Introduction to Reinforcement Learning

Swati Mishra

Applications of Machine Learning (4AL3)

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McMaster University

ENGINEERING

Tips on Planning for Final Project

- All project milestones can be submitted at **anytime** before the deadline. You do not have to wait until the deadline to finish it.

- Milestone III is all about making **small improvements** to your project. Most of your work is finished in Milestone II. As an example, if you experiment with 2 normalization techniques; Standard Scalar and Min Max, you can report results of 1 technique in milestone II and results of another technique in milestone III.

- There are 3 parts: Data + Model + Evaluation (distribute the workload evenly across team members).

- Try to stick with topics that have been covered in the class. Trying to learn something entirely new may take way more time and effort.

- Do not be too ambitious. It’s more important to complete the project. Please talk to me when in doubt.

Reinforcement Learning

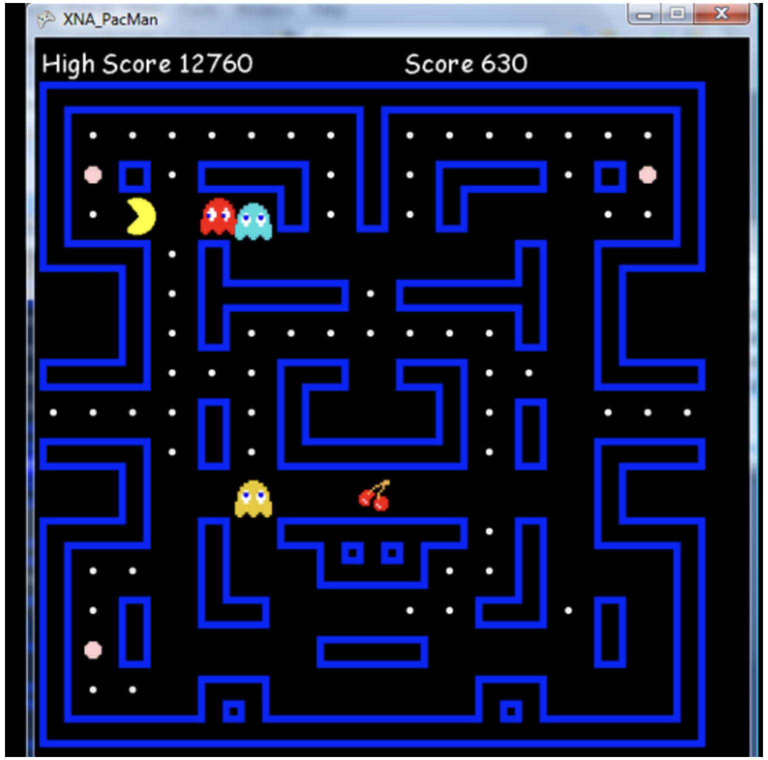
- A software agent
  - Makes observations,
  - Takes actions within an environment,
  - Receives a reward:
    - The reward maybe positive – award for taking the right /acceptable action.
    - The reward maybe negative – punishment for taking the wrong/inacceptable action.

- The goal of the agent is to maximize the reward and minimize the punishment.

- If you think about it, the process is entirely trial and error.

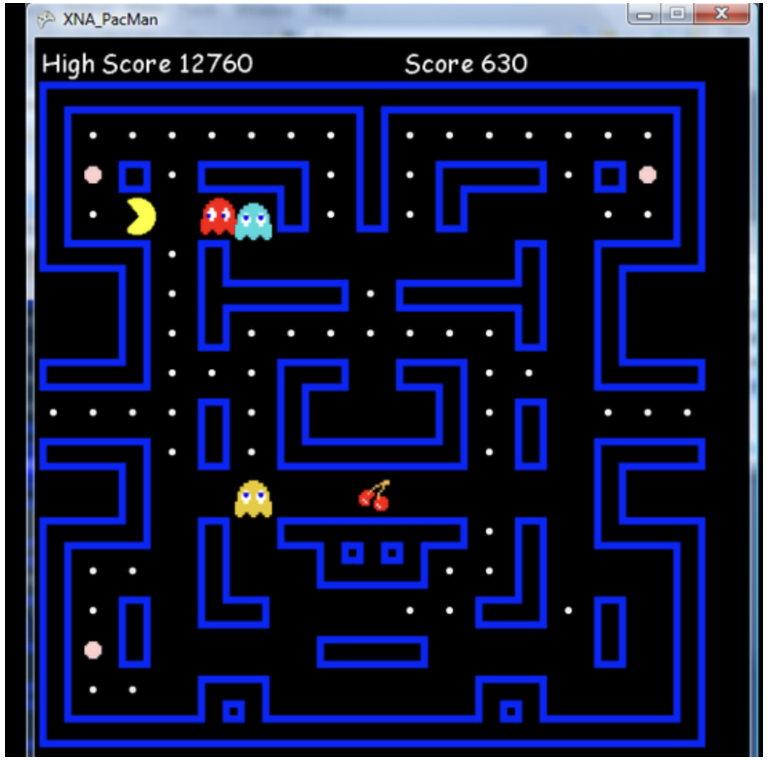
Reinforcement Learning

- Think Atari game Pac-man!
- The **environment** is
- The **agent** is
- The **actions** are
- The **reward** is
- The **observation** is



Reinforcement Learning

- Think Atari game Pac-man!
- The **environment** is the simulation of the Atari game.
- The **agent** is something that control the Ms. Pac-Man movements.
- The **actions** are possible directions in which the movements can occur (Up, Left, Right, Down).
- The **reward** is points earned or the game score.
- The **observation** is screenshots of the game stages.



