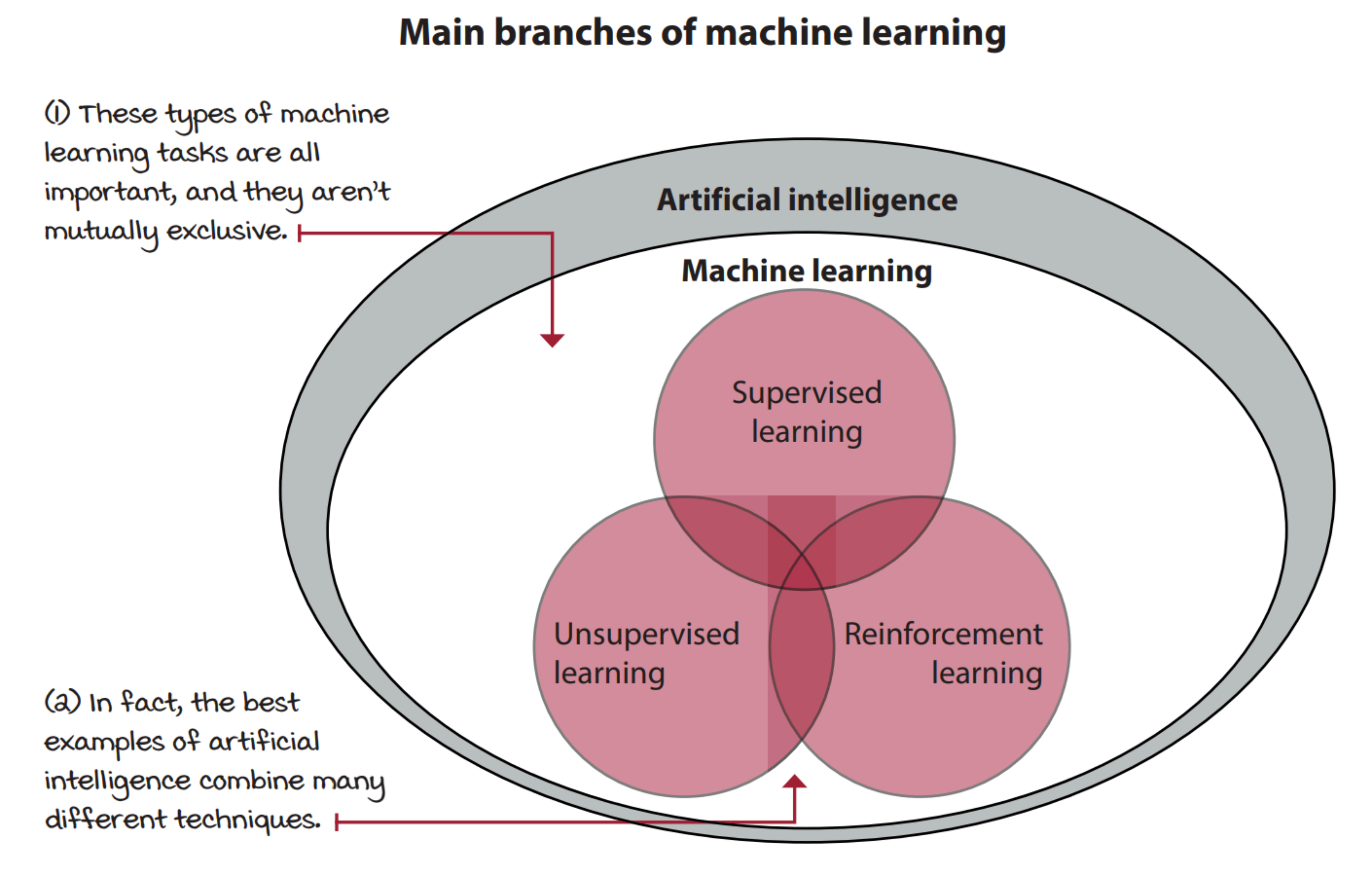
Reinforcement Learning Training 2025

Where is RL in ML?



Supervised Learning

- We know *all* the right answers (label)
- We teach machine.

Unsupervised Learning

- We don't know the answer.
- We let machine find structure in the data.

Reinforcement Learning

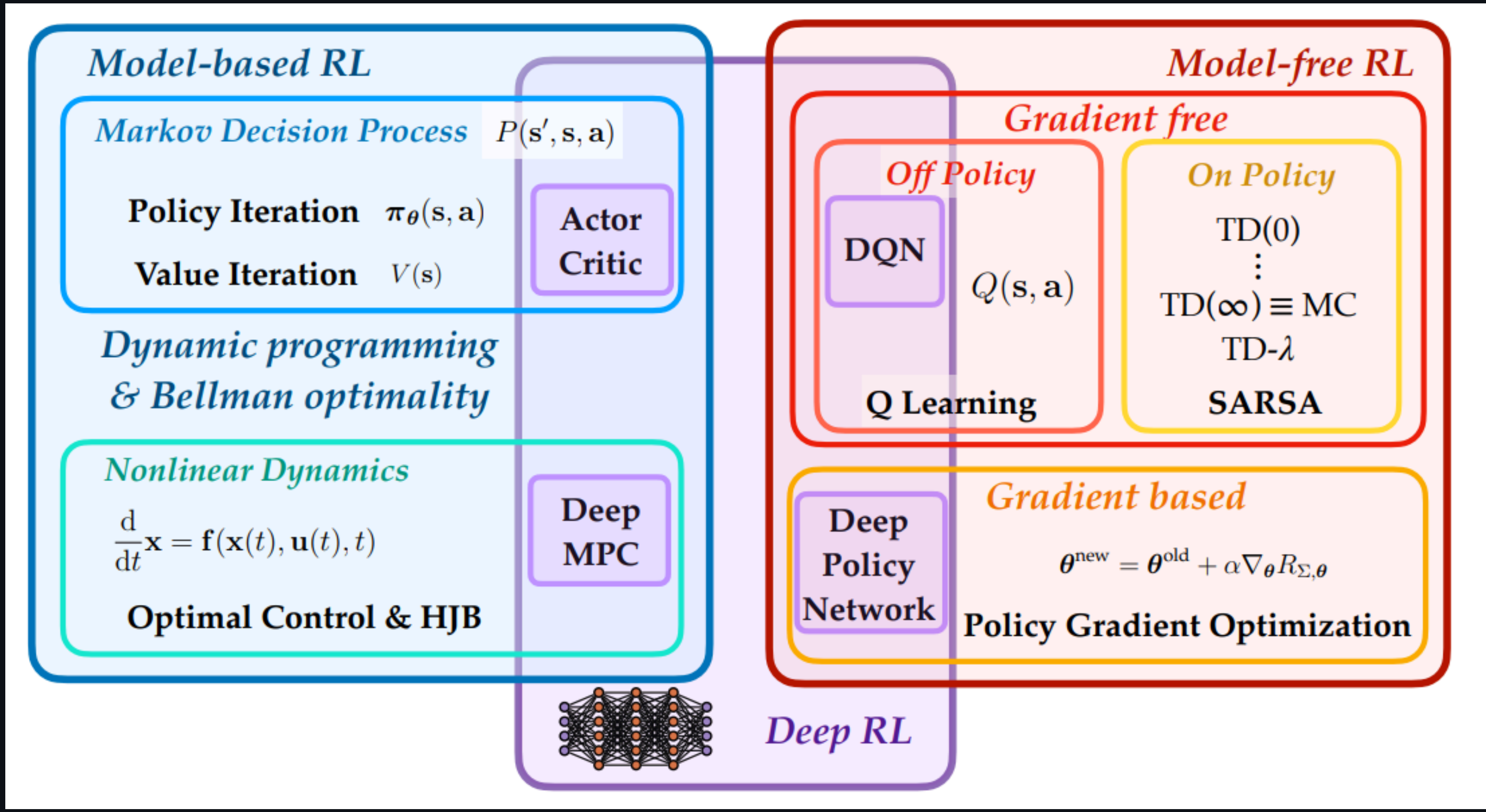
- We don't know *all* the right answer
  - but we have a way to conduct *trial-and-error* experiments.
- We let the machine *discover* the answers.

