Searching by learning: Exploring artificial general intelligence on small board games by deep reinforcement learning
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Appendix A

A.1 Symbols

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Type</th>
<th>Description</th>
<th>Ref.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma$</td>
<td>$0 \leq \gamma \leq 1$</td>
<td>the discount factor of $\max_a Q(s', a')$</td>
<td>Eq. (2.1)</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>$0 \leq \alpha \leq 1$</td>
<td>the learning rate of Q-learning</td>
<td>Eq. (2.2)</td>
</tr>
<tr>
<td>$\epsilon$</td>
<td>$0 \leq \epsilon \leq 1$</td>
<td>$\epsilon$-greedy for exploration and exploitation</td>
<td>Eq. (2.3)</td>
</tr>
<tr>
<td>$l$</td>
<td>$\mathbb{N}^+$</td>
<td>match number used to control decaying speed of $\epsilon$</td>
<td>Eq. (2.3)</td>
</tr>
<tr>
<td>$d$</td>
<td>$\mathbb{N}^+$</td>
<td>dimension of action space</td>
<td>Eq. (3.1)</td>
</tr>
<tr>
<td>$p$</td>
<td>$\mathbb{R}^d$</td>
<td>policy provided by the neural network</td>
<td>Eq. (3.1)</td>
</tr>
<tr>
<td>$\pi$</td>
<td>$\mathbb{R}^d$</td>
<td>improved estimate policy after performing MCTS</td>
<td>Eq. (3.1)</td>
</tr>
<tr>
<td>$v$</td>
<td>$\mathbb{R}$</td>
<td>state value prediction</td>
<td>Eq. (3.1)</td>
</tr>
<tr>
<td>$z$</td>
<td>${-1, 0, 1}$</td>
<td>real game end reward</td>
<td>Eq. (3.1)</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>$0 \leq \lambda \leq 1$</td>
<td>a weight to balance policy and value loss function</td>
<td>Eq. (4.1)</td>
</tr>
<tr>
<td>$\beta$</td>
<td>$\mathbb{R}$</td>
<td>a weight number to balance $U(s, a)$ and $U_{rave}(s, a)$</td>
<td>Eq. (5.4)</td>
</tr>
<tr>
<td>$L$</td>
<td>$\mathbb{N}^+$</td>
<td>the length of the reward list</td>
<td>Eq. (7.1)</td>
</tr>
<tr>
<td>$\tau$</td>
<td>$0 \leq \tau \leq 1$</td>
<td>a ratio to locate game length threshold in reward list</td>
<td>Eq. (7.1)</td>
</tr>
<tr>
<td>$r_\tau$</td>
<td>$\mathbb{N}^+$</td>
<td>threshold reward of game length to judge win or loss</td>
<td>Eq. (7.1)</td>
</tr>
</tbody>
</table>
# APPENDIX

## A.2 Abbreviations

<table>
<thead>
<tr>
<th>Abb.</th>
<th>Full Name</th>
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</thead>
<tbody>
<tr>
<td>AI</td>
<td>Artificial Intelligence</td>
</tr>
<tr>
<td>AGI</td>
<td>Artificial General Intelligence</td>
</tr>
<tr>
<td>MCS</td>
<td>Monte Carlo Search</td>
</tr>
<tr>
<td>MCTS</td>
<td>Monte Carlo Tree Search</td>
</tr>
<tr>
<td>GGP</td>
<td>General game playing</td>
</tr>
<tr>
<td>RAVE</td>
<td>Rapid Action Value Estimation</td>
</tr>
<tr>
<td>GDL</td>
<td>Game Description Language</td>
</tr>
<tr>
<td>DQN</td>
<td>Deep Q-networks</td>
</tr>
<tr>
<td>GM</td>
<td>Game Manager</td>
</tr>
<tr>
<td>TCP/IP</td>
<td>Transmission Control Protocol/Internet Protocol</td>
</tr>
<tr>
<td>UCT</td>
<td>Upper Confidence bound applied to Trees</td>
</tr>
<tr>
<td>AMAF</td>
<td>All Moves As First</td>
</tr>
<tr>
<td>RHEA</td>
<td>Rolling Horizon Evolutionary Algorithm</td>
</tr>
<tr>
<td>P-UCT</td>
<td>Policy-Upper Confidence bound applied to Trees</td>
</tr>
<tr>
<td>HPC</td>
<td>High Performance Computing</td>
</tr>
<tr>
<td>TSP</td>
<td>Travelling Salesman Problems</td>
</tr>
<tr>
<td>BPP</td>
<td>Bin Packing Problems</td>
</tr>
<tr>
<td>R2</td>
<td>Ranked Reward</td>
</tr>
<tr>
<td>MDP</td>
<td>Markov Decision Process</td>
</tr>
<tr>
<td>NRPA</td>
<td>Nested Rollout Policy Adaptation</td>
</tr>
</tbody>
</table>
A.3 Algorithms

