Effective Short-Term Opponent Exploitation in Simplified Poker

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Abstract

Uncertainty in poker stems from two key sources, the shuffled deck and an adversary whose strategy is unknown. One approach is to find a pessimistic game theoretic solution (i.e. a Nash equilibrium), but human players have idiosyncratic weaknesses that can be exploited if a model of their strategy can be learned by observing their play. However, games against humans last for at most a few hundred hands so learning must be fast to be effective. We explore two approaches to opponent modelling in the context of Kuhn poker, a small game for which game theoretic solutions are known. Parameter estimation and expert algorithms are both studied. Experiments demonstrate that, even in this small game, convergence to maximally exploitive solutions in a small number of hands is impractical, but that good (i.e. better than Nash or breakeven) performance can be achieved in a short period of time. Finally, we show that amongst a set of strategies with equal game theoretic value, in particular the set of Nash equilibrium strategies, some are preferable because they speed learning of the opponent's strategy by exploring it more effectively.

Introduction

Poker is a game of imperfect information against an adversary with an unknown, stochastic strategy. It represents a tough challenge to artificial intelligence research. Game theoretic approaches seek to approximate the Nash equilibrium (i.e. minimax) strategies of the game (Koller & Pfeffer 1997; Billings *et al.* 2003), but this represents a pessimistic worldview where we assume optimality in our opponent. Human players have weaknesses that can be exploited to obtain winnings higher than the game-theoretic value of the game. Learning by observing their play allows us to exploit their idiosyncratic weaknesses. This can be done either directly, by learning a model of their strategy, or indirectly, by identifying an effective counter-strategy. Several factors render this difficult in practice. First, real-world poker games like Texas Hold'em have huge game trees and the strategies involve many parameters (e.g. two-player, limit Texas Hold'em requires O(10^{18}) parameters (Billings *et al.* 2003)). The game also has high variance, stemming from the deck and stochastic opponents, and folding gives rise to partial observations. Strategically complex, the aim is not simply to win but to maximize winnings by enticing a weakly-positioned opponent to bet. Finally, we cannot expect a large amount of data when playing human opponents. You may play only 50 or 100 hands against a given opponent and want to quickly learn how to exploit them.

This research explores how rapidly we can gain an advantage by observing opponent play given that only a small number of hands will be played in total. Two learning approaches are studied: *maximum a posteriori parameter estimation* (*parameter learning*), and an "experts" method derived from Exp3 (Auer *et al.* 1995) (*strategy learning*). Both will be described in detail.

While existing poker opponent modelling research focuses on real-world games (Korb & Nicholson 1999; Billings *et al.*), we systematically study a simpler version, reducing the game's intrinsic difficulty to show that, even in what might be considered a best case, the problem is still hard. We start by assuming that the opponent's strategy is fixed. Tracking a non-stationary strategy is a hard problem and learning to exploit a fixed strategy is clearly the first step. Next, we consider the game of Kuhn poker (Kuhn 1950), a tiny game for which complete game theoretic analysis is available. Finally, we evaluate learning in a two-phase manner; the first phase exploring and learning, while the second phase switches to pure exploitation based on what was learned. We use this simplified framework to show that learning to maximally exploit an opponent in a small number of hands is not feasible. However, we also demonstrate that some advantage can be rapidly attained, making short-term learning a winning proposition. Finally, we observe that, amongst the set of Nash strategies for the learner (which are "safe" strategies), the exploration inherent in some strategies facilitates faster learning compared with other members of the set.

