

ON THE INFERENCE OF STRATEGIES

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ABSTRACT

We investigate the use of automata theory to model strategies for nonzero-sum two-person games such as the Prisoner's Dilemma. We are particularly interested in infinite tournaments of such games. In the case of finite-state strategies (such as ALL D or TIT FOR TAT) we use graph traversal techniques to show the existence of a (non-terminating) procedure for detecting our opponent's strategy and developing an "optimal" defense. We also investigate counter machine and Turing machine strategies. We show that the optimal defense to a counter machine strategy need not be finite-state, thus disproving a previous conjecture. We show that determining an optimal defense to an arbitrary Turing machine strategy is undecidable.

1. INTRODUCTION

Consider the following nonzero-sum two-person game, called the *Prisoner's Dilemma*, given by the payoff matrix in Figure 1. (In this description we follow closely the presentation given by Hofstadter [Hofs83].) In the payoff matrix with (i, j) entry $(P(i, j), Q(i, j))$, $P(i, j)$ represents the payoff to player X when X chooses move i and Y chooses move j . Similarly, $Q(i, j)$ represents the payoff to

Payoff		Player Y	
		C	D
Player X	C	(3,3)	(0,5)
	D	(5,0)	(1,1)

Figure 1

player Y .

The origin of the term Prisoner's Dilemma comes from the following hypothetical situation: Suppose you and an accomplice attempt to commit a crime and are caught. The prosecuting attorney offers each of you, independently, the following "deal." If neither of you confess (i.e., you both *cooperate* with each other), you will both be convicted and will each serve two years in prison. However, if either of you confesses (*defects* against your partner) and the other doesn't, the one who confesses will be released and the other will serve five years. If you both confess you will each serve four years. This situation can be described by the matrix of Figure 2 where $(-x, -y)$ means that you get x years in jail and your accomplice gets y years. If, for convenience, you avoid negative values by adding five to each element in Figure 2 you get the original matrix of Figure 1.

The dilemma of this game arises from the following analysis. If Y chooses C (to cooperate) the best choice for X is D (to defect), for X then will win 5 instead of 3. If Y chooses D then X still does best by choosing D , winning 1 instead of 0. Consequently, the best choice for X is to defect regardless of what Y does. The same analysis for player Y indicates that Y should also defect. Consequently, both players receive 1 unit when they both could have received 3 units by mutual cooperation.

The Prisoner's Dilemma has been used by Axelrod and Hamilton [AXEL81] and by Hofstadter [HOF83] to study the evolution of cooperation. Imagine that X and Y play an infinite sequence, or *tournament*, of games, each using the past history of the

Payoff		Accomplice	
		C	D
You	C	$(-2, -2)$	$(-5, 0)$
	D	$(0, -5)$	$(-4, -4)$

Figure 2

other player to determine its next move. The general condition for a Prisoner's Dilemma is a payoff matrix of the form given in Figure 3, where R is the reward for mutual cooperation, T is the temptation to defect, P is the punishment for mutual defection, and S is the sucker's payoff. The interesting case occurs when 1) $T > R > P > S$ and 2) $(T+S)/2 < R$. The first condition gives the dilemma. The second guarantees that if the two players get locked into out-of-phase alternations (i.e., on one move X defects and Y cooperates, on the next move X cooperates and Y defects, etc.) then both players will do worse than with mutual cooperation.

We will examine various strategies for playing such a tournament using standard computing devices, specifically, Turing Machines, counter machines and finite-state automata. In this model a player will choose a move, be informed of the other player's move, then perform some computation to choose its next move.

A finite-state strategy for player X can be represented by a directed graph similar to the well-known state diagram. Each vertex of the graph is labeled with the choice of player X . Each directed edge is labeled with a choice of player Y . So an edge labeled y_1 joining vertices x_1 to x_2 represents the fact that if player X is in the state indicated by the vertex labeled x_1 then he will choose move x_1 and if player Y makes a corresponding move of y_1 then player X next chooses move x_2 .

Various strategies for playing tournaments of the Prisoner's Dilemma were examined by Axelrod and subsequently by Hofstadter. Some of the simplest (and most interesting) of them are finite-state. We give a few strategies taken from Hofstadter [HOF83] along with their corresponding automata.

Payoff		Player Y	
		C	D
Player X	C	(R, R)	(S, T)
	D	(T, S)	(P, P)

Figure 3

ALL D: Defect every time. (Figure 4.)

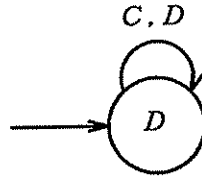


Figure 4

MRS: (Massive retaliatory strike.) Cooperate until Y defects, then defect every time. (Figure 5.)

