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## **Searching by learning: Exploring artificial general intelligence on small board games by deep reinforcement learning**

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### **Citation**

Wang, H. (2021, September 7). *Searching by learning: Exploring artificial general intelligence on small board games by deep reinforcement learning*. Retrieved from <https://hdl.handle.net/1887/3209232>

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**Author:** Wang, H.

**Title:** Searching by learning: Exploring artificial general intelligence on small board games by deep reinforcement learning

**Issue Date:** 2021-09-07

# Searching by Learning: Exploring Artificial General Intelligence on Small Board Games by Deep Reinforcement Learning

**Proefschrift**

ter verkrijging van  
de graad van doctor aan de Universiteit Leiden,  
op gezag van rector magnificus prof.dr.ir. H. Bijl,  
volgens besluit van het college voor promoties  
te verdedigen op dinsdag 7 september 2021  
klokke 16.15 uur

door

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geboren te Anhui, China

in 1992

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ISBN: 978-94-6419-253-7

Het onderzoek beschreven in dit proefschrift is uitgevoerd aan het Leiden Institute of Advanced Computer Science (LIACS, Universiteit Leiden).

This Research is financially supported by the China Scholarship Council (CSC), CSC No. 201706990015.

# Contents

<b>1</b>	<b>Introduction</b>	<b>1</b>
1.1	Background . . . . .	1
1.2	Research Questions . . . . .	5
1.3	Dissertation Outline . . . . .	7
<b>2</b>	<b>Classical Q-learning in GGP</b>	<b>11</b>
2.1	Introduction . . . . .	11
2.2	Related Work and Preliminaries . . . . .	12
2.2.1	GGP . . . . .	12
2.2.2	Reinforcement Learning . . . . .	13
2.2.3	Q-learning . . . . .	13
2.3	Design . . . . .	14
2.3.1	Classical Q-learning for Two-Player Games . . . . .	14
2.3.2	Dynamic $\epsilon$ Enhancement . . . . .	15
2.3.3	QM-learning Enhancement . . . . .	16
2.4	Experiments and Results . . . . .	17
2.4.1	Dynamic $\epsilon$ Enhancement . . . . .	17
2.4.2	QM-learning Enhancement . . . . .	20
2.5	Summary . . . . .	23
<b>3</b>	<b>Hyper-Parameters for AlphaZero-like Self-play</b>	<b>25</b>
3.1	Introduction . . . . .	25
3.2	Related work . . . . .	26
3.3	Test Game . . . . .	27
3.4	AlphaZero-like Self-play . . . . .	28
3.4.1	The Base Algorithm . . . . .	28
3.4.2	Loss Function . . . . .	30
3.4.3	Bayesian Elo System . . . . .	30

## CONTENTS

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3.4.4	Time Cost Function . . . . .	31
3.5	Experimental Setup . . . . .	32
3.5.1	Hyper-Parameter Sweep . . . . .	32
3.5.2	Hyper-Parameters Correlation Evaluation . . . . .	33
3.6	Experimental Results . . . . .	33
3.6.1	Hyper-Parameter Sweep Results . . . . .	34
3.6.2	Hyper-Parameter Correlation Evaluation Results . . . . .	38
3.7	Summary . . . . .	41
<b>4</b>	<b>Loss Functions of AlphaZero-like Self-play</b>	<b>43</b>
4.1	Introduction . . . . .	43
4.2	Related Work . . . . .	45
4.3	Test Games . . . . .	45
4.4	Loss Function . . . . .	47
4.4.1	Minimization Targets . . . . .	47
4.5	Experimental Setup . . . . .	47
4.5.1	Measurements . . . . .	48
4.6	Experiment Results . . . . .	48
4.6.1	Training Loss . . . . .	49
4.6.2	Training Elo Rating . . . . .	53
4.6.3	The Final Best Player Tournament Elo Rating . . . . .	55
4.7	Summary . . . . .	57
<b>5</b>	<b>Warm-Starting AlphaZero-like Self-Play</b>	<b>59</b>
5.1	Introduction . . . . .	59
5.2	Related Work . . . . .	61
5.3	AlphaZero-like Self-play Algorithms . . . . .	62
5.3.1	The Algorithm Framework . . . . .	62
5.3.2	MCTS . . . . .	64
5.3.3	MCTS Enhancements . . . . .	64
5.4	Initial Experiment: MCTS(RAVE) vs. RHEA . . . . .	66
5.5	Full Length Experiment . . . . .	67
5.5.1	Experiment Setup . . . . .	67
5.5.2	Results . . . . .	68
5.6	Summary . . . . .	69
<b>6</b>	<b>Adaptive Warm-Start AlphaZero-like Self-play</b>	<b>73</b>
6.1	Introduction . . . . .	73
6.2	Related Work . . . . .	75

6.3	Warm-Start AlphaZero Self-play . . . . .	76
6.3.1	The Algorithm Framework . . . . .	76
6.3.2	MCTS . . . . .	76
6.3.3	MCTS enhancements . . . . .	77
6.4	Adaptive Warm-Start Switch Method . . . . .	78
6.5	Experimental Setup . . . . .	79
6.6	Results . . . . .	80
6.6.1	MCTS vs MCTS Enhancements . . . . .	80
6.6.2	Fixed $I'$ Tuning . . . . .	81
6.6.3	Adaptive Warm-Start Switch . . . . .	83
6.7	Summary . . . . .	86
<b>7</b>	<b>Ranked Reward Reinforcement Learning</b>	<b>89</b>
7.1	Introduction . . . . .	89
7.2	Related Work . . . . .	90
7.3	Morpion Solitaire . . . . .	91
7.4	Ranked Reward Reinforcement Learning . . . . .	92
7.5	Experiment Setup . . . . .	94
7.6	Result and Analysis . . . . .	95
7.7	Summary . . . . .	97
<b>8</b>	<b>Conclusion</b>	<b>99</b>
8.1	Contributions . . . . .	100
8.2	Outlook . . . . .	102
<b>A</b>		<b>105</b>
A.1	Symbols . . . . .	105
A.2	Abbreviations . . . . .	106
A.3	Algorithms . . . . .	107
A.4	Elo Computation . . . . .	115
	<b>Bibliography</b>	<b>119</b>
	<b>English Summary</b>	<b>131</b>
	<b>Nederlandse Samenvatting</b>	<b>133</b>
	<b>Acknowledgements</b>	<b>135</b>
	<b>Curriculum Vitae</b>	<b>137</b>

## CONTENTS

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