ALPHAZERO-BASED PROOF COST NETWORK TO AID GAME SOLVING

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ABSTRACT

In recent years, the AlphaZero algorithm has achieved super-human playing levels for many games without hand-crafted expert knowledge. Researchers have taken advantage of AlphaZero's effectiveness at learning and playing games to help in solving them. However, a strong player is not necessarily a strong solver. This paper proposes a novel approach to solving problems by modifying the training target of the AlphaZero algorithm, such that it prioritizes solving the game quickly, rather than winning. We train a Proof Cost Network (PCN), where *proof cost* is a heuristic that estimates the amount of work required to solve problems. This matches the general concept of the so-called *proof number* from proof number search, which has been shown to be well-suited for game solving. We propose two specific training targets. The first finds the shortest path to a solution, while the second estimates the proof cost. We conduct experiments on solving 15x15 Gomoku and 9x9 Killall-Go problems with both MCTS-based and FDFPN solvers. Comparisons between using AlphaZero networks and PCN as heuristics show that PCN can solve more problems.

1 INTRODUCTION

There are two main goals in the pursuit of strong game-playing agents. The first is to push the boundaries of artificial intelligence since games can be seen as simplified models of the real world. The second involves finding *game-theoretic values*, or outcomes given optimal play, for various games (van den Herik et al., 2002). These two closely related yet separate goals are commonly referred to as *playing* and *solving* games, respectively. For playing, researchers have found success in building super-human level game-playing agents for many games, including Go (Silver et al., 2017; 2016), Chess, Shogi (Silver et al., 2018), and Atari games (Schrittwieser et al., 2020; Mnih et al., 2015). Achievements for solving include checkers (Schaeffer et al., 2007), Hex up to board sizes of 9x9 (Pawlewicz & Hayward, 2013; Henderson et al., 2009), Go for board sizes up to 5x6 (van der Werf & Winands, 2009), 15x15 Gomoku (Allis, 1994), among others.

Our focus is on solving games, which entails the exploration of all possibilities, rather than a select few strong moves at every level of the game tree, in order to derive the theoretical value correctly. Previously, researchers used hand-crafted heuristics with game-specific knowledge, combined with search methods such as Monte Carlo tree search (MCTS) (Winands et al., 2008), proof number search (PNS) (Allis et al., 1994), depth-first proof number search (DFPN) (Nagai, 2002; 1999), and threat-space search (Allis et al., 1993), to solve problems by massively pruning away unnecessary branches (Schaeffer et al., 2007; van der Werf et al., 2003; Allis et al., 1996; Allis, 1994). With the great success of AlphaGo and AlphaZero, there have been attempts to combine neural networks with previous solvers to further improve game solving. For example, Gao et al. (2017) incorporated an AlphaGo-like neural network into a state-of-the-art Hex solver to solve 8x8 Hex openings more quickly, which demonstrated that neural networks can have a positive impact when combined with previous techniques and heuristics. Meanwhile, McAleer et al. (2018) also trained an AlphaZero-like agent to solve the Rubik's Cube. In addition, game solving techniques were also shown to be viable for non-game applications (Kishimoto et al., 2019; Segler et al., 2018).

However, a limitation of using these techniques is that the networks trained with the objective of strong play may not be well-suited for obtaining game-theoretic values. Since the goal of a strong player is to play moves that maximize win rates (or the highest confidence for winning), as a heuristic

it often does not choose moves that result in the fewest nodes in the search tree when solving. As an example, Agostinelli et al. (2019) pointed out that AlphaZero-like systems tend to solve problems with longer solutions. For games with a singular end state, e.g. Rubik's cube and n-puzzles, they proposed an approach that trains a cost-to-go value function that approximates the cost of finding the shortest-path solution, which can be viewed as a kind of prioritized-sweeping (Moore & Atkeson, 1993) algorithm, starting from the end state (goal). However, singular end states are often only exploitable for puzzles. Indeed, in two-player zero-sum games such as Go, Hex, Gomoku, Connect6, and many others, the game may end in too many configurations to enumerate practically. This paper presents a novel approach to solving these problems, while still tending to choose moves that lead to the fastest solutions.

In our approach, we propose a new heuristic, referred to as the *proof cost*. We give two concrete examples of how proof cost can be designed. The first acts as a "shortest path" heuristic to a proof, while the second predicts solution tree sizes. Then, we use AlphaZero training to approximate this heuristic. The resulting network is referred to as the *Proof Cost Network* (*PCN*), which can be used as a heuristic with any AND/OR tree search algorithm to improve solving efficiency.

Experiments were conducted on 15x15 Gomoku and 9x9 Killall-Go problems. The results show that PCN outperforms AlphaZero when used as a heuristic with MCTS-based and Focused DFPN (Gao et al., 2017; Henderson et al., 2009) solvers, which are both commonly used to solve games.

2 BACKGROUND

2.1 THE GAME-THEORETIC VALUE AND PROOF TREES

For a one or two-player game, the *game-theoretic value* of a game state is the best outcome that can be obtained by all players if they play optimally. In this paper, we focus on two-player games, and simplify the outcome to only include win/loss; draws are considered losses for both players[1]. A game state is said to be *solved* when the game-theoretic value for the state is obtained, and *proved/disproved* if the player to play for the state has a winning/losing outcome. In a proof, the winning player needs to ensure a winning response to all possible actions by the losing player. A *proof tree* (Pijls & de Bruin, 2001; Stockman, 1979) is an AND-OR search tree representing a strategy of answering actions such that (a) all terminal nodes are wins, (b) the winning player (the OR-player) contains at least one winning action, (c) all losing player (the AND-player) actions are enumerated, and the OR-player needs to have winning responses to each AND-player action. A *disproof tree* is the dual case of the above (with win/loss and AND/OR reversed); a *solution tree* is a general term used to describe both proofs and disproofs.

2.2 MONTE CARLO TREE SEARCH

Monte Carlo tree search (MCTS) (Coulom, 2006; Kocsis & Szepesvári, 2006) is a heuristic best-first search algorithm that iteratively repeats the following four phases: selection, expansion, evaluation, and backpropagation. In the selection phase, starting from the root node, the algorithm chooses a child node according to a specified selection criterion until a leaf node is reached. Given a state s during selection, AlphaZero selects an action a by the PUCT equation (Silver et al., 2018; Rosin, 2011):

$$a = \arg\max_a \left\{ Q(s,a) + c_{PUCT} \times P(s,a) \times \frac{\sqrt{\sum_b N(s,b)}}{1 + N(s,a)} \right\}, \tag{1}$$

where $Q(s,a) = W(s,a)/N(s,a)$ is the estimated mean win rate, $N(s,a)$ is the number of times a is selected at s, $W(s,a)$ is the number of wins, c_{PUCT} is a weight for exploration, and $P(s,a)$ is a prior knowledge heuristic. The above selected leaf then expands all children which are added to the tree. The leaf node is then evaluated. In AlphaZero, a two-head network is trained such that it outputs a policy $p(s,a)$, and a value $v(s)$. The policy is a distribution that estimates how likely each child of s will be visited during selection; $p(s,a)$ can then be used as $P(s,a)$ in eq. 1. The scalar $v(s)$ is an estimate for the game-theoretic value of s. During backpropagation we move back up the

[1] We can solve the same problem twice, once for each player; if both outcomes are losses, then we know the outcome is a draw.

selection sequence and $Q(s_i, a_i)$ is updated for all ancestors s_i by $W(s_i, a_i) \leftarrow W(s_i, a_i) + v(s)$ and $N(s_i, a_i) \leftarrow N(s_i, a_i) + 1$. While originally designed for playing, MCTS can also be used to solve games with AND-OR Boolean backpropagation. MCTS has been used to solve games and problems for Lines of Action (Winands et al., 2010; 2008), Connect4, Seki in the game of Go (Cazenave & Saffidine, 2010), and Connect6 (Wei et al., 2015).

2.3 Proof Number Search

Proof number search (PNS) (Allis et al., 1994) is a best-first search algorithm that was designed specifically for solving games. Each node is associated with two numbers: the *proof number* (*PN*) and the *disproof number* (*DN*), which are heuristics that represent the minimum required number of leaf nodes that need to be expanded to prove and disprove the node respectively. PNS largely follows the same four phases as in MCTS. What is called the *most-proving node* (*MPN*) is selected during the selection phase. Specifically, the child with the lowest PN at each OR node, or the lowest DN at each AND node is selected; the resulting leaf node is then the MPN that needs to be evaluated. Following the definition of the PN/DN, PNS therefore builds the solution tree by expanding and evaluating the least number of nodes. There are many PNS variants, one of which is the so-called depth-first proof number search (DFPN) (Nagai, 2002; 1999), which addresses the large memory requirements for large searches.

PNS was originally designed such that all newly expanded nodes initialize PN/DN values to 1/1. To improve the heuristic, domain knowledge can be used to initialize PN/DN values differently, which speeds up the search for a solution (Winands & Schadd, 2010; Wu et al., 2010; Saito et al., 2006; Kishimoto & Müller, 2005; Allis, 1994). In addition, Henderson (2010) proposed Focused DFPN (FDFPN), which uses heuristics to direct the search toward promising solutions with a technique that is often referred to as progressive widening. Specifically, progressive widening involves prioritizing search on only a portion of all possible moves. The branching factor b at an internal search node is dynamically adjusted by $b = b_{base} + \lceil \mu \times |b_{livechildren}| \rceil$, where b_{base} is set to 1, $b_{livechildren}$ is the number of all yet unsolved children of the node, and μ is a weighting constant. With an accurate heuristic, FDFPN can solve problems while searching fewer nodes than unmodified DFPN. Further, Gao et al. (2017) proposed FDFPN-CNN by incorporating the policy and value outputs from an AlphaGo-based agent as heuristics to solve 8x8 Hex. Namely, the policy was used for move ordering and the value was used to control the branching factor by $b = b_{base} + \lceil f(s) \times |b_{livechildren}| \rceil$ and $f(s) = \min\{\mu, 1 + v(s)\}$.

2.4 The AlphaZero Algorithm

AlphaZero (Silver et al., 2018) is a general reinforcement learning algorithm that can achieve superhuman level playing strength for games without requiring any expert domain knowledge. The training routine consists of two phases: self-play and optimization. In a nutshell, a two-headed neural network that outputs a policy distribution p and a value scalar v is periodically optimized with data that is collected via self-play. Self-play games are generated by running a set number of MCTS simulations with the most recently optimized neural network. In order to explore the game state space more thoroughly during self-play, Dirichlet noise Dir(α) is added to p specifically for the MCTS root node. In the optimization phase, random positions are sampled from the latest self-play games, where the network is optimized by the following loss function:

$$L = (z - v)^2 - \pi^{\mathrm{T}} \log p + c\|\theta\|^2, \tag{2}$$

where z is the ground truth outcome of the game for that position, π is the MCTS search distribution, c is an L2 regularization weight, and θ represents the network parameters. As mentioned above, the optimized network will then be used to generate the next round of self-play games.

3 Our Approach

3.1 Estimating Proof Tree Sizes

We first examine the size of a proof tree, i.e. how many nodes need to be searched to obtain a proof for a given state. Given limited time and resources, it is almost always preferable to prove a

given state by traversing as small a search tree as possible, where the ideal case is called a *minimum proof tree*. A minimum proof tree, say rooted at a node representing state s, is defined as a proof tree containing the least possible number of tree nodes, denoted by $n(s)$, for the player at s to win. For a terminal state s_T, if the game-theoretic value is a win, $n(s_T) = 1$, otherwise, it is defined to be infinity. Suppose that s has b children s_1, s_2, ..., s_b. Then the inductive definition of $n(s)$ is $n(s) = 1 + \sum_{i=1}^{b} n(s_i)$.

