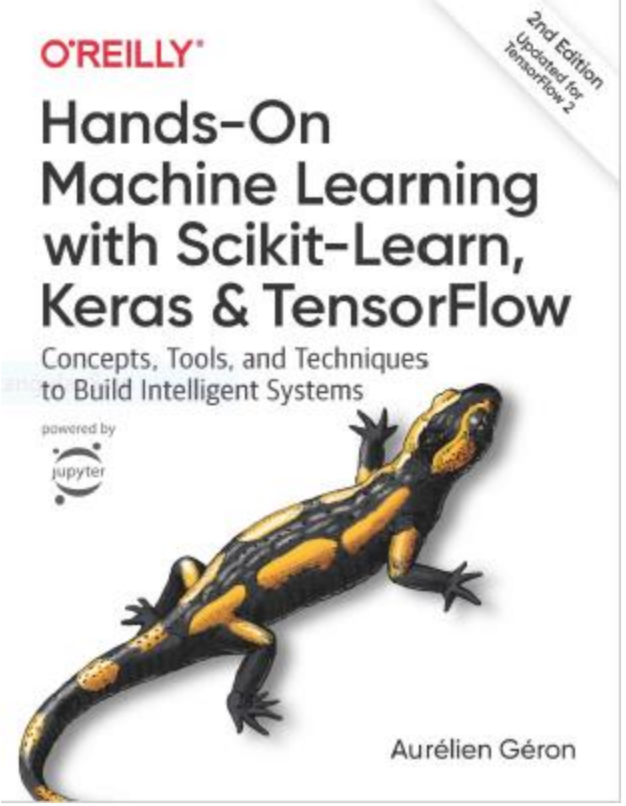
Reinforcement Learning

Prof. Gheith Abandah

Reference



- Chapter 18: **Reinforcement Learning**

- Aurélien Géron, **Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow**, O'Reilly, 2nd Edition, 2019
  - Material: https://github.com/ageron/handson-ml2

Outline

1. Introduction
2. Policy Search
3. OpenAI Gym
4. Neural Network Policies
5. The Credit Assignment Problem
6. Q-Learning
7. Exercises

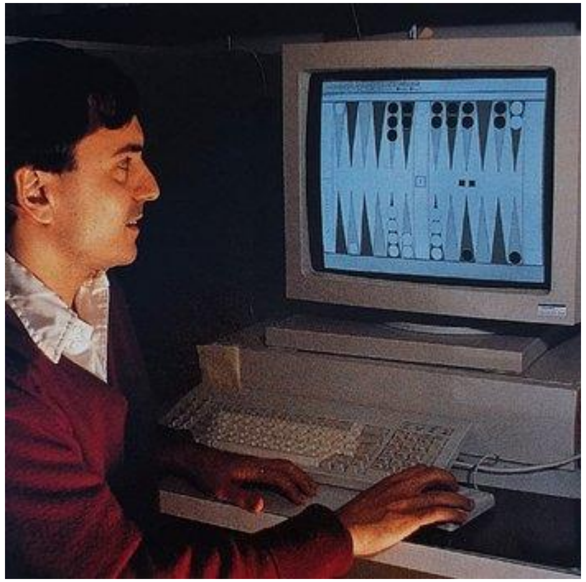
Introduction

- YouTube Video: **An introduction to Reinforcement Learning** from Arxiv Insights

