Decision Making III

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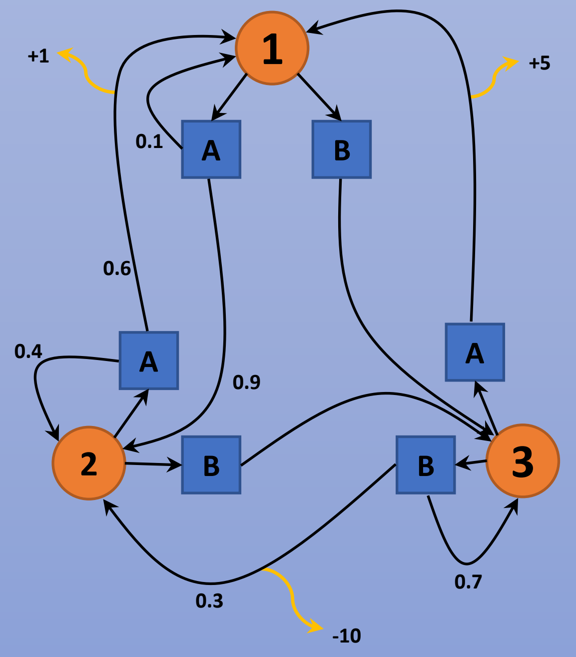
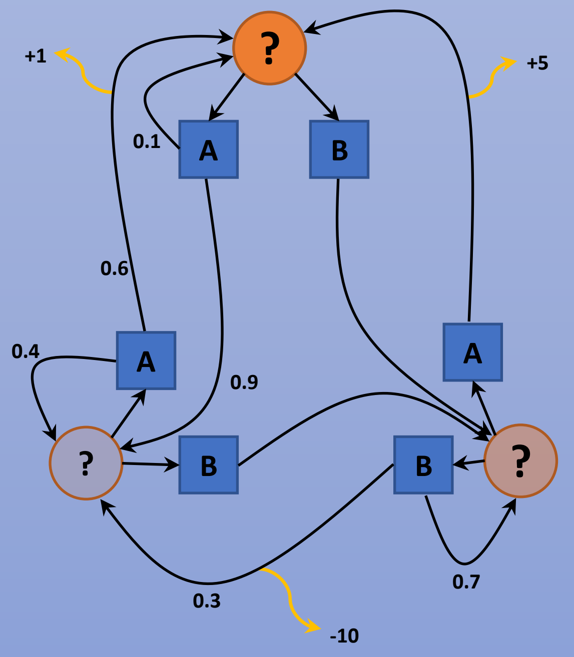
Markov Models

Markov Decision Processes (MDP)



