CS6364 – Artificial Intelligence Project – Nine Men Morris Variant

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Problem Statement:

To obtain the next best move for the maximizer playing a variant of Nine Men Morris game with a given input board position and ply using algorithms such as Minimax and Alpha-Beta pruning.

Modules:

The following are the list of files delivered.

	File name	Purpose	
Support	MorrisVariant.py	Contains all support functions	
Part I	MiniMaxOpening.py	Program for opening using minimax	
	MiniMaxGame.py	Program for game using minimax	
Part II	ABOpening.py	Program for opening using alpha-beta	
	ABGame.py	Program for game using alpha-beta	
Part III	MiniMaxOpeningBlack.py	Program for opening using minimax for	
		black player as maximizer	
	MiniMaxGameBlack.py	Program for game using minimax for	
		black player as maximizer	
Part IV	MiniMaxOpeningImproved.py	Program for opening using minimax	
		with improved static estimation	
	MiniMaxGameImproved.py	Program for game using minimax with	
		improved static estimation	
	MINIMAX	Support file for minimax algorithm	
Support	ALPHABETA	Support file for alpha-beta pruning	
		algorithm	
Test cases	S1.txt, S2.txt, S3.txt, S4.txt, S5.txt	Input text file for 5 different test cases	
	Project-test-cases.xlsx	Results for the above test cases	
Readme	readme	Instructions to run the program	
Report	Report_kxs200001.pdf	Document showing examples and	
		results	
Extras for tournament	ABOpeningImproved.py	Program for opening using alpha-beta	
		with improved static estimation	
	ABGameImproved.py	Program for game using alpha-beta	
		with improved static estimation	

Test cases and results:

The following image shows different test cases applied to different parts of the project. This can also be found in Project-test-cases.xlsx for better view.

