Training ANN to solve Ludo as a blackbox problem

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Abstract. This article is a hand in for the course AI2 at the University of Southern Denmark. It concerns the training of a neural network for playing LUDO. The approach is a black box approach were the network is to be trained without using any prior analysis of the LUDO game. Thus the goal is to analyse the abilities of simple training using backpropagation with moves from other LUDO players. Thus the state of the board is used without any preprocessing and no knowledge about the game is used. It is shown that the approach used is not able to cope with the complexity of LUDO. Backpropagation and trying to learn from players using GOFAI is not easily done. Though others have shown that simply using the raw input for ANN can create competent agents for solving various task. An aspect of the LUDO game is found in the effectiveness of always moving the same token when possible. This also explains why most neural networks initiated with random parameters will outperform a random player significantly.

Introduction

The idea for this article is to understand the limits of using artificial neural networks, ANN, to solve problems. Thus it is not the goal to simply create the LUDO player with the best performance, but to understand how the performance depends on the development of the network and the given input. [ME1] shows that it is possible to gain recognition and image understanding using pixels as input. Furthermore [GT1] shows that an ANN can be trained to play backgammon extremely well, where the dynamics of LUDO and backgammon are largely the same. Thus it is hypothesized that it is possible to create a LUDO player trained by backpropagation using the same information as a human player, the position of all tokens and the dice roll.

The complexity of the LUDO game, makes it impossible to make a analytical solution by simply creating a lookup table with every solution for every state [FA1]. This article tries to determine an appropriate neural network for an agent playing on level with other solutions.

The performance of the ludo player will be measured by the ratio of wins per play, thus only the amount of victories will be measured, all other positions than winner is seen as losing. To test this the LUDO player will play multiple games

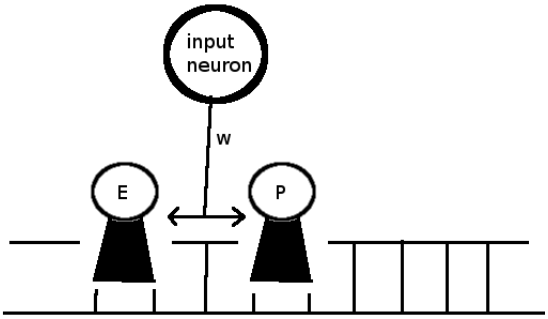


Fig. 1: Figure showing a possible preprocessed input taking the relative position of bricks into account. Thus one has decided that this factor is important for the performance of the LUDO player.

until a linearity is found, i.e. more plays wont change the relationship between wins.

The goal will be to avoid any preprocessing of parameters towards the creation of the neural network. Examples of such tweaking will be shown both to show it's strengths and why it is desirable to avoid. Neural networks are often created with preprocessed input [IC].

An example of such preprocessing can be seen by looking at the ludo game and it's dynamics. Every turn a piece is dictated to move forward, and except from stars and globes overall progress is the same. Thus one could speculate that the most important factor is hitting home. One could thus give the relationship of positions between pieces instead of all positions, as seen in figure 1.

The problem is that this isn't necessarily the best solution and could thus steer the network towards a suboptimal solution. Thus the idea is to create neural networks trained only by the knowledge that winning is positive. Seeing the LUDO game as a black-box problem.

The neural network

The neural networks were implemented using PyBrain described in [SR1]. This was done because of a desire to obtain the flexibility and ease of Python while still retaining the speed of C.

The implementation of the LUDO game was done using the simulator developed in effort with Rudi Hansen, Leon Larsen and Kent Stark Olsen. The simulator follows the rules of LUDO as described in [LU], though using danish rules with stars and globes, three tries for entry with no active pieces and always using four players.

Before training the neural networks their dimension must be decided. There exist no formal definition for how to chose the size of a network with unknown complexity. The more neurons the better it should be possible to fit the network

to the training data. Though to avoid over fitting the system when training, the network should not be to large. A standard element of neural networks is the perceptron which takes a weighted input and returns 0 or 1. Thus a combination of these could decide which brick to move. The problem is that a single layer perceptron is a linear separator and to avoid this a hidden layer is introduced [AI2]. [FM1] is an approach to train the size of perceptron networks, though given the complexity of LUDO this approach is deemed to complex.