Algorithm 8 Time Limited Monte Carlo Search Algorithm

1: function MONTECARLOSEARCH(time_limit)
2:     get legal actions set $A$ of current state $s$
3:     get next states set $S'$ where $s' \in S'$
4:     $z(s')=0$, $count(s')=0$
5:     while time_cost $\leq$ time_limit do
6:         for each $s'$ in $S'$ do
7:             outcome($s'$)$\leftarrow$random simulation from $s'$ to game end.
8:             $z(s')+=outcome(s')$
9:             $count(s')+=1$
10:        selected_action$\leftarrow$ getActionFromStates($s$, $\arg\max_{s'\in S'} \frac{z(s')}{count(s')}$)
11:     return selected_action
Algorithm 9 QM-learning Enhancement

1: function QMPLAYER(current state $s$, learning rate $\alpha$, discount factor $\gamma$, Q table: $Q(S, A)$) 
2:     for each match do 
3:         if $s$ terminates then 
4:             for each $(s, a)$ from end to the start in current match record do 
5:                 $R(s, a) = s′$ is terminal state? getGoal($s′$, myrole) : 0 
6:                 Update $Q(s, a) \leftarrow (1 - \alpha) Q(s, a) + \alpha (R(s, a) + \gamma \max_{a′} Q(s′, a′))$ 
7:         else 
8:             if $\epsilon$-greedy is enabled then 
9:                 selected_action = Random() 
10:             else 
11:                 selected_action = SelectFromQTable() 
12:                 if no s record in $Q(S, A)$ then 
13:                     MonteCarloSearch(time_limit) 
14:                 performAction($s$, selected_action) 
15:         return $Q(S, A)$ 


Algorithm 10 Neural Network Based MCTS with Only Rollout Simulation

Value

1: function Rollout($s, f_\theta$)
2: Search($s$)
3: $\pi_s \leftarrow \text{normalize}(Q(s, \cdot))$
4: return $\pi_s$
5: function Search($s$)
6: Return game end result if $s$ is a terminal state
7: if $s$ is not in the Tree then
8: Add $s$ to the Tree, initialize $Q(s, \cdot)$ and $N(s, \cdot)$ to 0
9: Get $P(s, \cdot)$ and $v(s)$ by looking up $f_\theta(s)$
10: Get result $v(s)$ by performing random rollout until the game ends
11: return $v(s)$
12: else
13: Select an action $a$ with highest UCT value
14: $s' \leftarrow \text{getNextState}(s, a)$
15: $v \leftarrow \text{Search}(s')$
16: $Q(s, a) \leftarrow \frac{N(s, a) \cdot Q(s, a) + v}{N(s, a) + 1}$
17: $N(s, a) \leftarrow N(s, a) + 1$
18: return $v$;
Algorithm 11 Neural Network Based MCTS with Only RAVE Value