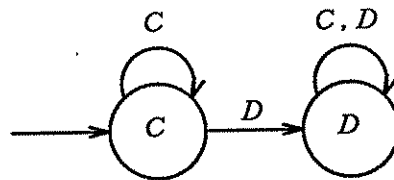


Figure 5

TIT FOR TAT: Cooperate on the first move, then mimic Y 's last move. (Figure 6.)

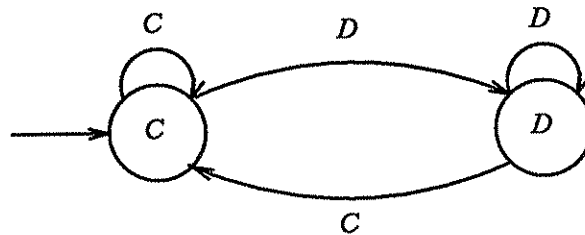


Figure 6

In computer tournaments TIT FOR TAT was found to be an extremely successful strategy. See Axelrod [AXEL84].

We also introduce another type of strategy which will aid our analysis.

TOT TIT FOR TAT: Cooperate if Y has cooperated at least as often as he has defected.

Note that this is not a good strategy in practice. An optimal defense against this strategy is to alternately cooperate and defect. We are interested in this strategy because it can be modeled with a counter machine which uses the counter to keep track of the difference between the number of times Y cooperated and the number of times he

defected.

In this paper we apply the techniques of Richards and Swart [RICH83] for graph traversal and identification to attempt to solve the following problems. We assume that Y is playing a deterministic strategy.

- 1) Determine Y 's strategy, by playing a tournament as X ,
- 2) Given Y 's strategy, produce an optimal strategy (or *defense*) for X .

We assume that each strategy can be modeled by a transducer, specifically either a finite-state machine (FSM), a counter machine (CM), or a Turing machine (TM). The input to the transducer represents the Y move and the output represents the subsequent X move.

2. TERMINOLOGY

The following notation, similar to Trakhtenbrot and Barzdin' [TRAK73] is helpful. Each player's strategy produces a sequence of moves which may depend on its particular opponent. Let the moves of player X be given by

$$X \text{ vs } Y = x_1, x_2, \dots$$

and let the moves of player Y be given by

$$Y \text{ vs } X = y_1, y_2, \dots$$

Then for $i \geq 2$, x_i depends on y_1, y_2, \dots, y_{i-1} , and y_i depends on x_1, x_2, \dots, x_{i-1} . (The sequences $X \text{ vs } Y$ and $Y \text{ vs } X$ are called nonanticipatory operators.) Suppose X and Y have each chosen their strategies. We define the *payoff sequence* $P(X \text{ vs } Y) = P_1(X \text{ vs } Y), P_2(X \text{ vs } Y), \dots$, where $P_i(X \text{ vs } Y)$ is $P(x_i, y_i)$, i.e., the payoff to player X after the i th move in the tournament.

For convenience, we often identify players with their strategies.

Next we must determine what we mean by a good strategy for X playing in an infinite tournament with Y . Simply adding the total payoffs to X is inadequate since this sum is usually infinite. We suggest the following definition. Consider two strategies X_1 and X_2 against a given strategy for player Y . Then strategy X_1 *dominates* X_2 with respect to Y , $X_1 \geq_Y X_2$, if and only if there exists an $n_0 \geq 1$ such that for

all $n \geq n_0$, $\sum_{i=1}^n P_i(X_1 \text{ vs } Y) \geq \sum_{i=1}^n P_i(X_2 \text{ vs } Y)$. This means that after some point, the total payoff to X_1 is never less than the total payoff to X_2 . The reason for not demanding that each partial sum dominate is to allow initial sacrifices which eventually provide a larger payoff. A strategy X is *strongly optimal* with respect to Y if for every strategy X' , $X \geq_Y X'$. As we shall show below, a strongly optimal strategy need not exist.

It is sometimes possible to prove another form of optimality. The (average) *value* of a strategy $V(X \text{ vs } Y) = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n P(X_i, Y_i)$ if this limit exists. Since each term in the partial sum is bounded above and below by values in the payoff matrix the averages of the partial sums are always bounded. So if the limit fails to exist then the average sums do not diverge but oscillate between two finite values. We say that X is *value optimal* against Y if the value of X exists and is at least as large as the value of any other strategy X' against Y .

In the following, when there is no chance of confusion, we shall refer to value optimal strategies simply as optimal.

3. STRATEGY INFERENCE

Next we examine the problem in which player X tries to determine player Y 's strategy by playing a tournament against him. This work is closely related to the area of *inductive inference*. This field deals with the process of guessing a general rule from examples. For instance, the guesser could be given, one by one, words from a context-free language and the guesser attempts to construct a grammar for the language. Or the guesser might have access to an "oracle" for the language. When provided with a word by the guesser, the oracle states whether or not that word is in the given language. As the guesser obtains more information about the language, he refines his prediction of the grammar for that language. The fundamental paper on this topic is Gold [GOLD67]. A good survey of the field may be found in Angluin and Smith [ANGL83].

