

Artificial Intelligence Techniques in Games
with Incomplete Information:
Opponent Modelling in Texas Hold'em

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Abstract

Games have been widely used as an application for Artificial Intelligence techniques because of their simplicity and well-defined rules but in the other hand, for their huge range of possible and complex strategies to reach the final objective.

In the last years, Artificial Intelligence study applied to games has focused more in games with incomplete information and non-deterministic games where players do not have complete information about the entire state of the game and where random events occur throughout the game.

The game of Poker is a perfect theme for studying this subject and thus it was selected for this Project. The most well known Poker variant is Texas Hold'em that combines simple rules with a huge amount of possible playing strategies.

The work is focused on developing algorithms for "Opponent Modelling" in Texas Hold'em Poker enabling to select the best strategy to play against each given opponent. This opponent modelling capabilities and playing strategy is implemented in an Intelligent Agent capable of observing opponents and to adapt his playing mode in function of their behaviour.

Several agents were developed in order to simulate typical Poker player's behaviour and one other agent was developed capable of use opponent modelling techniques in order to select the best playing strategy against each opponent.

Experiments were performed using the Texas Hold'em simulator previously developed, in order to verify the capabilities of the Intelligent Agent developed confirming its use of Artificial Intelligence techniques to classify opponents and adapt his game strategy. The tests performed proved that this agent has better results than a regular agent that doesn't use Opponent Modelling.

Although there is still much work to be done in order to obtain an Agent capable to play at human's level, the work done in this project was positive and could be used as a basis to develop some more sophisticated techniques in the game.

Resumo

Os jogos sempre tiveram um papel fundamental no estudo de Inteligência Artificial pela sua simplicidade e regras bem definidas, mas por outro lado pela complexidade e variedade de estratégias possíveis para alcançar o objectivo do jogo.

Nos últimos tempos, o domínio da Inteligência Artificial tem-se focado no estudo de jogos de informação incompleta e não determinísticos, ou seja, jogos em que o jogador não tem total informação sobre o estado do jogo e o elemento aleatório está constantemente presente.

O jogo de Poker enquadra-se perfeitamente neste estudo e por essa razão será analisado neste projecto. A variante do jogo mais habitual é Texas Hold'em que combina regras simples e bem definidas com uma grande variedade de estratégias possíveis.

Neste trabalho foram definidas estratégias de "Opponent Modelling" que pretendem dotar um Agente Inteligente da capacidade de observação de adversários e, conseqüentemente, adaptar o seu modo de jogo em função dos seus comportamentos.

Foram também desenvolvidos vários agentes que irão simular comportamentos típicos dos jogadores habituais e um agente principal capaz de utilizar capacidades de modelação de oponentes para seleccionar a melhor estratégia a utilizar contra cada um.

Foram também realizadas diversas experiências no simulador de Texas Hold'em, desenvolvido previamente, de forma a validar o trabalho desenvolvido. Verificou-se que o Agente Inteligente desenvolvido utiliza técnicas de Inteligência Artificial de forma a adaptar a sua estratégia de jogo em função do comportamento dos adversários. Os testes realizados demonstraram que este agente obtém melhores resultados do que um agente que não utiliza técnicas de "Opponent Modelling".

Apesar de haver ainda muito trabalho por realizar para obter um Agente Inteligente capaz de jogar ao nível de jogadores humanos, o resultado deste projecto foi positivo e pode ser utilizado como suporte para desenvolver outras técnicas, mais sofisticadas, de jogo.

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Chapter 1

1. Introduction

Poker has a number of attributes that make it very interesting to study from an Artificial Intelligence perspective. Incomplete knowledge, risk management, opponent modelling and dealing with unreliable information are topics that identify poker as an important research area in Artificial Intelligence (AI).

Unlike games of perfect information (such as chess) in which players are perfectly informed about the state of the game, in poker, players face hidden information from the opponents cards, and future actions.

In such a domain players face the need to use “Opponent Modelling” techniques in order to understand and adapt themselves to the opponents playing style. Distinct strategies may be optimal against different opponents.

In environments with more than one agent, the outcome of one agent may depend on the actions of the other agents. Consequently, in determining what action to take, an agent must consider the possible actions of the other agents. Game theory provides the mathematical foundation for explaining how rational agents should behave in such settings. Unfortunately, even in settings where game theory provides definitive guidance of an agent’s optimal behaviour, the computational problem of determining these strategies remains difficult [Schaeffer et al., 1992].

Opponent Modelling allows determining a probability distribution for the opponent’s hidden cards. In some previous work, it was considered a single model for all opponents in a given hand. Opponent modelling may be improved by modifying those probabilities based on collected statistics and betting history of each opponent.

The main goal of the project is to prove that an intelligent agent that considers the opponent strategy achieves better results than one that considers only a single model for all the players in a table.

The idea is to create several *pokerbots* with different strategies (that are used often by human players), and create an *observer bot* that analyses these strategies and use different algorithms to decide the action to take against each one.

1.1 Artificial Intelligence and Games

The term Artificial Intelligence was coined in 1956 by John McCarthy at the Massachusetts Institute of Technology [MIT, 2008]. Artificial intelligence includes, among other areas:

- Game playing: programming computers to play games such as chess and checkers;
- Expert systems: programming computers to make decisions in real-life situations (for example, some expert systems help doctors diagnose diseases based on symptoms);
- Natural language processing: programming computers to understand natural human languages and be able to generate it;
- Neural networks: systems that simulate intelligence by attempting to reproduce the types of physical connections that occur in animal brains;
- Robotics: programming computers to see and hear and react to other sensory stimuli and are able to act in the environment using some kind of actuators.

Currently, no computers exhibit full artificial intelligence (that is, are able to simulate human behaviour). However several successful approaches exist in well-defined areas. One of the greatest advances has occurred in the field of game playing. The best computer chess programs are now capable of beating the best chess human players. In May, 1997, an IBM super-computer called Deep Blue defeated world chess champion Gary Kasparov in a chess match [Newborn, 1997].

Artificial intelligence in games is usually used for creating player's opponents. The players give high-level strategic orders and the computer-controlled units take care of detail. At the same time, the full detail and dynamics of the game is maintained with the computer control of detail, rather than lost through abstraction.

Artificial Intelligence (A.I.) researchers have used games as research tests for a long time. Games have well-defined rules and goals that made them easy to explore and compare to other problems in Artificial Intelligence domain.

Games are categorized based on the accessibility of the game state to the players. If all players in a game have complete knowledge of the entire game state, it is called **a game**

with complete information. Otherwise, it is a **game with incomplete information.** Chess, checkers and backgammon are all games of perfect information because all the players have access to the entire game state by just looking at the board. On the other hand, poker, bridge, and Scrabble are examples of imperfect information games because each player has their own cards or tiles that are kept hidden from the other players in the game.

Both games can be also categorized based on whether or not they contain chance elements. A chance element, such as the roll of dice in backgammon or the deal of cards in poker, is an event that introduces randomness or no determinism into a game. If a game contains elements of chance, it is referred to as a **stochastic game.** Otherwise, it is referred to as a **deterministic game.**

In the past, most games-related A.I. research focused on decision-making in deterministic perfect information games, because they are easier to deal. This research made outstanding progress and resulted in many programs achieving a level of playing strength that is comparable to or superior to the best humans, the example of Deep Blue in chess [Newborn, 1997].

In recent years, A.I. researchers start focus on decision-making in domains that contain elements of chance and/or imperfect information. Again, games are an excellent domain for exploring these issues. From the computational decision-making point of view, these games promise great research potential because they offer many new and interesting challenges not present in traditional deterministic perfect information games.

1.2 Motivation

A study has revealed that the recent poker boom has not only reached casinos across the world, but computers world wide too. A study completed by consulting firm MECN analyses one of the hottest topics in the gambling industry – online poker.

As gambling reinvents itself constantly it seems online poker is the product that seems to be the current guarantor of future growth rates.

The success story of online poker began some years ago, and as Martin Oelbermann, co-author of the study, explains "Online poker is the perfect symbiosis of two mega trends in gambling: online gambling and poker."

What began as triumphant advance in the USA is now leading to a global poker wave on the Internet with tremendous potential:

- The amount gambled on poker websites around the world in 2005 is estimated to be more than USD 60 billion.

- More than 60% of the industry experts surveyed believe that online poker will be the dominant offer in online gambling in 2-3 years.
- 75% of the industry experts surveyed believe that the global annual rake/commission in the 2-3 years will be more than USD 4 billion.

When it comes to geographical expansion, Europe seems to be the place to go. 52% of the experts believe that Europe offers the greatest future potential for online poker. Market leader PartyPoker [Party Poker, 2008], for example, is planning to launch its presence on television throughout Europe very soon and already operates its site in one other language besides English, namely, German [MECN, 2008].

As we can see by the facts, poker as an important weight in economy and should be considered not just by the properties of Artificial Intelligence test bed, but also for the social and economic relevance in the modern society.

Besides the topics referred, the game also includes an important theme for science - The Human Behaviour. The behaviour of a person along a poker game is an interesting object for study in psychology and sociology [Ready By Bet, 2004].

This project doesn't intend to focus on these aspects, but just give an introduction to other aspect - the player modelling.

The major motivation for the approach of opponent modelling is the lack of studies in this topic of the game. Most of the work done in poker, focus mostly in the game strategy and the simple player modelling developed till now has an approach based in predicting the opponent moves, and not in predicting the opponent cards.

The approach done in this project intends to be new in the domain of Opponent Modelling in Poker but at the same type, useful to create an online poker player agent.

1.3 Goals

The main goal of the project is to prove that a poker agent that considers the opponent behaviour has better results than an agent that doesn't, even when playing the same betting strategy.

The first objective of this work is to study and use the previous work developed at LIAAC (Artificial Intelligence and Computer Science Laboratory) [LIACC, 2008] for testing and building the models for the project.

The second objective is to study and identify the type of players that we can find in a poker game and build some agents that simulate these players. The agents should have

similar behaviour of human players when it comes to choosing starting hands to play and betting strategies.

After the first two goals are done, an intelligent agent should be developed in order to observe the opponents, and adapt the strategy of the game for each one. The agent should keep the information of all the movements made by the opponents along the game and classify them. After the classification, the agent should adapt his strategy to the opponent(s) in the table.

The main goal should be reached by analysing the results of the different agents developed. Several games should be simulated with the different kind of agents and always with an observer agent.

1.4 Summary of contents

This project is structured in 5 chapters.

The first one is the introduction to the thesis. Games and Artificial Intelligence are presented in a simple approach, and it's explained the motivation for this kind of work.

In the second chapter the game is explained in detail and it's presented some previous work done in Artificial Intelligence applied to the game of Poker.

The third chapter shows the importance of Opponent Modelling at Poker. The classification of players is described in detail and it's presented a theory for starting hands probability of a specific kind of player.

The fourth chapter describes all the work done step-by-step and the difficulties found along the time.

The fifth chapter is an analysis to the results of the project. Some tables and graphs are presented to explain the work done.

The conclusion of the project is presented in the sixth and last chapter, as well an introduction to future work that can be done in order to complete this project.

Chapter 2

2. Games with Incomplete Information

Games have proven to be both interesting and rewarding for research in Artificial Intelligence (AI). Many success stories like Chinook (checkers) [Schaeffer et al., 1992], Logistello (Othello) [Buro, 1997], Deep Blue [Newborn, 1997] and Hydra [Hydra, 2008] (chess), TD Gammon (backgammon) [Tesauro, 1995], and Maven (Scrabble) [Sheppard, 2008] have demonstrated that computer programs can surpass all human players in skill. However, there remain many challenges in computer game-playing. Games such as Poker are difficult because of the elements of imperfect information and partial observability [Kan, 2006].

Games with incomplete information are games where the player doesn't have complete knowledge of the entire game state. Poker is an excellent game for testing incomplete knowledge because the players only have access to the information of their own cards and the predicting of opponent cards is a challenge in Artificial Intelligence domain.

Poker is also a stochastic game because of the shuffle of the deck introduces the chance element into the game state. Once again, this is a characteristic that turns poker into an excellent game to explore.

Von Neumann introduced game theory [Wikipedia, 2008] in 1940s and has since become one of the foundations of modern economics [Neumann, 1944]. He used the game of poker as a basic model for 2-player zero-sum adversarial games, and proved the first fundamental result, the famous Minimax Theorem. Many decision problems can be modelled using game theory, and it has been employed in a wide variety of domains in recent years.

The poker domain contains a wide variety of challenges to standard learning and decision-making algorithms. The domain is inherently noisy and uncertain.

All reasoning in poker must be probabilistic, as things are rarely ever certain. The cumulative sum of a series of games matter more than any individual game [Billings et al., 1998] [Davidson et al., 2000].

Poker is a non-cooperative multi-player game. A wealth of challenging problems exists in multi-player games that do not exist in two-player games.

Multi-player games are inherently unstable, due in part to the possibility of coalitions (i.e., teams), but those complexities are minimized in a non-cooperative game [Sturtevant, 2002] [Sturtevant, 2004].

2.1 Poker

Poker is a popular type of card game in which players bet on the value of the card combination ("hand") in their possession, by placing a bet into a central pot. The winner is the one who holds the hand with the highest value according to an established hand rankings hierarchy, or otherwise the player who remains "in the hand" after all others have folded (the player who makes an un-called bet.).

Poker has many variations, all following a similar pattern of play. Depending on the variant, hands may be formed using cards, which are concealed from others, or from a combination of concealed cards and community cards.

In casual play, the right to deal a hand typically rotates among the players and is marked by a token called a 'dealer' button (or "buck"). In a casino, a house dealer handles the cards for each hand, but the button (typically a white plastic disk) is rotated clockwise among the players to indicate a nominal dealer to determine the order of betting.

One or more players are required to make forced bets (usually called a 'blind' or an 'ante') to create an initial stake for which the players will contest. The dealer shuffles the cards, cuts, and deals the appropriate number of cards to the players, one at a time.

Cards may be dealt either face-up or face-down, depending on the variant of poker being played. After the initial deal, the first of what may be several betting rounds begins. Between rounds, the players' hands develop in some way, often by being dealt additional cards or replacing cards previously dealt. At the end of each round, all bets are gathered into the central pot.

At any time during a betting round, if one player bets and no opponents choose to call (match) the bet, the hand ends immediately, the bettor is awarded the pot, no cards are required to be shown, and the next hand begins. This is what makes bluffing possible.

Bluffing is a primary feature of poker, one that distinguishes it from other vying games and from other games that make use of poker hand rankings.

At the end of the last betting round, if more than one player remains, there is a showdown, in which the players reveal their previously hidden cards and evaluate their hands. The player with the best hand according to the poker variant being played wins the pot. A poker hand consists of five cards, but in some variants a player has more than five to choose from.

2.1.1 Poker Hands

The combinations of cards in Poker are described next, in order from the highest to lower.

Royal Flush: An Ace, King, Queen, Jack and Ten in the same suit.

In the event of a tie: Two or more Royal Flushes split the pot.



Fig 1: Royal Flush

Straight Flush: Five cards in sequence, of the same suit.

In the event of a tie: Highest rank at the top of the sequence wins.

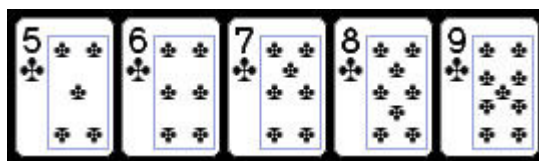


Fig 2: Straight Flush

Four of a Kind: Four cards of the same rank, and one side card.

In the event of a tie: Highest four of a kind wins. In community card games where players have the same four of a kind, the highest fifth side card ("kicker") wins.



