

INFO-F-311: Artificial Intelligence - Project 2:
Recherche adversariale

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1 Introduction

This report outlines the application of adversarial search techniques in graph search problems. For references, please refer to the project instructions and the project 1.

2 Better evaluation function

2.1 `get_available_actions_ordered`

Algorithm	Time Complexity
Minimax	$O(b^m)$
Alpha-Beta	$O(b^{m/2})$ to $O(b^m)$
Alpha-Beta with Perfect Ordering	$O(bm/2)$

In the `BetterValueFunction` class, this method orders the available actions based on certain conditions:

- Moves the action `STAY` to the end of the list.
- If not all gems are collected, it prioritizes actions that lead to a gem.
- If the agent's path intersects with dangerous lasers, it de-prioritizes such actions.

2.2 Method: `transition`

In this method, the value of a state is changed based on multiple factors:

- The distance of agents to gems and exit points.
- Whether all gems are collected or not.

3 Results

3.1 Fewer Nodes with Better Evaluation

3.1.1 First Map

.	G	S1
L0E	S0	.
X	@	X

. G S1
 L0E S0 .
 X @ X

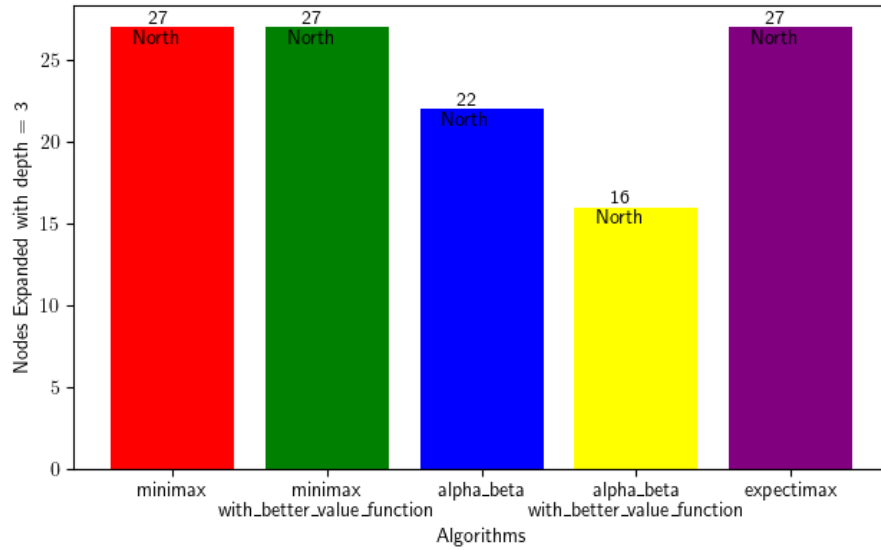


Figure 1: Map 1

Here we can see that, compared to `alpha_beta`, the number of nodes is reduced by 6. Additionally, compared to `minimax`, the number of nodes is reduced by 11. This is what we expected, because we have a better evaluation function.

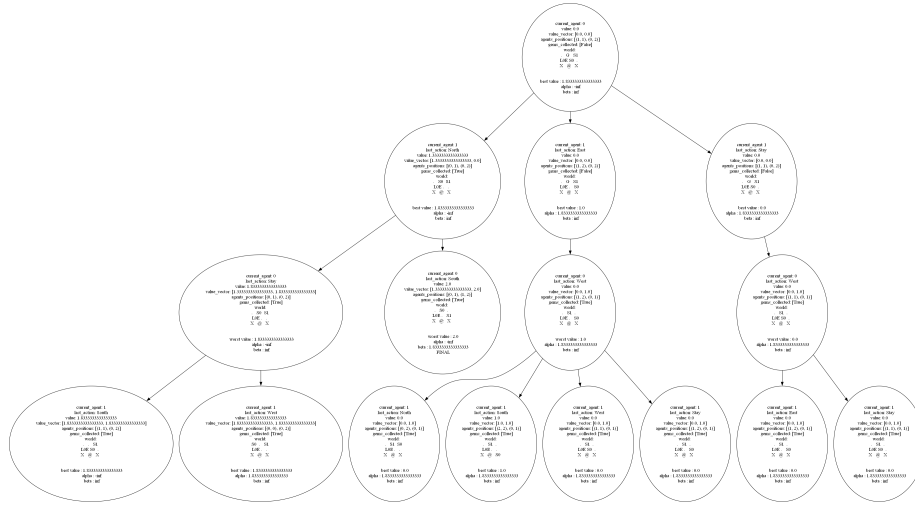


Figure 2: First map's Better Evaluation Markov Decision Process Tree

3.1.2 Second Map

.	X	G
@	@	S0
.	.	.
.	.	.
.	X	S1

Again, we can see that, compared to **alpha_beta**, the number of nodes is reduced and compared to **minimax**, the number of nodes is reduced by factor 2.

