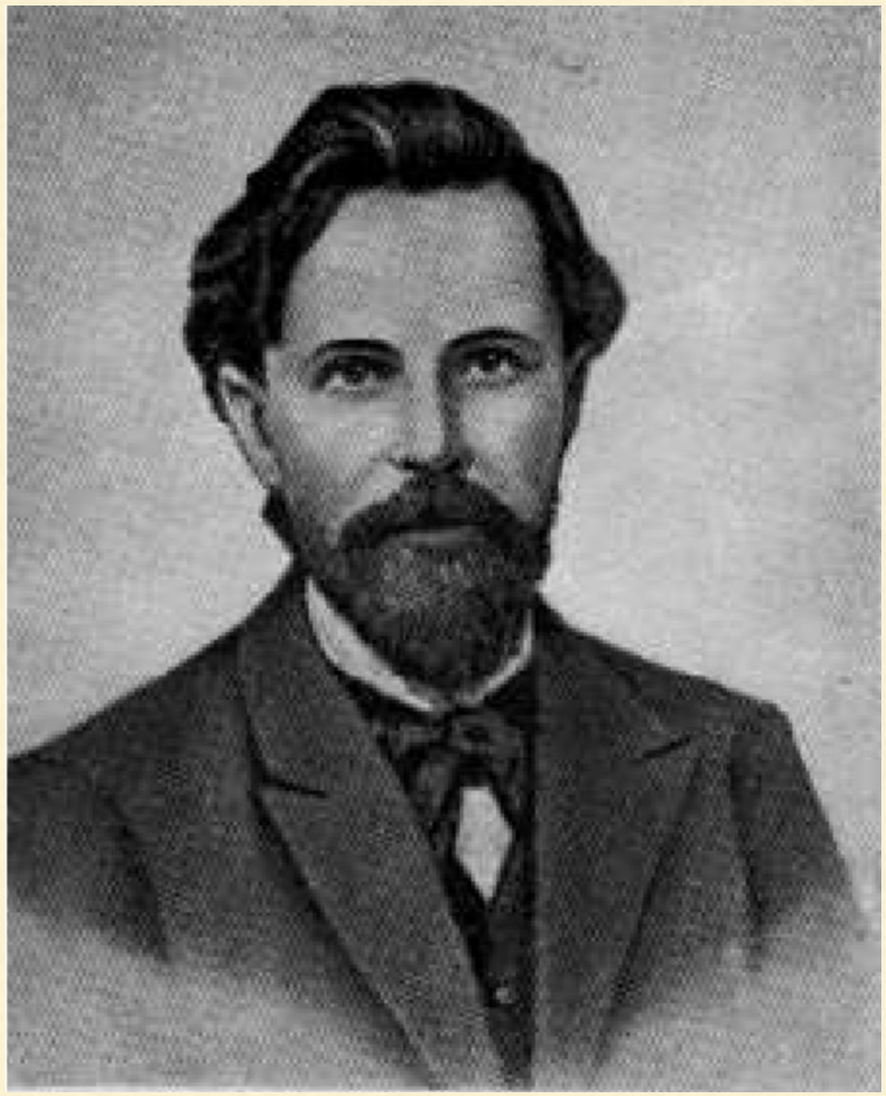
Here is one common variant of REINFORCE:

4. Finally, compute the mean of all the resulting gradient vectors, and use it to perform a Gradient Descent step.

Markov Decision Processes

Markov Chains

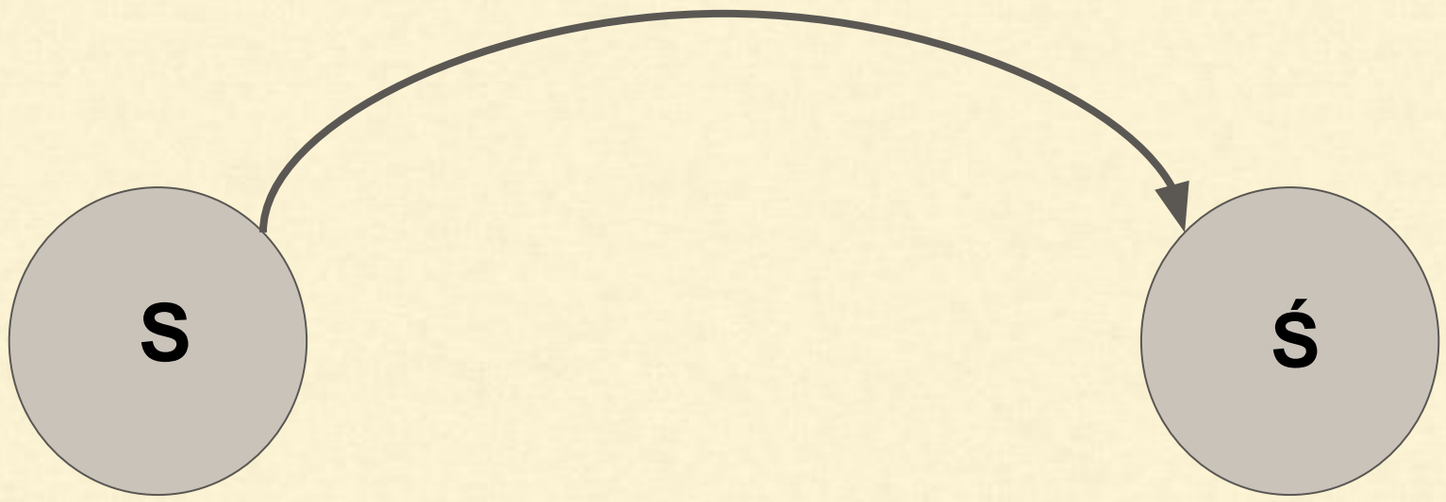
- In the early 20th century, the mathematician **Andrey Markov** studied stochastic processes with no memory, called **Markov chains**