Applications

- `ChatGPT`
  - Enhanced by reinforcement learning through a technique called Reinforcement Learning from Human Feedback (RLHF). [1] [2]
- `Spot`
  - Utilize reinforcement learning (RL) to enhance their locomotion and manipulation capabilities. [3]

Types of RL

- Don't worry. We will come back later.



RL Formalism

- Entities
  - Agent
  - Environment
- Communimation
  - Actions
  - Reward
  - Observation

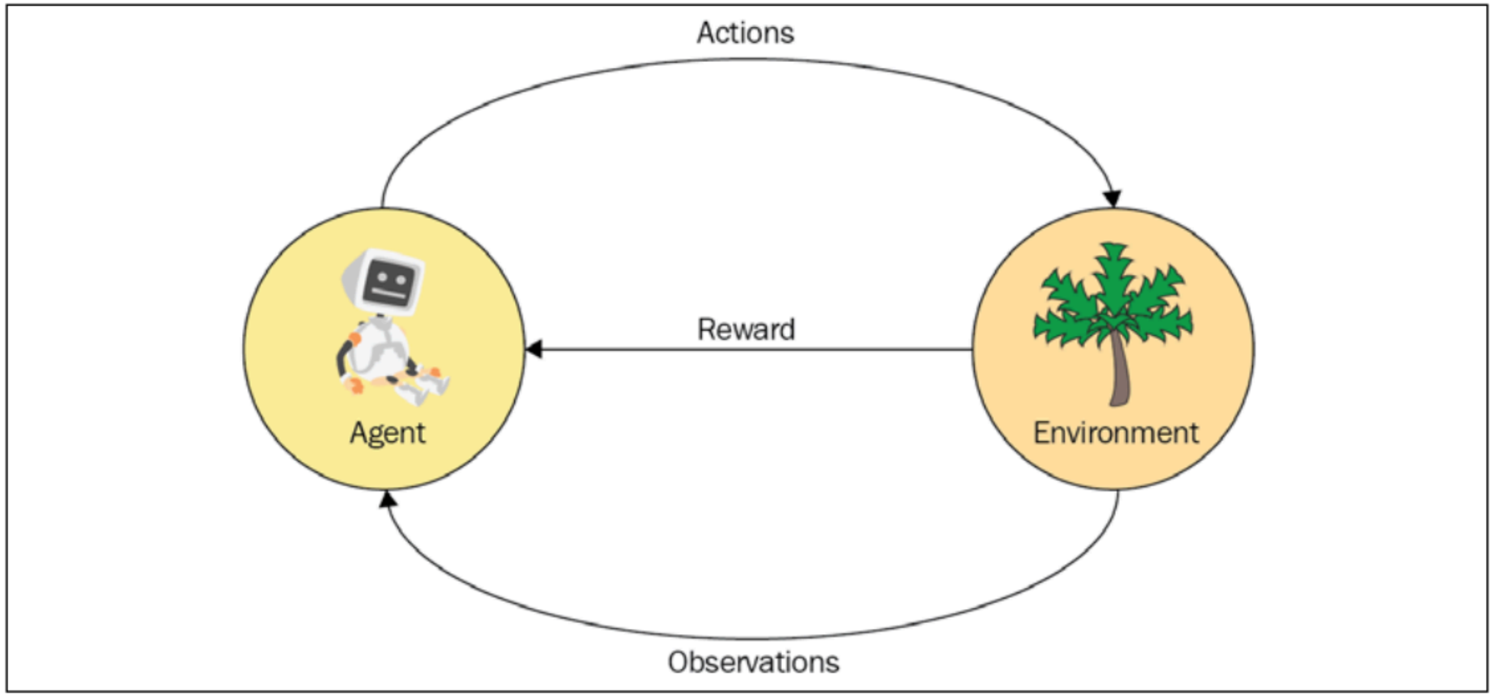


Figure 1.2: RL entities and their communication channels

Agent

- An agent is somebody or something that interact with the environment.
- *The thing that is going to solve our problem.*

Reward

- A scalar value we obtain periodically from the environment.
    - Can be positive or negative
- Tell our agent how well it has behaved.
- An agent wants to get the largest *accumulated* reward over its sequence of actions.

Environment

- The environment is everything outside of an agent.
- The agent's communication with the environment is limited to
  - Reward (obtained from the environment)
  - Actions (executed by the agent and given to the environment)
  - Observations (some information besides the reward that the agent receives from the environment).

Action

- Actions are things that an agent can do in the environment.
- Two types of actions
  - **Discrete actions** form the finite set of mutually exclusive things an agent can do, such as move left or right.
  - **Continuous actions** have some value attached to them, such as a car's action turn the wheel having an angle and direction of steering.

Observation

- Observations are pieces of information that the environment provides the agent with that say what's going on around the agent.
- *I am guessing it is something that agent can use to make action?*

Markov Processes (MP)

- Also called a Markov chain
- MP Models a system observed through a sequence of `states`.
    - You cannot influence the system, can only watch.

MP - Markov Property

- The future state depends only on the current state, not on the full history.
  - The current state is enough to predict the future.
- If you think you need history, you can add more quantities to the current state (e.g. adding velocity and acceleration, in addition to position, to model motion)

MP - Example (Weather Model)

- States: `{sunny, rainy}`
- Sequence example: `[sunny, sunny, rainy, sunny, …]`
- The Markov property means the probability of rain tomorrow depends only on today's weather, not previous days.
    - To improve this we can include season with weather states.