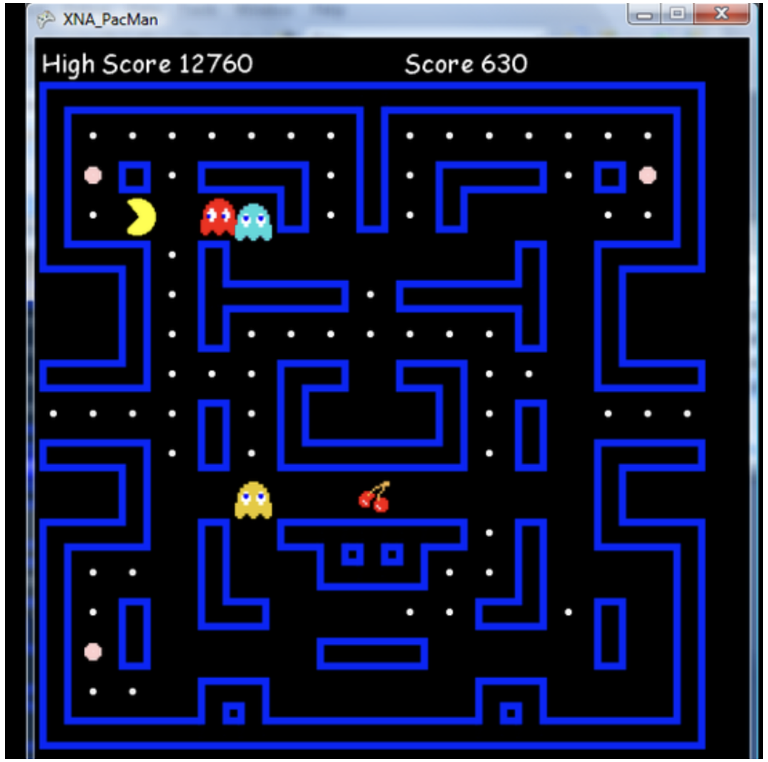
Picture Source: Wikipedia

Reinforcement Learning: Policy

- RL systems need a **policy function** to determine the behavior of the agent

- A policy defines the learning agent's way of behaving at a given time. It is defined as the **mapping from** perceived states of the **environment to actions** that the agent must takes when those states are encountered.

- Policy function can be a simple hash look up table, or a complex like some sort of search algorithm.



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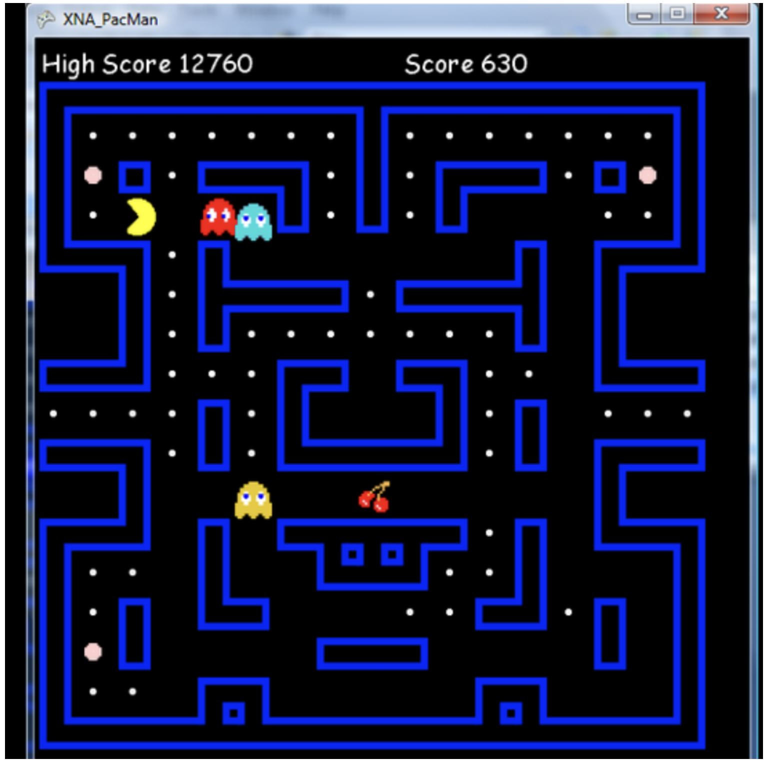