Markov Decision Processes

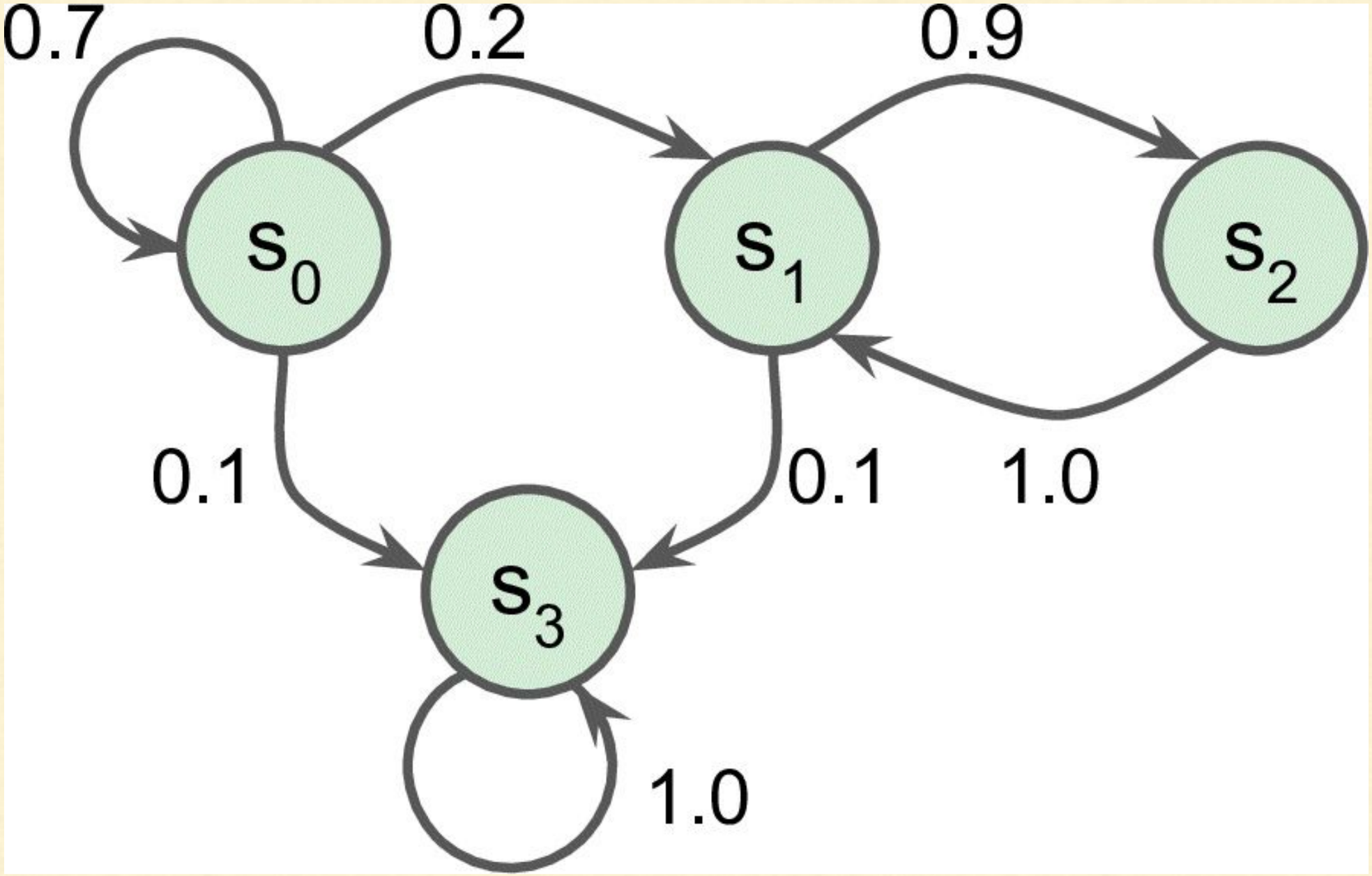
Markov Chains

- Such a process has a fixed number of states, and it randomly evolves from one state to another at each step
- The probability for it to evolve from a state **s** to a state **s′** is fixed, and it depends only on the pair **(s,s′)**, not on past states
- The system has no memory



