CSC411: Assignment #4

Due on Monday, April 2, 2018

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Part 1

Environment description
1. The grid is represented by a 2D array, displayed as 3x3 grid. Empty grids are represented with ".", while first and second player's move is represented with symbol "x" and "o" consecutively.

2. Attribute 'turn" represents who's turn is it. When it's player1, turn equals "1" and action will show as "x" on the grid; When it's player2, turn equals "2" and action will show as "o" on the grid.

3. Attribute "done" represents if the game is over. If done is false, then it's not over. If done is true, then one of the player wins or there's a tie.

4. Create a new environment, and play a game of Tic-Tac-Toe against yourself by calling the step(), and render() methods. Display the text output in picture below.

```
env.render()
...
...
...
====
env.step(4)
(array([0, 0, 0, 0, 1, 0, 0, 0, 0]), 'valid', False)
env.render()
...
.x.
...
====
env.step(0)
(array([2, 0, 0, 0, 1, 0, 0, 0, 0]), 'valid', False)
env.render()
o..
.x.
...
====
env.step(6)
(array([2, 0, 0, 0, 1, 0, 1, 0, 0]), 'valid', False)
env.render()
o..
.x.
x..
====
env.step(2)
(array([2, 0, 2, 0, 1, 0, 1, 0, 0]), 'valid', False)
env.render()
o.o
.x.
x..
====
env.step(1)
(array([2, 1, 2, 0, 1, 0, 1, 0, 0]), 'valid', False)
```

```
env.render()
oxo
.x.
x..
====
env.step(8)
(array([2, 1, 2, 0, 1, 0, 1, 0, 2]), 'valid', False)
env.render()
oxo
.x.
x.o
====
env.step(7)
(array([2, 1, 2, 0, 1, 0, 1, 1, 2]), 'win', True)
```

Part 2

Policy Implementation

Part A

```
class Policy(nn.Module):
    """
    The Tic-Tac-Toe Policy
    """
    def __init__(self, input_size=27, hidden_size=64, output_size=9):
        super(Policy, self).__init__()
        self.layer = nn.Sequential(
            nn.Linear(input_size, hidden_size),
            nn.ReLU(),
            nn.Linear(hidden_size, output_size),
        )

    def forward(self, x):
        x = self.layer(x)
        x = F.softmax(x, dim=-1)
        return x
```

Part B

There are 9 grids, and 3 possible values in each grid. In total there are 27 possibilities which forms a list of 27 elements that is the output from select_action.

The first 9 values of the output list from select_action is the indicator if the grids are empty. The second 9 values form the output list is the indicator if the grid has an ”x” on it. The last 9 values is the indicator if the grid has an ”o” on it.

```
Example 1:
   When all the grid is empty, the first 9 values all have value 1,
   indicates empty grids.
array([0, 0, 0, 0, 0, 0, 0, 0, 0])
state value listed below:
    1     1     1     1     1     1     1     1     1
    0     0     0     0     0     0     0     0     0
    0     0     0     0     0     0     0     0     0
[torch.FloatTensor of size 1x27]

Example 2:
array([0, 0, 2, 1, 0, 0, 0, 0, 0])
state value listed below:
    1     1     0     0     1     1     1     1     1
    0     0     0     1     0     0     0     0     0
    0     0     1     0     0     0     0     0     0
[torch.FloatTensor of size 1x27]
```

Part C

The output of this policy is a 9-dimensional vector. The value in each output represents the possibility each grid is the next move. The index of the highest value in the output is the index of the next move.

This policy is stochastic.

