DQN

저번
시간
에 얘
기했
던거

DQN vs. Deep Q-learning

Deep Q-learning은 그냥 Q를 neural network 로 non-linear function approximation 을 한 것 까지만 칭하는 것으로 봐도 되지 않을까..?

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음… paper에서 algorithm1 =
Deep Q-learning이라 한 걸 보면
DQN == Deep Q-learning 인듯
하기도 하고 ㅋㅋㅋ

논문
정리
하기

Problems with RL

1. Learning from scalar reward signal that is frequently sparse, noisy and delayed

2. Typically encounters sequences of highly correlated states

What is DQN:
basically….

1. Network trained with variant of Q-Learning

2. Stochastic gradient descent to update network weights

3. Experience replay mechanism

What is DQN:

Aim: single neural network agent that is able to learn to play as many of the games as possible

So… all hyperparameters were kept constant across all games

Except for frame reduction in one game – reduce to ¼ or 1/3 of the frames

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Non-linear function approximator = neural network

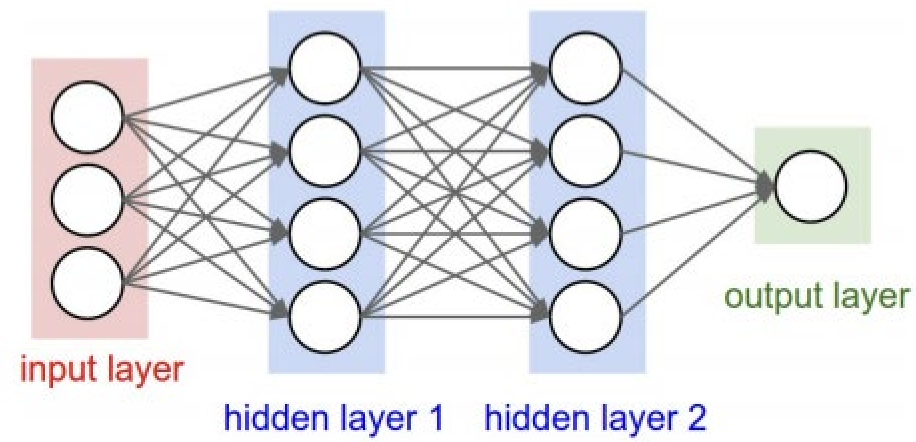
Note that pixels or other information that represents the state has been processed to some other parameters which still represents the state, but in a reduced form

So can we say it goes through two approximation procedures? Once for expressing the state and once for calc/estimating the Q(s, a)?

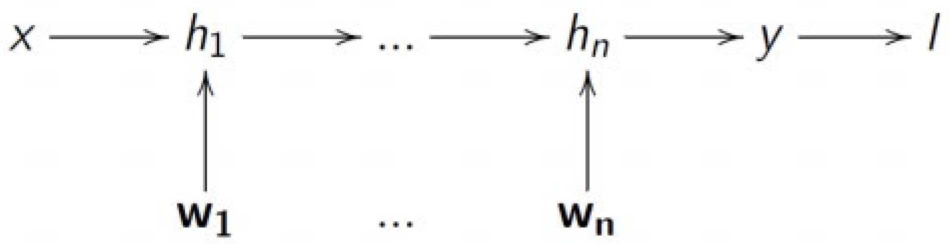
Linear function approximation

$$Q(s,a) = \theta_0 \cdot 1 + \theta_1 \phi_1(s,a) + \cdots + \theta_n \phi_n(s,a) = \theta^T \phi(s,a)$$

non-Linear function approximation : network



Backprogation to teach this network



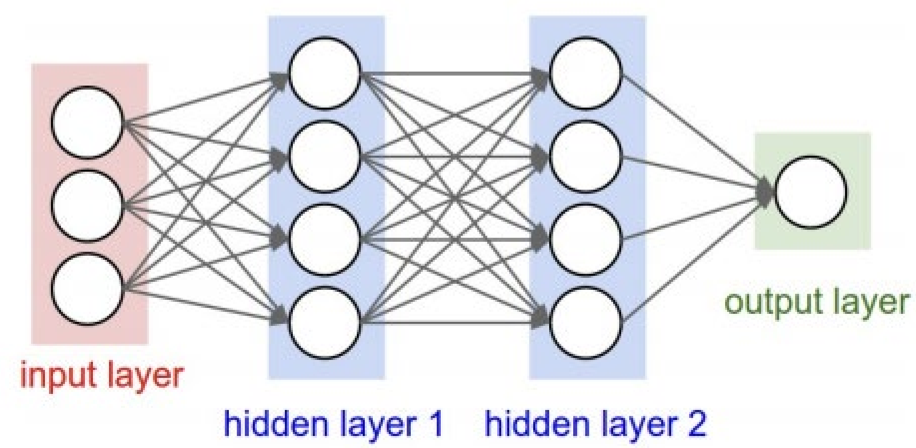
W = weight or theta

Where x = s, a pair

Output y will be prediction Q(s, a)