Fig 3: Four of a Kind (poker)

Full House: Three cards of the same rank, and two cards of a different, matching rank.

In the event of a tie: Highest three matching cards wins the pot. In community card games where players have the same three matching cards, the highest value of the two matching cards wins.



Fig 4: Full House

Flush: Five cards of the same suit.

In the event of a tie: The player holding the highest ranked card wins. If necessary, the second-highest, third-highest, fourth-highest, and fifth-highest cards can be used to break the tie.



Fig 5: Flush

Straight: Five cards in sequence.

In the event of a tie: Highest ranking card at the top of the sequence wins.

Note: The Ace may be used at the top or bottom of the sequence, and is the only card which can act in this manner.



Fig 6: Straight

Three of a kind: Three cards of the same rank, and two unrelated side cards.

In the event of a tie: Highest ranking three of a kind wins. In community card games where players have the same three of a kind, the highest side card, and if necessary, the second-highest side card wins.



Fig 7: Three of a Kind

Two pair: Two cards of a matching rank, another two cards of a different matching rank, and one side card.

In the event of a tie: Highest pair wins. If players have the same highest pair, highest second pair wins. If both players have identical pairs, highest side card wins.



Fig 8: Two Pair

One pair: Two cards of a matching rank, and three unrelated side cards.

In the event of a tie: Highest pair wins. If players have the same pair, the highest side card wins, and if necessary, the second-highest and third-highest side card can be used to break the tie.



Fig 9: One Pair

High card: Any hand that does not qualify under a category listed above.

In the event of a tie: Highest card wins, and if necessary, the second-highest, third-highest, fourth-highest and smallest card can be used to break the tie.



Fig 10: High Card

2.1.2 Poker Variants

The most popular poker variants are draw poker, stud poker and community card poker.

In **Draw Poker**, each player receives five — as in five-card draw — or more cards, all of which are hidden. They can then replace one or more of these cards a certain number of times.

In **Stud Poker**, each player receive five — as in five-card stud — or more cards; some cards are dealt face up, one at a time, and displayed to other players at the table. The key differences between stud and 'draw' poker are that players are not allowed to discard or replace any cards in stud poker and that part of a players' hand in stud is exposed rather than the entire hand being hidden as in draw.

In **Community Card Poker**, players combine individually dealt cards with a number of "community cards" dealt face up and shared by all players. Each player will attempt to make the best five card poker hand using the community cards and their own face down cards. Two or four individual cards are dealt in the most popular variations, Texas Hold'em and Omaha Hold'em, respectively.

2.2 Texas Hold'em

Texas Hold'em is the most popular poker game, and is the variant of Poker that we are going to consider in this project. Hold'em is a community card game where each player may use any combination of the five community cards and the player's own two hole cards to make a poker hand, in contrast to poker variants like stud or draw where each player holds a separate individual hand.

After slow but steady gains in popularity throughout the 20th century, hold'em's popularity surged in the 2000s due to exposure on television, on the Internet, and in popular literature [CGN, 2008].

Because each player only starts with two cards and the remaining cards are shared, it presents an opportune game for strategic analysis (including mathematical analysis). Hold'em's simplicity and popularity have inspired a wide variety of strategy books which provide recommendations for proper play.

This game is very easy to learn, each player receives two cards on the hand. The leaf of the player will be made later by 5 out of a total of 7 cards .

Hold'em is normally played using small and big blind bets – forced bets by two players. A dealer button is used to represent the player in the dealer position; the dealer button rotates clockwise after each hand, changing the position of the dealer and blinds. The

small blind is posted by the player to the left of the dealer and is usually equal to half of the big blind. The big blind, posted by the player to the left of the small blind, is equal to the minimum bet (fig 11).

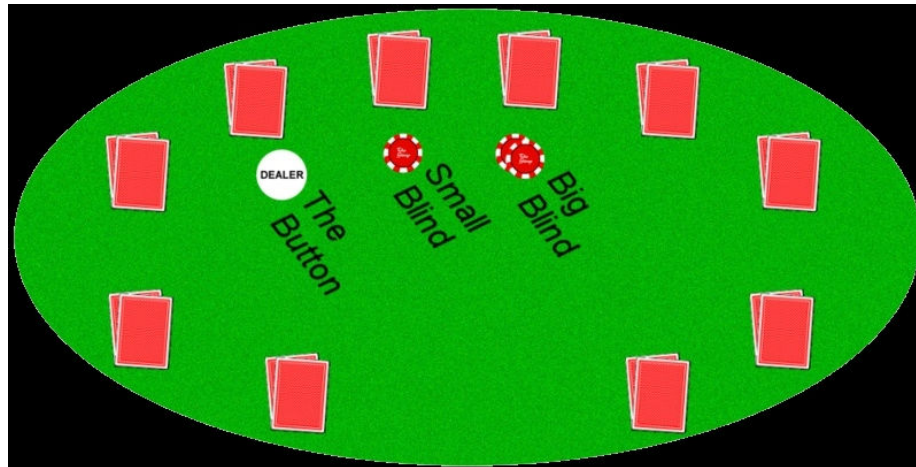


Fig 11: The positions at the table [wikimedia, 2008]

It follows an initial bidding for each player in turn must now consider what he and his two cards probably start. When bidding, the players always have the opportunity to keep (“hold”), to increase (“raise”) or abandon (“fold”).

Then three cards open in the middle. It follows a second bidding. Then a fourth card - closely followed by bidding - and then is the fifth card openly lying. As expected, once again it follows another bidding.

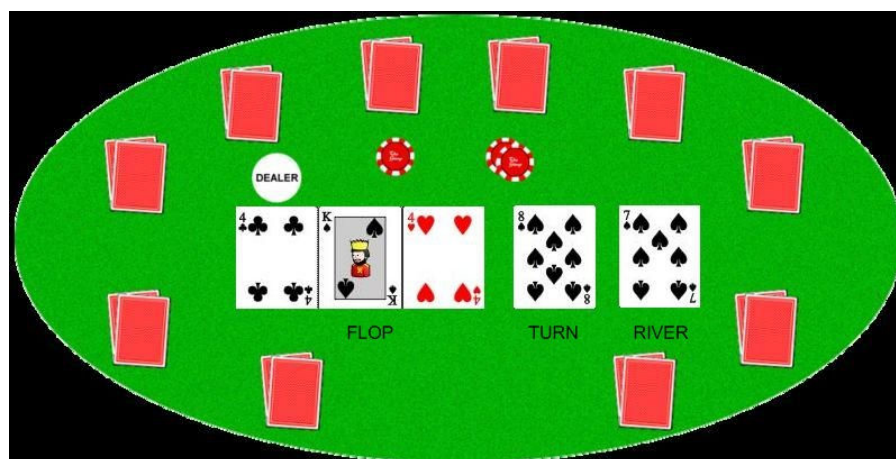


Fig 12: The flop, turn and river [wikimedia 2008, adapted]

After the fifth card is dealt, each one of the players knows exactly what his hand is worth. The hand for each player is the five card combination of seven possible cards to choose (five on the board and two from the player).

If more than one player remains after the last round, there is a “showdown”, in which the players reveal their previously hidden cards and evaluate their hands. The player with the best hand according to the poker variant being played wins the pot.

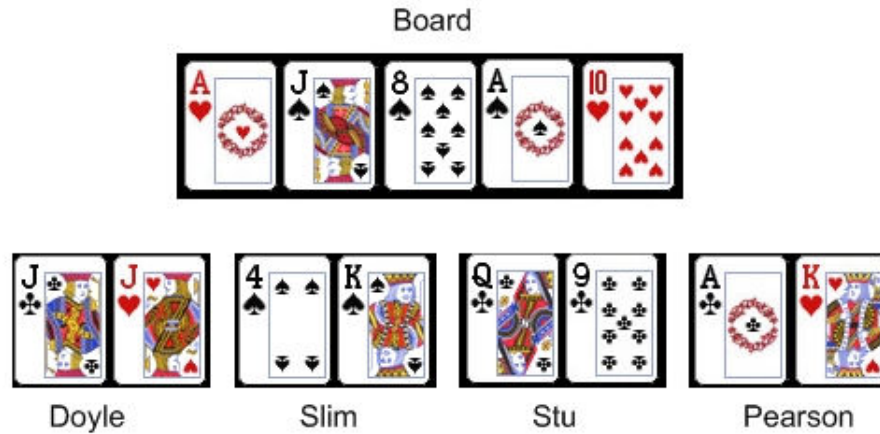


Fig 13: Sample showdown

Each one of the players plays the best 5 cards with the seven cards available.

The combinations of this showdown could be seen in figure 14.

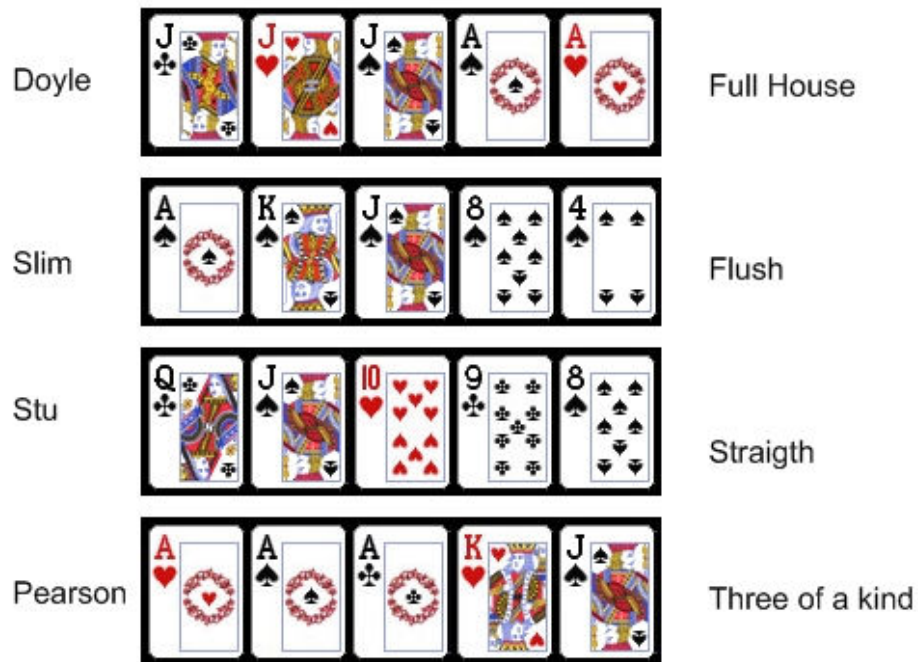


Fig 14: Combinations of cards at the showdown

In this case, Doyle's full house is the best hand, with Slim in 2nd (flush), Stu in 3rd (straight) and Pearson last (three of a kind) [Wikipedia, 2008].

2.3 Related Work

This project is essentially based on two previous works, the first one “Algorithms and Assessment in Computer Poker” from Darse Billings [Billings, 2006], is a very complete thesis about the work done at The University of Alberta Computer Poker Research Group [UA GAMES Group, 2008].

The second work that supports this project is a work done in FEUP at LIACC, which consists of a poker simulator software [Afonso and Silva, 2007]. It includes a server and a basic intelligent agent.

2.3.1 The U.A. Computer Poker Research Group

The University of Alberta Computer Poker Research Group (CPRG) is the major contributor to the academic literature on poker game-playing AI [CPRG, 2008].

The research began in 1992 with scientific foundations, methodologies, and research philosophy. This included a complete basic implementation, along with computer-oriented algorithms (rather than knowledge-based methods) for advanced hand assessment, simulation techniques, and other essential functions [Billings, 1995]. The CPRG was formed in 1997 to follow up on this work. Darse Billings [Billings et al., 1998] is the lead architect for the group, and the domain expert. He played poker professionally from 1996 to 1999, after several years of studying and extending poker theory [Billings et al., 1999].

The thesis “Algorithms and Assessment in Computer Poker” [Billings, 2006] describes the work done at University of Alberta. The most significant topics that influence this work are:

- Pre-flop strategies;
- Hand strength, hand potential and effective hand strength;
- Opponent Modelling.

The betting strategies developed at University of Alberta are essential to a basic agent capable of playing poker. They are divided in betting strategy before the flop and after the flop [Billings et al., 2002].

These betting strategies are significantly different. Before the flop the decision is very simple, because the agent only has to consider the two starting cards. After the flop the program should analyze how all possible opponent holdings combine with the given public cards.

There are 1326 possible hands **prior to the flop**. The value of one of these hands is called an income rate, and is based on a simple technique that is called a roll-out simulation. This is an off-line computation that consists of playing several million games (trials) where all players call the first bet. This does provide an approximation, and the relative values of the hands are reasonably accurate for the given situation [Papp, 1998] [Peña, 1999].

There is a strong correlation between Sklansky groups [Sklansky & Malmuth, 1994] and the results of the roll-out simulations (table 1) and since the differences are not large, it is clear that roll-out simulations provide an acceptable means of quantifying the pre-flop value of each hand.

Sklansky is a professional poker player and was the first to apply rankings to the starting 2-card hands, and place them in groupings with advice on how to play those groups. This subject will be analysed in Chapter 3.

Group 1		Group 2		Group 3		Group 4	
+2112	AA	+714	TT	+553	99	+481	T9s
+1615	KK	+915	AQs	+657	JTs	+515	KQo
+1224	QQ	+813	AJs	+720	QJs	+450	88
+935	JJ	+858	KQs	+767	KJs	+655	QTs
+1071	AKs	+718	AKo	+736	ATs	+338	98s
				+555	AQo	+449	J9s
						+430	AJo
						+694	KTs
Group 5		Group 6		Group 7		Group 8	
+364	77	+304	66	+214	44	-75	87o
+270	87s	+335	ATo	+92	J9o	+87	53s
+452	Q9s	+238	55	+41	43s	+119	A9o
+353	T8s	+185	86s	+141	75s	+65	Q9o
+391	Kj0	+306	KTo	+127	T9o	-129	76o
+359	QJo	+287	QTo	+199	33	-42	42s
+305	JTo	+167	54s	-15	98o	-83	32s
+222	76s	+485	K9s	+106	64s	+144	96s
+245	97s	+327	J8s	+196	22	+85	85s
+538	A9s			+356	K8s	-51	J8o
+469	A8s			+309	K7s	+206	J7s
+427	A7s			+278	K6s	-158	65o
+386	A6s			+245	K5s	-181	54o
+448	A5s			+227	K4s	+41	74s
+422	A4s			+211	K3s	+85	K9o
+392	A3s			+192	K2s	-10	T8o
+356	A2s			+317	Q8s		
+191	65s						

Table 1: Income Rate Values VS Sklansky Groups [Billings, 2006]

It was preferred to use the computed results, rather than transcribing the Sklansky rules, because of the wish to eliminate the use of human knowledge whenever possible, (b) the roll-out simulation information is quantitative rather than qualitative, and (c) the

algorithmic approach can be applied to many different specific situations (such as having exactly six players in the game), whereas Sklansky gives only a few recommendations for atypical circumstances [Billings, 2006].

The basic betting strategy **after the flop** is based on computing the hand strength (HS), positive potential (PPot), negative potential (NPot), and effective hand strength (EHS) of agent's hand relative to the board.

EHS is a measure of how well the agent's hand stands in relationship to the remaining active opponents in the game. It is a combination of the current hand strength (HS) and positive potential for the hand to improve (Ppot).

