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
"""
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)

def forward(self, x):
  x = F.relu(self.fc1(x))
  x = self.fc2(x)
  softmax = nn.Softmax()
  return softmax(x)
```

2(b)

Running the following script

```
  policy = Policy()

  # xoo
  # .x.
  # ..x
  # =====

  state = np.array([1, 2, 2, 0, 1, 0, 0, 0, 1)]

  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 indicat entries that are empty, the second nine dimensions indicate entries that are x's and the last nine dimensions indicate entires 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)

```python
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} + ..
"""
  G = [0] * len(rewards)

  for i in range(len(rewards)-1, -1, -1):
  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 s

Part 4

4(a)

The modified `get_reward(status)` function is included below:

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

4(b)

There are positive and negative rewards. Negative rewards are given for undesirable outcomes (invalid move, tie and lose) while positive rewards are given for winning and making a valid move. Initially the reward for tie was positive and comparable to the reward for winning but was then made negative to increase the win rate (we observed that the AI was going for ties and was effectively treating tie-ing the same as winning).

As far as the magnitude of the rewards go, the reward for winning was increased by a factor of 100 compared to the magnitudes of losing and tieing to incentivize the AI to win more. The reward for making an invalid move was initially -1 but was increased in magnitude to bring down the number of invalid moves during the game.

Part 5

5(a)

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)

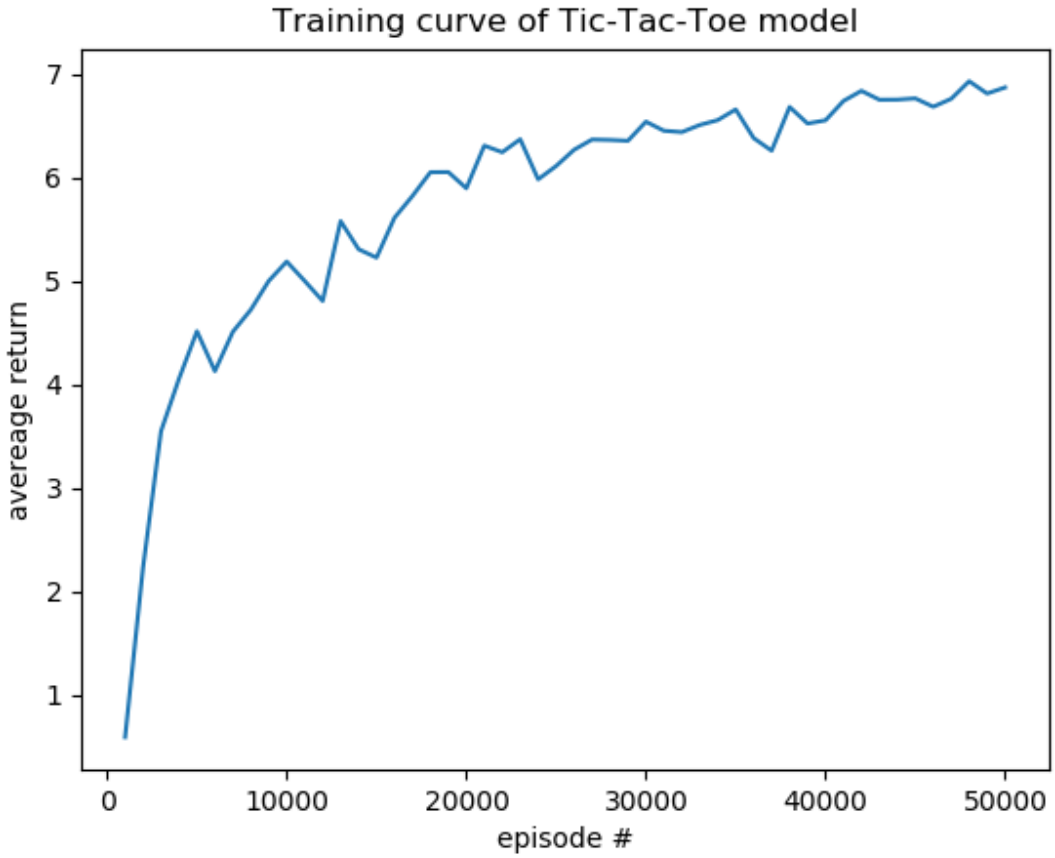


Figure 3: Training curve (# hidden units: 128)

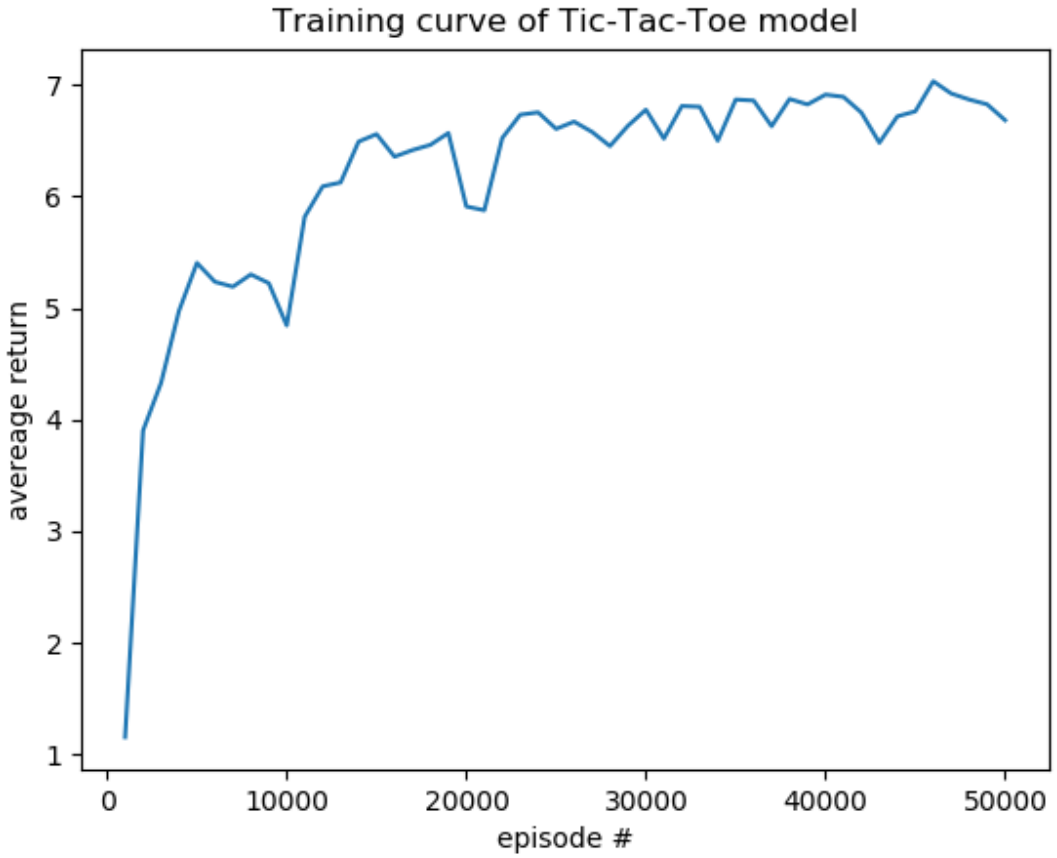
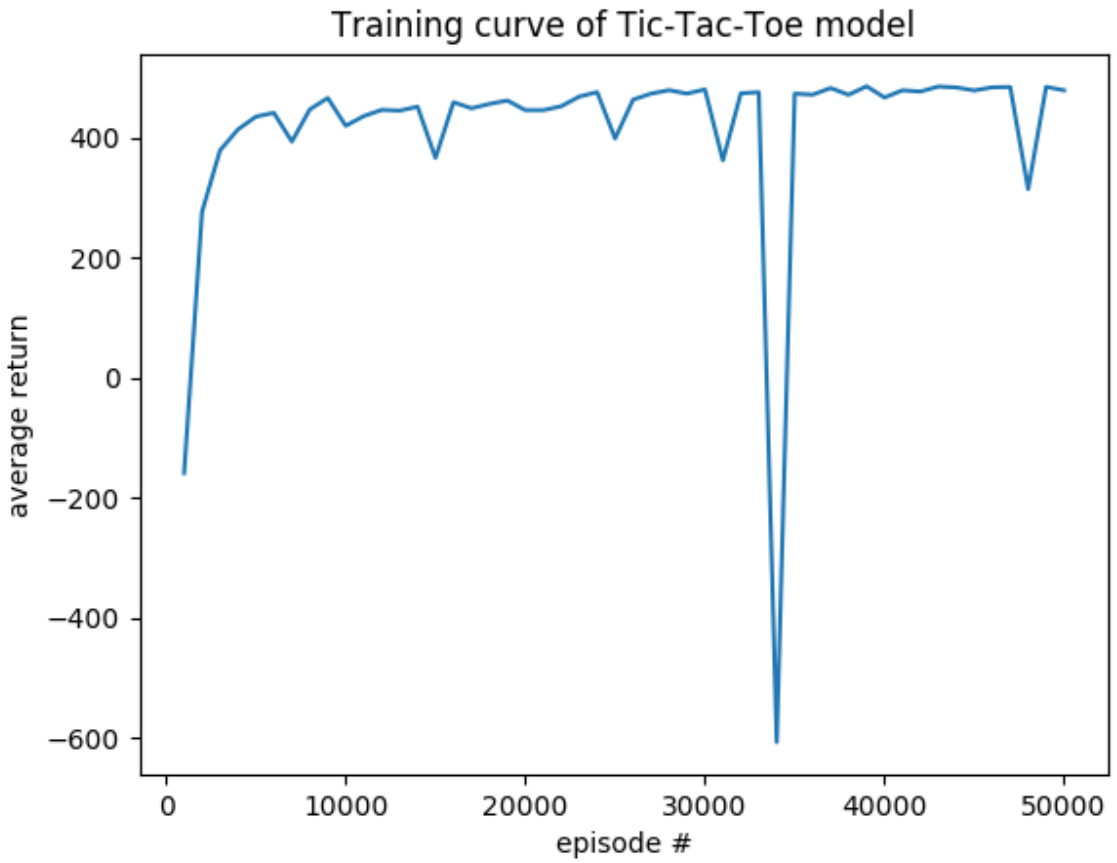


Figure 4: Training curve (# hidden units: 256)



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

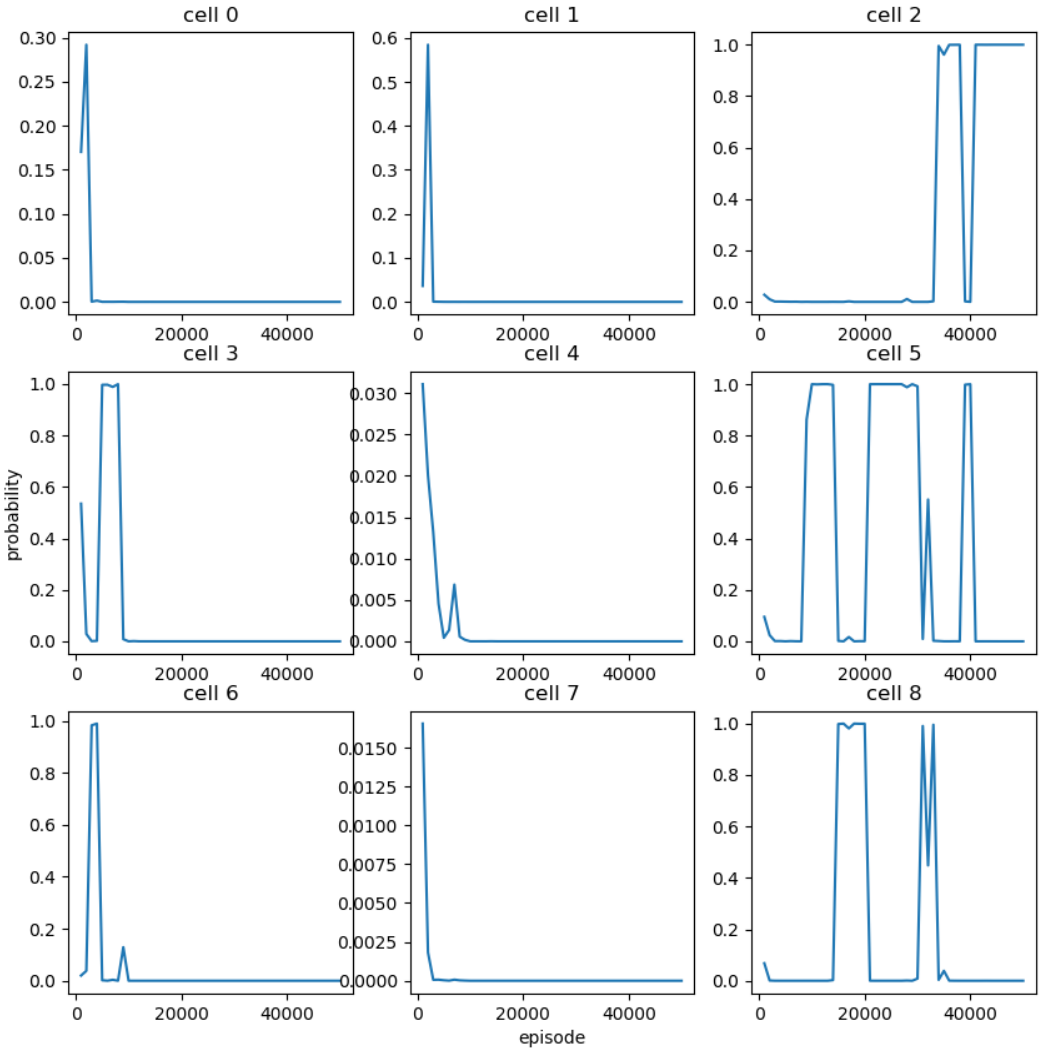
Refer to Figure 5.

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