Modeling Decision Times in Game Theory Experiments

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What makes us decide whether to cooperate or not? The answer to this fundamental question goes necessarily beyond a simple maximisation of individual utility. Recent studies contributed in this sense by using decision times to claim that intuitive choices are pro-social while deliberation yield to anti-social behavior [1]. These analysis are based on the rationale that short decisions are more intuitive than long one and summed up to keeping track of the average time taken by the subject of game theory experiment to make their decision under different conditions. Lacking any knowledge of the underlying dynamics, this simple approach might however lead to erroneous interpretations, especially on the light of our experimental evidence that the distribution of decision times is skewed and its moments strongly correlated.

Here we use the Drift Diffusion Model (DDM) [2] to outline the cognitive basis of cooperative decision making and characterise the evolution of subject's behavior when facing strategic choices in game theory experiments. In the DDM, at each moment subjects randomly collect evidence in favour of one of two alternative choices, which are in our case cooperation and defection. This accumulation has a stochastic character as a consequence of the noisy nature of the evidence [3]. The continuous integration of evidence in time is described by the evolution of $x(t)$ as a one-dimensional brownian motion with diffusion coefficient $\sqrt{D}$ and a drift v:

$$dx = vdt + \sqrt{D}\xi(t) \tag{1}$$

For each dt the quantity $x(t)$ is increased by vdt (drift term) plus a noise $\sqrt{D}\xi(t)$ (diffusive term), where v and $\sqrt{D} > 0$ are constant and $\xi(t)$ is a white noise. Given an initial condition $x(0) = x_0 > 0$ and two barriers at $x = 0$ and $x = a > x_0$ associated to the two alternative choices, the process is equivalent to the commonly called "gambler's ruin problem" [4], where $x_0 = z \cdot a$ represents the initial bankroll of the gambler, the absorption at $x = a$ represents the gambler leaving a possibly unfair game (if $v \neq 0$) after collecting her target winnings a, and the absorption at $x = 0$ represents the gambler's ruin. The probability distribution of the times at which the process reaches the origin $x = 0$ before reaching the exit value $x = a$ is known as Fürth formula for first passages:

$$P(t; v, a, z, D) = \frac{\pi\sqrt{D}}{a^2} \exp\left(-\frac{vza}{\sqrt{D}} - \frac{v^2 t}{2\sqrt{D}}\right) \times \sum_{k=1}^{\infty} k \exp\left(-\frac{k^2\pi^2\sqrt{D}t}{2a^2}\right) \sin(k\pi z)$$

This distribution has been successfully used to model decision time in a wide range of contexts [5]. Our findings extend this use to the strategic choices of iterated Prisoner's dilemma experiments. Analyzing the results of large-scale experiments [6] (169 subjects making 165 decision each) through the new lens of DDM and its characteristics free parameters (drift v, threshold a, and initial bias z) allows us to clearly discern between deliberation (described by the drift) and intuition (associated to the initial bias). Our results show that rational deliberation quickly becomes dominant over an initial intuitive bias towards cooperation, which is fostered by positive interactions as much as frustrated by a negative one. This bias appear however resilient, as after a pause it resets to its initial positive tendency.

The method we proposed here represents a novel tool for the analysis of decision times in experimental game theory from a neuro-economics [7] perspective and illustrate how an accurate modeling of decision times allows to get new detailed insight on human the decision process.

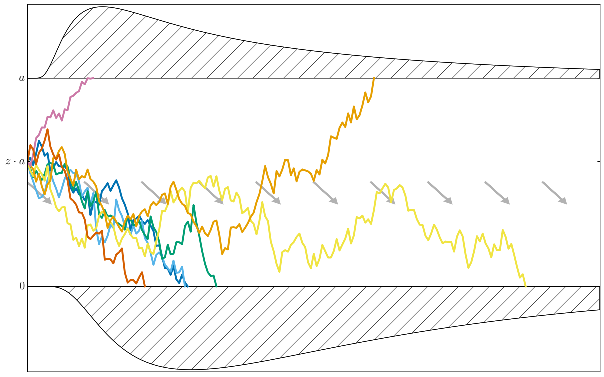

Figure 1: An illustration of the DDM: starting from an initial condition $z{\cdot}a$, the agents accumulate random evidence in favour of one of two alternative decisions. Once the amount of evidence reaches one of the thresholds, the associated decision is made. The arrows indicate the presence of a negative drift towards defection.

[1] D. G. Rand, J. D. Greene, M. A. Nowak, Nature **489**, 427 (2012).

[2] R. Bogacz, E. Brown, J. Moehlis, P. Holmes, J. D. Cohen, Psychological Review **113**, 700 (2006).

[3] B. W. Brunton, M. M. Botvinick, C. D. Brody, Science **340**, 95 (2013).

[4] W. Feller, *An introduction to probability theory and its applications* (Wiley, New York 1968).

[5] B. U. Forstmann, R. Ratcliff, E-J. Wagenmakers. Annual review of psychology **67**, 641-666 (2016).

[6] J. Grujić, C. Fosco, L. Araujo, J. A. Cuesta, A. Sánchez, PloS one **5**, e13749 (2010).

[7] P. W. Glimcher, Science **306**, 447 (2004).