Decision Processes

CISC 7404 - Decision Making

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Review

Markov Processes

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Decisions must make some change in the world

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- DNA sequences
- Cryptography
- History

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The **state space**	The **state transition function**
S	$\mathrm{Tr} : S \mapsto \Delta S$
Outcome space describing the state of our system	$\mathrm{Tr}(s_{t+1} \mid s_t) = \Pr(s_{t+1} \mid s_t)$ $s_{t+1} \sim \mathrm{Tr}(\cdot \mid s_t)$

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$$\begin{aligned}
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= &\begin{bmatrix} \Pr(C \mid C) & \Pr(R \mid C) & \Pr(S \mid C) \\ \Pr(C \mid R) & \Pr(R \mid R) & \Pr(S \mid R) \\ \Pr(C \mid S) & \Pr(R \mid S) & \Pr(S \mid S) \end{bmatrix}
\end{aligned}$$

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$$= \begin{bmatrix} 0.4 & 0.3 & 0.3 \\ 0.5 & 0.3 & 0.2 \\ 0.5 & 0.1 & 0.4 \end{bmatrix}$$

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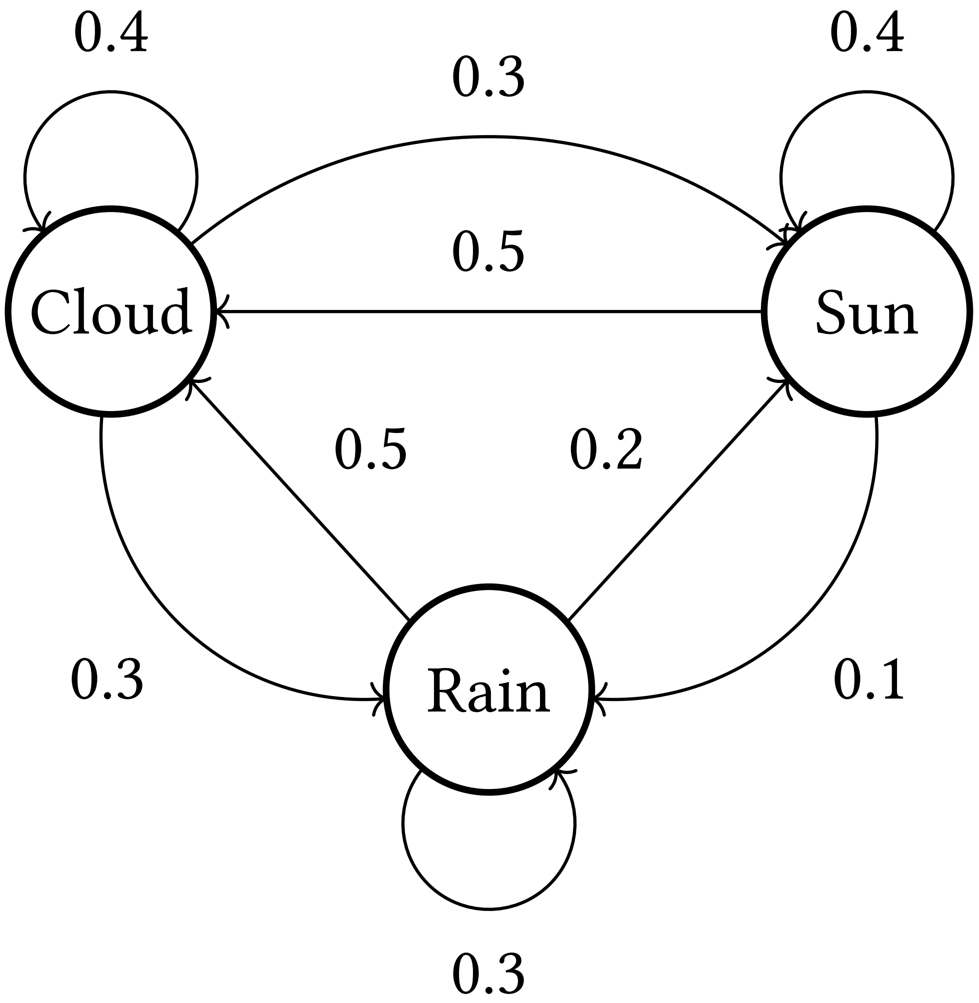

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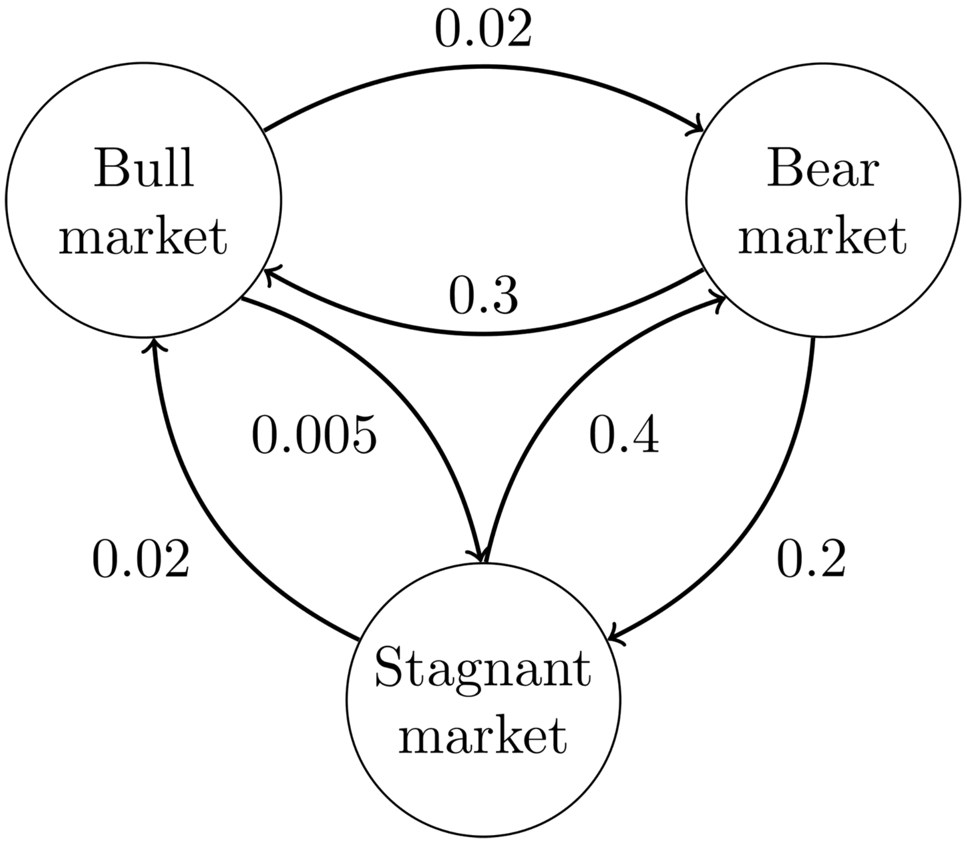

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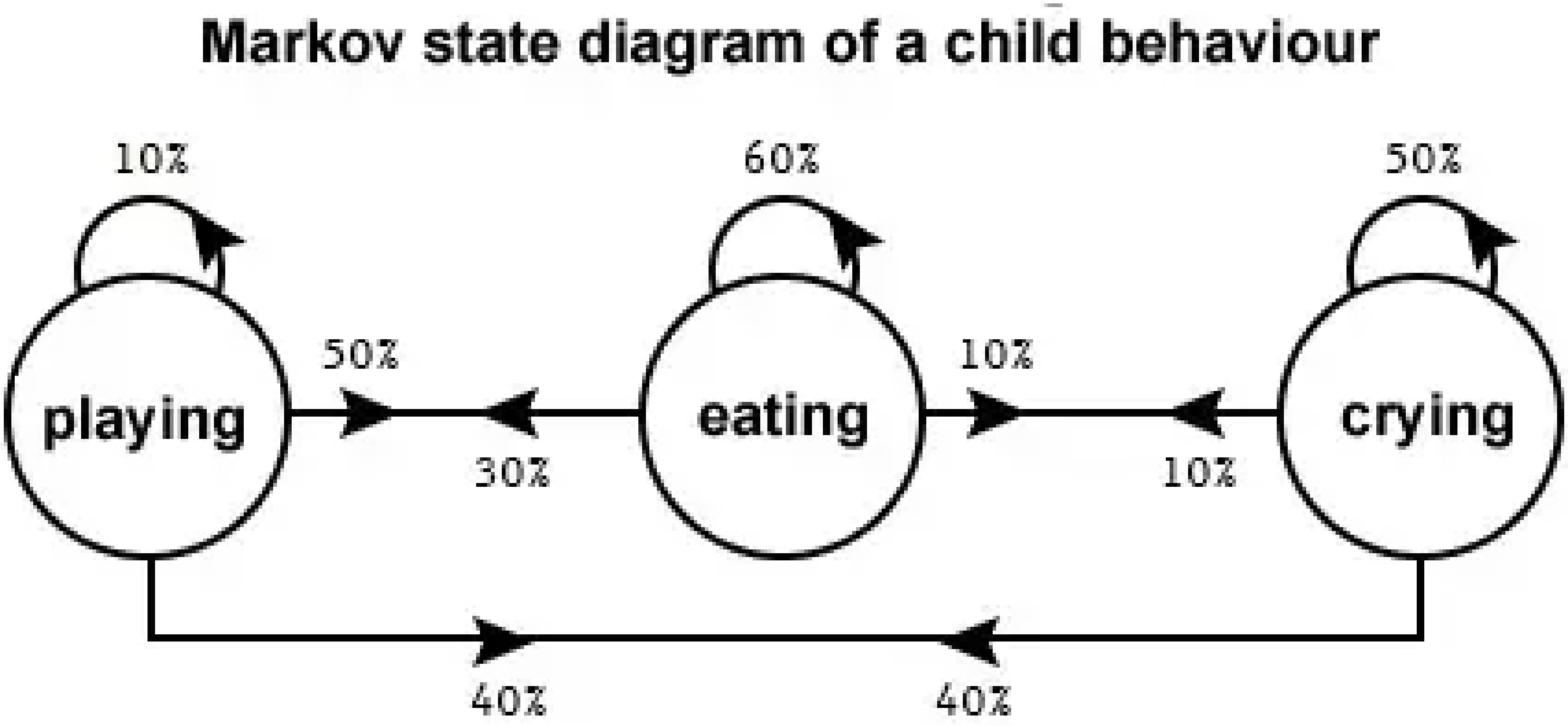

