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Imperfect Information Game – A Review

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Abstract: Card games are interesting for many reasons besides their connection with gambling. Among the huge variety of games, the researchers focus on those in which cards dealt randomly at the beginning of the game, with each player receiving a hand of cards that is not visible to the other players. Bridge is being a game of imperfect information, it is well defined and decision making game. The imperfect information games are contrasted with the perfect information game, where as the players are not having the complete knowledge of the game, where one player does not know exactly what cards the opponent hold. The Game of bridge provides lot of chance to conduct research to the researchers, because many components that constitutes the game. Hence researchers have much interested in this field especially in Double Dummy Bridge Problem (DDBP).

Keywords: Bridge Game, Imperfect Information game, Double Dummy Bridge Problem, FFNN, Bidding and Playing

I. INTRODUCTION

Artificial Neural Networks (ANNs) are non – linear mapping structures based on the function of the human brain. Neural networks are type of artificial intelligence that attempts to imitate the way a human brain works rather than using a digital model. In which all computations manipulates zeros and ones a neural networks by creating connections between processing elements, the computer equivalent of neurons [1]. Neural networks are particularly effective for predicting events when the networks have a large database of prior examples to draw on. Neural networks can be described as artificial intelligence models inspired along with the brain and possible in computer programs. They typically learn by exposure to a series of examples (a training set), strengths and connections between its nodes. They are then being able to do well not only on the original training set, but also when facing problems never encountered before. Artificial neural networks were used to solve the bridge problems particularly for the bidding phase of bridge game [2].

The feed forward neural networks are one of the most common types of neural network in use and these are often trained with stimulated annealing, genetic algorithms or one of the propagation techniques. Many of the feed forward neural networks were trained to solve the Double Dummy Bridge Problems in bridge game [3].

II. FEED FORWARD NEURAL NETWORK

A feed forward neural network is a biologically inspired classification algorithm. It consists of a number of simple neuron like processing units organized in layers. A simple neural network types were synapses are made from an input layer to zero or more hidden layers, and finally to an output layers. Every unit in a layer is connected with all the units in the previous layer. Data enters at the inputs and passes through the network, layer by layer, until it arrives at the outputs. During normal operation, it acts as a classifier and there is no feedback between layers i.e., the output of any layer does not affect the same or preceding layer [4]. Hence they are called feed forward neural networks. The feed forward neural network was the first and arguably simplest type of artificial neural network. The information moves in only one direction, forward from the input nodes through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the networks [5].

III. BRIDGE GAME

The Bridge game is the most fascinating trick-taking a card game that one can play. It is so skillful and can take a life time to master. Bridge is a tactical game of cards between for four people, who are split into two pairs; members of a single pair sit opposite one another and game is played between two partnerships with a standard deck of cards, each player being dealt 13 cards (4x13=52) and totally 52 cards. Bridge game has proceeds through Bidding and Playing phases. Each phase has its own rules, goals and interpretations [6].

The game bridge is no human knowledge, no rules and experience. Analysis of connections of trained neural networks is the possibility to explain some patterns using human knowledge of the game of bridge. This is also important aspect of human analysis of a deal, which allows taking into a possibility of FINESSE in the part of playing phase. There are five possible trump suits; Spades, Hearts, Diamonds, Clubs and No-Trump which is the term for contracts played without a trump [3].

IV. DOUBLE DUMMY BRIDGE PROBLEM

Double dummy bridge problems are solved by using feed forward neural networks. To estimate the number of tricks to be taken by one pair of bridge players is called double dummy bridge problem (DDBP). In the feed forward neural networks using resilient back propagation algorithm to help into estimate the number of tricks to be taken by players of NS (North South) in contract bridge game deal. The better networks were able to perfectly point the number of tricks in more than one third of deal on gain [7]. Feed forward networks assumption is to reduce human hand influence on neural networks to the minimum. This is the reason for avoiding special pre processing of deals. It is to be logical to present the networks information about short suits [8].