Markov Decision Processes

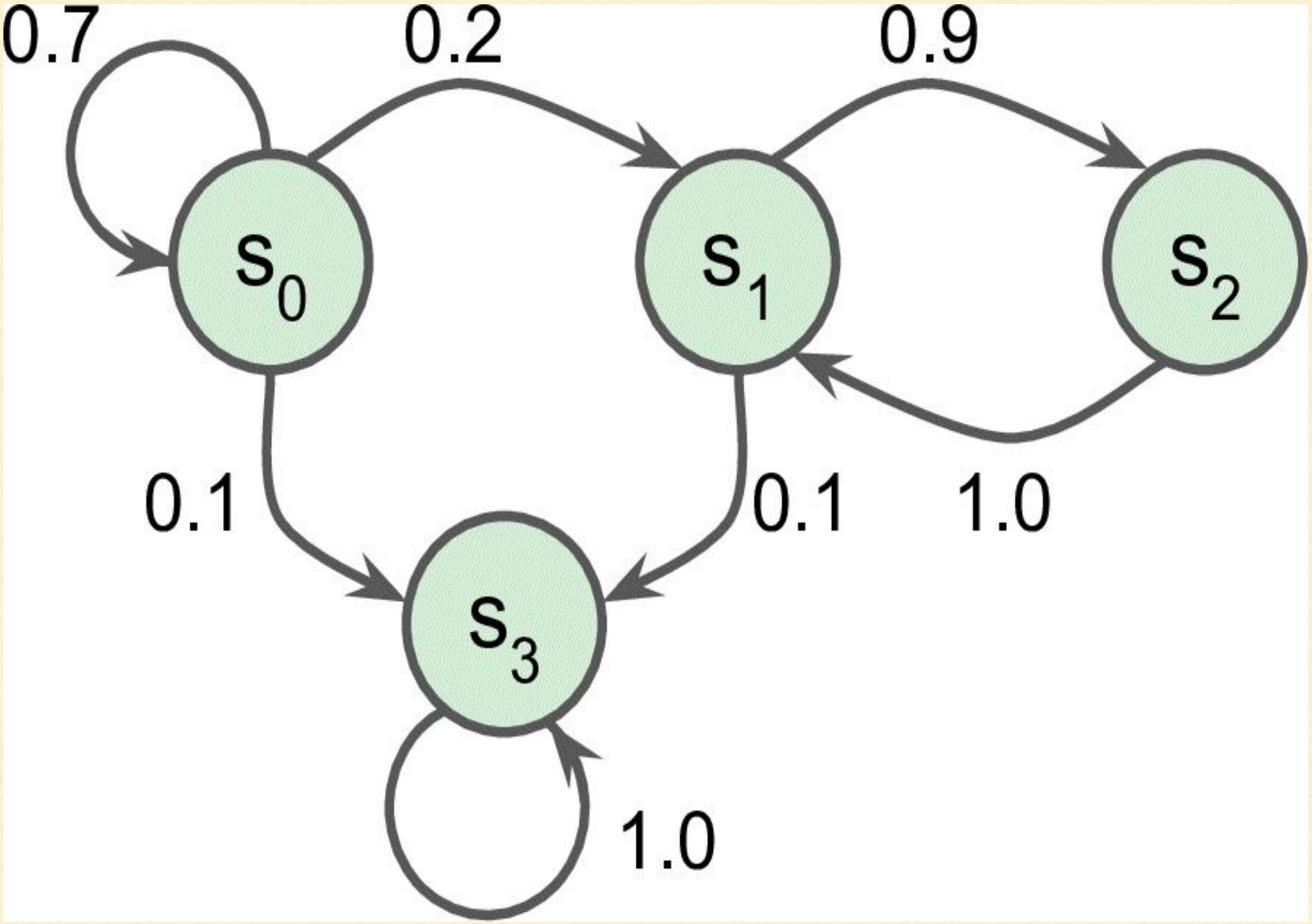
Markov Chains



An example of a Markov chain with four states

Markov Decision Processes

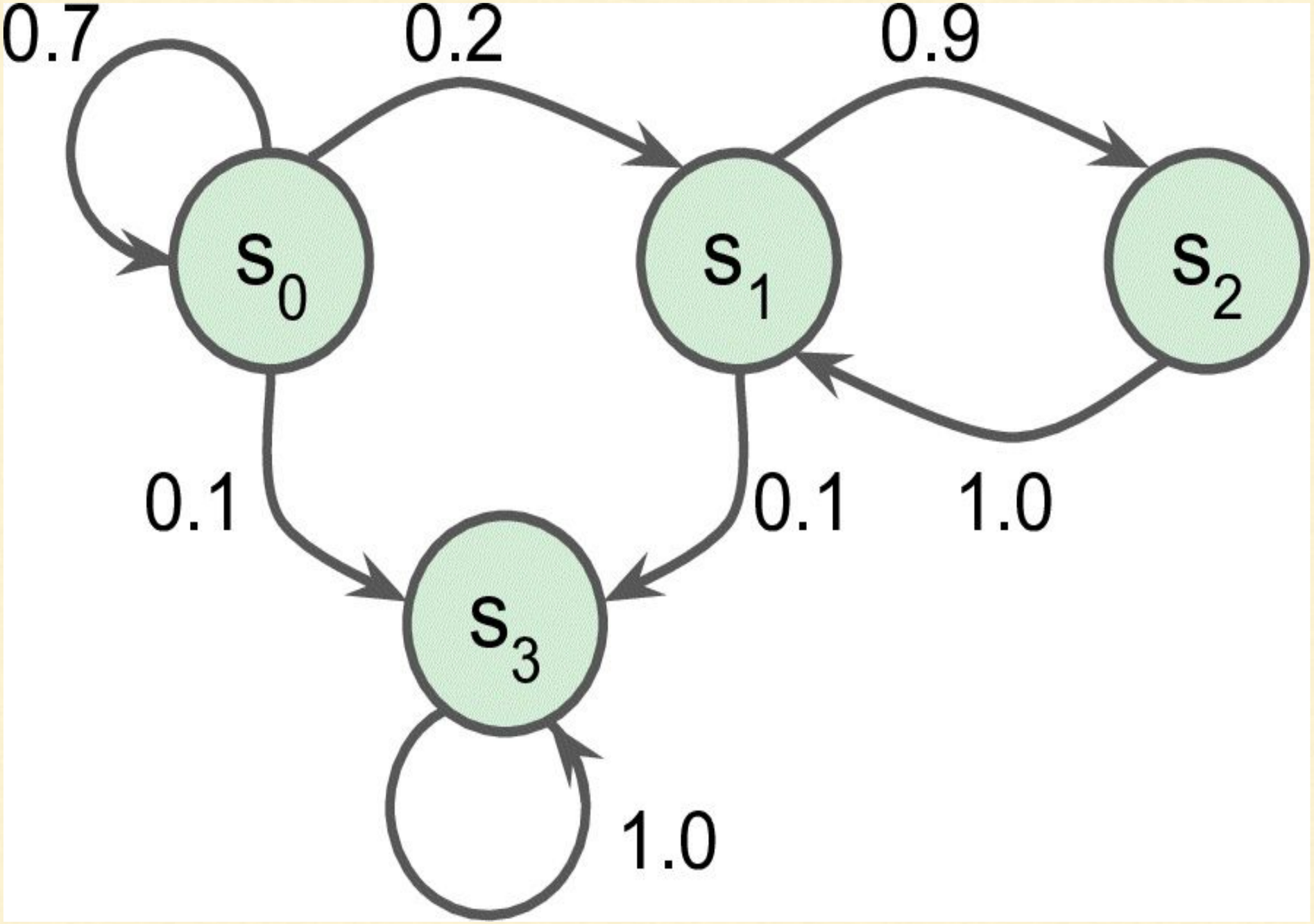
Markov Chains



Suppose that the process starts in state $\mathbf{s_0}$, and there is a **70%** chance that it will remain in that state at the next step

Markov Decision Processes

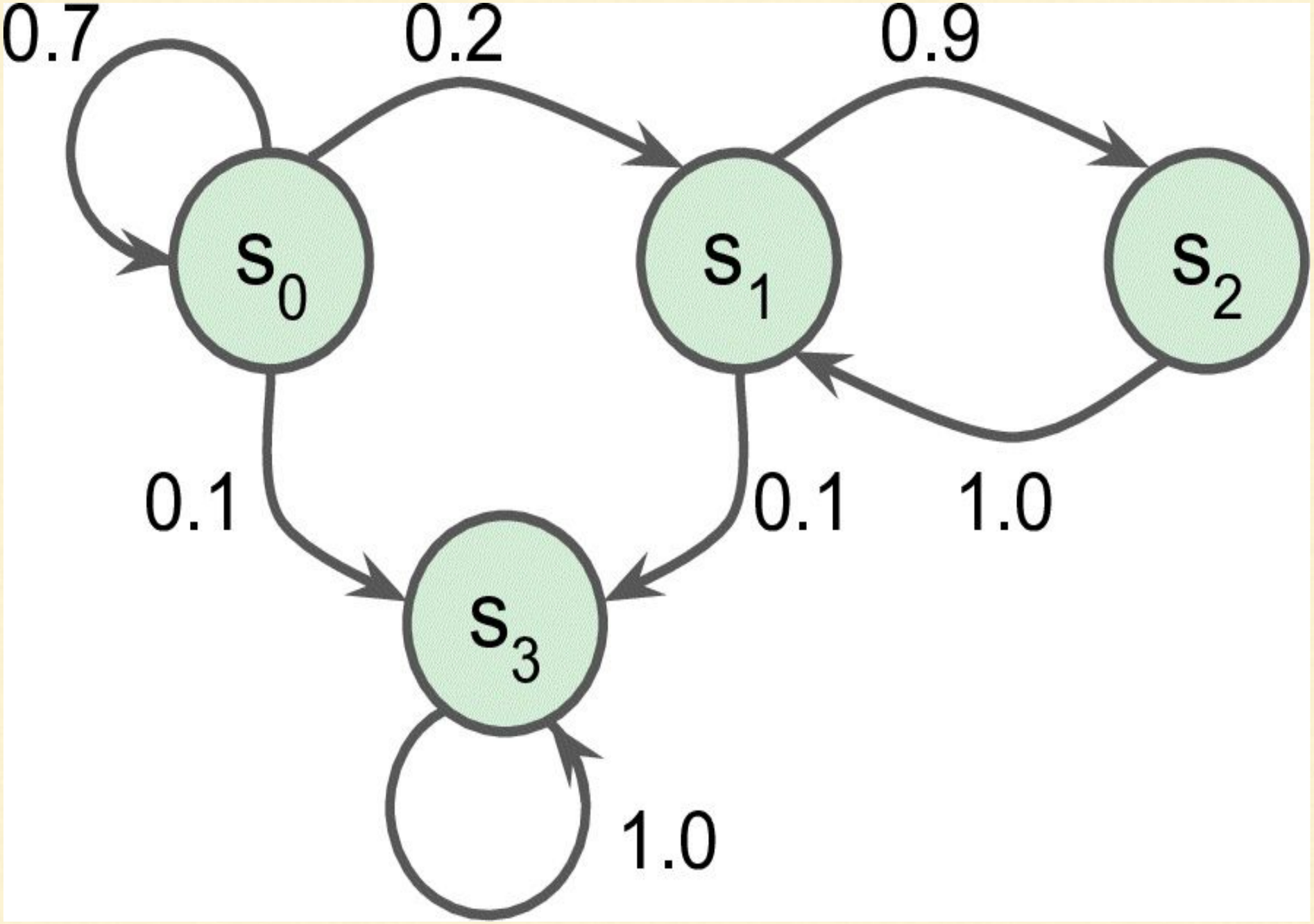
Markov Chains



Eventually it is bound to leave that state and never come back since no other state points back to s_0