1: function RAVE(s, f_θ)
2:     Search(s)
3:     π_s ← normalize(Q_{rave}(s, ⋅))
4:     return π_s
5: function Search(s)
6:     Return game end result if s is a terminal state
7:     if s is not in the Tree then
8:         Add s to the Tree,
9:         Initialize Q(s, ⋅), N(s, ⋅), Q_{rave}(s, ⋅) and N_{rave}(s, ⋅) to 0.
10:        Get P(s, ⋅) and v(s) by looking up f_θ(s)
11:    return v(s)
12: else
13:     Select an action a with highest UCT_{rave} value
14:     s′ ← getNextState(s, a)
15:     v ← Search(s′)
16:     Q(s, a) ← \frac{N(s,a)\times Q(s,a)+v}{N(s,a)+1}
17:     N(s, a) ← N(s, a) + 1
18:     N_{rave}(s_t, a_t) ← N_{rave}(s_t, a_t) + 1
19:     Q_{rave}(s_t, a_t) ← \frac{N_{rave}(s_t, a_t)\times Q_{rave}(s_t, a_t)+v}{N_{rave}(s_t, a_t)+1}
20:     ▷ where s_t ∈ VisitedPath, and a_t ∈ A(s_t), and for ∀t < t_2, a_t ≠ a_{t_2}
21:     return v;
A.3 Algorithms

Algorithm 12 Neural Network Based MCTS with Rollout Simulation and RAVE Value

1: function RoRa($s, f_\theta$)
2: Search($s$)
3: $\pi_s \leftarrow$ normalize($Q_{rave}(s, \cdot)$)
4: return $\pi_s$
5: function Search($s$)
6: Return game end result if $s$ is a terminal state
7: if $s$ is not in the Tree then
8: Add $s$ to the Tree,
9: Initialize $Q(s, \cdot)$, $N(s, \cdot)$, $Q_{rave}(s, \cdot)$ and $N_{rave}(s, \cdot)$ to 0.
10: Get $P(s, \cdot)$ and $v(s)$ by looking up $f_\theta(s)$
11: Get result $v(s)$ by performing random rollout until the game ends
12: return $v(s)$
13: else
14: Select an action $a$ with highest $UCT_{rave}$ value
15: $s' \leftarrow$ getNextState($s, a$)
16: $v \leftarrow$ Search($s'$)
17: $Q(s, a) \leftarrow \frac{N(s,a) \times Q(s,a) + v}{N(s,a) + 1}$
18: $N(s,a) \leftarrow N(s,a) + 1$
19: $N_{rave}(s_{t_1}, a_{t_2}) \leftarrow N_{rave}(s_{t_1}, a_{t_2}) + 1$
20: $Q_{rave}(s_{t_1}, a_{t_2}) \leftarrow \frac{N_{rave}(s_{t_1}, a_{t_2}) \times Q_{rave}(s_{t_1}, a_{t_2}) + v}{N_{rave}(s_{t_1}, a_{t_2}) + 1}$
21: ▷ where $s_{t_1} \in VisitedPath$, and $a_{t_2} \in A(s_{t_1})$, and for $\forall t < t_2, a_t \neq a_{t_2}$
22: return $v$;
Algorithm 13 Neural Network Based MCTS with Neural Network and Rollout Simulation Value

1: function WRO(s, fθ)
2:   Search(s)
3:   πs ← normalize(Q(s, ·))
4:   return πs
5: function Search(s)
6:   Return game end result if s is a terminal state
7:   if s is not in the Tree then
8:     Add s to the Tree, initialize Q(s, ·) and N(s, ·) to 0
9:     Get P(s, ·) and v(s)network by looking up fθ(s)
10:    Get result v(s)rollout by performing random rollout until the game ends
11:    v(s) = (1 − weight) * vnetwork + weight * vrollout
12:    return v(s)
13: else
14:   Select an action a with highest UCT value
15:   s′ ← getNextState(s, a)
16:   v ← Search(s′)
17:   Q(s, a) ← \frac{N(s,a)Q(s,a)+v}{N(s,a)+1}
18:   N(s, a) ← N(s, a) + 1
19: return v;
Algorithm 14 Neural Network Based MCTS with Neural Network, Rave and Rollout Simulation Value