MiniMax (M) 16, AlphaBeta (A) 16, Improved (I) 16, dep MiniMax (M) 13, AlphaBeta (A) 13,	, 3997, xWWxxxWWWBBWWBxxWB	depth2 (D2)	depth3 (03) 3416, 1, WhooxxWhooxxvBxxxx 450, 1, WhooxxWhooxxvBxxxx 3416, 4, xxxxxvWhoxxVhxBxxxx Scenario (52): BWWxxxWhXBxxxX depth3 (03) 738, 4979, BWWxxxWWXBBWWBxxWx 320, 4979, BWWxxxXWWXBBWWBxxWx 320, 4979, BWXxxxXWWXBBWWBxxWx 320, 4979, BWXxxxXWWXBBWWBxxWx 320, 4979, BWXxxxXWXBBWWBxxWx 320, 4979, BWXxxxXWXBBWWBxxWx 320, 4979, BWXxxxXWXBBWWBxxWx 320, 4979, BWXxxxXWXBBWWBxxWXXXXXXXXXXXXXXXXXXXXXX	depth4 (D4) 3469, 4977, BWWxxxWWWBBWWBxxWx 353, 4977, BWWxxxWWWBBWWBxxWx	3693, 10000, BxWWxxWxWBBWWBWxWB
AlphaBeta (A) 16, Improved (I) 13, AlphaBeta (A) 13, Improved (I) 16, Improved (I) 16, Improved (I) 17, Improved (I) 18, Impr	, 1, WrocoxWoocoxBooox , 5, xxxxxxWWBxxxxXXXXXXXXXXXXXXXXXXXXXXXXXX	30, 0, WhoocoXWxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx	450, 1, WiccocxWiccocxdBxcox 3416, 4, xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx	1396, 0, WooocxWooocxBxxxx 45944, 0, xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx	21961, 1, WiocooxWocooxBxxxx 603920, 2, xxxxxxxWxWixxxxXxxxxxxxxxxxxxxxxxxxxxxx
Improved (f) 16, 16, 16, 16, 17, 1	, 5, xxxxxxWWBbxxxWB pth1 (D1) , 3997, xWWxxxWWWBBWWBxxWB , 3997, xWWxxxWWWBBWWBxxWB	240, 1, xxxxxWxxxxxxxxxxxxxxxxxxxxxxxxxxxxx	3416, 4, xxxxx/xxxxxxxxxxxxxxxxxxxxxxxxxxxxx	45944, 0, xxxxxxxWxxxxxWxBxxxxxX B depth4 (D4) 3469, 4977, BWWxxxWWWBBWWBxxWx 353, 4977, BWWxxxXWWWBBWWBxWWx	603920, 2, xxxxxxxXXXXXXXXXXXXXXXXXXXXXXXXXXXX
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MiniMax (M) 13, AlphaBeta (A) 13,	, 3997, xWWxxxWWWBBWWBxxWB , 3997, xWWxxxWWWBBWWBxxWB	depth2 (D2) 48, 3995, xWWxxxWWWBBWWBxxWB 23, 3995, xWWxxxWWWBBWWBxxWB	depth3 (D3) 738, 4979, BWWxxxWWWBBWWBxxWx 320, 4979, BWWxxxWWWBBWWBxxWx	depth4 (D4) 3469, 4977, BWWxxxWWWBBWWBxxWx 353, 4977, BWWxxxWWWBBWWBxxWx	53420, 10000, BxWWxxWxWBBWWBWxW 3693, 10000, BxWWxxWxWBBWWBWxWB
MiniMax (M) 13, AlphaBeta (A) 13,	, 3997, xWWxxxWWWBBWWBxxWB , 3997, xWWxxxWWWBBWWBxxWB	depth2 (D2) 48, 3995, xWWxxxWWWBBWWBxxWB 23, 3995, xWWxxxWWWBBWWBxxWB	depth3 (D3) 738, 4979, BWWxxxWWWBBWWBxxWx 320, 4979, BWWxxxWWWBBWWBxxWx	depth4 (D4) 3469, 4977, BWWxxxWWWBBWWBxxWx 353, 4977, BWWxxxWWWBBWWBxxWx	53420, 10000, BxWWxxWxWBBWWBWxW 3693, 10000, BxWWxxWxWBBWWBWxWB
AlphaBeta (A) 13,	, 3997, xWWxxxWWWBBWWBxxWB	23, 3995, xWWxxxWWWBBWWBxxWB	320, 4979, BWWxxxWWWBBWWBxxWx	353, 4977, BWWxxxWWWBBWWBxxWx	
