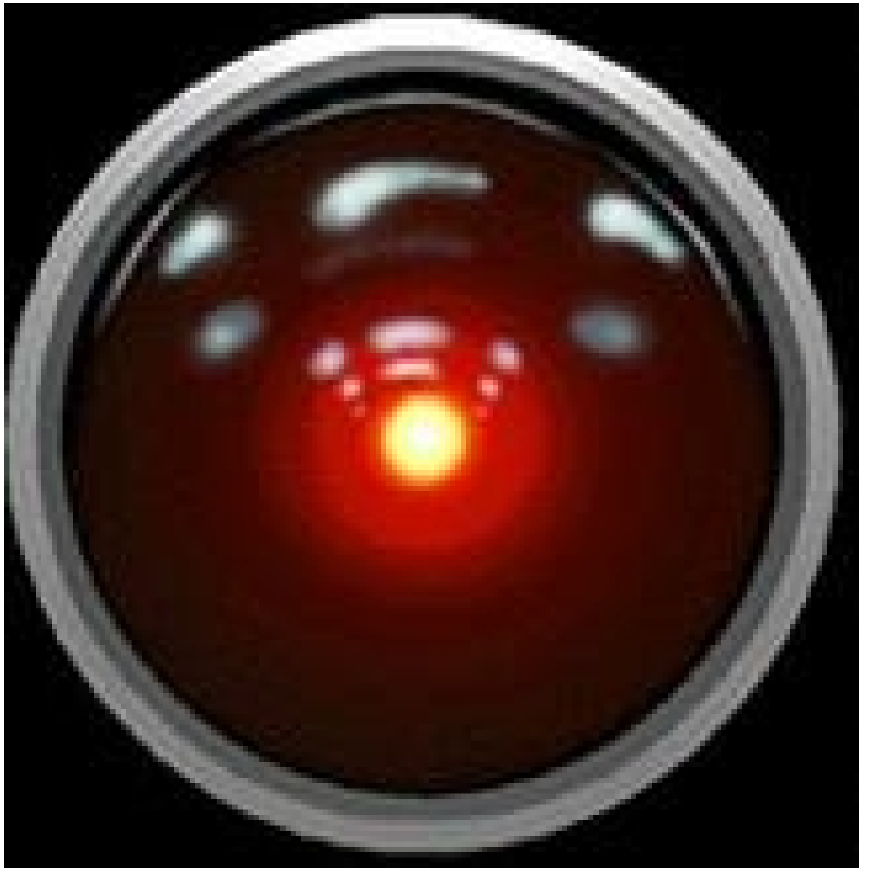
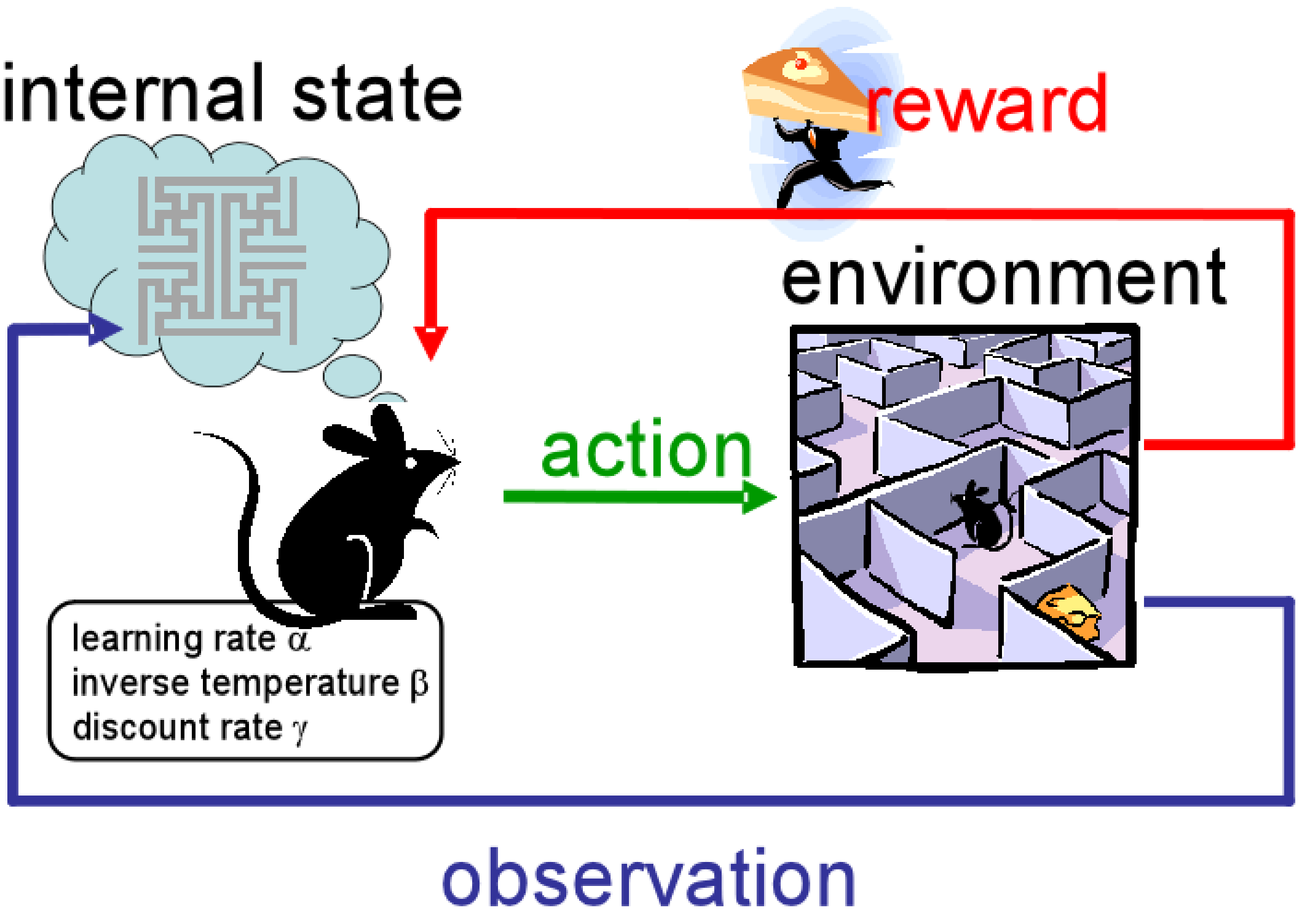


CS 378: Autonomous Intelligent Robotics FRI-II

Instructor: Jivko Sinapov

http://www.cs.utexas.edu/~jsinapov/teaching/cs378_fall2016/

Reinforcement Learning (Part 2)