Markov Decision Processes

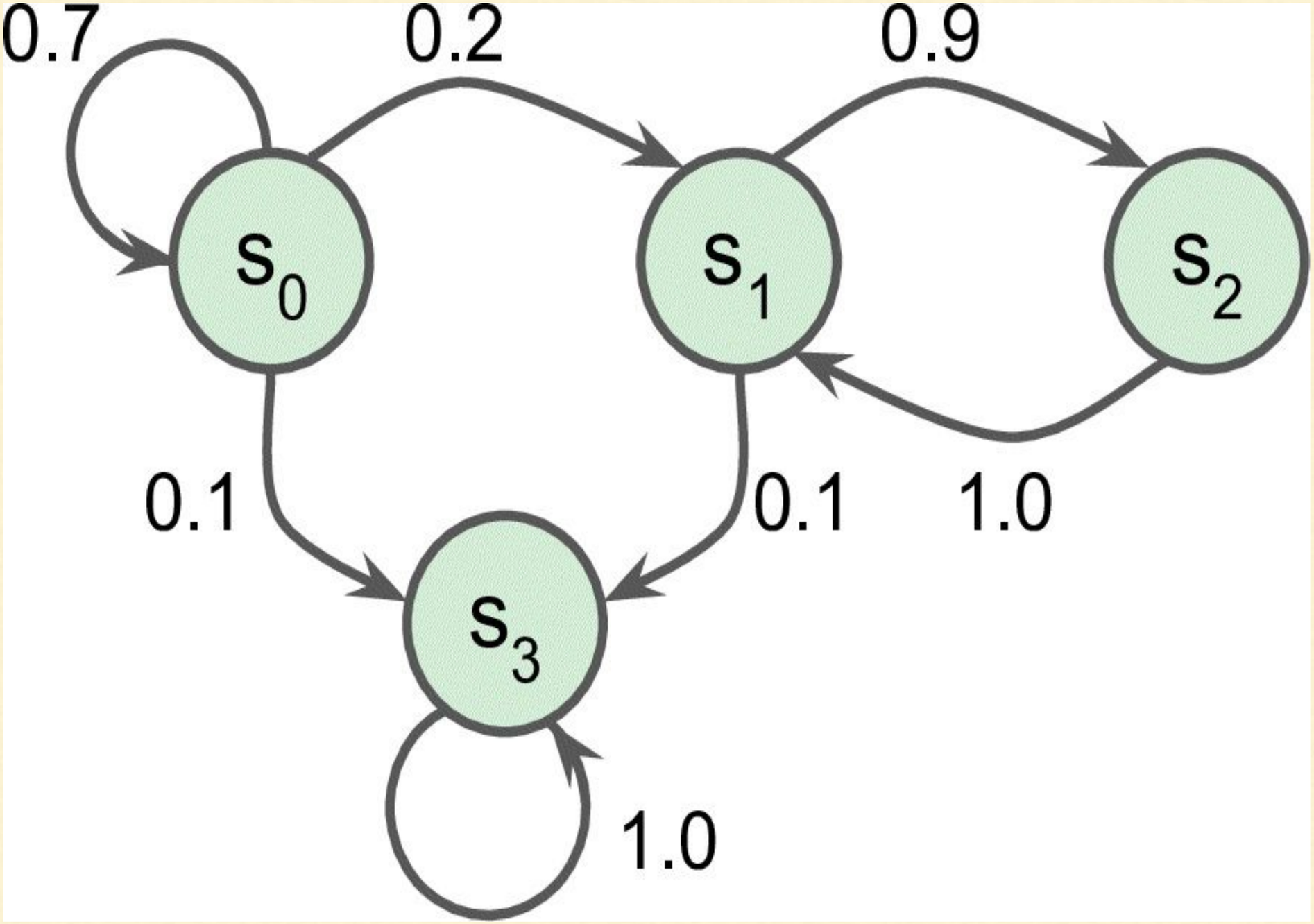
Markov Chains



If it goes to state s_1, it will then most likely go to state s_2 with **90% probability**, then immediately back to state s_1 with **100% probability**

Markov Decision Processes

Markov Chains



It may alternate a number of times between these two states, but eventually it will fall into state s_3 and remain there forever.

This is a **terminal state**

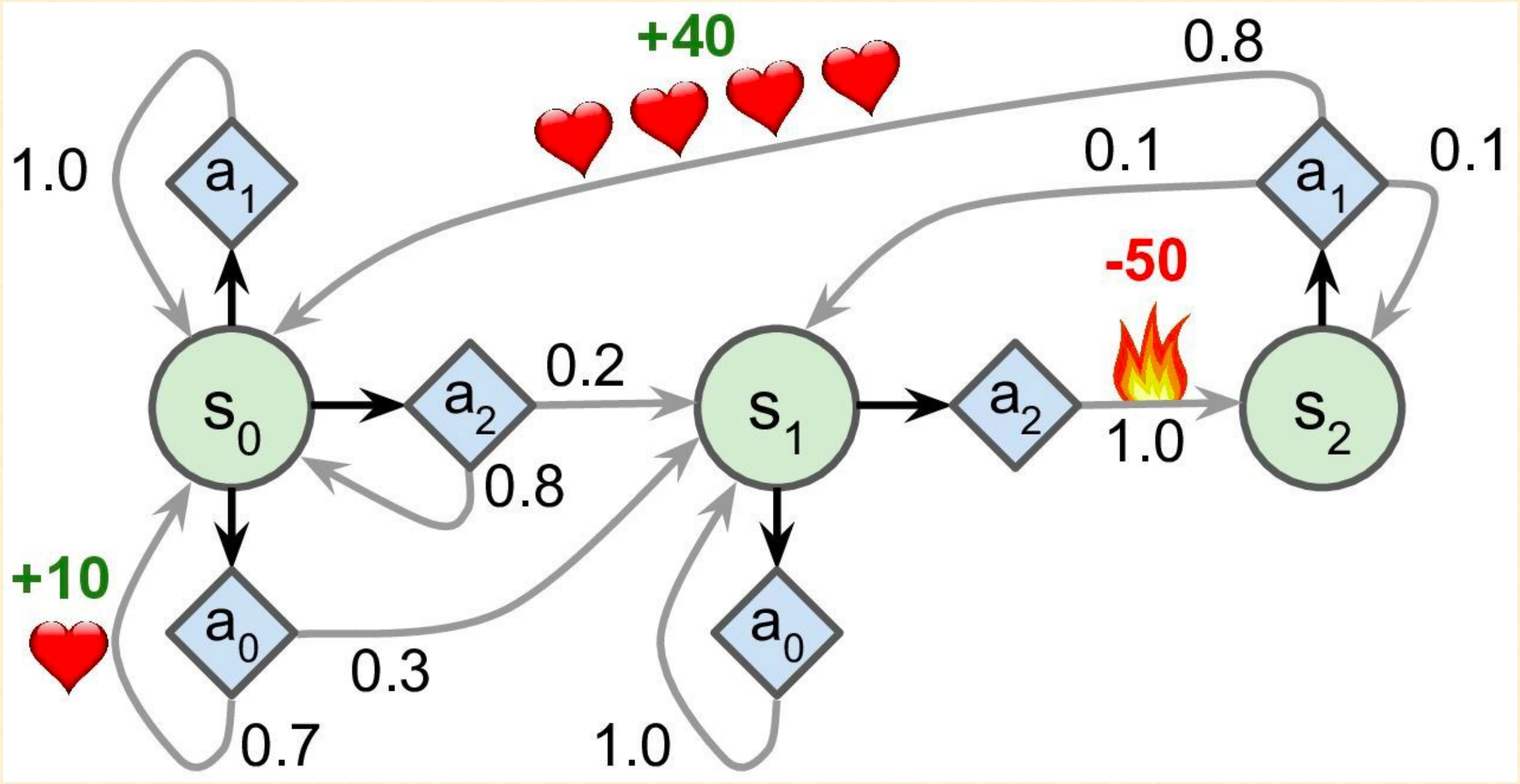
Markov Decision Processes

- Markov chains can have very different dynamics, and they are heavily used in thermodynamics, chemistry, statistics, and much more
- Markov decision processes were first described in the 1950s by **Richard Bellman**