The **hand strength (HS)**, figure 15, is the probability that a given hand is better than that of an active opponent. Suppose an opponent is equally likely to have any possible two hole card combination. All of these opponent hands can be enumerated, identifying hand is better (+1), tied (+1/2), or worse (0). Taking the summation and dividing by the total number of possible opponent hands gives the (unweighted) hand strength.

```

HandStrength(ourcards, boardcards, player_classification)
{
    ahead = tied = behind = 0
    ourrank = Rank(ourcards, boardcards)
    /* Consider all two-card combinations of the remaining cards. */
    for each case(oppcards)
    {
        opprank = Rank(oppcards, boardcards)
        if (ourrank>opprank) ahead += 1
        else if (ourrank==opprank) tied += 1
        else behind += 1
    }
    handstrength = (ahead+tied/2) / (ahead+tied+behind)
    return(handstrength)
}

```

Fig 15: Hand Strength Calculation

After the flop, there are still two more board cards to be revealed. On the turn, there is one and it's essential to determine the potential impact of these cards, figure 16. The **positive potential (PPot)** is the chance that a hand that is not currently the best improves to win at the showdown. The negative potential (NPot) is the chance that a currently leading hand ends up losing.

PPot and NPot are calculated by enumerating over all possible hole cards for the opponent, like the hand strength calculation, and also over all possible board cards. For all combinations of opponent hands and future cards, we count the number of times the agent hand is behind, but ends up ahead (PPot), and the number of times hand is ahead but ends up behind (NPot).

```

HandPotential(ourcards, boardcards, player_classification)
{
  /* Hand Potential array, each index represents ahead, tied, and behind. */
  integer array HP[3][3] /* initialize to 0 */
  integer array HPTotal[3] /* initialize to 0 */
  ourrank = Rank(ourcards, boardcards)
  /* Consider all two-card combinations of the remaining cards for opponent. */
  for each case(oppcards)
  {
    opprank = Rank(oppcards,boardcards)
    if(ourrank>opprank) index = ahead
    else if(ourrank==opprank) index = tied
    else index = behind
    HPTotal[index] += 1

    /* All possible board cards to come. */
    for each case(turn)
    {
      for each case(river)
      { /* Final 5-card board */
        board = [boardcards,turn,river]
        ourbest = Rank(ourcards,board)

        oppbest = Rank(oppcards,board)
        if(ourbest>oppbest) HP[index][ahead] += 1
        else if(ourbest==oppbest) HP[index][tied] += 1
        else HP[index][behind] += 1
      }
    }
  }

  /* PPot: were behind but moved ahead. */
  PPot = (HP[behind][ahead] + HP[behind][tied])/2
  + HP[tied][ahead]/2) / (HPTotal[behind]+HPTotal[tied]/2)
  /* NPot: were ahead but fell behind. */
  NPot = (HP[ahead][behind] + HP[tied][behind])/2
  + HP[ahead][tied]/2) / (HPTotal[ahead]+HPTotal[tied]/2)

  return(PPot,NPot)
}

```

Fig 16: Hand Potential Calculation

Computing the potential on the flop can be expensive, given the real-time constraints of the game (about one second per decision). There are 990 possible turn and river cards to consider for each possible two-card holding by the opponent. In practice, a fast approximation of the PPot calculation may be used, such as considering only the next one card to come.

The **effective hand strength (EHS)** combines hand strength and potential to give a single measure of the relative strength hand against an active opponent.

One simple formula for computing the probability of winning at the showdown is:

$$\mathbf{Pr(win)} = \mathbf{Pr(ahead)} \times \mathbf{Pr(opp\ not\ improve)} + \mathbf{Pr(behind)} \times \mathbf{Pr(we\ Improve)} \quad (Eq\ 1)$$

$$\mathbf{Pr(win)} = \mathbf{HS} \times \mathbf{(1 - NPot)} + \mathbf{(1 - HS)} \times \mathbf{PPot} \quad (Eq\ 2)$$

In practice, the correct act is bet when having the best hand, regardless of negative potential, so that an opponent with a marginal hand must either fold, or pay to draw. Hence, NPot is not as important as PPot for betting purposes. Since the interest is the probability of the hand is either currently the best, or will improve to become the best, one possible formula for EHS sets $\mathbf{NPot} = \mathbf{0}$, giving:

$$\mathbf{EHS} = \mathbf{HS} + \mathbf{(1 \times HS)} \times \mathbf{PPot} \quad (Eq\ 3)$$

This has the effect of betting a hand aggressively despite good draws being possible for opponent hands, which is a desirable behaviour.

For n active opponents, this can be generalized assuming that the same EHS calculation is the same for all opponents:

$$\mathbf{EHS} = \mathbf{HS}^n + \mathbf{(1 - HS}^n) \times \mathbf{PPot} \quad (Eq\ 4)$$

With this simple strategy the result is an agent that is capable of calculate the hand strength of all possible a hands in pre-flop. And also capable of calculate the Effective Hand Strength in each round after the flop.

Based on this capacity, it is possible to create several types of agents that use different strategies. Each one of them decides a different move for the hand strength in pre-flop or EHS post-flop.

At University of Alberta CPRG, a general system for opponent modelling was implemented with a neural network for predicting the opponent's next action in any given context [CPRG, 2008]. Guessing the next action is useful for planning advanced betting strategies, such as a check-raise, and is also used in each trial of a full-information simulation.

A standard feed-forward neural net was trained on contextual data collected from online games against real human opponents. The networks contain a set of nineteen inputs corresponding to properties of the game context, such as the number of active players, texture of the board, opponent's position, and so on. These are easily identified factors that may either influence, or are correlated with a player's next action.

The output layer consists of three nodes corresponding to the fold, call, and raise probabilities. Given a set of inputs, the network will produce a probability distribution of the opponent's next action in that context (by normalizing the values of the three output nodes) [Billings et al., 1998] [Davidson et al., 2000].

This approach of opponent modelling seems very useful in poker, since predicting the opponent's next action could give an edge over them. Meanwhile, in this project the Opponent Modelling strategy intends to give another approach. Predicting Opponent's cards. This strategy is different of the one developed at University of Alberta and is going to be explained in the next chapters.

2.3.2 The LIACC's Texas Hold'em simulator

Previous work about computer Poker has been developed at LIACC, including a software capable of simulating the Texas Hold'em game [Afonso & Silva, 2007]. It was based on a Server that communicates with Clients through sockets with a predefined communication protocol. The software was developed in C/C++.

The Client software has two versions, the first one could be controlled by a human, and the second which acts autonomously and is programmed to make the best move in function of the state of the game. This Intelligent Agent was developed based in the Betting strategy described at "Algorithms and Assessment in Computer Poker" by Billings [Billings, 2006].

The server accepts up to 10 players (clients) that can connect over the protocol TCP/IP. It has the option to choose the initial chips of the players, the value of the blinds, the port used to communicate, the number of simulations and the name of the log file.

These log files could be analysed after the game to get information about all the plays occurred and the chips of every player. Table 1 shows a part of a log file. This is an example of a game with 3 players. It's only an extract showing the first 10.

POKER TEXAS HOLD'EM				FEUP 2007					
Player 0			Player 1			Player 2			
Game	Bet	Won	Money	Bet	Won	Money	Bet	Won	Money
0	0	0	1000	10	-10	990	20	30	1010
1	20	-20	980	0	0	990	20	40	1030
2	10	-10	970	20	30	1000	0	0	1030
3	0	0	970	10	-10	990	20	30	1040
4	20	30	980	0	0	990	10	-10	1030
5	30	70	1020	20	-20	970	20	-20	1010
6	30	60	1050	10	-10	960	20	-20	990
7	20	-20	1030	20	50	990	10	-10	980
8	10	-10	1020	20	30	1000	0	0	980
9	0	0	1020	10	-10	990	20	30	990

Table 2: Log file from server

In table 2 we can see that in game 5, for example, the player 0 bets 30 chips and won 70, staying with 1020. The player 1 bets 20 chips and lost them, staying with 970. Player 2 bets 20 chips and also lost them, staying with 1010.

The communication protocol used is compatible with the one developed at University of Alberta Computer Poker Research Group [CPRG, 2008]. This makes possible the use of our agents in servers of other projects and even the participation in competitions like “2008 AAI Poker Competition” [AAAI’08, 2008].

The 2007 AAI Poker Competition consisted of 15 competitors from 7 countries and 43 bots. Matches were played on 32 machines running for a month, playing over 17 million hands of poker [AAAI’07, 2007].

The AAI Computer Poker Competition showcases state-of-the-art intelligent programs for playing poker. This is the premiere venue for demonstrating poker-playing software systems.

The poker variant considered in the 2008 competition will be Texas Hold'em poker. The competition will build on the success of the previous years' two-player (heads-up) competitions, with both limit and no-limit betting structures. New this year will be a multiplayer competition. This addition intends to significantly spur the development of new techniques since presently the most successful solution techniques for two-player games do not apply to multi-player games.

The communication protocol implemented is based on simple strings sent between server and clients as text messages.

After the connection between server and client is done, the client sent to the server the string (1) that gives the server the information of the version used. With this, the server knows that this client is now connected and gives him the lowest number available for identification.

“VERSION:1.0.1\n” (1)

After 2 or more clients have connected and the game has been activated, the server sends to all the clients the message (2).

“START:Q:W:E:R:T:Y\n” (2)

- Q – version of the game;
- W – maximum number of players
- E – binary number of active players (Ex: 7 = 0000000111, the first 3 players are in game)
- R – initial stack (money)

- T – value of small blind
- Y – value of big blind

After that, all the clients have the information needed to start the game. The server starts to send the cards to the first player.

“MATCHSTATE:0:0::Ah2d|” (3)

“MATCHSTATE:1:0::|Tc3s:f” (4)

The server sends string (3) to player 0 and string (4) to player 1, let’s analyse the string:

“(0):(1):(2):(3):(4):(5)”

- (0) – type of message;
- (1) – number of player that the message was sent;
- (2) – number of the game;
- (3) – current bets till the moment, separated rounds by “/” (Ex: rc/cf – 1 raise and 1 call in the pre-flop and 1 call and 1 fold in the flop);
- (4) – player cards, after the flop, the cards of the table are added and separated by “/” (Ex: |Ah2d/KsKhQc/Kc – player cards: Ah2d; flop: KsKhQc; turn: Kc);
- (5) – movement made by the player (c – call; r – raise; f - fold), only in the messages sent from client to server;

In (4), the “|” before the cards of the player means that the player is the dealer, all the other players have the “|” after the cards.

At the showdown, (4) will have all the cards of the players that remains in the game, starting from the player with the lowest number (Ex: Tc3s|Td4s|Ah2d/ KsKhQc/Kc/2s).

In figure 17, it’s shown the graphical interface of the server. In the right tab (debug) we can see the messages of the protocol that was explained previously.



Fig 17: The LIACC Poker Simulator – Server Application

Both of the software, server and client, have five classes essential for playing Texas Hold'em. Some other classes are implemented to support the application, but the main classes are:

- Card – returns the value and suit of the cards;
- Deck – responsible for shuffle up and deal the cards to the players and to the board;
- Game – controls the variables that refer to the state of the game (cards at the table, number of players, round, bets, ...)
- Player – controls the variables that refer to the players (bets, stack, number of player, ...)
- Parser – reads the messages received and parses in different variables;
- HandEvaluator – uses the cards from the board and the cards from a player to returns the value of the hand of this player.

The agent has also a class that is responsible for the decisions at the table - PokerAgent. This class basically implements the betting strategy developed in the University of Alberta Poker Research Group, explained previously.

In pre-flop, the function `Hand_Strength_Pre_Flop()` returns the income rate value (table 1) of the agent's cards. The decision of call, raise or fold is made in function of this value.

After the flop, for each new round, the functions `Hand_Strength()`, `Hand_Potential_Strength()` and `Effective Hand Strength()` returns values that will decides the movement call, raise or fold.

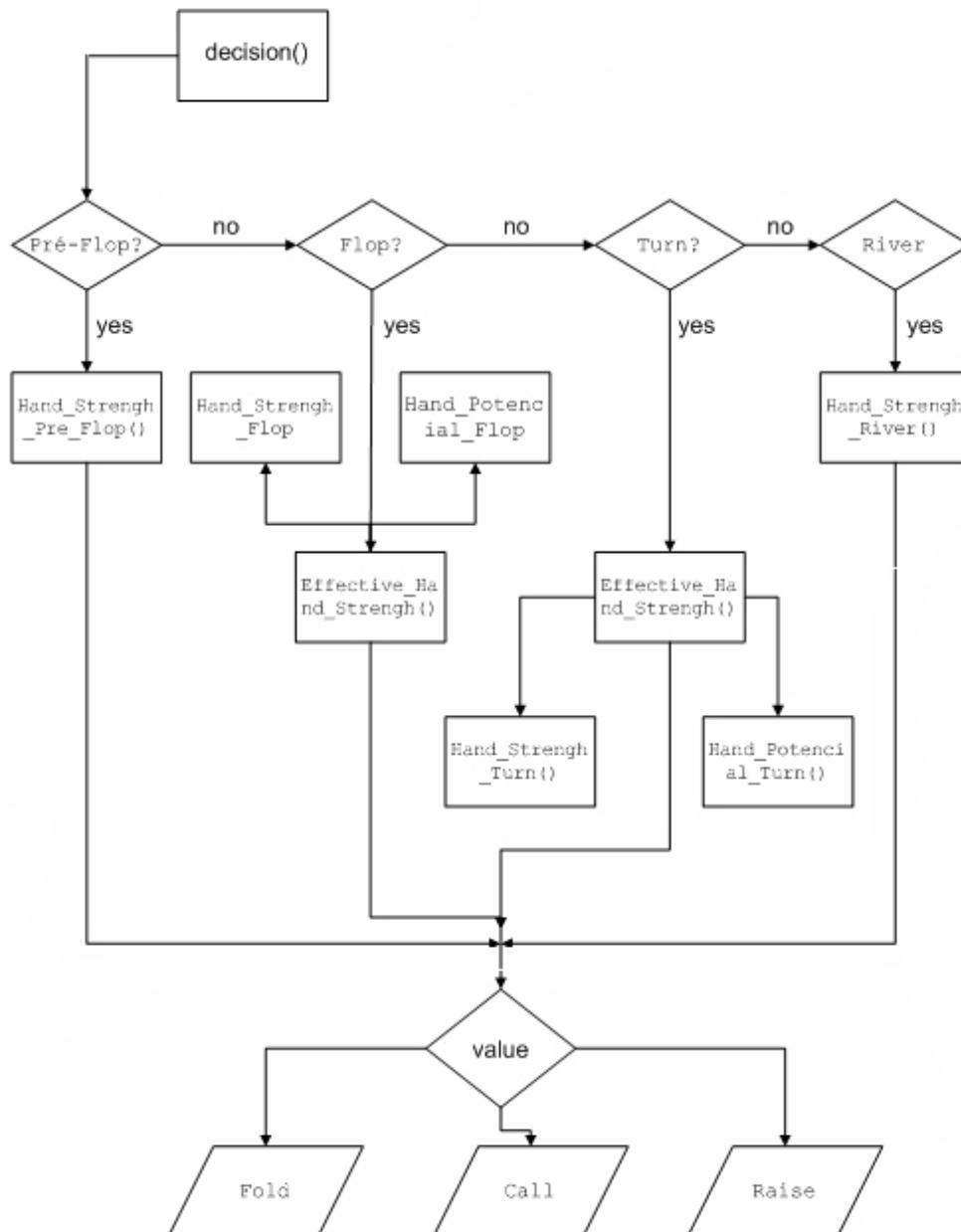


Fig 18: *PokerAgent Class Decision-Making Algorithm*

We can see in figure 18, for each round, a different function is used for Hand Strength and Hand Potential Strength.

Each one of this function returns a value that represents the probability of our hand wins the game considering our cards and, after the flop, also the board cards. Based on this value, it's possible to develop different agents that take different decisions based on the probability they have to win the game.