Announcements

Volunteers needed for robot study

Sign up sheet here:

https://docs.google.com/spreadsheets/d/1Gr2GqlPt8kdTJwlZ3FerxU0J8oIoGt0pEbeR37iCHqY/edit#gid=0

Further details will be made available on Canvas via an announcement

FAI Talk this Friday

"Turning Assistive Machines into Assistive Robots"

Brenna Argall

Northwestern University

Friday, Sept. 9th, 11 am @ GDC 6.302

[https://www.cs.utexas.edu/~ai-lab/fai/] or google "fai ut cs"

Robotics Seminar Series Talk

"Learning from and about humans using an autonomous multi-robot mobile platform"

Jivko Sinapov

UT Austin

Wed., Sept. 7th, 3 pm @ GDC 5.302

Robot Training

- Sign up for a robot training session next week at: https://docs.google.com/spreadsheets/d/1kz6QMPa-xkdFQNyV0Biif913JKf73GIUGx9bVSLo_R8/edit?usp=sharing

- Link will be posted as Announcement on Canvas

Preliminary Project “Presentations”

- Date: **September 13th**
- Form groups of 2-3 prior to the date
- Be prepared to talk about 2-3 project ideas for 5-10 minutes
- **Email me your group info, i.e., who is in it**

Project Ideas

Project Idea: Improve the robot's grasping ability

- Currently, the robot does not “remember” which grasps succeeded and which failed
- If the robot were to log the context of the grasp (e.g., the position of the gripper relative to the object's point cloud) and the outcome, it could incrementally learn a model to predict the outcome given the context
- The robot's current grasping software is described in http://wiki.ros.org/agile_grasp

Project Idea: Object Handover

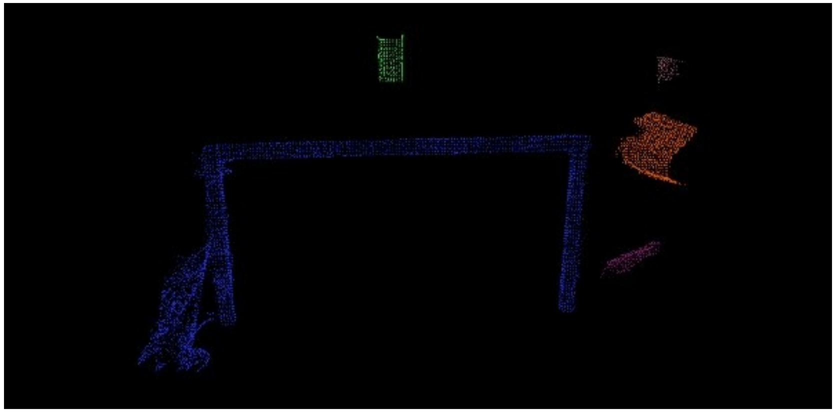
- Currently, the arm can let go of an object or close its fingers upon sufficient contact using haptic feedback
- Can you make it so that it can move towards an object held by a human and grasp it based on visual *and* haptic feedback?

Project Idea: Learning about objects from humans

- The robot is currently able to grasp an object from a table and navigate to an office
- Can we use the GUI to ask humans questions about objects and store this information in a database that can be used for learning recognition models?

Project Idea:
Large-Scale 3D object mapping

- Can we combine 3D Plane detection and Clustering to detect and map objects in the environment?



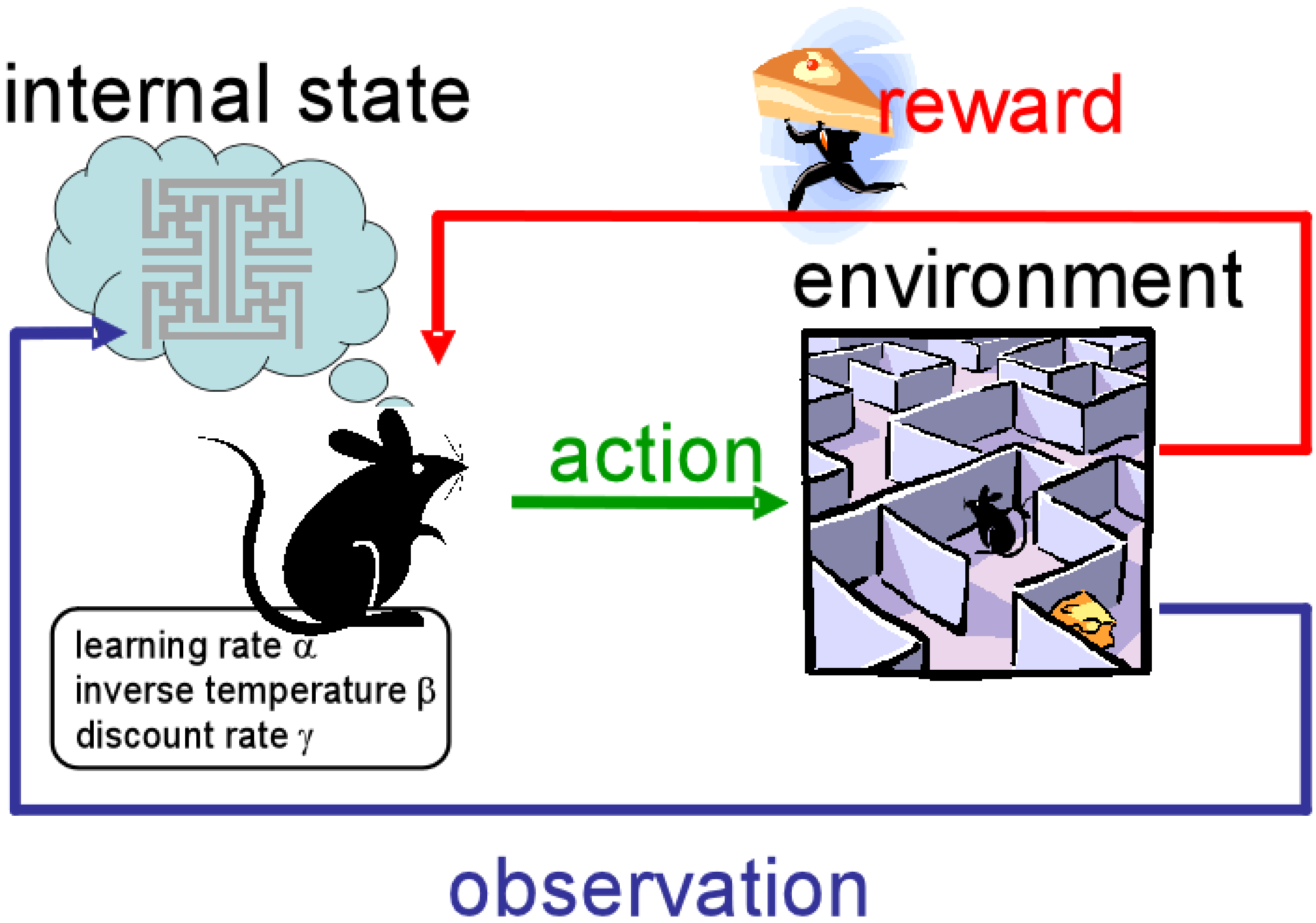
Project Idea: Learning an object manipulation skill