1: function WRoRa(s, θ)
2: Search(s)
3: \( \pi_s \leftarrow \text{normalize}(Q(s, \cdot)) \)
4: return \( \pi_s \)
5: function Search(s)
6: Return game end result if s is a terminal state
7: if s is not in the Tree then
8: Add s to the Tree,
9: Initialize \( Q(s, \cdot) \), \( N(s, \cdot) \), \( Q_{\text{rave}}(s, \cdot) \) and \( N_{\text{rave}}(s, \cdot) \) to 0.
10: Get \( P(s, \cdot) \) and \( v(s)_{\text{network}} \) by looking up \( f_\theta(s) \)
11: Get result \( v(s)_{\text{rollout}} \) by performing random rollout until the game ends
12: random rollout path added to VisitedPath
13: \( v(s) = (1 - \text{weight}) \times v_{\text{network}} + \text{weight} \times v_{\text{rollout}} \)
14: return \( v(s) \)
15: else
16: Select an action \( a \) with highest \( UCT_{\text{rave}} \) value
17: \( s' \leftarrow \text{getNextState}(s, a) \)
18: \( v \leftarrow \text{Search}(s') \)
19: \( Q(s, a) \leftarrow \frac{N(s, a) \times Q(s, a) + v}{N(s, a) + 1} \)
20: \( N(s, a) \leftarrow N(s, a) + 1 \)
21: \( N_{\text{rave}}(s_t_1, a_t_2) \leftarrow N_{\text{rave}}(s_t_1, a_t_2) + 1 \)
22: \( Q_{\text{rave}}(s_t_1, a_t_2) \leftarrow \frac{N_{\text{rave}}(s_t_1, a_t_2) \times Q_{\text{rave}}(s_t_1, a_t_2) + v}{N_{\text{rave}}(s_t_1, a_t_2) + 1} \)
23: \( \triangleright \) where \( s_t_1 \in \text{VisitedPath} \), and \( a_t_2 \in A(s_t_1) \), and for \( \forall t < t_2, a_t \neq a_t_2 \)
24: return \( v; \)
Algorithm 15 Rolling Horizon Evolutionary Algorithm

1: function RHEA(s, time_limit)
2:    Set up population of n valid action sequences of length l: A_{n,l}
3:    for all A_i < n do Evaluate(A_i)
4: repeat
5:    new action sequence A_j = mutate one randomly chosen action sequence
6:    f(A_j) = Evaluate(A_j)
7:    add A_j to population
8:    remove A_i with worst f(A_i) from population
9: until time_cost ≥ time_limit
10: return first action of best sequence in population
11: function Evaluate(A_i)
12: repeat
13:    Play action sequence in A_i
14:    Get result success, game_steps by performing random rollout until
15:    the game ends
16: until repetitions ≥ 2
17: compute fitness f(A_i) from average success probability with sequence
18: length penalty (line 117)
19: return f(A_i)
A.4 Elo Computation

In this dissertation, like AlphaZero series papers did, a whole history Bayesian Elo computation \[82\] is also employed to present the relative competence of playing the game of different trained models instead of a win or loss rate. In this section, a full computation process will be described in detail based on the Bayesian Elo computation system (called Bayeselo) provided on github \[131\].

Bayeselo is a free software tool to compute Elo ratings. It receives a file containing game records written in PGN (Portable Game Notation) format \[132\], and produces a rating list \[131\]. Therefore, a full process can be simply described in Fig. A.1.

An example of part of a PGN file (arena_othello_final.pgn) generated based on win/loss results recorded during AlphaZero-like self-play arena competition is shown as Fig. A.2.

