Inference of Opponent's Uncertain States in Ghosts Game using Machine Learning

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Abstract. Among many categories, board games can be classified into two main categories: Games with perfect information and games with imperfect information. The first category can be represented by the example of "Chess" game where the information about the board is open to both players. The second category can be determined with the "Ghosts" game. Players can see the position of the opponent's pieces on the board whereas the identity of the ghost pieces (good or bad) is hidden, which makes this game uncertain to apply search state space based technique. In this work, we have investigated the opponent game state with uncertainty for Ghosts using machine learning algorithms. From last year competition replay data, we extracted several features and apply various machine learning algorithms to infer game state. Also, we compare our experimental results to the previous prototype based approach. As a result, our proposed method shows more accurate results.

Keywords: Ghosts challenge · Uncertainty · Game AI · Machine learning · Feature extraction

1 Introduction

Games have been considered as one of the main source of digital entertainment now a day. There has been different type of games that are played against the other player or against the game AI (artificial intelligence). The purpose of playing games is not only to exercise the brain like making some strategies and winning/finishing the game but also to express the explicit thinking of the human mind. Therefore with the help of the games, the behavior of the human can be evaluated. There are several games in which the player wishes to play against other human player rather than playing against the AI. This is because of the limitations for computer-controlled opponents to build the strategy based decisions like humans. Computer-controlled opponent is a background program which is capable of automatically playing the game and can give the human players the feeling that they are interacting with other human players. It requires an enormous design effort in terms of strategies and interaction options. However, there have been a lot of game AI developed to predict future game state and can defeat the human in many games (i.e. Chess) [1].

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adfa, p. 1, 2011.

There are some board games that have been solved so perfectly that any program or human cannot win against the computer generated program [2]. However, there are still some board games which are under observation where the strategy of the human players cannot be easily evaluated. This is because of the imperfect information type of the board games. Since the information about the board game is missing, several search state space based techniques cannot be applied straightforward for strategy prediction. It can be possible to identify the game state and the opponent's strategy by applying the machine learning techniques using game play data [3, 4].

In this paper we found out the game state for the uncertain game named "Ghosts" using machine learning algorithms by collecting its game play logs. Although the Ghosts is a very simple board game, it is difficult to play because of uncertainty of opponent ghost's identity. We collected game play data over 1,400 games and applied various machine learning algorithms to build ghost identification inference model. Also we compare its results to previous approach used in [5]. As a result, our results show more accurate results.

2 Ghosts Challenge

"Ghosts" is a simple board game invented by Alex Randolph [6]. Its German name is Geister and is played between two players. Each player has a total of eight ghosts which are equally divided into two categories, good ghosts and bad ghosts. The identity of which are good ghosts and which are bad ghosts is hidden from the opponent as it is marked at the back side of the ghost which can only be seen by its own player. These ghosts have to be placed at middle of the least two rows on a 6×6 board as can be seen from the fig. 1.

The players can move their ghosts alternatively. The ghosts have limitation of not to take a step diagonally instead they can move one square forward, backward and sideways. The ghosts can capture the opponent ghosts (regardless of any identity) by landing onto the opponent's ghost position. Upon moving a ghost onto the same space, the nature of the latter ghosts is revealed to the capturing player. On the other hand, the player (whose ghost is captured) couldn't realize the identity of the capturing ghost.

Different winning strategies can be adopted as there are diverse conditions for winning: A player can win the game if it is eating/capturing all the good ghosts of the opponent. A player can win the game if the opponent eats/captures all the bad ghosts of the player (it can be possible to adopt a strategy so that the opponent is given a choice to eat our bad ghosts i.e. bluffing). A player can win the game if it reaches to the opponent's corner space (moving off the board) with its good ghost. Each corner of the board is marked with an arrow sign which indicate that the ghost (if it is good) reaching that corner is moving off the board and finishing the game. The length of the

