

Independent Study Module Report

An Investigation of Reinforcement Learning Algorithms for
Mastering the Game of Santorini

Aryan Sarswat - A0200521E
Lim Wei Liang - A0205466E
Roy Chua Dian Lun - A0199930N

University Scholars Programme
National University of Singapore

Contents

1	Introduction	2
1.1	Outline	2
1.2	Objective	2
2	Santorini	3
2.1	Game Rules	3
2.2	Game Code	3
3	Methods employed to create AI Agent	4
3.1	Combining Linear Value Function Approximation with Minimax Search .	4
3.2	Neural Networks (Value Function Approximation)	9
3.3	Neural Networks with Convolutional Layers (Value Function Approximation)	11
3.4	Monte Carlo Tree Search	14
3.5	Combining the Above	17
4	Results and Discussion	18
4.1	Loss against iteration for ANN and CNN Models	18
4.2	Loss against iteration for MCTS Models	19
4.3	Relative Performance of Trained Agents	20
4.4	Limitations of the above methods	23
5	Other Methods Explored	25
6	Conclusion	26

1 Introduction

1.1 Outline

The advent of Artificial Intelligence has allowed mankind to transcend what we thought is humanly possible, and many different approaches have been developed to create machines that can perform intelligent tasks previously thought to be limited only to humans, such as driving a car. Furthermore, these machines can do so at a speed and accuracy that transcend what the best humans can achieve.

An area of Artificial Intelligence, known as reinforcement learning, has seen increasing popularity recently, with one of its most recent successes being its use by Google DeepMind to develop AlphaGo, a computer programme which has defeated the Legendary Go player Mr Lee Sedol, the winner of 18 world titles. In essence, the technique of Reinforcement Learning works by training “agents” to take “actions” in an environment that maximise a predetermined “reward”.

1.2 Objective

The objective of this Independent Study Module (ISM) is to develop an agent which can effectively play the board game Santorini. This is largely novel as there is no accepted standard in developing an agent in the game of Santorini.

A wide variety of reinforcement learning techniques that have been shown to be effective in playing other two-player zero-sum games have been implemented, tested and compared with one another. Firstly, more traditional approaches making use of linear, feature-based, value function approximation combined with reinforcement learning and minimax search were implemented and tested. Then, more cutting-edge methods such as non-linear value function approximation were investigated using Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs), as well as a form of simulation-based search and self-play reinforcement learning shown to be successful in highly complex domains - Monte Carlo Tree Search. Finally, we attempted to combine parts of each approach in order to cope with some of the limitations encountered.

Evaluation of the implemented models was then undertaken by pitting them against each other in simulated games, which allowed us to discuss the relative merits of the techniques used. Finally, we consider some of the limitations of our investigation, such as the lack of processing power and professional games.

2 Santorini

2.1 Game Rules

Santorini is a 2-player board game on a 5x5 grid, with 3 distinct pieces: building blocks, the worker and the dome. Each player has two workers they can control, although only one can be moved in every turn.

Before the game begins, players will first select the coordinates for their initial worker placement. Then, on each turn, a player will select a worker to move, move their worker to an adjacent tile, (diagonal movement is acceptable) then place a building block on a tile adjacent to the moved worker. The building blocks can be stacked up to 3 levels, and at the beginning all tiles have no building blocks on them (i.e. level 0). The objective of the game is to move a worker to a level 3 tile. The player also wins if the opponent runs out of valid moves.

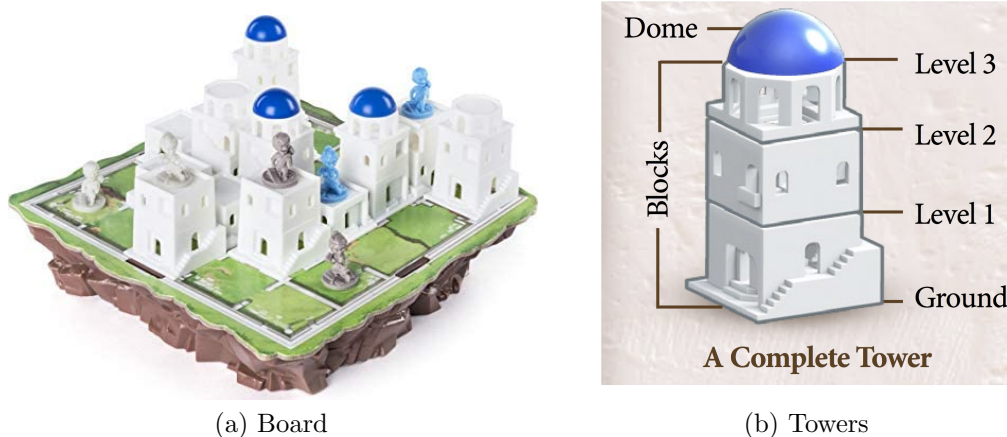


Figure 1: Santorini [8]

Workers can only traverse to an adjacent tile that is within 1 level above that of the worker's current tile (i.e. if the worker is on level 1, he can only move to an adjacent tile of level 0, 1 or 2). Particularly, workers can go down any number of levels. (i.e. level 2 to level 0) When there are 3 building blocks on a tile, a dome can be placed on top of those blocks to prevent an opponent from winning; this tile becomes impassable for the remainder of the game.

2.2 Game Code

An Object-Oriented Programming (OOP) approach was employed to simulate the board-game, as it was deemed as the most “user-friendly” approach, allowing ease of code review and overall game design. The main objects that were instantiated were: 1) Worker, 2) Square, 3) Board, and 4) Player. All of the game's code was done in Python 3.9.

1. **Worker Class**

The Worker class is a base class, representing a Worker object on the Board. The worker has two pieces of information stored: the player it belongs to, and its position on the board (represented by a tuple of x-y coordinates). It allows us to immediately determine the location of the workers to calculate possible future moves.

2. **Square Class**

The Square class represents a “square” on the board, having immutable x-y coordinates (represented as a tuple) as an attribute. It possesses two pieces of information: the level of buildings (represented as an integer ranging from 0 to 4), and whether a worker is present (represented by either a Worker object or None).

3. **Board Class**

The Board class represents the entire state of the board game, which is the main object used for interaction with the players. The space of the board (a 5x5 grid) is represented as a list of 25 Square objects. The Board class has methods for checking terminal states and validity of player actions.

4. **Player Class**

The Player class is a super class for all agents and human players. It possesses information about its Worker locations, as well as two methods: one to place its 2 workers at the start of the game, and one to simulate an action (movement of a worker piece, followed by placement of building).

A simulation of the board game will start with the creation of a Board object and 2 Player objects (either human or AI), and initialize worker placement depending on the Player object. The players (starting from Player A) will take turns doing an action until a terminal state is reached, where either player wins, of which the script will terminate for a single simulation.

3 **Methods employed to create AI Agent**

3.1 **Combining Linear Value Function Approximation with Minimax Search**

Minimax Search

Minimax Search is a well-established idea that can be used to create a game-playing AI [6]. In Minimax Search, one player is assigned to be the maximizing player, while the other is the minimizing player.