Markov Decision Processes

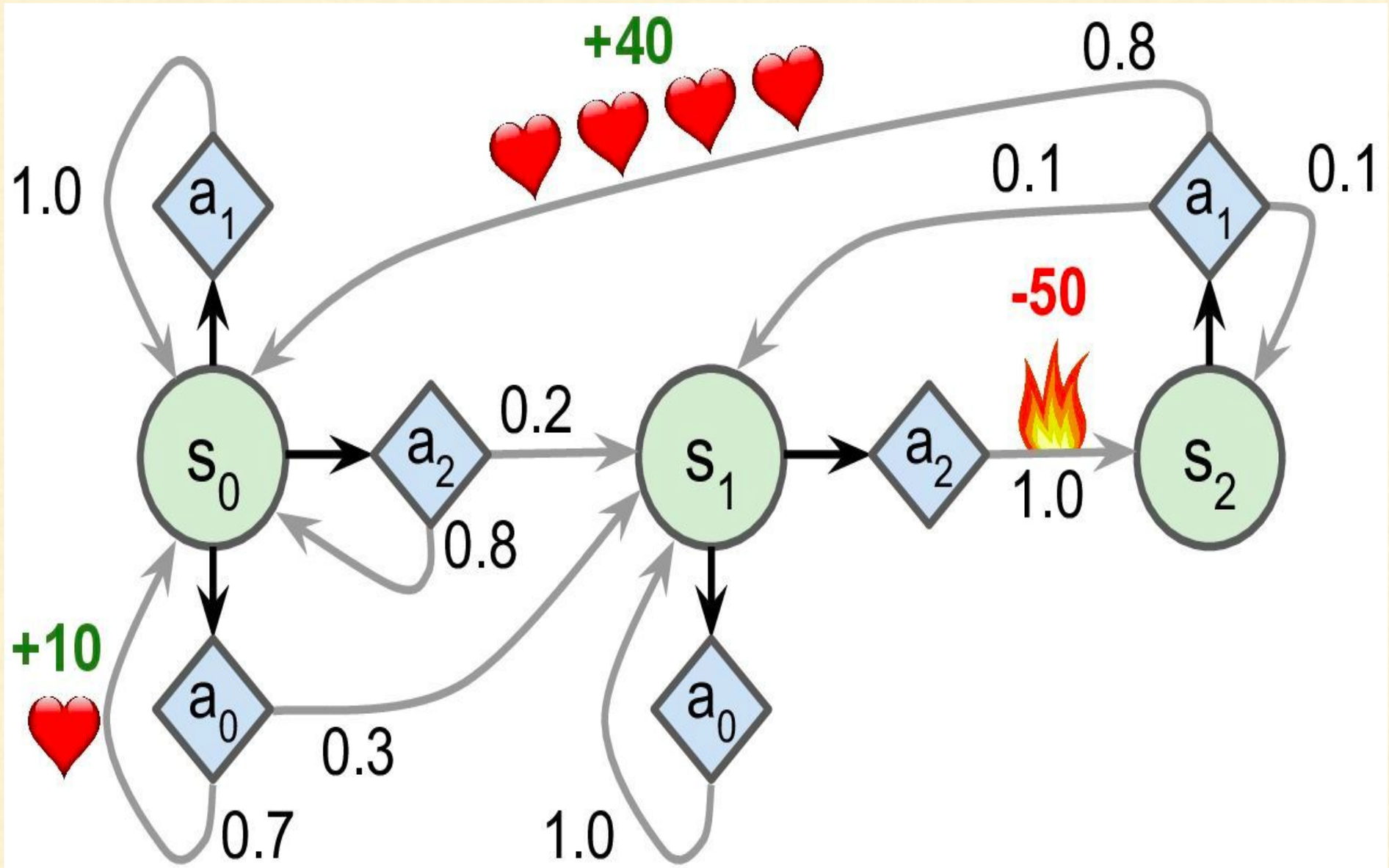
- They resemble Markov chains but with a twist:
  - At each step, an agent can choose one of several possible actions
  - And the transition probabilities depend on the chosen action
- Moreover, some state transitions return some reward, positive or negative, and the agent's goal is to find a policy that will maximize rewards over time

Markov Decision Processes



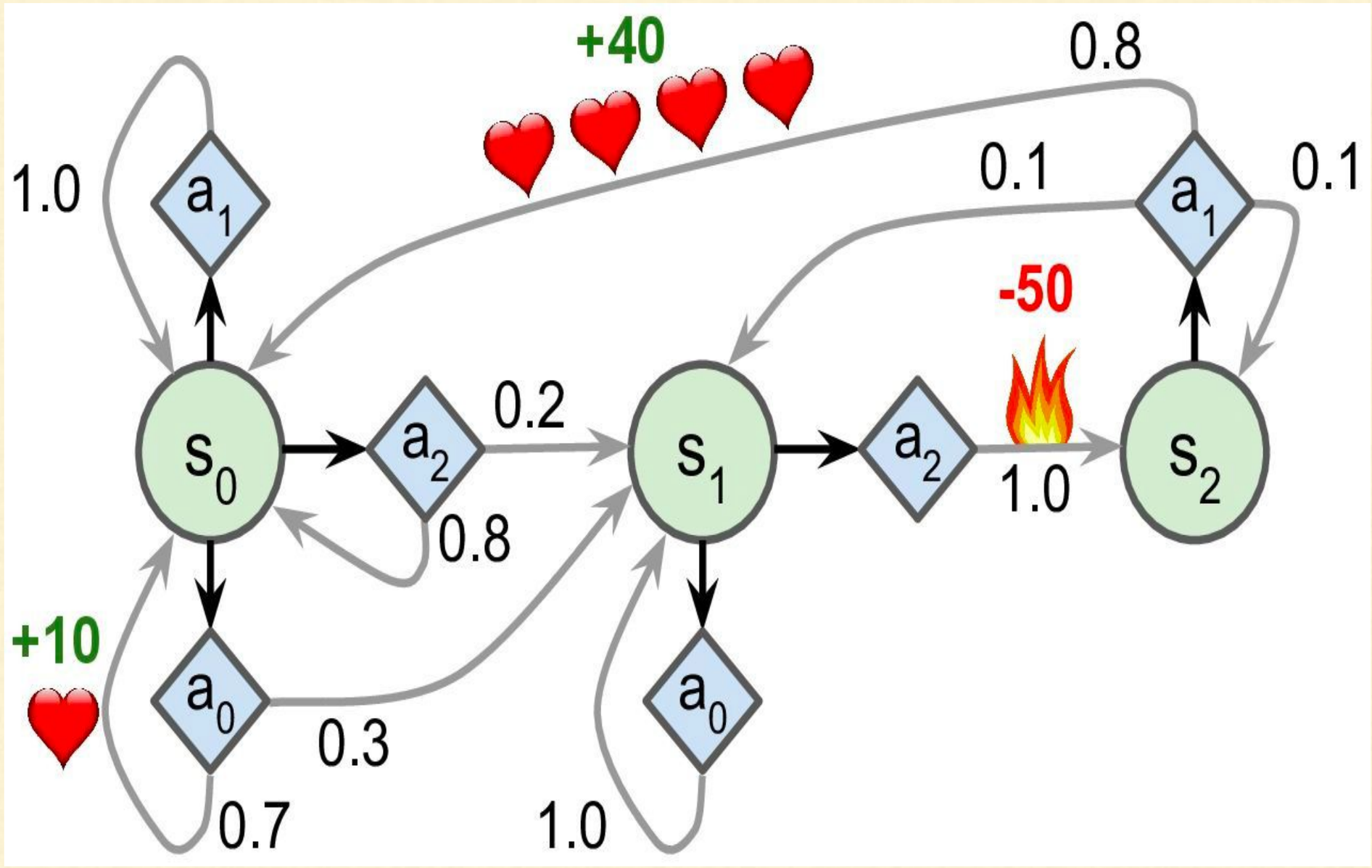
This Markov Decision Process has three states and up to three possible discrete actions at each step