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$$\Pr(\text{sun} \mid s_t = \text{rain}, s_{t-1} = \text{sun}) = 0.4$$

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$$\Pr(\text{sun} \mid s_t = \text{rain}, s_{t-1} = \text{sun}) = 0.4 \qquad \Pr(\text{sun} \mid s_t = \text{rain}) = 0.3$$

$0.3 \neq 0.4$, process is **not** Markov

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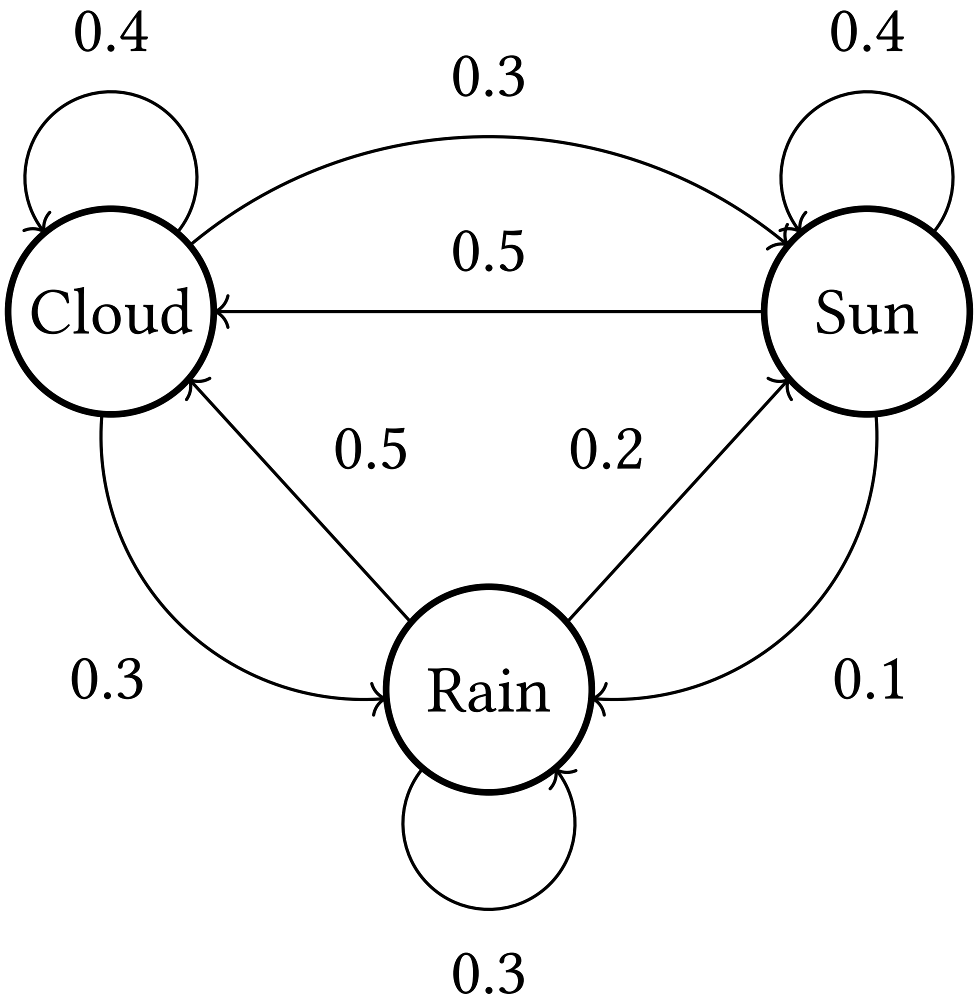

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Generalize to any timestep n

$$\Pr(s_n \mid s_0) = \sum_{s_1, s_2, \ldots s_{n-1} \in S} \prod_{t=0}^{n-1} \Pr(s_{t+1} \mid s_t)$$

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This expression tells us how the Markov process evolves over time

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Answer: We create a **terminal state** that we cannot leave

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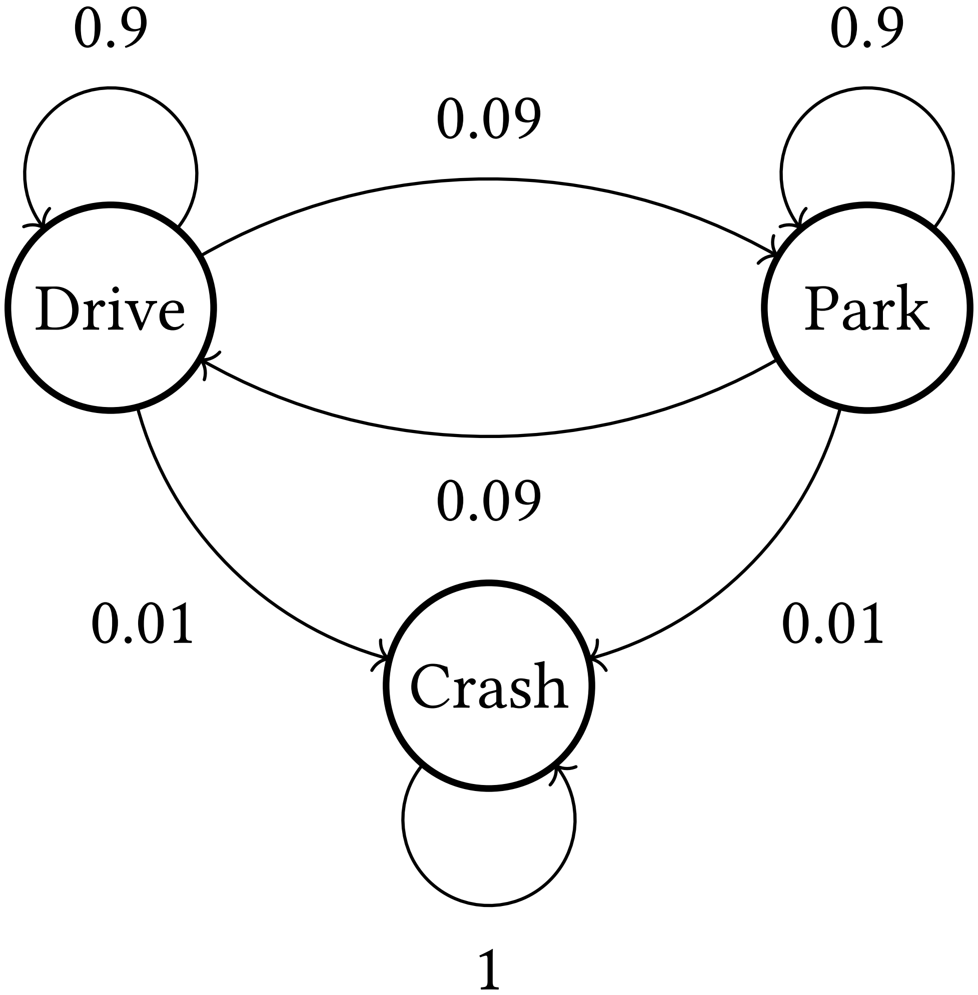