In the ideal case, each time it must make a decision the agent will construct a search tree with the current game state as the root node, branching into all possible states that the game can progress to depending on the moves that the agent and opponent make. The depth of the tree is defined to increase by 1 when either player makes a move. The tree reaches a terminal node when either player wins. These winning nodes are assigned either

an arbitrarily large positive or negative value depending on which player has won (in our case, we used 9999 for the maximizing player and -9999 for the minimizing player).

Then, starting from the parent nodes of the terminal nodes in the search tree, the best possible move for each player at a branching node is determined by them selecting the move that would lead to either the maximum or minimum possible value amongst the child nodes, depending on which player they are. This represents each player playing perfectly and allows us to assign values to non-terminal nodes. Proceeding up the search tree step-wise, we eventually reach the root node where we can now determine the best possible move to make. Such a state of play is optimal and achieves the Nash equilibrium.

Unfortunately, in most games (Santorini included), it is not possible to construct a search tree up to the winning nodes, given that a large number of possible moves at each state contribute to large branching factors in the search tree. Santorini specifically has a branching factor of up to 100, and it is larger at the start of a game when more moves are possible. Estimating the average to be 50 possible moves at each state, a Minimax Search tree would have an exponential time complexity of $O(50^n)$, where n is the search depth. Hence, it is only possible to search up to a fixed depth, and a means of approximating the state value is required at the terminal leaf nodes which do not represent a win.

Linear Value Function Approximation

One simple and effective way of approximating the value of a given game state would be using a linear value function approximator [1]. Linear approximators have a preset list of features used to evaluate a game state, as well as an array of weights, which represent the value of each feature. The state value will then be calculated by taking the dot product of the feature vector and weights vector. Such linear approximators have seen great success in other traditional board games, most notably in Chess, where IBM's Deep Blue beat the reigning world champion, Garry Kasparov [7].

As a preliminary investigation, a simple linear value function approximator for Santorini was constructed, comprising of the following 8 features that were normalized from 0 to 1:

1. Number of workers on Level 0
2. Number of workers on Level 1
3. Number of workers on Level 2
4. Centrality - Average worker distance from the board centre
5. Repeat features 1 - 4 for the other player

These simple features were constructed using some pre-existing knowledge and experience of the gameplay, being highly representative of the strength of a player's position. Worker height was considered since the game is won by having workers gradually ascend to level 3, and centrality because a player tends to have more possible moves and opportunities when their workers are at the centre of the board rather than at the edges. Pre-existing knowledge was also used to come up with a set of weights for each feature that seem to make logical sense, these weights had the values of $[0, 2, 4, -1, 0, -2, -4, 1]$. This essentially

means that greater heights are prioritized more (i.e. getting to Level 2 > Level 1 > Level 0), as well as keeping workers closer to the centre. Playing against an AI using these weights, we observe that it behaves extremely logically, and is fairly competent especially with deeper search depths. However, our initial implementation was greatly hampered by our inability to perform deep searches at acceptable speeds - a search at depth 3 took nearly 60 seconds just to come up with a move.

Optimizations in Minimax Search

It was also observed that one major factor greatly contributing to the strength of a game playing AI would be the search depth that it undertakes. Testing using the same set of weights, an AI with a minimax search depth of 3 won 95% of games against the same AI using a minimax search depth of 2. Hence, it would be highly beneficial to first make optimizations in this area before attempting to train an AI using reinforcement learning.

The first optimization technique implemented was alpha-beta pruning [6], which is a method of reducing the time complexity of a full minimax search by skipping calculations of nodes and entire branches in the search tree which are certain not to affect the final outcome. Additionally, further optimizations can be made to enhance alpha-beta pruning itself - one of these is known as move ordering, which involves sorting the list of all possible moves generated based on a heuristic so that moves likely to be stronger are considered first. This would result in pruning taking place earlier in the search tree, and hence fewer calculations being made. For Santorini, the list of all possible moves generated was sorted based on the sum of squares of the current player's worker heights, as typically moves that bring the worker up to higher floors tend to be stronger. Squaring the height automatically prioritizes moves to level 3 over level 2, 1 and 0.

Furthermore, the game's implementation was partially rewritten based on observed bottlenecks in the original code, one of which was due to the use of the rather slow deepcopy function when generating all possible moves. This problem was compounded as a minimax search tree easily generates and searches through a large number of (> 10000) possible moves every time the agent has to make a decision, and as mentioned above this number increases exponentially with search depth. Instead, the game state was changed to be represented by numpy arrays and lists of tuples while searching through the large number of possible moves, as they could be copied much more efficiently.

Collectively, these optimizations allowed for an optimized minimax search tree of depth 4 to be generated in about 2 seconds, as compared to the same amount of time needed just for depth 2 previously.

Learning Feature Weights through Reinforcement Learning

After the linear value function approximator was created and the search algorithm optimized, the possibility of the agent learning the weights through existing reinforcement learning techniques was investigated. In the paper 'Bootstrapping from Game Tree Search' [4], Veness et al., introduced new and improved algorithms for performing minimax search bootstrapping, which is the idea that a value function approximator can approximate the minimax value resulting from a deep game tree search without actually using computational power to perform said search. Game playing performance would then be significantly improved due to the greater effective search depth resulting from both the search actually performed and the bootstrapped search from the approximator. The algorithms introduced,

applied to a linear value function approximator of 1812 features, were demonstrated to be capable of learning from self-play and with randomly initialized weights in Chess, achieving master-level performance. This approach combines both reinforcement learning as well as the idea of searching for good moves using minimax, which is important in ‘highly tactical domains’ Hence, we apply the same approaches for the purpose of playing Santorini, which is also a tactical 2-player game.

The two main algorithms introduced in the paper [4], named RootStrap and TreeStrap, were thus implemented and used to train the weights for our linear function approximator. RootStrap and TreeStrap were used in 100 and 50 games of self-play respectively, starting from randomly initialized weights. The difference in the number of training games is a result of TreeStrap requiring significantly more time (about 10 times) for training per game as compared to RootStrap. This is due to the fact that our implementation of TreeStrap utilizes a regular minimax search tree without alpha-beta pruning, while RootStrap uses a pruned search tree, which contains fewer nodes and is thus much faster to create. A minimax search tree of depth 3 was used, as well as the same learning rates used in the research paper (10^{-5} for RootStrap and 10^{-6} for TreeStrap) The sketch of these training algorithms are given below. (see Algorithm 1 and 2)

Both algorithms update the linear value function approximator’s weights using ‘stochastic gradient descent on the squared error’ between the approximator’s predicted value, and the actual minimax search value. While RootStrap updates only the root node towards the calculated minimax value at that node, TreeStrap updates all nodes within the search tree towards their respective minimax search values.