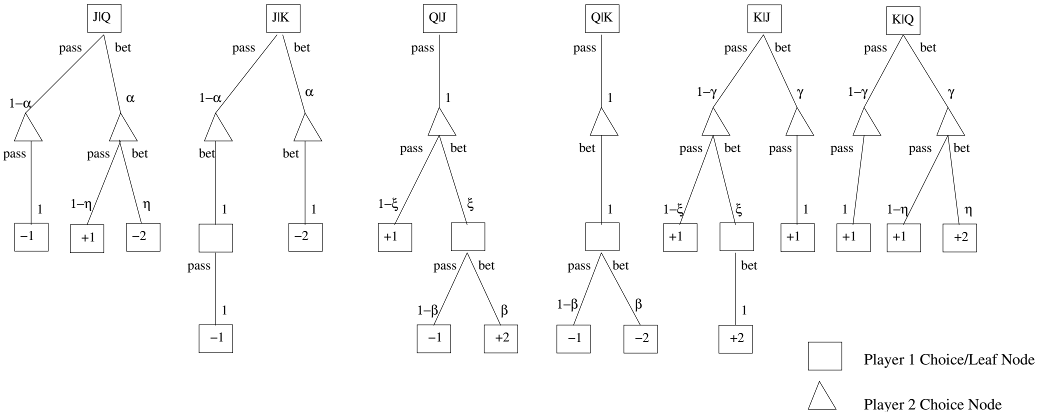

Figure 1: Kuhn Poker game tree with dominated strategies removed

Kuhn Poker

Kuhn poker (Kuhn 1950) is a very simple, two-player game (P1 - Player 1, P2 - Player 2). The deck consists of three cards (J - Jack, Q - Queen, and K - King). There are two actions available: *bet* and *pass*. The value of each bet is 1. In the event of a showdown (players have matched bets), the player with the higher card wins the pot (the King is highest and the Jack is lowest). A game proceeds as follows:

- Both players initially put an ante of 1 into the pot.
- Each player is dealt a single card and the remaining card is unseen by either player.
- After the deal, P1 has the opportunity to bet or pass.
  - If P1 bets in round one, then in round two P2 can:
    - bet (calling P1's bet) and the game then ends in a showdown, or
    - pass (folding) and forfeit the pot to P1.
  - If P1 passes in round one, then in round two P2 can:
    - bet (in which case there is a third action where P1 can bet and go to showdown, or pass and forfeit to P2), or
    - pass (game proceeds to a showdown).

Figure 1 shows the game tree with P1's value for each outcome. Note that the dominated strategies have been removed from this tree already. Informally, a dominated strategy is one for which there exists an alternative strategy that offers equal or better value in any given situation. We eliminate these obvious sources of suboptimal play but note that non-dominated suboptimal strategies remain, so it is still possible to play suboptimally with respect to a specific opponent.

The game has a well-known parametrization, in which P1's strategy can be summarized by three parameters (α, β, γ), and P2's by two parameters (η, ξ). The decisions governed by these parameters are shown in Figure 1. Kuhn determined that the set of equilibrium strategies for P1 has the form $(\alpha, \beta, \gamma) = (\gamma/3, (1+\gamma)/3, \gamma)$ for $0 \leq \gamma \leq 1$. Thus, there is a continuum of Nash strategies for P1 governed by a single parameter. There is only one Nash strategy for P2, $\eta = 1/3$ and $\xi = 1/3$; all other P2 strategies can be exploited by P1. If either player plays an equilibrium strategy (and neither play dominated strategies), then P1 expects to lose at a rate of $-1/18$ per hand. Thus P1 can only hope to win in the long run if P2 is playing suboptimally and P1 deviates from playing equilibrium strategies to exploit errors in P2's play. Our discussion focuses on playing as P1 and exploiting P2, so all observations and results are from this perspective.

The strategy-space for P2 can be partitioned into the 6 regions shown in Figure 2. Within each region, a single P1 pure strategy gives maximal value to P1. For points on the lines dividing the regions, the bordering maximal strategies achieve the same value. The intersection of the three dividing lines is the Nash strategy for P2. Therefore, to maximally exploit P2, it is sufficient to identify the region in which their strategy lies and then to play the corresponding P1 pure strategy. Note that there are 8 pure strategies for P1: $S_1 = (0,0,0), S_2 = (0,0,1), S_3 = (0,1,0), \ldots, S_7 = (1,1,0), S_8 = (1,1,1)$. Two of these ($S_1$ and S_8) are never the best response to any P2 strategy, so we need only consider the remaining six.

This natural division of P2's strategy space was used to obtain the suboptimal opponents for our study. Six opponent strategies were created by selecting a point at random from each of the six regions. They are $O_1 = (.25, .67), O_2 = (.75, .8), O_3 = (.67, .4), O_4 = (.5, .29), O_5 = (.25, .17), O_6 = (.17, 2)$. All experiments were run against these six opponents, although we only have space to show results against representative opponents here.