AlphaBeta (A) 13,	, 3997, xWWxxxWWWBBWWBxxWB	23, 3995, xWWxxxWWWBBWWBxxWB	320, 4979, BWWxxxWWWBBWWBxxWx	353, 4977, BWWxxxWWWBBWWBxxWx	3693, 10000, BxWWxxWxWBBWWBWxWB
		48, 4002, BWWxxxWWWBBWWBxxWx	738, 4990, BWWxxxWWWBBWWBxxWx	0.400 4005 DIAMA - MARKED DIAMAD - MI	
				3469, 4985, BWWxxxWWWBBWWBxxWx	53420, 10000, BxWWxxWxWBBWWBWxWB
		Opening Sc	enario (S3): xWxxxWxxBxxxxxBxxx		
der	pth1 (D1)	depth2 (D2)	depth3 (D3)	depth4 (D4)	depth5 (D5)
	. 2. xWxWxWxxxxxxxxxxxxxxxxxxxxxxxxxxxxx	197, 1, xWxWxWxxxxxxxxxxxxxxxxxx	2752, 2, xWxWxWxxxxxxxxBxxx	33924, 1, xWxWxWxxxxxxxxxxxx	431734, 2, xWxWxWxxxxxxxxBxxx
	. 2. xWxWxWxxxxxxxxxxxxxxxxxxxxxxxxxxxxx	40. 1. xWxWxWxxxxxxxxBxxx	260, 2, xWxWxWxxxxxxxxBxxx	1036, 1, xWxWxWxxxxxxxxxxxxxxxxxxxxxxxxxxxxx	4897, 2, xWxWxWxxxxxxxxBxxx
MiniMaxBlack (ends in B) 14.		208, 0, xWxBxWxxBxxxxxBxxx	2715, 1, xWxBxWxxBxxxxxBxxx	36360, 0 xWxBxWxxBxxxxxBxxx	444990, 1, xWxBxWxxBxxxxxBxxx
	, 6, xWxWxWxxxxxxxxxxxxxxxxxxxxxxxxxxxxx	197, 3, xWxWxWxxxxxxxxBxxx	2752, 5, xWxWxWxxxxxxxBxxx	33924, 1, xWxWxWxxxxxxxxxxxxxxxxxxxxxxxxxxxxx	431734, 3, xWxWxWxxxxxxxxBxxx
		Midgame/Endgam	ne Scenario (S4): xBBxxxWxxWxxBxBxxW		A Desired State of the Control of th
der	pth1 (D1)	depth2 (D2)	depth3 (D3)	depth4 (D4)	depth5 (D5)
MiniMax (M) 33,	, -1009, WBBxxxxxxWxxBxBxxW	352, -1012, WBBxxxxxxWxxBxBxxW	12150, -36, xBBxxxxxxWxWBxBxxW	143704, -36, xBBxxxxxxWxWBxBxxW	4922535, -36, WBBxxxxxxWxxBxBxxW
AlphaBeta (A) 33,	, -1009, WBBxxxxxxxWxxBxBxxW	192, -1012, WBBxxxxxxWxxBxBxxW	2130, -36, xBBxxxxxxWxWBxBxxW	3894, -36, xBBxxxxxxWxWBxBxxW	48829, -36, WBBxxxxxxWxxBxBxxW
MiniMaxBlack (ends in B) 11,	, 967, BxBxxxWxxWxxBxBxxW	363, 964, xBBxxxWxxWxBBxxxxW	3801, 964, xxBBxxWxxWxxBxBxxW	128112, -36, BxBxxxWxxWxxBxBxxW	1485986, -36, BxBxxxWxxWxxBxBxxW
Improved (I) 33,	, -1007, xBBxxxxxxWxWBxBxxW	352, -1010, xBBxxxWxxxxWBxBxxW	12150, -33, xBBxxxxxxWxWBxBxxW	143704, -35, xBBxxxxxxWxWBxBxxW	4922535, -36, WBBxxxxxxWxxBxBxxW
		Midgame/Endgan	ne Scenario (S5): WWxxWxxxBxBxxBxxxx		
der	pth1 (D1)	depth2 (D2)	depth3 (D3)	depth4 (D4)	depth5 (D5)
MiniMax (M) 38,	, 10000, WxWxWxxxxxBxxBxxxx	1327, 10000, WxWxWxxxxxBxxBxxxx	45441, 10000, WxWxWxxxxxBxxBxxxx	1627830, 10000, WxWxWxxxxxxBxxxBxxxx	
AlphaBeta (A) 38,	, 10000, WxWxWxxxxxxBxxxx	200, 10000, WxWxWxxxxxBxxBxxxx	2771, 10000, WxWxWxxxxxBxxBxxxxx	23317, 10000, WxWxWxxxxxBxxBxxxxx	207314, 10000, WxWxWxxxxxBxxBxxxx
Improved (I) 38,	, 10000, WxWxWxxxxxBxxxBxxxx	1327, 10000, WxWxWxxxxxBxxBxxxx	45441, 10000, WxWxWxxxxxBxxBxxxx	1627830, 10000, WxWxWxxxxxBxxxBxxxx	
		ons visited by static estimation, static es th peers from the discussion board in ele			

