# GAMES, game theory and artificial intelligence

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## Abstract

**Purpose** – The purpose of this paper is to illustrate how game theoretic solution concepts inform what classes of problems will be amenable to artificial intelligence and machine learning (AI/ML), and how to evolve the interaction between human and artificial intelligence.

**Design/methodology/approach** – The approach addresses the development of operational gaming to support planning and decision making. It then provides a succinct summary of game theory for those designing and using games, with an emphasis on information conditions and solution concepts. It addresses how experimentation demonstrates where human decisions differ from game theoretic solution concepts and how games have been used to develop AI/ML. It concludes by suggesting what classes of problems will be amenable to AI/ML, and which will not. It goes on to propose a method for evolving human/artificial intelligence.

**Findings** – Game theoretic solution concepts inform classes of problems where AI/ML 'solutions' will be suspect. The complexity of the subject requires a campaign of learning.

**Originality/value** – Though games have been essential to the development of AI/ML, practitioners have yet to employ game theory to understand its limitations.

**Keywords** Game theory, Games, Artificial intelligence

**Paper type** Conceptual paper

## Introduction

Playing games is a natural activity for humans and other animals to make sense of, explore, experiment and adapt to their environment [1]. The lusory play-mood of games encourages players to project imagination beyond their current physical circumstances, thus promoting creativity and innovation. Going beyond the physical to the metaphysical, from prehistory on, games have played roles in ritual, and animal bones have been used for both divination and early games of chance. The ancient Egyptians played chess-like board games using dice, presumably abstractions representing battle as were used by all advanced ancient societies (David, 1998).

With the exception of cards coming from ninth century China to Europe around 1,350 (David, 1998), games in different societies remained more similar than different until the Scientific Revolution in the seventeenth century where diplomat-scientist-philosopher-mathematician Gottfried Wilhelm (von) Leibniz combined the manipulation of symbols in language and games as a basis for logical truth, and wrote a paper anticipating computer languages. Leibniz sought to bring similar logical processes to his war game designs. He proposed a "German military system" in which:

> Newly invented war game, colonels and captains, also other commanders practice it instead of the chessboard and card game, and come to greater *science, speed and invention* [emphasized in original]; one could represent with certain game pieces certain battles and skirmishes, also the position of the forces, and the lay of the land, both at one's discretion and from history, for example if one wanted to play the Battle of Lützen, the skirmish with the French at Eisisheim and other historical events;

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> thereby on would often find what others missed and how we could gain wisdom from the losses of our forerunners (von Hilgers, 2012, p. 28)

The Prussian Kriegsakademie, founded by General Gerhard von Scharnhorst in 1801, eventually established such a system and adopted the von Reiswitzs' Kriegspiel adopted in 1824.

Contemporaneously, patrician and merchant Christopher Weikhmann developed the chess-like *Newly Invented Great King's Game* as an means to derive a "state and war council," whereby "the most necessary political and military axiomata, rules and ways of playing . . . without great effort and the reading of many books, are shown and presented as if in a compendio" to those who studied the game diligently [2]. Leibnitz's and Weikhmann's efforts were the first to make abstract gaming used for entertainment and improving strategic intuition into games for operational planning and decisions.

Scharnhorst's approach to military science and Prussian successes in the 1886 war against Austria and 1870–1871 war against France led to widespread adoption of their processes as war colleges and gaming proliferated among major military powers. Before First World War, a British political game contributed to the formation of the Triple Entante between the UK, France and Russia. Gaming demonstrated the weaknesses in the German war plans in the west and the Russian war plans in the east. The gaming and exercises conducted by the Germans between the World Wars laid the foundations for the rapid expansion of Wehrmacht beyond the limits set in the treaty ending First World War and their victories early in Second World War. In 1940, Soviet gaming again demonstrated weaknesses in their plans, but they were too slow to reorganize and adapt. Similarly, early Japanese victories in Second World War followed the course of their games. US Navy gaming and exercises led to a deep appreciation of the upcoming war in the Pacific, contributing to winning the war (Hanley, 1992).

War gaming did not have the same salience immediately following Second World War as US and Soviet war colleges turned to harvesting the lessons of the war and German and Japanese forces were restricted in their activities. However, business and government policy makers found operational gaming "a powerful method for simultaneously mastering complexity, enhancing communication, stimulating creativity, and contributing to consensus and a commitment to action (Duke and Geurts, 2004)." The mathematics of Operations Research developed and employed during Second World War displaced much of the US military analytic effort that had gone into war gaming, and accelerated with the development of computers. However, during the 1980s war gaming at the Naval War College and fleet exercises played a similar role in the development and implementation of the Maritime Strategy as it had during the interwar years (Hanley, 2014, pp. 11–29).

In addition to mathematical programming for optimization and stochastic processes that formed the core of the Operations Research discipline, game theory and computer science further developed during Second World War. Twentieth century mathematicians studied ways to play chess better. This led to John von Neumann proving a saddle-point minimax strategy as the best solution for two-person zero-sum games in 1928, and with Oskar Morgenstern publishing a comprehensive *Theory of Games and Economic Behavior* in 1944 extending the theory to cooperative and non-cooperative games other than constant sum, and with more than two people.

Computer advances and Alan Turing's writings on "thinking machines" led to a conference at Dartmouth College in 1956 where the term artificial intelligence (AI) was coined. Early work on AI explored neural nets and machine learning. By 1959, Arthur Samuel had developed a machine that could beat him at checkers using game theory as the basis for rational choice and employing novel techniques (Holland, 1998). Since then, game theory has played a major role in machine learning and electronic commercial games. Artificial intelligence has gone through several waves of enthusiasm and disappointment (Richbourg, 2018). With recent successes in machine learning with algorithms that can beat humans at *Go* and the Department of Defense's interest in AI, another wave is cresting. AI is finding many uses in areas from designing drugs to robots to social control in China and will have many commercial successes. However, game theory is key to understanding the kinds of problems having well founded solution concepts, and where to expect problems in AI used to inform decisions in situations involving paradoxes and dilemmas in competition and cooperation.