Unfortunately, in order to derive the *true* value of $n(s)$, we would need to traverse the game tree starting at s by induction as follows. Suppose s_T are terminal states. Then, $n(s_T) = 1$ if the player to play at s is winning, and $n(s_T) = \infty$ otherwise. Suppose s_{AND} are non-terminal AND nodes. Then, $n(s_{AND}) = 1 + \sum_{s_i} n(s_i)$ for all children s_i. Suppose s_{OR} are non-terminal OR nodes. Then, $n(s_{OR}) = 1 + \min_{s_i} n(s_i)$ for all children s_i. To obtain $\min_{s_i} n(s_i)$, we would need to search all children of non-terminal OR nodes; combined with having to search all children of non-terminal AND nodes, the conclusion is that the entire tree rooted at s will have to be searched.

In practice, when proving s, a heuristic $\bar{n}(s_i)$ that approximates $n(s_i)$ is often used. In the ideal case, $\bar{n}(s_i)$ perfectly preserves the order of $n(s_i)$, i.e. $\bar{n}(s_1) \leq \bar{n}(s_2)$ if and only if $n(s_1) \leq n(s_2)$. Then, for s_{OR}, we would only have to compute the heuristic $\bar{n}(s_i)$ for all children s_i, then choose to search the child with the smallest value. The difficulty, as is always the case in heuristic search, is in designing such a heuristic so that $\bar{n}(s_i)$ preserves the order of $n(s_i)$ as best as possible.

While prioritization according to $\bar{n}$ is straightforward for OR nodes, the AND node case requires some more thought. Theoretically, in this case $\bar{n}$ should have no effect on priority since all children need to be searched for AND nodes. In practice, with an imperfect heuristic, the order in which children of AND nodes are searched will still have implications on the solution size, regardless of which search algorithm is used (MCTS or PNS). We will discuss how the heuristic can be used for AND nodes in subsection 3.2.

3.2 The Proof Tree Size Estimate as a Training Target

Knowing that $\bar{n}(s)$ plays a critical role in the search size for OR nodes, this subsection presents our method of defining $\bar{n}(s)$. Let us assume that s is the root, is an OR node, has b children, $s_1, ..., s_b$, and that all $\bar{n}(s_i)$ are available with $\bar{n}(s_1) \leq \bar{n}(s_2) \leq ... \leq \bar{n}(s_b)$. We propose that $\bar{n}(s) := \bar{n}(s_1)$, similar to the way PNs are calculated for OR nodes in PNS. As a result, as described in subsection 3.1, the OR-player will prioritize searching s_1, or those s_i with small i. The dual case where the root is an AND node is $\bar{n}(s) := \sum_{i=1}^{b} \bar{n}(s_i)$ for all children s_i, following PNs for AND nodes in PNS. In order to design the heuristic $\bar{n}(s)$ such that it preserves the ordering of $n(s)$ as accurately as possible, a naive way as describe in the previous subsection would be to perform brute force search to obtain all the ground truths for machine learning. However, it is apparent that this is not feasible given how quickly the tree size grows as the depth increases.

Instead, we take advantage of the self-play phase in AlphaZero to collect game episodes, which are then used to learn $\bar{n}(s)$.

1. For the terminal state, the ground truths are set to 1 if the root player wins, and ∞ otherwise.
2. For all non-terminal OR nodes s_t and its child s_{t+1} in the episode, $\bar{n}(s_t)$ is set to $\bar{n}(s_{t+1})$.
3. For all non-terminal AND nodes s_t and its child s_{t+1} in the episode, $\bar{n}(s_t)$ is set to $b \times \bar{n}(s_{t+1})$, where b is the number of children for s_t.

We use $b \times \bar{n}(s_{t+1})$ for AND nodes as the training target since we do not know the values for all other siblings of s_{t+1} (recall that self-play generates single episodes), which makes it difficult to obtain $\sum_{i=1}^{b} \bar{n}(s_i)$. Effectively, we are assuming that the costs for all of s_t's children are equal to s_{t+1}'s. There are domain-specific improvements for many games to improve the accuracy of this estimate. As an example, the Gomoku position illustrated in Fig. 1 contains what is called a "four threat" (4T) for Black. We know that Black will achieve a 5-in-a-row and win if White does not block at A, so we can effectively reduce b to 1.

To differentiate the case where we use heuristics to reduce b like in the 4T example above, we will use b_{heur} to specify the number of valid children when heuristics are used, and b_{max} for the setting where we use the entire action space. We illustrate three examples for b in 15x15 Gomoku. First,

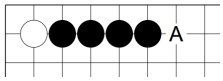


Figure 1: An illustration for different b.

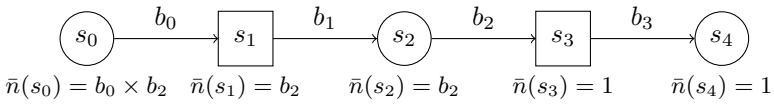


Figure 2: Estimate $\bar{n}(s)$ from an episode of a game.

b_{max} is always 225 since that is the maximum number of moves for the 15x15 board; next, if we use the game independent heuristic where we only consider legal moves, we set b_{heur} to the number of empty grids left on the board; last, if a 4T exists, as in Fig. 1, $b_{heur} = 1$.

An example episode is illustrated in Fig. 2. It starts from s_0 and ends at s_4 with a win (achieving the goal) for the OR-player; b_0 to b_3 are the branching factors of s_0 to s_3 respectively (with no loss of generality to whether b_{heur} or b_{max} is used). The heuristic function $\bar{n}(s)$ for the states in the episode are set to the following: $\bar{n}(s_3) = \bar{n}(s_4) = 1$, $\bar{n}(s_1) = \bar{n}(s_2) = b_2 \times \bar{n}(s_3) = b_2$, and $\bar{n}(s_0) = b_0 \times \bar{n}(s_1) = b_0 \times b_2$. Based on this calculation, we can see that every move counting backwards from the terminal node increases the proof cost by a factor of b equally when using b_{max}. Thus, the resulting heuristic can be seen as a measure of how many moves are left until the solution, so it can be useful for finding the shortest path to the solution.

There are some similarities and differences between our heuristic and the concept of PNs in PNS. First, PN/DN are meant to change as PNS progresses and new nodes are expanded and evaluated. In that sense, the PN/DN are a dynamic quantity used to signify the least number of nodes that need to be expanded to prove/disprove each node at that point in the search. In contrast, $\bar{n}(s)$ is a static estimate of an oracle number that represents the minimum proof tree size.

Second, PNS makes no assumptions as to which player is more likely to win, and so both PN/DN are used. In contrast, as the proof cost, $\bar{n}$ is only concerned with the difficulty of winning for one side. Since we already have self-play episodes to train from, we can add an auxiliary target $\bar{m}(s)$, which is similar to DNs. In Fig. 2, $\bar{m}(s_0) = \bar{m}(s_1) = \bar{m}(s_2) = \bar{m}(s_3) = \bar{m}(s_4) = \infty$.

Last, in PNS, the search arrives at the MPN by choosing the minimum PN at OR nodes, and the minimum DN at AND nodes. In our method, while OR nodes behave similarly in that the smallest $\bar{n}$ value is chosen, for AND nodes, we prioritize moves which have the maximum $\bar{n}$ value. The OR node estimate is most accurate when the OR-player chooses the move with the lowest $\bar{n}(s)$ value because $n(s) = 1 + \min n(s_i)$. To leverage the AlphaZero algorithm, where the two players' goals run counter to each other, the AND-player behavior should be designed such that it tries its best to oppose the OR-player, which in this case means it should pick the largest $\bar{n}$. Intuitively, the OR-player will try to prove a win as quickly as possible, while the AND-player will delay as much as it can. It is important to stress that this difference only affects how the heuristic network is trained, not how search algorithms work. In other words, the choice of the maximum $\bar{n}$ value for AND nodes is used only in the self-play phase described in subsection 2.4 when training the heuristic network.

3.3 Training the Proof Cost Network with AlphaZero

We train the Proof Cost Network (PCN) $f_\theta(s) = (p, v_n, v_m)$, with parameters θ, such that it predicts the policy distribution p, and the values v_n and v_m, corresponding to the proof cost $\bar{n}(s)$ and auxiliary $\bar{m}(s)$ for the state s. Intuitively, for p, moves with higher probabilities lead to faster solutions for s, either proof or disproof. Our method replaces the AlphaZero $v(s)$ output, which estimate the win rate (or outcome of the game z), with $v_n(s)$ and $v_m(s)$, which estimate $\bar{n}(s)$ and the auxiliary target $\bar{m}(s)$. In practice, since $\bar{n}(s)$ grows exponentially the closer s is to the root, we replace $\bar{n}(s)$ with the surrogate $l_n(s)$, where $l_n(s) = \log(\bar{n}(s))$, likewise with $\bar{m}(s)$.

With the single-sided proof cost heuristic $\bar{n}$, our method tends to perform stronger when we designate a specific player as the OR-player and attempt a proof (as opposed to solving problems without any assumptions as to the winner/loser). Thus, we need to first decide which are the AND/OR-players, e.g. knowing that Black is proven to be the winner for 15x15 Gomoku, we set Black as the OR and White as the AND-players. In the self-play phase, ideally, the OR-player should select $\arg\min_{a_i} \bar{n}(s_i)$ among all candidate moves a_i which lead to s_i. Intuitively this motivates

the self-play agent to solve s as quickly as possible. Meanwhile, the AND-player should select $\arg\max_{a_i} \bar{n}(s_i)$ to prevent the OR-player from solving the game quickly, as described in subsection 3.2.

To implement this behavior into the MCTS process for move selection during self-play, we make the following changes. In the MCTS selection phase, we still follow eq. 1, but now $Q(s, a)$ is a moving average of $v_n(s)$, representing the estimated overall mean cost of solving s with the action a. Since $Q(s, a)$ is not limited to $[-1, 1]$, we calculate $\bar{Q}(s, a)$ by normalizing $Q(s, a)$ with the following equation (similar to Schrittwieser et al. (2020)):

$$\bar{Q}(s, a) = 2 \times \frac{Q(s, a) - \min_{s,a \in Tree} Q(s, a)}{\max_{s,a \in Tree} Q(s, a) - \min_{s,a \in Tree} Q(s, a)} - 1. \tag{3}$$

Lastly, to motivate the OR/AND-player to choose small/large values of $\bar{n}$, we simply flip the value to $-\bar{Q}(s, a)$ for the OR-player.

During AlphaZero optimization, we randomly sample the self-play games and calculate $\bar{n}$ and $\bar{m}$ as described in subsection 3.2, then convert them to l_n and l_m accordingly. The network is optimized by a modified version of eq. 2, as follows:

$$L = \phi(v_n)^{\mathrm{T}} \log l_n + \phi(v_m)^{\mathrm{T}} \log l_m - \pi^{\mathrm{T}} \log p + c\|\theta\|^2, \tag{4}$$

where ϕ is a transformation function that changes scalar values to categorical representations (Schrittwieser et al., 2020).