Figure 1 Test Cases and Results

Part I MiniMaxOpening output:

From the Figure 1, Scenarios 1 and 3 are tested for opening game.

Example1: Scenario 1 for depth 2

INPUT:

Board Position: xxxxxxWxxxxxxBxxxx

OUTPUT:

Board Position: WxxxxxWxxxxxBxxxx

Positions evaluated by static estimation: 240

MINIMAX estimate: 0

Example2: Scenario 3 for depth 4

INPUT:

Board Position: xWxxxWxxBxxxxxBxxx

OUTPUT:

Board Position: xWxWxWxxxxxxxxBxxx

Positions evaluated by static estimation: 33924

MINIMAX estimate: 1

Part I MiniMaxGame output:

From the Figure 1, Scenarios 2, 4, and 5 are tested for midgame/endgame.

Example1: Scenario 2 for depth 2

INPUT:

Board Position: BWWxxxWxWBBWWBWxWB

OUTPUT:

Board Position: xWWxxxWWWBBWWBxxWB Positions evaluated by static estimation: 48

MINIMAX estimate: 3995

Example2: Scenario 4 for depth 3

INPUT:

Board Position: xBBxxxWxxWxxBxBxxW

OUTPUT:

Board Position: xBBxxxxxxWxWBxBxxW

Positions evaluated by static estimation: 12150

MINIMAX estimate: -36

Part II ABOpening output:

From the Figure 1, Scenarios 1 and 3 are tested for opening game. Same examples are used from the MiniMaxOpening, we can see that the ouput position and static estimate values are same, but number of positions evaluated is less.

Example1: Scenario 1 for depth 2

INPUT:

Board Position: xxxxxxWxxxxxxBxxxx

OUTPUT:

Board Position: WxxxxxWxxxxxxBxxxx Positions evaluated by static estimation: 30

AlphaBeta estimate: 0

Example2: Scenario 3 for depth 4

INPUT:

Board Position: xWxxxWxxBxxxxxBxxx

OUTPUT:

Board Position: xWxWxWxxxxxxxxBxxx

Positions evaluated by static estimation: 1036

AlphaBeta estimate: 1

Part II ABGame output:

From the Figure 1, Scenarios 2, 4, and 5 are tested for midgame/endgame.

Example1: Scenario 2 for depth 2

INPUT:

Board Position: BWWxxxWxWBBWWBWxWB

OUTPUT:

Board Position: xWWxxxWWWBBWWBxxWB Positions evaluated by static estimation: 23

AlphaBeta estimate: 3995

Example2: Scenario 4 for depth 3

INPUT:

Board Position: xBBxxxWxxWxxBxBxxW

OUTPUT:

Board Position: xBBxxxxxxWxWBxBxxW

Positions evaluated by static estimation: 2130

AlphaBeta estimate: -36

Alpha-Beta vs Minimax:

From the Figure 1, when we compare the results of MiniMax (M) and AlphaBeta (A), the number of positions evaluated is same at depth 1 and it significantly reduces for AlphaBeta as depth increases.

In scenario (S1), for depth5 (D5) MiniMax has evaluated 603920 nodes whereas AlphaBeta evaluated only 21961, we can see 96% reduction in the number, which is a huge savings in time. The same holds for other scenarios at depth5 (D5). In fact, the last scenario (S5) with a lot of empty spots in board was able to produce results at depth5 (D5) only using AlphaBeta pruning, as MiniMax was taking large amount of time.

Part III MiniMaxOpeningBlack output:

From the Figure 1, Scenarios 1 and 3 are tested for opening game. Here, the black coin is the maximizer. The board is inverted (whites become black and blacks become white) before and after executing the functions defined for white as maximizer.

