Reinforcement Learing on Board Games

A Project Report Submitted
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by

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under the guidance of

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CERTIFICATE

*This is to certify that the work contained in this thesis entitled "**Reinforcement Learing on Board Games**" is a bonafide work of **Vishal Kumar Chaudhary (Roll No. 111501030)**, carried out in the Department of Computer Science and Engineering, Indian Institute of Technology Palakkad under my supervision and that it has not been submitted elsewhere for a degree.*

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Abstract

In this project, learning through self-play algorithm has been explored and has been applied on connect4, 2048, cricket. Our task is to improve the training process of board games. During self-play, data is being generated for the model to learn. So if we create good data and explore more rewarding paths then our agent can learn quickly. For experiment purposes, we have tried the self-play algorithm in 2048 with a branching factor of 4. Further, in this project we worked on two important things.

We have introduced KL-Upper Confidence Bound (KL-UCB) and Thompson sampling for sequential game connect4. In Spite of these bound came from the solution of multi-arm bandit problem they show significant improvement over the existing bound which was being used in the algorithm.

Learning through self-play algorithm has been implemented for sequential games but we have applied this algorithm on cricket in the simultaneous environment. Simultaneous games are more complex game than its sequential form because there is always randomness involved about the opponent.

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Chapter 1

Introduction

Board games are one of the best way to test agents and reinforcement learning algorithms to test it viability.These are complex yet not too complex than that of agent in real environments. Example- chess is one of the complex game with state space of almost 10^{47} and decision tree of size 10^{123}. Similarly state space complexity of connect4 is 10^{12} and decision tree of 10^{21}. This motivates me to learn and contribute to algorithms in board games. The task of this project is to improve the learning rate of the algorithm. The traditional supervised machine learning method involves experts data and sometimes, it is not enough or the data is too noisy such that we cannot learn anything. In this project various games have been chosen depending upon its complexity to train agent within time constraints.

The project started with establishing fixing the baseline for some fixed game. We went directly to study the one of the most complex game chess. We thought to train agent with the help of dataset. But for training such network and work on big data has certain limitation. Like it requires huge computation (GPU and RAM requirements) and there should be enough examples for a certain stradegy to learn. This poses a problem that we don't know the quality of data though we had collected a good amount of data. So that stratdgy didn't worked.

We got to know about learning through self-play. We started trying to select a game that could suit our situation like low computation, trainable in days. We select 2048 game which has the branching factor of 4 which means at any given position we can have maximum of 4 valid moves. The motivation of chosing low branching factor game was to test the possibilty and scope of given algorithm. We tried and trained the 2048 and it was able to train in 2-3 hours with better results than the random moves. We tried with different type of neural network architecture. We found out that the irrespective of the network architecture, there was not significant change. So we move on applying the algorithm without changing the neural network architecture and we want to test the algorithm on some complex games with higher branching factor. We selected connect4 game with branching factor of 7. We tested and studied the algorithm of self-play and every piece of it on connect4. We established the baseline over this game and we will not change the neural network architecture in any experiments because of findings in the game 2048.

Connect4 is an example of sequential game in which player1 moves after the player2 has taken its action. So the task of agent is to take action which maximize its probability of winning. The advantage of training agent from self play is that it explores the game state space all by itself depending upon the reward it gets after taking those action.To make the probability space of more rewarding state higher, better bound should be choosen to select the action. We gave a shot to confidence interval of solutions of multi-arm bandit problem. KL-UCB [1] is found to be performing better than the Upper Confidence Bound (UCB). We applied this bound in the training process and got better results which excited us to seek for more better bound in the multi-arm bandit field. We found thompson sampling and experimented on it. We found out that it is performing as better as the KL-UCB. In the end our both results are being better than result of baseline which use UCB.

With the given achievement in sequential games, we also wanted to try on simultaneous games. Simultaneous games are the game in which both player make their move at the same time. So there is randomness involved and the agent have to choose action considering

the possible move made by adversary. There is only a very little work on this area. We have taken cricket game in simultaneous environment.So we have bowler team and they chooses which bowler to bowl for the over. We have also batting team which choses shot which can be go run for $0, 1, 2, 4, 6$ irrespective of the knowledge of the bowler. This shot from the batting team is fixed for the whole over for the simplicity of game. The motive of bowling network is to minimize the number of runs made instead number of matches won whereas the motive of batting network to score runs. Since we want to investigate the learning through self-play in simultaneous game which is much harder for network to learn than the sequential games, we made this cricket environment to be simple and easy to investigate.