Our work differs from inductive inference in that it is more interactive and dynamic. Even though the player's strategy is fixed his actual moves are not predetermined but are affected by his opponent's testing of his strategy. This work is very similar to the "black box identification" found in section five of Gold [GOLD67] and falls within the general model of identification suggested by section six of the same paper.

As is the case with graph traversal in Richards and Swart [RICH83] there are some inherent limitations to any attempt at strategy identification.

1) Cardinality

A general strategy can be represented as a nonanticipatory operator (Trakhtenbrot and Barzdin' [TRAK73]). Hence the set of oblivious strategies (those which make no use of the other player's moves) is in one-to-one correspondence with the set of infinite sequences, so is uncountable. Thus no procedure can identify all strategies.

2) Termination

There is no way to know when a general Turing machine strategy, or even a finite-state strategy, has been identified because there is always an incompletely specified finite-state strategy consistent with any finite sequence of moves. Suppose player X tries to identify strategy Y . Then for any finite sequences of moves x_1, x_2, \dots, x_n and y_1, y_2, \dots, y_n there is a graph of the form given by Figure 7. Therefore, a guesser will never know at any given point in time whether he has successfully determined the strategy or has merely identified an initial part of a more complicated strategy. So any attempt to identify a strategy must never terminate. We will do the best possible considering this restriction. Our procedure will converge

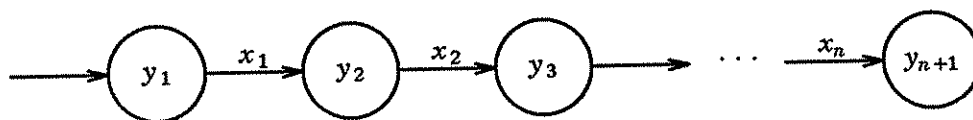


Figure 7

to the actual strategy in the sense that after a finite amount of time the procedure will suggest the actual strategy as a hypothetical strategy and the procedure will reject each alternate hypothetical strategy in a finite amount of time. In other words our procedure will find the correct strategy, but it will never stop verifying that it is indeed the correct strategy.

3) *Reachability*

Consider the following finite-state strategy for *Y*. Cooperate on the first move. Then if player *X* cooperated on his first move play TIT FOR TAT. Otherwise play ALL D. This strategy is indicated in Figure 8. This strategy cannot be identified, since the first test move by *X* restricts all future moves to one strongly connected component of the graph. This problem is general and not restricted to finite-state machines. Specifically, we can describe any Turing computable strategy by an infinite graph in which each vertex corresponds to a state of the machine (its instantaneous description) along with its choice of next move. Edges are labeled with the opponent's move. An edge from one vertex to another indicates that if the Turing Machine is in the configuration indicated by the first vertex and if the opponent chooses the move indicated by the label, then the Turing machine will be in the configuration given by the second vertex (possibly after considerable computation) when it selects its next

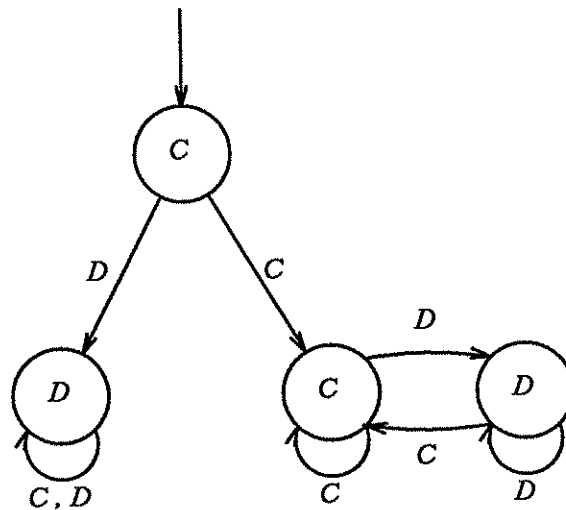


Figure 8

move. This graph is connected since it describes all configurations reachable from the initial state, but in general it is not strongly connected.

There are several reasonable approaches to handling this reachability problem.

- Allow the tester to "reset" the strategy he is testing, i.e., let him play several tournaments with Y .
- Consider only those strategies in which the starting configuration is reachable from any other configuration.
- Relax the meaning of identification of a strategy to mean identification of one strongly connected component of the strategy. This is essentially what Gold refers to as "weak learnability." (This is the approach we adopt in the last section.)

Our general approach for inferring a given strategy is the following. First we develop a procedure for generating a list of all strategies. (For example, for finite-state strategies it is possible to generate simpler strategies before more complex ones, according to the number of states used to describe the strategy.) These strategies are produced as needed below. We initialize by selecting the first strategy on the list as a candidate strategy S_c . We then repeat the following pair of steps forever.

