THE UNIVERSITY OF QUEENSLAND

AUSTRALIA

COM7702 - Artificial Intelligence

ASSIGNMENT 2 REPORT

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1 . MDP Design Problem

In this assignment, a program is designed to provide the estimated best instructions in a sequence for a car to travel through terrains of varying types and reach the goal within given steps. Since the action "continue moving" may result in a range of possible outcomes, stochasticity is introduced into the problem. The MDP problem can be defined as follows:

1.1. State Space

A state for this MDP problem captures information available to the agent at current step. It incorporates state of the car (car type, tyre model, fuel level, slip, breakdown, tyre pressure), the driver and the position of current terrain in the whole map. Using parameters denoted below:

- **pos** - The current position in the whole map, range from 1 to N
- **isSlip** - Boolean value indicating whether the car is currently in slip condition
- **isBrkDn** - Boolean value indicating whether the car is in breakdown condition or not
- **carType** - The current car type
- **fuelLvl** - The current fuel level, range from 0 to 50
- **tyrePrs** - The current tyre pressure, with 3 options being 50%, 75%, 100%
- **driver** - Current driver of the car
- **tyreMdl** - Current tyre model, options include all-terrain, mud, low-profile, etc...

The state can be denoted as:

$$S_i = \{pos_i, isSlip_i, isBrkDn_i, carType_i, fuelLvl_i, tyrePrs_i, driver_i, tyreMdl_i\}$$

The count of possible states for each level is calculated as per table below:

	Pos	Slip	BrkDn	Car	Fuel	Press.	Driver	Tyre	Total States
Level 1	10	2	2	2	1	1	2	4	640
Level 2	10	2	2	3	50	3	2	4	144.000
Level 3	30	2	2	5	50	3	5	4	1.800.000
Level 4	30	2	2	5	50	3	5	4	1.800.000
Level 5	30	2	2	5	50	3	5	4	1.800.000

Table 1.1.1 state space for varying levels

1.2. Action Space

- Action includes varying numbers of options based on input level, and each action will incur a cost in time measured by steps provided by input file.
- Some actions are only allowed in certain conditions. Eg. The car can perform A1 (continue moving) only if the fuel level is sufficient to support such an action.
- Apart from A1, all other actions are deterministic, that is, the results of such actions are fully predictable and non-stochastic.
- Some action items can be further split into smaller categories. Eg. Change tyre pressure can be split into: change tyre pressure to 50%, 75% and 100% level.

Possible actions are listed as follows with respective conditions

Action No.	Action Description	Sub Types	Action Result	Restriction
A1	Continue moving	No	The car may move forward, backward or remain at same position because of slip or breakdown condition.	cannot perform if fuel is insufficient or car is under slip/breakdown condition
A2	Change car	Yes (Toyota, Mazda, etc.)	Switch to another car from options	
A3	Change driver	Yes (eg. Change to Max / Tim)	Switch to another driver from options	
A4	Change tyres	Yes (all-terrain, low-profile, etc.)	Switch to another tyre model from options	
A5	Add fuel	Yes (amount of Fuel to add)	Increased fuel level	cannot perform when fuel is full
A6	Change tyre pressure	Yes (50%; 75% or 100%)	Change to another fuel pressure from options	
A7	A2 & A3	Yes	Change car type and driver from options	
A8	A4 & A5 & A6	Yes	Change tyre, add fuel and change tyre pressure from options	cannot perform when fuel is full

Table 1.2.1 Action summary

The count of possible actions available for each level is calculated as

*A7=A2*A3; A8=A4*A5*A6*

	A1	A2	A3	A4	A5	A6	A7	A8	Total Actions
Level 1	1	2	2	4	0	0	0	0	9
Level 2	1	3	2	4	5*	3	0	0	18
Level 3	1	5	5	4	5*	3	0	0	23
Level 4	1	5	5	4	5*	3	25	0	48
Level 5	1	5	5	4	5*	3	25	60	108

** Add Fuel is discretized into 10 units per step, reducing add fuel to 5 possible actions*

1.3. Transition Function

The transition is deterministic for all actions excluding A1 (continue moving). Assume S_i={pos_i, $isSlip_i$, $isBrkDn_i$, $carType_i$, $fuelLvl_i$, $tyrePrs_i$, $driver_i$, $tyreMdl_i$}, the transition matrix for action A2 – A8 is:

Action	Action Name	Current State	Next State
A2	Change Car	{,,,$carType_i$,$fuelLvl_i$,,,,}	{,,,$carType_j$,$fuelLvl_{max}$,,,,}
A3	Change Driver	{,,,,,,$driver_i$,}	{,,,,,,$driver_j$,}
A4	Change Tyre	{,,,,,,,$tyreMdl_i$}	{,,,,,,,$tyreMdl_j$}
A5	Add Fuel	{,,,,$fuelLvl_i$,,,,}	{,,,,$fuelLvl_i$,,,,}
A6	Change Pressure	{,,,,,$tyrePrs_i$,,}	{,,,,,$tyrePrs_j$,,}
A7	A2 & A3	{,,,$carType_i$,$fuelLvl_i$,,$driver_i$,}	{,,,$carType_j$,$fuelLvl_{Max}$,,$driver_j$,}
A8	A4 & A5 & A6	{,,,,$fuelLvl_i$,$tyrePrs_i$,,$tyreDdl_i$}	{,,,,$fuelLvl_j$,$tyrePrs_j$,,$tyreDdl_j$}

Omitted parameters are unchanged parameters.

The transition is non-deterministic for action A1 (continue moving), denoted as :

$$T(s, A_1, s') = P[S_{i+1} = S' \mid S_t = s, A_t = A_1]$$

That is, the next state of the action “continue moving” can be described as a probability distribution over 12 possible outcomes for a given state, with each probability calculated based on input slip factor of car, driver, tyre, pressure and terrain.

