Project: Sokoban

2012-10-10

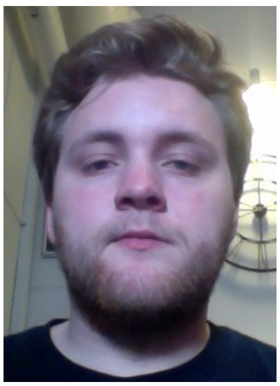
figure[h] 

Table 1: Jacob Håkansson, 890625-2914

figure

Abstract

This project was a part of the course DD2380 - Artifical Intelligence. The aim of the project was to create an agent that successfully solves instances (boards) of the game Sokoban. The overall approach was to use an A*-like algorithm, bipartite matchings and several deadlock detection heuristics to solve the problem.The result was an agent that proved to be quite efficient when solving certain kinds of boards, mostly boards with few boxes and few open spaces. The agent scored 18 solved boards out of 100.

1 Introduction

This report is a documentation of a project in the course "Artificial Intelligence" (DD2380). The goal of the project is to implement an agent that successfully solves Sokoban boards. Sokoban is a game where the goal is to push boxes on a game board to the specified goal points. The project relates to several topics in artificial intelligence, such as planning and observation, but the most critical property of this agent is decision-making.

Jens Arvidsson implemented the largest portion of the code, with input and ideas from the rest of the group. We got ideas for deadlock-handling from http://sokobano.de

2 Background

Sokoban is a game in which a player is supposed to move boxes in a warehouse. The warehouse is represented by a board, which specifies the positions of walls, boxes, empty spaces, the player and, of course, the goals. The player solves a board by pushing (no pulling allowed) all of the boxes to the separate goal points. The boxes and the player can only occupy empty spaces and goals. The problem is consequently to find the paths on which the player can push the boxes to the goals in a non-destructive way. A destructive path is a path which results in the box being immovable, this is called a deadlock. A deadlock makes the board unsolvable and as such must be avoided at all times. The problem of finding these paths might sound trivial, but is in fact very hard due to the branching factor of each step taken. This requires a lot of computing power, as each step makes up to 4 new steps available. For example, if we need to move 10 steps, this gives us up to $4^{1}0 = 1048576$ possible paths. Thankfully there are methods to cut this number down by prioritizing certain moves and eliminate moves that lead to deadlocks.

3 Approach

3.1 Initial idea

The task was to solve a sokoban board in a maximum of 60 seconds. We concluded that for boards small boards containing only a few boxes this should be pretty straight forward. We started out by implementing a player that just pushed each box in all directions possible, and saved the resulting states in a stack (a basic DFS search). Of course this did not work well at all. For the final solution we changed the search to prioritize moving boxes

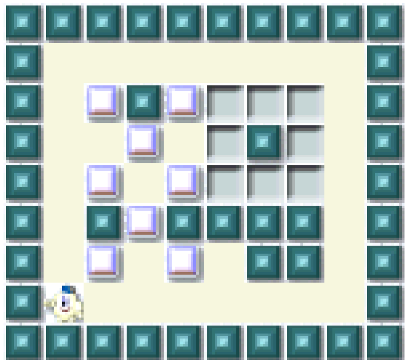


Figure 4: A typical Sokoban board

all the way to a goal area if possible, and using a priority queue to select which of the saved states to work on.

3.2 The board

The board is represented internally as a char matrix, and represents the game in one state. The board contains a list of the positions for all boxes and goals in the current game state. This later allows us to check the condition of all boxes in each state quickly.

Moving a box creates a new game state, and each time we make a move in one state we copy the old board, instruct it to make a move, and save the copy. The board representation is thus responsible for checking that the move made is legal, i.e. the player is not walking on top of boxes, walls or out of the board.

3.3 Deadlock detection

After loading a map into a game state, we try to detect deadlocks. If we could catch all deadlock situations we could eliminate a lot of the states that would not work anyways. The problem is that detecting deadlocks is very difficult, and if done incorrectly could eliminate states that actually contained the solution we were looking for. We divided deadlock detection into two groups: Static and Dynamic deadlocks.

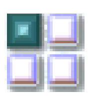
3.3.1 Static deadlocks

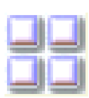
Static deadlocks are those that does not change during the game such as putting a box in a corner with no way to pushing it out of there. Finding static deadlocks is fairly straightforward and is only done once for each board, due to their nature of being static. This is done by simply checking all empty spaces for the following criterion: if it is a corner or if you can't pull a box from any of the goals to the space. This is true because pulling a box is the exact reverse of pushing it. Thus, if a box can't be pulled from any goal to a certain space, then a box can never be pushed to a goal from that space, and so it is a deadlock.

3.3.2 Dynamic deadlocks

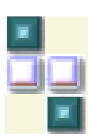
Dynamic deadlocks are all sorts of deadlocks that are caused by boxes blocking each other. A check for these is made whenever a box is moved, and if a deadlock is detected the state generated by the move is discarded.

The easiest example of a dynamic deadlock is when a move results in four box/wall tiles in a square (where at least one of the boxes are not on a goal): The agent also detects situations where a box is cornered by a wall





and a box, where that box is also cornered by a wall and the aforementioned box, as in the configurations below:



3.4 Hast table

It is very inefficient to evaluate the same states multiple times. To avoid this we implemented a hash function and a Hash table to store evaluated states in. The hash is, in its default configuration, calculated as the position of the boxes. It is very simple but unique for different box positions. A board with two boxes has the same hash even if the boxes switch positions. We decided to do it like this because switching positions of two boxes does not help our solution in anyway.

