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. It is concluded that preprocessing of data is an important aspect in learning algorithms. An interesting aspect found, in the effectiveness of not alternating the output. Which 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. 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 proverb: ”If you ain't first you're last” [1] , thus only the amount of victories will be measured. To test this the LUDO player will play multiple games 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

[1] $http://en.wikiquote.org/wiki/Talladega\_Nights:\_The\_Ballad\_of\_Ricky\_Bobby$

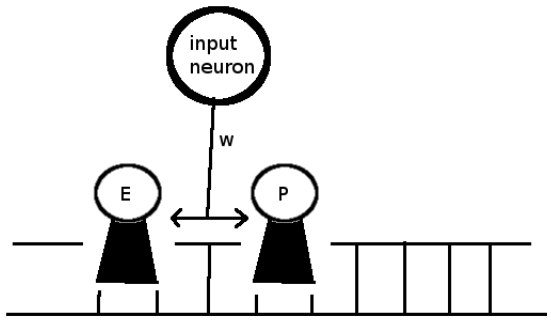


Fig. 1: Figure showing a possible preprocessed input taking the relative position of bricks into account. Thus one has decided that this factor is important for the performance of the LUDO player.

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 training data. Though to avoid over fitting the system when training, the dimension should not be to large. A standard element of neural networks is the perceptron taking 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 state and roll values. The values are scaled between 0 and 1. In ludo one cannot decide not to move any of the tokens and thus it 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. Thus 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 section.

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 create train a neuron 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.

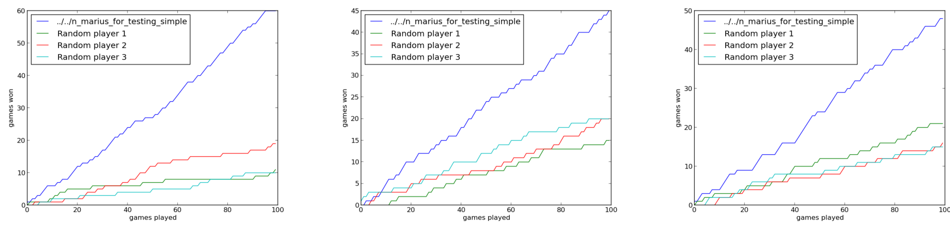
The training data for the human player can be found on Dropbox [2], it consist of 237 states with 17 input and 1 output scaled between 0 and 1, as a PyBrain ClassificationDataSet.

Results

For the backpropagation method the data set were split into a training and test set with a proportion of 0.25. Quite a lot of adjustments were made for the backpropagation, ending with a momentum 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% .

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

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.

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 some cases it was possible to train the network to be worse than the random player.

Randomly Winning

Though the human trained did perform good it could be interesting to train with a much larger dataset. Another test were performed to test the pack propagations possibility of learning simply from random games. Numerous games were played with random agents and for every game that resulted in a win, states chosen moves were collected for every round. Thus a dataset to win against random agents were created.

Method

To test what network best fitted such data, backpropagation were performed for increasingly larger neural network with along with an increasing number of training epochs. Using this data a player was created to compete against random players.

Using the optimal set of hidden neurons, an ANN was trained for 10 epochs, using a weight of 0.01 and a weight decay of 0.001. As this gave the best results.

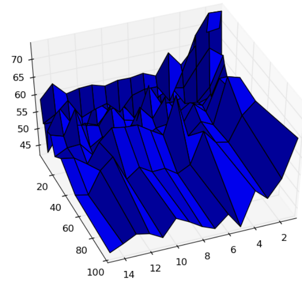


Fig. 3: Plot showing the error of the training set using different epochs and number of hidden neurons. Respectively on the right and left side.

Result

The test for lowest error can be seen in figure 3.

Fitting the data using automatically generated data. Trying to decide the optimal size to fit the data, i.e. the test data.

The result of the randomly generated player against.

Analysis and Discussion

Not surprisingly the more hidden neurons the better fit can be achieved.

Imitating Another Agent

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 from 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.

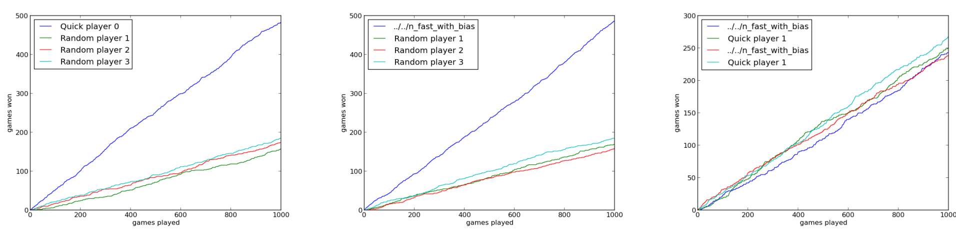
Method

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 momentum of 0.01 and a weight decay of 0.001 as it had to run through the large data set with size 36599. The backpropagation were run for 15 epochs effectively giving an error about 65 %.

