

CSC411: Project #4

Tic-Tac-Toe with Policy Gradient

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Part 1

Tic-Tac-Toe text output

```
>>> env.render()
...
...
...
====
>>> env.step(4)
(array([0, 0, 0, 0, 1, 0, 0, 0, 0]), 'valid', False)
>>> env.render()
...
.x.
...
====
>>> env.step(1)
(array([0, 2, 0, 0, 1, 0, 0, 0, 0]), 'valid', False)
>>> env.render()
.o.
.x.
...
====
>>> env.step(0)
>>> env.step(2)
(array([1, 2, 2, 0, 1, 0, 0, 0, 0]), 'valid', False)
>>> env.render()
xoo
.x.
...
====
>>> env.step(8)
(array([1, 2, 2, 0, 1, 0, 0, 0, 1]), 'win', True)
>>> env.render()
xoo
.x.
..x
=====
```

Part 2

2(a)

```

class Policy(nn.Module):
    """
    The Tic-Tac-Toe Policy
    """
5   def __init__(self, input_size=27, hidden_size=64, output_size=9):
        super(Policy, self).__init__()
        self.fc1 = nn.Linear(input_size, hidden_size)
        self.fc2 = nn.Linear(hidden_size, output_size)
10  def forward(self, x):
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        softmax = nn.Softmax()
15  return softmax(x)

```

2(b)

Running the following script

```

policy = Policy()

# x o o
# . x .
5 # ..X
# =====

state = np.array([1, 2, 2, 0, 1, 0, 0, 0, 1])
10 state = torch.from_numpy(state).long().unsqueeze(0)
state = torch.zeros(3, 9).scatter_(0, state, 1).view(1, 27)
print(state)

```

we yield the output

Columns 0 to 12

```
0      0      0      1      0      1      1      1      0      1      0      0      0
```

Columns 13 to 25

```
1      0      0      0      1      0      1      1      0      0      0      0      0
```

Columns 26 to 26

```
0
```

```
[torch.FloatTensor of size 1x27]
```

The output seems to imply that the first nine dimensions indicate entries that are empty, the second nine dimensions indicate entries that are x's and the last nine dimensions indicate entries that are o's.

2(c)

The output of the select_output function is a nine-dimensional vector indicates which position of the tic-tac-toe table to place that player's mark. The policy is stochastic.

Part 3

3(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} + ..  
    """  
    10 G = [0] * len(rewards)  
  
    for i in range(len(rewards)-1, -1, -1):  
        15 if i == len(rewards)-1: G[i] = rewards[i]  
        else: G[i] = rewards[i] + gamma * G[i+1]  
  
    return G
```

3(b)

We cannot update the weights in the middle of an episode because with just one move, we cannot know if it will lead to winning/losing/having a tie. The update to weights depends on the terminating status of an episode. This is why weights must be updated after each episode, and not in between.

Part 4

4(a)