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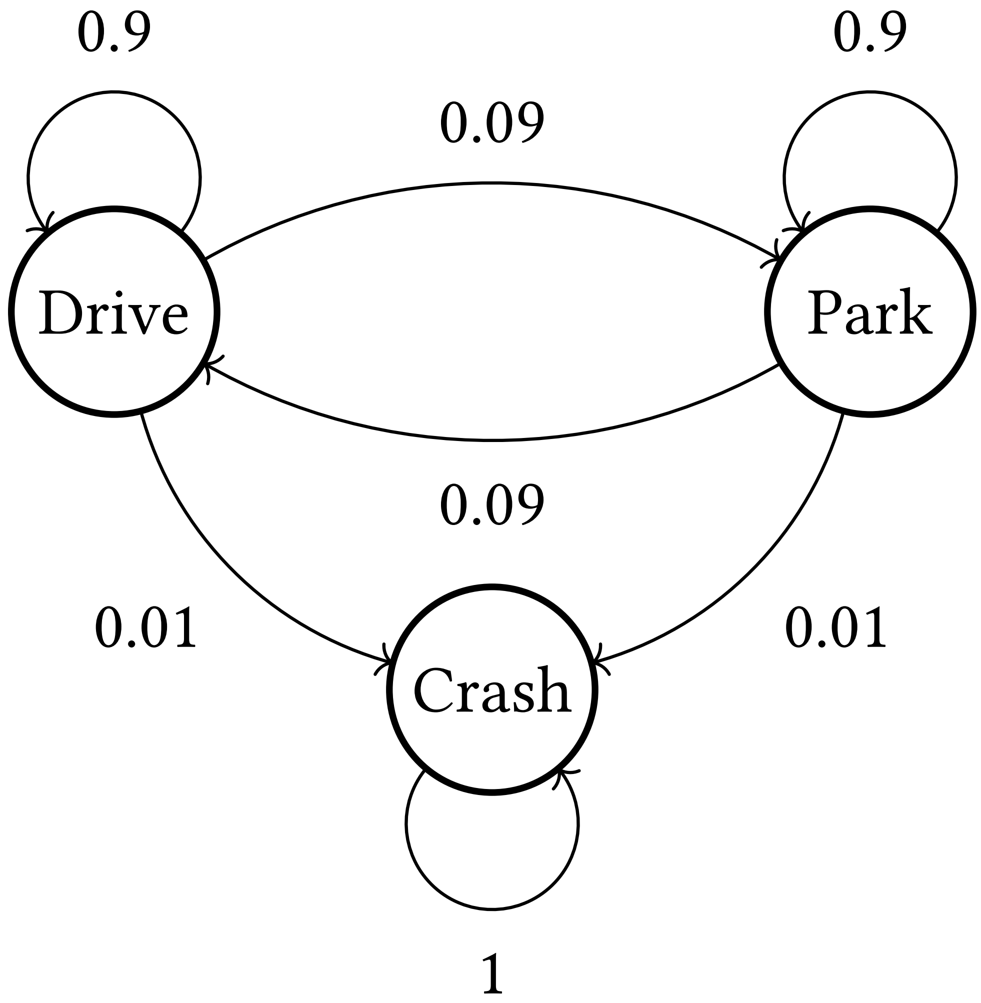

Upon reaching a terminal state, we get stuck

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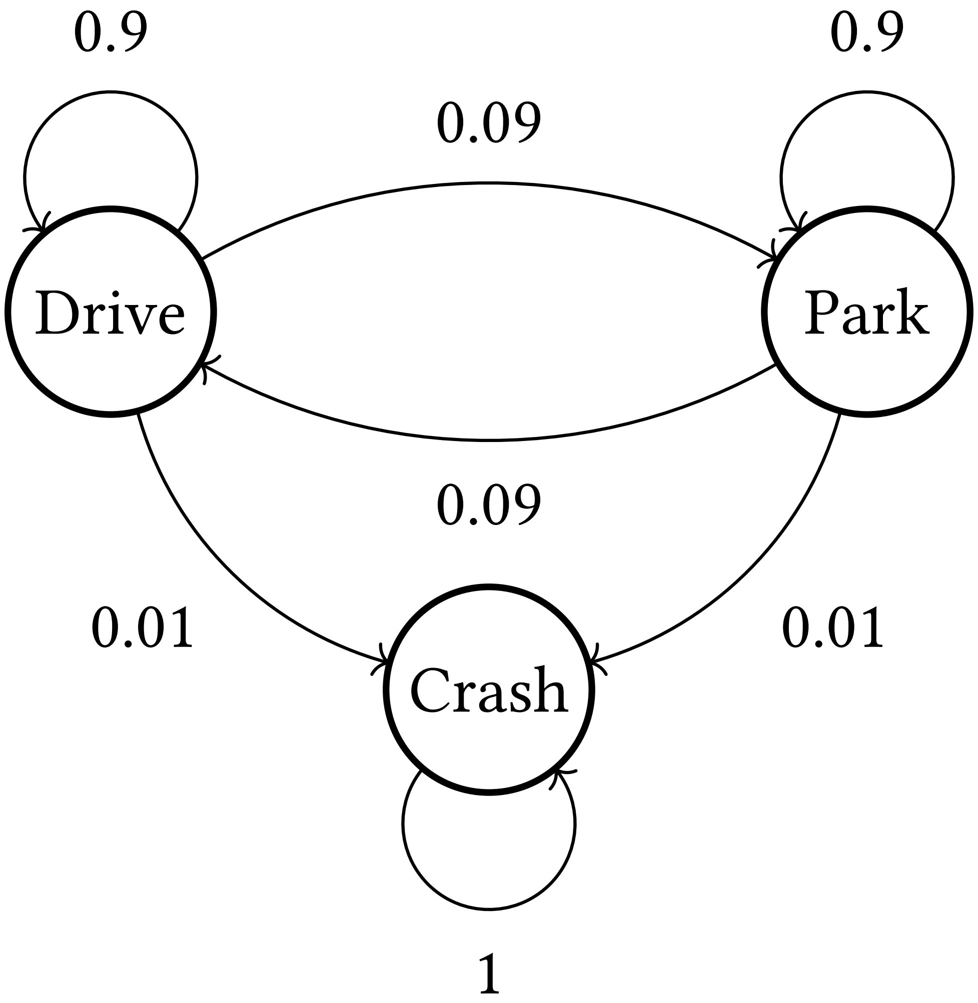

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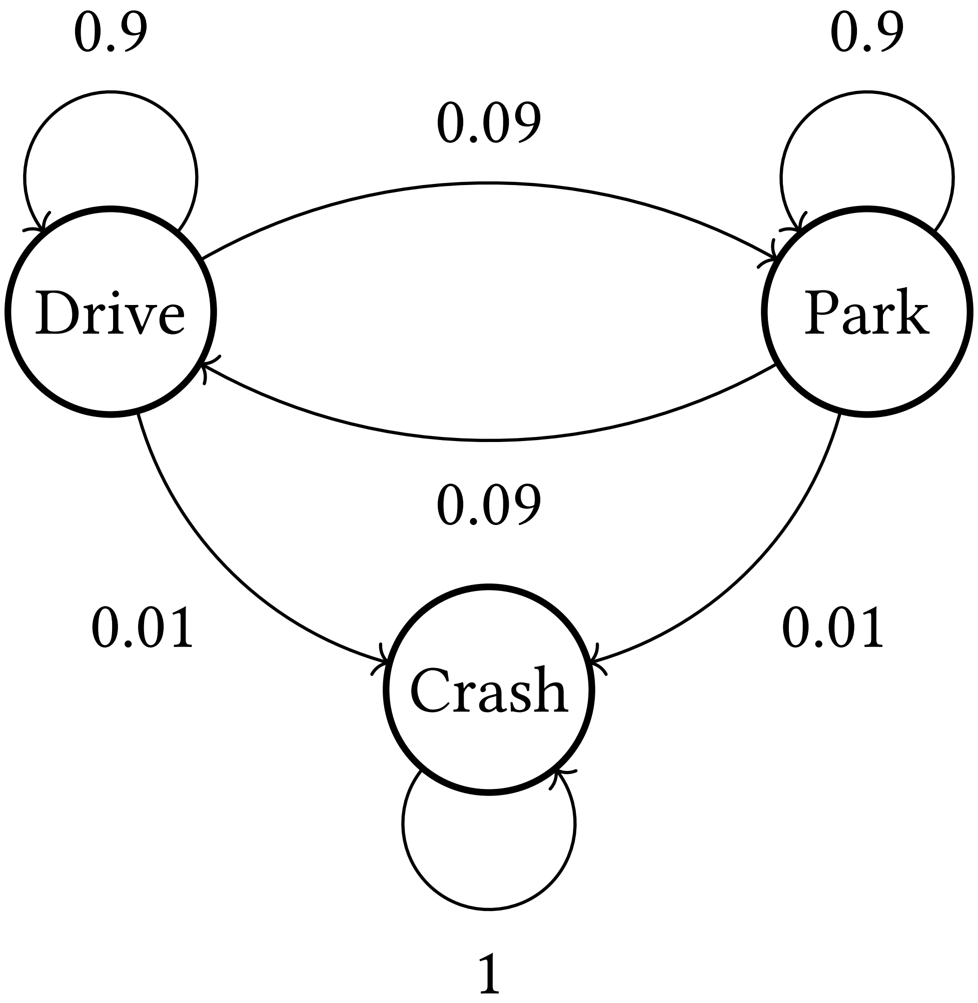

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The only transition from a terminal state is back to itself

$$\Pr(s_{\text{terminal}} \mid s_{\text{terminal}}) = 1.0$$

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- State transition function $\mathrm{Tr} = \Pr(s_{t+1} \mid s_t)$ for all s_t, s_{t+1}
- Create a terminal state
- Given a starting state s_0, what will your state distribution be for s_2?

