深度學習 HW2

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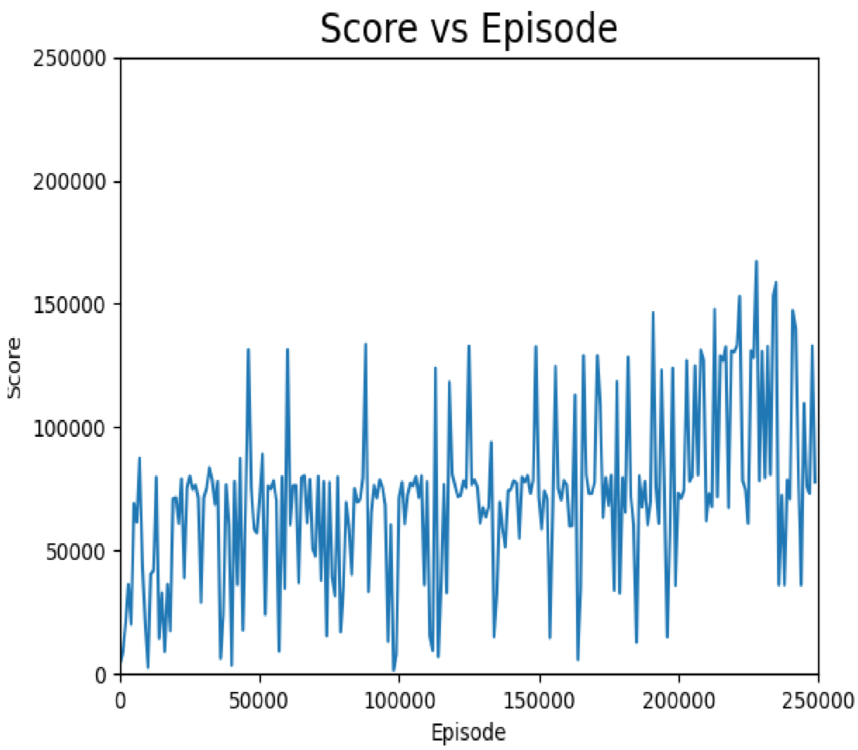
tags: 深度學習

Q1. A plot shows episode scores of at least 100,000 training episodes

```
8000     mean = 93757.7   max = 176412
         512      100%     (0.3%)
         1024     99.7%    (1.1%)
         2048     98.6%    (6.6%)
         4096     92%      (53.1%)
         8192     38.9%    (38.9%)
```

- In episodes 208000, we can get the best 2048 score for 98.6%

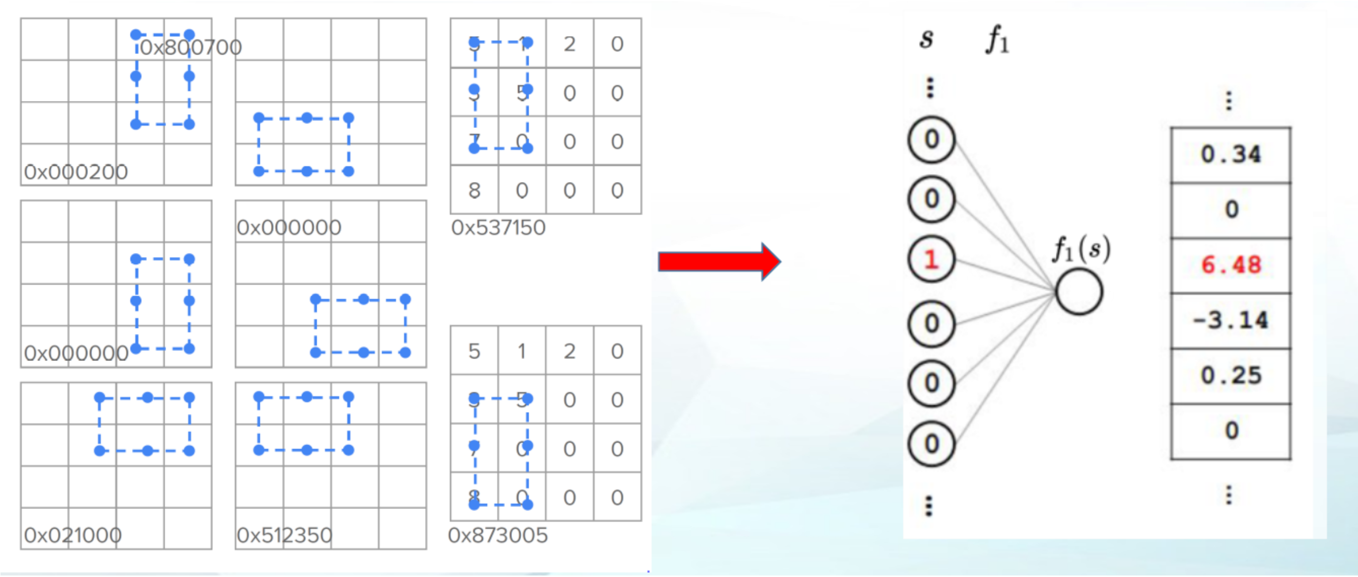


- Score plot for 250000 episodes (trained for 18 hours)
    - Change the learning_rate from 0.1 -> 0.01 after 200000 episodes