https://youtu.be/JgvyzIkgxF0

1. Introduction – History

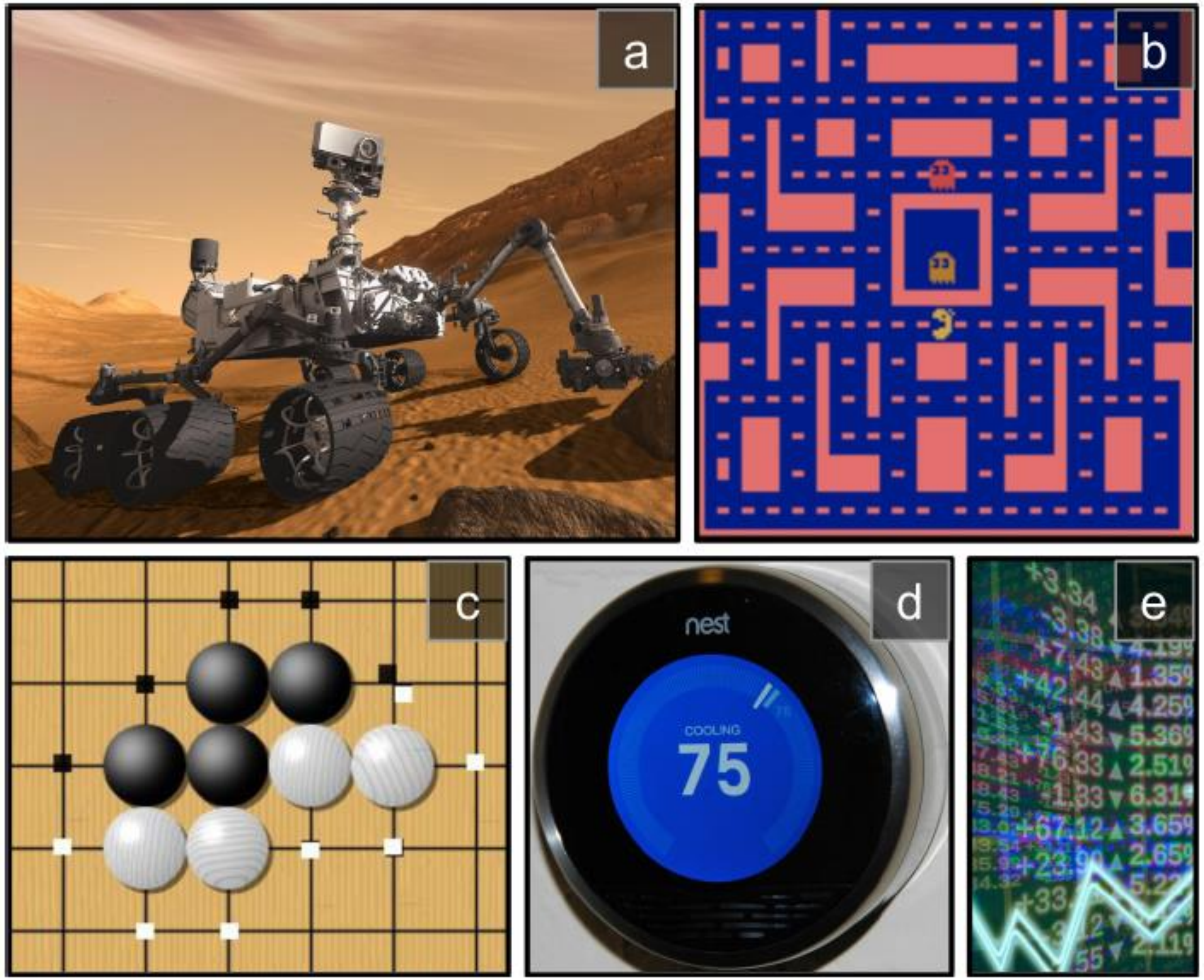
- RL started in **1950s**
- **1992**: IBM's TD-Gammon, a Backgammon playing program.
- **2013**: DeepMind demonstrated a system that learns to play Atari games from scratch.
- Use **deep learning** with raw pixels as inputs and without any prior knowledge of the rules of the games.
- **2014**: Google bought DeepMind for $500M.
- **2016**: AlphaGo beats Lee Sedol.



1. Introduction – Definition

- In Reinforcement Learning, a software **agent** makes **observations** and takes **actions** within an **environment**, and in return it receives **rewards**.
- Its objective is to learn to act in a way that will **maximize its expected long-term rewards**.
- In short, the agent acts in the environment and learns by trial and error to maximize its **pleasure** and minimize its **pain**.