This hash function, as described above, does not take into account the position of the player. Doing so would generate a lot of states for each player position for the same setup of boxes. However, there are times when player position should be taken into account, such as when boxes needs to be pushed back and forth through a tunnel. In these cases the application breaks after some states passed with no solution. Then we clear the hash table and re-run the application with the player position in the hash.

In the cases where we do not need the players position this is a great performance improvement, and where we do need the player position we get another try at completing the board.

3.5 Agent operation

The agent operates by taking each element in the priority queue, generate new states from it with different scores (for sorting the queue), putting these into the queue, and repeating. It generates new states in two steps: Matching and randomizing.

3.5.1 Matching

Matching is done by creating a bipartite graph from all available (that is, not standing on top of a goal) boxes and all free goals, using pushable paths between them as edges, and then solving its maximum matching by reducing it to the maximum flow problem and solving it with the Edmonds-Karp algorithm. Thus we get a maximum possible match between free boxes and free goals. The agent takes this matching, performs the first of the moves in it, and then makes a new such matching on the resulting board and repeating the process until no matching is found.

After every move made, the agent saves the resulting state in the priority queue with a modified score to push it to the front of the queue (as it is generally a good move).

3.5.2 Randomizing

After generating states from the matching process, the state also generates states by moving the box up, down, left, and right (assuming it is actually possible to do so) and saving these in the queue. These have a generally lower score than those generated by the matching, but are nevertheless necessary in order to explore all options.

3.5.3 Scoring states

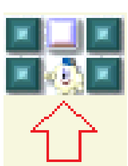
After a move has been made and a state is generated, the state is run through deadlock tests, and if it passes these, it is scored by weighing together distances from all boxes to any goal (closer is better), how many boxes are on goals, and how many steps were required to get to it (less is better). The state also inherits its parent's score (good moves should generally lead to better moves).

3.5.4 Looking for good signs

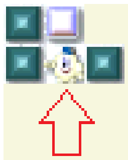
The last step after generating a state is looking for good situations generated by the move. We use two checks, goal pens and no influence push checks.

A goal pen is a goal square surrounded by three wall squares. If a move results in a box being pushed into such a square, it is awarded a high score and is, for all succeeding states, treated as a wall square (since no box can be pushed into it, and it cannot in most circumstances hinder any other box from reaching a goal).

A 'no influence' or 'tunnel' push is a push which has no impact on other boxes, and after which a second push in the same direction can only be beneficial. Two configurations lead us to draw the conclusion that a move was a tunnel push: If a move results in any of these configurations or their



rotated counterparts, we can safely push the box one step further in the same direction. In this manner, the agent can be said to consider tunnels as one square.



3.5.5 End of line

The agent keeps taking states and generating new ones in this manner until it finds one with a solved configuration, upon which it returns the path which it used to get to it as a LRUD string.

4 Results

Our matching algorithm combined with ranked random movements proved to be quite efficient at solving certain kinds of boards, especially boards with few boxes and few open spaces. This is in part because our agent quickly discovers which corners and tunnels create deadlock situations, and because the running time of the matching algorithm and the number of random movements made for each state depends solely on the number of boxes on the board.

On boards requiring a great deal of back and forth movement, our agent performs very badly, but it really shined in situations where paths to goals were not obscured by having to make a lot of movements. That is, if the board was such that a human observer could easily see a solution, our agent would find it almost immediately, regardless of how much distance there was to the goal or how many boxes there were.

The agent is particularly inefficient in open spaces. This is mainly because there are a lot more possible states in the open space, which causes the search tree to be much bigger. Because of this, the agent has problems with most open boards. On the other hand, the agent is very efficient in tight spaces. For example, it treats long tunnels as one position on the board. This means that the agent is able to solve tight boards, that may seem very complex, very efficiently.

In total, our agent managed to solve 18 out of the 100 test boards, which must be counted as sub-par performance.

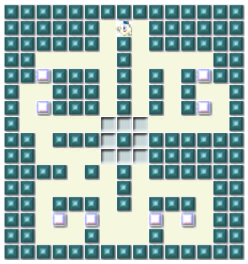


Figure 5: An easy board for our agent

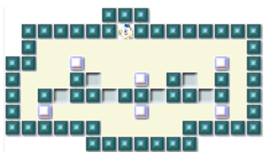


Figure 6: A hard board for our agent

5 Reflection

When we approached the problem we started out by separating the group into pairs. Each pair would implement their own agent, then the group would meet and share ideas and compare the performance of the agents. The best agent were chosen and developed further. We chose this approach because it seemed like the best allocation of time in the beginning of the project, when we didn't have enough material to start working on the report.

This approach failed in some sense, because one of the pairs failed to implement a working agent. If we could redo the project we would probably let one pair do most of the coding and one pair do the report, while having several regular brainstorming sessions with the whole group.

Our program is the result of using a basic idea about how the search is to be conducted, analyzing how it behaves in testing, and trying to find general patterns in behavior considered detrimental to solving the puzzle. Eliminating static deadlocks, and finding patterns that give a deadlocked state were generally the easiest challenges, since they are easily calculated in the beginning of the search and do not change during the rest of it. The hardest challenge was to determine and be sure of which moves were beneficial for the agent.