The LUDO player developed uses a neural network to decide which token to move given the board state and dice roll. The values are scaled between 0 and 1. In ludo one cannot decide not to move any of the tokens and thus it is necessary to guarantee that the move is legal. This is done by taking the best value that gives a change in states as the move. The number of and size of the hidden layers will be described in each test, though input and output size stays the same. To train the network towards the optimal multiple procedures were explored. These methods are described in the following sections.

Imitating Human Player

The backpropagation method uses a training signal to adjust the ANN. Thus it is necessary to provide a training signal for this approach. By looking at different ludo games and measuring the procedure of the winner one could train an ANN to make winner decisions. The system is still seen as a black box as no evaluation is done on the actual moves, they are simply used by the winner.

Methods

As no data set of ludo winner moves were available an imitation were performed. Evaluation data was collected by agents taking random moves playing against each other. By a chance of 1/200 the board state and dice roll were added to a dataset. A test person evaluates the data, and chose the "perceived" optimal move. Thus a learning set were created for the back propagation algorithm. The first test is to see whether it is possible to train a neural network using datasets with an answers provided by a human. More than 200 situations were evaluated before before the training began. Using pack-propagation the neural network were trained to fit the data set, and made to play against opponent.

The training data for the human player can be found on Dropbox [1], it consist of 237 states with 17 input and 1 output, scaled to be between 0 and 1 stored as a PyBrain ClassificationDataSet.

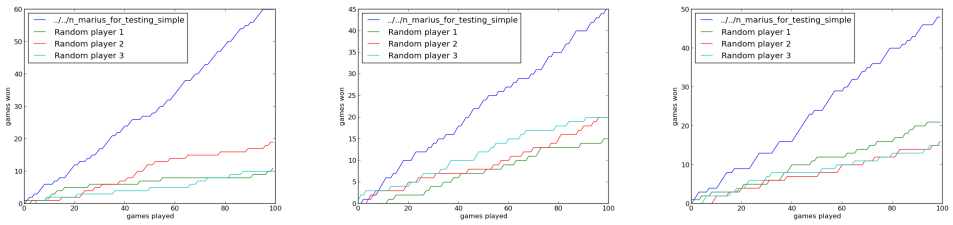
Results

For the backpropagation method the dataset were split into a training and test set with a proportion of 0.25. Quite a lot of adjustments were made for the

[1] `https://www.dropbox.com/s/i3fa0ewf9xxtyy5/marius_list_scaled.dat`

backpropagation, ending with a learning rate of 0.01 and a weight decay of 0.01. Similarly adjustments lead to a network of two hidden layers with 25 neurons using bias as this gave the best results. This gave a training error: 66.85% and a test error: 62.71% .

Figure 2 shows the result of three games 100 rounds of LUDO against three random players. It can be seen that though the neural network is not able to win all the games it is by far the most winning. Running 1000 games gives a win ratio of 0.44 for the trained agent.



(a) 100 games against 3 random opponents.

(b) 100 games against 3 random opponents.

(c) 100 games against 3 random opponents.

Fig. 2: Results of the agent trained by human input data, playing against random players. The wins for the agent is shown in blue, being the line with the steepest decent.

Analysis and Discussion

It is shown that it is possible to train a network to be able to beat the opponent. Quite a lot of tweaking were required to make the player win. And in many cases it was possible to train the network to be worse than the random player.

Imitating Another Agent

Though the human trained did perform well it could be interesting to train with a much larger dataset. A idea could be to play numerous games with random agents. For every game that resulted in a win, all data is collected, i.e. state of the board and the dice roll. Thus a dataset for wins against random agents is created.

The problem with imitating the random player is that it is not able to keep a consistent plan. As the backpropagation is trying to minimize the error between input and output. For example, when choosing which piece to move at the start after a roll of 6, the random players chose each one randomly. For a neural network it is impossible to imitate this and it would introduce error to the backpropagation fit.