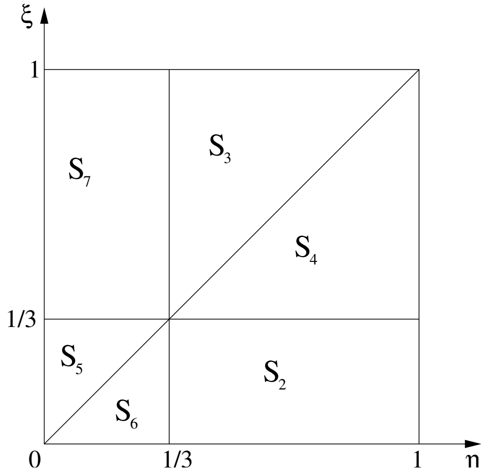

Figure 2: Partition of P2 Strategy-space by Maximal P1 Strategies

Parameter Learning

The first approach we consider for exploiting the opponent is to directly estimate the parameters of their strategy and play a best response to that strategy. We start with a Beta prior over the opponent's strategy and compute the *maximum a posteriori* (MAP) estimate of those parameters given our observations. This is a form of Bayesian parameter estimation, a typical approach to learning and therefore a natural choice for our study. In general poker games a hand either results in a showdown, in which case the opponent's cards are observed, or a fold, which leaves the opponent's cards uncertain (we only get to observe their actions, our own cards, and any public cards). However, in Kuhn poker, the small deck and dominated strategies conspire in certain cases to make the opponent's cards obvious despite their folding. Thus, certain folding observations (but not all) contain as much information as a showdown.

The estimation in Kuhn poker is quite straightforward because in no case does the estimate of any single player parameter depend on an earlier decision governed by some other parameter belonging to that player. The task of computing a posterior distribution over opponent strategies for arbitrary poker games is non-trivial and is discussed in a separate, upcoming paper. For the present study, the dominated strategies and small deck again render the task relatively simple.

Priors

We use the Beta prior, which gives a distribution over a single parameter that ranges from 0 to 1, in our case, the probability of passing vs. betting in a given situation (P2 has two parameters, η and ξ). Thus we have two Beta distributions for P2 to characterize our prior belief of how they play. A Beta distribution is characterized by two parameters, $\theta \geq 0$ and $\omega \geq 0$. The distribution can be understood as pretending that we have observed the opponent's choices several times in the past, and that we observed θ choices one way and ω choices the other way. Thus, low values for this pair of parameters (e.g. Beta(1,1)) represent a weak prior, easily replaced by subsequent observations. Larger values (e.g. Beta(10,10)) represent a much stronger belief.

A poorly chosen prior (i.e. a bad model of the opponent) that is weak may not cost us much because it will be quickly overwhelmed by observations. However, a good prior (i.e. a close model of the opponent) that is too weak may be thwarted by unlucky observations early in the game that belie the opponent's true nature. We examine the effects of the prior in a later section. The default prior, unless otherwise specified, is Beta(1,1) for both η and ξ (i.e. $\eta = 0.5$ and $\xi = 0.5$, pretending we have seen 2 decisions involving each).

Nash Equilibria and Exploration

Nash equilibrium strategies are strategies for which a player is guaranteed a certain minimum value regardless of the opponent's strategy. As such, they are "safe" strategies in the sense that things can't get any worse. As mentioned above, the Nash strategies for P1 in Kuhn poker guarantee a value of $-1/18$, and thus guarantee a loss. Against a given P2 strategy, some non-Nash P1 strategy could be better or worse. So, even though Nash is a losing proposition for P1, it may be better than the alternatives against an unknown opponent. It therefore makes sense to adopt a Nash strategy until an opponent model can be learned. Then the best means of exploiting that model can be tried.

In many games, and in Kuhn Poker P1's case, there are multiple equilibrium strategies. We explore the possibility that some of these strategies allow for faster learning of an opponent model than others. The existence of such strategies means that even though they offer identical game theoretic values, some strategies may be better than others against exploitable opponents.

Another interesting exploration approach is to maximize exploration, regardless of the cost. For this, we employ a "balanced" exploration strategy, $(\alpha = 1, \beta = 1, \gamma = .5)$, that forces as many showdowns as possible and equally explores P2's two parameters.