Let the state value given by the linear approximator be given by $V_approx(State, Weights)$

Algorithm 1: Algorithm for RootStrap($\alpha\beta$)

Result: Weights Trained

Randomly initialize starting weight vector W from -1 to 1 for each feature;

foreach *Game* **do**

foreach *state S* **do**

 Construct an $\alpha\beta$ pruned search tree of specified depth, evaluating terminal nodes using $V_approx(child_state, W)$;

 Find minimax value V given by the minimax search tree of the current state S ;

$Error \leftarrow V - V_approx(S, W)$;

$W \leftarrow W + learning_rate \times error \times feature_vector\ of\ S$;

 Pick best move by taking the argmax of minimax values of child nodes ;

 Execute move ;

if *either player wins* **then**

 Continue to next game;

else

 Carry on with next state as the other player ;

end

end

end

Algorithm 2: Algorithm for TreeStrap(Minimax)

Result: Weights Trained

Randomly initialize starting weight vector W from -1 to 1 for each feature;
foreach *Game* **do**
 foreach *state* S **do**
 Construct a full minimax search tree of specified depth, evaluating terminal nodes using $V_approx(child_state, W)$;
 $total_update \leftarrow 0$;
 foreach *State* S' *in the tree* **do**
 Find value V' given by the minimax search tree of that state S' ;
 $Error \leftarrow V' - V_approx(S', W)$;
 $total_update \leftarrow total_update + learning_rate \times error \times feature_vector$ of S' ;
 end
 $W \leftarrow W + total_update$;
 Pick best move by taking the argmax of minimax values of child nodes ;
 Execute move ;
 if *either player wins* **then**
 Continue to next game;
 else
 Carry on with next state as the other player ;
 end
 end
end

Having implemented and tested the algorithms, it was found that they were highly effective in learning a set of weights despite being trained only by self-play and starting from random initial weights. After 50 and 100 games respectively, the performance of both TreeStrap and Rootstrap's trained weights was effectively equal or even slightly better than that of the manually tuned weights, showing evidence that these algorithms were indeed able to effectively learn from automatically generated experience.

Further Improvements to the Linear Approximator-Based AI

As the basic minimax search, as well as reinforcement learning techniques used are effective despite the limited linear value function approximator, the next logical step was to expand the number of linear approximation features to allow for a more informative state value approximation. A new linear value function approximator was created containing 22 features, with 14 features capturing combinations of worker heights as well as worker centrality, and the remaining 8 features capturing the number of height-increasing and total moves that could be made from the current position.

Two separate sets of weights were trained using this expanded linear value function approximator, with one utilizing RootStrap and the other using TreeStrap. The training process involved 400 and 50 training games of self-play at search depth 3 for RootStrap and TreeStrap respectively. However, performance was significantly poorer as compared to the original linear function approximator with 8 features - playing at search depth 3, both algorithms are only capable of winning about 25% of games against their original

counterparts. It is possible that the additional features introduce more noise and variance, inhibiting the effectiveness of the state value approximation rather than improving it. Alternatively, it could also be the case that the more complex approximator requires a significantly increased amount of training. Taking into account our computational limitations and short timeframe, the final agent used in testing instead used the original linear value function approximator with only 8 features.

Additionally, there are also additional optimizations that may be made to further increase the speed of the minimax search, such as transposition tables for repeated moves, and a heuristic for enhancing alpha-beta pruning known as the killer heuristic. [6] The variant of TreeStrap used in our testing also only used the regular minimax search tree without alpha-beta pruning, which is slower to train, as the variant described in the research paper [4] which used alpha-beta pruning required transposition tables which we had not implemented.

Finally, to create an AI that truly learns on its own without requiring prior experience for feature creation, the possibility of an algorithm that generates and evaluates its own linear features based on commonly encountered patterns in the game state could be explored. That said, such a problem may be more easily solved through non-linear value function approximation methods, such as ANNs and CNNs, which we explore in the following sections.

3.2 Neural Networks (Value Function Approximation)

Using Linear Value Function Approximation with minimax is an extremely effective process. However, only in games where the branching factor is not very large, minimax can lead to optimal gameplay with a reasonable thinking time by the AI agent. Due to the relatively large branching factor of Santorini (up to 100 moves per turn), to achieve reasonably fast performance a linear agent can only perform a search up to a depth of 4 moves ahead. This severely handicaps the overall performance of the AI. This is one of the primary reasons to attempt to use a Neural Network to predict the value of a state instead.

Neural Networks are essentially seen as universal function approximators, which can be used to mimic any function. Thus by using the minimax algorithm we can find the true value of a state and use that as our training data. This training data will be fed into the neural network which will adjust its weights and bias to be able to create a function which can accurately determine how strong a certain state is. This will increase the speed at which our agent can predict the value of a state and consequently the optimal move. Since the minimax algorithm determines the value of the state by back-propagating the value from a terminal state, there is no need to look ahead to further states as they are already accounted for. This aspect of Neural Networks as function approximators significantly speed up the “thinking-time” of our agent.

One Hot Encoding was employed to turn the board state into a flattened array of size [1, 325] containing only ones and zeros. This was used to ensure that the height of the building is not given priority due to its large numbers (1-4).

ANN Architecture

1. Input

Consists of a $[1, 325]$ layer of Neurons as each board state contains 25 squares and there are 13 unique states thus a hot encoded flattened matrix would have 325 ones and zeros.

2. Neuron Layers

This is actually a hyperparameter which we can change, for our experiments there was one hidden layer consisting of 256 input neurons and 64 output neurons. This layer was chosen arbitrarily.

3. Output

The output consists of a tensor with one value. This value is between $[-1, 1]$ inclusively. The higher the value is the better the state is for Player 1 and the lower it is the better the state is for Player 2. A value of 0 implies that the state is equally strong for both players.

4. Activation Functions

The Rectified Linear unit (ReLU) activation function was employed to linearize the function and reduce its computational complexity. The *Tanh* function was also used in the output layer to ensure that the output was between $[-1, 1]$. This not only squashed the results into this range but also did it proportionally. Thus if the value of a state is extremely large it would be reduced to 1 which can be interpreted as a completely winning state for Player 1.

5. The Loss Function

The Mean Squared Error loss was employed, this ensured that the state values did not explode as it heavily punishes large differences between the true value and the value predicted by the neural network.

6. Optimizer

For updating the weights of the Neural Network the Stochastic gradient descent (SGD) was employed. Due to the large number of Neurons in each layer and the weights associated with each of these neurons, SGD is an appropriate optimizer as it reduces the computational burden allowing us to achieve faster training for a trade-off of lower convergence rate.

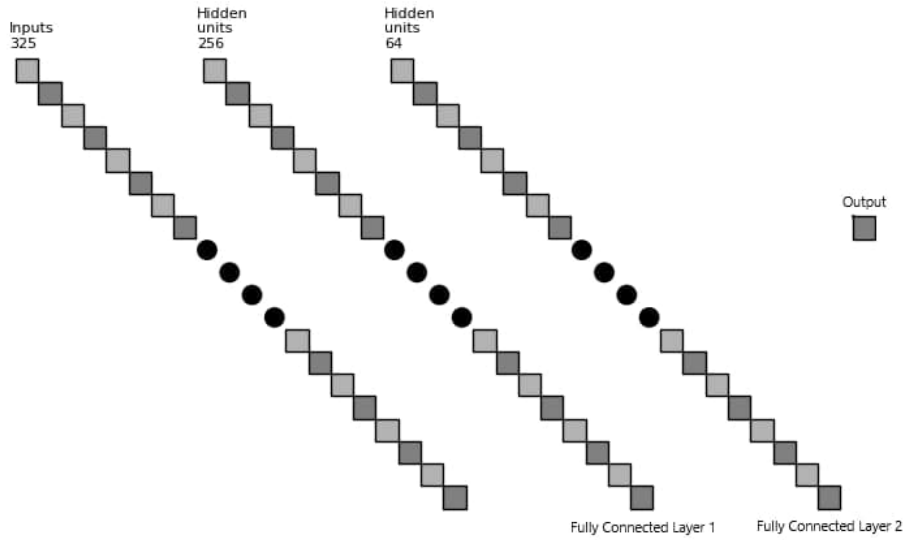


Figure 2: ANN Architecture

3.3 Neural Networks with Convolutional Layers (Value Function Approximation)

In order to make a value function approximator that is capable of converting board information to a state-value, a Convolutional Neural Network (CNN) was used to attempt to produce an accurate state-value given a board state. A CNN is capable of extracting relevant information from a multidimensional array. It is a type of neural network that is commonly employed in fields of Computer Vision, such as feature detection of images. One common example is facial recognition technology, where a CNN is trained and employed to detect facial features.