A better idea would be to imitate an agent that uses a consistent plan to win. Multiple agents using GOFAI were created and the QuickPlayer were chosen. The quick player uses a simple greedy approach of always moving the furthest token which can get closets to the goal.

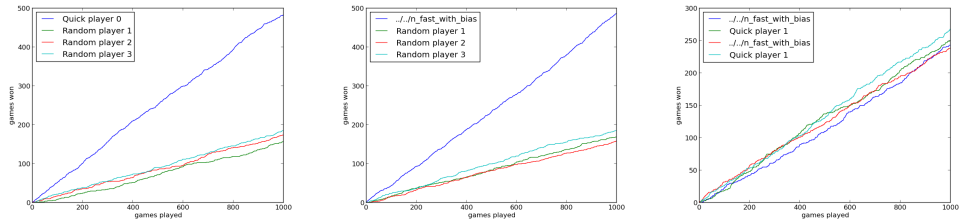
Method

To be able to predict the player better a much larger neural network were created. 100 games were played and every state and chosen move for the QuickPlayer were chosen. These were used as input for the back propagation.

Multiple runs with the backpropagation were used running with an learning rate of 0.01 and a weight decay of 0.001 as it had to run through the large data set with size 36599. With a 0.25 ratio split for testing. The backpropagation were run for 15 epochs effectively giving an error about 65 %.

Results

The results of the training can be seen in figure 3. Subfigure 3b shows the trained network against 3 random opponents. The win ratio is just below 0.5. The effectiveness of the trained network can be seen in subfigure 3b. It plays with almost the same effectiveness as the QuickPlayer with a ratio of below 0.5 wins per play. Subfigure 3c shows the two agents playing against each other. It can be seen that both QuickPlayers peform a little better than the trained networks.



(a) Result of 1000 for the QuickPlayer against 3 random opponents.

(b) Result of 1000 for the player trained by the QuickPlayers moves against 3 random opponents.

(c) 1000 games of two QuickPlayers against two trained networks.

Fig. 3: Two QuickPlayer agents against two instances of the trained ANN player.

Analysis and Discussion

Figure 3b shows very promising results towards training the network. Though the QuickPlayer is a very simple agent to train against. Especially because it

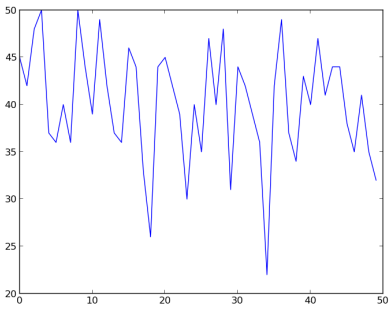


Fig. 4: Number of wins for 100 ludo games for 50 different randomly generated neural networks.

is simply dependent on which token can move to the furthest position. Thus if the bias is set so that it simply returns the same set of results every time the effect would be the same as bringing one player to the goal. When the player moves into the goal the agent would chose the token with the second best score. Effectively making it use the same strategy as the QuickPlayer, which could explain why it is able to play on equal terms. And when the ANN is trained towards this it would be very hard to correct this.

Random Neural Networks

It was seen that the trained networks did perform better than the random players. Though to test that this is actually the result of training, the effectiveness of simply using neural networks are to be tested. That is, how does any agent using randomly generated weights perform against random players.

Method

The network was made with a hidden layer of size 5 with no bias. The networks were made to be smaller as initial testing showed that networks of this size could also perform quite good, and this was intended as a simple test. Parameters were randomly generated with values between -1 and 1. 50 different neural networks playing against three random players for 100 games.

Results

The results of the multiple agents games can be seen in figure 4. Only in one of the games is the number of wins less than 25. The mean of multiple of such simulations never went below 40 wins.

Analysis and Discussion

It can be seen that simply having a plan makes the network perform better. It is possible that the scaling of inputs between -1 and 1 did have an effect in making the parameters good. Though most likely it simply stems from the fact that moving more consistently, when possible, is a better strategy than moving random.