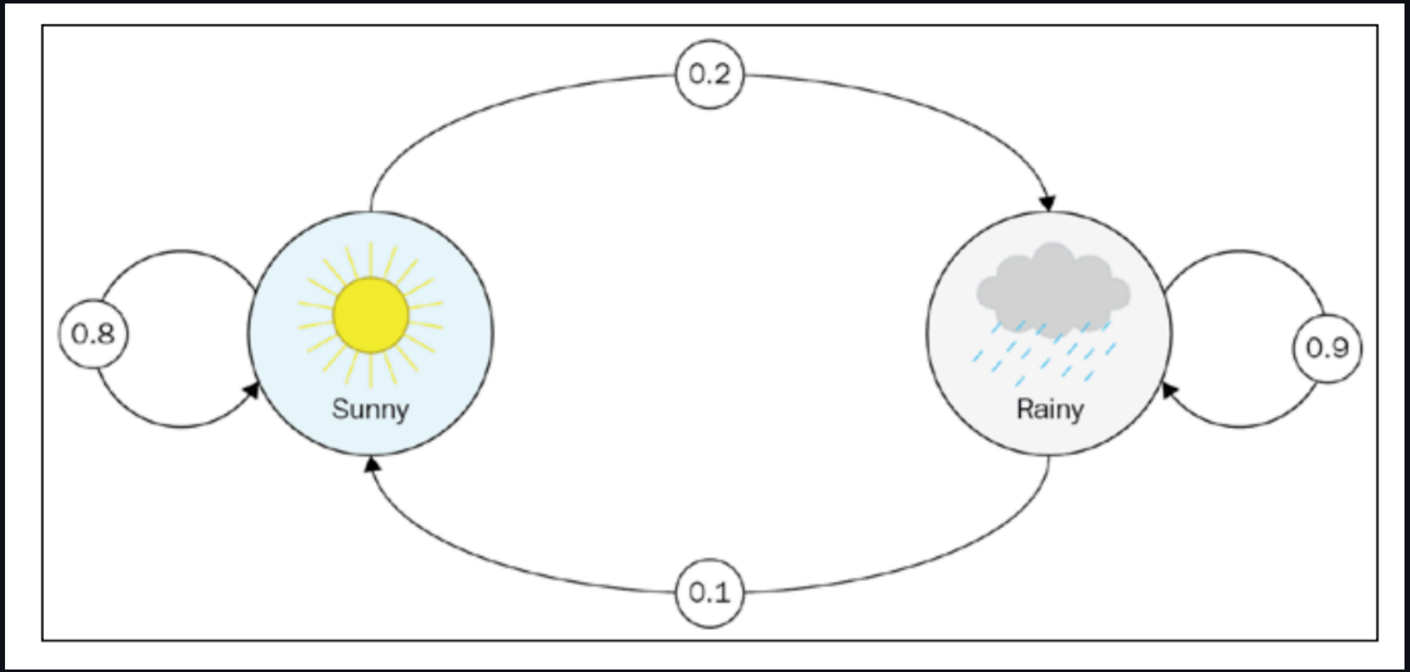
MP - Example (Weather Model)

- We can represents the probability of transitioning from state i to state j using the **trantition matrix**.

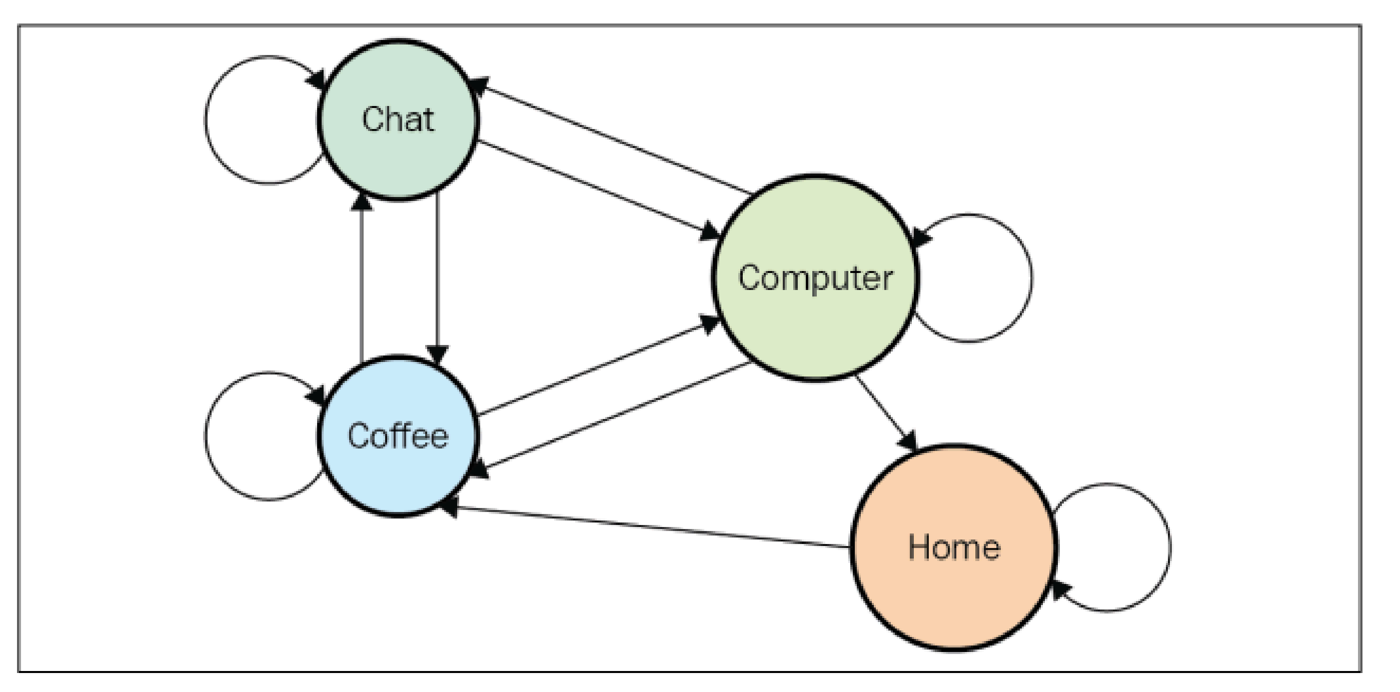
	Sunny	**Rainy**
Sunny	0.8	0.2
Rainy	0.1	0.9

MP - Example (Weather Model)

- Visual reprentation



MP - Example (Office Worker Model)



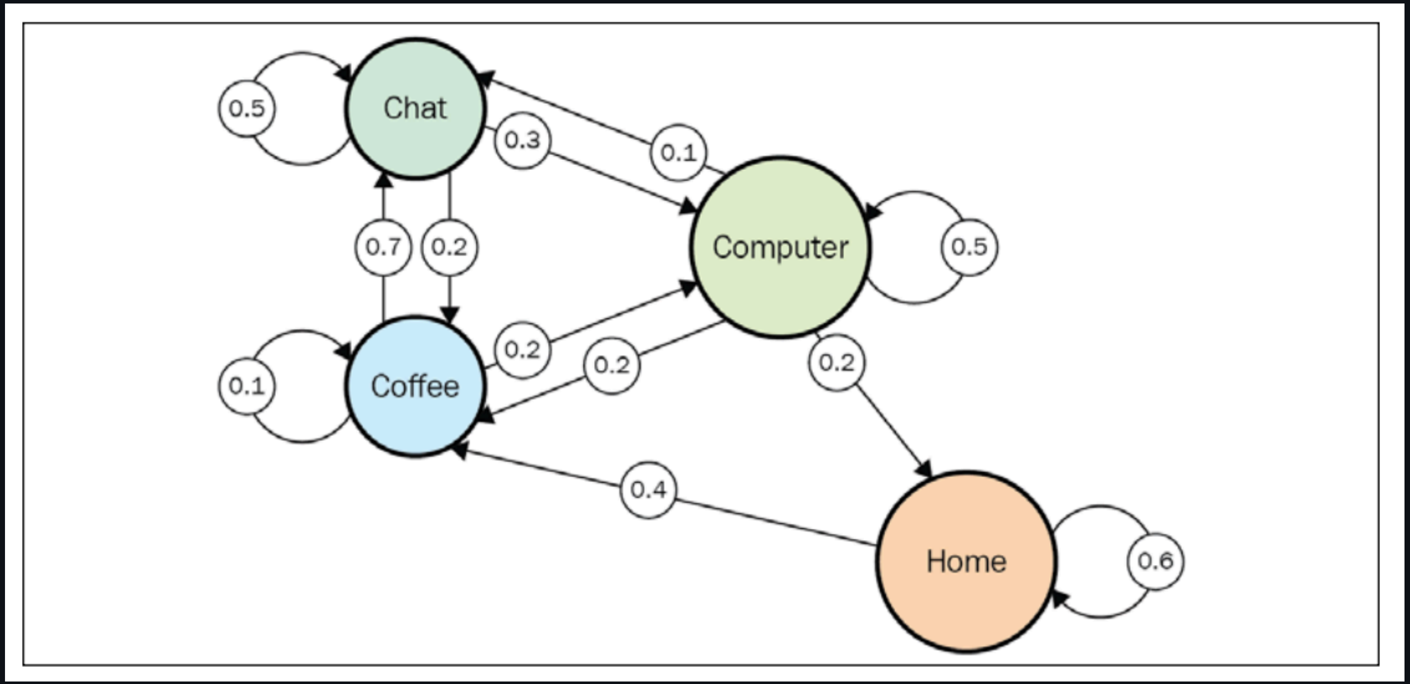
MP - Example (Office Worker Model)