Choose Alternate Strategy. Find the next strategy on the list which is consistent with the results of the tournament as played so far and which is distinguishable from S_c . Call this strategy S_a , the *alternate* strategy.

Eliminate One Strategy. Generate a distinguishing sequence of plays which will differentiate S_c from S_a . Run this sequence against the actual strategy to eliminate either S_c or S_a . Update S_c as necessary.

Certain conditions must hold for this procedure to be valid.

1. Possible strategies must be enumerable. This is true for strategies given by finite-state machines, counter machines and Turing machines.
2. A distinguishing sequence for non-equivalent machines must be found. If two

machines are known to be non-equivalent, such a sequence can always be found in an "off-line" manner. That is, the algorithm generates all sequences in lexicographical order and tests them by simulating the effect of each sequence on the two machines.

3. The equivalence of two given strategies must be decidable. For games with only two possible moves we can immediately reduce this problem to the standard machine equivalence problem by considering one move to correspond to an accepting state, the other to a non-accepting state. The equivalence problem for finite-state machines is well known to be decidable. Valiant and Paterson [VALI75] have shown that the equivalence problem for (deterministic) counter automata is decidable. The equivalence problem for Turing machines is well known to be undecidable.

Note that although the equivalence of Turing machines is undecidable, our approach could be modified to enumerate and test all pairs of descriptions of strategies and every sequence of plays. The procedure could work in a sequence of stages. At each stage a finite number of alternate machines are considered along with a finite set of test sequences and a finite time bound. Each test sequence is run on each alternate machine for at most the time bound to try to distinguish the alternate strategy from the candidate strategy. In each successive stage the number of alternate strategies and test sequences are increased and the time bound is raised. Thus each strategy which is demonstrably not equivalent to the actual strategy could be eliminated. However, infinitely many equivalent strategies would remain (including strategies which are consistent with the actual strategy for all moves produced but which do not terminate their computation for some test sequences.)

This analysis gives us the following result.

Theorem 1. A (non-terminating) procedure exists for identifying a finite-state strategy or a counter machine strategy.

4. OPTIMAL DEFENSES

In this section we suppose the strategy of Y has been identified. What defense should X choose to play with Y ? We have positive results when Y uses a finite-state strategy, and, not surprisingly, negative results when Y uses a Turing machine strategy. We have resolved a previous conjecture concerning counter machine strategies.

As we mentioned above, observe that a strongly optimal defense might not exist. For example, consider the following finite-state strategy for Y playing a Prisoner's Dilemma given in Figure 9. Y cooperates on the first move and then alternates between cooperation and defection. The first choice of X determines Y 's second move. Specifically, Y 's second move repeats X 's first move. After the first move Y 's moves are independent of X 's choices. X has only two reasonable strategies in the sense that any alternate strategy is dominated by one of these. They are:

X_1 : Cooperate on move one then defect forever.

X_2 : Defect forever.

The payoff sequences of the two strategies are:

$$P(X_1 \text{ vs } Y) = R, T, P, T, P, \dots$$

$$P(X_2 \text{ vs } Y) = T, P, T, P, T, \dots$$

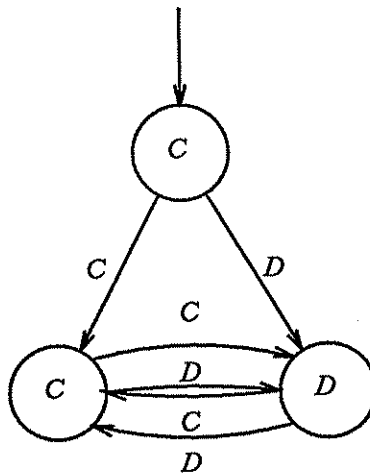


Figure 9.

The conditions of a Prisoner's Dilemma give us $T > R > P$. Since $R > P$, X_1 dominates X_2 after every even move, and since $T > R$, X_2 dominates X_1 after every odd move. Therefore a strongly optimal defense does not exist.

However, we are able to show, using a pumping argument, that a value optimal defense exists against a finite-state strategy.

Theorem 2. A value optimal defense against an FSM strategy exists and is finite-state. Furthermore, an algorithm exists for determining an optimal defense if a description of the FSM strategy is given.

Proof: Suppose Y uses a finite-state strategy. Form the graph corresponding to Y 's strategy. Give each edge in the graph weight equal to the payoff to X if that edge is chosen. Find a simple cycle which is reachable from the start state and which has the largest average payoff to X , i.e., find a cycle whose payoff per edge is maximal. Note that there may be several such cycles. Let the average payoff of such a cycle be p . Define the strategy \bar{X} to be one which takes Y to such a cycle and then stays in this cycle. Clearly the value of this strategy is p , and since the sequence of states generated is ultimately periodic, the strategy is finite-state. Next, let X' be any strategy against Y . Consider the set of states into which X' takes Y . At least one state, q , must occur infinitely often. So the behavior of the finite-state machine for Y consists of an initial sequence of moves ending in state q followed by an infinite sequence of (not necessarily distinct) cycles taking q to q . Since each of these cycles has an average payoff at most p , the value of this strategy $V(X' \text{ vs } Y)$ is at most p . Therefore, since $V(\bar{X} \text{ vs } Y) \geq V(X' \text{ vs } Y)$, \bar{X} is value optimal. \square

Notice that we have proved a slightly stronger result than that stated by the theorem in that we did not assume that strategy X' had a value. We proved that the value of \bar{X} was at least as large as a known upper bound on the average payoff of X' .

