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Modeling the Adversary and Success in Competition

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Abstract

Competition has been studied as something to be averted, yet rarely has it been asked what processes may be involved in successful competition. We tested whether more accurate modeling of an adversary can assist competitive success. Pairs played a zero-sum game with no specific skill component over 40 trials. We measured the relative accuracy of the players' second-order model (i.e., what I think about my opponent: R2MA), and third-order model (i.e., what I think my opponent thinks of me: R3MA), using responses to adjectives indicating personality traits. Performance correlated with both R3MA and having a better strategy (i.e., a better distribution of responses), but they contributed separately to performance variance. However, R2MA did not correlate with performance.

Modeling the Adversary and Success in Competition

Some important aspects of competition are thrown into stark relief by the card game poker. Thagard (1992) illustrated this with a story about miners from the gold fields of 1840's California on a slow ship to the east coast. To pass the time, they played poker with their gold dust. During one hand a player kept four cards and drew one, but as it was dealt to him he could only catch a glimpse of it before the wind blew it overboard. Immediately the player jumped into the water, swam to the card and was pulled out of the water holding it in his hand. On his return to the table, he bet all his gold dust. All the other players folded, assuming that the card must have completed a great hand. Why else risk drowning? It turned out that his hand consisted of four clubs and a very wet diamond. The miner won, not because he knew more about cards and probabilities, but because he accurately predicted how the other players would interpret his act. Critically, his opponents failed to do this.

Poker has rarely been used in studies of competition. Instead, many studies have used social dilemmas such as the *prisoner's dilemma* (see Axelrod, 1980). The main focus of this research has been on the factors leading to competition, but rarely has the question of what is the basis of *success* in competition been addressed. Yet this question could be interesting for multiple reasons. First, competition is a pervasive part of daily life, such that people even seek it out in games and sports. Second, competition could provide a useful domain for testing ideas about interaction in general, because people's goals are usually clear.

Competition has been studied in economics and game theory (see Rapoport, 1960). Yet much of this research has been normative, and has focused either on explaining or describing aggregate outcomes of competition, rather than the processes underlying competition. However, seeing competition as problem solving might suggest what these processes could be. Problem solving researchers have labeled competition *Adversarial Problem Solving* (APS), in order to emphasize the idea that competition can make similar cognitive demands to those normally associated with problem solving (see Gilhooly, 1988; Holding, 1989; Thagard, 1992). Unless the definition of problem solving is to be restricted, any general theory of problem solving must incorporate competitive tasks.

Thagard (1992) proposed a set of cognitive processes that could be involved in successful APS (i.e., competition). In particular, Thagard argued that it is the ability to model the opponent, and further to model how the opponent models you, that is critical for success. A mental model formed through interpersonal perception (a topic with a long history, see Kenny, 1994) can then be used to anticipate and counter the opponent's actions. However, to turn Thagard's proposal into a testable hypothesis, requires a focus on <u>accuracy</u> in modeling. Further, accurate modeling of the opponent should not be the critical determinant of success in any one competitive event; instead, the critical factor should be having a model of that particular opponent which is <u>more</u> accurate than the model that opponent has of you.

Information about an opponent's personality can influence cooperation in prisoner's dilemma games (see Wrightman, Baxter, Nelson, & Bilsky, 1972). Information about what another person received or what their price preferences are can influence bargaining (see Bazerman, White, & Loewenstein, 1995). Information specific to the game that is provided about an opponent is part of a players complete model of a competitive task. However, the focus of this paper is on whether being able to <u>perceive</u> a relatively more accurate model of an opponent is related to success in a game in which one must anticipate the opponent's choices.

<u>Components of Modeling</u>

Thagard (1992) suggested that the models that people build of their opponents may have more than one component. In particular, players need a model both of their opponent, and what they think their opponent thinks of them. In a very different context, this distinction was worked through by Laing, Phillipson, and Lee (1966). They studied couples experiencing difficulties in their marriage. However, in the same way as for competitors, what she thinks he thinks about her can be critical. So Laing et al. gave the husband a set of issues regarding the couple's interaction or interexperience (e.g., "She makes up my mind for me") and asked him three questions: How true do you think this is for you (i.e., direct perspective)? How would she answer (i.e., metaperspective)? How would she think you have answered (i.e., meta-metaperspective)? His wife independently answered the same questions from her point of view. By comparing their answers for each issue, Laing et al. could identify <u>agreement</u> (match of each person's direct perspective), <u>understanding</u> (match of own metaperspective to other's direct perspective), and <u>realization of understanding</u> (match of own meta-metaperspective to other's metaperspective) for each issue. They found that number of matches clearly differentiated on all three levels between couples in disturbed and nondisturbed marriages, and found all three levels important for detailed analysis.