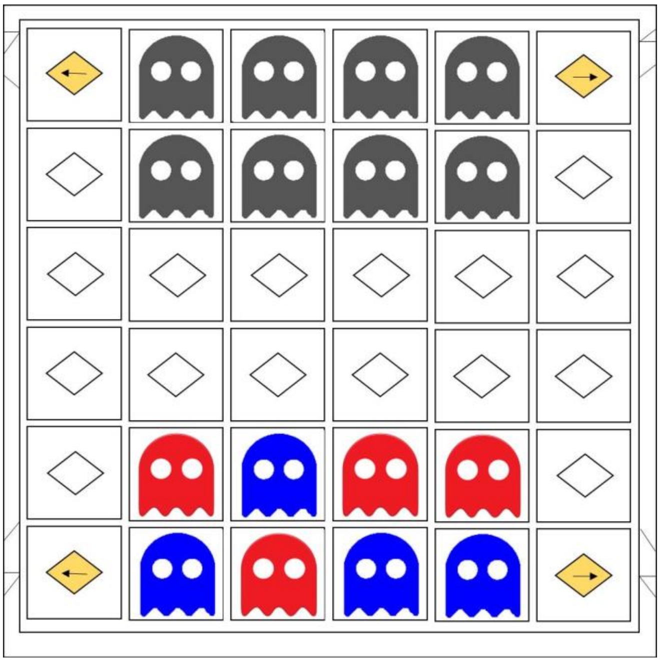

Fig. 1. Initial board setup for Ghosts (Top: Opponent)

game is limited to 100 plies where a "ply" means a single move of a player. The game is considered as tie if it reaches a length of 100 plies.

There have been a lot of game artificial intelligence competitions now a days organized by many game related international conferences all over the world. These competitions include first-person shooting games, real-time strategy games, board games and many other genres of games. The purpose of these competitions is to create autonomous bots/agents to play the game automatically without human intervention. "Ghosts Challenge[1]" is one of the recent simple board game competition based on "Ghosts" game organized by IEEE CIS Student Games-based Competition Committee in 2013. The competition continues its series and will hold again in 2014. The purpose of the competition is to develop an autonomous agent in order to play the game using computational intelligence techniques.

3 Background and Related Works

Games have different genres like platform games, arcade games, board games, card games, social games, real time strategy based games. On the other hand, there are other categories of games like perfect and imperfect information games. Focusing only to the imperfect information games in our study, there are different types of games where the players don't have the clear information about the state of the game.

1 https://ghosts-challenge.math.unipd.it/

Research on game AI character strategy and decision making emerged from the design of AI opponents in two-player games such as checkers and Othello. Othello in particular proved that computer-controlled opponents could be designed to not only compete with but also regularly defeat human players [7]. In these games, players take turns making moves on the board. With the passage of time, the table status can be used to predict the strategy. Since such games start with a specific initial position of pliers on the board, it is possible to use any state space based search technique to analyze the strategy.

Some other card games like "The Landlord Game" in which a player named Landlord fights against two other players called farmers' alliance [8, 9]. The task of each player is to play out all the cards before the other player finish its cards in hands. The best strategy is to get the right of playing the card at first. It will give you a chance to play the card of your choice. In order to get the right to play first, you should suppress others in the previous round. So, in this game we have to find out the probability of the type of the cards that the opponent can have in their hands. Because it is a kind of incomplete information game, we can only make judgment/guess. But since the information is revealing with the passage of time and with each turn of every player, we can use the revealed information to modify our strategy. Hence a machine learning approach is required that can mimic the human ability to analyze the game state and can evaluate the important information from the cards that one of the players has in his hands to predict the next possible play out of the opponent. It will be difficult to estimate the exact possible play out of other players as there are more than two players in this game. So, we have to estimate/consider some important features that can be used to train the system and the system then can predict the next outcome.

In Ghosts game, the information of identity of all the ghosts of the opponent is hidden, therefore, we need to use a heuristic judgment to play the game without the human. It is possible if we use some information from the board (i.e. the position of the ghosts and playing pattern of the opponent); we can plan the next possible move in the game and hence can evaluate the strategy of the opponent.

