### Tic Tac Toe

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#### Introduction

刚开学这一个月真是好忙啊,我都没什么时间来写博客。这几天看了点 Reinforcement Learning 相关的知识写个小总结。因为我自己的专业不是这方面所以为了避免瞎讲,我无法在这篇博客涉及太多的概念。大部分概念可以在 Reference 中看。

#### Code

Tic Tac Toe!

Reinforcement Learning是机器学习的一部分,这篇博文的目标是用 Reinfocement Learning 实现个玩 Tic Tac Toe 的游戏AI,完整的代码[7],我大部分的代码都是参照[2]。

我们先写个 Board 来作为一个游戏场地

```
import numpy as np
   import pandas as pd
3
4
   class Game:
5
       def __init__(self, row, col):
6
           self.row_size = row
7
           self.col_size = col
8
           # 0 for not end
9
           # 1 for winer is first player
10
           # 2 for winer is second player
11
           # 3 for tie
12
           self.end = 0
13
           self.board = np.zeros((self.row_size, self.col_size))
14
           self.size = self.board.size
           self.mapping = {0: " ", 1: "X", -1: "0"}
15
16
17
18
       def DrawCharForItem(self, item):
19
           # 0 for ' '
20
           # 1 for 'X'
21
           # -1 for '0'
           return self.mannina[item]
```

```
poara =
28
                 {} | {} | {}
29
30
                 {} | {} | {}
31
32
                 {} | {} | {}
            """.format(*items)
33
34
            print(board)
35
36
        def CheckWin(self):
37
            result = \Pi
38
39
            for i in range(self.row_size):
40
                result.append(np.sum(self.board[i, :]))
41
            for i in range(self.col_size):
42
                result.append(np.sum(self.board[:, i]))
43
44
            result.append(0)
45
            for i in range(0, self.col_size):
                result[-1] += self.board.item((i, i))
46
47
            result.append(0)
48
            for i in range(0, self.row_size):
49
                result[-1] += self.board.item((i, self.row_size - 1 - i))
50
51
            for i in result:
52
                if i == 3:
53
                    self.end = 1
54
                    return self.end
55
                if i == -3:
56
                    self.end = 2
57
                    return self.end
58
            sum = np.sum(np.abs(self.board))
59
            if sum == self.size:
60
                self.end = 3
            return self.end
61
62
63
       def End(self):
64
            return self.end
65
       def Step(self, order, action):
66
67
            if action[0] < 0 or action[0] > self.row_size-1 or action[1] < 0 or action[1] > self.column{1}{c}
68
                print("x or y invalid")
69
                return True
70
            if self.board[action[0], action[1]] != 0:
                print("this palce has already been taken")
71
72
                return True
73
            self.board[action[0], action[1]] = order
74
            self.CheckWin()
75
            self.Print()
76
            return False
```

接下来写个Agent类作为我们的AI。

```
1 class Agent
```

现在来介绍下我们这个AI的核心公式([8])



不过在编码这公式之前我们需要一个数据结构来存储我们的收益。

定义一个 state 来存储收益。这个 state 是一个 row\*col 的数组,这个数组存放当前情况下每一格的收益。

```
1 state, 当前情况下走 (0,1) 这个点的收益是 1.30938546e-07
2 [[ 1.30938546e-07 -4.93034771e-07 1.51138875e-04]
3 [-6.41862293e-08 -2.77494609e-08 -5.18934185e-07]
4 [-2.61877061e-07 -4.96284826e-05 2.59479593e-07]]
```

我们在定义一个字典来存每一种情况下的 state,为每一种情况生成一个hash,这个hash作为字典的 key

```
1
   def ComputeHash(board):
2
       board_ = board.flatten().tolist()
3
       return "".join([str(i) for i in board_])
4
5
   class Agent:
6
       def __init__(self, name, exploration_rate=0.33, learning_rate=0.5, discount_factor=0.01):
7
           self.states = {}
8
           # states stack
9
           self.state_order = []
10
           self.learning_rate = learning_rate
11
           self.exploration_rate = exploration_rate
12
           self.discount_factor = discount_factor
13
           self.name = name
```

这样我们的公式就变成了这样

接着定义一个reward函数,对于什么时候给予奖励有多种选择[9],在这个AI中我们选择在出现赢家的时候给予奖励。

```
class Agent:
2
       def set_state(self, board, action):
3
           hash = ComputeHash(board)
4
           self.state_order.append((hash, action))
5
6
       def OnReward(self, reward):
7
           hash, action = self.state_order.pop()
8
           if hash not in self.states:
               self.states[hash] = np.zeros((BOARD_ROWS, BOARD_COLS))
9
10
           self.states[hash].itemset(action,reward)
11
12
           while self.state_order:
13
               hash_prev, action_prev = self.state_order.pop()
               reward *= self.discount_factor
```

```
self.states[hash_prev] = np.zeros((BOARD_ROWS, BOARD_COLS))
reward = self.learn_by_temporal_difference(reward, hash, hash_prev).item(action)
self.states[hash_prev].itemset(action,reward)

hash = hash_prev
action = action_prev
```