- Example: Pressing a button

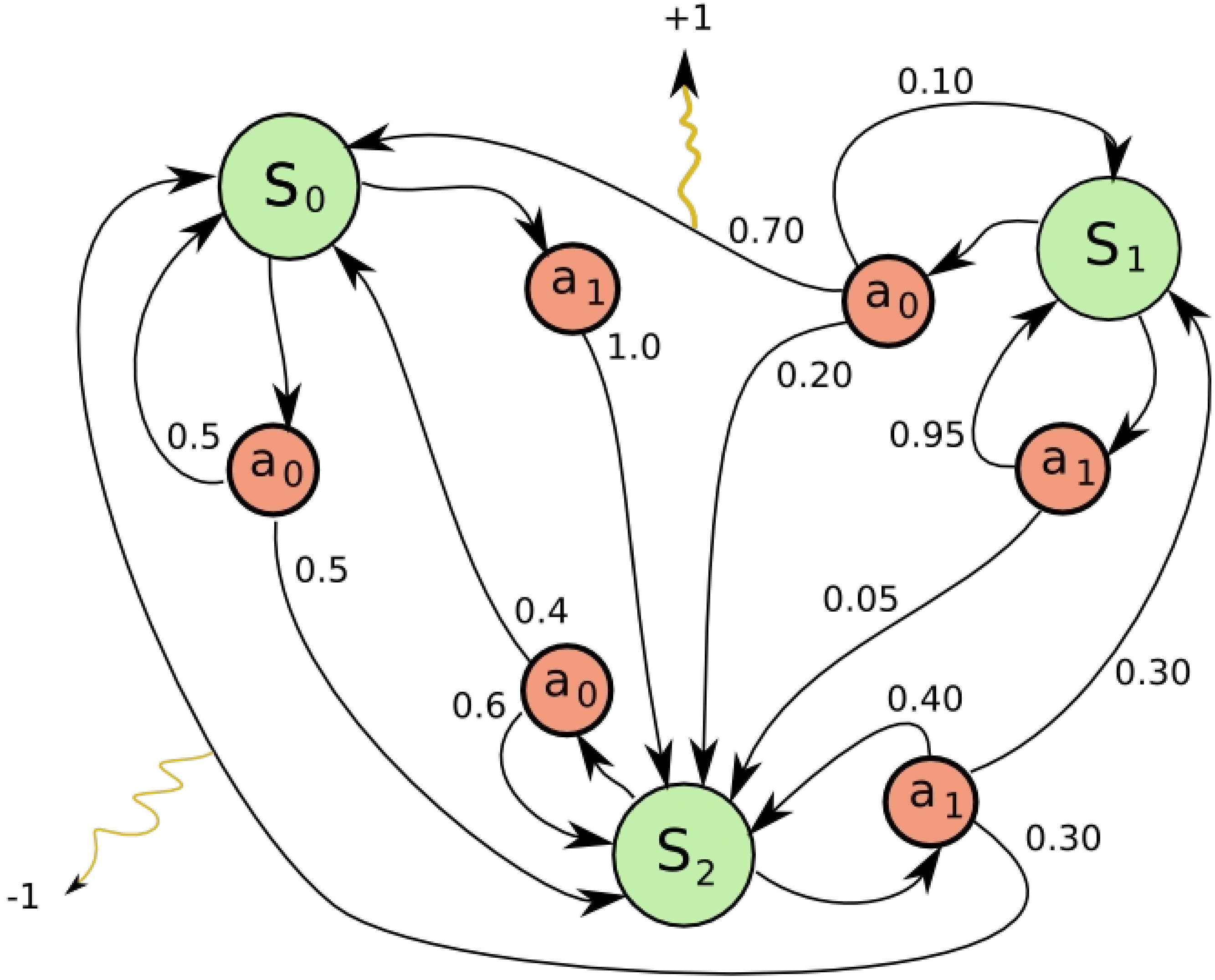
Project Idea: Enhance Virtour

www.cs.utexas.edu/~larg/bwi_virtour

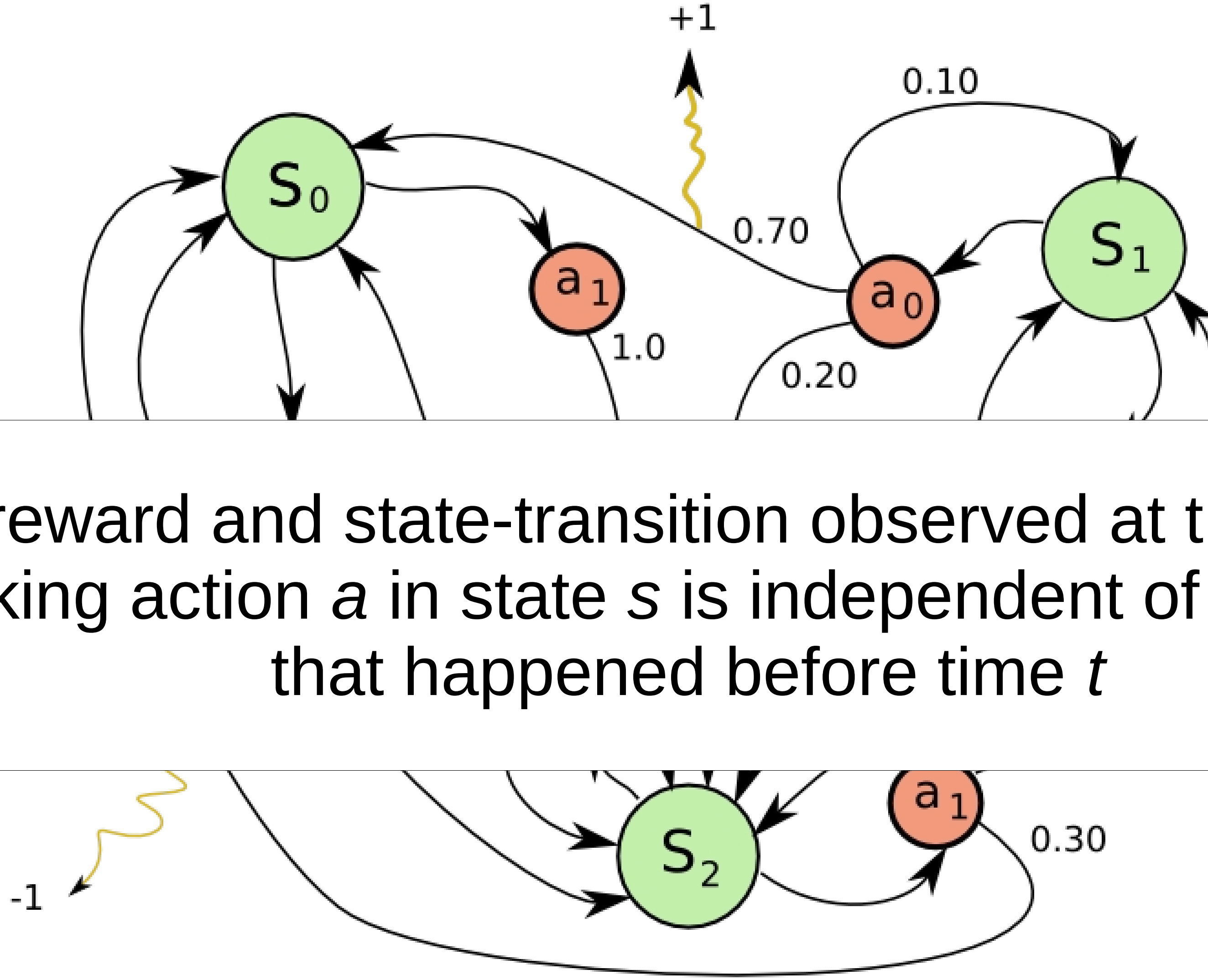
Reinforcement Learning (Part 2)



Markov Decision Process (MDP)

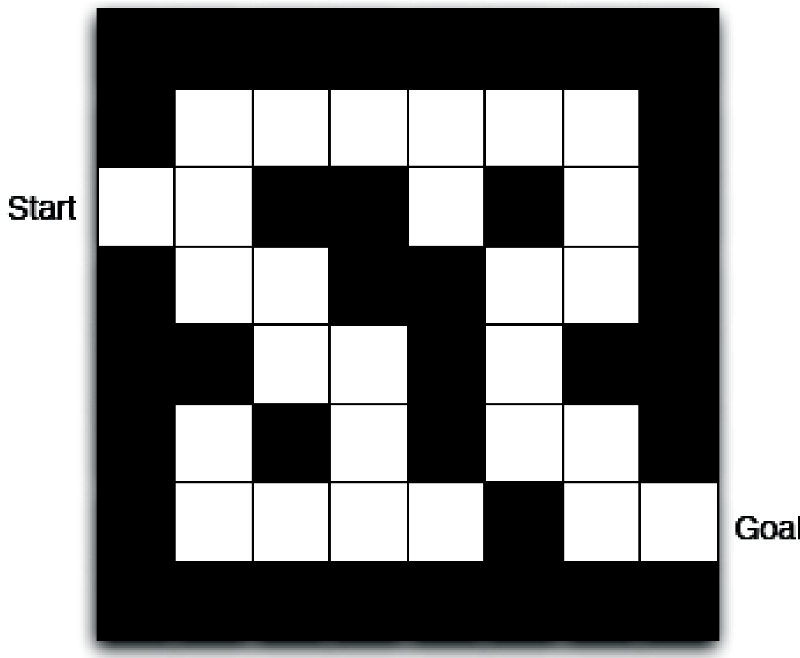


Markov Decision Process (MDP)