Laing et al.'s (1966) theory appears extendible to competition (they briefly consider international relations), particular given that realization of understanding is critical to deception (see Hymans, 1989). Dennet (1978) argued that deception involves beliefs about other people's intention, as deception requires believing that false impressions of one's own intentions can be created. Dennet (1978, pp. 274-275) put forward a useful distinction in that he proposed that beliefs about others' intentions are second-order intentions, while beliefs about what we believe others to believe about us, are third-order intentions. In a similar way, modeling an opponent can be divided into second- and third-order components: What we think of an opponent can be seen as <u>second-order modeling</u>, while how we believe the opponent is modeling us can be seen as <u>third-order modeling</u>. Laing et al.'s understanding and realization of understanding levels are equivalent to second- and third-order models.

A Methodology for Studying Competition

While it seems to make sense that modeling an opponent should play a role in success during competition, there is little empirical research that has tried to support this intuition. Even when it has been shown that modeling occurs in competition, this modeling has not then been related to success. For example, Ruscher and Fiske (1990) showed that individuals in competition focus more than non-competitors on trying to individuate their opponents, particularly with regard to task relevant attributes. This could be interpreted as showing that competitors tried to build a model of their opponent. However, Ruscher and Fiske did not examine whether trying to individuate the opponent improved performance.

A problem with examining factors leading to success in competition is that it often involves tasks that are too complex to produce testable hypotheses, given our ignorance regarding competition. Therefore, we needed a simple, manipulatible, competitive task in order to test hypotheses about competition. A possible candidate was the oft studied prisoner’s dilemma game. However, this game was used to study <u>why</u> people compete, because there is pressure towards both cooperation and competition. In contrast, when studying <u>how</u> people compete, it is best to know that participants are competing. Therefore, we used a purely adversarial game: a repeated, zero-sum, two-player game in which players simultaneously select the number ONE, TWO, or THREE. Table 1 presents the payoff matrix for this game. In this zero-sum game, we will refer to the two players as the <u>Chooser</u> and the <u>Avoider</u>. The Chooser player tries to select the number that he or she expects the Avoider player to select, while Avoider seeks to avoid selecting the number chosen by Chooser. Both players make their selections in secret, then each player is told what the opponent selected. If their selections coincide, then Chooser wins the amount of points that corresponds to the number they both selected and Avoider loses the same amount of points. If the players' numbers do not match then Avoider wins a point and Chooser loses a point. A point tally is updated over repeated trials and the winner is the player who finishes with positive points.

As can be seen, the game is different for the two players. Chooser can win up to three points, but Avoider can only ever win one point. To offset this, Avoider is expected to win more individual trials of the game. Using a game like this seemed to make it more interesting for the players, but its primary advantage was that it allowed us to set up a game in which one player has an advantage, even though neither player could be expected to be able to determine this with certainty. Thus, the pattern of results served as a check that players were trying to win. Completely random responding by both players would yield an expected score of zero, therefore the expected advantage would not emerge if players made no effort.

A Game Theory Analysis

Many games have been analyzed using game theory (see Rapoport, 1960, 1966). Game theory is essentially descriptive as it seeks to analyze a state of affairs that exists, or to predict a future equilibrium state. It does not address what processes bring about this state of affairs, thus, game theory can only predict the equilibrium point the players should tend towards. However, it is a useful tool for analyzing what should happen in our game.

For applying game theory to a zero-sum game with no saddle points (i.e., when no single selection is always the best) such as ours, the critical concept is that of a mixed strategy. A mixed strategy assumes that on each trial an alternative is chosen stochastically and independently of the previous selection. Von Neumann (1928) showed that for any finite, constant sum, two-person game, there exists a mixed-strategy equilibrium that specifies the probability distribution with which each selection should be randomly made (at equilibrium). This probability distribution depends on the payoff matrix of the game. The mixed-strategy equilibrium is defined as the probability distribution for both players, such that if both players use the specified distribution for random choices, then neither player can gain by changing their distribution. However, the mixed-strategy equilibrium is not necessarily a winning strategy, it yields either an equal expected score for both players, or it gives one an advantage. Nor necessarily does it yield the highest expected payoff. If your opponent is not at the mixed-strategy equilibrium, then a higher payoff can be gained from a different distribution of responses, although that leaves you open to being exploited in turn. Thus, the equilibrium is a stable point towards which players should tend, rather than a prescription.