- Transition matrix

From \ To	Home	Coffee	Chat	Computer
Home	60%	40%	0%	0%
Coffee	0%	10%	70%	20%
Chat	0%	20%	50%	30%
Computer	20%	20%	10%	50%

MP - Example (Office Worker Model)

- Visual representation



Estimating the transition matirx

- In real life, we don't know the transition matrix.
- Instead, we estimating transition matrix from **episodes** (sequences of states).
  - Count all observed transitions from each state to every other state.
  - Normalize these counts so that the probabilities from each state sum to 1.
  - With more episodes, our estimation improves.

Markov Reward Processes (MRP)

- We extend MP by associating a reward value with each state transition.
- For each **episode**, the return at time t (denoted as G_t) is the sum of future rewards, discounted by γ at each step:

$$G_t = R_{t+1} + \gamma R_{t+2} + \ldots = \sum_{k=0}^{\infty} \gamma^k R_{t+1+k}$$

- where γ is a scalar value between 0 and 1 called a `discount factor`.

MRP - Discount Factor

- γ determines how much future rewards are valued compared to immediate rewards.
  - $\gamma = 1$
    - The agent values all future rewards equally. This represents perfect foresight.
  - $\gamma = 0$
    - The agent only considers the immediate reward, ignoring all future rewards—total short-sightedness.

MRP

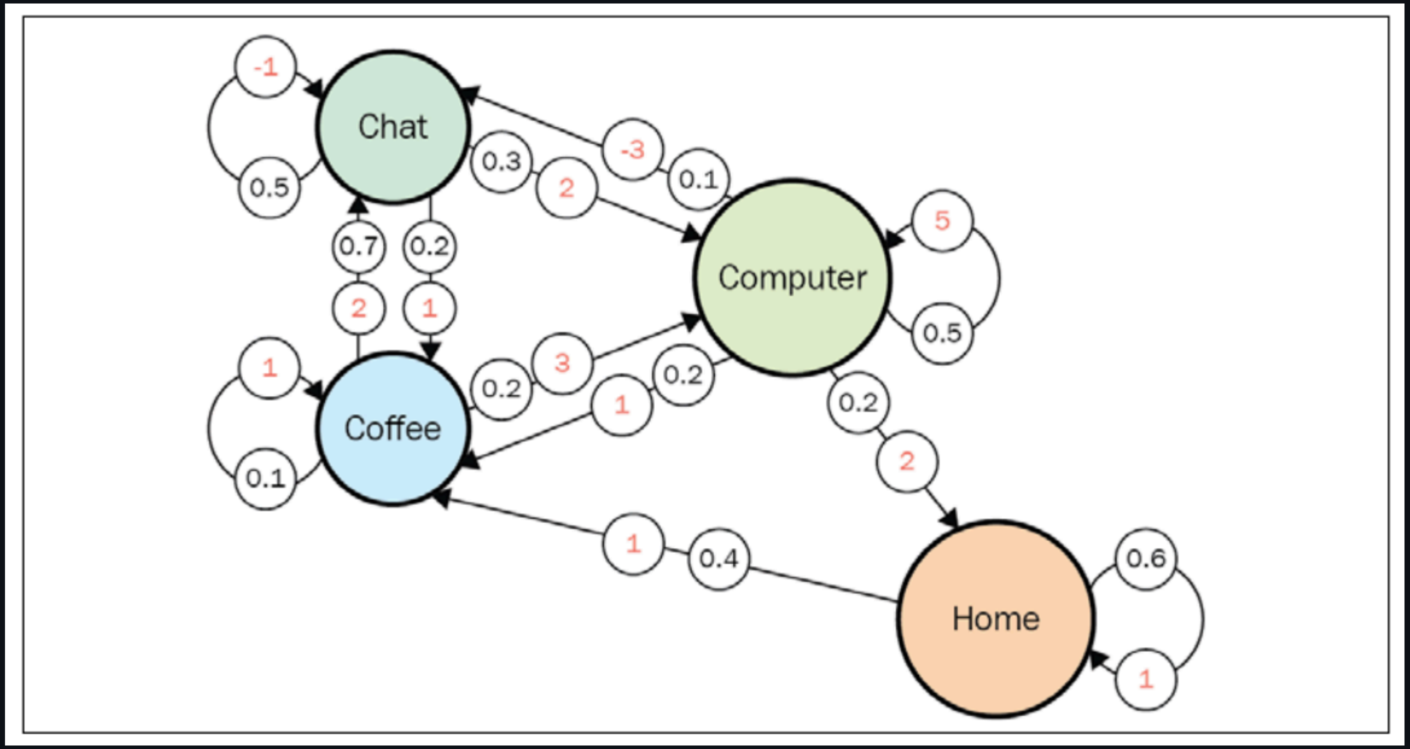
- Recall that state transition is probabilistic.
  - G_t can vary even for the same state.
- We want to know the **expected** return instead

$$V(s) = \mathbf{E}[G|S_t = s]$$

- Think about averaging return from many episodes.
- V is also called **value function**.