Next we consider counter machine strategies. Notice that the optimal defense against the CM strategy TOT TIT FOR TAT is $CDCDCD \dots$, which is finite-state.

Observations such as this led to the conjecture [SWAR84] that a value optimal defense against a CM strategy exists and is finite-state. We now give a counter-example to that conjecture along with a theorem that shows that approximate finite-state defenses exist against CM strategies.

Recall that a counter machine is a pushdown automaton which has only one stack symbol, with the exception of a bottom-of-stack marker. (See Hopcroft and Ullman [HOPC79].) The machine can push the symbol on the stack (increment the counter), pop the symbol from the stack (decrement a non-zero counter) and check to see if the count is zero (if the top stack symbol is the bottom-of-stack marker.)

We can use a generalization of the graph for finite-state strategies to represent CM strategies. Each vertex corresponds to the player's move. An edge joining two vertices is labeled by a triple. The first component is the opponent's move, just as with a finite-state strategy. The second component is a test for zero value on the counter (0 zero, $\neq 0$ not zero). The final component is the action to be taken on the counter (+ add one to the counter, $-$ subtract one from the counter, 0 no action).

Using this notation, consider the CM strategy for the Prisoner's Dilemma for player Y given by Figure 10. All unspecified edges take Y to an ALL D state.

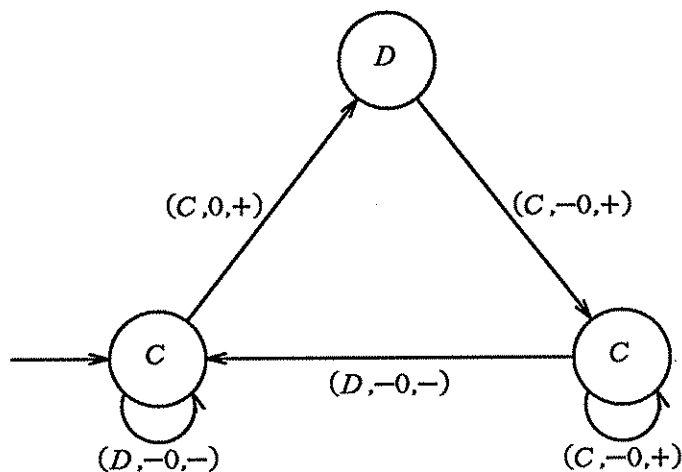


Figure 10

An simple interpretation of Y 's strategy can be given. Whenever the counter is zero Y cooperates once and then defects once, incrementing the counter both times. If X has cooperated on both these moves then Y continues to cooperate and increment the counter as long as X cooperates. When X defects Y continues to cooperate but decrements the counter. Y expects X to continue to defect until the counter is zero. When the counter again becomes zero Y begins this action all over again.

Now let's consider the best defense for player X . If X doesn't behave in the general fashion anticipated by Y (i.e., Y expects X to cooperate at least twice when the counter is zero and when X defects he is expected to continue defecting until the counter becomes zero), then Y plays ALL D, and so the value of any non-conforming strategy is at best P .

If however, X plays along with Y , then X must make a small initial sacrifice (by cooperating when he knows Y will defect) when the counter changes value from 0 to 1. If X cooperates n times then defects n times he receives a payoff of $R+S+(n-2)R+nT$. In this sequence of $2n$ moves X receives an average payoff per move of $\frac{R+T}{2} + \frac{S-R}{2n}$.

Note that if X simply increases Y 's counter forever he receives R, S, R, R, R, \dots , so the value of this strategy is R . Consequently, X does best by generating ever larger counter values for Y and each time defecting until the counter is zero. So, for instance the strategy of $C^2D^2C^3D^3C^4D^4 \dots$ has the optimal value of $\frac{R+T}{2}$.

A few more comments on this strategy are in order. Note that X never achieves the value of his defense since he must make infinitely many (but widely spaced) one-move sacrifices.

It is easy to see that no optimal defense to Y can be finite-state. Since any such defense must play along with Y , it must generate moves of the form C^pD^p for ever increasing p . When such a defense generates the p C 's Y will cooperate, defect,

then play $p-2$ C's. So if $p-2$ is greater than the number of states of the supposed finite automaton, then the machine will repeat a state, hence will cooperate forever. So for any FSM there is a bound on p and further there exists another FSM strategy which possesses a larger bound on p and hence can have greater value.