Calculating the mixed-strategy equilibrium for a game requires solving a set of simultaneous equations (see Luce & Raiffa, 1957). Such a calculation shows that the mixed-strategy equilibrium for this game for Avoider is selecting ONE with the probability .46 (more precisely, 6 out of every 13 trials), choosing TWO with the probability .31 (4/13), and THREE with the probability .23 (3/13). With this distribution, Avoider would be expected to win at least +.077 (1/13) points per trial, if Avoider imitates a stochastic process. In this game, the mixed-strategy equilibrium for Chooser is the same set of probabilities as those for Avoider, even though Avoider has an expected outcome of -.077 points per trial.

This analysis shows that Avoider has an advantage, but it would be surprising if the players worked through this analysis themselves. As Rapoport and Orwant (1962) pointed out, the concept of a mixed strategy is a sophisticated one. Its rationale is derived from profound mathematical ideas and its calculation is difficult. Perhaps this is why Colman’s (1982, ch. 5) review of the experimental literature on zero-sum games concluded that there was no tendency for people to use a mixed-strategy equilibrium. (However, in timing games in which the question is not what to do, but when to do it, such as duels, there is evidence that people use the mixed-strategy equilibrium, see Rapoport, Kahan, & Stein, 1976.)

Assessing modeling

To test our hypothesis, we had to decide on a method for assessing the participants' mental models of each other. Clearly, information of direct relevance to the game will be part of their models. For example, what distribution players think their opponent will use. However, if we directly asked this question, the answer would be likely to be based on the opponent's previous choices. Thus, there would be a fundamental confounding between players' modeling measures, and their opponents' previous distributions. For this reason, we looked for a way to assess players' modeling which could not be directly calculated from information available in the game, yet would assist in a fundamentally interactive game.

We reasoned that if players can accurately model their opponent, then they should be able to accurately assess their opponent. Thus, we had participants respond to a large set of word pairs that indicated their general assessment of their opponent, such as negative – positive. These items were answered on seven-point scales as in Osgood, Suci, and Tannenbaum (1957). We had our players rate sets of items for themselves (the self scale, representing the first-order model), their opponent (the opponent scale, representing the second-order model), and how they thought their opponent would rate them (the opponent-self scale, representing the third-order model).

It was not clear a priori which personal characteristics should be critical for successful competition. So we largely used items from Osgood et al.'s (1957) evaluation scale. However, our proposal was that the critical aspect of modeling for successful competition was how accurate you are in what you thought about your opponent. So the actual items which players rated may be less important than how accurate players were in their ratings. Therefore, we used the responses from all six scales -- the three scales from each player -- to derive the accuracy of a player's second- and third-order models of the opponent. Similar to Laing et al. (1966), to assess a player's second-order accuracy for modeling an opponent we compared the player's rating of the opponent (the *opponent scale*) with the opponent's rating of him or herself (the *self scale*), by summing the absolute differences between the ratings of the same item on these two scales. Third-order modeling accuracy for the player was derived by summing the absolute differences between items on the player's rating of 'how you think the opponent would rate you' (the *opponent-self scale*) and items on the opponent's actual rating of the player (the opponent's *opponent scale*).

For successful competitive performance, the absolute abilities of a player are not the critical factor, the outcome is determined by relative abilities. The second-best poker player in the world should still lose to the best. This implies that the unit of analysis for a competitive game should not be the individual, it should be the pair of players. Thus, to investigate the effects of modeling on performance, we used two measures of relative modeling accuracy calculated for each pair of players: the *relative second-order modeling accuracy* (to be referred to as *R2MA*), which was the Avoider's second-order modeling accuracy subtracted from the Chooser's second-order modeling accuracy; and, the *relative third-order modeling accuracy* (to be referred to as *R3MA*), which was the Avoider's third-order modeling accuracy subtracted from the Chooser's third-order modeling accuracy. Like R2MA and R3MA, all of our dependent measures were difference scores derived from the Avoiders' and Choosers' individual measures. Better performance on any measure was always stated in terms of the Avoider being better. So positive scores indicated the Avoider was better, and negative scores indicated the Chooser was better. This allowed us to always predict positive correlations.

Using a pair's relative modeling accuracy had a further advantage: It avoided (1955) criticism of the use of difference scores to assess the accuracy of person perception.