Chapter 2

Review

2.1 Reinforcement learning by self-play

The traditional algorithm involves training agent with help of expert data, guidance or hard coded heuristic in that domain. They also don't discover paths which was not present in data. Reinforcement learning through self-play [2] is the state of art algorithm for board game agent. In this algorithm, the agent learns new things by themselves without any human intervention. This algorithm has three parts, self-play, training, selection of new best agent. The agent tries to improve on the previous version of itself. This type of algorithm was not possible before because it requires a lot of computating power. It is very different to other supervised algorithms which requires a good source of data and the model is dependent upon the noise in data. But in the above algorithm it does not require data from outside, rather it create data by selecting highly probable and rewarding moves.

2.1.1 Self-play

The agent learns from the examples created by its previous version. There is one neural network f_θ which predicts actions probability and probability of winning if it played with

itself (meaning same policy) from that state.

$$(p, v) = f_\theta(s)$$

. So (p, v) is the prediction of the network. With the help of this network combined with tree search, it produces better strategy for agent in next iteration. The tree search involved is Monte Carlo Tree Search (MCTS) [2].

After doing serveral MCTS iterations, one can estimation action probability with the help of number of visits taken to other state after taking action a. $\pi_a \propto N(s, a)^\tau$ where $N(s, a)$ is the number of time a action has been taken from state s and τ is temperature parameter. z is win or lose at the end of game. So (π, z) is the examples created after the self play and π is supposed to be better policy than the p because of the tree search simulations. The exisiting method uses upper confidence bound for action selection. Our method differs here using different bound for action selection. The bound used are being KL-UCB [1] and Thompson sampling [3]

2.1.2 Training

As previously mentioned, there is one neural network with two head one predicting policy and other probability of wining. We train this neural network with (π, z) data.

$loss = (z - v)^2 + \pi^T log(p)$

2.1.3 Selection of Model

Selection of neural network is done with the help of tournaments between the new trained version of neural network and the previous neural network which was before training with the new data. Depending upon the thresold we decide the new network as our best network or not.

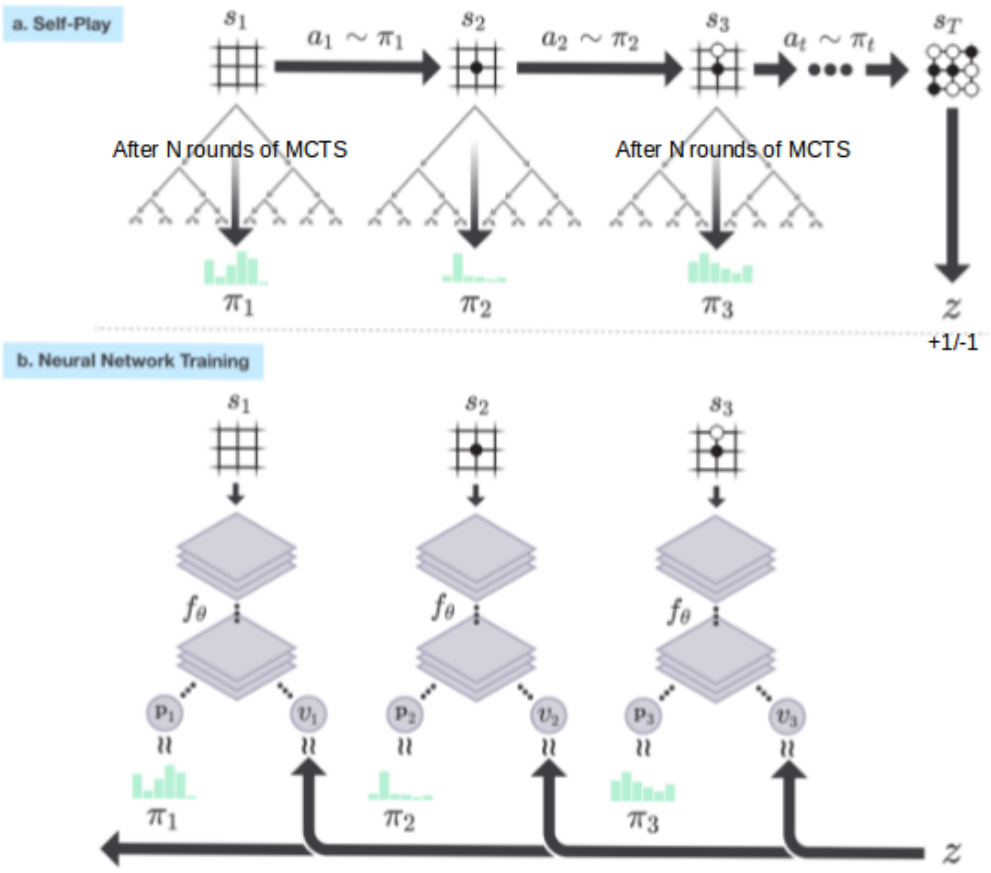

Fig. 2.1 a. self-play: each action $a \sim \pi$ is done after N simulation and single example is created with values depending upon lose or win and probability depending upon number of actions taken. b. Neural network is trained with the examples created during self-play

