# Alpha Zero For Connect4

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## 1 AlphaZero

### 1.1 Monte-Carlo Tree Search (MCTS)

#### 1.1.1 Upper Confidence Bound

$$U(s, a) = Q(s, a) + \sqrt{\frac{2 \ln \sum_{b} N(s, b)}{1 + N(s, a)}}$$

U(s,a) is the upper confidence bound for the current state s and action a

Q(s,a) is the expected reward by taking action a in state s

N(s,a) is the number of times we took action a from state s

 $\sum_{b} N(s,b)$  is the total number of plays from state s

#### 1.1.2 Upper Confidence Bound Alpha Zero

$$U(s,a) = Q(s,a) + c_{puct}P(s,a) \frac{\sqrt{\sum_b N(s,b)}}{1+N(s,a)}$$

U(s,a) is the upper confidence bound for the current state s and action a.

Q(s,a) is the expected reward by taking action a in state s.

 $c_{puct}$  is a constant that controls the amount exploration

 $\hat{P}(s,a)$  probability to take action a in state s as predicted by the neural network

N(s,a) is the number of times we took action a from state s

 $\sum_{b} N(s,b)$  is the total number of plays from state s

#### 1.1.3 Training Loss

$$l = (z - v)^2 - \pi^T \log p$$

z is the outcome of the game -1, 0, 1 for the current player

v is the value prediction of the value

 $\pi$  is the policy form the MCTS

p is the network prediction of the policy

#### 1.1.4 Alpha Zero Algorithm

```
while current iteration < iterations do
    for episode 1, M do
         while !game terminated do
             while current simulation < mctssimulations do
                  while !s leaf node do
                       if s root node then
                           p(s) = (1 - \epsilon)p(s) + \epsilon \eta_d(\alpha)
                      play move a = \operatorname{argmax}_a \left( Q(a, s) + c_{puct} p(s, a) \frac{\sqrt{(N(s))}}{1 + N(s, a)} \right)
                      N(s) \leftarrow N(s) + 1
                  {f if}\ s terminal game state {f then}
                      v \leftarrow z
                  else
                       evaluate s with the network to get v(s) and p(s)
                       v \leftarrow v(s)
                      if player BLACK then
                           v \leftarrow -v
                  for all state-action pairs (s, a) do
                      if player BLACK then
        v \leftarrow -v
Q(s, a) \leftarrow \frac{N(s, a)Q(s, a) + v}{N(s, a) + 1}
N(s, a) \leftarrow N(s, a) + 1
p(s, a) = \left(\frac{N(s, a)}{N(s)}\right)^{1/\tau}
        sample from p(s) to play next self-play move a
        add training example (s, p(s), v') to experience buffer
         get the true outcome z of the game
        for all training examples of game do
             if player WHITE then
                 v' \leftarrow z
             else
                  v' \leftarrow -z
```

train the neural network with the training examples from the experience buffer