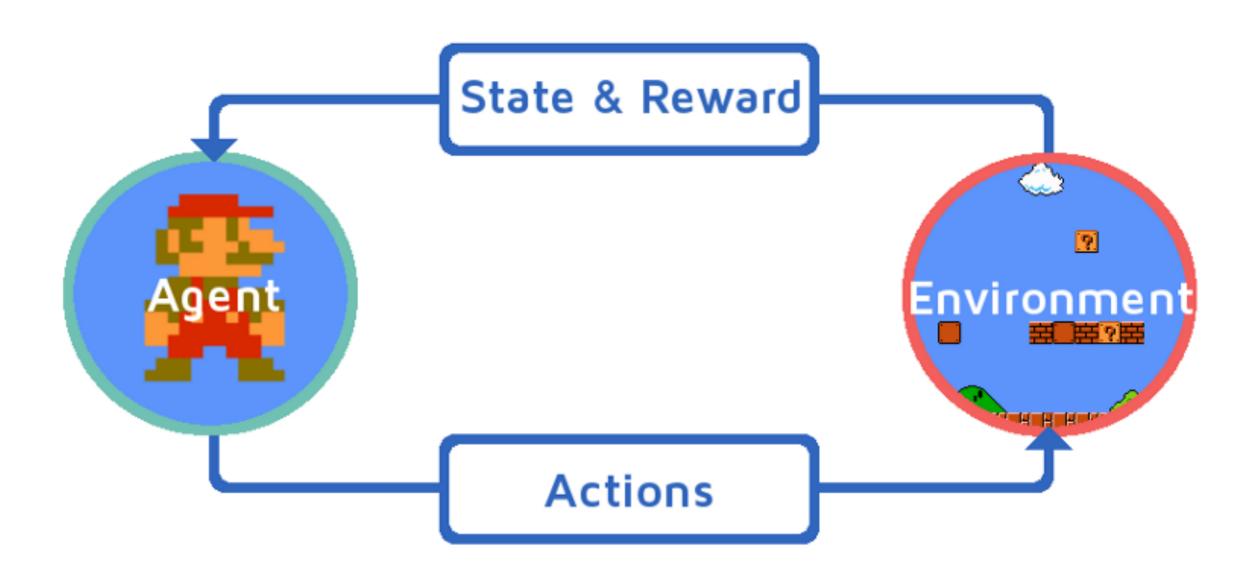
Reinforcement Learning

Saurabh Gupta

Agent Environment Interface



Reinforcement Learning

Markov Decision Process



Step Back

 a_t

 O_{t+1}

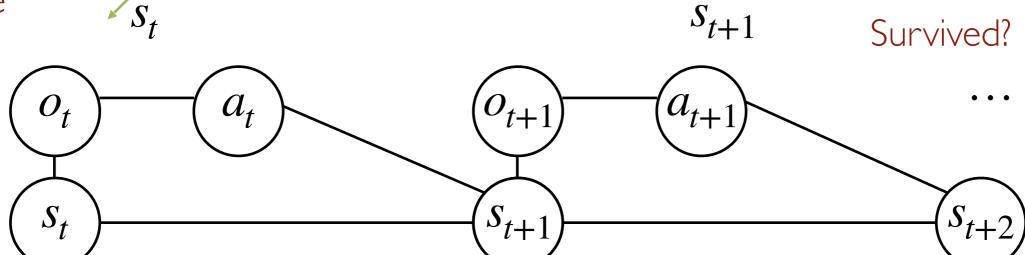
Transition Function

How you move, how the tiger moves?

Reward Function

Survived?





One step dynamics $p(s_{t+1}, r_{t+1} | s_t, a_t)$

Transition Function $p(s_{t+1} | s_t, a_t)$

$$p(s_{t+1} | s_t, a_t)$$

$$p(s_{t+2} | s_{t+1}, a_{t+1})$$

Reward Function
$$r_{t+1} = R(s_{t+1}, s_t, a_t)$$

$$r_{t+2} = R(s_{t+2}, s_{t+1}, a_{t+1})$$

Goal

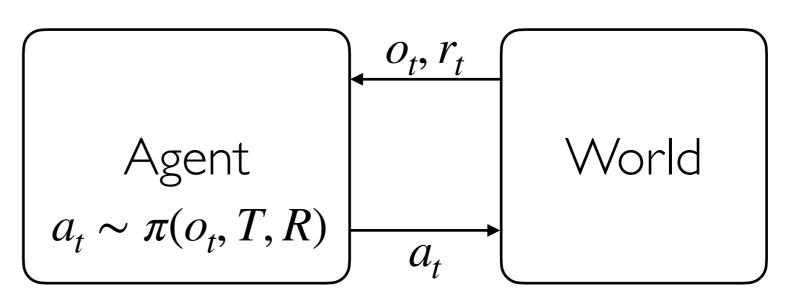
$$\operatorname{argmax}_{a_0,...,a_T} \sum \gamma^t r_t$$

Solving MDPs

Policy: $a_t \sim \pi(o_t)$

Most General Case

More Specific Case



Fully Observed System

$$o_t = s_t$$

Known Transition Function

Known Reward Function

$$s_{t+1} \sim T(s_t, a_t)$$

$$R(s_{t+1}, s_t, a_t)$$

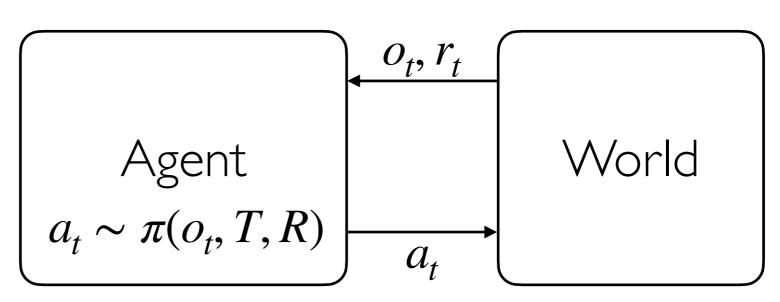
Solving MDPs

Policy: $a_t \sim \pi(o_t)$

Most General Case

 $\begin{array}{c} o_t, r_t \\ \\ Agent \\ a_t \sim \pi(o_t) \end{array} \qquad \begin{array}{c} o_t, r_t \\ \\ a_t \end{array}$

More Specific Case



Fully Observed System

$$o_t = s_t$$

Known Transition Function
Known Reward Function

$$s_{t+1} \sim T(s_t, a_t)$$

$$R(s_{t+1}, s_t, a_t)$$

Basics

Policy

Episodes

Returns

Value Functions

Action-value Functions

Solving MDPs via Dynamic Programming

Policy Evaluation

Policy Improvement

Policy Iteration

Value Iteration

Resources

Reinforcement Learning: An Introduction
Sutton and Barto
http://incompleteideas.net/book/the-book-2nd.html

David Silver's **Reinforcement Learning Course** https://www.davidsilver.uk/teaching/

Thank you