The first competition of Ghosts challenge held in November 2013 [10]. A total of eight teams participated in this competition. BLISS team took the victory while mutigers were the runner up. The replays of the competition between each of the participants are available at the website of the ghost challenge. BLISS team from China first converted the imperfect information of the Ghosts game to perfect information using the baseline approach and then used Upper Confidence Bounds (UCB) for decision making [11]. Whereas mutigers used hybrid computational intelligence to design their controller. At first they evaluated all the possible actions using goal-based fuzzy inference system, then used neural network to estimate the true nature of the ghosts and finally learned the parameters of the strategy using co-evolutionary system [12, 13]. Aiolli *et al* in [5] used the simple prototype based approach. He trained the machine learning methodology by considering 17 features and determined the prototype for good and bad ghosts by averaging the features. The badness score for the new feature vector is then calculated using the normalized Euclidean distance between the features of the profile vector and the prototype vector.

4 Proposed Method

To infer the state of game board, we assume that a player usually behaves the same for a particular situation during different games. If we could understand behavior of the player at a particular situation, we could use this information to plan a strategy against that player. Depending on the previous moves, the player has taken; we can analyze the type of the ghost and can use a suitable style to compete the opponent. There can be different playing styles like aggressive playing, attacking the opponent, defending from being killed and bluffing the opponent. It can be assumed that a player could adopt the same playing style. The current availability of in-game data (board position) and behavior style of the opponent can support the researcher to learn and predict the strategy using any machine learning algorithm.

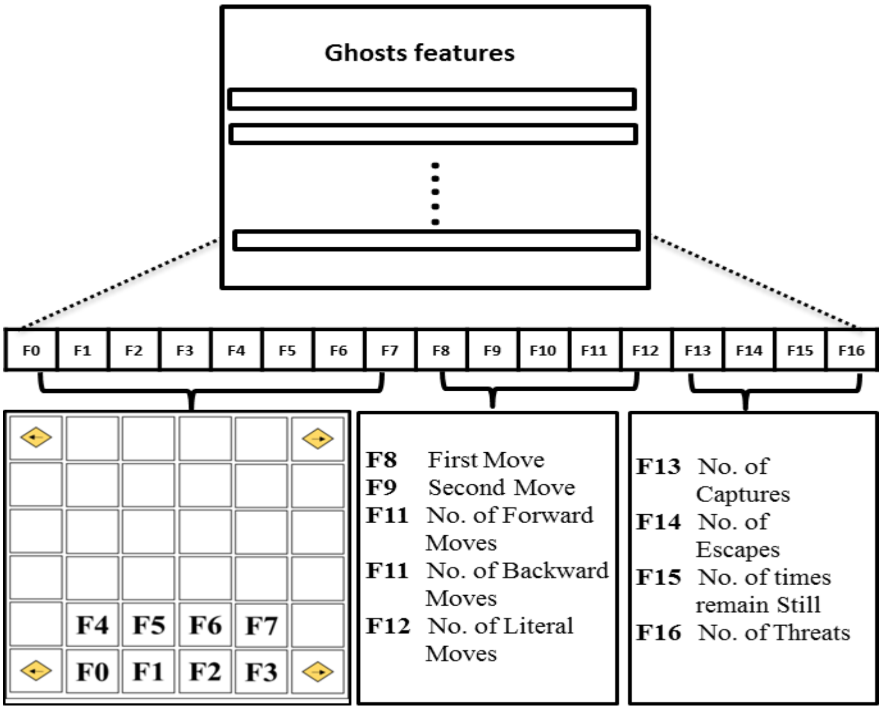

Fig. 2. Feature vector for Ghosts

To investigate the ghosts of the opponent in a particular game, we consider 17 features that can be used to profile the ghost. The impact and importance of these features is explained by Aiolli *et.al.* [5] Who used prototype based approach for the ghosts prediction. These features have been extracted from the replays of the previous year Ghosts challenge competitions. These replays are available at the website of Ghosts Challenge[2] in the form of XML format. These replays contain all the game

[2] https://ghosts-challenge.math.unipd.it/2013/matches

logs played between each participant. In total there are 28 logs (with 50 games between two players in each log). With the help of these game logs, we can evaluate the behavior, analyze the player strategies and train an AI system to learn player strategies.