3.4 Focused DFPN with Proof Cost Network

In this subsection, we present a method that incorporates PCN into the FDFPN solver (Henderson et al., 2009), called FDFPN-PCN. With the PCN, since the value outputs v_n and v_m are not scalars between $[-1, 1]$, we cannot directly apply them as heuristics like FDFPN-CNN (Gao et al., 2017), described in subsection 2.3.

We propose a separate method based on FDFPN and FDFPN-CNN that is able to use the PCN as a heuristic in the FDFPN solver. The fundamental search behaves just as DFPN would, including PN/DN calculation and the MPN selection mechanism, with two differences. First, we follow FDFPN-CNN where the policy output serves as move ordering, and FDFPN where the branching factor is limited by a parameter μ. Second, since v_n and v_m take inspiration from PN/DN, we can initialize PN/DN values with the PCN as follows. Let us assume we are expanding state s, at which point we will call $f_\theta(s)$. A naive way would be to set PN $= v_n(s)$ and DN $= v_m(s)$ directly. The problem is that we do not have $v_n(s_i)$ and $v_m(s_i)$ for every expanded child. Additionally, calling $f_\theta(s_i)$ for all s_i slows the entire search down. To conserve time, we initialize the PN/DN of s_i, then calculate the PN/DN of s with its children's values. If s is an OR node, we set PN $= v_n(s)$ and DN $= v_m(s)/b$ for all s_i, where b is the number of children for s. On the other hand, if s is an AND node, we set PN $= v_n(s)/b$ and DN $= v_m(s)$ for all s_i. This way, the PN/DN of s will then be $v_n(s)$ and $v_m(s)$, respectively.

4 Experiments

4.1 Training Settings

All experiments were performed by solving 15x15 Gomoku and 9x9 Killall-Go problems. We use two different *solvers*, one MCTS and the other FDFPN. The MCTS solver is an AlphaZero player with AND/OR tree logic to propagate win/loss information. The FDFPN solver follows the mechanism described in 3.4. Both solvers make use of transposition tables (Nelson, 1985) to conserve evaluation costs when identical positions are encountered during search[2].

For each experiment, we focus on comparing the number of solved problems by using different *networks* as heuristics on the same solvers. There are four network configurations: (1) no network, (2) $\alpha 0$ (AlphaZero), (3) PCN-b_{max}, and (4) PCN-b_{heur}. For fairness, we use the same training

[2]Note that we only consider the single-ko as repetition in 9x9 Killall-Go, as was the case in van der Werf et al. (2003) on solving small Go boards.

settings for each network configuration, described as follows. We run 400 MCTS simulations for each move during self-play, for a total of 1,500,000 games, and the network is optimized every 5,000 games. The network contains 5 residual blocks with 64 filters, is optimized by SGD with 0.9 for momentum, 1e-4 for weight decay, and a fixed learning rate of 0.02. We use 1080Ti GPUs for training, where the network is implemented with PyTorch (Paszke et al., 2019). Each 15x15 Gomoku training takes about 1,000 GPU-Hours, and for 9x9 Killall-Go, about 1,500 GPU-Hours. For simplicity, we select the last snapshot model for each network in our experiments.

Additional detailed settings for each game is listed as follows. In 15x15 Gomoku, the network input has 4 channels, including black and white stones in the current position, and two channels representing the turn color. The α for Dirichlet noise is set to 0.05. The maximum value (∞), used to set training targets, is set to 1600. There are two *variations* for 15x15 Gomoku: (1) NDK: no domain knowledge is provided, and (2) 4T: uses the four threat heuristic. For the NDK variation, all legal moves are considered in the solver; $b_{max} = 225$, and b_{heur} is the number of legal moves. For the 4T variation in Gomoku, whenever a 4T occurs, the solver will only consider blocking[3]; $b_{max} = 225$; $b_{heur} = 1$ with a 4T and is the number of legal moves else wise. Note that b_{max} and b_{heur} are not "branching factors" for the solver, but hyperparameters that define the training labels for $\bar{n}$ and $\bar{m}$.

9x9 Killall-Go (Cauwet et al., 2015) is similar to the game of Go except the following additional rules. Black plays four stones first on the board as shown in Fig. 4a, then White and Black play normally, as in standard Go. White wins if any white stones becomes unconditionally alive, otherwise Black wins. Namely, Black wins if and only if there are no white stones on the board at the end of the game. The network input for 9x9 Killall-Go has 18 channels, including black and white stones for the last 8 positions, and two channels representing the turn color. The α for Dirichlet noise is set to 0.2. The maximum value (∞) is set to 500. In 9x9 Killall-Go, we implement two heuristics for the solver to help the game end quickly; first is Benson's algorithm (Benson, 1976) which detects unconditional life, which we use to end the game immediately if White achieves unconditional life anywhere on the board[4]; second, we prohibit players to fill their own true eyes. There are also two variations for Go, one assuming White is the OR-player, and the other Black; recall that v_n is the proof cost estimate for the OR-player. For both variations, b_{max} is set to 82 ($9 \times 9 + 1$ for passing), and b_{heur} is set to the number of legal moves excluding filling in one's own eye.

4.2 Solving 15x15 Gomoku problems with MCTS-based Solver

A set of 77 problems are generated automatically for the experiment, described in detail in Appendix B. The results for the number of solved problems within 30 minutes are shown in Table 1. We list the node counts in Appendix C. From the table, when no domain knowledge is provided for 15x15 Gomoku, both PCN-b_{max} and PCN-b_{heur} outperform $\alpha 0$, with PCN-b_{max} being better than PCN-b_{heur}. However, by adding more knowledge, PCN-b_{heur} can close the gap in performance against PCN-b_{max} (73 vs. 77 with 4T, whereas in the NDK case, 38 vs. 43).

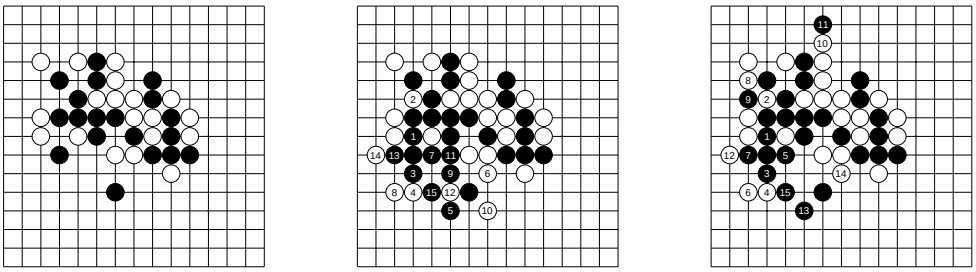
	No Network	$\alpha 0$	PCN-b_{max}	PCN-b_{heur}
15x15 Gomoku (NDK)	1 / 77	23 / 77	**43 / 77**	38 / 77
15x15 Gomoku (4T)	22 / 77	64 / 77	**77 / 77**	73 / 77
9x9 Killall-Go (OR: White)	1 / 81	28 / 81	**79 / 81**	76 / 81
9x9 Killall-Go (OR: Black)			38 / 81	**46 / 81**

Table 1: The number of problems that can be solved by MCTS-based solver within 30 minutes.

We use Fig. 3, one of the problems, to illustrate that with the help of 4T, PCN-b_{heur} can take advantage of the VCF (victory by continuous four) (gom, 2021) strategy more effectively. Fig. 3a is a problem where Black plays first and wins. Fig. 3b shows the solution following b_{heur} calculation, where Black wins using VCF. Namely, if White does not respond to any of Black's threats, Black wins directly. In b_{heur}, $l(s) \approx 0$ since the branching factor is reduced to 1 by 4T. Fig. 3c shows the solution found by PCN-b_{max}, which has the same length as PCN-b_{heur}, but move 7 (Black) is

[3]Since this changes the way the game behaves by removing all other branches, the networks training will also be affected.

[4]Like 4T, this affects the game tree, and therefore also the network training process.



(a) A 15x15 Gomoku problem. (b) Solving with PCN-b_{heur}. (c) Solving with PCN-b_{max}.

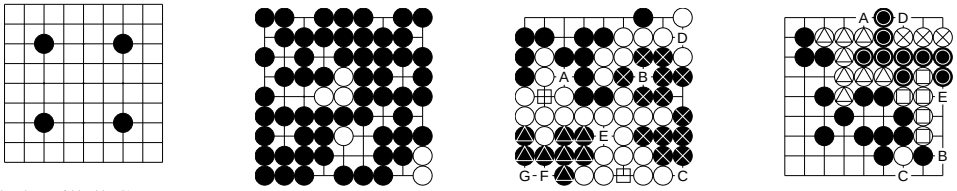
Figure 3: An illustration for using PCNs on solving 15x15 Gomoku problems.

not a 4T. This means that White has many choices, such as moves 8 and 10, that does not result in an immediate loss. All possibilities need to be searched to ensure a Black win, so limiting White choices narrows down the search and improves efficiency. With b_{max}, since the branching factor is always set to 225, the solver cannot identify 4Ts. As a result, PCN-b_{max} requires 7,090 nodes while PCN-b_{heur} only uses 2,283 to solve this problem. We expect that PCN-b_{heur} can perform even better when incorporating more domain knowledge, such as three-threats.

4.3 Solving 9x9 Killall-Go problems with MCTS-based Solver

Next, we try to solve 81 automatically generated problems for 9x9 Killall-Go. We exclude Black wins from the generated problem set because they are trivial for PCN for the following reason. The goal for Black in this game is to own the entire board. However, since we generate problems from self-play outcomes, for Black winning states close to the end of the game, e.g. in Fig. 4b, Black has many similar moves that lead to victory. In situations like these, AlphaZero-based agents are known to play passively, unnecessarily extending the game length, which is a well-known problem for MCTS-based players. In fact, the AlphaZero-based Leela Chess Zero program implemented a "moves left head" in its network to handle this issue (Forstén & Pascutto, 2019), which functions similarly to $\bar{n}$ when we use b_{max}. Whereas the "moves left head" is only used near the end of the game, PCN is used throughout a problem. As favorable as this is for PCN, it is not a fair comparison, so we excluded Black win problems from the Killall-Go set.

Now we observe results for White win problems. Both b_{max} and b_{heur} still outperform $\alpha 0$ as shown in Table 1. Note that since the baseline and $\alpha 0$ do not need to designate which side is the OR-player, they only have one result each. For the variation where White is set to be the OR-player, PCN-b_{max} can solve 79 problems while PCN-b_{heur} can solve 76 problems. Interestingly, for the variation where Black is set to be the OR-player (and v_m is used instead of v_n as the proof cost), it can still solve about half of the problems, despite the problem being White win and v_m being an auxiliary task.



(a) 9x9 Killall-Go opening. (b) A black win problem. (c) A white win problem. (d) A white win problem.

Figure 4: An illustration for using PCN and AlphaZero on solving 9x9 Killall-Go problems.

Fig. 4 shows two examples to illustrate the difference between $\alpha 0$ and our method. In Fig. 4c, a problem for White to play and win, White can become Benson safe by directly playing at A, which forms two eyes (square labels). Both PCN-b_{max} and PCN-b_{heur} only focus on A, which solves the problem directly. However, since White has many ways to win in this position, $\alpha 0$ will attempt other

moves, e.g. play at B, C, or D to kill the cross-marked black stones, or play at E, F, or G to kill the triangle-mark stones. Since the goal for AlphaZero is to win, and all of A to G can reach this goal, $\alpha 0$ does not focus on A only, spending more nodes to solve this problem.