The reward and state-transition observed at time *t* after picking action *a* in state *s* is independent of anything that happened before time *t*

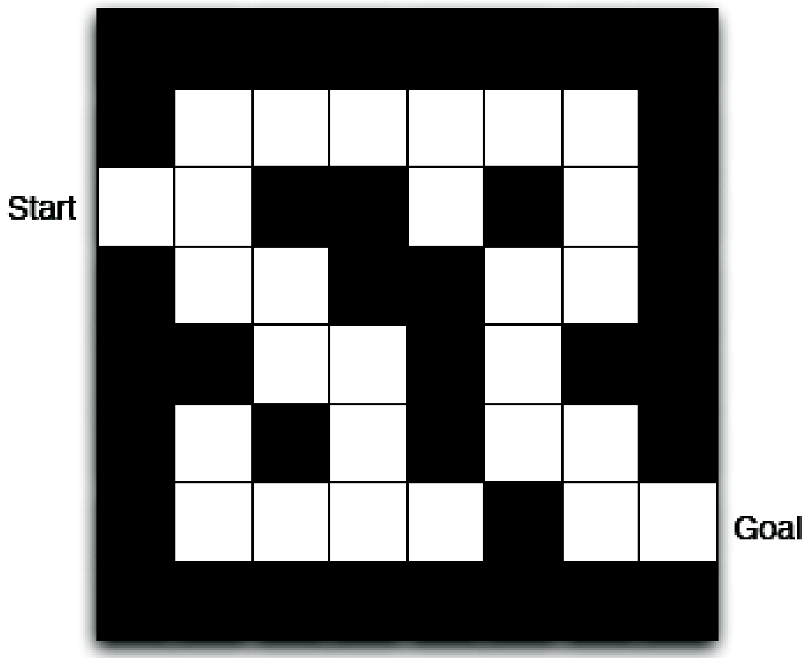
Maze World



- Rewards: -1 per time-step
- Actions: N, E, S, W
- States: Agent's location

[slide credit: David Silver]

