COMS10017 – SCOTLAND YARD PROJECT

Patrick Lee

**PART 1 – MODEL**

Outline

The first task was to build the ‘Game State’ and ‘Model’ Factory classes such that it would pass all the given tests to ensure they would act as foundations to the Scotland Yard game, essentially creating implementation for an object “game state” which would provide all details about a particular game state including the arrangement of pieces on the board and the moves available to them. This was linked with the “model” implementation which could register and notify any external observers about game events such as moves and if the game has ended.

Our implementation was completed successfully, passing all 83 of the given tests and making use of a variety of techniques and OOP concepts learned in the past few months.

Evaluation

**PART 2 – AI**

State and Action Classes

We decided to create our own implementations of Board and Move, ‘State’ and ‘Action’ such that these classes could also contain scores and relationships between moves and resulting positions. These classes both implement in the built in ‘Comparable” interface allowing them to be sorted by score. Initially, we thought about having these classes inherit from ‘Board’ and ‘Move’ so as to basically be able to extend those classes with the extra data but decided against that as we wanted to create completely separate objects in their own right. The State and Action classes have attributes and methods to deal with things like: scoring, the ‘Board’ and ‘Move’ instances which they relate to (on a one to one basis), a uniquely generated key (for the State – explained further down) and an object reference to the next state (for the Action).

We also created a data structure called an ‘Action Set’ which is able to store a list of actions, sorted by the score of the state they lead to. This is sorted in descending order if maximizing MrX and ascending otherwise.

These classes aim to encapsulate all necessary attributes and methods required for a given AI agent to reason about the game in terms of ‘Actions’ and their resulting ‘States’, in a similar fashion to an API, as well as create cleaner ‘MyAI’ class where the focus can be on the AI logic itself as opposed to game data.

Scoring Function

We implemented a basic scoring function which would provide a rating for each move explored in the game tree as well as giving a base case when either the tree has reached a maximum depth or a winning/losing position is found. In the case of a MrX win, the score for the board configuration would be 100, and -100 in the case of a loss. Otherwise, the score would be the weighted sum of the average distance between MrX and the detectives, found using Dijkstra’s algorithm, and the number of moves available to him (this would be subtracted if a detective move was being evaluated). Whilst exploring the game tree, the score for each move is the weighted sum of this function being applied to whatever board configuration the move leads to, and the maximum score which can be achieved from a subsequent move, generated from the next layer down in the tree. This is loosely inspired by Q-learning, in which the ranking for a given state (or board in this case) is partially based on the expected value of the subsequent state. In our case, each player has full control over what move they will make next and therefore we can just use the value of the best (or worst if minimizing) subsequent state that the player can end up in.

Minimax Algorithm

Due to the turn-based and perfect information (from MrX’s perspective) nature of Scotland Yard, we felt an algorithm based on MiniMax would be a good fit, seeking to maximise the score of a move when processing MrX’s turn and minimising it otherwise. The algorithm essentially plays out all possible sequences of moves up to a certain number of turns (defined by the depth parameter). One thing which became apparent straight away was that the size of the resulting recursion tree meant the problem became intractable for greater tree depths due to having a complexity O(n^x) where n and x roughly equate the average number of possible moves and depth of the tree respectively. In an attempt to optimize the algorithm, we did the following:

Optimizations

**Reducing the move list**

It is often the case that more than one of the moves available to a player will lead to the same destination due to being able to use different means of transport. As these will lead to the same board configuration, these moves become redundant and can be removed from the list of moves to evaluate, speeding up the execution time of minimax. In our implementation, excess moves are removed from the list based on the scarceness of the required ticket(s) i.e. rarer tickets, such as double tickets and secret tickets are preserved where possible, unless they are the only way to get to a certain destination.

**Ordering the moves list by likelihood of a good score**

The moves available to the agent are initially sorted by heuristic score, i.e. the scoring function mentioned earlier is applied to the board state reached by each move, and then each move is sorted using merge sort such that the moves with the highest heuristic appear first in the list. This sorting process is also done at each layer in the game tree, massively increasing the efficiency of alpha-beta pruning.

**Transposition table to contain scores for already seen moves**

When a particular board state is being evaluated in the minimax tree, it is looked up in a table to see if a score for the position has already been found. If so, it will use this value instead of going deeper down the recursion tree. A basic hashing algorithm is used to access the table whereby the key is the sum of the detective locations each multiplied by an increasing power of the total number of nodes in the graph, subsequently being multiplied again by this total and then added to MrX’s location. It is analogous to a binary shift. The fomula for the algorithm is expressed as follws:

Where *X* is MrX’s location, *N* is the total number of nodes in the game graph, *D* is the sorted array of detective locations of size *n.*

**Timeout**

The time taken to explore the Minimax tree varies with depth, branching factor i.e. how many moves and whether many moves have been logged in the transposition table. This time can be considerably longer than the time allowed for a move for a great depth with a sparsely populated table. As such, we developed a mechanism for terminating minimax when this time limit is reached. The minimax algorithm returns a pair consisting of a Boolean and the score value as an integer. The Boolean is returned as true if the time taken is within 5% of the time limit so the recursion tree can essentially ‘unwind’ and return the current maximum score found at the top without exploring the tree further.

**Alpha Beta Pruning**

Alpha Beta pruning increases the efficiency of minimax by eliminating less-promising subtrees meaning the game tree can be explored deeper down the routes which are more likely to end in a maximised score. The ordering of moves mentioned makes it easier for the alpha beta pruning to eliminate branches. Overall, this decreasing of the branching factor made a noticeable decrease in time taken to explore the game tree to a greater depth.

**Parallelisation**

Making use of threading offered a significant increase speed. We created a ‘MinimaxThread’ class which could be instantiated and run as a thread, containing all attributes and methods necessary for minimax to run recursively within it. When picking a move, a thread is created for each move available and the game trees for each move are then explored in parallel. Each thread will exit either when the time limit is reached (the minimax function will return) or after the tree is fully explored

Evaluation

There was some level of success in AI; when playing, the agent would generally move away from detectives and avoid cornering himself but this was less effective when more detectives were playing. Five or six detectives would often result in the agent only being able to look one move ahead for himself as the combinations of moves from the remaining detectives would, in most cases, mean the game tree would have more layers than could be fully processed within the time limit for making a move, even with the optimisations.

The AI seems to be effective against less than 4 detectives, but would rarely win games against 5 or 6 detectives.