Under perfect information, the average branching factor of a full 52 card deal of bridge makes the state space too large to solve problems. The problem of designing a fast double dummy bridge game (i.e., a simplified bridge game with perfect information) solver and the hash table techniques to share the lower and higher bounds of the maximal trick for nodes frequently visited or nodes with larger depth in the search tree may be promising in reducing the size of each tree. Effective moves ordering and pruning heuristics, most double bridge hands can be solved within a reasonable amount of time [9].

V. CONTRACT BRIDGE

Estimating hands strength is a crucial aspect of the bidding phase of the game of bridge, since contract bridge is game with incomplete information. In contract Bridge, a player makes a bid to convey information about the pattern of the thirteen cards in hand and not having the prior knowledge of the rest of the cards in other hands. In the Double Dummy Bridge Problem, it is advisable to train neural networks independently for no - trump – contract and suit contract.

No-Trump contract and suit contracts were compared and the reliability test shows to prove the result in confidence in the learning process is high, and the training results are repeatable. The reasonable explanation based on human experience in the game of bridge shows potential, taking into consideration the possibility of automatic and unguided discovering of knowledge hidden in the connection weights [10].

The work point count is also important for suit contract; moreover in this case additional information about lengths of suit must be applied to best result. An extraction of human knowledge on neural network output depends on the deal. The results revealed that, the outputs achieved by neural networks for spades contract are better than output for no-trump contract [11].

A. Bidding:

The auction in contract bridge is a game with incomplete information. Bids in auction bridge can be broadly divided into partnership bidding and competitive bidding. An agent model was proposed based on common sense in bidding by human and hypothetical reasoning capability [12].

B. Aim of Bidding:

The aim of a bidding system is to convey the maximum amount of information for cases which are most frequent. Bidding in bridge is to cooperatively estimate the playing strength of two hands held by a partnership, and arrive at an optimal final contract. The bidding in bridge has two purposes. The primary purpose is to share information about the cards between the partners to select a most advantageous final contract. A secondary purpose is to interrupt the opponents to get an optimal final contract. For achieving this purpose, a wide variety of bidding “languages” have been developed. The purpose of bidding phase is to identify trumps, declarer and contract. Trumps, card that belongs to the suit that has been chosen to have the highest value in a particular game; a trump can take any card of any other suit. Declarer is defined as, the player who is the first to bid the suit (or no trump) of the final contract. Contract is the final bid of the auction. A bid becomes the contract when it is followed by three passes. During the bidding phase, various contracts are proposed. Each contract suggests a particular trump suit [13].

Most of the previous attempts to write bridge playing programs were failure due to the reasons viz., not having clear knowledge, pragmatics, probabilities and proper plans [14]. The architecture, which has defined bids by using a rule, based bidding inference, a stochastic simulation of deals and neural net for contract evaluation, also presented a sketch for playing component which uses single - suit brute force analysis and global analysis by plan combination [15].

C. Partnership Bidding:

In the bidding phase of bridge, the player makes an effort to arrive at a better contract through collaboration involving the exchange of information restricted bids. The partnership in the bidding process is modeled as a communication between two agents with common knowledge and hypothetical reasoning mechanisms. The basis of the partnership is rules which are understood between two players. In partnership bidding, that is the case where there is no disturbance from the opponents. Model of partnership bidding construct an image of the partners hand and then determines its own next bid on the image. Model of partnership bidding was implemented by using constraint logic programming language. These languages are unique, that have both the capability of problem representation inbuilt to a logic programming language and the capability of consistency technique to solve the problem efficiently. The experimental result revealed that, deep mutual inference of the partners through process, such as how the partners responds to one’s own bid, realize a best partnership [16].

D. Competitive Bidding:

In competitive bidding a partnership must be prepared for the opponents attempt to interrupt a perfectly normal and logical bidding sequence with an intervening bid. Competitive bidding rules such as overcalls, preemptive bids and doubles, in addition to the opening response and rebids as means of cooperating with the partner. The criterion for the action of each agent is defined as “maximizing gain by co-operating with partners and minimizing the loss by competing with the opponents”. The hands of both sides are estimated from the course of bidding by hypothetical inference and bids are made in an effort to obtain the contract with the greatest score gain or smallest loss. The results revealed that the information transmitted by the partner and hinder the information exchange between the opponents is useful [17].