Cronbach pointed out that the agreement between a judge's and a target's ratings was partly the agreement of their response biases (e.g., the extent to which the judge and target tend to give high or low ratings in general). However, the effect of this agreement will be equivalent for both players, by definition. Therefore, the bias is eliminated by subtracting the opponent's accuracy from the player's own accuracy, in order to yield relative accuracy.

A Test of this Methodology

Burns (1993) briefly reported an attempt to apply this methodology to competition with 48 pairs of players. These pairs interacted together for 10 minutes, then played the game for 25 minutes (mean number of trials: 33.0, *SD* = 7.10). Before starting, they completed the self and opponent scales, then the opponent and opponent-self scales at the end of the game.

As predicted by game theory, the Avoider players had a clear advantage, in that they won 31 of the 48 games. Further, the mean proportions with which Avoider selected ONE (*M* = .42, *SD* = .12), TWO (*M* = .30, *SD* = .08), and THREE (*M* = .28, *SD* = .10) were close to the mixed-strategy equilibrium (proportions .46, .30, .23, respectively). However, the Chooser players' proportions did not fit to the mixed-strategy equilibrium (for ONE, *M* = .33, *SD* = .10; for TWO, *M* = .34, *SD* = .11; for THREE, *M* = .34, *SD* = .10), which game theory predicted should have been the same as the Avoiders' proportions.

Relative modeling accuracies were calculated as outlined above. There was no evidence that R2MA correlated with performance in the game (measured by the cumulative score after the final trial of the game), *r*(48) = .02, *p* = .88. However, success and R3MA correlated, *r*(48) = .29, *p* = .05, although this correlation was not significantly different to that for R2MA, *z* = 1.23, *p* = .22 (using Olkin's, 1967, test for differences between non independent correlations, as was used for all comparisons of such correlations in this paper). Thus, it appeared that modeling was associated with success, but only the third-order component could be shown to be important. None of the raw responses to any single item on the scale was associated with success, nor was the relative accuracy on any one item particularly associated with performance, instead, only the overall accuracy was predictive.

Thus, this experiment demonstrated the utility of the proposed methodology. Firstly, we observed that players did try to win this game even though they could apply no previous skills and received no reward. Evidence of the players' motivation was that, as expected, the Avoider won: Unthinking responding would have resulted in no expected difference between the players. Informal observation of players supported the conclusion that they were trying to win. Perhaps competition is motivating in itself: Flood (1958) used a nonzero-sum participation game, but found that participants appeared more concerned with maximizing the difference in their payoffs, than maximizing their own monetary payoff. Secondly, the results were consistent with our main hypothesis, that relative modeling accuracy would be associated with success in competition. However, there were some problems with interpreting this study. First, the opponent-self scale was only given at the end of the task, therefore the R3MA measure based on it, could be a reaction to success or failure rather than a predictor of performance. Second, the amount of time spent playing the game was fixed, but the number of trials was allowed to vary. Perhaps speed of play correlates with other factors, so given that expected score increases with number of trials, unknown biases may have affected the data.

An alternative prediction

The game theory analysis suggested a source of success that does not involve modeling the opponent: using a relatively better distribution of responses. Selecting each number equally often should not be the best strategy. Therefore, players who fail to discovered this should perform poorly in the game. We would not expect players to derive the exact mixed-strategy equilibrium, but they may infer that it is beneficial to choose ONE more than either TWO or THREE. Therefore, performance may correlate with the degree to which players used a more extreme distribution (i.e., one that deviates away from using each selection with equal probability) than their opponent. In itself, such a correlation would not contradict our hypothesis regarding modeling and performance, unless the correlation accounted for the relationship between modeling accuracy and performance.

Using a relative measure of a pair's distributions has a weakness: If one player uses the equilibrium strategy, then the expected outcome is the same regardless of the other player's distribution. However, we did not expect many players to use the equilibrium distribution. First, as already pointed out, it is unlikely that players will calculate this equilibrium. Second, an examination of the studies of experiments with zero-sum games reviewed by Colman (1982), showed a clear tendency for players to be conservative. They had distributions closer to equal probability for each selection, rather than the equilibrium distribution. In particular, Kaufman and Becker (1961) found that the more extreme the equilibrium strategy a game required, the more players deviated from it in favor of conservatism. Such a conservative tendency will reward an opponent's extremity even more, thus greater relative extremity should be associated with better performance. Players who use the equilibrium strategy will, however, add noise to a relative extremity distribution measure.