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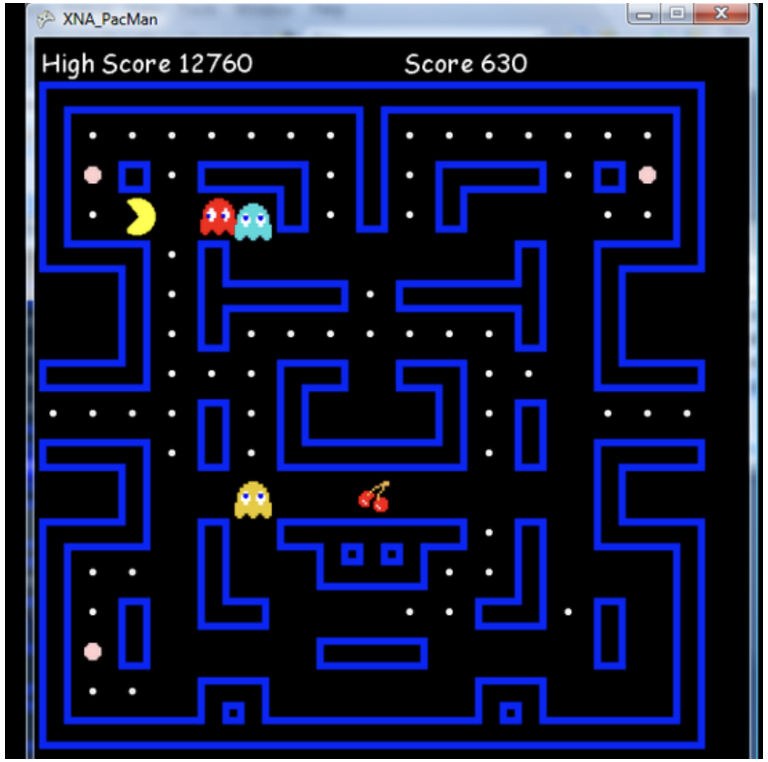

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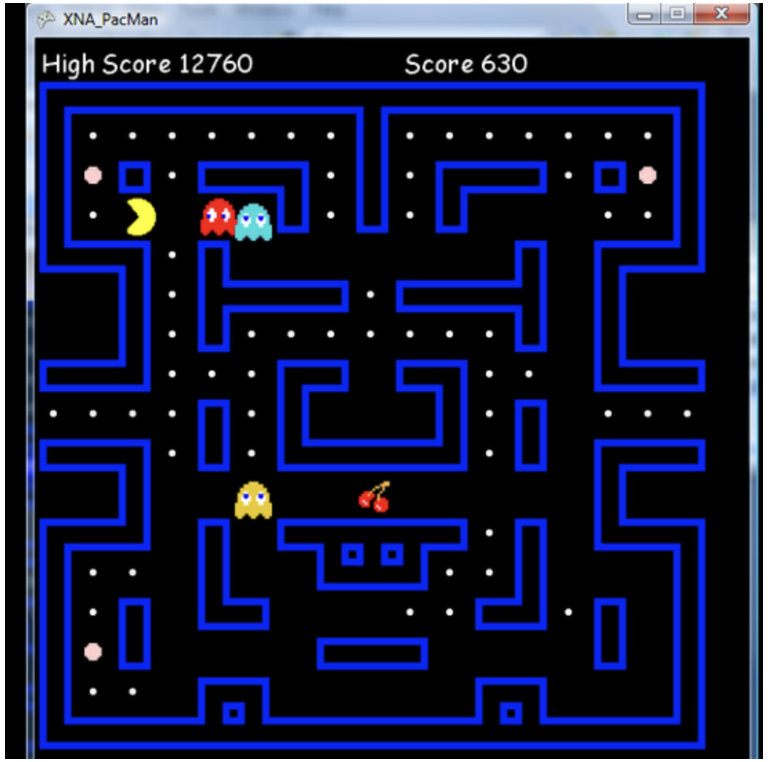
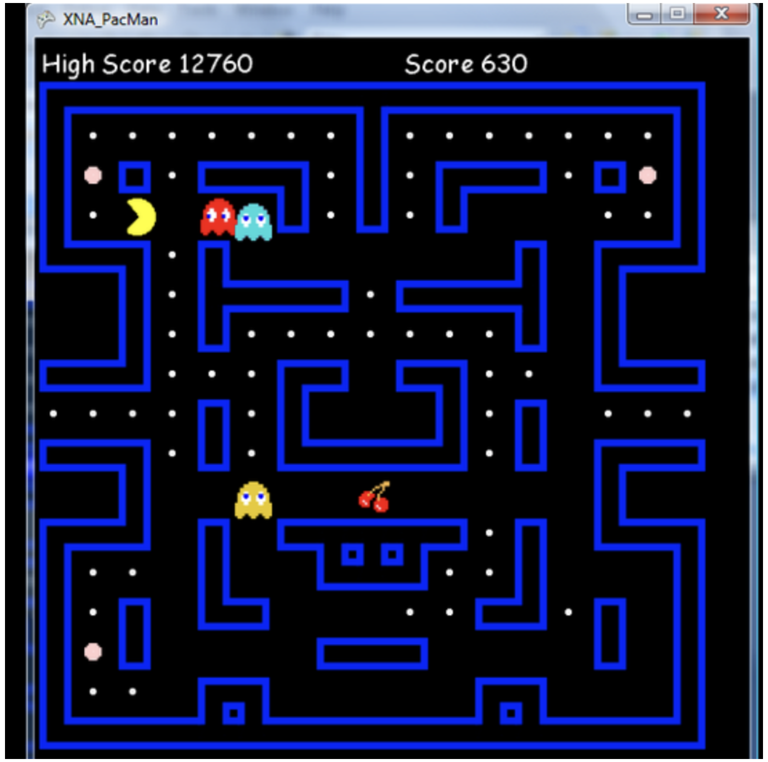