VI. BIDDER AGENT

Auction in the game of bridge is an interesting field and the bid may have various meanings according to the context. The goal of each bidder agent is to reach reasonable contract in the auction. The important feature of the bidder agent is a hypothetical reasoning mechanism. The agent generates an image of the other agent’s hidden hands by abduction from the observed bidding sequence. Each agent selects his bid and cooperates with the partner to get maximum profit and compete against opponents to minimize the loss. The action criteria were set so that the difference between one's own real hand and its image in a partner's knowledge motivates an agent to continue bidding to reach a reasonable contract. The result reported that, the reasoning by an agent to select a sacrifice bid where the expected score of the bid is better than the score of an opponent's possible contract [18].

VII. OPENING BID PROBLEM

In contract bridge, a player makes a bid to convey information about the pattern of thirteen cards in his hand. A person first to make a bid is called Opening Bid that is the player has no prior knowledge of the rest of the cards in others hand. Opening bid problem was solved by evolutionary programming with the help of feed forward neural networks. An evolutionary programming based neural networks construction algorithm, which efficiently configures feed forward neural networks in terms of optimum structure and optimum parameter set. Construction algorithm, which was tested on a contract bridge opening bid problem. In the evolutionary programming based method, more than one solution is generated initially, and the solutions are repeatedly adapted by adding and deleting the hidden nodes or by small perturbation of weighs and bias values. The self organization capability of construction algorithm, due to which, it is able to find the proper number of hidden nodes even though it starts with an inappropriate number of hidden nodes. The results concluded that, the classification efficiency of the construction algorithm is 3.83% greater than the conventional back propagation algorithm on the same test set. It demonstrates the better generalization capability of the network trained by the evolutionary programming based Gradient decent method [19].

A Probabilistic Neural Network (PNN) has made a popular alternative to feed forward networks trained by Back propagation algorithm. An evolutionary programming based clustering technique was used to determine the optimum parameter set of the Gaussian mixture model. The clustering algorithm was tested on a contract bridge Opening bid problem. During the structural mutation only one cluster is added or deleted at a time. The result reported that the number of hidden nodes decrease significantly in the conventional Probabilistic Neural Network (PNN) to modified PNN. The clustering started with wrong number of clusters and incorrect position of the cluster centers, due to self organization capability, the Evolutionary Programming based algorithm did not find any problem in clustering. When comparing the classification efficiency of conventional PNN and the modified PNN on the same test set, modified PNN showing better result and increase the efficiency of 3.70% and demonstrates the better generalization capability [20].

The classification task involved in the game of bridge bidding is inherently fuzzy. A rough-fuzzy set based measure is proposed to evaluate the importance of the each feature. While considering the importance of particular features, other features, player's experience, vulnerability etc., Rough – Fuzzy set measure is used to bias the input representation of each hand so that more important features get more weightage, and eventually result in a better classification. Since membership assignment should be possibilistic in order to extract the maximum advantage of fuzzy set, the fuzzy K-NN (K-Nearest Neighbors) algorithm was modified to possibilistic K-NN algorithm. To check the effectiveness of the rough- fuzzy set, two experiments were conducted on the opening bid problem. The result reported that, the classification performance of original and modified Rough-Fuzzy set on a same test are 79.81% and 82.95% respectively and the training time was improved by 18%. The result also revealed that the classification efficiency on the same test was improved by 2.8% [21].

Train a monolithic feed forward neural network for whole classification task is very difficult. Fuzzy integral approach is considered to be independent of the other information sources. Fuzzy-Rough set theoretic technique is used to determine the importance of each subset of the information sources from the incomplete knowledge. Modular neural network is more appropriate for the bidding task than single monolithic network. Fuzzy-Rough method is better than the frequency based method while comparing the classification performance [22].