## A game theory primer for gamers

Game theory provides an "elaborate mathematical development centered solely in the social sciences (Luce and Raiffa, 1957)." It begins with utility theory to provide an approach for quantifying the value of known, certain outcomes for each individual [3].

### *Types of games*

Reflecting their interest in economic and social coalitions, von Neumann and Morgenstern distinguished between "inessential" games in which coalitions and side-payments between partners play no role, and "essential" games where they do. Inessential games include two-person, zero-sum games where one person gains what the other loses and two-person, non-zero-sum non-cooperative games where the sum of the outcomes for the players is not zero, making them not strictly competitive, and where mutual gain is always a possibility, but no pre-play communication between players is permitted. In repeated plays of the second type, observing the other player's choices provides a means for signaling within the game, but no other messages may be sent.

Essential games include two-person cooperative games where pre-play messages are transmitted without distortion, all agreements are binding and enforceable by the rules of the game, and a player's evaluations of the outcomes are not affected by the pre-play negotiations; and n-person games where going beyond two people allows for the formation of coalitions [4]. Where assumptions about pre-play negotiations or other communications not affecting the evaluation of outcomes are too strong, one can revise the formulation of the game to explicitly include negotiations and communications, though coding written and verbal language, expressions and behavior are a challenge for any quantitative method.

### *Information conditions*

The information that each player, and umpires, have performs a determinative role in game theory to the point that changing the information conditions changes the game. The information conditions address what information is available to each player at every stage of the game, what is the role of a player being informed about the other player's strategy, and about the entire theory of the game (von Neumann and Morgenstern, 2004, p. 47).

*Complete information.* To "divide the difficulties" of assuming otherwise, von Neumann and Morgenstern assumed that the subjects under consideration "are completely informed about the physical characteristics of the situation in which they operate and are able to perform all statistical, mathematical, etc. operations which this knowledge makes possible (von Neumann and Morgenstern, 2004, p. 30)." Incomplete information is where this assumption does not apply.

*Perfect information.* Where at every point of time during the play of a game each player with a decision to make knows all of the previous moves of the other players when making a move. *Chess* is an example of a game with perfect information (von Neumann and Morgenstern, 2004, p. 51). Simultaneous moves where previous moves are known provides "almost perfect" information. Lacking perfect information, players need to randomize their decisions to achieve the best outcomes (von Neumann and Morgenstern, 2004, pp. 183–184; Shubik, 1982, p. 37).

*Imperfect recall.* In games like *Bridge* players decide upon their bids not knowing the contents of their partner's hand. Games involving teams representing a player may not know of moves other teammates have made or the information on which those moves were based. In games with imperfect recall, players may need to make a random choice of strategy at the beginning of play, so that the actions of their agents will be properly correlated. In games with perfect recall, randomizing decisions can be deferred until actual decision points are reached. Mixed strategies of this kind with on-the-spot randomizations are called "behavioral strategies" in the literature, and are far easier to work with, both in theory and practice, than general mixed strategies (Shubik, 1982, pp. 37–38). Imperfect recall leads to "direct" signaling in *Bridge* as opposed to "inverted signaling," or bluffing, in *Poker* (von Neumann and Morgenstern, 2004, p. 54).

Game theory primarily treats exogenous uncertainty from random processes as "nature's moves." For calculation, it treats the associated probabilities as known. Decision theories make greater distinctions between decisions under "risk" where probabilities are known, and uncertainty where the probabilities are more subjective (Luce and Raiffa, 1957).

### *Game-theoretic forms*

The theory provides for three forms to represent a game: extensive, strategic (or normal) form and the characteristic function. The first level of application of game theoretic analysis is in the selection of which way to represent the game.

*Extensive form.* Modeling games in extensive form captures the timing of the players' moves relative to relevant events and representations of what the players knew about other's choices when they selected their move. Figure 1 illustrates two simple games in extensive form involving players Red (R) and Blue (B) making sequential moves in 1a, where Blue knows Red's choice when making its move, and "simultaneous" moves in 1b, where both

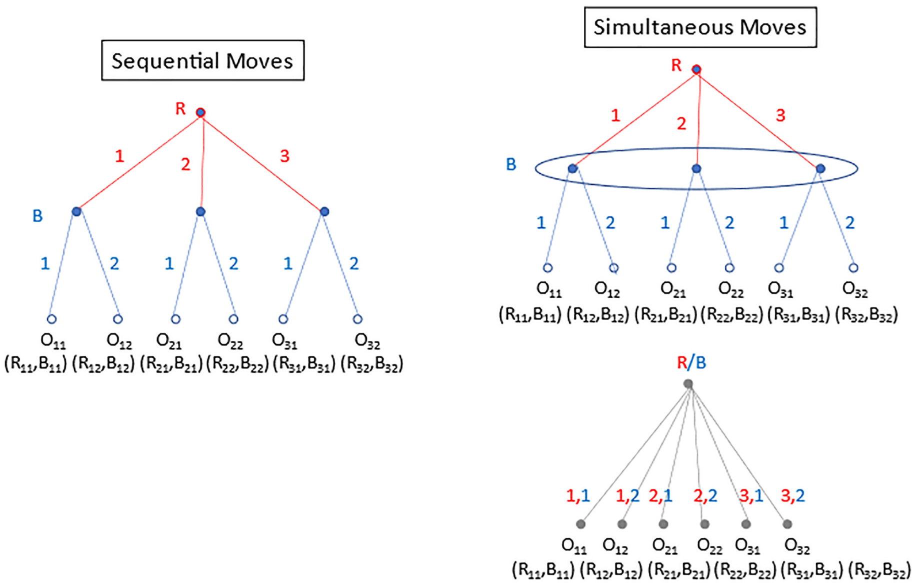


**Figure 1.**
Games in extensive (tree) form

sides select their move without knowing the other's choice [5]. For simplicity, these games represent Red having three and Blue having two alternatives, one "branch" representing each alternative. A move involves choosing one of the possible alternatives.