A Study

We tried to replicate and extend the modeling accuracy findings from Burns (1993) by asking participants to complete all three rating scales (self, opponent, and opponent-self) at the beginning of the game, half-way through, and at the end of the game. Thus, we could ask if the relative third-order modeling accuracy was predictive of the game's result or was only a reaction to the result. In addition, rather than restricting the amount of time that participants played the game, the number of trials was fixed at 40. This eliminated any biases due to varying numbers of trials, and permitted an analysis of players' relative distributions.

To test if modeling accuracy was associated with success, we tested the hypothesis that R3MA would be positively correlated with performance (as it was in Burns, 1993). However, we also examined when this relationship arose, was it at the beginning, during, or only at the end of the game? We again tested the hypothesis that R2MA would correlate with performance, but Burns' result suggested we must also test the hypothesis that the R3MA and R2MA correlations with performance would differ. In addition, we analyzed the relative extremity of players' distributions. We tested whether this factor was related to performance, and whether it could account for a relationship between modeling accuracy and performance.

Method

Participants. Seventy-five pairs of students (75 male, 75 female) from the University of California, Los Angeles, subject pool participated for partial course credit.

Procedure. Participants initially interacted together for ten minutes while trying to solve insight problems. Thus, they had some familiarity with their opponent before they started to play the game. Participants then were seated in the same room with a large screen separating them, and given the instructions for how to play the game. These included the payoff matrix shown in Table 1, although shown in a way that fit with a participant's assigned role (either Chooser or Avoider, randomly assigned). Once each participant understood the task, they were given the self, opponent, and opponent-self scales to complete. Each scale consisted of the same ten items, and each item consisted of a pair of words which anchored the ends of a seven-point scale. The pairs were chosen from the twenty given in Burns (1993) on the basis that in that study they were found to have the ten highest correlations (although not significant) between score in the game and relative third-order modeling accuracy. Of the ten pairs, eight were from Osgood et al.'s (1957) evaluation scale (*humorous* – *serious*; *negative* – *positive*; *hard* – *soft*; *foolish* – *wise*; *weak* – *strong*; *pessimistic* – *optimistic*; *severe* – *lenient*; *cruel* – *kind*), one was from their oriented activity scale (*rational* – *intuitive*), and one was designed to be relevant to this game (*risk-taking* – *risk-avoiding*). We also asked participants whether they knew their opponent. After completing the three scales, participants played the game for 20 trials, then filled out all three scales again. After 20 more trials (their score carried over from the first 20), they filled out the three scales a third time.

Players had as much time as they liked on each trial to select a number. Once each player had made a selection, they were informed of the opponent's selection. They then wrote down the selection on a scoring sheet, and updated their current score (using Table 1). Thus, they always had access to the history of selections. To avoid endgame strategies, participants were not told how many trials the game lasted. After the fortieth trial, they were told that the game was over, unless the game was tied. In that case, they played one more trial, then the game was over. Thus, players should have felt that the game came to a definite conclusion.

Results

Unlike Burns (1993), participants played the game in the same room. It was observed that the screen separating them did not eliminate all possible communication (i.e., sounds rather than words), and that in particular, friends were more likely to make such sounds. Therefore, we analyzed only the 54 pairs who did not know each other. Of these 54 pairs, 40 (74%) of the games were won by the Avoider, replicating the advantage found by Burns for the Avoider player (65% win-rate). Although the Avoider player won 74% of the games, the mean score in favor of Avoider was only 1.70 points ($SD = 9.27$). However, this was not significantly different from the 3.07 points the mixed-strategy predicted for a 40 trial game, $t(53) = 1.07$, $p = .28$. Note that all statistical tests we report were two-tailed and used an alpha level of .05.

Modeling and Performance. Relative accuracies of second- and third-order modeling (in favor of Avoider) were calculated in the way outlined above. In detail, the following calculation was made for a player's absolute second-order modeling accuracy: For each item on a player's opponent scale, the absolute difference between its rating and the same item's rating on the self scale was calculated, then the differences for the ten items were summed. Therefore, a low sum indicated accurate modeling. In order to calculate R2MA, the absolute second-order accuracy for the Avoider player was subtracted from the absolute accuracy for the Chooser player. Thus, a positive R2MA indicated that Avoider was a more accurate second-order modeler, the higher the better. Given that the final score was positive if Avoider won, a positive correlation was predicted between performance and modeling. The R3MA measure was calculated in the same way, except that it was based on the absolute differences calculated between items on a player's opponent-self scale and the opponent's opponent scale. Because the scales were completed at three different points -- the beginning, after 20 trials, and after the end -- three R2MA and R3MA measures (each derived from items answered at the same time point) were calculated. The correlations between each of these six relative modeling accuracy measures and the final score in the game are presented in Table 2. One player did not complete the items at the end of the game, therefore that pair was excluded from analyses of R2MA and R3MA at the end. It was also calculated whether R3MA measures for any single item were consistently correlated with success, but no item was.

