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Final Project

**“May the odds be ever in your favor”:**

*An N-person customizable Game Theory model, built to explore the power and effects of different decision making processes*

The motivation for this project began with my curiosity about the basic principles of Game Theory. Game Theory is defined as a model of optimality taking into consideration not only the benefits and costs, but also the interactions between participants. Furthermore, it attempts to look at the relationships between players in a particular model and predict their optimal decisions. In a “game”, there is a set of players, each with their own personal set of strategies, or possible choices. Depending on the decisions that every player makes, each participant receives some payoff value, also known as utility. A strategy is *strictly dominant* to another if it always produces a higher utility value for the player, regardless of what strategies the other players choose. A profile of chosen strategies is a Nash Equilibrium if no player would like to change their strategy given the strategies of other players. In other words, players seek to maximize their utility when they know the other player’s strategies; and if every player has maximized their utility given the current profile of strategies, then a Pure Strategy Nash Equilibrium has been achieved. However, in many games, it is not reasonable to assume that a player will make the same decision each time given a profile of strategies. Instead, each player will have a certain probability of choosing each strategy. For example, consider the game of a penalty kick in soccer. Let’s simplify the game by saying that the kicker can either shoot right or left and the goalie can either dive right or left. If they both choose the same direction, the goalie wins. If they choose different directions, the kicker wins. However, if one of them makes the same decision time after time, then that individual becomes predictable and, therefore, easily defeated. As a result, a probability distribution for their strategies emerges. In this case, the kicker and the goalie each choose left or right with a probability of 50%. This solution, while logical, is analytically determined by a mathematical model. While the model is effective for its purpose, it fails to take into account the fact that people are frequently illogical, and furthermore, don’t perfectly randomize the decisions that they make. To expand on this idea, people carry many biases with them that mold and guide their decisions. For example, a soccer player may not have equal ability in shooting the ball either left or right, so he tends towards the side with which he feels more comfortable. With this in mind, the analytical model becomes a bit unrealistic. There are many different types of people in the world and are, therefore, many different types of decision making processes. The Netlogo model intends to capture a select few of these decision making processes to see how different types of people respond to various situations and to see which strategy results in the largest expected payoff.

 The goal of this model is to emergently determine the best decision making strategy, as well as how often each player chooses each strategy. Furthermore, it will seek to determine how the number of people employing each type of decision making strategy affects the aforementioned results. The model will be focusing on the most basic type of game. It will be looking at games consisting of two players, each with a set of two strategies. Furthermore, the analysis will be focusing on two specific games, a cooperation game and a competition game, as opposed to the BehaviorSpace of games. While there will only be two types of players, there will be a large number of participants to allow players with different decision making strategies to interact with one another. While one could imagine a large number of deep and complex decision making strategies, three will be focused on. The first group of people is called the “utility-maximizers”. When they enter a game and make a decision, they look at the payoff they received and the payoff they could have received had they made the other decision. If they received a larger payoff than their potential, then they become more likely to make the same decision again. However, if they could have done better by making the other choice, then they become more likely to make that other decision. This group lives in the moment and is purely self-interested. The next group of people is called the “fair-seekers”. When they enter a game and make a decision, they look at the payoff they received and the payoff their partner received. If they did as good as or better than their partner, then they become more likely to make the same decision again. If, however, they lost to their partner, then they become more likely to choose their other strategy the next time around. This is a purely competitive group that is merely focused on winning. The final group of people is called the “predictors”. This group thinks out their decisions a bit harder. Upon playing a game, they look at the payoff that their partner received and the payoff their partner could have received from choosing the other strategy. The player assumes that his partner will tend to make the better decision, and then assesses what’s best for himself given such a situation. At this point, the player becomes more likely to make his best decision in response to the decision prediction for his partner. This group of players is the only one to employ predictive abilities in their decision making process. None of the players have previous knowledge of the game, so they all start indifferent towards their strategies.