2.2 Confidence bound

So far Upper confidence bound is being using during the Monte Carlo Tree Search (MCTS)[4] which minimize the regret.

$$A_t = argmax_i \left\{ Q_i(t-1) + \sqrt{\frac{2 * \log N}{N_i}} \right\}$$

A_t is action taken at time t, Q_i is average reward after taking i^{th} action, N is total number of simulations and N_i is number of time i^{th} action has been taken.

2.3 Simultaneous game

There is only little work done on reinforcement learning on simulataneous game. One work we found is on the game Goofspiel. We wanted to know whether this learning setup through self-play with MCTS can be applied over this kind of games also or not.

2.4 Conclusion

This UCB [**?**] variant called UCB1 which reaches to its optimal value i.e minimizing regrets asymtotically. The method for action selection during self-play in Monte Carlo Tree Search is done with this confidence bound and it is the core part of Tree search. So improving or using better confidence interval promises better results.

Also exploring the scope of the algorithm to more random field(simultaneous games) can be fruitful.

Chapter 3

Confidence Bound

Game which have been used to test the validity of the algorithm is connect4. Connect4 is a two player game. So the agent have to chose one valid action depending on the board state in such way that he will win the game. This problem is similar to multi-arm bandit problem in which one has to chose arm to maximise the reward or which minimize the regret.

3.1 KL-UCB

During the self play and doing Monte Carlo Tree Search(MCTS), we are using KL-UCB to select action given the history of rewards. In multi-arm bandit problem, KL-UCB has less regret than the UCB. We want to see whether this also work and improves the learning time of agent.

For each state and action of game we store reward during self play and the create data for agent to learn upon those examples.

Step 1: For a state having k valid actions

Step 2: Choose every action once.

Step 3: Then choose A_t action at t - time

$$A_t = argmax_i \ \max \left\{ x \in [0,1] : d(\hat{x}_i(t-1), x) <= \frac{\log N}{N_i} \right\}$$

3.2 Baseline results

Baseline for above algorithm is using UCB1 as it confidence bound in MCTS during self-play. The rest of the setup like Neural Network Architecture, hyperparameters remains same for both the experiments.

3.3 Experiment

Instead of using UCB in the action selection process during MCTS we are using KL-UCB. All other environment parameters remain same as that of Baseline. We calculate training loss and compare with the baseline. Moreover we also do tournament matches between baseline and new model for ensuring the result.

Baseline in master branch and kl-ucb on this branch.

`https://github.com/vishalkumarchaudhary/connect4/tree/kl-ucb`

3.3.1 Results

Moreover when the KL-UCB models had tournament with UCB1 models, 52 wins , 39 loses and 9 draws were the average roundup results over 10 such models. This show that the new model is learning at faster and better rate than the previous model.