A strategy in game theory means a complete description of how a player intends to play a game, from the beginning to the end. "The test of completeness of a strategy is whether it provides for all contingencies that can arise, so that a secretary or agent or programmed computer could play the game on behalf of the original player, without having to return for instructions (Shubik, 1982, p. 34)." In policy making and the military the term course of action (COA) represents following one path down the game tree. COA is used below to avoid confusion with other concepts of strategy.

The alternatives are numbered and the outcomes indicated with subscripts relating to the player's choice of that alternative; e.g. $O_{IJ}$ indicates the outcome should Red select COA $i$ and Blue select its COA $j$. The payoffs to Red and Blue are indicated similarly by $R_{ij}$ and $B_{ij}$ respectively. The payoffs are the value (utility) of the outcome to each player [6]. Should the value of all outcomes be equal and opposite for Red and Blue (i.e. $R_{ij} = -B_{ij}$ for all Red COAs $i$ and Blue COAs $j$), the game would be zero-sum. In general, though some situations, such as winning or losing a duel, may be usefully modeled as a zero-sum game, the more considerations involved in the outcome, the less valuable modeling the game as zero-sum is likely to be.

Figure 1b also illustrates two ways for representing simultaneous moves, and the information available to players when they chose their next move. The bubble (ellipse) around the positions at which Blue selects its move indicates that Blue does not know which move Red has selected when it makes its choice. The set of points enclosed is called an information set (Shubik, 1982, p. 42). For simultaneous moves the information set consists of one point. The lower figure is an alternative representation of Blue with one information set that shows it is the equivalent of the players choosing simultaneously among their alternatives.

In a game with more than two players, the sequence of player alternatives and moves is represented adding to the detail above. Nature and game adjudicator decisions are treated similarly to a player, representing their adjudications as moves in the game.

The positional form is a variant of the extensive form useful for reducing redundancy in the many games such a *Checkers*, *Chess* or *Go* where pieces can reach the same physical positions through various sequences of moves and the history of the game is not relevant to the play. A directed graph, network structure, allowing different lines of play to merge is one way to capture the moves in such a game. Since the positions of the pieces are used to evaluate future moves in machine learning and artificial intelligence, the positional form may save computations. This form resembles a flow diagram for a computer program. As with computers, loops can result in moves of infinite duration. Chance and simultaneous moves can be treated as before, but all nodes with multiple incoming edges are assumed to have the same information. Most positional games in the literature have perfect or almost perfect information. Also, players may make a different choice when re-arriving at a node, complicating the enumeration of strategies. "Stationary strategies' are where the player uses selects the same alternative at each opportunity to move. In games like *Monopoly* arriving at a position leads to a "spot payment," which when summed up leads to ruin or survival. The chance events associated with the roll of dice make the game stochastic (Shubik, 1982, pp. 48–57).

*Strategic form.* If the focus of the analysis is on strategy and payoffs, representing a game in strategic form may be more useful than the extensive form. A two-person game in strategic form (also called the normal form) is represented as a two-dimensional matrix. Each player represents a dimension, requiring games with three players to be drawn as cubes, and games with more than three players being even more challenging to illustrate. Figure 2 illustrates the same games as Figure 1, but in strategic form.

Going to the strategic from the extensive form loses many details of the move sequence and information structure. However, the strategic form of these simple games shows the importance of intelligence of the other players move. Blue has many more COAs available when acting with knowledge of Red's COA than without that knowledge. Here the strategies, or COAs, available to Blue going from the simultaneous to the sequential game go from selecting either COA 1 or 2 to selecting among eight along the lines of (1,1); (1,2); (1,3), which means Blue selects 1 if Red selects 1; Blue selects 2 if Red selects 1; Blue selects 3 if Red selects 1, etc. In general, the number of Blue's strategies is the number of its alternatives raised to the power of number information sets at the point of choice. Transitioning from a multi-move game in extensive form to one in strategic form requires careful book keeping. Accounting for all of the combinations of possible COAs in games with many moves is daunting and produces very large matrices.

*Characteristic function.* In considering cooperation among more than two players in his original work on game theory in 1928, Von Neumann formulated the notion of a characteristic function that assigns a value to every coalition that can be formed in a game [7]. Table 1 illustrates such a game with three players. $V(i)$ indicates the value that player $i$ could achieve acting alone. $V(ij)$ indicates the value that players $i$ and $j$ could achieve acting together in a coalition. $V(123)$ indicates the value that all three players could receive if they all participated in a coalition. The characteristic function is a pre-solution, as matters of how the players should share the gains from a coalition require further analysis. This form leaves behind all