 To get into more detail about the model, it all starts with the creation of the game. As I mentioned before, the focus lies on two player, two strategy games. Each player receives a utility value for each strategy profile, which means that there are 8 utility values that have to be set to initiate a game. The model is customizable by the user, which means that the user controls the setup of the game. More specifically, all of the utility values are controlled by sliders in the range of negative 10 to positive 10. This means that the model allows for almost 38 billion (21^8) different games to be analyzed! Once the game is set, the user now has to decide how many of each type of group to include in the simulation. These values are all controlled by sliders in the range of zero to fifty. All of these turtles then randomly assign themselves to either be a player 1 or a player 2, represented by their color. Furthermore, they also assign themselves a label to distinguish what group they are in. Utility-maximizers set themselves to be a “1”. Fair-seekers set themselves to be a “2”. And finally, Predictors set themselves to be a “3”. Turtles were chosen for this model because they are capable of movement, thus allowing for randomized spatial interactions. This means that they are able to interact and play games with all of the different types of turtles, providing a more realistic representation of how people interact in the real world. At this point, the user presses “go” and the turtles begin to aimlessly wander around the map. As previously mentioned, the turtles start indifferent towards their strategies, meaning that the probabilities of choosing each strategy are equal. Each turtle stores these probabilities as turtles-own variables to allow each individual to uniquely learn throughout the simulation. In order to play a game, a turtle must be spatially located adjacent to an opposing player. If this is the case, the two turtles “partner-up” and pick strategies based on their current probability distributions. Now, they may assess their payoff, their potential payoff, their partner’s payoff, and their partner’s potential payoff, depending on the learning mechanism that they employ. The players then adjust their likelihoods of choosing each strategy and proceed to release their partners and search for a new one. However, these probabilities adjustments are weighted different ways for each type of decision making strategy. The Utility-maximizers weight their adjustments according to the difference between the utility they received and the potential utility they could have received. Without this weighting, the group won’t necessarily tend towards a better decision or tend towards any decision at all. In other words, without the weighting, a turtle may not recognize the difference between a payoff of 2 and a payoff of 10, a very important distinction for this model to produce valid results. The Fair-seekers weight their adjustments according to the difference between their and their partner’s payoffs. This means that when a turtle feels that they’ve been very unfairly treated (i.e. their payoff is much less than that of their partner), they move away from that strategy choice a proportional amount to their negative sentiment. Finally, the Predictors weight their adjustments based on how confident they are that their partner will make the better decision. To be more specific, the player will look at the difference between their partner’s payoff and their partner’s potential payoff, and weight their personal best decision proportional to this. Throughout the learning process, the expected utilities of each group of each player are monitored and recorded. The expected utility is calculated by looking at how likely a turtle is to make each decision, how likely the other players are to make each decision, and the payoffs associated with each strategy profile. Along with a plot of the expected utilities for each group of each player, the average probability distributions will be monitored as well. This is to visualize the time it takes for each group to reach equilibrium with their decision making. When this occurs, the model can be stopped. This concludes the implementation and function of the model.

 The first game that is going to be considered is a variation of the classic cooperation game. The setup is as follows:

* If both players choose strategy 1, they each receive a payoff of 5
* If both players choose strategy 2, they each receive a payoff of 2
* If the players choose different strategies, they each receive a payoff of 0

It is quickly easy to see that it is optimal for both players to purely pick strategy 1, as this strategy profile results in the largest payoff for each of them time after time. This game was chosen to see how effective the turtles are at working and learning together in order to collectively optimize their payoffs. When analyzing the emergent expected utilities, many different population combinations are considered in order to see the impact of the size of each group. It is also worth noting that only player 1’s expected utilities are being monitored. This is because the game is symmetrical, so player 2 will have the same results. The following graph depicts the final expected utilities of each group for 125 different population combinations.

The first thing that stands out is the consistency of the ranking of the groups at each run. The graph clearly illustrates that the Predictors receive the highest expected payoffs, followed by the Utility-maximizers, and finally the Fair-seekers. This implies that the population dynamics have no impact on determining the optimal decision making strategy. However, this graph does seem to show a general increase in expected utilities as the run number increases. This is a result of the sorting of the group sizes. In developing this plot, the data was first sorted by an increasing level of the number of Predictors, then by an increasing level of the number of Fair-seekers, and finally by an increasing level of the number of Utility-maximizers. It is also worth noting that five population sizes (1, 11, 21, 31, 41) were looked at for each group. This is evident by the five “groupings” of data across the chart, along with the five groupings within those groupings (especially evident in runs 1-25). The trends within all of these are important to consider. As previously mentioned, there is a general increase in utility from one large grouping to the next as the run number increases. This is a result of the number of Predictors increasing. In other words, an increase in Predictors is better for the entire population. This is because the Predictors are capable of quickly finding the optimal choice and sticking with it over time. This can’t be said about either of the two other groups. The Fair-seekers have the opposite effect of the Predictors. From looking at the smaller group to group changes, an increase in Fair-seekers consistently results in a decrease in expected utility across all decision making strategies. This is an expected result given that the Fair-seekers never feel the need to adjust their probability distributions. Therefore, an increasing number of Fair-seekers pulls down the mean probability of choosing strategy 1. This results in lower expected utilities for all decision making strategies. The last trend to consider is that of the increasing population of Utility-maximizers. This is a good strategy, but not quite as effective as a predictive strategy. This means that when the amount of Predictors is low when compared to the amount of Utility-maximizers, the Utility-maximizers have the effect of increasing everybody’s expected utilities. However, it is clear that populations with large proportions of Predictors tend to be the most successful. This means that when the number of Predictors is comparable or greater than the number of Utility-maximizers, then increasing the amount of Utility-maximizers results in a lower proportion of Predictors and lower expected utilities across all groups. In conclusion, a predictive strategy is best both for the individual and the community. This is followed by Utility-maximization, which is also good both for the individual and the community. And the worst strategy for a cooperation game is to seek fairness, as the player remains indifferent to their strategies and becomes a detriment to the community.