The rationale of employing a CNN in the determination of the state-value of a board is mainly due to the capability of a CNN in retaining the 2-dimensional structure of an “image” of a board, whilst generating and preserving 2D spatial features that a normal ANN is not capable of. This is because a board is fundamentally 2-dimensional in nature, and the player is traversing in a 2D-board space (3D if the buildings are included). Therefore, features of the Santorini board, like the grouping of high-level buildings, or the proximity of a player to a building, is better extracted by a CNN rather than a simple 1D neural network structure. The feature extraction capability of a CNN is pivotal in determining how much “value” the board is to a player.

CNN Architecture

The neural network was split into two distinct sections, the CNN layers (for feature extraction) and the ANN layers (for state-value determination).

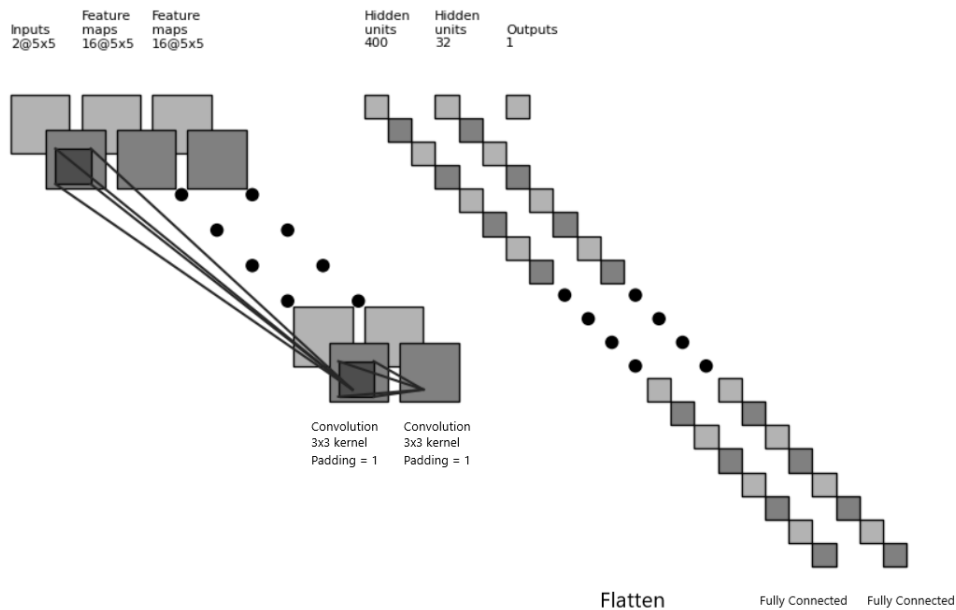


Figure 3: CNN architecture for first value function approximator

1. Input

From the board, two sources of information were determined to be essential for the neural network to output an accurate state-value: worker position and building level. Hence, the input layer had 2 input features. The board was converted into 2 layers. Each layer is a 2-dimensional 5×5 array, representing the board structure. The first layer consisted of building data, where the possible building levels of 0 to 4 were min-max normalized (0 representing ground level, 0.25 representing level 1 etc). The second layer consisted of worker data, where the player's worker was denoted as 1, and the opponent's worker was denoted as -1.

2. Output

The output was a tensor with a single value that represented the state-value of the board, with the maximum value of 1 being favourable for the player (aka a winning state) and the minimum value of -1 being not favourable.

3. CNN Layers

The first CNN layer had an input feature value of 2, representing the building levels and worker positions. It outputted 16 feature channels, with a default stride value of 1. The second CNN layer had similar hyperparameters to the first layer, the only difference being the input features to be 16, corresponding to the out channels of the first layer.

4. Batch Normalization

Batch normalization was implemented after every convolutional layer to coordinate

the updating of weights at the end of every batch.

5. Pooling

Pooling was not implemented in the CNN as the value function should retain as much information about the board as possible.

6. Kernel Size

A kernel size of 3 was adopted to capture the possible features of the board, as the worker could move in the adjacent 8 squares, hence the features that are extracted will be more relevant for the player's worker.

7. Padding

Padding with a value of 1 was used to capture the information of the board corners more accurately.

8. Activation Function

The Rectified Linear unit (ReLU) activation function was adopted for both the CNN and ANN layers (bar the second ANN layer), for less computational complexity and its linear behaviour.

9. Loss Function

The Loss Function used was the MSE loss function, with a rationale similar to that of the ANN (as explained in Section 3.2).

Training of the first CNN Model

The first CNN model was trained on a random agent (who made random worker movements and worker placements) for 10,000 iterations. Each iteration represents a complete game of Santorini. For each state, the CNN agent will generate all possible next states, evaluate the states through the CNN, and output the state-value for each possible state. Based on an epsilon-greedy policy, it will then either make a random move or make a move based on the state with the highest state-value. The state-value of the next state (either the random state or the state with the highest state-value) is saved in an array for backpropagation at the end of the iteration. As the reward given to the agent is only known at the end of the iteration, there is no update of weights to the CNN until the end of one iteration.

Algorithm 3: Training CNN Model

Result: Model Trained

```
foreach Episode do
    while game is not terminal do
        Generate all possible states;
        Generate all possible state-values for all states;
         $r \leftarrow$  generate random number;
        if  $r > \epsilon$  then
            | Make action with the highest state-value;
        else
            | Make random action;
        end
        Store state-value of action made;
    end
     $\epsilon \leftarrow \epsilon \times (\epsilon - \text{decay});$ 
     $R \leftarrow 1$  (Agent Win) or  $-1$  (Agent Loss);
    Backpropagate loss based on  $R$ ;
end
```

3.4 Monte Carlo Tree Search

The Monte Carlo Tree Search algorithm is a variant of the standard Monte Carlo method where a search tree is constructed creating a sort of policy network for an agent to follow. It relies on rollouts to be able to successfully determine the value of a state. This is a very popular algorithm used in many board games; It was successfully implemented by researchers at Deep-Mind to develop AlphaGo an AI which was able to reach grandmaster level Elo at the game of Go [3]. Monte Carlo Tree search is executed by 4 key steps; Selection, Expansion, Simulation and Backup. In one run of the algorithm, first Selection occurs and if the node is a leaf node (i.e has no children) it is expanded, after which a number of games are simulated from that leaf node. Finally the values obtained from simulating these games are backpropagated up to the root node. These four steps will be elaborated upon in detail below:

1. Selection:

Beginning at the root node, select a child node based on heuristics which involve the visit count and value of the child state. For our experiment, the Upper Confidence Bound (UCB1) was utilised. More specifically the UCB1 algorithm was used, where along with the value of the state, the number of visits of the child node and the parent node are also used to determine the criteria for selecting a child node. This algorithm allows for the selection of nodes which have not been visited and thus promotes exploration. This algorithm also contains a hyperparameter c which is known as the exploration parameter and it is usually determined empirically, however we have used the accepted theoretical value of $\sqrt{2}$ [1].

$$v_i + c \sqrt{\frac{\ln N_p}{n_i}}$$

2. Expansion

Once a leaf node is reached, the tree is expanded by adding children to the leaf node. These children are all the possible next states which may follow. This allows for the growth of the search tree. However, if the leaf node is terminal, it will not be expanded and in some cases. One may choose not to expand a leaf node completely.