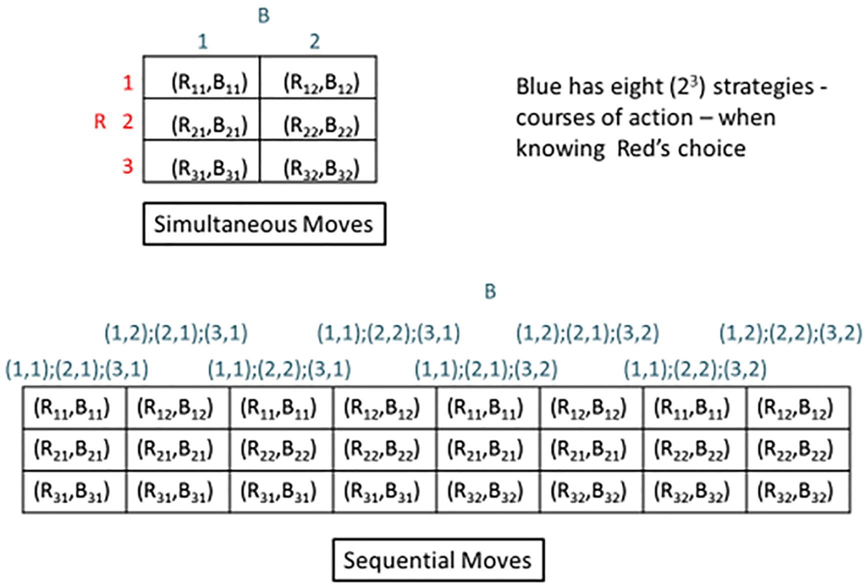


**Figure 2.**
Game in strategic, or normal, form

**Table 1.**
Game in characteristic form

| | | |
|---|---|---|
| $V(1) = 1$ | $V(2) = 1$ | $V(3) = 2$ |
| $V(12) = 4$ | $V(13) = 4$ | $V(23) = 7$ |
| | $V(123) = 11$ | |

questions of tactics, information and physical transactions to deal with essential features of n-person problems. This form must be modified or abandoned when addressing strategic with coalitional questions (Shubik, 1982, p. 129).

*Solution concepts.* In introducing their theory of games and economic behavior, von Neumann and Morgenstern devoted careful attention to their meaning of a solution concept (von Neumann and Morgenstern, 2004, pp. 31–45). Game theoretic solution concepts involve mathematically complete principles of "rational behavior" for the participants in a social economy to derive general characteristics of that behavior. To allow mathematical treatment, "rational behavior" involves maximizing individual "utility," as formulated for the theory. The definition of a solution:

> must be precise and exhaustive in order to make a mathematical treatment possible. The construct must not be unduly complicated, so that the mathematical treatment can be brought beyond the mere formalism to the point where it yields complete numerical results. Similarity to reality is needed to make the operation significant. And this similarity must usually be restricted to a few traits deemed "essential" pro tempore – since otherwise the above requirements would conflict with each other.

Recognizing the difficulty of finding principles valid in all situations, they sought to find solutions for some special cases.

The concept of a solution "is plausibly a set of rules for each participant which tell him how to behave in every situation that may conceivably arise." These rules account for the irrational conduct on the part of others in the sense that irrational conduct produces less utility for that participant than rational behavior would have. Using utility, the solution summarizes how much the participant under consideration could get by behaving "rationally," recognizing that more could be obtained if other participants behaved irrationally.

Ideally, the game would lead to a solution that had just one set of payoffs [8]. In his 1928 paper von Neumann proved that two-person, zero-sum games have a saddle-point where the minimizing the maximum (the minimax) that one player receives equals maximizing the minimum (the max-min) that the other player receives. Realizing this point may require randomizing between two strategies rather than adopting a single strategy. But this solution only occurs in two-person zero-sum games.

Moving on to two-person variable sum, then to more than two people (which allows cooperation against the third party – leads to multiple sets, and sets of sets, of feasible payoffs for each player) [9]. A dominant strategy is where one player can achieve their goals no matter what other players do presents an obvious choice. However, that rarely occurs. Nash equilibria, named after John Nash, where no player can improve their position given the other players' choices is another common aspect of a solution, but multiple equilibria in a game is not uncommon [10]. In general, though concepts for solutions to all types of games exist, as one moves from two-person, zero-sum games the possible solutions are not unique and additional rules for what constitutes a solution must be added, which limits the solution to cases where that set of rules applies [11].

To summarize, game theory solutions are mathematical constructs. Game theoretic solutions deduce the set of outcomes that are consistent with the embedded assumptions about individual and group behavior (Shubik, 1975, p. 91). "As long as the logic is sound, a solution cannot be wrong *per se*. However, a solution can be irrelevant in the sense that it fails to provide reasonable normative advice and is of little use in predicting behavior (Shubik, 1975, p. 276)." Game theorists understand that "multi-person games cannot be properly analyzed or solved until adequate information is provided about the social climate – in particular, about the possibilities for communication, compensation, commitment, and trust. Given this sociological information, one can proceed to the selection of a suitable solution concept (Shubik, 1982, p. 24)." An accurate criticism of game-theoretic solutions, as with other mathematical models, is that this may not be possible without far more detailed knowledge than is usually available, and then the solution applies only to the narrow set of conditions modeled.

Experimentation provides some insight into the relevance of various solution concepts. Game theory provides a theoretical framework for extending experimental psychology to interpersonal and social relations. The theory provides constructs that sharpen concepts of "conflict and co-operation, trust and suspicion, power of bargaining, balance of bargaining advantage, and equity … (Rapoport, 1960, p. 214)" Experiments identify actual norms of behavior. "The game theory is extremely useful in setting up the game, but the running of the game is our means to explore behavior (Shubik, 1975, p. 92)."

*Experimenting with games and results*

Designing and using games in the study of game theory and social behavior dates from the early 1950s. At Princeton graduate students including John Nash, Lloyd Shapley and Martin Shubik informally discussed the use of games in the study of game theory and devised "so long sucker" to illustrate the vital roles of coalition formation and double-crossing [12]. Shubik also created the "dollar auction" as a demonstration of escalation. In this game both the winning bidder and the second highest bidder have to pay their bids for the dollar. The game is a way for instructors to make some money on the side while teaching game theory.