In the problem in Fig. 4d, there is a capturing race between the three white blocks (marked as cross, triangle, and square) and the black block (marked as circle). White can win the capturing race by directly playing at A (for Black D, reply E, and for E, reply D). For another sure win, White can first extend liberties for the square-marked white blocks by making an *exchange*, a common technique in Go, where White plays at B and Black replies at C. For both winning moves at A and B, we observe that $\alpha 0$ tends to make the exchange at B first to increase the win rate, while PCN prefers the faster A. Again, exploring all possibilities is costly. So much so that $\alpha 0$ takes nearly three times the node count of PCN to solve this problem.

4.4 Solving with the FDFPN Solver

In this subsection, we try to use the FDFPN solver as described in subsection 3.4 to solve the same problems in previous subsections.

Table 2 shows the results for baseline FDFPN[5] and the three types of networks to solve problems on 15x15 Gomoku and 9x9 Killall-Go. In FDFPN, we set $\mu = 0.1$ on both 15x15 Gomoku and 9x9 Killall-Go. The result shows that both PCN-b_{max} and PCN-b_{heur} still outperform $\alpha 0$. When comparing MCTS and FDFPN solvers directly, we find that there is no clear winner. FDFPN can solve the same number of problems for 9x9 Killall-Go, while MCTS-based solver is slightly better for 15x15 Gomoku. The fact that neither DFPN nor MCTS dominates the other in solving has been corroborated by previous research (Ewalds, 2012; Wei et al., 2015). However, in either case, PCN has a positive impact on efficiency. We therefore expect PCN to be extendable to other search algorithms.

	No Network	$\alpha 0$	PCN-b_{max}	PCN-b_{heur}
15x15 Gomoku (NDK)	6 / 77	15 / 77	45 / 77	**48 / 77**
15x15 Gomoku (4T)	34 / 77	41 / 77	**71 / 77**	69 / 77
9x9 Killall-Go (OR: White)	32 / 81	76 / 81	**79 / 81**	77 / 81
9x9 Killall-Go (OR: Black)			66 / 81	68 / 81

Table 2: The number of problems that can be solved by FPNS solver within 30 minutes.

5 Discussion

The experiments demonstrate that, in general, AlphaZero-like networks can be used to enhance solving without expert knowledge. In addition, with the Gomoku 4T experiment, the results indicate that both PCN configurations can benefit from simple expert knowledge. This implies there is potential in combining hand-crafted heuristics with our general AlphaZero-assisted solving method. We note that 15x15 Gomoku has been solved by a combination of PNS, dependency-based search, and threat-space search (Allis, 1994). Nonetheless, we choose to perform experiments on Gomoku because it is a straight-forward benchmark that is well-known and often used in games. By excluding the highly specific dependency-based and threat-space search in our experiments, and by including experiments for the yet unsolved 9x9 Killall-Go, we wish to demonstrate PCN's generality and positive impact on solving efficiency, regardless of whether expert knowledge is provided. Combining PCN with powerful, highly game-specific heuristics is left as a future topic of research. A strong case that supports the idea that neural networks do not clash with hand-crafted heuristics in solving is the results presented by Gao et al. (2017), where a highly game-specific engine was combined with networks to enhance solving on 8x8 Hex. We expect that PCN can be used to solve more challenging game problems in the future with the introduction of more sophisticated knowledge. Lastly, PCN may be helpful for domains in which heuristics can be difficult to design, e.g. planning, chemistry, material science, among others.

[5]FDFPN relies on networks to provide heuristics for progressive widening and move orderings, so without a network, the baseline is implemented as DFPN.

Ethics Statement We do not foresee any subtleties in regards to ethical concerns for this research at this time.

Reproducibility Statement All experiments can be reproduced by following the instructions in the README file in the supplementary materials, including source code, problem sets, MCTS and FDFPN solvers, and the trained models used in this paper.

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A PLAYING STRENGTH

Although our method does not optimize for strongest playing strength, it is an interesting question worth investigating, since we expect playing and solving to be correlated tasks. With PCN the OR-player tends to solve (win) the game as soon as possible, which coincides with strong play. On the other hand, the goal for the AND-player is to maximum $\bar{n}(s)$; it receives the maximum reward (∞) if it wins the game. This encourages the AND-player to win the game if possible, and prevent the OR-player from winning the game as much as possible otherwise. Overall, PCN optimization preserves playing strength while prioritizing game solving.

Interestingly, the results in Table 3 show that our method is stronger than $\alpha 0$ for 9x9 Killall-Go (with a win rate of 60%), and has nearly the same playing strength as $\alpha 0$ in 15x15 Gomoku. Each experiment contains 250 games with alternating Black and White assignment.

		Win Rate (WR)	Black WR	White WR
15x15 Gomoku (NDK)	PCN-b_{max}	50.40% $\pm$ 6.21%	100.00%	0.80%
15x15 Gomoku (NDK)	PCN-b_{heur}	50.80% $\pm$ 6.21%	100.00%	1.60%
15x15 Gomoku (4T)	PCN-b_{max}	50.40% $\pm$ 6.21%	96.80%	4.00%
15x15 Gomoku (4T)	PCN-b_{heur}	50.00% $\pm$ 6.21%	100.00%	0.00%
9x9 Killall-Go	PCN-b_{max} (OR: White)	50.00% $\pm$ 6.21%	34.40%	65.60%
9x9 Killall-Go	PCN-b_{heur} (OR: White)	60.80% $\pm$ 6.07%	66.40%	55.20%
9x9 Killall-Go	PCN-b_{max} (OR: Black)	62.25% $\pm$ 6.03%	60.00%	64.52%
9x9 Killall-Go	PCN-b_{heur} (OR: Black)	60.08% $\pm$ 6.06%	53.23%	66.94%

Table 3: Comparing the playing strength between PCNs and $\alpha 0$.

B PROBLEM SET GENERATION

We generate self-play games to create the problem sets. For each self-play game, we start from the last move at the end of game and try to solve the game by using the three networks ($\alpha 0$, PCN-b_{max}, PCN-b_{heur}) with an MCTS solver. If the problem can be solved within 5 minutes, we rollback two moves and try solving the resulting larger problem. To generate problems with strong discriminating power, we repeat this process until one of the three programs cannot solve the problem within 5 minutes, upon which the problem is added into the problem set.

For 15x15 Gomoku, we choose Yixin (Sun, 2018), a strong Gomoku program that won several championships from 2012 to 2018, as the problem generating program. Self-play games were generated with one second per move. Since 15x15 Gomoku has been proven as Black win (Allis, 1994), and Yixin plays almost optimally, we only select problems with Black wins. We collect 77 problems for Black wins from two variations, 43 and 34 problems from the NDK and 4T respectively. Generally, the 34 problems is harder than 43 problems.

For 9x9 Killall-Go, since there are no open-source 9x9 Killall-Go programs, we simply use $\alpha 0$ and PCN-b_{max} to generate self-play games. The self-play games were generated with 400 simulations per move. In addition, the Dirichlet noise is maintained in order to increase the diversity of self-play games. We collect 81 problems for White wins, 39 and 42 problems from the self-play games by $\alpha 0$ and PCN-b_{max} respectively. Black wins are trivial for PCN but difficult for $\alpha 0$ (as we mention in subsection 4.3), so we exclude them from our problem set. All problem sets are included in the supplementary materials.

C DETAILS FOR SOLVING PROBLEM SETS WITH DIFFERENT SOLVERS

Table 4 to 7 and Table 8 to 11 list the node count and the time for solving 15x15 Gomoku and 9x9 Killall-Go with different network settings as heuristics on both MCTS-based and FDFPN solvers. In the table, the fewest node counts and the shortest time to solve the problems among the different settings are bolded, where dashes represent settings where the problems cannot be solved within 30 minutes. Note that the "no network" configuration searches more nodes than any of the configurations where networks are used, within the same amount of time. Each solver runs with one

CPU and one NVIDIA Tesla V100. In 15x15 Gomoku, the solver without networks can visit nearly 10,000 and 30,000 nodes on MCTS-based and FDFPN solvers respectively, while the solver with networks can only visit 600 and 1,000 nodes on MCTS-based and FDFPN solvers respectively. In 9x9 Killall-Go, the solver without networks can visit nearly 5,600 and 15,000 nodes on MCTS-based and FDFPN solvers respectively, while the solver with networks can only visit 600 and 950 nodes on MCTS-based and FDFPN solvers respectively. Despite this massive difference in node counts, network-assisted solvers can still solve more problems.

To further improve network-assisted solvers, we can use asynchronous evaluation between CPU and GPU. By doing so, the solver no longer needs to wait for the GPU to compute during evaluation. The FDFPN-CNN Hex solver by Gao et al. (2017) is one such example. In regards to the slower CNN evaluations, they state that the runtime overhead of CNN evaluation is not an issue, since the sophisticated hand-crafted Hex heuristics can be up to 10 times slower than the CNN evaluations in early positions. As a result, FDFPN-CNN can solve problems more quickly than DFPN and FDFPN (both without networks) in the same amount of time.

For 15x15 Gomoku, problems 1 to 43 are generated by NDK and problems 44 to 77 are generated by 4T. The NDK problem set is determined to be easier to solve than the 4T set because all NDK problems are solvable by the three networks trained with 4T, except for problem 6. All of these experiments can be reproduced by following the instructions in the README file in the ”PCN” directory of our supplementary code.

ID	NDK				4T			
	No Network	$\alpha 0$	PCN-b_{max}	PCN-b_{heur}	No Network	$\alpha 0$	PCN-b_{max}	PCN-b_{heur}
1	-	-	903,544	**836,419**	-	4,492	**3,051**	3,164
2	-	1,012,028	**686,546**	749,374	8,480,868	2,437	2,938	**2,416**
3	-	-	**783,765**	940,395	9,422,154	3,014	**1,962**	2,015
4	-	908,688	**635,155**	652,825	512,488	**2,571**	2,668	2,706
5	-	-	**687,892**	758,434	-	5,501	**4,063**	5,815
6	-	653,312	**638,560**	-	-	699,398	**10,735**	-
7	-	1,119,700	470,906	**433,757**	2,781,342	2,219	**1,288**	1,981
8	-	**534,685**	591,610	957,519	5,518,358	2,382	3,503	**2,006**
9	-	-	**515,801**	751,947	12,757,192	**2,700**	2,707	3,608
10	-	**862,561**	938,374	-	1,201,265	5,936	4,232	**2,851**
11	-	559,413	**361,723**	-	-	**1,681**	4,215	2,460
12	-	**94,659**	839,179	-	2,266,157	8,307	7,798	**3,484**
13	-	1,113,649	**287,016**	386,683	-	2,206	1,796	**1,268**
14	-	-	**685,446**	715,306	-	**2,868**	5,105	3,452
15	-	-	672,121	**644,224**	2,662,073	3,777	**1,680**	2,571
16	-	680,569	**568,632**	698,349	5,666,572	**4,090**	6,236	4,254
17	-	926,956	**784,247**	809,173	-	3,112	2,949	**2,878**
18	-	1,032,936	**639,561**	1,014,679	-	8,837	**2,234**	13,235
19	-	1,000,189	**93,057**	273,953	-	18,424	7,090	**2,283**
20	-	990,392	**781,816**	935,157	507,186	**2,782**	2,799	2,802
21	-	-	**651,847**	830,393	-	5,679	**4,735**	6,405
22	-	1,030,986	770,577	**639,290**	264,069	**2,577**	2,776	3,043
23	-	-	450,445	**431,117**	-	4,631	1,320	**1,281**
24	-	-	**420,275**	454,366	-	5,271	**1,758**	3,367
25	-	**395,492**	987,041	-	6,959,837	**1,618**	2,738	8,177
26	-	1,156,791	**653,604**	757,952	-	4,576	**1,717**	3,054
27	-	-	712,891	**509,584**	11,033,791	5,159	4,675	**2,758**
28	-	1,103,090	862,540	**796,669**	13,049,802	**3,423**	4,066	3,786
29	-	-	861,855	**834,637**	293,187	**2,789**	3,867	3,538
30	-	-	**652,067**	865,387	198,562	4,097	**2,097**	2,464
31	-	231,797	**69,152**	1,028,435	1,808,145	5,014	**3,957**	4,035
32	-	-	**172,368**	577,034	-	**20,016**	78,047	92,014
33	-	-	**530,040**	648,157	-	6,658	**1,775**	1,944
34	-	-	**487,206**	504,550	-	3,368	**1,254**	1,257
35	-	-	**399,652**	593,615	-	6,204	**1,788**	2,849
36	-	-	**603,235**	666,346	-	8,290	**2,770**	6,285
37	13,955,507	**465,375**	799,030	953,092	93,510	1,273	**682**	983
38	-	-	**583,851**	646,149	13,734,784	3,771	3,198	**2,951**
39	-	1,106,087	747,578	**719,157**	2,091,312	2,348	2,938	**2,115**
40	-	1,036,870	**466,665**	807,696	-	1,865	1,897	**1,861**
41	-	-	**539,523**	548,735	11,774,261	3,964	1,384	**983**
42	-	1,049,955	**719,127**	912,464	-	158,302	2,622	**2,345**
43	-	-	889,495	**762,337**	-	5,004	3,134	**2,751**