 The next game that is going to be looked at is known as the hawk-dove model, but in this case will be considered a model for aggressive vs. passive behavior. The idea is that the two players are competing for a resource (R), but if both players are aggressive, they incur a cost (C). This cost is greater than the value of the resource. The setup of the game is as follows:

* If both players choose strategy 1 (aggressive), they receive a payoff of (R-C)/2
* If one player is aggressive and the other passive, the aggressor receives a payoff of R, while the passive player receives a payoff of 0
* If both players choose to be passive, then they each receive a payoff of R/2
* For the analysis, R=6 and C=8

An optimal decision isn’t as straightforward in this case. The largest potential payoff goes to an aggressor, but an aggressor may also incur the largest cost. Because of this, there is no strictly dominant strategy in this game. As opposed to the cooperation game, this game was chosen to see how turtles learn and compete with one another. Once again, a multitude of population combinations are considered and only player 1 is being tracked during the analysis. In this case, however, the final probabilities of choosing strategy 1 are being monitored, along with the final expected utilities. The following graph illustrates these final probabilities.

This is a peculiar result, as the Predictors almost purely choose strategy 2, while the Fair-seekers almost purely choose strategy 1. Subsequently, the Utility-maximizers get confused and choose to mix their strategies, with a tendency towards strategy 1. The Predictors are purely choosing strategy 2 because their analysis of the game shows them that their partners are typically going to choose strategy 1. As a result, the Predictors would rather net even by choosing strategy 2, than incur a cost by choosing strategy 1. The Fair-seekers, however, aren’t quite as risk averse. They look at the game and realize that they can’t “win” by choosing a passive strategy; thus, they tend to be aggressors. As for the Utility-maximizers, recall that they adjust their probabilities proportional to the difference in their payoffs and potential payoffs. If their partner were to choose strategy 1, then this payoff difference equals 1 (-1 – 0). If their partner were to choose strategy 2, then this payoff difference equals 3 (6 – 3). Because they are initially indifferent to their choices, they take 3 “steps” towards strategy 1 for every one “step” towards strategy 2. Therefore, it’d be expected that this group would ultimately choose strategy 1 roughly 75% of the time. This is backed up by the mean probability of this group choosing strategy 1 being 76.8%. The following graph plots the expected utilities for various population combinations to illustrate which group is more successful over time.

While the rankings aren’t perfectly consistent across each round, the data shows that the Fair-seekers tend to do the best, with the Utility-maximizers close behind and the Predictors coming in last. Once again, this implies that the population dynamics have a minimal effect on the emergent ranking. However, the population dynamics do have an effect on the value of each expected payoff. To remain consistent, the aforementioned ordering of runs was used in this analysis as well. First and foremost, the expected utilities still increase as the number of Predictors increases. This occurs because both aggressive players and passive players benefit from competing with a greater number of passive players. More specifically, in such a matchup, an aggressive partner will receive the full value of the resource (his best outcome), and a passive partner will receive half the value of the resource (his best outcome as well). A similar argument can be made for the effects of increasing the number of Fair-seekers. It is clear that as this value gets larger, all of the expected utilities tend to get smaller. This occurs because neither aggressive players nor passive players benefit from competing with a greater number of aggressive players. To clarify, in such a matchup, an aggressive partner will incur a cost (his worst outcome), and a passive partner won’t receive anything (his worst outcome as well). The last trend to consider is that of an increasing amount of Utility-maximizers. This increase doesn’t result in any significant pattern, however. This is a result of the Utility-maximizers randomizing their decisions. In conclusion, the competitive minded Fair-seekers have the most success in an aggressive vs. passive game. That said, they are a detriment to the community as more and more of them join the game. The Utility-maximizers do the next best and have no discernible impact on the community. And finally, the Predictors end up doing the worst, but have a positive impact on the community as a whole.

 Both the cooperation game and the competition game provide an intriguing insight into the power and effects of various decision making processes, but the results are only valuable if the model is feasibly valid. Furthermore, validity is required if the user wishes to extend it to some of the 38 billion other potential games.