1.4. Reward Function

The reward function is based on how far the agent can move forward from the previous condition (eg: current car, current driver, and current fuel level). When the agent reaches the goal, it will be rewarded with extra bonus that is equivalent to being able to move 5 cells ahead. If the Agent cannot reach the goal in the given step count during simulation, it will not receive any bonus. The reward function is calculated as :

$$Reward\ Point = (Current\ Position - Start\ Position) + Goal\ Bonus$$

The default policy of rollout simulation implemented is to continue moving until out of fuel, so as to provide a general guidance on action and reduce action space.

2. BotMate Agent at Conceptual Level

2.1. Data Structure

Every action is stored in a **TreeNode** data structure, which is a generic class containing properties including action, parent node, children nodes, value and visitCount. The states will not be stored in our data structure, instead, it will be created on-the-fly by the simulator with actions stored in parent nodes. The states consist of position, tyre pressure, driver, tyre model, fuel, slip or breakdown information.

```
public class TreeNode {

    private Action action;
    private TreeNode parent;
    private List<TreeNode> children;
    private double value;
    private int visitCount;
```

- **value** - Value of a node which is updated when back-propagation method is called
- **visitCount** - Records the times the current node is visited
- **parent** - A reference to the parent node from the current node
- **children** - A collection of all the children of the current node

2.2. MCTS Implementation

Game-changing problem is solved by using an online method using MCTS because of the enormous state space and action space from input of higher levels. As mentioned previously, the count of states is around 1.800.000 from level 3 to 5, requiring huge computational resources using the offline method. Four core components of our MCTS implementation is described as per below:

2.2.1. Selection

Selection is a function to choose the best action based on the upper confidence bound (UCB) value. The node with maximum UCB value will be selected.

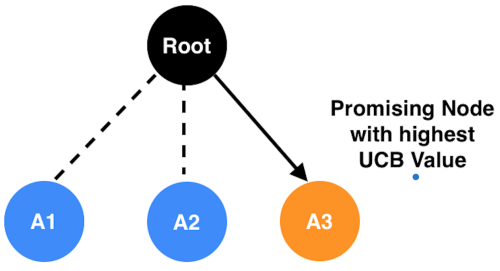


Figure 2.2.1.1: Select the promising node based on UCB value

Upper Confidence Bound (UCB value) for every node is calculated with this formula, then the agent selects the node with the highest UCB Value.

$$UCBValue = childValue + CONSTANT + \sqrt{\frac{\log(parentVisitCount)}{childVisitCount}}$$

The UCB value will be stored in every node after back-propagation from a leaf node.

2.2.2. Expansion

Expansion is a function to add children nodes to a particular node based on available actions at current state.

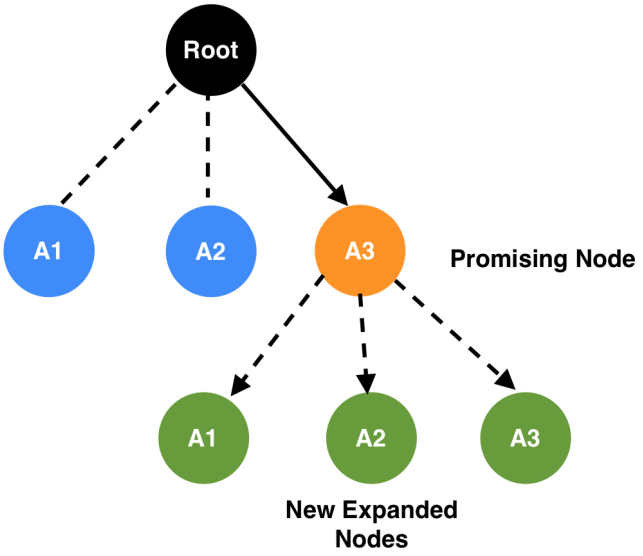


Figure 2.2.2.1 : Expansion to create new children nodes

2.2.3. Simulation

Simulation is a function to simulate a newly added node to estimate its value. In this implementation, the default policy is to always move forward until it reaches the goal, or run out of fuel, or reaching max step. The value of current node is measured by the distance covered by the car within simulation steps until out of fuel.

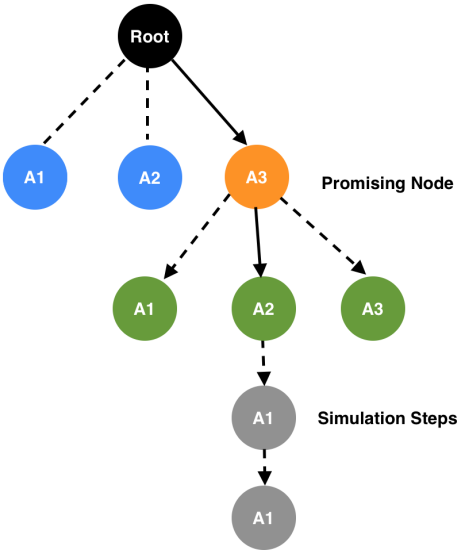


Figure 2.2.3.1 : Simulation from the current node

2.2.4. Back-propagation

Back-propagation is a function to update the value of the predecessor nodes from children nodes. The value of a parent node is updated whenever new iteration finishes upon its children. Formula for such a relation is represented as :

$$Parrent\ Value = \frac{Parent\ Value \times Parent\ Visit + Child\ Value}{Parent\ Visit + 1}$$

The Back-propagation process is illustrated as follow

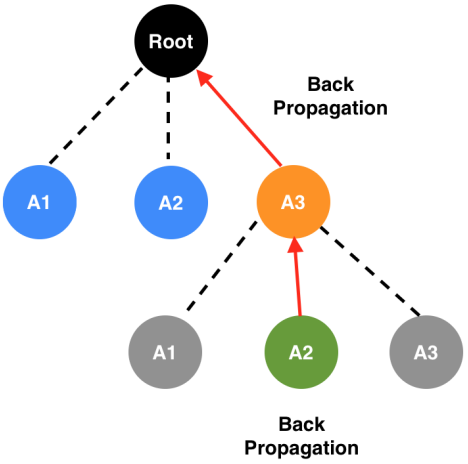


Figure 2.2.4.1 : Backpropagation is a function to update every value of nodes

Back-propagation function is called after a rollout simulation. This algorithm iterates through the ascendant nodes of the leaf node to update their values.