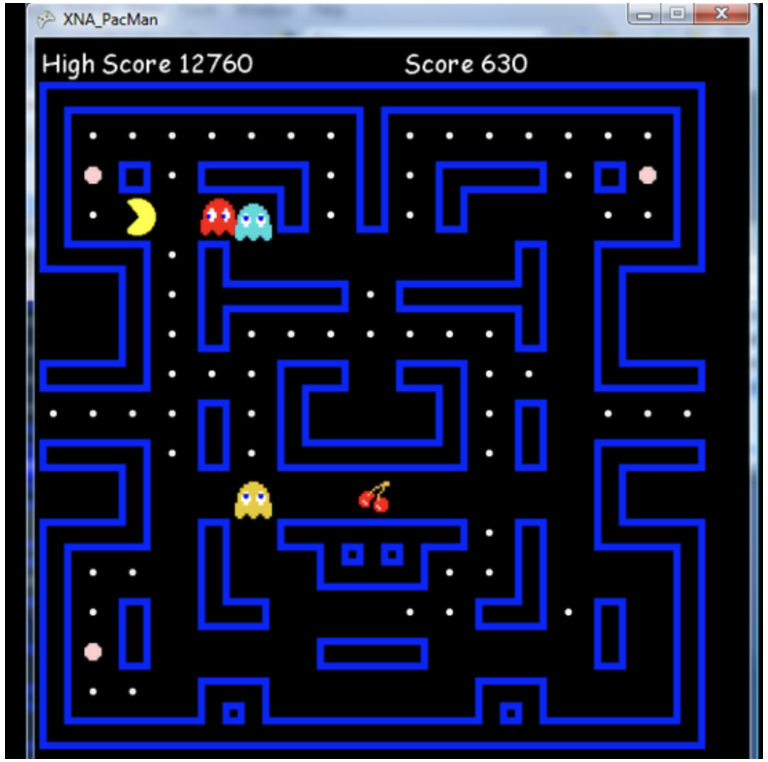
Reinforcement Learning: Reward

- At each time step, the agent receives a “numeric” reward, and it’s goal is to maximize it.
- Reward at a given time step depends on the current action, and current observation.
- The agent may learn a policy based on reward, not the other way round.
- If in the current state, the policy selected gives low rewards, then policy is changed for the future state.
- Reward signal indicates what is good in current state.



Reinforcement Learning: Value

- Value function indicates what is advantageous in the long run.
- It indicates the long-term-desirability of a given state in the environment.
- A state with low immediate reward does not necessarily yield bad score, because maybe it is helpful in the long run.
- Value function is estimated through observations and reward.
- Usually, the goal is to seek a state of highest value, not highest reward.



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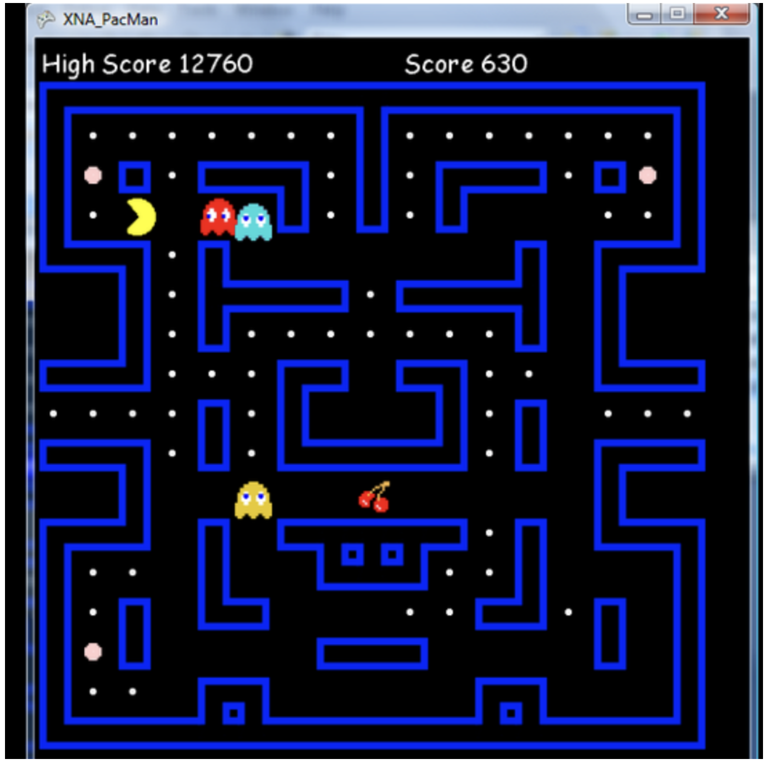
Reinforcement Learning: Model

- This is the simulation of the environment and mimic its behavior in real time.
- For a given state and action, a model might predict the next state and next reward.
- Models are useful for planning a set of actions to anticipate the states an agent might experience even before they are encountered.
- Model-based methods use a model and planning, model-free methods do not use model and planning.