Strategy Learning

The other learning approach we examine here is what we will call *strategy learning*. We can view a strategy as an *expert* that recommends how to play the hand. Taking the six pure strategies shown in Figure 2 plus a single Nash strategy $(\alpha = \frac{1}{6}, \beta = \frac{1}{2}, \gamma = \frac{1}{2})$, we use the Exp3 algorithm (Auer *et al.* 1995) to control play by these experts. Exp3 is a *bounded regret* algorithm suitable for games. It mixes exploration and exploitation

Algorithm 1 Exp3

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1. Initialize the *scores* for the $K$ strategies: $s_i = 0$
2. For $t = 1, 2, \ldots$ until the game ends:
    (a) Let the probability of playing the $i$th strategy for hand $t$ be $p_i(t) = (1-\psi)\frac{(1+\rho)^{s_i(t)}}{\sum_{j=1}^{K}(1+\rho)^{s_j(t)}} + \frac{\psi}{K}$
    (b) Select the strategy to play $u$ according to the distribution $\mathbf{p}$ and observe the hand's winnings $w$.
    (c) $s_i(t+1) = \begin{cases} s_i(t) + \frac{\psi w}{K p_i(t)} & \text{if } u = i \\ s_i(t) & \text{if } u \neq i \end{cases}$
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in an online fashion to ensure that it cannot be trapped by a deceptive opponent. Exp3 has two parameters, a learning rate $\rho > 0$ and an exploration rate $0 \leq \psi \leq 1$ ($\psi = 1$ is uniform random exploration with no online exploitation). See Algorithm 1 for details.

Exp3 makes very weak assumptions regarding the opponent so that its guarantees apply very broadly. In particular, it assumes a non-stationary opponent that can decide the payoffs in the game at every round. This is a much more powerful opponent than our assumptions dictate (a stationary opponent and fixed payoffs). A few modifications were made to the basic algorithm in order to improve its performance in our particular setting (note that these do not violate the basic assumptions upon which the bounded regret results are based).

One improvement, intended to mitigate the effects of small sample sizes, is to replace the single score (s_i) for each strategy with multiple scores, depending on the card they hold. We also keep a count of how many times each card has been held. So, instead of just s_i, we have $s_{i,J}$, $s_{i,Q}$, and $s_{i,K}$, and counters $c_{i,J}$, $c_{i,Q}$, and $c_{i,K}$. We then update only the score for the card held during the hand and increment its counter. We now compute the expert scores for Algorithm 1's probabilistic selection as follows: $s_i = \frac{1}{3}s_{i,J}/c_{i,J} + \frac{1}{3}s_{i,Q}/c_{i,Q} + \frac{1}{3}s_{i,K}/c_{i,K}$. This avoids erratic behaviour if one card shows up disproportionately often by chance (e.g. the King 10 times and the Jack only once). Naturally, such effects vanish as the number of hands grows large, but we are specifically concerned with short-term behaviour. We are simply taking the sum of expectations instead of the expectation of a sum.

Another improvement is to "share" rewards amongst those strategies that suggest the same action in a given situation. We simply update the score and counter for each agreeing expert. This algorithm bears a strong resemblance to Exp4 (Auer *et al.* 1995).

In all experiments reported here, $\rho = 1$ and $\psi = 0.75$. These values were determined by experimentation to give good results. Recall that we are attempting to find out how well it is *possible* to do, so this parameter tuning is consistent with our objectives.

Experimental Results

We conducted a large set of experiments using both learning methods to answer various questions. In particular, we are interested in how quickly learning methods can achieve better than Nash equilibrium (i.e. winning rate $\geq -1/18$) or breakeven (i.e. winning rate ≥ 0) results for P1 , assuming the opponent is exploitable to that extent. In the former case, P1 is successfully exploiting an opponent and in the latter, P1 can actually win if enough hands are played. However, we aim to play well in short matches, making expected winning rates of limited interest. Most of our results focus on the total winnings over a small number of hands (typically 200, although other numbers are considered).

In our experiments, P1 plays an exploratory strategy up to hand t, learning during this period. P1 then stops learning and switches strategies to exploit the opponent. In parameter learning, the "balanced" exploratory strategy mentioned earlier is used throughout the first phase. In the second phase, a best response is computed to the estimated opponent strategy and that is "played" (in practice, having both strategies, we compute the exact expected winning rate instead). For strategy learning, modified Exp3 is run in the first phase, attempting some exploitation as it explores, since it is an online algorithm. In the second phase, the highest rated expert plays the remaining hands.

We are chiefly interested in when it is effective to switch from exploration to exploitation. Our results are expressed in two kinds of plot. The first kind is a *payoff rate plot*, a plot of the expected payoff rate versus the number of hands before switching, showing the rate at which P1 will win **after** switching to exploitation. Such plots serve two purposes; they show the long-term effectiveness of the learned model, and also how rapidly the learner converges to maximal exploitation.