3. Simulation

From the selected node or from a node which has been expanded, a complete episode starting from that node is simulated until the state is terminal. After which, a reward is returned. This is also known as a rollout and the games are simulated with a certain policy; this policy could be a Linear Value Function, a random Policy or even a policy from a Neural Network which has been trained with expert games. Other than the node selected for the simulation, none of the other states in the simulation are stored. This significantly reduces the memory requirements compared to other methods such as Q-tables.

4. Backup

The return obtained from the simulated episode is then backed up the path taken to reach the leaf node. If it is the first node in the tree, it is used to initialize the value for the node. These values are then added up for each simulation in each node in a value sum variable, and this will provide an indication of how good or bad the state is. This is one of the key steps of the MCTS algorithm as instead of using randomly generated episodes, where the goal is to explore as many states as possible, it enriches this data and even though lesser states are explored, the data contains more refined information than that of a randomly generated episode.

The figure below visually depicts how the algorithm runs

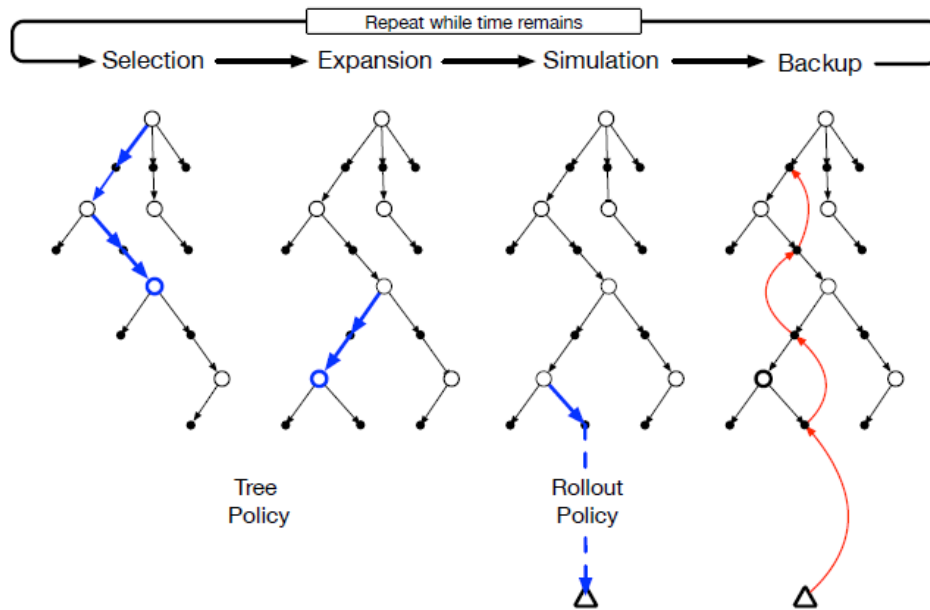


Figure 4: One iteration of MCTS algorithm [1]

Algorithm 4: Monte Carlo Tree Search

Input: root
Output: root
Result: One Iteration of MCTS
while *time/resource left* **do**
 if *root is not expanded* **then**
 Expand Root;
 else
 $search_path \leftarrow [root]$;
 $current_node \leftarrow root$;
 while *current_node is expanded* **do**
 $current_node \leftarrow \text{Select child from } current_node$;
 $search_path.append(current_node)$;
 end
 for $Simulation \in \{1, 2, 3, \dots, \text{Number of Simulations}\}$ **do**
 Reward \leftarrow Rollout from $current_node$;
 Backpropagate Reward;
 end
 if *Current_node is not terminal* **then**
 Expand $current_node$;
 end
 end
end

This algorithm continues to run until either a time limit is reached or some other computational resource such as memory is depleted. After the algorithm stops running the tree can be used as a policy to be able to play games. For each node, the child node with the highest value can be selected. This works because if the visit count and the value of the state are high. It implies that during the simulation, the tree had often selected this node. This means that it often wins in this state.

In addition to the above, the previous tree can be improved upon by selecting a leaf node which has not terminated and setting that node as the new root node to construct another MCTS tree. This will allow for greater exploration and better approximation of the value of states. However, due to our computational constraints we were unable to run the MCTS algorithm for a significant amount of time. This is due to the fact that for the value of any node to converge, we need a high number of simulations. This is not easily achievable on standard computers as they make take up to 4 to 5 days to complete the construction of one MCTS tree. Thus we developed a variation of the MCTS tree which considers the breadth of the tree instead of the depth.

The Algorithm is as follows: for each node, all the child nodes are selected one by one and for each of these node games are simulated to obtain a value of how good this state is. This value is normalized by the number of games simulated. After all the games have been simulated for all the child nodes, using the UCB1 algorithm a child node is selected which has the highest value. This child node then becomes the new root node. For each iteration, this repeatedly results in a higher depth explored. This algorithm significantly cuts down on the computational resources required. However, this comes at a cost, since

we are using the new child nodes as the new root nodes for another tree, we are essentially doing a one-step look ahead, the values will not be backed up all the way to the root node, and this reduces the chances of the value of the state to converge. Furthermore, it constricts the number of nodes it explores as it only searches down the path with the highest UCB1 value.

3.5 Combining the Above

In an attempt to address the limitation of each of the methods described above and the lack of experiment games we decided to combine the defining aspects of each method into one model. This was done using the MCTS tree to generate a game tree using the Linear RL agent’s policy for the rollouts. Multiple trees were generated up to a certain depth which were then fed into a neural network containing convolutional layers. The network was trained for multiple epochs after.

The hope was to be able to use the MCTS tree to simulate professional games by following the Linear RL agent’s policy, which using its features was able to emulate some of the considerations human players take into account while playing a game. This process, when applied to multiple simulations allows us to determine the correct value of a state accurately. This produces a dataset with a reliable set of state values. With these states and state values, the CNN network should be able to identify features in a winning state or a losing state, allowing the network to learn more advanced features.