Q2. Describe the implementation and the usage of n-tuple network

Every single position can have the probability to be $[null, 2, 4, 8, 16, 32, 64, 128, 256, 512, 1024, 2048, \dots]$. Total will be at least 12^{16} combinations. It is impossible to store all these possiblities in computer.

Compared to recording all the state of boards, **n-tuple network can use multiple small tuples for caculation** because a tuple can present the characteristic of board. It is also easy for caculations and saves a lot of spaces.



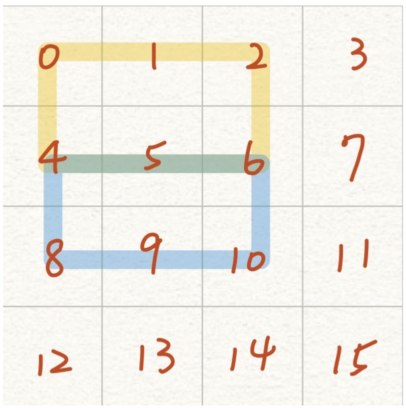
可以看到我們宣告了一個 6-tuple 然後根據鏡像以及旋轉，可以得到八種不同的結果。六個位置可以對應到一組 index，然後可以從 network中找到對應的value，例如： **fig.3 右側的網路就是以第三種版面為例子，所以可以看到第三種版面為 1 ，其餘都是 0，我們即可拿到第三種版面的權重，相乘就可以得到估計值**，因此八種版面估計值加總，就可以成為此版面的價值了！

我們可以在多取一點feature，助教的sample code 有四種，那我又自己加上三種，總共有七種 feature。

fig.3 新增 窗形 2 x 3 feature

```
// ---
// ---
tdl.add_feature(new pattern({ 0, 1, 2, 4, 5, 6 }));
tdl.add_feature(new pattern({ 4, 5, 6, 8, 9, 10 }));
```

fig.4 黃色與藍色分別代表窗形feature的兩種情況。



Q3. Explain the mechanism of TD(0).

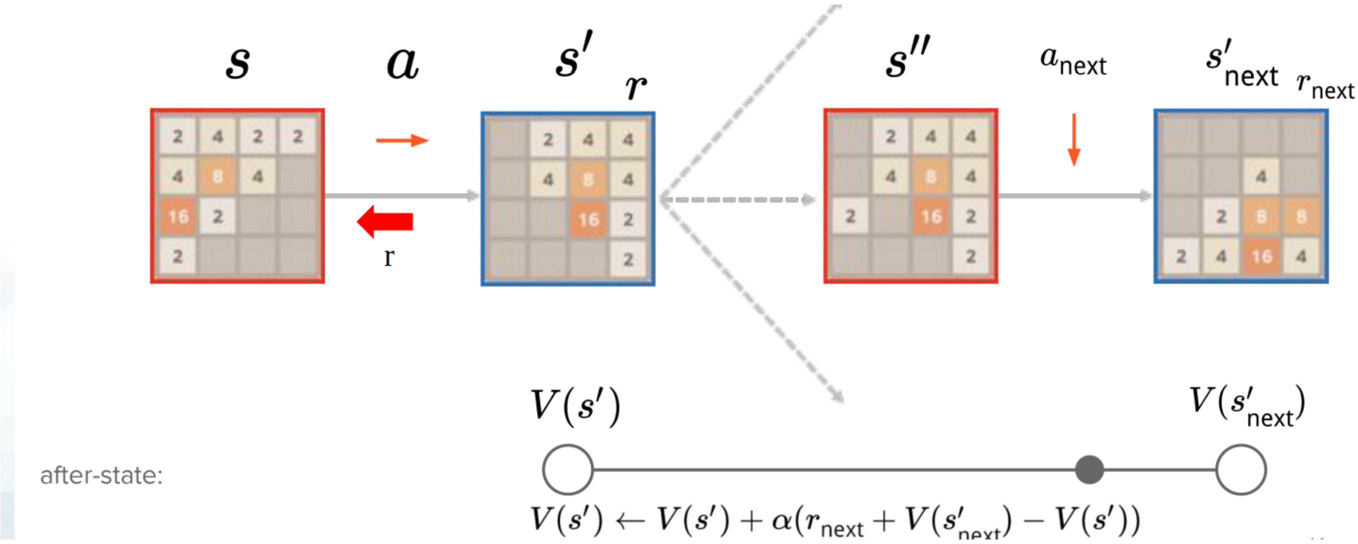
TD(0) is special case of TD(λ)，it will look one step ahead. Unlike the MC, we will get the immediate reward plus the discount estimate value of 1 step ahead.