Practical example of $V(s)$

- Let $\gamma = 0$, calculate $V(s)$

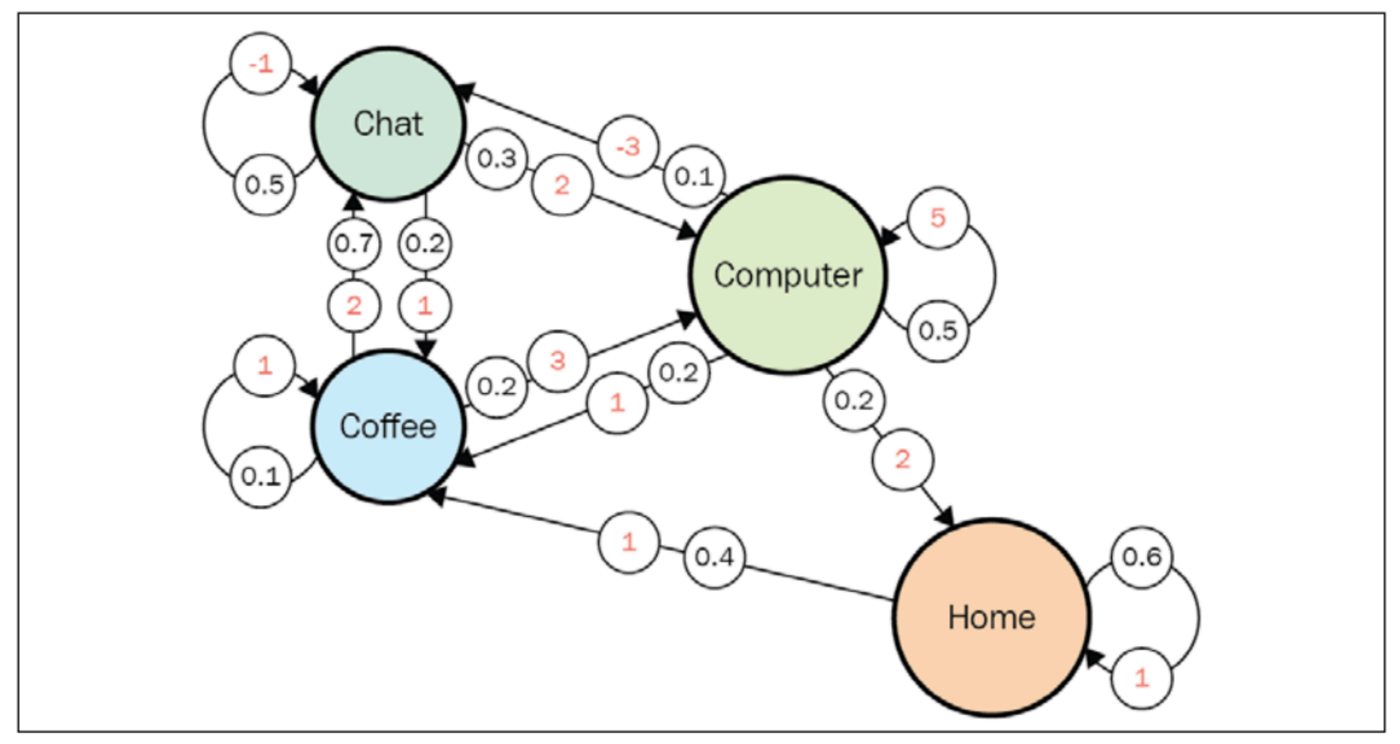


Practical example of $V(s)$

$$V(chat) = -1 \times 0.5 + 2 \times 0.3 + 1 \times 0.2 = 0.3$$
$$V(coffee) = 2 \times 0.7 + 1 \times 0.1 + 3 \times 0.2 = 2.1$$
$$V(home) = 1 \times 0.6 + 1 \times 0.4 = 1.0$$
$$V(computer) = 5 \times 0.5 + (-3) \times 0.1 + 1 \times 0.2 + 2 \times 0.2 = 2.8$$

- Computer is the most valuable state to be in.

Practical example of $V(s)$



- If $\gamma = 1$, then $V(s) = \infty$
- This is why we usually introduce $\gamma < 1$ in MRP.

Markov Decision Process

- Add a set of actions (A)
- Agent can now choose an action to take.
- Our transition matrix will now have "action" dimension.