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We will modify the Markov process for decision making

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We introduce the **agent** to make decisions that change the environment

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Let us see an example

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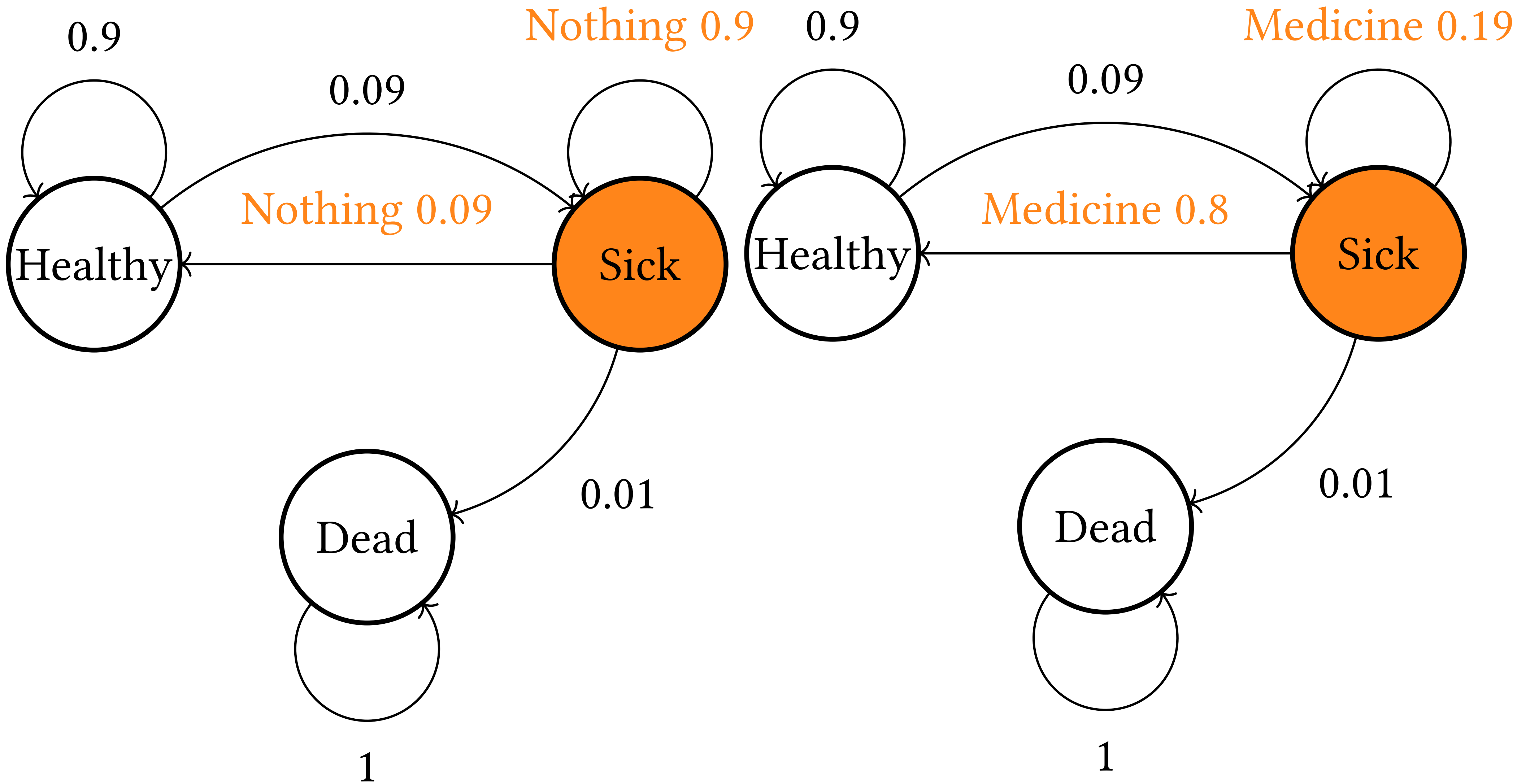

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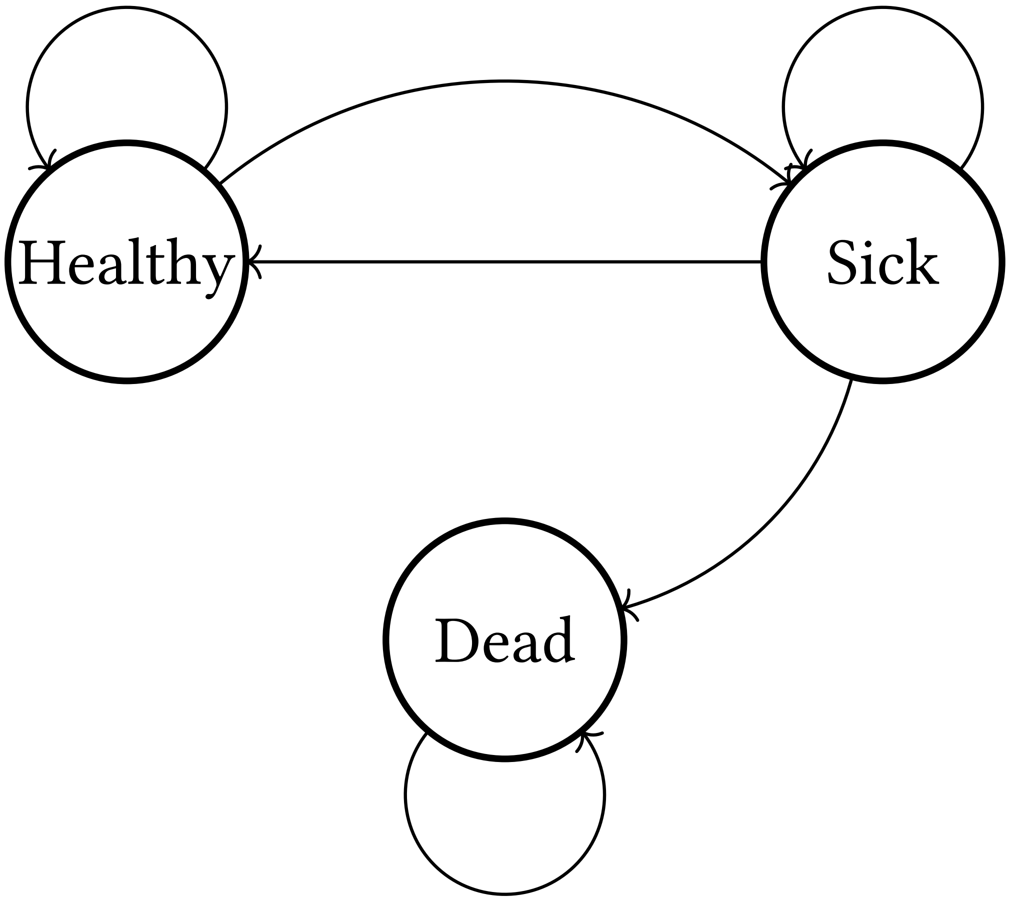

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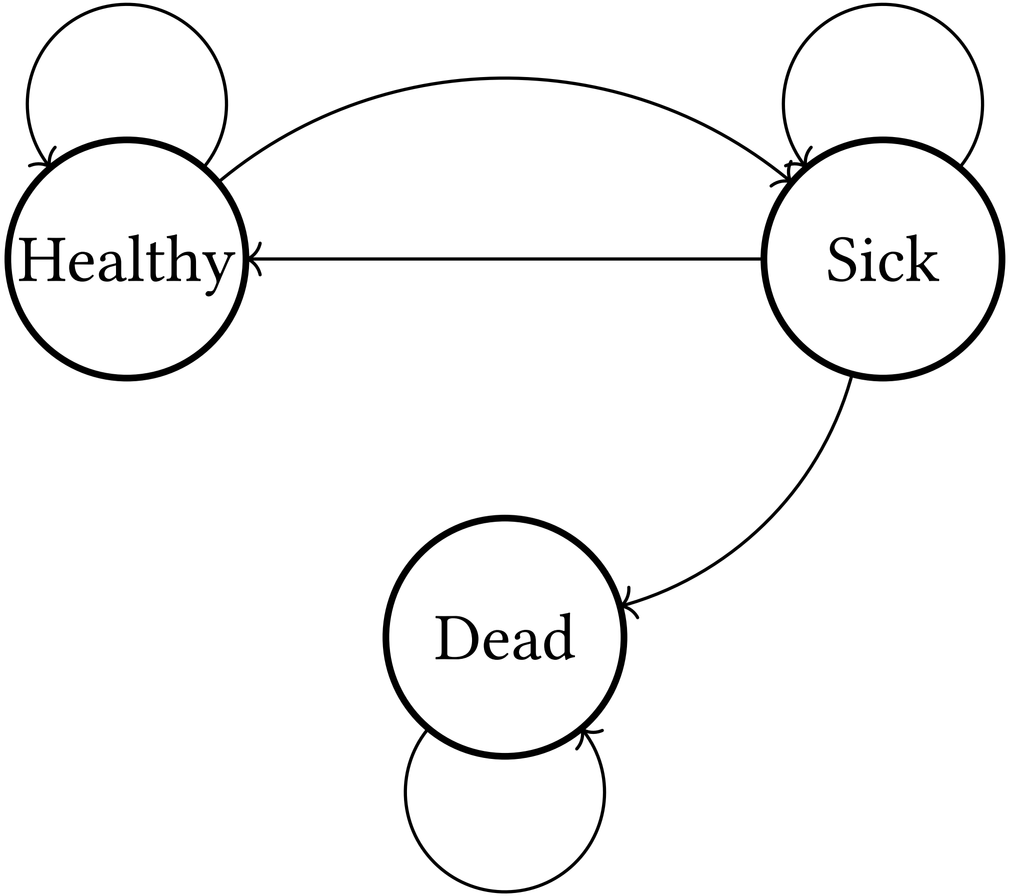