Based on these features, we created two standard 17-D vectors to describe the good and bad ghosts. Among these 17 features, first eight features represent the initial position of the board. We believe that the initial setting of the ghosts in the board is the most important part of the strategy. Since we are not sure about the identities of the opponent ghosts (even though the identities are revealed in the game logs), we try to extract the initial position from the initial setup of the game. It is a rule that the ghosts has to set up initially in the middle of the least two rows in the board, we have fixed the least row dimensions as their initial configuration for any ghost as can be seen in fig. 2. The position of the pliers (ghosts) is represented with the binary values (0 or 1).

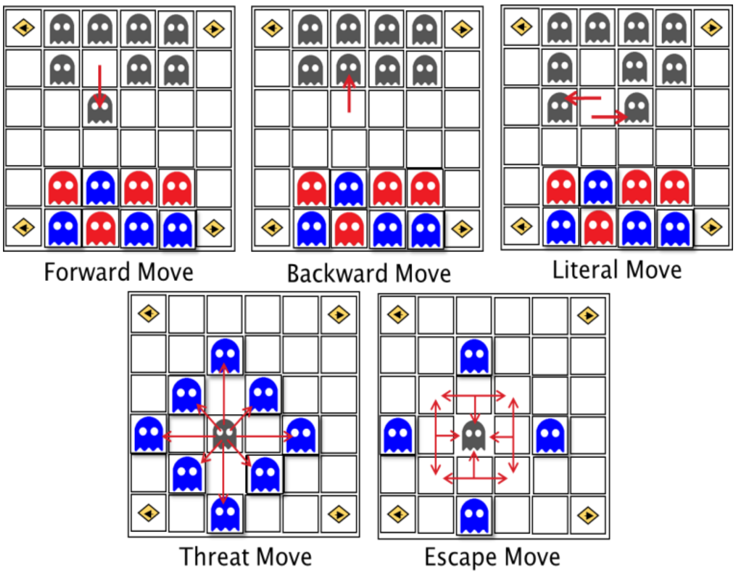

Fig. 3. Ghosts moves and behavior prediction

Next five features represent the movements of the pliers on the board in the game session: if this piece is moved at first move, if this piece is moved as second move, how many numbers of moves does the piece moved forward?, how many numbers of moves does the piece moved backward?, how many numbers of moves does the piece moved sideways? In order to find out how many number of moves does a ghost taken, we use the configuration of the table after each ply. The table configuration provides information about the latest position of ghosts after each turn. By comparing the two consecutive table configurations, the movement of the ghosts are identified and marked.

Last four features represent the behavior of the pieces: How many numbers of pieces are stalked by the piece? (Capturing the opponent's ghost), how many times does the piece take a move to escape from the opponent's attack?, how many times does the piece remain still? (No move) and how many times does the piece take a move to threat the opponent ghost? The number of captured pieces and the number of still moves are calculated by counting the missing pieces and no moves for each ghost, respectively. The number of threats are counted out by checking the second space of each ghosts in all directions (forward, backward and literal) and first diagonal space. The number of escapes is counted by checking the first space around the ghost. The initial positions, the moves and the behavior of the ghosts can be seen in fig. 3.

The features are extracted based on the XML data provided in the website. In order to extract the data, XML format file is first converted into an excel format for a quick and better understanding of the data. The Game IDs, Initial position and Table columns are then used to design and play the game. While playing the game, the features (movements and behavior) are calculated using the technique explained above. We have created 16 feature vectors (consisting of 17 features each) for every ghost in one game as can be seen in fig.2. A data set of $22{,}400 \times 16$ is then used for our experiments.