2.4 Summary

In this chapter it was presented the game of Poker and its Texas Hold'em popular variant. It was also explained how the LIACC basic poker server system, composed by simple intelligent agents and server application works. Related work developed at the University of Alberta Poker group was also analysed.

Besides having a good poker strategy implemented, another topic that should influence the decision of the intelligent agent is Opponent Modelling. In real poker games against humans, distinct strategies seem to work better with different opponents. However, before implementing this topic, it's necessary to understand the theory of player classification and starting hand selection. Chapter 3 will give a presentation of this theme.

Chapter 3

3. Opponent Modelling

As explained in the previous chapter, poker is a game that involves many topics like incomplete knowledge, risk management or opponent modelling. Each one of these topics is very important for a good poker player. Meanwhile, this work, as stated in the objectives, will focus mostly in opponent modelling methodologies for Poker playing agents.

No poker strategy is complete without a good opponent modelling system [Southey et al., 2005]. A strong poker player must develop a dynamically changing (adaptive) model of each opponent, to identify potential weaknesses.

In perfect information games, it has been sufficient to play an objectively best move, without special regard for the opponent. If the opponent plays sub optimally, then continuing to play good objective moves will naturally exploit those errors.

In poker, the situation is different. Two opponents can make opposite kinds of errors and both can be exploited, but it requires a different response for each. Even very strong players can employ radically different styles, so it is essential to try to deduce each opponent's basic approach to the game, regardless of how well they play [Billings et al., 2002].

Understanding the strategy of the opponent is essential for winning at the tables. In this project, it's intended to develop an Intelligent Agent that observes the moves of the other players in the table. There are many possible approaches to opponent modelling [Davidson, 2002] [Carmel & Markovitch] [Davidson et al., 2000], but in this work the observation model is based on basic observation of the starting moves of the players, so it could be created an estimated guess of their starting hands in future rounds.

Players could be classified generally in four models that depend of two variables: **loose/tight** and **passive/aggressive**. As soon as the intelligent agent identifies the

opponents, the calculation of the hand strength would be more precise, because the opponent possible hands are reduced to a small range.

3.1 Player Classification

Player classification, in the simplest of words, comes from knowing the poker strength of opponents. Player classification includes, but is not limited to:

1. Knowing what kinds of hole cards all of your opponents routinely play;
2. Knowing how often each player bluffs, and in what circumstances;
3. Knowing your opponents' general "style" of play: tight/aggressive, tight/passive, loose/aggressive, unpredictable, etc.

Knowing the types of hole cards various players tend to play, and in what position, is probably the start point of Opponent Modelling. Having information of tight/loose tendencies of each player at the table will make decisions easier.

Knowing how often players bluff, and in what circumstances, is very useful as well. The poker playing world is filled with players who love to bluff, for whatever reason. Some do it merely for the thrill, or to setup a bullying stance at the table, or to establish a loose/aggressive image at the table only to change it once it is set in.

3.2 Loose/Tight and Passive/Aggressive

Understanding these concepts is essential to a basic opponent modelling. Most poker players use these concepts to understand the behaviour of their opponents, even that sometimes unconsciously.

We classify a player as **loose** or **tight** according to the percentage of hands that he plays. These two basic concepts are obtained analysing the percentage of the time a player puts money into a pot to see a flop in Hold'em - VP\$IP.

VP\$IP is expressed as a percentage of the games a player puts money into a pot to see a flop in Hold'em. The big blind is not considered voluntary, so if a player checks his big blind, that is not considered in the VP\$IP calculation. However, if the big blind calls a raise, then it is considered for VP\$IP.

A player with a VP\$IP of about 28% or less is considered a **tight player**. If the percentage is above 28% or so the player is probably a **loose player**. Loose doesn't mean that the player loses more, is just a term that classifies opponents that plays a lot.

The players are also classified as **passive** or **aggressive**. These concepts are obtained analysing the Aggression Factor (AF). This is a ratio (not a percentage) which describes the nature of a player's bets. The formula is given by:

$$(bets + raises) / calls \quad (\text{Eq 5})$$

Bets, raises, and calls are all "money bets." Bets and raises, however, are aggressive (increasing the cost of playing) and calls are passive. Folds are not in the equation because they are not bets.

An AF of 1.0 implies that the person makes bets about as often as they call bets. Generally speaking, an AF dropping below 1 is to getting **passive**; an AF over 1 or so is generally getting **aggressive** (figure 19).

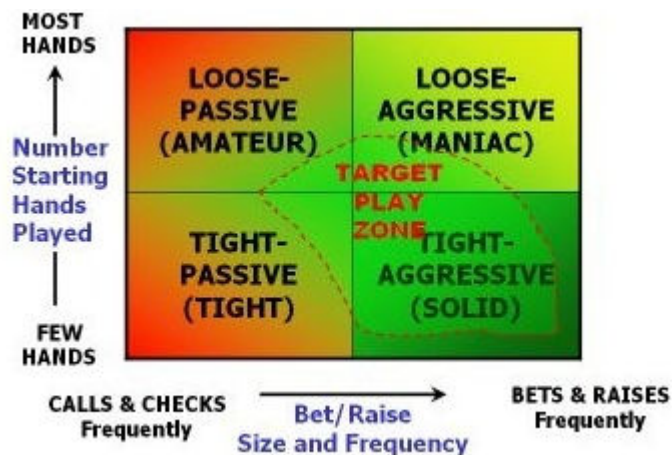


Fig 19: Player Classification

Knowing an opponent's style is essentially a fusion of the aforementioned aspects. Let's look at the basic types of playing styles individually.

3.2.1 Loose Aggressive

A Loose Aggressive player raises a good deal of hands in pre-flop and calls the rest. If his bet is raised, he will usually re-raise.

In a tight game, the loose aggressive may actually win games by stealing the blinds and flops enough to make up for all the times he is called down. When handling a strong hand however, it is hard to tell because his betting behaviour will be the exact same.

In a loose game with many players playing much hands, the loose aggressive player usually can't win by bluffing people out and ends up increasing the pot for the winning hand.

This player almost never folds when holding any hand with strength.

The best way of playing against a loose aggressive player is:

- Call their bets to the river will lose often but usually win more often than lose, so it's worth it.
- Any strong hand (top pair or better) should be bet out with the hope that this player re-raises and make the pot rentable.
- There is usually no threat unless the loose aggressive is a selective raiser. The correct choice should be to raise him right back and expect it to be capped to the river.
- Against a very loose aggressive player, the best position would be sitting to the right in order to see the action of the field before it comes around.
- In terms of starting hands however, sitting to the right has issues, since he will raise the blinds and other limping hands raised before the flop.

3.2.2 Loose Passive

These players use to play lots of hands and normally just by calling and rarely bet. They are what are known as “calling stations”. They tend to see almost every flop.

Pre-flop hands from these players are usually quite varied, because they usually don't have the knowledge about the real value of their cards .

The only advantage a loose passive has is that the strength of their hand is almost always unknown since they usually play most hands. Bluffing them is hard but not impossible as many of them will call to the river.

The best way of playing against a loose passive player is:

- Since calling is their usual move, any raise should be carefully considered and opponents should fold or at least not raise back unless holding a very good hand;
- Raising this players only when having a strong hand or a good possibility to draw one in order to make worth the pot won;

3.2.3 Tight Passive

The Tight Passive player understands the concept of playing only good hands, but pays little or no attention to what other players are doing. These players often fold to aggressive player's bets, and many will often fold winning hands. They are very cautious, as a rule.

Many play strong cards and calculate the best possible hands and whether or not they have them or not.

Usually a consistent showdown winner, this player won't try to make any moves, call down a bluffer or try to play any kind of poker other than simply playing their cards. They could easily be recognized because they don't see many flops and many of the flops they do see they fold.

These players play well in a loose game where players are not observing each other. By playing usually only the winning hands, these players have an edge over players who don't understand all the odds in poker.

The best way of playing against a tight passive player is:

- Take advantage of their predictable type of playing, they are only going to see the flop with very strong cards. If the board shows low cards with no strong straight or flush possibilities, this player folds pretty easily;
- Play carefully when this player bets, since they rarely do it. If this player called on the flop/turn and then bet out on the turn/river, that is almost a sure sign this player has very good hand;
- Betting is good, because tight players usually fold when they don't hold strong hands. A bet is also an information gatherer, because a call from this player indicates strength, while a raise is almost always a major hand.

3.2.4 Tight Aggressive

A tight/aggressive stance is the essential strategy of all strong players. Because of this, it is extremely important to identify these players as soon as possible. Players who have mastered this style of play will put the pressure on opponents at just the right time. They calculate the odds quickly. However, tight aggressive players can be predicted and beaten.

These players play a lot like Tight passive players when it comes to hand selection pre-flop, but after the flop, they play in a completely different style.

These players are good in tight games and loose games, but usually are best in mixed games.

The best way of playing against a tight aggressive player is:

- Wait for the right opportunity, when they get too aggressive and fall into a mode of trying to bluff more pots than they should, they start losing, especially on loose tables;
- Observe the position they have at the table, as general rule, the earlier the position bet the stronger the hand;
- Raising is actually one of the plays that will best deal with a tight aggressive. A normal play often seen is raising with the flush draw in late position;
- This player's weakness is being overly aggressive. Their bets are more often real than for show;

Although players fall essentially into those four categories, there are players who are just so unpredictable it's hard to classify. The best option is to treat these players as a tight/aggressive player. Really outstanding players will change their stance to fit the table, to give off the impression of a poor player, or, for the most obvious reason, just to be unpredictable.

3.3 Sklansky Groups

One of the most difficult and yet crucial decisions when playing Texas Hold'em is whether to even play or not the starting hand. Hitting the needed card on the flop only to end up with the second best hand can be very costly. So, first of all, only the best hands should be considered to play. David Sklansky and Mason Malmuth, co-authors of "Hold'em Poker and Advanced Hold'em Poker", were the first to apply rankings to the starting 2-card hands, and place them in groupings with advice on how to play those groups [Sklansky, 1992] [Sklansky and Malmuth, 1994].

There are some computer simulations developed to test Sklansky's hand rankings. They created multiple table environments, ranging from extremely tight to loose, and let them play millions of hands. They've suggested some alterations to Sklansky's hand rankings and groupings. But in general, the classification is very similar.

Group 1:	AA KKQQ JJ AKs
Group 2:	TT AQs AJs KQs AK
Group 3:	99 KTs QJs KJs ATs AQ
Group 4:	A8s KQ 88 QTs A9s AT AJ JTs
Group 5:	77 Q9s KJ QJ JT A7s A6s A5s A4s A3s A2s J9s T9s K9s KT QT
Group 6:	66 J8s 98s T8s 55 J9 43s 75s T9 33 98 64s 44 K8s K7s K6s K5s K4s K3s K2s Q8s 22 87s 97s
Group 7:	87 53s A9 Q9 76s 42s 32s 96s 85s J8 J7s 65 54 74s K9 T8 76 65s 54s 86s
Group 8:	all the other 2 cards combination

Table 3: Sklansky Groups – rankings of the 2-card hands

This classification (table 3) allows the player to choose what strength is needed for what situation and position. In their book they go into detail on what circumstances call for which group. In general, Groups 1-2 are powerful hands (high pairs, high suited cards), Groups 3-5 are medium hands (medium pairs) and Groups 6-8 are weaker hands.

3.4 Summary

As explained in the beginning of this chapter, a player is classified as loose or tight according to the percentage of hands that he plays (VP\$IP). If we consider the Sklansky groups, it's easy to conclude what starting hands a tight player usually plays. If the VP\$IP of the player is below 28%, he is probably playing hands from group 1 and 2, some of 3 and 4, and rarely from the other groups. In the other hand, if a player is a loose player, he's probably playing almost every hand from groups 1 to 4, some of 5 and 6 and even a few hands from the lower groups.

With this simple analysis, it's easy to exclude some of the hands that our opponents could have. Joining this theory to the betting strategy presented at Chapter 2, it is now possible to develop a better Intelligent Agent that observes the moves of the opponents and decides his movements based on the player classification made. Chapter 4 will show how this can be done in detail.

Chapter 4

4. Intelligent Agents

As referred in Chapter 2, this project is based on the simulator developed at LIACC. The basic agent is capable of determine the hand strength in pre-flop and the Effective Hand Strength after the flop. The first part of the work is to create different agents that emulate the behaviour of poker players defined in Chapter 3. As described in that chapter, players are classified generally by the VP\$IP and by AF. The idea is to create agents passives or aggressives and tight or loose based on the moves made.

4.1 Opponent Simulators

Based on player classification, were created 8 intelligent agents, two for each player style described in Chapter 2:

- Loose Aggressive Agents (Maniac and Gambler);
- Loose Passive Agents (Fish and Calling Station);
- Tight Aggressive Agents (Fox and Ace);
- Tight Passive Agents (Rock and Weak Tight);

Each of these agents will be described in detail in the following sections.

4.1.1 Loose Aggressive Agents

The first style analyzed was Loose Aggressive. For this style were created the agents “Maniac” and “Gambler”. Both of these agents will play lots of hands and they will raise or bet more often than call.

The Maniac was programmed to raise any hand from group 1, 2 or 3 in pre-flop. It will also raise a percentage of hands from group 4, 5 and 6, and call the rest. The hands from groups 7 and 8 will be raised but very few times.

The Gambler will act in a very similar way, but was programmed to play less hands from the lowest groups.

4.1.2 Loose Passive Agents

For this type of players, were created the agents “Fish” and “Calling Station”. These agents were programmed to play almost every hand till group 6 and a few from groups 7 and 8. They will raise only hands from group 1 and very few from other groups.

The difference between them is the percentage of hands played. “Fish” will play more hands from 7 and 8 than “Calling Station”.

4.1.3 Tight Passive Agents

“Rock” and “Weak-Tight” were the agents programmed to simulate tight passive players. These agents play only good hands from group 1 and 2. Sometimes they play hands from group 3 and few from other groups.

The difference between them is that Rock will play just a little more aggressive and raises more hands than “Weak-Tight”.

4.1.4 Tight Aggressive Agents

For this style, were created the agents “Fox” and “Ace”. These agents will play hands mostly from group 1, 2 and 3 like the tight passive agents, but almost every time they will raise those hands. They will also play hands from group 4 and 5, sometimes call and sometimes raise.

In order to avoid being predictive, they will raise a small percentage of hands from weaker groups. Table 2 shows the relation between the group hands and the actions in pre-flop of each one of the agents. The values presented in the table are chosen in order to force the players to play according the type of players tight, loose, aggressive and passive.

	Gambler	Maniac	Fish	Calling Station	Rock	Weak Tight	Fox	Ace
Group1	Raise	Raise	Raise 90% Call 10%	Raise	Raise	Raise	Raise	Raise
Group2	Raise	Raise	Call 80% Fold 20%	Raise 20%	Raise 70%	Raise 50%	Raise 90%	Raise 90%
Group3	Raise	Raise		Call 60%	Call 20%	Call 30%	Call 10%	Call 10%
				Fold 20%	Fold 10%	Fold 20%		
Group4	Raise 30%	Raise 50%			Raise 10%	Call 70%	Raise 30%	Raise 20%
Group5	Call 30%	Call 30%			Call 40%	Fold 30%	Call 10%	Call 10%
	Fold 40%	Fold 20%			Fold 50%		Fold 70%	Fold 70%
Group6							Raise 10%	Raise 10%
Group7	Raise 10%	Raise 10%	Call 20%	Call 20%			Fold 90%	Fold 90%
Group8	Call 10%	Call 10%	Fold 80%	Fold 80%				
	Fold 80%	Fold 80%						

Table 4: Agent's pre-flop movements

The movements described at table 4, guarantee that all the agents maintain the correct levels of VP\$IP and AF along most of the time they are playing.