Less obvious is the fact that any optimal defense to Y 's strategy is not a CM strategy. The intuition behind this result is that X must generate longer and longer sequences and also must know when Y has a zero counter; a single counter cannot do this simultaneous bookkeeping.

Lemma 1. A CM with constant input has a fixed bound (depending only its number of states) on the the number of steps from one zero counter to the next zero counter.

Proof: Consider the behaviour of the CM between zero counters. Since the input can effectively be ignored and no zero counters occur the behaviour depends only the states. Define a configuration to be a state and counter value pair. If a configuration is repeated then the behaviour of the CM would loop. So if the largest counter value is bounded then the number of configurations will be bounded as well.

We claim that the counter value is bounded by the number of states. To see this consider the sequence of states the CM is in the first time the counter value becomes 1,2,3,.... If there were two configurations with the same state and the second configuration had a larger counter value it follows that the behaviour of the CM would loop and the counter would grow without bound. \square

Theorem 3. There exists a CM strategy for which no optimal defense is a CM strategy.

Proof: We show that the strategy in Figure 10 is such a strategy. Assume that X has an optimal CM strategy against Y . As discussed above X must play along with Y and so must produce, for arbitrary p , a sequence of more than p C's before switching to a sequence of more than p D's and then switching back to a C, and throughout the input is constant (after the second C). The CM needs some internal

cue to switch its output since the input is constant. First, notice that for p large enough the CM must produce a zero counter during the C 's since, otherwise, by using a pumping argument, it follows that the CM's behaviour must loop and it will not change to a sequence of D 's. Similarly during the sequence of D 's a zero counter must occur. Second, by the same reasoning used in the proof of Lemma 1, there is a fixed bound on the number of moves between the last time the counter is zero in a sequence of D 's and the next time that X chooses a C . This follows because with constant input there is a bound on the stack height the CM can attain before reaching the configuration in which it next chooses to cooperate. Hence the CM will produce a series of zero counters while the input is kept constant. At least one of these counters occurs on a C choice and one occurs a bounded distance from the end of the D choices.

There are two cases. If for all p it produces a number of zero counters that is less than or equal to the number of states then, for large enough p , we can find a pair of consecutive zero counter configurations separated by a number of steps larger than any fixed bound. This contradicts Lemma 1. Therefore, for some p , it produces more zero counters than states. In this case some state must repeat in the zero counter configuration. Therefore, the CM must loop. Its looping behaviour may be all C 's, all D 's, or a combination of the two, but in all cases it either does not play along with Y or generates bounded length sequences of C 's and D 's \square

Finally, note that X can get as close as he wishes to the optimal value of this game by simply choosing a large enough n and playing the finite-state strategy $C^n D^n C^n D^n \dots$. This situation generalizes to the following theorem.

Theorem 4. Suppose player Y uses a CM strategy and suppose X has a value optimal defense against Y with value v . Let $\epsilon > 0$ be given. Then X has a finite-state strategy against Y with value at least $v - \epsilon$.

Proof: Suppose X plays its value optimal defense against Y . Then Y 's moves can be described by a sequence of pairs (s_i, h_i) , where s_i is the state of Y and h_i is the

height of the counter. There are two cases to consider.

a) $h_i=0$ infinitely often (i.e., the counter is zero infinitely often). Since the CM has only finitely many states there must be some state, say s_i such that the pair $(s_i,0)$ occurs infinitely often. Therefore, the sequence of Y 's moves can be partitioned into a finite initial segment and infinitely many segments, each of finite length and each starting with $(s_i,0)$ and ending just before the next $(s_i,0)$. See Figure 11. We claim that at least one of these segments has an average payoff per move of at least $v-\epsilon$. If every segment had average payoff strictly less than $v-\epsilon$ then by adding all the payoffs of all the segments we would get a value for X 's optimal strategy which is bounded above by $v-\epsilon$, contrary to hypothesis. Suppose that the k th segment has value at least $v-\epsilon$. Then by choosing a strategy for X which is the same as the value optimal one for the first $k-1$ segments and then repeatedly chooses the moves which produced segment k , we get a defense which has value at least $v-\epsilon$. Since this strategy is ultimately periodic, it is finite-state.

b) $h_i=0$ finitely often. A similar argument works. There must be some state s_i and some infinite subsequence which begins somewhere after the last time the counter is 0. $(s_i, h_0), (s_i, h_1), \dots$ such that $h_j \leq h_{j+1}$ for each j . See Figure 12. Again, the sequence of Y 's moves can be partitioned into a finite initial segment and infinitely many