ID	NDK				4T			
	No Network	$\alpha 0$	PCN-b_{max}	PCN-b_{heur}	No Network	$\alpha 0$	PCN-b_{max}	PCN-b_{heur}
44	-	-	-	-	-	948,612	**11,816**	136,827
45	-	-	-	-	-	-	32,691	**28,290**
46	-	-	-	-	-	-	**63,209**	364,122
47	-	-	-	-	-	**233,314**	294,051	549,238
48	-	-	-	-	-	660,045	657,619	**651,482**
49	-	-	-	-	-	879,833	**536,679**	584,436
50	-	-	-	-	-	-	418,675	**209,113**
51	-	-	-	-	-	1,008,722	**35,214**	61,311
52	-	-	-	-	-	-	**478,926**	911,914
53	-	-	-	-	-	-	**61,331**	317,466
54	-	-	-	-	-	-	273,710	**249,321**
55	-	-	-	-	-	633,981	479,537	**453,190**
56	-	-	-	-	-	-	268,991	**238,730**
57	-	-	-	-	-	854,630	287,420	**284,574**
58	-	-	-	-	-	1,147,125	**464,559**	891,960
59	-	-	-	-	-	**261,682**	581,801	361,861
60	-	-	-	-	-	553,491	**72,787**	587,483
61	-	-	-	-	-	535,287	**328,709**	1,005,042
62	-	-	-	-	-	802,585	**585,090**	-
63	-	-	-	-	-	-	831,631	**294,646**
64	-	-	-	-	-	1,042,594	**342,084**	411,711
65	-	-	-	-	-	199,122	**120,191**	-
66	-	-	-	-	-	-	342,094	**304,327**
67	-	-	-	-	-	**84,050**	794,435	150,296
68	-	-	-	-	-	**198,359**	438,366	866,356
69	-	-	-	-	-	-	**376,675**	489,782
70	-	-	-	-	-	527,975	**505,992**	719,737
71	-	-	-	-	-	310,169	**267,580**	654,385
72	-	-	-	-	-	-	538,784	**272,023**
73	-	-	-	-	-	-	354,198	**304,270**
74	-	-	-	-	-	1,048,393	**415,890**	437,995
75	-	-	-	-	-	95,530	**77,530**	-
76	-	-	-	-	-	**329,171**	928,163	675,018
77	-	-	-	-	-	-	**544,247**	673,300

Table 4: The number of nodes for solving 15x15 Gomoku problems by MCTS-based solver within 30 minutes.

ID	No Network	$\alpha 0$	OR: White		OR: Black	
			PCN-b_{max}	PCN-b_{heur}	PCN-b_{max}	PCN-b_{heur}
1	-	-	437,427	**339,633**	-	785,525
2	-	-	**4,618**	33,160	-	-
3	-	-	**192,309**	211,574	-	-
4	-	-	6,555	**5,379**	10,642	12,223
5	-	1,133,362	554,846	**233,965**	877,935	1,061,766
6	-	-	156,314	**70,436**	-	-
7	-	-	**349,935**	421,157	-	925,416
8	-	-	**409,362**	449,030	-	-
9	-	-	**160,034**	201,496	-	-
10	-	-	437,794	**429,521**	-	-
11	-	-	529,023	**400,903**	-	-
12	-	-	**156,672**	182,602	586,437	440,626
13	-	-	403,117	405,541	**397,002**	454,119
14	-	-	69,294	**50,143**	-	-
15	-	61,204	**46,534**	355,033	55,525	-
16	-	-	455,218	**405,530**	-	497,717
17	-	-	**227,845**	274,924	-	791,601
18	-	666,273	**576,607**	605,017	-	693,361
19	-	-	**570,149**	574,660	-	917,036
20	-	-	70,939	**68,671**	120,887	75,346
21	-	-	491,865	**363,363**	-	-
22	-	-	453,038	**245,053**	-	830,380
23	-	-	476,680	**453,657**	-	-
24	-	**259,634**	544,990	-	-	-
25	-	-	257,715	**193,855**	1,020,210	-
26	4,009,437	-	**1,981**	2,851	137,263	3,990
27	-	-	102,884	51,444	**20,350**	45,310
28	-	550,715	368,897	**352,836**	855,787	719,720
29	-	-	**14,519**	19,203	18,116	108,653
30	-	-	325,283	**233,978**	484,467	612,807
31	-	-	340,825	**321,689**	-	536,506
32	-	1,072,229	650,540	506,066	**483,832**	507,081
33	-	699,976	670,141	658,158	790,459	**647,781**
34	-	1,152,164	136,569	**94,909**	182,727	237,083
35	-	682,934	**210,127**	330,116	549,703	335,215
36	-	889,594	362,456	**327,290**	606,410	470,420
37	-	690,280	319,203	**214,199**	241,502	249,145
38	-	660,857	782,389	656,469	**604,494**	836,375
39	-	**188,863**	1,014,805	214,094	458,387	285,908

ID	No Network	$\alpha 0$	OR: White		OR: Black	
			PCN-b_{max}	PCN-b_{heur}	PCN-b_{max}	PCN-b_{heur}
40	-	-	**391,510**	646,069	590,645	723,964
41	-	-	**381,749**	425,425	-	757,229
42	-	-	**603,583**	722,377	-	-
43	-	-	**360,083**	385,016	-	-
44	-	835,478	**134,934**	372,879	-	-
45	-	-	**49,328**	94,117	-	-
46	-	-	-	**1,016,020**	-	-
47	-	-	766,115	**618,161**	-	833,902
48	-	-	456,166	**289,890**	980,939	700,542
49	-	598,013	313,586	321,995	-	**205,000**
50	-	-	661,909	**499,206**	-	-
51	-	-	544,187	**455,409**	-	-
52	-	1,058,102	458,325	**237,500**	-	-
53	-	1,079,923	**71,166**	127,477	-	625,432
54	-	-	**165,955**	210,692	-	-
55	-	524,162	**258,051**	270,910	418,062	406,587
56	-	681,781	**294,556**	-	416,460	-
57	-	-	**429,972**	763,296	-	-
58	-	-	361,453	**278,488**	664,460	646,122
59	-	702,626	176,605	**123,341**	600,530	323,570
60	-	-	263,338	279,139	431,096	**249,955**
61	-	656,951	**10,355**	187,801	207,440	121,996
62	-	-	306,116	**241,333**	1,032,826	958,818
63	-	-	**545,717**	782,683	-	779,757
64	-	-	**353,096**	438,834	-	421,204
65	-	952,956	478,213	**463,806**	615,836	566,792
66	-	979,685	748,465	**654,854**	709,501	804,058
67	-	-	815,722	**462,405**	-	-
68	-	-	896,922	**547,063**	-	-
69	-	773,437	**85,371**	97,659	-	-
70	-	-	**536,289**	656,174	-	-
71	-	-	**758,350**	800,725	913,483	-
72	-	-	**305,553**	352,893	544,303	-
73	-	761,161	**403,713**	445,774	680,177	553,268
74	-	-	**564,561**	-	-	-
75	-	830,266	37,573	**34,223**	594,617	161,846
76	-	-	**315,803**	332,915	-	-
77	-	-	**541,111**	-	-	-
78	-	712,686	553,105	**451,014**	892,304	606,382
79	-	-	779,636	**320,105**	-	-
80	-	333,202	-	-	**144,310**	-
81	-	-	**305,263**	480,568	528,225	543,474

Table 5: The number of nodes for solving 9x9 Killall-Go problems by MCTS-based solver within 30 minutes.

ID	NDK				4T			
	No Network	$\alpha 0$	PCN-b_{max}	PCN-b_{heur}	No Network	$\alpha 0$	PCN-b_{max}	PCN-b_{heur}
1	-	-	543,160	**300,826**	2,177,195	28,632	12,195	**7,225**
2	-	1,052,180	**339,216**	575,363	390,282	3,202	**2,406**	8,729
3	-	-	**179,216**	264,336	-	-	**2,394**	2,532
4	-	-	262,151	**224,069**	2,688,024	54,325	2,610	**2,383**
5	-	-	426,690	**261,045**	1,245,999	13,423	**3,748**	4,916
6	-	-	566,537	**510,176**	-	-	10,133	**9,760**
7	-	1,081,268	180,677	**131,859**	1,459,111	3,310	**1,248**	2,092
8	-	512,308	361,114	**196,655**	1,409,132	2,689	3,627	**855**
9	-	-	375,162	**174,019**	-	292,830	**2,078**	2,498
10	-	-	**158,011**	160,819	1,437,840	26,542	2,797	**889**
11	-	**242,705**	432,620	398,452	87,376	**1,271**	3,745	3,694
12	1,187,021	**5,326**	250,782	205,715	2,497	**58**	3,990	5,932
13	-	-	265,696	**189,882**	6,610,347	164,078	**1,215**	2,867
14	-	-	**382,906**	529,466	2,022,077	11,191	**3,480**	4,308
15	-	-	**248,953**	375,955	23,691,221	2,972	**2,024**	2,035
16	-	-	646,271	**516,882**	21,022,574	7,978	**4,748**	9,440
17	-	-	**441,738**	527,535	-	199,248	5,792	**3,355**
18	-	-	254,980	**83,524**	-	4,173	**877**	8,192
19	2,076,725	**136,831**	339,247	285,687	22,819	**1,298**	4,688	8,163
20	-	-	**286,949**	318,495	894,652	13,950	**2,782**	**2,782**
21	-	-	839,876	**281,356**	-	-	**6,815**	16,147
22	-	-	323,425	**114,274**	23,531,128	3,492	**2,330**	2,472
23	6,674,096	**140,310**	419,757	196,482	18,671	**292**	1,164	2,336
24	-	-	322,051	**159,776**	34,292,960	4,162	**1,588**	**1,588**
25	-	-	1,452,491	**453,056**	-	-	**4,104**	4,389
26	-	-	641,847	**209,837**	3,227,357	**1,556**	1,606	3,296
27	-	615,044	496,379	**115,182**	975,205	5,759	**1,165**	1,167
28	-	-	508,185	**261,287**	-	-	**2,523**	2,873
29	-	363,656	741,413	**277,864**	99,310	**2,563**	5,855	4,823
30	-	-	1,241,236	**234,492**	4,750,995	13,191	**2,058**	**2,058**
31	423,196	443,681	526,924	**329,662**	3,767	**14**	6,793	7,824
32	2,698,810	156,409	**5,573**	16,313	9,891	**986**	1,942	2,499
33	-	-	**130,813**	226,744	-	839,813	**1,239**	2,520
34	-	-	253,464	**121,042**	24,304,241	44,919	**1,194**	**1,194**
35	-	430,639	**294,400**	482,790	5,816,694	**3,297**	6,354	4,420
36	-	-	1,459,236	**1,308,142**	7,288,513	1,295,829	10,432	**5,081**
37	49,658,836	159,883	44,904	**41,163**	1,007,093	465	**400**	401
38	-	-	**138,609**	258,479	-	-	**4,723**	10,196
39	-	462,126	450,905	**177,037**	235,960	2,377	**1,674**	2,471
40	-	-	**210,674**	212,195	2,526,582	61,503	2,100	**1,953**
41	-	426,269	654,285	**85,745**	34,663	1,101	**814**	1,274
42	-	-	1,378,481	**186,671**	37,091,680	625,646	**1,759**	2,770
43	-	-	645,077	**206,283**	-	4,295	3,642	**2,042**