2.3. Pseudocode

2.3.1. Selection phase

```
Algorithm selectPromisingNode(currentNode)
selectedNode <- first child of current node
bestValue <- selectedNode.getValue()
a <- currentNode.visitCount
for each childNode in currentNode.getChildren()
    if childNode.visitCount == 0 return childNode
    b <- childNode.visitCount
    UCBValue = childNode.getValue() + CONSTANT * sqrt(log(a/b))
    if UCBValue >= bestValue
        selectedNode <- childNode
        bestValue <- UCBValue
return selectedNode
```

2.3.2. Expansion phase

```
Algorithm expandNode(leafNode)
currentState <- simulator.getCurrentState()
for each action in generateActions(currentState)
    newNode <- new treeNode(action)
    newNode.setParent(leafNode)
    leafNode.addChild(newNode)
```

2.3.3. Simulation phase

```
Algorithm rollOut(LeafNode, remainingStep)
currentState <- simulator.getCurrentState()
car <- getCurrentCar(currentState)
while simulator.getStep() <= remainingStep
    terrain <- getCurrentTerrain(currentState)
    if currentState.getFuel() < getFuelUsage(car, terrain)
        break
    if isGoalState(currentState)
        return ps.getN() - startPos + CAR_MAX_MOVE;
    currentState <- sim.step(new Action(ActionType.MOVE))
return currentState.getPos() - startPos;
```

2.3.4. Back-propagation phase

```
Algorithm backPropagation(leafNode)
currentNode <- leafNode
while currentNode != NULL
    currentNode.visitCount <- currentNode.visitCount + 1;
    q <- currentNode.getValue
    parentNode = currentNode.getParent
    if parentNode != NULL
        c <- parentNode.getVisitCount()
        parentNode.Value <- (parentNode.getValue * c + q) / (c + 1)
        currentNode = parentNode;
```

3. Time and Memory Complexity Analysis

3.1. Time Complexity

3.1.1. Time Complexity for One Iteration Calculation

Let **a** be the number of Possible Actions in action space, let **t** be the maximum allowed steps and let **d** be the depth of the tree. We can calculate the computational step for one iteration from the following components:

- Select Node: takes **a * d** primitive operations (for each level, select one node and iterate over all its children to select the promising node)
- Expand Node: takes **a** primitive operation (create new node for every action)
- Simulation: takes **t** primitive operations, one for each default action until it reach the maximum number of step (worst case)
- Back-propagation: takes **d** primitive operations (iterate over one ascendant at once)

So the time complexity for one iteration would be

$$Number\ of\ Calculation = a \times d + a + t + d$$

Since the **Depth of the MCTS Tree** is **Expected** to be equal to the **Max Number of Steps,** one iteration has the time complexity of **O(Number of Action * Max Number of Steps)** or **O(a*t)**

3.1.2. Experiments for Time Complexity for One MCTS iteration

To understand how problem size affects the time consumption for one MCTS iteration. Repetitive experiments are conducted for input files of all levels. To estimate the time spent over one iteration, our approach is to count total iteration of a single execution and the total time spent over the iterations. Then

$$Time\ Per\ Iteration = \frac{Total\ Run\ Time}{Total\ Iteration\ Count}$$

For each difficulty level, the program is executed 10 times to obtain average values. The sample data is taken across inputs from all levels. For instance, our level 5 experimental record is:

Level 5 problem with 5 second planning time (on a 16G RAM computer)

Execution (lv5)	Cell Count	Iteration Count	total time (sec)	time per iteration (nano sec)	total steps	max step	peak memory usage	reached goal
1st	30	59,491,507	195.63s	3288ns	48	80	2948	yes
2nd	30	68,330,421	225.41s	3298ns	50	80	2902	yes
3rd	30	56,525,746	175.66s	3107ns	41	80	2838	yes
4th	30	54,932,175	175.98s	3203ns	37	80	2965	yes
5th	30	71,138,430	230.85s	3245ns	49	80	3071	yes
6th	30	72,097,015	225.83s	3132ns	51	80	2887	yes
7th	30	77,296,369	245.64s	3177ns	52	80	2933	yes
8th	30	74,546,293	235.66s	3161ns	54	80	2985	yes
9th	30	71,846,865	230.77s	3211ns	49	80	3110	yes
10th	30	86,369,589	276.21s	3198ns	59	80	2897	yes
Avg	**30**	**69,257,441**	**221.76s**	**3202ns**	**49**	**80**	**2954**	**100%**