The scope of experimentation includes attempts to directly verify the worth of various game-theoretic solution concepts for relatively abstract games; social psychological experimentation; the study of behavioral characteristics of individuals in loosely structure games; the analysis of human factors; logistics and military research for large operational games, and the investigation of social factors and basic learning procedures in the study of the effectiveness of gaming for teaching (Shubik, 1975, pp. 209–210). Experimental gaming has been used with success in psychology and economics, and to a lesser extent in organizational theory and political science (Shubik, 1975, p. 10).

*Classic 2 × 2 non-constant-sum games.* Because 2 × 2 games are relatively few in number and can be used to illustrate several of the paradoxes involving the relationship between individual isolated and interactive behavior, they are frequently used in experimentation [13]. Some of the 2 × 2 games have been given names. Classic among these games are the Prisoners' Dilemma, the Battle of the Sexes and the game of Chicken.

Prisoner's Dilemma is a game where two completely rational individuals might not cooperate, even though cooperation would produce a better outcome. The story that goes with the game is that two members of a criminal gang are arrested and imprisoned. The prisoners are separated with no means of communicating with the other. The prosecutors lack sufficient evidence to convict the pair on the principal charge, but they have enough to convict both on a lesser charge. Simultaneously the prosecutors offer each prisoner a bargain. Each prisoner is given the opportunity to either betray the other by testifying that the other committed the crime, or to cooperate with the other by remaining silent. The possible outcomes are:

(1) If R and B each betray the other, each of them serves two years in prison

(2) If R betrays B but B remains silent, R will be set free and B will serve three years in prison (and vice versa)

(3) If A and B both remain silent, both of them will serve only one year in prison (on the lesser charge)

In strategic form the matrix is as shown in Table 2 with representative payoffs.

The game demonstrates where choosing what is individually rational provides other than what may be considered a socially rational outcome. The only non-cooperative equilibrium for the Prisoner's Dilemma is for both to betray each other, since that is the least bad outcome given that neither knows what the other will do. The prisoners would be better off with cooperation.

In the Battle of the Sexes a man and a woman must agree on one of two possible activities (such as which movie to see) where their preferences differ. If they do not agree, they do neither activity, but are unhappy with each other. Table 3 shows a payoff matrix of the value to them for going to her movie, his movie or disagreeing and not going out.

In the Game of Chicken two hot-rodders drive towards each other on a collision course. If they stay on course, they both crash. If one veers and the other stays on course the later "wins" and the former is chicken. If both veer their mutual shame cancels out. Table 4 shows representative payoffs.

*Control and context.* The participants in the experiments are individuals, often students, "who come equipped with social conditioning, language and memory of individual experience. When they come to an experiment their memories and conditioning cannot be wiped out." In their work on game theory Shapley and Shubik suggested that the condition of "external symmetry" be made explicit in game models (Shubik, 1982, p. 16). This condition indicates that unless explicitly modeled otherwise, all aspects of the players are assumed to be the same. In fact, they never are. At best the experimenter can suggest that as a first order approximation the individuals are sufficiently similar. When little in the way of context is provided, the influence of differences in wording instructions is magnified.

Von Neumann began his explorations into game theory by illustrating a completely rational solution to a zero-sum game. Thus, from experimental data on zero-sum games one can draw conclusions about how the actual behavior of people departs from rationality in a completely competitive situation. However, "Even at the level of two-person zero-sum games context and professional training appear to be relevant. An early PhD thesis of Simon (1967) utilized business school and military science majors playing a two-person, zero-sum game with three scenarios for the quantitatively same game. One scenario was based on business, one was military and one was abstract. Different results were obtained in all instances." That

**Table 2.** Prisoner's Dilemma payoff matrix

| | B Remains silent | B betrays R |
|---|---|---|
| R remains silent | −1, −1 | −3, 0 |
| R betrays B | 0, −3 | −2, −2 |

**Table 3.** Battle of the Sexes payoff matrix

| | Choose her movie | Choose his movie |
|---|---|---|
| Choose her movie | 2, 1 | −1, −1 |
| Choose his movie | −1, −1 | 1, 2 |

**Table 4.** Game of Chicken payoff matrix

| | Stay on course | Veer |
|---|---|---|
| Stay on course | −10, −10 | 5, −5 |
| Veer | −5, 5 | 0, 0 |

said, "The pure strategy saddle point when it exists provides a reasonably good prediction of how people behave (Shubik, 1975, p. 245)"

An extensive literature exists on cooperation in repeated plays of the Prisoner's Dilemma. Other experiments used different communication conditions (no communication, communication, reversible decision and non-simultaneous decisions) and three orientations (cooperative emphasizing joint maximization, individualistic where each player was told to look out for himself, competitive where each player was made to feel that he played against the other). Results of the experimentation demonstrated the value of communication and performing a trusting act in achieving cooperation, though betrayal continued to occur in all communication conditions. Players' orientations also significantly affected their choices, as did the presence of an "obnoxious" person present as an observer (Rappaport, pp. 218–222).

One set of experiments involved showing students the payoff matrices of the three classical games without descriptions of the choices and having them assign the three names to the matrices. There appears to be some support that "numbers tell a story" for the Battle of the Sexes but little for the Prisoner's Dilemma or the Game of Chicken. After the students were told of the names of the games, they for the most part agreed that the names were "reasonable." But the percentage of correct guesses indicated at best a fairly weak association (Shubik, 2001b, p. 10). Experiments changing the name of the Prisoner's Dilemma have produced different levels of cooperation and betrayal.

*Interpersonal comparison.* The three games above have symmetric payoffs for the players. Experiments routinely demonstrate that payoffs that are not symmetric, though strategically equivalent in having the same equilibrium point (such as multiplying one player's payoffs by 100), affects choice as players compare their payoffs to others rather than choosing what strategy guarantees their best outcome (Shubik, 2001b, p. 11). Choosing based upon the difference in payoffs changes a two-person, non-zero-sum game into zero-sum.