After the flop, all the agents have the same strategy of decision. They will raise if the Effective Hand Strength (figure 18 - chapter 2) is equal or above 0.8 and call if less than 0.8 and above 0.5. Less than 0.5 all the agents fold. This is an approach that basically keeps the agents in game when having positive chances to win the game and make them fold when it's more probable they will loose. This strategy was not very explored for these agents, because the project is focused in analysing behaviour at pre-flop in hand selection.

The observer agent developed in the next level have the ability to check these variables and will validate the classification of the agents along the game.

4.2 Observer Agent

The main objective of this project is to create an agent that observes the behaviour of opponents. This agent, that we will call “Observer” was created with small differences from the rest. This agent is capable of:

- Keeping the information of every move made from the opponents;
- Analysing the information and calculating the VP\$IP and AF of each opponent in every moment of the game;
- Identifying which of the players are playing the round and knowing what kind of player each opponent is;
- Calculating Hand Strength in function of the opponent(s) for each game and each round after the flop.

These capabilities will enable the observer agent to play differently against each opponent type. Figure 20 shows the implemented interface for the Observer agent.



Fig 20: Observer Agent - Graphical Interface

4.2.1 Strategy

Every agent was programmed to receive information from the server about the moves of all the players in the table. The information received is the one described at the protocol

in chapter 2.3.2, the text message sent by the server to the agents includes the number of the game, the cards in the board (if available) and the moves made till the moment for all the players at the table.

A basic agent only processes this information in order to know when it's his time to play and how much chips were in the pot.

The Observer was also programmed to count the times each player folds, call or raise in order to calculate the Aggression Factor. It keeps the number of times each player call or raise in pre-flop to calculate the VP\$IP. Those variables are kept till the end of the game and are analysed every time the Observer has to make a decision.

When the observer's turn comes, he knows which of the opponents are in the game and predicts, based on the available information, what kind of player they are.

In order to follow any change of behaviour from the opponents, only the last 100 matches are considered to calculate the VP\$IP and AF.

This number has reached performed some tests with the observer agent playing in a table with different agents, playing different strategies. When considering only the last 50 or 60 games it's concluded that many times the opponents were wrongly classified. These numbers of games doesn't give the opponents the possibility to show their real strategy because the number of hands received tends to be or good or bad. Increasing this number of games, it's observed that the classification tends to be more precise.

After 100 games each one of the players received approximated the same number of good and bad hands, this number was considered in the rest of the project since it permits good classification and in other hand follows changes of behaviour.

The opponents are classified in the 4 types of players analysed at chapter 3. So, an opponent with VP\$IP above 28% is considered **loose**, otherwise, the player is considered **tight**. With an AF above 1, the player is considered **aggressive** and less than 1 is considered **passive** (table 5).

	AF<=1	AF>1
VP\$IP>=28%	Loose Passive (classification1)	Loose Aggressive (classification2)
VP\$IP<28%	Tight Passive (classification3)	Tight Aggressive (classification4)

Table 5: Player Classification

This classification could be observed at figure 20. Note that the observer software has a lateral tab in the right that shows the parameters of classification for each opponent.

After player classification and, based on the information referred in chapter 3.2, the agent could consider a different range of possible hands for different opponents. These considerations are based in the behaviour discussed at Chapter 3 for each kind of player.

A possible consideration is that **loose aggressive** players plays hands from group 1 to group 8 but only raises hands in pre-flop from groups 1 to 3 and a percentage (less than 50%) from groups 3 to 6.

From **loose passive** players, the agent could consider that the players are playing hands from group 1 to 8, but only raising from group 1, and a small percentage (less than 30%) from group 2 to 4.

Obviously, for tight players, the range of hands to consider is much smaller.

So, for **tight passive** players, the range of hands to consider is from groups 1 to 6 and a raise should be considered a hand from group 1 or 2 and a small percentage from group 3.

For **tight aggressive** players the agent should only consider hands from group 1 to 5, and raises from group 1 to 3 and also a percentage from groups 4 and 5 (less than 30%).

In order to pass this information to Hand Strength calculation, for each player is determined a parameter that was called “sklansky” (figure 21). This parameter is a float number that represents the lowest value of a hand (view figure 16 from chapter 2 – Income Rate) that belongs to the most probable range of hands that the player plays with that specific movement (call or raise).

```

Sklansky(player_classification, player_move)
{
    random = (rand() % 10) + 1; /*random number between 1 and 10*/
    switch(player_classification)
    {
        case(1): /*loose passive*/
            if(player_move==raise)
            {
                if(random<=3) {return 26.2;} /*last hand from group 3*/
                else {return 44.2;} /*last hand from group 1*/
            }
            else if(player_move==call)
            {
                return -100.0; /* all the possible hands */
            }
        case(2): /*loose aggressive*/
            {
                ...similar to case 1 but with diferent values
            }
    }
}

```

Fig 21: Lowest value from probable opponent's hand

With conscience that many times the correct hand of the opponent is wrongly ignored, the better approach of Effective Hand Strength calculation given with this technique should give a better result that compensates this.

Note that the fact of not considering the opponent hand doesn't necessary means that the agent will loose the play.

4.2.2 Effective Hand Strength

The Hand Strength and Potential Hand Strength could now be calculated with a better approach. They are calculated only for active players and only considering the hands with a rank better than the "sklansky" parameter. The Effective Hand Strength is a combination of all these calculations.

The formulas seen in chapter 3 could be reformulated in the formulas shown at the figures 22 and 23.

We can see marked in blue (figure 22) the changes to the initial Hand Strength calculation. The algorithm only considers the hands that the opponent probably has.

```

HandStrength(ourcards,boardcards, player_classification)
{
    ahead = tied = behind = 0
    ourrank = Rank(ourcards,boardcards)
    /* Consider all two-card combinations of the remaining cards. */
    for each case(oppcards)
    {
        if(oppcards belong to player_starting_hands_range) /* change!*/
        {
            opprank = Rank(oppcards,boardcards)
            if(ourrank>opprank) ahead += 1
            else if(ourrank==opprank) tied += 1
            else behind += 1
        }
    }
    handstrength = (ahead+tied/2) / (ahead+tied+behind)
    return(handstrength)
}

```

Fig 22: Hand Strength Calculation with Opponent Modelling

The same consideration is used to calculate Hand Strength Potential (figure 23).

```

HandPotential(ourcards,boardcards,player_classification)
{
    /* Hand Potential array, each index represents ahead, tied, and behind. */
    integer array HP[3][3] /* initialize to 0 */
    integer array HPTotal[3] /* initialize to 0 */
    ourrank = Rank(ourcards,boardcards)
    /* Consider all two-card combinations of the remaining cards for opponent. */
    for each case(oppcards)

```

```

{
    if(oppcards belong to player_starting_hands_range) /*Change!*/
    {
        opprank = Rank(oppcards,boardcards)
        if(ourrank>opprank) index = ahead
        else if(ourrank=opprank) index = tied
        else index = behind
        HPTotal[index] += 1
    }

    /* All possible board cards to come. */
    for each case(turn)
    {
        for each case(river)
        { /* Final 5-card board */
            board = [boardcards,turn,river]
            ourbest = Rank(ourcards,board)
            if(oppbest belong to player_starting_hands_range)
            { /*Change!*/
                oppbest = Rank(oppcards,board)
                if(ourbest>oppbest) HP[index][ahead] += 1
                else if(ourbest==oppbest) HP[index][tied] += 1
                else HP[index][behind] += 1
            }
        }
    }
}

/* PPot: were behind but moved ahead. */
PPot = (HP[behind][ahead] + HP[behind][tied])/2
+ HP[tied][ahead]/2) / (HPTotal[behind]+HPTotal[tied]/2)
/* NPot: were ahead but fell behind. */
NPot = (HP[ahead][behind] + HP[tied][behind])/2
+ HP[ahead][tied]/2) / (HPTotal[ahead]+HPTotal[tied]/2)

return(PPot,NPot)
}

```

Fig 23: Hand Potential Calculation with Opponent Modelling

The Effective Hand Strength for each one of the opponents is given by the equation 6.

$$\mathbf{EHS}_i = \mathbf{HS}_i + (1 - \mathbf{HS}_i) \times \mathbf{PPot}_i \quad (\text{Eq 6})$$

Besides a better approach of the Effective Hand Strength, the agent could also decides his movement considering all the movements made before his turn to act.

4.3 Summary

At the end of this chapter we have several intelligent agents capable of simulating a Poker game. Eight different agents have different decisions for the Effective Hand Strength calculation which puts each one of them in one of the four player classifications studied.

We also have now an agent capable of observe the opponents and take decisions based on this observation. This new strategy only considers the possible cards of the opponent to calculate the Effective Hand Strength.

In the next chapter it will be described the tests done with all this agents. The results will show the differences between agents observers and non observers.

Chapter 5

5. Results

As referred previously, poker is a noisy domain. The element of chance is always present and obtaining significant results is a hard task. Thus a huge set of experiments has been performed in order to test the model developed. The methodology used to test the approach was performing game simulations in complete tables with poker agents playing different strategies. This was similar to a simulation of a real game with the objective to analyse the differences between the performance of an observer agent and a non observer agent. Both agents were set to play at the same table using the same strategy of pre-flop hand selection.

5.1 Game Simulation

In order to obtain some results, several simulations were made with the agents created. There are 8 normal agents and 1 observer, so the simulations were performed with 9 players at each table. The seats have the order shown in table 6.

Position	Player
Player 0	Observer
Player 1	Gambler
Player 2	Rock
Player 3	Fish
Player 4	Weak-tight
Player 5	Fox
Player 6	Calling station
Player 7	Ace
Player 8	Maniac

Table 6: Positions at the table

The simulations are done with 9 players at the table because of the purpose of the project – Opponent Modelling. The intention is to give the Observer Agent the possibility to play in a table with different kind of players. The Observer will have the chance to test his new strategy against different players several times along a complete simulation.

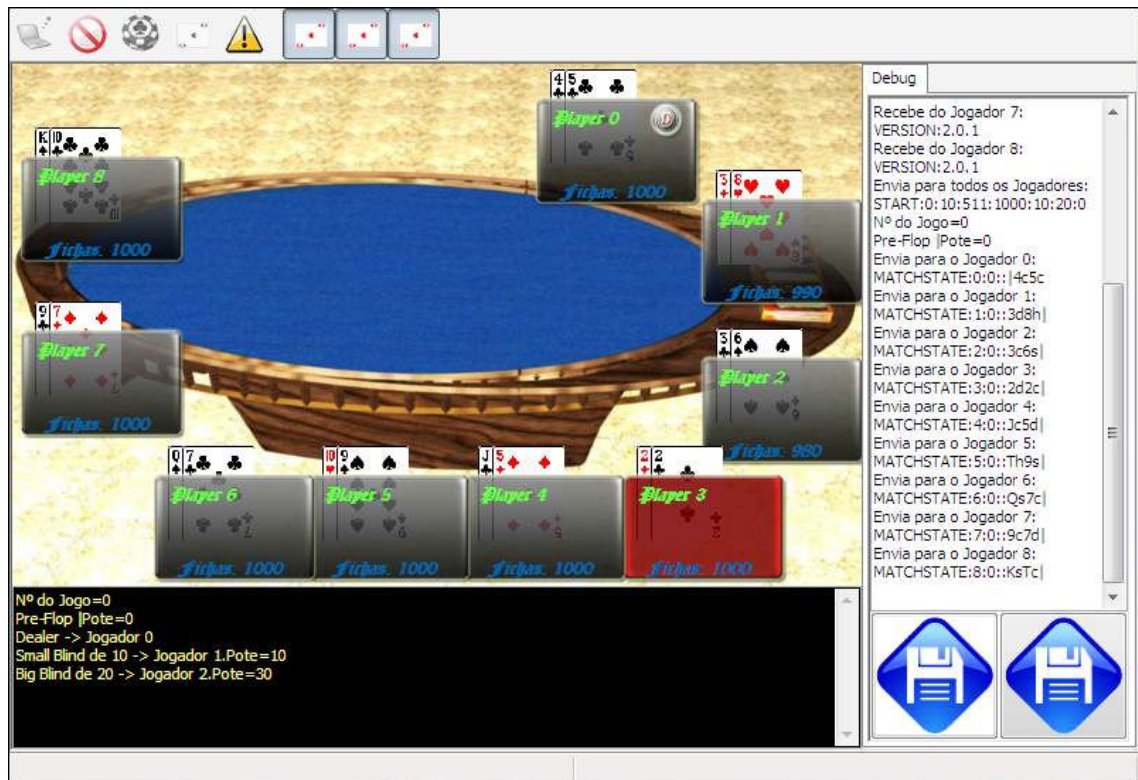


Fig 24: Simulation 1 – Server Graphical Interface

The figure 24 shows the server interface at the beginning of a simulation, the dealer is the player 0, and the player 1 is the small blind, and already has paid 10 chips, the player 2 is the big blind and has paid 20 chips. The rest of the players keep the initial stack of 1000 chips.

In the first simulation, the Observer (player 0) was programmed to act like a Gambler. This means that the hand selection in the pre-flop of the Observer will be equal to the one made by the Gambler agent (player 1).

The player 1 was also a gambler. These two players use the same strategy for choosing the starting cards, but after that, the player 0 decides all his moves based on opponent modelling while Gambler plays regularly like described in Chapter 4.

The results observed in the log files of the server should confirm that opponent modelling improves the strategy of an Intelligent Agent.

After the first simulation with the observer playing like a Gambler, the next simulations would have observers acting like 3 other players (table 7).

To avoid long time simulations, only four agents were adapted to observers, one for each kind of player:

- Gambler represents **loose aggressive** players.
- Rock represents **tight passive** players.
- Fox represents **tight aggressive** players.
- Calling Station represents **loose passive** players.

Each one of the simulations performed was repeated 3 times in order to reduce the effect of luck in the final results. The simulation ends up when one of the two agents loses all his bankroll or when the simulation reaches the game 2000 or more in some (extraordinary) cases where is necessary. This is done in order to avoid long time simulations that take too much time. The ideal simulation should continue till one of the agents loses all his chips, but the conditions of this project are limited by time. About 2000 games should be sufficient to take some conclusions. In this number of games, each one of the agents probably receives the same number of good and bad hands.

The objective of all those simulations is to verify if opponent modelling is always a benefit for a poker agent or if depends of the style of player that's doing the modelling. Table 7 describes the simulation games performed.

Simulation	Observer acting like a:	Position of similar agent at the table:
1,2,3	Gambler	1
4,5,6	Calling Station	6
7,8,9	Fox	5
10,11,12	Rock	2

Table 7: Game Simulation

The results are presented in the form of graphs showing the bankroll of the two agents to be compared, the observer and the non observer agent. Although the graphs only shows two lines representing these two agents, it's important to keep in mind that the games are simulated always with nine players (table 6).

5.2 Loose Aggressive Observer

The game simulations to test loose aggressive agents were represented by a “Gambler Observer”. In the figures 25, 26 and 27, we can see 3 graphs that represent the bankroll of the two Gambler agents (observer and non observer) in the 3 game simulations.