Note that such non-linear approximations could cause Q-network to diverge (never converge to a fixed value which can give the answer)

non-Linear function approximation : network



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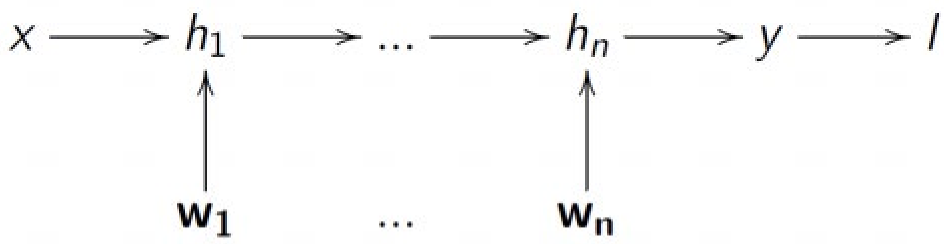

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gradient $$\nabla_{\theta_i} L_i(\theta_i) = \mathbb{E}_{s,a\sim\rho(\cdot);s'\sim\mathcal{E}}\left[\left(r + \gamma \max_{a'} Q(s', a'; \theta_{i-1}) - Q(s, a; \theta_i)\right)\nabla_{\theta_i} Q(s, a; \theta_i)\right]. \quad (3)$$

Applying gradient to weight by learning rate alpha

$$\mathbf{w}_{t+1} = \mathbf{w}_t + \alpha\Big[R_{t+1} + \gamma \max_a \hat{q}(S_{t+1}, a, \mathbf{w}_t) - \hat{q}(S_t, A_t, \mathbf{w}_t)\Big]\nabla \hat{q}(S_t, A_t, \mathbf{w}_t), \quad (16.3)$$

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Replay memory

Experience replay

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"Q function instead works on fixed length representation of histories produced by a function phi"

Vs.

"the input to the neural network consists is an 84X84X4 image produced by phi"

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Phi:
- RGB → grey-scale
- 210 X 160 → downsample 110X84 → crop 84X84
- Applied to last 4 frames of a history

Still not sure why

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Still not sure why it is a combination as shown, how do you calc the purple above is there is a and s combined?

guess

Is it like if there are multiple possible s or phi(s) even with same image x but different previous history s and a executed at current state? == multiple versions of phi that can have same value but considered different if a and st is different?

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There are several possible ways of parameterizing Q using a neural network. Since Q maps history-action pairs to scalar estimates of their Q-value, the history and the action have been used as inputs to the neural network by some previous approaches [20, 12]. The main drawback of this type of architecture is that a separate forward pass is required to compute the Q-value of each action, resulting in a cost that scales linearly with the number of actions. We instead use an architecture in which there is a separate output unit for each possible action, and only the state representation is an input to the neural network. The outputs correspond to the predicted Q-values of the individual action for the input state. The main advantage of this type of architecture is the ability to compute Q-values for all possible actions in a given state with only a single forward pass through the network.

After DQN selected an action, the action was executed by the game emulator, which returned a reward and the next video frame. The frame was preprocessed and added to the four-frame stack that became the next input to the network. Skipping for the

From Sutton and barto

Seems to be simplified
so not easy to see how
it is actually processed
by deepmind

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1. Process and approx. state phi/pho(s)

Loop

1. E-greedy pick a
2. Do action
3. Pick up r and x:image (observ)
4. Preprocess next state
5. Store in replay memory
6. Pick random from replay memory
7. Learn theta for Q : SGD
   a. Target is forward pass with Q-learning algo

End if term

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+ reward scale +- 1 or 0
+ frame skipping k = 4 or 3

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So.. Evaluating DQN...

Checking on total reward obtained by agent in an episode

Average reward can be very noisy : since small change policy weight = large change in state the agent visits

Rather evaluate with expected reward == Q value
For which state action pair?
average of max predic Q from set of states obtained by random policy (not the policy in training)

참고

DQN cartpole https://github.com/seungeunrho/minimalRL

DQN lunarlanding https://github.com/philtabor/Youtube-Code-Repository/tree/master/ReinforcementLearning/DeepQLearning

코드

https://github.com/laphisboy/RL_fall/tree/master/fall_week_2