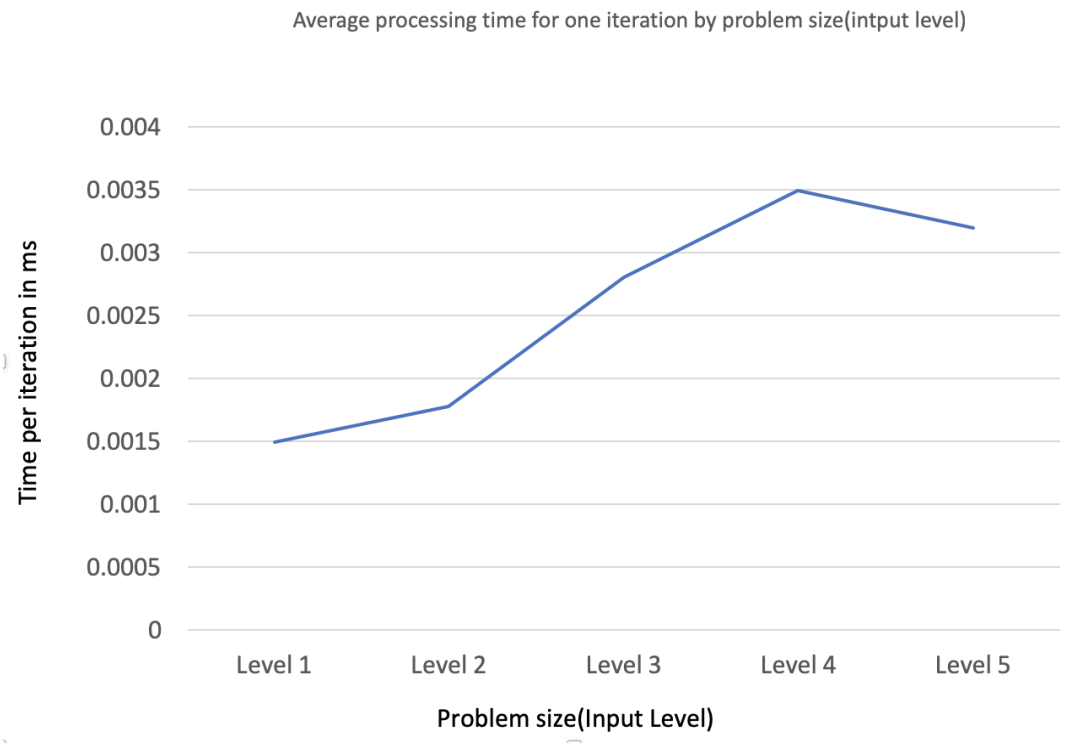
Table 3.1.2.2 Stats from 10 executions for level 5

After collecting data from all input levels, here is the relation of problem size(level) and time consumption for one iteration:

Level	Average Iteration	Average Time	Avg Time per Iteration	Average Steps	Average Memory	Reach Goal Percentage
1	38.482.466	57.681s	1498ns	12.1	3303MB	100%
2	34.741.950	62.154s	1789ns	13.8	2982MB	100%
3	56.764.422	159.89s	2816ns	36.1	3329MB	100%
4	60.184.897	210.71s	3501ns	46.2	3030MB	100%
5	69.257.441	221.76s	3202ns	49.0	2953MB	100%

Table 3.1.2.3 The memory consumption with 5 second planning time

Based on the data collected above, the chart is plotted to illustrate the relation between average time for one iteration of different input levels:



It can be observed from the chart that in general the time consumption for one iteration on average increases along with problem size, reaching maximum (at around 3500ns) on level 4 and then drops slightly on level 5.

One possible reason for time consumption decrease on level 5 input is that the level 5 input file has maximum step as 80 while the level 4 maximum step is 90. In our implementation, the rollout simulation step count (rollout depth) is proportional to the maximum step from input, so the agent is constructing and traversing more nodes during the rollout in level 4 than level 5, thus impacting the time spent on each iteration as it needs to traverse longer distance.

To prove this, the previous level 5 is modified with max step as 90 steps. After multiple executions, the average time on one iteration for this modified level 5 input is 3754 ns. The new plot with modified level 5 input file.

As observed, the average time consumption for one MCTS iteration gradually increases along with the problem size consistently after modifying the maximum step allowed on level 5 input.

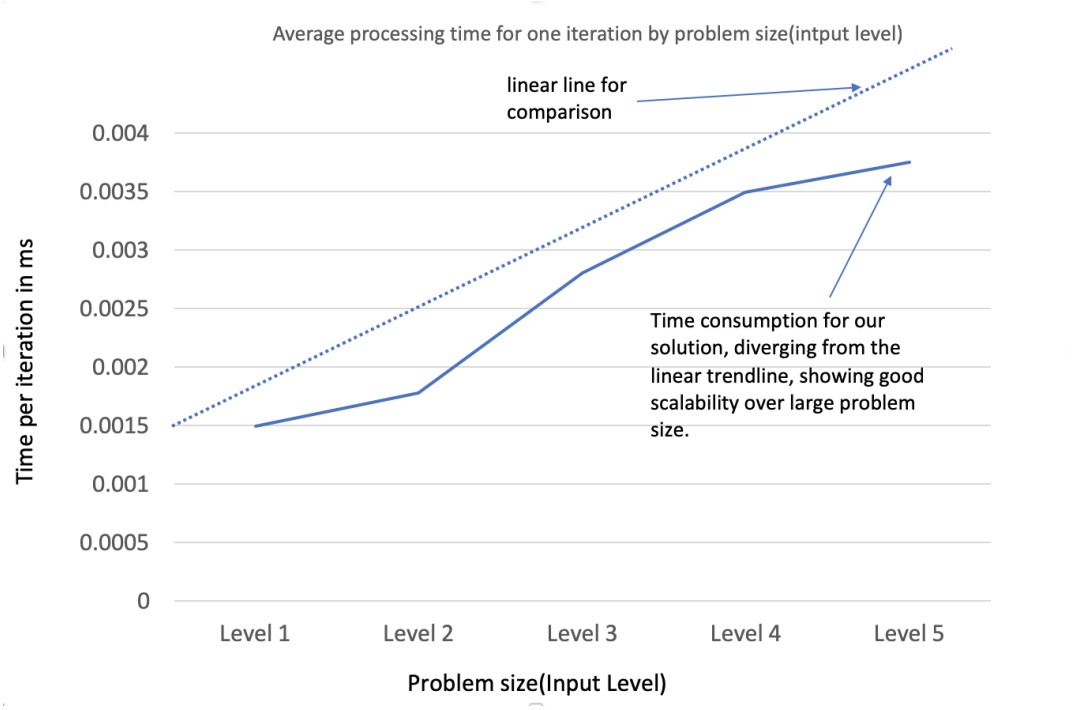


Figure 3.1.2.2 : Time consumption chart after using consistent max step input.