ID	NDK				4T			
	No Network	$\alpha 0$	PCN-b_{max}	PCN-b_{heur}	No Network	$\alpha 0$	PCN-b_{max}	PCN-b_{heur}
44	-	-	-	**1,792,382**	-	-	**251,433**	267,422
45	-	-	-	-	-	-	56,306	**44,743**
46	-	-	541,211	**183,799**	34,104,016	439,562	37,161	**4,239**
47	-	-	-	-	-	-	**93,820**	159,739
48	-	-	-	-	-	-	**81,989**	1,790,298
49	-	-	-	-	-	-	480,072	**386,461**
50	-	-	-	-	-	-	-	**1,610,384**
51	-	-	-	-	-	-	**298,338**	1,033,424
52	-	-	-	-	-	-	-	**1,798,644**
53	-	-	-	-	-	-	**88,042**	125,743
54	-	-	-	-	-	-	-	-
55	-	-	-	-	-	-	356,504	**337,247**
56	-	-	-	-	-	-	-	-
57	-	-	-	-	-	-	-	-
58	-	-	-	-	-	-	**948,526**	1,584,855
59	-	-	-	-	-	1,438,345	**468,174**	982,546
60	-	-	-	-	-	-	**92,478**	114,131
61	-	-	-	-	-	-	**1,068,376**	-
62	-	-	-	-	-	-	**519,382**	958,805
63	-	-	-	-	-	-	594,017	**281,991**
64	-	-	-	-	-	-	**460,714**	597,067
65	-	-	-	-	-	-	1,081,090	**578,086**
66	-	-	-	-	21,638,030	-	**1,300,876**	-
67	-	-	-	**1,374,985**	-	69,420	57,288	**26,993**
68	-	-	-	-	-	-	**611,155**	1,490,409
69	-	-	-	-	-	-	**709,441**	1,297,859
70	-	-	**654,994**	-	-	-	**60,078**	1,507,901
71	-	-	-	-	-	-	705,697	**318,132**
72	-	-	-	**1,822,097**	-	-	**102,770**	251,269
73	-	-	-	-	-	-	-	-
74	-	-	-	-	-	-	**709,832**	-
75	-	-	-	-	-	-	**143,401**	204,409
76	-	-	-	-	-	-	**1,359,561**	-
77	-	-	-	**1,257,882**	-	130,946	88,314	**34,050**

Table 6: The number of nodes for solving 15x15 Gomoku problems by FDFPN solver within 30 minutes.

ID	No Network	$\alpha 0$	OR: White		OR: Black	
			PCN-b_{max}	PCN-b_{heur}	PCN-b_{max}	PCN-b_{heur}
1	-	**105,581**	-	251,446	-	-
2	440,072	1,185,075	**85,304**	849,589	-	1,517,593
3	-	165,180	66,414	**48,006**	282,534	254,917
4	156,629	**11,862**	25,744	58,257	402,391	598,018
5	12,225,417	134,212	**49,372**	82,856	899,547	384,364
6	**94,776**	-	229,484	-	-	-
7	-	88,568	49,381	**42,336**	327,931	92,959
8	-	324,258	99,992	**84,942**	550,406	1,204,383
9	-	91,815	**38,332**	58,377	904,472	576,223
10	-	-	**168,602**	-	-	-
11	-	**76,156**	707,040	439,179	-	-
12	-	109,511	**47,928**	65,455	166,016	158,398
13	-	91,202	**68,399**	70,416	78,761	69,916
14	913,926	139,042	**30,826**	38,837	344,542	-
15	714,249	-	594,300	-	**440,596**	-
16	-	74,575	**56,884**	73,200	716,529	649,376
17	-	104,483	67,225	**52,809**	269,910	326,266
18	-	**371,360**	404,028	764,740	-	994,024
19	-	236,576	**153,104**	175,386	538,322	454,310
20	-	**49,697**	52,844	81,449	840,154	52,794
21	-	229,227	414,353	**112,112**	-	-
22	-	68,046	352,552	**37,635**	349,411	85,562
23	-	201,110	154,734	**108,834**	-	854,835
24	-	**55,827**	-	92,276	1,152,654	735,299
25	5,751,181	**70,464**	72,376	73,656	228,755	151,235
26	**18,955**	155,636	308,769	119,415	311,918	210,555
27	267,915	**17,387**	30,025	24,954	26,811	27,820
28	-	94,007	77,754	**73,580**	1,073,040	246,813
29	160,073	20,682	4,142	**4,140**	25,690	32,209
30	6,306,634	**19,652**	41,903	41,139	116,303	74,733
31	-	123,465	176,841	**61,750**	184,350	575,231
32	-	204,057	77,380	**74,878**	432,883	207,227
33	-	453,994	455,168	**142,337**	368,747	292,738
34	9,370,462	76,096	169,268	**40,835**	173,576	-
35	18,455,057	92,739	125,019	**90,691**	959,719	207,097
36	-	130,105	187,389	**115,271**	-	555,793
37	-	365,501	191,485	**39,745**	41,332	59,091
38	-	171,239	**75,797**	92,581	153,552	96,992
39	1,325,967	**40,338**	309,778	243,186	451,765	61,551

ID	No Network	$\alpha 0$	OR: White		OR: Black	
			PCN-b_{max}	PCN-b_{heur}	PCN-b_{max}	PCN-b_{heur}
40	1,568,427	**11,062**	68,513	62,227	121,919	119,334
41	5,582,584	85,341	77,923	**49,357**	239,248	80,325
42	12,159,258	**208,083**	250,075	727,195	1,515,988	297,450
43	-	398,535	**104,223**	109,207	155,762	393,325
44	7,868,261	**51,794**	116,171	95,303	105,250	127,852
45	-	42,763	**26,045**	59,236	260,910	1,155,942
46	-	**332,714**	481,330	470,446	517,647	481,537
47	-	153,737	178,395	324,031	**105,871**	649,895
48	3,546,708	**61,985**	190,729	63,435	570,575	119,572
49	3,463,904	-	60,819	**33,260**	542,081	363,988
50	-	119,373	59,956	**57,896**	172,871	226,773
51	-	202,341	86,683	**75,376**	-	1,194,333
52	-	60,529	**27,602**	623,511	932,927	-
53	2,532,381	931,158	49,522	**43,069**	-	141,410
54	7,796,804	96,960	**28,603**	38,995	127,005	216,658
55	23,427,876	78,237	44,023	**42,123**	51,499	61,907
56	-	62,164	**58,695**	229,139	84,872	230,724
57	-	**297,229**	298,112	563,293	1,277,324	567,529
58	-	**45,637**	67,159	60,974	131,614	174,553
59	-	-	**35,303**	-	-	247,154
60	-	**76,577**	96,680	134,284	396,421	99,898
61	3,228,036	180,397	1,000,430	551,266	**45,367**	1,004,425
62	1,732,495	95,734	67,390	**53,681**	84,854	67,360
63	-	136,273	**51,063**	86,901	164,990	98,916
64	19,265,809	**94,870**	199,416	193,159	212,520	166,488
65	-	226,771	81,651	83,622	**81,599**	308,324
66	-	101,958	**52,661**	169,573	53,265	64,568
67	-	191,855	120,125	**92,385**	948,000	-
68	-	453,862	130,535	247,408	**128,594**	143,000
69	3,538,272	**40,611**	389,813	268,809	1,212,621	761,402
70	-	184,262	**141,848**	226,816	-	754,497
71	-	345,270	338,292	**135,537**	323,659	952,482
72	16,519,842	113,105	**63,087**	491,455	-	-
73	-	241,979	**108,124**	112,510	231,873	1,488,998
74	-	329,613	478,603	**108,690**	338,535	707,935
75	4,266,281	39,189	177,188	**26,459**	61,456	108,976
76	-	216,528	**162,290**	222,421	516,084	591,543
77	5,212,057	74,484	372,793	283,878	**57,896**	-
78	-	101,740	890,386	1,313,460	**75,293**	214,671
79	3,951,997	913,206	**538,557**	1,560,344	-	-
80	5,556,840	**51,665**	189,705	137,227	688,728	431,534
81	-	203,609	258,430	**116,320**	250,402	130,868

Table 7: The number of nodes for solving 9x9 Killall-Go problems by FDFPN solver within 30 minutes.