Before: MP

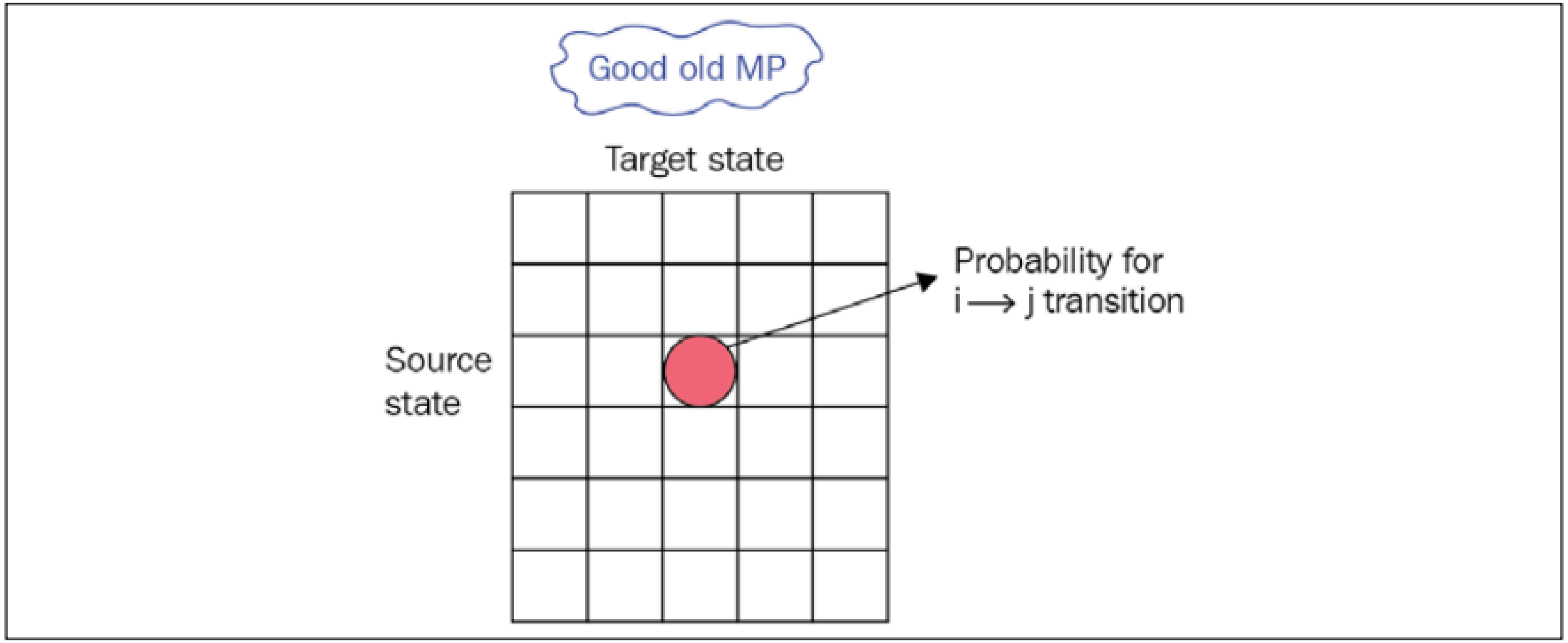


Figure 1.8: The transition matrix in square form

After: MDP

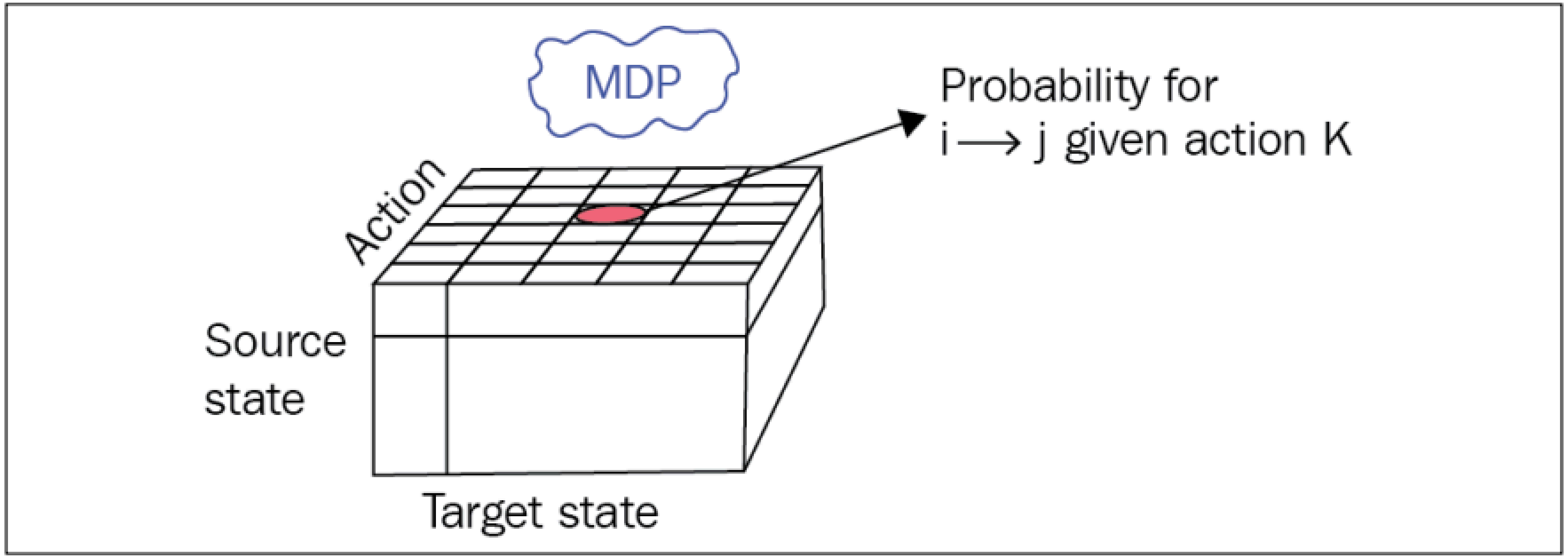


Figure 1.9: Transition probabilities for the MDP

MDP: Example (Grid World)

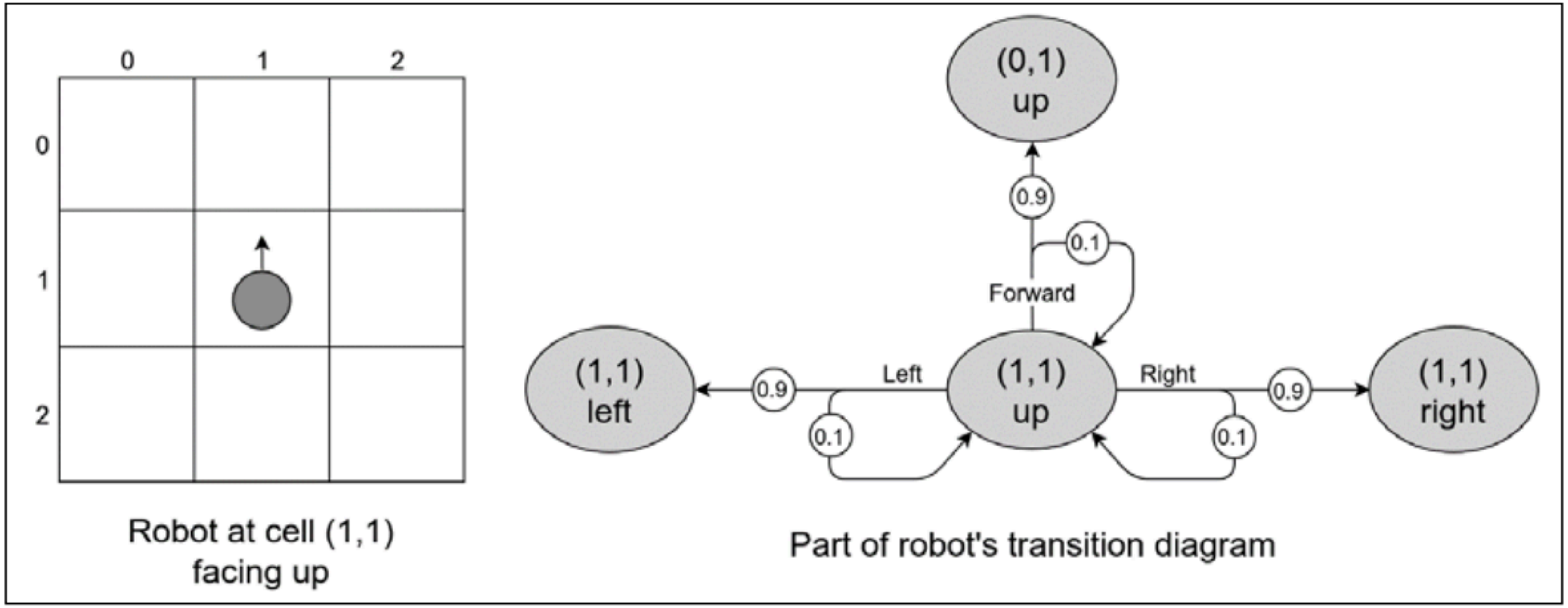


Figure 1.10: A grid world environment

MDP: Example (Grid World)

- State = [Robot Position] + [Orientation]
- Action = `turn left`, `turn right`, `go forward`
- Even if robot execute action (e.g. `up`), there is a chance that the robot stay the same (due to motor imperfection).

Policy

- Rule that control agent behavior.
- In the robot example, policies can be
  - Always turn right when the state is `(0, 1, left)`. (**Deterministic**)
  - `turn right` 50% of the time and `go forward` 50% of the time when the state is `(0, 0, up)`. (**Stochastic**)
  - Randomly move 10% of the time, but for the rest of the time, `turn right` when the state is `(0, 1, left)` (**Stochastic** / **Explorative**)