Maze World

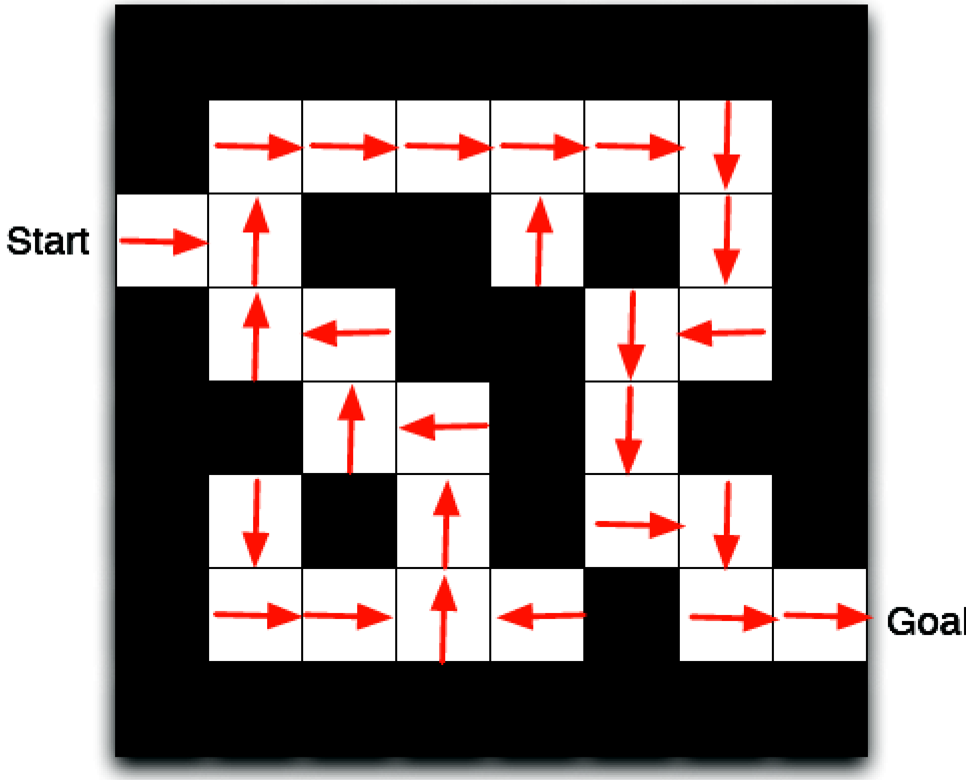


- Rewards: -1 per time-step
- Actions: N, E, S, W
- States: Agent's location

State Representation:
Factored vs. **Tabula Rasa**

[slide credit: David Silver]

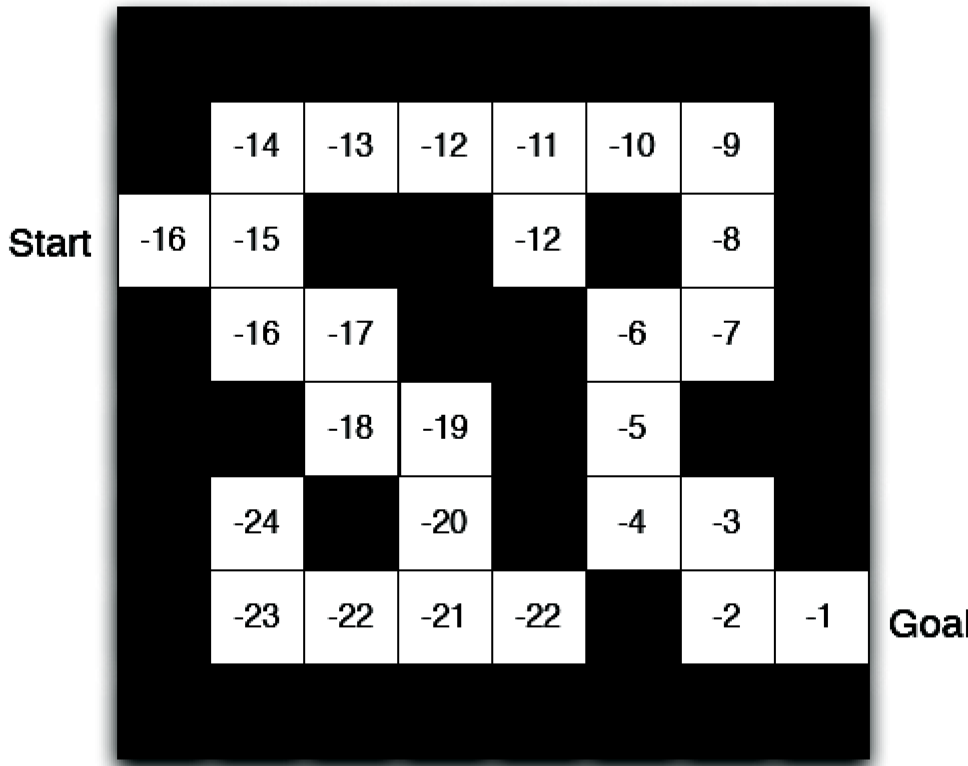
Maze Example: Policy



- Arrows represent policy $\pi(s)$ for each state s

[slide credit: David Silver]

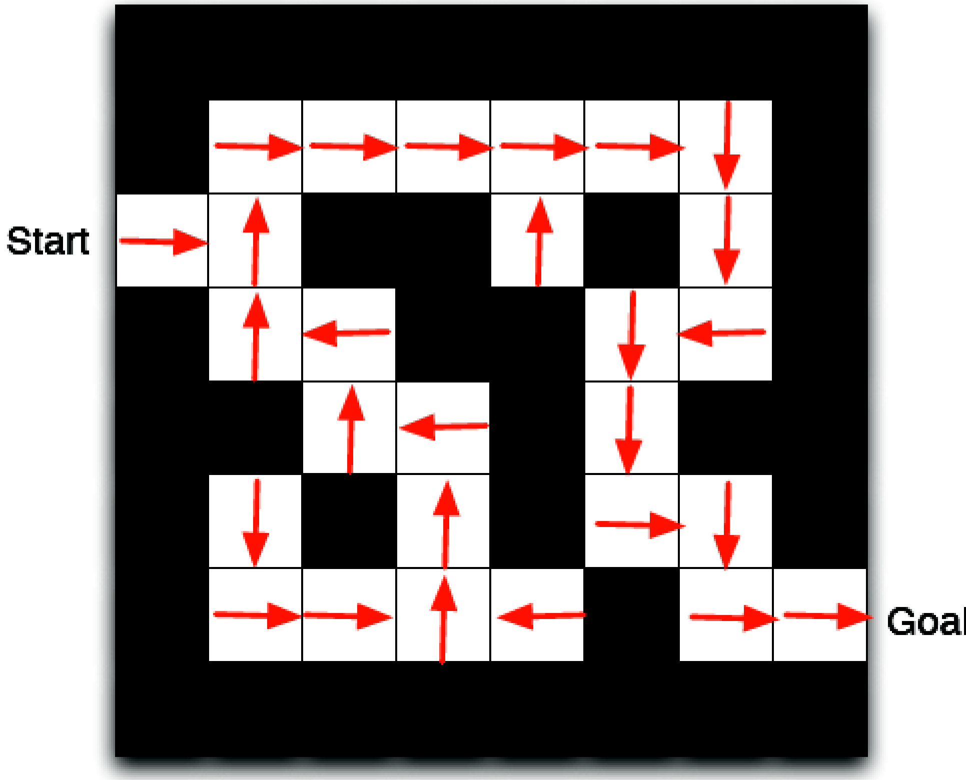
Maze Example: Value Function



- Numbers represent value $v_\pi(s)$ of each state s

[slide credit: David Silver]