ID	NDK				4T			
	No Network	$\alpha 0$	PCN-b_{max}	PCN-b_{heur}	No Network	$\alpha 0$	PCN-b_{max}	PCN-b_{heur}
1	-	-	1,641.85	**1,391.13**	-	6.91	**5.24**	5.26
2	-	1,603.53	**1,164.22**	1,211.55	909.63	**3.79**	4.76	4.06
3	-	-	**1,285.74**	1,575.19	960.39	4.81	**3.42**	3.56
4	-	1,359.59	**1,086.16**	1,089.31	49.73	**4.16**	4.56	4.62
5	-	-	**1,156.20**	1,300.91	-	8.29	**6.80**	9.62
6	-	**985.13**	1,111.49	-	-	1,043.69	**17.64**	-
7	-	1,679.10	762.32	**713.26**	303.18	3.62	**2.41**	3.44
8	-	**818.23**	996.76	1,617.30	635.09	3.79	5.92	**3.52**
9	-	-	**872.64**	1,236.99	1,508.31	**4.40**	4.60	6.11
10	-	**1,302.95**	1,588.18	-	117.27	8.89	6.91	**5.00**
11	-	849.36	**612.68**	-	-	**2.74**	7.08	4.18
12	-	**143.59**	1,459.04	-	252.64	12.48	12.49	**5.89**
13	-	1,764.95	**473.21**	643.69	-	4.20	3.13	**2.37**
14	-	-	**1,390.14**	1,407.12	-	**4.36**	8.31	5.74
15	-	-	1,145.41	**1,110.29**	276.29	5.82	**2.92**	4.35
16	-	1,046.80	**970.73**	1,155.58	619.56	**6.34**	10.14	7.06
17	-	1,361.17	**1,341.06**	1,425.94	-	**4.90**	4.95	4.94
18	-	1,556.42	**1,133.75**	1,747.26	-	13.35	**3.89**	21.70
19	-	1,494.58	**156.03**	457.72	-	26.66	11.88	**3.89**
20	-	1,471.13	**1,323.64**	1,587.48	49.84	**4.34**	4.76	4.77
21	-	-	**1,132.25**	1,422.36	-	8.45	**7.92**	10.42
22	-	1,549.52	1,296.35	**1,055.47**	25.47	**4.38**	4.65	5.08
23	-	-	753.05	**727.39**	-	7.14	**2.41**	2.42
24	-	-	**711.89**	755.30	-	8.29	**3.07**	5.81
25	-	**606.42**	1,654.57	-	685.59	**2.62**	4.63	13.23
26	-	1,739.03	**1,103.72**	1,237.65	-	7.01	**3.04**	5.15
27	-	-	1,193.00	**827.29**	1,191.56	7.78	7.68	**4.65**
28	-	1,701.56	1,480.14	**1,336.36**	1,550.17	**5.14**	6.75	7.60
29	-	-	1,478.13	**1,373.58**	24.06	**4.41**	6.50	5.83
30	-	-	**1,051.20**	1,428.38	18.52	6.42	**3.76**	4.20
31	-	353.11	**115.50**	1,722.87	161.98	7.75	**6.60**	6.67
32	-	-	**292.02**	1,004.17	-	**29.57**	127.56	144.17
33	-	-	**887.65**	1,196.47	-	9.90	**3.10**	3.38
34	-	-	**789.29**	825.19	-	5.21	**2.31**	2.35
35	-	-	**680.09**	988.54	-	9.47	**3.20**	5.00
36	-	-	**1,011.33**	1,127.02	-	14.79	**4.76**	10.34
37	1,546.59	**727.96**	1,367.75	1,539.05	7.41	2.17	**1.41**	1.89
38	-	-	**944.65**	1,051.17	1,444.89	5.76	5.35	**5.04**
39	-	1,655.04	1,255.56	**1,201.15**	210.16	3.81	5.01	**3.68**
40	-	1,553.98	**798.03**	1,346.00	-	**3.02**	3.40	3.32
41	-	-	910.09	**900.26**	1,339.80	7.40	2.51	**1.95**
42	-	1,588.72	**1,444.92**	1,498.58	-	282.98	5.35	**4.05**
43	-	-	1,654.17	**1,261.58**	-	7.69	5.39	**4.72**

ID	NDK				4T			
	No Network	$\alpha 0$	PCN-b_{max}	PCN-b_{heur}	No Network	$\alpha 0$	PCN-b_{max}	PCN-b_{heur}
44	-	-	-	-	-	1,416.51	**18.58**	219.25
45	-	-	-	-	-	-	53.10	**47.68**
46	-	-	-	-	-	-	**107.05**	609.18
47	-	-	-	-	-	**342.41**	483.62	934.34
48	-	-	-	-	-	**963.28**	1,295.06	1,106.29
49	-	-	-	-	-	1,287.97	**908.03**	1,001.88
50	-	-	-	-	-	-	730.09	**354.13**
51	-	-	-	-	-	1,477.58	**56.31**	103.56
52	-	-	-	-	-	-	**848.60**	1,605.55
53	-	-	-	-	-	-	**103.88**	556.51
54	-	-	-	-	-	-	437.53	**404.02**
55	-	-	-	-	-	915.69	791.14	**742.92**
56	-	-	-	-	-	-	436.69	**390.40**
57	-	-	-	-	-	1,292.87	**478.50**	491.27
58	-	-	-	-	-	1,765.34	**820.44**	1,565.14
59	-	-	-	-	-	**382.00**	1,114.89	623.94
60	-	-	-	-	-	823.72	**117.10**	1,002.04
61	-	-	-	-	-	836.36	**566.13**	1,788.09
62	-	-	-	-	-	1,181.13	**998.12**	-
63	-	-	-	-	-	-	1,475.81	**510.46**
64	-	-	-	-	-	1,569.05	**554.86**	691.11
65	-	-	-	-	-	307.41	**204.81**	-
66	-	-	-	-	-	-	573.36	**503.69**
67	-	-	-	-	-	**127.16**	1,592.37	258.61
68	-	-	-	-	-	**296.08**	772.00	1,534.01
69	-	-	-	-	-	-	**646.82**	835.70
70	-	-	-	-	-	**770.25**	872.30	1,241.65
71	-	-	-	-	-	456.92	**447.29**	1,099.47
72	-	-	-	-	-	-	948.82	**477.99**
73	-	-	-	-	-	-	574.38	**495.11**
74	-	-	-	-	-	1,564.80	**680.49**	739.09
75	-	-	-	-	-	145.03	**129.98**	-
76	-	-	-	-	-	**488.09**	1,541.00	1,129.12
77	-	-	-	-	-	-	**931.98**	1,120.48

Table 8: The number of seconds for solving 15x15 Gomoku problems by MCTS-based solver within 30 minutes.

ID	No Network	$\alpha 0$	OR: White		OR: Black	
			PCN-b_{max}	PCN-b_{heur}	PCN-b_{max}	PCN-b_{heur}
1	-	-	717.29	**550.25**	-	1,308.06
2	-	-	**7.64**	53.68	-	-
3	-	-	**310.45**	455.50	-	-
4	-	-	10.95	**8.91**	17.15	19.88
5	-	1,699.97	883.03	**373.53**	1,407.40	1,716.12
6	-	-	257.29	**112.90**	-	-
7	-	-	**593.42**	692.15	-	1,574.53
8	-	-	**678.70**	760.72	-	-
9	-	-	**249.15**	318.21	-	-
10	-	-	**720.91**	743.88	-	-
11	-	-	859.67	**670.63**	-	-
12	-	-	**251.54**	314.89	960.04	701.50
13	-	-	657.45	637.39	**624.48**	728.20
14	-	-	112.69	**80.58**	-	-
15	-	92.62	**76.34**	589.04	90.74	-
16	-	-	865.33	**670.93**	-	803.47
17	-	-	**361.44**	454.74	-	1,283.96
18	-	1,016.10	**947.34**	980.16	-	1,141.83
19	-	-	930.83	**927.06**	-	1,562.77
20	-	-	114.96	**110.13**	194.30	135.16
21	-	-	859.63	**594.28**	-	-
22	-	-	710.73	**408.30**	-	1,404.40
23	-	-	776.83	**745.13**	-	-
24	-	**397.35**	923.48	-	-	-
25	-	-	409.48	**306.63**	1,665.77	-
26	713.71	-	**3.43**	4.87	219.22	6.67
27	-	-	166.86	88.92	**32.27**	73.49
28	-	813.48	590.50	**576.55**	1,420.97	1,189.86
29	-	-	**23.39**	30.57	29.27	171.38
30	-	-	516.90	**376.76**	766.32	976.99
31	-	-	562.35	**525.96**	-	885.91
32	-	1,642.09	1,051.68	848.82	**777.79**	948.32
33	-	1,055.87	1,089.96	**1,047.25**	1,287.27	1,057.17
34	-	1,786.24	226.78	**151.43**	293.71	380.98
35	-	1,047.99	**337.09**	533.51	876.26	545.96
36	-	1,413.90	699.19	**527.28**	983.93	749.81
37	-	1,026.93	525.22	**349.81**	382.59	393.80
38	-	1,021.81	1,319.52	1,045.71	**993.30**	1,335.96
39	-	**286.99**	1,639.58	346.67	753.18	486.64

ID	No Network	$\alpha 0$	OR: White		OR: Black	
			PCN-b_{max}	PCN-b_{heur}	PCN-b_{max}	PCN-b_{heur}
40	-	-	**609.87**	1,055.59	972.74	1,154.97
41	-	-	**624.47**	789.08	-	1,225.60
42	-	-	**969.97**	1,151.57	-	-
43	-	-	**581.76**	726.57	-	-
44	-	1,254.88	**214.95**	600.15	-	-
45	-	-	**82.95**	151.06	-	-
46	-	-	-	**1,691.70**	-	-
47	-	-	1,244.11	**989.85**	-	1,345.12
48	-	-	747.32	**478.10**	1,620.92	1,119.28
49	-	965.99	499.94	523.49	-	**336.27**
50	-	-	1,083.70	**819.99**	-	-
51	-	-	902.41	**734.51**	-	-
52	-	1,606.60	742.37	**375.71**	-	-
53	-	1,709.32	**113.59**	208.31	-	1,059.81
54	-	-	**270.97**	334.19	-	-
55	-	769.36	**426.23**	432.22	682.90	650.82
56	-	1,043.89	**473.24**	-	683.99	-
57	-	-	**703.08**	1,228.99	-	-
58	-	-	593.03	**459.56**	1,099.31	1,071.77
59	-	1,095.48	306.37	**195.31**	950.30	529.00
60	-	-	422.89	449.17	699.77	**404.72**
61	-	1,000.77	**17.10**	314.45	354.66	195.99
62	-	-	495.79	**377.44**	1,659.71	1,544.58
63	-	-	**853.85**	1,253.60	-	1,316.05
64	-	-	**582.64**	727.92	-	674.43
65	-	1,435.88	786.31	**730.44**	984.65	943.31
66	-	1,444.08	1,227.15	**1,057.24**	1,163.36	1,333.39
67	-	-	1,339.81	**739.78**	-	-
68	-	-	1,503.63	**961.99**	-	-
69	-	1,184.15	**140.69**	162.64	-	-
70	-	-	**856.74**	1,087.59	-	-
71	-	-	**1,205.52**	1,314.98	1,496.59	-
72	-	-	**501.21**	578.36	882.80	-
73	-	1,219.56	**634.80**	736.14	1,077.52	899.74
74	-	-	**903.23**	-	-	-
75	-	1,269.77	60.95	**55.17**	954.76	267.81
76	-	-	**512.92**	540.63	-	-
77	-	-	**989.07**	-	-	-
78	-	1,096.09	873.19	**720.92**	1,461.39	996.62
79	-	-	1,322.26	**556.49**	-	-
80	-	496.93	-	-	**237.71**	-
81	-	-	**503.55**	796.72	873.12	887.82

Table 9: The number of seconds for solving 9x9 Killall-Go problems by MCTS-based solver within 30 minutes.