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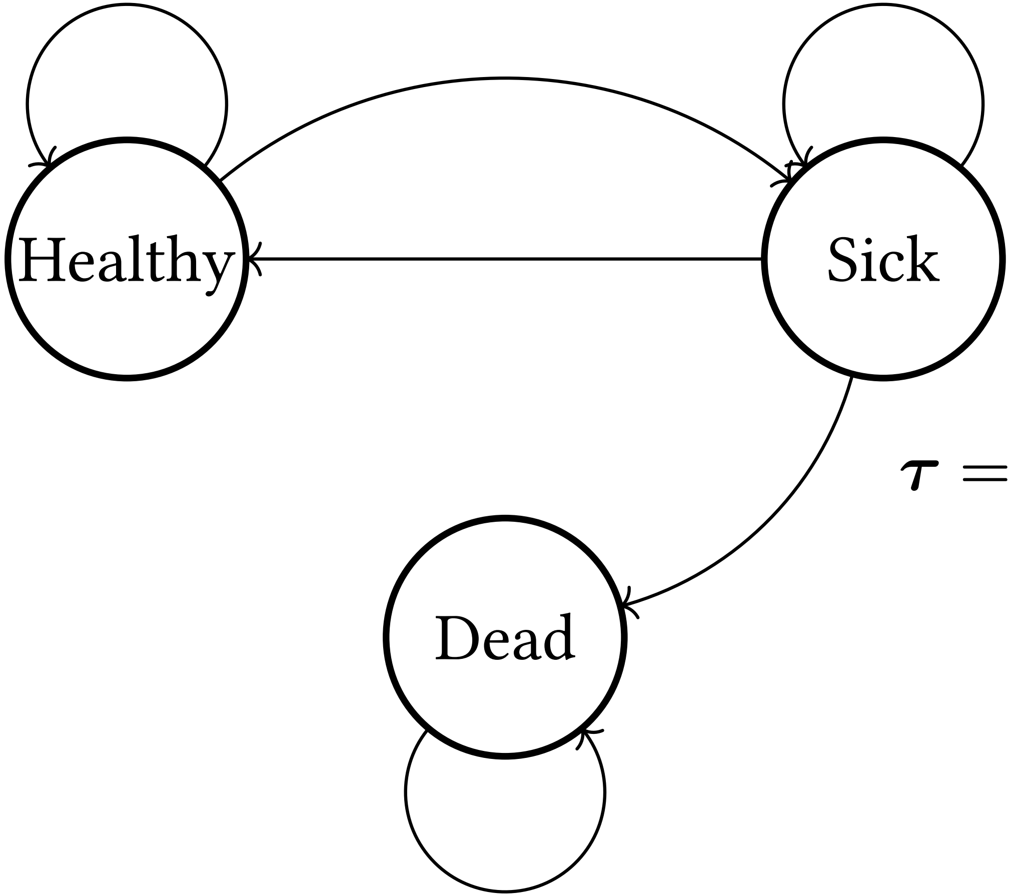

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$$\boldsymbol{\tau} = \begin{bmatrix} s_0 & a_0 \\ s_1 & a_1 \\ s_2 & a_2 \\ \vdots & \vdots \\ s_{n-1} & a_{n-1} \\ s_n & \emptyset \end{bmatrix}$$

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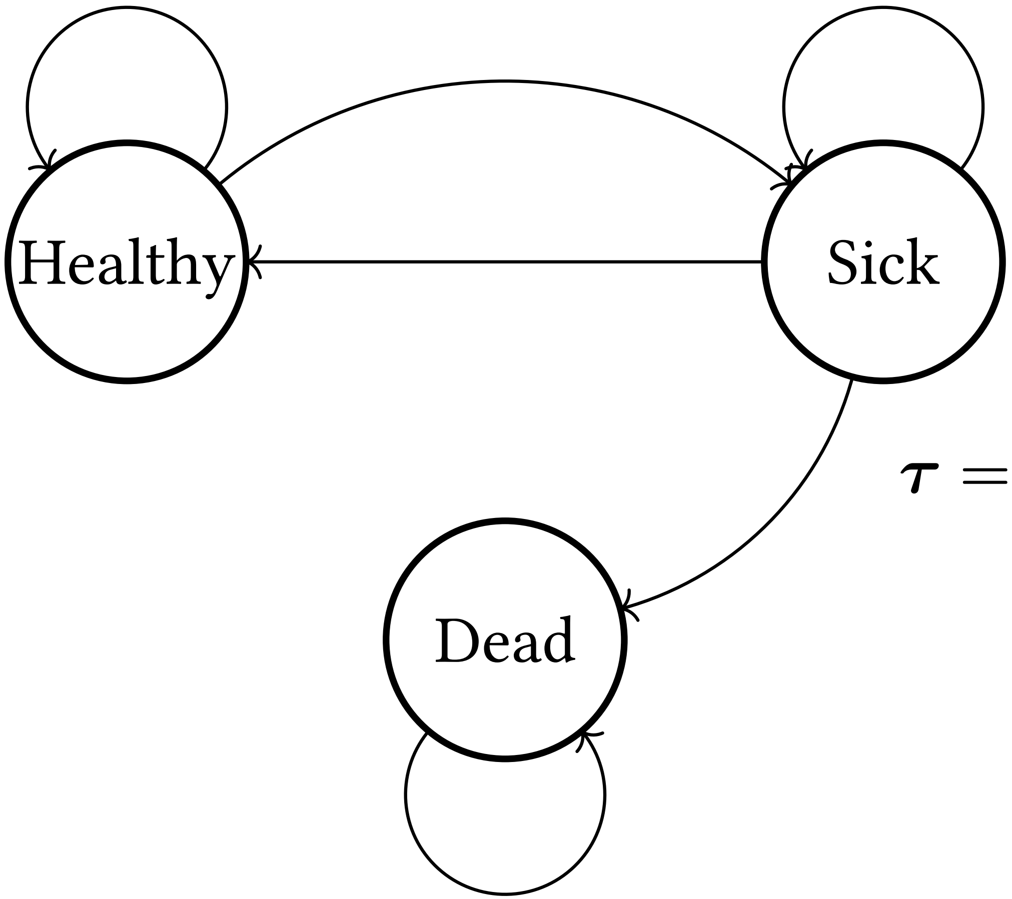

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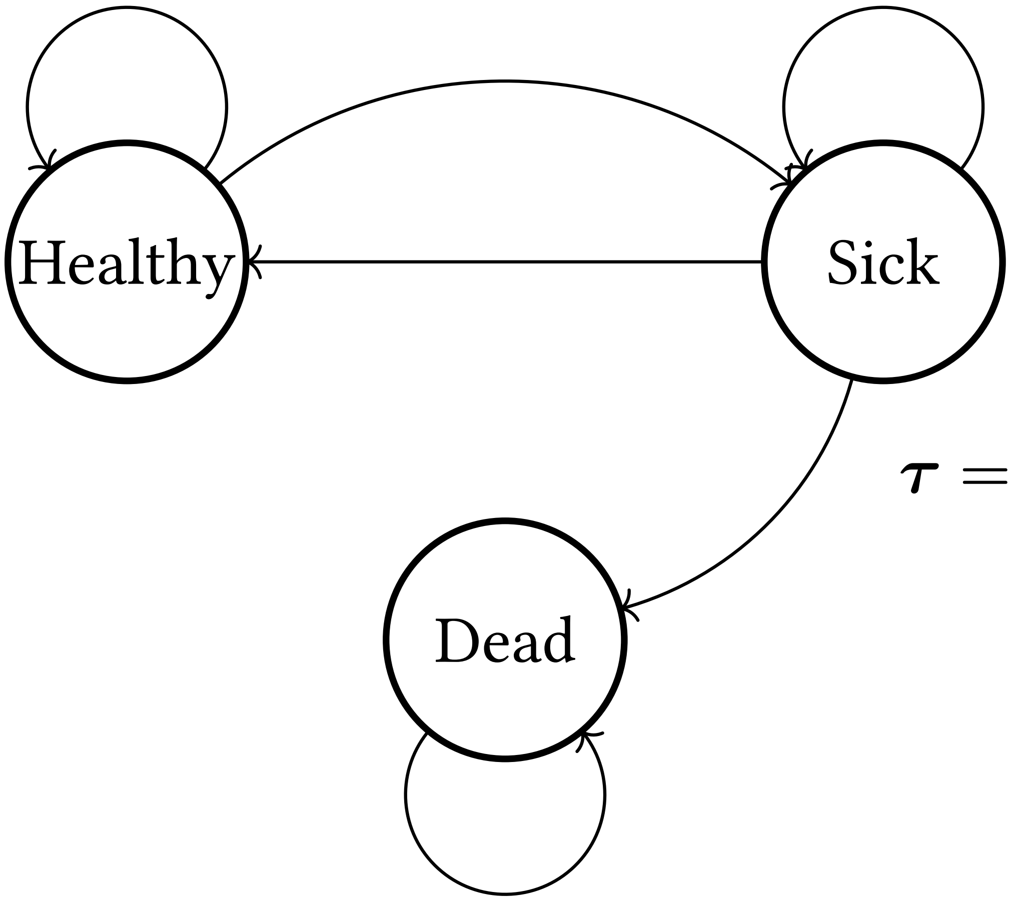