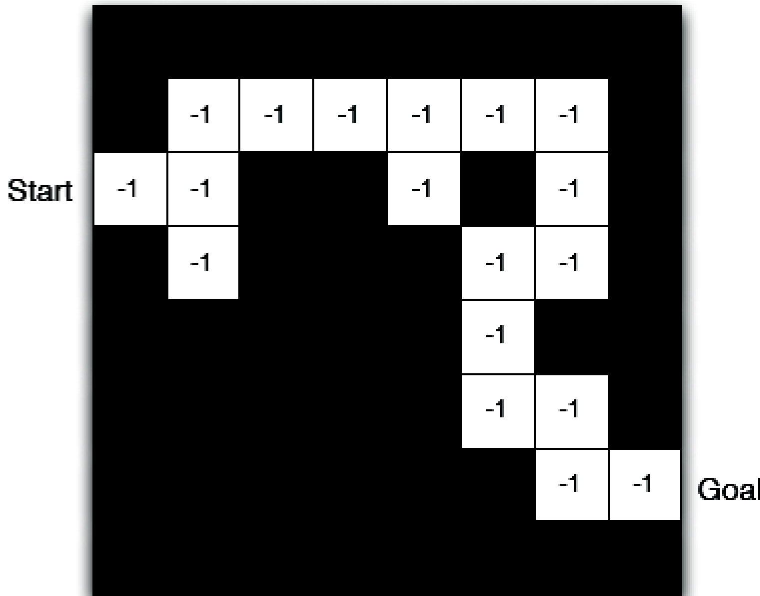
Maze Example: Policy



- Arrows represent policy $\pi(s)$ for each state s

[slide credit: David Silver]

Maze Example: Model



- Agent may have an internal model of the environment
- Dynamics: how actions change the state
- Rewards: how much reward from each state
- The model may be imperfect

- Grid layout represents transition model $\mathcal{P}^a_{ss'}$
- Numbers represent immediate reward $\mathcal{R}^a_s$ from each state s (same for all a)

[slide credit: David Silver]

Sparse vs. Dense Reward

Notation and Problem Formulation

- Overview of notation in TEXPLORE paper

Notation

Set of States: $\mathcal{S}$

Set of Actions: $\mathcal{A}$

Transition Function:

$$\mathcal{P} : \mathcal{S} \times \mathcal{A} \mapsto \Pi(\mathcal{S})$$

Reward Function:

$$\mathcal{R} : \mathcal{S} \times \mathcal{A} \mapsto \mathbb{R}$$

Action-Value Function

$$Q^*(s,a) = \mathcal{R}(s,a) + \gamma \sum_{s'} \mathcal{P}(s'|s,a) \max_{a'} Q^*(s',a')$$

Action-Value Function

Discount factor (between 0 and 1)

Probability of going to state *s'* from *s* after *a*

$$Q^*(s,a) = \mathcal{R}(s,a) + \gamma \sum_{s'} \mathcal{P}(s'|s,a) \max_{a'} Q^*(s',a')$$

The value of taking action *a* in state *s*

The reward received after taking action *a* in state *s*

a' is the action with the highest action-value in state s'

Action-Value Function

$$Q^*(s,a) = \mathcal{R}(s,a) + \gamma \sum_{s'} \mathcal{P}(s'|s,a) \max_{a'} Q^*(s',a')$$

Common algorithms to learn the action-value function include Q-Learning and SARSA

The policy consists of always taking the action that maximize the action-value function

Q-Learning Grid World Example

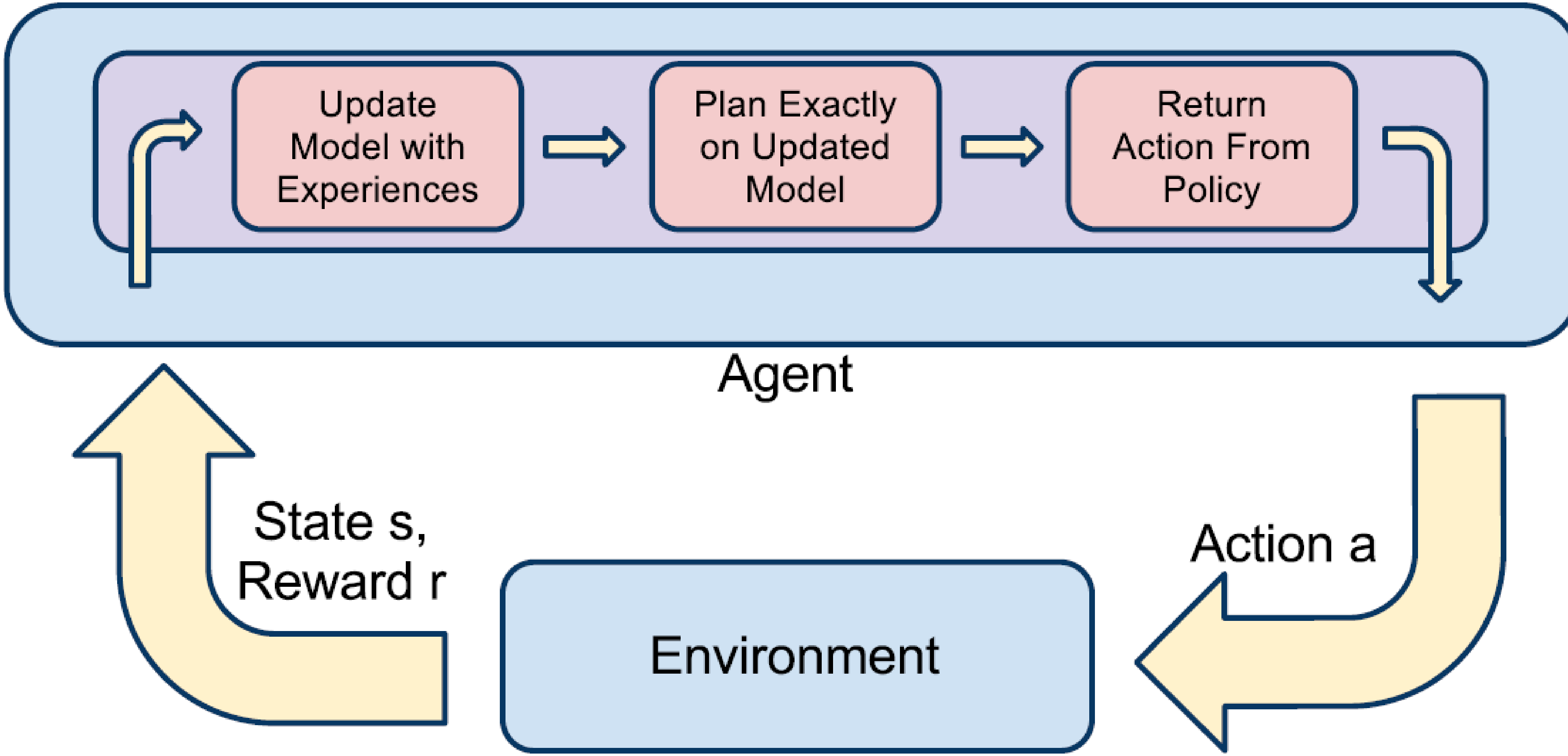
https://www-s.acm.illinois.edu/sigart/docs/QLearning.pdf