Policy

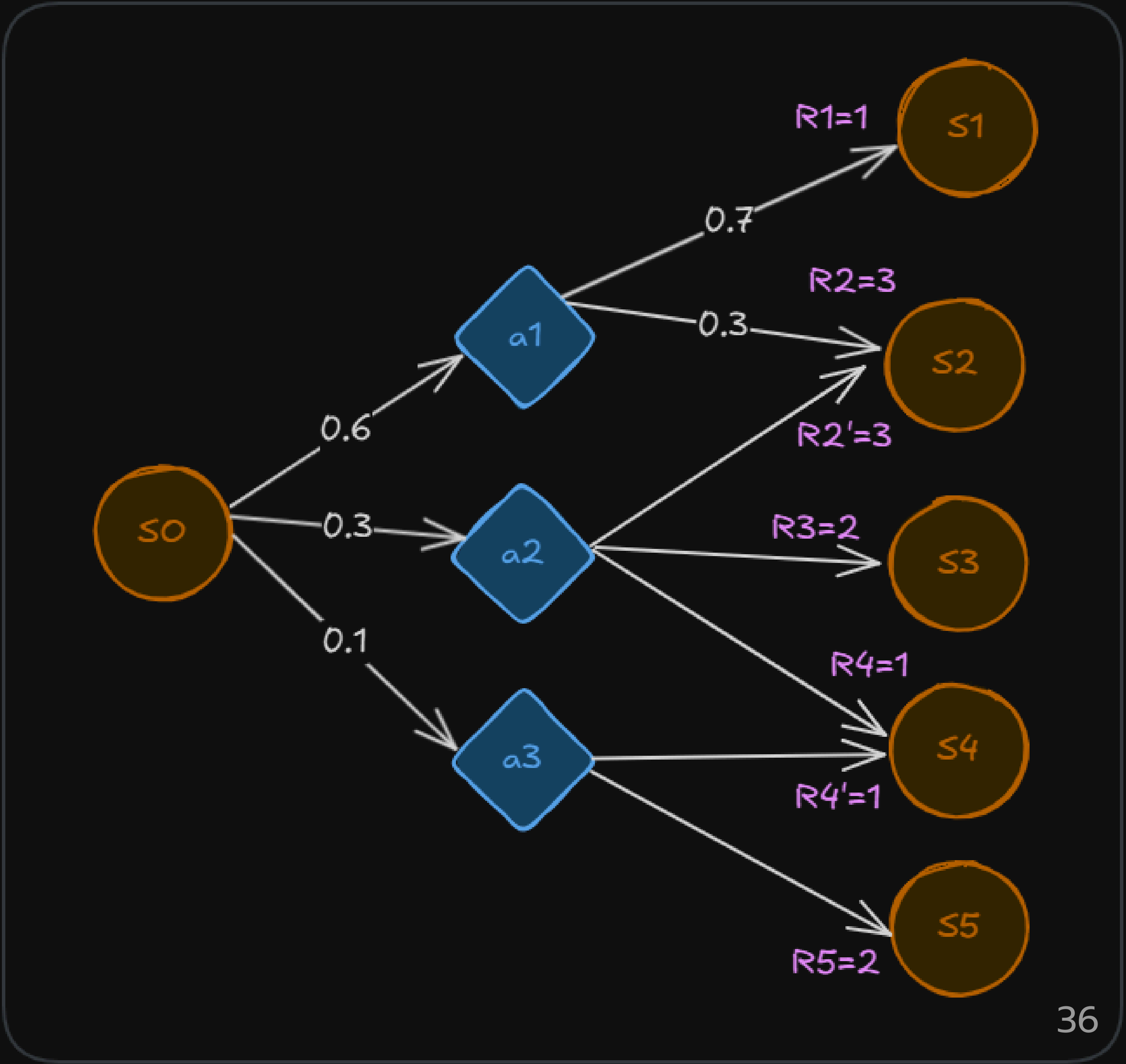
- Formally

$$\pi(a|s) = \mathtt{P}[A_t = a|S_t = s]$$

- Policy can be deterministic and stochastic.
- If policy is not chaning, MDP becomes MRP.

MDP Example

- Stochastic policy
- Given $\gamma = 0$
- Calculate $V(S_0)$



Solution

$$
\begin{aligned}
V(S_0) &= 0.6 \times (0.7R_1 + 0.3R_2) + 0.3 \times (0.2R_2' + 0.3R_3 + 0.5R_4) \\
&\quad + 0.1 \times (0.6R_4' + 0.4R_5) \\
&= 0.6 \times (0.7 + 0.9) + 0.3 \times (0.6 + 0.6 + 0.5) + 0.1 \times (0.6 + 0.8) \\
&= 0.6 \times (1.6) + 0.3 \times (1.7) + 0.1 \times (1.4) \\
&= 1.61
\end{aligned}
$$

Recap

- Our policy is the choose a_1, a_2, a_3 with `[60%, 30%, 10%]` chance
    - We get $V = 1.61$
- Can you do better?

Reformulation

Recall

$$V(S_0) = 0.6 \times (0.7R_1 + 0.3R_2) + 0.3 \times (0.2R_2' + 0.3R_3 + 0.5R_4) \\ + 0.1 \times (0.6R_4' + 0.4R_5)$$

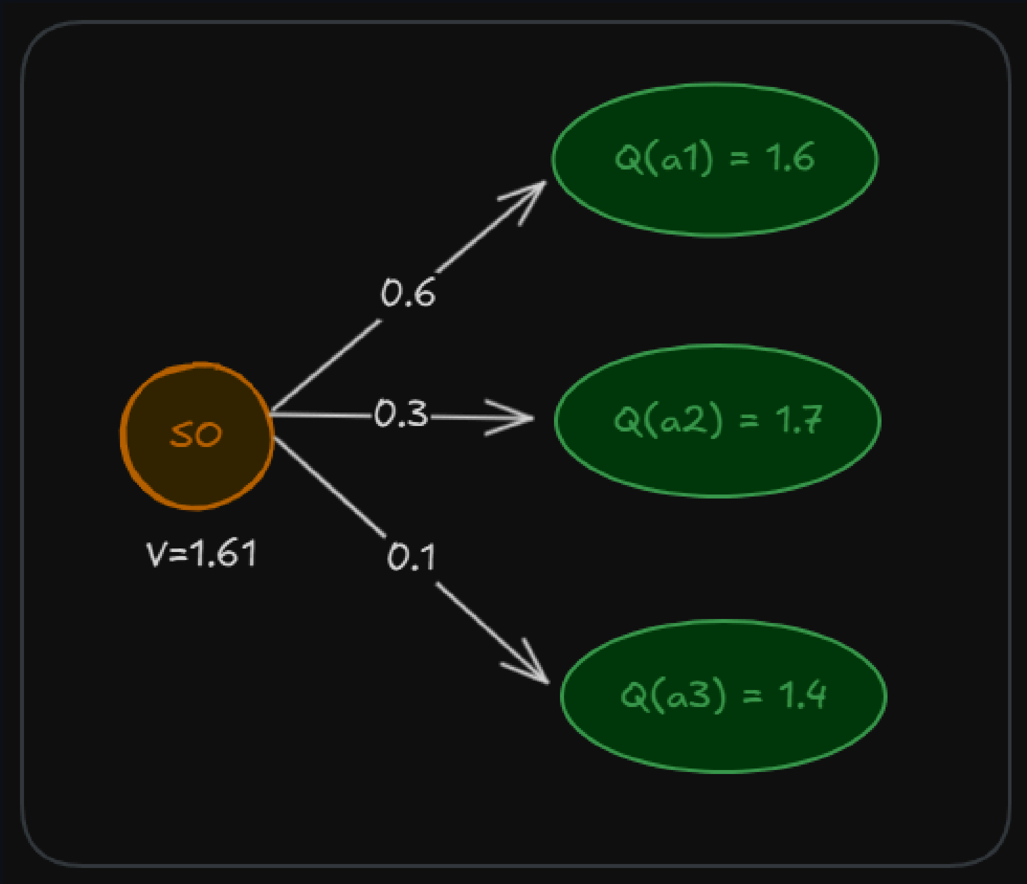
We can write

$$\begin{aligned} V(S_0) &= 0.6 \times [\text{Reward from } a_1] + 0.3 \times [\text{Reward from } a_2] \\ &\quad + 0.1 \times [\text{Reward from } a_3] \\ &= 0.6 \times Q(a_1) + 0.3 \times Q(a_2) + 0.1 \times Q(a_3) \end{aligned}$$

where $Q(a_1) = 1.6$, $Q(a_2) = 1.7$, and $Q(a_2) = 1.4$.

