Solve Lunar Lander with Deep Q Learning

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***Abstract*—In this project, an agent will be implemented and trained to successfully land the "Lunar Lander" in OpenAI gym. Deep reinforcement learning [1] is adopted.**

***Index Terms*—Lunar Lander, Deep Q Learning**

I. Introduction

"Lunar Lander" can be simulated by OpenAI Gym [2]. The lunar lander is trying to land onto the lunar ground without crashing, see Fig. 1. After rounds of tries and learning, the lander will gradually learn how to land. Deep reinforcement learning [1] is a suitable solution to this landing problem.

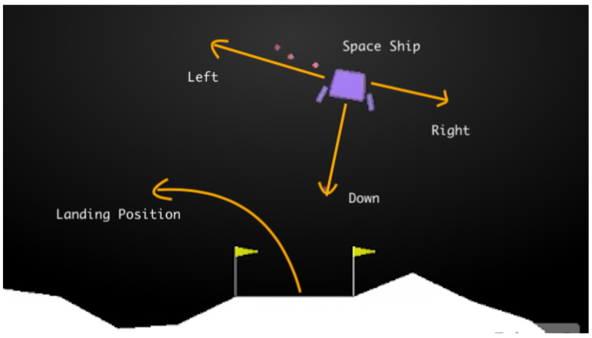

Fig. 1. Lunar Lander in Opengym.

II. Problem Statement

The "Lunar Lander" problem consists of an 8-dimensional continuous state space s and a discrete action space a, $(x, y, vx, vy, \theta, v\theta, leg_L, leg_R)$. x and y are the x and y-coordinates of the lunar lander's position. vx and vy are the lunar lander's velocity components on the x and y axes. θ is the angle of the lunar lander. θ is the angular velocity of the lander. leg_L and leg_R are binary values to indicate whether the left leg or right leg of the lunar lander is touching the ground. So the states are six dimensional continuous state space with the addition of two more discrete variables. The four discrete actions available are: do nothing, fire the left orientation engine, fire the main engine, fire the right orientation engine.

The landing pad is always at coordinates (0,0). Coordinates consist of the first two numbers in the state vector. The total reward for moving from the top of the screen to the landing pad ranges from 100 - 140 points varying on the lander placement on the pad. If the lander moves away from the landing pad it is penalized the amount of reward that would be gained by moving towards the pad. An episode finishes if the lander crashes or comes to rest, receiving an additional -100 or +100 points respectively. Each leg ground contact is worth +10 points. Firing the main engine incurs a -0.3 point penalty for each occurrence. Landing outside of the landing pad is possible. Fuel is infinite,

Problem in this project is how to let an agent learn to land the lunar ground on its first attempt.

III. Solution

The problem is considered solved when the reward in one run achieving a score of 200 points or higher on average over 100 consecutive runs.

The agent is in a state s and has to choose one action a, upon which it receives a reward r and come to a new state s', see equation (1). The way the agent choosing actions is called $policy$. If the agent knows the expected reward of each action at every step, it will know exactly which action to perform at each step and finally learn the $policy$ that can achieve target.

All states that come in between an initial-state and a terminal-state is called one $episode$. The agent's goal it to maximize the total reward it receives during an episode.

$$s \xrightarrow{\text{a}} r, s' \tag{1}$$

Deep Q learning is the solution for this project. Deep Q learning uses neural network based on Q learning. In this report, Q learning (Section III-A) will be introduced first to facilitate the understanding of deep Q learning in (Section III-B).

A. Q learning

In Q learning, the agent will perform the sequence of actions that will eventually generate the maximum total reward.