RL in a nutshell

Algorithm 1 Sequential Model-Based Architecture

Input: S, A ▷ S: state space, A: action space
Initialize M to empty model
Initialize policy π randomly
Initialize s to a starting state in the MDP
loop
    Choose $a \leftarrow \pi(s)$
    Take action a, observe r, s'
    $M \Rightarrow \text{UPDATE-MODEL}(\langle s, a, s', r \rangle)$ ▷ Update model M with new experience
    $\pi \leftarrow \text{PLAN-POLICY}(M)$ ▷ Exact planning on updated model
    $s \leftarrow s'$
end loop

RL in a nutshell



Q-Learning

- Guest Slides

Pac Man Example

Linear Function Approximator of Q*

$$Q^*(s,a) = \mathcal{R}(s,a) + \gamma \sum_{s'} \mathcal{P}(s'|s,a) \max_{a'} Q^*(s',a')$$

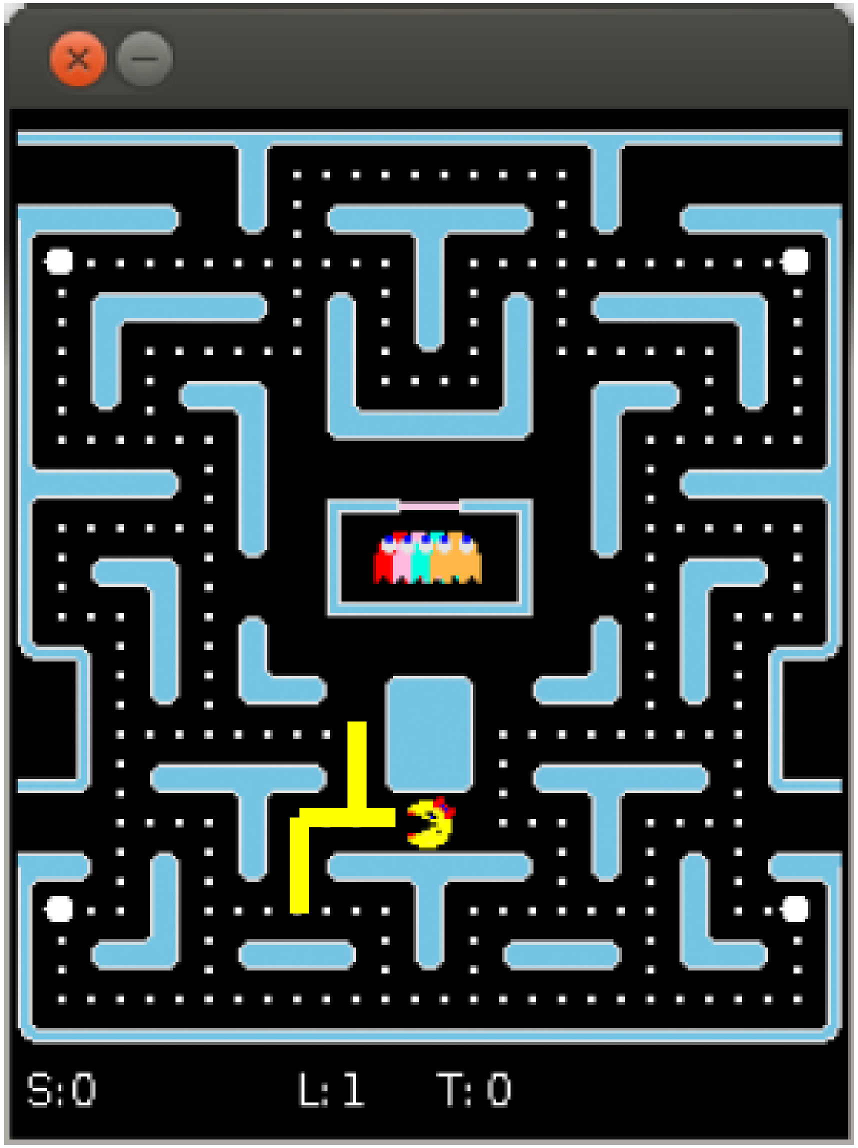
$\Phi(s,a)$ = **x** where **x** is an *n*-dimensional feature vector