 At the micro level, it is vital to consider the feasibility of the rules of each of the decision making strategies. From a philosophical perspective, people enter the world a blank slate and it is, therefore, fair to consider them indifferent to their initial choices. As soon as an individual enters the world, though, learning begins. While learning is a complex process, let it first be separated into two categories: observational learning and experiential learning. In other words, people learn from what they see or they learn from what they do. This is where the Utility-maximization strategy becomes relevant. This strategy is purely based on experiential learning. A person makes a decision, receives an outcome, then both consciously and sub-consciously decides if they made a good choice or not. For example, the person who grabs a piping hot cookie sheet with their bare hands will suffer a painful burn and, consequently, become more cautious in the future. While simple, the Utility-maximization strategy directly reflects this experiential learning and is, therefore, a viable learning method at the micro level. The Predictive strategy extends this idea to allow a person to consider what is best for them given what they believe is best for another. In other words, they observe the options of others to see if they made a good decision or not, look at their payoffs for their own possible strategies, and choose a strategy based on how confident they are in the other’s decision. For example, consider the penalty kick game. Suppose, however, that the goalie knows that the kicker has more success when he shoots to the left. Therefore, the goalie assumes that the kicker will shoot left. After weighing his own options, it is clear that the goalie’s best response is to dive left. This learning comes from having observed the opposing player and from having experienced the utilities of both blocking and allowing a goal. While a bit more involved, the Predictive strategy accurately reflects this form of learning and is, thus, another viable learning mechanism. Finally, the Fair-seeking strategy is more based on emotional learning than either observational or experiential. In this sense, a person learns from how they feel about an outcome, as opposed to the outcome itself. For example, consider an example where an individual and his friend are competing on an upcoming test. They can choose to study or not study. The individual will get a B if he studies and a C if he doesn’t, but the friend will get an A if he studies and a D if he doesn’t. The individual will learn that not studying allows him to beat his friend, so he prefers this decision, despite it giving him a worse grade. While this is a specific case, there are many situations in which people will avoid the rational decision because their emotions hold more value. The Fair-seeking strategy is reflective of this type of learning and is, therefore, a final viable option at the micro level. With all three strategies valid at the micro level, it’s also imperative to consider the macro level behavior of the population.

 For assessing macro level validity, consider the results of the cooperation game and the competition game. The cooperation game shows that prediction is the best strategy, followed by utility-maximization, and finally fair-seeking. It is expected that Fair-seekers would come in last because they “feel” nothing, as each strategy profile results in an equal outcome. Therefore, they remain indifferent to their two choices, resulting in the lowest expected payoff. The next group to consider is the Predictors. In a game that depends on working with a partner to achieve an optimal result, it is logical that predicting the partner’s decision will quickly lead to a successful strategy. Finally, while Utility-maximization succeeds in learning that strategy 1 is the optimal decision, it’s a much slower process than predictive learning. Furthermore, with the Fair-seekers remaining indifferent to their decisions, the Utility-maximizers are forced to consider strategy 2 as the optimal choice half of the time. While this model is impossible to empirically validate, on face, it appears to produce expected and logical results. Next, consider the results of the competition game. First and foremost, it is rational that a competitive minded individual will have the most success in a competitive game. The aggressors can’t lose, so it easily predicted that all Fair-seekers will purely choose an aggressive strategy. As previously discussed, a Predictor sees that an aggressive strategy is going to be his partner’s best decision over time and, therefore, opts for a passive strategy to avoid incurring a cost. While a passive strategy is their logical choice, the Predictors end up getting used for the benefit of the rest of the population and, ultimately, finish with the lowest expected utilities. From a real world perspective, those who actively take risk and pursue what they want will have more success than those who wait for opportunities to come to them. Finally, as previously discussed, the Utility-maximizers choose a mixed strategy approach that depends on the value of the resource and the cost of competition. Once again, this result is difficult to empirically validate, but on face, it does tend to match up with inherent aggressive vs. passive behavior. The outcomes of both the cooperation game and the competition game are easily predicted and understood, allowing this model to be valid at the macro level.

 All in all, this model demonstrates that no single pure decision making strategy is optimal across all situations. Rather, the best strategy is situation specific, and this evident from the reversed rankings of the cooperation and the competition game. However, one consistent result is that the community benefits from those who rationally think out their decisions, while the community suffers from those who make purely emotional decisions. Ultimately though, the surface has only been scratched with this model, as there are “games” being played with every decision that is made every day. And with roughly 38 billion variations, this model still has plenty of more room for interpretation and analysis.