Markov Decision Processes



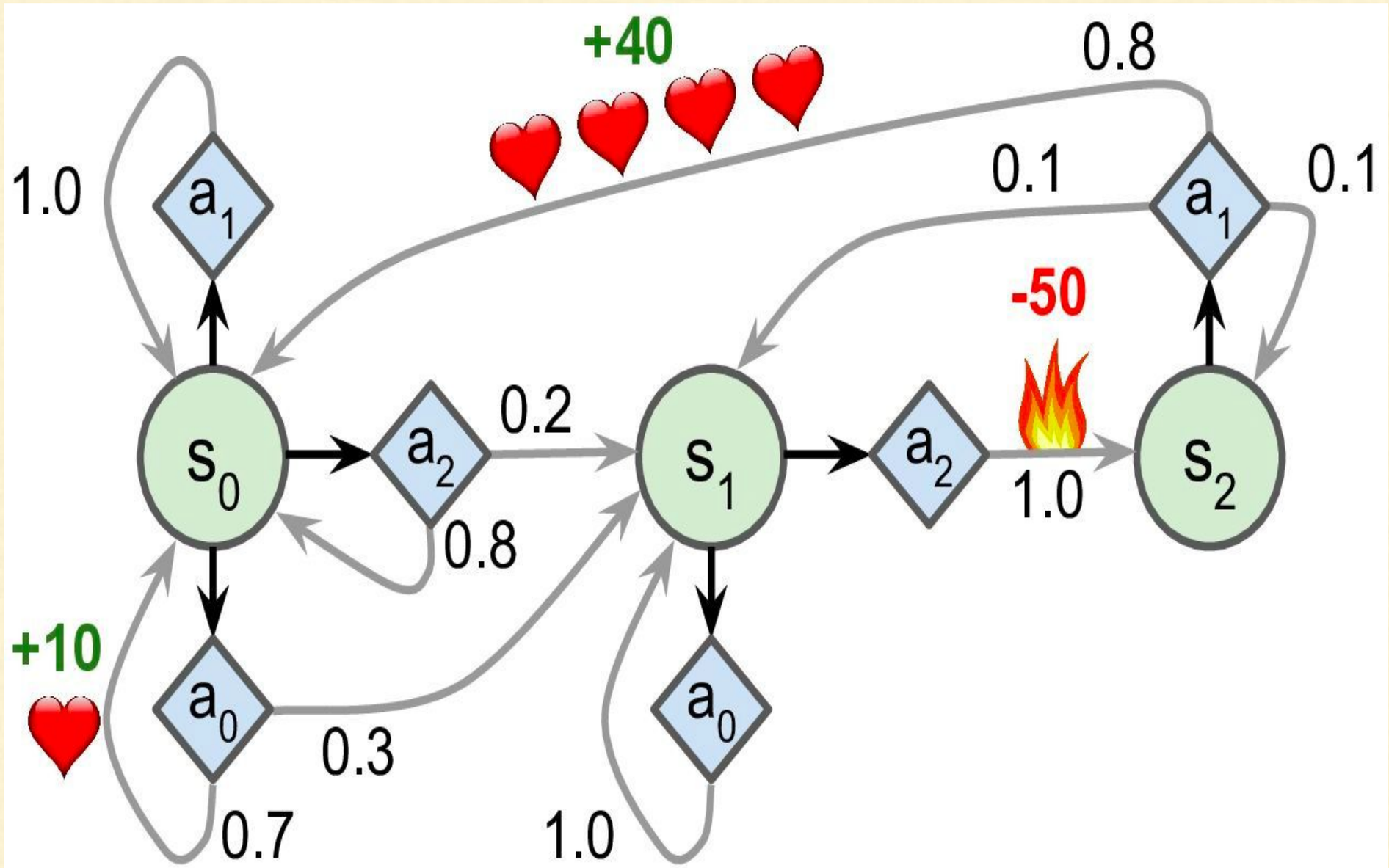
If it starts in state $\mathbf{s_0}$, the agent can choose between actions $\mathbf{a_0}$, $\mathbf{a_1}$, or $\mathbf{a_2}$. If it chooses action $\mathbf{a_1}$, it just remains in state $\mathbf{s_0}$ with certainty, and without any reward

Markov Decision Processes



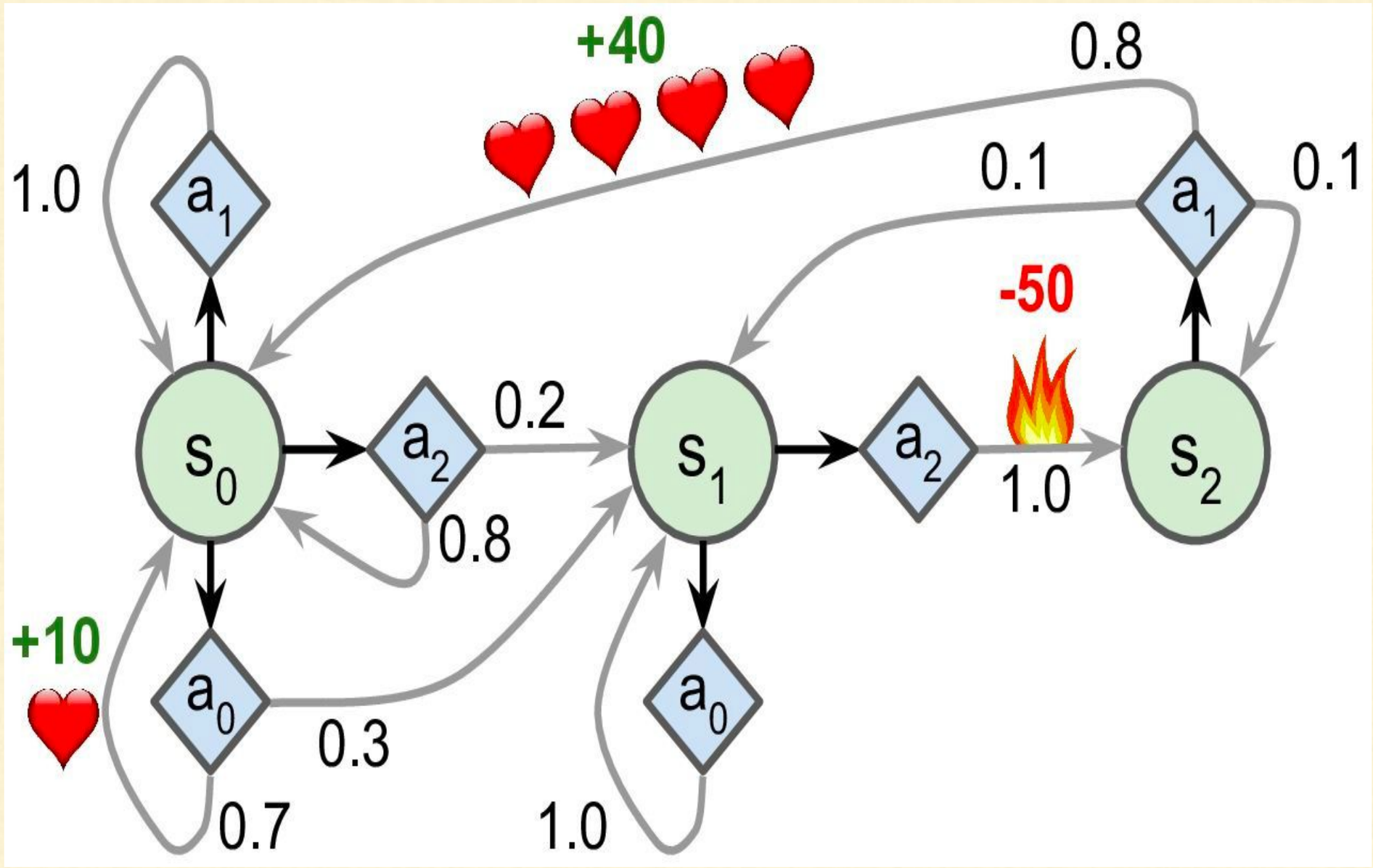
It can thus decide to stay there forever if it wants. But if it chooses action $\mathbf{a_0}$, it has a **70%** probability of gaining a reward of **+10**, and remaining in state $\mathbf{s_0}$