$Q(s, a)$ yielded from being at state s and performing action a, is the immediate reward r(s,a) plus the highest Q-value possible from the next state s', see in equation (3). γ is a discount factor and $\gamma < 1$, it makes sure that the sum in the formula is finite. The lower the discount factor is, the less important future rewards are, and the agent will tend to focus on actions on immediate rewards only. $Q(s', a)$ recursively depends on $Q(s'', a)$, see equation (4).

$$Q(s, a) = r(s, a) + \gamma \text{max}_a Q(s', a) \tag{3}$$

$$Q(s, a) \rightarrow \gamma Q(s', a) + \gamma^2 Q(s'', a) ...... + \gamma^n Q(s^{'' \cdots n}, a) \tag{4}$$

Algorithm 1: Deep Q-learning

Initialize replay memory D to a FIFO queue of capacity N;
Initialize action-value function Q with random weights;
Construct neural network mapping from states to rewards;
for *episode* = *1*, M **do**
    Reset game environment;
    Reward = 0 ;
    for *step* = *1*, *STEP* **do**
        Select an action a;
            Select a random action with probability ϵ;
            Otherwise select a = argmax$'_a$Q(s,a');
        Store $< s, a, r, s' >$ in replay memory D after apply action a;
        Reward = Reward + r;
        s = s';
        if *replay memory buffer size* $>= N$ **then**
            Collect train batch randomly from replay memory;
            Train neural network using $(r - Q(s,a))^2$ as loss function and ;
        end
        if *Done* **then**
            Break
        end
    end
    ϵ = ϵ * decay;
    if *Last 200 episodes rewards average* $>$ 200 **then**
        Break
    end
end

$$\bigtriangledown_{\theta_i} L_i(\theta_i) = \mathrm{E}_{s,a\sim\rho(.);s'\sim\epsilon}\left[(r + \gamma \mathrm{max}_{a'}\mathrm{Q}(s',a';\theta_{i-1}) - (Q)(s,a;\theta_i)) \bigtriangledown_{\theta_i} \mathrm{Q}(s,a;\theta_i)\right] \tag{2}$$

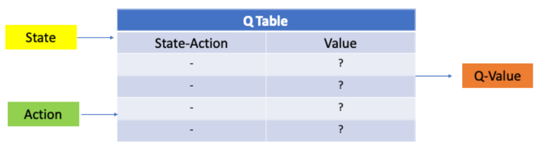

Fig. 2. Q Learning.

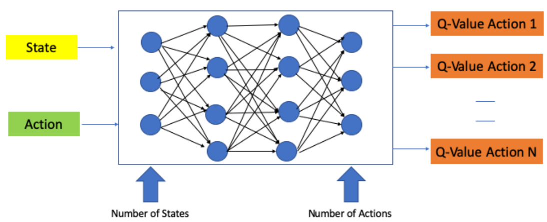

Fig. 3. Deep Q Learning.

The agent constantly performs the action that is believed to achieve the highest expected reward. The agent needs to try many different actions in many different states in order to try and learn all available possibilities and find the *policy* which will maximize its overall reward, this is known as exploration, as the agent explores the environment. However, the agent should also use the informationit learned. The agent need to exploit and explore its knowledge to maximize the rewards it receives. Greedy policy, ϵ-Greedy Policy allows agent to randomly explore. A number ϵ in the range of [0,1] is selected, if that number is larger than ϵ, the greedy action is selected while a random action is selected if the number is lower. If ϵ = 0, the policy becomes the greedy policy, and if ϵ = 1, always explore. Such value iteration algorithm converge to the optimal action value function, $Q_i \rightarrow Q*$ as $i \rightarrow \infty$. Finally, a Q table will be built for states to choose expected best action from, see Fig.2.

B. Deep Q Learning

The continues states and descrete actions in 'Lunar Lander' OpenAI Gym scenario, require deep reinforcement learning [1] to avoid the complexity of store Q table. Instead, the Q values are calculated by neural network by states and corresponding action rewards, see in Fig.3.

The algorithm can be described in algorithm 1. As reinforcement learning tasks have no pre-generated training sets which they can learn from, the agent must keep records of batches of the state-transitions it encountered in the replay memory buffer so it can learn from them later.