*Tacit communications.* Recognizing the limitations of the assumptions of game theory and focused on situations involving mixed motivations for competition and cooperation, Thomas Schelling sought to extend game theory into a theory of interdependent decision. He experimented with situations where the players had common or differing interests, and where they could not communicate or could explicitly bargain. He found that even without communication people could "often concert their intentions or expectations with others if each knew the other was trying to do the same (Schelling, 1960, p. 57)." Schelling concluded that in situations where collaboration is advantageous, even where conflict of interest is also present but where direct bargaining is impossible, tacit agreements will take place, provided the two parties can seize on some prominent, preferably unique feature of the situation, which one has reason to believe the other will also seize upon. Also, significantly, the impossibility of explicit bargaining precludes quantitative compromises, typical of the results of haggling. Even with explicit bargaining, the "solutions" that people arrive at involve some special feature of the situation, such as status quo ante. Rather than a continuous range of possibilities from most to least advantageous for either side, people are better able to recognize qualitative rather than quantitative differences that are lumpy and discrete.

Using game theory, repeating a $2 \times 2$ game once produces an $8 \times 8$ matrix of strategies. The size of the matrix grows dramatically with each repetition of play. Providing the players with a large matrix of strategies to decide on their course of action is not the same as having them repeatedly play the game, where their play provides a form of tacit communication [14].

Recent research shows that human's ability to detect patterns stems in part from the brain's goal to represent things in the simplest way possible, balancing accuracy with simplicity when making decisions. Errors in making sense of patterns are essential to getting a glimpse of the bigger picture, as when looking closely at a pointillist painting, and then stepping back to get a sense of the overall structure (Lynn *et al.*, 2020). This theme of balancing the level of detail to arrive at an appropriate scale for identifying patterns is a common theme in language, play, gaming, mathematics and studying emergence in complex adaptive systems.

*Cooperative games and coalitions.* Three-person nonconstant-sum games provide many ways to form coalitions and divide the proceeds of coalitions that are formed. The characteristic function describes the value of each possible coalition and feasible divisions of the proceeds. Game theory provides many possible solutions for dividing the proceeds, making these games a rich source for experimenting with the merit of the various solutions. In general, when the set of feasible divisions is large, players select a feasible solution. The smaller this set, the less often players select a feasible solution (Shubik, 1975, pp. 262–269, 2001b).

### *Some implications for game design, observation and analysis*

Game theory can be employed at high-church, low-church and folk levels [15]. High-church game theory is found in publications such as *Mathematics of Operations Research*. Low-church game theory employs simplified features of game theory to explore the logic of particular contingencies. Folk-level game theory is at the level of the narratives that go with these classic $2 \times 2$ non-constant-sum games that allow win-win and lose-lose solutions.

All three have had impact. But it is the third which has caught the imagination of the public. These classical games suggest that game designers, controllers and analysts should employ folk-level game theory to address fundamental features of narrative used in the scenario framing the contingency under study. Is it a situation where trust is required to accomplish the best outcomes for the players? Is it a case where cooperation is required, recognizing that one party will accept the other obtaining a greater gain, or both will lose possible gains? Is it a situation where not losing means dying? One test of rational play is whether the players choose to accept worse outcomes rather than make the required compromises.

Of course, one must have the information to understand what the player considers a worse outcome. Many examples of individuals selecting other than “objectively” rational behavior exist. One recent example is young Koreans choosing *shibal biyong* “fuck-it expense” as a means to vent their frustration with their future prospects, a trend that applies to other nation’s millennials (Kim, 2019).

## Artificial intelligence and games

Continuing his work in set theory, von Neumann’s development of game theory followed Ernest Zermelo, Emile Borel and others’ efforts seeking mathematical approaches for determining a method of play better than all others in chess and other games without any reference to psychology (Leonard, 2010). As the speed of computations has increased, computers have been used to experiment on better ways of playing games. One prominent view defines artificial intelligence as “the study and construction of rational agents,” thus establishing the connection to game theory when multiple agents are involved (Norvig and Russell, 2003).

Working on the Defense Calculator in 1952, John Holland and his colleague Arthur Samuel found that the computer opened possibilities for exploring models far beyond what could be done with pencil, paper and an adding machine (Holland, 1998). They aimed to write programs that could *learn* as their calculations explored alternatives, that would allow them to tell the computer what to do without telling it how to do it. Holland attacked the problem through the metaphor of neural nets while Samuel developed a technique he named Machine Learning. Following the work of von Neuman and others on chess, they chose to look at board games; in this case *Checkers*.

Rather than following the neural net approach of trying to understand how humans make decisions, Samuel chose to focus on winning strategies. The novelty of his approach was in identifying and assigning weights to features of the game (e.g. pieces ahead, kings, penetration), anticipating the opponent's moves, looking ahead several moves to adjust the weights assigned to match a future state of the game and work towards a minimax outcome, minimizing the maximum damage that the opponent can inflict. Bootstrapping by having the checkersplayer play against itself was an additional technique. By 1959 he had produced a program that could beat him at checkers. Though computational capacities and speeds have increased geometrically consistent with Moore's Law, Samuels technique provides the foundations for current Machine Learning.

Computer competitions have determined better schemes for playing an iterated Prisoner's Dilemma and test ideas for teamwork in general agent systems (Anon, 2004). Building on the success of IBM's Deep Blue, programs on commercial software now can defeat even the most talented human chess players. Recently, Google's AlphaZero has outperformed both humans and other programs in playing the games of *Go, Chess and Shogi* (a Japanese form of chess) as efforts to apply machine learning to a broader range of subjects have accelerated. Unlike previous prototypes like AlphaGo, the program iterates using the rules of the game rather than attempting to mimic natural, human game play. However, changing the rules mid-game flummoxes the program (Wu, 2018).