4 Results and Discussion

4.1 Loss against iteration for ANN and CNN Models

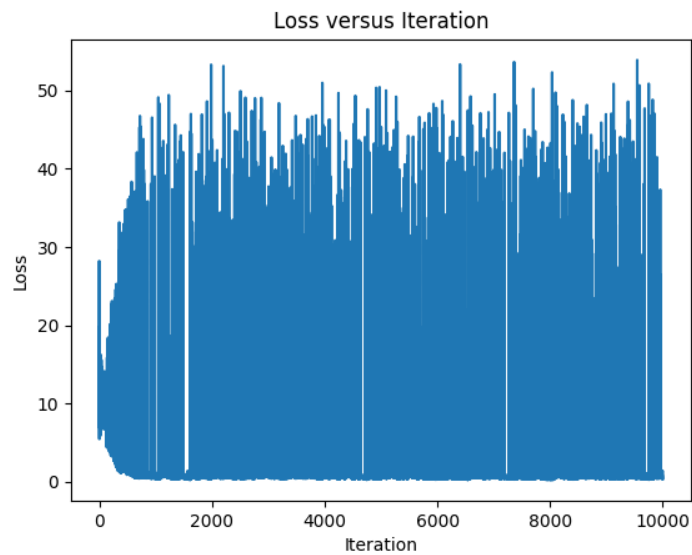


Figure 5: Loss against iteration for ANN model, trained against a random agent

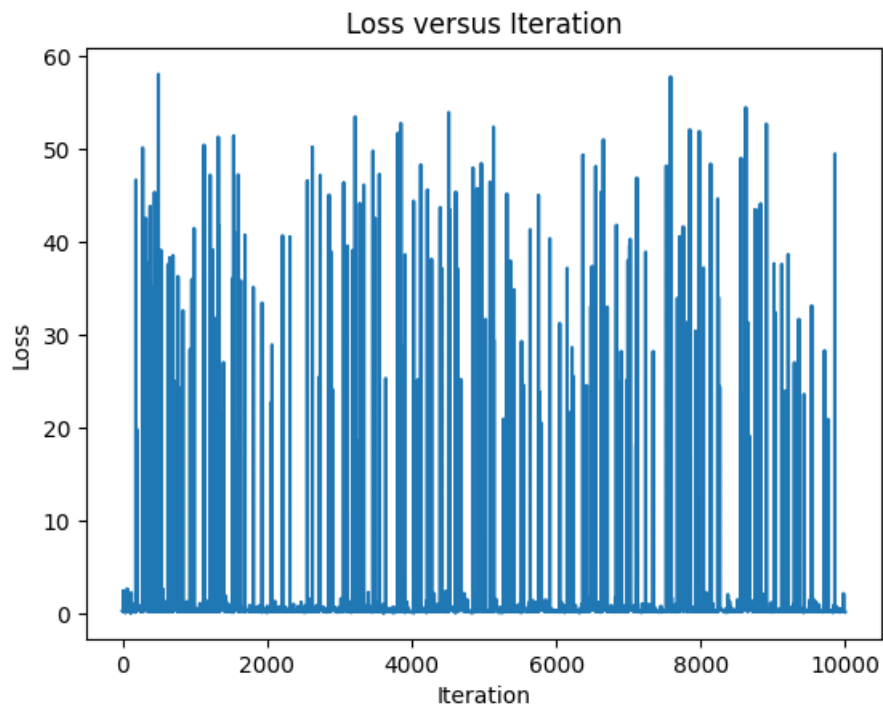


Figure 6: Loss against iteration for CNN model, trained against a random agent

The ANN and CNN value functions were trained against a random agent for 10,000 iterations, with 1 iteration being a complete Santorini game. The algorithm used to generate the reward for each state, as well as to backpropagate the loss, is mentioned in Algorithm 3. The loss displayed in the graph is the cumulative loss for each iteration. From the graph, there is a slight decreasing trend at the initial part of the graph for both ANN and CNN models, plateauing at a value close to 0.

There are also many “spikes” that can be seen protruding from the general trendline. The model, in these iterations, has not explored these states before, and this results in a state-value that is extremely different from the true state-value, thus contributing to the high loss value for each evaluated state per iteration. The cumulative sum of these losses for that iteration resulted in the spike for 1 iteration.

4.2 Loss against iteration for MCTS Models

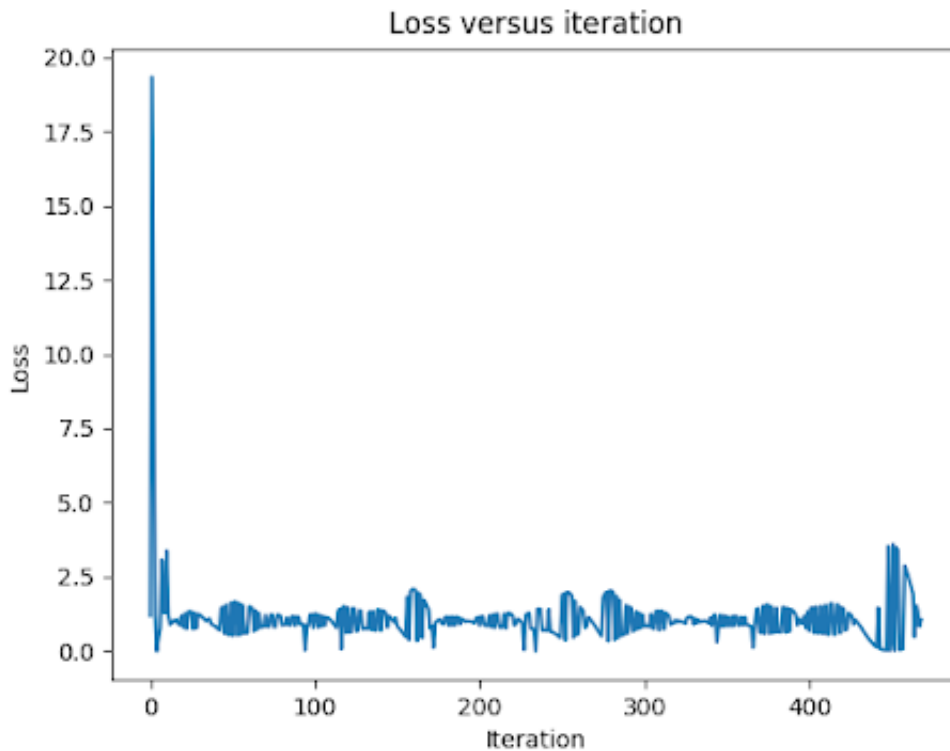


Figure 7: Loss against iteration for MCTS ANN model, trained against a random agent

The ANN model was trained using training data produced from a MCTS search tree. In total, approximately 500 nodes were explored and with each node there were about 30 simulations, this means in total the algorithm had explored about 1500 states. The loss from each node is the mean squared Error loss and is represented in Figure 5. As expected the initial loss is high in the 20s, this is due to the random weights which are

initialized whenever a new Neural Network is created. Soon after the loss quickly reduced to lower values.

As mentioned earlier, the erratic peaks and falls during the latter half of the training are primarily due to the fact that new states are encountered and the neural network needs to adjust its weights to account for this novel state.