5 Experimental Results

Instead of setting up new programming environments or designing a prototype based approach, we use built-in open source software named "Weka" which is a well-suited for data mining tasks. Weka[3] contains a collection of machine learning algorithms that are suitable for classification [14]. We have considered the most promising machine learning algorithms in our research. These algorithms are K-Star, Bagging, PART (decision list), J48 (C4.5), RSS (Random Subspace), RC (Random Committee), LMT(Logistic Model Tree), CART (Classification and Regression Tree), IBK(K-Nearest Neighbor classifier) and RF (Random Forest), We run the experiment several times with different size of data sets. To measure the accuracy of the machine learning algorithms, we adopt a ten-fold cross validation. Since we extracted the features from the game replays and these game replays are available up-till the end of the game, we also extract the features for half-length of the game, first 10-turns length of the game and first 5-turns length of the game in order to validate the accuracy of machine learning algorithms. We also run the experiment using our data set for a prototype based algorithm explained in [5]. The results are explained below.

5.1 Evaluation with full-length game replays

In this experiment, we use the data set of the complete game. Fig. 4 shows the percentage of the correct instances for each machine learning algorithm. The correct

[3] http://www.cs.waikato.ac.nz/ml/weka/

instance means the system recognized the good ghost as good and bad ghost as bad. In this experiment, we have considered all the games between each player. Among many machine learning algorithms in Weka, we have considered top ten algorithms based on their performance. K- Star machine learning algorithm showed the highest performance in this experiment. K-Star is an instance based classifier that determines similar instances by using Entropy based distance function. Normally probabilistic approaches (Naïve Bayesian, Bayesian logistic Regression, naïve Bayes Updateable and so on) are promising in uncertainty handling. However, in our experiments, they have shown very low performance than those shown in the figures.

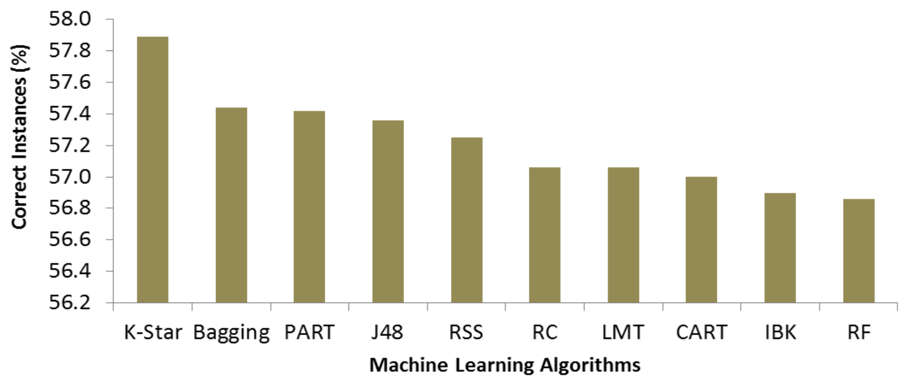

Fig. 4. Performance with complete game replays

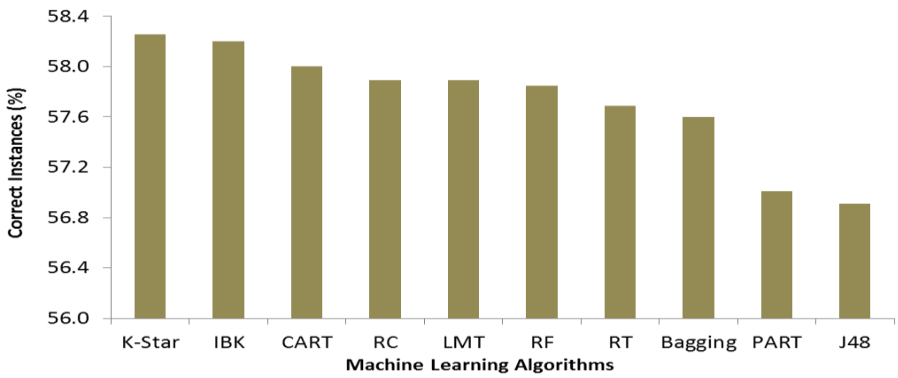

Fig. 5. Performance with half-length game replays

5.2 Evaluation with half-length game replays

In this experiment, we have extracted the features up-till half of the length of the game. Fig. 5 shows the percentage of the correct instances for each machine learning algorithm. It is seen that the performance of these experiments is not very promising (maximum performance is 58%). This is because we have considered the game replays of all the participants in the previous year competition. However, some bots performed very low in the Ghosts challenge.