Part 3

Part A

```
def compute_returns(rewards, gamma=1.0):
    """
    Compute returns for each time step, given the rewards
      @param rewards: list of floats, where rewards[t] is the reward
                      obtained at time step t
      @param gamma: the discount factor
      @returns list of floats representing the episode's returns
          G_t = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + ...

    >>> compute_returns([0,0,0,1], 1.0)
    [1.0, 1.0, 1.0, 1.0]
    >>> compute_returns([0,0,0,1], 0.9)
    [0.7290000000000001, 0.81, 0.9, 1.0]
    >>> compute_returns([0,-0.5,5,0.5,-10], 0.9)
    [-2.5965000000000003, -2.8850000000000002, -2.6500000000000004, -8.5, -10.0]
    """
    size = len(rewards)
    result = [0] * size
    i = size - 1
    while i >= 0:
        if i == size - 1:
            result[i] = float(rewards[i])
        else:
            result[i] = rewards[i] + gamma * result[i+1]
        i -= 1
    return result
```

Part B

We cannot compute backward pass and update weights while the game is not done, because we don't have a definite reward until the game is done. While the game is still playing, we can only know if a move is valid but cannot know whether the move is a good or bad one since we don't know the result of the game. That's why the reward won't be definite until the game is done.

Part 4

Part A

```python
def get_reward(status):
    """Returns a numeric given an environment status."""
    return {
            Environment.STATUS_VALID_MOVE  : 10,
            Environment.STATUS_INVALID_MOVE: -10,
            Environment.STATUS_WIN         : 50,
            Environment.STATUS_TIE         : -5,
            Environment.STATUS_LOSE        : -50
    }[status]
```

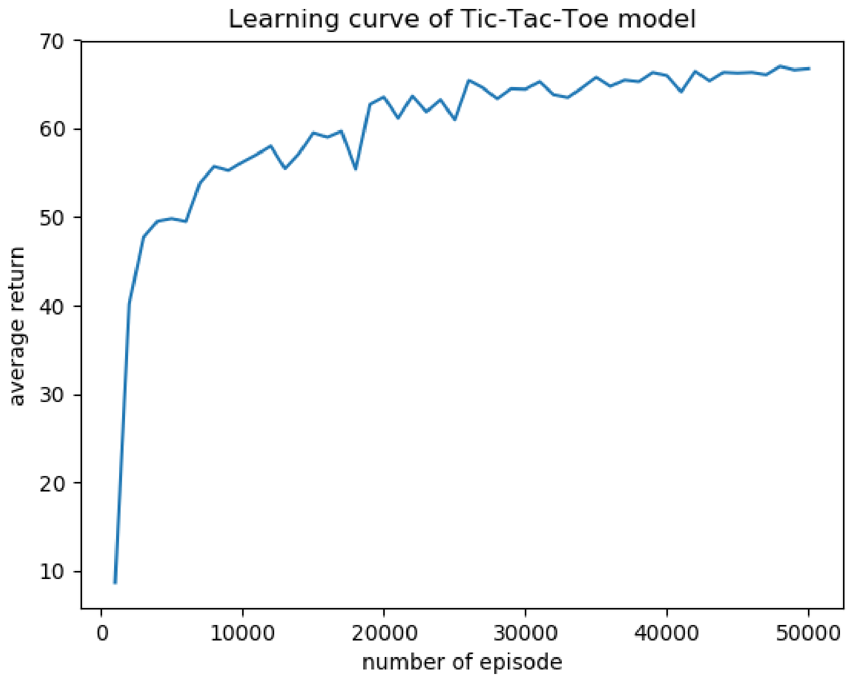
Part B

Explain the choices that we made in 4(a): 1. Valid move and invalid move contradict each other. Therefore, a valid move is rewarded 10 points and an invalid move is penalized -10 points.
2. Win, Loose and Tie are a group of status. For win we reward 50 points, while lose is penalized the same amount of points (-50). As for tie, it's (-5) reward points because it's better than lose. But it's still not something we want. 3. The magnitude of the rewards is selected based on the importance of the status. Win is a better result than valid move, therefore it has 5 times the score as valid move. Others are scaled accordingly.

We have also tested among several different sets of values to see which one leads to better performance of the agent.

Part 5

Part A

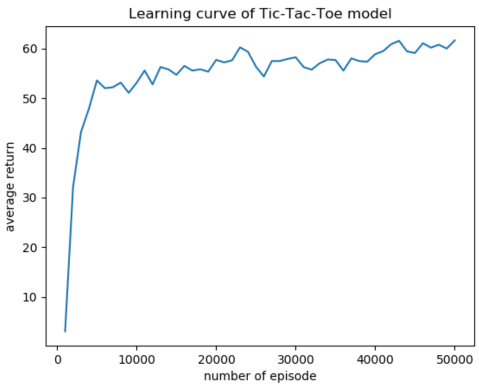


We changed gamma to 0.70. We tried other hyper parameters like 0.9, 0.8, 0.75, 0.6. Among different gamma values, 0.70 gives the best performance.

