# Learning Reinforcement Learning with OpenAl Gym

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# Did you get into IT because you wanted to be a game dev?

Anyone familiar with this image?



# What about this one?



$$V_{\pi}^{(t)}(s) \leftarrow \sum_{s'} T(s, \pi(s), s') [R(s, \pi(s), s') + \gamma V_{\pi}^{(t-1)}(s')]$$





	<b>1</b> -	File Edit Se	lection View Go Run Terminal Help	CreateData.py - FallGuys - Visual Studio Code — 🛛 🔍 🗙
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	~		import cv2	
	J.S.		import time	
		4	import os	
	\$ <sup>&gt;</sup>			
	₿		from utils.grabscreen i	mport grab_screen
	7 from utils.getkeys impor			t key check
			file_name = "C:/Users/p	rogrammer/Desktop/FallGuys/data/trainin
		11	file_name2 = "C:/Users/	programmer/Desktop/FallGuys/data/target
		12		
		13		
		14	<pre>def auto_canny(image, s</pre>	igma=0.33):
		15	# compute the media	n of the single channel pixel intensiti
		16	v = np.median(image	)
		17	# apply automatic C	anny edge detection using the computed
		18	lower = int(max(0,	(1.0 - sigma) * v))
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Source: https://www.youtube.com/watch?v=GS_0ZKzrvk0			# 0.03490014891052246 Seconds	



Source: https://www.popularmechanics.com/technology/a19844/googles-alphago-ai-wins-first-round-against-go-champion/





# A Whirlwind Tour of Reinforcement Learning

# 🜲 Stanford CS221: Artificial Intelligence



#### Lecture 7: Markov Decision Processes - Value Iteration | Stanford CS221: AI (Autumn 2019)

91K views • 1 year ago

#### stanfordonline

For more information about Stanford's Artificial Intelligence professional and graduate programs, visit: https://stanford.io/3pUNqG7 ... 8:08 Um, and in the middle, I'm going to talk about policy evaluation, which is not an inference algorithm but it's kind of a step toward... Subtitles



#### Lecture 8: Markov Decision Processes - Reinforcement Learning | Stanford CS221: AI (Autumn 2019) 26K views • 1 year ago

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For more information about Stanford's Artificial Intelligence professional and graduate programs, visit: https://stanford.io/2Zv1JpK ...

49:00 So in MDPs, we saw that policy evaluation allows you to get Q Pi; value iteration get- allows you to get Q opt. And now, we're ... Subtitles

### Markov Decision Process

- States
- $s_{start} \in States$
- Actions(s)
- T(s, a, s')
- Reward(s, a, s')
- IsEnd(s)
- $0 \le \gamma \le 1$



### Reinforcement Learning

- States
- $s_{start} \in States$
- Actions(s)

- IsEnd(s)
- $0 \le \gamma \le 1$



$$V_{\pi}^{(t)}(s) \leftarrow \sum_{s'} T(s, \pi(s), s') [R(s, \pi(s), s') + \gamma V_{\pi}^{(t-1)}(s')]$$

# Model-based Monte Carlo

# Do we have to explore all states?

# SARSA & Q-Learning



### **Evaluation vs Iteration**

SARSA

On each (s, a, r, s', a'):

$$\hat{Q}_{\pi}(s,a) \leftarrow (1-\eta) \hat{oldsymbol{Q}}_{\pi}(s,a) + \eta(r+\gamma \hat{Q}_{\pi}(s',a'))$$

### Q-learning

On each (s, a, r, s'):

$$\hat{Q}_{ ext{opt}}(s,a) \leftarrow (1-\eta) \hat{Q}_{ ext{opt}}(s,a) + \eta (r + \gamma \max_{a' \in \operatorname{Actions}(s')} \hat{Q}_{ ext{opt}}(s',a'))]$$

### Reinforcement Learning

- States
- $s_{start} \in States$
- Actions(s)

- IsEnd(s)
- $0 \le \gamma \le 1$



Unlike classical ML, you don't really have scikit-learn and ImageNet / Kaggle

# OpenAl Gym

#### Environments Documentation



Gym is a toolkit for developing and comparing reinforcement learning algorithms. It supports teaching agents everything from walking to playing games like Pong or Pinball.

View documentation > View on GitHub >





RandomAgent on Ant-v2

#### Environments Documentation

#### 

#### Algorithms Atari Box2D Classic control MuJoCo Robotics Toy text EASY

Third party environments 🗷

#### MuJoCo

Continuous control tasks, running in a fast physics simulator.



Ant-v2 Make a 3D four-legged robot walk.



HalfCheetah-v2 Make a 2D cheetah robot run.



Hopper-v2 Make a 2D robot hop.



Humanoid-v2 Make a 3D two-legged robot walk



HumanoidStandup-v2 Make a 3D two-legged robot standun



InvertedDoublePendulumv2 Balance a pole on a pole on

## Examples



#### ••••

```
import gym
env = gym.make('CartPole-v0')
for i_episode in range(20):
    observation = env.reset()
    for t in range(100):
        env.render()
        print(observation)
        action = env.action_space.sample()
        observation, reward, done, info = env.step(action)
        if done:
            print("Episode finished after {} timesteps".format(t+1))
            break
env.close()
```

# Demo

### **Evaluation vs Iteration**

SARSA

On each (s, a, r, s', a'):

$$\hat{Q}_{\pi}(s,a) \leftarrow (1-\eta) \hat{oldsymbol{Q}}_{\pi}(s,a) + \eta(r+\gamma \hat{Q}_{\pi}(s',a'))$$

### Q-learning

On each (s, a, r, s'):

$$\hat{Q}_{ ext{opt}}(s,a) \leftarrow (1-\eta) \hat{Q}_{ ext{opt}}(s,a) + \eta (r + \gamma \max_{a' \in \operatorname{Actions}(s')} \hat{Q}_{ ext{opt}}(s',a'))]$$

# Function approximation

 $\hat{Q}_{ ext{opt}}(s,a;\mathbf{w}) = \mathbf{w}\cdot oldsymbol{\phi}(s,a)$ 

Q can be approximated as weights x features

$$\mathbf{w} \leftarrow \mathbf{w} - \eta [ \hat{Q}_{ ext{opt}}(s,a;\mathbf{w}) - \underbrace{(r+\gamma \hat{V}_{ ext{opt}}(s'))}_{ ext{target}} ] \phi(s,a)$$

On each (s, a, r, s'), fix the weights

# Combining with Deep Learning

# **RL** Applications

. . .

- Game playing 🚣 🚎
- Multi-armed bandits
- Dialogue systems 💬

### Learning Resources

- 1. <u>Stanford CS221: Artificial Intelligence</u>
- 2. <u>DeepMind/UCL: Reinforcement Learning</u> by David Silver
- 3. <u>UC Berkeley CS285: Deep Reinforcement Learning</u> by Sergey Levine
- 4. <u>Reinforcement Learning: An Introduction</u> by Sutton & Barto

## Conclusions

- 1. RL is often overlooked in ML syllabi because of the hassles ••
- OpenAI Gym can help you teach/learn RL from Q-learning to DQN!
- 3. Learning by doing is the best 🔤 🐱 💻 👰

# Thank you @aliakbars