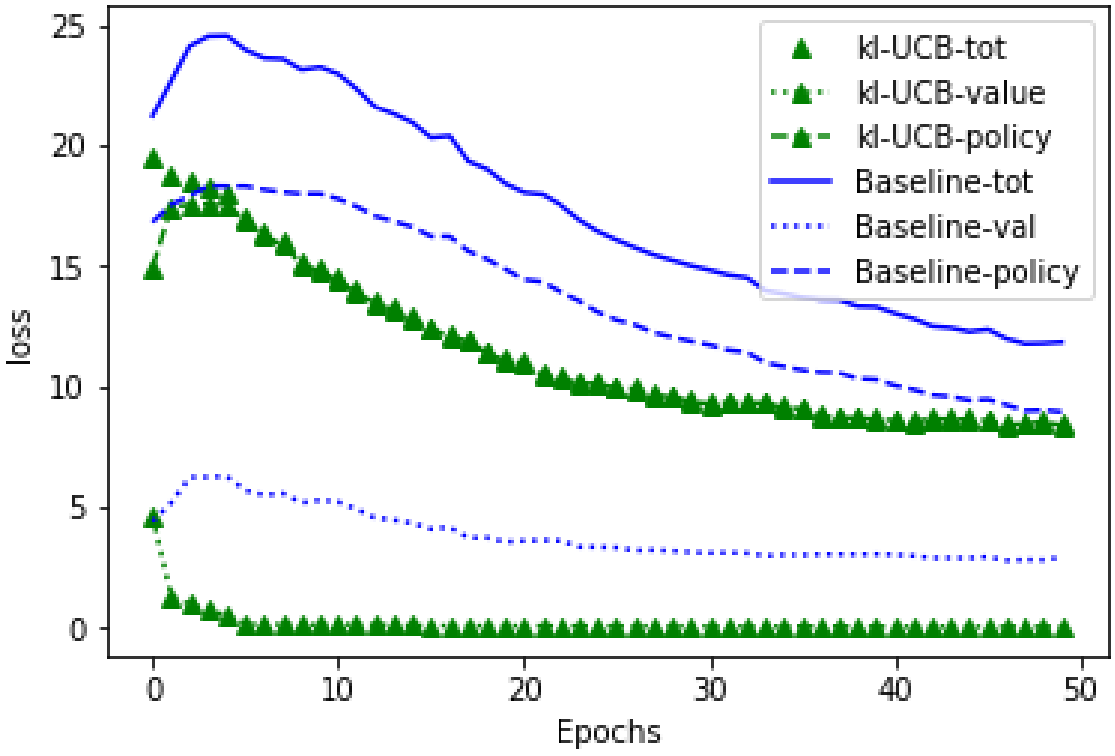

Fig. 3.1 Loss function during the training of Neural Network with $KL-UCB$ confidence bound compared with UCB1 confidence bound

3.4 Thomson sampling confidence bound

While applying this bound with the assumption that the reward $Q(a)$ follows $Beta(\alpha, \beta)$ distribution. We have reward which are success or failures so reward for each iteration comes from bernoulli distribution. So the posterior distribution is again $Beta$ distribution with α and β parameters changed. The value of $Beta(\alpha, \beta)$ is in interval of [0,1] and α and β is the count of success and failure respectively. So

$$q_i \sim Beta(\alpha_i, \beta_i)$$

$$A_t = argmax_i \{q_i\}$$

A_t is the action taken at time t q_i is the reward of i^{th} action. So A_t is the action which gives maximum reward after sampling from all distribution.

Some salient features of Thomspon sampling :

1. Robust to delay rewards because this is randomised algorithm.
2. Use of prior into solution can be easily incorporated and it is not possible in KL-UCB bound.
3. Easier to implement than KL-UCB because no optimization is required other than sampling whereas in KL-UCB requires optimization and being used is Netwon-Raphson optimization.

3.5 Experiment

Instead of using UCB in the action selection process during MCTS we are using Thompson sampling method. All other environment parameters remain same as that of Baseline. We calculate training loss and compare with the baseline. Moreover we also do tournament matches between baseline and new model for ensuring the result.

This model in Thomson-sampling branch. `https://github.com/vishalkumarchaudhary/connect4/tree/thompson-sampling`