R3MA had a consistent positive relationship to performance. Final performance was significantly correlated with R3MA measured half-way through the game and the end, although it was not significant at the beginning of the game. At the beginning, players had only had ten minutes to interact (However, the correlation between performance and R3MA did not differ between the beginning and the end of the game, $z = 1.28$, $p = .20$). Again R2MA measures did not significantly correlate with performance. Although R2MA and R3MA correlations did not differ at the beginning, $z = 1.76$, $p = .08$, they did differ after 20 trials, $z = 2.68$, $p = .009$, and at the end of the game, $z = 2.66$, $p = .009$.

To investigate further if final R3MA had its basis in modeling during the game, or was simply a reaction to winning or losing, we calculated the correlation between R3MA at different times. There were significant correlations between R3MA measured at the beginning of the game and after 20 trials, $r(54) = .34$, $p = .013$, and between R3MA measured after 20 trials and after the end of the game, $r(53) = .55$, $p < .001$. This showed that R3MA differences did not only arise once players knew the result, but instead were based on earlier differences.

Distribution of Responses. We calculated the proportion of trials on which Avoiders and Choosers gave each of the three selections. The mean proportions were very similar to the mean proportions found by Burns (1993). For Avoiders, the mean number of times that ONE was selected was .41 ($SD = .11$), for TWO, $M = .32$ ($SD = .070$), and for THREE, $M = .27$ ($SD = .086$). This was again similar to the mixed-strategy equilibrium. In contrast, Chooser players, as in Burns, gave each selection about equally often: for ONE, $M = .32$ ($SD = .073$); for TWO, $M = .34$ ($SD = .095$); and for THREE, $M = .34$ ($SD = .087$).

Although collectively the Avoiders approximated the mixed-strategy equilibrium, very few did individually. This was clear from the standard deviations of their proportions, but was made clearer by examining how many Avoiders came close to using this distribution. To do this, we defined *close* arbitrarily as proportions within .05 (plus or minus) of the equilibrium. For selections of ONE, only 13 of 54 Avoiders were in this range (.41 to .51); for TWO, 29 of 54 met the criterion (.25 to .35); and for THREE, 21 of 54 met the criterion (.18 to .28). Only six Avoiders met the criterion for all selections. As the means indicate, Choosers were even less likely to meet these criteria: Only two of the 54 Choosers were within the three ranges.

To test if players with a relatively better distribution of selections would have more success, we calculated a *relative distribution extremity* (RDEX) measure. To calculate this measure, we assumed that the game theory analysis of this game was valid: players should select ONE more than one-third of the time and TWO and THREE each less than one-third of the time. Therefore, first we calculated *absolute distribution extremity* by using each player's actual distribution of responses and applying the following formula:

absolute distribution extremity = (ONE - .333) + (.333 - TWO) + (.333 - THREE)

where ONE, TWO, and THREE represent the proportions of trials on which each selection was made. Thus, a positive score indicated that a player deviated away from choosing each selection equally often, and in the direction of the equilibrium. We then subtracted Chooser's deviation from Avoider's deviation to yield RDEx. So a positive RDEx indicated that Avoider had a more extreme distribution. RDEx correlated positively with the final score, $r(53) = .39$, $p = .004$, and almost significantly with R3MA at the end of the game, $r(53) = .26$, $p = .060$. Thus, using a better distribution than the opponent was another factor associated with success.

The finding that the extremity of a player's distribution was associated with both final score and almost with R3MA suggested that the quality of a player's distribution could be responsible for the R3MA correlation with final score. To examine this possibility we performed a multiple regression analysis for final score on RDEx and R3MA (after end). This yielded a significant equation, multiple $R = .48$, $F(2, 50) = 7.31$, $p = .0016$; for RDEx, $\beta = .31$, $t(52) = 2.41$, $p = .020$; and for R3MA, $\beta = .29$, $t(52) = 2.25$, $p = .029$. Thus, relative accuracy measures of distribution quality and third-order modeling each appeared to account for significant, but separate, components of the variance in performance.

Discussion

This study found that relative third-order modeling accuracy (R3MA) was associated with success in a purely competitive game. However, again there was no significant correlation with relative second-order accuracy (R2MA). Thus, as in Burns (1993), we had no evidence that second-order modeling was important for success.