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If there is no terminal state, the trajectory can be infinitely long!

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How can we make optimal decisions if we cannot tell how good a decision is?

We need something to tell us how good it is to be in a state!

Markov Decision Processes

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For now, I will use the simplest one

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You can always make these equivalent by modifying the MDP

Markov Decision Processes

Markov process

$$(S, T)$$

$$T : S \mapsto \Delta S$$

Markov Decision Processes

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Markov decision process

$$(S, A, T, R, \gamma)$$

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Markov Decision Processes

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$$\boldsymbol{E} = \begin{bmatrix} s_0 & a_0 & r_0 \\ s_1 & a_1 & r_1 \\ \vdots & \vdots & \vdots \\ s_{n-1} & a_{n-1} & r_{n-1} \\ s_n & \emptyset & \emptyset \end{bmatrix} = [\boldsymbol{\tau} \;\; \boldsymbol{r}]$$

Markov Decision Processes

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We can write this mathematically as

$$\arg\max_{s \in S} R(s)$$

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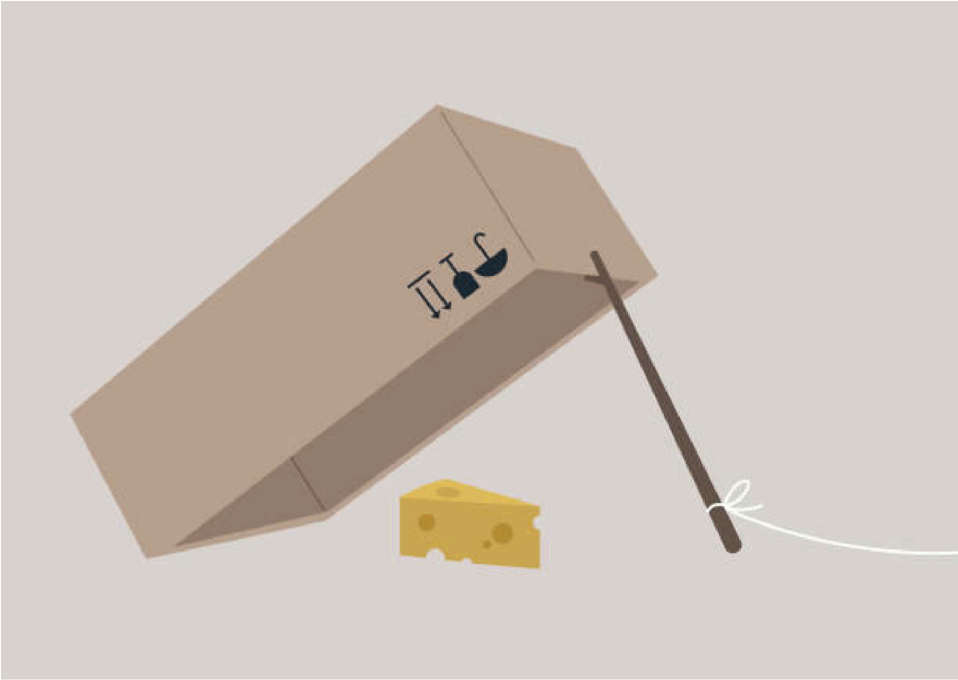

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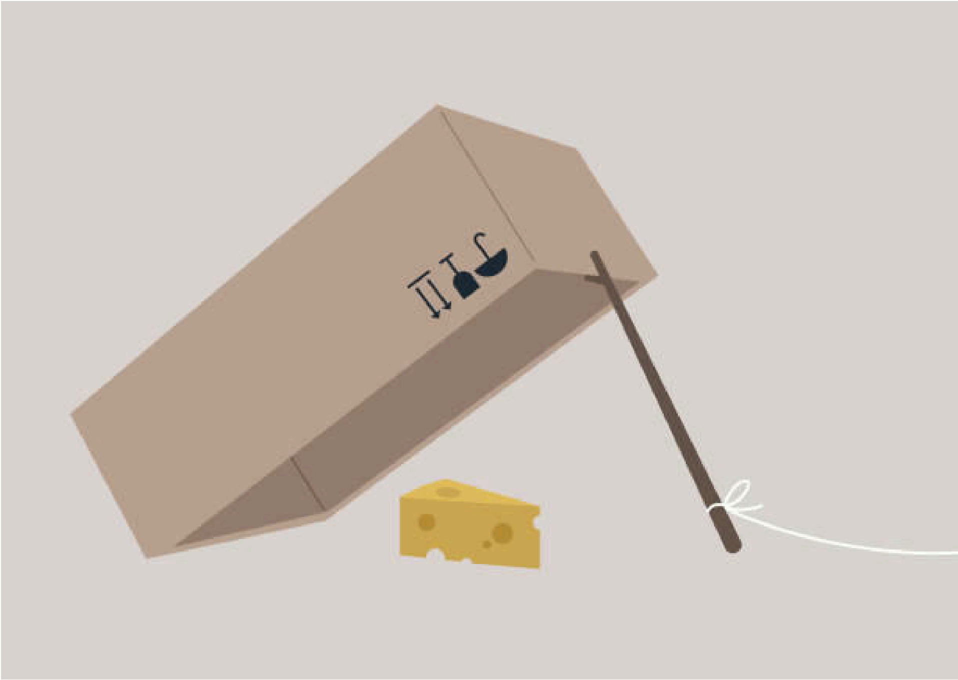

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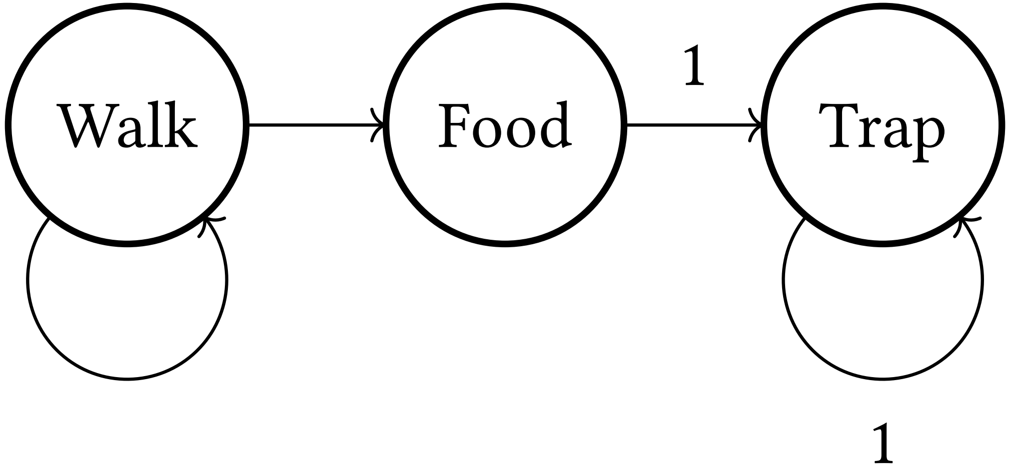