1. Introduction – Examples



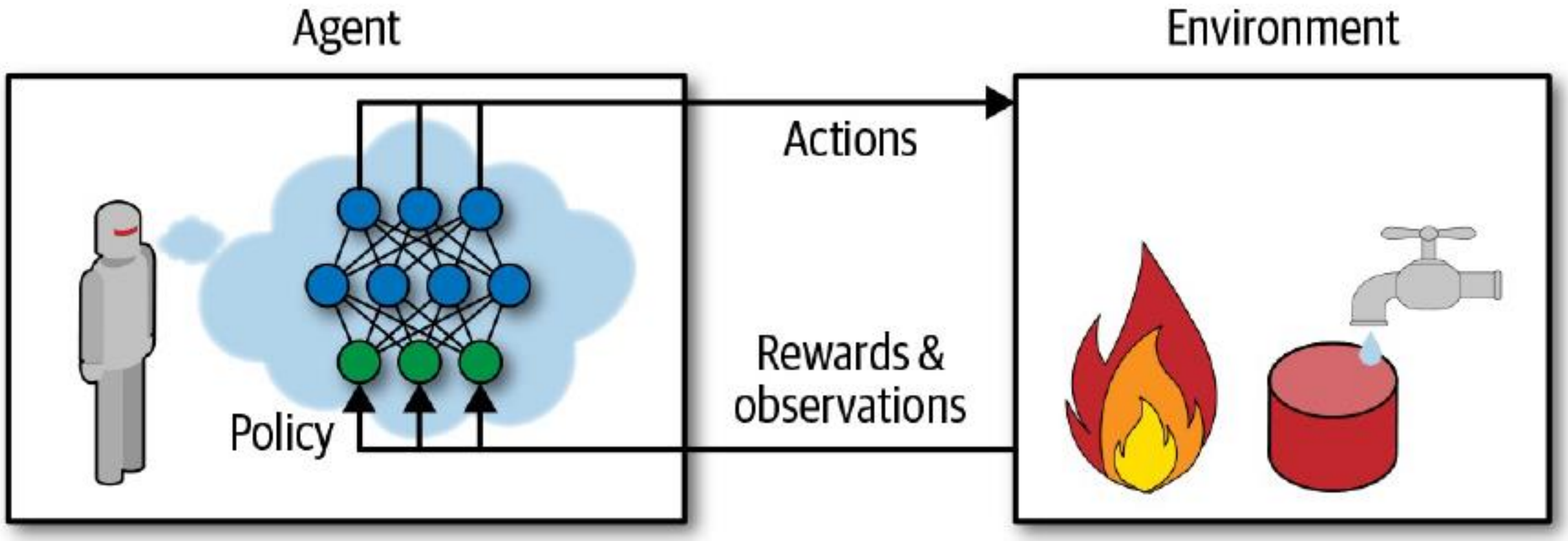
(a) robotics
(b) Ms. Pac-Man
(c) Go player
(d) thermostat
(e) automatic trader

Outline

1. Introduction
2. Policy Search
3. OpenAI Gym
4. Neural Network Policies
5. The Credit Assignment Problem
6. Q-Learning
7. Exercises

2. Policy Search

- The algorithm used by the software agent to determine its actions is called its **policy**.
- The policy can be **deterministic** or **stochastic**.
- **Policy search techniques**: Brute force, Genetic algorithm, Policy Gradient (PG), Q-Learning.



Outline

1. Introduction
2. Policy Search
3. OpenAI Gym
4. Neural Network Policies
5. The Credit Assignment Problem
6. Q-Learning
7. Exercises

3. OpenAI Gym

- OpenAI Gym is a toolkit that provides **simulated environments** (Atari games, board games, 2D and 3D physical simulations, …).
- OpenAI is a nonprofit AI research company funded in part by Elon Musk. Got $1 billion investment from Microsoft.

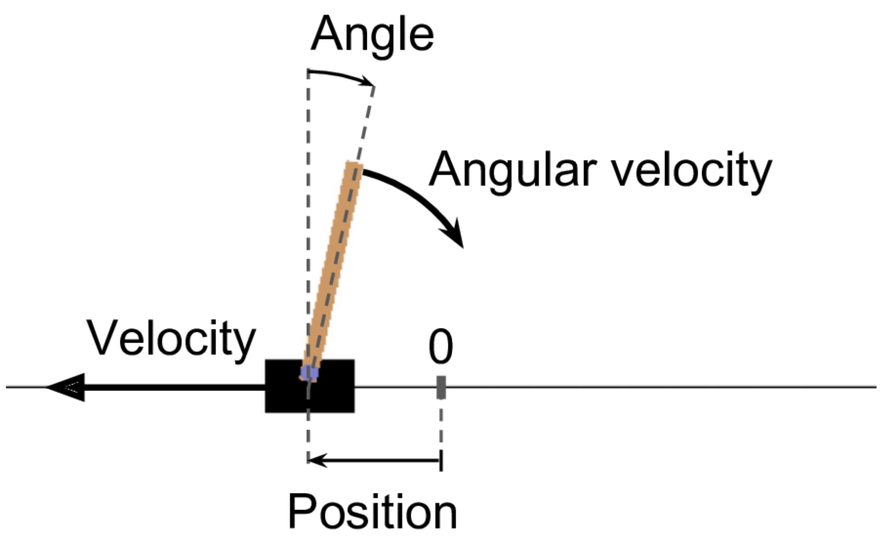
```
$ pip3 install --upgrade gym
```

Cart position, cart speed, pole angle, pole velocity

```
>>> import gym
>>> env = gym.make("CartPole-v1")
>>> obs = env.reset()
>>> obs
array([-0.012586, -0.001566, 0.042077, -0.001805])
```