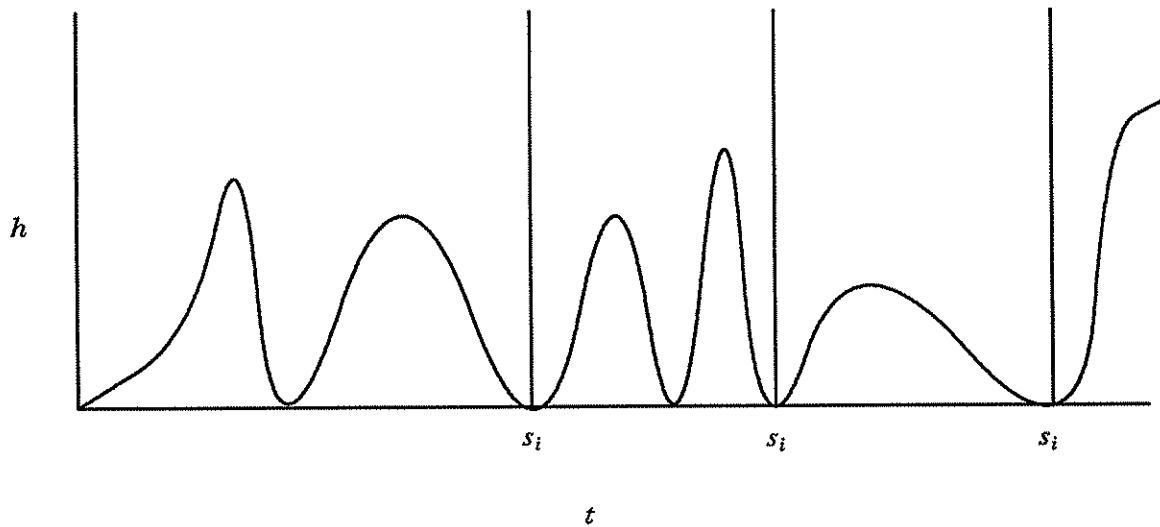


Figure 11

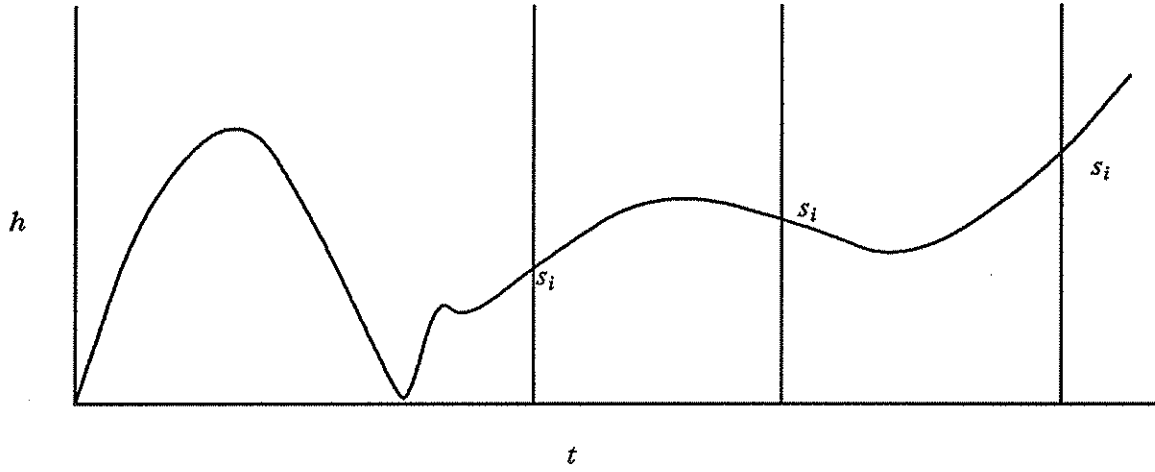


Figure 12

segments, each of finite length, starting with $(s_i, h_0), (s_i, h_1), \dots$. As before, at least one of these segments, say the k th, has value at least $v - \epsilon$. Choose a strategy for X which is the same as the value optimal one for the first $k-1$ segments and then repeatedly chooses the moves which produced segment k . Notice that segment k started with the counter at value h_{k-1} and ended with value h_k and that at no time did the counter become zero while Y was playing in this segment. When the moves which produced segment k are repeated, the new segment $k+1$ starts with the counter at value h_k and ends with the counter at value $2h_k - h_{k-1}$. Since $h_{k-1} \leq h_k$, the initial counter value at the start of segment $k+1$ is at least as large as the initial counter value at the start of segment k , so all moves in the new segment have counter values at least as large as corresponding moves in the k th segment. Hence the counter is never zero in segment $k+1$. So the behavior of Y in playing segment $k+1$ is identical to its behavior in segment k . In particular the average payoff per move is the same. Continuing this sequence of moves gives us an ultimately periodic strategy of value at least $v - \epsilon$. \square

Notice that in this theorem we have assumed that a value optimal strategy exists. It is an open question whether every CM strategy has a value optimal defense.