3.1.3. Overall Time Complexity

The overall time complexity is analysed based on execution time required to solve varying levels of the game. We compare the overall time consumption of different levels to explore how time can be affected by increased state space and action space(problem size).

Screenshot for sample taking as below:

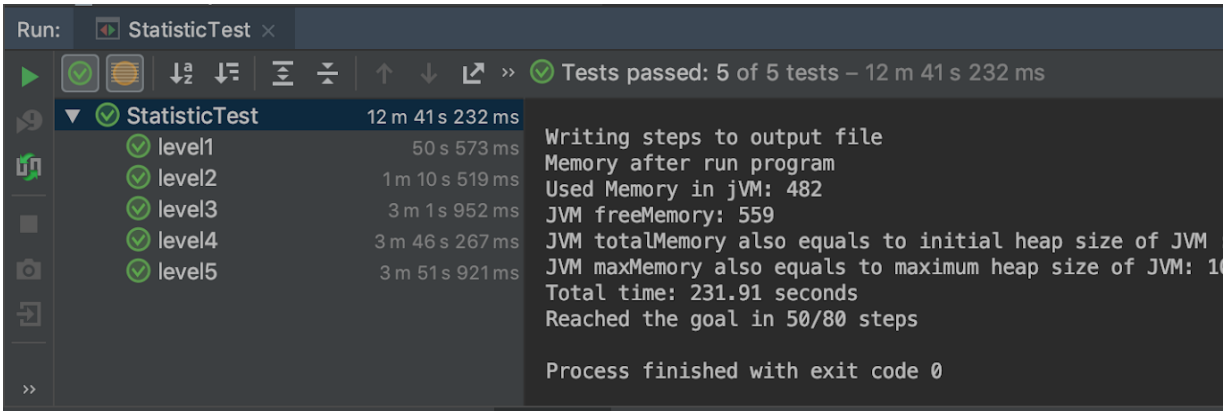


Figure 3.1.2.1 : Repetitive test for all levels

```
Step: 12 - State: [ Pos=16 | Car=mach-6 | Driver=toad | Tire=ALL_TERRAIN | Pressure=100% | Fuel=37 ]
A1(94395|7.807) A7(50005|7.345) A7(51697|7.374) A7(49285|7.334) A7(51409|7.369) A7(47989|7.311) A7(48545|7.320) A7(51176|7.365)
A7(50096|7.347) A7(52843|7.392) A7(51090|7.363) A7(52489|7.386) A7(52741|7.391) A7(49321|7.333) A7(50797|7.358) A7(48493|7.320)
A7(41762|7.186) A7(45549|7.265) A7(45654|7.265) A7(43326|7.220) A7(50617|7.356) A7(56269|7.443) A7(53749|7.406) A7(47557|7.303)
A7(47053|7.293) A8(47770|7.306) A8(49646|7.339) A8(47534|7.302) A8(48004|7.309) A8(1772|-0.093) A8(1261|-1.886) A8(1819|-0.008)
A8(1272|-1.787) A8(1819|0.027) A8(1272|-1.789) A8(31481|6.904) A8(35671|7.031) A8(31955|6.920) A8(36548|7.058) A8(28206|6.784) A
8(31085|6.890) A8(13803|5.810) A8(12864|5.696) A8(13811|5.815) A8(13883|5.821) A8(14312|5.869) A8(12288|5.615)
MOVE | Value: 7.807 | Average: 6.038 | Visit: 94395 | Total: 1761983 | Percentage: 5% | Nodes: 47)
```

Figure 3.1.2.2 : Output for single step

	Level 1		Level 2		Level 3		Level 4		Level 5	
#Iter.	Time	Steps	Time	Steps	Time	Steps	Time	Steps	Time	Steps
1	55.3s	11	65.2s	19	108s	21	299s	67	314s	69
2	75.1s	21	68.7s	15	149s	33	204s	47	353s	79
3	60.1s	12	55.2s	11	191s	45	192s	43	156s	31
4	60.7s	12	70.4s	18	185s	44	238s	55	358s	75
5	45.4s	9	130s	25	213s	47	173s	40	215s	45
6	55.5s	12	75.8s	19	201s	44	227s	44	199s	40
7	50.3s	10	55.5s	11	141s	30	176s	41	317s	64
8	60.2s	13	200s	17	167s	35	183s	40	236s	49
9	65.3s	13	60.4s	12	177s	35	192s	42	213s	45
10	50.3s	11	45.2s	9	183s	38	262s	53	259s	59
Average	**57.8s**	**12.4**	**82.6s**	**15.6**	**171s**	**37.2**	**214s**	**47.2**	**262s**	**55.6**

Table 3.1.2.2 Average time and steps for every level

- In this program, the time to solve a problem can always be calculated as:

$$Total\ Time = ExploreationTime(predefined) \times Number\ of\ Steps$$

- ExplorationTime is set as 5 second for every action decision, and step count to reach the goal is proportional to input cell count. This can be observed from the table above as the ratio of total time to step count is a constant≈5.
- As expected, the increase in problem size also increases steps to reach the goal as well as the overall execution time.