A function approximator is used to estimate the action-value function in deep Q learning, $Q(s, a; \theta) \approx Q^*(s, a)$. In the continuous agent state and discrete actions environment, a neural network function approximator with weights θ constructs a Q network. A Q network can be trained by minimising a sequence of loss functions $L_i(\theta_i)$ that changes at each iteration i,

$$L_i(\theta_i) = E_{s,a \sim \rho(.)}[(y_i - Q(s, a; \theta_i))^2] \quad (5)$$

where $y_i = E_{s' \sim \epsilon}[r + \gamma \text{max}_{a'} Q(s', a', \theta_{i-1})|s, a]$ is the target for iteration i and $\rho(s, a)$ is a probability distribution over sequences s and action a which is called behaviour distribution. Differentiating the loss function with respect to the weights.

Equation (5) is computationally expedient to optimise the loss function by stochastic gradient descent. The learning agent is following the Q learning algorithms [3] with the neural network's assistance.

The deep Qlearning is described in Algorithm I (1). Each step of batch experience is potentially used in many weight updates. Considering strong correlations between samples, randomizing the samples can break correlations and reduces the variance of the updates. When learning on-policy the current parameters determine the next data sample that the parameters are trained on.

Based on the theory of deep Q learning, the training result of 'Lunar Lander' is shown in Section IV.

IV. RESULT

In the training, neural network is built with Keras [4]. First, rewards at each training episode are demostrated in section IV-A. Then, hyperparameters differences' impact on the training is discussed in section IV-B. Results will be also simulated in section IV-C while neural network adopts various structures.

A. Rewards

In this subsection, the neural network has input layer with the number of neurons equaling to the number of states and relu activation function, first hidden layer with 512 neurons and relu activation function, second hidden layer with 256 neurons and relu activation, output layer with the number of naurons equaling to the number of actions and linear activation function.

The parameters for this experiment is set as: learning rate = 0.001, $\epsilon = 1.0$, decay of $\epsilon = 0.995$, $\gamma = 0.99$,

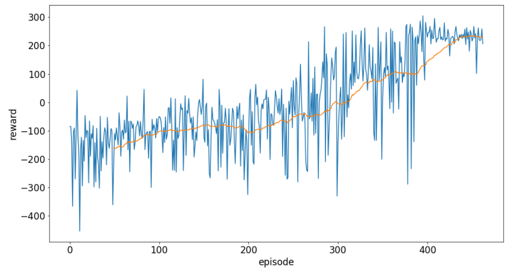

Fig. 4. Reward per episode for 8-512-256-4 linear activation layers

the maximum number of training episodes is set to be 2000.

As seen in Fig 4, the rewards are gradually increasing from about -450 to above 200. And when the number of training episode achieves around 400, the rewards are considered converge to above 200, which achieve the success landing definition in the 'Lunar Landing' project. Then the agent based on deep Q learning is considered to be trained successfully.

Next the trained agent is tested in complete different 100 consecutive randomly generalized scenarios of 'Lunar Landing', the rewards versus episode is plotted in Fig. 5. It can be seen that the average rewards of the test scenarios is around 220.

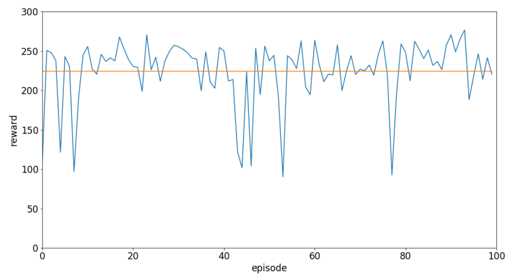

Fig. 5. Reward per episode for 100 consecutive episodes using trained agent.

B. Hyperparameters

Hyperparameters like neural network learning rate, future Q value discount factor γ and ϵ decay value will be discussed in this part.

1) Neural network learning rate: Neural network learning rate is a hyperparameter that controls how much to change the model in response to the estimated error each round the model weights θ are updated. Too small learning rate may result in a long trainign process. Too large learning rate may result in a suboptimal set of weights or an unstable training process.

The parameters for this experiment is set as: learning rate ranges in [0.0001, 0.001, 0.01, 0.05, 0.1], $\epsilon = 1.0$, decay of $\epsilon = 0.995$, $\gamma = 0.99$, the maximum number of training episodes is set to be 1000.