$$V(S_t) \Leftarrow V(S_t) + \alpha[R_{t+1} + \gamma V(S_{t+1}) - V(S_t)]$$

In the project, the discount fector is set to 1, We will keep update our value function in each state. The transition is $s \rightarrow s''$. We wait until arrive the next time step s'' and then **combine immediate reward r in state s and prediction $V(s'')$ to update our $V(s)$.**

$$V(s) \leftarrow V(s) + \alpha(r + V(s'') - V(s))$$

Q4. Explain the TD-backup diagram of V(after-state).



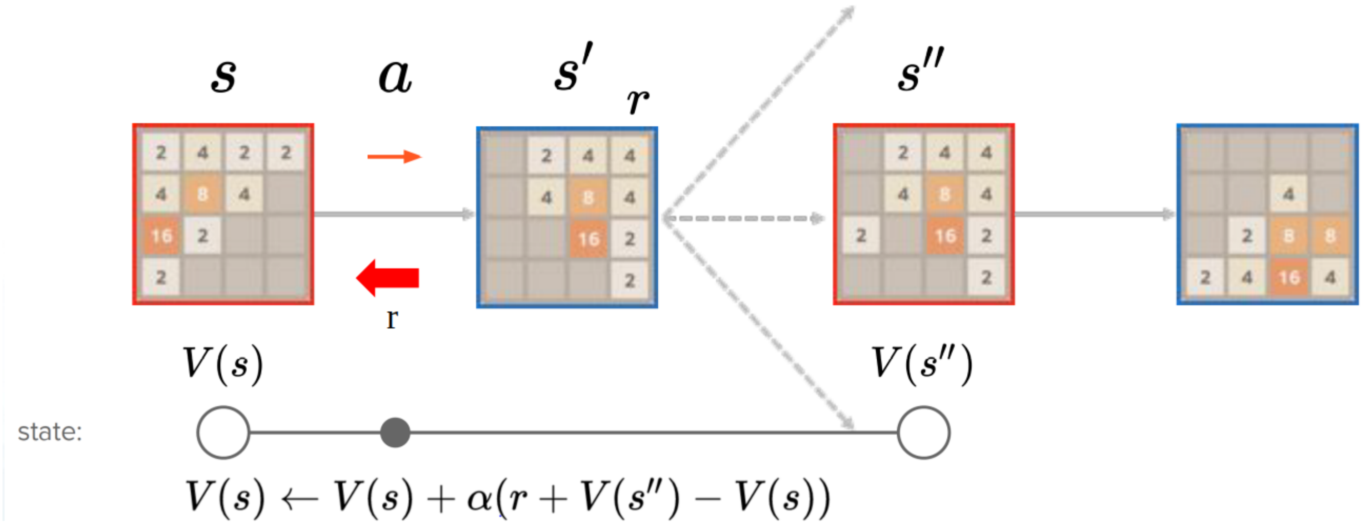
The after-state method only cares about the after state. We want to update $V(s')$ by selecting a_{next} and chooseing TD target as $r_{next} + V(s'{next}). ThenwecangetTDerrorby (r{next} + V(s'_{next}) - V(s')). FinallyupdateV(s')bymultiplyingthelearning_rate\alpha$.

Q5. Explain the action selection of V(after-state) in a diagram.

To select the best action, it will caculate all possible actions and select the action that can go to state with highest value function.

function EVALUATE(s, a)
  $s', r \leftarrow$ COMPUTE AFTERSTATE(s, a)
  return $r + V(s')$

Q6. Explain the TD-backup diagram of V(state).



The before-state method cares about the state "after the transition" or "before the action". We want to update $V(s)$ by selecting a and chooseing TD target as $r + V(s'')$. Then we can get TD error by $(r + V(s'') - V(s))$. Finally update $V(s)$ by multiplying the learning_rate α.

Q7. Explain the action selection of V(state) in a diagram.