5.3 Evaluation with ten-turn length game replays

In this experiment, we have extracted the features up-till first ten turns of each game. The purpose of this experiment was to train our system with very little information about the features of the ghosts and to predict the identity of the ghost within the game. In previous experiments (i.e. Full-length and half-length), the length of each game is different. Few games finished very early while few games were draw because none of the team could win against each other. In this experiment, we decided to fix the length of each game and hence we consider first ten turns in each game. Fig. 6 shows the percentage of the correct instances for each machine learning algorithm. The results are somewhat related to the previous experiments. This is because most of the features (Initial positions (binary), first move (binary), second move (binary), threats (very less threats in first few moves), escapes (very less escapes), still moves (since the length of the game is very short, so there are very less still moves), captures (very few captures) are common in almost all the games.

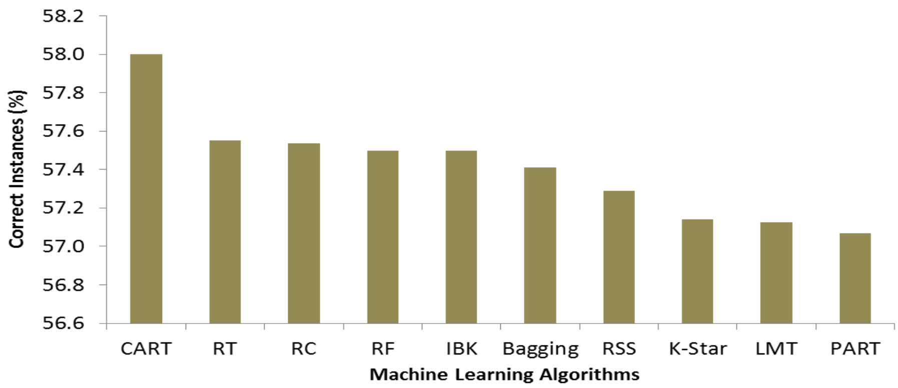

Fig. 6. Performance with ten-turn length game replays

5.4 Evaluation with five-turn length game replays

In this experiment, we have extracted the features up-till first five turns of each game. The main focus of this experiment was to predict the identity of the ghosts based on the initial positions in order to understand the importance of the initial ghosts' settings. Since the game is in its initial stages and movement features and the behavior features of the ghost are not identified at this early stage of the game, we can say that the system can predict the identity of the opponent ghost based on the initial set-up of the ghosts. Fig. 7 shows the percentage of the correct instances for each machine learning algorithm.

5.5 Evaluation and comparison using prototype based approach

We also use our data set to implement the prototype based approach discussed in [5]. The prototype for good or bad piece is determined by taking the average among the feature vectors and a badness score is calculated using normalized Euclidean distance between the average feature vector and the new profile vector. We used ten-fold cross validation in this prototype based approach in order to compare the performance results with other machine learning algorithms. We also compare the results of prototype approach with our all experiments. In the prototype based approach, the prediction is made based on the normalized Euclidean distance between the profile vector of the unknown ghosts and the average feature vector defined for good and bad ghosts.

