**Move Performance Optimisation for Large Search Space using Decision Tree Learning with the Minimax Algorithm and Alpha-Beta Pruning**

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**Abstract – The Minimax algorithm with alpha-beta pruning is commonly used in machine playing of two-player games such as Tic-tac-toe and chess.**(1)

**In this paper, we show that an agent using the alpha-beta pruning algorithm can be improved by implementing machine learning. We attempt to improve the performance of the algorithm by applying Decision Tree learning and capturing sets of good moves to be used in later games. Finally the agent will be compared with just the Minimax alpha-beta pruning algorithm to determine whether there is an improvement in the agent’s play. The results showed that there is promise in theory however it doesn’t seem to be feasible in this implementation.**

**[NEED TO INCLUDE WHAT WE FOUND HERE]**

*Keywords:* Minimax, Alpha-Beta Pruning, MixMeta4, Decision Tree, Learning

**1 Introduction**

The Minimax algorithm with alpha-beta pruning or simply just alpha-beta pruning algorithm is more commonly used in machine playing games than the naïve Minimax algorithm. It general performs better than just Minimax by pruning away search paths and thus reducing the size of the search space.

In the MixMeta4 environment, an agent that utilises the alpha-beta pruning algorithm is expected to win a game against an agent that simply chooses random moves. However, when played against more intelligent agents such as Hal, its endgame performance is lacking, often producing moves backwards or away from the opposition, losing the game.

In this paper, we investigate the effect of allowing the agent to learn better moves from playing agents such as Hal, where the result set are gathered using Decision Trees and stored for future games.

Therefore our hypothesis is that an Agent that uses the Decision Tree learning technique will make beneficial moves that will improve its game playing performance over an agent that simply uses only Alpha-Beta Pruning.

In section 2 we describe our method for capturing *good* moves using Decision Tree learning, and in section 3 show the effect of applying this *learnt knowledge* against agents such as Hal that have historically performed well against a Alpha-Beta Pruning agent.

Finally we discuss in a more general sense what implications our results have for not only game playing, but also machine learning.

**2 Method**

**2.1 Decision Tree Training Sets**

To effectively "teach" our Agent a good set of moves given the current state of the environment, we asked it to "learn" decision trees, something known as Decision Tree Induction.

We started by building a training set; a database of Attributes and their associated Goals.

Each node within the tree is called an Attribute, and can be thought of as the input. Each resulting decision is called the Goal.

To maintain a feasible experiment we chose relatively simple, but pertinent Attributes to compute, such as if our Agent could take a piece or be taken by a piece.

[INSERT SAMPLE Attributes & Goals here]

The Goals were provided by a human "expert" or an Agent known to be better than Alpha-Beta pruning playing games. We captured the result of the Agent performing each combination of Attributes.

Originally we hoped to provide all Goals via human experts, but due to the volume of data, generated Goals from known better performing players were used.

Each training set was built from data captured from multiple games and stored within a training set directory. The aggregate results are used to produce associated probabilities for each tree node being a good move.

**2.2 The jaDTi Library**

Once our training set was complete, we then fed this raw data into the jaDTi library (2) to produce our actual Decision Trees.

We used the jaDTi library in interest of time, and because we didn’t want to “reinvent the wheel.” Although we did actually first attempt to write a Decision Tree library ourselves, the jaDTi library proved to produce the results we were looking for.

To feed data into the library, we first had to write a utility to convert our training set of raw data files into a Java Database readable by the library.

Using jaDTi also allowed us to visualise the Decision Trees built as shown below.

[INSERT DECISION TREE FIGURE HERE]

(3)[NEED TO SPECIFY THAT THE FIGURE IS GENERATED BY GRAPHVIZ]

Once the database was built, upon initialisation of our Agent we run jaDTi over the data, generating actual Decision Tree objects along with their associated probability results. At this stage the Agent has “learnt” the moves of the “expert.”

**2.3 Choosing a Move**

During game play, we generate a test set of data for all next set of possible moves using the Attributes specified earlier. We then compare this test set of moves against the set in our Decision Tree data. If a suggested move from a piece differs from the move suggested by the Decision Tree, we reject that piece. This effectively reduces the search space for the agent, by removing pieces believed to have bad moves as per our Decision Tree data.

**3 Results**

Figure 1. Branching expansion with and without DT learning results.

**4 Discussion**

may or may not reject the null hypothesis

- with time constraint, may reject it

- implementation of decision tree

- not enough knowledge about the implementation of D.tree

- getActions method from Board class (may be wrong)

- affect the final results we generated

- may need to prove it to cara by giving snap shot of the game in the report

- MAY NEED TO TAKE THIS OFF!!

- results may depend on machine specs

- more CPU power, we can search deeper

**4.1 Alpha-Beta Pruning  
4.2 Game Playing  
4.3 Decision Tree Learning**

**[we could save more time perhaps for bigger ply]**

**4.4 Machine Learning**

**5 Conclusion**

**References**

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