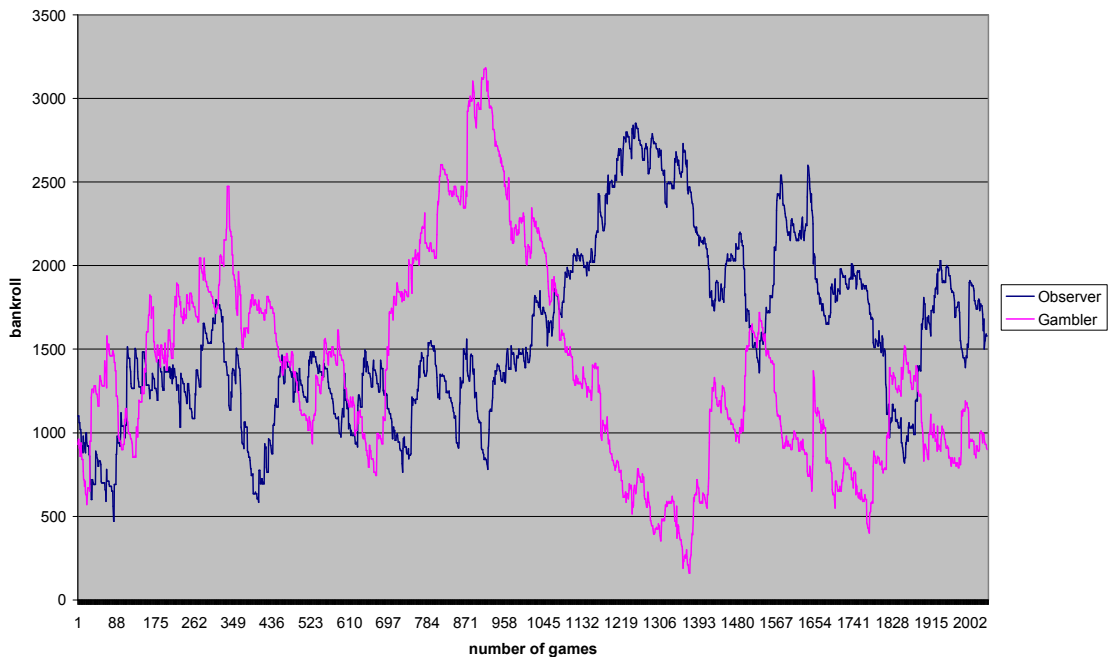


Fig 25: Bankroll variation of the Observer and Gambler Agent in the first simulation

In the first simulation (fig 25), we can observe that opponent modelling doesn't seem to improve the performance of the Gambler player. The bankroll of the two agents doesn't have much differences along the games played. After the 2000 games we can see that Observer keeps more chips than the non observer agent but this simulation is not very conclusive.

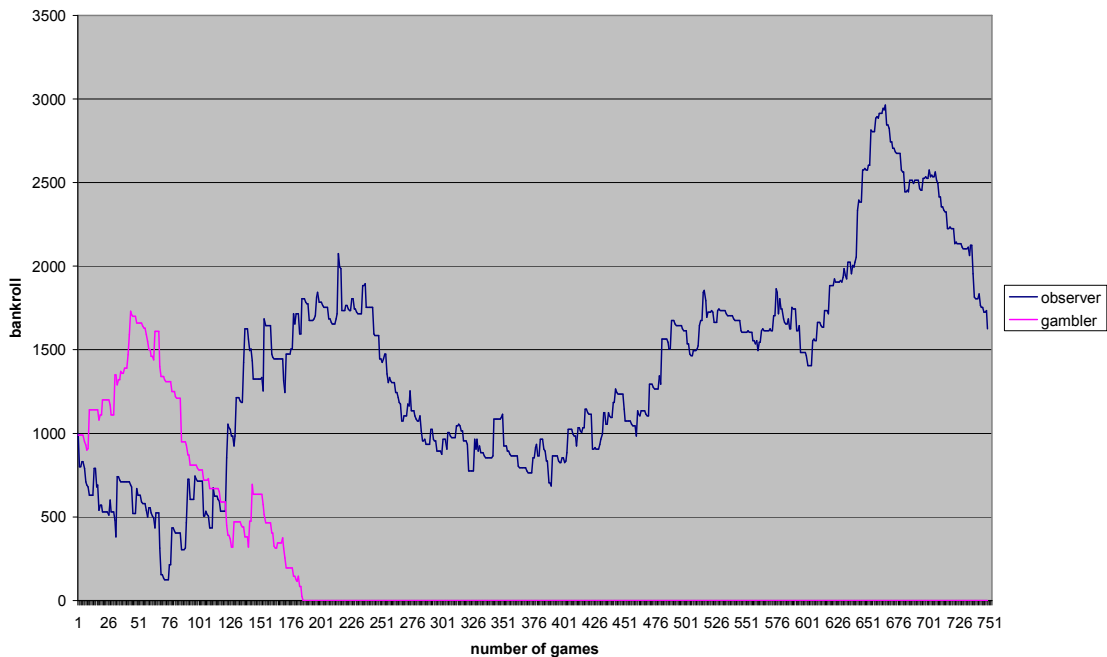


Fig 26: Bankroll variation of the Observer and Gambler Agent in the second simulation

In the second simulation (fig 26) we can observe that both of the agents start to lose much of the bankroll in the first hundred games. This is typical from a loose aggressive player, the great percentage of games played and the “aggressively” of the bets causes large variations of bankroll.

Because of the opponent modelling strategy, the Observer bets carefully after the flop and loses less chips when doesn't have a good game, so the observer can keep a stable number of chips better than a non observer agent.

In this simulation, opponent modelling clearly proves to be an advantage.

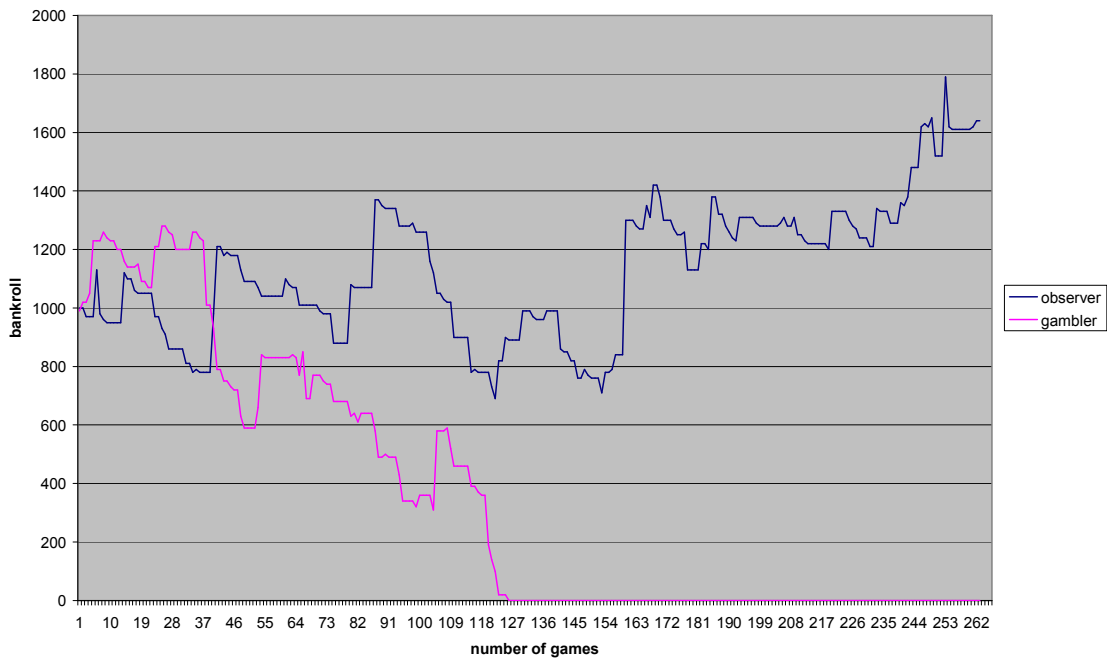


Fig 27: Bankroll variation of the Observer and Gambler Agent in the third simulation

This simulation (figure 27) is very similar to the previous one. Once again, the non observer agent lost his bankroll very quickly and the observer agent keeps his chips for long time.

The fact that the third simulation was very similar to the second, reinforce the idea of the advantage of opponent modelling.

5.3 Loose Passive Observer

The game simulations to test loose aggressive agents were represented by a “Calling Station Observer”. In the figures 28, 29 and 30, we can see 3 graphs that represent the bankroll of the two Calling Station agents (observer and non observer) in the 3 game simulations.

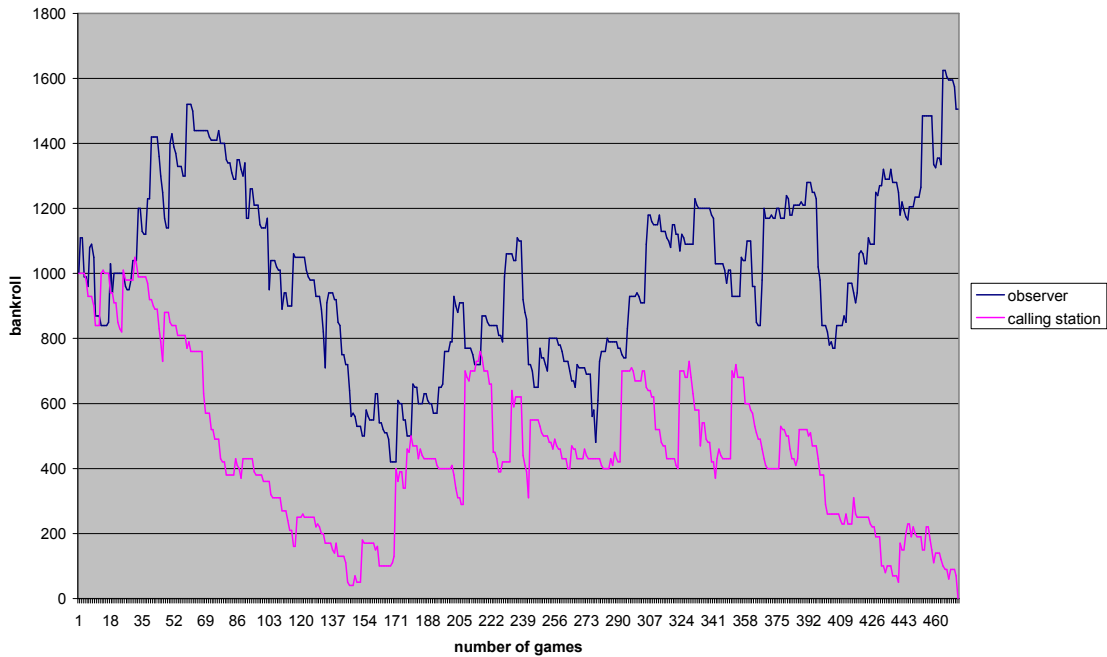


Fig 28: Bankroll variation of the Observer and Calling Station Agent in the first simulation

The first simulation with loose passive agents (Calling Station) is shown on fig 28. We can see by the graph that both of the agents doesn't earn too much chips and rarely have more than the initial bankroll.

The Observer can keep a stable bankroll along the time and almost at game 500 he has more than 1500 chips. At this time the non observer agent loses the game.

In this simulation, opponent modelling helps to keep a stable strategy of betting and proves to be helpful in the game of Calling Station agents.

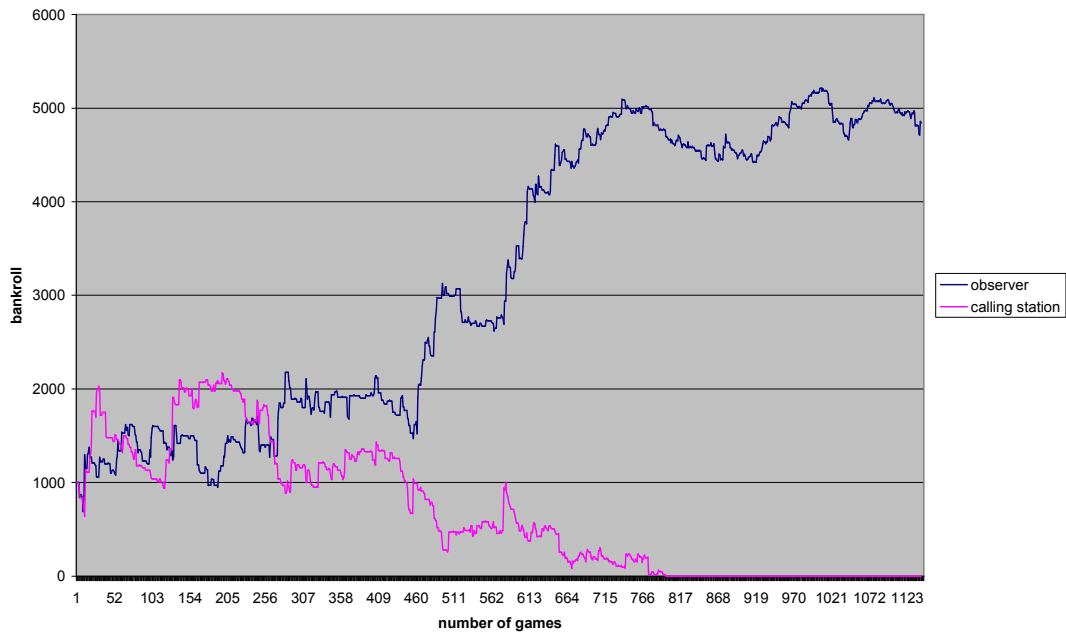


Fig 29: Bankroll variation of the Observer and Calling Station Agent in the second simulation

In the first 300 games of the second simulation (figure 29), both of the agents keep a similar bankroll, but after that, the agent non observer starts to loose lots of chips contrarily to the observer agent that had a great performance in this game even reaching more than 5000 chips in the later games, 5 times the initial bankroll.

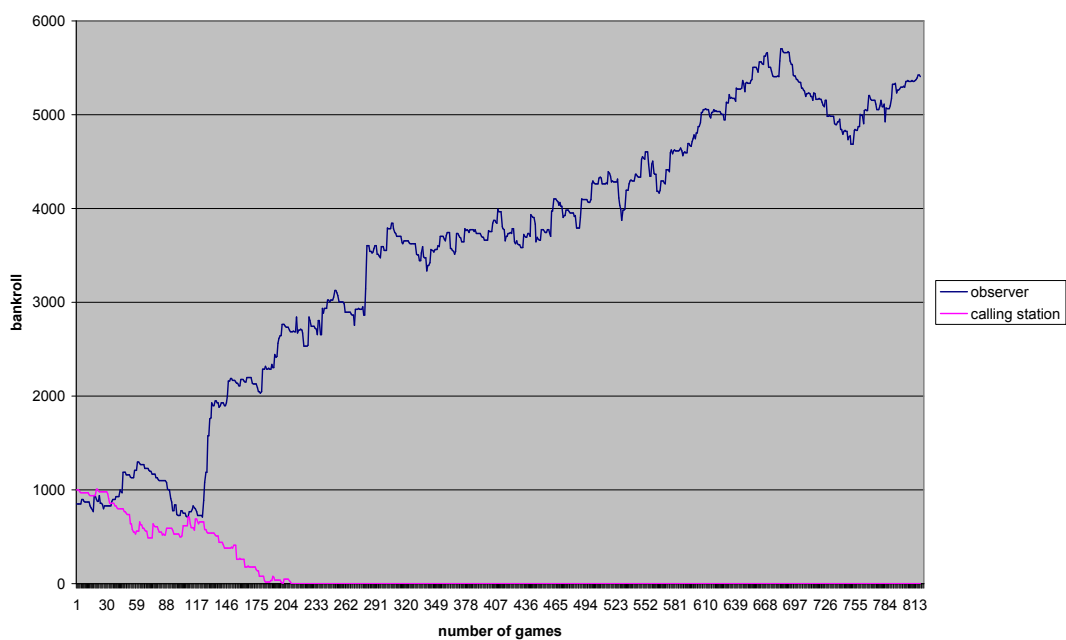


Fig 30: Bankroll variation of the Observer and Calling Station Agent in the third simulation

The third simulation (figure 30) is very similar to the second one. In this one, the non observer agent lost all his bankroll very quickly. It's a normal situation for a loose player. He plays lots of hands and without a good strategy of betting it is normal loose many chips. Once again, the observer agent shows a great performance, reaching the 5000 chips.