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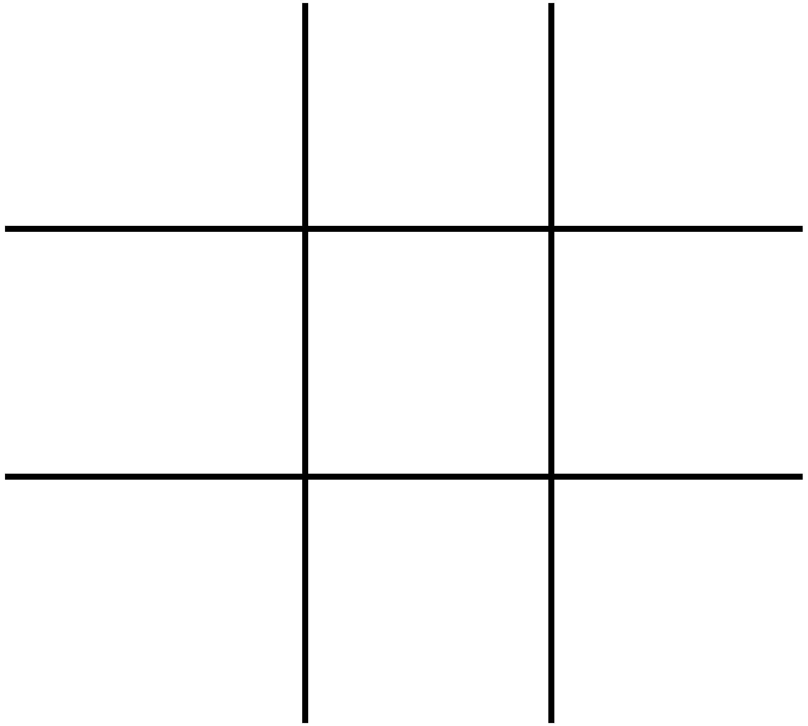
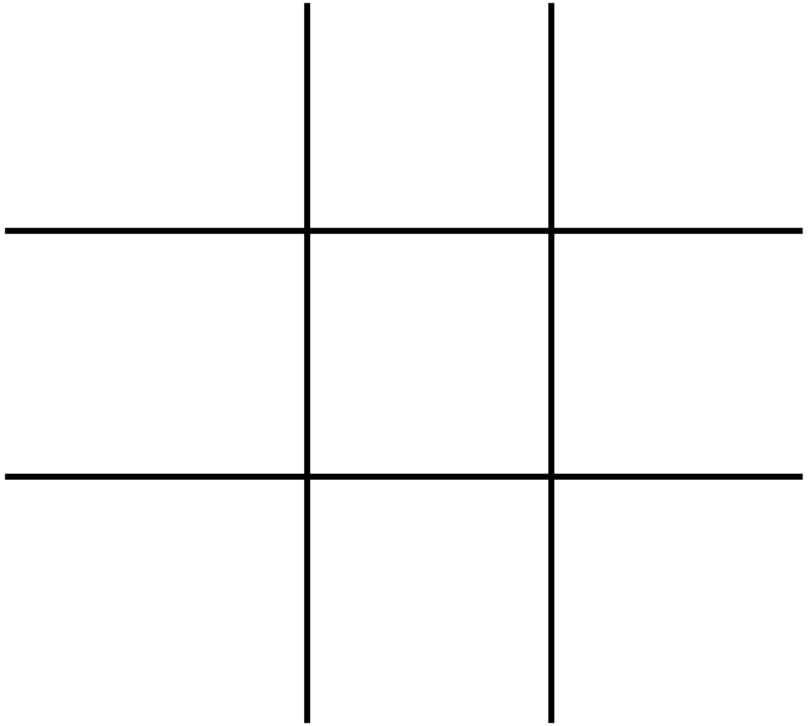
Reinforcement Learning



Let’s play Tic-Tac-Toe!

Reinforcement Learning

Starting Position: Empty board



Minmax solution from game theory:

$$\max_{x \in X} \min_{y \in Y} f(x, y) = \min_{y \in Y} \max_{x \in X} f(x, y)$$

Reinforcement Learning

Starting Position: Empty board

Possible moves : **0**
Move by A : **0**

0	0	0
0	0	0
0	0	0

Minmax solution from game theory:

$$\max_{x \in X} \min_{y \in Y} f(x, y) = \min_{y \in Y} \max_{x \in X} f(x, y)$$

Reinforcement Learning

Starting Position: Empty board

Possible moves : **0**
Move by A : **0**

Possible moves : **X**
Move by B : **X**

0	X	X
X	X	X
X	X	X

Minmax solution from game theory:

$$\max_{x \in X} \min_{y \in Y} f(x, y) = \min_{y \in Y} \max_{x \in X} f(x, y)$$