Finally, we consider general Turing machine strategies. We extend the technique used for FSM strategies to show that a general TM strategy need not have a value

optimal defense, and then show that even if a value optimal or strongly optimal defense exists finding it is undecidable.

Theorem 5. A value optimal defense against a TM strategy need not exist. There is a TM strategy which has neither a strongly optimal nor a value optimal defense.

Proof: Consider the following TM strategy for Y playing the Prisoner's Dilemma. Starting with its second move Y plays strategy A for two moves, then plays strategy B for four moves, then strategy A for eight moves, etc. On the first move, Y cooperates and if X cooperates A is TIT FOR TAT and B is ALL D. If X defects on the first move A is ALL D and B is TIT FOR TAT (cooperate then mimic Y 's move). Again X has two reasonable strategies in the sense that any other strategy is dominated by one of these:

X_1 : $C \ CD \ DDDD \ CCCCCCD$ etc., and

X_2 : $D \ DD \ CCDD \ DDDDDDD$ etc.

(Note that both strategies defect on Y 's last move in each TIT FOR TAT sequence.) Neither of these strategies has a value. X_1 has an average payoff which approaches P after moves $2^{2n+1} - 1$ and R after moves $2^{2n} - 1$. Similarly, the average payoff for strategy X_2 approaches R after moves $2^{2n+1} - 1$ and P after moves $2^{2n} - 1$. So a value optimal defense doesn't exist. Finally, since neither X_1 nor X_2 dominate one another a strongly optimal strategy doesn't exist. \square

The existence of strategies such as this discourages us from simply defining the value of a strategy to be the lim sup of the average of the partial sums. Such a definition has the advantage that all strategies associated with finite games have a value, but it has the disadvantage that the average of the partial sums could be very far from that value infinitely often.

Our final result in this area is that even if an optimal strategy exists, there is no algorithm to determine it.

Theorem 6. There is no algorithm which, given a description of a TM strategy, produces an optimal defense, even if it is known that such a defense exists.

Proof: We show that the existence of such a strategy would imply the solution to the blank tape halting problem. Consider the following Turing machine strategy for player Y , which uses the description of an arbitrary Turing machine H as additional input and plays a Prisoner's Dilemma tournament. Y cooperates on the first play. If X cooperates Y plays TIT FOR TAT. If X defects Y uses a scratch tape to simulate H when started on a blank tape. Y defects once for each step H makes. If H halts then Y cooperates in all future plays. Again, X has two reasonable strategies, completely determined by his first move. If X chooses to cooperate on his first move, Y will play TIT FOR TAT. The optimal defense to this strategy is to cooperate forever, (ALL C), so if X chooses this his payoff sequence is R, R, R, \dots . If, however, X defects on his first move, then Y 's future moves are independent of X 's, so the best strategy for X is ALL D. This strategy has payoff P, P, P, \dots if H never halts since then Y will play ALL D forever. The same strategy has payoff $P, P, \dots, P, T, T, T, \dots$ with n P 's if H halts after n moves, since after n defections, Y will cooperate forever. So the value of ALL C is R and the value of ALL D is either P if H never halts or T if H halts. Recall that $P < R < T$ so that ALL D is optimal if H halts and ALL C is optimal if H doesn't halt. \square

5. COMBINING IDENTIFICATION WITH OPTIMAL DEFENSE

In Richards and Swart [RICH83] we combined graph identification with graph traversal. A similar situation occurs in the case of game strategies. When methods exist for identifying a strategy and computing an optimal defense, then in some sense it is possible to do both simultaneously. The basic idea is straightforward. Modify the identification procedure to alternate between identification and defense playing. Every time the identification procedure finishes one pass through the steps *Choose Alternate Strategy* and *Eliminate One Strategy* (i.e., it has either reconfirmed the old candidate strategy or selected a new candidate strategy) it computes the optimal defense against the candidate strategy and spends some time playing that strategy. Since the procedure eventually identifies the correct strategy, it eventually plays the correct

defense. The major difficulty with this approach is assuring that more moves are spent playing than testing. For instance, it is conceivable that each new test takes more moves than all the previous moves made up to that test. In some cases one can prevent this by predicting the maximum length of the next distinguishing sequence and playing long enough in advance. By careful prediction one can assure that any desired fraction (less than one) of the time is spent playing the defense and that in the limit this fraction can be made to go to one.

In the case of finite-state strategies, this goal is achievable. Suppose M_c , the automaton for the candidate strategy S_c has n states and that M_a , the automaton for the next consistent, distinguishable alternate strategy has m states. Before playing the optimal defense against strategy S_a , for each pair (i, j) we compute a sequence which distinguishes M_c starting in state i from M_a starting in state j . Whenever we finish playing we know that one of these sequences will distinguish S_c from S_a . Therefore, the longest of these nm sequences gives us a uniform upper bound on our next test sequence. We can use this bound to determine how long to play our defense before resuming testing.

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