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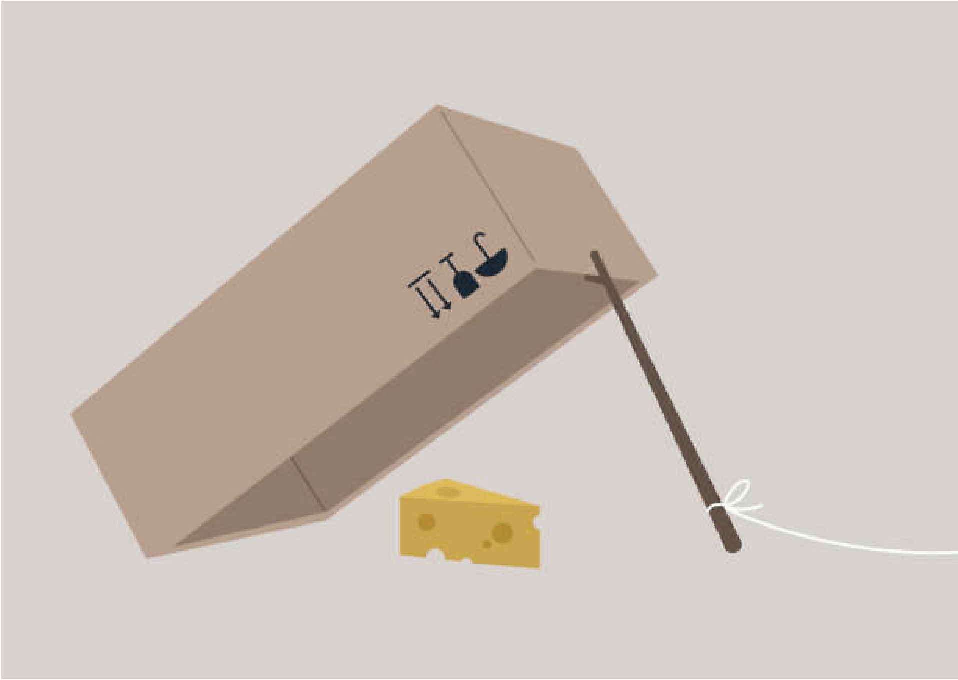

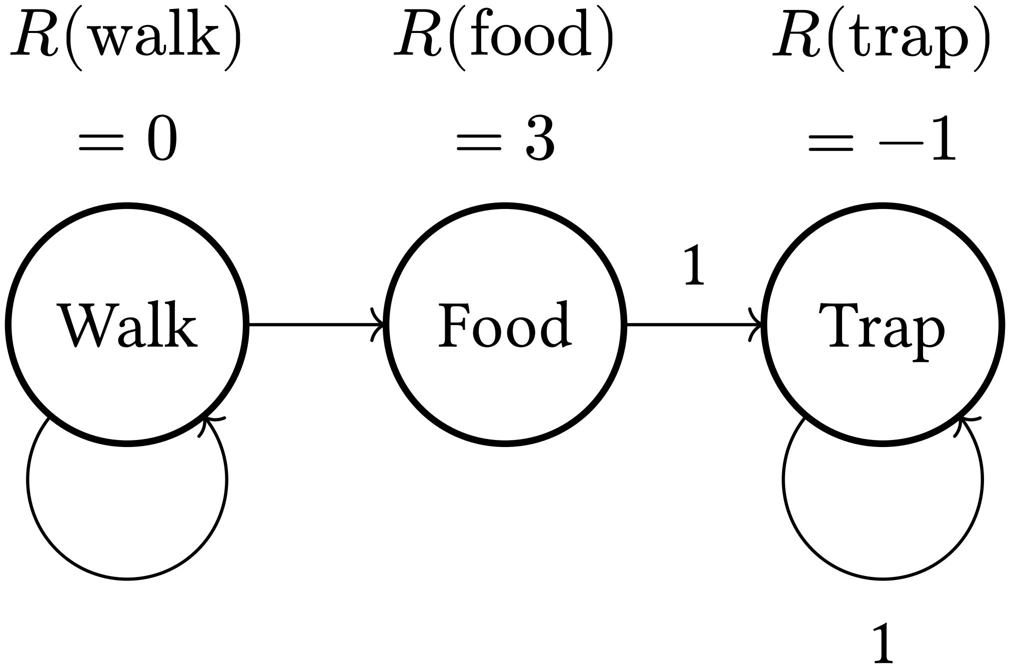

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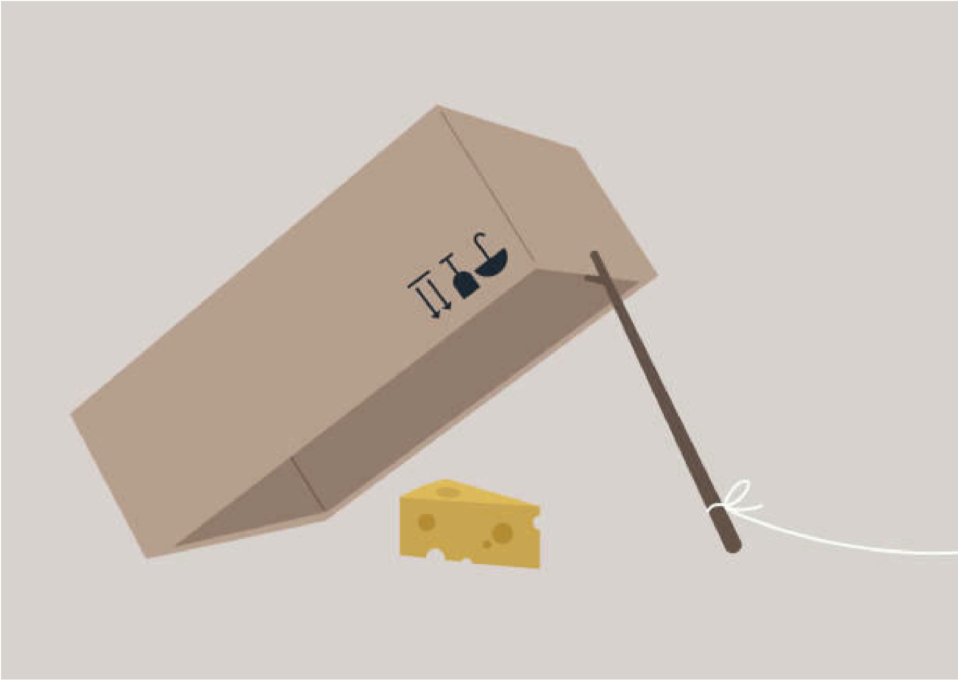

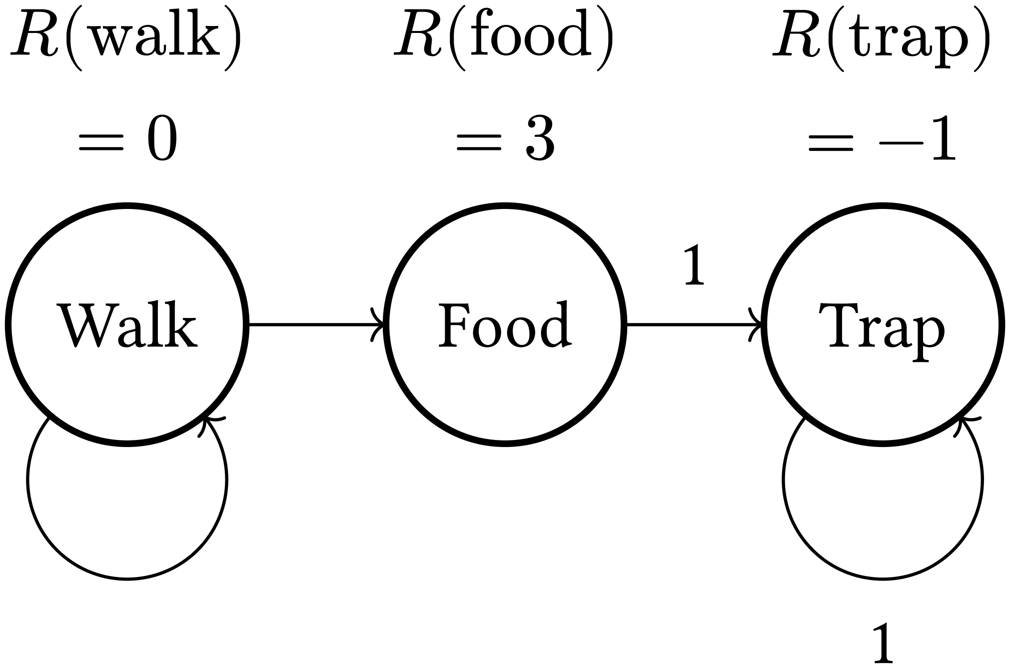

$$\arg\max_{s \in S} R(s) = \text{food}$$

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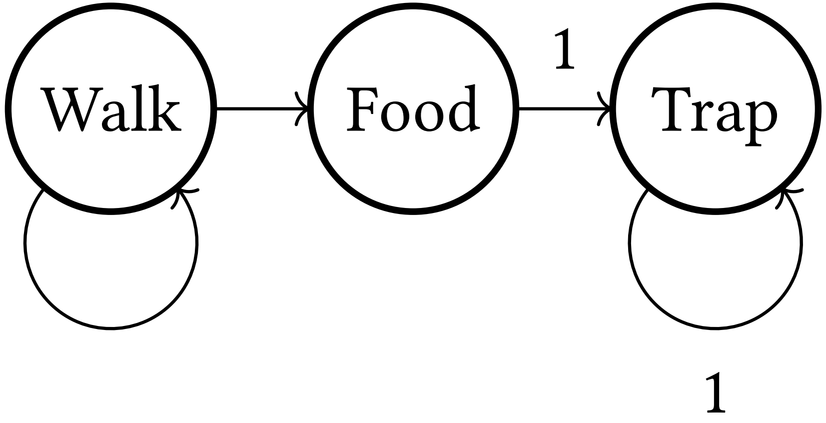

