

A Game Theoretical Exploration of Open Science

Robert Olendorf¹ and Steve Koch²

¹University Libraries, University of New Mexico

²Department of Physics and Astronomy, University of New Mexico

May 14, 2012

The value of sharing data and other research products is increasingly recognized. Many funding agencies, such as NSF and NIH now require that data created through their grants be made available to others in a reasonable amount of time. Additionally, many journals now require or encourage that the data used as a basis for a manuscript be made available. Universities, including University of New Mexico, are working to create data repositories to help researchers make the products of their research available.

While acknowledging the public good of making their data more available, many if not most individual researchers are still reluctant to make their data available. There are several reasons for this attitude. First and foremost is researchers fear that others will publish from their data before them. Additionally, researchers worry that their data will be used without proper attribution and that their data will be misunderstood or used inappropriately. Essentially, researchers believe that while making their data more open may benefit society, there are few personal benefits and considerable personal risks to doing so. This dichotomy between the wish to make research more open for the public good, and to keep data closed for personal interest creates a tension between funding agencies, policy makers and others hoping to make research more open, and individual researchers who create the content.

In this manuscript we will use game theoretical arguments, specifically work based on the well researched Prisoners' Dilemma to explore how we can create an atmosphere where researchers feel they receive direct benefits to making their data more open. We will show that it is possible that even in the current environment openness in research directly benefits researchers. We will also explore ways to further increase direct benefits to researchers. Finally, we will provide examples from our own experiences in open research, as well as experimental examples from the literature that show how openness can be encouraged.

		Player 1	
		C	D
Player 2	C	7 / 7	0 / 10
	D	10 / 0	3 / 3

Figure 1: A sample example matrix for the Prisoners' Dilemma. The players can either Cooperate(C) or Defect(D). Numbers above the diagonal represent payoffs to Player 1, numbers below the diagonal represent payoffs to Player 2.

1 Theory

1.1 The Prisoners' Dilemma and Open Science

We will use the Prisoners' Dilemma to explore open science. The Prisoners' Dilemma is a game theoretical construct developed in the RAND corporation by Merrill Flood and Melving Dresher in 1950 [4,5] to study situations where there is both a strong incentive to cooperate, but also a strong temptation to defect. Figure 1 shows a specific example of the Prisoners' Dilemma (PD). In the PD each player can do one of two actions, Cooperate, or Defect (cheat). Mutual cooperation yields a relatively high reward. However, if a player can defect while the other player cooperates, they get an even higher reward (the big payoff) the other player gets the lowest possible payoff (the suckers payoff). There are a few constraints on the payoff matrix. The big payoff to a Defector against a Cooperator needs to be higher than mutual cooperation. If mutual cooperation is higher, then cooperating is always favored. Second, mutual cooperation must be higher than the average of the big payoff and the sucker's payoff. In the example shown in Figure 1, the payoff for mutual cooperation is seven, while the average of the big payoff and the sucker's payoff is 5 $((10+0)/2)$. This prevents an alternating strategy from being favored in the Iterated Prisoners' Dilemma discussed below.

If the game is to be played only once, then the only rational move is to defect. If Player 1 knows that Player 2 will cooperate, then she maximizes her reward by defecting and yielding 10. On the other hand, if Player 1 knows that Player 2 will defect, then she should still defect because then she will get at least 3 rather than 0. Player 2

follows the same logic and the equilibrium is for both players to defect. This is known as a Nash Equilibrium, defined as a situation when neither player benefits by changing strategies [4].

The Prisoners' Dilemma serves as a useful paradigm for exploring open research for a number of reasons. First, is often the model used to explore situations where individuals must trade personal gain for a public good. More importantly, if as we will argue, that open research presents both personal rewards as well as risks, this model captures this dynamic.

1.2 Tit-For-Tat

If the game is to be played for some unknown number of times (Iterated Prisoners' Dilemma or IPD), then the situation becomes much more complicated because the players are now able to base their decisions both on past behavior and expectations of future behavior. It is important that the number of interactions is not known to the players, otherwise the last interaction is played just like a single play Prisoners' Dilemma and both players defect. Since both players know that the last move is to defect, they use similar logic on the second to last interaction, continuing until the first interaction where both players defect.

In 1981 Axelrod and Hamilton [2] conducted a tournament where strategies for playing the IPD were pitted against one another. Surprisingly, the simplest submission won, Tit-For-Tat (TFT). The TFT strategy cooperates on the first move then simply repeats the other player's last move thereafter. Subsequent analysis and tournaments suggest that TFT is successful because of three traits. First it is nice in that it cooperates by default. Second, it is retaliatory, in that it defects if the other player defects. Finally, it is forgiving because it cooperates if the other player then cooperates on future moves. Subsequent work has shown that other successful strategies also share these traits [1,3,5].