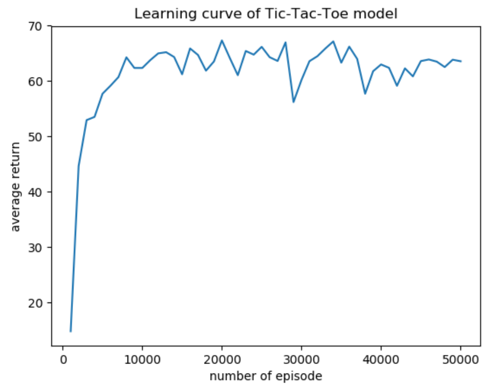
Part B

We tried three hidden units number and plot the learning curve of it.

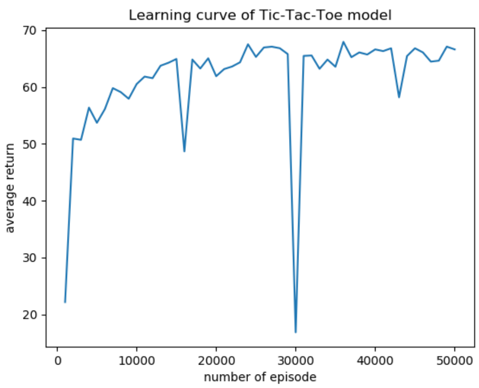
1. Hidden Unit Number = 30.



2. Hidden Unit Number = 120.



3. Hidden Unit Number = 240.

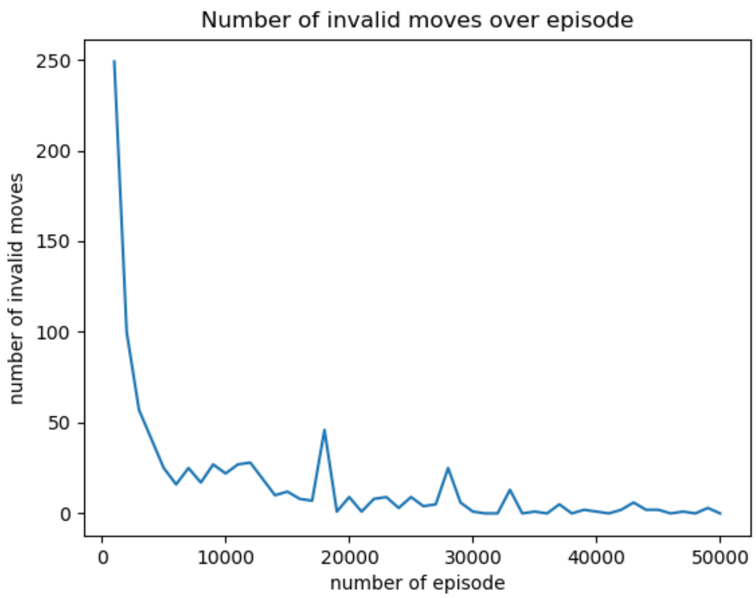


Conclusion: Too large or too small hidden unit length does not perform as well as 64 hidden unit length. The one with larger number of hidden units performed worse.

Part C

We tried two ways to analyze when our algorithm learn to stop playing invalid moves.

1. Firstly, by plotting the invalid move against number of episodes. The resulted graph is shown below. We can see that the number of invalid moves has dropped significantly as iterations increases and converges to zero at around 35000 episodes and on-wards.



2. Secondly we identified decrease of invalid move by analyzing the learning curve in part(a). The slope became more smooth at 35000 episode and it is increasing in a steady path, which means that we stopped getting invalid moves.

Part D

1. Play 100 Games against Random.
From the result of fcuntion **games_play_against_random(policy, env)**.
The agent won 94 times, lost 5 times, and tied 1 time.