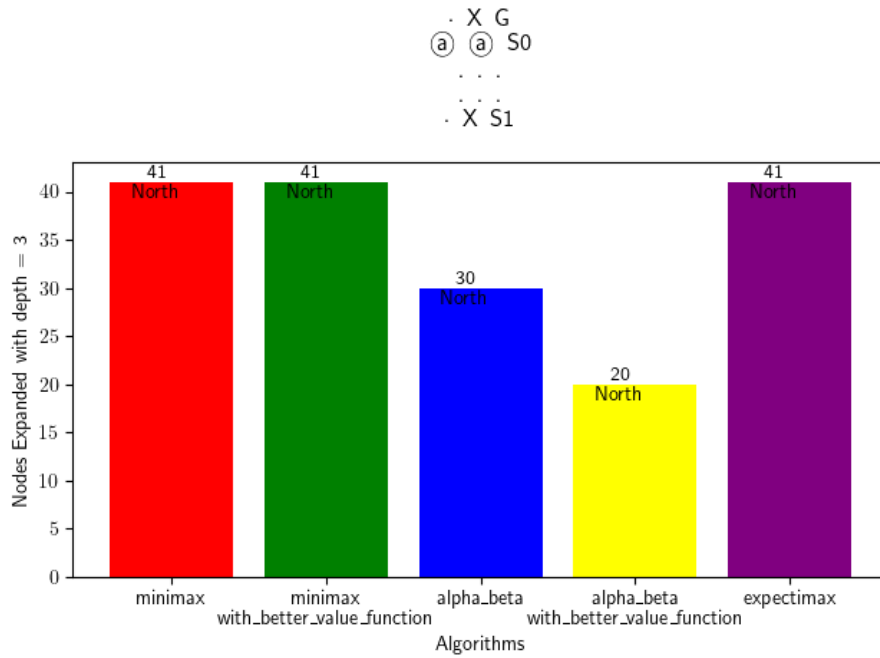


Figure 3: Map 2

3.1.3 Third Map

G	G
X	.	G	S2	S0	G
.	.	G	X	S1	X
.	.	G	.	.	.

Here again, with a slightly bigger map and with a much bigger difference with factors of 2 and 7. It is to note that **expectimax**, without any heuristic, has the lowest number of nodes, with correct action.

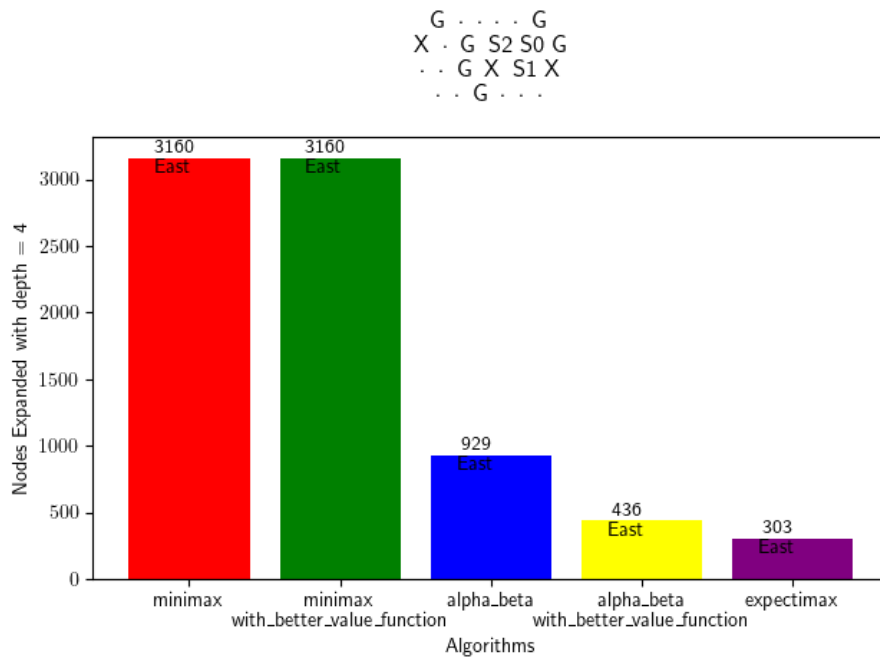


Figure 4: Map 3

3.2 Fourth Map

S0	S2	X
	G	
@		G
	S1	
	X	X

This case shows that better evaluation function does not always mean fewer nodes.