3.5.1 Results

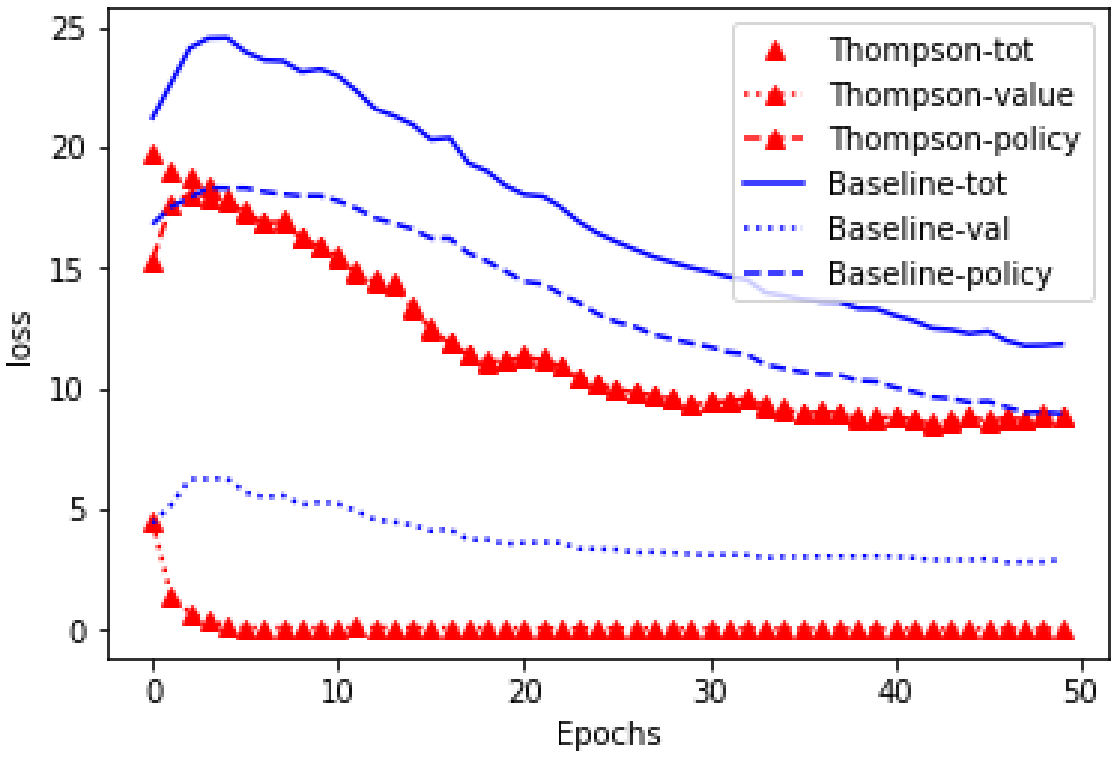

Fig. 3.2 Comparison between Thompson and UCB of training loss with respect to number of Epochs

The tournament between the new model and old model remains same as that of KL-UCB model with decrease in 3 win which is very marginal and cannot be compared. So for this connect4 problem Thompson sampling does as better as KL-UCB but it literature it says that it has better bounds than the KL-UCB.

3.5.2 Conclusion

Comparing the two new bounds which performs almost similar has the following loss function average over 10 experiments. These two also suggest that thier capacity of generating

good examples or the exploration of probability space of rewarding action is same.

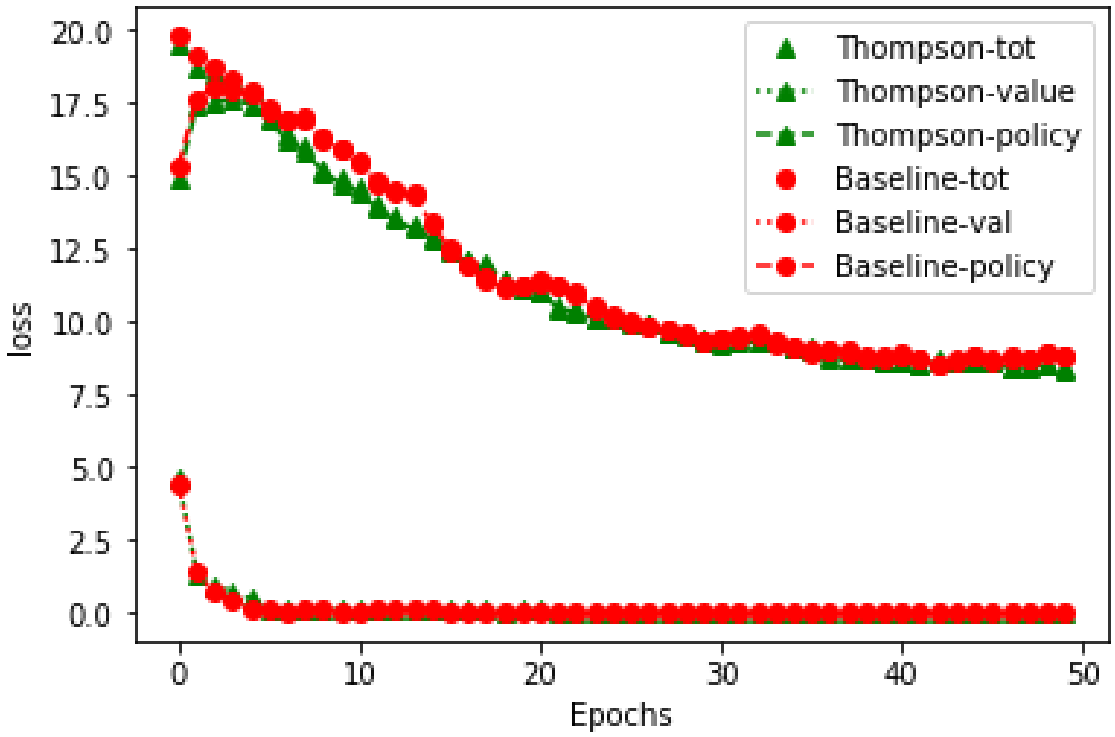

Fig. 3.3 Loss function during the training of Neural Network with $KL - UCB$ confidence bound compared with KL-UCB confidence bound

Chapter 4

Simultaneous Game

4.1 Construction

4.2 Conclusion

Chapter 5

Conclusion and Future Work

write results of your thesis and future work.

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