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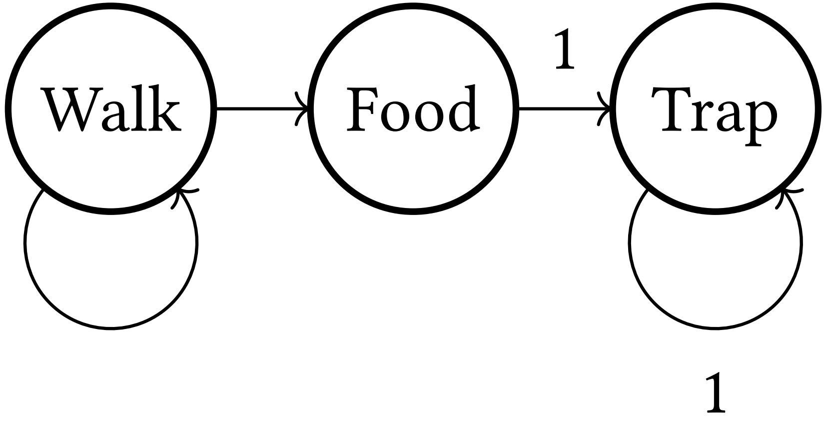

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Markov Decision Processes

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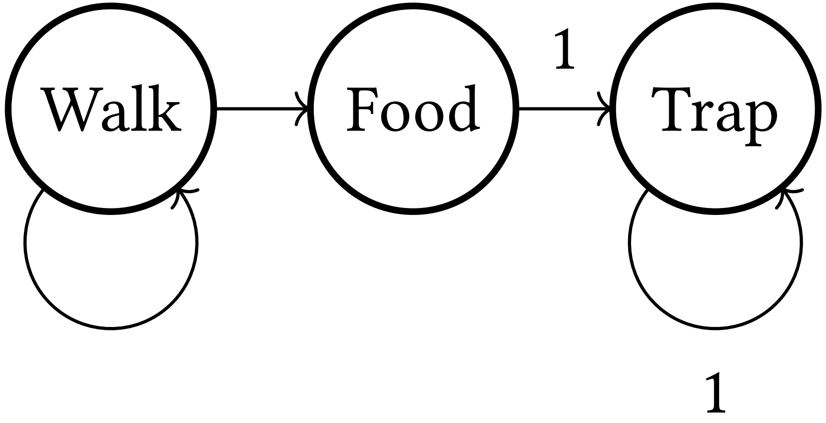

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Now, we make better decisions!

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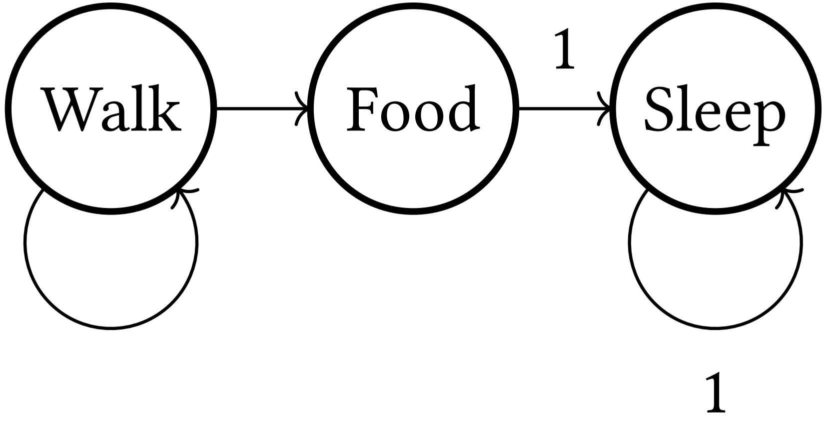

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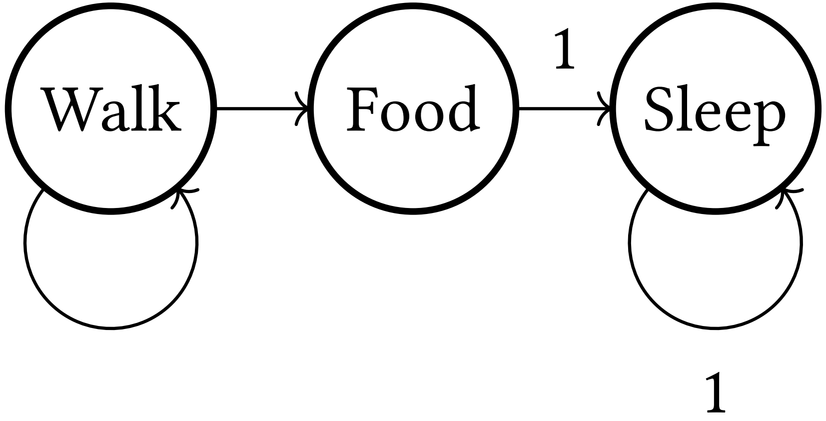

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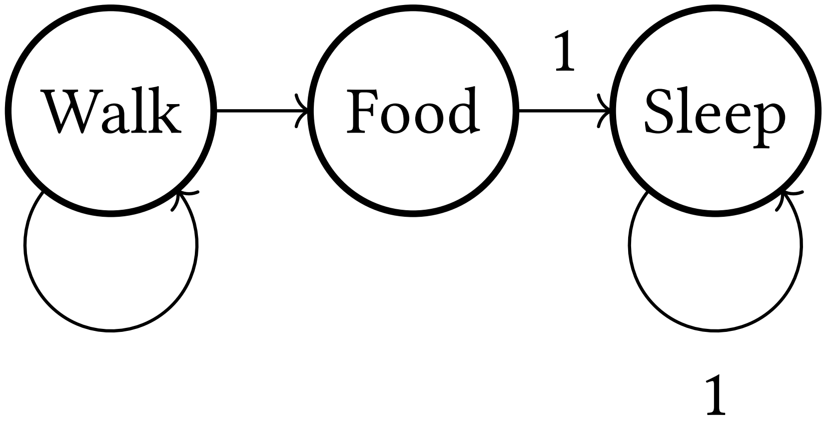

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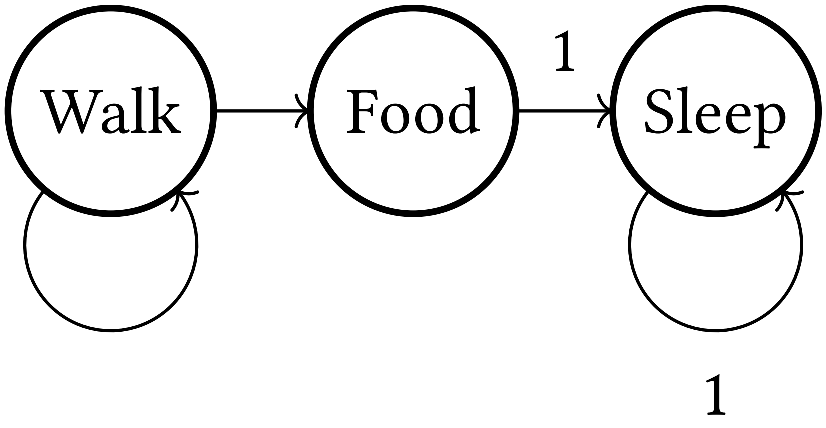

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Order matters, humans prefer reward sooner rather than later

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Markov Decision Processes

Without γ | With γ

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For the rest of the course, we maximize the discounted return

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You must understand the discounted return!

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Make sure you understand MDPs!

Exercise

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Design a Super Mario Bros MDP

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- State space S

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- State space S
- Action space A

Exercise

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- State space S
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Compute discounted return for:

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Compute discounted return for:

- Eat mushroom at $t = 10$

Exercise

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Compute discounted return for:

- Eat mushroom at $t = 10$
- Collect coins at $t = 11, 12$

Exercise

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- Discount factor γ

Compute discounted return for:

- Eat mushroom at $t = 10$
- Collect coins at $t = 11, 12$
- Die to bowser at $t = 20$

Coding

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https://gymnasium.farama.org/api/env/

Coding

Gymnasium uses **observations** instead of **states**

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Question: What was the Markov condition for MDPs?

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Gymnasium uses observations, but for MDPs we treat them as states

Coding

```
import gymnasium as gym

MyMDP(gym.Env):
  def __init__(self):
    self.action_space = gym.spaces.Discrete(3) # A
    self.observation_space = gym.spaces.Discrete(5) # S

  def reset(self, seed=None) -> Tuple[Observation, Dict]

  def step(self, action) -> Tuple[
    Observation, Reward, Terminated, Truncated, Dict
  ]
```

Coding

https://colab.research.google.com/drive/1rDNik5oRl27si8wdtMLE7Y41U5J2bx-I#scrollTo=9pOLI5OgKvoE

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Too many A's last term, exam will be **difficult**