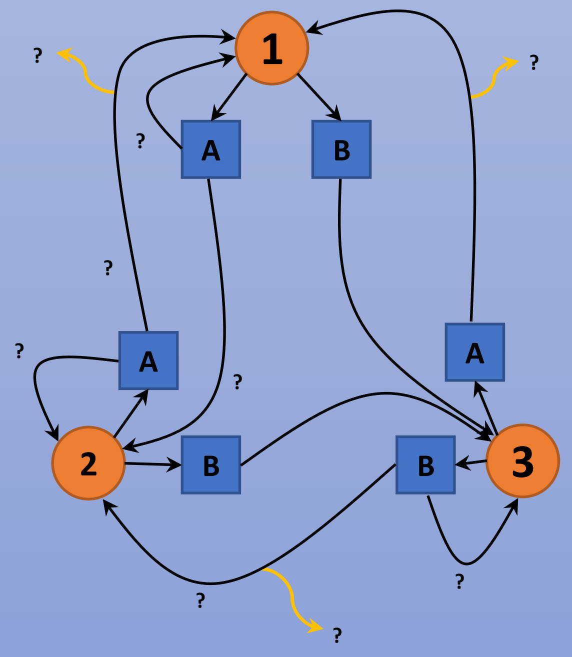
Uncertainty in effects of actions

Partially Observable MDP



Uncertainty in current state

Reinforcement Learning



Uncertainty in model

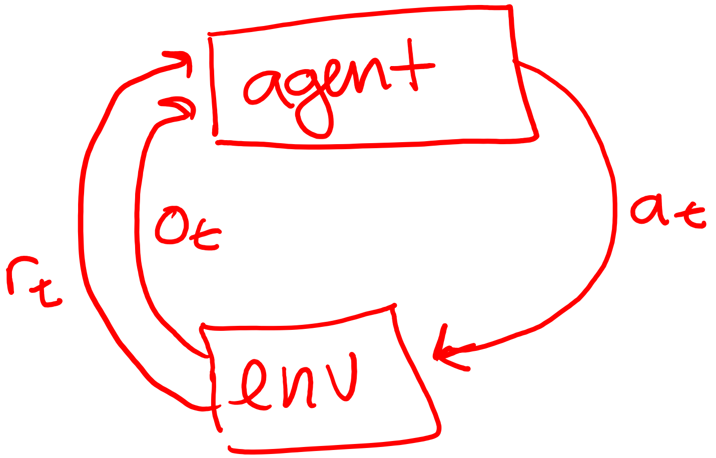
Challenges for Reinforcement Learning

1. **Exploration** of the world must be balanced with **exploitation** of the knowledge gained through previous experience
2. Reward may be received long after important choices have been made, so **credit must be assigned to earlier decisions**
3. Must **generalize** from limited experience

There are many solutions to this problem!

For a comprehensive overview, check out *Reinforcement Learning: An Introduction* by Sutton and Barto.

Reinforcement Learning



not given T or R directly
→ must learn through experience

Goal: determine optimal actions that maximize expected reward

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

solution methods:

- model based
- model free

Q-learning: Model-free method: Q-Learning

- Agent gathers experience: (s, a, r, s')
- Q-function returns the expected reward of that action at that state
- *Temporal Differences* to estimate optimal value Q^* for each state
- Agent maintains Q-table of all Q values for each state s and action a

Incremental Estimation

suppose we have a random variable X

how to estimate mean given samples $x_{1:n}$?

$$\hat{x}_n = 1/n \sum_{i=1}^{n} x_i$$

we can show that

$$\hat{x}_n = \hat{x}_{n-1} + 1/n (x_n - \hat{x}_{n-1})$$

$\alpha(n) \rightarrow$ learning rate, often constant

$$\hat{x} \leftarrow \hat{x} + \alpha (x - \hat{x})$$

temporal difference error

Incremental Estimation Example

current mean estimate of $3 = \hat{x}$

new sample: $x = 7$

$$\hat{x} \leftarrow \hat{x} + \alpha(x - \hat{x})$$

if $\alpha = .1$

$$\hat{x} \leftarrow 3 + .1(7-3) = 3.4$$

if $\alpha = .5$

$$\hat{x} \leftarrow 3 + .5(7-3) = 5$$

Q-Learning (1)

key idea: apply incremental estimation to Bellman eq.

$$Q(s,a) = R(s,a) + \gamma \sum_{s'} T(s'|s,a) U(s')$$

$$= R(s,a) + \gamma \sum_{s'} T(s'|s,a) \max_{a'} Q(s',a')$$

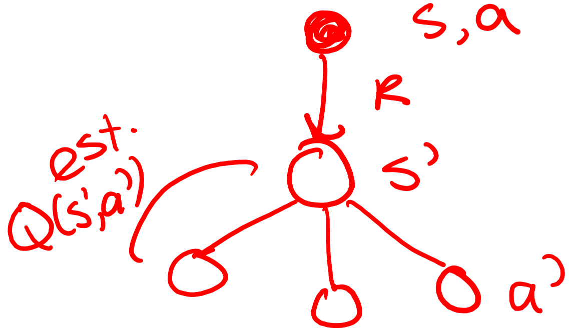
since we don't have T or R, use observed next state s' + r to estimate the Q values

use the following incremental update rule:

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left(r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right)$$

Q-Learning (2)

Q-Learning Algorithm



function Qlearning

$t \leftarrow 0$

s_0 ←initial state

Initialize Q

loop

Choose action a_t based on Q and some exploration strategy

Observe new state s_{t+1} and reward r_t

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha\left(r_t + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t)\right)$$

$t \leftarrow t + 1$

s a r s' a'