Number of valid moves

It was seen that even a randomly generated network gives a good performance against the random player. It is thus of interest to see what kind of moves is actually returned from the neural network. That is does it give valid moves and is there any difference towards different input.

Method

To test the valid moves 100 games are played and every time the agent makes a move the ANN's priority of this move is checked. To check the consistency of the ANN 1000 different states are sampled and the output is compared.

Results

For the human and QuickPlayer trained networks the ratio of valid moves were 0.332 and 0.325 respectively. Testing the networks output for the 1000 randomly generated inputs between 0 and 1 gave the completely same result. For the QuickPlayer generated the output was [0.30486155 0.31426025 0.33858957 0.04048108] and for the human trained the output was [0.36656972 0.334266 0.06157172 0.23690873].

Analysis and Discussion

From the randomly generated data input it is seen that the trained networks simply are a clone of the QuickPlayer. Thus no actual choices are made as the bias simply overrules the input. Effectively the ANN's are simply 'dead' networks with no reaction.

Performance against other Agents

To test the effectiveness of the trained players a LUDO player developed by Leon Larsen was borrowed. This agent is also trained, but use a very different approach of learning. The opponent is a sequentially trained player using both Temporal Difference learning, TD [RS1], and backpropagation.

The learning is split into two parts to cover what is defined as the static and dynamic parameters. The static parameters are as follows, jumping by landing

on a star, requirement of the correct dice roll to enter the goal and that a dice roll of six is required to leave the start. These are seen as static parameters as they do not change during the game, landing on a star will always move one to the next star independently of the state of the game.

The dynamic parameters are the concept of hitting home tokens, and the fact that a token cannot be hit home if it is on a globe or stands together with another token. These are determined to be dynamic as the concept of hitting home is determined by the state of the game, i.e. it is only advantageous to move to a globe if there is a possibility of being hit home.

The rewards of the tiles are updated while playing the game. Only the goal is set to a reward other than zero, thus when the token encounters the goal, the tile from where it came is updated according to the learning rate. Thus are the tiles updated, while stars get a higher score as they lead to the goal more quickly, and correct dice rolls lead to the stars which gives them a higher weight. Thus an optimal path for moving towards the goal given a specific dice roll.

For training the dynamic parameters backpropagation is used. The input for the network is the immediate positions around the token, i.e. five backwards and six forwards. An enemy token gives a positive threat and a friendly token gives a negative threat. Moves are evaluated based on the threat scores on new positions. Thus using the input and the according weights a threat score is calculated. After the move is performed, the result is found, i.e. 1 hit other player home, -1 token hit home or 0 nothing happened. This signal is then used to train the weights of the network.

As it possibly takes multiply turns before a token is hit home, and thereby changing the training signal from 0. The neurons are able to store their activation for training when an actual training signal occurs. Though this is only used for training and is not part of the decision making.

Methods

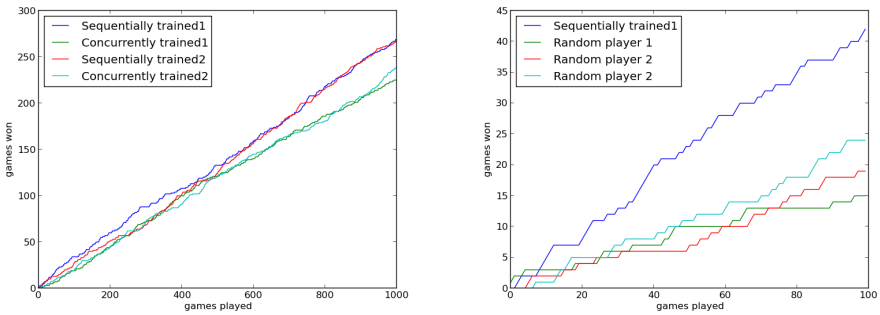
Before testing the agents against each other the Sequential player had to be trained. The Sequential player plays 100 games using and training only the static parameters. Thereafter it plays 100 games using and training the dynamic parameters. The concurrently trained run the same training, but with all training active at the same time.