Reinforcement Learning

Starting Position: Empty board

Possible moves : **0**
Move by A : **0**

Possible moves : **X**
Move by B : **X**

Possible moves : **0**
Move by A : **0**

0	X	0
0	0	0
0	0	0

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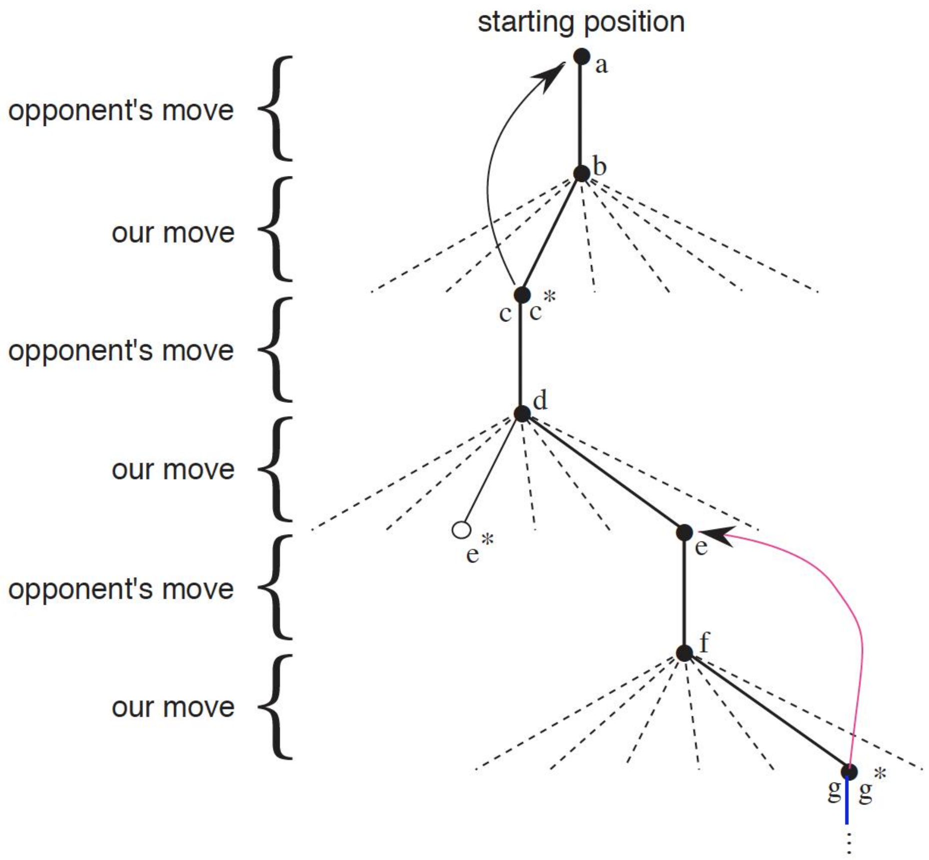
Reinforcement Learning



0	X	0
0	0	0
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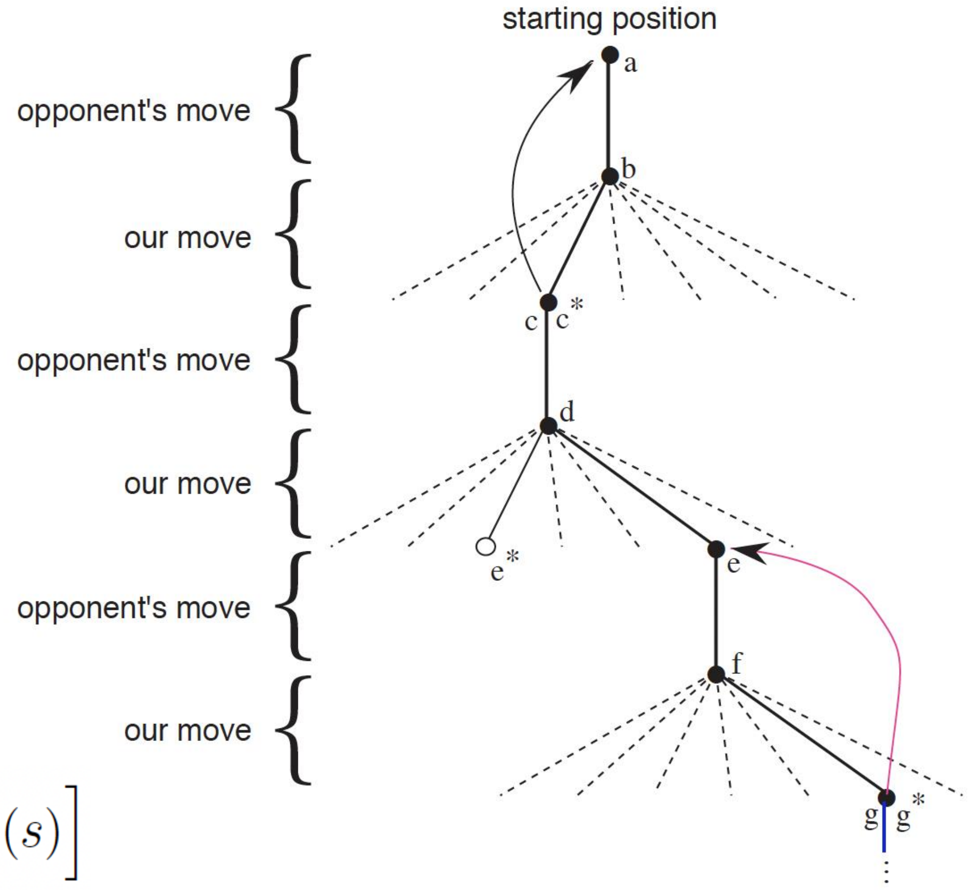
Minmax solution from game theory:

