Lab7: Temporal Difference Learning

Lab Objective:

In this lab, you will learn temporal difference learning (TD) algorithm by solving the 2048 game using an n-tuple network.

Important Date:

1. Experiment report submission deadline: 06/15 (Mon) 23:55
(No demo)

Turn in:

1. Experiment report (.pdf)
2. Source code [NOT including model weights]

Notice: zip all files with name "DLP_LAB7_StudentId_Name.zip",
e.g.: 「DLP_LAB7_0856032_鄭余玄.zip」

Lab Description:

- Understand the concept of (before-)state and after-state.
- Learn to construct and design an n-tuple network.
- Understand TD algorithm.
- Understand Q-learning network training.

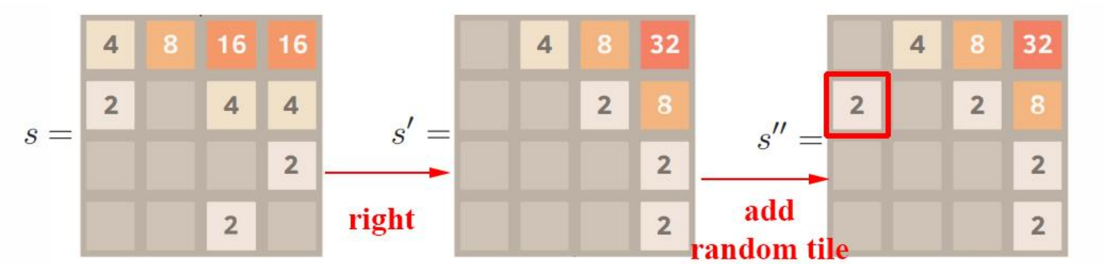
Requirements:

- Implement TODO in template
  - n-tuple network estimate and update
  - V(state) action selection
  - V(state) update
- Understand mechanisms
  - Construction of n-tuple network
  - V(state) and V(after state)
  - Action selection according to the n-tuple network
  - TD-target and TD-error

Game Environment – 2048:

- Introduction: 2048 is a single-player sliding block puzzle game. The game's objective is to slide numbered tiles on a grid to combine them to create a tile with the number 2048.
- Actions: **Up**, **Down**, **Left**, **Right**
- Reward: The score is the value of new tile when two tiles are combined.

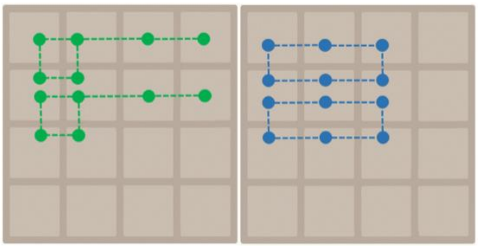
- A sample of two-step state transition



Implementation Details:

Network Architecture

- n-tuple patterns: 4×6-tuples with all possible isomorphisms



Training Arguments

- Learning rate: 0.1
    - Learning rate for features of n-tuple network with m features: $0.1 \div m$
- Train the network 500k ~ 1M episodes

Algorithm:

A pseudocode of the game engine and training. (modified backward training method)

function PLAY GAME
  $score \leftarrow 0$
  $s \leftarrow$ INITIALIZE GAME STATE
  while IS NOT TERMINAL STATE(s) **do**
    $a \leftarrow \underset{a' \in A(s)}{\text{argmax}}$ EVALUATE(s, a')
    $r, s', s'' \leftarrow$ MAKE MOVE(s, a)
    SAVE RECORD(s, a, r, s', s'')
    $score \leftarrow score + r$
    $s \leftarrow s''$
  for (s, a, r, s', s'') FROM TERMINAL DOWNTO INITIAL **do**
    LEARN EVALUATION(s, a, r, s', s'')
  return $score$

function MAKE MOVE(s, a)
  $s', r \leftarrow$ COMPUTE AFTERSTATE(s, a)
  $s'' \leftarrow$ ADD RANDOM TILE(s')
  return (r, s', s'')

TD-state

function EVALUATE(s, a)
  $s', r \leftarrow$ COMPUTE AFTERSTATE(s, a)
  $S'' \leftarrow$ ALL POSSIBLE NEXT STATES(s')
  return $r + \Sigma_{s'' \in S''} P(s, a, s'') V(s'')$

function LEARN EVALUATION(s, a, r, s', s'')
  $V(s) \leftarrow V(s) + \alpha(r + V(s'') - V(s))$

TD-after-state

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

function LEARN EVALUATION(s, a, r, s', s'')
  $a_{next} \leftarrow \underset{a' \in A(s'')}{\text{argmax}}\, EVALUATE(s'', a')$
  $s'_{next}, r_{next} \leftarrow COMPUTE\ \ AFTERSTATE(s'', a_{next})$
  $V(s') \leftarrow V(s') + \alpha(r_{next} + V(s'_{next}) - V(s'))$

Rule of Thumb:

- You can design your own n-tuple network, but do NOT try CNN.
- 2048-tile should appear within 10,000 episodes.

Scoring Criteria:

Show your work, otherwise no credit will be granted.

- Report (70%)
  - A plot shows episode scores of at least 100,000 training episodes (10%)
  - Describe your implementation in detail. (10%)
  - Describe the implementation and the usage of n-tuple network. (10%)
  - Explain the TD-backup diagram of V(state). (5%)
  - Explain the action selection of V(state) in a diagram. (5%)
  - Explain the TD-backup diagram of V(after-state). (5%)
  - Explain the action selection of V(after-state) in a diagram. (5%)
  - Explain the mechanism of temporal difference learning. (5%)
  - Explain whether the TD-update perform bootstrapping. (5%)
  - Explain whether your training is on-policy or off-policy. (5%)
  - Other discussions or improvements. (5%)
- Performance (30%)
  - The 2048-tile win rate in 1000 games, $\lceil \text{winrate}_{2048} \rceil$.

References:

[1] Szubert, Marcin, and Wojciech Jaśkowski. "Temporal difference learning of N-tuple networks for the game 2048." 2014 IEEE Conference on Computational Intelligence and Games. IEEE, 2014.

[2] Kun-Hao Yeh, I-Chen Wu, Chu-Hsuan Hsueh, Chia-Chuan Chang, Chao-Chin Liang, and Han Chiang, Multi-Stage Temporal Difference Learning for 2048-like Games, accepted by IEEE Transactions on Computational Intelligence and AI in Games (SCI), doi: 10.1109/TCIAIG.2016.2593710, 2016.

[3] Oka, Kazuto, and Kiminori Matsuzaki. "Systematic selection of n-tuple networks for 2048." International Conference on Computers and Games. Springer International Publishing, 2016.

[4] moporgic. "Basic implementation of 2048 in Python." Retrieved from Github: https://github.com/moporgic/2048-Demo-Python.

[5] moporgic. "Temporal Difference Learning for Game 2048 (Demo)." Retrieved from Github: https://github.com/moporgic/TDL2048-Demo.

[6] lukewayne123. "2048-Framework" Retrieved from Github: https://github.com/lukewayne123/2048-Framework.