VIII. PLAYING

Once bidding has finished, as a declarer need to make the required number of tricks to achieve the contract, or as a defender need to stop the declarer. The aim of declarer is to take at least the number of tricks announced during bidding phase. The hand of declarer's partner is displayed face up on the table after the opening lead has been made by the member defending side to the left of the declarer; the displayed hand is referred to as the dummy and is played by the declarer [23].

A. Planning in Bridge playing:

In contract bridge a domain in which many of the issues involved in real world problems can be addressed without simplification in representation. Planning in the game of bridge took away from the traditional methods. A two stage mechanism for planning used contract bridge as the domain. In the first stage partial plans are recommended by knowledge structures called Thematic Acts (TA), and another stage is a scheduler combines the actions suggested by the TAs into a coherent plan. The scheduler is basically a weak method than the first stage of thematic planning. Implementation strategy of means – ends – analysis has been adopted, as it is well suited to the domain of planning in bridge [24].

Bridge is an imperfect-information game taken the advantage of the planning nature of bridge by adapting and extending some ideas from Task-Network Planning (TNP). To represent the tactical and strategic schemes of card-playing in bridge, the multi-agent methods are used similar to the task decompositions which were used in hierarchical single-agent planning system. Forward pruning works best in situations where there is a high correlation among the minimal values of sibling nodes. The prototype system *Tignum* was implemented and used in the game of bridge during card playing. The prototype *Tignum* produces game trees small enough that it can search them all the way to the end of the game. It can successfully solve typical bridge problems that matched situations in its knowledge base [25].

B. Game tree search in bridge playing:

Game tree search is less suitable for imperfect information game such as contract bridge. The lack of knowledge about the opponent's possible moves gives the game tree a very large branching factor, making it impossible to search a significant portion of the game tree in a reasonable amount of time. By using techniques adapted from task-network planning forward pruning reduces the large branching factors that results from uncertainty in contract bridge [26].

Traditional game tree search techniques do not work so well in bridge; hence bridge is an imperfect information game. An implementation called Tignum -2 was developed which use an adaptation of Hierarchical Task Network (HTN) planning techniques to plan declarer play in contract bridge. Tignum-2 used to represent the locations of cards about which declarer is certain and to represent the probabilities associated with the locations of cards about which declarer is not certain. To generate game trees Tignum-2 planning algorithm used to build up game tree [27].

Partition search and conventional methods are used to comparing the number of nodes expanded in the game of Bridge. Partition search brings dependency maintenance techniques accept on problems in adversary search. The principal difficulty that has arisen in the application of dependency techniques generally is that there is no convenient way to store the conclusions drawn as the search proceeds this is frequently not an issue in adversary search. Hence transposition tables are constructed and maintained in any event. Partition and conventional cases, a binary zero-window search was used to determine the exact value to be assigned to the hand. In which the rules of bridge constrain ranging from 0 to ¼ times the number of cards in play [28].

C. Algorithms used in bridge playing phase:

There are three heuristic algorithms used for games with imperfect information viz., Monte – Carlo sampling, Vector minimaxing and payoff - reduction minimaxing (prm). These algorithms were compared theoretically and experimentally using simple game trees and a large data base of problems from the game of bridge. The Bridge game has been heavily analyzed by human experts, who have produced texts that describe the optimal play in large number of situations. The availability of such reference provides a natural way of assessing the performance of automated algorithms. The results demonstrate that vector minimaxing is little bit superior to Monte - Carlo sampling and payoff – reduction minimaxing algorithm dramatically out – performs the other two, both on simple random game trees and for an extensive set of problems from the game of bridge. In the single suit bridge problems, prm's speed and level performance was good enough to allow and to detect errors in the analysis of human experts [29].