The second kind of plot, a *total winnings plot,* is more germane to our goals. It shows the expected total winnings versus the number of hands before switching, where the player plays a fixed total number of hands (e.g. 200). This is a more realistic view of the problem because it allows us to answer questions such as: if P1 switches at hand 50, will the price paid for exploring be offset by the benefit of exploitation. It is important to be clear that the x-axis of both kinds of plot refers to the number of hands before switching to exploitation.

All experiments were run against all six P2 opponents selected from the six regions in Figure 2. Only representative results are shown here due to space constraints. Results were averaged over 8000 trials for parameter learning and 2000 trials for strategy learning. The opponent is O_6 unless otherwise specified, and is typical of the results obtained for the six opponents. Similarly, results are for parameter learning unless otherwise specified, and consistent results were found for strategy learning, albeit with overall lower performance.

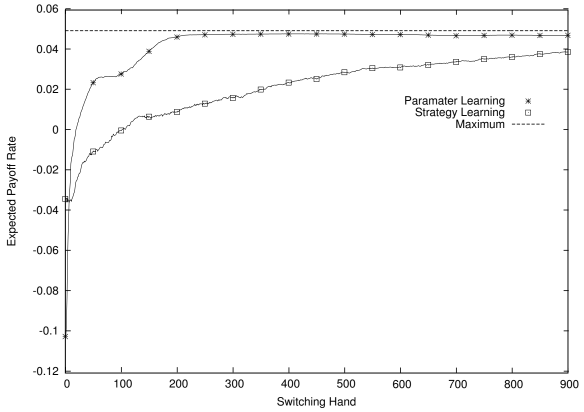

Figure 3: Convergence Study: Expected payoff rate vs. switching hand for parameter and strategy learning

Convergence Rate Study

Figure 3 shows the expected payoff rate plot of the two learning methods against a single opponent. The straight-line near the top shows the maximum exploitation rate for this opponent (i.e. the value of the best response to P2's strategy). It takes 200 hands for parameter learning to almost converge to the maximum and strategy learning does not converge within 900 hands. Results for other opponents are generally worse, requiring several hundred hands for near-convergence. This shows that, even in this tiny game, one cannot expect to achieve maximal exploitation in a small number of hands. The possibility of maximal exploitation in larger games can reasonably be ruled out on this basis and we must adopt more modest goals for opponent modellers.

Game Length Study

This study is provided to show that our total winnings results are robust to games of varying length. While most of our results are presented for games of 200 hands, it is only natural to question whether different numbers of hands would have different optimal switching points. Figure 4 shows overlaid total winnings plots for 50, 100, 200, and 400 hands using parameter learning. The lines are separated because the possible total winnings is different for differing numbers of hands. The important observation to make is that the highest value regions of these curves are fairly broad, indicating that switching times are flexible. Moreover, the regions of the various curves overlap substantially. Thus, switching at hand 50 is a reasonable choice for all of these game lengths, offering close to the best possible total winnings in all cases. This means that even if we are unsure, *a priori*, of the number of hands to be played, we can be confident in our choice of switching time. Moreover, this result is robust across our range of opponents. A switch at hand 50 works well in all cases.

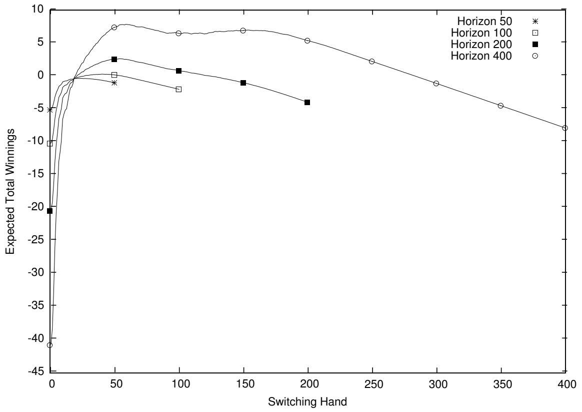

Figure 4: Game Length Study: Expected total winnings vs. switching hand for game lengths of 50, 100, 200, and 400 hands played by parameter learning

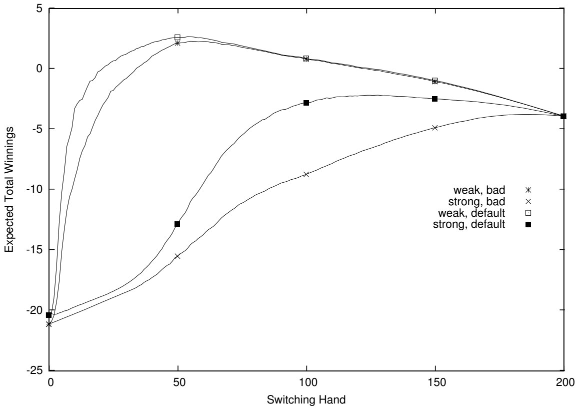

Figure 5: Prior Study: Four different priors for parameter learning against a single opponent.