5.4 Tight Aggressive Observer

The game simulations to test loose aggressive agents were represented by a “Fox Observer”. In the figures 31, 32 and 33 we can see 3 graphs that represent the bankroll of the two Fox agents (observer and non observer) in the 3 game simulations.

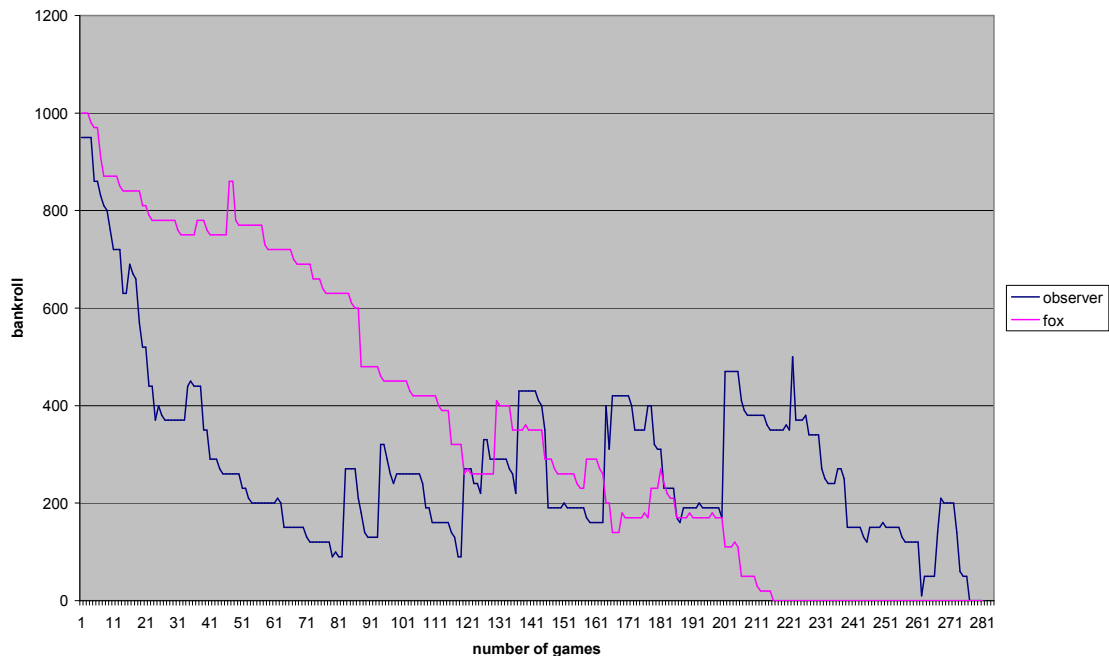


Fig 31: Bankroll variation of the Observer and Fox Agent in the first simulation

The first simulation is very inconclusive because of the fact that both of the agents lost all their chips very soon.

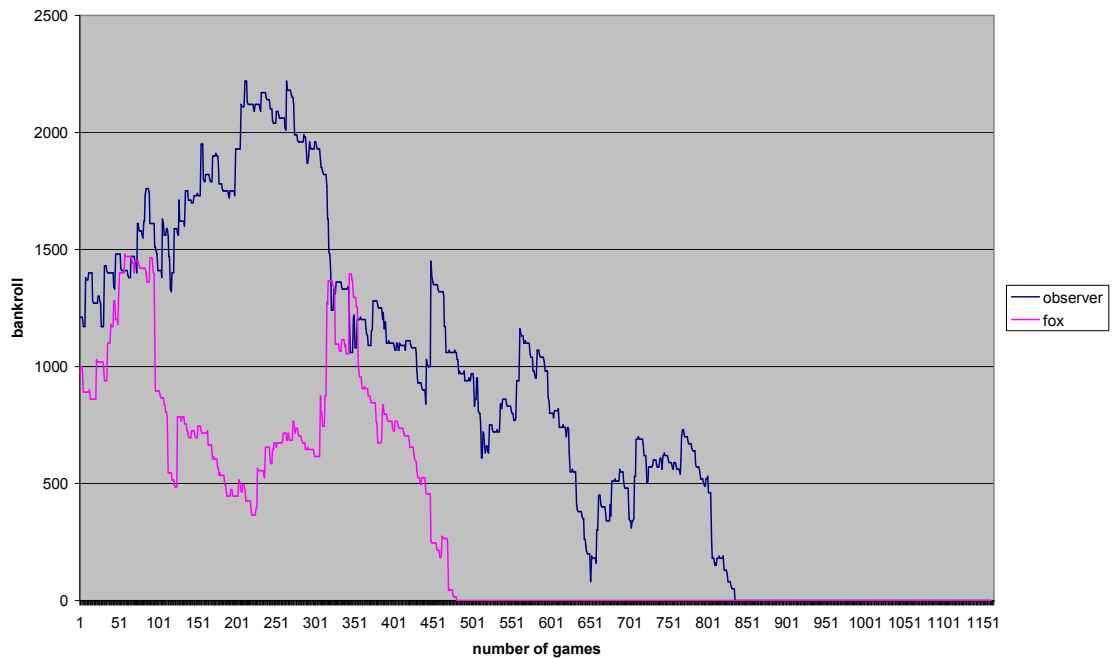


Fig 32: Bankroll variation of the Observer and Fox Agent in the second simulation

In this simulation, the agents don't have good results once again, although we can check that the observer agent keeps more time in the game, proving that his strategy improves the results and helps keeping bankroll for a long time.

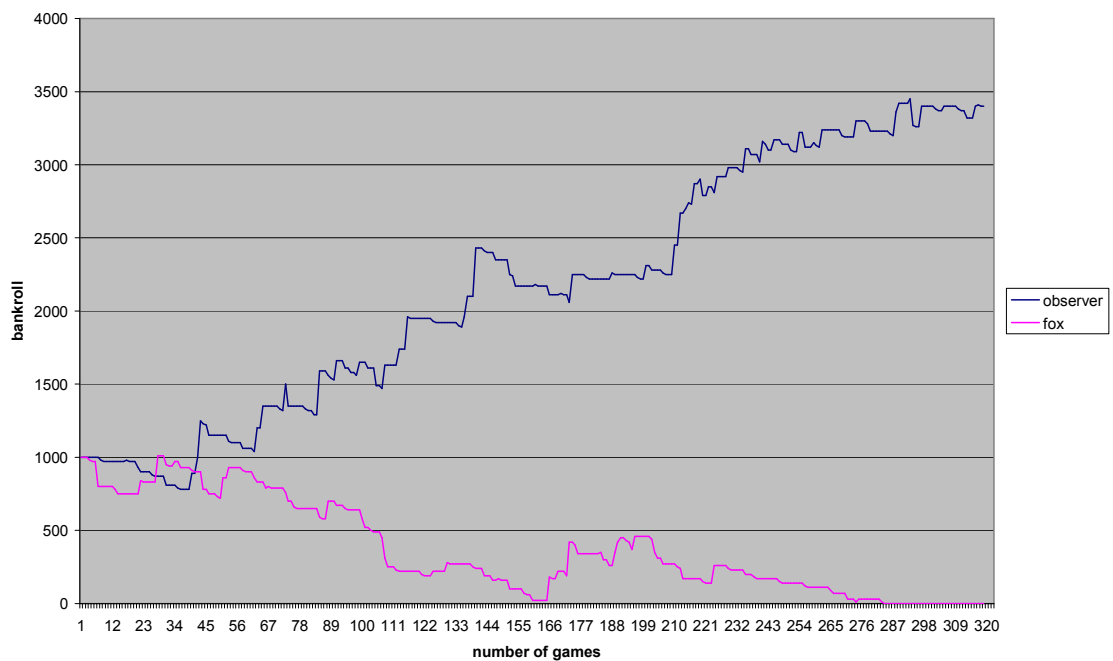


Fig 33: Bankroll variation of the Observer and Fox Agent in the third simulation

In the third simulation (figure 33), the non observer agent once again lost his bankroll very soon, but in this simulation, the observer improves his game and obtains good results reaching more than 3 times the initial chips.

5.5 Tight Passive Observer

The game simulations to test loose aggressive agents were represented by a “Rock Observer”. In the figures 34, 35 and 36, we can see 3 graphs that represent the bankroll of the two Rock agents (observer and non observer) in the 3 game simulations.

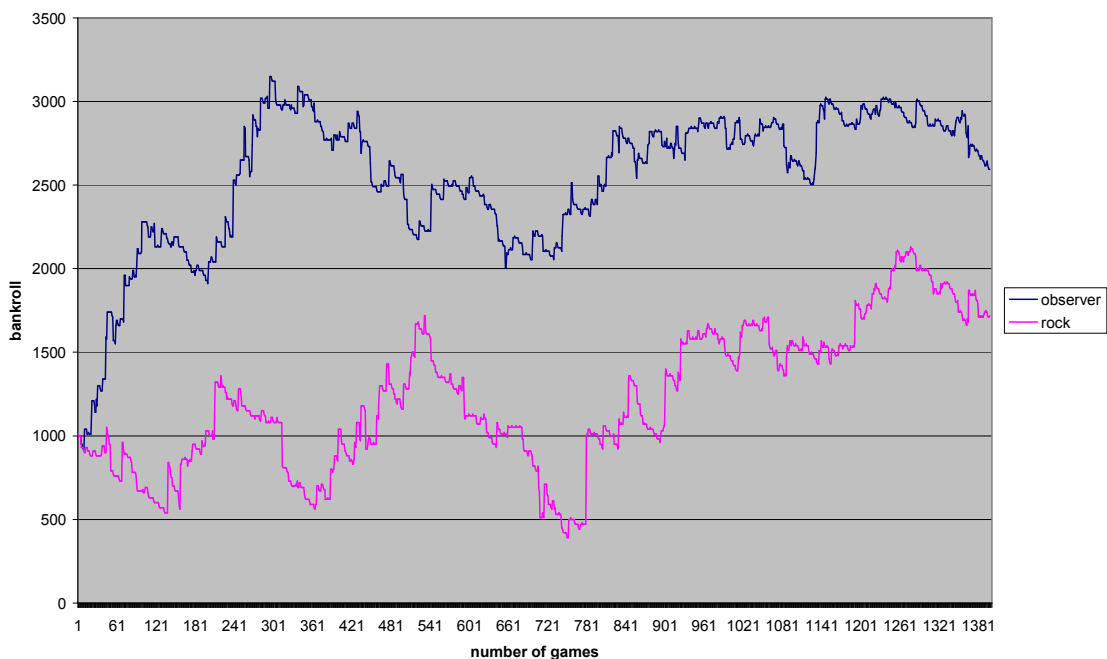


Fig 34: Bankroll variation of the Observer and Rock Agent in the first simulation

The agent “Rock” is very “careful“ choosing his starting hands, for that reason most of the times he can keep his bankroll for a long time. In this simulation (fig 34) we can confirm this fact, but we also can check that the observer agent besides keeping his chips also earns a significant number reaching the 3000. The next simulation has more games simulated in order to observe what happens after that.

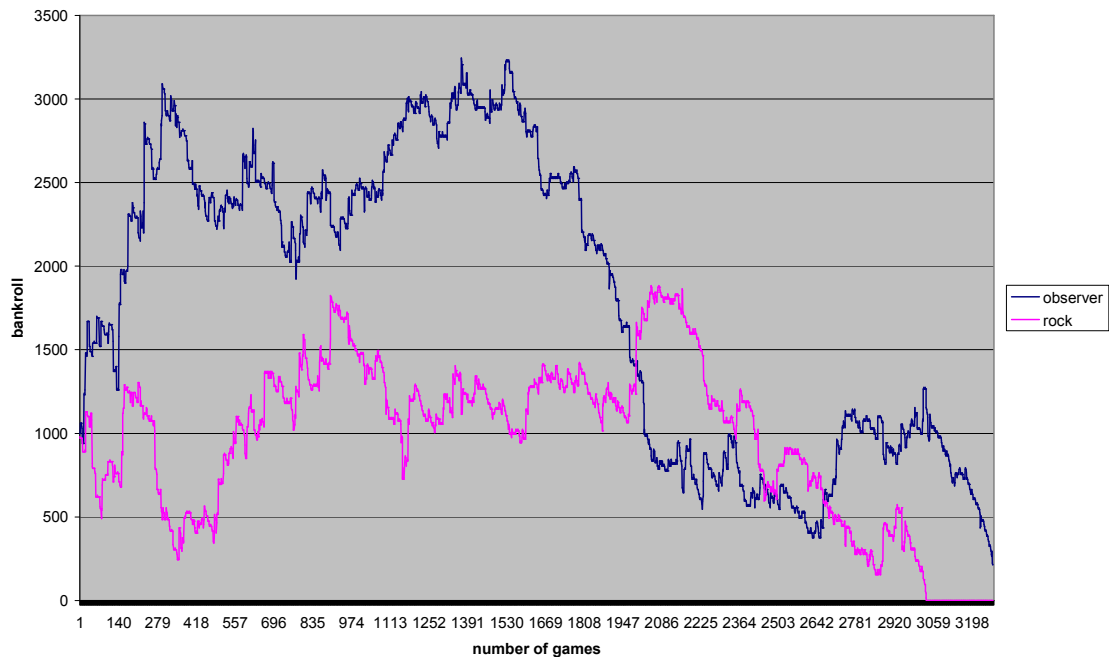


Fig 35: Bankroll variation of the Observer and Rock Agent in the second simulation

The second simulation (fig 35) seems to be very similar to the first one, but in this case we let one of the agents loose the game. As we can observe, like in the first simulation, the two agents keep their bankroll stable for long time (till game 2000), but after that they start loosing very quickly. This is probably due to the number of players at the table in that moment. The table at that time only has 5 and later 4 players. This turns the game more aggressive, and an agent like Rock can't keep the bankroll in this conditions.

The objective of these simulations has been reached, proving that the observer has better results than the non observer agent once again.

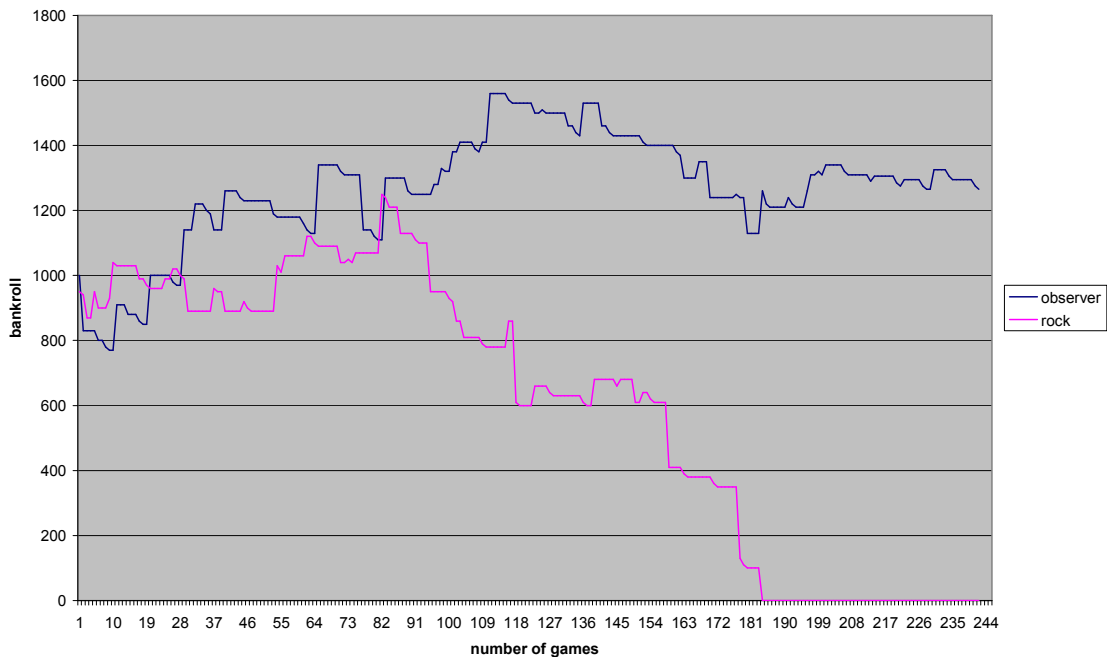


Fig 36: Bankroll variation of the Observer and Rock Agent in the third simulation

The third simulation (figure 36) of this case shows how the element of chance could affect every player in poker. In this case, the agent Rock even playing very carefully lost all his bankroll very soon before the game 200. The reason could be one of the players at the table is winning great part of the games.