Example1: Scenario 1 for depth 2

INPUT:

Board Position: xxxxxxWxxxxxxBxxxx

OUTPUT:

Board Position: BxxxxxWxxxxxxBxxxx

Positions evaluated by static estimation: 240

MINIMAX estimate: 0

Example2: Scenario 3 for depth 4

INPUT:

Board Position: xWxxxWxxBxxxxxBxxx

OUTPUT:

Board Position: xWxBxWxxBxxxxBxxx

Positions evaluated by static estimation: 36360

MINIMAX estimate: 0

Part III MiniMaxGameBlack output:

From the Figure 1, Scenarios 2, 4, and 5 are tested for midgame/endgame.

Example1: Scenario 2 for depth 2

INPUT:

Board Position: BWWxxxWxWBBWWBWxWB

OUTPUT:

Board Position: xWWxxxWxWBBWWBWBWB Positions evaluated by static estimation: 26

MINIMAX estimate: -4014

Example2: Scenario 4 for depth 3

INPUT:

Board Position: xBBxxxWxxWxxBxBxxW

OUTPUT:

Board Position: xxBBxxWxxWxxBxBxxW

Positions evaluated by static estimation: 3801

MINIMAX estimate: 964

Part IV: MiniMaxOpeningImproved and MiniMaxGameImproved:

The original static estimate function doesn't given importance to few special cases which might improve the game. The current function would always try to give the left most node as the best node. The function is improved by the following two ways.

- The original static estimation function doesn't given importance to special spots in the board such as e4, f5, and g6 where the number of possible mills is 3 for each. Therefore, the number of possible mills (if the corresponding spots forming mill are either empty or occupied by the maximizer) are calculated and added into the static estimate value giving such nodes higher weightage than the others. This is very important in opening move.
- 2. The tree that is being generated through these algorithms for the Morris game is not a complete tree, that is, the leaf nodes (winning position, either the number of minimizer coins are less than or equal to 2 or the minimizer is out of moves) don't always fall on the same depth. The leaf nodes can be located at any depths and therefore should carry different weights. Closer the leaf node to the root higher should be its weight as the maximizer can win soon if it reaches the closest leaf node. Therefore, the depth at which the leaf node is found is being subtracted from the static estimate value. Higher the depth higher is the penalty and lower will be the static estimate value.

Example 1:

In Figure 1 Scenario 1 (S1) depth 1 (D1), which is an opening position the original static estimation is estimating the same value (that is 1) for all the positions in next move and places the White coin in the left mode empty spot (a0) which is intuitively the worst possible opening spot. Whereas the improved static function places the White coin at spot (e4) which is a good opening move as the player can try to form more mills in upcoming moves.

MiniMaxOpening.py Output for Scenario 1 and depth 1:

INPUT:

Board Position: xxxxxxWxxxxxxBxxxx

OUTPUT:

Board Position: WxxxxxWxxxxxBxxxx Positions evaluated by static estimation: 16

MINIMAX estimate: 1

MiniMaxOpeningImproved.py Output for Scenario 1 and depth 1:

INPUT:

Board Position: xxxxxxWxxxxxxBxxxx

OUTPUT:

Board Position: xxxxxxWxxxxWxBxxxx

Positions evaluated by static estimation: 16

MINIMAX estimate: 5

Example 2:

In Figure 1 Scenario 2 (S2) depth 1 (D1), which is a midgame/endgame position, the output result for static estimate value and board position are different for original and improved versions, but the number of positions evaluated by static estimation is same.

MiniMaxOpening Output for Scenario 2 and depth 1:

INPUT:

Board Position: BWWxxxWxWBBWWBWxWB

OUTPUT:

Board Position: xWWxxxWWWBBWWBxxWB Positions evaluated by static estimation: 13

MINIMAX estimate: 3997

MiniMaxOpeningImproved Output for Scenario 2 and depth 1:

INPUT:

Board Position: BWWxxxWxWBBWWBWxWB

OUTPUT:

Board Position: BWWxxxWWWBBWWBxxWx Positions evaluated by static estimation: 13

MINIMAX estimate: 4007