Q-Learning Challenges

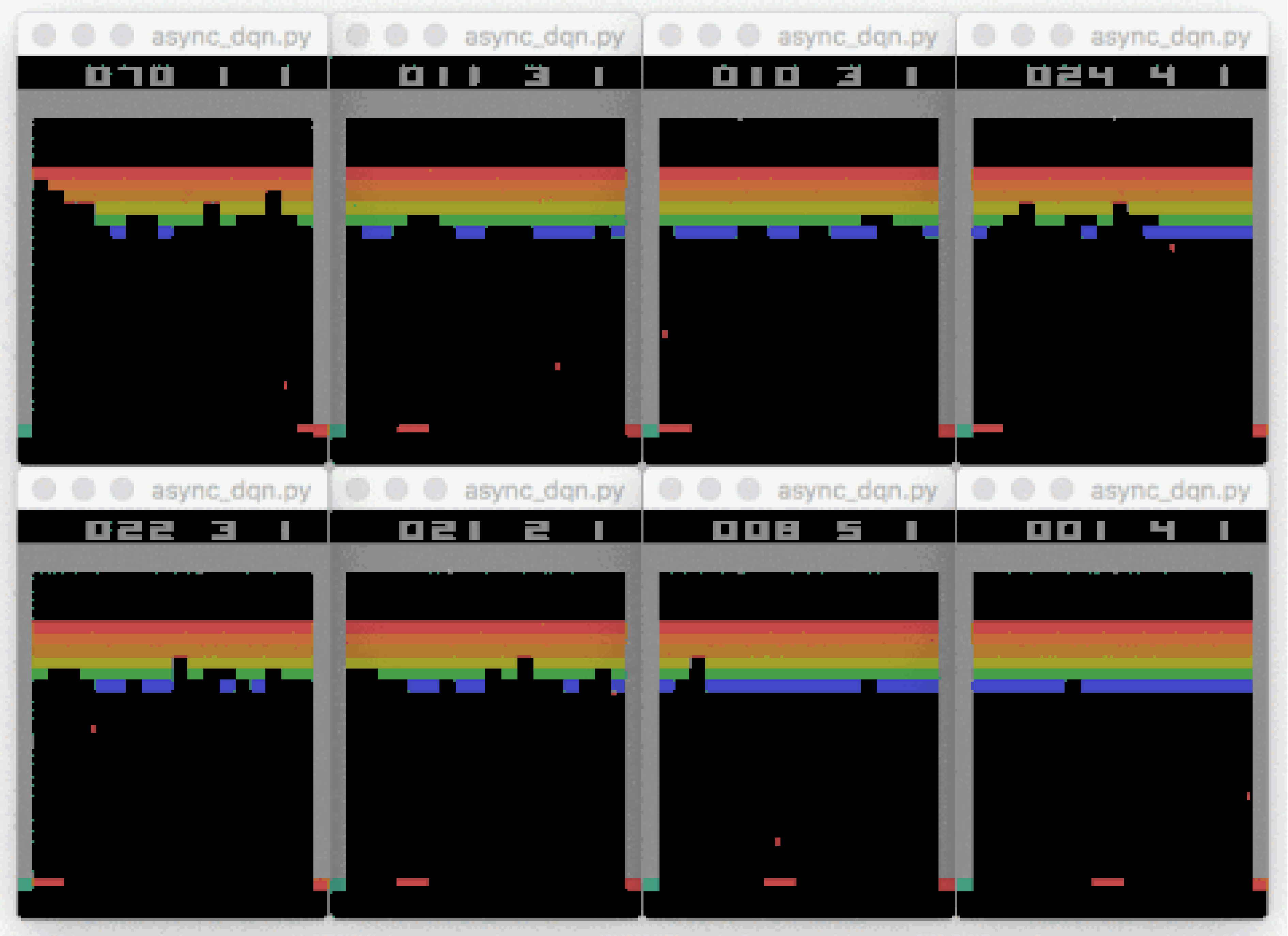
- How should an agent decide which actions to choose to explore?
- One way to define probabilistic exploration strategy, using the Boltzmann distribution:

$$P(\mathrm{a}|\mathrm{s}) = \frac{\mathrm{e}^{Q(s,a)/k}}{\sum_j e^{Q(s,a_j)/k}}$$

The k parameter (called temperature) controls probability of picking non-optimal actions. If k is large, all actions are chosen uniformly (explore), if k is small, then the best actions are chosen.