2. Display five games that our trained agent plays against the random policy. Explain any strategies that you think your agent has learned.

```
Game1:
...
.xo
...
====
...
.xo
o.x
====
x..
.xo
o.x
```

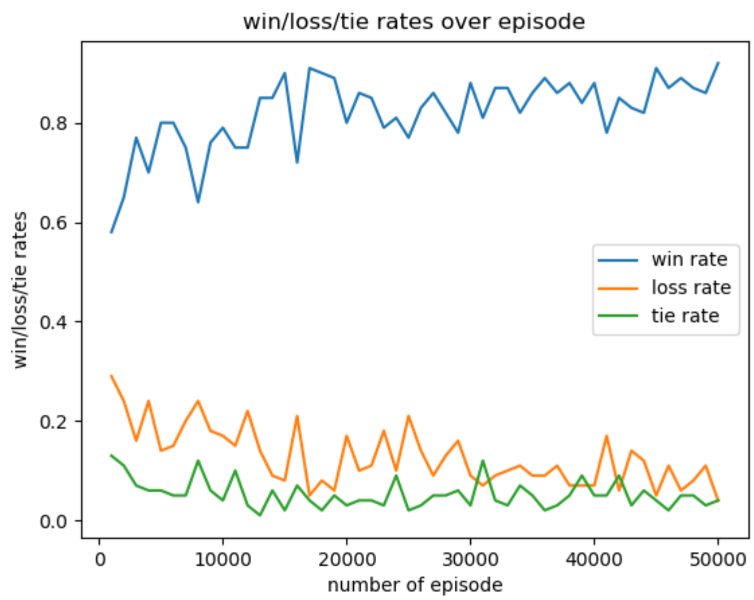
```
====
*****************
Game2:
...
.xo
...
====
x..
.xo
..o
====
x.x
.xo
.oo
====
x.x
.xo
xoo
====
*****************
Game3:
o..
.x.
...
====
o.x
.x.
o..
====
oox
xx.
o..
====
oox
xxx
o..
====
*****************
Game4:
...
.x.
..o
====
..x
.xo
..o
====
..x
.xo
x.o
====
*****************
Game5:
```

```
o..
.x.
...
====
o.x
ox.
...
====
o.x
ox.
x..
====
*****************
```

Conclusion: there are are several strategies that we believe the agent has learned.
1. Always start in the middle of the grid. The first move is always the middle one.
2. The second move of "x" should always be on one of the corners that gives more paths to win.
3. The third move of "x" is to aim to block "o" to win, as we called is as "blocking move".

Part 6

We compute the learning rate form 100 random games for each episode. Each iteration of episode we used the current policy to play 100 games and calculate the win/loose rate. The result over episode iteration is shown in graph below:



Conclusion: We can see that the win rate has improved from around 60% to 90% over 50000 episodes. The tie rate is always low and decreasing slowly and the loss rate decreased from around 25% to around 0.2%.