这里 state\_order 是我们存所走过的每一步的一个栈,存的是 (state的hash,这一步的坐标)。这个函数的组要目的是把计算出的收益存储在 self.states 中。

接下来我们定义 exploit 和 explore 函数

```
class Agent:
2
        def exploit(self, board):
3
            state_value = self.states[ComputeHash(board)]
4
            x, y = np.where(state_value == state_value.max())
5
            best_choices = [(a, b) \text{ for } a, b \text{ in } zip(x, y)]
6
            return best_choices[np.random.choice(len(best_choices))]
7
8
        def explore(self, board):
9
            x, y = np.where(board == 0)
10
            vacant = [(a, b) \text{ for } a, b \text{ in } zip(x, y)]
11
            return vacant[np.random.choice(len(vacant))]
```

最后定义个用来选择走那一步的函数,何时选择探索具体可以参考[5]中的2.2

```
class Agent:
1
2
       def SelectMove(self, board):
3
           action = None
4
           exploration = np.random.random() < self.exploration_rate</pre>
5
           if exploration or hash not in self.states:
                print("%s exploit" % self.name)
6
7
                action = self.explore(board)
8
           else:
9
                print("%s exploit" % self.name)
10
                action = self.exploit(board)
11
           # update state
12
           self.set_state(board, action)
13
           return action
```

训练下这个AI

```
def Train(round, bot1, bot2):
2
       win_trace = pd.DataFrame(data=np.zeros(
3
            (round, 2)), columns=["bot1", "bot2"])
4
       for i in range(round):
5
           print("-"*100)
6
           print("Round:{}".format(i+1))
7
           game = Game(BOARD_ROWS, BOARD_COLS)
8
           turn = 1
9
           while game.End() == 0:
10
                if turn == 1:
11
                    action = bot1.SelectMove(game.board)
12
                    game.Step(1, action)
13
                    turn = 2
14
                else:
15
                    action = bot2.SelectMove(game.board)
```

```
21
               bot2.0nReward(-1)
22
               win_trace.set_value(i, 'bot1', 1)
23
           elif game.End() == 2:
24
               bot1.0nReward(-1)
25
               bot2.0nReward(1)
26
               win_trace.set_value(i, 'bot2', 1)
27
       return win_trace
28
29 if __name__ == "__main__":
30
       bot1 = Agent("bot1")
31
       bot2 = Agent("bot2")
32
       Train(5000, bot1, bot2)
```

#### 最后跟它玩下

```
Bot first!
   bot1 exploit
3
4
                | | X
5
6
                7
8
                9
10 Your turn(enter x,y):1,1
11
12
                 | | X
13
14
                 101
15
                \perp
16
17
18 bot1 exploit
19
20
                 | | X
21
22
                 | 0 |
23
24
                 | X
26 Your turn(enter x,y):1,2
27
                 28
29
30
                 | 0 | 0
31
32
                | | X
33
34 bot1 exploit
35
36
                 | | X
37
38
               X \mid 0 \mid 0
39
40
                | X
41
42 Your turn(enter x,y):0,1
43
44
                 I O I X
```

```
51
52
                       I O I X
53
54
                    X \mid 0 \mid 0
55
56
                     X \mid X
57
58
    Your turn(enter x,y):2,1
59
60
                       \mid 0 \mid X
61
62
                     X \mid 0 \mid 0
63
64
                     X \mid O \mid X
65
66 You win
```

尝试了比较多的次数,只有一次训练出来的智商过关(结果忘保存结果)。感觉训练的次数不够并且需要把规则教给AI,不然训练的速度太慢。

#### Reference

- [1] https://en.wikipedia.org/wiki/Reinforcement\_learning
- [2] https://github.com/AmreshVenugopal/tic\_tac\_toe/blob/master/Tic%20tac%20toe.ipynb
- [3] https://github.com/ShangtongZhang/reinforcement-learning-an-introduction/blob/master/chapter01/tic\_tac\_toe.py
- [4] https://en.wikipedia.org/wiki/Temporal\_difference\_learning
- [5] http://tokic.com/www/tokicm/publikationen/papers/AdaptiveEpsilonGreedyExploration.pdf
- [6] https://detailed.af/a-game-of-tic-tac-toe/
- [7] https://github.com/lceware/blog\_code/blob/master/2018/tic\_tac\_toe.py
- [8] http://incompleteideas.net/book/the-book.html
- [9] https://medium.freecodecamp.org/an-introduction-to-reinforcement-learning-4339519de419

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