Q-Learning Challenges

- How should an agent decide which actions to choose to explore?
- The Q Table can be thought of as a cheat sheet. How many states and actions must be stored for a game of chess?
- Another issue generally in RL: How to know if reward is correct? How do we best shape the reward to get a desirable outcome? Is that okay?


async_dqn.py
070 1 1
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022 3 1
async_dqn.py
021 2 1
async_dqn.py
008 5 1
async_dqn.py
001 4 1

DQN: approximate Q with deep network

- $\text{target} = R(s, a, s') + \gamma \max_{a'} Q_k(s', a')$
- $Q_{k+1}(s, a) \leftarrow (1 - \alpha) Q_k(s, a) + \alpha[\text{target}]$
- Goal is to approximate our Q table with a deep network that will act as a Q Function

function DQN
  s_0 ←initial state
  Initialize Q_0
  for k = 1,2,…
    Choose action a_t / Observe new state s_{t+1} and reward r_t
    $\text{target} = R(s, a, s') + \gamma \max_{a'} Q_k(s', a')$
    $\theta_{k+1} \leftarrow \theta_k + \alpha \nabla \mathbb{E}_{s' \sim P(s'|s,a)} [\mathrm{Q}_\theta(s, a) - \text{target}(\mathrm{s}')] \Big|_{\theta=\theta_k}$
    $s \leftarrow s'$

DQN Challenges

- Deep learning works for supervised learning under these conditions:
  - Samples are i.i.d., meaning that each batch has the same distribution and all samples are independent within the batch
  - For some input, the label is consistent across time

- In RL, these typically do not hold
  - Target is unstable!
  - Not iid: when parameters are updated, local states are also effected
  - Actions are chosen by estimated Q (we choose what to explore or exploit), this means our target output (action) is constantly changing as well

function DQN
  s_0 ←initial state
  Initialize Q_0
  for k = 1,2,…
    Choose action a_t / Observe new state s_{t+1} and reward r
    $\text{target} = R(s,a,s') + \gamma \max_{a'} Q_k(s',a')$
    $\theta_{k+1} \leftarrow \theta_k + \alpha \nabla \mathbb{E}_{s' \sim P(s'|s,a)}[Q_\theta(s,a) - \text{target}(s')]\big|_{\theta=}$
    $s \leftarrow s'$

nonstationary

correlation within trajectories

DQN Solutions

- Experience Replay
  - Say you store 10^6 transitions and use a batch size of 32 to train the network.
  - Sampling from this buffer forms a dataset that is close to iid and therefore stable
- Target network:
  - Use two deep networks! θ^- and θ.
  - First retrieves Q values and the second updates in the training. By temporarily fixing the Q-value targets, the moving target issue is solved.
  - $L_i(\theta_i) = \mathbb{E}_{s,a,s',r\sim D}\left(r + \gamma \max_{a'} Q(s', a'; \theta_i^-) - Q(s, a, ; \theta_i)\right)^2$

DQN Algorithm

Algorithm 1: deep Q-learning with experience replay.

Initialize replay memory D to capacity N
Initialize action-value function Q with random weights θ
Initialize target action-value function $\hat{Q}$ with weights $\theta^- = \theta$
For episode = 1, M **do**
  Initialize sequence $s_1 = \{x_1\}$ and preprocessed sequence $\phi_1 = \phi(s_1)$
  For t = 1,T **do**
    With probability ε select a random action a_t
    otherwise select $a_t = \text{argmax}_a Q(\phi(s_t), a; \theta)$
    Execute action a_t in emulator and observe reward r_t and image x_{t+1}
    Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$
    Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in D
    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from D
    Set $y_j = \begin{cases} r_j & \text{if episode terminates at step } j+1 \\ r_j + \gamma \max_{a'} \hat{Q}(\phi_{j+1}, a'; \theta^-) & \text{otherwise} \end{cases}$
    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ with respect to the network parameters θ
    Every C steps reset $\hat{Q} = Q$
  End For
End For

ε-greedy

$$P(a|s) = \begin{cases} \varepsilon/m + 1 - \varepsilon, & \text{if } a^* \\ \varepsilon/m, & \text{ow} \end{cases}$$