ID	NDK				4T			
	No Network	$\alpha 0$	PCN-b_{max}	PCN-b_{heur}	No Network	$\alpha 0$	PCN-b_{max}	PCN-b_{heur}
1	-	-	452.58	**250.79**	92.40	34.36	14.90	**10.23**
2	-	1,089.85	**287.76**	486.31	19.31	**5.97**	6.27	13.83
3	-	-	**147.90**	219.14	-	-	5.95	**4.52**
4	-	-	225.64	**187.48**	112.61	70.03	4.27	**4.24**
5	-	-	373.72	**214.83**	57.89	17.62	**6.50**	6.62
6	-	-	483.94	**426.65**	-	-	**13.08**	13.44
7	-	1,050.54	150.95	**111.42**	67.48	5.39	**3.35**	3.98
8	-	500.92	290.77	**174.87**	64.05	4.71	5.57	**3.01**
9	-	-	315.60	**148.64**	-	353.89	**3.96**	4.40
10	-	-	131.21	**129.81**	62.44	29.35	4.42	**3.10**
11	-	**228.54**	381.68	344.47	6.07	**3.10**	5.48	5.29
12	38.44	**8.55**	204.32	171.83	2.44	**2.28**	7.15	7.14
13	-	-	225.16	**158.58**	277.23	161.44	**3.27**	5.08
14	-	-	**386.61**	428.26	87.17	16.28	**4.99**	5.81
15	-	-	**204.07**	343.96	995.42	6.11	**3.90**	3.93
16	-	-	553.34	**422.95**	935.03	12.68	**6.53**	9.81
17	-	-	**362.46**	538.79	-	265.95	7.08	**5.06**
18	-	-	213.73	**69.44**	-	7.56	**3.39**	13.55
19	**59.33**	169.88	289.70	244.17	**2.69**	4.76	6.78	9.13
20	-	-	**234.84**	279.29	41.60	16.44	**4.69**	5.61
21	-	-	701.95	**230.92**	-	-	**10.40**	18.68
22	-	-	267.92	**94.72**	952.18	6.51	**4.23**	4.37
23	196.64	171.50	339.06	**160.70**	2.71	**2.58**	3.18	4.25
24	-	-	267.21	**130.39**	1,500.09	6.97	**3.50**	3.56
25	-	-	1,344.21	**373.23**	-	-	6.21	**5.90**
26	-	-	533.24	**175.49**	137.86	4.40	**3.55**	5.78
27	-	572.92	400.28	**96.45**	43.25	8.08	**3.15**	3.15
28	-	-	419.59	**217.19**	-	-	**4.55**	4.88
29	-	309.18	645.21	**236.40**	6.10	**4.11**	7.44	6.59
30	-	-	1,082.56	**193.67**	218.66	16.67	4.00	**3.86**
31	**13.94**	389.29	447.95	272.70	2.45	**2.18**	8.07	9.72
32	77.56	150.14	**7.54**	17.33	**2.26**	3.83	4.25	5.70
33	-	-	**108.39**	187.57	-	1,036.16	**3.24**	4.62
34	-	-	229.58	**102.62**	1,047.46	48.76	3.40	**3.31**
35	-	500.48	**244.87**	396.00	257.96	6.10	9.04	**5.85**
36	-	-	1,476.63	**1,135.60**	259.40	1,704.00	13.61	**6.96**
37	1,708.60	159.03	39.99	**35.99**	45.19	2.53	2.72	**2.51**
38	-	-	**115.46**	257.76	-	-	**8.38**	12.98
39	-	462.48	462.54	**168.51**	12.81	4.15	**3.53**	4.46
40	-	-	178.03	**173.06**	105.34	68.63	**4.25**	5.05
41	-	415.11	543.92	**72.02**	3.55	3.50	4.04	**3.23**
42	-	-	1,322.47	**152.56**	1,748.07	712.34	**4.53**	6.47
43	-	-	534.58	**169.33**	-	7.06	7.06	**4.01**

ID	NDK				4T			
	No Network	$\alpha 0$	PCN-b_{max}	PCN-b_{heur}	No Network	$\alpha 0$	PCN-b_{max}	PCN-b_{heur}
44	-	-	-	**1,531.60**	-	-	**231.69**	254.88
45	-	-	-	-	-	-	54.78	**44.81**
46	-	-	479.45	**154.43**	1,365.49	552.57	35.40	**6.32**
47	-	-	-	-	-	-	**93.92**	147.53
48	-	-	-	-	-	-	**73.80**	1,535.73
49	-	-	-	-	-	-	428.07	**355.17**
50	-	-	-	-	-	-	-	**1,467.75**
51	-	-	-	-	-	-	**260.30**	975.85
52	-	-	-	-	-	-	-	**1,573.53**
53	-	-	-	-	-	-	**82.38**	122.28
54	-	-	-	-	-	-	-	-
55	-	-	-	-	-	-	323.44	**303.80**
56	-	-	-	-	-	-	-	-
57	-	-	-	-	-	-	-	-
58	-	-	-	-	-	-	**834.94**	1,385.13
59	-	-	-	-	-	1,747.38	**422.92**	1,119.64
60	-	-	-	-	-	-	**81.03**	98.32
61	-	-	-	-	-	-	**932.23**	-
62	-	-	-	-	-	-	**452.09**	857.88
63	-	-	-	-	-	-	550.55	**274.11**
64	-	-	-	-	-	-	**426.04**	559.13
65	-	-	-	-	-	-	1,260.36	**558.35**
66	-	-	-	-	**929.66**	-	1,194.21	-
67	-	-	-	**1,146.29**	-	81.16	50.39	**27.80**
68	-	-	-	-	-	-	**583.33**	1,385.67
69	-	-	-	-	-	-	**614.95**	1,148.70
70	-	-	**559.80**	-	-	-	**52.98**	1,421.51
71	-	-	-	-	-	-	606.93	**280.18**
72	-	-	-	**1,531.69**	-	-	**98.30**	229.78
73	-	-	-	-	-	-	-	-
74	-	-	-	-	-	-	**609.68**	-
75	-	-	-	-	-	-	**144.79**	215.34
76	-	-	-	-	-	-	**1,159.34**	-
77	-	-	-	**1,075.57**	-	149.06	87.45	**34.11**

Table 10: The number of seconds for solving 15x15 Gomoku problems by FDFPN solver within 30 minutes.

ID	No Network	$\alpha 0$	OR: White		OR: Black	
			PCN-b_{max}	PCN-b_{heur}	PCN-b_{max}	PCN-b_{heur}
1	-	**123.57**	-	240.92	-	-
2	**31.58**	1,427.51	83.20	942.16	-	1,695.97
3	-	198.97	62.60	**46.13**	291.05	253.62
4	**13.43**	15.10	25.76	56.57	417.85	601.96
5	886.54	156.85	**49.55**	80.30	1,144.13	406.89
6	**7.89**	-	250.80	-	-	-
7	-	103.60	49.37	**41.54**	318.74	89.22
8	-	371.78	98.65	**81.89**	581.53	1,339.79
9	-	109.20	**37.78**	55.22	900.34	587.29
10	-	-	**153.40**	-	-	-
11	-	**84.11**	725.33	463.33	-	-
12	-	130.78	**46.56**	61.71	156.09	152.95
13	-	114.65	**65.08**	71.93	77.01	68.35
14	61.45	144.57	**32.69**	37.78	334.21	-
15	**54.44**	-	624.53	-	431.13	-
16	-	85.17	**56.61**	73.32	732.51	680.38
17	-	119.74	65.52	**51.85**	261.32	314.09
18	-	434.44	**385.28**	766.47	-	1,041.93
19	-	284.36	**166.35**	179.28	549.76	446.55
20	-	64.16	**51.23**	77.72	901.22	51.33
21	-	273.99	384.46	**101.71**	-	-
22	-	69.99	325.36	**38.38**	331.10	83.25
23	-	219.83	148.88	**105.60**	-	921.71
24	-	**66.71**	-	104.04	1,166.18	728.24
25	231.02	82.18	75.33	**74.93**	278.38	157.90
26	**3.20**	183.71	319.49	119.51	338.69	225.64
27	26.03	**20.94**	31.05	26.29	31.74	28.56
28	-	104.69	75.16	**73.88**	1,093.91	246.79
29	16.22	24.03	6.18	**5.83**	25.89	31.84
30	623.01	**24.35**	40.71	39.76	115.49	70.90
31	-	144.15	183.09	**60.75**	205.21	624.58
32	-	221.47	74.58	**68.91**	453.48	194.93
33	-	582.08	477.68	**142.69**	377.24	301.71
34	960.28	91.37	172.93	**42.44**	186.74	-
35	1,198.23	104.04	121.52	**85.38**	1,052.79	203.96
36	-	151.65	184.78	**128.23**	-	545.87
37	-	434.39	185.82	39.34	**38.79**	57.92
38	-	183.02	**73.48**	88.23	148.20	93.28
39	86.48	**50.87**	314.47	232.05	440.41	61.29

ID	No Network	$\alpha 0$	OR: White		OR: Black	
			PCN-b_{max}	PCN-b_{heur}	PCN-b_{max}	PCN-b_{heur}
40	184.11	**14.31**	66.06	58.98	115.94	111.50
41	252.70	99.94	85.21	**53.00**	250.28	88.53
42	838.71	263.73	**252.75**	740.79	1,770.01	326.05
43	-	474.60	**101.17**	104.18	150.20	366.13
44	345.29	**57.68**	127.94	96.94	103.44	125.41
45	-	48.26	**26.04**	57.68	295.36	1,129.93
46	-	**432.77**	491.31	465.43	528.22	499.04
47	-	185.87	164.82	302.55	**99.48**	618.58
48	202.32	72.18	186.28	**63.25**	565.44	120.45
49	202.00	-	68.18	**36.49**	605.91	384.63
50	-	131.79	**56.36**	56.53	161.66	223.69
51	-	241.02	84.23	**77.15**	-	1,224.39
52	-	73.73	**30.88**	624.36	976.04	-
53	233.12	1,153.92	50.00	**41.29**	-	150.20
54	430.20	106.41	**26.53**	38.03	134.80	214.86
55	844.70	92.66	49.99	**46.33**	65.48	75.00
56	-	69.00	**56.28**	224.92	79.94	214.85
57	-	350.69	**281.45**	585.07	1,392.13	584.82
58	-	**54.89**	77.31	59.04	128.94	172.72
59	-	-	**36.58**	-	-	266.44
60	-	96.72	91.44	140.39	370.75	**89.89**
61	286.99	208.00	951.63	519.76	**44.48**	1,043.74
62	166.89	105.47	75.49	**54.51**	84.17	66.29
63	-	178.92	**50.21**	81.57	170.67	94.54
64	1,079.18	**108.55**	212.10	194.94	218.66	178.36
65	-	270.09	**78.17**	84.74	78.95	281.10
66	-	126.95	55.17	165.01	**51.84**	71.56
67	-	230.61	116.47	**93.38**	956.85	-
68	-	706.19	123.35	230.51	**118.42**	140.59
69	264.20	**45.12**	382.15	296.52	1,568.31	785.38
70	-	214.32	**141.80**	220.62	-	729.76
71	-	401.63	336.30	**129.38**	314.37	955.69
72	1,117.88	157.31	**63.33**	481.37	-	-
73	-	309.80	**104.24**	109.34	241.93	1,449.46
74	-	401.79	494.81	**105.64**	348.10	680.13
75	368.85	46.48	170.07	**25.79**	57.99	101.98
76	-	239.43	**153.76**	217.91	526.48	632.97
77	349.00	81.59	372.46	286.34	**54.16**	-
78	-	120.78	916.71	1,374.30	**105.49**	214.10
79	**212.18**	1,161.57	631.20	1,695.10	-	-
80	377.69	**63.16**	189.77	140.90	725.64	437.09
81	-	236.54	268.44	**113.45**	276.19	125.98

Table 11: The number of seconds for solving 9x9 Killall-Go problems by FDFPN solver within 30 minutes.