3. OpenAI Gym

```
>>> env.render()
```



- **render()** can also return the rendered image as a NumPy array.

```
>>> img = env.render(mode="rgb_array")
>>> img.shape # height, width, channels (3 = RGB)
(800, 1200, 3)
```

3. Balancing the pole

```
>>> env.action_space
Discrete(2)
```

The possible actions are integers 0 and 1, which represent accelerating left (0) or right (1).

```
>>> action = 1 # accelerate right
>>> obs, reward, done, info = env.step(action)
>>> obs
array([-0.012617, 0.192928, 0.042041, -0.280921])
>>> reward
1.0
>>> done
False
>>> info
{}
```

3. Balancing the pole

```
def basic_policy(obs):
        angle = obs[2]
        return 0 if angle < 0 else 1

totals = []
for episode in range(500):
    episode_rewards = 0
    obs = env.reset()
    for step in range(200):
        action = basic_policy(obs)
        obs, reward, done, info = env.step(action)
        episode_rewards += reward
        if done:
            break
    totals.append(episode_rewards)
```

Accelerates left when the pole is leaning left and accelerates right when the pole is leaning right.

3. Balancing the pole

- Even with 500 tries, this policy never managed to keep the pole upright for more than 68 consecutive steps.

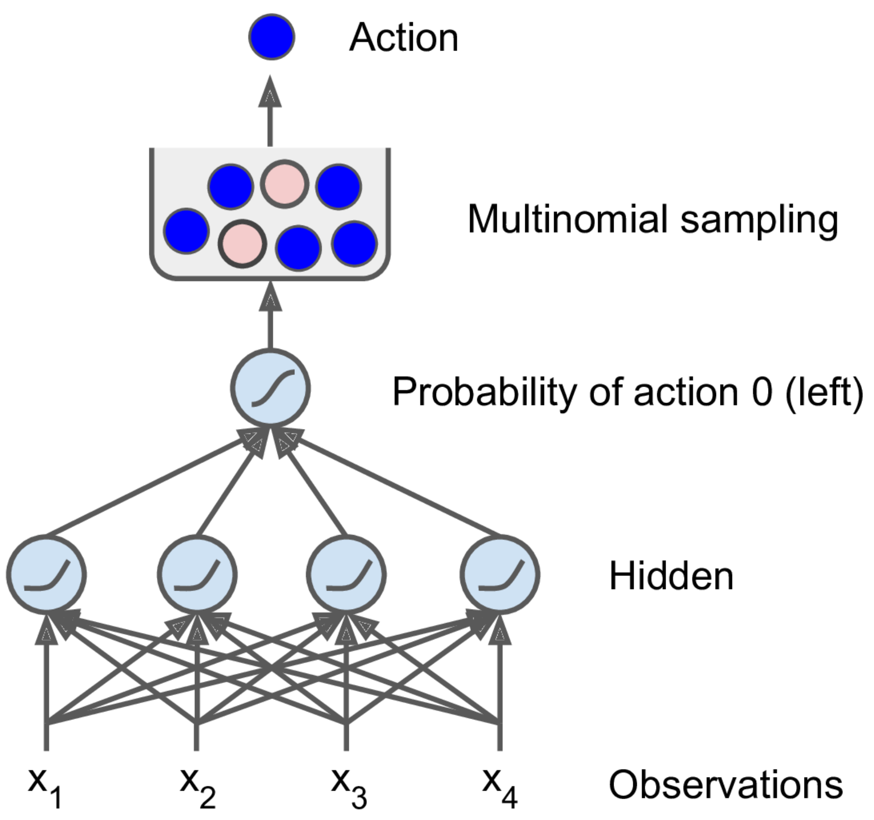
```
>>> import numpy as np
>>> np.mean(totals), np.std(totals), np.min(totals),
              np.max(totals)
(41.718, 8.858356280936096, 24.0, 68.0)
```

Outline

1. Introduction
2. Policy Search
3. OpenAI Gym
4. Neural Network Policies
5. The Credit Assignment Problem
6. Q-Learning
7. Exercises