We found some support for the claim that modeling accuracy was predictive of performance, rather than just being a reaction to success. While accuracy at the end of the game had the highest correlation with performance, there was also a significant correlation between R3MA measured half-way and final performance. Only the start of the game R3MA correlation with final performance was not significance. Further, there was evidence that relative modeling accuracy did not only arise suddenly once the result of the game was known. Instead, R3MA at the start of the game was predictive of R3MA after 20 trials, which was in turn predictive of the final R3MA. If final R3MA was just a response to the final result of the game, then it should not have been strongly associated with earlier relative accuracy. Thus, modeling accuracy appeared not simply to be a reaction to success or failure.

Adding support to the claim that more accurate modeling was a factor for success, was the failure to find evidence that the R3MA correlation with performance could be accounted for by a third factor. We did find that using a better distribution of selections (as measured by RDEx) was associated with better performance. So it was critical to show that our measure of relative modeling accuracy was not just a substitute for this factor. Regression analysis showed that the influence of RDEx on final score was separate from that of R3MA.

We have not completely eliminated the possibility that some unmeasured factor could actually be responsible for the performance-modeling relationship. For example, intelligence or motivation could be correlated with both. However, quality of distribution would appear to be the likely mechanism via which these factors would affect performance. Yet quality of distribution accounted for separate variance in performance to modeling accuracy. The barrier for any speculated third factor is to propose a mechanism through which it could affect performance other than via modeling or quality of the distribution.

What is the Nature of the Model? If modeling is important for success in competition, what is the nature of this model? We found no evidence that accuracy on any one personality item was particularly important. The main purpose of this study was to find evidence that accurate modeling of an opponent was associated with success. Therefore, we did not systematically test different items. It could be that our measures are just a manifestation of a general modeling ability. However, there are ways in which modeling accuracy on our items could translate into success. Its possible that evaluative items relate to whether a player will stay with a strategy or change, or that the items relate to some intuitive feel that players have. Accuracy on the item risk-taking -- risk-avoiding might guide selections, so a set of risk items might have a measurable association with success. These are questions for future research.

The consistent finding that third-order modeling accuracy, but not second-order, was related to competitive performance, could be because third-order modeling is critical for deception. However, we should be cautious about interpreting the null results for R2MA as showing that second-order modeling is unimportant. First, we only showed that differences in second-order modeling did not distinguish between players. It could be that second-order modeling is critical, but perhaps second-order modeling is so pervasive, that differences are only weakly predictive. Good third-order modeling may be rarer, and thus confer a clearer advantage on its better practitioners.

Second, we are limited to conclusions based on a particular measure. For our R2MA measure we assumed that self-ratings were accurate. However, if opponents gave inaccurate ratings of themselves, then this accuracy measure would be flawed. Therefore, we must be conservative in the conclusions we draw, because the accuracy of self-reported measures of the self is a matter of debate (see Kenny, 1994).

<u>Further Issues</u>. This study has not attempted to determine the size of the contribution of modeling accuracy to success in competition. To do so would have required trying to develop the best possible measure of modeling, which was not the aim of this study. The importance of modeling may depend on the particular game and its demands, and probably on how evenly matched the competitors are on other factors. In our game, we tried to make players as evenly matched as possible by removing all obvious skill components from the game, but still found that quality of distribution and modeling accuracy were components of success. (Perhaps these are actually general skills applicable to many games.) Yet our game provided little information on which to base a model of the opponent. In normal competitive situations, more information is available, and thus the opportunity for those who can exploit it should be greater. Therefore, it is possible that modeling accuracy could account for more performance variance than we have calculated here.

Our game was artificial, yet many forms of competition have the characteristic that our game embodied in a pure form: repeated choices and an opponent who must not discover your choice, but who cannot cover all choices. For example, a football player decides to run left or right with the ball, and the tackler decides which way to move first; this week’s military convoy has to be sent down the low road or the high road, while the guerrillas decide which road to wait on; a firm plans a product line to emphasize, and its weaker competitor tries to pick a different niche. Our results suggest that if you can get inside the head of the opponent and anticipate his or her choices, then you can obtain an edge

Conclusions

In one sense, given the anecdotal evidence that modeling is important in competition, our results were not surprising, although finding that third-order modeling was particularly important goes beyond the anecdotes. However, we have demonstrated a methodology capable of empirically supporting this intuition and suitable for beginning to study this phenomenon. Research on competition has often focused on factors that cause competition rather than cooperation. It has been assumed that success in competition is simply a product of the attributes of the competitors, rather than itself being a social phenomenon. Our results suggested that modeling is an important component of successful competition just as interpersonal perception has been seen as an important component of other social situations. Kelley and Thibaut (1969) suggested that pure competition is rare in social interactions, yet they also pointed out that many interactions are a mixture of competition and cooperation, therefore the factors behind successful competition may have an impact on many social interactions. Finally, this work presents a challenge to problem solving research and theory: to address a whole new domain which has been ignored, that of interactive tasks.