Markov Decision Processes



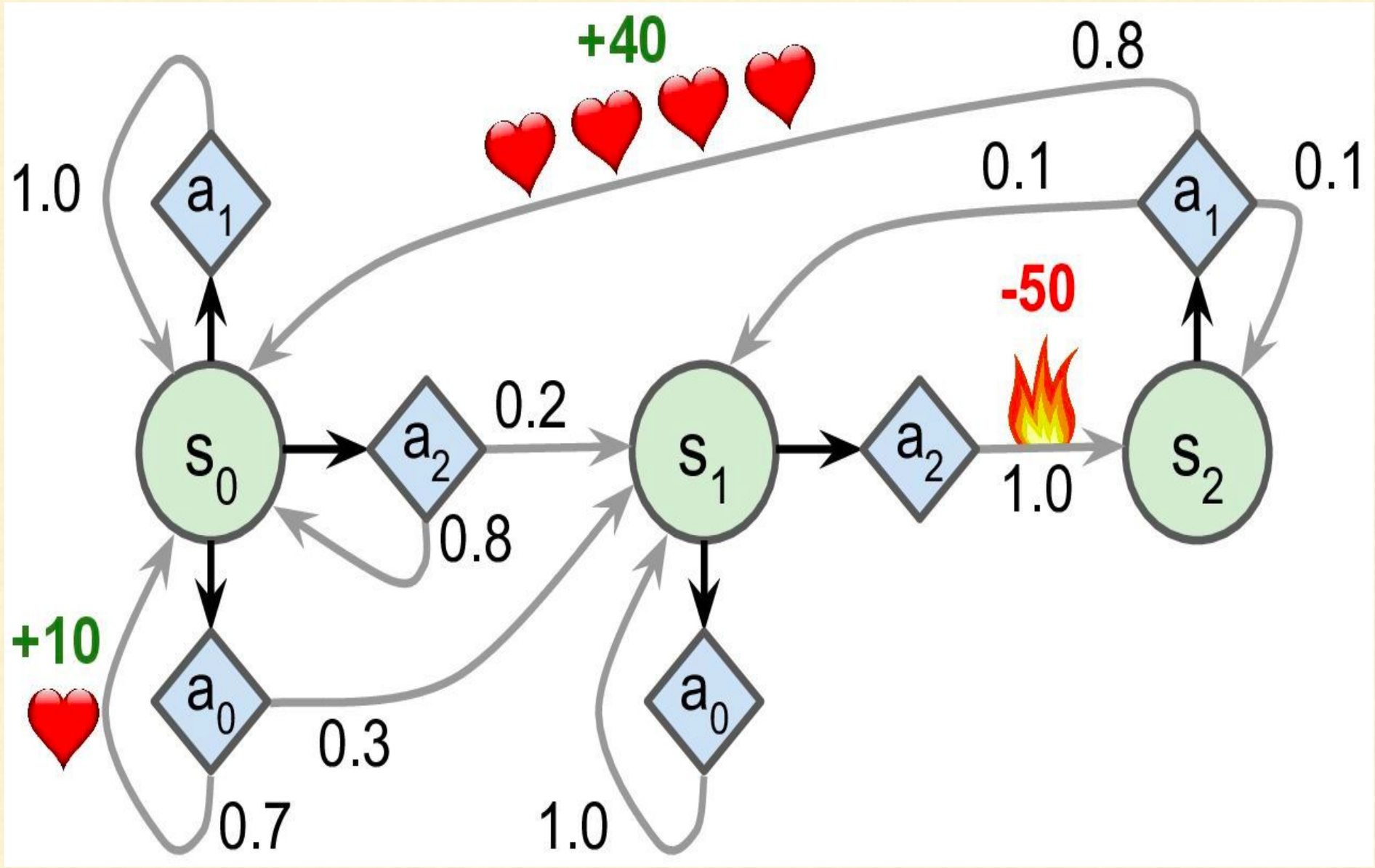
It can then try again and again to gain as much reward as possible. But at one point it is going to end up instead in state $\mathbf{s_1}$ In state $\mathbf{s_1}$ it has only two possible actions: $\mathbf{a_0}$ or $\mathbf{a_2}$

Markov Decision Processes



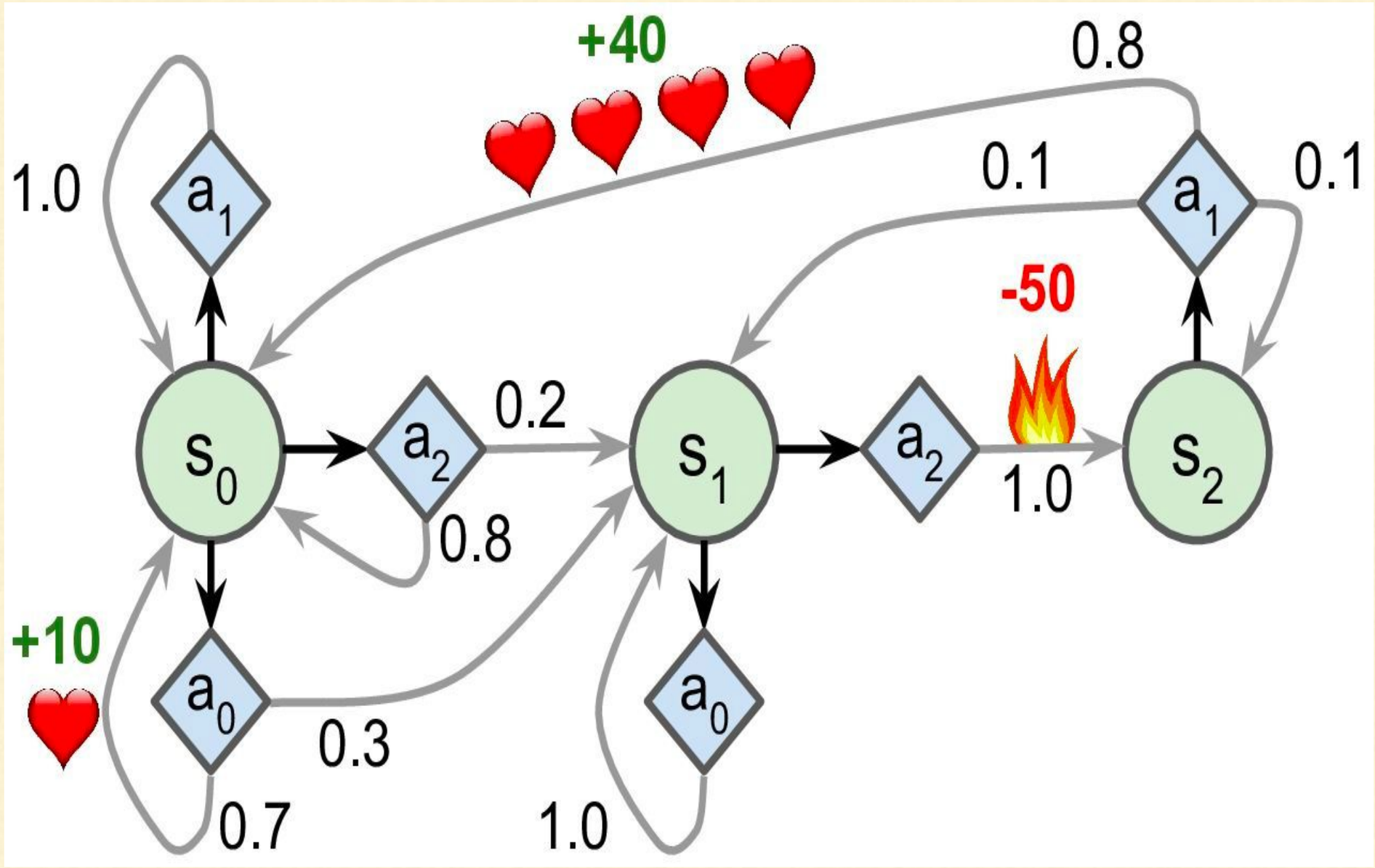
It can choose to stay put by repeatedly choosing action $\mathbf{a_0}$, or it can choose to move on to state $\mathbf{s_2}$ and get a negative reward of **–50**