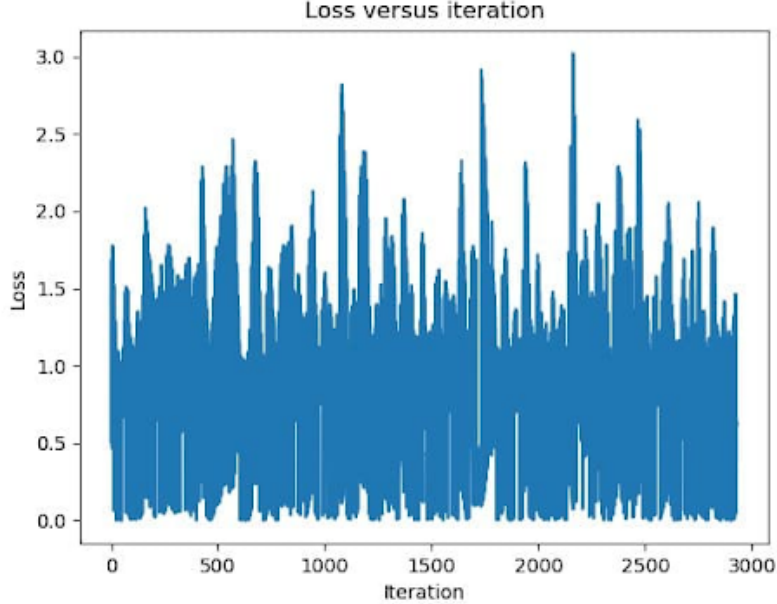


Figure 8: Loss against iteration for MCTS CNN model, trained against a random agent

The CNN model was trained using training data produced from a MCTS search tree. In total, approximately 2800 nodes were explored and with each node there were about 30 simulations, this means that about 84000 total states were explored during training. The loss from each node is the mean squared error loss and is represented in Figure 6. However, unlike with the ANN, the training loss for the MCTS CNN model is quite different. This can partly be attributed to the fact the CNN may be overestimating the value of certain features which were encountered in previous training iterations, and the time for which the MCTS algorithm ran was not long enough for the values of the different states to converge.

4.3 Relative Performance of Trained Agents

In order to assess the relative performance of the various trained agents, 200 games were simulated between each pair of agents, with the agents spending an equal amount of time in each match-up as Player A and B. (i.e. 100 games) Then, the win rate of each match-up was calculated and recorded below within Table 1. For the Linear agents, search depth was fixed at 3 throughout. The human row in the table is indicated by a Yes if a human player could beat the agent in the 3 games played against it, and No if the agent was able to win atleast 1 game played against the human player.

Win Rates										
	Random	ANN	CNN	MCTS_ANN	MCTS_CNN	Combined	Linear TreeStrap	Linear RootStrap	Linear Manual	Human
Random										
ANN	92%									
CNN	98%	60%								
MCTS_ANN	99%	54%	52%							
MCTS_CNN	100%	72%	67%	84%						
Combined	100%	94%	90%	89%	85%					
Linear (TreeStrap)	100%	88%	89%	89%	89%	67%				
Linear (RootStrap)	100%	92%	100%	91%	90%	61%	52.5%			
Linear (Manual)	100%	86%	84%	88%	87%	56%	49.5%	46%		
Human	Yes	Yes	Yes	Yes	Yes	No	No	No	No	

Table 1: Win Rate of Each Agent

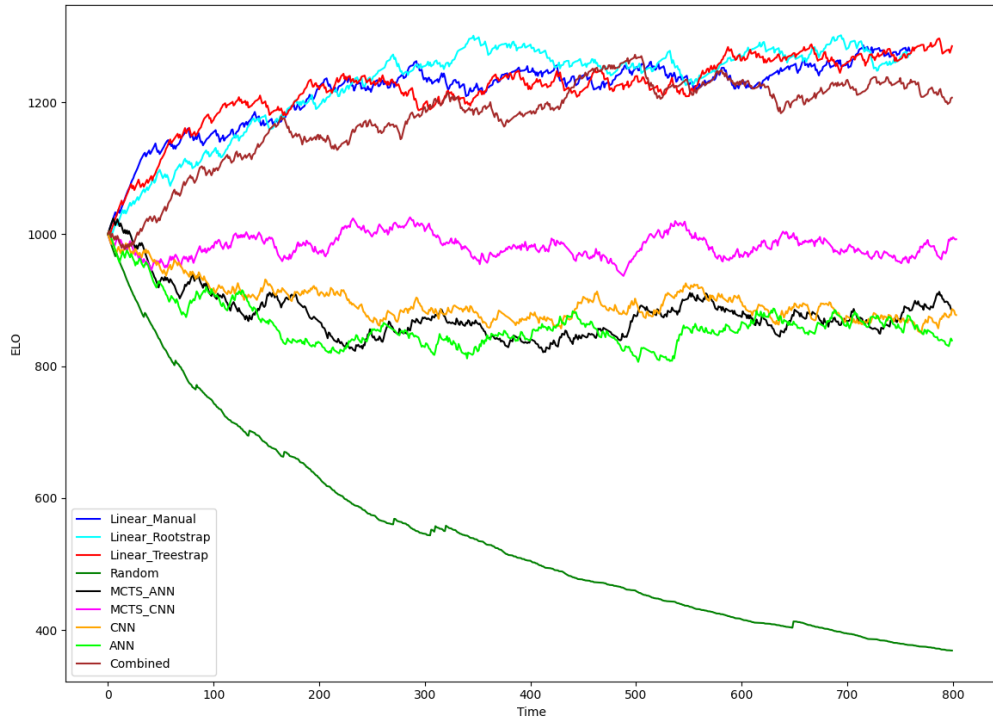


Figure 9: ELO Game Results



Figure 10: ELO Time Simulation Results

The above figures (Fig. 9 and 10) illustrate the performance of the different agents against each other. An ELO rating system was established where each agent had a base ELO rating of 1000. The first graph (Figure 9) shows the results of the win rate table in a graphical form, where each of the games played by an agent was used as the basis for the final ELO rating of that agent. The second graph (Figure 10) uses each agent's probability of winning against other agents to simulate a random tournament which lasts for a certain time t . This particular graph has t set to 30 seconds, and this was employed in the attempt to find the ELO at which each agent converges to given the win-rates in Table 1.

The Final ELO rating from the win-rate simulation are as follows:

1. Linear Rootstrap (Cyan) Final ELO : 1348
2. Linear Treestrap (Red) Final ELO : 1291
3. Linear Manual (Blue) Final ELO : 1282
4. Combined (Brown) Final ELO : 1211
5. MCTS CNN (Magenta)Final ELO : 990
6. CNN (Orange) Final ELO : 873
7. MCTS ANN (Black) Final ELO : 871

8. ANN (Lime) Final ELO : 844

9. Random (Green) Final ELO : 292

As seen from the ranking of the agents, the Linear agents did significantly better as compared to the other non-linear agents using Neural Networks, due to the fact that Neural Networks need to be trained on a very large amount of data. Although we could produce a significant amount of data, most of the data produced was using random games which do not emulate expert play. Thus the Neural Networks needed to go through multiple iterations by learning from previous versions of itself which improved upon random play. This required immense computing power which we did not have; to overcome this we used the policy created by the linear agents with the Monte Carlo Tree Search to train a Convolutional Neural Network. This approach is what we called the combined approach, and from the results, we observe that although the combined approach could not outperform the linear agents, the fact that it has performed better than its other counter-parts tells us that it had learnt the policy created by the features of the linear model (there is evidence of learning).

4.4 Limitations of the above methods

General Limitation

This study had a few limitations that were common across all methods employed. These limitations restricted further optimization and hyperparameter tuning of the models. This section will be using AlphaGo as a benchmark for model training and optimization, as AlphaGo is seen as one of the most successful agents trained using reinforcement learning for playing a board game.