```
def get_reward(status):  
    """Returns a numeric given an environment status."""  
    return {  
        Environment.STATUS_VALID_MOVE : 1,  
5      Environment.STATUS_INVALID_MOVE: -250,  
        Environment.STATUS_WIN        : 500,  
        Environment.STATUS_TIE         : -3,  
        Environment.STATUS_LOSE        : -3  
    }[status]
```

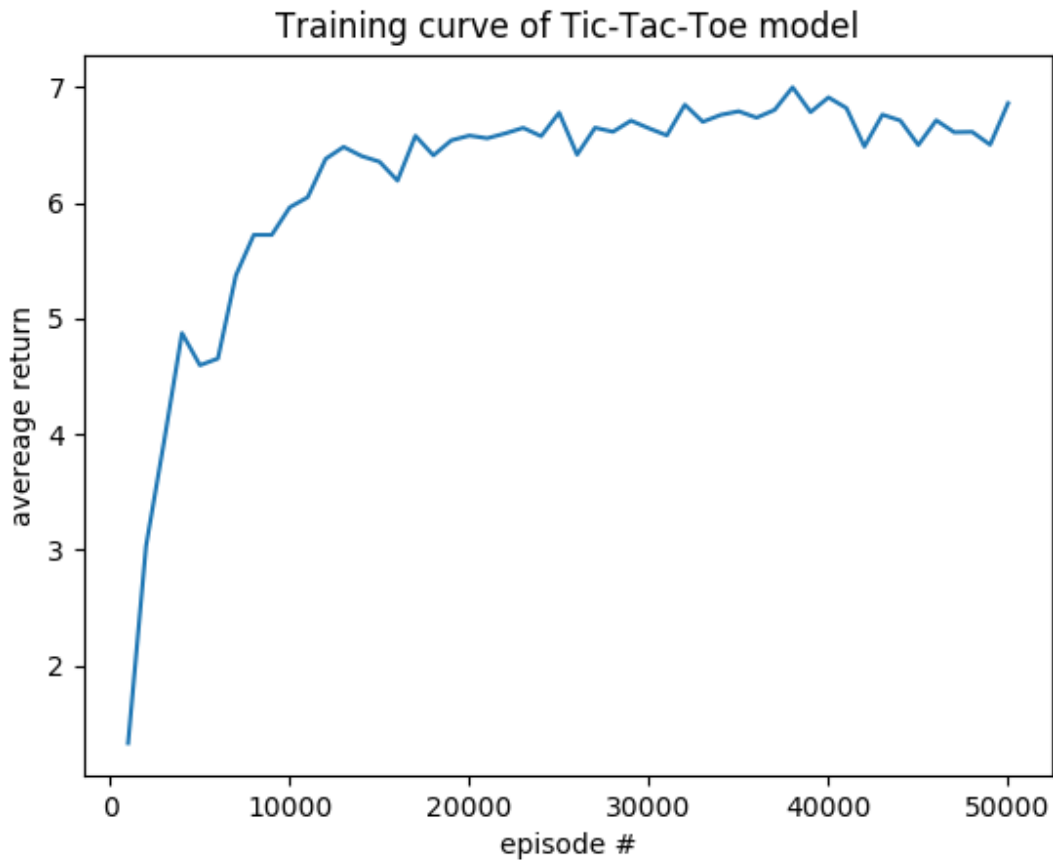
4(b)

Part 5

5(a)