To address games where no best strategy exists, such as *rock-paper-scissors*, imperfect information, actions that pay off only after many moves, continuous play rather than alternate turns and a large action space, AlphaStar took on the challenge of playing *StarCraft II*. Beginning with strategies derived from human play and using a set of reinforcement learning techniques, Long-Short Term Memory and other techniques, AlphaStar was able to defeat top human players. Like Samuel's checkersplayer, AlphaStar discards risky strategies to find approaches that are least likely to go wrong, thus improving the safety and robustness of the AI. The final AlphaStar agent employs a Nash distribution of the most effective mixture of strategies discovered. The intent is to apply these techniques to the "fundamental problem of making complex predictions over very long sequences of data appears in many real world challenges, such as weather prediction, climate modelling, language understanding and more (The AlphaStar Team, 2019)."

Multi-agent artificial intelligence (AI) systems, imitation and reinforcement learning and adversary training in Generative Adversarial Networks (GANs) compute minimax solutions for zero-sum games and Nash equilibria for non-zero-sum games (Ippolito, 2019). Such developments have led to a growing literature in "algorithmic game theory" addressing topics such as game playing, social choice, and mechanism design. Recent directions in mechanism design address resistance to manipulations enabled by anonymous Internet connection (Elkind and Leyton-Brown, 2010). Designing auctions employs inverse game theory where the game is designed around the behavior of rational participants.

Artificial intelligence is an essential aspect of commercial video games. Rather than attempting to beat the human player, the objective for this AI is to provide virtual competition in a way that enhances a player's experience. To do this in a way that players do not notice, the AI must provide proper reactions to specific stimuli. One of the most widely used techniques is call the Finite State Machine (FSM) algorithm. The game designer anticipates all the possible situations that an AI could encounter, and then specifies a future state as a reaction to each situation. Thus, the AI reacts to the human with pre-programmed behavior. Many successful games such as *Battle Field, Call of Duty, Tomb Raider* and *Super Mario* use FSM AI. In using this technique, the game designer is essentially using the game-theoretic extensive form to program the game. This technique provides predictability.

Other games, such as *Civilization* where players compete to develop a city in competition with an AI doing the same thing, uses a Monte Carlo Search Tree (MCST) algorithm that randomizes among possible responses to overcome the repeatability aspect of FSM and make the game more enjoyable. Deep Blue used MCST to consider possible moves and the opponent's responses through several iterations, select the most promising and then repeat the process following the opponent's move. Essentially, this approach randomizes among possible responses when the set becomes too large to anticipate. Video game developers are cautious when randomizing as the play of the game to avoid unexpected AI behaviors that could impair the experience of a human player (Lou, 2017). A technique used in *Alien: Isolation* adds another level of a Director AI whose job is to keep the game enjoyable, and an Alien AI as the virtual opponent. The Director controls the information that the Alien has about the human player to affect the Alien's behavior. Some games are incorporating neural nets, GANs and other techniques to allow the AI and the player to learn through iterative play.

This work transfers to the real world as games like *Grand Theft Auto* have been used for instrumental purposes to provide a safe and realistic environment for testing self-driving car algorithms (Shummon Maass, 2019). Also, *Assassin's Creed* has been used to develop scenes to help train AI algorithms, and *Minecraft* has been used to conduct research into machine learning. As massive-multiplayer online role-playing video games become a prolific source for "big data," both video gaming and AI development will contribute to each other (Rue, 2019).

### *Summary of experimental results*

Game theory provided structure for behavioral scientists to frame questions and experiments related to the underlying assumptions. Also, experimentation using games allowed game theorists to understand better the relevance of solution concepts and factors to consider in improving them, leading to better applications of game theory.

"The success of game theory in supplying the language for the study of information and providing the basic concept of strategy has led to our understanding the limitations implicit in the model of the fully informed rational individual decision-maker. The vistas opened up by the formalization of the concepts of player, information set, strategy space, and extensive form led us into experimental and operational gaming, simulation and artificial intelligence (Shubik, 2001a)." Experimentation demonstrated the need to account for individuals with limited capacity, optimizing locally in many special contexts where expertise and learning count.

Game theory has been useful in AI to identify what decisions are "rational." Players in experimental games tend to use the saddle point in two-person zero-sum games where it occurs in pure strategies, and to select a feasible distribution of proceeds in cooperative games if the core of feasible solutions is large enough. However, game-theoretic solutions are not a good predictor of human decisions in many two-person, non-constant-sum games (Shubik, 1975, p. 169, 2000). The absence of reliable game theoretic solutions for rational decision and rational action in mixed motive situations (e.g. minimizing collateral or unintended damage while pursuing a military mission) should suggest cautions when using AI in autonomous weapons.

Another approach is to introduce behavioral considerations explicitly. "In a given population sample one can expect that some will resort to "tacit communication" when such is called for; some will not. In a mixed motive game, some will behave cooperatively, some competitively. In a coalition game, coalitions *will* form and will persist, winnings will be divided in ascertainable ways, even though classical game theory has very little to say *specifically* about such situations. Thus, we may expect to learn something about behavior in situations of strategic conflict which is outside the scope of game theory in the present state. Nevertheless, game theory is distinctly suggestive for interpreting and systematizing the results (Rapoport, 1960, p. 214)." When the results of gaming experiments are not adequate approximations of game theoretic solutions the first step is to go back to game theory and extend the solution concept. Thus, experimentation has been used to validate hypotheses, to generate new ones, to generate new theory, and for the employment and enjoyment of academics. Challenges such as interpersonal comparison of utility and social choice exposed by game theory also inform limitations of artificial intelligence.