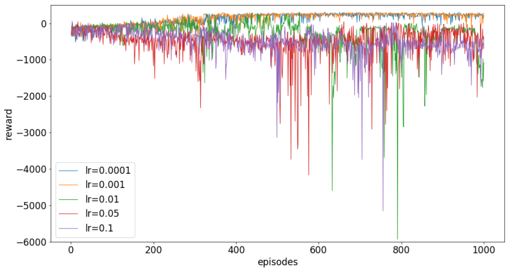

Fig. 6. Reward per episode for different learning rates.

It can be seen in Fig 6, learning rate 0.001 outperforms other values. Learning rate 0.0001 can also achieve rewards 200 in around episodes 400 but rewards in episodes varies much. However, learning rate 0.01, 0.05 and 0.1 do not result in a convergence.

2) Discount factor γ: Discount factor γ quantifies how much importance future rewards weighing. It is also handy to approximate the noise in future rewards.

In this experiment, parameters are set as: γ ranges in [0.99, 0.9, 0.8, 0.7], learning rate = 0.001, ϵ = 1.0, ϵ decay = 0.995, training episodes = 1000.

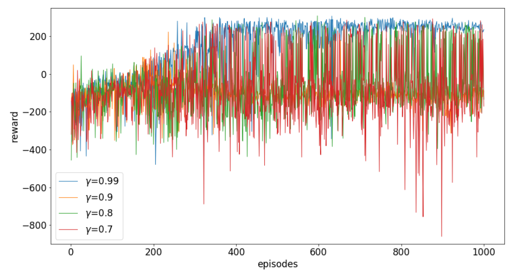

Fig. 7. Reward per episode for different γ values.

It can be seen in Fig 7, γ 0.99 is the best value that achieves rewards convergence. γ 0.7 result in the worst performance. That means in the 'Lunar Lander' environment, future rewards are important for the current action decision.

3) ϵ decay: ϵ is associated with how random the agent take an action. As the learning goes on, ϵ should be decayed to stabilize and exploit the learned policy which converges to an optimal one, so that higher Q-values can be found in higher probability.

In this experiment, parameters are set as: ϵ decay ranges in [0.999, 0.995, 0.990, 0.9], neural network learning rate = 0.001, ϵ = 1.0, γ = 0.99, training episodes = 1000.

It can be seen in Fig 8, high ϵ decay like 0.999 does not achieve reward 200. 0.9 is a good learning process but the worst reward for 0.9 ϵ delay learning is as low as -820. 0.99 ϵ decay learning process's reward cannot converge as early as 0.995 ϵ decay learning process.

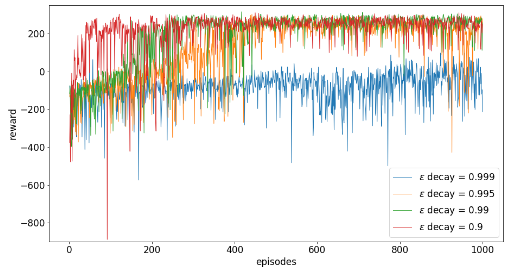

Fig. 8. Reward per episode for different decay values.

C. Neural network structure

Extra experiments have been done to explore the performance of different neural network architectures.

1) Neural network setting 1: Simpler Setting: In this subsection, the neural network has a simpler setting: input layer with the number of neurons equaling to the number of states and relu activation function, first hidden layer with 128 neurons and relu activation function, second hidden layer with 64 neurons and relu activation, output layer with the number of neurons equaling to the number of actions and linear activation function.

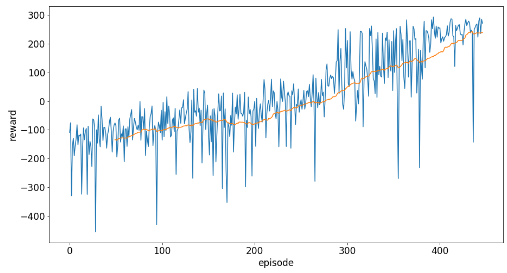

Fig. 9. Reward per episode for 8-128-64-4 linear activation layers.