Part 7

First Move Analysis

1. For the final trained model, $\pi(a|s_0)$ - the learned distribution over the first move is shown as below:

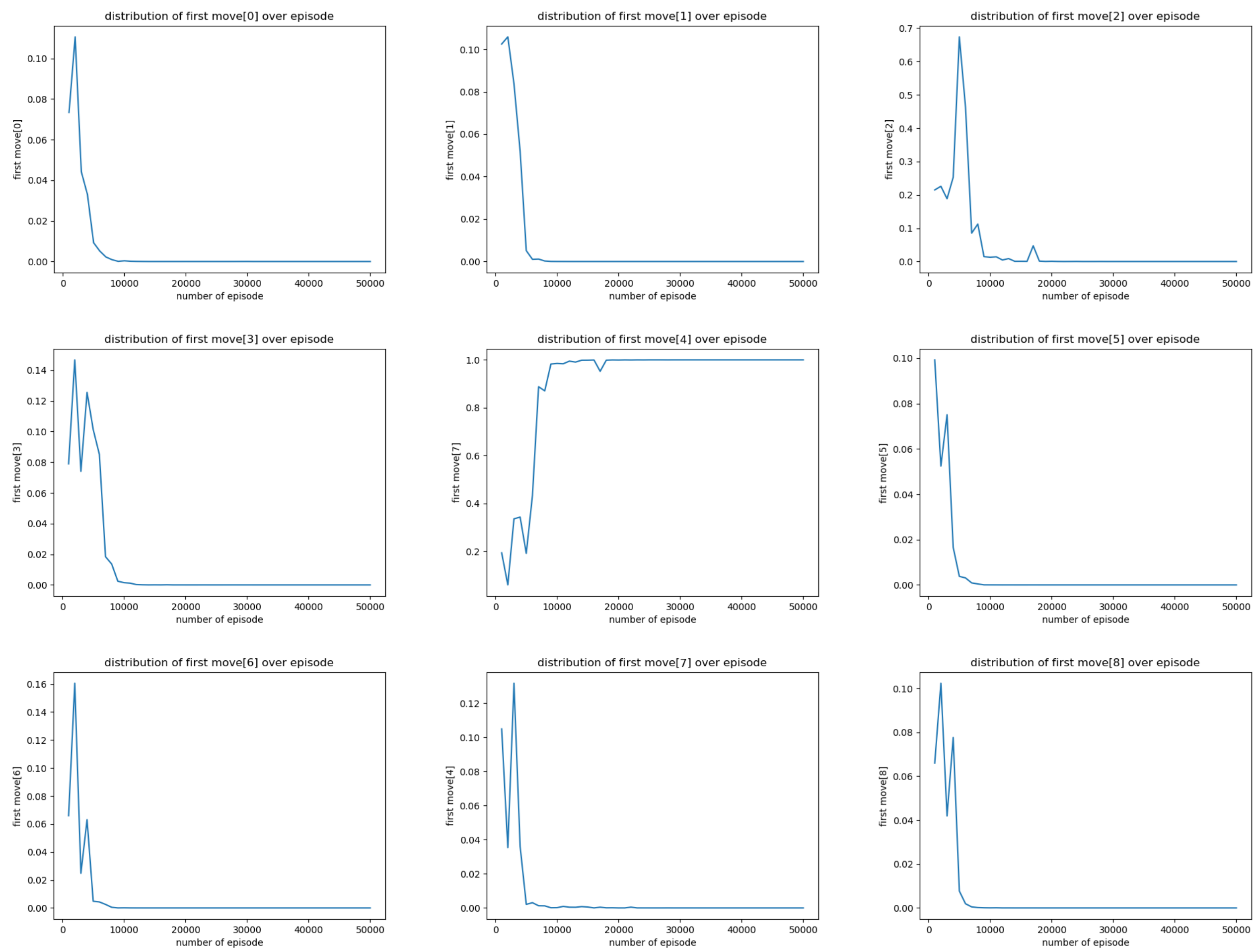
```
Columns 0 to 5
 3.5264e-05  4.9005e-07  4.5341e-05  3.7189e-08  9.9972e-01  4.5391e-08

Columns 6 to 8
 5.0122e-06  1.7546e-04  2.3234e-05
```

From the result we can see that the value at index 4, which is the indicator of the middle gird has significantly higher value than other values.

2. Conclusion: Our Modal has learned that we should always start in the middle (i.e: the first "x" should always be at index 4, the middle of the grid.)

I think it make sense because by landing the first move in the middle, the player1 has the most chance to win.

3. To explore how the distribution over the first move has changed throughout training, we plotted nine graphs for each of the index in $\pi(a|s_0)$ in order to show how the distribution has changed:



Conclusion: The values fluctuates at the beginning but become more stable at the end. The value at index 4 is increasing and all other values at other indexes are decreasing as number of episode increases.

Part 8

Limitations

One of the mistakes the agent make is that the agent did not predict or consider the possible moves of the opponent before the agent decides his moves.

Also, the agent does not play the optimal move sometimes. For example:

```
.x.
...
.o.
====
.x.
.x.
oo.
====
```

The agent shouldn't put 'x' at position [4] at his second step since there's already an 'o' at position [7] and position [1][4][7] cannot provide a 'x' row anymore.