3.2. Memory Complexity

3.2.1. Memory Complexity for One Iteration Calculation

For every iteration, the agent has to store all the explored nodes within MCTS tree, the number of tree node can be calculated as below:

Let **a** be the number of possible actions in action space, **t** be the maximum allowed steps and **d** be the depth of the tree. We can calculate the computational step for one iteration:

$$Number\ of\ Nodes = Number\ of\ Action^{(Depth\ of\ Tree+1)} = a^{(d+1)}$$

Since the **Depth of the MCTS Tree** is **Expected** to be the **Max Number of Steps** so that one iteration will have the memory complexity of **O(Number of Action Max * Number of steps)** or **O(a*t)**.

3.2.2. Overall Memory Complexity

The overall memory consumption measured by the average of 10 executions in every level of the game. Multiple execution for same level is performed with the purpose to prevent a very lucky/unlucky case representing the memory usage for that level.

Level	# 1	#2	#3	#4	# 5	#6	#7	#8	#9	#10	Average
1	442	519	538	495	457	597	472	541	393	546	**501 MB**
2	565	652	437	476	571	633	534	496	995	618	**597 MB**
3	648	757	676	545	686	535	524	497	511	722	**610 MB**
4	628	653	728	902	773	540	731	452	767	704	**687 MB**
5	503	419	740	749	493	496	411	731	566	602	**571 MB**

Table 3.2.2.1 The average memory consumption for all levels on 8G RAM computer

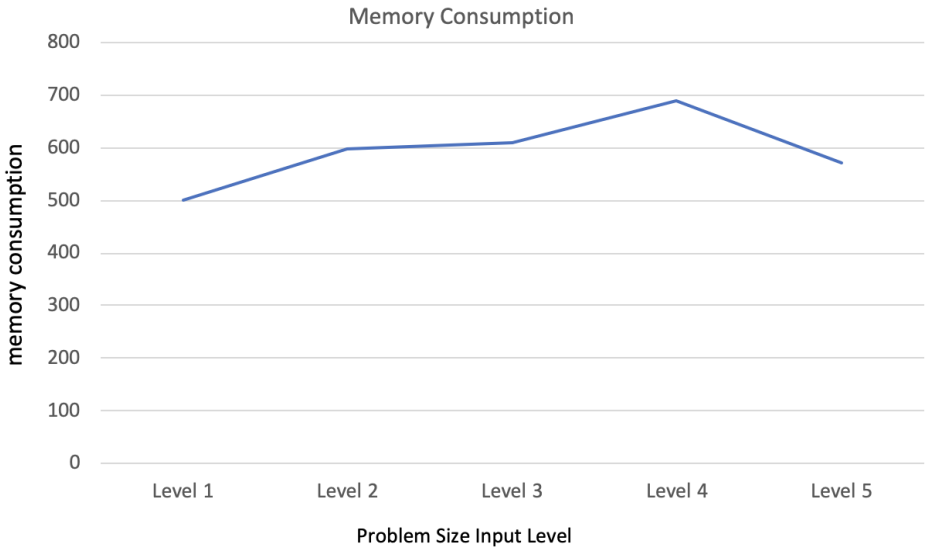


Figure 3.2.2.2 : Graph of memory consumption across all levels

As can be seen on from the graph above, the memory consumption increases gradually from level 1 to level 4. After that memory consumption decreases because the maximum step allowed in level 5(being 80) is smaller than level 4(being 90). This could be caused by the same reason that time consumption drops at level 5 in previous analysis (section 3.1.2).

To prove that it is caused by max step, the max step of level 5 test case is modified to 90. With the new input, here are the graphs below:

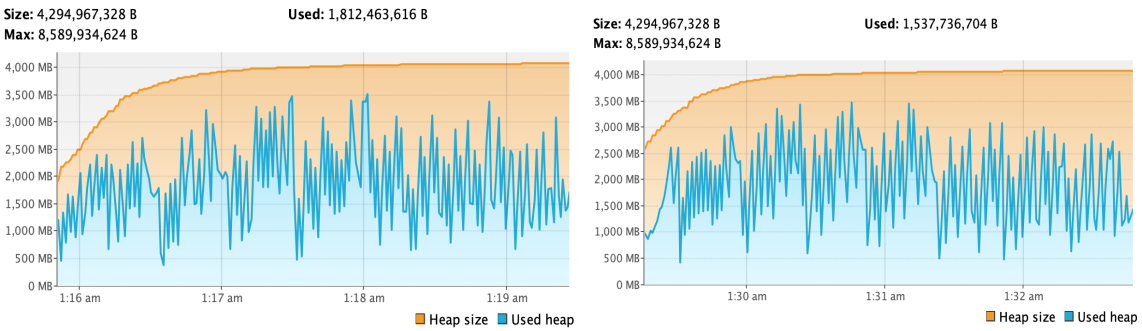


Figure 3.2.2.3 : Level 4 & 5 re-comparison after modifying max step limit

As can be seen from the graph comparison above, after setting max step of level 5 to the same value as level 4, the memory consumption for level 4 input (on the left) is approximately the same as level 5(on the right). Possible reasons are as below:

1. The test case of level 5 is easier than level 4 despite having more branching factors.
2. Memory allocation by operating system might have reached a limit.
3. More samples of various input may provide different consumption data.

3.3. Performance for Varying Planning Time

In the assignment, time consumption over decision for action is controlled by parameter EXPLORATION_TIME. Increasing time limit for one action decision will also increase the iteration times for that decision, thus the decision is made with more information and often leads to better result.