Bridge is a game with imperfect information and having enormous search spaces. Analysis of Single-Suit bridge problems is challenging even for master-level players. Computer can use a set of patterns to find and explain optimal strategies for single-suit play. A *vector propagation* algorithm that backs up sets of vectors so that the outcome of each possible strategy in a nodes sub tree is represented by one of the vectors in the set produced at that node. Number of vectors produced by *vec-prop* at any MAX and MIN node will be the same as the number of strategies in the sub tree rooted on the node. In imperfect information game *vector propagation* algorithm that quickly finds the optimal solutions even though the task being NP-complete in the size of the game tree [30].

A game with incomplete information formalized a best defence model of bridge games based on the assumptions typically made when incomplete information problems are analysed authoritative bridge text. An equilibrium point strategies for optimal card play exist for best defence model and an algorithm called *Exhaustive Strategy Minimisation* capable of computing such strategies. The result concluded that, formalization of exhaustive strategy minimization allowed pinpointing exactly the sources of sub-optimality in repeated minimaxing; strategy fusion results from combining different MAX strategies in different possible words and non-locality results from examining only partial strategies at internal nodes of a game tree. The experimental evidence showed that non-locality occurs often in actual systems. The results provided a clear understanding the performance of *Exhaustive Strategy Minimisation* algorithms against the commonly used model of expert bridge play and used to judge the practical merits of systems designed for man-machine play [31].

D. Bridge Playing Techniques:

GIB (Ginsberg's Intelligent Bridge Player) is very good game playing program, identifying specific possibilities that will allow a contract to be made or defeated. GIB works differently, instead of modeling its play on techniques used by humans. The success of Brute-Force techniques such as GIB suggested that the small but frequent errors made by a Monte-Carlo Sampling approach are to no barrier to competing with the strong human bridge players [32].

The computer bridge system FINESSE was built, which finds the optimal strategies for single-suit Bridge problems. To explain FINESSE strategies, an approach was developed based on three steps viz., Collapsing, Pruning and Pattern Matching of game trees. The collapsing stage is reducing the size of the tree and the strategy was identified from the possible sequences of MAX plays explaining a game tree is to extract the branches that form part of the optimal strategy. The strategy was achieved by collapsing the input game tree into a tree whose paths are a subset of the original. In pruning stage identifies and removes branches from collapsed trees based on the two concepts like "Particularly Bad Moves" and "Particularly Easy to Play" which are clearly game specific. Pattern matching is the final step which automatically explaining strategies. In this step that is responsible for mapping the branches of collapsed and pruned trees into English text. The natural English text was produced with the aid of both game general and game specific patterns and idioms that can explain each MAX and MIN move. The trees of the tactics produced by FINESSE are simply compact representations of a subset of the space of possible moves [33].

Monte-Carlo Sampling is the technique which handled the imperfect information game. Monte-Carlo Sampling consists of guessing a possible world and then ignoring the pay offs associated with the remaining worlds. The performance of Monte Carlo sampling was examined on simple binary game trees, demonstrating that as the depth of the game tree increases and the error were rapidly approaches maximum percent (100%). These errors were explained in terms of strategy fusion and non locality. The strategy fusion and non locality affected the analysis of bridge, despite the way that Monte Carlo sampling largely reflects the best defence assumptions commonly made when analyzing bridge problems. To find out the optimal play against best defense is NP – complete in the size of the game tree, and introduced the new heuristics of *vector minimaxing, payoff – reduction minimaxing, beta-reduction minimaxing, beta – reduction* and *interative biasing.* The effectiveness of these heuristics were demonstrated the *iprm-beta* made fewer errors than the human experts that produced the model solutions and this is the first search algorithm consistently performing either at or above, expert level on a significant aspect of bridge card-play [34].

IX. CONCLUSION

Artificial neural networks are very effective in estimating the number of tricks to be taken by one pair of players in Double Dummy Bridge Problem. The bridge bidding program is skillful and intelligent performance to improve initial bridge player. In playing phase, the hand strength values must be properly communicated between the pair of players. When playing bridge game the players get better probability to assume the hand strength of the opponent if the partners using the playing techniques and languages between them.

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