Refer to Figure 1. One hyperparameter that was changed was γ . Initially it was set to $\gamma = 1$, but changing it to $\gamma = 0.75$ incentivized the AI to finish the game in shorter number of turns, which helped penalize ties and invalid moves.

Figure 1: Training curve (# hidden units: 64)



5(b)

The number of hidden units were reset to values 32, 128 and 256 to obtain the following training curves:

Figure 2: Training curve (# hidden units: 32)

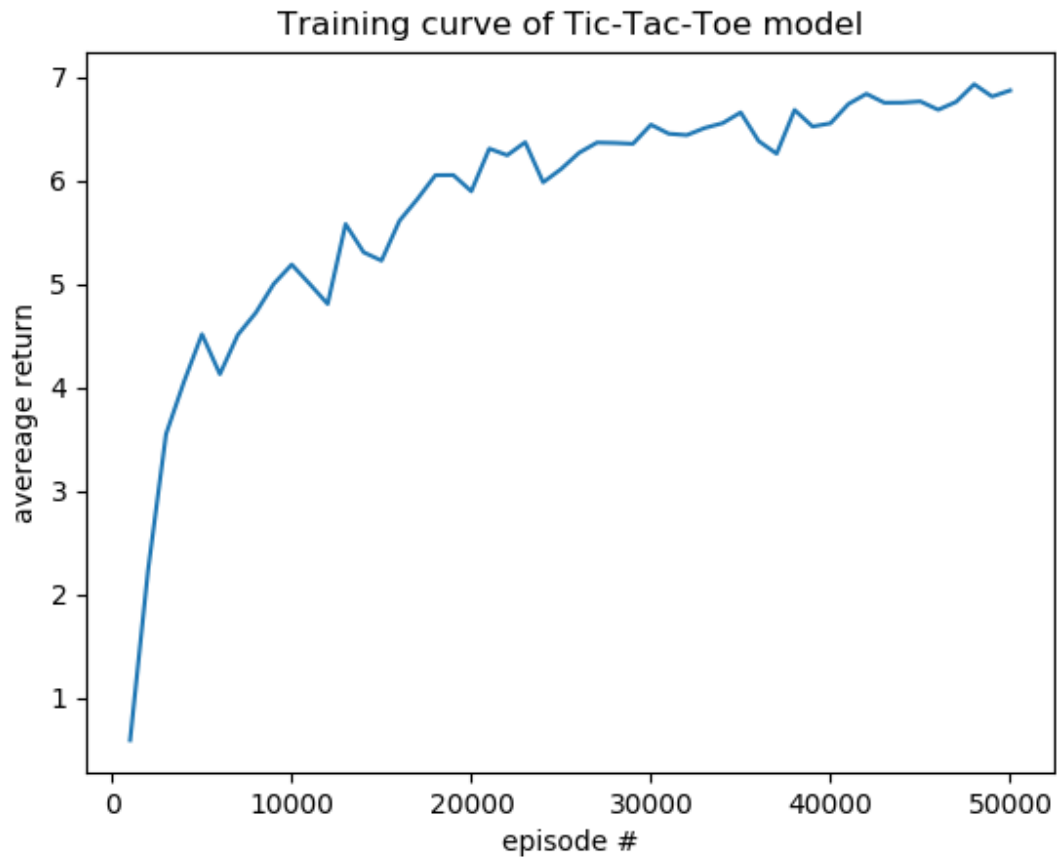