Parameter Learning Prior Study

In any Bayesian parameter estimation approach, the choice of prior is clearly important. Here we present a comparison of various priors against a single opponent ($O_6 = (.17, .2)$). Expected total winnings are shown for four priors: a weak, default prior of (.5,.5), a weak, bad prior of (.7,.5), a strong, default prior of (.5,.5), and a strong, bad prior of (.7,.5). The weak priors assume 2 fictitious points have been observed and the strong priors assume 20 points. The "bad" prior is so called because it is quite distant from the real strategy of this opponent. Figure 5 shows that the weak priors clearly do better than the strong, allowing for fast adaptation to the correct opponent model. The strong priors perform much more poorly, especially the strong bad prior.

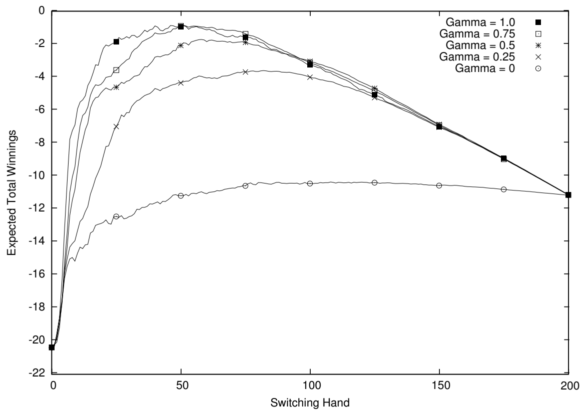

Figure 6: Nash Study: Expected total winnings vs. switching hand for parameter learning with various Nash strategies used during the learning phase.

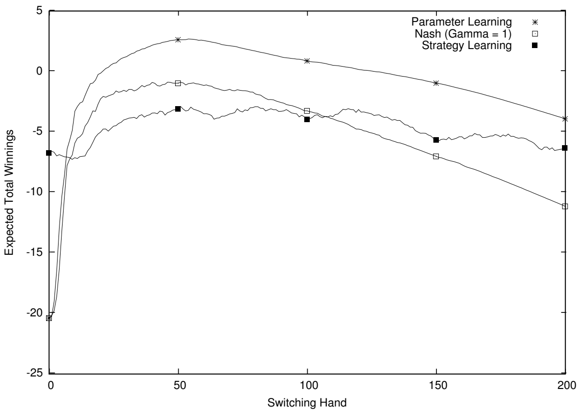

Figure 7: Learning Method Comparison: Expected total winnings vs. switching hand for both parameter learning and strategy learning against a single opponent.

Nash Exploration Study

Figure 6 shows the expected total winnings for parameter learning when various Nash strategies are played by the learner during the learning phase. The strategies with larger γ values are clearly stronger, more effectively exploring the opponent's strategy during the learning phase. This advantage is typical of Nash strategies with $\gamma > 0.7$ across all opponents we tried.

Learning Method Comparison

Figure 7 directly compares strategy and parameter learning (both balanced and Nash exploration ($\gamma = 1$)), all against a single opponent. Balanced parameter learning outperforms strategy learning substantially for this opponent. Over all opponents, either the balanced or the Nash parameter learner is the best, and strategy learning is worst in all but one case.

Conclusions

This work shows that learning to maximally exploit an opponent, even a stationary one in a game as small as Kuhn poker, is not generally feasible in a small number of hands. However, the learning methods explored are capable of showing positive results in as few as 50 hands, so that learning to exploit is typically better than adopting a pessimistic Nash equilibrium strategy. Furthermore, this 50 hand switching point is robust to game length and opponent. Future work includes non-stationary opponents, a wider exploration of learning strategies, and larger games. Both approaches can scale up, provided the number of parameters or experts is kept small (abstraction can reduce parameters and small sets of experts can be carefully selected). Also, the exploration differences amongst equal valued strategies (e.g. Nash) deserves more attention. It may be possible to more formally characterize the exploratory effectiveness of a strategy. We believe these results should encourage more opponent modelling research because, even though maximal exploitation is unlikely, fast opponent modelling may still yield significant benefits.

Acknowledgements

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