**Figure A.1:** a full Bayesian Elo Computation Process.
APPENDIX

......
[Event "arena_othello_final.pgn"]
[Iteration "926"]
[Site "liacs server, Leiden"]
[Round "6"]
[White "bestmodel_mcts_rave_run2"]
[Black "bestmodel_mcts_rave_run5"]
[Result "1-0"]
Here are detailed game moves for [Iteration "926, round6"]

[Event "arena_othello_final.pgn"]
[Iteration "926"]
[Site "liacs server, Leiden"]
[Round "7"]
[White "bestmodel_mcts_rave_run2"]
[Black "bestmodel_mcts_rave_run5"]
[Result "0-1"]
Here are detailed game moves for [Iteration "926, round7"]

[Event "arena_othello_final.pgn"]
[Iteration "926"]
[Site "liacs server, Leiden"]
[Round "8"]
[White "bestmodel_mcts_rave_run2"]
[Black "bestmodel_mcts_rave_run5"]
[Result "0-1"]
Here are detailed game moves for [Iteration "926, round8"]

[Event "arena_othello_final.pgn"]
[Iteration "926"]
[Site "liacs server, Leiden"]
[Round "9"]
......

**Figure A.2:** Small Part of PGN file arena_othello_final.pgn. The file contains much such format iterative arena competition information. Each pair of White and Black players played 20 rounds.

An example of elo rating list generated by operating Bayeselo system with PGN file (arena_othello_final.pgn) as input is shown as follows. See Fig. [A.3]. The figures of elo ratings in this dissertation are visualized based on such elo rating lists.
### Table A.3: An example of Generated Elo Rating List by Bayeselo

<table>
<thead>
<tr>
<th>Rank</th>
<th>Name</th>
<th>Elo</th>
<th>+</th>
<th>-</th>
<th>games</th>
<th>score</th>
<th>oppo.</th>
<th>draws</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>bestmodel_mcts_rave_rollout_run6</td>
<td>117</td>
<td>22</td>
<td>22</td>
<td>960</td>
<td>62%</td>
<td>-2</td>
<td>0%</td>
</tr>
<tr>
<td>2</td>
<td>bestmodel_weight_mcts_rave_rollout_run5</td>
<td>102</td>
<td>21</td>
<td>21</td>
<td>960</td>
<td>57%</td>
<td>-2</td>
<td>0%</td>
</tr>
<tr>
<td>3</td>
<td>bestmodel_weight_mcts_rave_rollout_run2</td>
<td>100</td>
<td>21</td>
<td>21</td>
<td>960</td>
<td>58%</td>
<td>-2</td>
<td>0%</td>
</tr>
<tr>
<td>4</td>
<td>bestmodel_weight_mcts_rollout_run5</td>
<td>97</td>
<td>22</td>
<td>21</td>
<td>960</td>
<td>58%</td>
<td>-2</td>
<td>0%</td>
</tr>
<tr>
<td>5</td>
<td>bestmodel_mcts_rave_run1</td>
<td>86</td>
<td>21</td>
<td>21</td>
<td>960</td>
<td>58%</td>
<td>-2</td>
<td>0%</td>
</tr>
<tr>
<td>6</td>
<td>bestmodel_weight_mcts_rave_rollout_run8</td>
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<tr>
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<td>21</td>
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<td>61%</td>
<td>-2</td>
<td>0%</td>
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<td>21</td>
<td>21</td>
<td>960</td>
<td>54%</td>
<td>-1</td>
<td>0%</td>
</tr>
<tr>
<td>9</td>
<td>bestmodel_mcts_rave_rollout_run2</td>
<td>62</td>
<td>21</td>
<td>21</td>
<td>960</td>
<td>57%</td>
<td>-1</td>
<td>0%</td>
</tr>
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<td>21</td>
<td>960</td>
<td>53%</td>
<td>-1</td>
<td>0%</td>
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<td>-1</td>
<td>0%</td>
</tr>
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<td>21</td>
<td>21</td>
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<td>-1</td>
<td>0%</td>
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<td>21</td>
<td>21</td>
<td>960</td>
<td>50%</td>
<td>-1</td>
<td>0%</td>
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<td>51%</td>
<td>-1</td>
<td>0%</td>
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<td>21</td>
<td>21</td>
<td>960</td>
<td>51%</td>
<td>-1</td>
<td>0%</td>
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<td>21</td>
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<tr>
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Bibliography


[76] Iwata, S., Kasai, T.: The Othello game on an \( n \times n \) board is \( \text{PSPACE} \)-complete. Theoretical Computer Science 123 (1994) 329–340


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128