Once again, the observer agent proves to have a better strategy by not being affected in this case, keeping his chips as the non observer is losing.

5.6 Observer Performance

In the 12 tests done (more than 10 000 games) with observer agents, the Observer has better results than the non observer agent that uses the same hand selection in pre-flop. Even with no significant advantage in some of the simulations, the global result of Opponent Modelling reveals to be positive.

The most conclusive results are with passive agents, Rock and Calling Station. When testing the Rock behaviour, Observer always seems to have a significant advantage compared to the non observer. Even when both agents start to loose, the observer can keep in game for long time.

In the Calling Station simulations, Observer besides having always a big advantage from non observer, the results are also very good, reaching a good level of bankroll in two simulations.

With aggressive agents, the simulations seem to be a bit inconclusive due to the fact of an aggressive betting strategy causes big variations of bankroll and sometimes causes the end of the game too soon for a player.

In Gambler simulation, the non observer agent lost too quickly 2 of the simulations contrarily to the Observer, but in one of them, both of the agents have reached the game 2000, although, the variations of bankroll are not very conclusive. We can only conclude that Opponent Modelling could help the agent to keep in game for a long time, but doesn't seem to be helpful in winning many chips.

The last simulations to analyse are from Fox, once again both of the agents lost all their chips very soon, but the observer agent proves to be more conservative and keep his bankroll for long time than non observer.

5.7 Summary

In this chapter were performed several simulations to test the model developed. The results were positive and proved that the Observer Agent definitely has better performance than a non observer agent.

The project was finished with this tests and the result is an Intelligent Agent capable of apply some techniques of observation at a Poker table. Although, the agent needs to be better explored in Opponent Modelling and other topics of the game. The next chapter will present a conclusion and future work to be done.

Chapter 6

6. Conclusions and Future Work

This work intended to present Artificial Intelligence techniques applied to games with incomplete information. The game chosen was Texas Hold'em because of its characteristics presented in chapter 2 that turn the game in an interesting test bed for Artificial Intelligence techniques.

The rules of the game were explained and some typical Poker playing strategies were also referred. One important strategy is Opponent Modelling, not just in Texas Hold'em but in most of the games with incomplete information. This work was focused on this topic of the game, and the main goal was to verify if the approach developed improved the results achieved by an intelligent agent playing at a complete Poker table.

The first goal of this project was to study and adapt the simulator software to become a test ground to the work of opponent modelling. After testing and developing some versions of the software, this goal was accomplished and the software was able to simulate several games with different agents without any problems at the last stage of the project.

The second goal was to develop different kinds of agents that emulate the different kind of playing styles of players in the domain of Texas Hold'em. Eight different agents were created with different strategy of hand selection and their behaviour along the simulations seems to accomplish what it was intended to be developed. When it comes to choosing the starting hands, all the agents seem to behave like normal poker players in their choices.

The main objective was developing a technique that considers the opponent behaviour and adapts the betting strategy to each one of them. An Observer agent was created capable of adding opponent modelling capabilities to the intelligent agents developed. The Observer agent created is capable of keeping information about all the players at the table during the entire game. This information is analysed each time the agent has to make a decision to improve its playing capabilities.

The results of the Opponent Modelling techniques were presented in chapter 5 showing the usefulness of the approach. In most of the tests it is possible to verify that the Observer agent has better results than a non observer agent, even when the strategy of hand selection is not very good.

The technique presented and developed in this project proves to be an important technique to be applied to an Intelligent Agent capable of playing poker at high level.

In this project several other techniques were not considered. So, the agent developed is not, globally, a great poker player if compared with good human poker players. However, the main objective was reached and the agent is capable of modelling opponents and effectively using the models to improve its playing style which is an added value to a future work in this area.

Future work done in Artificial Intelligence applied to poker may use the work done in this project and the conclusions achieved. The agent developed till the moment must be explored in several other topics, like learning to play in function of the position at the table and bluffing. These topics could be better explored considering also, always, Opponent Modelling.

In the domain of player classification, future projects could tune the approach done in this work. The opponent Modelling described intended to be very simple and basic like a first approach.

Future work in Opponent Modelling at Texas Hold'em could:

- Consider more than the 4 type of players described in this project;
- Analyse other player style variables besides VP\$IP and AF;
- Retrieve some information from the cards shown at showdown;
- Examine patterns of betting behaviour.

Lots of work must be done in order to obtain an Intelligent Agent capable of playing Poker at High Level, but at the end of this project, we have a good, stable simulator to test future work and an Observer Agent capable of playing poker at an acceptable level, improving the capabilities of the original agent, that is prepared to be explored, introducing new functionalities.

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Appendix A – Glossary of Poker Terms

- **All-in.** To have one's entire stake committed to the current pot. Action continues toward a side pot, with the all-in player being eligible to win only the main pot.
- **All-in Equity.** The expected value income of a hand assuming the game will proceed to the showdown with no further betting (i.e., a fraction of the current pot, based on all possible future outcomes).
- **Bad Beat.** An unlucky loss. In particular, losing a game where the opponent probably should have folded, but instead got extremely lucky to win.
- **Bet.** To make the first wager of a betting round (compare raise).
- **Bet for Value.** To bet with the expectation of winning if called (compare bluff).
- **Big Bet.** The largest bet size in Limit poker (e.g., \$20 in \$10-\$20 Hold'em).
- **Big Blind** (sometimes called the Large Blind). A forced bet made before the deal of the cards (e.g., \$10 in \$10-\$20 Hold'em, posted by the second player to the left of the button).
- **Blind.** A forced bet made before the deal of the cards (see small blind and big blind).
- **Bluff .** To play a weak hand as though it were strong, with the expectation of losing if called (see also semi-bluff and pure bluff , compare bet for value).
- **Board** (or Board Cards). The community cards shared by all players.
- **Board Texture.** Classification of the type of board, such as having lots of high cards, or not having many draws (see dry).
- **Button.** The last player to act in each betting round in Texas Hold'em. Also called the dealer button, representing the person who would be the dealer in a home game.
- **Call.** To match the current level of betting. If the current level of betting is zero, the term check is preferred.
- **Cap.** (a) The maximum number of raises permitted in any single round of

betting (typically four in Limit Hold'em, but occasionally unlimited). (b) (vt) To make the last permitted raise in the current betting round (e.g., after a bet, raise, and re-raise, a player caps the betting).

- **Check.** To decline to make the first wager of a betting round (compare call).
- **Check-Raise.** To check on the first action, with the intention of raising in the same betting round after an opponent bets.
- **Community Cards.** The public cards shared by all players.
- **Connectors.** Two cards differing by one in rank, such as 7-6. More likely to make a straight than other combinations.
- **Dominated.** A Hold'em hand that has a greatly reduced chance of winning against another because one or both cards cannot make a useful pair (e.g., KQ is dominated by AK, AQ, AA, KK, and QQ, but not by AJ or JJ).
- **Draw.** A holding with high potential to make a strong hand, such as a straight draw or a flush draw (compare made hand).
- **Draw Potential.** The relative likelihood of a hand improving to be the best if it is currently behind.
- **Drawing Dead.** Playing a draw to a hand that will only lose, such as drawing to a flush when the opponent already holds a full house.
- **Drawing Hand.** A hand that has a good draw (compare made hand).
- **Dry.** Lacking possible draws or betting action, as in a dry board or a dry game.
- **Equity (or Pot Equity).** An estimate of the expected value income from a hand that accounts for future chance outcomes, and may or may not account for the effects of future betting (e.g., all-in equity).
- **Expected Value (EV)** (also called mathematical expectation). The average amount one expects to win in a given game situation, based on the payoffs for each possible random outcome.
- **Flop.** The first three community cards dealt in Hold'em, followed by the second betting round (compare board).
- **Fold.** To discard a hand instead of matching the outstanding bet, thereby losing any chance of winning the pot.
- **Fold Equity.** The equity gained by a player when an opponent folds. In particular, the positive equity gained despite the fact that the opponent's fold was entirely correct.

- **Forward Blinds.** The logical extension of blinds for heads-up (two-player) games, where the first player posts the small blind and the second player (button) posts the big blind (compare reverse blinds). (Both rules are seen in practice, with various casinos and online card rooms having different policies for multi-player games that have only two active players).
- **Free-Card Danger.** The risk associated with allowing an opponent to improve and win the pot without having to call a bet (in particular, when they would have folded).
- **Free-Card Raise.** To raise on the flop intending to check on the turn.
- **Game.** (a) A competitive activity in which players contend with each other according to a set of rules (in poker, a contest with two or more players). (b) A single instance of such an activity (in poker, from the initial dealing of the cards to the showdown, or until one player wins uncontested).
- **Game Theory.** Among serious poker players, game theory normally pertains to the optimal calling frequency (in response to a possible bluff), or the optimal bluffing frequency. Both depend only on the size of the bet in relation to the size of the pot.
- **Hand.** (a) A player's private cards (e.g., two hole cards in Hold'em). (b) One complete game of poker (see game (b)).
- **Heads-up.** A two-player (head-to-head) poker game.
- **Hole Card.** A private card in poker (Texas Hold'em, Omaha, 7-Stud, etc.).
- **Implied Odds.** (a) The pot odds based on the probable future size of the pot instead of the current size of the pot (positive or negative adjustments). (b) The extra money a strong hand stands to win in future betting rounds (compare reverse implied odds).
- **Kicker.** A side card, often deciding the winner when two hands are otherwise tied (e.g., a player holding Q-J when the board is Q-7-4 has top pair with a Jack kicker).
- **Large Blind** (usually called the Big Blind). A forced bet made before the deal of the cards (e.g., \$10 in \$10-\$20 Hold'em, posted by the second player to the left of the button).
- **Loose Game.** A game having several loose players.
- **Loose Player.** A player who does not fold often (e.g., one who plays most hands at least to the flop in Hold'em).

- **Made Hand.** A hand with a good chance of currently being the best, such as top pair on the flop in Hold'em (compare draw).
- **Mixed Strategy.** Handling a particular type of situation in more than one way, such as to sometimes call, and sometimes raise.
- **Offsuit.** Two cards of different suits (also called unsuited, compare suited).
- **Open-Ended Draw.** A draw to a straight with eight cards to make the straight, such as 6-5 with a board of Q-7-4 in Hold'em.
- **Outs.** Cards that will improve a hand to a probable winner (compare draw).
- **Pocket Pair.** Two cards of the same rank, such as 6-6. More likely to make three of a kind than other combinations (see set).
- **Post-flop.** The actions after the flop in Texas Hold'em, including the turn and river cards interleaved with the three betting rounds, and ending with the showdown.
- **Pot.** The common pool of all collected wagers during a game.
- **Pot Equity** (or simply Equity). An estimate of the expected value income from a hand that accounts for future chance outcomes, and may or may not account for the effects of future betting (e.g., all-in equity).
- **Pot Odds.** The ratio of the size of the pot to the size of the outstanding bet, used to determine if a draw will have a positive expected value.
- **Pre-flop.** The first round of betting in Texas Hold'em before the flop, beginning with the posting of the blinds and the dealing of the private hole cards.
- **Pure bluff** . A bluff with a hand that can only win if the opponent folds (compare semi-bluff).
- **Pure Drawing Hand.** A weak hand that can only win by completing a draw, or by a successful bluff.
- **Raise.** To increase the current level of betting. If the current level of betting is zero, the term bet is preferred.
- **Raising for a Free-card.** To raise on the flop intending to check on the turn.
- **Rake.** A portion of the pot withheld by the casino or host of a poker game, typically a percentage of the pot up to some maximum, such as 5% up to \$3.
- **Re-raise.** To increase to the third level of betting after a bet and a raise.
- **Reverse Blinds.** A special rule sometimes used for heads-up (two-player) games, where the second player (button) posts the small blind and the first

player posts the big blind (compare forward blinds). (Both rules are seen in practice, with various casinos and online card rooms having different policies for multi-player games that have only two active players).

- **Reverse Implied Odds.** The unaccounted (negative) money a mediocre hand stands to lose in future betting rounds (compare implied odds (b)).
- **River.** The fifth community card dealt in Hold'em, followed by the fourth (and final) betting round.
- **Semi-bluff** . A bluff when there are still cards to be dealt, with a hand that might be the best, or that has a reasonable chance of improving to the best if it is called (compare pure bluff).
- **Second pair.** Matching the second highest community card in Hold'em, such as having 7-6 with a board of Q-7-4.
- **Session.** A series of games, typically lasting several hours in length.
- **Set.** Three of a kind, formed with a pocket pair and one card of matching rank on the board. A very powerful and well-disguised hand (compare trips).
- **Short-handed Game.** A game with less than the full complement of players, such as a Texas Hold'em game with five or fewer players.
- **Showdown.** The revealing of cards at the end of a game to determine the winner.
- **Side pot.** A second pot for the remaining active players after another player is all-in.
- **Slow-play.** To check or call a strong hand as though it were weak, with the intention of raising in a later betting round (compare smooth-call and checkraise).
- **Small Bet.** The smallest bet size in Limit poker (e.g., \$10 in \$10-\$20 Hold'em).
- **Small Blind.** A forced bet made before the deal of the cards (e.g., \$5 in \$10-\$20 Hold'em, posted by the first player to the left of the button).
- **Smooth-call.** To only call a bet instead of raising with a strong hand, for purposes of deception (as in a slow-play).
- **Suited.** Two cards of the same suit, such as both Hearts. More likely to make a flush than other combinations (compare offsuit or unsuited).
- **Table Image.** The general perception other players have of one's play.

- **Table Stakes.** A poker rule allowing a player who cannot match the outstanding bet to go all-in with his remaining money, and proceed to the showdown (also see side pot).
- **Texture of the Board.** Classification of the type of board, such as having lots of high cards, or not having many draws (see dry).
- **Tight Player.** A player who usually folds unless the situation is clearly profitable (e.g., one who folds most hands before the flop in Hold'em).
- **Time Charge.** A fee charged to the players in a poker game by a casino or other host of the game, typically collected once every 30 minutes.
- **Top Pair.** Matching the highest community card in Hold'em, such as having Q-J with a board of Q-7-4.
- **Trap.** To play a strong hand as though it were weak, hoping to lure a weaker hand into betting. Usually a check-raise, or a slow-play.
- **Trips.** Three of a kind, formed with one hole card and two cards of matching rank on the board. A strong hand, but not well-disguised (compare set).
- **Turn.** The fourth community card dealt in Hold'em, followed by the third betting round.
- **Unsuited.** Two cards of different suits (also called offsuit, compare suited).
- **Value Bet.** To bet with the expectation of winning if called (compare bluff).
- **Wild Game.** A game with a lot of raising and re-raising. Also called an action game.