In summary:

> it is almost impossible to extend the normative theory of games, because the criteria of rationality become confused by the clash between individual and group norms and because "equilibria" are either nonexistent or not very relevant to the players. On the contrary, an empirical (descriptive) approach to bargaining situations (including coalition formation) seems full of promise. . . . All these questions related to theory construction based on experimental evidence. It cannot be emphasized too strongly that classical game theory is not based on experimental evidence. It represents an attempt to build a normative theory on a foundation of strategic logic. We have also seen how such a foundation becomes difficult if not impossible to erect without invoking specific norms of behavior. These norms are not logical but arbitrary and can be exceedingly varied. From this point on, therefore, there can be no single game theory but only a great variety of such theories, each based on different norms. Here the experimental scientist should naturally take over to explore the norms actually operating in human affairs. (Rapoport, 1960, pp. 224–225)

AI seeks to provide rational decision and rational action. Though game theory is inadequate, rational decision and rational action is in the eye of the beholder absent meeting the criteria for game theoretic solutions. Though AI has been successful in inessential games, whether it can extend to essential games is an open question.

## SO, what to do?

Return to the origins of military science; a campaign of learning. Just as Scharnhorst instituted rigorous study of quantitative and qualitative techniques, critical analysis of military history augmented by intellectual exercises such as staff rides to project how forces would be used in a particular terrain and circumstance; followed by gaming to explore concepts against active opponents on a map, followed by field exercises to experiment and evaluate the concepts in situations using actual forces in a campaign of learning, the Department of Defense should employ a campaign of learning in developing and deploying AI-enabled systems. Getting prototypes from the laboratory, into operational contexts and games employing the AI algorithms, and then into exercises and operations in the context of learning is a scheme for rapid concept and technology development while avoiding unintended consequences.

More broadly, military gamers and gaming centers will need to become more proficient in employing electronic games similar to commercial games. Much can be learned from manual games. However, if the US military wants to lead, it will need to move beyond nineteenth century techniques and incorporate twentieth century advances in computers and game, chaos and complexity theories.

Recently, the Department of the Navy initiated an education for seapower initiative to enhance the intellectual capability of the Navy and Marine Corps team, stating that it "will be the primary military differentiator between our nation and its adversaries and the true foundation of any credible deterrent to war (Secretary of the Navy, 2020)." It then cut budgets for its educational institutions. Funding for artificial intelligence (AI) has increased. AI can solve specific problems for which it has been trained. It can explore alternatives within the rules encoded in its algorithms. However, it cannot imagine. It has no subconscious intuition. It cannot conduct critical inquiry and encompass intangible aspects of a situation and reframe an approach to wicked problem. In short, it has no coup d'œil, no real talent, no genius. Investing in AI and machine learning at the expense of a campaign of learning that provides individuals and organizations with the talent and adaptive capacity they need to meet complex challenges and conceive of opportunities in those challenges is a dangerous mistake.

## Notes

1. Brian Arthur attributed this phrase to John Holland during a presentation to the International Conference on Complex Systems, 29 July 2020.
2. Also see Sayre (1910). *Map Maneuvers and Tactical Rides*. Third edition. Ft. Leavenworth: The Army Service Schools Press, p. 6.
3. Individual decision making where risk is present where the probability distributions for alternative outcomes are known, or uncertainty where the probability distributions are unknown require extensions to von Neumann's and Morgenstern's utility theory; Luce and Raiffa, p. 13.
4. Luce and Raiffa devotes a chapter to each of these topics, along with critiques.
5. Game theory generally assumes that each player knows the other the other players' possible courses of action and evaluation of outcomes, which rarely occurs in actual circumstances. Some work has been done on evaluating games with misperceptions. The analysis is challenging enough, and may be sufficient for the purposes of the model without going to this level. The purpose of the analysis determines the level of complexity required (Shubik, 1982, Chapter 1).
6. von Neumann and Morgenstern include a method for expressing the utility of an outcome to an individual player as a specific quantity. However, this method is difficult to employ, and is made conceptually and practically much more difficult when attempting to quantify a single utility for multiple players representing different organizations or groups of individuals (Shubik, 1982, Chapter 5).
7. von Neumann (1928). "Zur theorie der Gesellschaftespiele." *Mathematische Annalen* 100: pp. 295–320; Luce and Raiffa; (Shubik, 1975). *Games for Society, Business and War: Towards a Theory of Gaming*. New York: Elsevier; (Shubik, 1982); and von Neumann and Morgenstern are all excellent sources for discussion of the characteristic function and critiques of its use.
8. Economics calls the set of payoffs an imputation (Shubik, 1982, p. 111).
9. The mathematics of game theory involves set theory more than other forms of mathematics (von Neumann and Morgenstern, 2004, pp. 60–73).
10. Formally, an equilibrium point is "a vector of strategies such that no one player, regarding the others as committed to their choices, can improve his lot." John Nash formulated this solution concept in his doctoral dissertation, so it is commonly called the Nash equilibrium (Shubik, 1982, p. 240).
11. Shubik (1982, pp. 365–366) provides useful table summarizing solutions and their characteristics.
12. Nash and Shapley received Nobel prizes in economics for their uses of game theory.
13. There are 78 strategically different $2 \times 2$ games with no ties in individual preferences (Shubik, 1975, Chapter 11).
14. The repeated Prisoner's Dilemma has multiple equilibrium points, all of which are rational solutions (Shubik, 1982, p. 259).
15. Martin Shubik refined these terms to high-church, low-church, and conversational game theory in Shubik (2002). "Game Theory and Operations Research." *Research Gate*. January. Accessed May 18, 2021. https://www.researchgate.net/publication/242932751_Game_Theory_And_Operations_Research_Research

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## Further reading

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