4. Neural Network Policies

- Takes an **observation as input**, and **outputs** the **probability** for **each action**
- We **select an action** randomly, according to the estimated probabilities.
- **Explore and exploit**



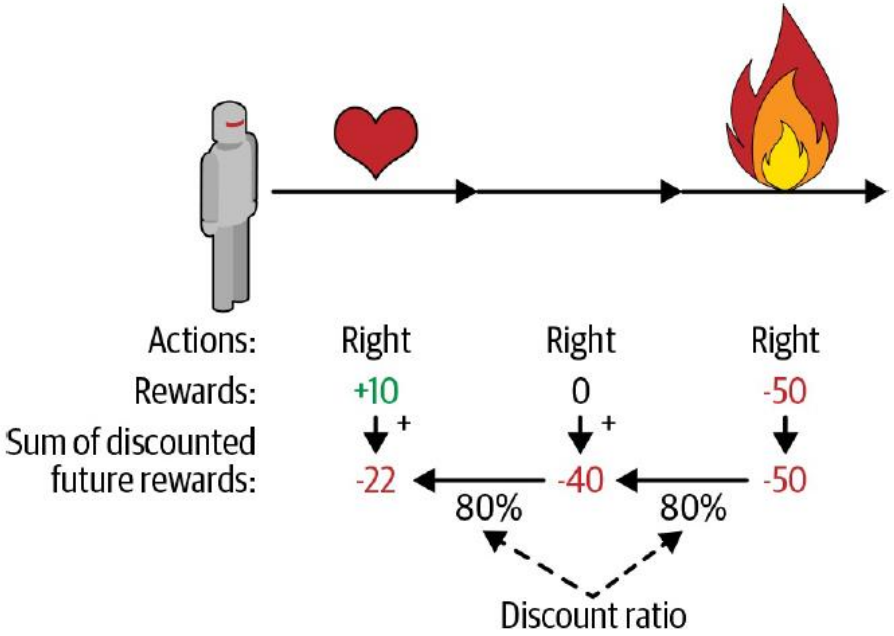
4. Neural Network Policy in Keras

```
# Building a polity network is easy
import tensorflow as tf
from tensorflow import keras

n_inputs = 4 # == env.observation_space.shape[0]

model = keras.models.Sequential([
      keras.layers.Dense(5, activation="elu",
          input_shape=[n_inputs]),
      keras.layers.Dense(1, activation="sigmoid"),
])
# Training it is something else
```

Outline

5. The Credit Assignment Problem

- Rewards are typically **sparse** and **delayed**.
- **Credit assignment problem**: when the agent gets a reward, it is hard for it to know which actions should get credited (or blamed) for it.
- Evaluate an action based on the sum of all the rewards that come after it, usually applying a **discount rate** γ at each step.



Outline

1. Introduction
2. Policy Search
3. OpenAI Gym
4. Neural Network Policies
5. The Credit Assignment Problem
6. Q-Learning
7. Exercises

6. Q-Learning

- Reference: Keon Kim, Deep Q-Learning with Keras and Gym, https://keon.io/deep-q-learning/
- Deep reinforcement learning (deep Q-learning) example to play a CartPole game using Keras and Gym.
- Google's DeepMind published Playing Atari with Deep Reinforcement Learning where they introduced the algorithm **Deep Q Network** (DQN) in 2013.
- In **DQN**, the **quality function** Q is used to approximate the reward based on a state. $Q(s,a)$ calculates the expected future value from state s and action a.
- A neural network is used to approximate the reward based on the state.

6. Q-Learning

- Carry out an action a, and observe the reward r and resulting new state s'.
- Calculate the maximum target Q and then discount it so that the future reward is worth less than immediate reward by γ.
- Add the current reward to the discounted future reward to get the target value.
- Subtracting our current prediction from the target gives the loss.
- Squaring this value allows us to punish the large loss value more and treat the negative values same as the positive values.

$$loss = \Big(\underbrace{\overset{\text{Reward}}{\mathrm{r}} + \overset{\text{Decay Rate}}{\gamma} \max_{a'} \hat{Q}(s',a')}_{\text{Target}} - \underbrace{Q(s,a)}_{\text{Prediction}}\Big)^2$$

6. DQN – Imports and Definitions

```
import random
import gym
import numpy as np
from collections import deque
from keras.models import Sequential
from keras.layers import Dense
from keras.optimizers import Adam

EPISODES = 5000
```