- In order to compare the performance with regards to varying planning time (eg. 1, 5, 10 seconds per action),10 executions on each difficulty level with 1, 5, 10 second planning time is performed respectively.
- By comparing the success rate (percentage of reaching goal by given max step limit) and the average step count to reach the goal, the relation between performance and planning time per action can be revealed.
- To prevent the agent always reaching goal, we deliberately reduced the max step allowed to cause extra difficulty, so the improvement of performance can be easily observed. Specifically, 53 is set as the max step allowed for a level 5 problem.
- The number 53 (max allowed step) is obtained from the average steps reaching the goal of a level 1 problem after 10 executions. By using this number as maximum allowed step, it is expected that around 50% of level 1 attempts would fail.
- The expectation of such a comparison experiment is that, by increasing planning time, the rate of reaching goal would probably increase and the steps used to reach the goal would probably decrease.

The data collected for this experiment is represented in table below:

Iteration	1 second		5 seconds		10 seconds	
#1	Pass	48/53 steps	Pass	50/53 steps	Pass	37/53 steps
#2	Pass	52/53 steps	Failed	N/A	Pass	31/53 steps
#3	Pass	50/53 steps	Pass	41/53 steps	Pass	37/53 steps
#4	Pass	43/53 steps	Pass	42/53 steps	Pass	44/53 steps
#5	Failed	N/A	Pass	45/53 steps	Pass	38/53 steps
#6	Pass	51/53 steps	Pass	45/53 steps	Pass	29/53 steps
#7	Failed	N/A	Pass	43/53 steps	Pass	44/53 steps
#8	Pass	51/53 steps	Pass	37/53 steps	Pass	40/53 steps
#9	Failed	N/A	Pass	43/53 steps	Pass	45/53 steps
#10	Failed	N/A	Failed	N/A	Pass	38/53 steps
Avg	**60%**	**49/53 steps**	**80%**	**43/53 steps**	**100%**	**37/53 steps**

Table 3.3.1.1 The success rates and the number of steps with various planning time

Based on the last row of the table it can be observed that the increase in the planning time will affect the result in two aspects:

1. Increase rate of reaching the goal.
2. Decrease average step for reaching the goal

To avoid exceeding time limit, only 1, 5, 10 seconds planning is included in the chart. It is expected that the steps for reaching goal would converge to optimal if the planning time is sufficiently large (starting from the elbow point of the step/planning time curve). However, convergence is not observed in this experiment even if 15-second planning (with average steps reaching goal being 33) is included into the scope.

3.4.1 Memory Consumption with Varying Planning Time

Memory consumption of varying planning time can be seen from charts below. It is clear that memory usage increases along with the planning time. This is because increased planning time for each action leads to more iterations, constructing of a bigger MCTS tree, which requires more nodes to be stored in RAM.