$Q^*(\Phi(s,a)) =$

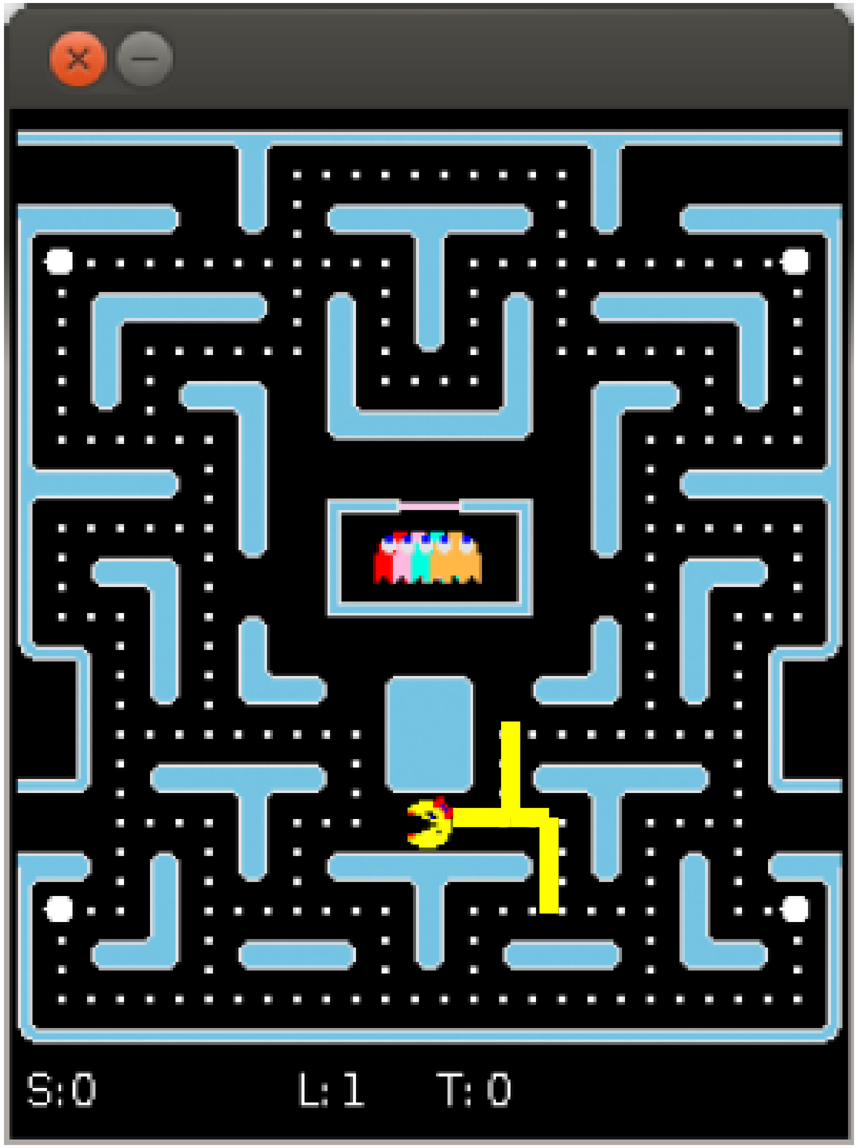
$$w_1 * x_1 + w_2 * x_2 + \ldots + w_n * x_n$$

How does Pac-Man "see" the world?

How does Pac-Man “see” the world?



How does Pac-Man “see” the world?



Linear Function Approximator of Q*

$$Q^*(s,a) = \mathcal{R}(s,a) + \gamma \sum_{s'} \mathcal{P}(s'|s,a) \max_{a'} Q^*(s',a')$$

Φ*(s,a)* = **x** where **x** is an *n*-dimensional feature vector

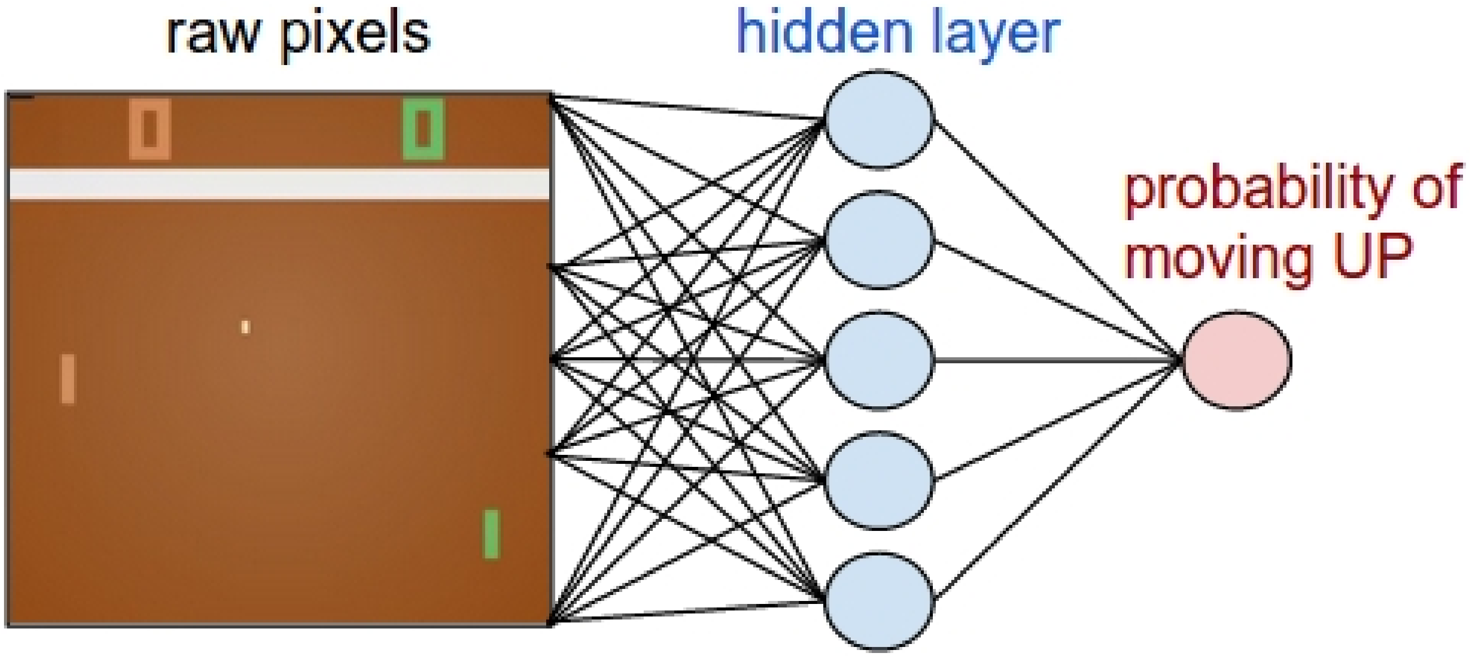
*Q**(Φ*(s,a)*) =

$$w_1 * x_1 + w_2 * x_2 + \ldots + w_n * x_n$$

The task now is to find the optimal weight vector **w**

Can RL learn directly from images?

- Yes it can:
- http://karpathy.github.io/2016/05/31/rl/



Video on Updating a NN's Weights

Neural Networks Demystified [Part 3: Gradient Descent]

https://www.youtube.com/watch?v=5u0jaA3qAGk

Video of TAMER

http://labcast.media.mit.edu/?p=300

Using RL: Essential Steps

1) Specify the state space or the state-action space

- Are the states and/or actions discrete or continous?

2) Specify the reward function

- If you have control over this, dense reward is better than sparse reward

3) Specify the environment (e.g., a simulator or perhaps the real world)

4) Pick your favorite RL algorithm that can handle the state and action representation

Resources

- BURLAP: Java RL Library: http://burlap.cs.brown.edu/
- Reinforcement Learning: An Introduction

  http://people.inf.elte.hu/lorincz/Files/RL_2006/SuttonBook.pdf