It can be seen in Fig 9, the rewards line still can converge to 200.

2) Neural network setting 2: Complex Setting: In this subsection, the neural network has an more complex setting: input layer with the number of neurons equaling to the number of states and relu activation function, hidden layers with 1024, 512, 256, 128, 64 neurons and relu activation function, output layer with the number of neurons equaling to the number of actions and linear activation function.

It can be seen in Fig 10, the rewards line cannot converge to 200 and even worse till -3000. That means the agent does not learn anything from the past experiences and environment. It means the complex neural network is not a suitable choice in the 'Lunar Lander' environment.

3) Neural network setting 3: Softmax Activation: In this subsection, the neural network change the output layer activation function to softmax: input layer with

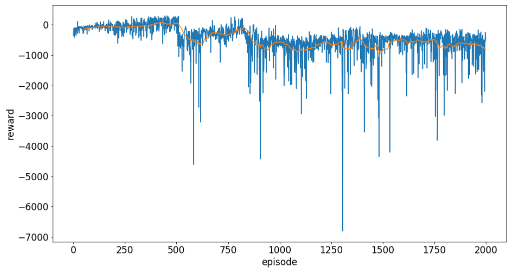

Fig. 10. Reward per episode for 8-1024-512-256-128-64-4 linear activation layers.

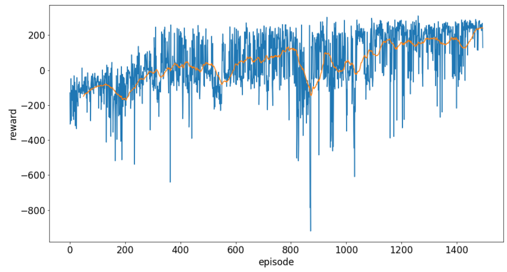

Fig. 12. Reward per episode for 8-512-256-4 linear activation layers with dropout 0.2.

the number of neurons equaling to the number of states and relu activation function, first hidden layer with 128 neurons and relu activation function, second hidden layer with 64 neurons and relu activation, output layer with the number of neurons equaling to the number of actions and softmax activation function.

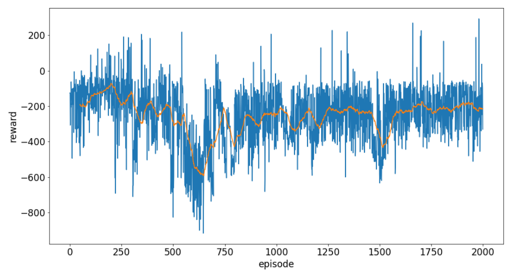

Fig. 11. Reward per episode for 8-512-256-4 softmax activation layers.

It can be seen in Fig 11, the rewards line cannot converge to 200 in the output layer with softmax as activation function.

4) Neural network setting 4: Dropout Effect: In this subsection, an experiment has been done to observe the dropout layer effect on the neural network. The other network layer settings are the same as subsection IV, besides an additional dropout layers with dropout rate of 0.2 is added before the output layer. Dropout is remarkably effective regularization method to reduce overfitting and improve generalization error in deep neural networks.

As can be seen in Fig 12, the rewards converge in episode 1490, far from the converge number of 400 in the original experiment shown in subsection IV. That means in the network contructed in subsection IV, there is no need to do dropout regularization.

V. Related work

Currently, there are several works, that have noticed the dropback of the neural network training batch evenly randomly selection from replay memory buffer. There are kinds of training data selection algorithms, which consist of keeping training over its new behavior [5] or conditioning each agent's value function on a fingerprint that disambiguates the age of the data sampled from the replay memory [6]. Advanced designs of deep RL techniques lead to even lesser number of episodes for agent to learn the environment.

VI. Conclusion

In this project, 'Lunar Lander' problem in OpenAI Gym is solved by deep reinforcement learning. Multiple experiments have been done to explore the effect to the learning process caused by different hyberparameters and different neural network desgins.

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