$$\max_{x\in X}\min_{y\in Y} f(x,y) = \min_{y\in Y}\max_{x\in X} f(x,y)$$

Reinforcement Learning: Learning

- The idea is to play many games with the opponent.
- We observe the result from each move and many times, select states that lead to greatest value.
- As we progress, we change the values of our current state.
- To make more accurate estimates of the probability of success (e.g. maximizing the reward), we “back up” the value of state after each greedy move.
- s = state before greedy move,
  s’ = state after the move,
  V = estimated value of s

$$V(s) \leftarrow V(s) + \alpha\Big[V(s') - V(s)\Big]$$



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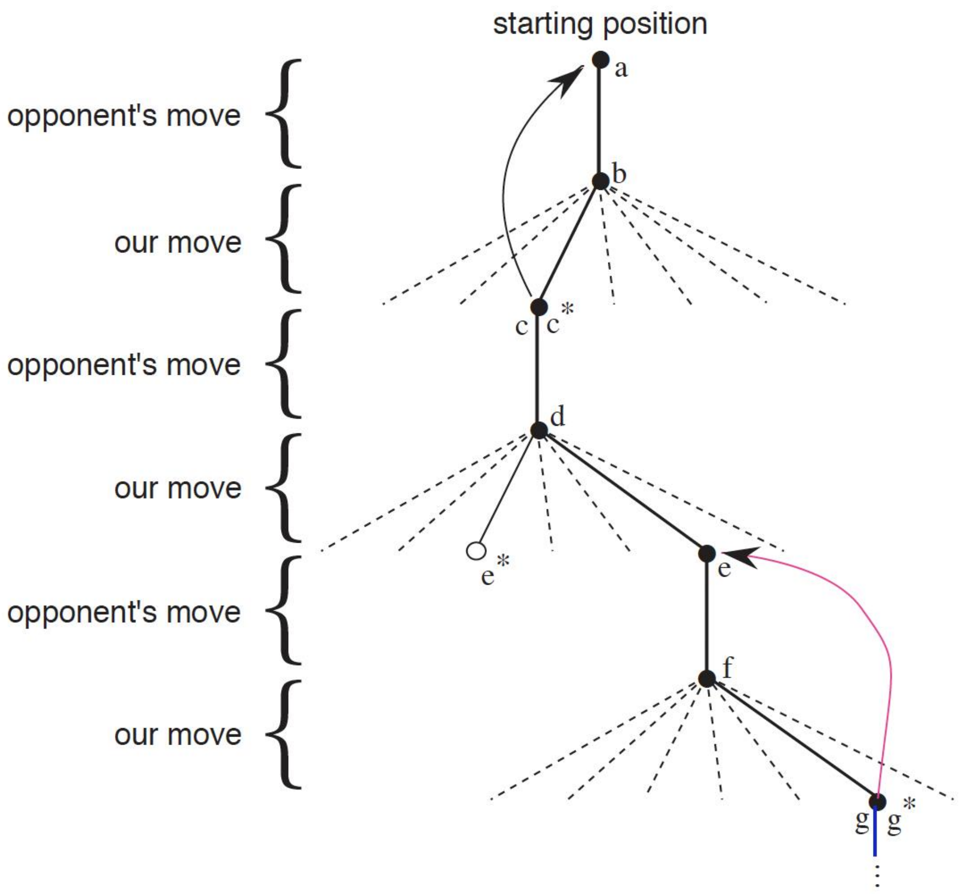