Markov Decision Processes



In state $\mathbf{s_2}$ it has no other choice than to take action $\mathbf{a_1}$, which will most likely lead it back to state $\mathbf{s_0}$, gaining a reward of **+40** on the way

Markov Decision Processes

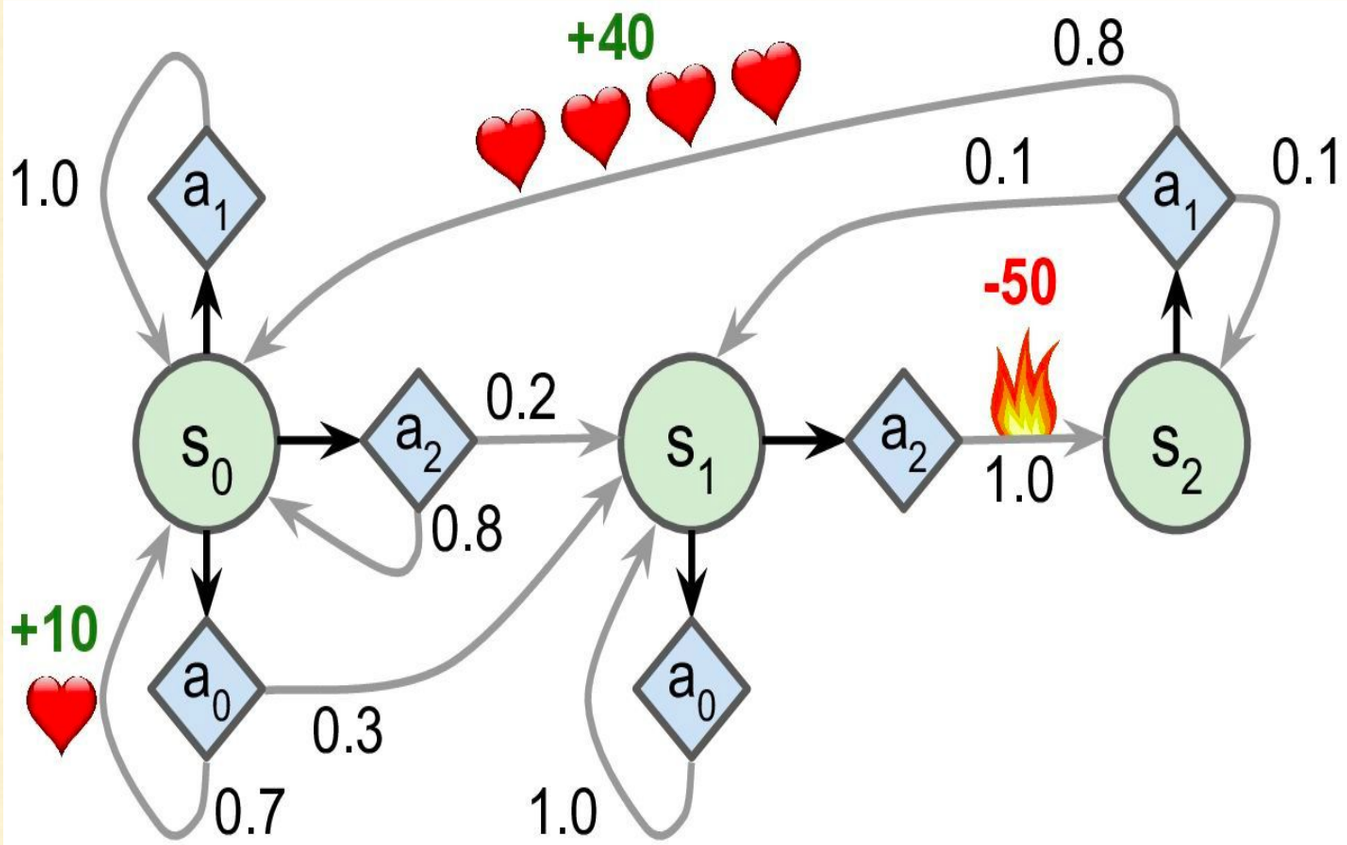


Question

By looking at this MDP, can we guess which strategy will gain the most reward over time?

Markov Decision Processes

- In state $\mathbf{s_0}$ it is clear that action $\mathbf{a_0}$ is the best option
- And in state $\mathbf{s_2}$ the agent has no choice but to take action $\mathbf{a_1}$
- But in state $\mathbf{s_1}$ it is not obvious whether the agent should stay put $\mathbf{a_0}$ or go through the fire $\mathbf{a_2}$



So how do we estimate the optimal state value of any state s ??

Markov Decision Processes

- **Bellman** found a way to estimate the optimal state value of any state **s**, noted **V*(s)**, which is the sum of all discounted future rewards the agent can expect on average after it reaches a state **s**, assuming it acts optimally
- He showed that if the agent acts optimally, then the **Bellman Optimality Equation** applies

$$V^*(s) = \max_a \sum_{s'} T(s, a, s')[R(s, a, s') + \gamma . V^*(s')] \quad \text{for all } s$$

Markov Decision Processes

$$V^*(s) = \max_a \sum_{s'} T(s, a, s')[R(s, a, s') + \gamma . V^*(s')] \quad \text{for all } s$$

This recursive equation says that

- *If the agent acts optimally, then the optimal value of the current state is equal to the reward it will get on average after taking one optimal action, plus the expected optimal value of all possible next states that this action can lead to*

Markov Decision Processes

Let's understand this equation

$$V^*(s) = \max_a \sum_{s'} T(s, a, s')[R(s, a, s') + \gamma . V^*(s')] \quad \text{for all } s$$

- **T(s, a, s′)** is the transition probability from **state s** to **state s′**, given that the agent chose **action a**
- **R(s, a, s′)** is the reward that the agent gets when it goes from **state s** to **state s′**, given that the agent chose **action a**
- **γ** is the discount rate

Questions?

https://discuss.cloudxlab.com

reachus@cloudxlab.com