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similarity." Psychological Bulletin, 52, 177-193.

Dennet, D. C. (1978). Brainstorms: Philosophical essays on mind and psychology. Montgomery, VT: Bradford Books.

Flood, M. M. (1958). Some experimental games. Management Science, 5, 5-26,

Gilhooly, K. J. (1988). Thinking: Directed, undirected and creative (2nd ed.). San Diego, CA: Academic Press.

Holding, D. H. (1989). Adversarial problem solving. In K. J. Gilhooly (Ed.), Human and machine problem solving (pp. 83-122). New York: Plenum Press.

Hymans, R. (1989). The psychology of deception. Annual Review of Psychology, 40, 133-154.

Kaufman, H., & Becker, G. M. (1961). The empirical determination of game-theoretical strategies. Journal of Experimental Psychology, 61, 462-468.

Kelley, H. H., & Thibaut, J. W. (1969). Group problem solving. In G. Lindzey & E. Aronson (Eds.), Handbook of social psychology (Vol. 4, 2nd ed., pp. 1-101). Reading, MA: Addison-Wesley.

Kenny, D. A. (1994). Interpersonal perception: A social relations analysis. New York: Guilford

Press.

Laing, R. D., Phillipson, H., & Lee, A. R. (1966). *Interpersonal perception: A theory and a method of study*. New York: Springer.

Luce, R. D., & Raiffa, H. (1957). *Games and decisions*. New York: Wiley.

Olkin, J. (1967). Correlation revisited. In J. C. Stanley (Ed.), *Improving experimental design and statistical analysis* (pp. 102-128). Chicago: Rand McNalley.

Osgood, C. E., Suci, G. J., & Tannenbaum, P. H. (1957). *The measurement of meaning*. Urbana, IL: University of Illinois Press.

Rapoport, A. (1960). *Fights, games, and debates.* Ann Arbor, MI: University of Michigan Press.

Rapoport, A. (1966). *Two-person game theory.* Ann Arbor, MI: University of Michigan Press.

Rapoport, A., Kahan, J. P., & Stein, W. E. (1976). Decisions of timing in experimental probabilistic duels. *Journal of Mathematical Psychology, 13*, 163-191.

Rapoport, A. & Orwant, C. (1962). Experimental games: A review. *Behavioral Science, 7*, 1-37.

Ruscher, J. B., & Fiske, S. T. (1990). Interpersonal competition can cause individuating processes. *Journal of Personality and Social Psychology, 58*, 832-843.

Thagard, P. (1992). Adversarial Problem Solving: Modeling an opponent using explanatory coherence. *Cognitive Science, 16*, 123-149.

Von Neumann, J. (1928). Zur Theorie der Gesellschaftspiele [On a theory of games]. *Mathematische Annalen, 100*, 295-320.

Wrightman, L. S., Baxter, G. W., Nelson, R. H., & Bilsky, L. (1972). Effects of information about other player and other player's game behavior upon cooperation in a mixed-motive game. In

L. S. Wrightman, J. O’Conner, & G. W. Baxter, Cooperation and competition: Readings on mixed motive games (pp. 211-224). Belmont, CA: Brooks/Cole.

Table 1.

Payoff matrix for the game. Outcome for Chooser is the first number in the pair while the second number is the outcome for Avoider.

		Avoider's selection		
Chooser's selection		ONE	TWO	THREE
	ONE	+1 / -1	-1 / +1	-1 / +1
	TWO	-1 / +1	+2 / -2	-1 / +1
	THREE	-1 / +1	-1 / +1	+3 / -3

Table 2.

Correlations between the final score in the game with R2MA and R3MA measured at the start of the game, after 20 trials, and after the end of the game, together with probability levels.

	At start	After 20 trials	After end of game
	(N = 54)	(N = 54)	(N = 53)
Final score:			
with R2MA	-.21, p = .13	-.26, p = .062	-.19, p = .18
with R3MA	.17, p = .21	.27, p = .047	.37, p = .006