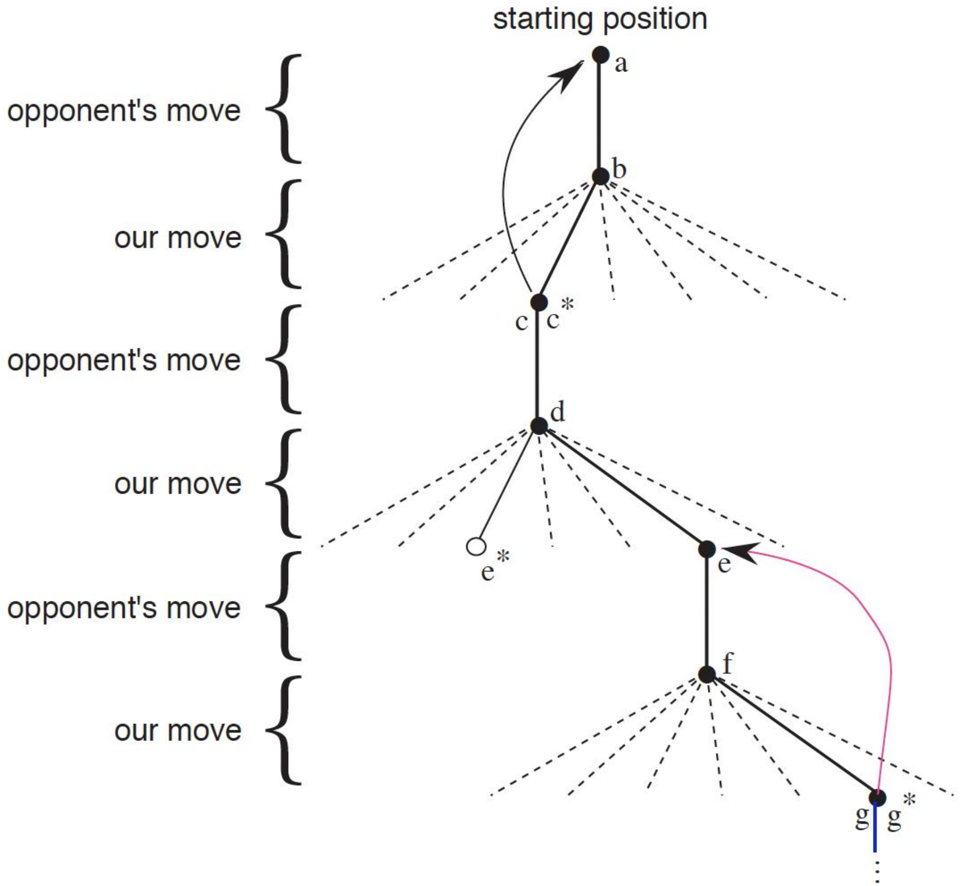
Reinforcement Learning: Learning

- s = state before greedy move,
  s’ = state after the move,
  V = estimated value of s

$$V(s) \leftarrow V(s) + \alpha\Big[V(s') - V(s)\Big]$$

- If the step-size parameter is reduced properly over time, this method converges, for any fixed opponent

- If the step-size parameter is not reduced all the way to zero over time then this player also plays well against opponents that slowly change their way of playing.



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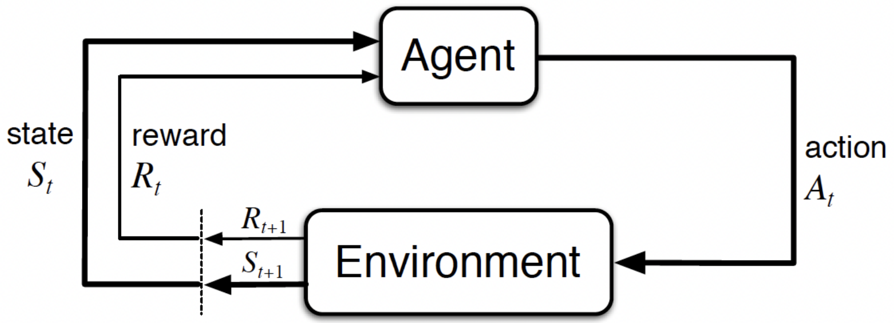
Reinforcement Learning: Policy Evaluation

- How do we compute the state- value of an arbitrary policy?

$$
\begin{aligned}
v_\pi(s) &= \mathbb{E}_\pi\big[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \cdots \mid S_t = s\big] \\
&= \mathbb{E}_\pi[R_{t+1} + \gamma v_\pi(S_{t+1}) \mid S_t = s] \\
&= \sum_a \pi(a|s) \sum_{s',r} p(s',r|s,a)\Big[r + \gamma v_\pi(s')\Big],
\end{aligned}
$$

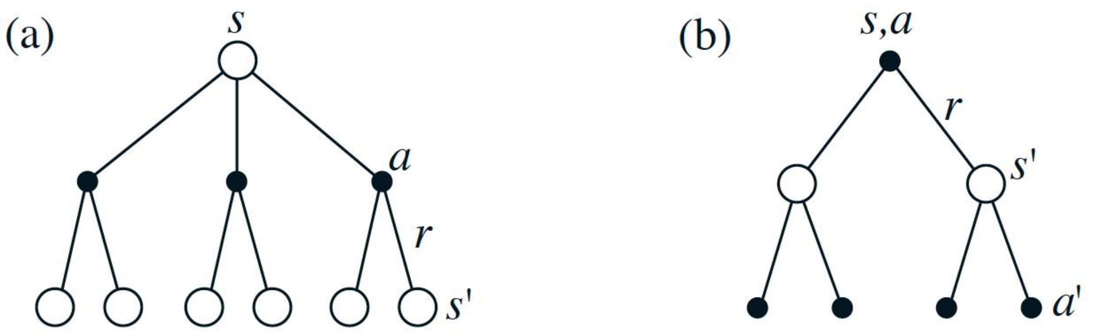


If the environment's dynamics are completely known, then above is a system of |S| simultaneous linear equations.

Reinforcement Learning: Policy Evaluation

- How do we compute the state- value of an arbitrary policy
  - Using the Bellman equation for: $$= \sum_a \pi(a|s) \sum_{s',r} p(s',r|s,a)\Big[r + \gamma v_\pi(s')\Big]$$

The Bellman equation averages over all the possibilities, weighting each by its probability of occurring.



Backup diagrams for (a) value function and (b) back up policy

Reinforcement Learning: Policy Evaluation

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\begin{aligned}
v_{k+1}(s) &= \mathbb{E}_\pi[R_{t+1} + \gamma v_k(S_{t+1}) \mid S_t = s] \\
&= \sum_a \pi(a|s) \sum_{s',r} p(s',r|s,a)\Big[r + \gamma v_k(s')\Big]
\end{aligned}
$$

In principle, iterative solution methods are most suitable.

Readings

Reference Reading:

- Uploaded on Avenue

Thank You