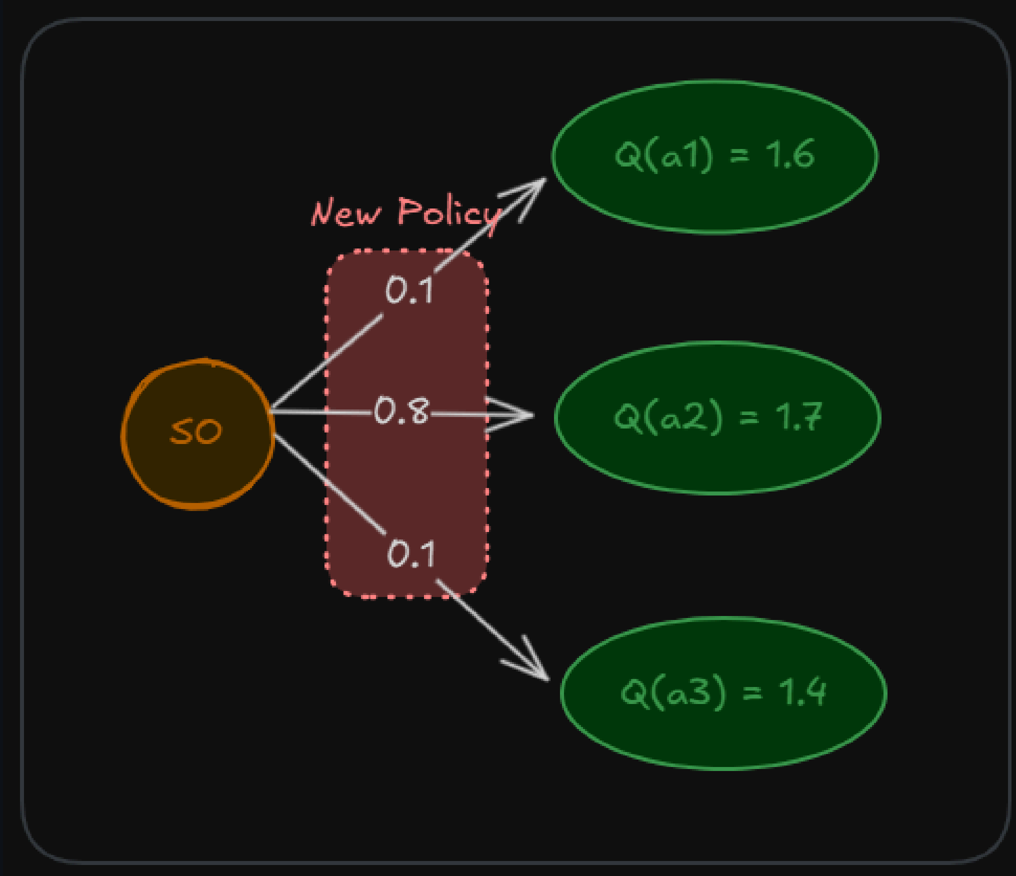
Reformulation

- We can then rewrite the diagram like this.
- Q is called **action-value functions**.
    - It tells you how good the action is.



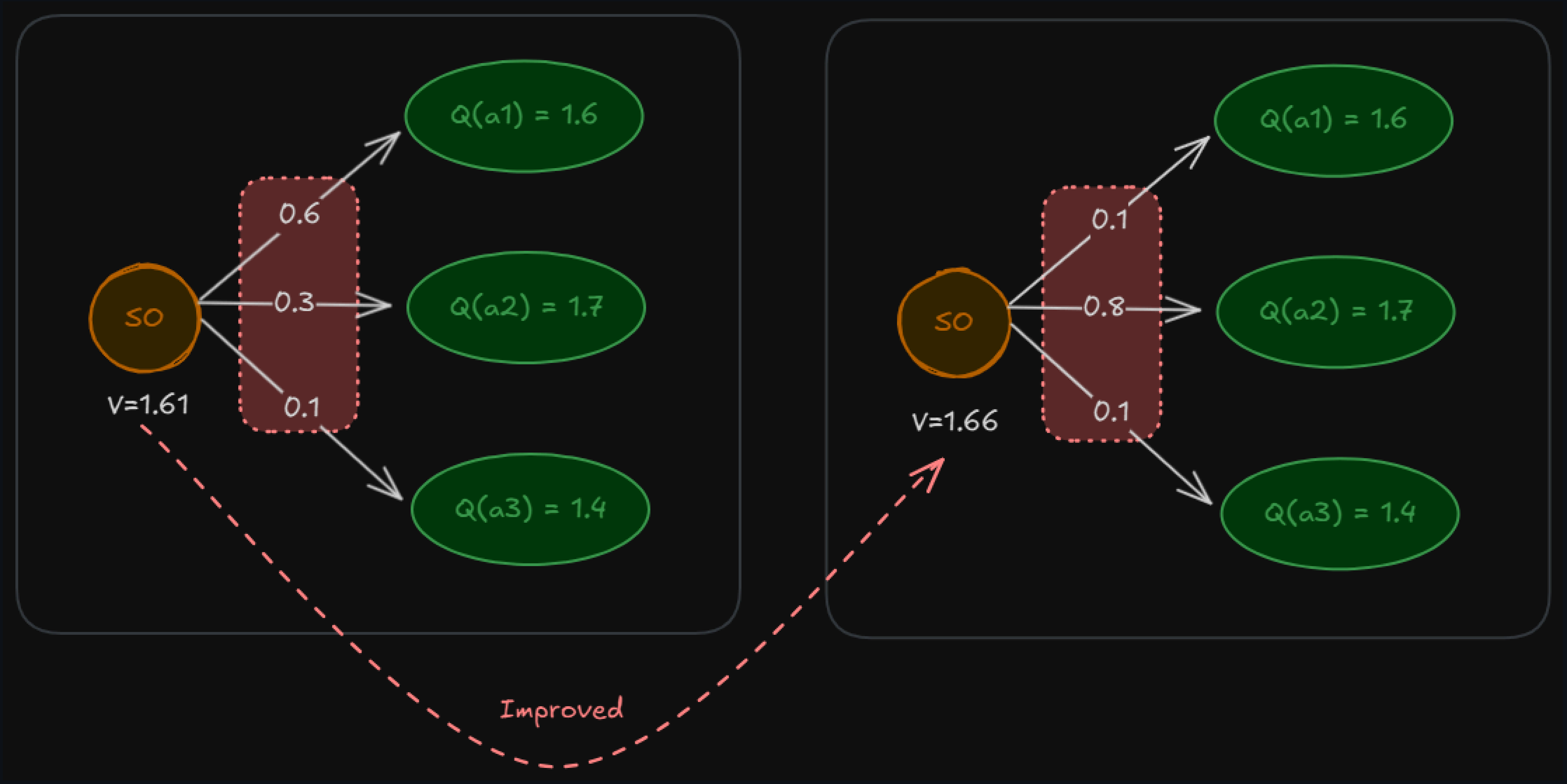
Policy Improvement

- Let's try a new policy.
- What is V?



Policy Improvement

$$\begin{aligned} V(S_0) &= 0.1Q(a_1) + 0.8Q(a_2) + 0.1Q(a_3) \\ &= 0.1 \times 1.6 + 0.8 \times 1.7 + 0.1 \times 1.4 \\ &= 1.66 \end{aligned}$$


SO
V=1.61
0.6
0.3
0.1
Q(a1) = 1.6
Q(a2) = 1.7
Q(a3) = 1.4
Improved
SO
V=1.66
0.1
0.8
0.1
Q(a1) = 1.6
Q(a2) = 1.7
Q(a3) = 1.4

Optimal Policy

- If we can find a policy that can improve V, that policy must be better than the previous policy.
- The best policy is the policy that **maximize** V.
- Can you find the **optimal** policy in our example?

Optimal Policy

- The optimal policy is just choose action a_2 all the time.
    - Essentially, this is acting greedily.
- We can write more formally

$$\pi^* = \underset{a}{\operatorname{argmax}}\, Q(a)$$

Discussion

- Notice that the optimum policy is deterministic.
- If fact, in most cases you will find that most environment that can be modelled by a MDP has an optimal policy which is deterministic.
- However, if the environment is adversarial and can exploit predictable behavior, adopting a stochastic policy can actually be more advantageous.
    - This environment violate Markov property (non-stationary).