6. DQN – Agent Class (1/4)

```python
class DQNAgent:
    def __init__(self, state_size, action_size):
        self.state_size = state_size
        self.action_size = action_size
        self.memory = deque(maxlen=2000)
        self.gamma = 0.95    # discount rate
        self.epsilon = 1.0  # exploration rate
        self.epsilon_min = 0.01 # min exploration rate
        self.epsilon_decay = 0.995
        self.learning_rate = 0.001
        self.model = self._build_model()
```

6. DQN – Agent Class (2/4)

```
def _build_model(self):
    model = Sequential()
    model.add(Dense(24, input_dim=self.state_size,
         activation='relu'))
    model.add(Dense(24, activation='relu'))
    model.add(Dense(self.action_size, activation='linear'))
    model.compile(loss='mse',
         optimizer=Adam(lr=self.learning_rate))
    return model
```

4

2

6. DQN – Agent Class (3/4)

```python
def remember(self, state, action, reward, next_state, done):
    # Queue of previous experiences to re-train  the model
    self.memory.append((state, action, reward, next_state, done))

def act(self, state):
    # Returns an action randomly or from the model
    if np.random.rand() <= self.epsilon:
        return random.randrange(self.action_size)
    act_values = self.model.predict(state)
    return np.argmax(act_values[0])
```

6. DQN – Agent Class (4/4)

```
def replay(self, batch_size):
    minibatch = random.sample(self.memory, batch_size)
    for state, action, reward, next_state, done in
      minibatch:
        target = reward
        if not done:
            target = (reward + self.gamma * np.max(
                self.model.predict(next_state)[0]))
        target_f = self.model.predict(state)
        target_f[0][action] = target
        self.model.fit(state, target_f, epochs=1,
          verbose=0)
    if self.epsilon > self.epsilon_min:
        self.epsilon *= self.epsilon_decay
```

`Replay()` trains the neural net with experiences in the memory

$$loss = \left(\mathrm{r} + \gamma \max_{a'} \hat{Q}(s', a') - Q(s,a) \right)^2$$

Learn to predict the reward

6. DQN – Setup

```
if __name__ == "__main__":
    env = gym.make('CartPole-v1')
    state_size = env.observation_space.shape[0] # 4
    action_size = env.action_space.n            # 2
    agent = DQNAgent(state_size, action_size)
    done = False
    batch_size = 32
```

6. DQN – Training

```
for e in range(EPISODES):
    state = env.reset()
    state = np.reshape(state, [1, state_size])
    for time in range(5000):
        action = agent.act(state)
        next_state, reward, done, _ = env.step(action)
        reward = reward if not done else -10
        next_state = np.reshape(next_state, [1, state_size])
        agent.remember(state, action, reward, next_state, done)
        state = next_state
        if done:
            print("episode: {}/{}, score: {}"
                  .format(e, EPISODES, time))
            break
        if len(agent.memory) > batch_size:
            agent.replay(batch_size)
```

6. DQN – Results

```
episode: 1/5000, score: 27
episode: 2/5000, score: 11
episode: 3/5000, score: 34
episode: 4/5000, score: 33
episode: 5/5000, score: 8
episode: 6/5000, score: 22
episode: 7/5000, score: 47
episode: 8/5000, score: 22
episode: 9/5000, score: 54
episode: 10/5000, score: 16
```

```
episode: 284/5000, score: 1331
episode: 285/5000, score: 124
episode: 286/5000, score: 259
episode: 287/5000, score: 138
episode: 288/5000, score: 170
episode: 289/5000, score: 13
episode: 290/5000, score: 365
episode: 291/5000, score: 1499
episode: 292/5000, score: 274
episode: 293/5000, score: 498
episode: 294/5000, score: 529
episode: 295/5000, score: 284
episode: 296/5000, score: 1355
episode: 297/5000, score: 911
episode: 298/5000, score: 1414
```

Exercises

18.1. How would you define Reinforcement Learning? How is it different from regular supervised or unsupervised learning?

18.2. Can you think of three possible applications of RL that were not mentioned in this chapter?

18.For each of them, what is the environment? What is the agent? What are some possible actions? What are the rewards?

18.3. What is the discount factor? Can the optimal policy change if you modify the discount factor?

18.4. How do you measure the performance of a Reinforcement Learning agent?

18.5. What is the credit assignment problem? When does it occur? How can you alleviate it?

18.6. What is the point of using a replay buffer?

Summary

1. Introduction
2. Policy Search
3. OpenAI Gym
4. Neural Network Policies
5. The Credit Assignment Problem
6. Q-Learning
7. Exercises