Taking the best performing player from the performance test, it is tested against the two trained ANN. 100 games is played against them and the performance is measured.

Results

The results of the training can be seen in figure 5. Subfigure 5a shows the result of the sequentially and concurrently trained agents playing against each other. It is seen that the sequential players outperforms the concurrently with a small margin. Subfigure 5b shows the result of the best performing sequential network

against three random players. Though it shows better performance than the random players, it is not able to win overwhelmingly.



(a) Outcome of 1000 games of the sequentially and concurrently trained playing against each other.

(b) Result of 100 games for the sequentially trained against 3 random players.

Fig. 5: Evaluation of the sequentially trained LUDO player.

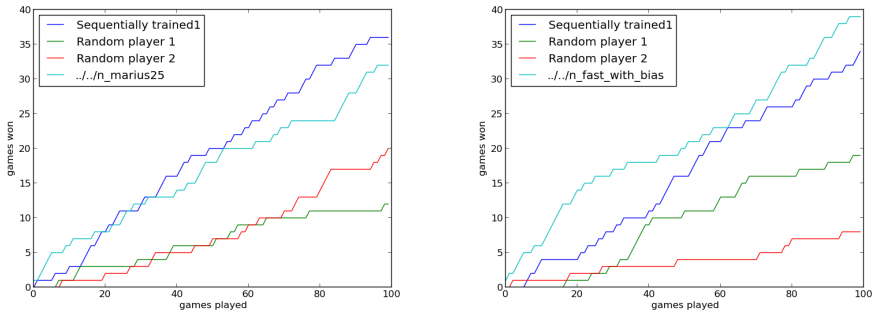
Figure 6 shows the result of the two 'dead' ANN playing against the sequentially trained network. Subfigure 6a shows that the sequentially trained network wins by a small margin whereas subfigure 6b shows that the ANN trained towards the QuickPlayer outperforms the sequentially trained player.

Analysis and Discussion

This is a very interesting result showing the effectiveness of moving one token into the goal before starting to move the next one. Though the sequential network was not trained for very long and could possibly show much better results.

Conclusion

Using the backpropagation to copy the advanced players was in this case not possible. The number and connections of the neurons could of course have been completely wrong. Though a lot of adjustments were made to the parameters and no immediate solutions were found for changing the network. The tests give an insight into the limits of artificial neural networks. To be able to train the networks properly one needs to have a proper insight to the system designing the network for. Another interesting result is the effectiveness of using a consistent plan for the LUDO player. Even though the ANN networks effectively didn't make any choices based on the input.



(a) Result of 100 games for the agent trained by human input against the Sequentially trained and 2 random opponents.

(b) Result of 100 games for the network trained towards QuickPlayer against the Sequentially trained and 2 random opponents.

Fig. 6: Results of the two trained networks against the best performing sequential network.

Perspective

Interesting results were also seen from the competition against the Sequential Player. It was actually outperformed by the ANN trained by the QuickPlayer. This gives an idea about the complexity of the LUDO game as a simple "dead" player could outperform the active player using preprocessed input. Though being able to train against the ANN trained by the QuickPlayer the Sequential could possibly outperform it drastically.

The complete set of states is a very large input. It was simply to complicated for the backpropagation used to find any consistency when using the given ANN size. Preprocessing the input could drastically reduce the input size and complexity thus making it much easier to find consistency. [KC1] shows that using genetic algorithms it is possible create a near expert level checker player. This indicates that it is not neseacarry to use preprocessed input to create a proper agent event with complex input. Indicating that this should also be the case for the implementation of LUDO.

The article [ME1] showed that pixels can be used as input for recognition. Thus creating a LUDO player taking the raw input should be possible.

It could be very interesting to test the ability to train towards GOFAI players using other approaches with the input preprocessed towards their solution. Possibly starting with a more simple version of the LUDO game to determine how to preprocess the data and determine the effectiveness of different setups. [FM1] was avoided because of the complexity of the LUDO input. Though given proper preprocessed data this would be an interesting approach to build components to determine the the fitness of moves.

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