1.3 Population Dynamics

In most cases players are not just playing against one player, but exist in a population of players. We must therefore consider the dynamics of strategies in the IPD played against a population of strategies. To do this we must redefine our equilibrium from a situation where neither player benefits by changing strategies to the situation where a population of players, cannot be invaded by any alternative strategy that is initially rare. This is known as an Evolutionarily Stable Strategy (ESS) first developed by J. Maynard Smith [6]. An ESS is actually a Nash equilibrium extended for the case of a population rather than two individuals.

We can determine the expected payoff for each interaction to each strategy with the following formulas. We use the payoff per interaction to allow us to compare between long and short expected numbers of interactions.

$$\omega_D = \frac{\mu * (1 - F_D)(P_{CD}) + F_D * P_{DD}}{\mu} \quad (1a)$$

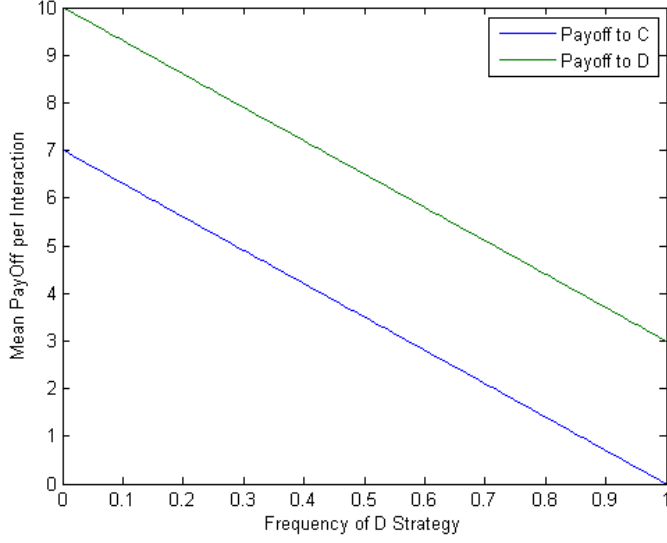


Figure 2: The payoffs to Cooperate and Defect strategies as a function of the frequency of Defectors in the population.

cancels out so the pay off is independent of the number of times the players expect to interact.

$$\omega_D = (1 - F_D)(P_{CD}) + F_D * P_{DD} \quad (1b)$$

and likewise, the expected payoff to Cooperating is

$$\omega_C = (1 - F_D)(P_{CC}) + F_D * P_{DC} \quad (2)$$

where μ is the expected number of times players play the game together, ω_x is the expected payoff to strategy x , F_x is the frequency of strategy x in the population and P_{XY} is the pay off to Player Y when the othe Player plays X . In the simple case of a Cooperators and Defectors we can see in Figure 2 that while the expected payoff to both strategies decreases as the number of defectors increases. Also, both strategies achieve a higher payoff in an environment with more Cooperators, but because Defectors always achieve a higher payoff the population is only stable with pure defection. This is essentially the same result as we saw with only two players.

We approach the determining the payoffs in a similar way, the payoff to Defecting in a population of Defectors and TFT players is

$$\omega_D = \frac{(1 - F_D * P_{CD} + F_D * (\mu - 1) * P_{DD})}{\mu} \quad (3)$$

and the payoff to TFT is

$$\omega_D = \frac{1 - F_D * P_{CC} + F_D * (P_{DC} + (\mu - 1) * P_{DD})}{\mu} \quad (4)$$

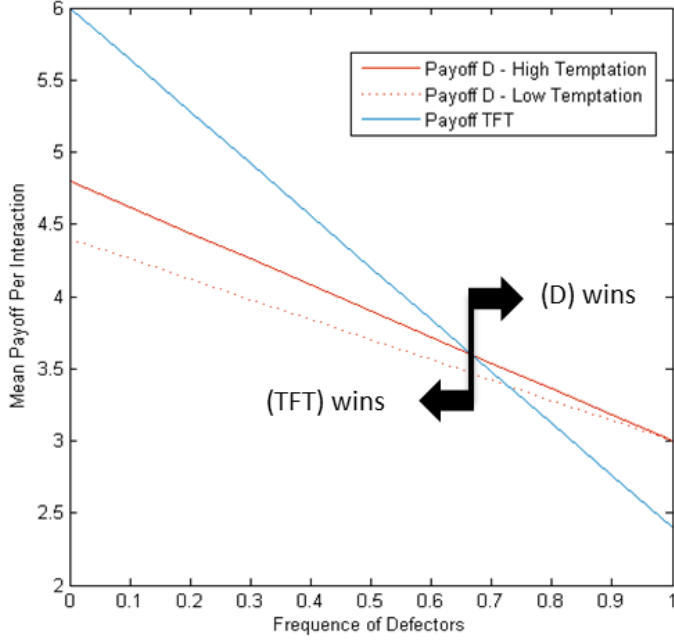


Figure 3: The payoffs to TFT and Defect as a function of the frequency of Defectors in the population.