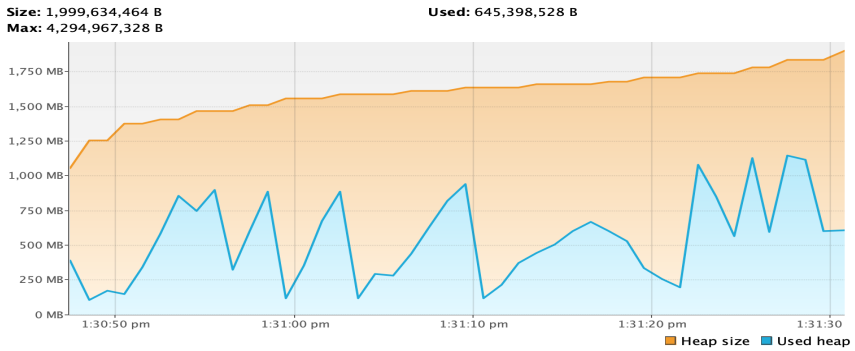


Figure 3.4.1.1 : Memory consumption for 1 second planning time

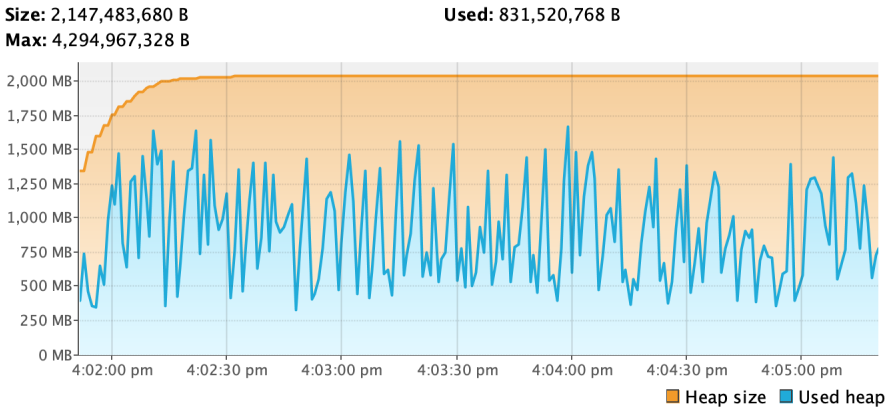


Figure 3.4.1.2 : Memory consumption for 5 second planning time

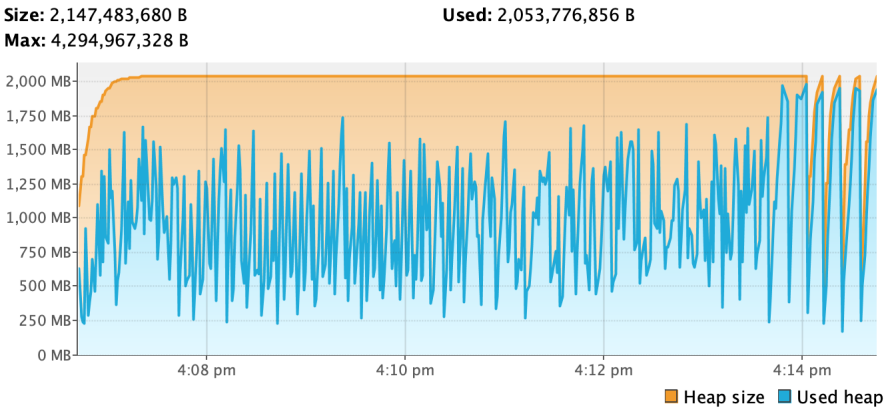


Figure 3.4.1.3 : Memory consumption for 5 second planning time

3.4.2 Memory Consumption Chart by Java Virtual VM

- Java Virtual VM is used as one of our methods to record the memory consumption. This tool provides consistent data with the statistics generated along with the agent execution, but providing better graphic representations.
- A brief comparison experiment is performed with this tool, for planning time 1 and 5 second across all level of difficulties.
- The result graphs provide consistent evidence with previous analysis, as the memory consumption increases when the state space and action space increase.

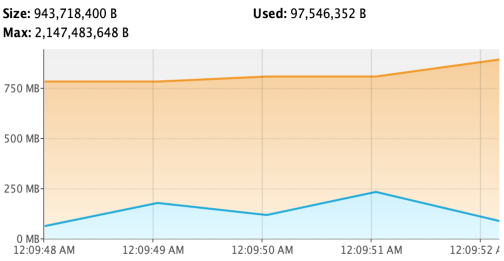
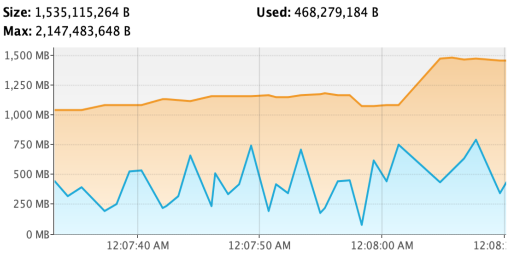
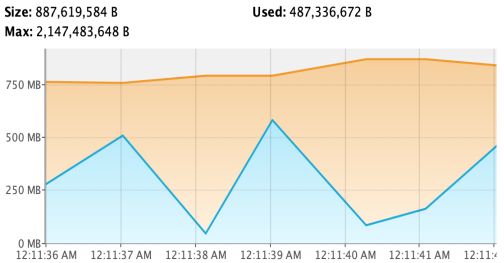
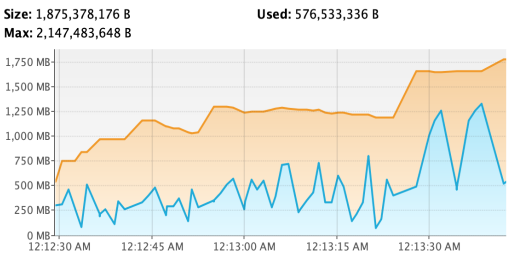
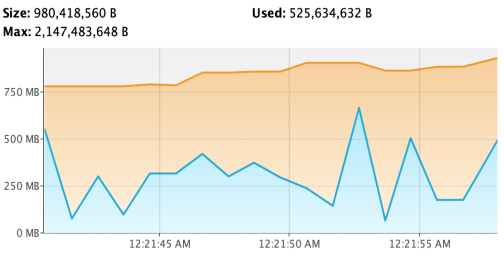
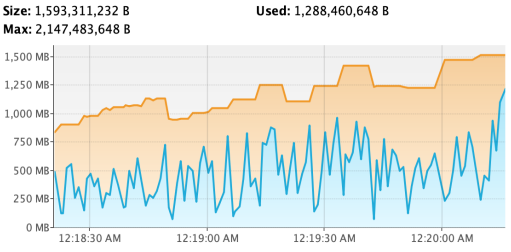
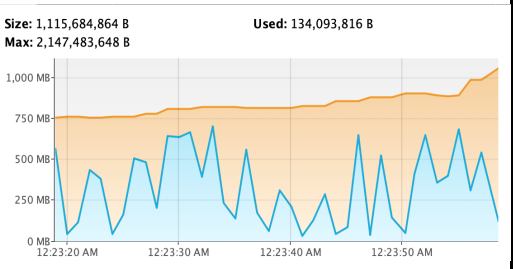
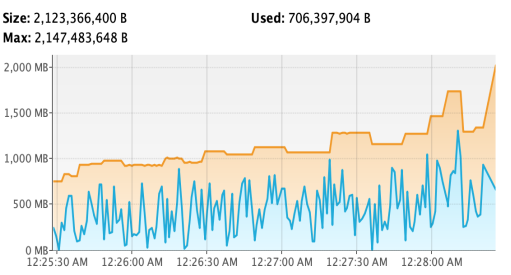
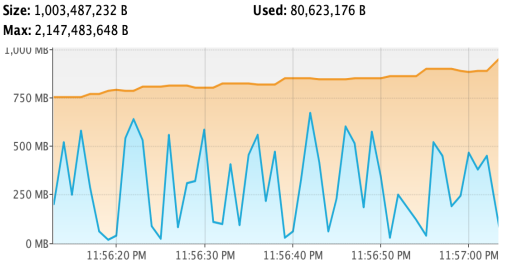
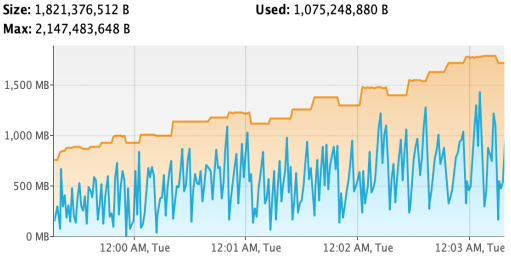
Level	1 Second Planning Time	5 Second Planning Time
1		
2		
3		
4		
5		

Figure 3.4.2.2 : Memory consumption for 1 and 5 second planning time across all levels