Action selection will take all possible action (up, down, left, right) and go through all the possible transition to next state s''. Then we can choose the best action with the highest state-action value function.

function EVALUATE(s, a)

$s', r \leftarrow$ COMPUTE AFTERSTATE(s, a)

$S'' \leftarrow$ *ALL POSSIBLE NEXT STATES*(s')

return $r + \Sigma_{s'' \in S''} P(s, a, s'') V(s'')$

Q8. Describe your implementation in detail.

In this lab, I change the following function :

- select_best_move :
  - To select best action, build a for loop that will take all actions and build an inner for loop to caculate the expectation of choosing that action

1. define a vector to store the empty position on board

```
// check all possible s'' will occur (empty position)
std::vector<int> empty_position;

// record all empty position
for (int i = 0; i<16;i++){
    if (move->after_state().at(i) == 0){
        empty_position.push_back(i);
    }
}
```

2. Run a for loop to run through all possible action. **Choose one possible action and run through all possible transition to predict the expectation of choosing that action**. (Remember: the probability of popup 4-tile is 10% but 2-tile is 90%)

```
for (int i =0; i < empty_count ; i++){

    // initialize the future state
    S_future = move->after_state();
    // if popout 2 in empty position
    S_future.set(empty_position[i],1);
    // the chance is 0.9/empty_position_count
    val += estimate(S_future) * 0.9 / empty_count;

    // initialize the future state
    S_future = move->after_state();
    // if popout 4 in empty position
    S_future.set(empty_position[i],2);
    // the chance is 0.1/empty_position_count
    val += estimate(S_future) * 0.1 / empty_count;
}
```

3. Return the best action with the highest value function

```
// value is immediate reward and the expectation of all possible value in next state
move->set_value(move->reward() + val);
```

- update_episode :

function LEARN EVALUATION(s, a, r, s', s'')

$V(s) \leftarrow V(s) + \alpha(r + V(s'') - V(s))$

```
path.pop_back();
state& move_final = path.back();
// Terminal state
// v(s) <- v(s) + alpha(r + V(s'') - V(s))
float previous_state = 0 - estimate(move_final.before_state());

// loop through all path
for (path.pop_back() /* terminal state */; path.size(); path.pop_back()) {
    state& move = path.back();
    float error =  previous_state - estimate(move.before_state()) + move.reward();
    previous_state = update(move.before_state(), alpha * error);
}
```

1. Caculate the value function of terminal state
2. Loop through the path by updating the value function
3. Then you can get the new value function of the whole path!

- main :
    - 跑程式
    - 自己加上新的 feature

```
// initialize the features
// ----
tdl.add_feature(new pattern({ 0, 1, 2, 3}));
tdl.add_feature(new pattern({ 4, 5, 6, 7}));

// ---
//  -
tdl.add_feature(new pattern({ 0, 1, 2, 5}));
tdl.add_feature(new pattern({ 4, 5, 6, 9}));

// --
// --
tdl.add_feature(new pattern({ 0, 1, 4, 5}));
tdl.add_feature(new pattern({4, 5, 8, 9}));
tdl.add_feature(new pattern({1, 2, 5, 6}));
tdl.add_feature(new pattern({5, 6, 9, 10}));

//-
//---
tdl.add_feature(new pattern({0, 4, 5, 6}));
tdl.add_feature(new pattern({1, 5, 6, 7}));
tdl.add_feature(new pattern({4, 8, 9, 10}));
tdl.add_feature(new pattern({5, 9, 10, 11}));
```

```
//--
// --
tdl.add_feature(new pattern({0, 1, 5, 6}));
tdl.add_feature(new pattern({1, 2, 6, 7}));
tdl.add_feature(new pattern({4, 5, 9, 10}));
tdl.add_feature(new pattern({5, 6, 10, 11}));

// ----
// --
tdl.add_feature(new pattern({ 0, 1, 2, 3, 4, 5 }));
tdl.add_feature(new pattern({ 4, 5, 6, 7, 8, 9 }));

// ---
// ---
tdl.add_feature(new pattern({ 0, 1, 2, 4, 5, 6 }));
tdl.add_feature(new pattern({ 4, 5, 6, 8, 9, 10 }));
```

Q9. Other diccussions or improvement

1. We can adjust the learning rate after 100000 episodes, turn 0.1 to 0.01 can get a better performance

2. To draw the score and episode graph, define a function to automatically save score in txt file so we can plot from python or matlab!

```
void write_score(size_t episode, int score){

    std::ofstream file;
    file.open("./record_final.txt", std::ios::app);
    file << "ep: " << episode << " , score: " << score << std::endl;

}
```