Figure 3: Training curve (# hidden units: 128)

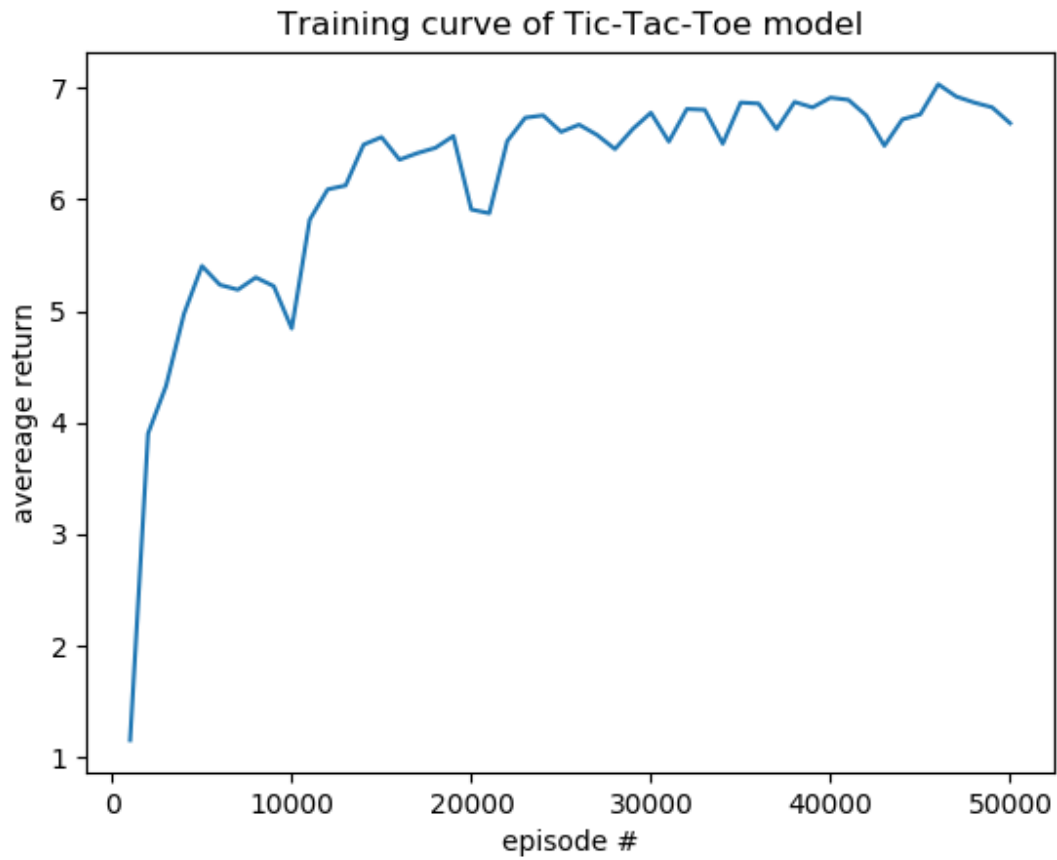
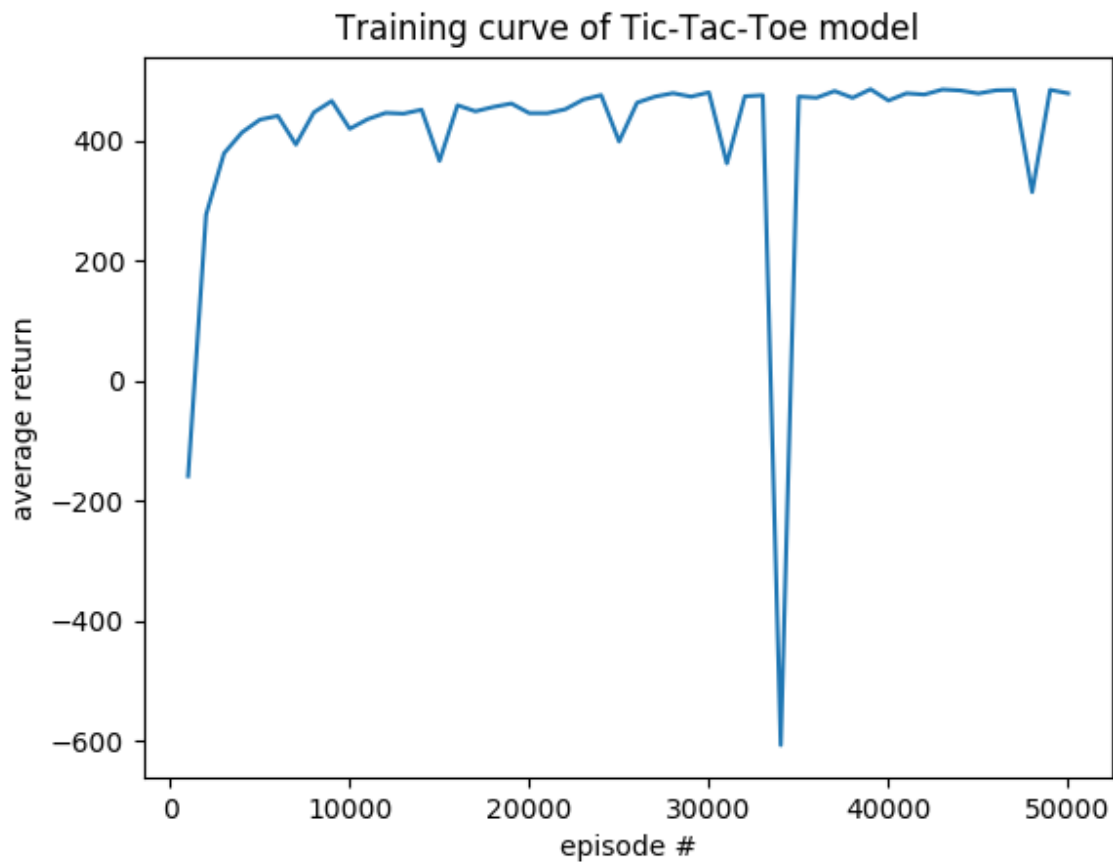


Figure 4: Training curve (# hidden units: 256)



5(c)

From Figure 1, it seems as though the policy never played invalid moves.

5(d)

Using the final learned policy, the agent wins 98/100 games and ties 2/100. This can be seen in Figure 5. Five of the 100 sample games are displayed below:

Game: 0	Game: 19	Game: 57	Game: 76	Game: 95