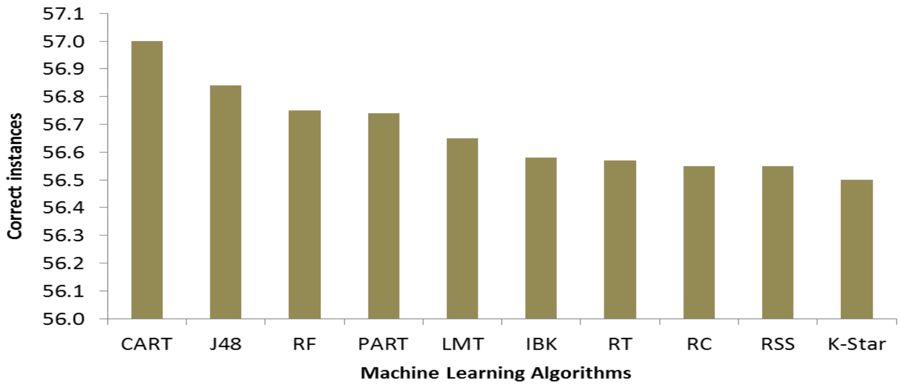

Fig. 7. Performance with five-turn length game replays

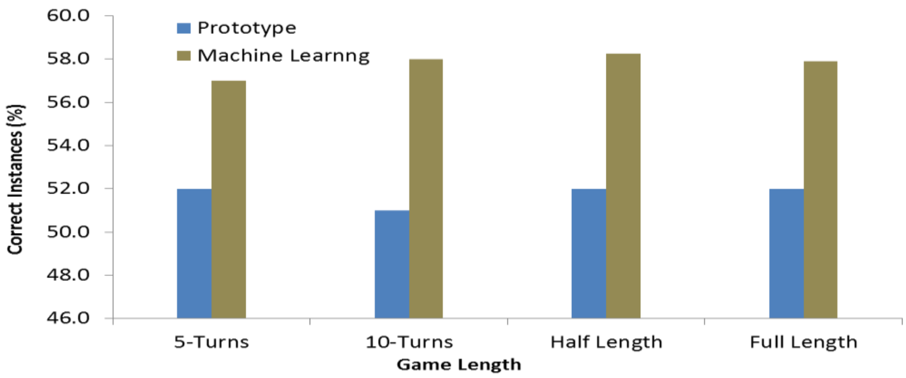

Fig. 8. Comparison of performance of
Prototype based approach vs. machine learning algorithm

It can be seen that the performance of the machine learning algorithms is less in five turns and 10 turns experiment because of the less information about the features and the game states. However, the performance also decreased at the full length experiment. This is because the performance of the bots participated in the Ghosts challenge is not similar. Few are very good (like BLISS or MuTigers) while some have shown very poor performance (like Tsengine and WAIYNE1). The comparison of prototype based approach and the machine learning algorithms is shown in fig. 8.

6 Conclusion and Future Works

In this work, we have investigated the uncertain opponent game state for Ghosts game using machine learning algorithms. We use last year Ghosts competition game play data and apply various machine learning algorithms to infer uncertain game state. Also we compare our experimental results to previous prototype based approach. As a result, our proposed method shows more accurate result about six percent than the prototype based approach.

Game designers are creating highly skilled computer-controlled players that can provide challenging opportunities to game players. Instead of encoding classical AI rules, it is possible to design adaptive computer-controlled opponents which are capable of learning by imitating human players. We tried to infer game state in Ghosts game by training our system with the previous played game replays. Since the replays in the Ghosts Challenge are not human players, and the strategies that are adapted by previous year participants based on their individual learning techniques, it is challenging to realize the strategy in these replay games. However, with the help of the replays and using machine learning algorithms, we can at least train our system for a certain level to predict the unknown ghost's identity based on the feature vectors. In this work, we have used different length game replays to find out the identity of the ghosts using built in machine learning algorithms in Weka.

The performance was based on the identification of the correct instances by the algorithms. Different machine learning algorithms showed different performance on the same data. CART performance was the highest in five-turn and ten-turn length game replays while K-Star showed highest performance in half-length and full-length game replays. In this experiment, we have used all the game replays which include the replays of those participants whose bot didn't perform well in the last year competition which cause the reduction of overall performance. Also, in this experiment, we only have used 17 features. We can also find some obscure features that can help to correctly identify the ghosts.

Our long-term goal is to design a computer-controlled opponent that can learn player strategies, styles and employ them in game bot against human players. Since these game replays are not played by humans, instead the bots designed by humans, we are not sure to imitate human strategies exactly. Further experiments can be done on the data sets extracted using only the final match (i.e. BLISS vs. Mutigers) or by collecting the data using human players. It is also possible to implement further state-of-the-art machine learning techniques on the extracted datasets to find out the most important features among the feature vectors.

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