1. Processing Power

The CPUs that were used to train the models were extremely limited in processing power. The models were trained mainly on a single CPU. Parallel programming was not employed due to time constraints. The GPUs that were used to perform calculations for the neural networks was a consumer-grade Nvidia GeForce GTX1060.

In comparison, the AlphaGo AI was trained using up to 1920 CPUs. The AlphaGo neural network calculations were also performed on Google's own proprietary hardware, the Tensor Processing Unit (TPUs), designed specifically for neural network training, which significantly boosted training speed [3].

- **Effects on Model Performance**

Limited processing power restricted the hyperparameter tuning that could be done for the various models.

For the CNN model, a kernel size of 3 was used, however, a kernel size of 2 could also be considered. The usage of padding could also have been evaluated. The number of features for feature map generation could not be too large, thus limiting the model's capability of detecting an increased number of features on the board. All of the above restricted the optimization of the CNN model, as

the various permutations of the hyperparameters could not be done to obtain the most optimized and best-performing model.

For the MCTS algorithm, it severely increased the run time for one iteration. With our computer specification, it would take 7 days of continuous training to be able to construct a moderately adequate search tree for training. This resulted in us having to cut down on some of the core steps of the algorithm, making a toned down version that is only able to search a depth of 8-10. These limitations also led to a reduction in the efficacy of our AI.

For the models relying on minimax search, lack of computing power limited the search depth the models could be trained at to 3, which limits eventual performance. Furthermore, hyperparameter tuning on parameters such as learning rates would be difficult to perform given the long time taken just to train one model.

2. Lack of Professional Games

Professional games between experts are essential for an agent’s learning, especially in certain methods tried out that are less effective being trained by self-play. Initially, AlphaGo was trained to simulate professional players, and this was done by training it on 30 million moves [3]. This sped up the learning process, as the agent can learn to play at a decently high level by “mimicking” professionals.

As Santorini is not played competitively, and does not have a professional competitive scene, there was a lack of data of professional games for the models to be trained on. Thus, the initial training of the models was mostly done using a random agent who made random moves, instead of ones that were logical and “winning” in nature.

• Effects on Model Performance

The initial training of agents against a random agent greatly hampered the learning rate of the models. This was due to the randomness in the random agent’s movement, such as not playing a winning move, or moving into a position of less value, which resulted in “false” wins for the agents (as the agents would have lost if it was a “rational”, or human, player), hence giving the agents a positive reward for the states when the states were actually of neutral or negative value. Therefore, this will result in a much slower convergence to the true state-value (for neural networks value function approximator) or the optimal weights for the linear features (for a linear approximator).

Additionally, the lack of available literature on Santorini also limits the amount of features that can be implemented with regards to the linear value function approximator, given that the ability to come up with informative features is heavily reliant on possessing a deep understanding of the tactics involved in playing Santorini.

3. Limitations of Pure-ANN and CNN model training

As these models were only value function approximator and do not have a policy

networks. Their performance against more robust models, such as the linear approximator is severely handicapped. This is due to the fact that the linear model had features such as centrality and number of workers on a certain level, as well as a minimax policy with a certain lookahead depth. There was no lookahead for these models as they only evaluated the next possible states (acting like a depth 1 agent), thus not learning to consider opponent moves, as well as learning to prevent the opposition from winning (such as placing a level 4 block to prevent the opponent from winning).

Training a CNN on only a random agent also prevented it from learning the true state-value, as mentioned previously. Attempts to train the CNN against itself also did not succeed, as the loss per iteration did not converge, and its performance was comparable to the CNN model trained on the random agent.

Nevertheless, the CNN model did perform well against the random agent, implying that it is learning to win by building “staircases” (moving the worker upwards, and placing consecutive building blocks to build a staircase-like structure).

5 Other Methods Explored

1. Actor-Critic and Q-learning methods

For the pure ANN and CNN models, one huge limiting factor, as mentioned in Section 4.4, is the lack of lookahead during gameplay, essentially only performing a 1 step lookahead. This severely impacted the performance of these models, compared to those with higher depths, such as the MCTS and linear models, where they looked ahead up to depth 3.

As such, for the pure value function approximators, an actor-critic method can be applied, in which there is an “actor” (a policy network) to guide the agent to make optimal actions, instead of purely relying on value function approximation.

A Deep-Q network could have also been applied to train the agent on the best possible action, instead of evaluating the state-value.

2. Genetic Algorithm

Another popular technique used in optimization problems involves the use of genetic algorithms to find an optimal set of weights for any model. This is one alternative to using Reinforcement Learning techniques. Genetic Algorithms (GA) function based on the principles of natural selection, and by emulating the biological process we can “create” an agent which is stronger than its latter forms. [5]

More specifically, the implementation of GA in Santorini requires us to create a set of N agents, all initialized with random weights. These agents can then participate in a tournament where they go against each other for a certain number of games G . At the end of G games, the winner of the tournament is selected and its weights are used to create a new generation of N agents with random changes to those weights, after which the tournament between the agent are carried out again, and this process repeats until a certain end condition like time or number of generation is met. These random changes to the winner weights resemble mutations in the natural selection process

6 Conclusion

To conclude, we have investigated various techniques for creating an AI capable of effectively playing the board game Santorini. Amongst the various techniques that were experimented with, tried-and-tested methods combining Minimax Search with RL-trained Linear Value Function Approximators were the most effective as compared to Neural Network-based methods, and this result may be attributed to our limited computational resources. However, a final combined approach which involved MCTS, linear agents, and a CNN also proved to be effective and promising. Future studies could look into other techniques that we have not tried, such as Genetic Algorithms or Deep Q-Networks, or make further enhancements and optimizations to the methods used.

References

- [1] Sutton, R. S. (2018). *Reinforcement Learning, Second Edition: An Introduction*. Cambridge, MA: The MIT Press.
- [2] Liang, Shiyu, and R. Srikant. *Why Deep Neural Networks for Function Approximation?* ArXiv:1610.04161 [Cs], Mar. 2017. arXiv.org, <http://arxiv.org/abs/1610.04161>
- [3] Silver, D., Huang, A., Maddison, C. J., Guez, A., Sifre, L., Van den Driessche, G., Hassabis, D. (2016). *Mastering the game of Go with deep neural networks and tree search*. *Nature*, 529(7587), 484-489. doi:10.1038/nature16961
- [4] Veness, J., Silver, D., Blair, A., & Uther, W. (2009). *Bootstrapping from Game Tree Search*. In *Advances in Neural Information Processing Systems*. Curran Associates, Inc..
- [5] Mallawaarachchi, V. (2020, March 01). *Introduction to genetic algorithms - including example code*. Retrieved April 14, 2021, from <https://towardsdatascience.com/introduction-to-genetic-algorithms-including-example-code>
- [6] Russell, S. J., & Norvig, P. (2010). *Artificial Intelligence: A Modern Approach* (3rd ed.). Upper Saddle River, New Jersey: Prentice-Hall.
- [7] Campbell, M., Hoane Jr, A. J., & Hsu, F. H. (2002). *Deep Blue*. *Artificial intelligence*, 134(1-2), 57-83.
- [8] Santorini game rules. (n.d.). Retrieved April 15, 2021, from <https://www.ultraboardgames.com/santorini/game-rules.php>