..X	O.X	..X	.OX	..X
...	...	O..
O..O
====	====	====	====	====
O.X	O.X	O.X	.OX	.OX
...	O..	O..X.
O.X	..X	..X	.OX	..O
====	====	====	====	====
O.X	O.X	O.X	.OX	.OX
..X	O.X	O.X	..X	.X.
O.X	..X	..X	.OX	X.O
====	====	====	====	====

Part 6

Refer to Figure 5.

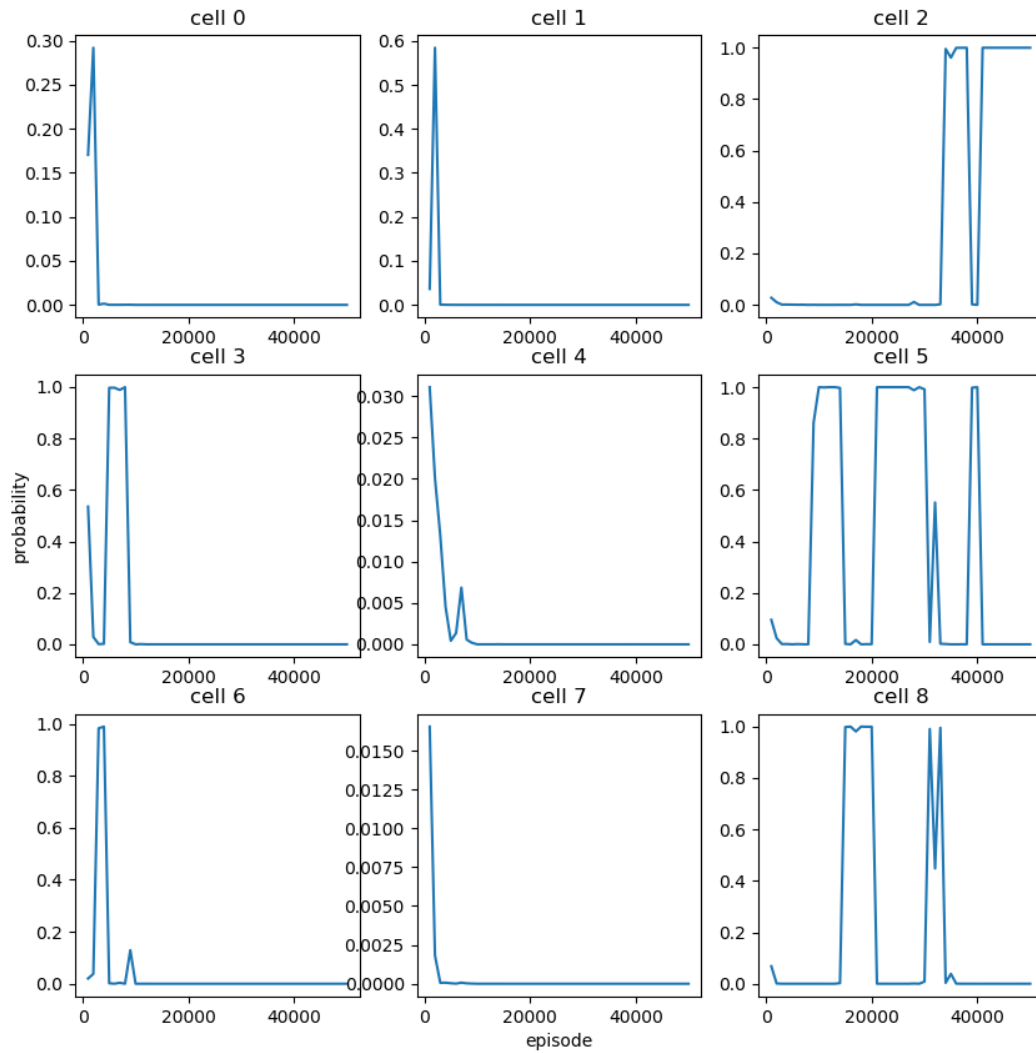
Figure 5



Part 7

Refer to Figure 6.

Figure 6: Evolution of first move probability for each of the 9 cells of the tic-tac-toe board



Part 8