Results

The results of the training can be seen in figure 4. Subfigure 4b 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 4b. It plays with almost the same effectiveness as the QuickPlayer with a ratio of below 0.5 wins per play. Subfigure 4c 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. 4: Two QuickPlayer agents against two instances of the trained ANN player.

Analysis and Discussion

Figure 4b shows very promising results towards training the network. Though the QuickPlayer is a very simple agent to train against. Especially because it 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.

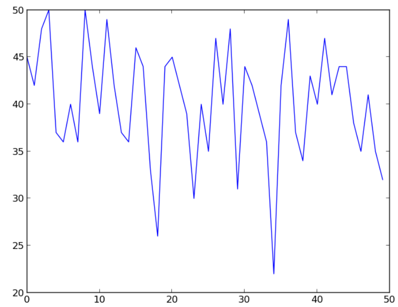


Fig. 5: Number of wins for 100 ludo games for 50 different randomly generated neural networks.

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. They were made to be simple as the weight were random [3] 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 5. 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 simply having a plan makes the network 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.

[3] why exactly

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 1000 randomly generated input between 0 and 1 gave the completely same result. I.e. 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.

Playing against other Agents

To test the effectiveness of the trained players another LUDO player was borrowed from Leon Larsen. This agent is also trained but does use quite a different approach. The opponent is a sequentially trained player using both Temporal Difference, TD [GT1], learning and backpropagation.

The learning is split into two parts to cover what is defined as static and dynamic parameters. The static parameters are as follows, jumping by landing on a star, the correct number of moves 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, land on a star will always move one to the other star independent 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. Hitting another player home depends on wheter the other

The static parameters are trained by TD learning. By moving the brick around it is calculated how ofte Whenever a game is won, the rewards of the tiles visited during the game are updated. This way the system learns about tiles that leads to victory and a strategy to maximise the rewards can be formulated.

Dynamic

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 would give a positive threat and a friendly token would give a negative threat. Moves are evaluated based on the threat scores on new positions.

Since the teacher signal is only present when an event has occurred (ie. a token was hit home) learning will only take place in that case.

To accommodate this the said neurons have been given a pseudo-recurrency property meaning that a fraction of their activation is remembered for training purposes, but are not part of the output.

Training

The ANN weights are initialised to fixed values close to zero. Four instances of the agent are trained for 200 games and then competes for 1.000 games without learning only exploiting what was learned in the training phase. Two instances are trained sequentially by running 100 games with only static rules active followed by 100 games with only dynamic rules active. The other two instances are trained for 200 games with all rules active.

Results

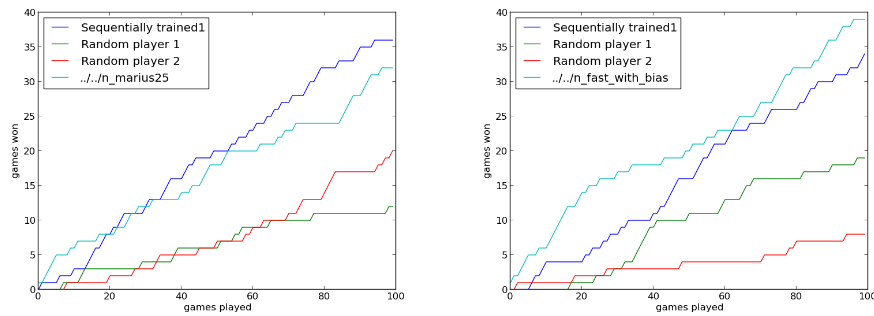
The results of the training can be seen in figure 4.

Subfigure 4b 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 4b. It plays with almost the same effectiveness as the QuickPlayer with a ratio of below 0.5 wins per play. Subfigure 4c shows the two agents playing against each other. It can be seen that both QuickPlayers peform a little better than the trained networks.

Analysis and Discussion

From the initial generation of datasets with random parameters it can be seen that all most all of them outperform the random approach. This indicates that using somewhat of a plan will outperform a completely random approach. Though testing of the trained players showed that the ANN didn't respond to any of the input, but simply relied on the fact that if the desired output wasn't possible the second best would be chosen.

Though the effect of this approach especially against the Sequentially trained player.



(a) Result of 100 for the player trained against the Sequentially trained and 2 random opponents.

(b) Result of 100 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.

Conclusion

Using the backpropagation to copy the advanced players does not seem to be able to work. The number of and shape could of course have been completely wrong. As the article [ME1] showed that pixels can be used as input for recognition.

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.

And interesting results were also seen from the fight against the Sequential Player. It was actually outperformed by the ANN simply 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 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. [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 fitness of moves.

The tests gives 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. One needs to chose proper parameters as input if the network should be able find any consistency. Thus the black box approach for training ANN seems very infeasible. [KC1] shows that using proper preprocessing it is possible to solve the LUDO problem quite effectively using neural networks thus indicating that this should also be the case for the implementation of LUDO.

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 game to determine how to preprocess the data and determine the effectiveness of different setups.

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Marius Hagelskjaer, my little brother, for sitting through and judging more than 200 different ludo states.

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