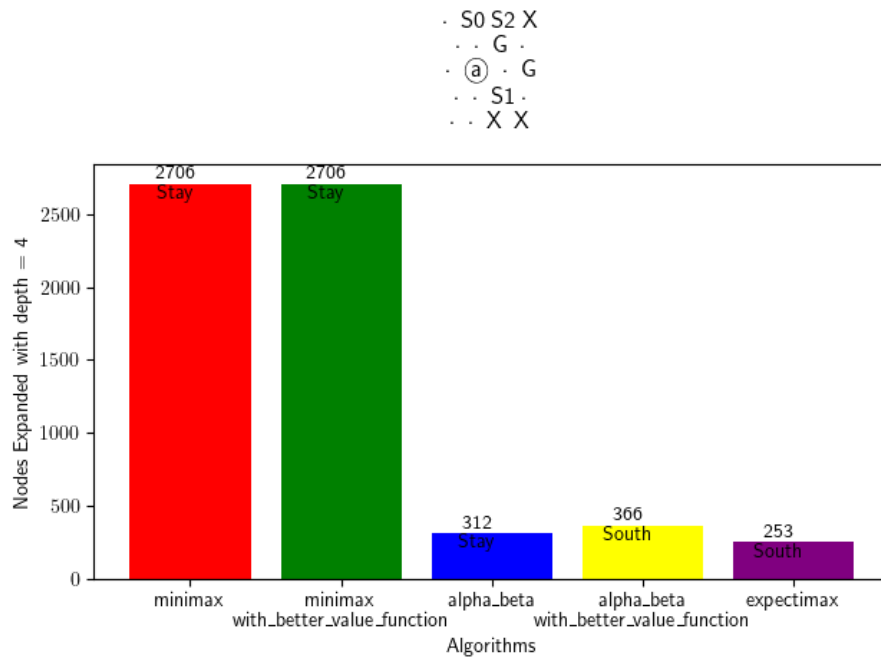


Figure 5: Map 4

3.3 Fifth Map

.	.	L0S	.	.	S2
X	L1S	.	S1	.	.
X	.	.	@	S0	X

Again, better evaluation function is not the best.

But what makes it very interesting is that **expectimax** has, again, the lowest number of nodes, but also, is the only one to output the optimal action.

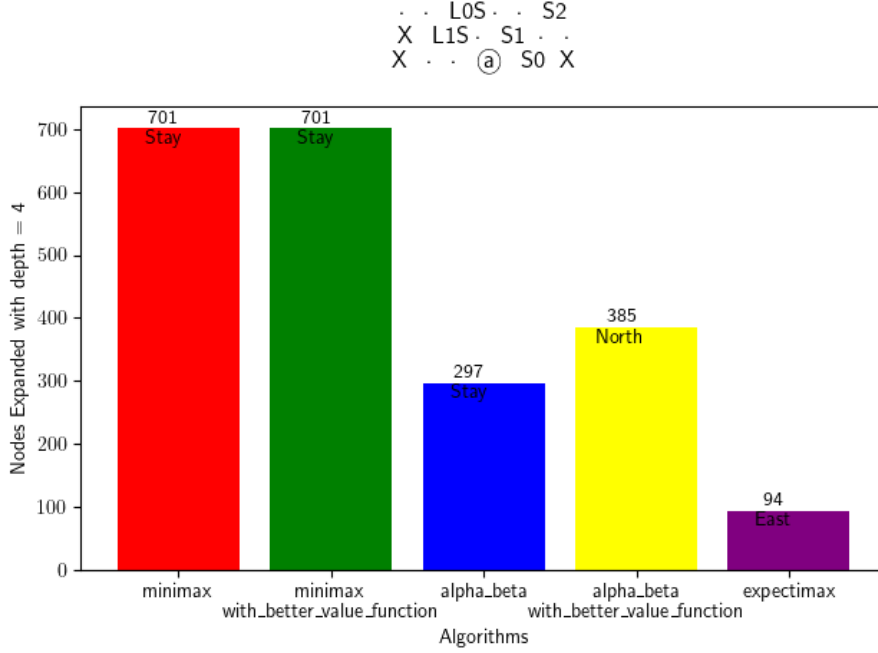


Figure 6: Map 5

4 Discussion

4.1 Limitations of High-Level Heuristics

While the use of high-level heuristics in action ordering generally improves performance, it is not always fine enough for every case. As a result, in some cases, the **BetterValueFunction** may not actually result in fewer nodes being expanded compared to basic evaluation functions.

4.2 Use of Expectimax

Interestingly, the **Expectimax** algorithm often resulted in fewer nodes being expanded while also selecting the optimal action. This suggests that stochastic models offer benefits in environments with high levels of uncertainty.

4.3 Future Work

Recent advancements in adversarial search algorithms have started to incorporate machine learning techniques to dynamically adapt the heuristics used for action selection. This represents a potential avenue for further improving the performance of our algorithms.

5 ChatGPT Usage

The project was made with ChatGPT.