There are a number of things to notice. First, as shown in Figure 3, Defectors are not always favored. When the TFT line is above the Defectors line, TFT is favored and eventually come to dominate the population at equilibrium. The point where the lines cross is a threshold point where if the frequency of Defectors is less than this point, TFT will be favored and come to dominate, while if the frequency of Defectors is higher than this point, Defectors are favored. This derives from two factors. First, while Defectors enjoy a long string of high payoffs against Cooperators, they only enjoy this high payoff once against TFT strategists. Similarly, TFT strategists only suffer the suckers payoff once against a Defector, while a Cooperator endures a potentially long string of suckers payoffs.

Extending this affect is the influence the expected interaction length has on the threshold point. Figure 4, shows how with very short expected interaction lengths, the threshold for Defectors to dominate is very low, while increasing the expected interaction length rapidly increases this threshold. This results from the fact that Defectors only get one big payoff on their first interaction with a TFT. Thereafter, both TFT and Defectors defect realizing a relatively low payoff. At the same time, TFT only get the suckers payoff once, and thereafter get the low, but still higher, mutual defection payoff. The longer two players interact, the less important the initial payoff becomes to each player and the affect of the mutual defection payoff dominates the mean payoff.

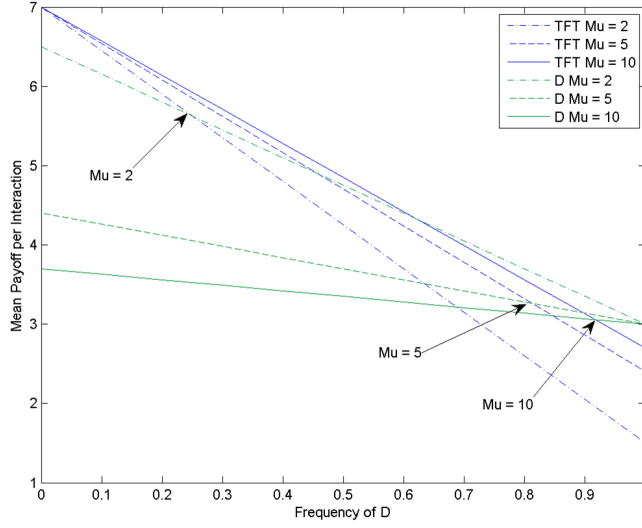


Figure 4: The affect of increasing expected interaction length in TFT versus D populations.

Also, as shown in Figure reftftvsd the temptation to defect (the payoff to a player when she defects while the other player cooperates) influences this threshold. The higher the temptation to defect, the lower the threshold value is meaning that Defectors are favored at a lower frequency. Also, while the expected number of interactions with another player was not an issue when Defectors and Cooperators were competing (μ cancels out in equations 1b and 2), the expected number of interactions is a factor when TFT and Defectors compete.

2 Analysis

We will now turn to using this body of theory to explore how open research functions now and more importantly how researchers, institutions, funding agencies, journals and other interested parties can modify their behaviors to favor a more open environment in research. We will first describe the current research environment and discuss where the costs and benefits to open research come from. We will then suggest how current practices can be changed to further facilitate an atmosphere of openness.

2.1 Current Environment for Researchers

References

- [1] R. Axelrod and D. Dion. The further evolution of cooperation. *Science*, 242(4884):1385–1390, 1988. Times Cited: 263.

- [2] R. Axelrod and W. D. Hamilton. The evolution of cooperation. *Science*, 211(4489):1390–1396, 1981. Times Cited: 2119.
- [3] Lee Alan Dugatkin and Hudson Kern Reeve. *Game theory and animal behavior*. New York, Oxford University Press, 2000.
- [4] R. Duncan Luce and Howard Raiffa. *Games and decisions; introduction and critical survey*. New York, Wiley, 1957.
- [5] W. Poundstone. Prisoners dilemma. 1992.
- [6] J. M. Smith and G. R. Price. Logic of animal conflict. *Nature*, 246(5427):15–18, 1973.